




# Modelling Open Curves with Neural Implicit SDF

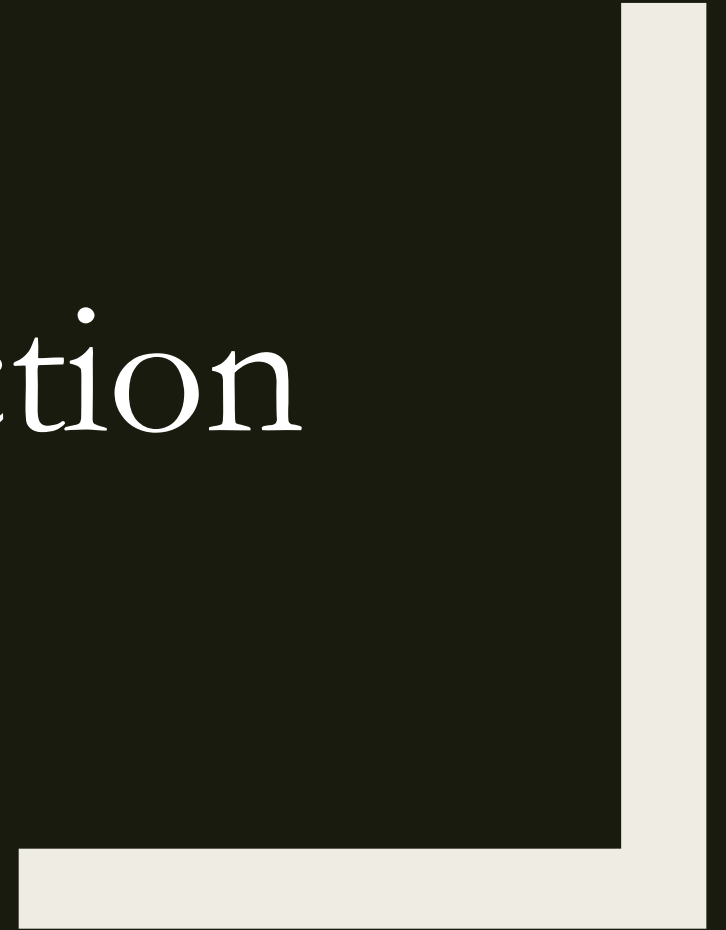
31-08-2021 Lu Meng



# Content

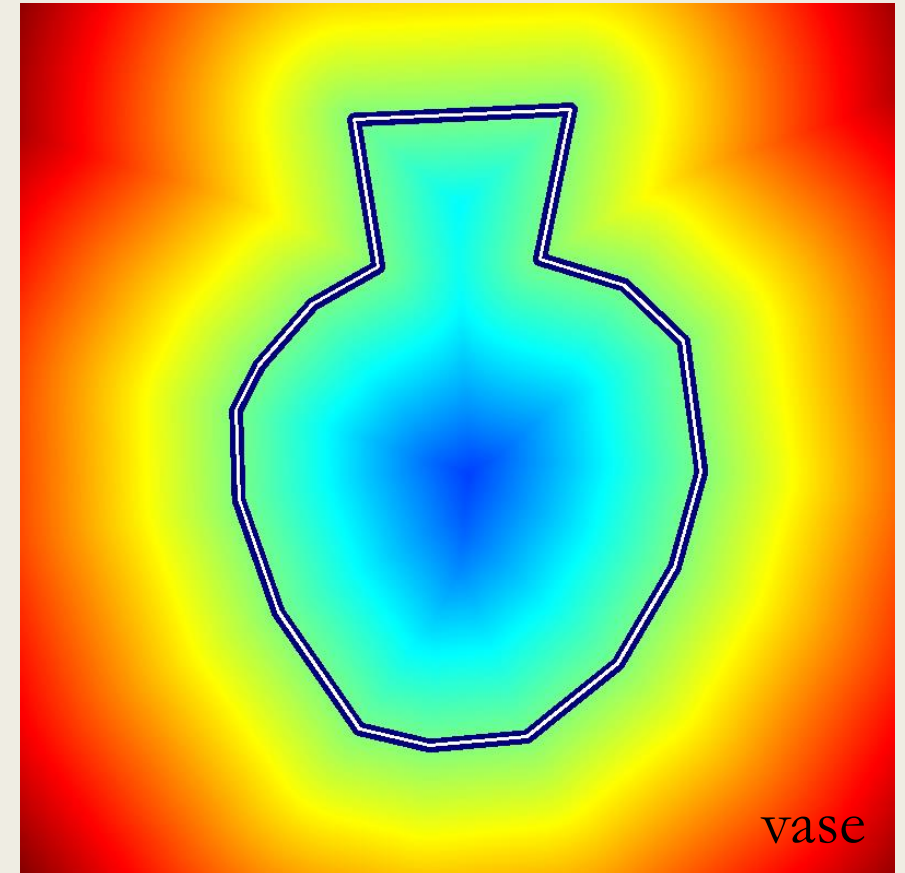
1. Introduction
2. Network
3. Problems
4. Solutions
5. Results
6. Future work

# Introduction



# Introduction: Signed distance function (SDF)

- Definition:
  - The signed distance function determines the **distance** of a given point  $x$  from the boundary of a curve  $\Omega$ .
  - The function is **negative** inside  $\Omega$  and **positive** outside.
- The zero-value contour is the **boundary** of the curve.
- We can derive any curve from its SDF.



Red area: positive SDF

Blue area: negative SDF

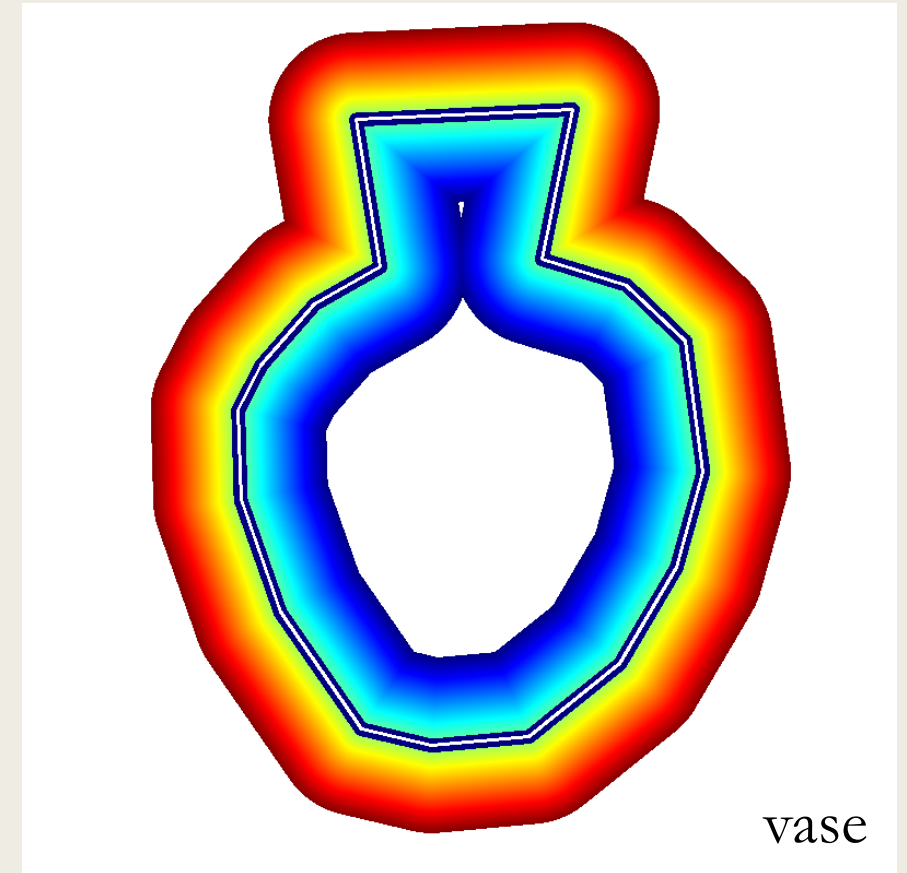
Black line: zero-value SDF contour

White line: true curve

# Introduction: Truncated signed distance function (TSDF)

$$TSDF = \text{clamp}(SDF, \text{threshold})$$

- The zero-value contour is the **boundary** of the curve.



Red area: positive SDF

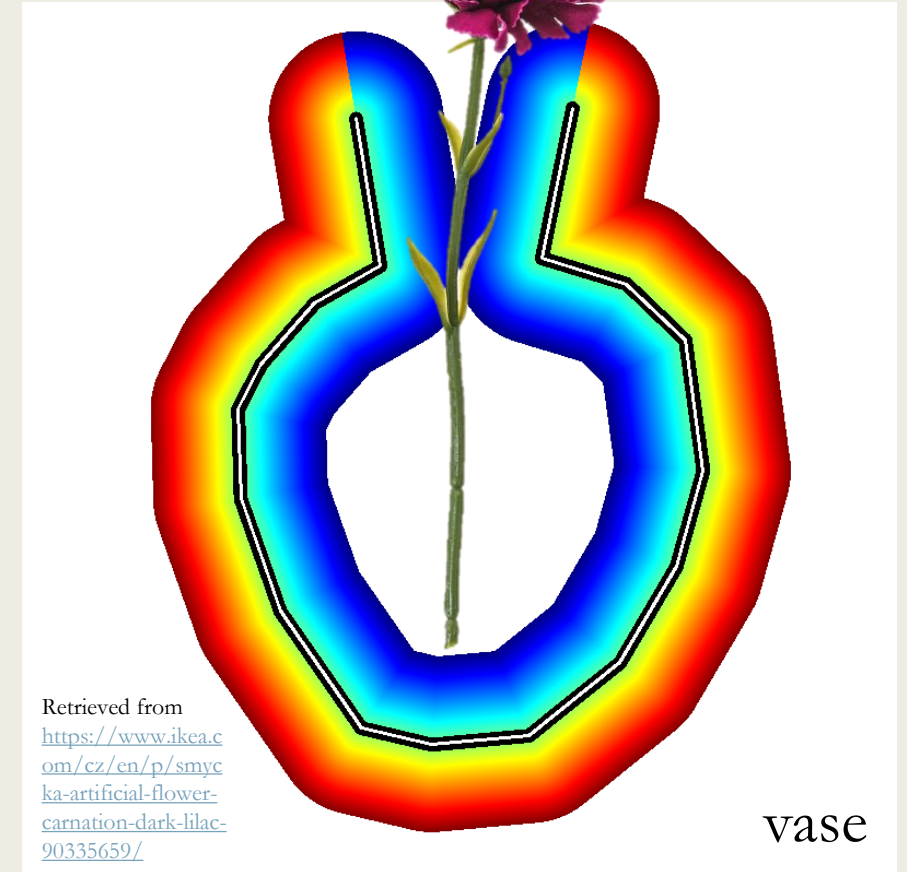
Blue area: negative SDF

Black line: zero-value SDF contour

White line: true curve

# Introduction: TSDF of open curves

- The open curve is assigned a **direction**.
- The **sign** is determined by whether a point  $X$  is on the **left** or **right** of the curve.



Red area: positive SDF

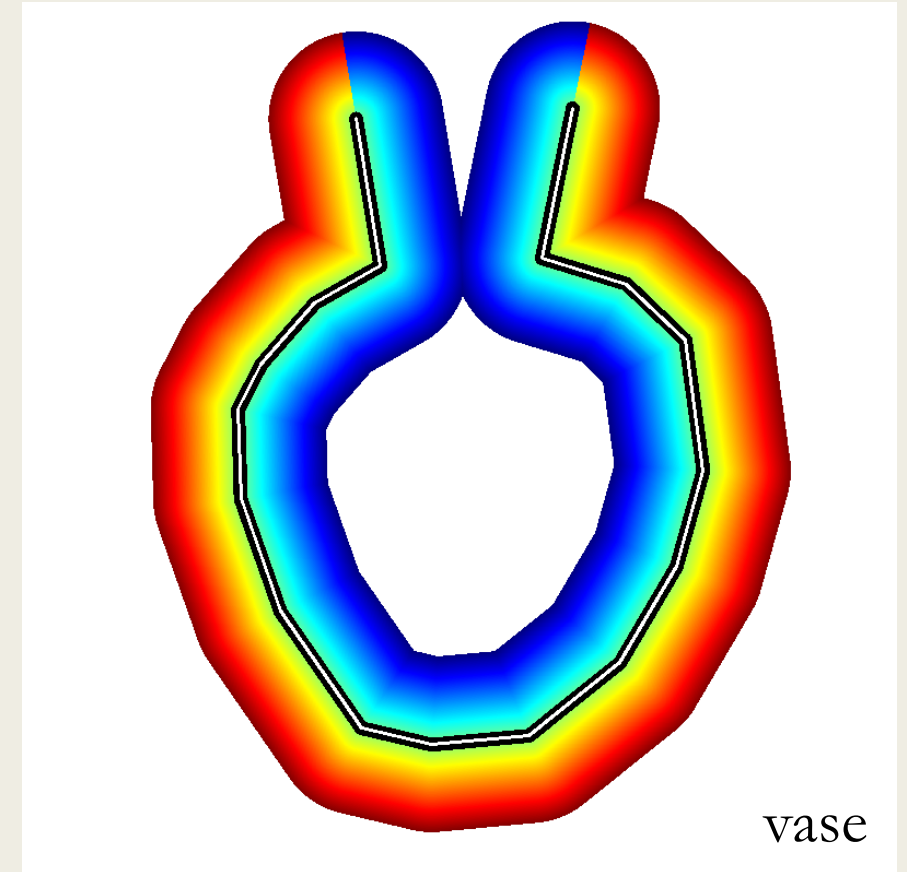
Blue area: negative SDF

Black line: zero-value SDF contour

White line: true curve

# Introduction: TSDF of open curves

- The open curve is assigned a **direction**.
- The **sign** is determined by whether a point  $x$  is on the **left** or **right** of the curve.



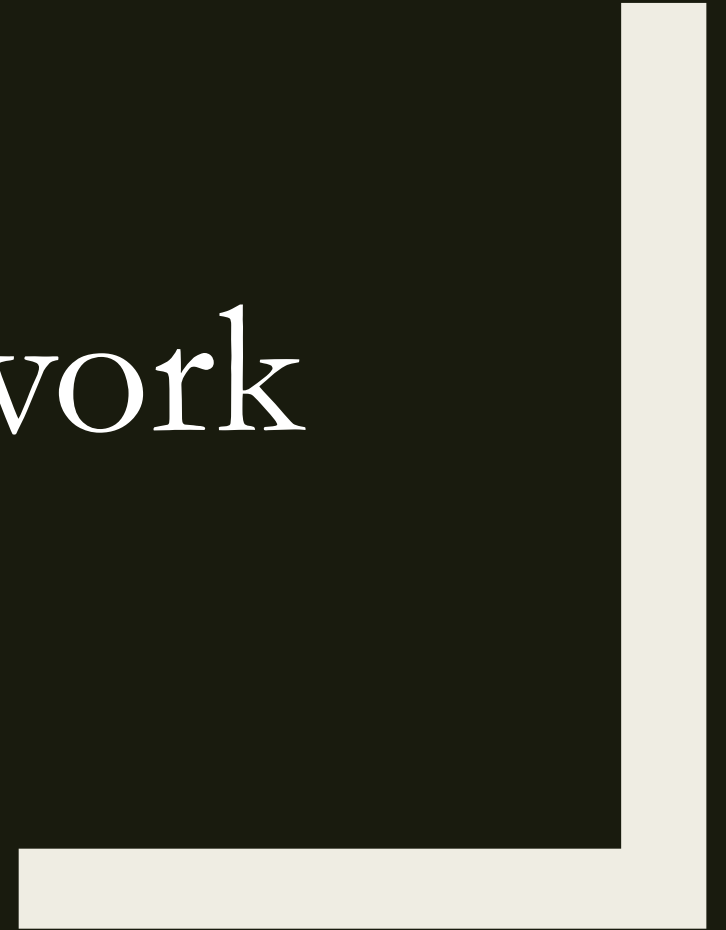
Red area: positive SDF

Blue area: negative SDF

Black line: zero-value SDF contour

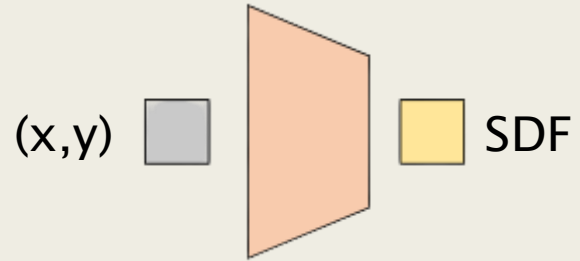
White line: true curve

Network



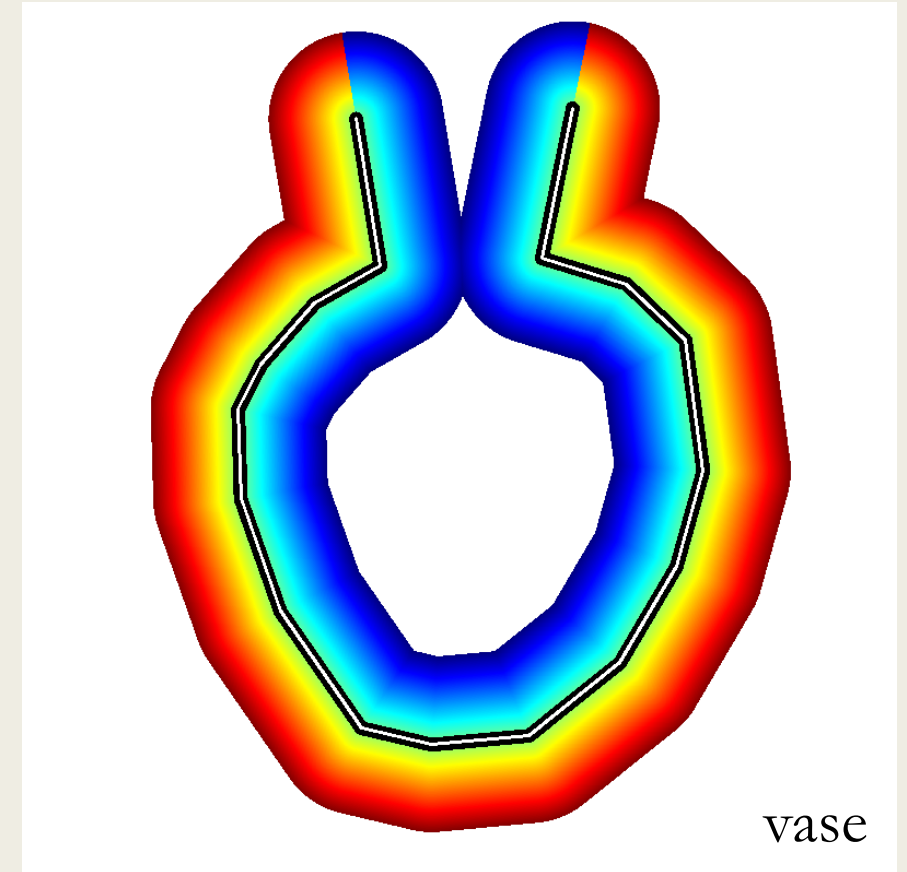


# Network: Idea



$$f_{\theta}(\mathbf{x}) \approx TSDF(\mathbf{x}), \forall \mathbf{x} \in \Omega$$

- Use a **neural network** to model the TSDF of a certain curve.
- The **curve information** is contained in the weight  $\theta$  of the network.



Red area: positive SDF

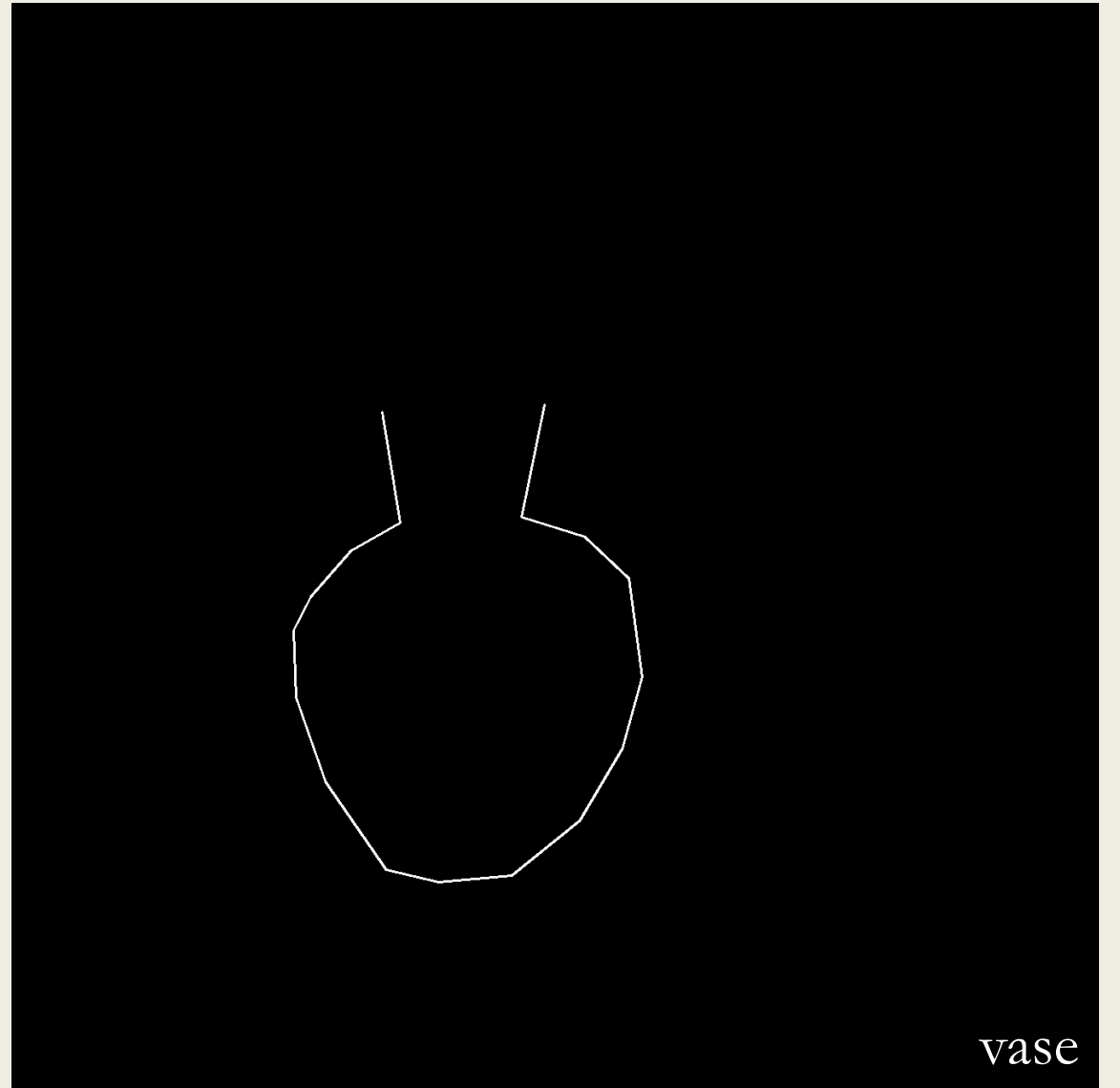
Blue area: negative SDF

Black line: zero-value SDF contour

White line: true curve

# Network: Data preparation

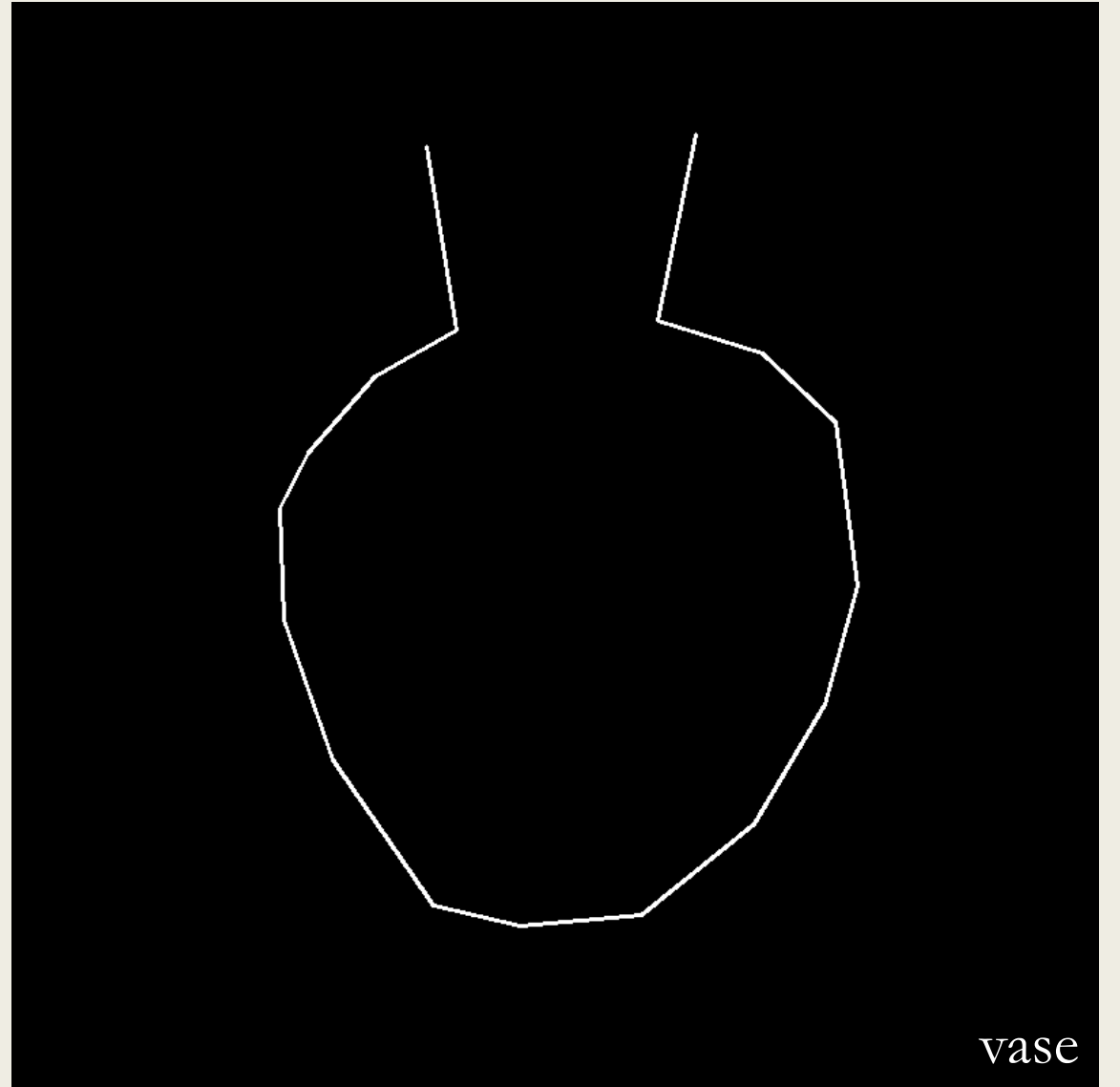
$$X := \{(\mathbf{x}, s) : SDF(\mathbf{x}) = s\}$$



# Network: Data preparation

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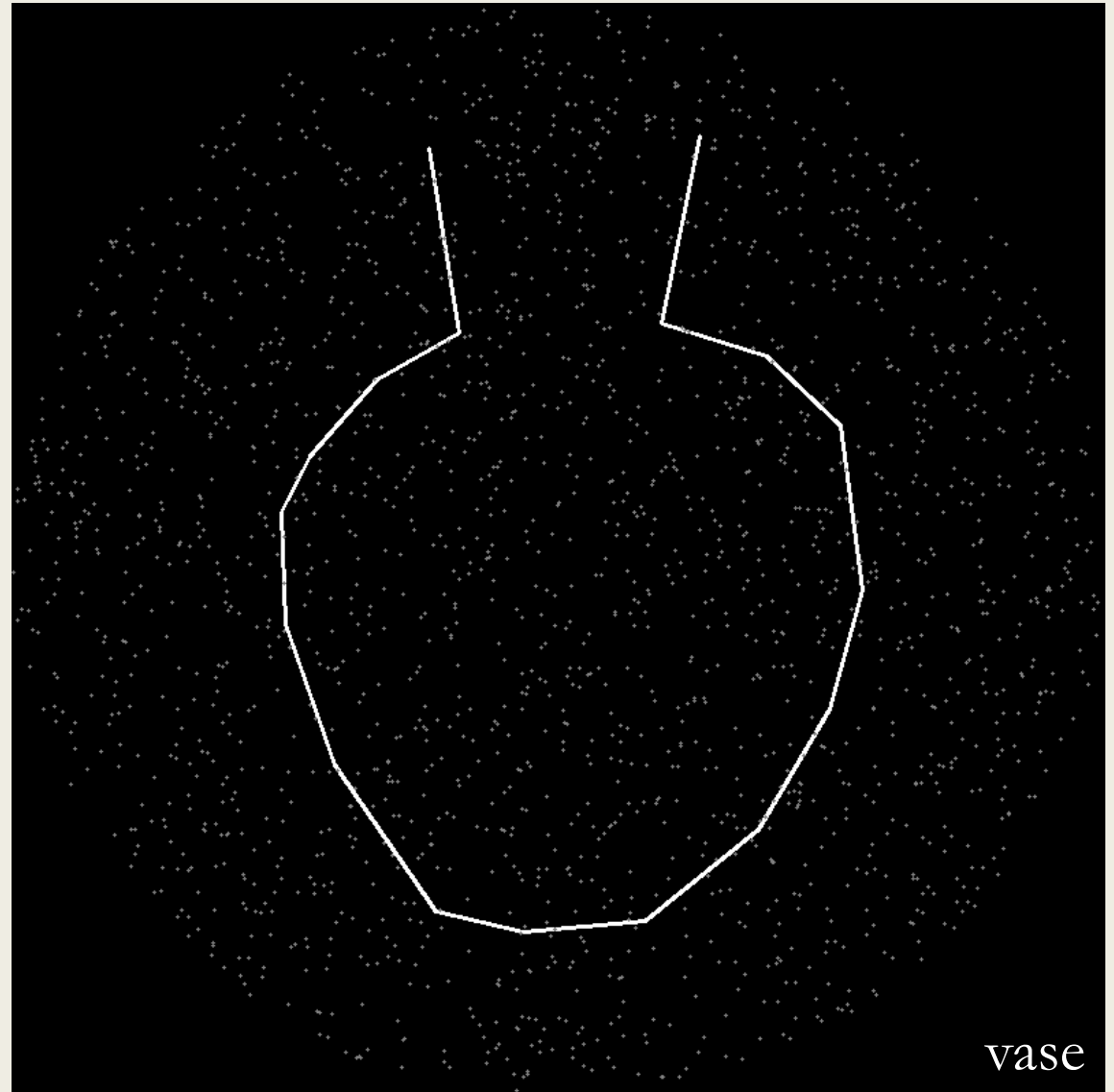
- **Normalize** the curve so that it is bounded by a unit circle.



# Network: Data preparation

$$X := \{(\mathbf{x}, s) : SDF(\mathbf{x}) = s\}$$

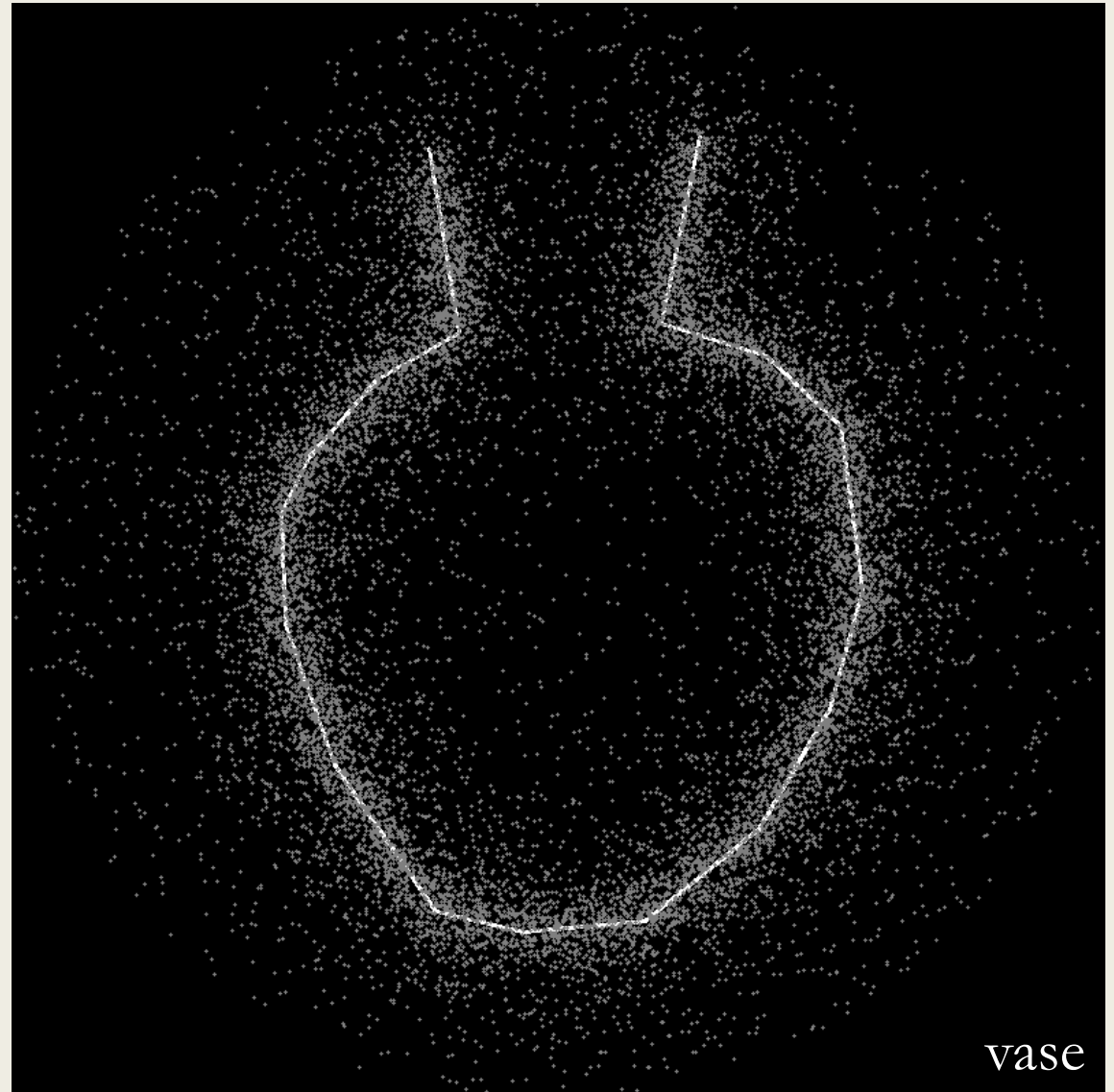
- **Normalize** the curve so that it is bounded by a unit circle.
- Generate 2,000 **uniform** sampling points.



# Network: Data preparation

$$X := \{(\mathbf{x}, s) : SDF(\mathbf{x}) = s\}$$

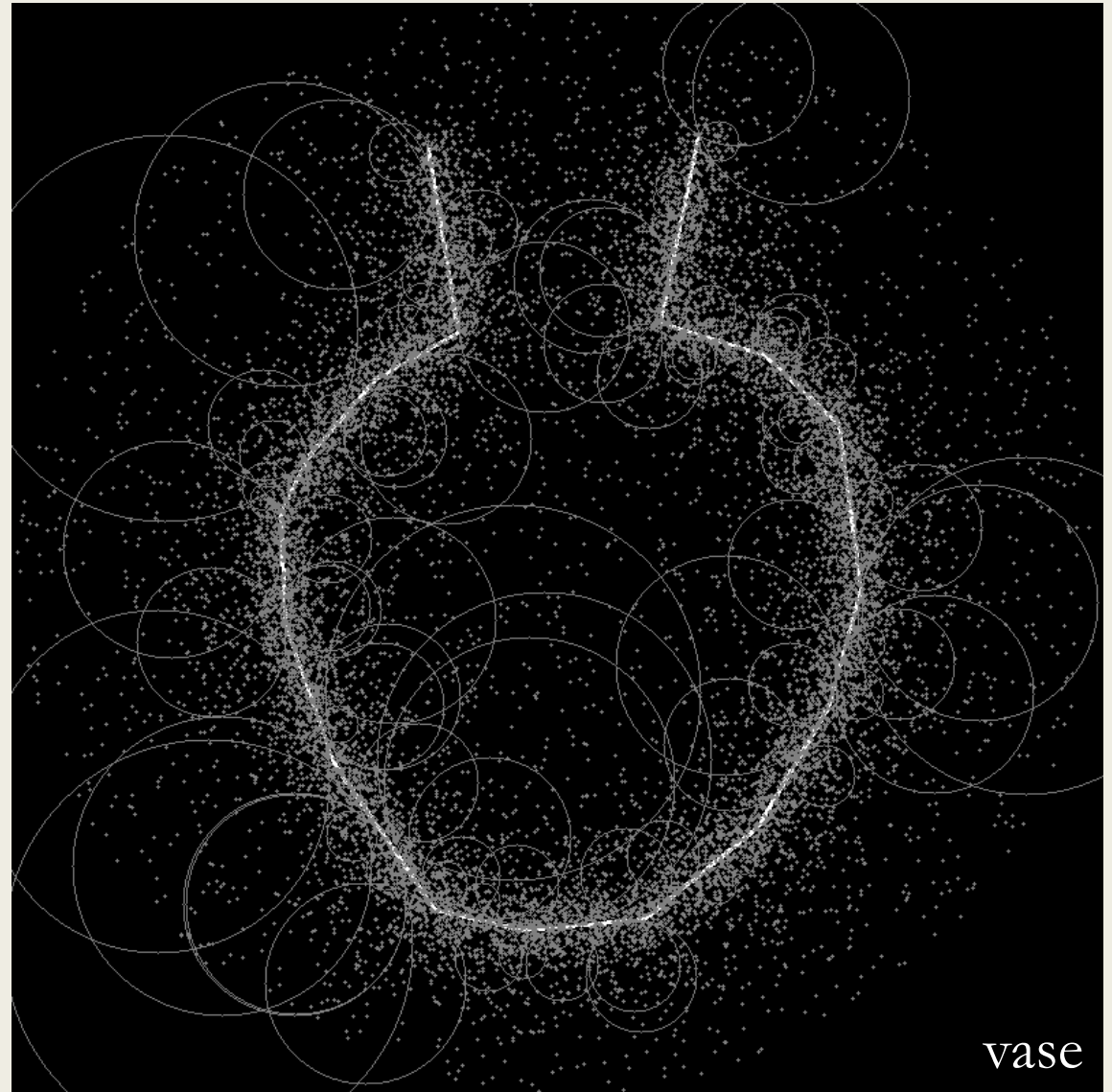
- **Normalize** the curve so that it is bounded by a unit circle.
- Generate 2,000 **uniform** sampling points.
- Generate 12,000 **Gaussian** sampling points.
- Obtain more information about the **zero-value set**.



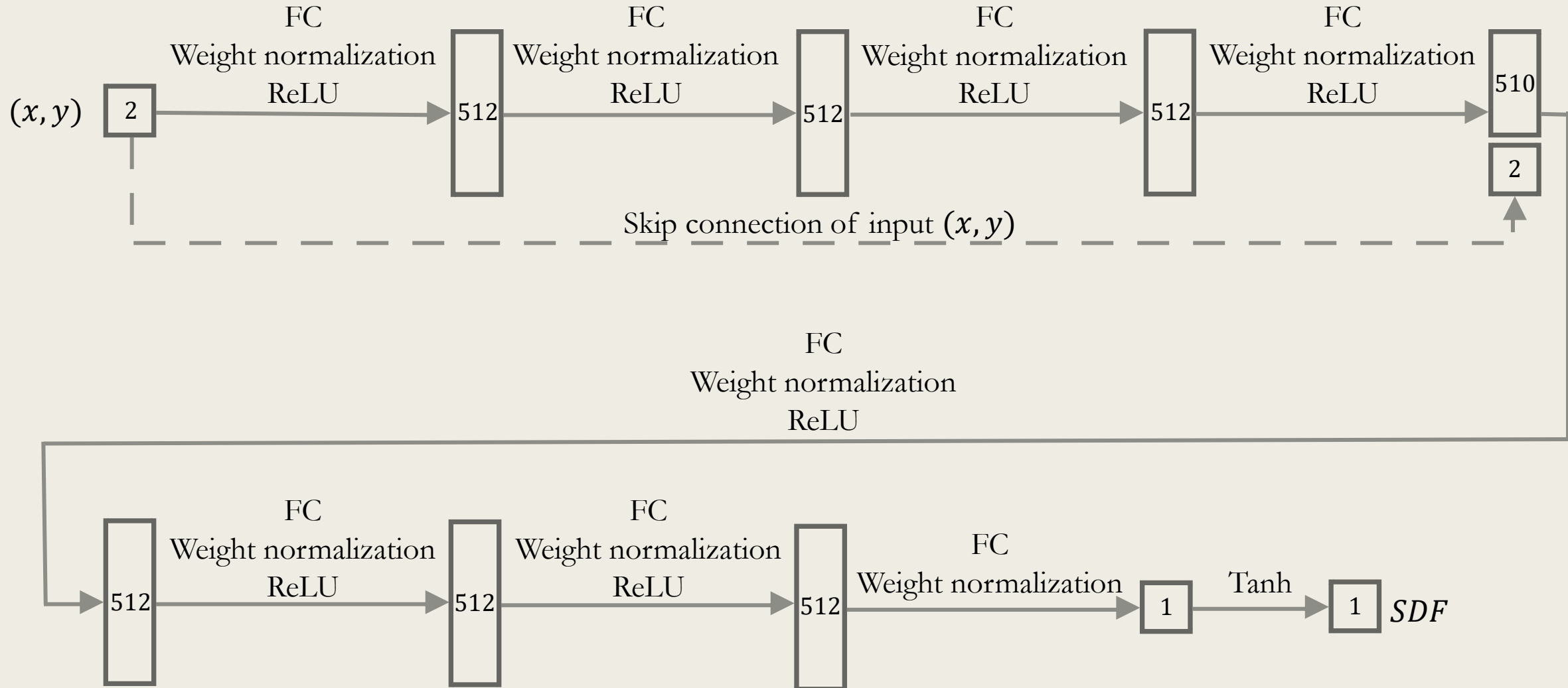
# Network: Data preparation

$$X := \{(\mathbf{x}, s) : SDF(\mathbf{x}) = s\}$$

- Calculate the corresponding **ground truth SDF**.
  - Find the **minimum value** among the distances from the point to each segment.
  - Determine the **sign** according to which side of the curve the point is on.



# Network: Structure



# Network: Training details

- Loss function:

- $\mathcal{L}(f_{\theta}(\mathbf{x}), s) = |\text{clamp}(f_{\theta}(\mathbf{x}), \delta) - \text{clamp}(s, \delta)|$

- Optimizer:

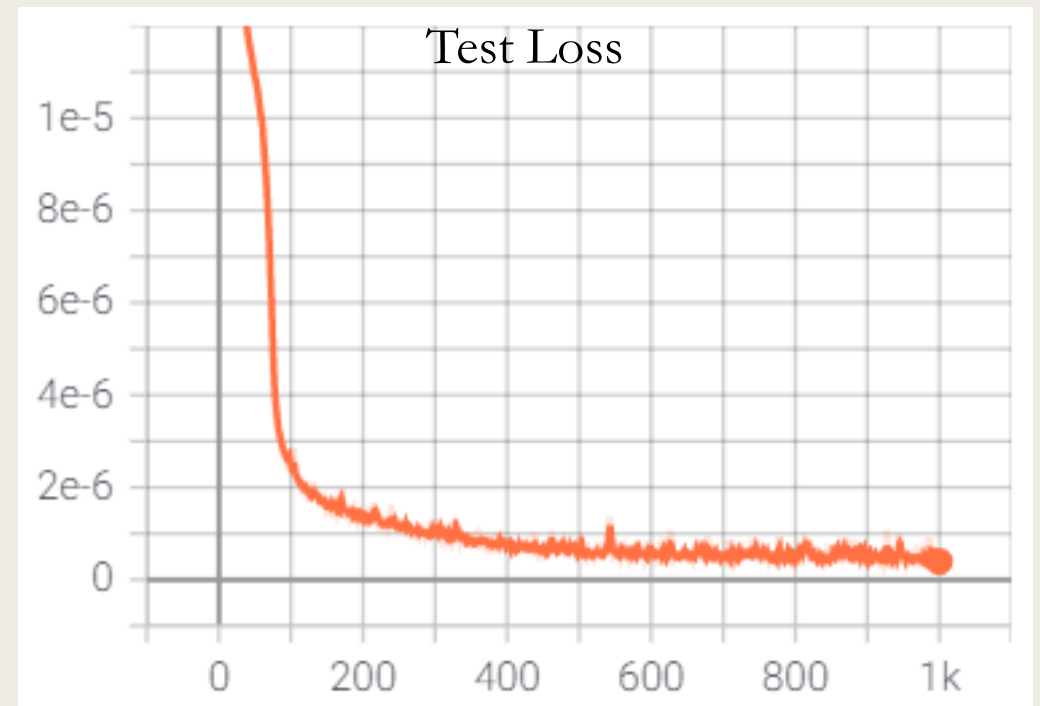
- Adam

- Configs:

- Learning rate:  $1e-5$

- Epochs: 1,000

- Batch size: 100



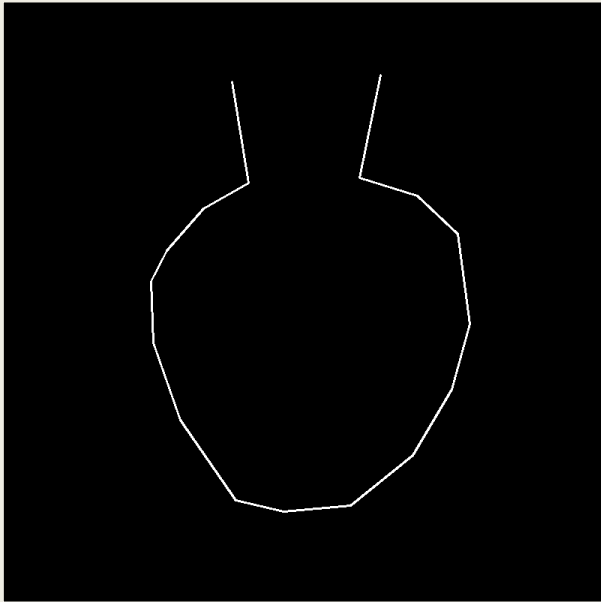


# Problems & Solutions

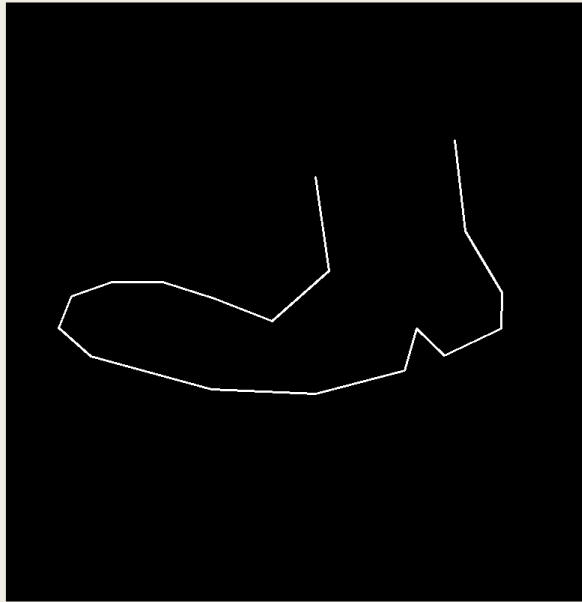


# Problems: Curves

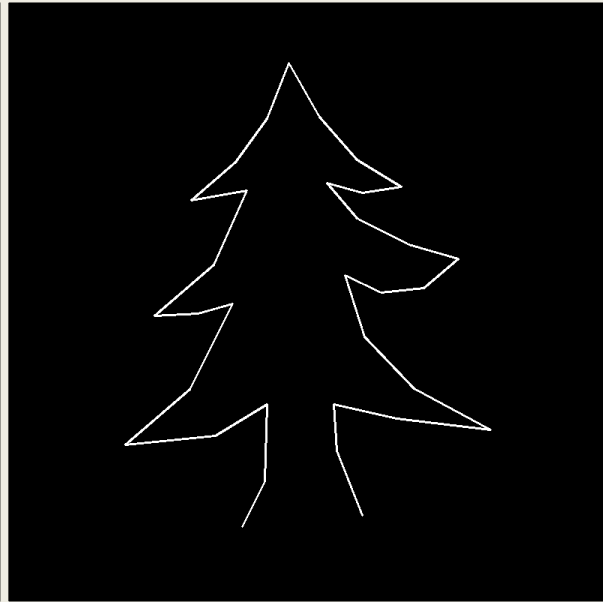
## Normalized Curves



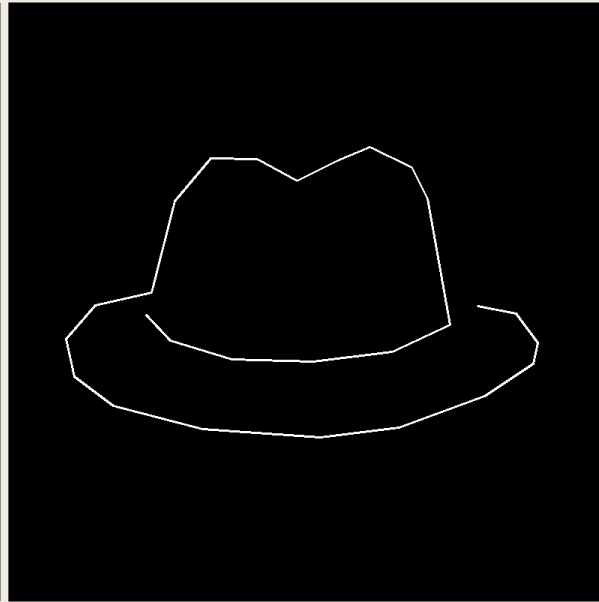
vase



shoe



tree



hat

# Problems: Outliers

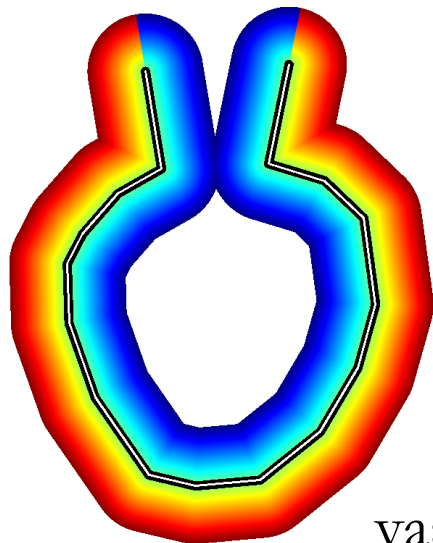
Red area: positive SDF

Blue area: negative SDF

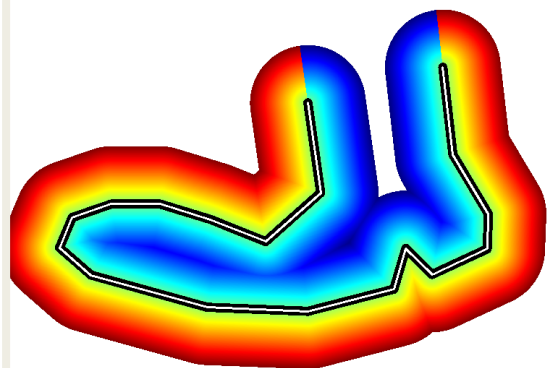
Black line: zero-value SDF contour

White line: true curve

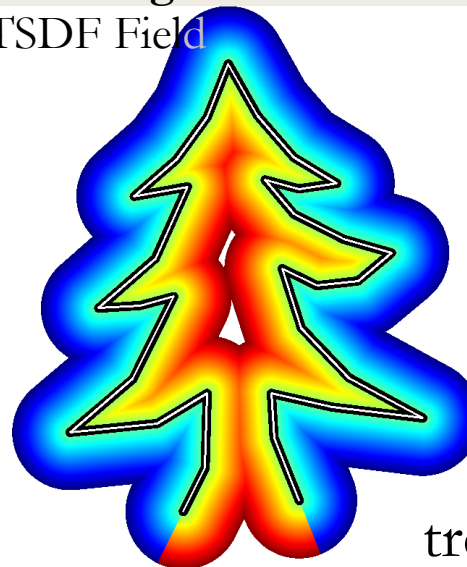
Ground Truth TSDF Field



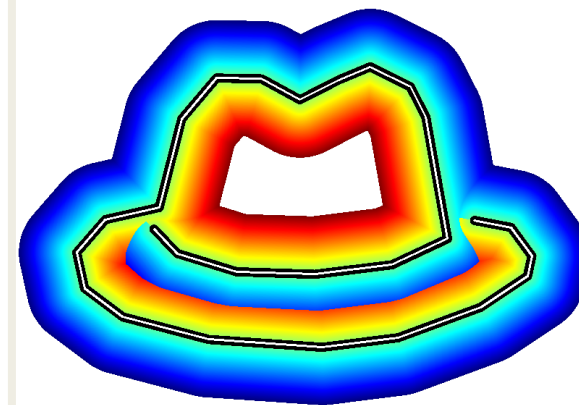
vase



shoe



tree



hat

Avg. L1 error:  $2.364e - 3$

$1.445e - 3$

$1.585e - 3$

$8.365e - 4$

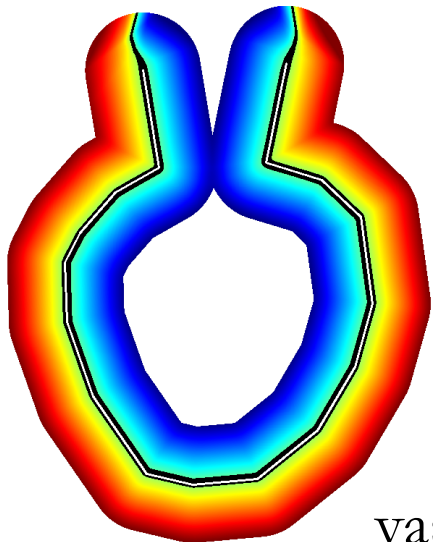
Max L1 error:  $1.309e - 1$

$1.127e - 1$

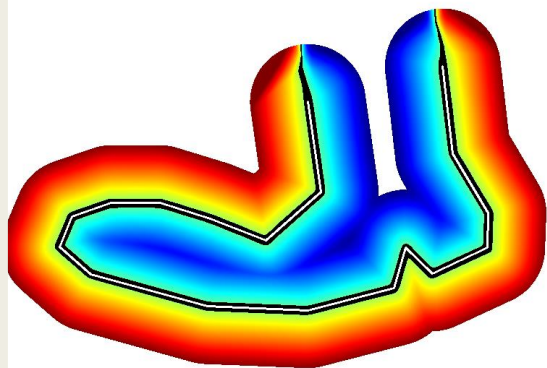
$1.196e - 1$

$1.340e - 1$

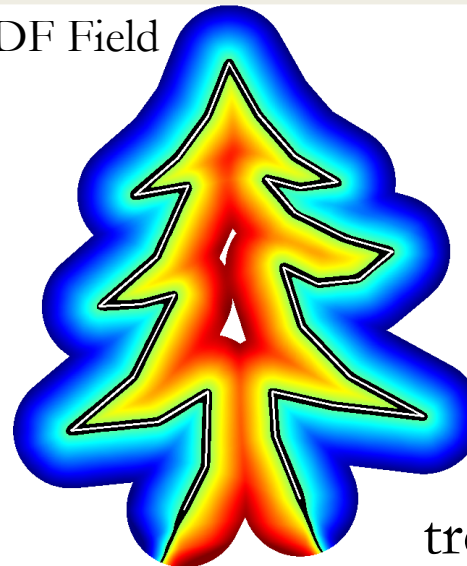
Predicted TSDF Field



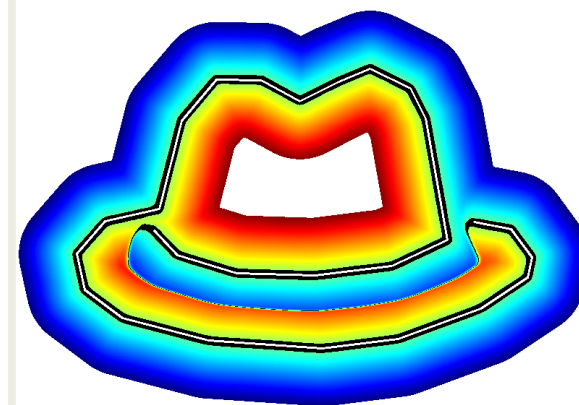
vase



shoe



tree



hat

# Problems: Outliers

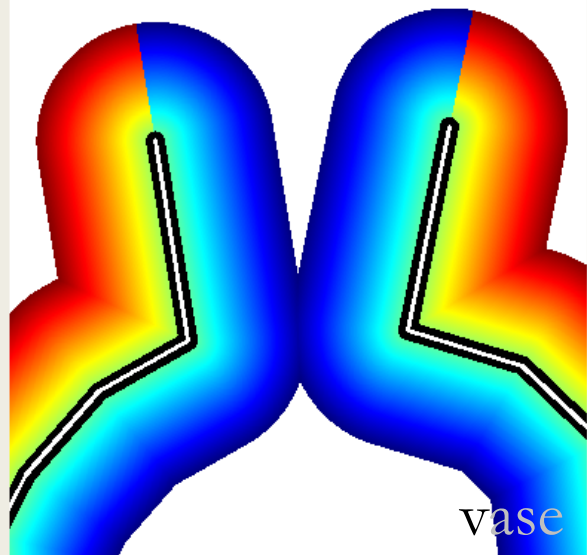
Red area: positive SDF

Black line: zero-value SDF contour

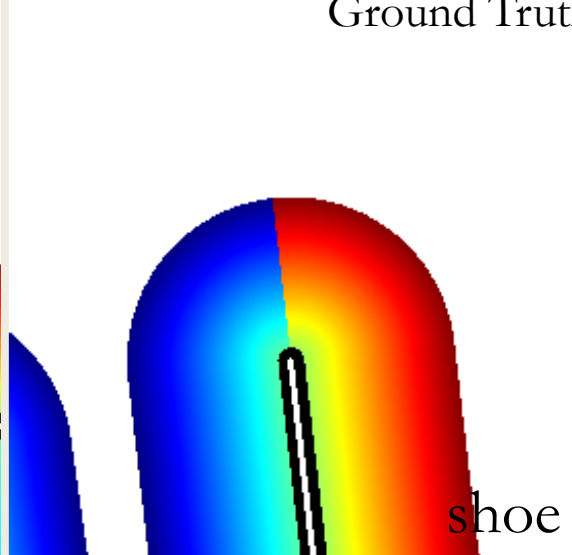
Blue area: negative SDF

White line: true curve

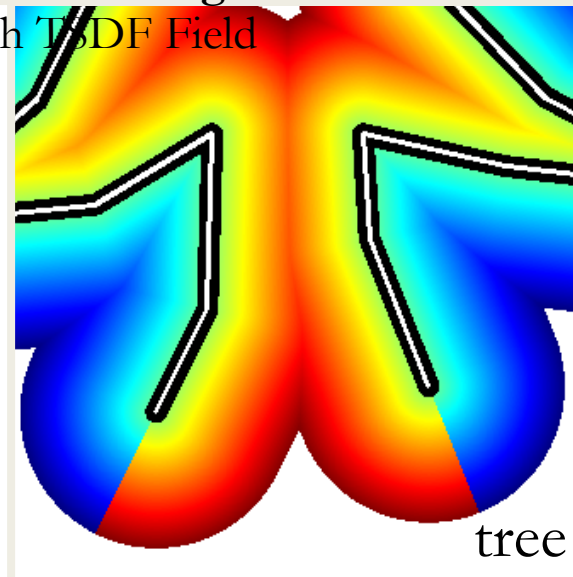
Ground Truth TSDF Field



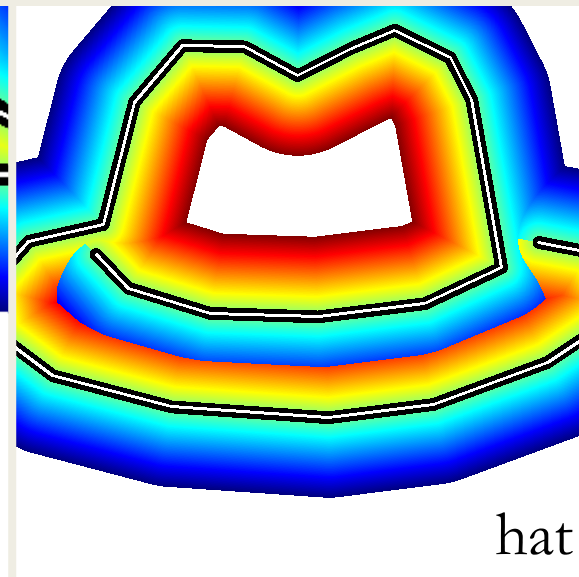
vase



shoe



tree



hat

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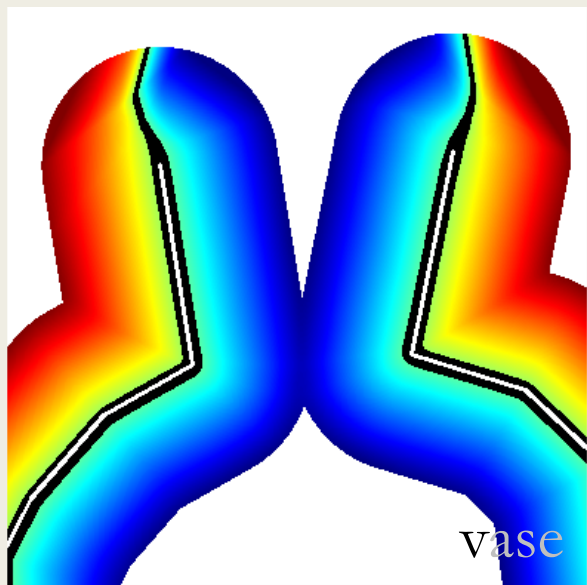
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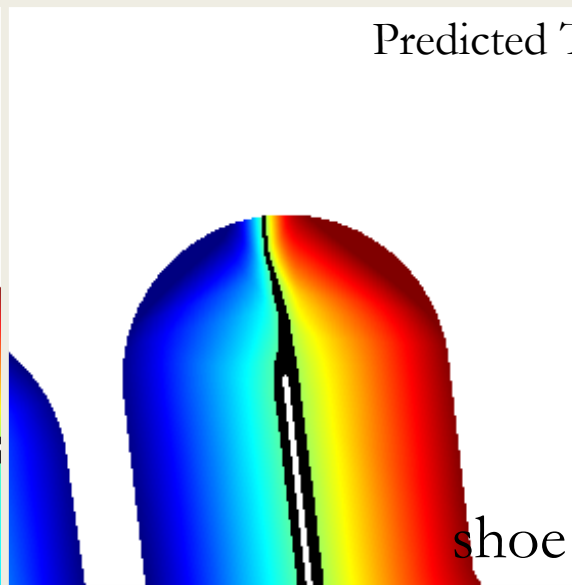
$1.196e - 1$

$1.340e - 1$

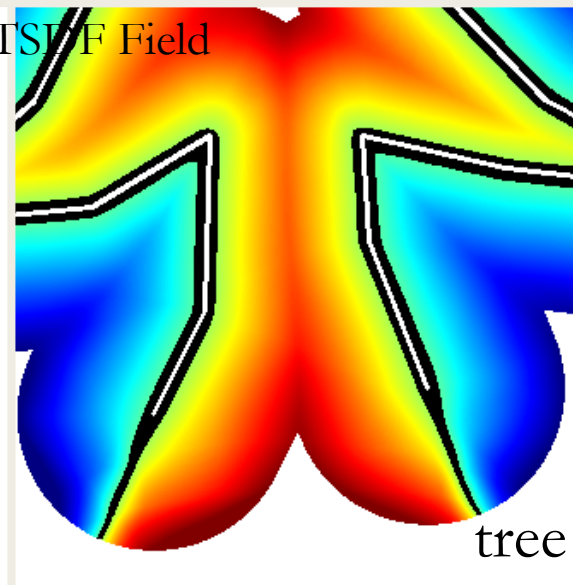
Predicted TSDF Field



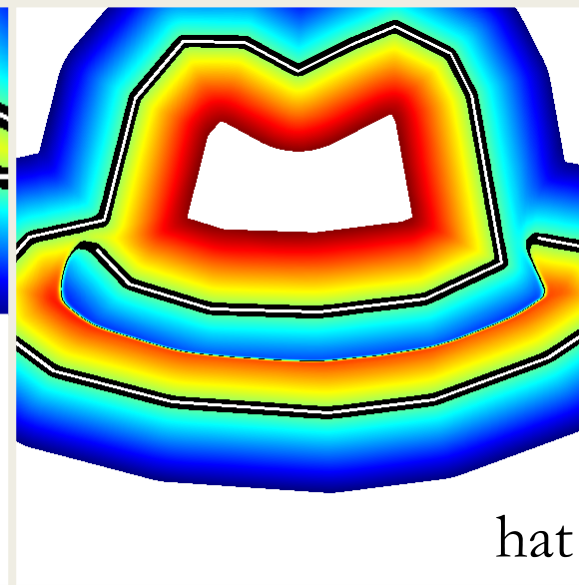
vase



shoe

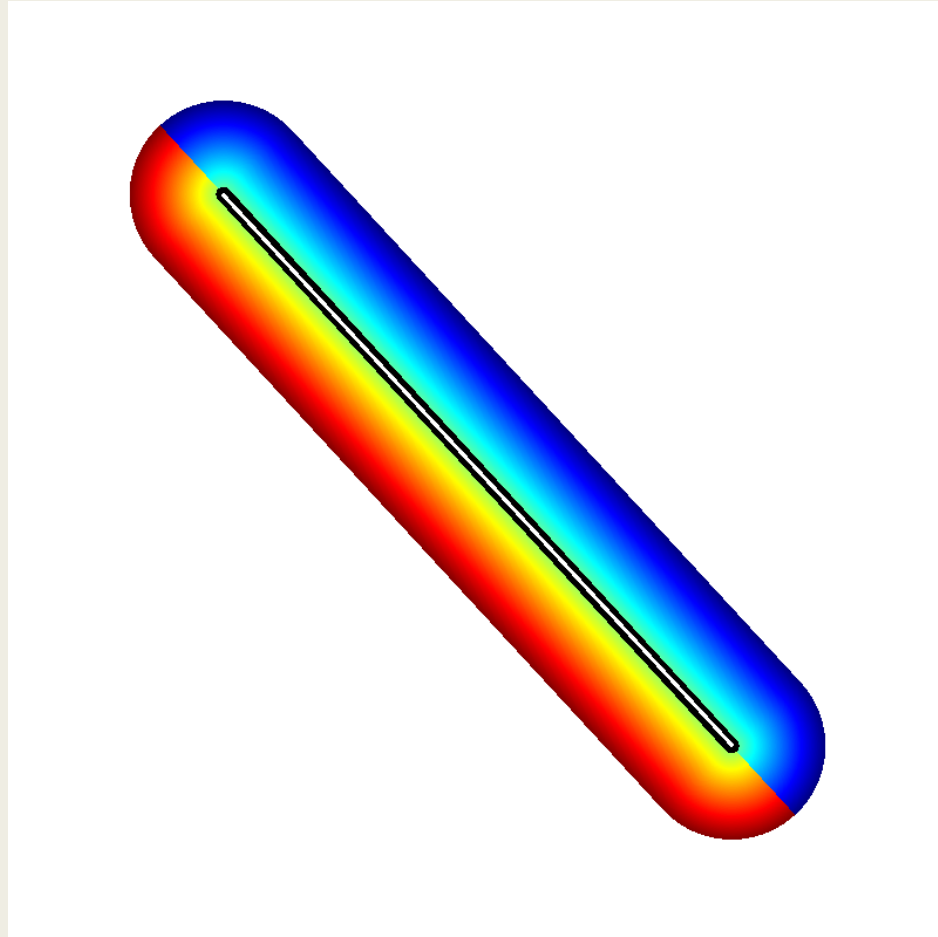


tree

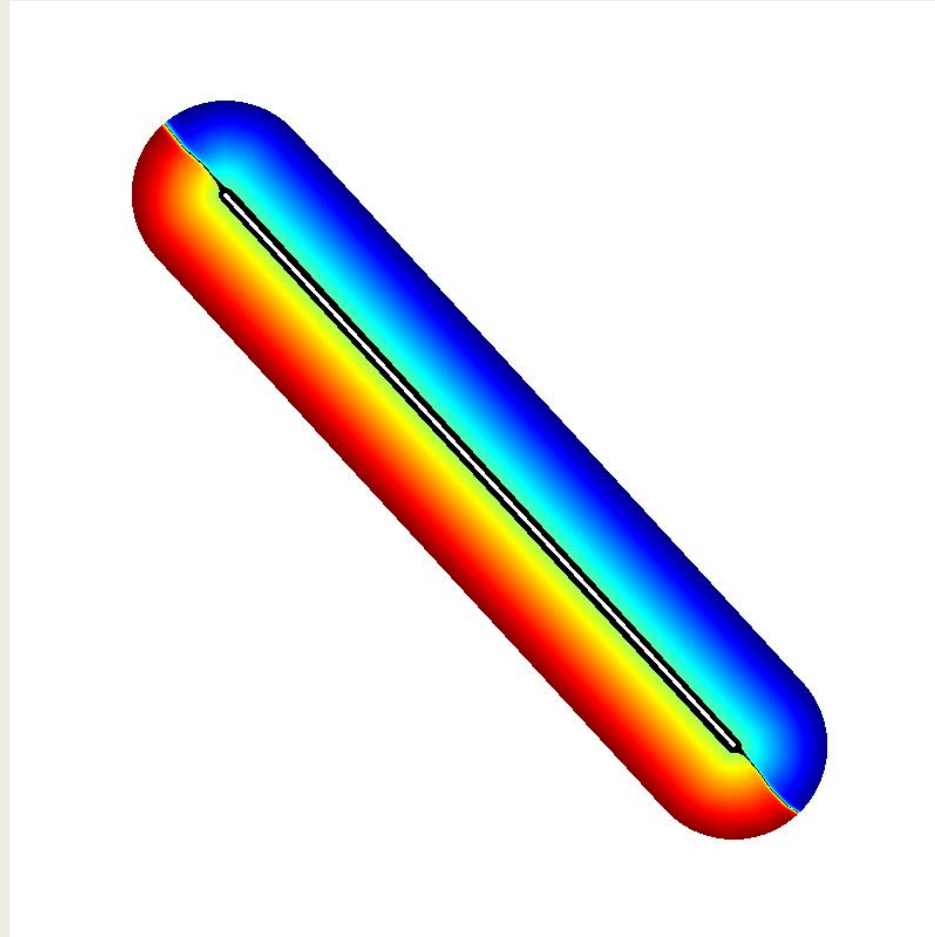


hat

# Problems: Outliers around endpoints (Type I)



Ground Truth TSDF Field

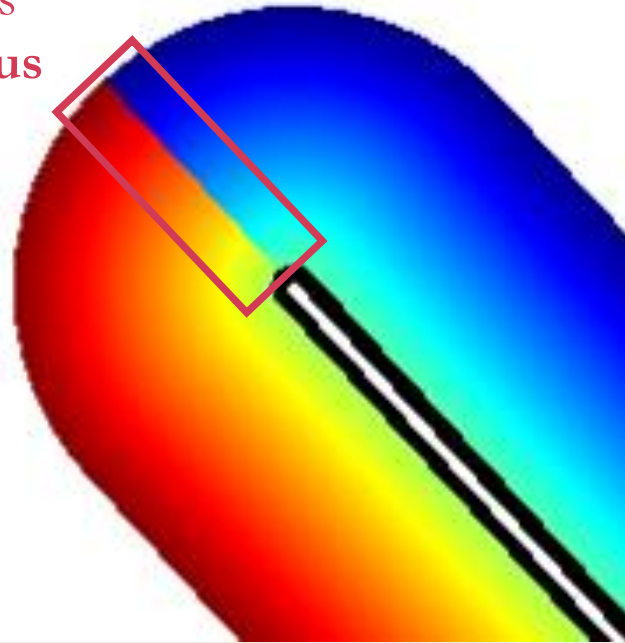


Predicted TSDF Field

Red area: **positive** SDF  
Blue area: **negative** SDF  
Black line: **zero-value**  
SDF contour  
White line: true curve

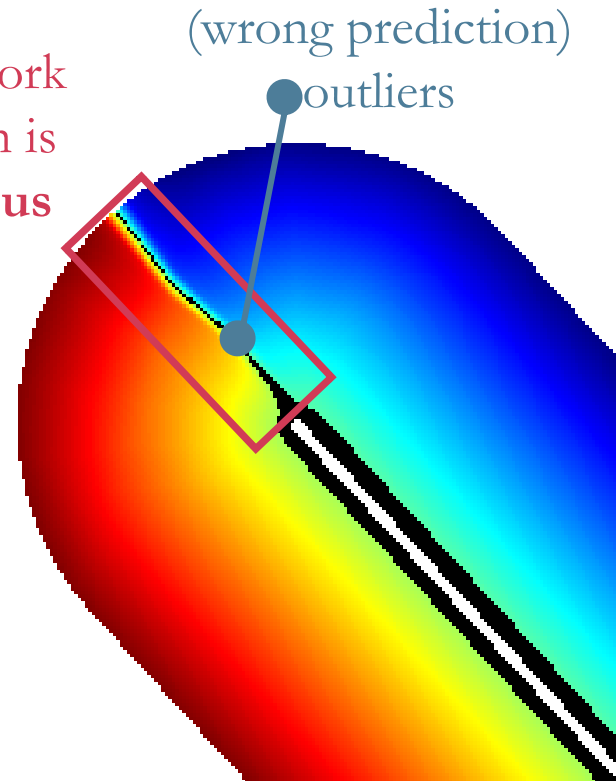
# Problems: Outliers around endpoints (Type I)

The ground truth TSDF is **discontinuous**



Ground Truth TSDF Field

The network prediction is **continuous**



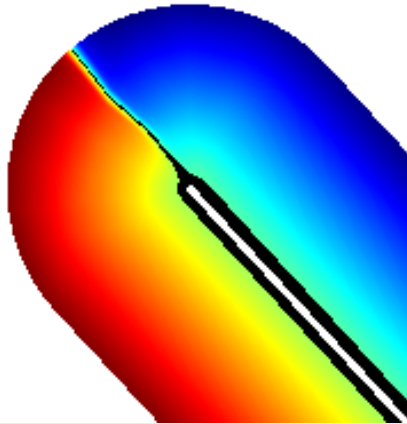
Predicted TSDF Field

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Black line: **zero-value** SDF contour  
White line: true curve

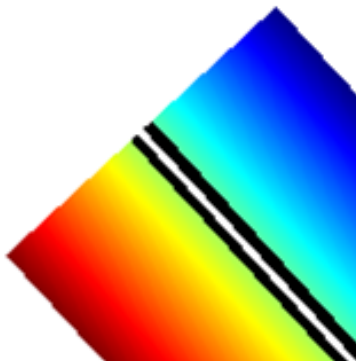


# Solutions: Cut-off at endpoints

Predicted TSDF before Cut-off

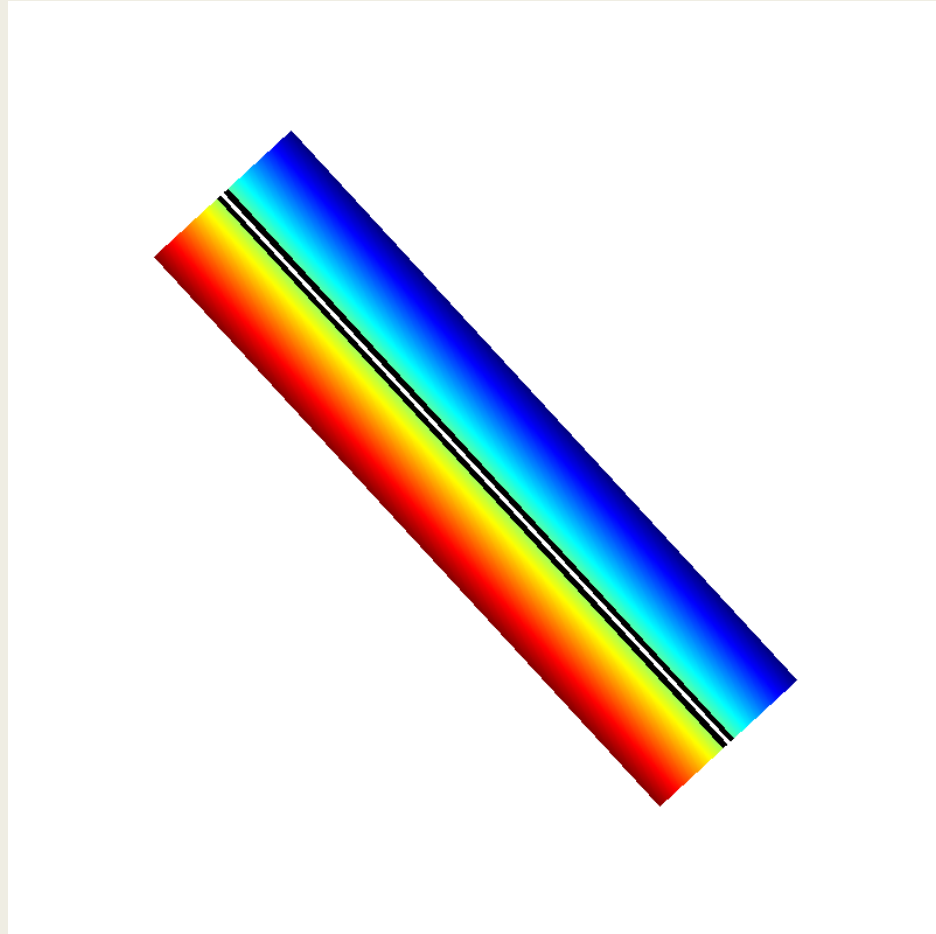


Predicted TSDF after Cut-off

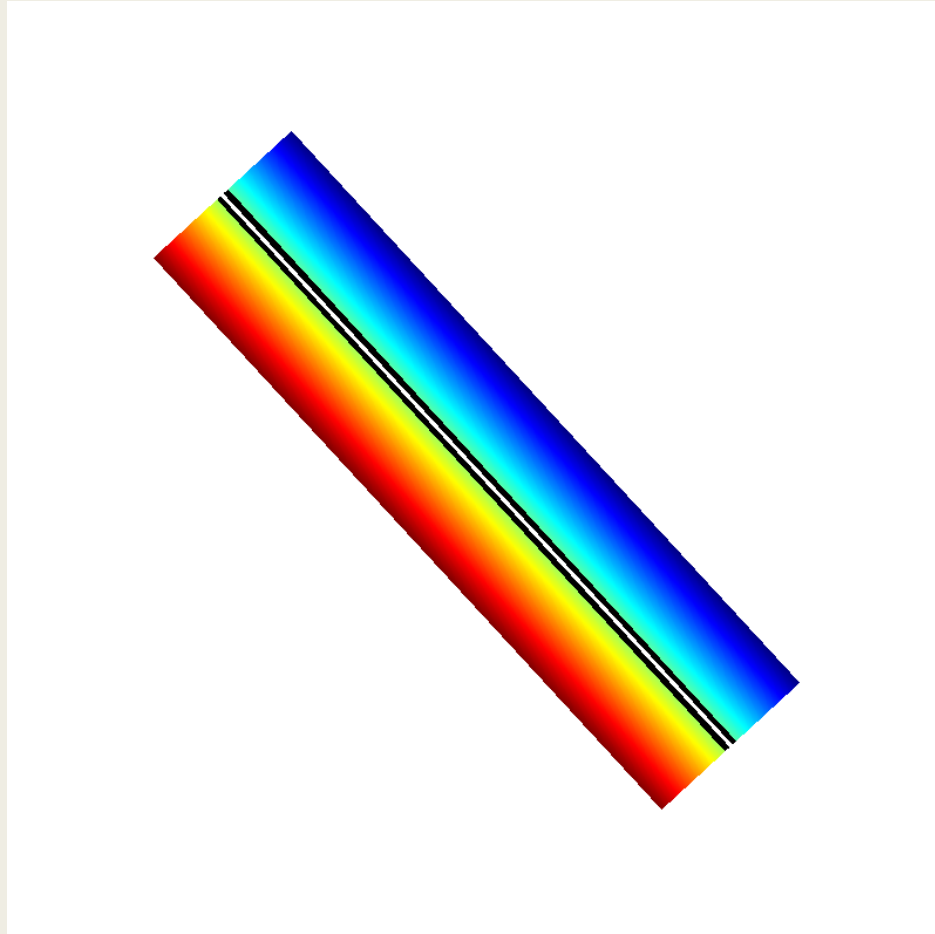


- **Type I outliers:** Outliers near endpoints
  - The **positive-negative conjunction** is caused by an endpoint.
- **Idea:**
  - Cut off the **half circle** at endpoints.
- **Methodology:**
  - Filter out points whose **nearest point on the curve** is one of the endpoints.

# Solutions: Cut-off at endpoints



Ground Truth TSDF Field

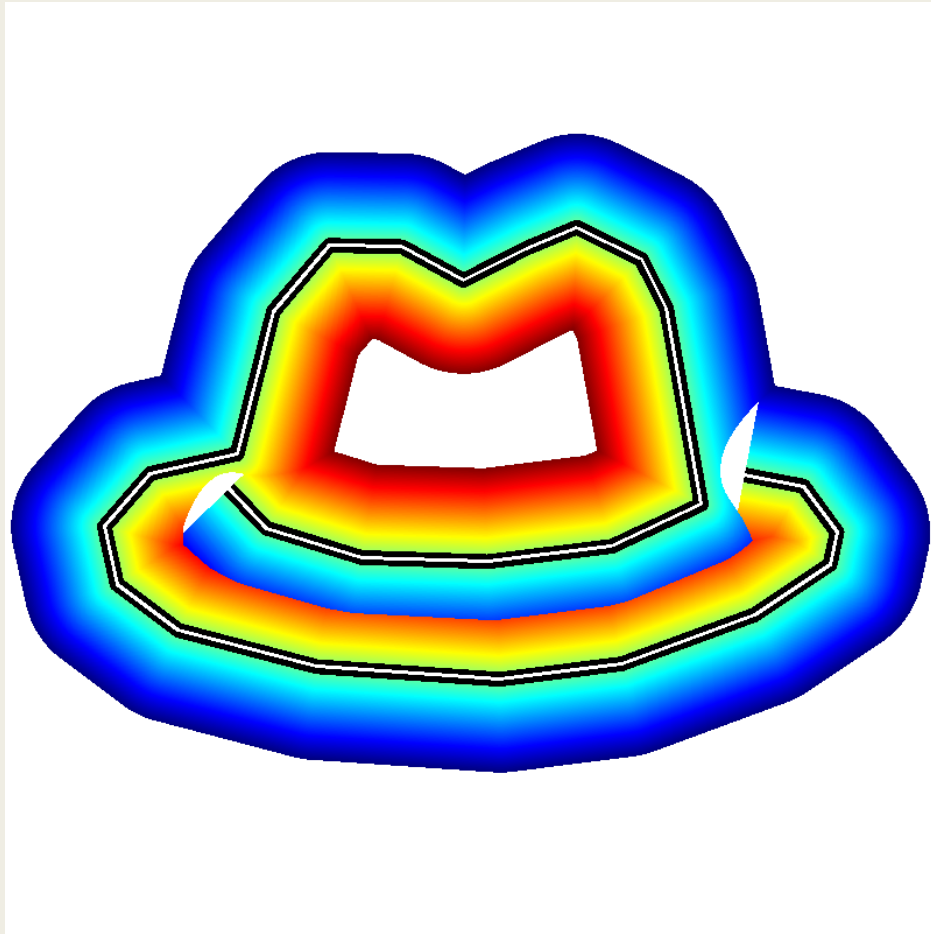


Predicted TSDF Field

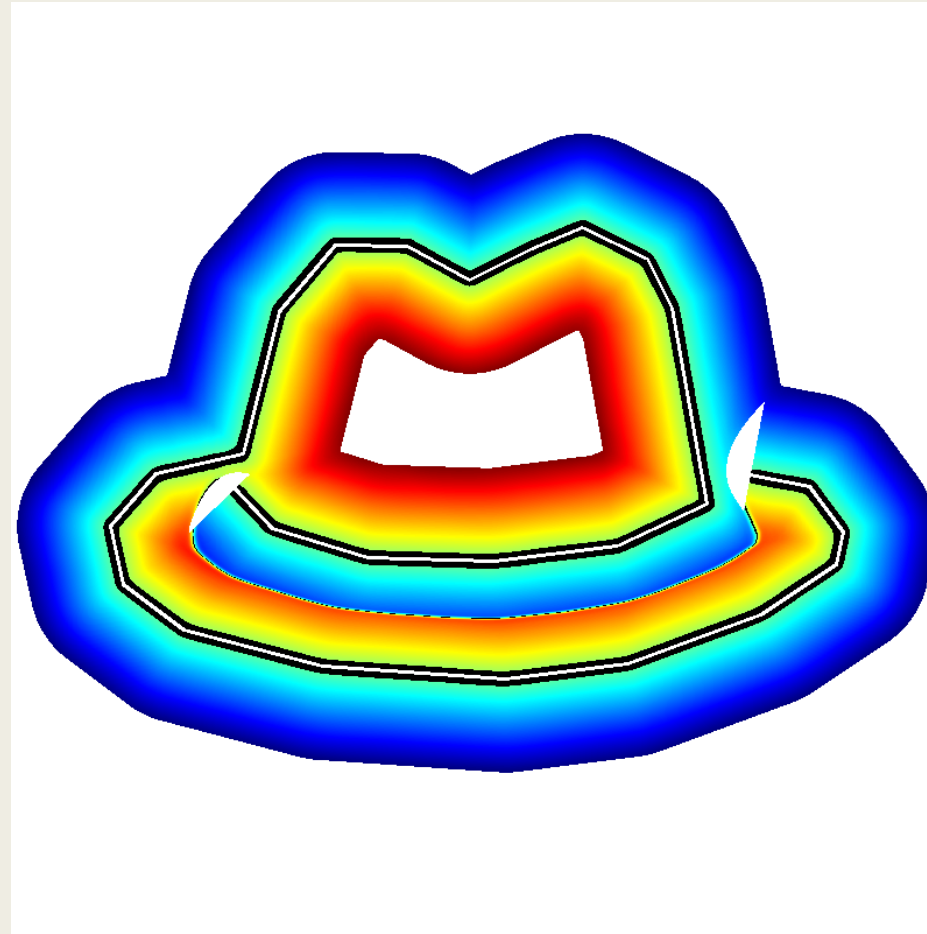
Red area: **positive** SDF  
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Black line: **zero-value**  
SDF contour  
White line: true curve



# Problems: Outliers between two segments (Type II)



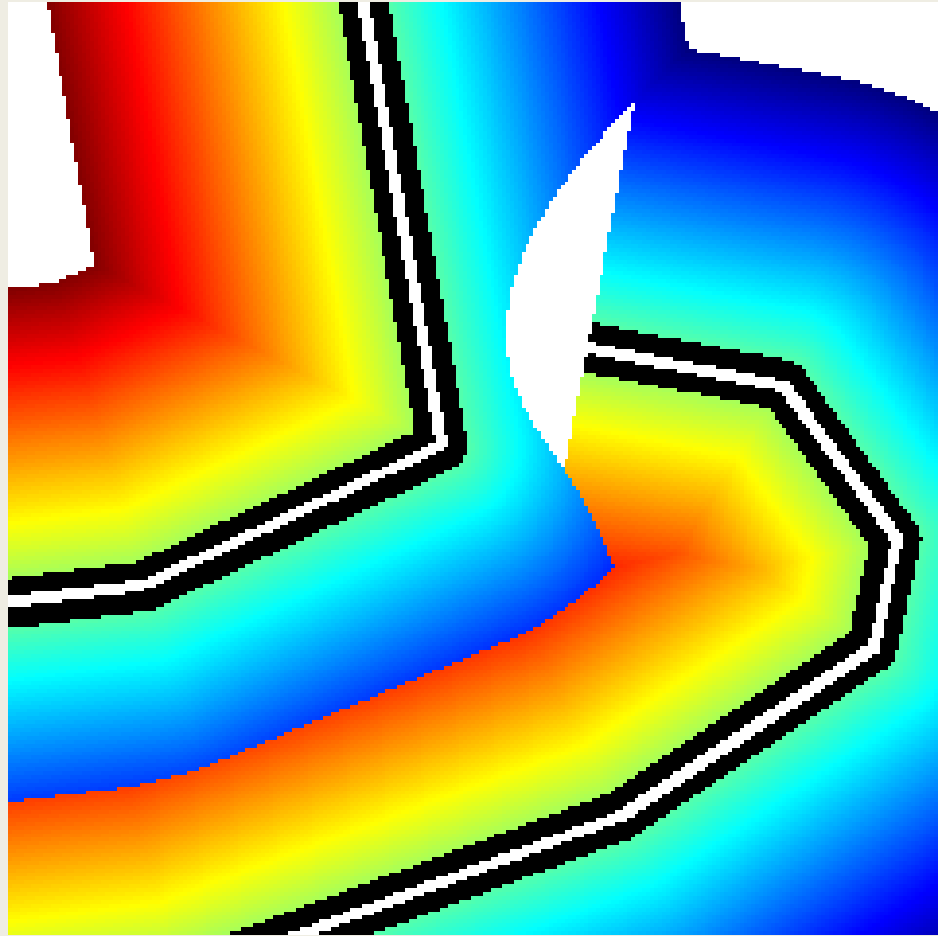
Ground Truth TSDF Field



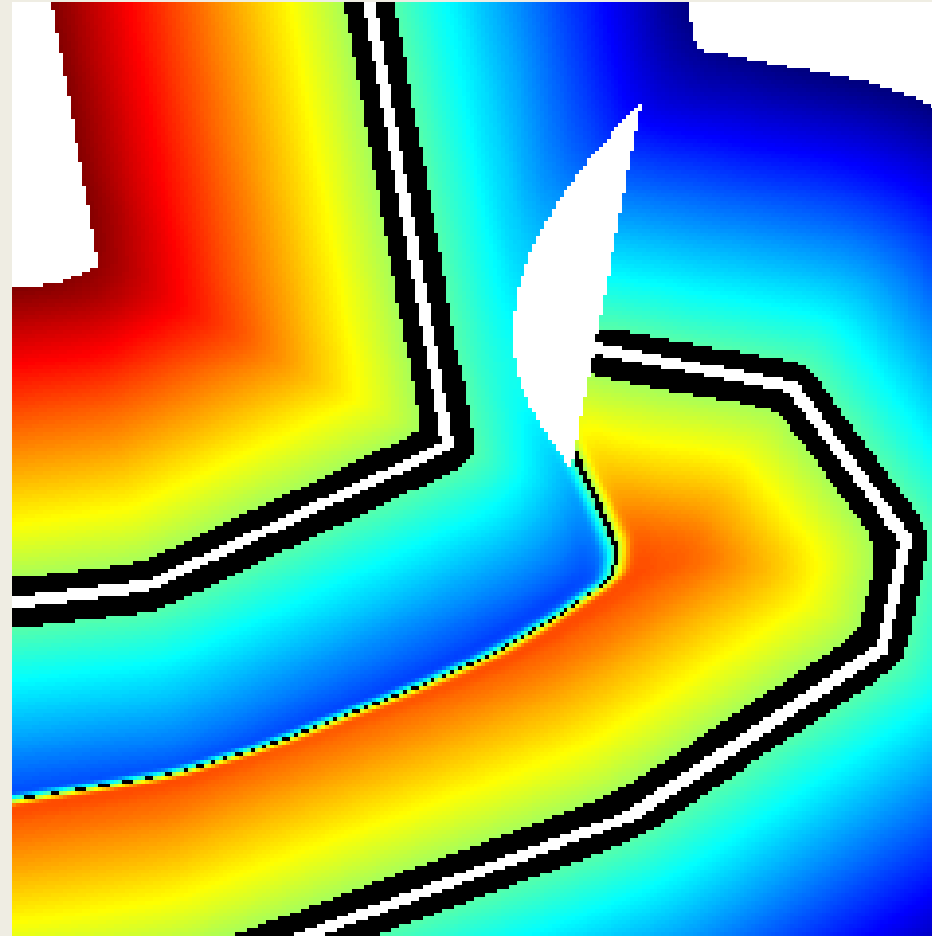
Predicted TSDF Field

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SDF contour  
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# Problems: Outliers between two segments (Type II)



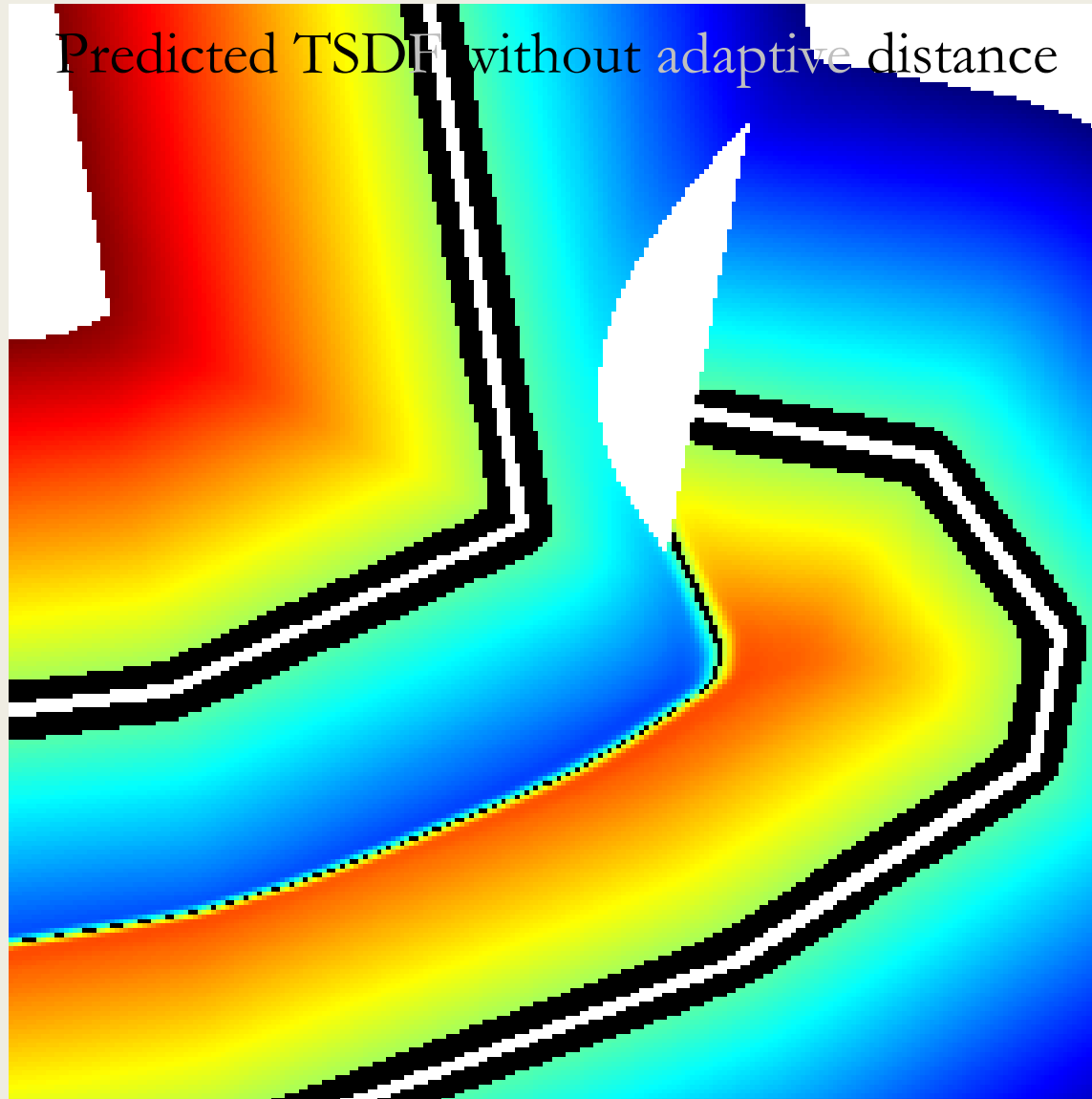
Ground Truth TSDF Field



Predicted TSDF Field

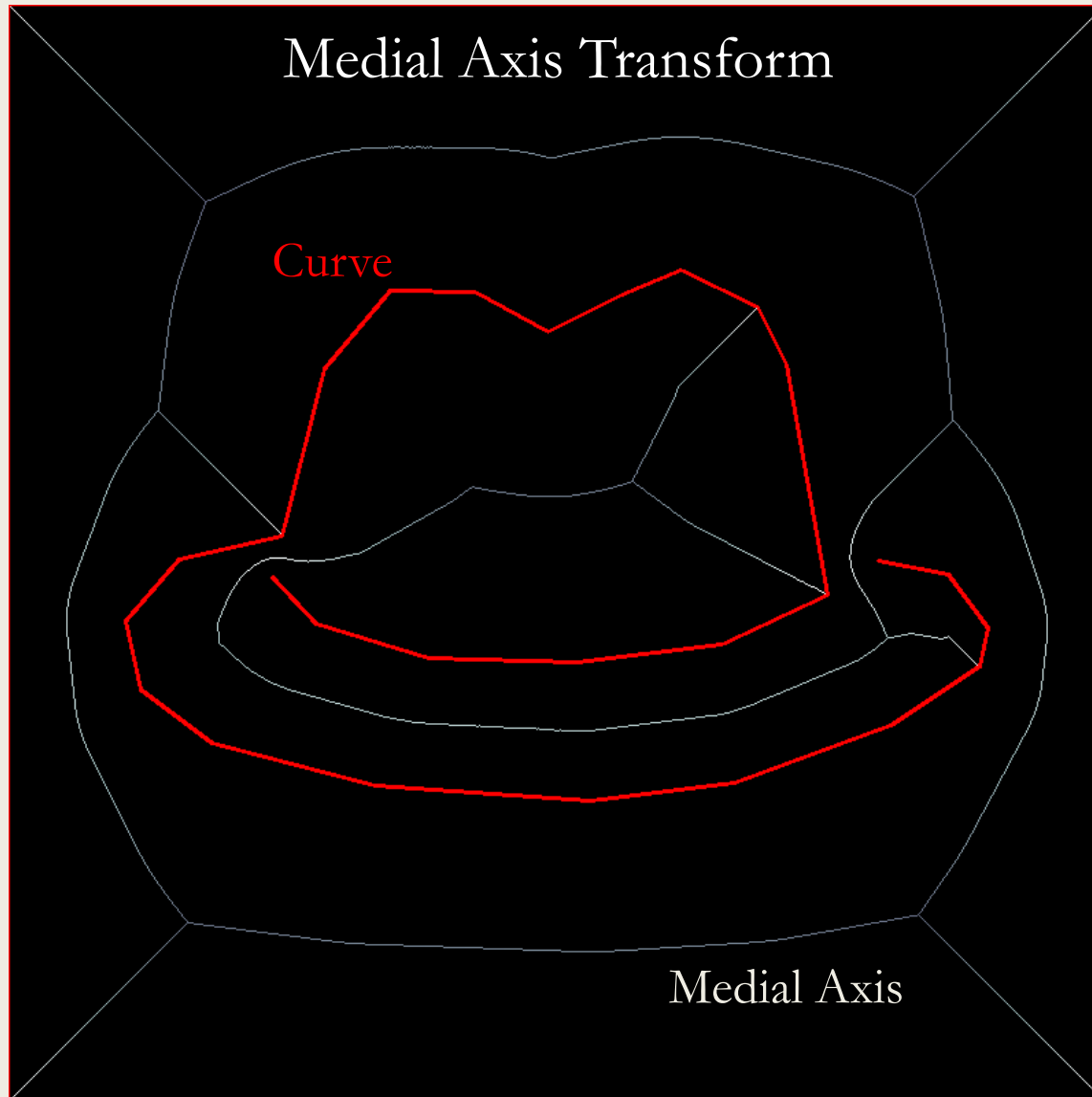
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# Solutions: Adaptive truncation distance



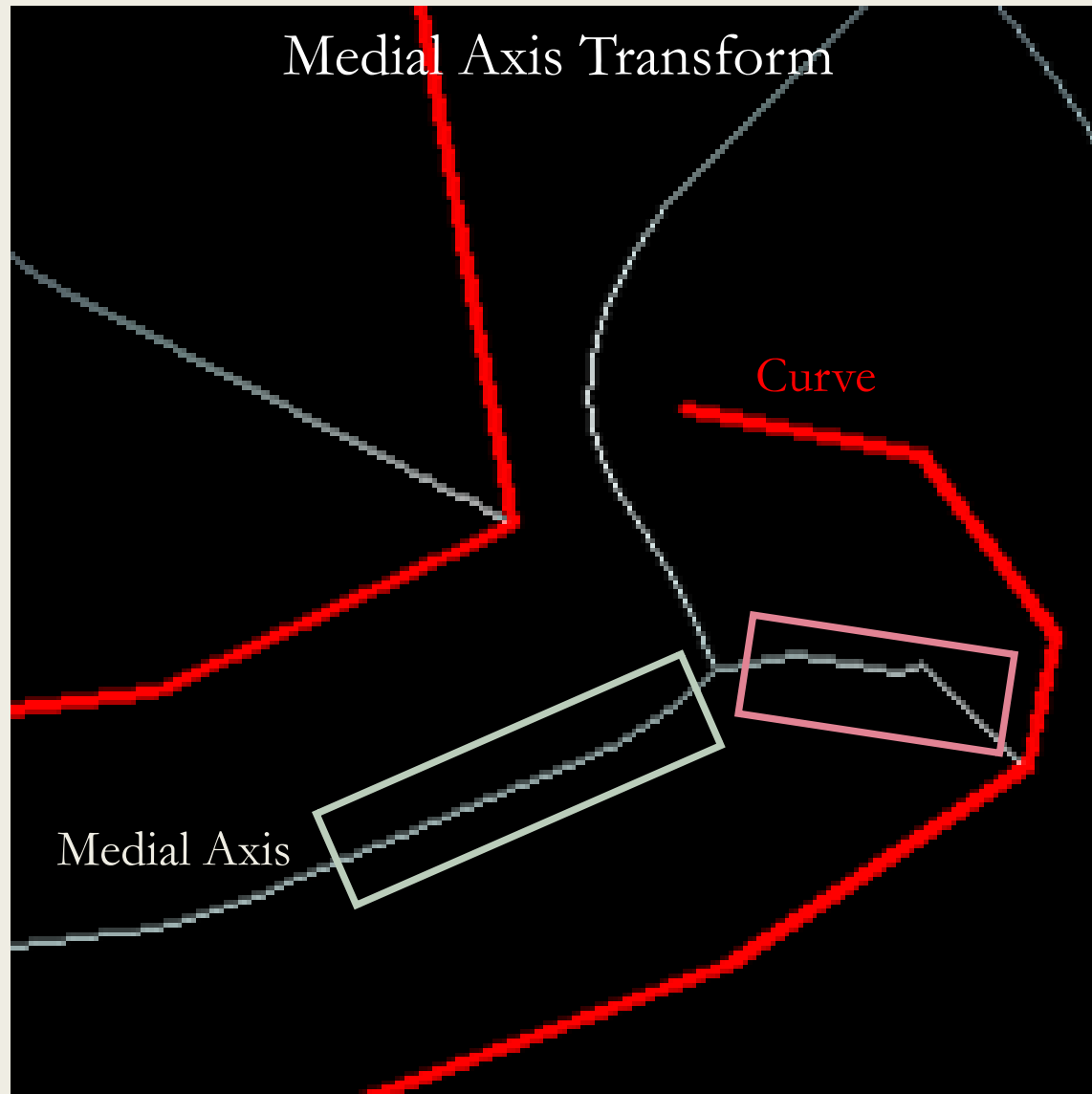
- **Type II outliers:** Outliers between two segments
  - The positive-negative conjunction is caused by two parts of the curves.
- **Idea:**
  - Implement an **adaptive truncation distance**.

# Solutions: Adaptive truncation distance



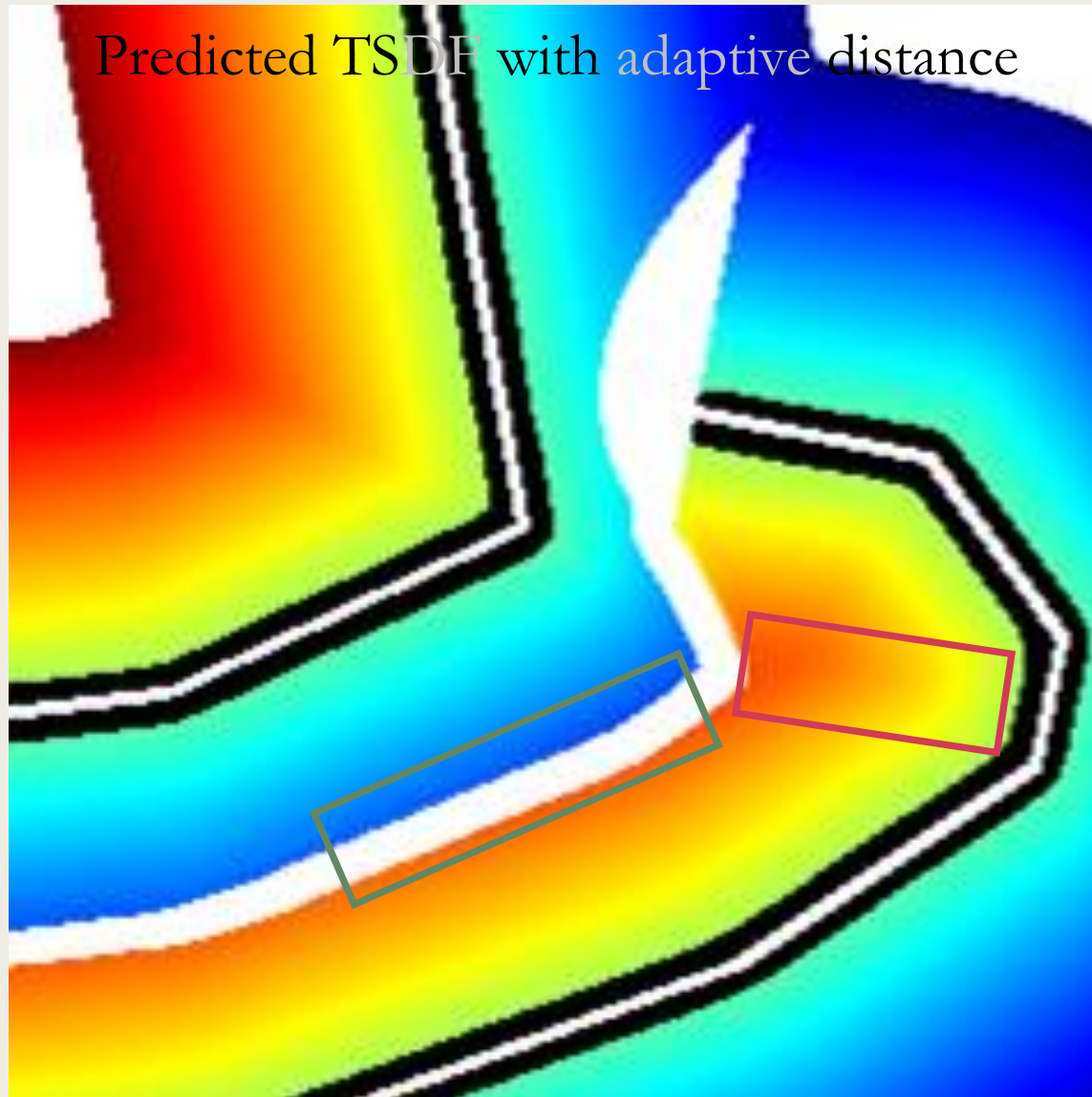
- **Medial Axis Transform:**
  - The **medial axis** is the set of all points **having more than one closest point** on the curve's boundary.
- **Methodology:**
  - For every point on the **medial axis**, if the point is near the **positive-negative junction**, we filter out **nearby points**.

# Solutions: Adaptive truncation distance



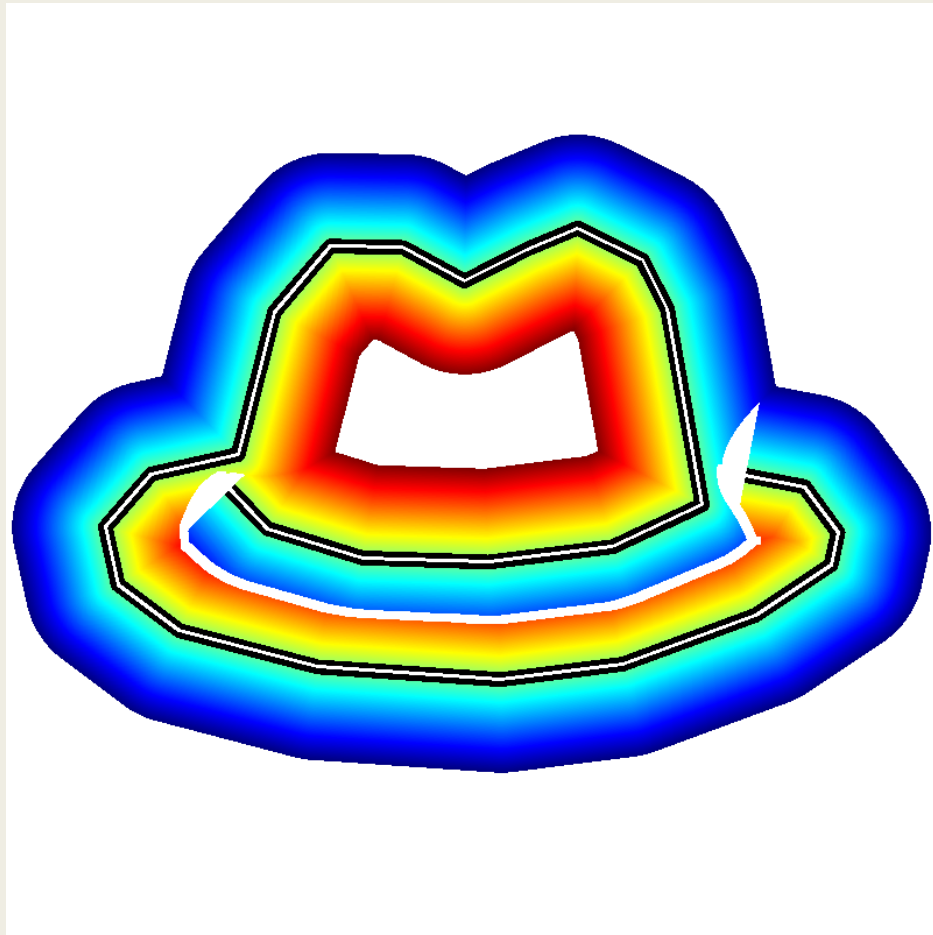
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# Solutions: Adaptive truncation distance

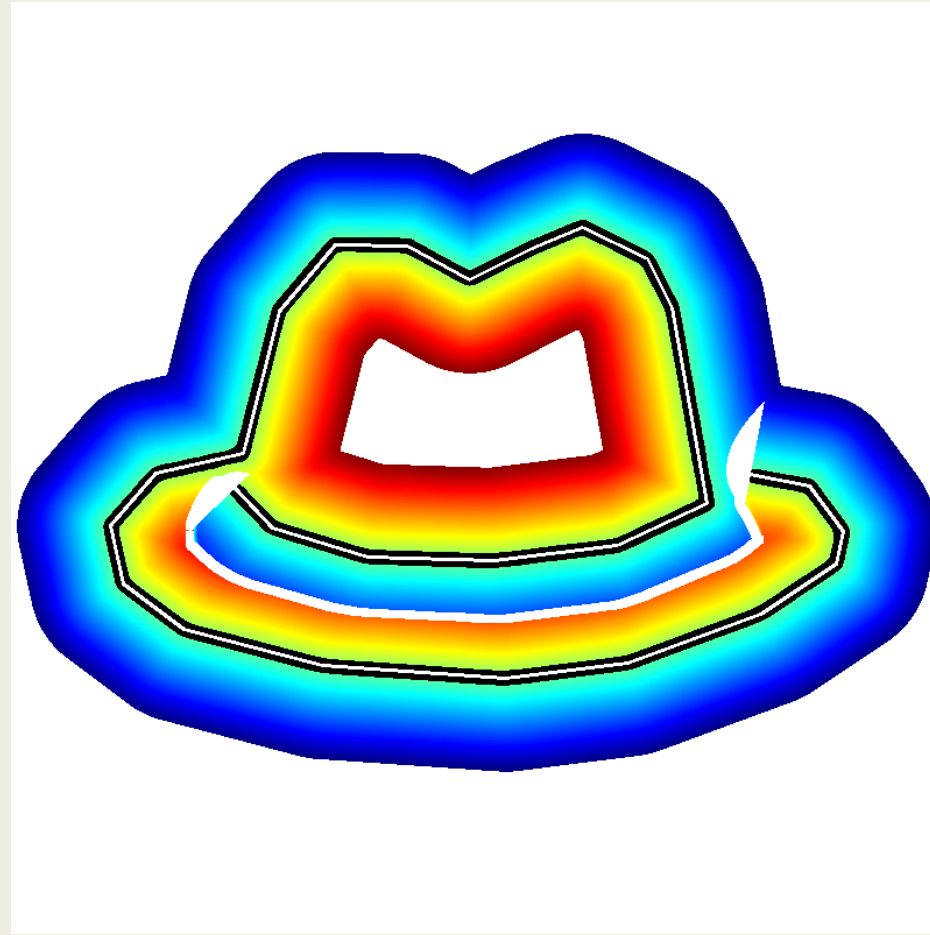


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# Solutions: Adaptive truncation distance



Ground Truth TSDF Field



Predicted TSDF Field

Red area: **positive** SDF  
Blue area: **negative** SDF  
Black line: **zero-value**  
SDF contour  
White line: true curve

# Results





# Results: No outliers

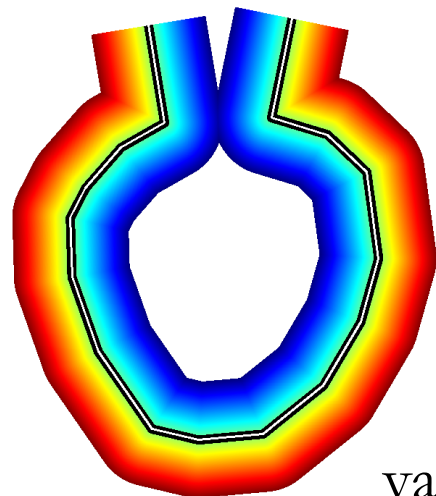
Red area: positive SDF

Blue area: negative SDF

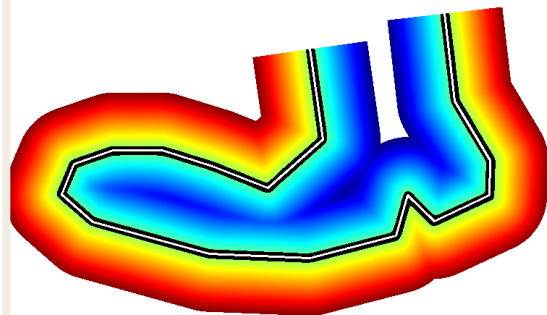
Black line: zero-value SDF contour

White line: true curve

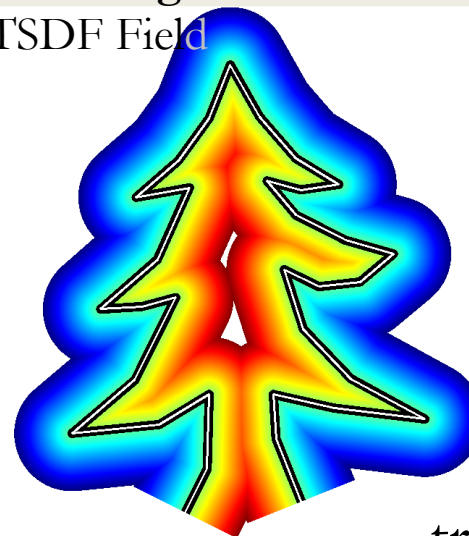
Ground Truth TSDF Field



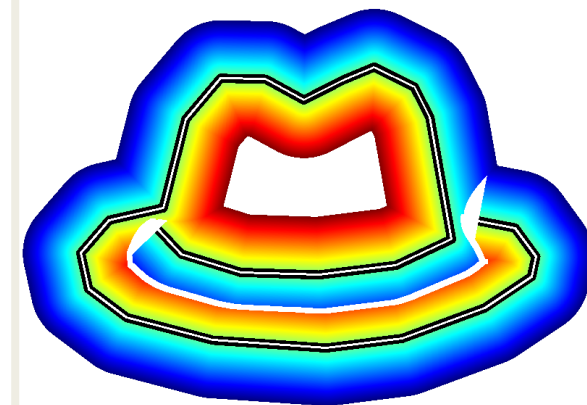
vase



shoe



tree



hat

Avg. L1 error:

$2.364e-3 \rightarrow 1.666e-3$

$1.445e-3 \rightarrow 5.893e-4$

$1.585e-3 \rightarrow 1.041e-3$

$8.365e-4 \rightarrow 4.520e-4$

Max L1 error:

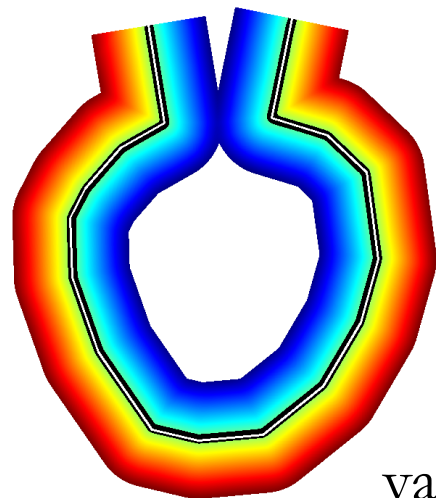
$1.309e-1 \rightarrow 8.080e-3$

$1.127e-1 \rightarrow 5.428e-2$

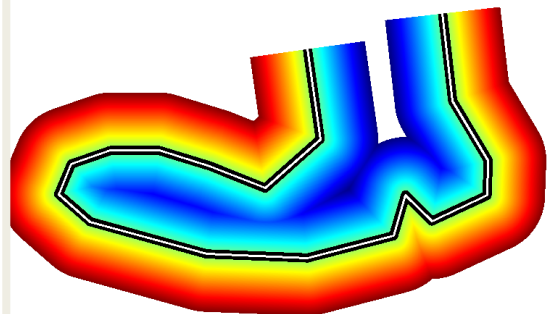
$1.196e-1 \rightarrow 1.195e-2$

$1.340e-1 \rightarrow 7.647e-2$

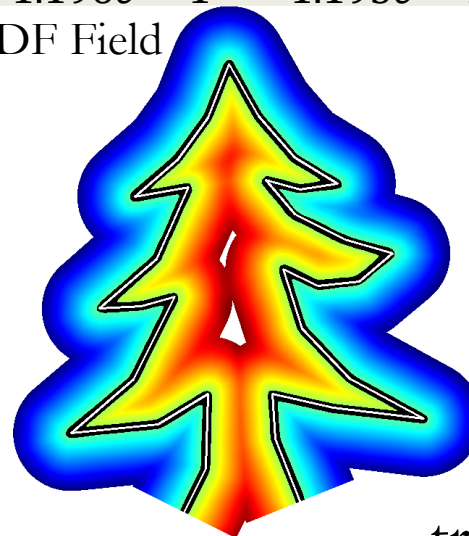
Predicted TSDF Field



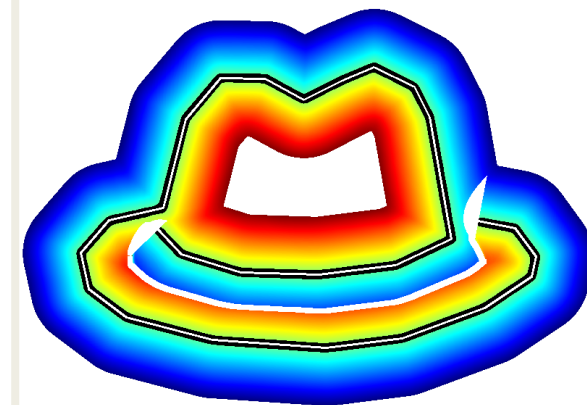
vase



shoe



tree



hat

# Results: No outliers

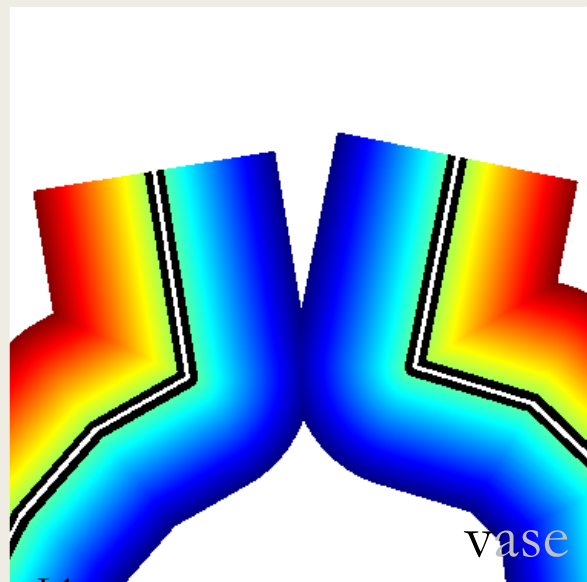
Red area: positive SDF

Black line: zero-value SDF contour

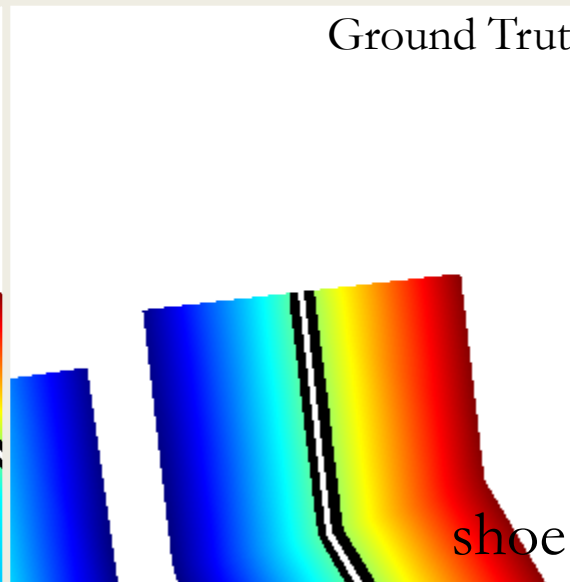
Blue area: negative SDF

White line: true curve

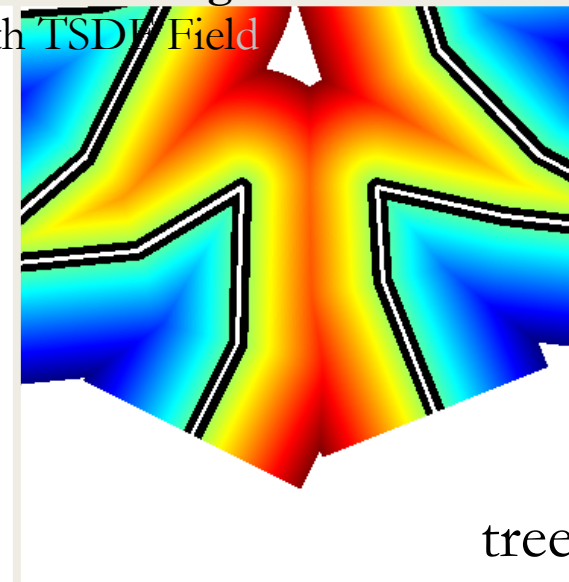
Ground Truth TSDF Field



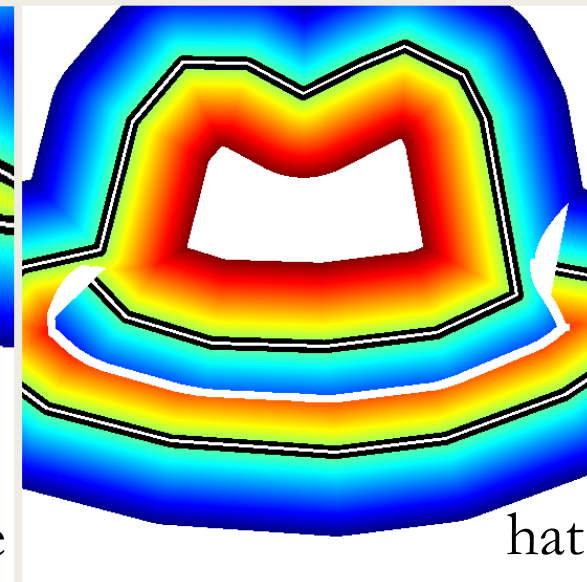
vase



shoe



tree



hat

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$2.364e-3 \rightarrow 1.666e-3$

$1.445e-3 \rightarrow 5.893e-4$

$1.585e-3 \rightarrow 1.041e-3$

$8.365e-4 \rightarrow 4.520e-4$

Max L1 error:

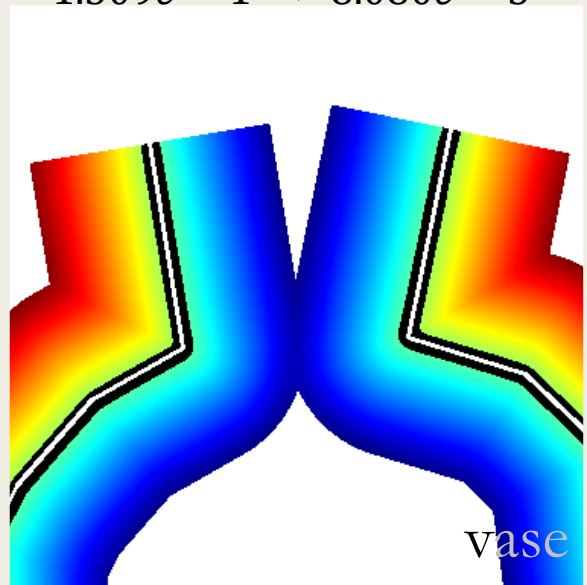
$1.309e-1 \rightarrow 8.080e-3$

$1.127e-1 \rightarrow 5.428e-2$

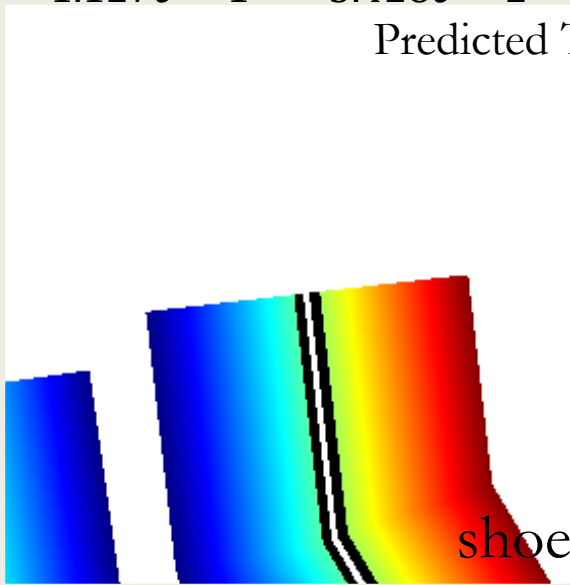
$1.196e-1 \rightarrow 1.195e-2$

$1.340e-1 \rightarrow 7.647e-2$

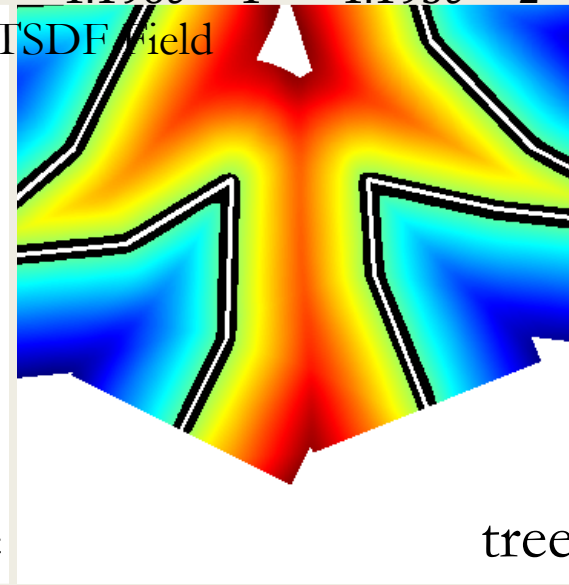
Predicted TSDF Field



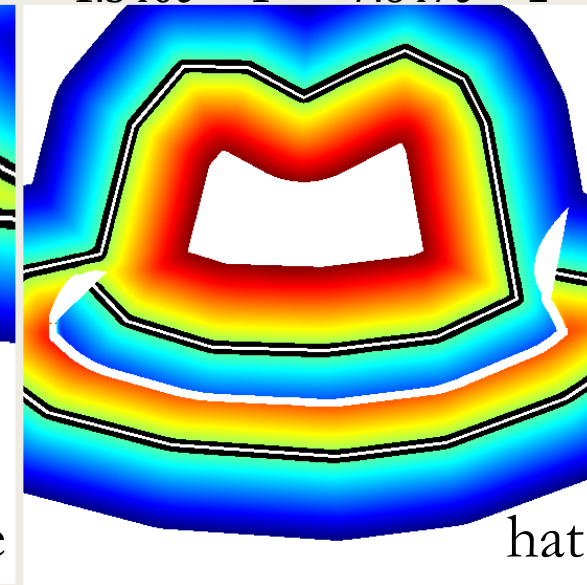
vase



shoe



tree



hat

# Results: Comparison

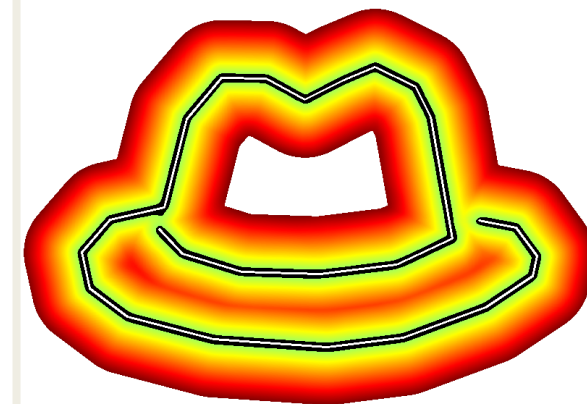
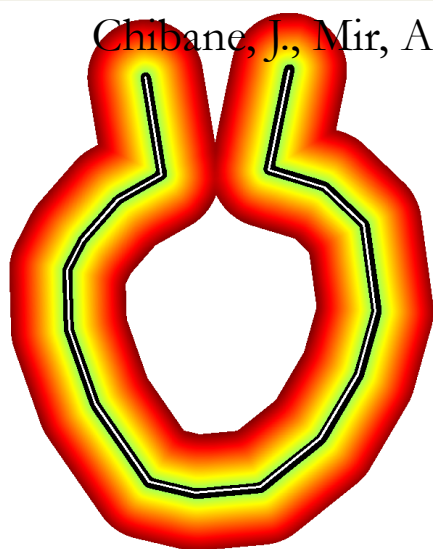
Red area: positive SDF

Black line: zero-value SDF contour

Blue area: negative SDF

White line: true curve

Chibane, J., Mir, A., & Pons-Moll, G. (2020). Neural unsigned distance fields for implicit function learning.



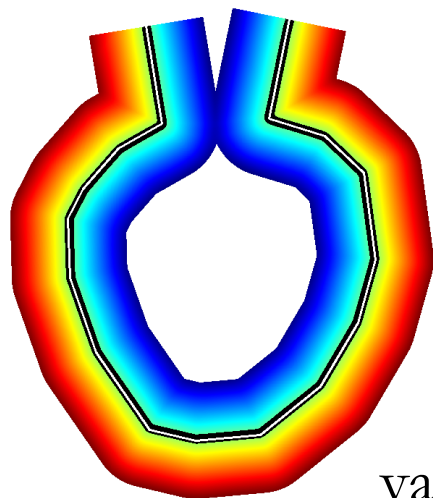
Avg. L1 error:  $1.465e-3$   
 $1.666e-3$

$7.052e-4$   
 $5.893e-4$

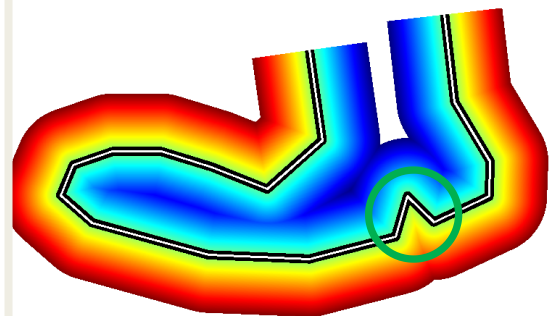
$1.416e-3$   
 $1.041e-3$

$3.639e-4$   
 $4.520e-4$

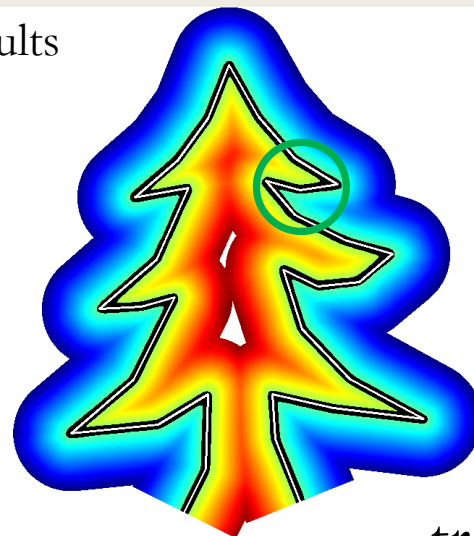
My Results



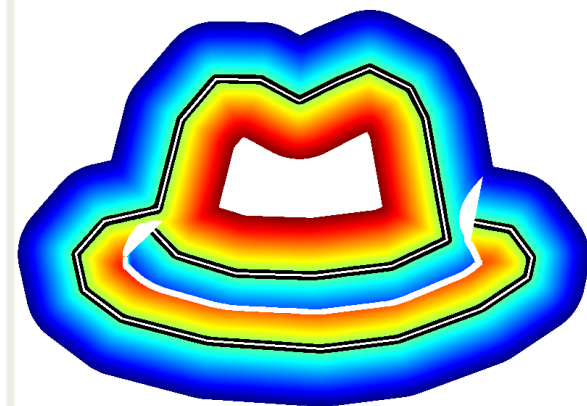
vase



shoe

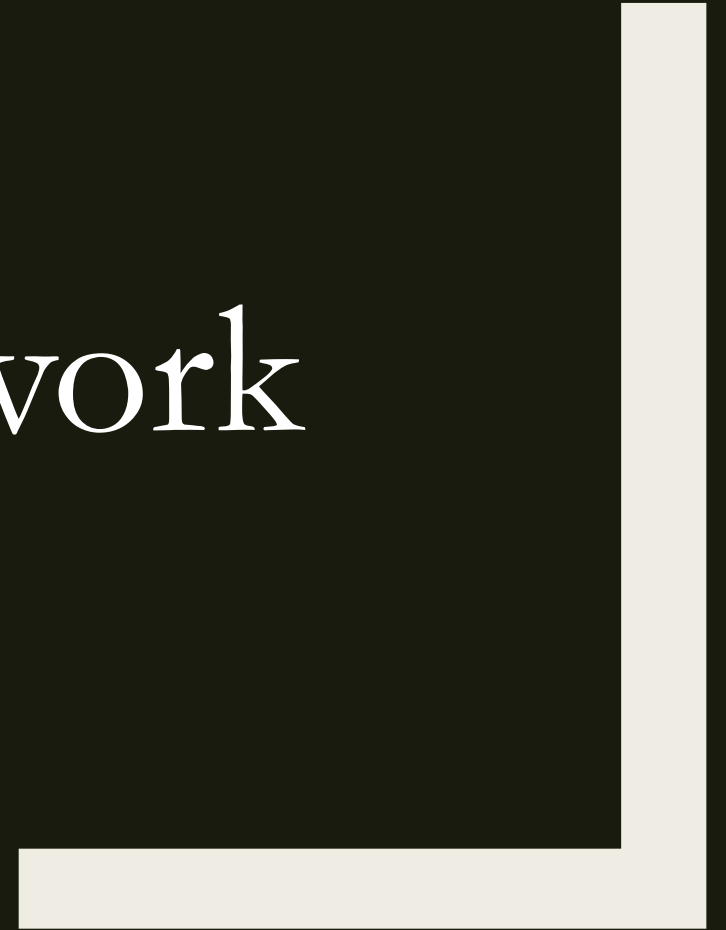


tree



hat

Future work



# Future work: Applications & Extensions

## ■ Applications:

- Collision detection using **neural representations**.

## ■ Extensions:

- Extension to **3D open surfaces**.
- Endpoints of open curves → **Boundary** of open surfaces
- Medial axis transform in 2D → **Medial axis transform** in 3D



The end



# Bibliography

- Chibane, J., Mir, A., & Pons-Moll, G. (2020). Neural unsigned distance fields for implicit function learning. arXiv preprint arXiv:2010.13938.
- Park, J. J., Florence, P., Straub, J., Newcombe, R., & Lovegrove, S. (2019). DeepSDF: Learning continuous signed distance functions for shape representation. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (pp. 165-174).