



DeepSketch: Sketch-based 3D shape Retrieval

Cecilia Zhang, Weilun Sun

Department of Electrical Engineering and Computer Science
UC Berkeley, CA 94720

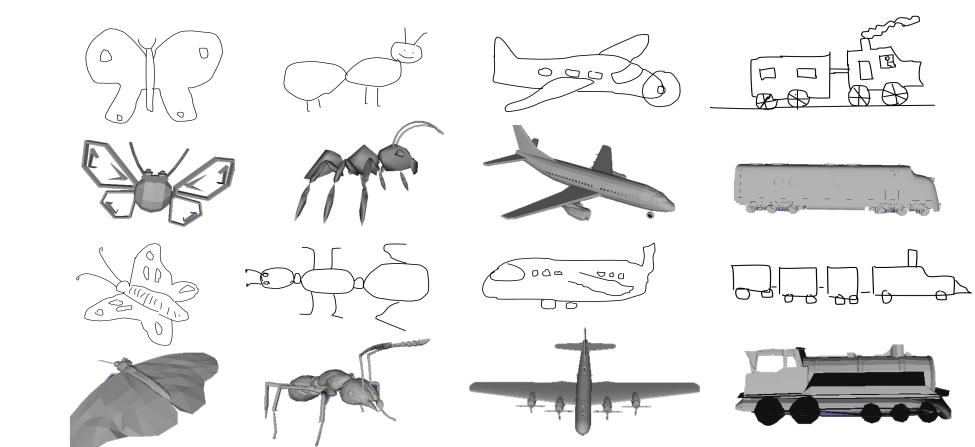
Introduction

In this project, we present a system for cross-domain similarity search that helps us with sketch-based 3D shape retrieval. We propose our DeepSketch neural network that is built on Siamese network to learn features that are basis for later similarity search using K-nearest Neighbor (KNN).

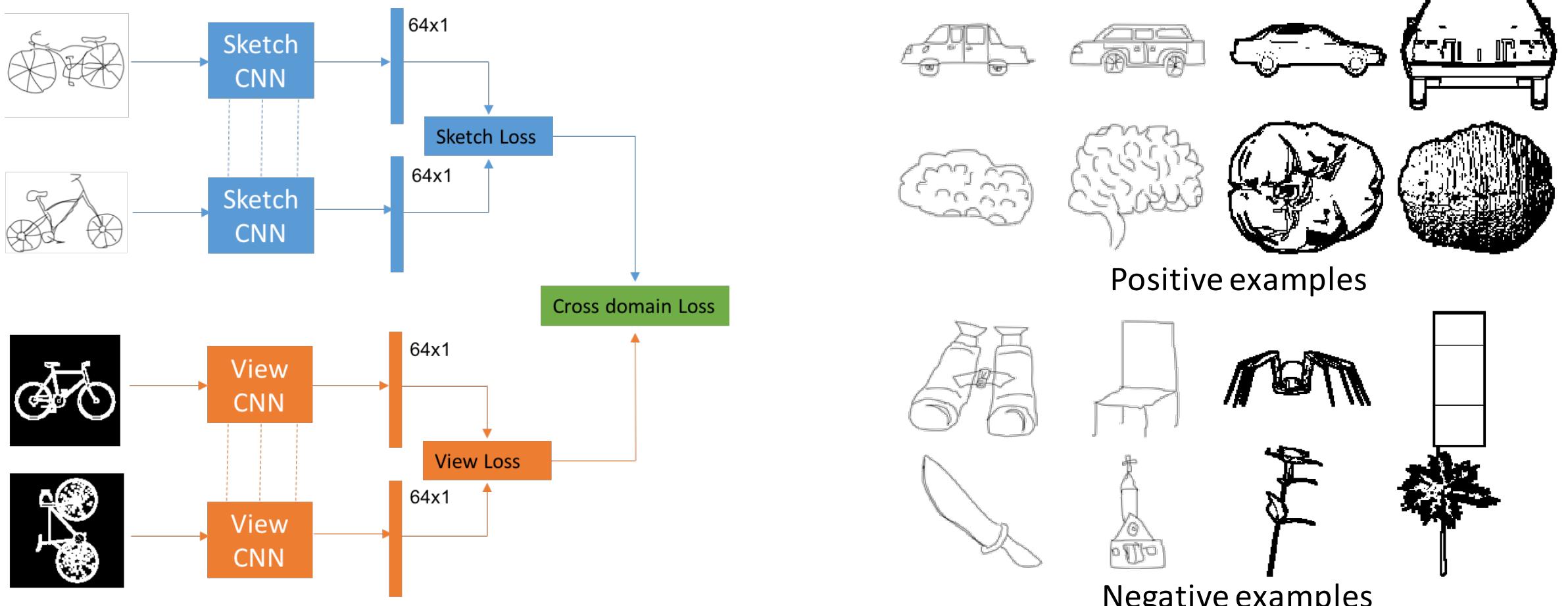
We further did analysis on how individual strokes of a sketch image affect retrieval results, and also inspected features learned from our DeepSketch network.

System Design

Dataset: we used **SHREC 13** to evaluate our method. The dataset contains **90** object classes; each class has **80** sketch images with **50** to be training and **30** to be testing. There are **1258** 3D models for the 90 classes. Some examples of the SHREC 13 dataset are shown on the right.



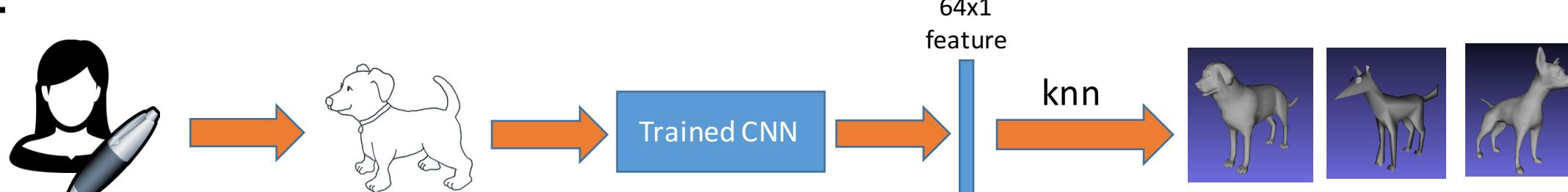
Network architecture: our DeepSketch network is composed of two separate Siamese network, one for view images and the other for sketch images. We used contrastive loss as our loss function for all three loss: sketch loss, view loss and cross domain loss.



Dataset preparation: assume S_1 and S_2 are the two sketch images and V_1 and V_2 are the two view images, $y(S_1, S_2) = 1$ if S_1 and S_2 are from the same class, and $y(V_1, V_2) = 1$ if V_1 and V_2 are from the same class; $y(S_1, S_2, V_1, V_2) = 1$ if all inputs are from the same class. Some positive and negative training data are shown above right.

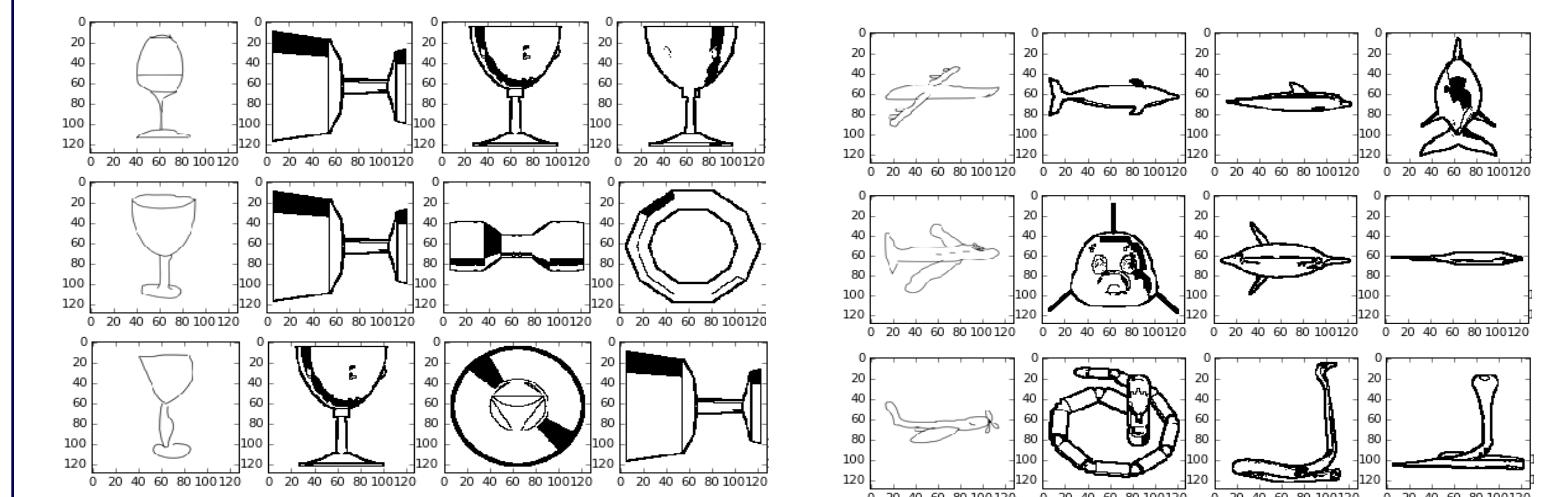
Specifically, we trained on **54000** sets, in which the ratio between positive and negative examples is **1:5**. The testing dataset contains **2700** sets. Our evaluation is based on top 1 and top 3 retrieval accuracy.

UI Design:



Results

Retrieval accuracy: we did sketch-sketch retrieval and sketch-view retrieval after using the learned features.



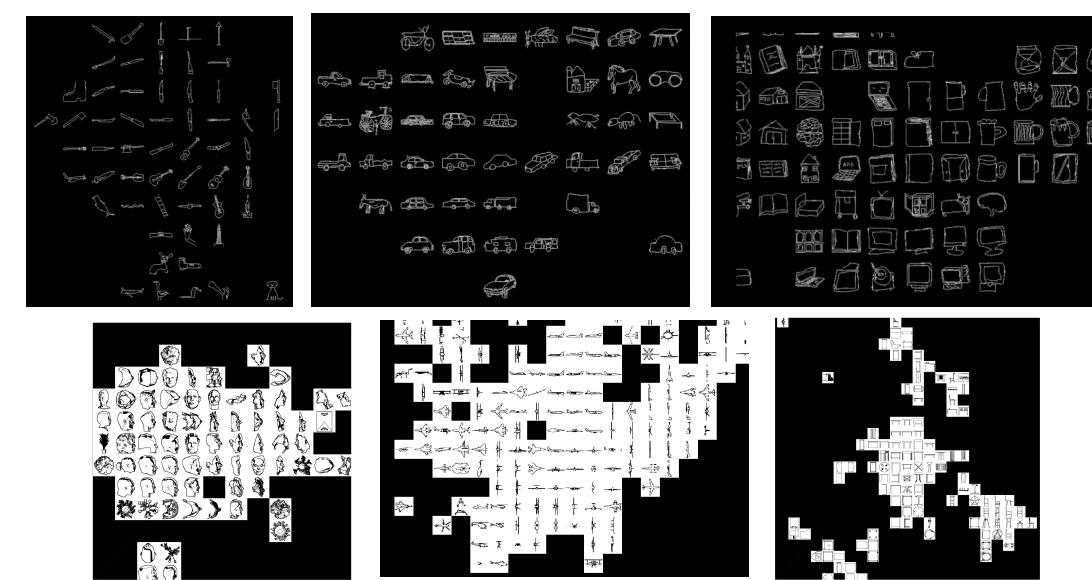
Positive retrieval results

Negative retrieval results

Retrieval accuracy

	Top 1	Top 3
Sketch-sketch	38.26%	52.26%
Sketch-view	32.63%	45.68%

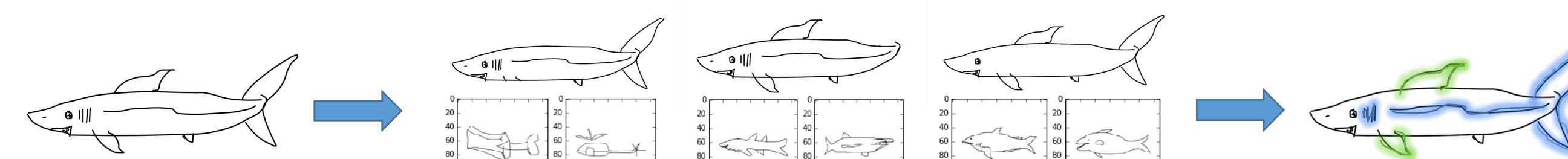
T-SNE Visualization for sketch and view feature space



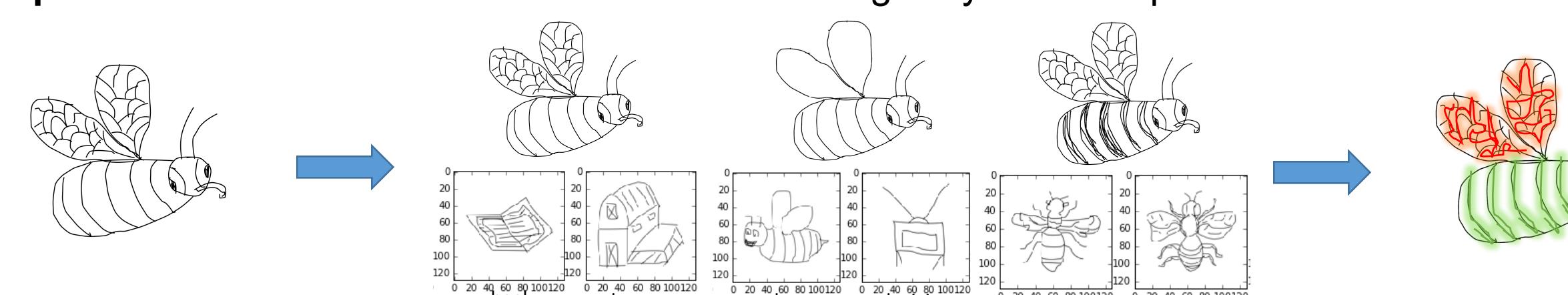
Analysis

Importance of each stroke: we inspect on the importance of each individual stroke made by the user. To do this, we remove certain stroke(s) of the sketch image and did inference again to get retrieval results. Green strokes are helpful strokes; Red strokes are non-helpful strokes; Blue strokes are neutral strokes.

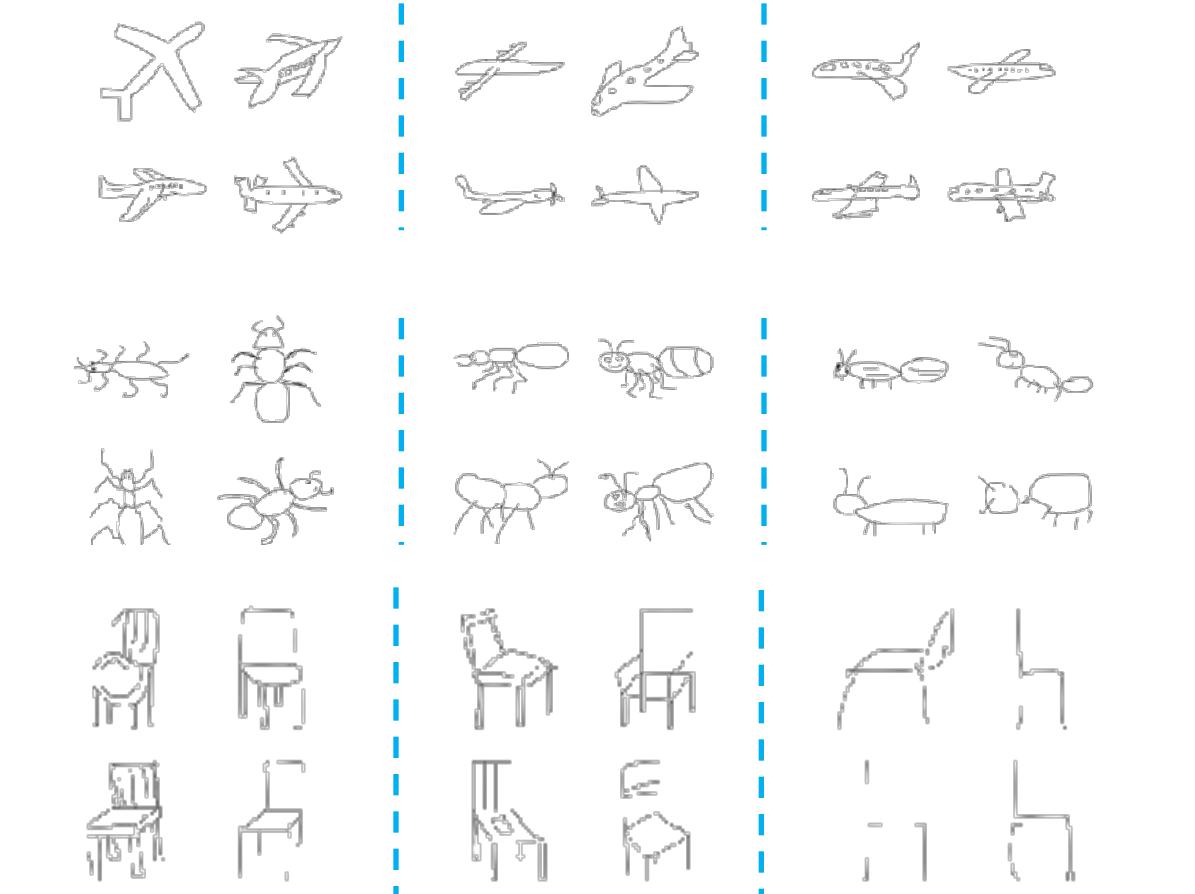
Examples 1: remove strokes on a sketch that originally has good performance



Examples 2: remove/add strokes on a sketch that originally has bad performance



K-means clustering in sketch feature space



Discussion

- The dataset used here is bias due to 1) the limited number of categories 2) non-balanced 3D models per category, there are classes with >100 3D models while classes with 5 models
- We also trained sketch images individually and used the network to do retrieval on view images, and the result shows the filters learned for sketch are transferable to view
- We only enforce class-level similarity but not instance-level similarity; the retrieval cannot necessarily return the closest 3D view in the retrieved class
- The learned features correspond to individual strokes as seen from our stroke analysis. Different strokes weigh differently
- The features learned contain view information even if we did not explicitly set constraint on it

References

- [1] Wang, Fang, Le Kang, and Yi Li. "Sketch-based 3d shape retrieval using convolutional neural networks." *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*. 2015.
- [2] Schneider, Rosália G., and Tinne Tuytelaars. "Sketch classification and classification-driven analysis using fisher vectors." *ACM Transactions on Graphics (TOG)* 33.6 (2014): 174.
- [3] Seddati, Omar, Stéphane Dupont, and Said Mahmoudi. "Deepsketch: deep convolutional neural networks for sketch recognition and similarity search." *Content-Based Multimedia Indexing (CBMI), 2015 13th International Workshop on*. IEEE, 2015.