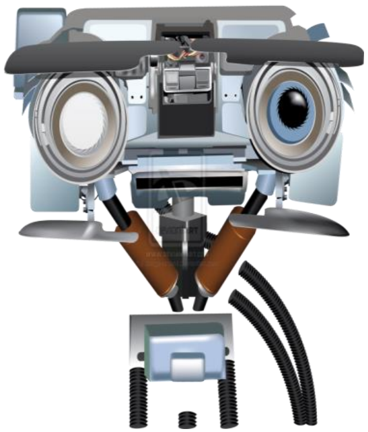
Announcements

Reminder: pset5 self-grading form and pset6 out, due Today 11/19 11:59pm Boston Time

- Class challenge out Today (will discuss in class)



Semi-Supervised Learning

Slides credit: Jerry Zhu, Aarti Singh

Supervised Learning

Feature Space $\mathcal{X}$ **Label** Space $\mathcal{Y}$

Goal: Construct a **predictor** $f : \mathcal{X} \to \mathcal{Y}$ to minimize

$$R(f) \equiv \mathbb{E}_{XY}[\text{loss}(Y, f(X))]$$

Optimal predictor (Bayes Rule) depends on unknown P_{XY}, so instead *learn* a good prediction rule from training data $\{(X_i, Y_i)\}_{i=1}^n \overset{\text{iid}}{\sim} P_{XY}$(unknown)

Training data $\{(X_i, Y_i)\}_{i=1}^n$ ⇒ **Learning algorithm** ⇒ Prediction rule $\widehat{f}_n$

Labeled

Labeled and Unlabeled data

“Crystal” “Needle” “Empty”

“0” “1” “2” …

Human expert/
Special equipment/
Experiment

“Sports”
“News”
“Science”
…

Unlabeled data, X_i

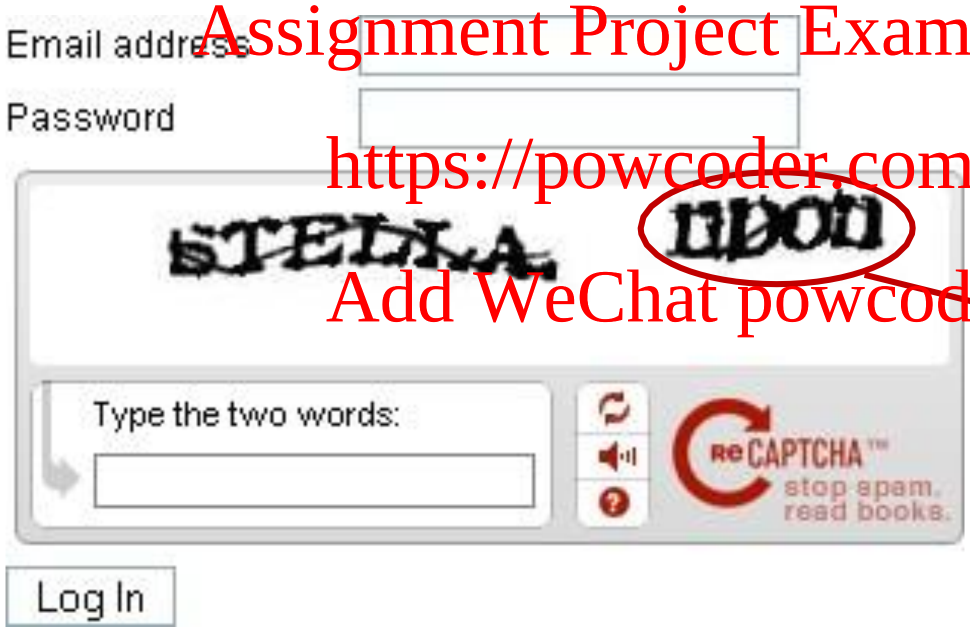
Labeled data, Y_i

Cheap and abundant !

Expensive and scarce !

Free-of-cost labels?

Luis von Ahn: Games with a purpose (ReCaptcha)



Word challenging to OCR
(Optical Character Recognition)

You provide a free label!

Semi-Supervised learning

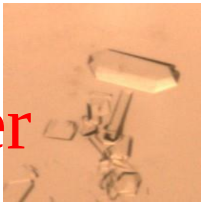
Training data $\Rightarrow$ **Learning algorithm** $\Rightarrow$ Prediction rule

$\{(X_i, Y_i)\}_{i=1}^n$ $\qquad$ $\widehat{f}_{n,m}$

$\{X_i\}_{i=1}^m$

Supervised learning (SL)

Labeled data $\{X_i, Y_i\}_{i=1}^n$



“Crystal”

X_i $\qquad$ Y_i

Semi-Supervised learning (SSL)

Labeled data $\{X_i, Y_i\}_{i=1}^n$ **and** Unlabeled data $\{X_i\}_{i=1}^m$ $\qquad$ $m \gg n$

Goal: Learn a better prediction rule than based on labeled data alone.

Semi-Supervised learning in Humans

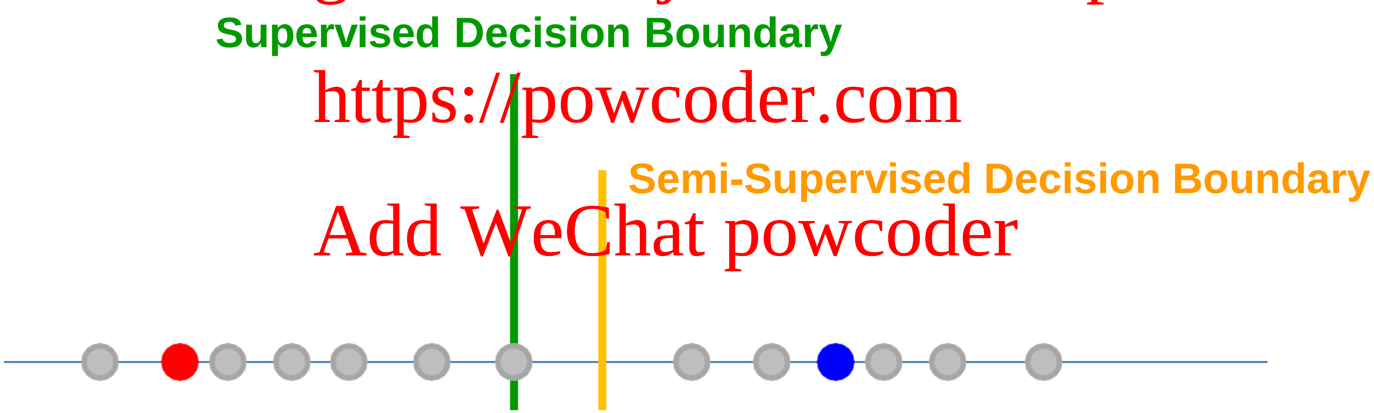
Cognitive science

Computational model of how humans learn from labeled and unlabeled data.

- concept learning in children: $\mathbf{x}$=animal, y=concept (e.g., dog)
- Daddy points to a brown animal and says "dog!"
- Children also observe animals by themselves

Can unlabeled data help?

- Positive labeled data
- Negative labeled data
- Unlabeled data

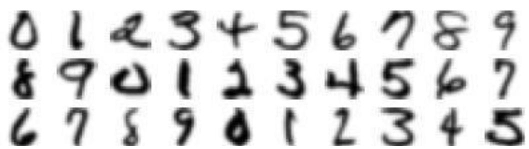


Assume each class is a coherent group (e.g. Gaussian)

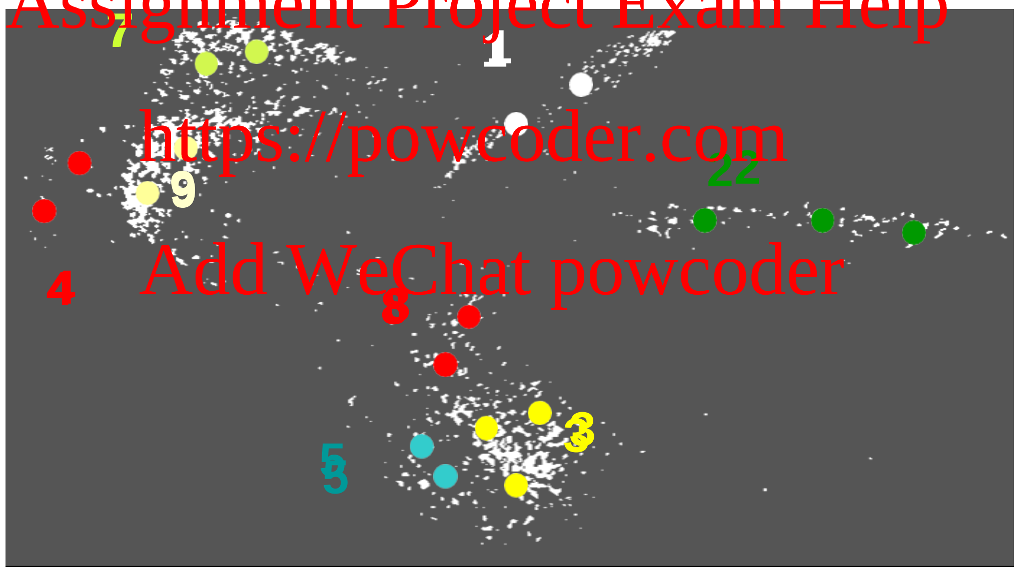
Then unlabeled data can help identify the boundary more accurately.

Can unlabeled data help?

Unlabeled Images

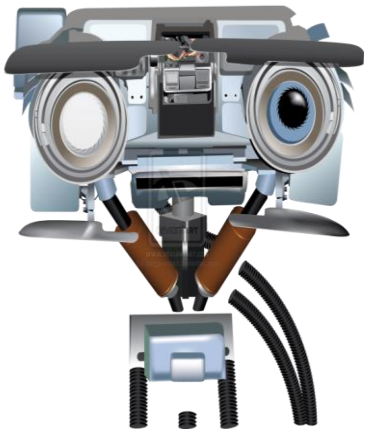


Labels “0” “1” “2” …



This embedding can be done by manifold learning algorithms, e.g. tSNE

“Similar” data points have “similar” labels



Algorithms

Semi-Supervised Learning

Slides credit: Jerry Zhu, Aarti Singh

Some SSL Algorithms

- Self-Training
- Generative methods, mixture models
- Graph-based methods
- Co-Training
- Semi-supervised SVM
- Many others

Notation

- instance $\mathbf{x}$, label y

- learner $f : \mathcal{X} \mapsto \mathcal{Y}$
- labeled data $(X_l, Y_l) = \{(x_{1:l}, y_{1:l})\}$

- unlabeled data $X_u = \{\mathbf{x}_{l+1:l+u}\}$, available during training. Usually $l \ll u$. Let $n = l + u$

- test data $\{(x_{n+1\ldots}, y_{n+1\ldots})\}$, not available during training

Self-training

Our first SSL algorithm:

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

1. Initially, let $L = \{(\mathbf{x}_i, y_i)\}_{i=1}^{l}$ and $U = \{\mathbf{x}_j\}_{j=l+1}^{l+u}$.
2. Repeat:

3. Train f from L using supervised learning.
4. Apply f to the unlabeled instances in U.

5. Remove a subset S from U; add $\{(\mathbf{x}, f(\mathbf{x})) | \mathbf{x} \in S\}$ to L.

Self-training is a *wrapper* method

- the choice of learner for f in step 3 is left completely open
- good for many real world tasks like natural language processing
- but mistake by f can reinforce itself

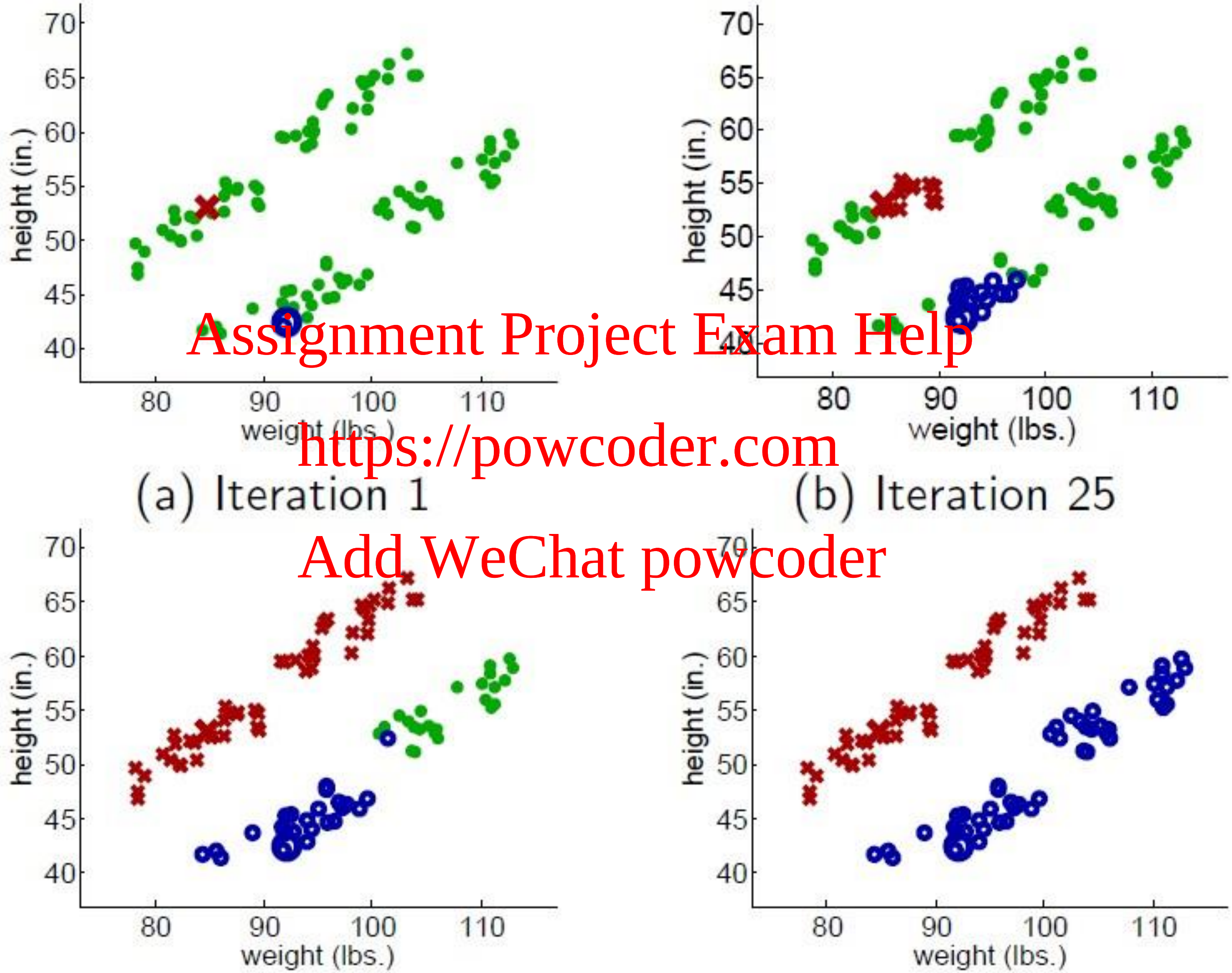
Self-training Example

Propagating 1-NN

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 $\mathbf{x} = \mathrm{argmin}_{\mathbf{x} \in U} \min_{\mathbf{x}' \in L} d(\mathbf{x}, \mathbf{x}')$.
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.

Propagating 1-Nearest-Neighbor: now it works

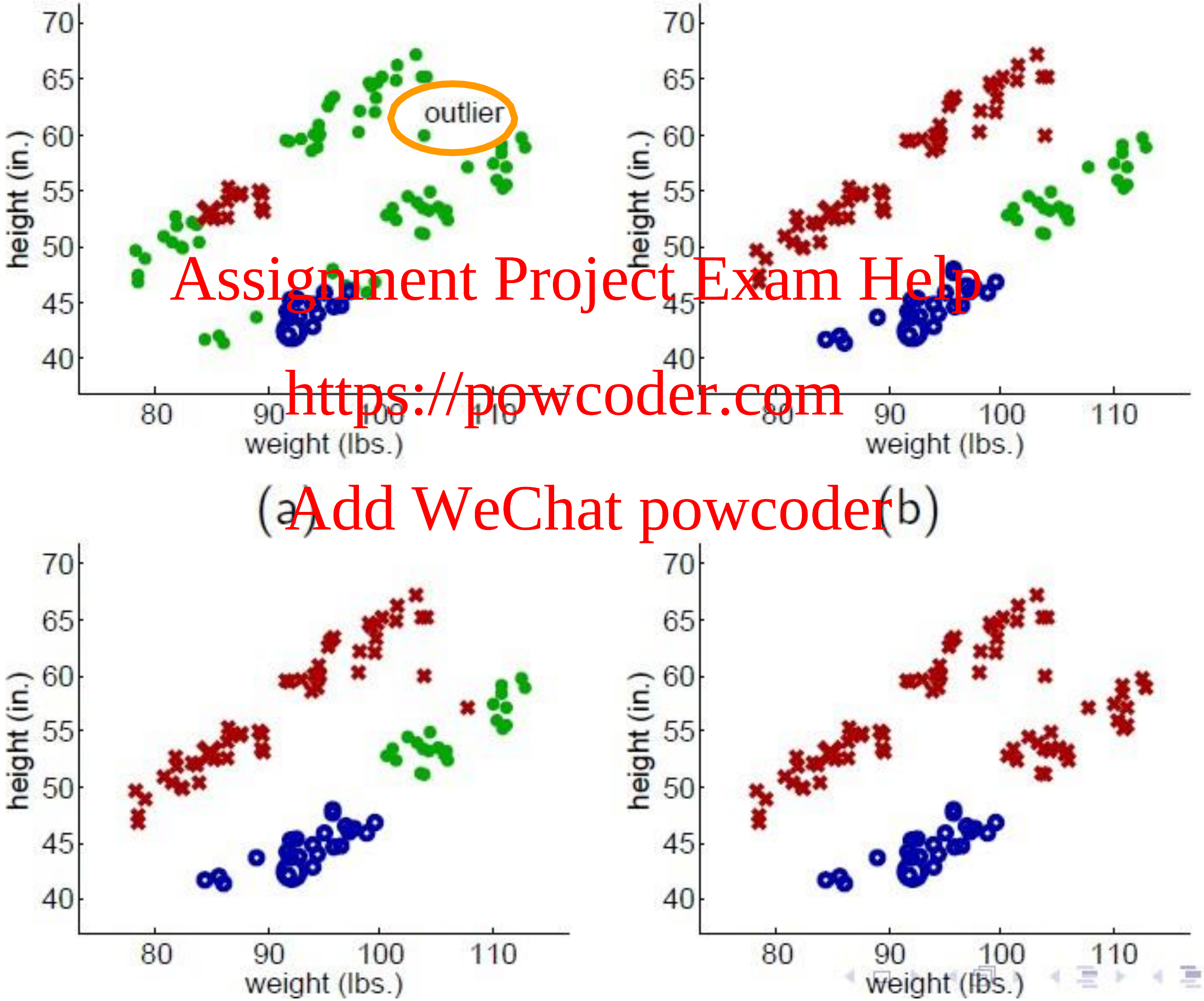


(a) Iteration 1 (b) Iteration 25

(c) Iteration 74 (d) Final labeling of all instances

Propagating 1-Nearest-Neighbor: now it doesn't

But with a single outlier...



Related: Cluster and Label

Input: $(\mathbf{x}_1, y_1), \ldots, (\mathbf{x}_l, y_l), \mathbf{x}_{l+1}, \ldots, \mathbf{x}_{l+u}$,
a clustering algorithm $\mathcal{A}$, a supervised learning algorithm $\mathcal{L}$

1. Cluster $\mathbf{x}_1, \ldots, \mathbf{x}_{l+u}$ using $\mathcal{A}$.
2. For each cluster, let S be the labeled instances in it:

3. Learn a supervised predictor from S: $f_S = \mathcal{L}(S)$.
4. Apply f_S to all unlabeled instances in this cluster.

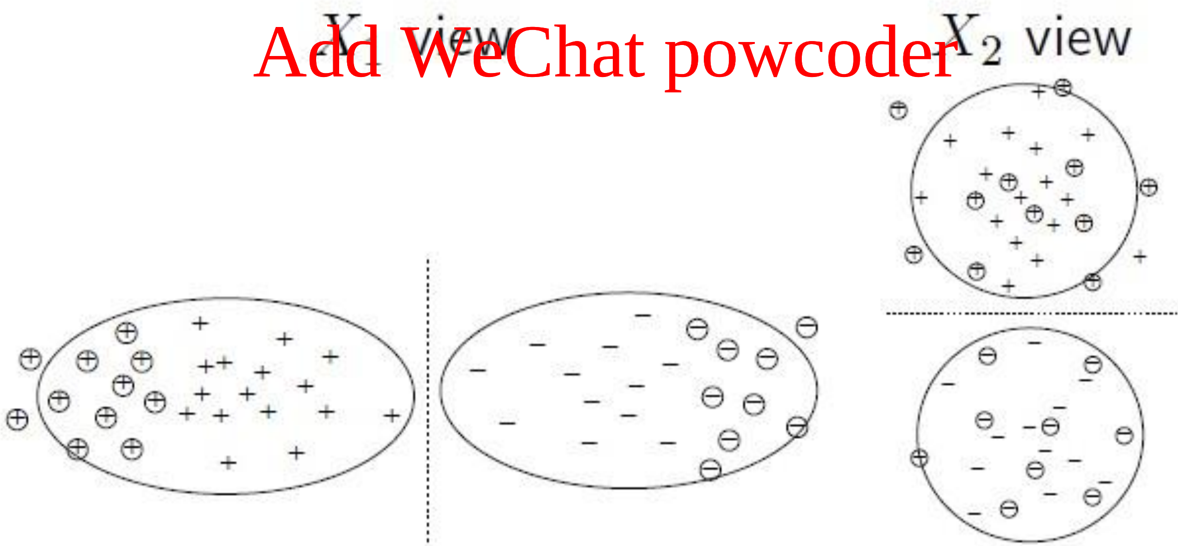
Output: labels on unlabeled data $y_{l+1}, \ldots, y_{l+u}$.

But again: **SSL sensitive to assumptions**—in this case, that the clusters coincide with decision boundaries. If this assumption is incorrect, the results can be poor.

Co-training

Assumptions

- feature split $x = [x^{(1)}; x^{(2)}]$ exists
- $x^{(1)}$ or $x^{(2)}$ alone is sufficient to train a good classifier



Co-training Algorithm

Co-training (Blum & Mitchell, 1998) (Mitchell, 1999) assumes that

(i) features can be split into two sets;

(ii) each sub-feature set is sufficient to train a good classifier.

- Initially two separate classifiers are trained with the labeled data, on the two sub-feature sets respectively.

- Each classifier then classifies the unlabeled data, and 'teaches' the other classifier with the few unlabeled examples (and the predicted labels) they feel most confident.

- Each classifier is retrained with the additional training examples given by the other classifier, and the process repeats.

Co-training Algorithm

Blum & Mitchell'98

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

each instance has two views $\mathbf{x}_i = [\mathbf{x}_i^{(1)}, \mathbf{x}_i^{(2)}]$,

and a learning speed k.

1. let $L_1 = L_2 = \{(\mathbf{x}_1, y_1), \ldots, (\mathbf{x}_l, y_l)\}$.
2. Repeat until unlabeled data is used up:
3. Train view-1 $f^{(1)}$ from L_1, view-2 $f^{(2)}$ from L_2.
4. Classify unlabeled data with $f^{(1)}$ and $f^{(2)}$ separately.
5. Add $f^{(1)}$'s top k most-confident predictions $(\mathbf{x}, f^{(1)}(\mathbf{x}))$ to L_2.
   Add $f^{(2)}$'s top k most-confident predictions $(\mathbf{x}, f^{(2)}(\mathbf{x}))$ to L_1.
   Remove these from the unlabeled data.

Semi-Supervised Learning

- Generative methods
- Graph-based methods
- Co-Training
- Semi-Supervised SVMs
- Many other methods

SSL algorithms can use unlabeled data to help improve prediction accuracy **if data satisfies appropriate assumptions**

Next Class

Practical Advice for Applying ML

Machine learning system design; feature engineering; feature pre-processing; learning with large datasets; SGD and mini-batch GD