Data Synthesis For Object Recognition

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Overview

- Motivation.
- Introduction and novel contributions.
- Data synthesis in data space.
- Features to learn from synthetic data
- Eliminating synthetic gap.
- Data synthesis in feature space.
- Conclusion

- Motivations and Importance of the problem.
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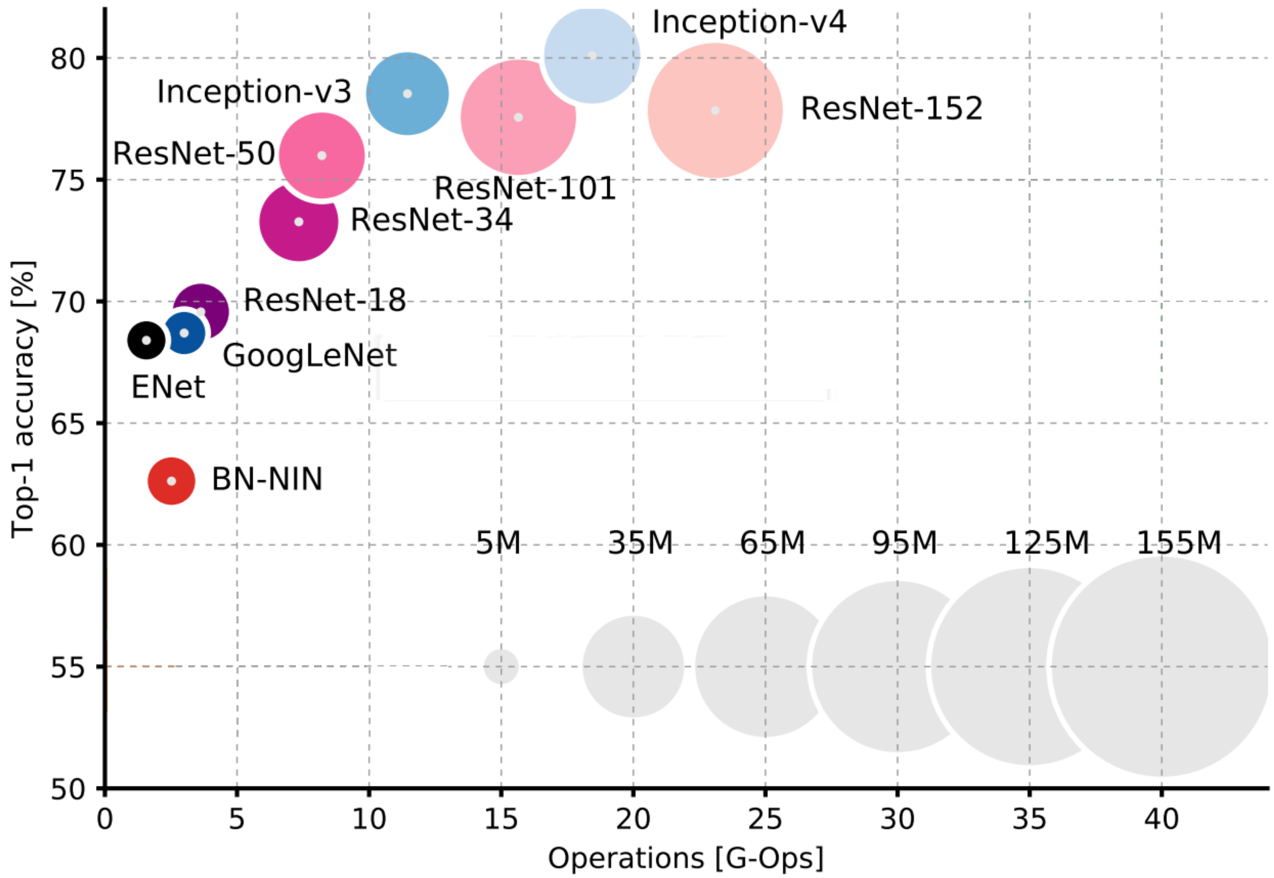
Motivation

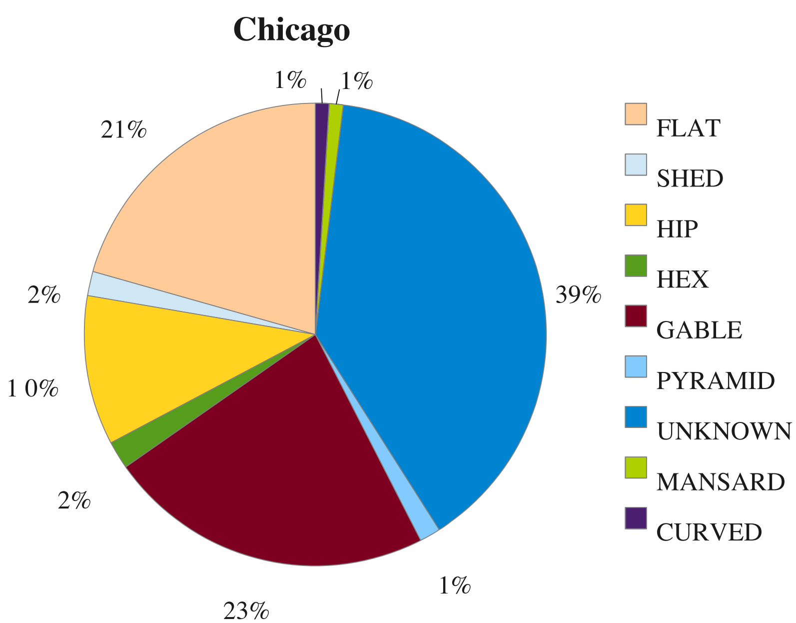


Model complexity V.S. Accuracy On ImageNet dataset

Fig cited from: A. Canziani etc. An analysis of deep neural network models for prectical applications, 2017

1) To gain a good performance of a machine learning process, more high quality data is always desired.

- ❖ Rare cases (absolute rarity)
- ❖ Rare classes (relative rarity)



Curved

Mansard

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2) Supervised learning requires high quality labeled data.

- Time consuming, expensive.
- Sometimes, impossible

2) Supervised learning requires high quality labeled data.

- Time consuming, expensive.
- Sometimes, impossible

2D optical flow

3D point cloud

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Solution:

Synthesizing data which will be used as training data.

Challenges:

- Where to synthesize? (As image or as features)
- How to synthesize?
- How to use synthesized data?

Novel contributions:

1. Data synthesis in data space.
2. Features to learn from synthetic data
3. Eliminating synthetic gap.
4. Data synthesis in feature space.

- Motivations and Importance of the problem.
- Introduction and novel contributions.
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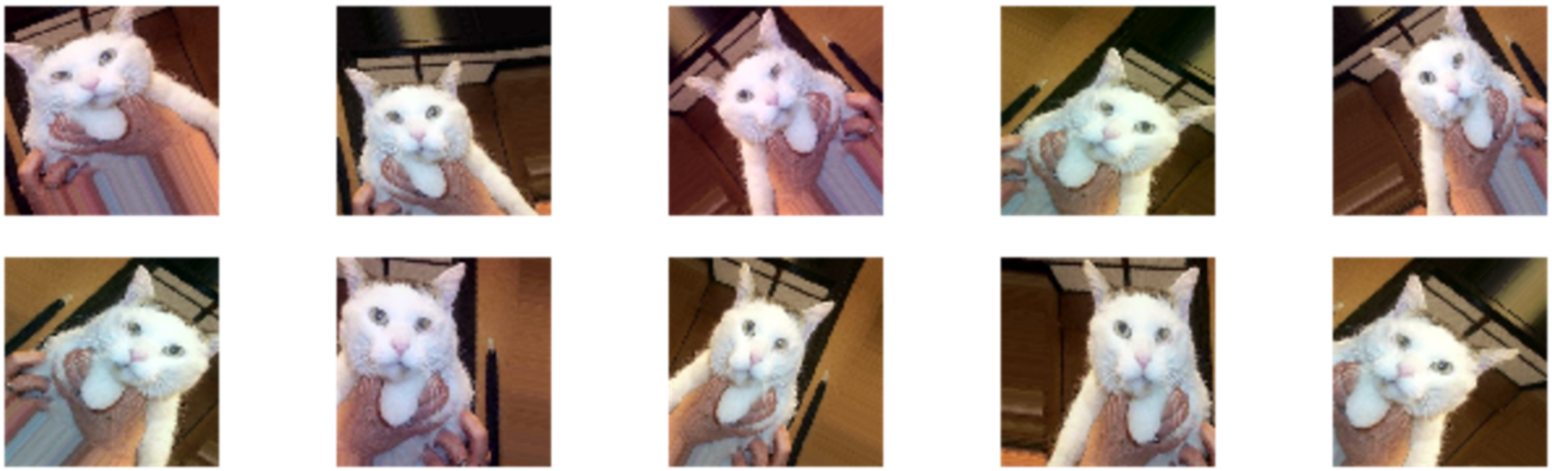
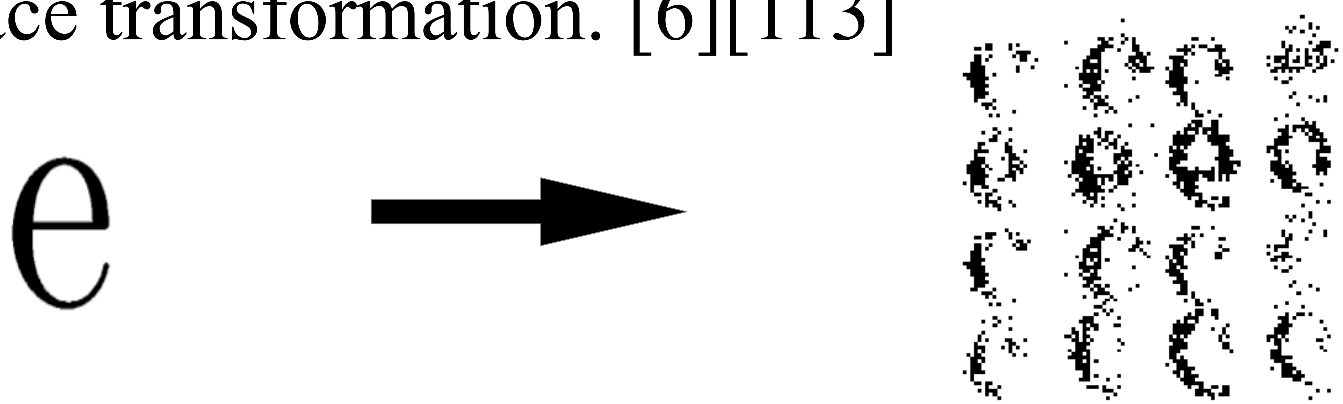
Existing methods.

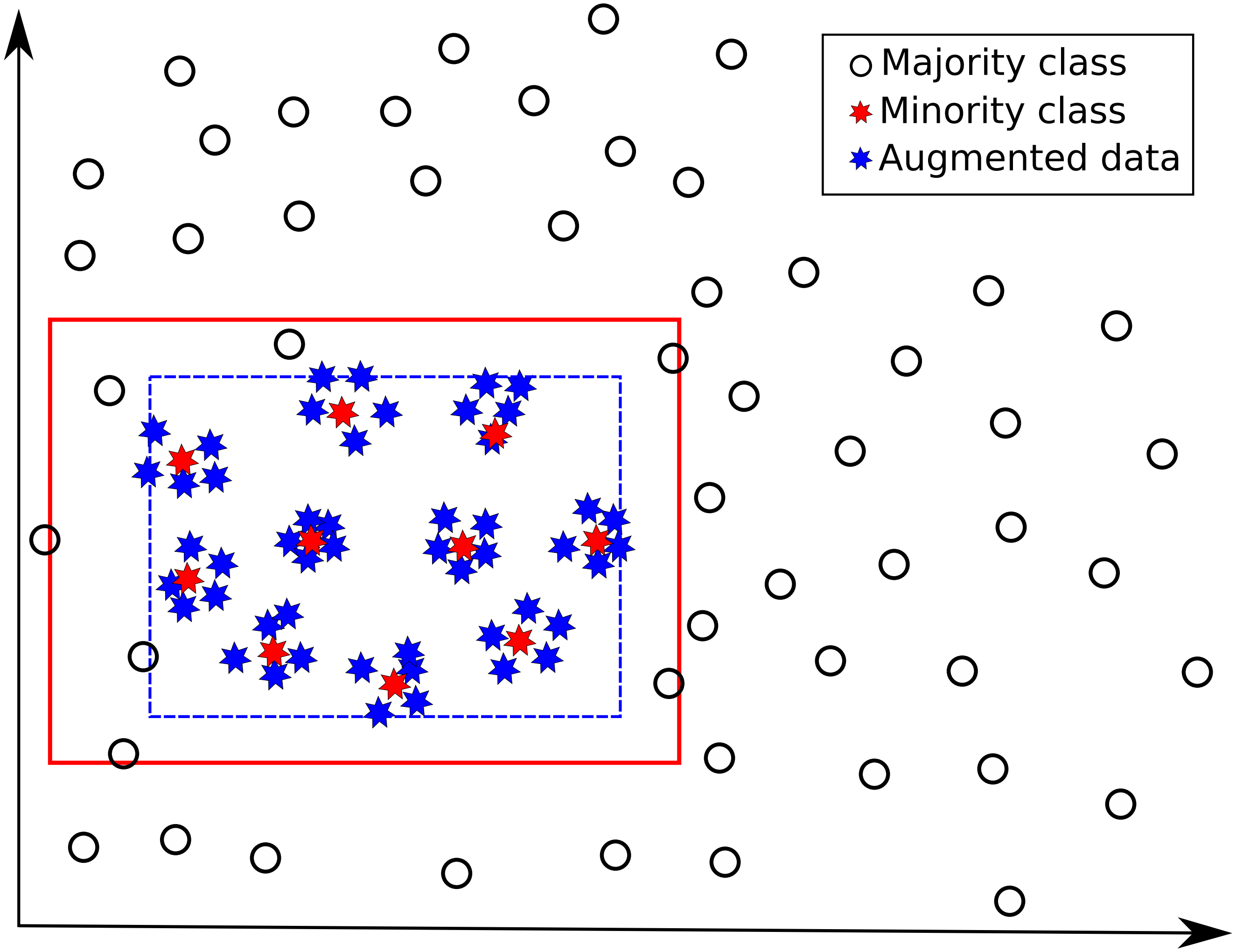
- Geometric transformation. [138][139]



- Color space transformation. [6][113]



- Disadvantage of existing methods.

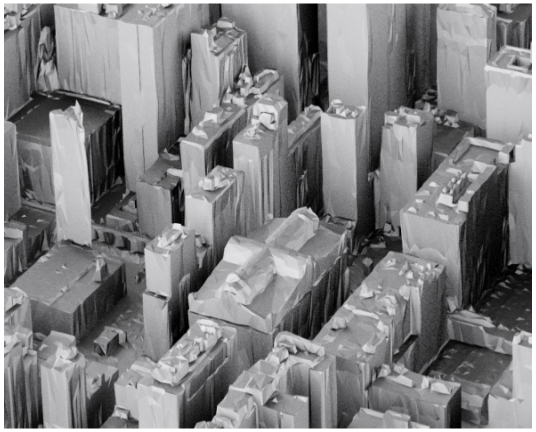


The Proposed Approach

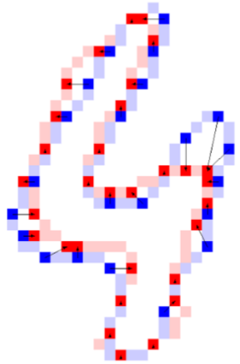
In contrast to existing methods, two approaches are used in my research:

1. Generate data.
   - Generation based on specified templates.
   - Generation based on learned templates.
   - Combination of specified and learned templates.
2. Generate labels.
   - Generating labels based on unsupervised learning.

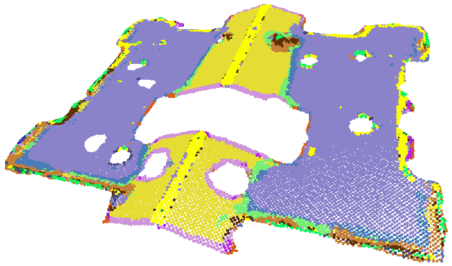
Generate data



Aerial LiDAR roof style classification [20]



Handwritten digits recognition [25]

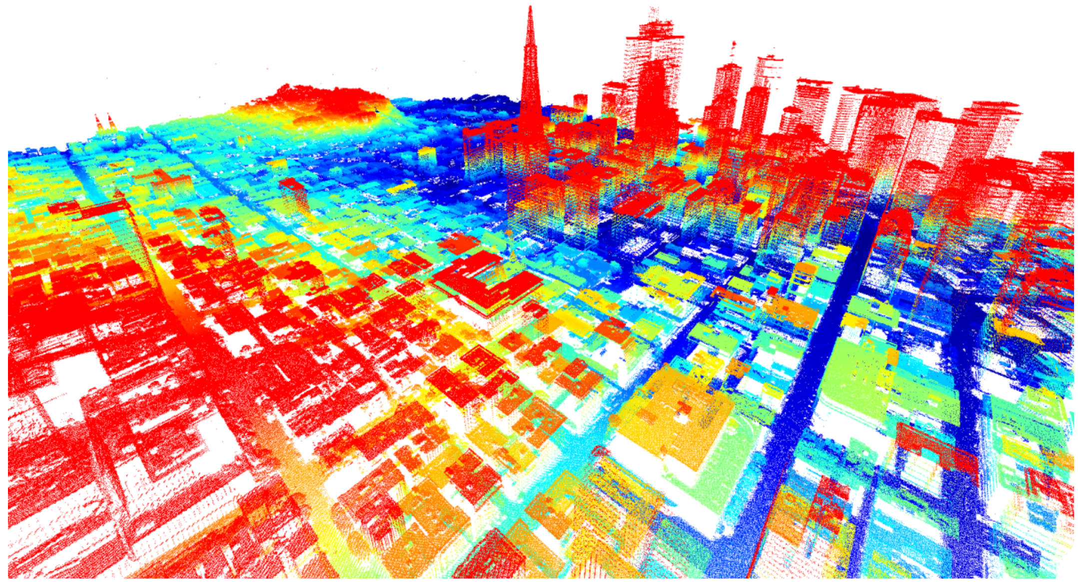


Point cloud roof points classification [20]

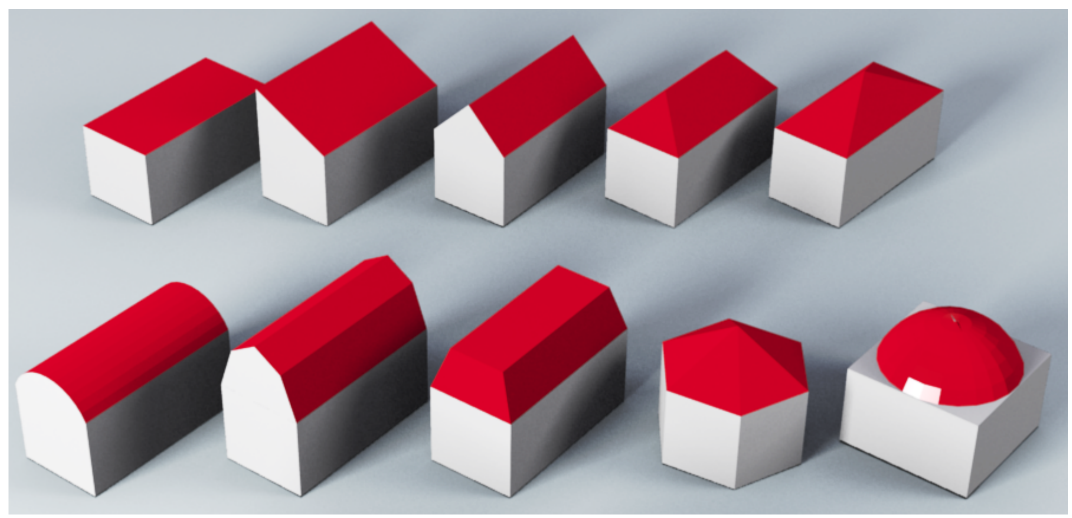
Generation based on specified templates

Aerial LiDAR

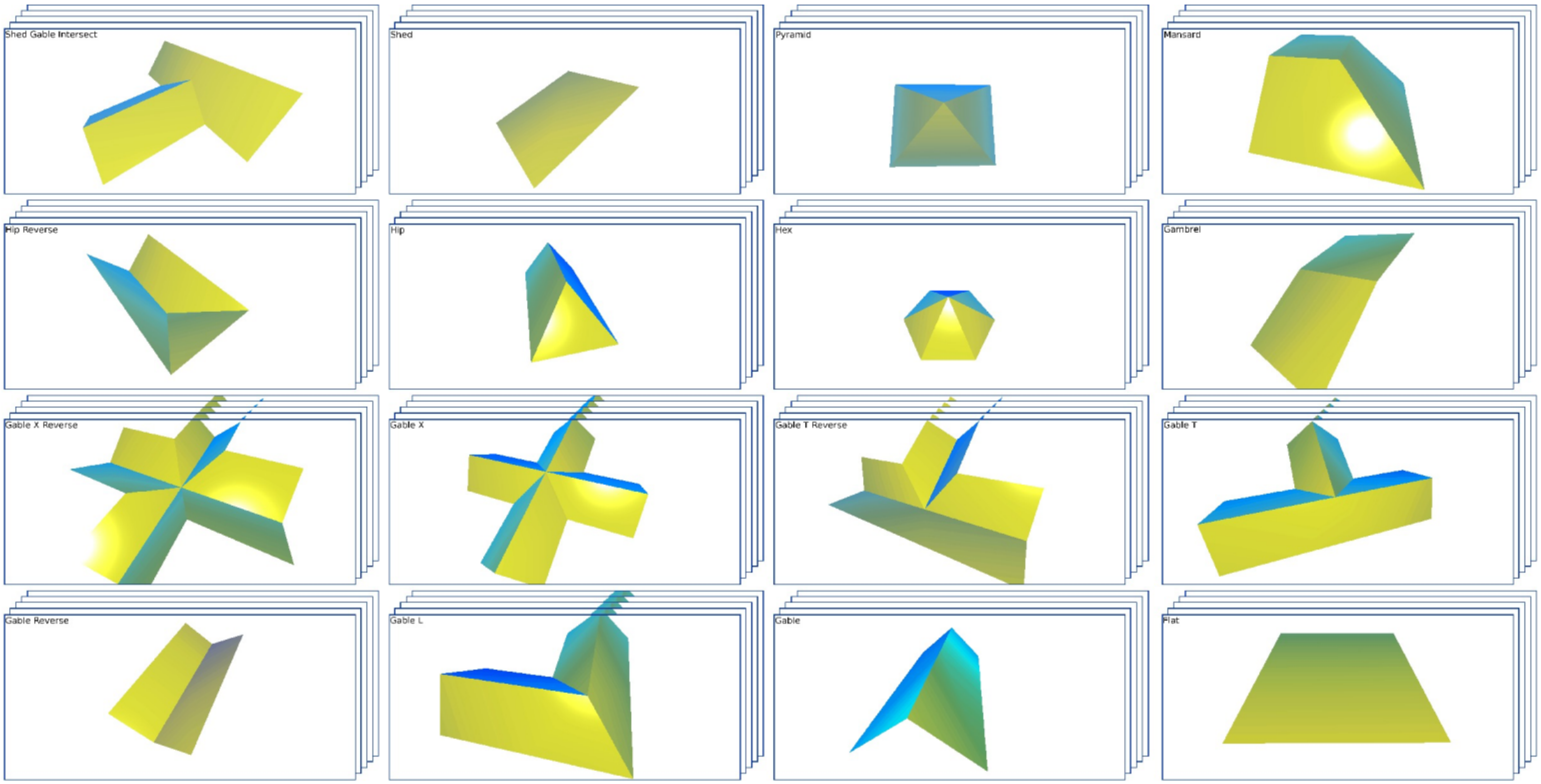
Downtown San Francisco



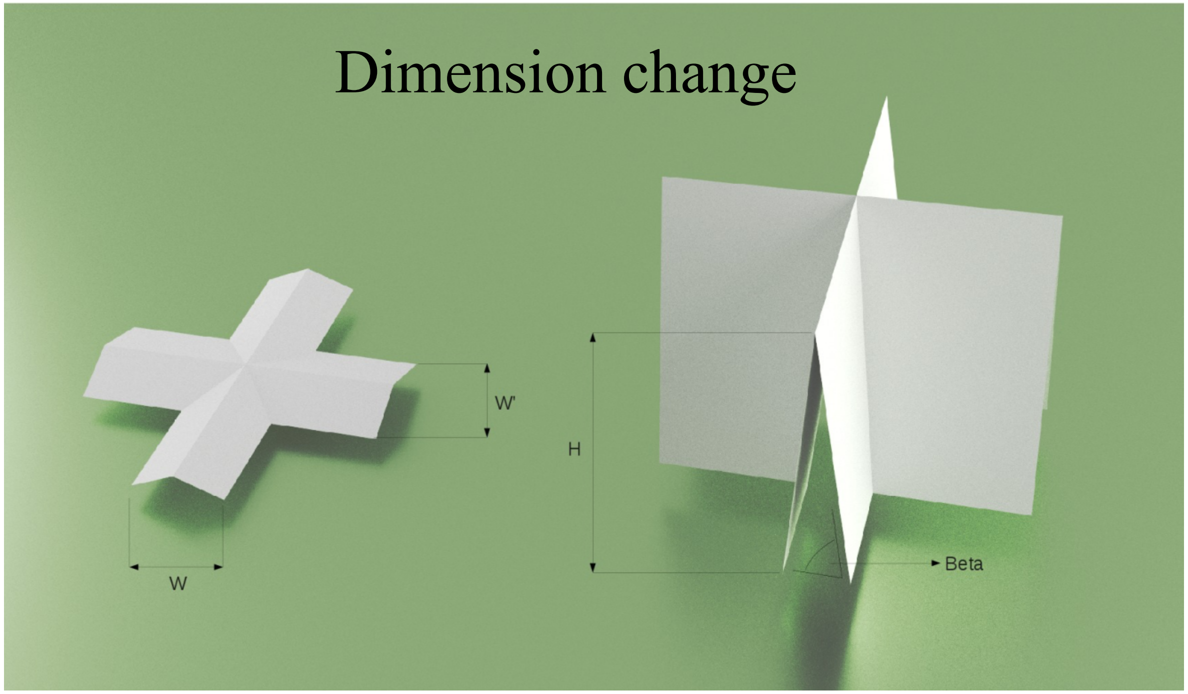
Candidate roof styles

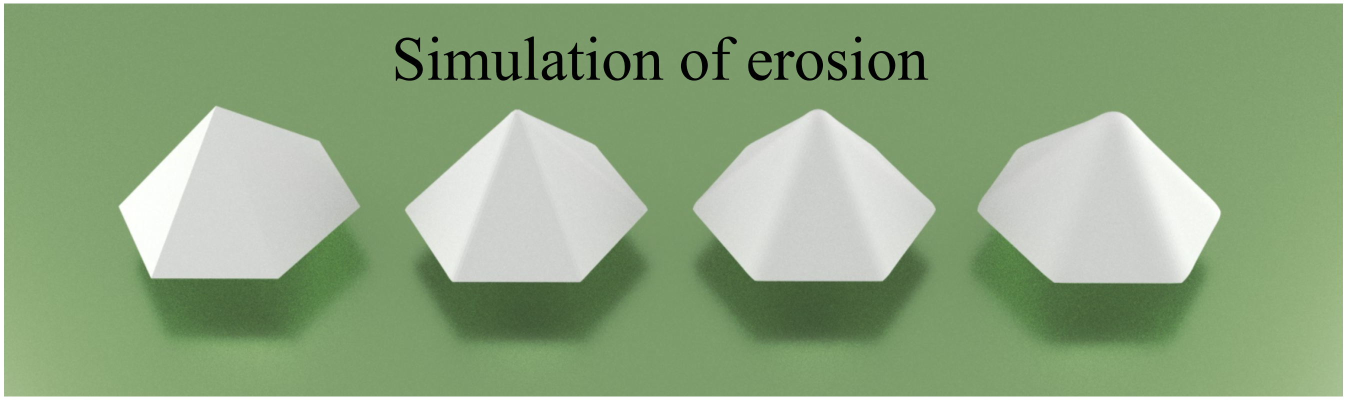


- Build prototypes.



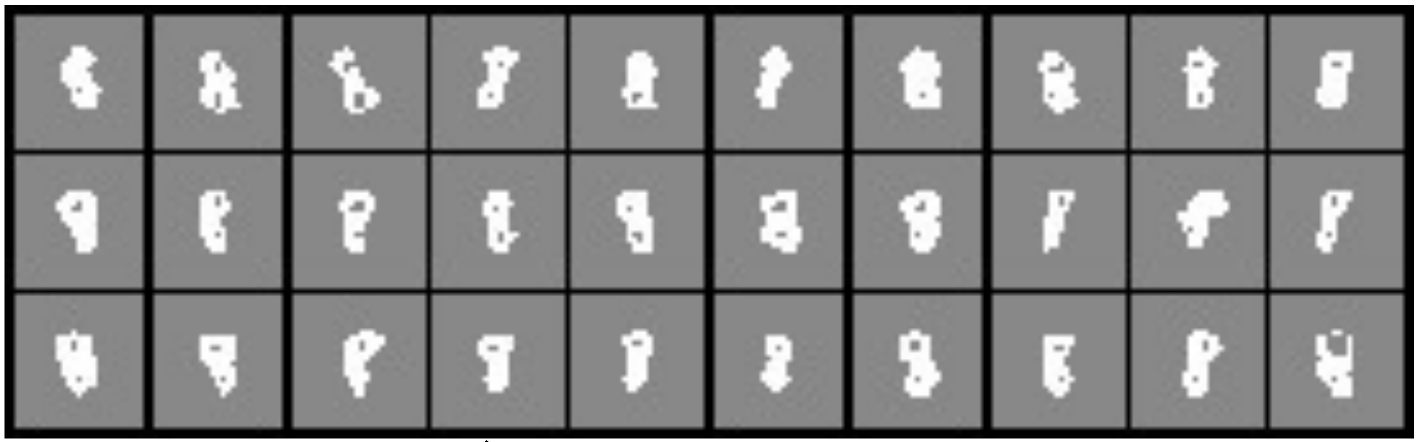
- Derive more data.

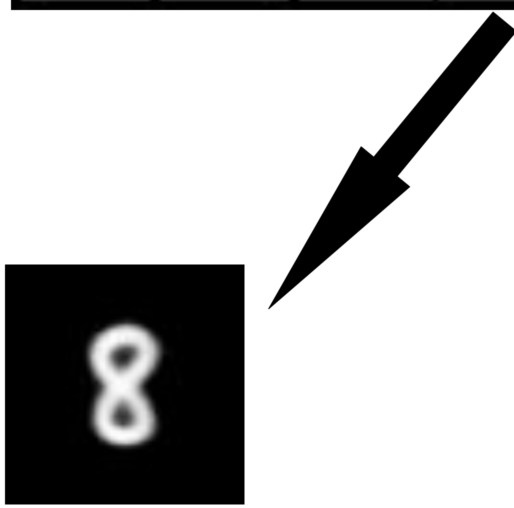




Generation based on learned templates

- Generate prototype by unifying images.

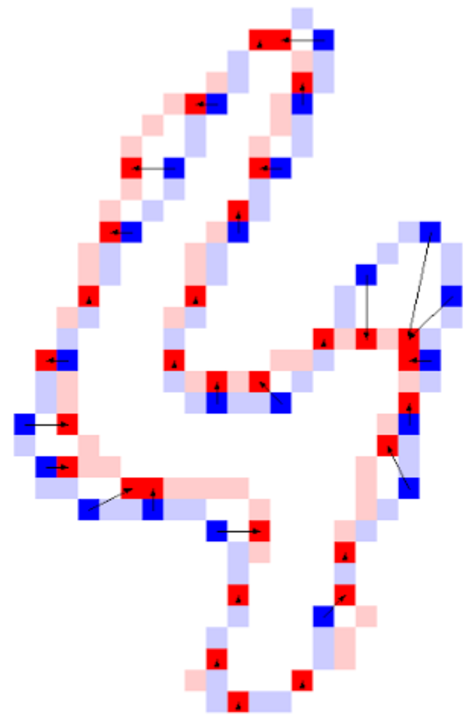




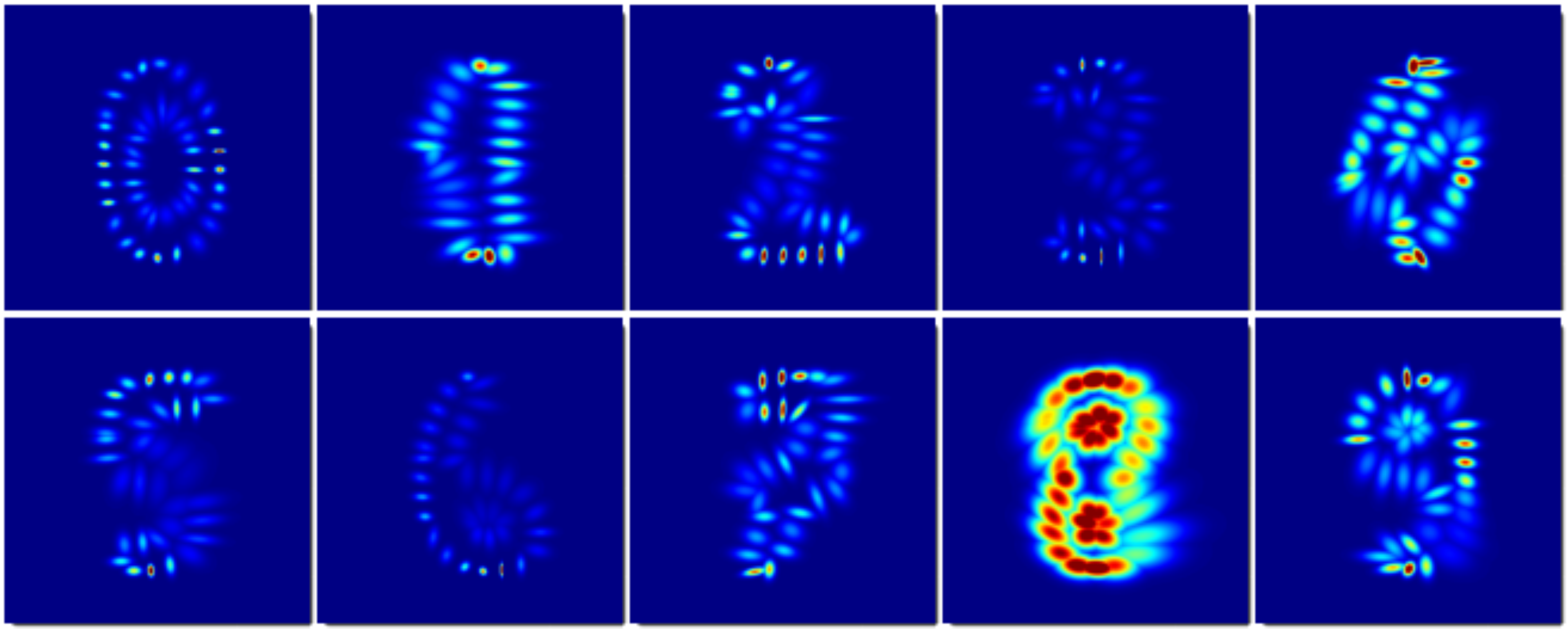
For N images $\{I_i\}_{i=1}^{N}$ with the same digit, solve for transformations $\{T_i\}_{i=1}^{N}$, that $\{T_i \cdot I_i\}_{i=1}^{N}$ minimize joint entropy

Building correspondence among data.

- Set control points on prototype.
- Find corresponding control points on each data.



- Data synthesis by drawing samples from a computed distribution.



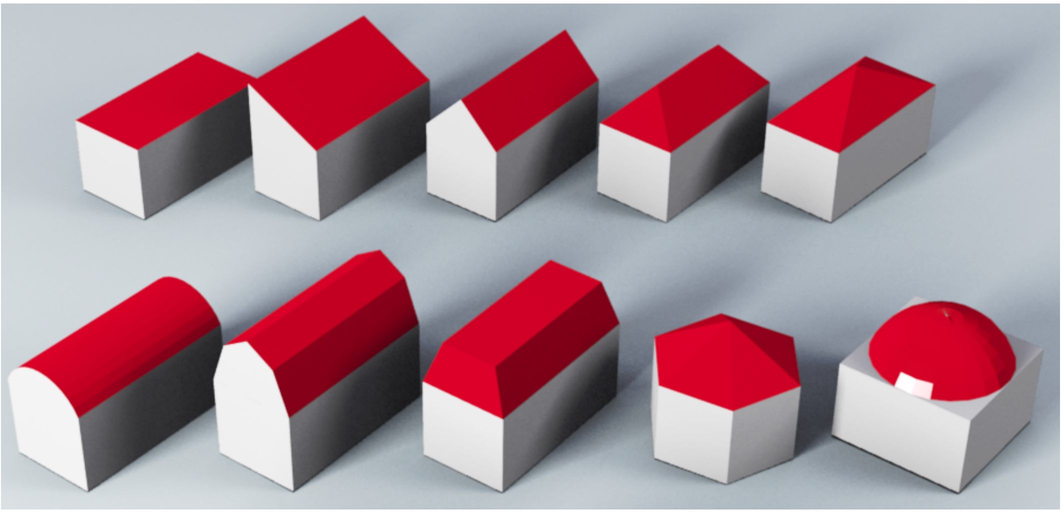
- Data synthesis by interpolation/extrapolation between nearest neighbors.

- Boost the performance by adding synthetic data.

	Real	Syn	Real+Syn
CNN	0.65	0.68	0.70
SVM	0.77	0.78	0.80
Samples #	2000	20000	2000+20000

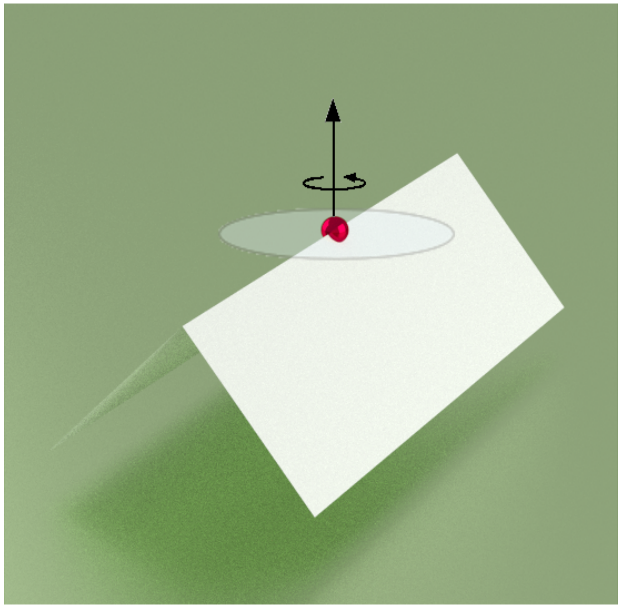
F1 score of classification results

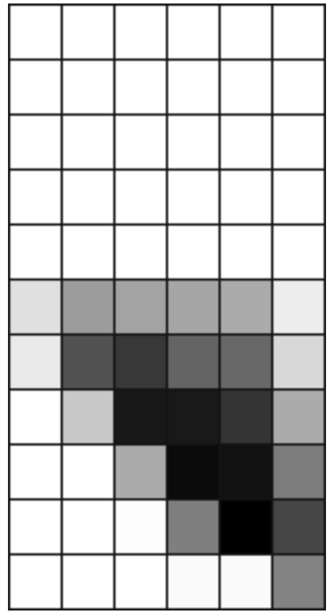
Combination of specified and learned templates.



Roof type classification from point cloud

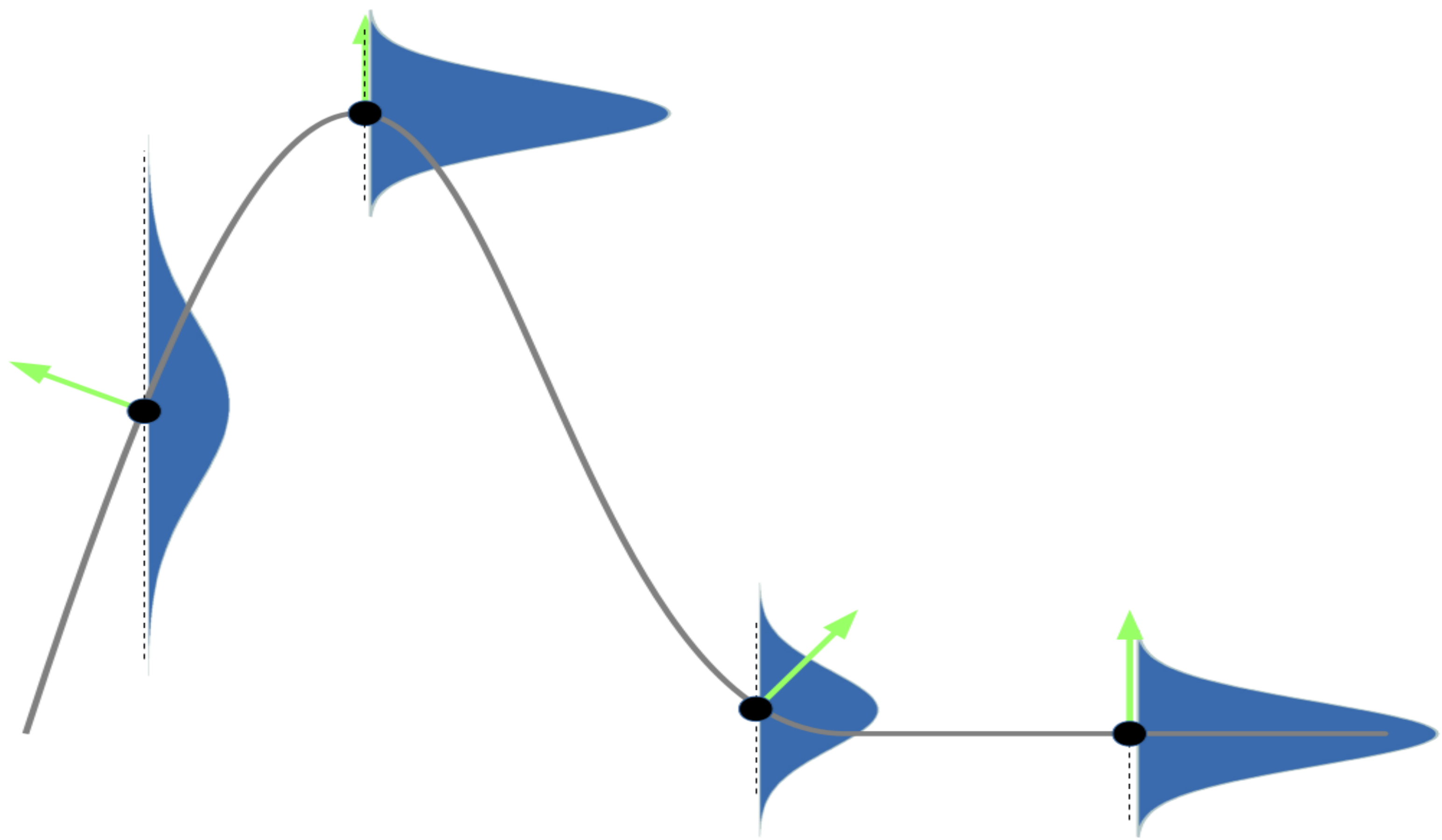
- Extract features that characterize local geometry.



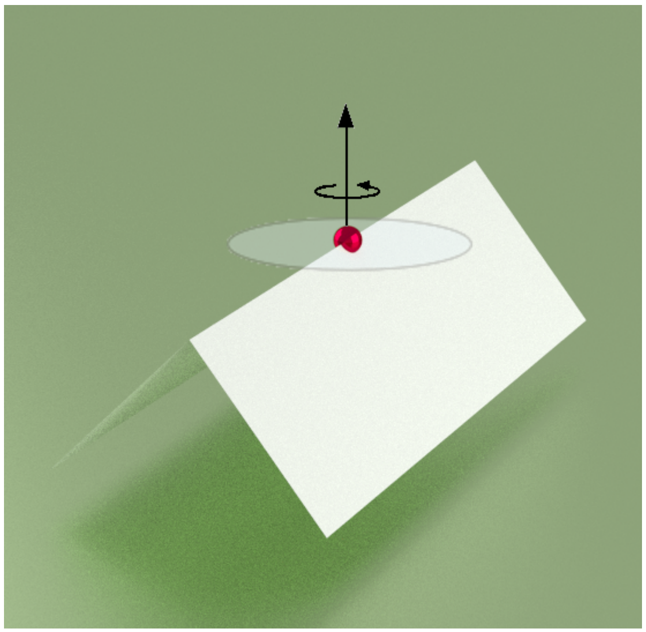


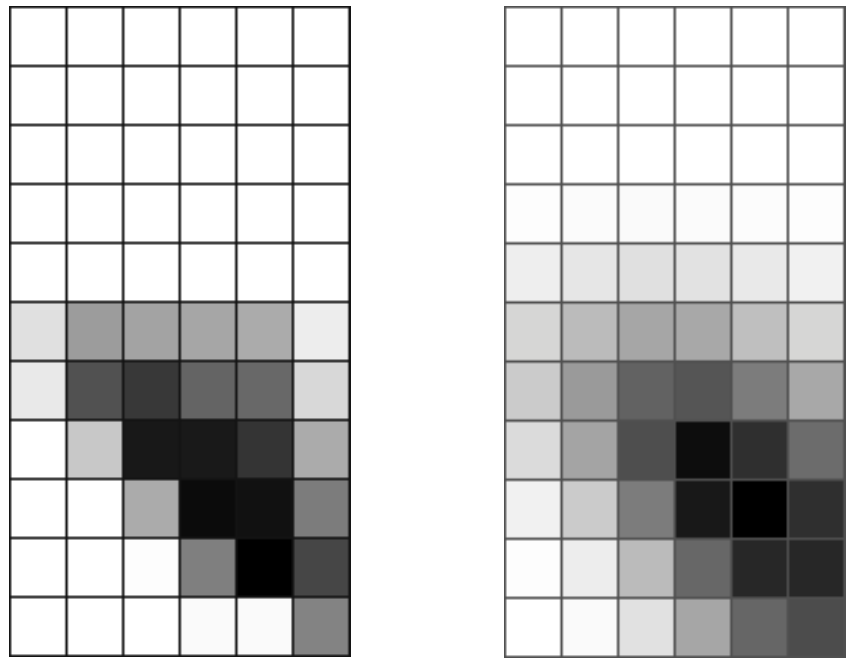
Spin image

- Learning bumpiness as a function of surface slope.



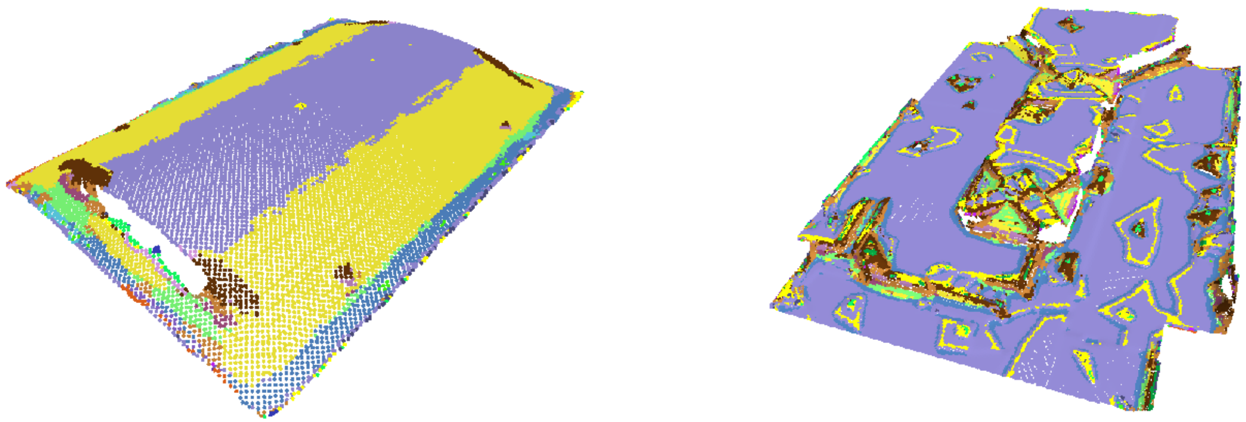
- Add random noise to synthetic data using knowledge learned.



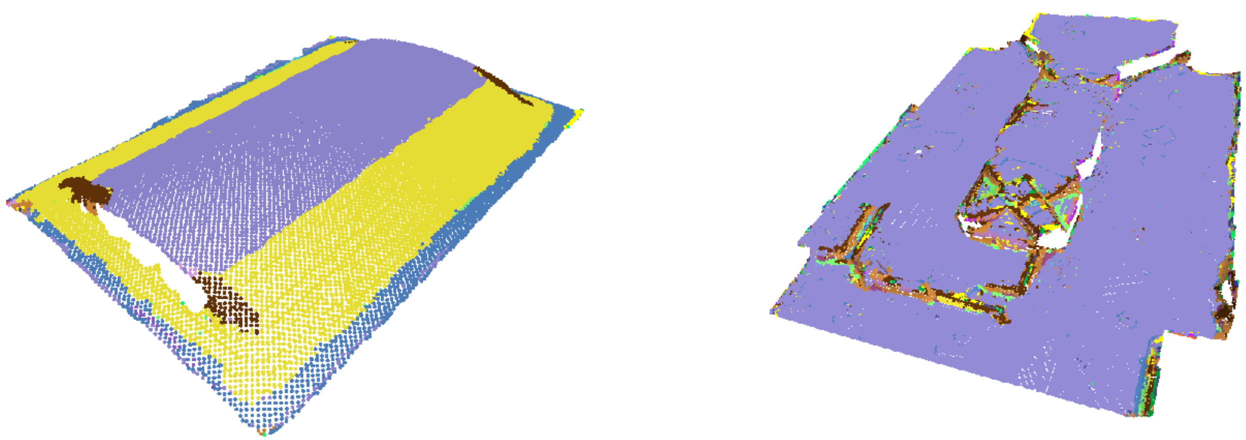


Spin image

- Point semantics classification results.

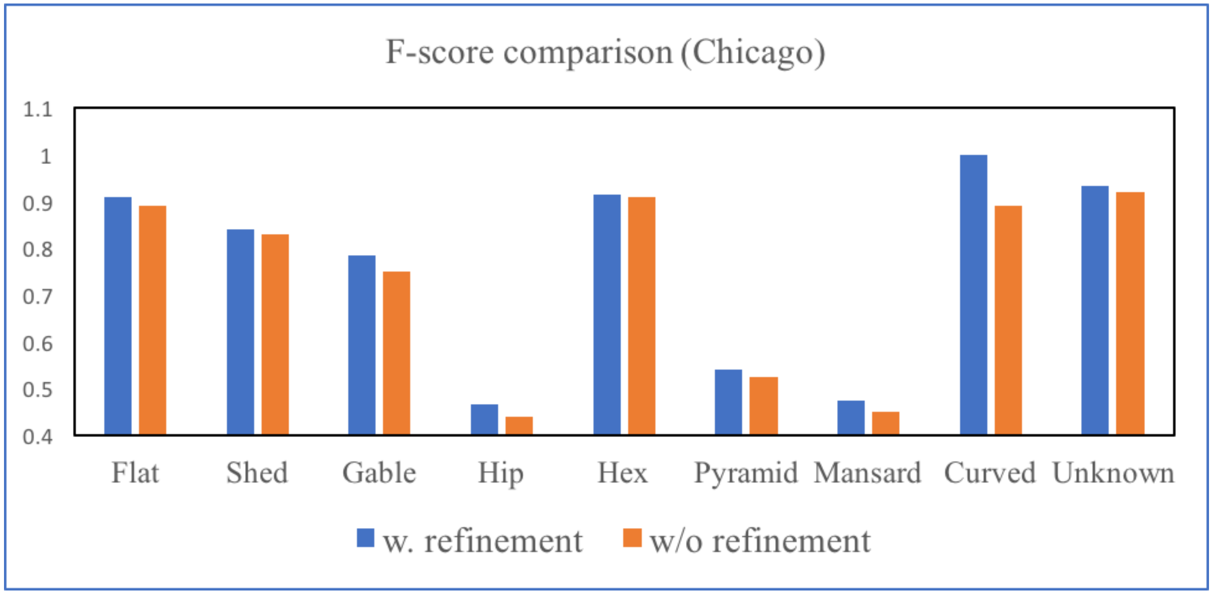


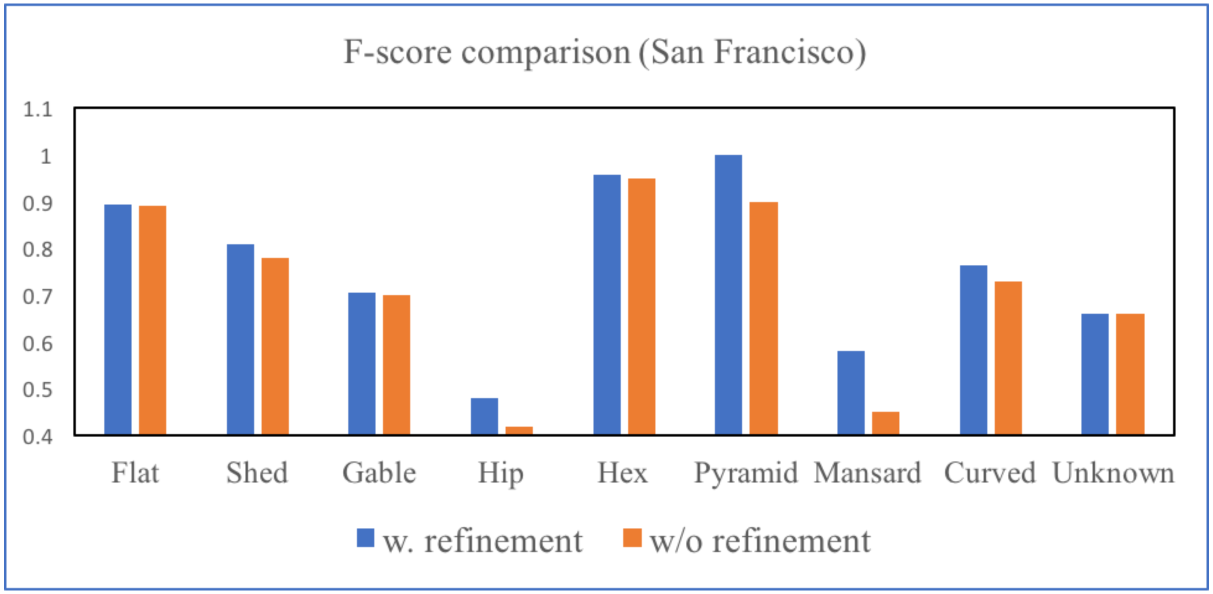
Without feature refinement



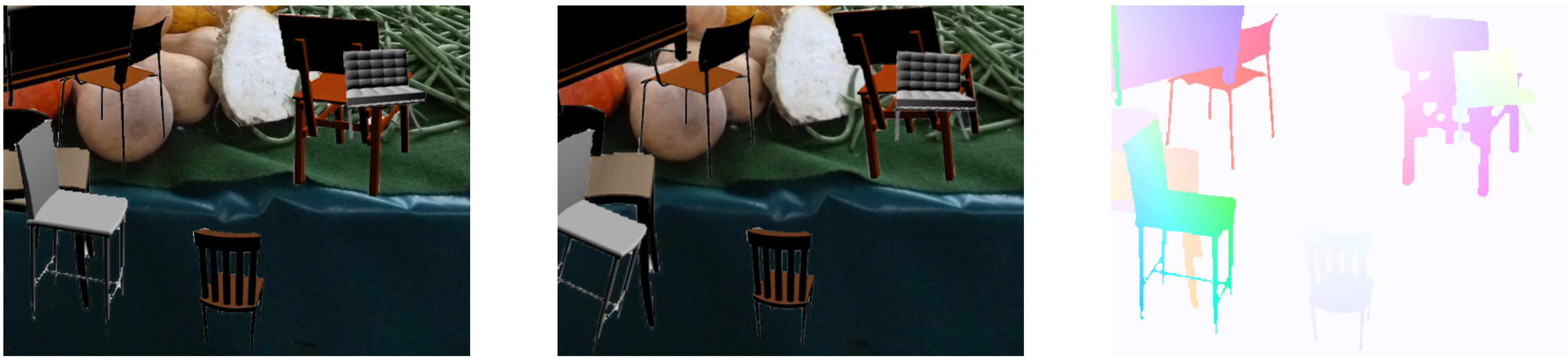
With feature refinement

Recognition rate by adding refinement to point features.



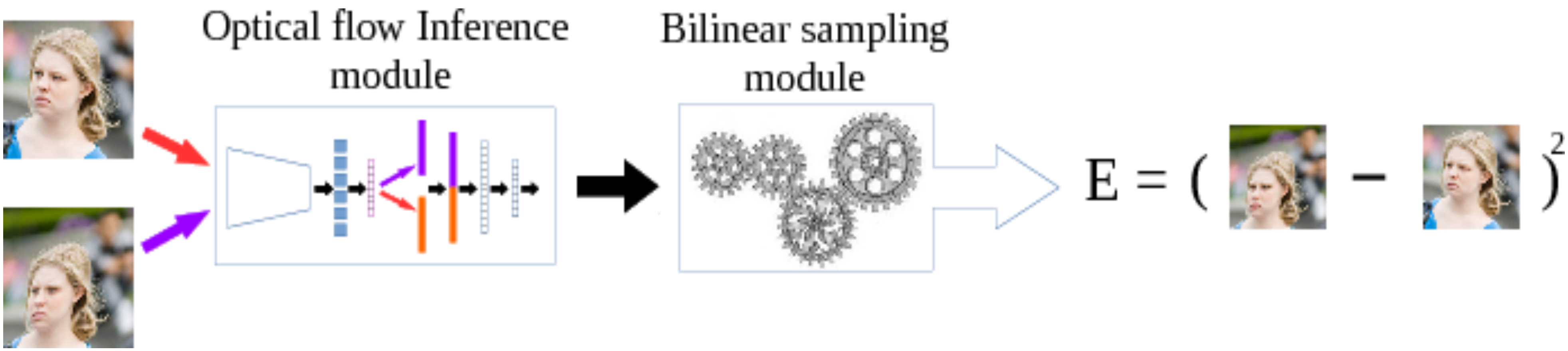


Generating labels based on unsupervised learning

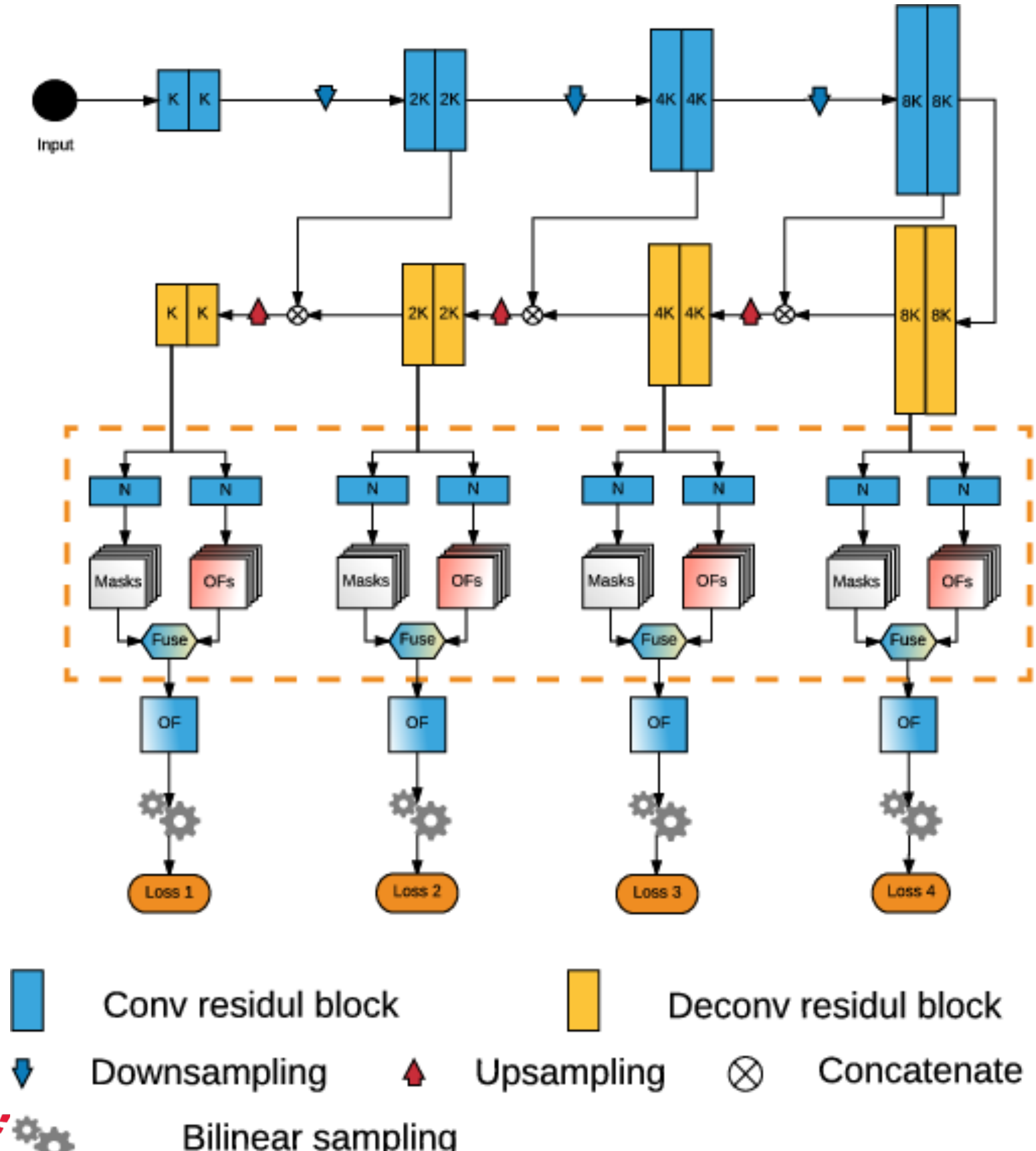


Unsupervised learning of optical flow using neural networks. [23]

- Framework of unsupervised optical flow learning



❖ Introduction of using mask modules



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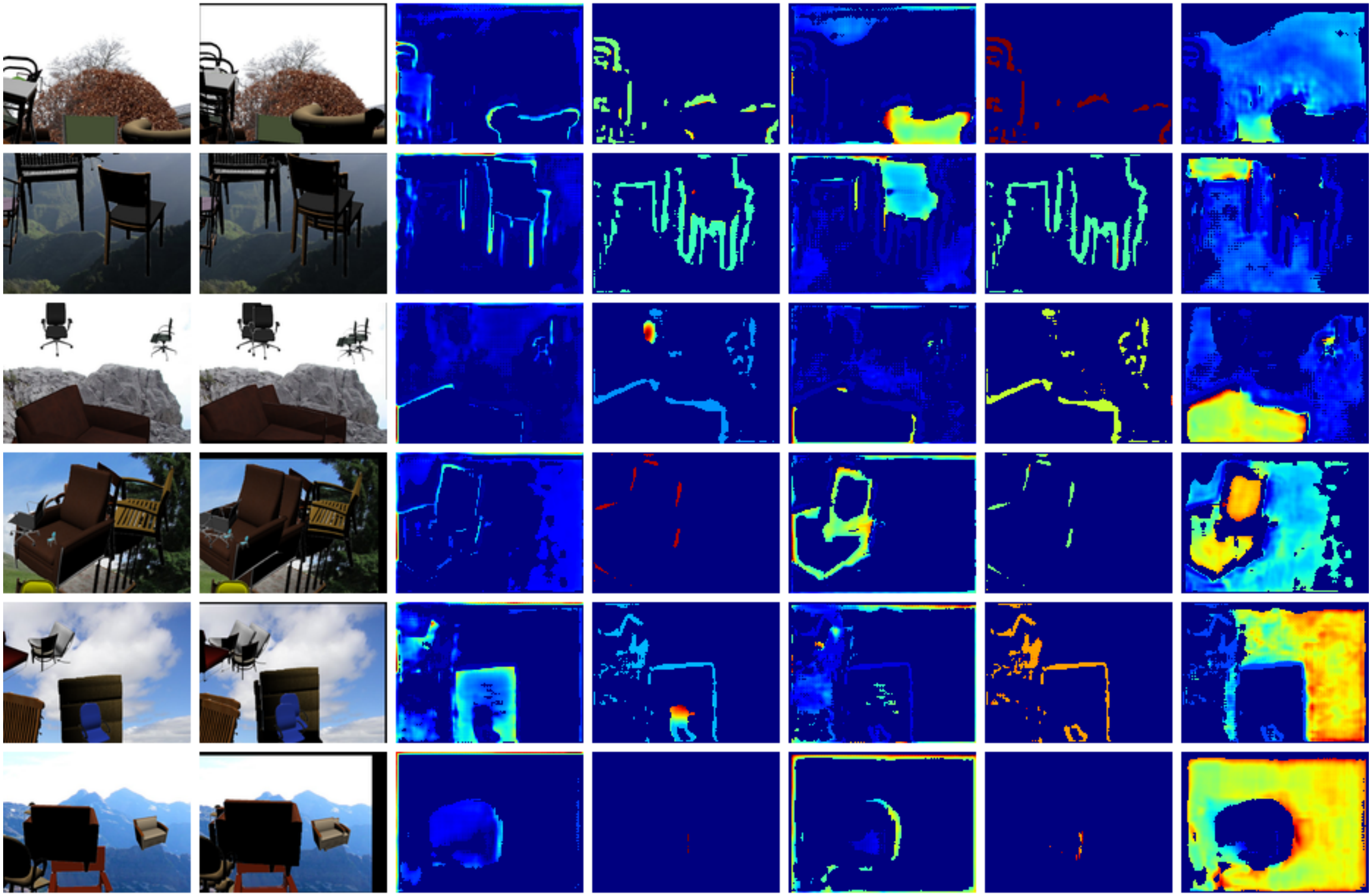
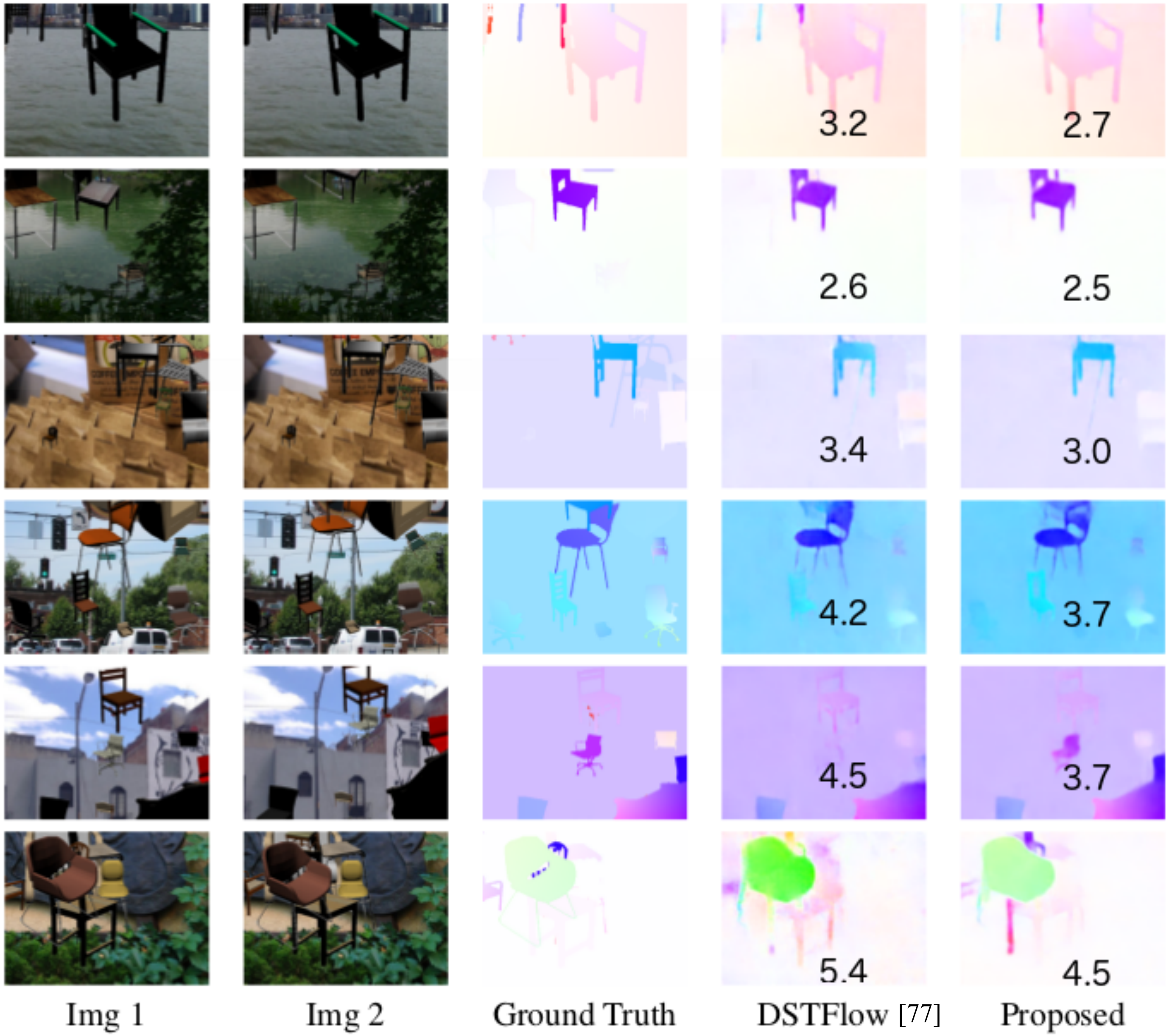
- Learned masks.



❖ Results


3.2
2.7
2.6
2.5
3.4
3.0
4.2
3.7
4.5
3.7
5.4
4.5
Img 1
Img 2
Ground Truth
DSTFlow [77]
Proposed

❖ Results

Training set	Test set	FlowNet
KITTI labeled data (200)	KITTI labeled test set (200)	5.23
KITTI labeled data (200) + Chairs labeled data (20k)	KITTI labeled test set (200)	4.43
KITTI w. pred' labels (40k) + Chairs labeled data (20k)	KITTI labeled test set (200)	**2.31**
KITTI w. pred' labels (40k) + KITTI labeled data (200) + Chairs labeled data (20k)	KITTI labeled test set (200)	**2.21**

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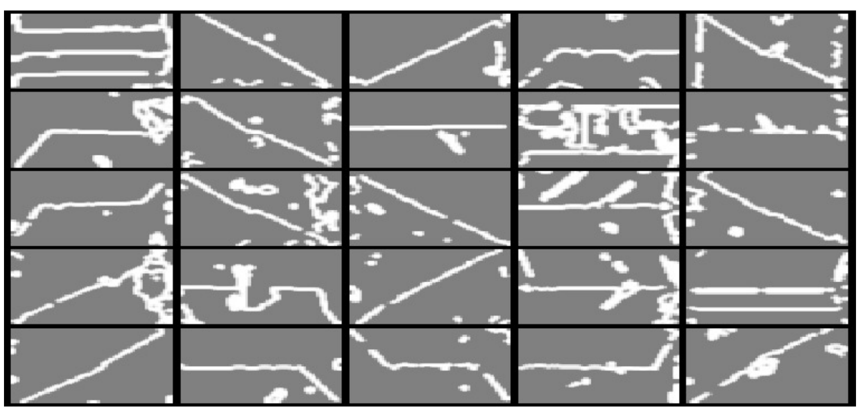
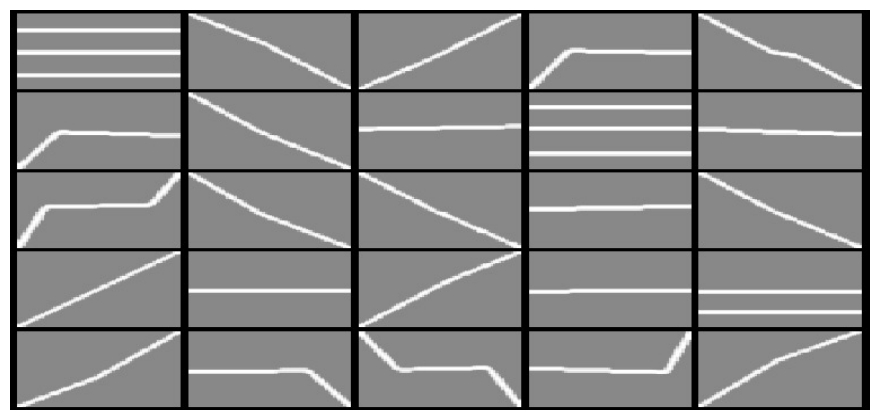
A Challenging task.



Actual data



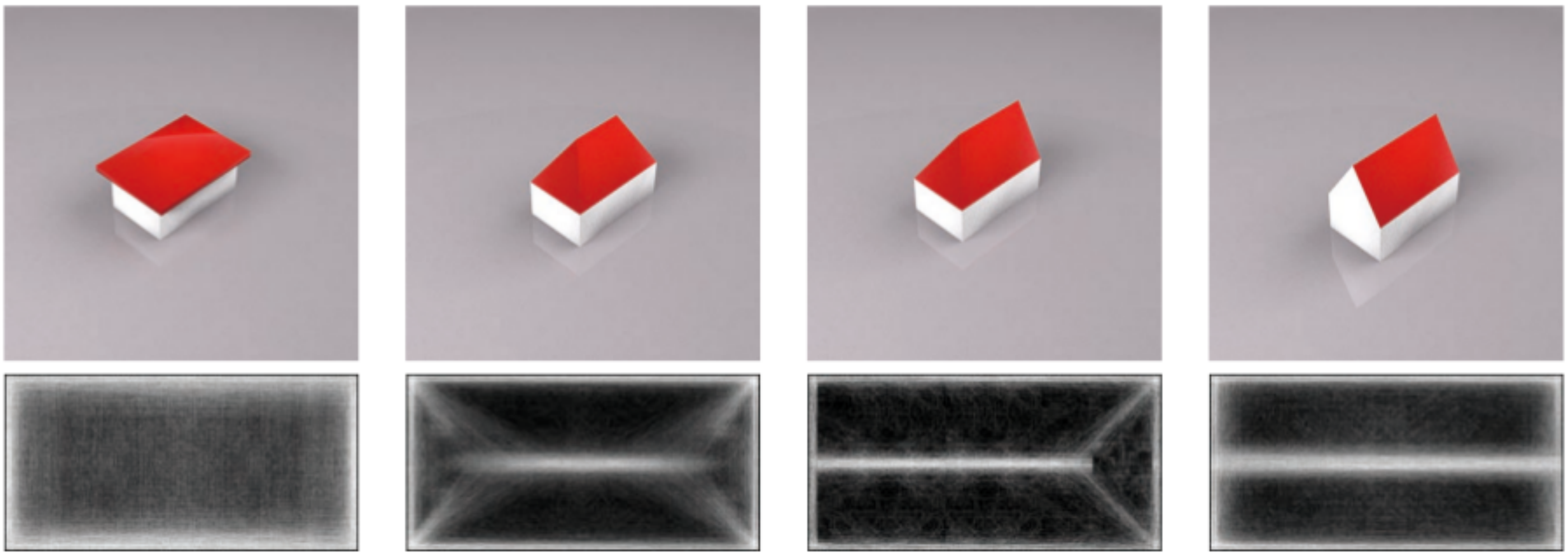
Synthetic data

Previous work.

- They all treat synthetic data as actual ones.[68][136][114][138][139]

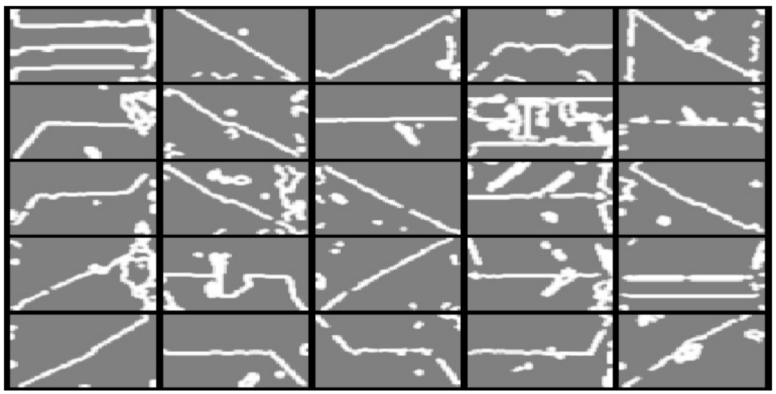
The proposed approach.

- Design features that would be insensitive to differences between synthesized and actual data

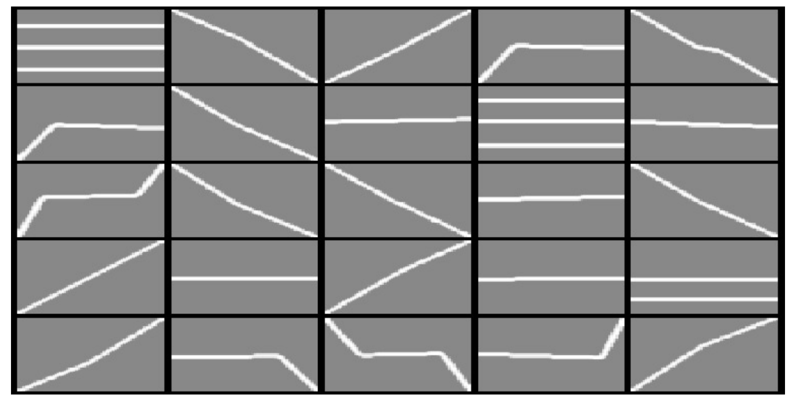


Roof type classification from satellite images [21]

- Satellite image roof style classification.



Actual data

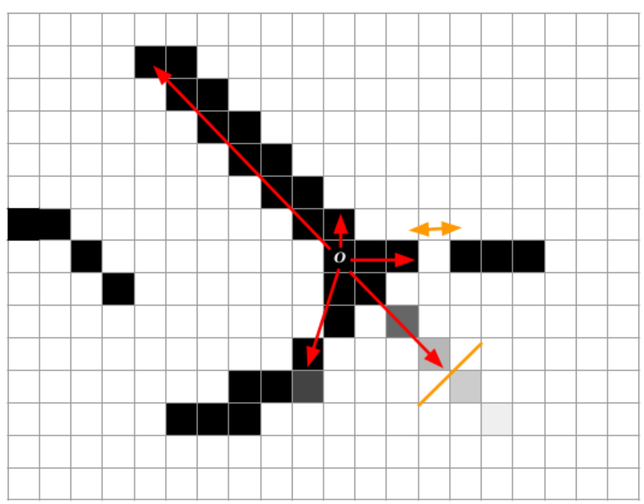


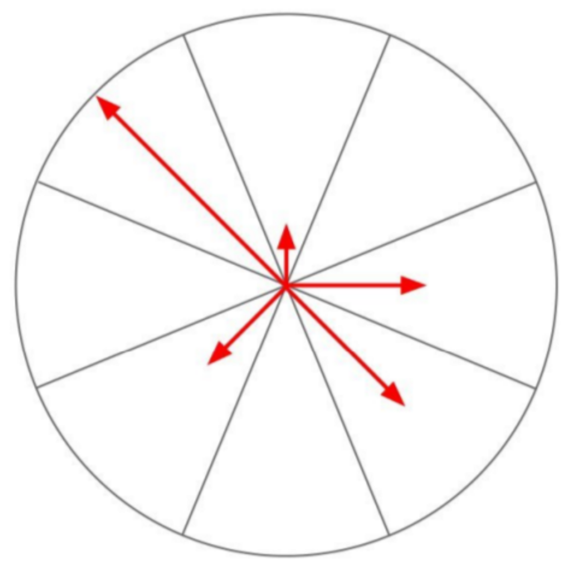
Synthetic data

Features expected:

- Ignore small blobs in actual data.
- Highlight the most evident structure of roofs.

- We proposed a feature called Histogram of Ray (HOR) in [21] to highlight edge length and direction.
- Translation, scale, rotation invariant.





- Compare with several well-known image features:

	HIP	GABLE	FLAT	HALFHIP
HOG	0.805	0.882	0.954	0.597
SC	0.350	0.828	0.959	0.140
HOR	0.898	0.950	0.968	0.632
LBP	0.000	0.986	0.631	0.000
HOR+HOG	0.931	0.959	0.982	0.667
HOR+SC	0.619	0.891	0.959	0.436
HOG+SC	0.752	0.959	0.945	0.474

F1 score of classification results

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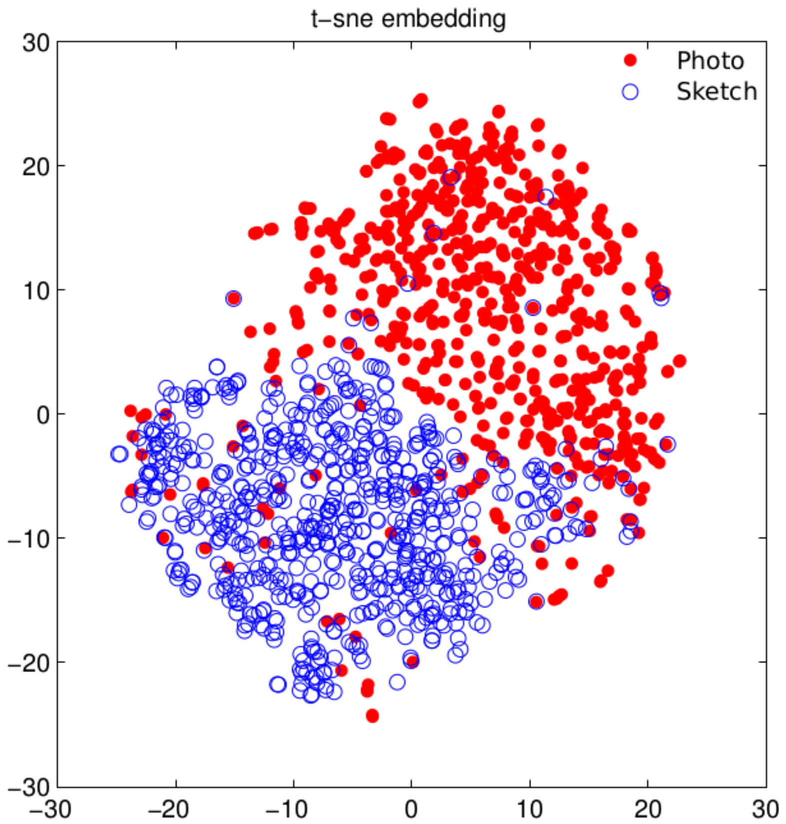
Eliminate Synthetic Gap

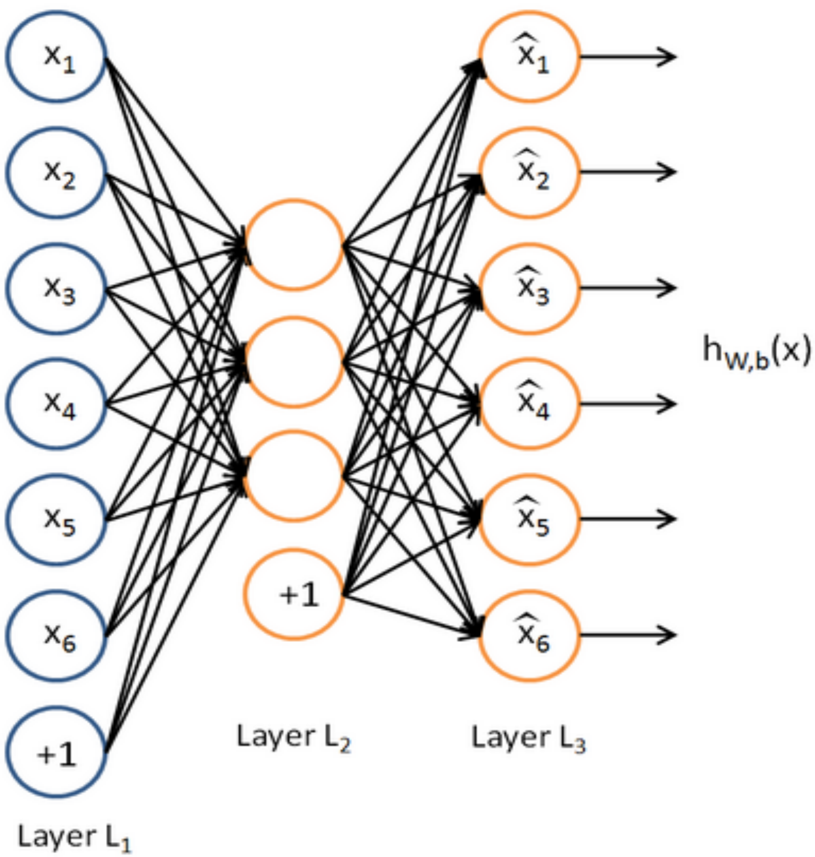


Previous work.

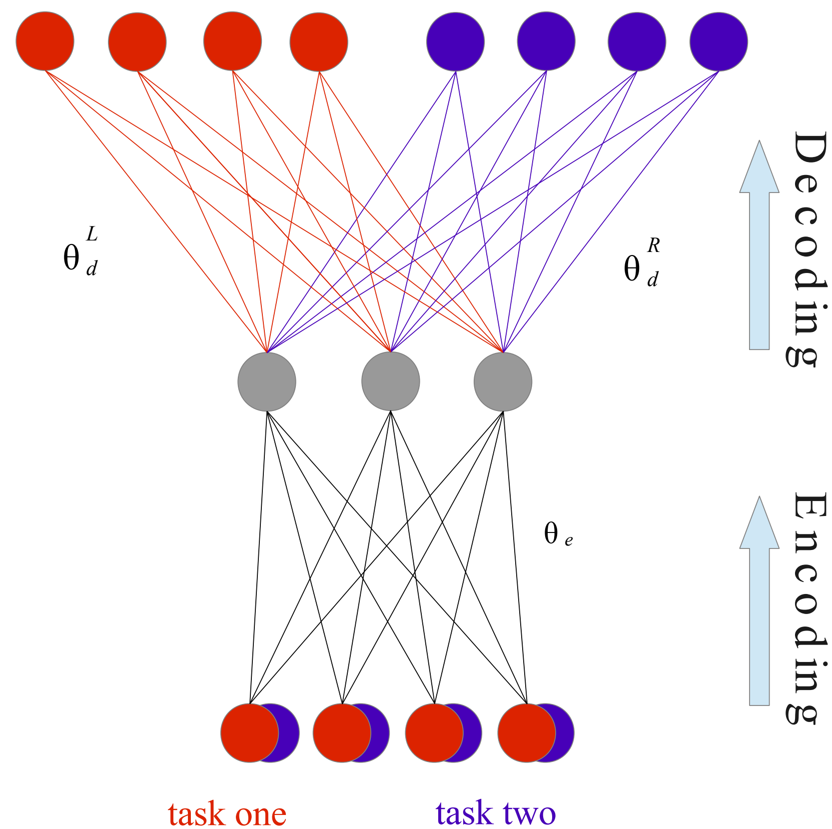
- Eliminate distribution means in Kernel Reproducing Hilbert Space (KRHS). [12][46]
- Subspace alignment. [35][24]
- Deep neural network using KRHS as domain loss. [32][19]

- I proposed Multi-Channel Autoencoder (MCAE)

- I proposed **Multi-Channel Autoencoder (MCAE)**

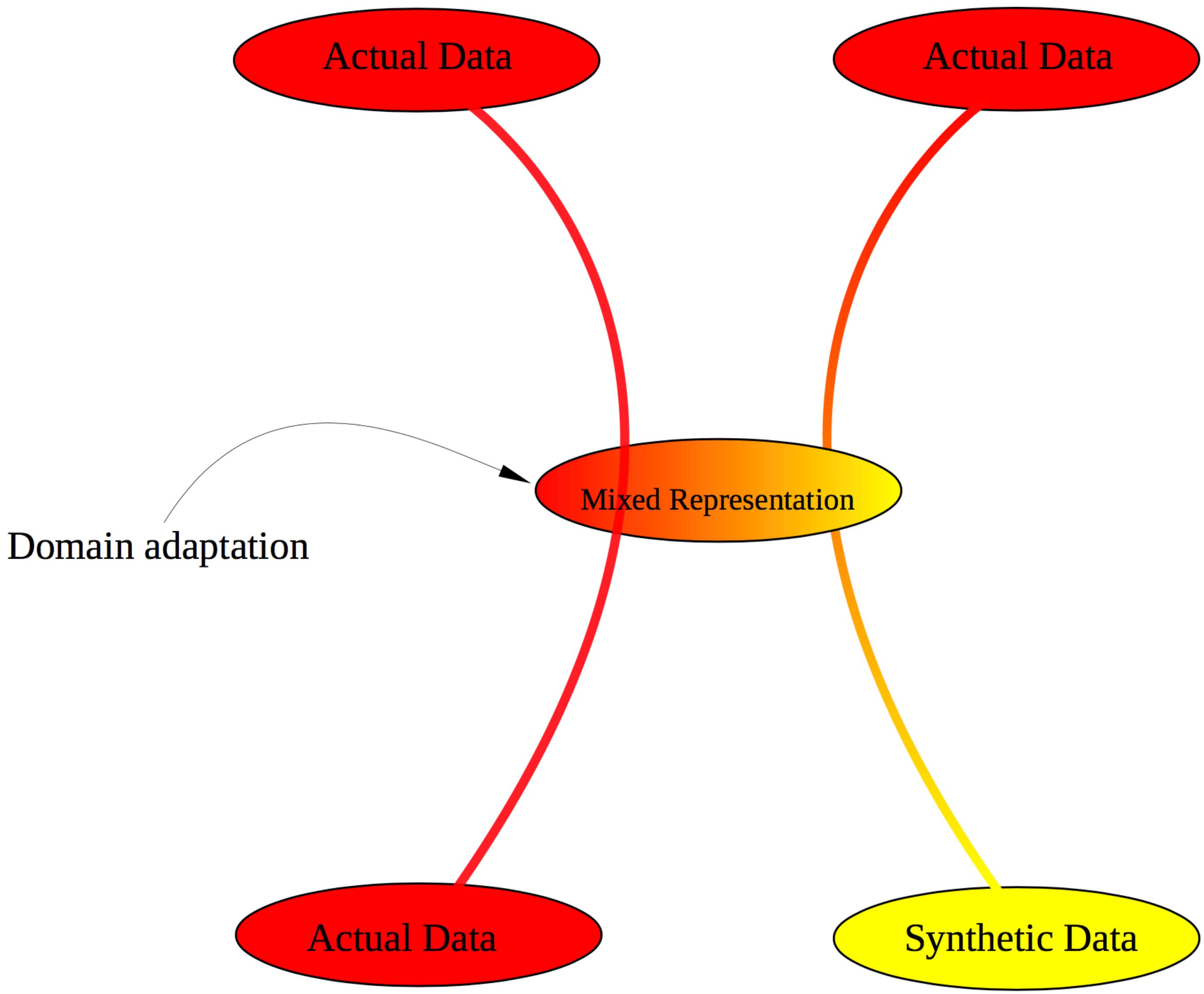


Traditional AutoEncoder



MCAE

- Configuration of MCAE



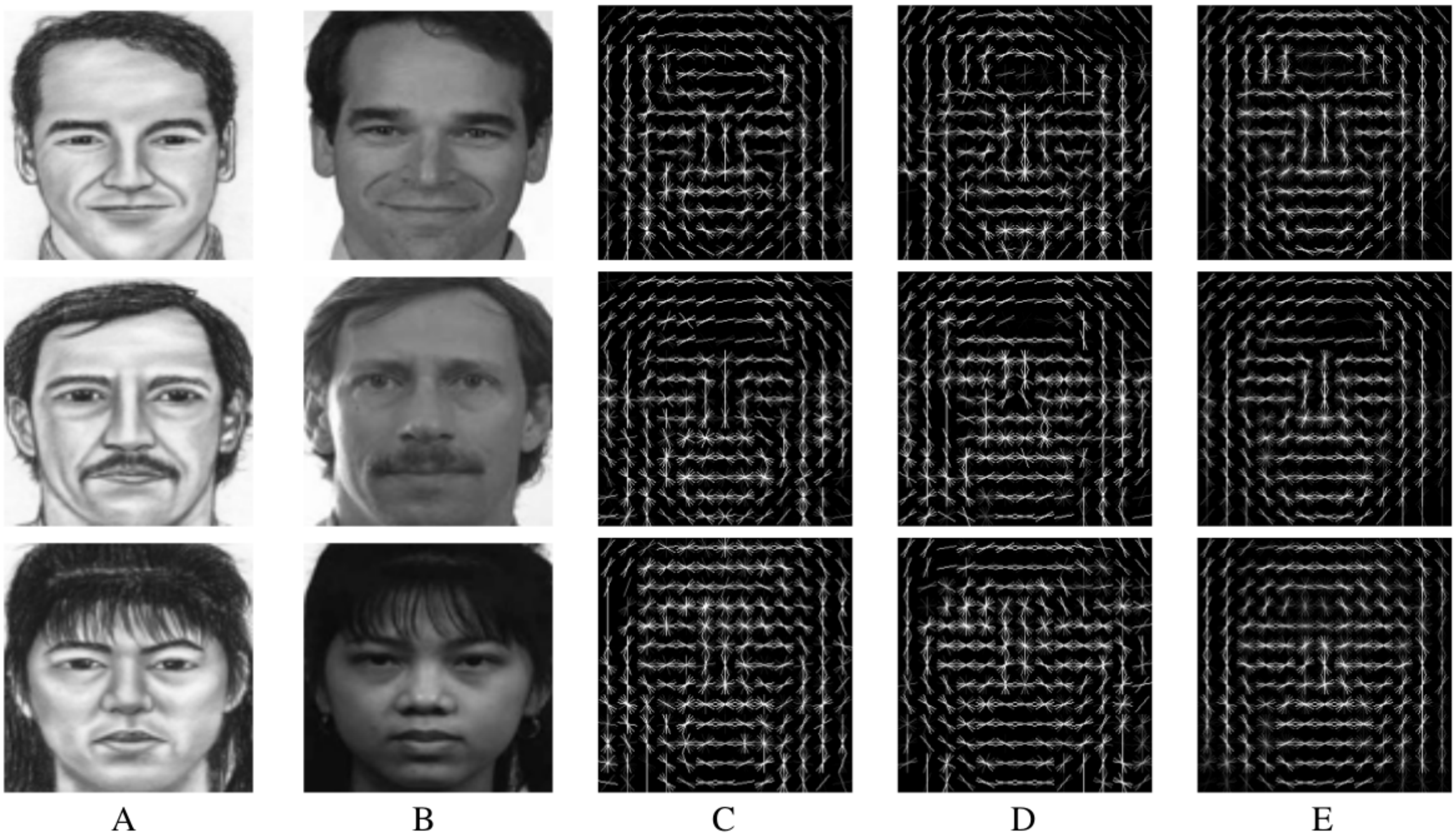
- MCAE
- Jointly learn two tasks, left and right, together.

$$E = J^L(\theta_e, \theta_d^L) + J^R(\theta_e, \theta_d^R) + \gamma\Psi$$

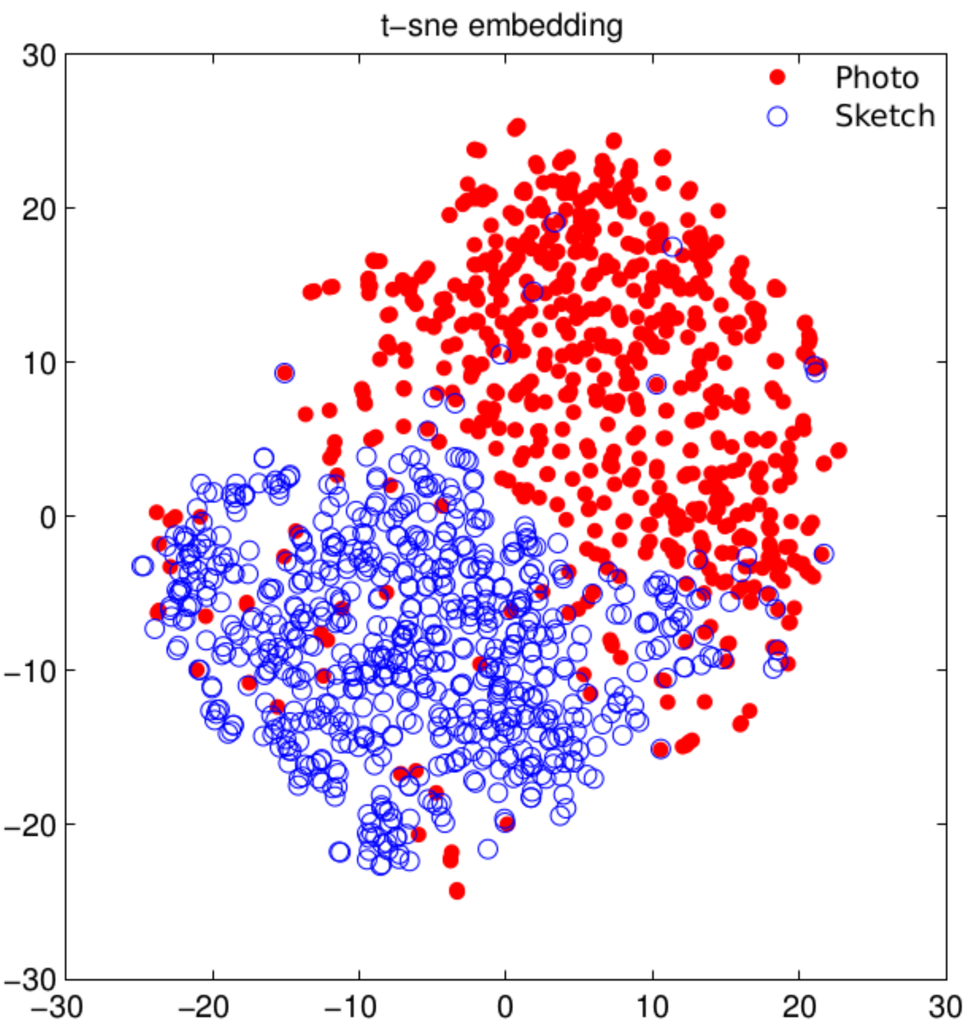
where

$$\Psi = \frac{1}{2}(J^L(\theta_e, \theta_d^L) - J^R(\theta_e, \theta_d^R))^2$$

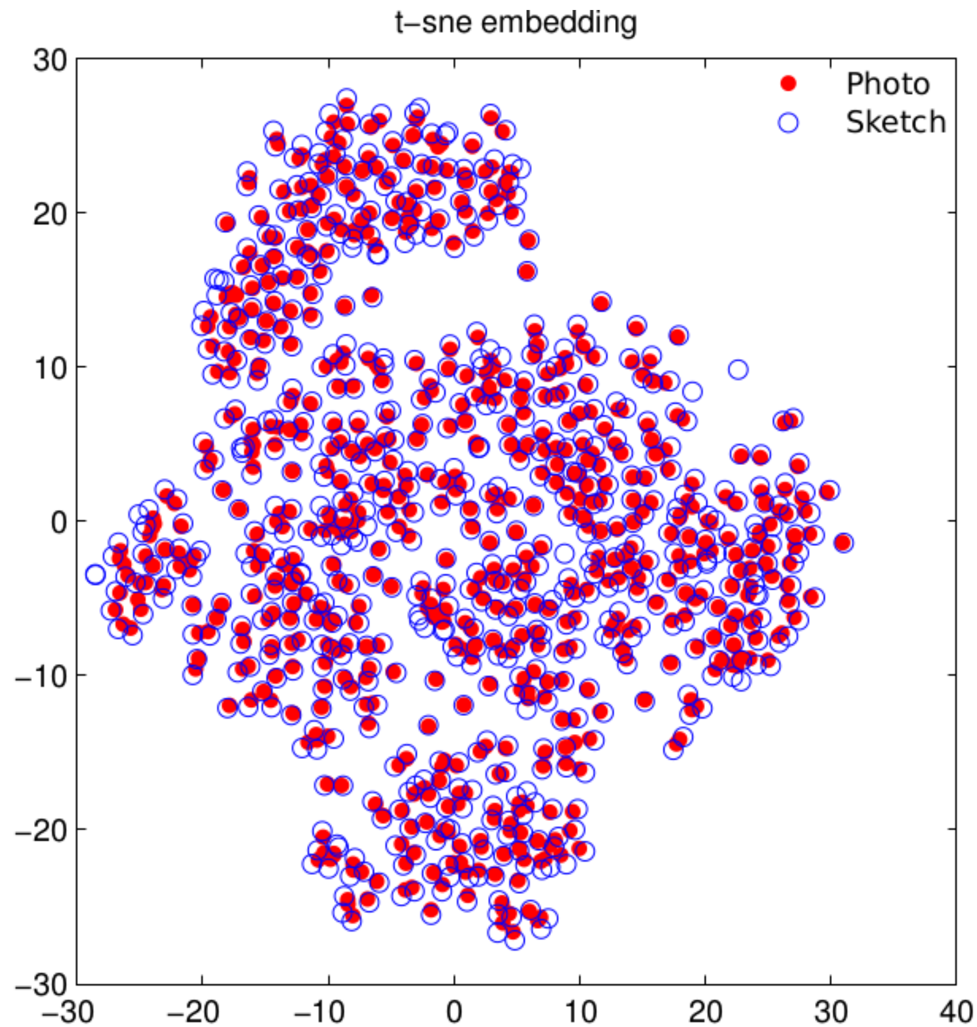
- Visualization of domain adaptation. [25]



A: Sketch. B: Photo. C: Original sketch HOG. D: Photo HOG. E: Transformed sketch HOG.

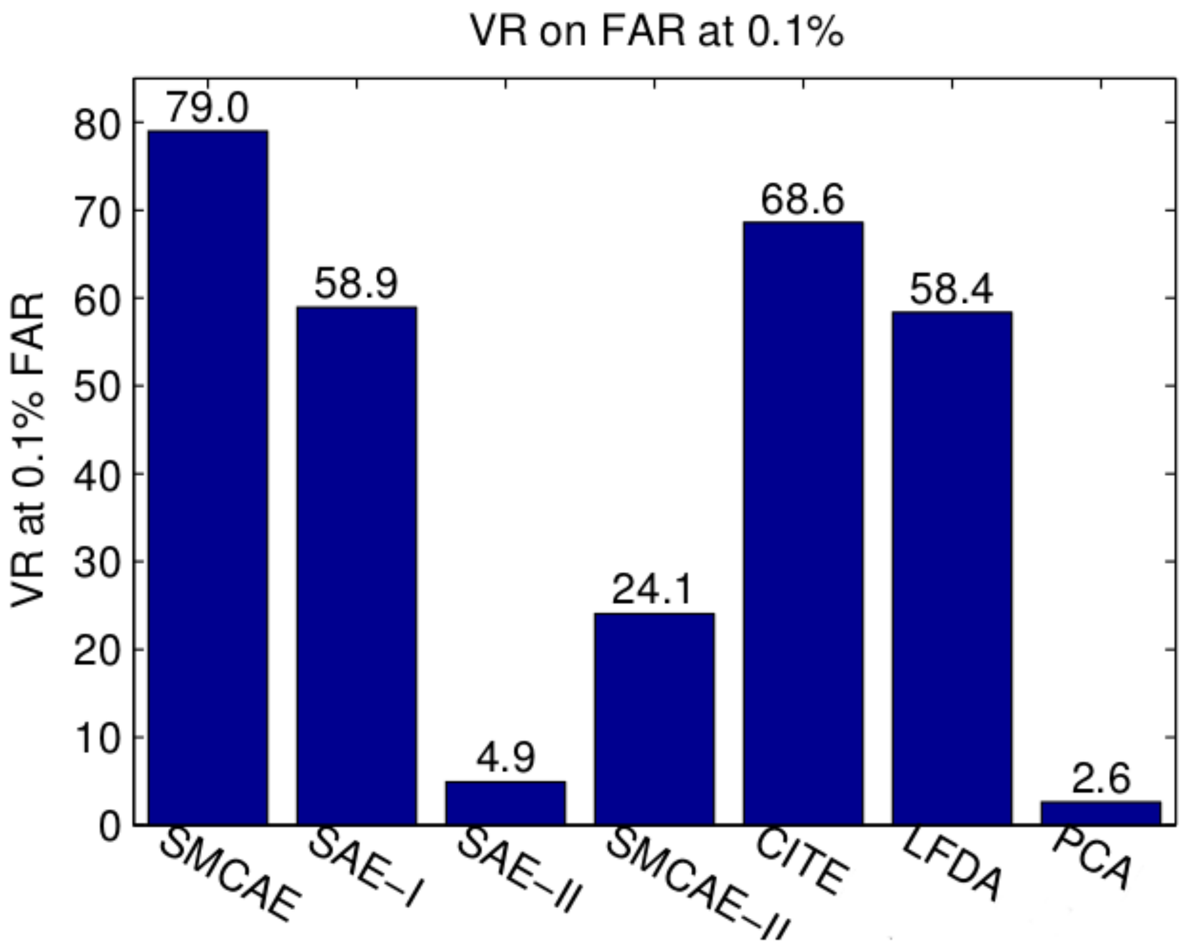


Original



Transformed

❖ Classification results



Results are evaluated on CUFSF data from [119]

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- **Data synthesis in feature space.**
- Conclusion.

Uneven distribution of data in classification

With uneven data distribution in classification problem, it usually require imbalanced data has an ability to compromise the performance of classification algorithm.

- ❖ It is hard to detect patterns, regularities within a minority class
- ❖ The general bias used in many classification algorithm make it hard to learn from the minority class.
- ❖ Noise impacts more to the minority class.

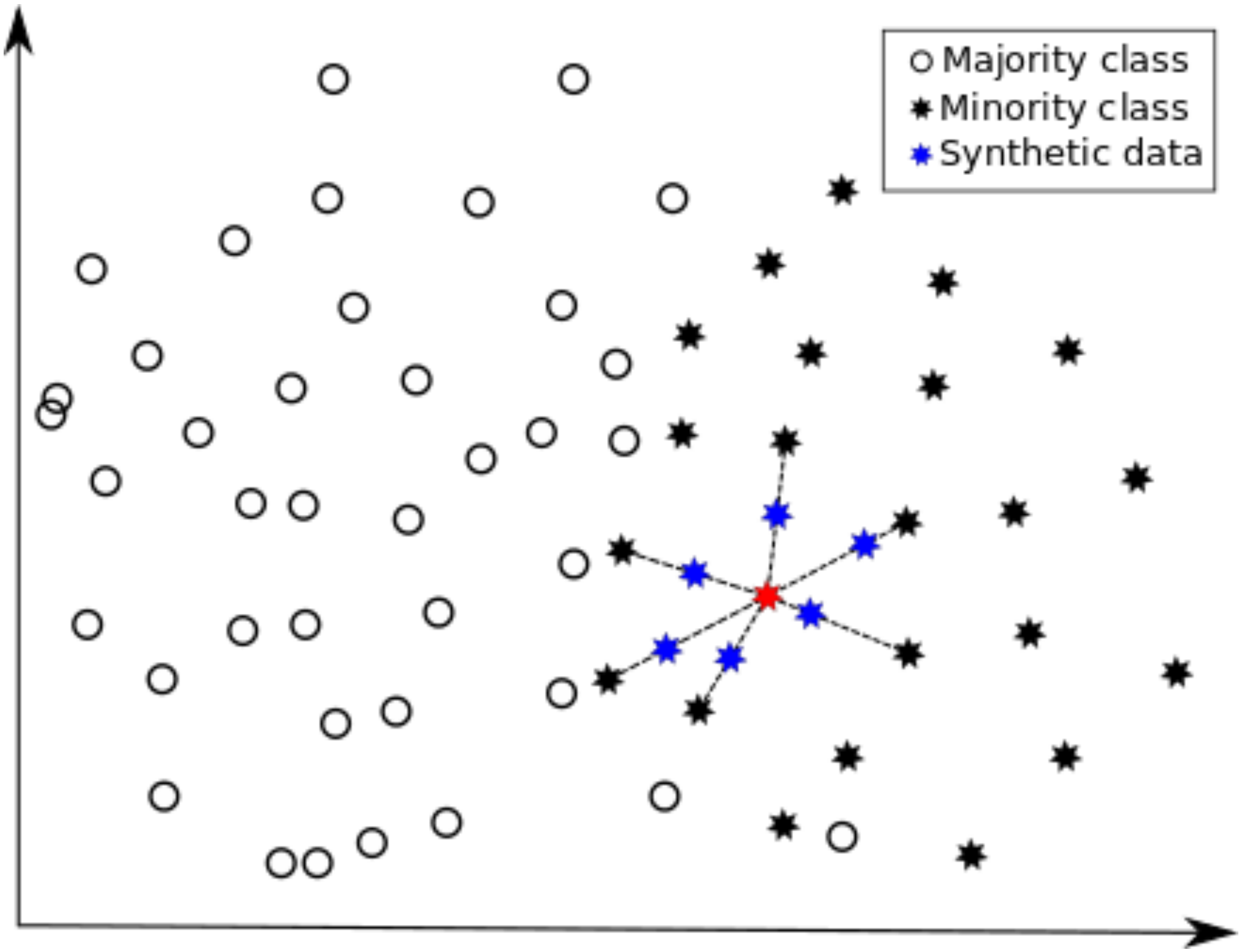
Solving uneven data distribution through data synthesis in feature space.

Existing work:

There are primarily three groups of methods that can solve imbalanced learning problems [19].

- Cost sensitive methods.
- Kernel methods.
- Sampling methods. ★

SMOTE [4] and its variants [2][7][17][18] etc.



The proposed approach – CGMOS [27]

What is CGMOS

- CGMOS is an oversampling technique that uses the same framework proposed by SMOTE.

- CGMOS can synthesize new samples that will improve the overall *certainty* of the entire dataset in classification.

- CGMOS is theoretically proved to work better than SMOTE during training when using Bayesian classification.

Definition of certainty

Given Bayes rule in a binary classification problem:

$$P(l|x_j) = \frac{P(x_j|l)P(l)}{P(x_j)}; \quad l \in \{l_{\text{mjr}}, l_{\text{mnr}}\}$$

For a data sample (x_j, y_j) representing features and class label. The certainty for this sample in the majority and minority class are respectively defined as:

$$C(y_j = l_{\text{mjr}}|x_j) = P(y_j = l_{\text{mjr}}|x_j)$$

$$C(y_j = l_{\text{mnr}}|x_j) = P(y_j = l_{\text{mnr}}|x_j)$$

Relative Certainty Change

- The weight $W(x_i)$ is computed as a *relative certainty change* comparing the certainty before and after a new sample is added.
- Given relative certainty change for sample (x_j, y_j) by adding a new sample at location x_i the relative certainty change is defined as:

$$R_{+i}(y_j|x_j) = \frac{C_{+i}(y_j|x_j) - C(y_j|x_j)}{C(y_j|x_j)}$$

Weight computation for seed selection

- The weight $W(x_i)$ is computed as a sum of *relative certainty change* from all samples in dataset if adding a new sample to x_i

- CGMOS selects a seed according to a weight $W(x_i)$ assigned to the seed.

Weight is computed as:

$$W(x_i) = 1 + \frac{1}{n}\sum_{j=1}^{n} R_{+i}(y_j|x_j)$$

Theoretical guarantee over SMOTE

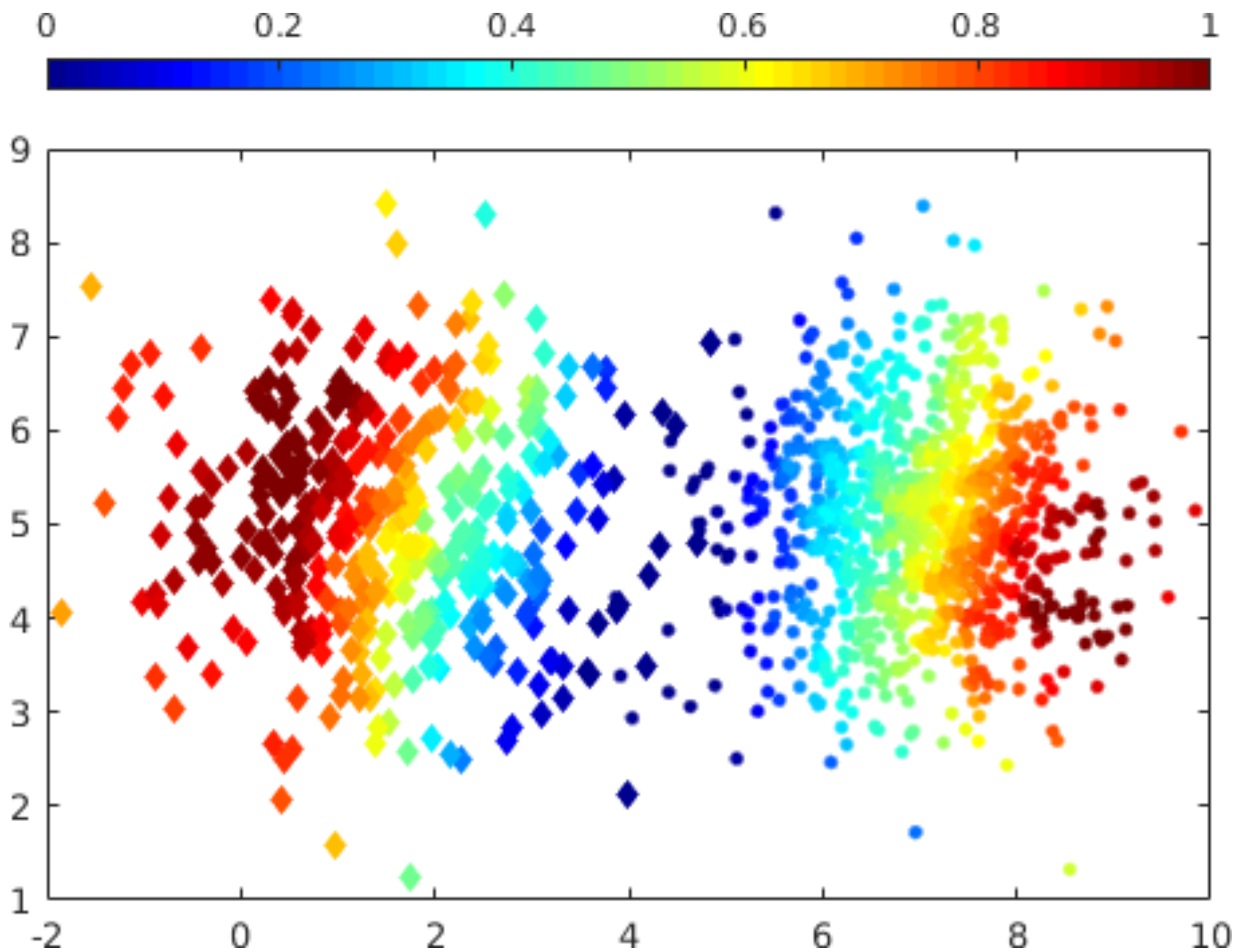
Definition (Average gain): The average gain when adding sample x_i is defined by:

$$\bar{r}_{+i} = \frac{1}{n}\sum_{j=1}^{n} r_{+i}(y_j|x_j)$$

where

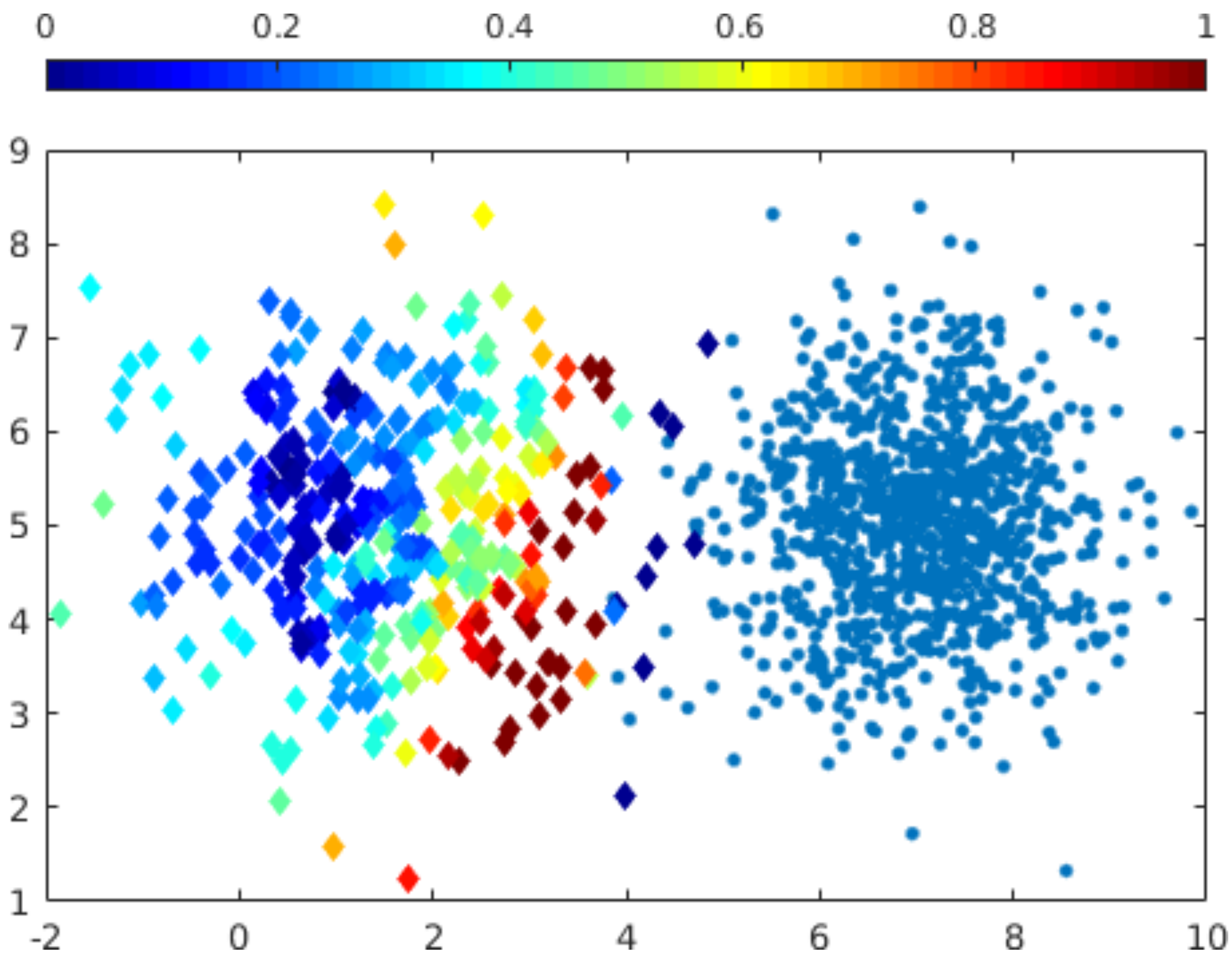
$$r_{+i}(y_j|x_j) = 1 + R_{+i}(y_j|x_j).$$

Theorem: *The expected average gain in CGMOS is higher or equal to that of SMOTE.*



Certainty

Left: Minority class, Right: Majority class



Relative certainty change

Left: Minority class, Right: Majority class

Results

Datasets: 30 datasets downloaded from UC Irvine machine learning repository corresponding to existing evaluations [160].

Compared approaches: No addition, Duplication, SMOTE [35], Boarderline-SMOTE [36], ADASYN [37], MWMOTE [156], and RAMOBoost [154].

Classifiers: Bayes with KDE, K nearest neighbors, Adaboost.M1, SVM, Neural networks, Random forest according to existing evaluations.

	CGMOS	Original	Dup	SMOTE	B-SMOTE	MWMOTE	ADASYN	RAMOboost
BankMarket	**0.728**	0.661	0.708	0.718	0.710	0.721	0.710	0.723
BloodService	**0.733**	0.653	0.648	0.649	0.651	0.720	0.714	0.728
BreastCancer	0.992	0.992	**0.993**	0.992	0.989	0.991	0.991	0.992
BreastTissue	**0.984**	0.899	0.946	0.932	0.917	0.937	0.908	0.943
CarEvaluation	**0.997**	0.995	0.845	**0.997**	0.994	0.996	**0.997**	0.995
Card'graphy	**0.977**	0.976	0.939	0.962	0.956	0.925	0.957	0.960
CharacterTraj	0.985	0.962	0.717	0.985	0.978	0.981	**0.988**	0.909
Chess	**0.977**	0.974	0.959	0.973	**0.977**	0.974	0.975	0.959
ClimateSim	**0.908**	**0.908**	0.861	0.902	0.863	0.901	0.901	0.882
Contraceptive	**0.724**	0.705	0.699	0.712	0.702	0.705	0.702	0.705
Fertility	**0.673**	0.615	0.594	0.634	0.592	0.604	0.639	0.638
Haberman	**0.651**	0.623	0.577	0.600	0.593	0.594	0.587	0.586
ILPD	0.707	0.687	0.693	**0.715**	0.703	0.702	0.693	0.703
ImgSeg	**0.999**	0.998	**0.999**	0.997	0.998	0.998	0.997	0.998
Leaf	**0.908**	0.880	0.782	0.852	0.775	0.836	0.839	0.821
Libras	**0.945**	0.922	0.859	0.929	0.886	0.936	0.923	0.883
MultipleFs	**0.998**	**0.998**	0.997	**0.998**	0.997	0.997	0.996	0.997
Parkinson	0.841	0.676	0.692	0.834	0.791	0.837	**0.842**	0.760
PlanRelax	0.472	0.457	0.494	0.469	0.445	0.467	**0.488**	0.464
QSAR	**0.901**	0.886	0.879	0.895	0.863	0.886	0.886	0.882
SPECT	**0.820**	0.772	0.803	0.808	0.811	0.752	0.801	0.799
SPECTF	0.819	0.819	0.800	0.805	0.816	0.812	**0.825**	0.795
SeismicBumps	**0.743**	0.735	0.712	0.727	0.740	0.732	0.715	0.691
Statlog	**0.998**	0.992	0.996	**0.998**	0.990	0.996	0.976	0.996
PlatesFaults	**0.956**	0.928	0.844	0.954	0.920	0.943	**0.956**	0.881
TAEvaluation	**0.748**	0.682	0.644	0.703	0.671	0.707	0.665	0.657
UserKnowledge	**0.958**	0.837	0.919	0.953	0.947	0.951	0.950	0.888
Vertebral	**0.890**	0.839	0.869	0.855	0.829	0.860	0.794	0.872
Customers	**0.952**	0.930	0.943	0.946	0.884	0.902	0.946	**0.952**
Yeast	**0.925**	0.792	0.844	0.907	0.898	0.900	0.906	0.851
Average	**0.864**	0.827	0.808	0.844	0.830	0.842	0.842	0.830

- Motivations and Importance of the problem.
- Introduction and novel contributions.
- Data synthesis in data space.
- Learning from synthetic data.
- Eliminating synthetic gap.
- Data synthesis in feature space.
- **Conclusion.**

Conclusion

Goals:

Use data synthesis techniques to

- Boost performance of object recognition.
- Ease ground truth labeling process.

Novel contributions:

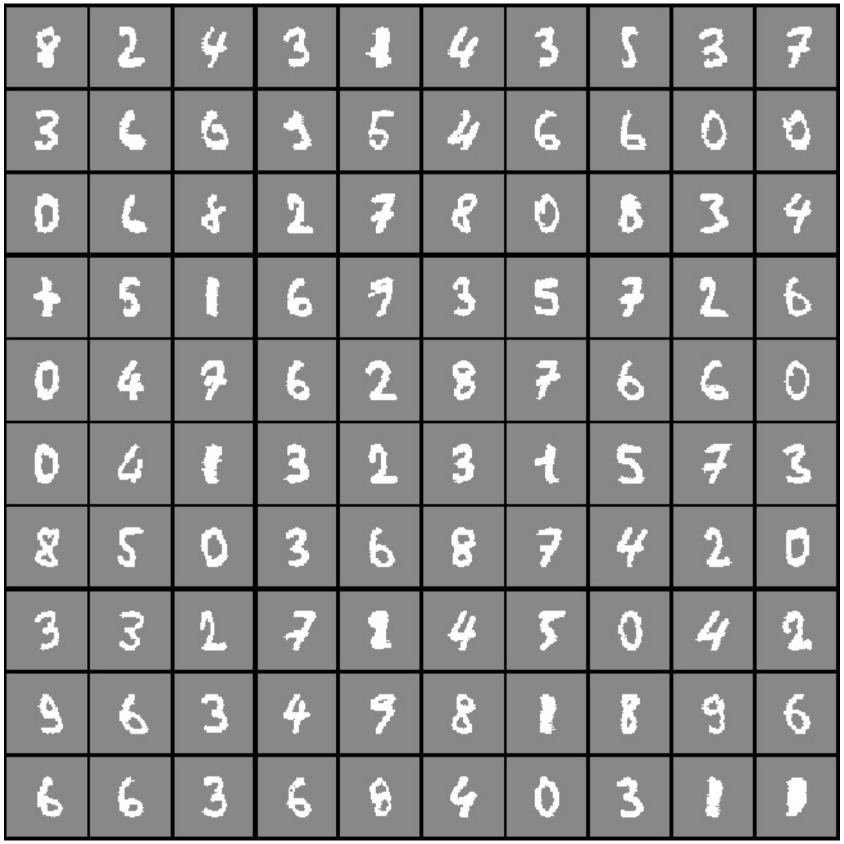
- Data synthesis in data space.
- Features to learn from synthetic data
- Eliminating synthetic gap.
- Data synthesis in feature space.

Future works:

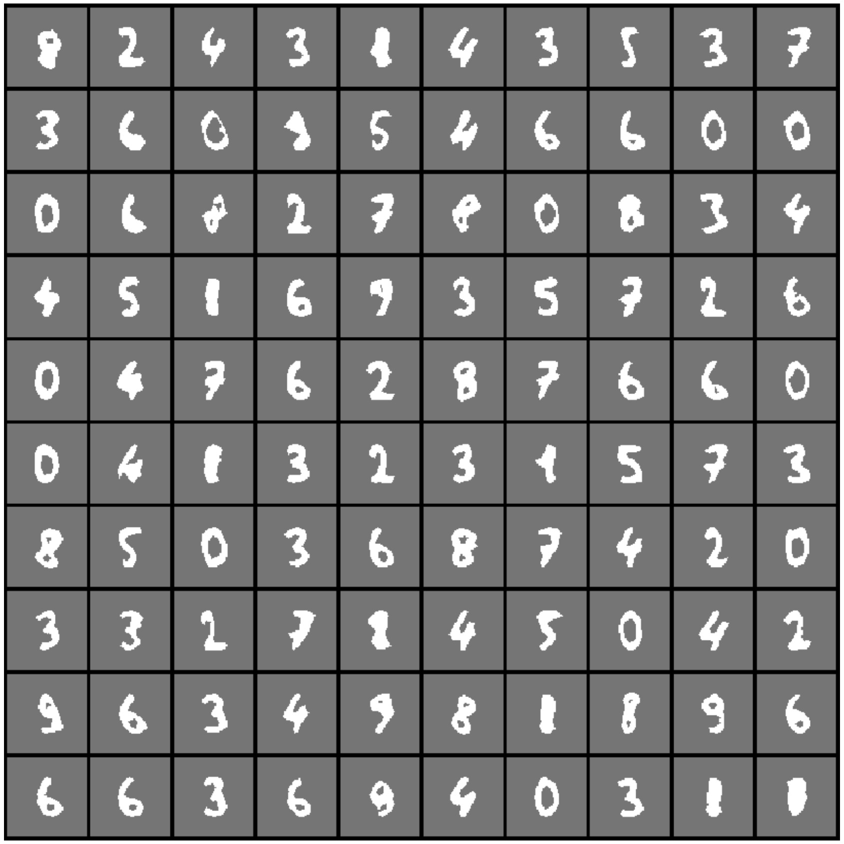
- Deep learning based data synthesis.
- Automatically synthesize more complicated data such as video, 3D object, etc..

Thank you very much

Questions and Comments?



Real Data



Synthesized Data

- Roof style classification results compared to unsupervised approaches.

	Chicago						San Francisco					
	Precision			Recall			Precision			Recall		
	GMM	KM	Ours	GMM	KM	Ours	GMM	KM	Ours	GMM	KM	Ours
FLAT	0.87	0.85	0.92	0.88	0.90	0.90	0.88	0.88	0.86	0.93	0.93	0.93
SHED	0.94	0.94	0.91	0.57	0.64	0.78	0.87	0.91	1.00	0.43	0.68	0.68
GABLE	0.62	0.67	0.71	0.86	0.84	0.88	0.57	0.61	0.65	0.71	0.69	0.77
HIP	0.65	0.63	0.63	0.16	0.36	0.37	0.55	0.61	0.70	0.22	0.28	0.31
HEX	0.87	0.86	0.93	0.87	0.81	0.90	0.90	0.80	0.92	0.83	0.66	1.00
PYRAMID	0.83	0.66	1.00	0.20	0.16	0.37	0.87	0.83	1.00	0.87	0.93	1.00
MANSARD	1.00	0.75	1.00	0.25	0.18	0.31	0.50	0.66	1.00	0.05	0.11	0.41
CURVED	1.00	0.93	1.00	0.87	0.93	1.00	0.71	0.70	0.74	0.77	0.71	0.79
UNKNOWN	0.84	0.85	0.97	0.88	0.85	0.90	0.62	0.59	0.66	0.63	0.64	0.66
Average	0.85	0.79	0.89	0.62	0.63	0.71	0.72	0.73	0.84	0.60	0.63	0.73

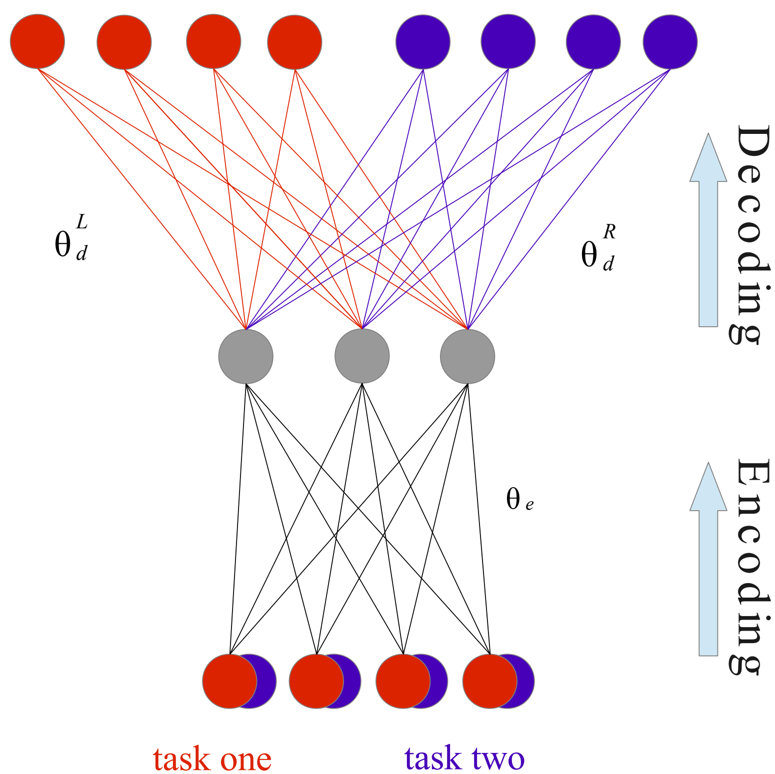
❖ Results

	Chairs	KITTI	SC occ	SC noc	SF occ	SF noc	Time (sec)
Epicflow †[87]	2.94	1.52	4.12	1.36	6.29	3.06	16
Deepflow † [88]	3.53	1.53	5.38	1.77	7.21	3.34	17
FlowNetS (C+S)*[2]	3.04	5.23	6.96	N.A.	7.76	N.A.	0.08
DSTFlow [77]	5.11	4.02	10.40	5.20	11.11	5.92	0.1
NoMask	5.03	4.11	10.78	6.22	12.32	6.03	0.1
Proposed	4.53	3.67	9.56	4.89	10.21	4.84	0.17

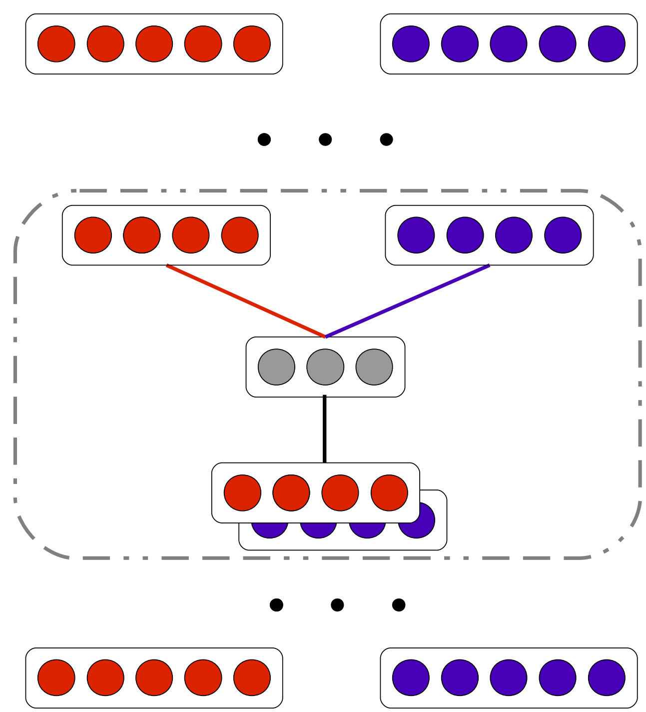
❖ Results

	Train	Fine Tune	Test	EPE
Exp. 1 (sup)	KITTI w. labels	N.A.	KITTI test set	5.23
Exp. 2 (sup)	Chairs w. labels	KITTI w. labels	KITTI test set	4.43
Exp. 3 (sup)	Chairs w. labels + KITTI w. labels	N.A.	KITTI test set	4.69
Exp. 4 (unsup)	KITTI raw w/o. labels	N.A.	KITTI test set	3.67
Exp. 5 (sup)	Chairs w. labels + KITTI w. predicted labels	N.A.	KITTI test set	2.21
Exp. 6 (sup)	Chairs w. labels + KITTI w. predicted labels	KITTI w. labels	KITTI test set	2.28
Exp. 7 (sup)	Chair w. labels + KITTI w. predicted labels + KITTI w. labels	N.A.	KITTI test set	2.31

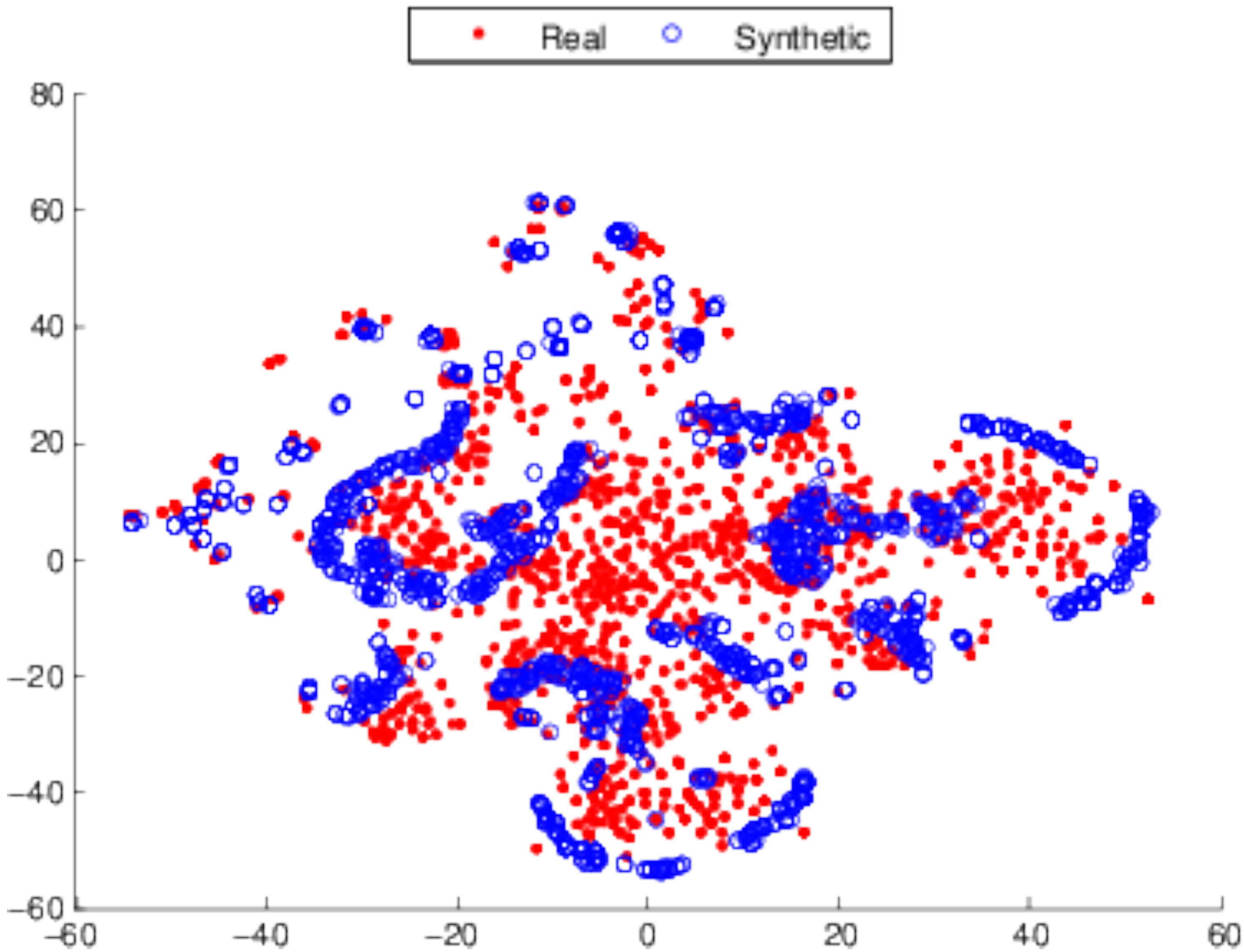
The proposed MCAE



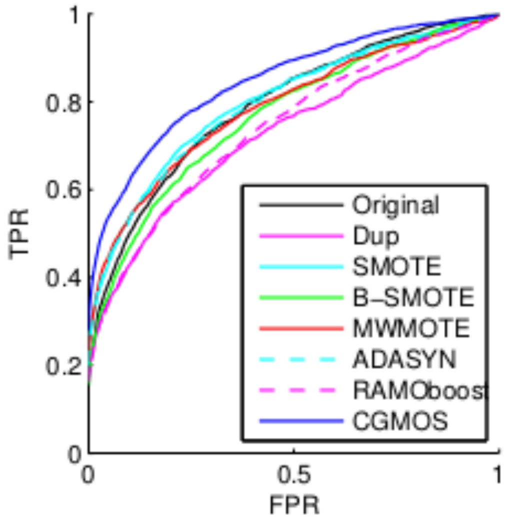
Basic structure



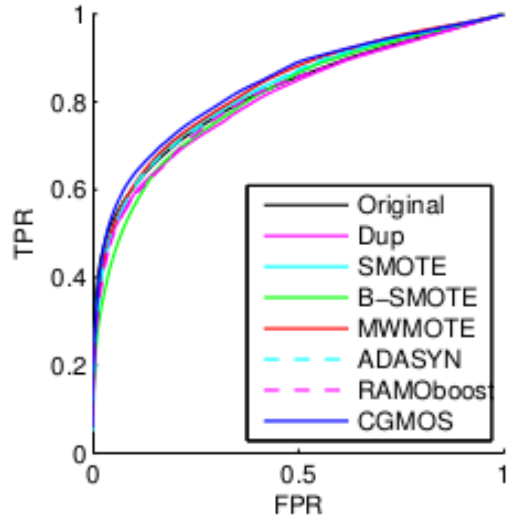
Stacked up


Real
Synthetic
80
60
40
20
0
−20
−40
−60
−60
−40
−20
0
20
40
60

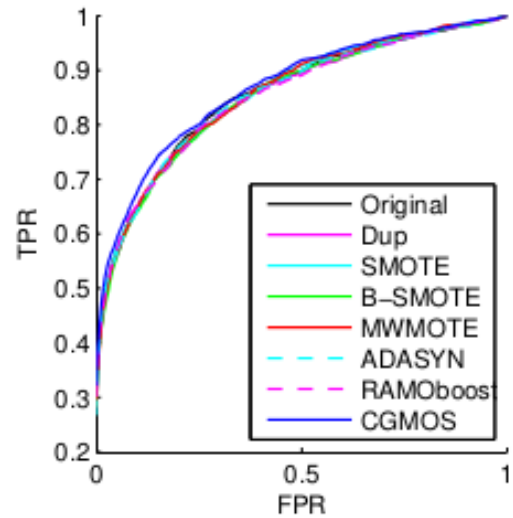
ROC curves



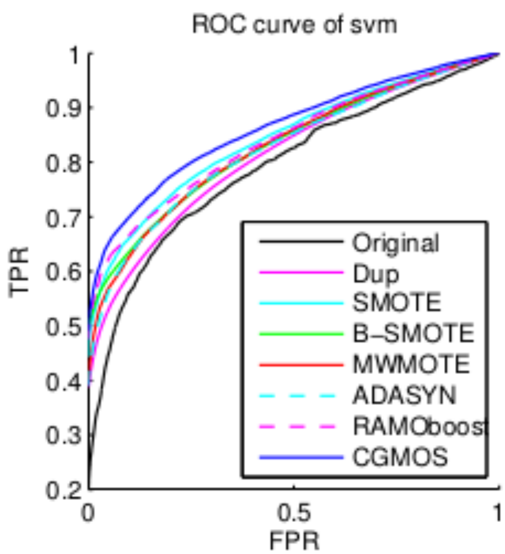
b-kde



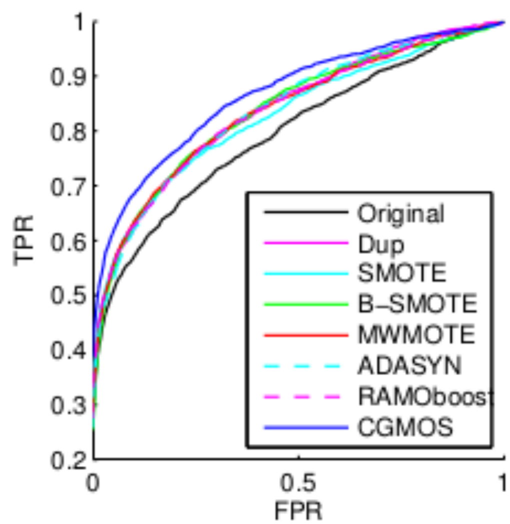
knn



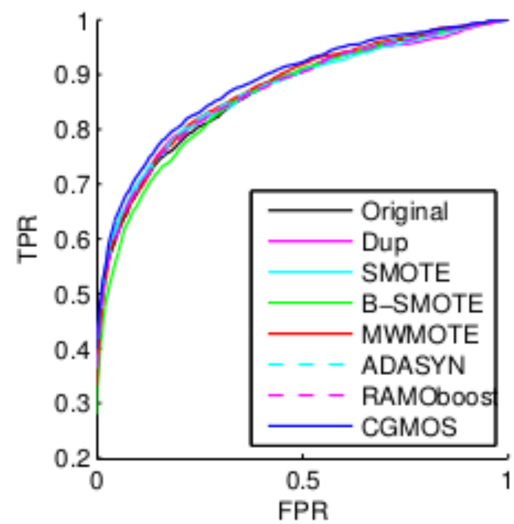
Adaboost.M1



svm



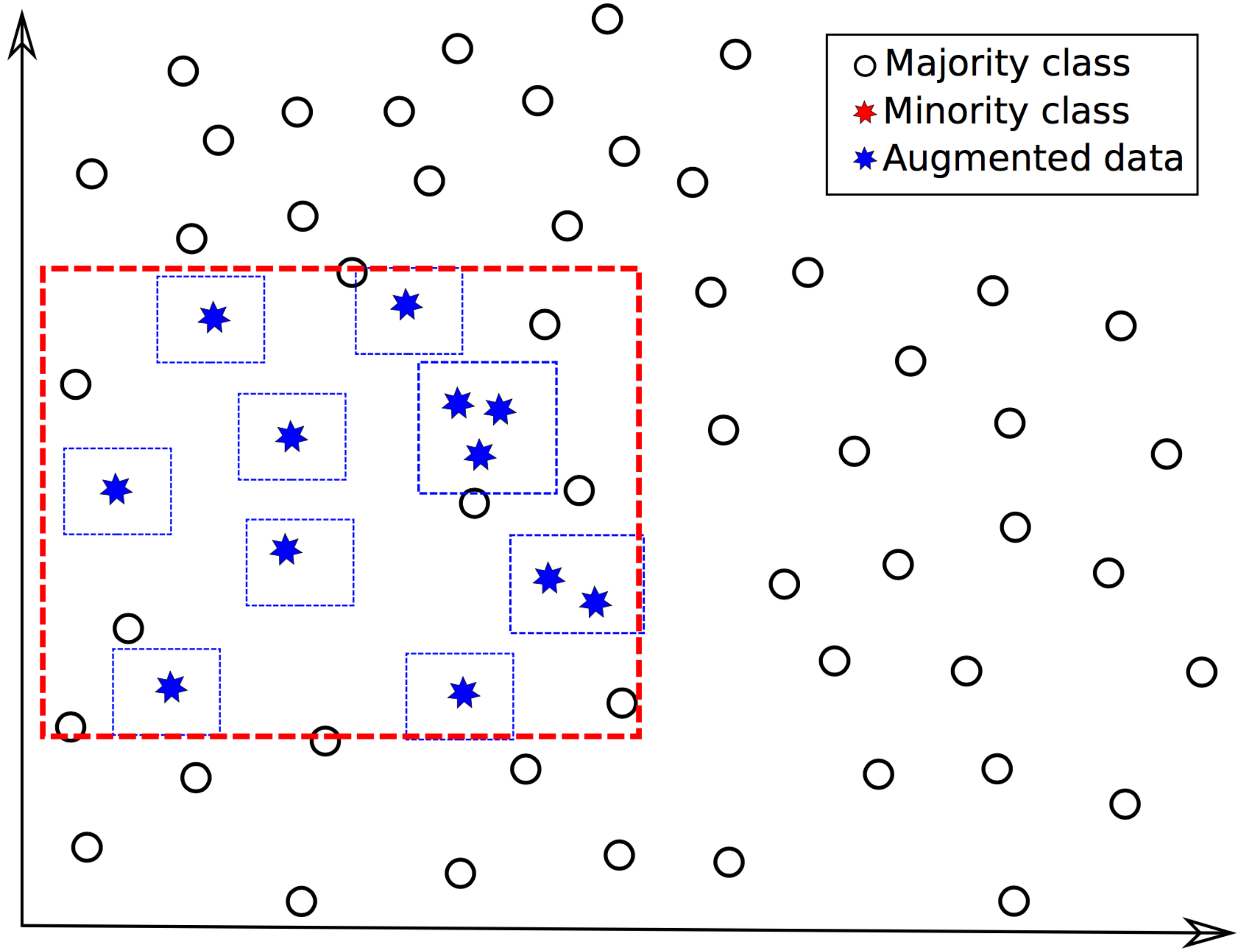
nn



rf

Existing sampling methods

1) Creating identical samples.



Statistical significance analysis

Given the significance level as 5%, we compute the p-values of statistical significance tests of classification results using CGMOS against the compared methods:

	Knn	Rf	B-kde	Nn	Svm	Boost
Original	5e-5	1e-4	0.004	1e-4	0.026	0.04
Dup	2e-6	5e-5	3e-6	0.03	0.049	0.004
SMOTE	0.003	2e-4	6e-6	0.018	0.006	0.046
B-SMOTE	4e-6	7e-6	2e-5	5e-4	0.047	5e-4
MWMOTE	0.046	4e-5	1e-5	0.003	0.005	0.007
ADASYN	8e-6	7e-5	9e-5	0.005	1e-4	0.003
RAMOboost	2e-6	5e-5	3e-6	0.001	0.045	0.035

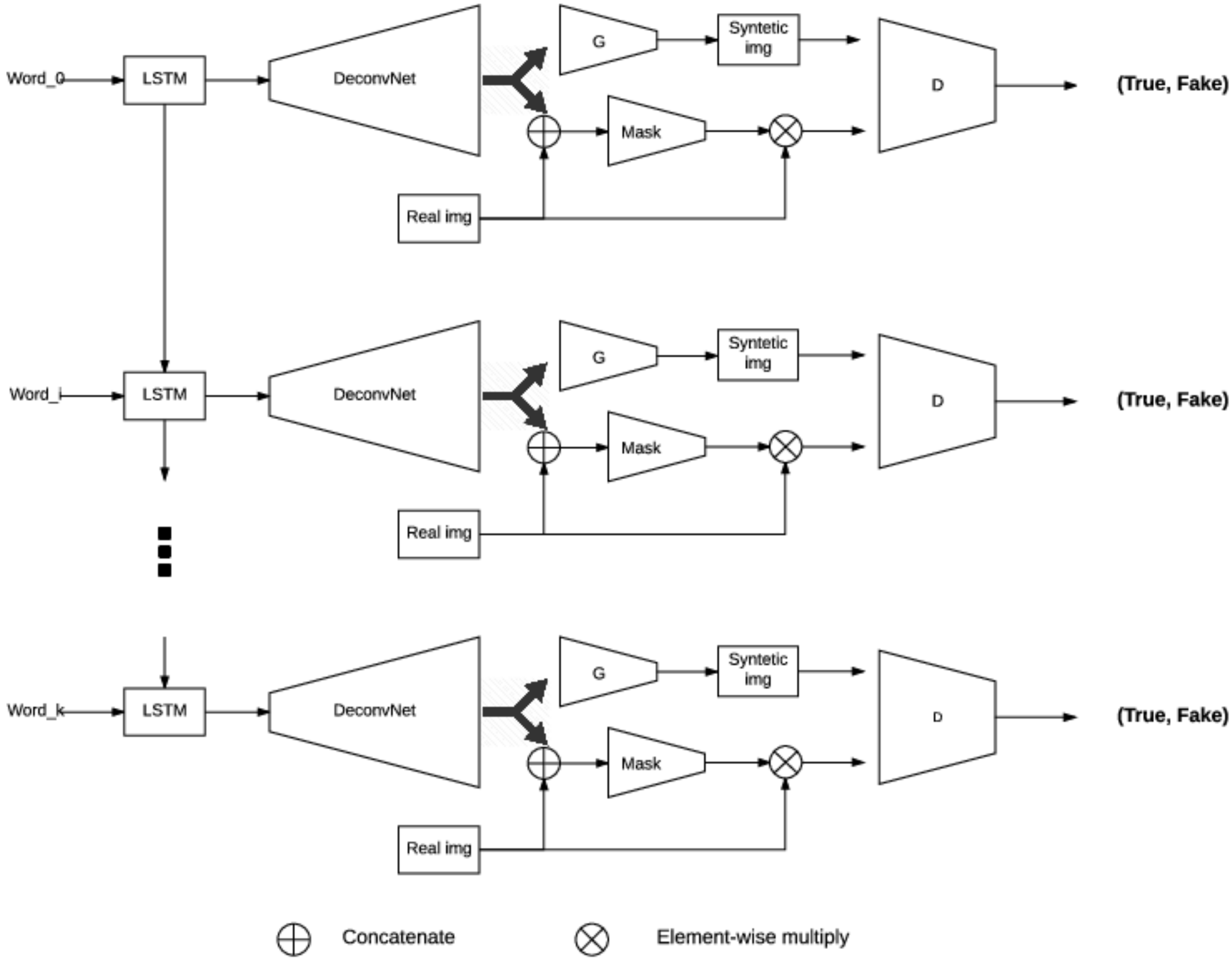
CGMOS is statistical significantly better then the compared methods regardless of classifiers selected.

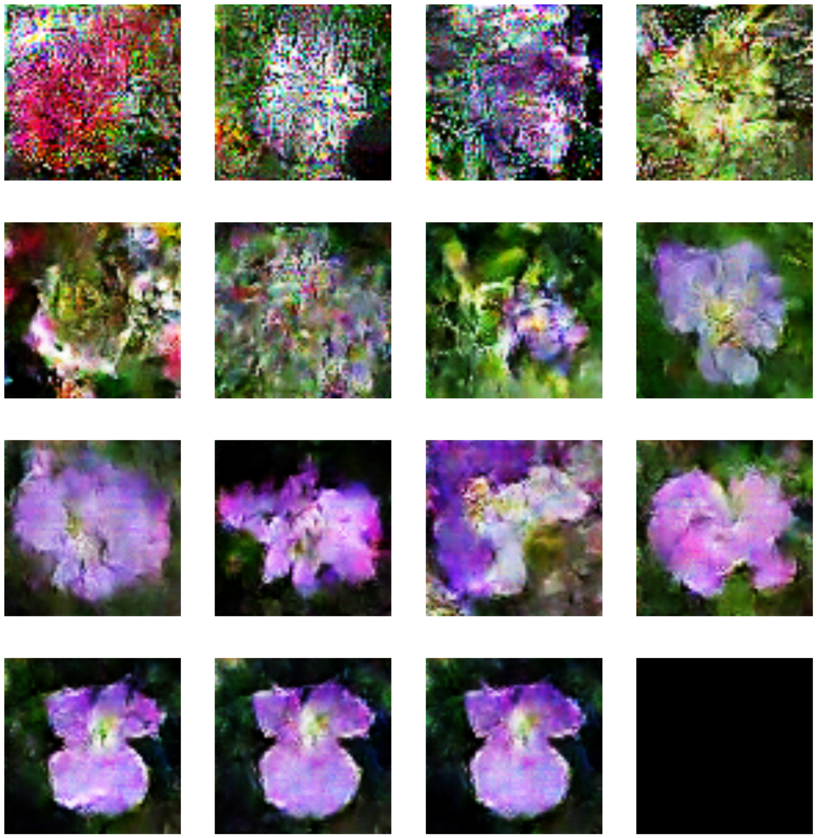
Text to image synthesis [22]

2.4.3.1 GAN. Generative adversarial networks are composed of a generator G and discriminator D, which are co-trained in a competitive manner. D learns to discriminate real images from fake ones generated by G, while G learns to generate fake images from latent variables z and tries to fool D. In other words, G and D play the following two-player minimax game with value function $V(G, D)$:

$$\min_G \max_D V(D,G) = E_{x \sim p_{data}(x)}[\log D(x)] + E_{z \sim p_z(z)}[\log(1 - D(G(z)))] \quad (2.2)$$

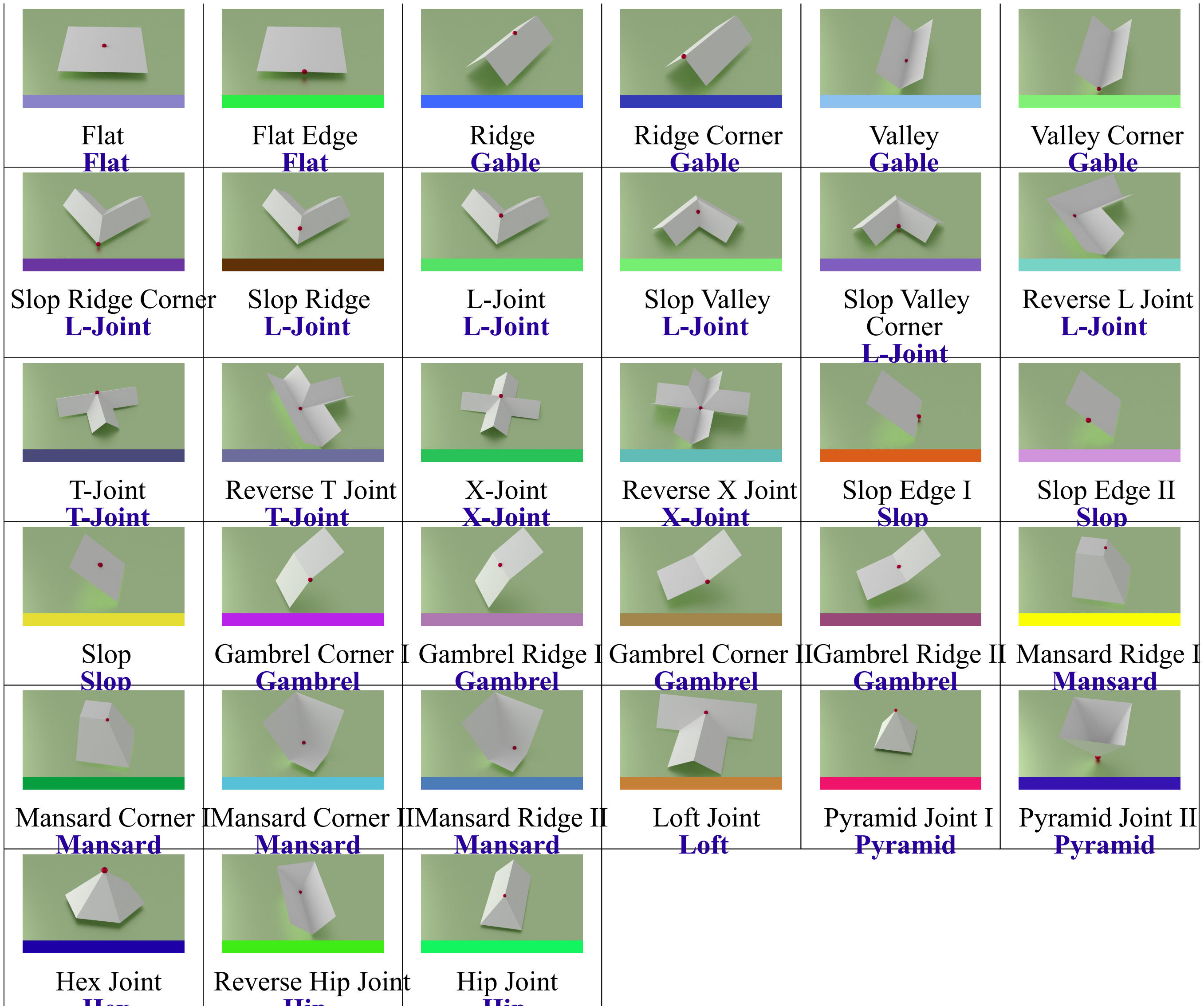
Text to image synthesis [22]



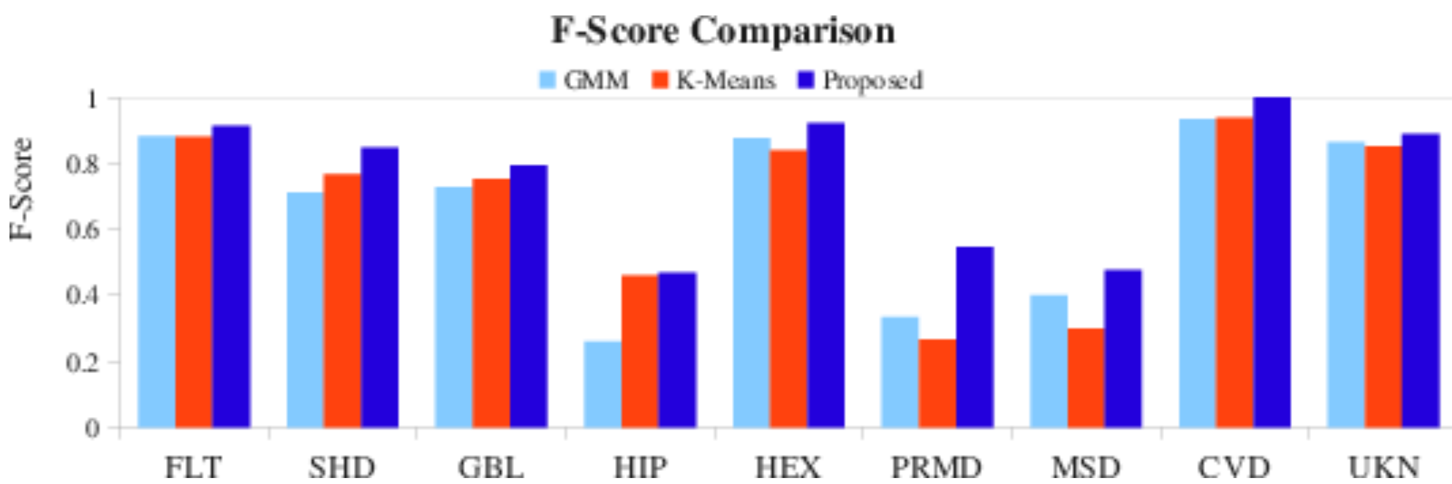


This flower has one large purple and white petal with one yellow and orange receptacle.

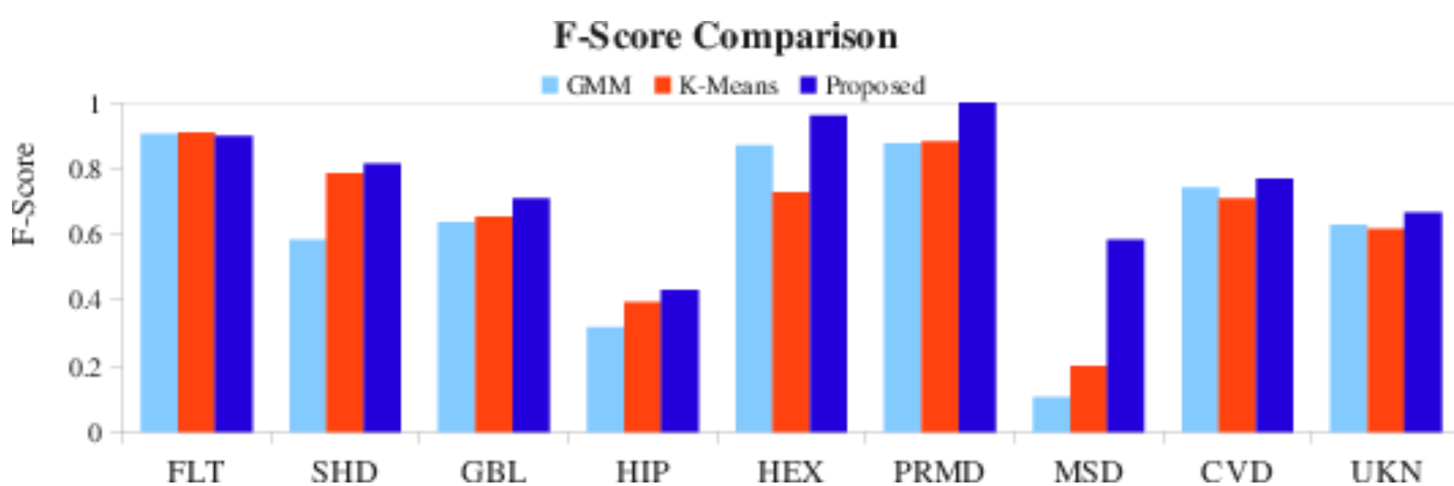
This flower has flat long and skinny yellow petals in one slightly upturned ring configuration.


Flat
Flat
Flat Edge
Flat
Ridge
Gable
Ridge Corner
Gable
Valley
Gable
Valley Corner
Gable
Slop Ridge Corner
L-Joint
Slop Ridge
L-Joint
L-Joint
L-Joint
Slop Valley
L-Joint
Slop Valley Corner
L-Joint
Reverse L Joint
L-Joint
T-Joint
T-Joint
Reverse T Joint
T-Joint
X-Joint
X-Joint
Reverse X Joint
X-Joint
Slop Edge I
Slop
Slop Edge II
Slop
Slop
Slop
Gambrel Corner I
Gambrel
Gambrel Ridge I
Gambrel
Gambrel Corner II
Gambrel
Gambrel Ridge II
Gambrel
Mansard Ridge I
Mansard
Mansard Corner I
Mansard
Mansard Corner II
Mansard
Mansard Ridge II
Mansard
Loft Joint
Loft
Pyramid Joint I
Pyramid
Pyramid Joint II
Pyramid
Hex Joint
Hex
Reverse Hip Joint
Hip
Hip Joint
Hip

- Boost recognition rate by adding synthetic data.



Chicago



San Francisco