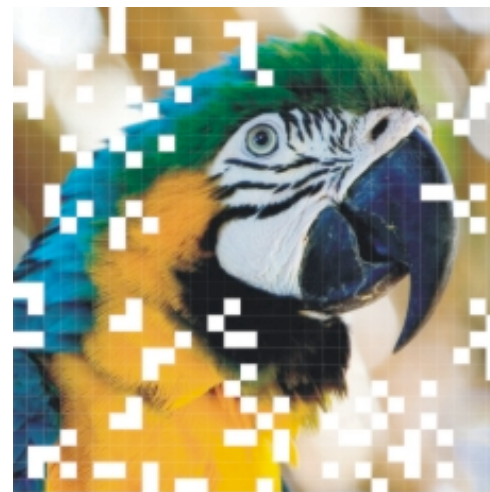


Fitting Surfaces to Polygonal Meshes using Parametric Pseudo-Manifolds

Tutorial 3



SIBGRAP²⁰⁰⁸

XXI BRAZILIAN SYMPOSIUM ON COMPUTER
GRAPHICS AND IMAGE PROCESSING

CAMPO GRANDE/MS - BRAZIL

October 12-15, 2008

Instructors



Prof. Jean Gallier, Ph.D., 1978

Department of Computer and Information Science

University of Pennsylvania

Philadelphia, PA, USA

jean@cis.upenn.edu

<http://www.cis.upenn.edu/~jean>

Instructors

Prof. Dimas M. Morera, Dr., 2006



Instituto de Matemática

Universidade Federal de Alagoas

Maceió, AL, Brasil

dimasmm@gmail.com

<http://www.impa.br/~dimasmm>

Instructors

Prof. Gustavo Nonato, Dr., 1998

Instituto de Ciências Matemáticas e de Computação

Universidade de São Paulo

São Carlos, SP, Brasil

gnonato@icmc.usp.br

<http://www.icmc.usp.br/~gnonato>



Instructors



Prof. Marcelo Siqueira, Ph.D., 2006

Departamento de Computação e Estatística

Universidade Federal de Mato Grosso do Sul

Campo Grande, MS, Brasil

marcelo@dct.ufms.br

<http://www.dct.ufms.br/~marcelo>

Instructors

Prof. Luiz Velho, Ph.D., 1994

Instituto de Matemática Pura e Aplicada (IMPA)

Rio de Janeiro, RJ, Brasil

lvelho@impa.br

<http://w3.impa.br/~lvelho/>



Instructors



Prof. Dianna Xu, Ph.D., 2002

Computer Science Department

Bryn Mawr College

Bryn Mawr, PA, USA

dxu@cs.brynmawr.edu

<http://www.cs.brynmawr.edu/~dxu>

Introduction

Marcelo Siqueira
UFMS

Outline

- The Surface Fitting Problem
- Traditional Approaches
- The Manifold-Based Approach
- What's Next?

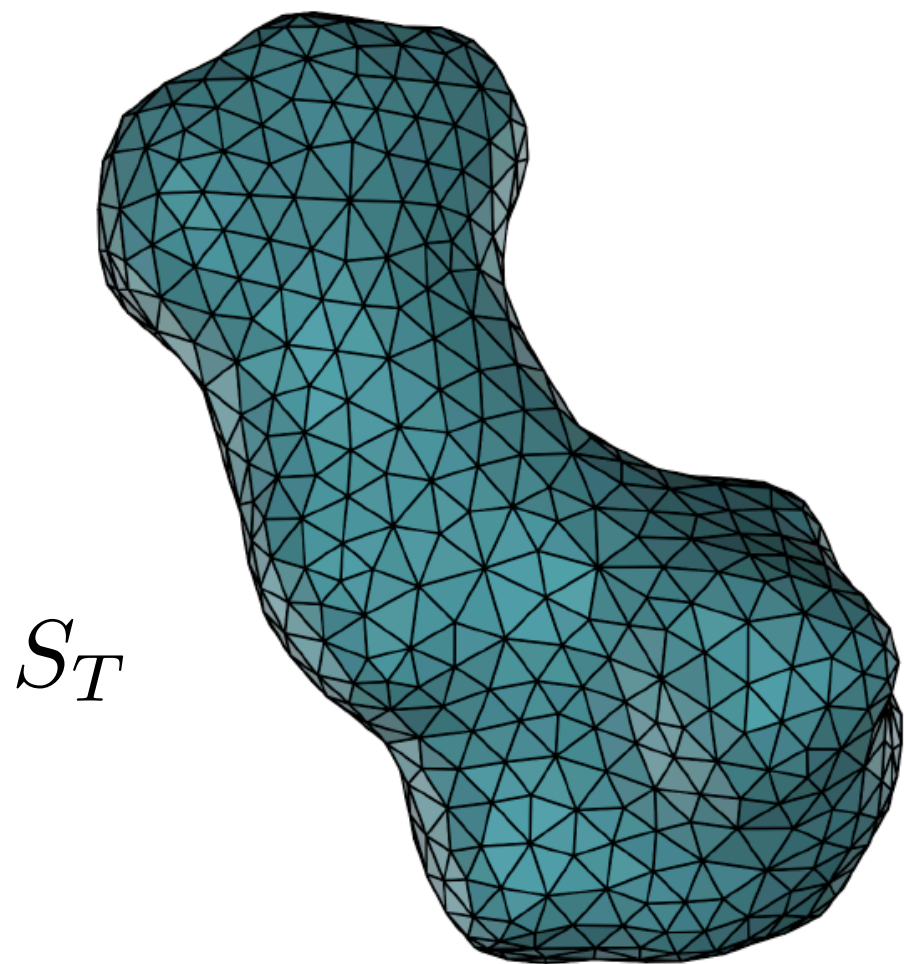
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We are given a piecewise-linear surface, S_T , in \mathbb{R}^3 , with an empty boundary, a positive integer k , and a positive number ϵ , . . .

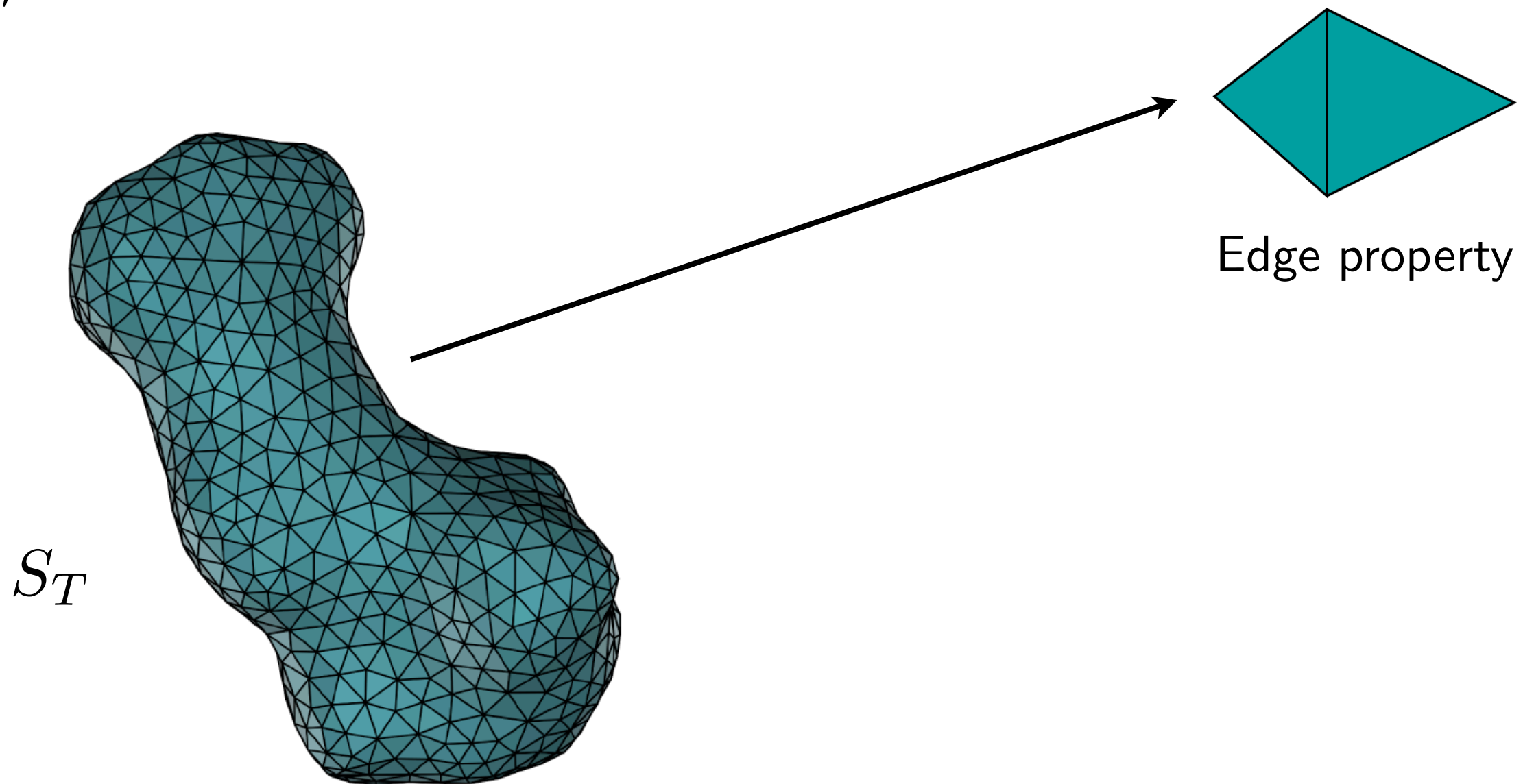
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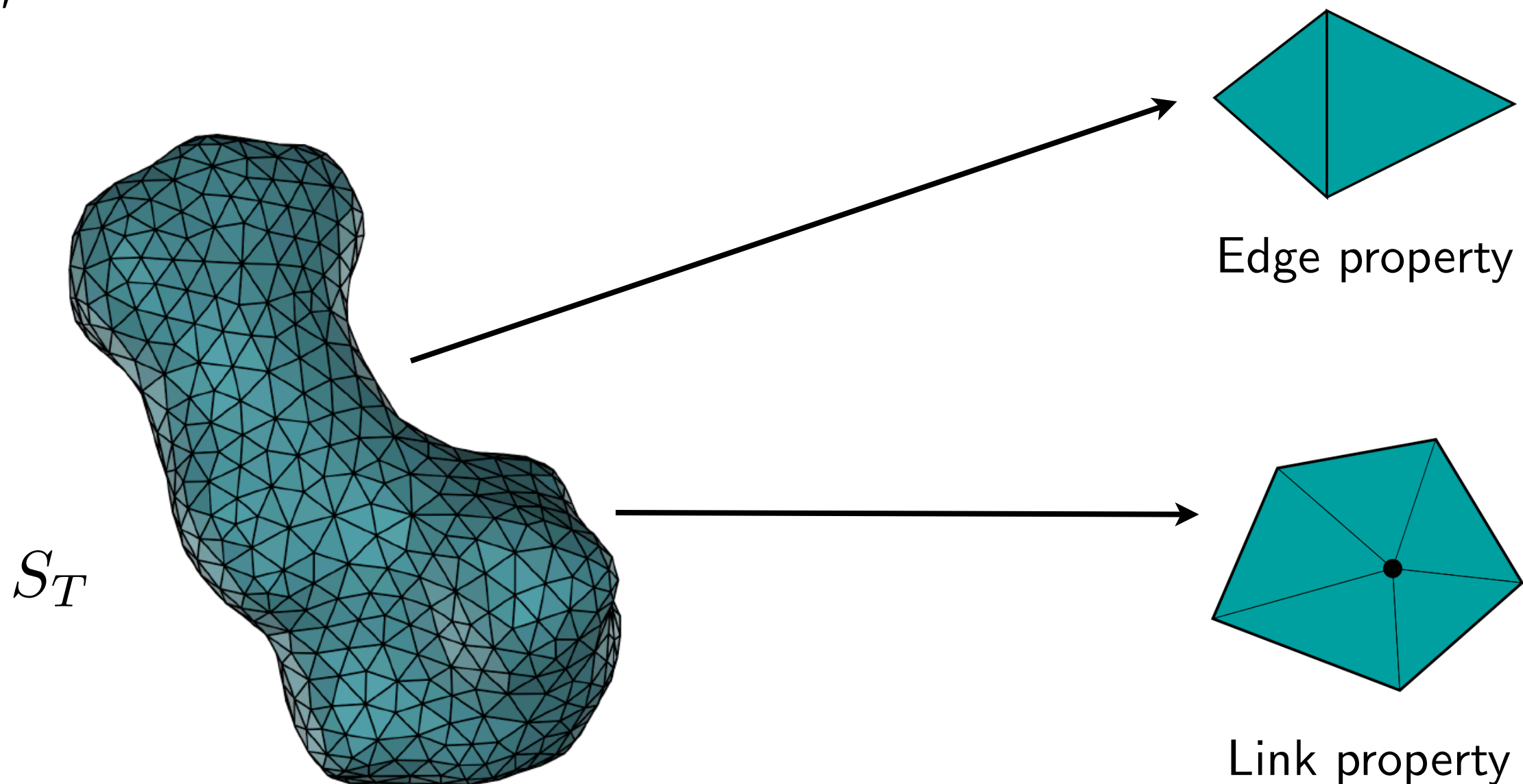
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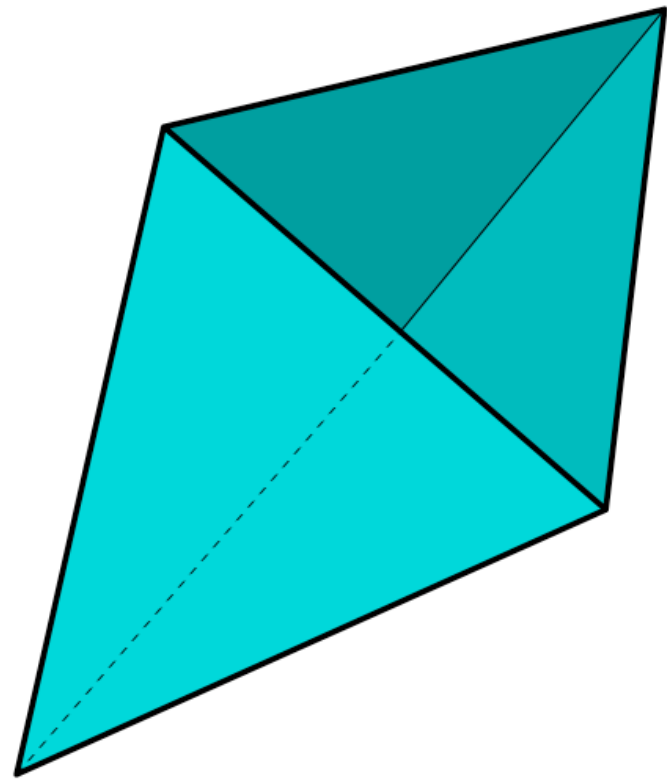
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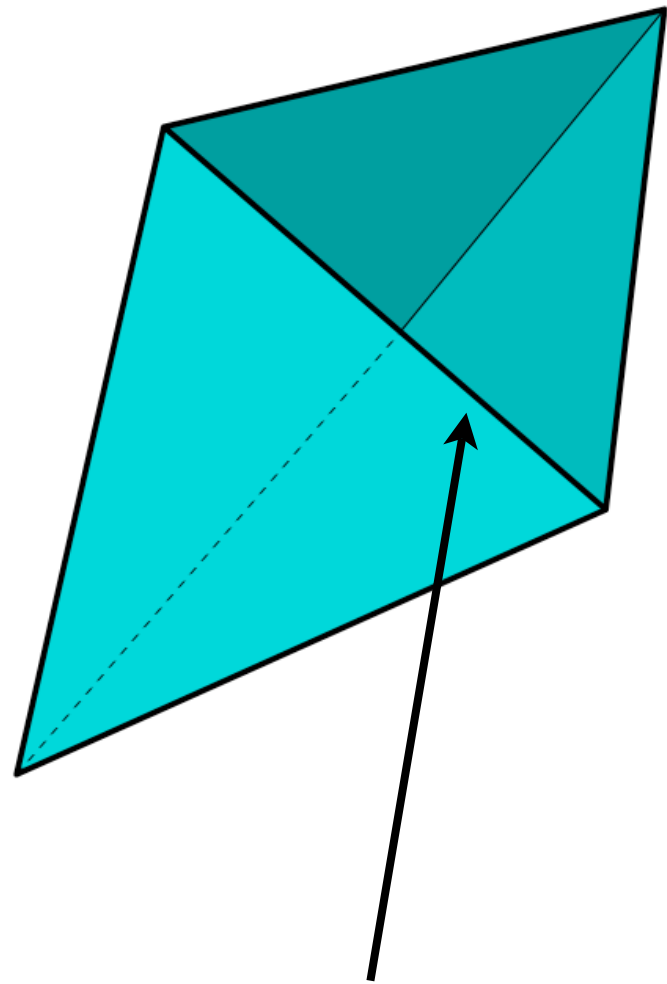


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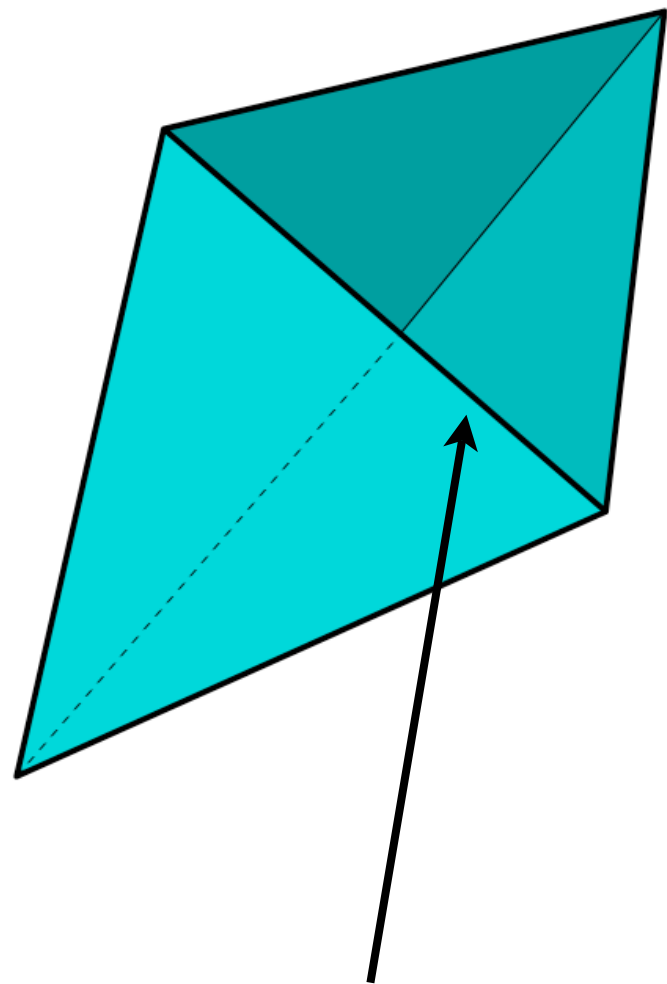


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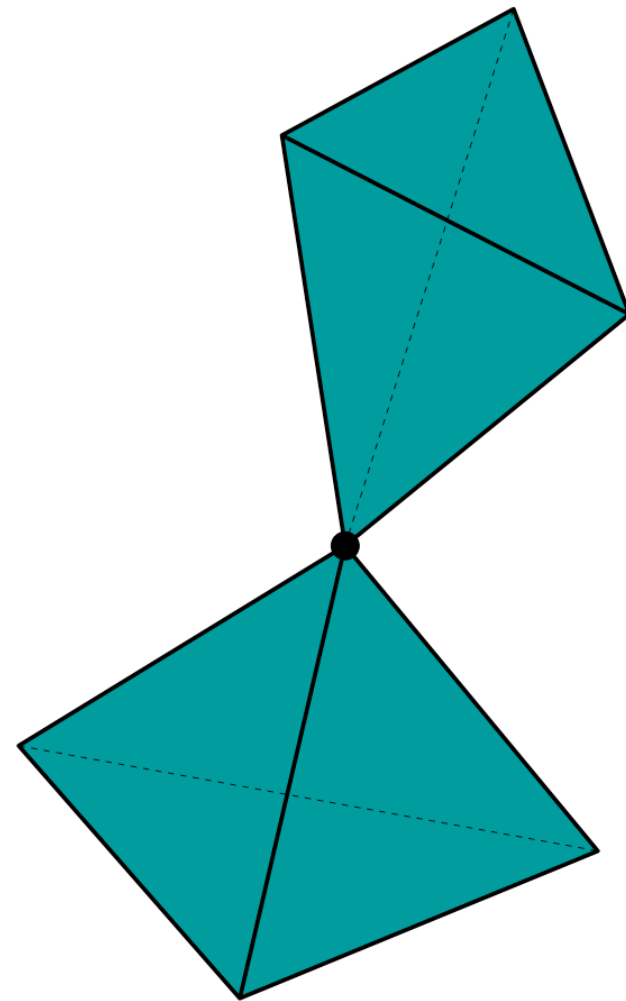


Violates edge property!

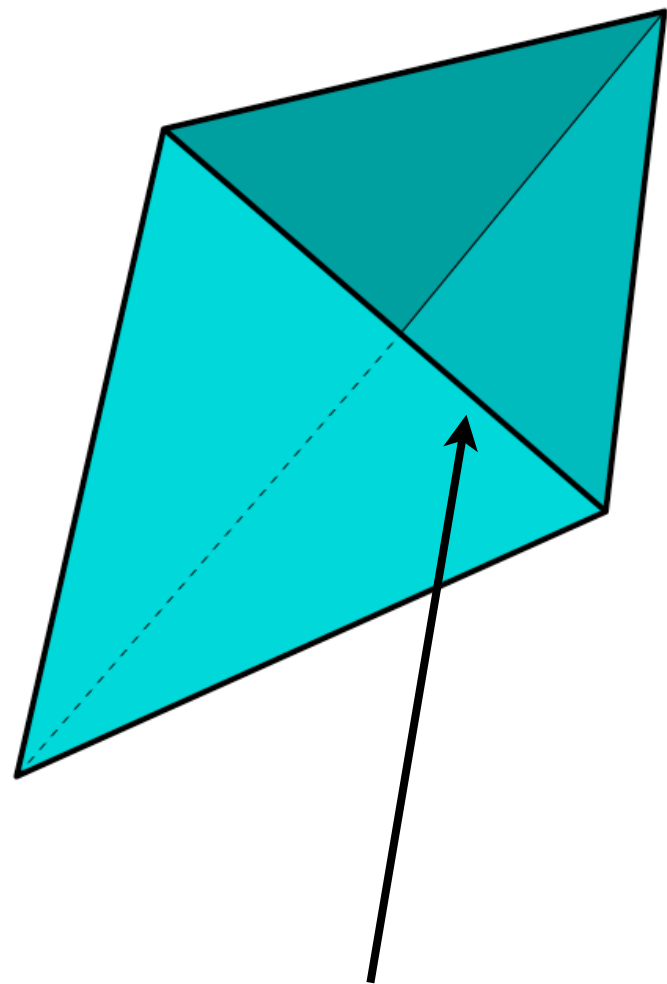
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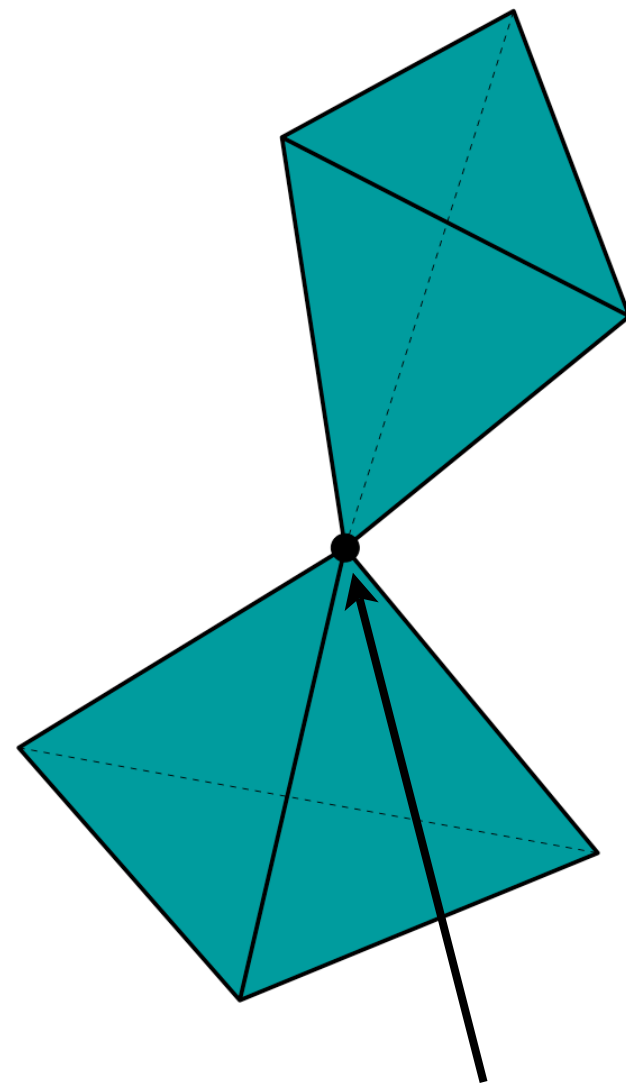
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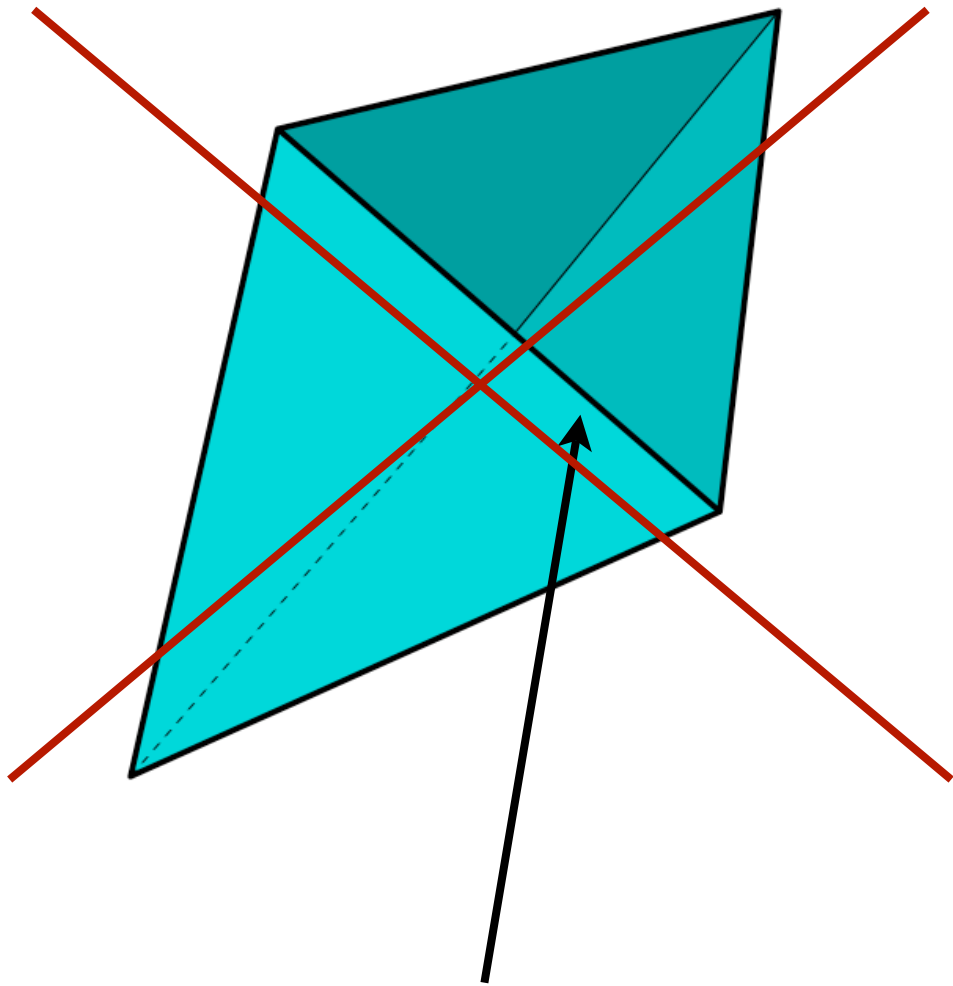


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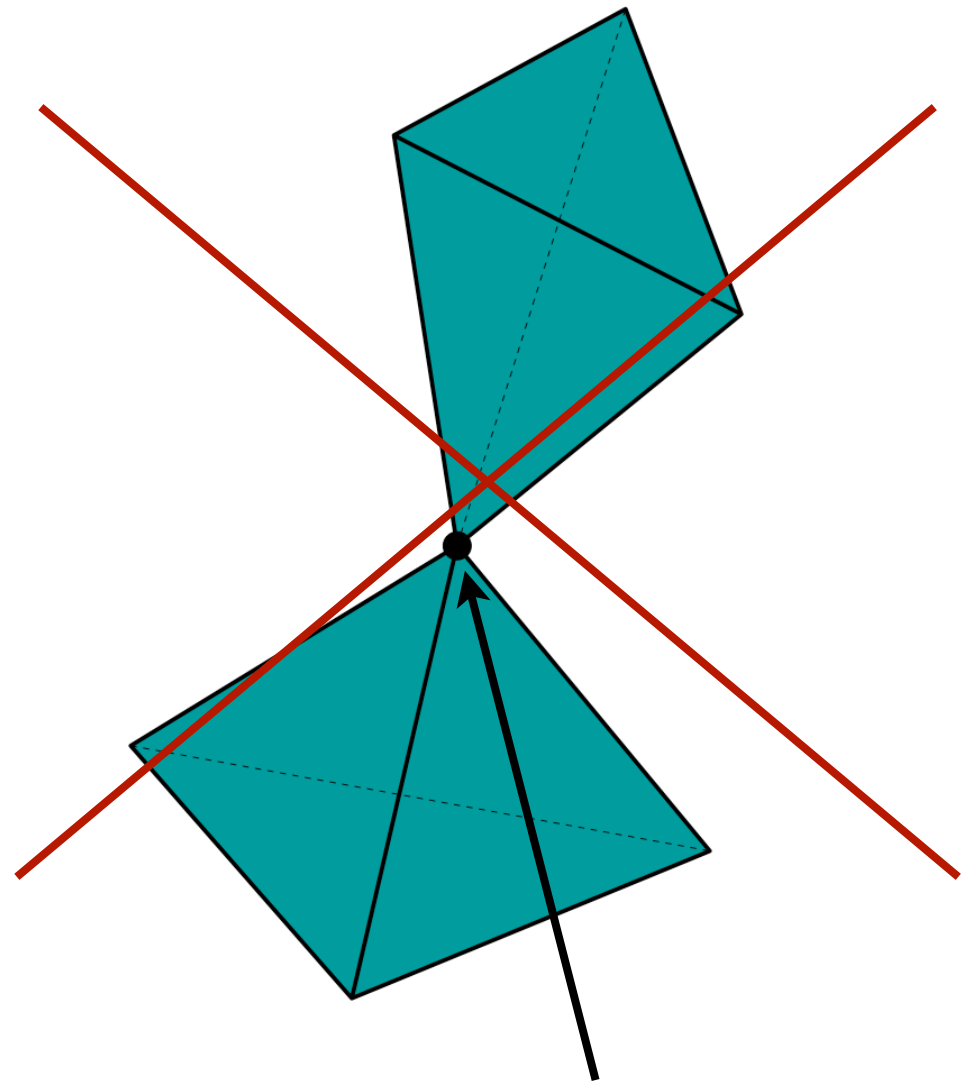


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The Surface Fitting Problem



Violates edge property!



Violates link property!

They are NOT piecewise-linear surfaces

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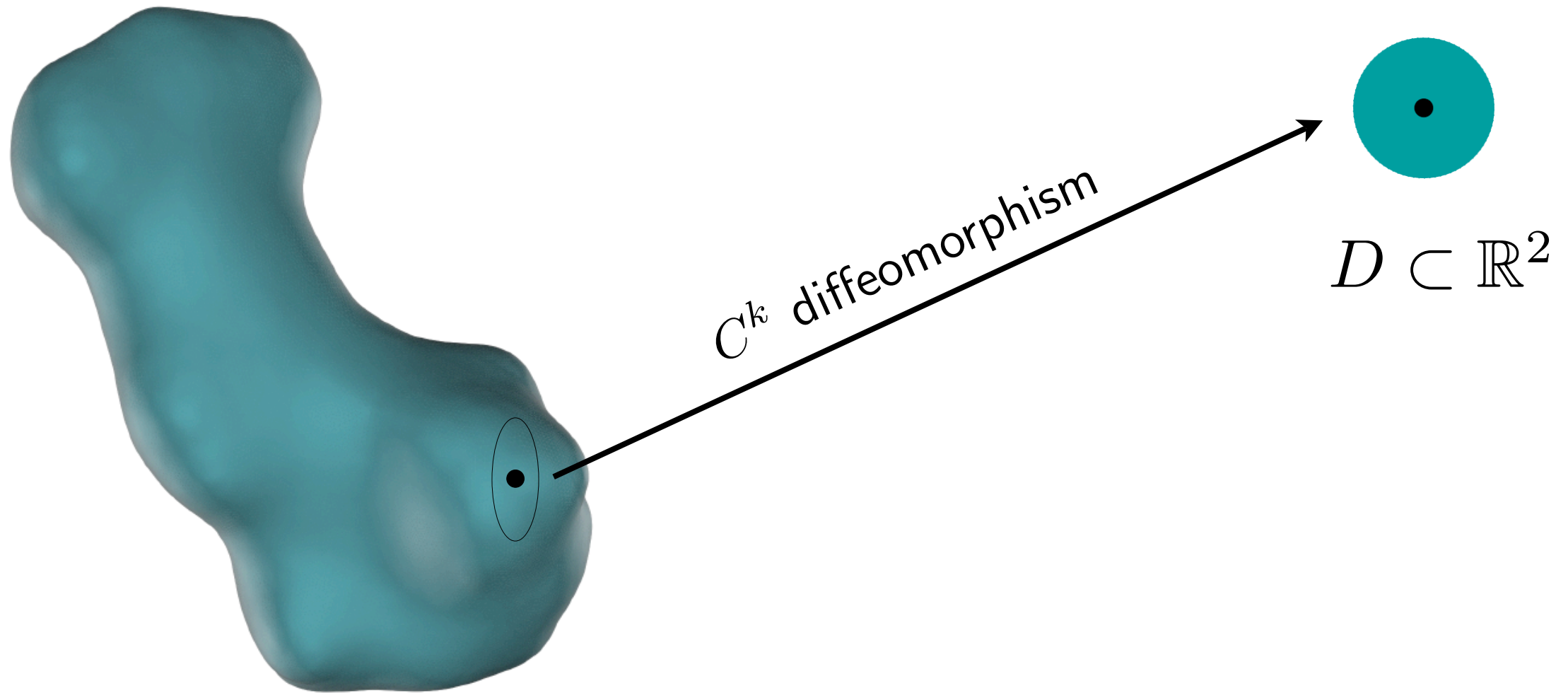
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The Surface Fitting Problem

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The Surface Fitting Problem

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such that there exists a homeomorphism, $h : S \rightarrow |S_T|$, satisfying

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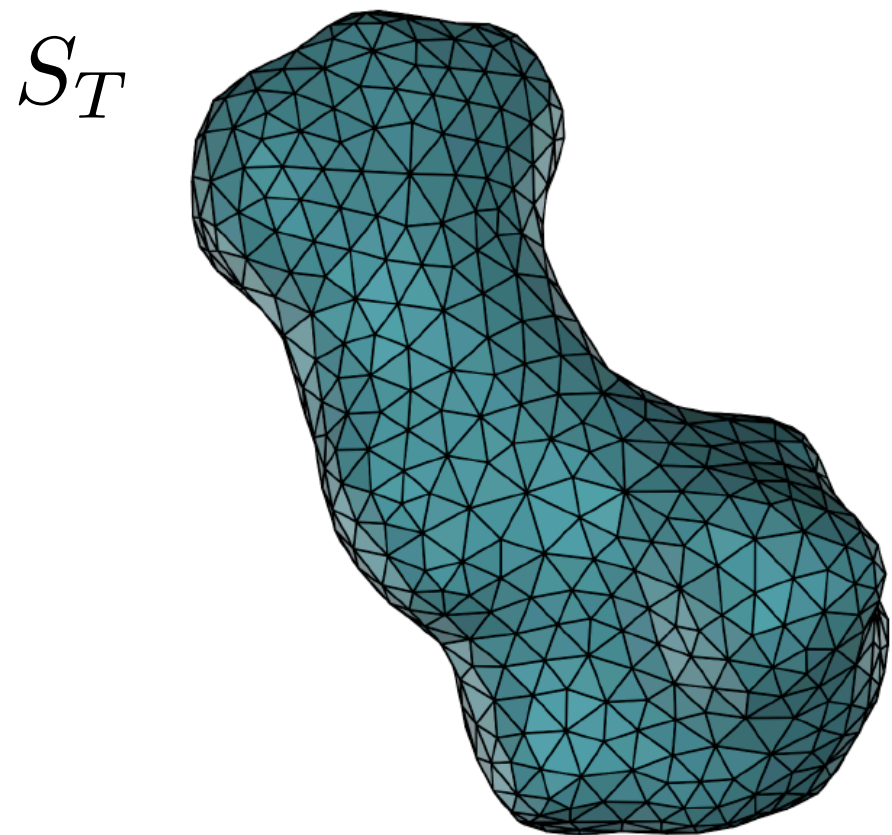
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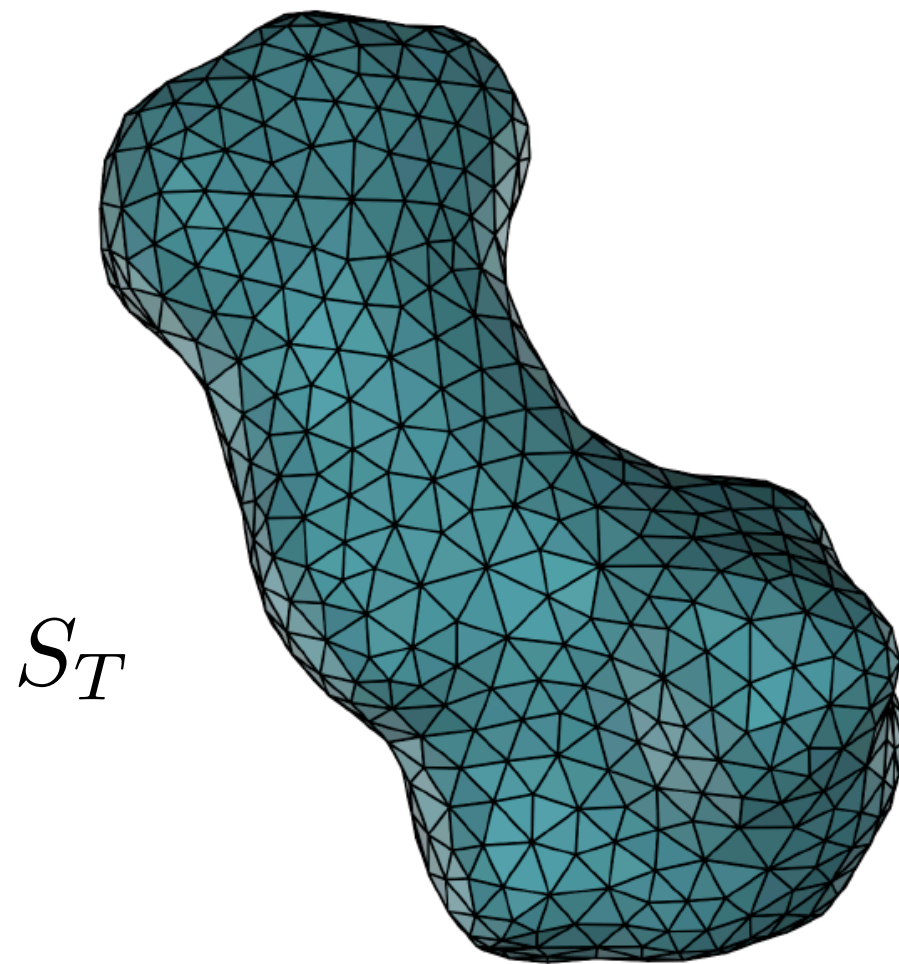


Topological and geometric guarantees!

The Surface Fitting Problem

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From now on, we will refer to S_T as a **polygonal mesh**.



The Surface Fitting Problem

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- Higher values of k are desirable in many applications.

Traditional Approaches

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The most popular approach is certainly the parametric surface one.

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Key idea:

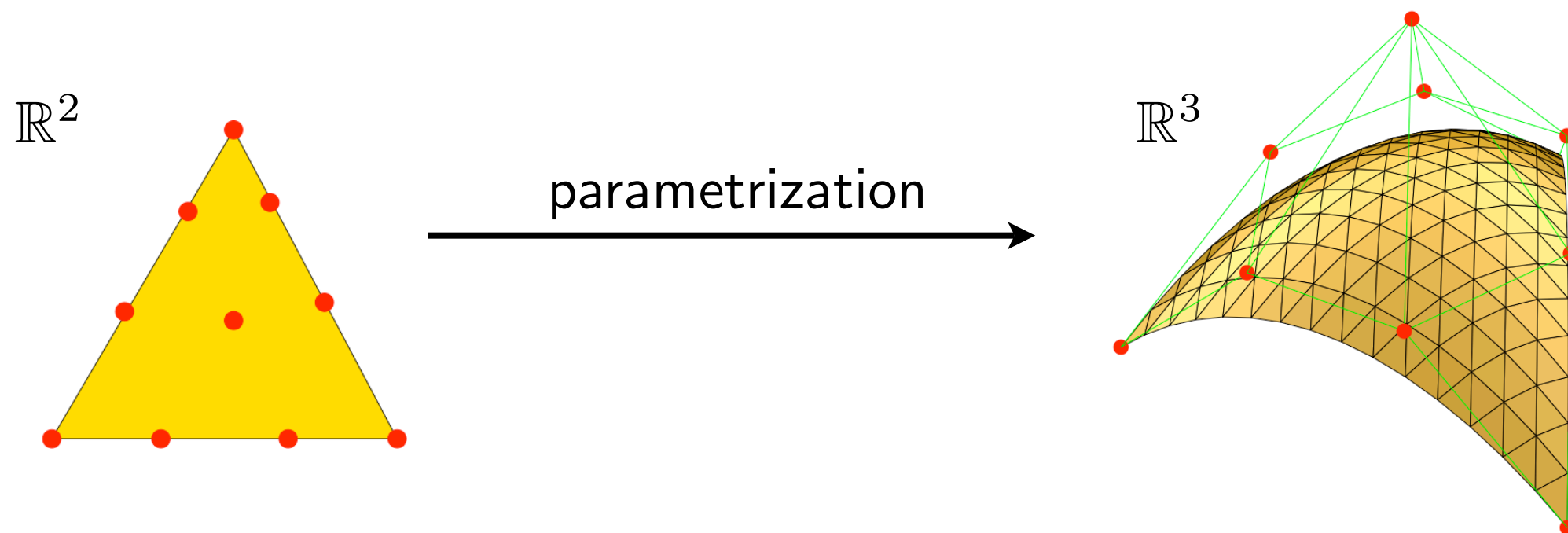
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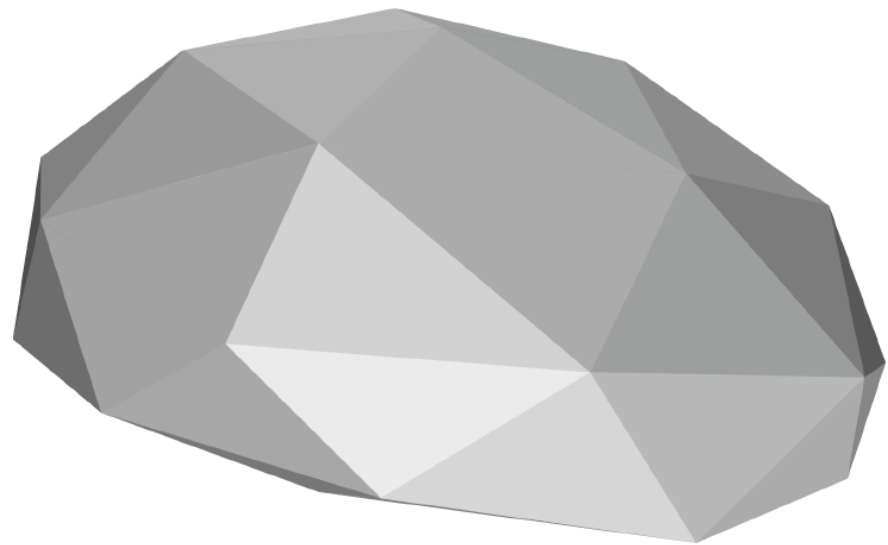
and

- stitch the patches together along their common edges and vertices.

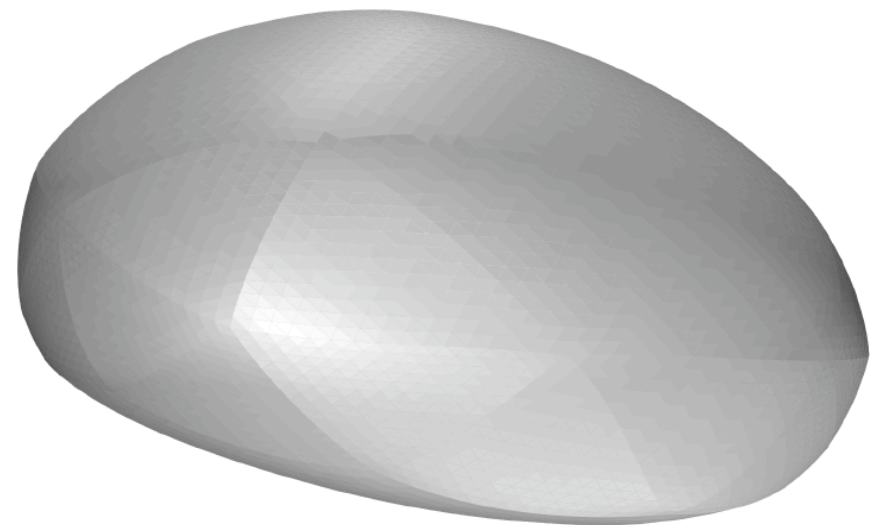
Traditional Approaches

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S_T



S

Continuity is enforced by control point placement!

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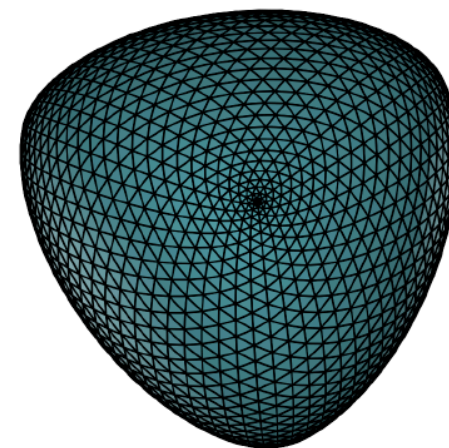
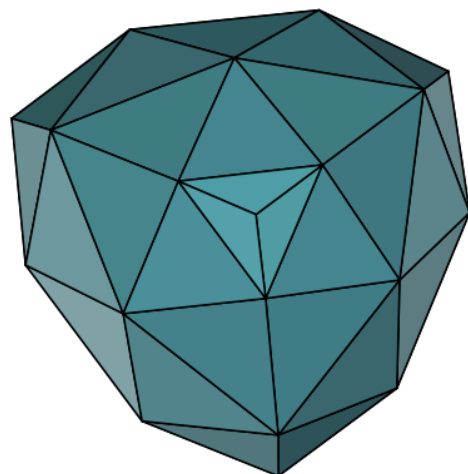
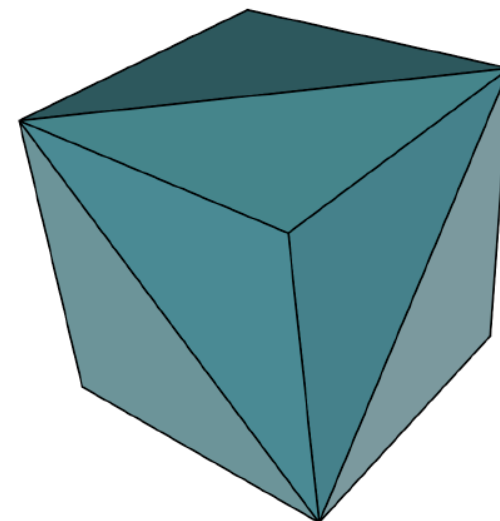
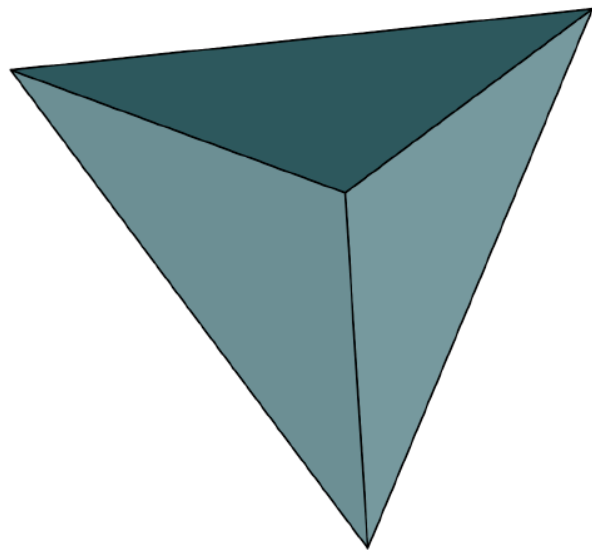
- The larger d is, the larger the number of control points and the more difficult the problem of control point placement.
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[Loop and DeRose, 1989], [Seidel, 1994], [Prautzsch, 1997], and [Reif, 1998] give C^k parametric approaches for arbitrary k .

Traditional Approaches

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Another popular approach consists of using subdivision surfaces.



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See [Warren, 2002].

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Then, one can use RBF, MPU, moving least squares, etc.

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See [Shen, O'Brien, and Shewchuk, 2004] and [Kolluri, 2005].

Implicit and parametric surfaces have complementary features.

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The manifold approach has also some advantages over the traditional approaches when it comes to certain applications, such as texture synthesis and the solution of equations on surfaces.

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Here, we

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Here, we

- describe the manifold-based approach for the surface fitting problem,
- review the main existing solutions and their limitations, and
- point out some applications and research challenges in Computer Graphics, Image Processing, and Computer Vision that can be more naturally tackled by using manifolds.

What's Next?

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II. Manifolds

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III. Constructing Manifolds

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IV. Fitting Surfaces to Polygonal Meshes – Part I

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II. Manifolds

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IV. Fitting Surfaces to Polygonal Meshes – Part I

Coffee break

What's Next?

What's Next?

V. Fitting Surfaces to Polygonal Meshes – Part II

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V. Fitting Surfaces to Polygonal Meshes – Part II

VI. Adaptive Manifold Fitting – Part I

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VIII. Applications of Manifolds and Research Challenges

Manifolds

Jean Gallier
UPenn

Outline

- Manifolds: Brief History
- Informal definition
- Formal definition
- Examples
 - The Sphere
 - Real Projective Space
- Conclusions

Origins of Manifolds

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- In the early 1900's, Dehn, Heegaard, Veblen and Alexander routinely used the term **manifold**.
- Hermann Weyl was among the first to give a rigorous definition (1913).

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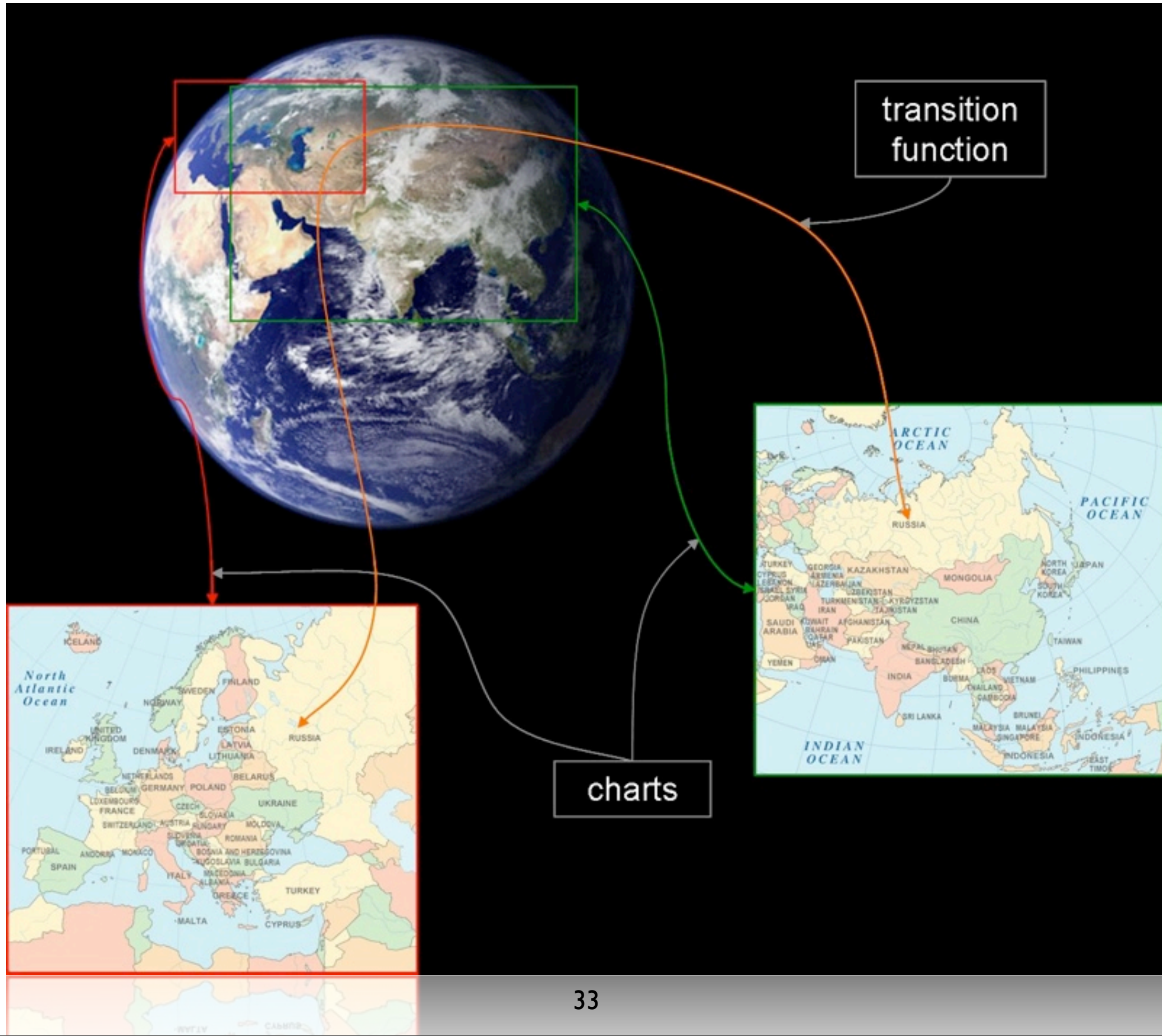


Hassler Whitney
1907-1989



Manifold: An Intuitive Picture

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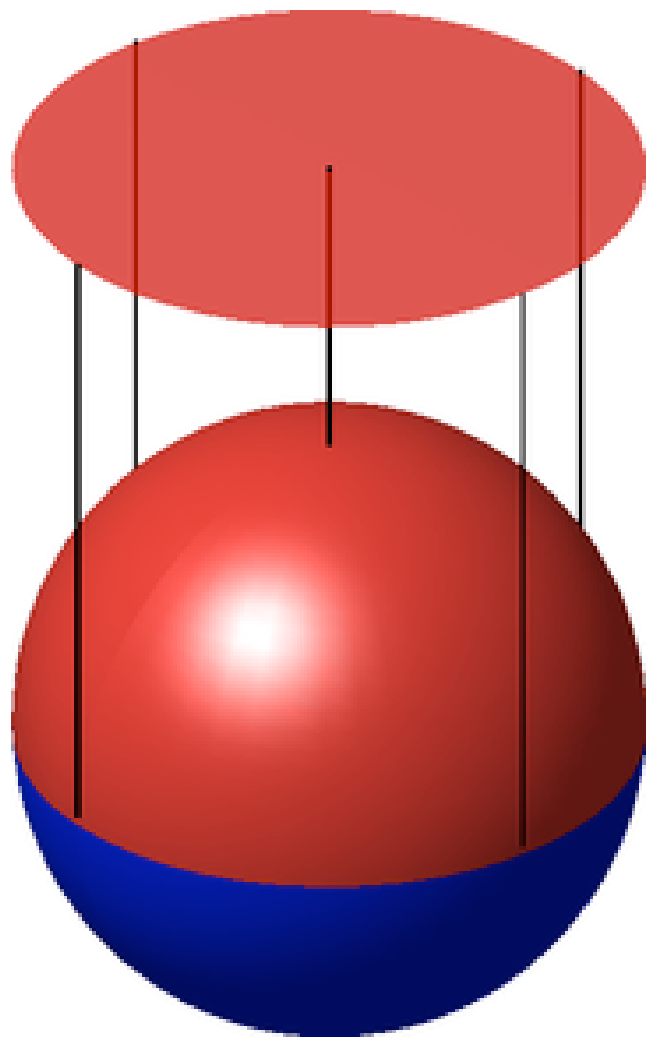
Manifolds: Informal Definition

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- A manifold is a topological space with an open cover so that every open set in this cover “looks” like an open subset of \mathbb{R}^n .

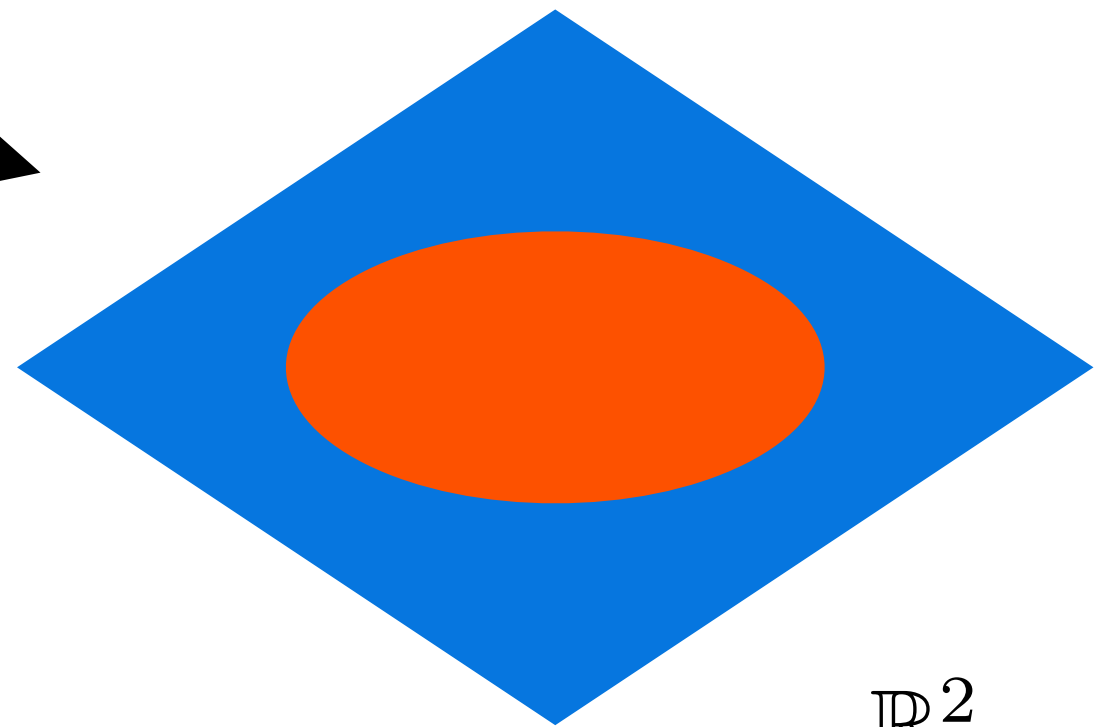
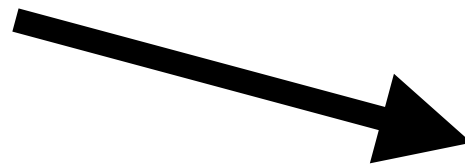
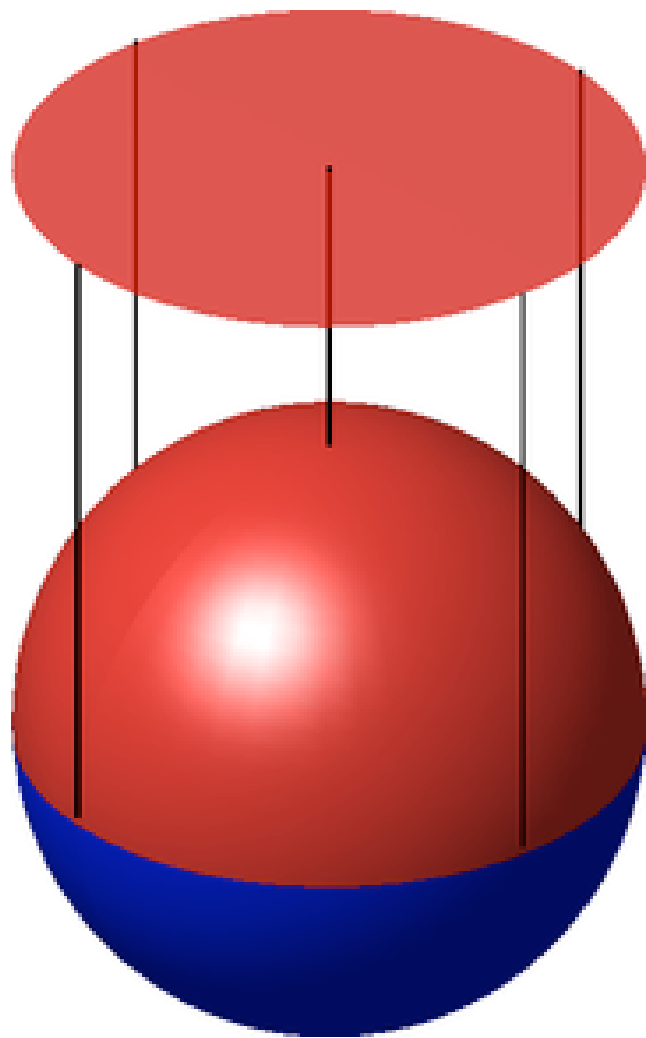
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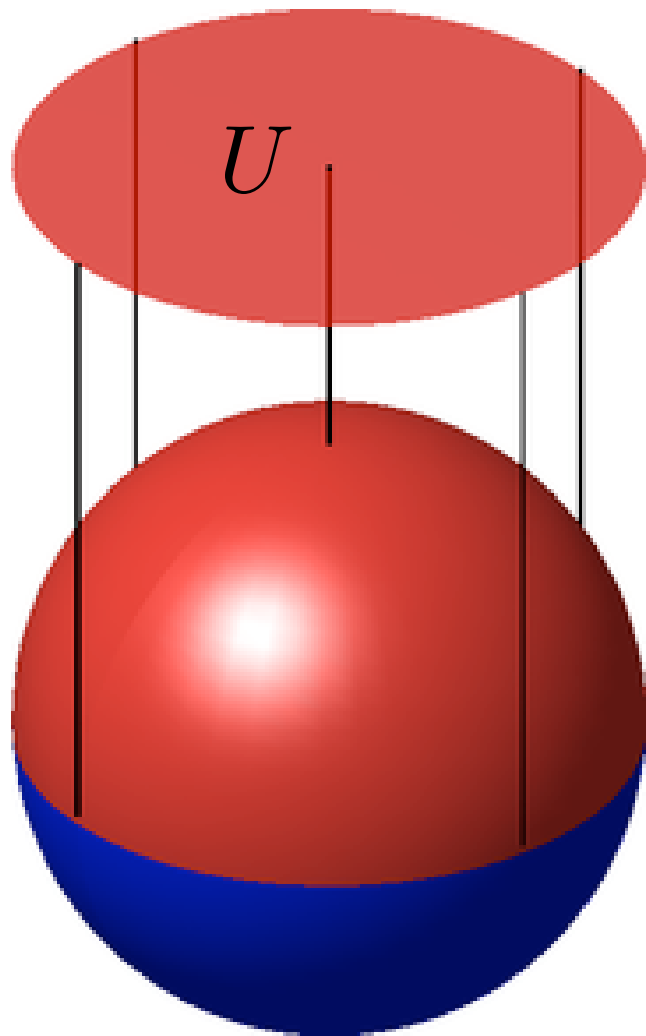
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- To make our informal notion precise, we use homeomorphisms, $\varphi : U \rightarrow \Omega$, where $\Omega \subseteq \mathbb{R}^n$ is an open subset of \mathbb{R}^n .

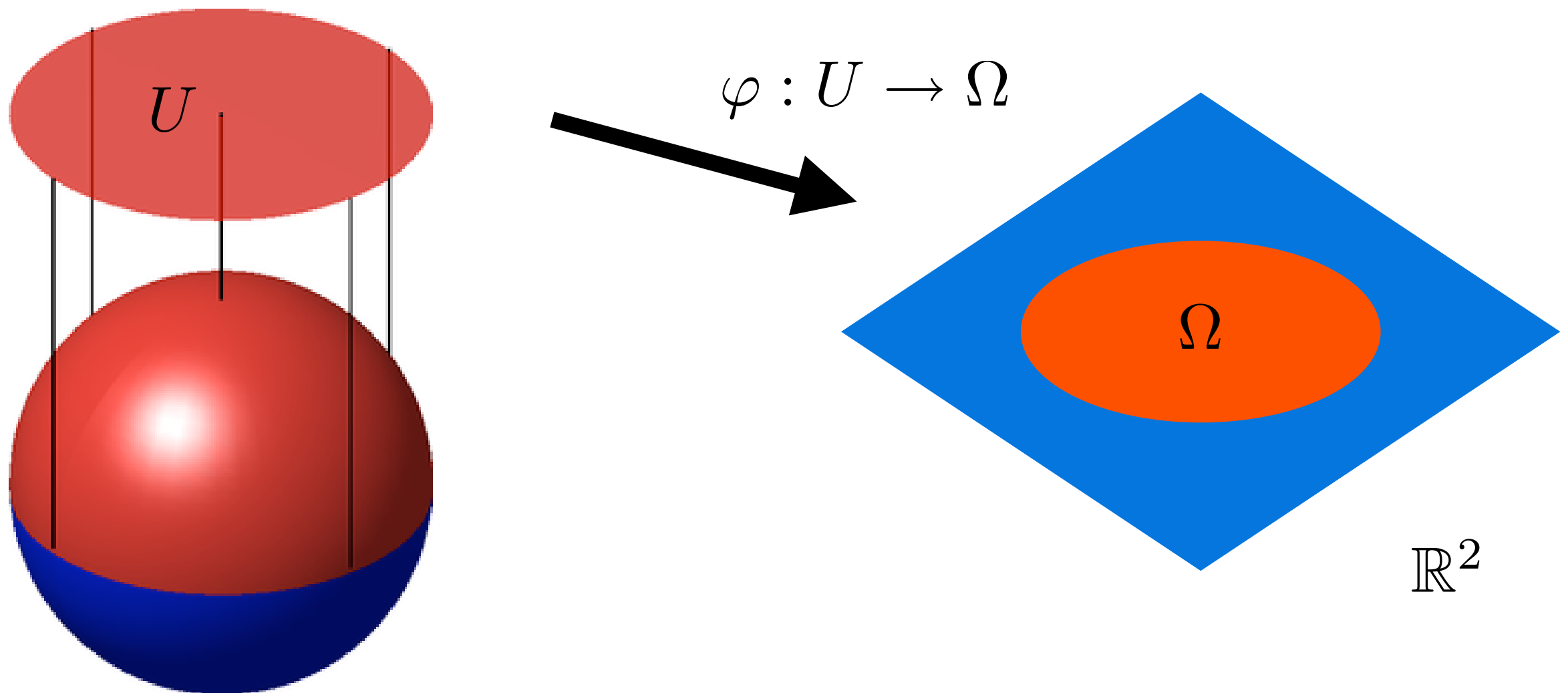
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- We also want to be able “to do calculus” on our manifolds. For this we need some conditions on **overlaps** of open sets.

Manifolds: Informal Definition

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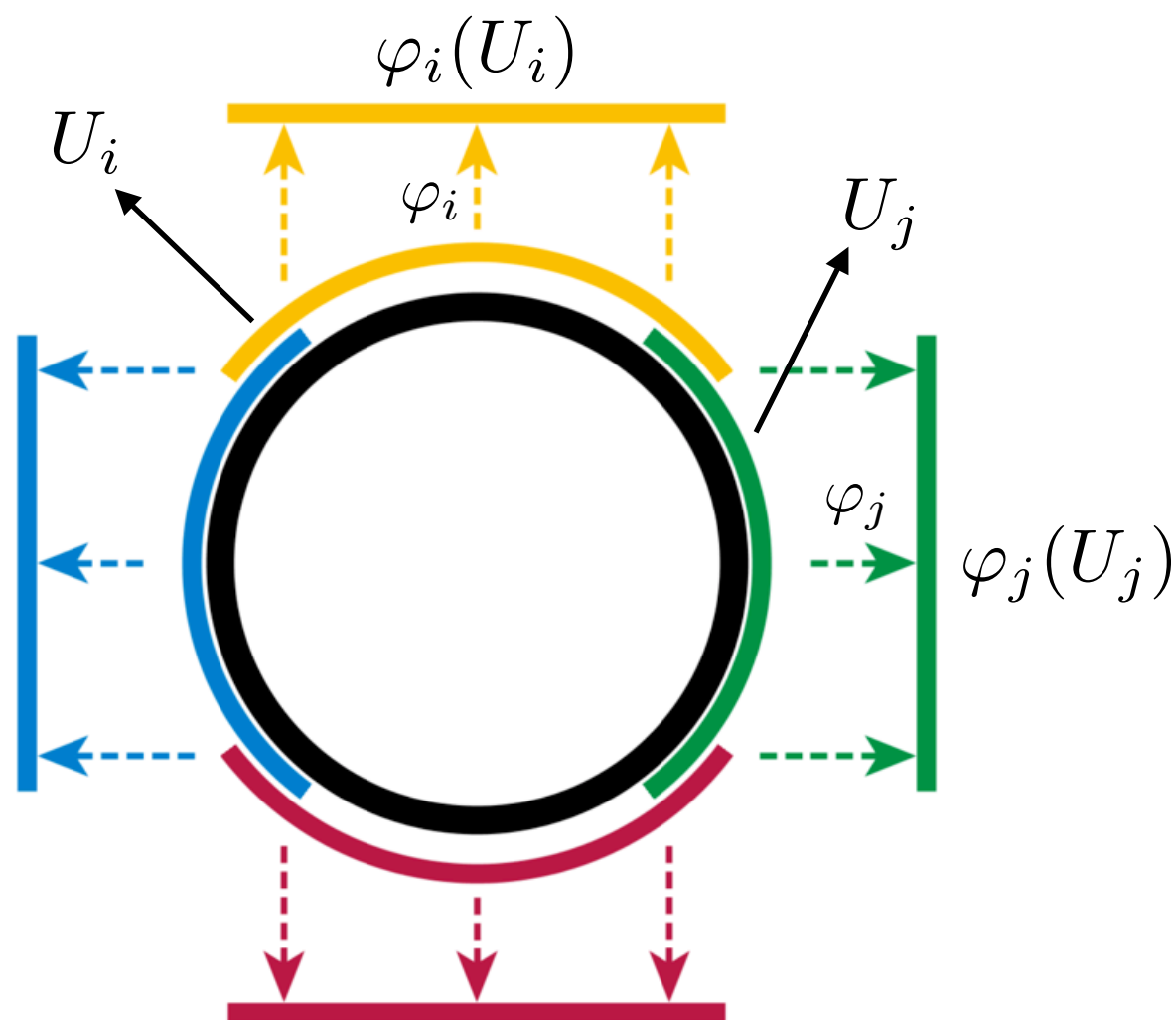
- Whenever $U_i \cap U_j \neq \emptyset$, we need some condition on the **transition function**,

$$\varphi_{ji} = \varphi_j \circ \varphi_i^{-1} : \varphi_i(U_i \cap U_j) \rightarrow \varphi_j(U_i \cap U_j).$$

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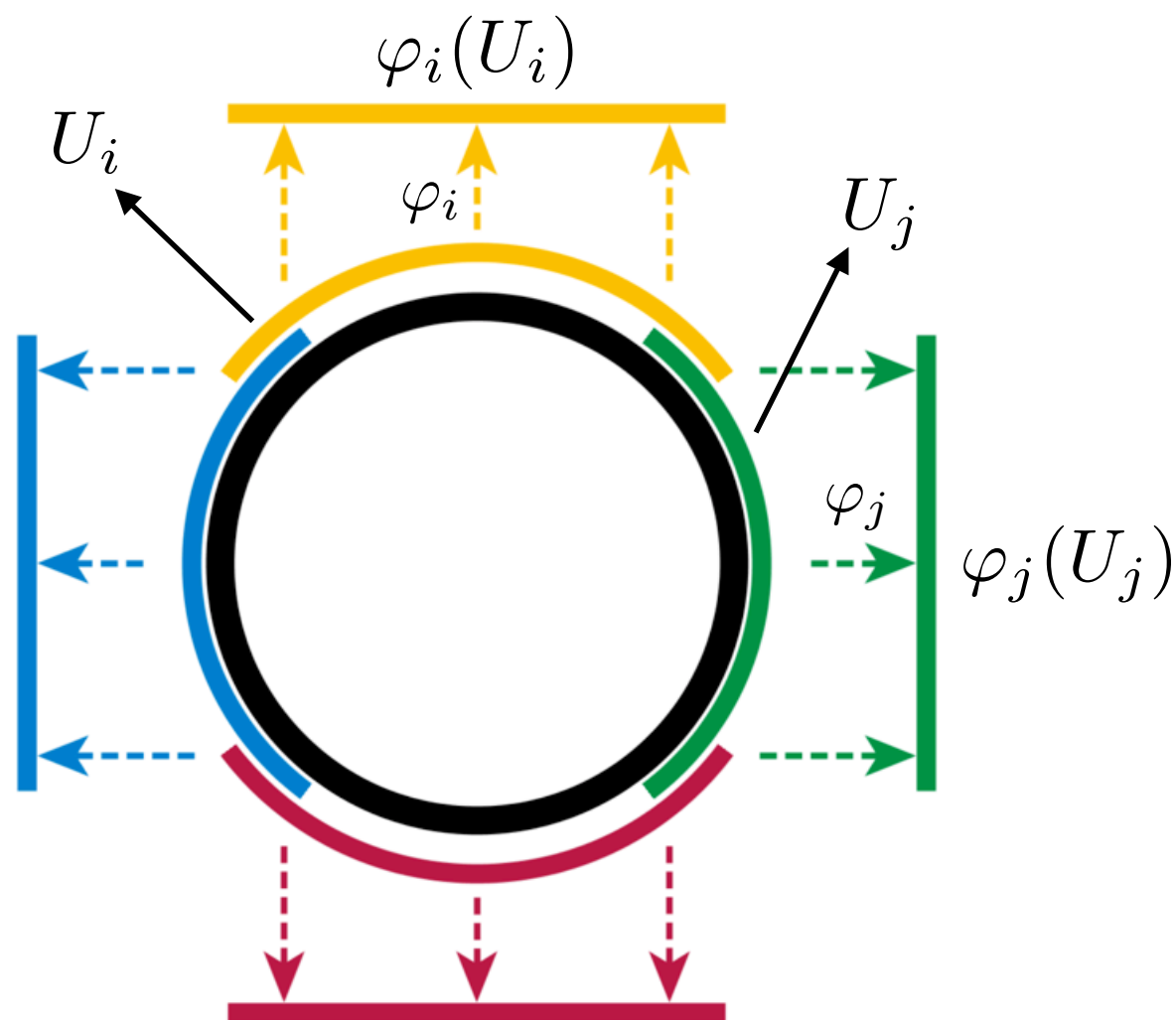
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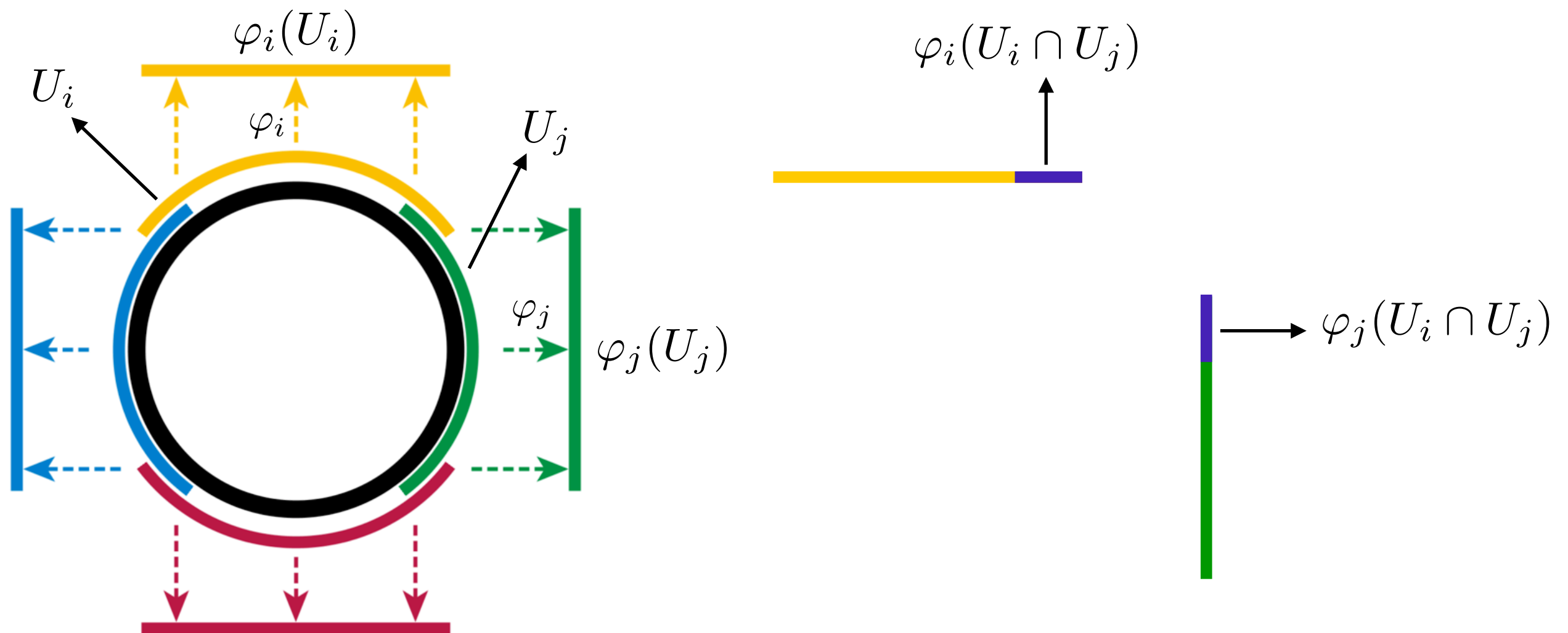
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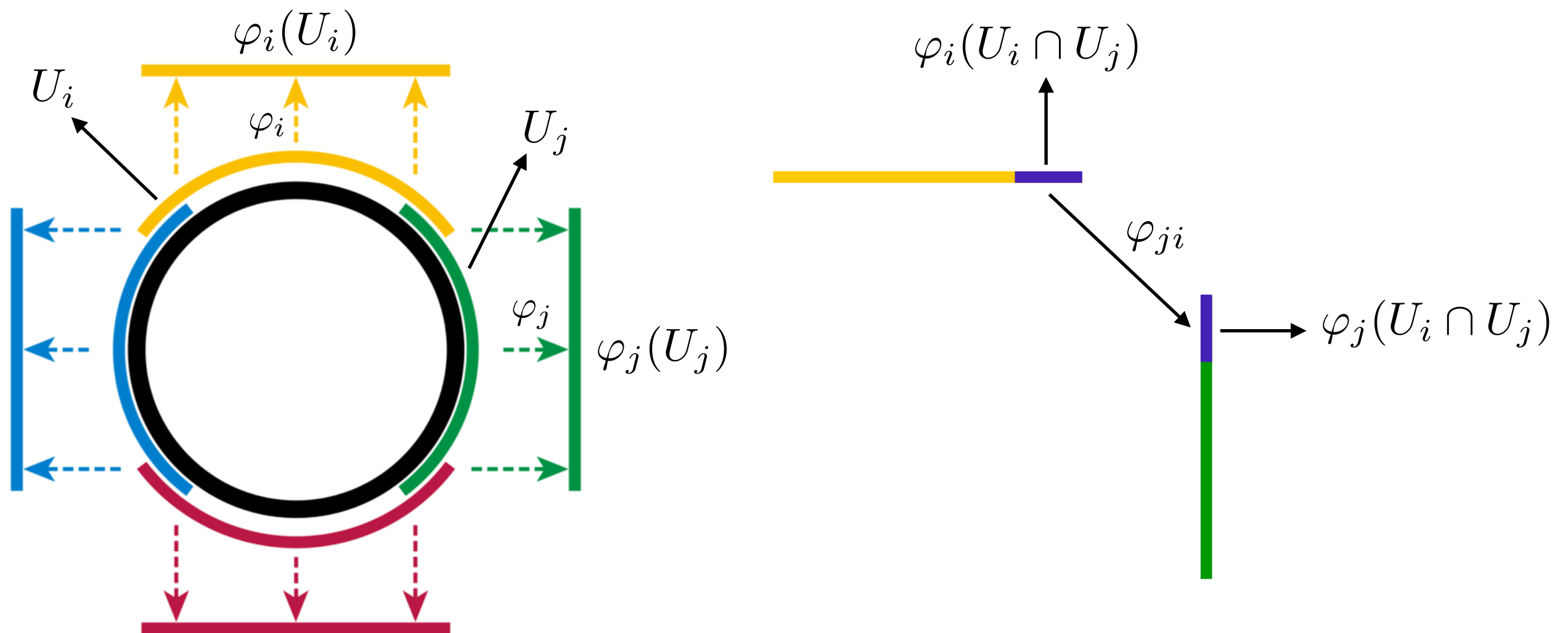
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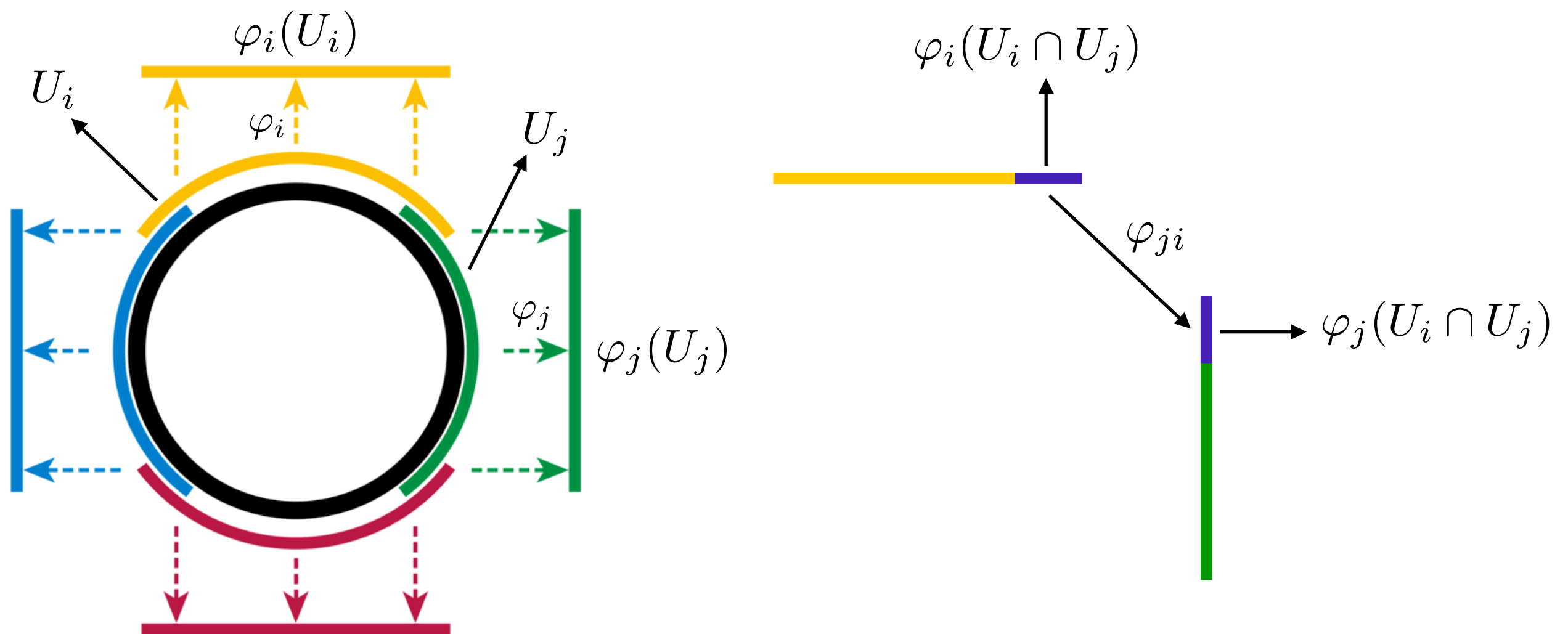
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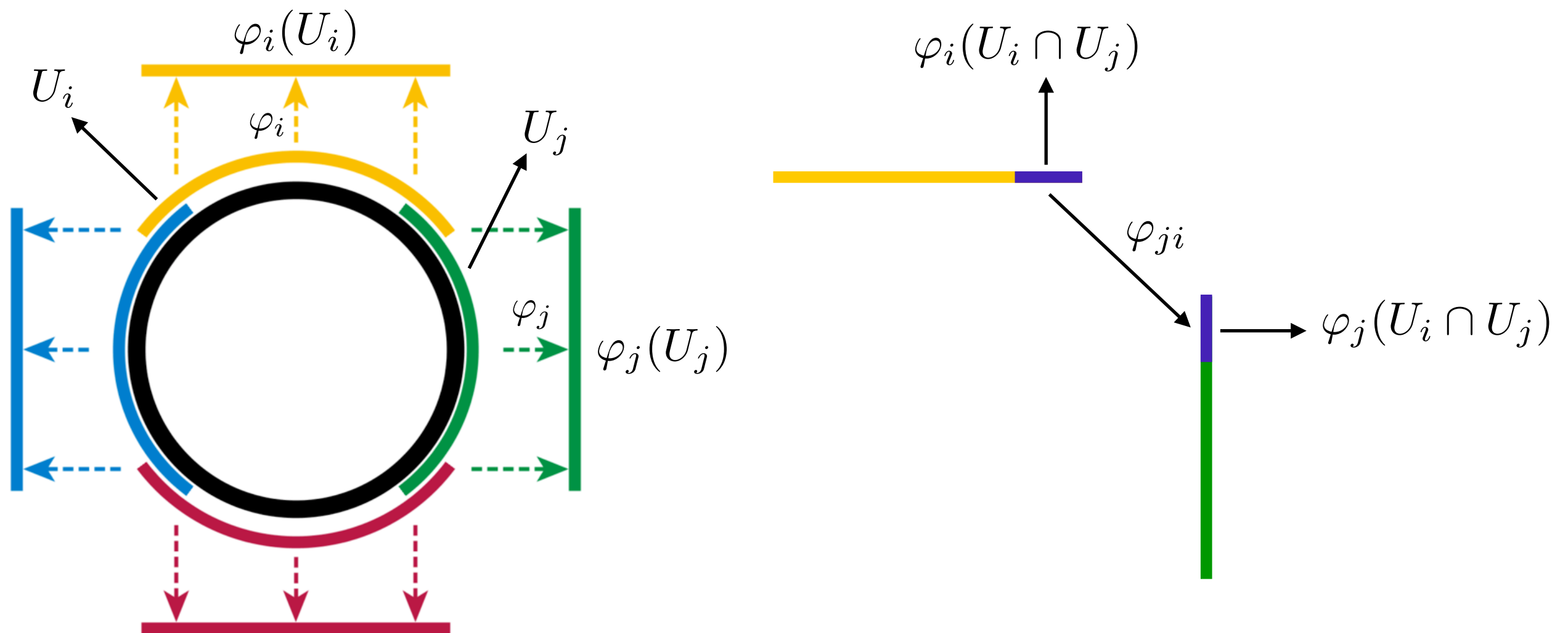


Manifolds: Informal Definition



Manifolds: Informal Definition

- This is a map between two open subsets of \mathbb{R}^n and we require it possess a certain amount of **smoothness**.



Manifolds: Formal Definition

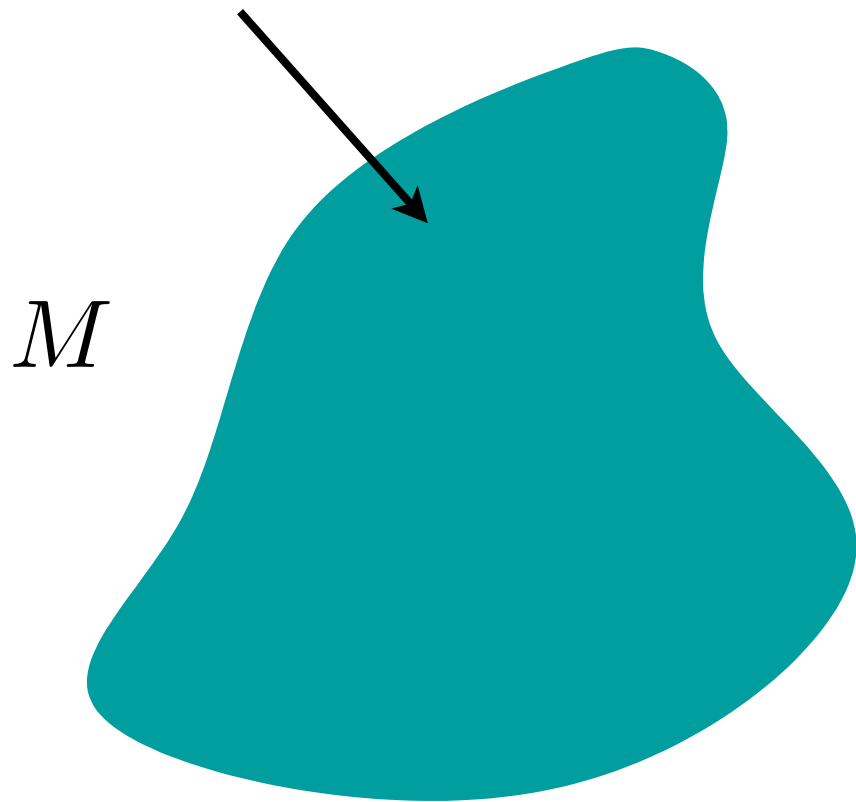
Manifolds: Formal Definition

Recall the definition of a manifold...

Manifolds: Formal Definition

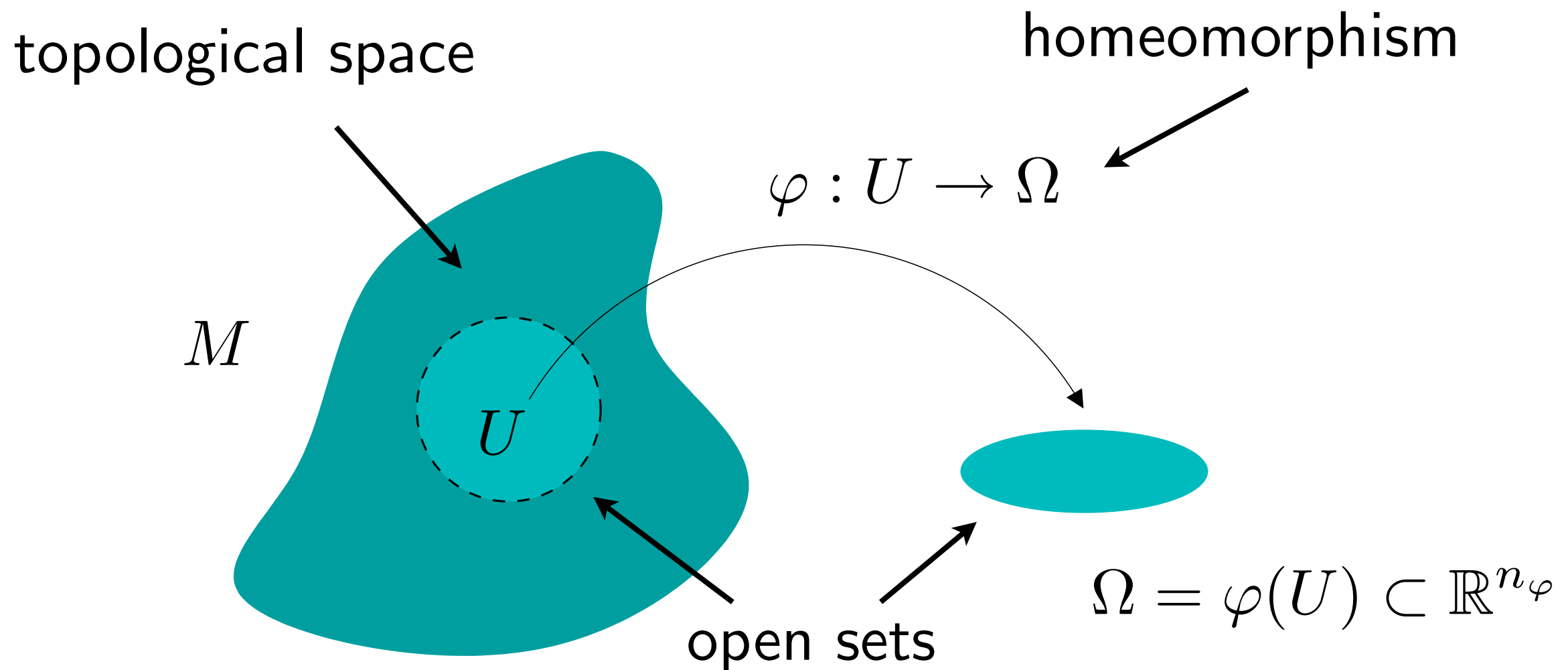
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topological space



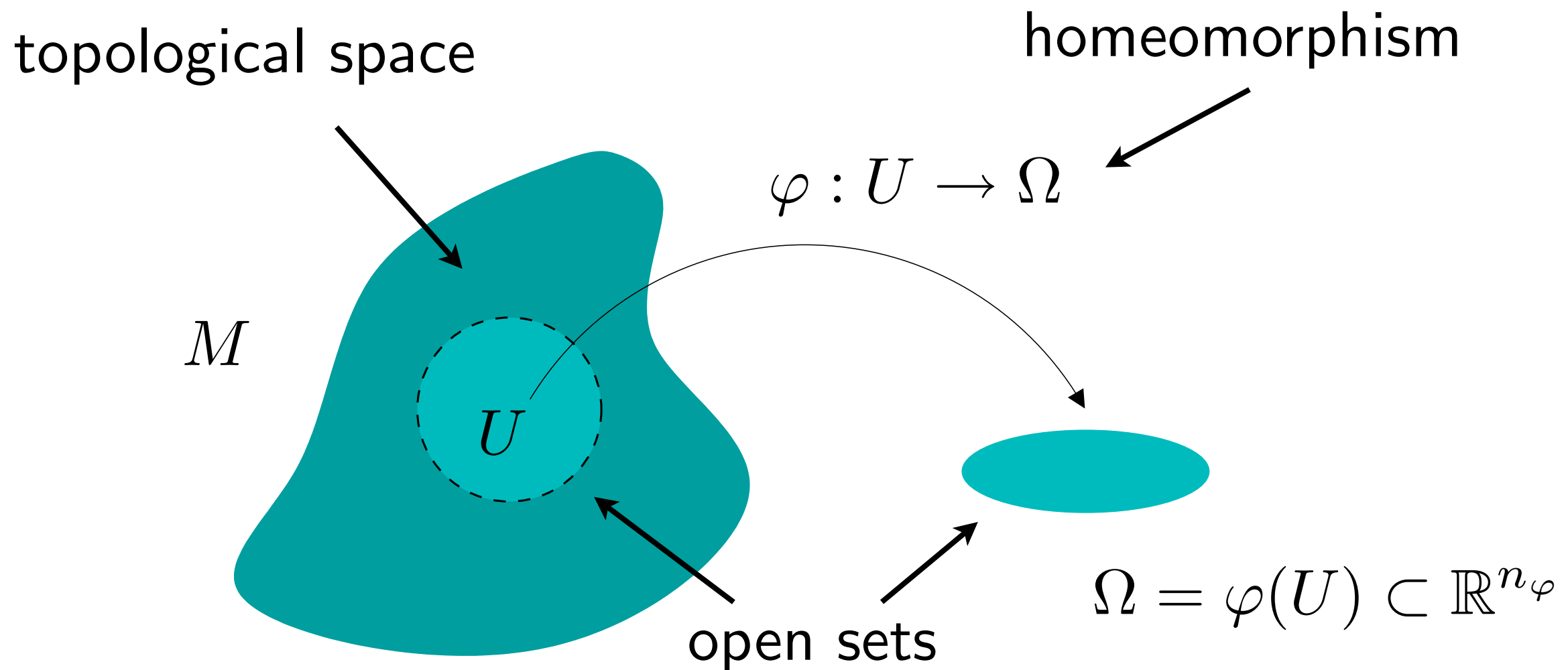
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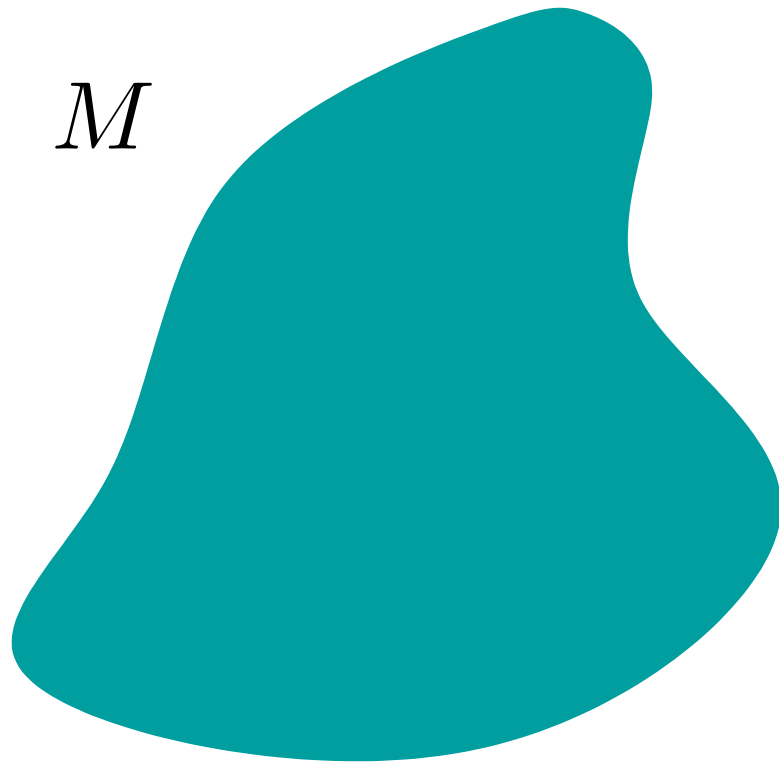
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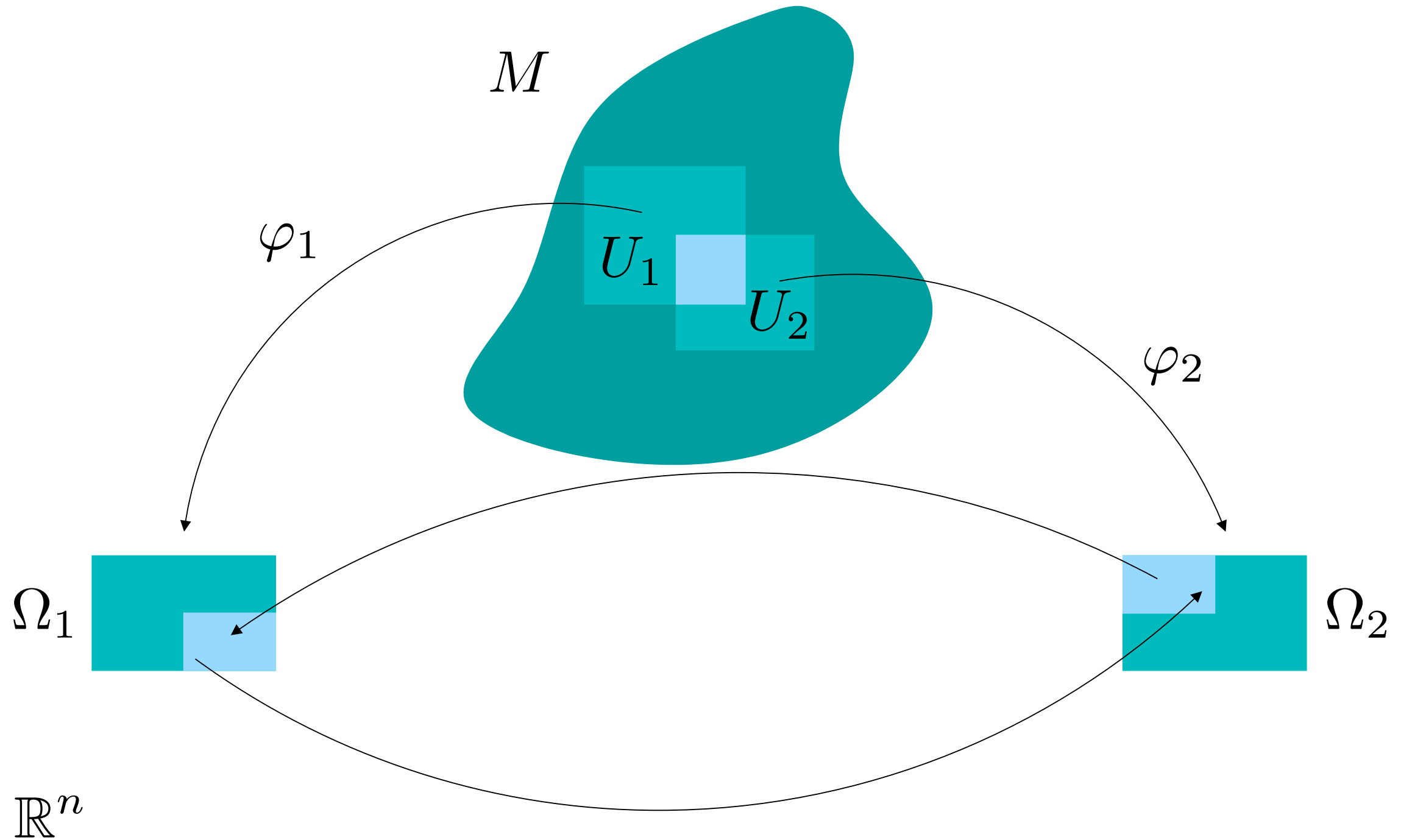
(U, φ) is called a **chart**.

Manifolds: Formal Definition

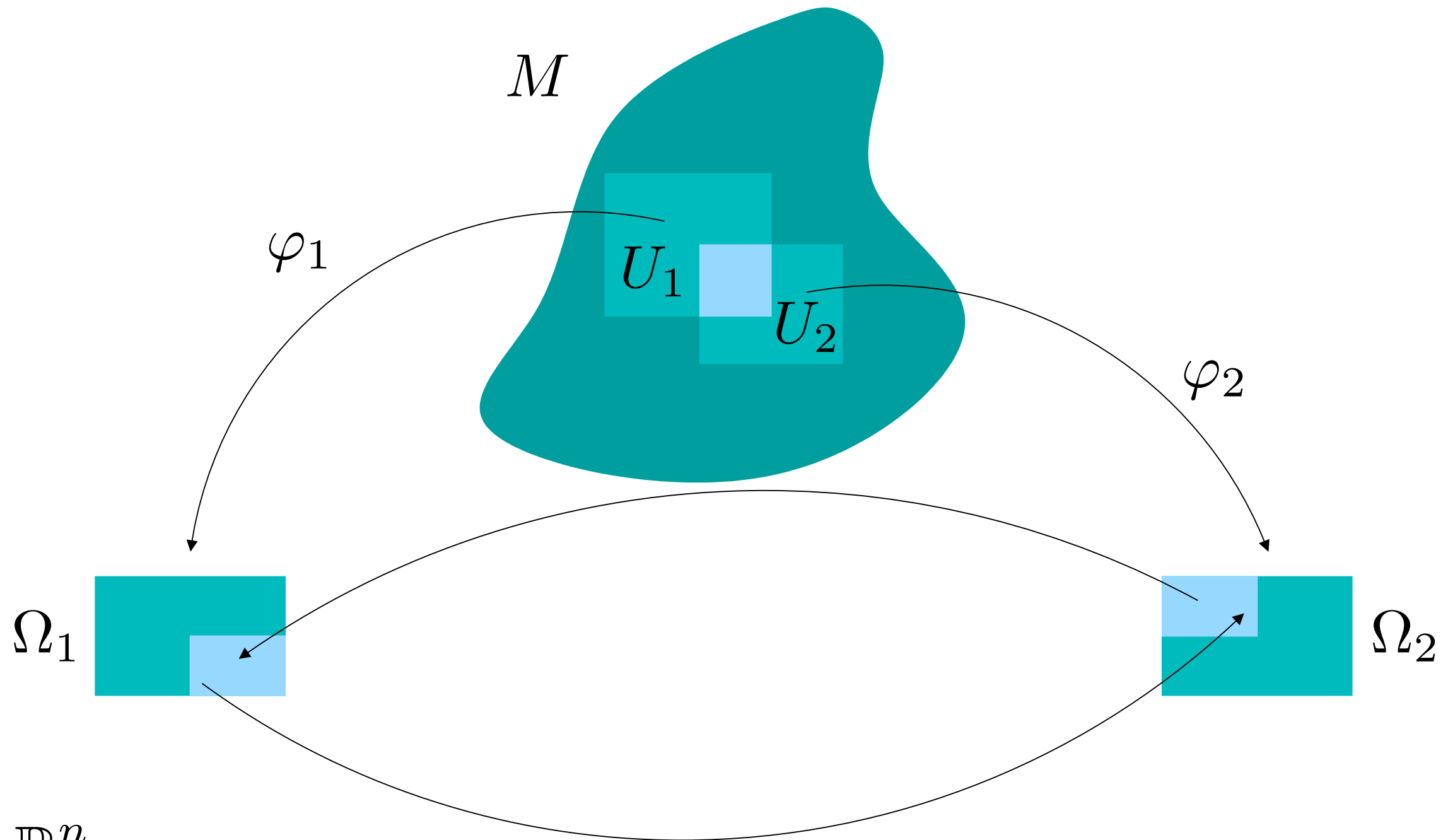
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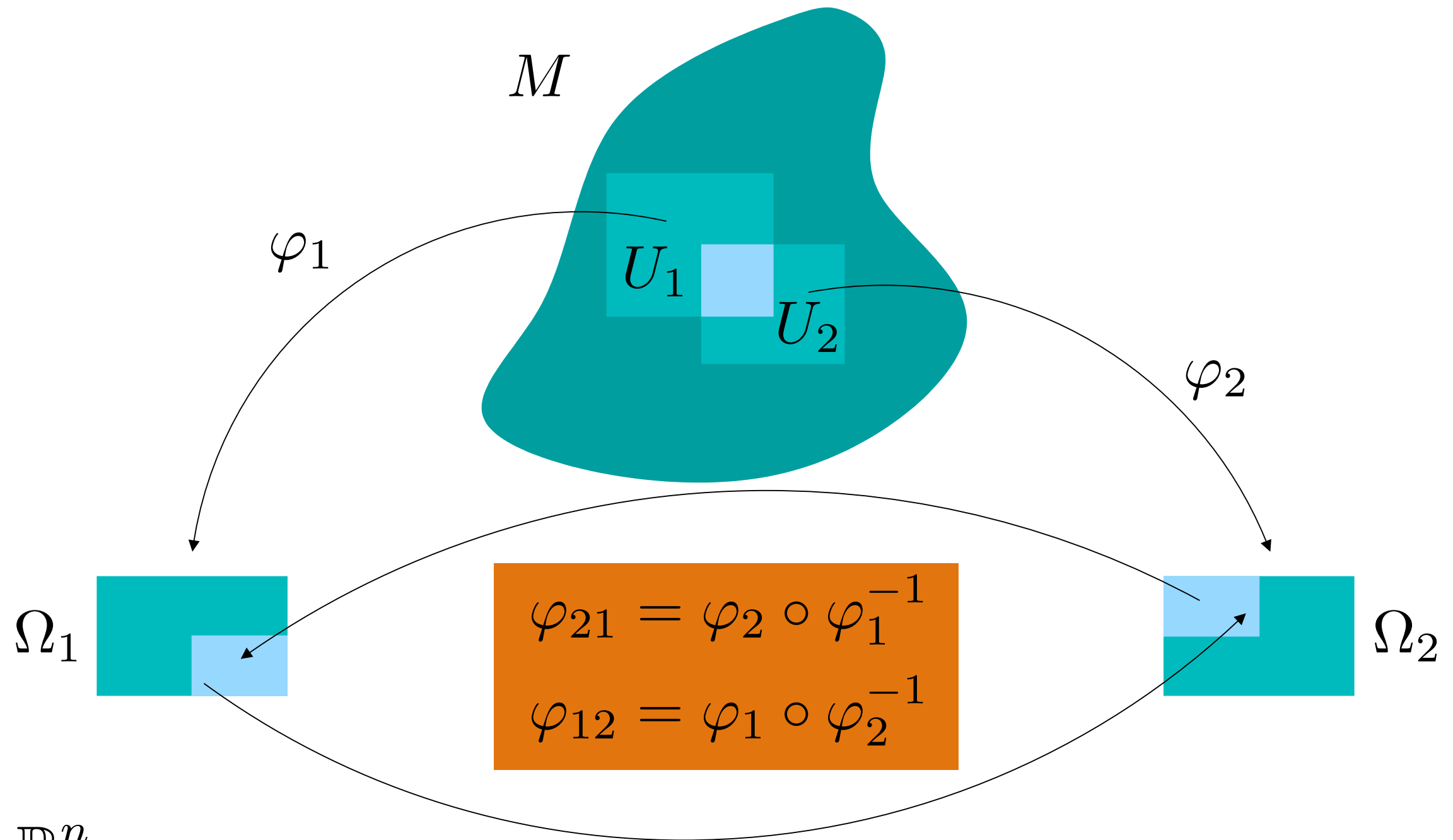
Manifolds: Formal Definition



$$\varphi_{21} : \varphi_1(U_1 \cap U_2) \rightarrow \varphi_2(U_1 \cap U_2)$$

$$\varphi_{12} : \varphi_2(U_1 \cap U_2) \rightarrow \varphi_1(U_1 \cap U_2)$$

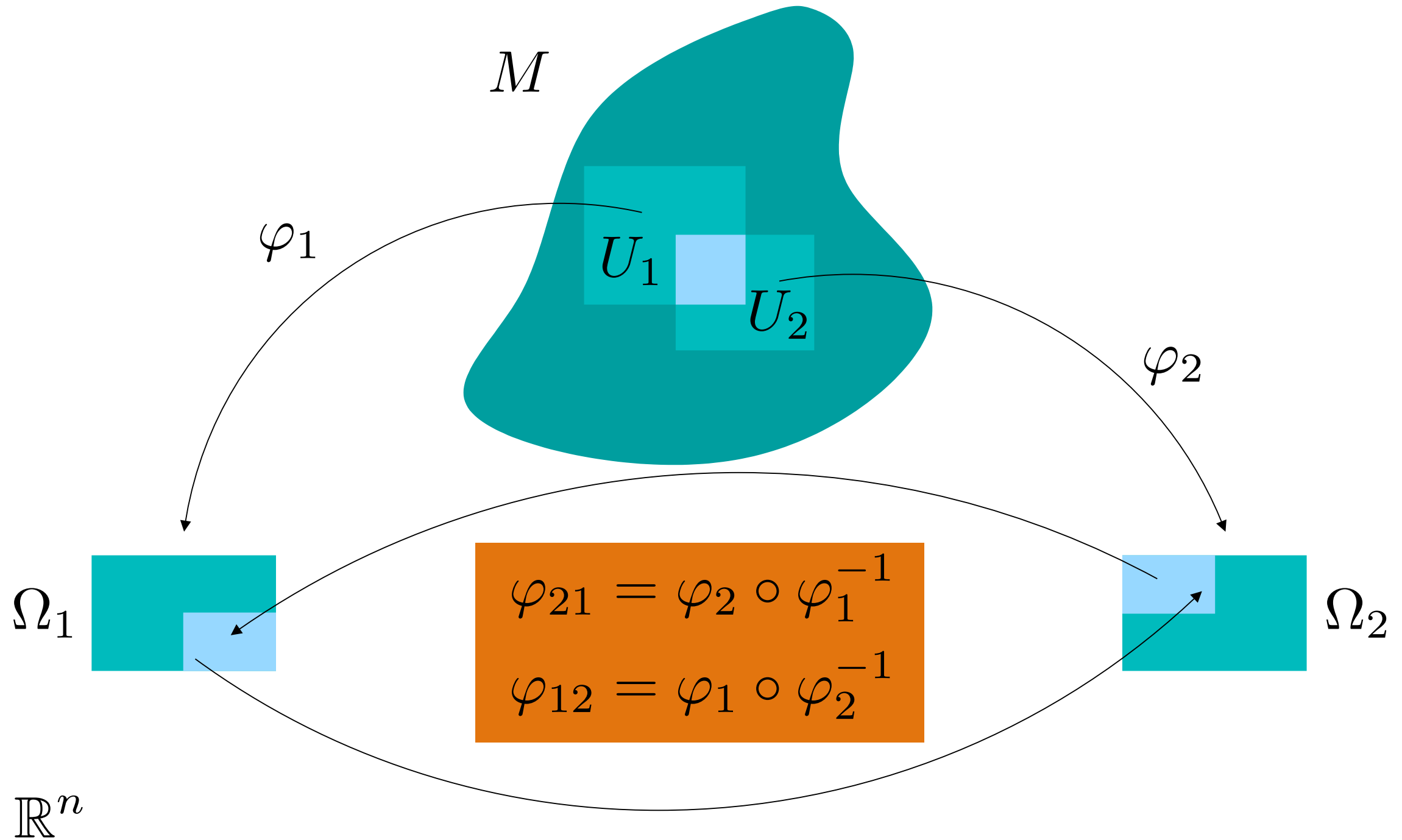
Manifolds: Formal Definition



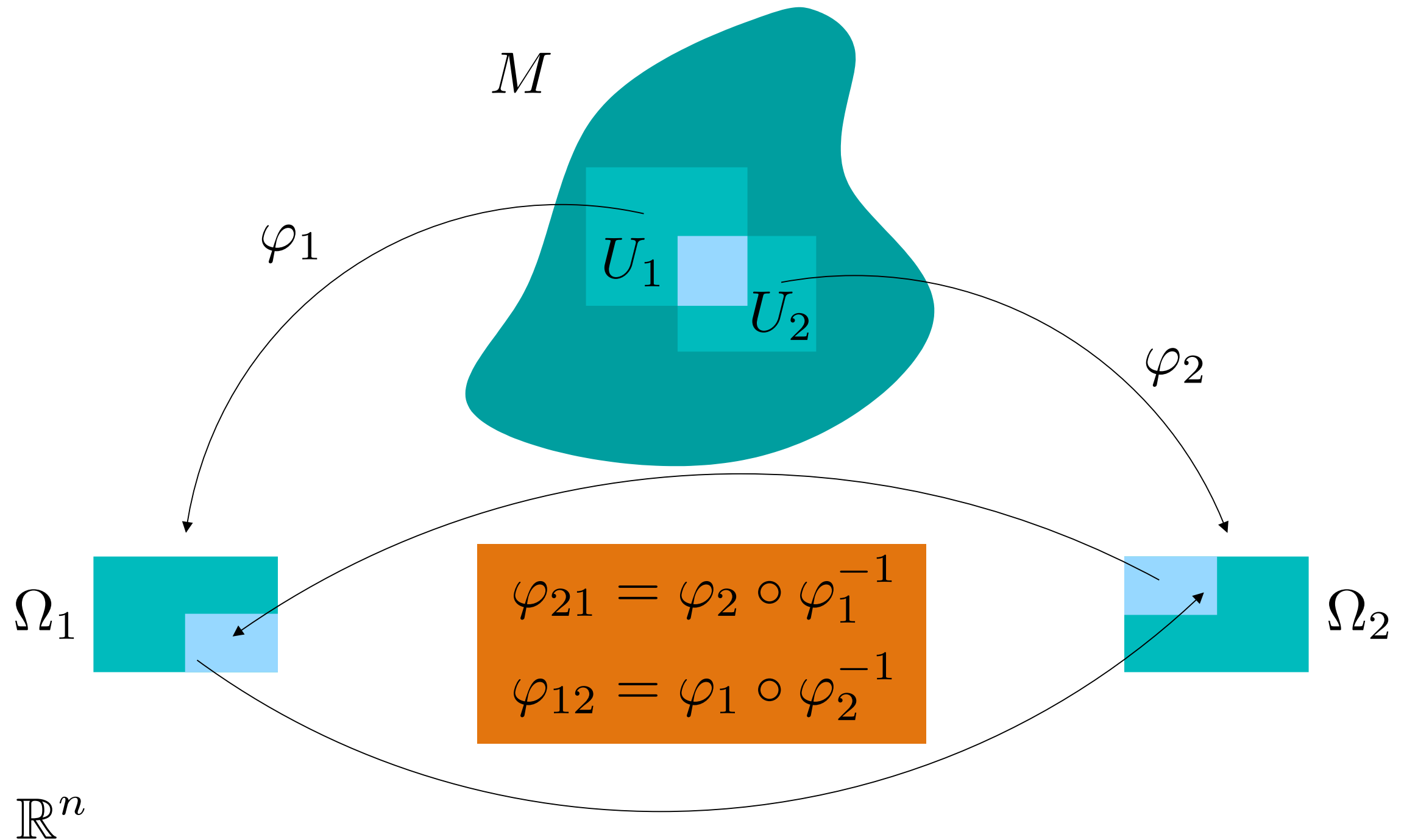
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φ_{21} and φ_{12} are the transition functions.

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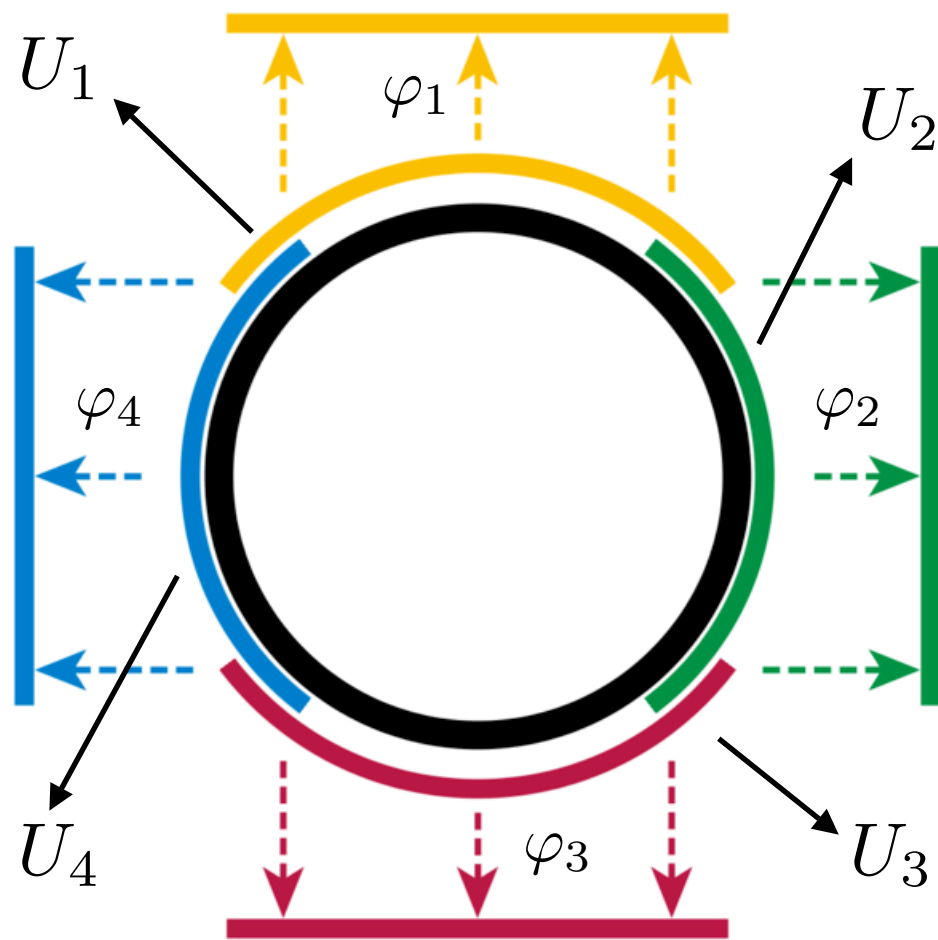
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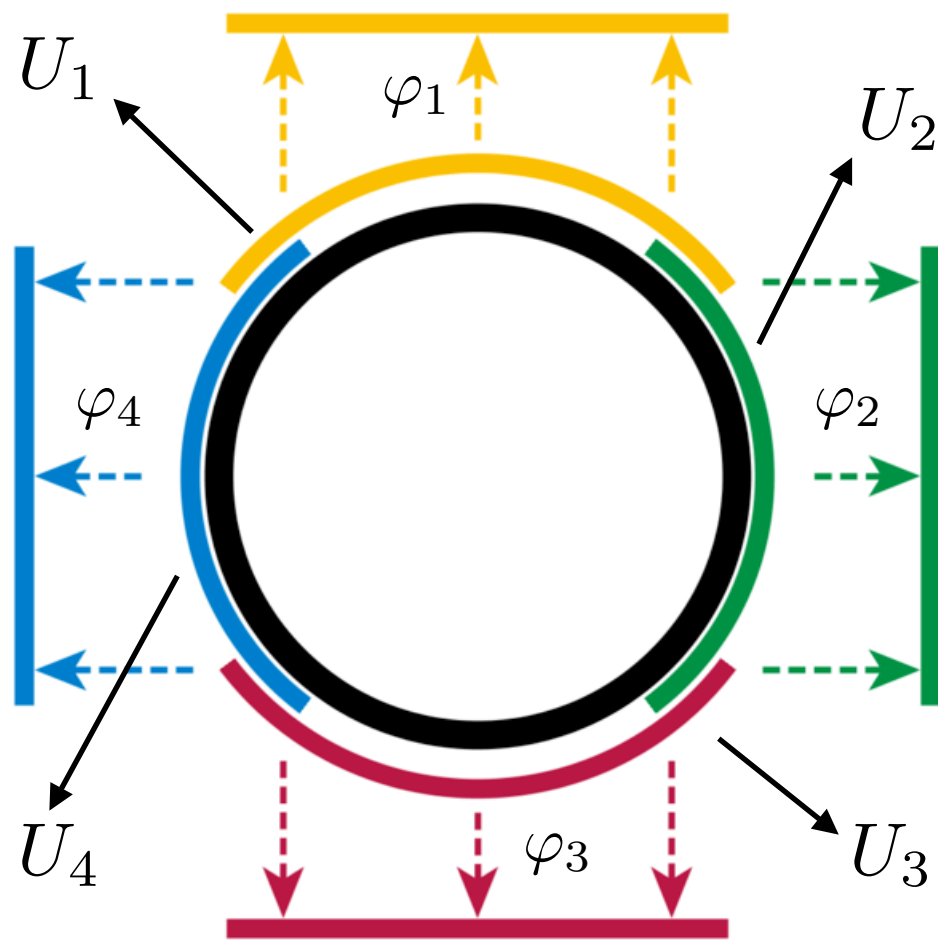
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Atlas: $\{(U_1, \varphi_1), (U_2, \varphi_2), (U_3, \varphi_3), (U_4, \varphi_4)\}$

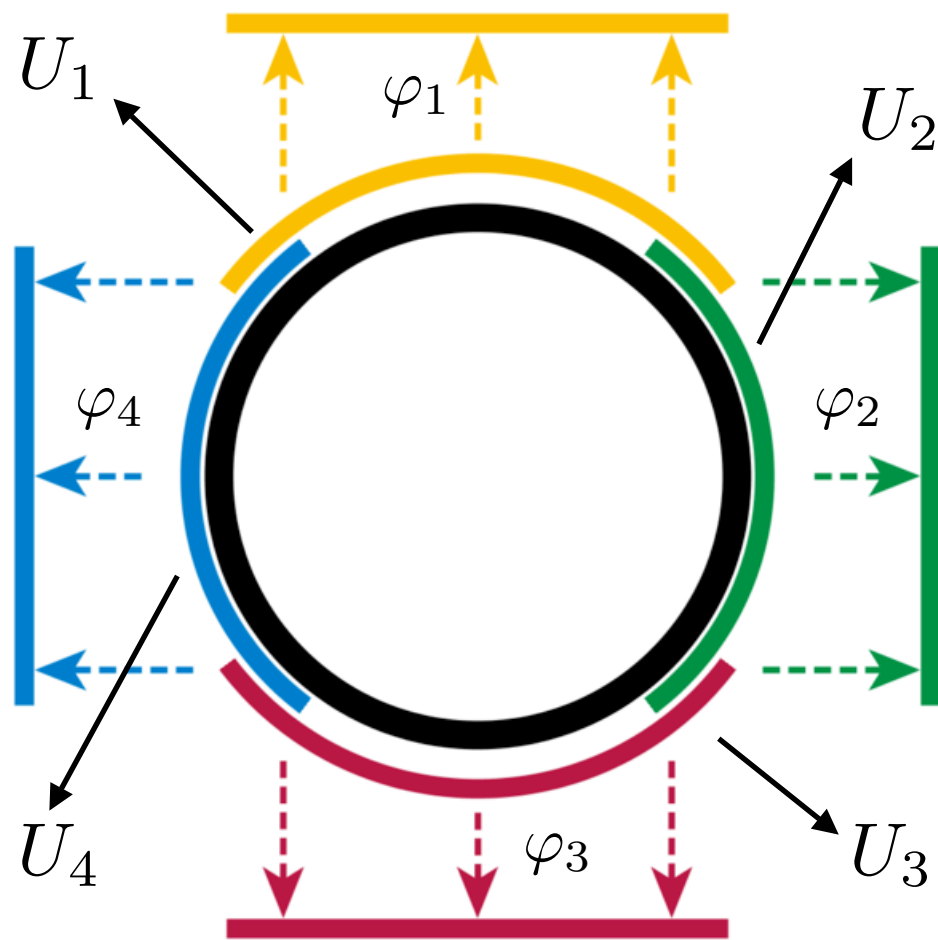
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$$M = \bigcup_{i=1}^4 U_i$$

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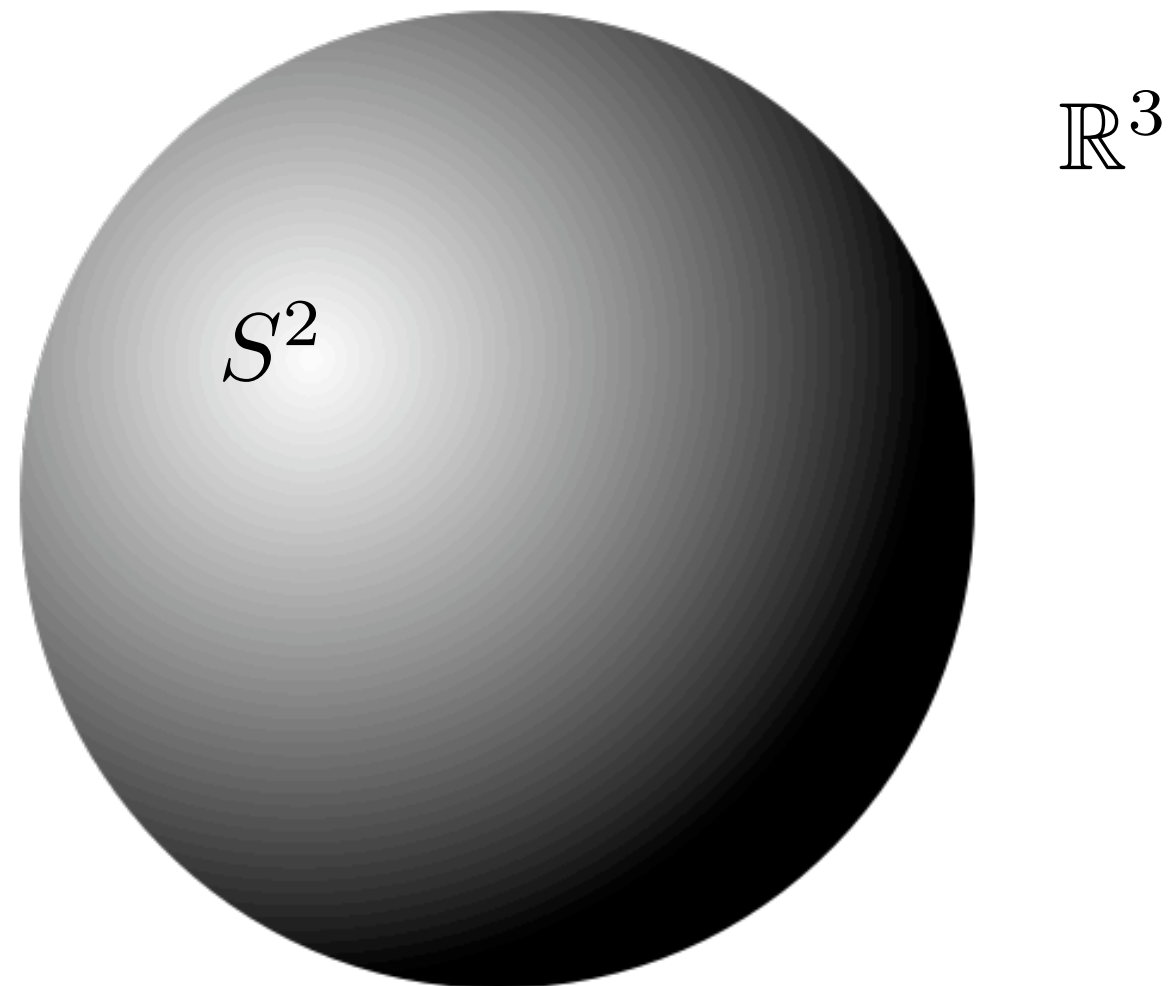
To avoid pathological cases and to ensure that a manifold is always embeddable in \mathbb{R}^n , for some $n \geq 1$, we further require that the topology of M be **Hausdorff** and **second-countable**.

Examples

Examples

- The sphere

$$S^{n-1} = \{(x_1, \dots, x_n) \in \mathbb{R}^n \mid x_1^2 + \dots + x_n^2 = 1\}.$$



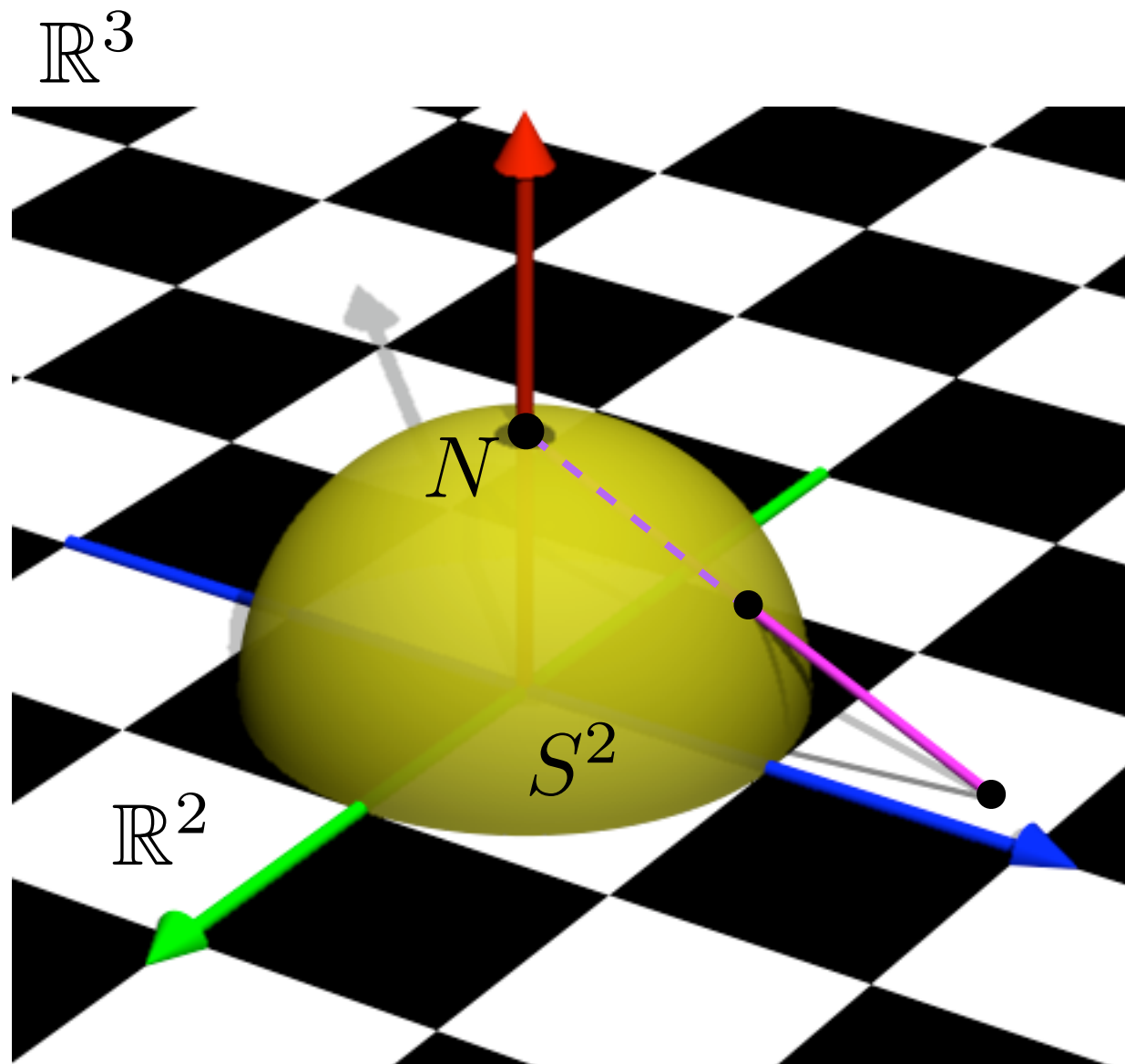
Examples

Examples

- We use stereographic projection from the north pole . . .

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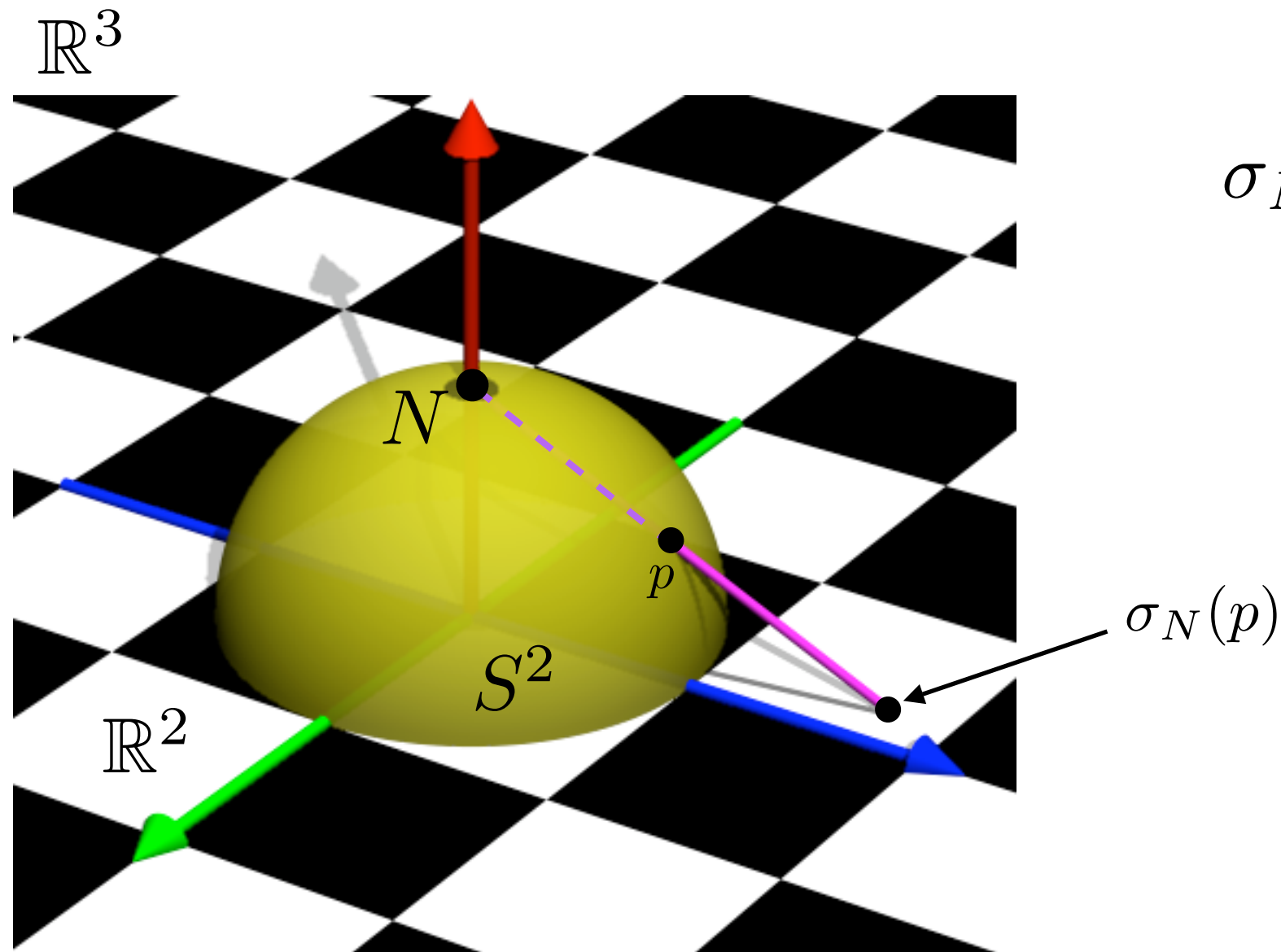
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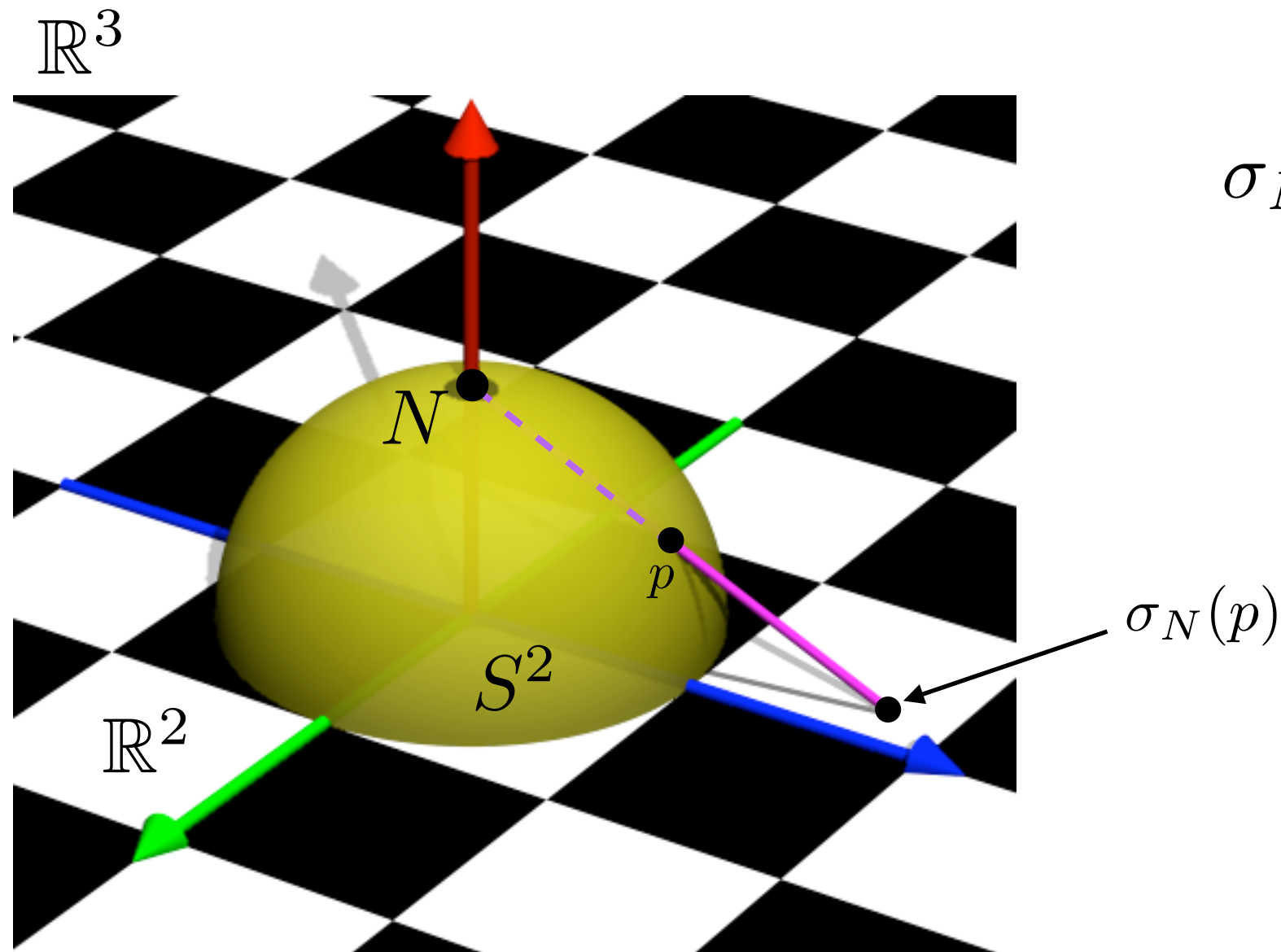
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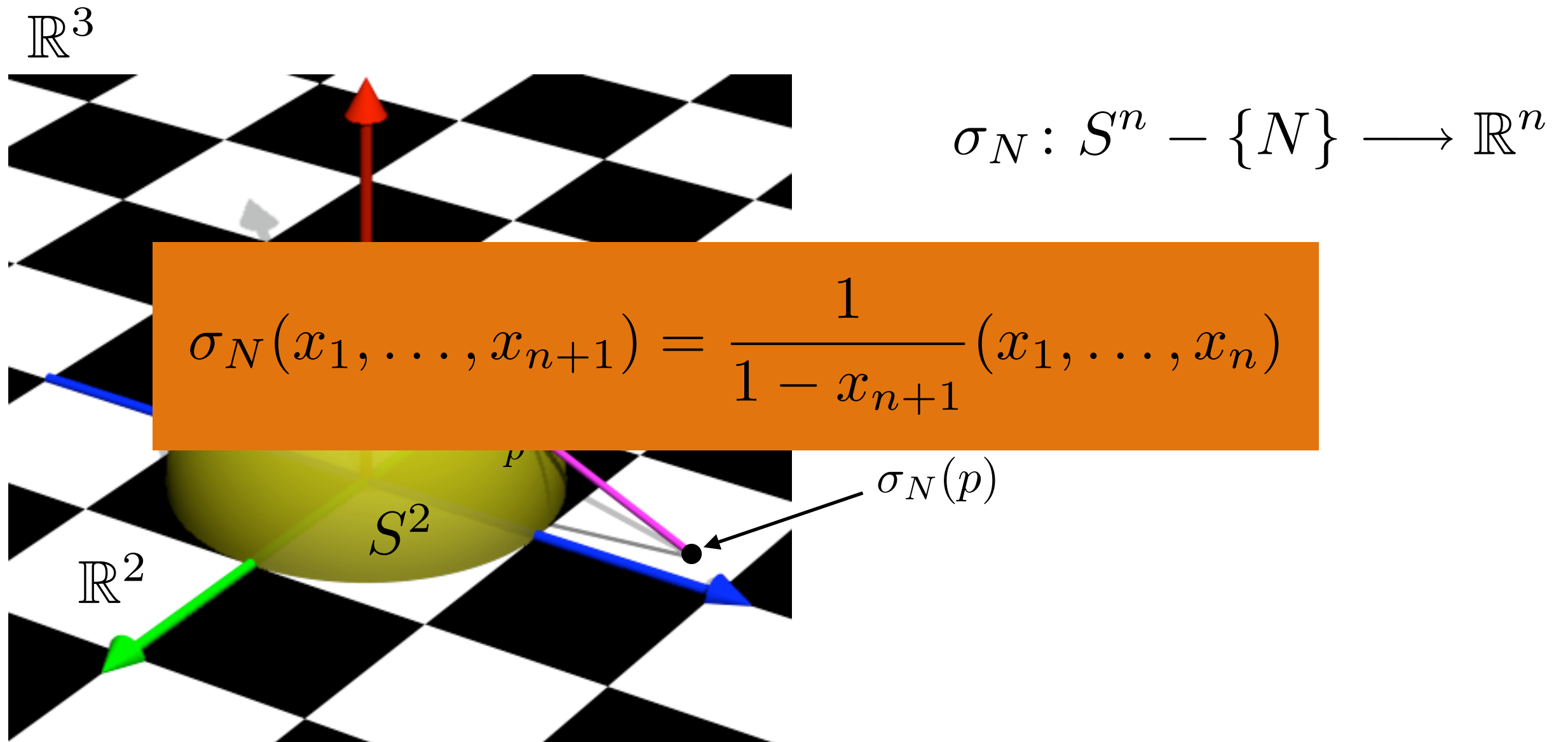
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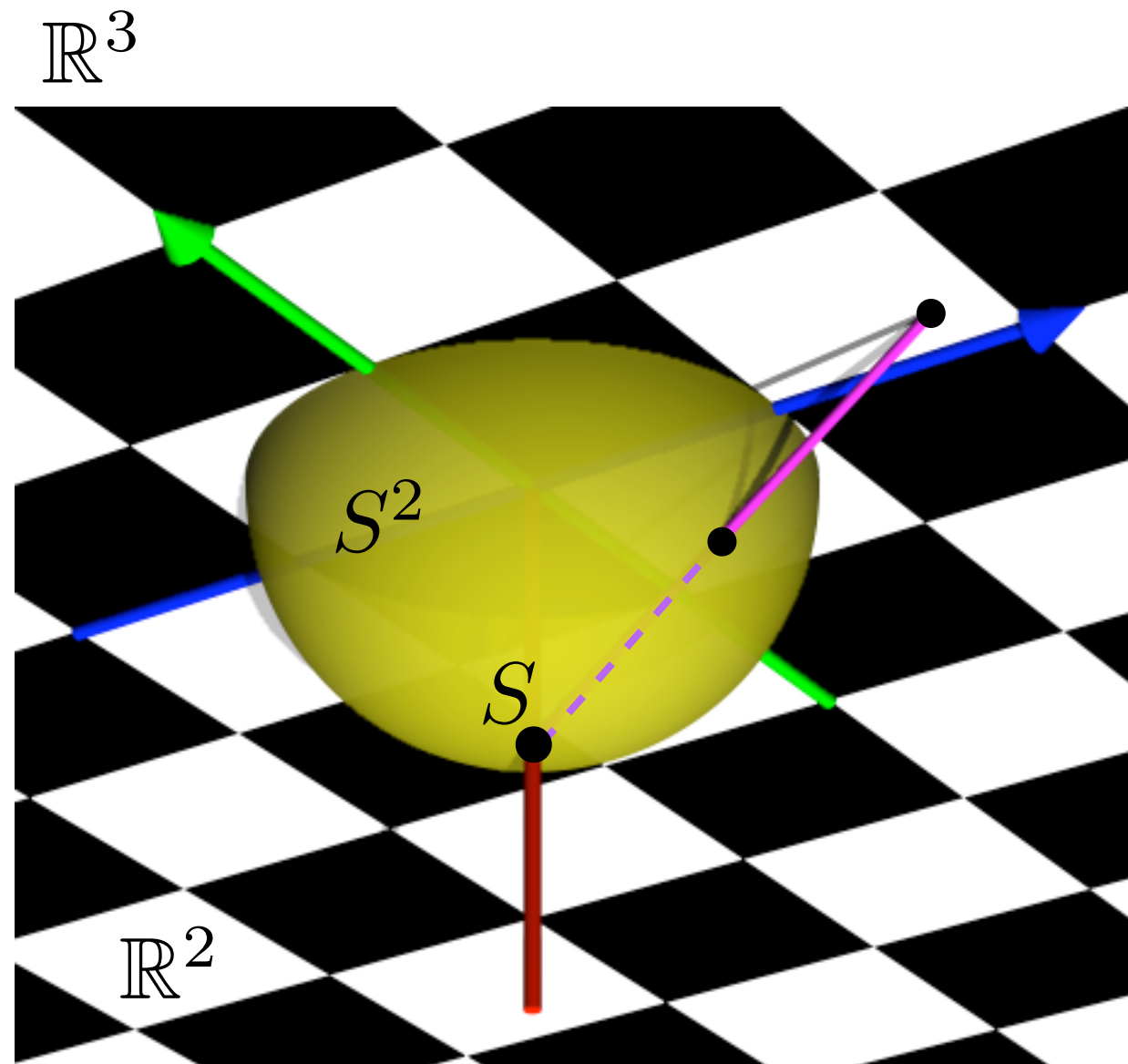
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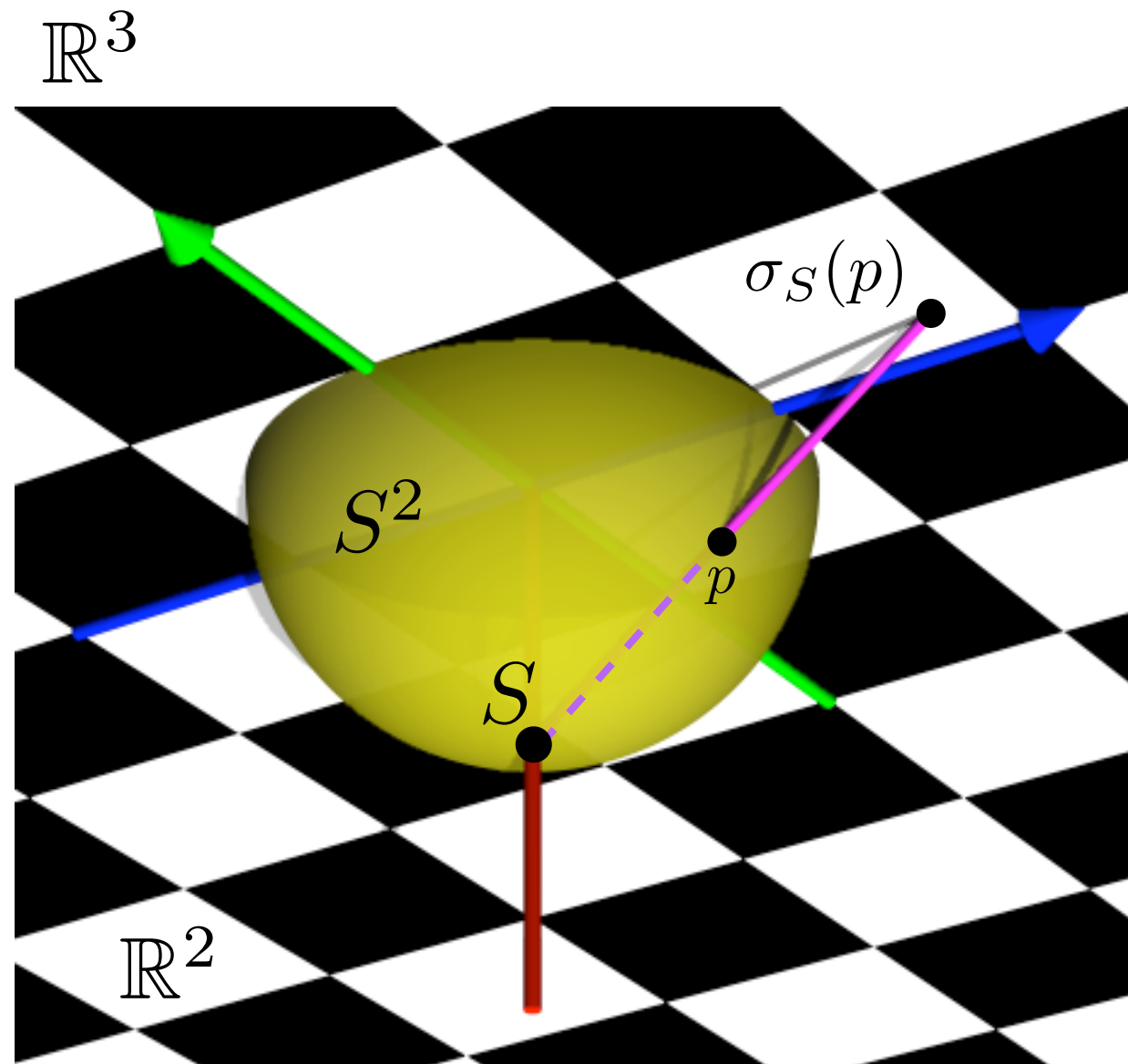
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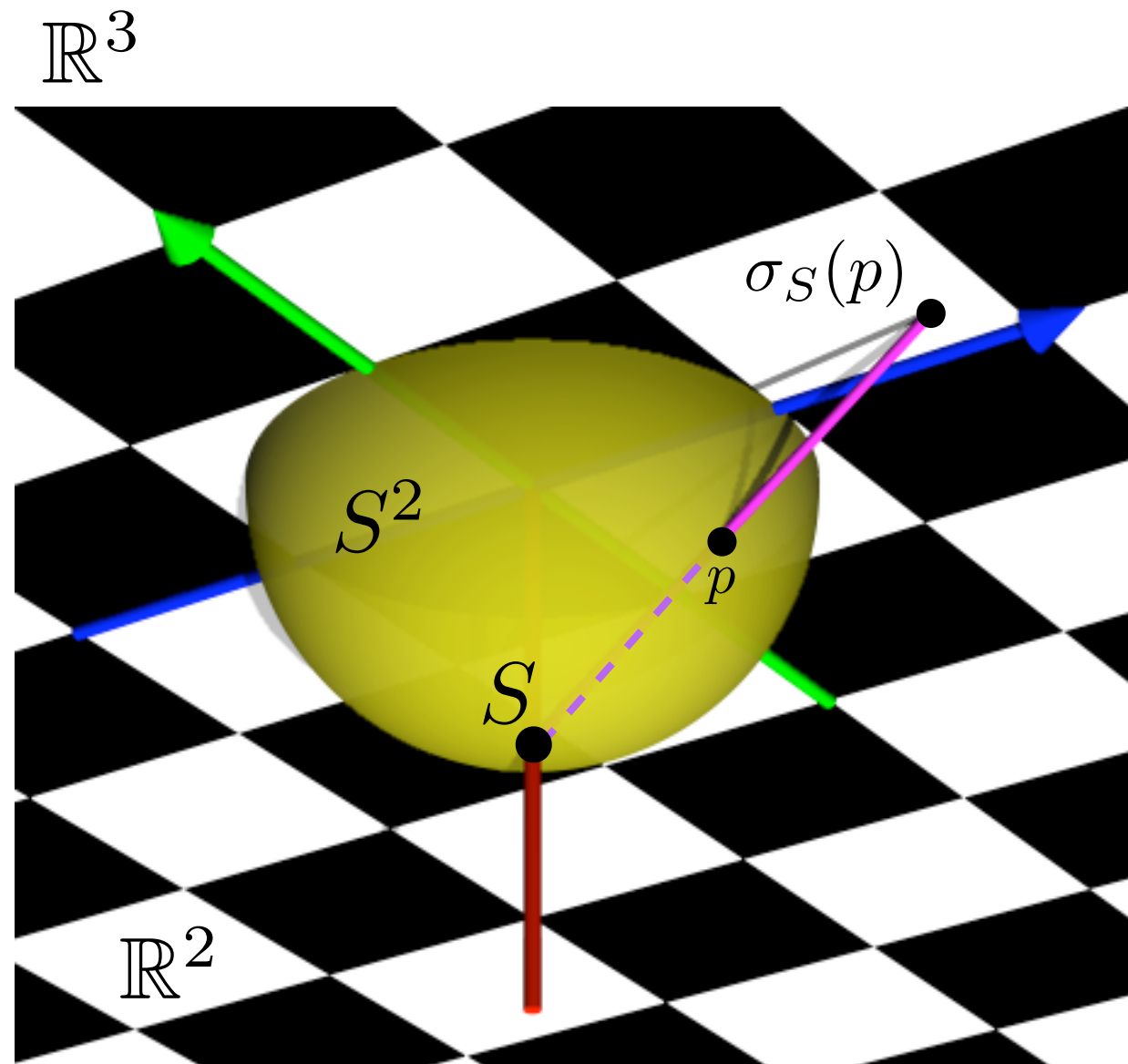
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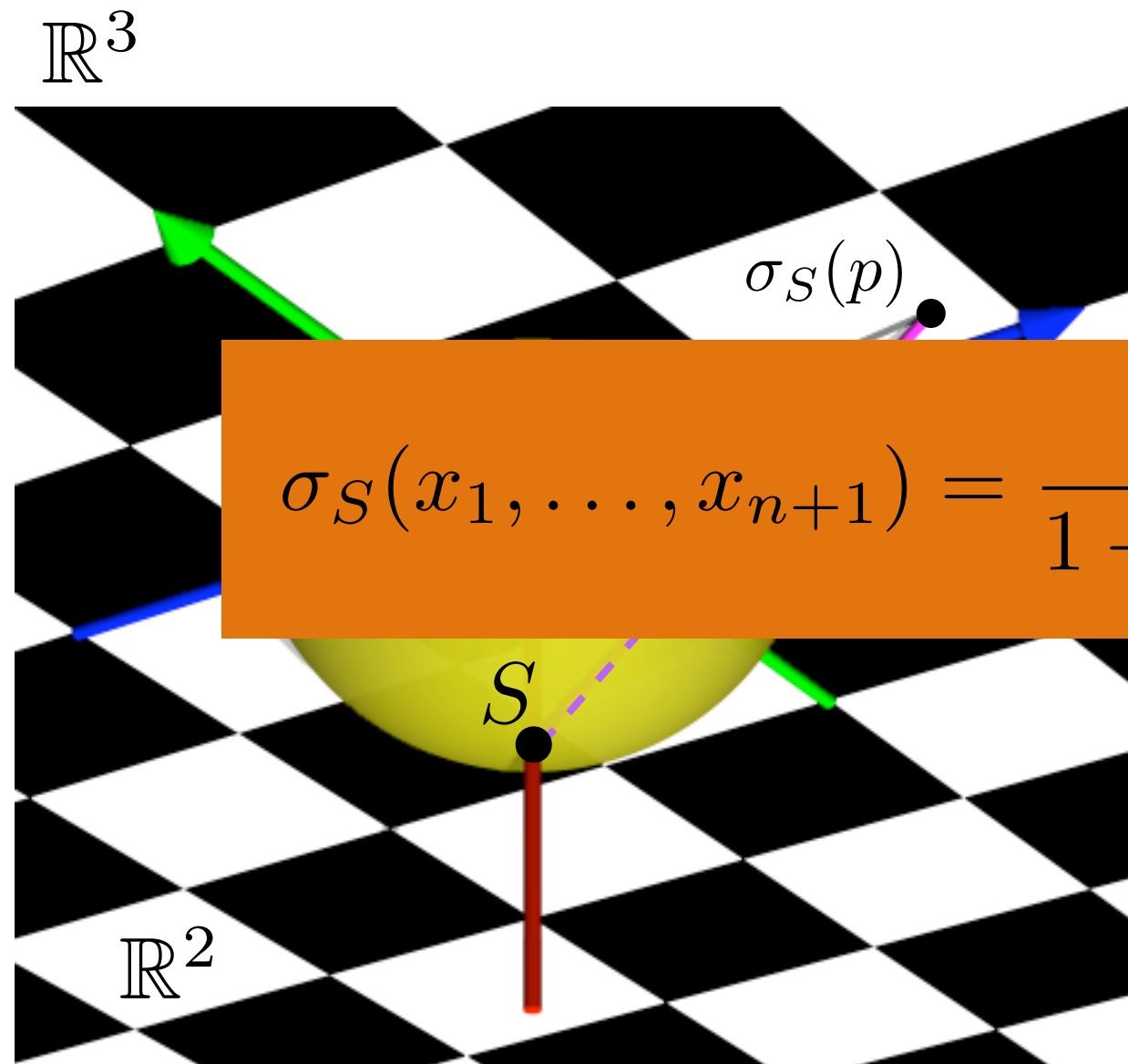
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$$\sigma_S(x_1, \dots, x_{n+1}) = \frac{1}{1 + x_{n+1}} (x_1, \dots, x_n)$$

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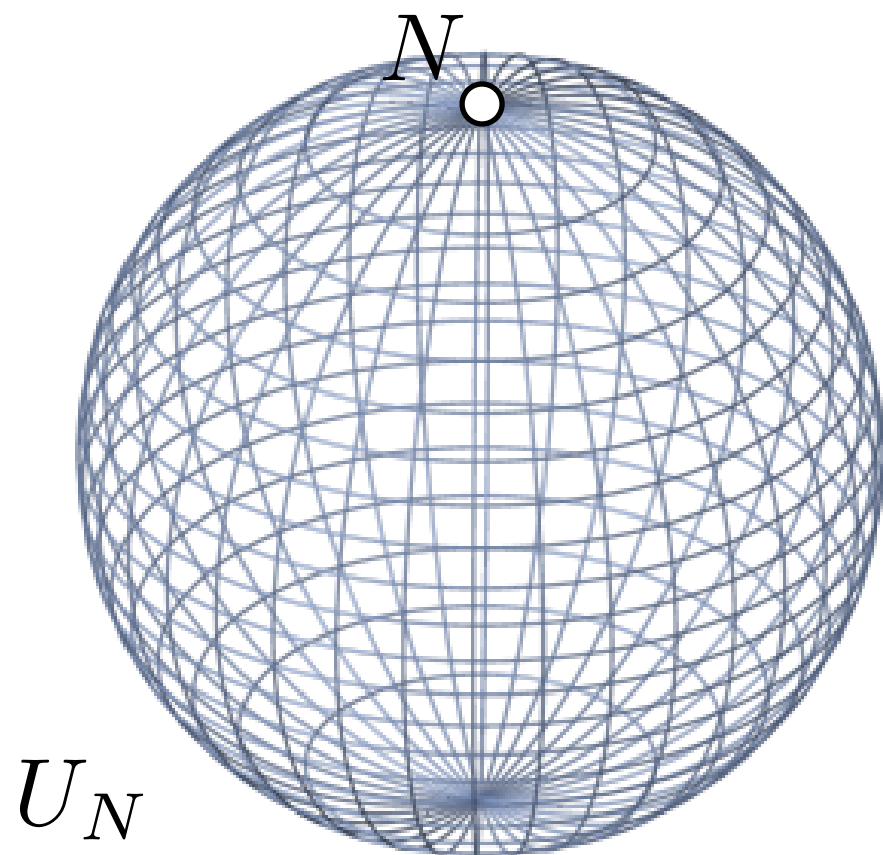
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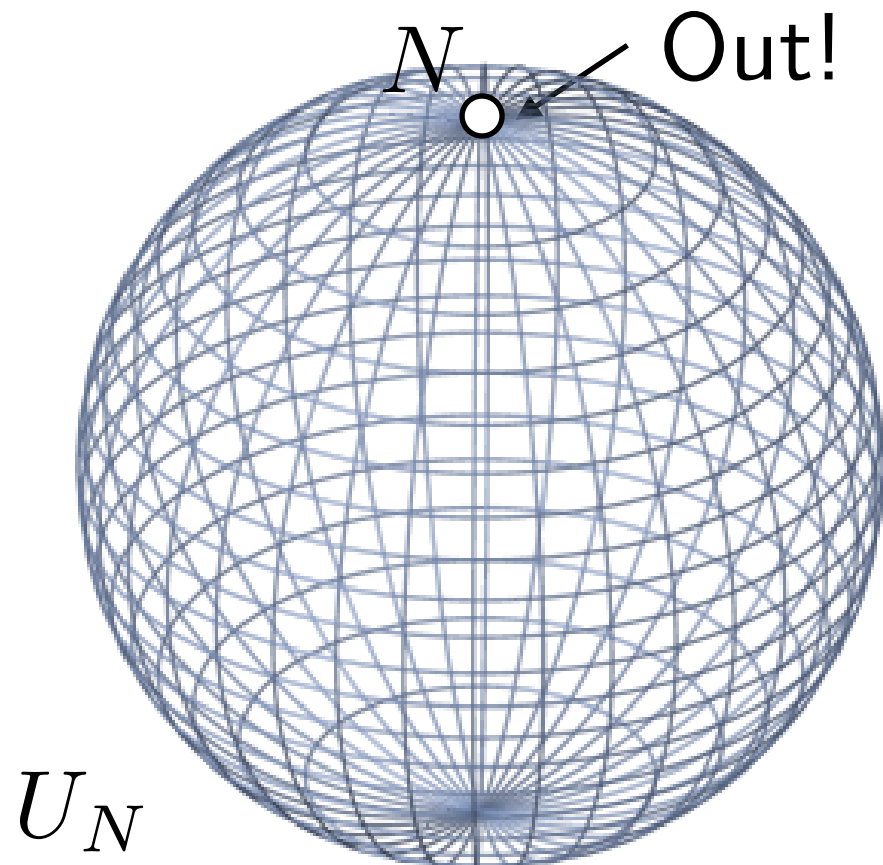
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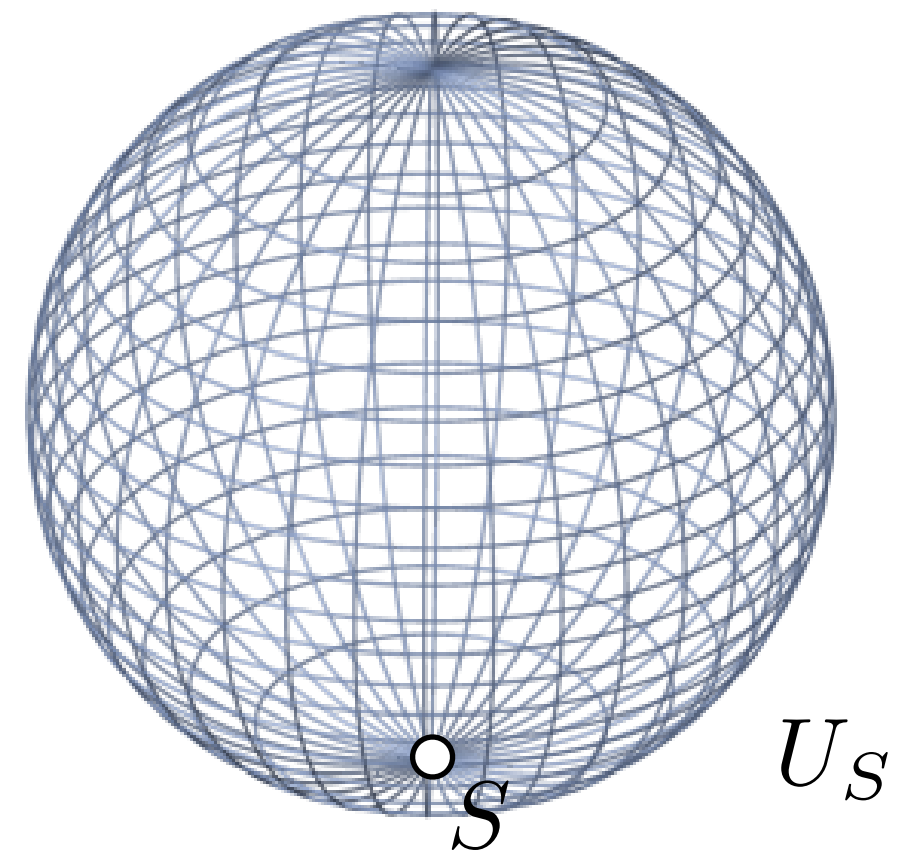
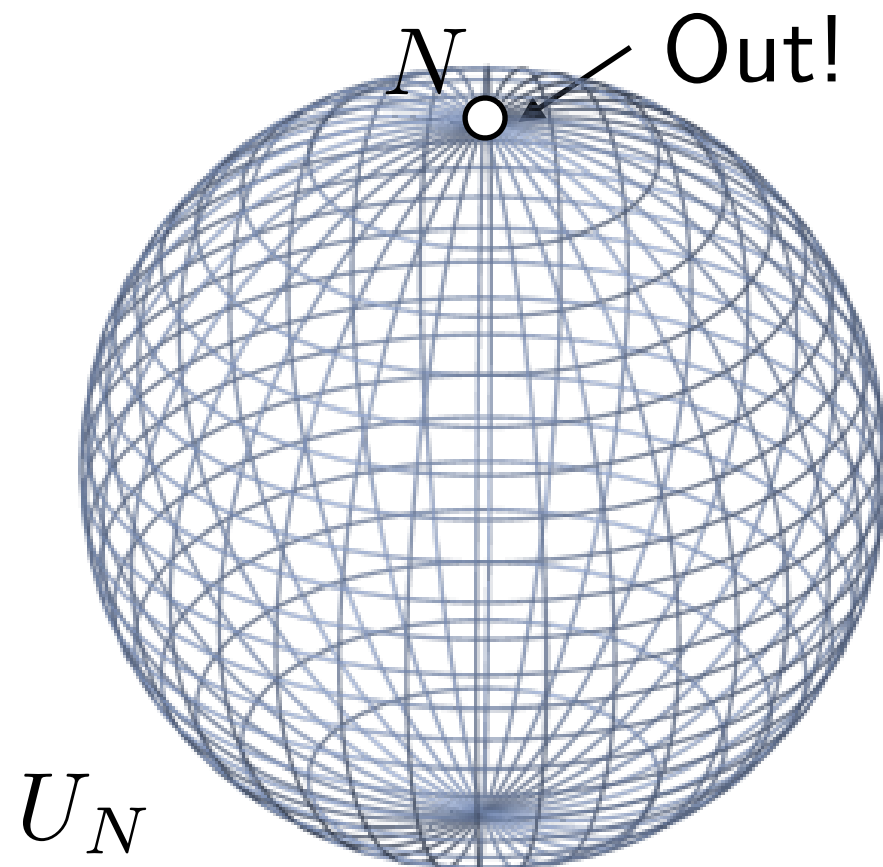
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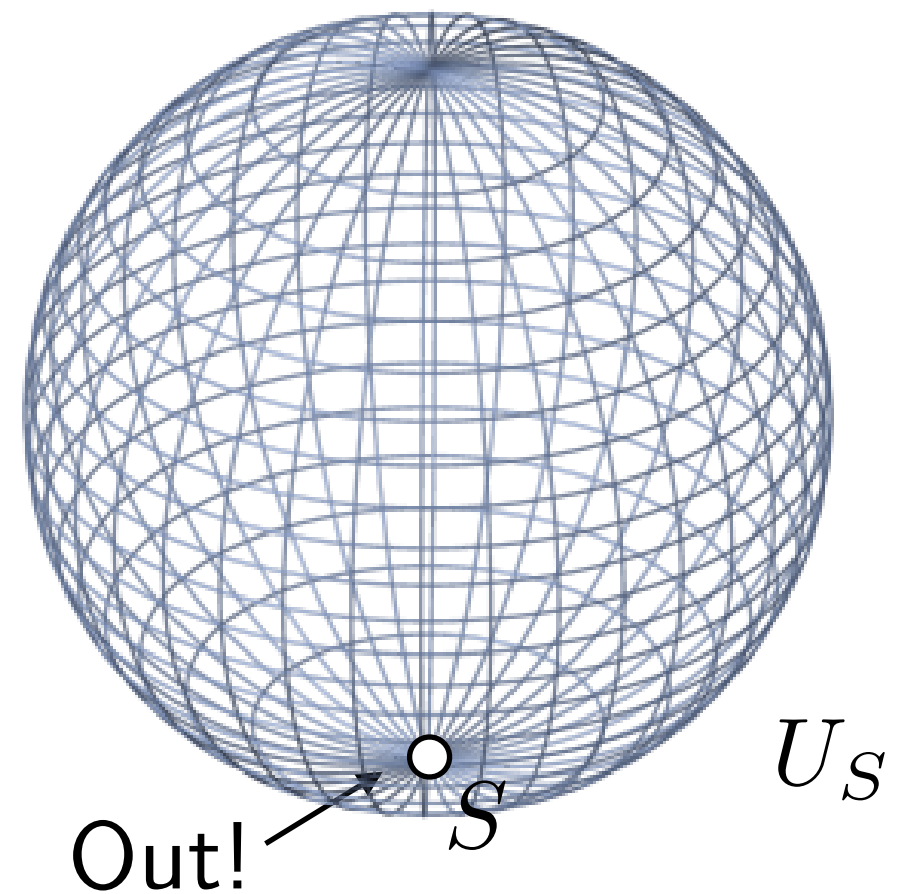
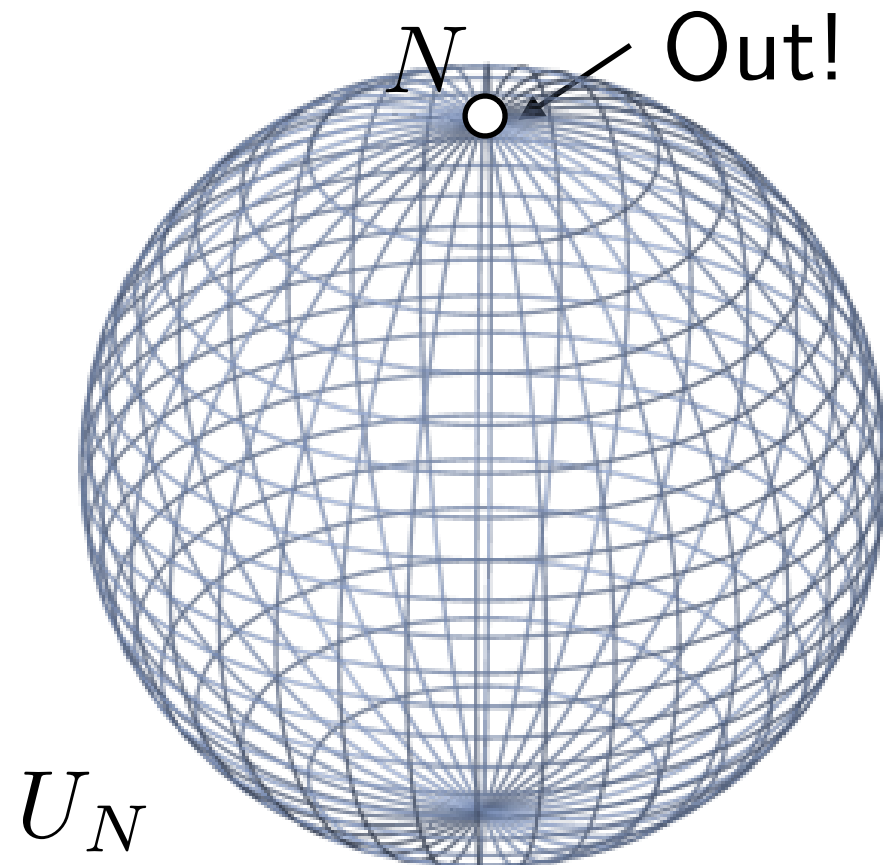
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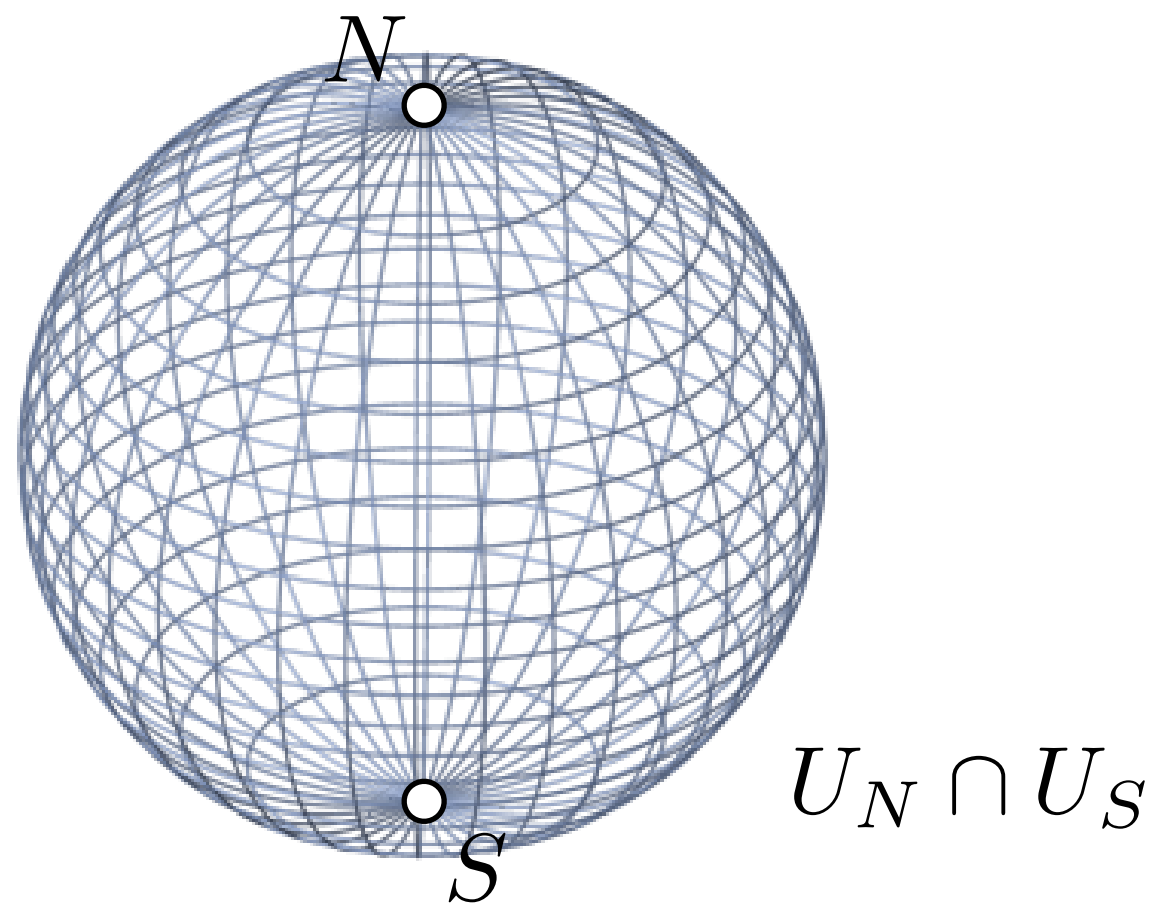
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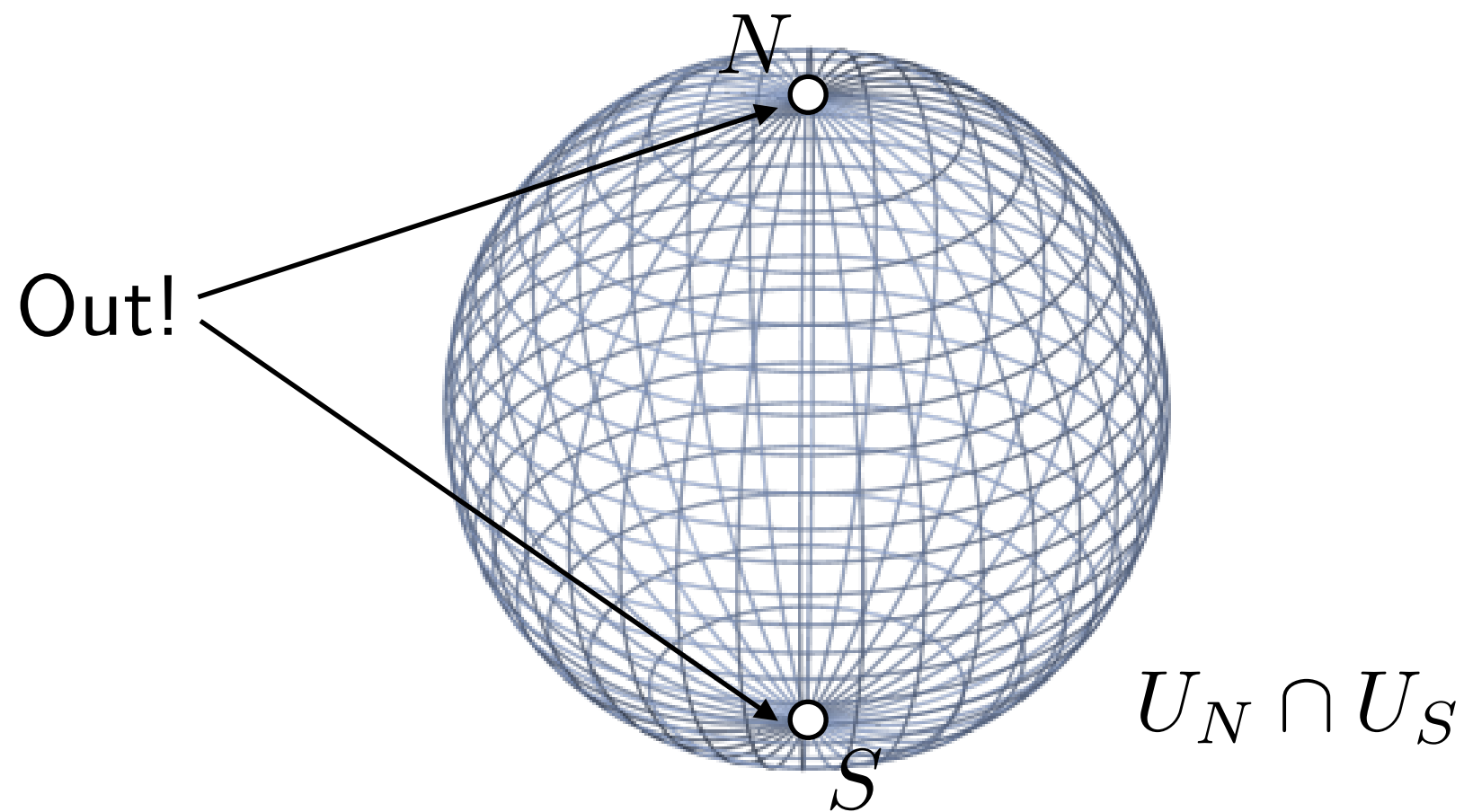
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are given by

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- So, the sphere is a smooth manifold.

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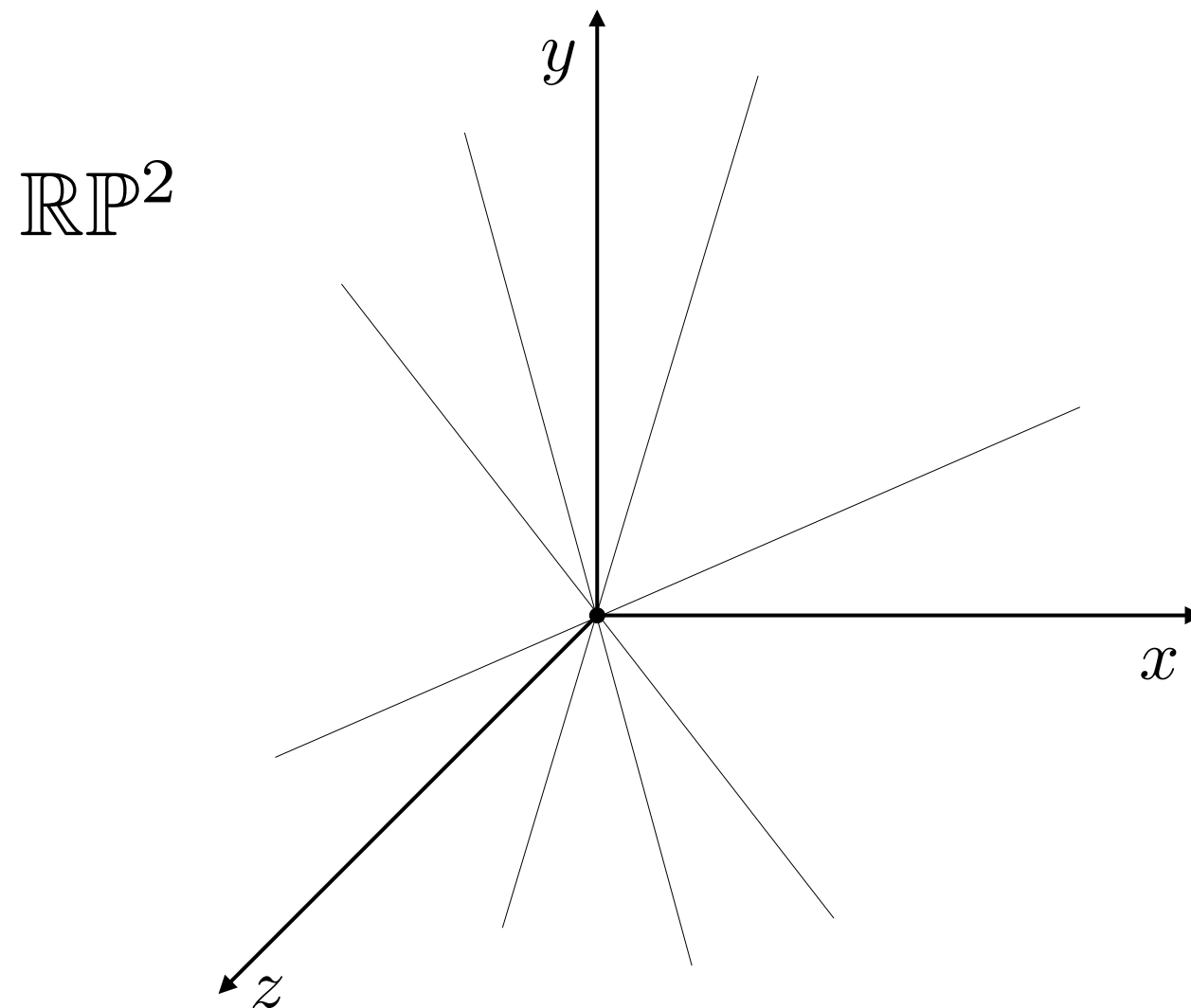
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Define an equivalence relation on nonzero vector in \mathbb{R}^{n+1} as follows:

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- Denote the equivalence class of (x_1, \dots, x_{n+1}) by

$$(x_1 : \dots : x_{n+1})$$

also called homogeneous coordinates.

Examples

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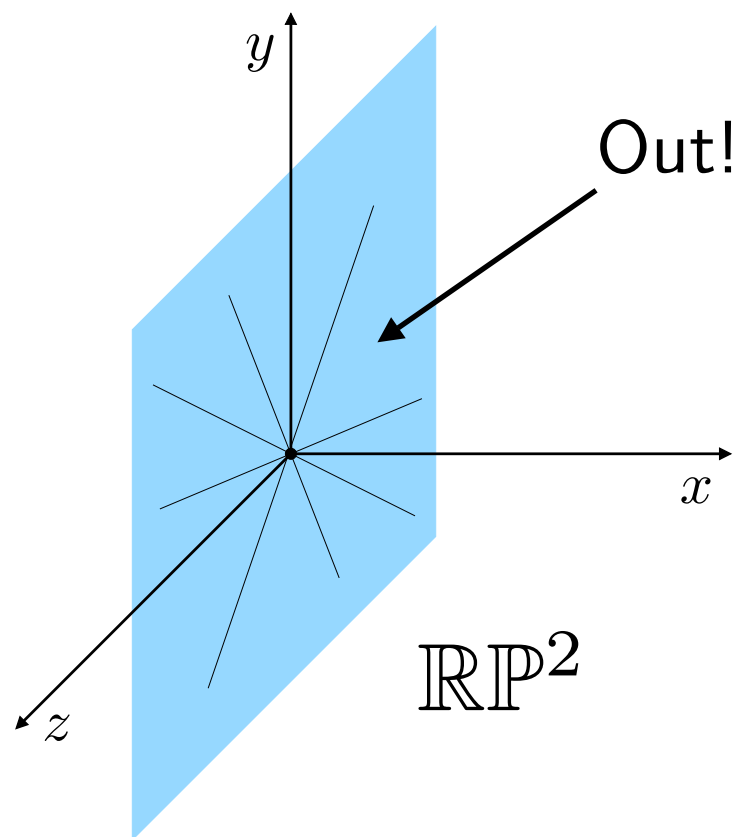
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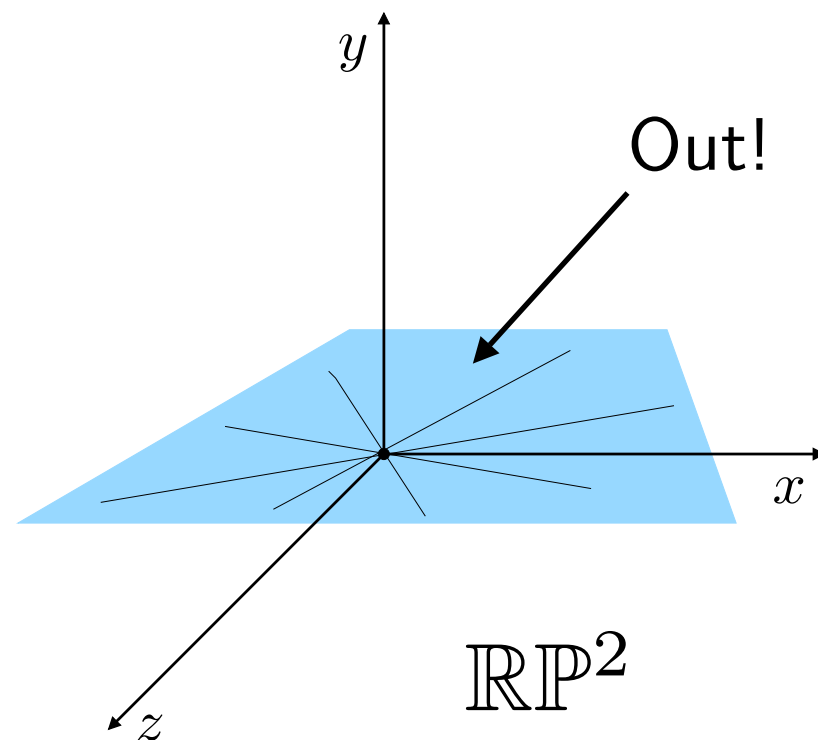
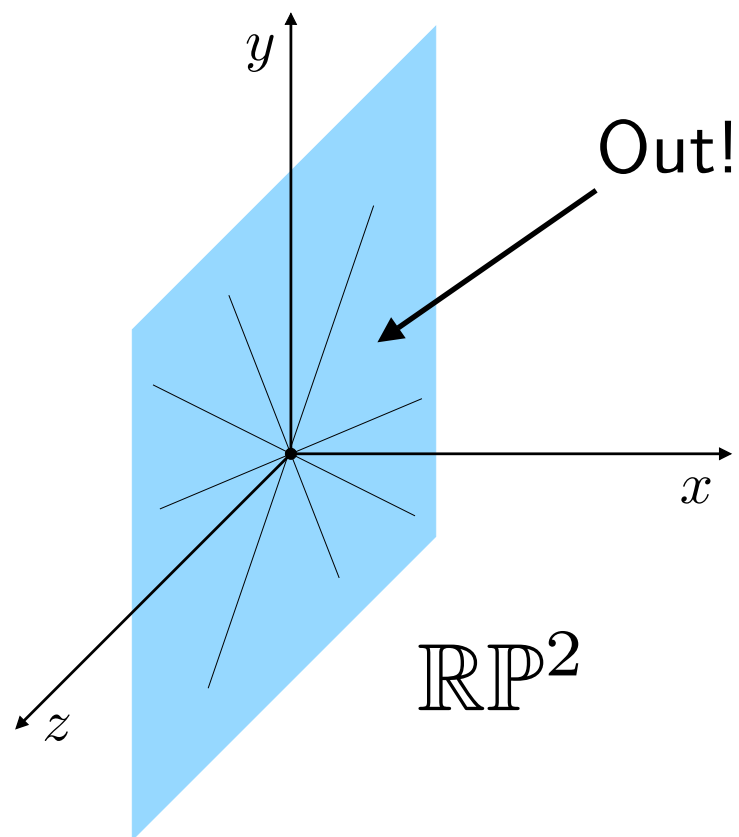


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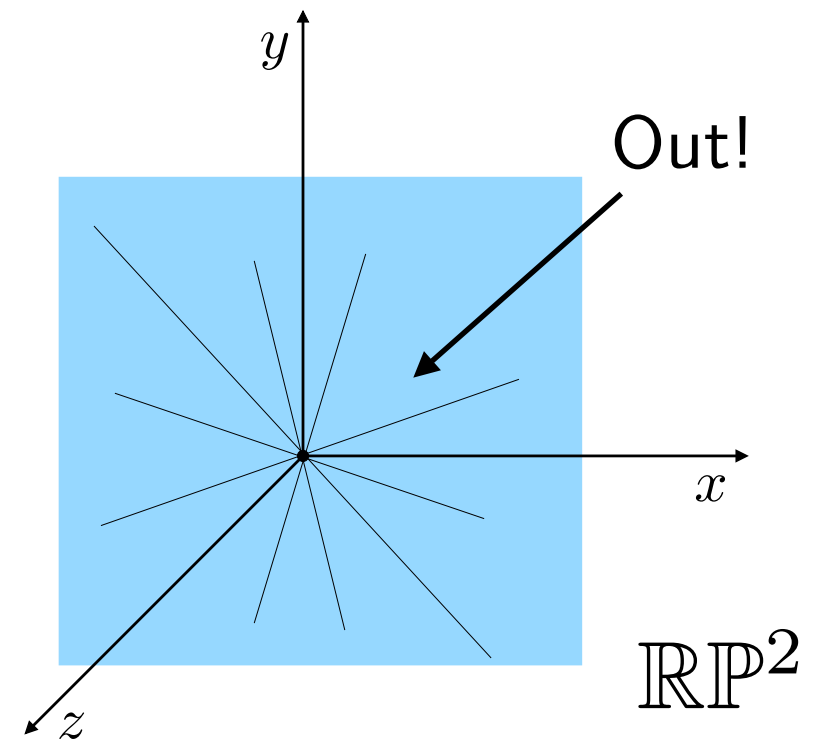
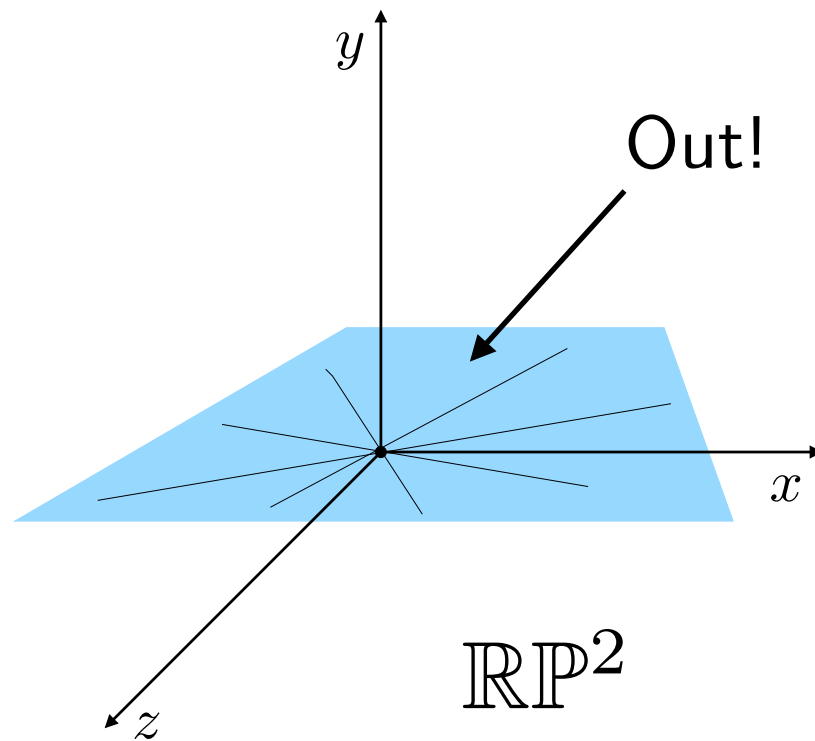
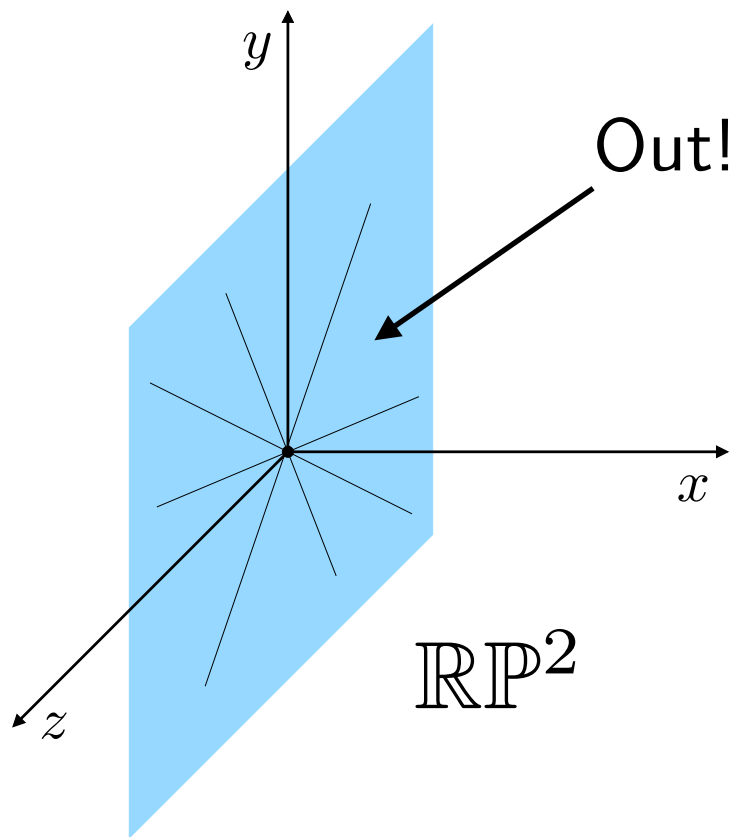
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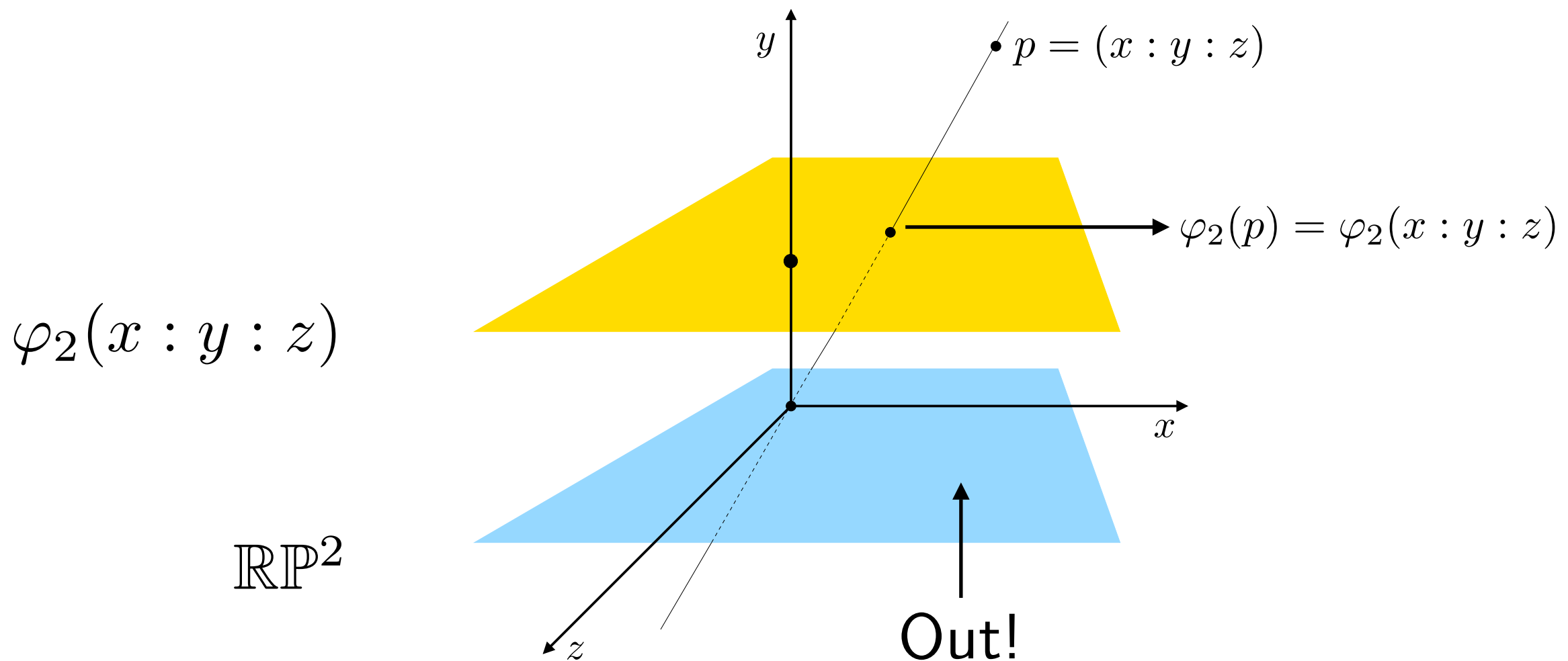
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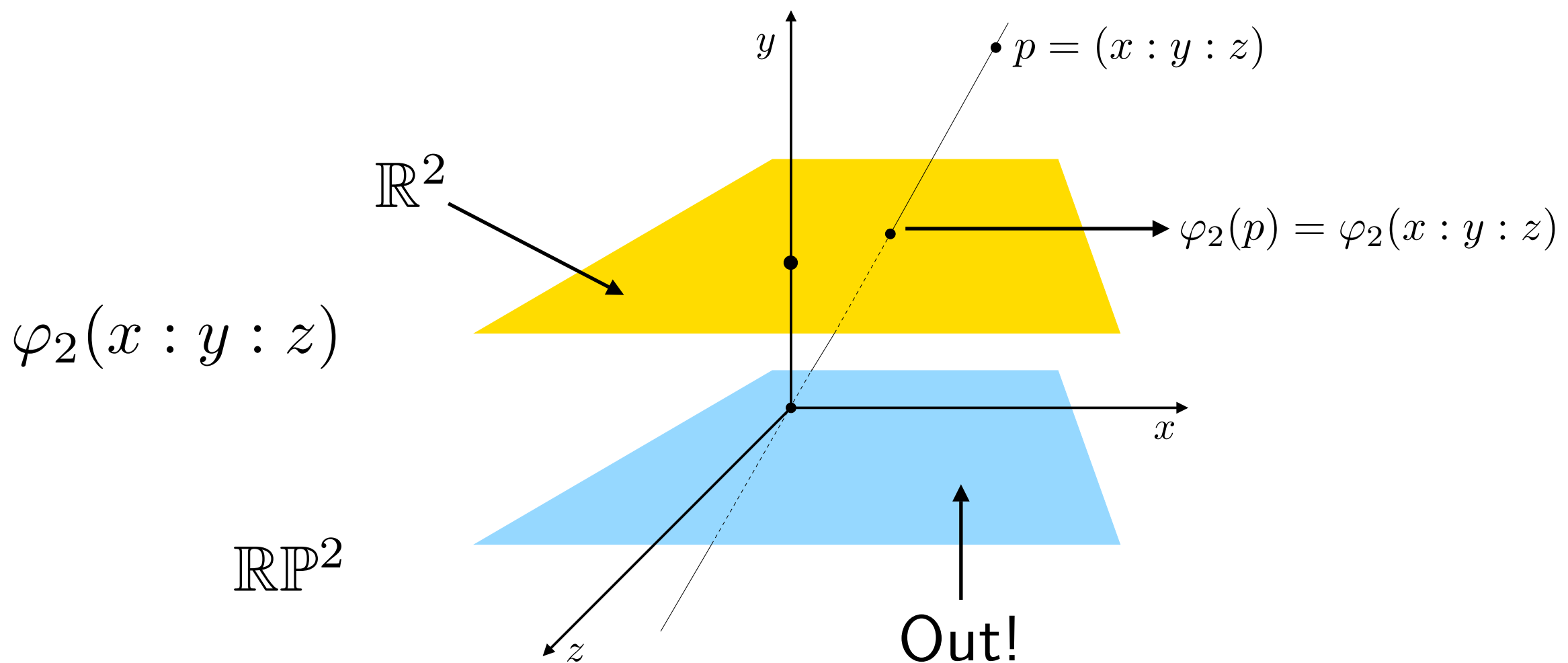
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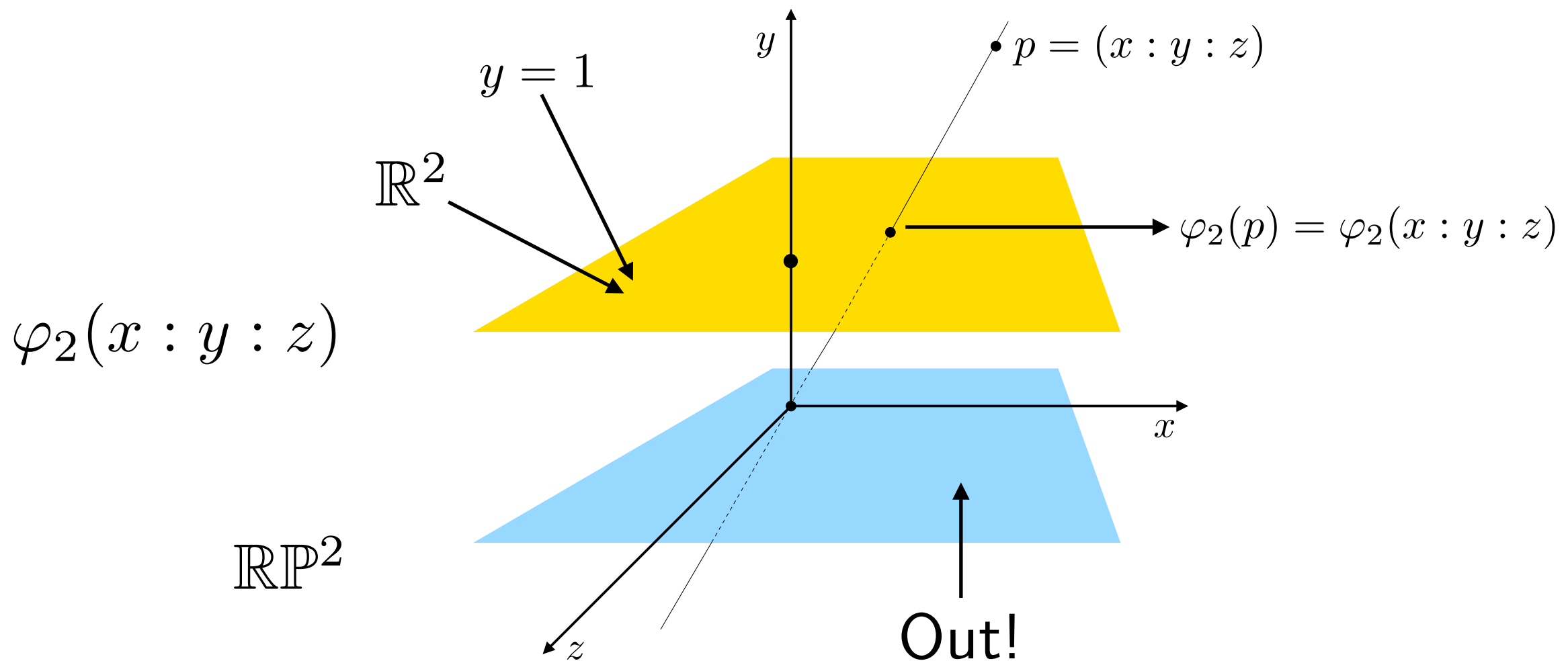
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- As these maps are smooth, real projective space is a smooth manifold.

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- Such a construction was first proposed by Andre Weil around 1944 in his book, *Foundations of Algebraic Geometry*.
- A similar approach was used to construct fiber bundles in the 1950's (Steenrod).

Constructing Manifolds from Sets of Gluing Data

Jean Gallier
UPenn

Outline

- Motivations
- Sets of gluing data
- Transition functions
- The cocycle condition
- Parametric pseudo manifolds (PPM's)
- Conclusions

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- Our plan is to define S constructively by **building a manifold**.

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THE KEY IDEA:

The notion of a **set of gluing data**.

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A set of gluing data is a triple

$$\mathcal{G} = \left((\Omega_i)_{i \in I}, (\Omega_{ij})_{(i,j) \in I \times I}, (\varphi_{ji})_{(i,j) \in K \times K} \right)$$

satisfying the following properties, where I and K are countable sets and I is non-empty:

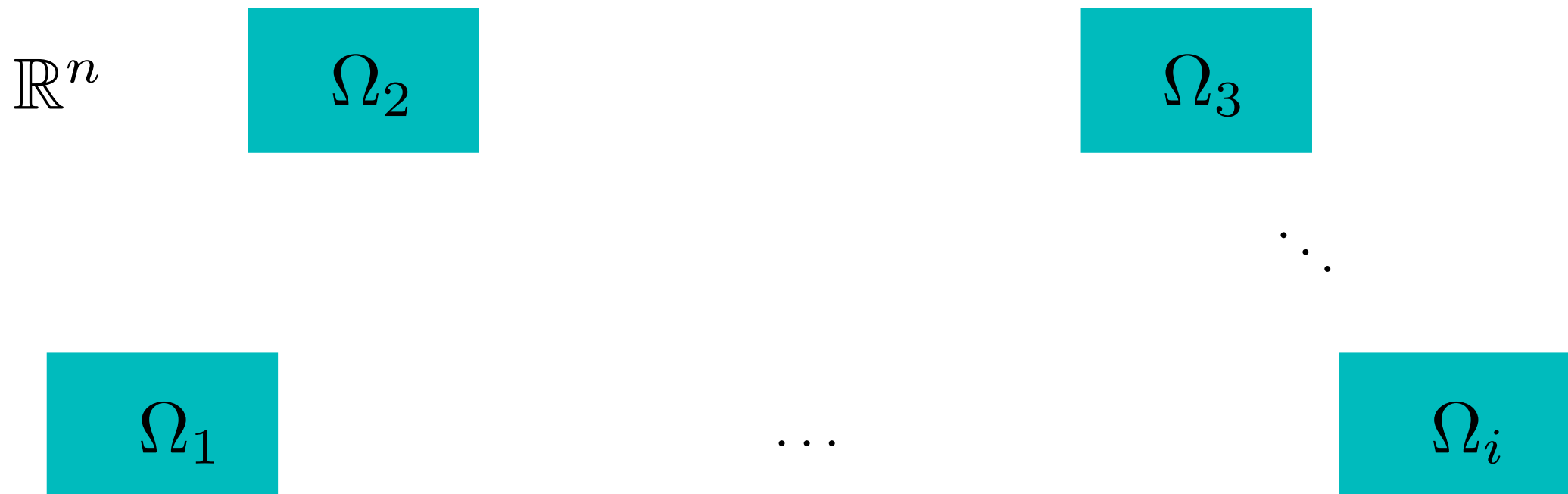
Sets of Gluing Data

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- (1) For every $i \in I$, the set Ω_i is a non-empty open subset of \mathbb{R}^n called **parametrization domain**, for short, **p -domain**, and the Ω_i are pairwise disjoint (i.e., $\Omega_i \cap \Omega_j = \emptyset$ for all $i \neq j$).

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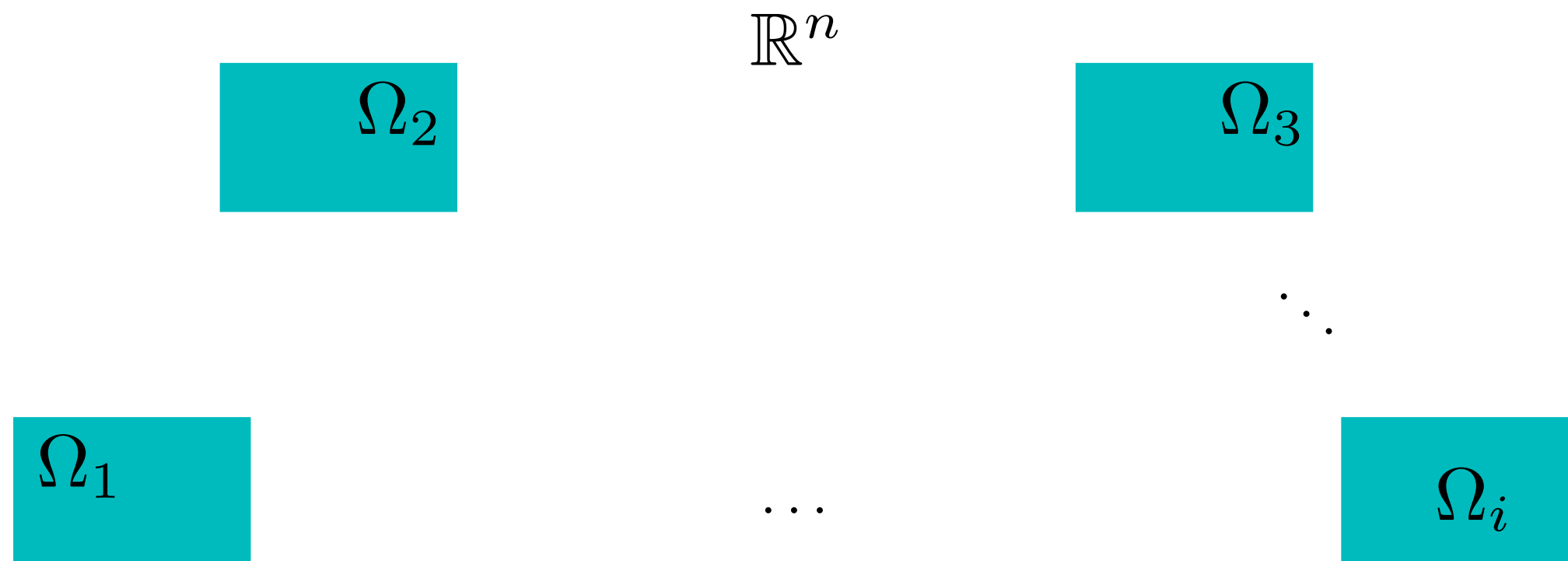
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- (2) For every pair $(i, j) \in I \times I$, the set Ω_{ij} is an open subset of Ω_i . Furthermore, $\Omega_{ii} = \Omega_i$, and $\Omega_{ji} \neq \emptyset$ if and only if $\Omega_{ij} \neq \emptyset$. Each non-empty Ω_{ij} (with $i \neq j$) is called **gluing domain**.

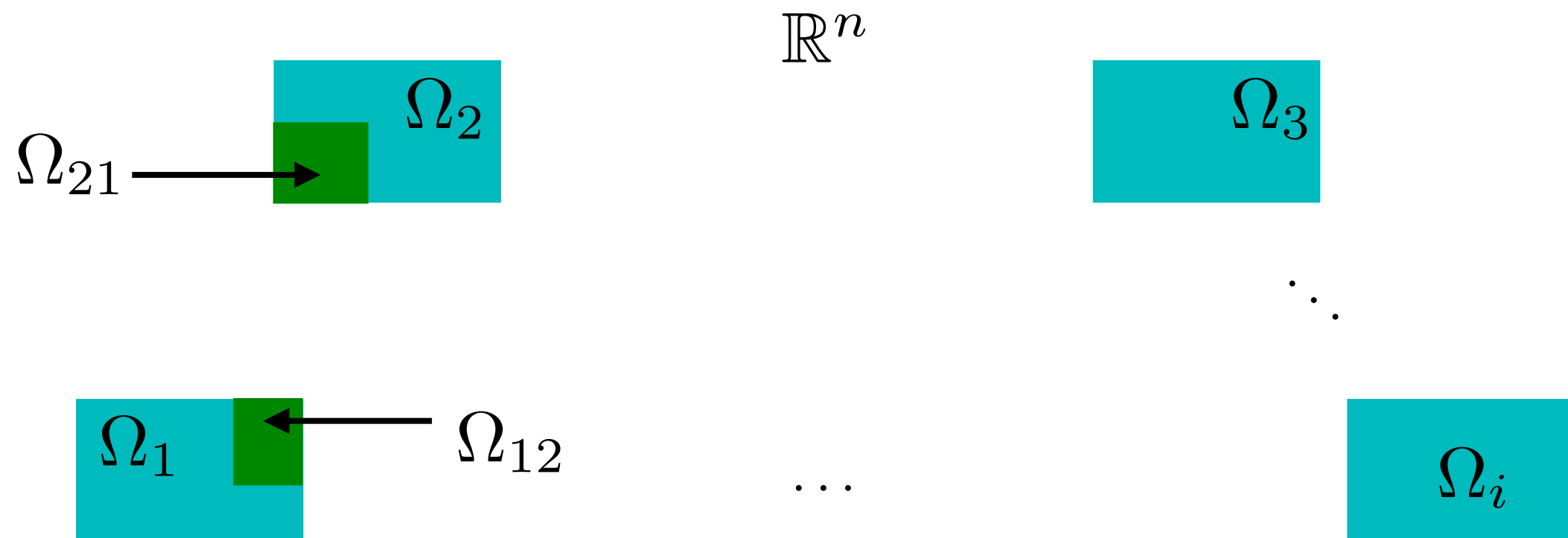
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- (2) For every pair $(i, j) \in I \times I$, the set Ω_{ij} is an open subset of Ω_i . Furthermore, $\Omega_{ii} = \Omega_i$, and $\Omega_{ji} \neq \emptyset$ if and only if $\Omega_{ij} \neq \emptyset$. Each non-empty Ω_{ij} (with $i \neq j$) is called **gluing domain**.



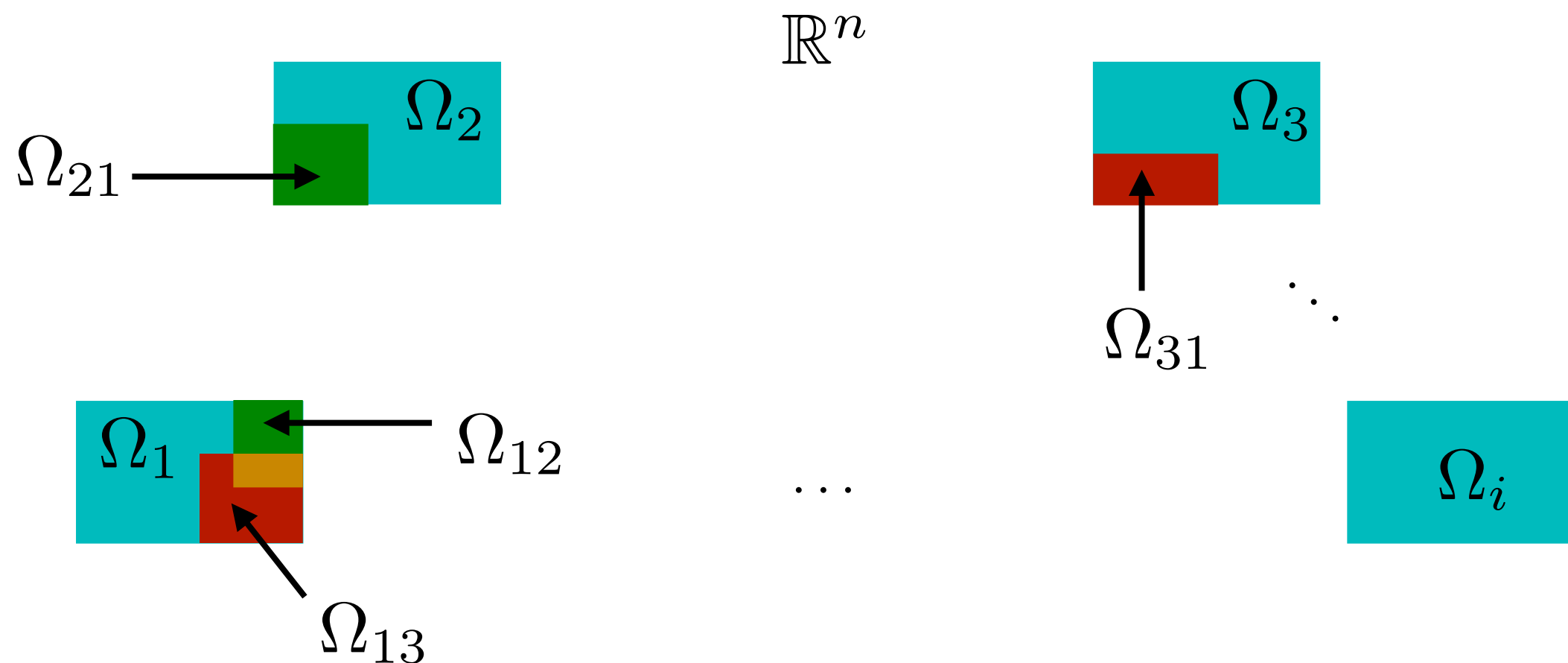
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Sets of Gluing Data

Sets of Gluing Data

(3) If we let

$$K = \{(i, j) \in I \times I \mid \Omega_{ij} \neq \emptyset\},$$

then

$$\varphi_{ji} : \Omega_{ij} \longrightarrow \Omega_{ji}$$

is a C^k bijection for every $(i, j) \in K$, called a **transition function** or **gluing function**.

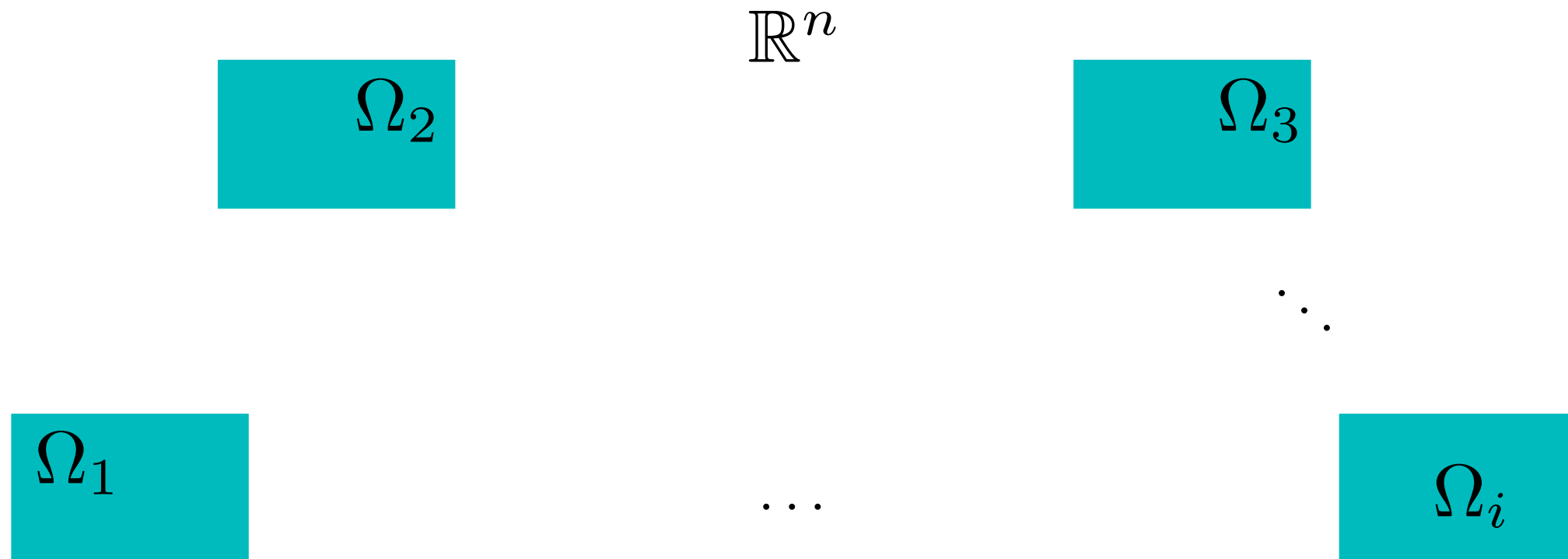
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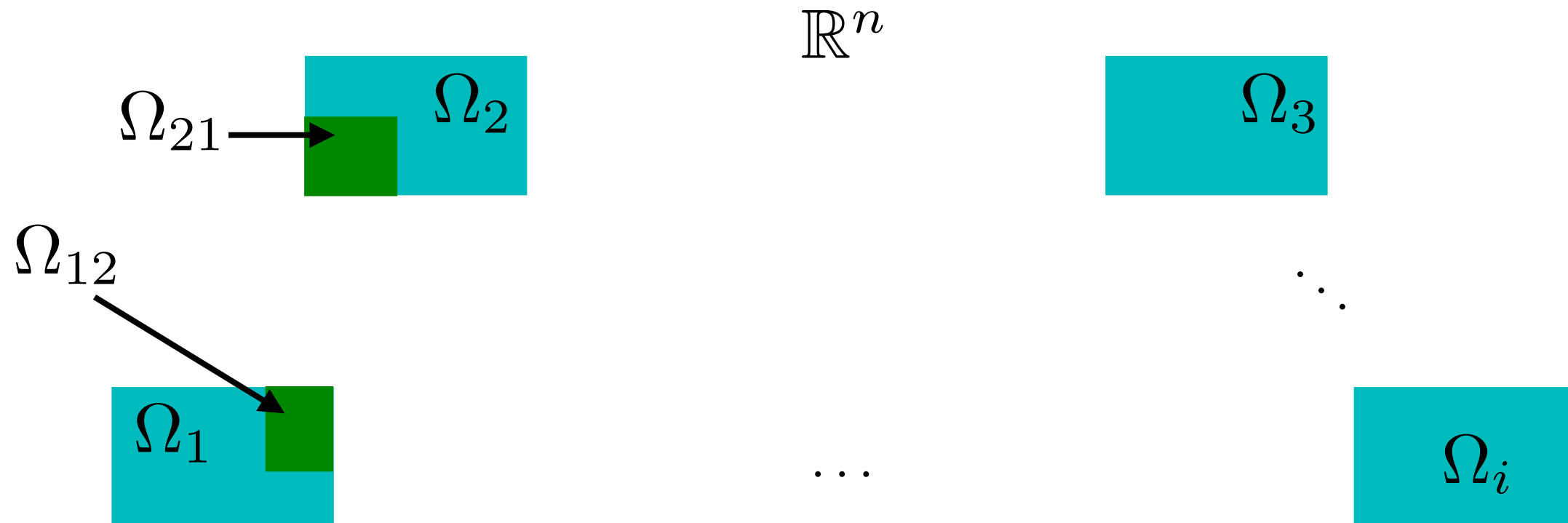
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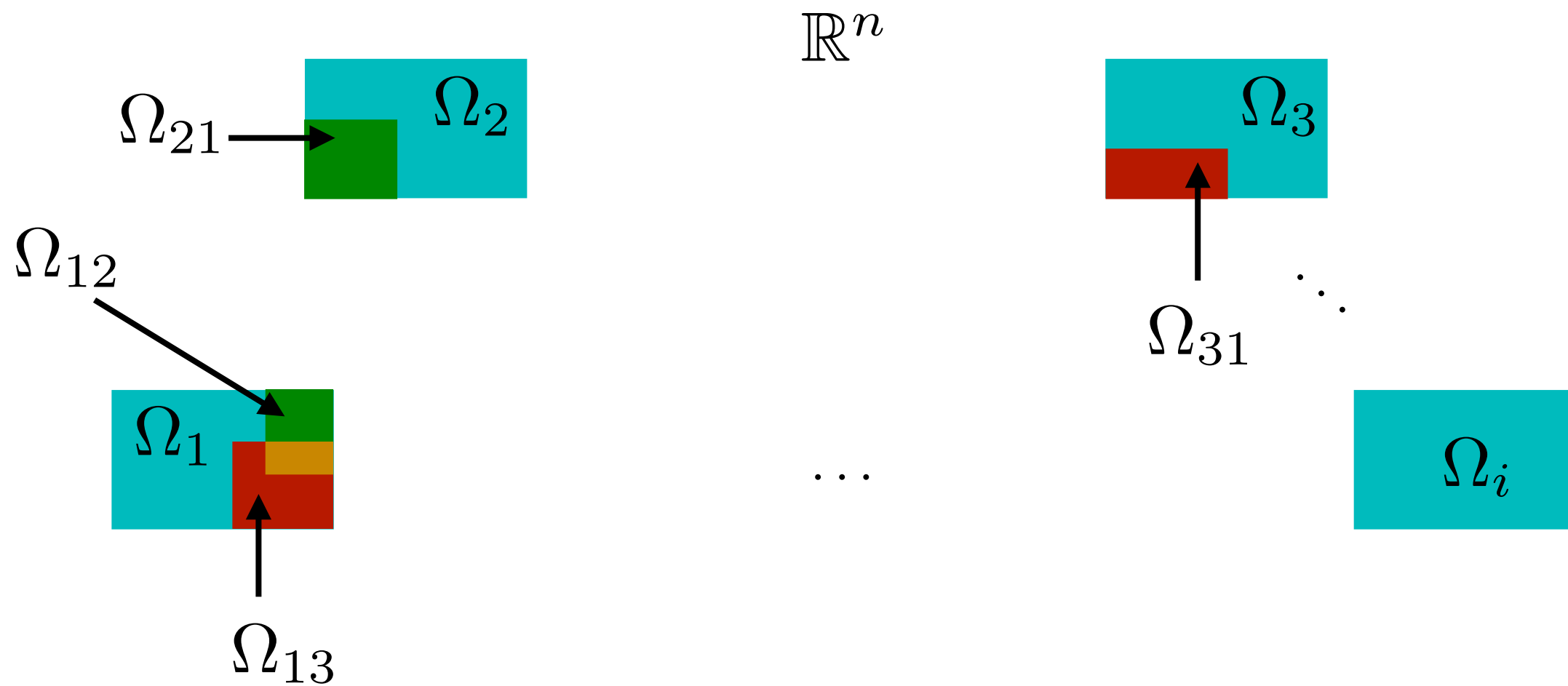
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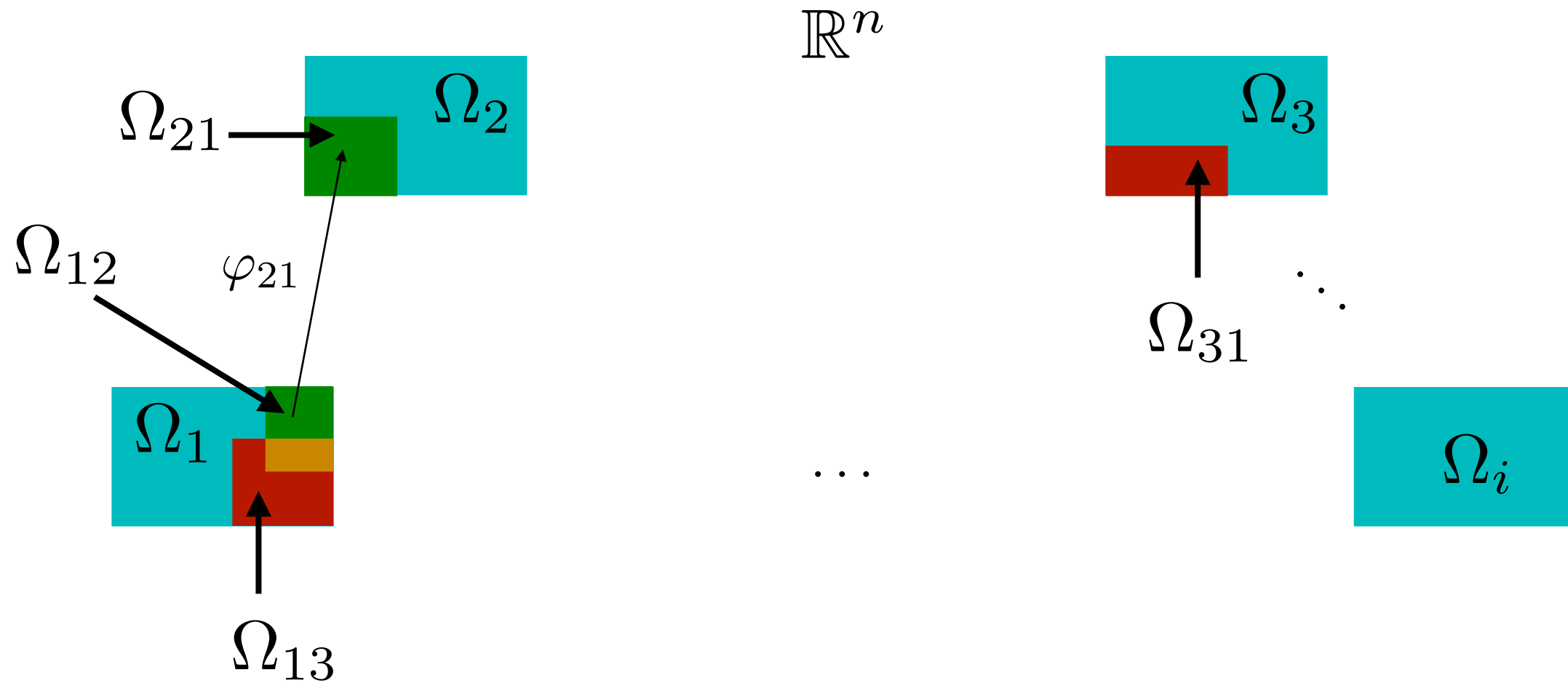
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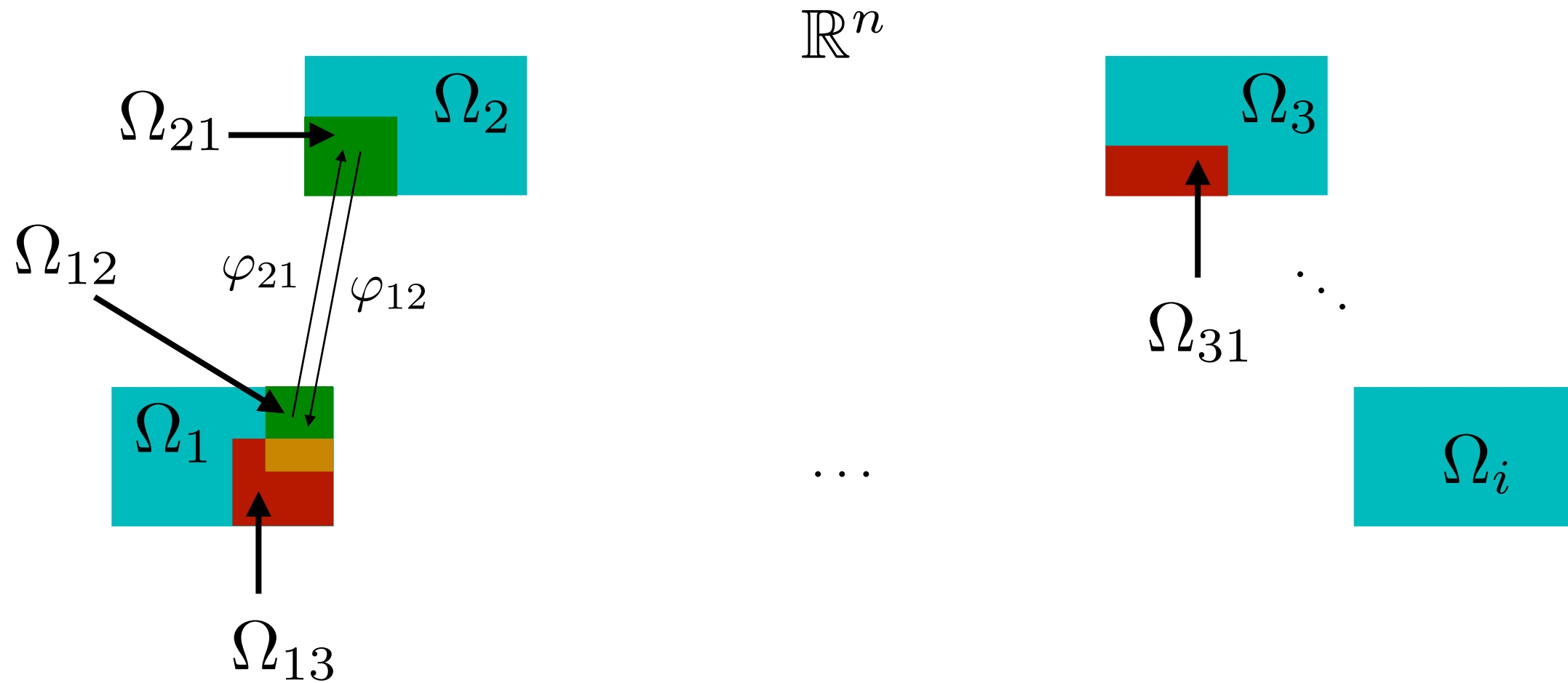
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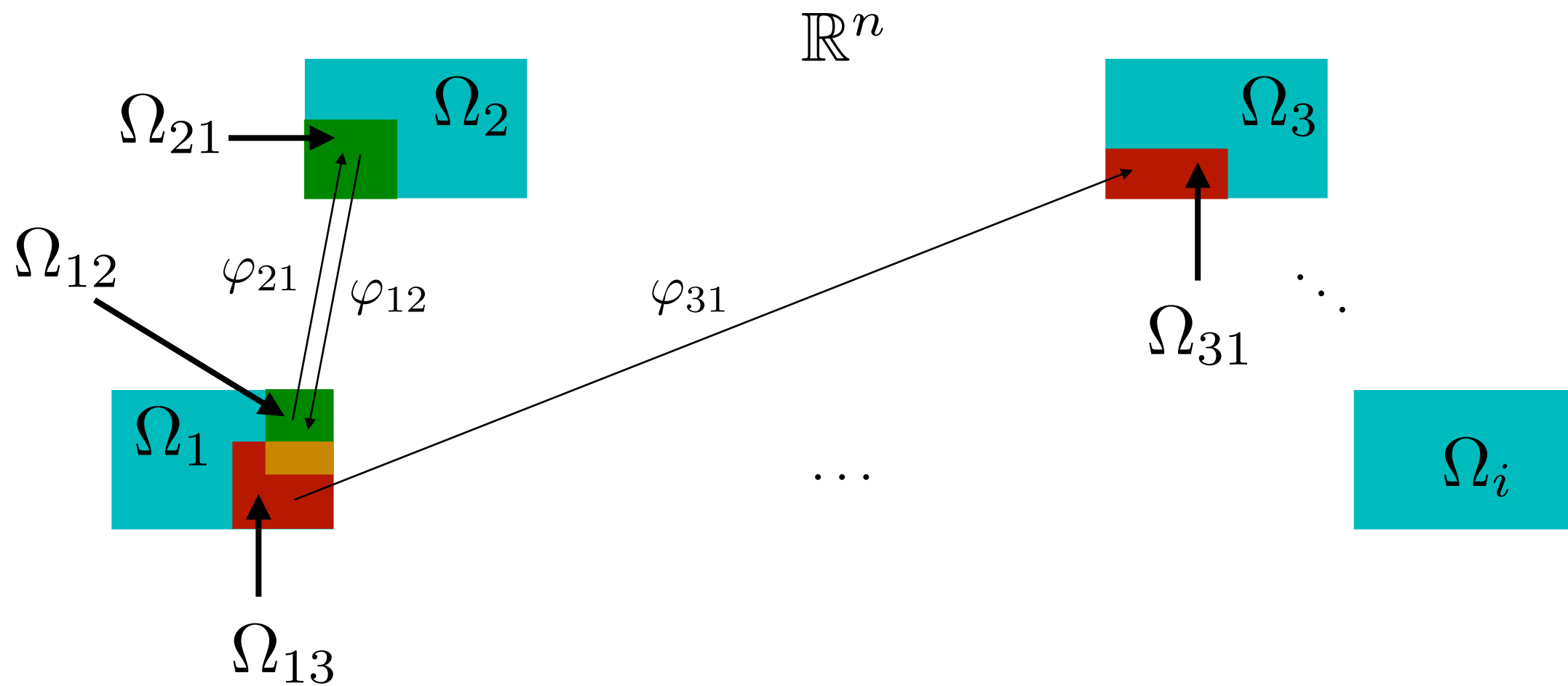
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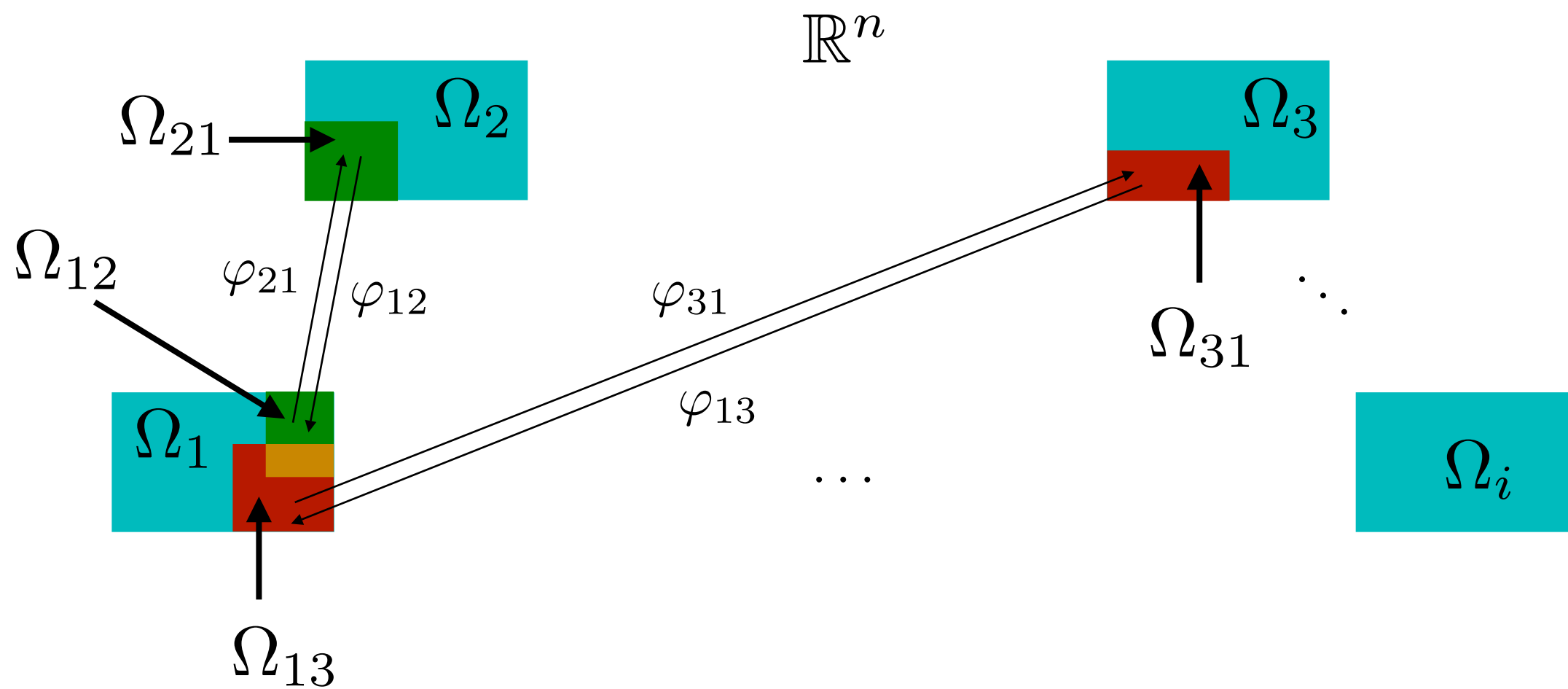
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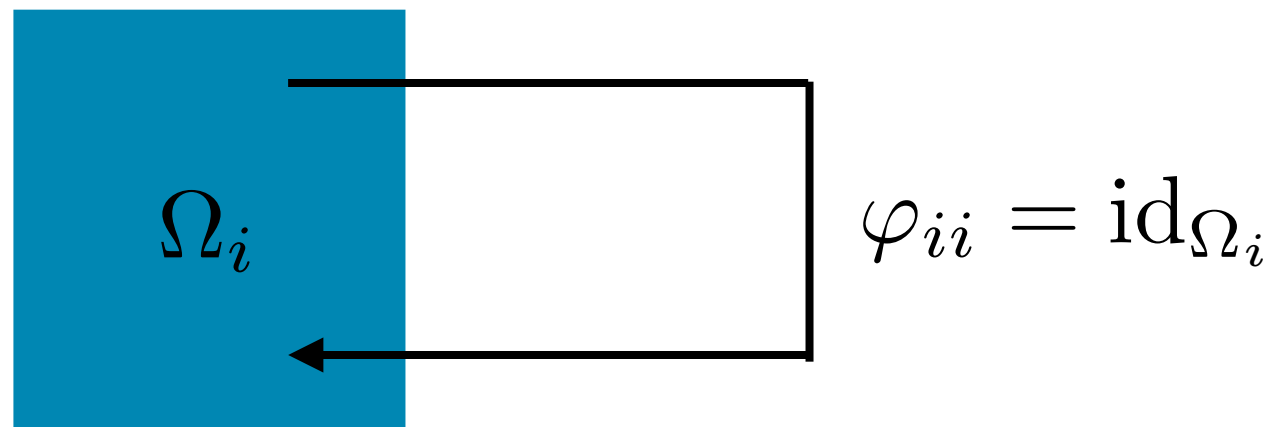
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(a) $\varphi_{ii} = \text{id}_{\Omega_i}$, for all $i \in I$,



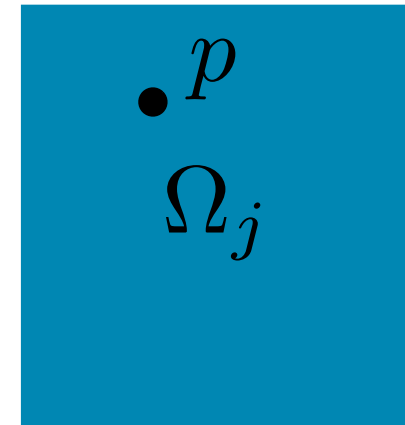
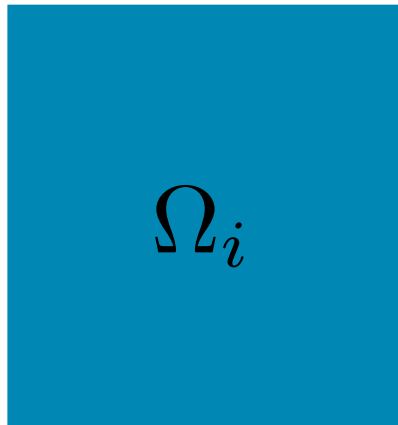
Transition Functions

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(b) $\varphi_{ij} = \varphi_{ji}^{-1}$, for all $(i, j) \in K$, and

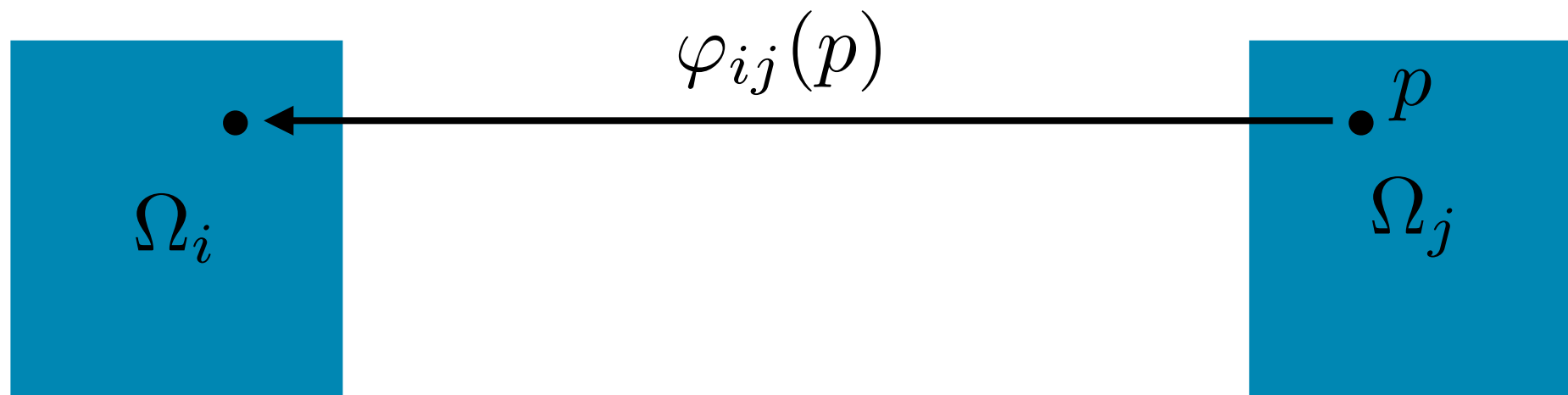
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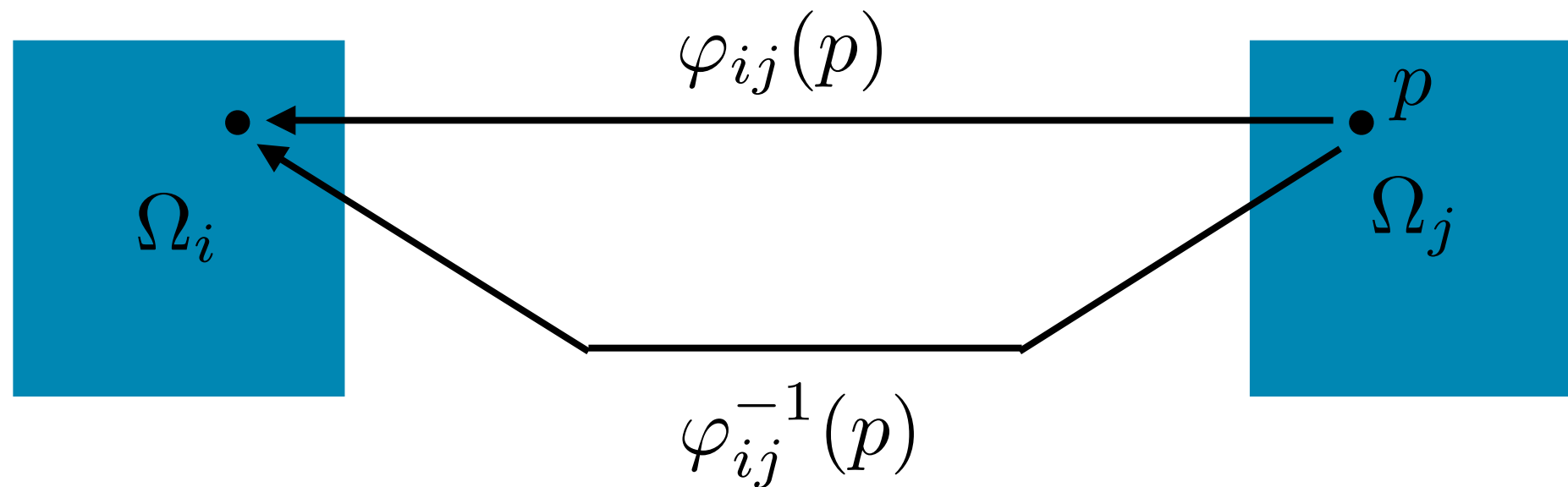
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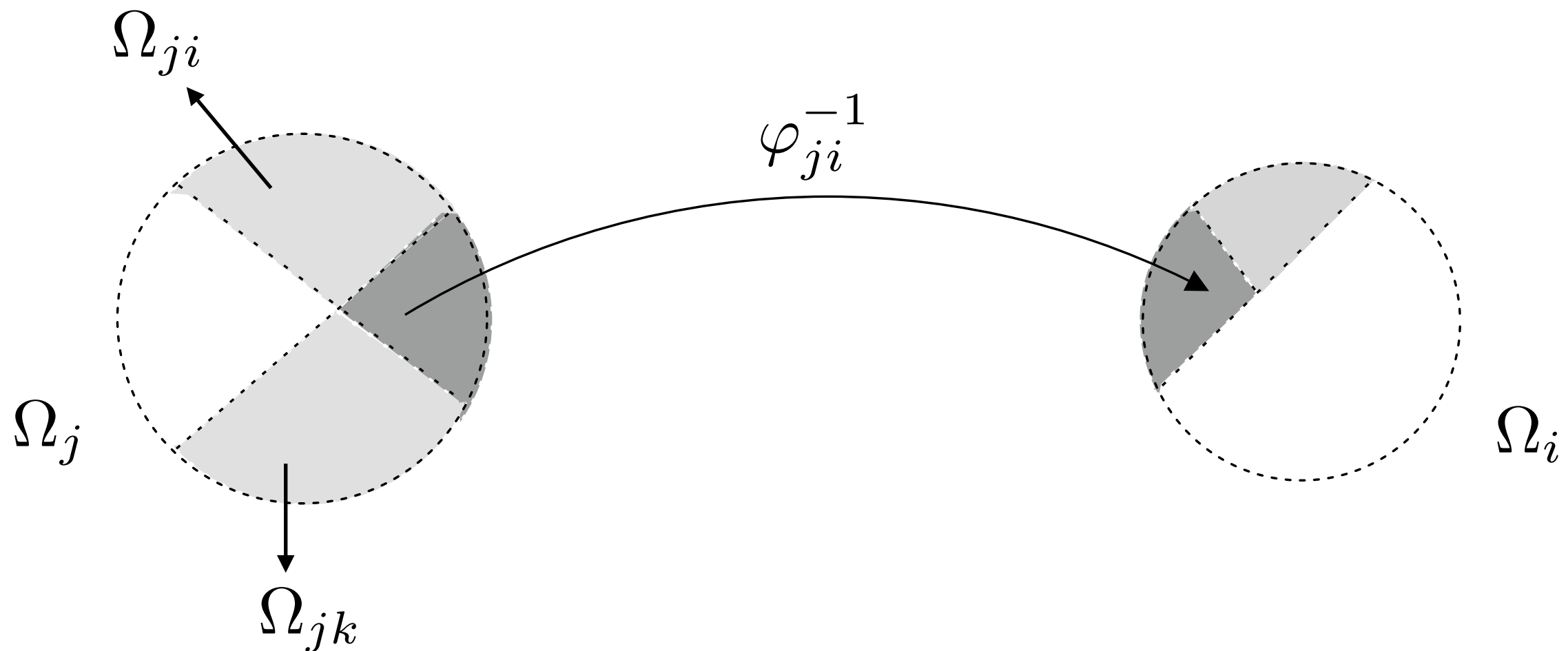
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(c) for all i, j , and k , if $\Omega_{ji} \cap \Omega_{jk} \neq \emptyset$ then $\varphi_{ji}^{-1}(\Omega_{ji} \cap \Omega_{jk}) \subseteq \Omega_{ik}$ and $\varphi_{ki}(x) = \varphi_{kj} \circ \varphi_{ji}(x)$, for all $x \in \varphi_{ji}^{-1}(\Omega_{ji} \cap \Omega_{jk})$.

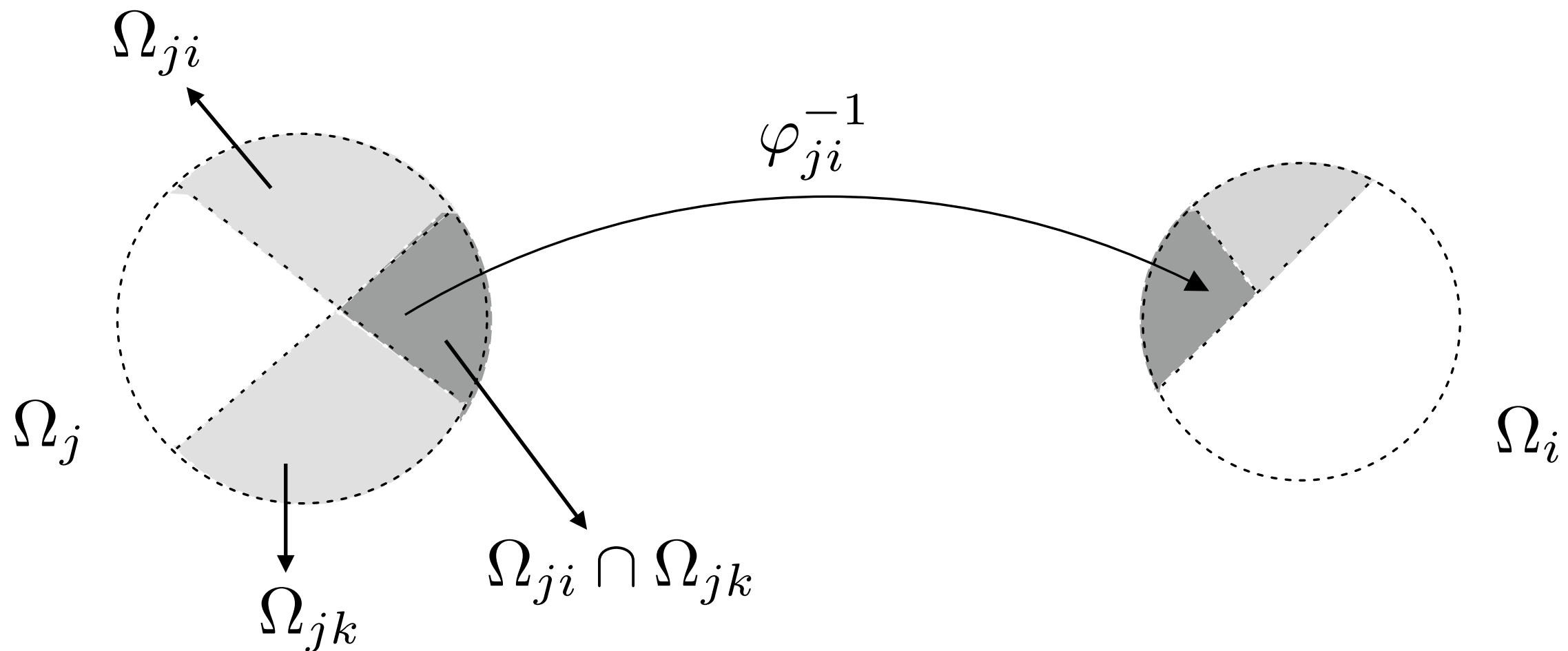
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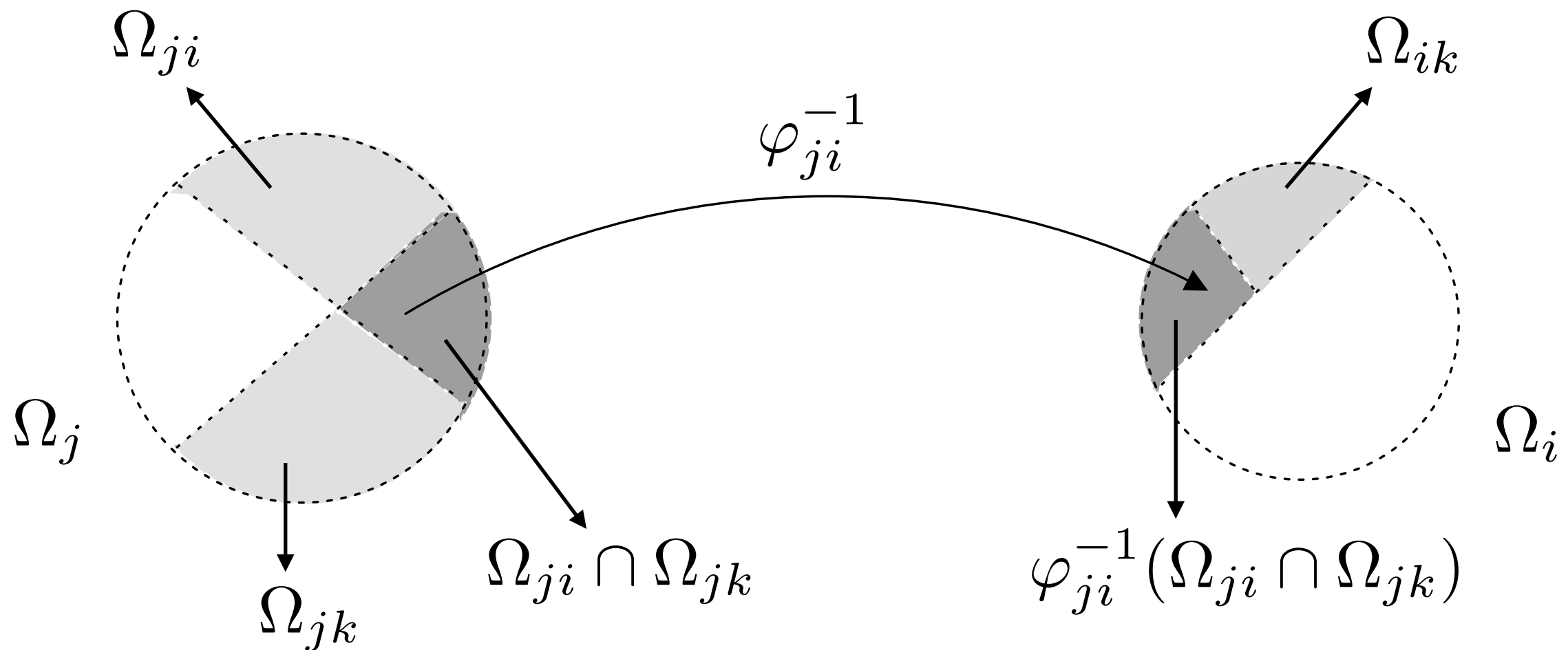
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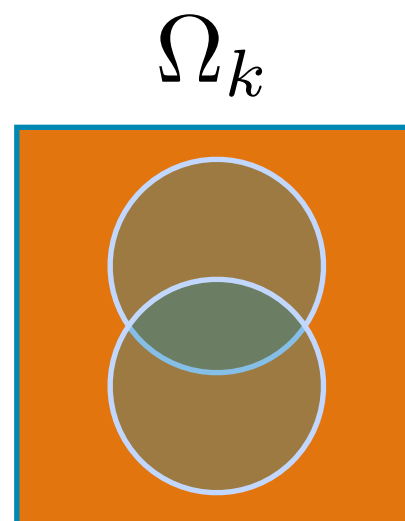
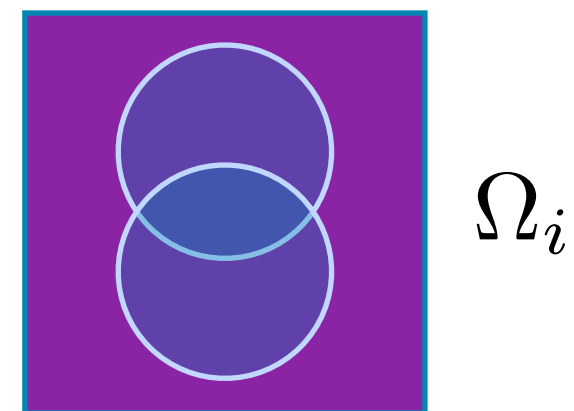
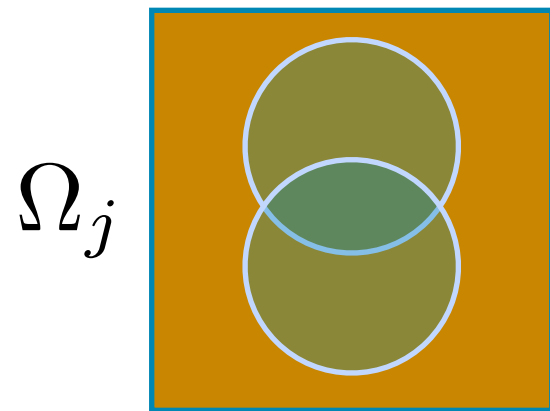
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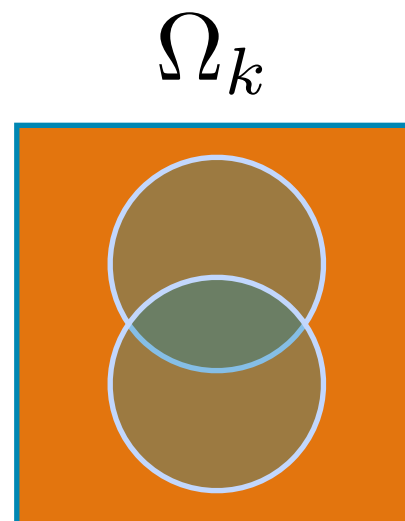
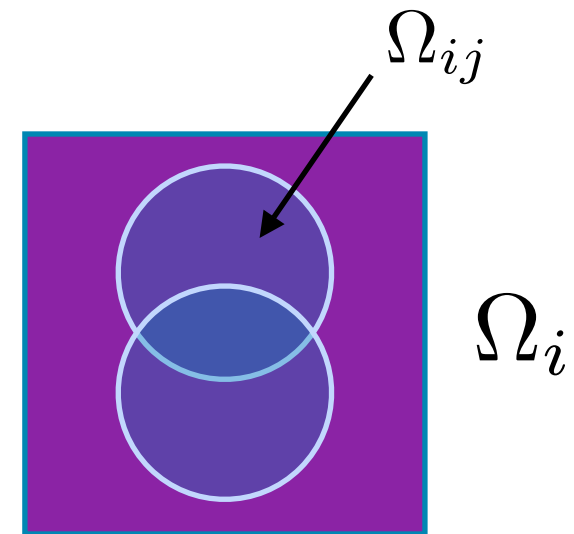
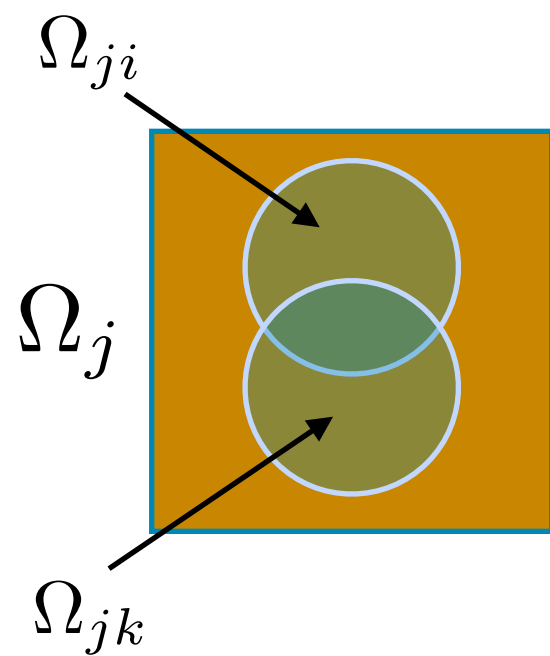
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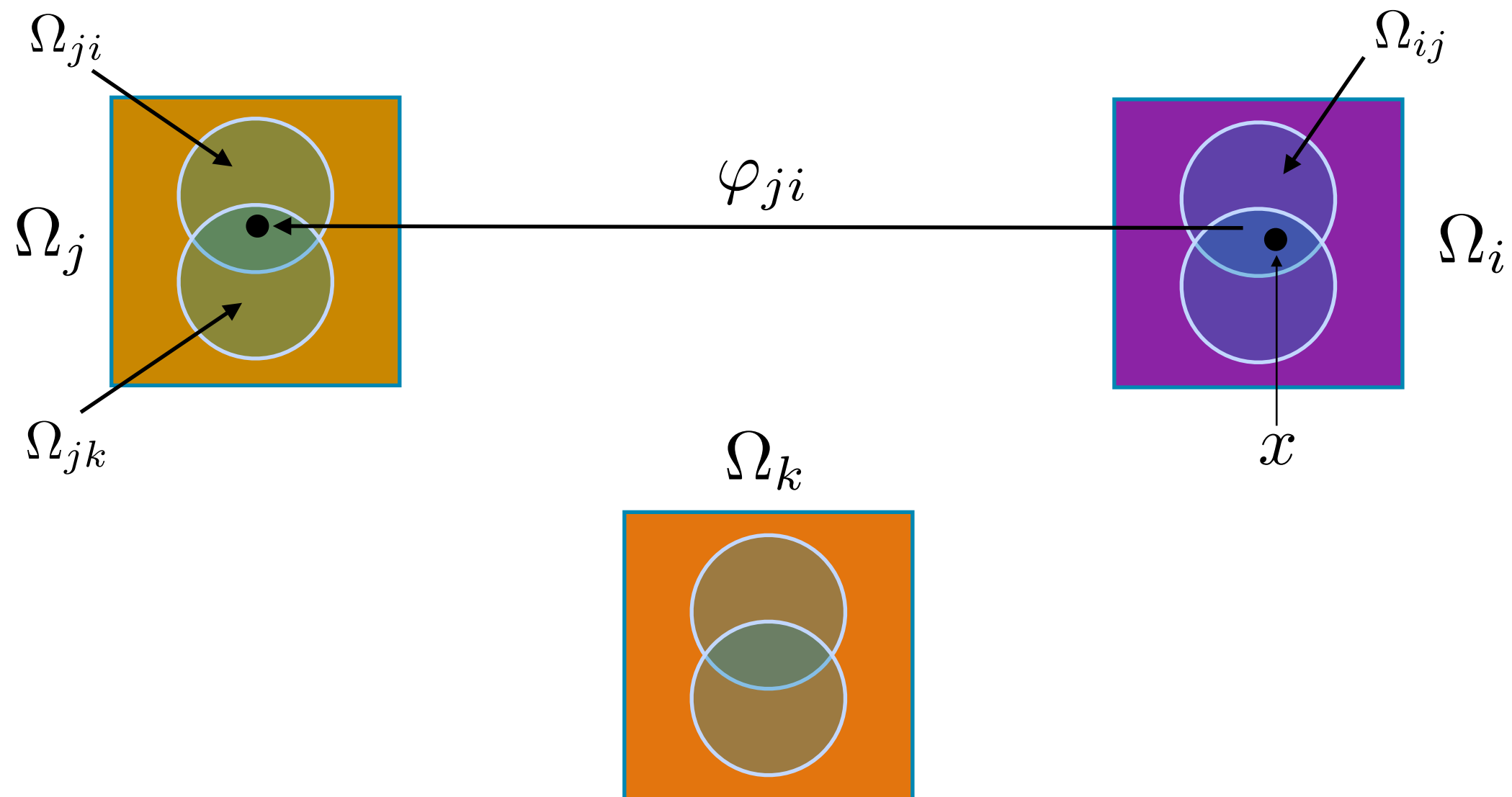
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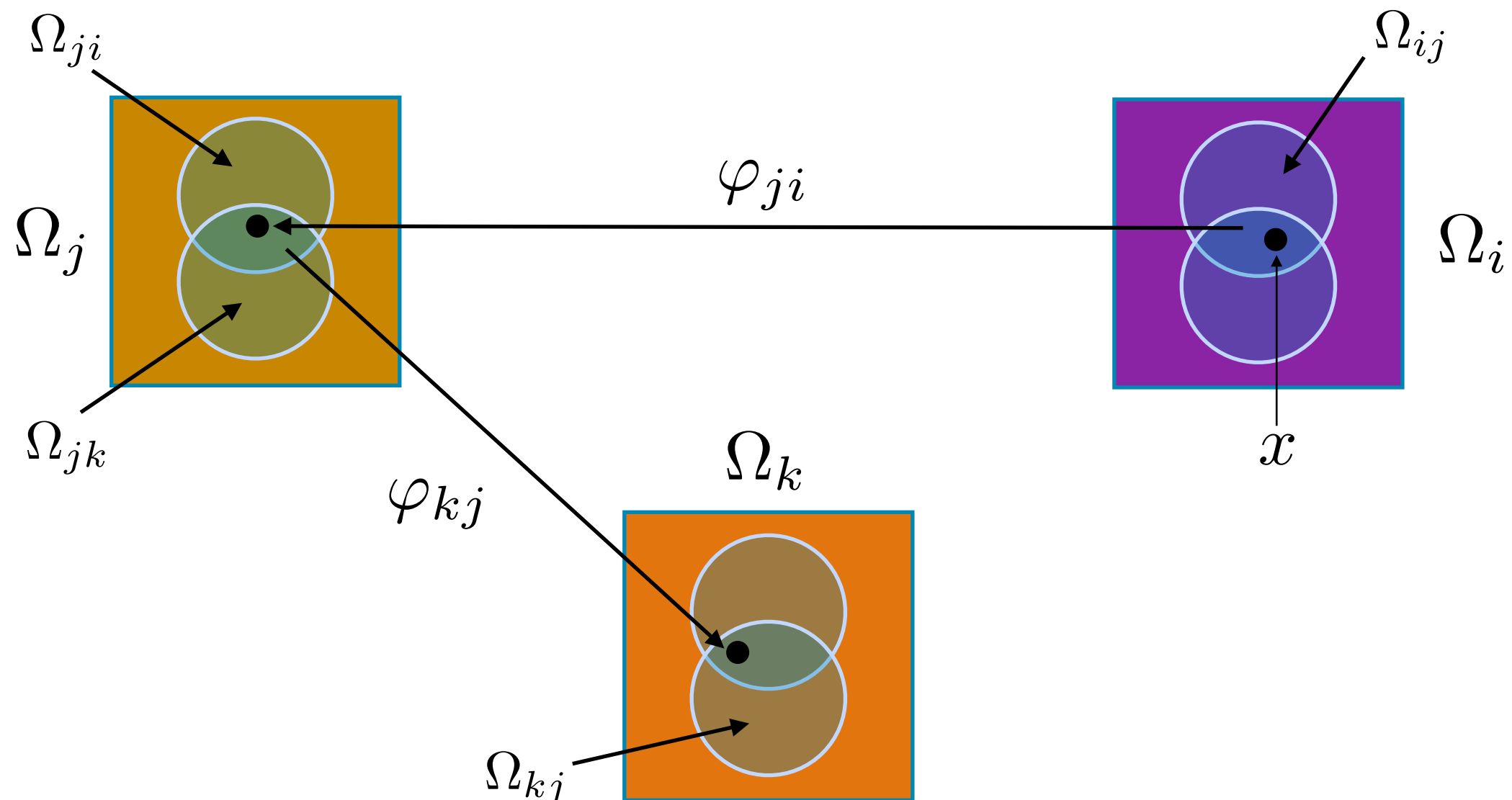
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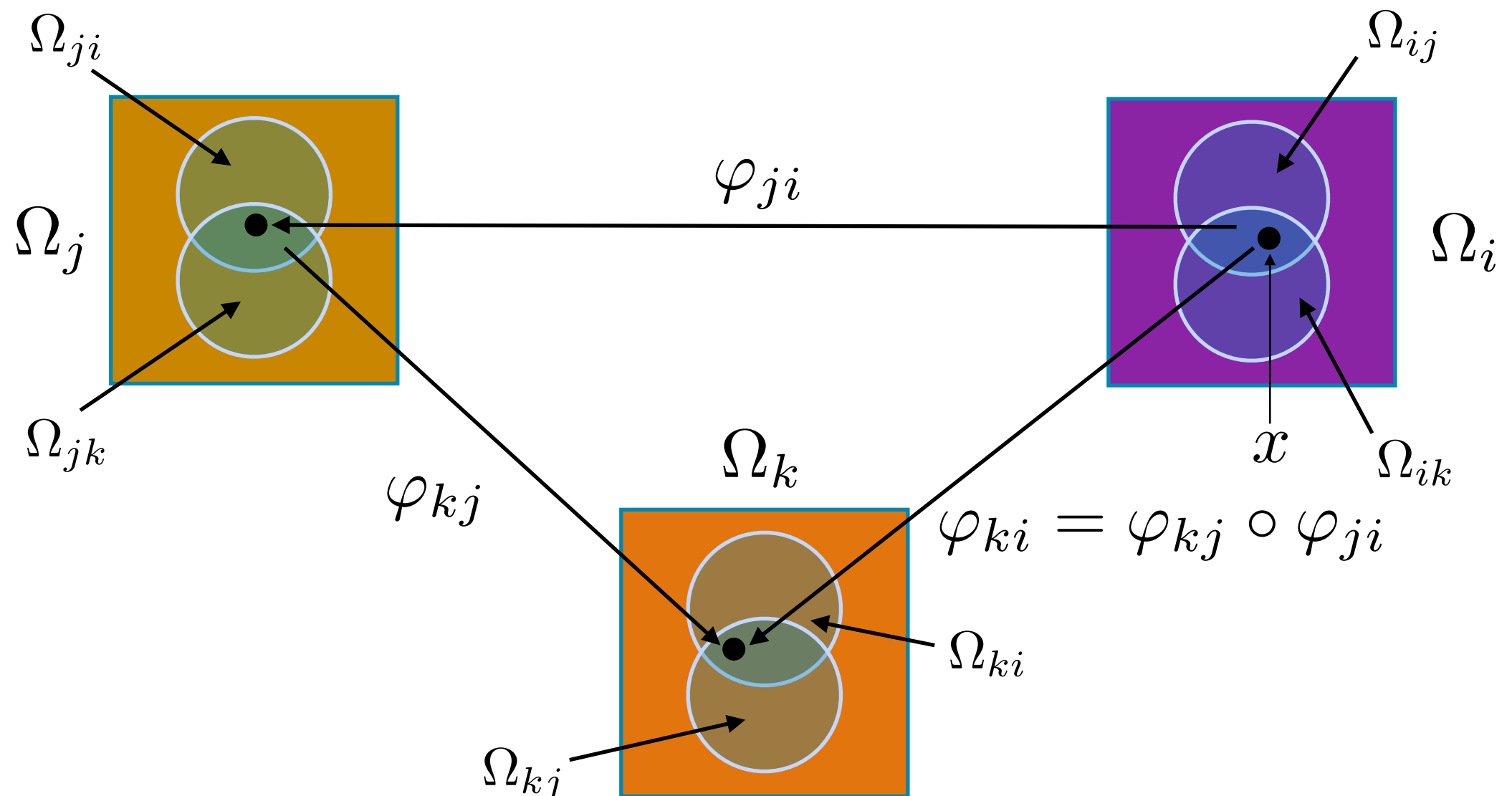
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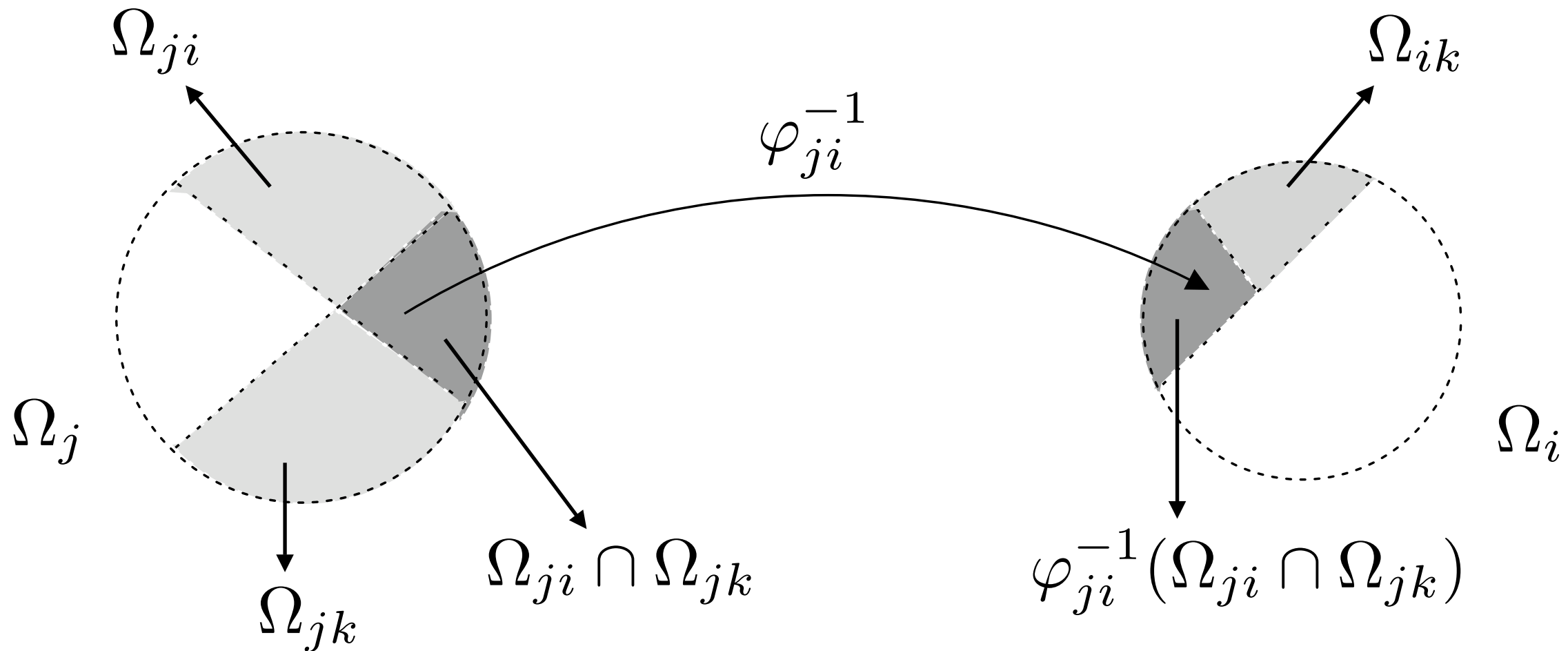
- The cocycle condition implies conditions (a) and (b).
- Previous versions found in the literature are often incorrect.

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- Indeed, such a manifold is built by a **quotient construction**.
- We form the disjoint union of the Ω_i and we identify Ω_{ij} with Ω_{ji} using φ_{ji} , an equivalence relation, \sim . We form the quotient

$$M_{\mathcal{G}} = \left(\coprod_i \Omega_i \right) / \sim, .$$

Parametric Pseudo-Manifolds

Parametric Pseudo-Manifolds

Theorem 1 [Gallier, Siqueira, and Xu, 2008]

For every set of gluing data,

$$\mathcal{G} = \left((\Omega_i)_{i \in I}, (\Omega_{ij})_{(i,j) \in I \times I}, (\varphi_{ji})_{(i,j) \in K \times K} \right),$$

there is an n -dimensional C^k manifold, $M_{\mathcal{G}}$, whose transition functions are the φ_{ji} 's.

Parametric Pseudo-Manifolds

Parametric Pseudo-Manifolds

REMARK:

A condition on the gluing data is needed to make sure that $M_{\mathcal{G}}$ is Hausdorff. Since it is quite technical, we will not show it here.

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So, the question that remains is **how** to build a *concrete* manifold.

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So, the question that remains is **how** to build a *concrete* manifold.

Let us first formalize our notion of “concreteness”.

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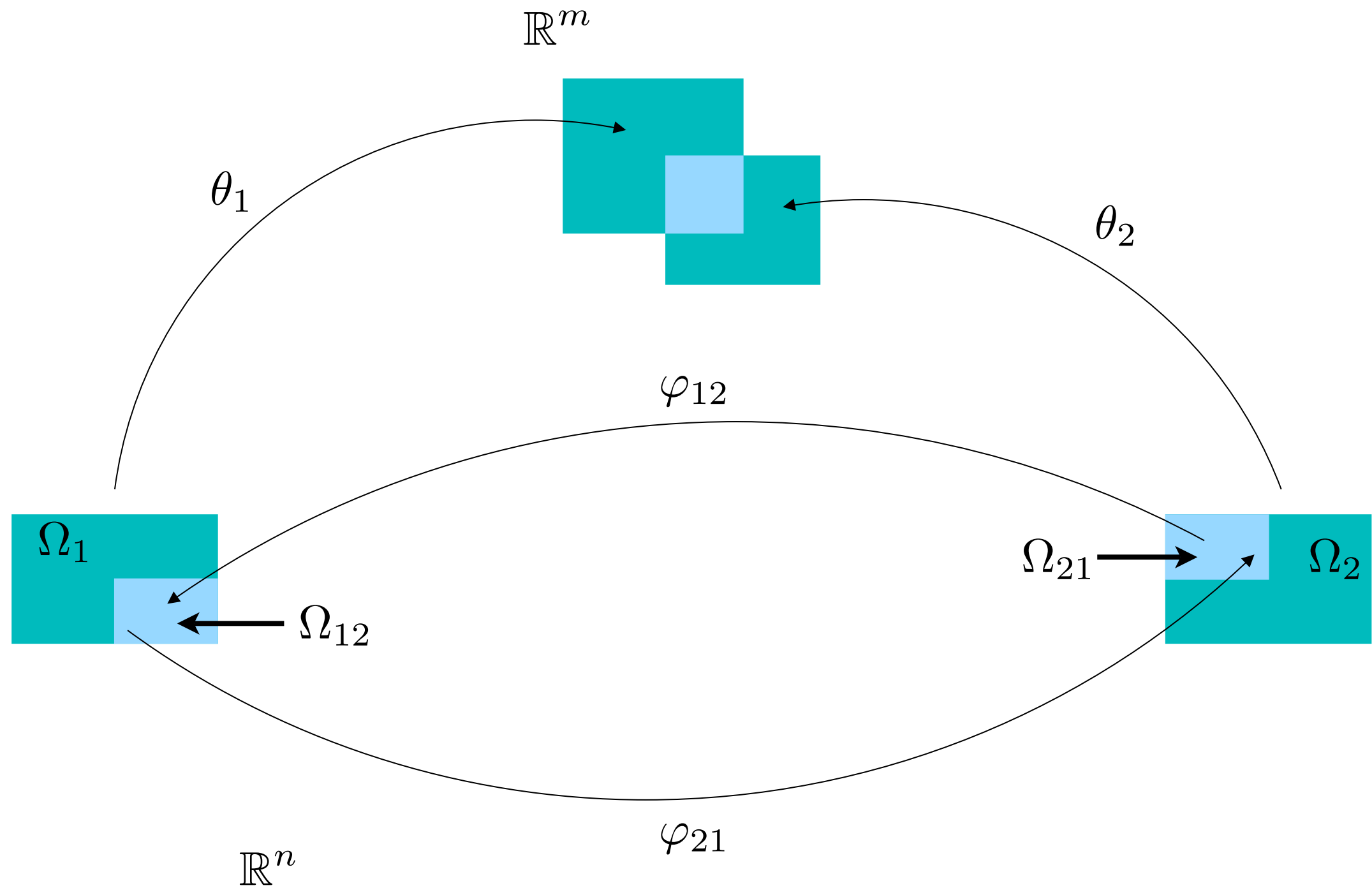
A **parametric C^k pseudo-manifold of dimension n in \mathbb{R}^m** is a pair,

$$\mathcal{M} = (\mathcal{G}, (\theta_i)_{i \in I}) ,$$

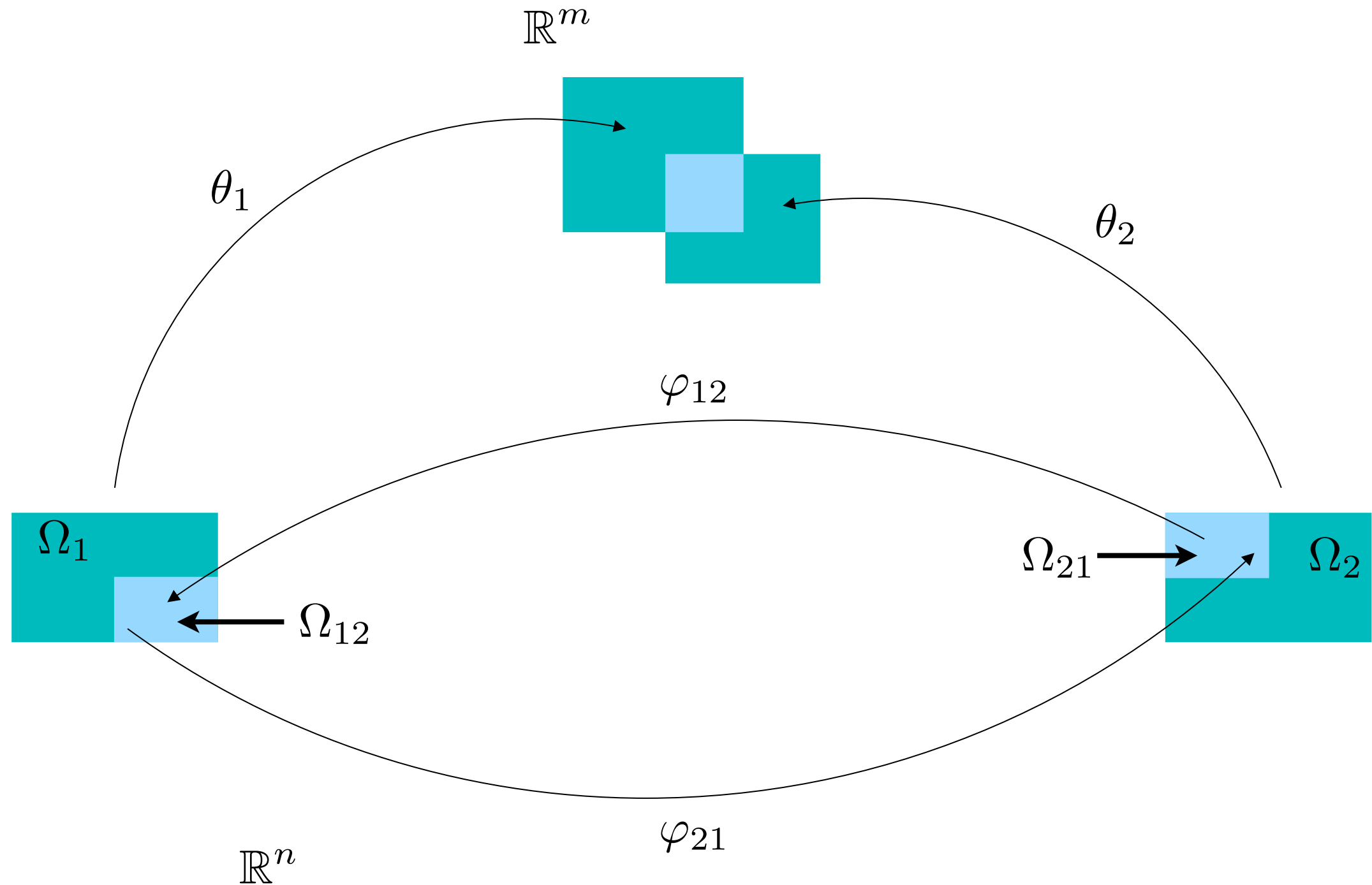
such that $\mathcal{G} = ((\Omega_i)_{i \in I}, (\Omega_{ij})_{(i,j) \in I \times I}, (\varphi_{ij})_{(i,j) \in K \times K})$ is a set of gluing data, for some finite I , and each θ_i is a C^k function, $\theta_i : \Omega_i \rightarrow \mathbb{R}^m$, called a **parametrization** such that the following holds:

Parametric Pseudo-Manifolds

Parametric Pseudo-Manifolds



Parametric Pseudo-Manifolds



- When $m = 3$ and $n = 2$, we say that \mathcal{M} is a **parametric pseudo-surface**.

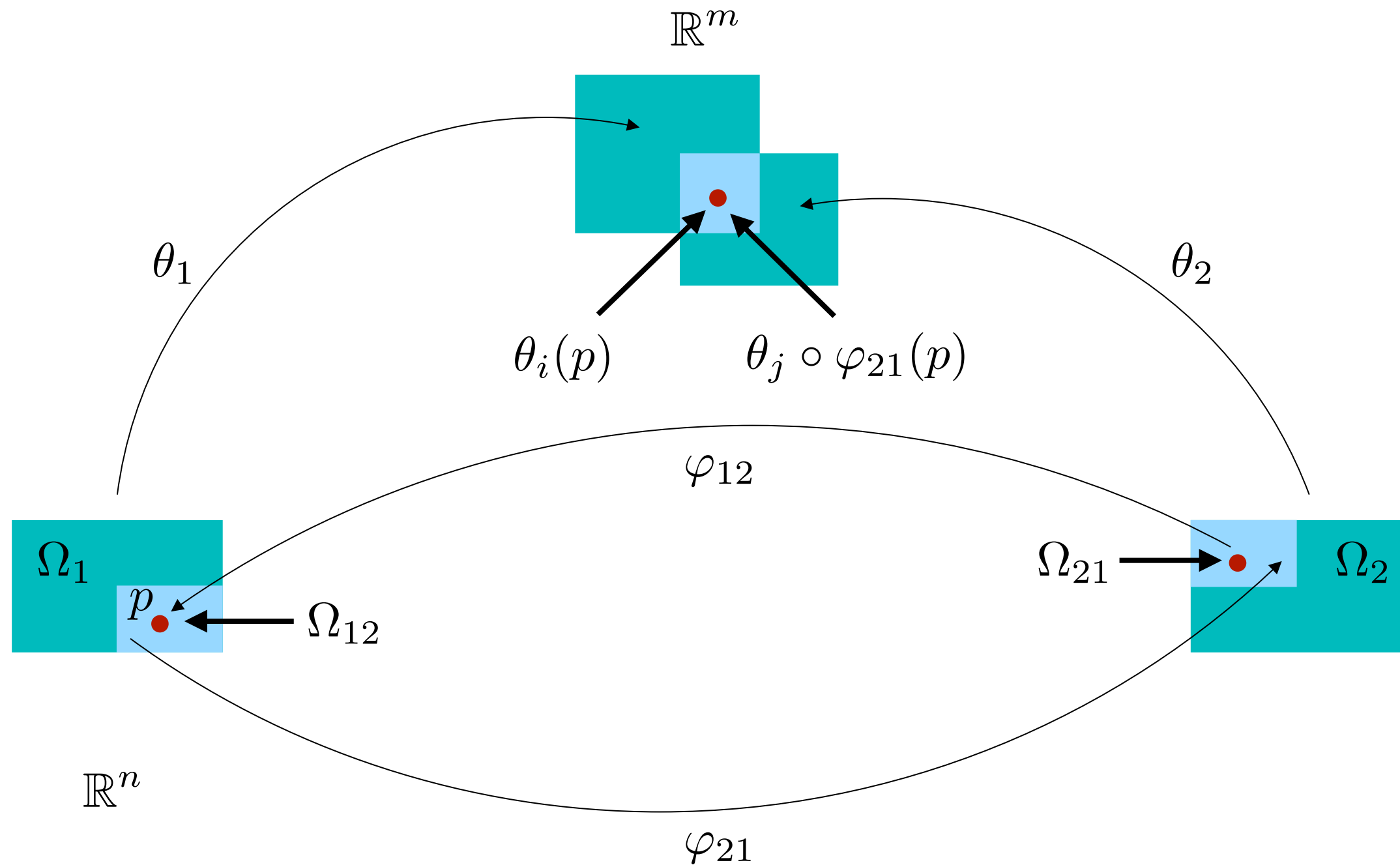
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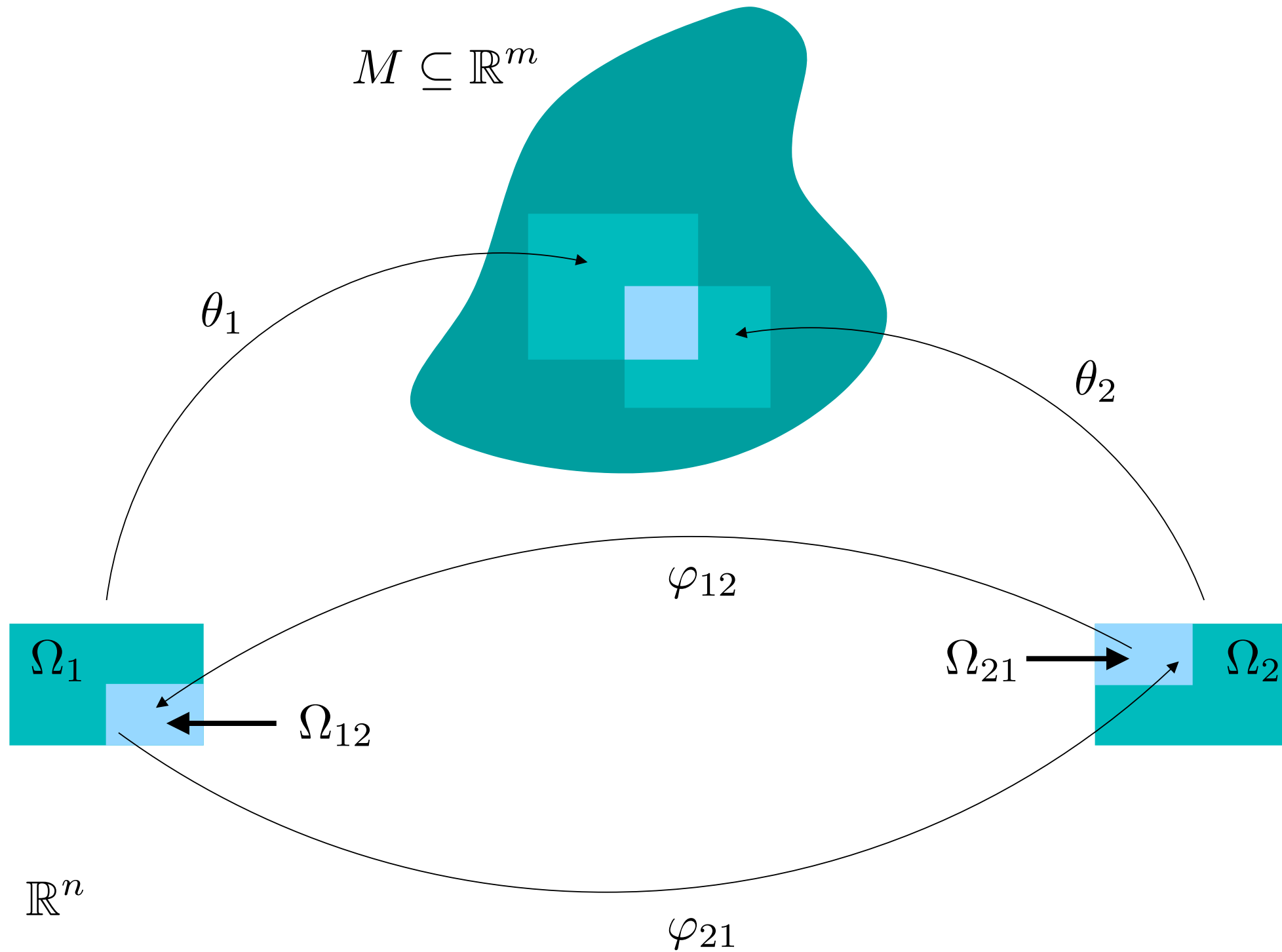
- The subset

$$M = \bigcup_{i \in I} \theta_i(\Omega_i)$$

of \mathbb{R}^m is called the **image** of the parametric pseudo-manifold.

Parametric Pseudo-Manifolds

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Parametric Pseudo-Manifolds

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REMARK:

There is a (unique) surjective map:

$$\Theta : M_{\mathcal{G}} \longrightarrow M .$$

Parametric Pseudo-Manifolds

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(C'') For all $(i, j) \notin K$,

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Conclusions

- We can *build* a parametric pseudo-manifold (PPM) from a set of gluing data and, *under certain conditions*, the image of a PPM can be given the structure of a manifold.
- In the following lecture, we describe a new constructive approach to define a set of gluing data from a triangle mesh.
- We also describe how to build a parametric C^∞ pseudo-surface from the set of gluing data. The image of this parametric pseudo-surface approximates the vertices of the mesh.

Fitting Surfaces to Polygonal Meshes (Part I)

Marcelo Siqueira
UFMS

Outline

- The Surface Fitting Problem
- Building a Set of Gluing Data

The Surface Fitting Problem

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Given a mesh S_T in \mathbb{R}^3 , a positive integer k , and a positive real number ϵ , our goal here is to fit a C^k surface, S , in \mathbb{R}^3 to S_T .

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The Manifold-Based Approach:

We solve the fitting problem by defining a C^k parametric pseudo-surface, \mathcal{M} , such that S is the image, M , of \mathcal{M} in \mathbb{R}^3 .

The Surface Fitting Problem

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Key Idea:

The Surface Fitting Problem

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GEOMETRY

Building a Set of Gluing Data

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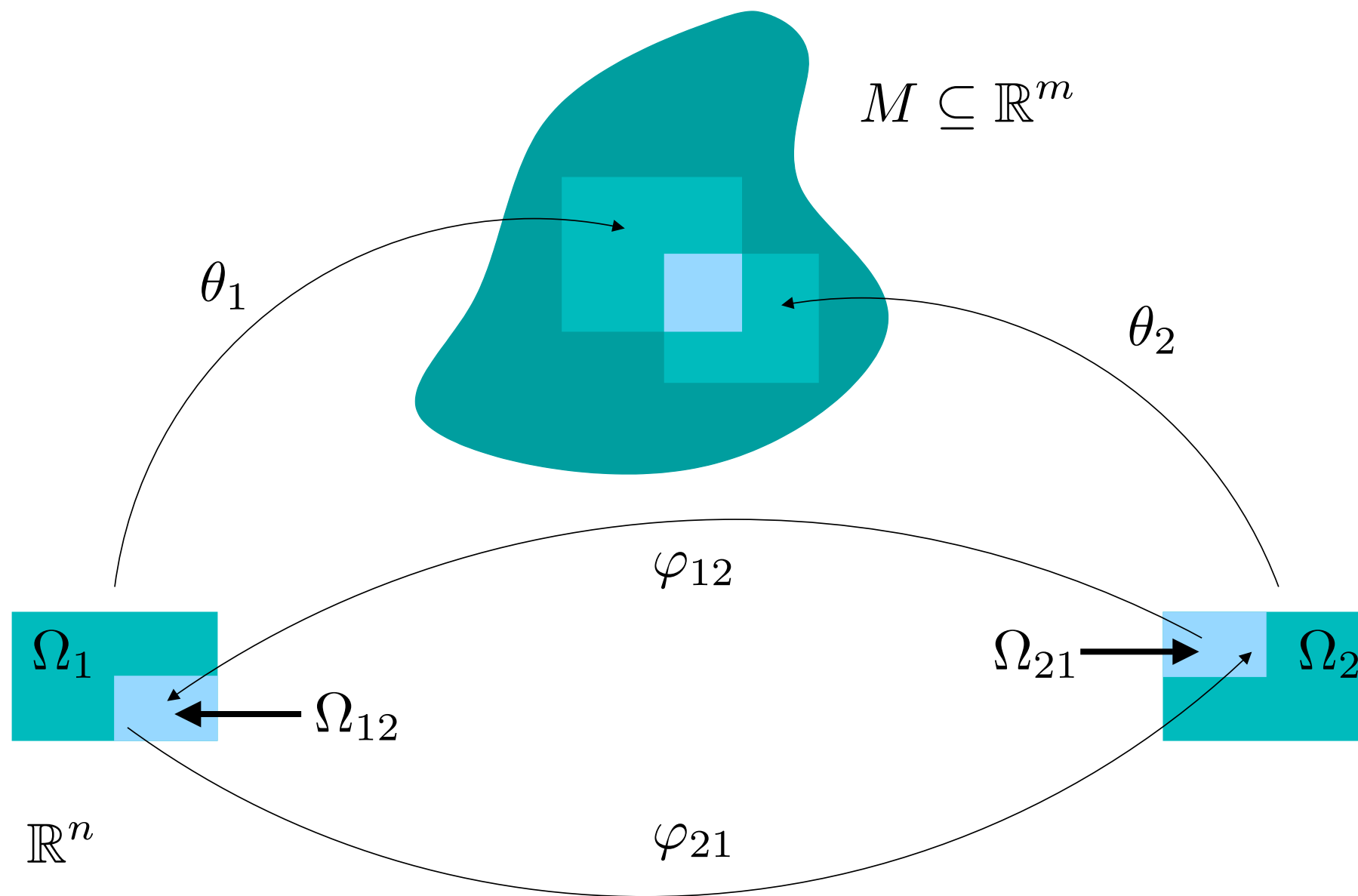
- define the p -domains, $(\Omega_i)_{i \in I}$,
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- define the transition functions, $(\varphi_{i,j})_{(i,j) \in K \times K}$.

$$\mathcal{G} = ((\Omega)_{i \in I}, (\Omega_{i,j})_{(i,j) \in I \times I}, (\varphi_{i,j})_{(i,j) \in K \times K})$$

Building a Set of Gluing Data

Building a Set of Gluing Data

The BIG PICTURE



Building a Set of Gluing Data

Building a Set of Gluing Data

p-Domains

Building a Set of Gluing Data

p -Domains

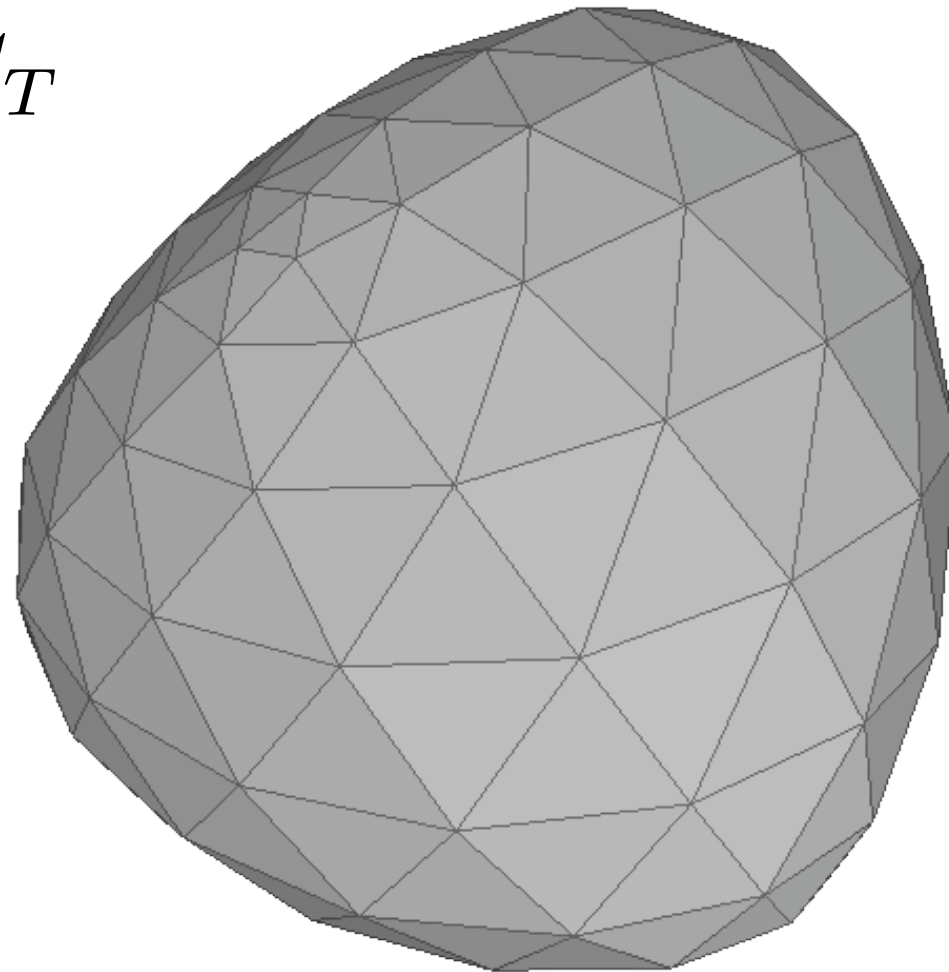
Assume that S_T is a **triangle** mesh (i.e., a simplicial surface).

Building a Set of Gluing Data

p -Domains

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S_T



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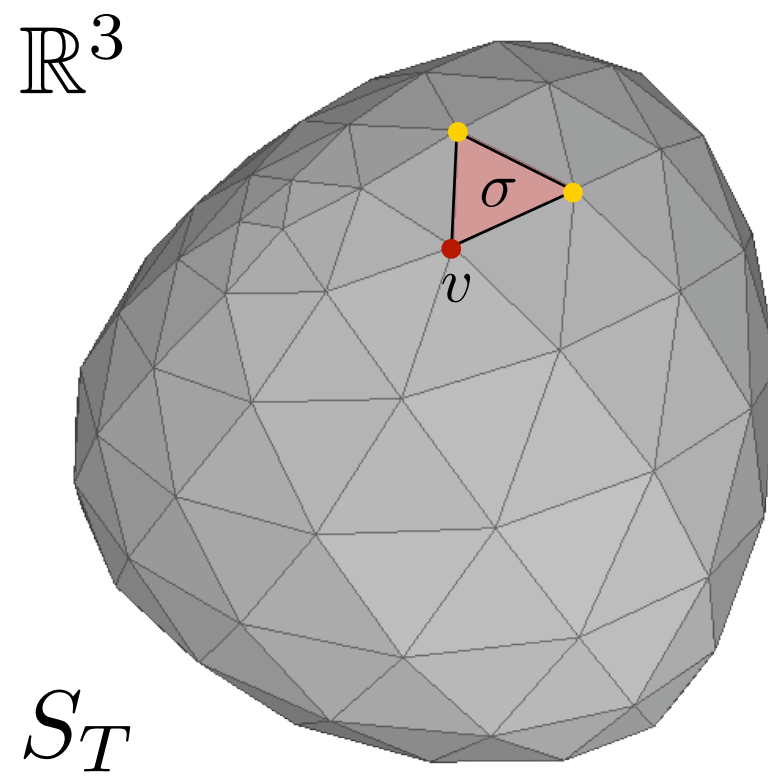
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$$I = \{(\sigma, v) \mid \sigma \text{ is a triangle of } S_T \text{ and } v \text{ is a vertex of } \sigma\}.$$

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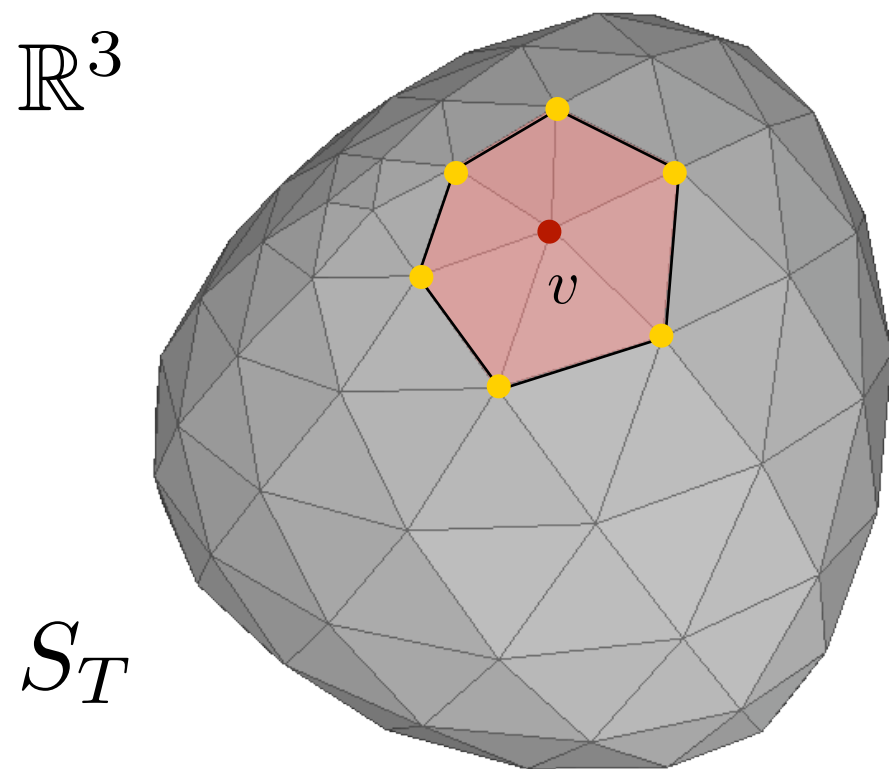
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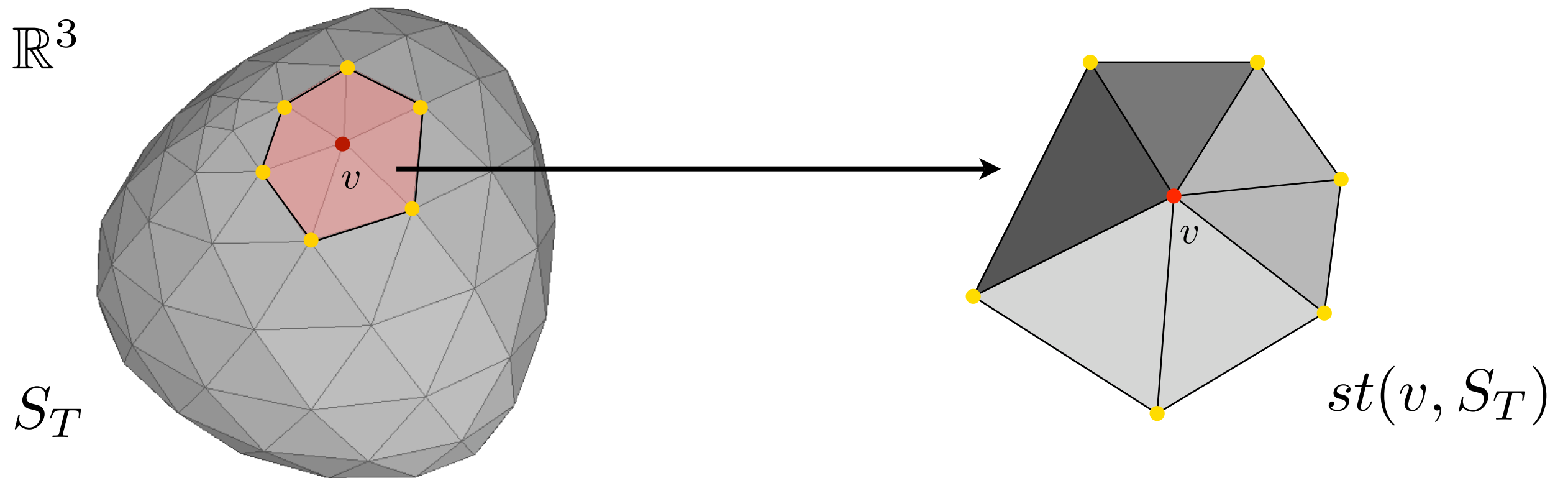
Building a Set of Gluing Data

For every vertex, v , of S_T , consider its **star**, $st(v, S_T)$:



Building a Set of Gluing Data

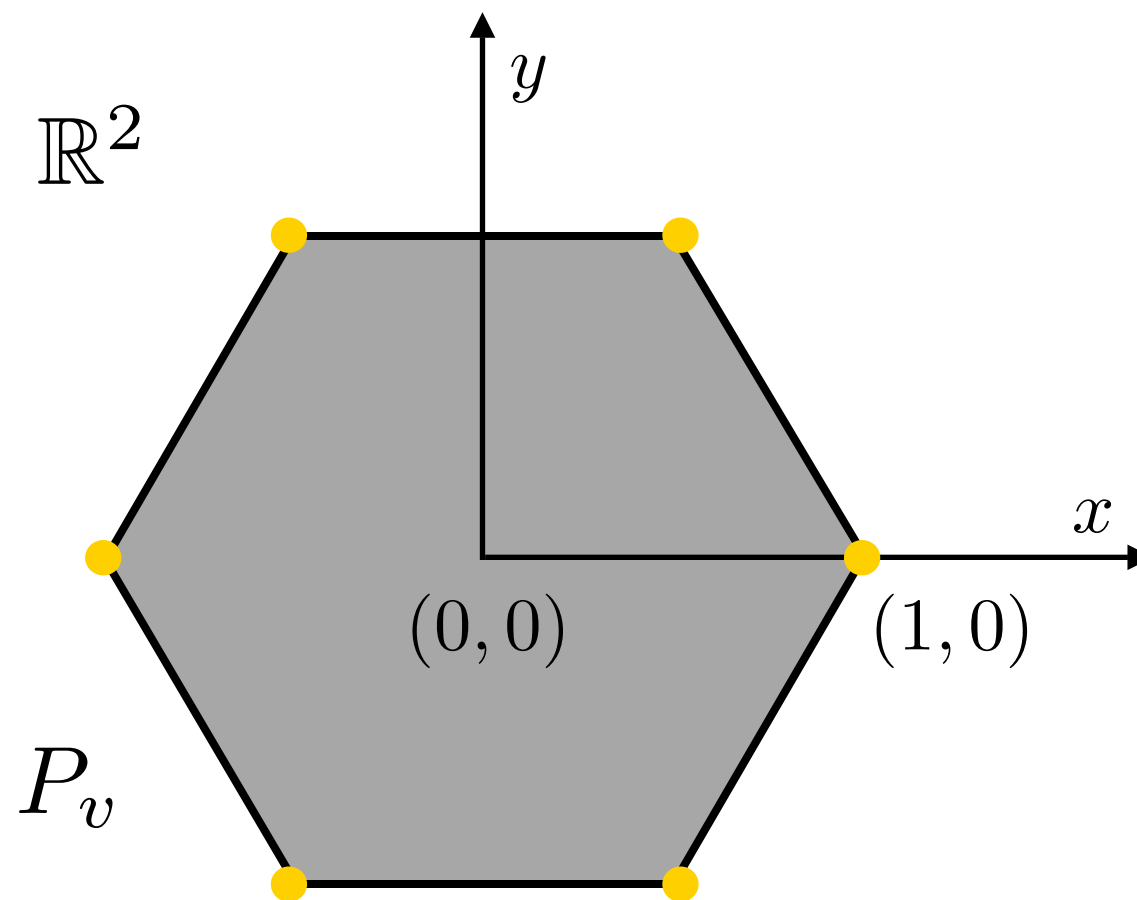
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Building a Set of Gluing Data

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Define the **P-polygon**, P_v , associated with v as the m_v -gon inscribed in the circle of radius 1 and centered at the origin in \mathbb{R}^2 :



m_v is the **degree** of v in S_T .

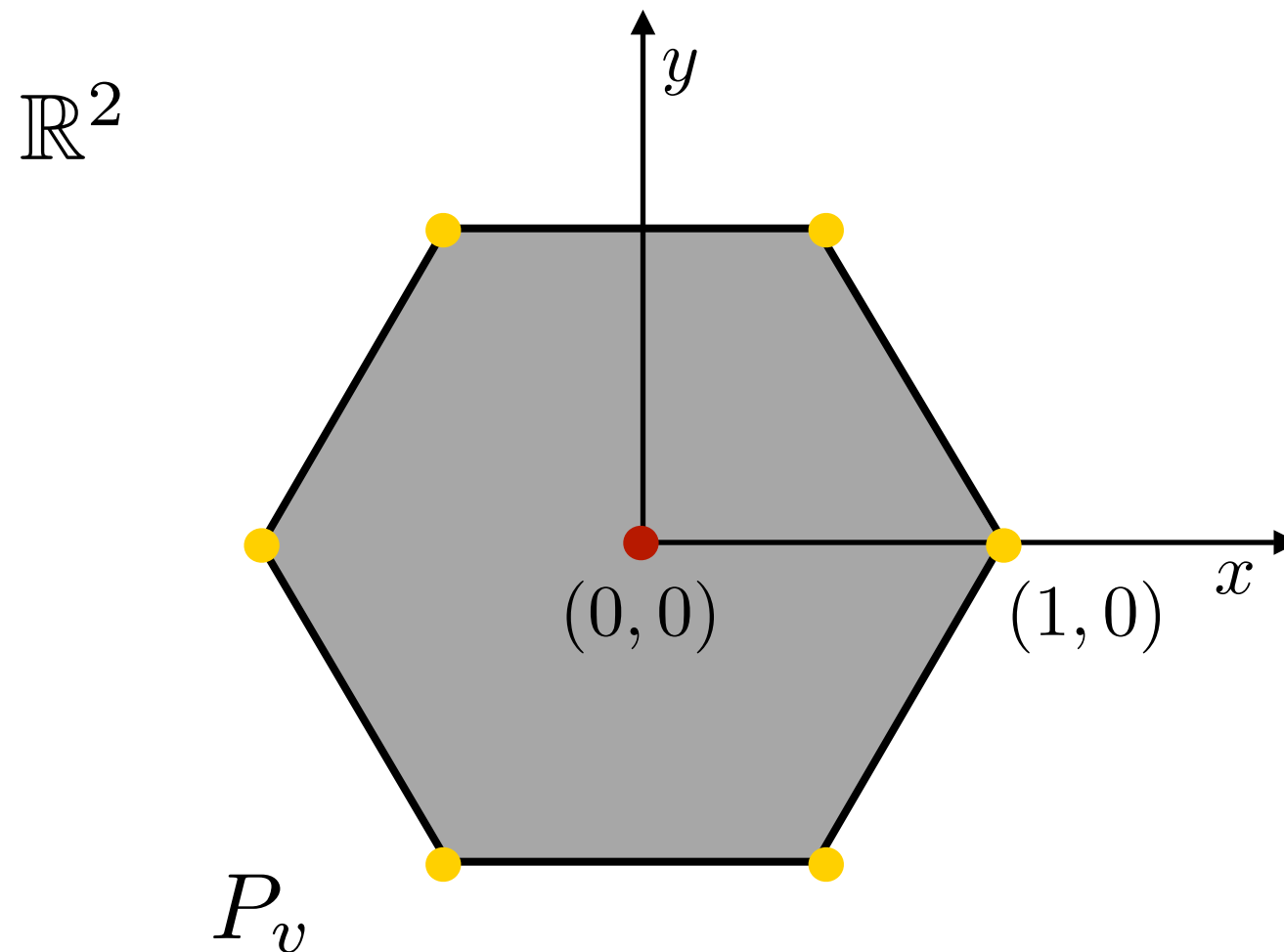
Building a Set of Gluing Data

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Define the **triangulation**, T_v , **associated with** v by adding straight edges (diagonals) connecting the barycenter of P_v to its vertices:

Building a Set of Gluing Data

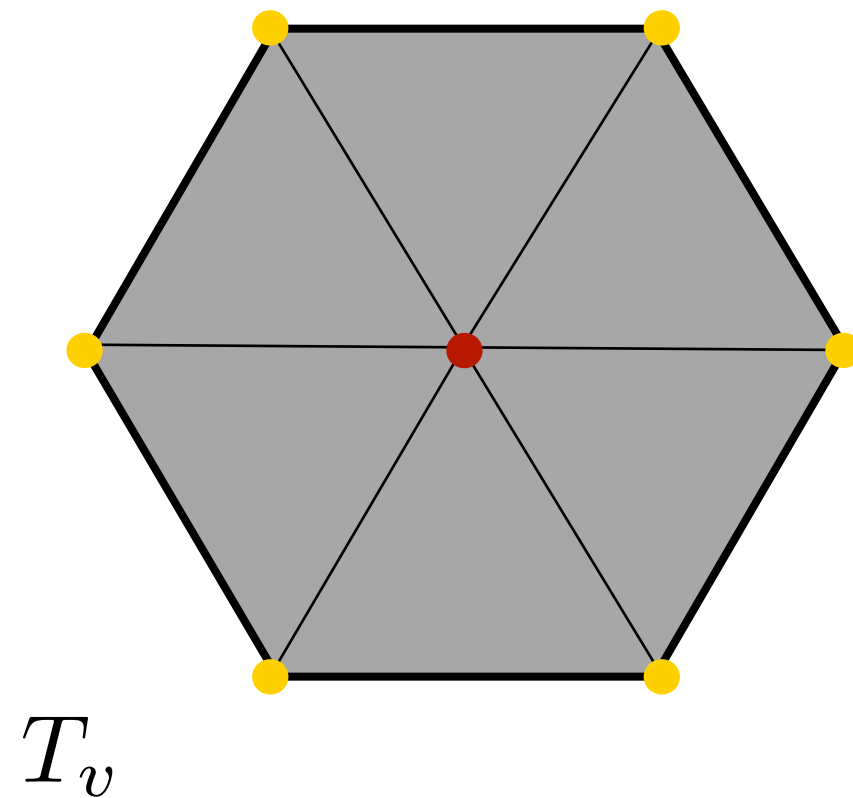
Define the **triangulation**, T_v , associated with v by adding straight edges (diagonals) connecting the barycenter of P_v to its vertices:



Building a Set of Gluing Data

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\mathbb{R}^2

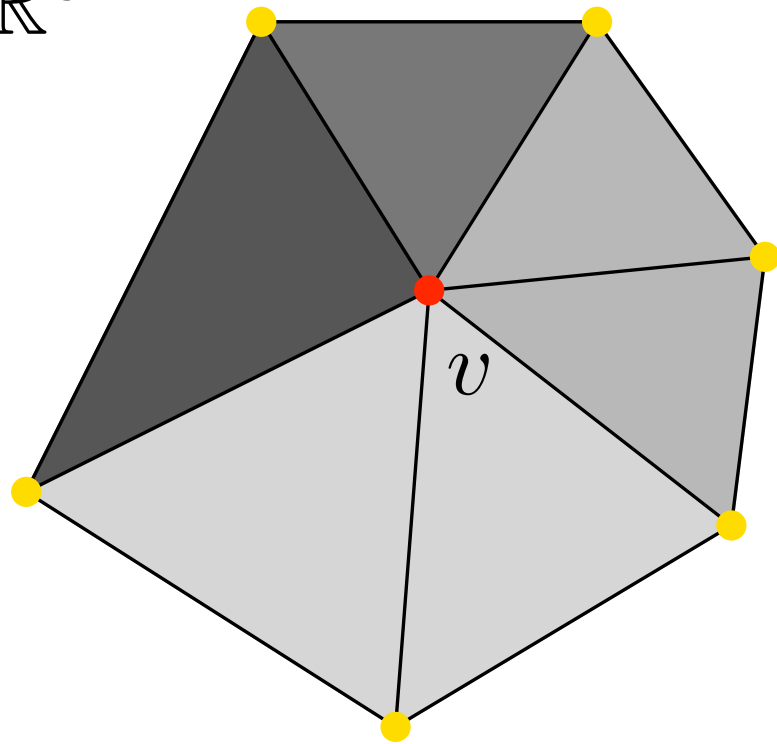


Building a Set of Gluing Data

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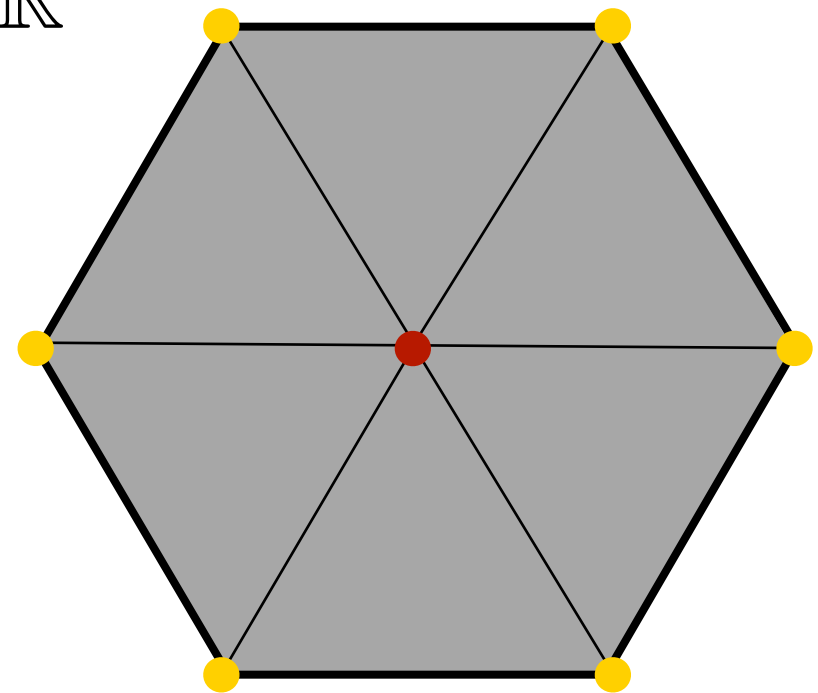
Remark: T_v is a parametrization of $st(v, S_T)$ in \mathbb{R}^2 :

\mathbb{R}^3



$st(v, S_T)$

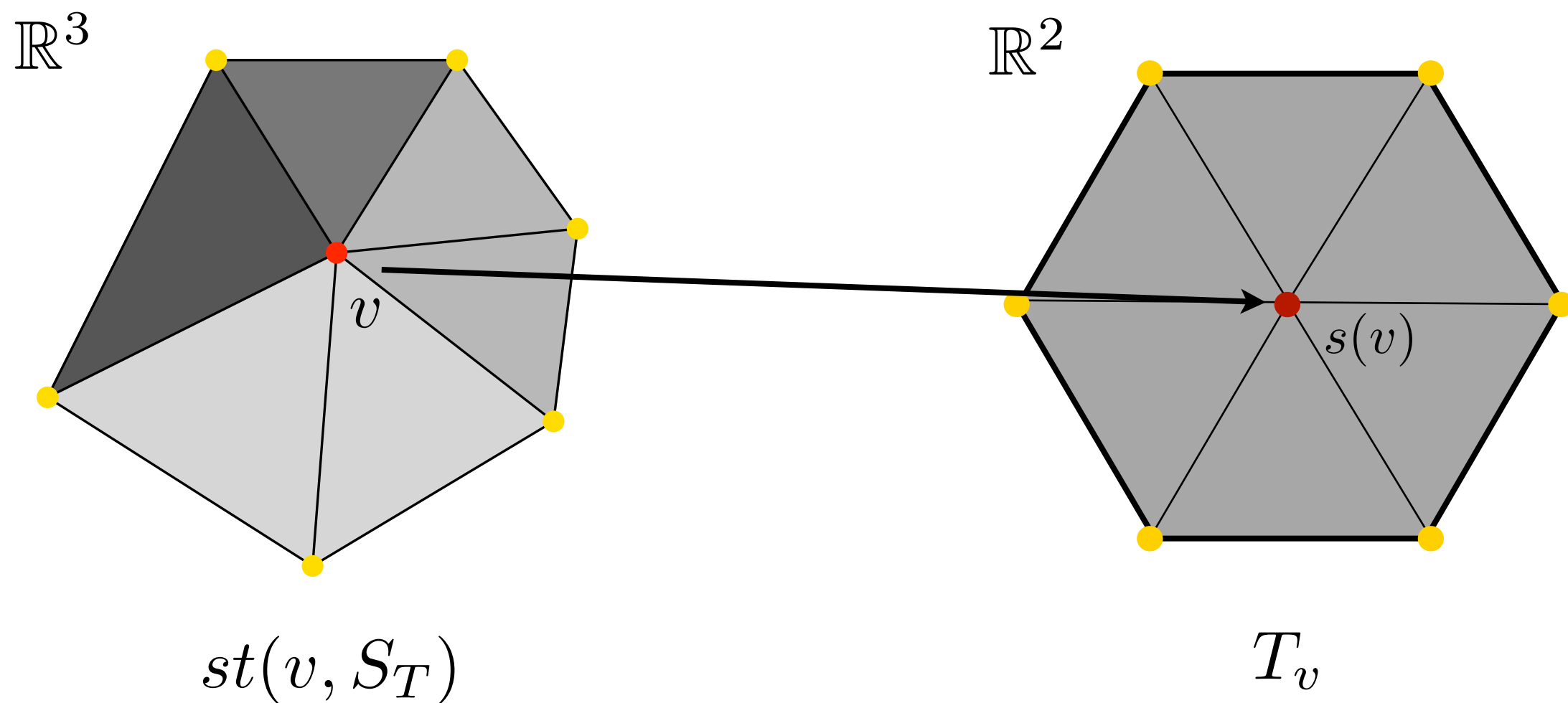
\mathbb{R}^2



T_v

Building a Set of Gluing Data

Remark: T_v is a parametrization of $st(v, S_T)$ in \mathbb{R}^2 :



$$s : st(v, S_T) \rightarrow T_v$$

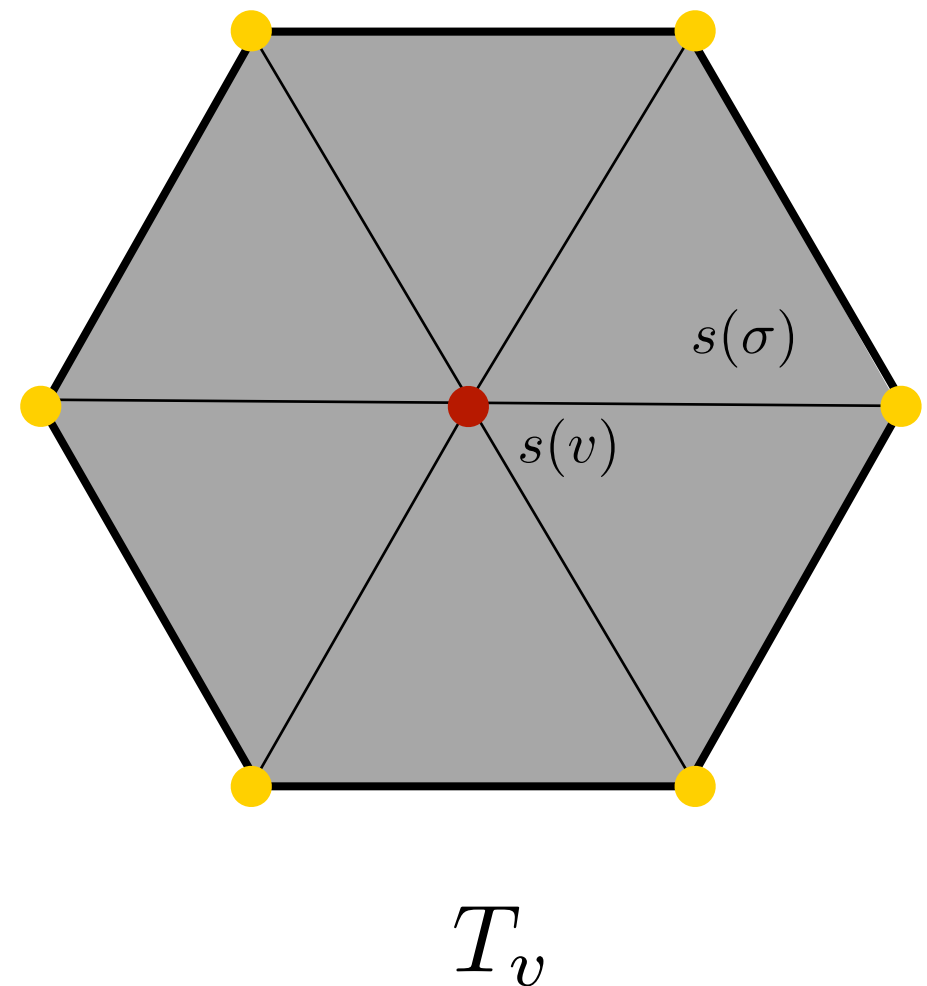
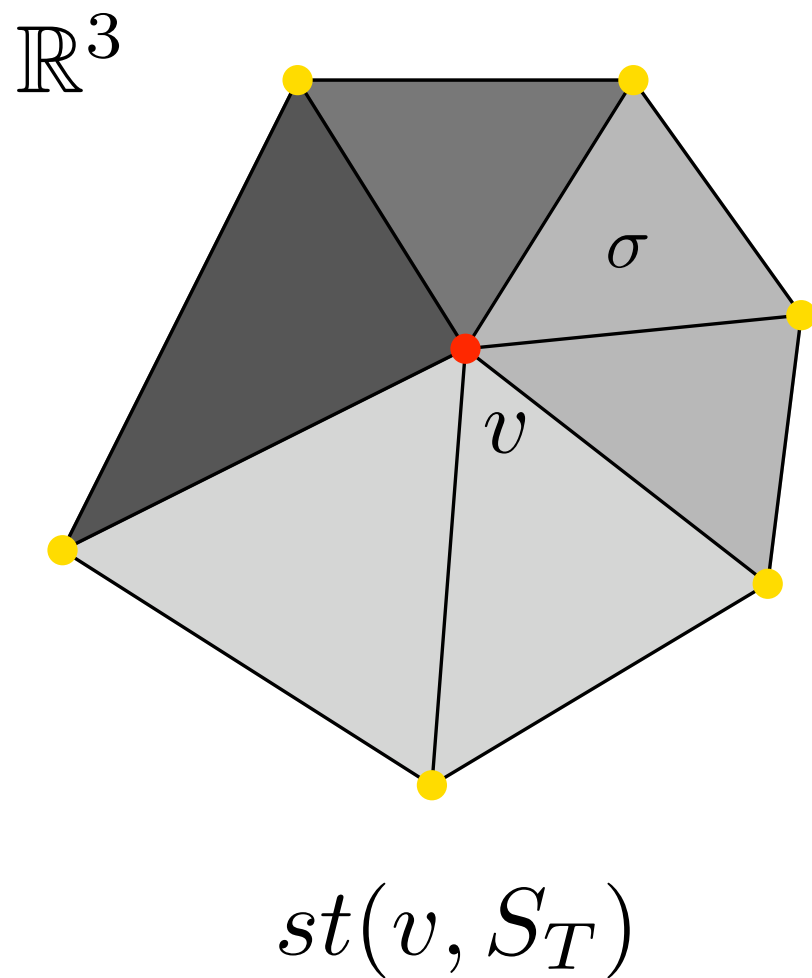
Building a Set of Gluing Data

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For each triangle σ of S_T and vertex v of σ , we define the **overlapping point**, $r_{v,\sigma}$, associated with $s(\sigma)$ in T_v , as follows:

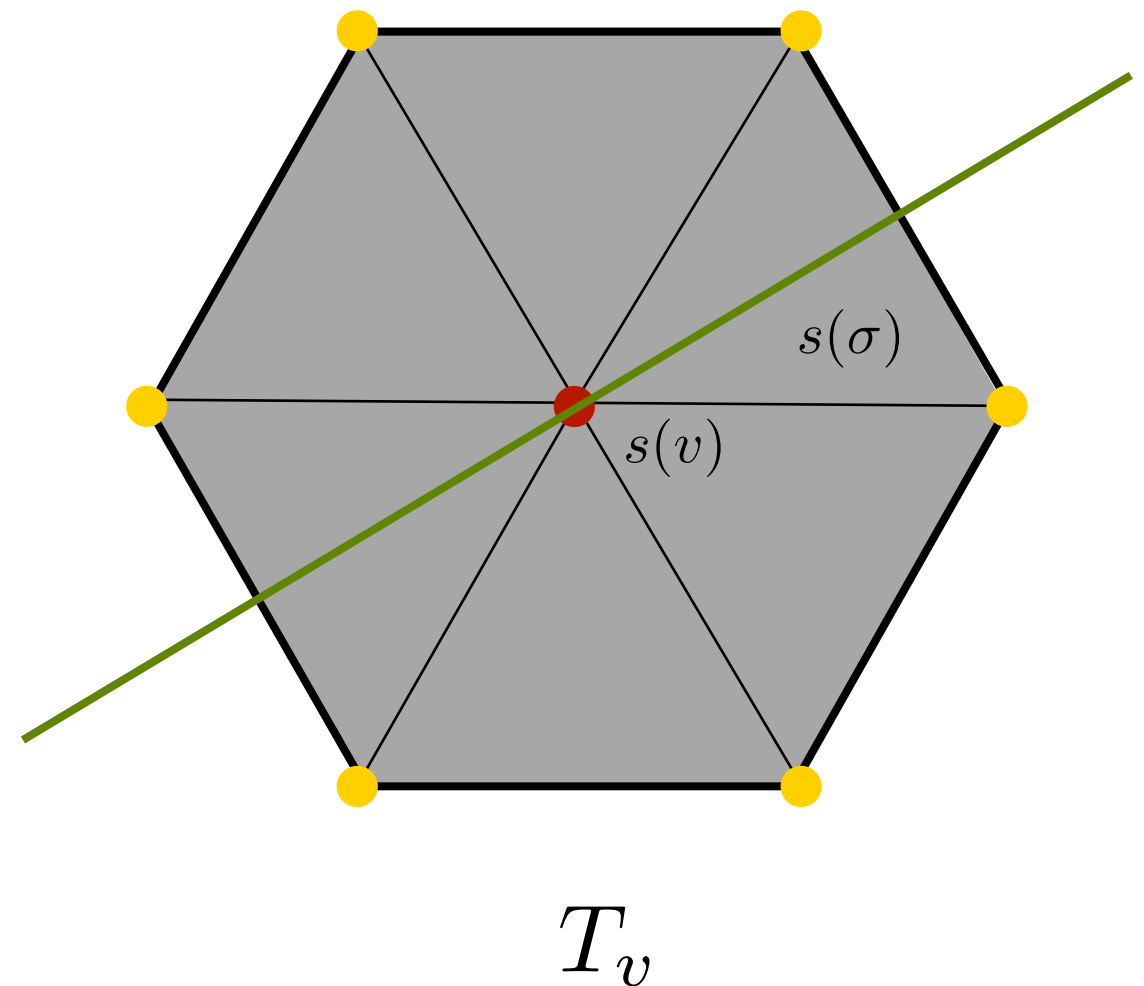
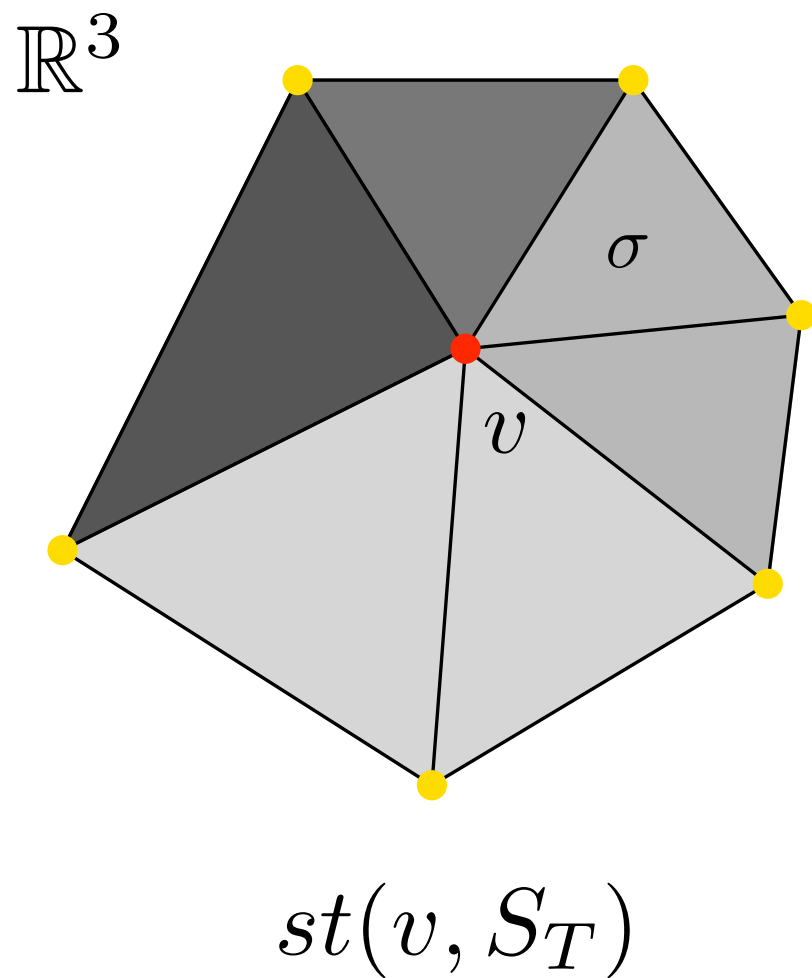
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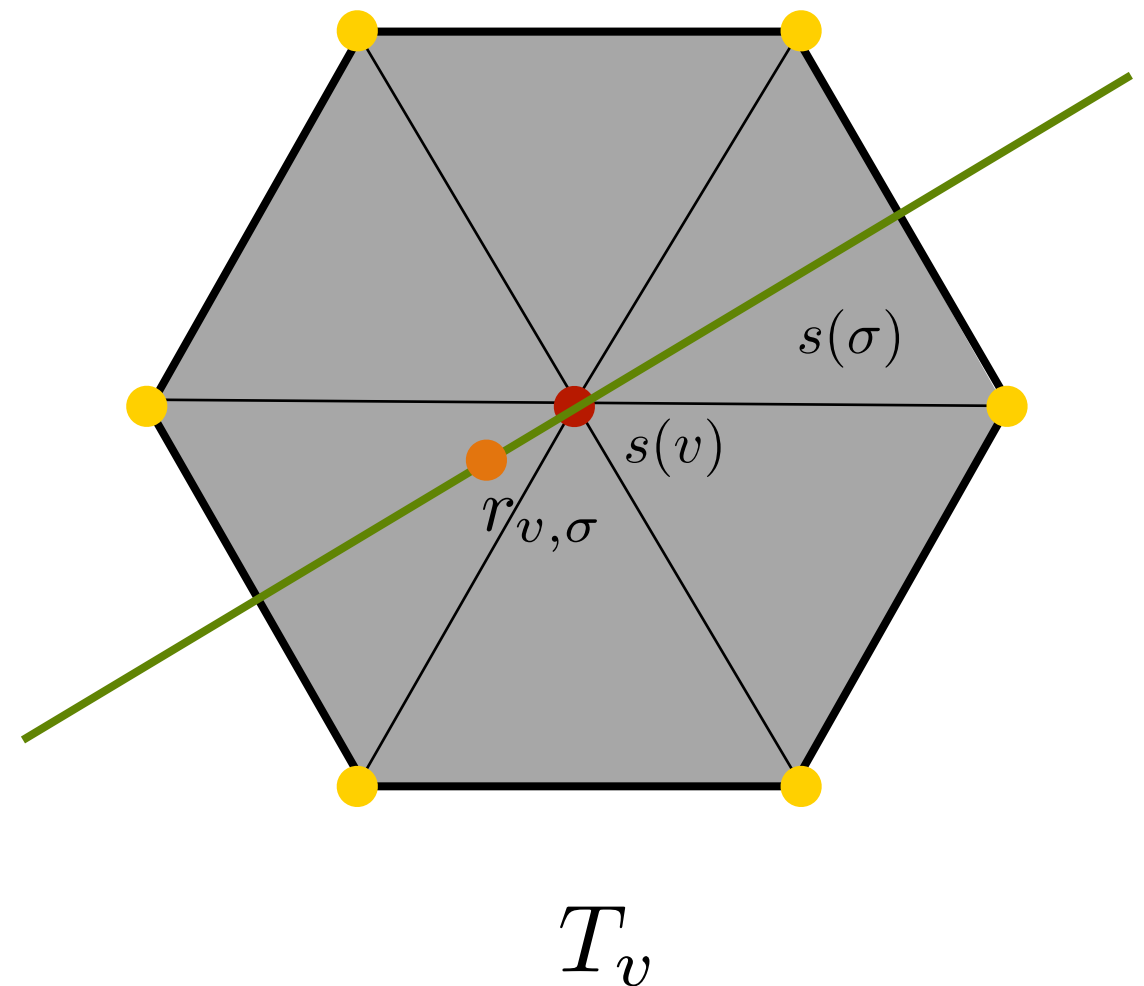
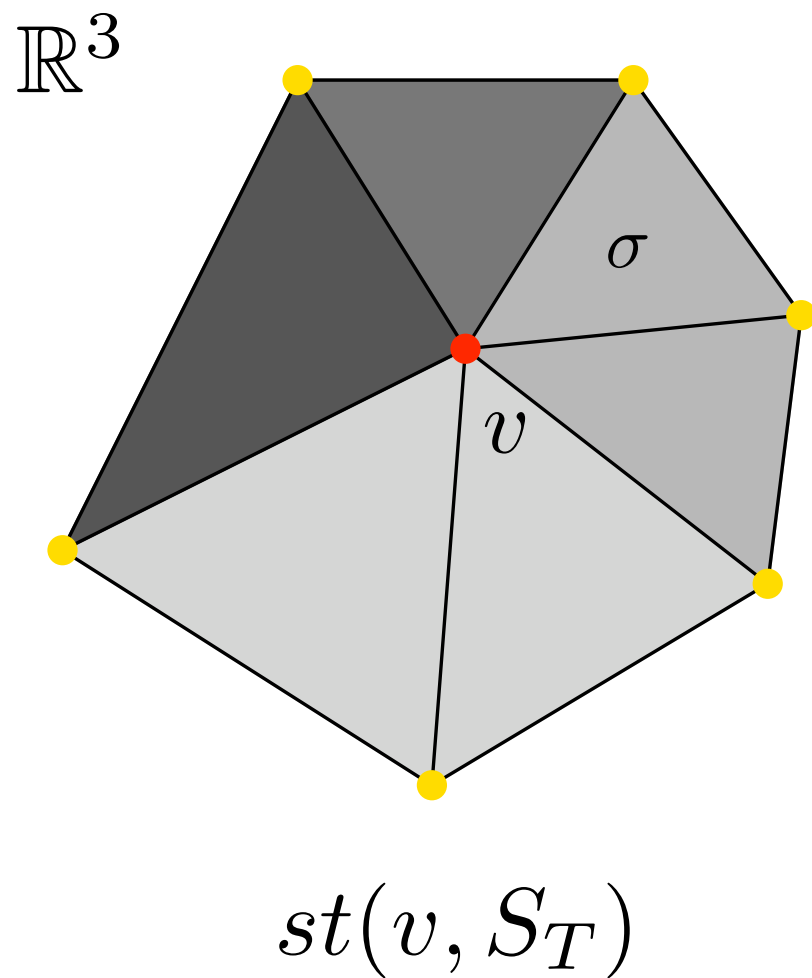
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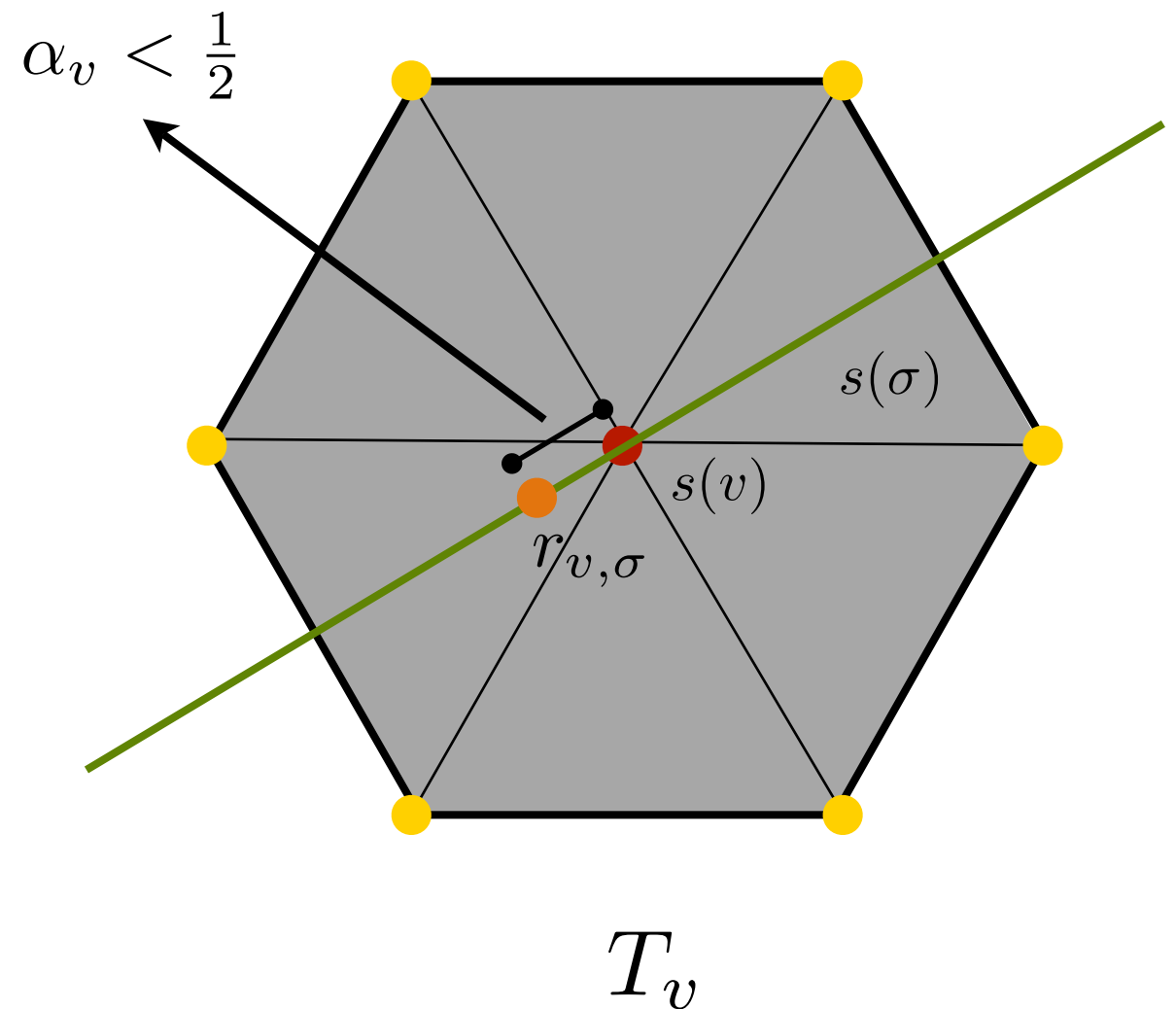
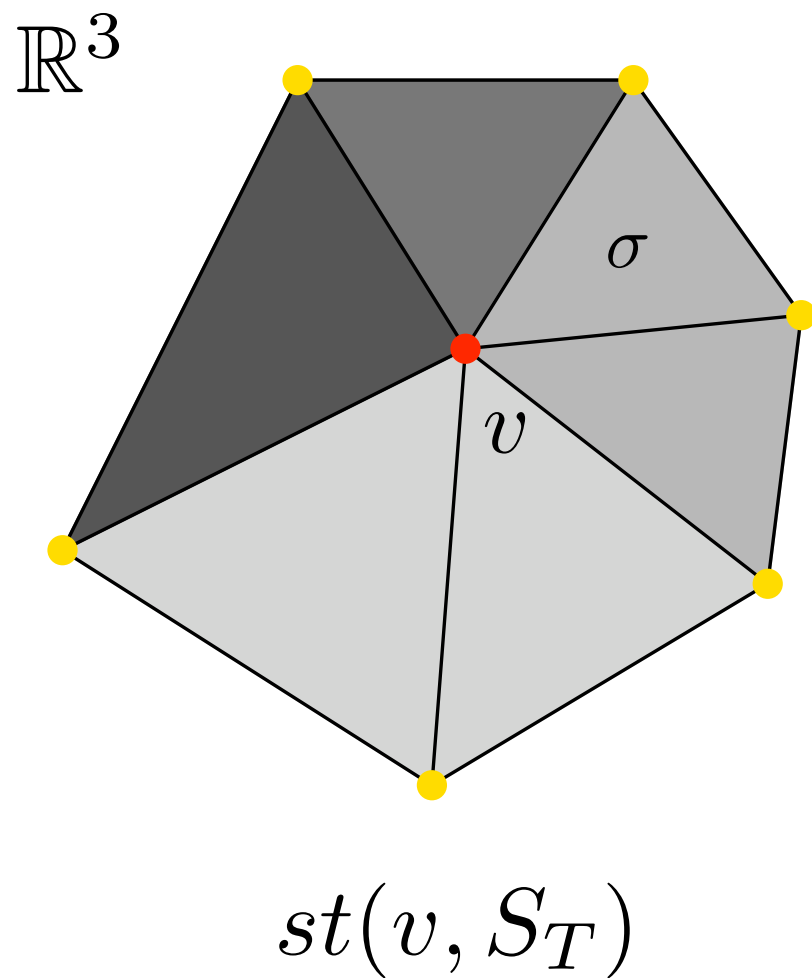
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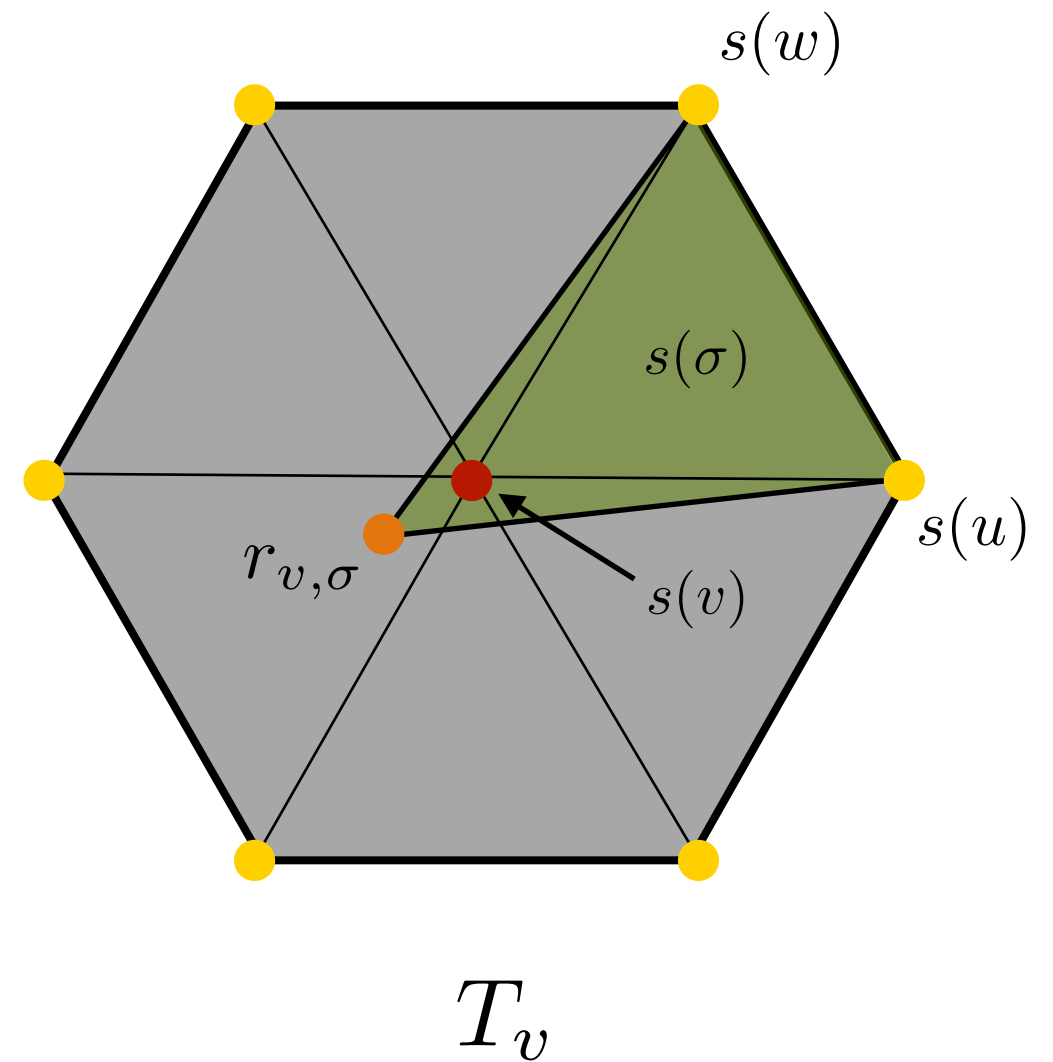
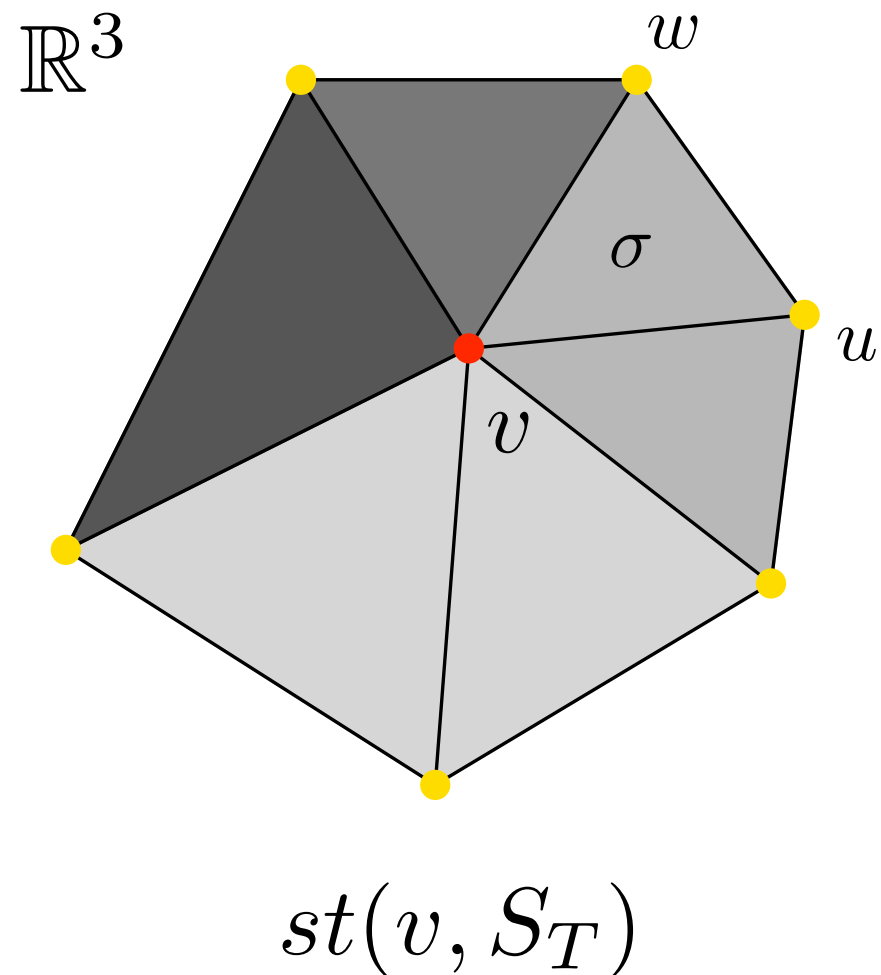
Building a Set of Gluing Data

Building a Set of Gluing Data

If $\sigma = [v, u, w]$ then consider the triangle $[r_{\sigma, v}, s(u), s(w)]$:

Building a Set of Gluing Data

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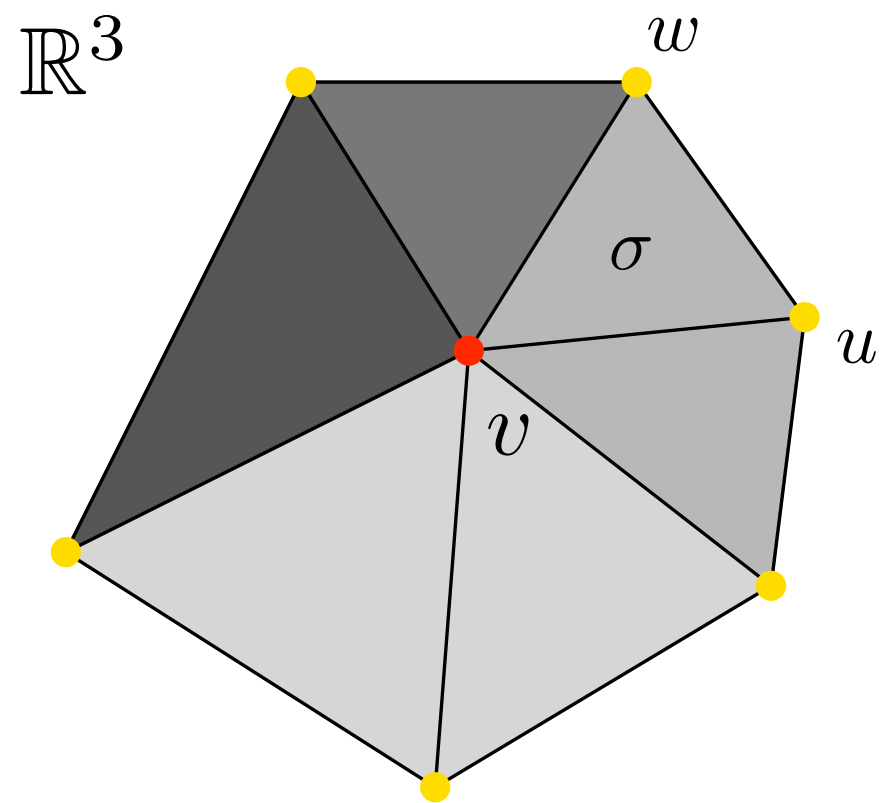
Building a Set of Gluing Data

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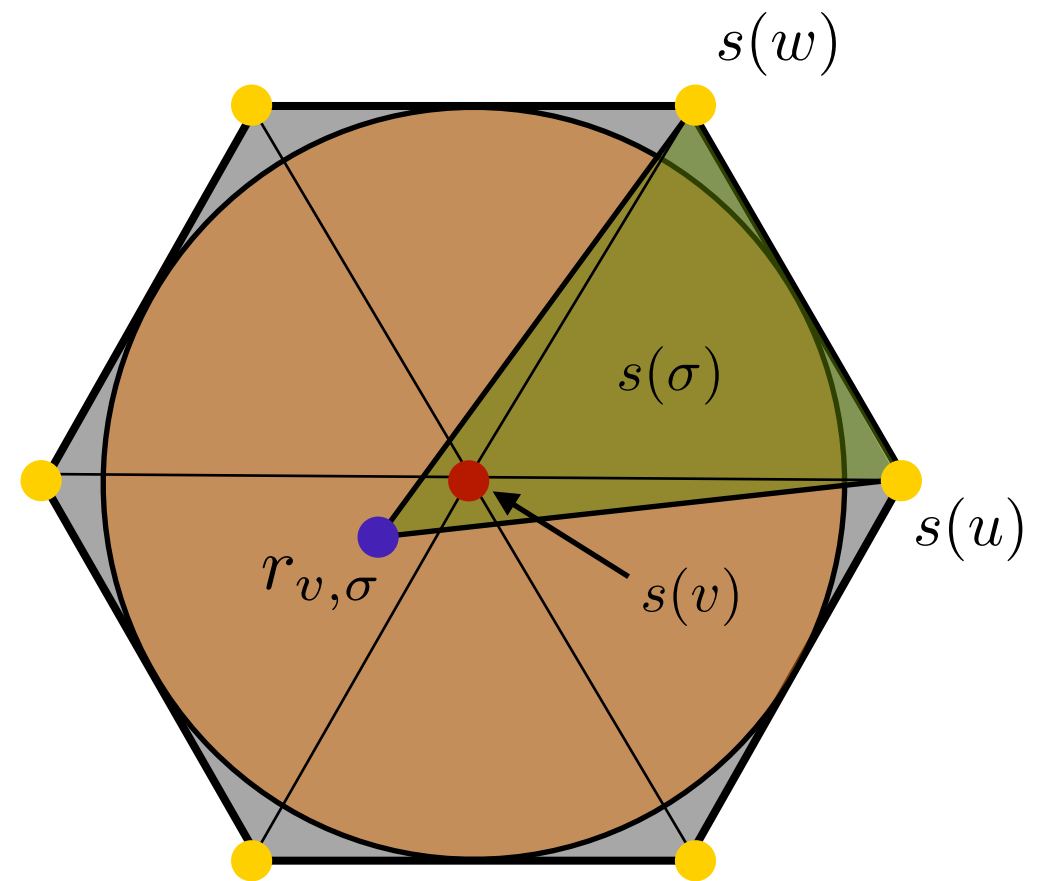
Consider the circle, C_v , inscribed in P_v :

Building a Set of Gluing Data

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$st(v, S_T)$



T_v

Building a Set of Gluing Data

Building a Set of Gluing Data

We let $\Omega_{(\sigma,v)}$ be

$$C_v \cap \text{int}([r_{v,\sigma}, s(u), s(w)]),$$

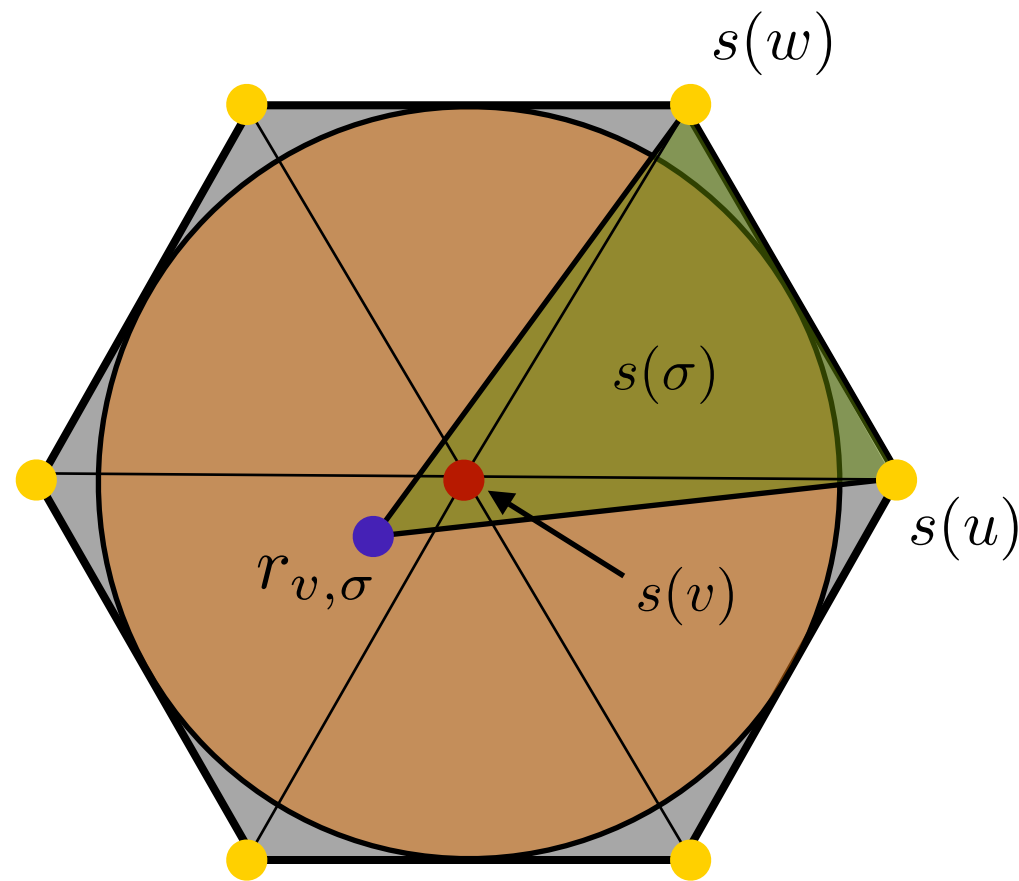
where $\text{int}([r_{v,\sigma}, s(u), s(w)])$ is the interior of $[r_{v,\sigma}, s(u), s(w)]$.

Building a Set of Gluing Data

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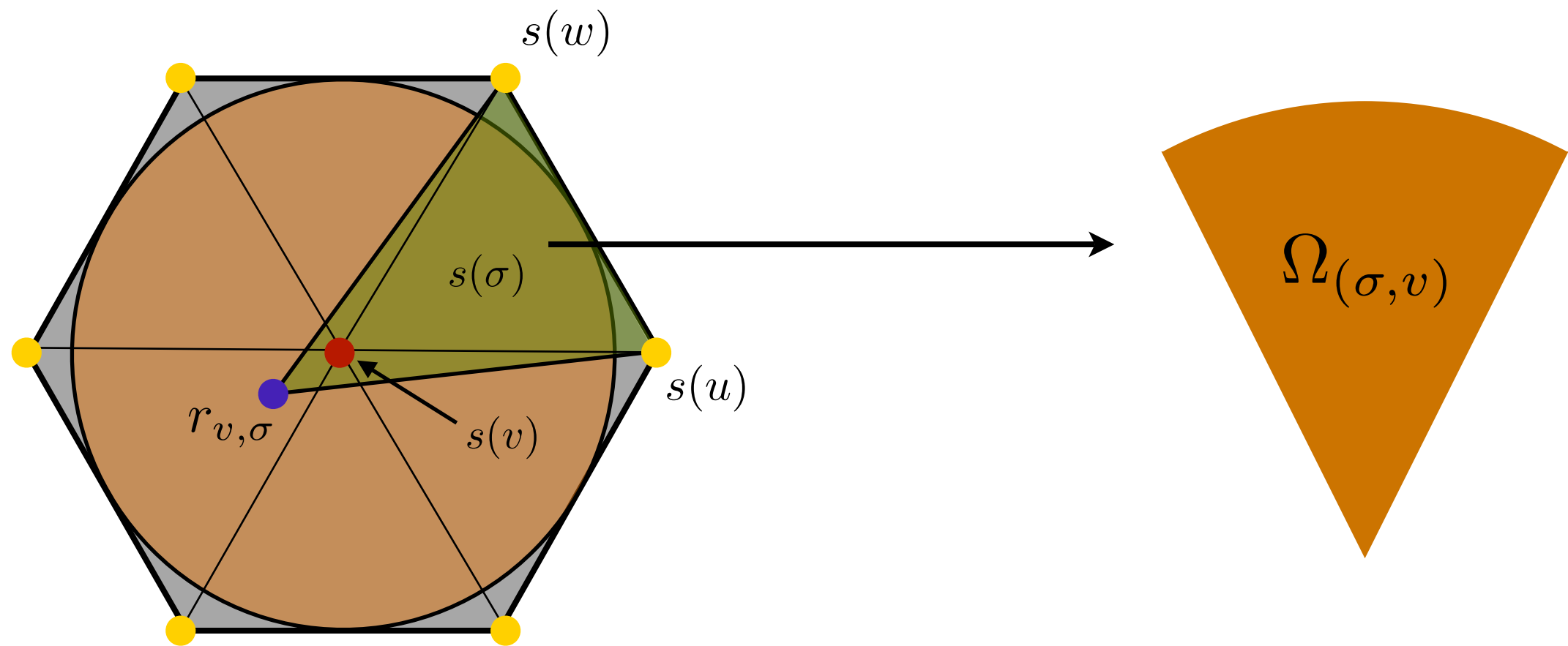


Building a Set of Gluing Data

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where $\text{int}([r_{v,\sigma}, s(u), s(w)])$ is the interior of $[r_{v,\sigma}, s(u), s(w)]$.



Building a Set of Gluing Data

Remark:

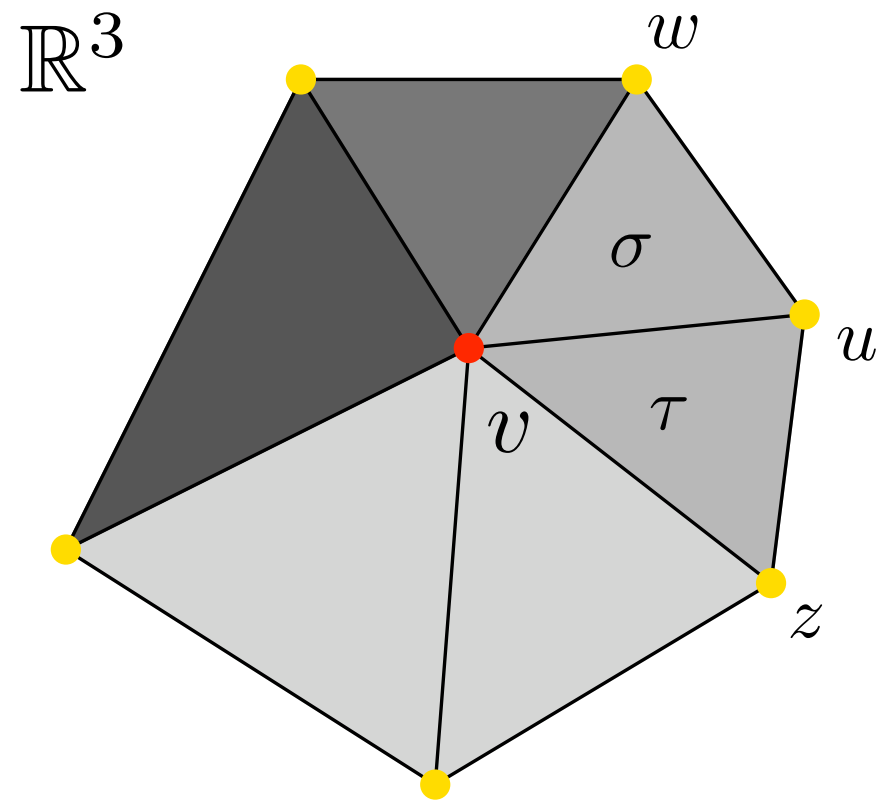
From Jean Gallier's lecture, we should have

$$\Omega_{(\sigma, v)} \cap \Omega_{(\tau, u)} = \emptyset,$$

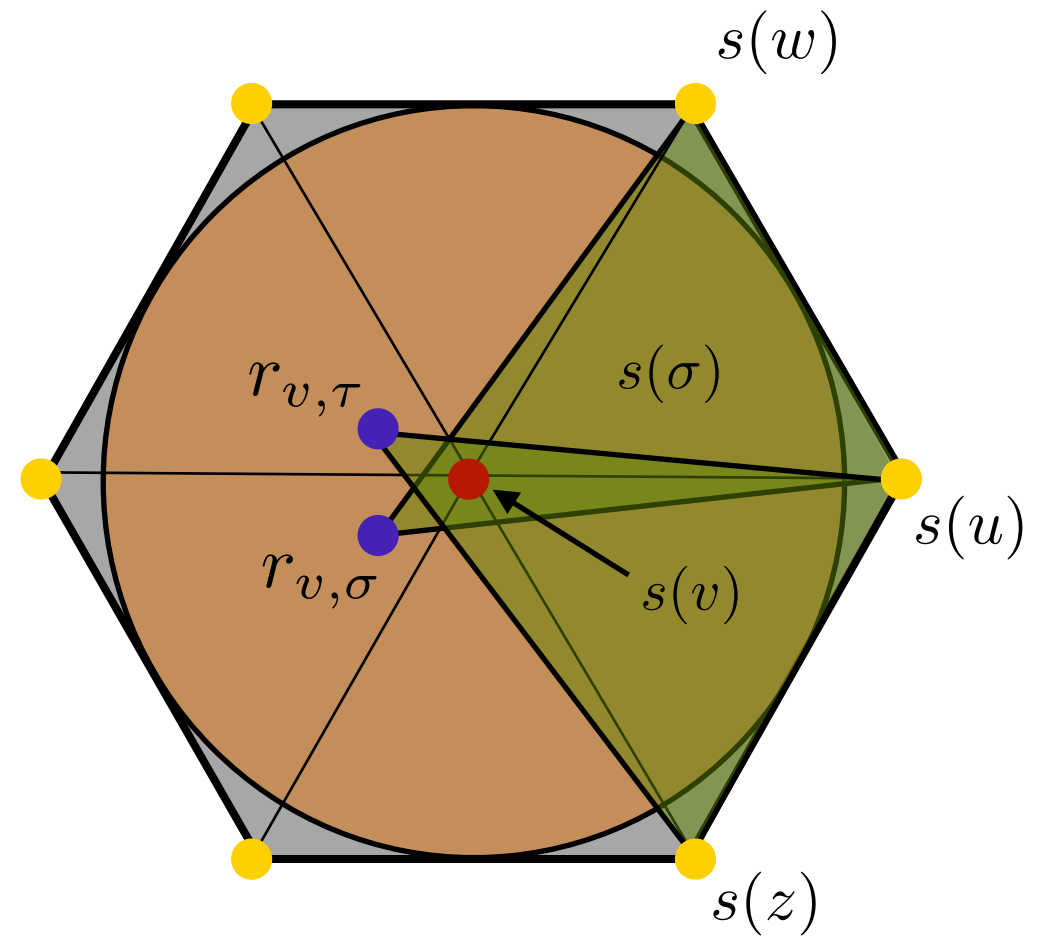
for any two pairs, (σ, v) and (τ, u) , in I . Did I make it right?

Building a Set of Gluing Data

Building a Set of Gluing Data

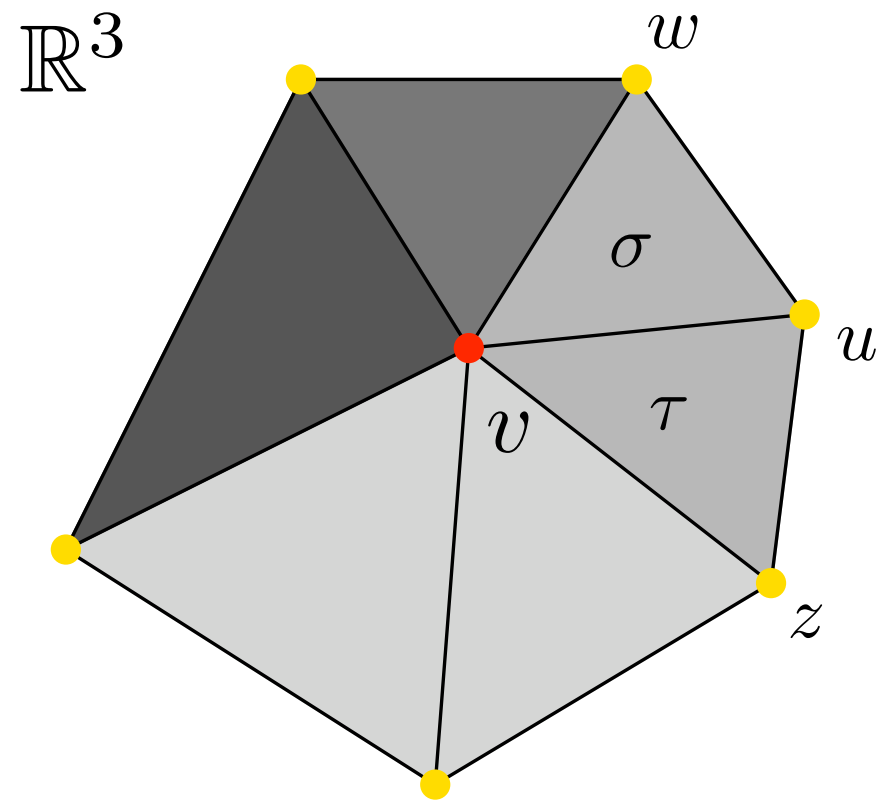


$st(v, S_T)$

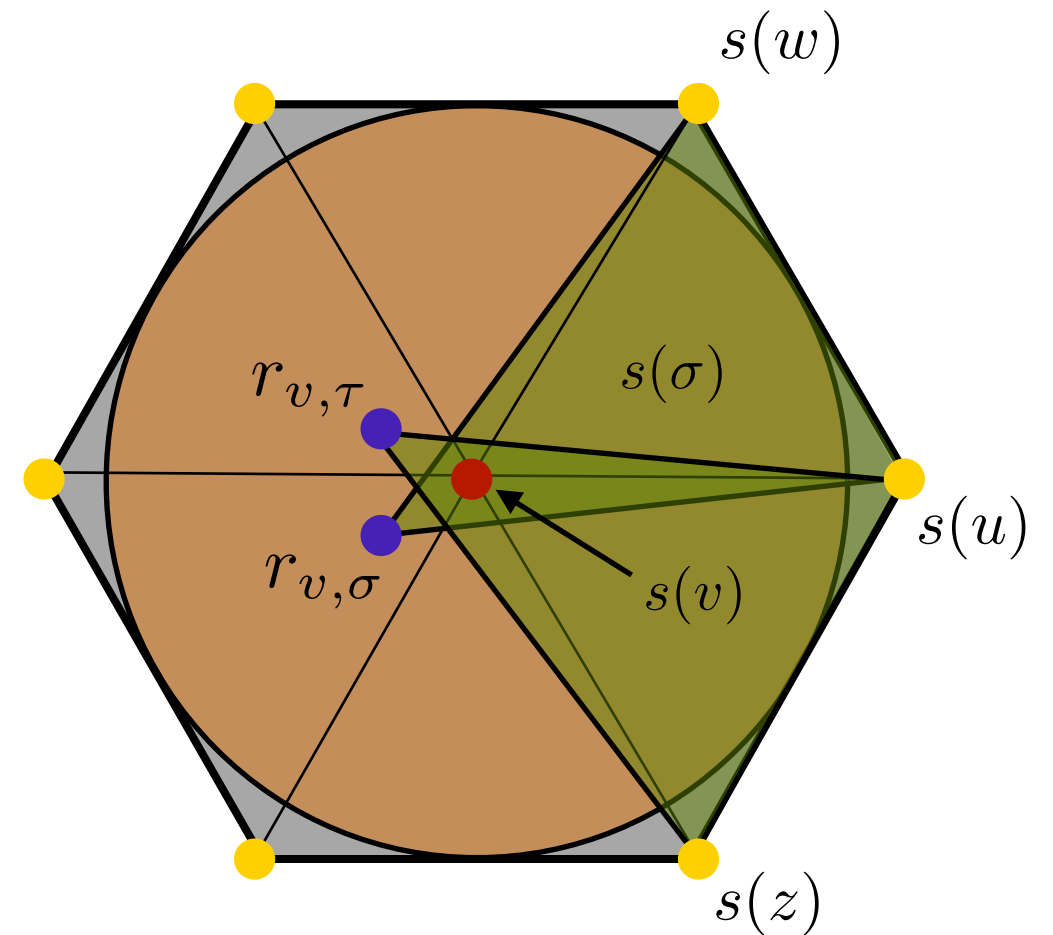


T_v

Building a Set of Gluing Data



$st(v, S_T)$



T_v

Clearly, $\Omega_{(\sigma,v)} \cap \Omega_{(\tau,v)} \neq \emptyset$.

Building a Set of Gluing Data

Building a Set of Gluing Data

So, I did NOT make it right.

Building a Set of Gluing Data

So, I did NOT make it right.

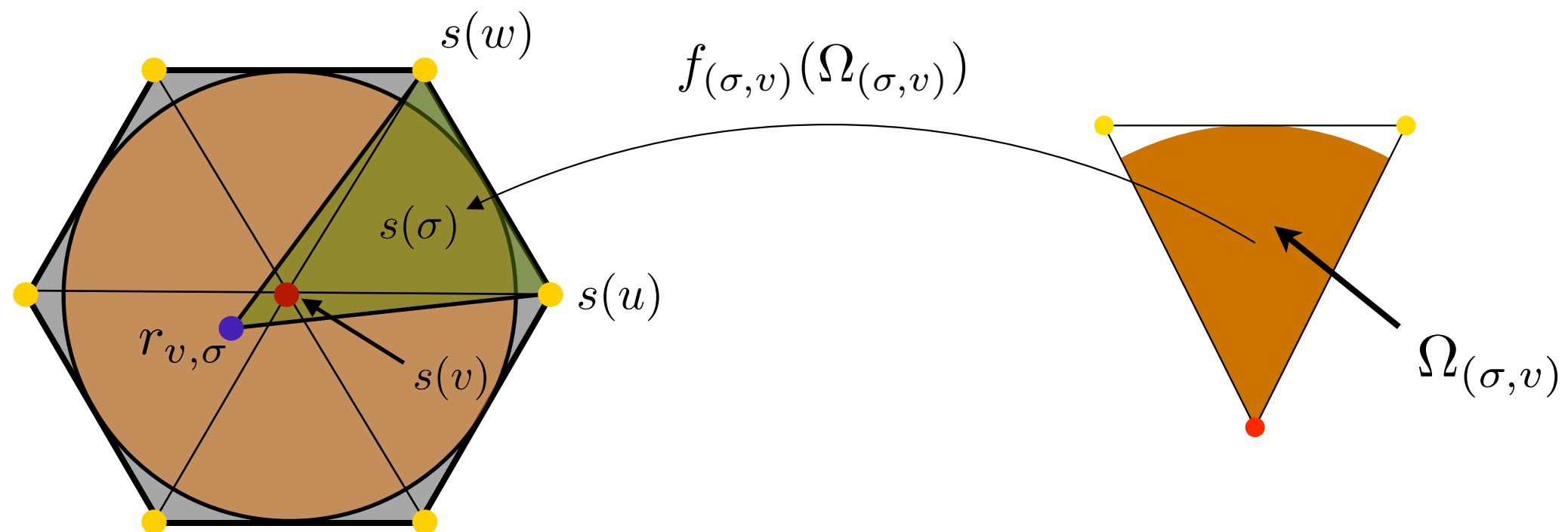
What now?

Building a Set of Gluing Data

So, I did NOT make it right.

What now?

We can *fix* that by letting $\Omega_{(\sigma,v)}$ be a set inside a triangle which is the inverse image of $[r_{v,\sigma}, s(u), s(w)]$ under a rigid transformation!



Building a Set of Gluing Data

Building a Set of Gluing Data

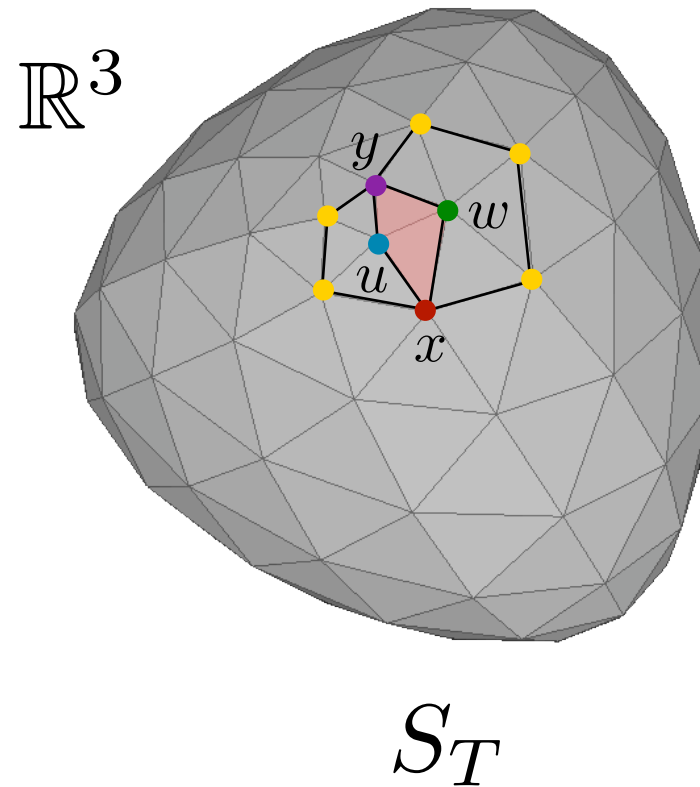
Since I is a finite set and the “enclosing” triangles are compact, we can certainly separate each p -domain from the others in \mathbb{R}^2 .

Building a Set of Gluing Data

Gluing domains

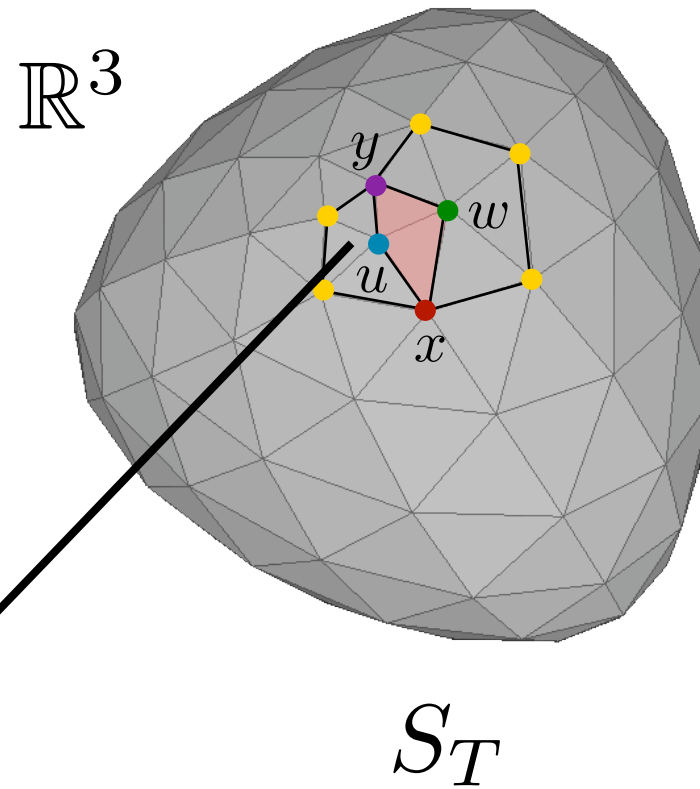
Building a Set of Gluing Data

Gluing domains

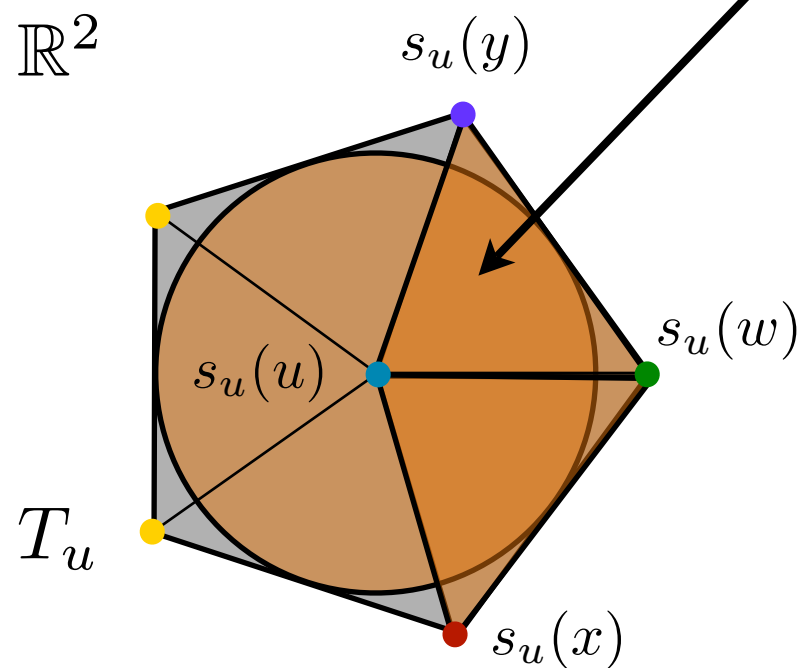


Building a Set of Gluing Data

Gluing domains

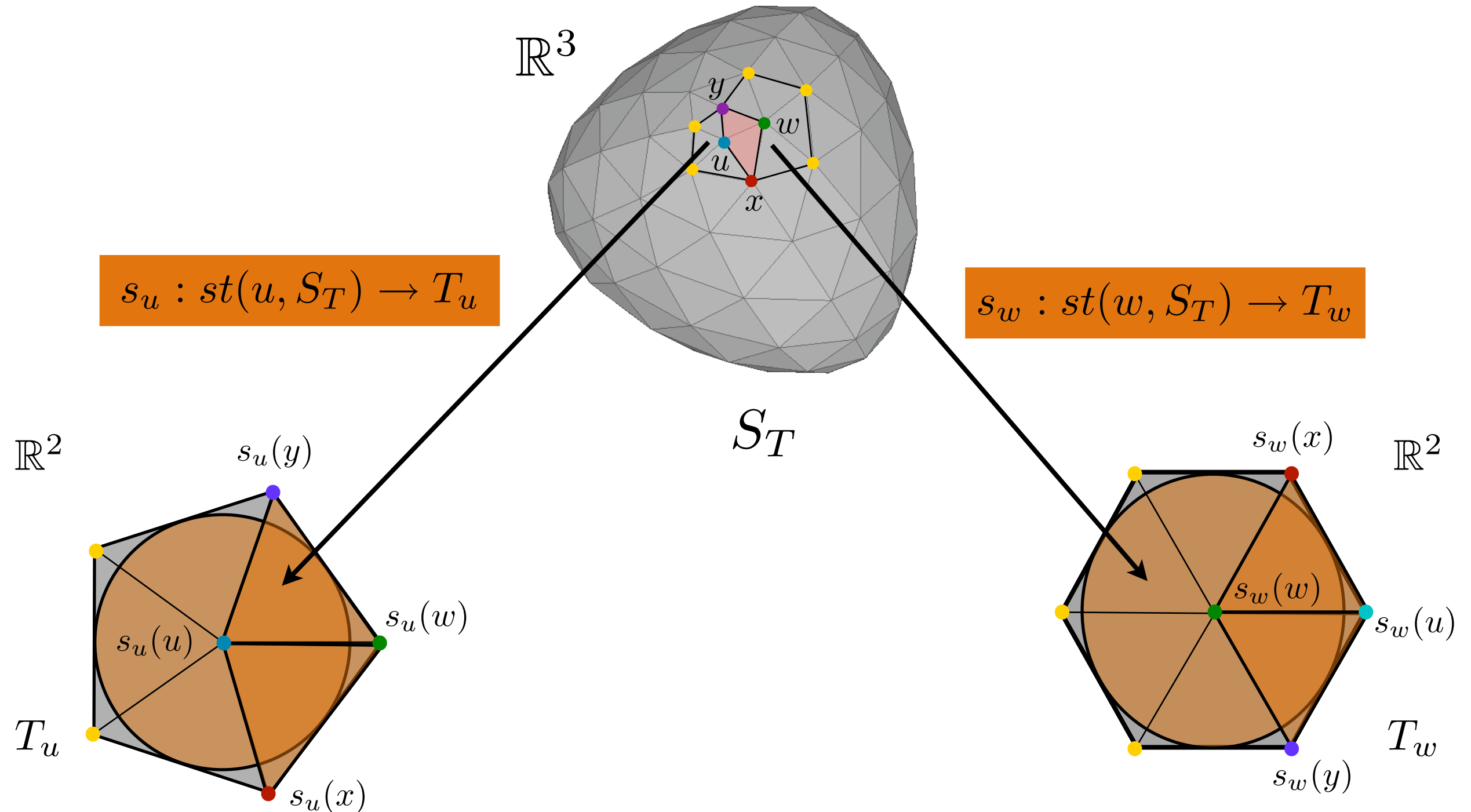


$$s_u : st(u, S_T) \rightarrow T_u$$



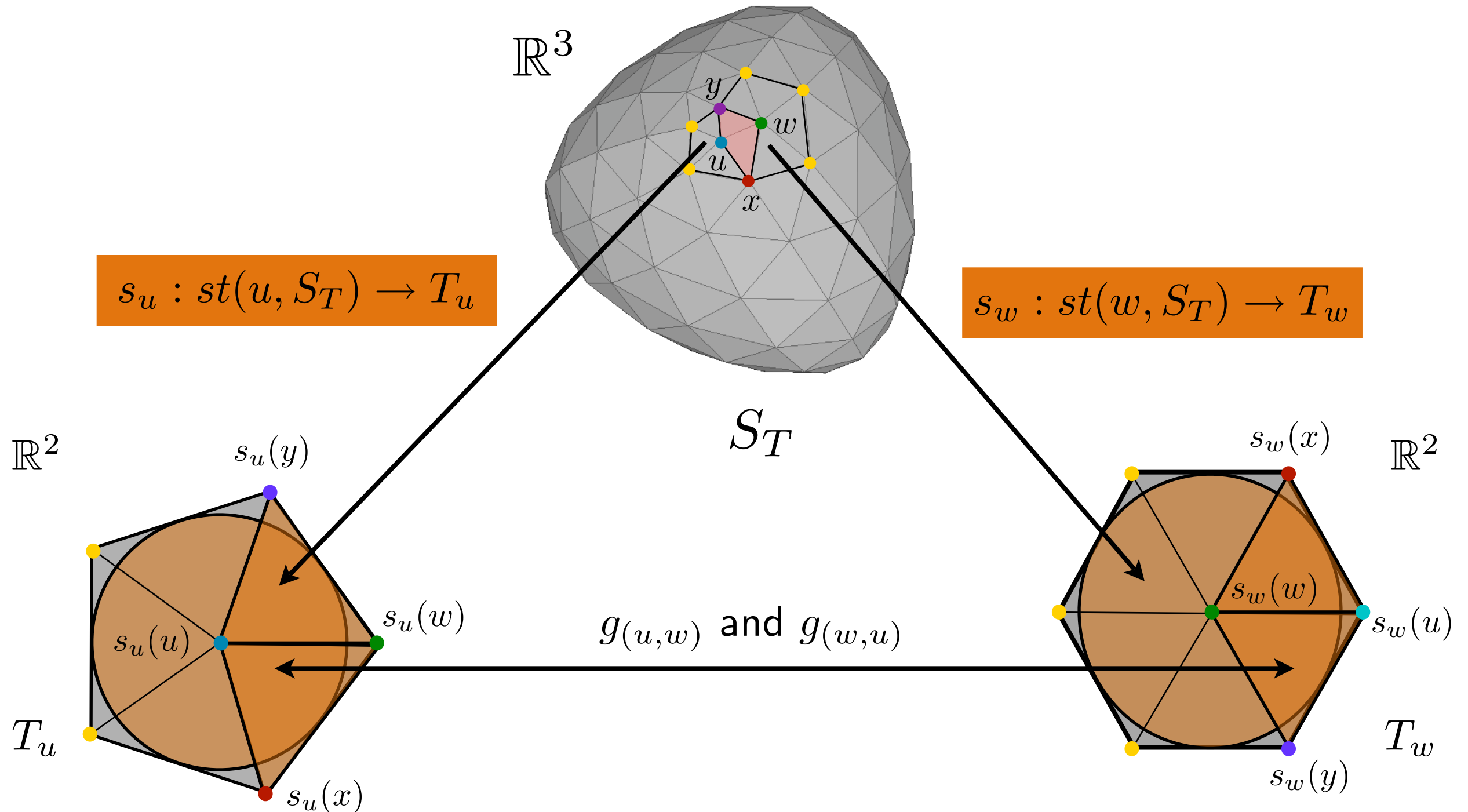
Building a Set of Gluing Data

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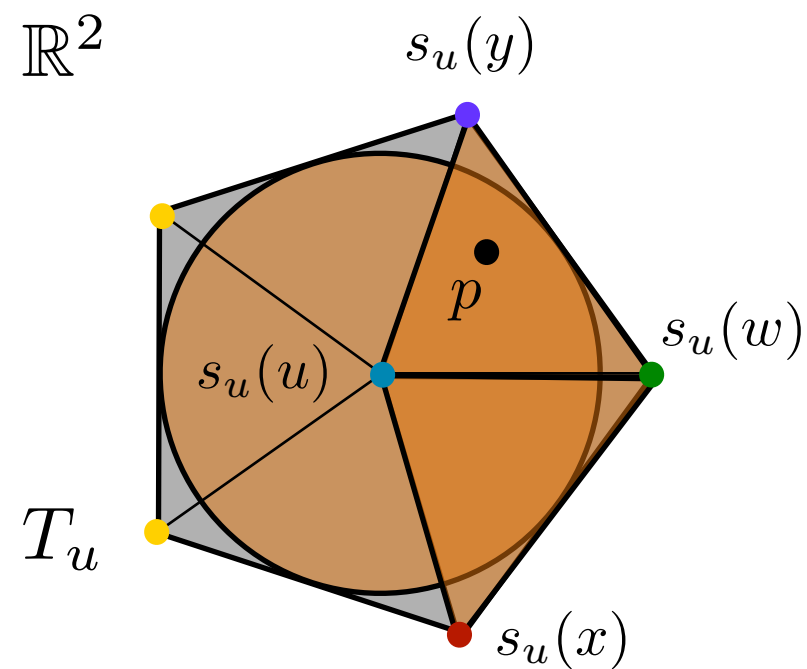
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Building a Set of Gluing Data

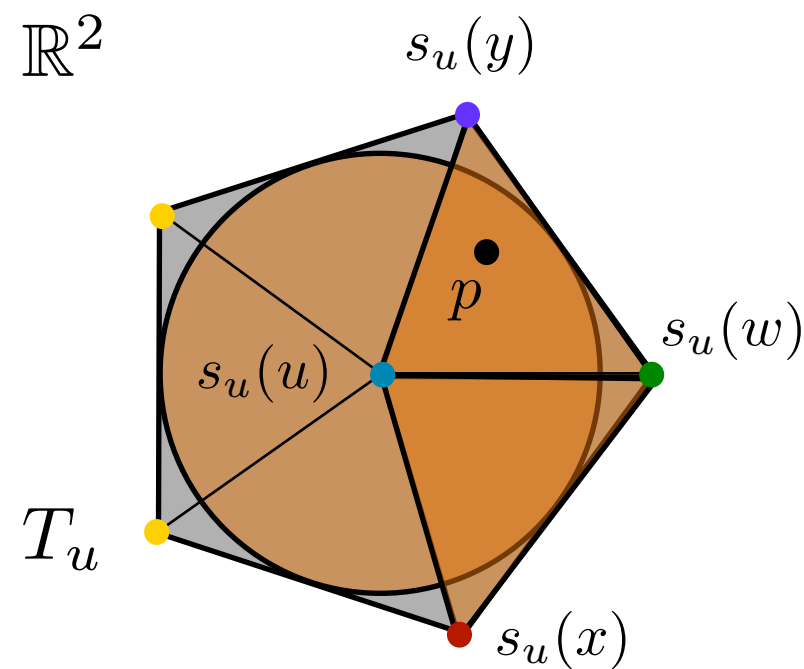
Building a Set of Gluing Data

Let p be a point in the region $C_u \cap [s_u(u), s_u(x), s_u(w), s_u(y)]$.



Building a Set of Gluing Data

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Let (θ, r) be the polar coordinates of point p with respect to the local coordinate system of P_u (i.e., origin at $s_u(u) = (0, 0)$).

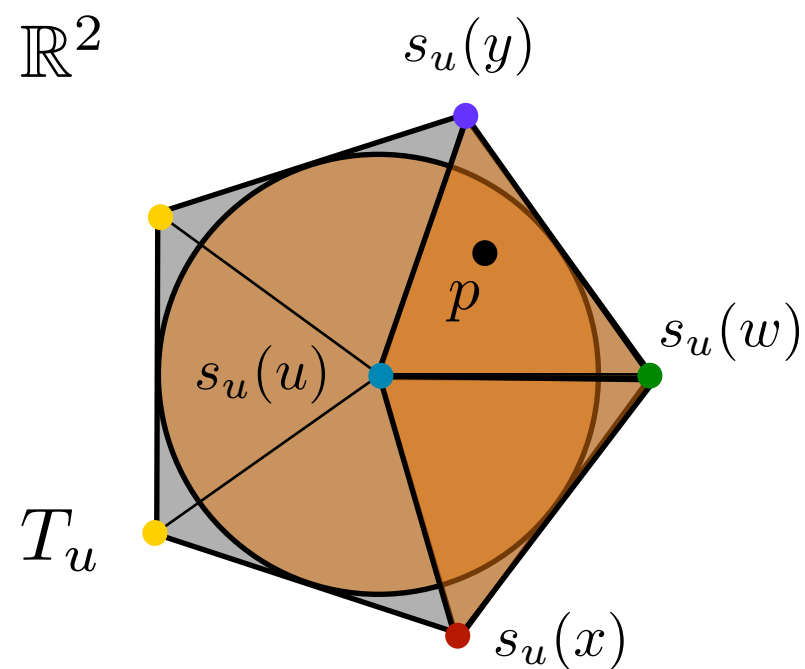
Building a Set of Gluing Data

Building a Set of Gluing Data

Let $g_u : [0, 2\pi) \times \mathbb{R}_+ \rightarrow [0, 2\pi) \times \mathbb{R}_+$ be the map

$$g_u(p) = g_u((\theta, r)) = \left(\frac{6}{m_u} \cdot \theta, \frac{\cos(\frac{\pi}{6})}{\cos(\frac{\pi}{m_u})} \cdot r \right),$$

where m_u is the degree of u .

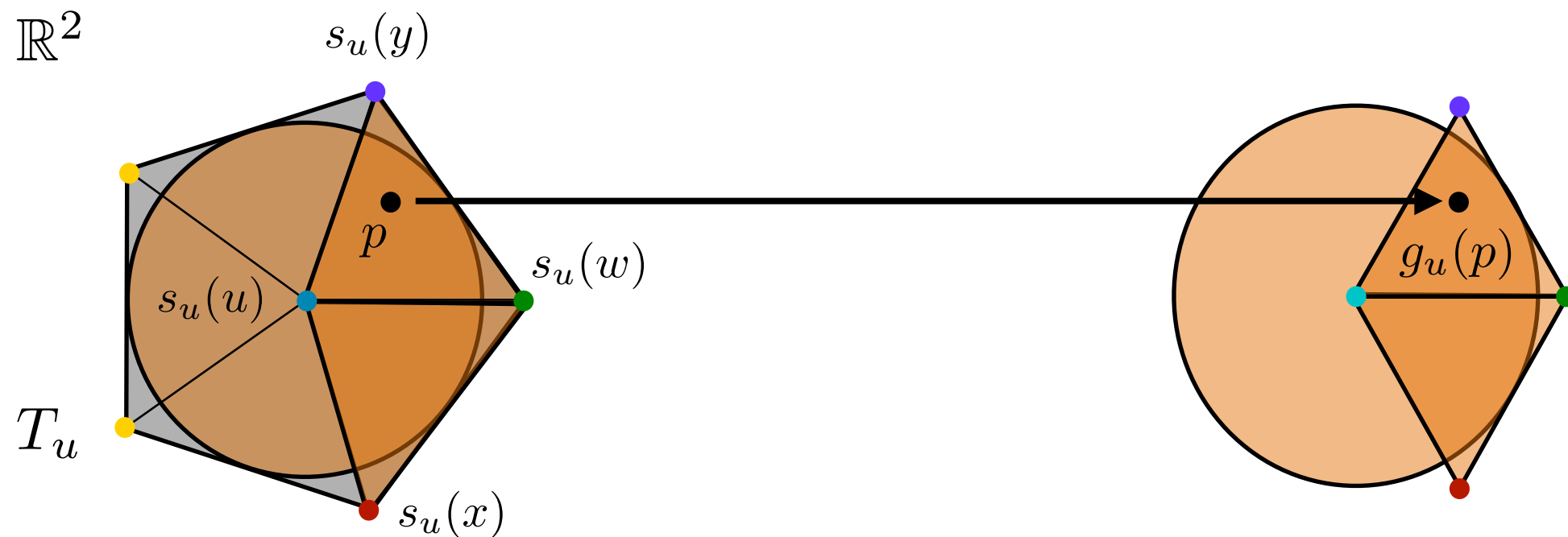


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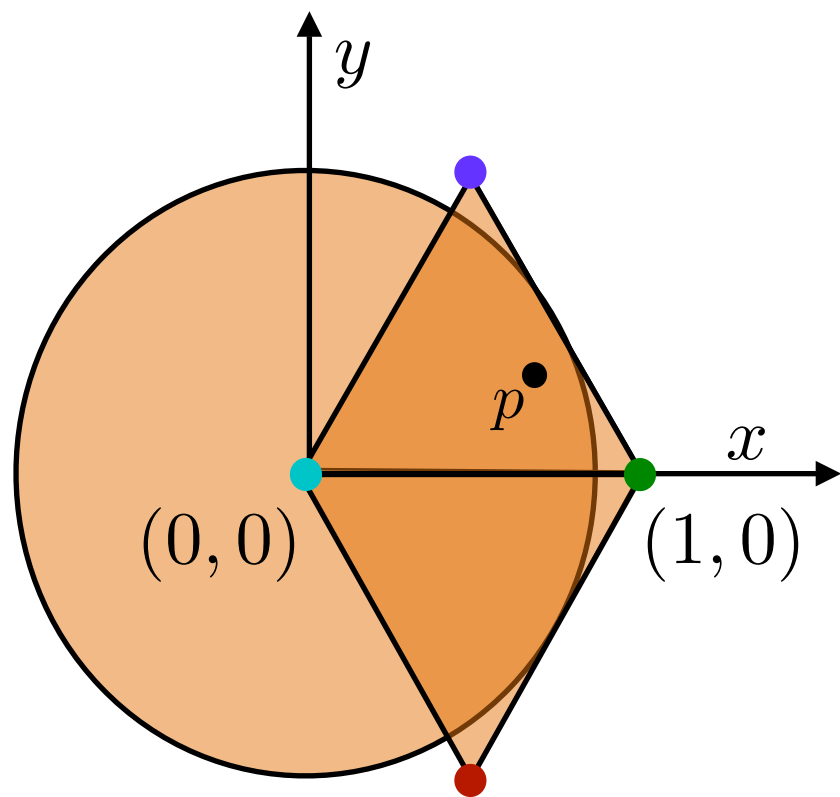
Building a Set of Gluing Data

Building a Set of Gluing Data

Let $h : \mathbb{R}^2 \rightarrow \mathbb{R}^2$ be the map $h(p) = h((x, y)) = (1 - x, -y)$:

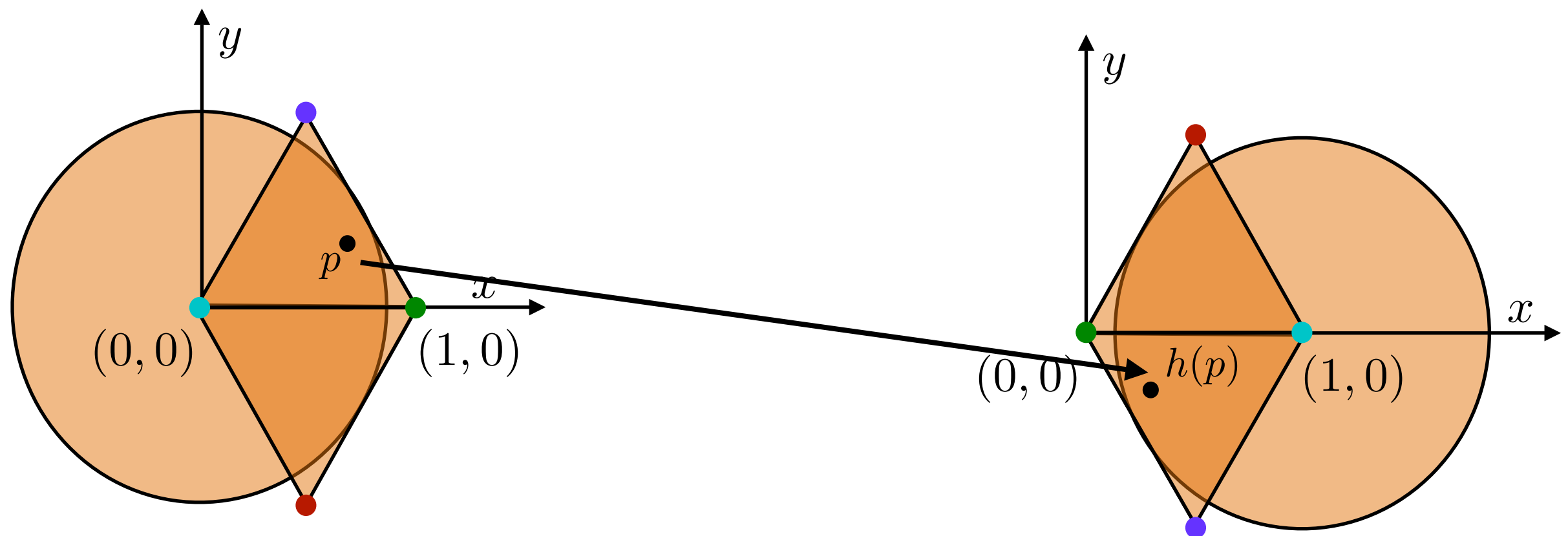
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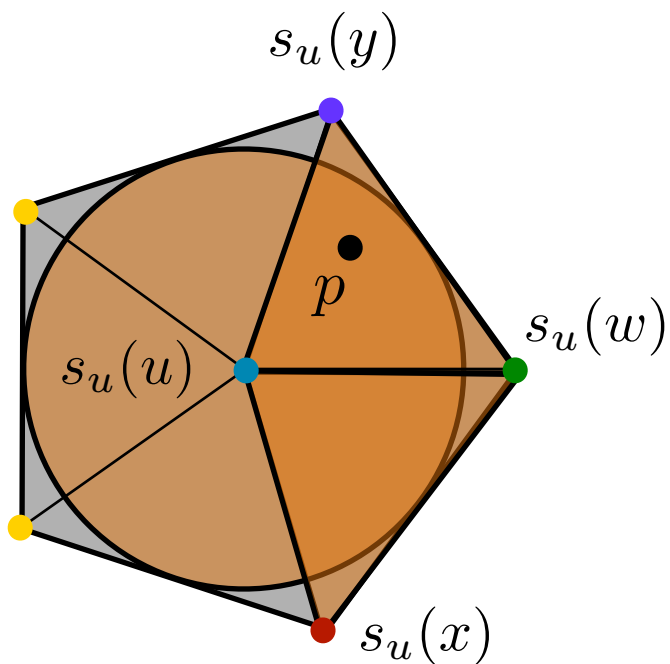
Finally, we define $g_{(u,w)} : [0, 2\pi) \times \mathbb{R}_+ \rightarrow [0, 2\pi) \times \mathbb{R}_+$ as

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Building a Set of Gluing Data

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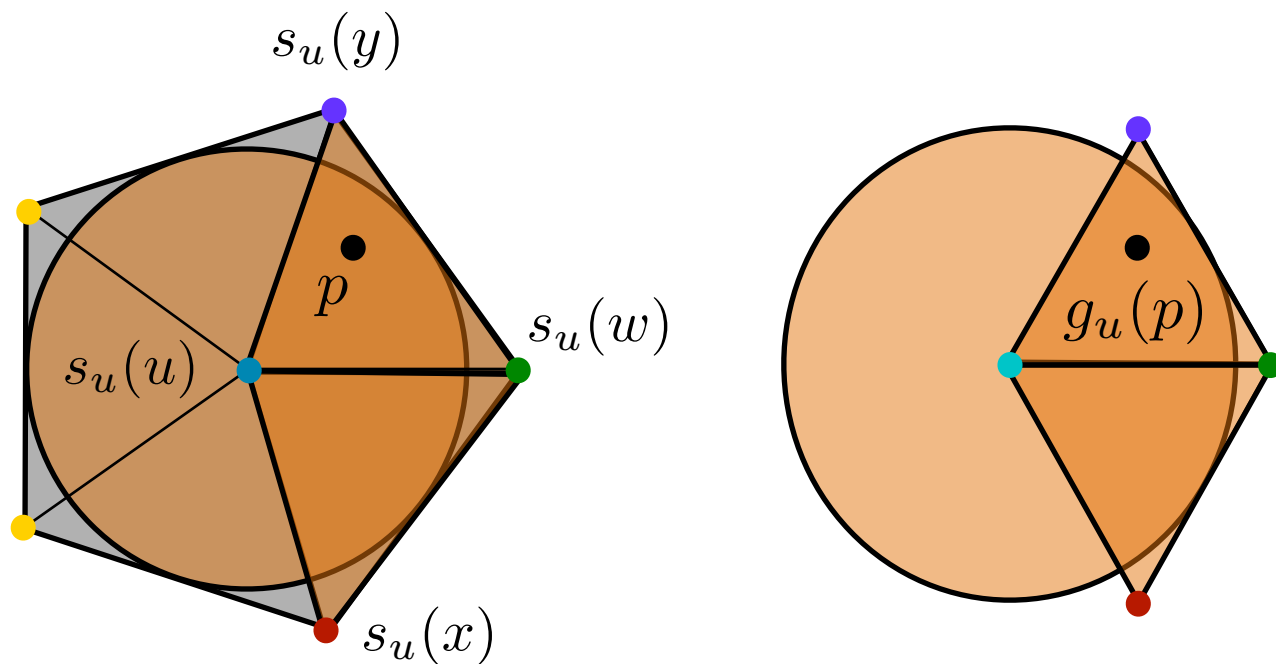
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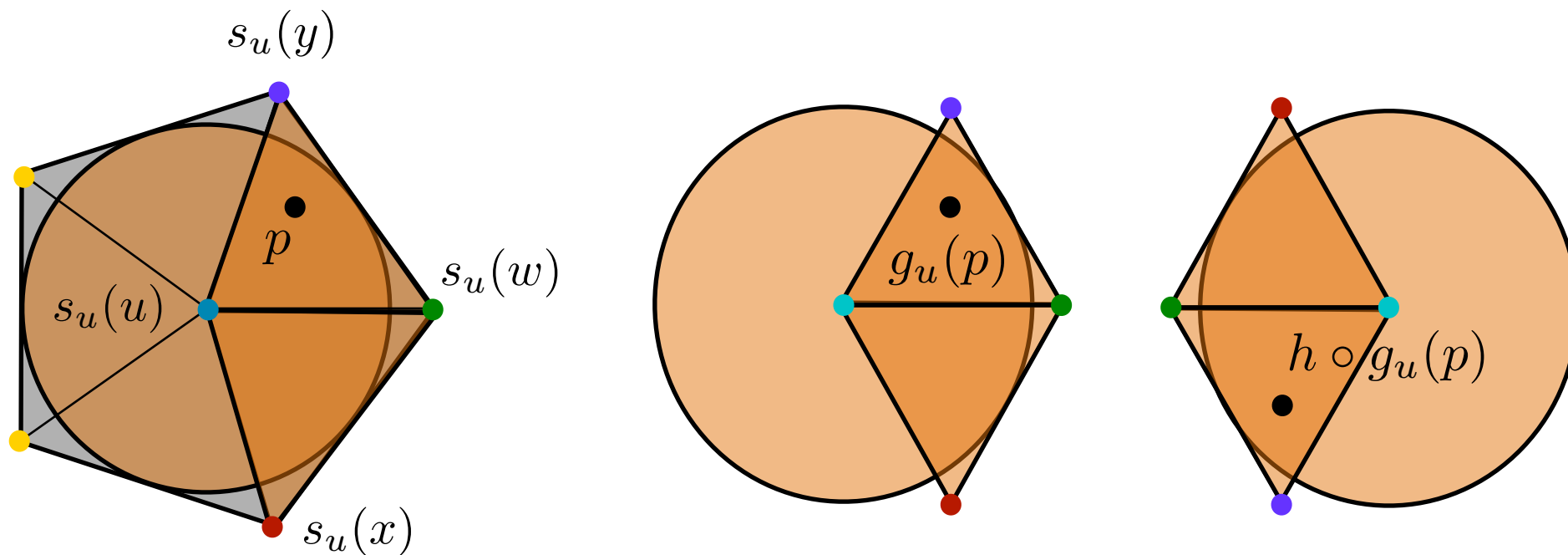
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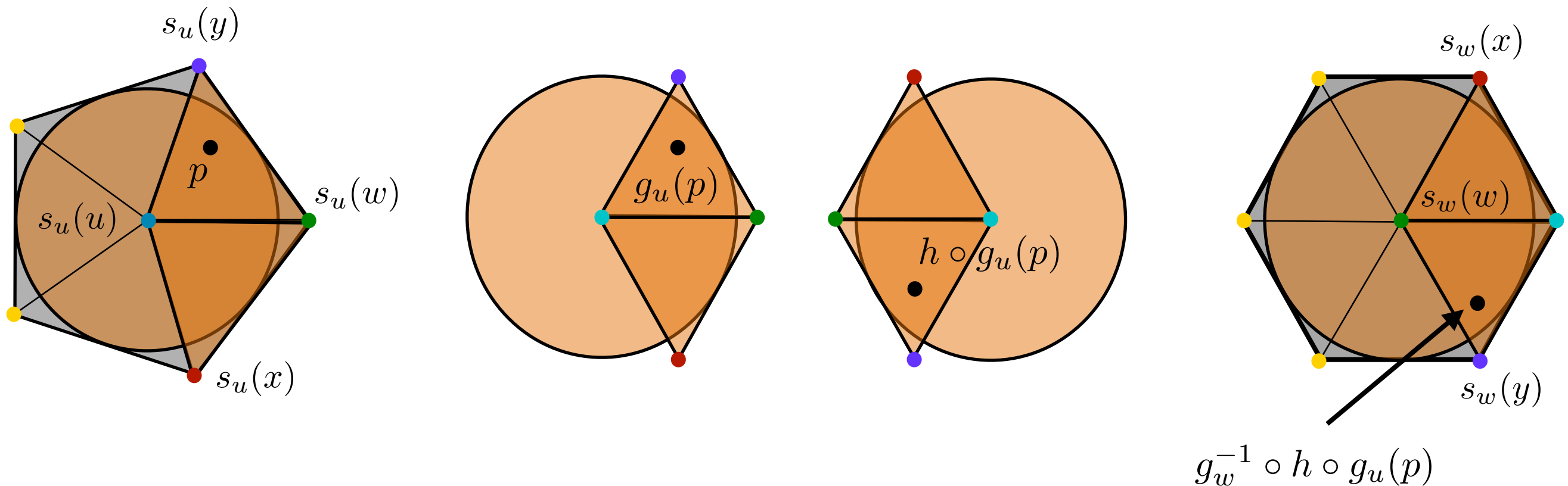
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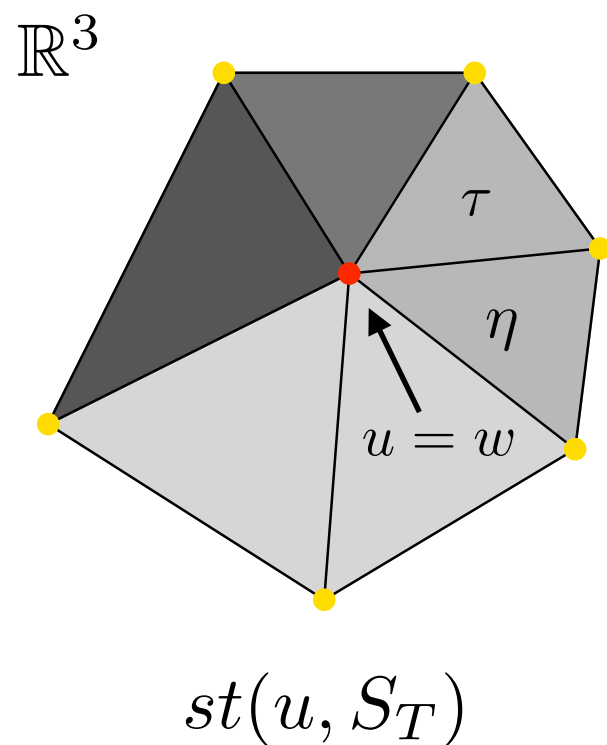
Building a Set of Gluing Data

For any two $(\tau, u), (\eta, w) \in I$, we define $\Omega_{(\tau, u)(\eta, w)}$ as follows:

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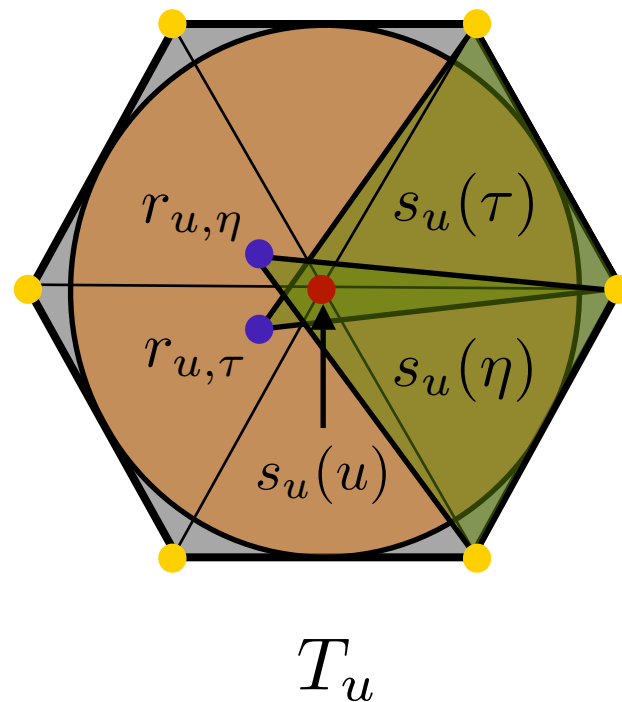
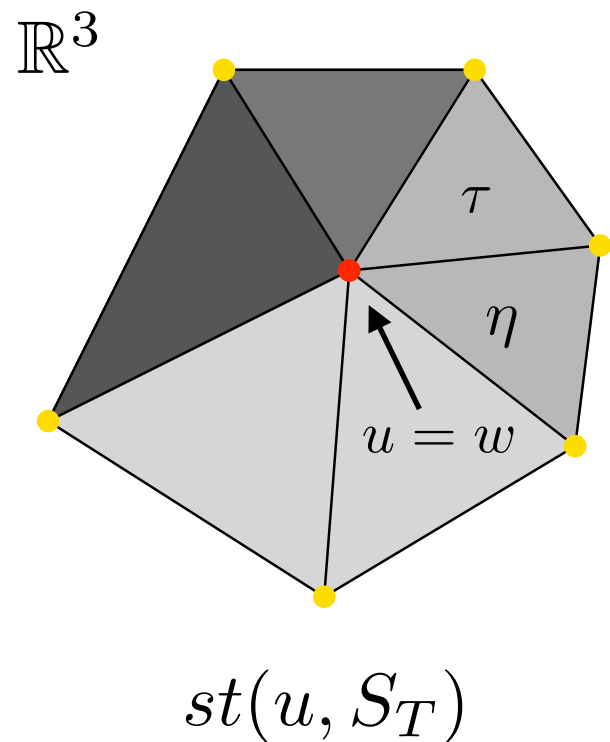
(1) $u = w$



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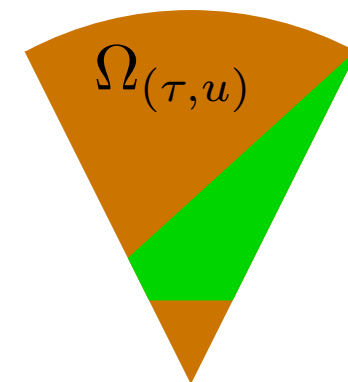
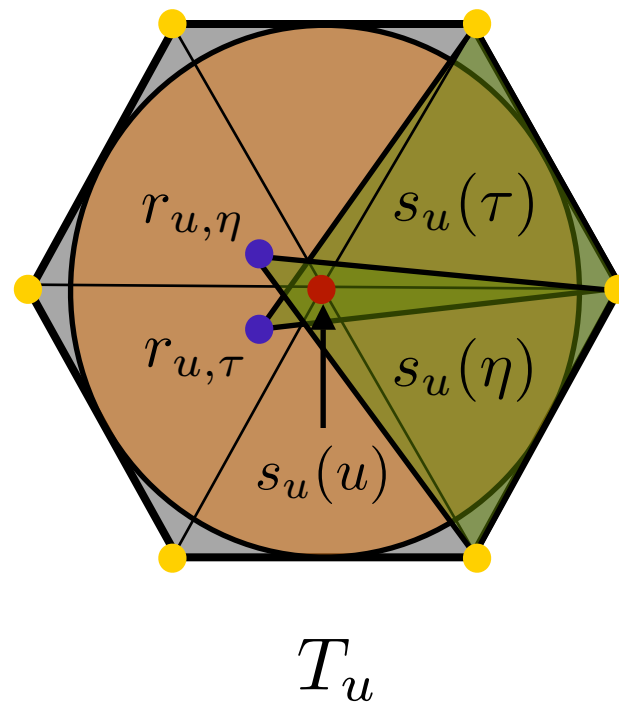
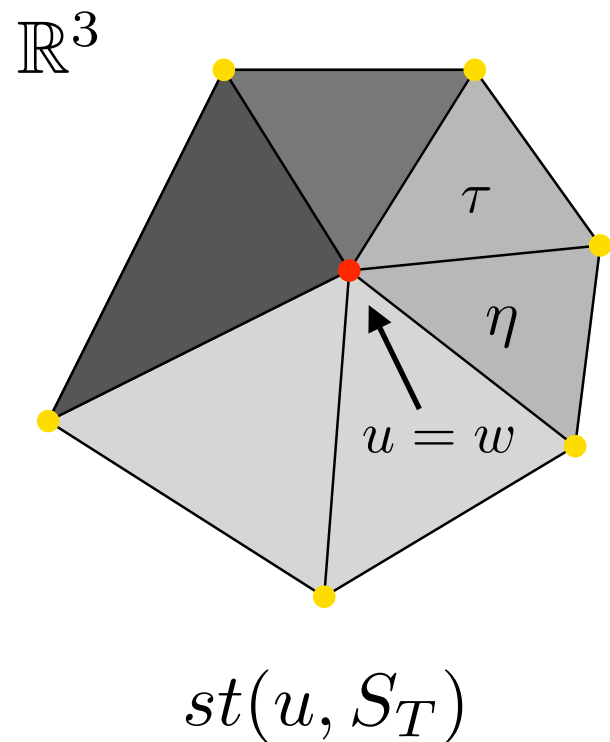
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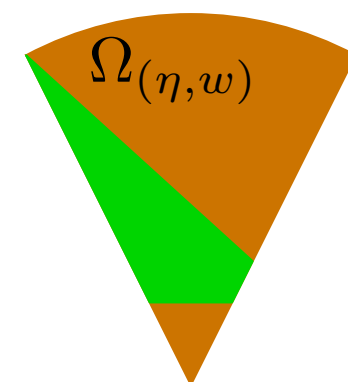
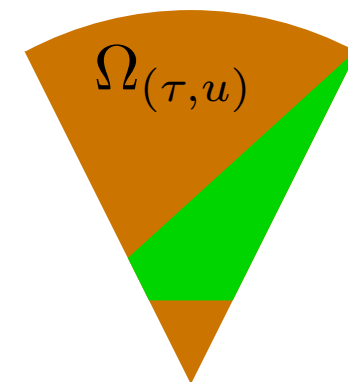
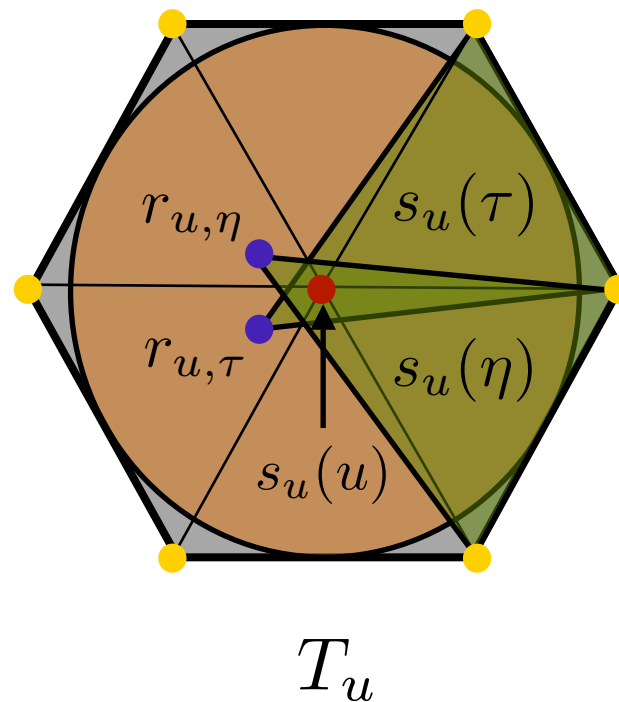
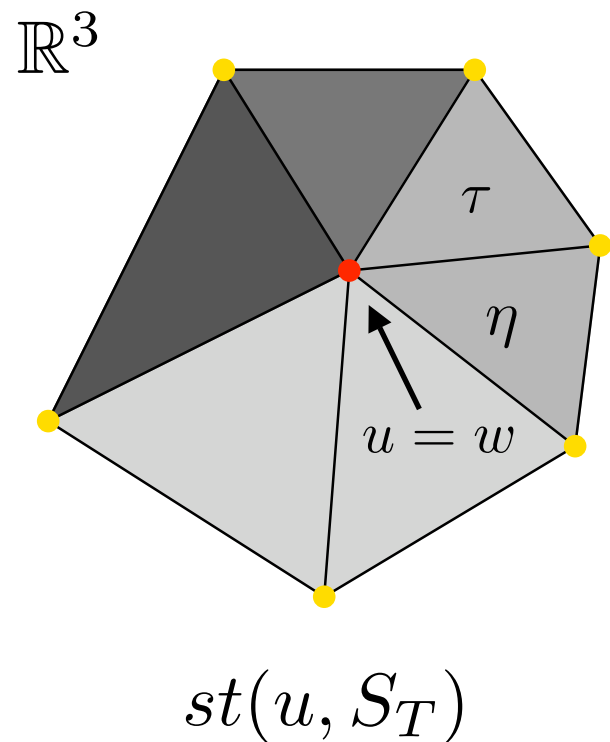
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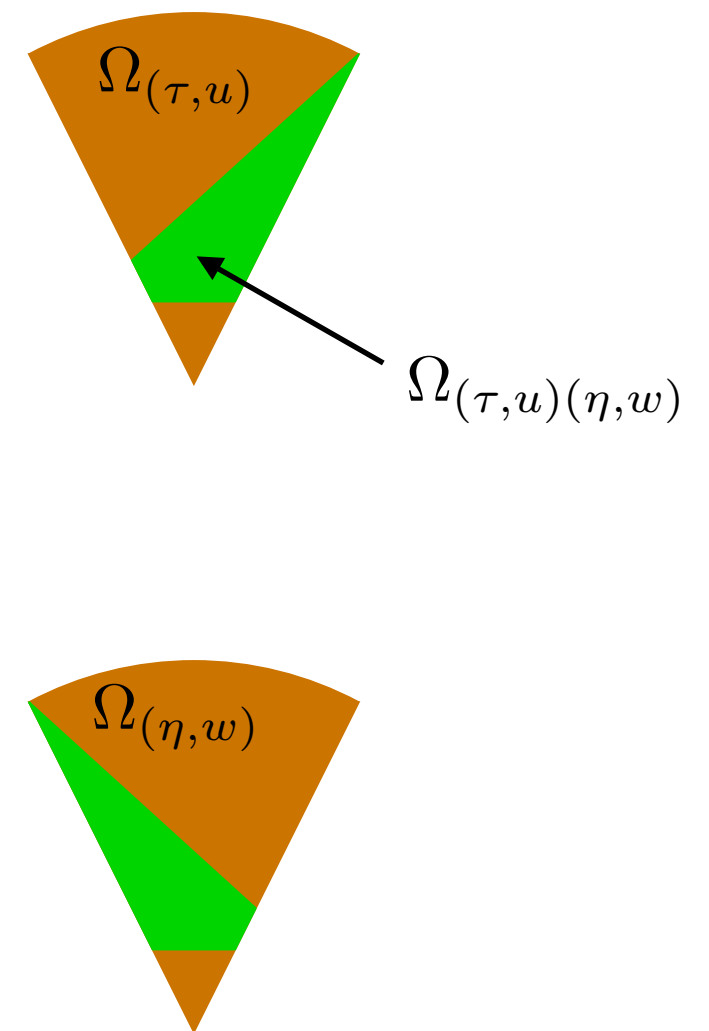
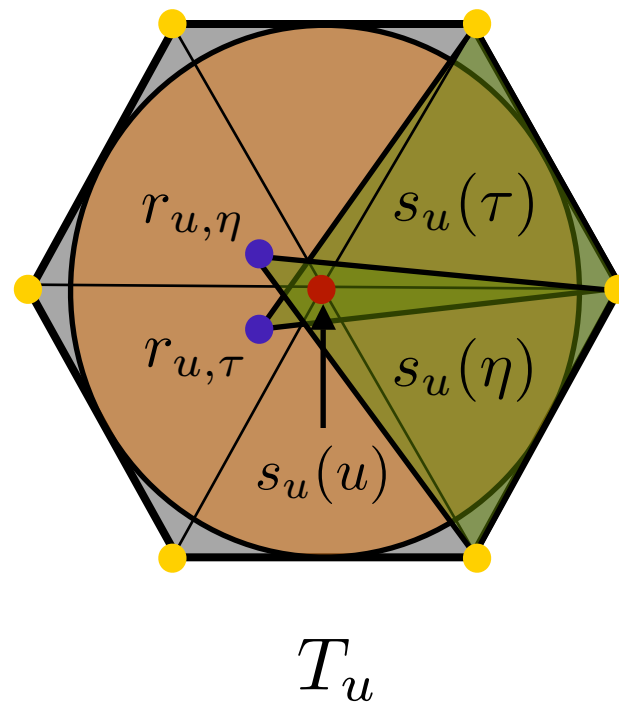
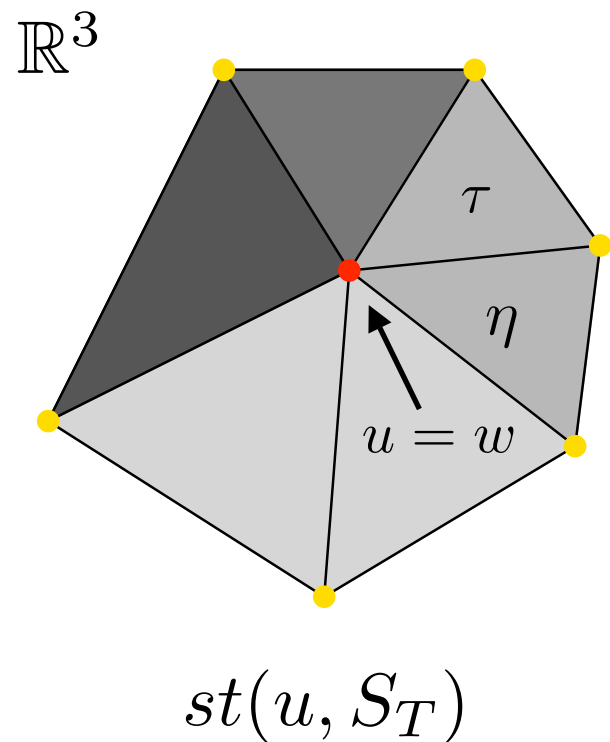
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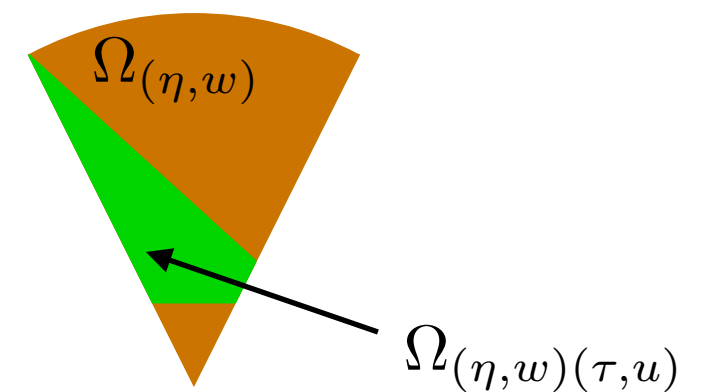
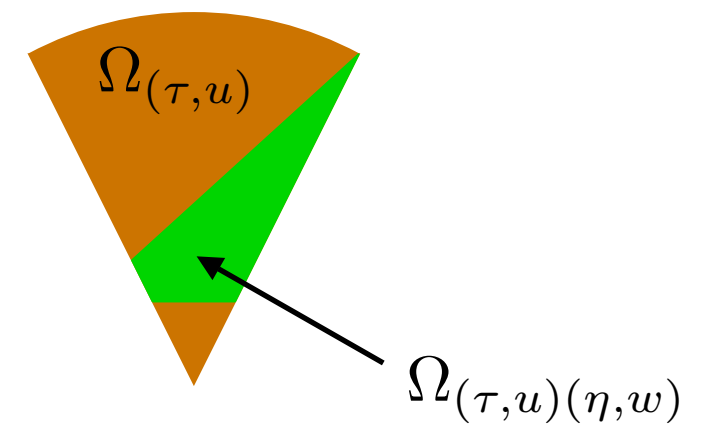
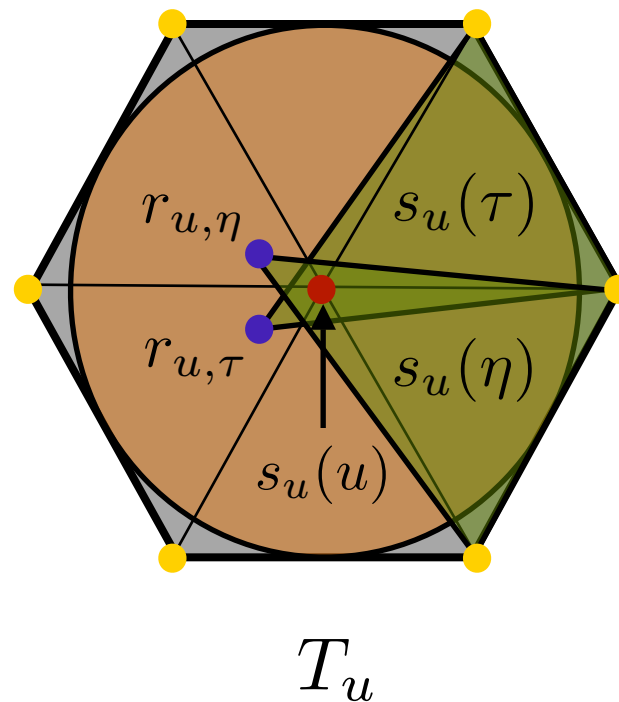
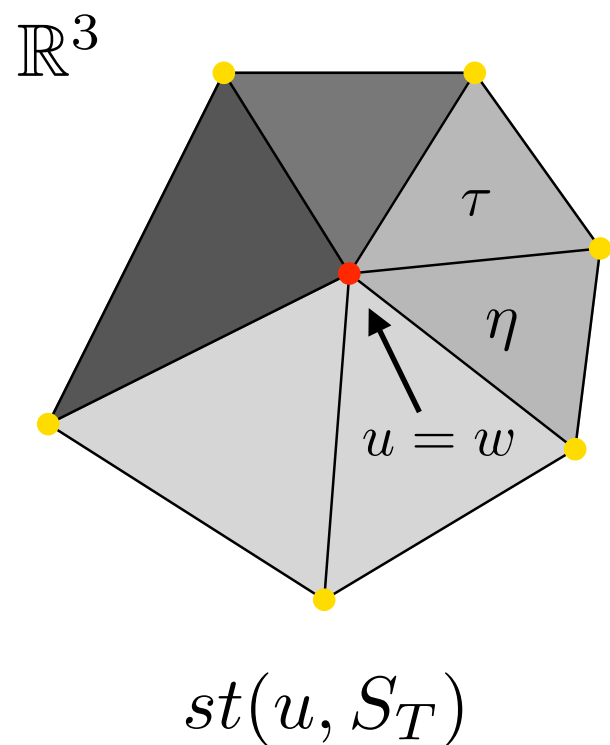
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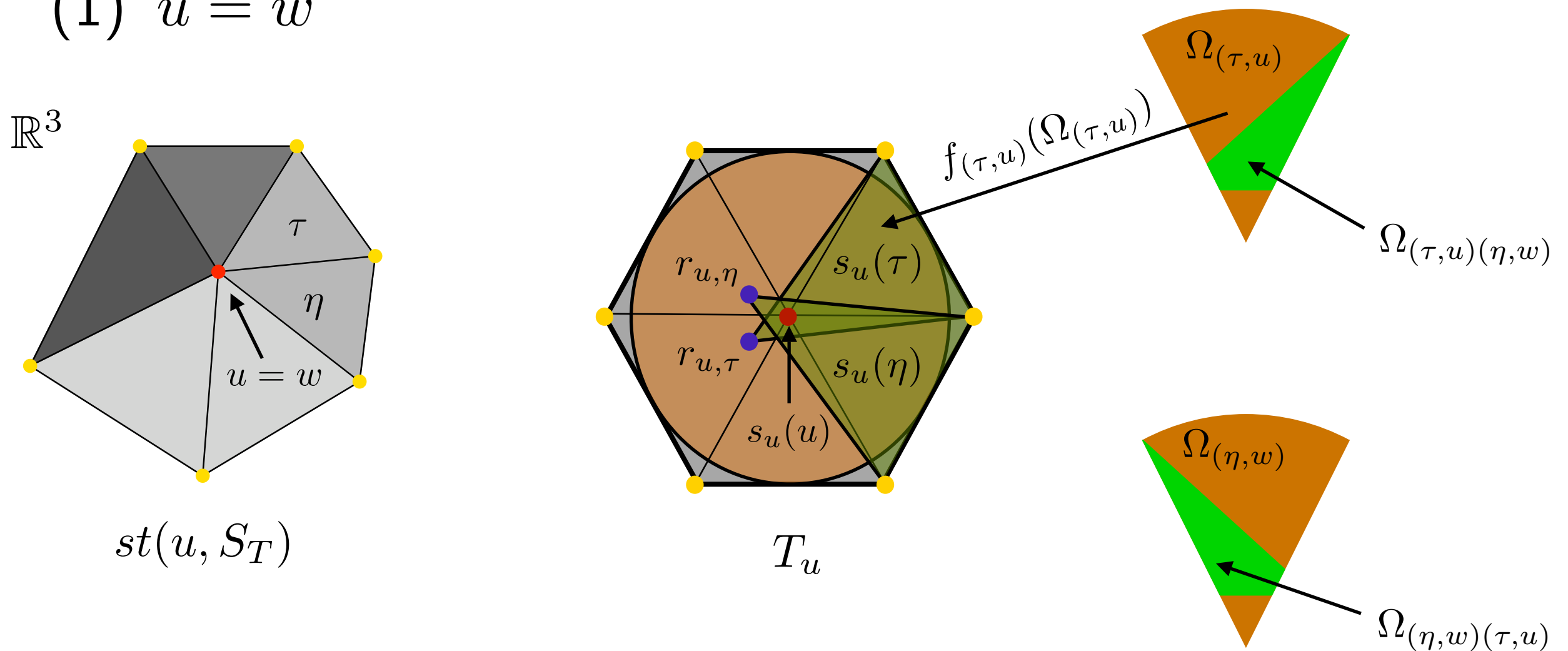
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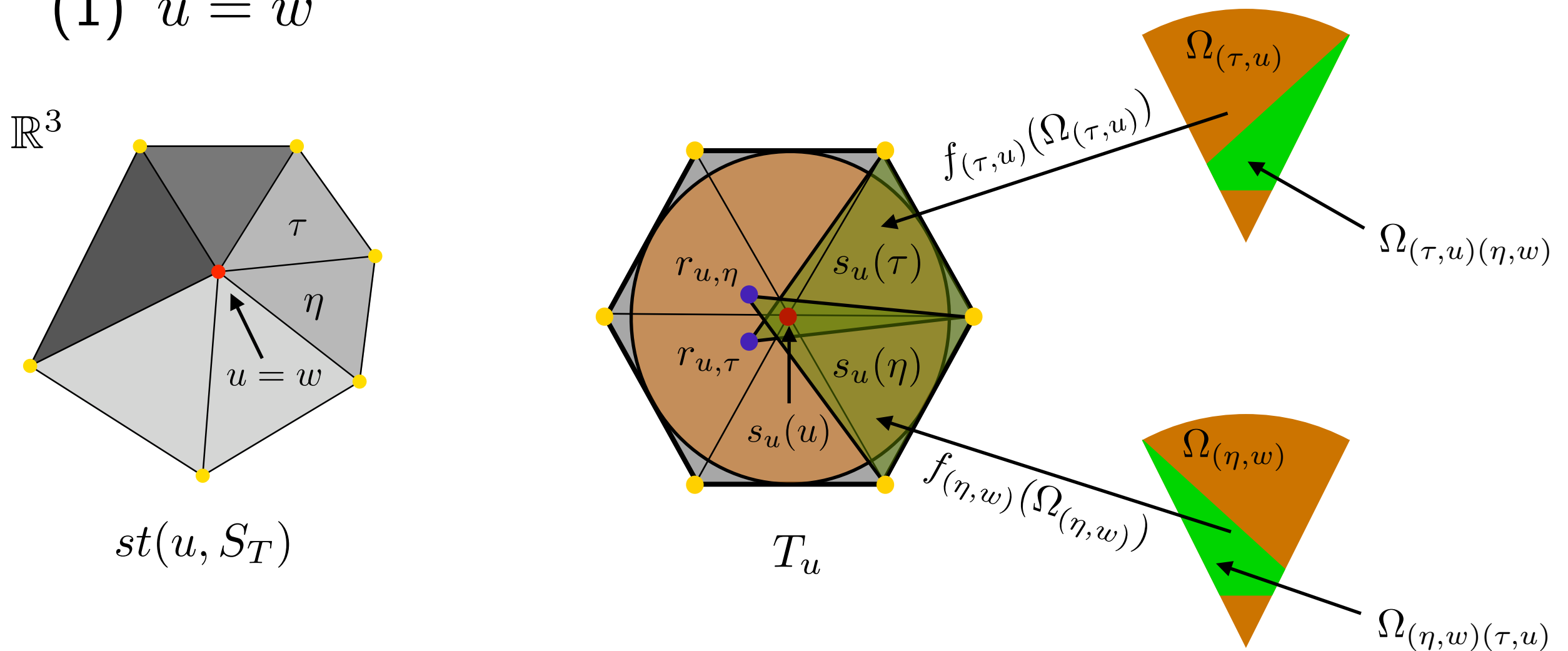
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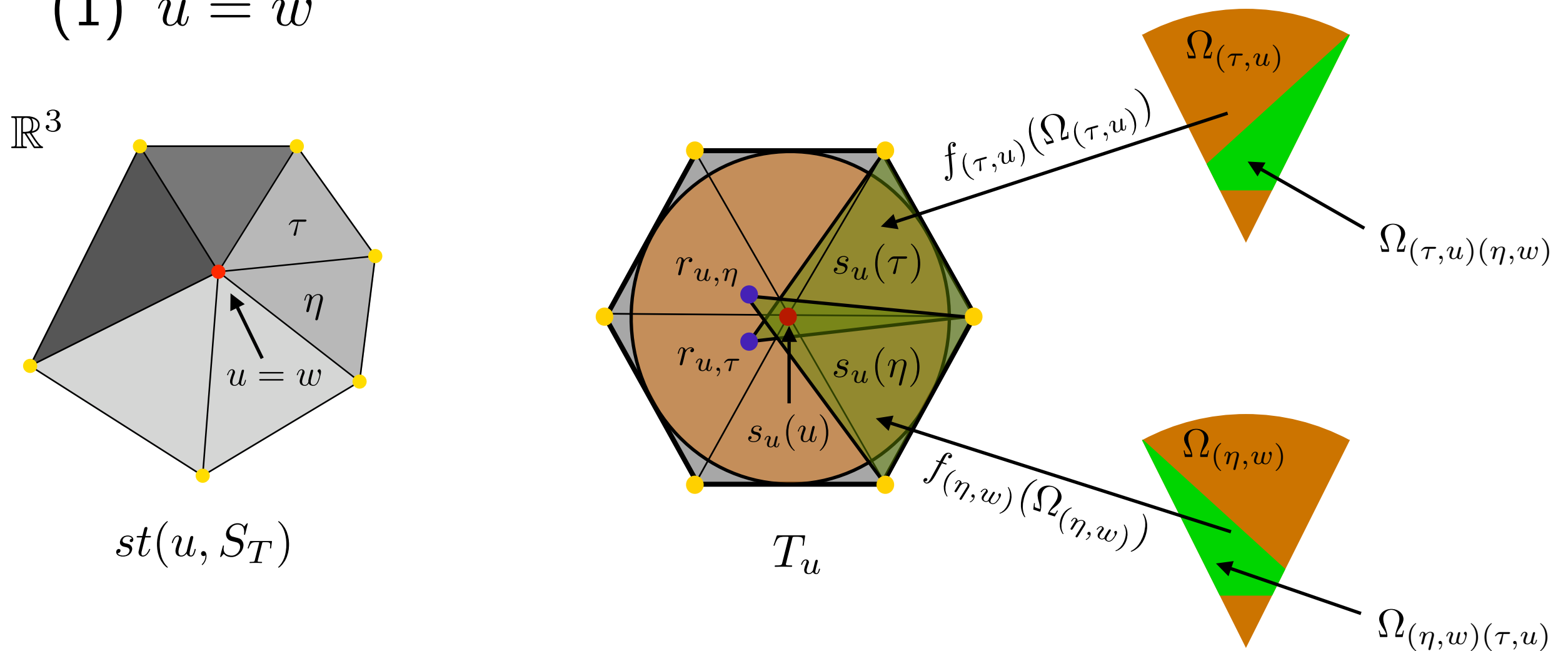
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(1) $u = w$



$$\Omega_{(\tau, u)(\eta, w)} = f_{(\tau, u)}^{-1} (f_{(\tau, u)}(\Omega_{\tau, u}) \cap f_{(\eta, w)}(\Omega_{\eta, w}))$$

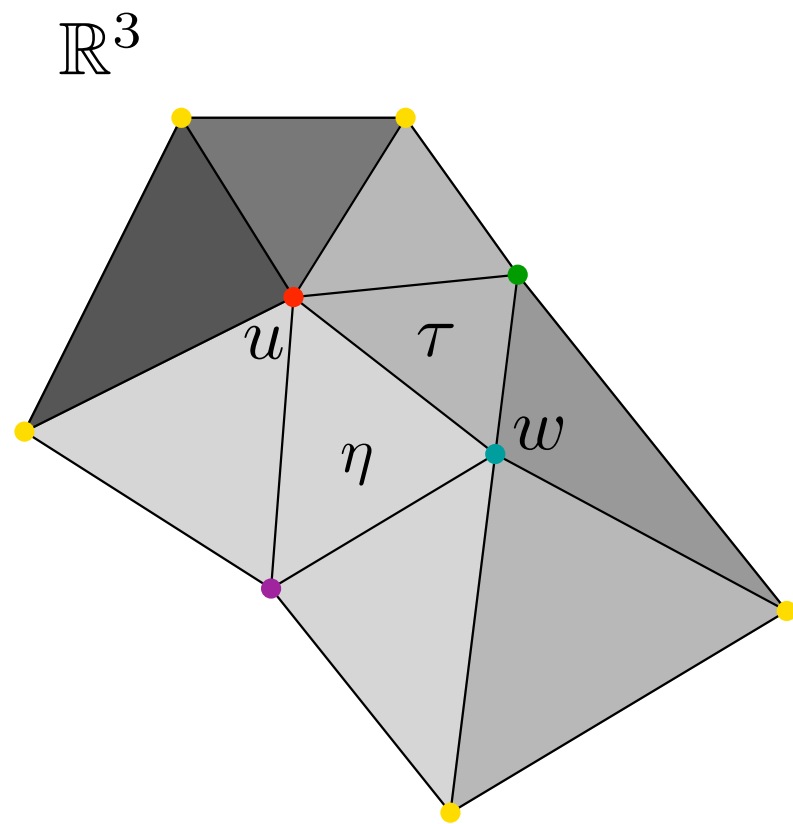
Building a Set of Gluing Data

Building a Set of Gluing Data

(2) $u \neq w$ and w is a vertex of τ or u is a vertex of η

Building a Set of Gluing Data

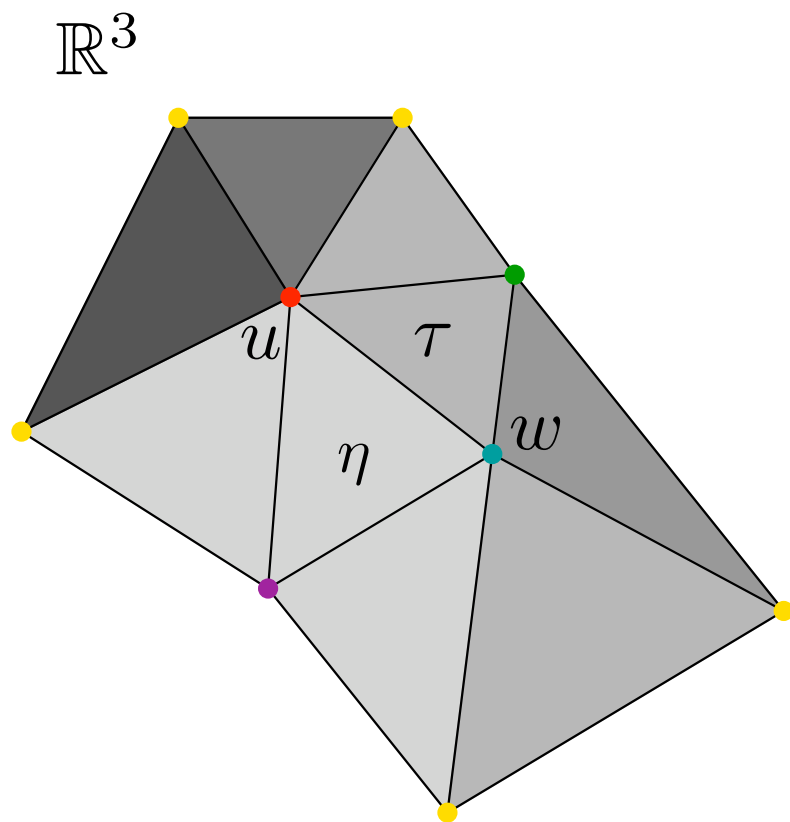
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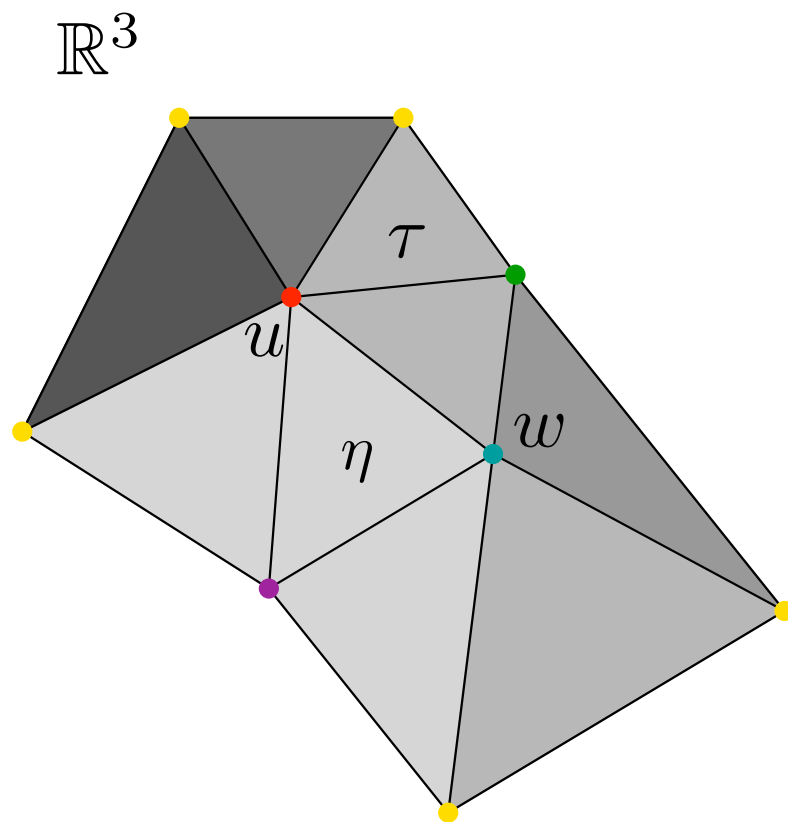
$$st(u, S_T) \cup st(w, S_T)$$

Building a Set of Gluing Data

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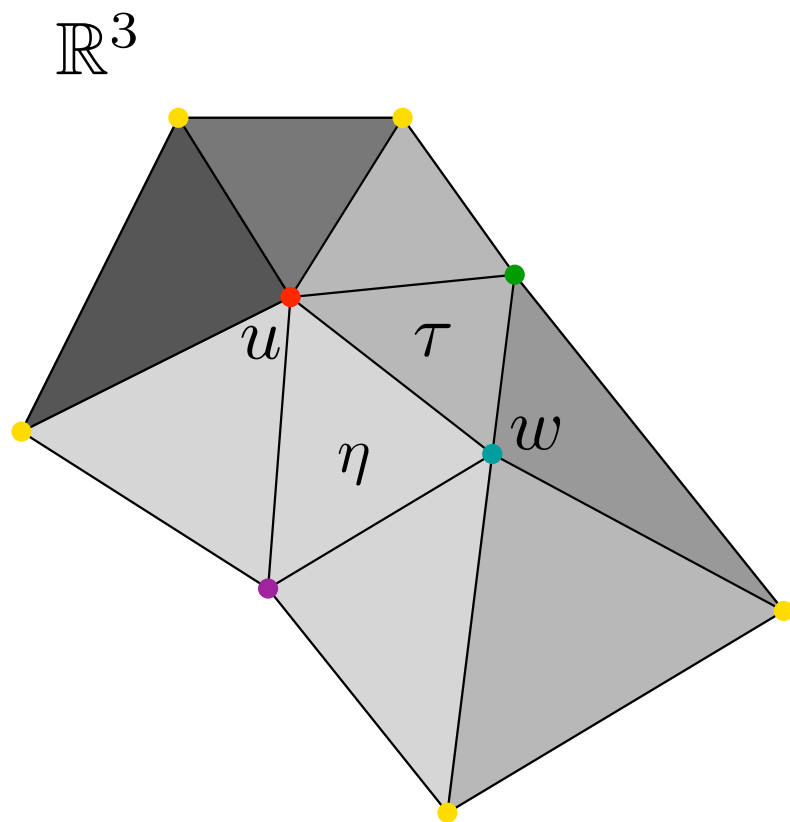
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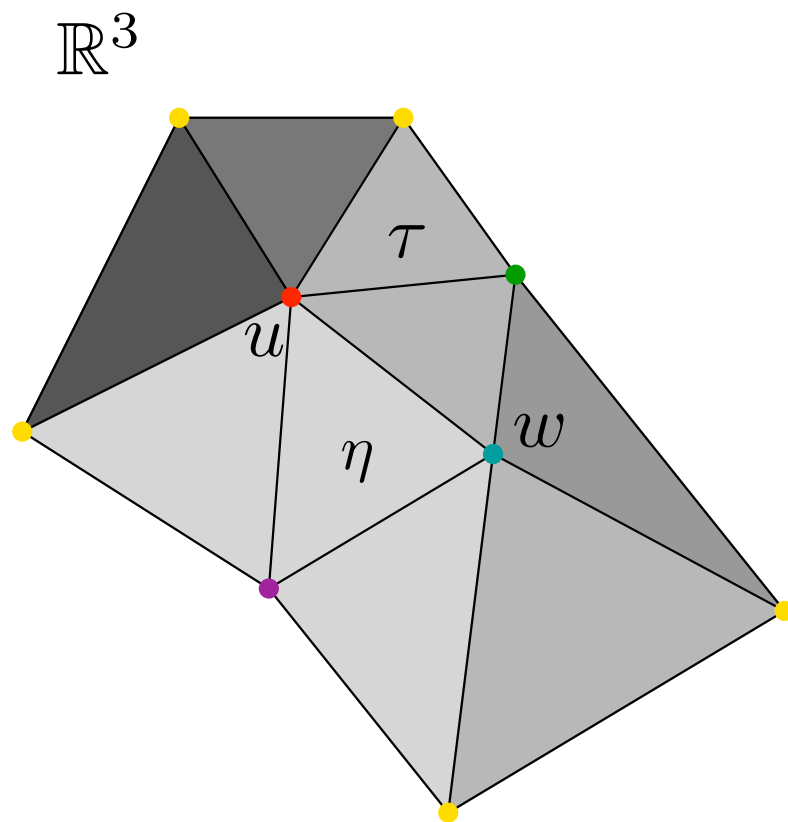
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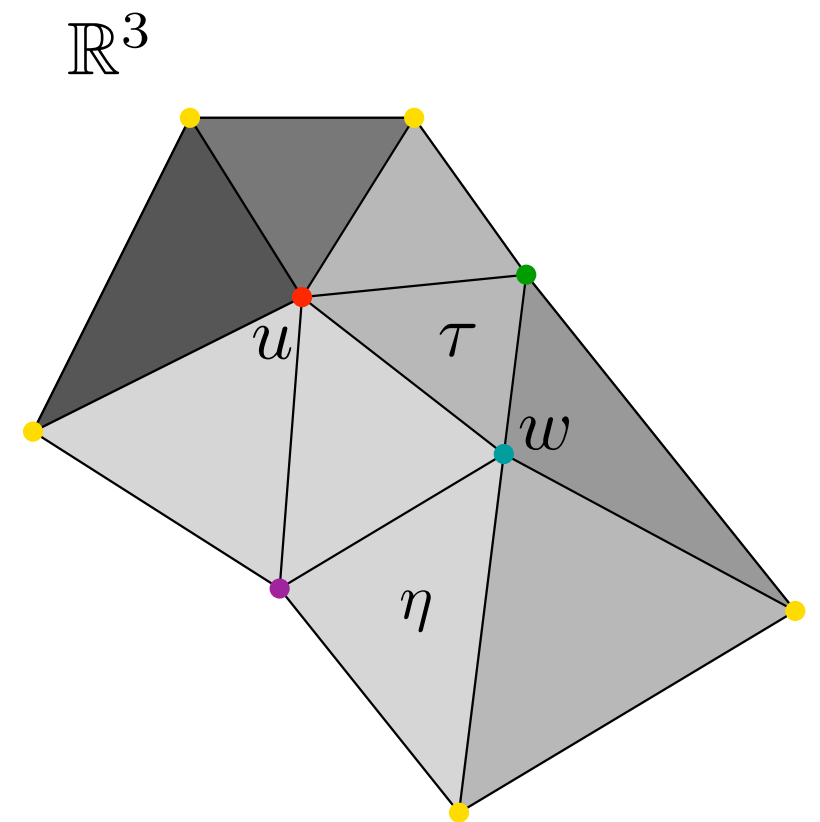
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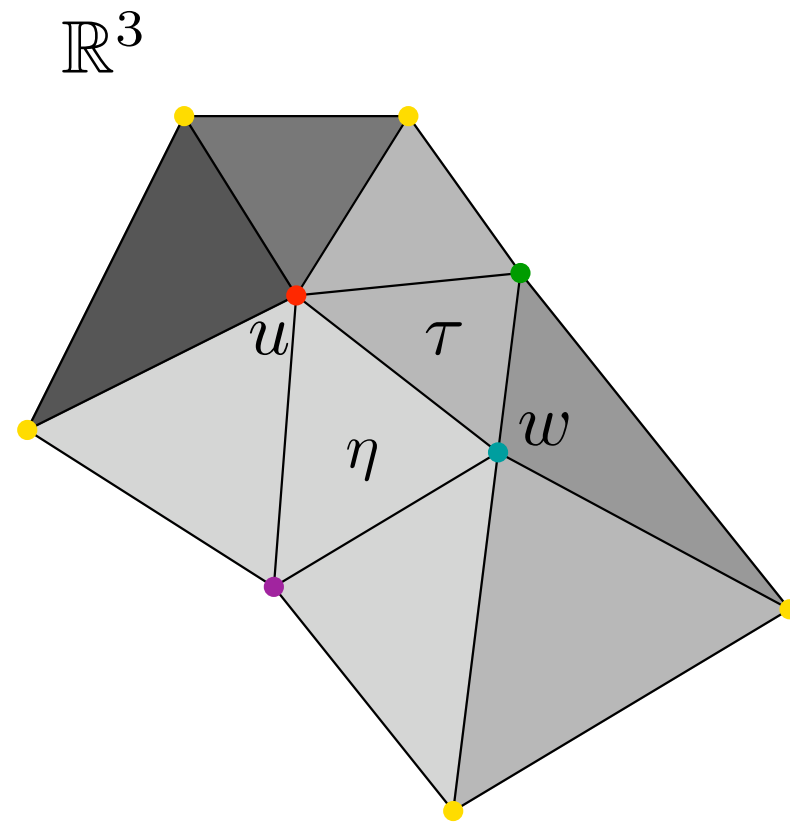
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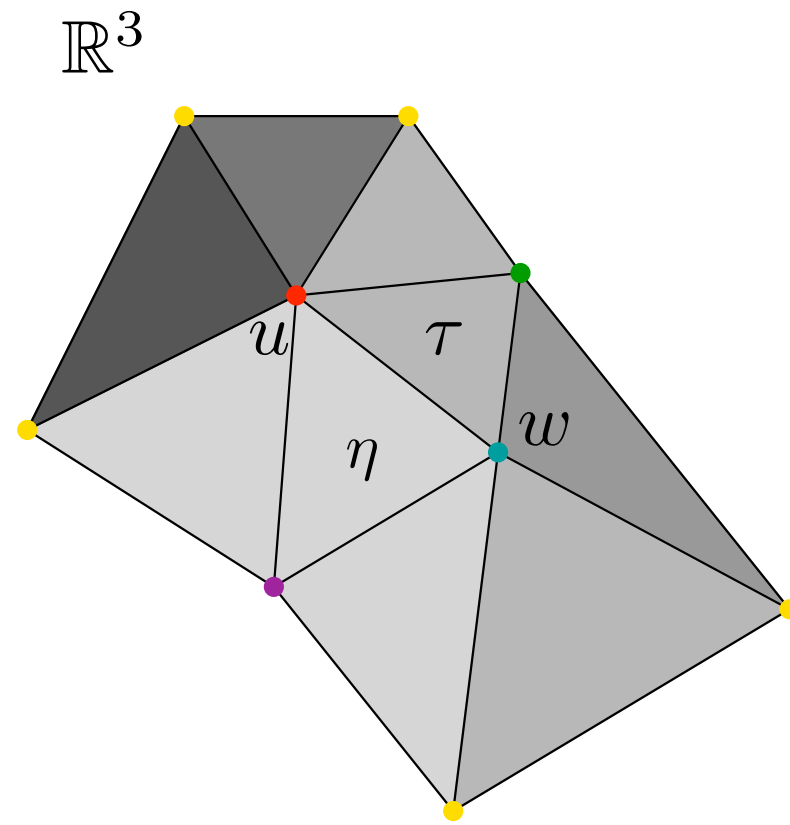
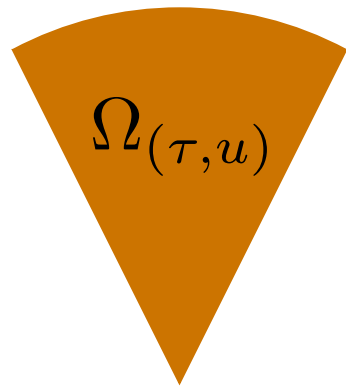
Building a Set of Gluing Data

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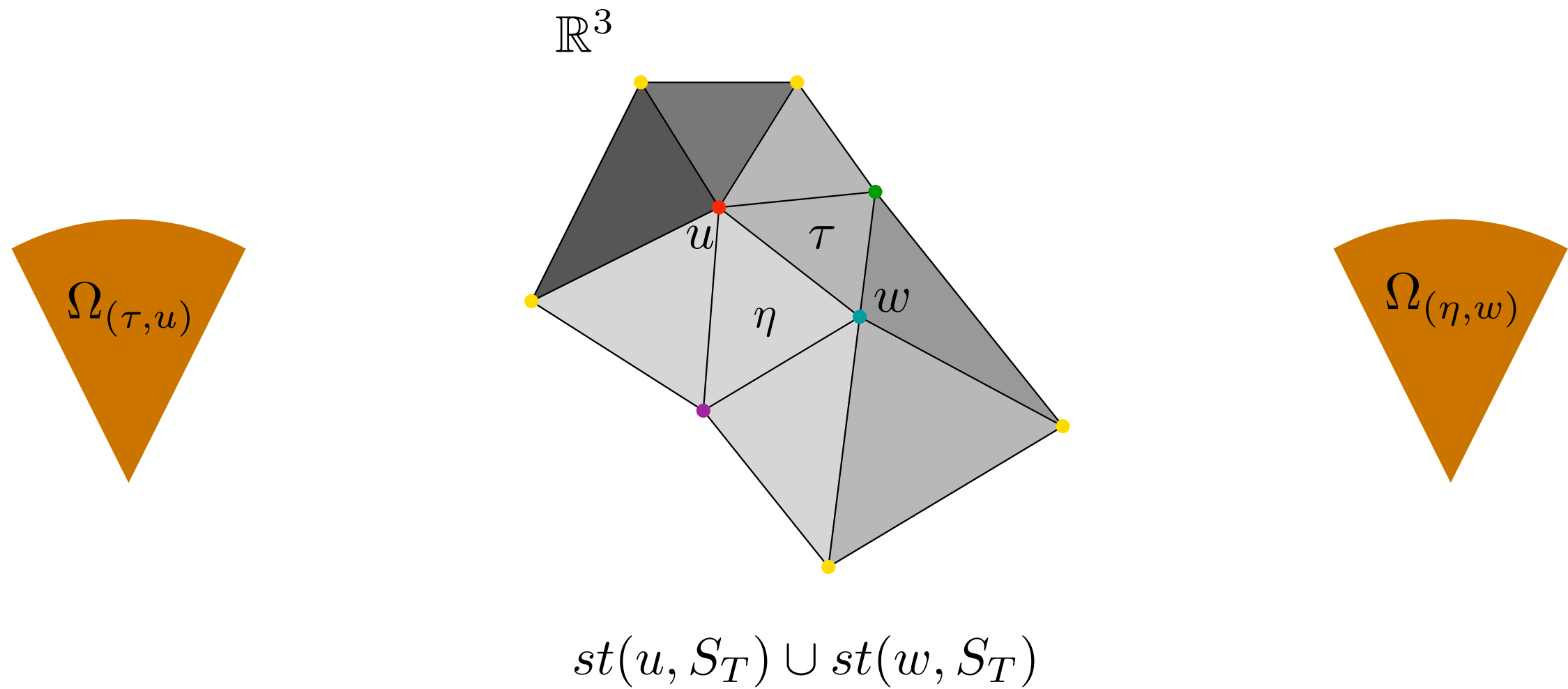
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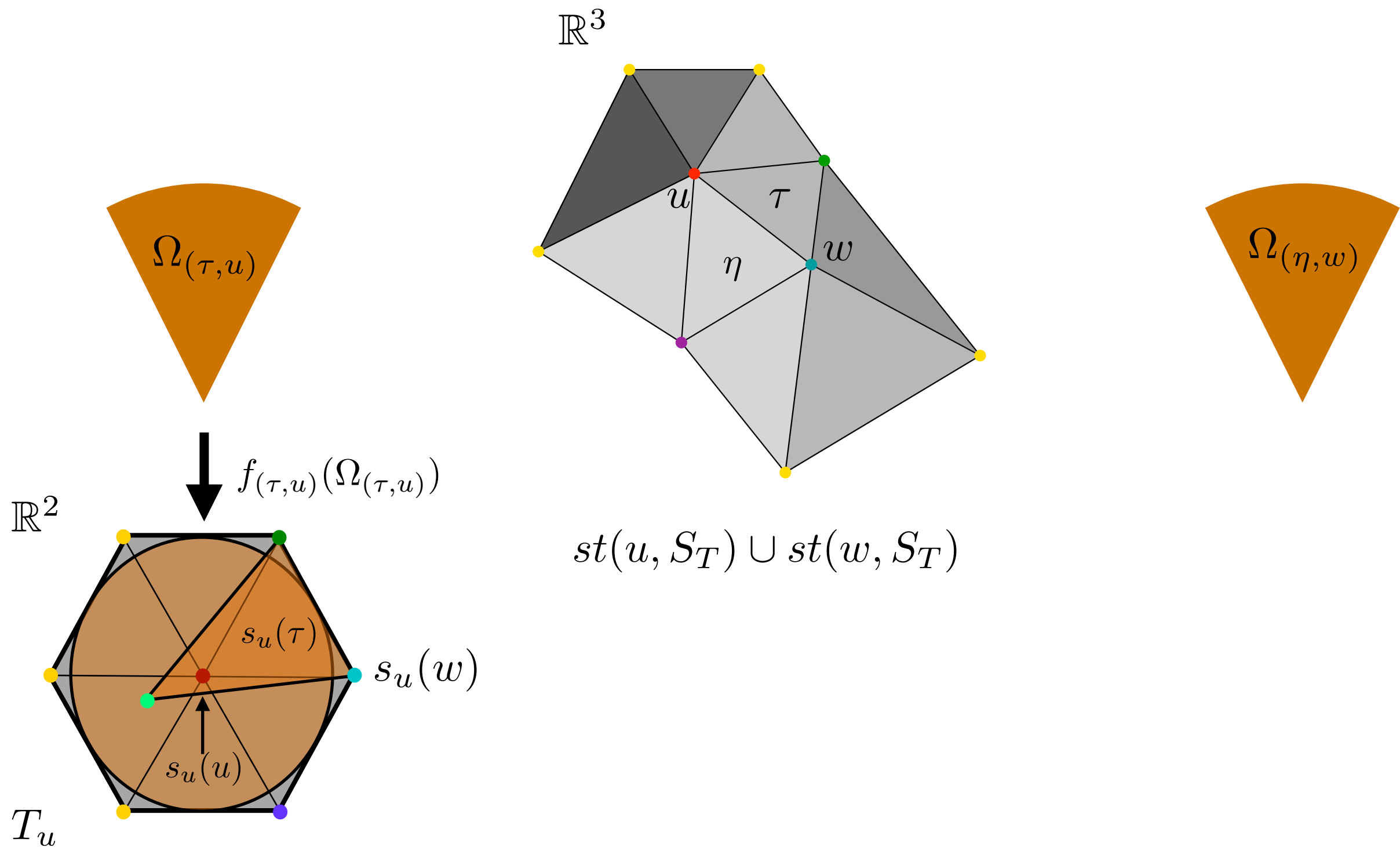


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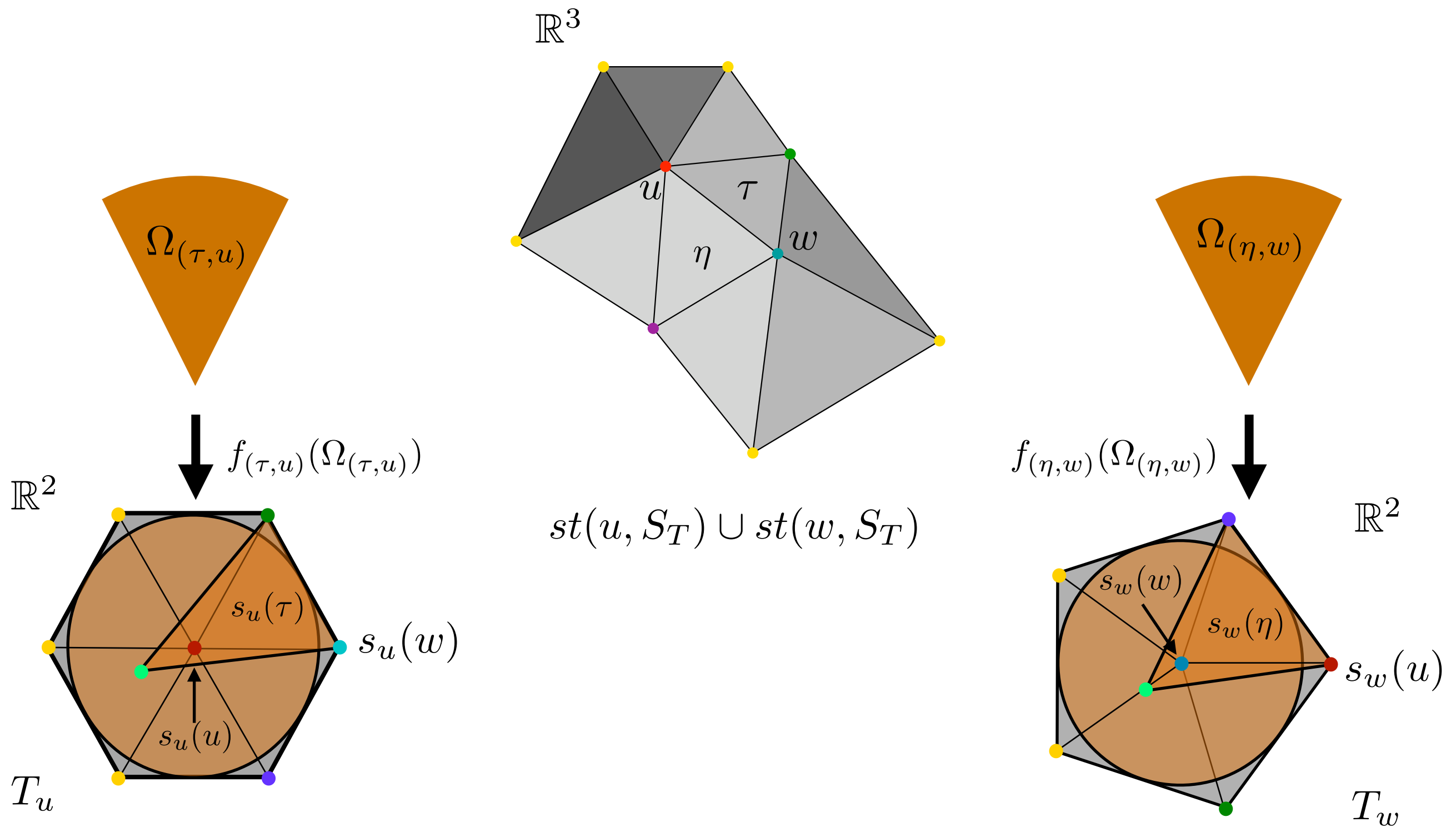
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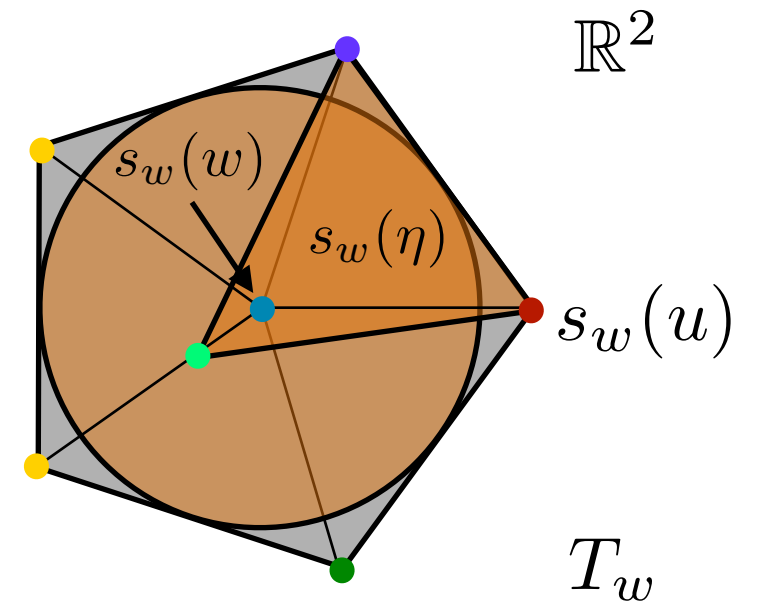
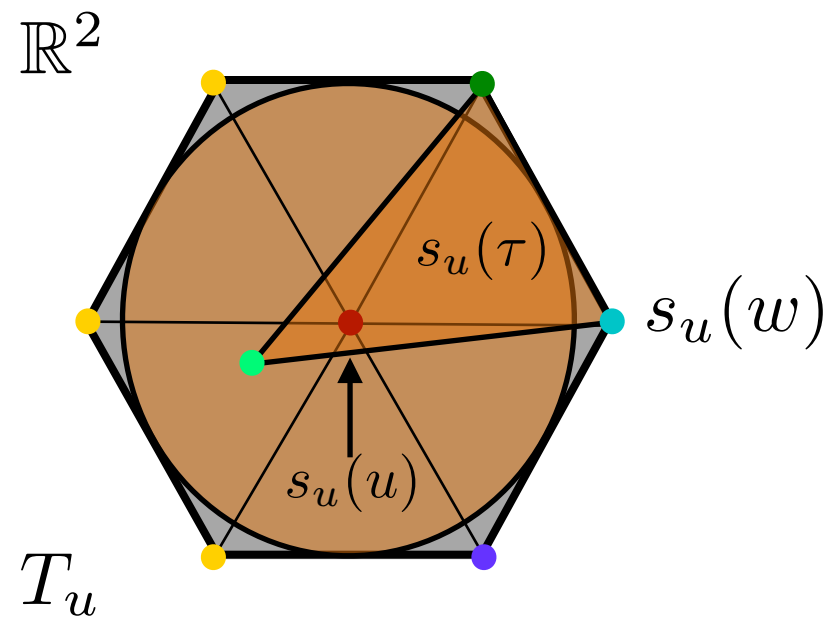


Building a Set of Gluing Data

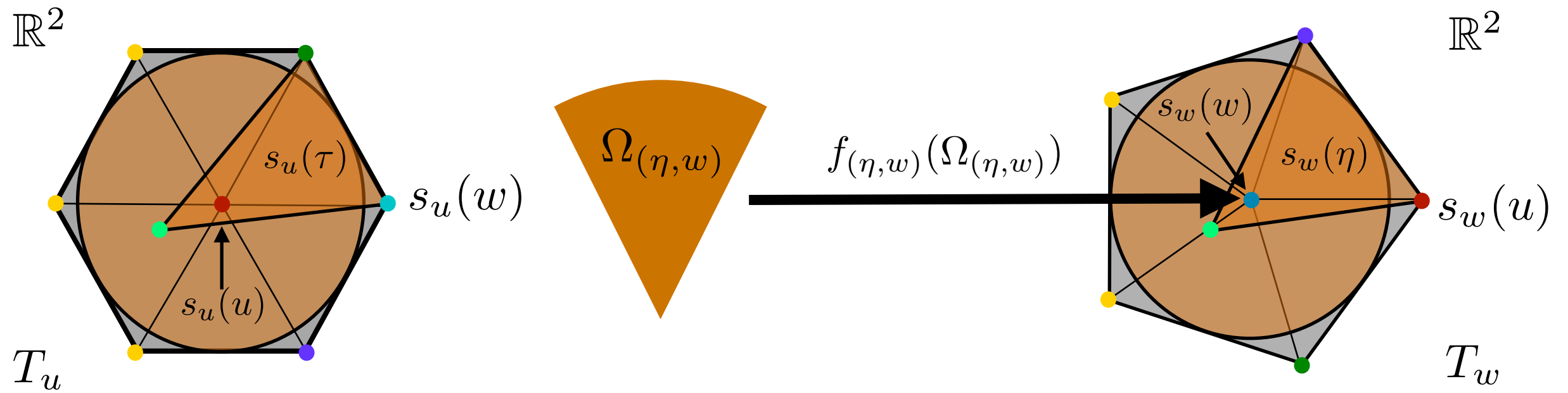


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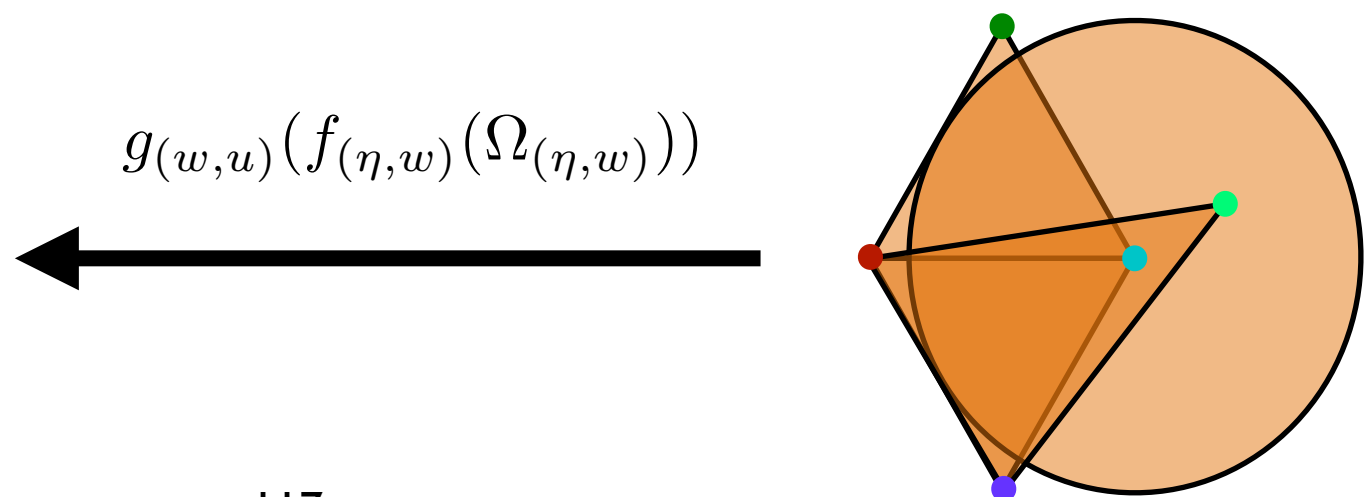
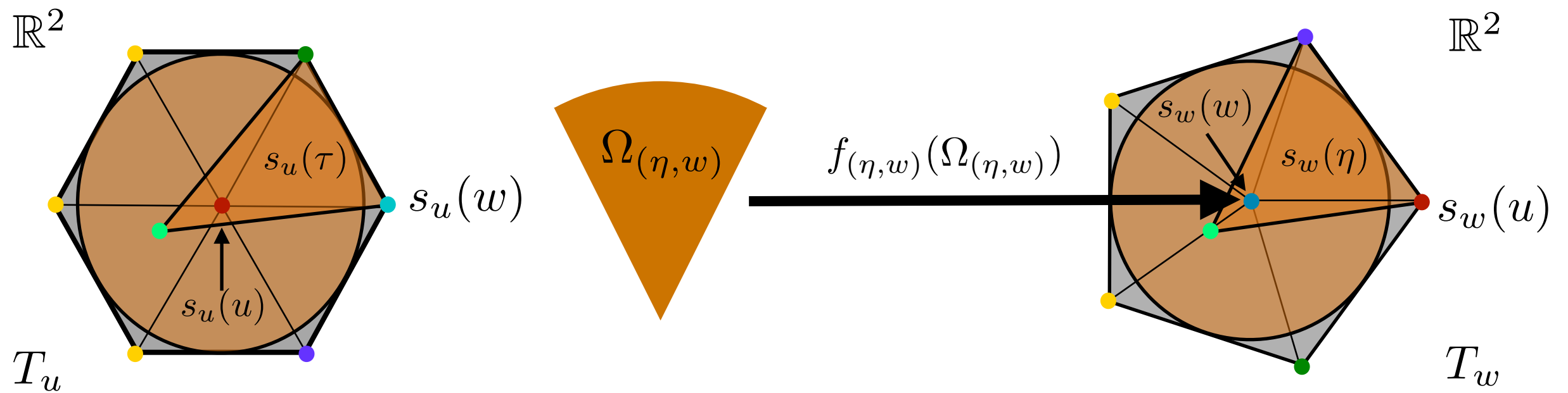
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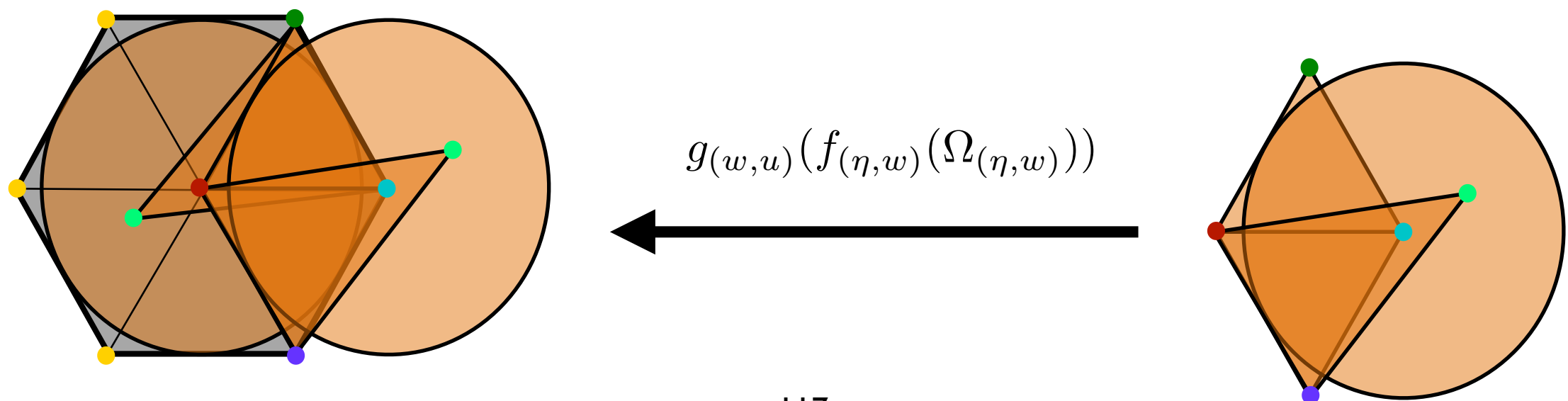
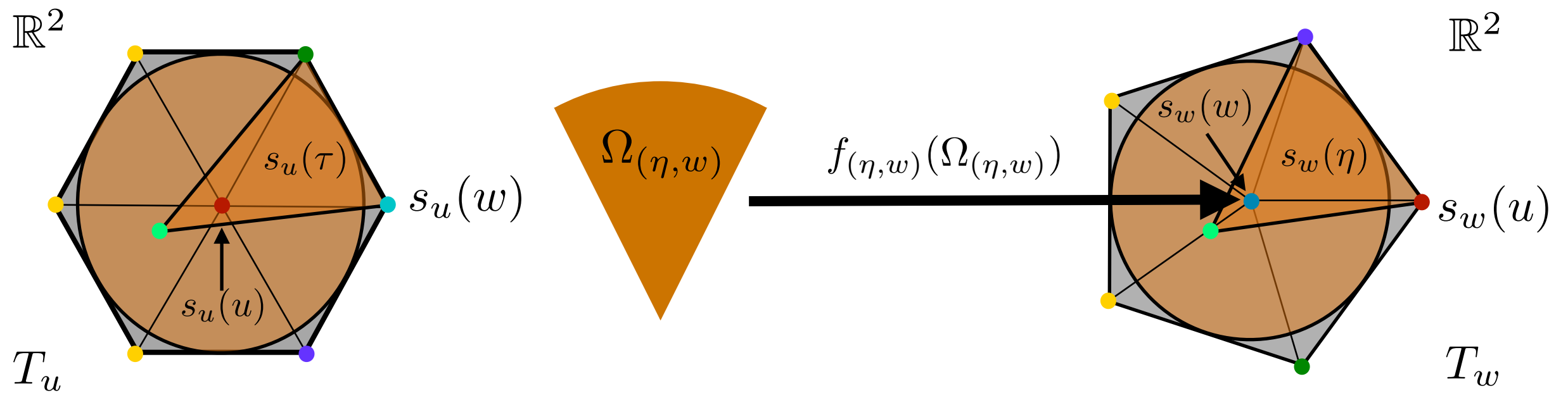
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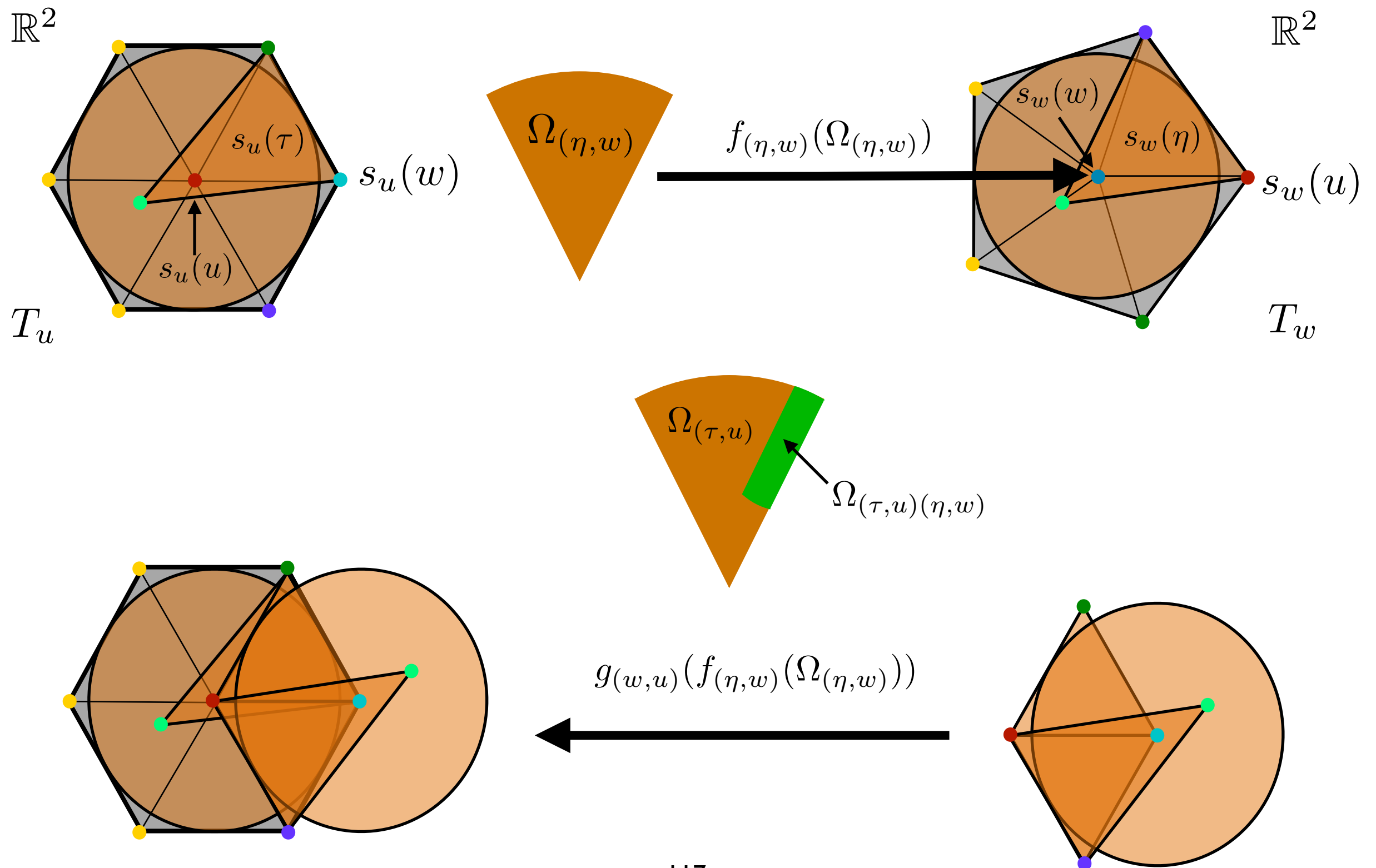
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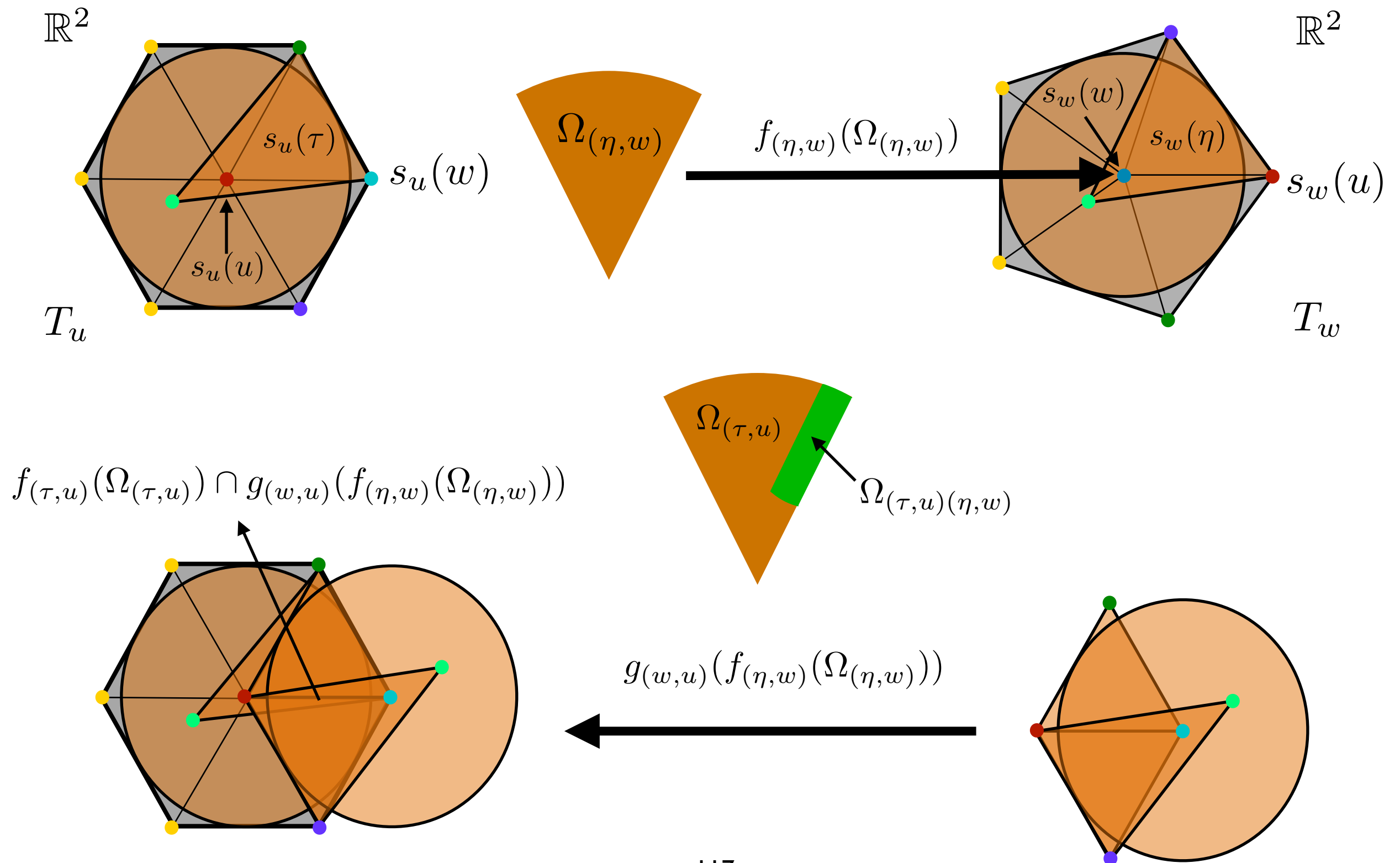
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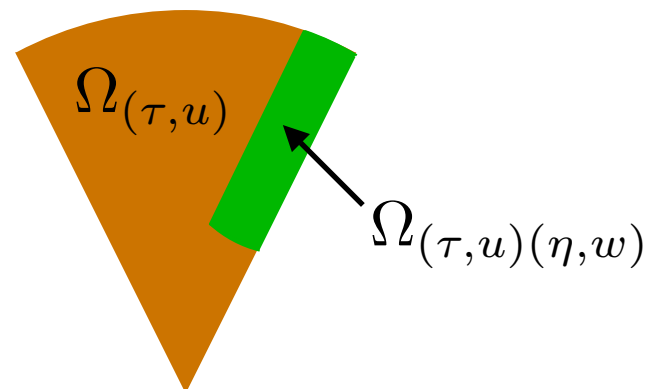
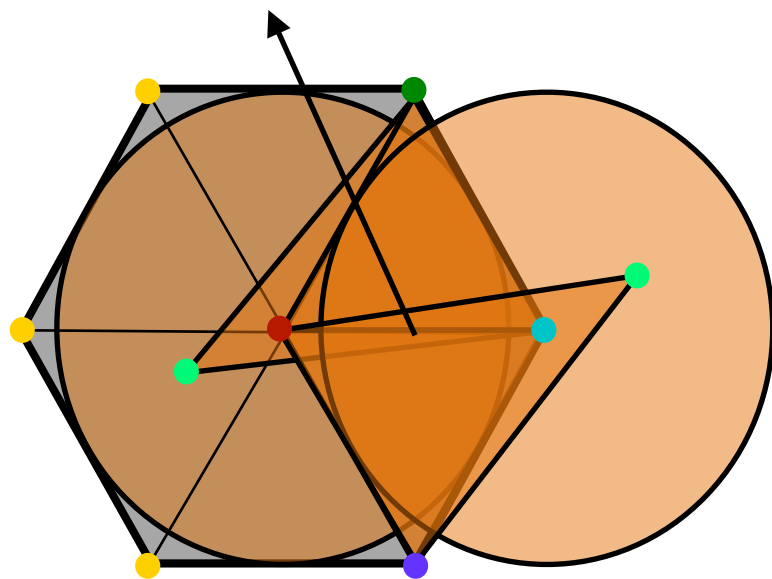
Building a Set of Gluing Data



Building a Set of Gluing Data

$$\Omega_{(\tau,u)}(\eta,w) = f_{(\tau,u)}^{-1} (f_{(\tau,u)}(\Omega_{(\tau,u)}) \cap g_{(w,u)}(f_{(\eta,w)}(\Omega_{(\eta,w)})))$$

$$f_{(\tau,u)}(\Omega_{(\tau,u)}) \cap g_{(w,u)}(f_{(\eta,w)}(\Omega_{(\eta,w)}))$$



Building a Set of Gluing Data

Building a Set of Gluing Data

(3) $u \neq w$ and w is not a vertex of τ nor u is a vertex of η

Building a Set of Gluing Data

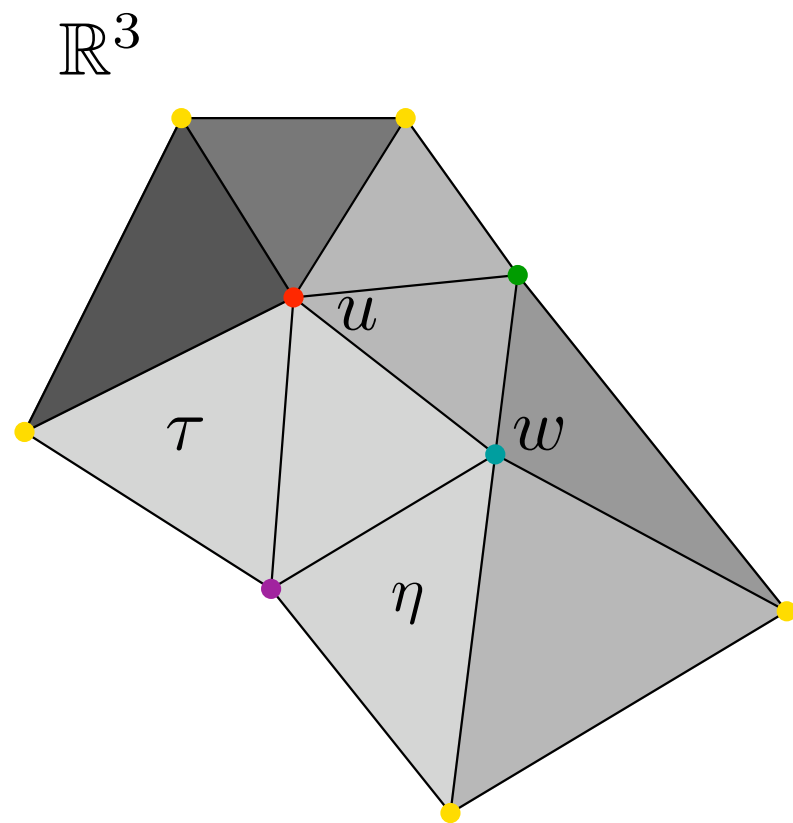
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Building a Set of Gluing Data

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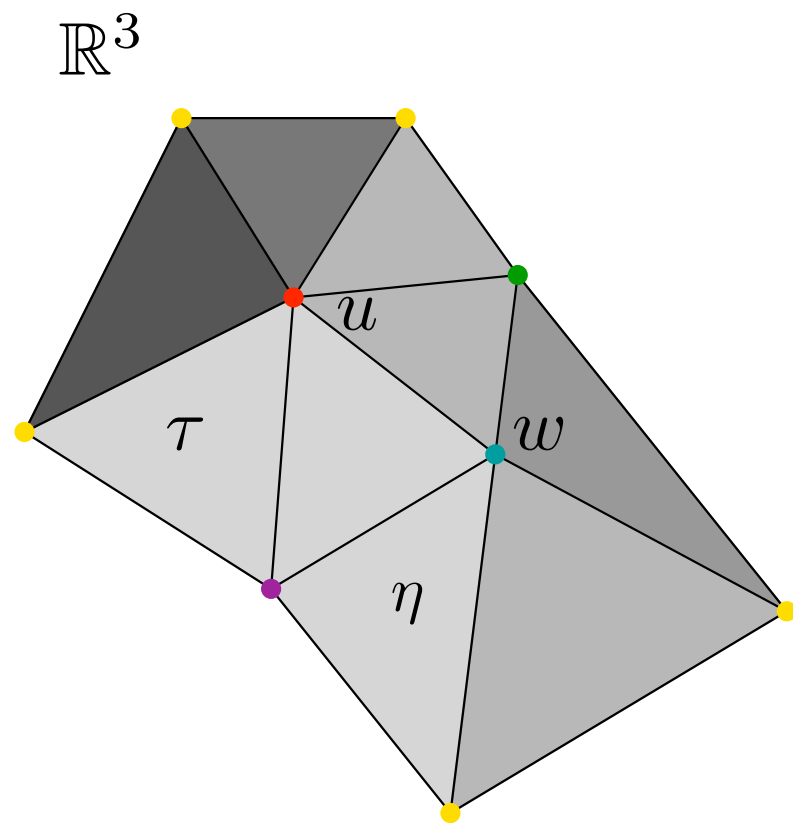


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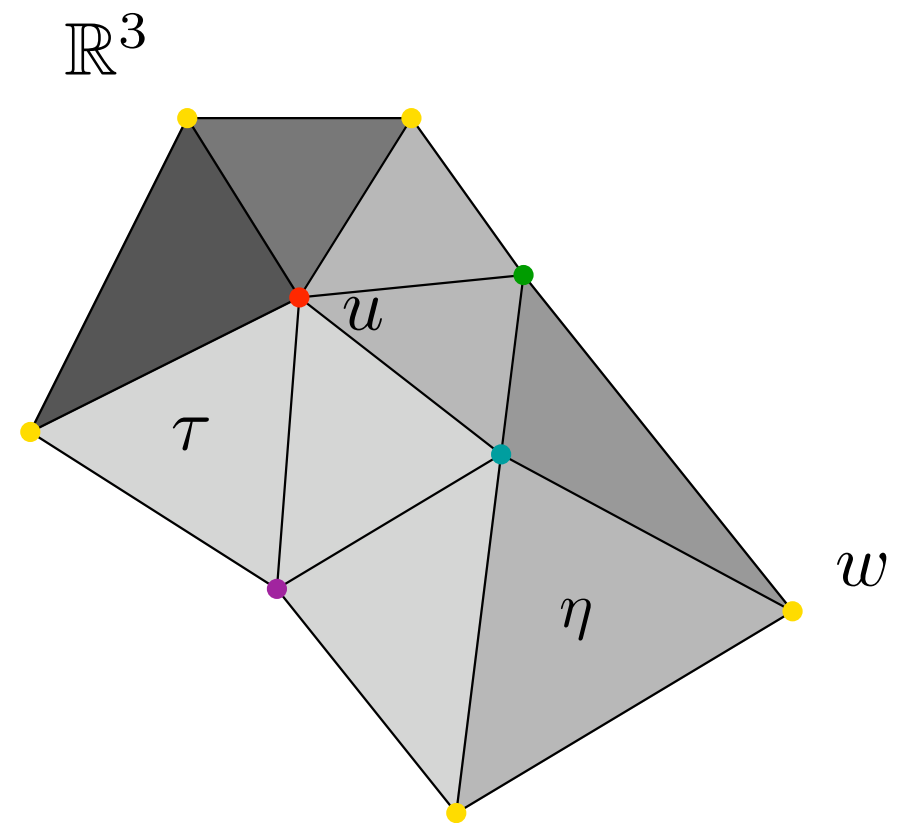
Building a Set of Gluing Data

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Building a Set of Gluing Data

Building a Set of Gluing Data

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Building a Set of Gluing Data

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- (2) For every pair $(i, j) \in I \times I$, the set Ω_{ij} is an open subset of Ω_i . Furthermore, $\Omega_{ii} = \Omega_i$ and $\Omega_{ji} \neq \emptyset$ if and only if $\Omega_{ij} \neq \emptyset$.

Fitting Surfaces to Polygonal Meshes (Part II)

Marcelo Siqueira
UFMS

Outline

- Building a Set of Gluing Data
- The User's Perspective
- Building Parametrizations
- Results
- Conclusions

Building a Set of Gluing Data

Building a Set of Gluing Data

Transition functions

Building a Set of Gluing Data

Transition functions

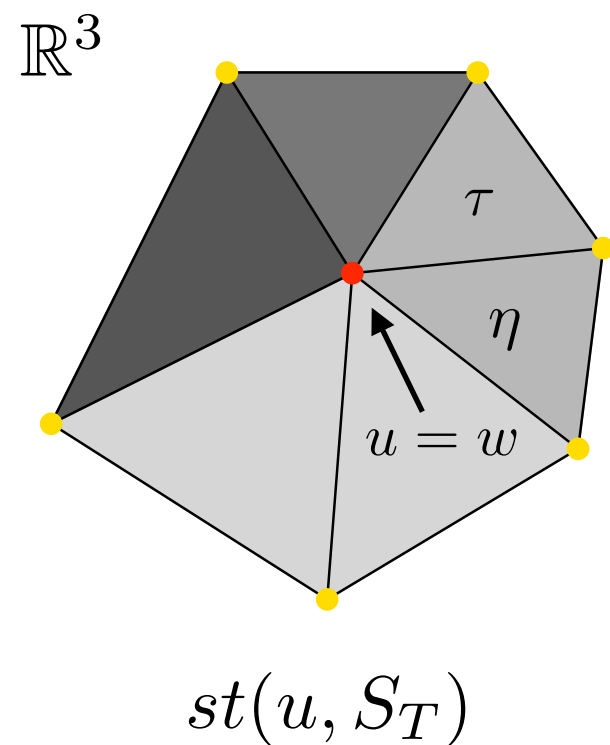
Let

$$K = \{((\tau, u), (\eta, w)) \in I \times I \mid \Omega_{(\tau, u), (\eta, w)} \neq \emptyset\}.$$

Building a Set of Gluing Data

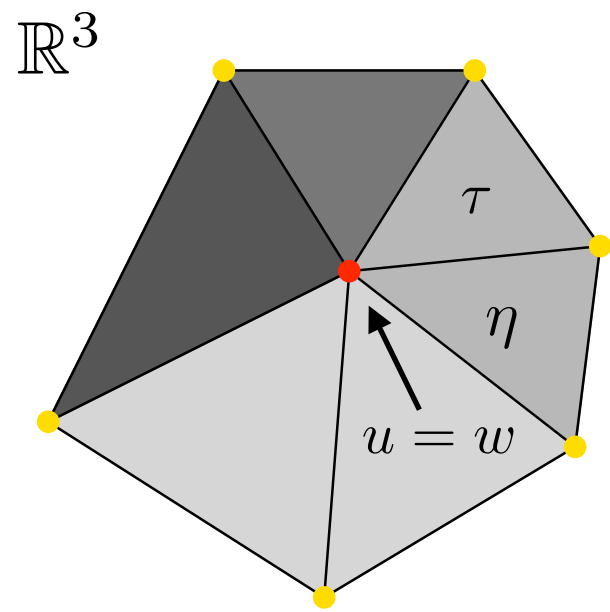
Building a Set of Gluing Data

$$(1) \quad u = w$$

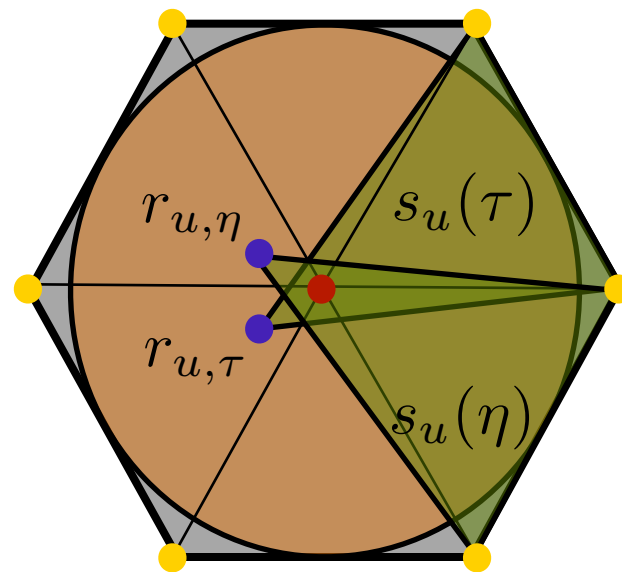


Building a Set of Gluing Data

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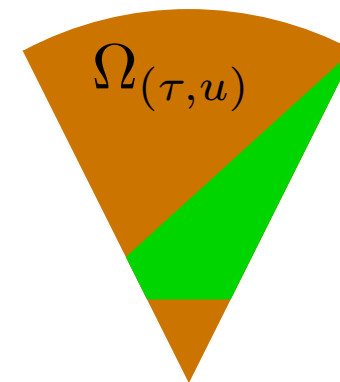
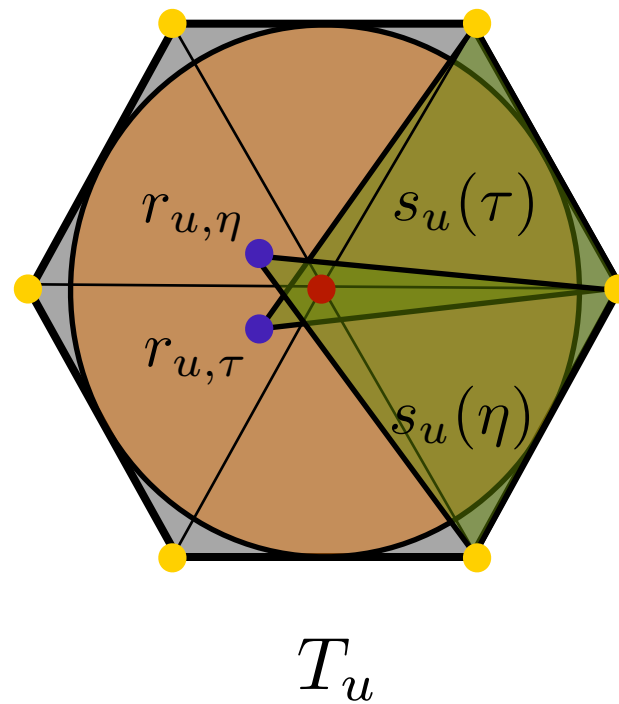
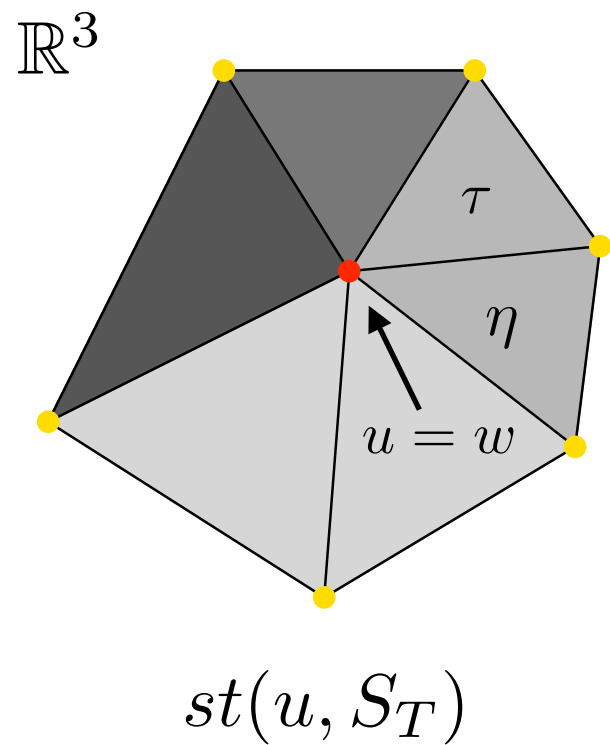
$st(u, S_T)$



T_u

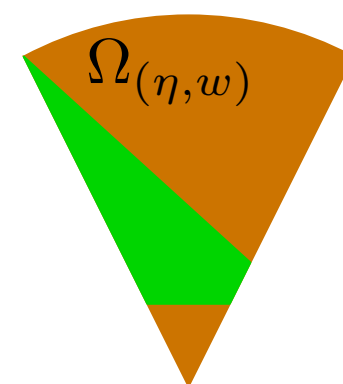
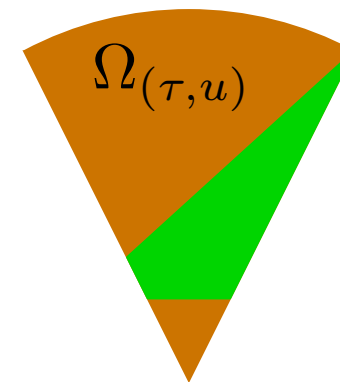
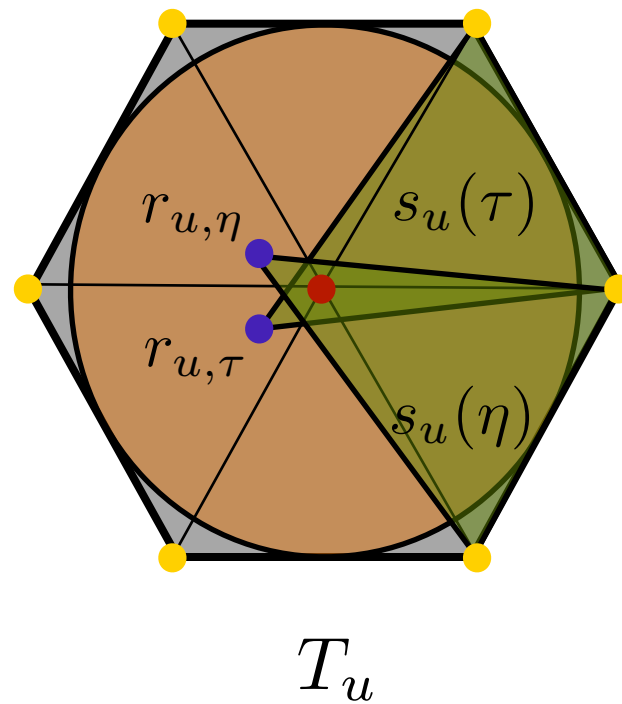
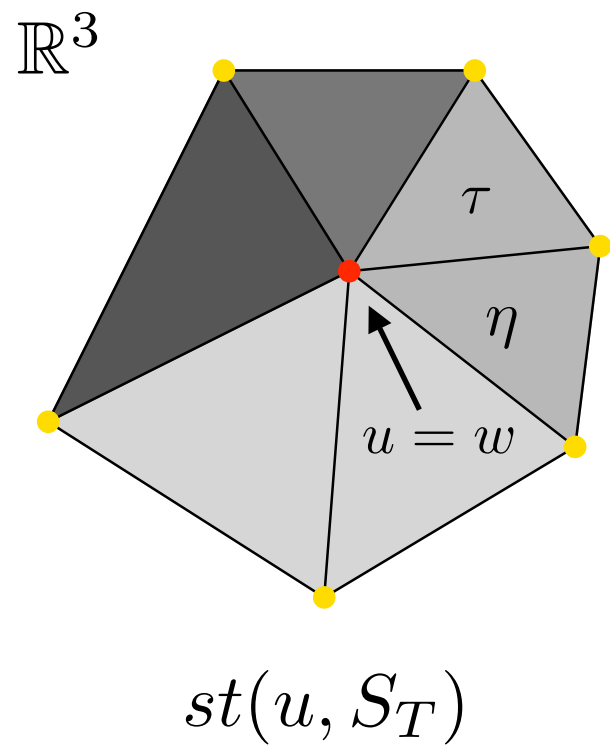
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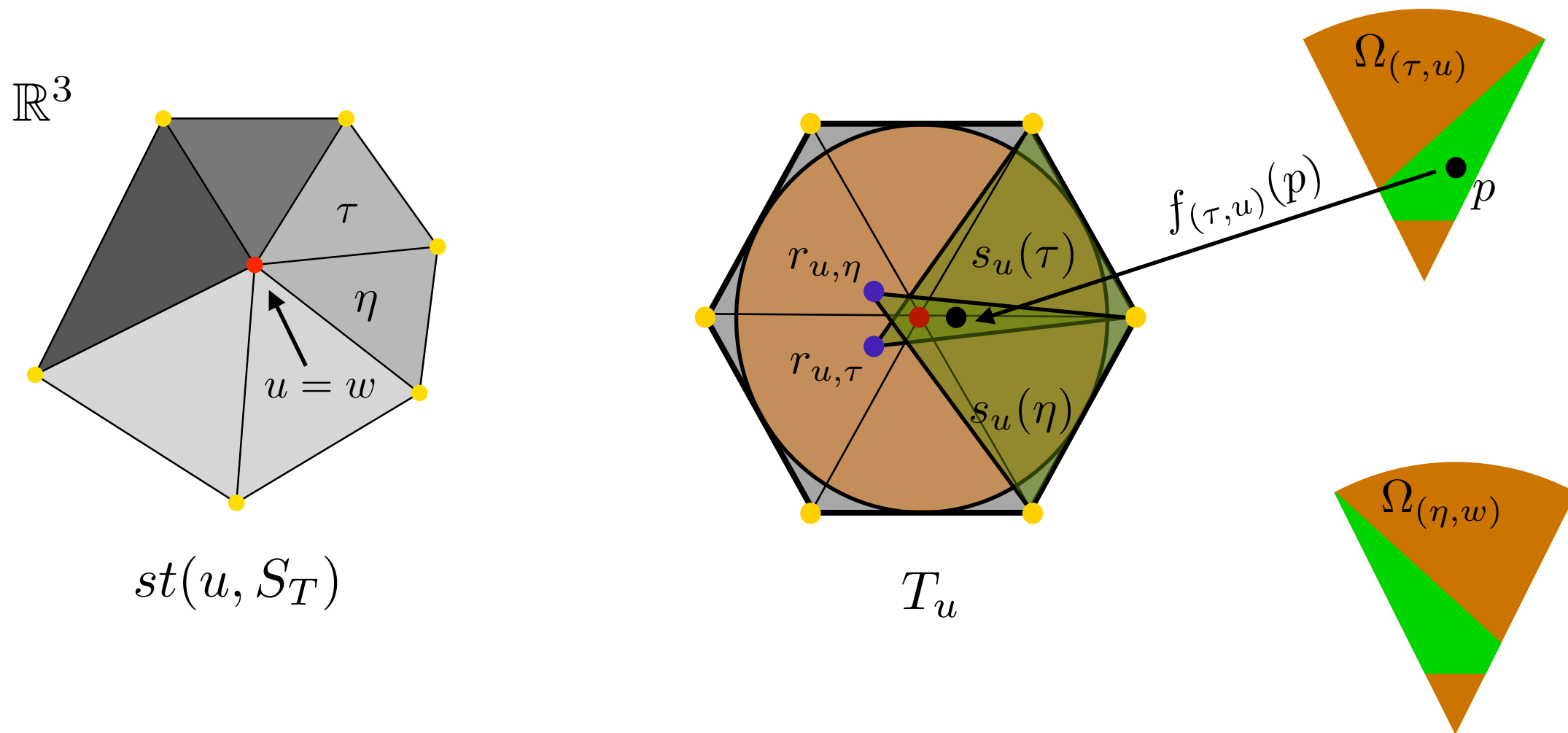
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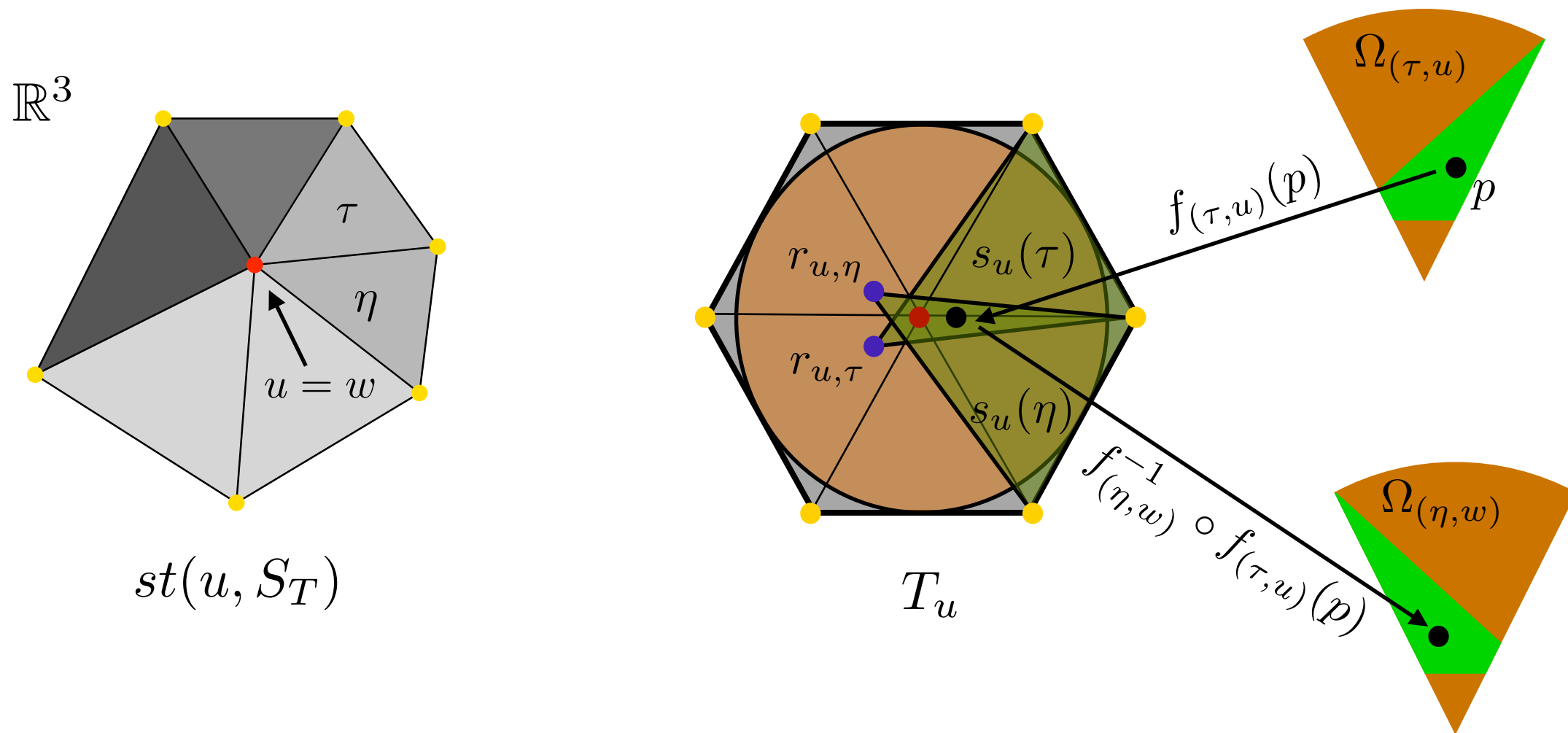
Building a Set of Gluing Data

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Building a Set of Gluing Data

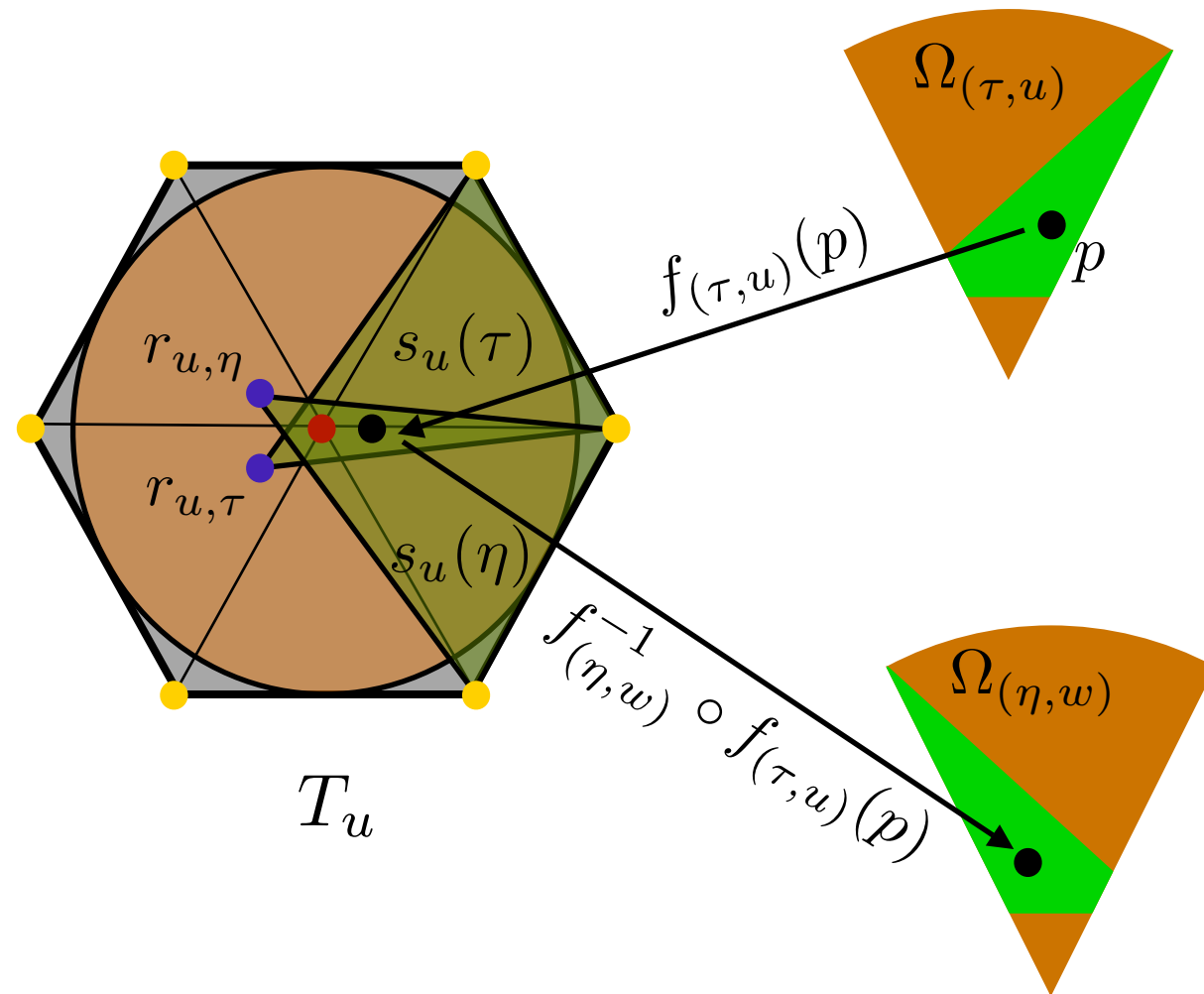
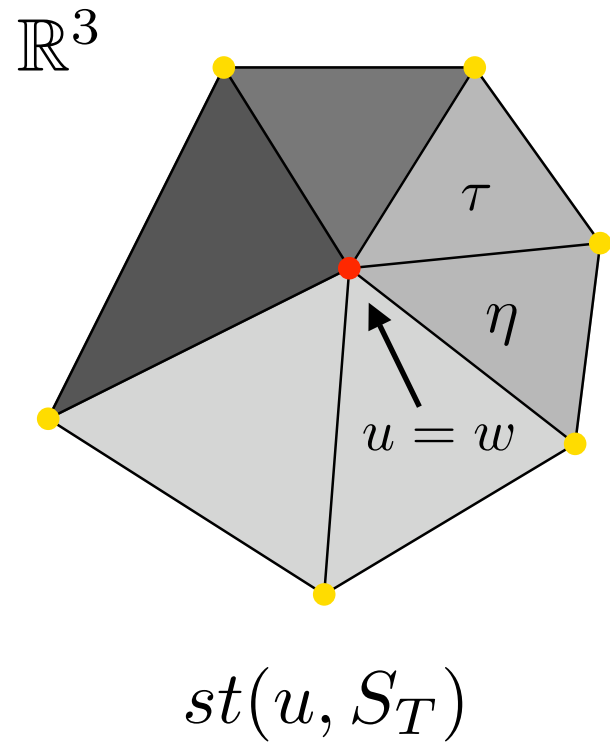
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Building a Set of Gluing Data

(1) $u = w$

$$f_{(\eta,w)}^{-1} \circ f_{(\tau,u)}(p)$$



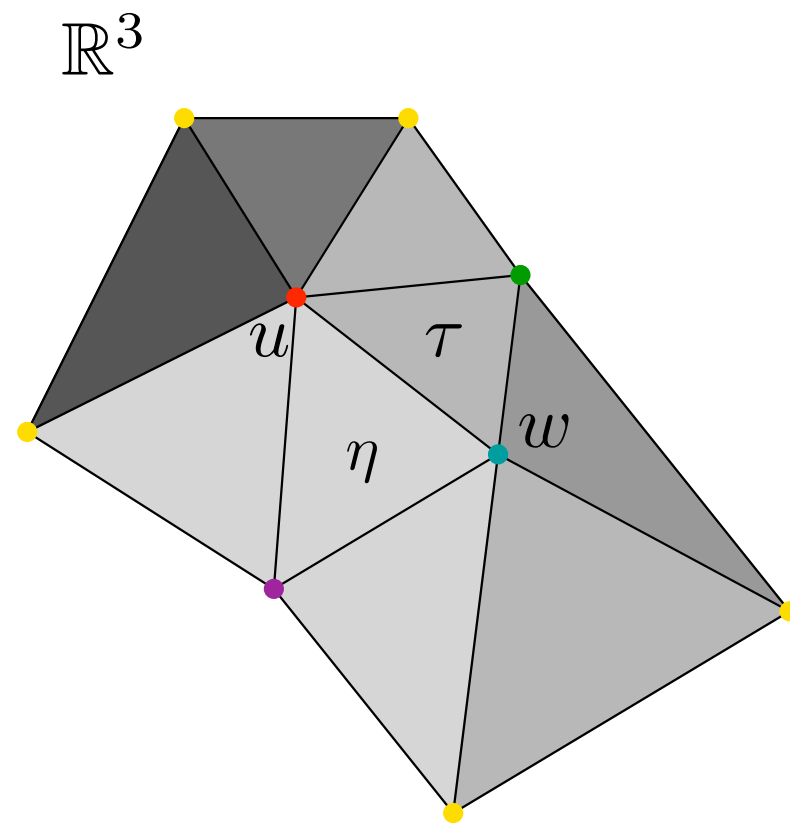
Building a Set of Gluing Data

Building a Set of Gluing Data

(2) otherwise

Building a Set of Gluing Data

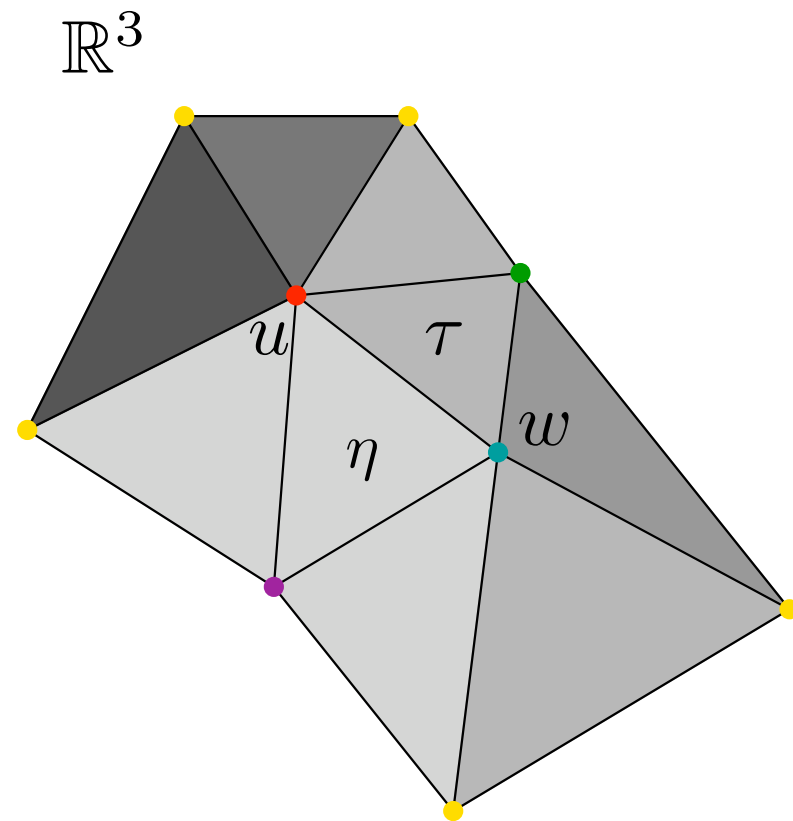
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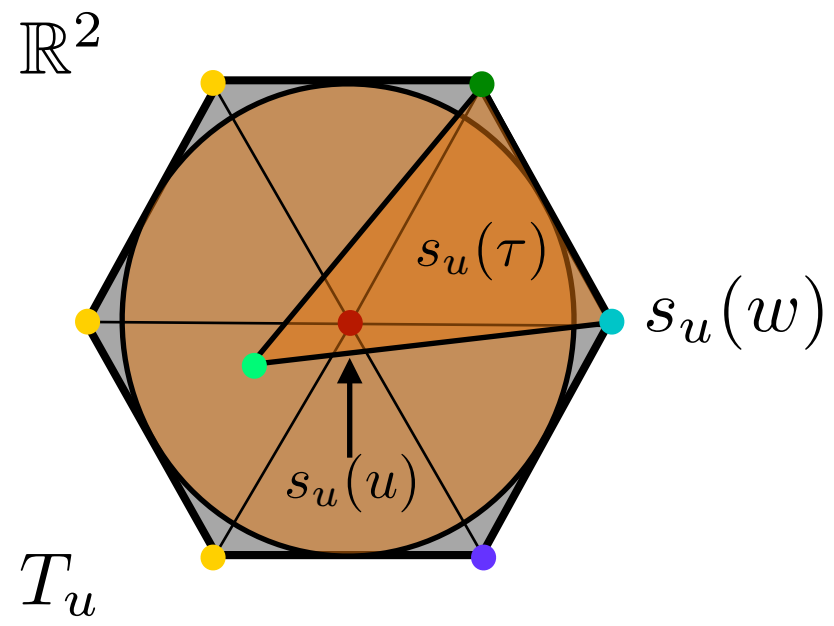
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Building a Set of Gluing Data

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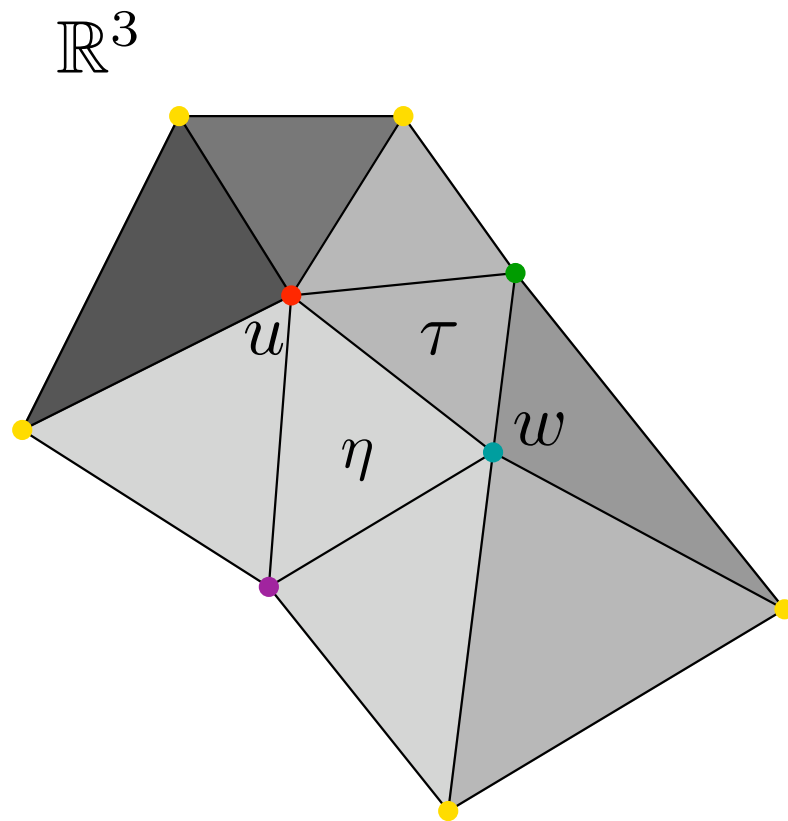


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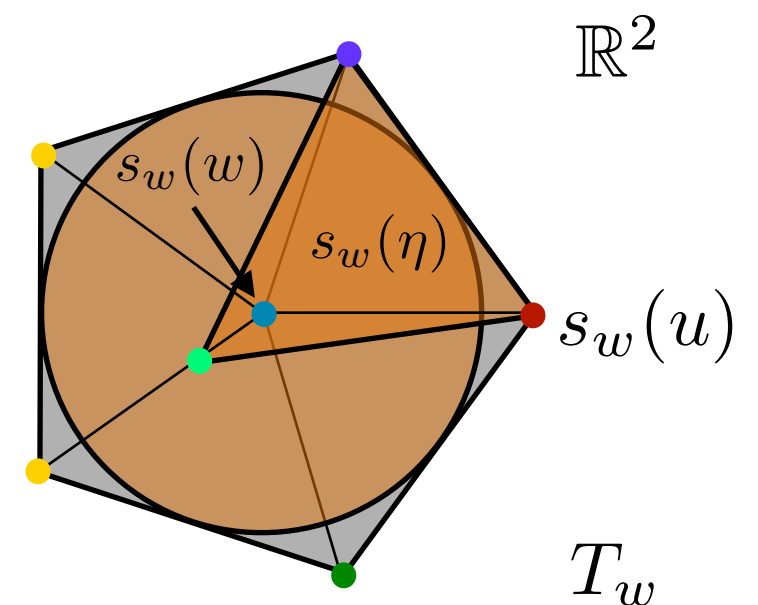
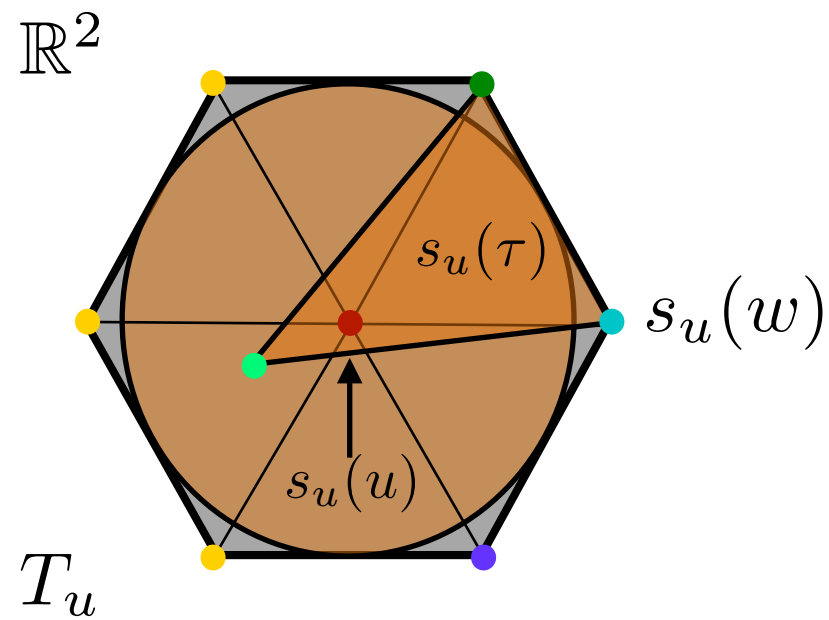


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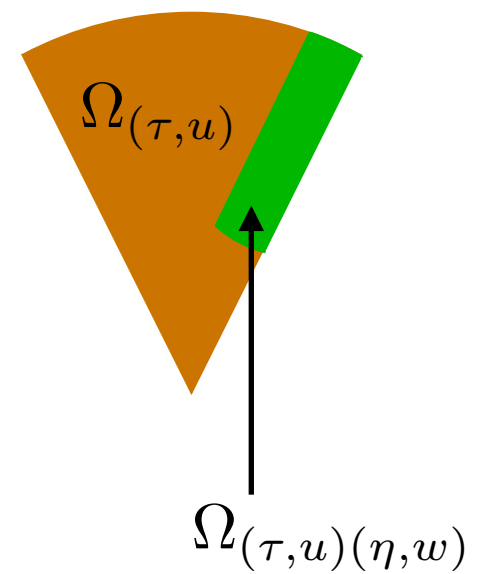
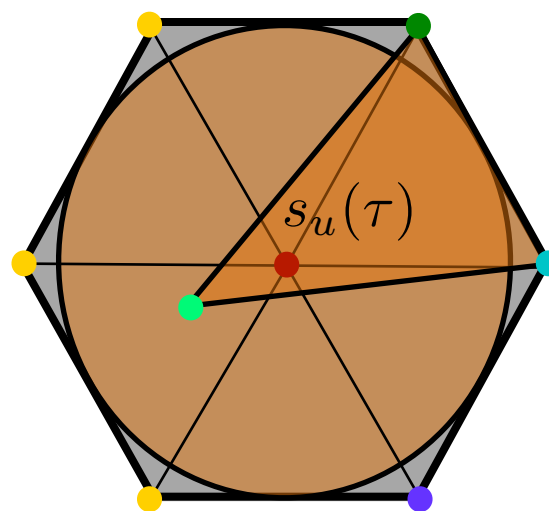


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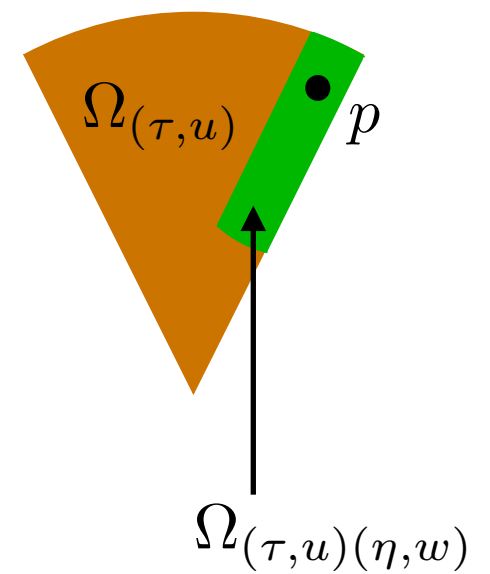
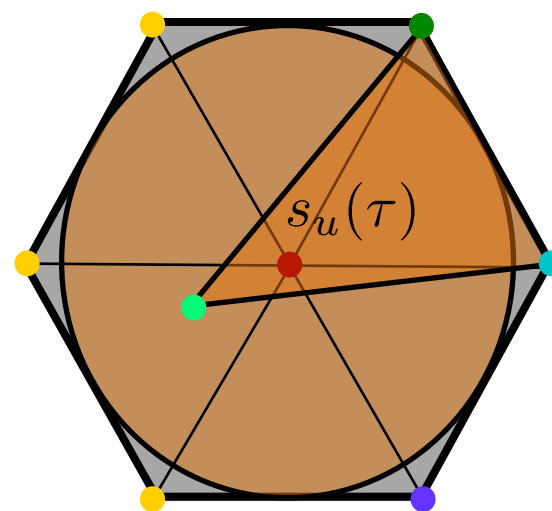


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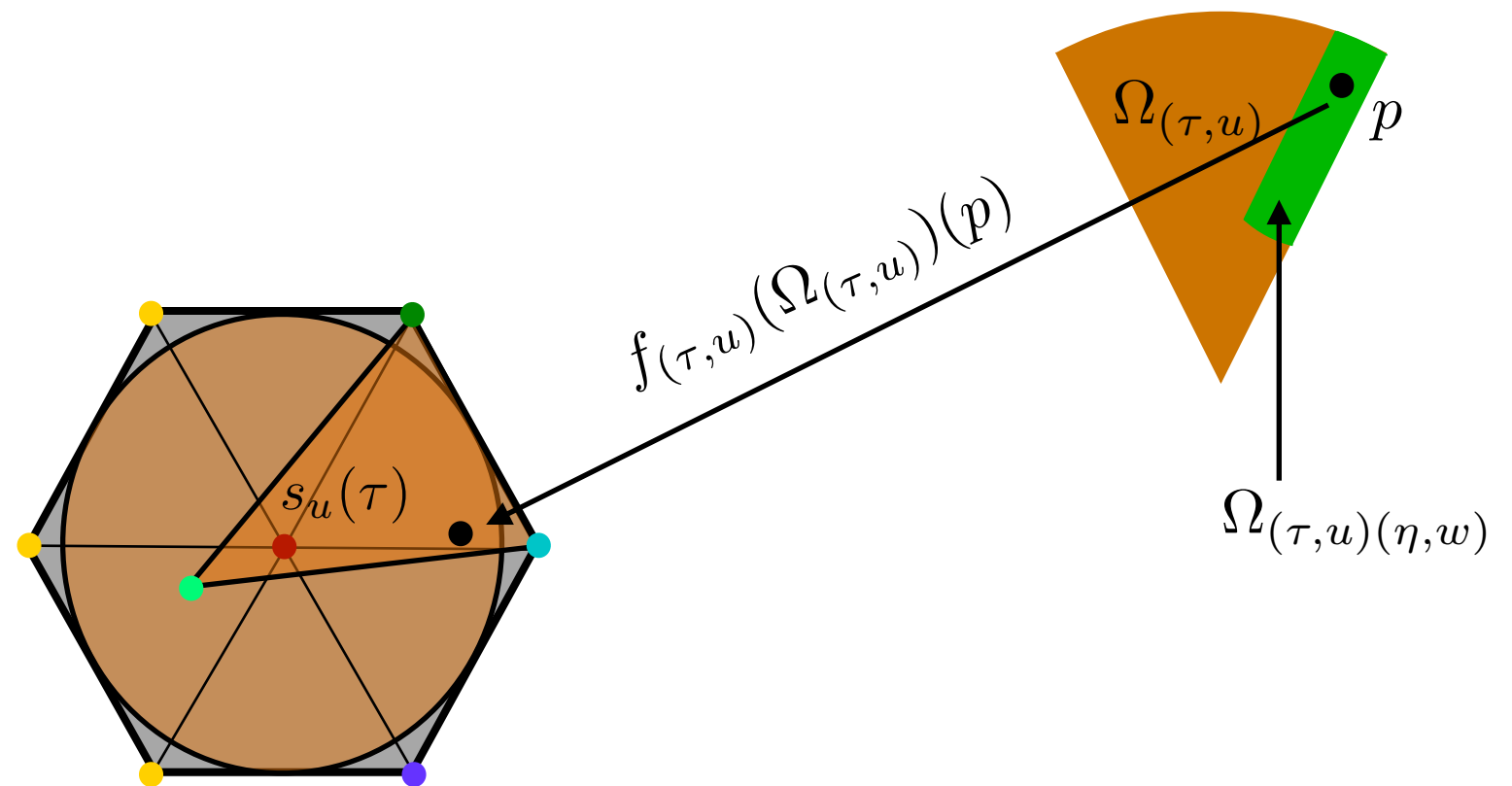
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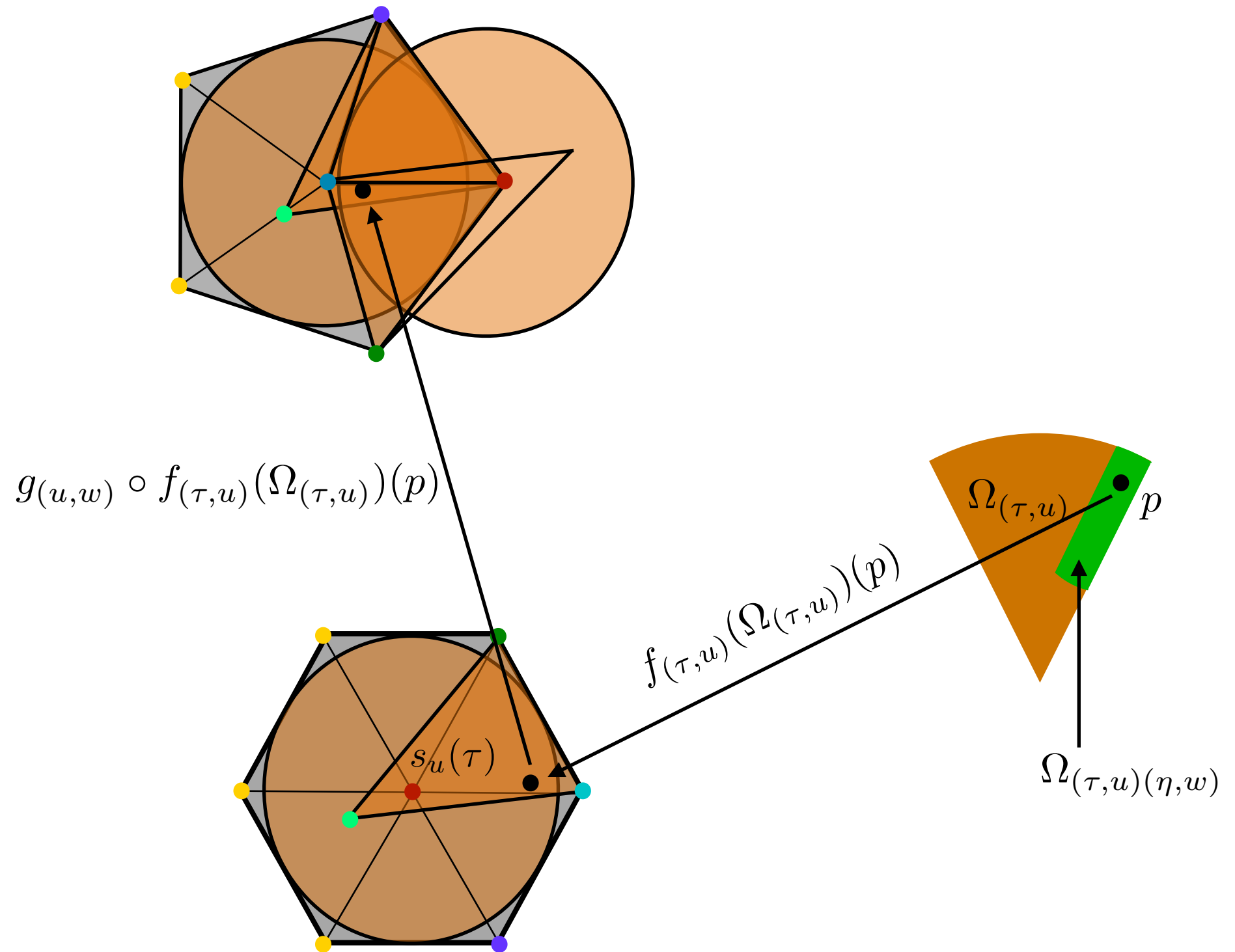
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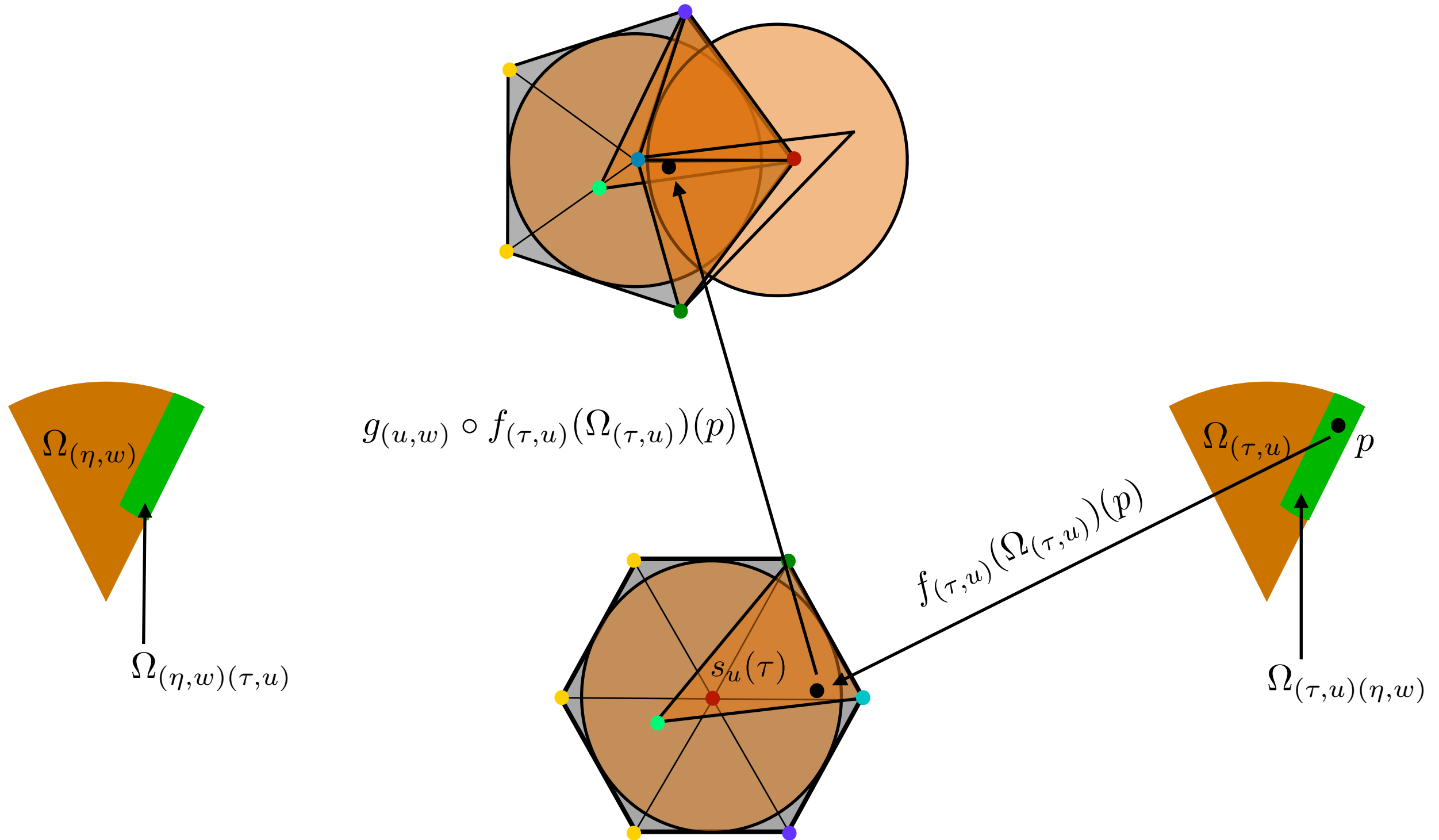
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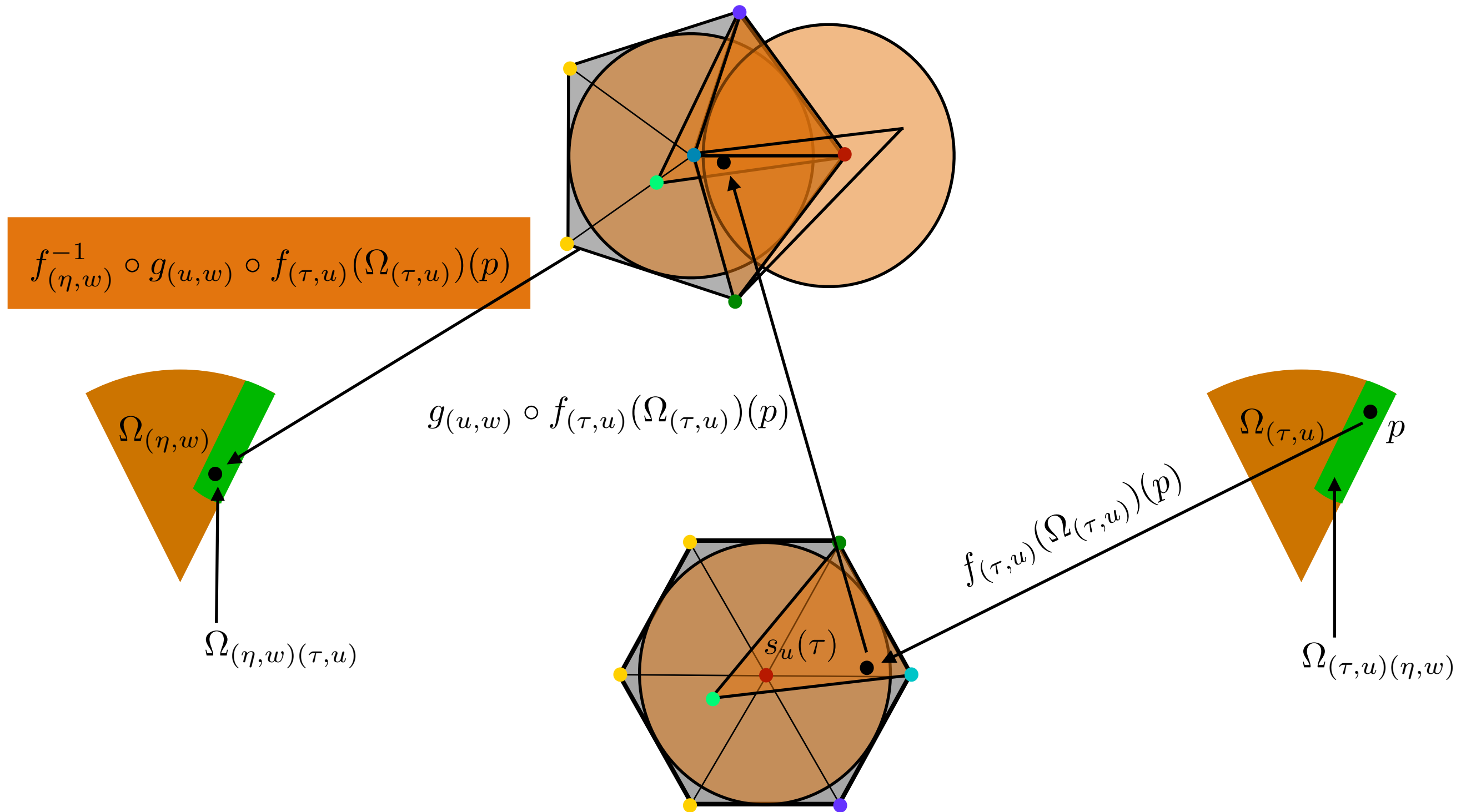
Building a Set of Gluing Data



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Building a Set of Gluing Data

Building a Set of Gluing Data

For every $((\tau, u), (\eta, w)) \in K$, we define

$$\varphi_{(\eta, w)(\tau, u)} : \Omega_{(\tau, u), (\eta, w)} \longrightarrow \varphi_{(\eta, w)(\tau, u)},$$

the transition function from $\Omega_{(\tau, u)}$ to $\Omega_{(\eta, w)}$, to be

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the transition function from $\Omega_{(\tau, u)}$ to $\Omega_{(\eta, w)}$, to be

$$\varphi_{(\eta, w)(\tau, u)}(p) = \begin{cases} f_{(\eta, w)}^{-1} \circ f_{(\tau, u)}(p) & \text{if } u = w \\ f_{(\eta, w)}^{-1} \circ g_{(u, w)} \circ f_{(\tau, u)}(p) & \text{otherwise,} \end{cases}$$

for every $p \in \Omega_{(\tau, u)(\eta, w)}$.

Building a Set of Gluing Data

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We can show that the above definition of transition functions satisfies conditions (3)(a)-(c) of the definition of sets of gluing data:

Building a Set of Gluing Data

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(a) $\varphi_{ii} = \text{id}_{\Omega_i}$, for all $i \in I$,

(b) $\varphi_{ij} = \varphi_{ji}^{-1}$, for all $(i, j) \in K$, and

(c) for all i, j , and k , if $\Omega_{ji} \cap \Omega_{jk} \neq \emptyset$ then $\varphi_{ji}^{-1}(\Omega_{ji} \cap \Omega_{jk}) \subseteq \Omega_{ik}$ and $\varphi_{ki}(x) = \varphi_{kj} \circ \varphi_{ji}(x)$, for all $x \in \varphi_{ji}^{-1}(\Omega_{ji} \cap \Omega_{jk})$.

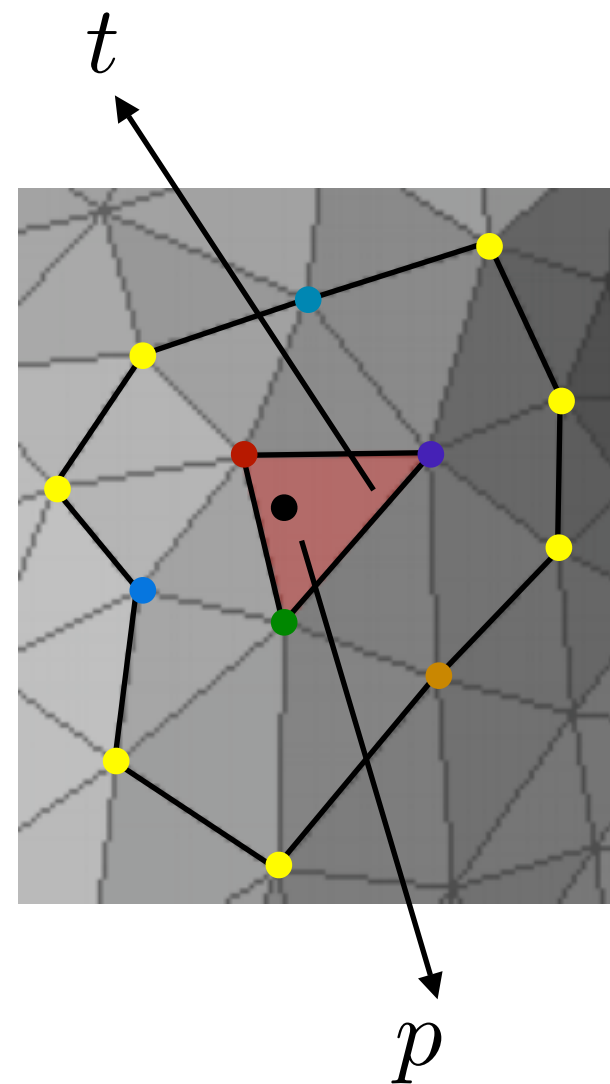
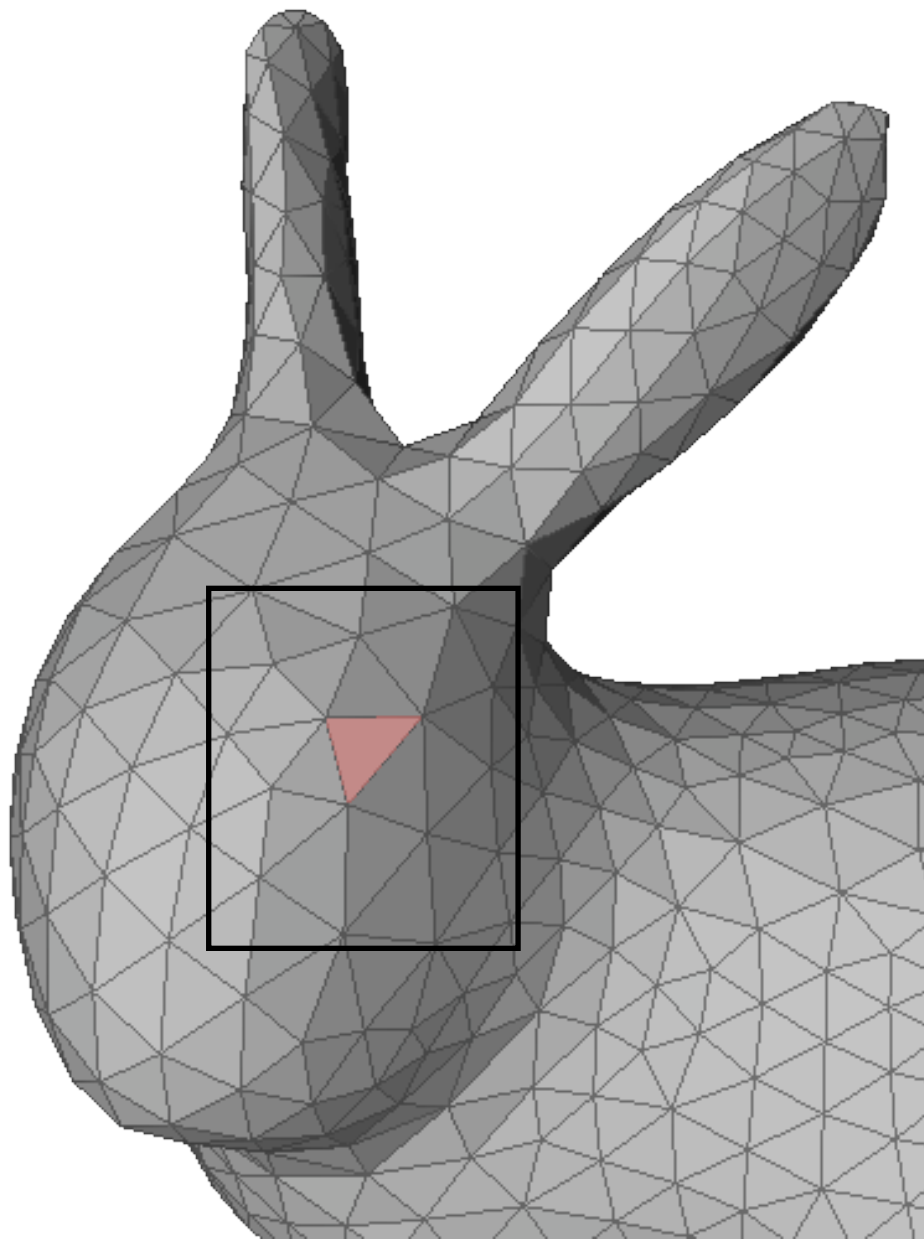
User's Perspective

User's Perspective

Let t be a triangle in S_T and p be any point in t :

User's Perspective

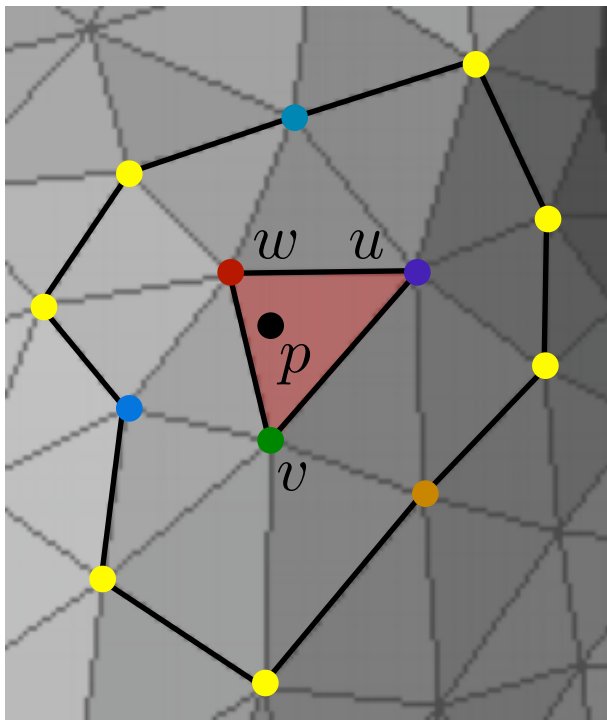
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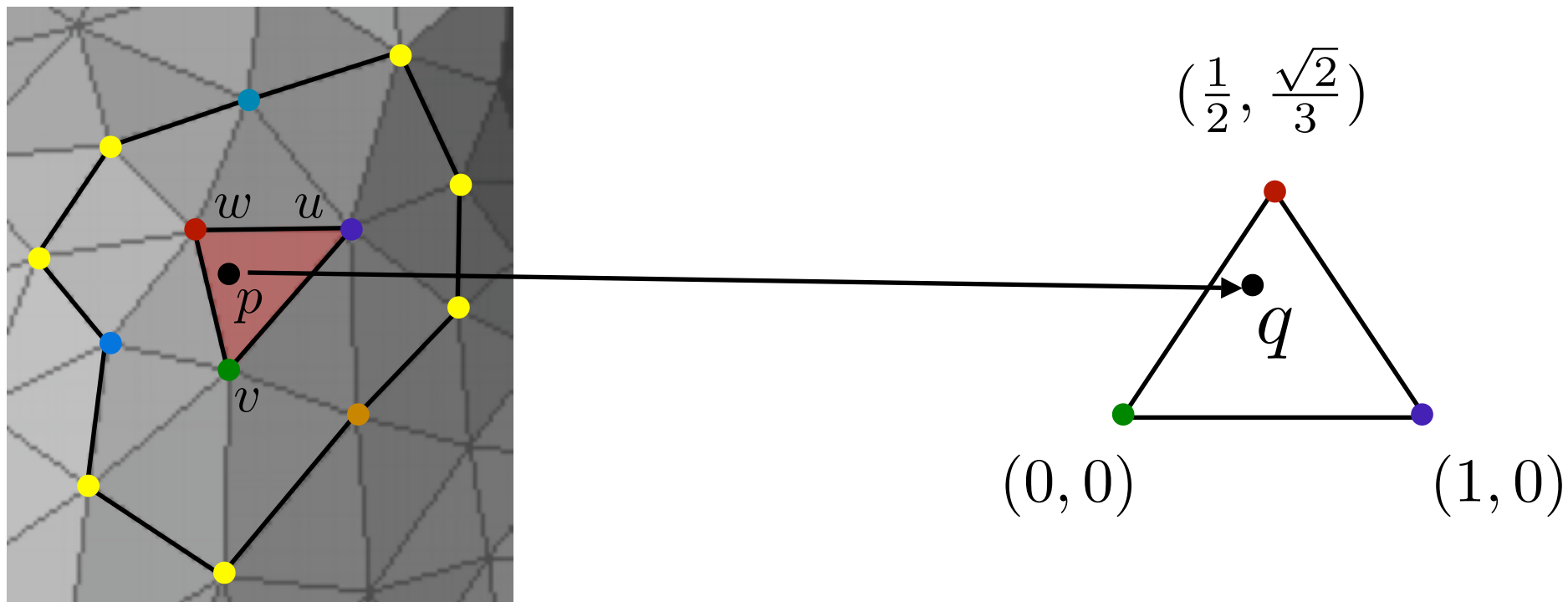
User's Perspective

Map p to an equilateral triangle in \mathbb{R}^2 .



User's Perspective

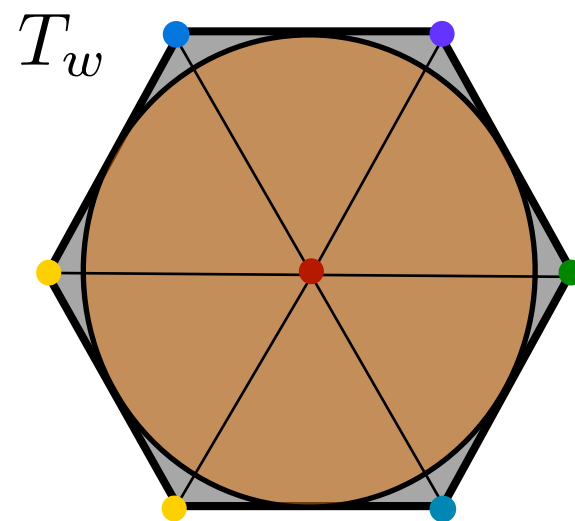
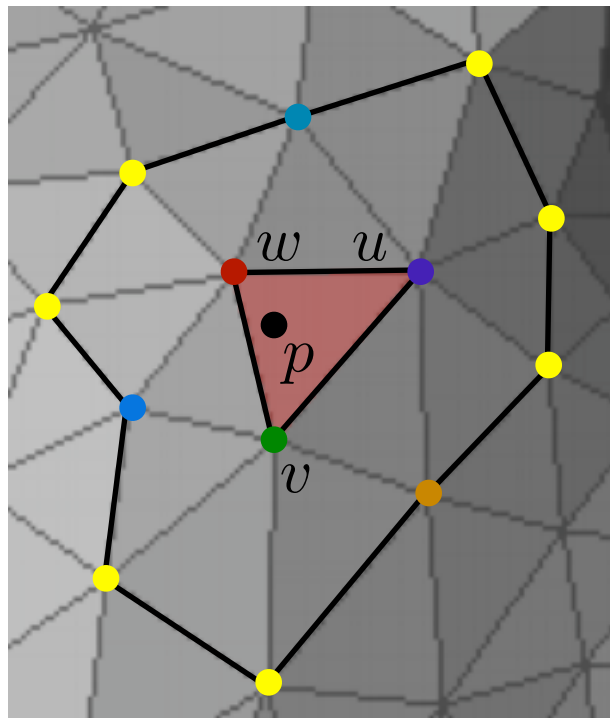
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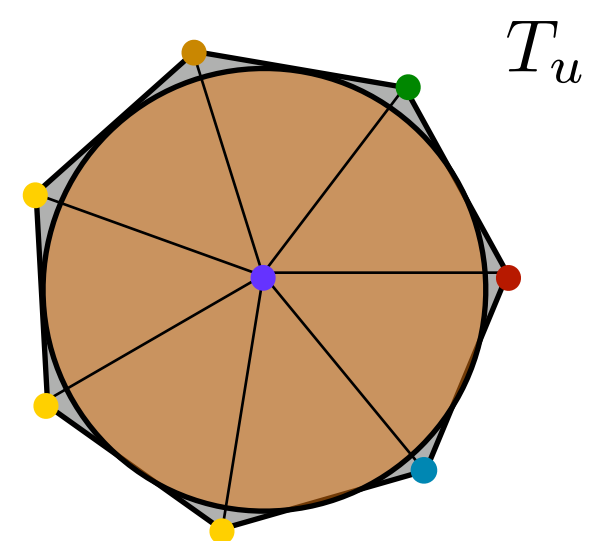
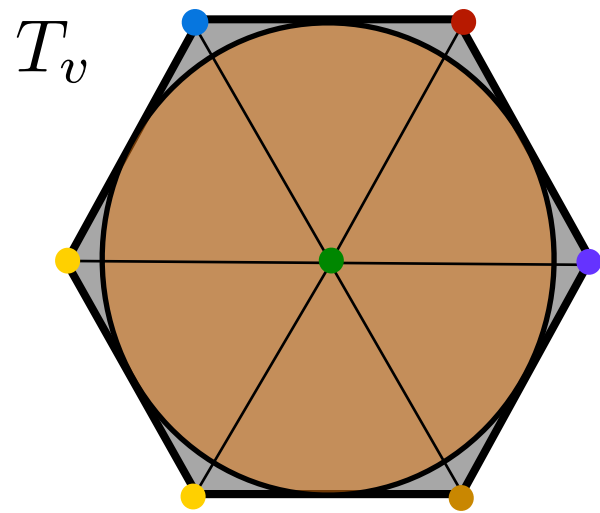
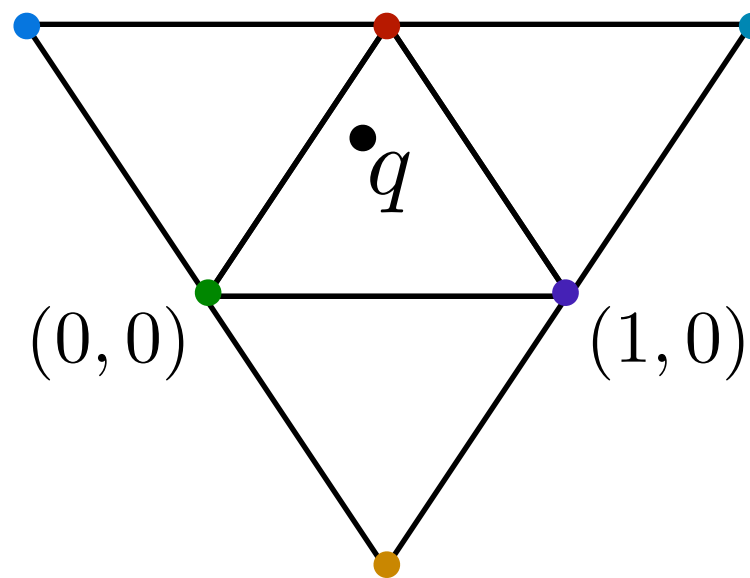
We can do that by using barycentric coordinates.

User's Perspective

User's Perspective

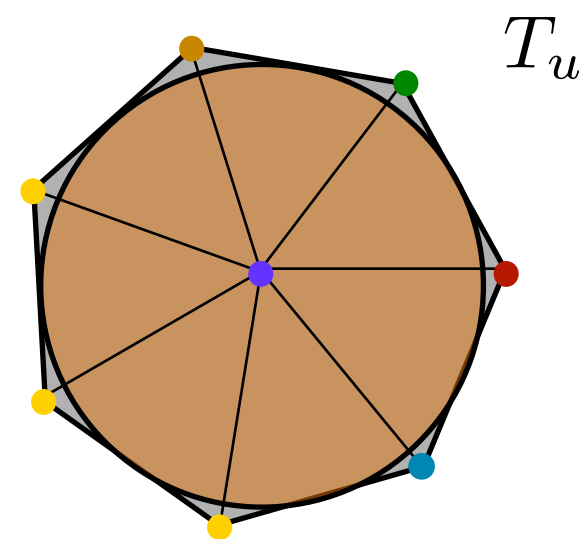
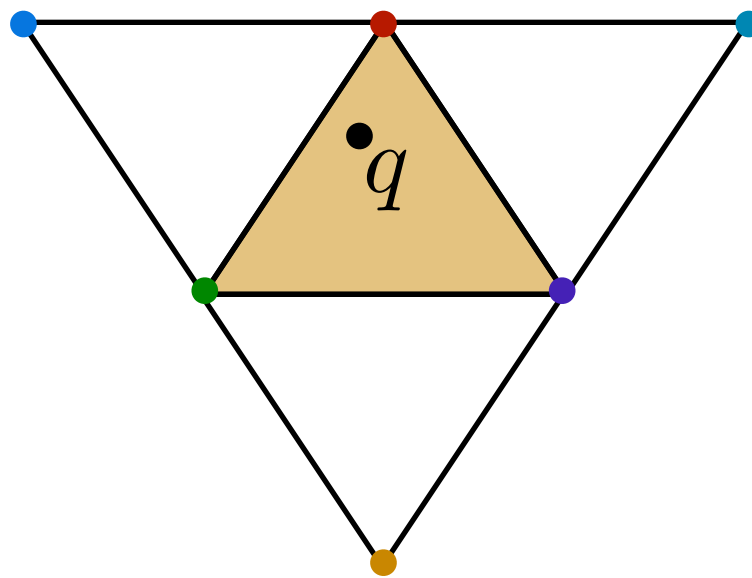
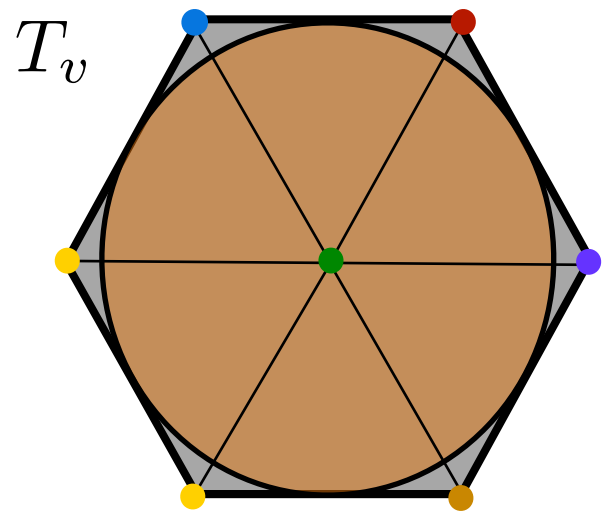
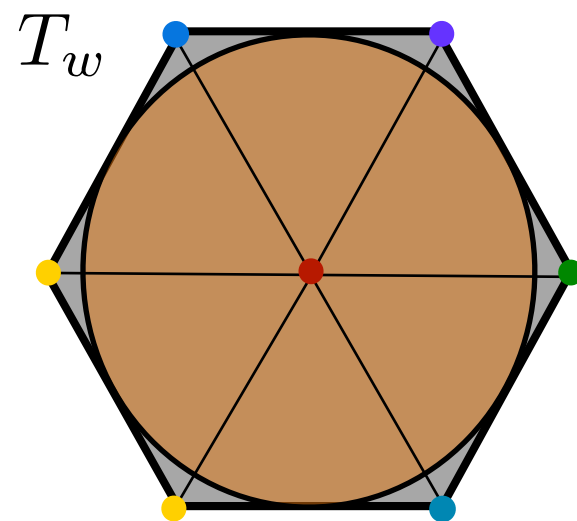
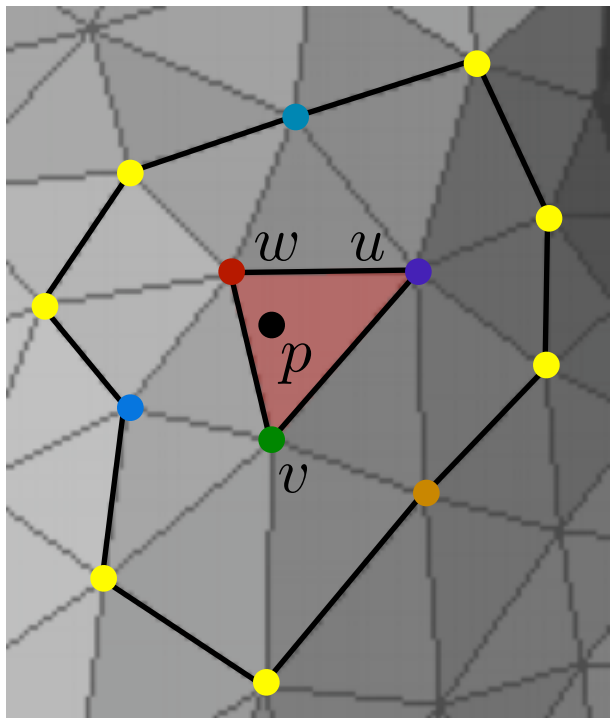


$$\left(\frac{1}{2}, \frac{\sqrt{2}}{3}\right)$$

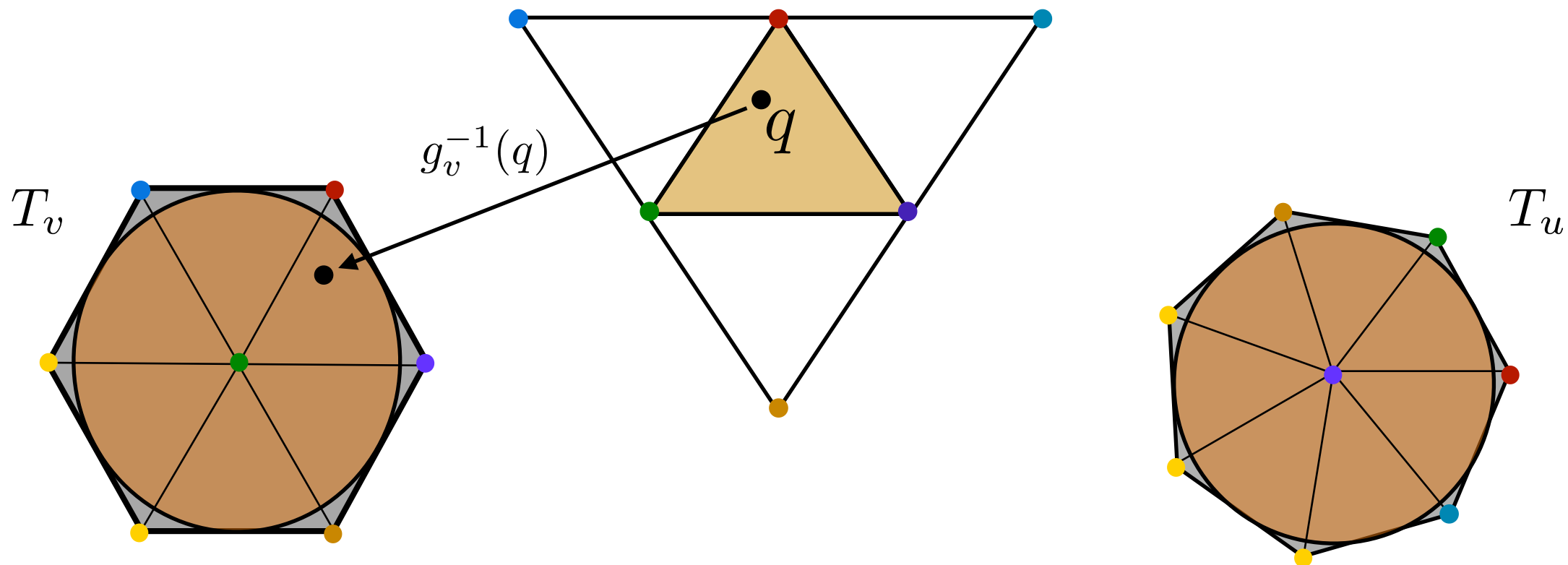
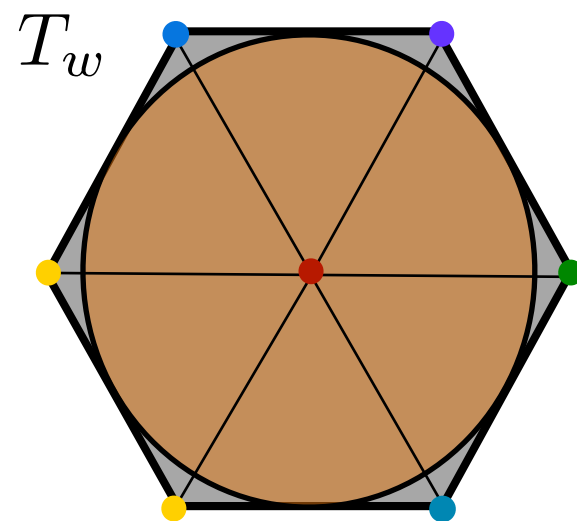
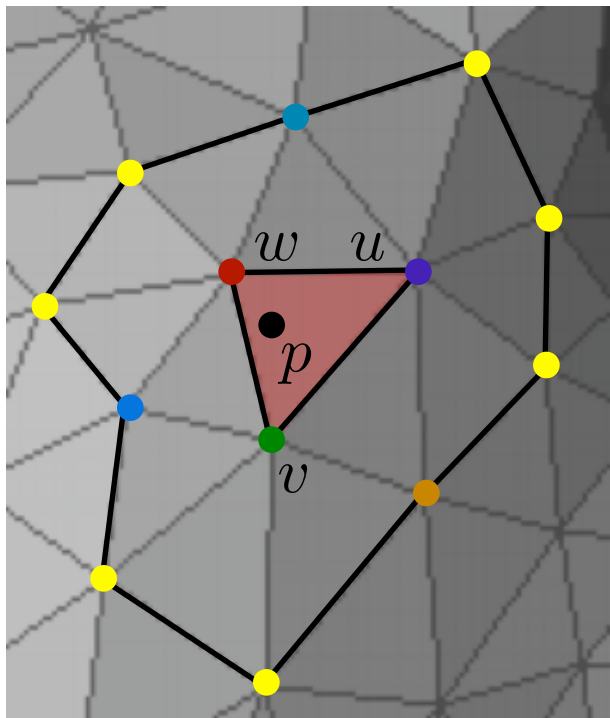


User's Perspective

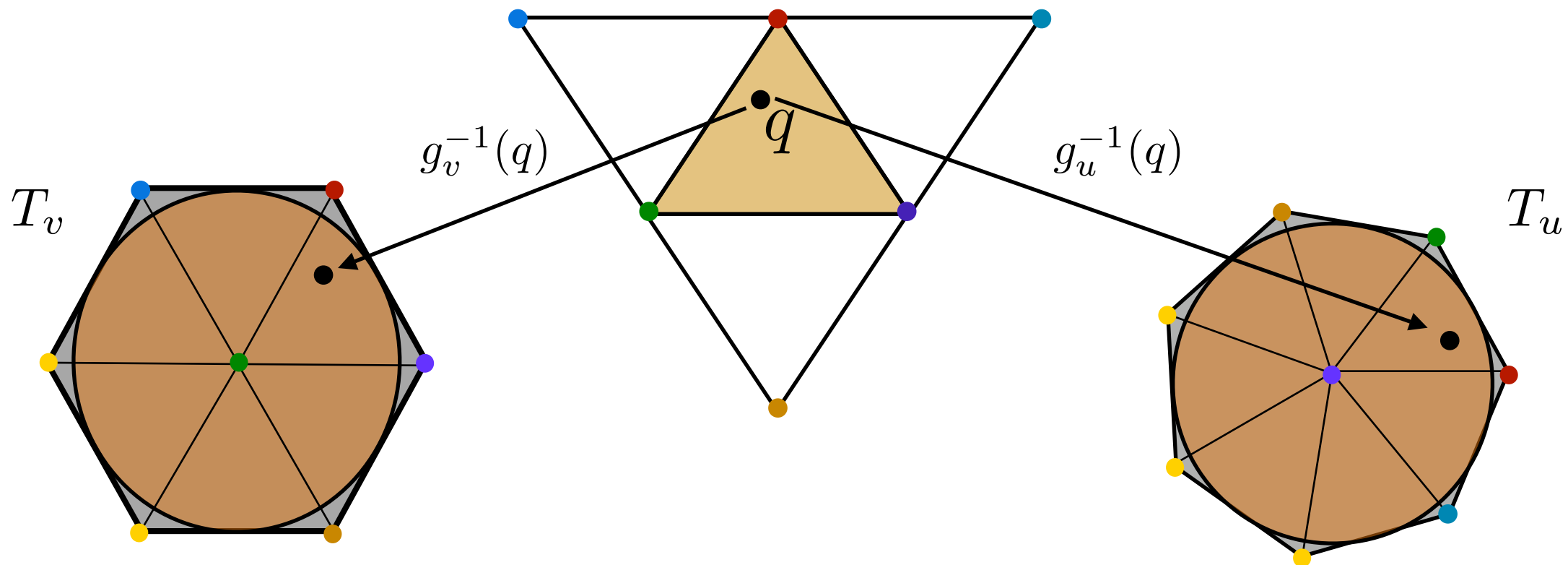
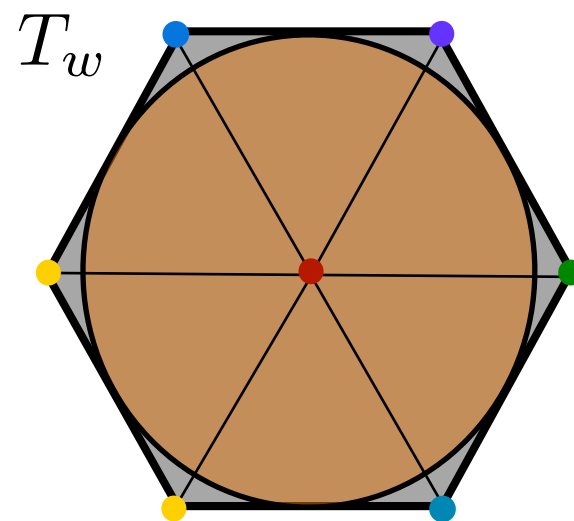
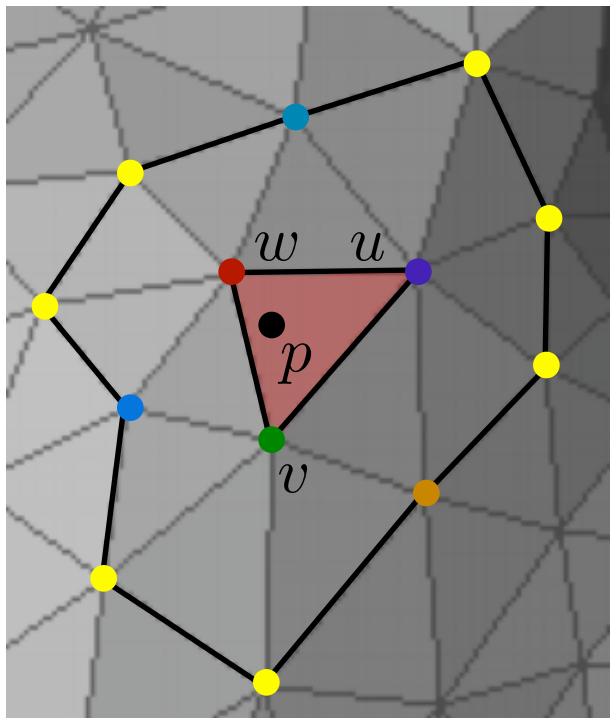
User's Perspective



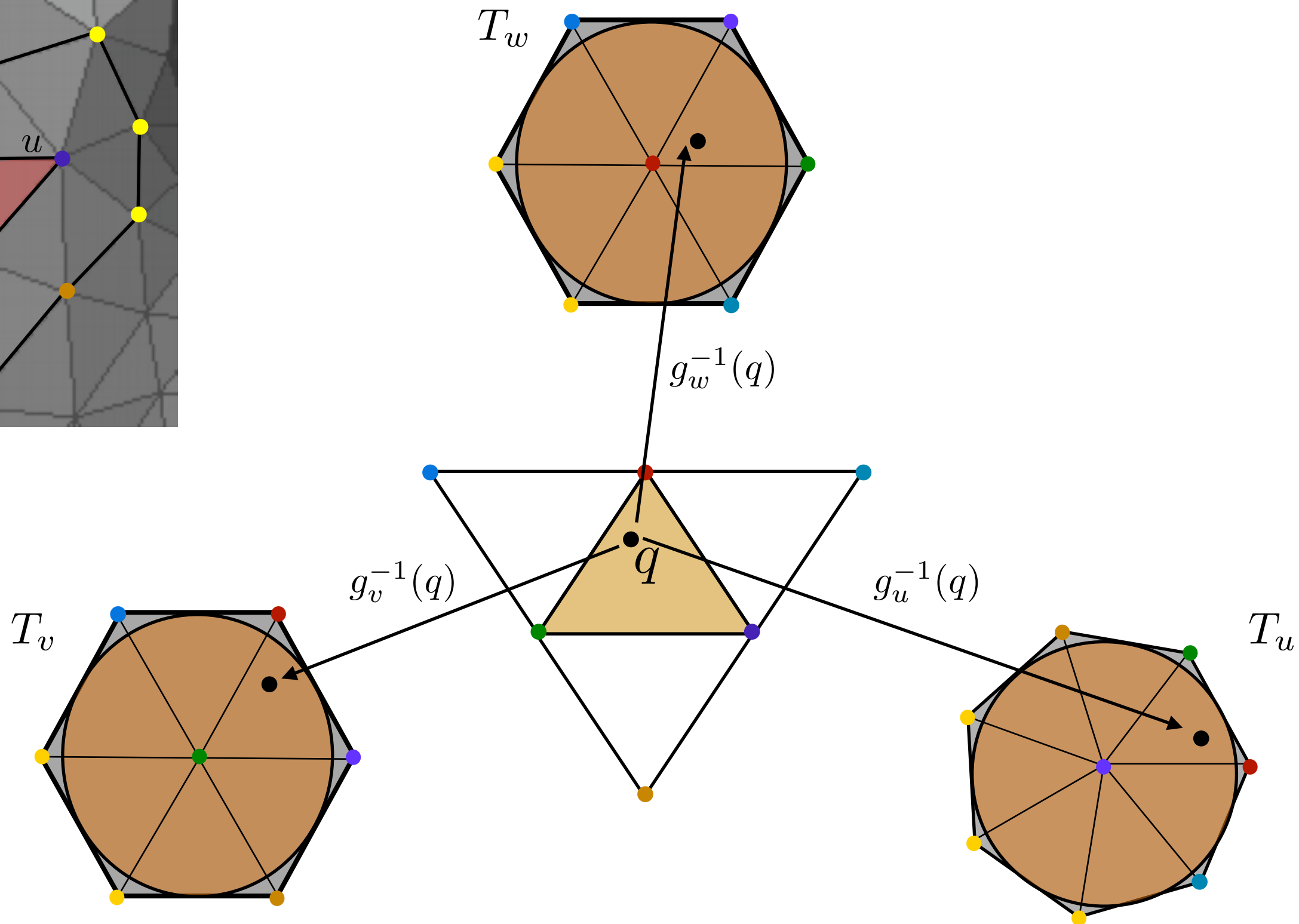
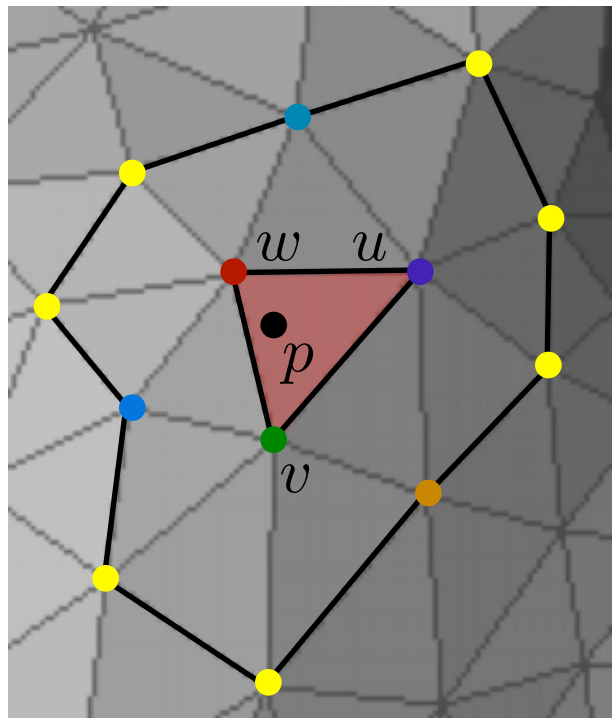
User's Perspective



User's Perspective

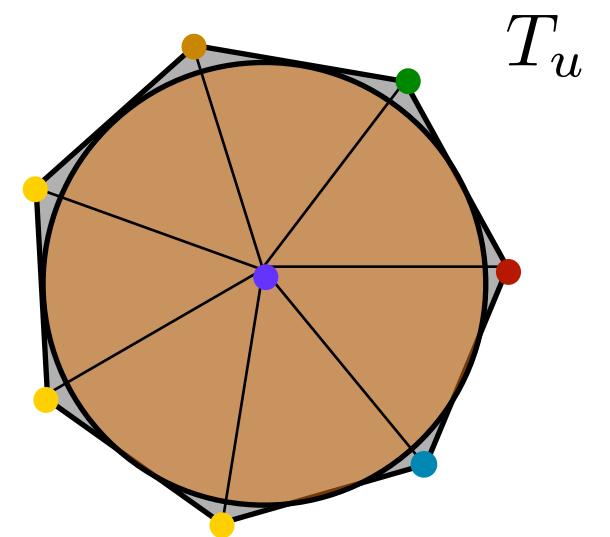
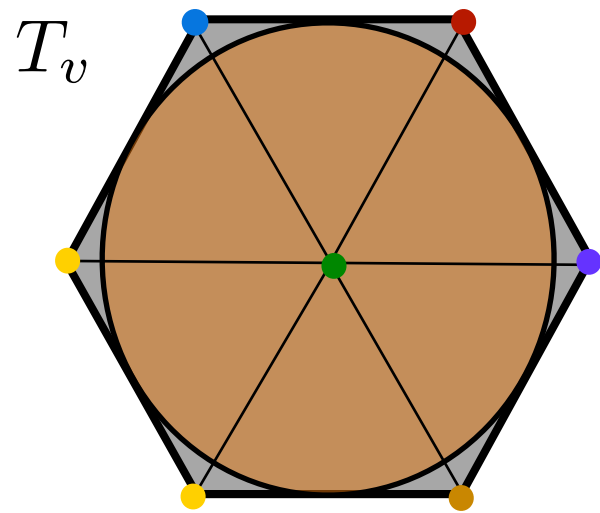
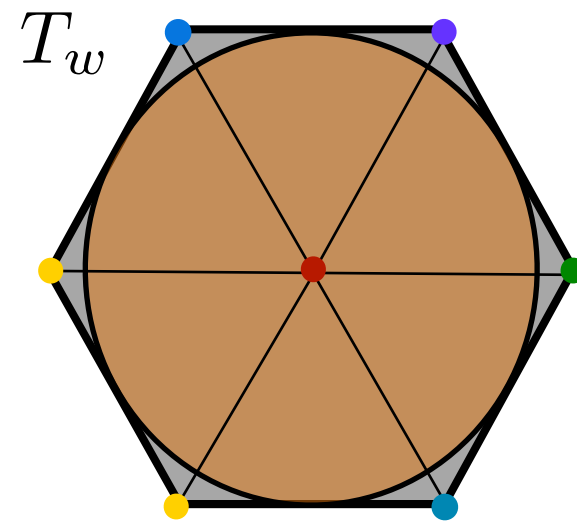
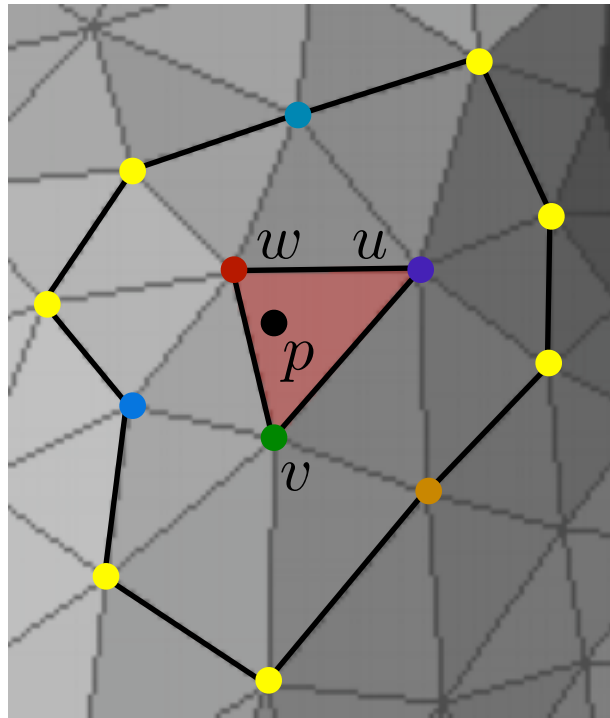


User's Perspective

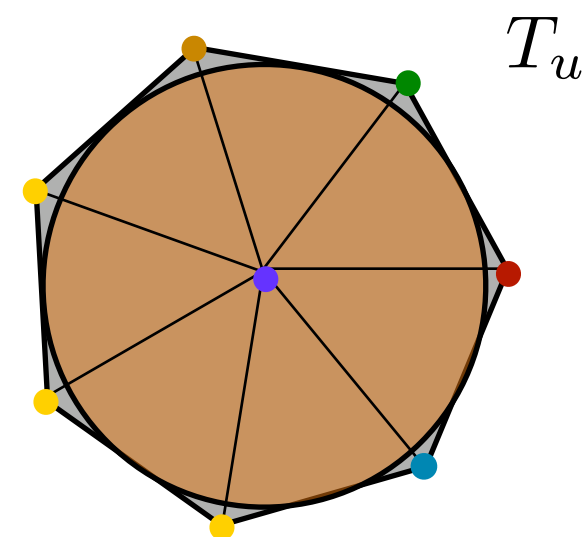
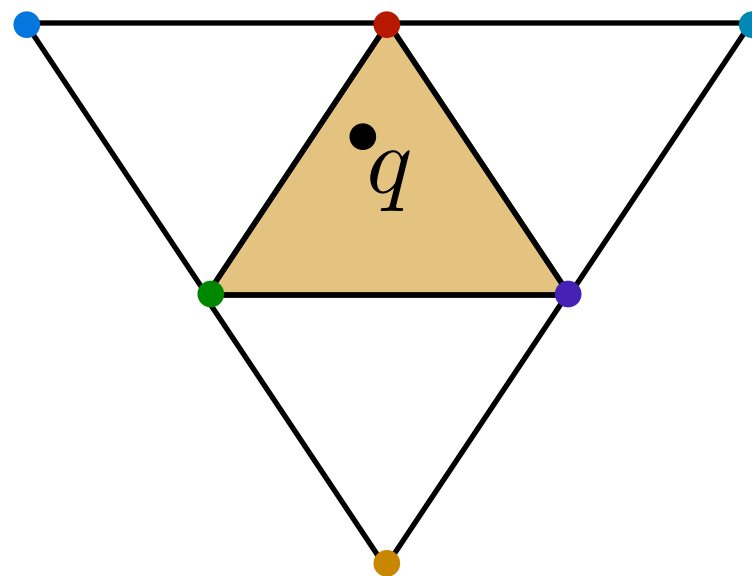
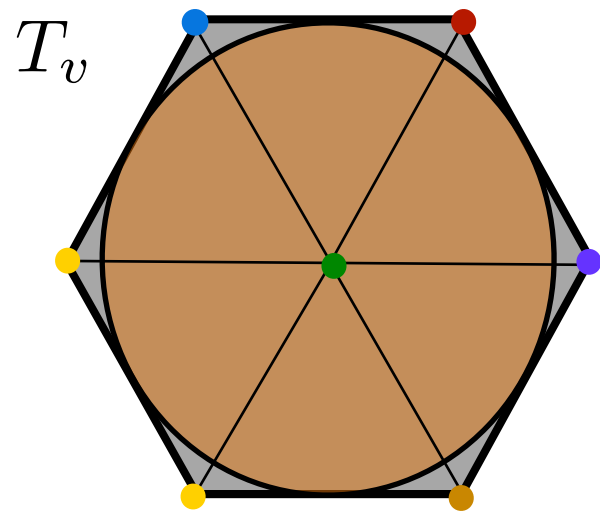
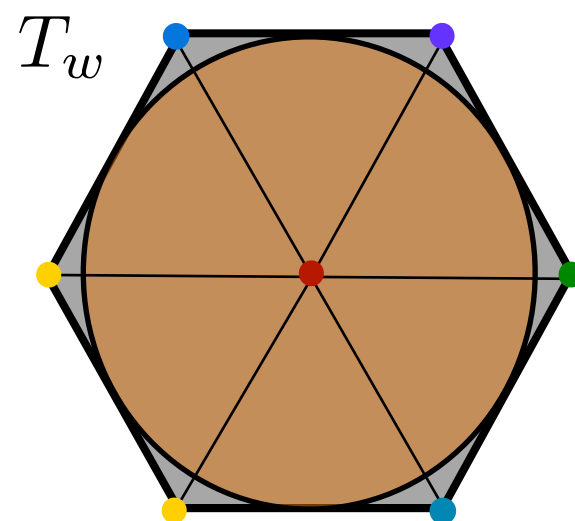
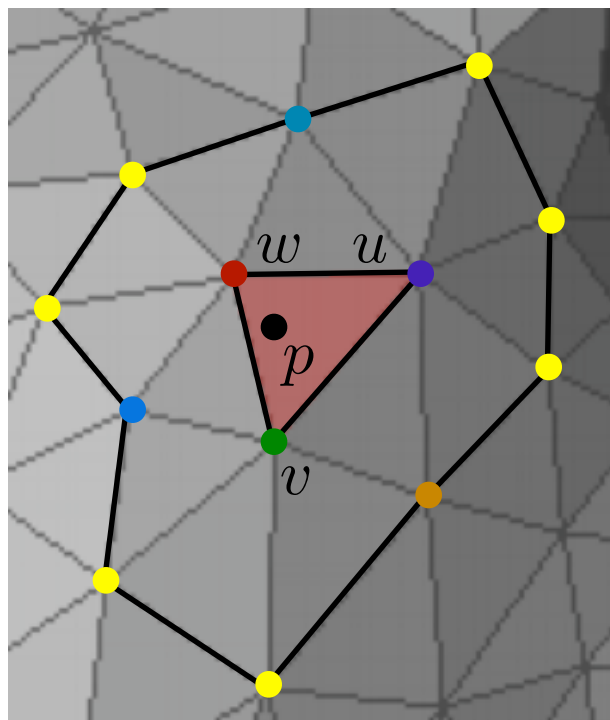


User's Perspective

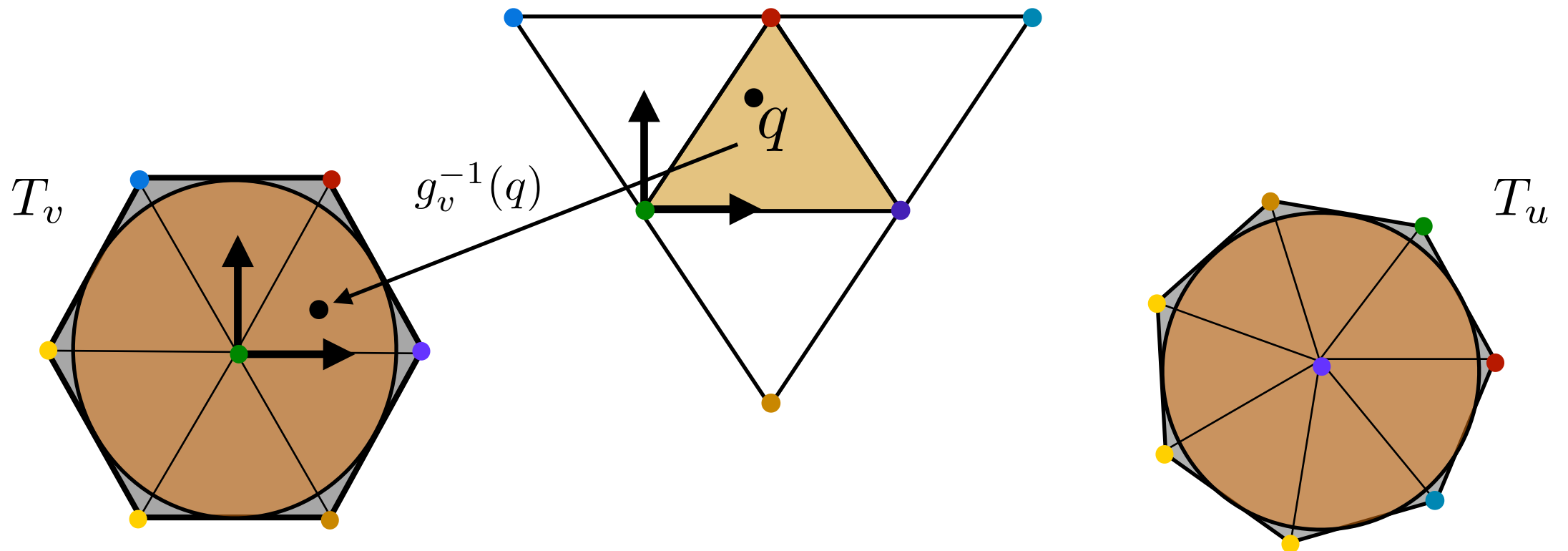
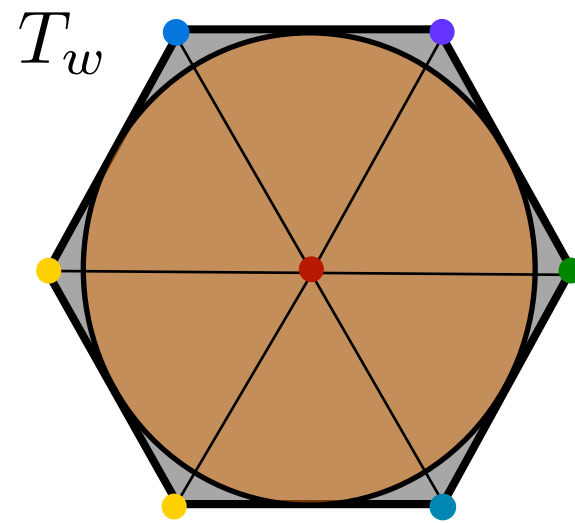
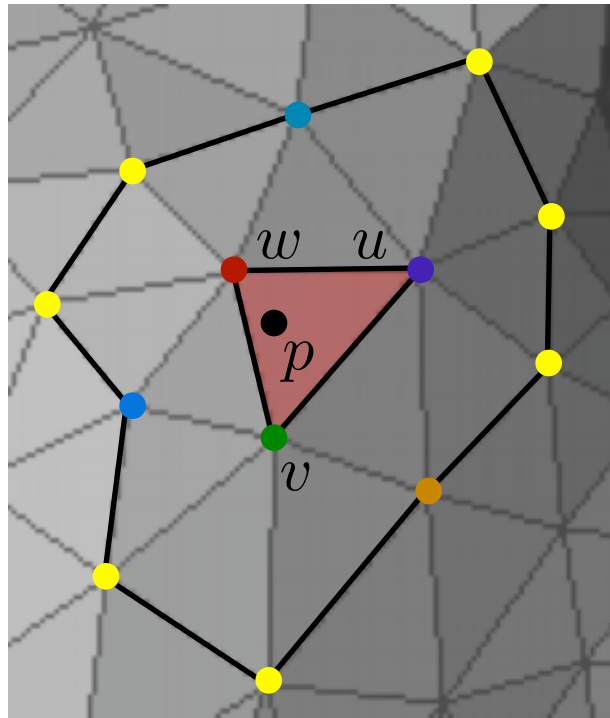
User's Perspective



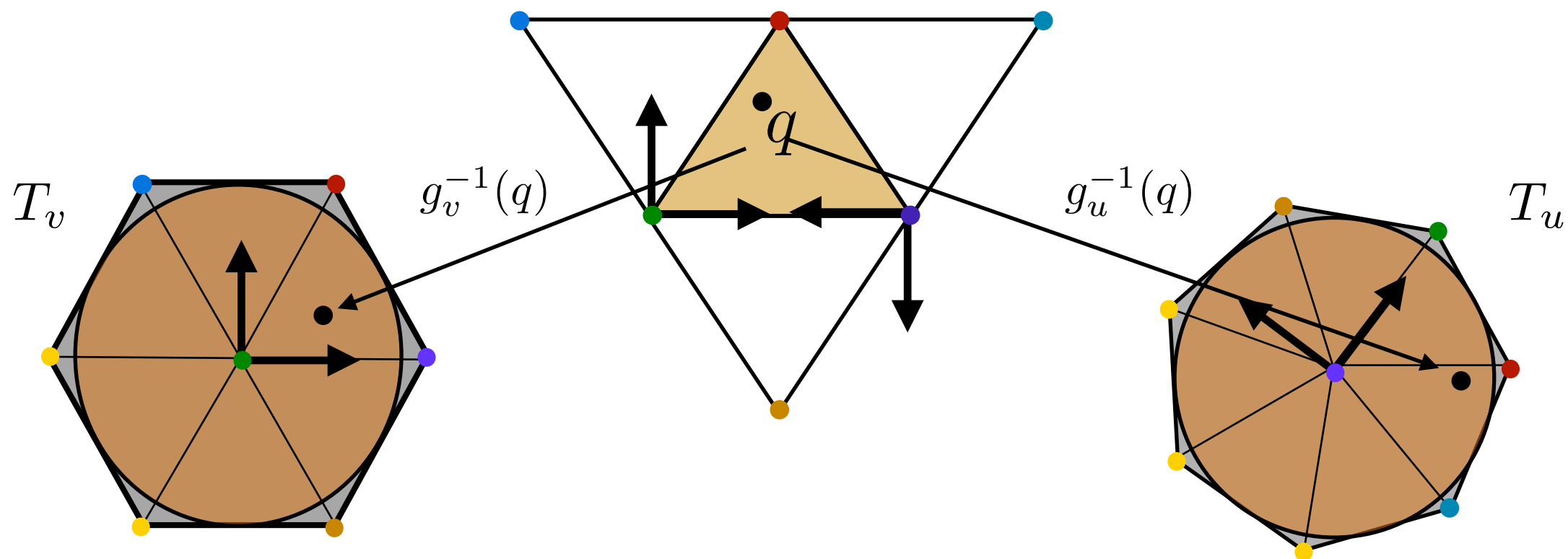
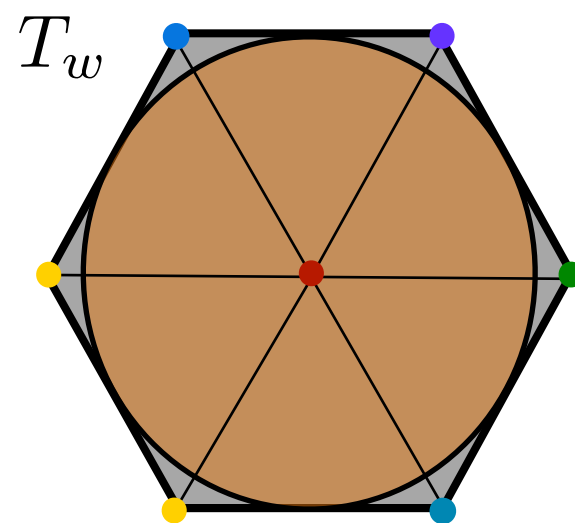
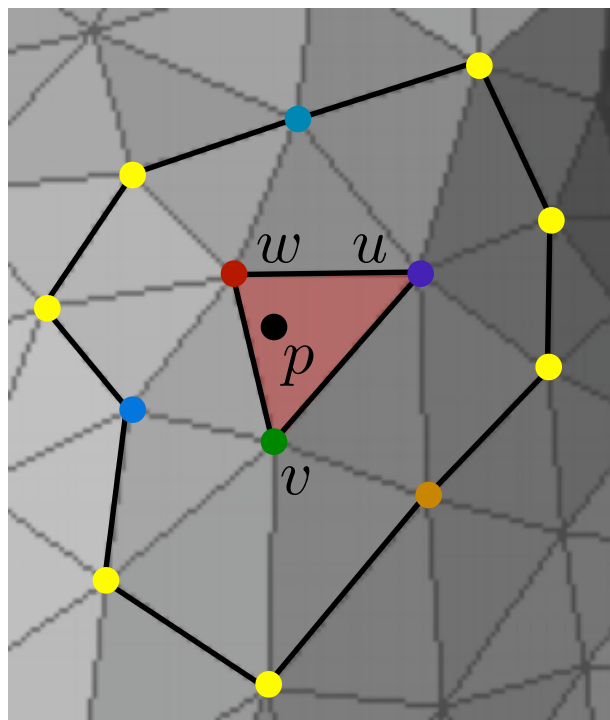
User's Perspective



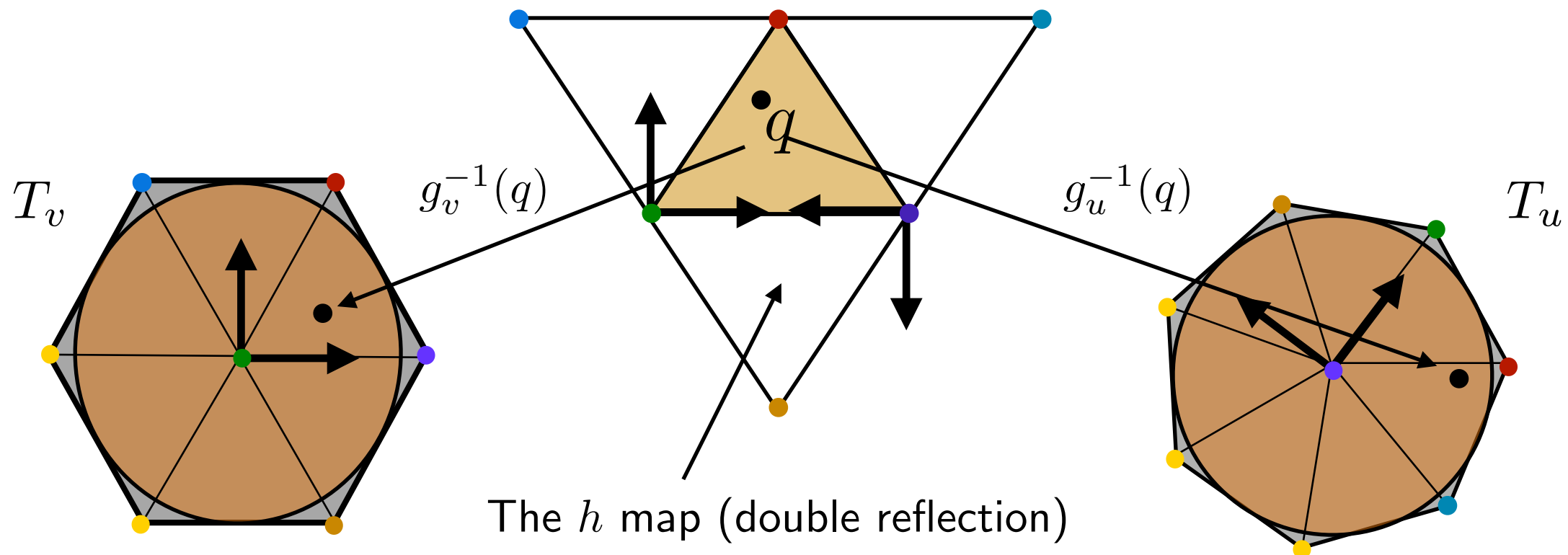
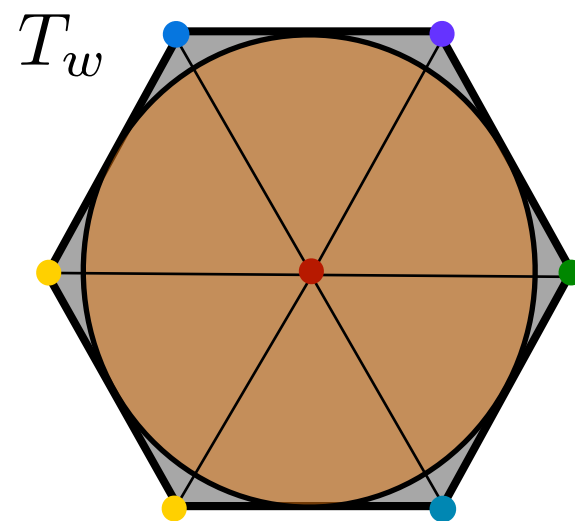
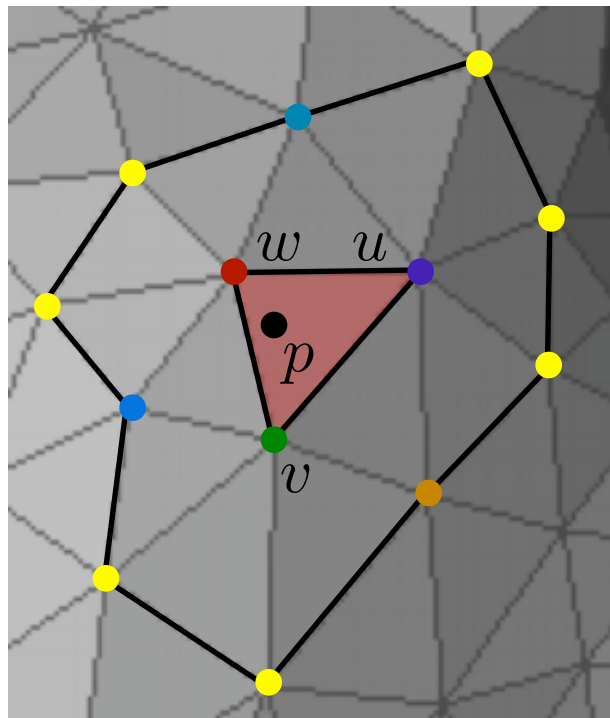
User's Perspective



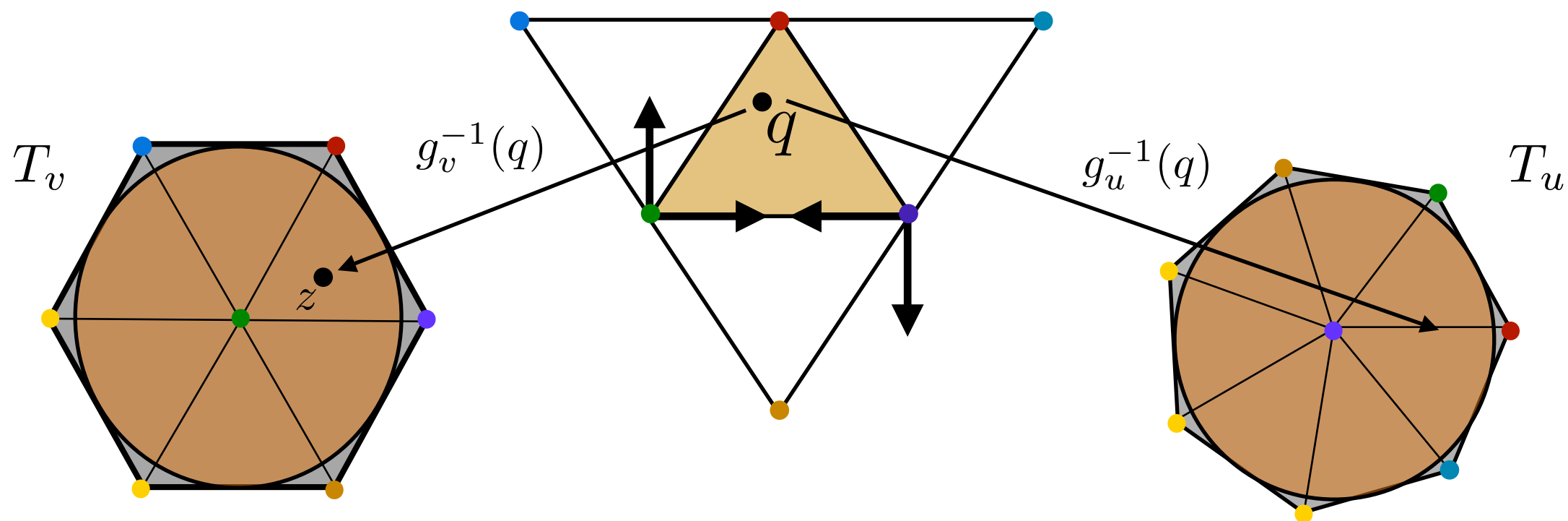
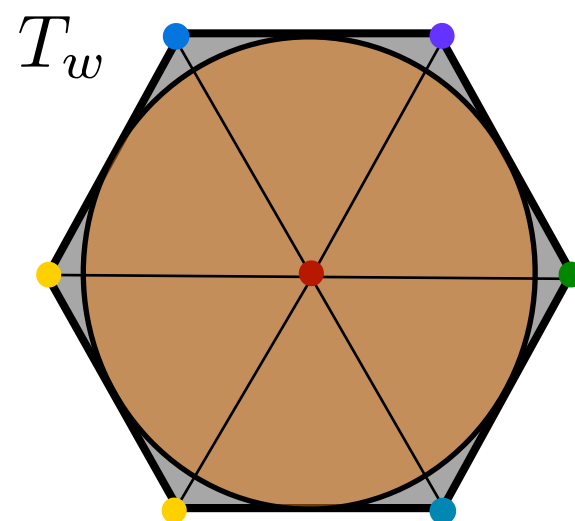
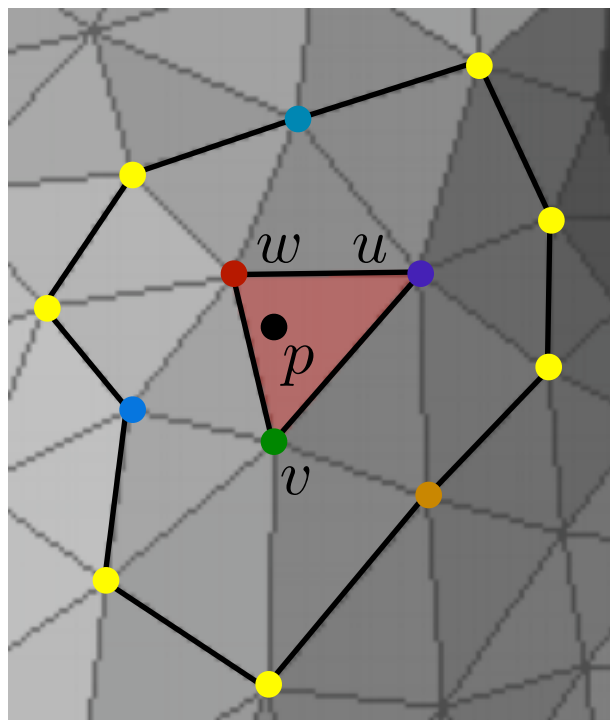
User's Perspective



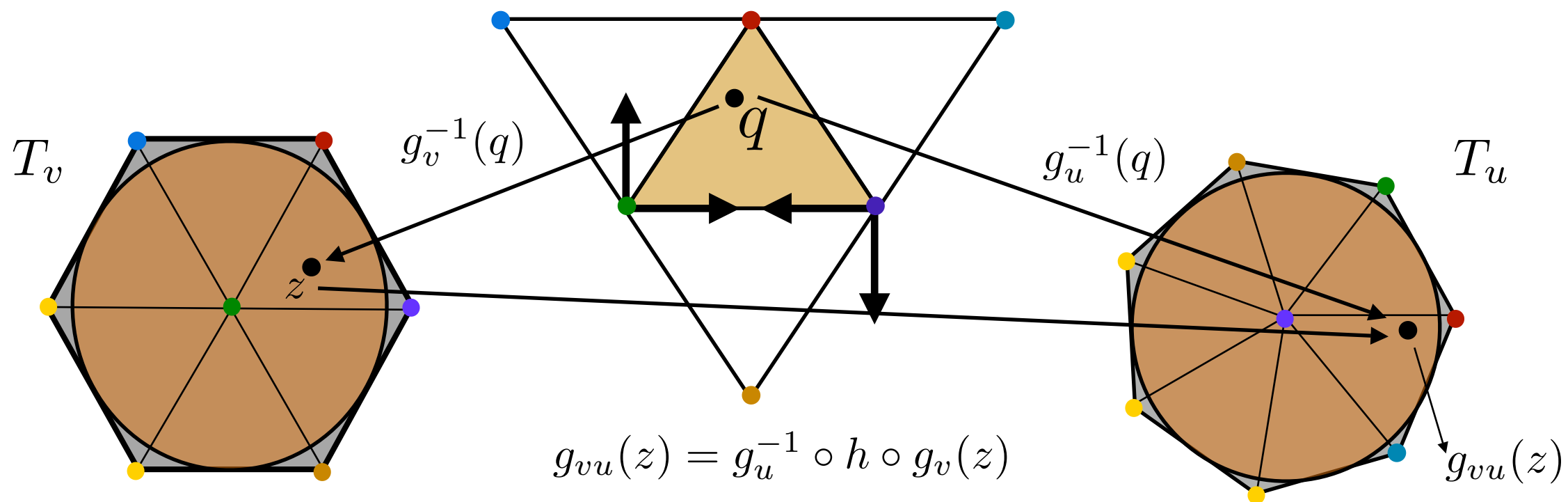
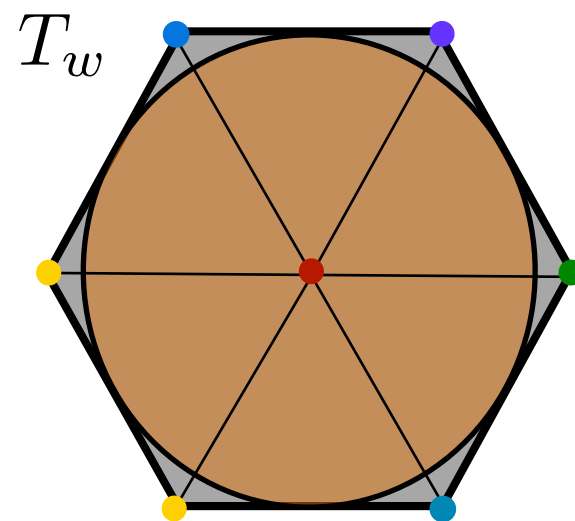
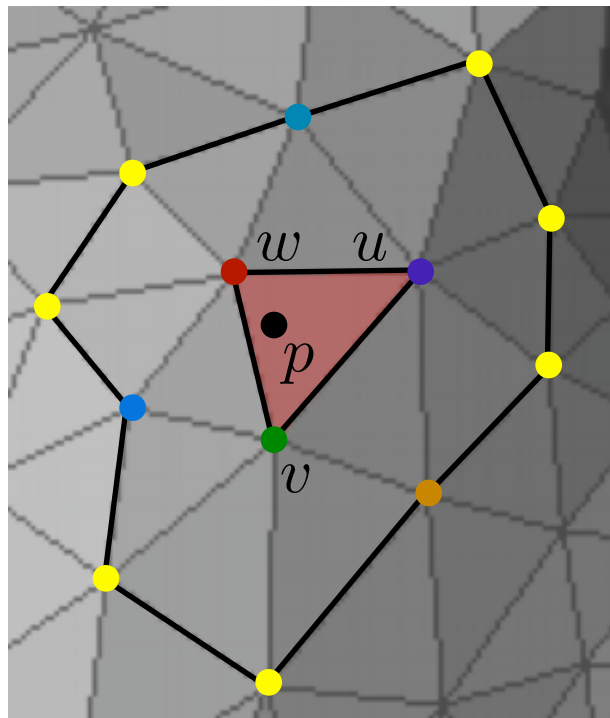
User's Perspective



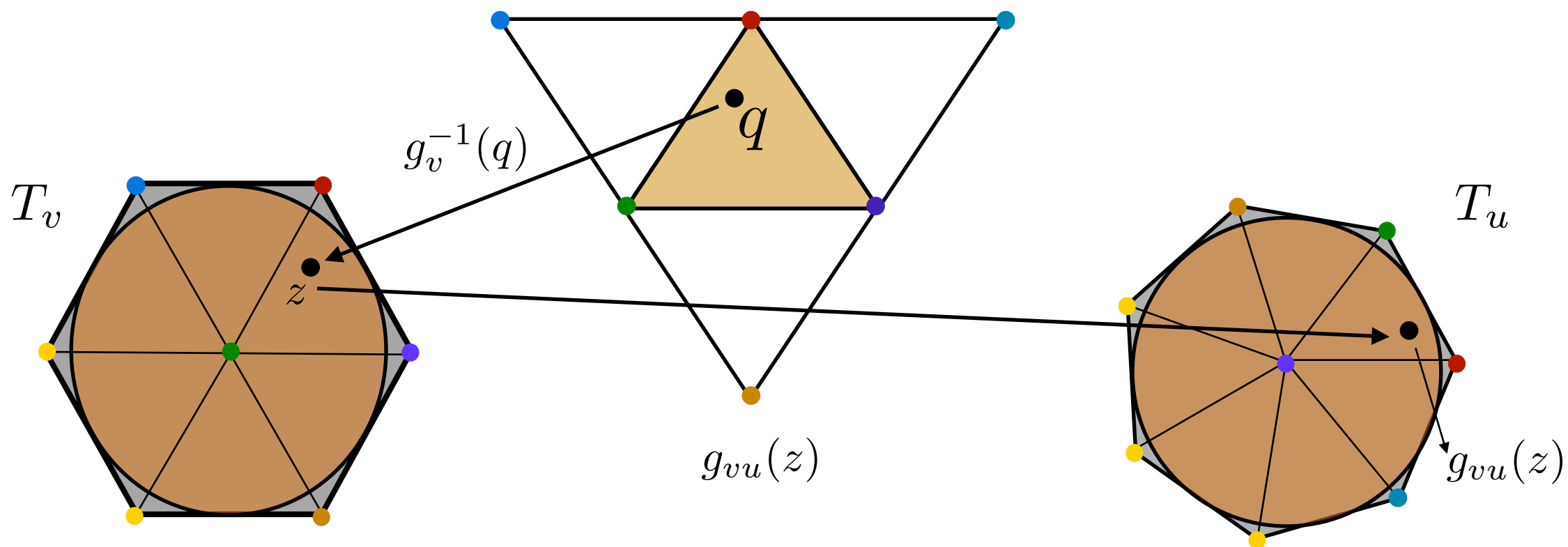
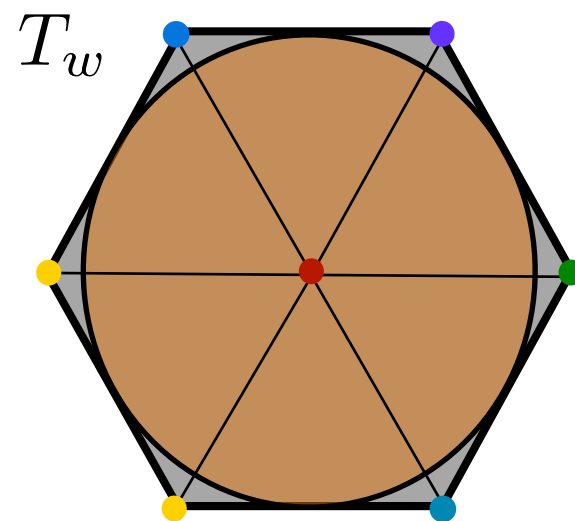
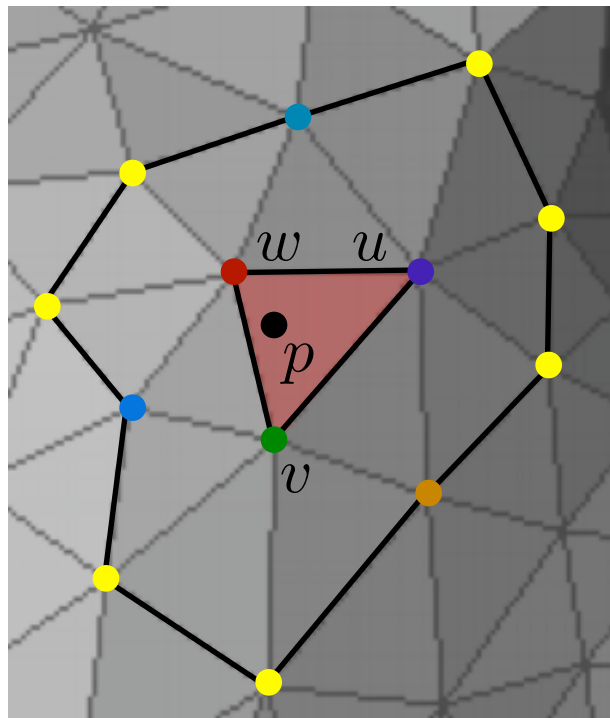
User's Perspective



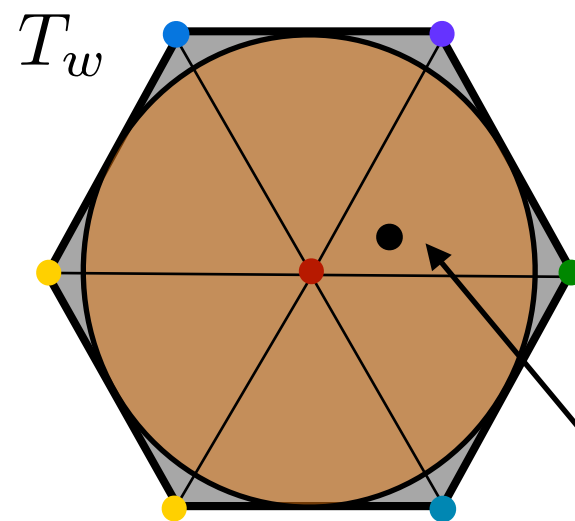
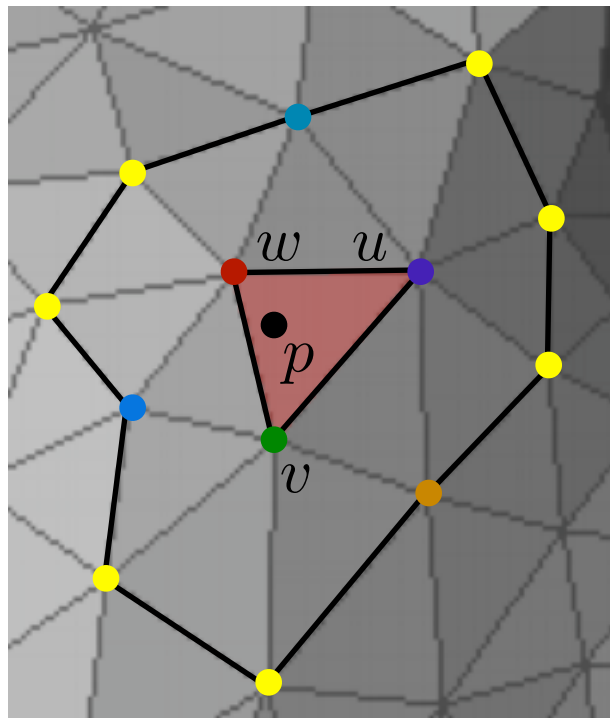
User's Perspective



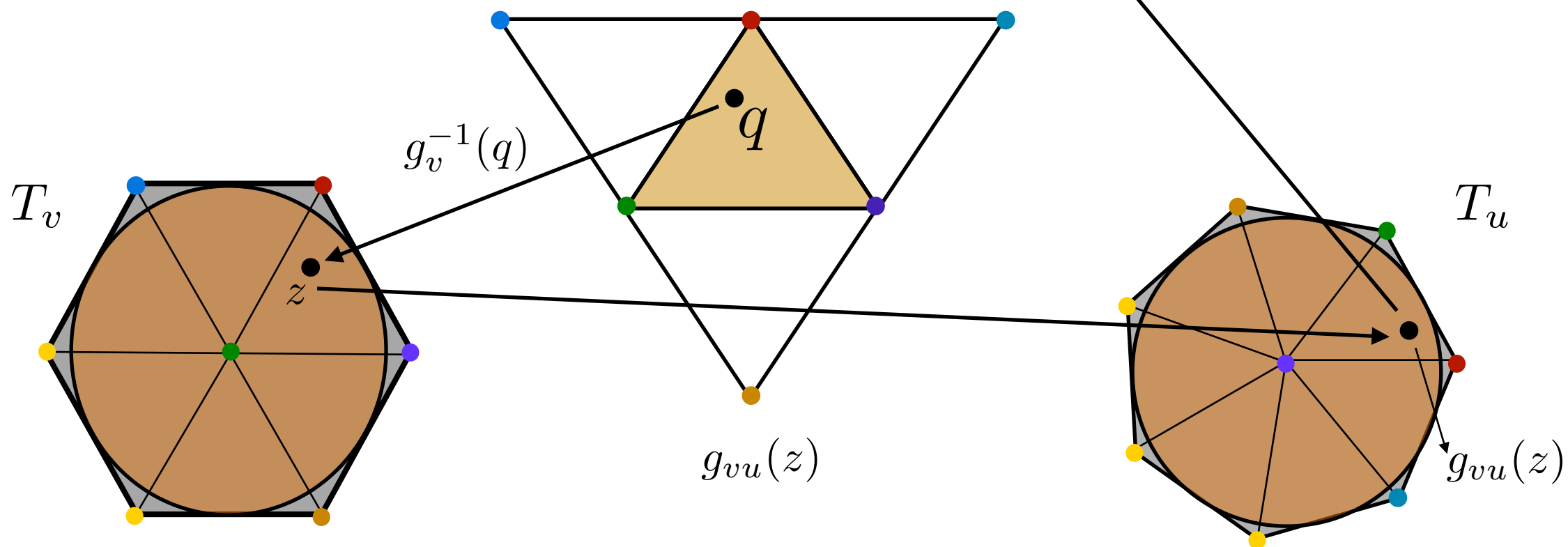
User's Perspective



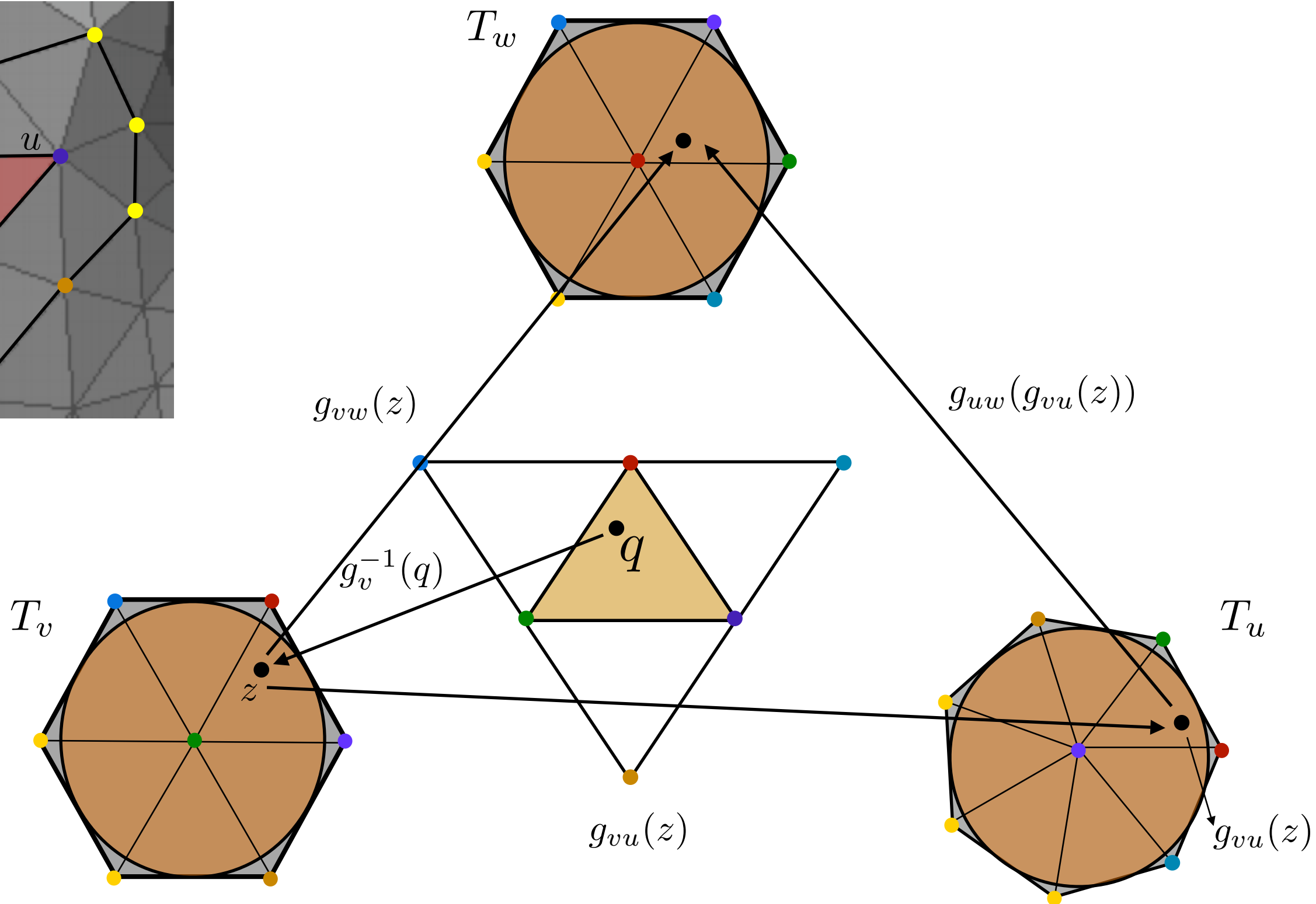
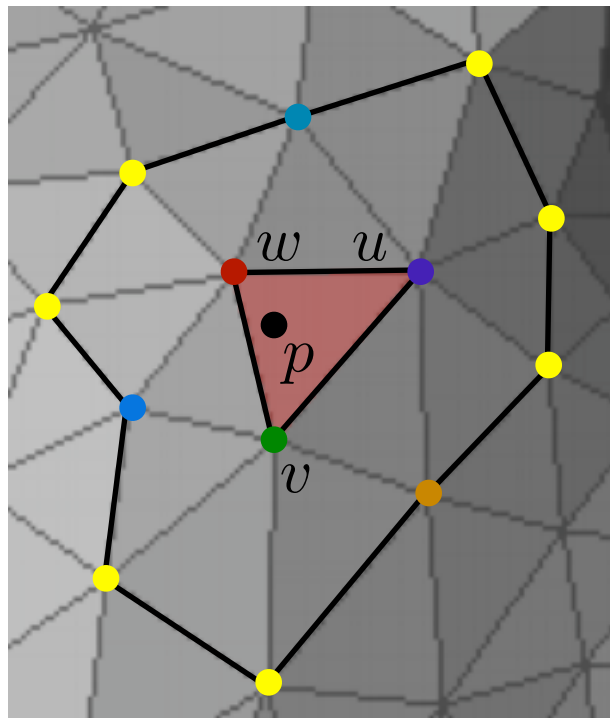
User's Perspective



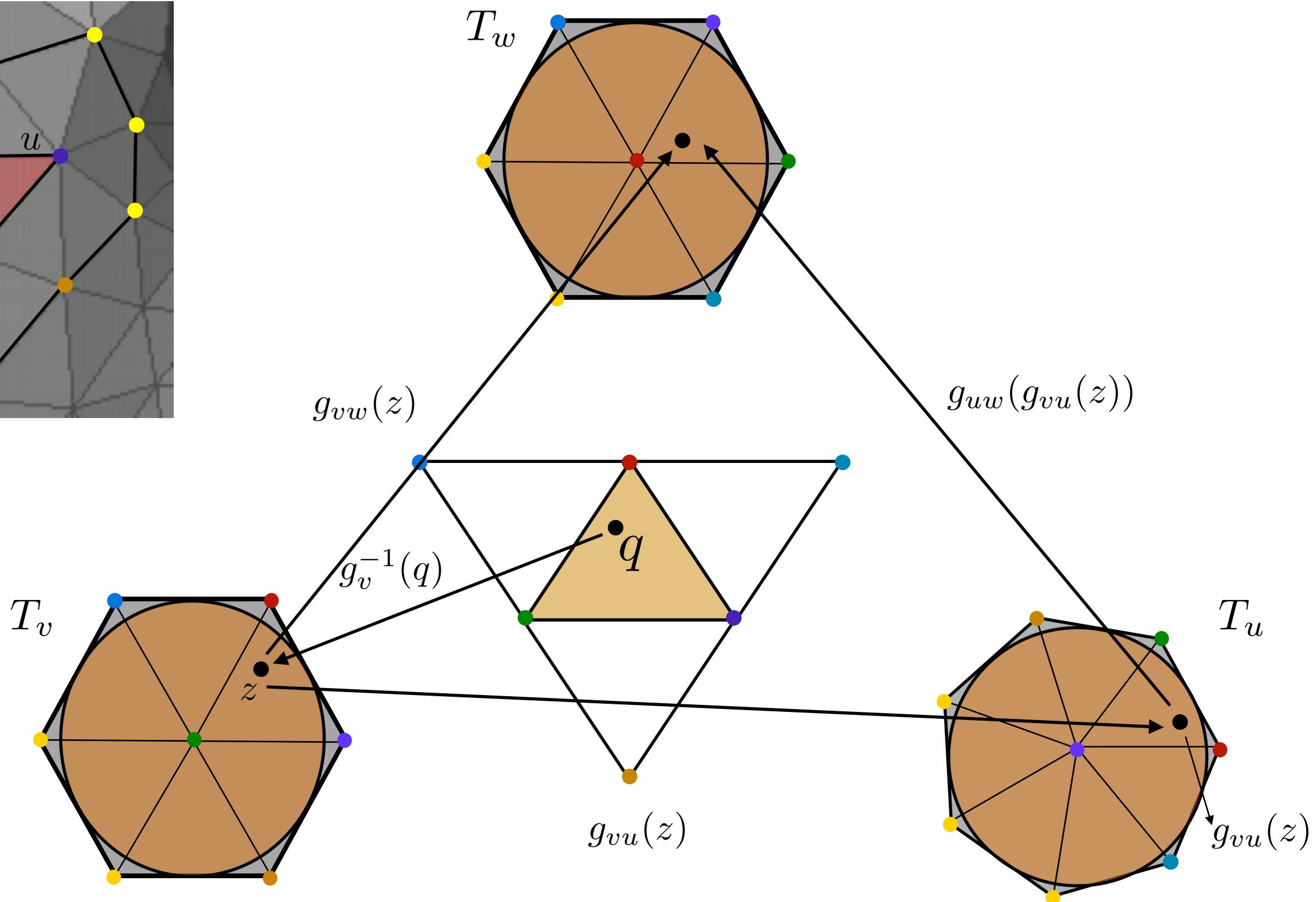
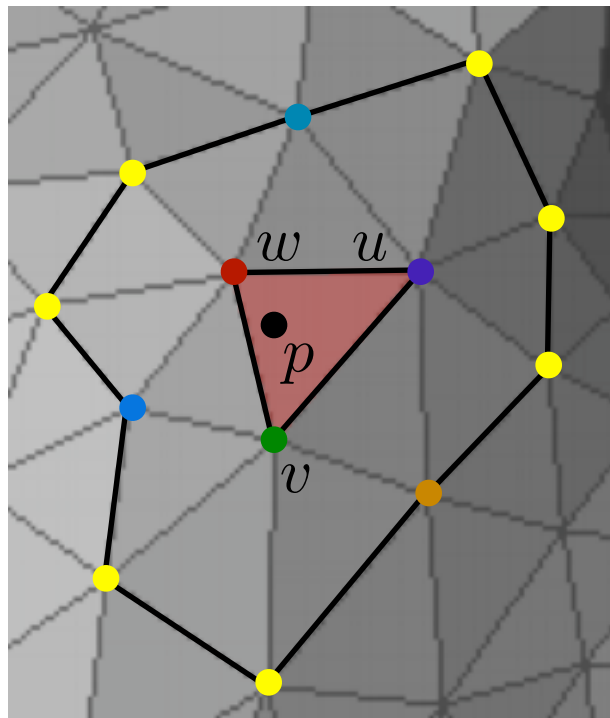
$g_{uw}(g_{vu}(z))$



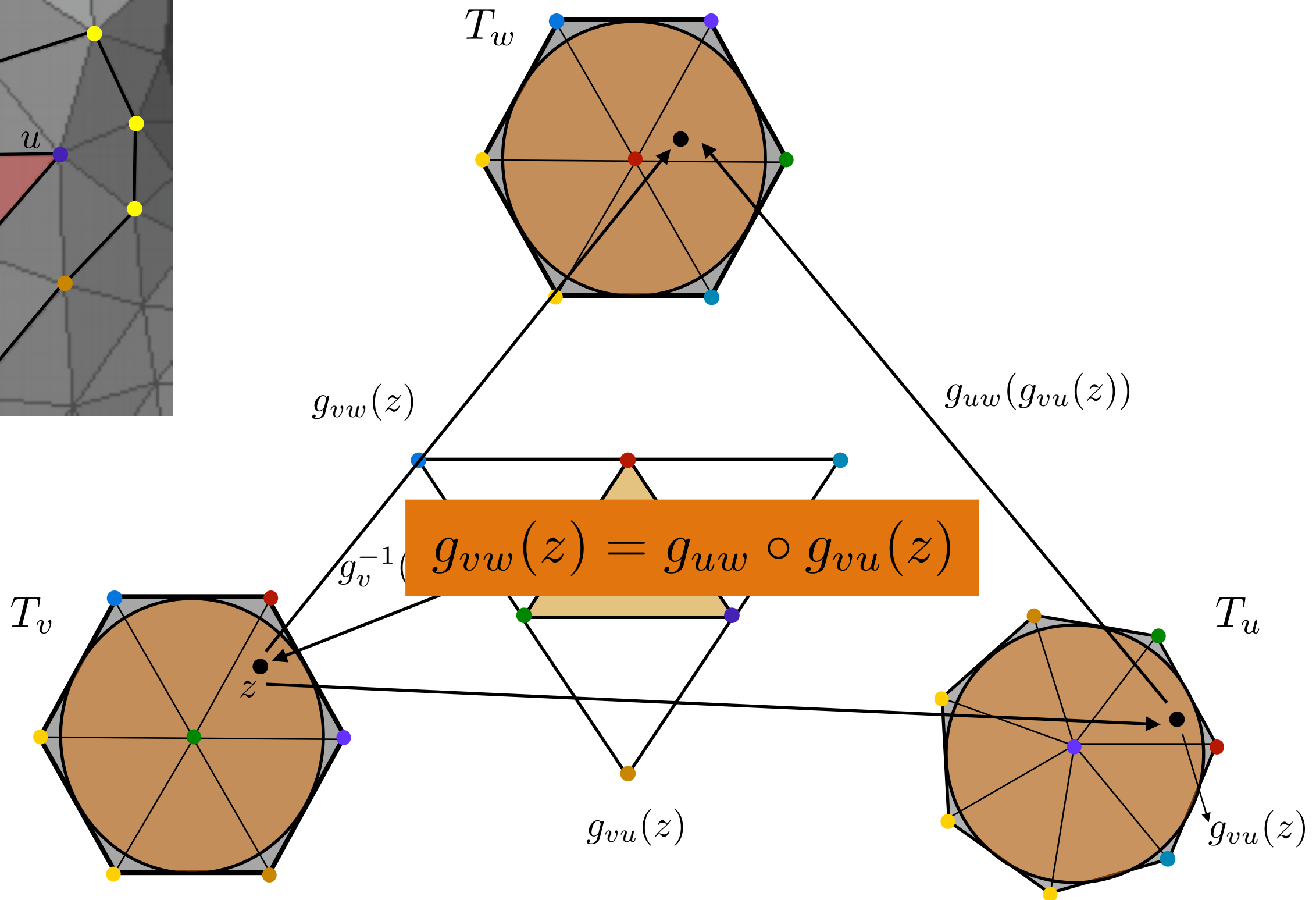
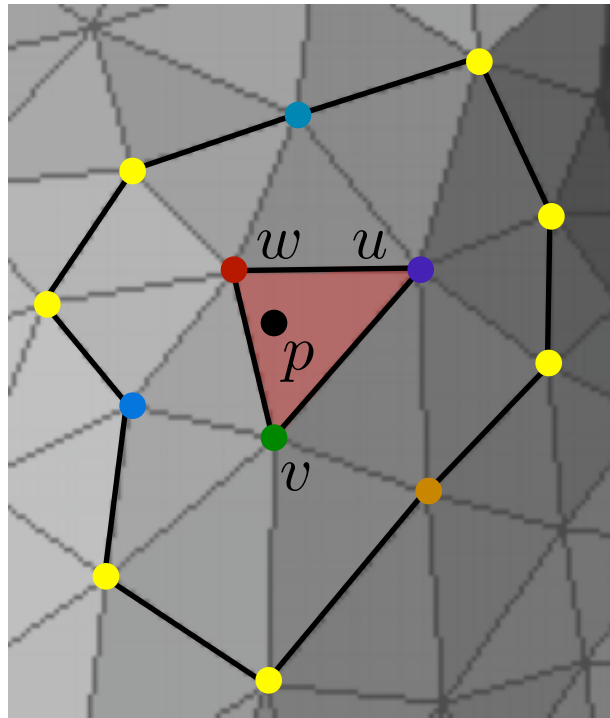
User's Perspective



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User's Perspective



Building Parametrizations

Building Parametrizations

For each $(\sigma, \nu) \in I$, we define a **weight function**,

$$\gamma_{(\sigma, \nu)} : \mathbb{R}^2 \rightarrow \mathbb{R},$$

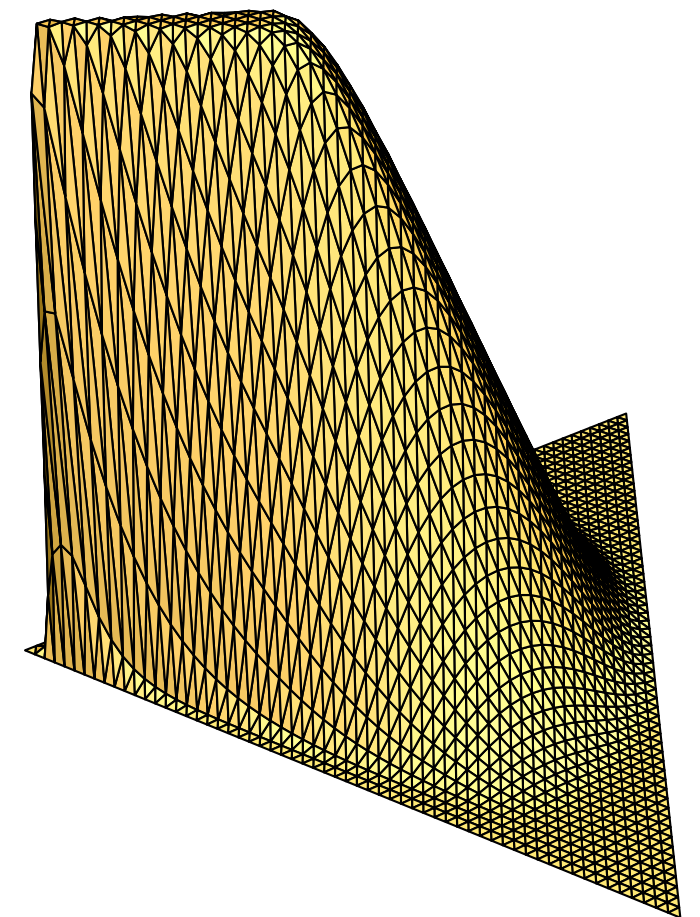
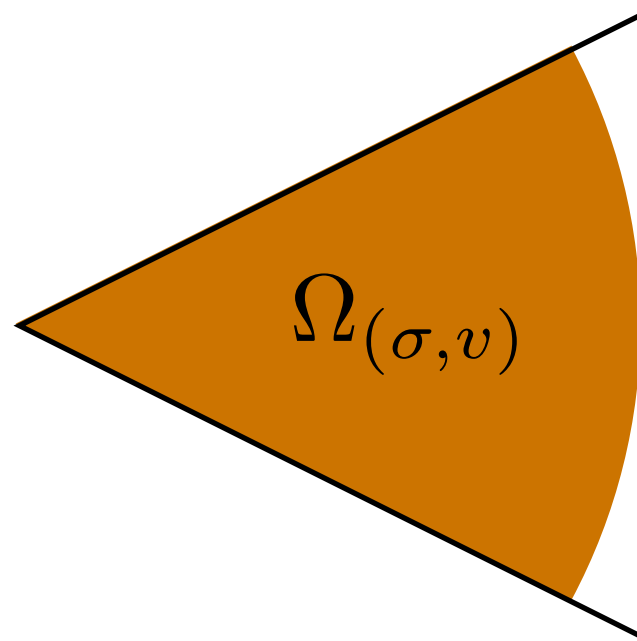
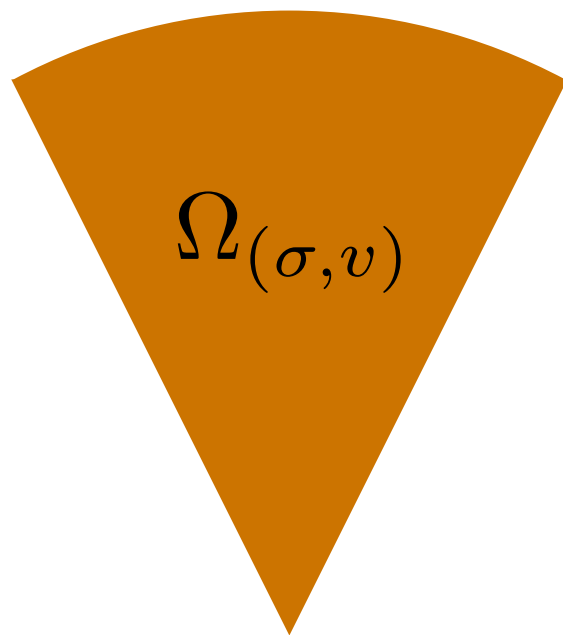
which is the product of two C^∞ curves (and therefore, C^∞ too).

Building Parametrizations

For each $(\sigma, v) \in I$, we define a **weight function**,

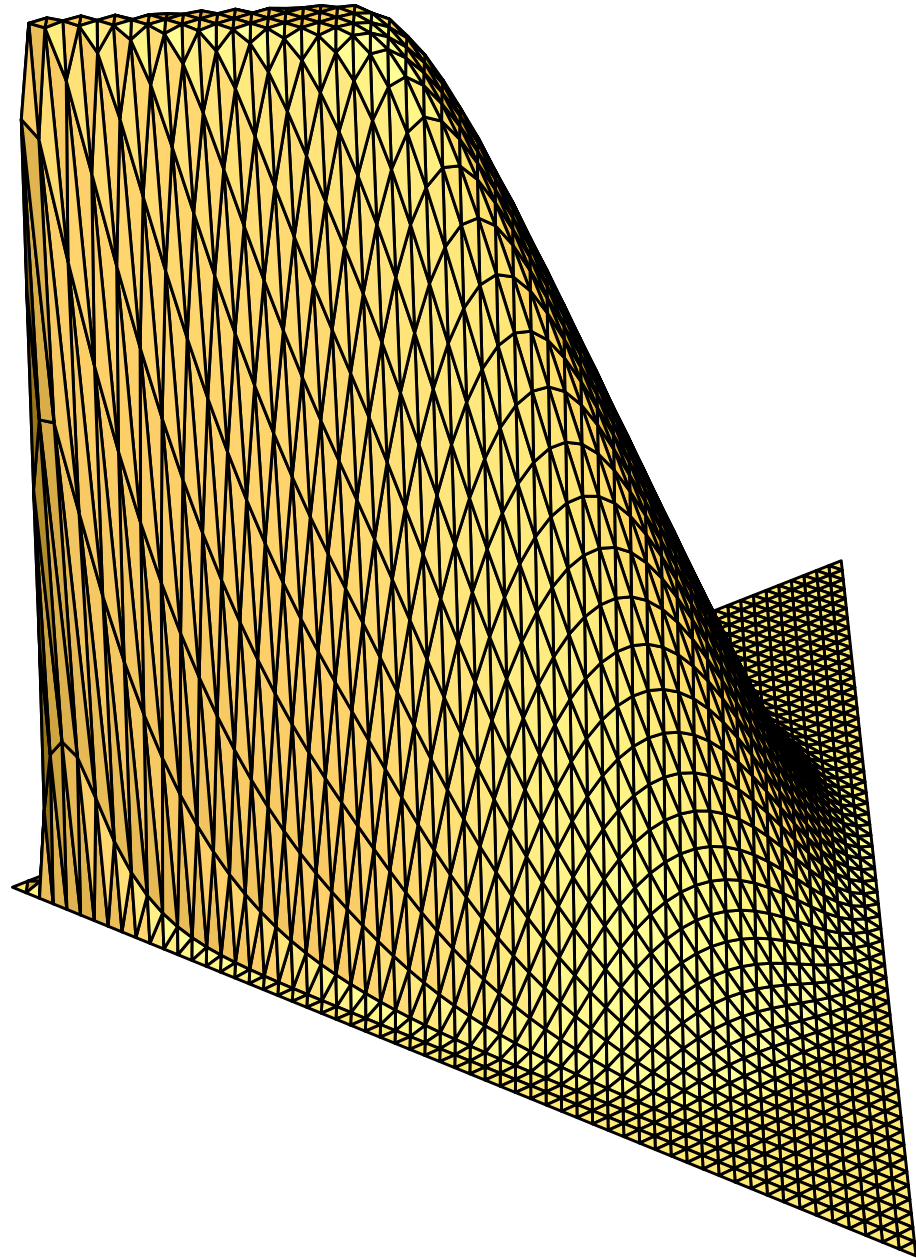
$$\gamma(\sigma, v) : \mathbb{R}^2 \rightarrow \mathbb{R},$$

which is the product of two C^∞ curves (and therefore, C^∞ too).

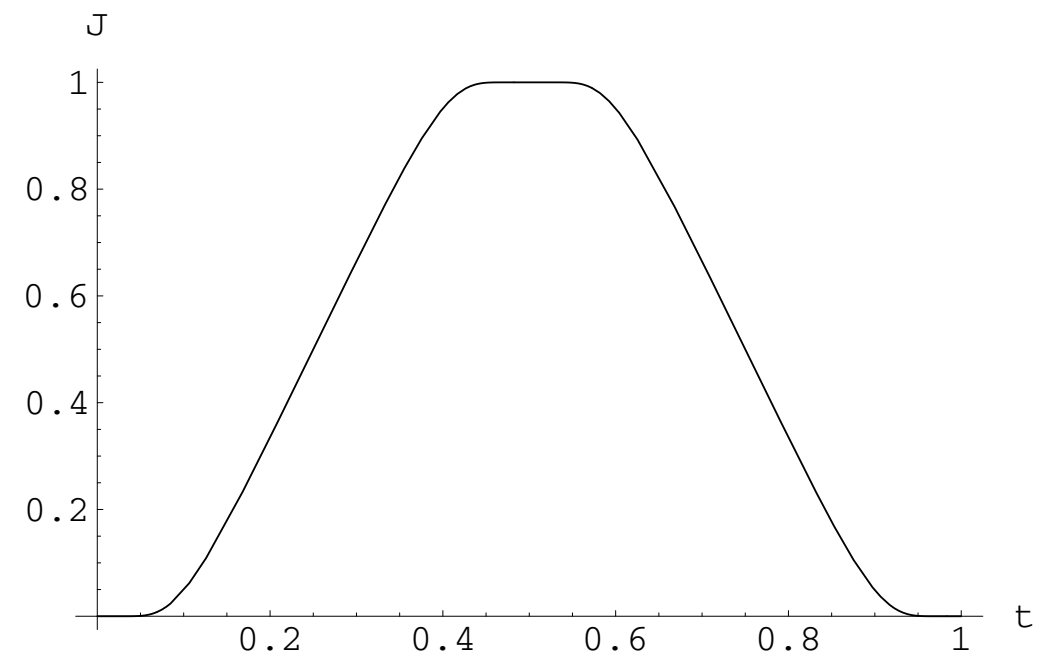
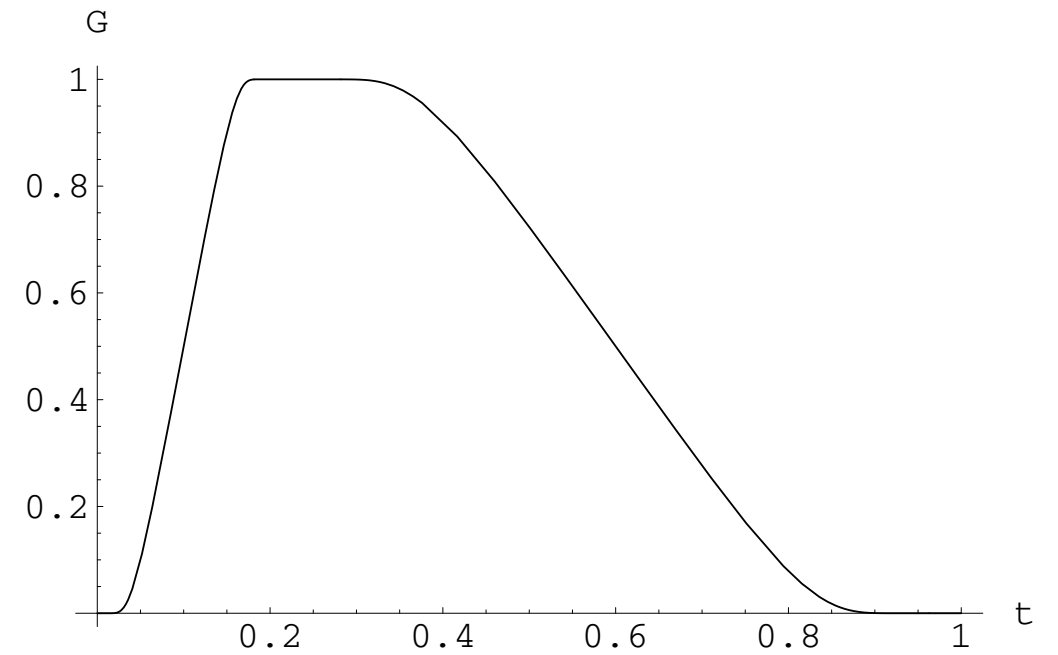
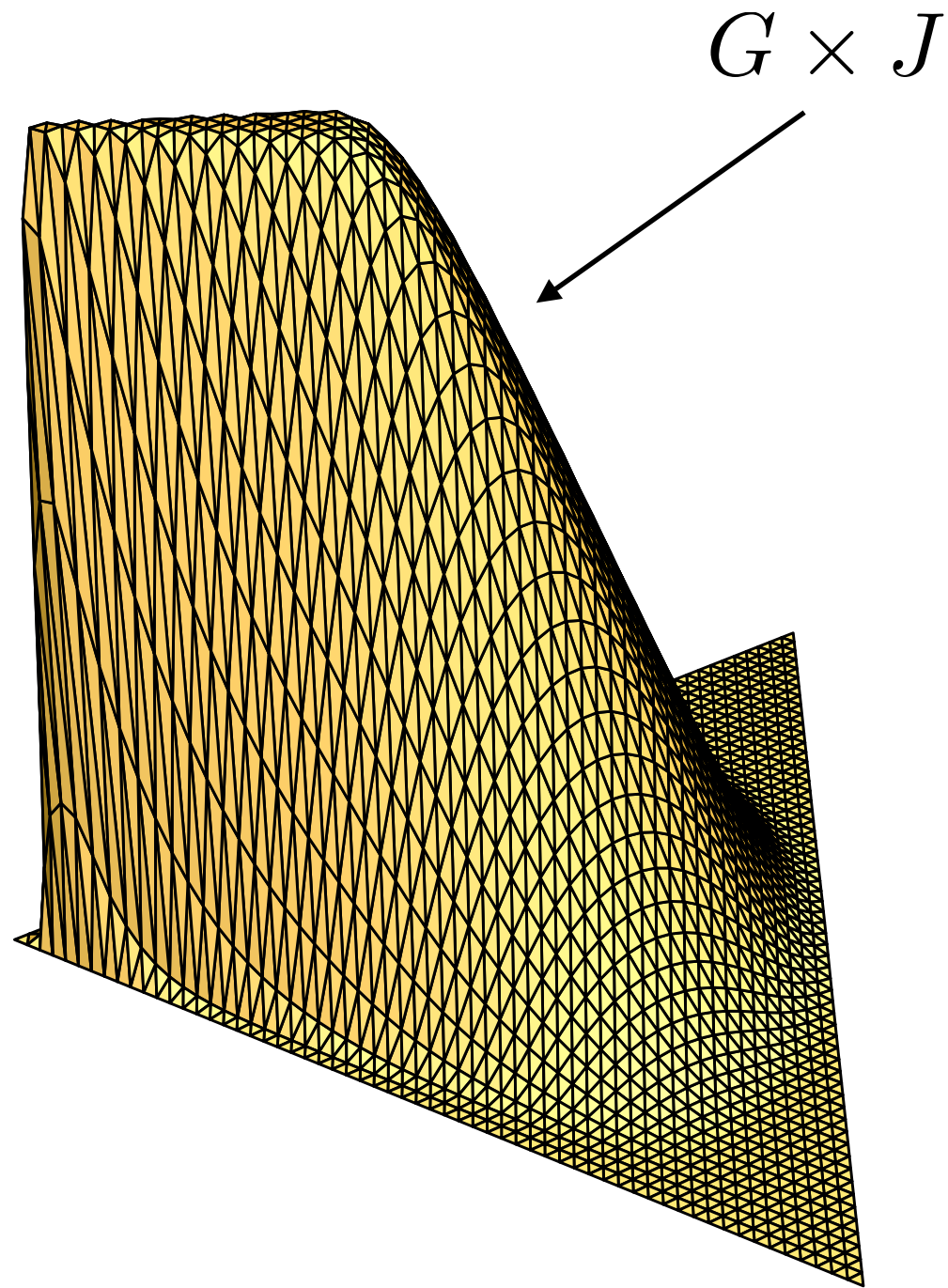


Building Parametrizations

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Building Parametrizations

Building Parametrizations

For each $(\sigma, v) \in I$, we define a **Bézier patch**,

$$\psi_{(\sigma, v)} : \mathbb{R}^2 \rightarrow \mathbb{R}^3 ,$$

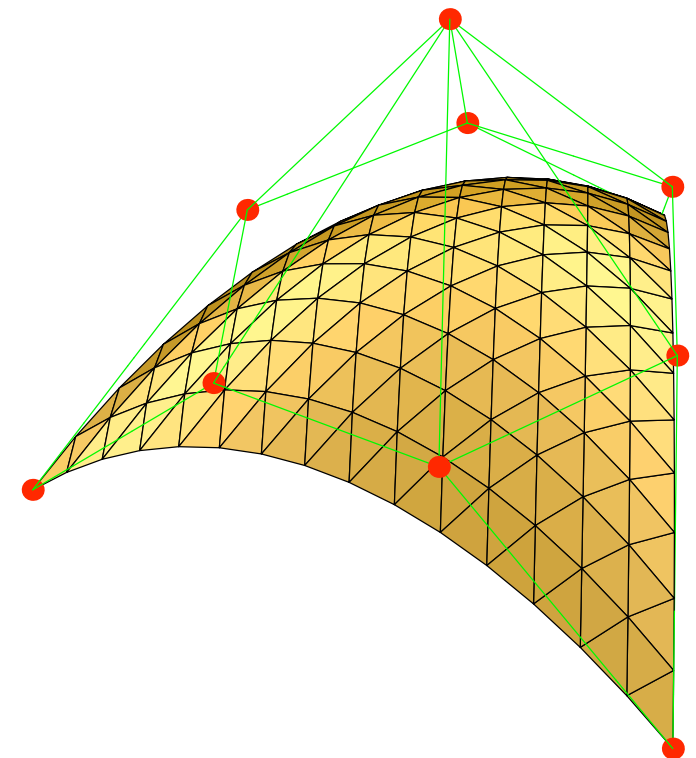
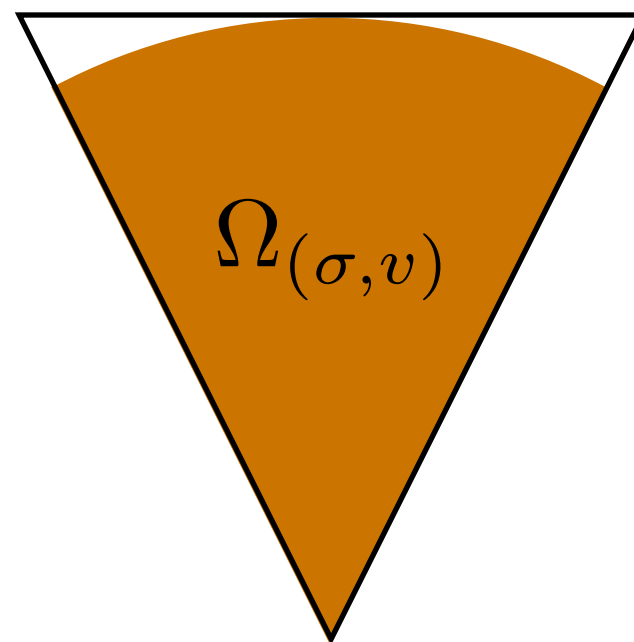
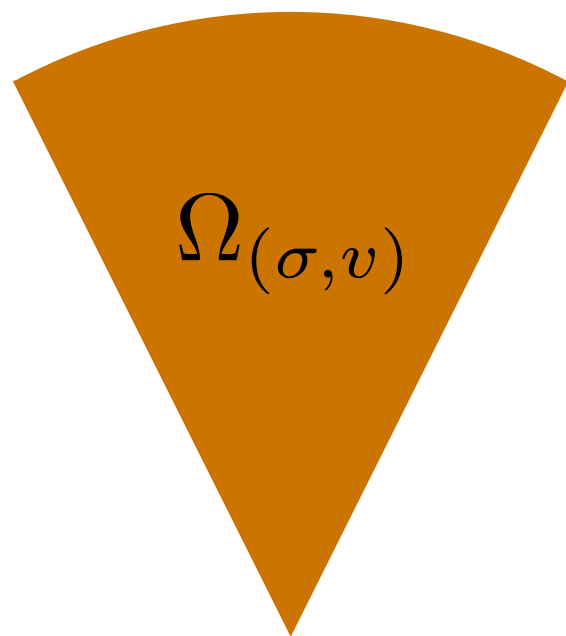
whose control points are defined in the “envelope” triangle of $\Omega_{(\sigma, v)}$.

Building Parametrizations

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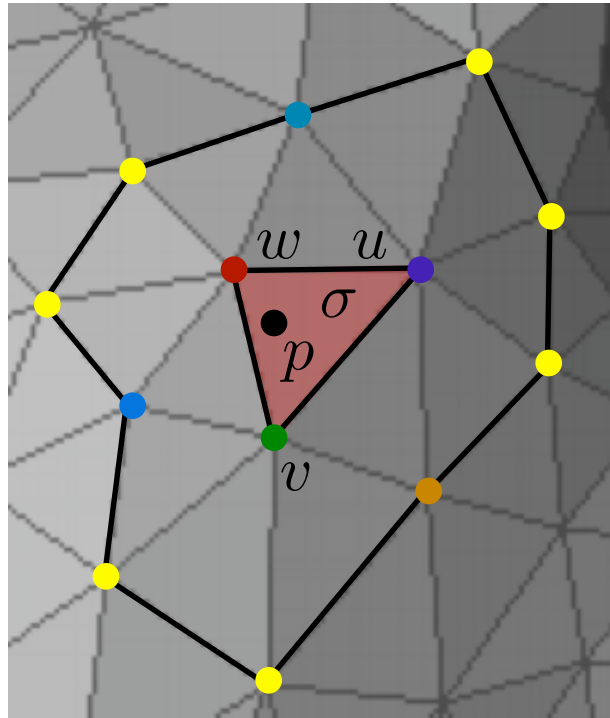
$$\psi_{(\sigma, v)} : \mathbb{R}^2 \rightarrow \mathbb{R}^3,$$

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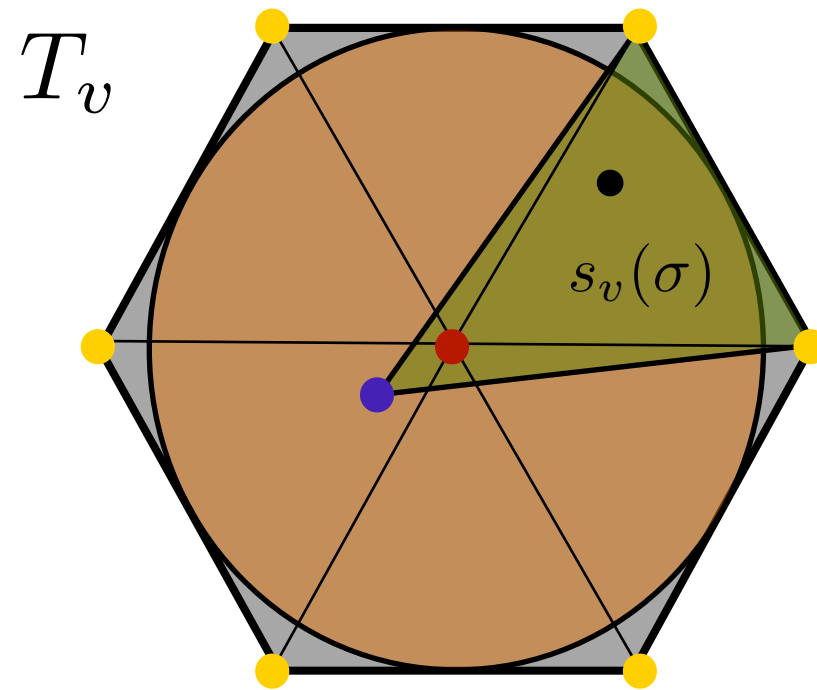
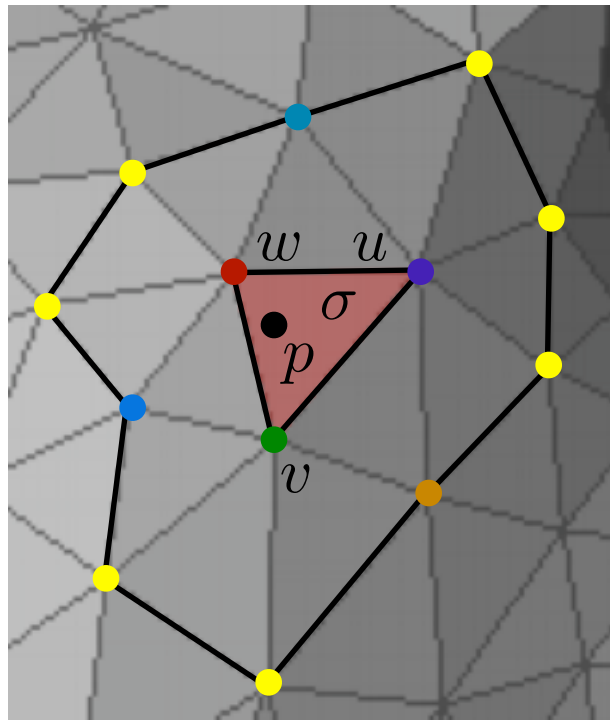


Building Parametrizations

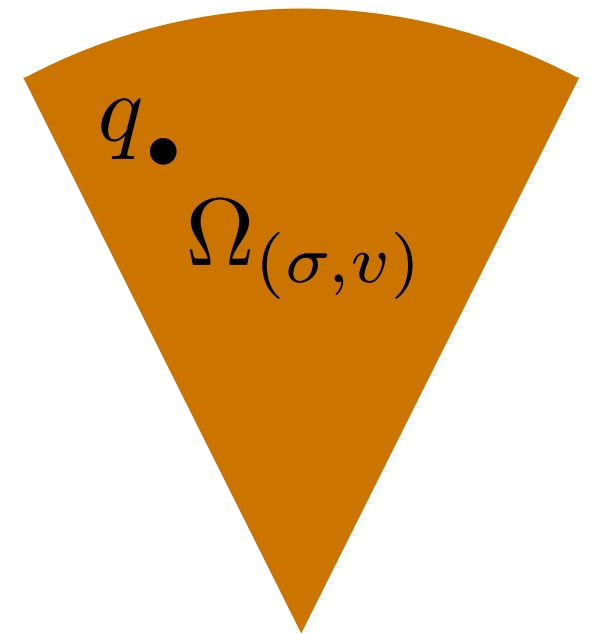
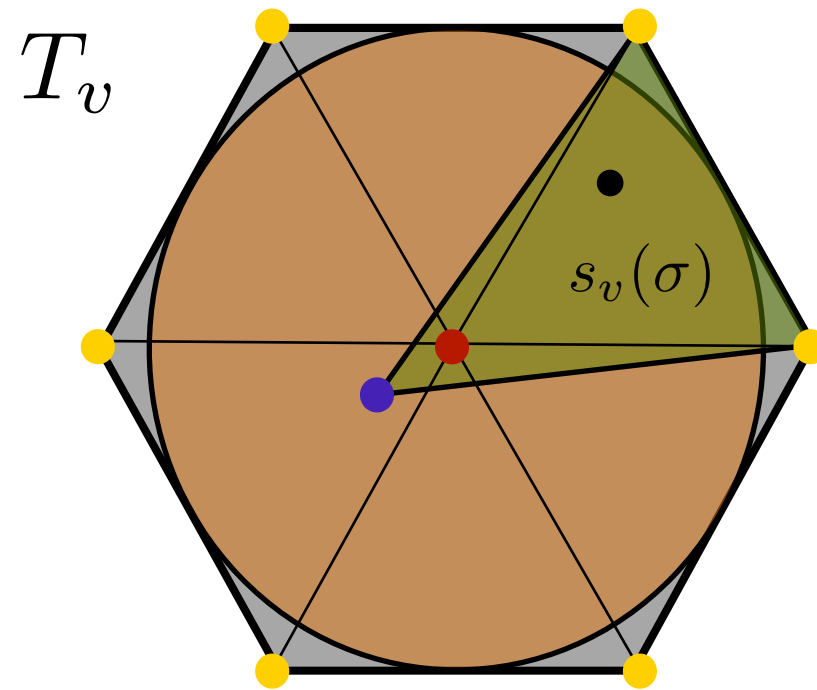
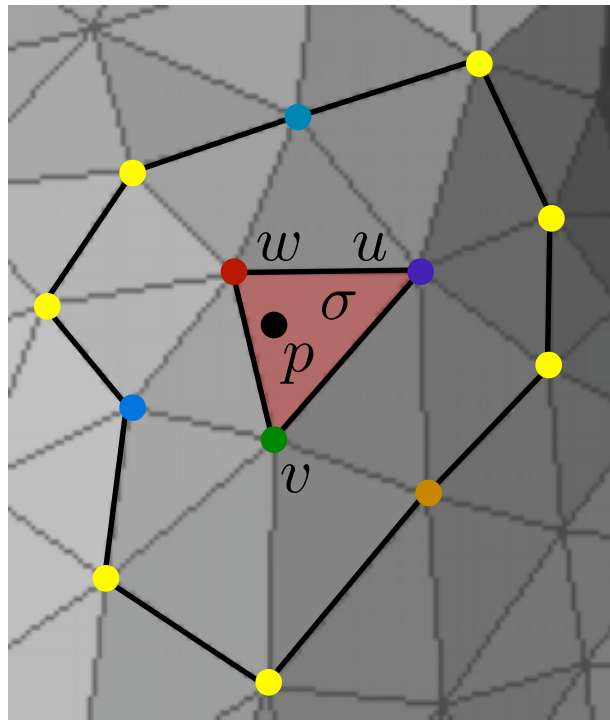
Building Parametrizations



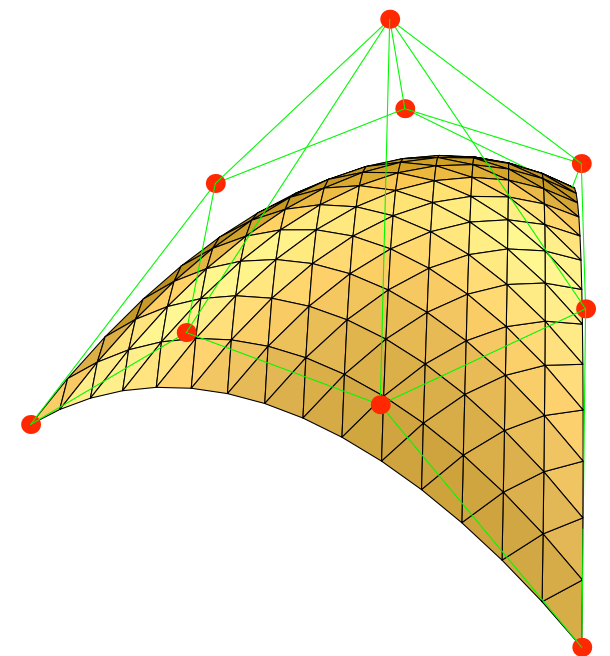
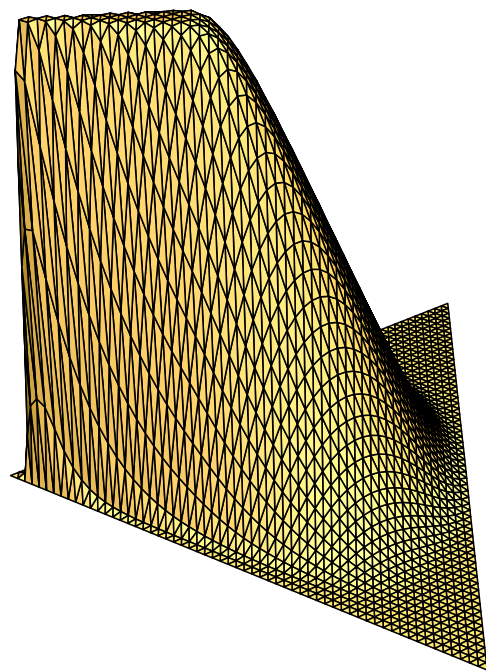
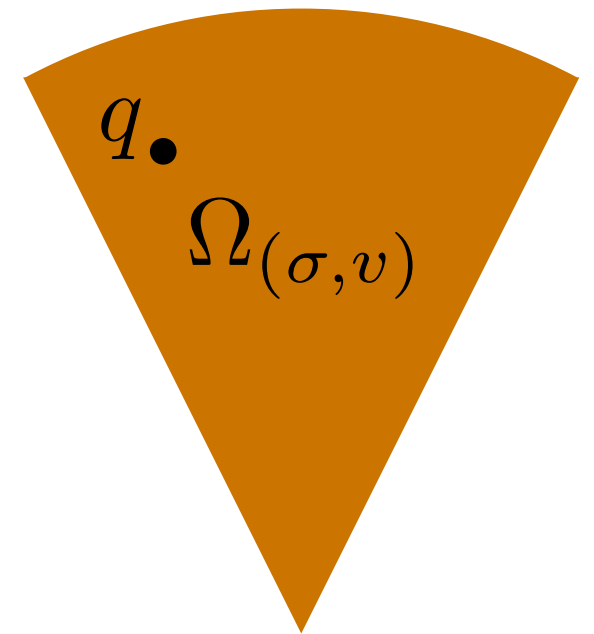
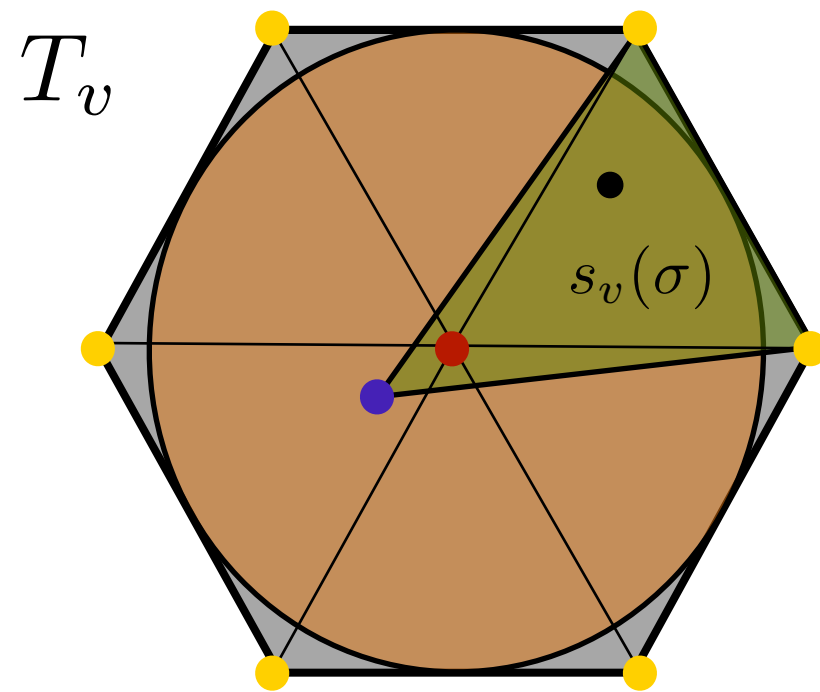
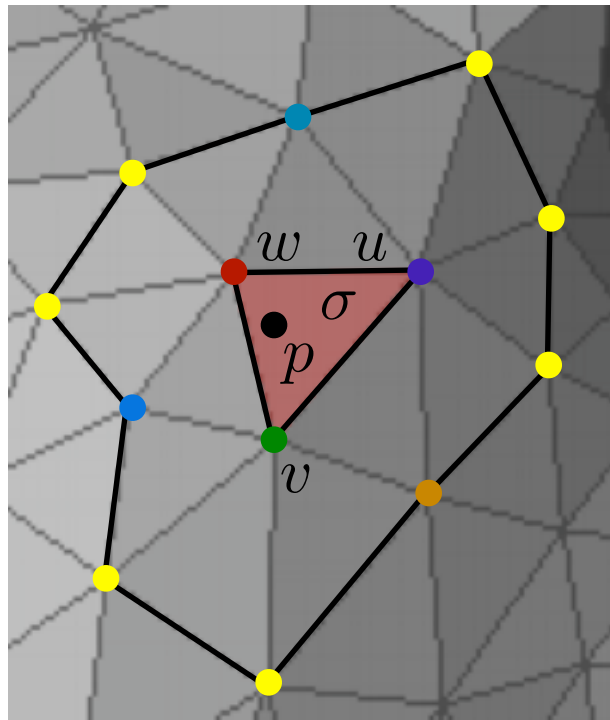
Building Parametrizations



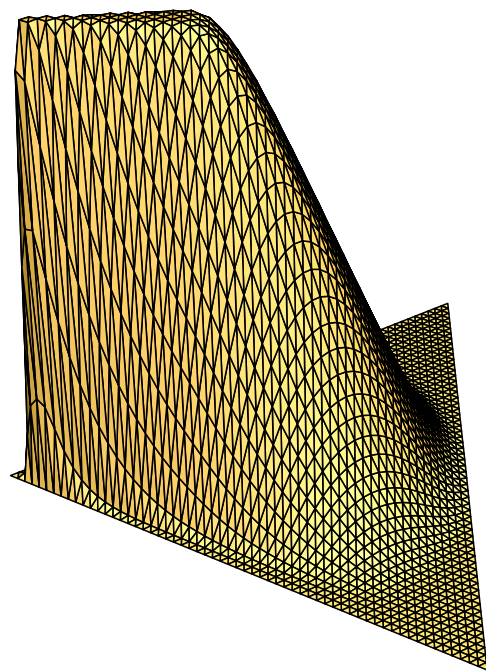
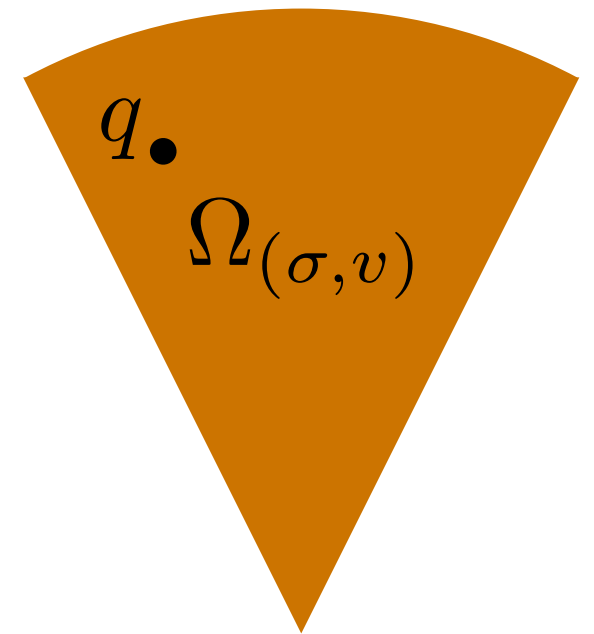
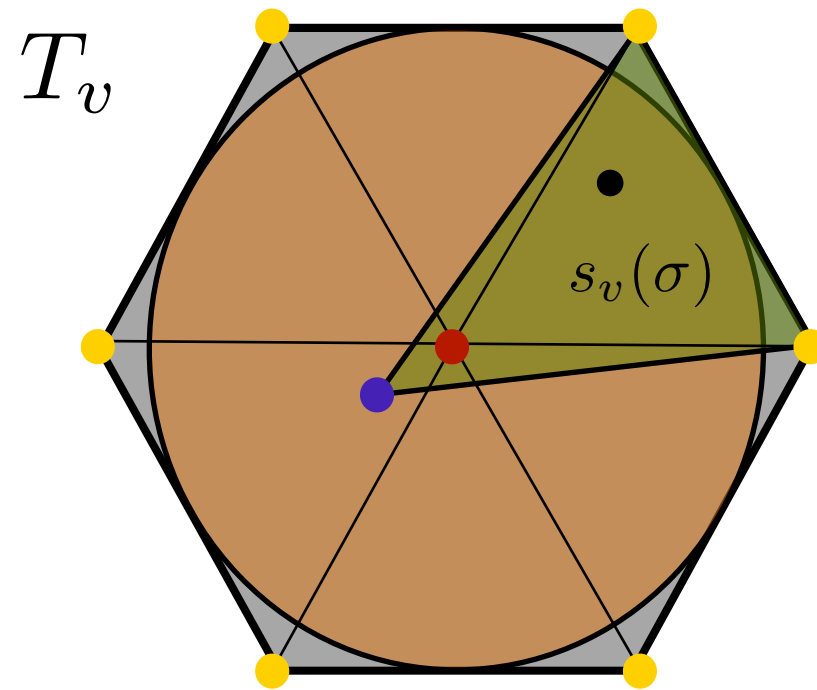
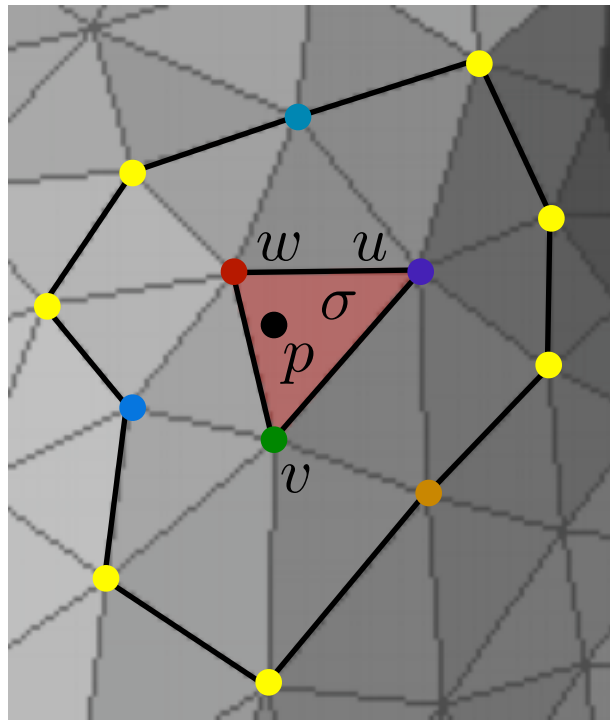
Building Parametrizations



Building Parametrizations

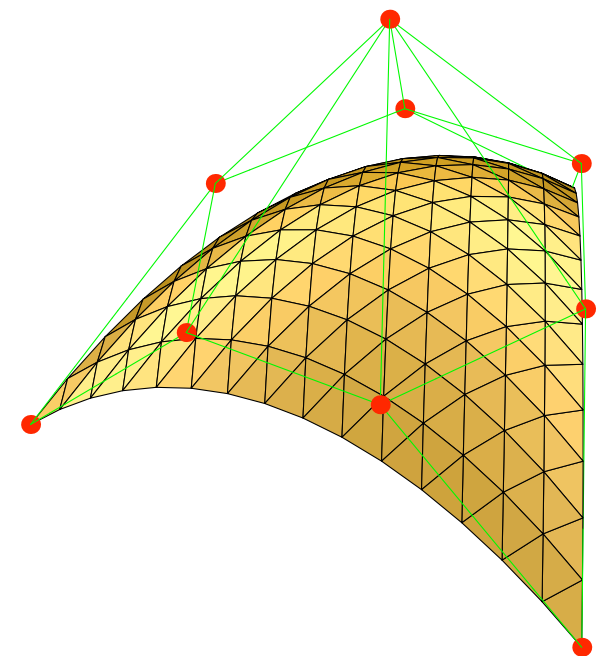


Building Parametrizations



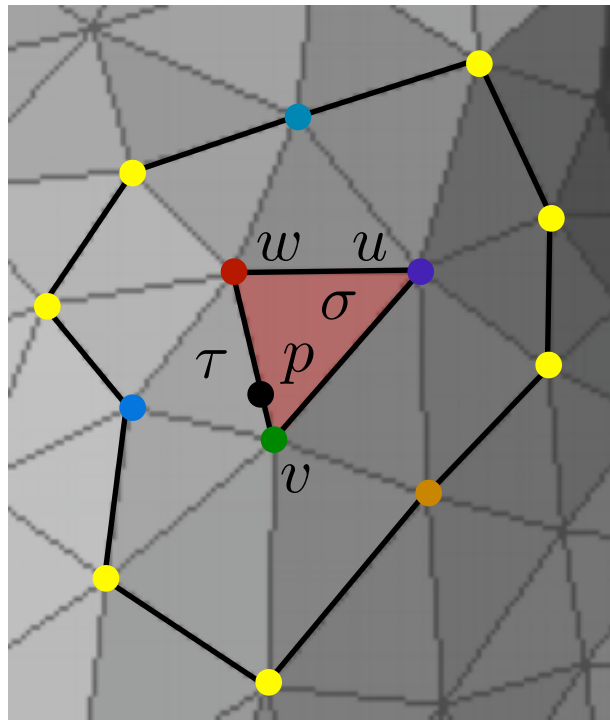
Contribution of $\Omega_{(\sigma, v)}$:

$$\gamma_{(\sigma, v)}(q) \cdot \psi_{(\sigma, v)}(q)$$

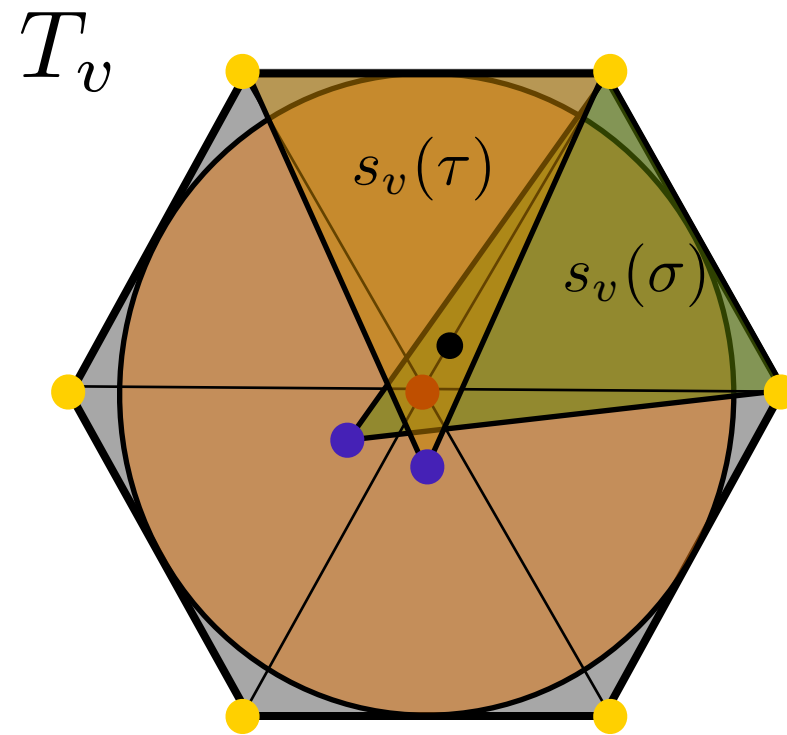
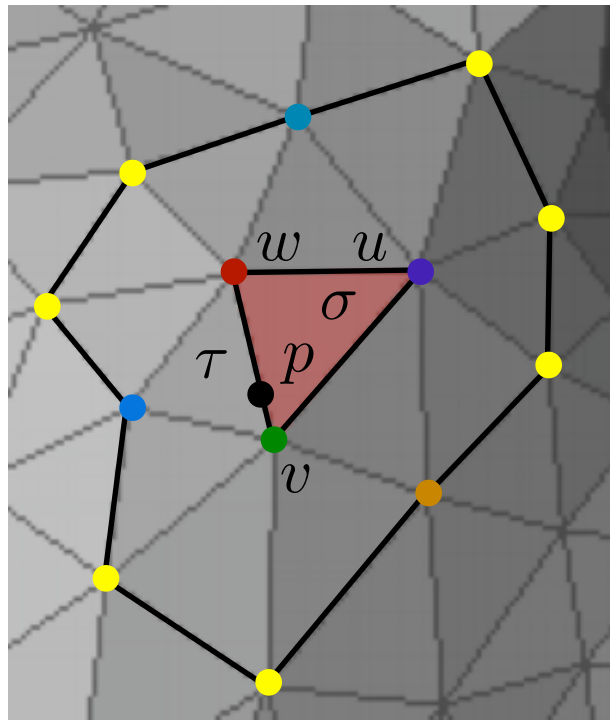


Building Parametrizations

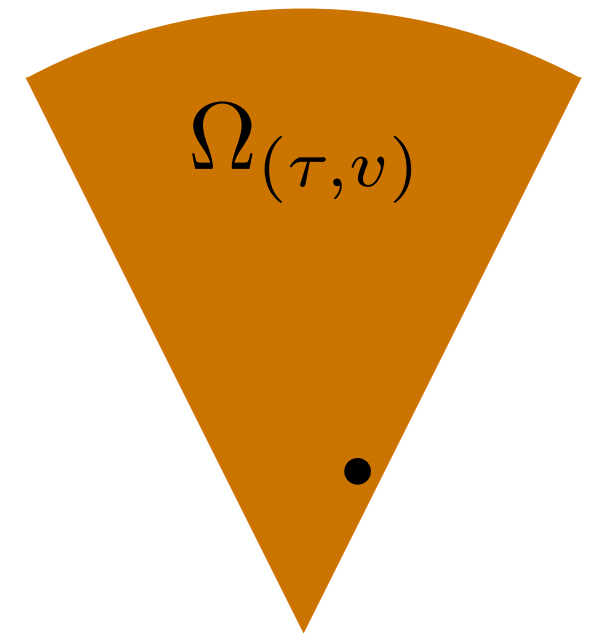
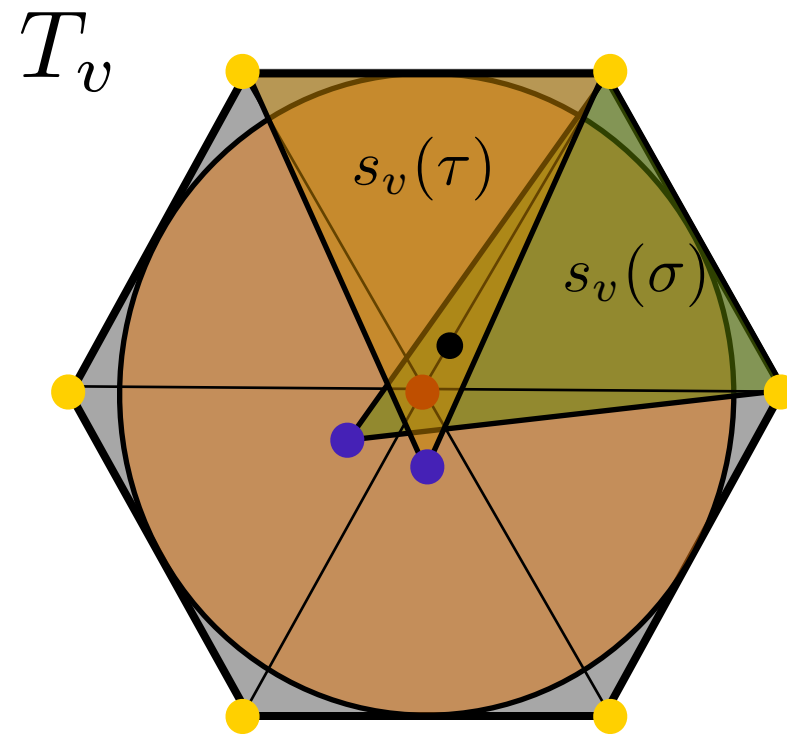
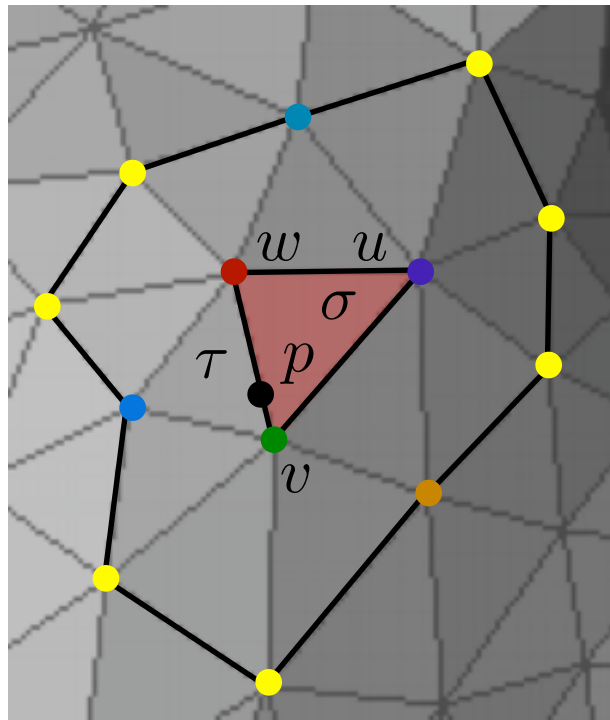
Building Parametrizations



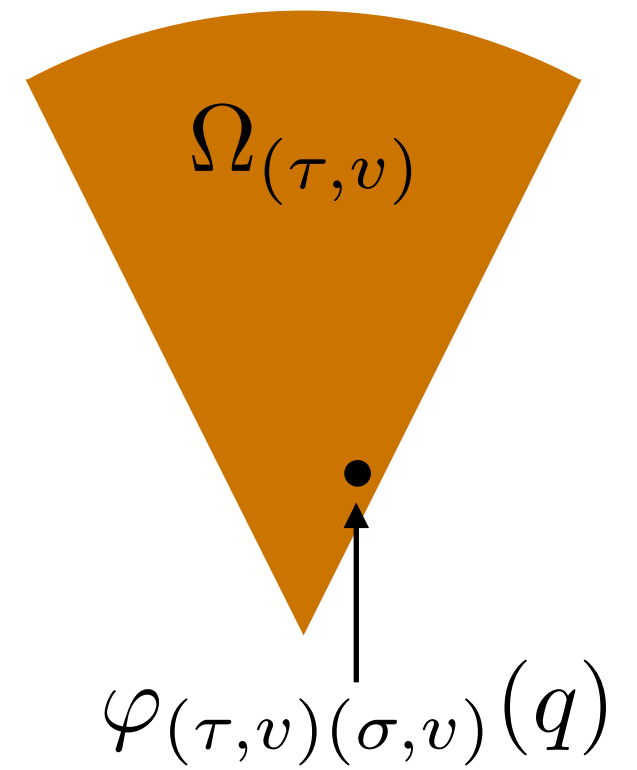
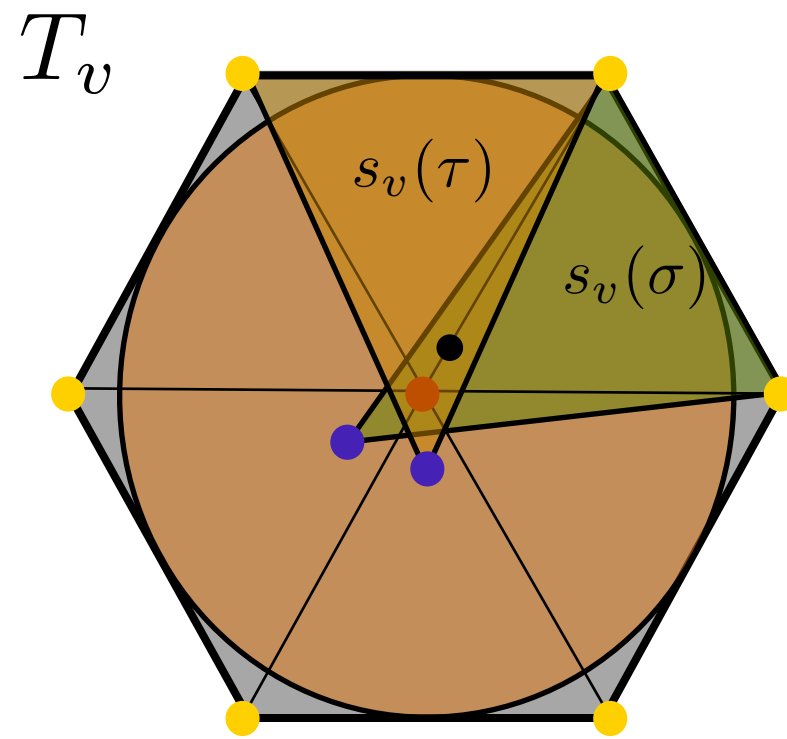
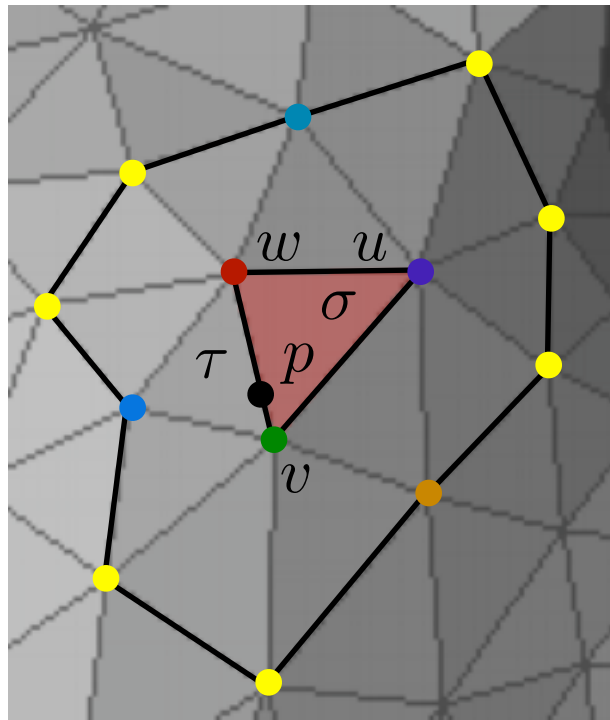
Building Parametrizations



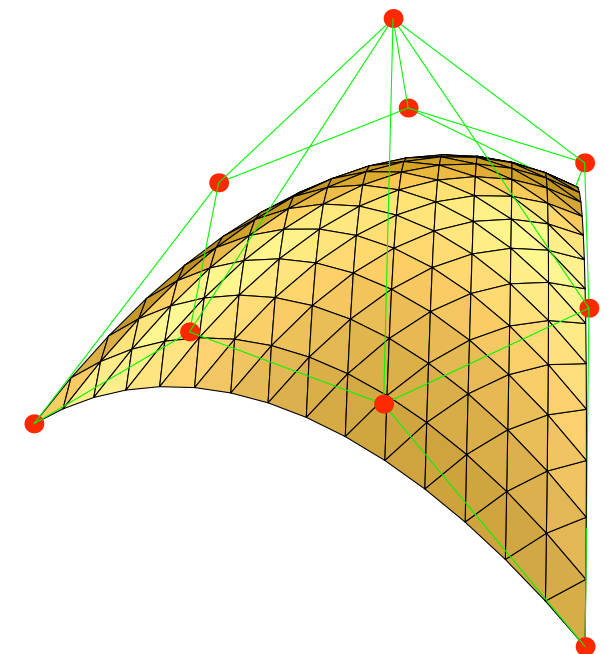
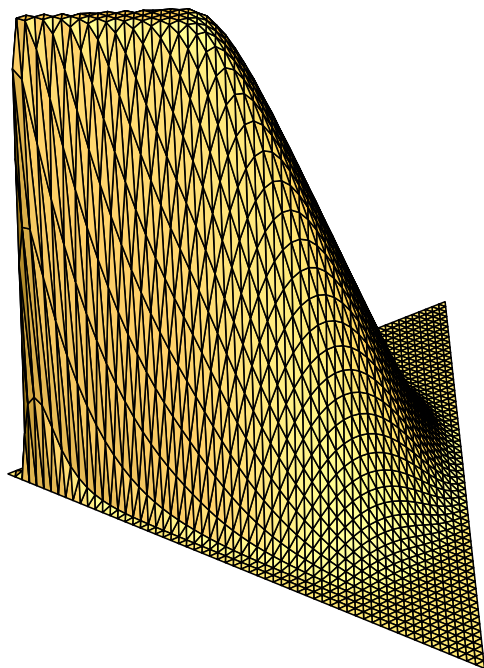
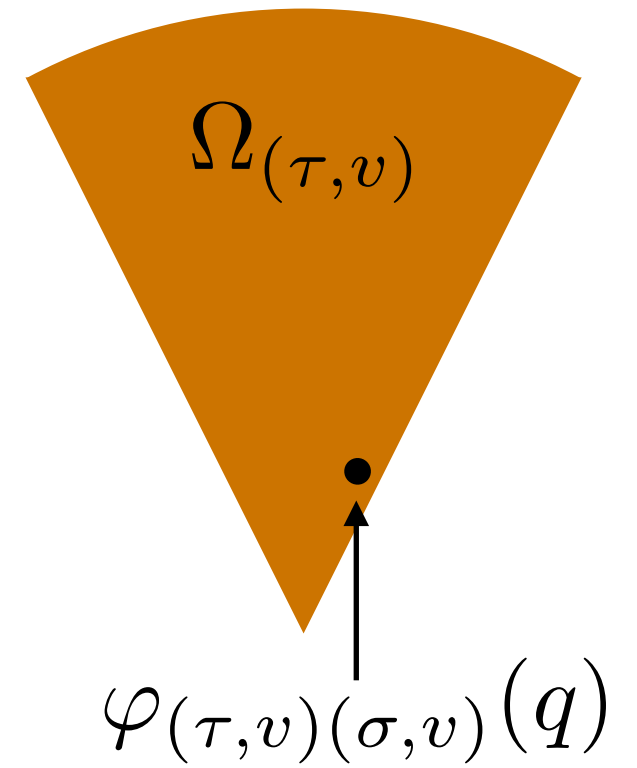
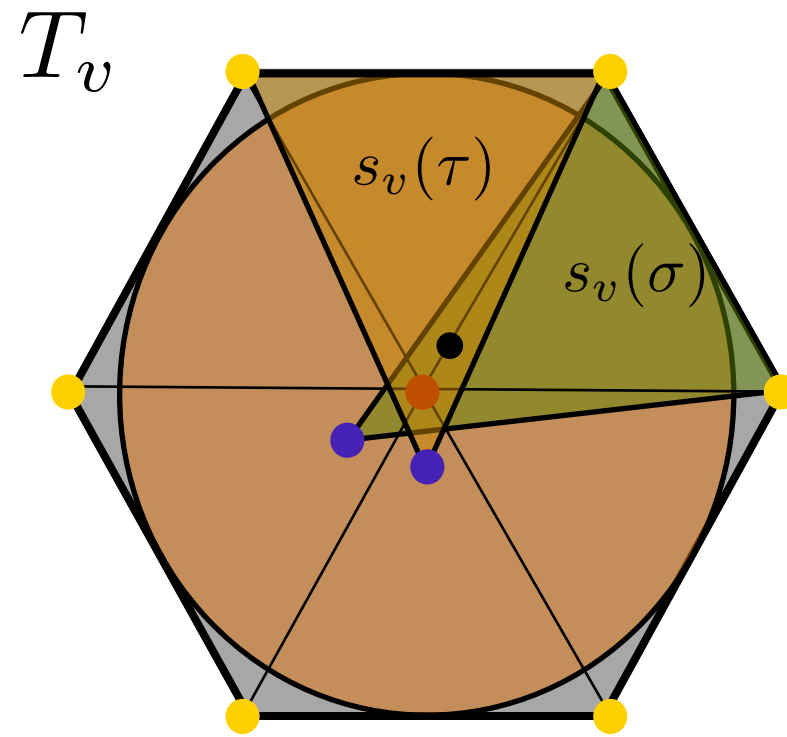
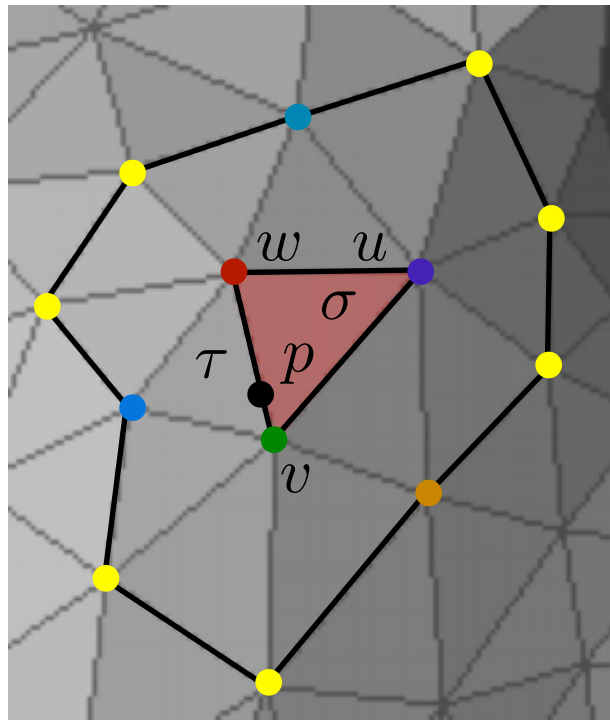
Building Parametrizations



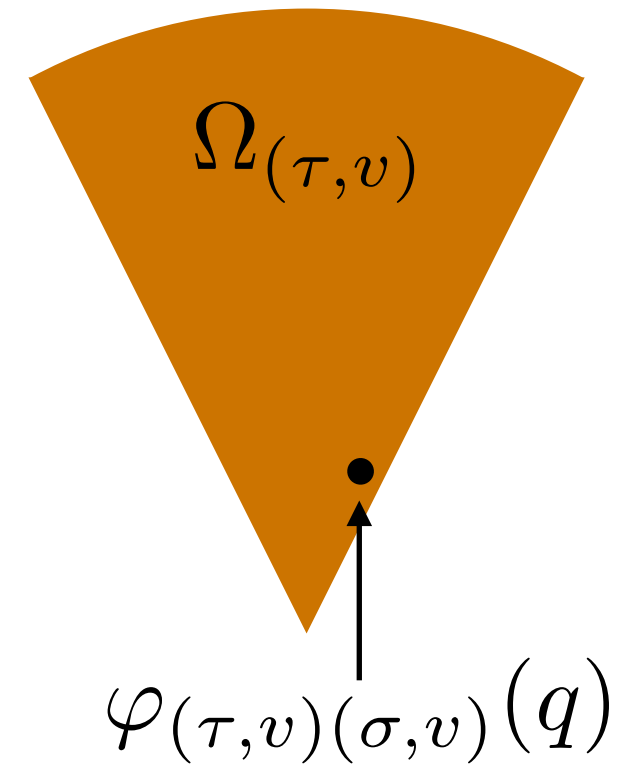
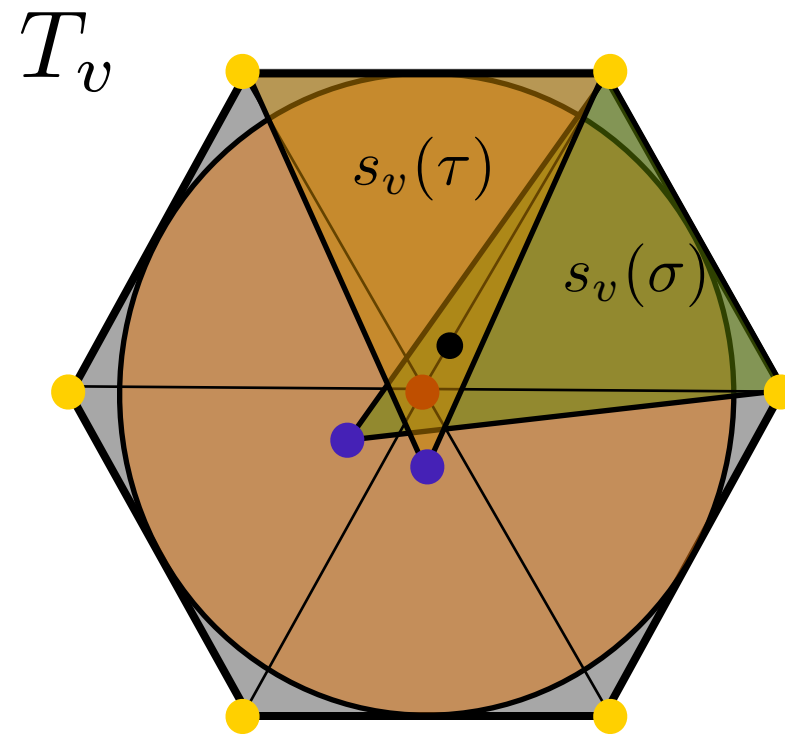
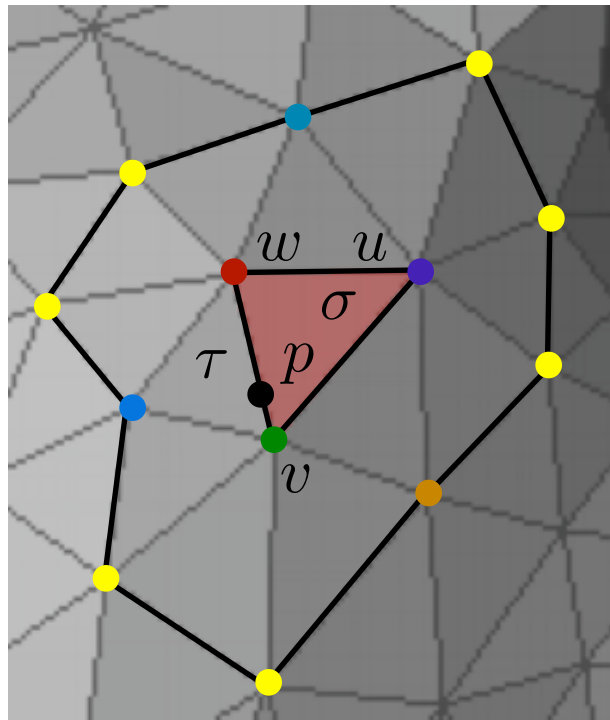
Building Parametrizations



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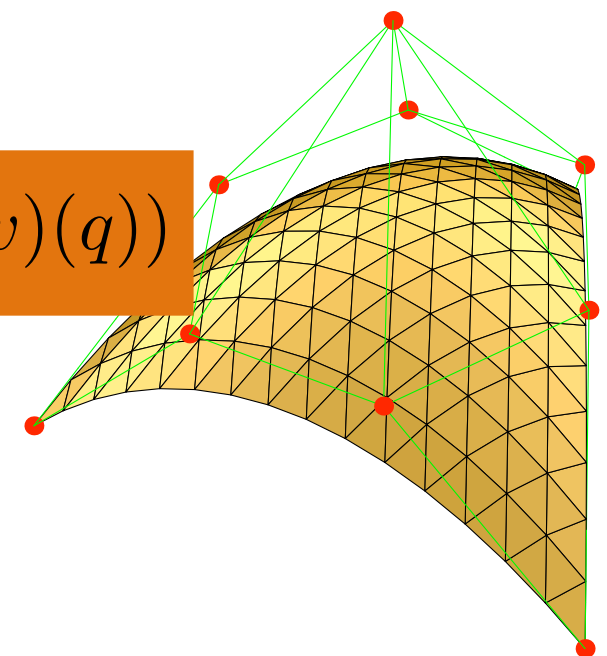
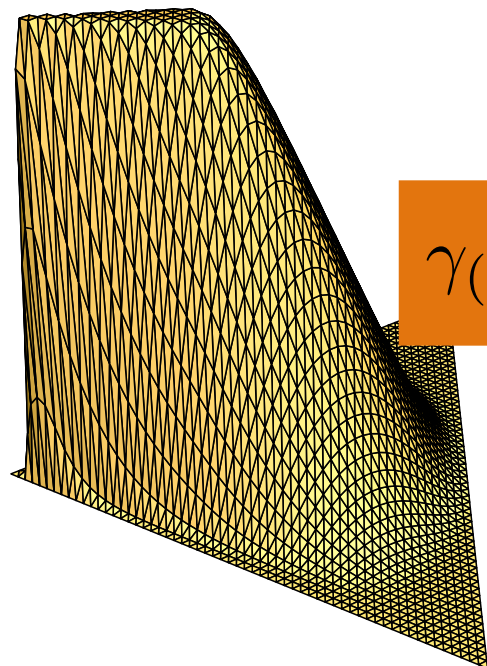


Building Parametrizations



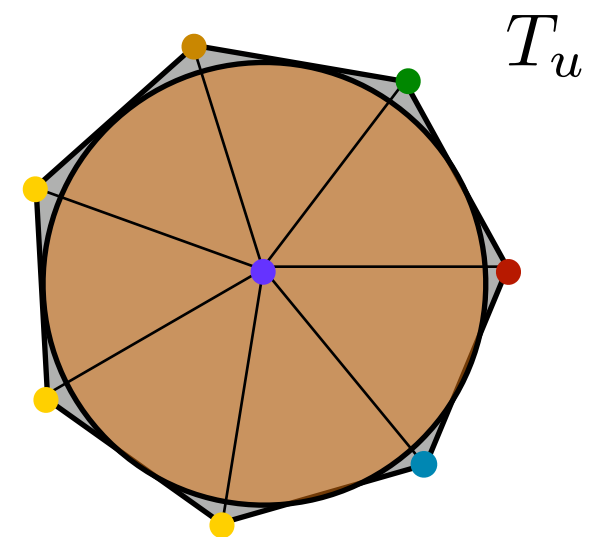
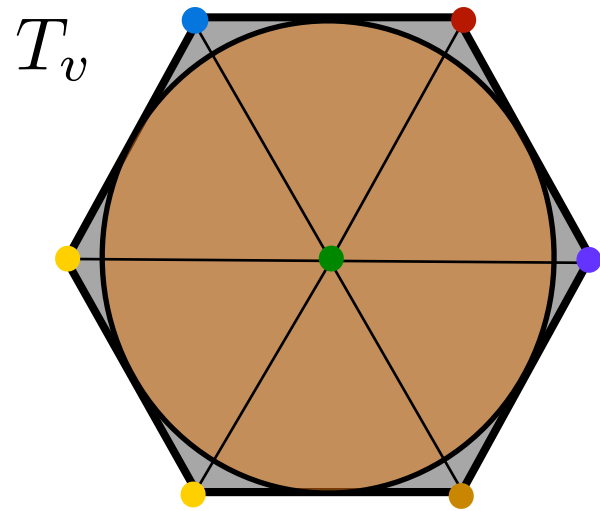
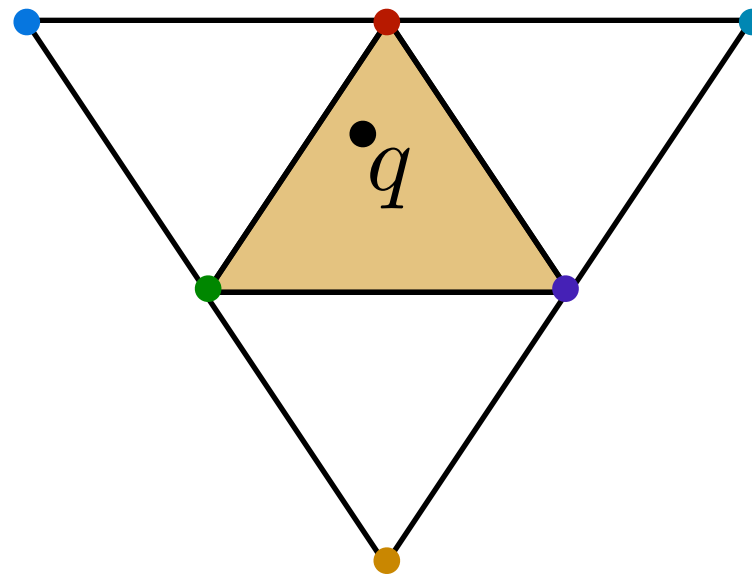
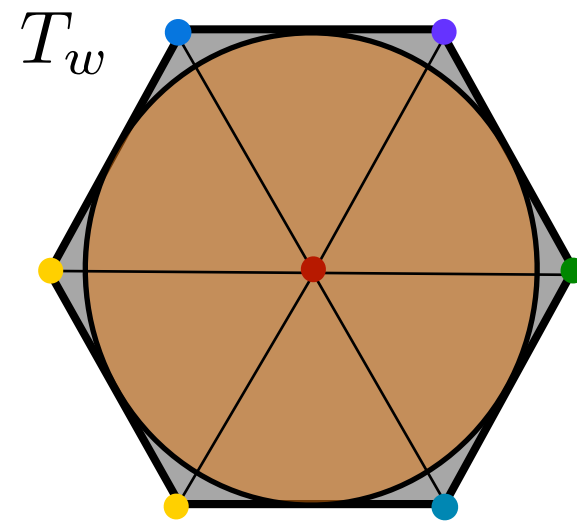
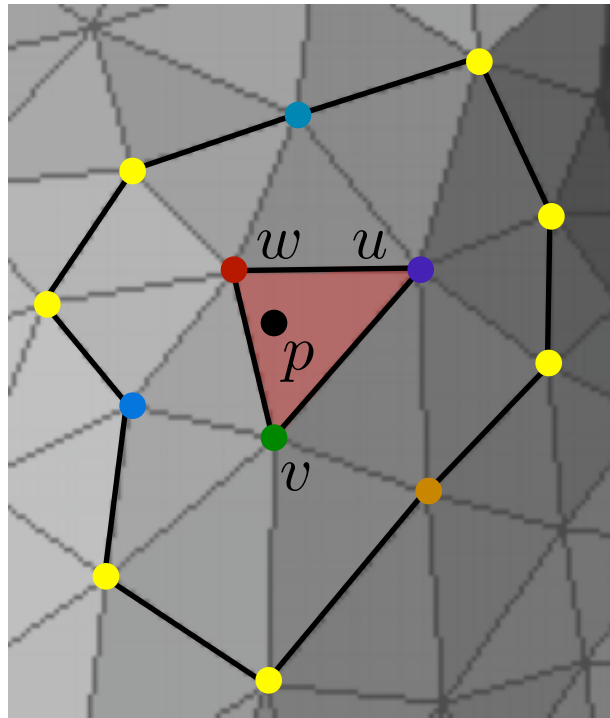
Contribution of $\Omega_{(\tau, v)}$:

$$\gamma_{(\tau, v)}(\varphi_{(\tau, v)}(\sigma, v)(q)) \cdot \psi_{(\tau, v)}(\varphi_{(\tau, v)}(\sigma, v)(q))$$

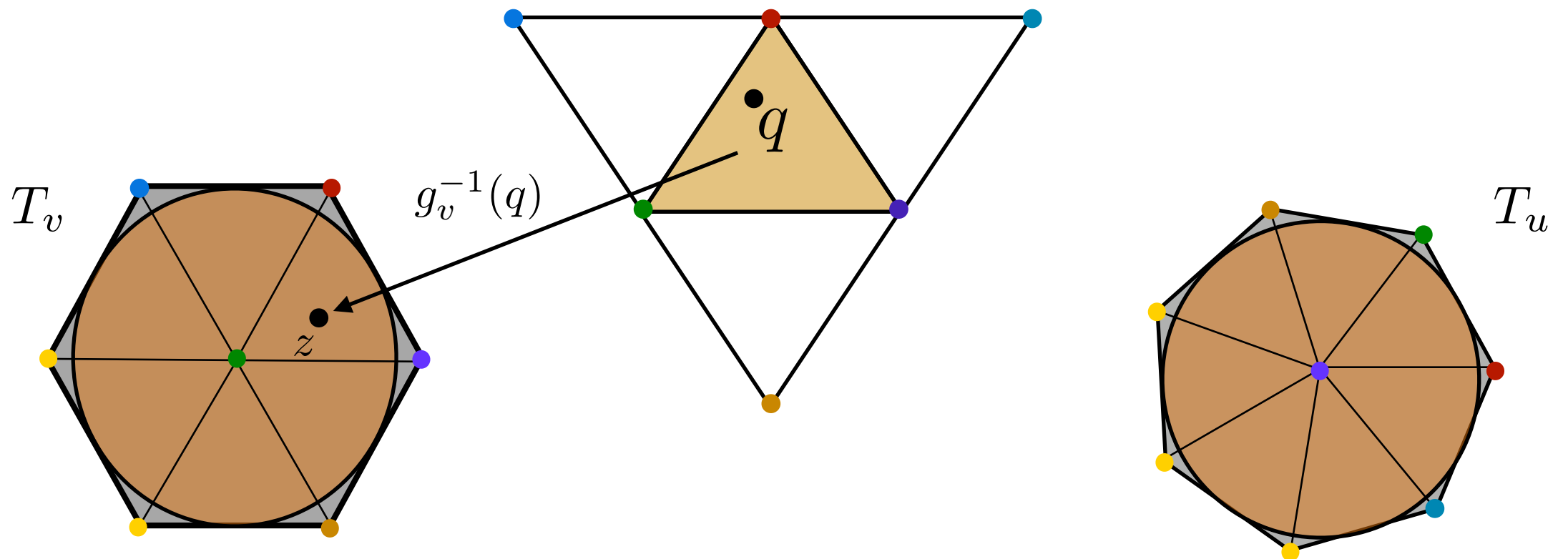
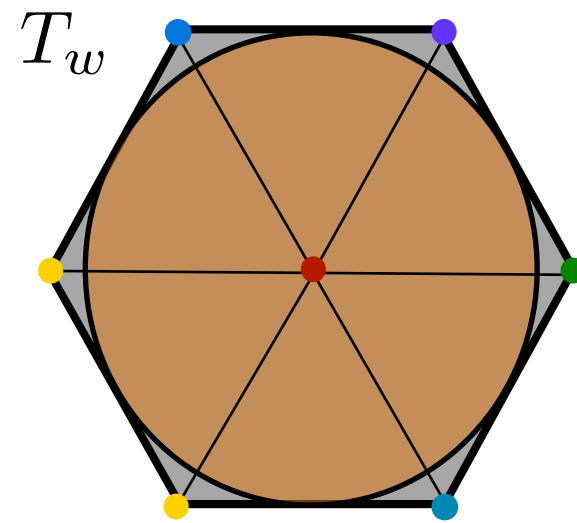
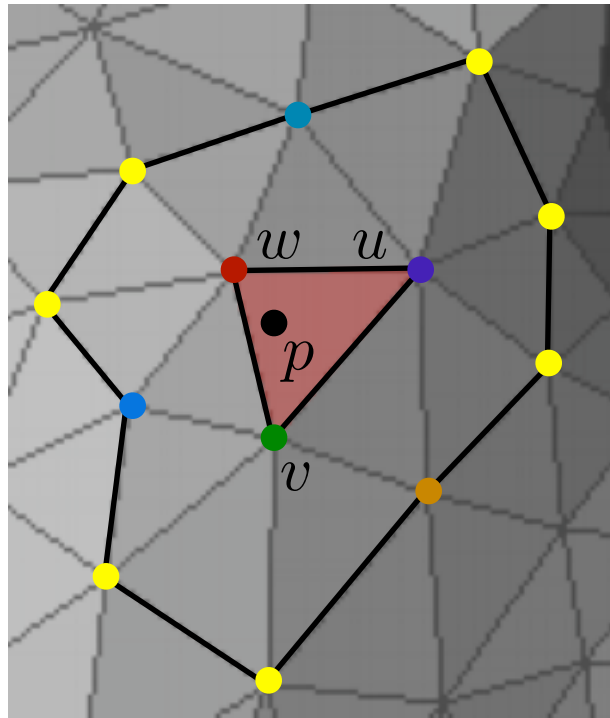


Building Parametrizations

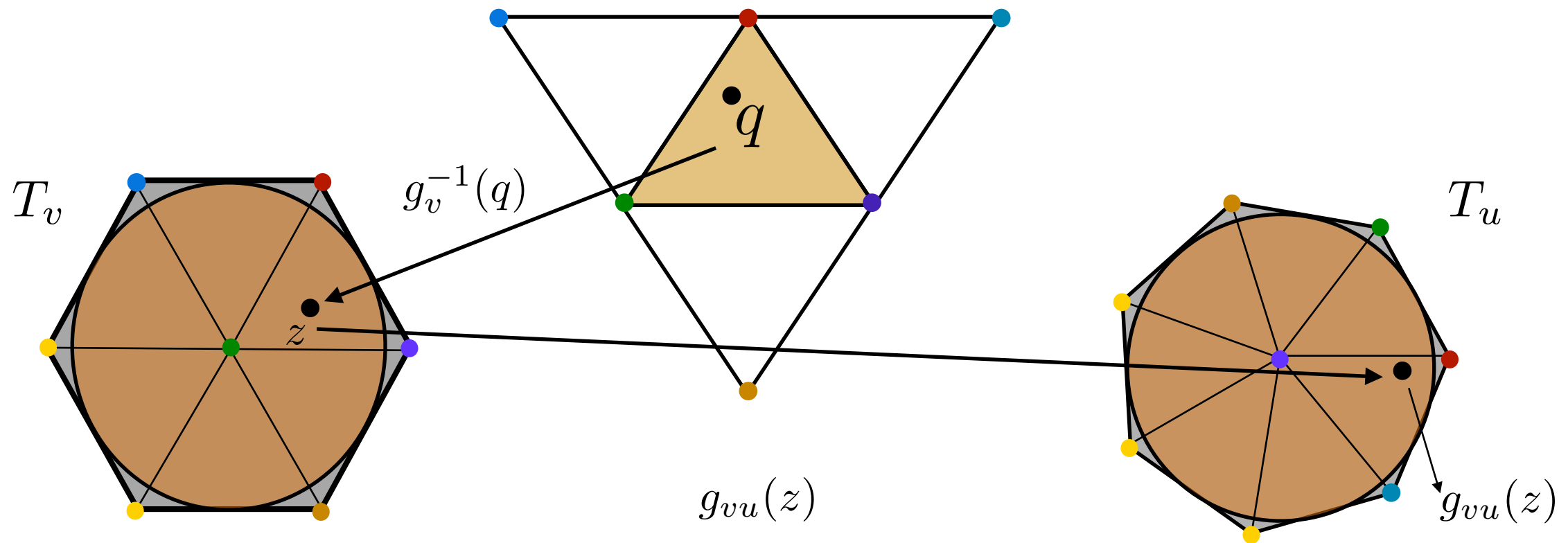
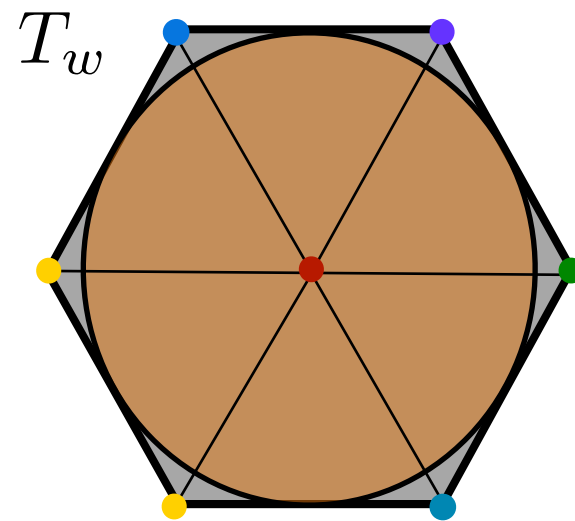
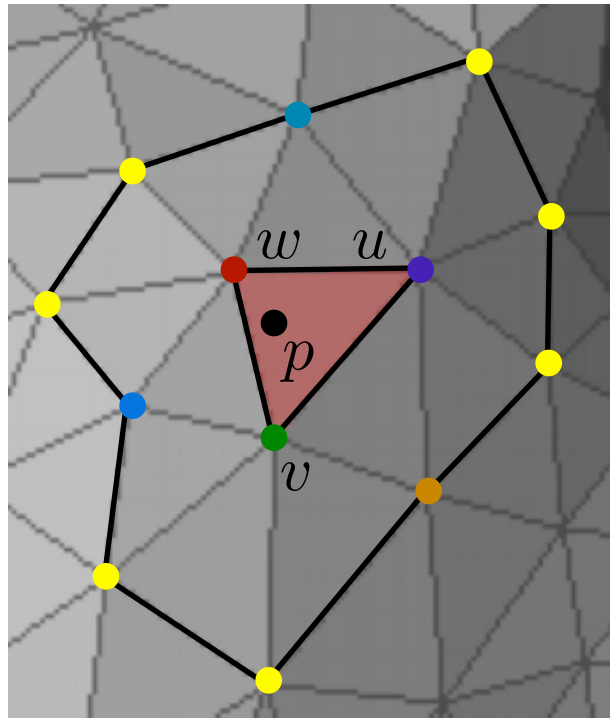
Building Parametrizations



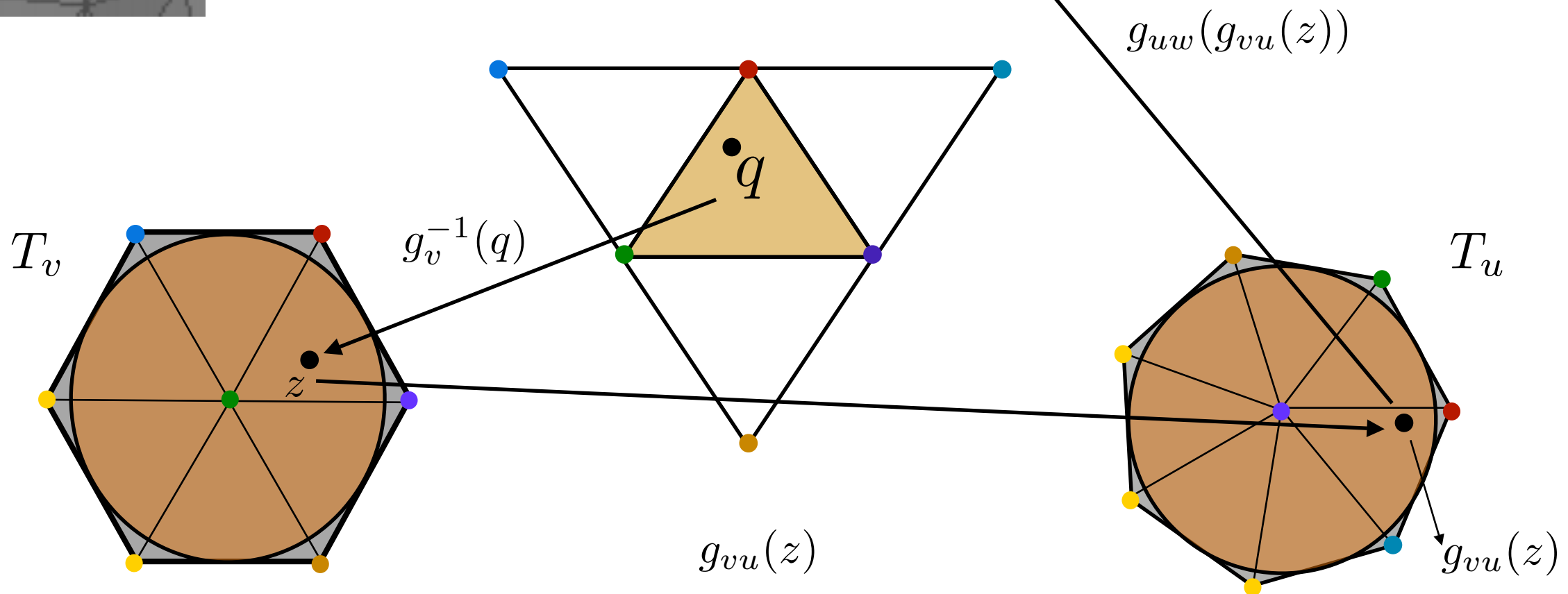
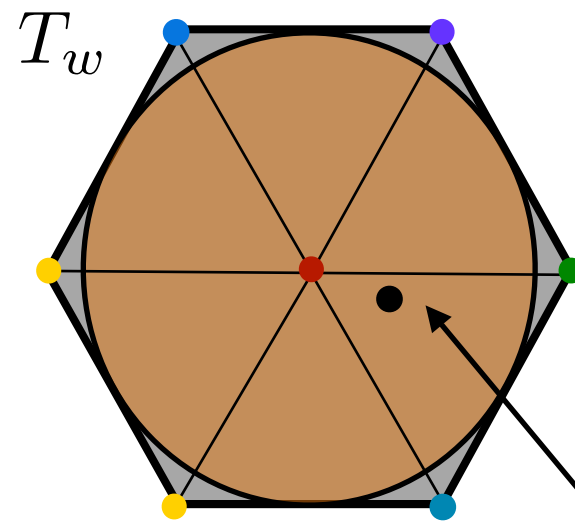
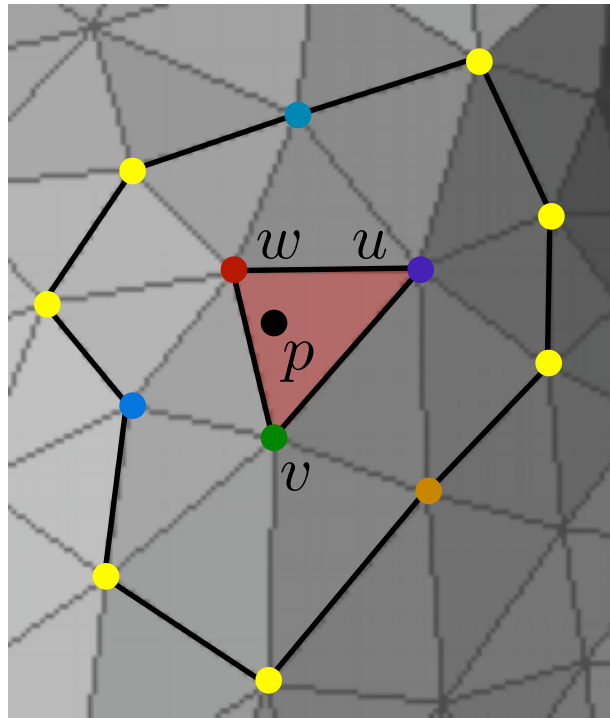
Building Parametrizations



Building Parametrizations



Building Parametrizations



Building Parametrizations

Building Parametrizations

For each $(\sigma, v) \in I$, we define a **parametrization**,

$$\theta_{(\sigma, v)} : \Omega_{(\sigma, v)} \rightarrow \mathbb{R}^3,$$

such that for every $p \in \Omega_{(\sigma, v)}$,

$$\theta_{(\sigma, v)}(p) = \sum_{(\tau, u) \in J(p)} \nu_{(\tau, u)}(p) \cdot \psi_{(\tau, u)}(\varphi_{(\tau, u)}(\sigma, v)(p)),$$

where

Building Parametrizations

Building Parametrizations

$$\nu_{(\tau,u)}(p) = \frac{\gamma_{(\tau,u)}(\varphi_{(\tau,u)}(\sigma,v)(p))}{\sum_{(\eta,w) \in J(p)} \gamma_{(\eta,w)}(\varphi_{(\eta,w)}(\sigma,v)(p))}$$

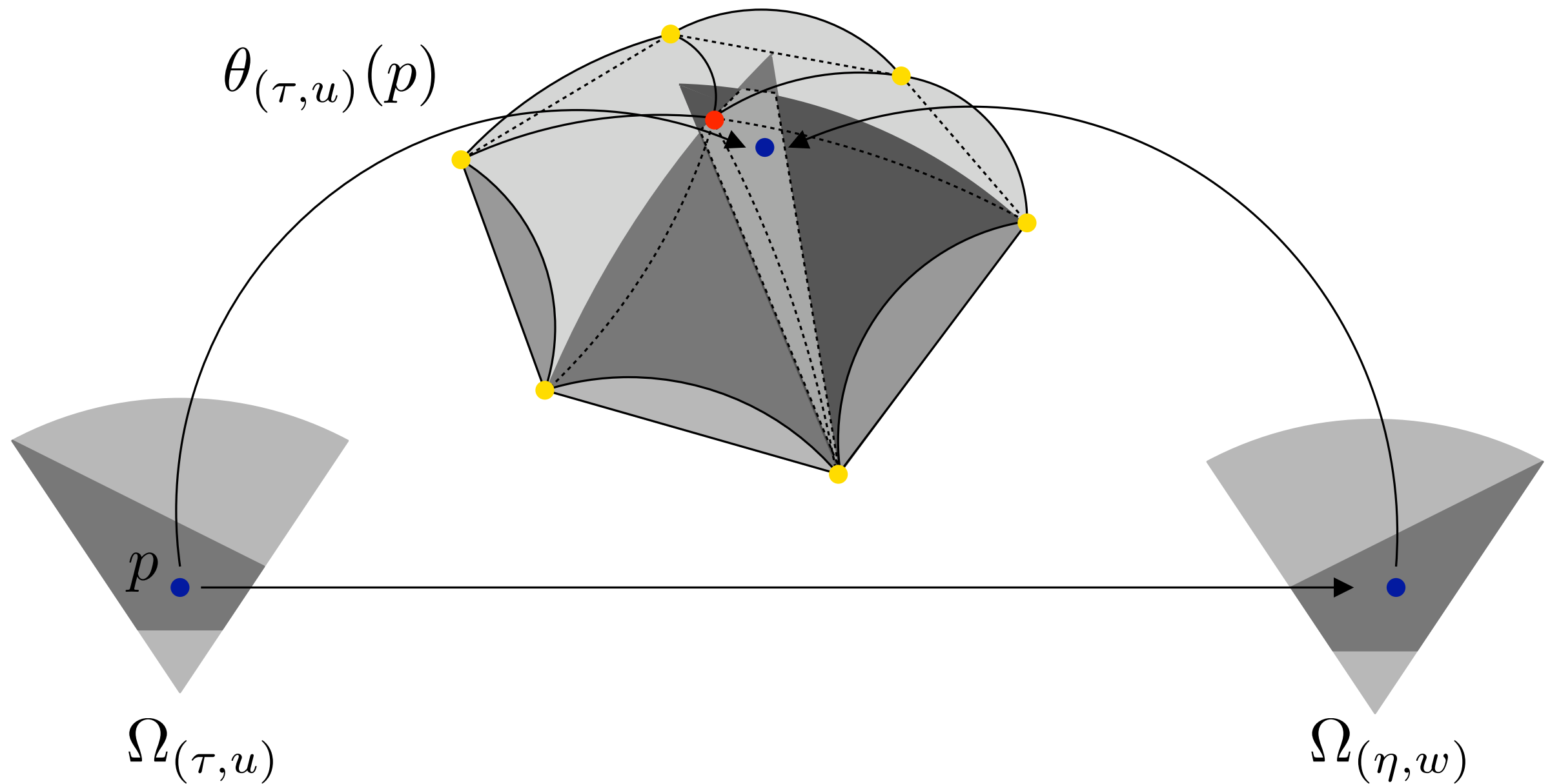
and

$$J(p) = \{(\eta, w) \in I \mid p \in \Omega_{(\sigma,v)}(\eta,w)\}.$$

Building Parametrizations

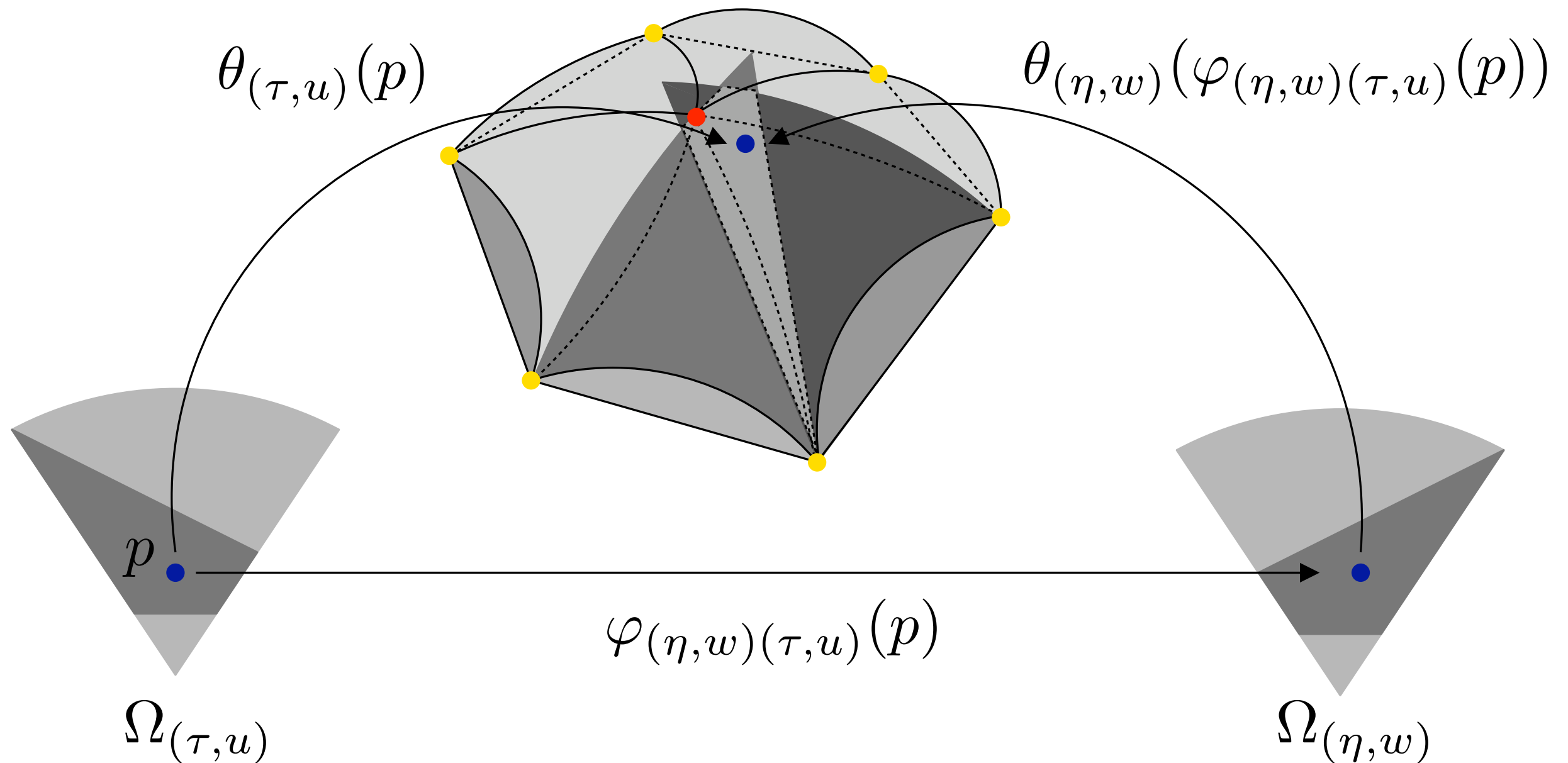
Building Parametrizations

Parametrizations are consistent!



Building Parametrizations

Parametrizations are consistent!

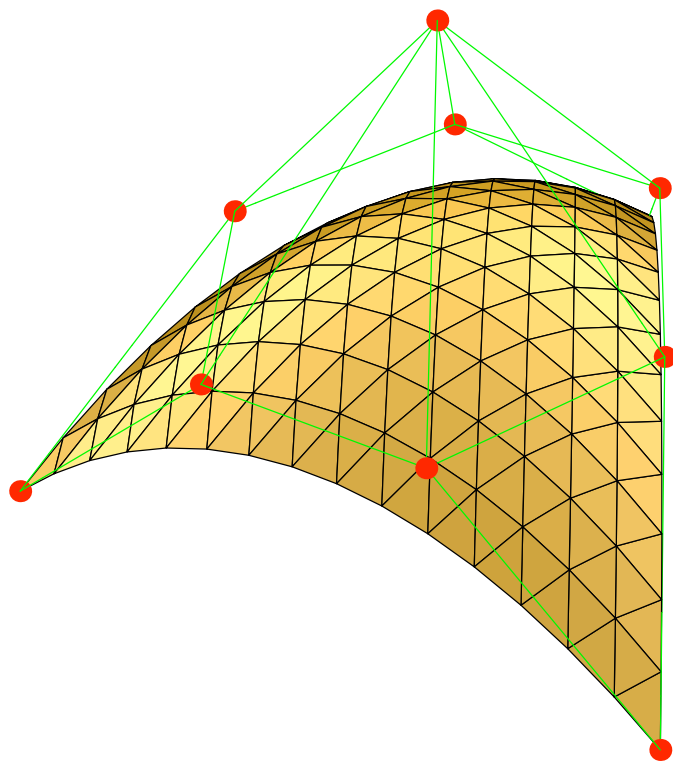


Building Parametrizations

$$\psi_{(\tau,u)}(\Omega_{(\tau,u)})$$

Building Parametrizations

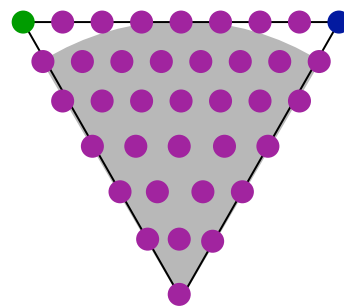
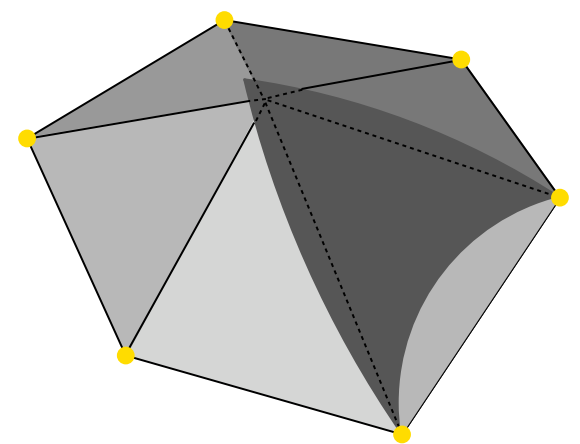
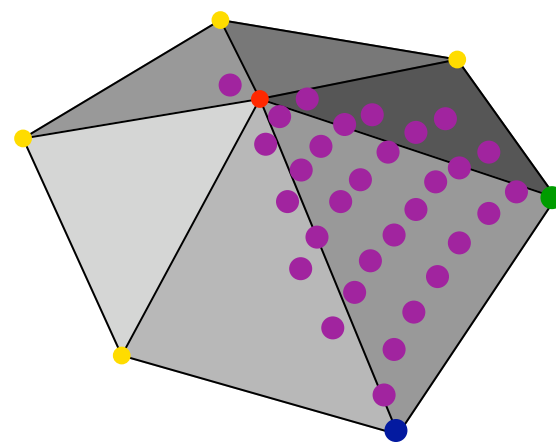
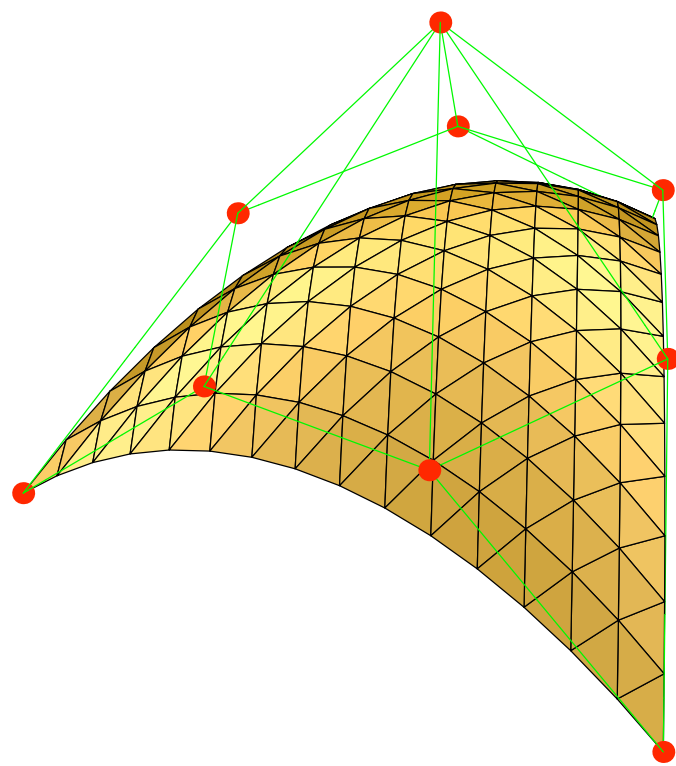
The control points of $\psi_{(\tau,u)}$ are the solutions of a least squares problem.



$$\psi_{(\tau,u)}(\Omega_{(\tau,u)})$$

Building Parametrizations

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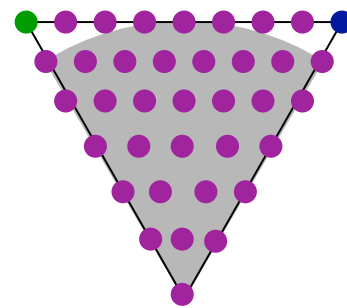
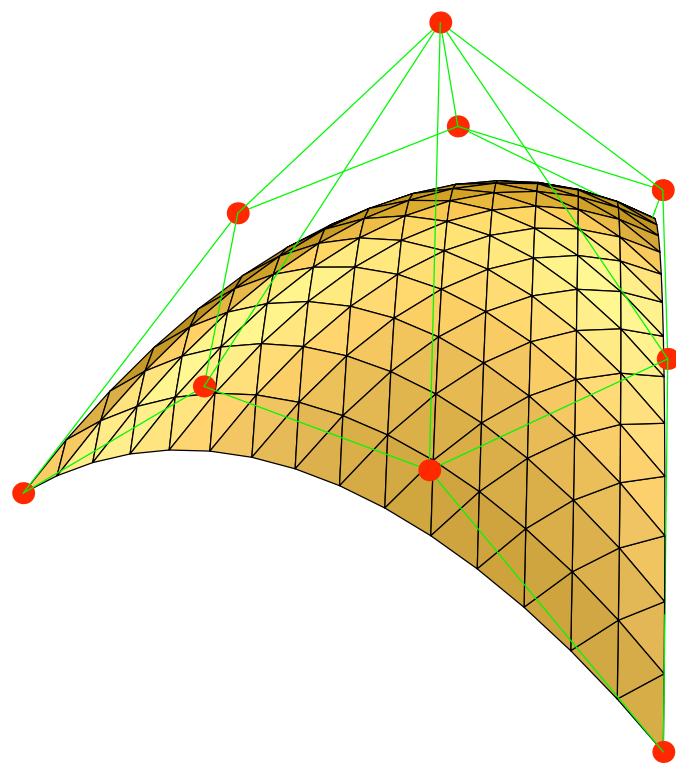


$$\Omega(\tau, u)$$

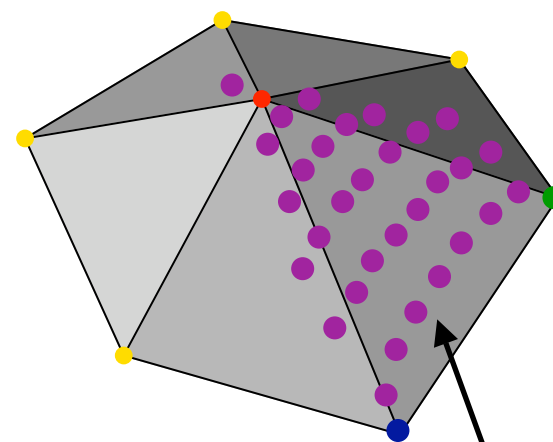
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Building Parametrizations

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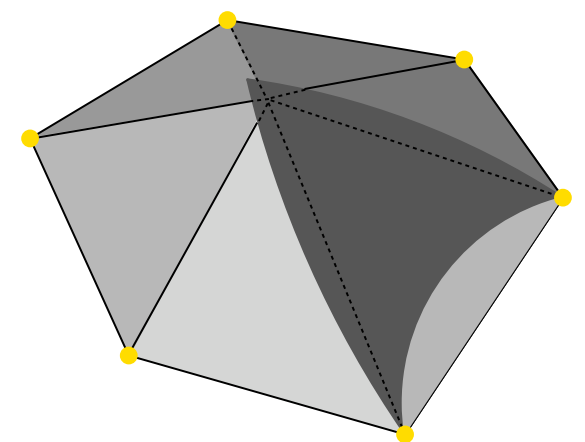


$$\Omega_{(\tau, u)}$$



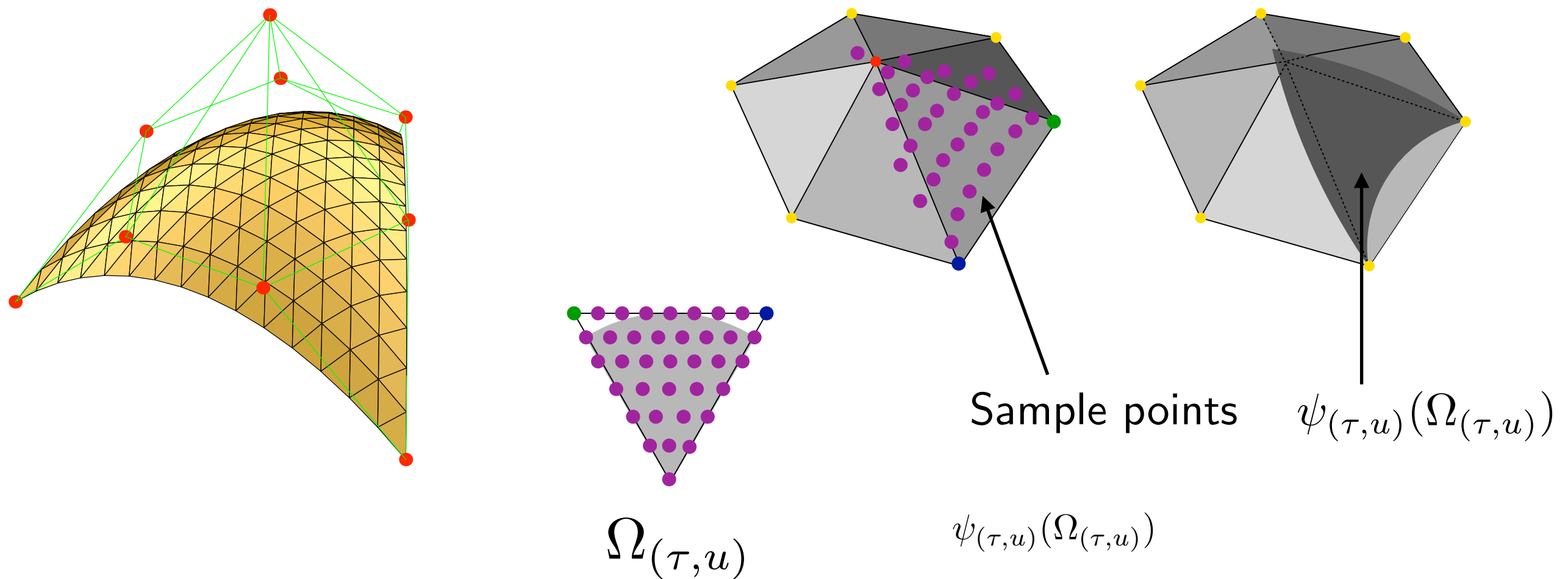
Sample points

$$\psi_{(\tau, u)}(\Omega_{(\tau, u)})$$



Building Parametrizations

The control points of $\psi_{(\tau,u)}$ are the solutions of a least squares problem.



Building Parametrizations

Building Parametrizations

How can we find the sample points to start with?

Building Parametrizations

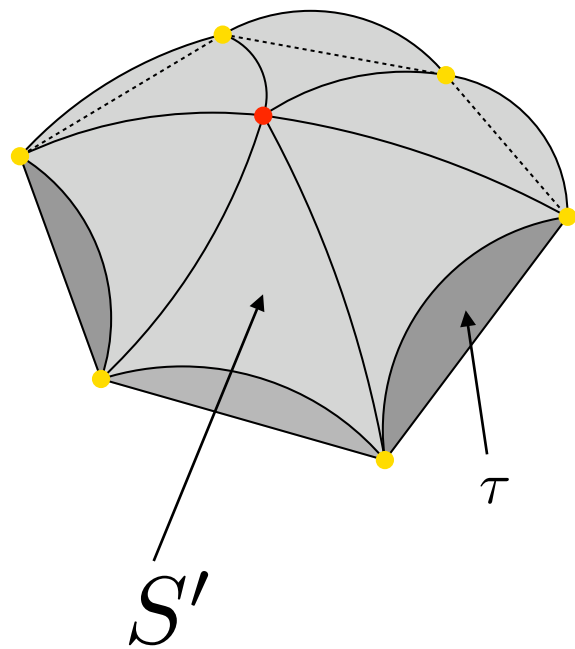
How can we find the sample points to start with?

Fit a “curved” surface, S' , to S_T and then sample it!

Building Parametrizations

How can we find the sample points to start with?

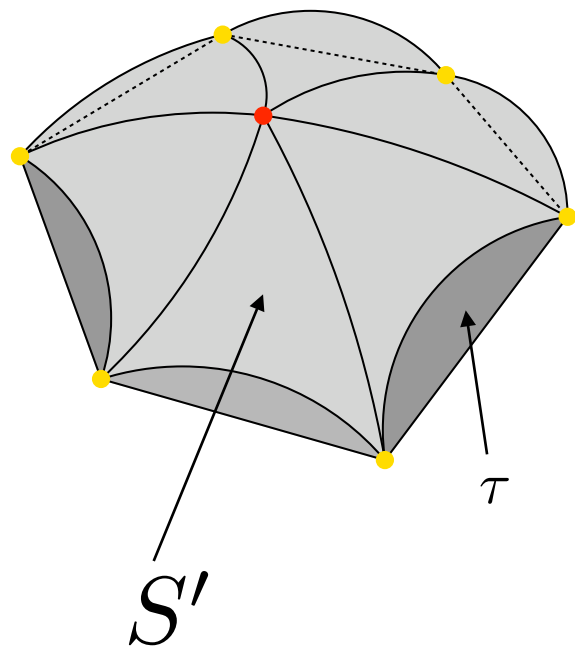
Fit a “curved” surface, S' , to S_T and then sample it!



Building Parametrizations

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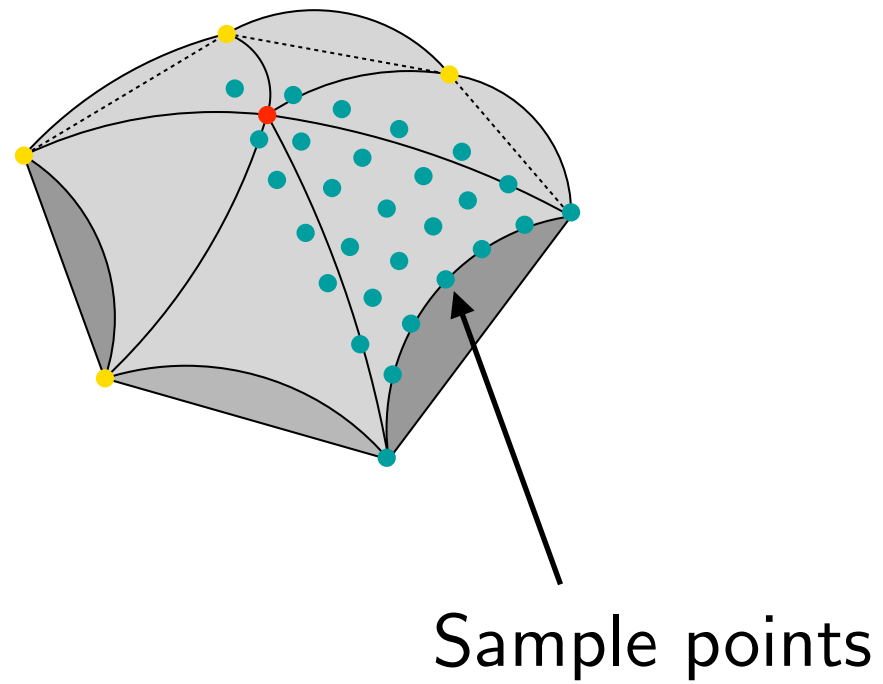
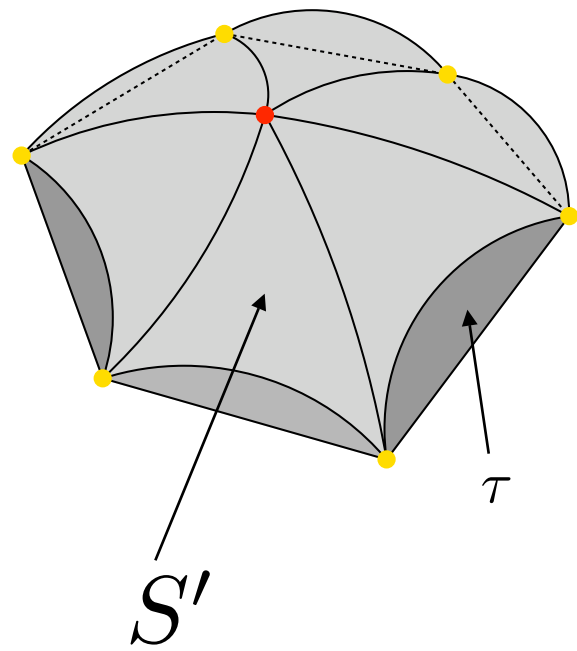


Good choices:

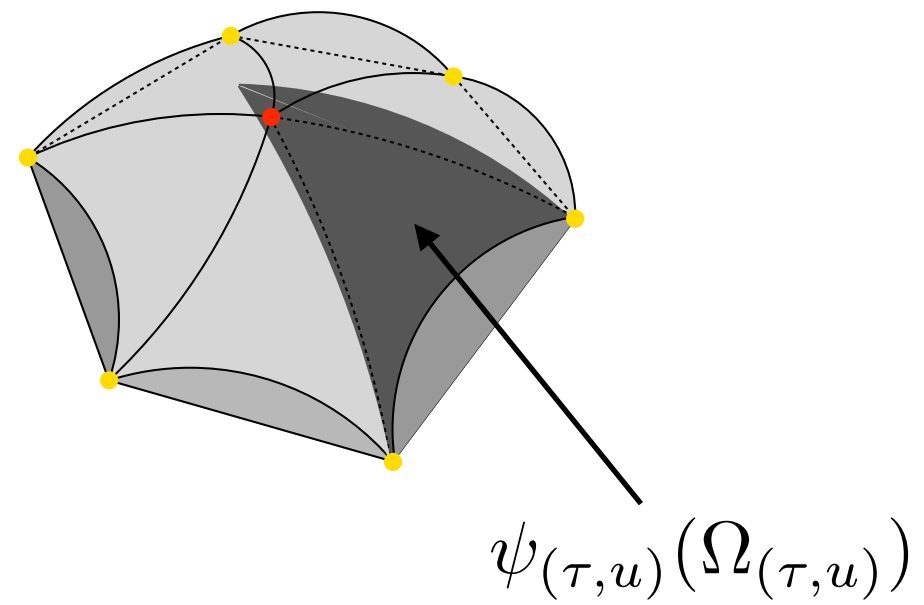
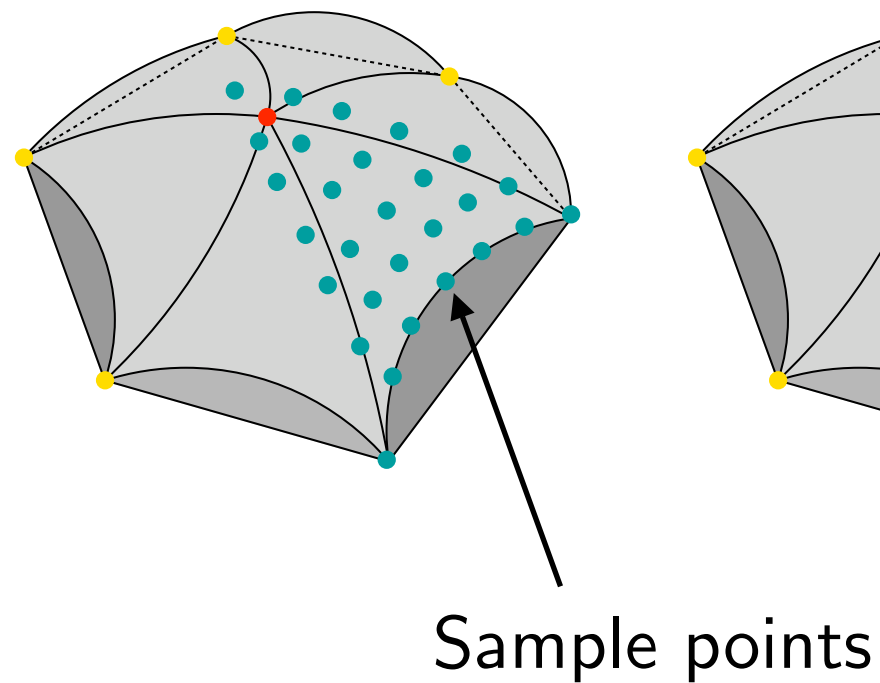
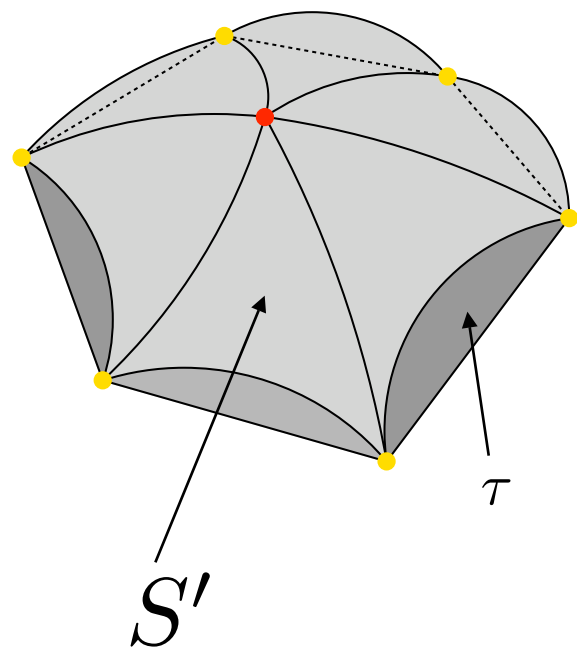
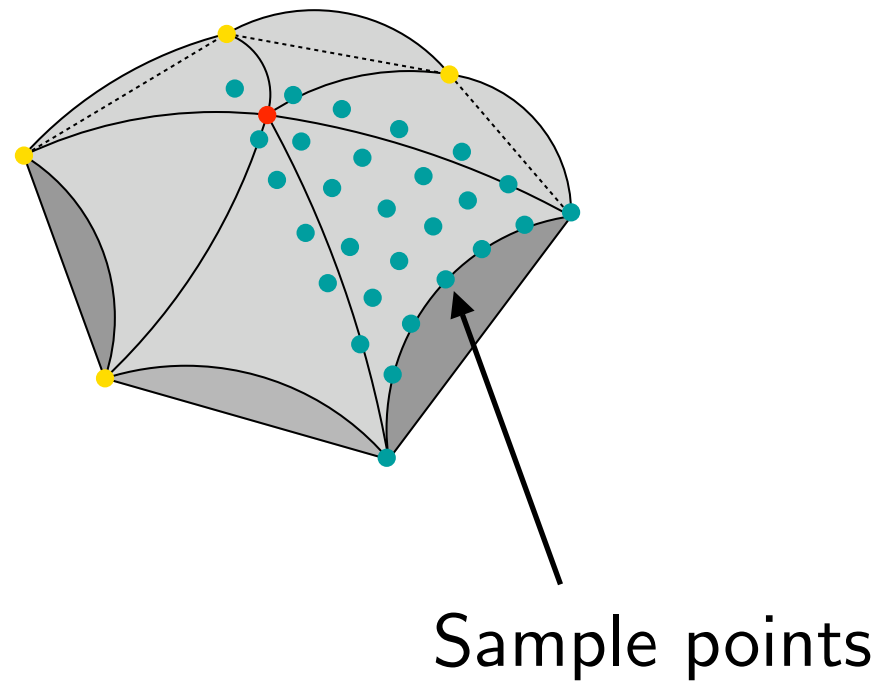
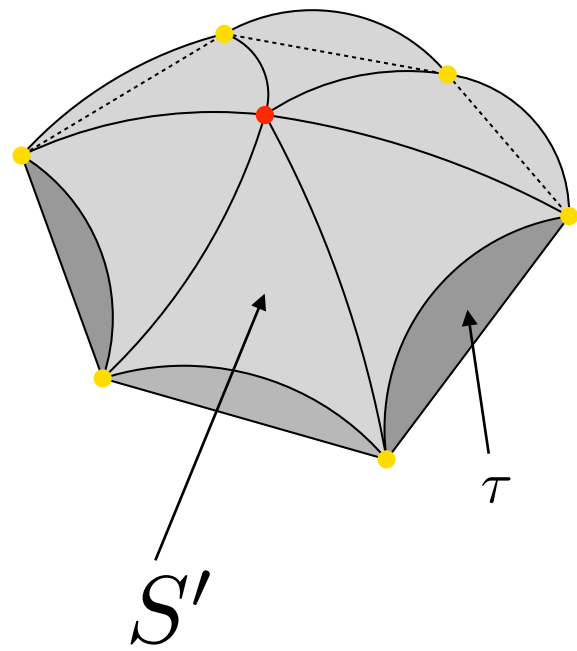
- PN triangle surfaces
- Subdivision surfaces

Building Parametrizations

Building Parametrizations

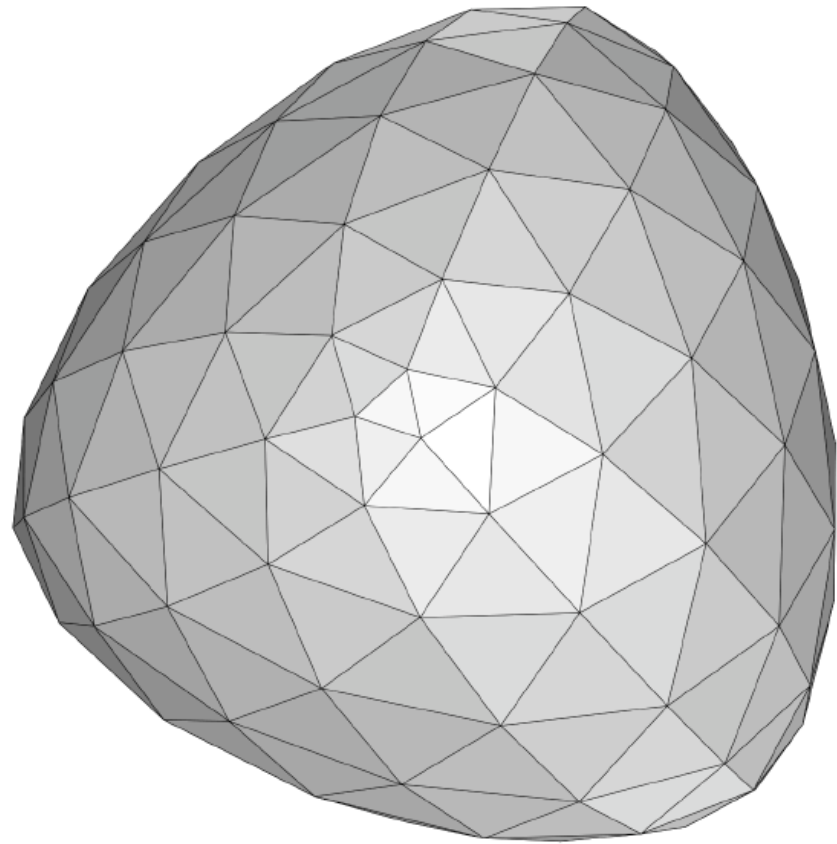


Building Parametrizations



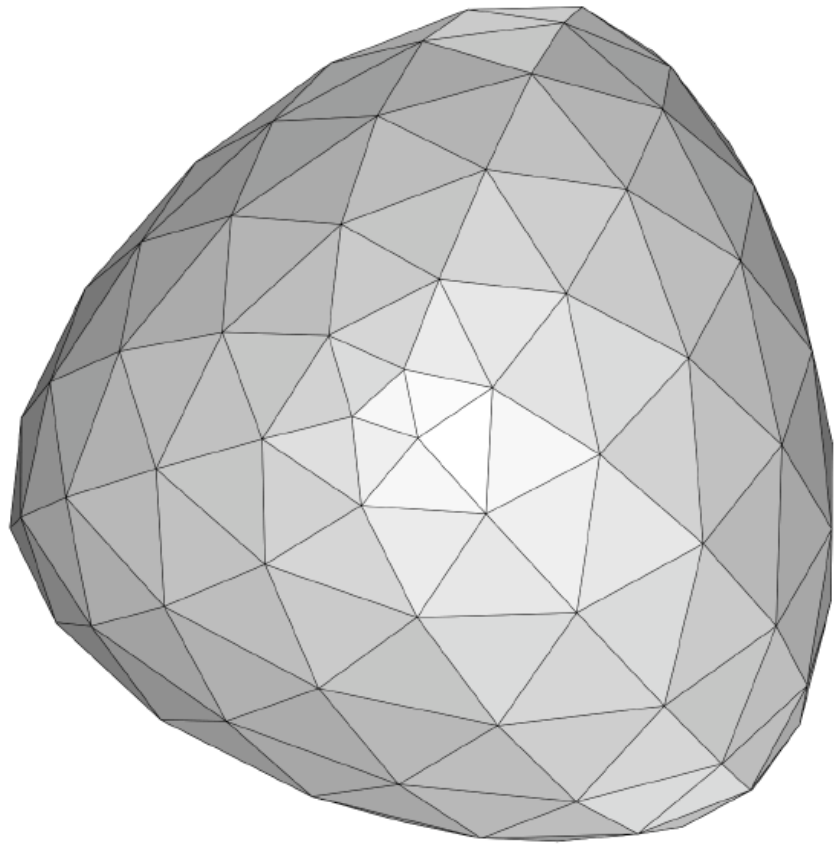
Results

Results

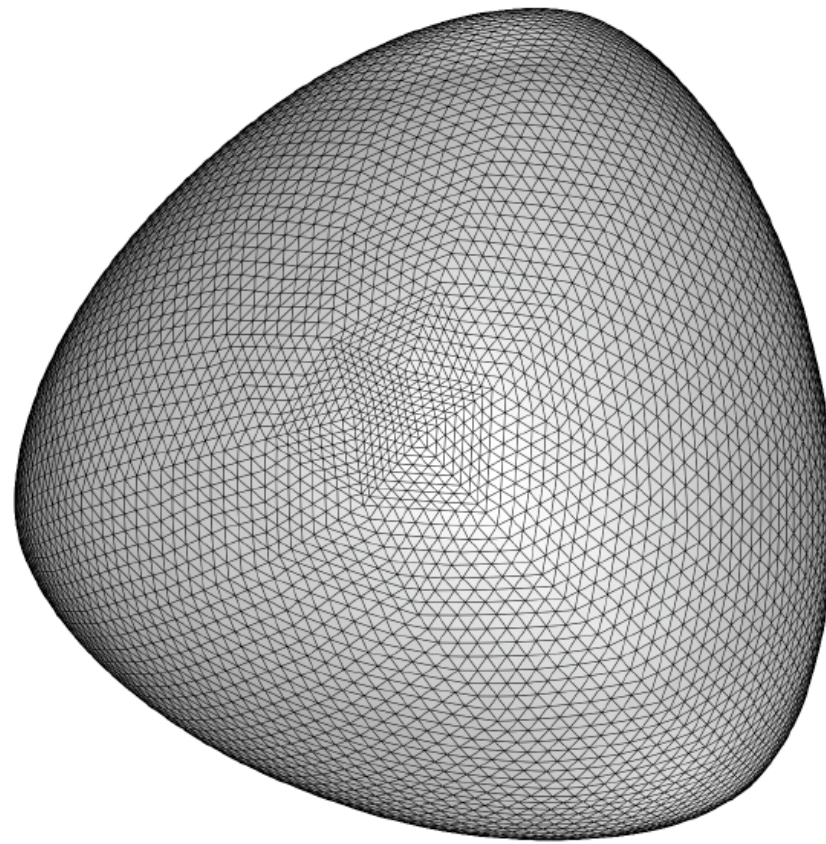


Mesh

Results

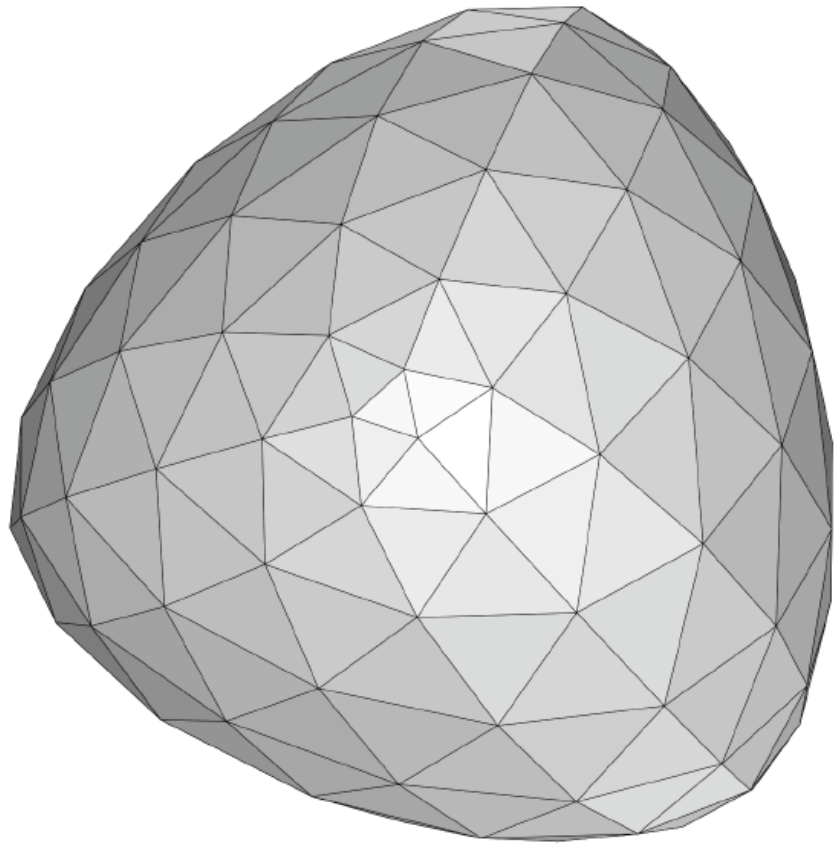


Mesh

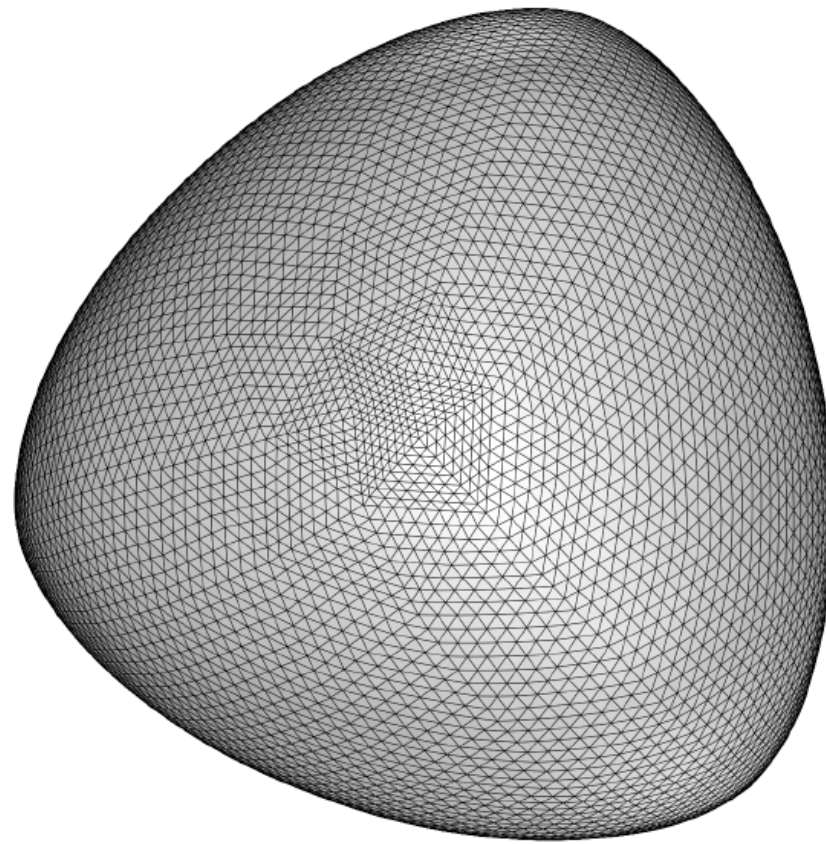


PN triangle

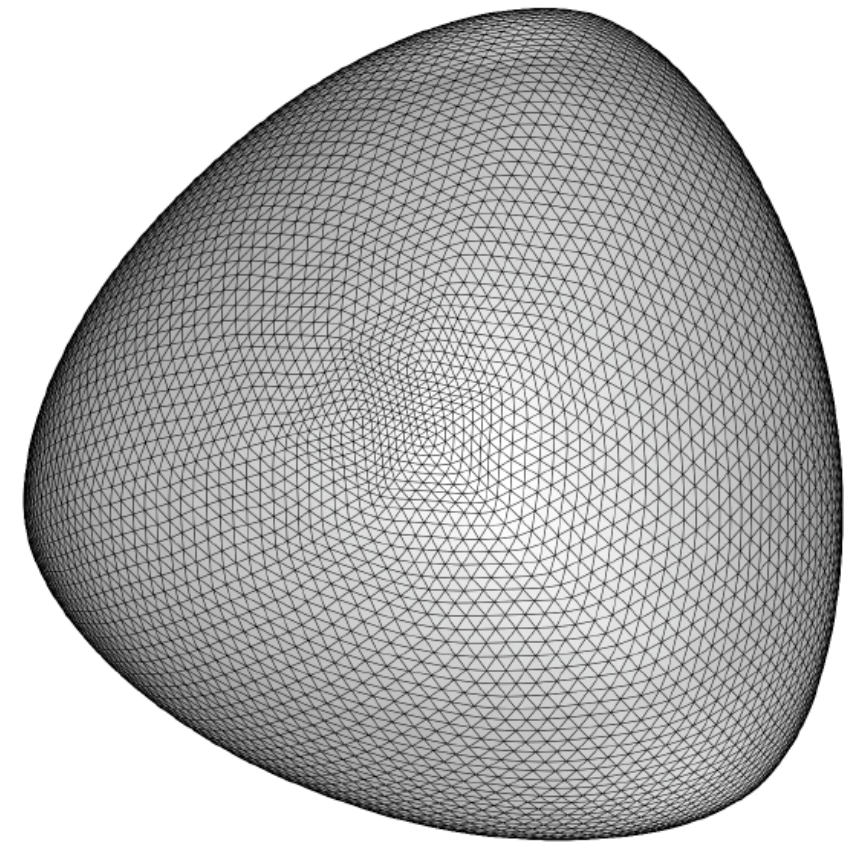
Results



Mesh



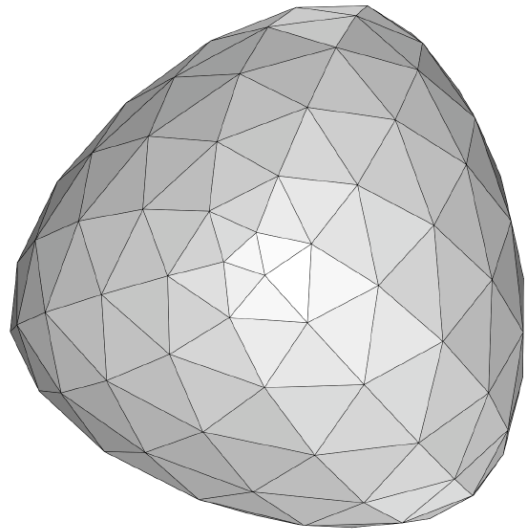
PN triangle



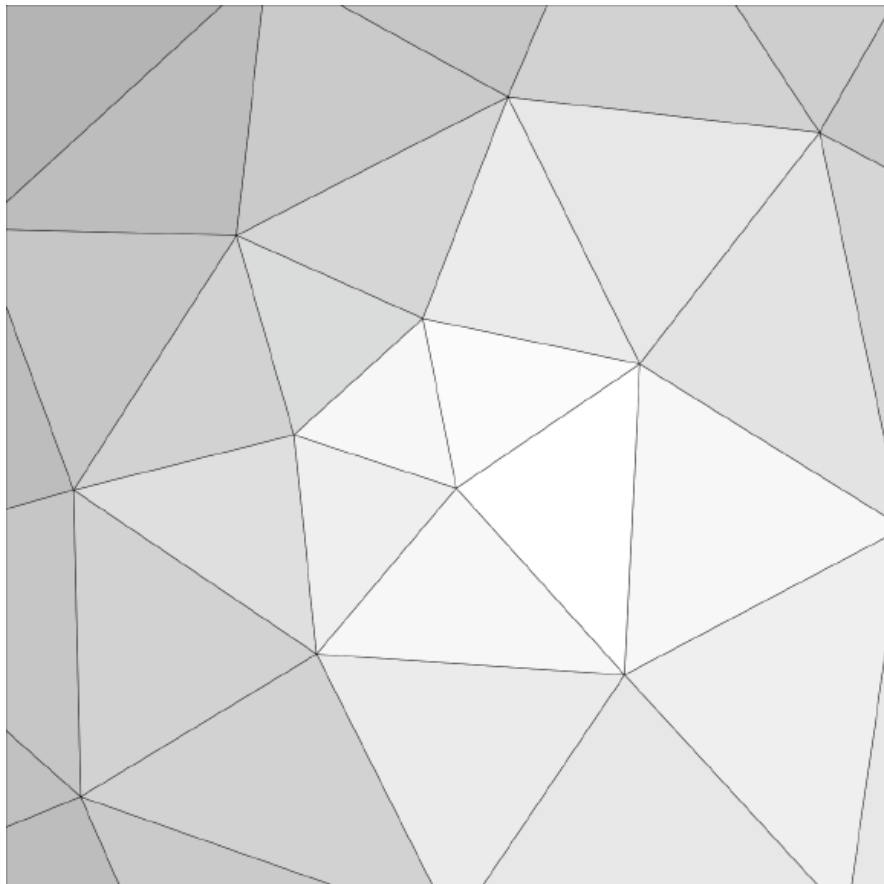
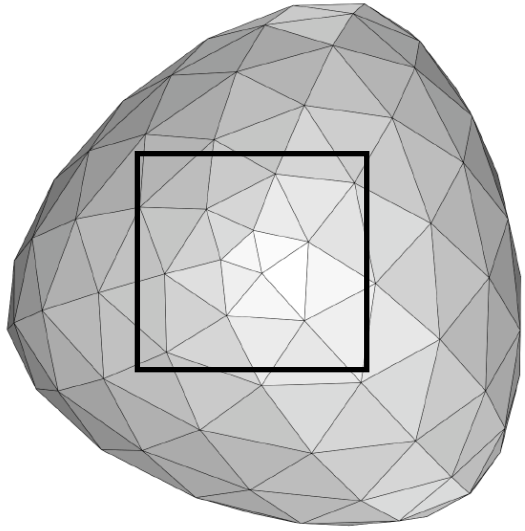
PPS

Results

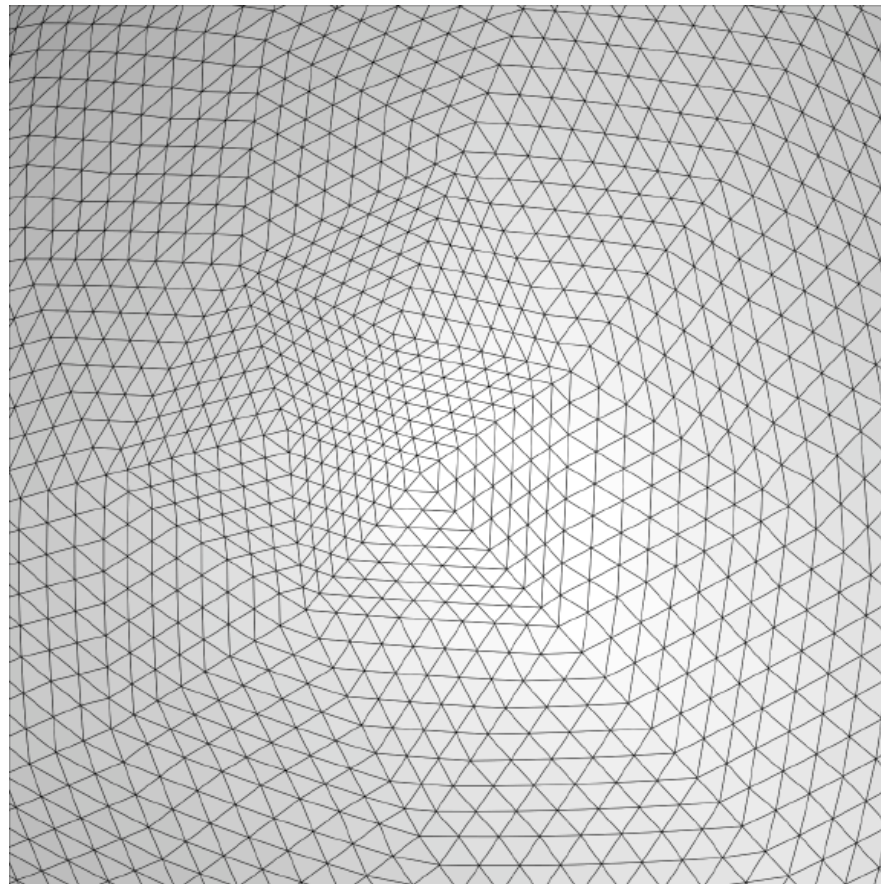
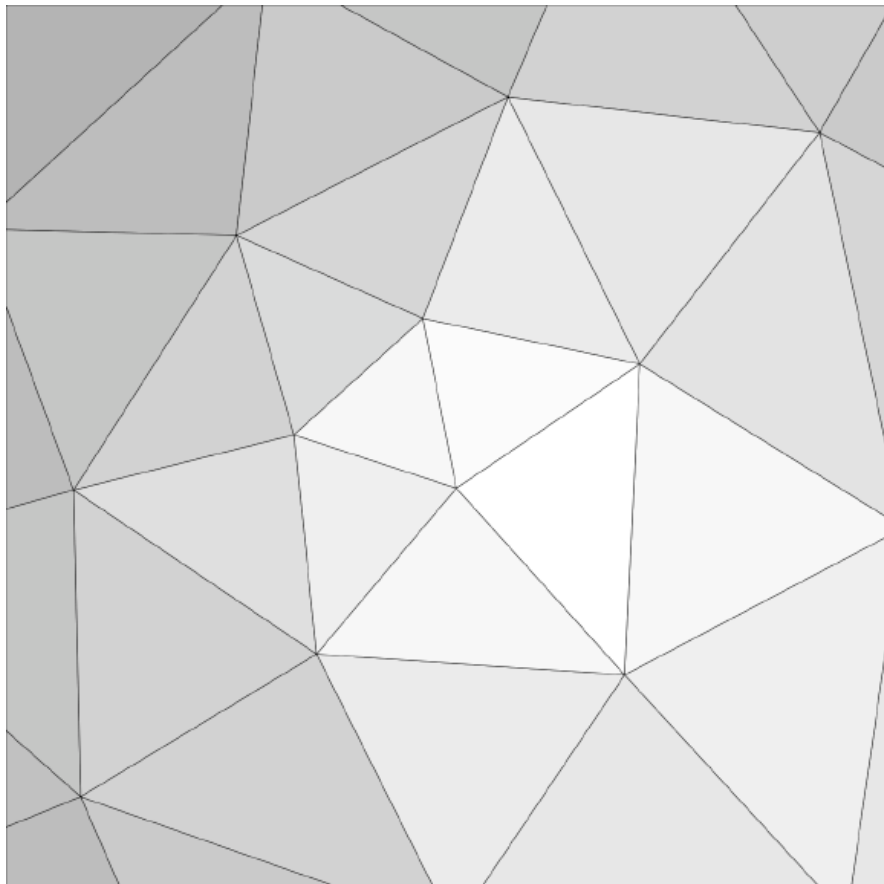
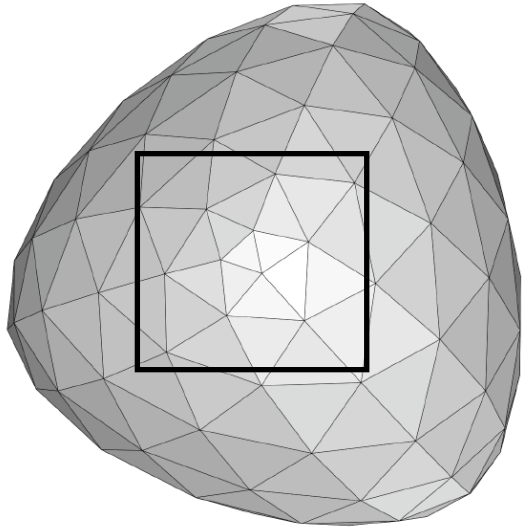
Results



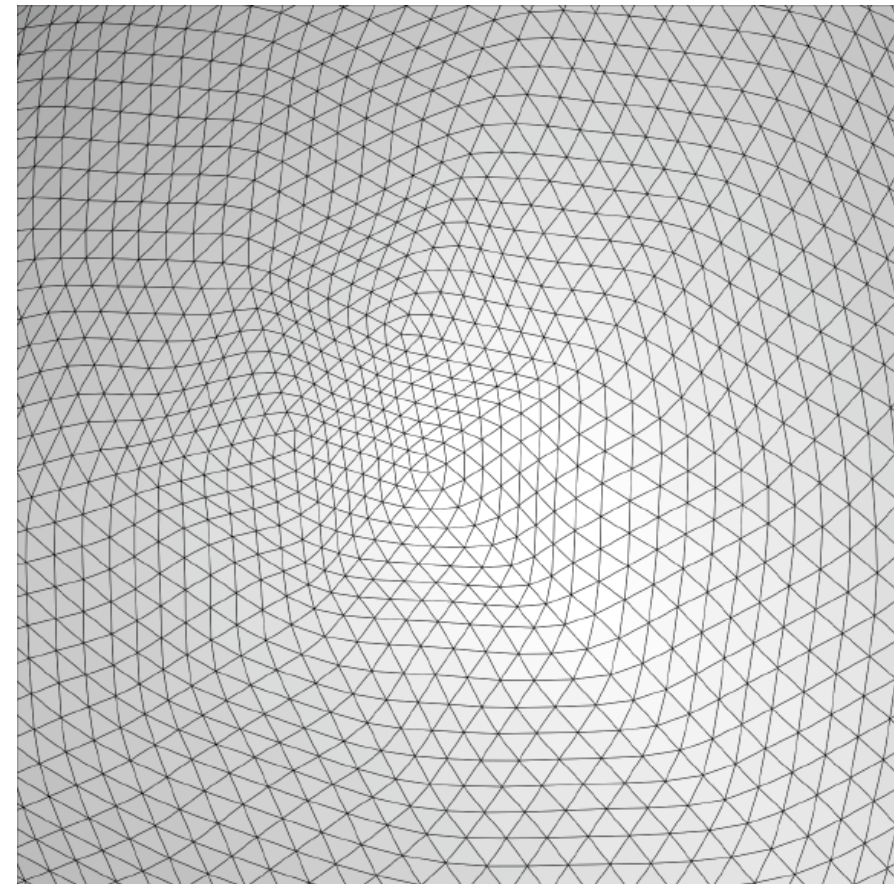
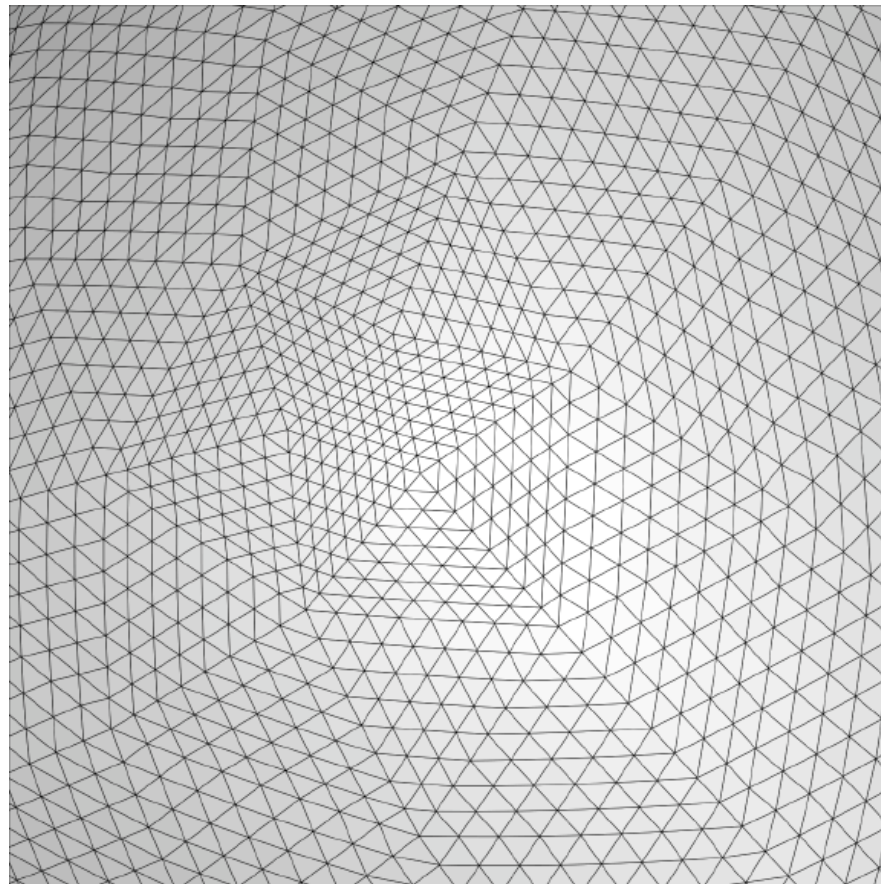
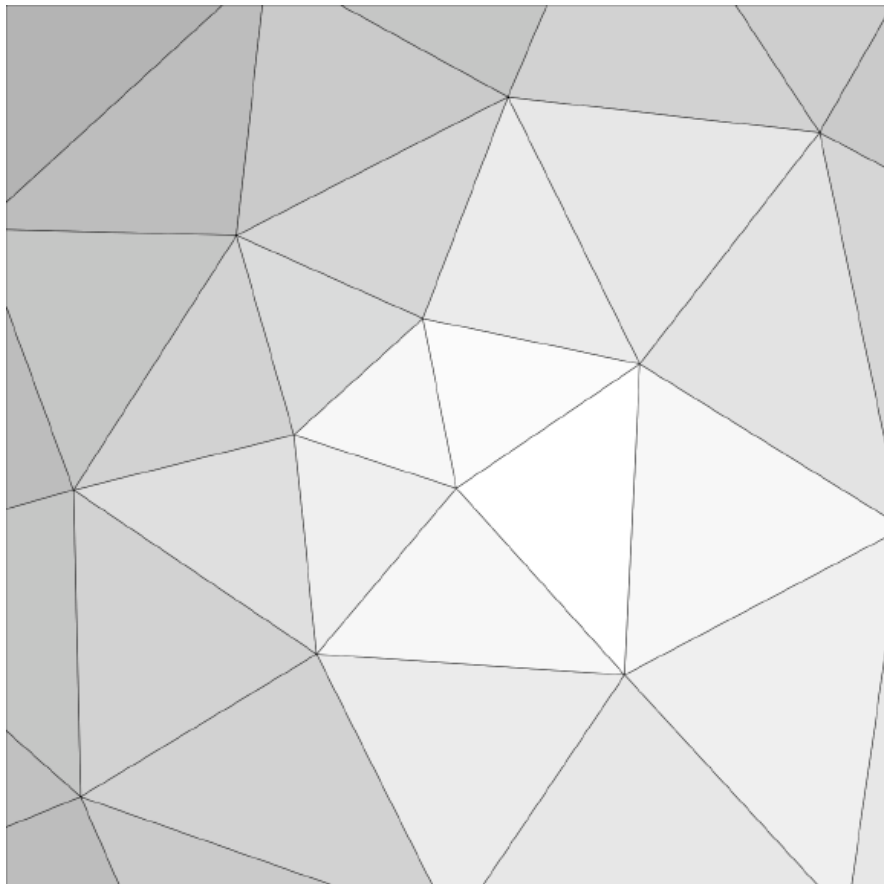
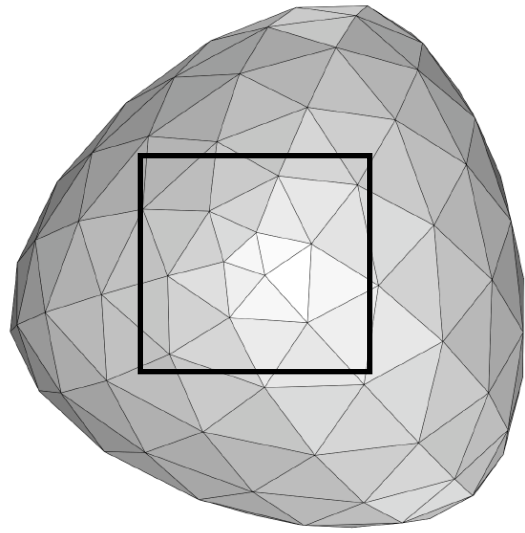
Results



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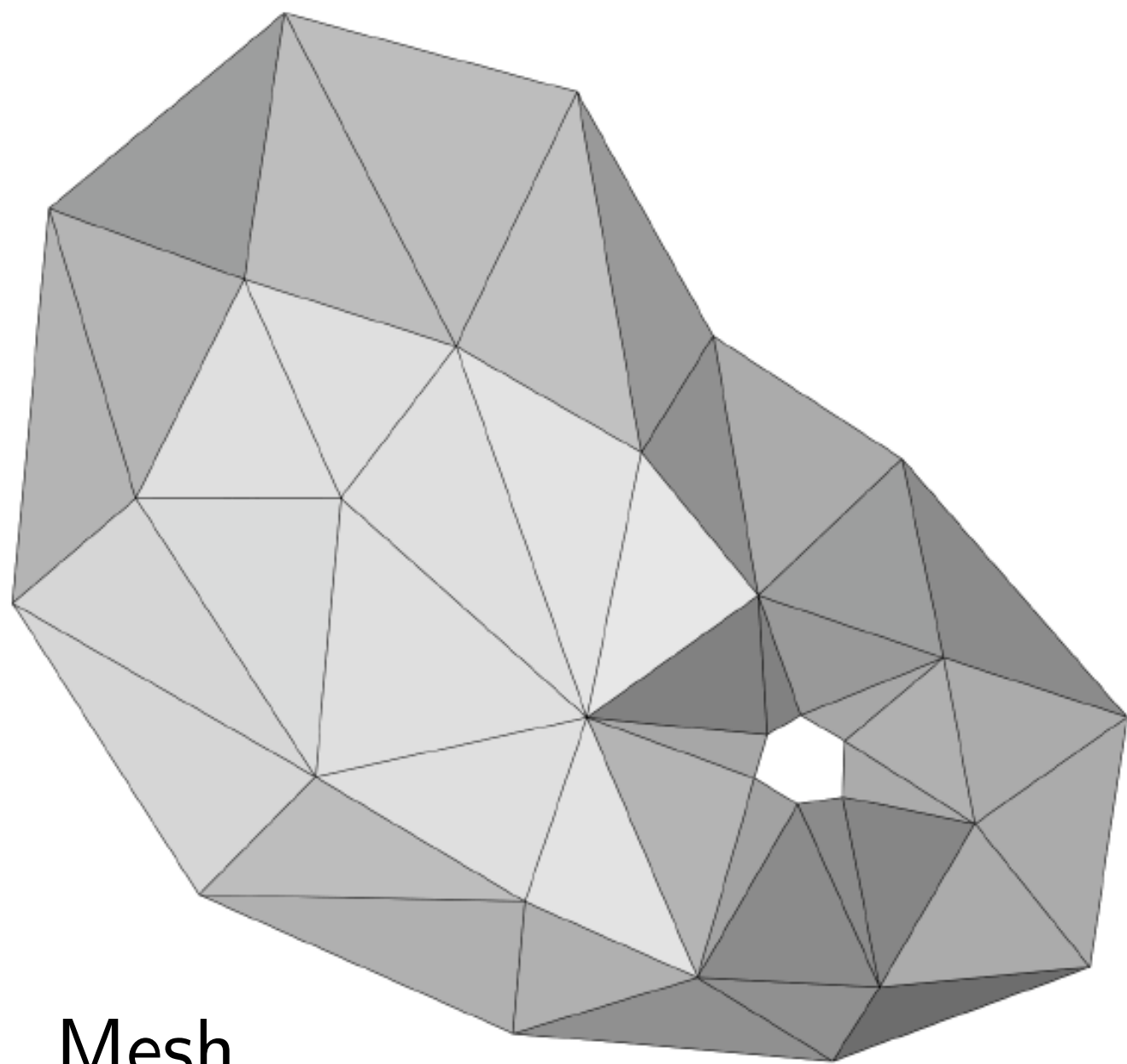


Results



Results

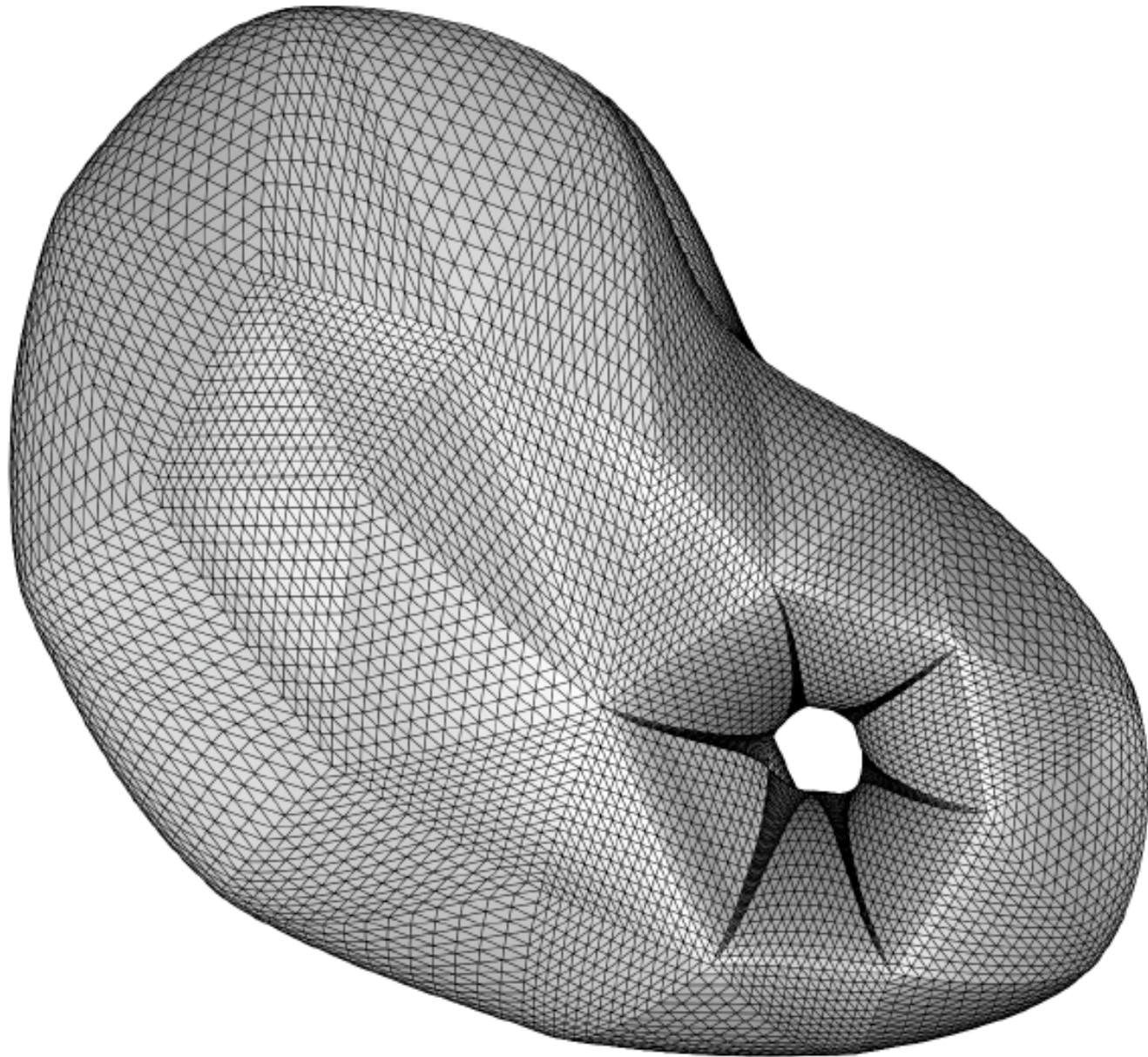
Results



Mesh

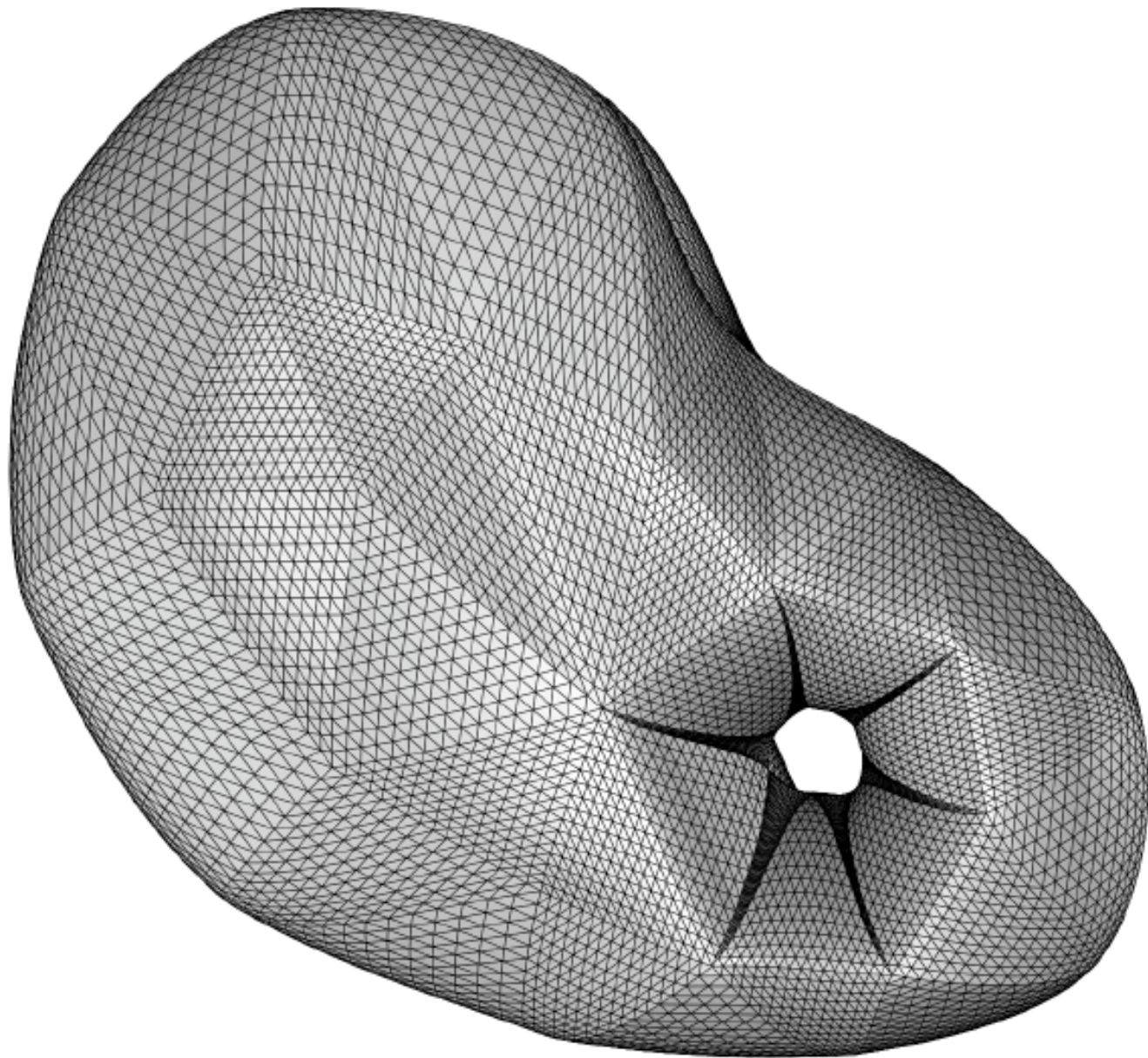
Results

PN triangle

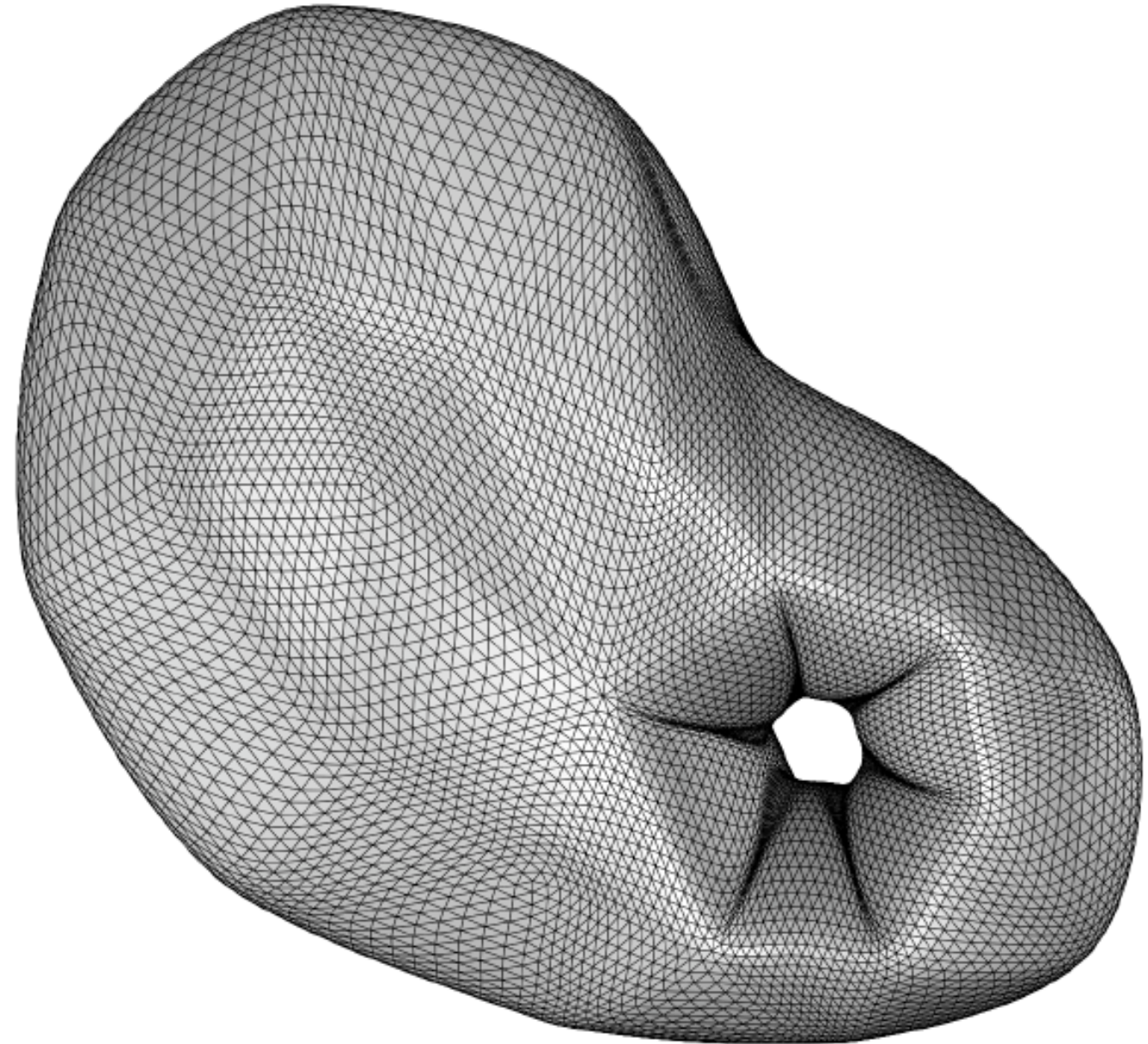


Results

PN triangle



PPS



Results

Results



Mesh

Results



Mesh



PN triangle

Results



Mesh



PN triangle

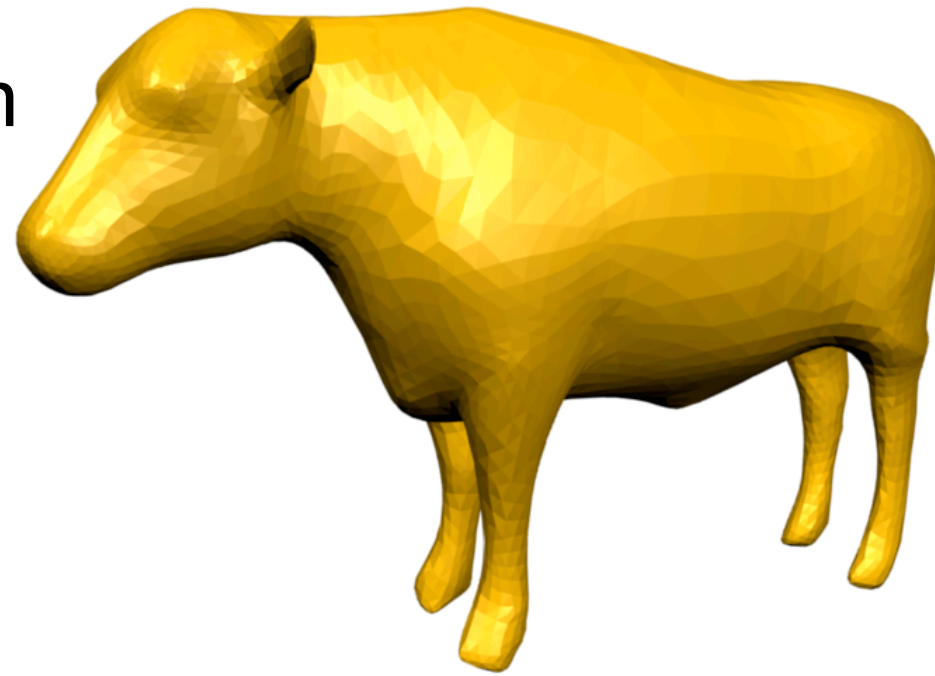


PPS

Results

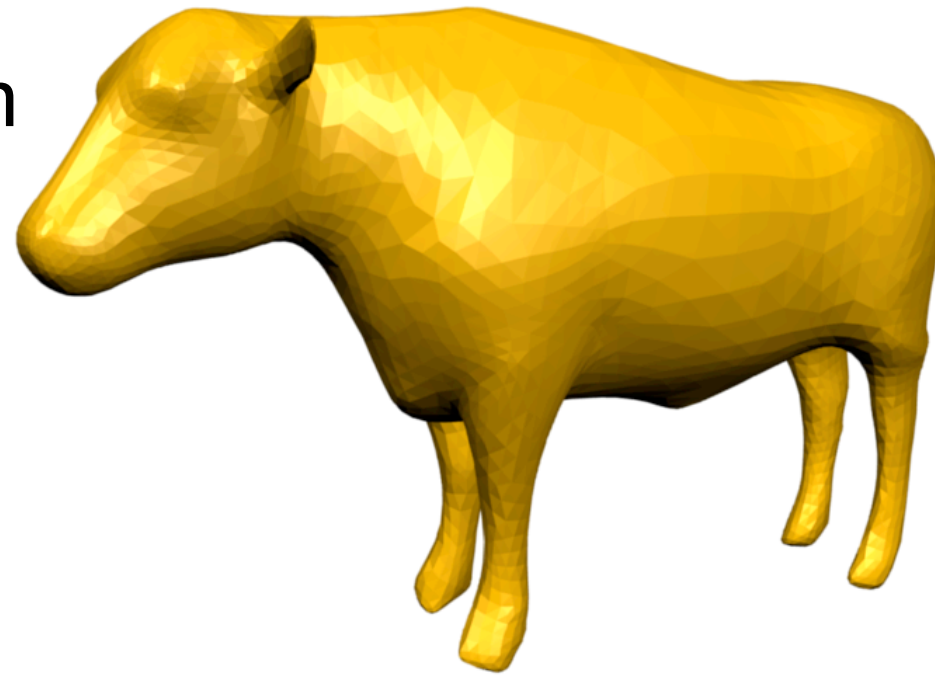
Results

Mesh



Results

Mesh

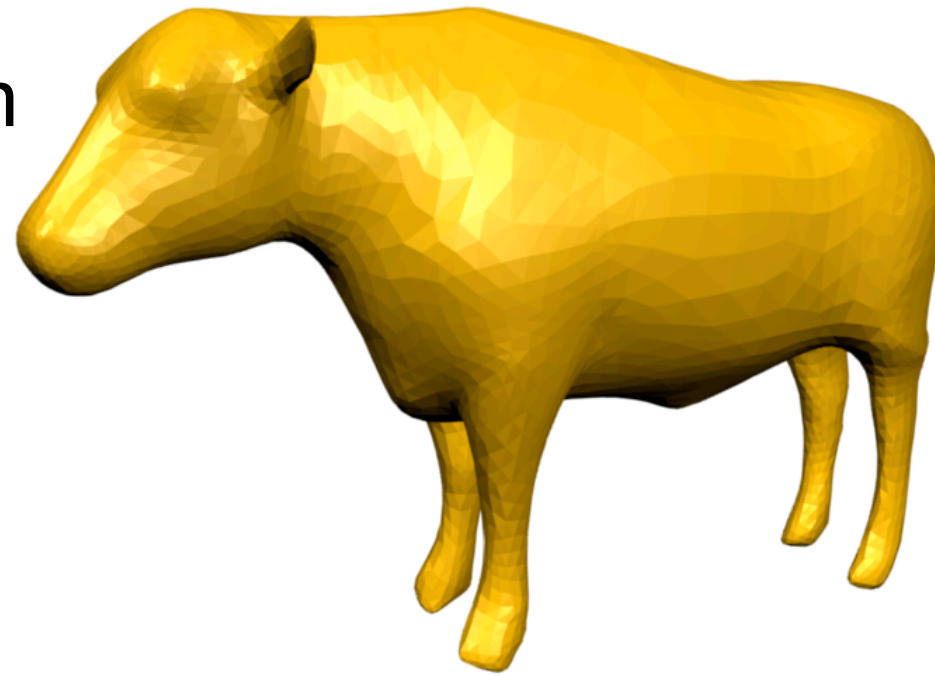


PN triangle



Results

Mesh



PN triangle



PPS



Results

Results

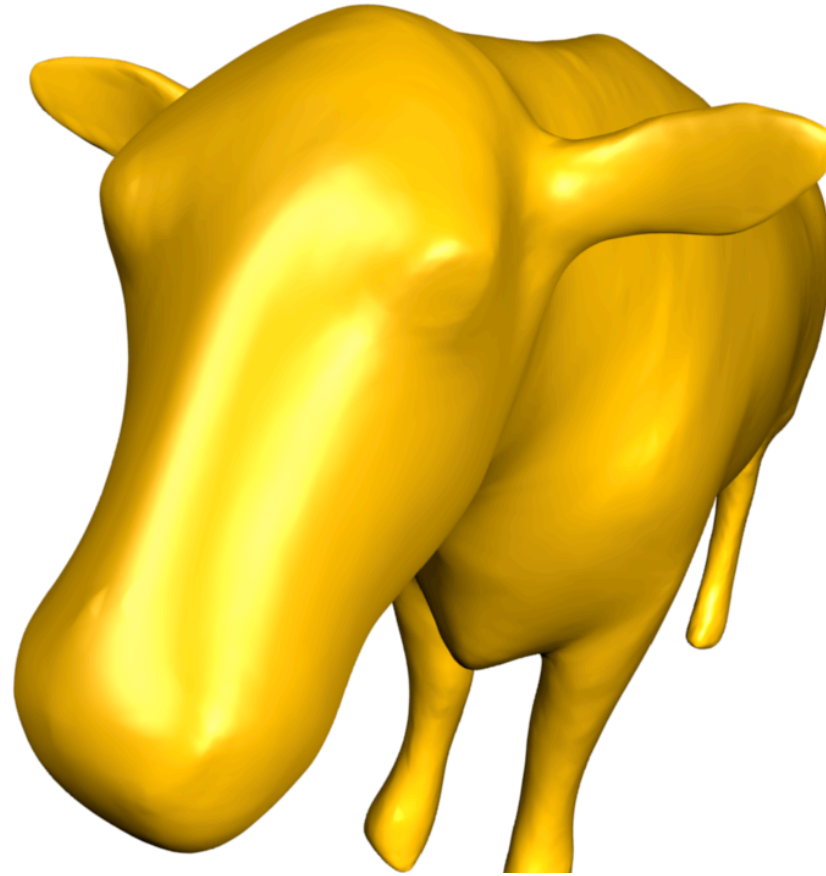


Mesh

Results



Mesh

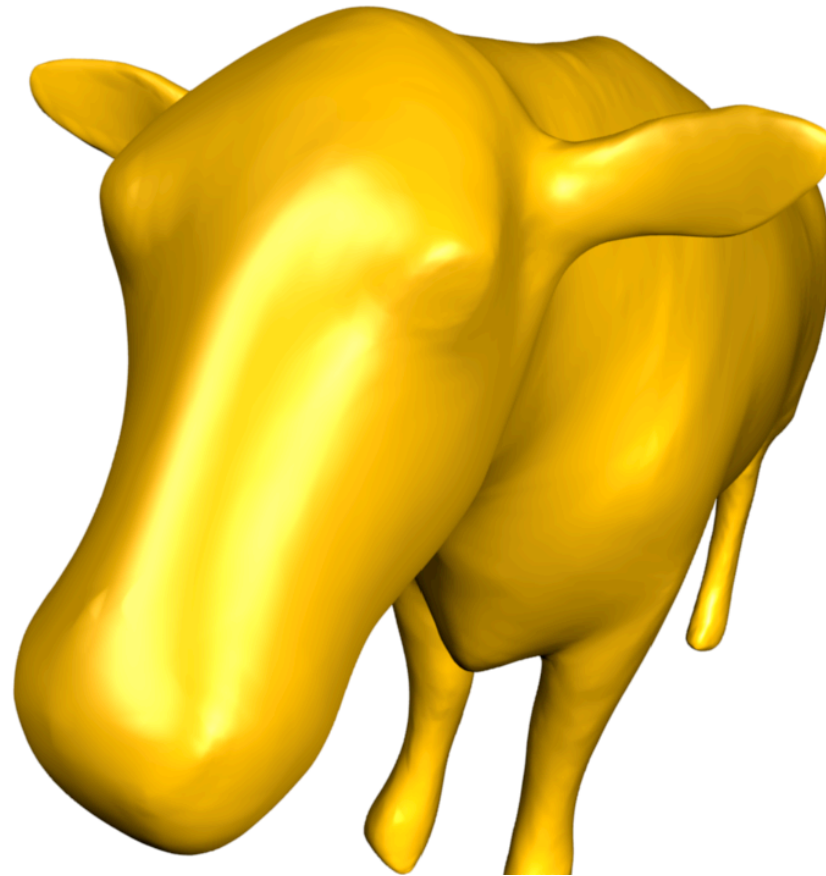


PN triangle

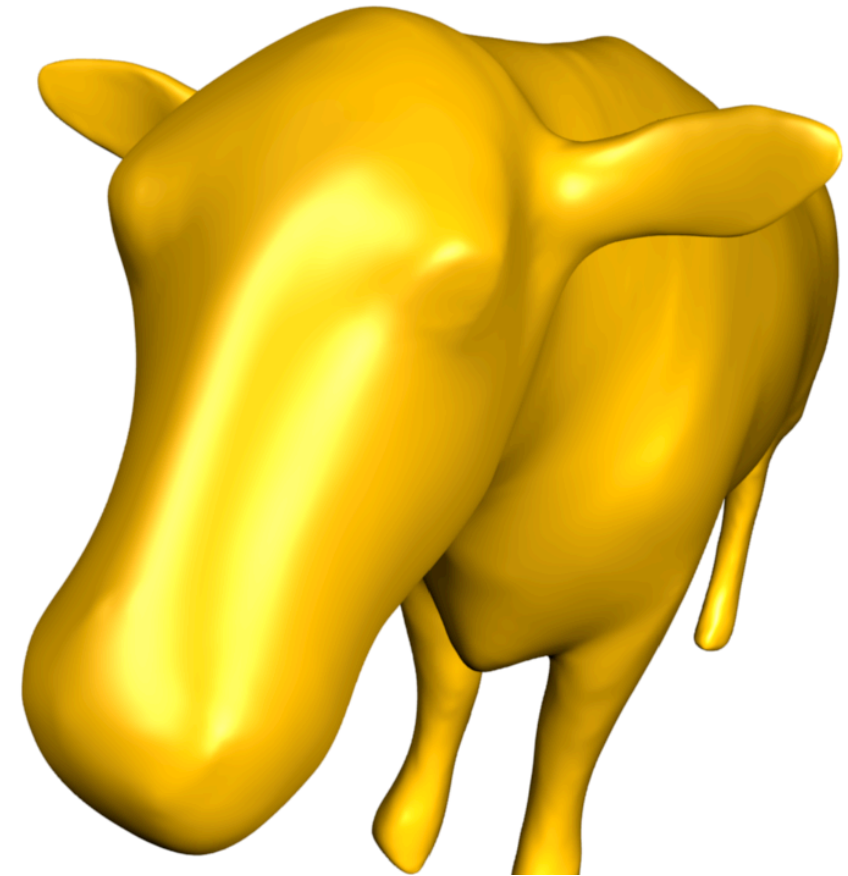
Results



Mesh



PN triangle



PPS

Results

Results



Mesh

Results



Mesh



PN triangle

Results



Mesh



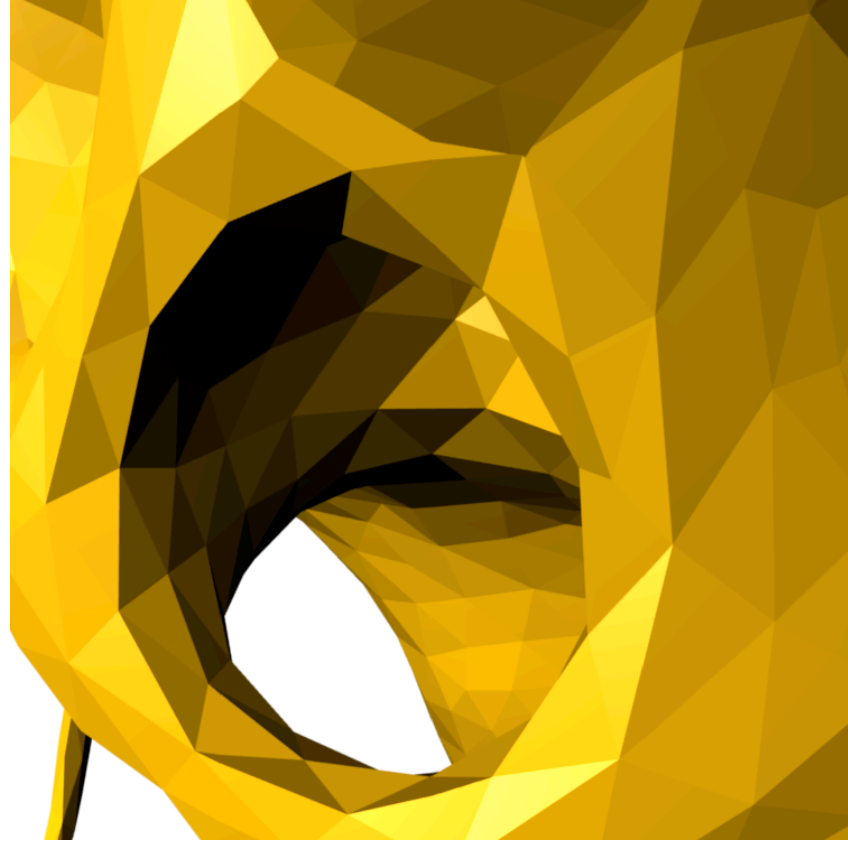
PN triangle



PPS

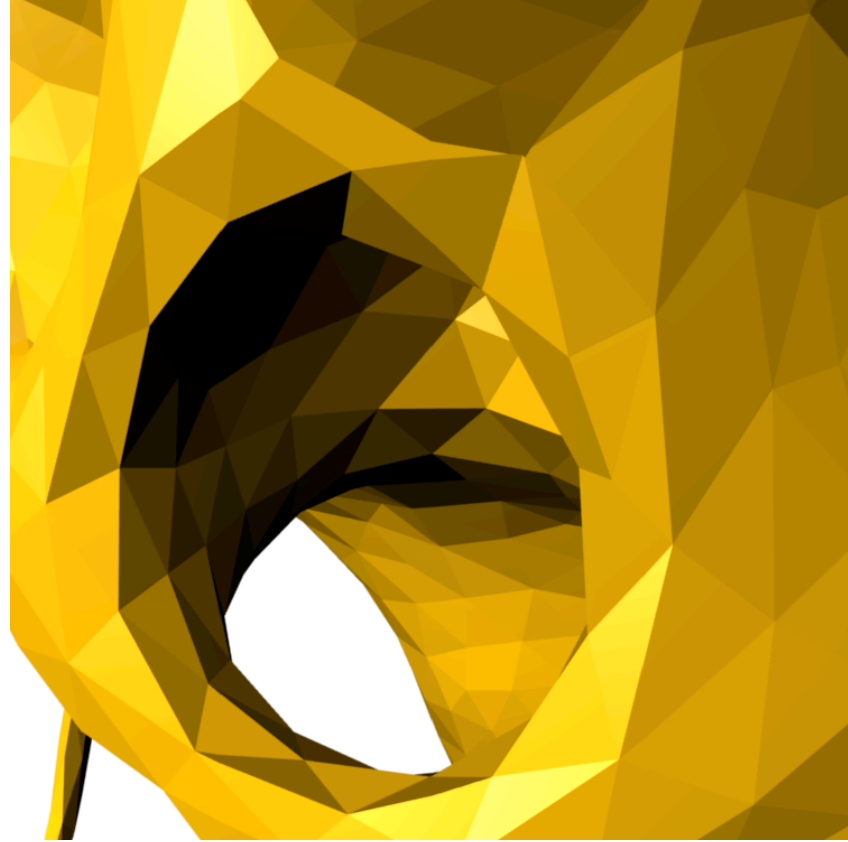
Results

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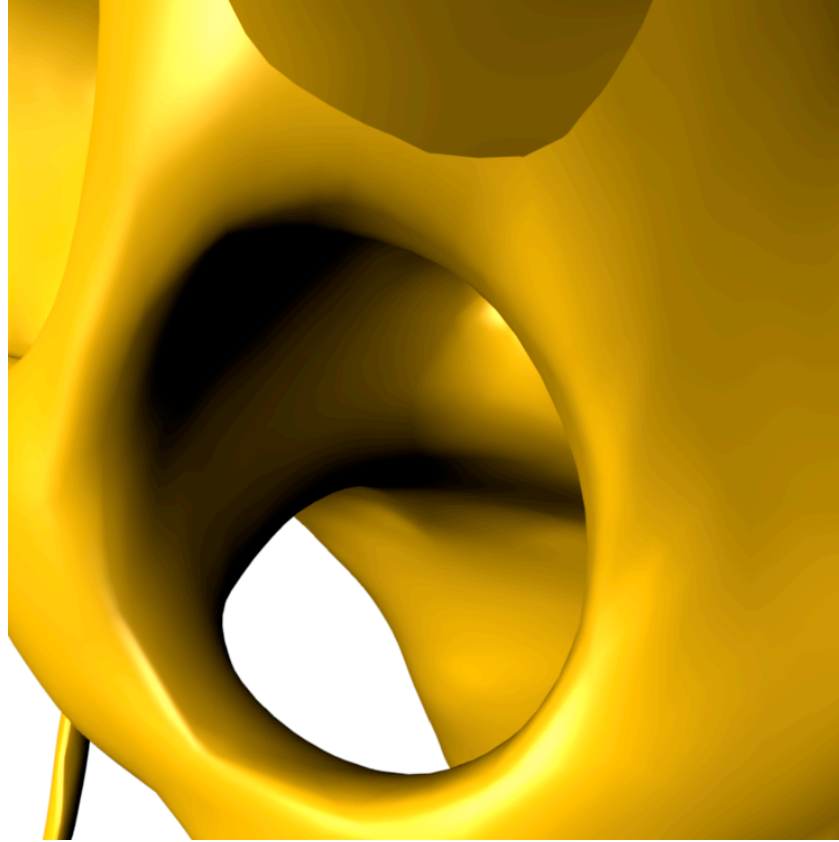


Mesh

Results



Mesh

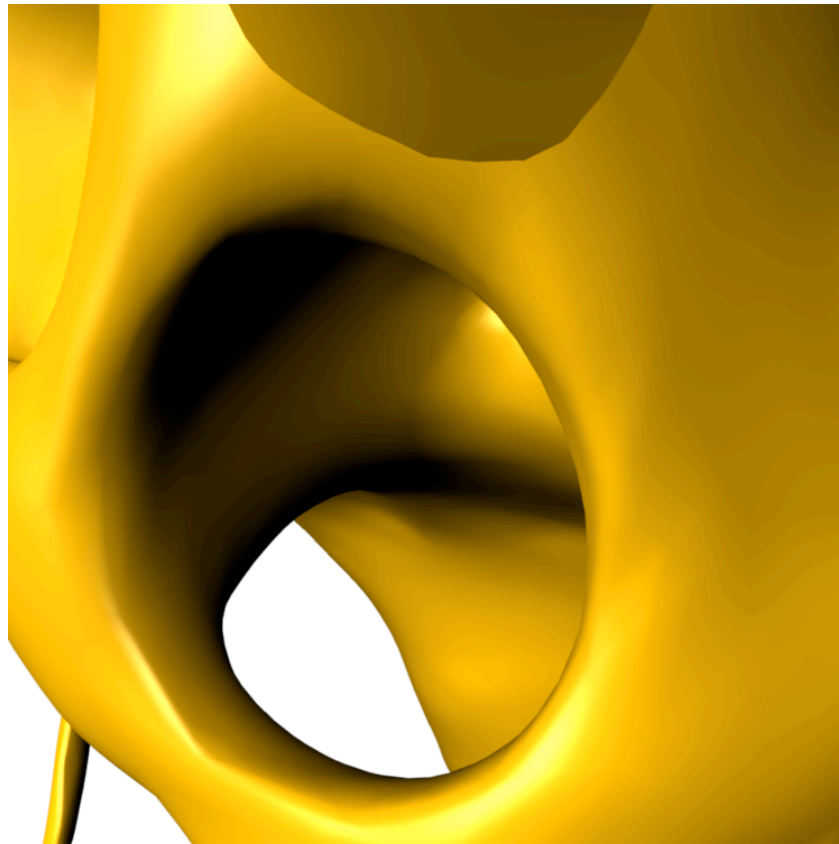


PN triangle

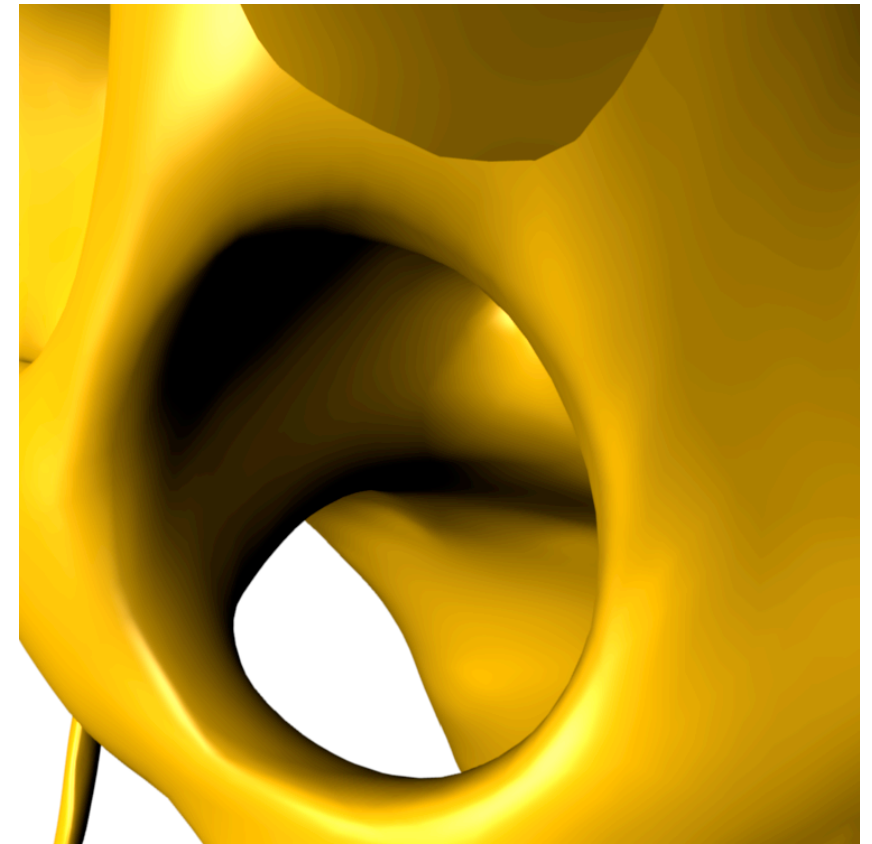
Results



Mesh



PN triangle



PPS

Conclusions

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The image of our C^k parametric pseudo-surface is given by

$$M = \bigcup_{(\sigma, v)} \theta_{(\sigma, v)}(\Omega_{(\sigma, v)}) .$$

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Conclusions

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$$M = \bigcup_{(\sigma, v)} \theta_{(\sigma, v)}(\Omega_{(\sigma, v)}).$$

The map $\theta_{(\sigma, v)}$ is actually C^∞ .

There are $3 \times n_t$ p -domains and Bézier patches in our construction, where n_t is the number of triangles of the input mesh, S_T .

Conclusions

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Unfortunately, the map $\theta_{(\sigma, v)}$ is NOT polynomial.

Conclusions

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OPEN PROBLEM: Can we make it polynomial?

Conclusions

Conclusions

Recall that

$$\theta_{(\sigma, v)}(p) = \sum_{(\tau, u) \in J(p)} \nu_{(\tau, u)}(p) \cdot \psi_{(\tau, u)}(\varphi_{(\sigma, v)}(\tau, u)(p)),$$

where

$$\nu_{(\tau, u)}(p) = \frac{\gamma_{(\tau, u)}(\varphi_{(\tau, u)}(\sigma, v)(p))}{\sum_{(\eta, w) \in J(p)} \gamma_{(\eta, w)}(\varphi_{(\eta, w)}(\sigma, v)(p))}$$

and

$$J(p) = \{(\eta, w) \in I \mid p \in \Omega_{(\sigma, v)}(\eta, w)\}.$$

Conclusions

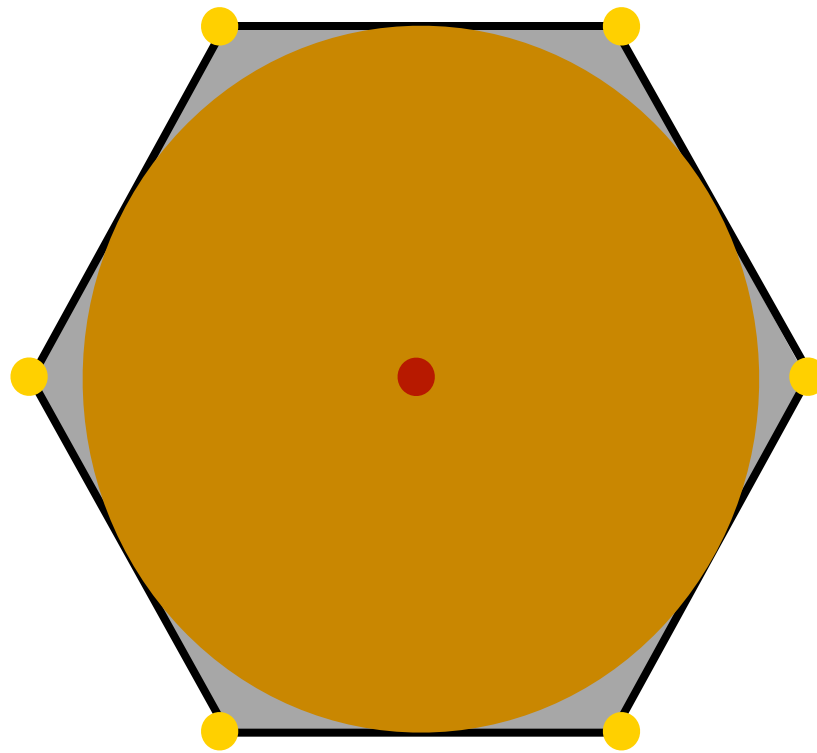
We can easily make $\gamma_{(\tau,u)}$ a C^k rational polynomial, for any finite k .

However, the difficult lies in making $\varphi_{(\tau,u)(\sigma,v)}$ (rational) polynomial!

Conclusions

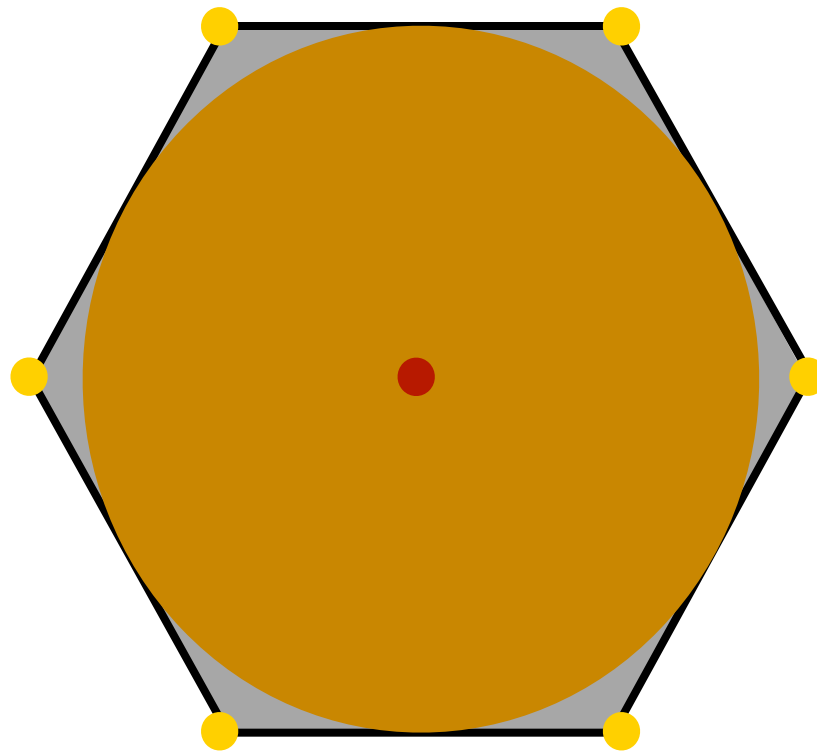
Conclusions

We can create a much simpler construction by letting the p -domains be the inscribed circles of the P -polygons, as shown below:



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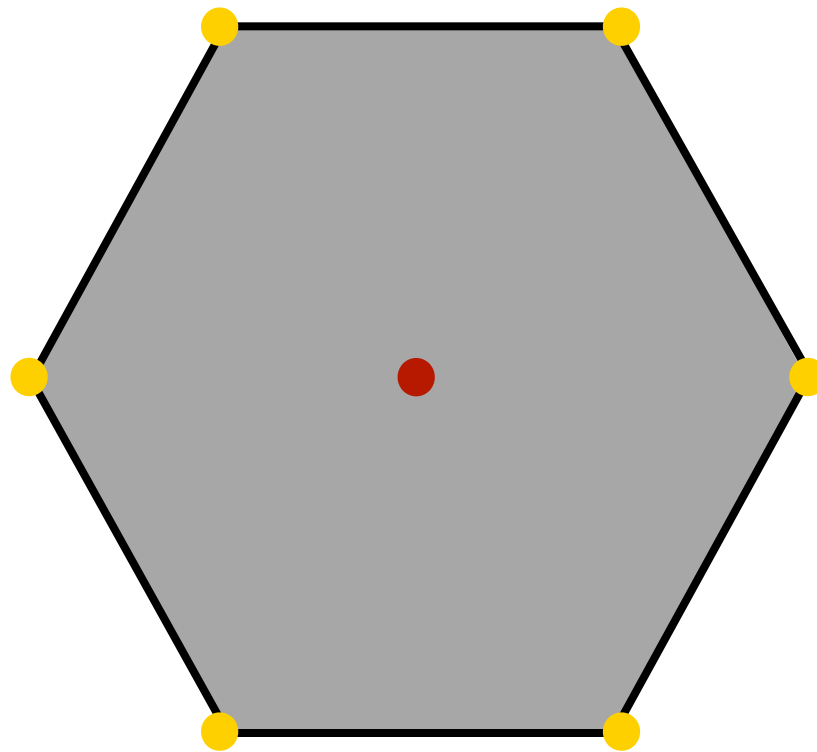


The transition maps do not change, but the shape functions do!

Conclusions

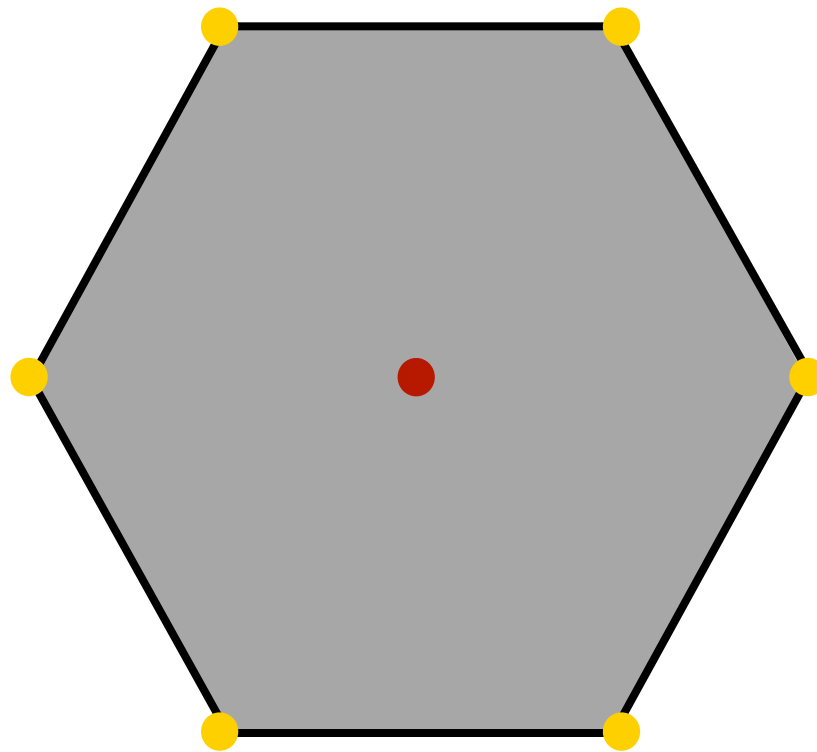
Conclusions

Why didn't we let the interior of the P -polygons be the p -domains?



Conclusions

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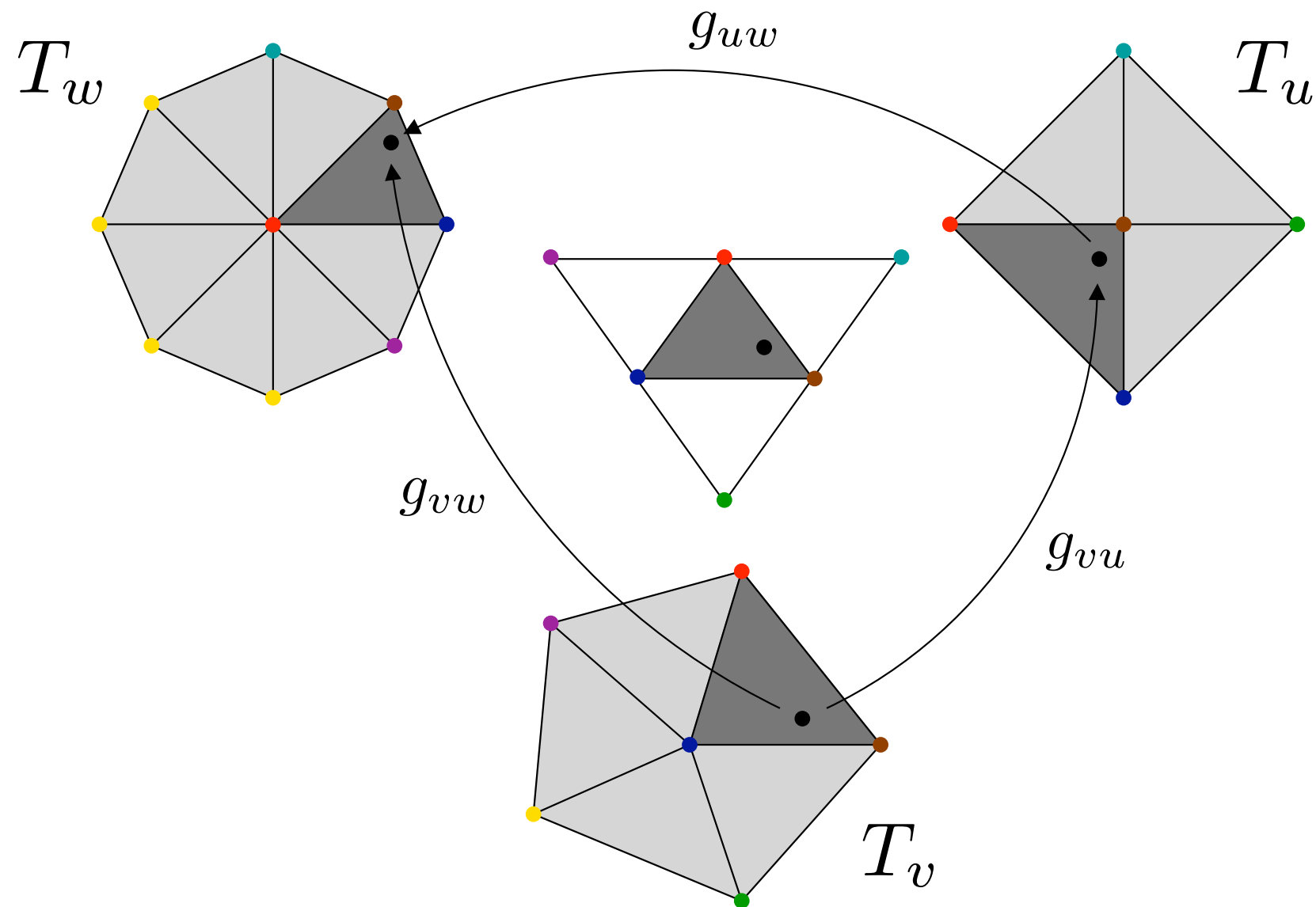


Simple answer: we failed to figure out the transition maps!

Conclusions

Conclusions

OPEN PROBLEM: Can you find a **simple** C^∞ bijective map g satisfying $g_{vw} = g_{uw} \circ g_{vu}$ (this has to do with the cocycle condition)?



Conclusions

Conclusions

For a good survey on the existing constructions, see

- Cindy M. Grimm and Denis Zorin. Surface Modeling and Parametrization with Manifolds. In ACM SIGGRAPH 2006 Courses (SIGGRAPH'06), pages 1-81, New York, NY, USA, 2006. ACM Press.

Adaptive Manifold Fitting (Part I)

Luiz Velho
IMPA

Outline

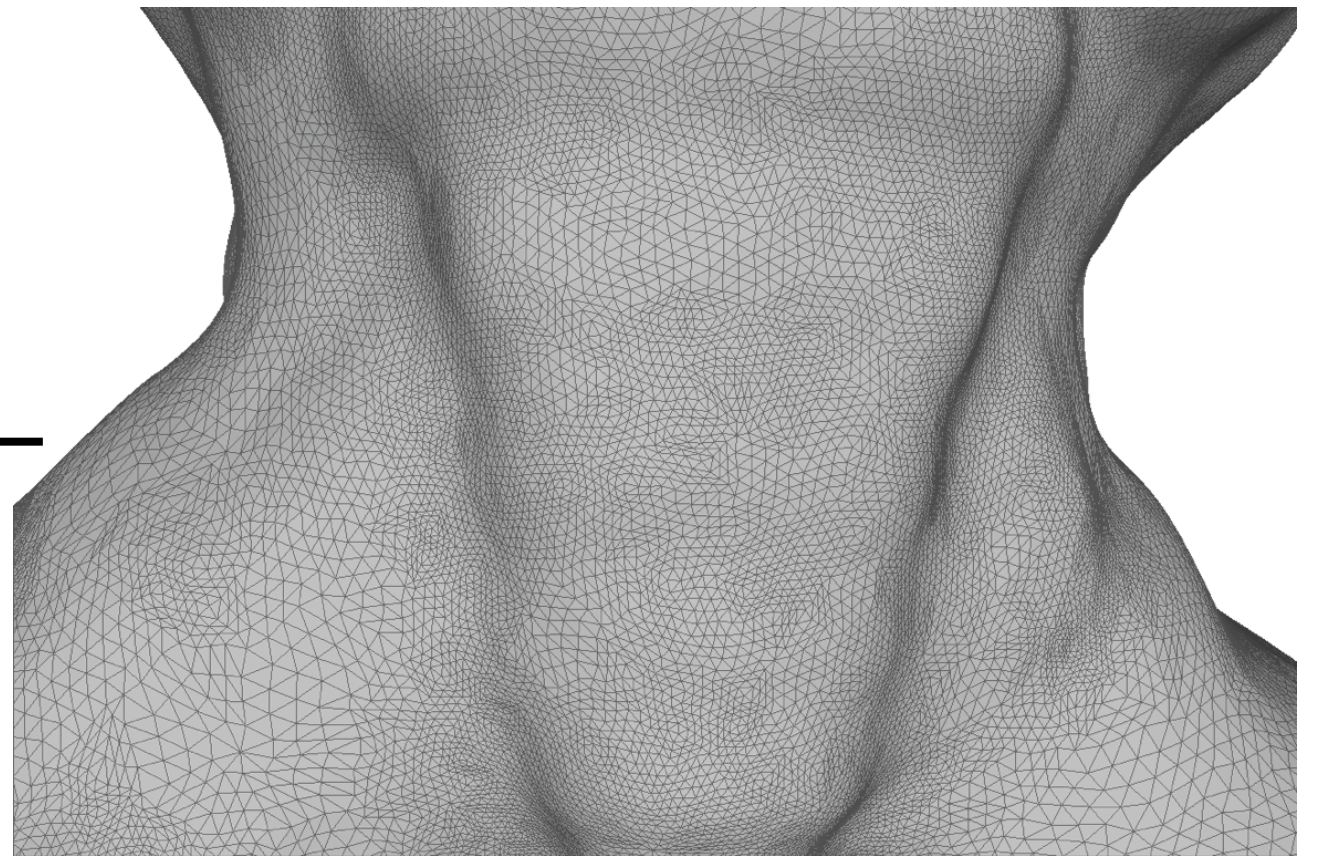
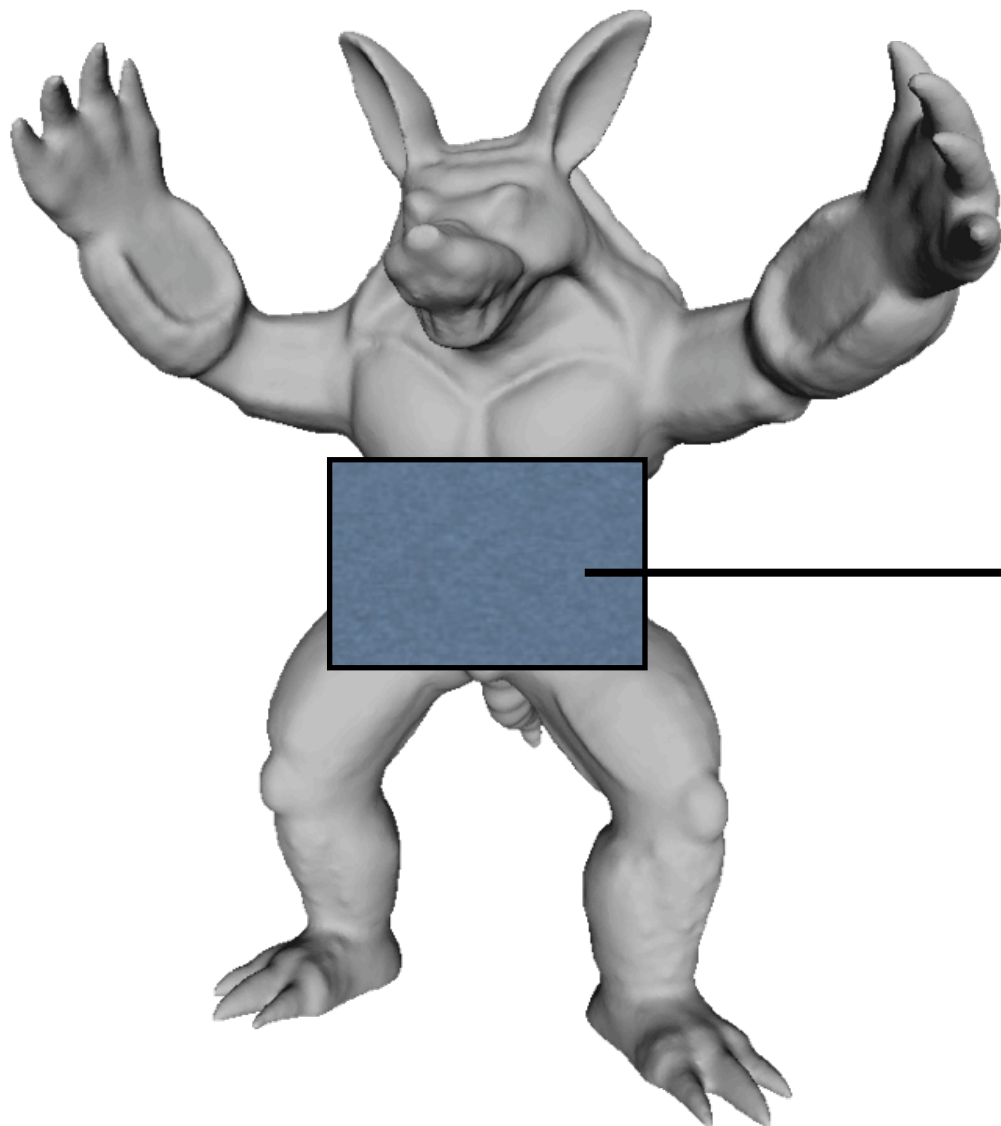
- Fitting Surfaces to Very Large Meshes
- Multiresolution Operators
- Building Base Meshes by Simplification
- Adaptive Mesh Refinement
- Conclusions

Surface Fitting

- Very Large Meshes (10^6 vertices)
 - Challenging Problem!

Surface Fitting

- Very Large Meshes (10^6 vertices)
 - Challenging Problem!



Manifolds and Fitting

- Basic Setting
 - Gluing Data proportional to Mesh Size
- Problem: *Very Large Meshes*
 - Computationally Inefficient
 - Do not Exploit Approximation Power
- Solution:
 - Adaptation

Adaptive Fitting

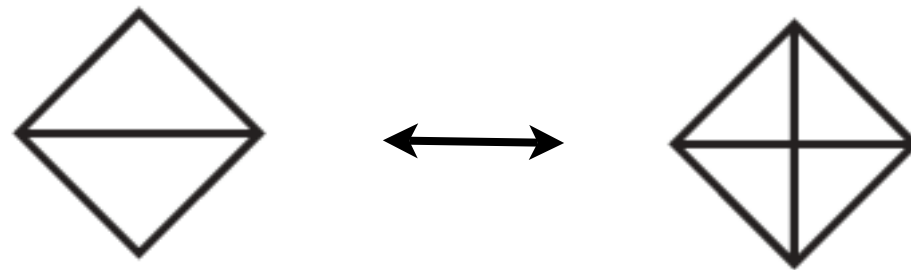
- Optimization Formulation:
 - Given an Approximation Error ϵ
 - Find \mathcal{M} with Smallest Number of Charts
- Strategy:
 - Combine
 - Multiresolution Structure
 - Manifold Surface Approximation

Multiresolution Framework

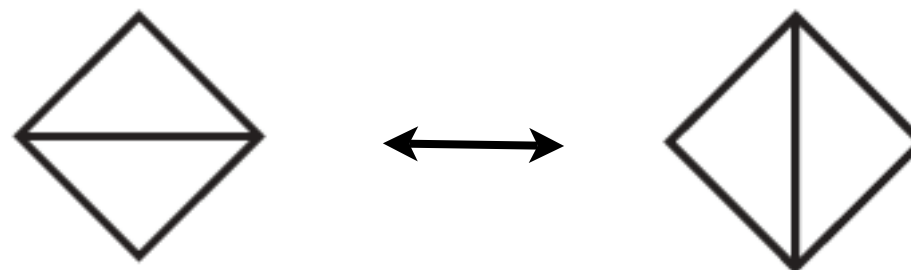
- Simplicial Multi-triangulation
 - Stellar Theory
- Building Base Meshes
 - Surface Simplification
- Adaptive Fitting
 - 4-8 Refinement

Stellar Theory

- Topological Operators
- Edge Split and Weld
 - ▬ Change Mesh Resolution



- Edge Flip
 - ▬ Change Mesh Connectivity



Stellar Simplification

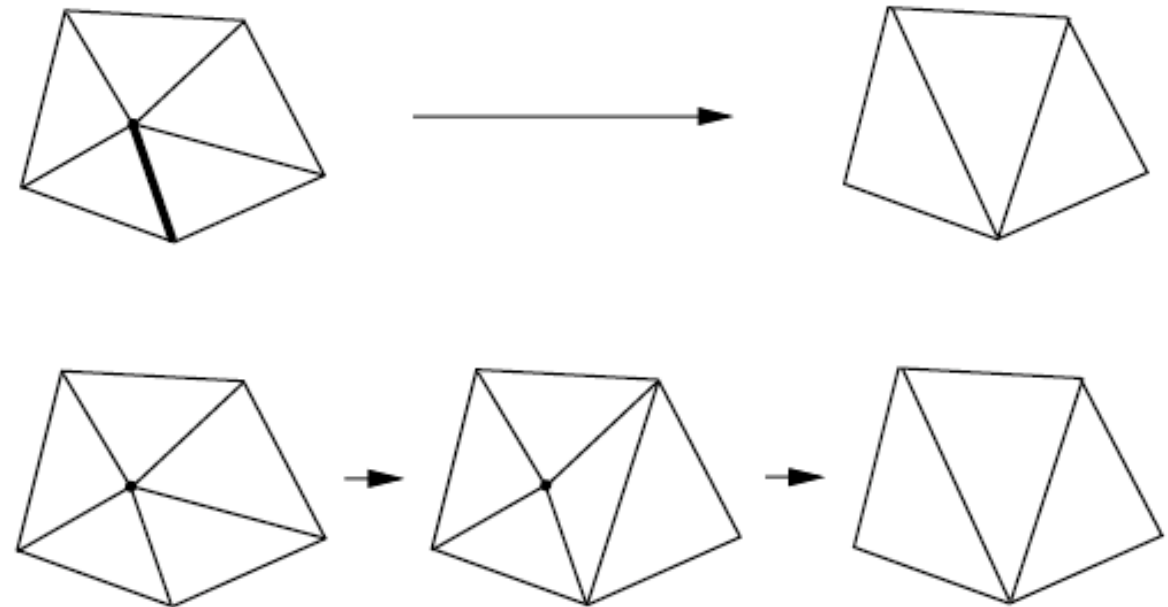
- Basic Elements:

I. Operator Factorization

- Edge Collapse



- Flip + Weld



II. Quadric Error Metric

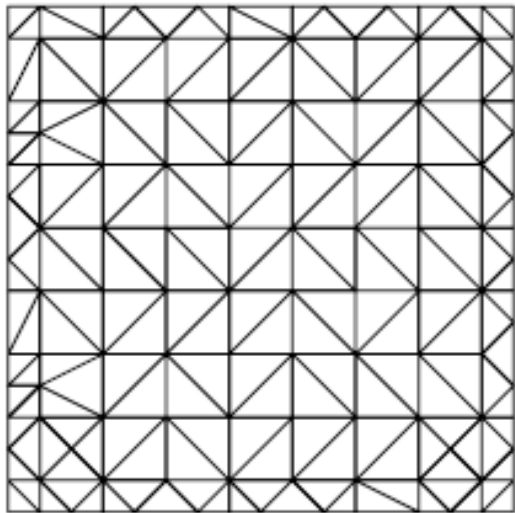
Basic Algorithm

- Repeat for N Resolution Levels
 1. Rank Vertices Based on Quadric Error
 2. Select Independent Set of Clusters
 3. Simplify Mesh using Stellar Operators

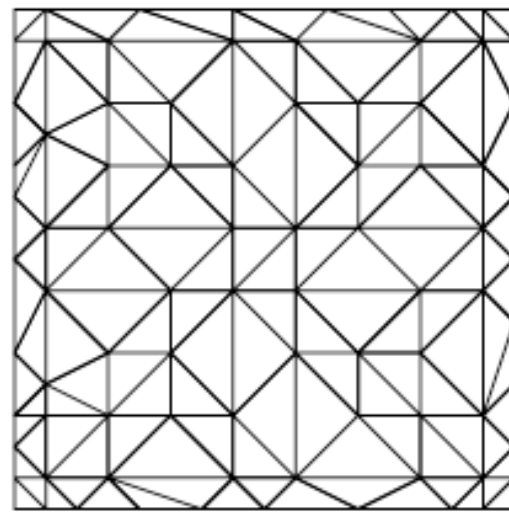
* *Properties*

- *Logarithmic Height*
- *Good Aspect Ratios*

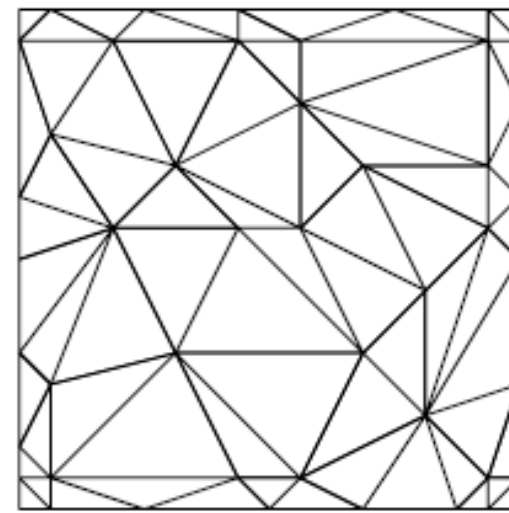
Example I: Plane



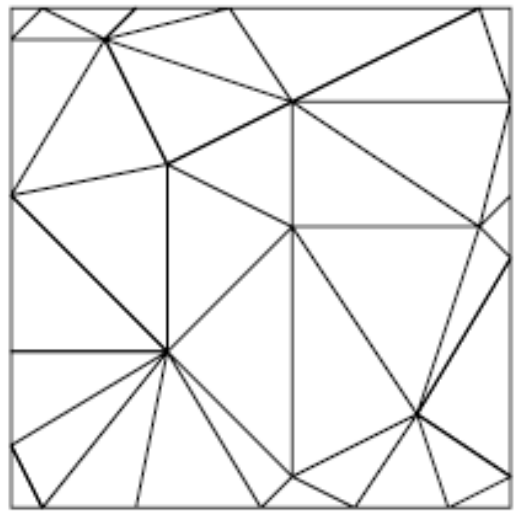
(a) original mesh



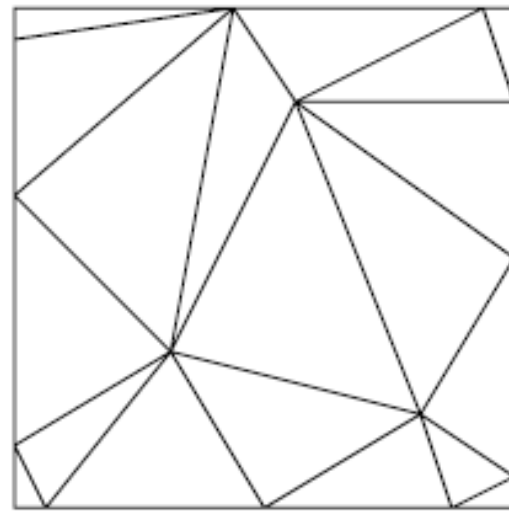
(b) level 1



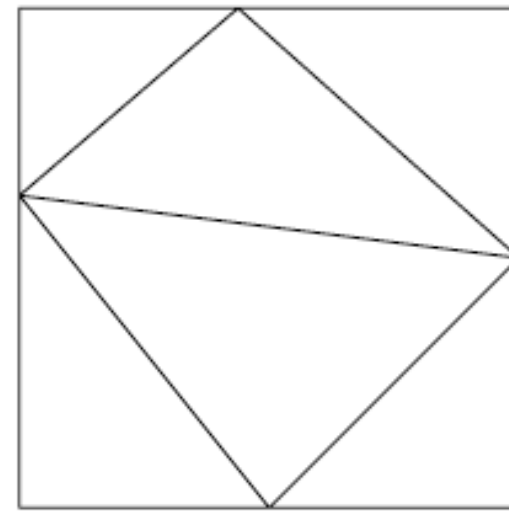
(c) level 3



(d) level 5

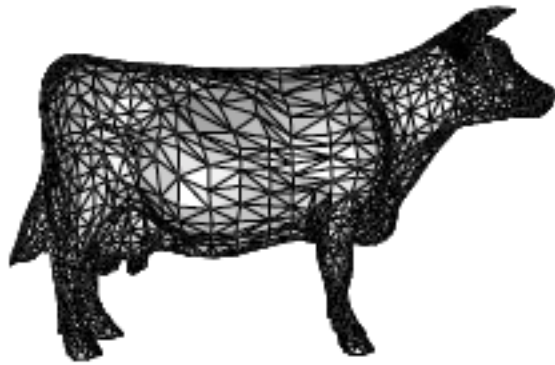


(e) level 7

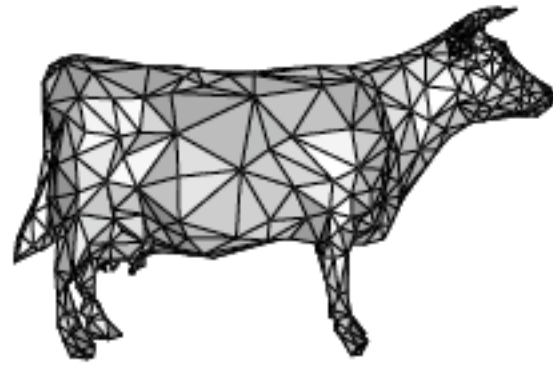


(f) level 9

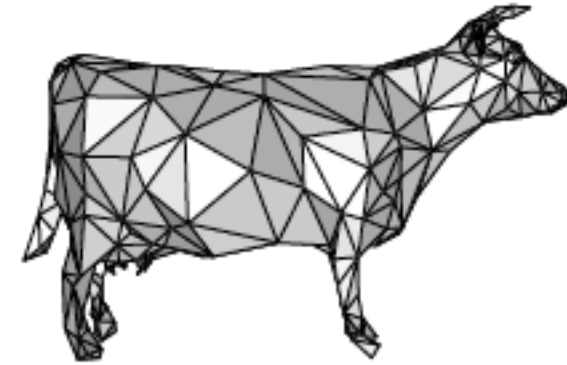
Example 2: Cow



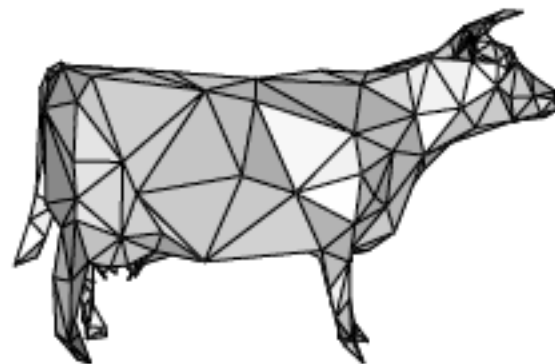
(a) original mesh



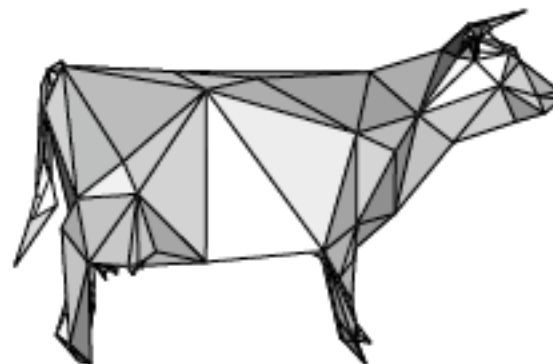
(b) level 1



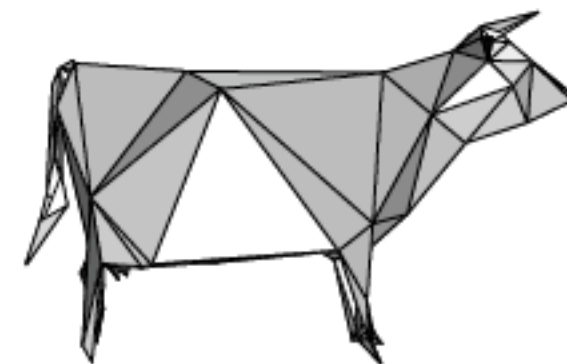
(c) level 3



(d) level 5



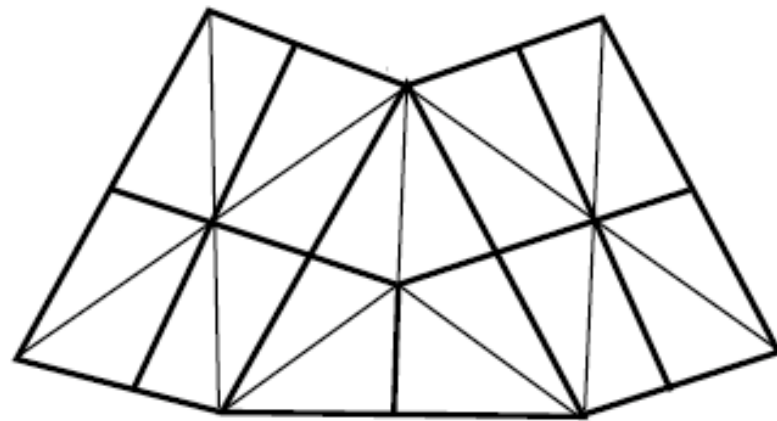
(e) level 7



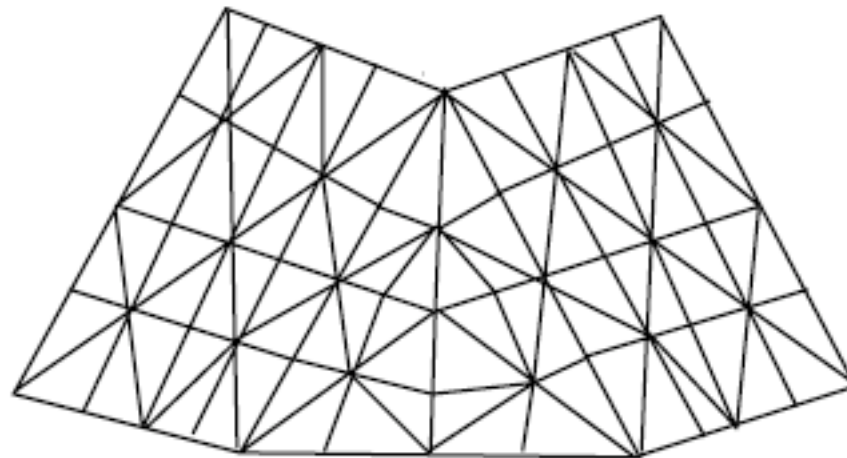
(f) level 9

Variable Resolution Mesh

- Underlying Semi-Regular Structure
 - Tri-quad Base Mesh

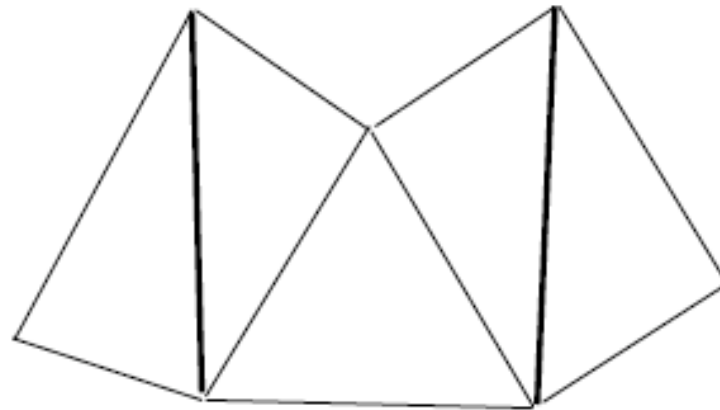


- 4-8 Subdivision

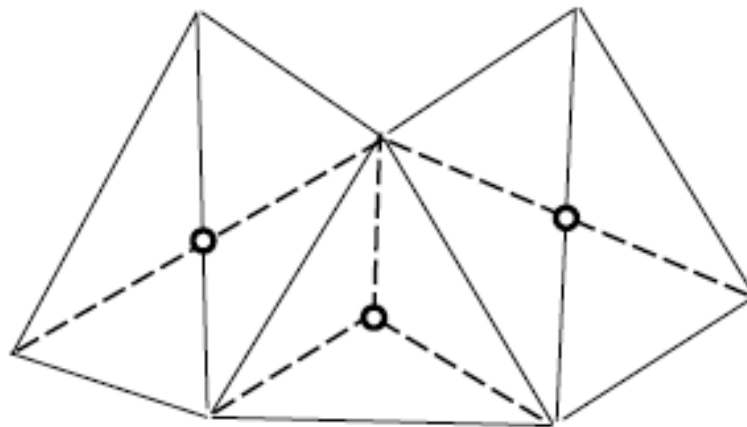


Building the Base Mesh

1. Two-Face Clusters + Single Triangles

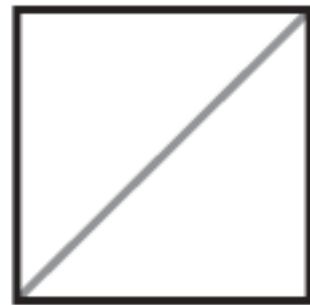


2. Barycenter Subdivision



4-8 Subdivision

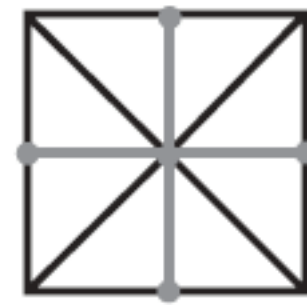
- Interleaved Binary Subdivision



i

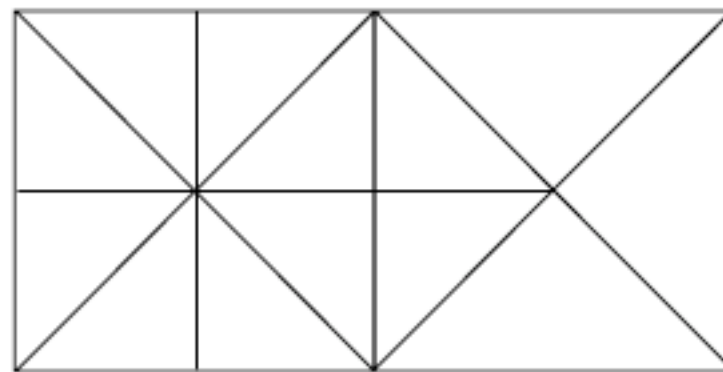


$i+1$

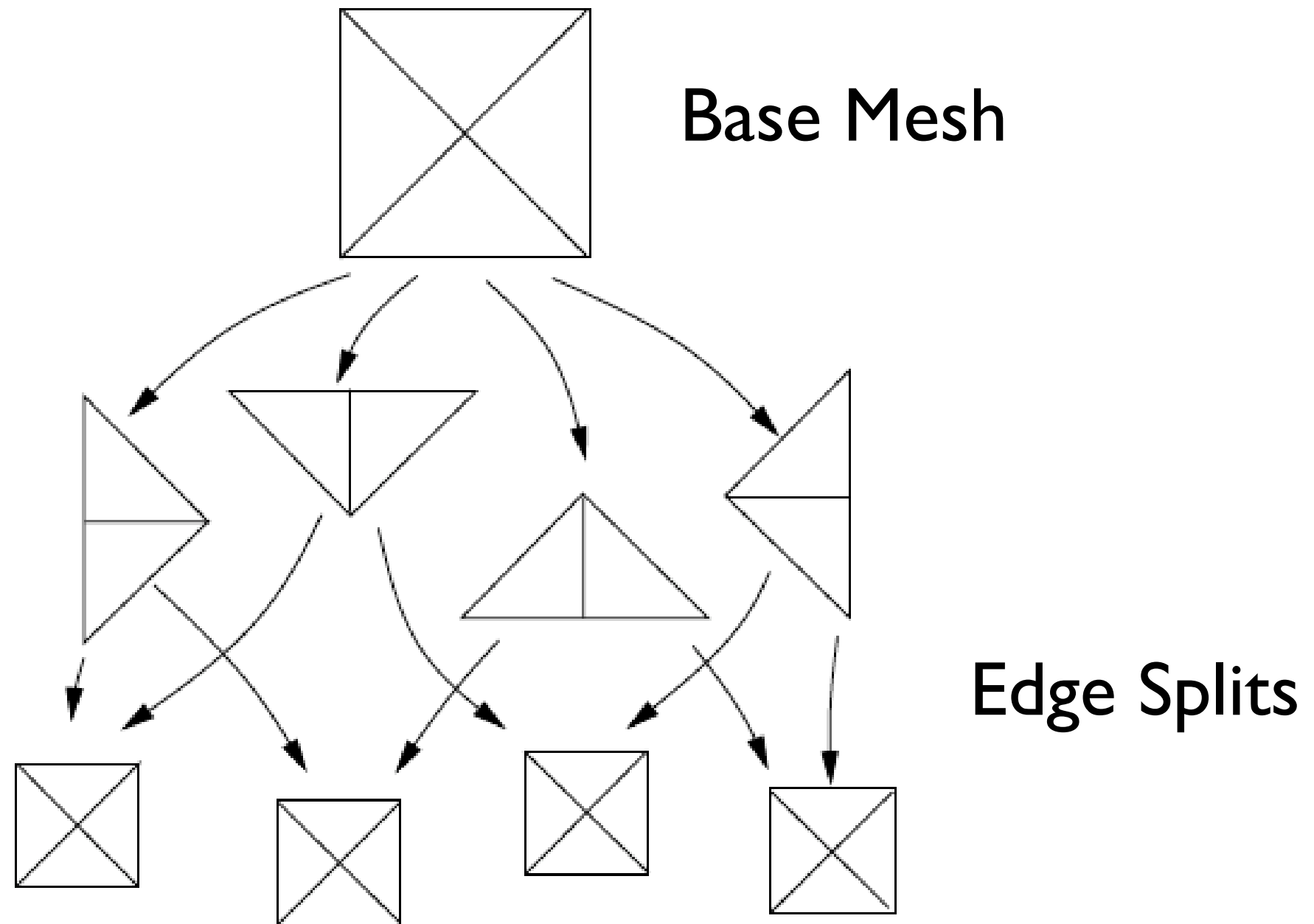


$i+2$

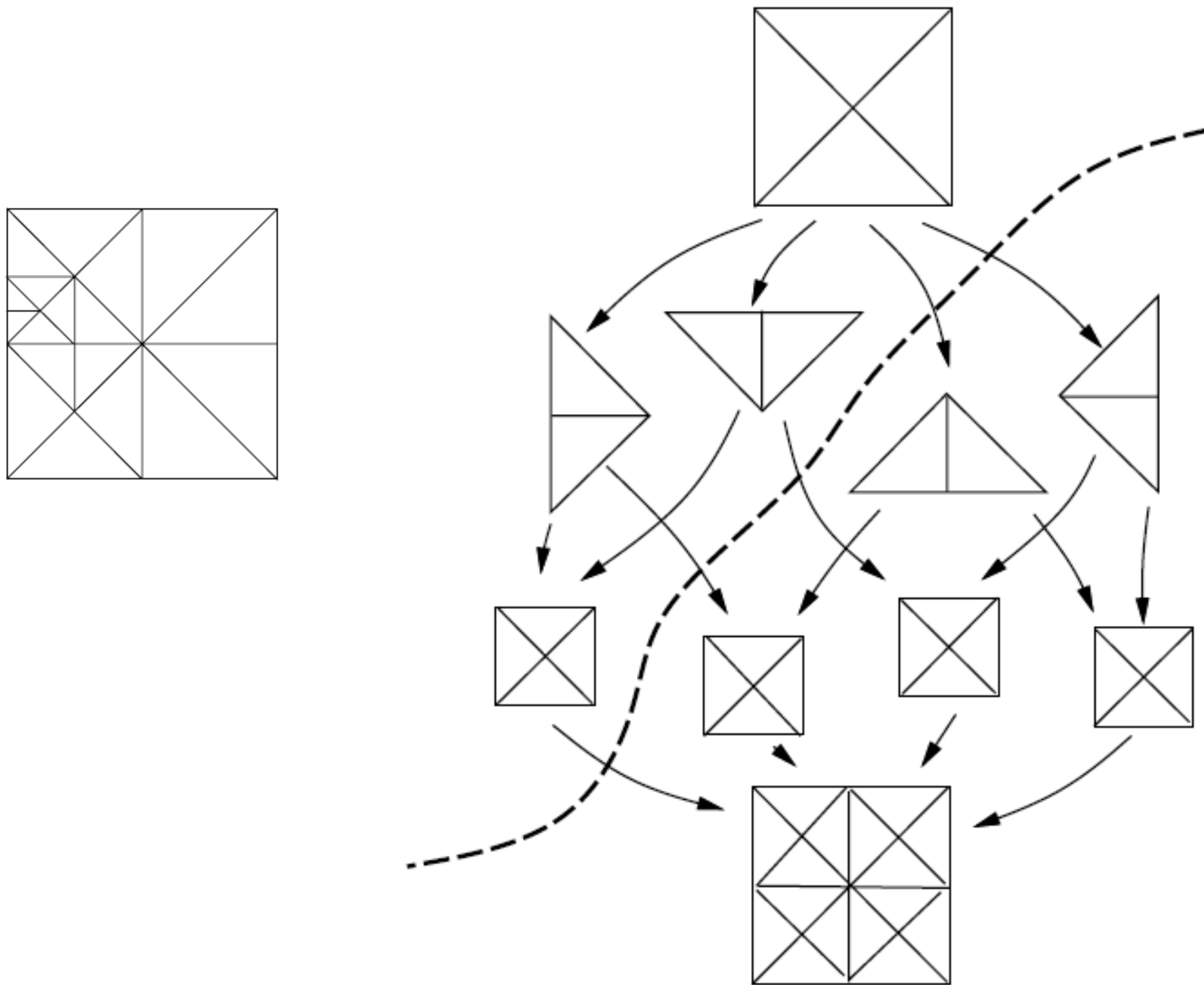
- Non-Uniform Refinement



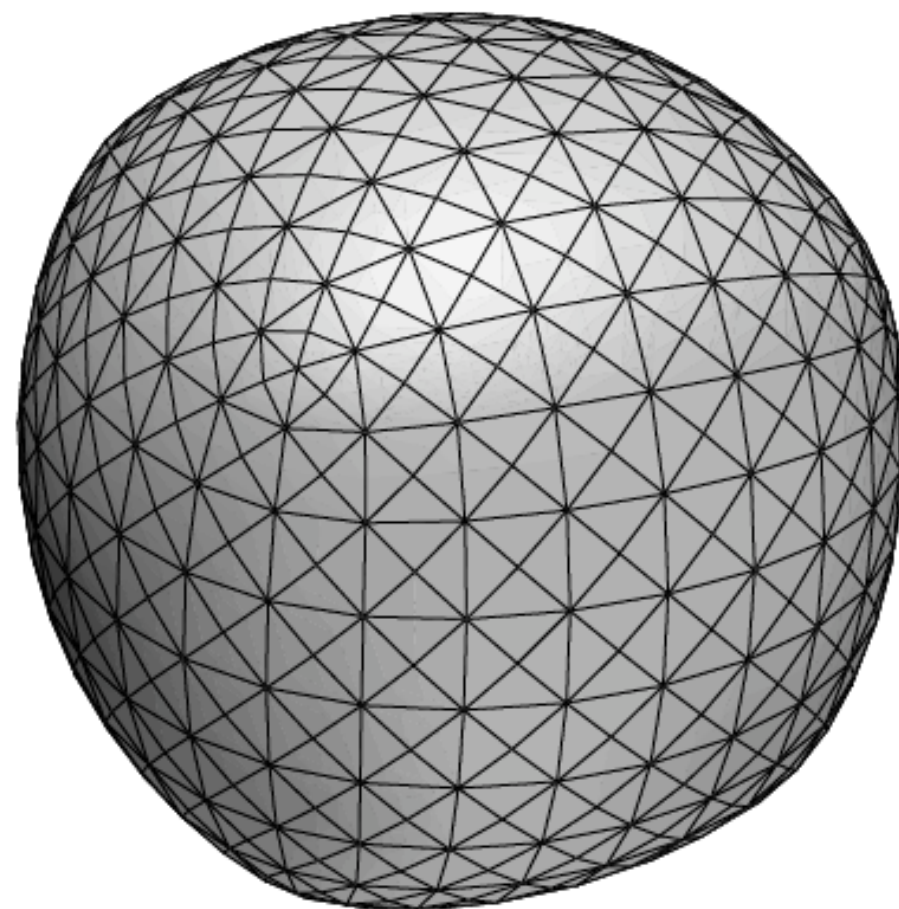
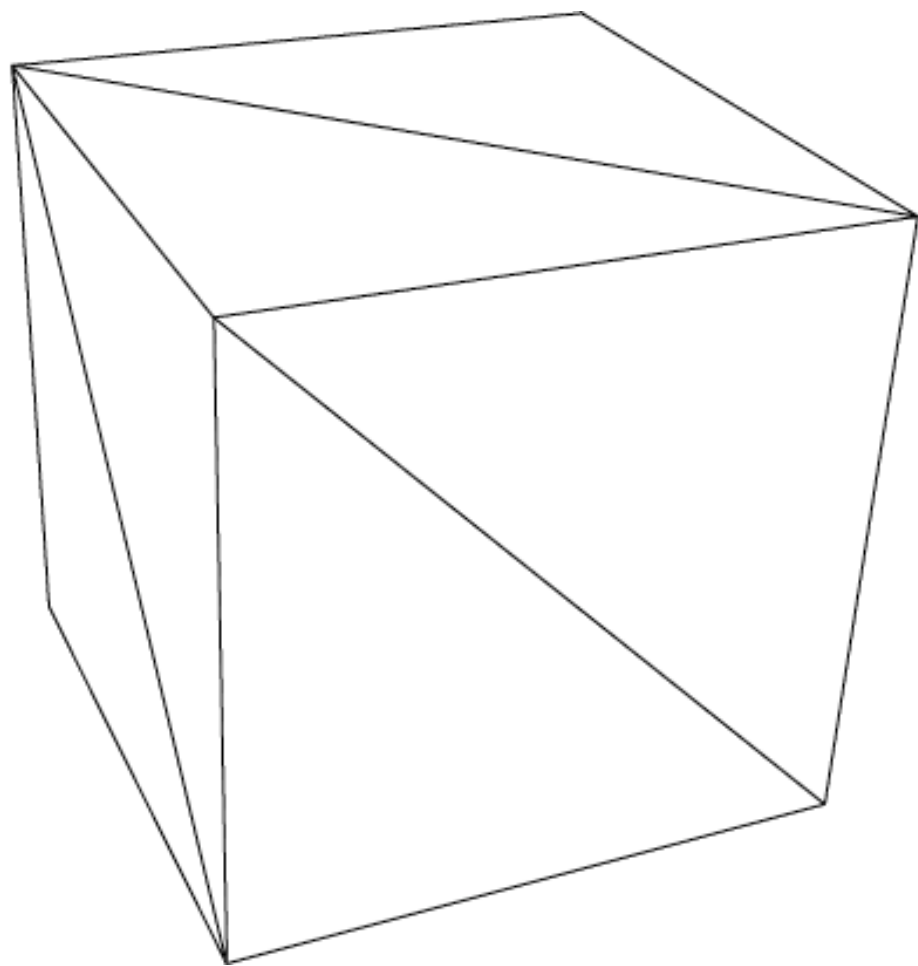
Binary Multi-Triangulation



Adaptive Refinement

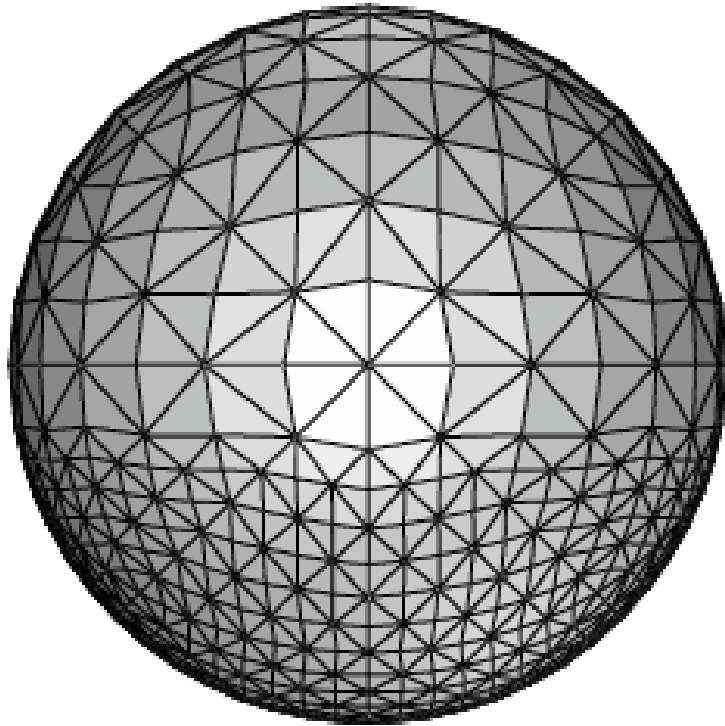


Example 1: Uniform

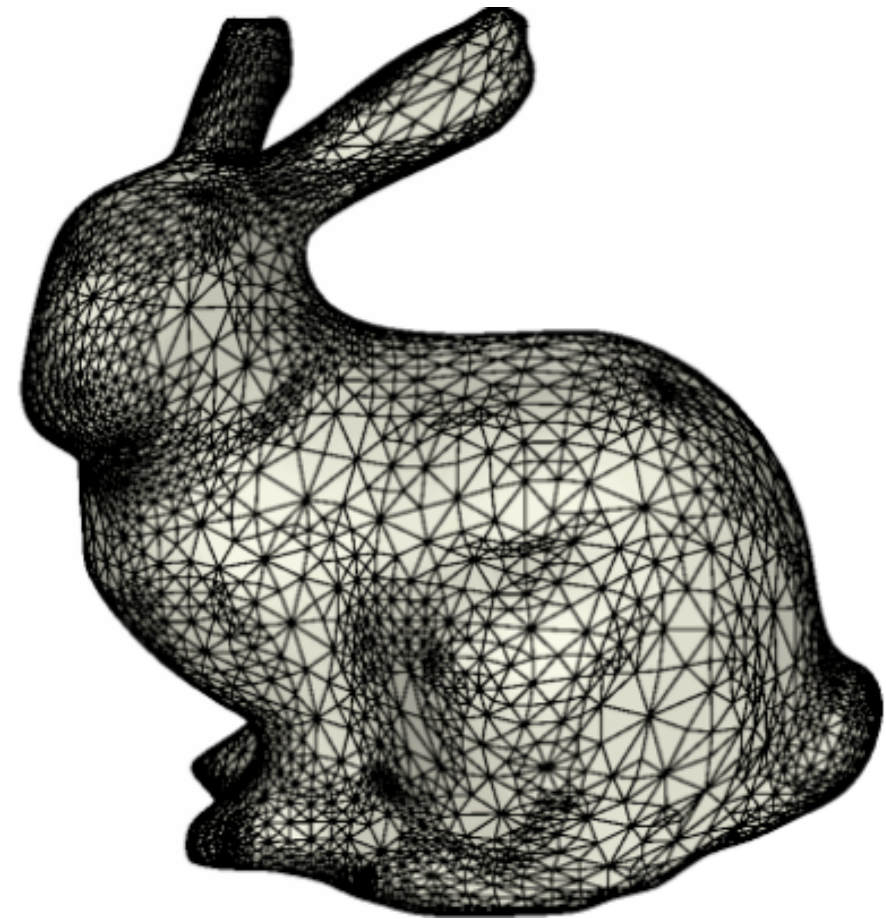


Example 2: Adaptive

- Application-Dependent Criteria



Spatial Selection



Curvature

Conclusions

- **Simplicial Multiresolution**
 - **Powerful Mechanism for Adaptation**
- **First Part of the Solution for Surface Fitting**
 - **Simplification**
 - **Adaptive Refinement**
- **Second Part (Next)**
 - **Geodesic Parametrization**
 - **Bezier Approximation**

Adaptive Manifold Fitting (Part II)

Dimas Martínez Morera
UFAL

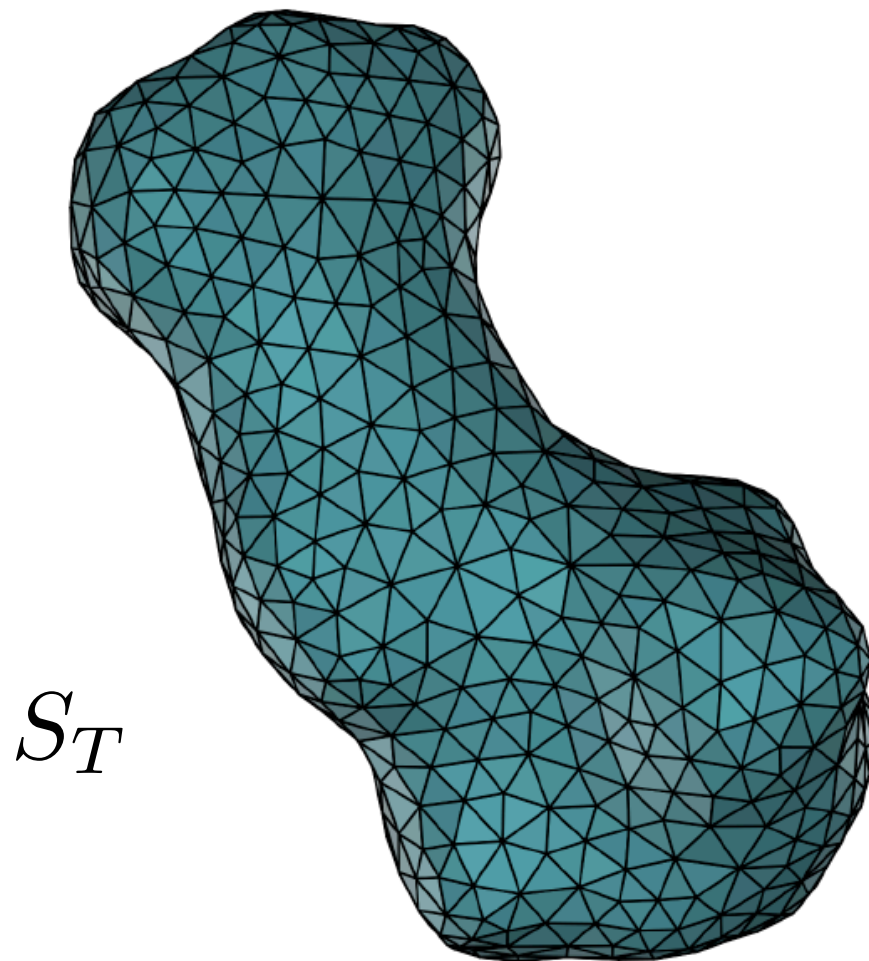
Outline

- The Surface Fitting Problem
- Adaptive Fitting
- Discrete Geodesics
- Conclusions

The Surface Fitting Problem

The Surface Fitting Problem

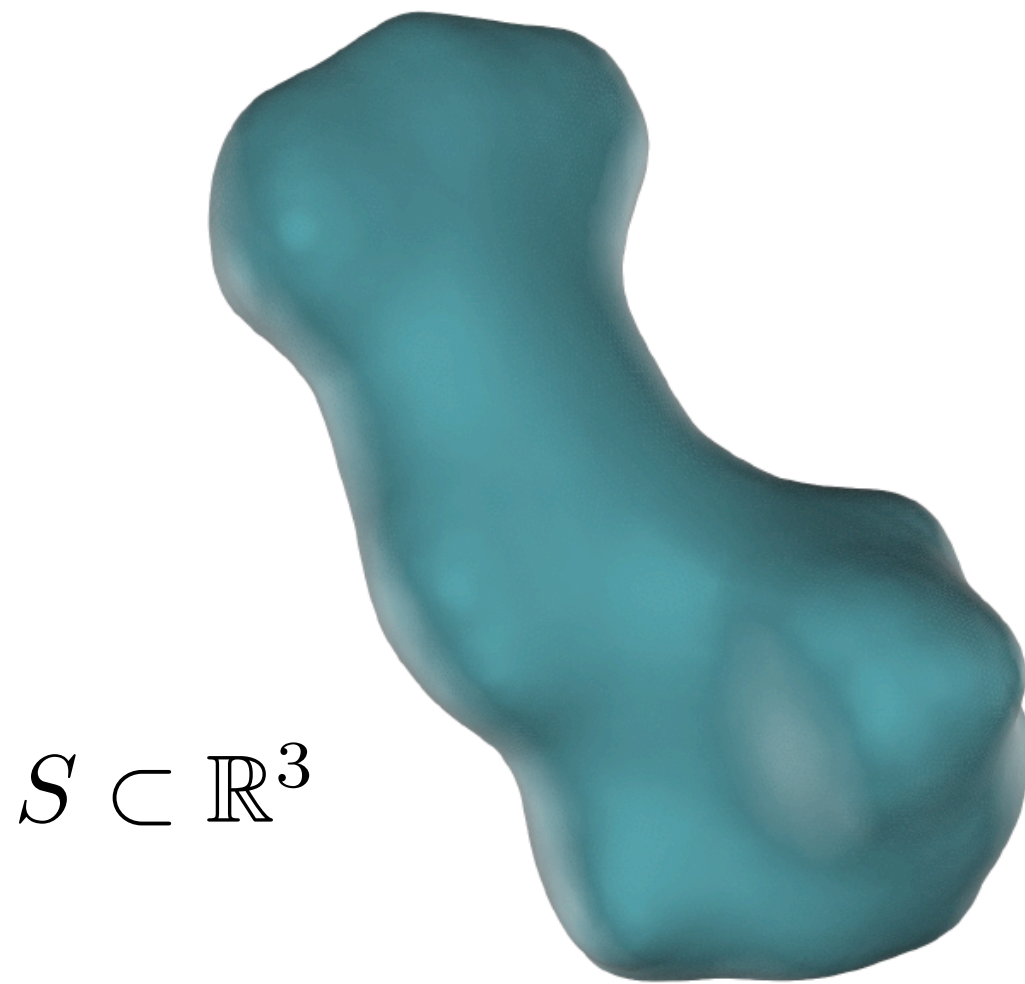
We are given a piecewise-linear surface, S_T , in \mathbb{R}^3 , with an empty boundary, a positive integer k , and a positive number ϵ , . . .



The Surface Fitting Problem

The Surface Fitting Problem

We want to find a C^k surface $S \subset \mathbb{R}^3$...



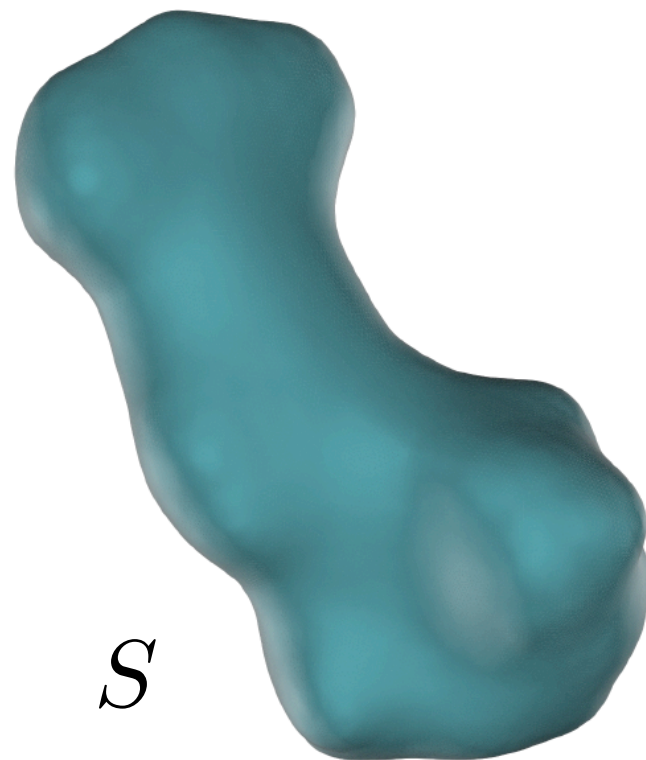
The Surface Fitting Problem

The Surface Fitting Problem

such that there exists a homeomorphism, $h : S \rightarrow |S_T|$, satisfying

$$\|h(v) - v\| \leq \epsilon,$$

for every vertex v of S_T .

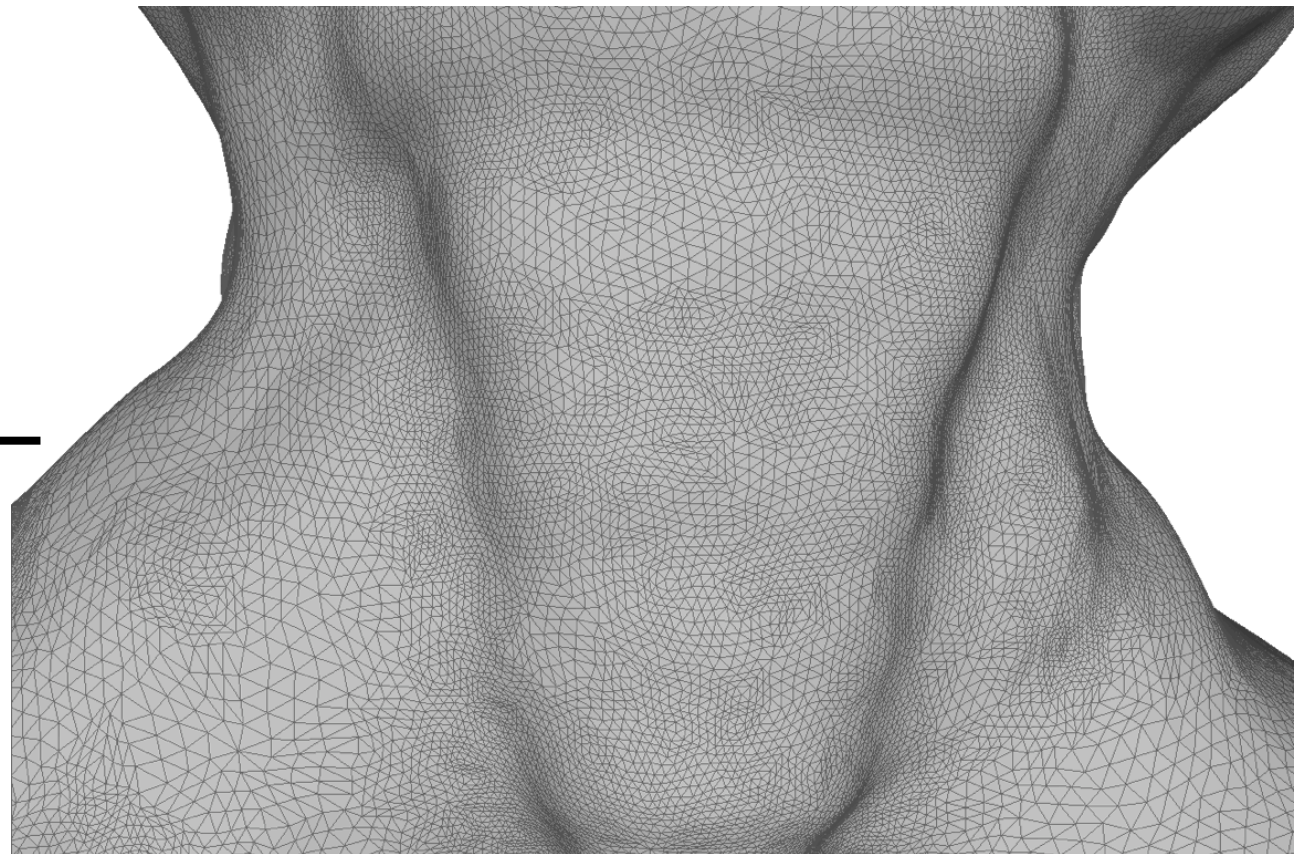
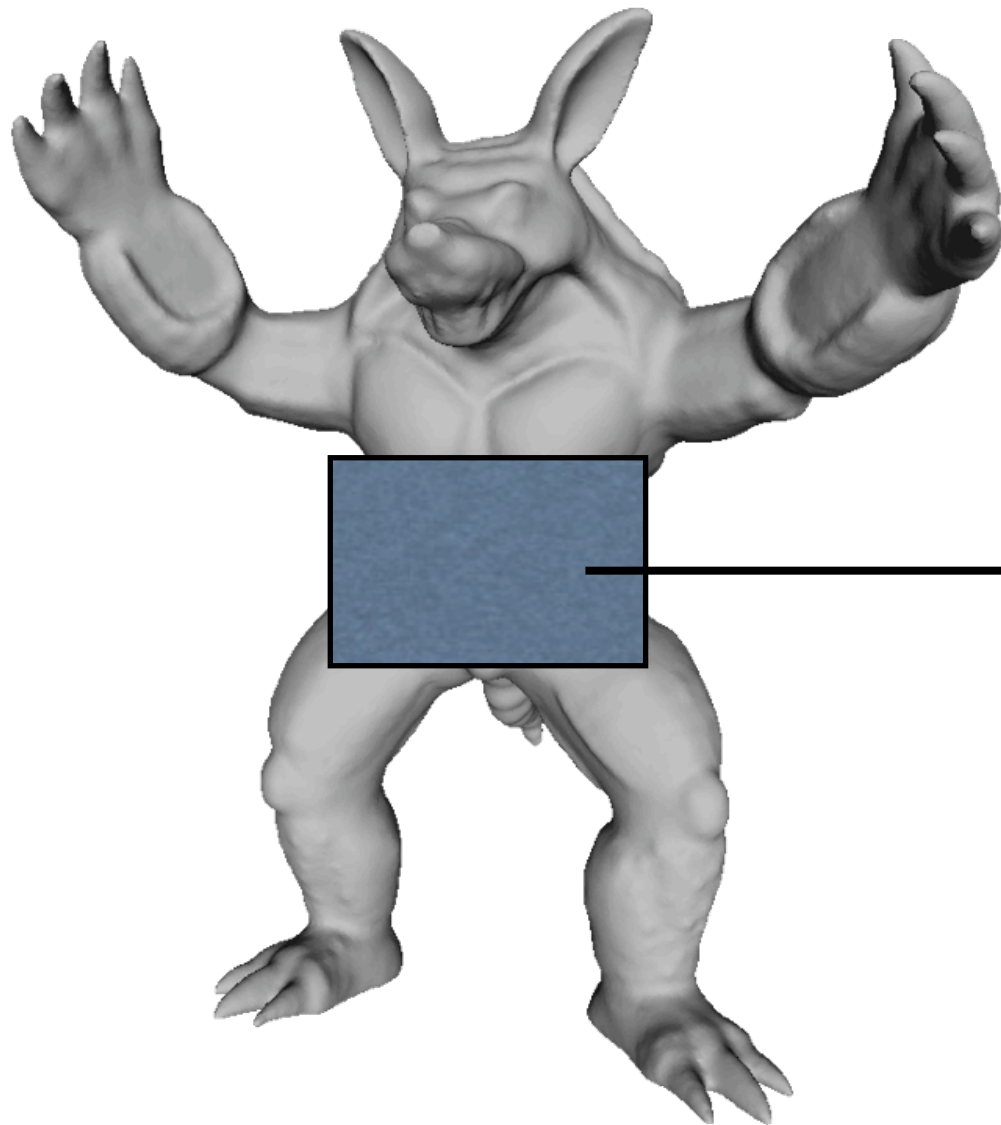


The Surface Fitting Problem

The Surface Fitting Problem

REMARK:

S_T is expected to be “very large” ($\sim 10^6$ vertices).



Adaptive Fitting

Adaptive Fitting

PIPELINE

Adaptive Fitting

S_T

PIPELINE

Adaptive Fitting

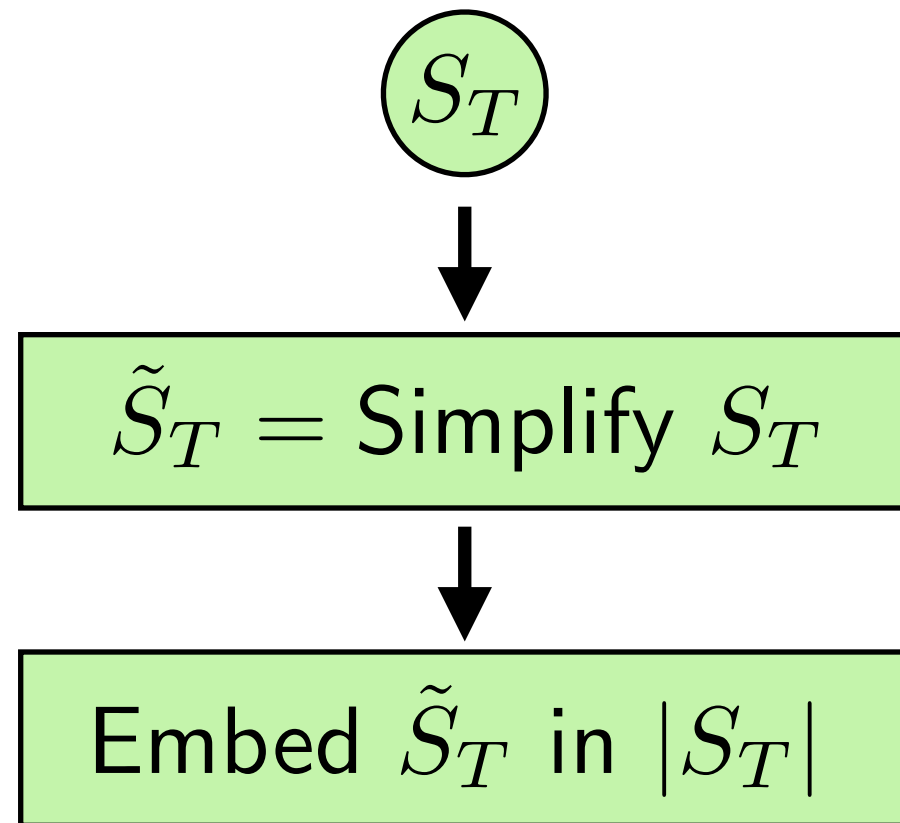
S_T



$\tilde{S}_T = \text{Simplify } S_T$

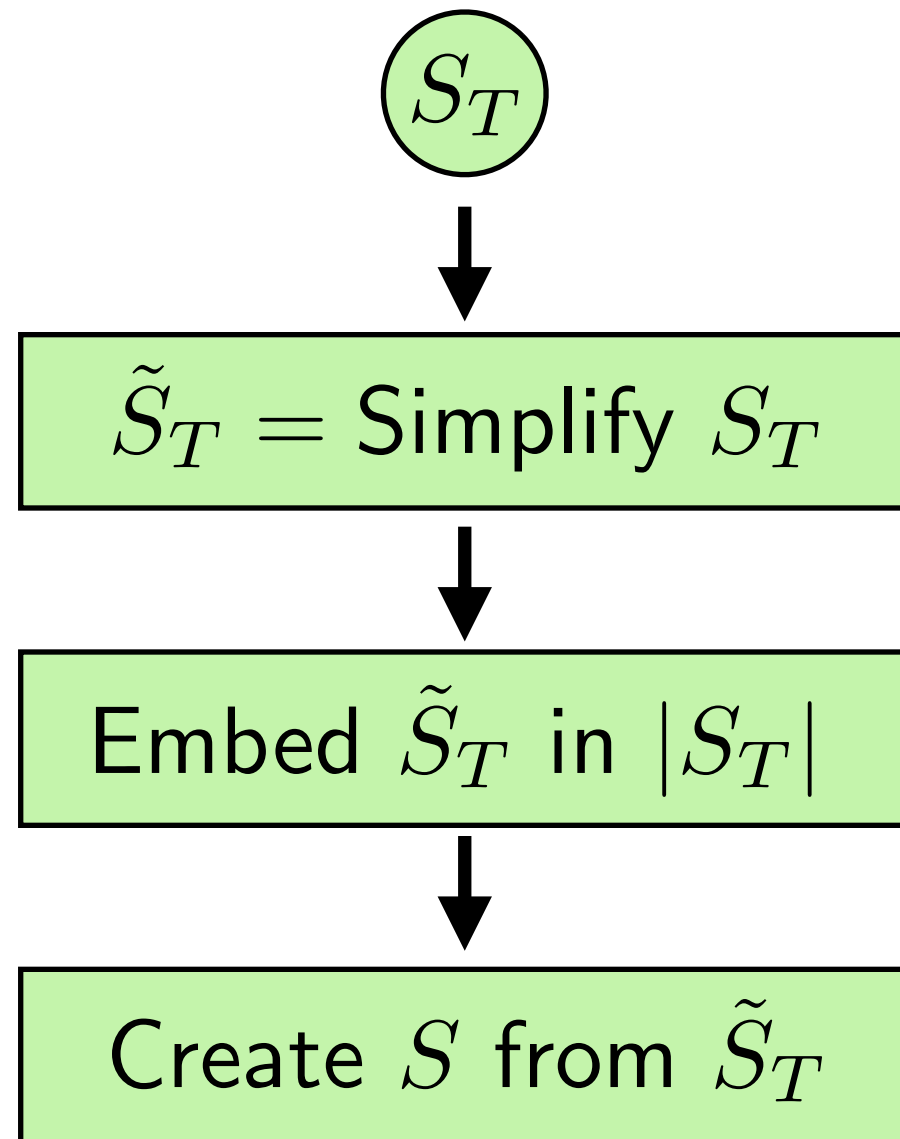
PIPELINE

Adaptive Fitting



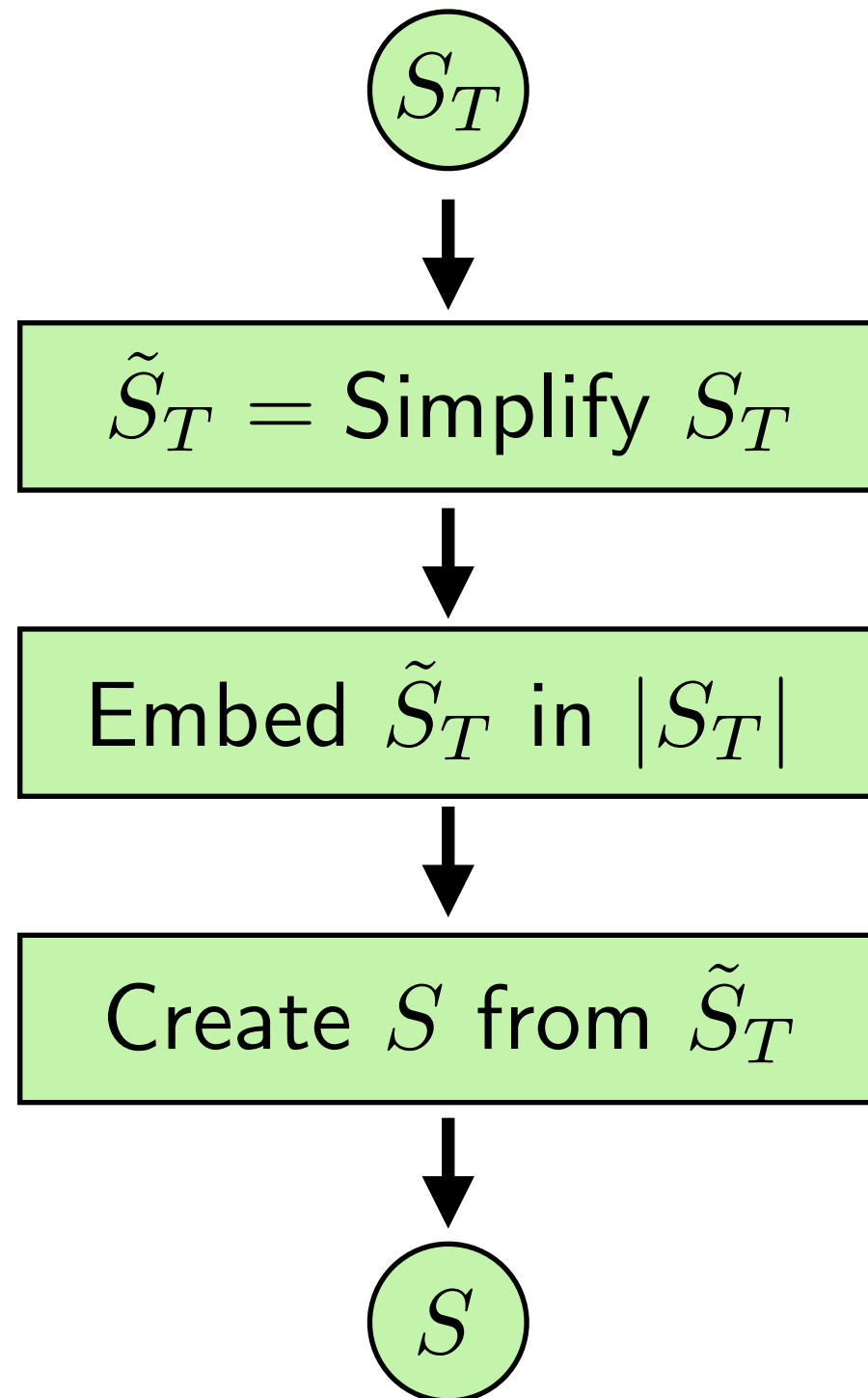
PIPELINE

Adaptive Fitting



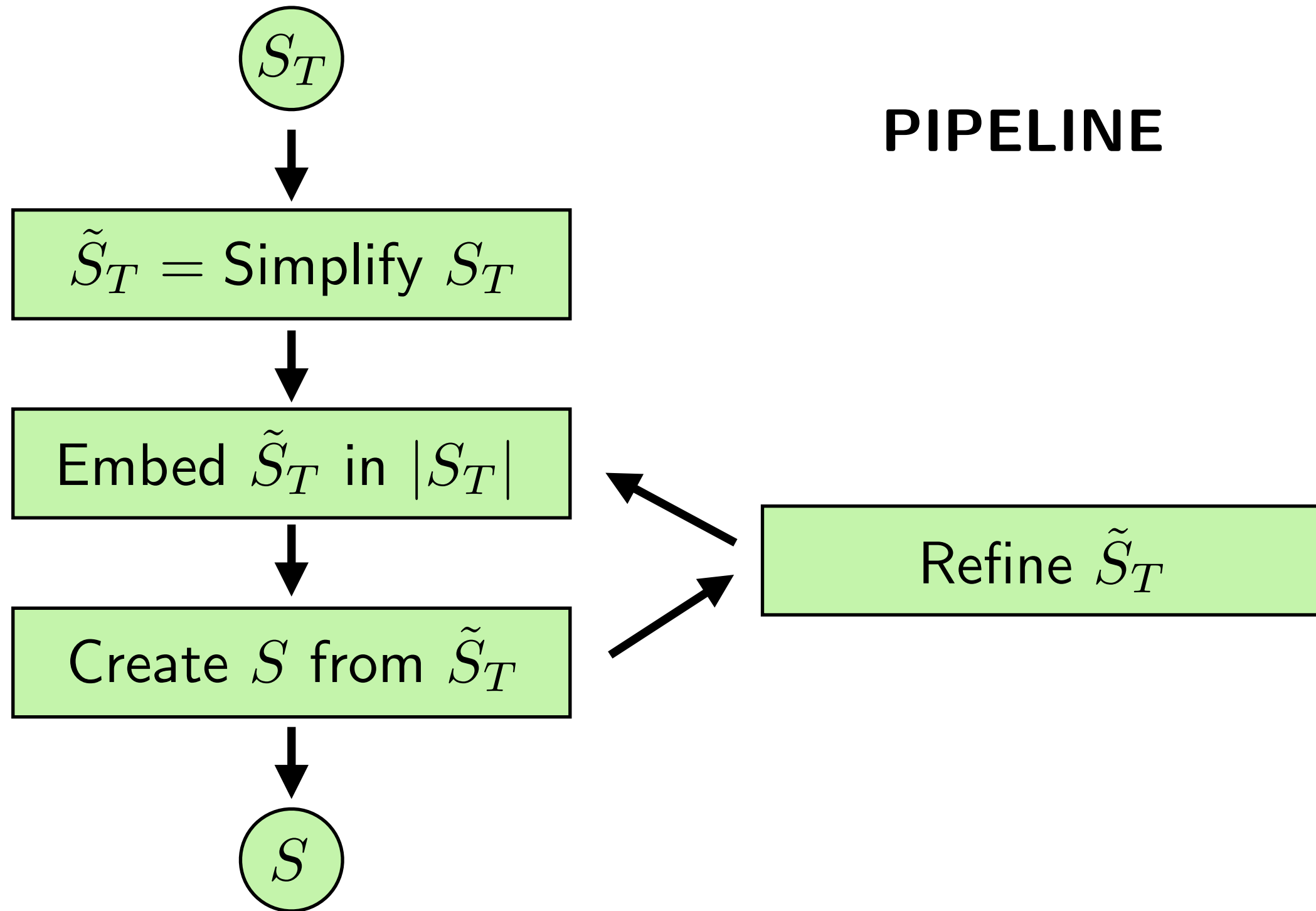
PIPELINE

Adaptive Fitting

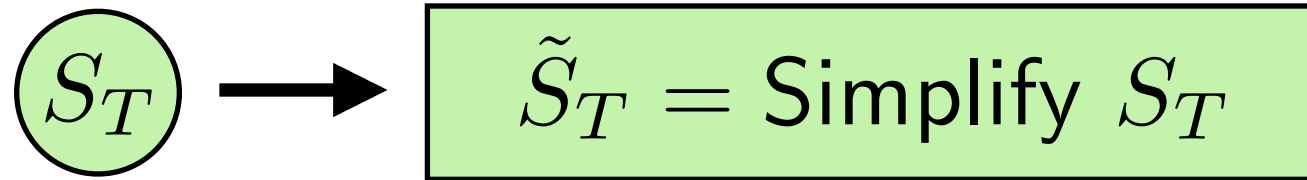


PIPELINE

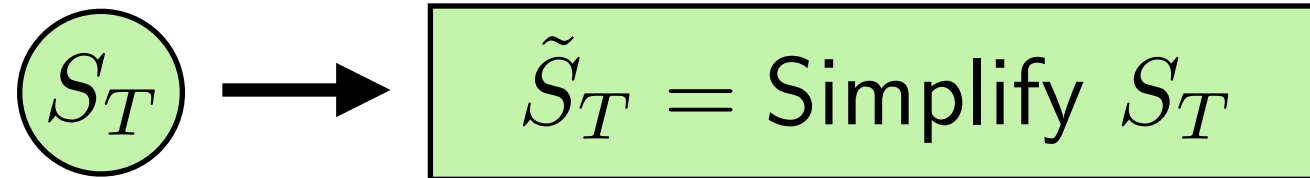
Adaptive Fitting



Adaptive Fitting



Adaptive Fitting

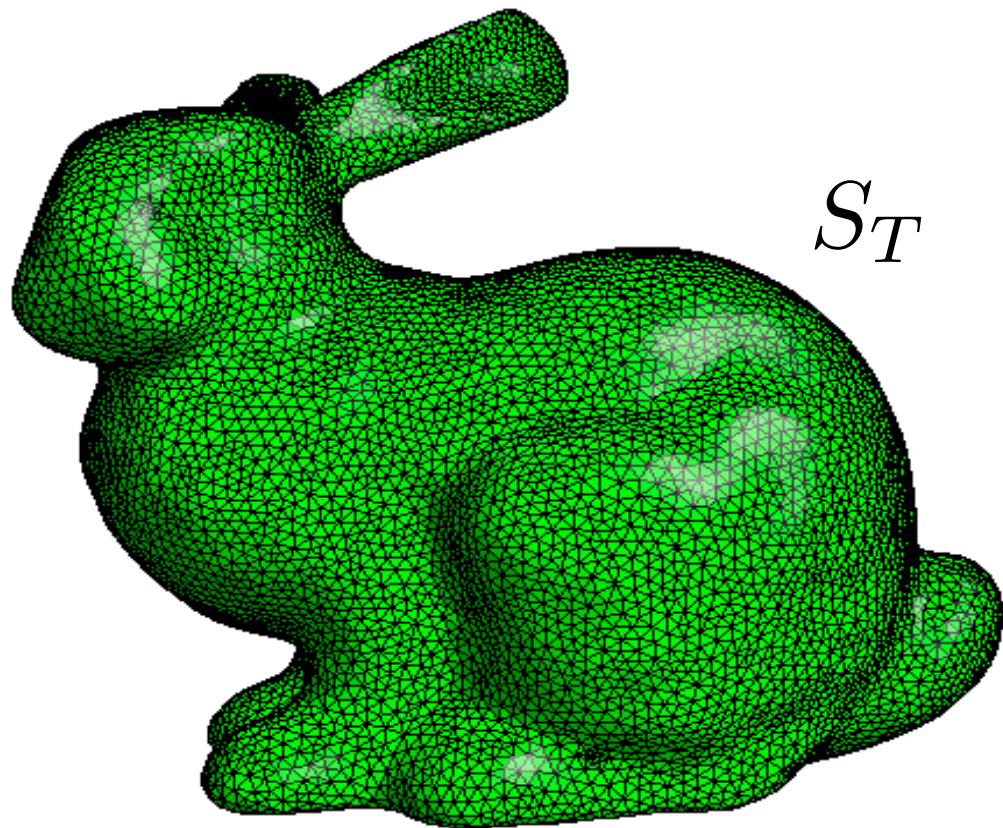


- Four-Face Clusters Algorithm

Adaptive Fitting

$$S_T \rightarrow \tilde{S}_T = \text{Simplify } S_T$$

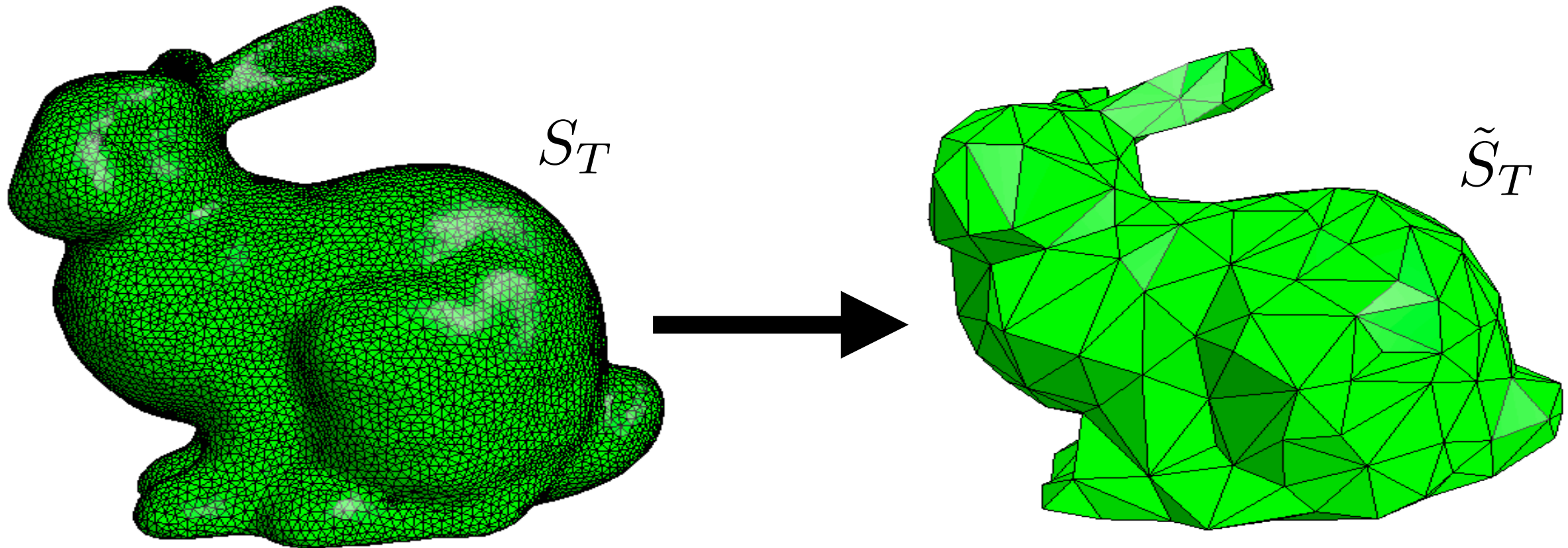
- Four-Face Clusters Algorithm



Adaptive Fitting

$$\textcircled{S_T} \longrightarrow \boxed{\tilde{S}_T = \text{Simplify } S_T}$$

- Four-Face Clusters Algorithm



Adaptive Fitting

Adaptive Fitting

Embed \tilde{S}_T in $|S_T|$

Adaptive Fitting

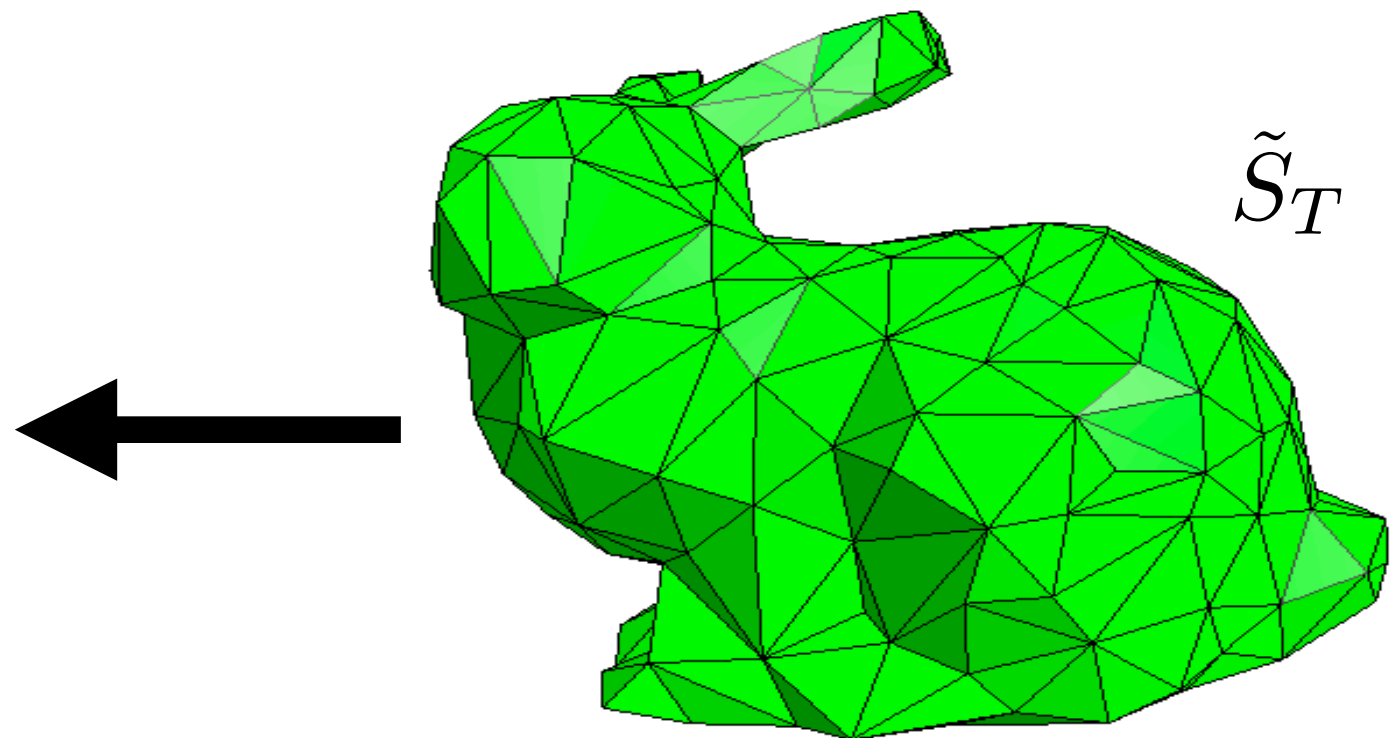
Embed \tilde{S}_T in $|S_T|$

- Each edge of \tilde{S}_T is embedded in $|S_T|$ as a “geodesic”.

Adaptive Fitting

Embed \tilde{S}_T in $|S_T|$

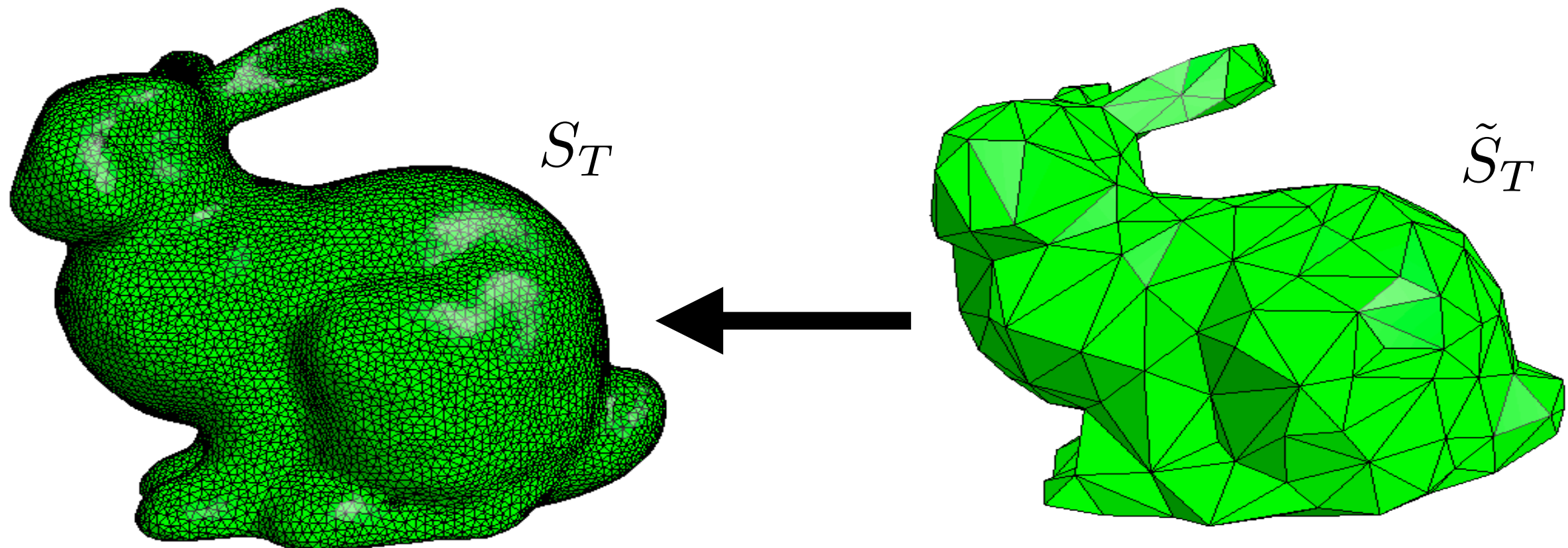
- Each edge of \tilde{S}_T is embedded in $|S_T|$ as a “geodesic”.



Adaptive Fitting

Embed \tilde{S}_T in $|S_T|$

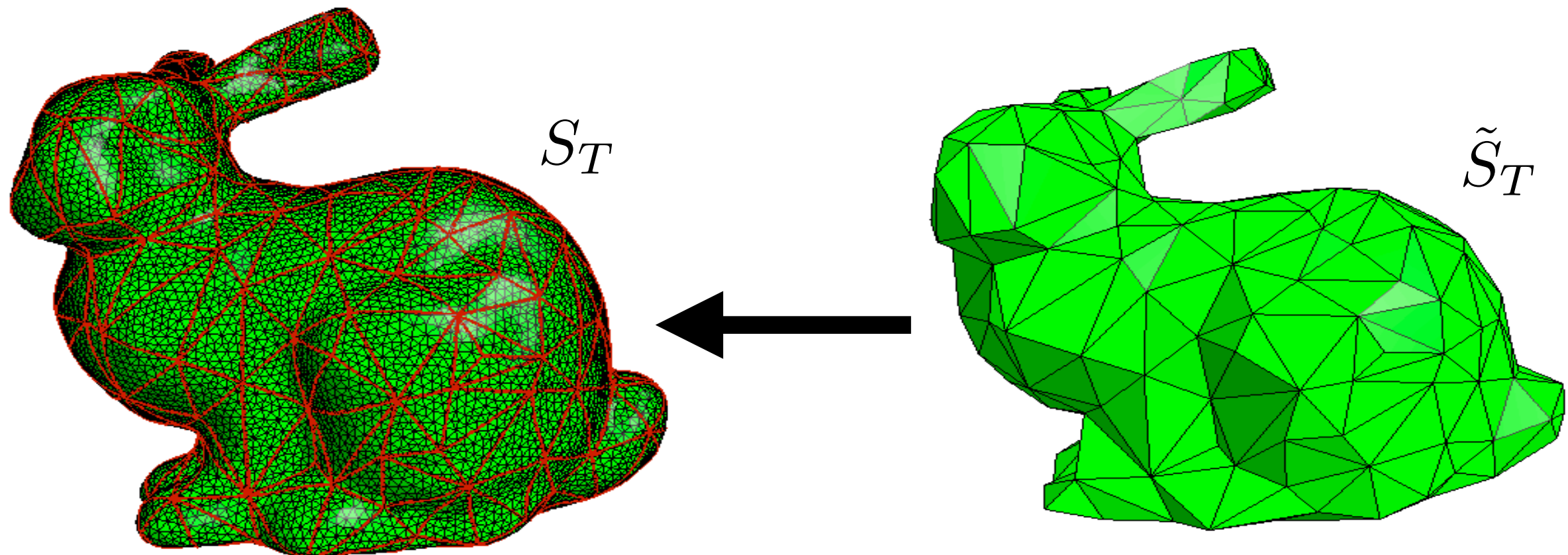
- Each edge of \tilde{S}_T is embedded in $|S_T|$ as a “geodesic”.



Adaptive Fitting

Embed \tilde{S}_T in $|S_T|$

- Each edge of \tilde{S}_T is embedded in $|S_T|$ as a “geodesic”.

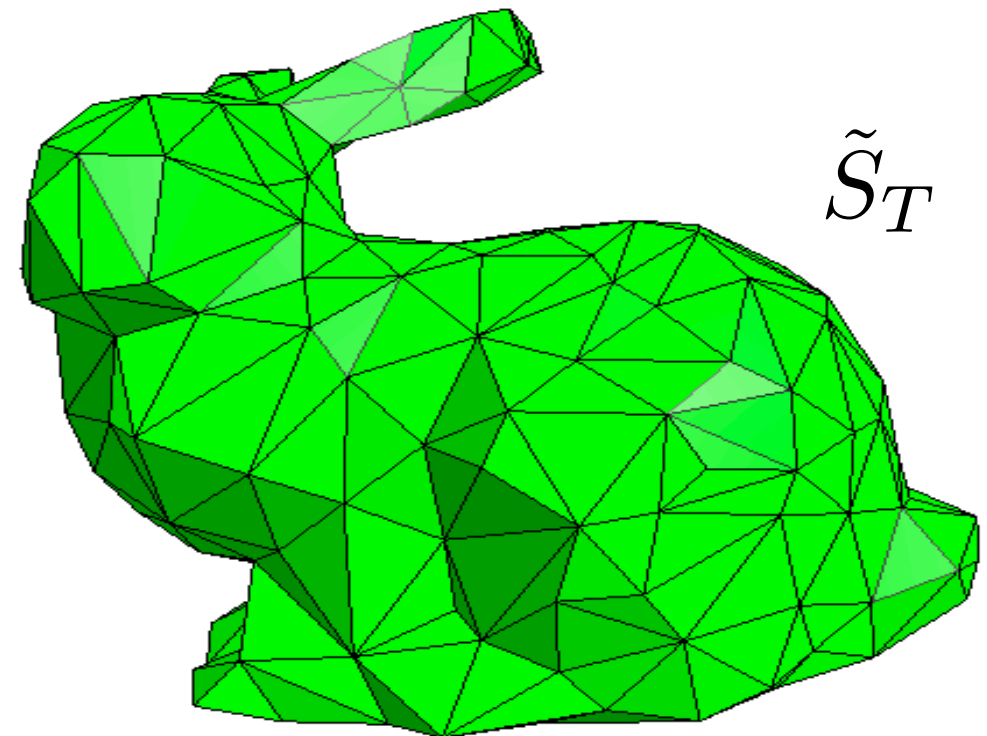
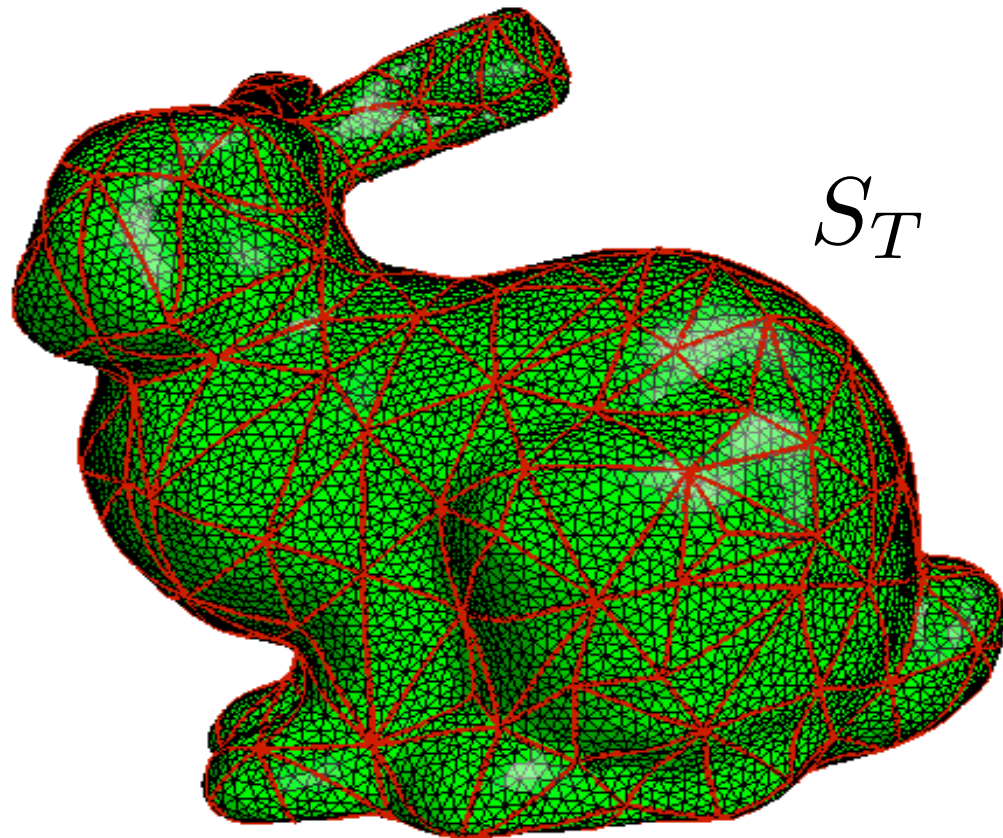


Adaptive Fitting

Adaptive Fitting

REMARK:

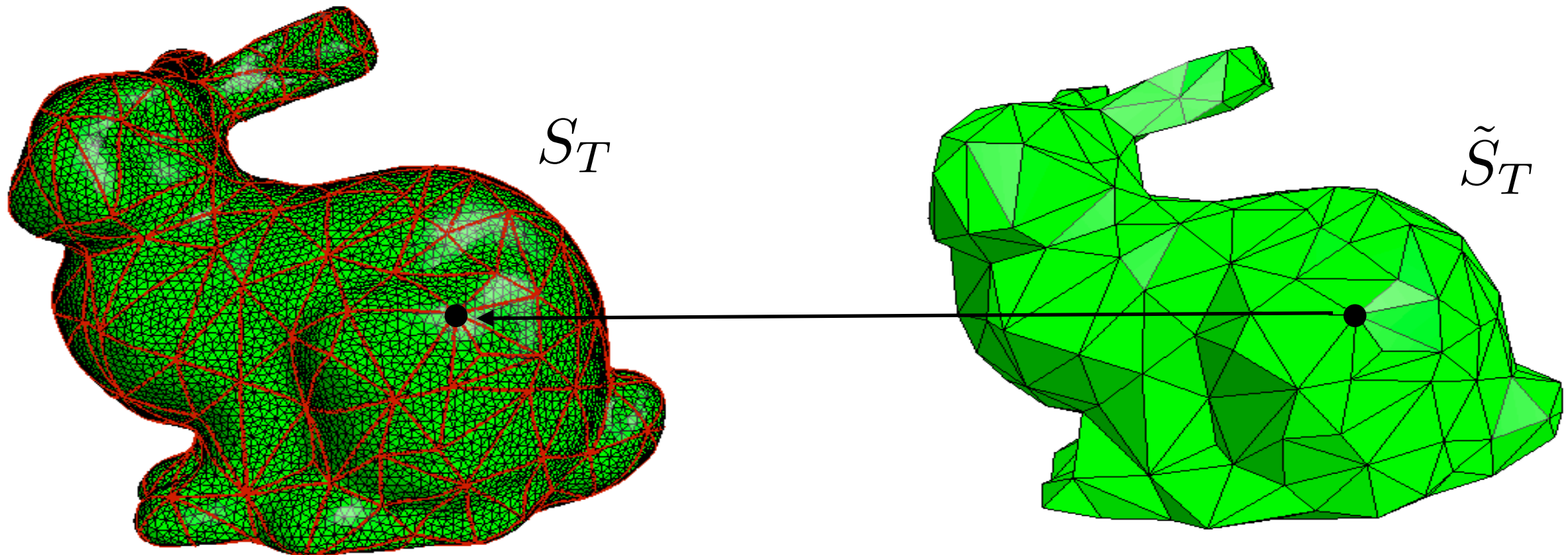
The vertices of \tilde{S}_T ARE vertices of S_T .



Adaptive Fitting

REMARK:

The vertices of \tilde{S}_T ARE vertices of S_T .



Adaptive Fitting

Adaptive Fitting

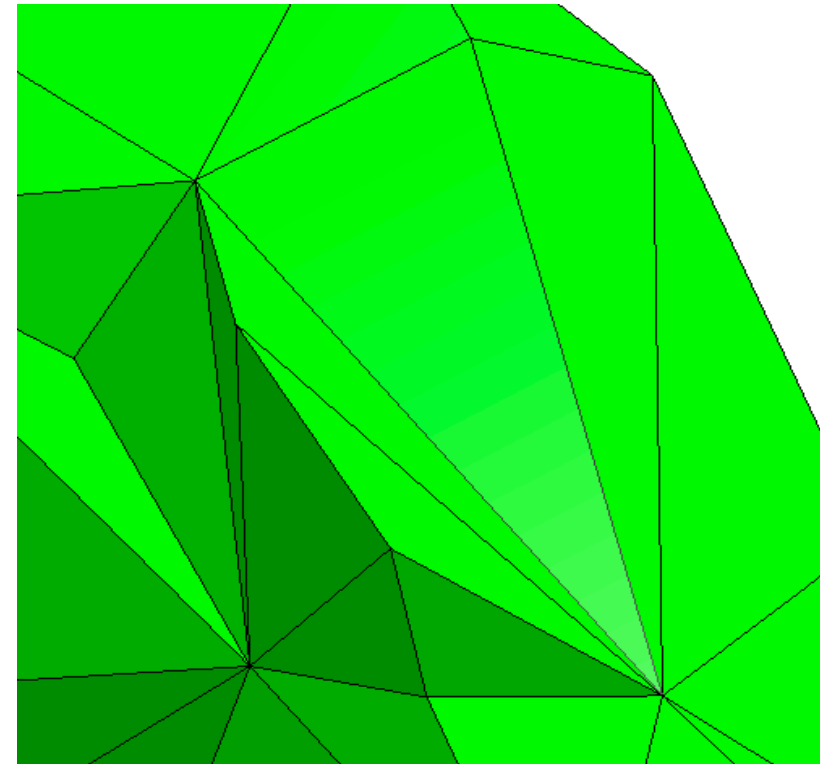
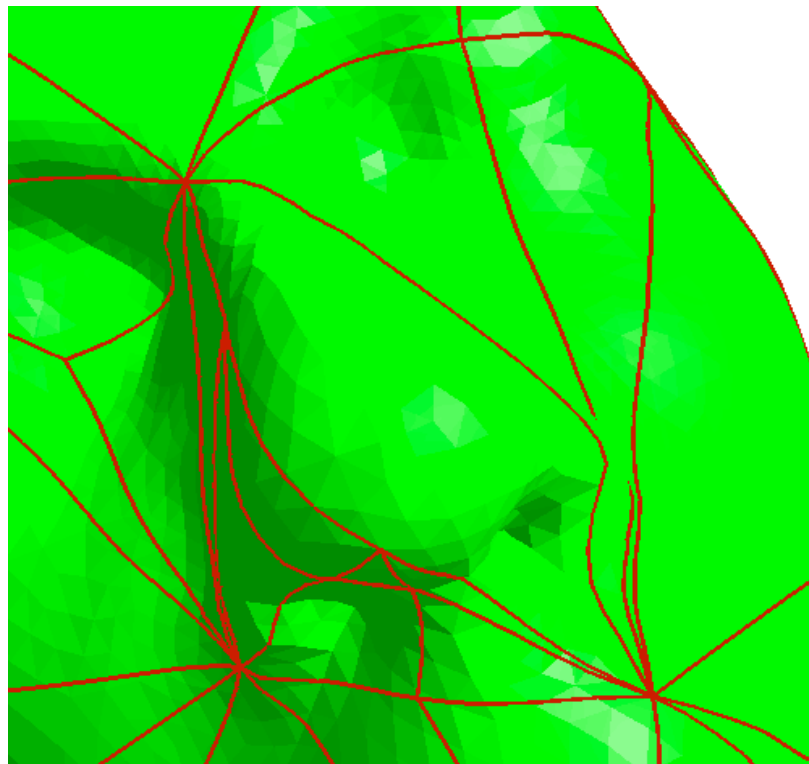
PROBLEM:

When defining geodesic triangles, we can violate the manifold property of the geodesic mesh, as illustrated by the figure below:

Adaptive Fitting

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Adaptive Fitting

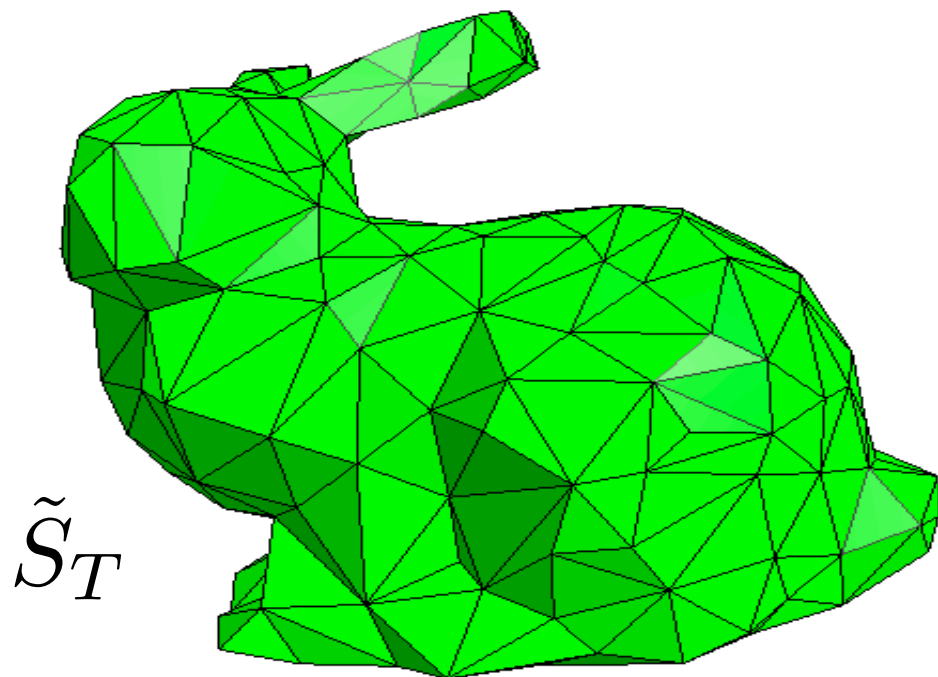
Adaptive Fitting

Create S from \tilde{S}_T

Adaptive Fitting

Create S from \tilde{S}_T

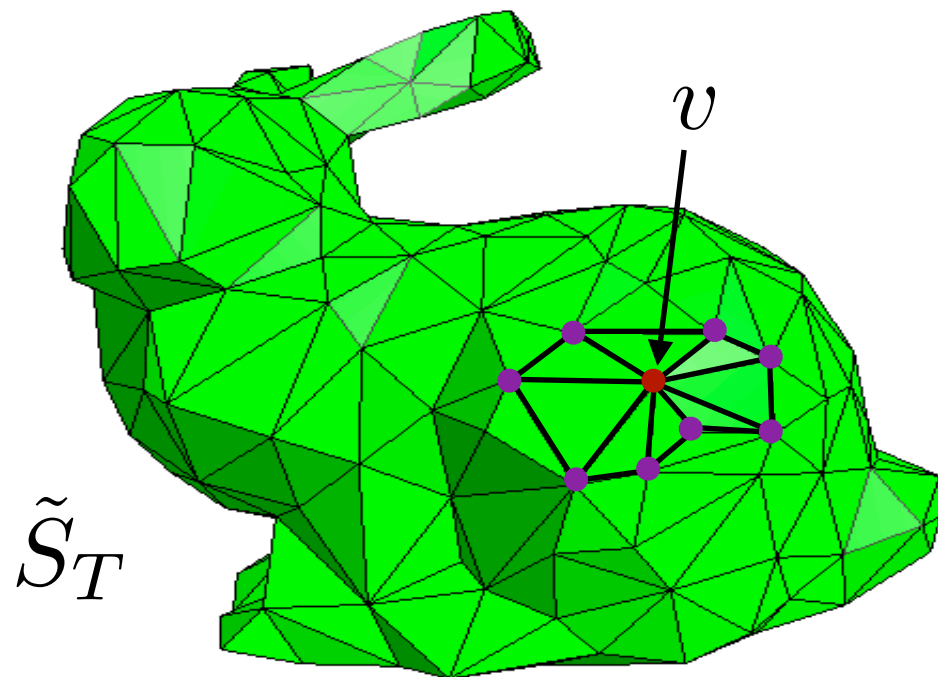
- For each vertex v of \tilde{S}_T , we consider the P-polygon, P_v , of v in \mathbb{R}^2 , and the standard triangulation, T_v , of the P-polygon P_v .



Adaptive Fitting

Create S from \tilde{S}_T

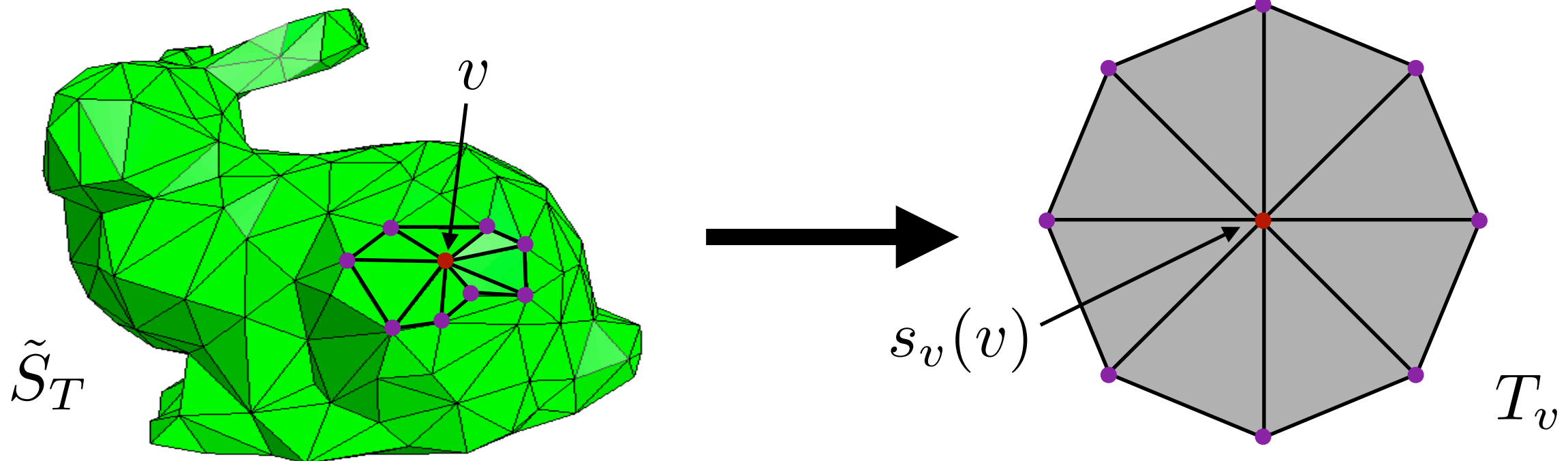
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Adaptive Fitting

Create S from \tilde{S}_T

- For each vertex v of \tilde{S}_T , we consider the P-polygon, P_v , of v in \mathbb{R}^2 , and the standard triangulation, T_v , of the P-polygon P_v .



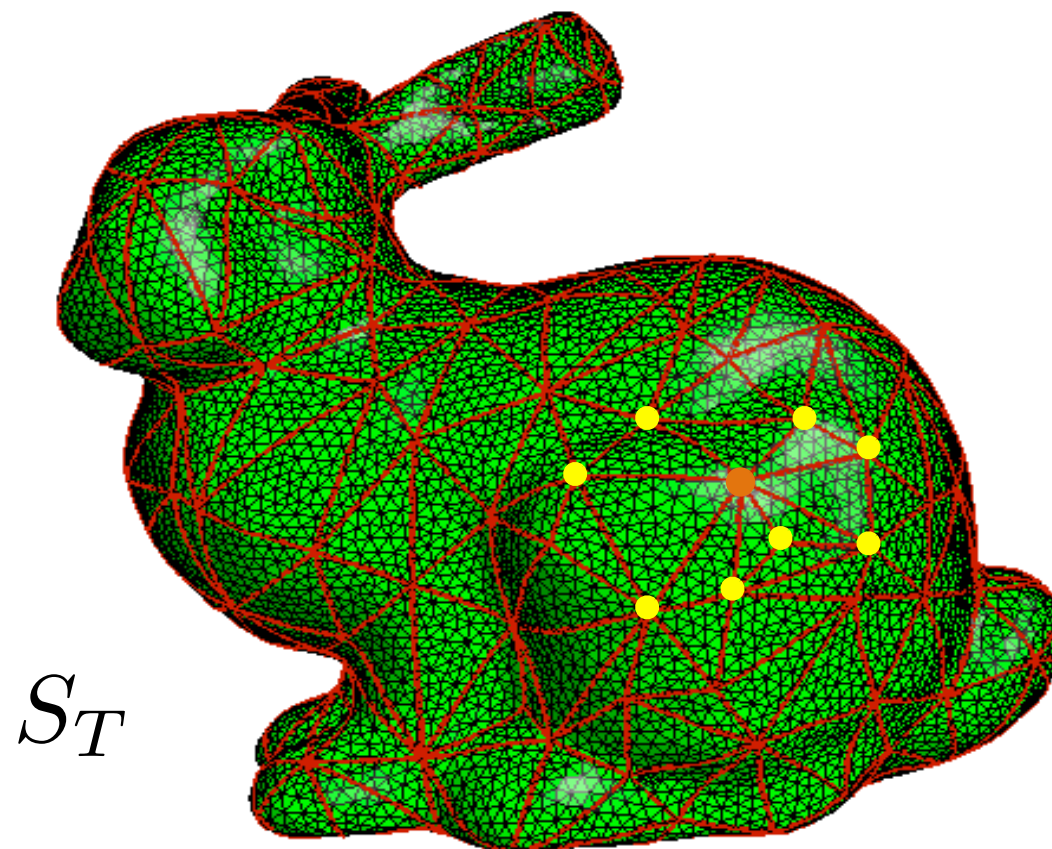
Adaptive Fitting

Create S from \tilde{S}_T

Adaptive Fitting

Create S from \tilde{S}_T

- Consider the embedding of the star, $st(v, \tilde{S}_T)$, of v in S_T .



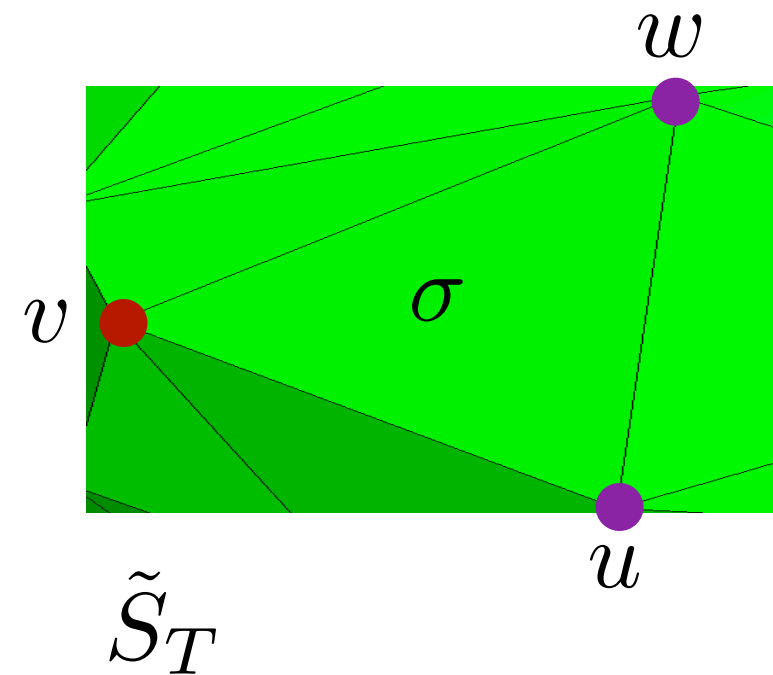
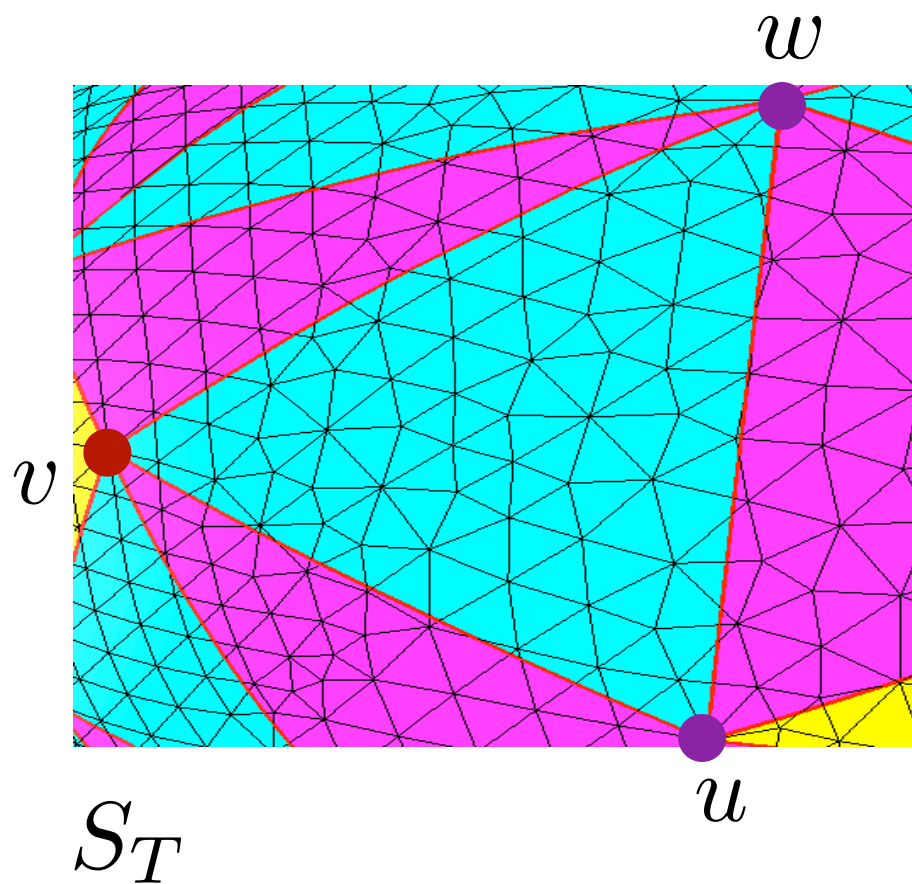
Adaptive Fitting

Create S from \tilde{S}_T

Adaptive Fitting

Create S from \tilde{S}_T

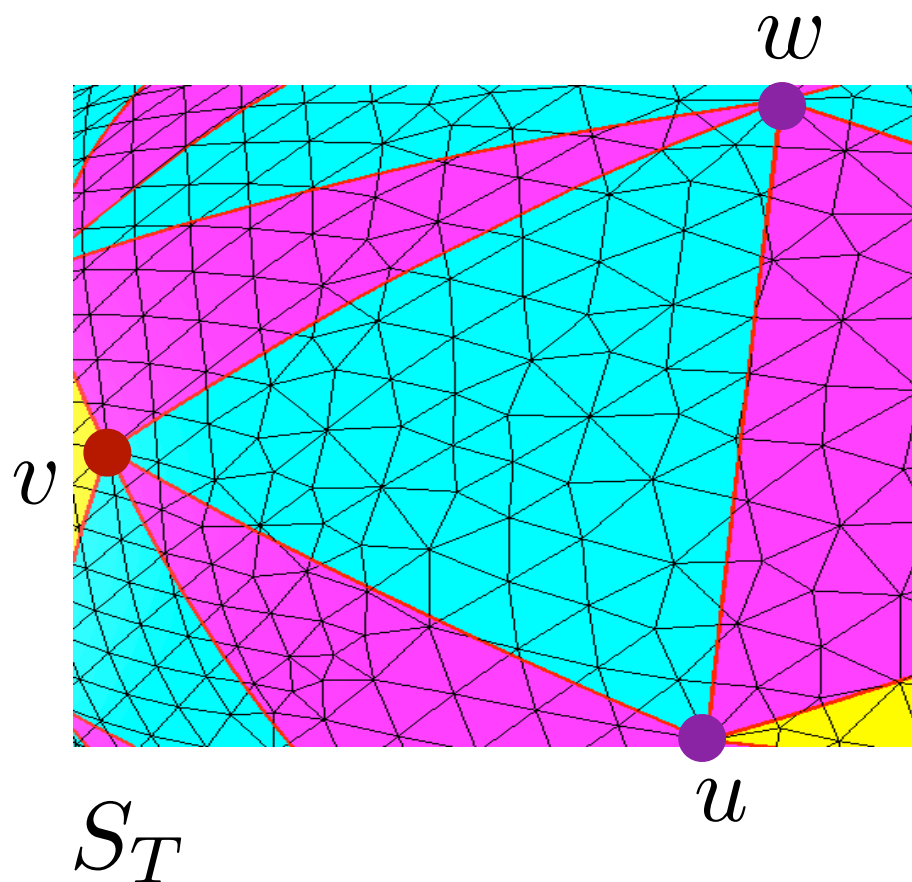
- Map the vertices of S_T bounded by the embedding of $st(v, \tilde{S}_T)$ to T_v .



Adaptive Fitting

Create S from \tilde{S}_T

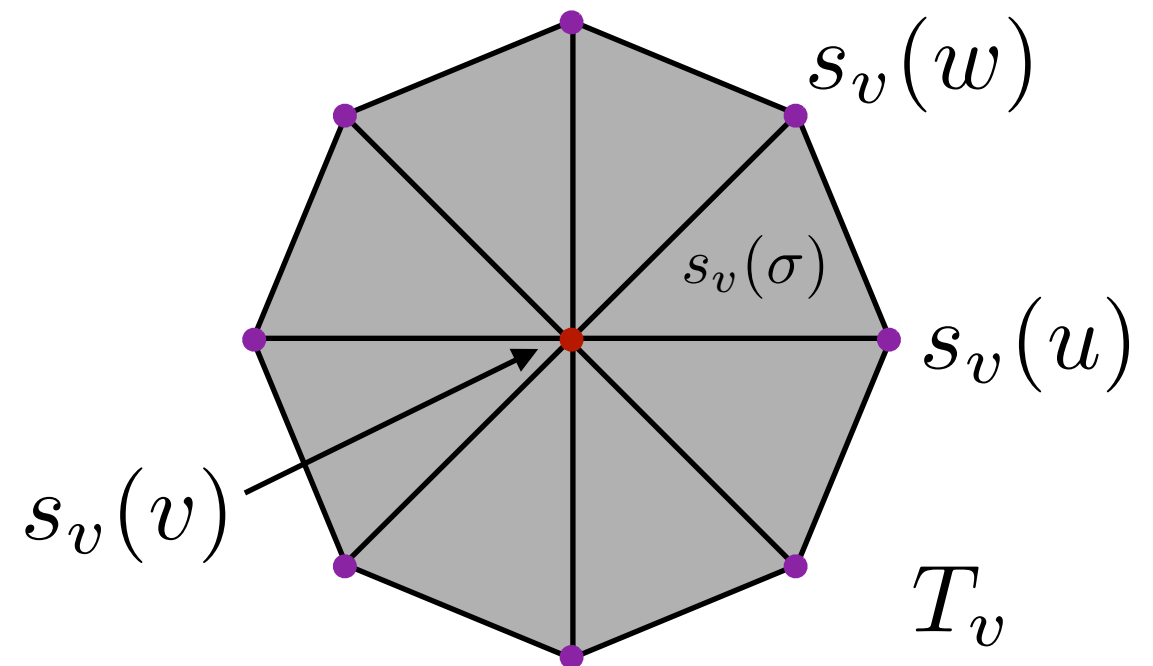
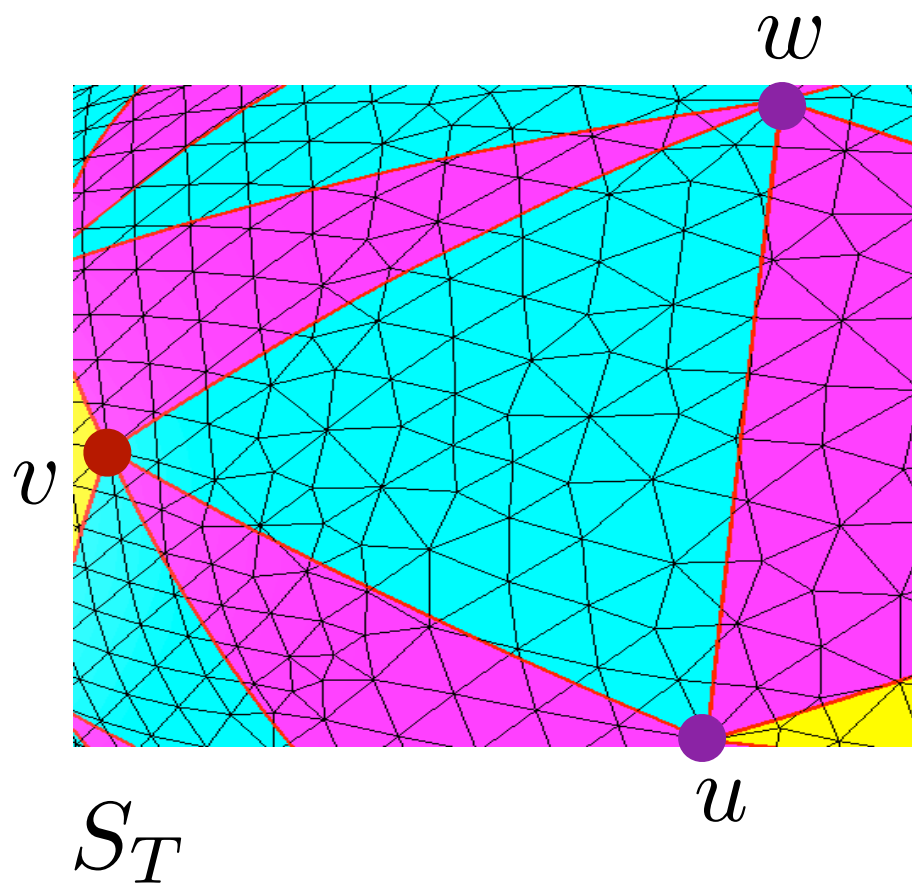
- Map the vertices of S_T bounded by the embedding of $st(v, \tilde{S}_T)$ to T_v .



Adaptive Fitting

Create S from \tilde{S}_T

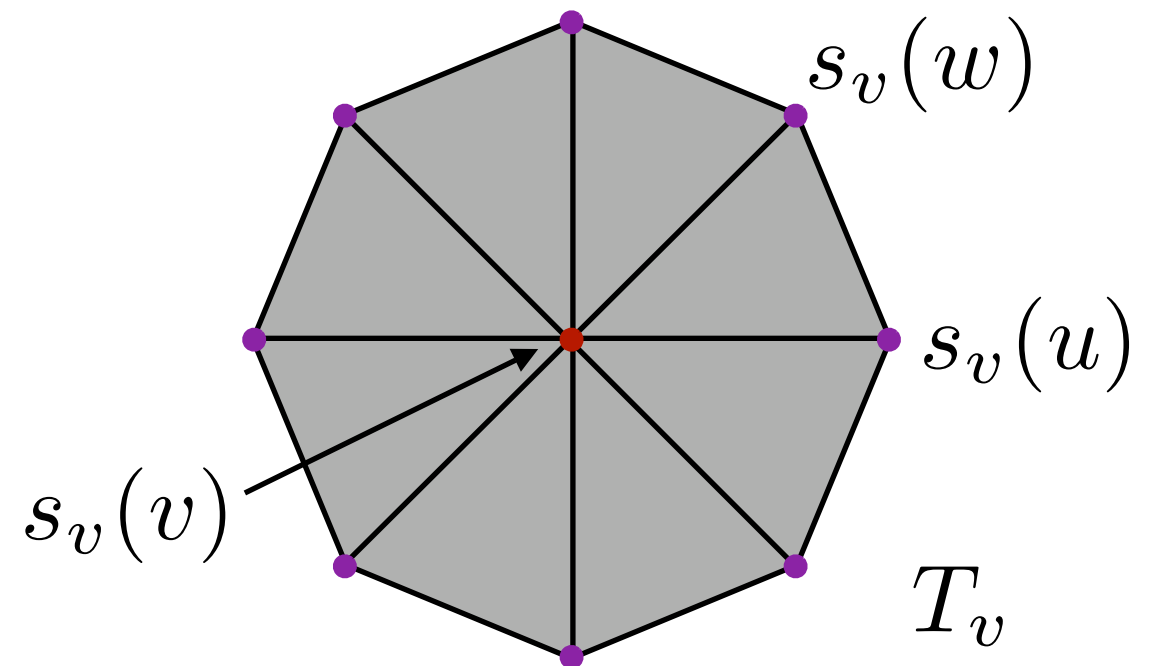
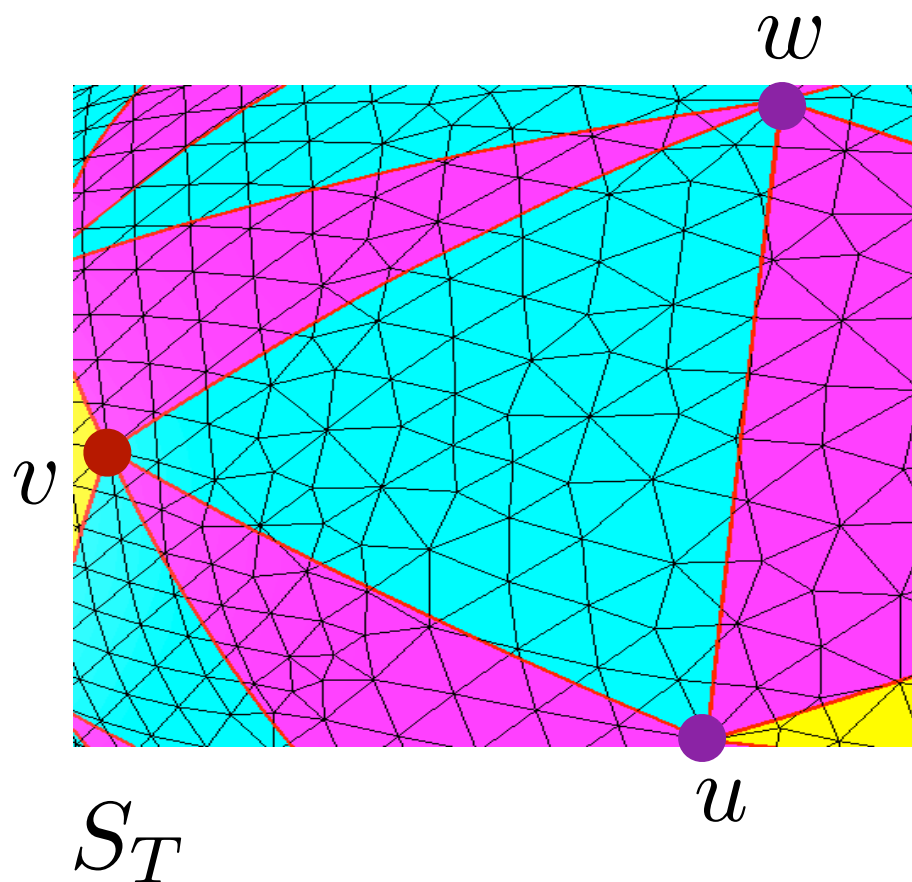
- Map the vertices of S_T bounded by the embedding of $st(v, \tilde{S}_T)$ to T_v .



Adaptive Fitting

Create S from \tilde{S}_T

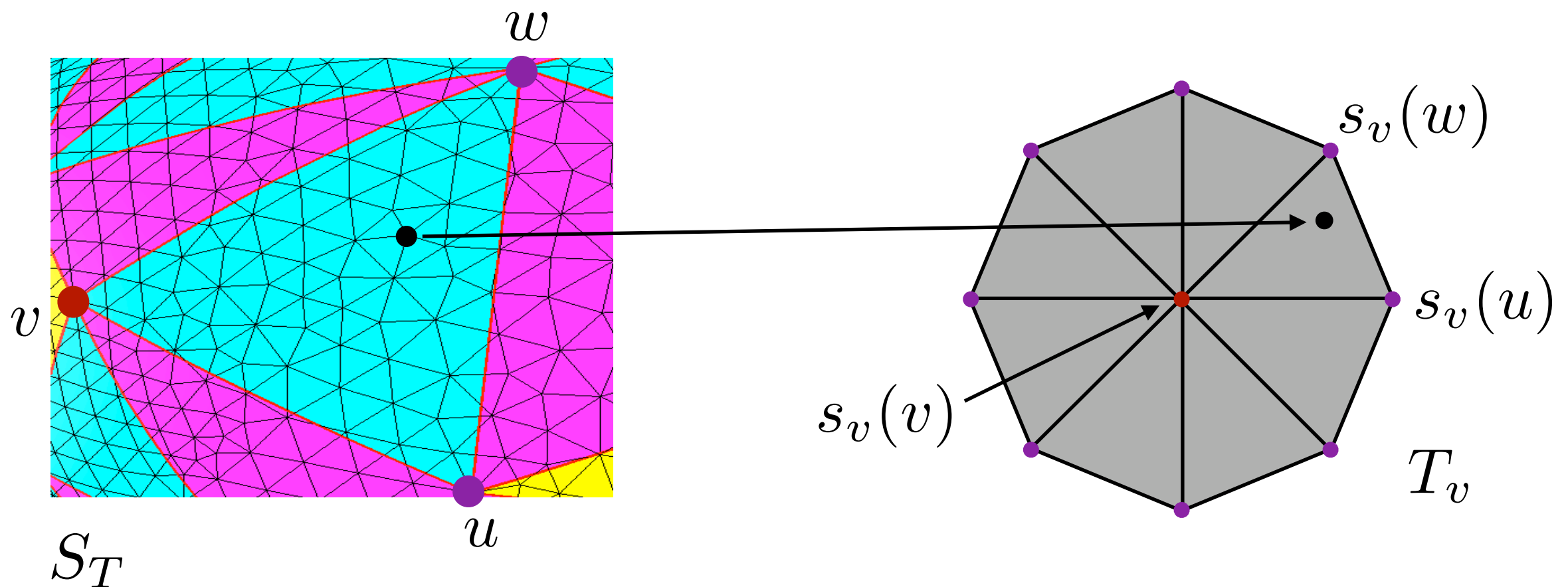
- Map the vertices of S_T bounded by the embedding of $st(v, \tilde{S}_T)$ to T_v .



Adaptive Fitting

Create S from \tilde{S}_T

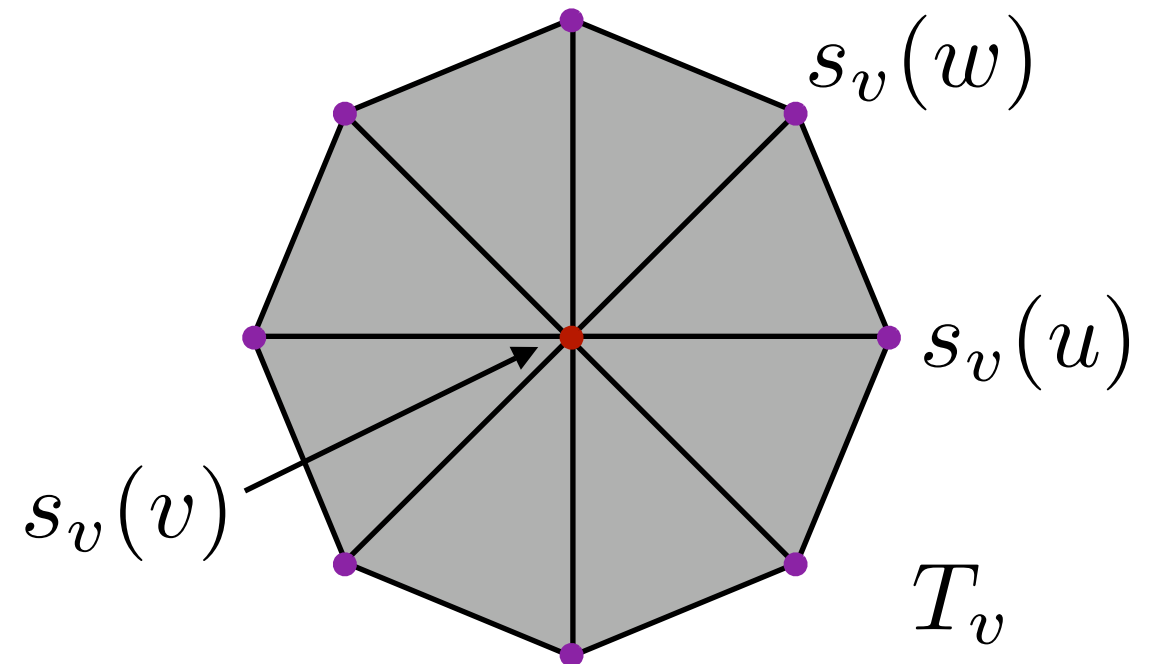
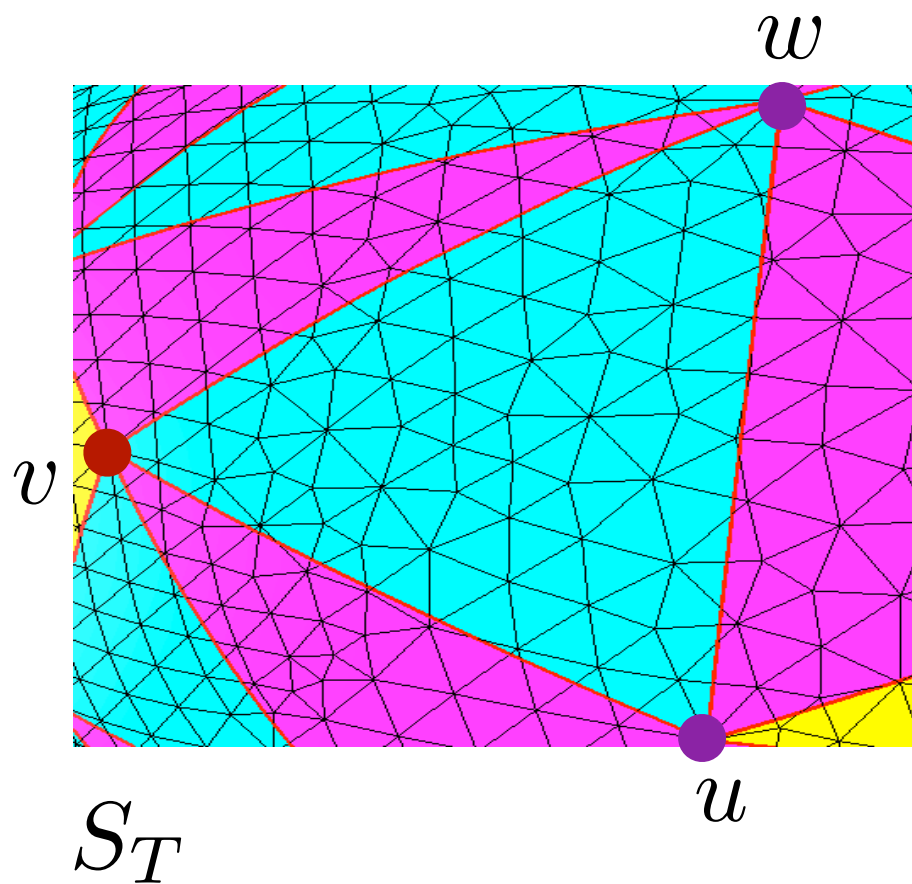
- Map the vertices of S_T bounded by the embedding of $st(v, \tilde{S}_T)$ to T_v .



Adaptive Fitting

Create S from \tilde{S}_T

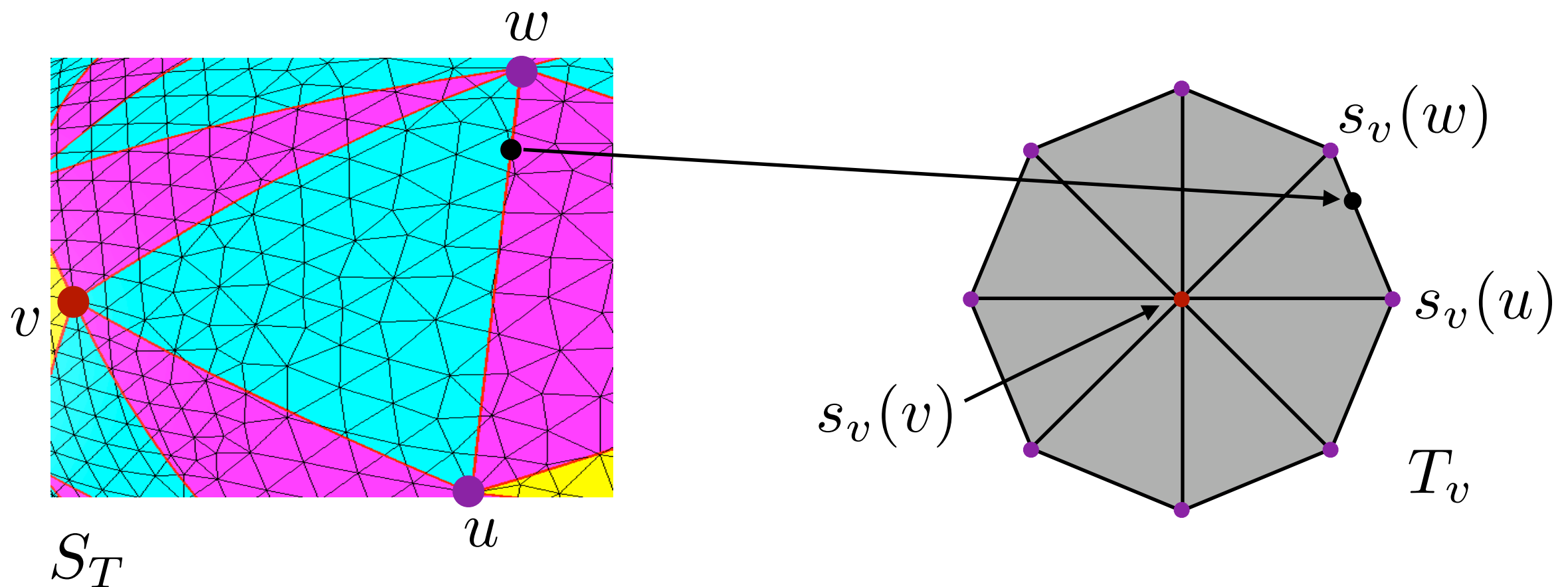
- Points where geodesics intersect edges of S_T are also mapped to T_v .



Adaptive Fitting

Create S from \tilde{S}_T

- Points where geodesics intersect edges of S_T are also mapped to T_v .



Adaptive Fitting

Create S from \tilde{S}_T

Adaptive Fitting

Create S from \tilde{S}_T

- How is this mapping done?

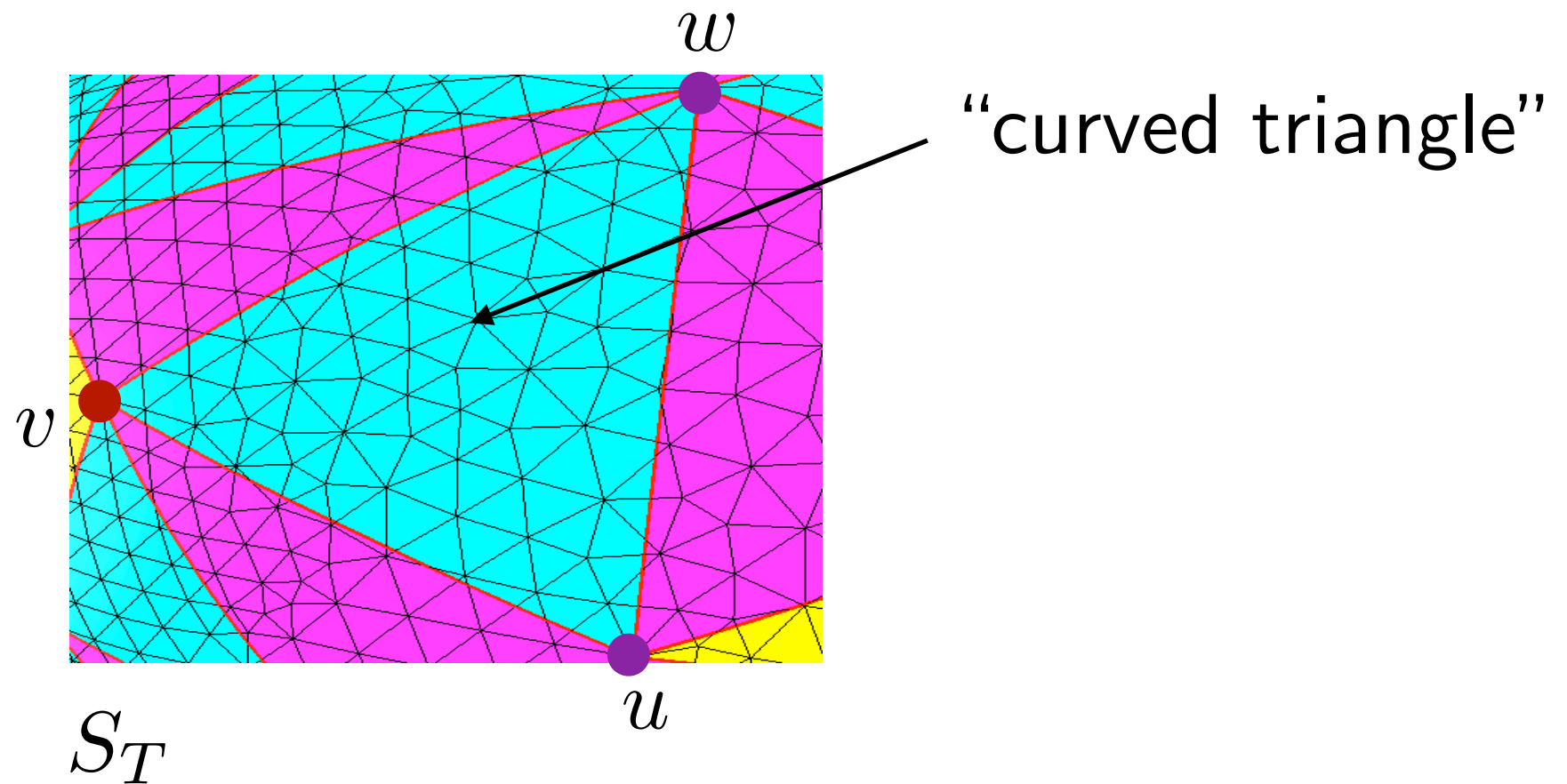
Adaptive Fitting

Create S from \tilde{S}_T

Adaptive Fitting

Create S from \tilde{S}_T

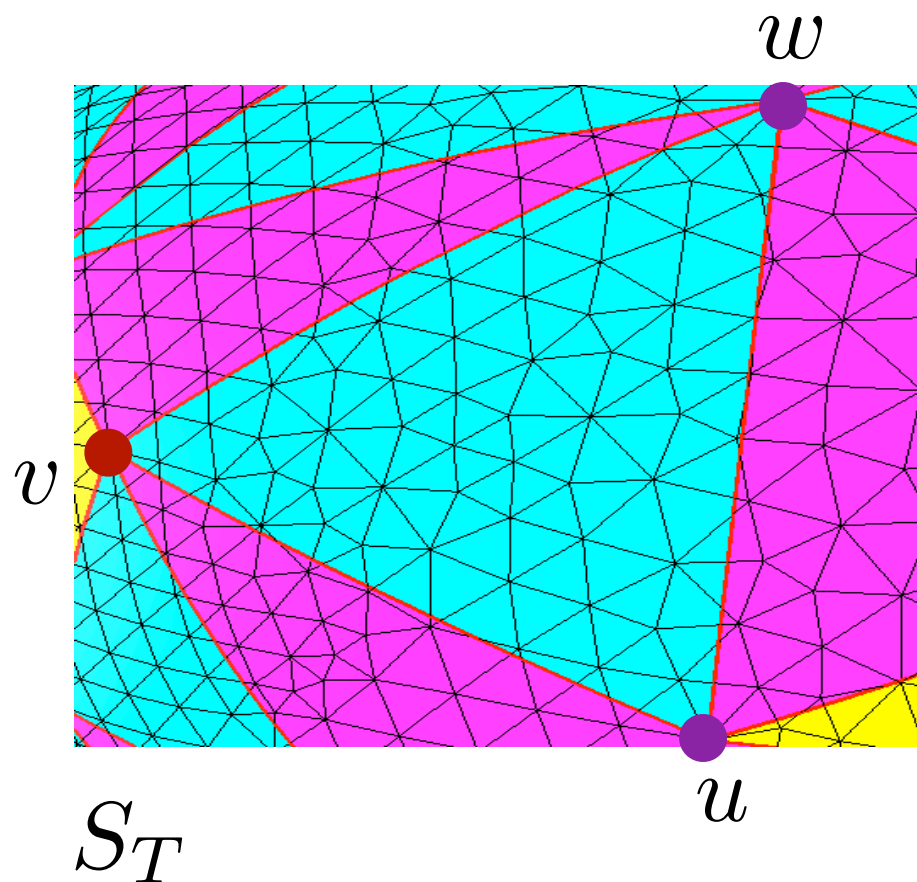
- We map the vertices in each “curved” triangle separately.



Adaptive Fitting

Create S from \tilde{S}_T

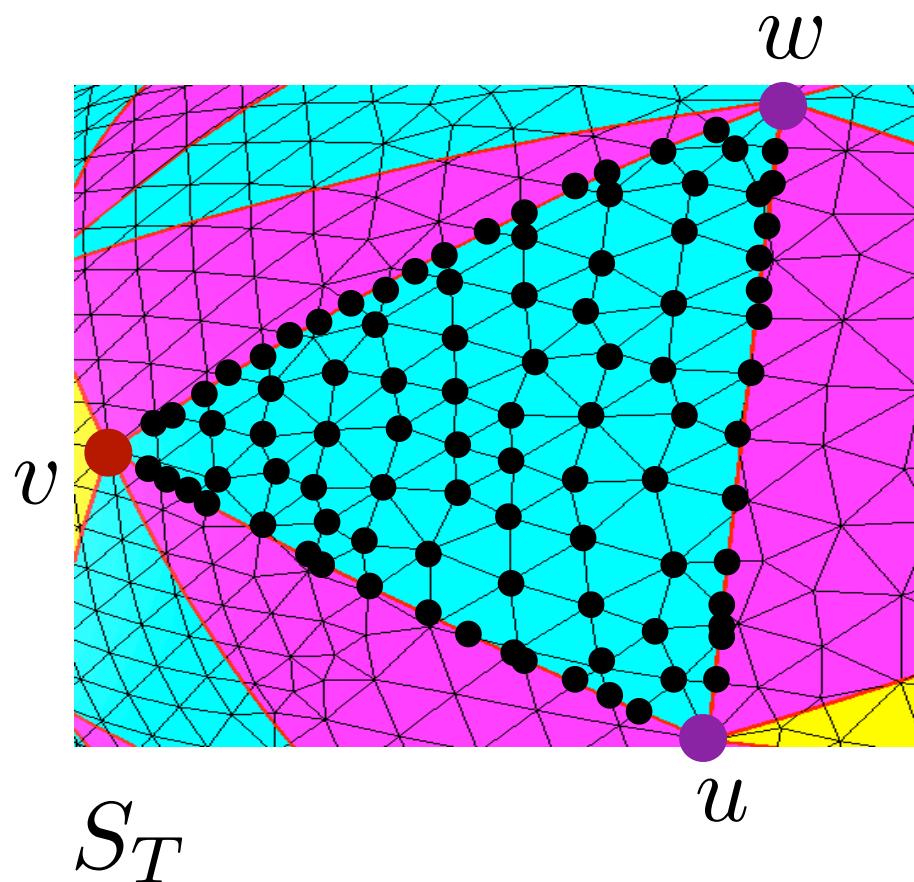
- We use Floater's parametrization to build the map for each "curved" triangle.



Adaptive Fitting

Create S from \tilde{S}_T

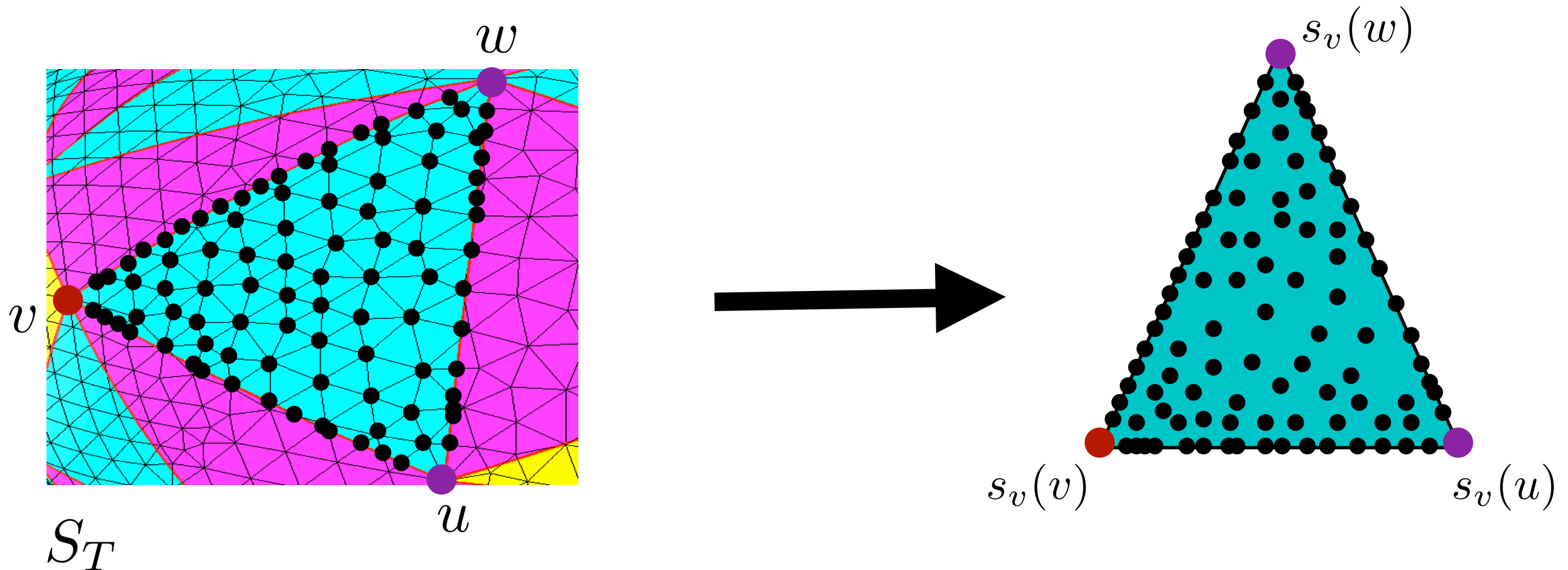
- We use Floater's parametrization to build the map for each "curved" triangle.



Adaptive Fitting

Create S from \tilde{S}_T

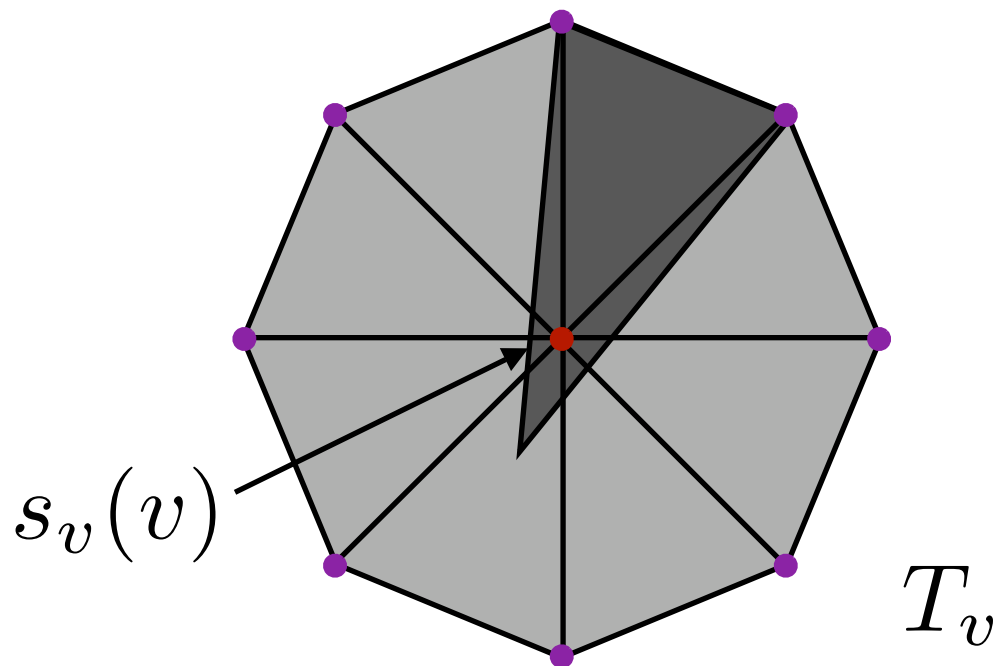
- We use Floater's parametrization to build the map for each "curved" triangle.



Adaptive Fitting

Create S from \tilde{S}_T

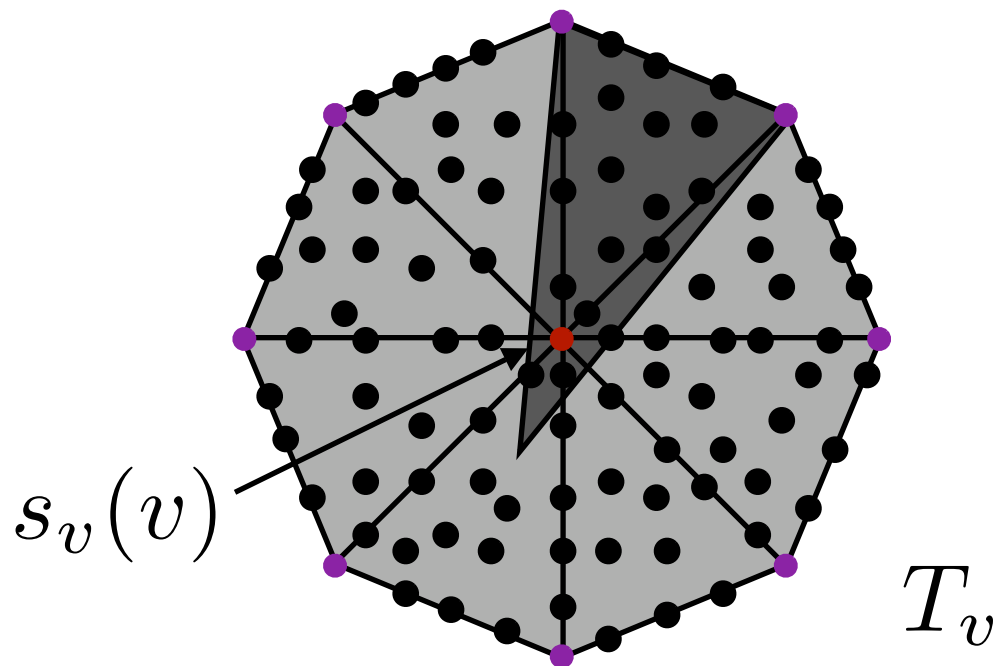
- For each triangle in $st(v, \tilde{S}_T)$, compute the shape function $\psi_{(\sigma, v)}$.



Adaptive Fitting

Create S from \tilde{S}_T

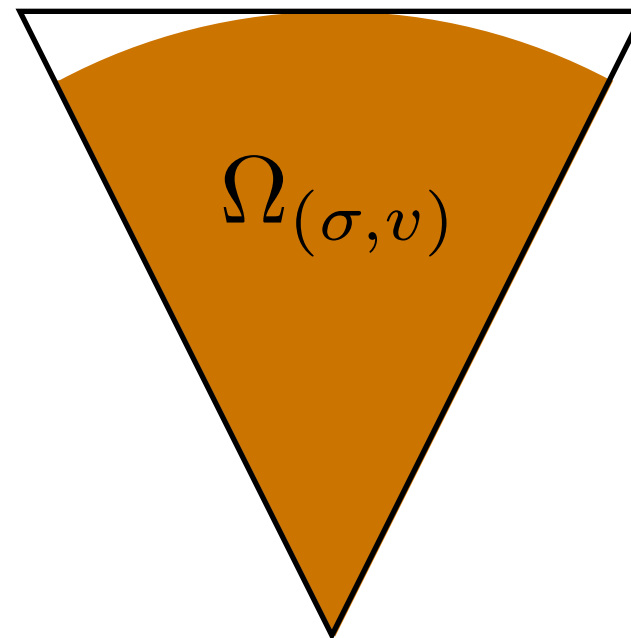
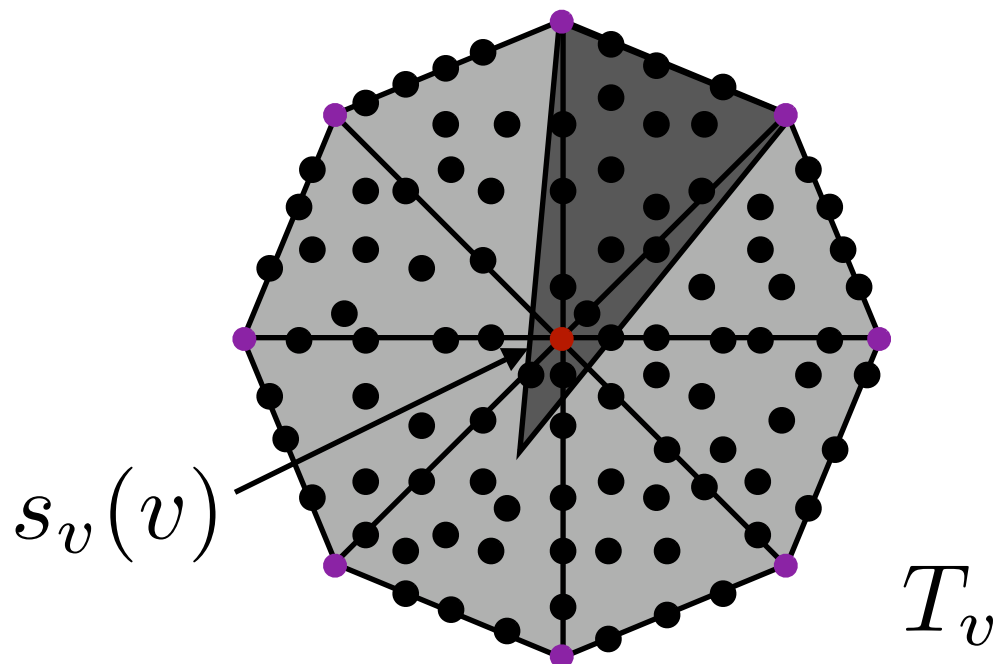
- For each triangle in $st(v, \tilde{S}_T)$, compute the shape function $\psi_{(\sigma, v)}$.



Adaptive Fitting

Create S from \tilde{S}_T

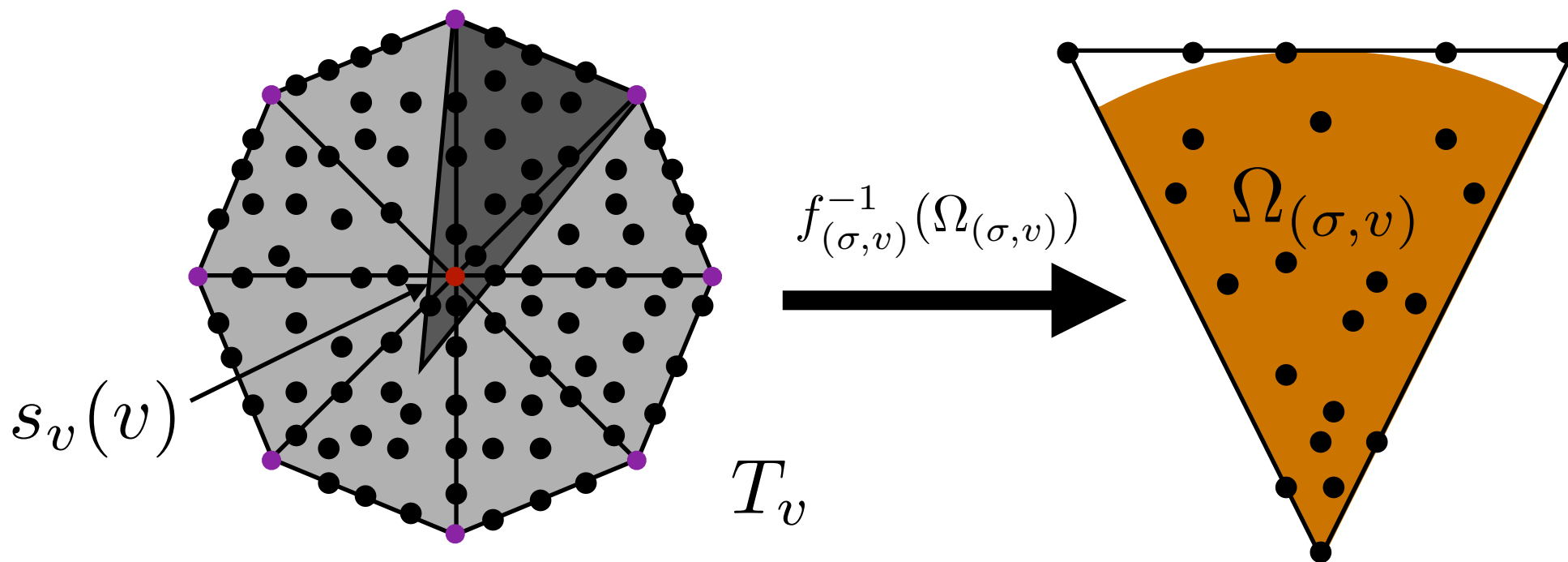
- For each triangle in $st(v, \tilde{S}_T)$, compute the shape function $\psi_{(\sigma, v)}$.



Adaptive Fitting

Create S from \tilde{S}_T

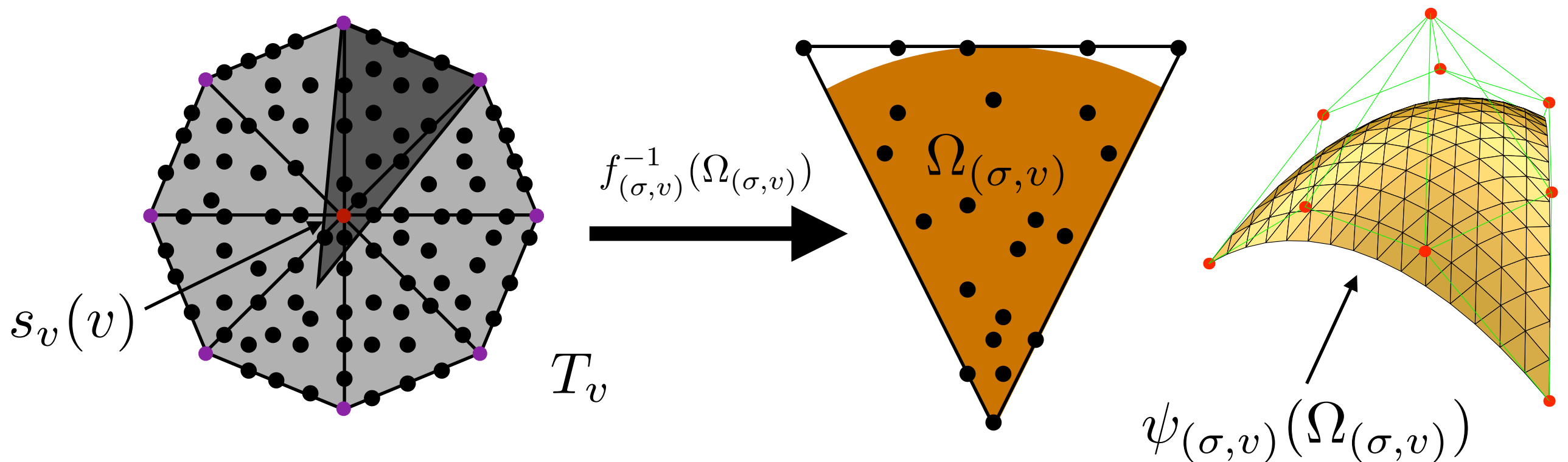
- For each triangle in $st(v, \tilde{S}_T)$, compute the shape function $\psi_{(\sigma, v)}$.



Adaptive Fitting

Create S from \tilde{S}_T

- For each triangle in $st(v, \tilde{S}_T)$, compute the shape function $\psi_{(\sigma, v)}$.



Adaptive Fitting

Create S from \tilde{S}_T

Adaptive Fitting

Create S from \tilde{S}_T

- Control points of $\psi_{(\sigma, v)}$ are computed by a least squares procedure.

Adaptive Fitting

Create S from \tilde{S}_T

- Control points of $\psi_{(\sigma, v)}$ are computed by a least squares procedure.
- But, this time, the sample points are the vertices of S_T that correspond to the points in T_v through Floater's parametrization!

Adaptive Fitting

Create S from \tilde{S}_T

Adaptive Fitting

Create S from \tilde{S}_T

- For each point p in T_v , we compute the **approximation error**,

$$\|q - \psi_{(\sigma, v)}(p)\|,$$

where q is the vertex of S_T corresponding to p through Floater's parametrization.

Adaptive Fitting

Create S from \tilde{S}_T

- For each point p in T_v , we compute the **approximation error**,

$$\|q - \psi_{(\sigma, v)}(p)\|,$$

where q is the vertex of S_T corresponding to p through Floater's parametrization.

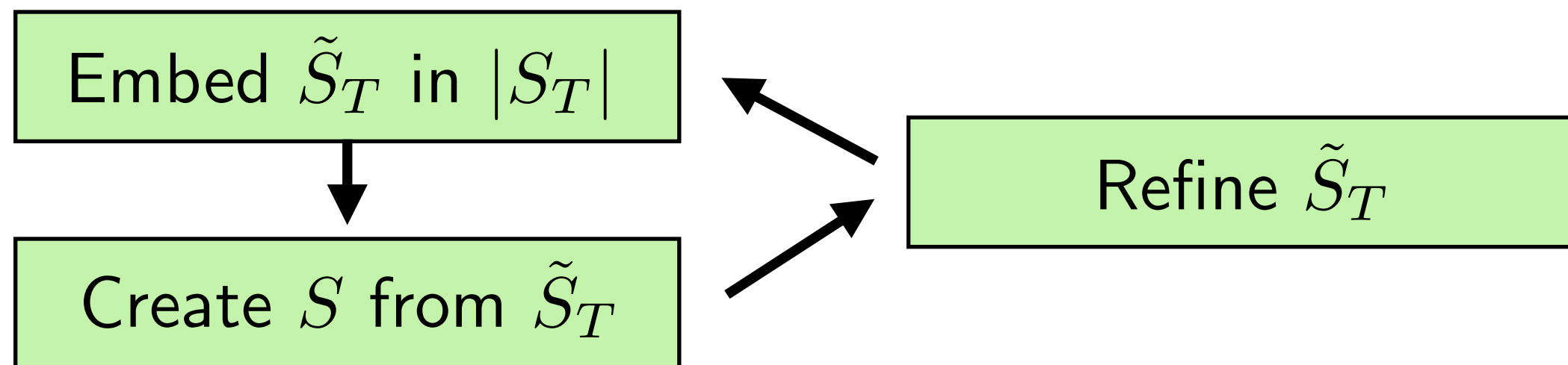
- If the above error is smaller than the given number ϵ , we keep computing $\psi_{(\tau, u)}$, for all pairs $(\tau, u) \in I$. Otherwise, we stop this process and go to the refinement step.

Adaptive Fitting

Adaptive Fitting

Refine \tilde{S}_T

- We locally refine \tilde{S}_T using the stellar operations and the 4-8 refinement, and then embed the resulting \tilde{S}_T in $|S_T|$ again.



Discrete Geodesics

Discrete Geodesics

- **Locally Shortest Geodesic:**

A curve joining two points, A and B , on a polyhedral surface. It is a local minimum of the length functional.

Discrete Geodesics

- **Locally Shortest Geodesic:**

A curve joining two points, A and B , on a polyhedral surface. It is a local minimum of the length functional.

- **Straightest Geodesic:**

A curve beginning at point A and moving in the direction of the tangent vector. It has zero *discrete geodesic curvature* everywhere.

Discrete Geodesics

Discrete Geodesics

Locally shortest geodesics:

Discrete Geodesics

Locally shortest geodesics:

Exact algorithms:

- Mitchell, Mount, and Papadimitriou (1987)
- Chen and Han (1996)
- Kapoor (1999)
- Surazhsky, Surazhsky, Kirsanov, Gortler, and Hoppe (2005)

Discrete Geodesics

Locally shortest geodesics:

Discrete Geodesics

Locally shortest geodesics:

Approximate algorithms:

- Kimmel and Sethian (1998)
- Martínez, Velho, and Carvalho (2004)
- Surazhsky, Surazhsky, Kirsanov, Gortler, and Hoppe (2005)

Discrete Geodesics

Discrete Geodesics

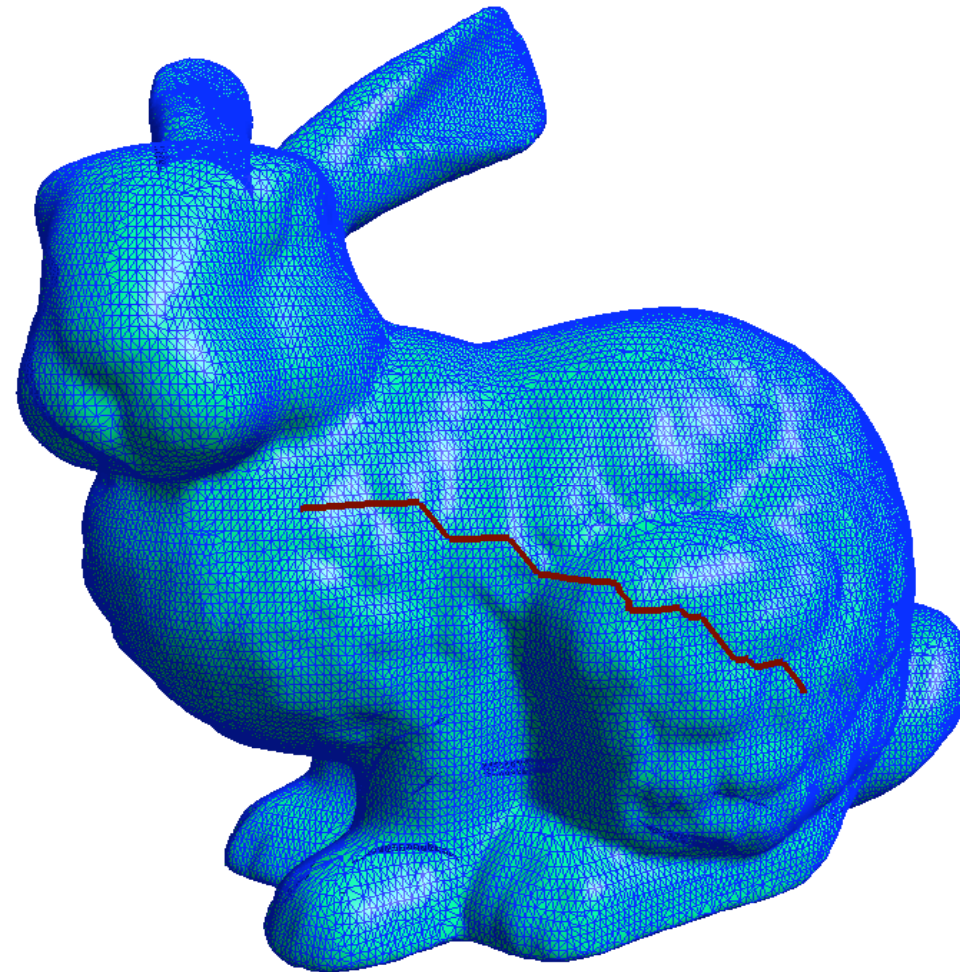
A Two-Step Algorithm:

Discrete Geodesics

A Two-Step Algorithm:

Step 1:

Find an initial curve joining A and B .



Discrete Geodesics

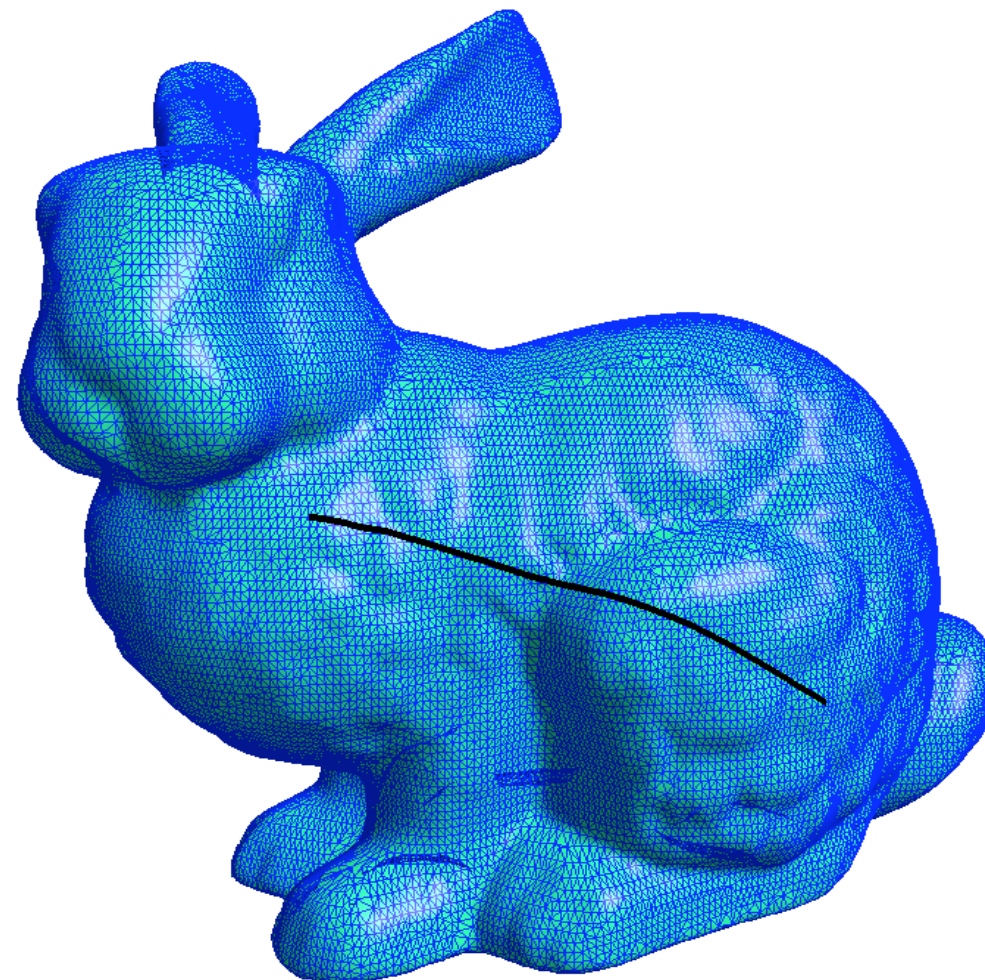
A Two-Step Algorithm:

Discrete Geodesics

A Two-Step Algorithm:

Step 2:

Iteratively modify the position of each curve vertex.



Discrete Geodesics

Discrete Geodesics

Step 1:

Find an initial curve joining A and B .

Discrete Geodesics

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- Fast Marching Method

Discrete Geodesics

Step 1:

Find an initial curve joining A and B .

- Fast Marching Method
- Define a distance function at the vertices, $d(v) = \text{dist}(A, V)$, using an approximation of the eikonal equation

$$|\nabla d| = 1.$$

Discrete Geodesics

Step 1:

Find an initial curve joining A and B .

Discrete Geodesics

Step 1:

Find an initial curve joining A and B .

- Back-integrate the differential equation:

$$\begin{cases} \frac{d\Gamma_0}{ds}(s) & = & -\nabla d(\Gamma_0(s)) \\ \Gamma_0(0) & = & B. \end{cases}$$

Discrete Geodesics

Discrete Geodesics

Step 2:

Iteratively modify the position of each curve vertex.

Discrete Geodesics

Step 2:

Iteratively modify the position of each curve vertex.

- Given a curve Γ_i , we want to get a shorter curve, Γ_{i+1} , with the same endpoints.

Discrete Geodesics

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- Given a curve Γ_i , we want to get a shorter curve, Γ_{i+1} , with the same endpoints.
 - a geodesic should be a line segment in the interior of a face;

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 - the algorithm will correct the position of the curve nodes;

Discrete Geodesics

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- Given a curve Γ_i , we want to get a shorter curve, Γ_{i+1} , with the same endpoints.
 - a geodesic should be a line segment in the interior of a face;
 - the curve will be a polygonal with nodes belonging to the edges of the mesh;
 - the algorithm will correct the position of the curve nodes;
 - distinct behavior for “edge nodes” and “vertex nodes”.

Discrete Geodesics

Step 2:

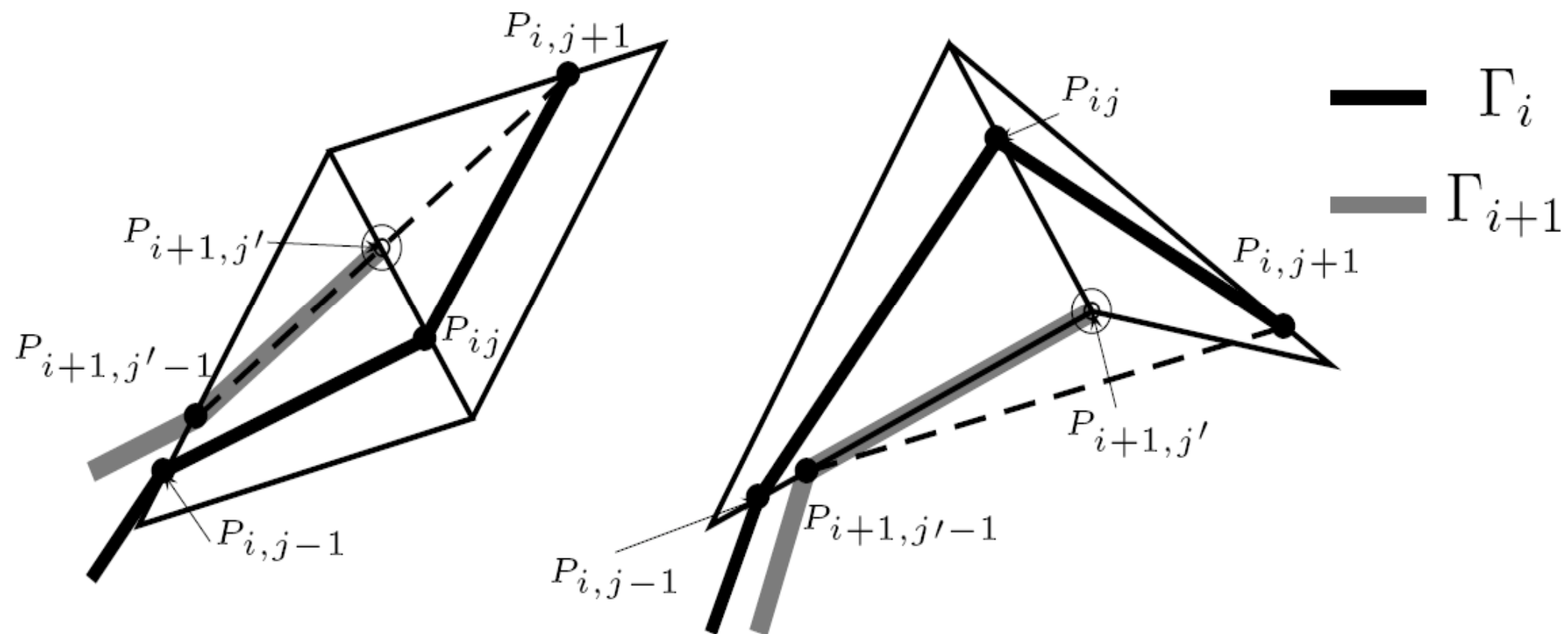
Iteratively modify the position of each curve vertex.

Discrete Geodesics

Step 2:

Iteratively modify the position of each curve vertex.

Edges nodes:



Discrete Geodesics

Step 2:

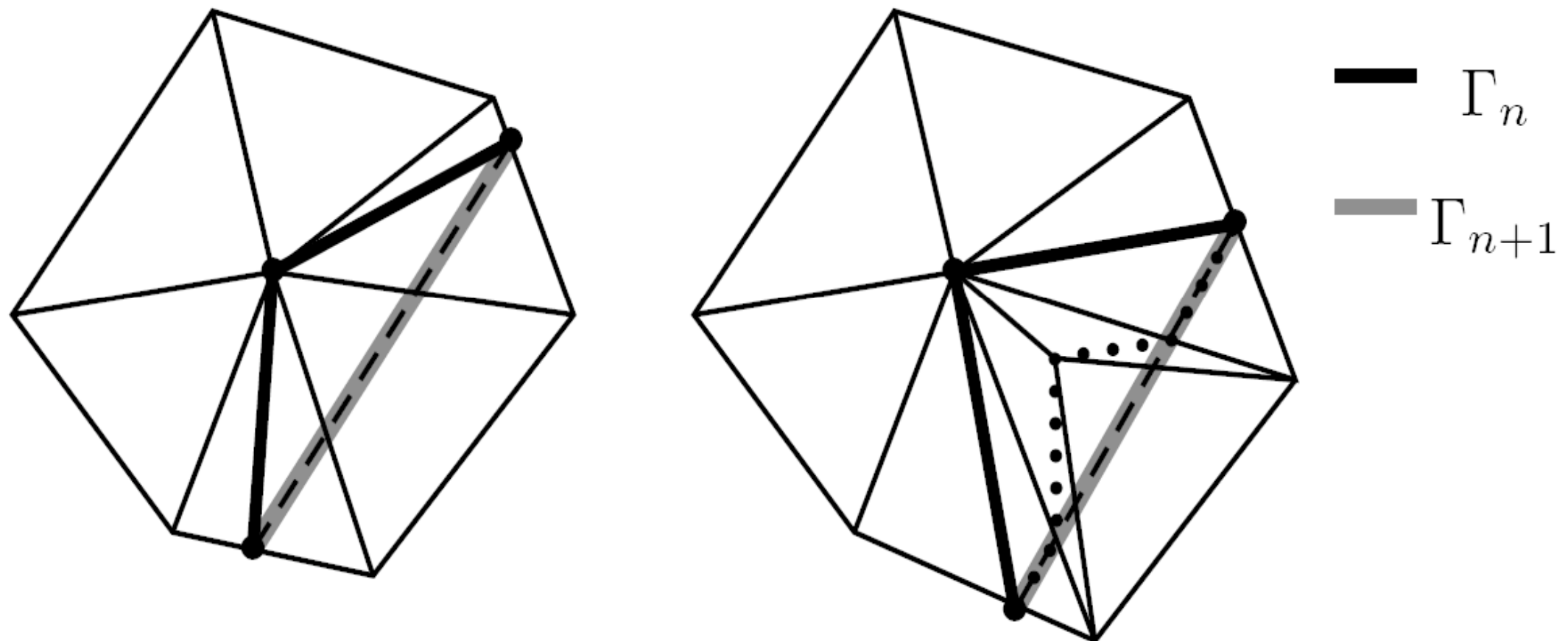
Iteratively modify the position of each curve vertex.

Discrete Geodesics

Step 2:

Iteratively modify the position of each curve vertex.

Vertex nodes:



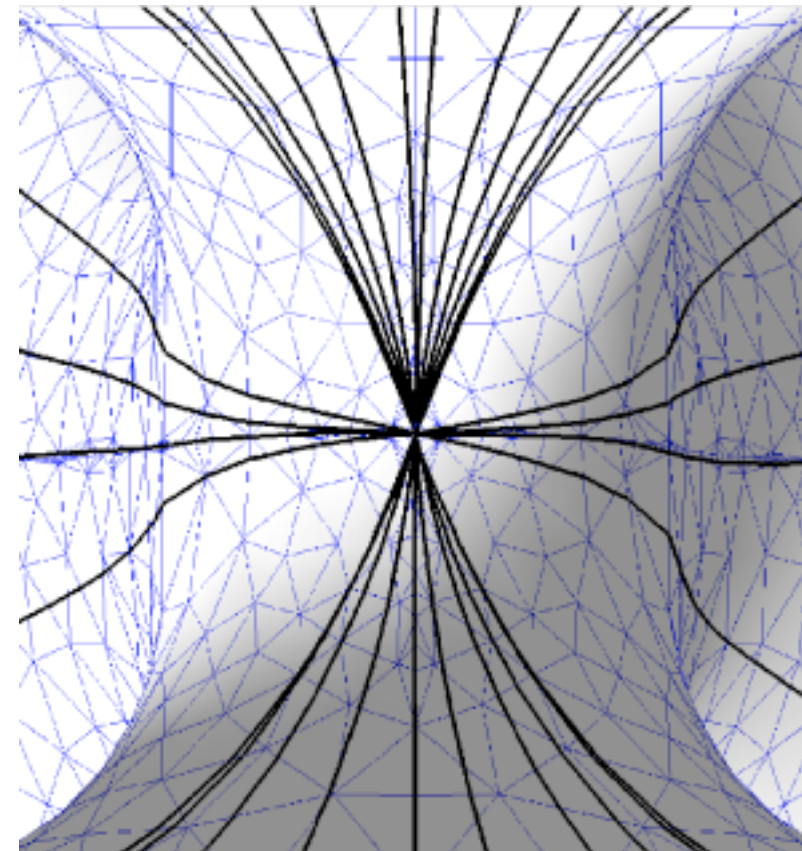
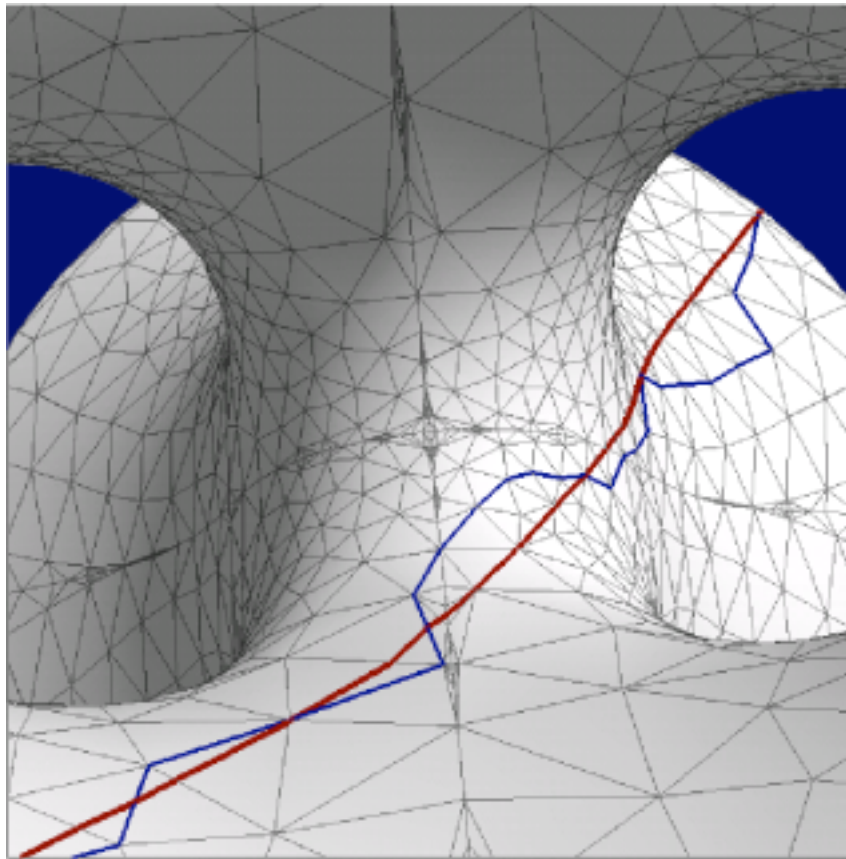
Discrete Geodesics

Discrete Geodesics

Examples:

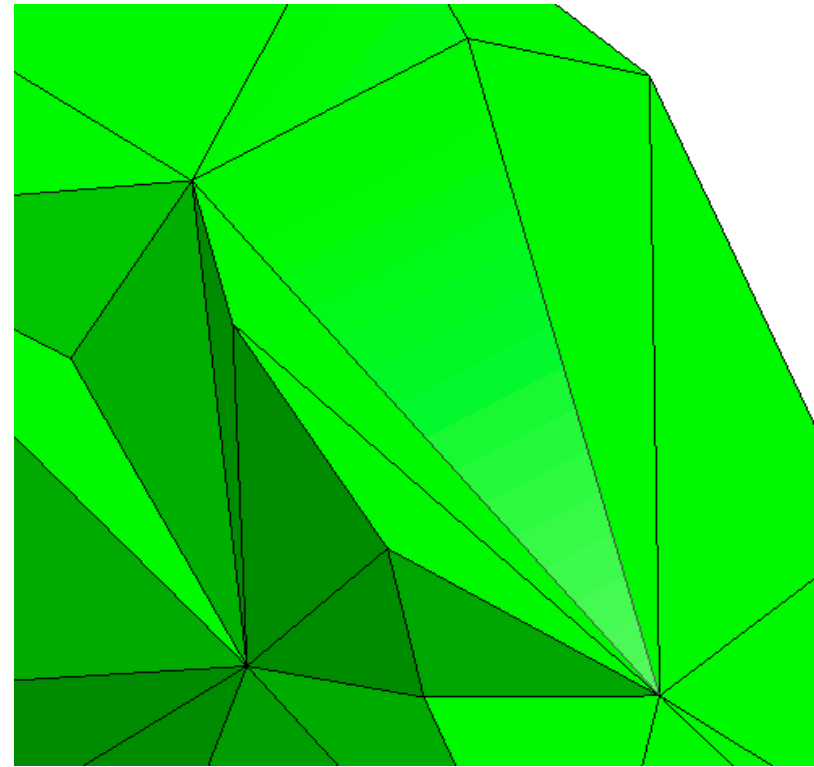
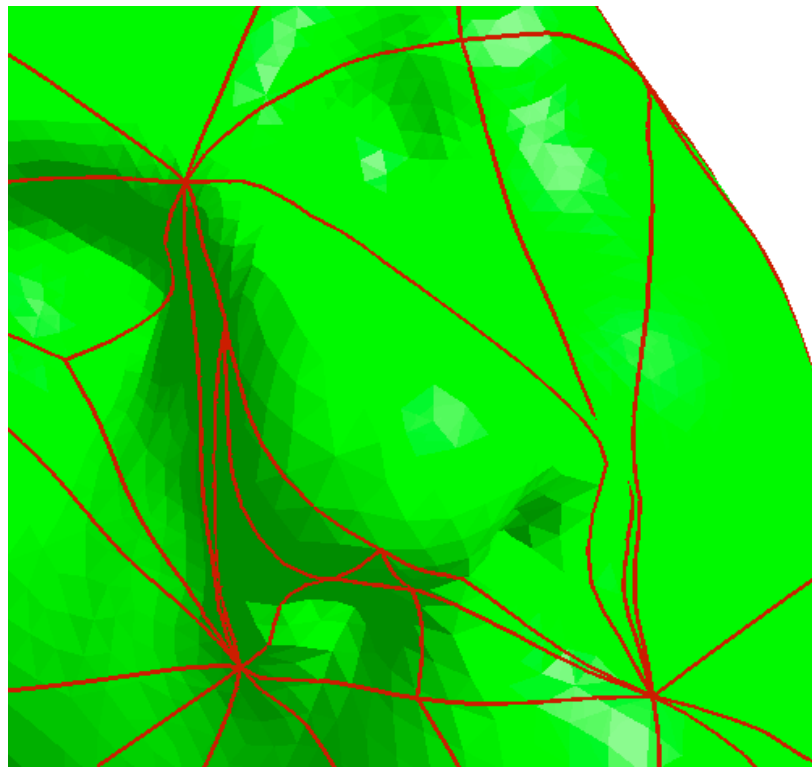
Discrete Geodesics

Examples:



Discrete Geodesics

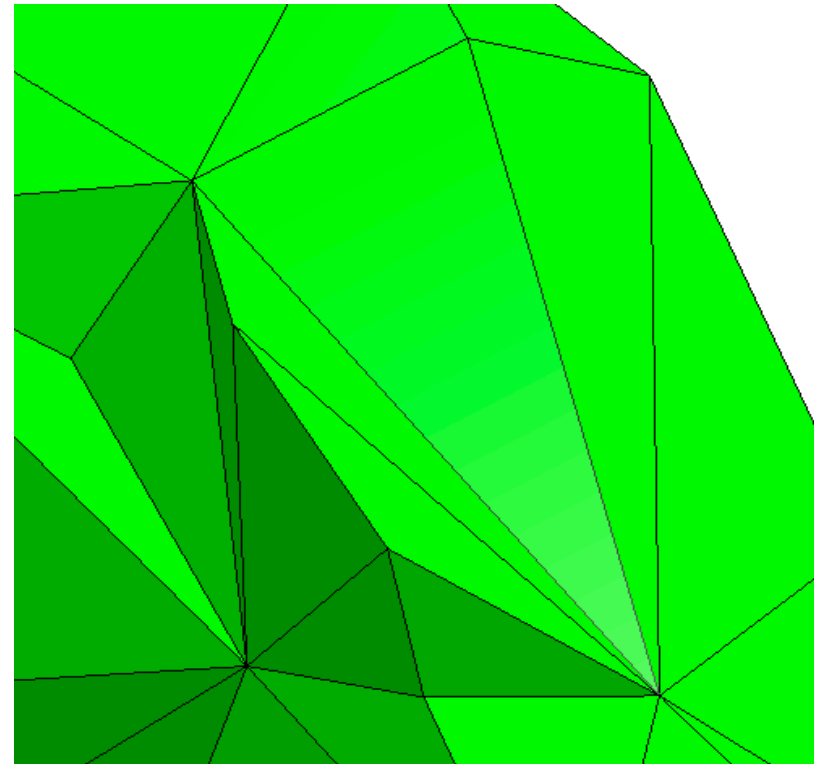
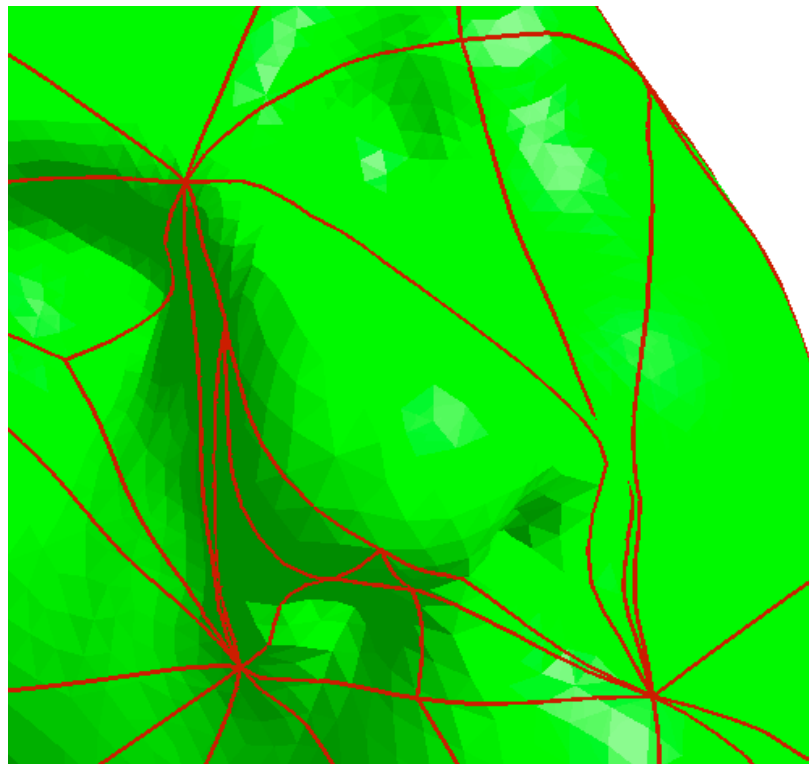
Discrete Geodesics



Discrete Geodesics

Adaptive Fitting:

When defining geodesic triangles, we can violate the manifold property of the geodesic mesh, as illustrated by the figure below:



Discrete Geodesics

Discrete Geodesics

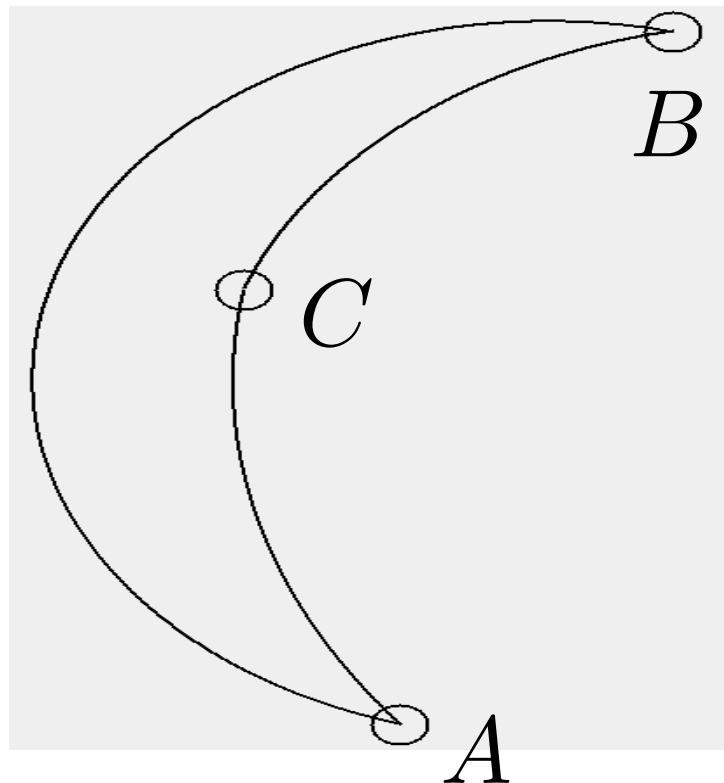
Solution:

Compute the geodesic curve AB as the geodesic resulting from using the concatenation of geodesics AC and CB as initial approximation:

Discrete Geodesics

Solution:

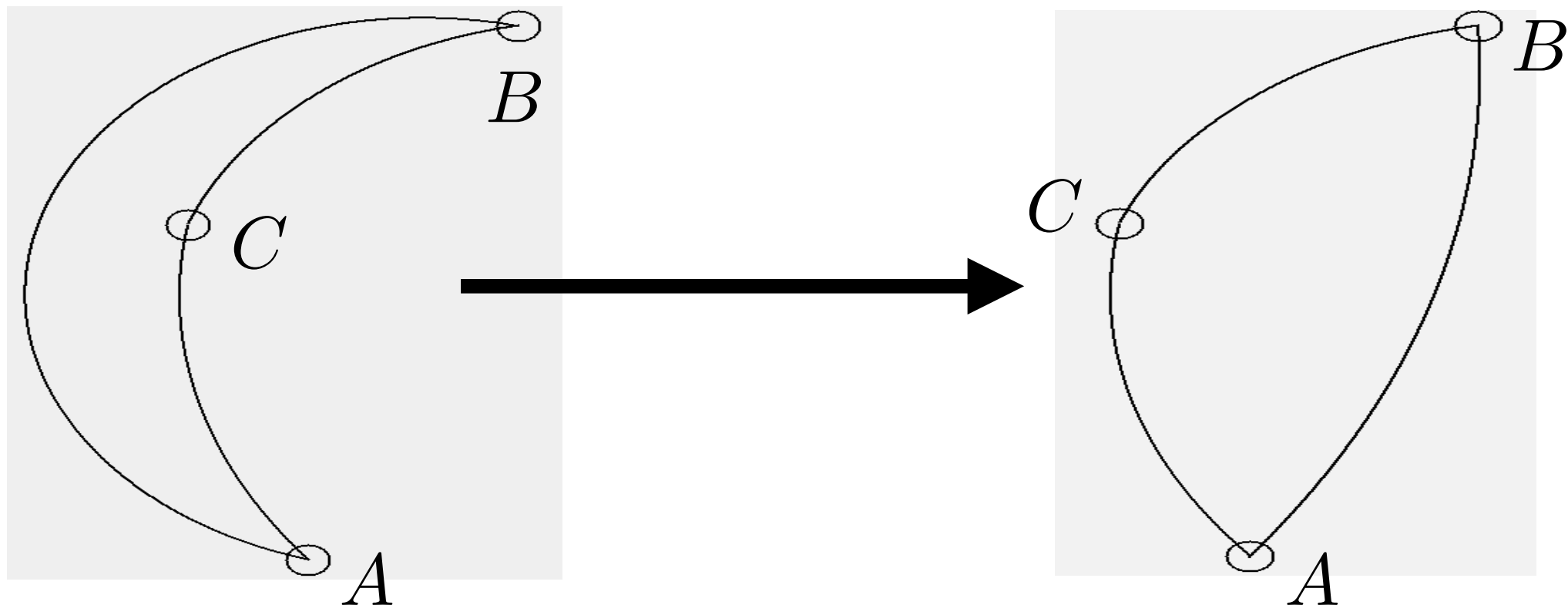
Compute the geodesic curve AB as the geodesic resulting from using the concatenation of geodesics AC and CB as initial approximation:



Discrete Geodesics

Solution:

Compute the geodesic curve AB as the geodesic resulting from using the concatenation of geodesics AC and CB as initial approximation:



Conclusions

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- This is the “real deal” when it comes to comparisons between smooth surfaces and very dense polygonal meshes.
- Implementation of the adaptive fitting is still under development.
- More specifically, the refinement step has not been completed.

Applications of Manifolds and Research Challenges

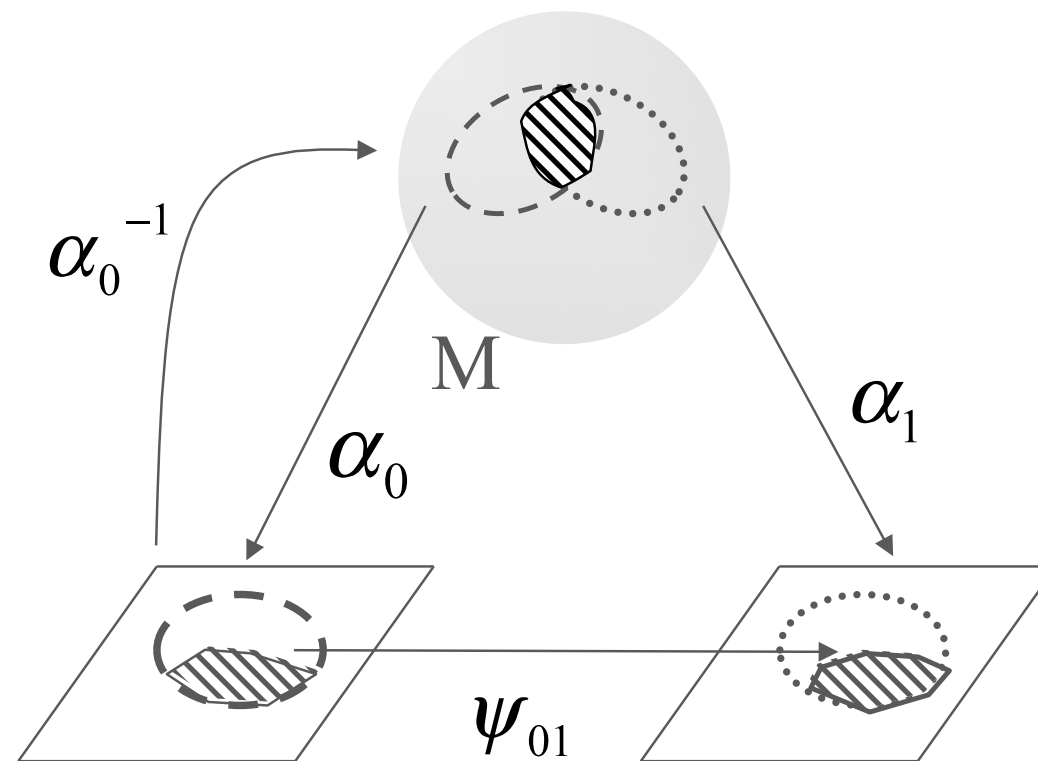
Luiz Velho
IMPA

Outline

- Concepts
- Illumination
- Appearance
- Simulation
- Faces
- Manifold Learning
- Wrap-up

Manifolds & Parametrization

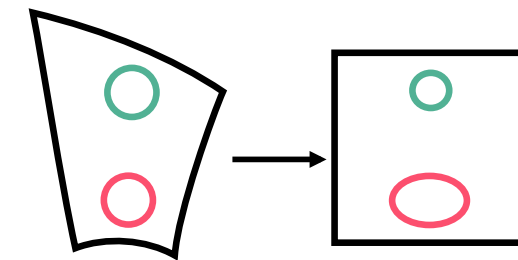
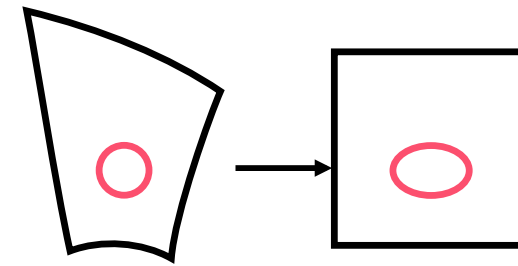
- Two Points of View
 - Functions on surfaces
 - Functions defining surfaces



Desirable Properties

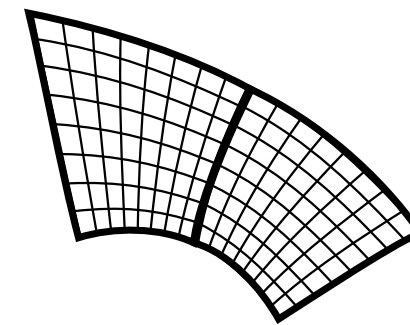
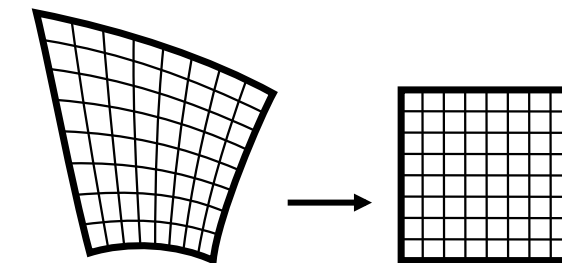
- Minimal Distortion

- Angle
- Area



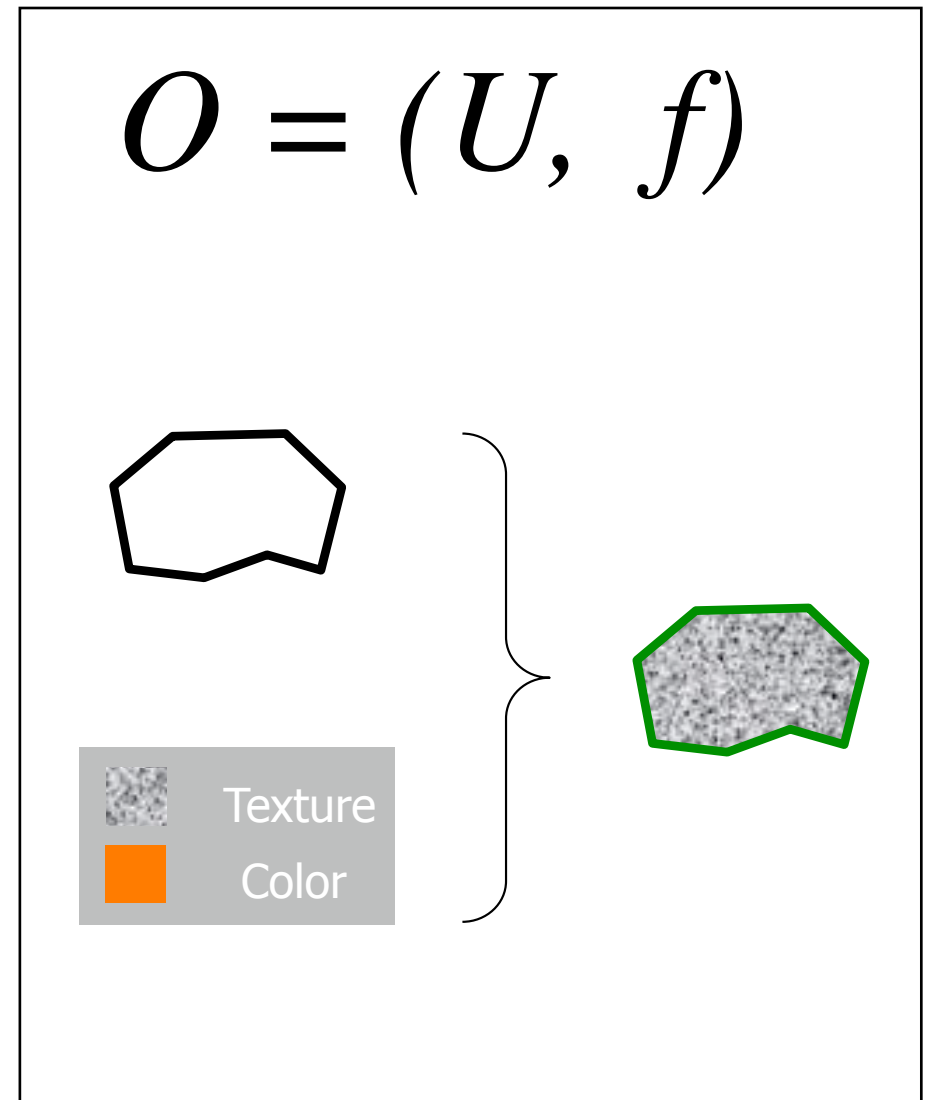
- Smoothness

- Differentiability
- Continuity



Graphical Objects

- Shape U
 - Topology (*domain*)
 - Abstract Manifold
 - Geometry (*function*)
 - Embedding
- Attributes f
 - Functions (*co-domain*)



G.O. Manifold Setting

- Canonical Surfaces
 - Fixed Shape (defined *a priori*)
 - Variable Functions (complex)
 - *ex: Sphere*
- Arbitrary Surfaces
 - Complex Shape
 - Computation on Surfaces (attributes)
 - Building / Transforming (shape)
 - *ex: Triangle Meshes*

Applications

- Illumination
 - Canonical Manifold + Functions
- Appearance and Simulation
 - Pseudo-Manifold + Attributes
- Faces
 - Manifold + Geometric Deformation
- Surface Reconstruction
 - Pseudo-Manifold / Topology Estimation

Illumination

- Functions on the Sphere
 - Light Fields / BRDFs
- Applications
 - Capture / Synthesis
- Construction [Grimm 2002]

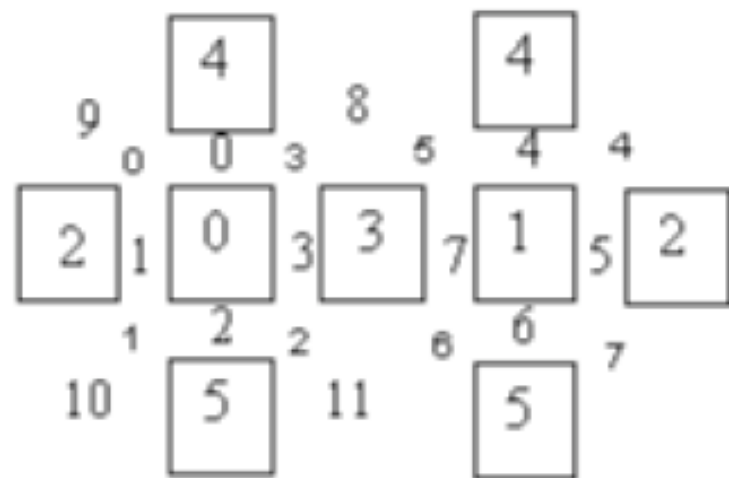
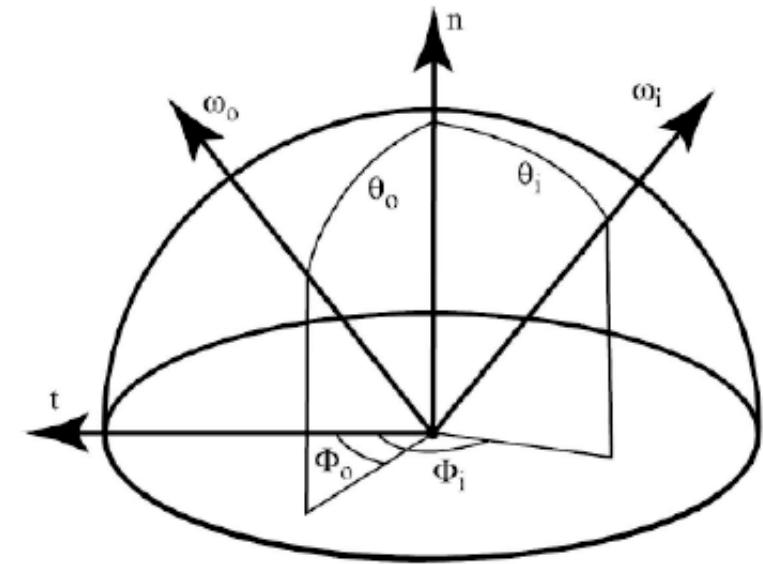
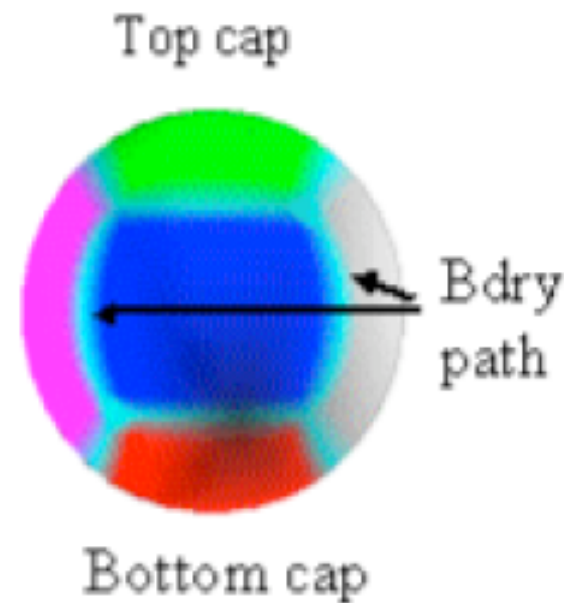
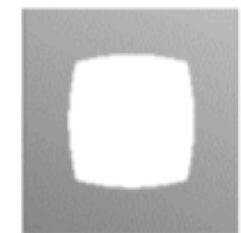


Chart (squares), edge, and



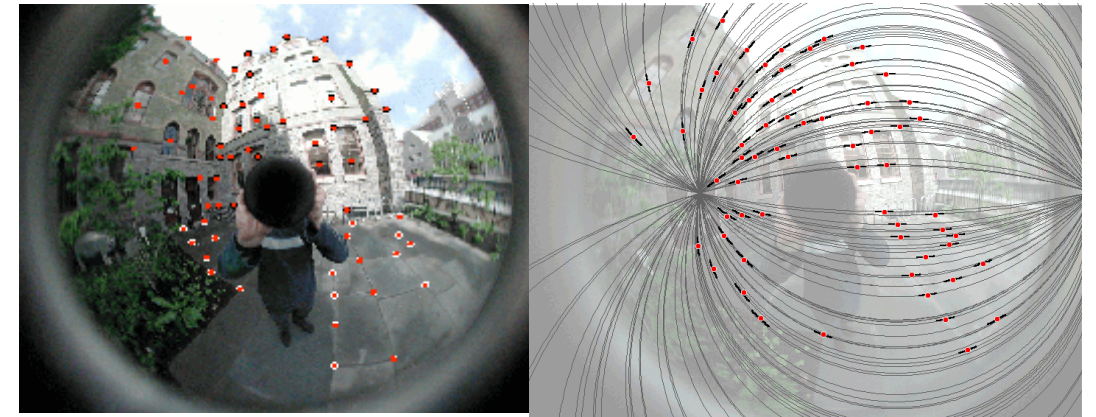
Bottom cap



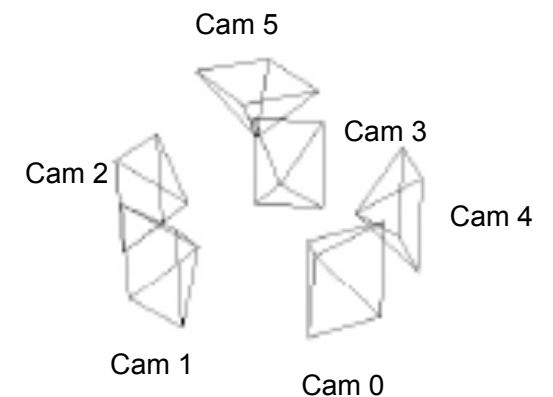
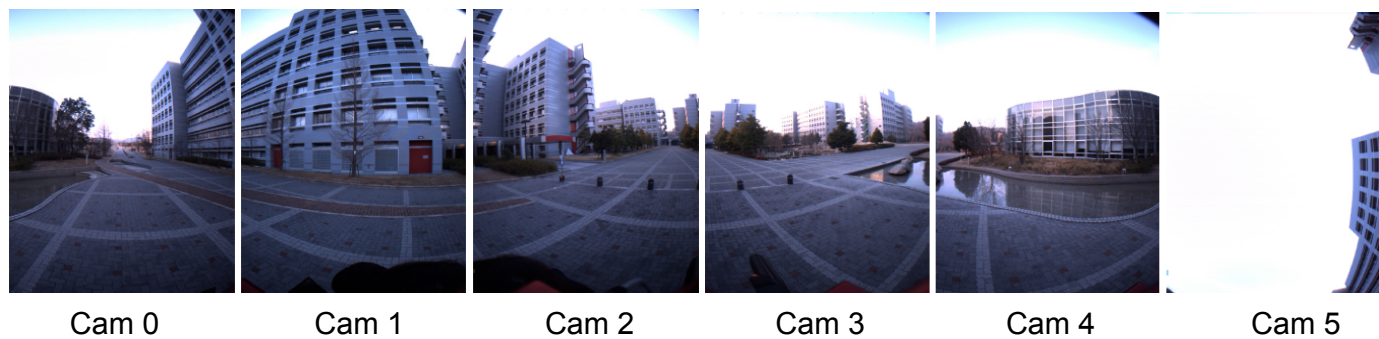
A single chart on the sphere

Omnidirectional Images

- Panoramic Cameras
 - Processing

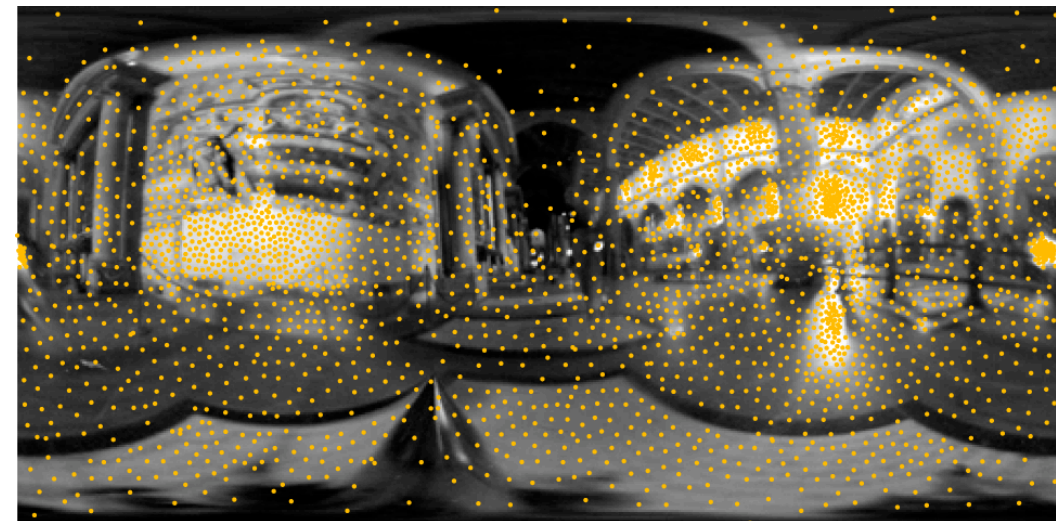
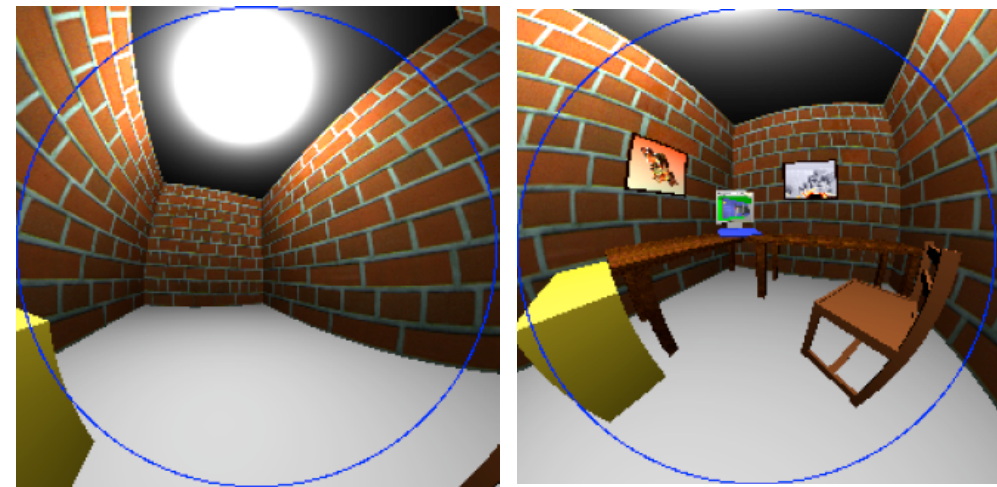


- Multi-Camera Assembly
 - Stitching / Blending



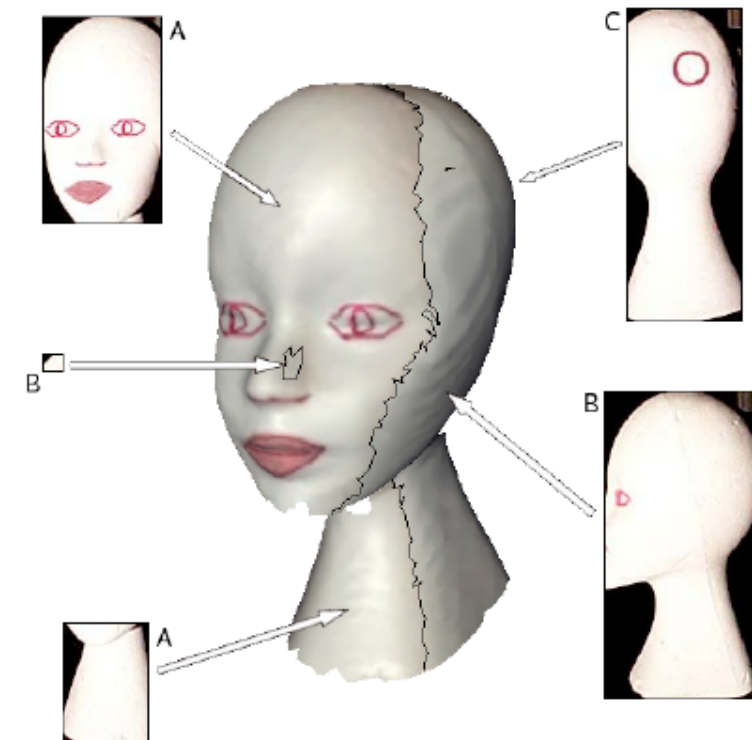
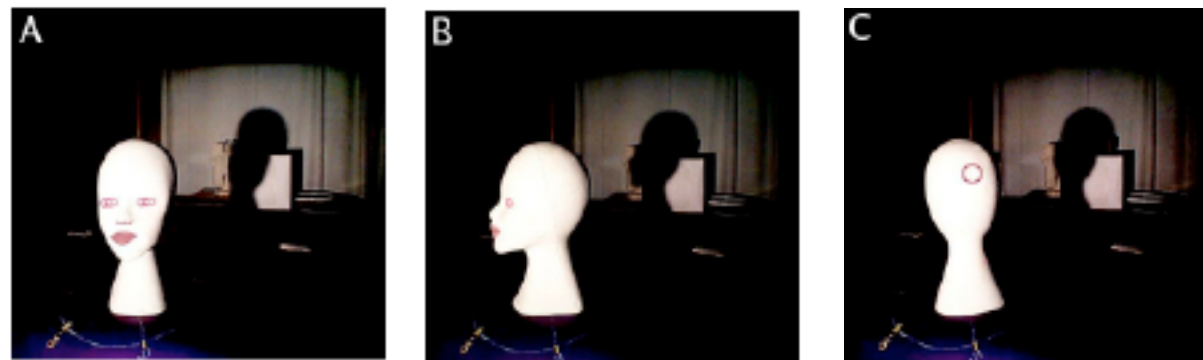
Illumination Maps

- Environment Maps
 - Area Sampling
- Light Maps
 - Stratification



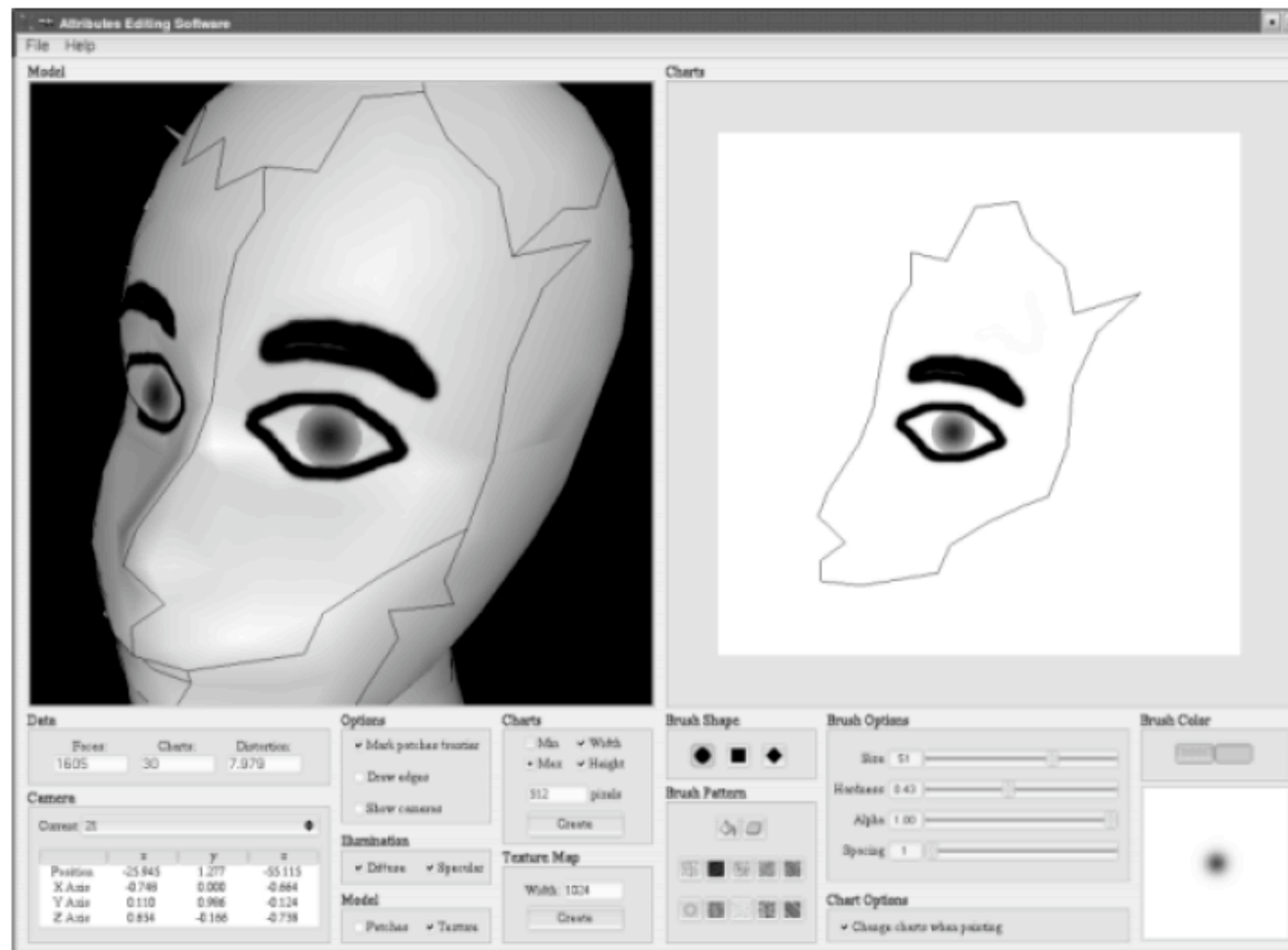
Surface Properties

- Texture Atlas
 - Albedo
 - Normal Field
- Building from Images
 - Projective Map



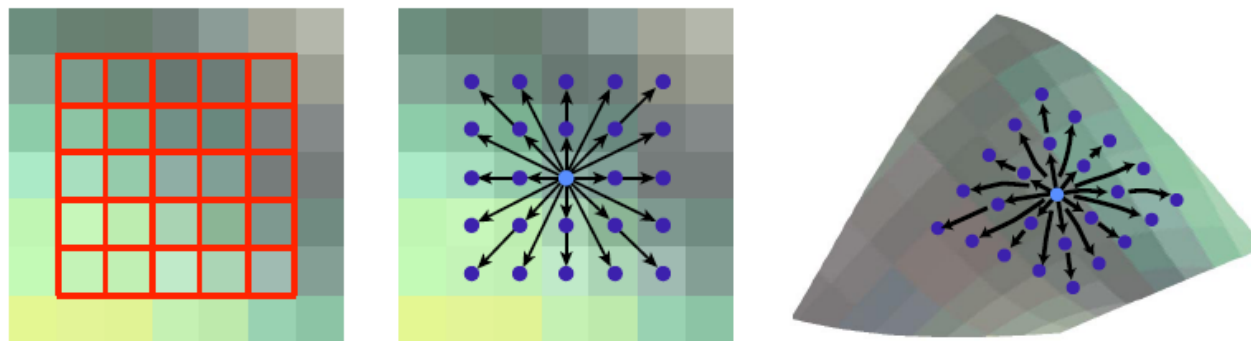
Painting

- Color
- Normals



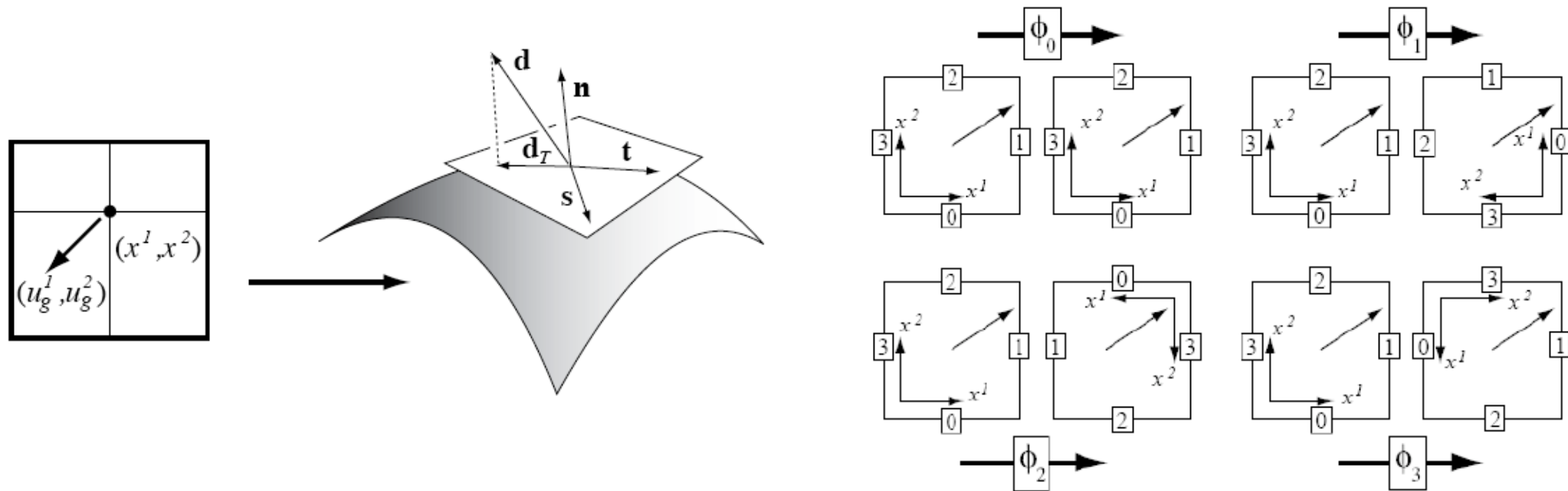
Texture Synthesis

- Stationary / Quasi Stationary



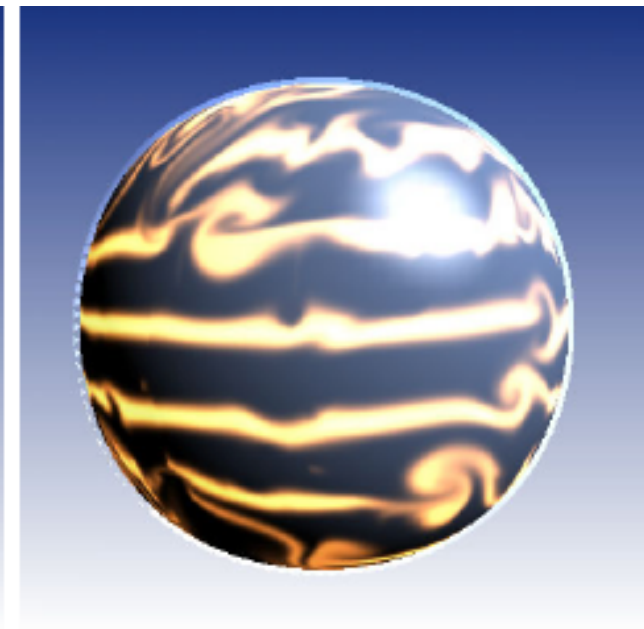
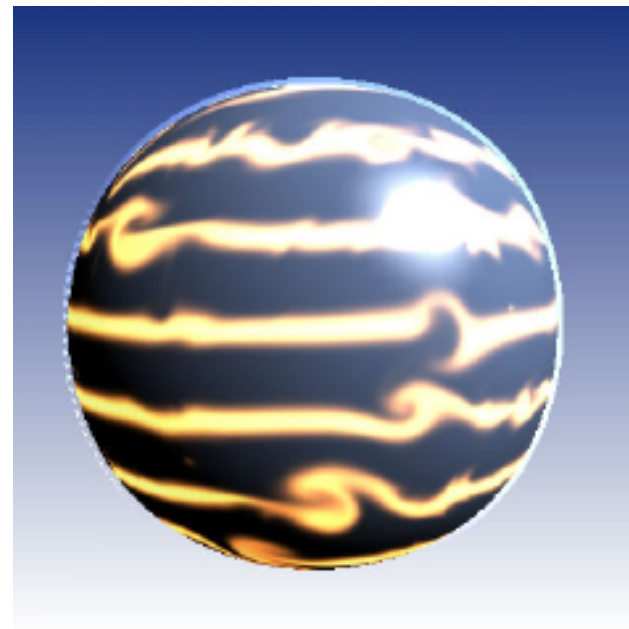
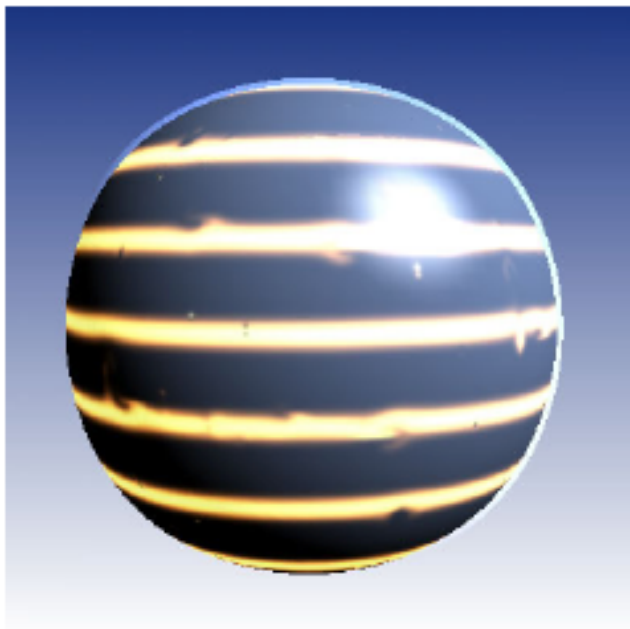
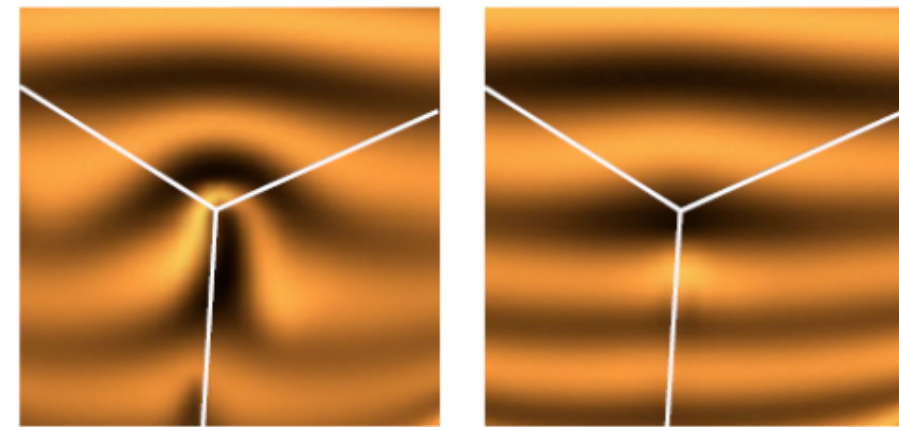
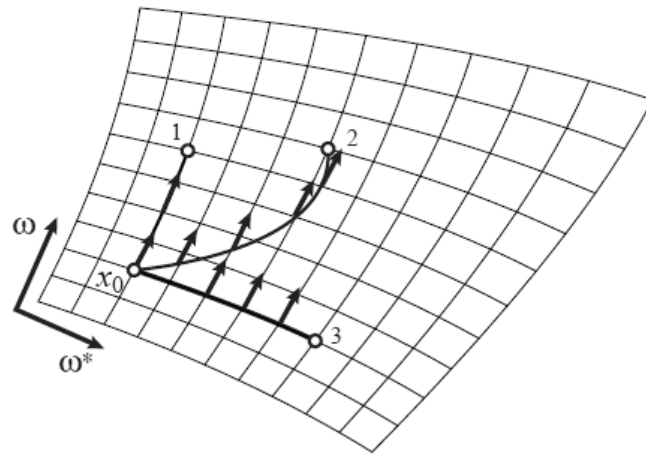
Simulation

- Solving Equations on Manifolds
 - Surface Points
 - Local Neighborhoods



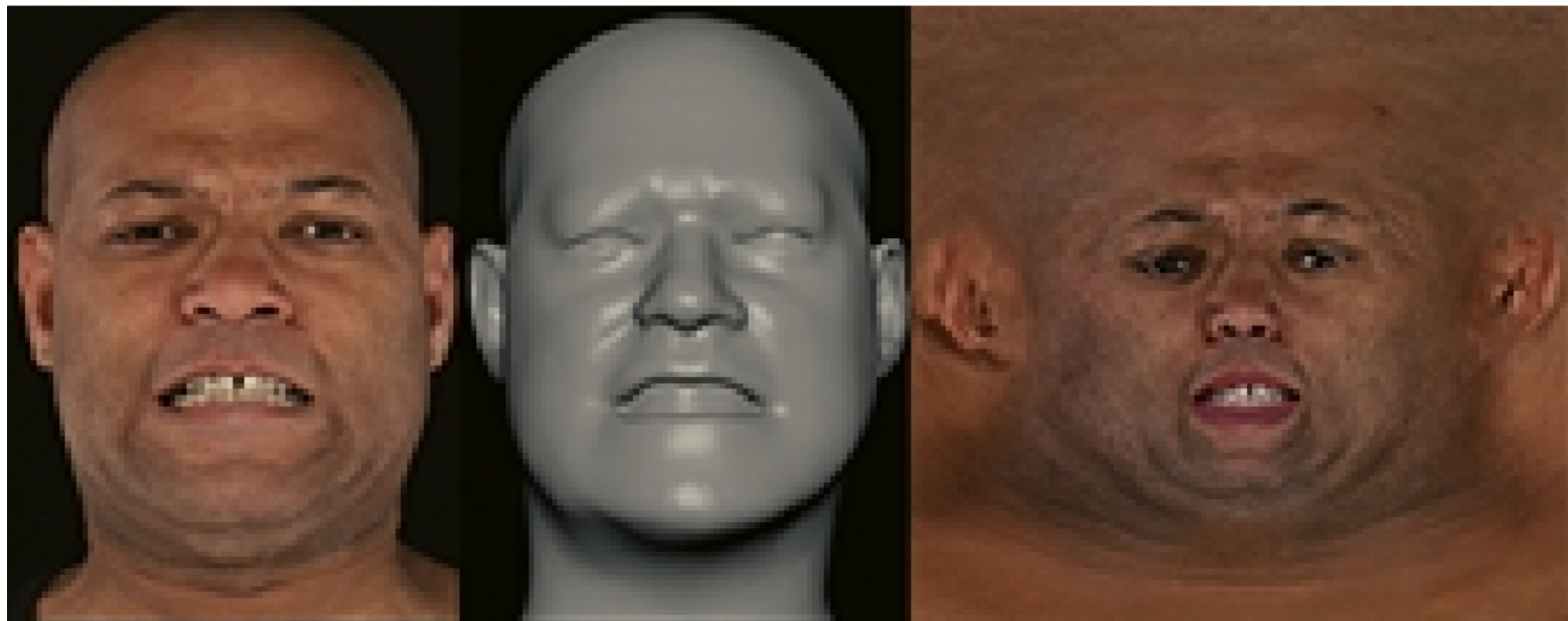
Fluids

- Vector Fields on Surfaces



Faces

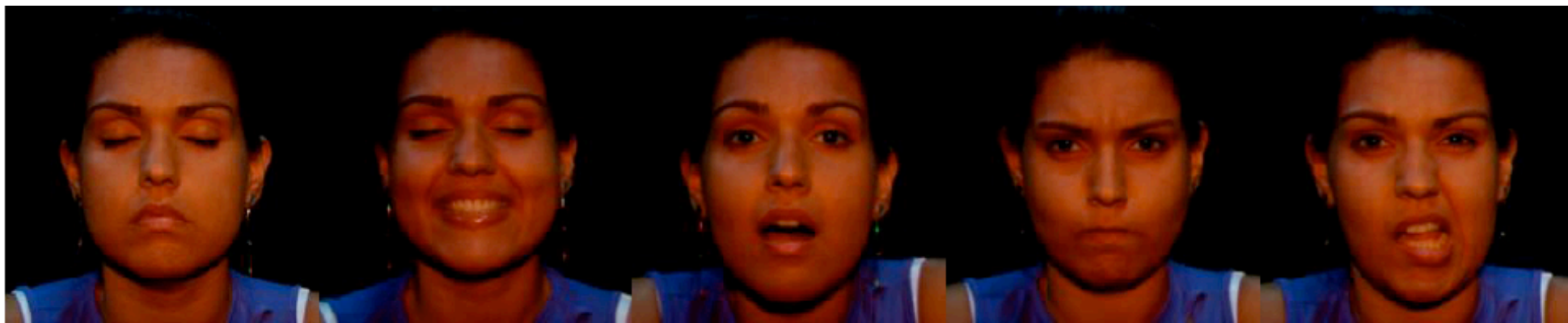
- Geometry + Appearance



[G. Borshukov et al SIGGRAPH 2003]

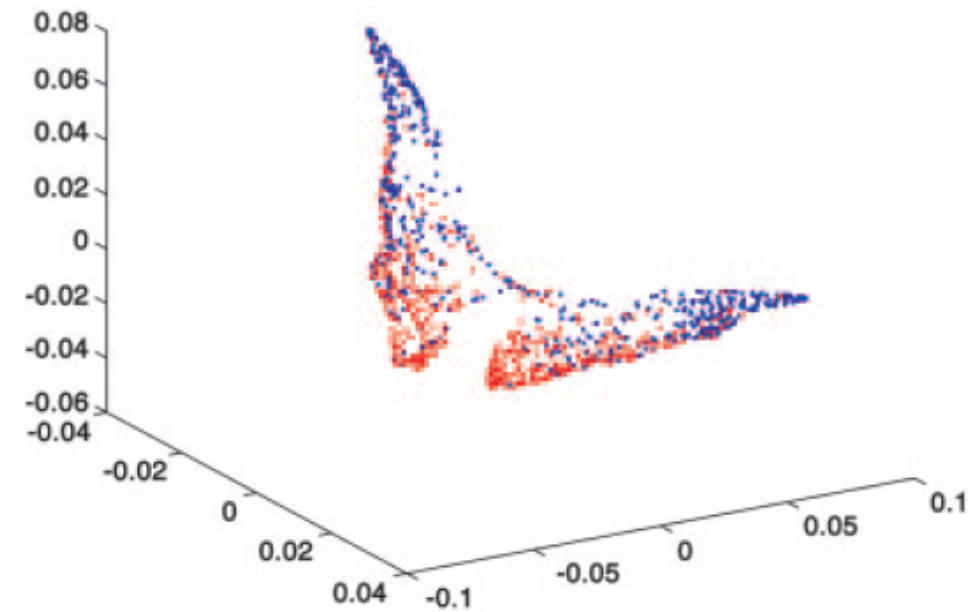
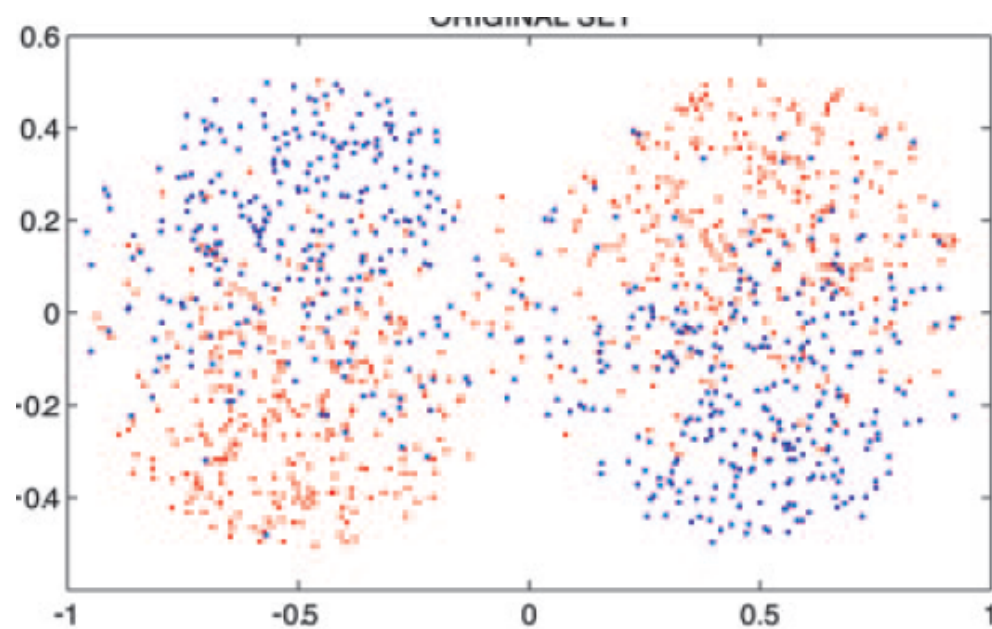
Facial Expressions

- Deformations



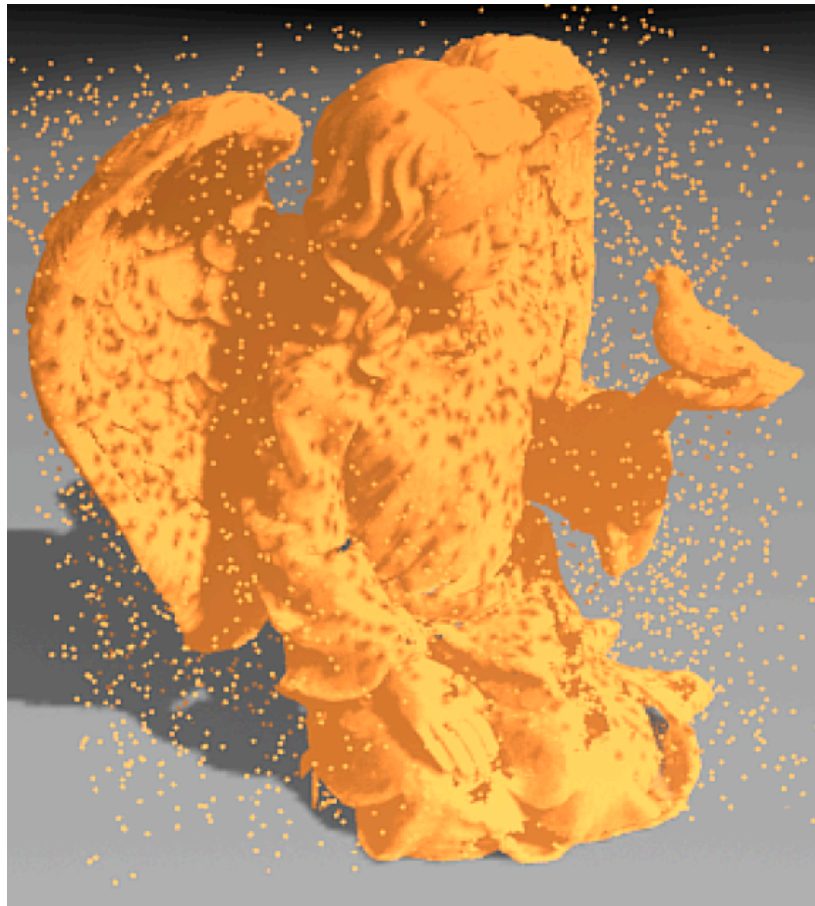
Manifold Learning

- Estimate from Data Samples
 - Topology
 - Geometry



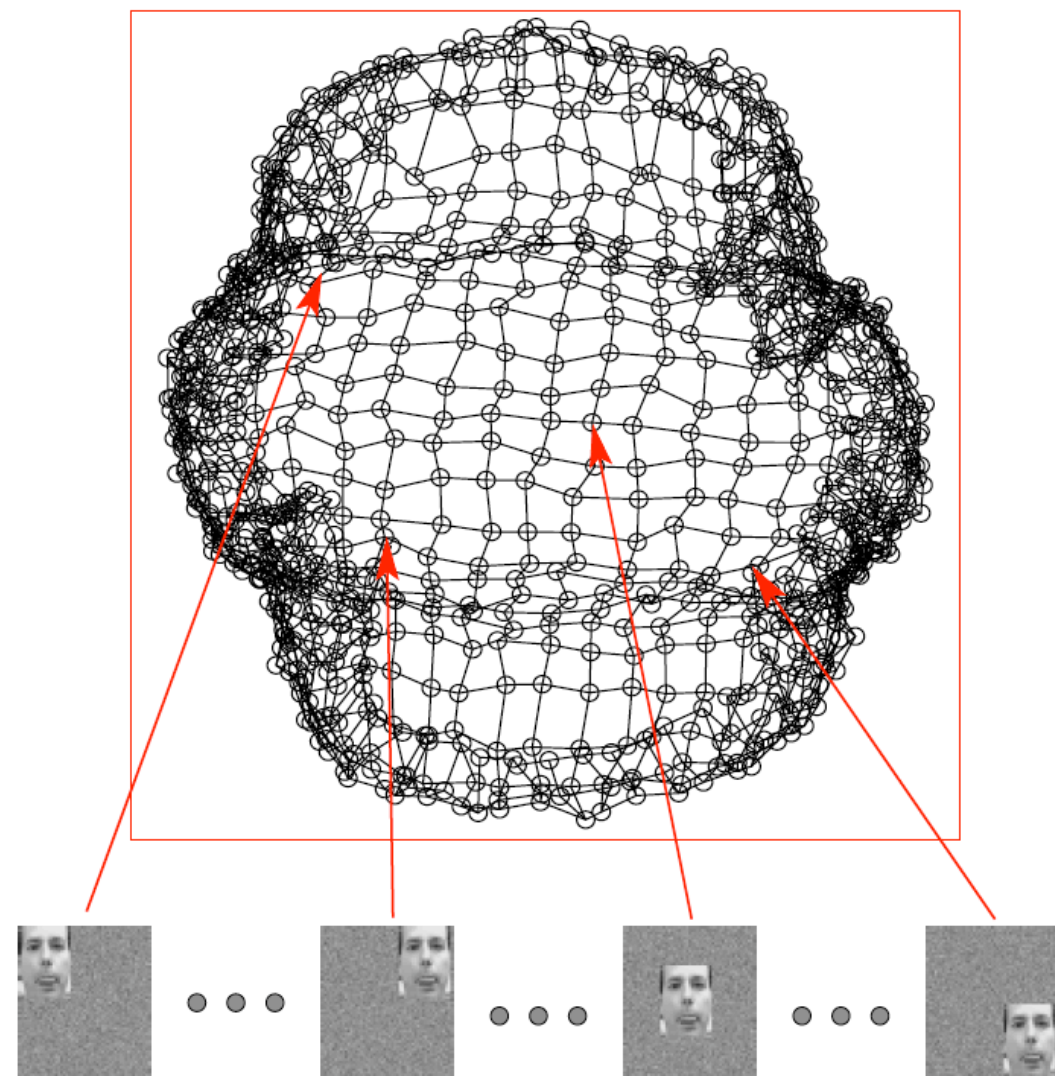
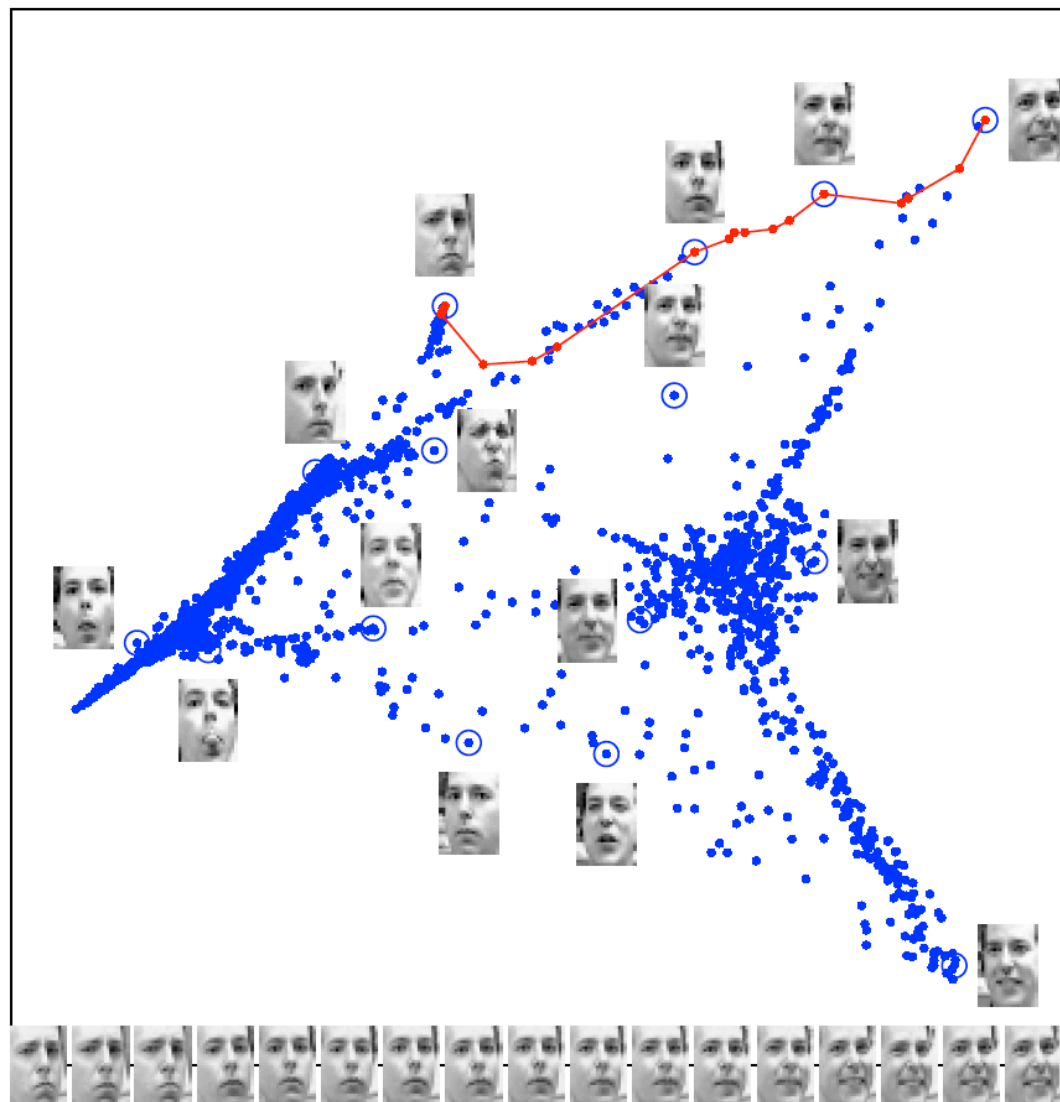
Surfaces

- Point Sets



N-Dimensional Case

- ex: Facial Expressions



Challenges

- Multi-Resolution
 - Hierarchical Atlas
 - Dynamic Setting

- API
 - Intuitive
 - General

Questions ?