Learning Shape Completion from Bounding Boxes with CAD Shape Priors

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Master Thesis
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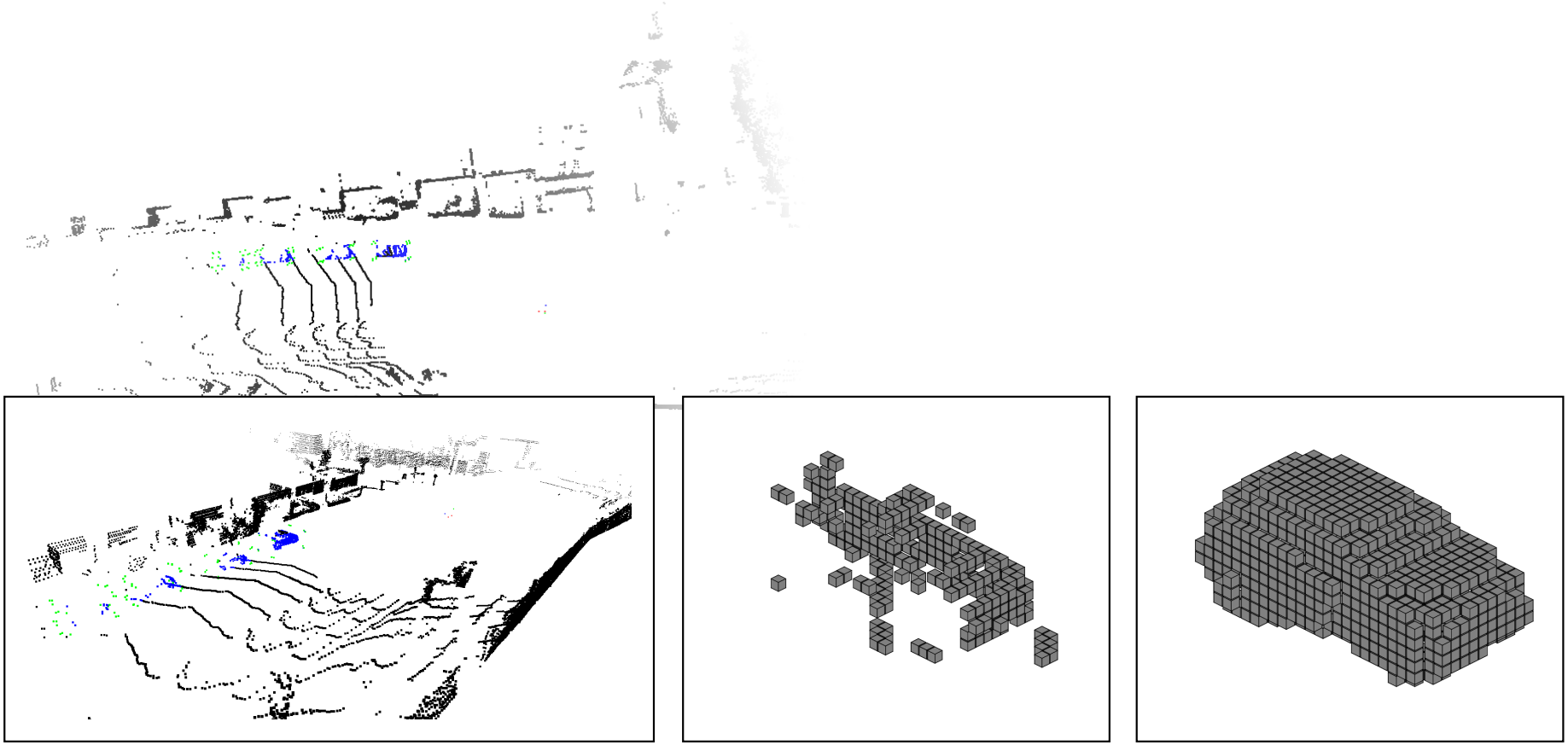
Outline

- Problem
- Related Work
- Proposed Approach
  - Shape Prior
  - Shape Inference
- Experiments
- Conclusion

Problem

Problem Overview

Shape completion from point clouds.



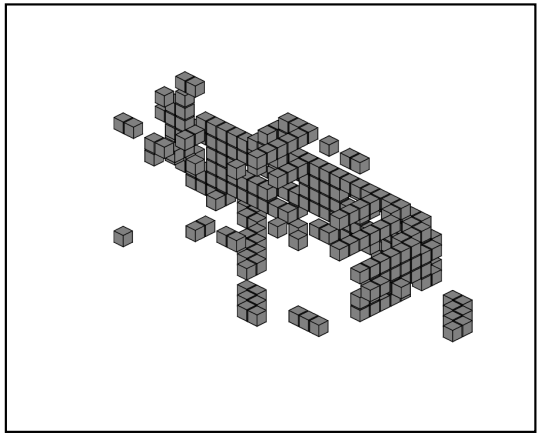
Voxelized Observation

Voxelized Shape

Problem Definition

Problem

Given observations $\mathcal{X} = \{x_1, \ldots, x_N\}$ *and reference shapes* $\mathcal{Y} = \{y_1, \ldots, y_M\}$*, learn a mapping* $x_n \mapsto y(x_n)$ *such that* $y(x_n)$ *fits the unknown target shape* y_n^**.*



Observation x_n

Problem Definition

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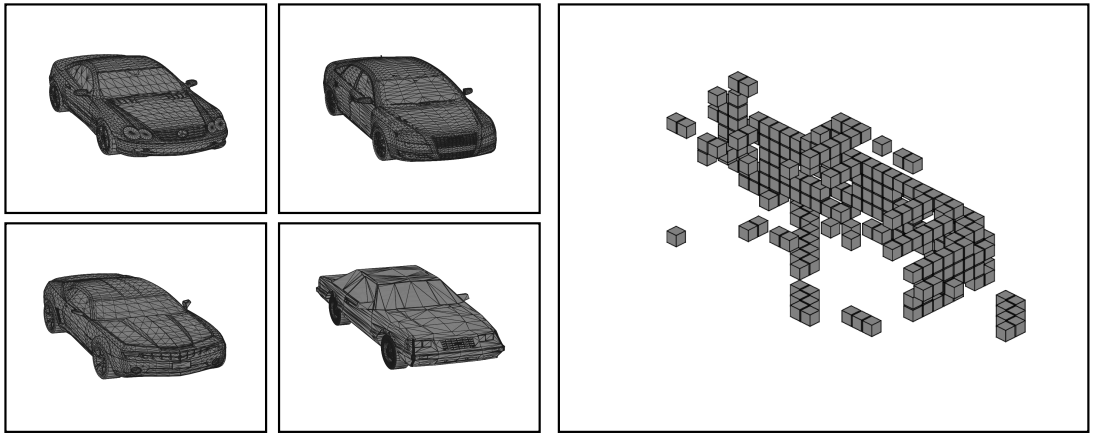

Reference Shapes y_m Observation x_n

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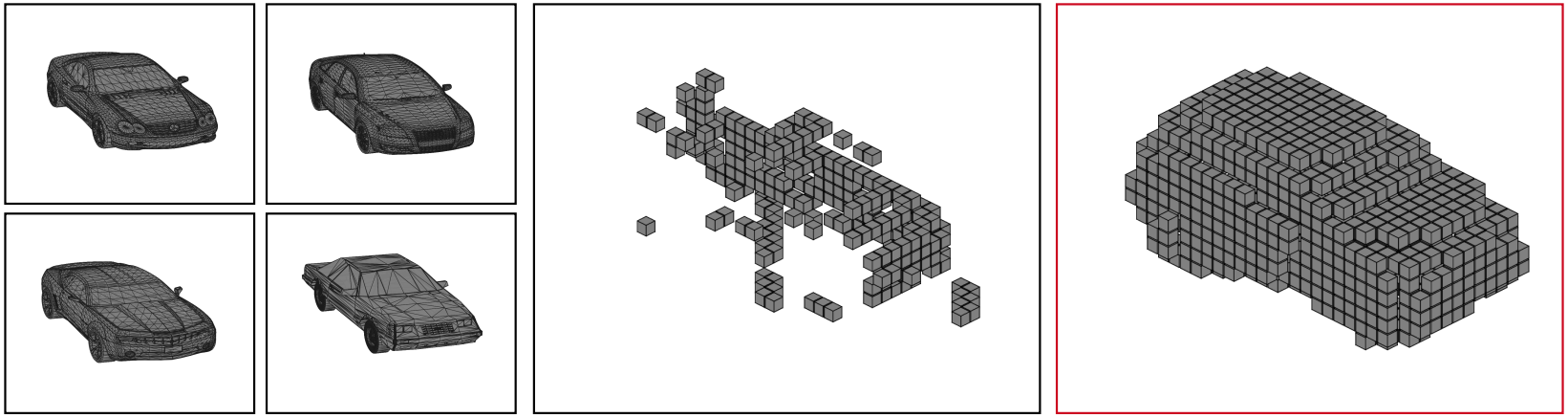

Reference Shapes y_m Observation x_n Unknown Shape y_n^*

Problem Definition

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Given observations $\mathcal{X} = \{x_1, \ldots, x_N\}$ *and reference shapes* $\mathcal{Y} = \{y_1, \ldots, y_M\}$*, learn a mapping* $x_n \mapsto y(x_n)$ *such that* $y(x_n)$ *fits the unknown target shape* y_n^**.*

Weakly-supervised:

- known object category;
- and bounding boxes required on real data.

Related Work

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Generative shape modeling, including [Wu et al., 2015, Wu et al., 2016].

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Generative shape modeling, including
[Wu et al., 2015, Wu et al., 2016].

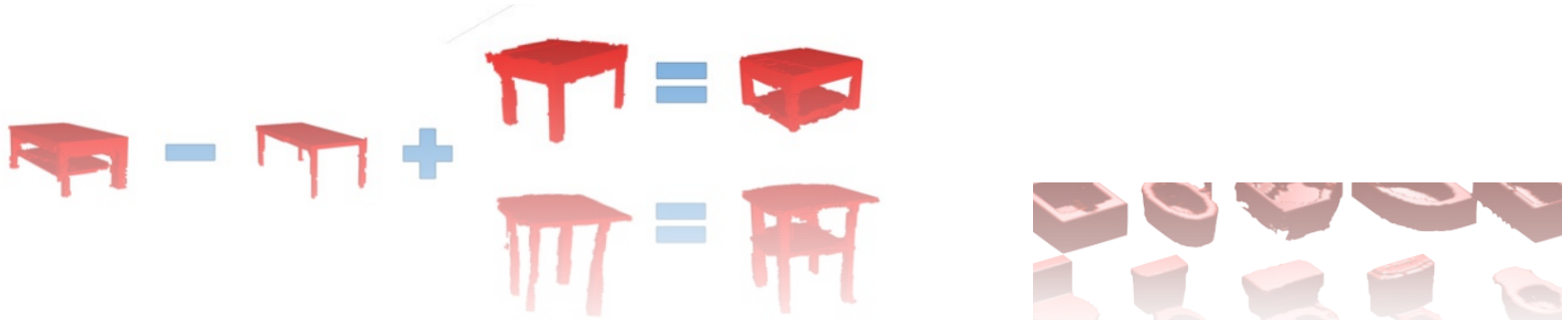
Shape completion, following [Sung et al., 2015]:

- symmetry based approaches;
- data-driven approaches, including
  [Dame et al., 2013, Engelmann et al., 2016];
- and recently learning-based approaches, including
  [Dai et al., 2016].

Selected Related Work

Generative shape modeling, *e.g.* [Wu et al., 2015, Wu et al., 2016]:

- Learn a generative model of shapes, *e.g.* using generative adversarial networks [Wu et al., 2016];
- and use for shape classification, manipulation and generation.

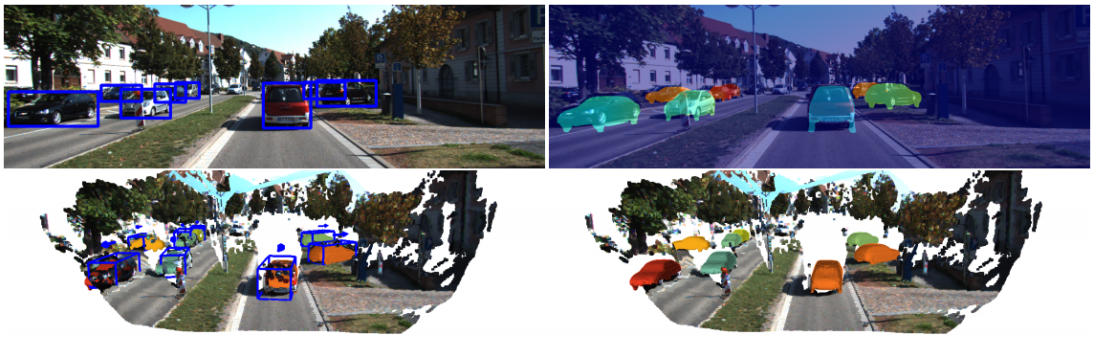


[Wu et al., 2016] [Wu et al., 2015]

Selected Related Work

Data-driven shape completion, *e.g.* [Dame et al., 2013, Engelmann et al., 2016]:

- Learn shape prior, *e.g.* using PCA or GP-LVM;
- and pose shape completion as energy minimization.

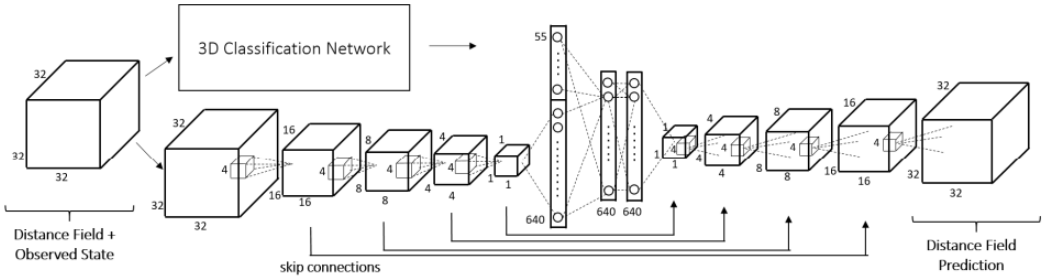


[Engelmann et al., 2016]

Selected Related Work

Learning-based shape completion, *e.g.* [Dai et al., 2016]:

- Learn an encoder-decoder network on synthetic data;
- and post-process if necessary.



[Dai et al., 2016]

Discussion

Two “philosophies”:

- data-driven approaches are applicable to real data, but shape completion involves energy minimization;
- learning-based approaches need supervision, but shape completion is “just a forward pass”.

Discussion

Question

Do strong shape priors allow us to learn shape completion under weak supervision?

Goal:

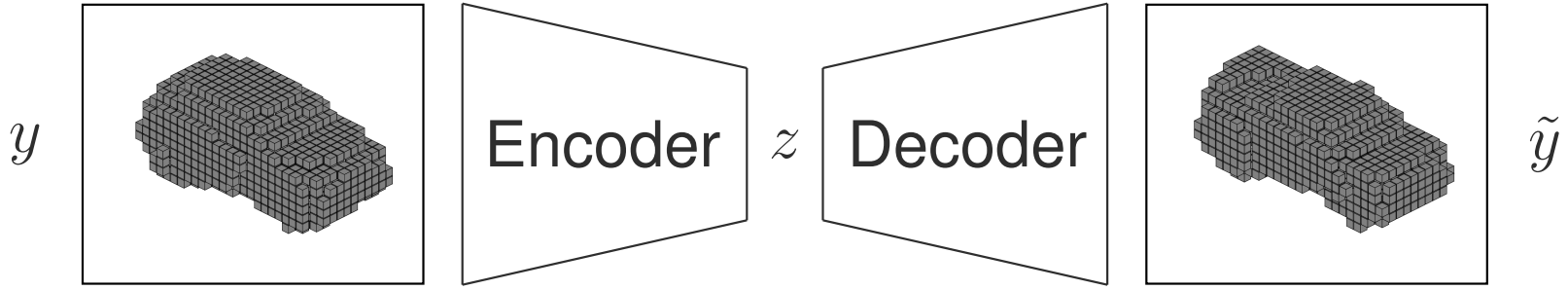
- Efficient shape completion;
- and learning on real data.

Proposed Approach

Proposed Approach

Shape prior.

Learn a variational auto-encoder
[Kingma and Welling, 2013]:



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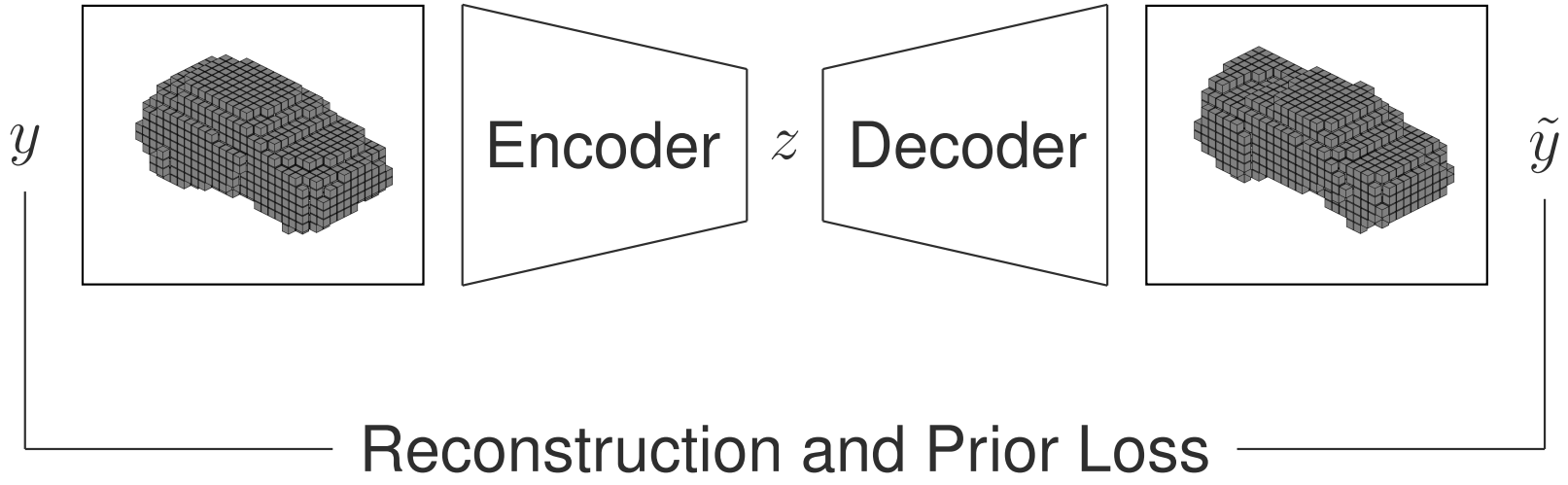

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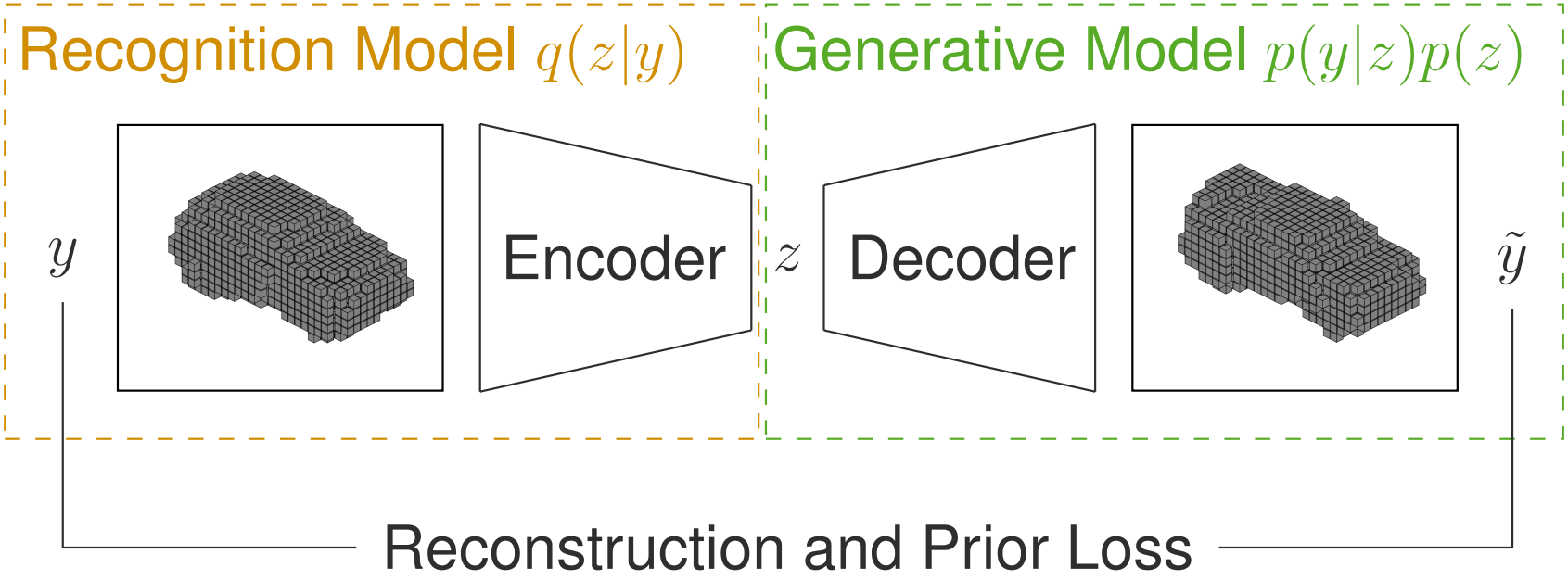
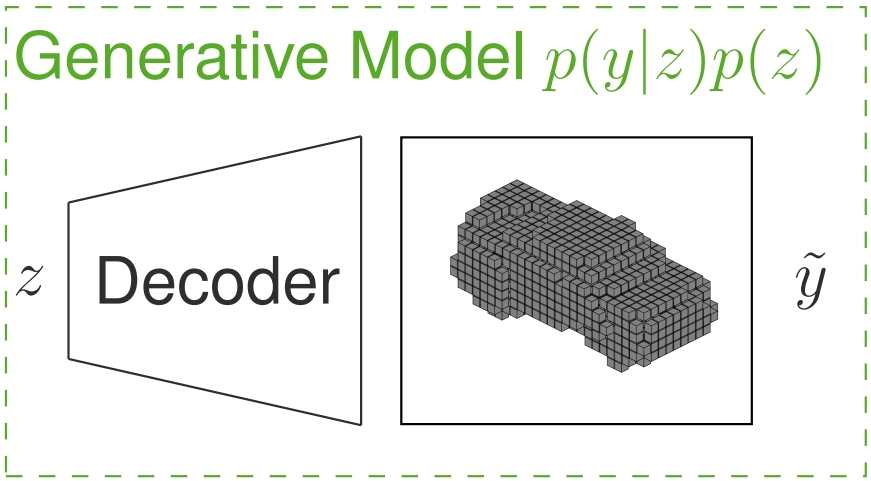


Proposed Approach

Shape inference.

Perform maximum likelihood:



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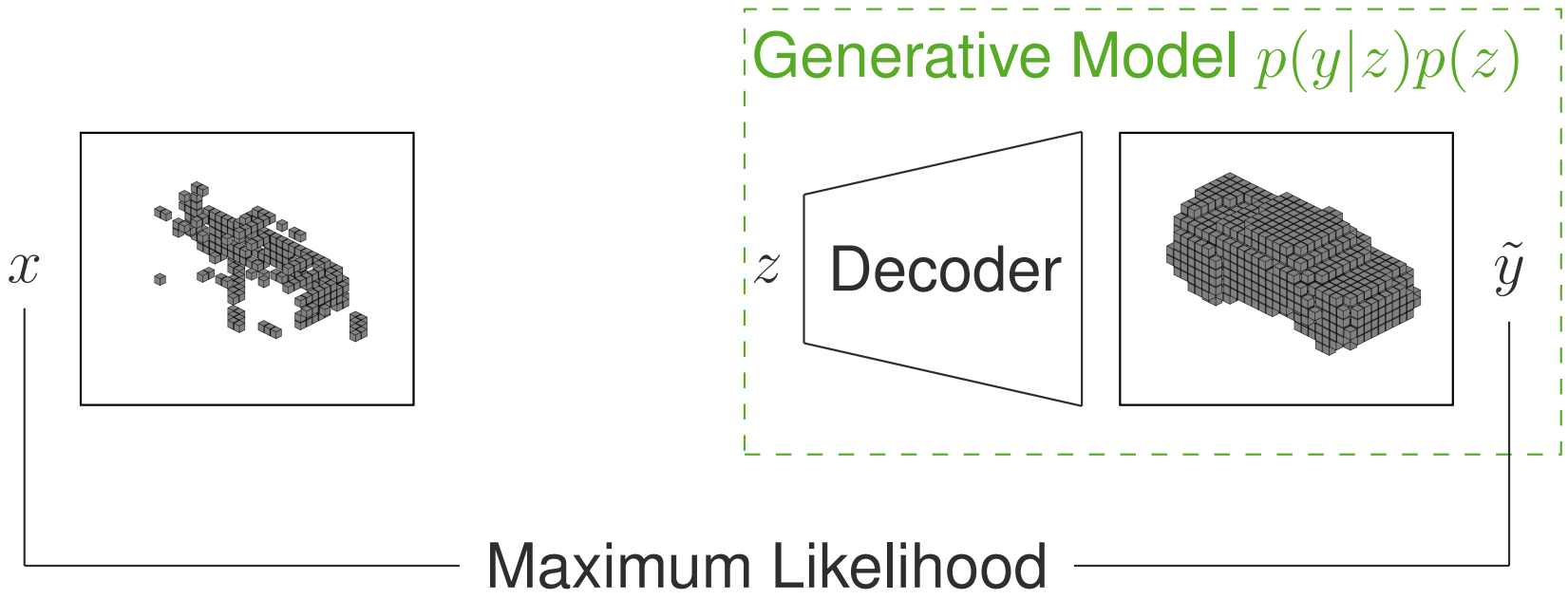
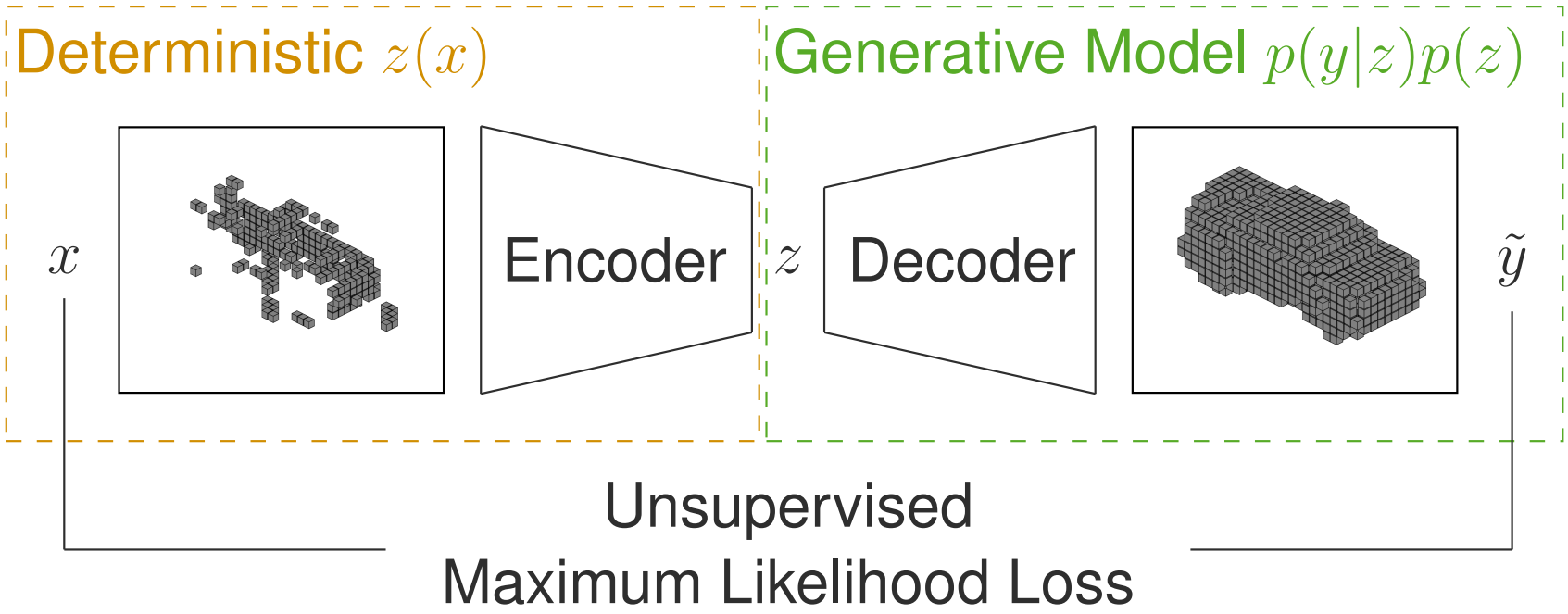


Proposed Approach

Shape inference.

~~Perform~~ Learn – *i.e.* amortize – maximum likelihood:



Shape Prior

Shape Prior

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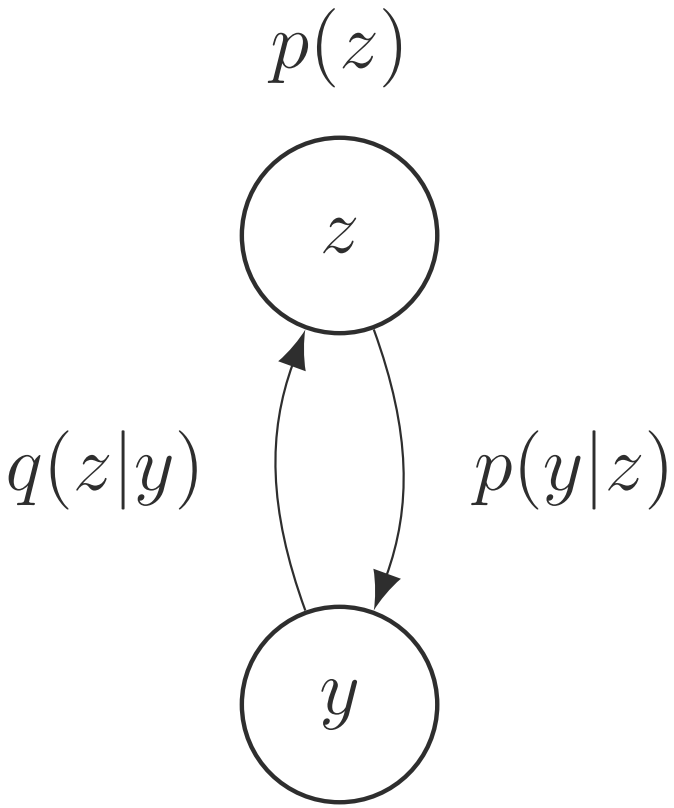

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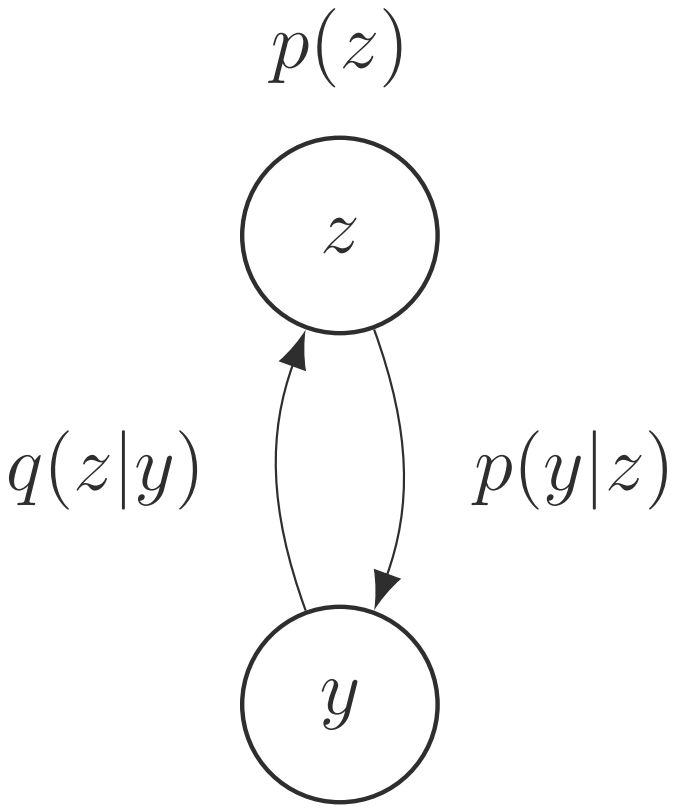

Prior $p(z) = \mathcal{N}(z|0, I)$

Shape Prior

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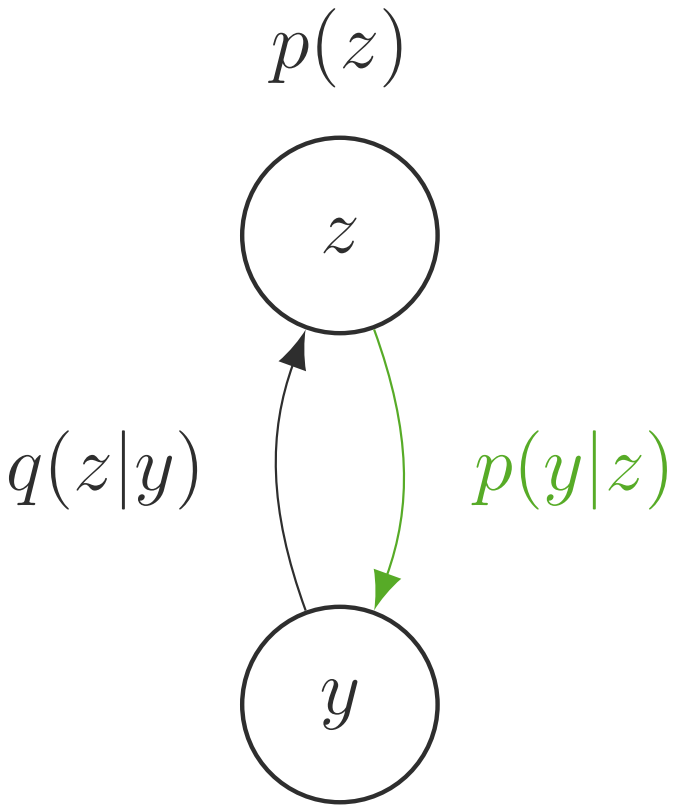

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Decoder/Generative Model

$$p(y|z) = \prod_i \text{Ber}(y_i|\theta_i(z))$$

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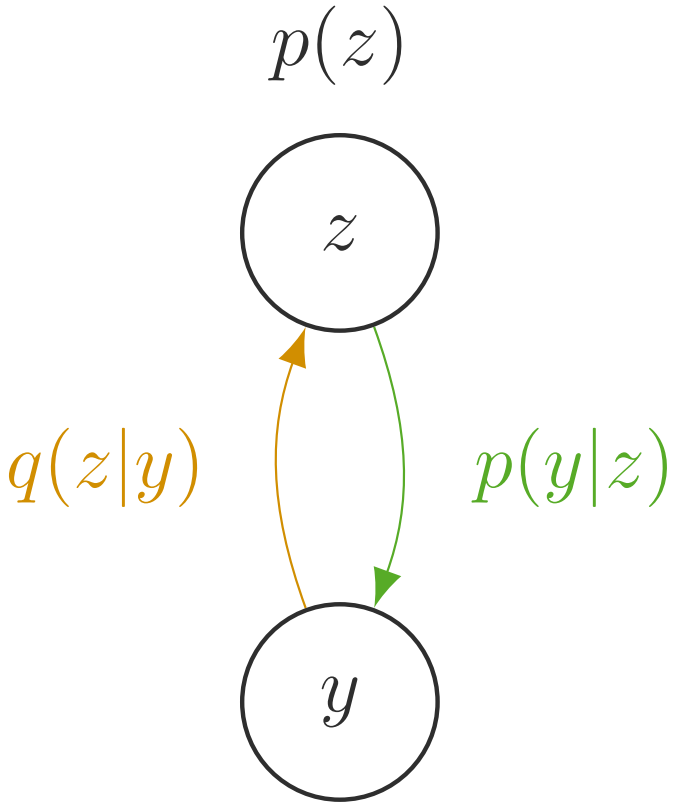

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$$p(y|z) = \prod_i \text{Ber}(y_i|\theta_i(z))$$

Encoder/Recognition Model

$$q(z|y) = \mathcal{N}(z|\mu(y), \sigma^2(y))$$

Shape Prior

Maximum likelihood leads to:

$$\mathcal{L}_{\text{ELBO}} = -\mathbb{E}_{q(z|y)}[\log p(y|z)] + \text{KL}(q(z|y)|p(z))$$

- Encoder: $q(z|y) = \mathcal{N}(z|\mu(y), \sigma^2(y))$;
- and decoder: $p(y|z) = \prod_i \text{Ber}(y_i|\theta_i(z))$.

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Maximum likelihood leads to:

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Shape Prior

Maximum likelihood leads to:

reconstruction

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Shape Prior

Maximum likelihood leads to:

$$\mathcal{L}_{\text{ELBO}} = \sum_i \mathcal{L}_{\text{BCE}}(\underset{\substack{\shortparallel \\ \theta_i(z)}}{\tilde{y}_i}, y_i) + \mathcal{P}_{\text{Reg}}(\mu(y), \sigma^2(y))$$

- Encoder: $q(z|y) = \mathcal{N}(z|\mu(y), \sigma^2(y))$;
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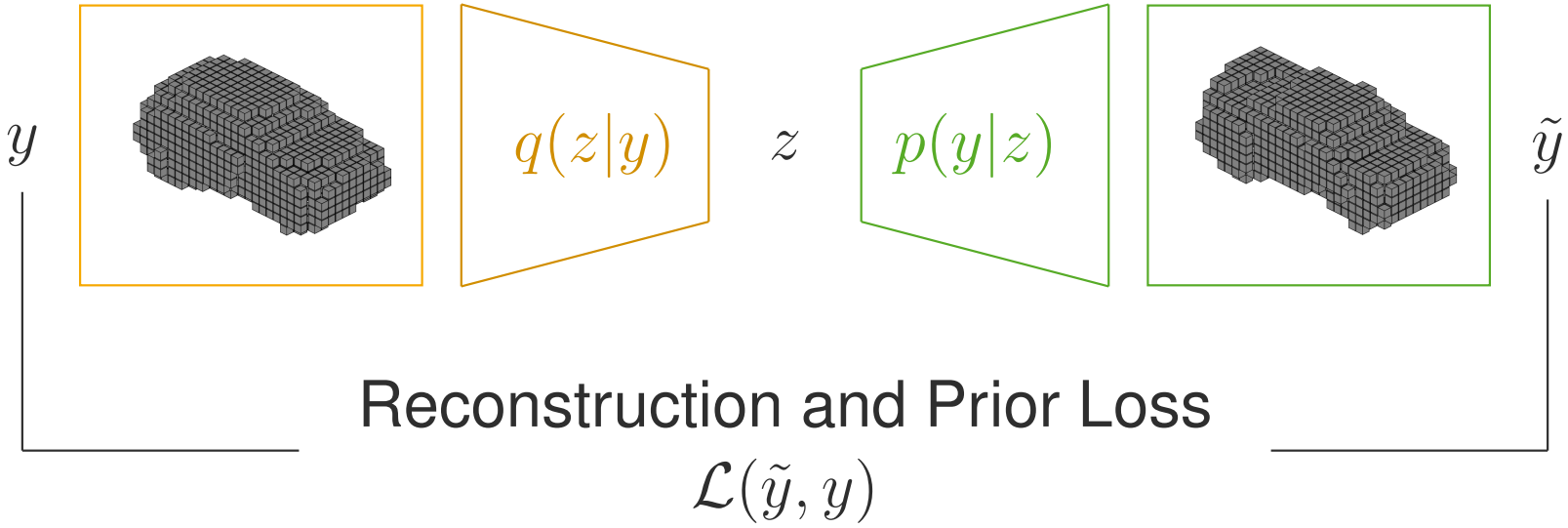
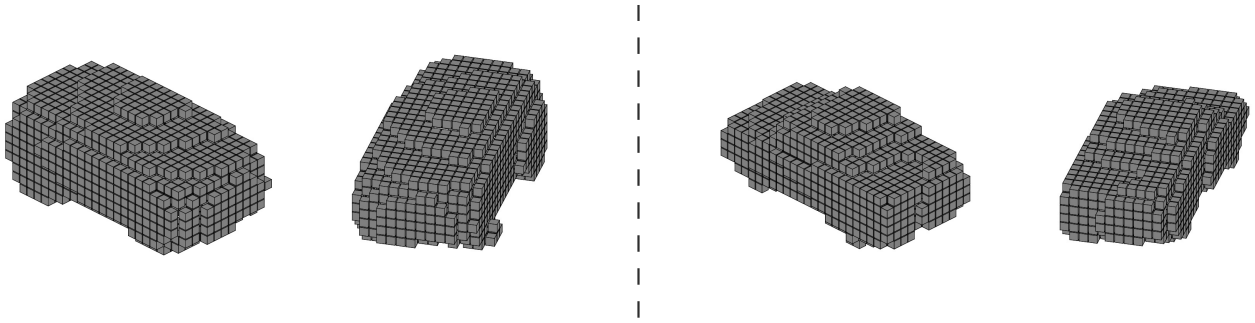
Shape Prior

Training a variational auto-encoder:



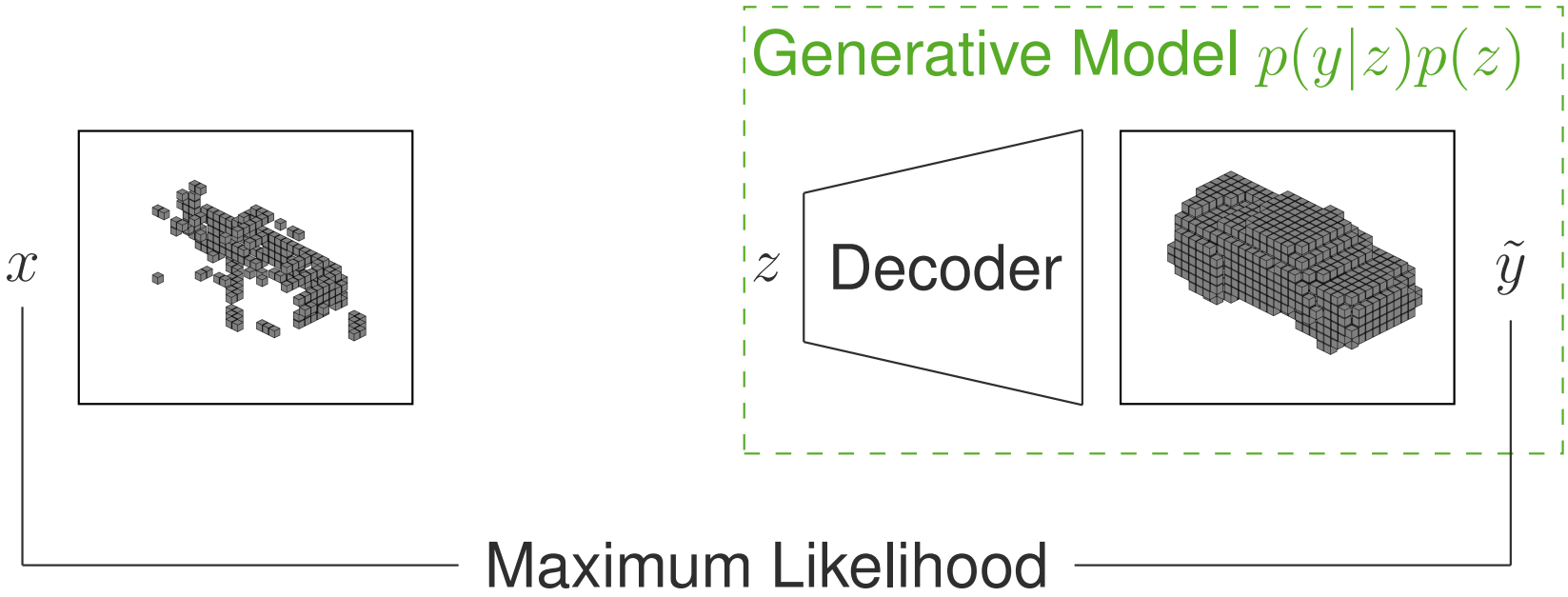
Generating random shapes:



Shape Inference

Shape Inference

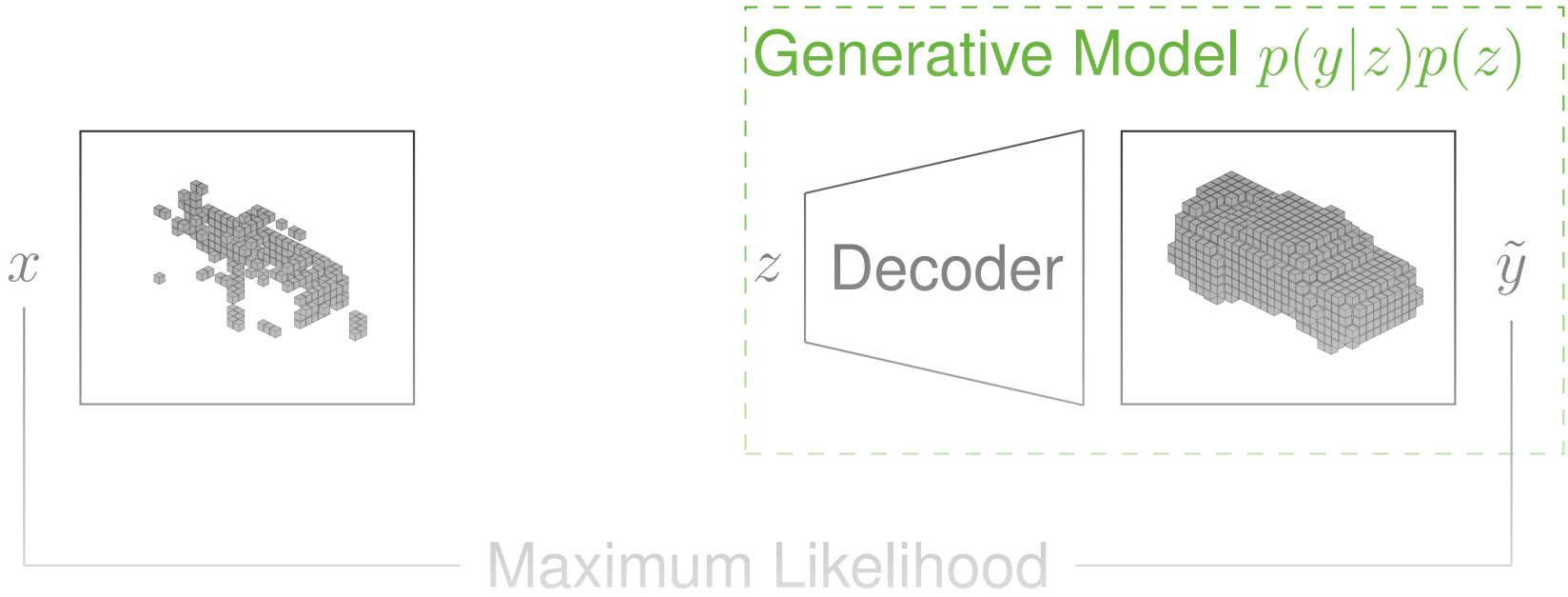
Maximize the likelihood of observation x over the latent space:



Shape Inference

Minimize the negative log-likelihood of observation x over the latent space:

$$\begin{aligned} &\underset{z}{\operatorname{argmin}} - \ln p(y = x, z) \\ &= \underset{z}{\operatorname{argmin}} - \sum_i \ln p(y_i = x_i | z) - \ln p(z) \end{aligned}$$



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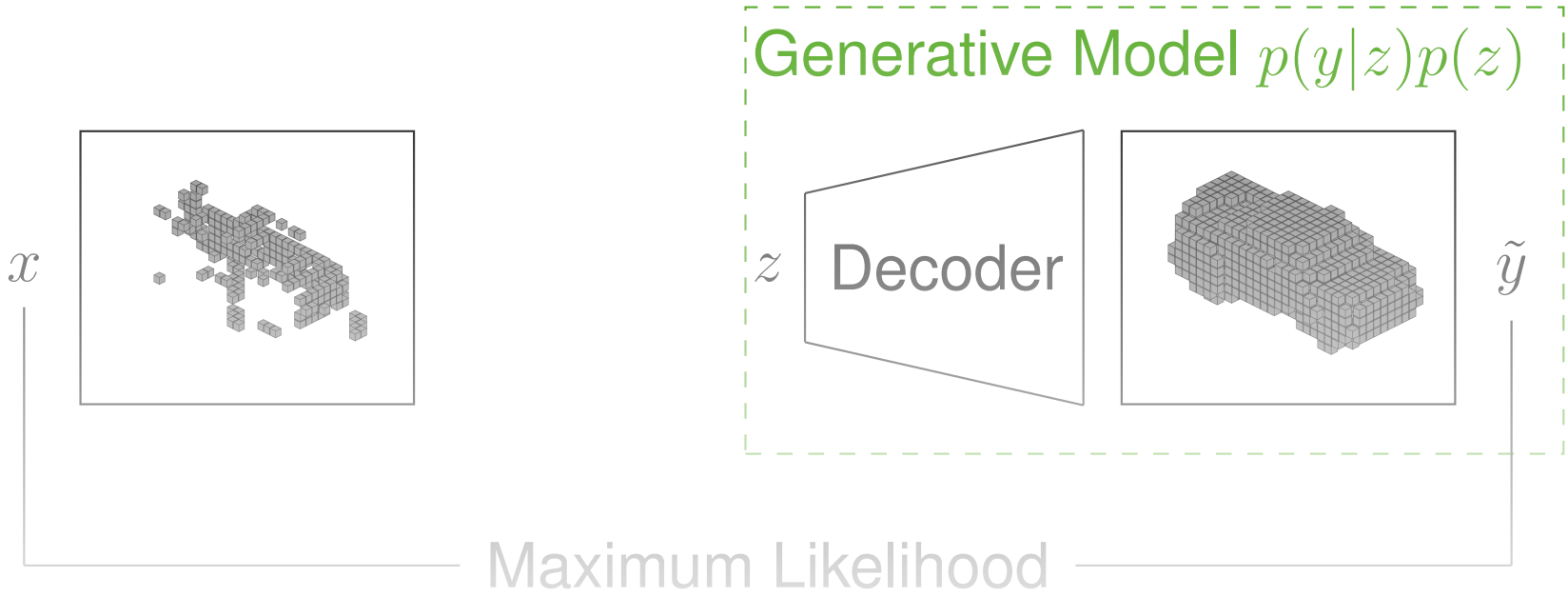

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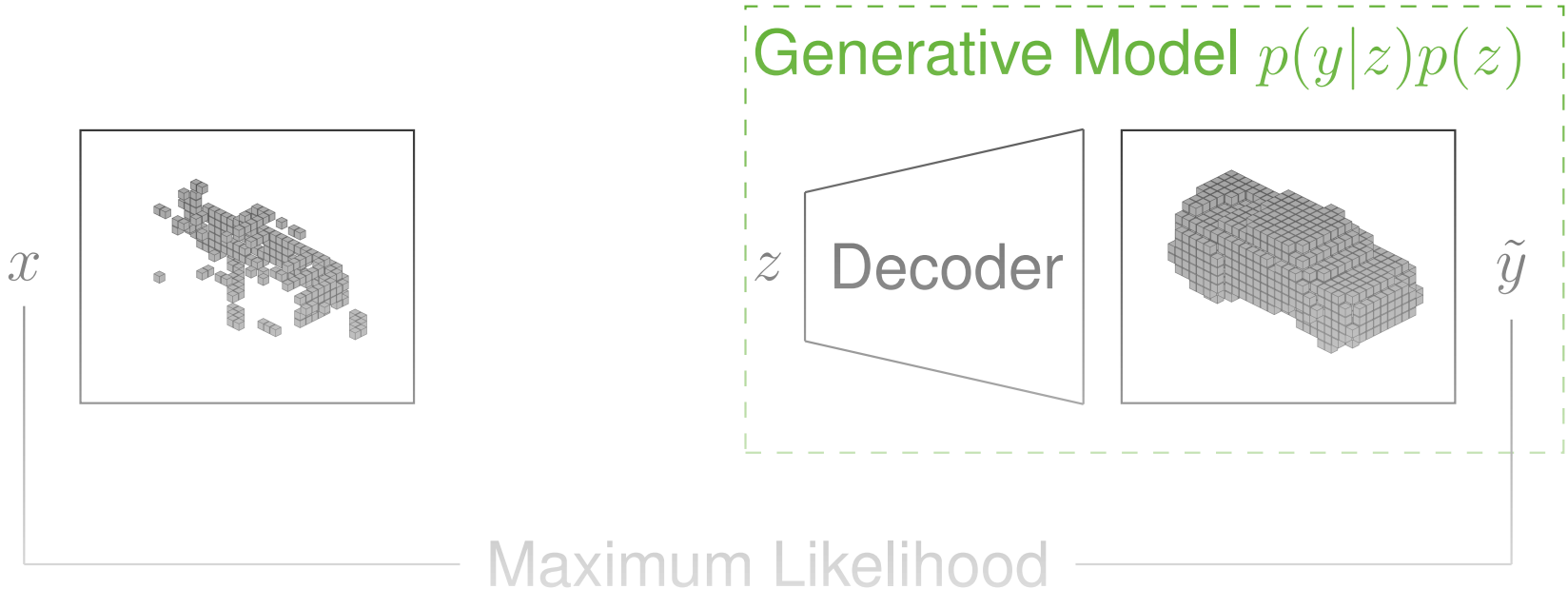
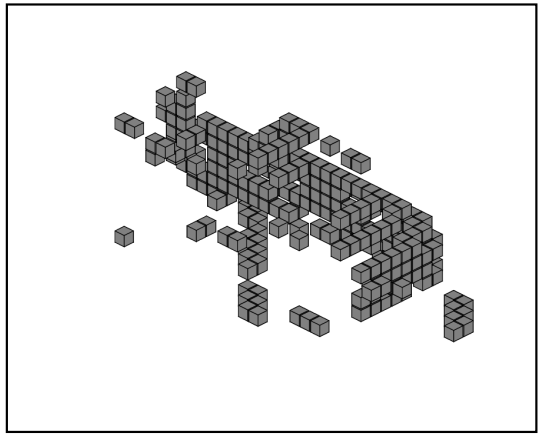


Shape Inference

What observations do we have?

- Occupied voxels $x_i = 1$ (from observed points);

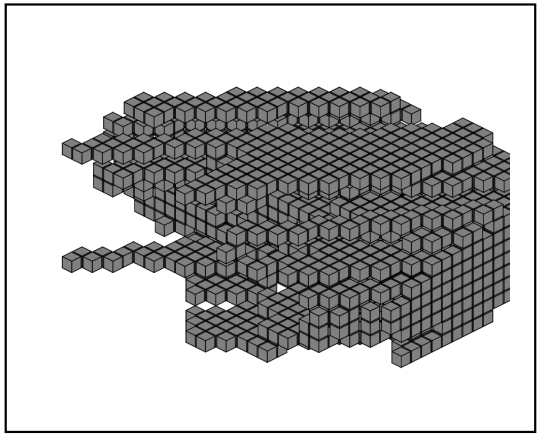


Occupied
Voxels $x_i = 1$

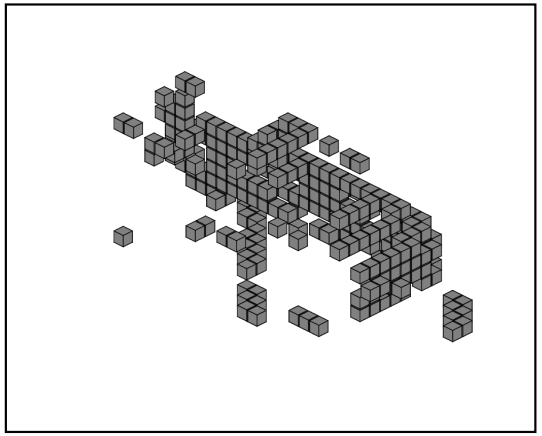
Shape Inference

What observations do we have?

- Occupied voxels $x_i = 1$ (from observed points);
- unoccupied voxels $x_i = 0$ (from free space);



Free Space
Voxels $x_i = 0$

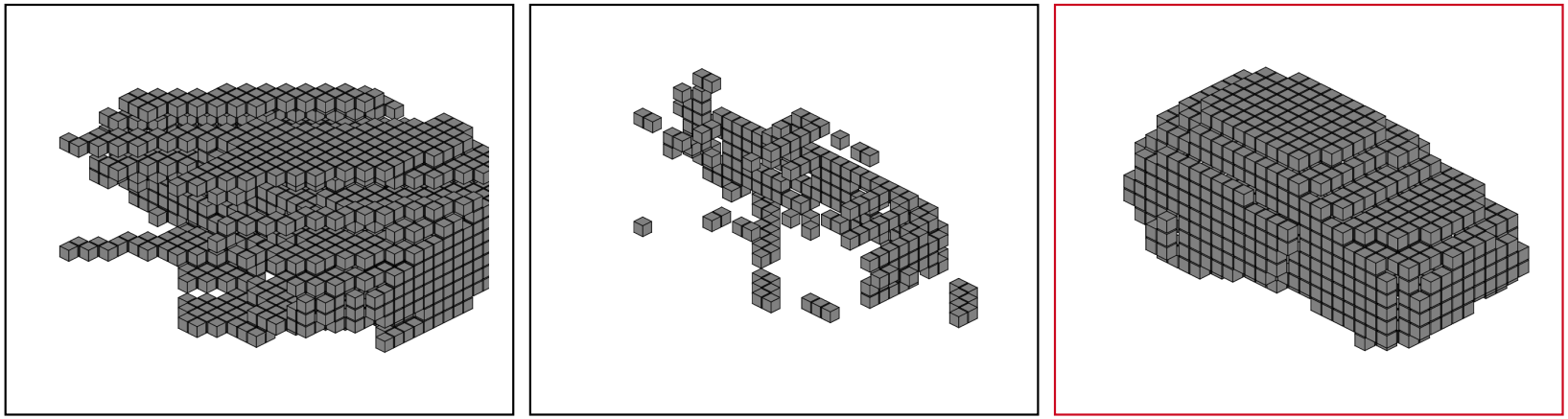


Occupied
Voxels $x_i = 1$

Shape Inference

What observations do we have?

- Occupied voxels $x_i = 1$ (from observed points);
- unoccupied voxels $x_i = 0$ (from free space);
- and unknown voxels "$x_i = \perp$".



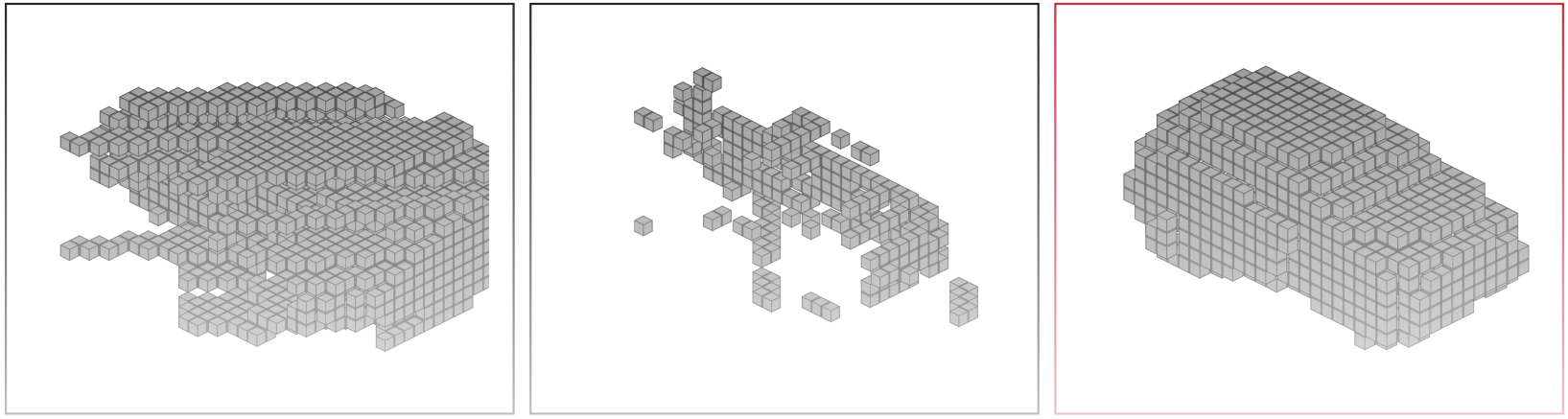
Free Space Voxels $x_i = 0$ | Occupied Voxels $x_i = 1$ | Unknown Shape y^*

Shape Inference

Minimize the negative log-likelihood of observation x over the latent space:

$$\underset{z}{\operatorname{argmin}} - \ln p(y = x, z)$$

$$= \underset{z}{\operatorname{argmin}} \sum_{x_i \neq \perp} \mathcal{L}_{\text{BCE}}(\tilde{y}_i, x_i) + \text{const} + \frac{1}{2}\|z\|_2^2$$



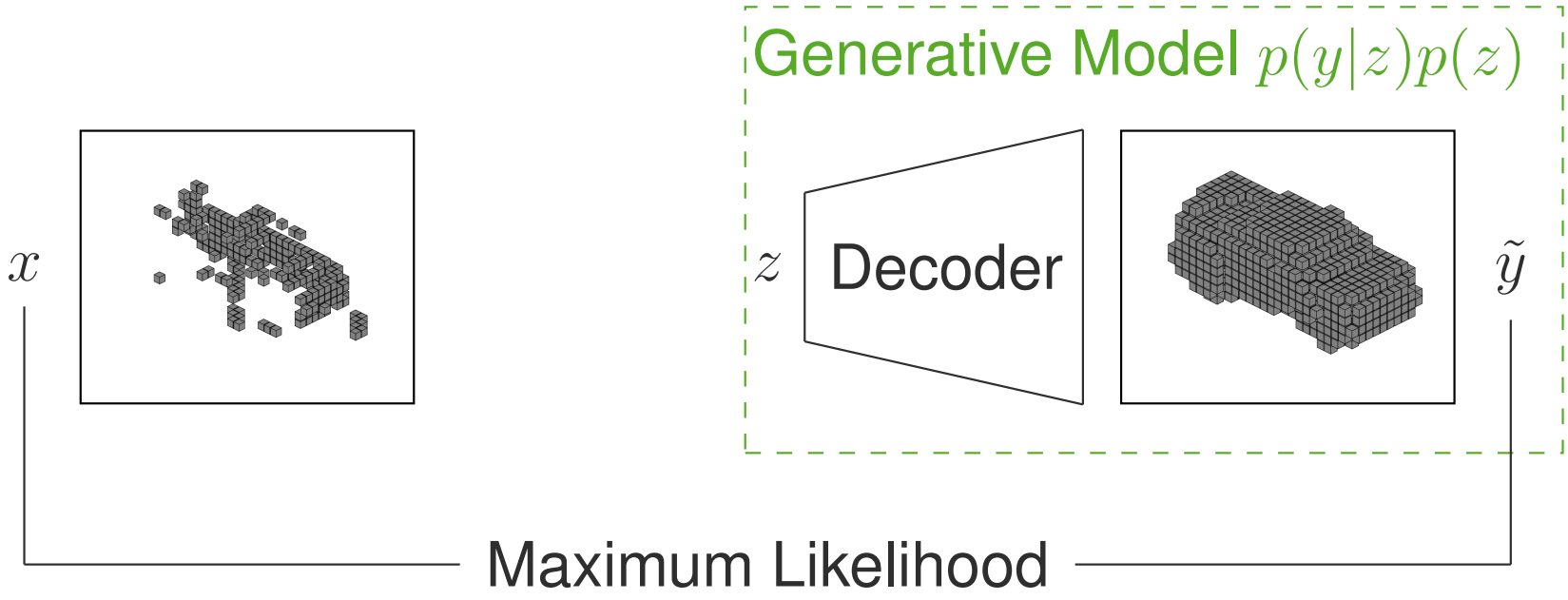
Free Space
Voxels $x_i = 0$

Occupied
Voxels $x_i = 1$

Unknown Shape y^*

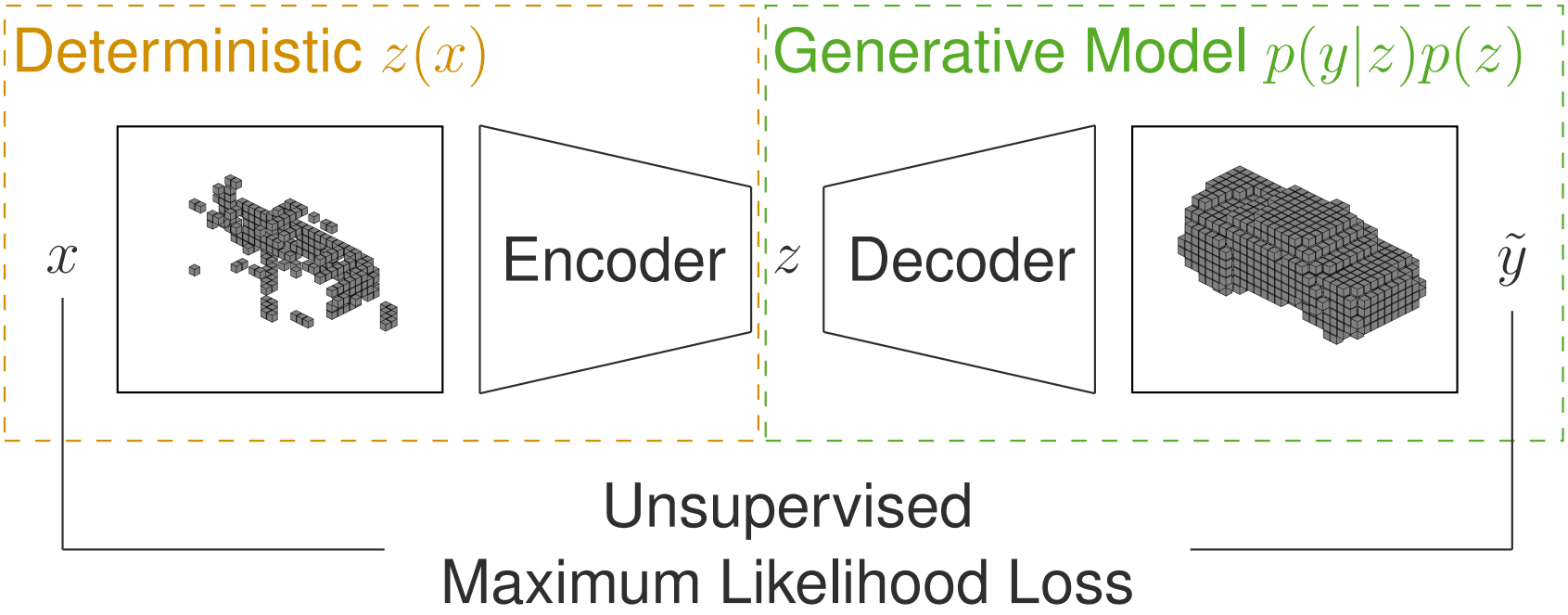
Shape Inference

Minimize the negative log-likelihood of observation x over the latent space:



Shape Inference

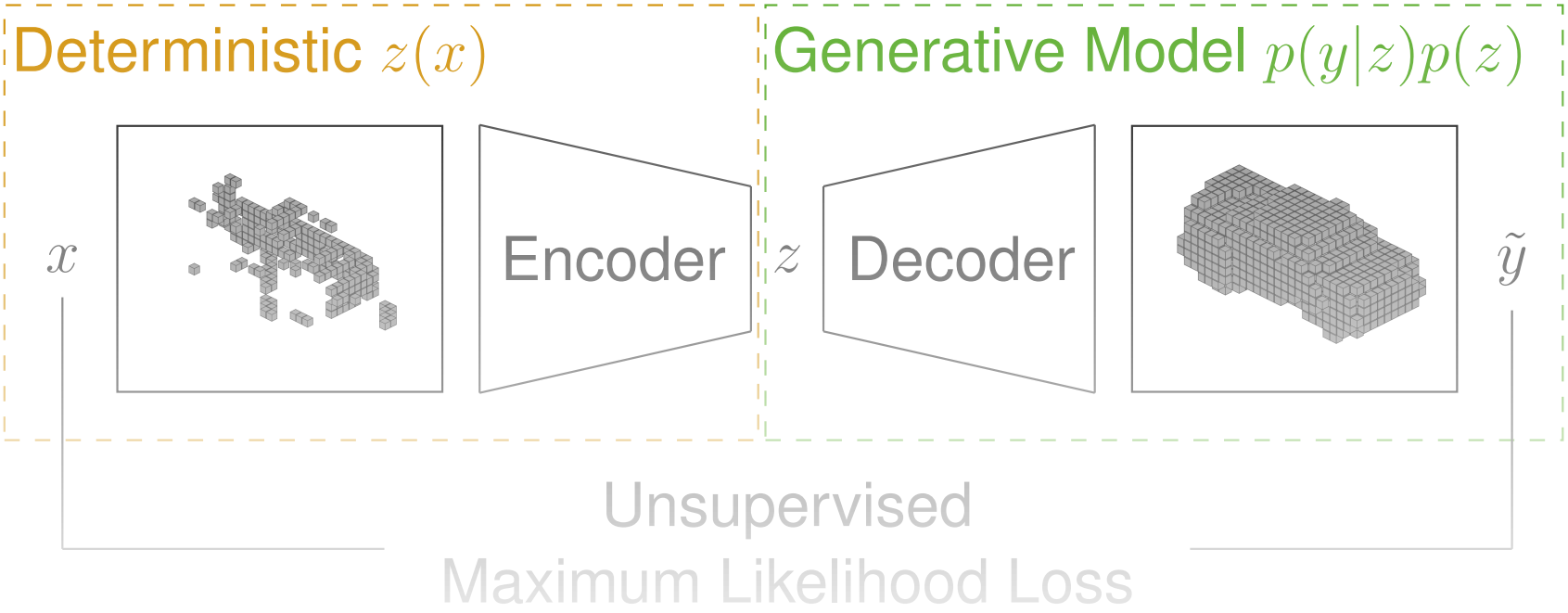
Learn to minimize the negative log-likelihood of observation x over the latent space:



Shape Inference

Learn to minimize the negative log-likelihood of observation x over the latent space:

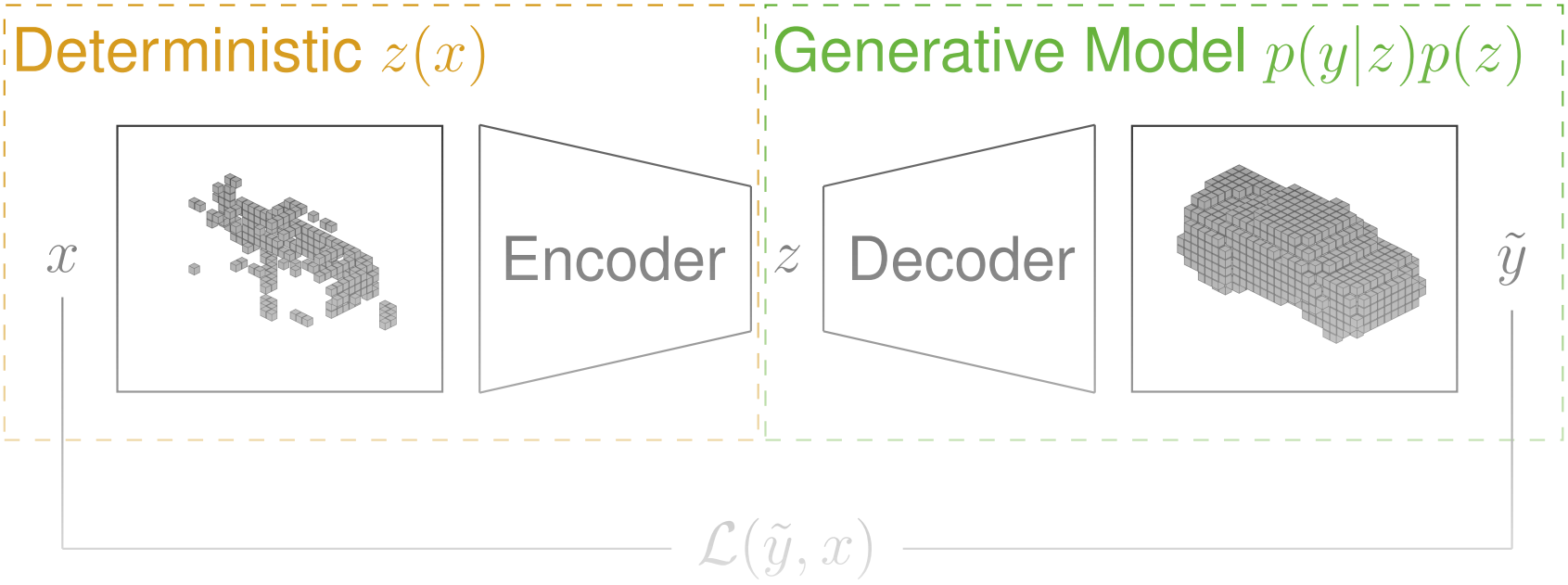
$$x \mapsto \tilde{z}(x) \approx \operatorname*{argmin}_{z} - \sum_{x_i \neq \perp} \ln p(y_i = x_i | z) - \ln p(z)$$



Shape Inference

Learn to minimize the negative log-likelihood of observation x over the latent space:

$$\mathcal{L}(\tilde{y}, x) = -\sum_{x_i \neq \perp} \ln p(\tilde{y}_i = x_i | z) - \ln p(z)$$



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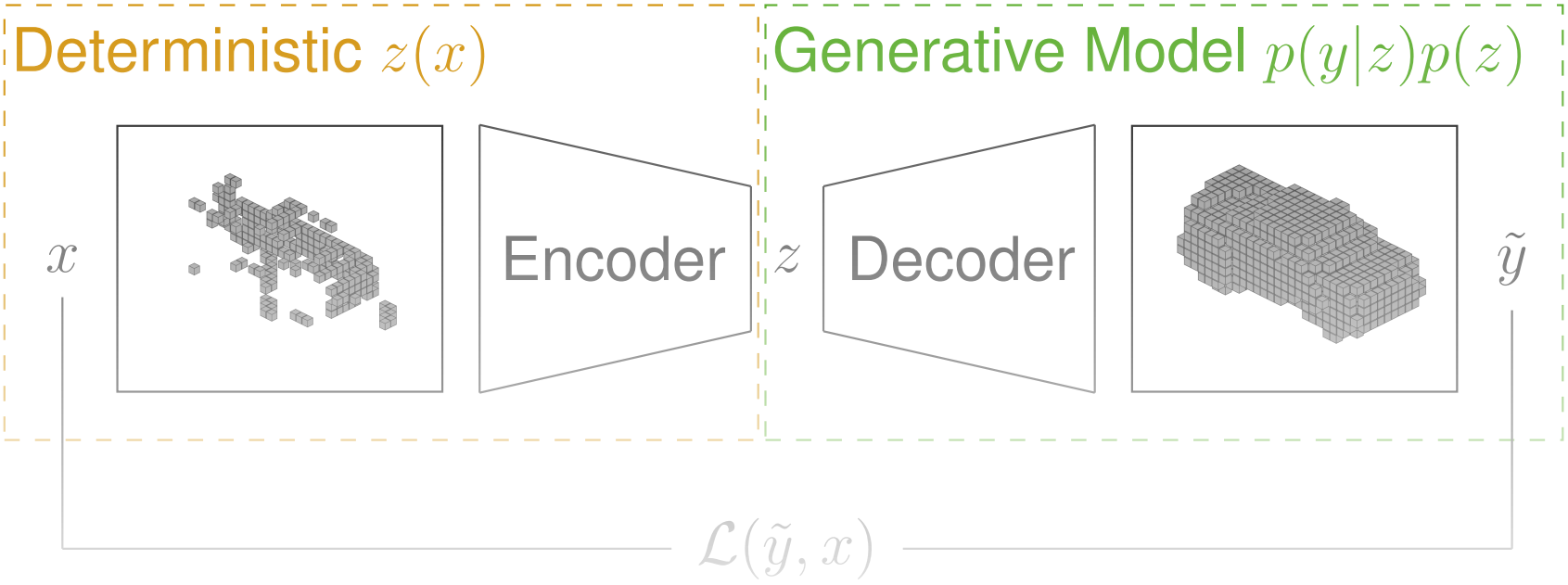

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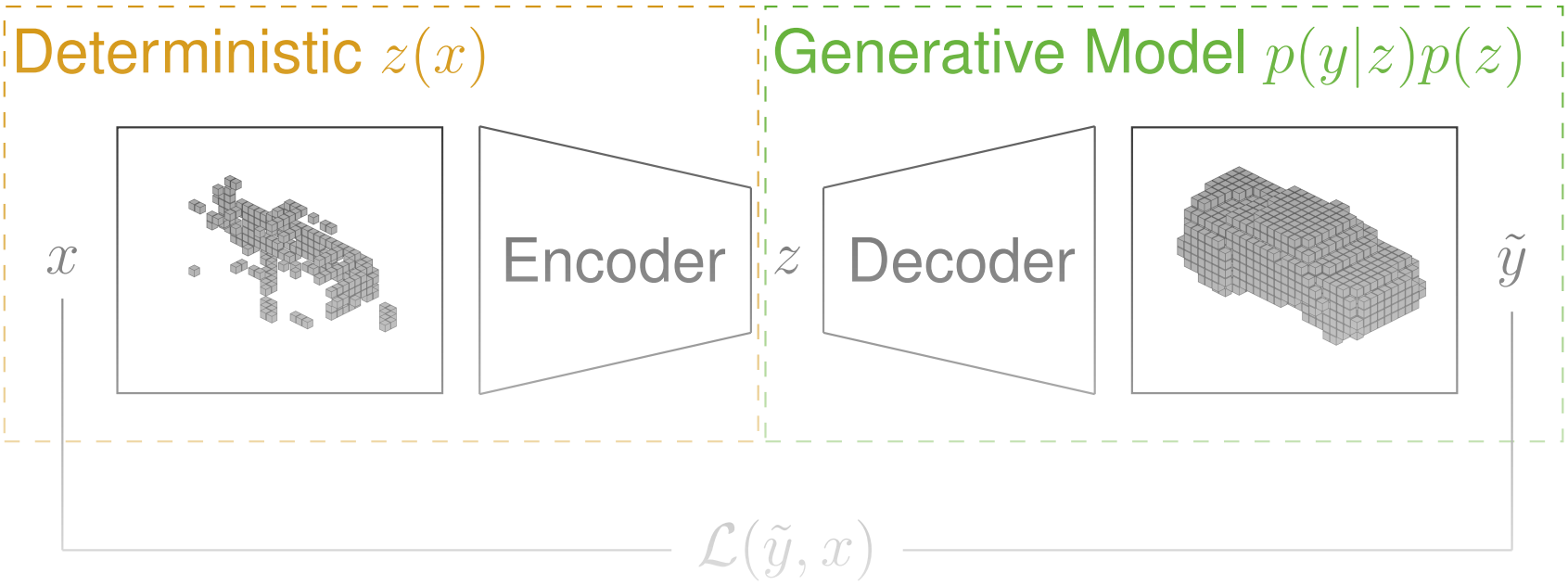
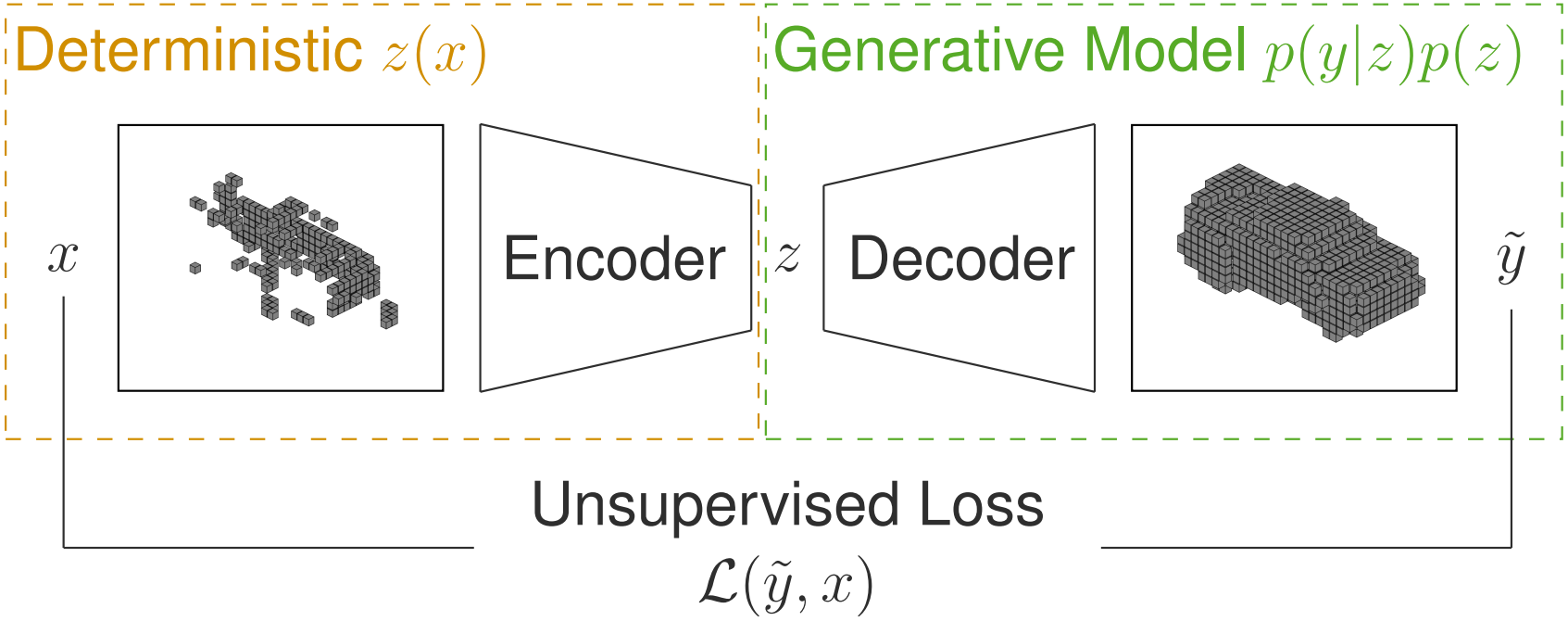


Shape Inference

Amortized maximum likelihood:

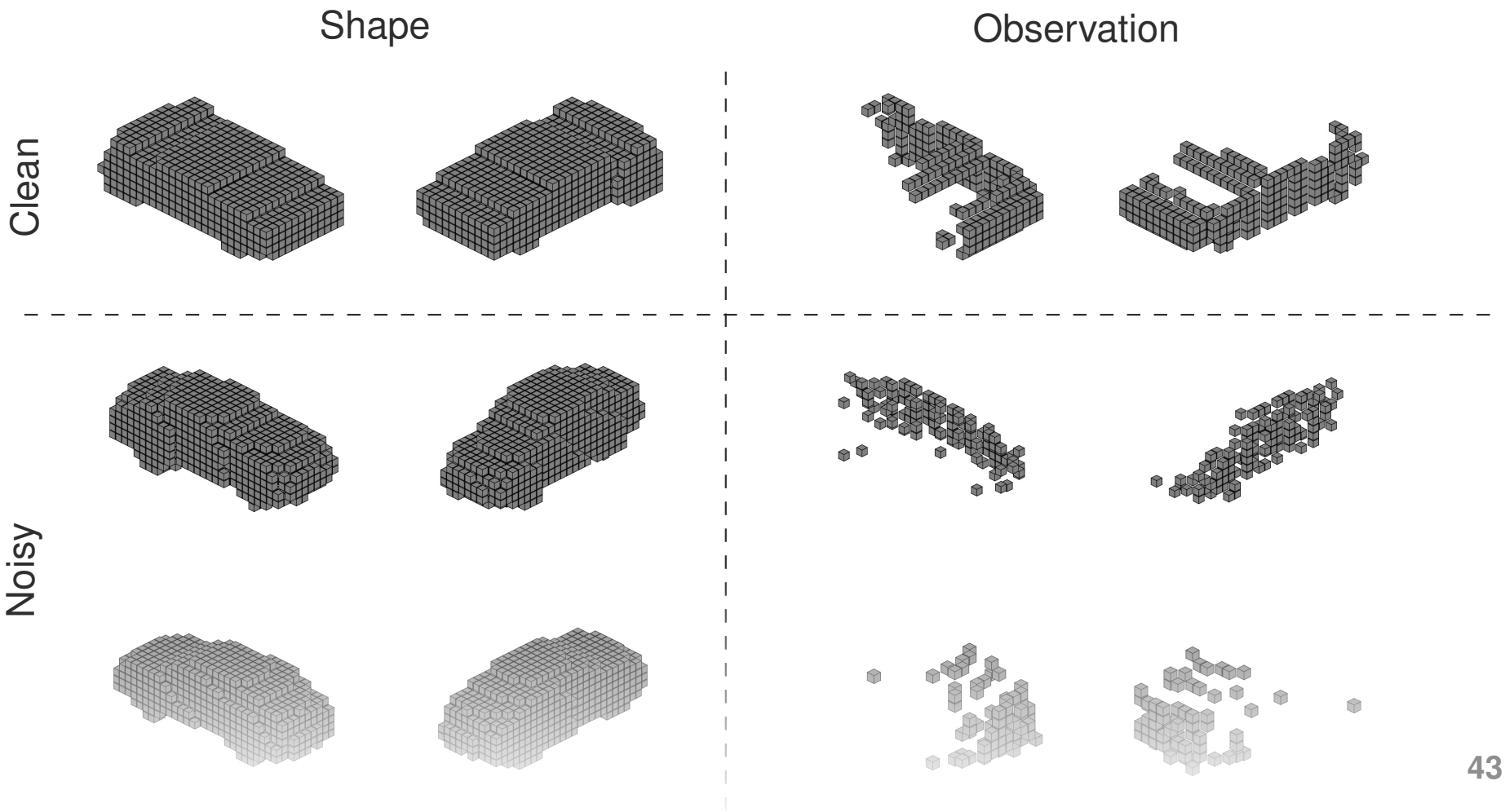


- Can be extended to signed distance functions;
- learning on real data and efficient inference.

Experiments

ShapeNet

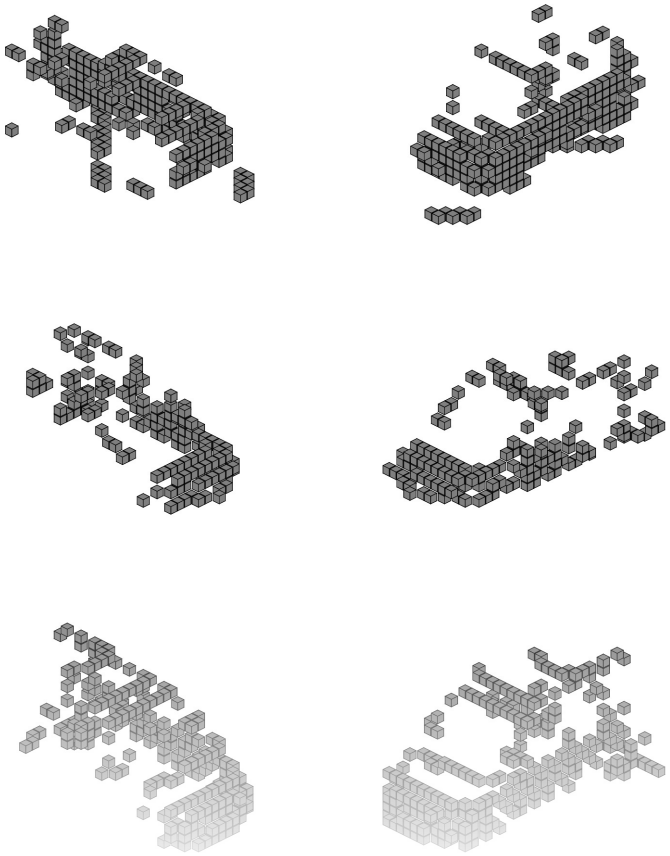
[Chang et al., 2015]; $\sim 3k$ car models, voxelized to 32^3, and synthetically generated observations.



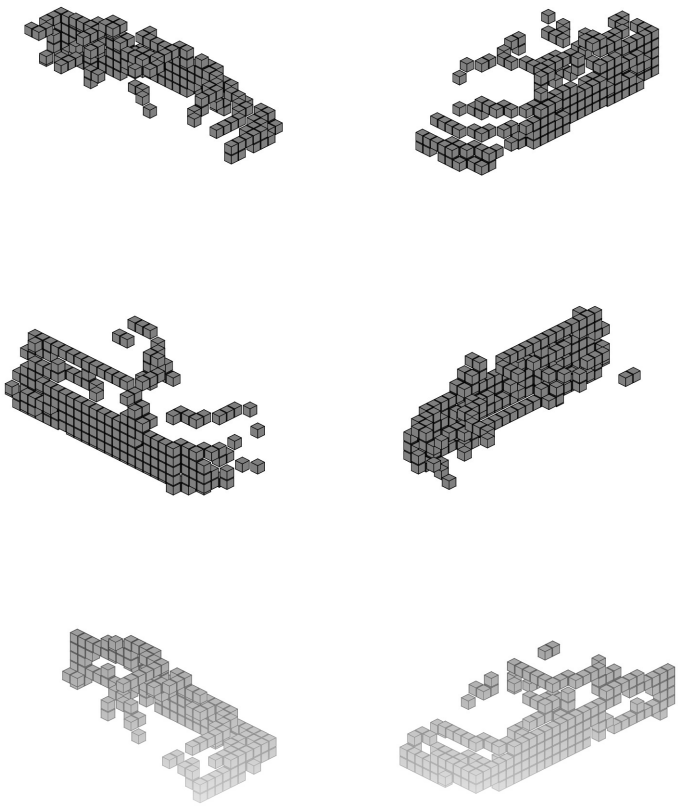
KITTI

[Geiger et al., 2012]; ground truth 3D bounding boxes, voxelized to 32^3, without target shapes.

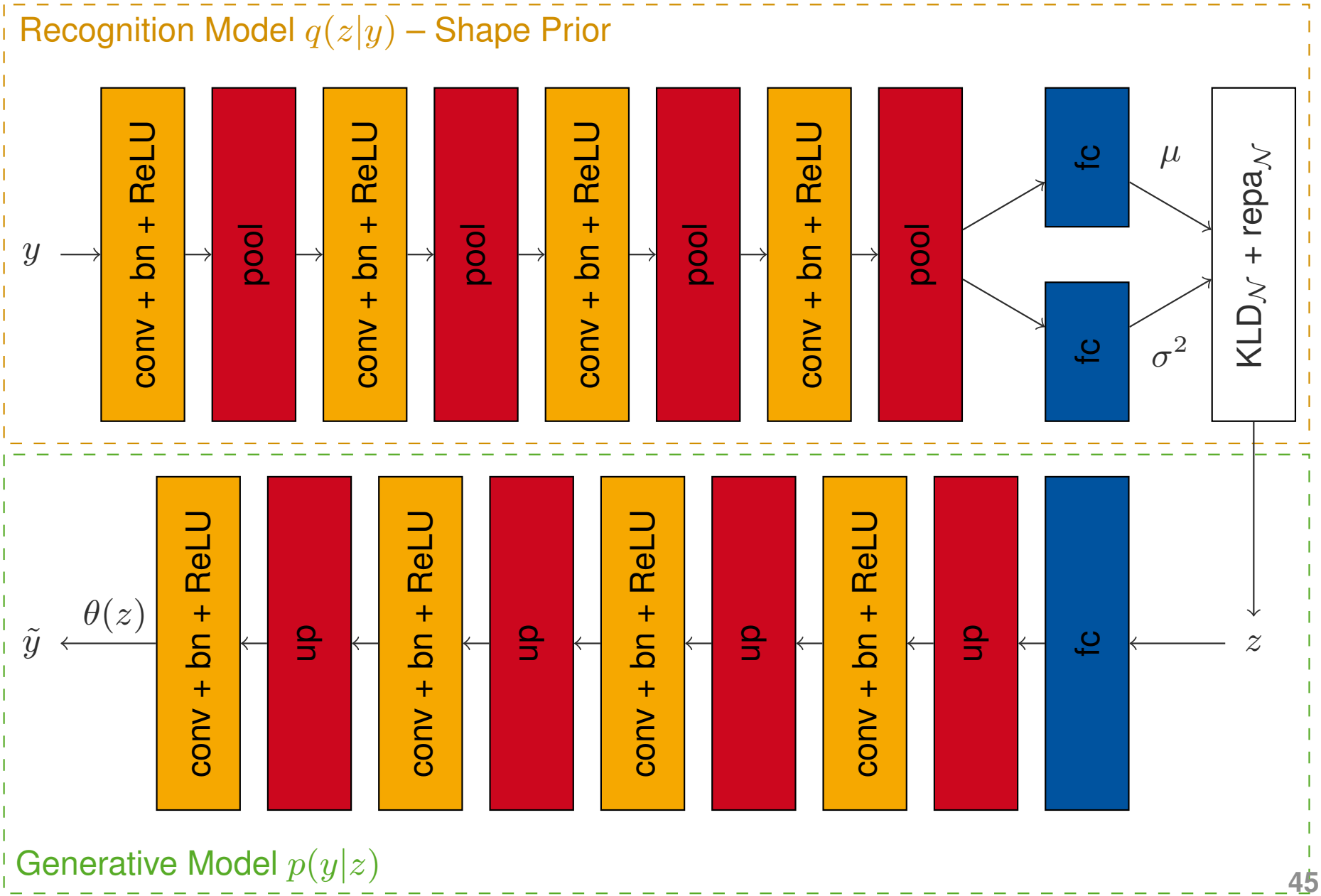
Observation



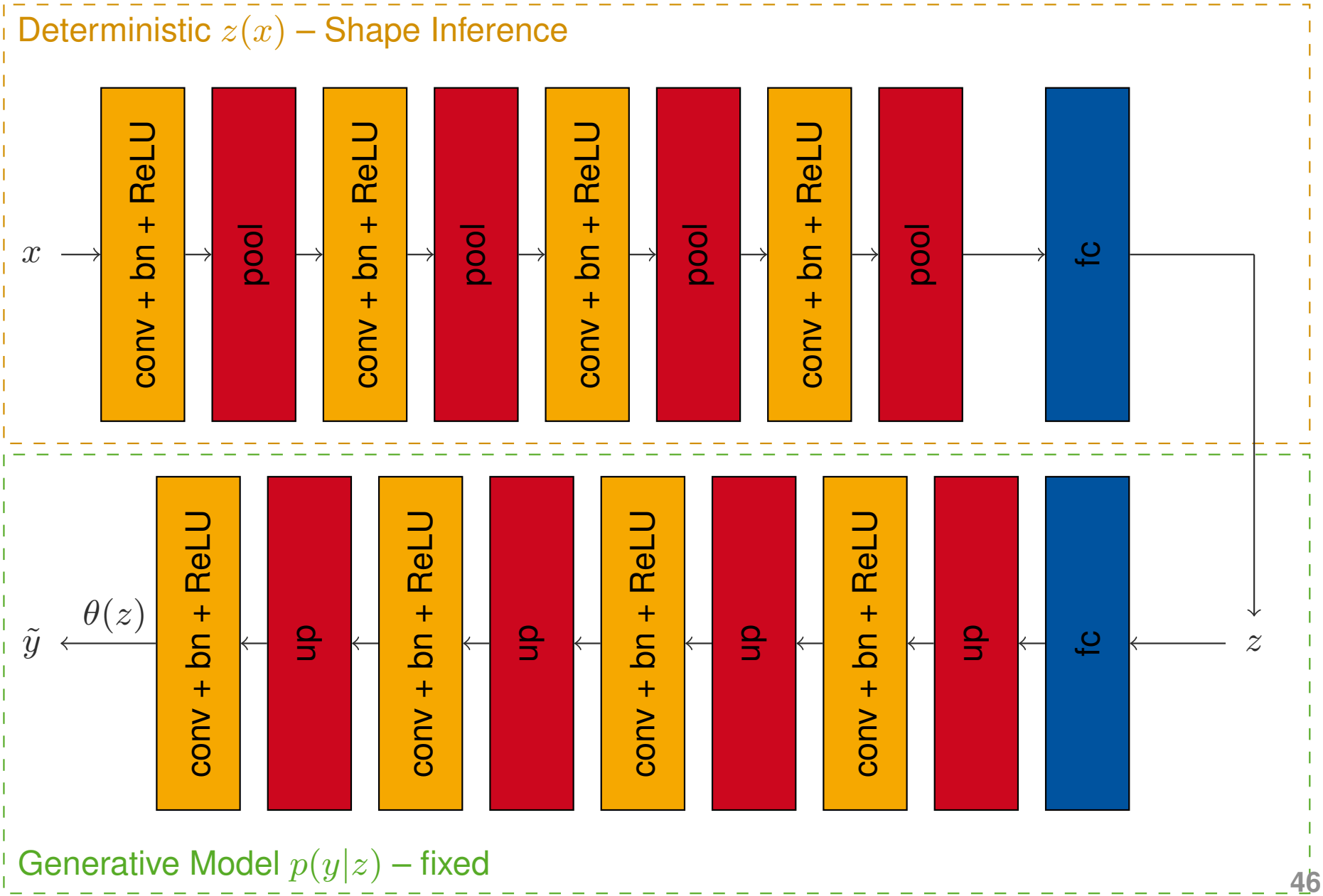
Observation



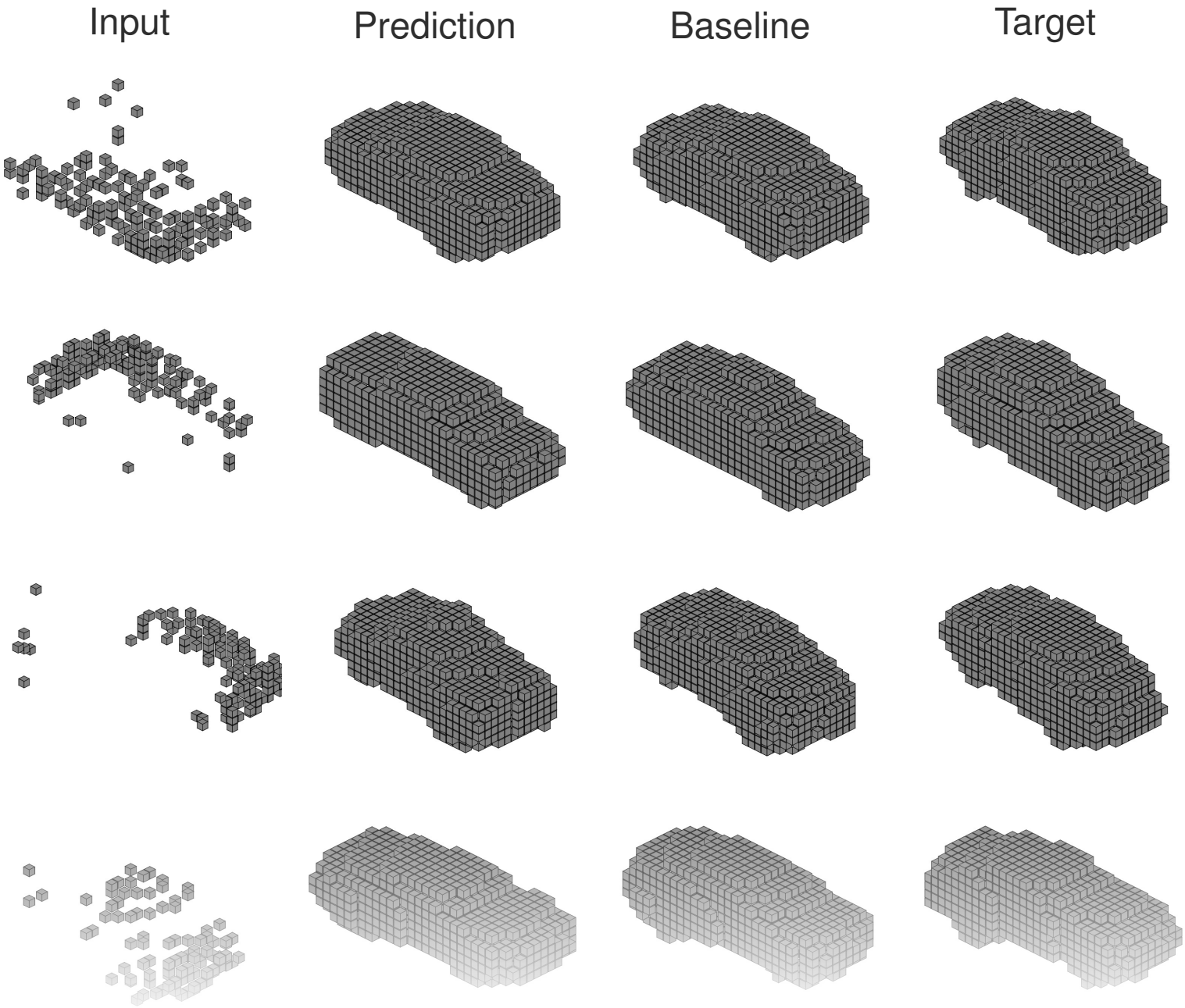
Architecture



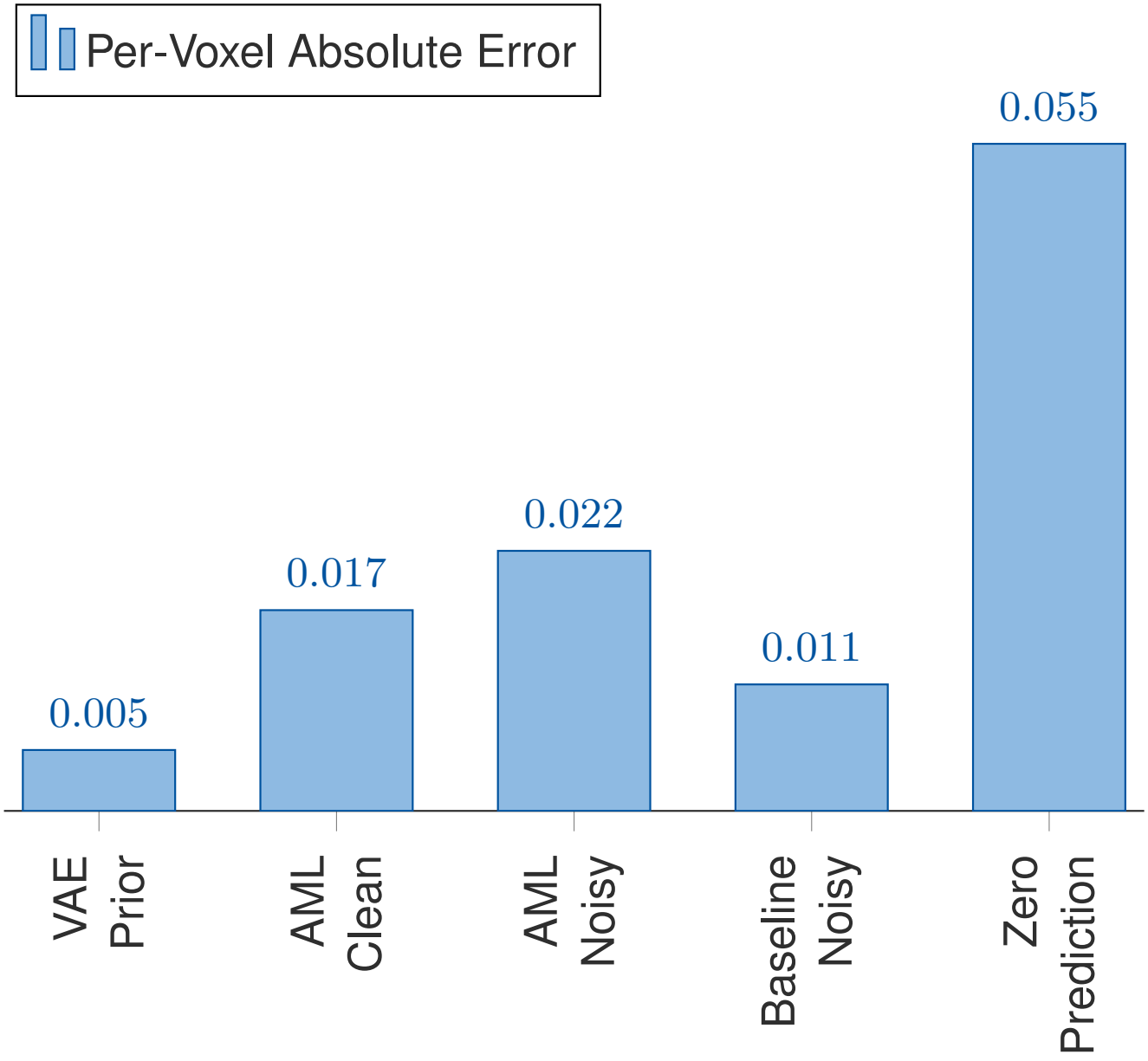
Architecture



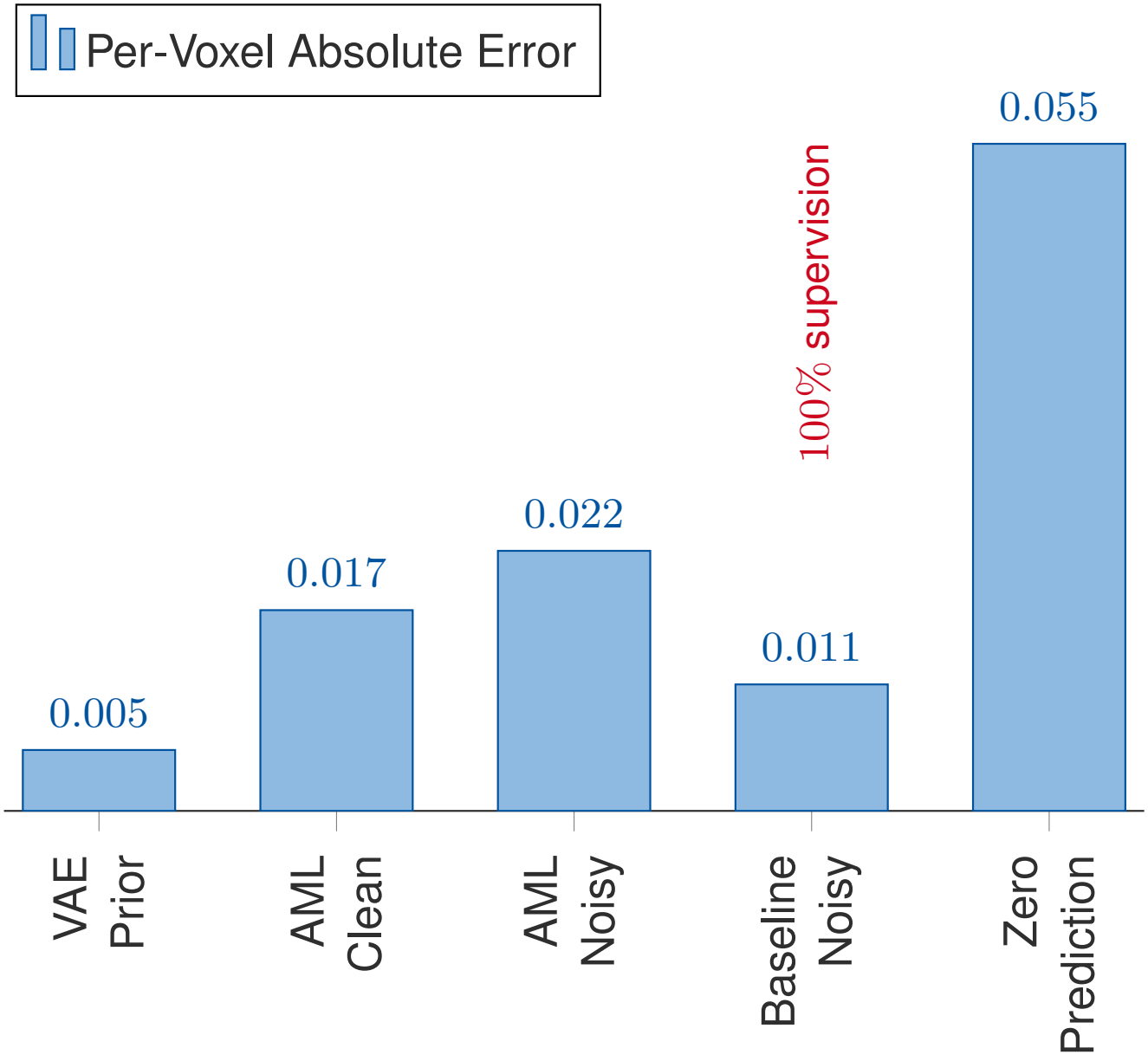
Results on ShapeNet



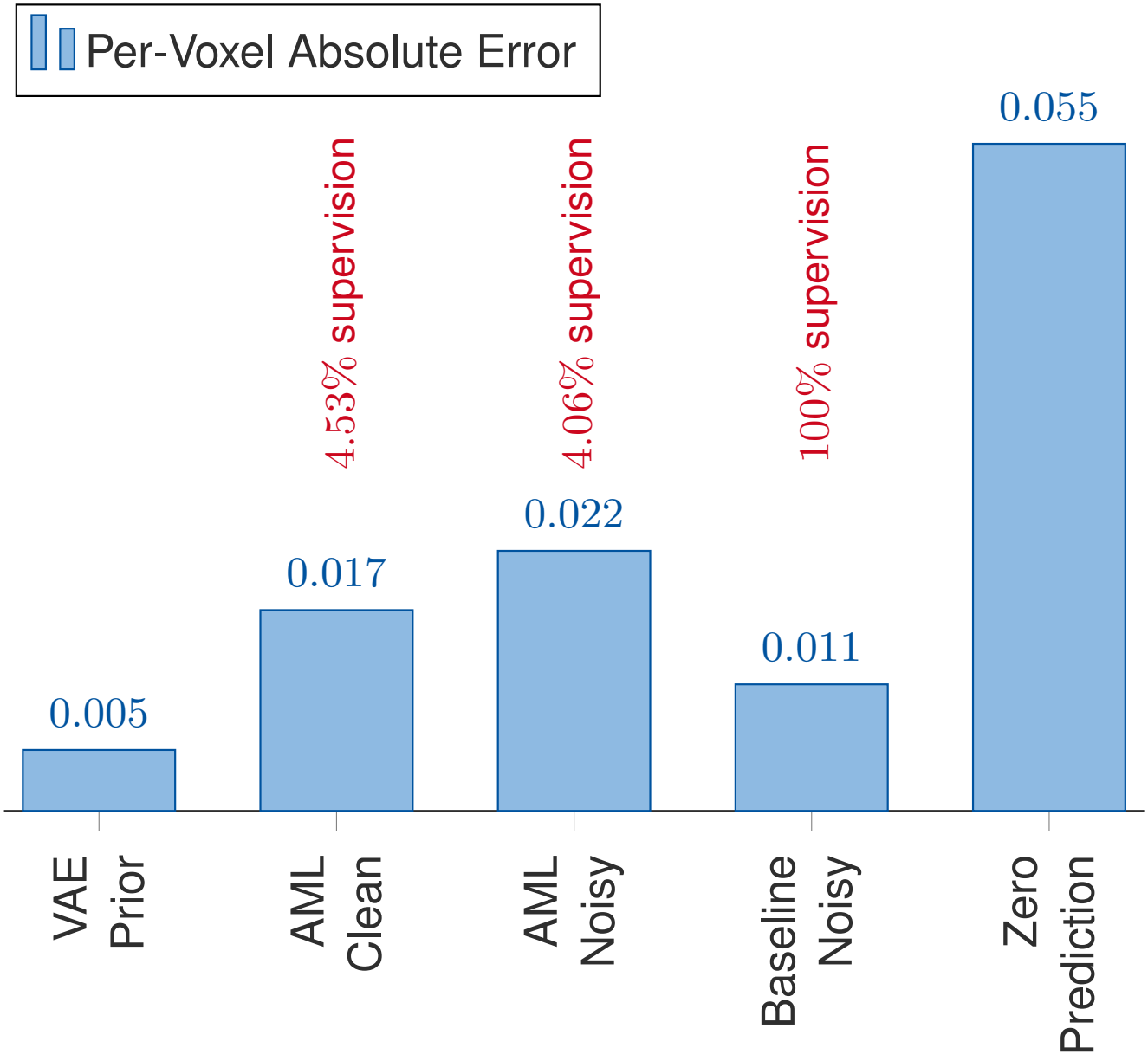
Results on ShapeNet



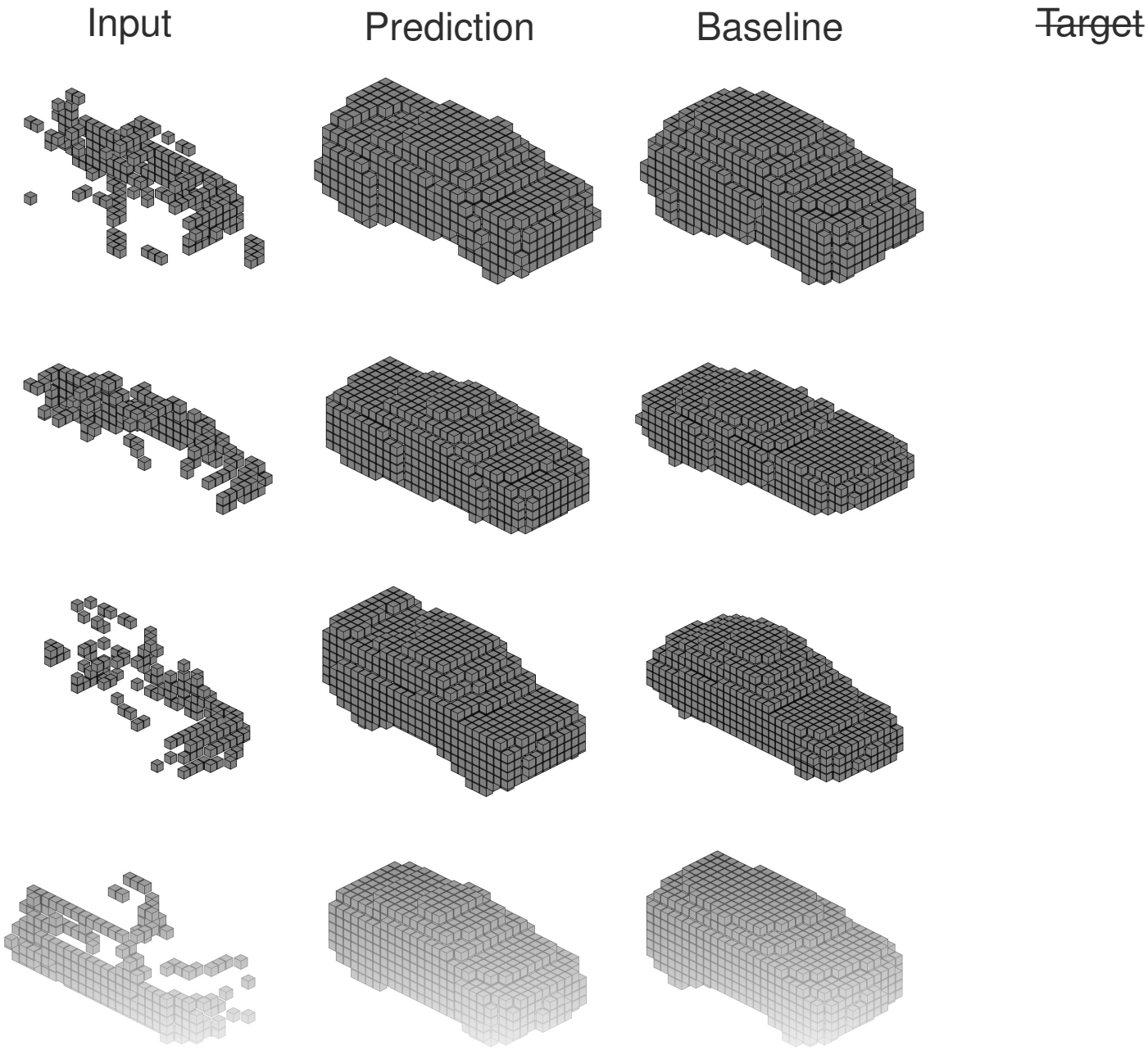
Results on ShapeNet



Results on ShapeNet



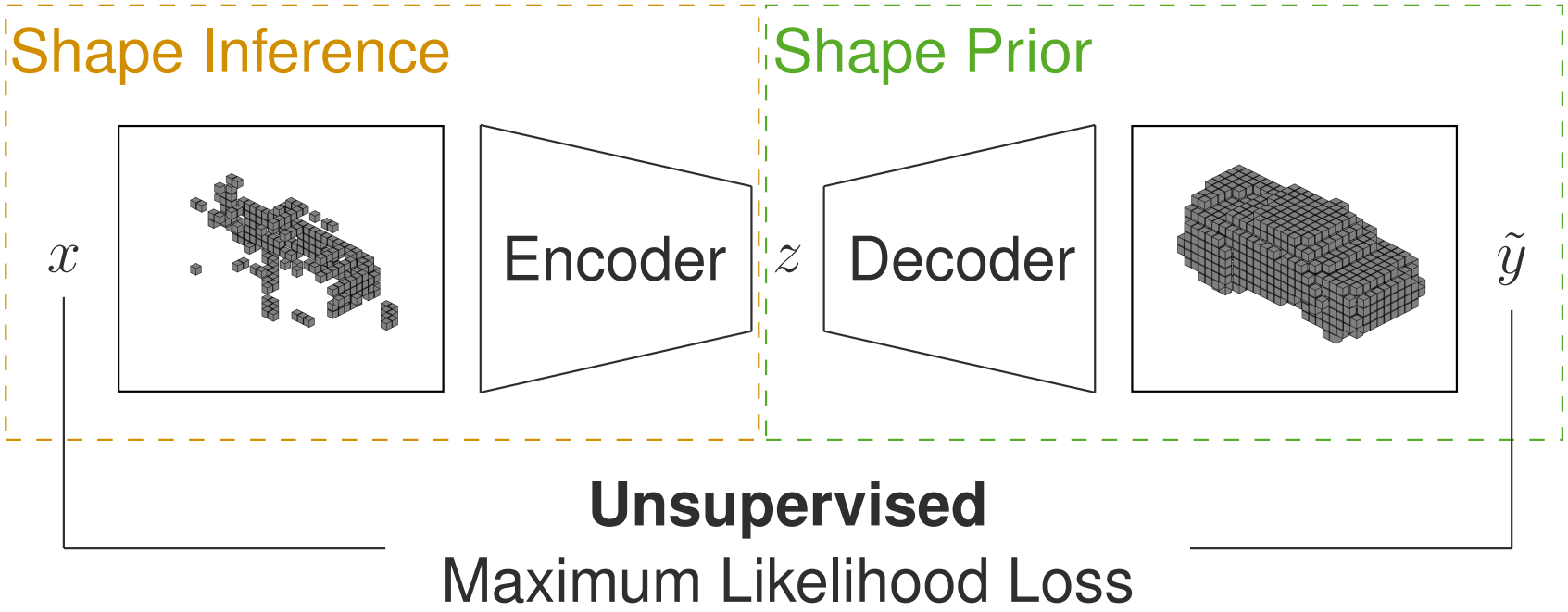
Results on KITTI



Conclusion

Summary

We proposed an amortized maximum likelihood framework for **learning** shape completion in a **weakly-supervised** setting.



Conclusion

Our experiments suggest that:

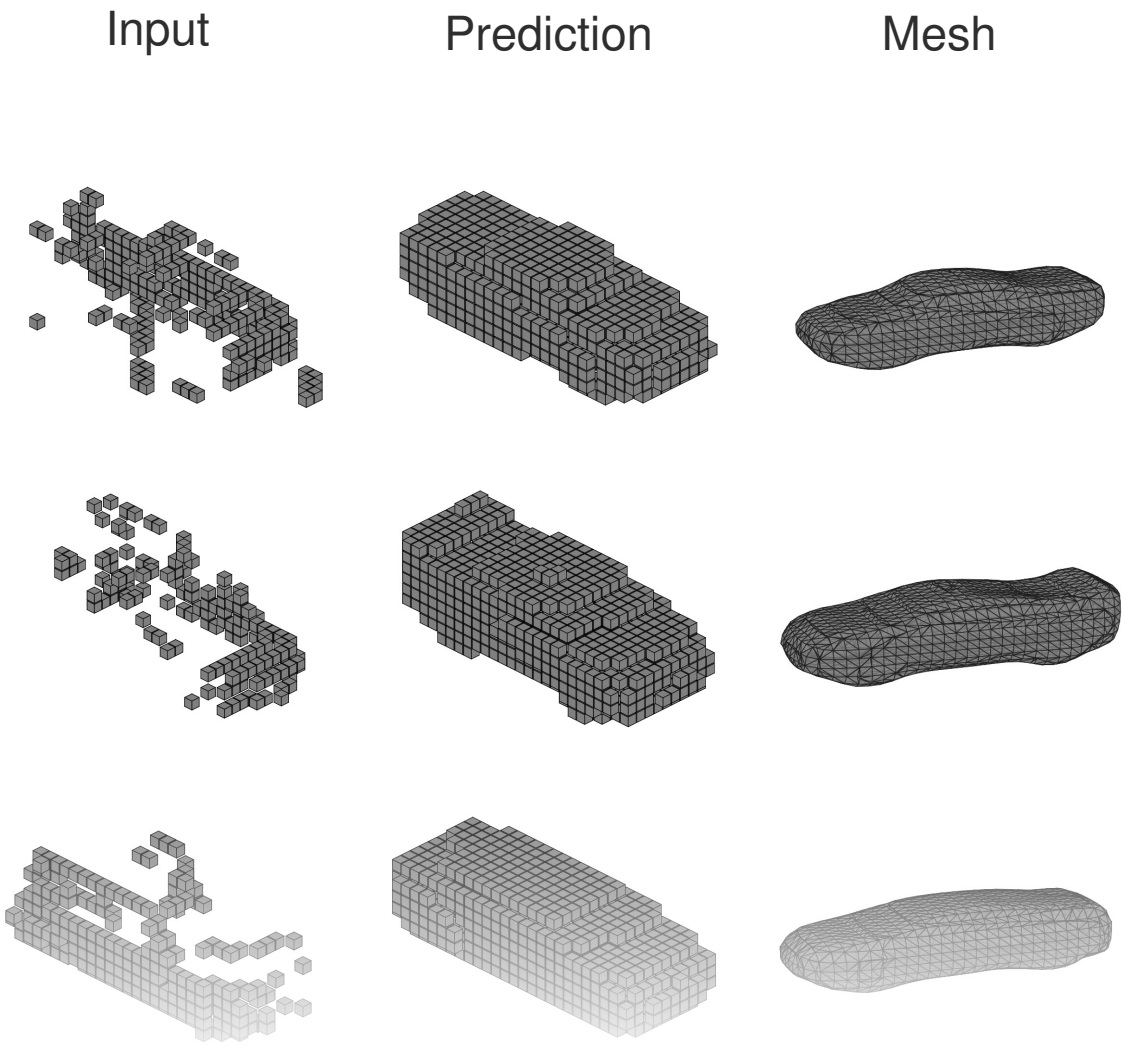
Hypothesis

Strong shape priors allow to learn shape completion under weak supervision.

- Additionally, inference involves “a simple forward pass”.

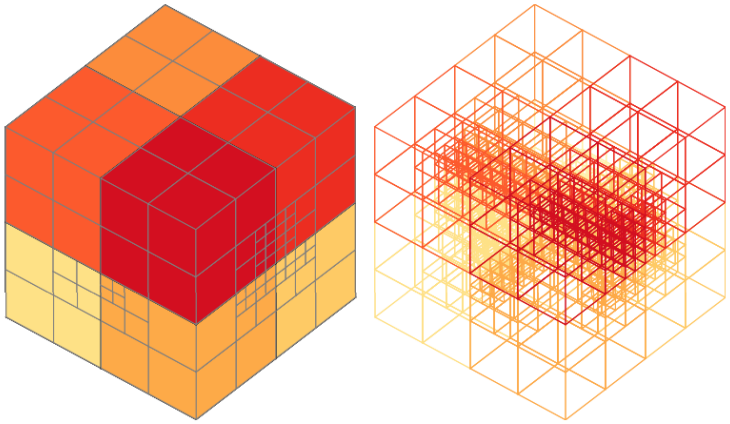
Future Work

Improve proposed amortized maximum likelihood framework on signed distance functions.

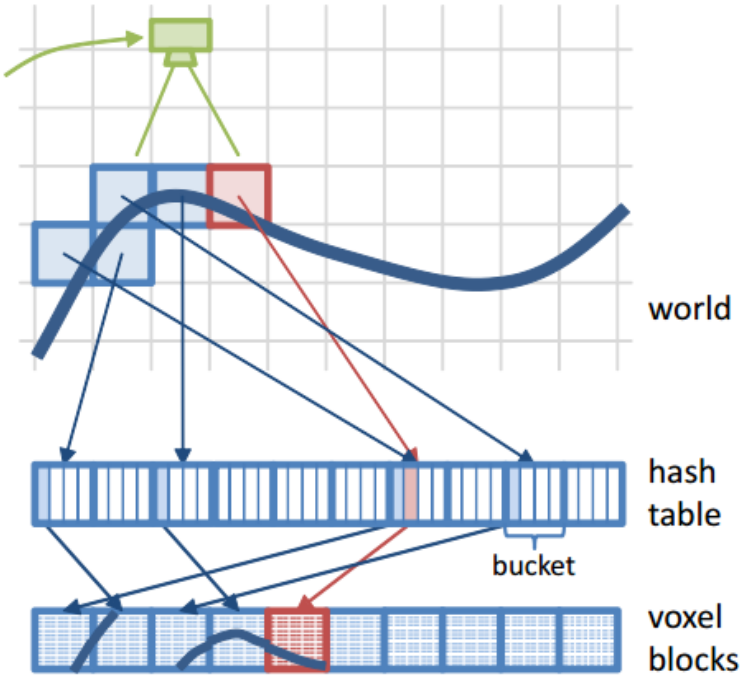


Future Work

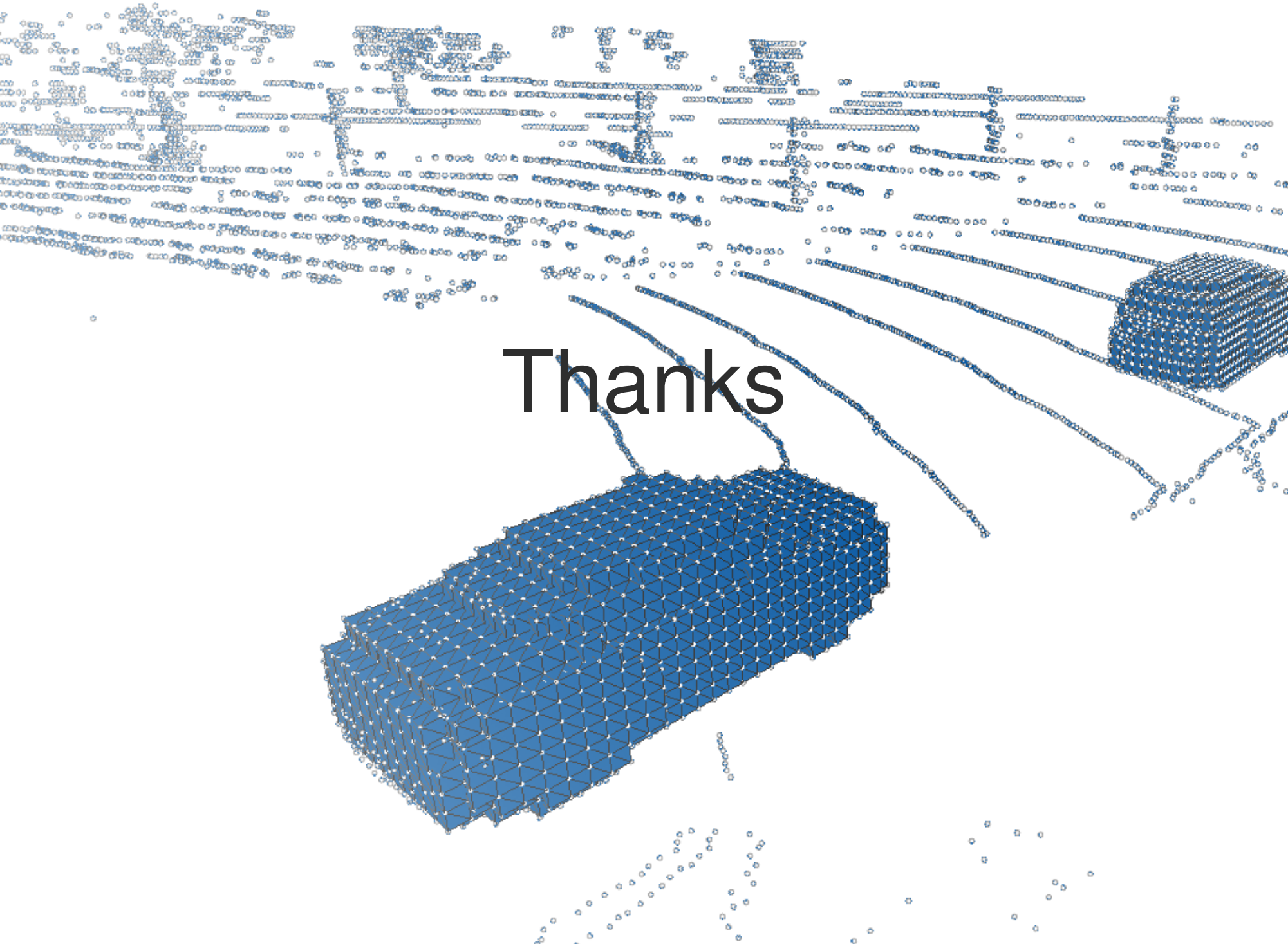
Increase resolution to learn details.



Input Reconstructed 3D point cloud



[Riegler et al., 2016] [Nießner et al., 2013]
[Fan et al., 2016]

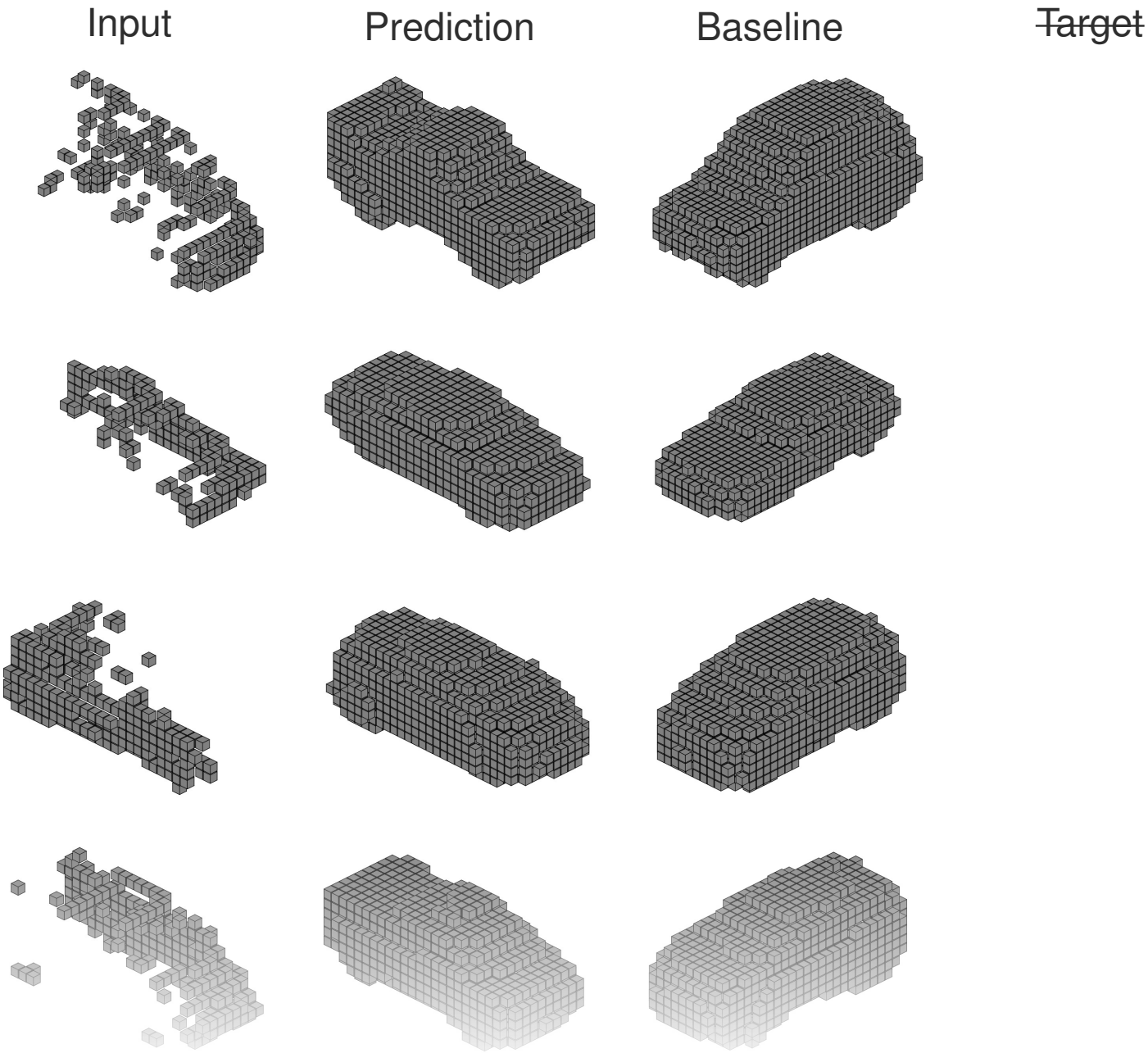

Thanks

Appendix – Related Work

Rough categorization following [Sung et al., 2015]:

- symmetry based approaches, *e.g.* [Thrun and Wegbreit, 2005, Pauly et al., 2008, Zheng et al., 2010, Kroemer et al., 2012];
- data-driven approaches, *e.g.* [Pauly et al., 2005, Li et al., 2015, Nan et al., 2012, Gupta et al., 2015, Dame et al., 2013, Engelmann et al., 2016];
- and recently learning-based approaches, *e.g.* [Firman et al., 2016, Smith and Meger, 2017, Dai et al., 2016, Sharma et al., 2016, Rezende et al., 2016, Fan et al., 2016].

Appendix – Results on KITTI



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