# Data Synthesis For Object Recognition

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# Overview

- 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

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# Motivation

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

   a. Rare cases (absolute rarity)

   b. Rare classes (relative rarity)

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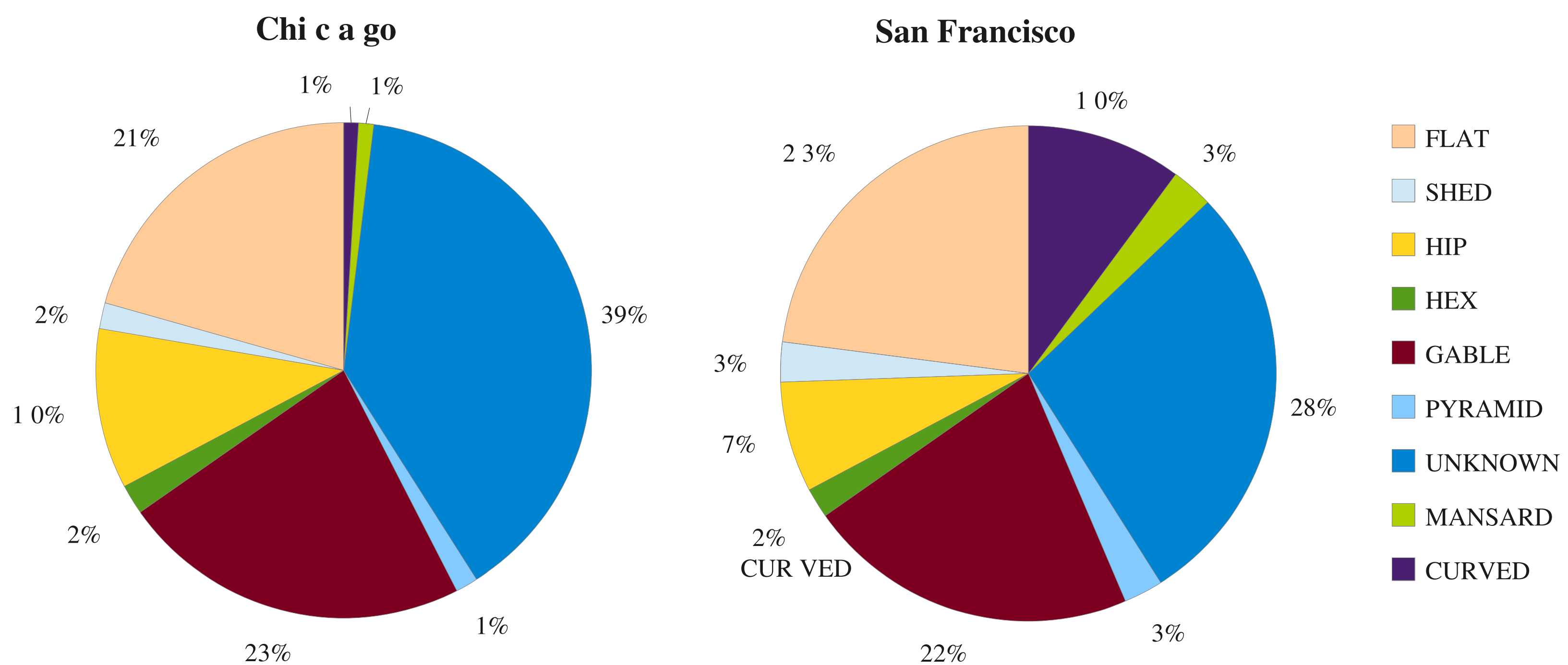
a. Rare cases (absolute rarity)

b. Rare classes (relative rarity)



2) Supervised learning requires high quality labeled data

a. Time consuming, expensive.

b. Sometimes, impossible

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# Introduction & Novel Contribution

- Solution: Data synthesis

- Challenges:

  1) Where to synthesize.

  2) How to synthesize.

- Novel contributions:

1)Data synthesis in data space.

2)Learning from synthetic data.

3)Eliminating synthetic gap.

4)Data synthesis in feature space.

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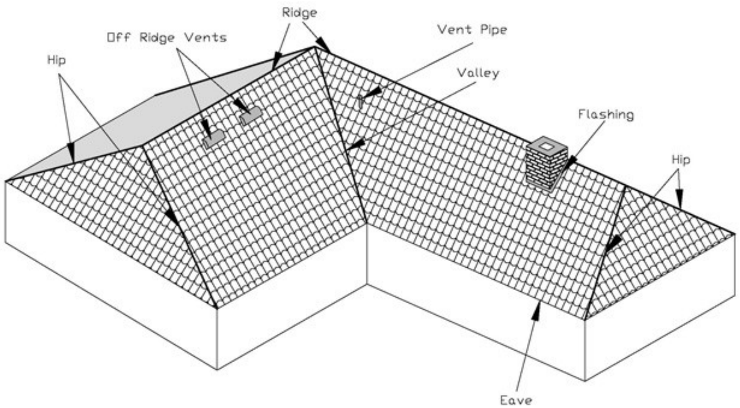
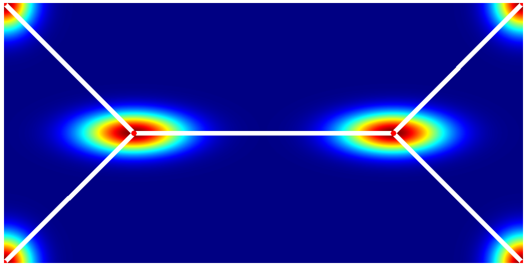
# Data Synthesis in Data Space

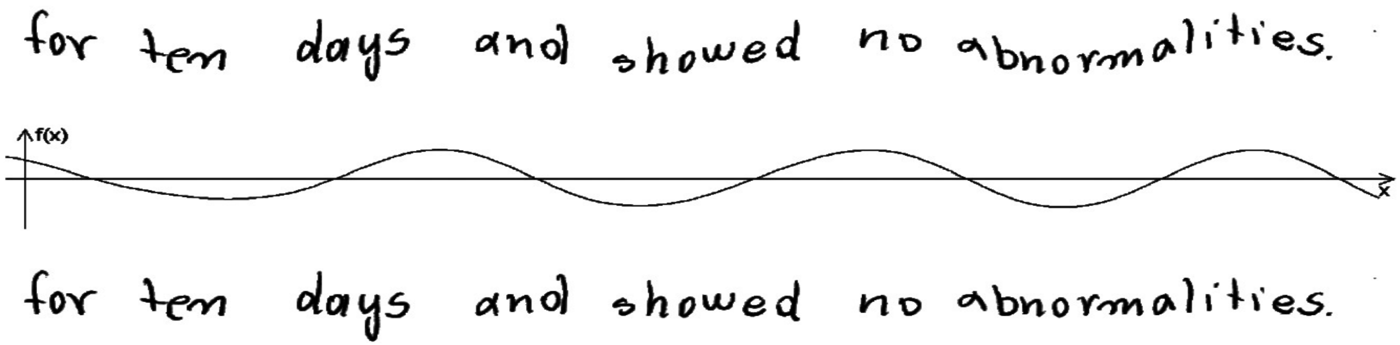
- Why in data space?
  - Most intuitive.
  - Sometime, easiest way.



- But, some limitations too.
  - Require good prototype.
  - Application specific.

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



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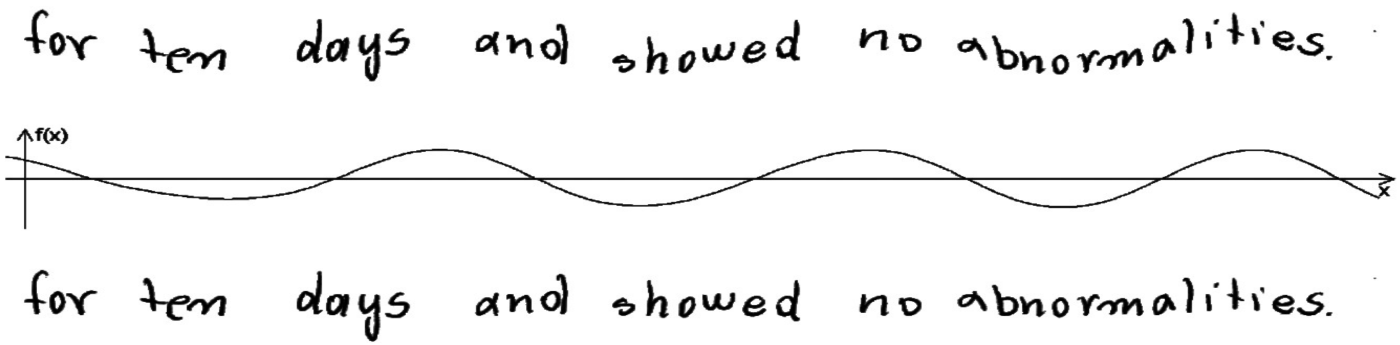
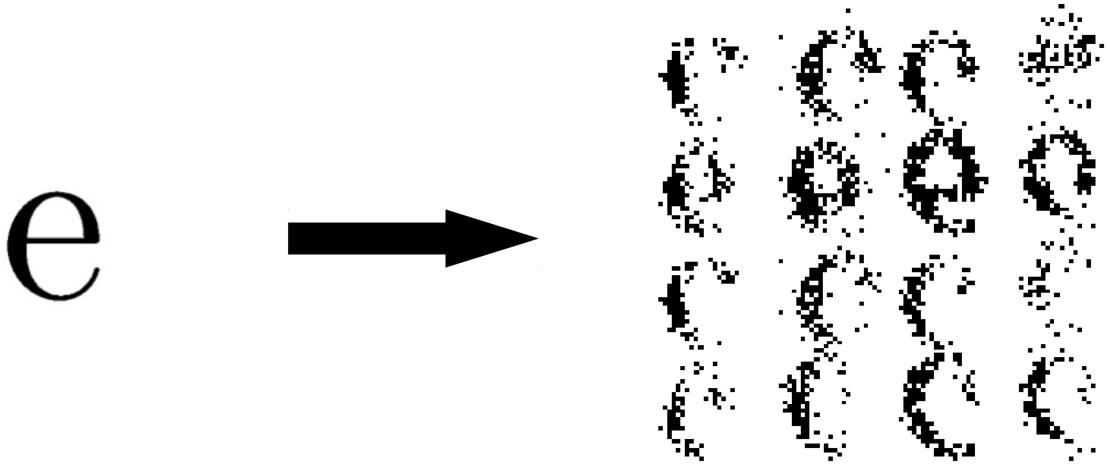
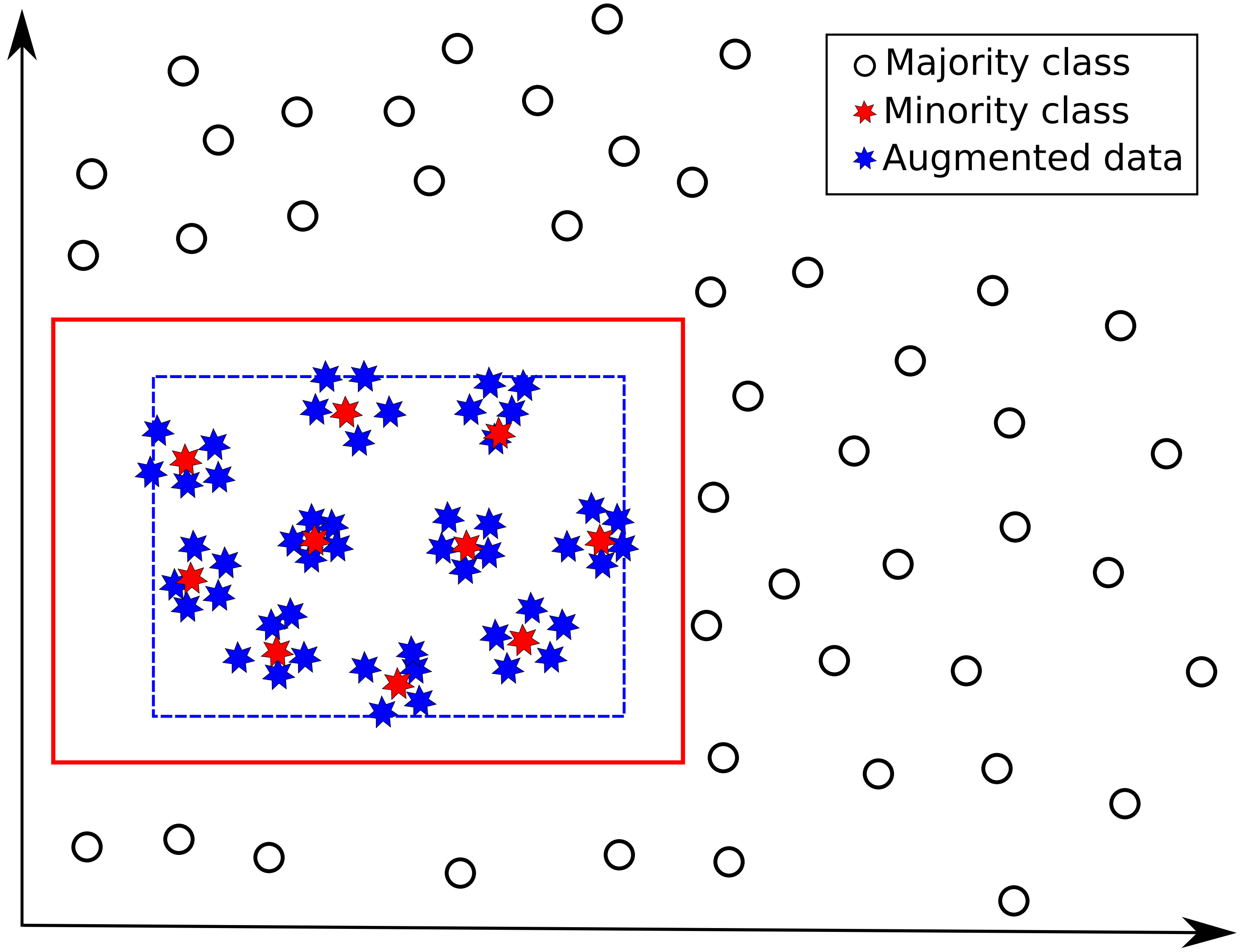



  - Image degradation. [4][65]



- Disadvantage of existing methods.

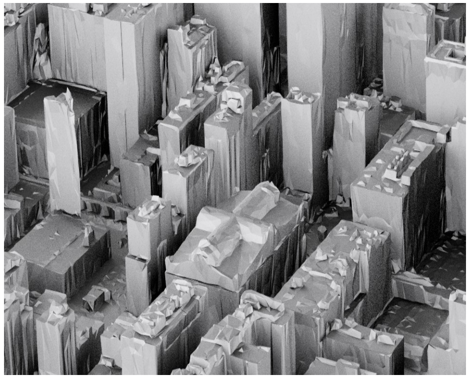


# The Proposed Approach

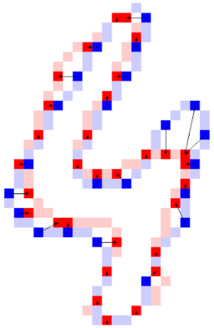
In contrast to existing methods, my approach:

- Generate templates/prototypes from data.
  - Automatically.
  - Semi-automatically.
- Synthesize more data using templates.

Satellite image roof style classification [100][105]



Aerial LiDAR roof style classification [106]



Handwritten digits recognition [105]

# Showcase One

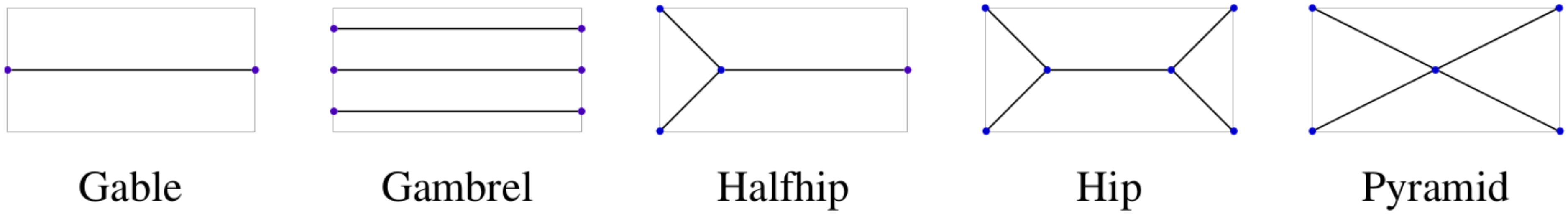
- Satellite image roof style classification.

  Decompose roof if necessary.

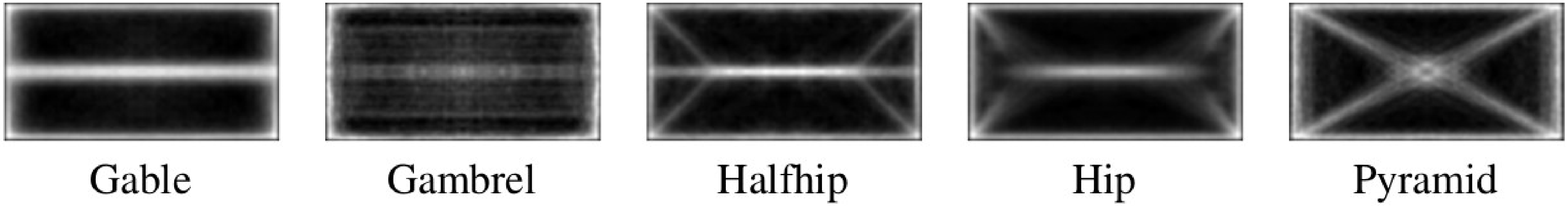
- Preprocessing to refine, scale and align images.

## Showcase One

- Prototype by design.
  - In [100], I manually designed prototypes.

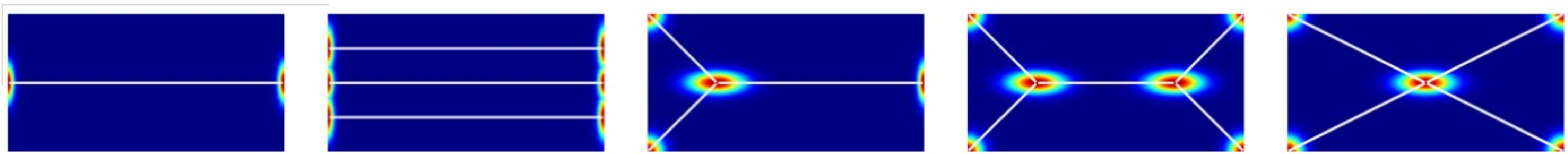



- Prototype by computation.
  - Identification of control points done automatically.



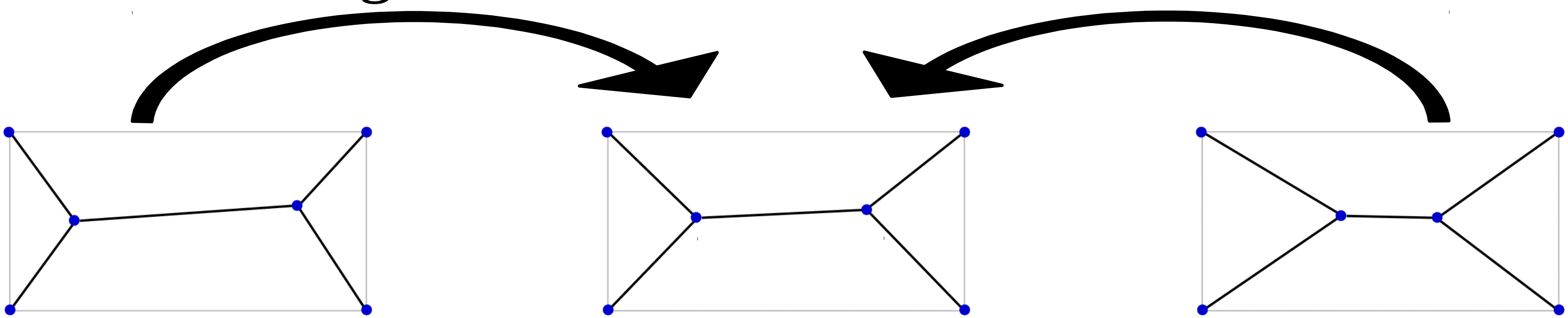
# Showcase One

- Data synthesis by distribution of control points.



Gable　Gambrel　Halfhip　Hip　Pyramid

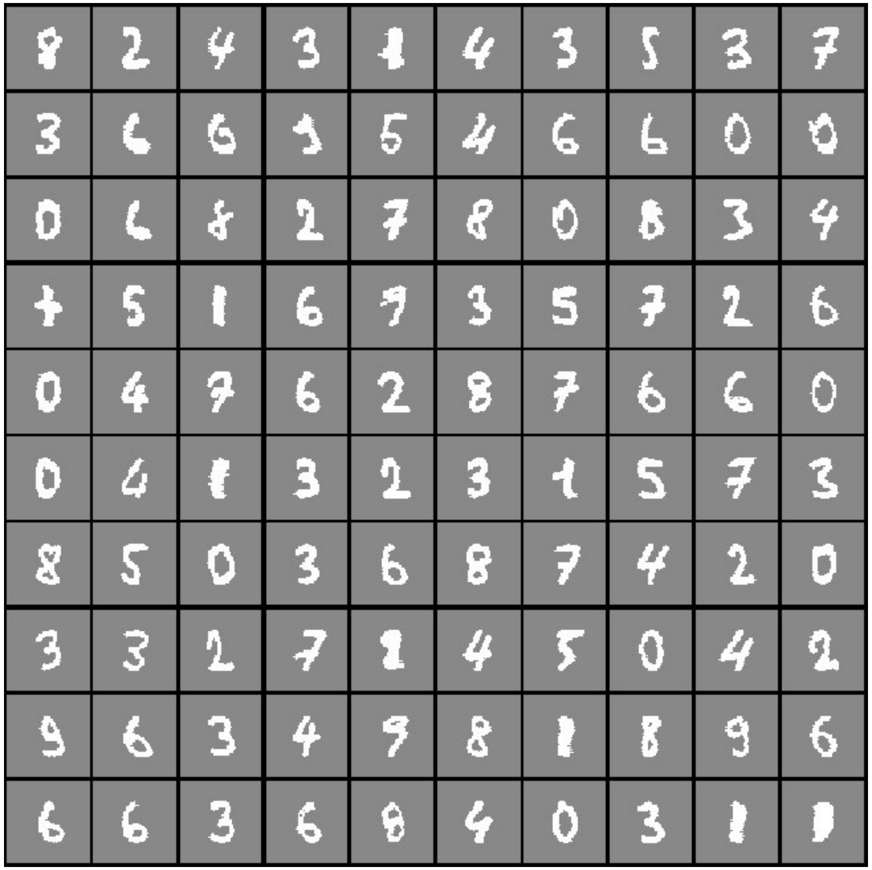
- Data synthesis by interpolation/extrapolation between nearest neighbors.



Source 1　Synthetic　Source 2

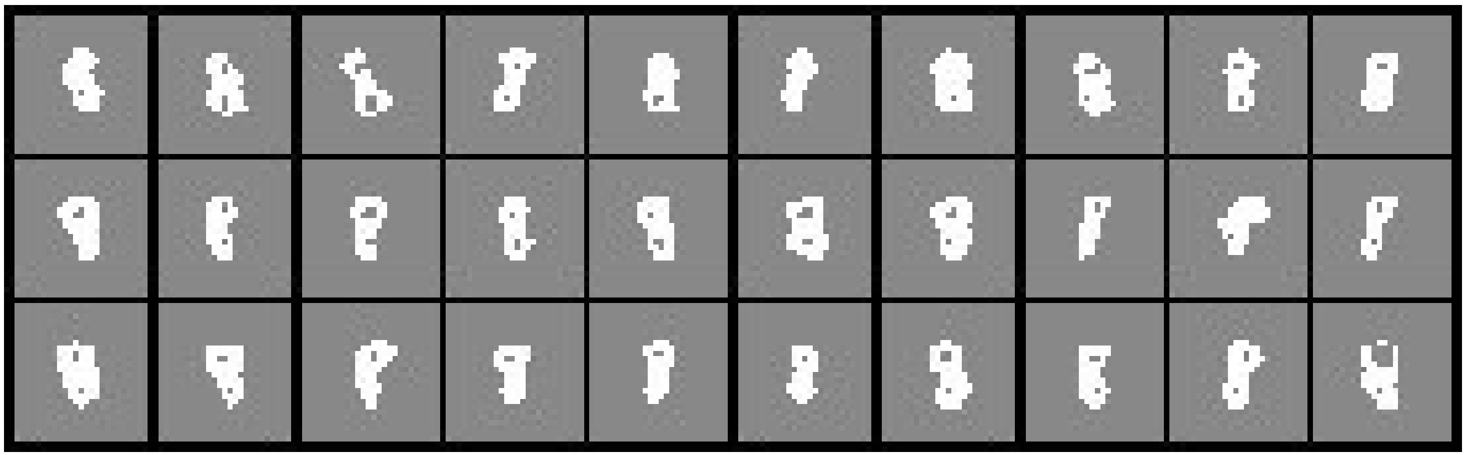
# Showcase Two

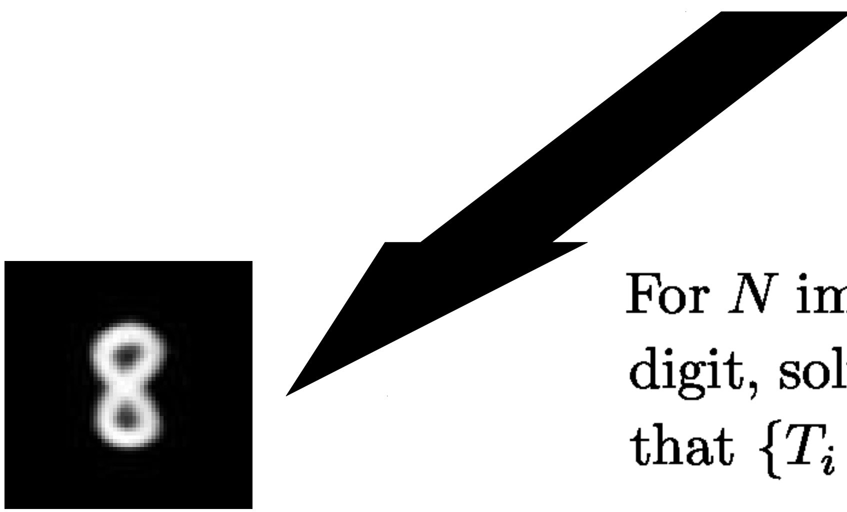
- Absolute rarity, digit from 0 ~ 9, each has around 200 samples.



# Showcase Two

- Generate prototype by congealing. [61]

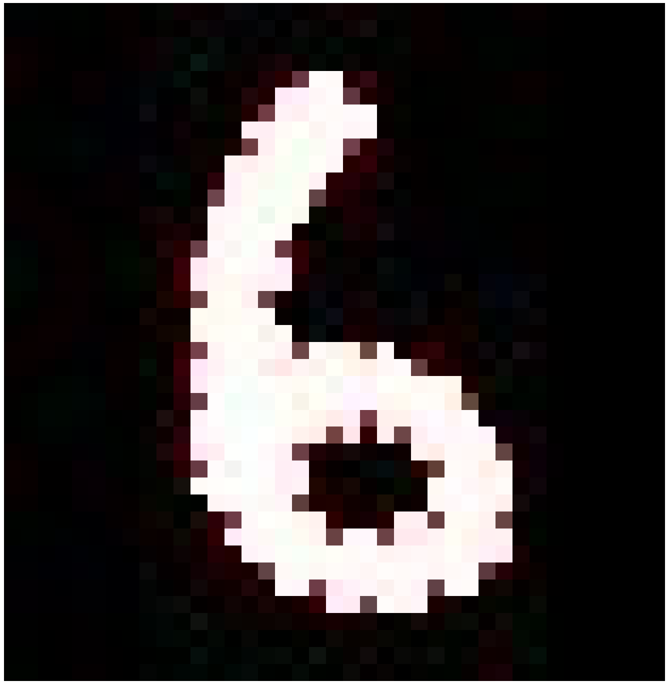




For $N$ images $\{I_i\}_{i=1}^{N}$ with the same digit, solve for transformations $\{T_i\}_{i=1}^{N}$, that $\{T_i \cdot I_i\}_{i=1}^{N}$ minimize joint entropy

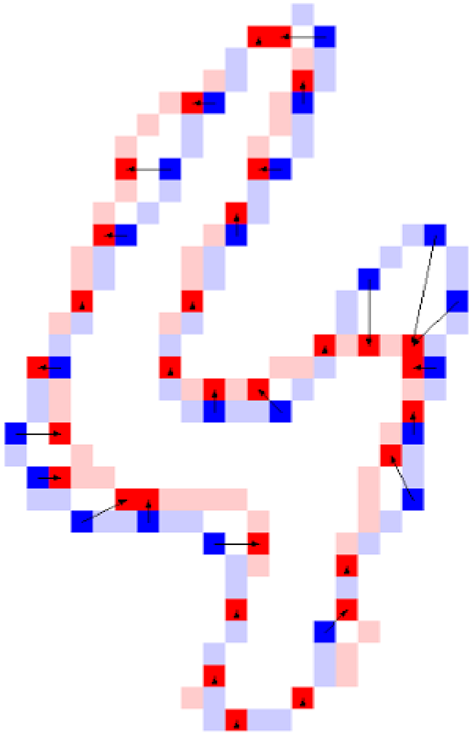
# Showcase Two

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



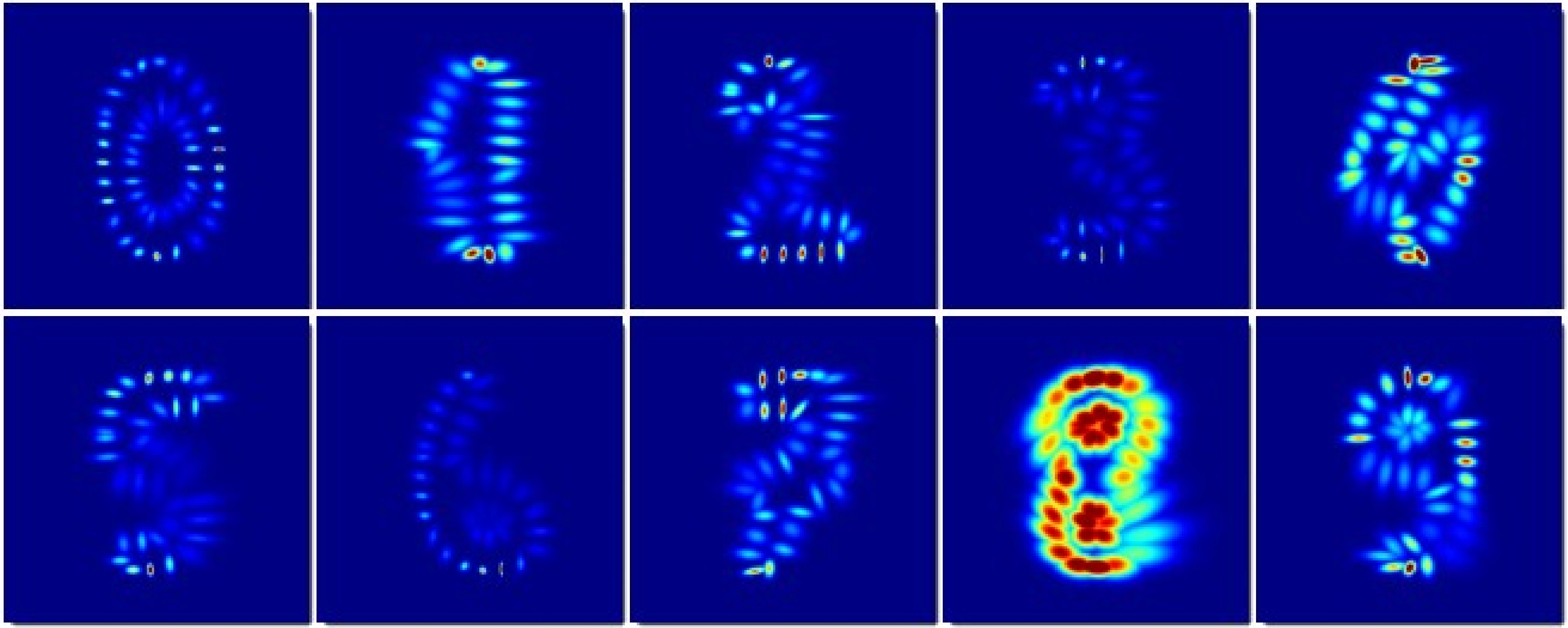
# Showcase Two

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



# Showcase Two

- Data synthesis by distribution of control points.



- Data synthesis by interpolation/extrapolation between nearest neighbors.

# Showcase Two

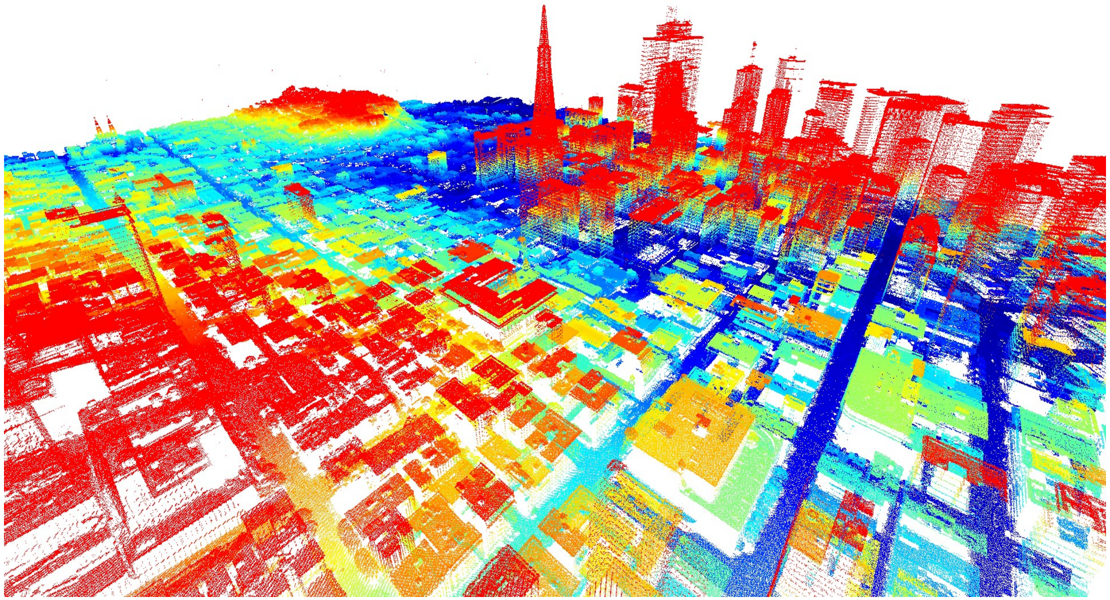
- Boost the performance by adding synthetic data.

| | Real | Syn | Real+Syn |
|---|---|---|---|
| **CNN** | 0.65 | 0.68 | 0.70 |
| **SVM** | 0.77 | 0.78 | 0.80 |

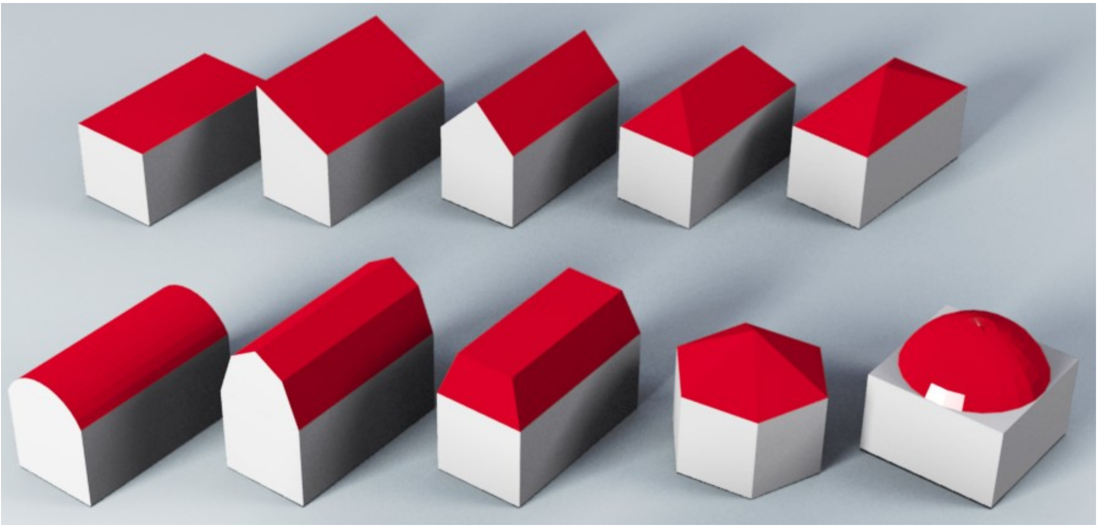
# Showcase Three

Aerial LiDAR

Downtown San Francisco

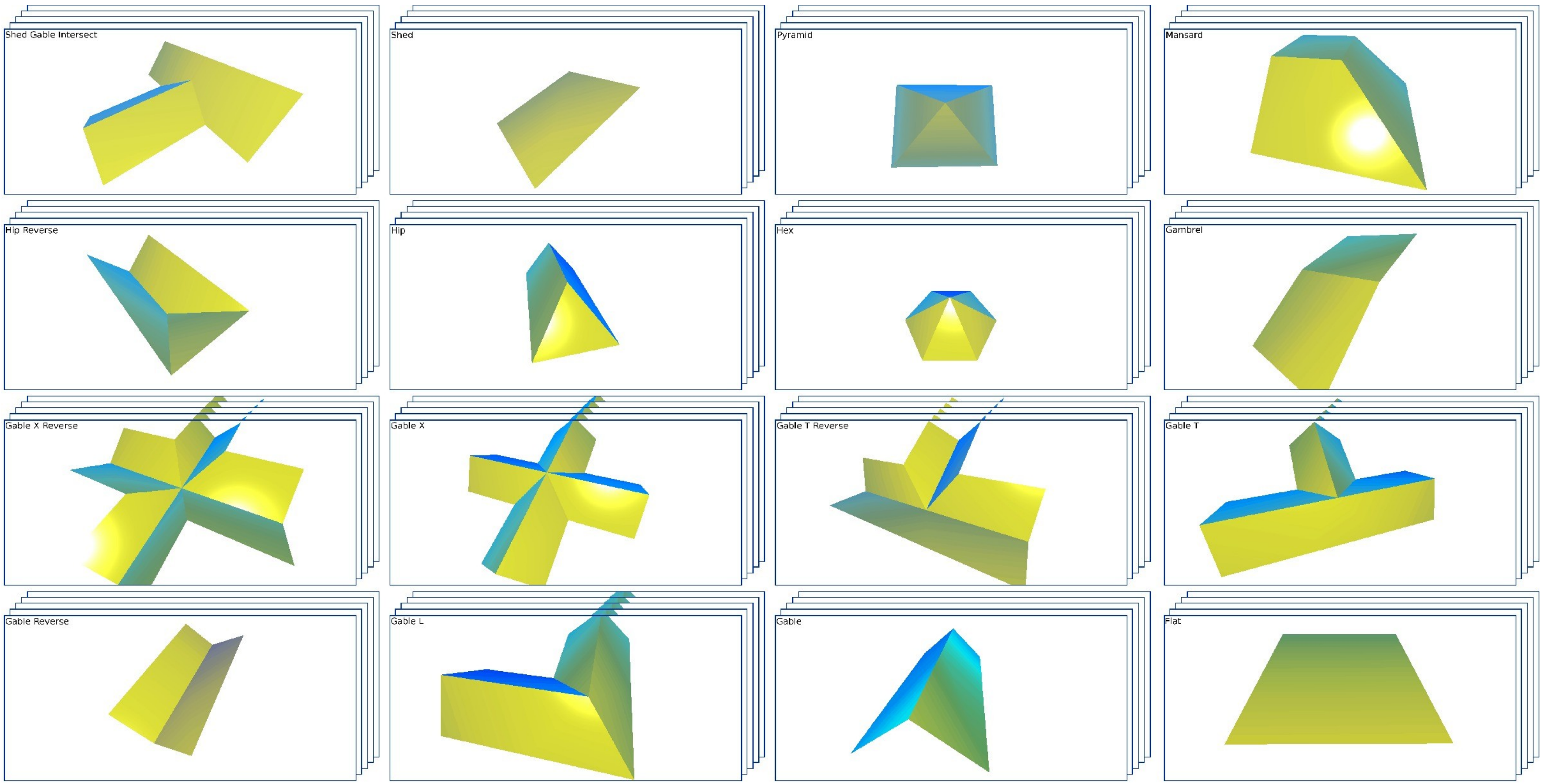


Candidate roof styles



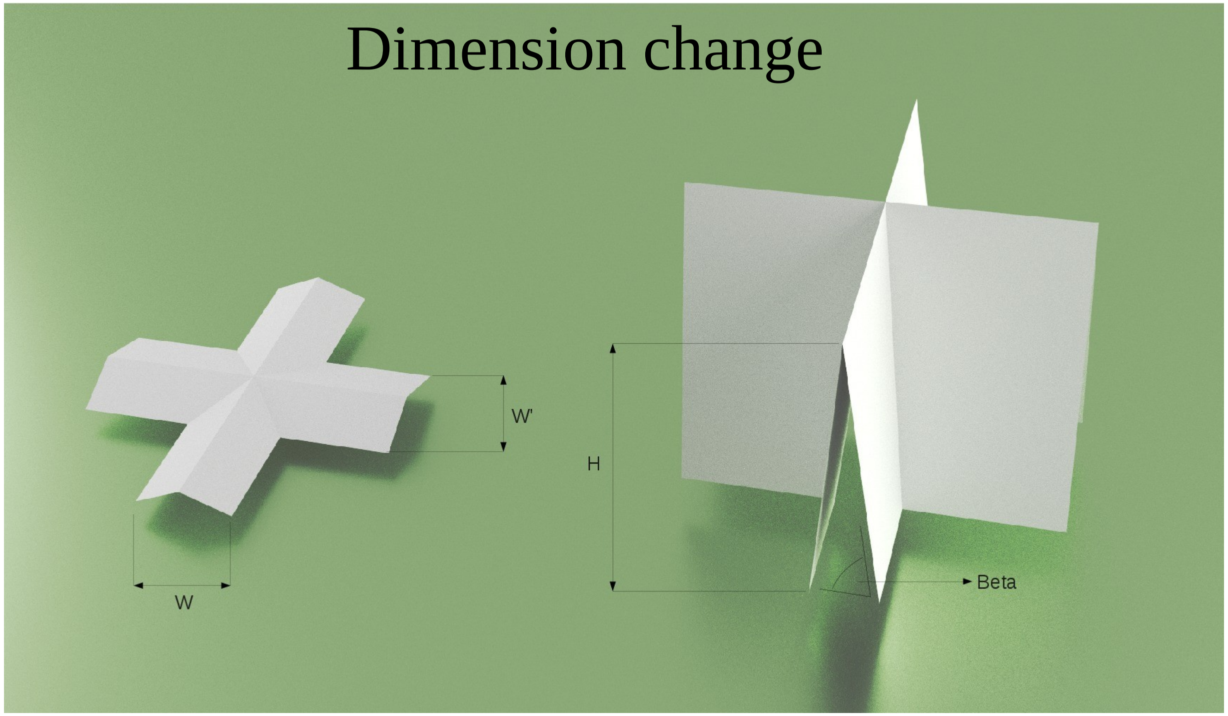
# Showcase Three

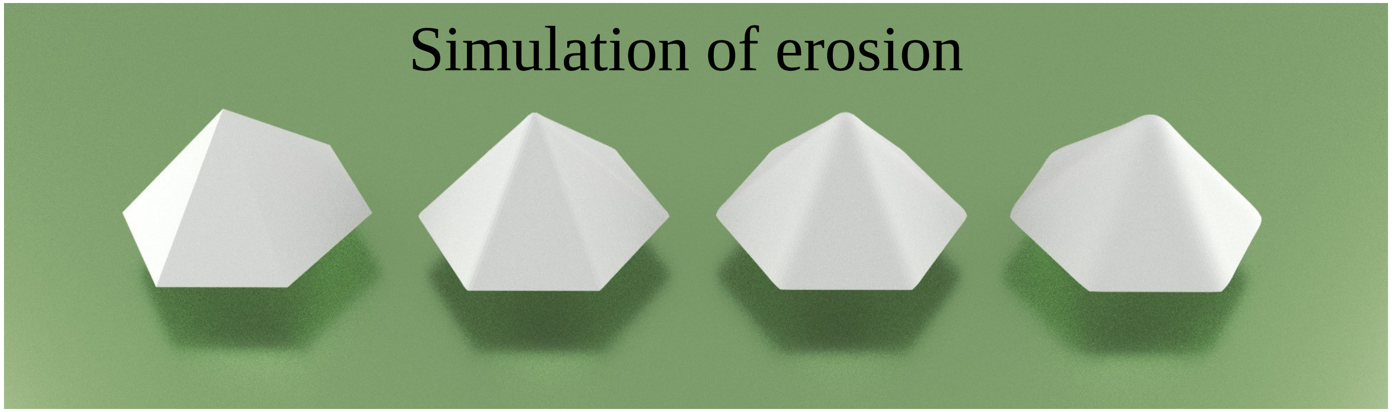
- Build prototypes.



# Showcase Three

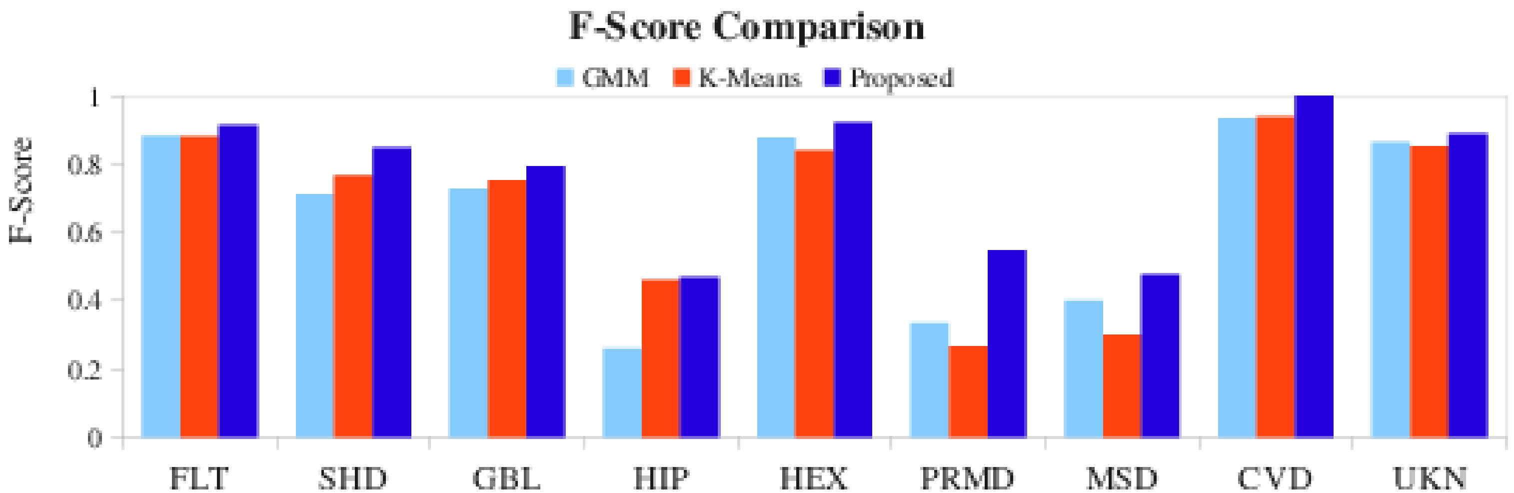
- Derive more data.



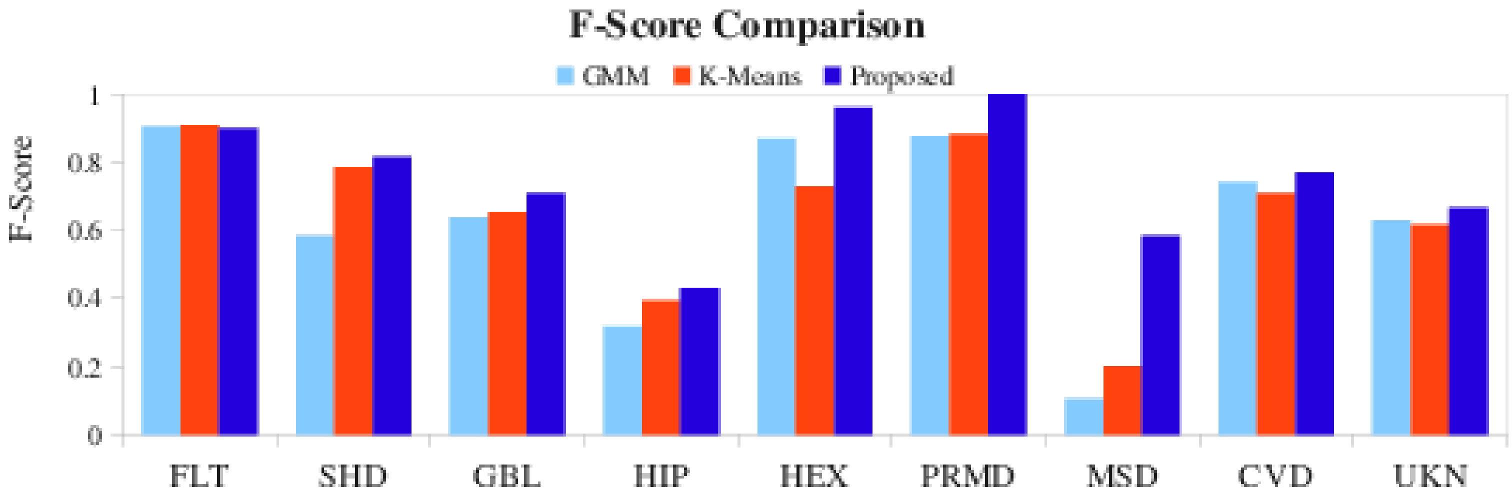



# Showcase Three

- Boost recognition rate by adding synthetic data.




Chicago




San Francisco

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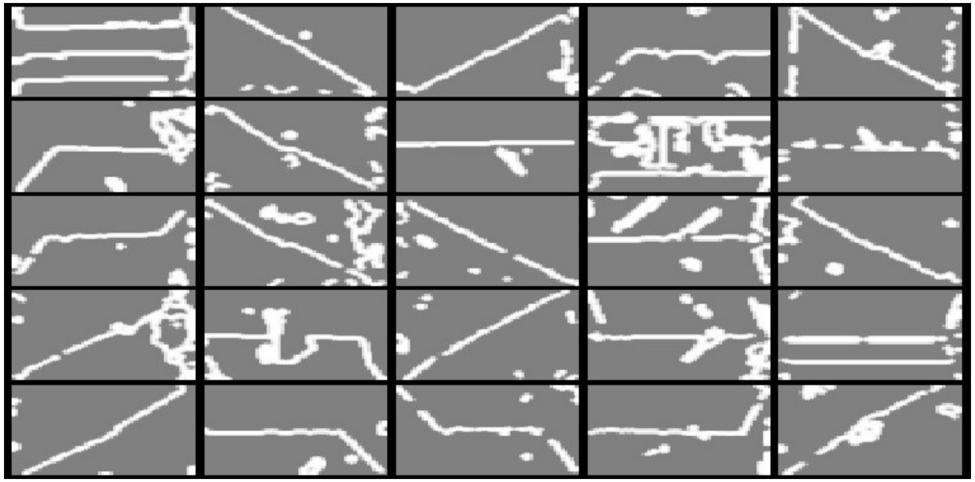
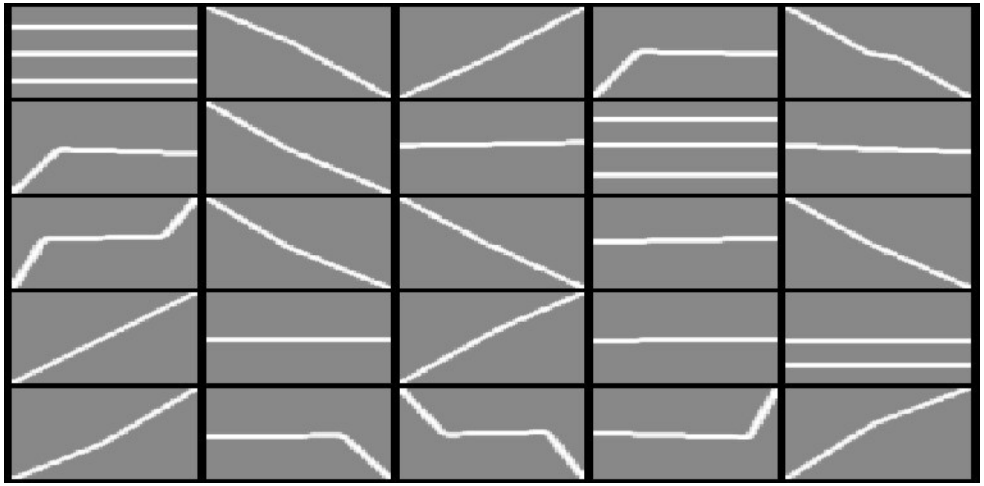
# Learning from Synthetic Data

- Challenging task.

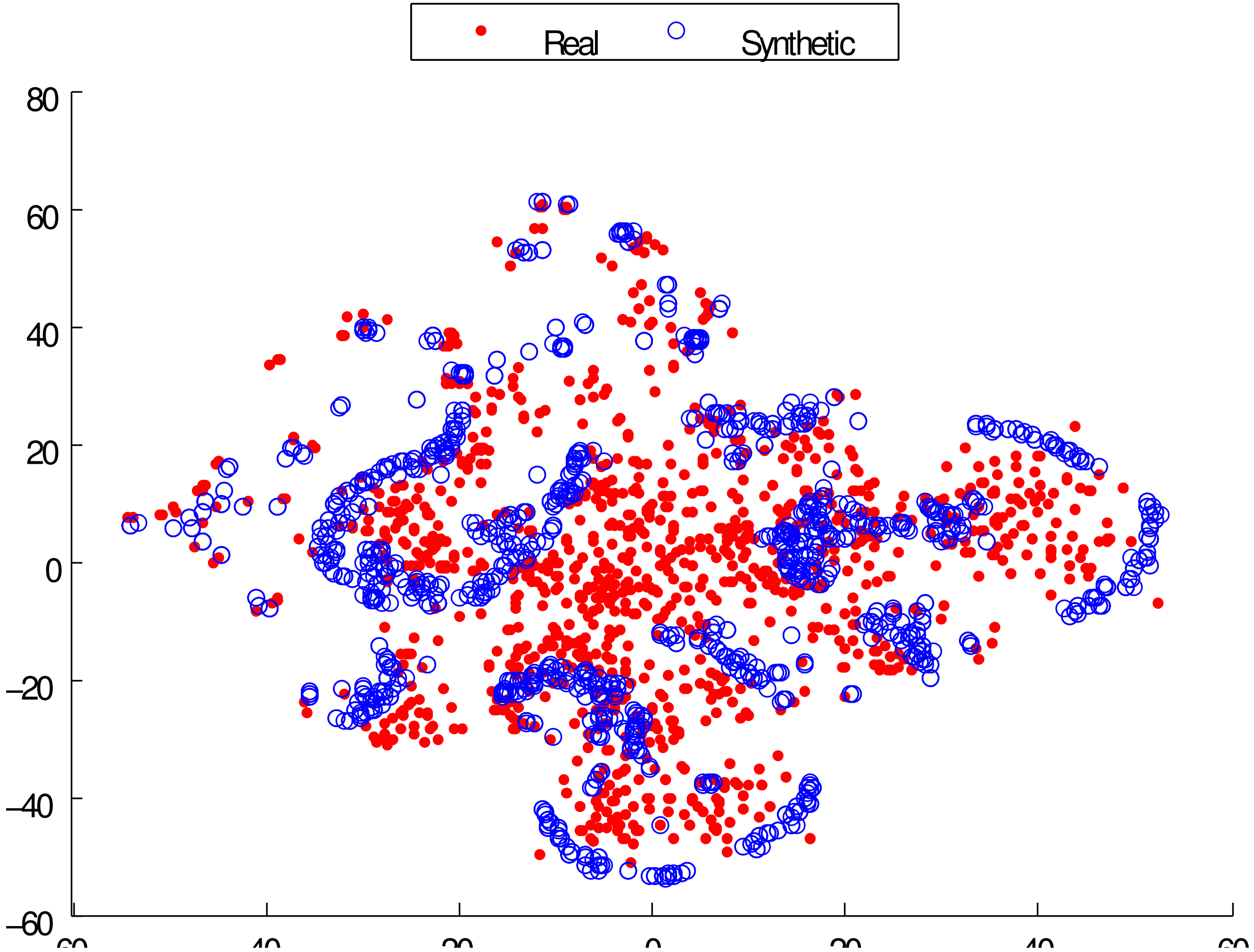


Actual data



Synthetic data

- Challenging task.



- 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.

Two types of features:

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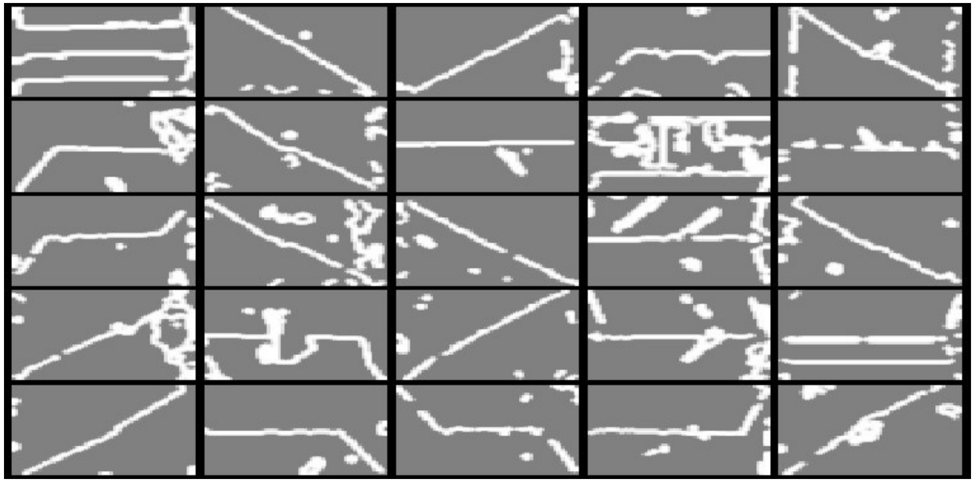
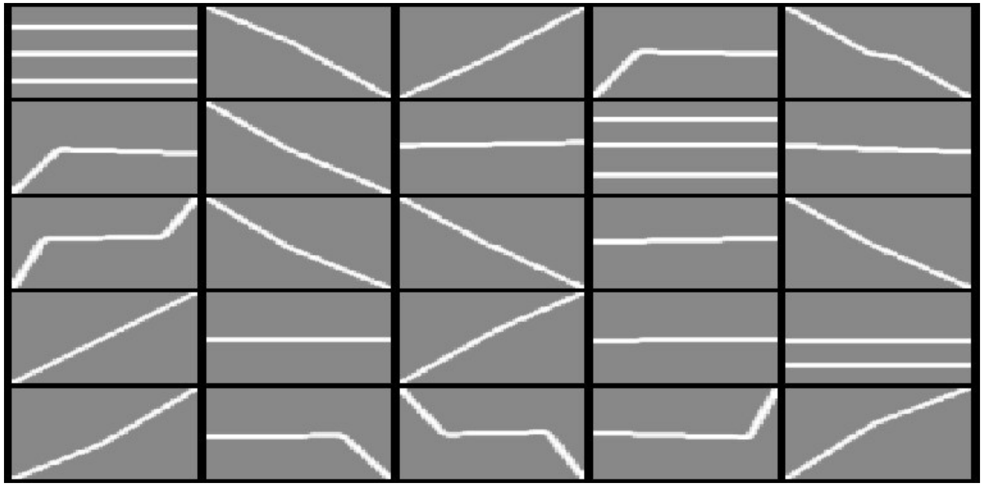
# Showcase One

- Satellite image roof style classification.



Actual data

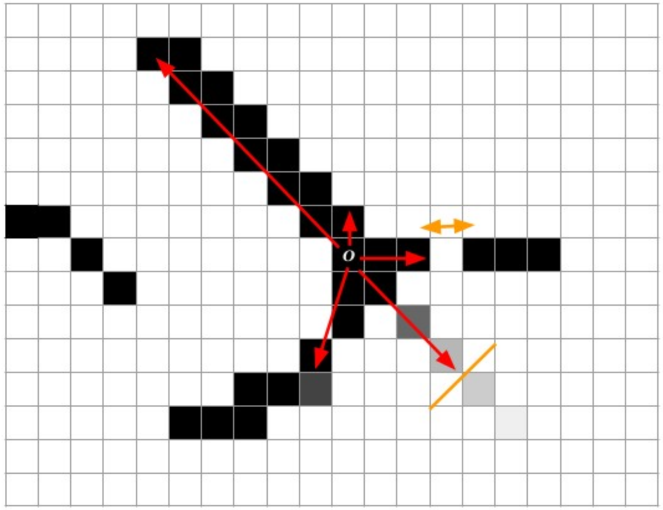


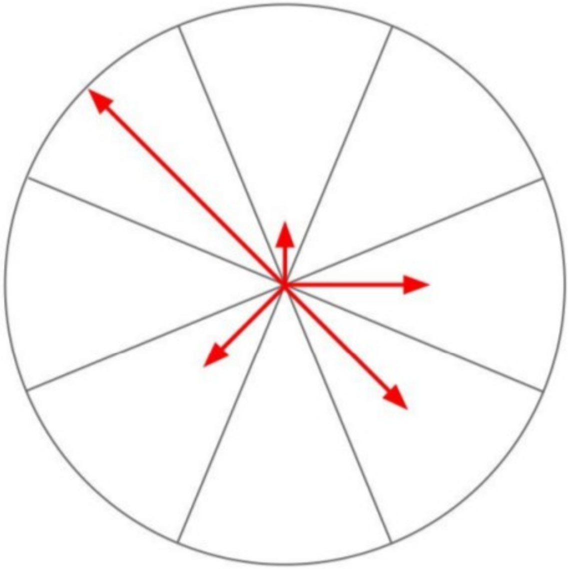
Synthetic data

- 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:

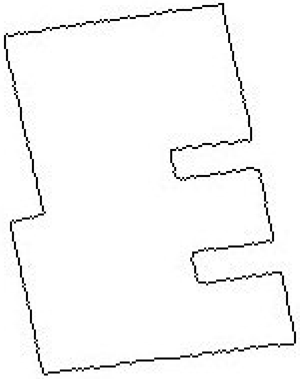
| | HIP | GABLE | FLAT | HALFHIP |
|---|---|---|---|---|
| HOG | 0.805 | 0.882 | 0.954 | 0.597 |
| SC | 0.350 | 0.828 | 0.959 | 0.140 |
| HOR | 0.898 | 0.950 | 0.968 | 0.632 |
| LBP | 0.000 | 0.986 | 0.631 | 0.000 |
| HOR+HOG | 0.931 | 0.959 | 0.982 | 0.667 |
| HOR+SC | 0.619 | 0.891 | 0.959 | 0.436 |
| HOG+SC | 0.752 | 0.959 | 0.945 | 0.474 |
| SC | 0.743 | 0.869 | 0.963 | 0.509 |

# Showcase Two

- Retrieve the most matching satellite building image for synthetic building footprint. [104]
- Challenges: Noise, occlusion and shape difference.

Original actual image

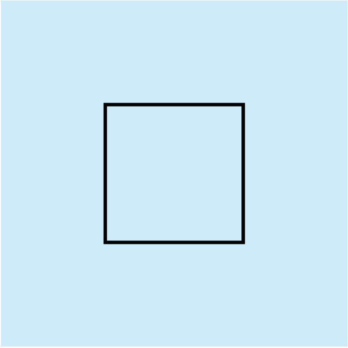
Edge extracted

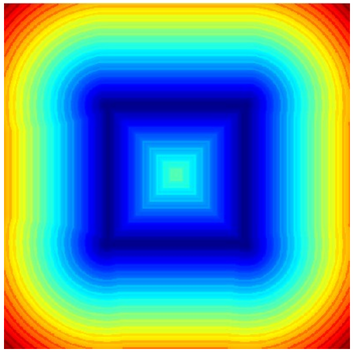


Synthetic building footprint

# Showcase Two

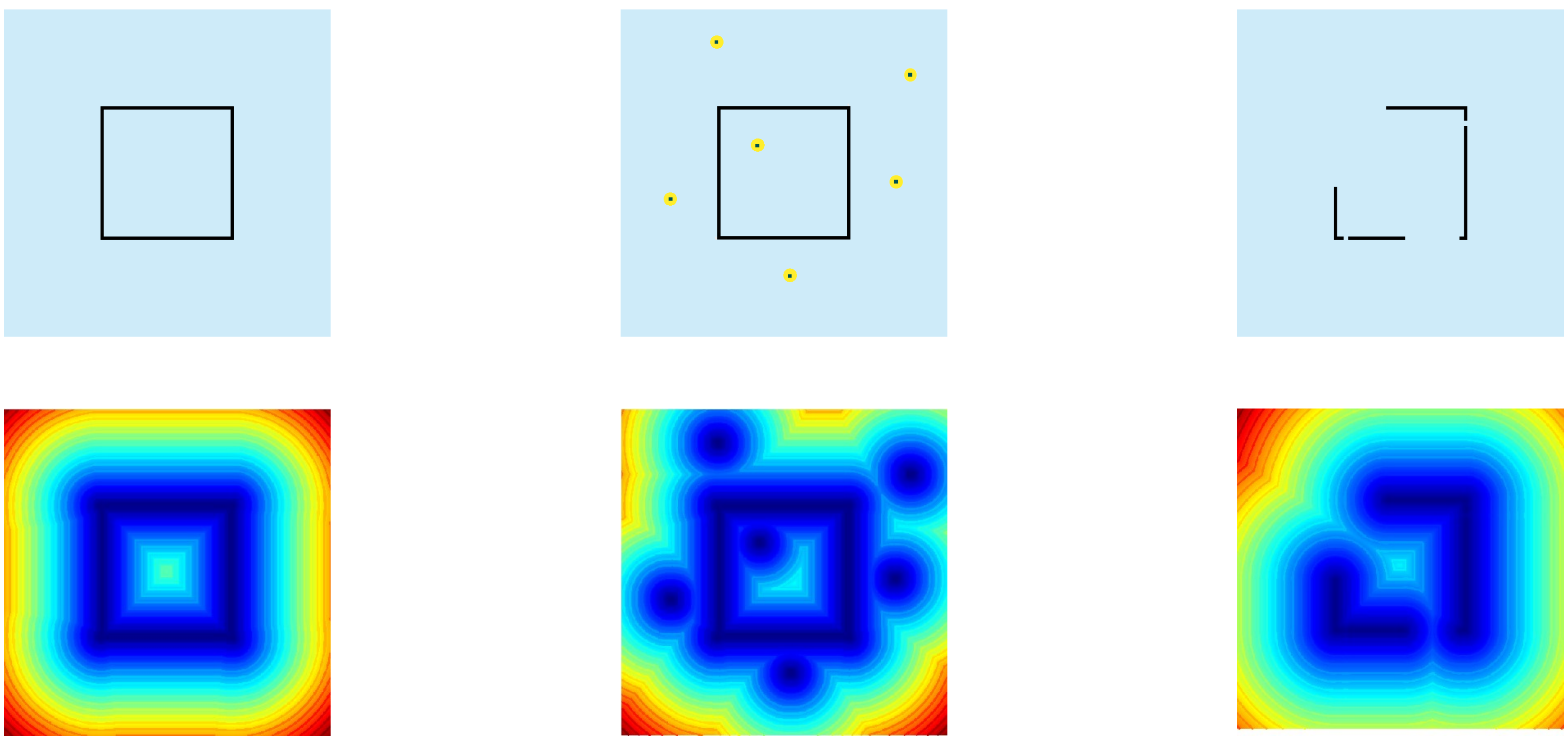
- Matching metric is derived from classic Chamfer matching.





# Showcase Two

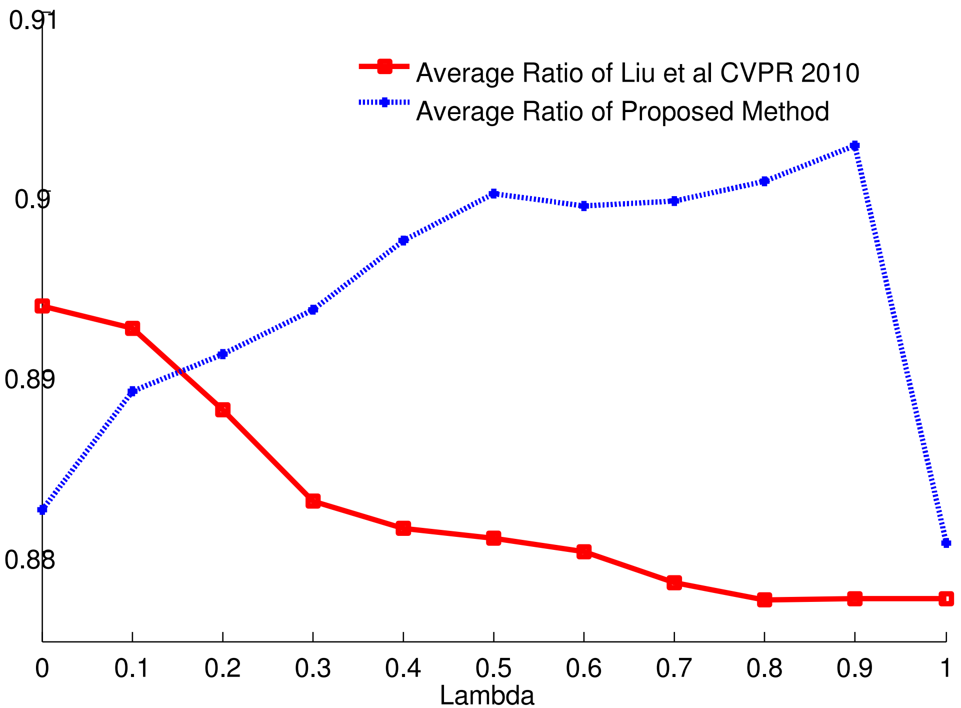
- Matching metric is derived from classic Chamfer matching.
- However



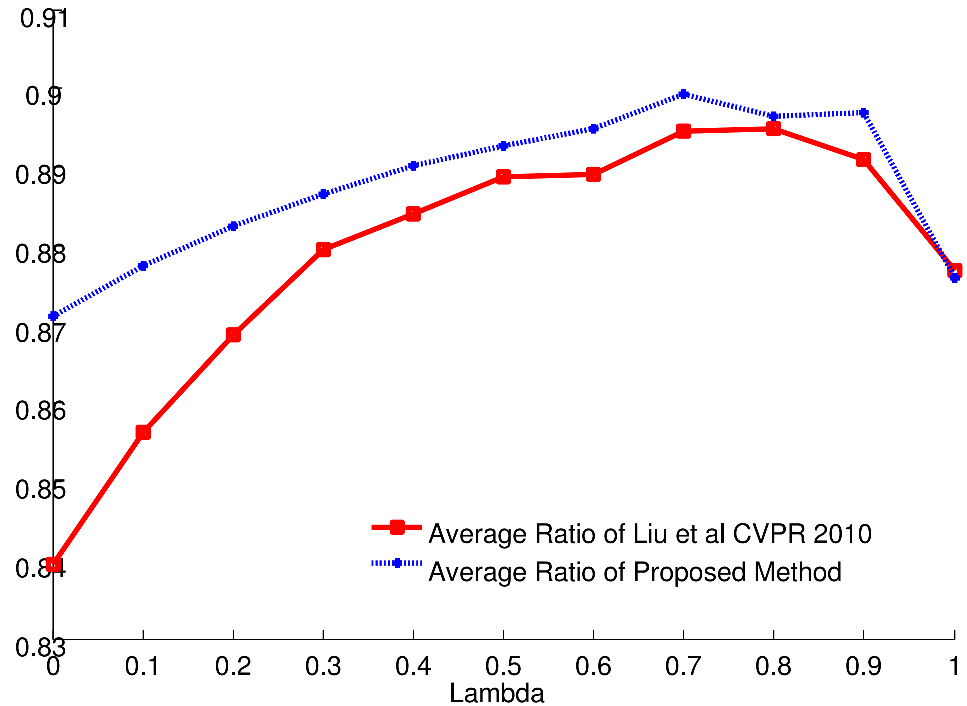
## Showcase Two

- I extend Chamfer matching from three aspects.
  - Add edge orientation to distance metric.
  - Add edge distance variance to distance metric.
  - Mechanism to matching incomplete targets.

# Showcase Two



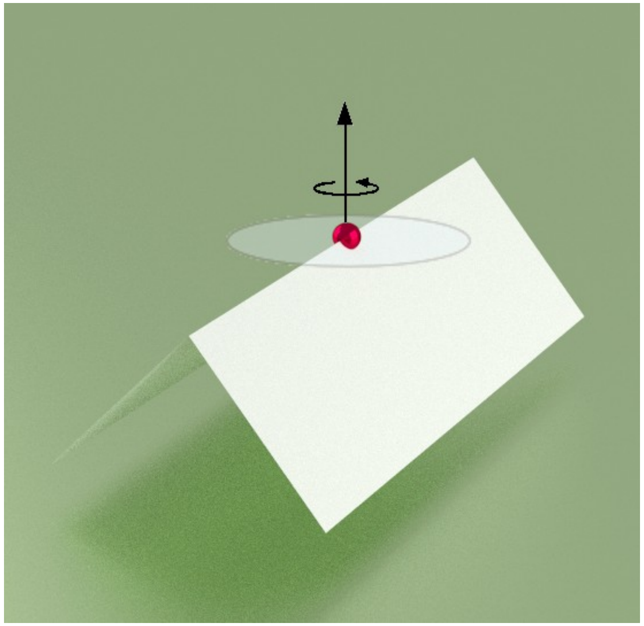

Chicago

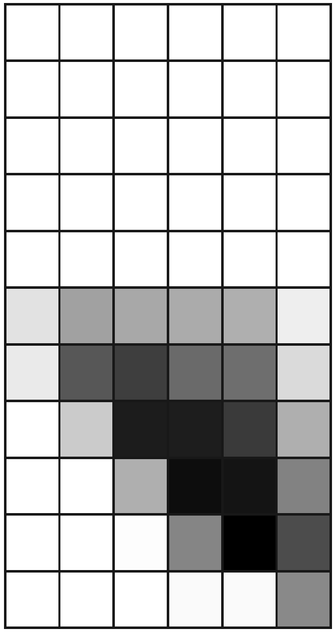



San Francisco

# Showcase Three

- Extract features that characterize local geometry.





Spin image

# Showcase Three

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

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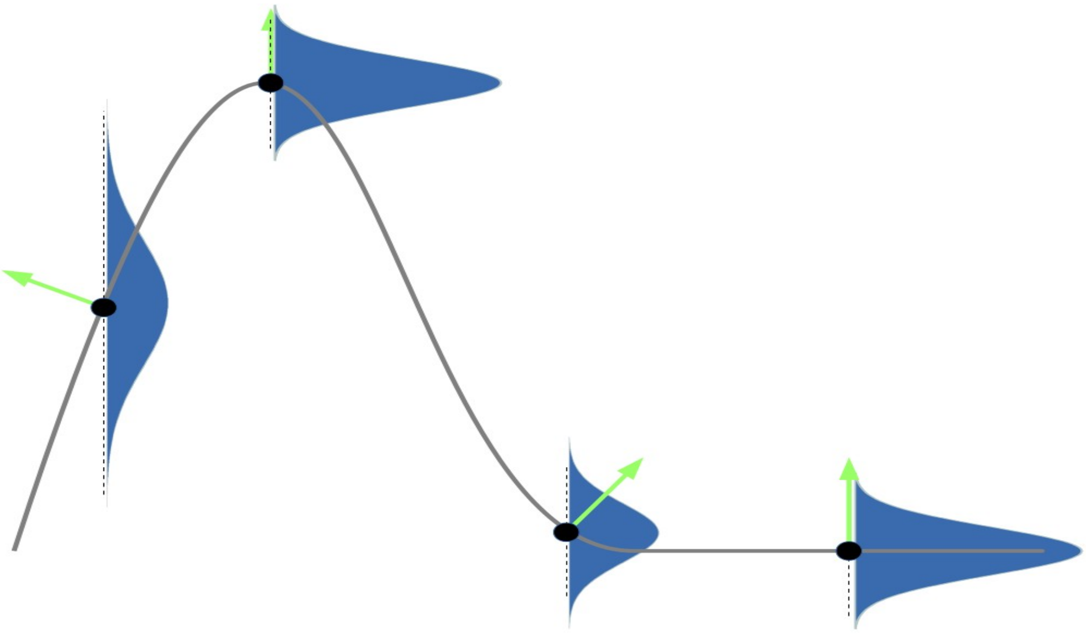
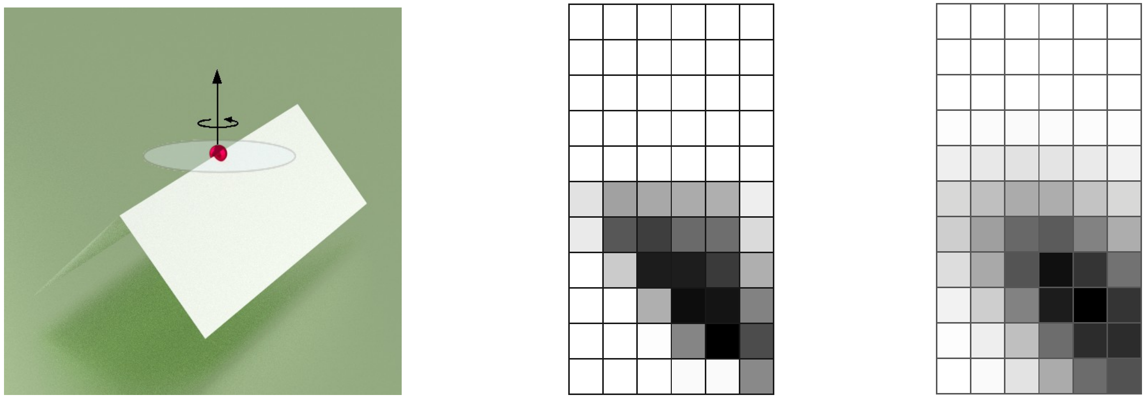
- Extract features that characterize local geometry.
- However, too regular and smooth.
- Learning bumpiness as a function of surface slope.



## Showcase Three

- 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

# Showcase Three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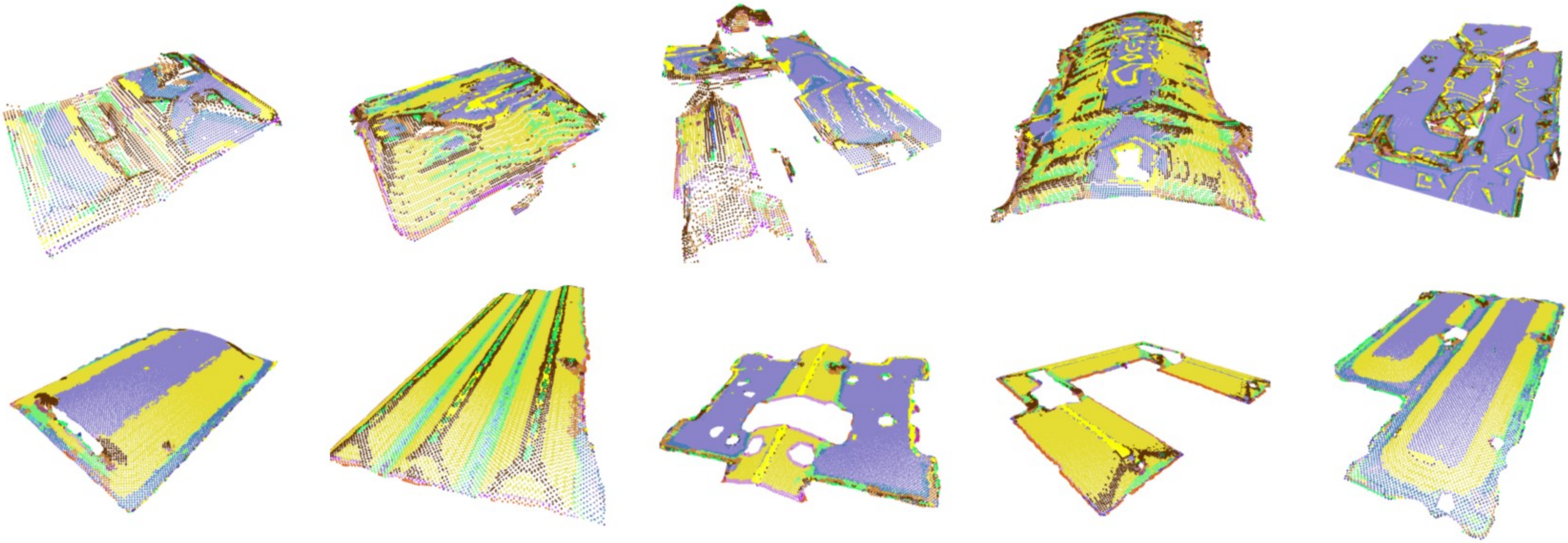
## Showcase Three

- Point semantics classification results.



# Showcase Three

- 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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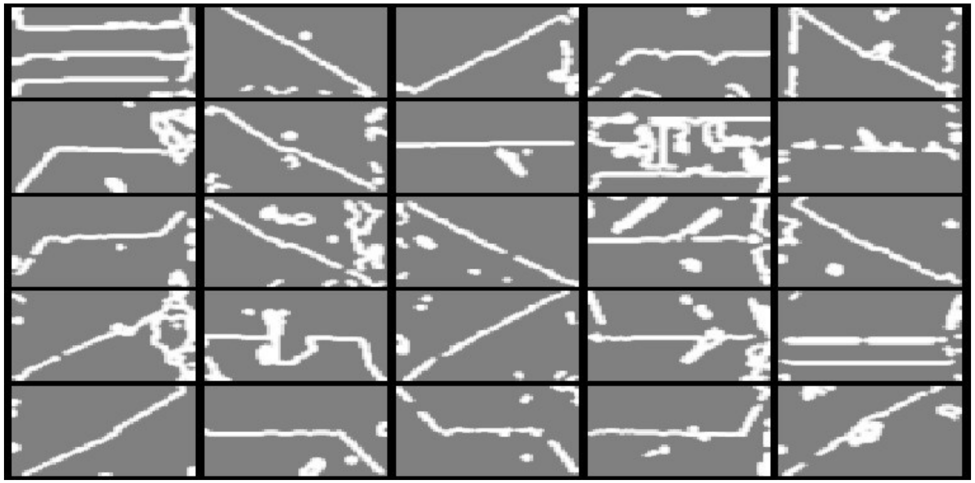
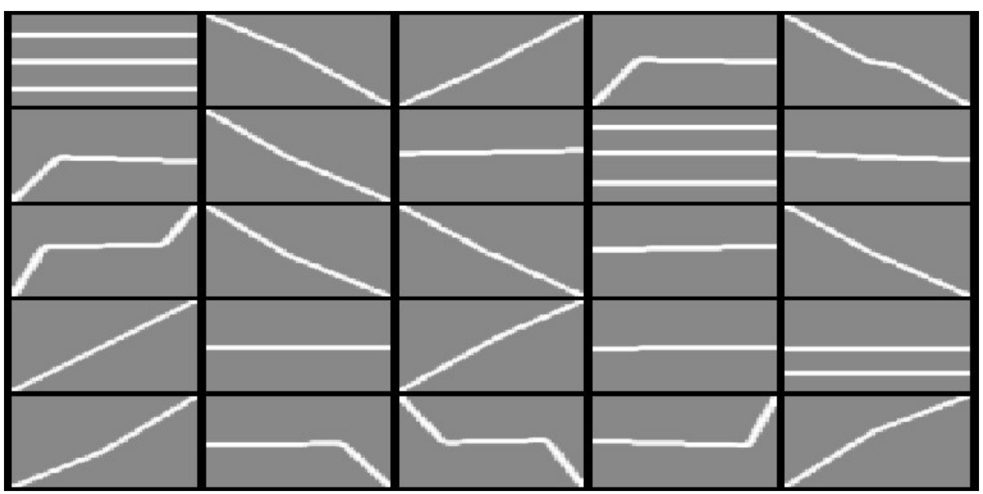
# Eliminate Synthetic Gap

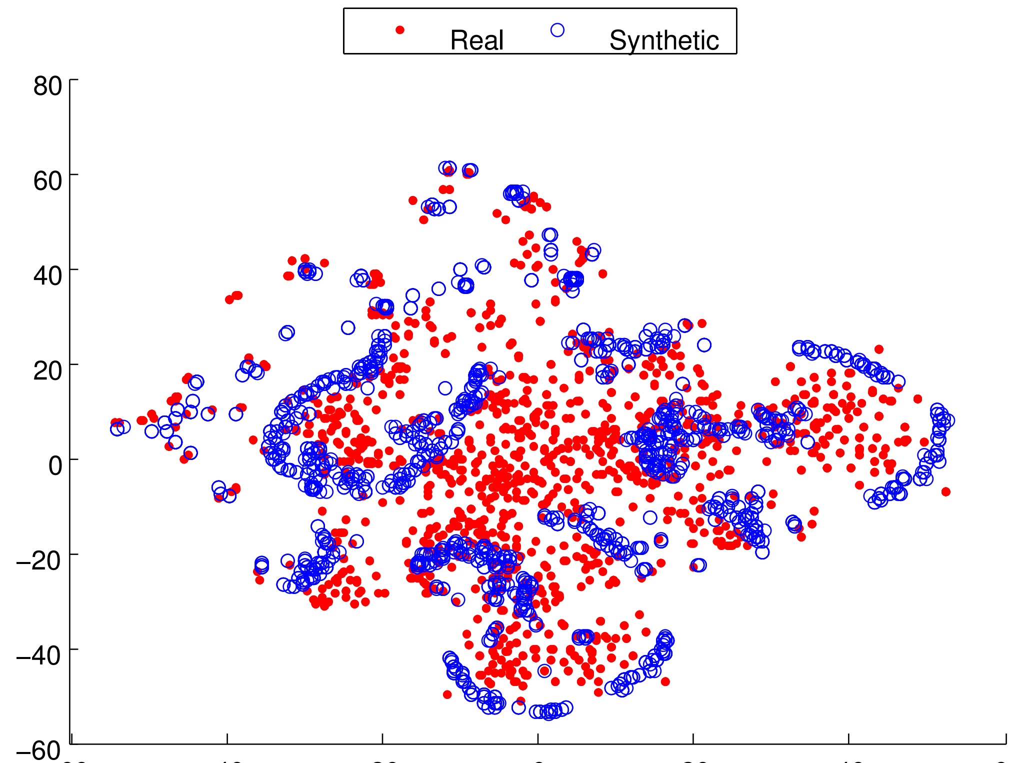
- Synthetic gap.



Actual data



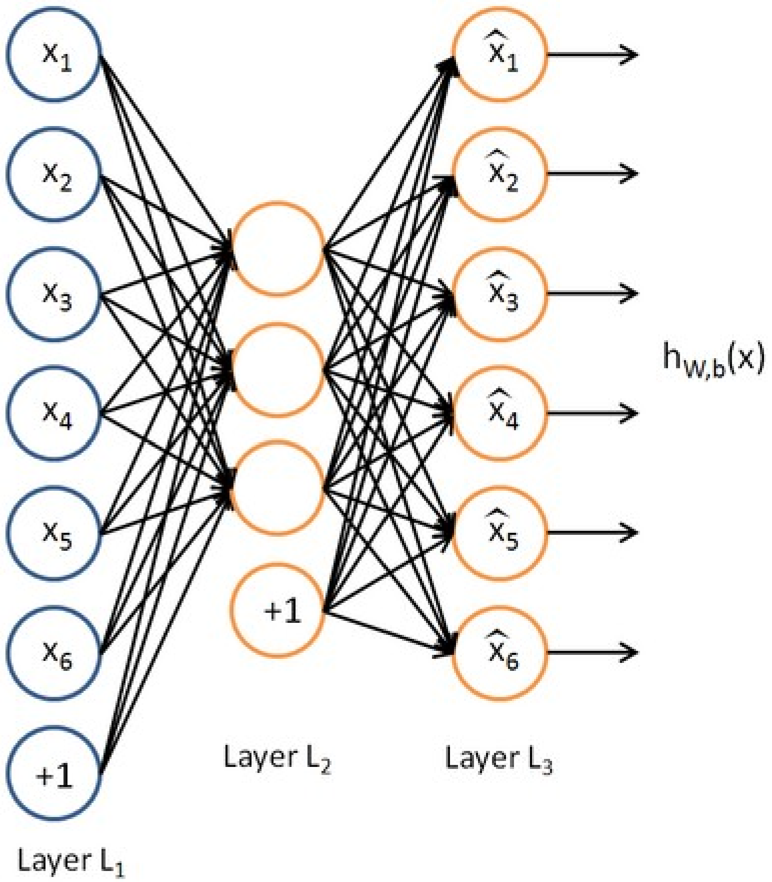
Synthetic data

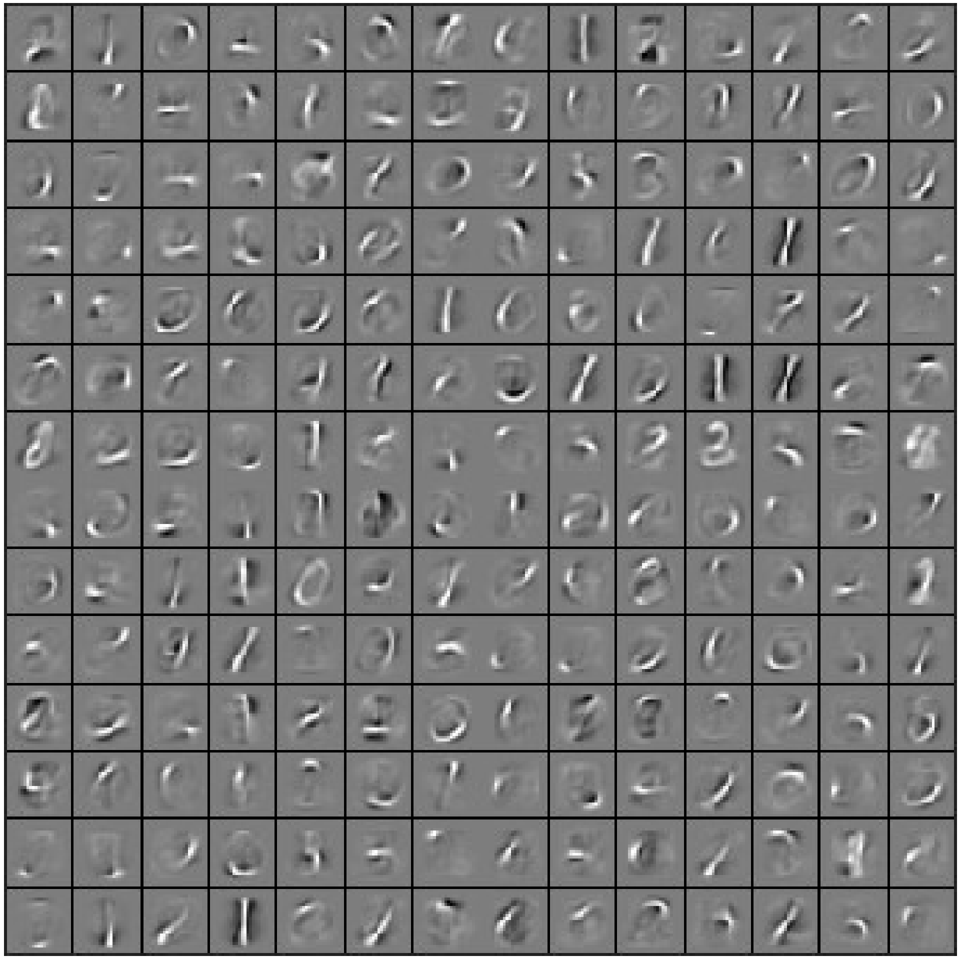


- Previous work.
  - Eliminate distribution means in Kernel Reproducing Hilbert Space (KRHS). [12][46]
  - Subspace alignment. [35][24]
  - Deep neural network using KRHS as domain loss. [32][19]

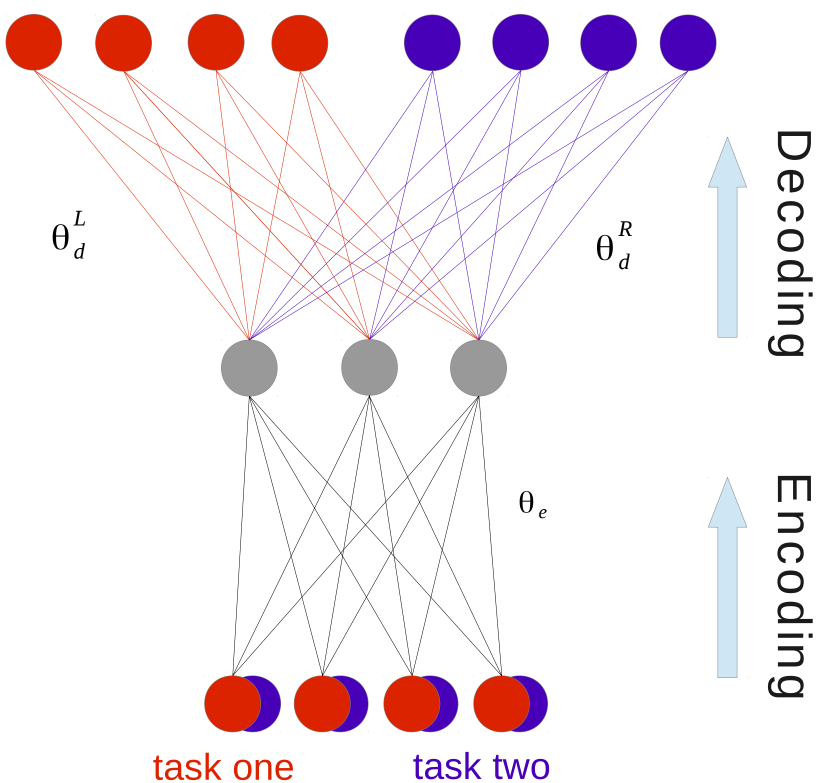
- The proposed approach.
  - Multi-Channel Autoencoder (MCAE)

- Traditional autoencoder

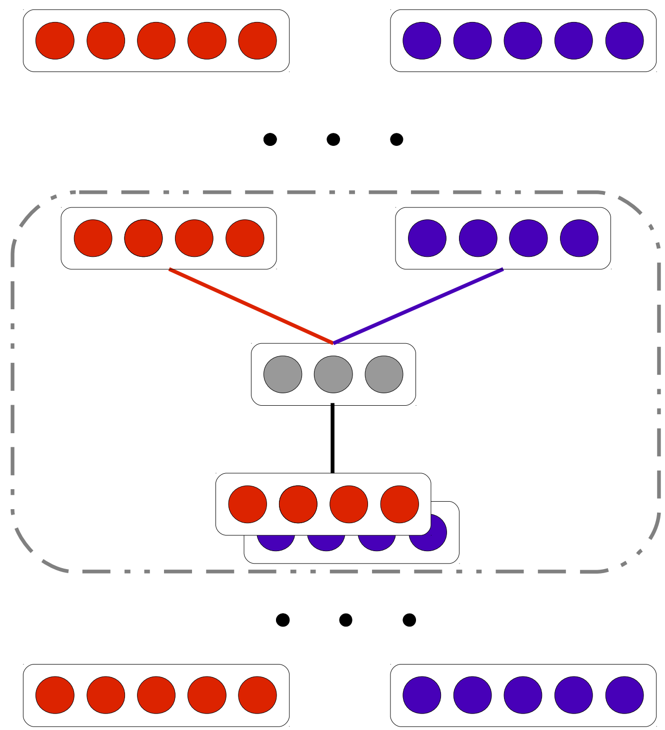


- The proposed MCAE




Basic structure



Stacked up

- MCAE

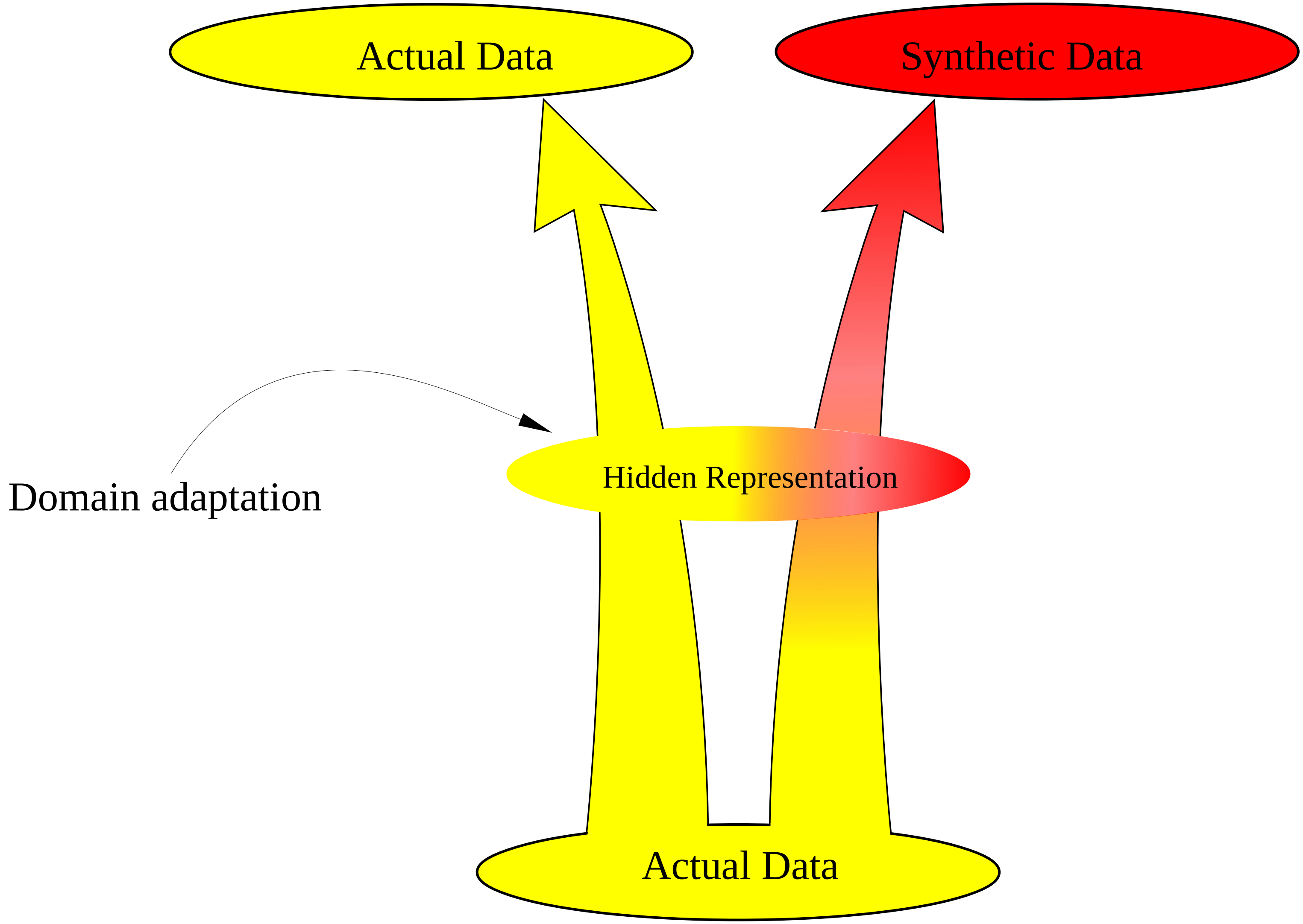
Jointly learn two tasks, left and right, together.

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

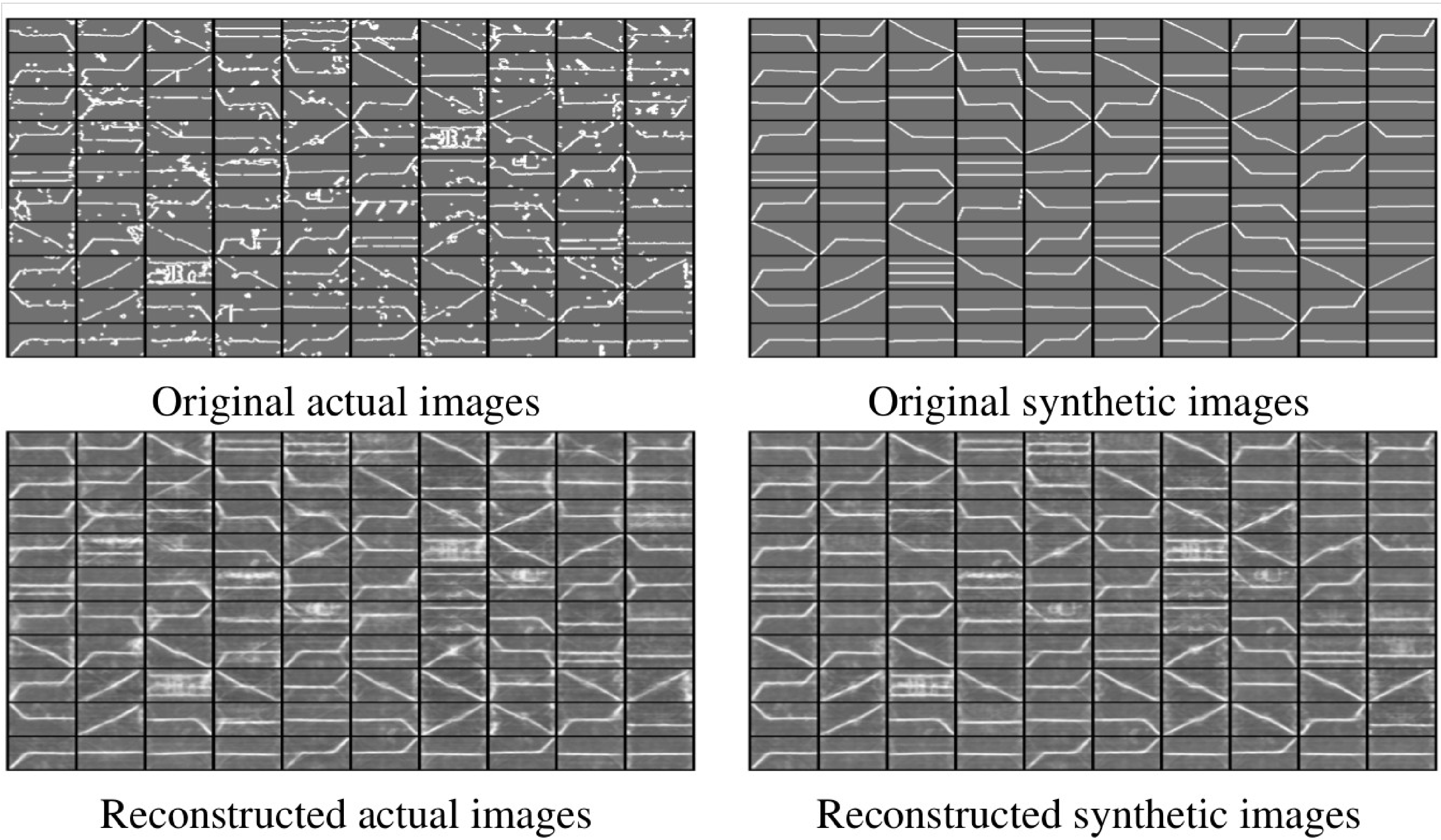
where

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

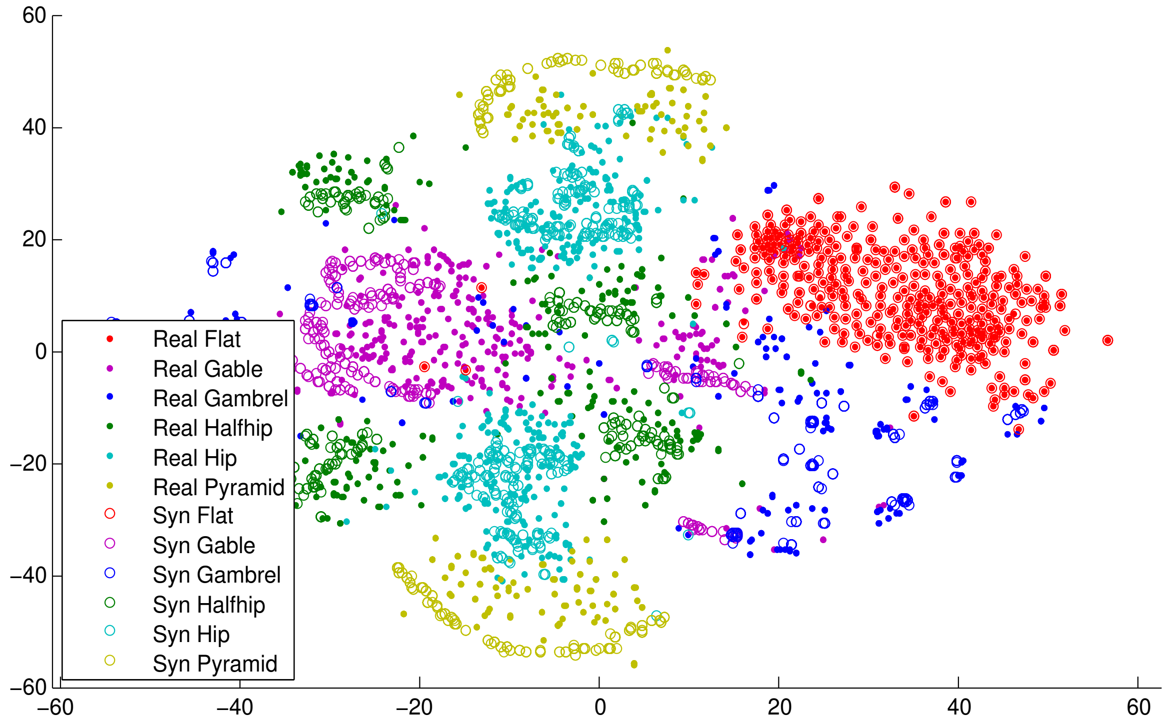
- Configuration of MCAE



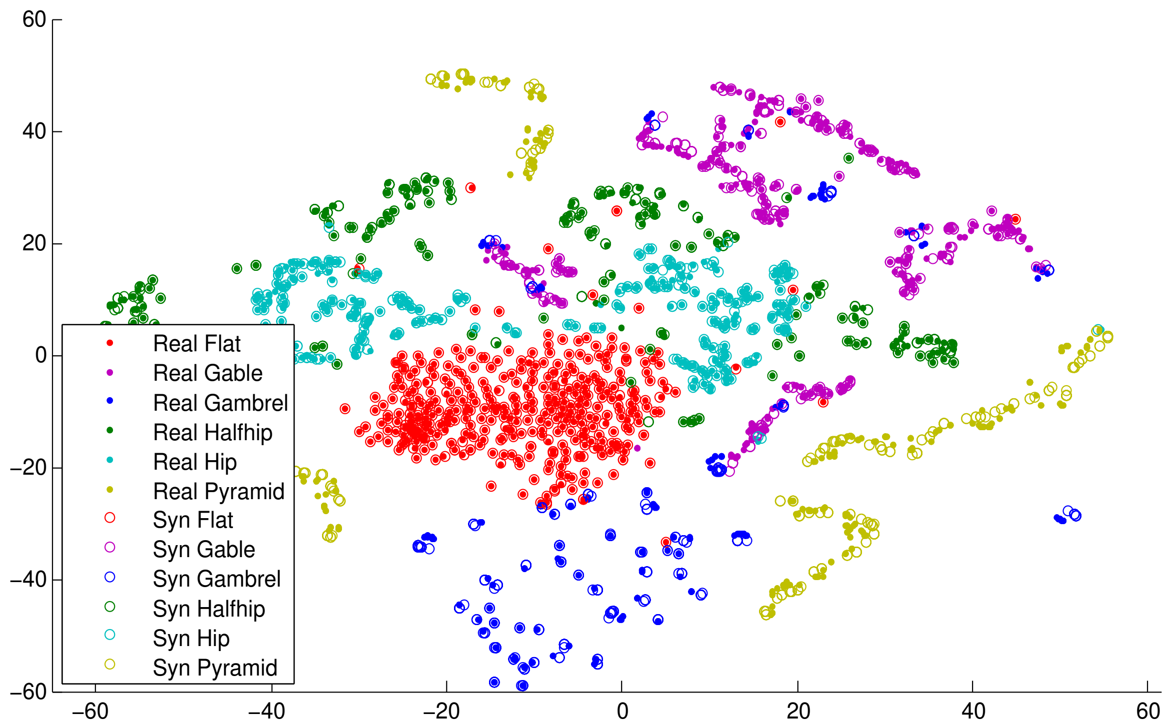
- Visualization of domain adaptation.



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 |

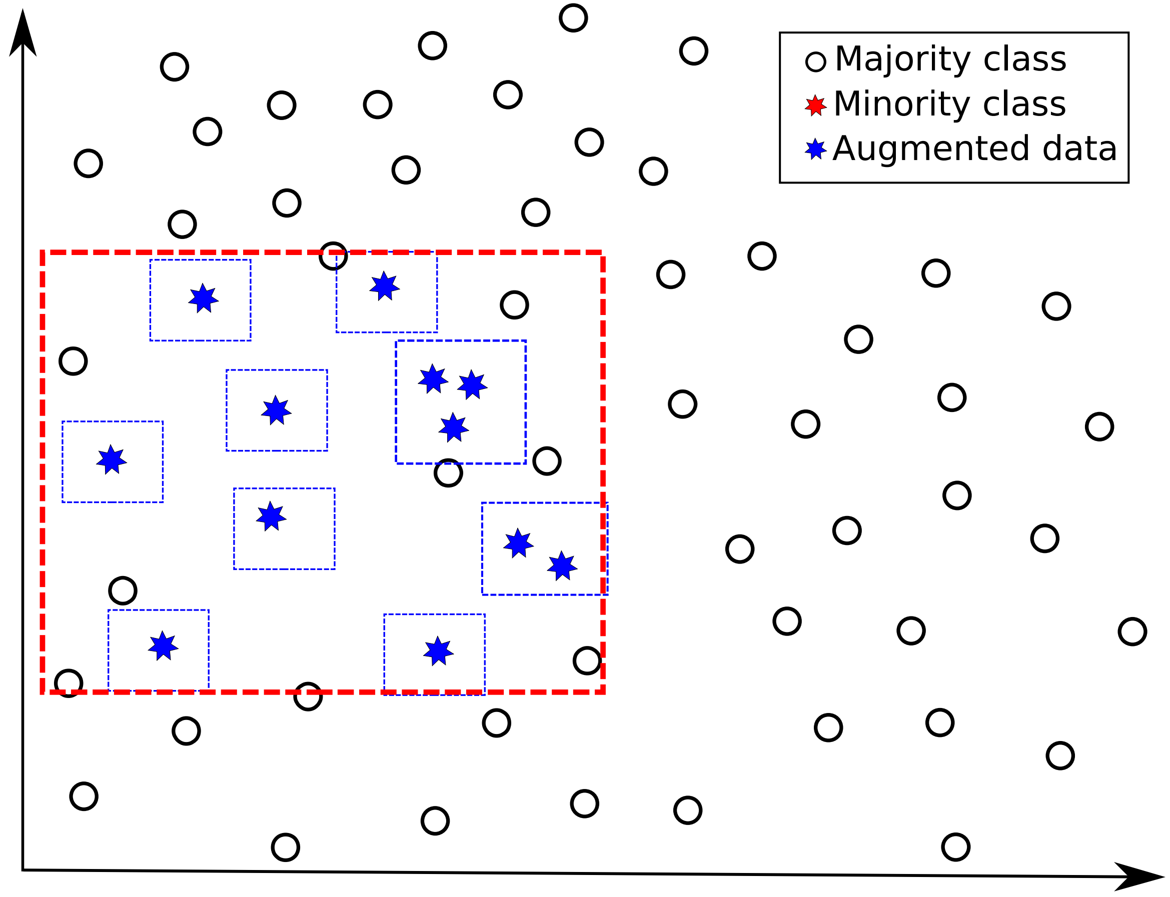
Handwritten digit dataset

- 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.

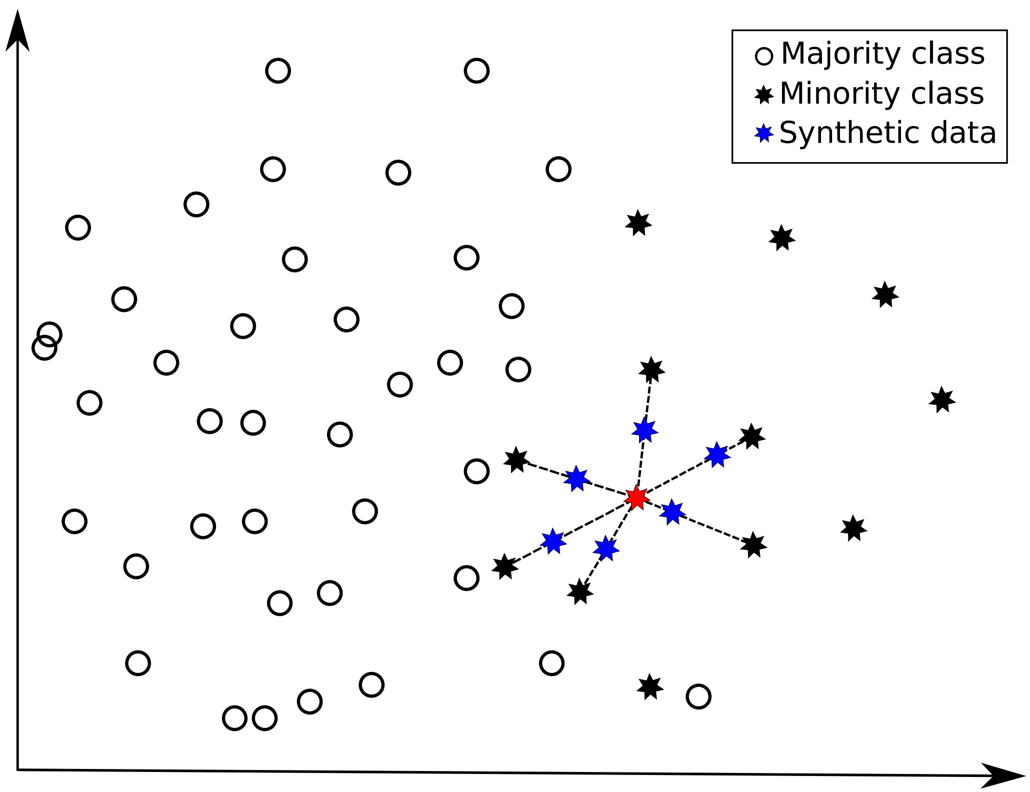
# Data Synthesis in Feature Space

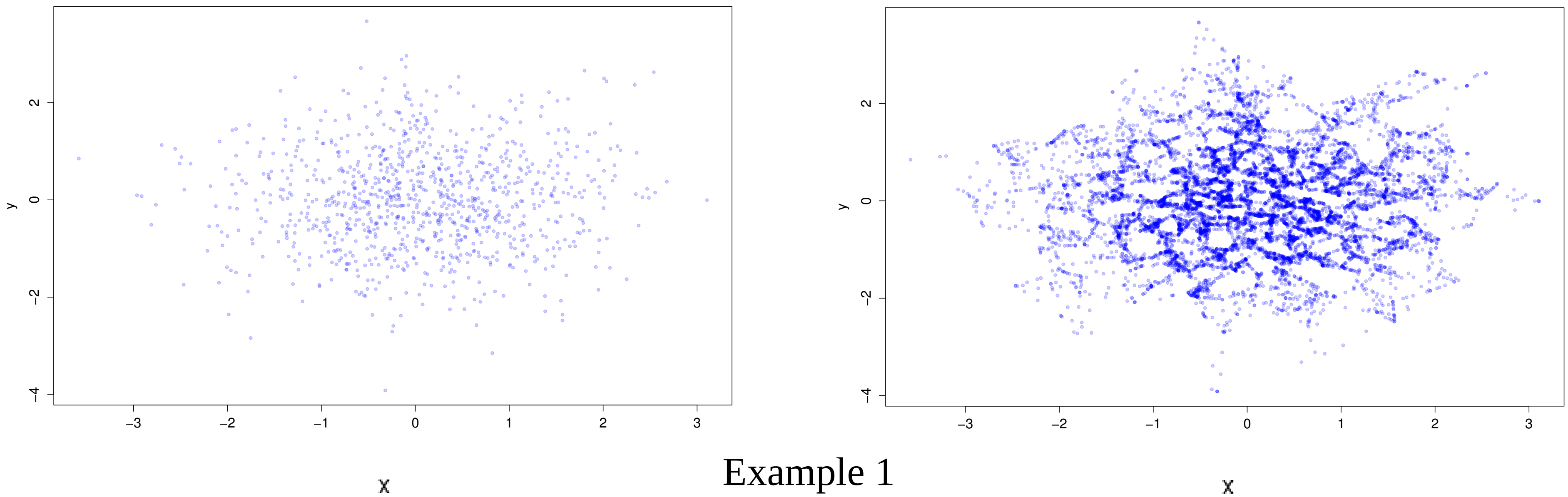
- Why in feature space:
  - Limitation for data synthesis in data space.
  - An universal approach for most problems.
  - Sometimes easier to detect patterns and relationship between data.
- Challenges:
  - Data representation is too abstract in feature space. To derive more data has to look at entire dataset.

- Previous work.
  - Creating identical samples.

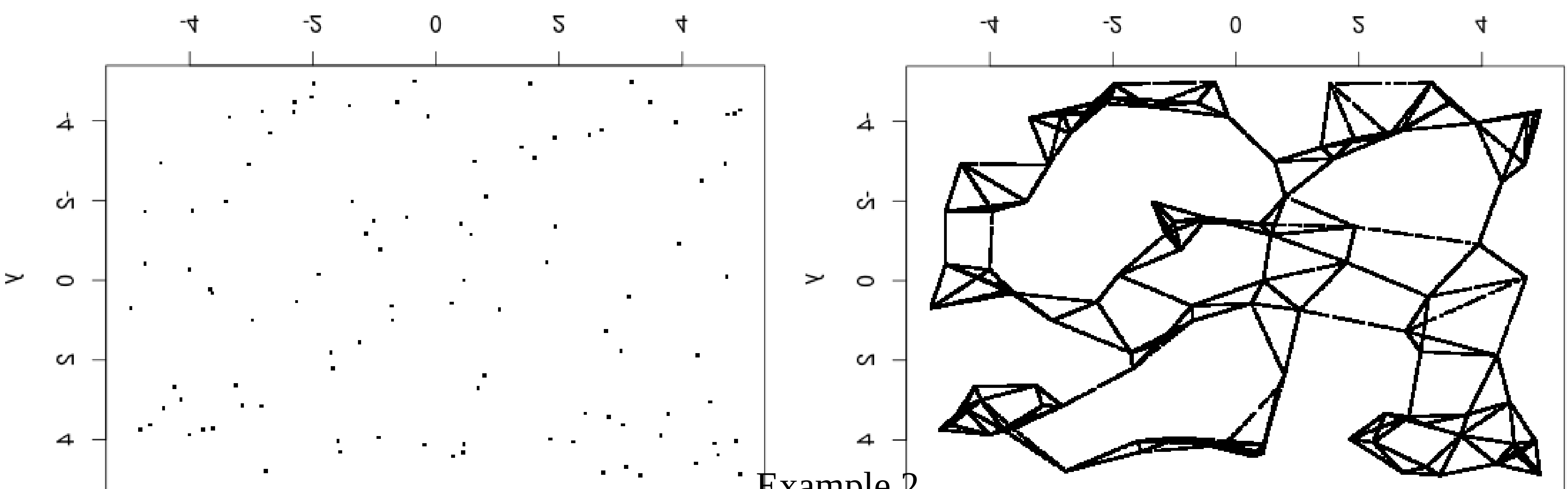


- Previous work.
  - Creating identical samples.
  - Synthetic minority oversampling technique (SMOTE)






Example 1

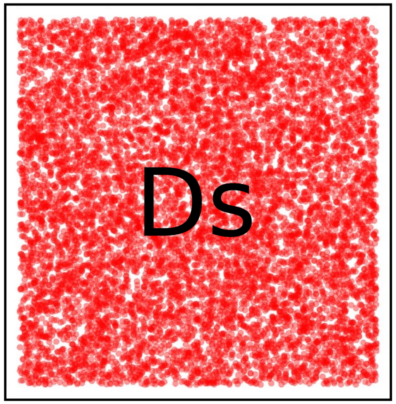


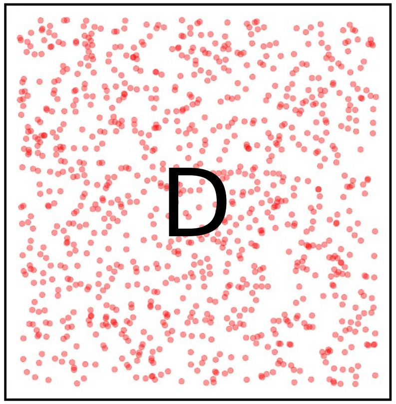
Example 2

- The proposed approach.
    - Up-sampling by keeping global structure of the dataset.

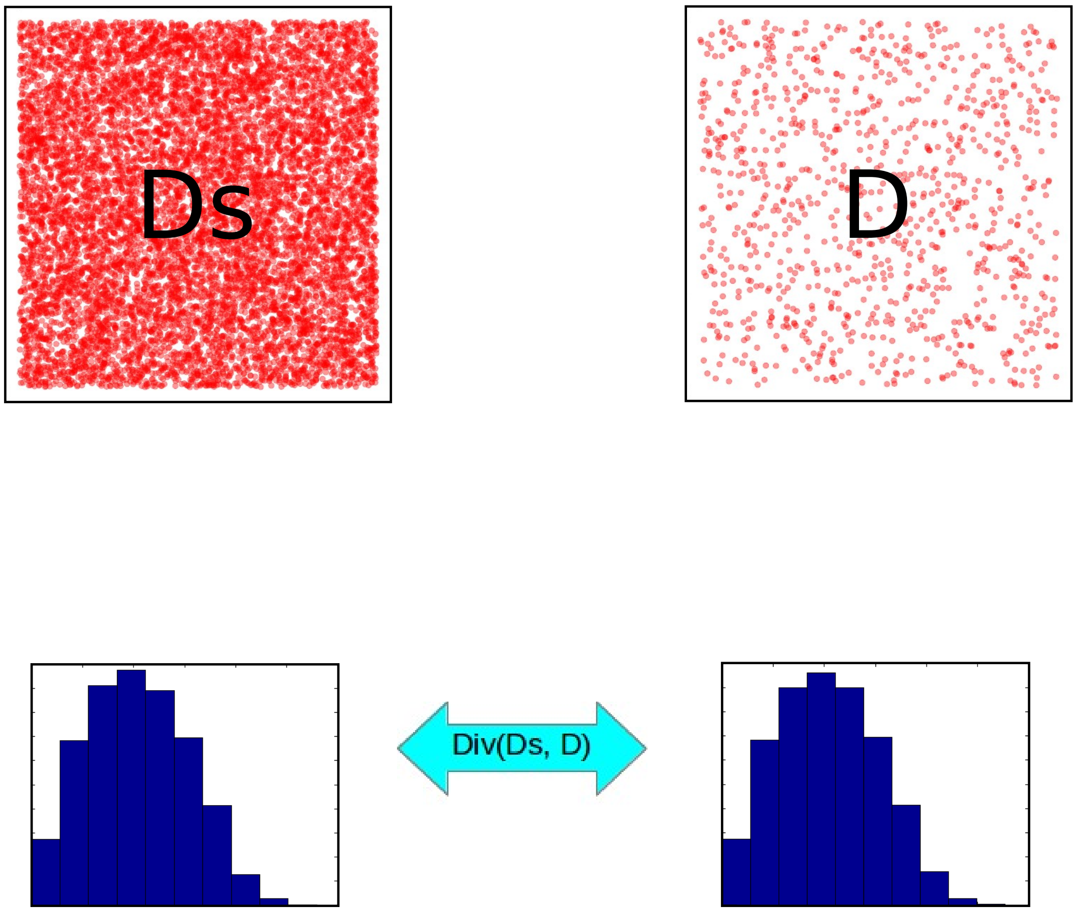
      Suppose we are given a dataset called $D$, the goal is to find out a dataset $Ds$ which is a up-sampled version of $D$

- The proposed approach.

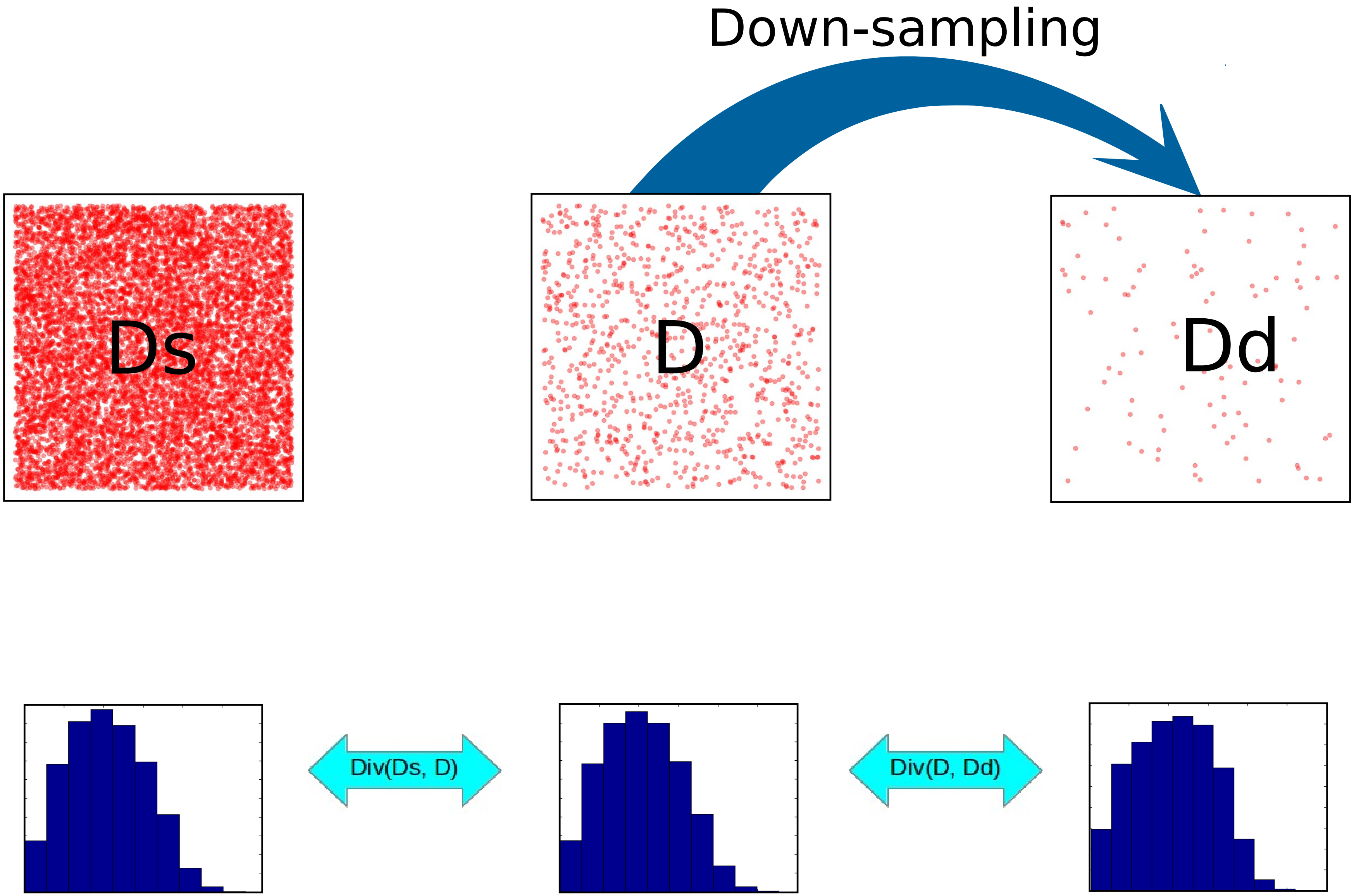


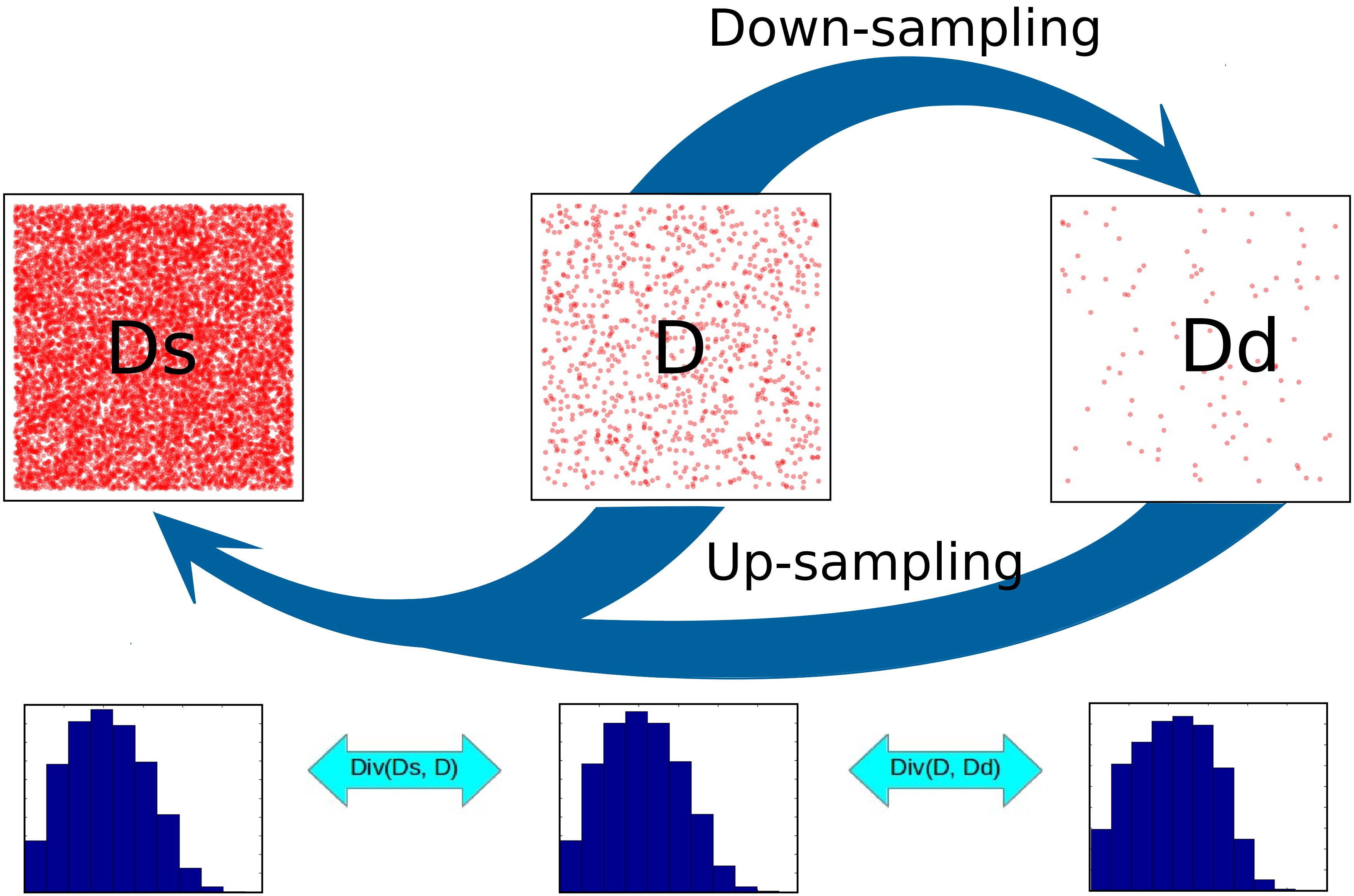
- The proposed approach.



- The proposed approach.



- The proposed approach.



- The proposed approach.

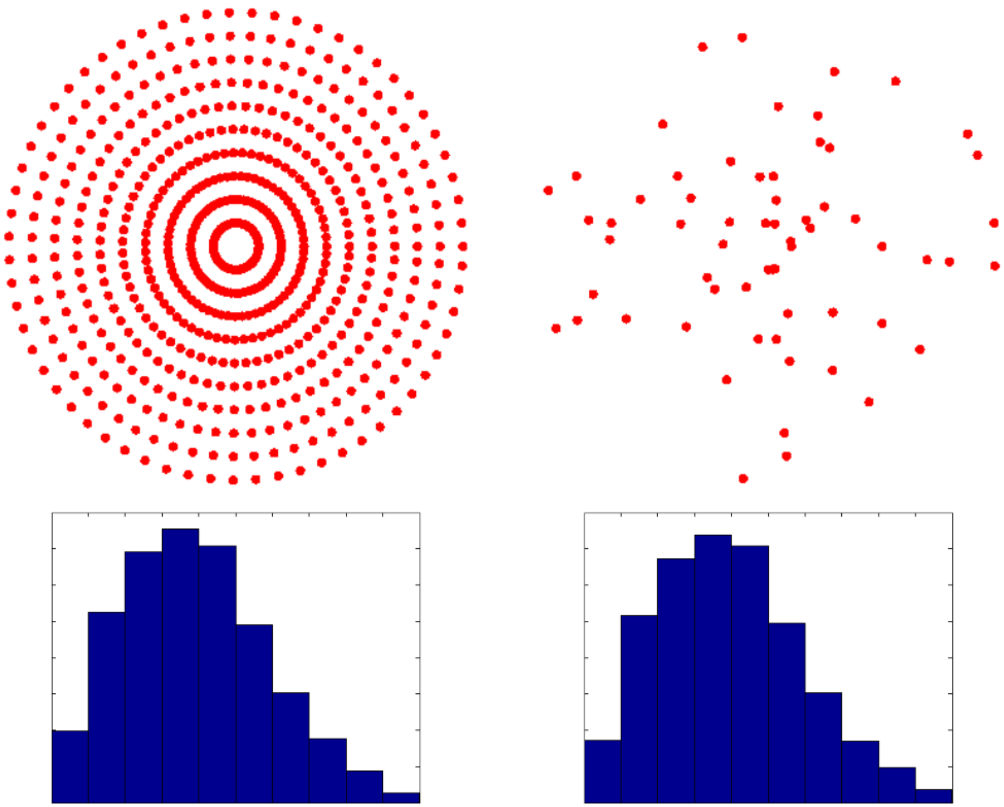
  1) Down-sampling: Minimize Kullback-Leibler divergence between two datasets.

$$E = Div(H(D), H(D_d)) = \sum_{i}^{k} b_{\mathrm{D}}^{i} \ln \frac{b_{\mathrm{D}}^{i}}{b_{\mathrm{Dd}}^{i}} + b_{\mathrm{Dd}}^{i} \ln \frac{b_{\mathrm{Dd}}^{i}}{b_{\mathrm{D}}^{i}}$$

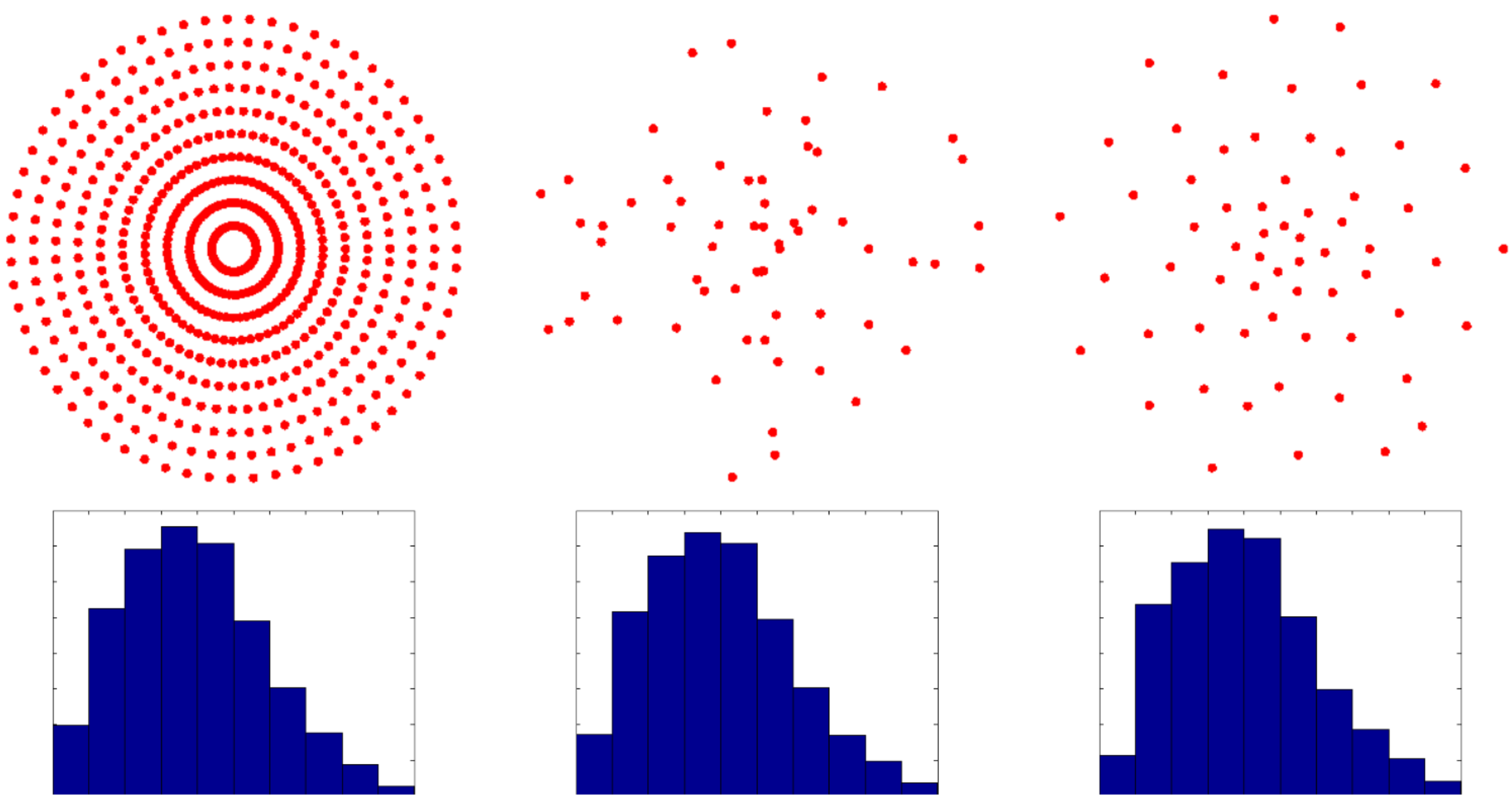
- Down-sampling

Minimize Kullback-Leibler divergence between two datasets.

$$E = Div(H(D), H(D_d)) = \sum_{i}^{k} b^i_{\mathrm{D}} \ln \frac{b^i_{\mathrm{D}}}{b^i_{\mathrm{Dd}}} + b^i_{\mathrm{Dd}} \ln \frac{b^i_{\mathrm{Dd}}}{b^i_{\mathrm{D}}}$$



$$E = Div(H(D), H(D_d)) = \beta \sum_{i}^{k} b^i_{\mathrm{D}} \ln \frac{b^i_{\mathrm{D}}}{b^i_{\mathrm{Dd}}} + b^i_{\mathrm{Dd}} \ln \frac{b^i_{\mathrm{Dd}}}{b^i_{\mathrm{D}}} + \underbrace{(1-\beta) \sum_{i}^{n} \left( \frac{k^i_{\mathrm{Dd}}}{|N_{d^i_{\mathrm{D}}}|} - r^{\downarrow}_{\mathrm{DDd}} \right)^2}_{\text{Sampling adaptively}} \quad (5.2)$$



• Comparison of classification results.

| KNN (k=5) | fps | kmeans | kmeansrand | rand | my |
|---|---|---|---|---|---|
| Abalone | 0.0908 | 0.1366 | 0.1427 | 0.1405 | 0.1961 |
| Banknote | 0.9963 | 0.9963 | 1 | 0.9993 | 1 |
| Blood | 0.4973 | 0.6049 | 0.6001 | 0.5929 | 0.6171 |
| Bcancer | 0.6139 | 0.6355 | 0.6444 | 0.638 | 0.6424 |
| CT | 0.9731 | 0.9683 | 0.9715 | 0.9661 | 0.967 |
| CMS | 0.4778 | 0.4778 | 0.4773 | 0.4778 | 0.4778 |
| CNAE-9 | 0.7051 | 0.7445 | 0.7699 | 0.819 | 0.8367 |
| Diabetes | 0.6215 | 0.7053 | 0.7053 | 0.7082 | 0.7254 |
| Haberman | 0.4841 | 0.6325 | 0.622 | 0.6331 | 0.6431 |
| Iono | 0.4076 | 0.5483 | 0.8036 | 0.8387 | 0.8105 |
| V.S. | 0.6643 | 0.6585 | 0.65 | 0.6433 | 0.6704 |
| Wine | 0.9155 | 0.9193 | 0.9221 | 0.9161 | 0.9196 |

| RANDFOREST | fps | kmeans | kmeansrand | rand | my |
|---|---|---|---|---|---|
| Abalone | 0.5658 | 0.5801 | 0.5899 | 0.5379 | 0.5838 |
| Banknote | 0.9999 | 0.9994 | 0.991 | 0.9917 | 0.9971 |
| Blood | 0.7024 | 0.7069 | 0.7337 | 0.7301 | 0.7573 |
| Bcancer | 0.6482 | 0.6528 | 0.6523 | 0.6493 | 0.6562 |
| CT | 0.9948 | 0.9907 | 0.9905 | 0.9863 | 0.9873 |
| CMS | 0.7433 | 0.7439 | 0.7674 | 0.7482 | 0.7603 |
| CNAE-9 | 0.946 | 0.9549 | 0.925 | 0.9291 | 0.9637 |
| Diabetes | 0.7975 | 0.8413 | 0.827 | 0.8202 | 0.8359 |
| Haberman | 0.7052 | 0.7749 | 0.7143 | 0.7295 | 0.7627 |
| Iono | 0.8706 | 0.9396 | 0.9535 | 0.9502 | 0.9562 |
| V.S. | 0.825 | 0.8445 | 0.8299 | 0.8278 | 0.8468 |
| Wine | 0.9972 | 0.9947 | 0.994 | 0.994 | 0.9952 |

- Down-sampling

Minimize Kullback-Leibler divergence between two datasets.

$$E = Div(H(D), H(D_d)) = \beta \sum_{i}^{k} b_{\mathrm{D}}^{i} \ln \frac{b_{\mathrm{D}}^{i}}{b_{\mathrm{Dd}}^{i}} + b_{\mathrm{Dd}}^{i} \ln \frac{b_{\mathrm{Dd}}^{i}}{b_{\mathrm{D}}^{i}} + (1-\beta) \sum_{i}^{n} \left( \frac{k_{\mathrm{Dd}}^{i}}{|N_{d_{\mathrm{D}}^{i}}|} - r_{\mathrm{DDd}}^{\downarrow} \right)^2 \quad (5.2)$$

- Up-sampling:

$$H(D_s) = H(D) + \alpha(H(D) - H(D_d))$$

# Conclusion