

Sketch Me That Shoe

Heechan Shin

CS688

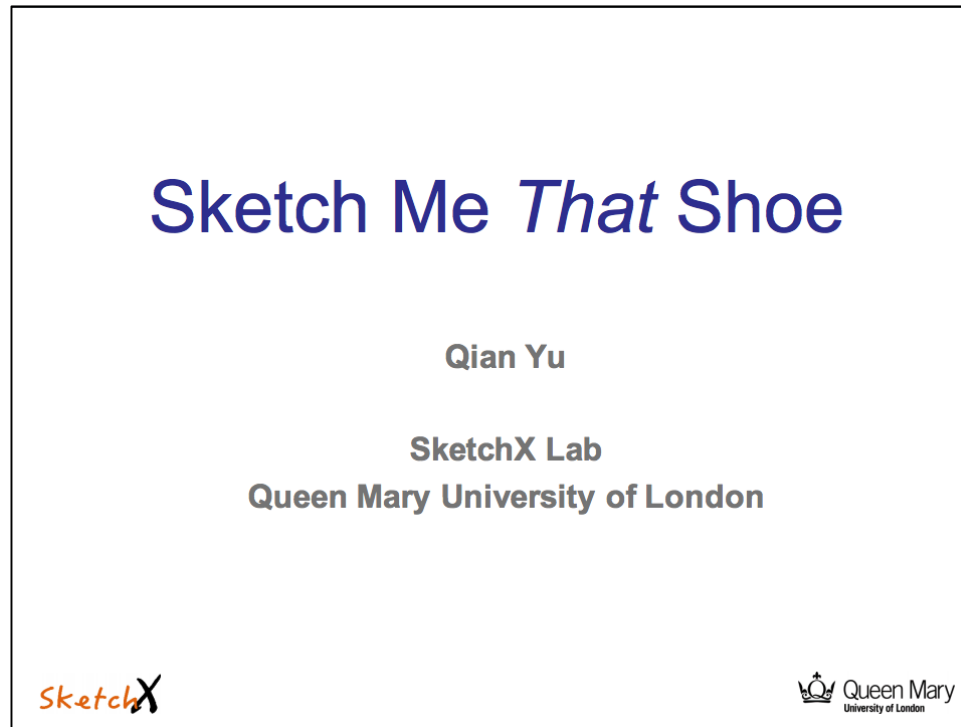
Student paper presentation

Contents

- **Problems**
- **Solution**
 - Dataset
 - Methodology
- **Experiment**

Announcement

- Most of contents of this presentation comes from materials of author's CVPR presentation.



Problems

- Sketch Based Image Retrieval (SBIR)



Problems

- SBIR
 - Pros
 - No need for complicated description
 - No need for photos
 - Cons
 - Sketch is highly abstract
 - Heterogeneous domains (sketch \leftrightarrow image)

Problems

- Previous works
 - Eitz, Mathias, et al. “*An evaluation of descriptors for large-scale image retrieval from sketched feature lines.*” Computers & Graphics, 2010
 - Eitz, Mathias, et al. “*Sketch-based image retrieval: Benchmark and bag-of-features descriptors.*” TVCG, 2011
 - Hu, Rui, et al. “Gradient field descriptor for sketch based retrieval and localization.” ICIP, 2010

 Category-level SBIR

Problems



Category-level SBIR

vs.



Instance-level SBIR

This work wants to find **fine-grained instance-level SBIR**

Problems

- Sketch Based Image Retrieval (SBIR)

- Sketch

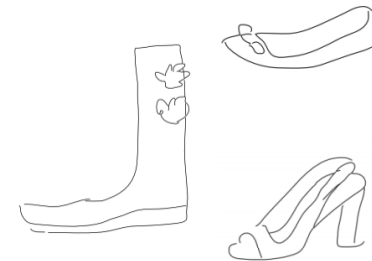
- Edge maps (automatically generated)



- Professional drawings (skilled artist)



- Free-hand sketches (amateur)



Problems

- Reasons of challenging
 - Sketch is highly abstract
 - Heterogeneous domains (sketch \leftrightarrow image)
- Want to capture the **fine-grained** similarities with free-hand sketches
- No large-scale dataset exists

} Cons of SBIR

Solutions

- Contributions
 - Constructing fine-grained SBIR dataset
 - Pre-training with sketch-specific data augmentation

Solutions

- Constructing fine-grained SBIR dataset

1. Data collection

- 1) Collecting photo images

- 419 shoe images from UT-Zap50K, 297 chairs from IKEA, Amazon and Taobao

- 2) Collecting sketches

- Recruiting 22 volunteers



Solutions

- Constructing fine-grained SBIR dataset
 2. Data annotation
 - 1) Attribute annotation
 - 2) Generating candidate photos for each sketch
 - 3) Triplet annotation



Solutions

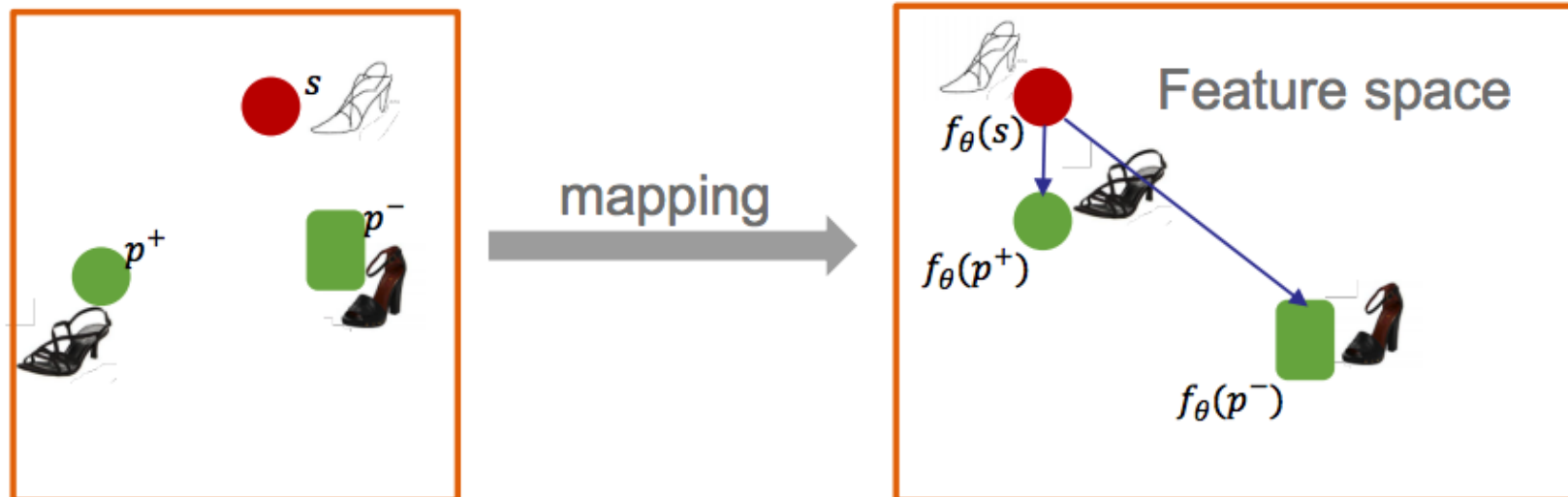
- Learn a feature space using triplet loss

- Always, $D(f_\theta(s), f_\theta(p^+)) < D(f_\theta(s), f_\theta(p^-))$

- Loss function :

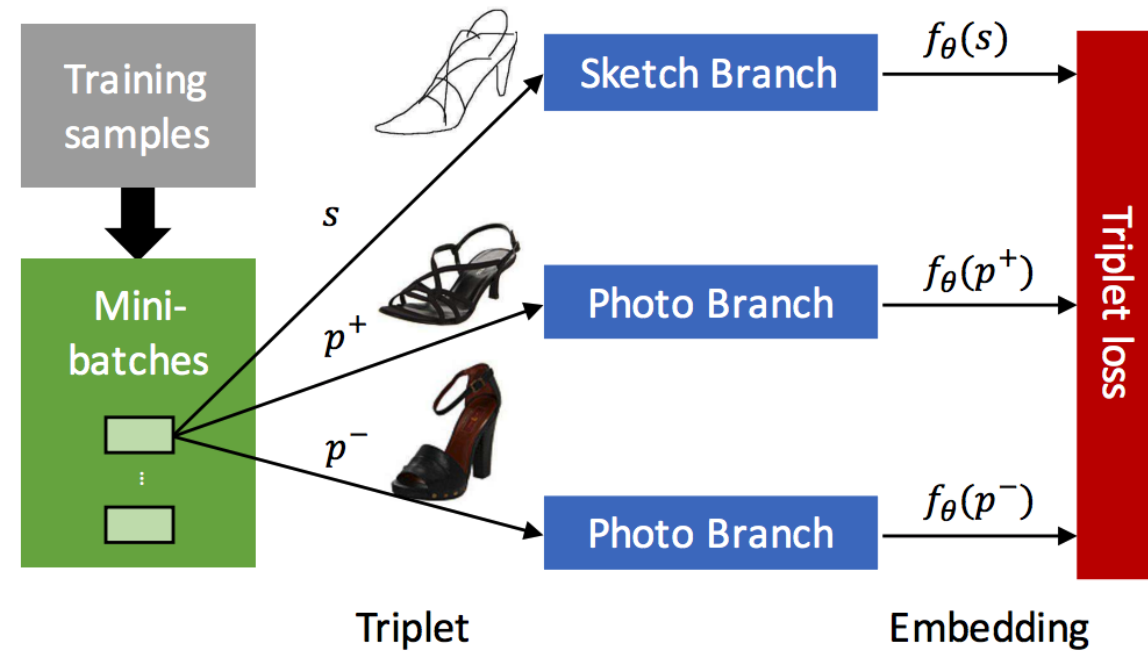
$$L_\theta(s, p^+, p^-) = \max\left(0, \Delta + D(f_\theta(s), f_\theta(p^+)) - D(f_\theta(s), f_\theta(p^-))\right)$$

Where, $D(\cdot)$ is euclidean distance, $f_\theta(\cdot)$ is feature embedding function



Solutions

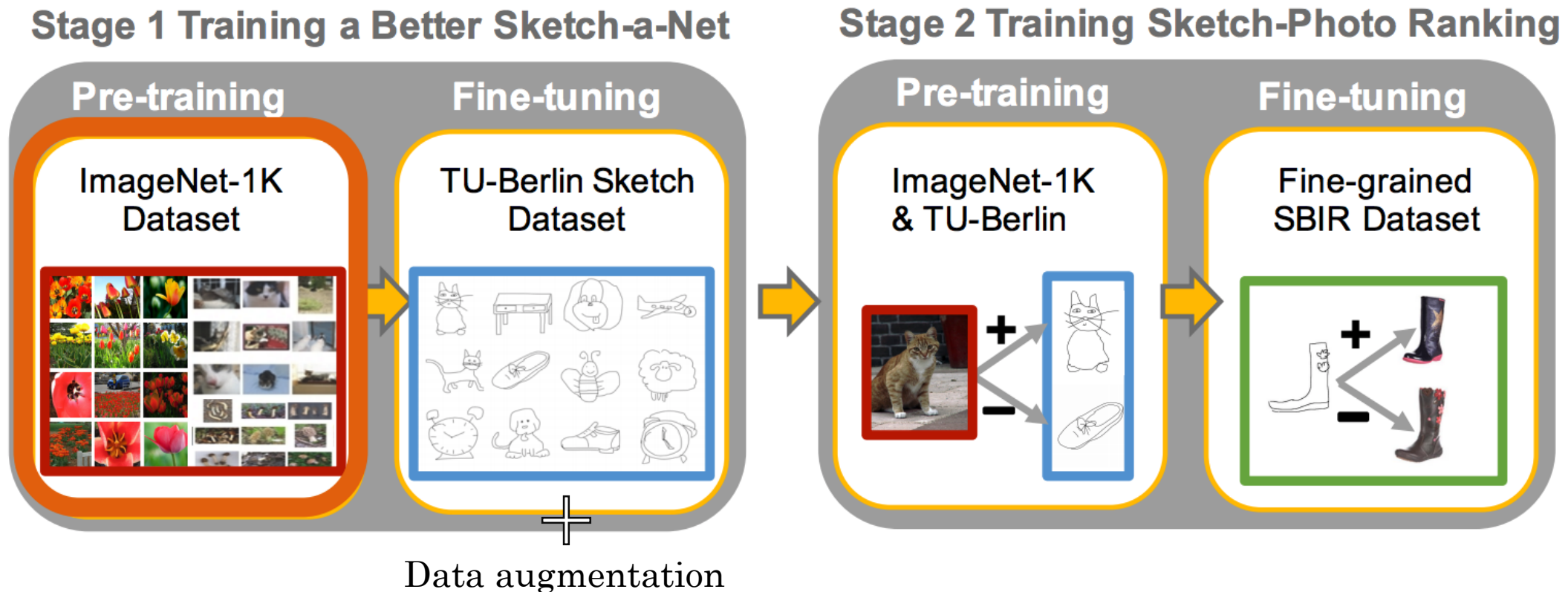
- Using three identical Sketch-a-Net* CNNs with Siamese network approach



* Q. Yu, et. al., "Sketch-a-net that beats humans" BMVC, 2015

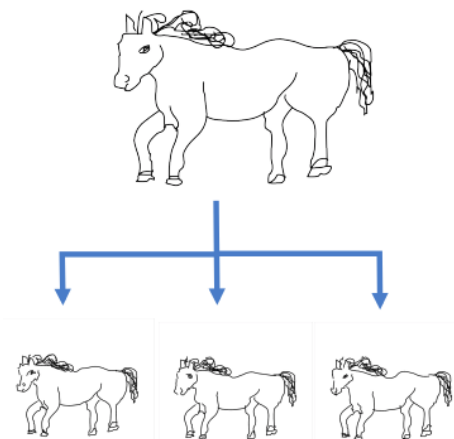
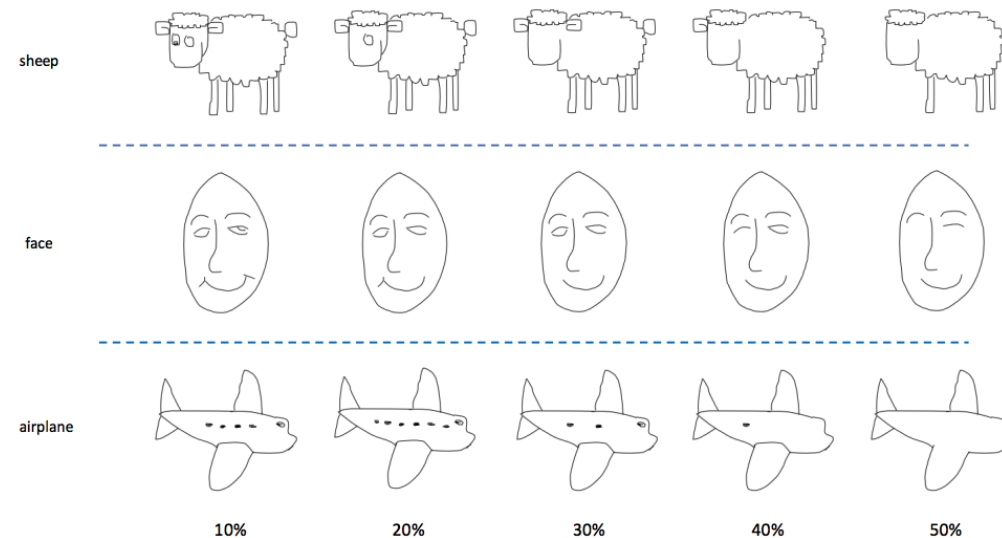
Solutions

- Re-train each Sketch-a-Net with



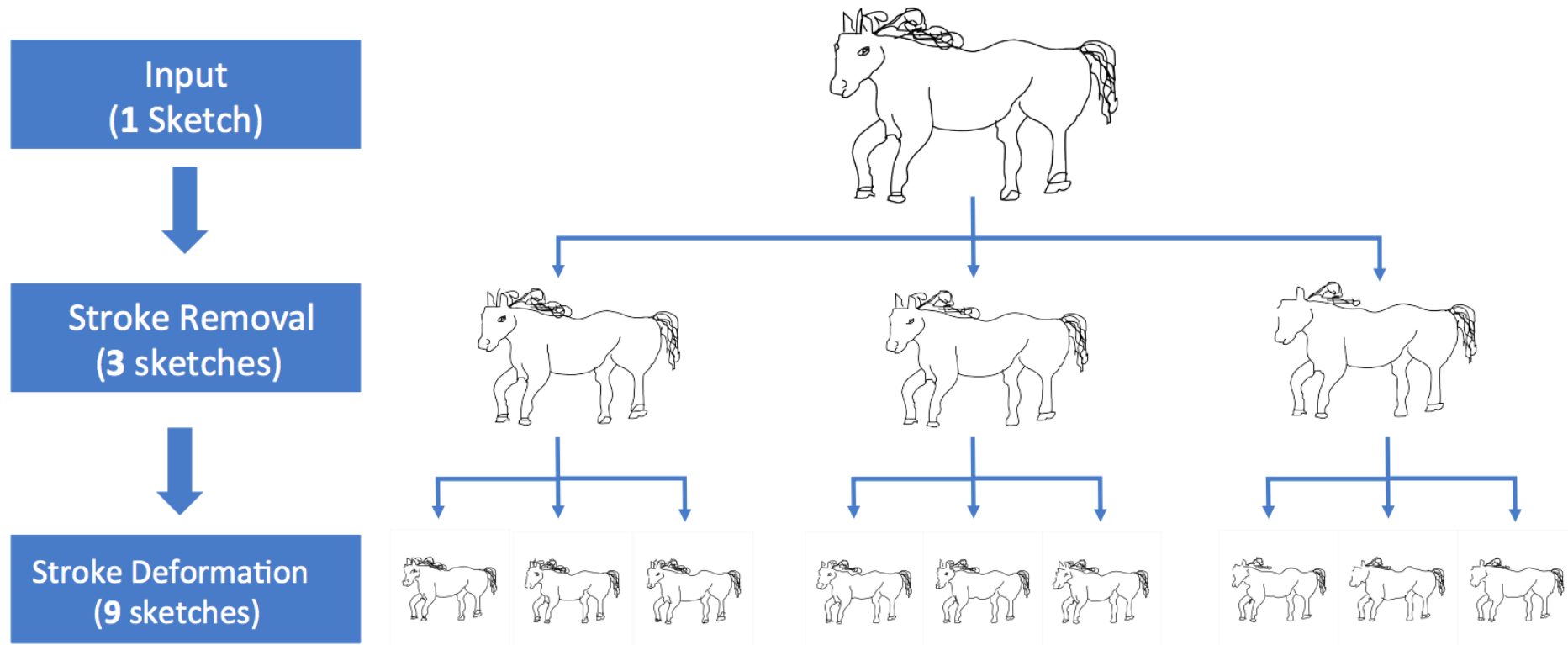
Solutions

- Data augmentation
 - Stroke removal
 - Broad outline is important
 - Longer line is important
 - Sketch is drawn from outside
 - Stroke deformation
 - Using Moving Least Square algorithm



Solutions

- Data augmentation



Experiment

- Settings
 - Data
 - 419 shoes (304 for training + 115 for testing)
 - 297 chairs (200 for training + 97 for testing)
 - Implementation setting
 - Caffe
 - 32 CPU with 2 Nvidia Tesla K80
 - Learning rate : 0.001
 - Batch size : 128
 - During training, randomly crop 225×225 sub-images and flip them with 0.5 probability

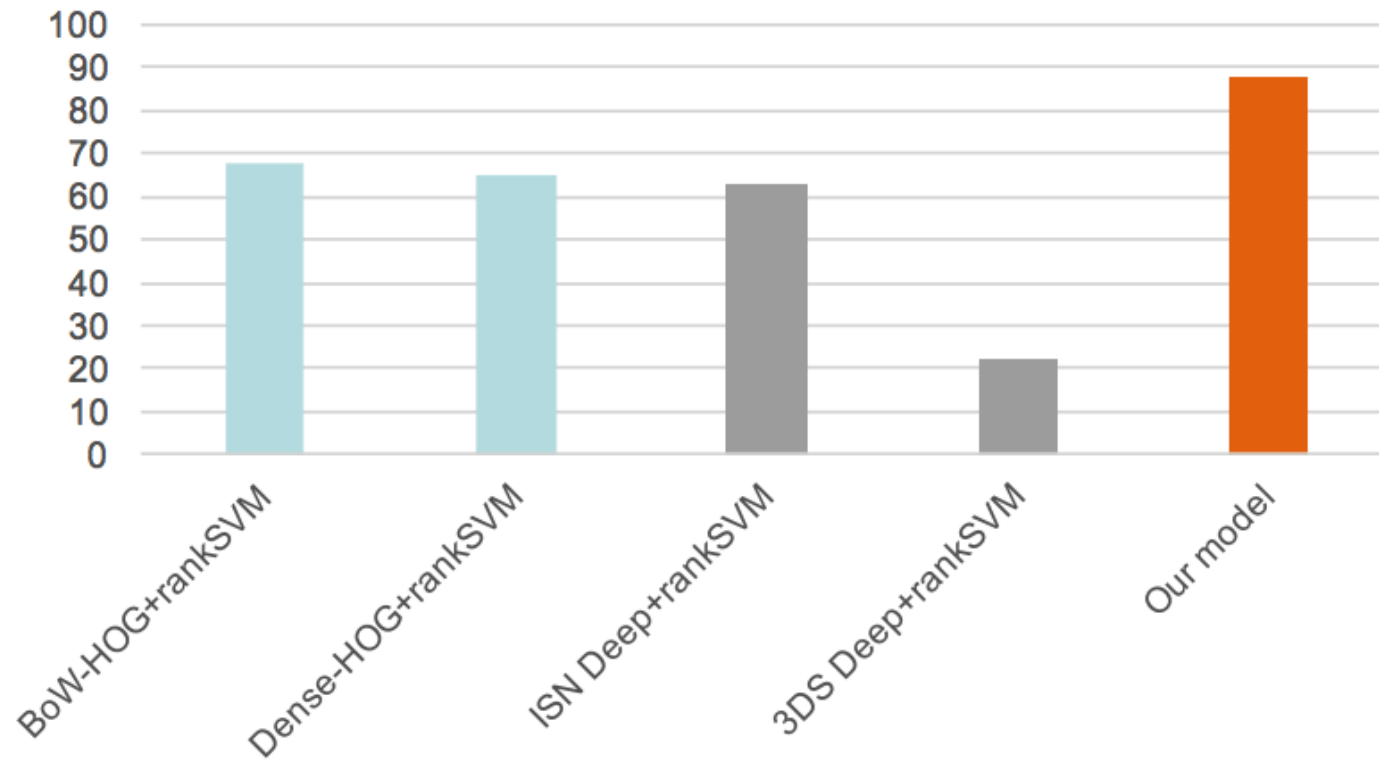
Experiment

Shoe Dataset	acc. @ 1	acc. @ 10	%corr.
BoW-HOG + rankSVM	17.39%	67.83%	62.82%
Dense-HOG + rankSVM	24.35%	65.22%	67.21%
ISN Deep + rankSVM	20.00%	62.61%	62.55%
3DS Deep + rankSVM	5.22%	21.74%	55.59%
Our model	39.13%	87.83%	69.49%
Chair Dataset	acc. @ 1	acc. @ 10	%corr.
BoW-HOG + rankSVM	28.87%	67.01%	61.56%
Dense-HOG + rankSVM	52.57%	93.81%	68.96%
ISN Deep + rankSVM	47.42%	82.47%	66.62%
3DS Deep + rankSVM	6.19%	26.80%	51.94%
Our model	69.07%	97.94%	72.30%

Triplet-ranking prediction

Experiment

Accuracy@10



Experiment



30ms per one retrieval

<https://sketchx.eecs.qmul.ac.uk>

Thank you

- Quiz

1. Which is the target of this work?

- ① Category – level SBIR
- ② Instance – level SBIR
- ③ Siamese – level SBIR

2. In the data augmentation section, what did they do?

- ① Region removal & region deformation
- ② Stroke removal & stroke deformation
- ③ Context removal & context deformation