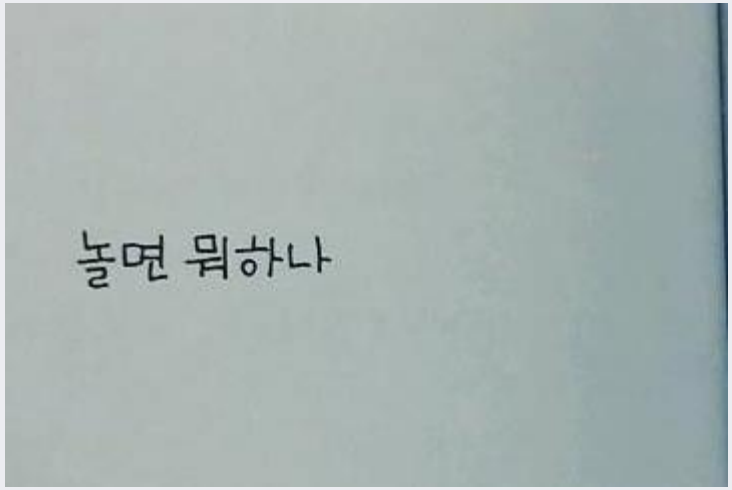



# Lecture 5: Semi-supervised Learning

Pilsung Kang
School of Industrial Management Engineering
Korea University

# AGENDA

# Machine Learning Categories

- Category of learning
  - ✓ According to the existence of target

### Supervised Learning

A given dataset **X** & **Y**

| | Var. 1 | Var. 2 | ... | Var. d | | Y |
|---|---|---|---|---|---|---|
| Ins. 1 | .. | .. | ... | .. | | .. |
| Ins. 2 | .. | .. | ... | .. | $y = f(x)$ | .. |
| ... | ... | ... | ... | ... | | ... |
| Ins. N | .. | .. | .. | .. | | .. |

### Unsupervised Learning

A given dataset **X**

| | Var. 1 | Var. 2 | ... | Var. d |
|---|---|---|---|---|
| Ins. 1 | .. | .. | ... | .. |
| Ins. 2 | .. | .. | ... | .. |
| ... | ... | ... | ... | ... |
| Ins. N | .. | .. | .. | .. |

### Semi-supervised Learning

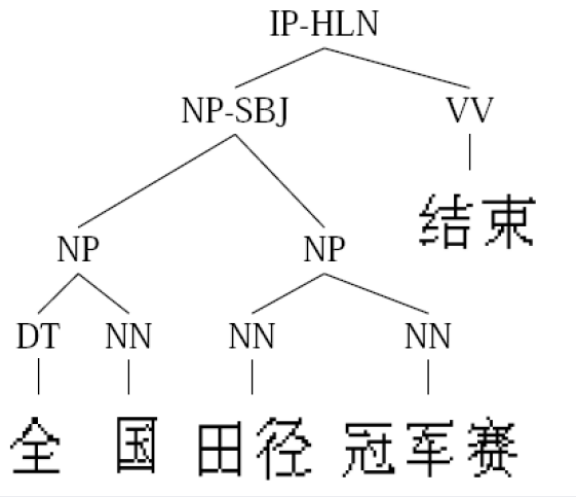
A given dataset **X** & **Y**

| | Var. 1 | Var. 2 | ... | Var. d | | Y |
|---|---|---|---|---|---|---|
| Ins. 1 | .. | .. | ... | .. | | .. |
| Ins. 2 | .. | .. | ... | .. | $y = f(x)$ | .. |
| ... | ... | ... | ... | ... | | ... |
| Ins. N | .. | .. | .. | .. | | .. |
| ... | ... | ... | ... | ... | | |
| ... | ... | ... | ... | ... | | |
| ... | ... | ... | ... | ... | | |
| ... | ... | ... | ... | ... | | |
| Ins. M | .. | .. | .. | .. | | |

# Backgrounds

Zhu (2007)

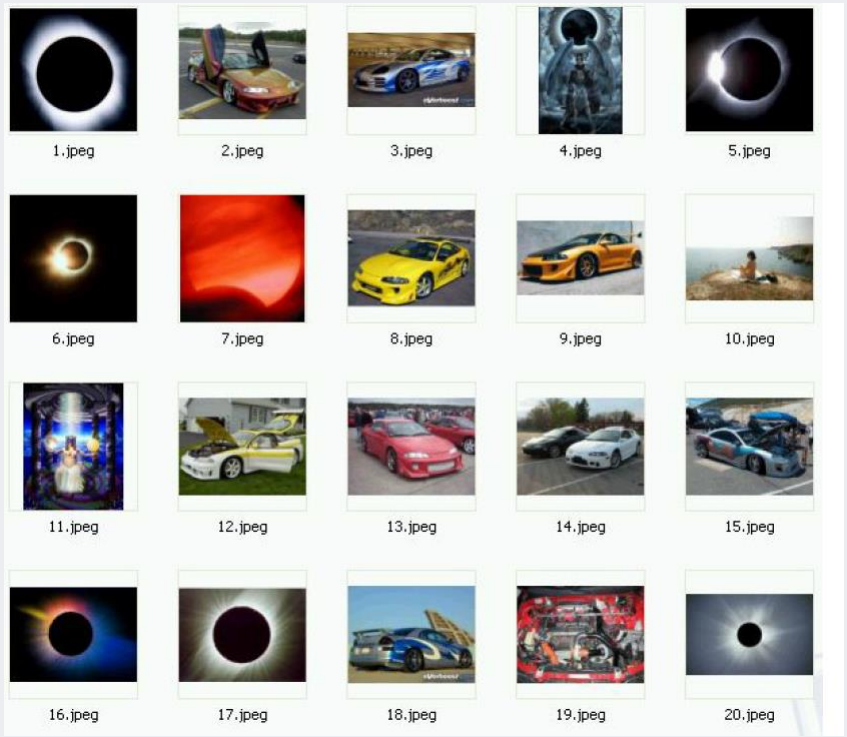
- People want better performance for free
  - ✓ Unlabeled data is cheap
  - ✓ Labeled data can be hard to get
    - human annotation is boring
    - labels may require experts
    - labels may require special devices
    - your graduate students is on vacation!!!
- Natural language parsing task (Penn Chinese Treebank)
  - ✓ 2 years for 4,000 sentences



# Backgrounds

Zhu (2007)

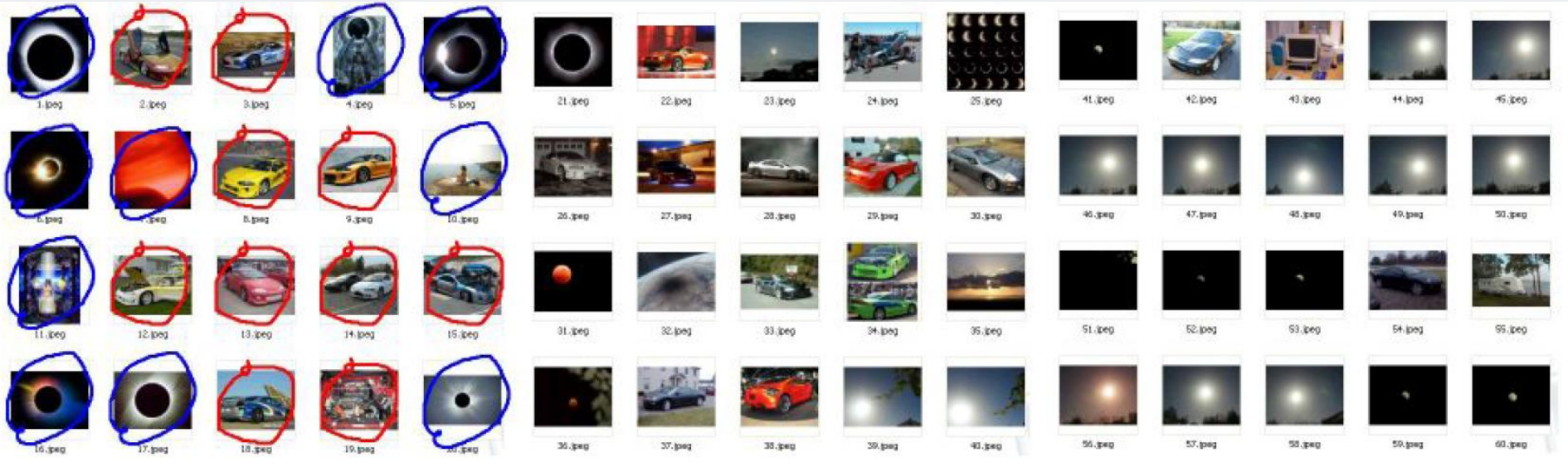
- For some tasks, it may not be too difficult to label 1000+ instances
  - ✓ Image categorization of **"eclipse"**




# Backgrounds

Zhu (2007)

- Example of not-so-hard-to-get labels
  - ✓ Nonetheless…



  - ✓ We still have bunch of other images that are not labeled yet…

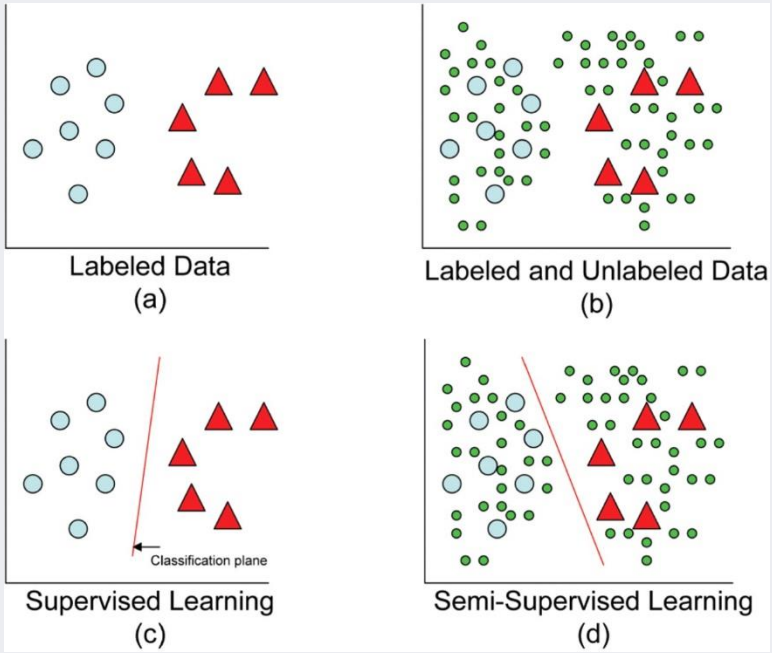
How can we utilize those unlabeled data

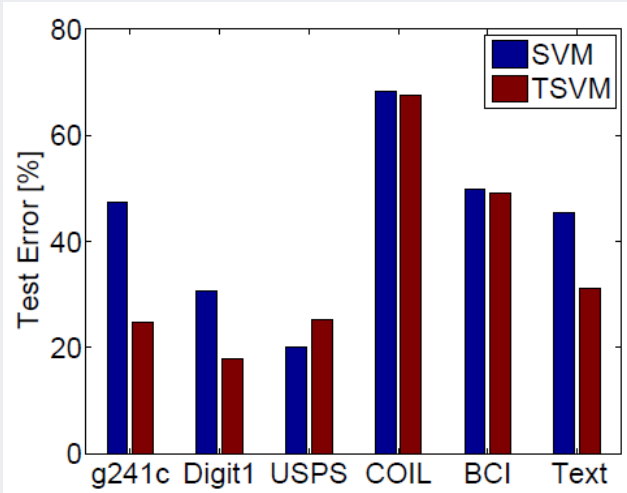
to improve the performance of supervised learning task?

# Purpose

Zien (2008)

- Purpose
  - ✓ Using both labeled and unlabeled data to build better learners, than using each of alone.
- Can it be possible?




10 labeled points
~1400 unlabeled points

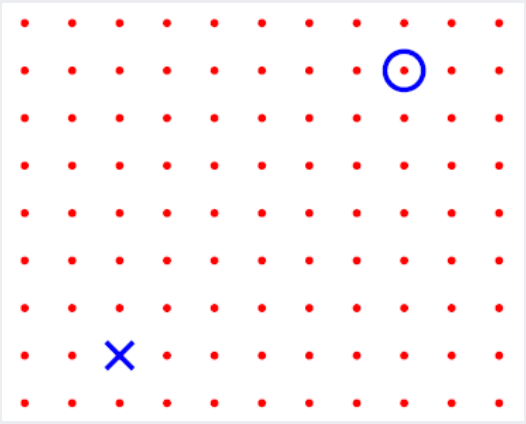
SVM: supervised
TSVM: semi-supervised

http://bioinformatics.oxfordjournals.org/content/24/6/783/F1.expansion.html

# Semi-supervised Learning

Zien (2008)

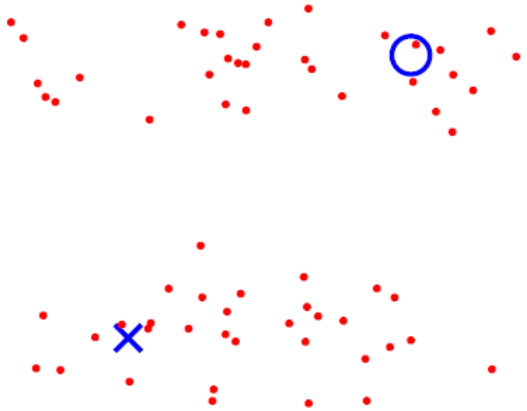
- Why would unlabeled data be useful at all?
  - ✓ Uniformly distributed data do not help
  - ✓ Must use properties of Pr(x)



vs

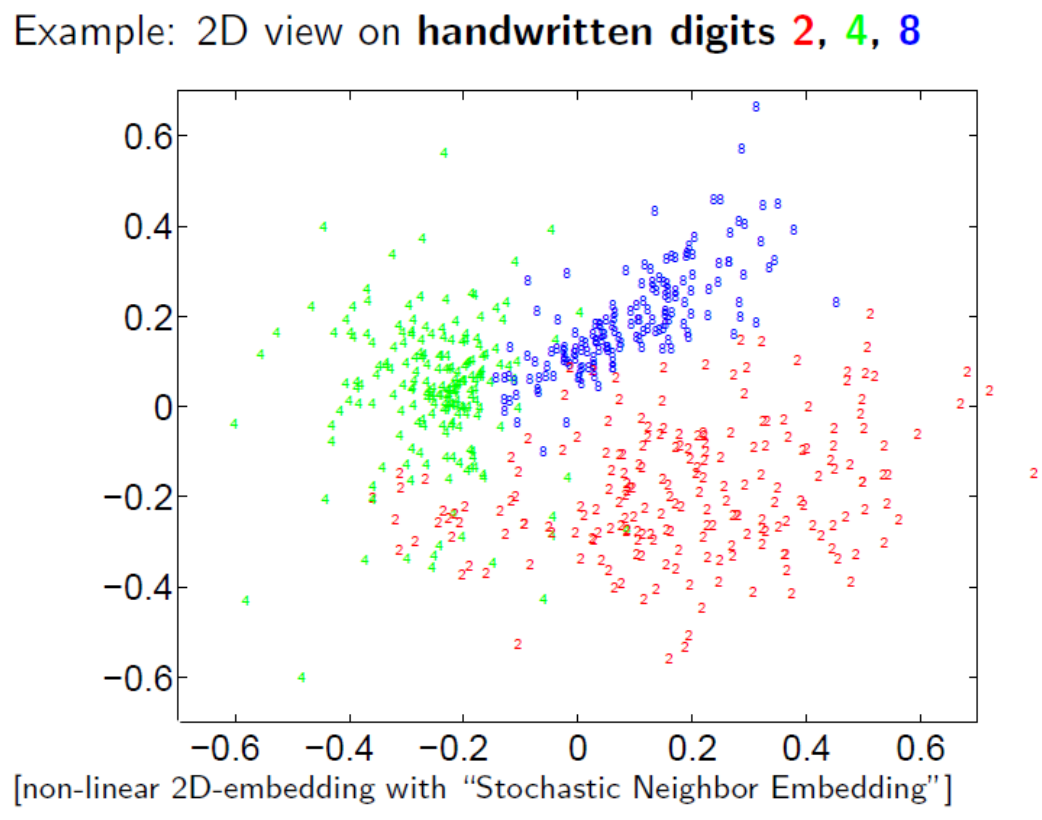
**Cluster Assumption**

1. The data form clusters.
2. Points in the **same cluster** are likely to be of the **same class**.



# Semi-supervised Learning

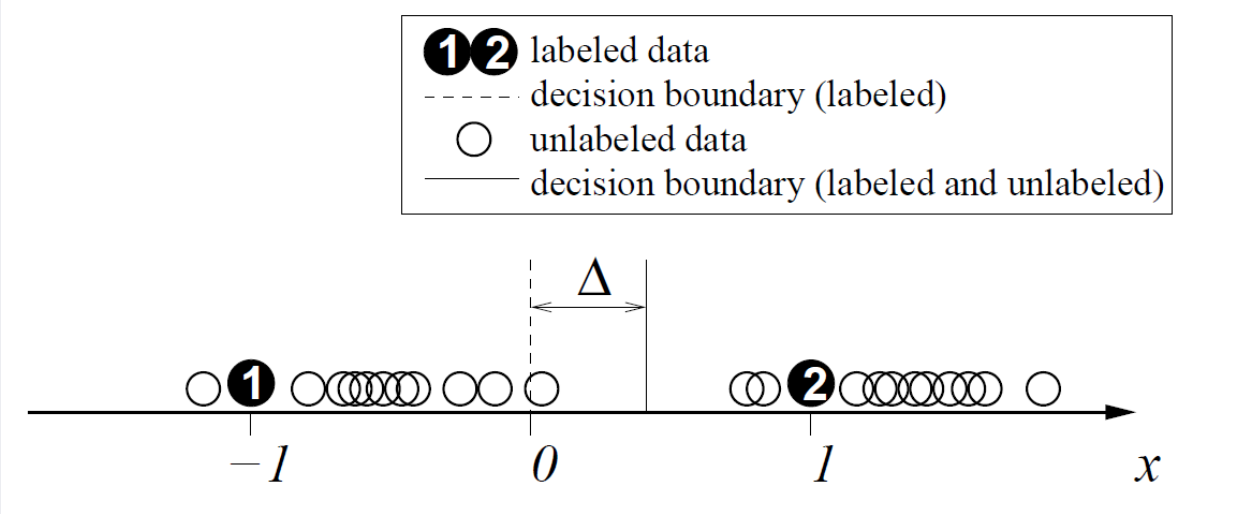
- Why would unlabeled data be useful at all?
  - ✓ The cluster assumption seems to hold for many real data sets
  - ✓ Many SSL algorithms (implicitly) make use of it



# Semi-supervised Learning

Zhu (2007)

- Why would unlabeled data be useful at all?
  - ✓ With and without unlabeled data: decision boundary shift




- Does unlabeled data always help?
  - ✓ Unfortunately, this is not the case, yet. (Ben-David et al. (2008) and Singl et al. (2008).)

# Semi-supervised Learning

Zhu (2007)

- Notations
  - ✓ Input instance $\mathbf{x}$, label $y$
  - ✓ Learner $f : \mathcal{X} \mapsto \mathcal{Y}$
  - ✓ Labeled data $(\mathbf{X}_l, \mathbf{y}_l) = \{(\mathbf{x}_{1:l}, y_{1:l})\}$
  - ✓ Unlabeled data $\mathbf{X}_u = \{(\mathbf{x}_{l+1:n}\}$, available during training
  - ✓ Usually $l \ll n$
  - ✓ Test data $\mathbf{X}_{test} = \{(\mathbf{x}_{n+1:}\}$, not available during training
- SSL vs. Transductive learning

**Semi-supervised learning**

is ultimately applied to the test data (inductive).

**Transductive learning**

is only concerned with the unlabeled data.

# Semi-supervised Learning

- Semi-supervised vs. Transductive

| Setting | Input to the algorithm (Distribution *D*) | Algorithm output | Performance of the algorithm | Examples |
|---|---|---|---|---|
| Supervised Learning | labeled examples | a function that maps points to labels | expected error on an unseen point | Support Vector Machines, AdaBoost |
| Unsupervised Learning | unlabeled examples | a function that maps points to labels | expected error on an unseen point | Clustering |
| Semi-supervised Learning (SSL) | labeled & unlabeled examples | a function that maps points to labels | expected error on an unseen point | |
| Transductive Learning | labeled & unlabeled examples | labels of the unlabeled examples | average error on unlabeled examples | Transductive SVMs, Graph regularization |

http://cs.nyu.edu/~rostami/ml/2008/rastogi-ssl.pdf

# Semi-supervised Learning

Zhu (2007)

- Semi-supervised vs. Transductive

**supervised learning** (classification, regression) $\{(x_{1:n}, y_{1:n})\}$

$\updownarrow$

**semi-supervised classification/regression** $\{(x_{1:l}, y_{1:l}), x_{l+1:n}, x_{test}\}$

**transductive classification/regression** $\{(x_{1:l}, y_{1:l}), x_{l+1:n}\}$

$\updownarrow$

**semi-supervised clustering** $\{x_{1:n}$, must-, cannot-links$\}$

$\updownarrow$

**unsupervised learning** (clustering) $\{x_{1:n}\}$

# AGENDA

01 Semi-supervised Learning: Overview

02 Self-Training

03 Generative Models

04 Graph-based SSL

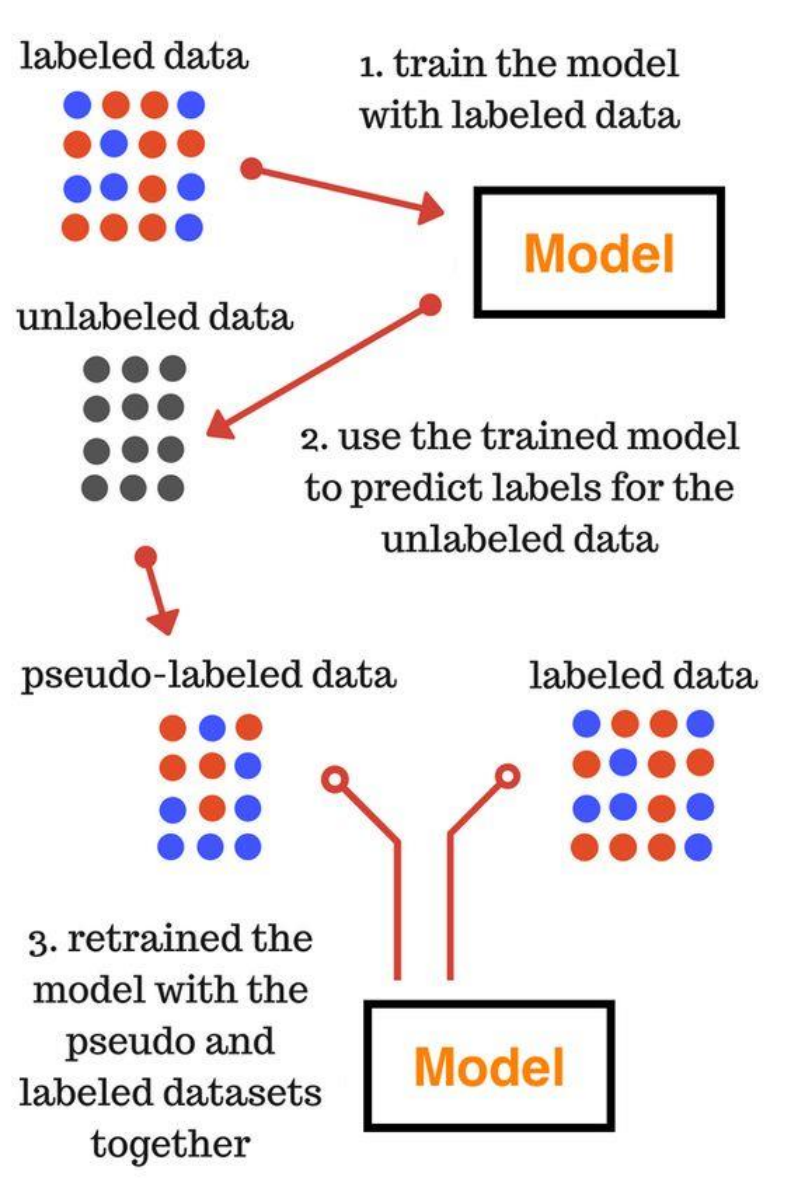
05 Multi-view Algorithms (Co-Training)

# Self-Training

- Assumption in the self-training
  - ✓ One's own high confidence predictions are correct
- Basic self-training algorithm
  - ✓ Train $f$ from $(\mathbf{X}_l, \mathbf{y}_l)$
  - ✓ Predict on $\mathbf{x} \in \mathbf{X}_u$
  - ✓ Add $(\mathbf{x}, f(\mathbf{x}))$ to labeled data
  - ✓ Repeat
- Variations in self-training
  - ✓ Add a few most confident $(\mathbf{x}, f(\mathbf{x}))$ to labeled data
  - ✓ Add all $(\mathbf{x}, f(\mathbf{x}))$ to labeled data
  - ✓ Add all $(\mathbf{x}, f(\mathbf{x}))$ to labeled data, weigh each by confidence

# Self-Training

- Procedure




https://www.pinterest.co.kr/pin/540713499003163569/

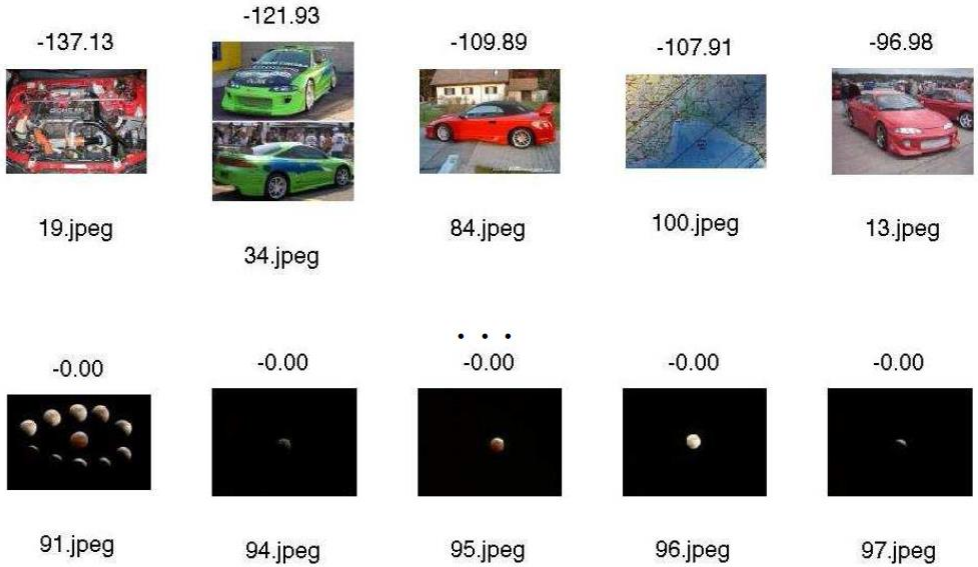
# Self-Training: Example 1

Zhu (2007)

- Image Categorization

1. Train a naïve Bayes classifier on the two initial labeled images

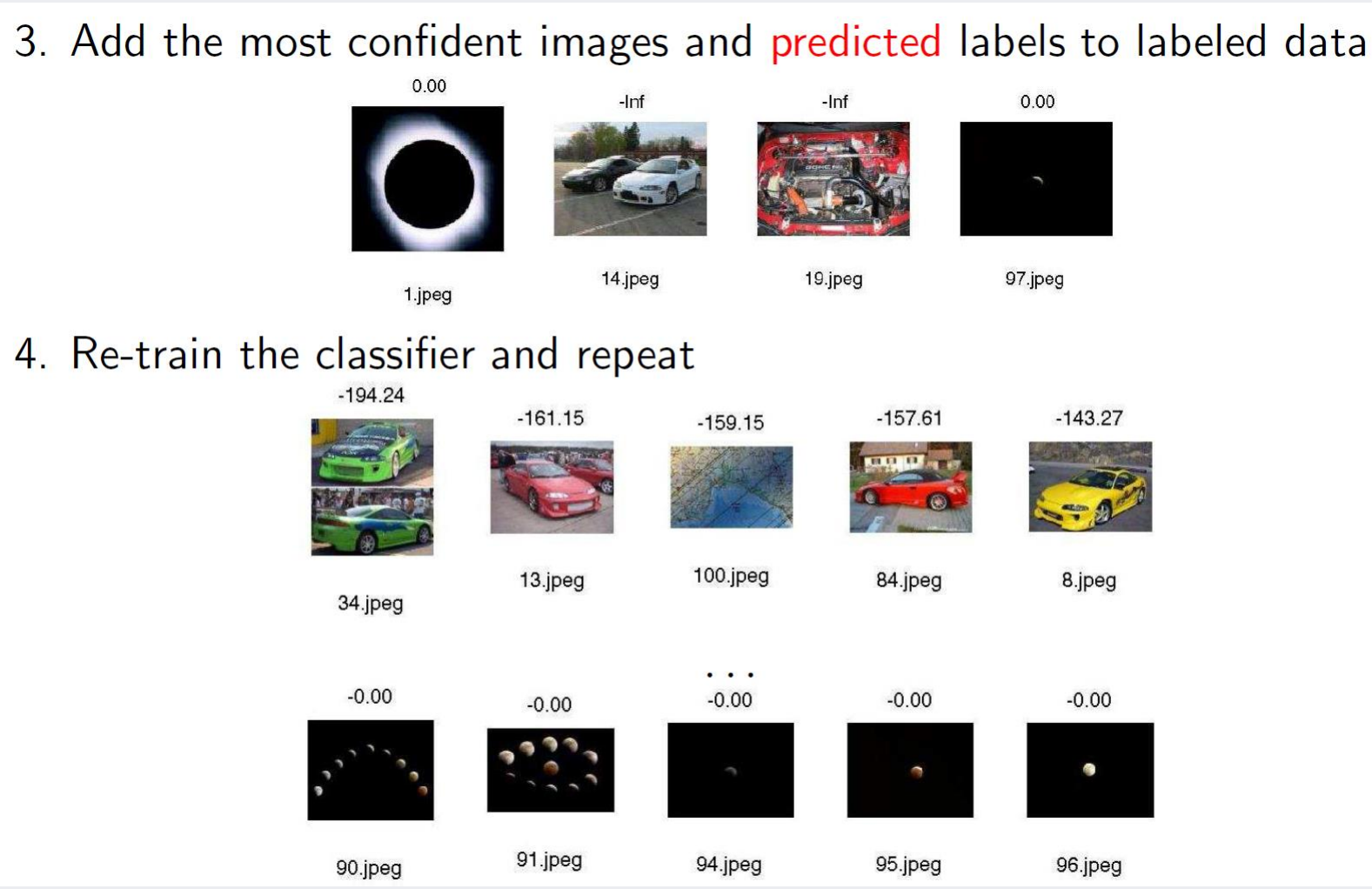

2. Classify unlabeled data, sort by confidence $\log p(y = \text{astronomy} | x)$



# Self-Training: Example 1

Zhu (2007)

- Image Categorization



# Self-Training: Example 2

Zhu (2009)

- Propagating 1-Nearest Neighbor

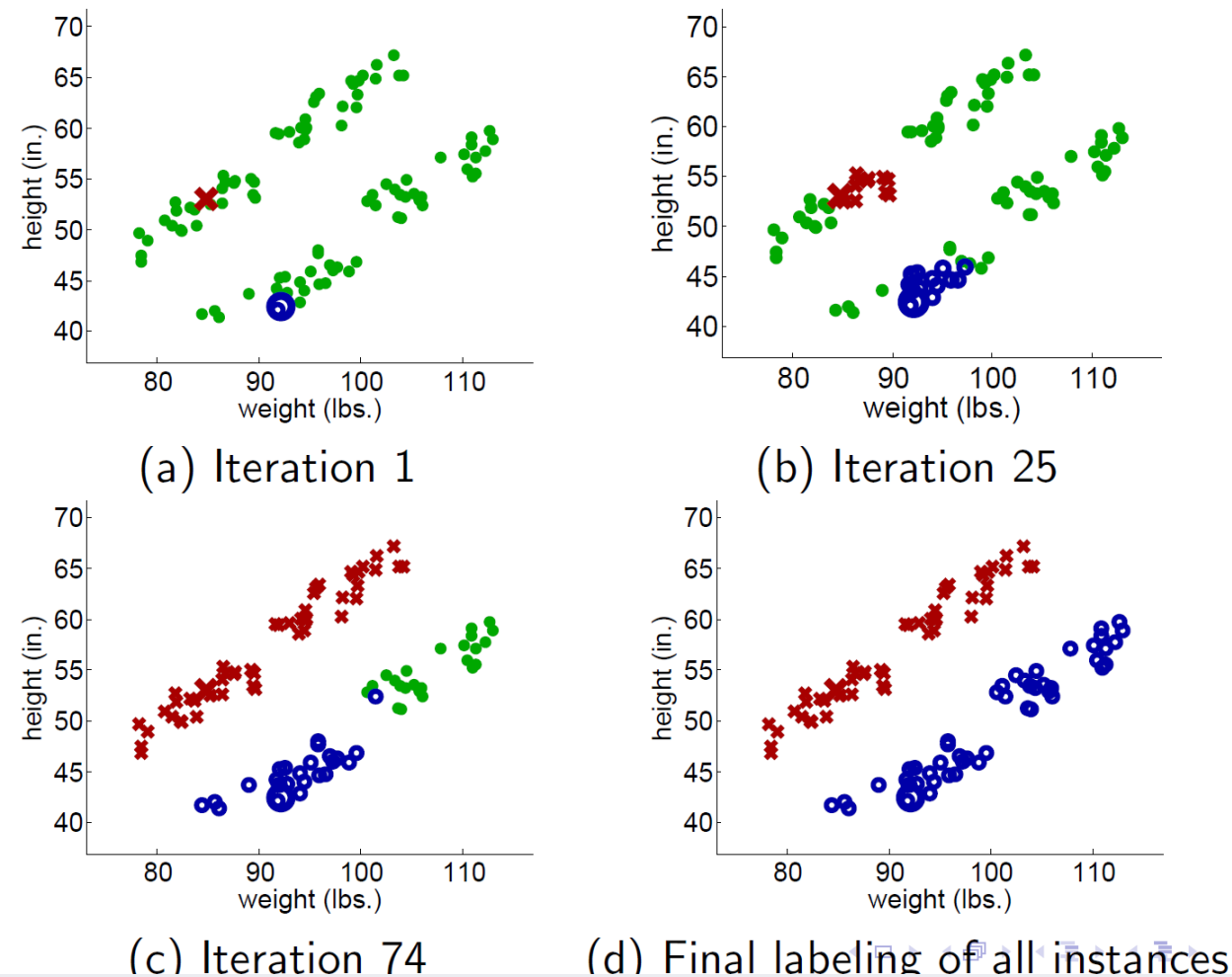
Input: labeled data $\{(\mathbf{x}_i, y_i)\}_{i=1}^{l}$, unlabeled data $\{\mathbf{x}_j\}_{j=l+1}^{l+u}$, distance function $d()$.

1. Initially, let $L = \{(\mathbf{x}_i, y_i)\}_{i=1}^{l}$ and $U = \{\mathbf{x}_j\}_{j=l+1}^{l+u}$.
2. Repeat until $U$ is empty:
3. Select $\mathbf{x} = \text{argmin}_{\mathbf{x} \in U} \min_{\mathbf{x}' \in L} d(\mathbf{x}, \mathbf{x}')$.
4. Set $f(\mathbf{x})$ to the label of $\mathbf{x}$'s nearest instance in $L$. Break ties randomly.
5. Remove $\mathbf{x}$ from $U$; add $(\mathbf{x}, f(\mathbf{x}))$ to $L$.

# Self-Training: Example 2

Zhu (2009)

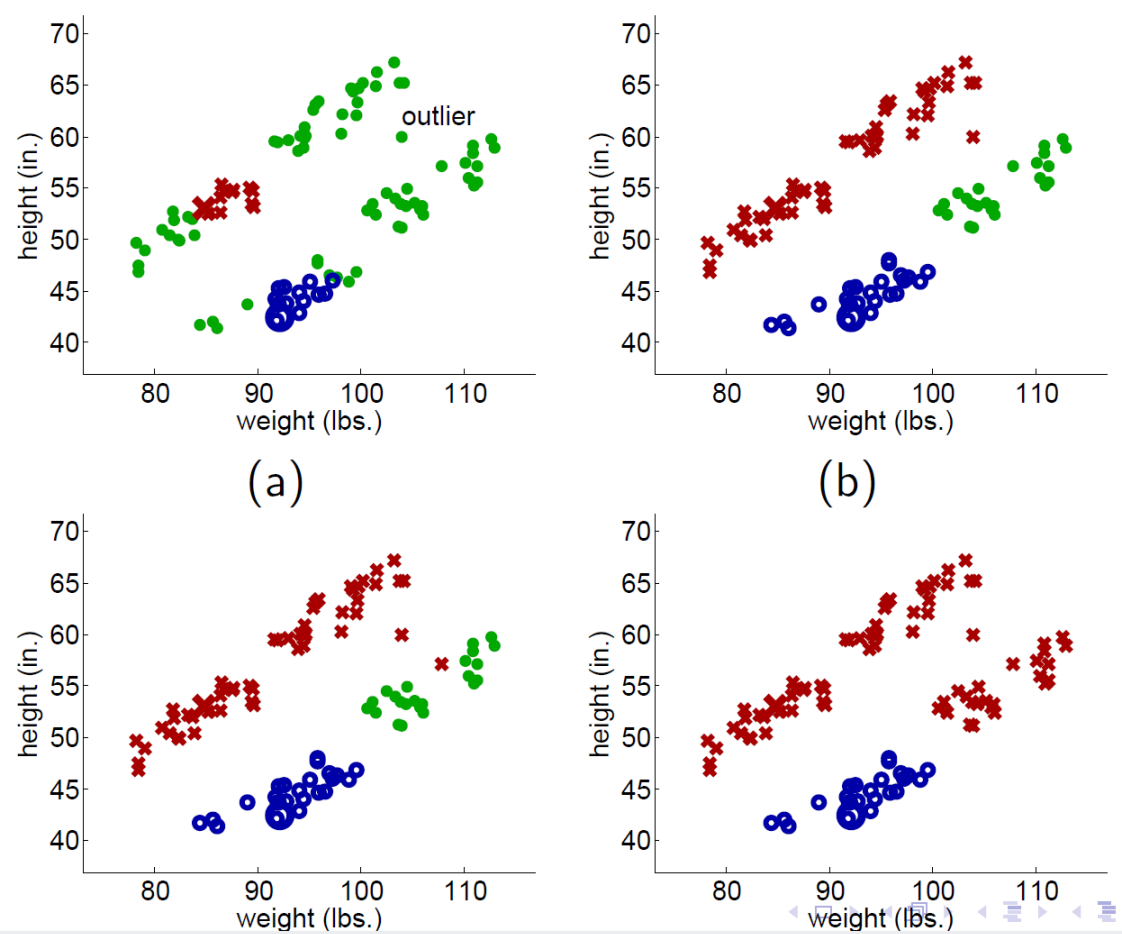
- Propagating 1-Nearest Neighbor



# Self-Training: Example 2

Zhu (2009)

- Propagating 1-Nearest Neighbor (with a single outlier)



# Self-Training: Summary

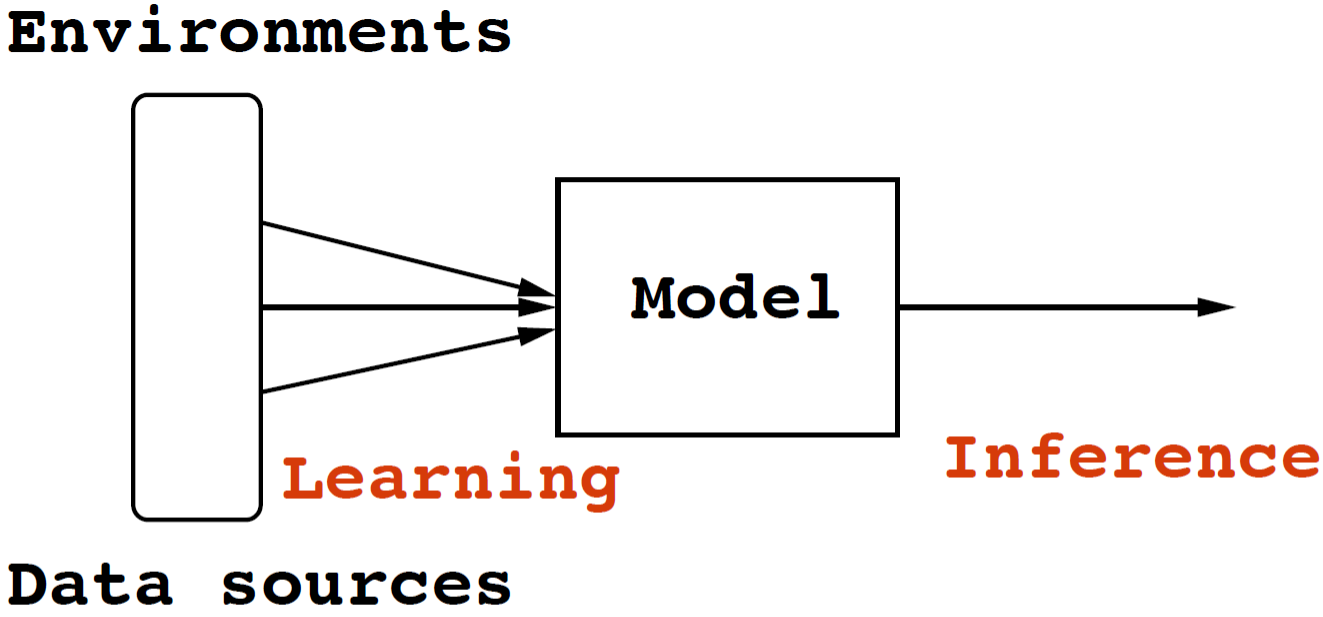
- Advantages
  - ✓ The simplest semi-supervised learning method
  - ✓ A wrapper method, applies to existing (complex) classifiers
  - ✓ Often used in real tasks like natural language processing

- Disadvantages
  - ✓ Early mistakes could reinforce themselves
  - ✓ Cannot say too much in terms of convergence

# AGENDA

# Discriminative vs. Generative

Choi (2015)

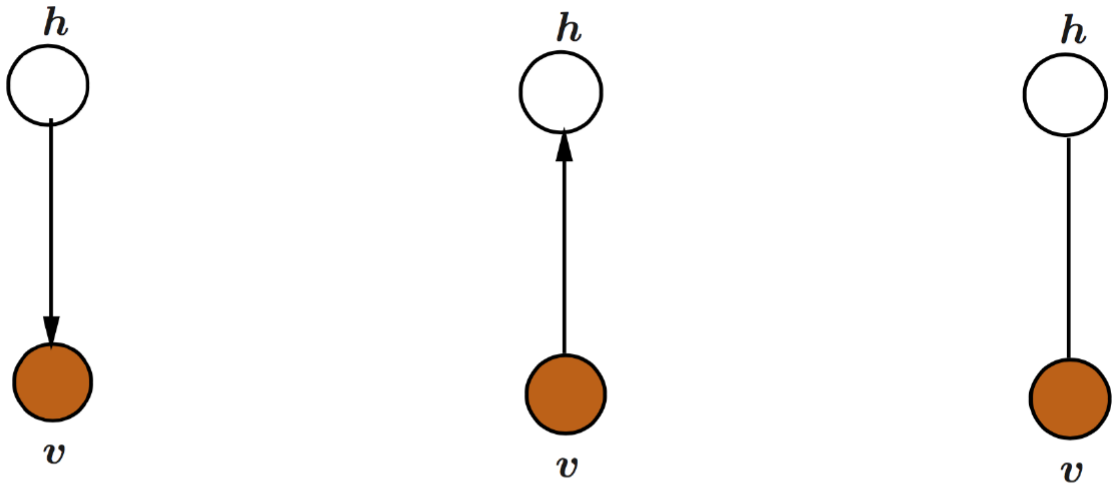



Machine Learning: A scientific discipline that is concerned with the design and development of algorithms that allow computers to learn from empirical data (sensor data or database) and to make predictions.

# Discriminative vs. Generative

Choi (2015)

Generative model | Discriminative model | Undirected model



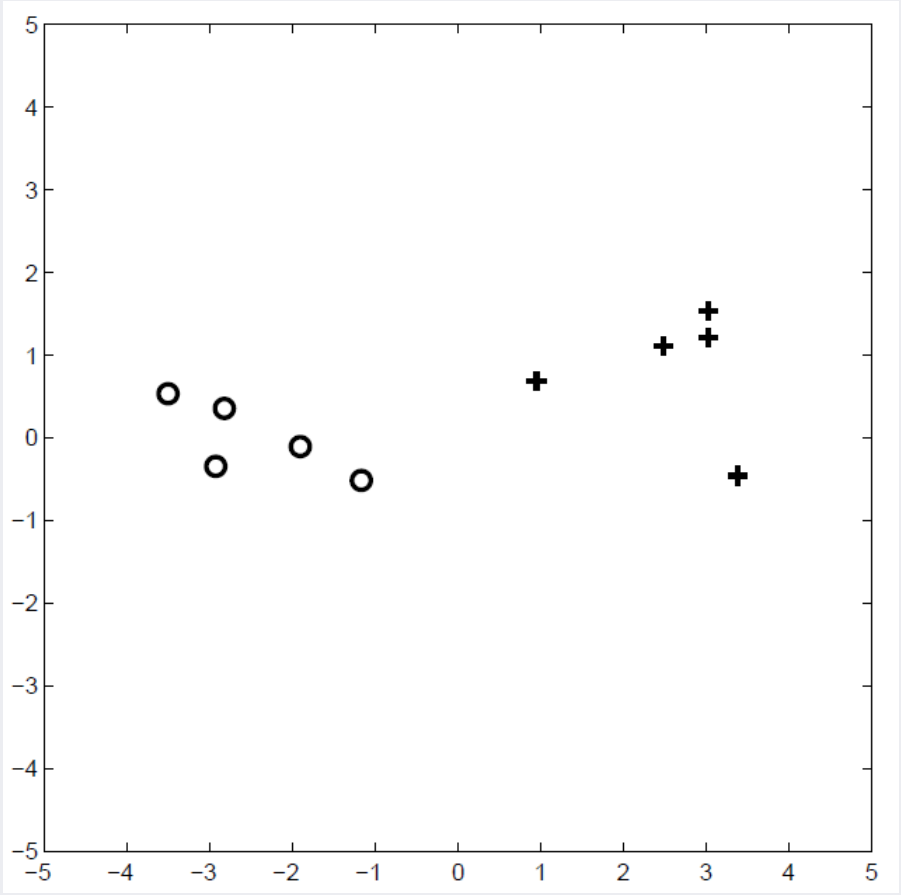

- Generative model: Joint distribution $p(\boldsymbol{v}, \boldsymbol{h}) = p(\boldsymbol{v}|\boldsymbol{h})p(\boldsymbol{h})$
- Discriminative model: Directly model $p(\boldsymbol{h}|\boldsymbol{v})$
- Undirected model: Energy-based model

$$p(\boldsymbol{v}, \boldsymbol{h}) = \frac{\exp\left\{-E\left(\boldsymbol{v}, \boldsymbol{h}\right)\right\}}{\sum_{\boldsymbol{v}', \boldsymbol{h}'} \exp\left\{-E\left(\boldsymbol{v}', \boldsymbol{h}'\right)\right\}}$$

# Generative Models

Zhu (2007)

- Example
  - ✓ Assuming each class has a Gaussian distribution, what is the decision boundary?




$$\text{Model parameters :}$$

$$\theta = \{w_1, w_2, \mu_1, \mu_2, \Sigma_1, \Sigma_2\}$$

$$p(x, y|\theta) = p(y|\theta)p(x|y, \theta)$$

$$= w_y \mathcal{N}(x; \mu_y, \Sigma_y)$$

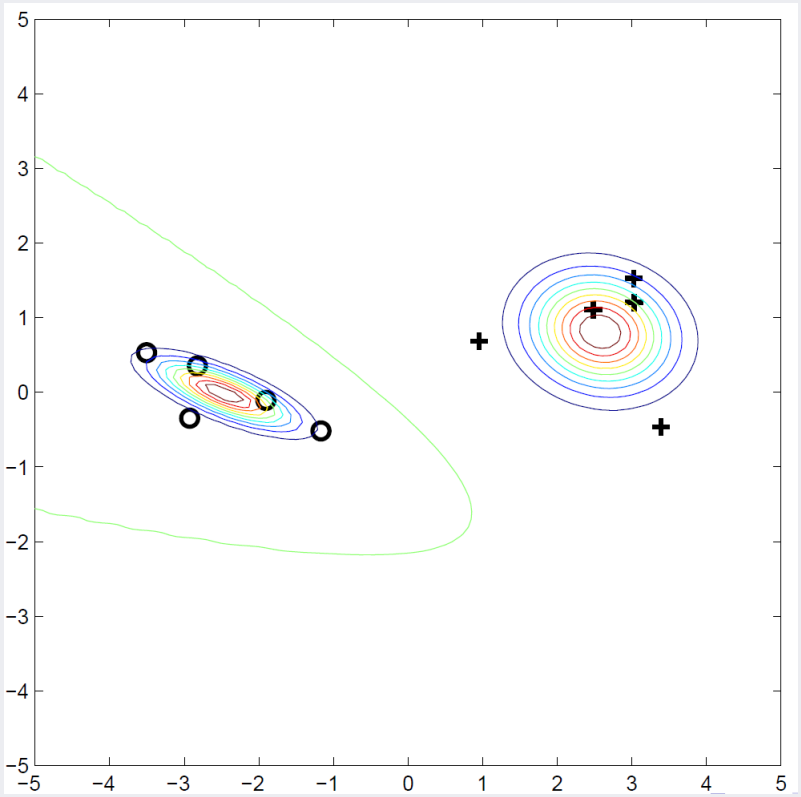
$$\text{Classification :}$$

$$p(y|x, \theta) = \frac{p(x, y|\theta)}{\sum_{y'} p(x, y'|\theta)}$$

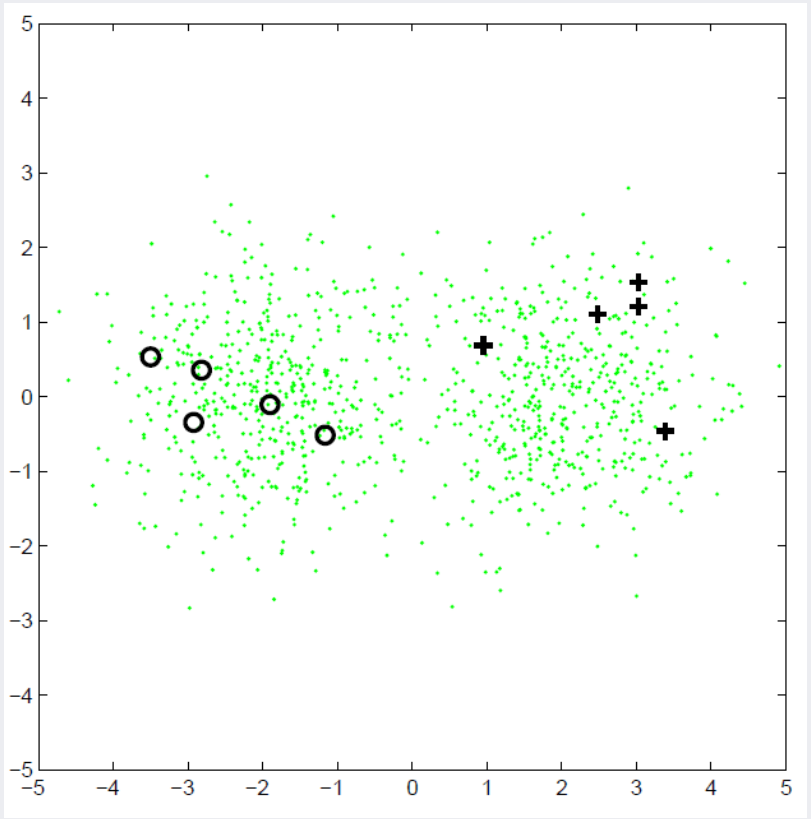
# Generative Models

Zhu (2007)

- Example
  - ✓ The most likely model, and its decision boundary:



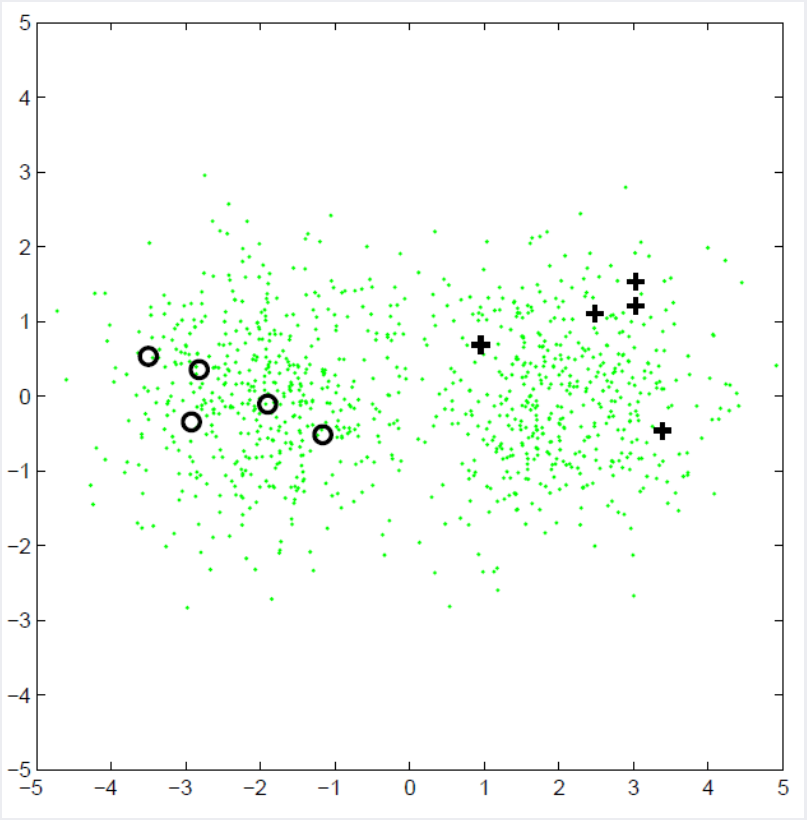

Add unlabeled data

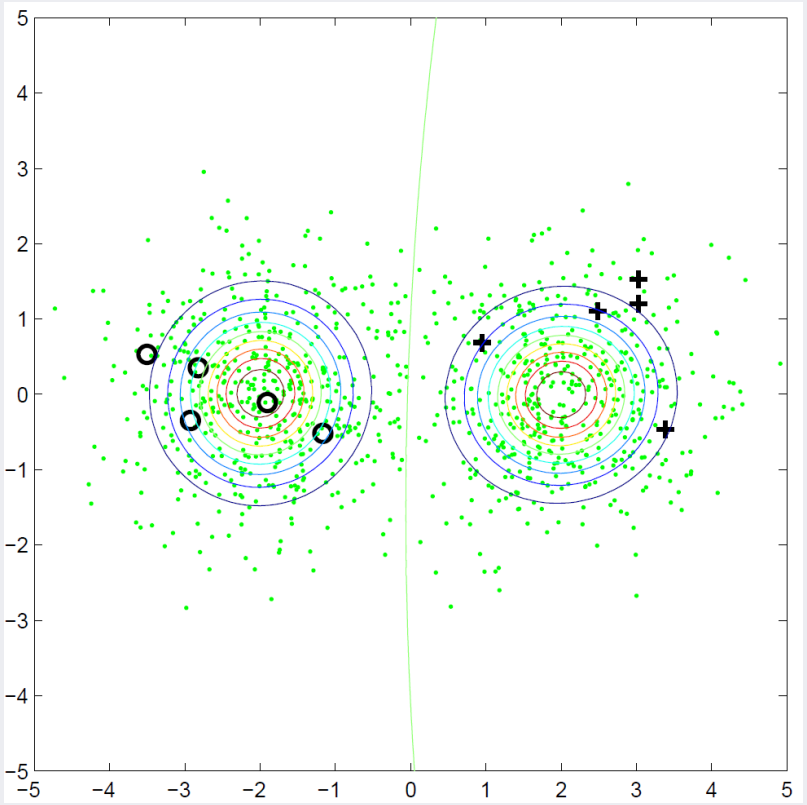


# Generative Models

Zhu (2007)

- Example
  - ✓ The most likely model, and its decision boundary:

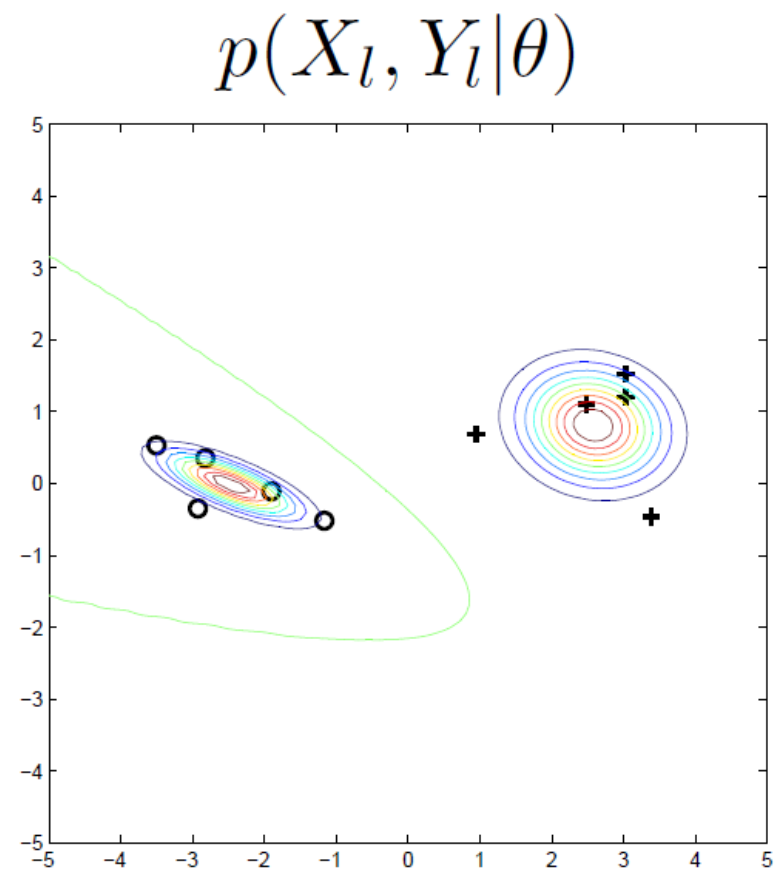


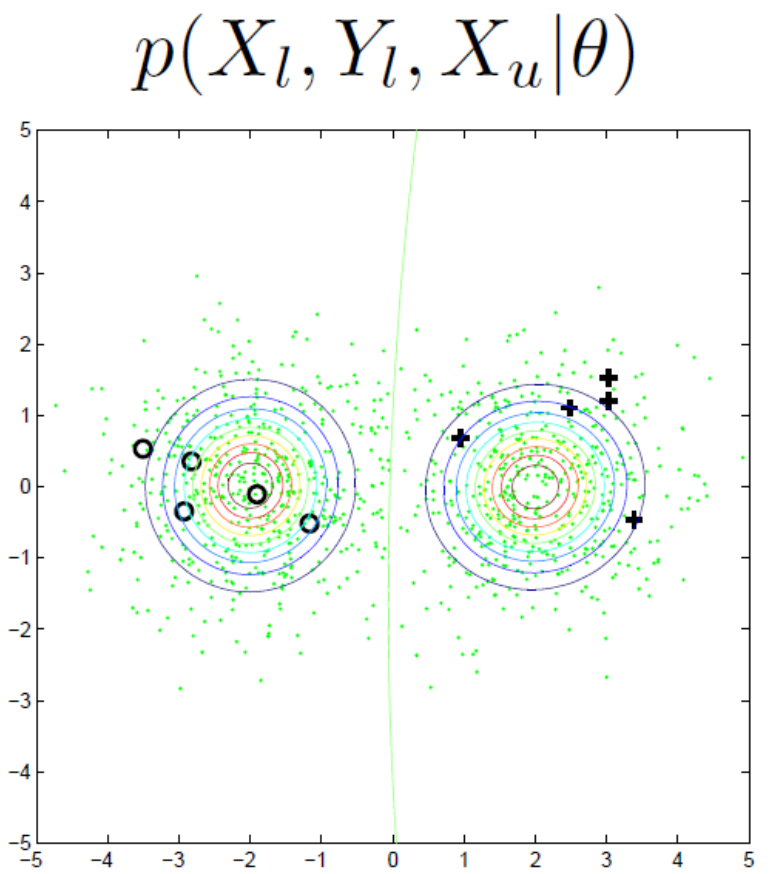


# Generative Models

Zhu (2007)

- Example
  - ✓ They are different because they maximize different quantities



# Generative Models

Fox-Roberts and Rosten (2014), Kingma et al. (2014)

- Assumption: The full generative model $p(\mathbf{X}, \mathbf{y}|\theta)$
  - ✓ Generative model for semi-supervised learning:
    - Quantity of interests:

$$p(\mathbf{X}_l, \mathbf{y}_l, \mathbf{X}_u|\theta) = \sum_{\mathbf{y}_u} p(\mathbf{X}_l, \mathbf{y}_l, \mathbf{X}_u, \mathbf{y}_u|\theta)$$

    - Find the maximum likelihood estimate (MLE) of θ, the maximum a posteriori (MAP) estimate, or be Bayesian
  - ✓ Examples of some generative models
    - Mixture of Gaussian distribution (GMM): Image classification (EM algorithm)
    - Mixture of multinomial distribution (Naïve Bayes): Text categorization (EM algorithm)
    - Hidden Markov Models (HMM): Speech recognition (Baum-Welch algorithm)

# Generative Models

Zhu (2007)

- Gaussian Mixture Model
  - ✓ For simplicity, consider binary classification with GMM using MLE
    - Labeled data only

$$p(\mathbf{X}_l, \mathbf{y}_l|\theta) = \sum_{i=1}^{l} \log p(y_i|\theta)p(\mathbf{x}_i|y_i, \theta)$$

      - MLE for is θ trivial (frequency, sample mean, sample covariance)
    - Labeled and unlabeled data

$$p(\mathbf{X}_l, \mathbf{y}_l, \mathbf{X}_u|\theta) = \sum_{i=1}^{l} \log p(y_i|\theta)p(\mathbf{x}_i|y_i, \theta) + \sum_{i=l+1}^{l+u} \log \left( \sum_{y=1}^{2} p(y|\theta)p(\mathbf{x}_i|y, \theta) \right)$$

      - MLE is difficult because of hidden variables
      - The Expectation-Maximization (EM) algorithm is used to find a local optimum

# Generative Models

Zhu (2007)

- The EM algorithm for GMM
  - ✓ Step 0: Start from MLE $\theta = \{w, \mu, \Sigma\}_{1,2}$ on $(\mathbf{X}_l, \mathbf{y}_l)$, repeat
  - ✓ Step 1: The E-Step: compute the expected label for all $\mathbf{x} \in \mathbf{X}_u$

$$p(y|\mathbf{x}, \theta) = \frac{p(\mathbf{x}, y|\theta)}{\sum_{y'} p(\mathbf{x}, y'|\theta)}$$

    - label $p(y = 1|\mathbf{x}, \theta)$ -fraction of **x** with class 1
    - label $p(y = 2|\mathbf{x}, \theta)$ -fraction of **x** with class 2
  - ✓ Step 2: The M-Step: update MLE θ with (now labeled) $\mathbf{X}_u$
    - $w_c$ : proportion of class c
    - $\mu_c$ : sample mean of class c
    - $\Sigma_c$ : sample covariance of class c
- Can be viewed as a special form of self-training

# Generative Models

Zhu (2007)

- The EM algorithm in general
  - ✓ Set up:
    - Obtain data $\mathcal{D} = (\mathbf{X}_l, \mathbf{y}_l, \mathbf{X}_u)$
    - hidden data $\mathcal{H} = \mathbf{y}_u$

      $$p(\mathcal{D}|\theta) \sum_{\mathcal{H}} = p(\mathcal{D}, \mathcal{H}|\theta)$$

  - ✓ Goal: find θ to maximize $p(\mathcal{D}|\theta)$
  - ✓ Properties
    - EM starts from an arbitrary $\theta_0$
    - The E-step: $q(\mathcal{H}) = p(\mathcal{H}|\mathcal{D}, \theta)$
    - The M-step: maximize $\sum_{q(\mathcal{H})} \log p(\mathcal{D}, \mathcal{H}|\theta)$
    - EM iteratively improves $p(\mathcal{D}|\theta)$
    - EM converges to a local maximum of θ

# Generative Models

Zhu (2007)

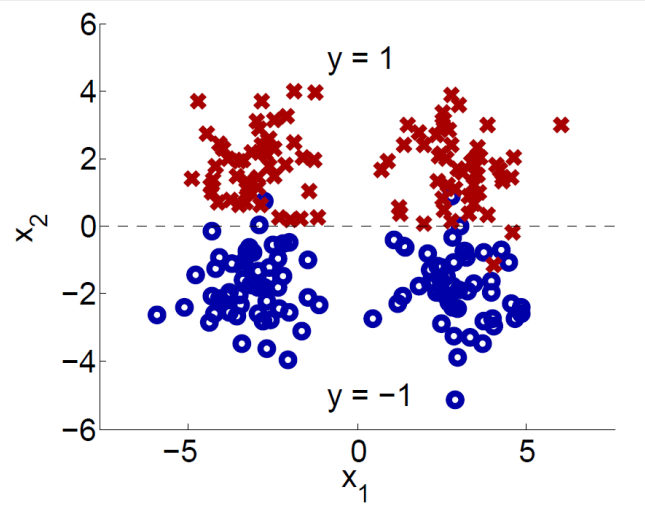
- The EM algorithm in general
  - ✓ Key is to maximize the posterior probability
  - ✓ EM is just one way to maximize it; other ways to find parameters are possible (variational approximation, direct optimization, etc.)

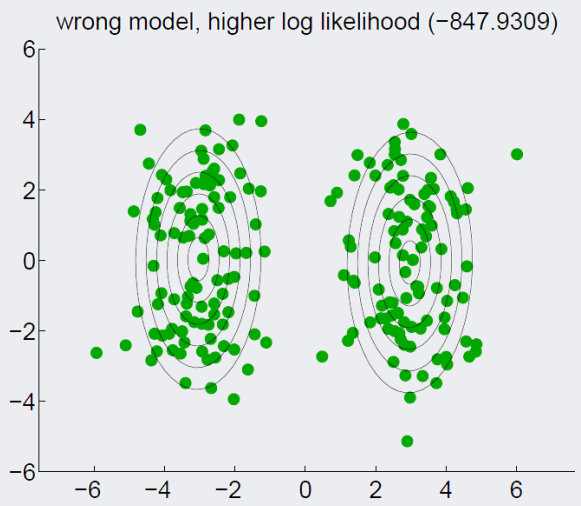
- Advantages
  - ✓ Clear, well-studied probabilistic framework
  - ✓ Can be extremely effective, if the model is close to correct

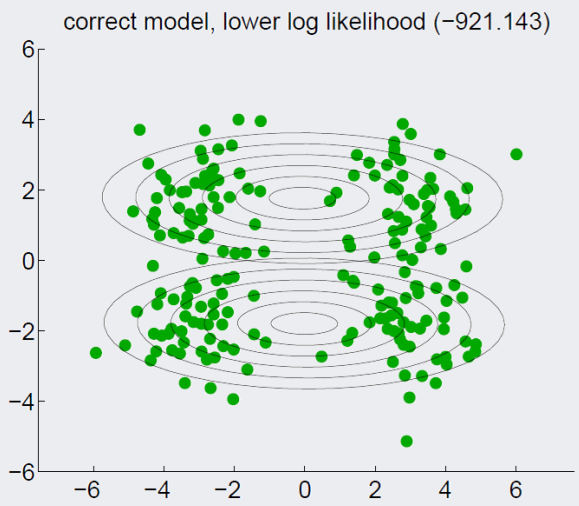
# Generative Models

Zhu (2007)

- Disadvantages
  - ✓ Often difficult to verify the correctness of the model
  - ✓ Model identifiability, local optima of the EM algorithm
  - ✓ Unlabeled data may hurt if generative model is wrong



# AGENDA

01 Semi-supervised Learning: Overview

02 Self-Training

03 Generative Models

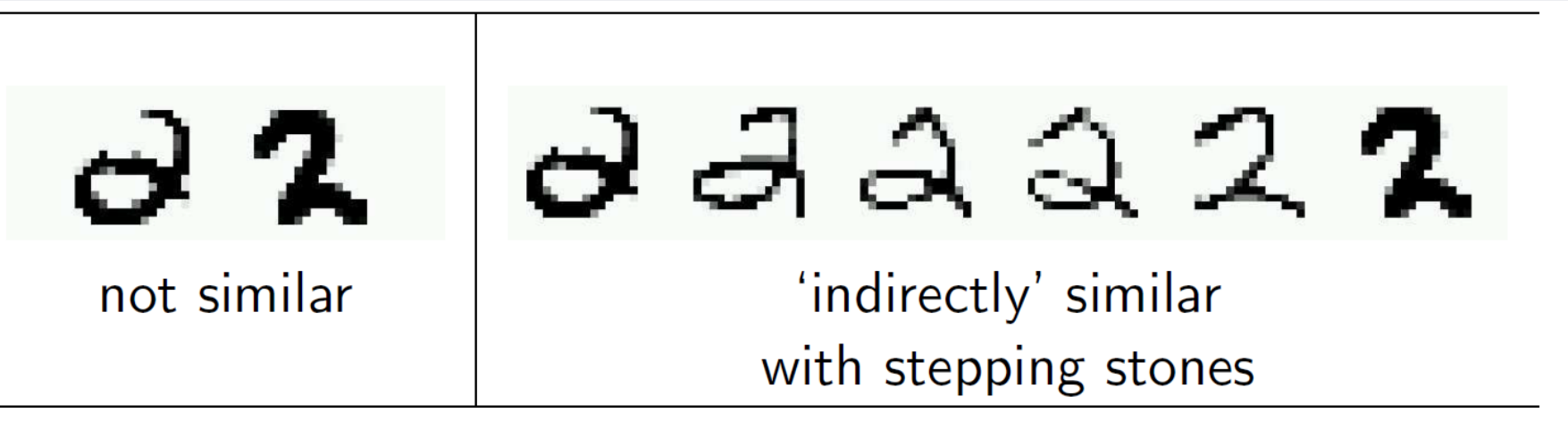
04 Graph-based SSL

05 Multi-view Algorithms (Co-Training)

# Graph-based SSL

Zhu (2007)

- Example: Handwritten digit recognition with pixel-wise Euclidean distance




- Assumption
  - ✓ A graph is given on the labeled and unlabeled data
  - ✓ Instances connected by heavy edge tend to have the same label

# Graph-based SSL

Zhu (2007)

- Graph construction
  - ✓ Nodes: $\mathbf{X}_l \cup \mathbf{X}_u$
  - ✓ Edges: similarity weights computed from features, e.g.,
    - k-nearest-neighbor graph, unweighted (0, 1 weights)
    - fully connected graph, weight decays with distance

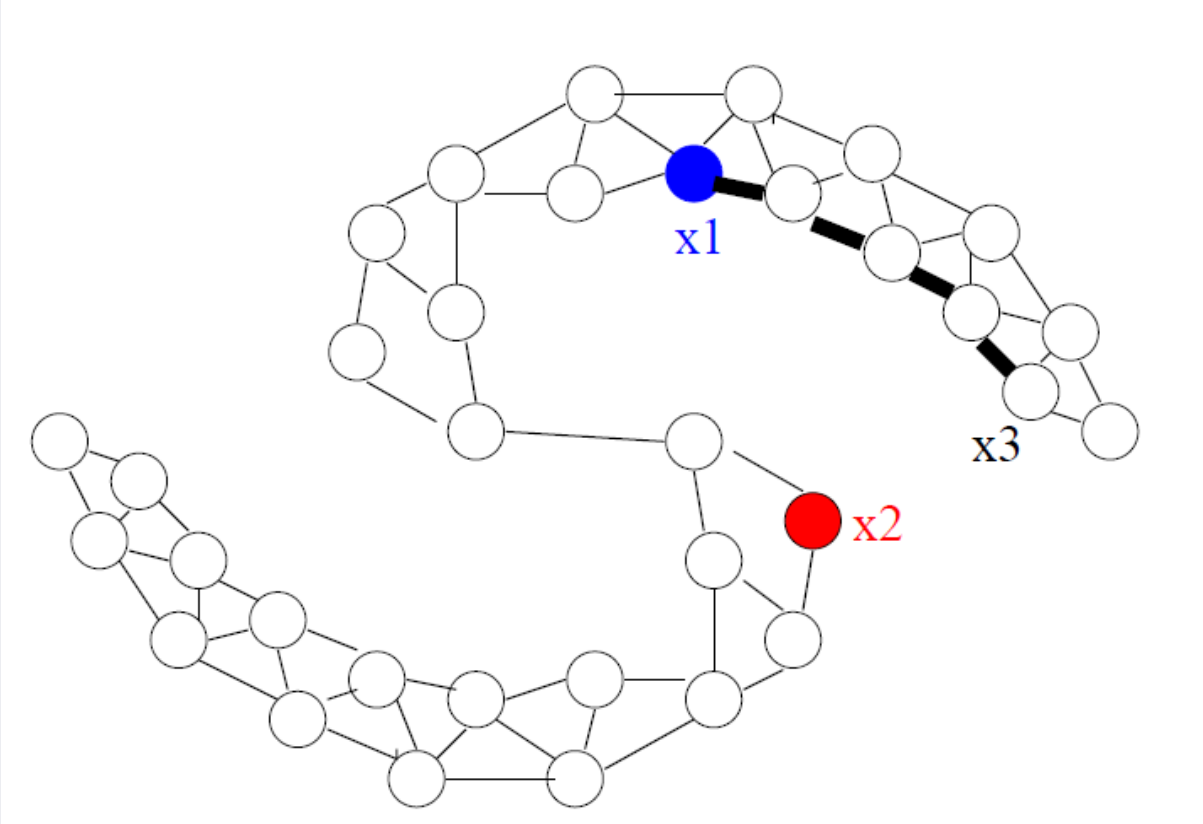
$$w_{ij} = \exp\left(\frac{-||\mathbf{x}_i - \mathbf{x}_j||^2}{\sigma^2}\right)$$

    - ε-radius graph
  - ✓ Assumption: Instances connected by heavy edge tend to have the same label

# Graph-based SSL

Zhu (2007)

- Assumption: Instances connected by heavy edge tend to have the same label



# Graph-based SSL

Zhu (2007)

- The mincut algorithm
  - ✓ Fix $\mathbf{y}_l$, find $\mathbf{y}_u \in \{0,1\}^{n-l}$ to minimize $\sum_{i,j} w_{ij}|y_i - y_j|$
  - ✓ Equivalently, solve the optimization problem

$$\min_{\mathbf{y}\in\{0,1\}^n} \infty \sum_{i=1}^{l} (y_i - \mathbf{y}_{li})^2 + \sum_{i,j} w_{ij}(y_i - y_j)^2$$

  - ✓ Combinatorial problem, but has polynomial time solution

# Graph-based SSL

Zhu (2007)

- Harmonic function
  - ✓ Relaxing discrete labels to continuous values in $\mathbb{R}$, the harmonic function $f$ satisfies

$$f(\mathbf{x}_i) = y_i \text{ for } i = 1, ..., l$$

    - $f$ minimizes the energy

$$\sum_{i \sim j} w_{ij} (f(\mathbf{x}_i) - f(\mathbf{x}_j))^2$$

    - the mean of a Gaussian random field
    - average of neighbors

$$f(\mathbf{x}_i) = \frac{\sum_{j \sim i} w_{ij} f(\mathbf{x}_j)}{\sum_{j \sim i} w_{ij}}, \ \forall \ \mathbf{x}_i \in \mathbf{X}_u$$

# Graph-based SSL

Zhu (2007)

- The graph Laplaican
  - ✓ We can also compute $f$ in closed form using the graph Laplacian
    - $n \times n$ weight matrix $\mathbf{W}$ on $\mathbf{X}_l \cup \mathbf{X}_u$
      - Symmetric, non-negative
    - Diagonal degree matrix: $\mathbf{D} : \mathbf{D}_{ij} = \sum_{j=1}^{n} \mathbf{W}_{ij}$
    - Graph Laplacian matrix $\mathbf{\Delta} = \mathbf{D} - \mathbf{W}$
    - The energy can be rewritten as

$$\sum_{i \sim j} w_{ij} (f(\mathbf{x}_i) - f(\mathbf{x}_j))^2 = \mathbf{f}^T \mathbf{\Delta} \mathbf{f}$$

# Graph-based SSL

Zhu (2007)

- Harmonic solution with Laplacian
  - ✓ The harmonic solution minimizes energy subject to the given labels

$$\min_{\mathbf{f}} \infty \sum_{i=1}^{l} (f(\mathbf{x}_i) - y_i)^2 + \mathbf{f}^T \boldsymbol{\Delta} \mathbf{f}$$

  - Partition the Laplacian matrix $\boldsymbol{\Delta} = \begin{bmatrix} \boldsymbol{\Delta}_{ll} & \boldsymbol{\Delta}_{lu} \\ \boldsymbol{\Delta}_{ul} & \boldsymbol{\Delta}_{uu} \end{bmatrix}$
  - Harmonic solution

$$\mathbf{f}_u = -\boldsymbol{\Delta}_{uu}^{-1} \boldsymbol{\Delta}_{ul} \mathbf{y}_l$$

  - The normalized Laplacian is often used

$$\mathcal{L} = \mathbf{D}^{-\frac{1}{2}} \boldsymbol{\Delta} \mathbf{D}^{-\frac{1}{2}} = \mathbf{I} - \mathbf{D}^{-\frac{1}{2}} \mathbf{W} \mathbf{D}^{-\frac{1}{2}}$$

# Graph-based SSL

Zhu (2007)

- Problems with harmonic solution
  - ✓ It fixes the given labels $\mathbf{y}_l$
    - What if some labels are wrong?
    - Want to be flexible and disagree with given labels occasionally
  - ✓ It cannot handle new test points directly
    - $f$ is only defined on $\mathbf{X}_u$
    - We have to add new test points to the graph, and find a new harmonic solution

➢ Allow $f(\mathbf{X}_l)$ to be different from $\mathbf{y}_l$ but penalize it

➢ Introduce a balance between labeled data fit and graph energy

$$\min_{\mathbf{f}} \sum_{i=1}^{l} (f(\mathbf{x}_i) - y_i)^2 + \lambda \mathbf{f}^T \mathbf{\Delta} \mathbf{f}$$

# Graph-based SSL

- Solution

$$\min(\mathbf{f}-\mathbf{y})^T(\mathbf{f}-\mathbf{y})+\lambda\mathbf{f}^T\boldsymbol{\Delta}\mathbf{f} \qquad \mathbf{y}=[\mathbf{y}_l;\ \underbrace{0;\ \ldots\ ;\ 0}_{N.\text{of unlabeled examples}}]$$

$$\frac{\partial E}{\partial \mathbf{f}}=(\mathbf{f}-\mathbf{y})+\lambda\boldsymbol{\Delta}\mathbf{f}=0$$

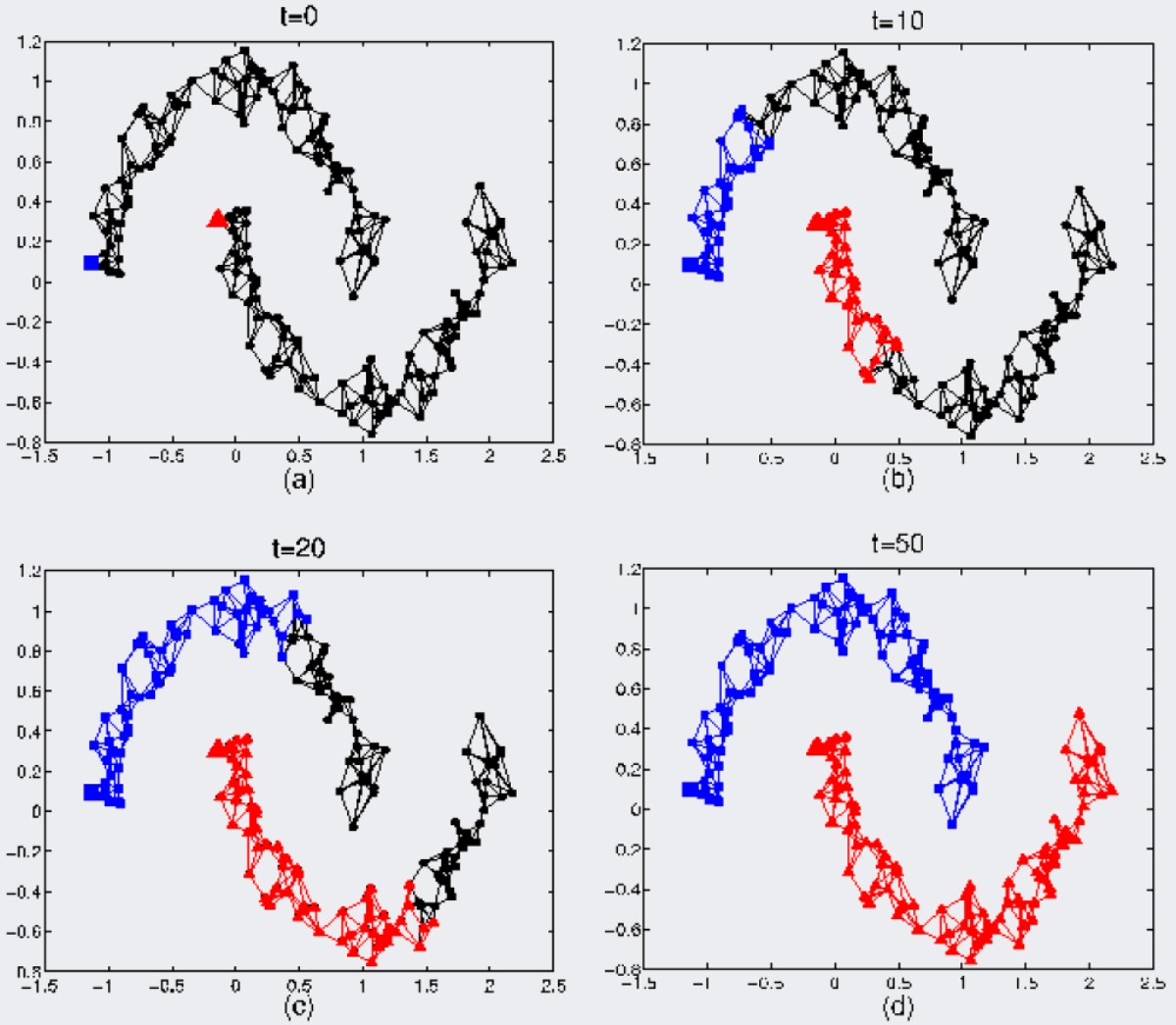
$$(\mathbf{I}+\lambda\boldsymbol{\Delta})\mathbf{f}=\mathbf{y} \quad \Rightarrow \quad \mathbf{f}=(\mathbf{I}+\lambda\boldsymbol{\Delta})^{-1}\mathbf{y}$$

- ✓ If $\lambda$ is large, then the effect of $\lambda\boldsymbol{\Delta}$ increases → more focused on the smoothness
- ✓ If $\lambda$ is small, then the effect of $\lambda\boldsymbol{\Delta}$ decreases → more focused on the accuracy of labeled data

# Graph-based SSL

Zien (2008)

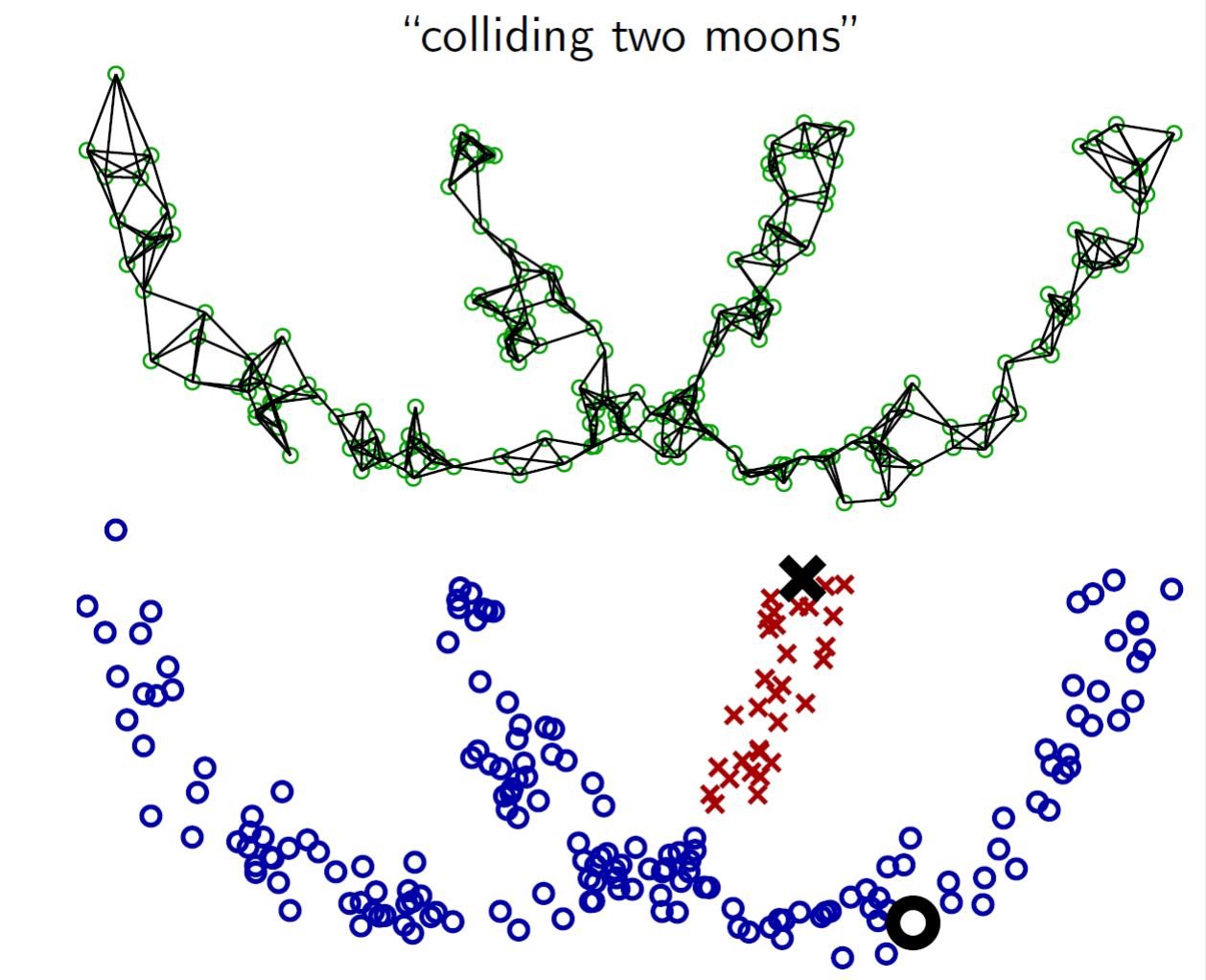
- Examples: Label Progapation



# Graph-based SSL

Zhu (2009)

- When the graph assumption is wrong



# AGENDA

# Multi-view Algorithms

Blum and Mitchell (1998), Yu et al. (2011)

- Co-training
  - ✓ Two views of an item: image and HTML text

# Multi-view Algorithms

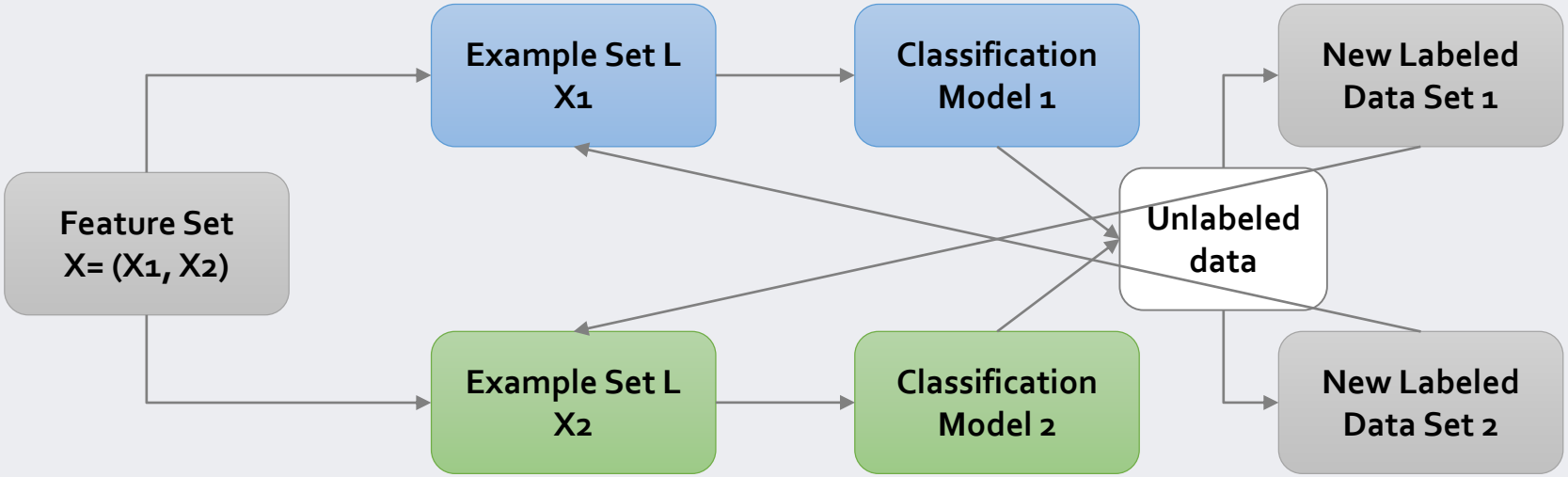
- Feature split

Each instance is represented by two sets of features $x = [x^{(1)}; x^{(2)}]$

- $x^{(1)}$ = image features
- $x^{(2)}$ = web page text
- This is a natural feature split (or multiple views)

Co-training idea:

- Train an image classifier and a text classifier
- The two classifiers teach each other



# Multi-view Algorithms

Blum and Mitchell (1998)

- Co-Training (Basic algorithm, for classification with Naïve Baye's Classifier)
  - ✓ Given
    - A set L of labeled training examples
    - A set of U of unlabeled examples
  - ✓ Create a pool U' of example by choosing u examples at random from U
  - ✓ Loop for k iterations
    - Use L to train a classifier $h_1$ that considers only the $x_1$ portion of x
    - Use L to train a classifier $h_2$ that considers only the $x_2$ portion of x
    - Allow $h_1$ to label p positive and n negative examples from U'
    - Allow $h_2$ to label p positive and n negative examples from U'
    - Add these self-labeled examples to L
    - Randomly choose 2p+2n examples from U to replenish U'

# Multi-view Algorithms

Zhou and Li (2005)

- Co-Training (with k-NN regression)

ALGORITHM: COREG

INPUT: labeled example set $L$, unlabeled example set $U$,
number of nearest neighbors $k$,
maximum number of learning iterations $T$,
distance orders $p_1, p_2$

PROCESS:

$L_1 \leftarrow L$; $L_2 \leftarrow L$

Create pool $U'$ by randomly picking examples from $U$

$h_1 \leftarrow kNN(L_1, k, p_1)$; $h_2 \leftarrow kNN(L_2, k, p_2)$

**Repeat** for $T$ rounds:

  **for** $j \in \{1, 2\}$ **do**

    **for** each $\mathbf{x}_u \in U'$ **do**

      $\hat{\mathbf{y}}_u \leftarrow h_j(\mathbf{x}_u)$

      $\Omega \leftarrow Neighbors(\mathbf{x}_u, k, L_j)$

      $h'_j \leftarrow kNN(L_j \cup \{(\mathbf{x}_u, \hat{\mathbf{y}}_u)\}, k, p_j)$

      $\Delta_{\mathbf{x}_u} \leftarrow \sum_{\mathbf{x}_i \in \Omega} \left( (\mathbf{y}_i - h_j(\mathbf{x}_i))^2 - (\mathbf{y}_i - h'_j(\mathbf{x}_i))^2 \right)$

    **end of for**

    **if** there exists an $\Delta_{\mathbf{x}_u} > 0$

    **then** $\tilde{\mathbf{x}}_j \leftarrow \arg\max_{\mathbf{x}_u \in U'} \Delta_{\mathbf{x}_u}$; $\tilde{\mathbf{y}}_j \leftarrow h_j(\tilde{x}_j)$

      $\pi_j \leftarrow \{(\tilde{\mathbf{x}}_j, \tilde{\mathbf{y}}_j)\}$; $U' \leftarrow U' - \pi_j$

    **else** $\pi_j \leftarrow \emptyset$

  **end of for**

  $L_1 \leftarrow L_1 \cup \pi_2$; $L_2 \leftarrow L_2 \cup \pi_1$

  **if** neither of $L_1$ and $L_2$ changes **then exit**

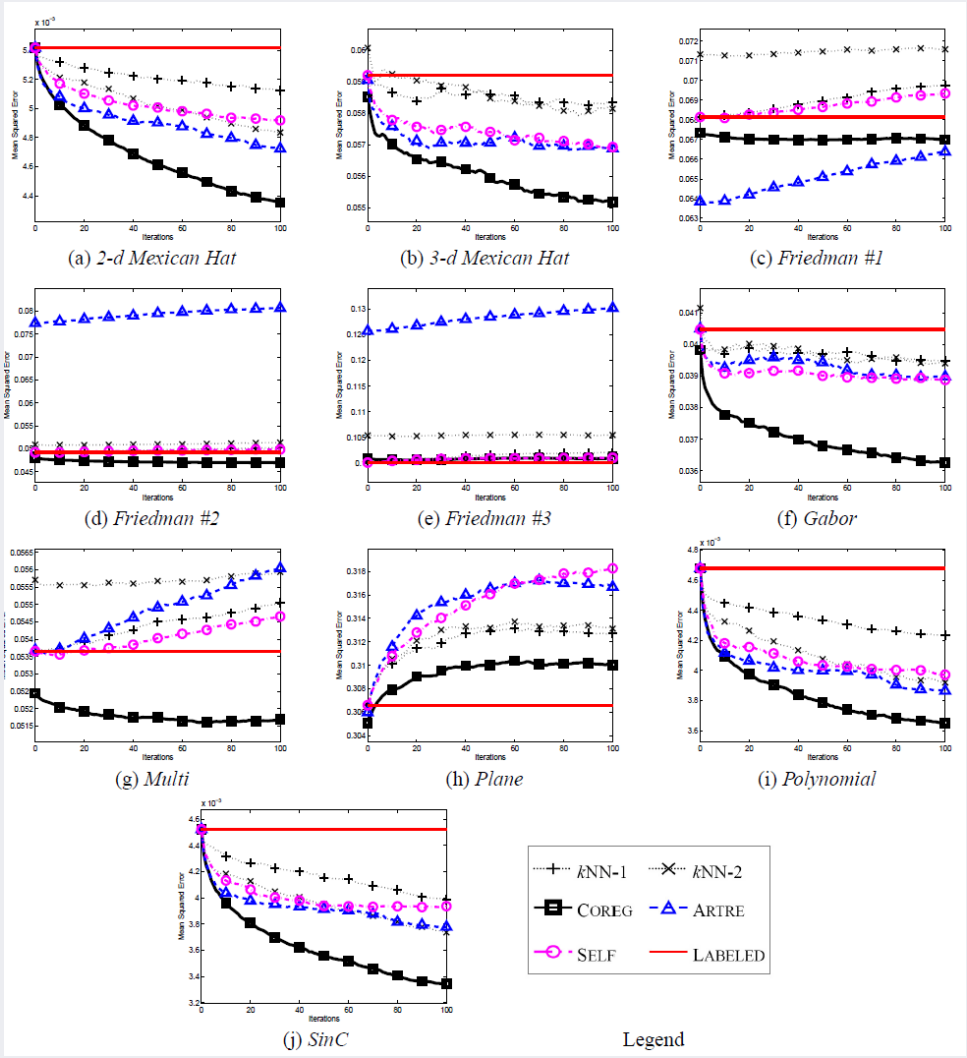
  **else**

    $h_1 \leftarrow kNN(L_1, k, p_1)$; $h_2 \leftarrow kNN(L_2, k, p_2)$

    Replenish $U'$ by randomly picking examples from $U$

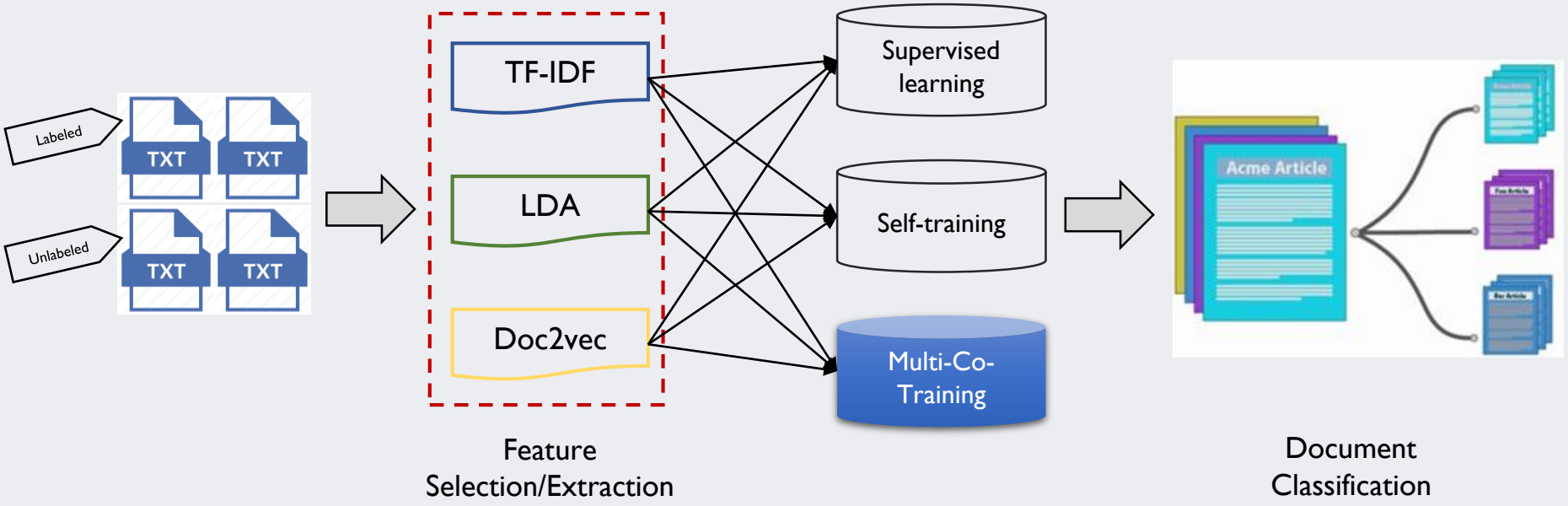
**end of Repeat**

OUTPUT: regressor $h^*(\mathbf{x}) \leftarrow \frac{1}{2}(h_1(\mathbf{x}) + h_2(\mathbf{x}))$



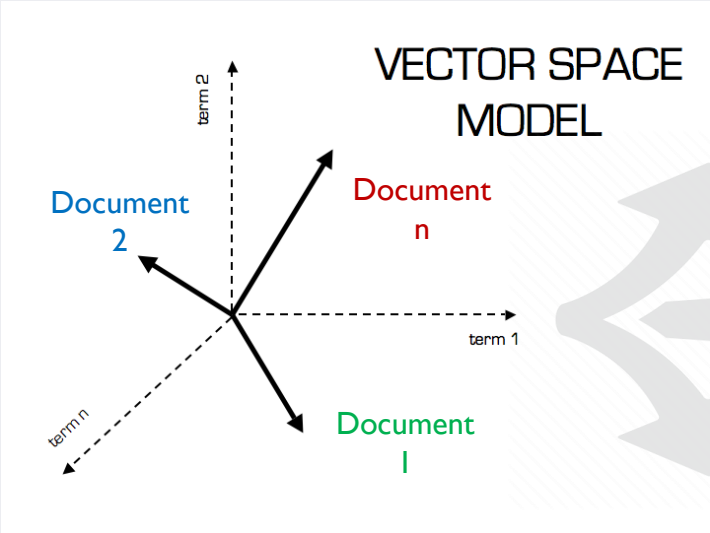
# Multi-view Algorithms

- Multi-Co-Training for Text Classification



# Multi-view Algorithms

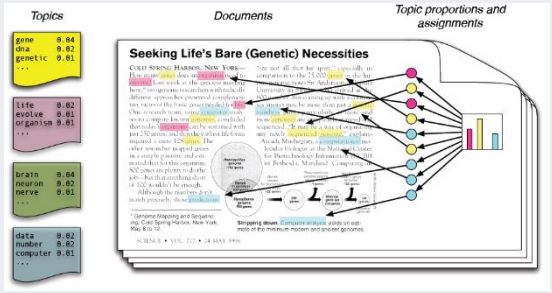
- Multi-Co-Training for Text Classification



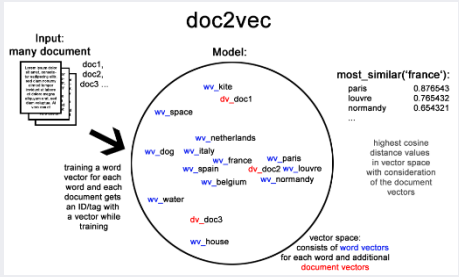

TF-IDF

| Document1 | | | | | |
|---|---|---|---|---|---|
| Word | TF | N | DF | IDF | TF-IDF |
| This | 4 | 3 | 3 | 1/3 | 1.33 |
| is | 5 | 2 | 3 | 1/3 | 1.67 |
| an | 3 | 3 | 3 | 1/3 | 1 |
| Example | 2 | 3 | 1 | 1 | 2 |

LDA

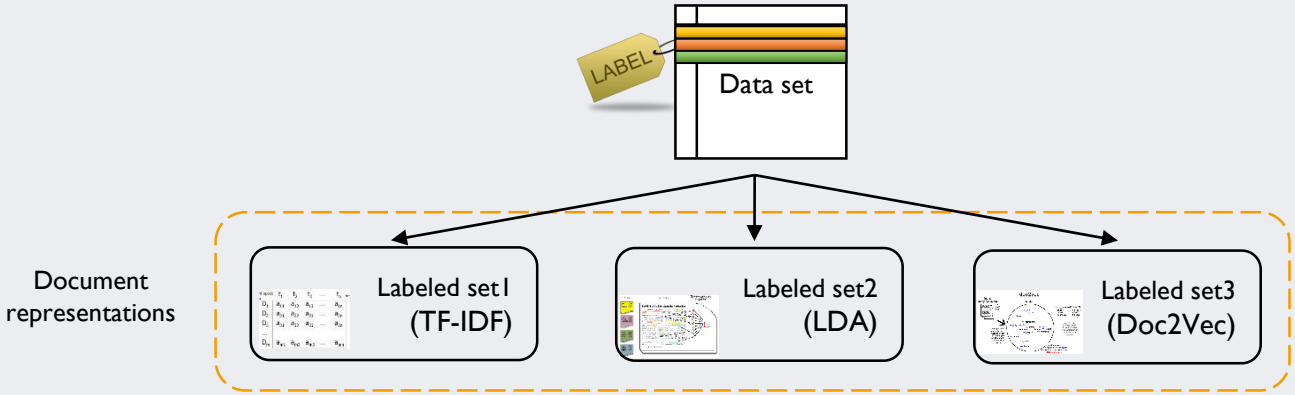



Doc2vec



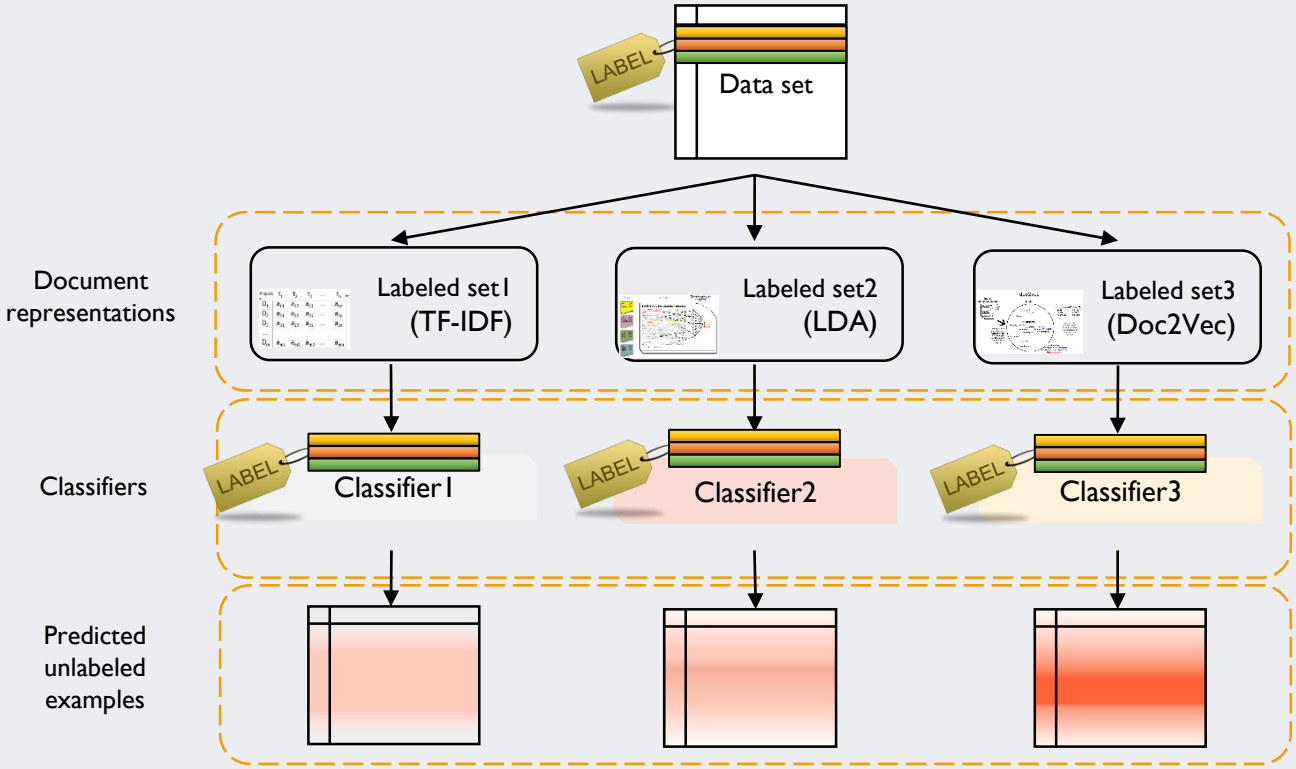
# Multi-view Algorithms

- Multi-Co-Training for Text Classification
  - ✓ Step1) Create multi-views: TF-IDF, LDA and Doc2vec



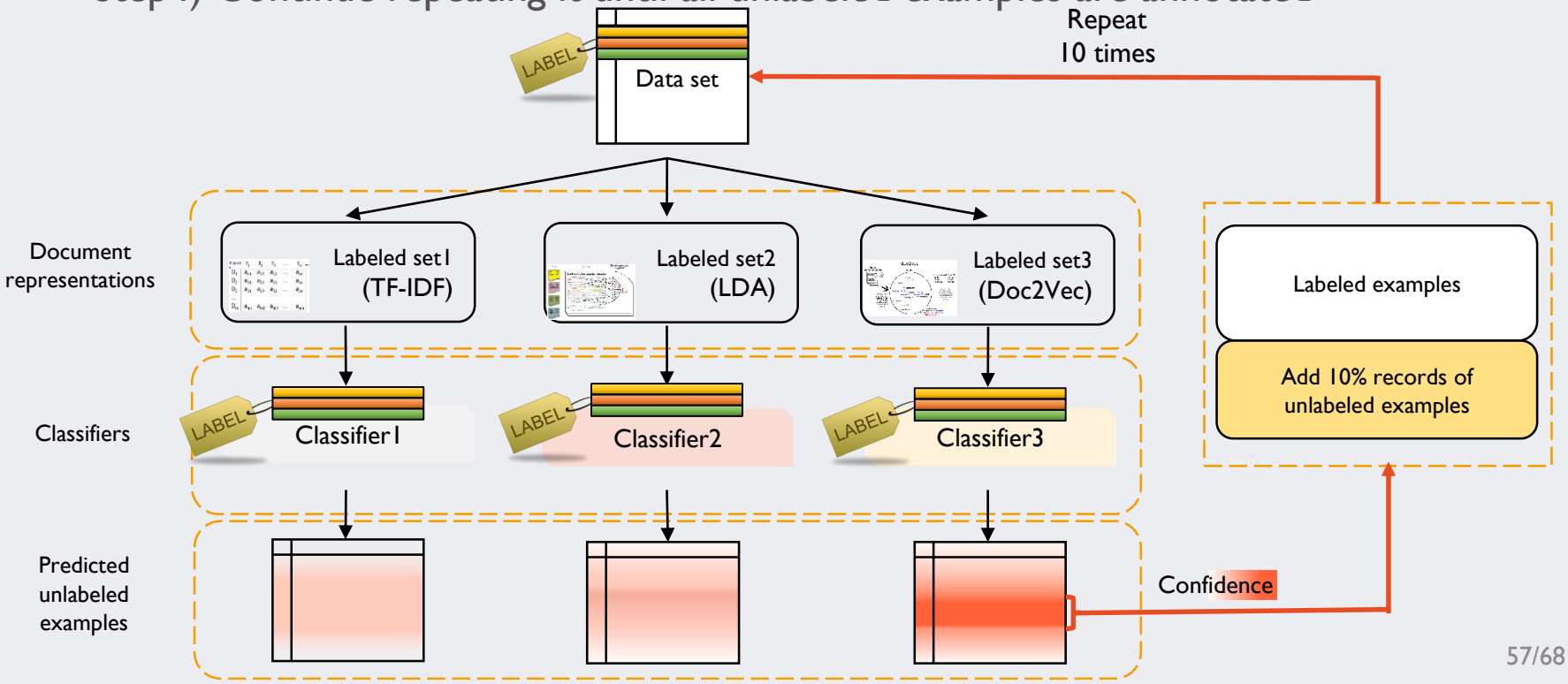
# Multi-view Algorithms

- Multi-Co-Training for Text Classification
  - ✓ Step1) Create multi-views: TF-IDF, LDA and Doc2vec
  - ✓ Step2) Build models and then predict unlabeled examples



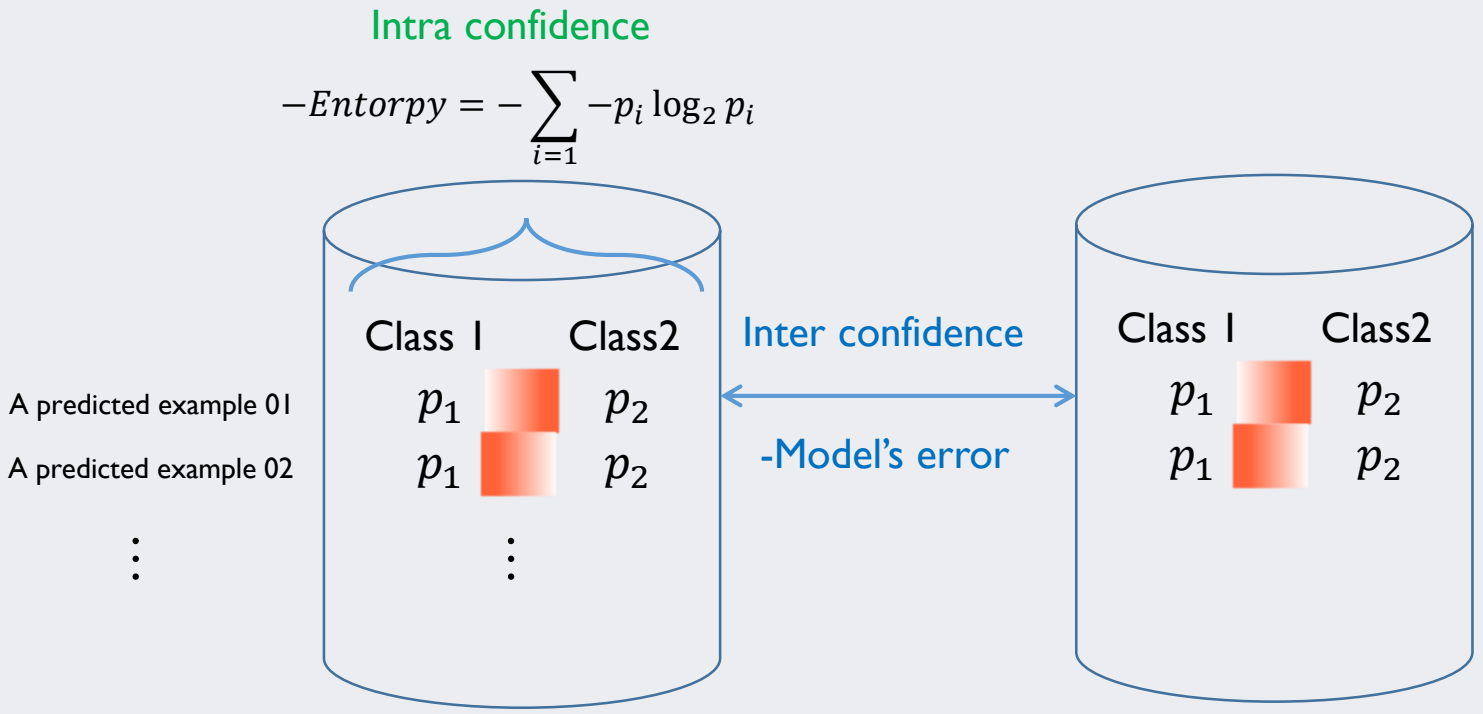
# Multi-view Algorithms

- Multi-Co-Training for Text Classification
  - ✓ Step1) Create multi-views: TF-IDF, LDA and Doc2vec
  - ✓ Step2) Build models and then predict unlabeled examples
  - ✓ Step3) Add the predicted examples with high confidence to labeled examples
  - ✓ Step4) Continue repeating it until all unlabeled examples are annotated



# Multi-view Algorithms

- Confidence measure with Naïve Bayesian
  - ✓ Intra confidence: $-Entropy$
  - ✓ Inter confidence: $-Training\ error$
  - ✓ Confidence measure = $-Entropy \times -Training\ error$



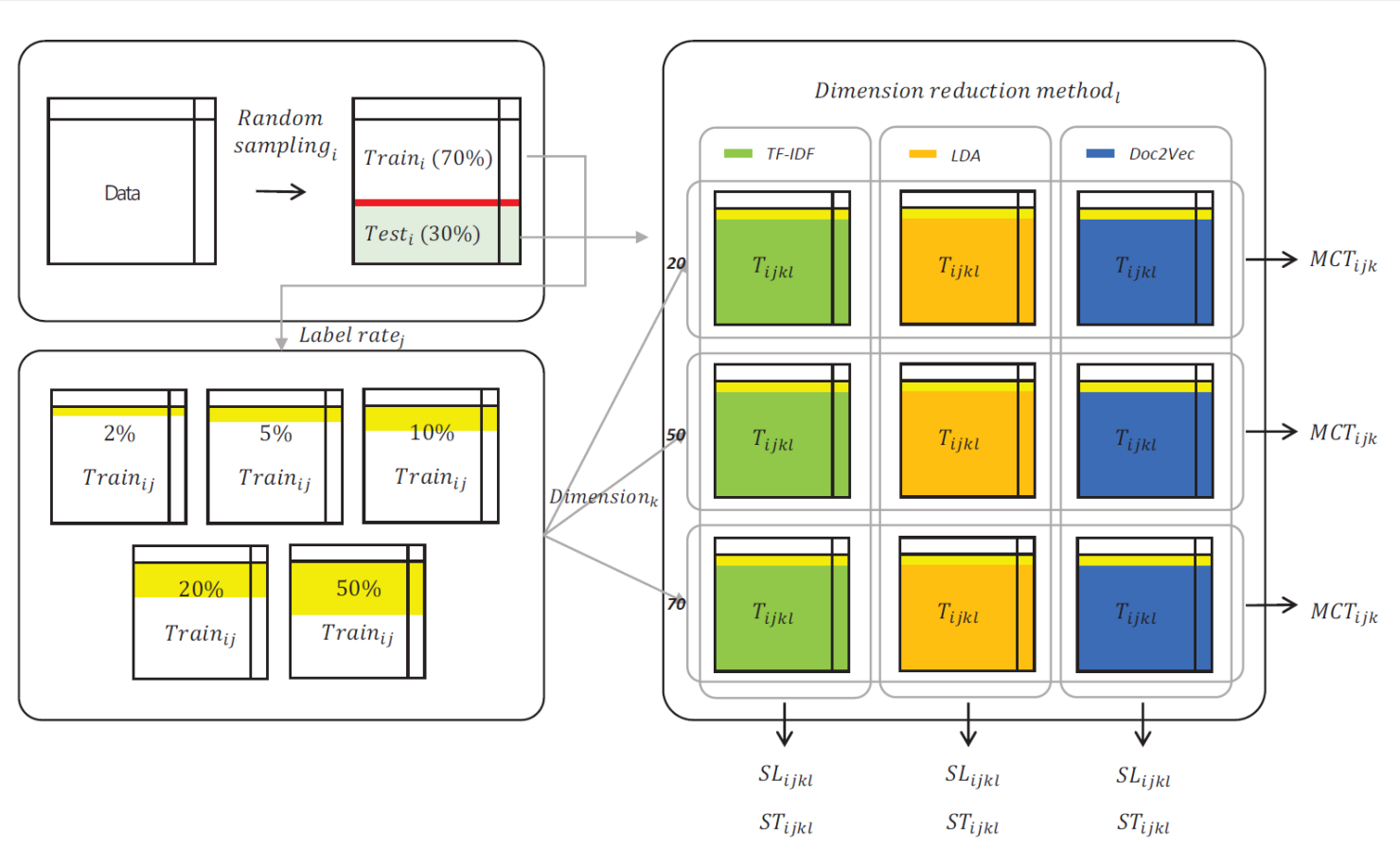
# Multi-view Algorithms

- Experiment: Data sets

| Data | Description | Category | No. of documents |
|---|---|---|---|
| Economic | Whether a news article data is associated with the US economy | No : 6,458 (82.12%)<br>Yes : 1,406 (17.88%) | 7,864 |
| 20 Newsgroup | Data of 20,000 messages collected from 20 different news categories | Computer : 4,863 (30.40%)<br>Recreation : 3,957 (24.74%)<br>Science : 3,933 (24.59%)<br>Talk : 3,244 (20.27%) | 15,997 |
| Ohsumed | Article-related abstracts of medical data | C04 : 2,630 (50.77%)<br>C14 : 2,550 (49.23%) | 5,180 |
| Reuters | 21,578 documents obtained from the Reuters news data | Earn : 3,953 (51.67%)<br>Non-earn : 4,697 (48.33%) | 8,650 |

# Multi-view Algorithms

- Experiment: Evaluation procedure
  - ✓ Evaluate the average and its standard deviation of Balanced Classification Rate (BCR)



# Multi-view Algorithms

- Experiment: Results

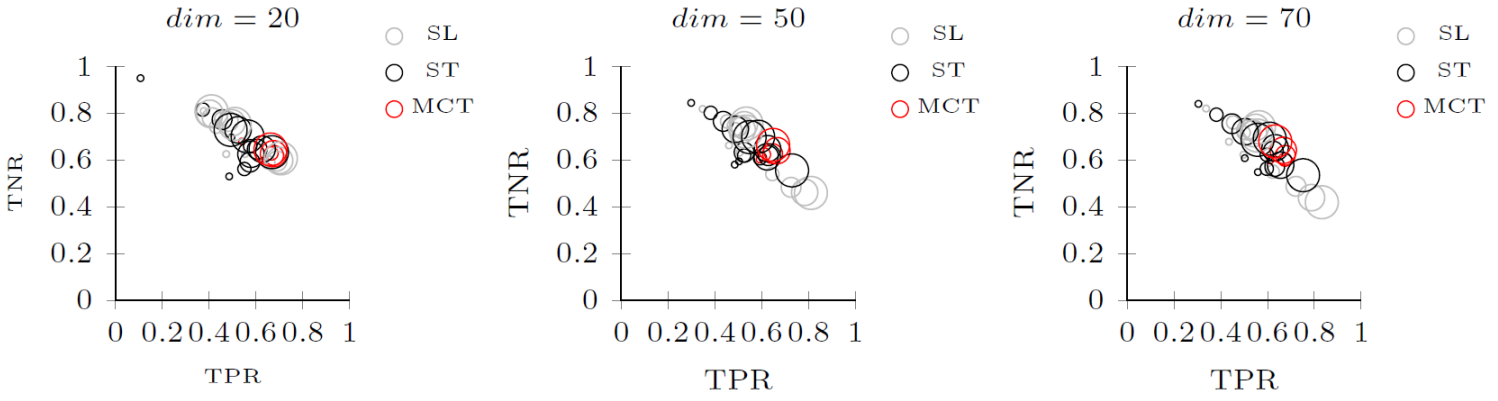



**Fig. 7** TPR—TNR plots for SL, ST, and MCT for Economic dataset (Size = label(%))

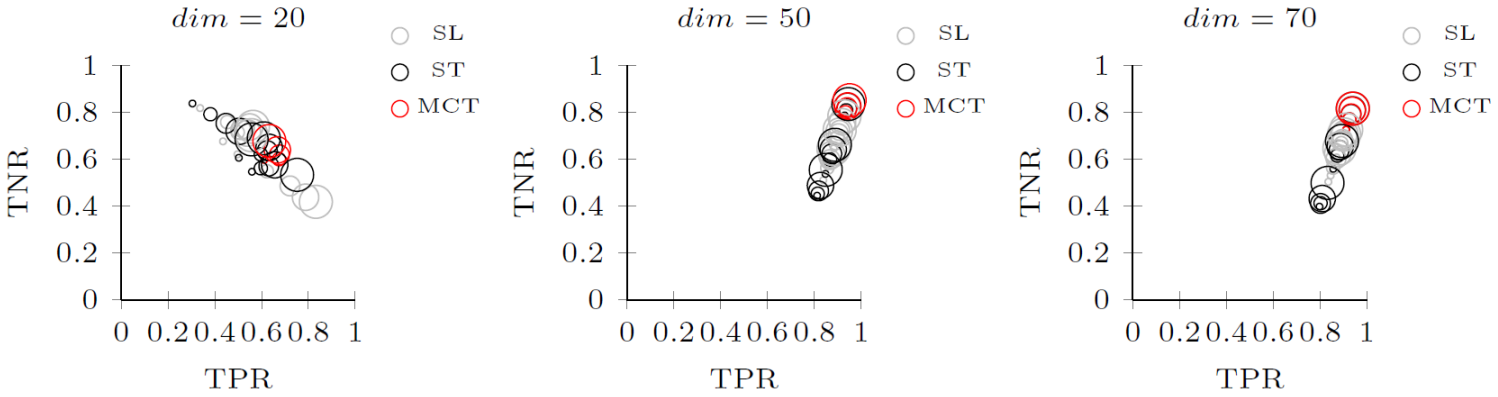



**Fig. 8** TPR—TNR plots for SL, ST, and MCT for Newsgroup dataset (Size = label(%))

# Multi-view Algorithms

- Experiment: Results

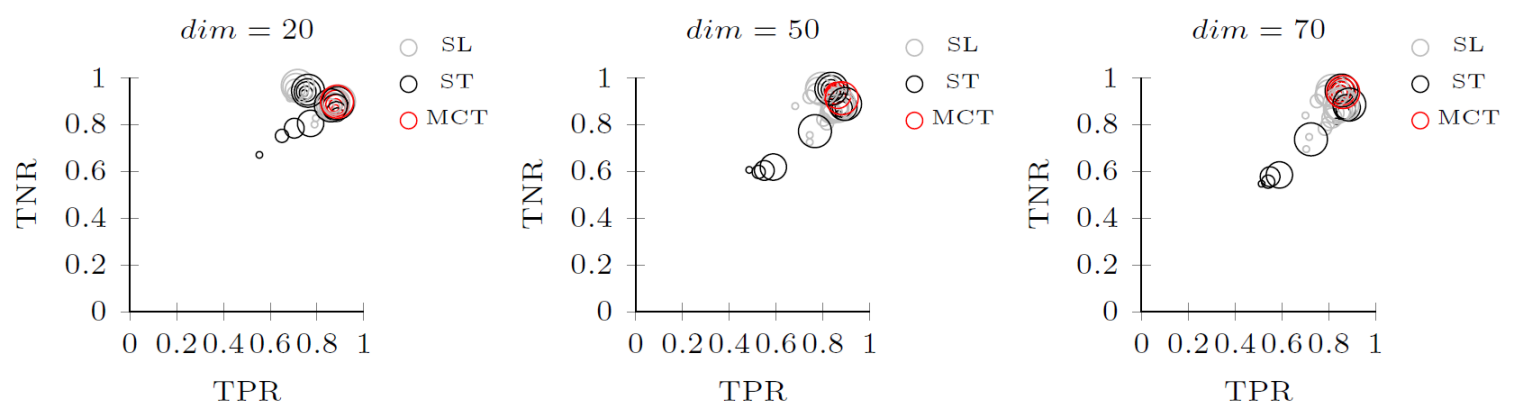



**Fig. 9** TPR—TNR plots for SL, ST, and MCT for Ohsumed dataset (Size = label(%))

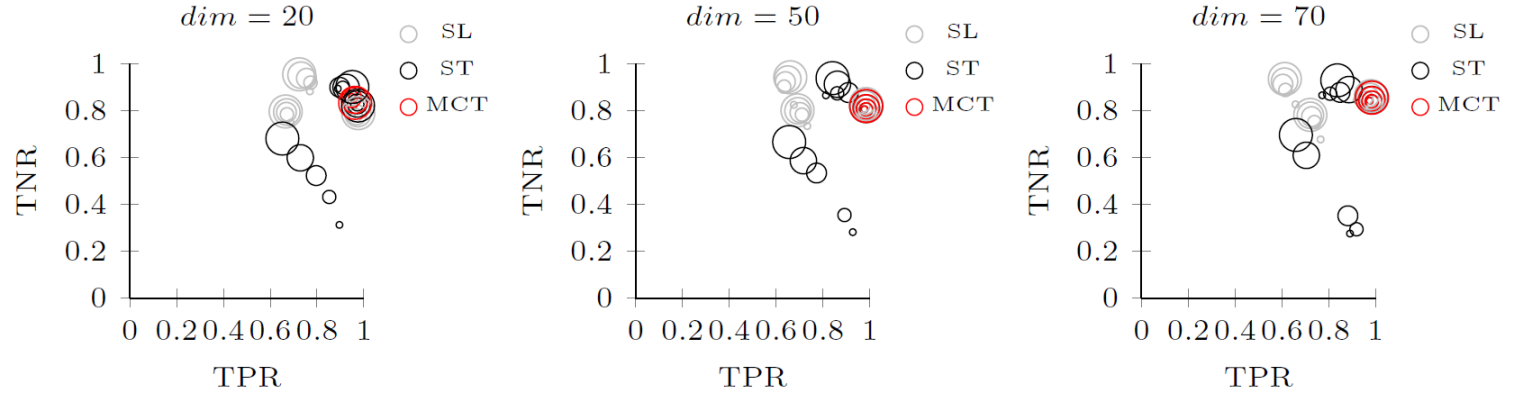



**Fig. 10** TPR—TNR plots of SL, ST, and MCT for Reuters dataset (Size = label(%))


Q & A

# References


Research Papers

- Ben-David, S., Lu, T., & Pál, D. (2008, July). Does Unlabeled Data Provably Help? Worst-case Analysis of the Sample Complexity of Semi-Supervised Learning. In *COLT* (pp. 33-44).
- Bennett, K., & Demiriz, A. (1999). Semi-supervised support vector machines. *Advances in Neural Information processing systems*, 368-374.
- Blum, A., & Mitchell, T. (1998, July). Combining labeled and unlabeled data with co-training. In *Proceedings of the eleventh annual conference on Computational learning theory* (pp. 92-100). ACM.
- Fox-Roberts, P., & Rosten, E. (2014). Unbiased generative semi-supervised learning. *The Journal of Machine Learning Research*, *15*(1), 367-443.
- Kim, D., Seo, D., Cho, S., & Kang, P. (2017+). Multi-co-training for document classification using various document representations: TF-IDF, LDA, and Doc2Vec. under review.
- Kingma, D. P., Mohamed, S., Rezende, D. J., & Welling, M. (2014). Semi-supervised learning with deep generative models. In *Advances in Neural Information Processing Systems* (pp. 3581-3589).
- Singh, A., Nowak, R., & Zhu, X. (2009). Unlabeled data: Now it helps, now it doesn't. In *Advances in neural information processing systems* (pp. 1513-1520).
- Yu, S., Krishnapuram, B., Rosales, R., & Rao, R. B. (2011). Bayesian co-training. *The Journal of Machine Learning Research*, *12*, 2649-2680
- Zhou, Z. H., & Li, M. (2005, July). Semi-Supervised Regression with Co-Training. In IJCAI (Vol. 5, pp. 908-913).

# References


Other materials

- Figures in the first page: 하상욱 단편시집 – 서울 시
- Zhu, X. (2007). Semi-Supervised Learning Tutorial. International Conference on Machine Learning (ICML 2007).
- Choi, S. (2015). Deep Learning: A Quick Overview. Deep Learning Workship. KIISE.
- Zien, A. (2008). Semi-Supervised Learning. Summer School on Neural Networks.
- Zhu, X. (2009). Tutorial on Semi-Supervised Learning. Theory and Practice of Computational Learning.