Learning with Deficient Supervision-II

CS771: Introduction to Machine Learning
Purushottam Kar



Announcements

- End sem examination: November 17, 1600-1900, L18,19,20, ERES
 - Open notes (handwritten only)
 - Please bring a pencil and eraser with you
 - Seating arrangement same as midsem will announce again
- Project presentation schedule open for slot choice
 - 15 minute presentations for each group
 - Please choose a slot by November 18 1159 hrs
 - Please do not overwrite each other's slots
- Final project report due November 26 1159PM IST (premidnight)
 - No late submission deadline since grade submission is overdue by then
 - Please refer to Piazza post on how to write and structure your report

Recap

- We saw how label imbalance impacts classification problems
 - Binary, multi-class and multi-label
- For binary classification problems we saw three solutions
 - Resampling
 - Oversample rare class or undersample popular class
 - Not nice as either throws away data or bloats up training set
 - Not extendable to multi-class and multi-label settings elegantly
 - Reweighted learning
 - Assign different weights to point of different classes
 - Nicely extends to multi-class settings
 - Changing the evaluation/training loss function
 - F-measure, AUC etc
 - Algorithms more involved but the extra work does pay off!
- Today: learning with weak, active, and semi-supervision



Learning with Weak Supervision





Refers to supervision at a high level



- Refers to supervision at a high level
- Related concepts distant supervision, multi-instance learning

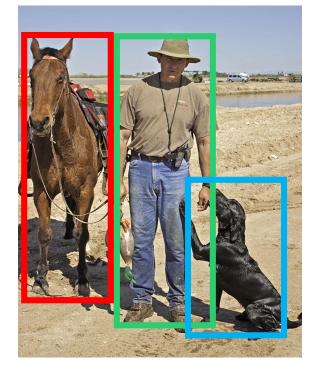


- Refers to supervision at a high level
- Related concepts distant supervision, multi-instance learning





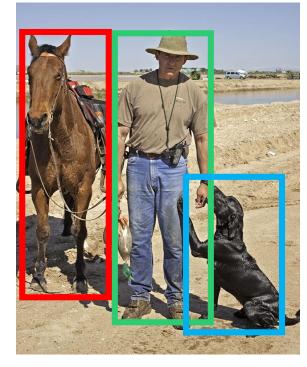
- Refers to supervision at a high level
- Related concepts distant supervision, multi-instance learning



Man, Horse, Dog



- Refers to supervision at a high level
- Related concepts distant supervision, multi-instance learning

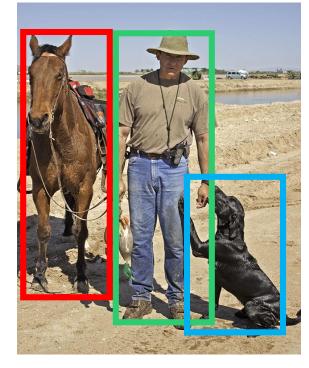


Man, Horse, Dog





- Refers to supervision at a high level
- Related concepts distant supervision, multi-instance learning



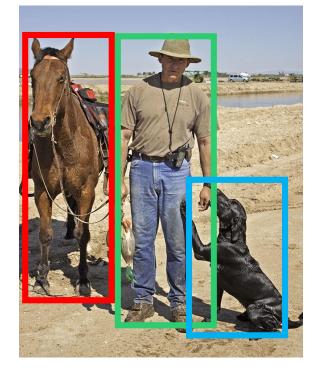
Man, Horse, Dog



Man, Horse, Dog



- Refers to supervision at a high level
- Related concepts distant supervision, multi-instance learning



Man, Horse, Dog



Man, Horse, Dog





Refers to supervision at a high level

Related concepts – distant supervision, multi-instance

Weak supervision

Less effort to label



Man, Horse, Dog



Man, Horse, Dog

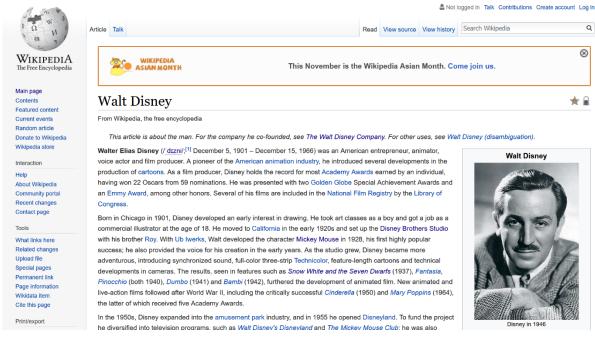


- Refers to supervision at a high level
- Related concepts distant supervision, multi-instance learning



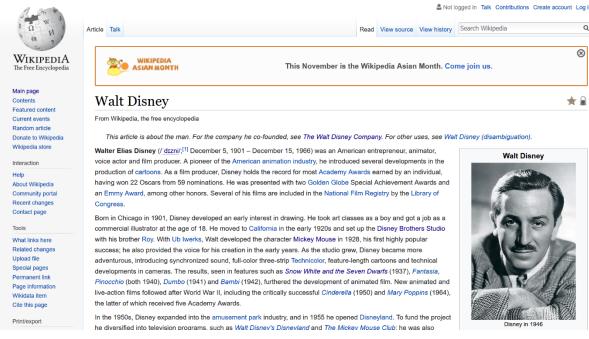
Nov 15, 2017 wikipedia.com

- Refers to supervision at a high level
- Related concepts distant supervision, multi-instance learning





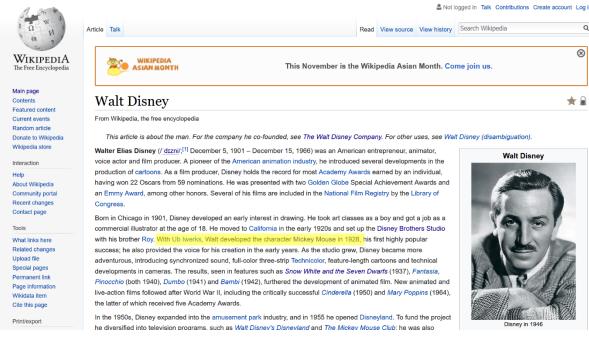
- Refers to supervision at a high level
- Related concepts distant supervision, multi-instance learning



CREATE(WALT DISNEY, MICKEY MOUSE)



- Refers to supervision at a high level
- Related concepts distant supervision, multi-instance learning

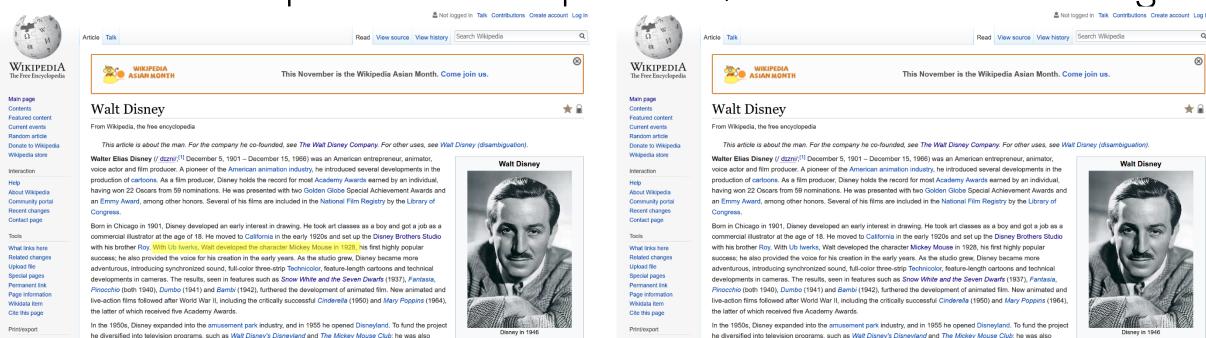


CREATE(WALT DISNEY, MICKEY MOUSE)



Refers to supervision at a high level

• Related concepts – distant supervision, multi-instance learning

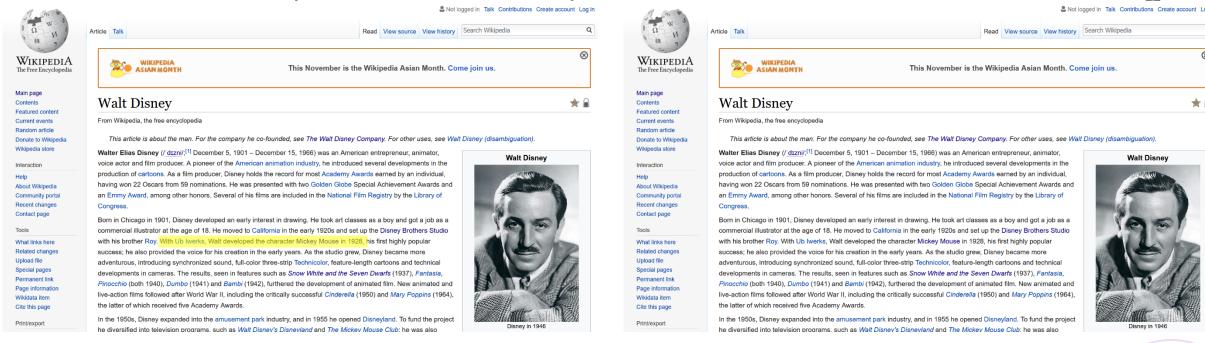


CREATE(WALT DISNEY, MICKEY MOUSE)



Refers to supervision at a high level

• Related concepts – distant supervision, multi-instance learning



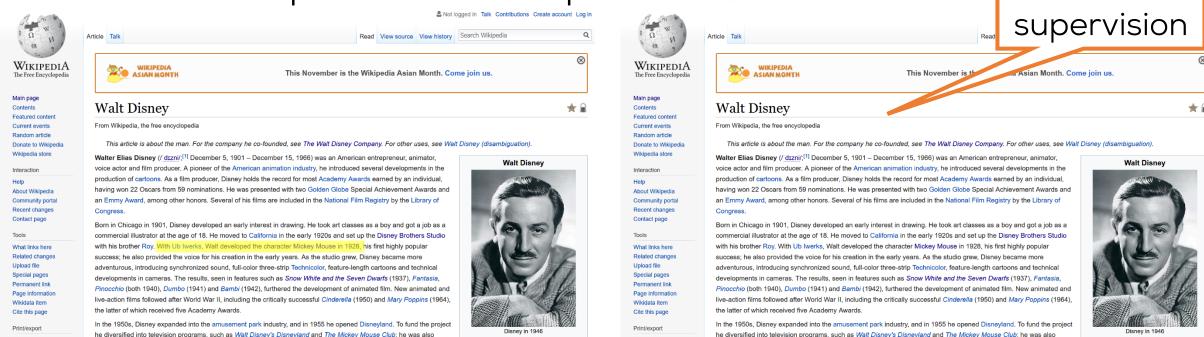
CREATE(WALT DISNEY, MICKEY MOUSE)

CREATE(WALT DISNEY, MICKEY MOUSE)

Nov 15, 2017 wikipedia.com CS771: Intro to ML

Refers to supervision at a high level

Related concepts – distant supervision, multi-instance



CREATE(WALT DISNEY, MICKEY MOUSE)

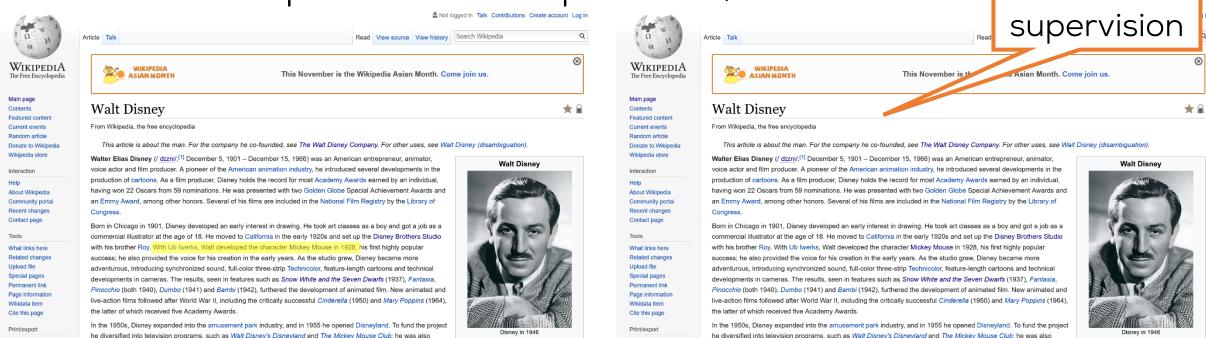
CREATE(WALT DISNEY, MICKEY MOUSE)

Nov 15, 2017 wikipedia.com

Weak

Refers to supervision at a high level

Related concepts – distant supervision, multi-instance



CREATE(WALT DISNEY, MICKEY MOUSE)

CREATE(WALT DISNEY, MICKEY MOUSE)

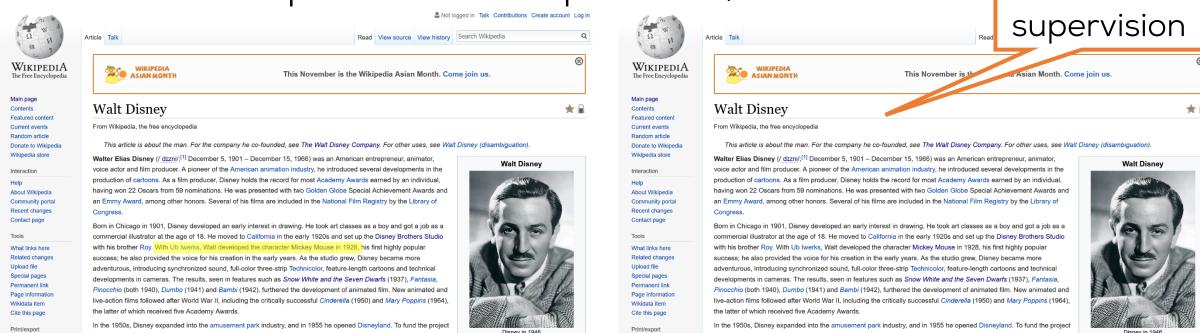
No human labeller needed if encyclopedia present

Nov 15, 2017 wikipedia.com

Weak

Refers to supervision at a high level

Related concepts – distant supervision, multi-instance



CREATE(WALT DISNEY, MICKEY MOUSE)

Relation extraction problem

CREATE(WALT DISNEY, MICKEY MOUSE)

No human labeller needed if encyclopedia present

Nov 15, 2017 wikipedia.com

Weak

- Supervision at high level distant superv., multi-instance learning
- Multi-instance learning: every data point is a "bag" of m "items" $x^i = \left\{x^{i,1}, x^{i,2}, \dots, x^{i,m}\right\}$
 - Every possible bounding box is an item. Their collection is the image
 - Every sentence is an item. Their collection is the Wikipedia document
- The "bag" has a multi-label $\mathbf{y}^i \in \{0,1\}^L$
 - Labels in the image example could be man, horse, dog, cat, tree, river, ...
 - A bit more tricky to define labels for relation extraction so skip it for now
- ullet Not told which item(s) caused individual labels \mathbf{y}_k^i to turn on or off
 - Which bounding box contains the dog?
 - Which sentence signals the relationship b/w Disney and Mickey?
- "Fine" supervision could have, for e.g., labelled every item in the bag

Nov 15, 2017

Solutions?

- Can often be elegantly cast as latent variable learning problems
- For every bounding box/sentence, latent vars. $z^{i,j,k}$, $j \in [m]$, $k \in [L]$
- $z^{i,j,k} = +1$ if that item is of "interest" w.r.t. label k else $z^{i,j,k} = 0$
- Final label can be $\mathbf{y}_k^i = \text{UNION}(z^{i,1,k}, z^{i,2,k}, \dots, z^{i,m,k})$
 - $\mathbf{y}_k^i = 1$ if any item declares that label to be present
 - Other "aggregation" techniques possible ask at least 2 items to declare
- Learn models for joint inference of latent variables and final label
- Alternative is a two-stage process
 - First find item that are of interest i.e. for which $z^{i,j} \neq 0$
 - Use object detection techniques to find useful bounding boxes
 - Use entity detection techniques to find mentions
 - Label each interesting item and aggregate to get labels for bag



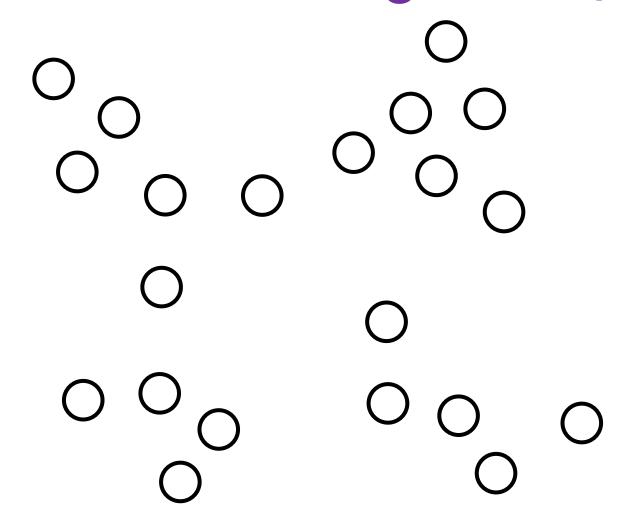
Active Learning



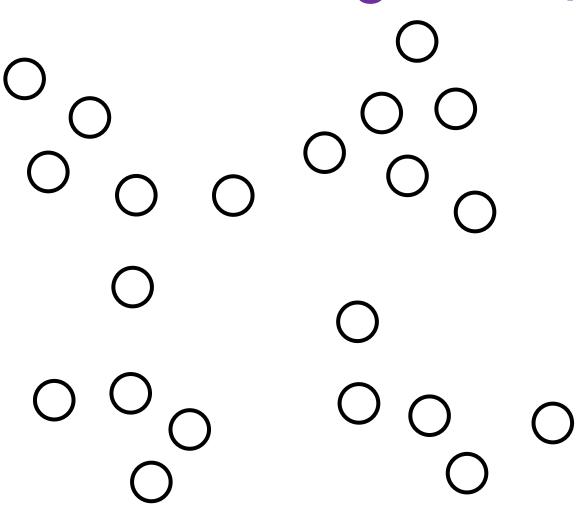
The active teacher

- The algorithm only gets unlabelled data points $S = \{x^1, ..., x^n\}$
- However, labels can be requested for $k \ll n$ points "on demand"
 - Need not ask all labels in a single go
 - Can ask for one label, process that, then ask for another label, and so on
- \bullet k must be small since most often, an actual human is involved
- We have only studied "passive" models till now where teacher retires after presenting the data
- Lots of techniques available for active learning
 - Most rely on some form of expected knowledge gain
 - Which unlabelled data point expected to surprise me the most?
 - Very "active" area (pun intended) dedicated workshops at NIPS, ICML
 - Very useful in guiding consumer surveys cannot have a lot of them!
 - Carefully choose which customers to entice into revealing more info



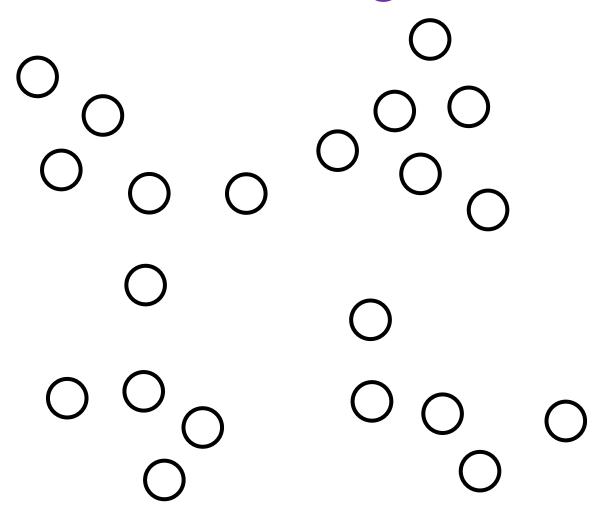






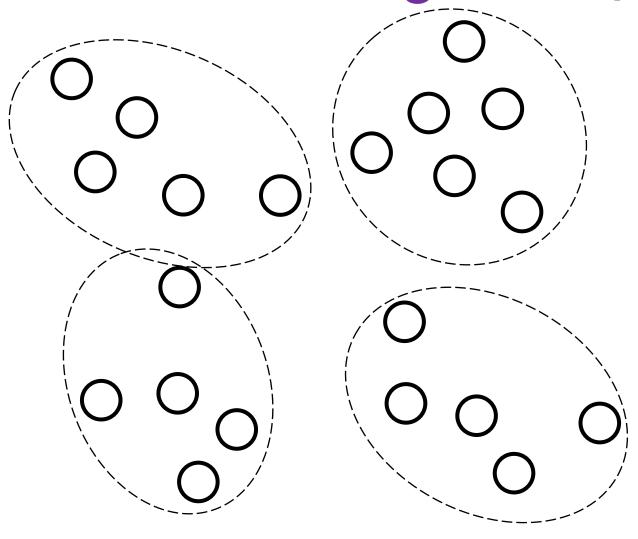
 Suppose data is has k clusters and each cluster is pure (only red or only green)





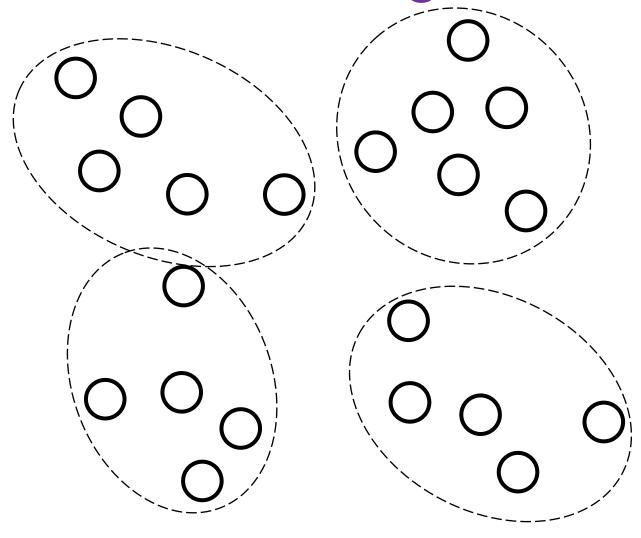
- Suppose data is has k clusters and each cluster is pure (only red or only green)
- Apply clustering (k-means, agglomerative, kernel k-means)





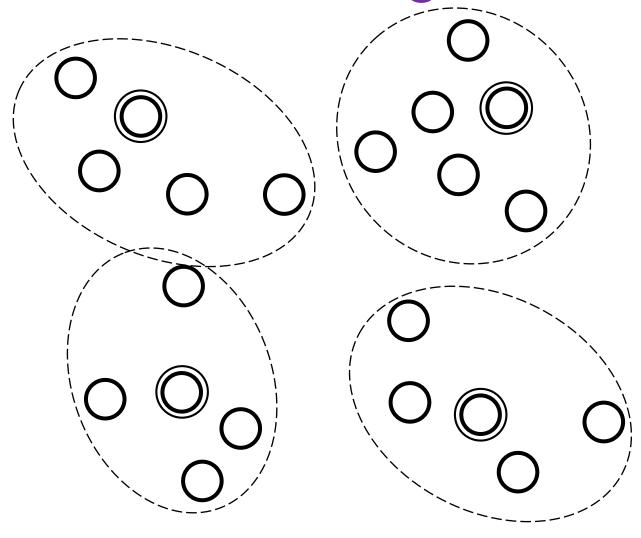
- Suppose data is has k clusters and each cluster is pure (only red or only green)
- Apply clustering (k-means, agglomerative, kernel k-means)





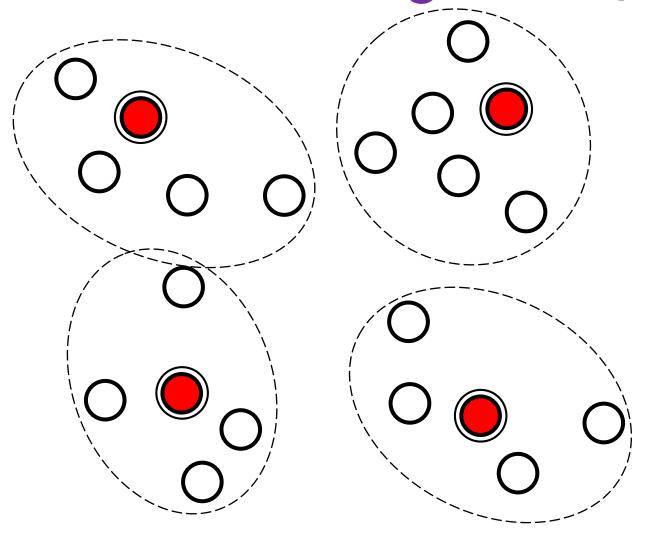
- Suppose data is has k clusters and each cluster is pure (only red or only green)
- Apply clustering (k-means, agglomerative, kernel k-means)
- Choose one data point from each cluster and query its label





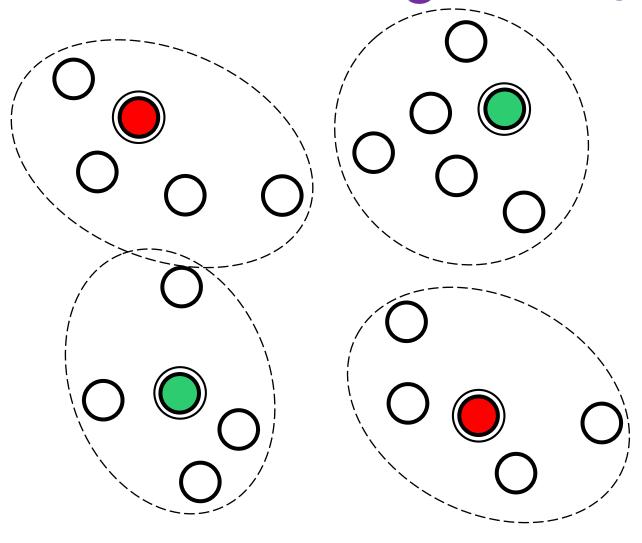
- Suppose data is has k clusters and each cluster is pure (only red or only green)
- Apply clustering (k-means, agglomerative, kernel k-means)
- Choose one data point from each cluster and query its label





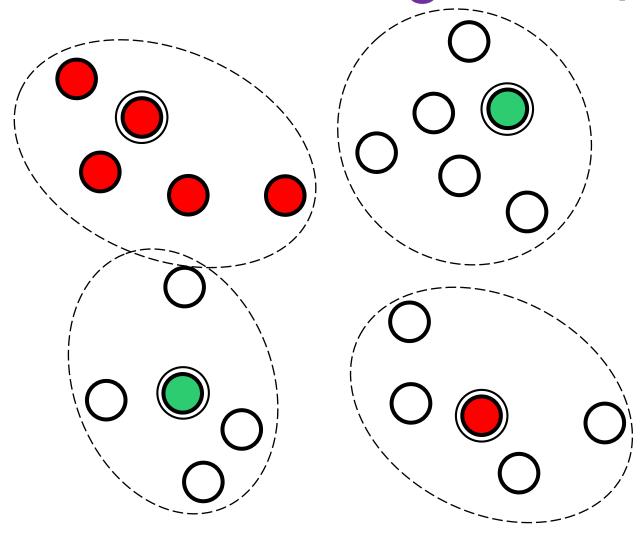
- Suppose data is has k clusters and each cluster is pure (only red or only green)
- Apply clustering (k-means, agglomerative, kernel k-means)
- Choose one data point from each cluster and query its label





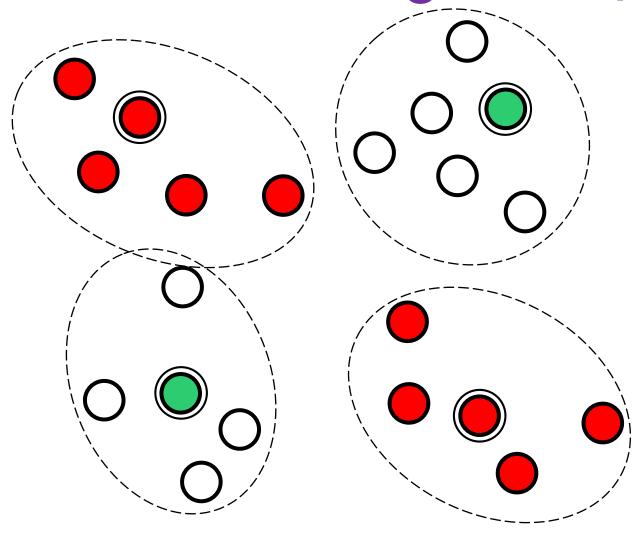
- Suppose data is has k clusters and each cluster is pure (only red or only green)
- Apply clustering (k-means, agglomerative, kernel k-means)
- Choose one data point from each cluster and query its label
- Label the cluster!





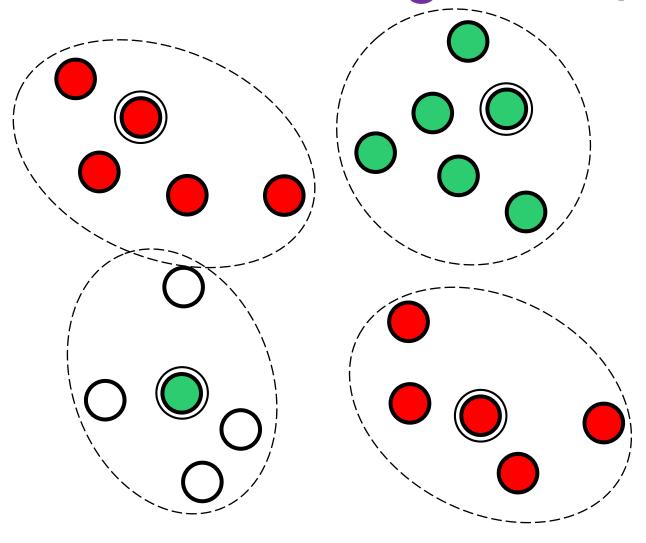
- Suppose data is has k clusters and each cluster is pure (only red or only green)
- Apply clustering (k-means, agglomerative, kernel k-means)
- Choose one data point from each cluster and query its label
- Label the cluster!





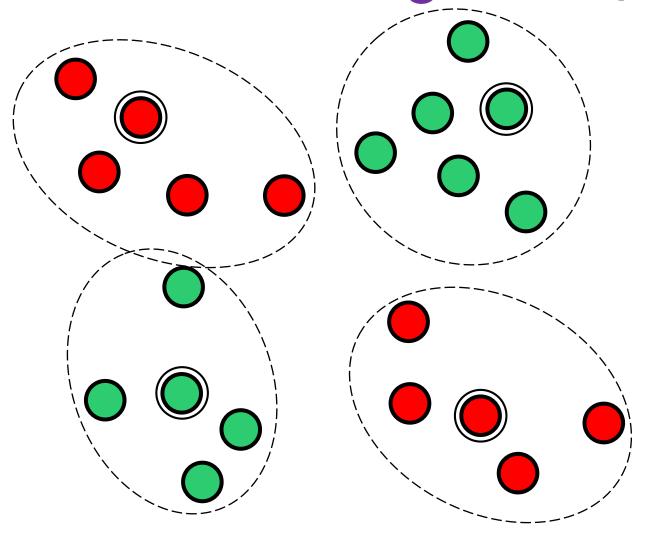
- Suppose data is has k clusters and each cluster is pure (only red or only green)
- Apply clustering (k-means, agglomerative, kernel k-means)
- Choose one data point from each cluster and query its label
- Label the cluster!





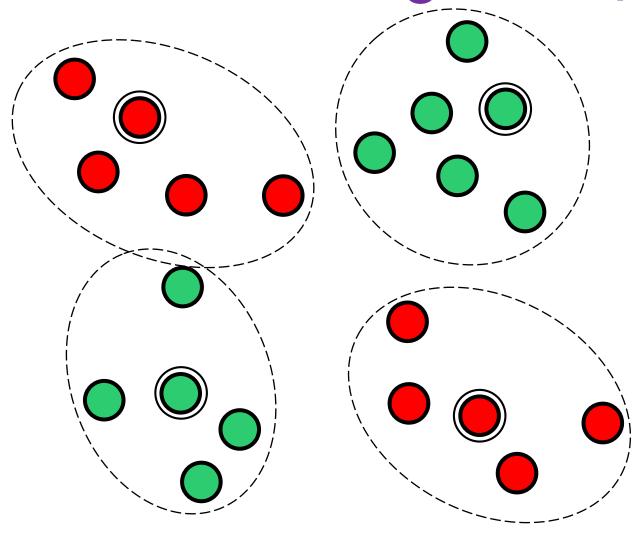
- Suppose data is has k clusters and each cluster is pure (only red or only green)
- Apply clustering (k-means, agglomerative, kernel k-means)
- Choose one data point from each cluster and query its label
- Label the cluster!





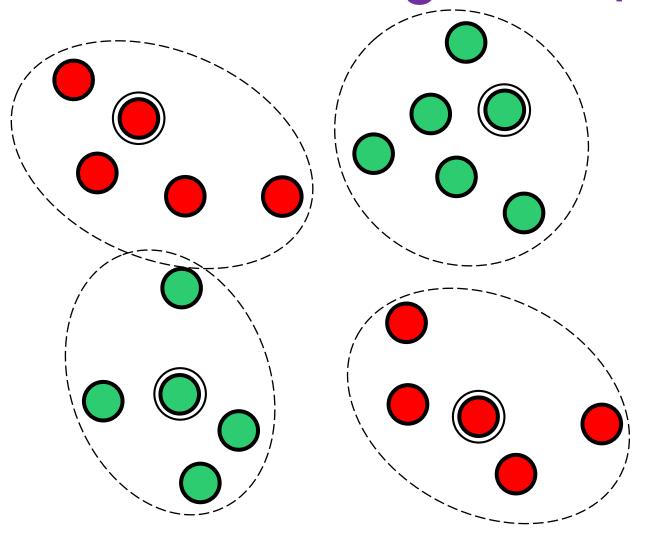
- Suppose data is has k clusters and each cluster is pure (only red or only green)
- Apply clustering (k-means, agglomerative, kernel k-means)
- Choose one data point from each cluster and query its label
- Label the cluster!



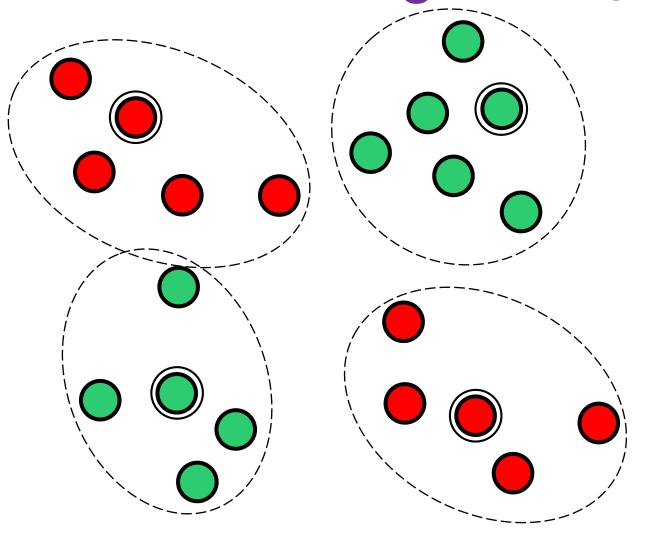


- Suppose data is has k clusters and each cluster is pure (only red or only green)
- Apply clustering (k-means, agglomerative, kernel k-means)
- Choose one data point from each cluster and query its label
- Label the cluster!
- Many challenges

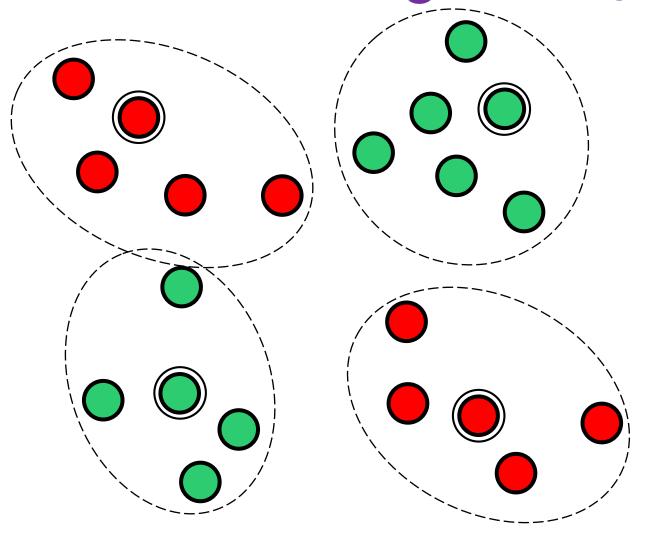




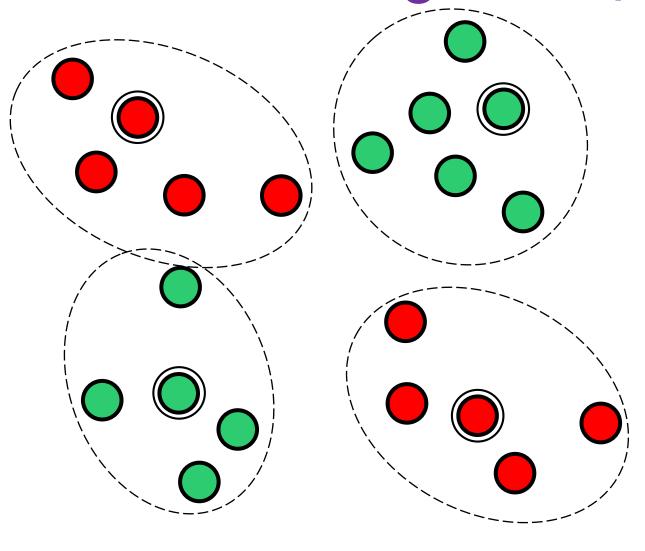
- Suppose data is has k clusters and each cluster is pure (only red or only green)
- Apply clustering (k-means, agglomerative, kernel k-means)
- Choose one data point from each cluster and query its label
- Label the cluster!
- Many challenges
 - Clusters not pure in general



- Suppose data is has k clusters and each cluster is pure (only red or only green)
- Apply clustering (k-means, agglomerative, kernel k-means)
- Choose one data point from each cluster and query its label
- Label the cluster!
- Many challenges
 - Clusters not pure in general
 - Clustering is itself a tricky problem

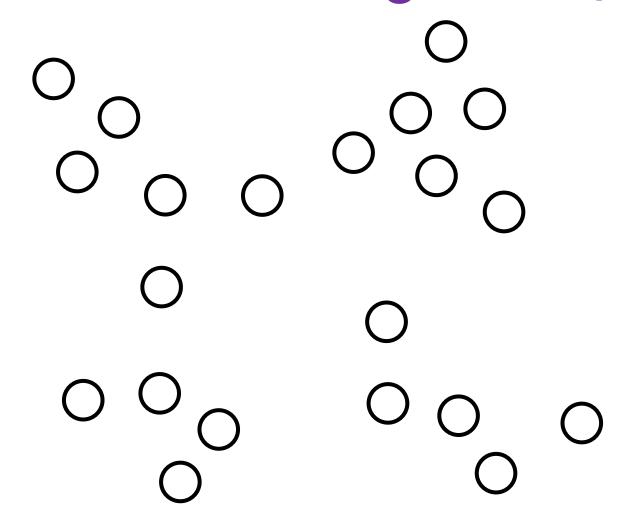


- Suppose data is has k clusters and each cluster is pure (only red or only green)
- Apply clustering (k-means, agglomerative, kernel k-means)
- Choose one data point from each cluster and query its label
- Label the cluster!
- Many challenges
 - Clusters not pure in general
 - Clustering is itself a tricky problem
 - Clustering mistakes disastrous

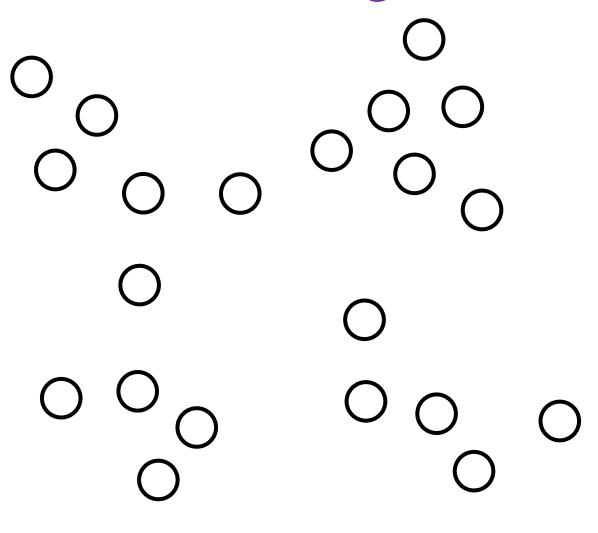


- Suppose data is has k clusters and each cluster is pure (only red or only green)
- Apply clustering (k-means, agglomerative, kernel k-means)
- Choose one data point from each cluster and query its label
- Label the cluster!
- Many challenges
 - Clusters not pure in general
 - Clustering is itself a tricky problem
 - Clustering mistakes disastrous
- Many solutions discuss one²⁷

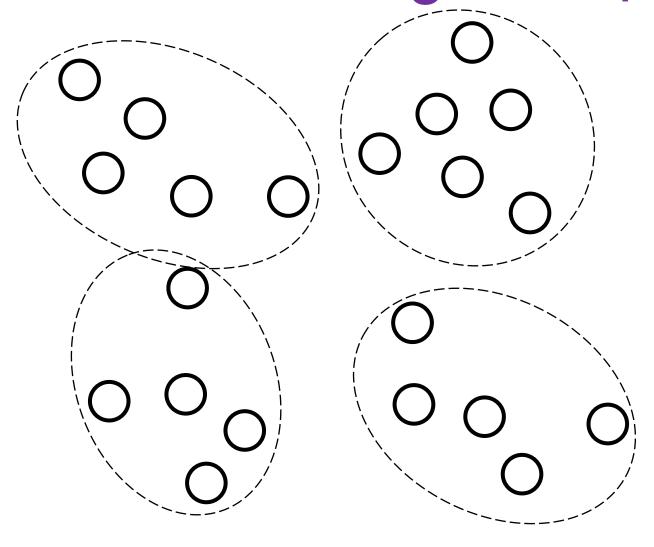




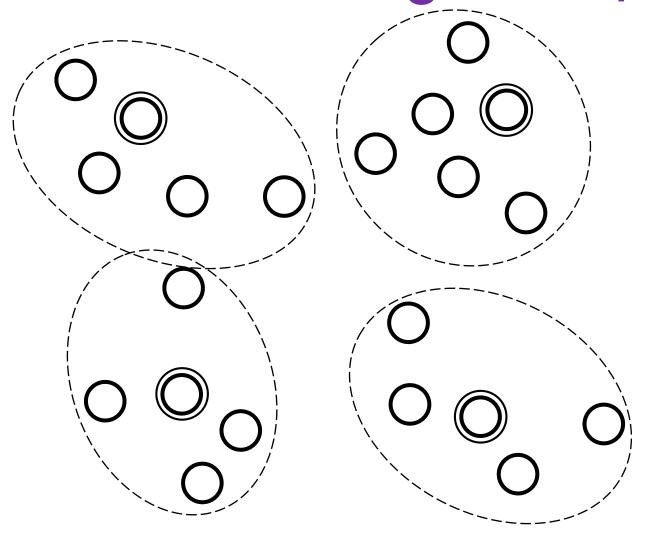




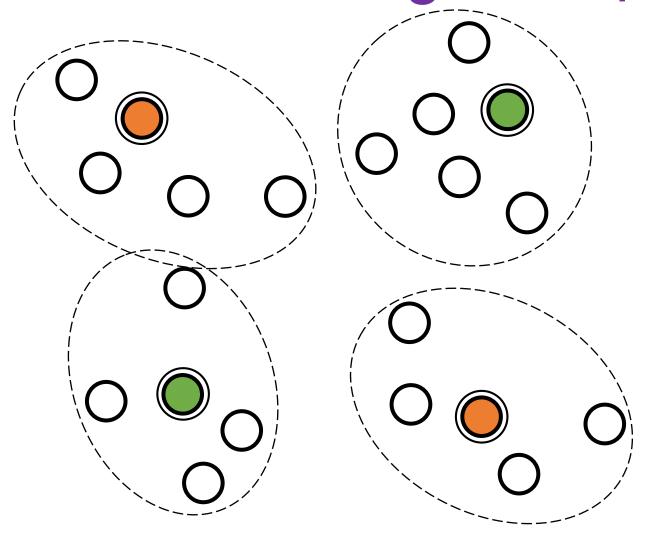




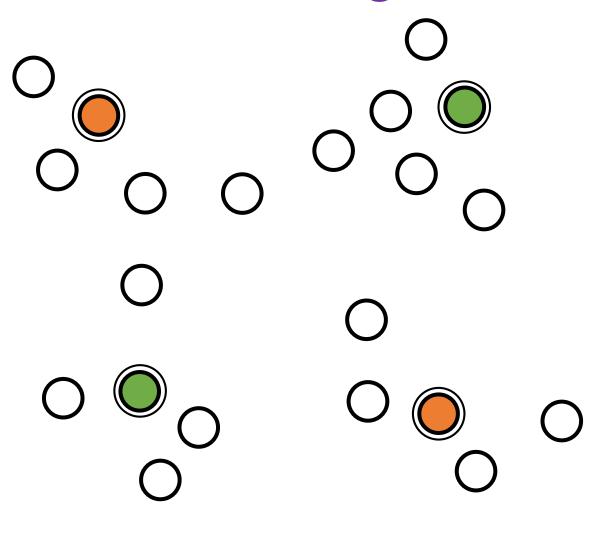




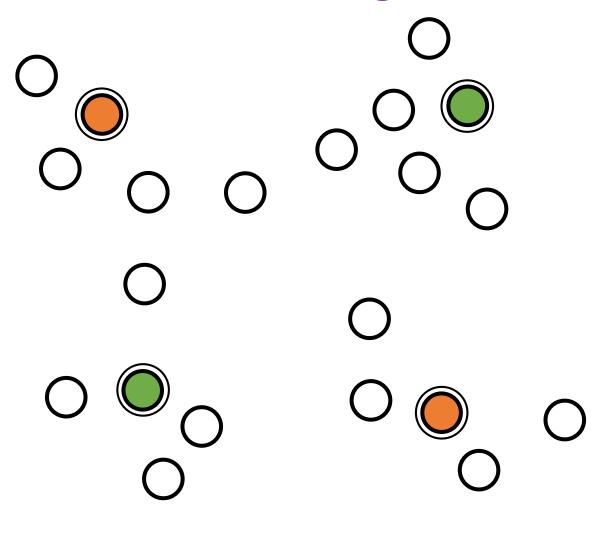






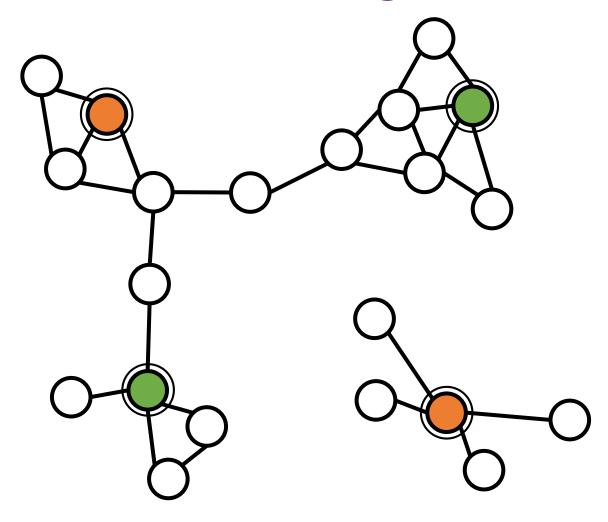






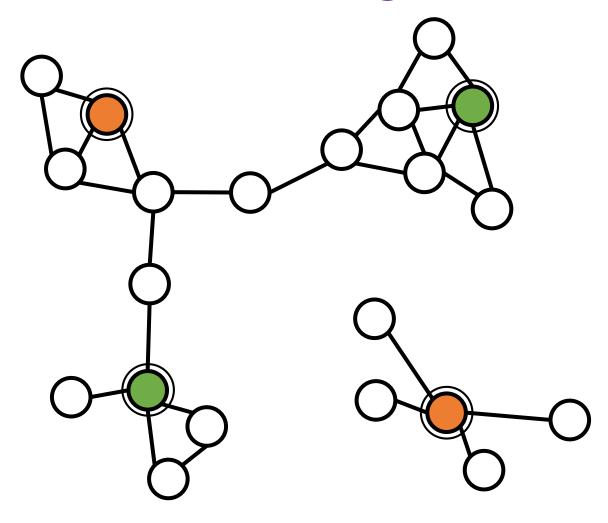
- Cluster and get labels for cluster representatives
- Create a "similarity graph" over data points





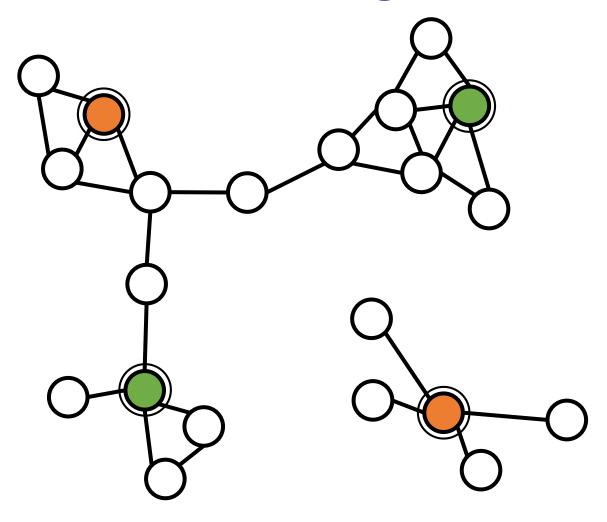
- Cluster and get labels for cluster representatives
- Create a "similarity graph" over data points





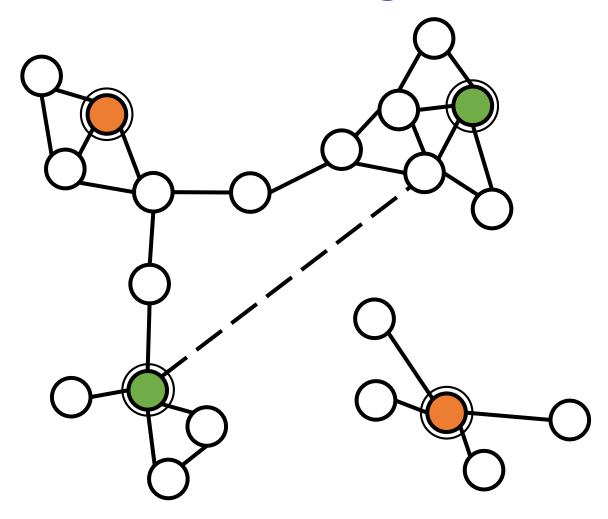
- Cluster and get labels for cluster representatives
- Create a "similarity graph" over data points
 - May use a Mercer kernel for edge weights





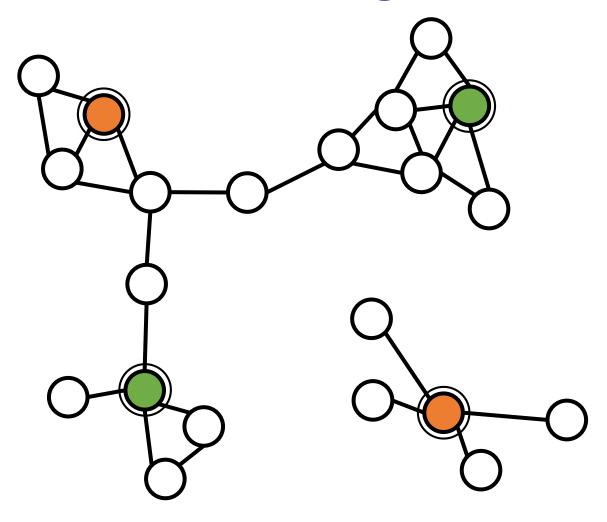
- Cluster and get labels for cluster representatives
- Create a "similarity graph" over data points
 - May use a Mercer kernel for edge weights
 - Don't include edges with very small weight sparse graph!





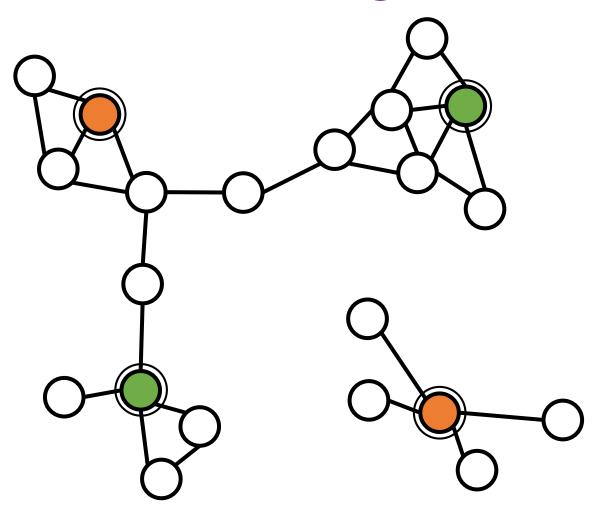
- Cluster and get labels for cluster representatives
- Create a "similarity graph" over data points
 - May use a Mercer kernel for edge weights
 - Don't include edges with very small weight – sparse graph!





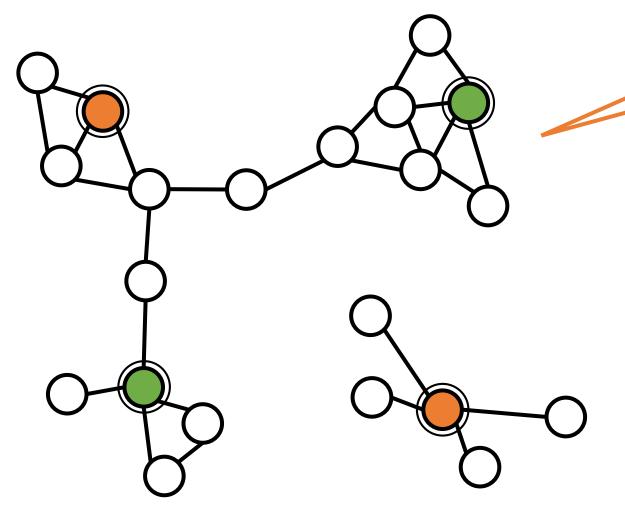
- Cluster and get labels for cluster representatives
- Create a "similarity graph" over data points
 - May use a Mercer kernel for edge weights
 - Don't include edges with very small weight sparse graph!





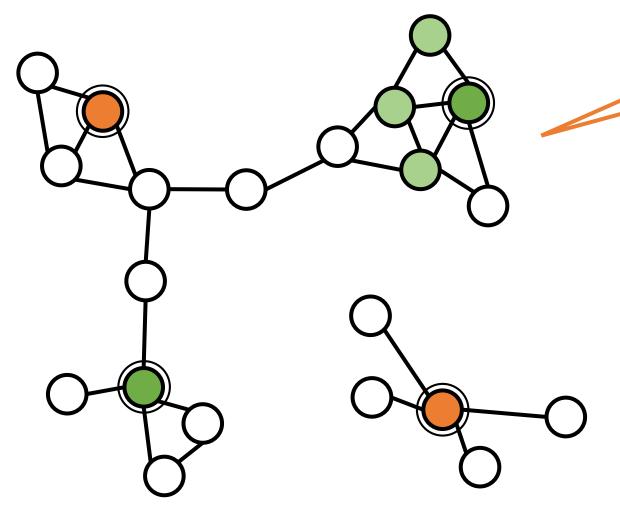
- Cluster and get labels for cluster representatives
- Create a "similarity graph" over data points
 - May use a Mercer kernel for edge weights
 - Don't include edges with very small weight – sparse graph!
- "Propagate" labels from labelled to unlabelled points





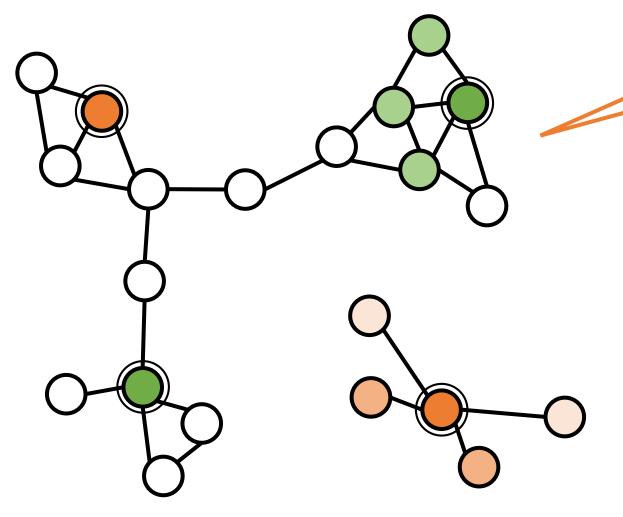
- Create a "similarity graph" over data points
 - May use a Mercer kernel for edge weights
 - Don't include edges with very small weight – sparse graph!
- "Propagate" labels from labelled to unlabelled points





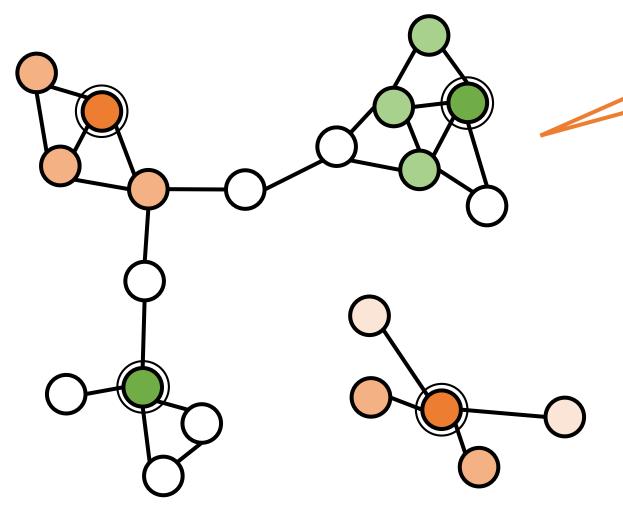
- Create a "similarity graph" over data points
 - May use a Mercer kernel for edge weights
 - Don't include edges with very small weight – sparse graph!
- "Propagate" labels from labelled to unlabelled points





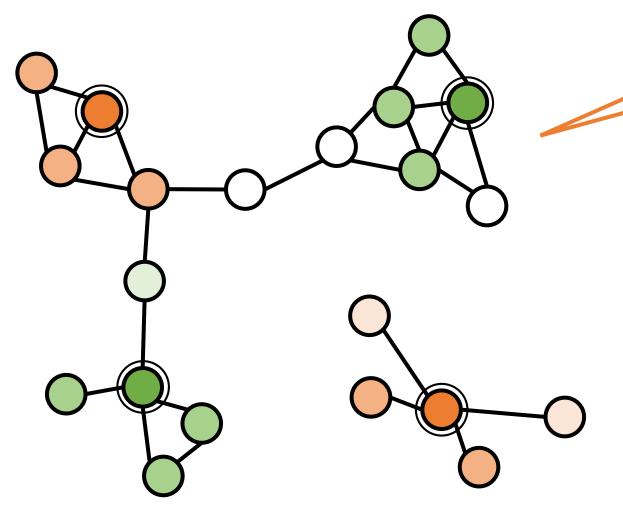
- Create a "similarity graph" over data points
 - May use a Mercer kernel for edge weights
 - Don't include edges with very small weight – sparse graph!
- "Propagate" labels from labelled to unlabelled points





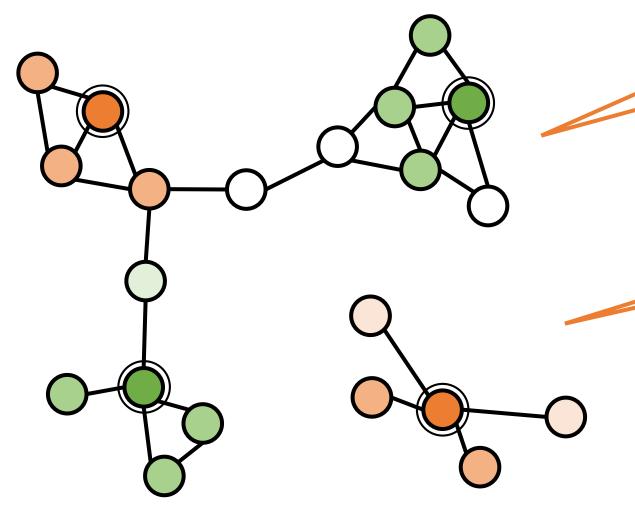
- Create a "similarity graph" over data points
 - May use a Mercer kernel for edge weights
 - Don't include edges with very small weight – sparse graph!
- "Propagate" labels from labelled to unlabelled points





- Create a "similarity graph" over data points
 - May use a Mercer kernel for edge weights
 - Don't include edges with very small weight – sparse graph!
- "Propagate" labels from labelled to unlabelled points





Many possibilities e.g. each node passes its label ±1 to its neighbours multiplied by weight of the edge

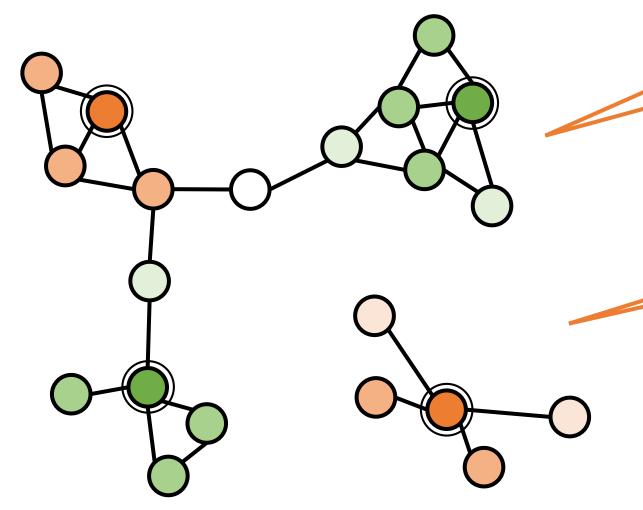
• Credovei

Neighbors pass them on in successive iterations – "message passing"

.ge weights

- Don't include edges with very small weight – sparse graph!
- "Propagate" labels from labelled to unlabelled points





Many possibilities e.g. each node passes its label ±1 to its neighbours multiplied by weight of the edge

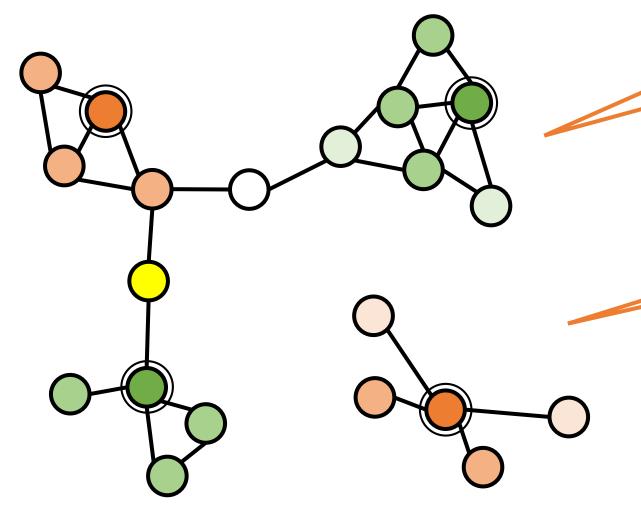
Credover

Neighbors pass them on in successive iterations – "message passing"

.se weights

- Don't include edges with very small weight – sparse graph!
- "Propagate" labels from labelled to unlabelled points





Many possibilities e.g. each node passes its label ±1 to its neighbours multiplied by weight of the edge

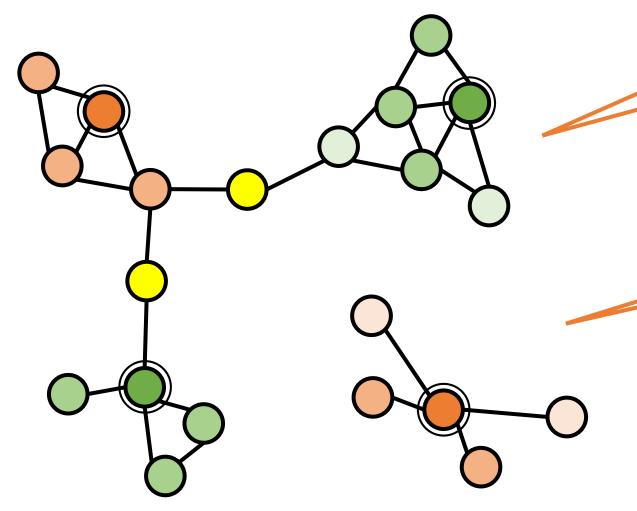
Credover

Neighbors pass them on in successive iterations – "message passing"

.ge weights

- Don't include edges with very small weight – sparse graph!
- "Propagate" labels from labelled to unlabelled points





Many possibilities e.g. each node passes its label ±1 to its neighbours multiplied by weight of the edge

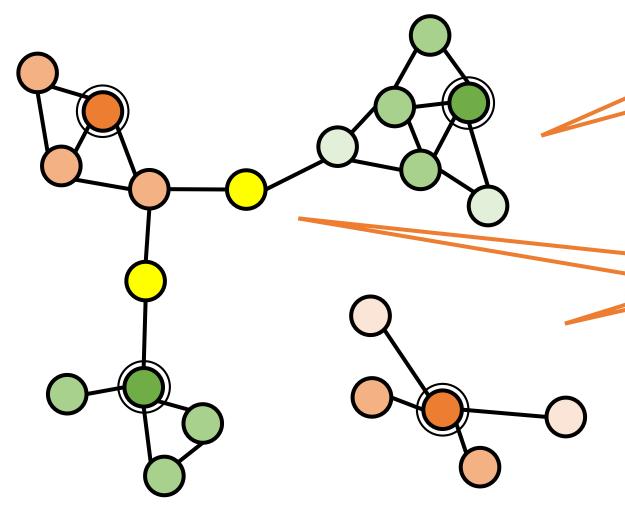
• Credovei

Neighbors pass them on in successive iterations – "message passing"

.ge weights

- Don't include edges with very small weight – sparse graph!
- "Propagate" labels from labelled to unlabelled points





Many possibilities e.g. each node passes its label ±1 to its neighbours multiplied by weight of the edge

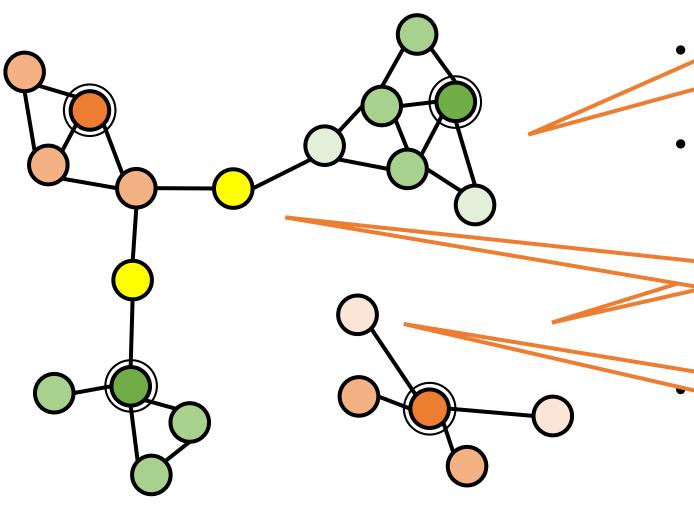
Crec ^N over

Neighbors pass them on in successive iterations – "message passing"

Some nodes may end up getting mixed messages

 "Propagate" labels from labelled to unlabelled points





Many possibilities e.g. each node passes its label ±1 to its neighbours multiplied by weight of the edge

Over Successive iterations - "message passing"

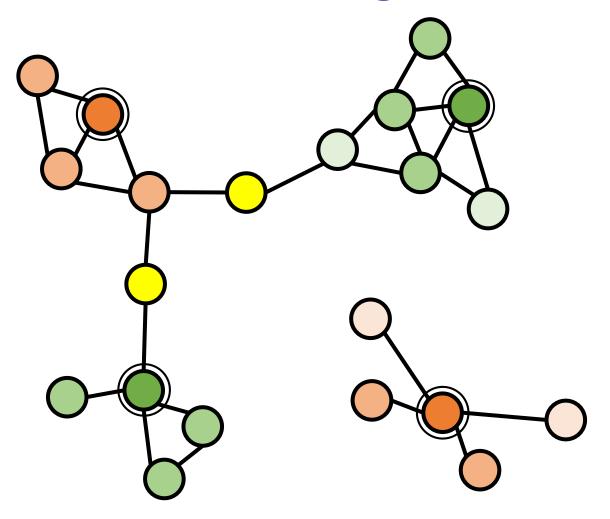
Some nodes may end up getting mixed messages

labellea

200

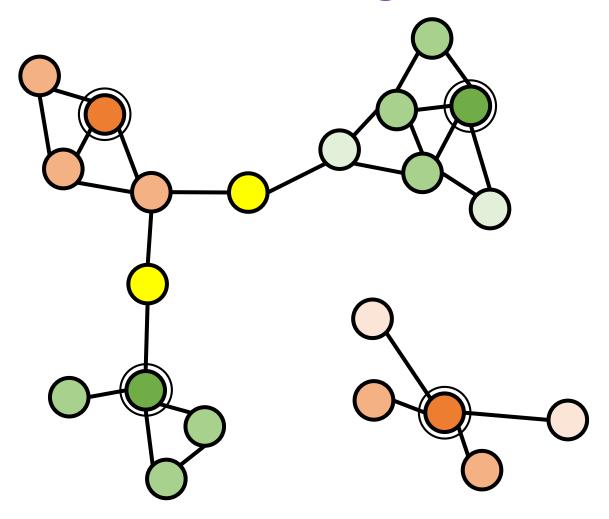
... or be very unsure of their label



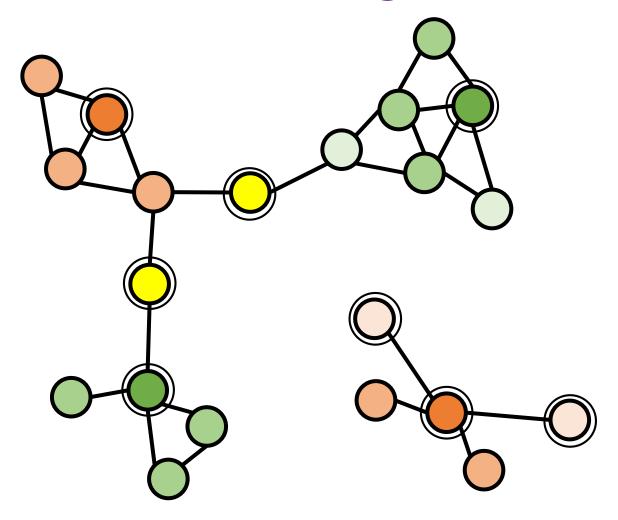


- Cluster and get labels for cluster representatives
- Create a "similarity graph" over data points
 - May use a Mercer kernel for edge weights
 - Don't include edges with very small weight – sparse graph!
- "Propagate" labels from labelled to unlabelled points



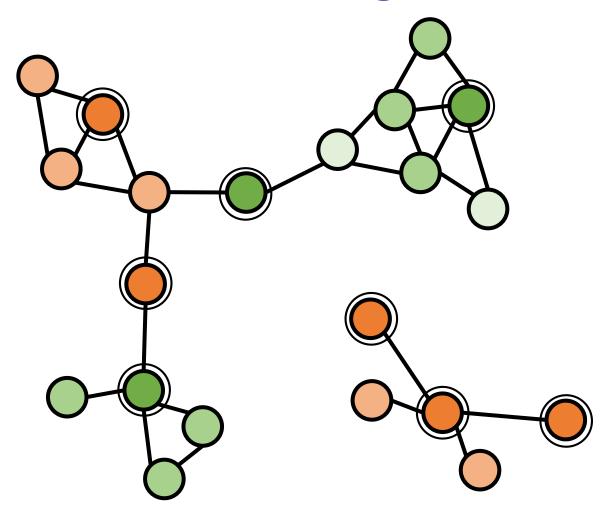


- Cluster and get labels for cluster representatives
- Create a "similarity graph" over data points
 - May use a Mercer kernel for edge weights
 - Don't include edges with very small weight – sparse graph!
- "Propagate" labels from labelled to unlabelled points
- Query unlabelled data points that are "confused"



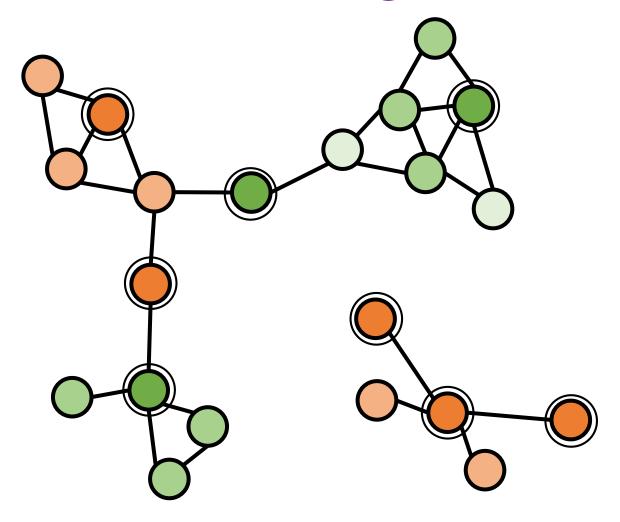
- Cluster and get labels for cluster representatives
- Create a "similarity graph" over data points
 - May use a Mercer kernel for edge weights
 - Don't include edges with very small weight – sparse graph!
- "Propagate" labels from labelled to unlabelled points
- Query unlabelled data points that are "confused"

Active Learning Attempt I



- Cluster and get labels for cluster representatives
- Create a "similarity graph" over data points
 - May use a Mercer kernel for edge weights
 - Don't include edges with very small weight – sparse graph!
- "Propagate" labels from labelled to unlabelled points
- Query unlabelled data points that are "confused"

Active Learning Attempt I

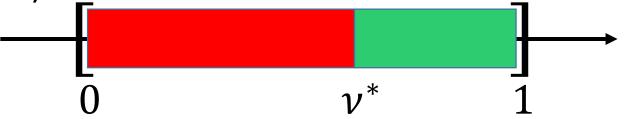


- Cluster and get labels for cluster representatives
- Create a "similarity graph" over data points
 - May use a Mercer kernel for edge weights
 - Don't include edges with very small weight – sparse graph!
- "Propagate" labels from labelled to unlabelled points
- Query unlabelled data points that are "confused"
- Repeat!

Active Learning Attempt II

Learning theoretic result

- To learn classifier with ϵ error, SVM/NN need $\mathcal{O}\left(\frac{1}{\epsilon}\right)$ labeled data pts
- Suppose data $S \subset [0,1]$ and true classifier is a threshold $y=2\cdot \mathbb{I}\{x\geq \nu^*\}-1$
- Notice that we can perform binary search to estimate ν^*
- Let a = 0, b = 1
- For t = 1, 2, ...



- Query the label of the data point (a + b)/2
- If label is -1 let $a \leftarrow (a+b)/2$ else let $b \leftarrow (a+b)/2$
- If $b a < \epsilon$, stop and output $\hat{v} = (a + b)/2$
- We queried only $\log(1/\epsilon)$ labels and yet ensured $|\hat{\nu} \nu^*| < \epsilon$
- Exponential improvement in number of labelled samples needed!

Active Learning Attempt II

- This is the most simple form of version space search
- Search the space of all classifiers
 - In the previous example, classifiers corresponded to thresholds
- Can get tricky to do this efficiently even over linear classifiers
- Also tricky to handle cases that are not linearly separable
- Can't we do boosting or bagging to solve this problem?
- Yes, search for ActBoost (the name is lame but the algo isn't)



Active Learning

- Many other techniques to query labels
- If working with a Bayesian model, query data point whose predictive posterior variance is largest
- Query-by-committee maintain a committee of several models and query data point on which committee disagrees the most
- Related concept of disagreement coefficient
- Expected model drift maintain a single model but query the data point whose label, if known, will change the model the most



Semi-supervised Learning



Semi-supervision

- Labeled data is expensive since manual effort often involved
- Unlabelled data often free to obtain by crawling repo/www
- Why is unlabelled data of any use?
- Since it gives us valuable access to $\mathbb{P}[x]$
- If we have a super awesome model of $\mathbb{P}[x]$ then under some assumptions, a few labelled data points enough to learn $\mathbb{P}[y,x]$
- Assumptions?? Yes, SSL usually works by imposing a heavy inductive bias
 - Points deemed similar by blah notion of similarity have similar labels
 - Points in the same cluster given by blah clustering algo have same labels
 - Some assumption necessary to relate labelled and unlabelled data
- If assumption is inappropriate then SSL method suffers

SSL Attempt I - Generative Learning

- Labelled $L = \left\{x^i, y^i\right\}_{i=1,\dots,n}$ and unlabeled data $U = \left\{x^j\right\}_{j=n+1,\dots,n+m}$
- Learn a generative model Θ that models $\mathbb{P}[x]$ and $\mathbb{P}[y \mid x] \log \mathbb{P}[L \cup U \mid \Theta] = \log \mathbb{P}[L \mid \Theta] + \log \mathbb{P}[U \mid \Theta]$

$$= \sum_{i=1}^{n} \log \mathbb{P}[y^{i} \mid x^{i}, \Theta] + \log \mathbb{P}[x^{i} \mid \Theta] + \sum_{j=n+1}^{n+m} \log \mathbb{P}[x^{j} \mid \Theta]$$

• Introduce latent variables $z^j \in [C]$ to model labels of points in U

$$= \sum_{i=1}^{n} \log \mathbb{P}[y^{i} \mid x^{i}, \Theta] + \log \mathbb{P}[x^{i} \mid \Theta] + \sum_{j=n+1}^{n+m} \log \left(\sum_{z^{j}=1}^{C} \mathbb{P}[z^{j} \mid x^{j}, \Theta] \cdot \mathbb{P}[x^{j} \mid \Theta] \right)$$

• Have fun executing the EM algorithm on this ©

SSL Attempt II - Bootstrapping

- Basically the hard-assignment version for the previous slide
- Makes sense even in non-PML settings though
- ullet Use any nice algo on L to learn a classifier $f^{\,0}$
- For t = 1, 2, ...
 - Use f^{t-1} to label data points in U i.e. $z^{t,j}=f^{t-1}(x^j), j=n+1,\ldots,$
 - Use the nice algo on the dataset $L \cup \{x^j, z^{t,j}\}$ to learn f^t
 - Stop when tired
- Very simple to try out first before attempting more fancy methods
- Be careful may reinforce wrong predictions
- No way to even detect if f^t getting better on U or not



SSL Attempt III - Regularization

- Incorporate a prior to force "similar" points to have similar labels
- Lets switch to a regression problem for simplicity
- Assume a notion of similarity between points $a_{ij} = K(x^i, x^j)$
 - ullet Should not depend on the label i.e. can be computed over U as well
- Want $f(x^i)$ to be close to $f(x^j)$ if a_{ij} is large
- Can enforce this by asking $a_{ij} \cdot \left(f(x^i) f(x^j) \right)^2$ to be small

$$\arg\min_{f} \sum_{i=1}^{n} \ell(f(x^{i}), y^{i}) + \sum_{i,j=1}^{m+n} a_{ij} \cdot (f(x^{i}) - f(x^{j}))^{2}$$

• Can also incorporate a usual regularizer r(f)



SSL Attempt III - Regularization

- Incorporate a prior to force
- Lets switch to a regression
- Assume a notion of similarit
- If $f(\mathbf{x}) = \langle \mathbf{w}, \mathbf{x} \rangle$ and $r(\mathbf{w}) = \lambda \cdot ||\mathbf{w}||_2^2$, then Assume a notion of similarit where $X = [\mathbf{x}^1, ..., \mathbf{x}^{m+n}] \in \mathbb{R}^{d \times (m+n)}$. Find $X = [\mathbf{x}^1, ..., \mathbf{x}^{m+n}] \in \mathbb{R}^{d \times (m+n)}$. Find $X = [\mathbf{x}^1, ..., \mathbf{x}^{m+n}] \in \mathbb{R}^{d \times (m+n)}$.
- Want $f(x^i)$ to be close to $f(x^j)$.
- Can enforce this by asking $a_{ij} \cdot \left(f(x^i) f(x^j)\right)^2$ to be small

$$\arg\min_{f} \sum_{i=1}^{n} \ell(f(x^{i}), y^{i}) + \sum_{i,j=1}^{m+n} a_{ij} \cdot (f(x^{i}) - f(x^{j}))^{2}$$

• Can also incorporate a usual regularizer r(f)



Additional regularization $\mathbf{w}^{\mathsf{T}}XLX^{\mathsf{T}}\mathbf{w}$. Overall regularization $\mathbf{w}^{\mathsf{T}}R\mathbf{w}$ where $R = XLX^{\mathsf{T}} + \lambda \cdot I$

- Incorporate a prior to force
- Lets switch to a regression
- Assume a notion of similarit
 - Should not depend on the lake
- If $f(\mathbf{x}) = \langle \mathbf{w}, \mathbf{x}, \mathbf{w} \rangle = \lambda \cdot ||\mathbf{w}||_2^2$, then $\arg\min_{\mathbf{w}} \sum_{i=1}^{\infty} \ell(\langle \mathbf{w}, \mathbf{x}^i \rangle, y^i) + \lambda \cdot ||\mathbf{w}||_2^2 + \mathbf{w}^{\mathsf{T}} X L X^{\mathsf{T}} \mathbf{w}$ where $X = [\mathbf{x}^1, ..., \mathbf{x}^{m+n}] \in \mathbb{R}^{d \times (m+n)}$. Find L?
- Want $f(x^i)$ to be close to $f(x^j)$.
- Can enforce this by asking $a_{ij} \cdot \left(f(x^i) f(x^j) \right)^2$ to be small

$$\arg\min_{f} \sum_{i=1}^{n} \ell(f(x^{i}), y^{i}) + \sum_{i,j=1}^{m+n} a_{ij} \cdot (f(x^{i}) - f(x^{j}))^{2}$$

• Can also incorporate a usual regularizer r(f)



SSL Attempt IV - Transductive SVM

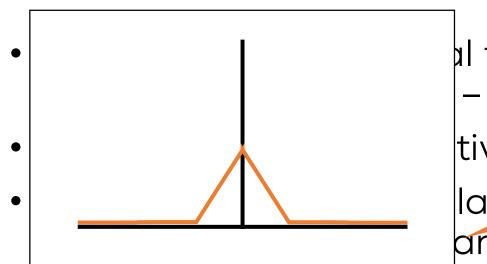
- Transduction is a special form of learning where test features are used to train the model – note, test labels still taboo to look at
- However, the "transductive" SVM works in SSL settings too
- Minimizes hinge loss on labelled points and keeps unlabelled points away from the hyperplane on at least one side

$$\min_{\mathbf{w}, \{\xi_i\}} \frac{1}{2} ||\mathbf{w}||_2^2 + \sum_{i=1}^{m+n} \xi_i
y^i \cdot \langle \mathbf{w}, \mathbf{x}^i \rangle \ge 1 - \xi_i, i = 1, ..., n
|\langle \mathbf{w}, \mathbf{x}^j \rangle| \ge 1 - \xi_j, j = n + 1, ..., m + n
\xi_i \ge 0, i = 1, ..., n, n + 1, ..., m + n$$

• Results in a non-convex optimization problem – difficult to solve

Nov 15, 2017

SSL Attempt IV – Transductive SVM



Can show that for unlabelled points, TSVM uses the symmetric hinge loss function $\ell(\mathbf{w}, \mathbf{x}^j) = \min\left\{ \left[1 - \langle \mathbf{w}, \mathbf{x}^j \rangle \right]_+, \left[1 + \langle \mathbf{w}, \mathbf{x}^j \rangle \right]_+ \right\}$

ane on at least on

m+n

label a points an Note that if $|\langle \mathbf{w}, \mathbf{x}^j \rangle| \ge 1 - \xi_i$ then $z^j \cdot \langle \mathbf{w}, \mathbf{x}^j \rangle \ge 1 - \xi_i$ for either $z^j = 1$ or $z^j = -1$

$$\min_{\mathbf{w}, \{\xi_i\}} \frac{1}{2} \|\mathbf{w}\|_2^2 + \sum_{i=1}^{j} \xi_i$$

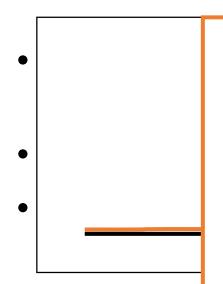
$$y^i \cdot \langle \mathbf{w}, \mathbf{x}^i \rangle \ge 1 - \xi_i, i = 1, ..., n$$

$$|\langle \mathbf{w}, \mathbf{x}^j \rangle| \ge 1 - \xi_j, j = n + 1, ..., m + n$$

$$\xi_i \ge 0, i = 1, ..., n, n + 1, ..., m + n$$

• Results in a non-convex optimization problem – difficult to solve

SSL Attempt IV – Transductive SVM



Exercise: show TSVM actually solves

$$\min_{\mathbf{w},\{\xi_i\},\{z^j\}} \frac{1}{2} \|\mathbf{w}\|_2^2 + \sum_{i=1}^{m+n} \xi_i$$

$$y^i \cdot \langle \mathbf{w}, \mathbf{x}^i \rangle \geq 1 - \xi_i, i = 1, \dots, n$$

$$z^j \cdot \langle \mathbf{w}, \mathbf{x}^j \rangle \geq 1 - \xi_j, j = n+1, \dots, m+n$$

$$\xi_i \geq 0, i = 1, \dots, m+n$$

$$z^j \in \{-1,+1\}, j = n+1, \dots, m+n$$
i.e. jointly optimizes latent vars and model

points, TSVM ss function $+\langle \mathbf{w}, \mathbf{x}^j \rangle]$

 $|\mathbf{x}^j\rangle| \ge 1 - \xi_j$ $\rangle \ge 1 - \xi_j$ for or $z^j = -1$

 $|\langle \mathbf{w}, \mathbf{x}^j \rangle| \ge 1 - \xi_j, j = n$ m + n

Results in a non-convex optimization p

 $\xi_i \ge 0, i = 1, ..., n, n + 1$, Bootstrapping using an SVM would have solved the same problem using hard AltMin

Time to Wrap Up!

A whirlwind tour of topics we did not discuss



Many topics we did not cover

- Bayesian learning (applicable to several problem areas CS775)
- Graphical models (model interactions within data feat. CS772)
- Transfer learning (when exam syllabus may have a "drift")
- Reinforcement learning (learn from an evolving teacher CS773)
- Multi-task learning (solve several problems on the same data)
- Multi-view learning (different feature rep. of the same data)
- Sparse recovery (learn space-efficient models CS772/CS777)
- Time series modelling (HMMs, AR, ARMA, RNNs)
- Learning theory (provable goodness of learnt models CS777)
- Learning on data streams (experts, bandits CS773)
- Advanced Optimization Techniques (CS774/CS777)

Please give your Feedback

http://tinyurl.com/ml17-18afb

