Data Synthesis For Object Recognition

Xi Zhang

Advisor: Professor Agam

xzhang22@hawk.iit.edu

Computer Science Department

Illinois Institute of Technology

Overview

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

- Motivations and Importance of the problem.
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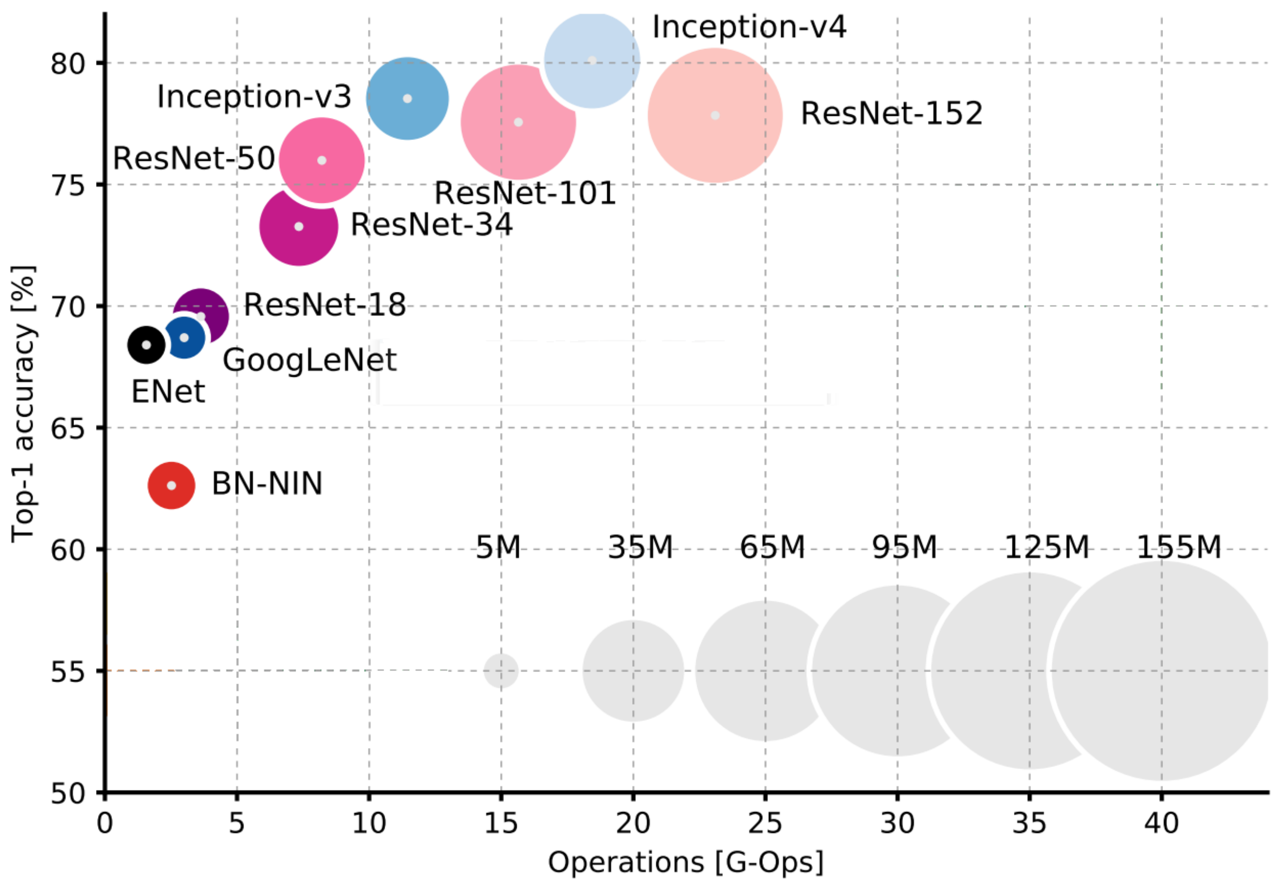
Motivation



Model complexity V.S. Accuracy

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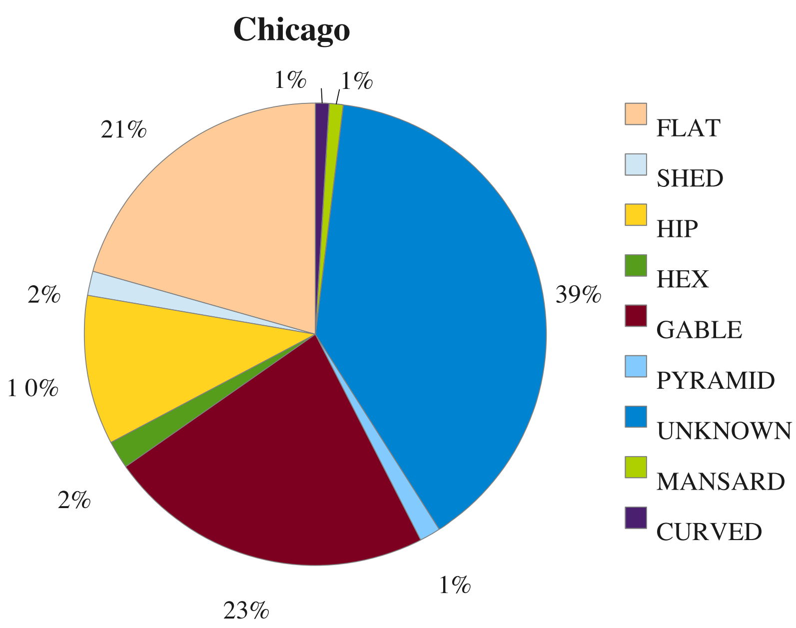
Fig cited from: A. Canziani etc. An analysis of deep neural network models for prectical applications, 2017

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

2) Supervised learning requires high quality labeled data.

- Time consuming, expensive.
- Sometimes, impossible

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2D optical flow

3D point cloud

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- Solution:

Data synthesis

- 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. Learning from synthetic data.
  3. Eliminating synthetic gap.
  4. Data synthesis in feature space.

- Motivations and Importance of the problem.
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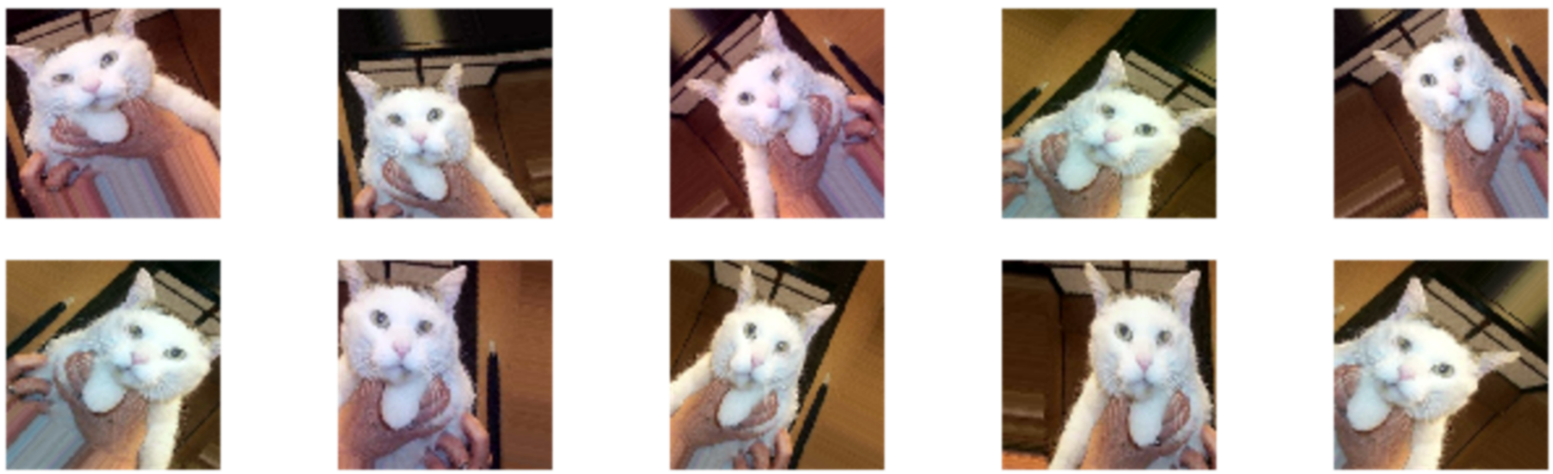
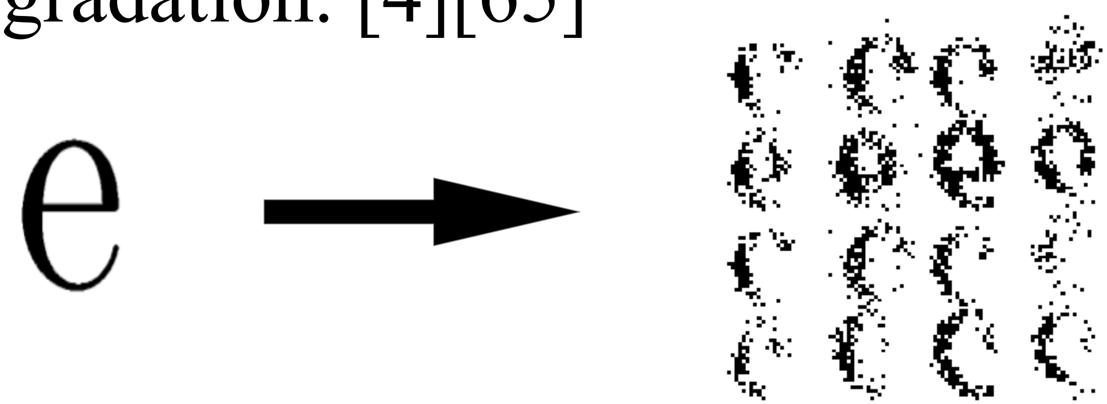
Introduction

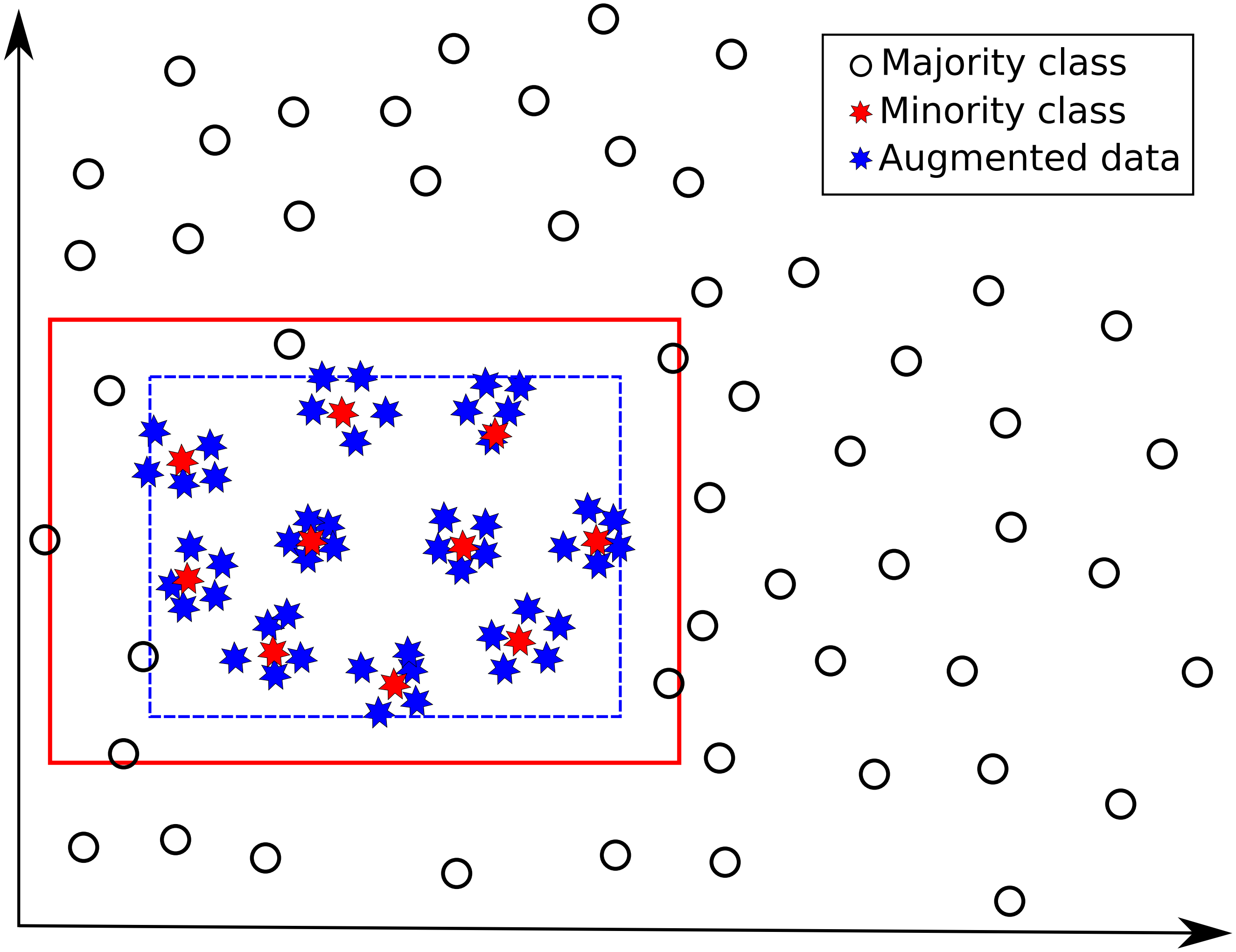
- Existing methods.
- Geometric transformation. [89][90]



- Image degradation. [4][65]



- Disadvantage of existing methods.



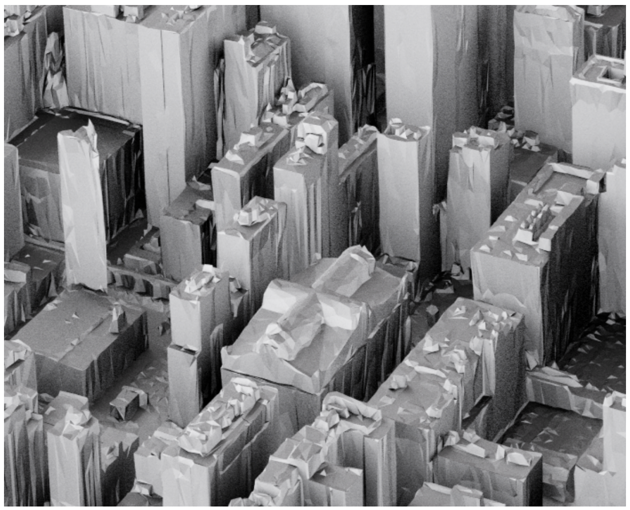
Overfitting

The Proposed Approach

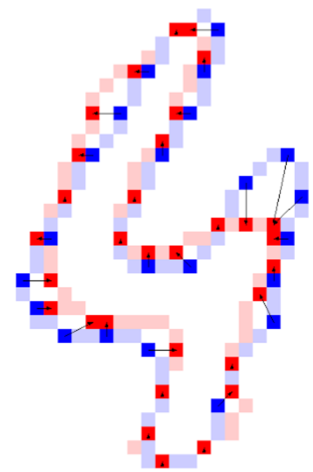
In contrast to existing methods, my approach:

1. Generate a conclusive templates from data.
2. Synthesizing data by inferring from unsupervised learning.

Examples of Using Template



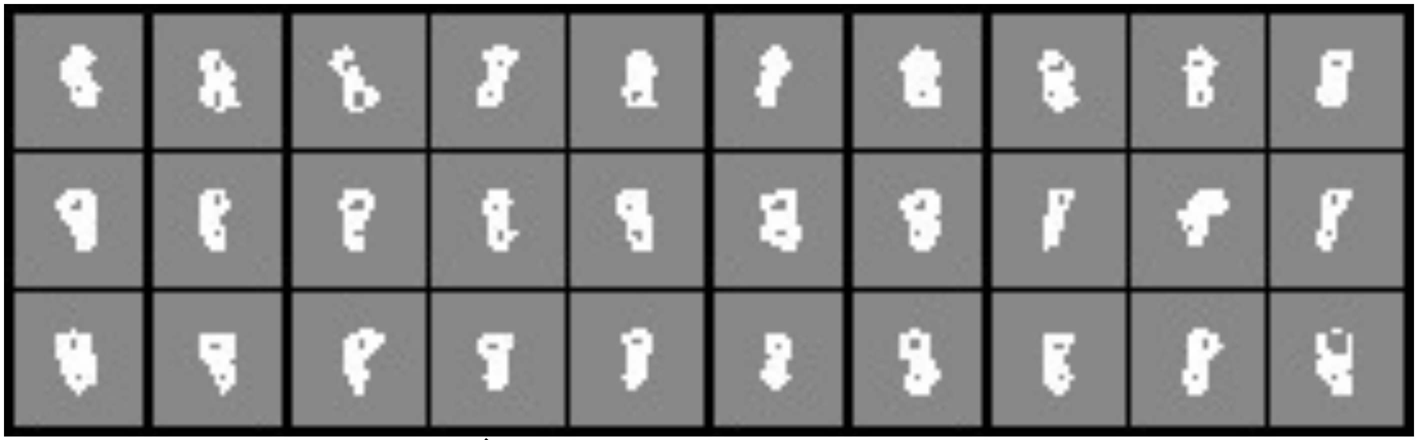
Aerial LiDAR roof style classification [106]

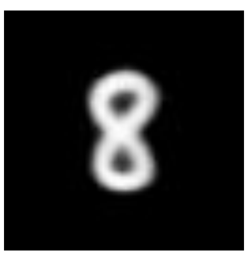


Handwritten digits recognition [105]

Showcase One – Digit Recognition

- Generate prototype by congealing.

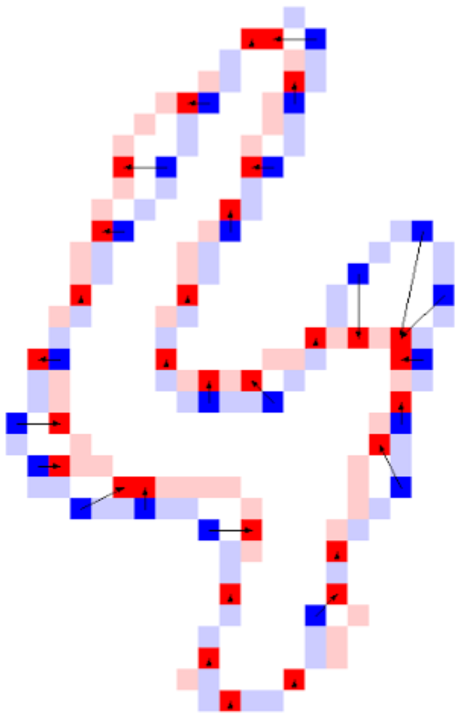




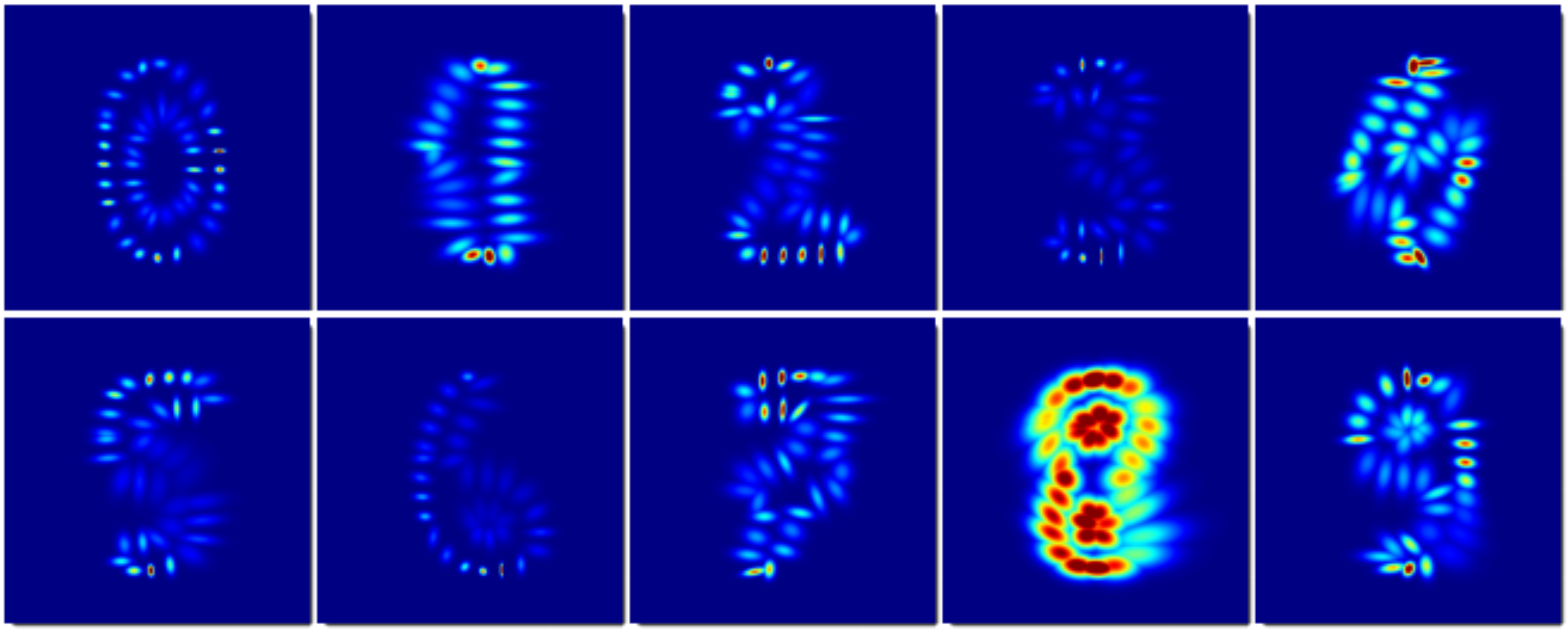
For N images $\{I_i\}_{i=1}^{N}$ with the same digit, solve for transformations $\{T_i\}_{i=1}^{N}$, that $\{T_i \cdot I_i\}_{i=1}^{N}$ minimize joint entropy

- Building correspondence among data.
- Set control points on prototype.

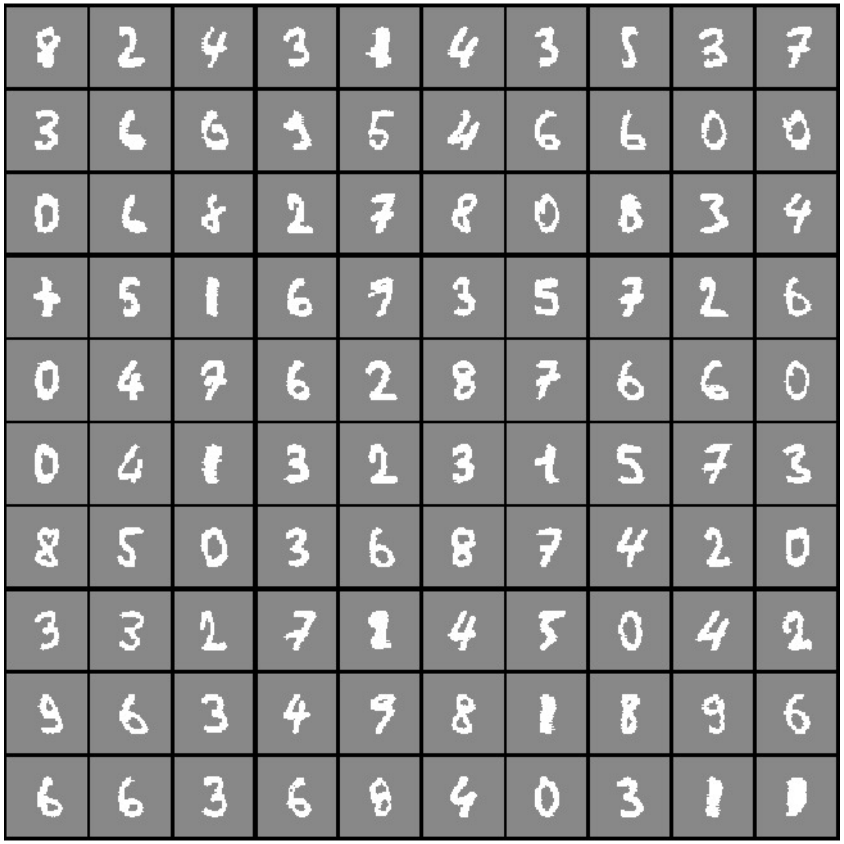
- Building correspondence among data.
- Set control points on prototype.
- Find corresponding control points on each data.



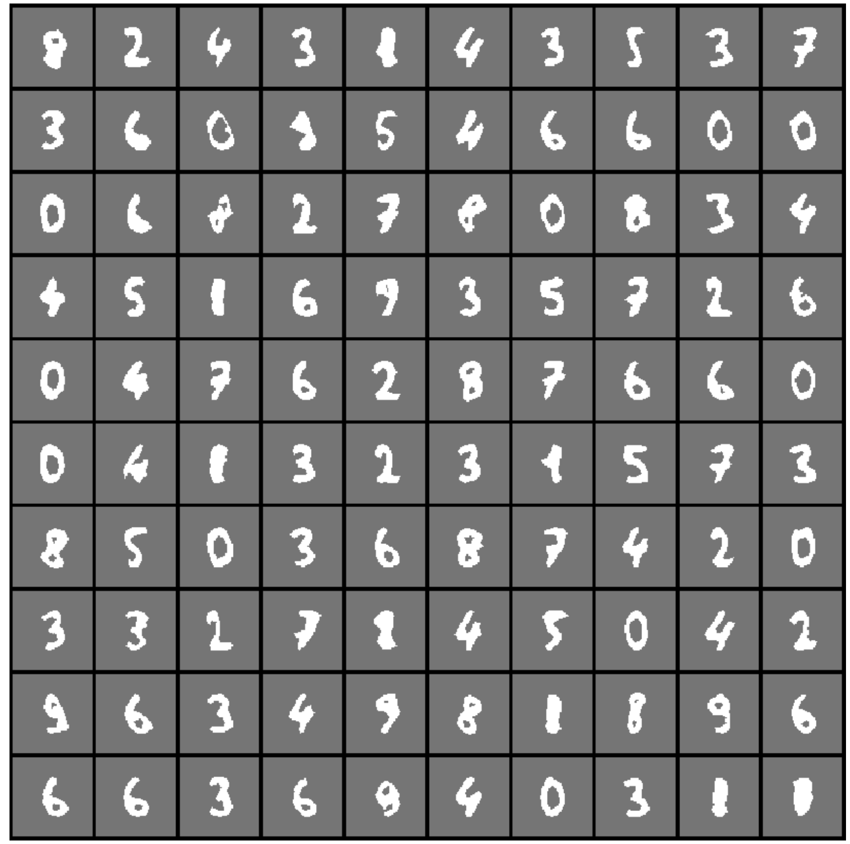
❖ Data synthesis by distribution of control points.



❖ Data synthesis by interpolation/extrapolation between nearest neighbors.



Real Data



Synthesized Data

- Boost the performance by adding synthetic data.

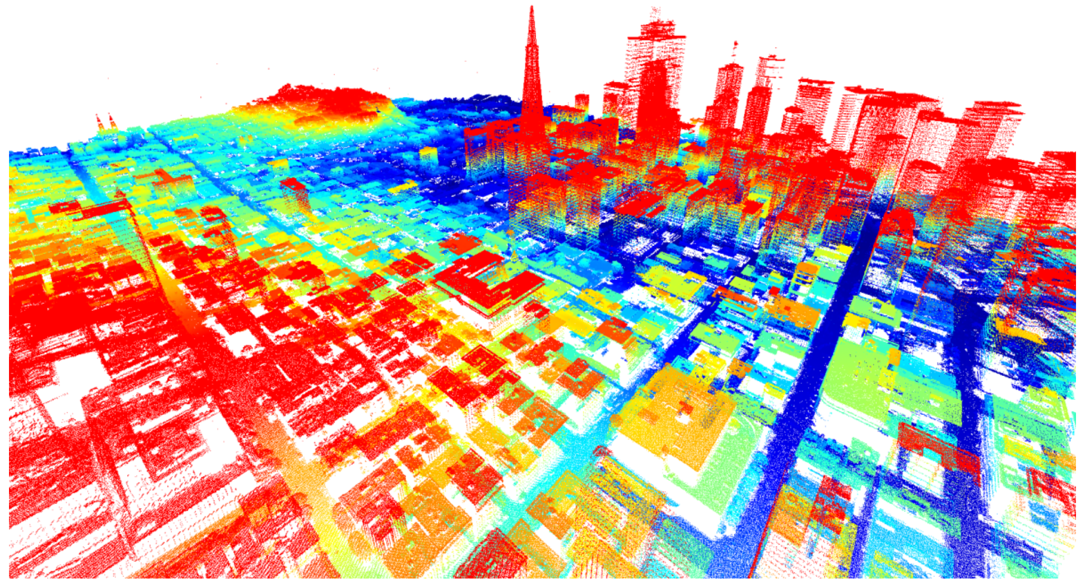
	Real	Syn	Real+Syn
CNN	0.65	0.68	0.70
SVM	0.77	0.78	0.80

F1 score of classification results

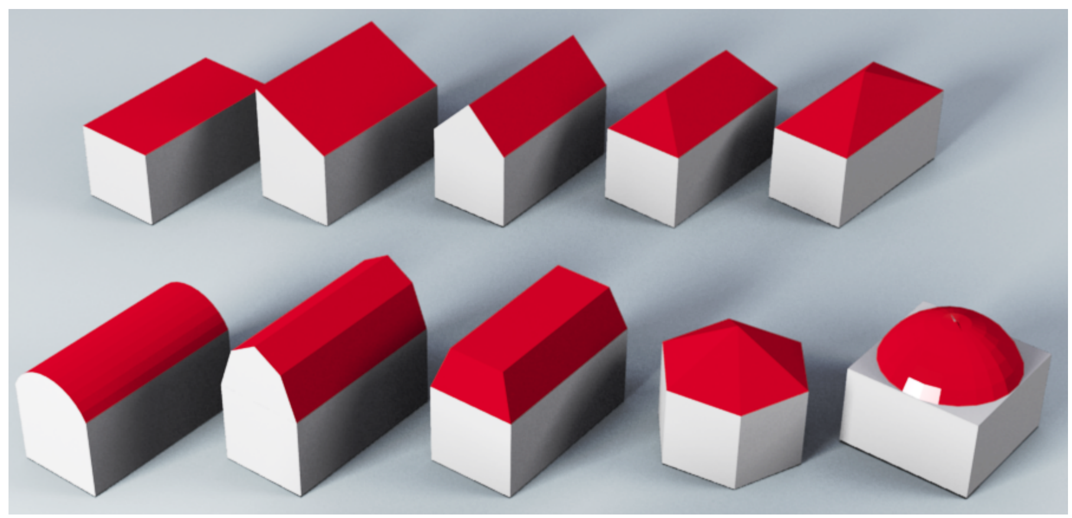
Showcase Two – Roof Recognition

Aerial LiDAR

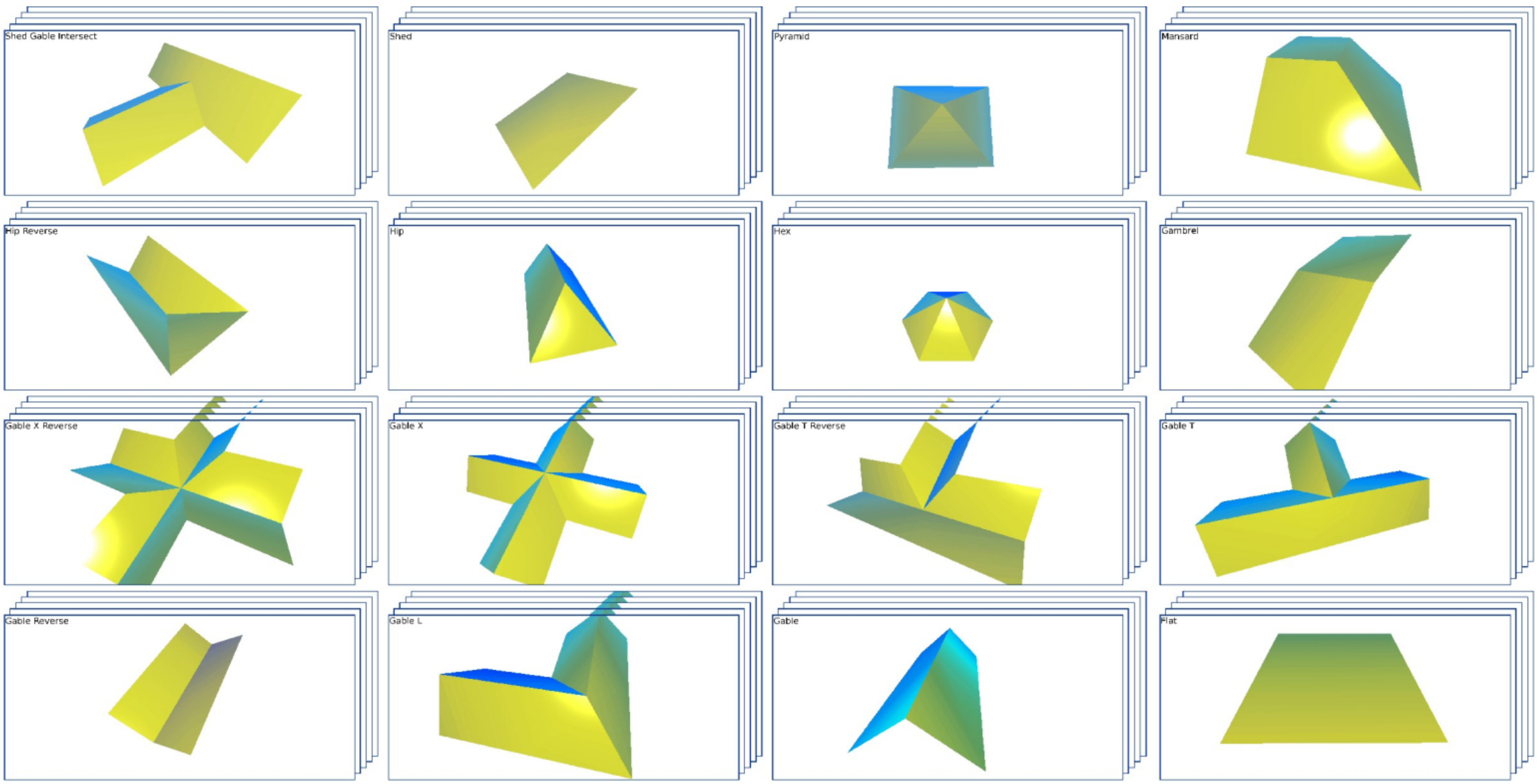
Downtown San Francisco



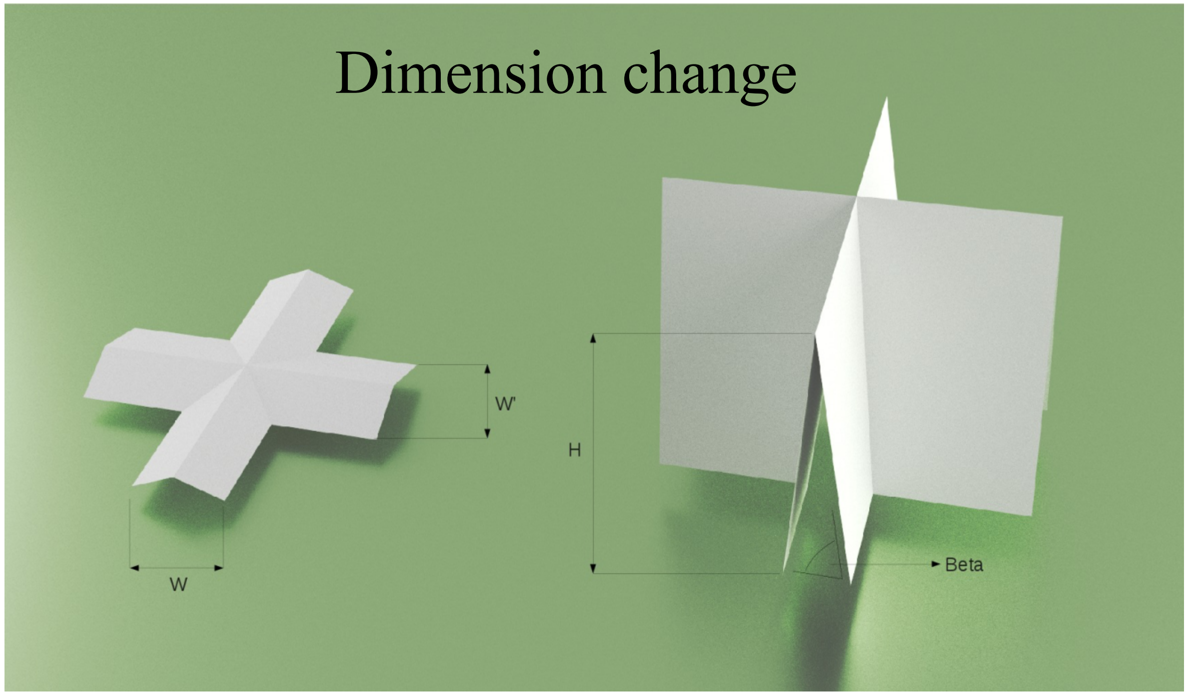
Candidate roof styles

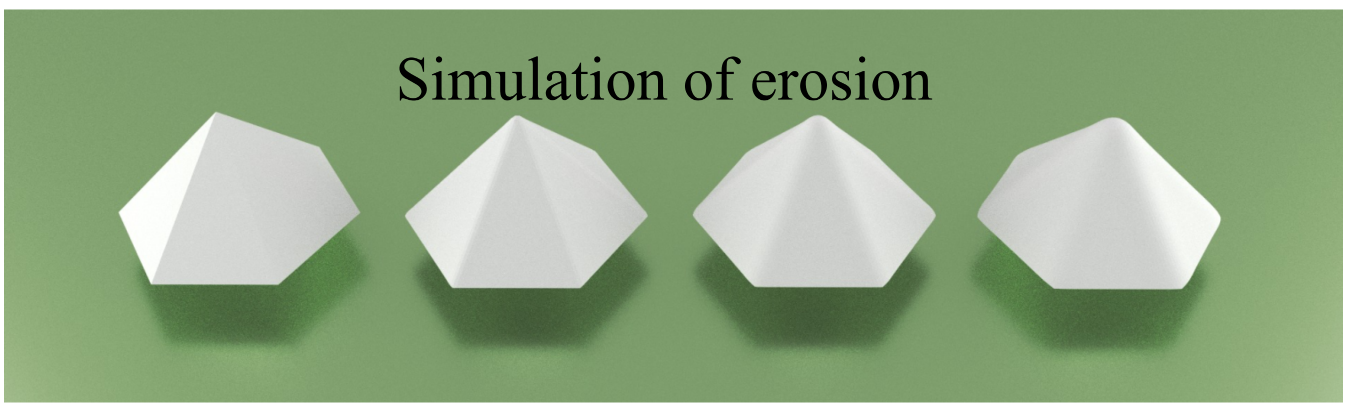


- Build prototypes.

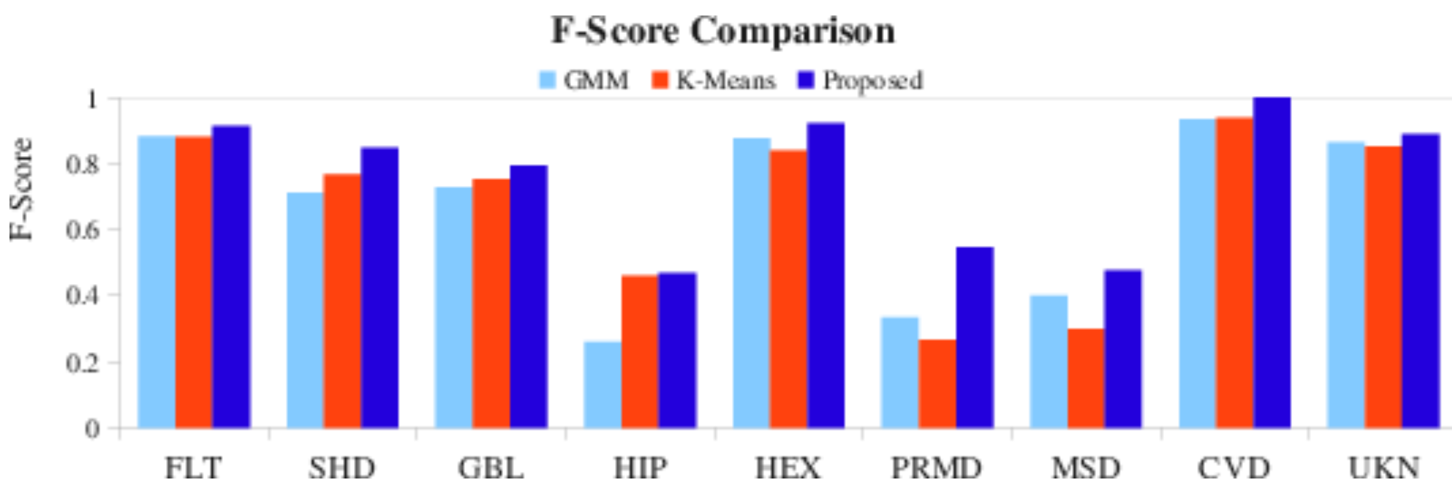


- Derive more data.

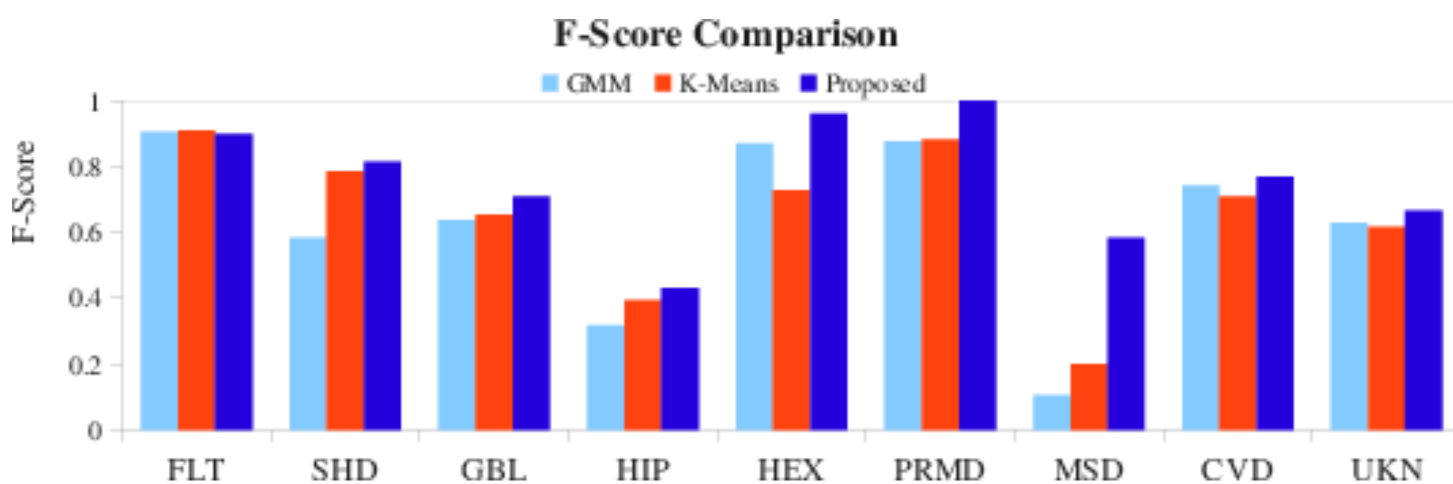




❖ Boost recognition rate by adding synthetic data.

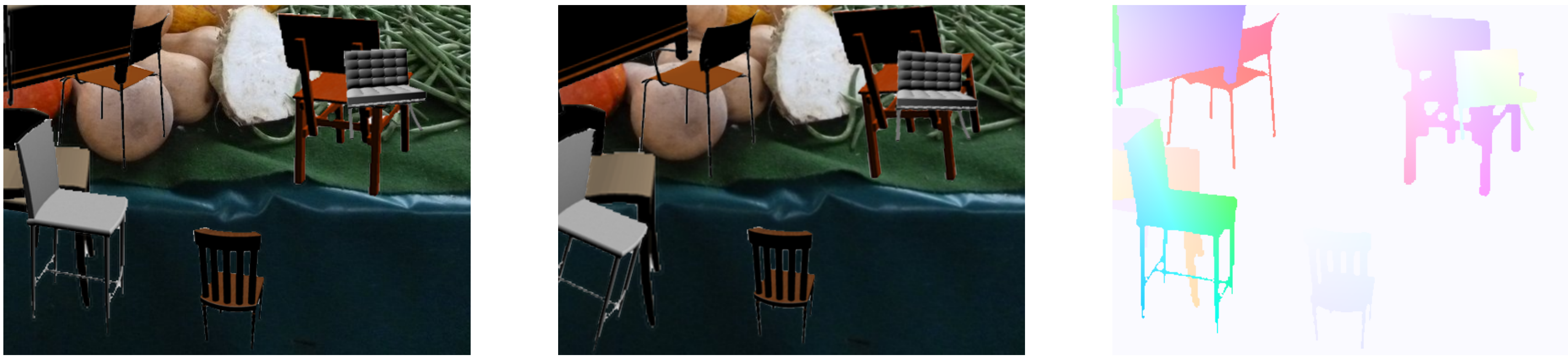


Chicago



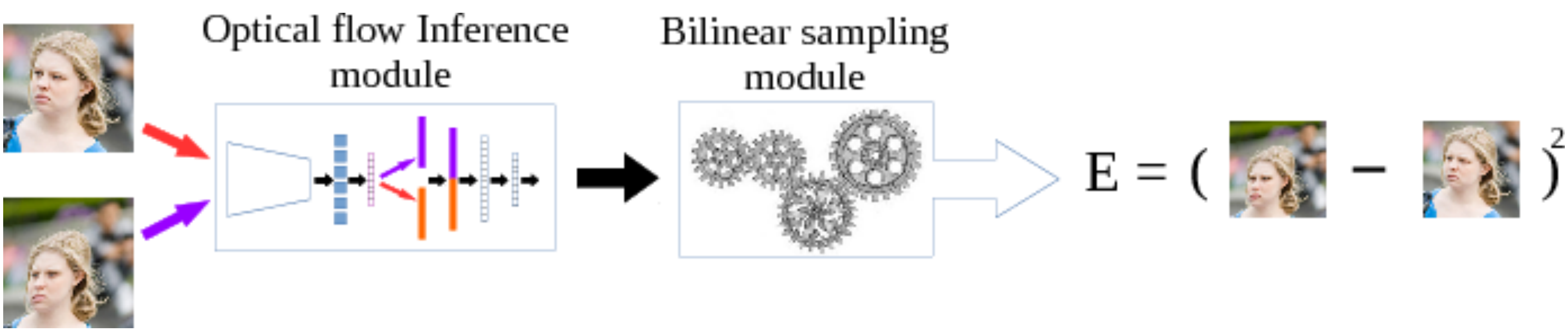
San Francisco

Examples of Inferring from Unsupervised learning

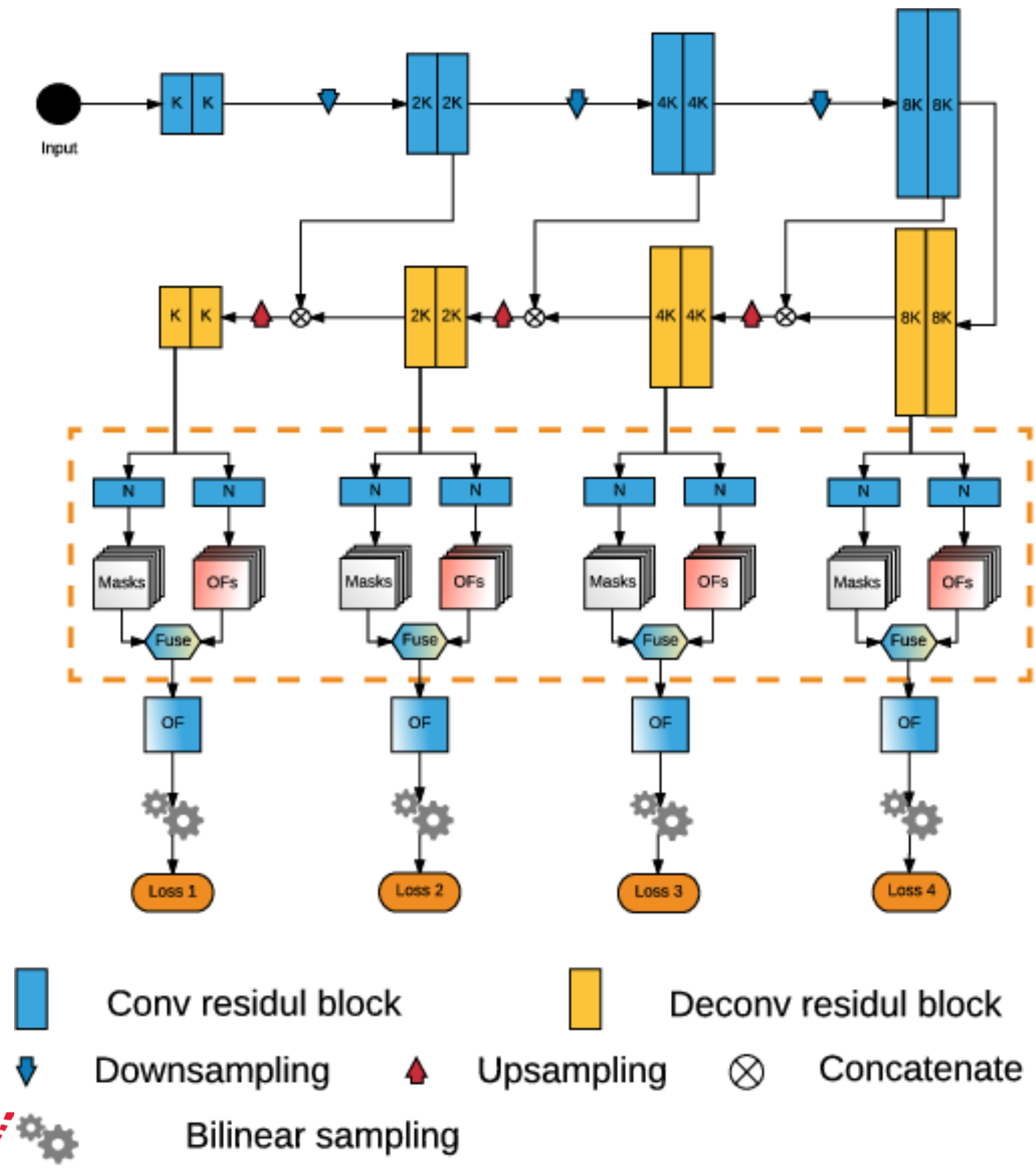


Unsupervised learning of optical flow using neural networks.

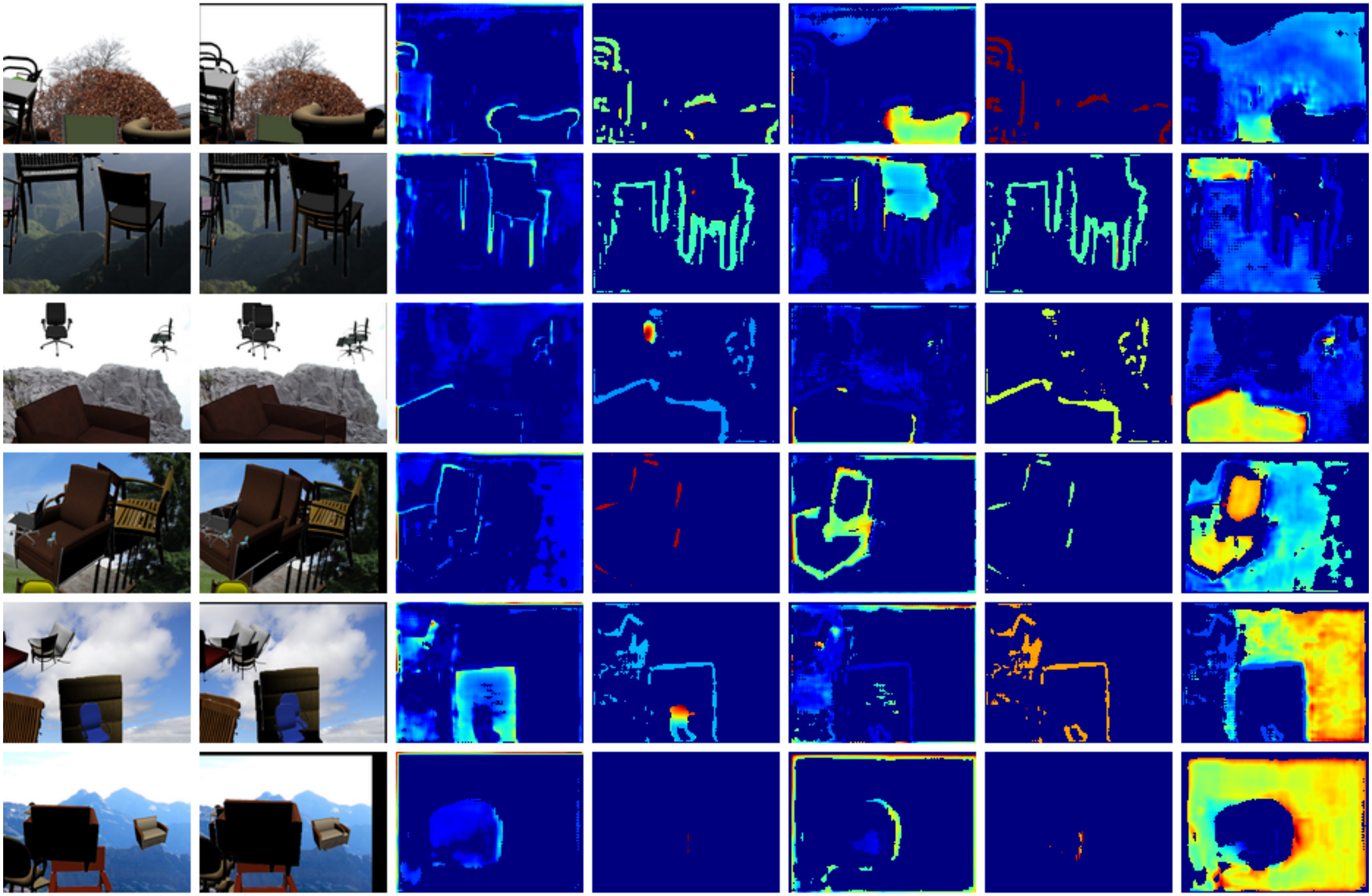
❖ Framework of unsupervised optical flow learning



Introduction of using mask modules



❖ Learned masks.



❖ Results

Img 1 | Img 2 | Ground Truth | DSTFlow | Proposed

❖ Results

	Chairs	KITTI	SC occ	SC noc	SF occ	SF noc	Time (sec)
Epicflow †	2.94	1.52	4.12	1.36	6.29	3.06	16
Deepflow †	3.53	1.53	5.38	1.77	7.21	3.34	17
FlowNetS (C+S)*	3.04	5.23	6.96	N.A.	7.76	N.A.	0.08
DSTFlow	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

- Motivations and Importance of the problem.
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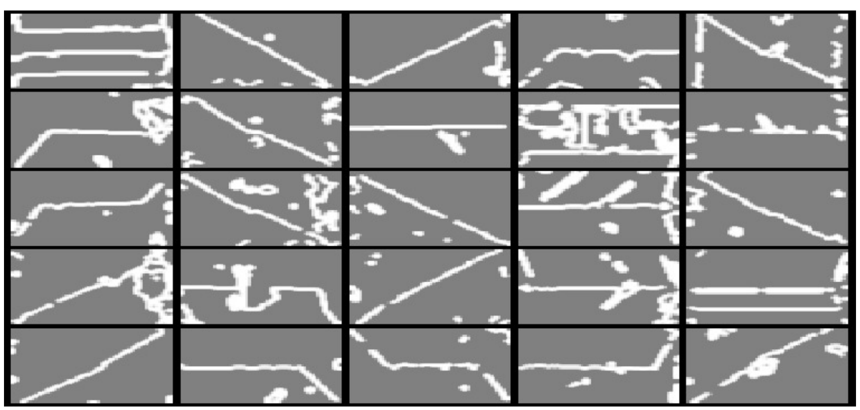
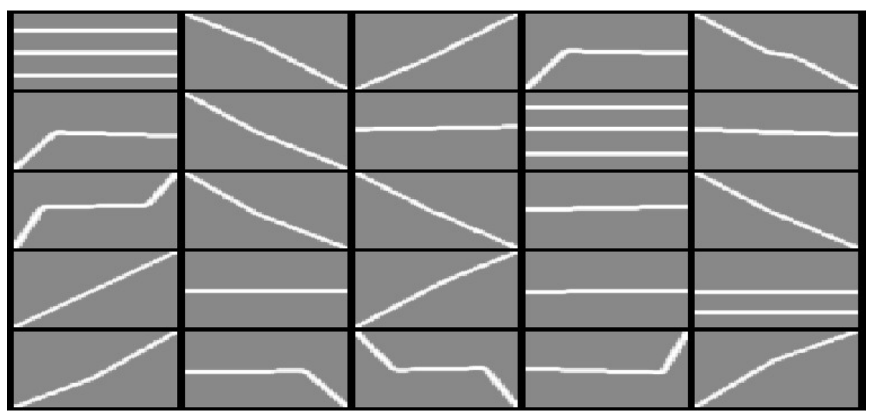
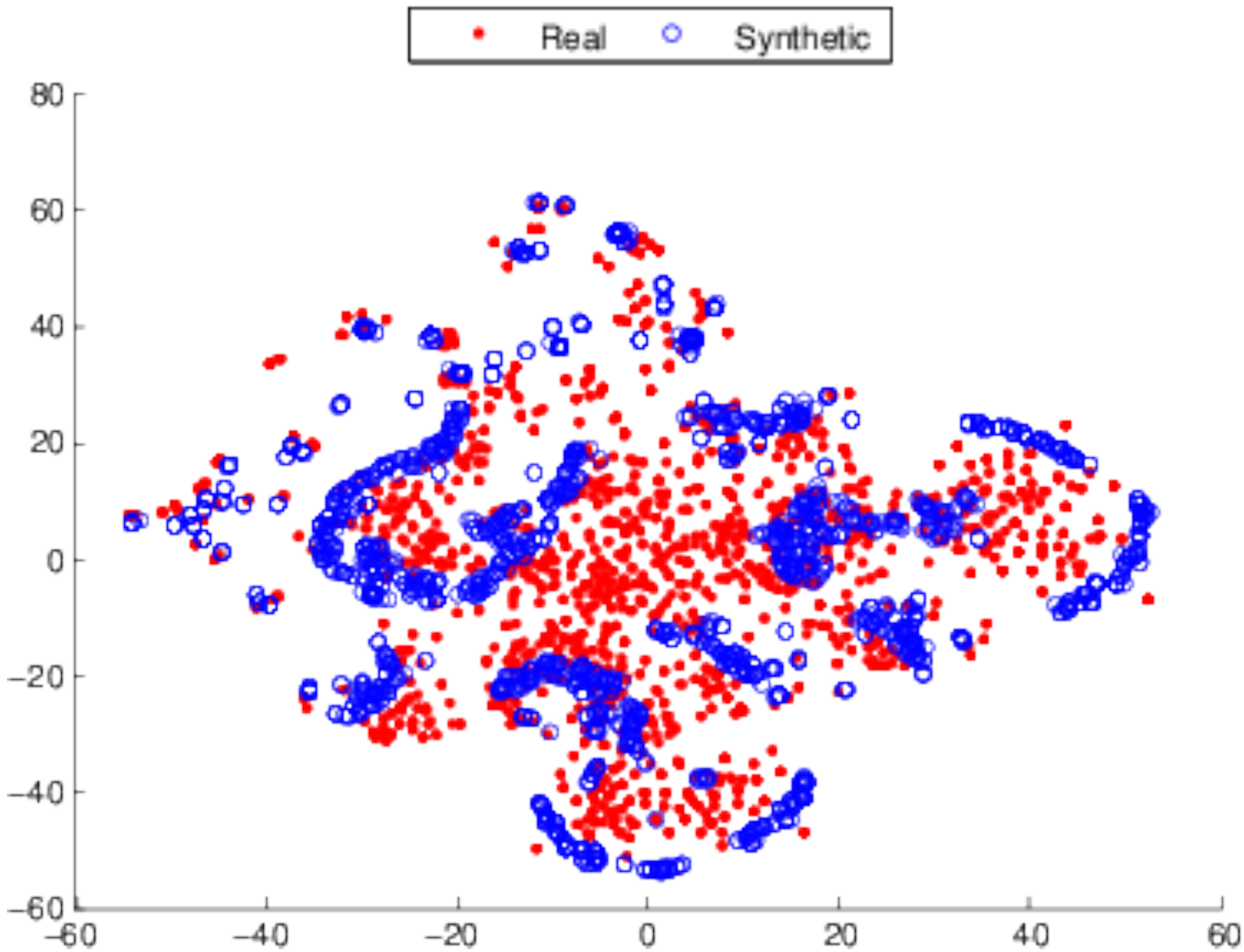
A Challenging task.



Actual data



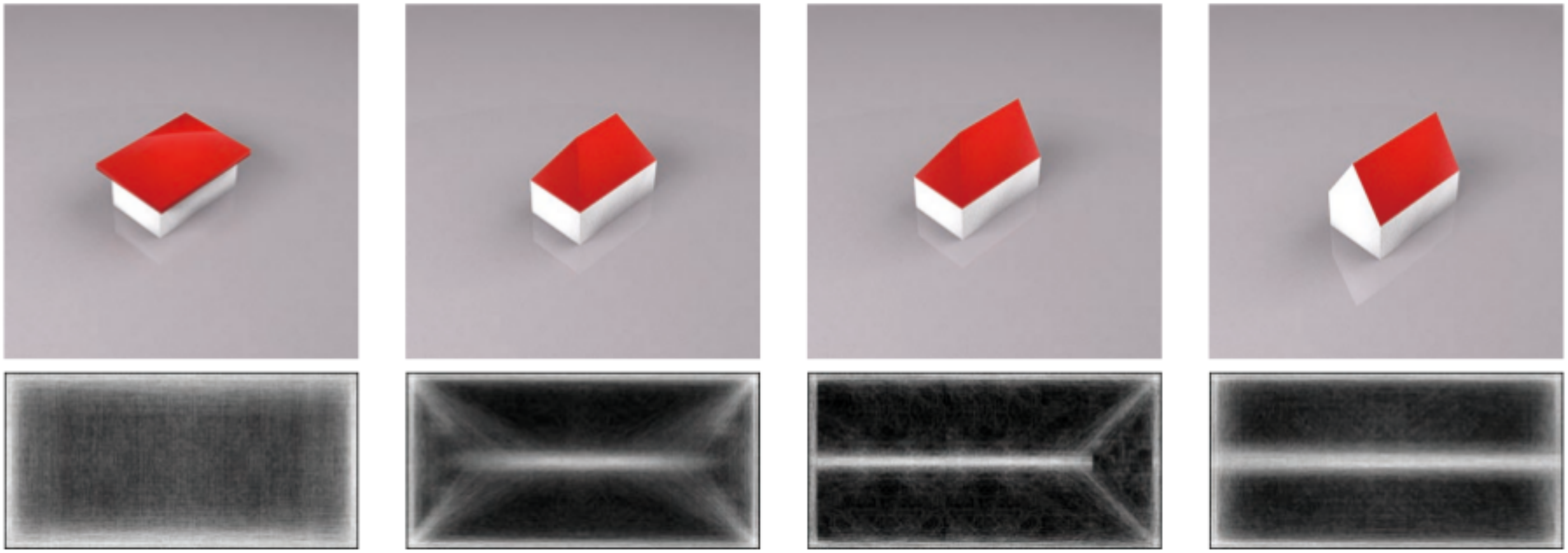
Synthetic data


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

- Previous work.
- They all treat synthetic data as actual ones.[39][87][66][89][90][65]

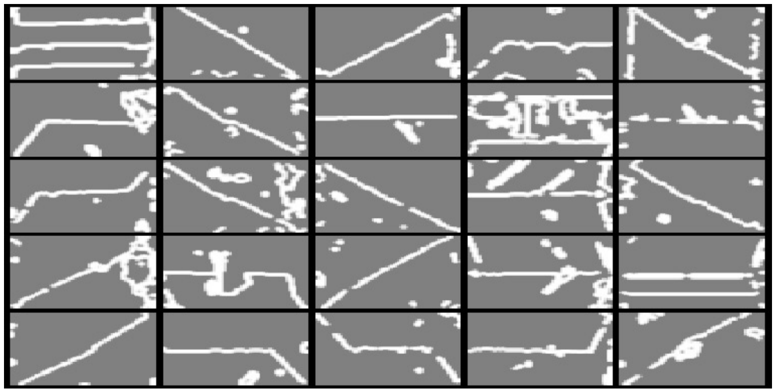
- **The proposed approaches.**
  - I build features that contain equivalent amount of information between synthetic data and actual data.
- **Two types of features**
  - Type I: Ignore additional information in actual data.
  - Type II: Compensate additional information for synthetic data.

Examples of ignoring additional information in actual data.

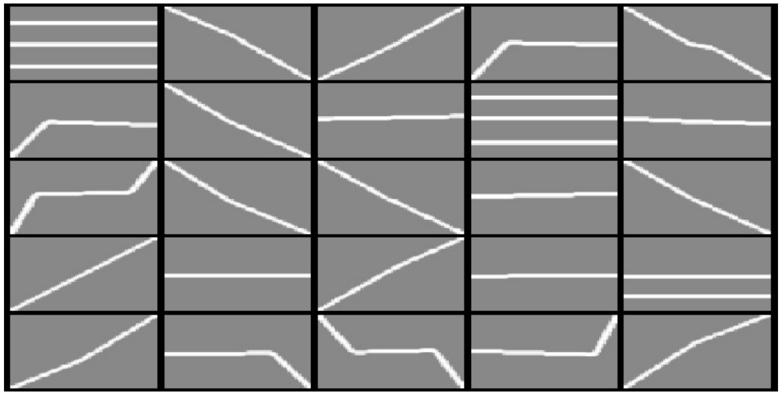


Roof type classification from satellite images

- Satellite image roof style classification.



Actual data

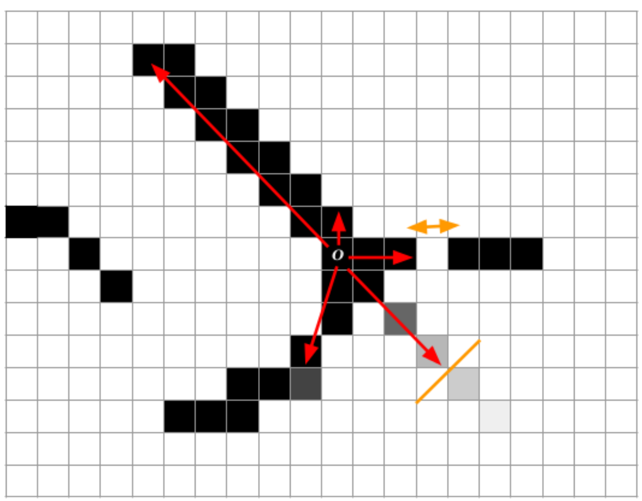


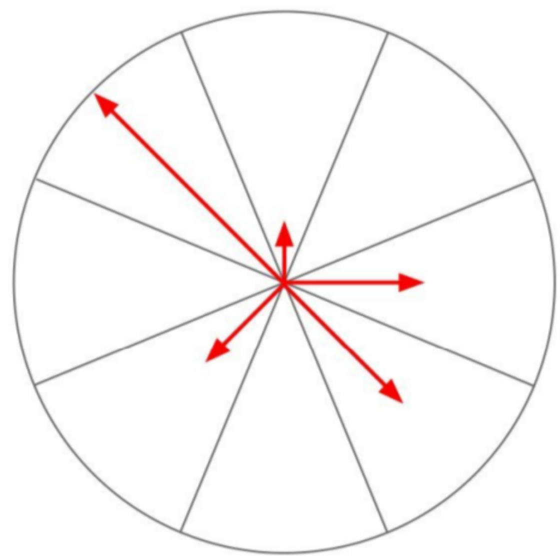
Synthetic data

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

Showcase One

- We proposed a feature called Histogram of Ray (HOR) in [100]
- Highlight edge length and direction in [100].
- Translation. scale. rotation invariant.





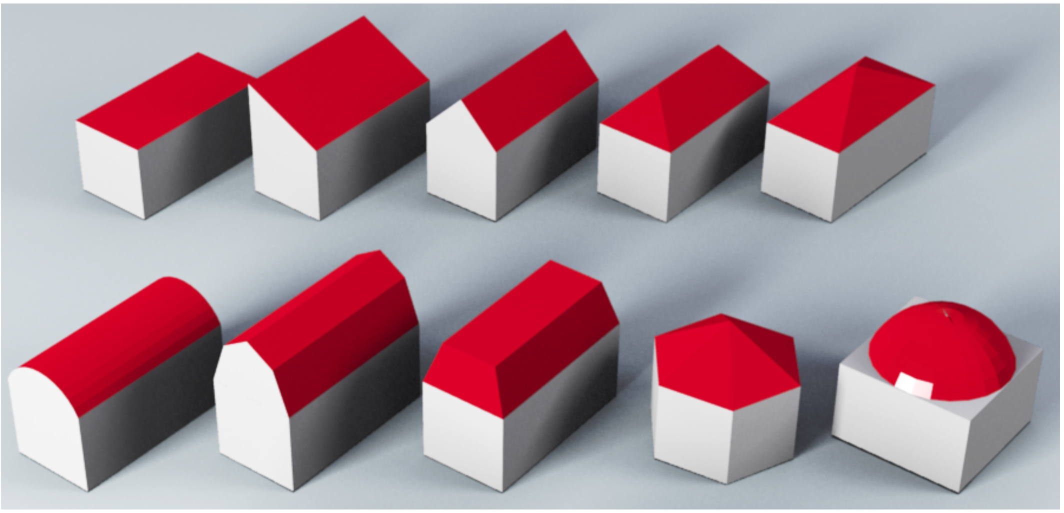
Showcase One

- 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
SC	0.743	0.869	0.963	0.509

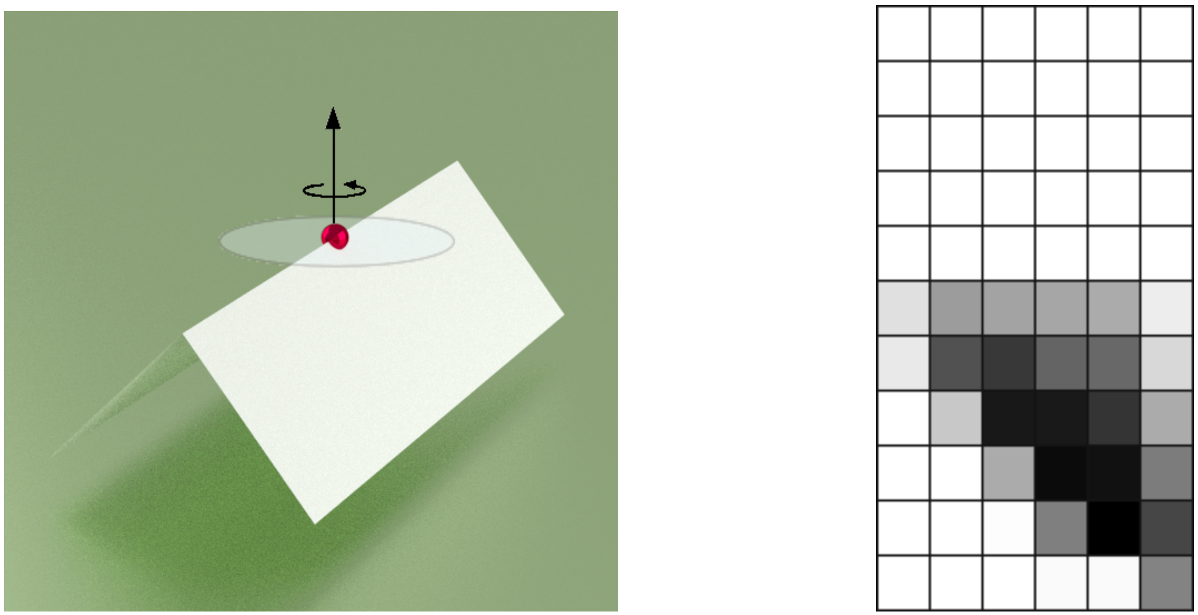
F1 score of classification results

Compensate additional information for synthetic data.



Roof type classification from point cloud

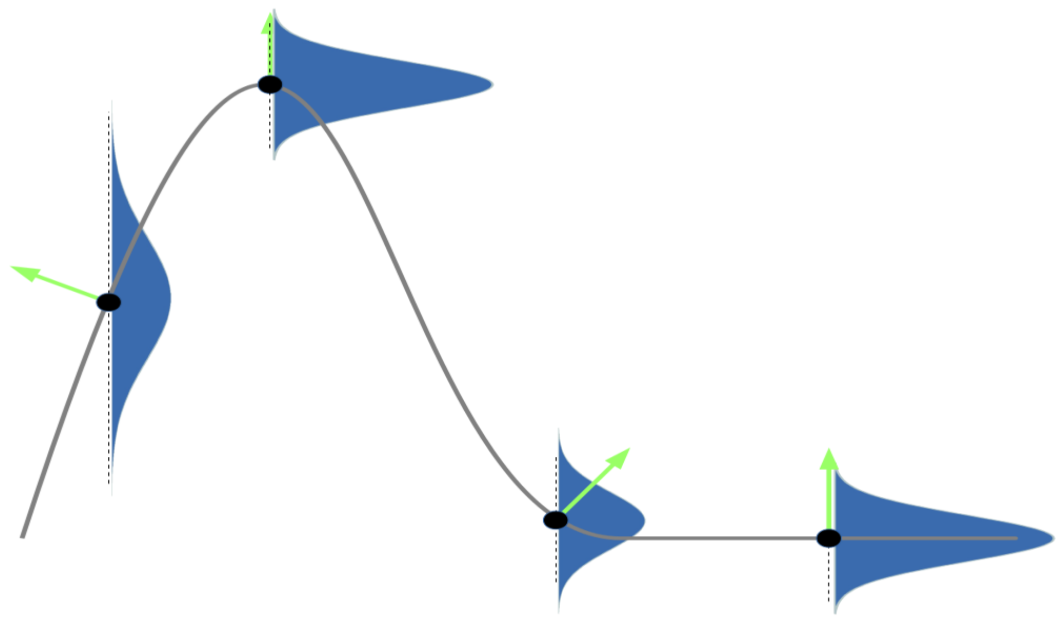
- Extract features that characterize local geometry.



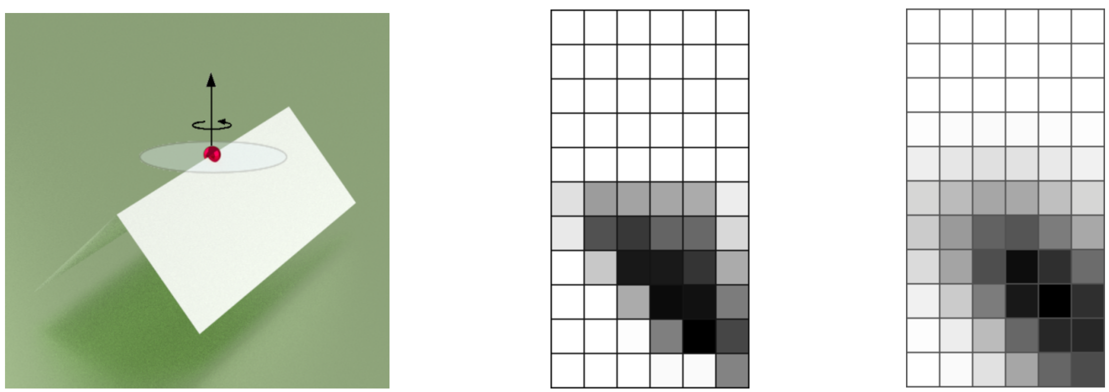
Spin image

- Extract features that characterize local geometry.
- However, too regular and smooth.

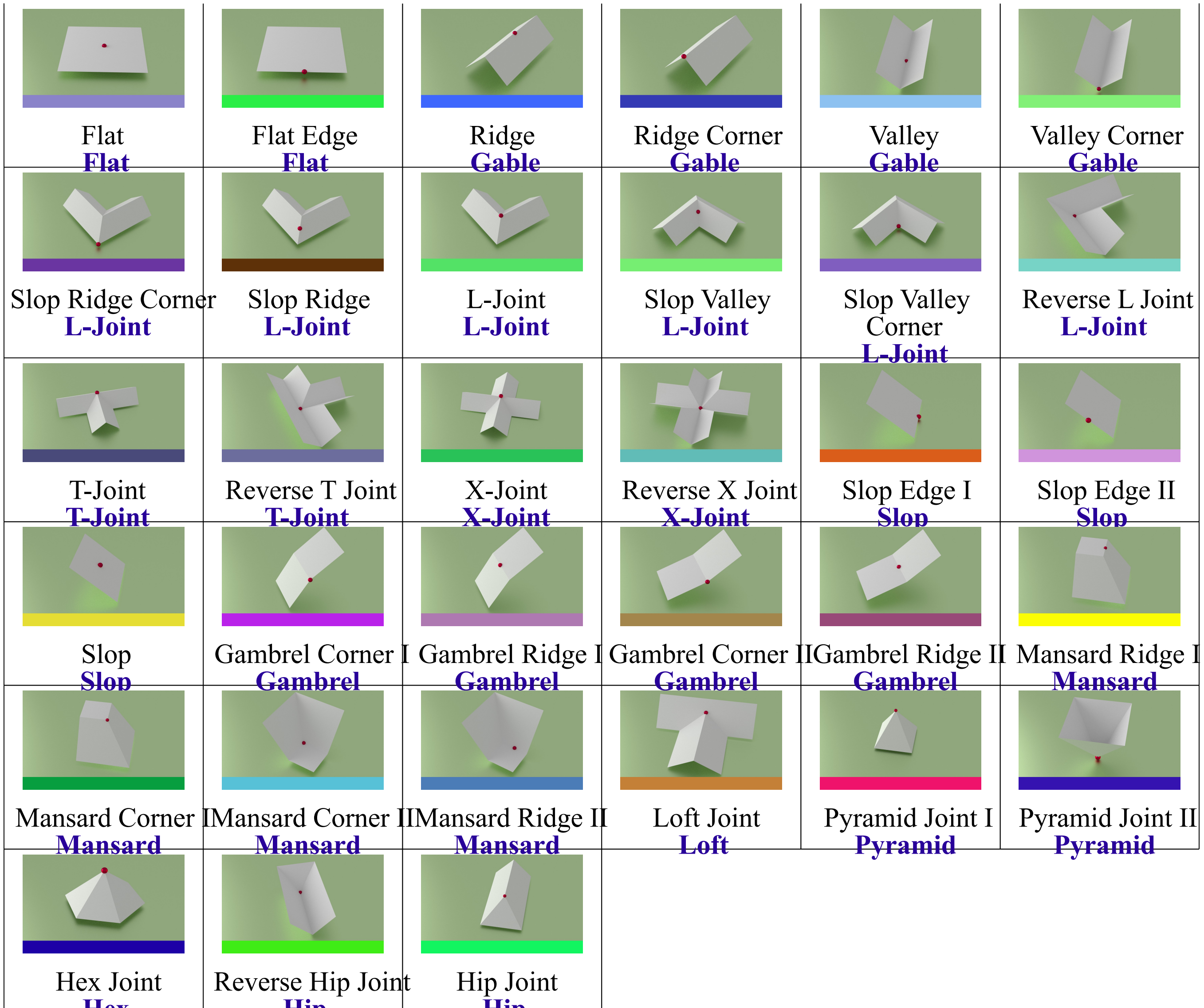
- Extract features that characterize local geometry.
- However, too regular and smooth.
- Learning bumpiness as a function of surface slope.



- Extract features that characterize local geometry.
- However, too regular and smooth.
- Learning bumpiness as a function of surface slope.
- Add random noise to synthetic data using knowledge learned.

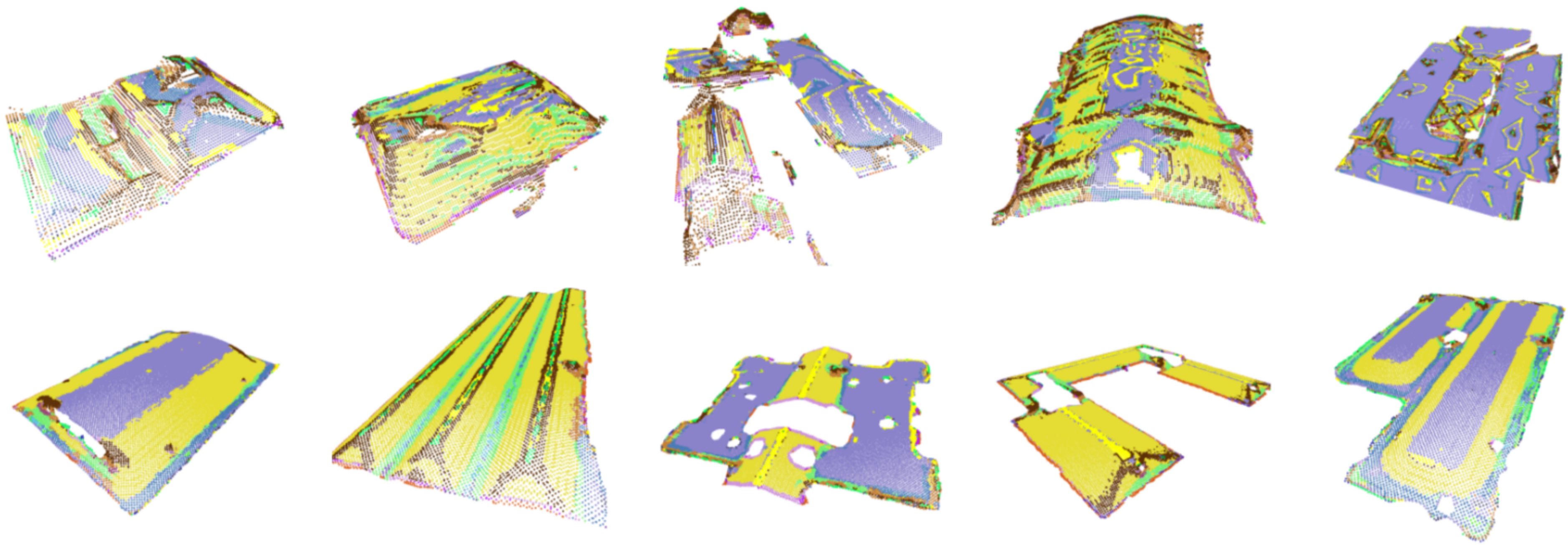


Spin image



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

- Point semantics classification results.



- 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

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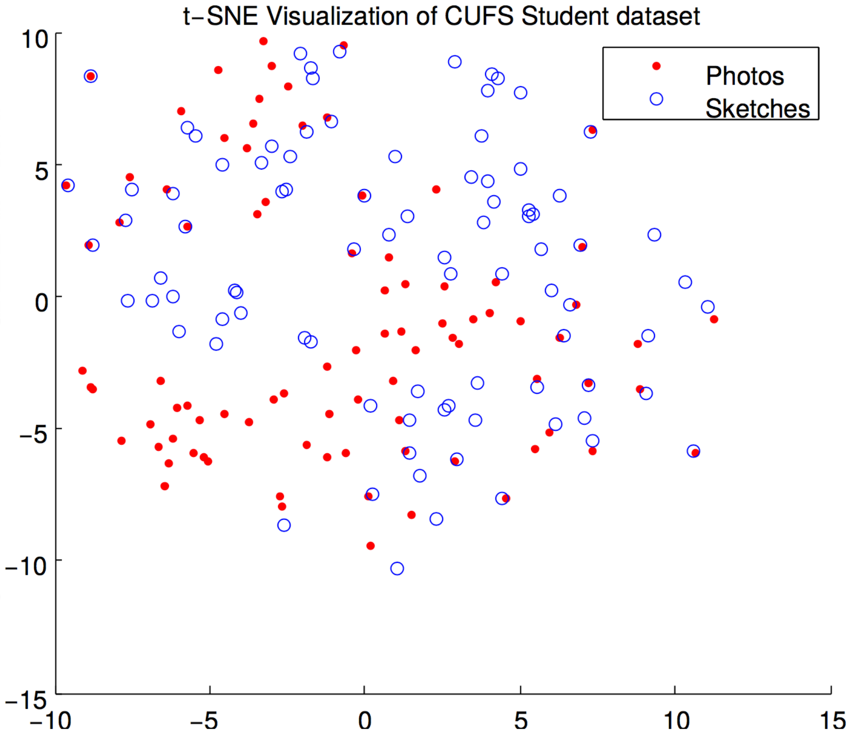
Eliminate Synthetic Gap

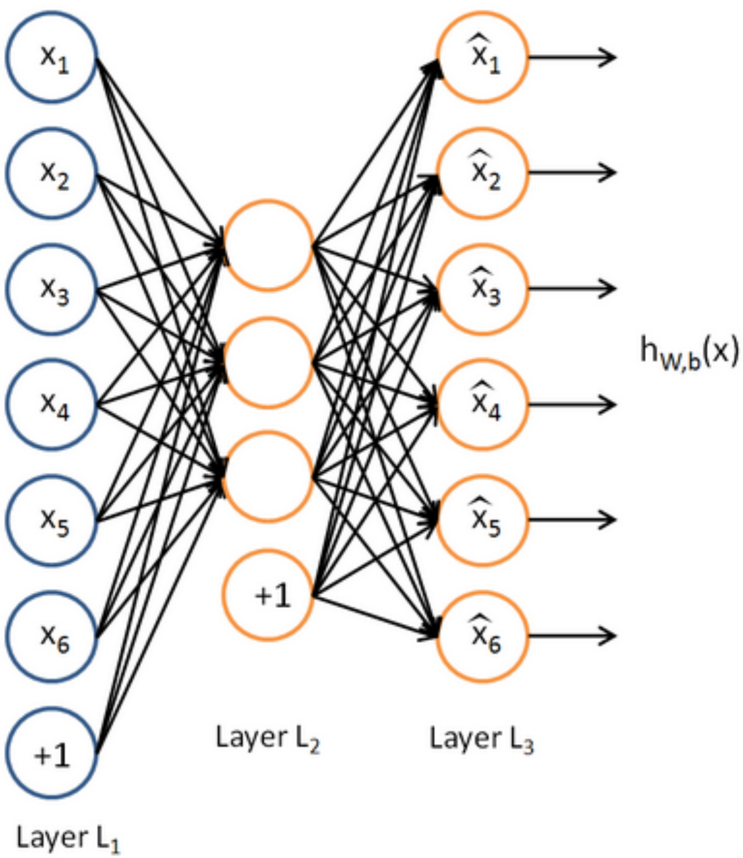
- Synthetic gap.

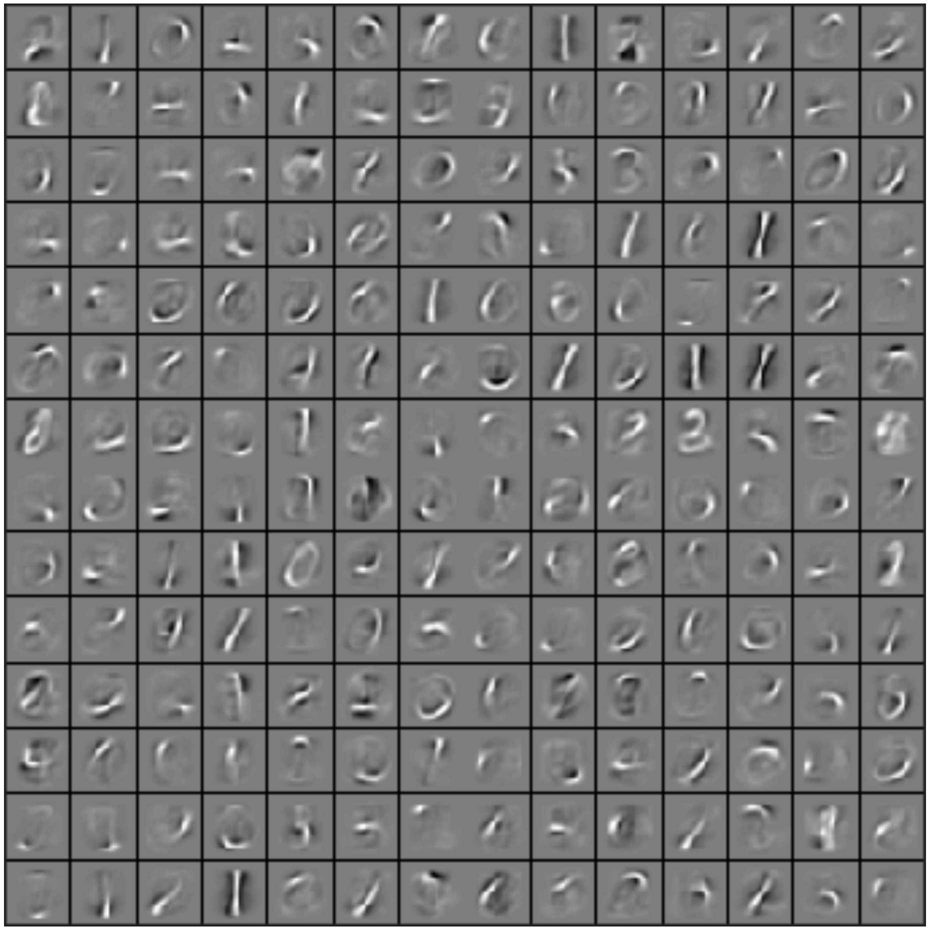


- Previous work.
- Eliminate distribution means in Kernel Reproducing Hilbert Space (KRHS). [12][46]
- Subspace alignment. [35][24]
- Deep neural network using KRHS as domain loss. [32][19]

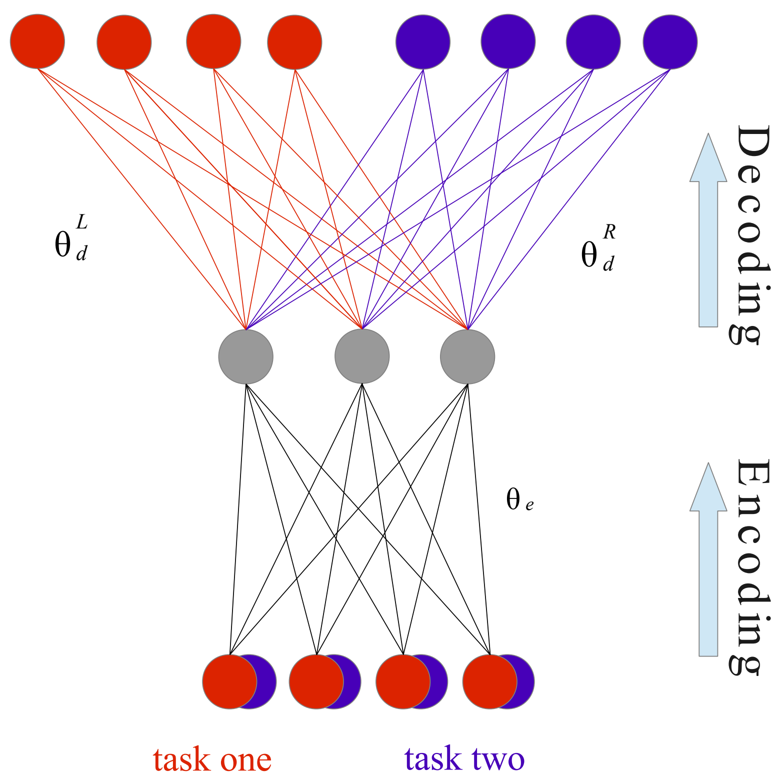
- The proposed approach.
- Multi-Channel Autoencoder (MCAE)

❖ Traditional autoencoder

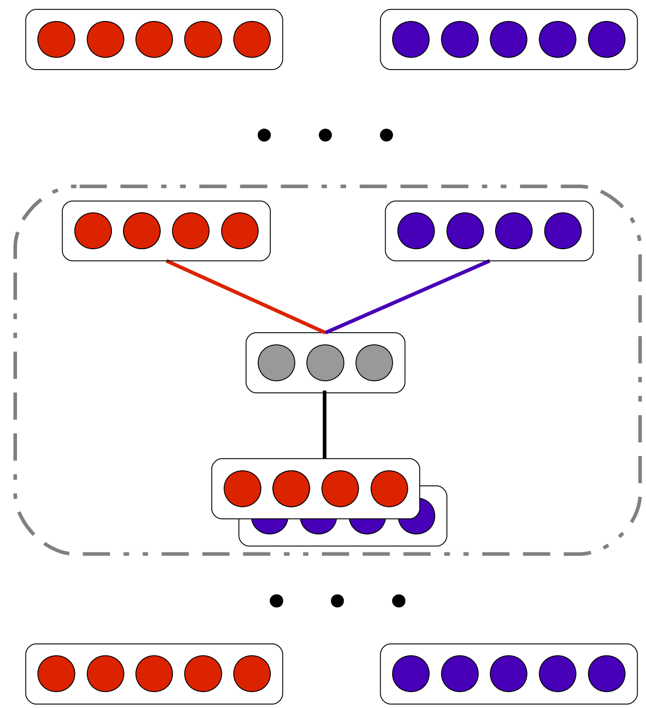




❖ The proposed MCAE



Basic structure



Stacked up

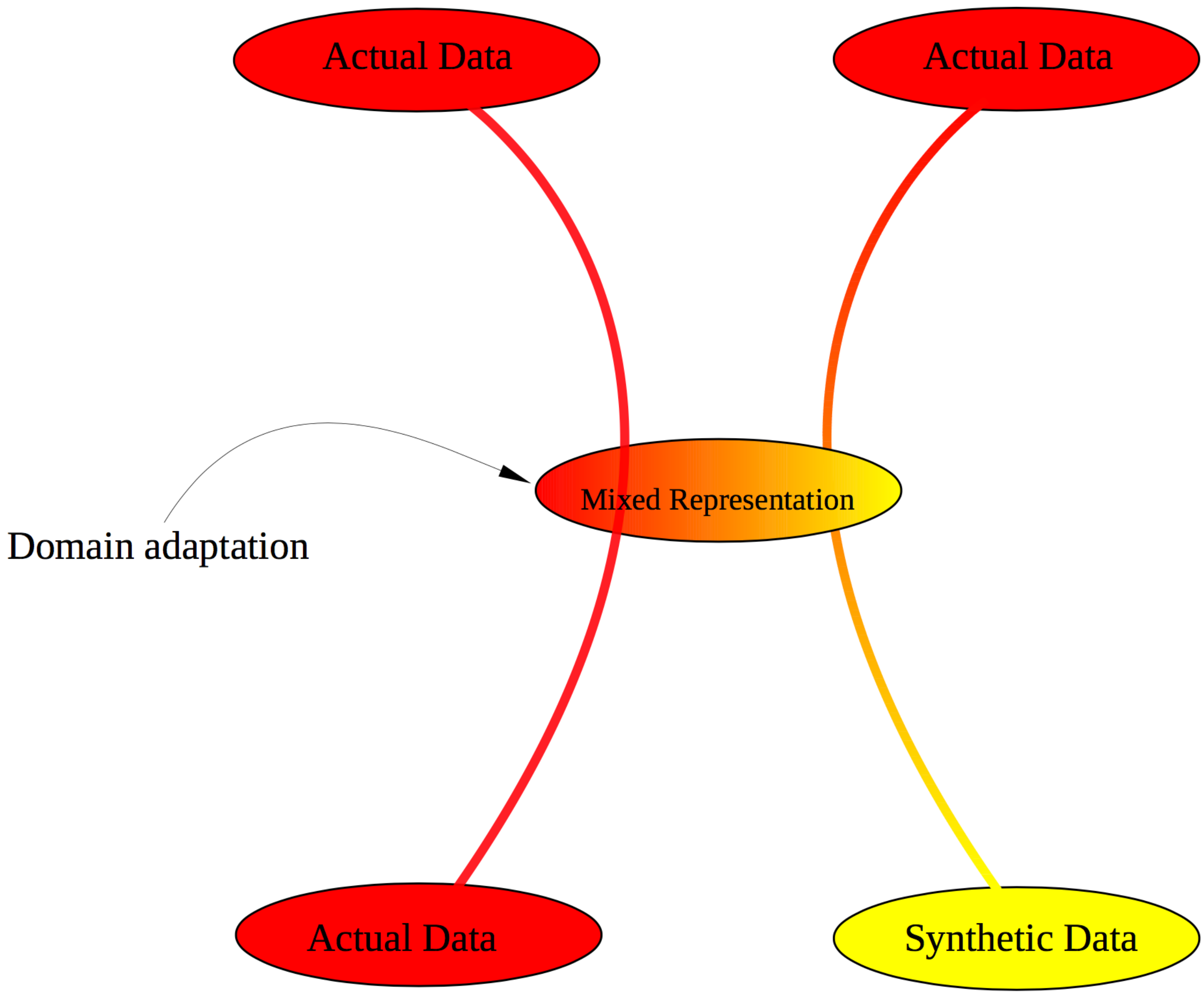
- MCAE
- Jointly learn two tasks, left and right, together.

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

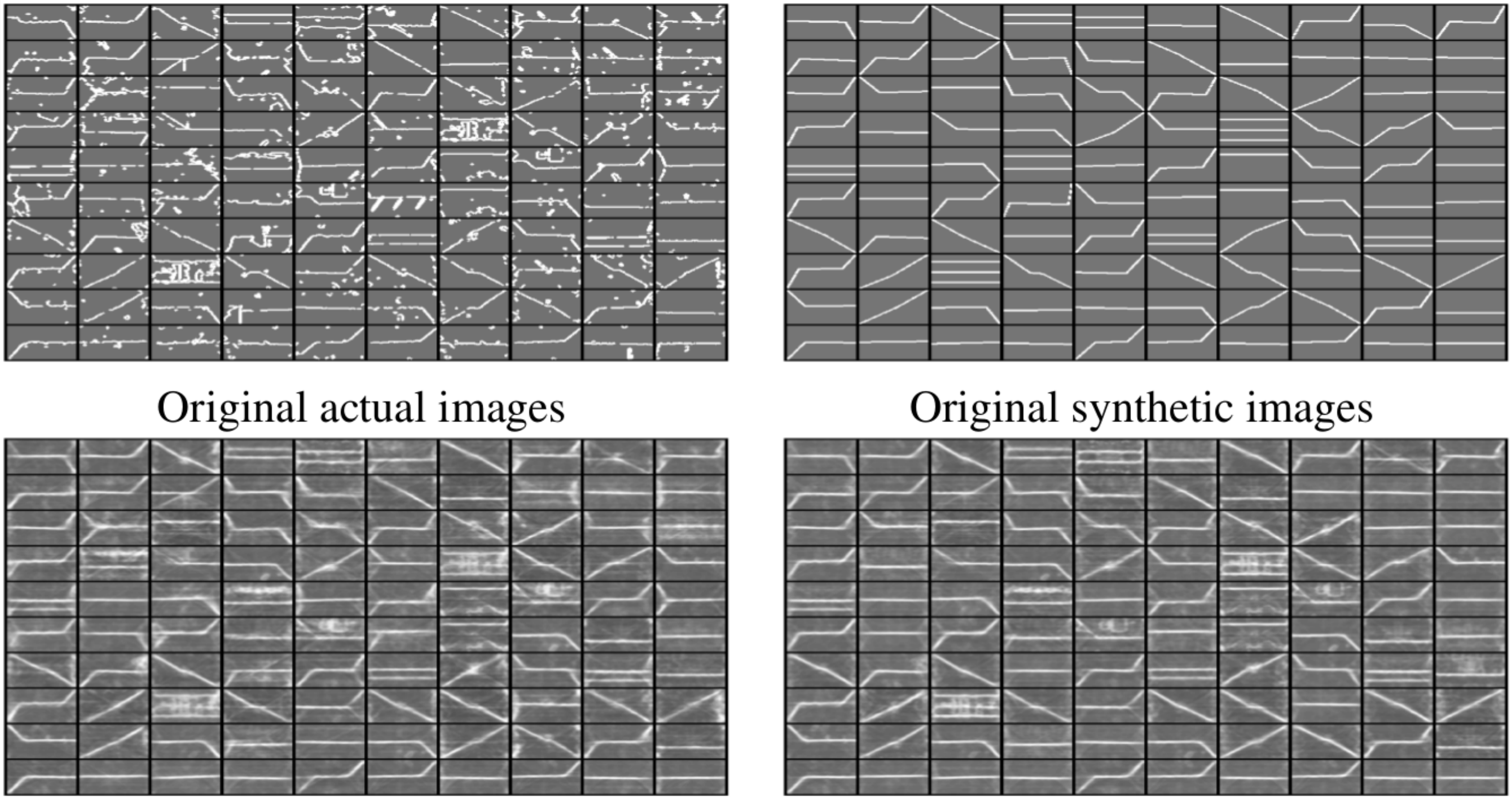
where

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

❖ Configuration of MCAE



- Visualization of domain adaptation.



Original actual images

Original synthetic images

Reconstructed actual images

Reconstructed synthetic images

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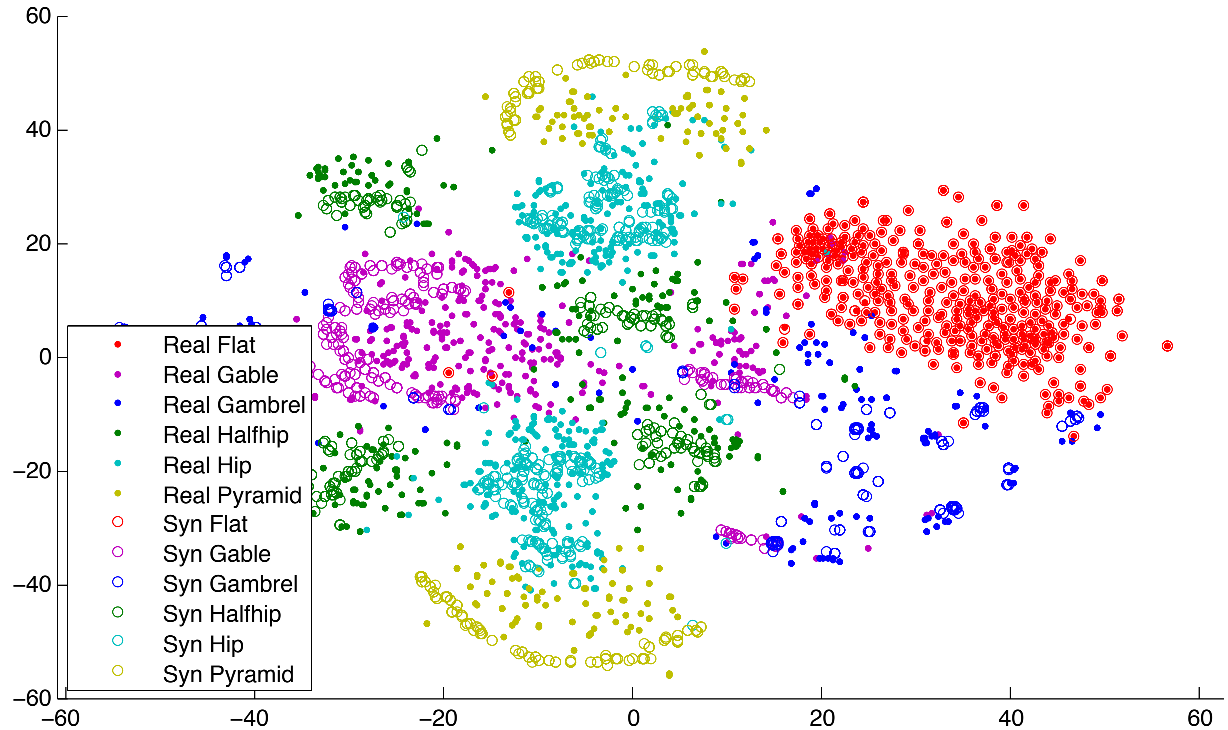
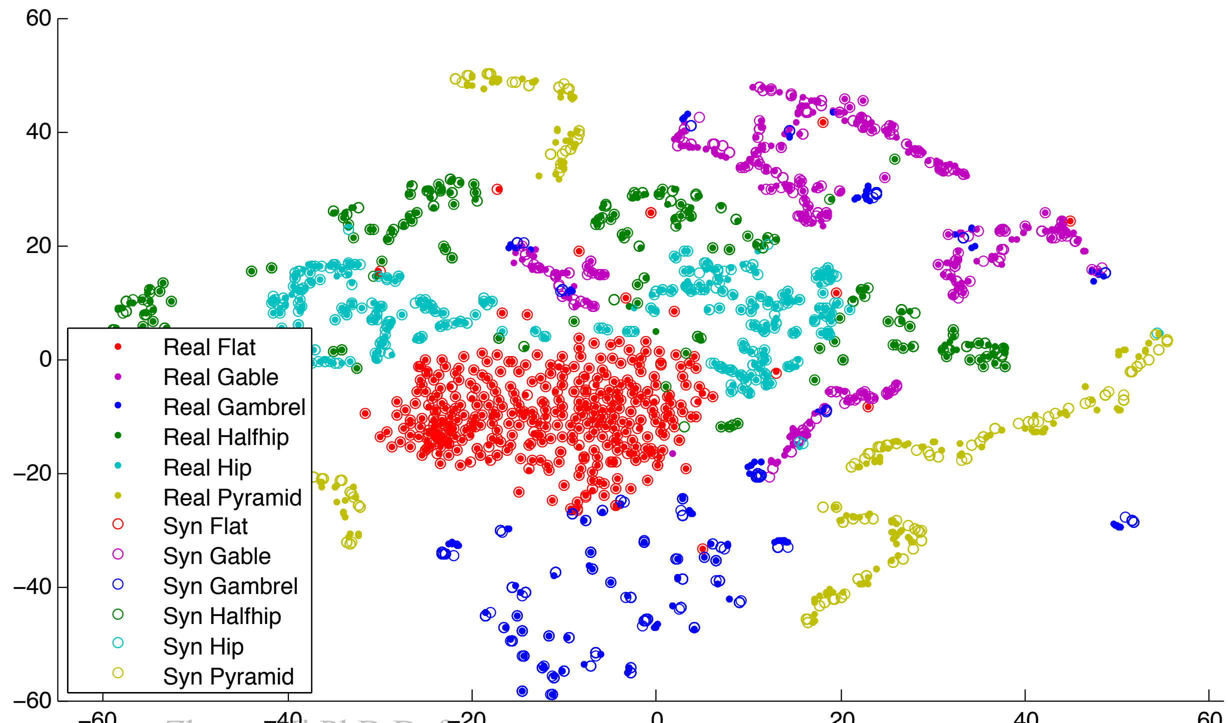
Without domain adaptation



With domain adaptation



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Classification results

	Data to train autoencoder	CNN Reconstructed	SVM Encoded
MCAE	$\langle$i:*Syn I*, t:Real$\rangle^L$ $\langle$i:Real, t:Real$\rangle^R$	**0.68**	**0.80**
CIAE	$\langle$i:*Syn I* + Real, t:*Syn I* + Real$\rangle$	0.68	0.78
SAE	$\langle$i:*Syn I*, t:*Syn I*$\rangle$	0.63	0.59
SAE	$\langle$i:Real, t:Real$\rangle$	0.62	0.62

Roof style dataset

	Data to train autoencoder	CNN Reconstructed	SVM Encoded
MCAE	$\langle$i:*Syn I*, t:Real$\rangle^L$ $\langle$i:Real, t:Real$\rangle^R$	**0.98**	**0.96**
CIAE	$\langle$i:*Syn I* + Real, t:*Syn I* + Real$\rangle$	0.97	0.96
SAE	$\langle$i:*Syn I*, t:*Syn I*$\rangle$	0.94	0.91
SAE	$\langle$i:Real, t:Real$\rangle$	0.95	0.65

Handwritten digit dataset

- 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.

Motivation

The fundamental issue in imbalanced learning is the ability of imbalanced data to compromise the performance of classification algorithm.

- ❖ It is hard to detect 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.

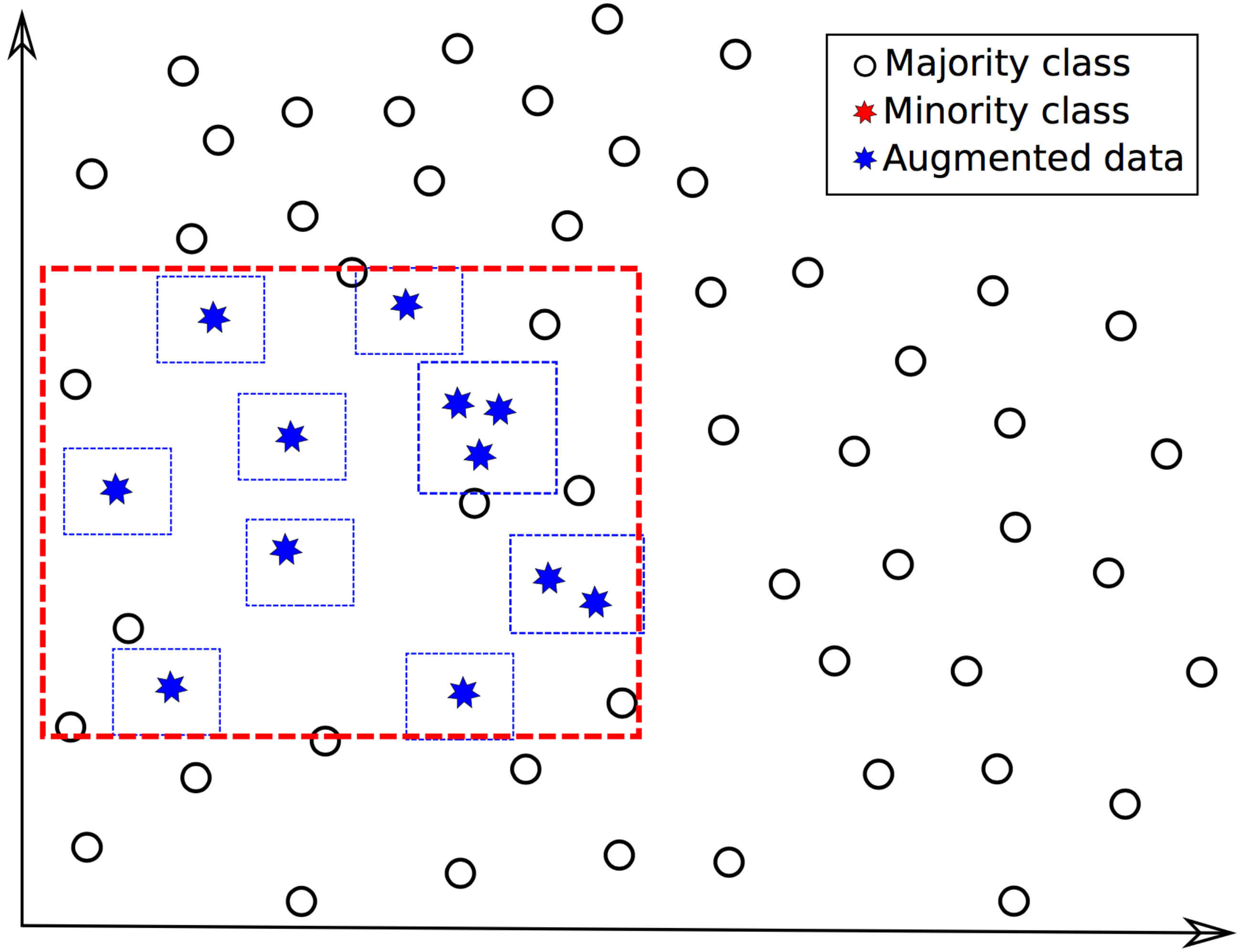
Existing work

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

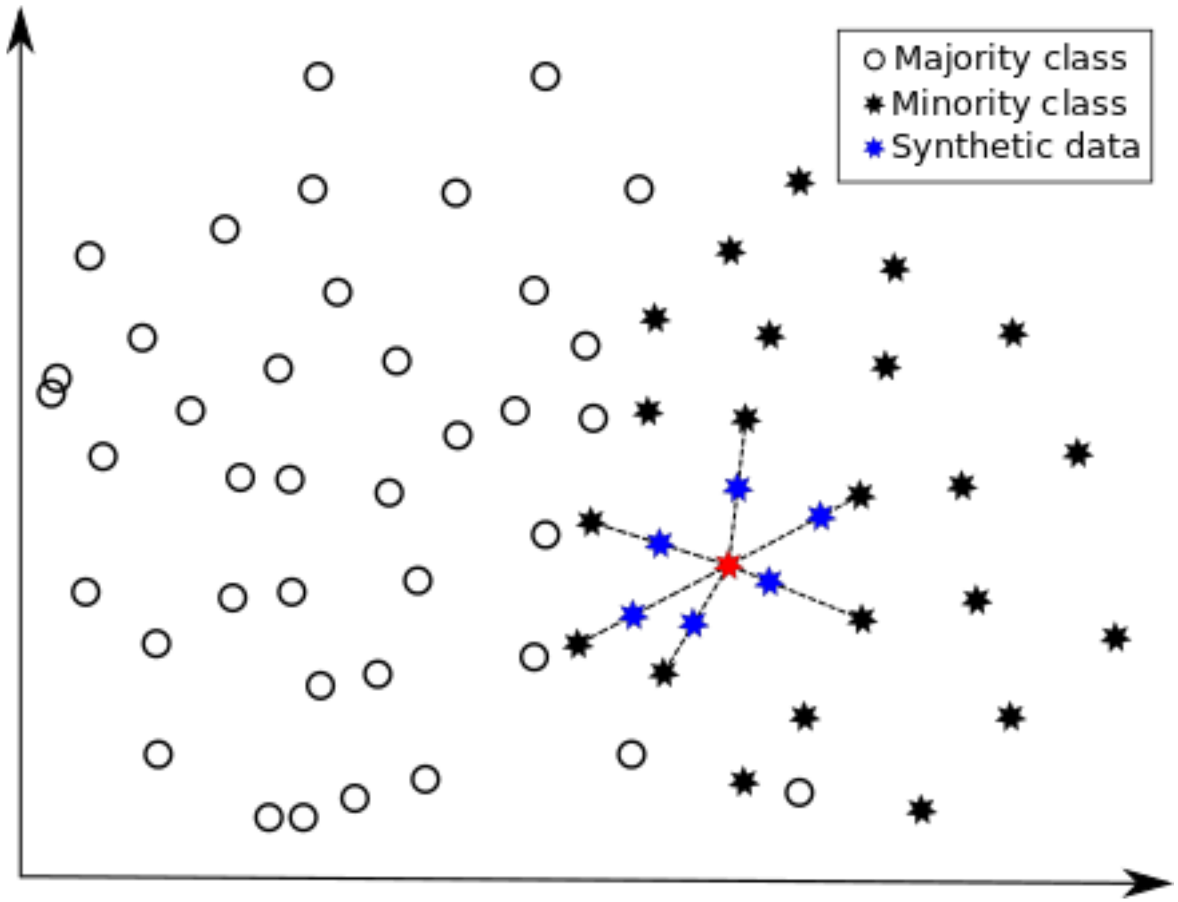
- Cost sensitive methods.
- Kernel methods.
- Sampling methods.

Existing sampling methods

1) Creating identical samples.



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



The proposed approach – CGMOS

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:

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

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

Strategy of choosing sampling seeds

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

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

Theoretical guarantee over SMOTE

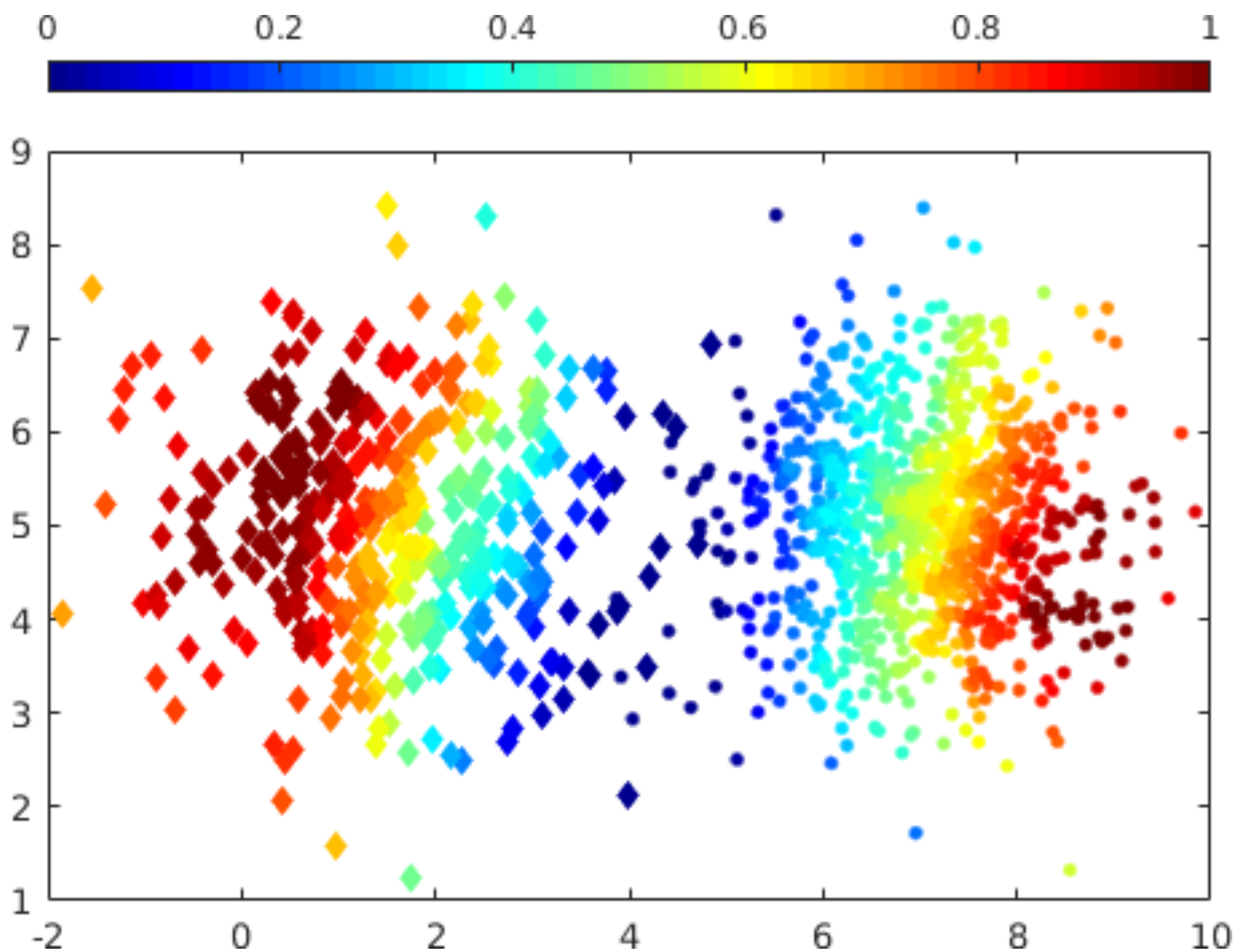
Definition (Average gain): The average gain when adding sample x_i is defined by:

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

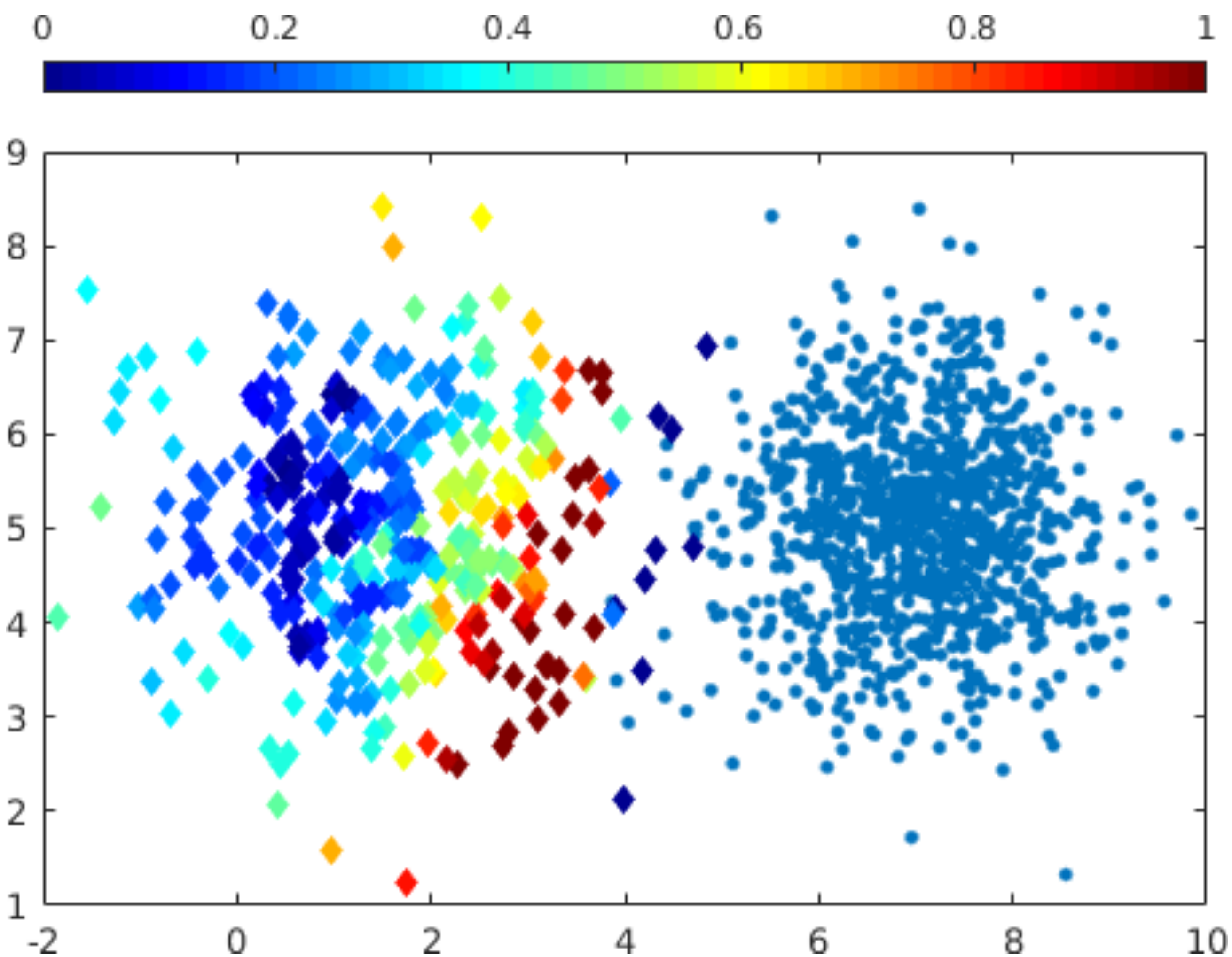
where

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

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



Certainty



Relative certainty change

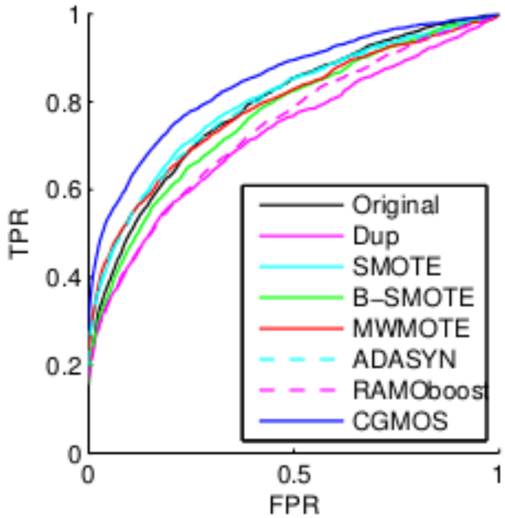
~~Results~~

Datasets: 30 datasets downloaded from UC Irvine machine learning repository corresponding to existing evaluations. [2][7][18]

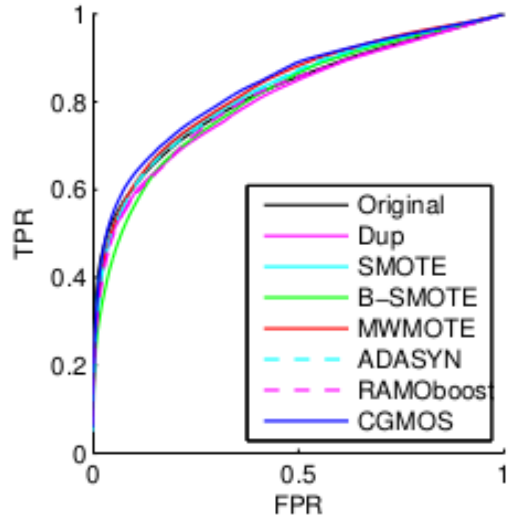
Compared approaches: No addition, Duplication, SMOTE [4], Boarderline-SMOTE [17], ADASYN [18], MWMOTE [2], RAMOBoost [7].

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

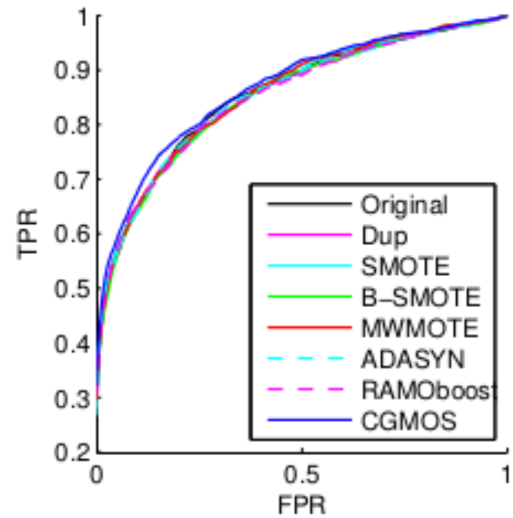
ROC curves



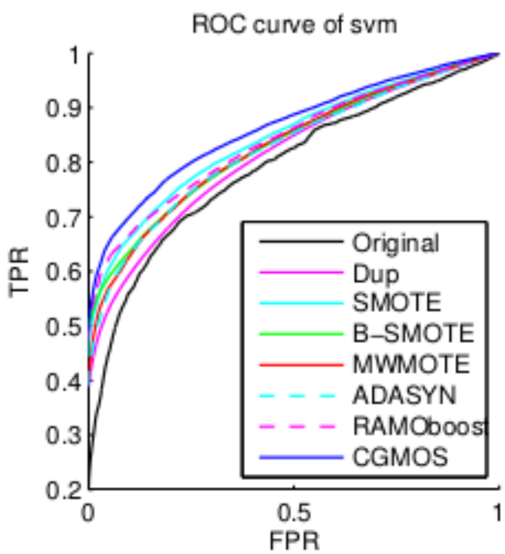
b-kde



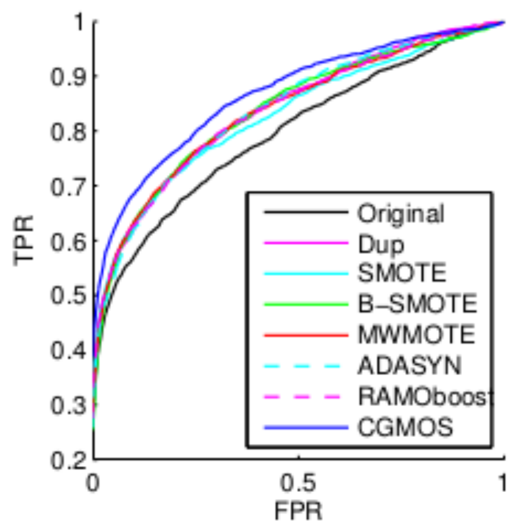
knn



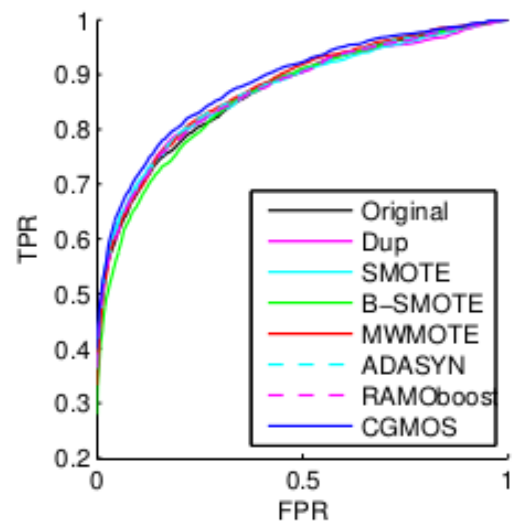
Adaboost.M1



svm



nn



rf

	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

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.

Conclusion

- Goal:
  - Boost performance of object recognition.
  - Ease ground truth labeling process.
- Solution:
  - Data synthesis.
- Novel contributions:
  - Data synthesis in data space.
  - Learning from synthetic data.
  - Eliminating synthetic gap.
  - Data synthesis in feature space.