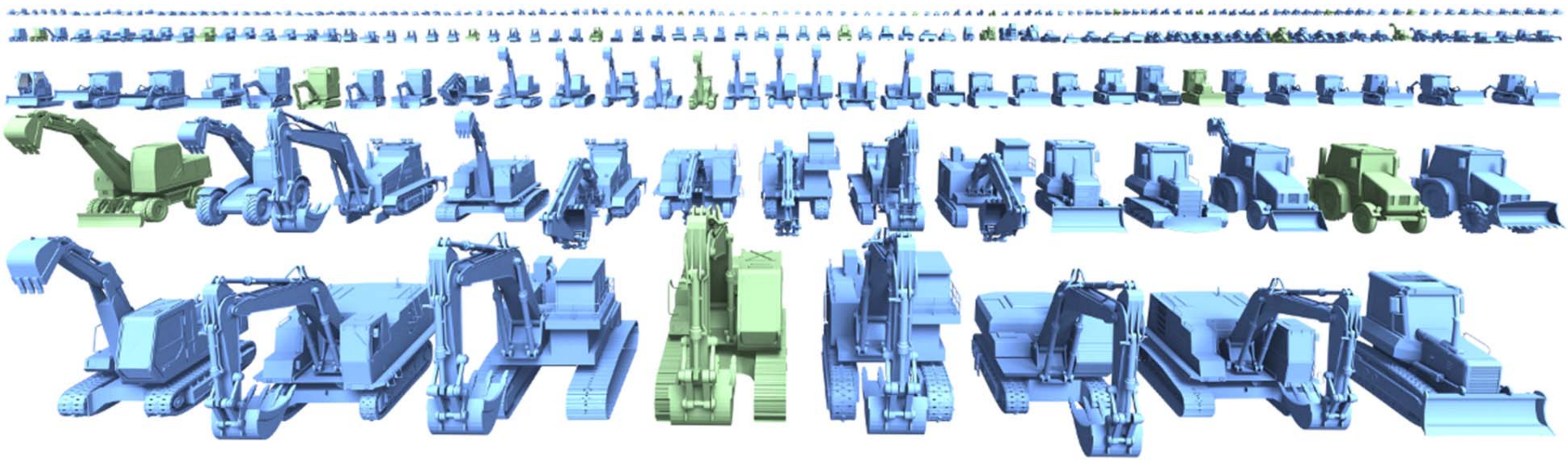
A Probabilistic Model for Component-Based Shape Synthesis



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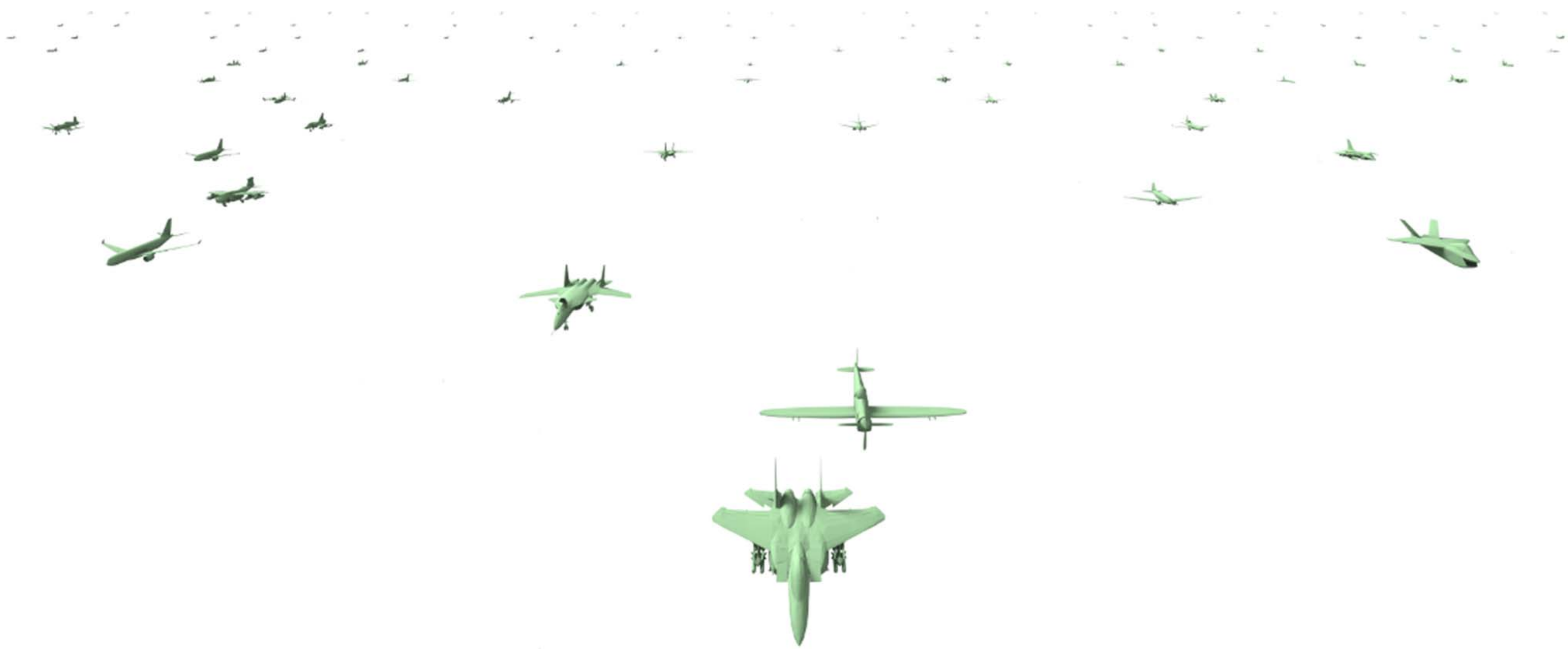
Daphne Koller, Vladlen Koltun

Stanford University

Goal: generative model of shape



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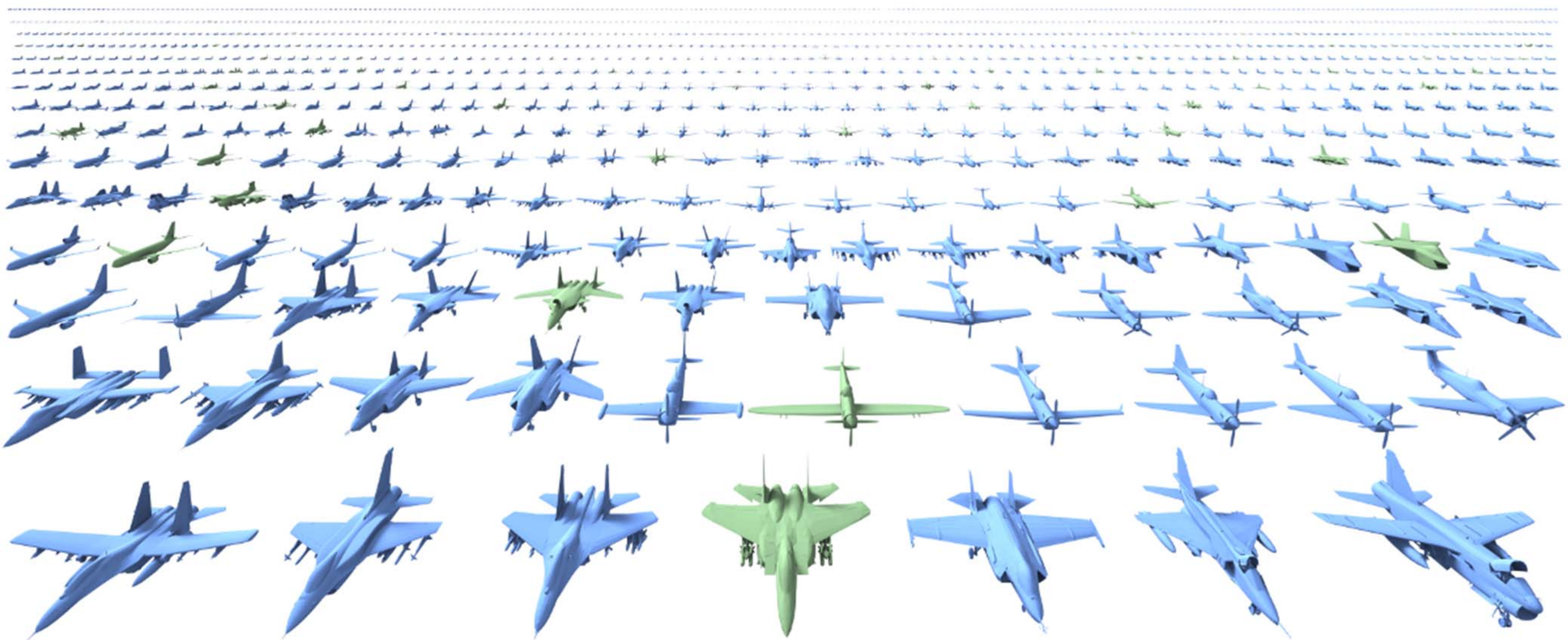
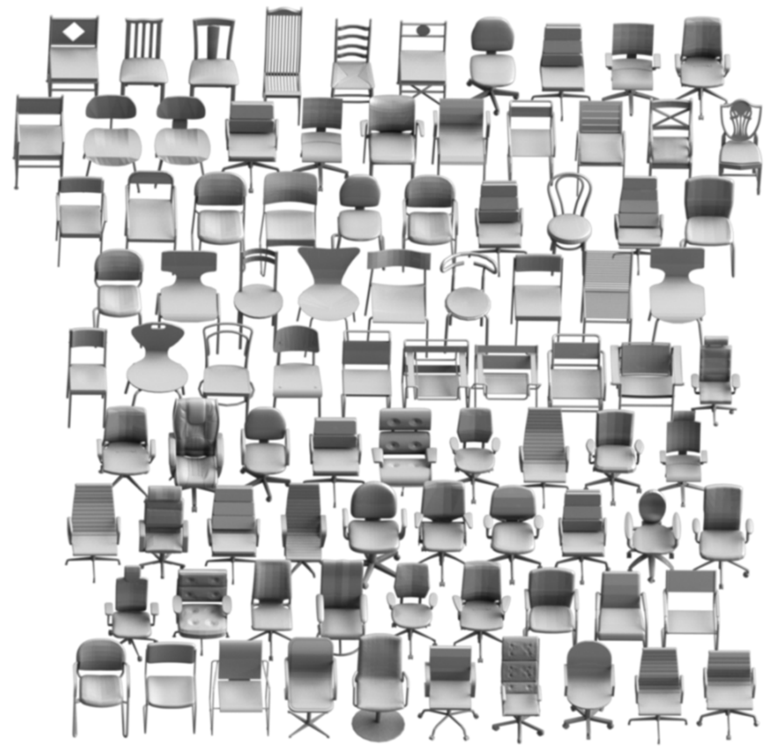


Challenge: understand shape variability

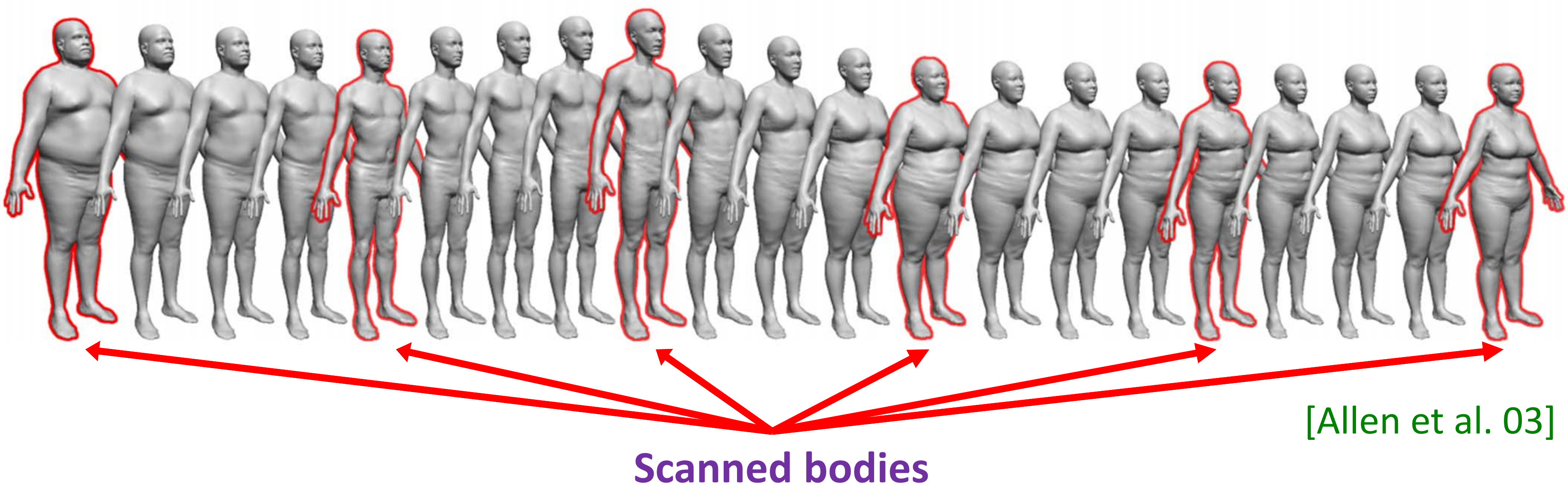
- Structural variability
- Geometric variability
- Stylistic variability



Our chair dataset

Related work: variability in human body and face

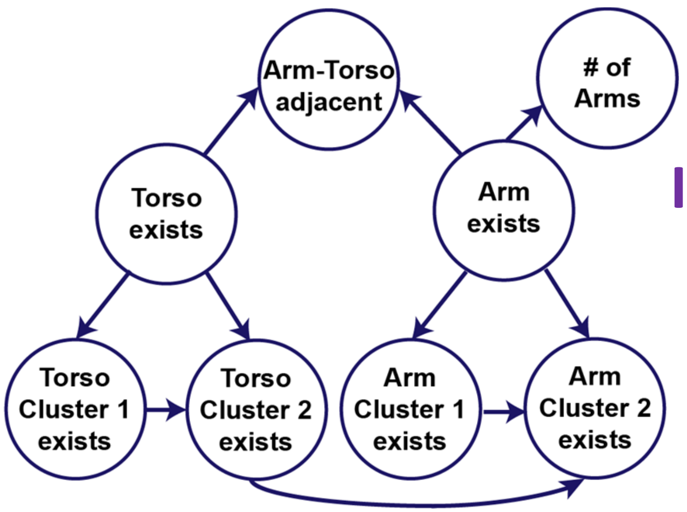
- A morphable model for the synthesis of 3D faces [Blanz & Vetter 99]
- The space of human body shapes [Allen et al. 03]
- Shape completion and animation of people [Anguelov et al. 05]



[Allen et al. 03]

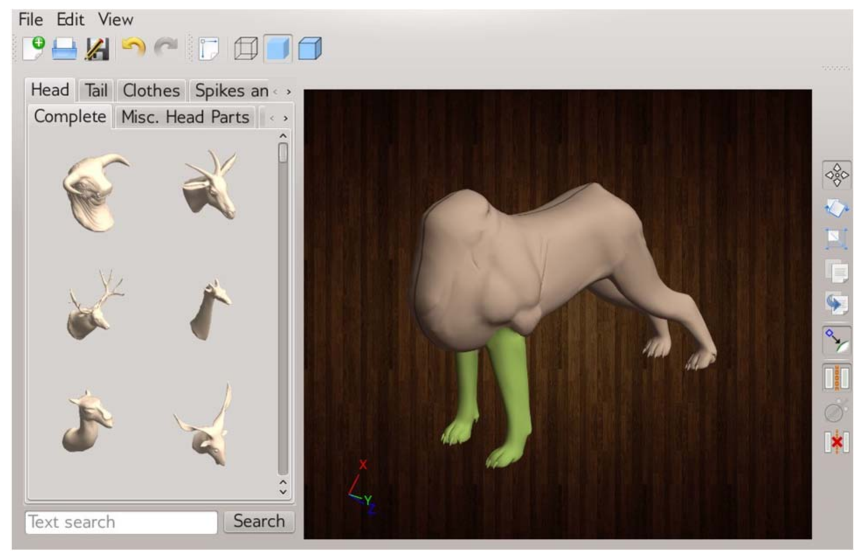
Related work: probabilistic reasoning for assembly-based modeling

[Chaudhuri et al. 2011]



Probabilistic model

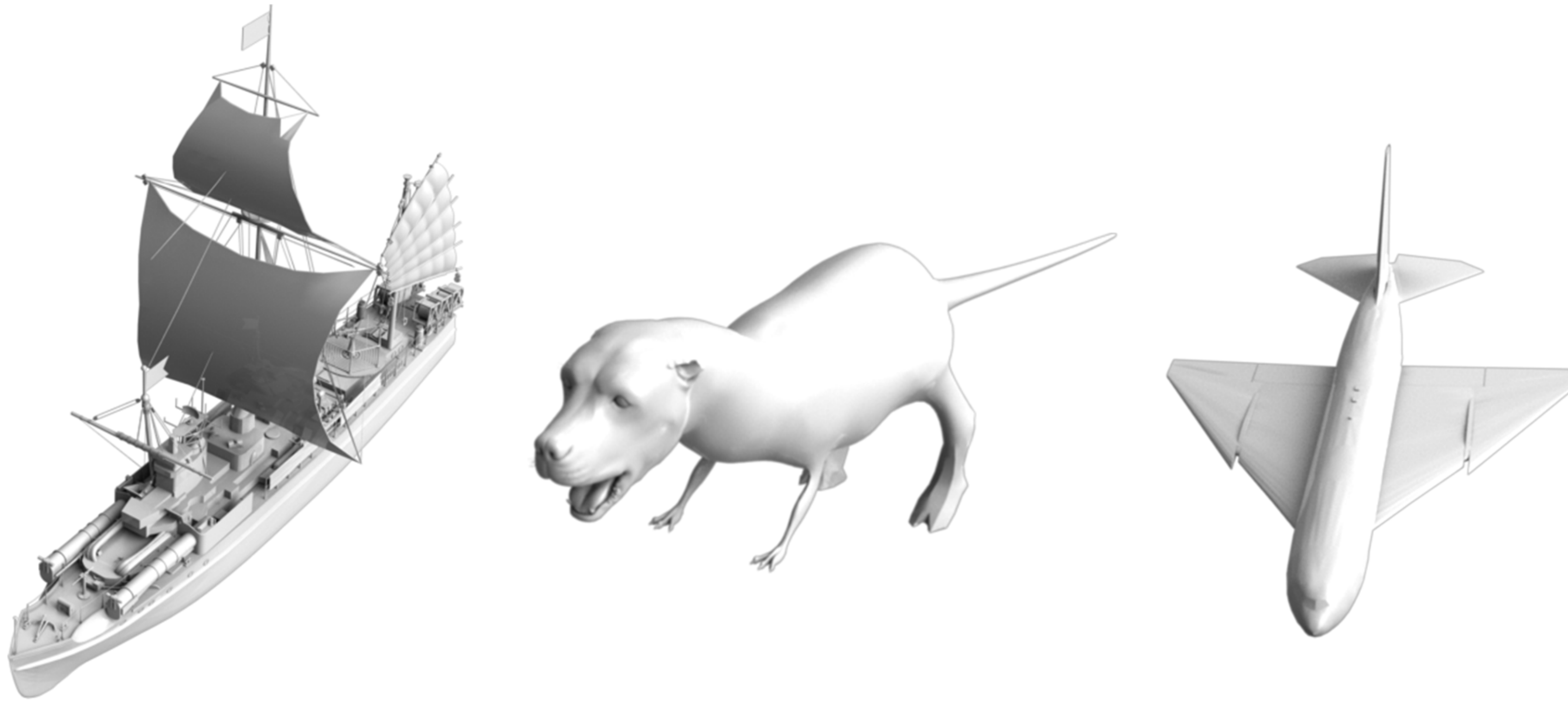
Inference



Modeling interface

Related work: probabilistic reasoning for assembly-based modeling

Randomly shuffling components of the same category



Our probabilistic model

- Synthesizes **plausible and complete shapes automatically**

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- Represents shape variability at **hierarchical levels of abstraction**

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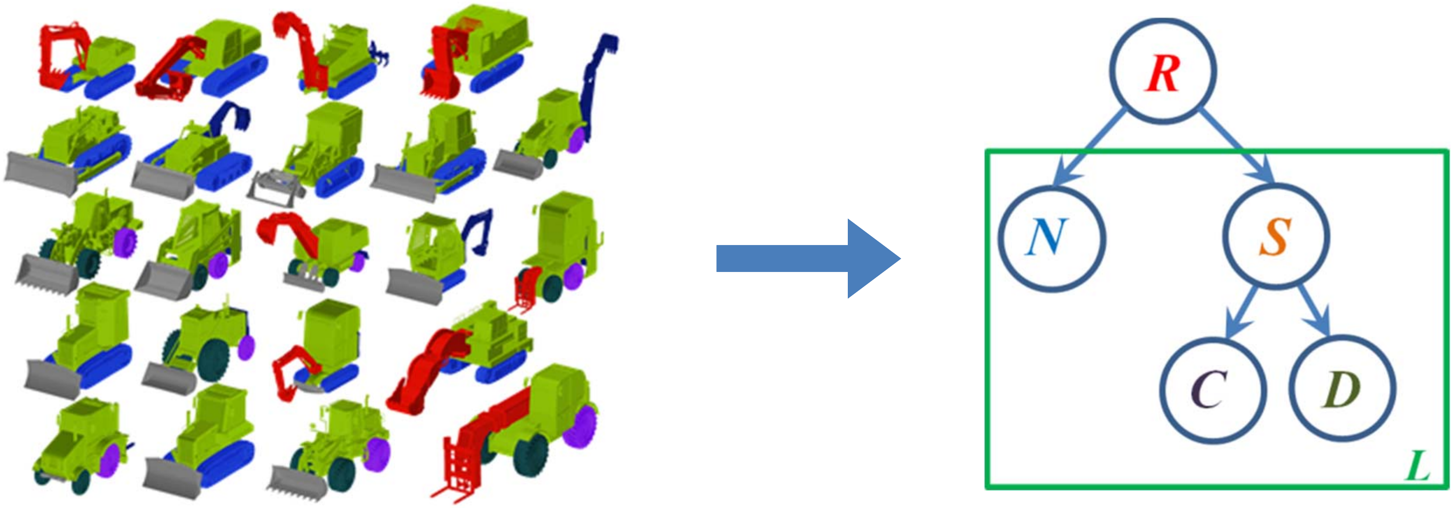
- Understands **latent causes of structural and geometric variability**

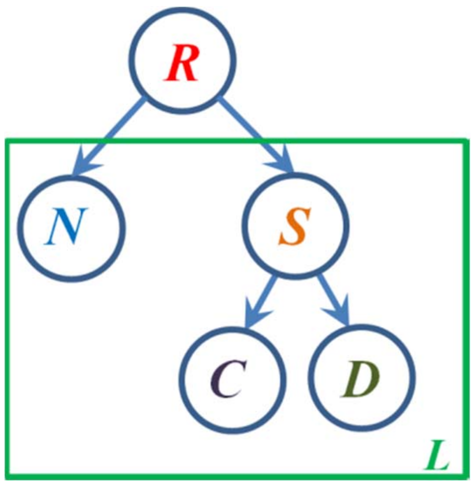
Our probabilistic model

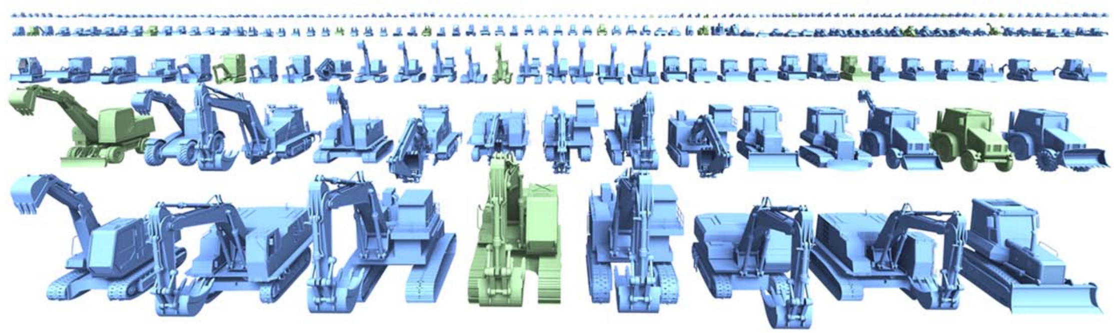
- Synthesizes **plausible and complete shapes automatically**
- Represents shape variability at **hierarchical levels of abstraction**
- Understands **latent causes of structural and geometric variability**
- Learned **without supervision** from a set of segmented shapes

Learning stage



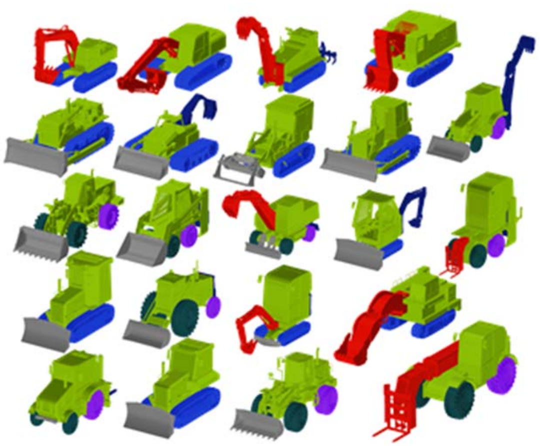
Synthesis stage





Learning shape variability

We model attributes related to **shape structure:**



Shape type

Component types

Number of components

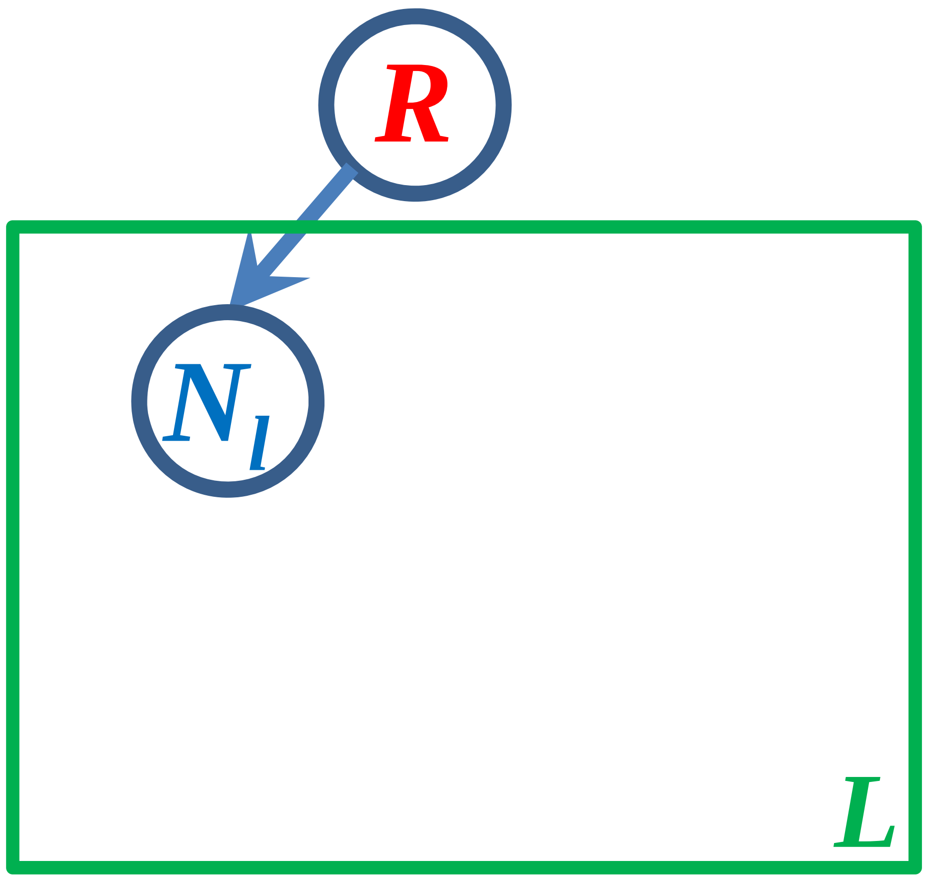
Component geometry

$$\Rightarrow P(R, S, N, G)$$

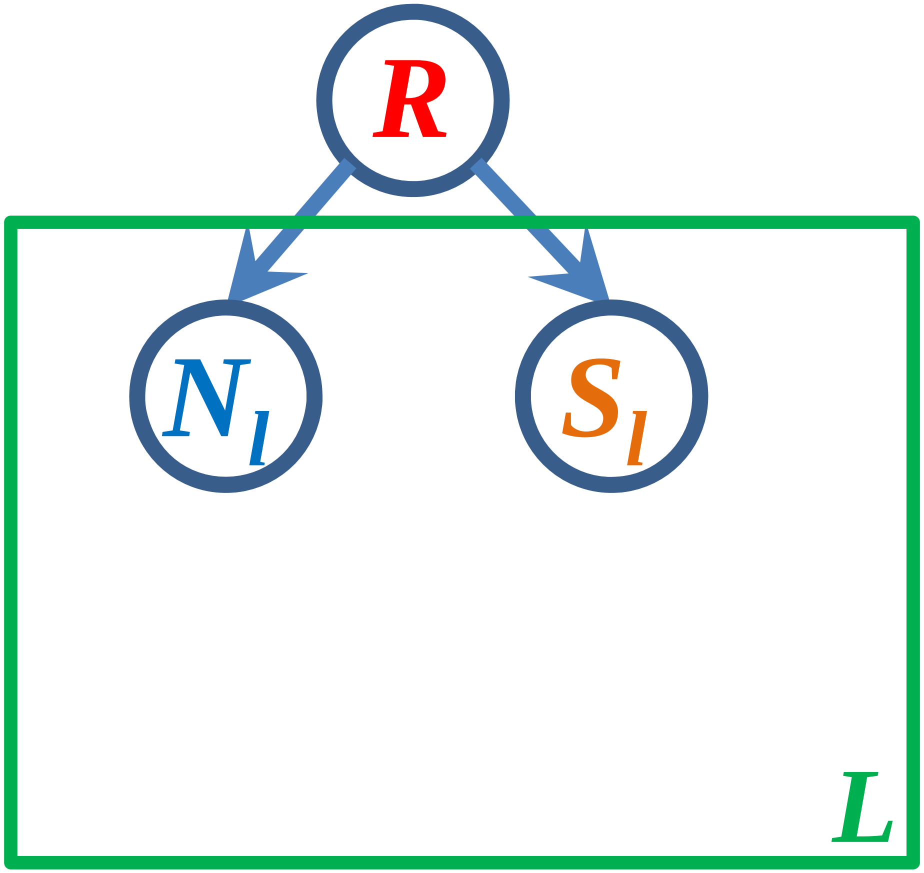
$P(R)$

R

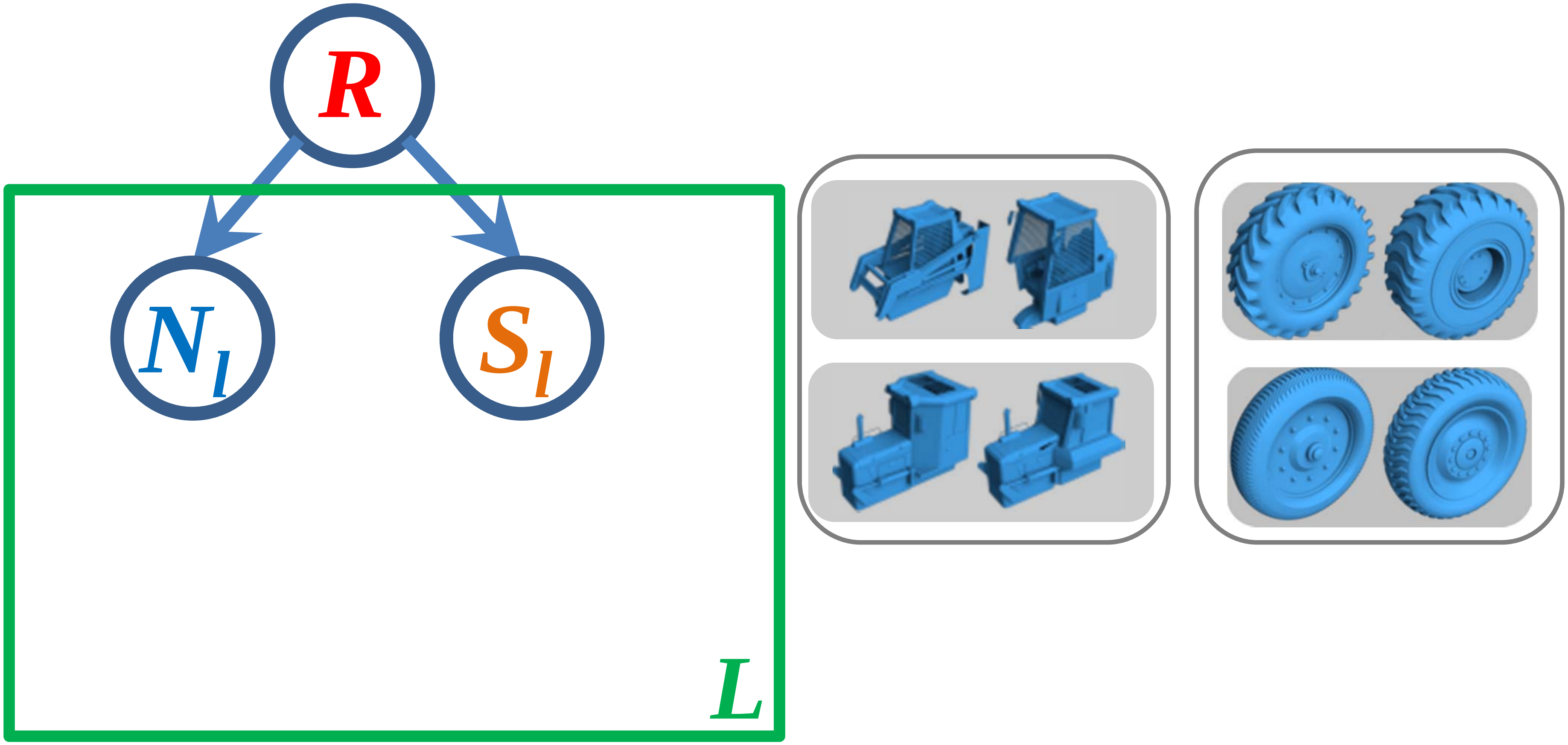
$P(R)$



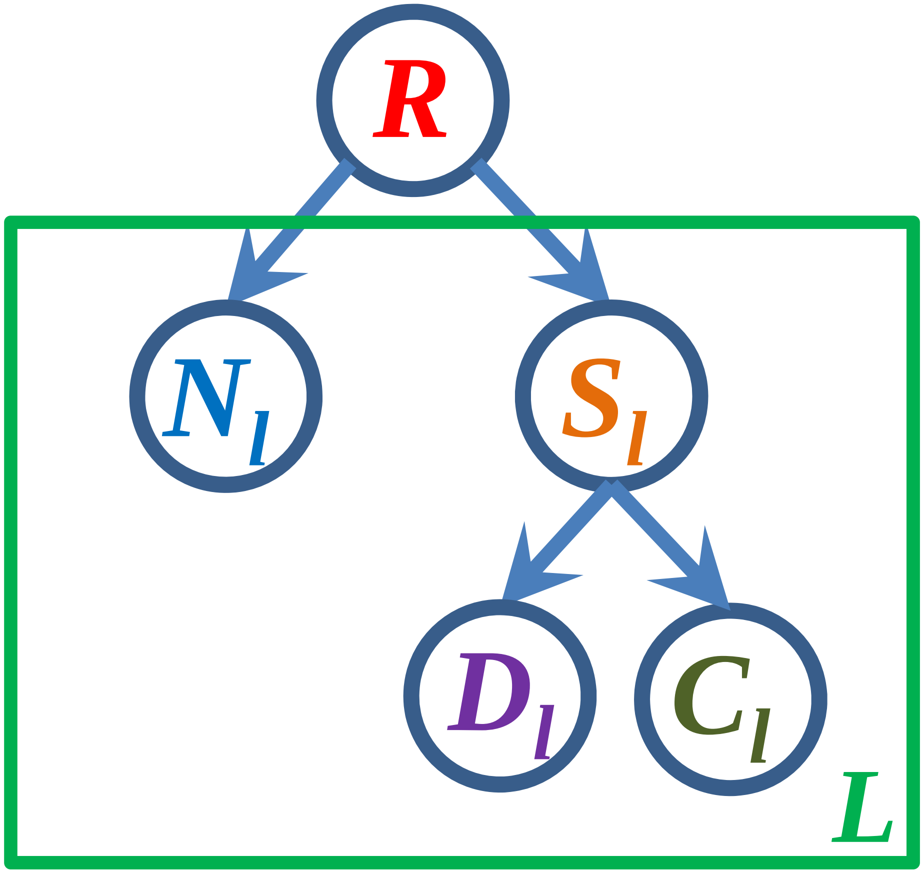
$$P(R)\prod_{l \in L}\left[P(N_l \mid R)\right]$$



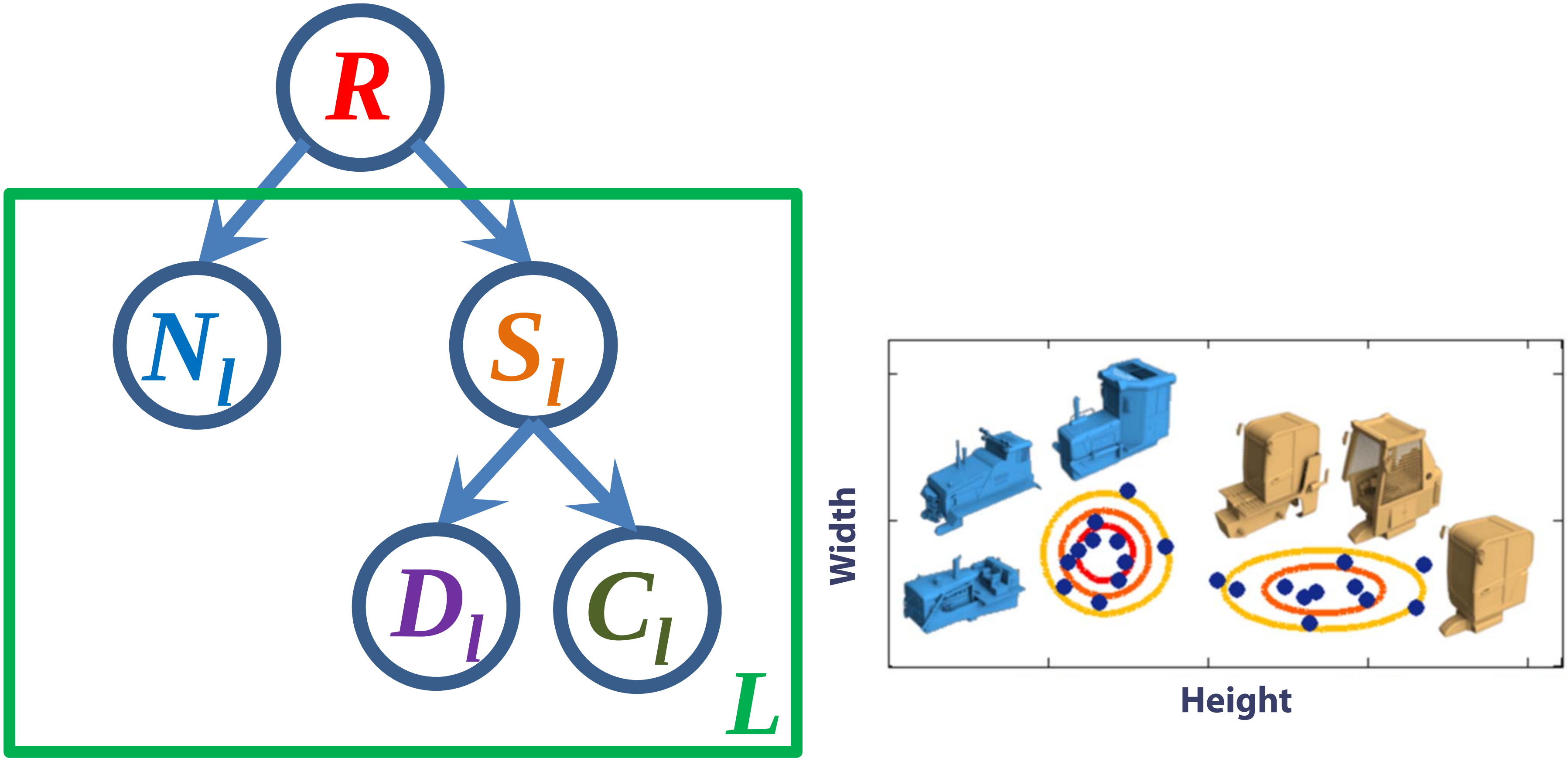
$$P(R)\prod_{l\in L}\left[P(N_l \mid R)\,P(S_l \mid R)\right]$$



$$P(R)\prod_{l\in L}\left[P(N_l \mid R)\,P(S_l \mid R)\right]$$



$$P(R) \prod_{l \in L} \left[P(N_l \mid R)\, P(S_l \mid R)\, P(D_l \mid S_l)\, P(C_l \mid S_l) \right]$$



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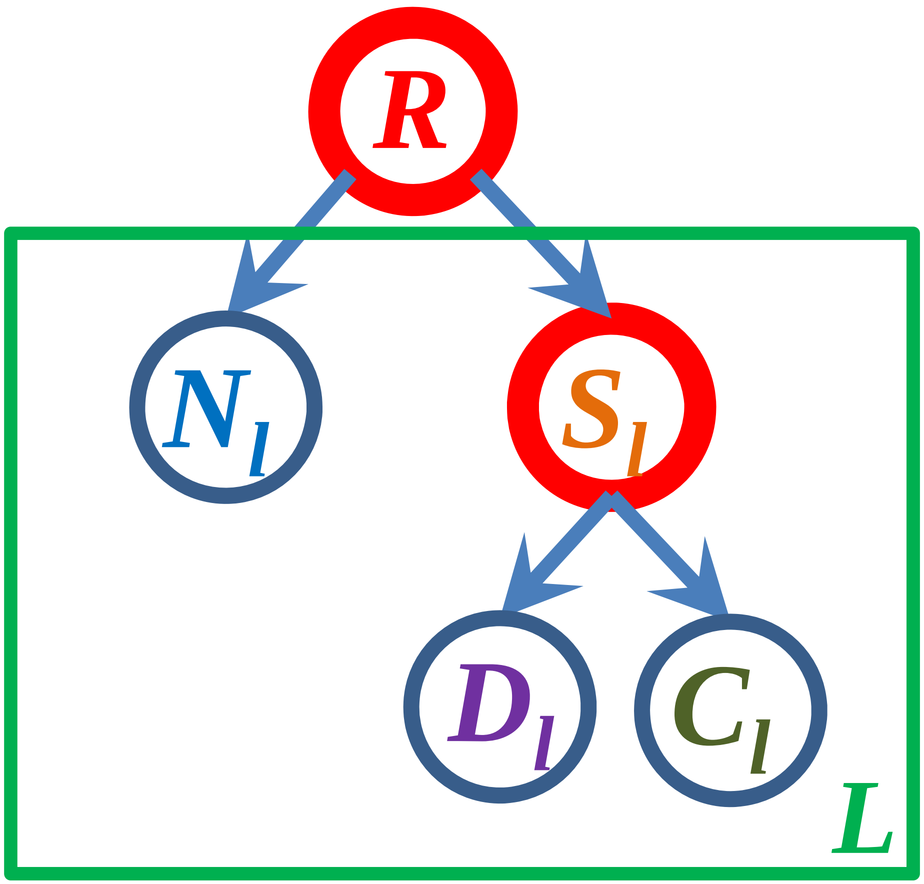
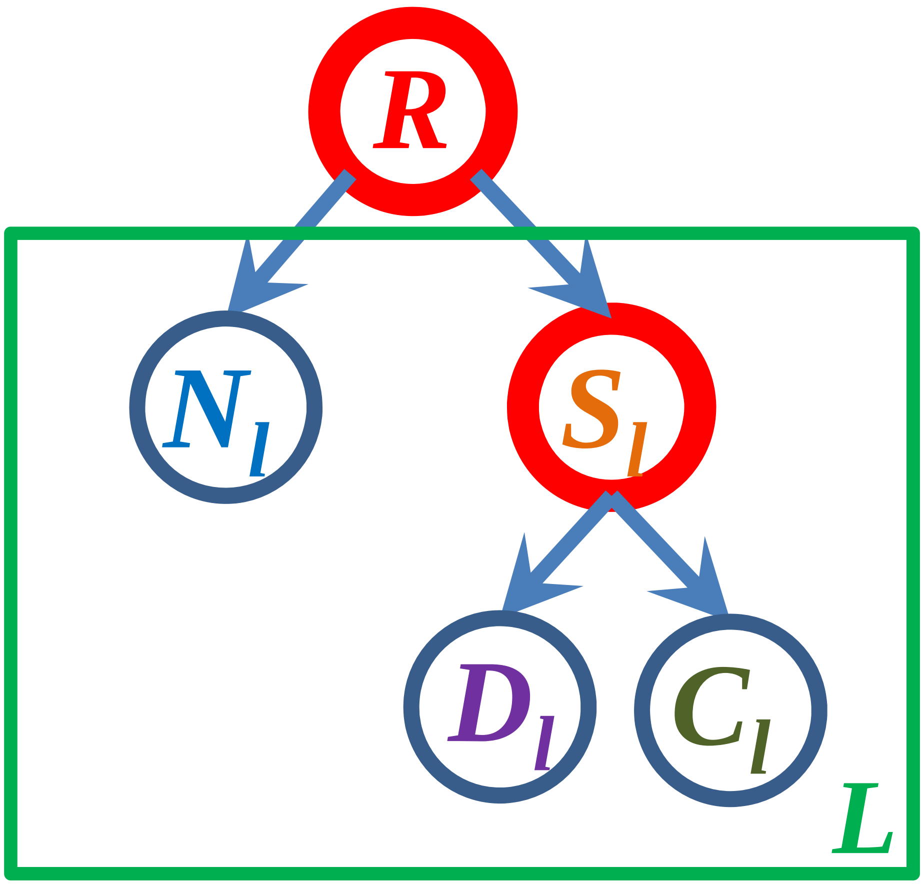
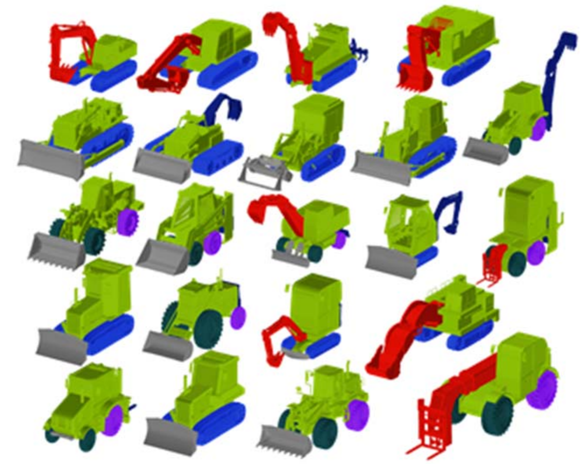


Latent object style

Latent component style

$$P(R)\prod_{l \in L}\left[P(N_l \mid R)\,P(S_l \mid R)\,P(D_l \mid S_l)\,P(C_l \mid S_l)\right]$$





Learn from training data:

latent styles

lateral edges

parameters of CPDs

Learning

Given observed data $\mathbf{O}$, find structure $\mathbf{G}$ that maximizes:

$$\boxed{P(G \mid \mathbf{O}) = \frac{P(\mathbf{O} \mid G)P(G)}{P(\mathbf{O})}}$$

Learning

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Assuming uniform prior over structures, maximize **marginal likelihood**:

$$P(\mathbf{O} \mid G) = \sum_{R,\mathbf{S}} \int_{\Theta} P(\mathbf{O}, R, \mathbf{S} \mid \Theta, G) P(\Theta \mid G)\, \mathrm{d}\Theta$$

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Parameter priors

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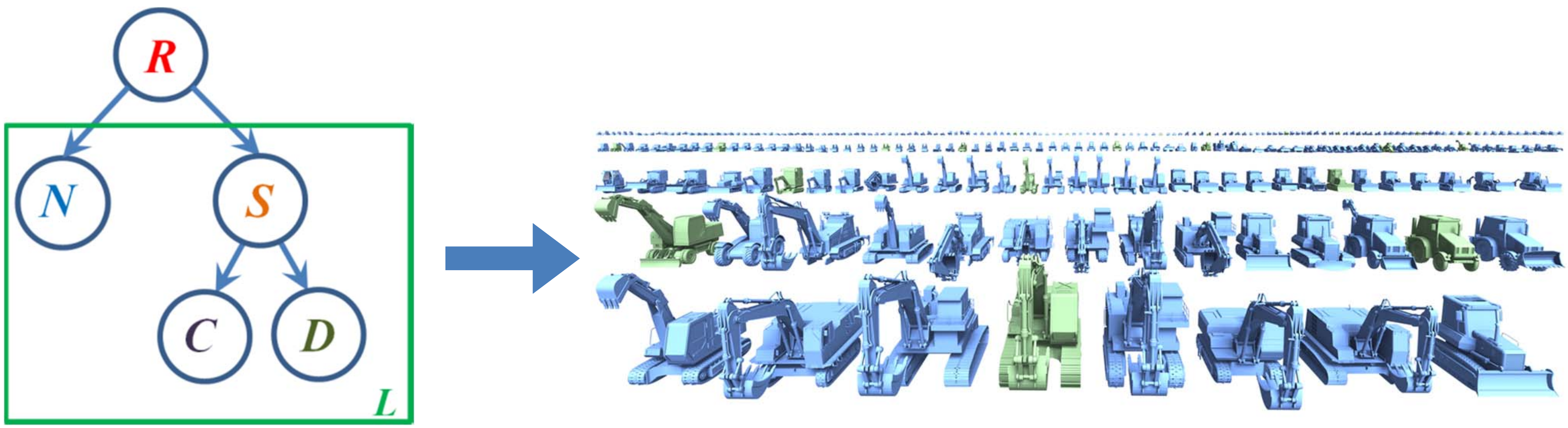
➡ ***Cheeseman-Stutz approximation***

Our probabilistic model: **synthesis stage**



Shape Synthesis

Enumerate high-probability instantiations of the model

$$
\begin{tikzcd}
 & & & \{\} \arrow[dll] \arrow[drr] & & & \\
 & \{R=1\} \arrow[dl] \arrow[dr] & & & & \{R=2\} \arrow[dl] \arrow[dr] & \\
\{R=1,S_1=1\} & & \{R=1,S_1=2\} & & \{R=2,S_1=2\} & & \{R=2,S_1=2\}
\end{tikzcd}
$$

...

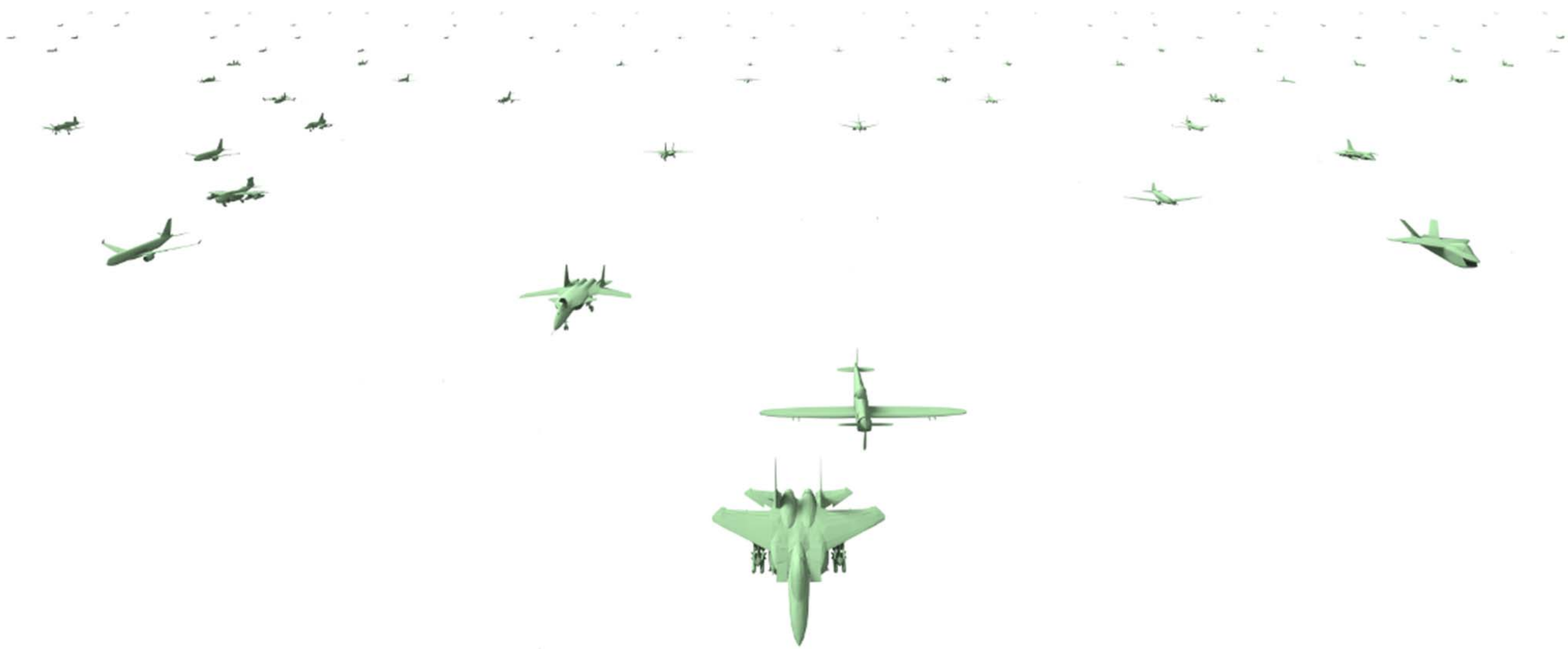
Component placement

Source shapes

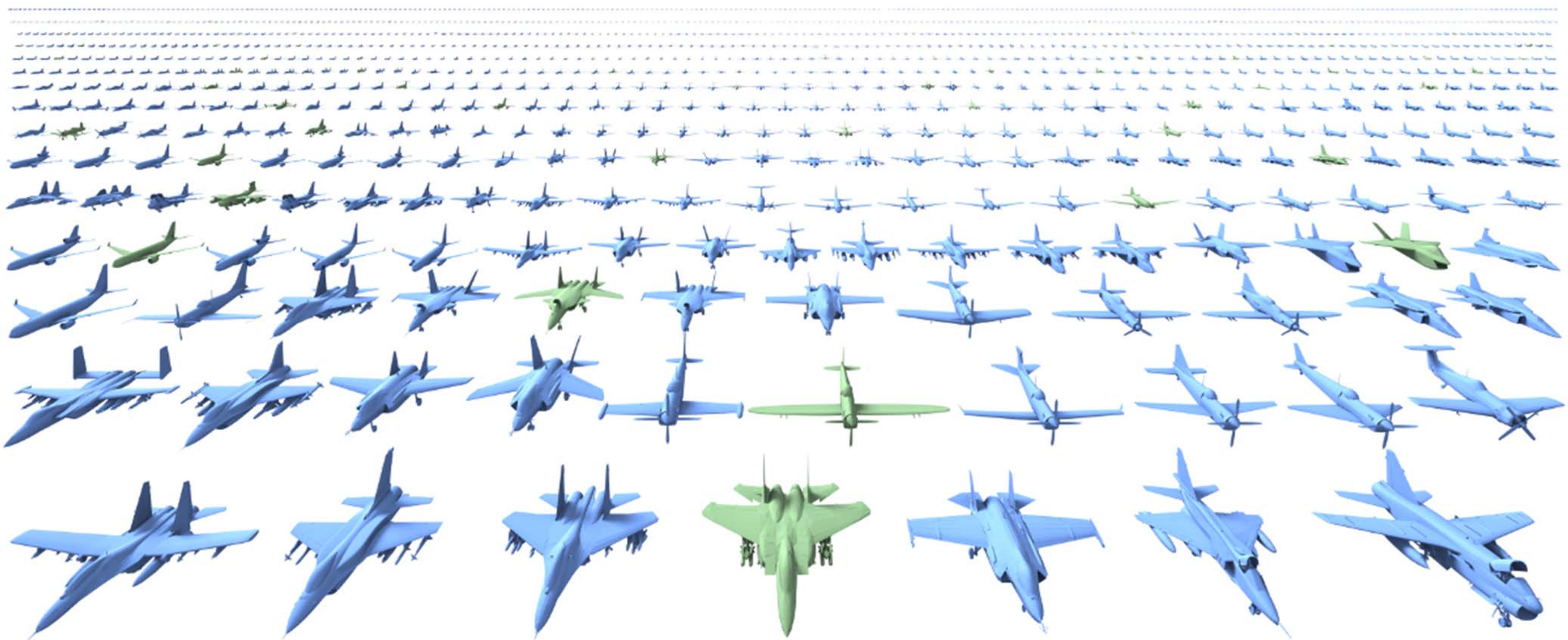
Unoptimized new shape

Optimized new shape

Database Amplification - Airplanes



Database Amplification - Airplanes



Database Amplification - Chairs

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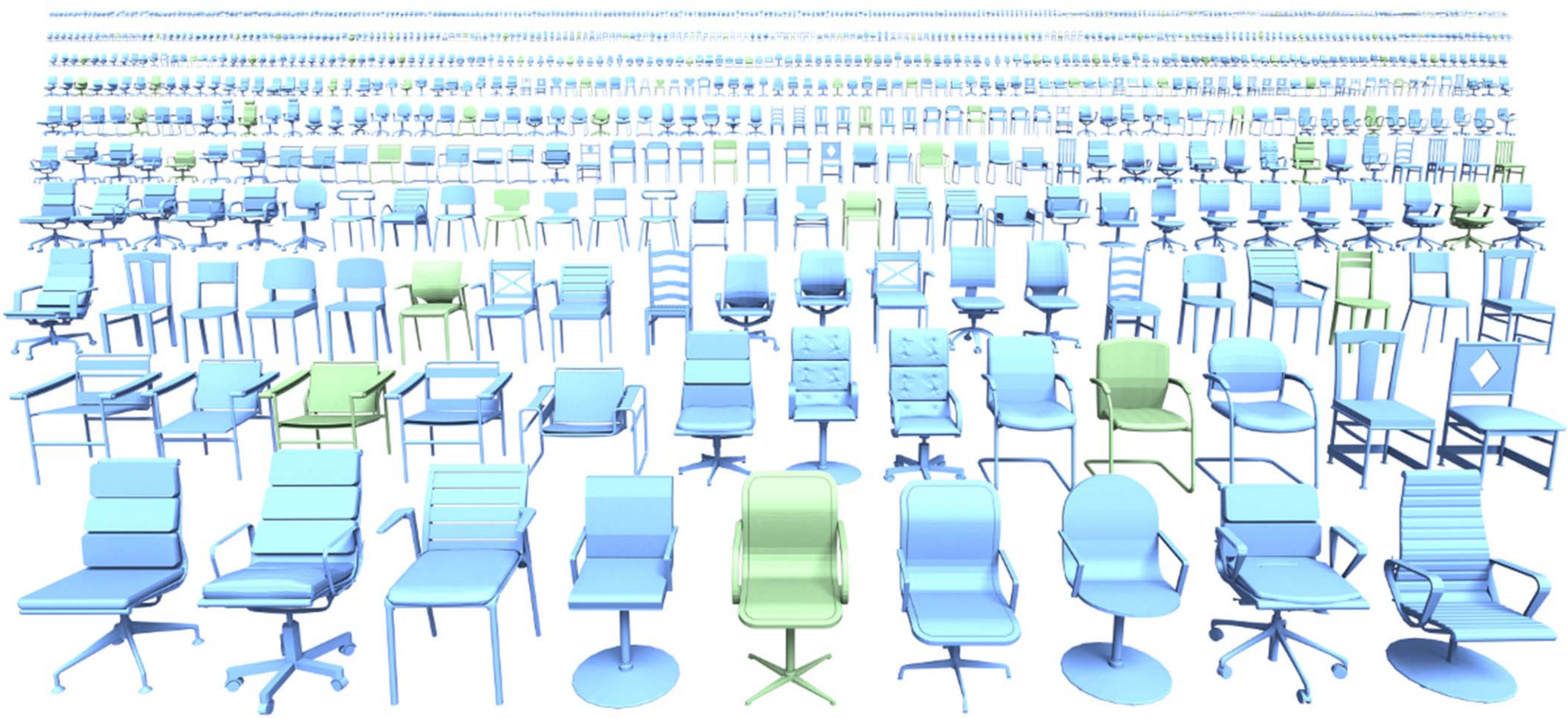
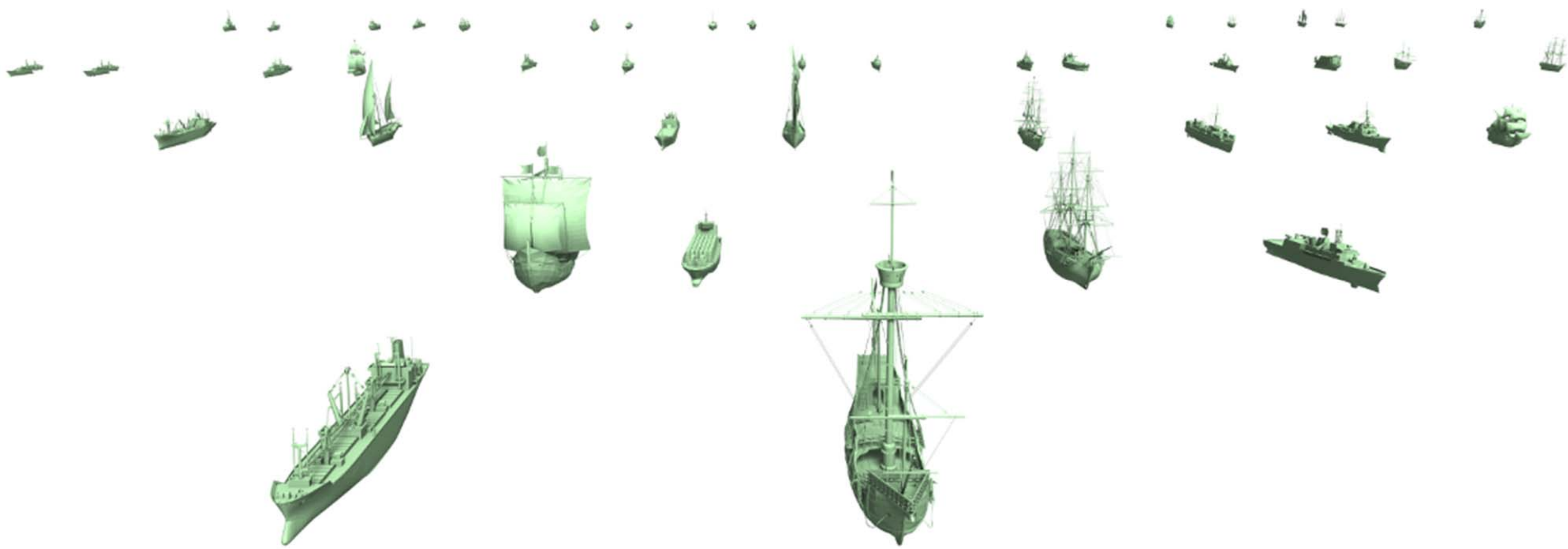
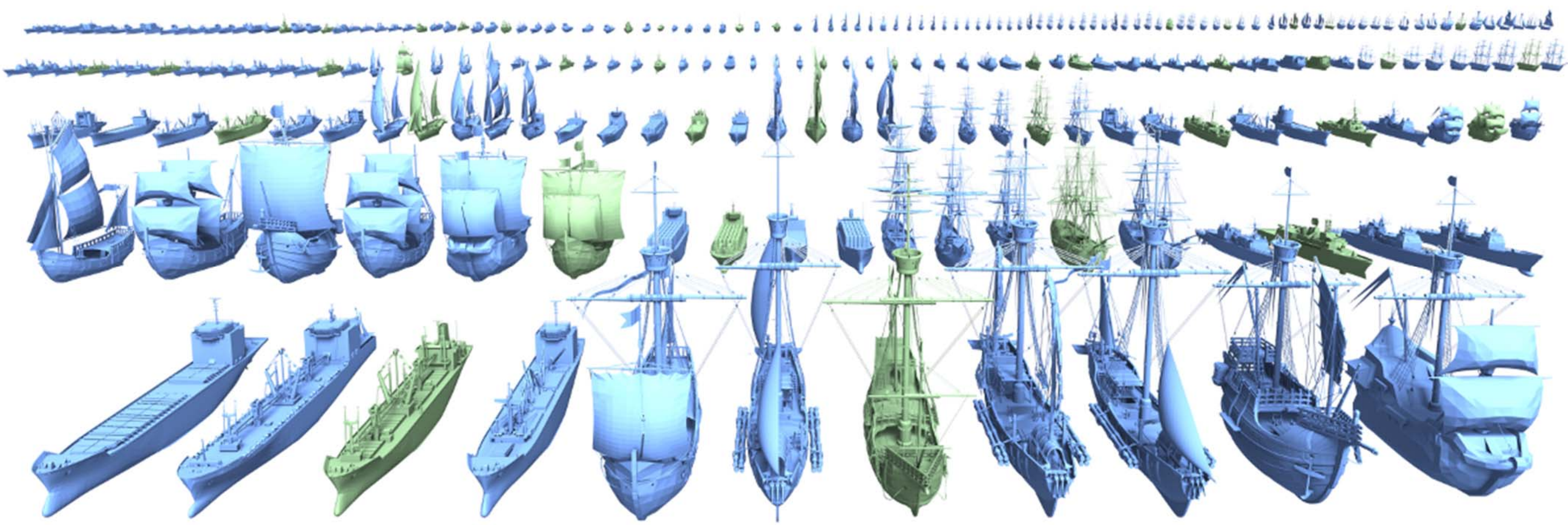


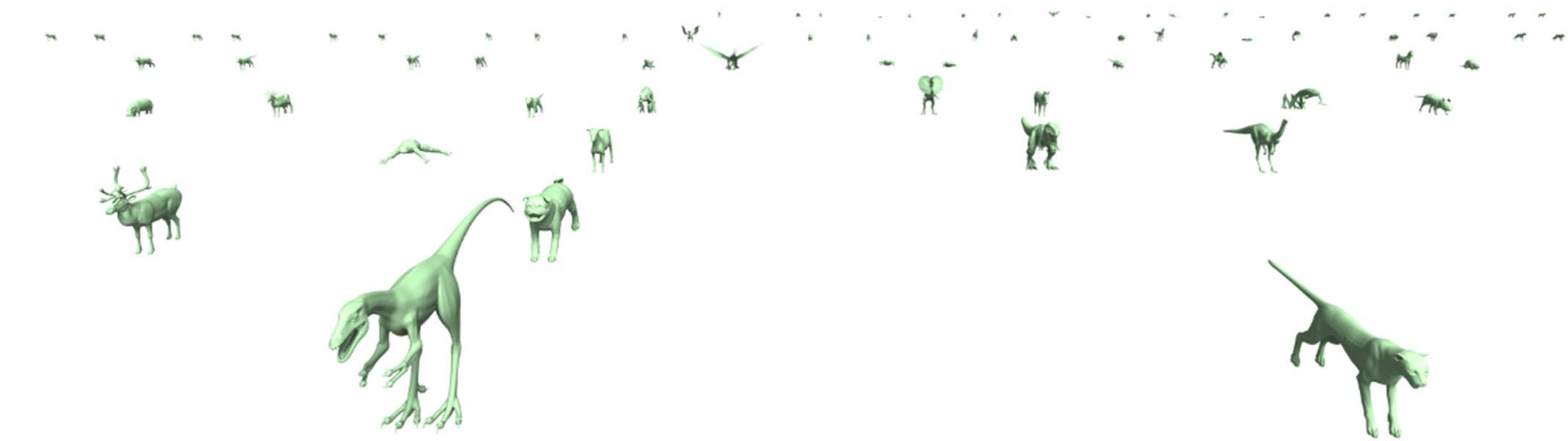
Database Amplification - Ships



Database Amplification - Ships

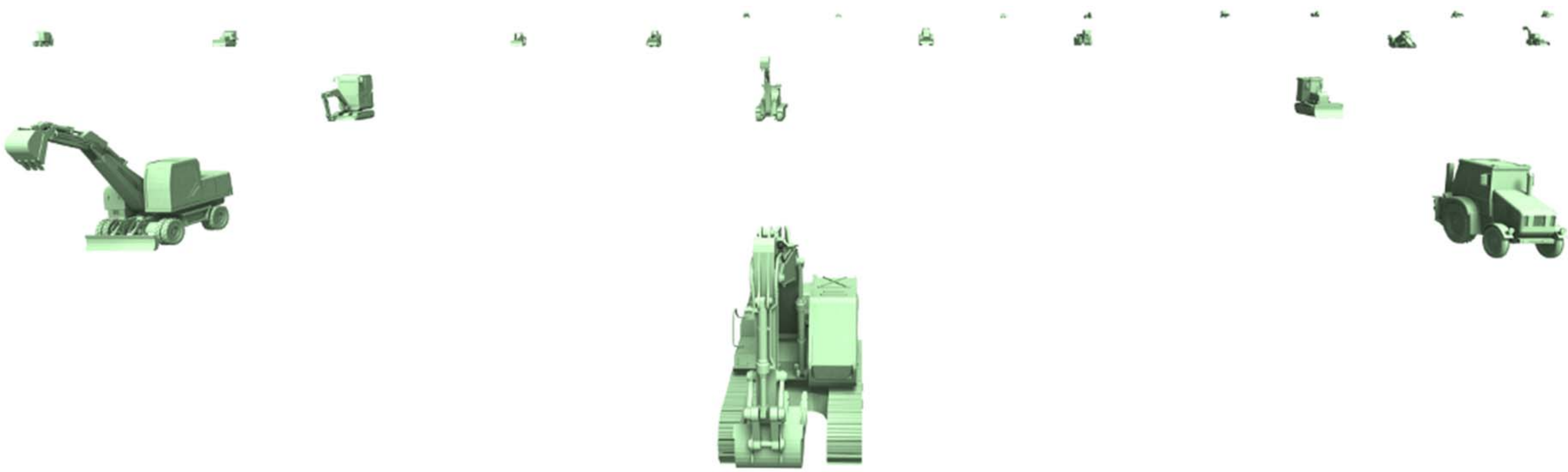


Database Amplification - Animals

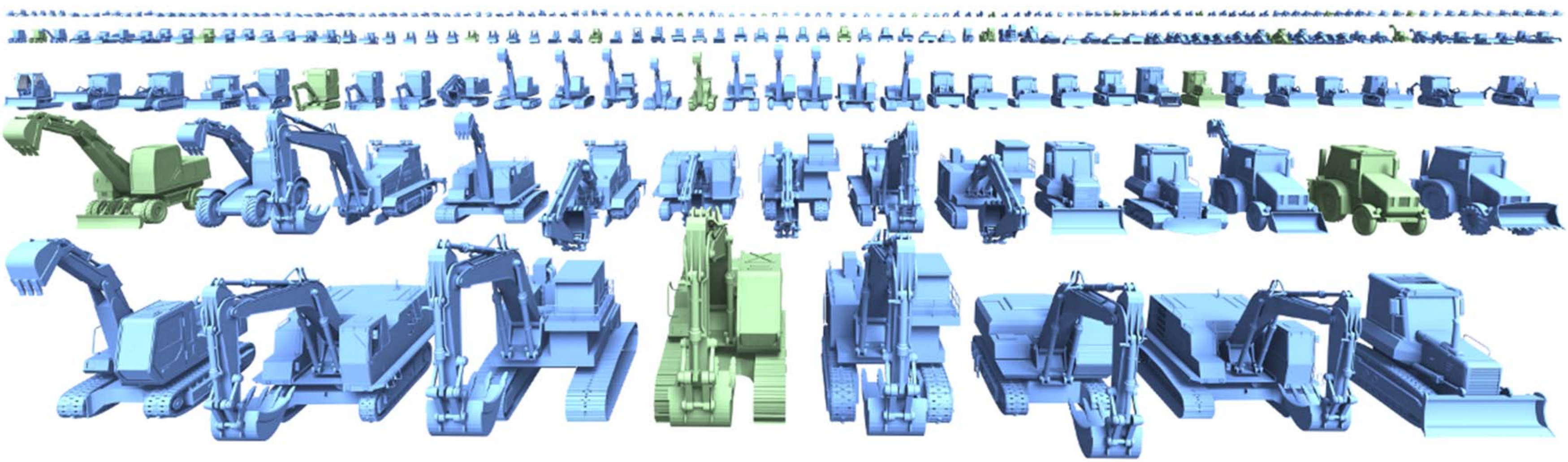


Database Amplification - Animals

Database Amplification – Construction vehicles

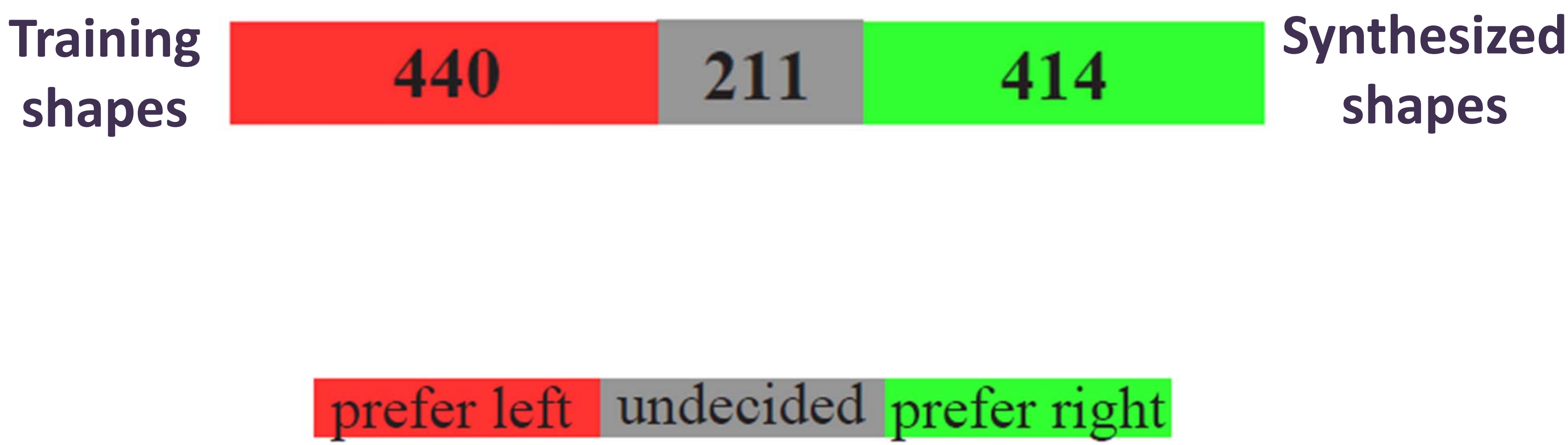


Database Amplification – Construction vehicles

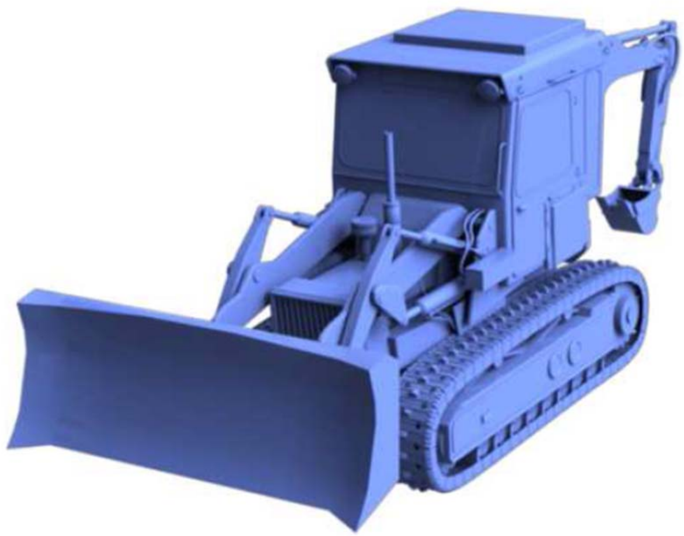


Interactive Shape Synthesis

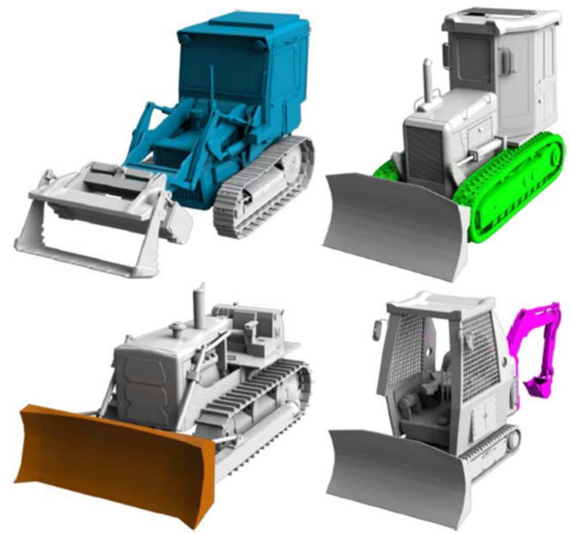
User Survey


Training shapes
440
211
414
Synthesized shapes
prefer left
undecided
prefer right

Results



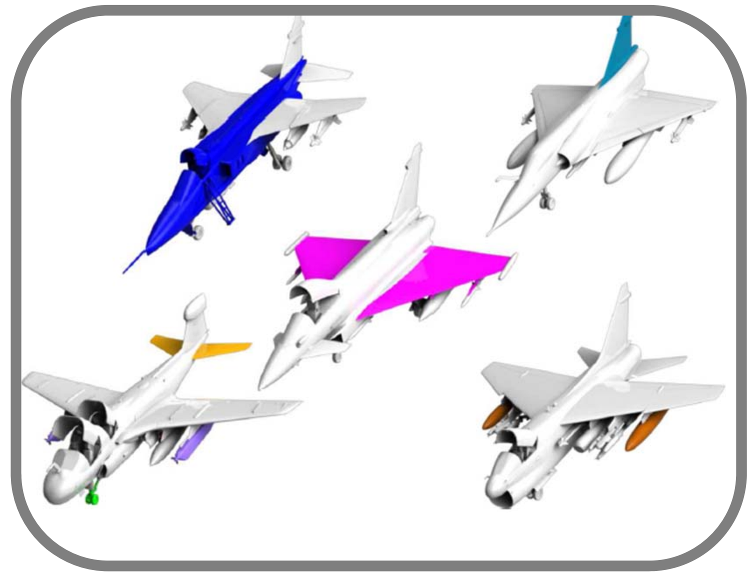
New shape



Source shapes (colored parts are selected for the new shape)

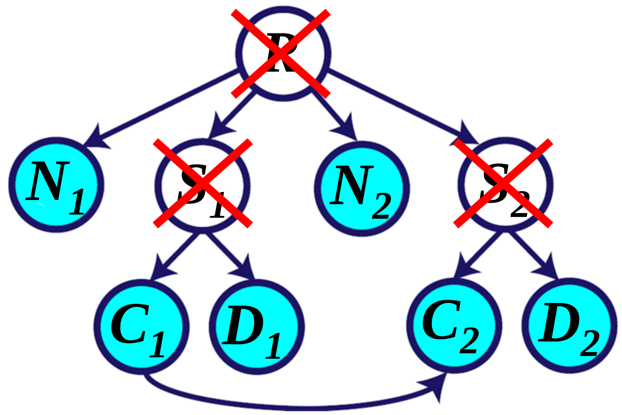
Results

New shape

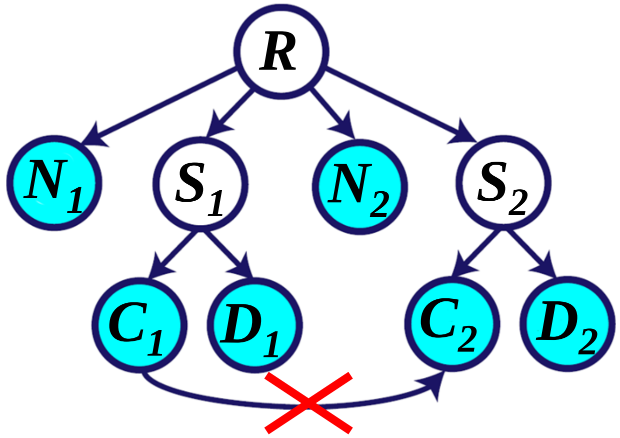


Source shapes
(colored parts are selected for the new shape)

Results of alternative models: no latent variables



Results of alternative models: no part correlations



Summary

- **Generative model** of component-based shape synthesis
- **Automatically synthesizes new shapes** from a domain demonstrated by a set of example shapes
- **Enables shape database amplification** or interactive synthesis with **high-level user constraints**

Future Work

- Our model can be used as a shape prior - applications to **reconstruction** and **interactive modeling**
- Synthesis of shapes with **new geometry** for parts
- Model **locations** and **spatial relationships** of parts

Thank you!

Acknowledgements: ***Aaron Hertzmann, Sergey Levine, Philipp Krähenbühl, Tom Funkhouser***

Our project web page:

http://graphics.stanford.edu/~kalo/papers/ShapeSynthesis/