The University of Texas at Austin
Electrical and Computer Engineering
Cockrell School of Engineering

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INTRODUCTION TO COMPUTER VISION

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Learning for episodic tasks

- **Machine Learning:**
  - Getting a computer to do well on a task without explicitly programming it
  - Improving performance on a task based on experience

- We first consider the “easier” problem of learning in episodic environments
  - The agent gets a series of unrelated problem instances and has to make some decision or inference about each of them
  - In this case, “experience” comes in the form of *training data*

- We may also look at learning in sequential environments

Example: Image classification

input **desired output**

apple

pear

tomato

cow

dog

horse

Training data:

apple

pear

tomato

cow

dog

horse

Example 2: Spam filter

Dear Sir.

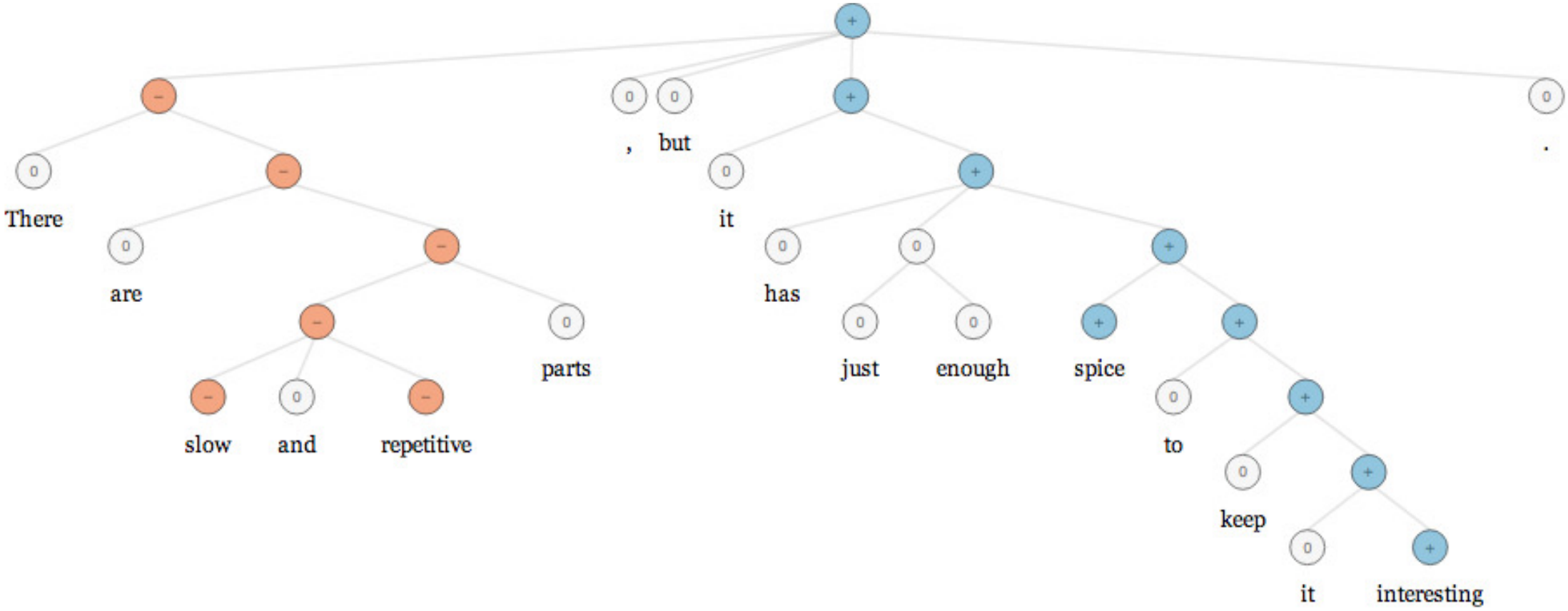
First, I must solicit your confidence in this transaction, this is by virture of its nature as being utterly confidencial and top secret. …

TO BE REMOVED FROM FUTURE MAILINGS, SIMPLY REPLY TO THIS MESSAGE AND PUT "REMOVE" IN THE SUBJECT.

99 MILLION EMAIL ADDRESSES
FOR ONLY $99

Ok, Iknow this is blatantly OT but I'm beginning to go insane. Had an old Dell Dimension XPS sitting in the corner and decided to put it to use, I know it was working pre being stuck in the corner, but when I plugged it in, hit the power nothing happened.

Example 3: NLP Sentiment analysis



http://gigaom.com/2013/10/03/stanford-researchers-to-open-source-model-they-say-has-nailed-sentiment-analysis/

http://nlp.stanford.edu:8080/sentiment/rntnDemo.html

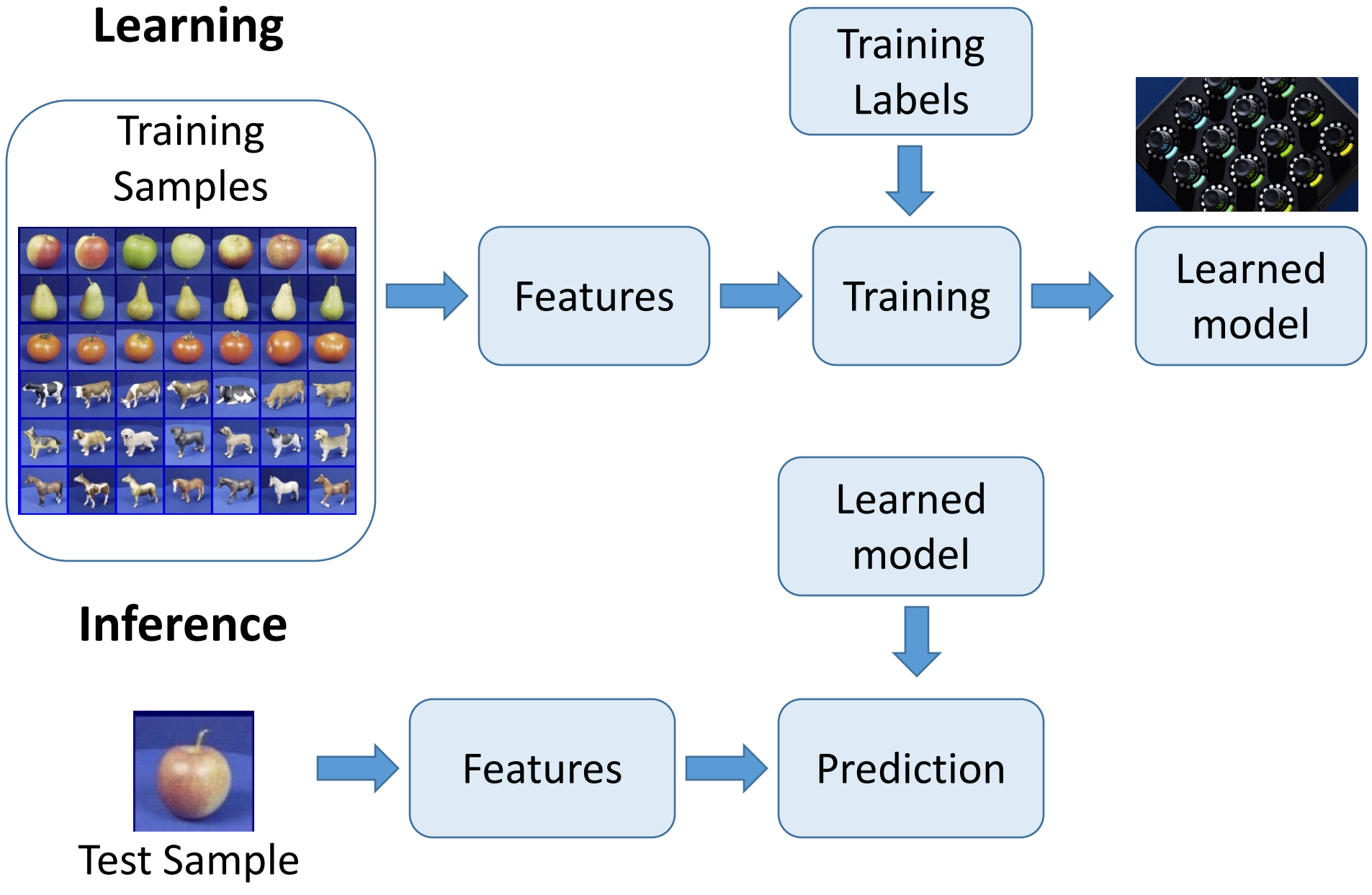
The basic *supervised learning* framework

$$y = f(\mathbf{x})$$

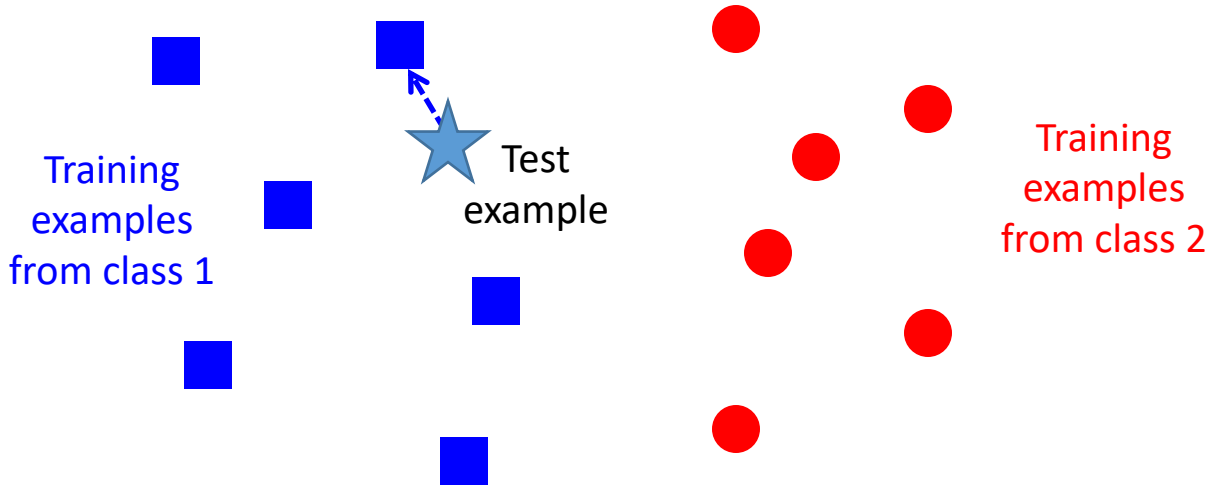
output | classification function | input

- **Learning:** given a *training set* of labeled examples $\{(\mathbf{x}_1, y_1), \ldots, (\mathbf{x}_N, y_N)\}$, estimate the parameters of the prediction function f
- **Inference:** apply f to a never before seen *test example* $\mathbf{x}$ and output the predicted value $y = f(\mathbf{x})$

Learning and inference pipeline



Nearest neighbor classifier

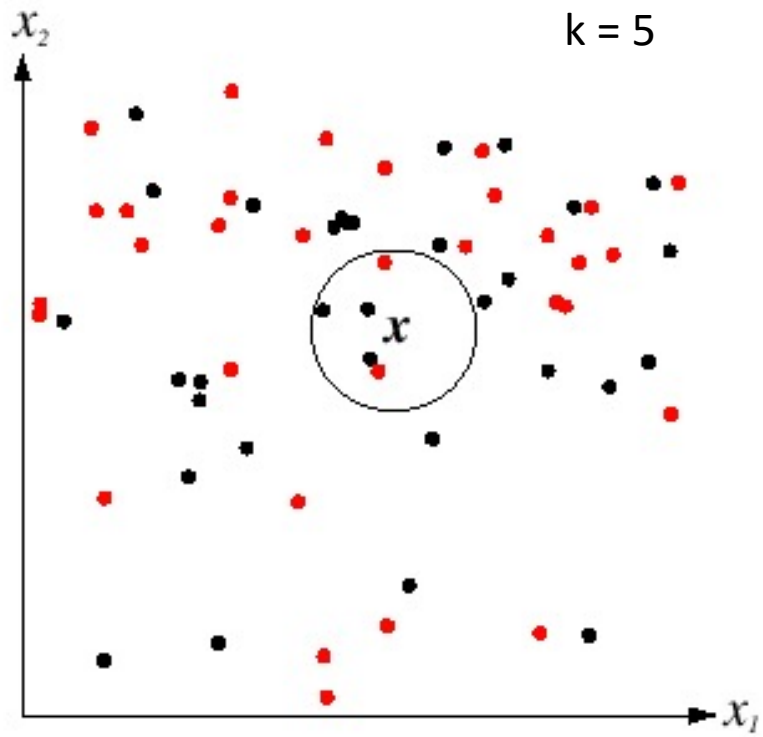


f(**x**) = label of the training example nearest to **x**

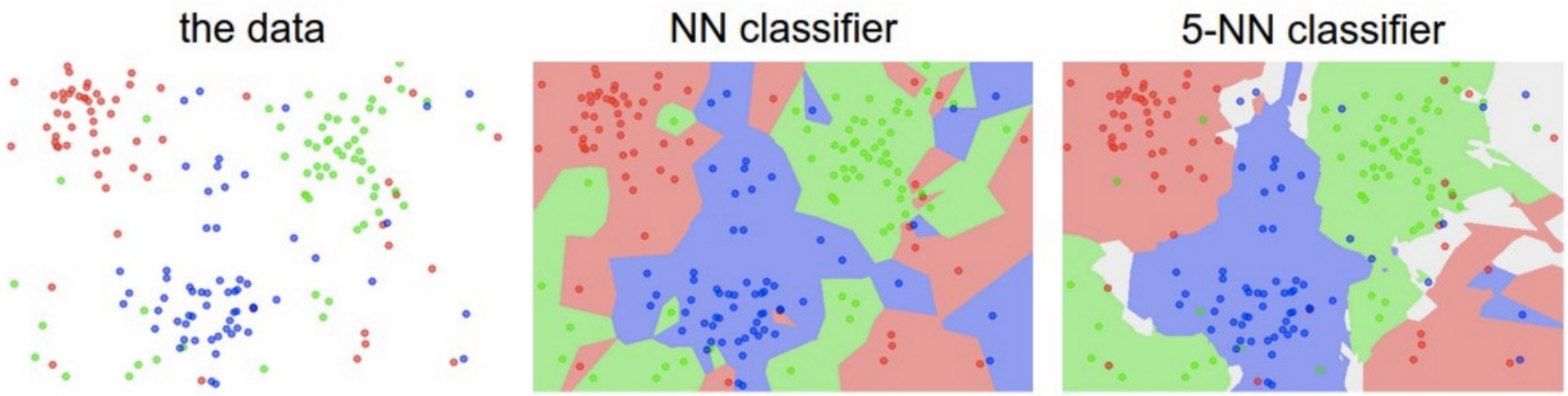
- All we need is a distance function for our inputs
- No training required!

K-nearest neighbor classifier

- For a new point, find the k closest points from training data
- Vote for class label with labels of the k points



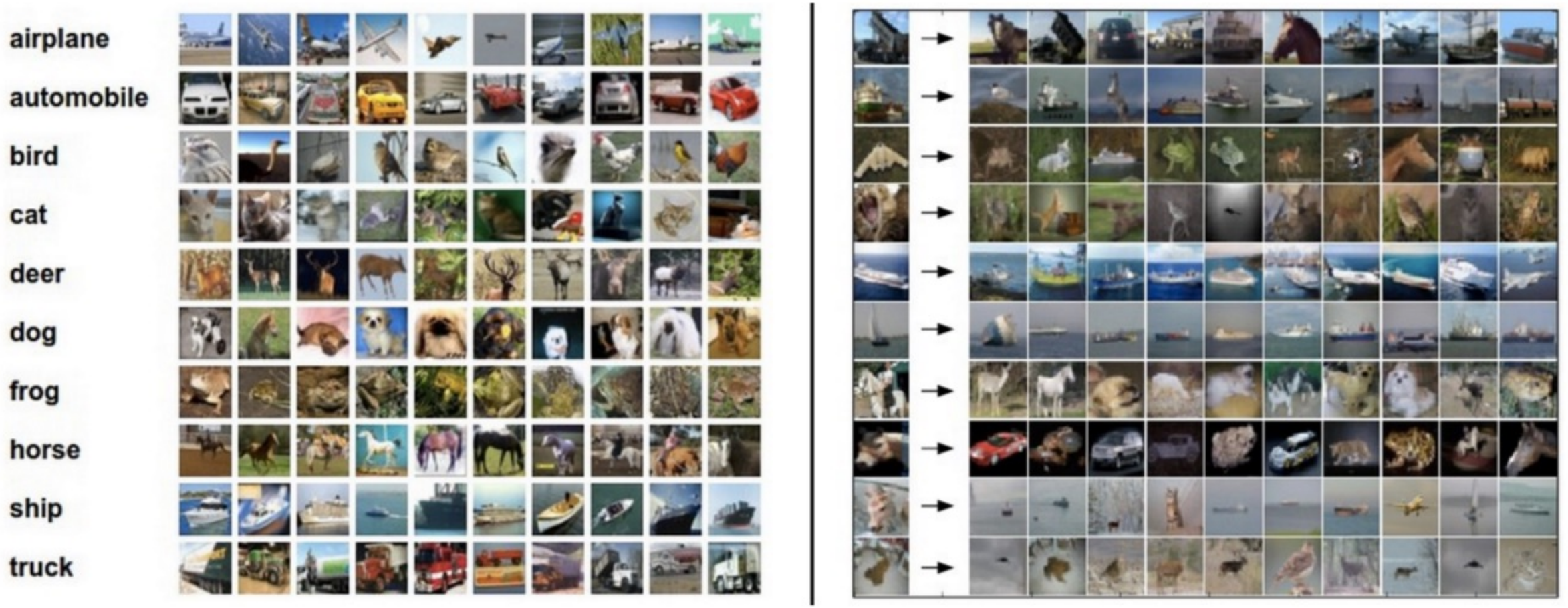
K-nearest neighbor classifier



- Which classifier is more robust to *outliers*?

Credit: Andrej Karpathy, http://cs231n.github.io/classification/

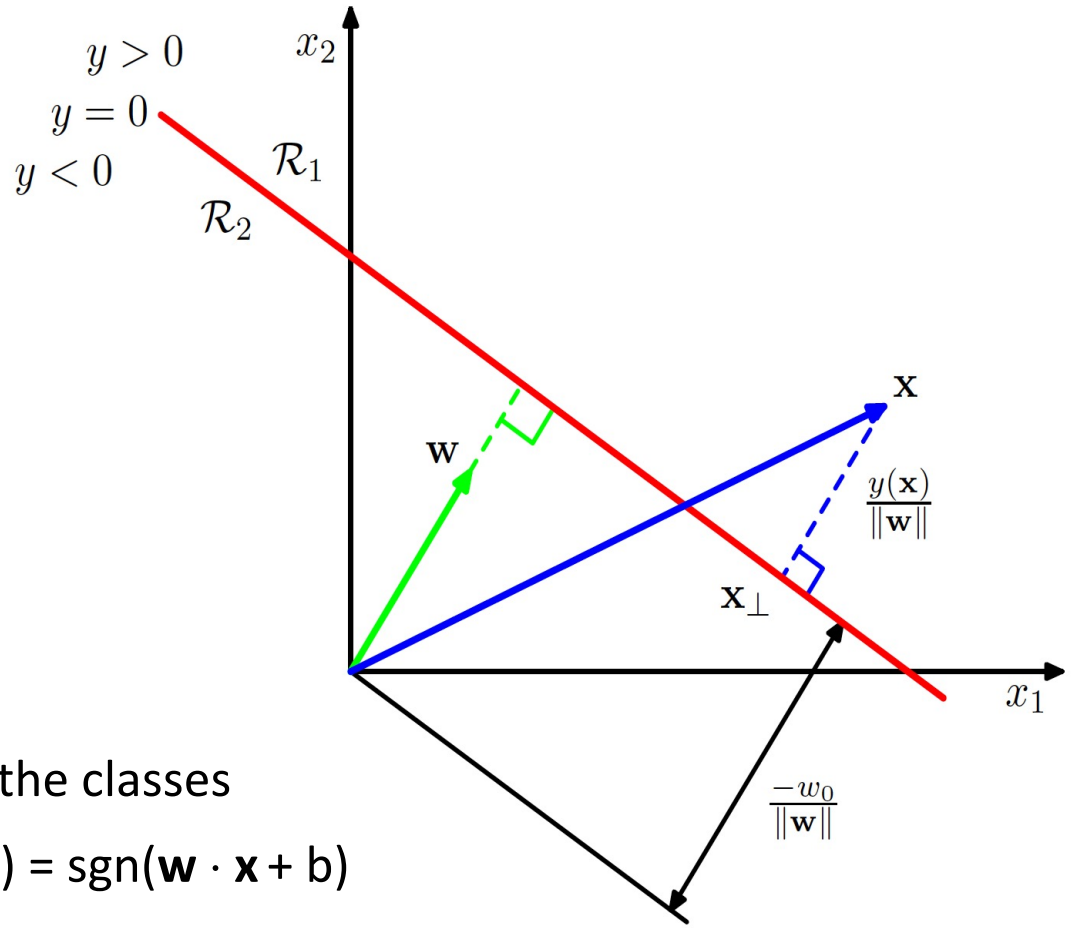
K-nearest neighbor classifier



Left: Example images from the CIFAR-10 dataset. Right: first column shows a few test images and next to each we show the top 10 nearest neighbors in the training set according to pixel-wise difference.

Linear classifier

The Classification Boundary marked in Red (Decision Hyperplane)



- Find a *linear function* to separate the classes

$f(\mathbf{x}) = \text{sgn}(w_1x_1 + w_2x_2 + \ldots + w_Dx_D + b) = \text{sgn}(\mathbf{w} \cdot \mathbf{x} + b)$

Probabilistic Classification Model

- Probabilistic Generative Model
  Model the class-conditional densities $p(\mathbf{x}|\mathcal{C}_k)$ and prior probabilities $p(\mathcal{C}_k)$, and compute $p(\mathcal{C}_k|\mathbf{x})$ using Bayes' theorem

$$p(\mathcal{C}_k|\mathbf{x}) = \frac{p(\mathbf{x}|\mathcal{C}_k)p(\mathcal{C}_k)}{p(\mathbf{x})}$$

- Probabilistic Discriminative Model
  Maximize a likelihood function defined through the conditional distribution $p(\mathcal{C}_k|\mathbf{x})$
- Advantages of Discriminative Models
  - Fewer adaptive parameters need to be determined.
  - Performance will be improved, especially when the class-conditional density assumption gives a poor approximation to the true distributions.

Logistic Regression

- In two-class problem, the posterior probability of class $\mathcal{C}_1$ can be written as a logistic sigmoid acting on a linear function of the feature vector ϕ so that

$$p(\mathcal{C}_1|\phi) = y(\phi) = \sigma(\mathbf{w}^T\phi).$$

- $\sigma(.)$ is the logistic sigmoid function.
- $p(\mathcal{C}_2|\phi) = 1 - p(\mathcal{C}_1|\phi)$
- In statistics, the model is known as **logistic regression**.
- The model is for **classification**, not for regression.
- In logistic regression, we estimate the parameter **w** directly.

Logistic Regression

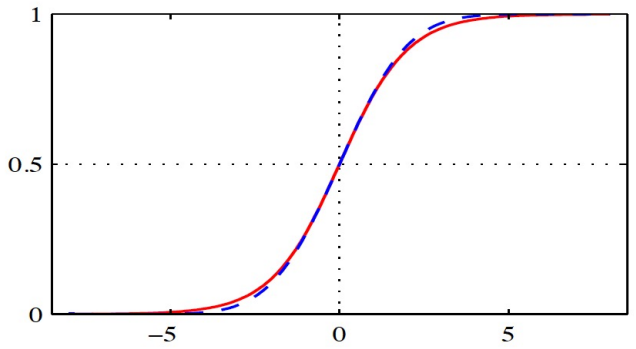
- Definition of **Logistic Sigmoid** function $\sigma(a)$:

$$\sigma(a) = \frac{1}{1 + \exp(-a)}$$

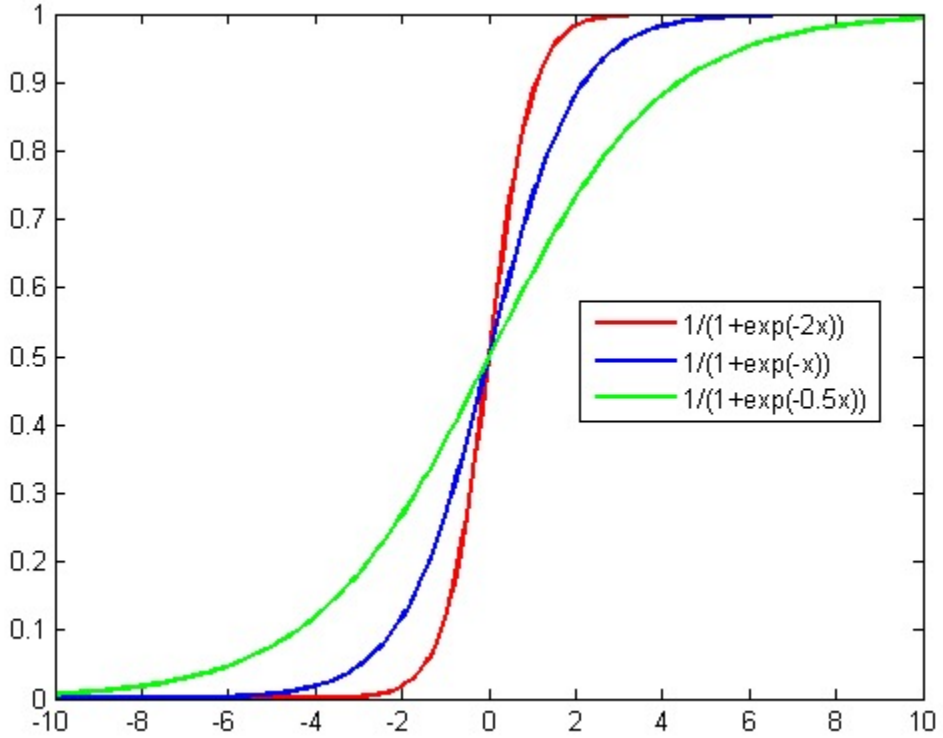
- Properties of Logistic Sigmoid function $\sigma(a)$:

$$\sigma(-a) = 1 - \sigma(a)$$

$$\frac{d\sigma}{da} = \sigma(1 - \sigma)$$

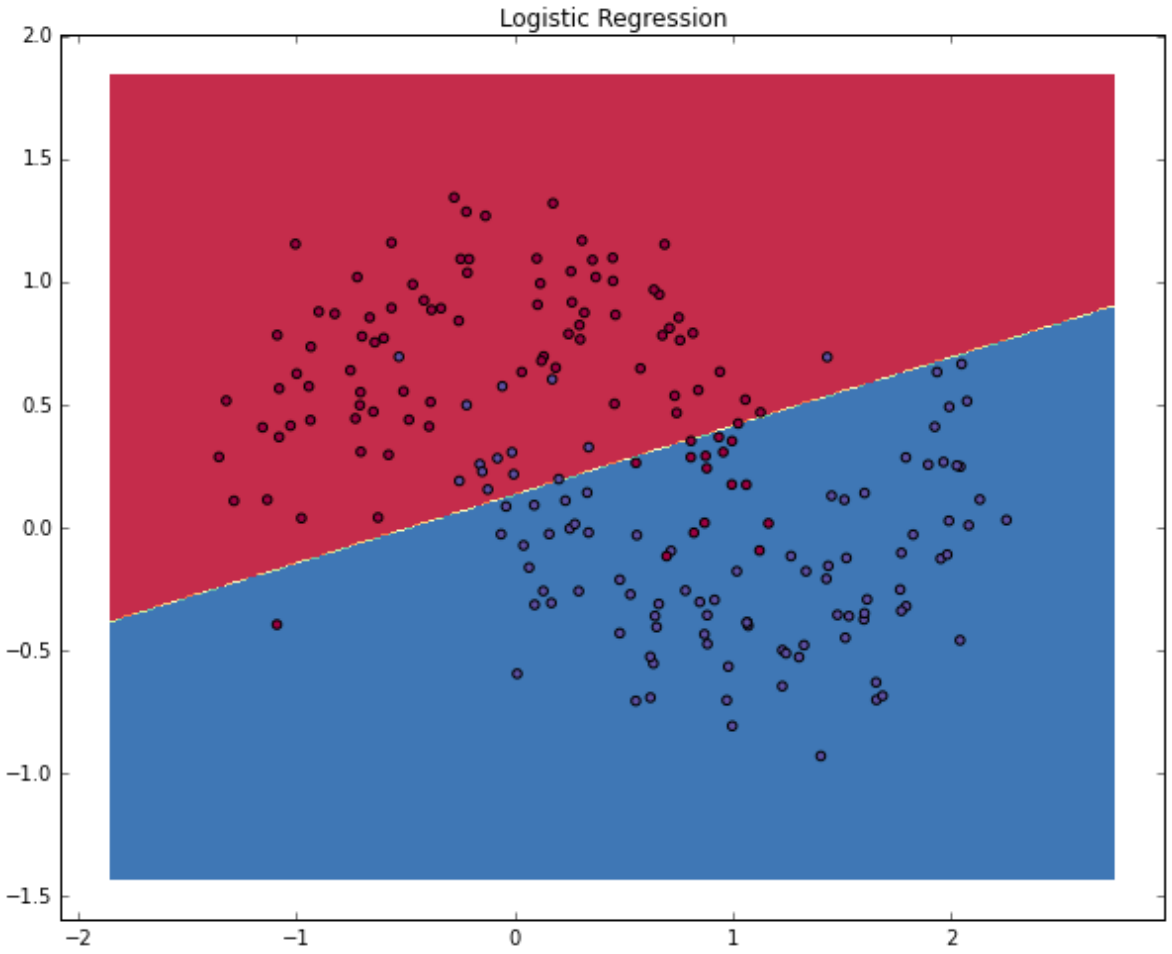


Plot of the logistic sigmoid function $\sigma(a)$ (Red Line)



A Continuously Differentiable Approximation of the 0-1 loss

Logistic Regression



Linear Decision Boundary! Why?

Logistic Regression

- For a training data set $\{\phi_n, t_n\}$ where $t_n \in \{0, 1\}$ and $n = 1, 2, , N$, the likelihood function is

$$p(\mathbf{t}|\mathbf{w}) = \prod_{n=1}^{N} y_n^{t_n}(1 - y_n)^{1-t_n} \tag{3}$$

- Definitions of $t_n, \mathbf{t}$ and y_n

$$t_n = \begin{cases} 1 \text{ if } n \in \mathcal{C}_1 \\ 0 \text{ if } n \in \mathcal{C}_2 \end{cases}$$

$$\mathbf{t} = (t_1, t_2, \ldots, t_N)^T$$

$$y_n = p(\mathcal{C}_1|\phi_n) = \sigma(\mathbf{w}^T\phi_n)$$

Logistic Regression

- The error function is the negative logarithm of the likelihood, namely, **Cross-entropy** error function:

$$E(\mathbf{w}) = -\ln p(\mathbf{t}|\mathbf{w}) = \sum_{n=1}^{N} \{t_n \ln y_n + (1 - t_n) \ln(1 - y_n)\}$$

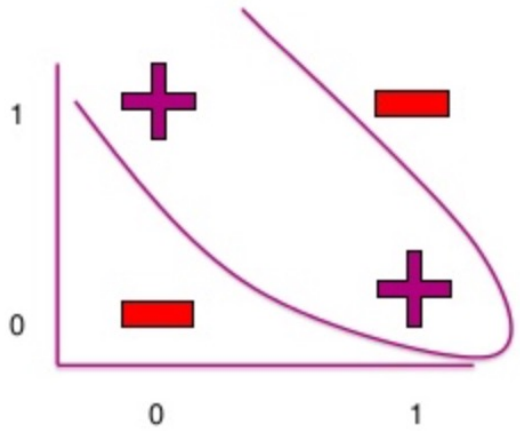
The gradient of cross entropy function with respect to $\mathbf{w}$ is

$$\nabla E(\mathbf{w}) = \sum_{n=1}^{N} (y_n - t_n)\phi_n$$

NN vs. linear classifiers

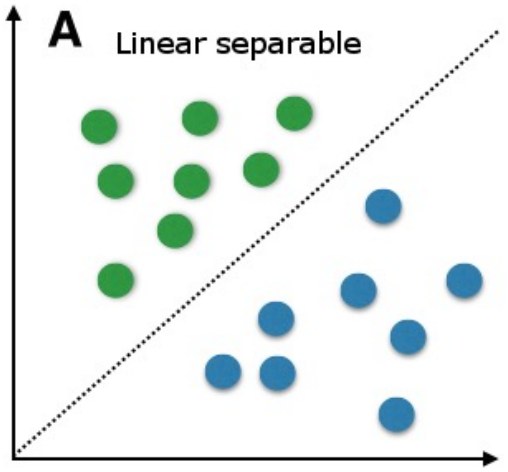
- NN pros:
  - + Simple to implement
  - + Decision boundaries not necessarily linear
  - + Works for any number of classes
  - + *Nonparametric* method
- NN cons:
  - Need good distance function
  - Slow at test time
- Linear pros:
  - + Low-dimensional *parametric* representation
  - + Very fast at test time
- Linear cons:
  - Works for two classes
  - How to train the linear function?
  - What if data is not linearly separable?

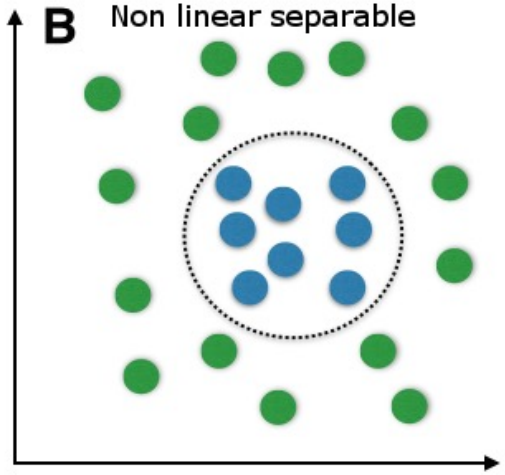
Limitation of Linear Classifiers



XOR

Need non-linear features





Multi-Class Classification

- Strategy 1: One-versus-All
  - Use *K - 1* two-class classifiers
- Strategy 2: One-versus-One
  - Use *K(K – 1)/2* two-class classifiers
- Strategy 3: Define a single K-class discriminant comprising K linear functions

$$y_k(\mathbf{x}) = \mathbf{w}_k^T \mathbf{x} + w_{k0}$$

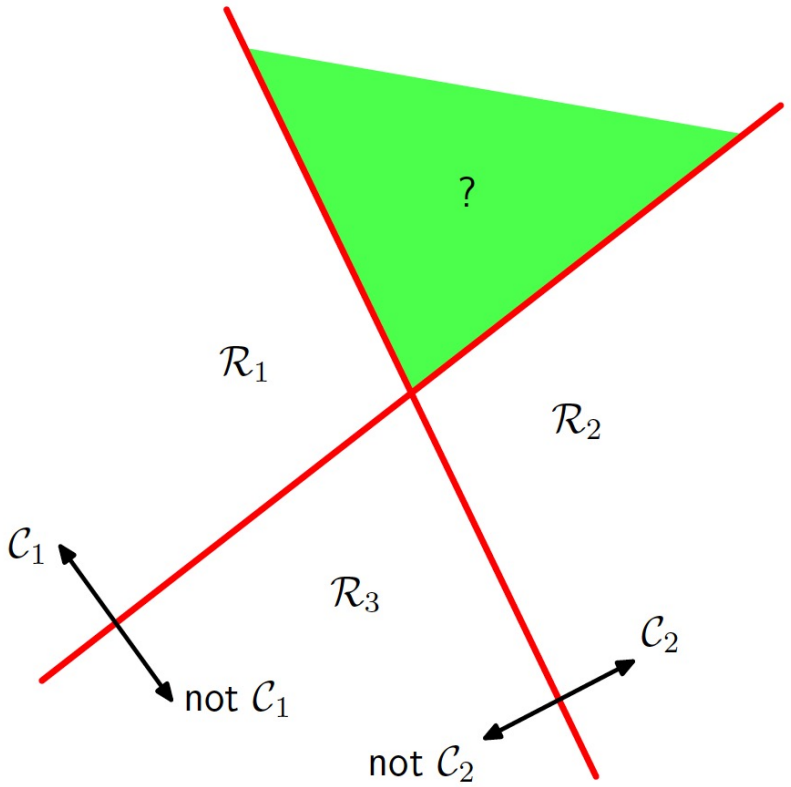
- Decision Rule
  Assigning a point $\mathbf{x}$ to class $\mathcal{C}_k$ if $y_k(\mathbf{x}) > y_j(\mathbf{x})$ for all $j \neq k$
- The decision boundary between class $\mathcal{C}_k$ and class $\mathcal{C}_j$

$$y_k(\mathbf{x}) = y_j(\mathbf{x})$$

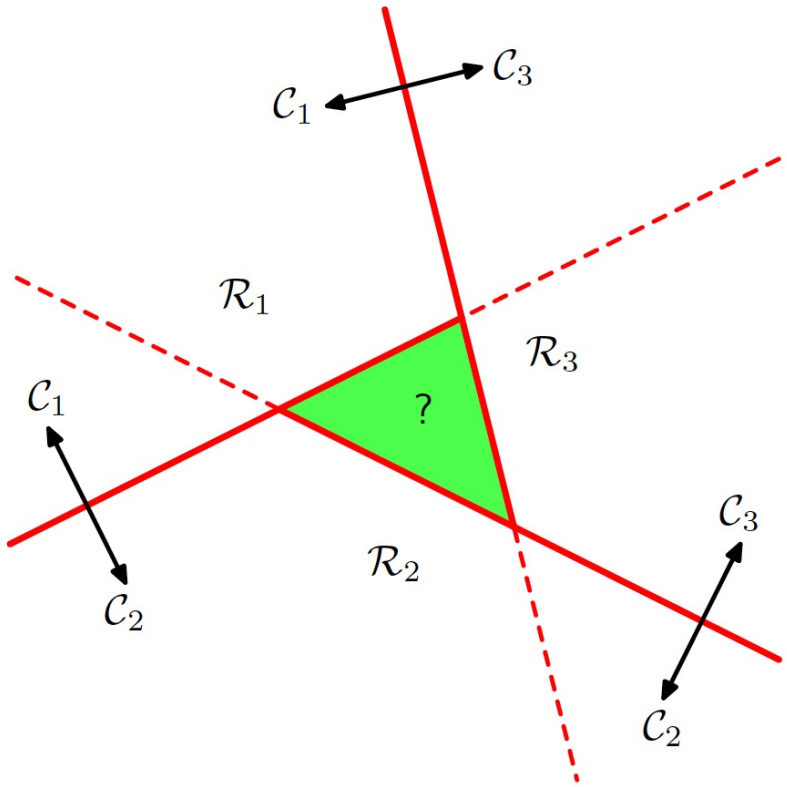
This boundary is $(D-1)$-dimensional hyperplane defined by

$$(\mathbf{w}_k - \mathbf{w}_j)^T \mathbf{x} + (w_{k0} - w_{j0}) = 0$$

Multi-Class Classification



Dilemma of One-versus-All



Dilemma of One-versus-One

Softmax Regression

- The Multi-Class version of Logistic Regression (popular in deep learning)
  (Reference: http://ufldl.stanford.edu/tutorial/supervised/SoftmaxRegression/)

$$h_\theta(x) = \frac{1}{1 + \exp(-\theta^\top x)},$$

$$h_\theta(x) = \begin{bmatrix} P(y = 1|x;\theta) \\ P(y = 2|x;\theta) \\ \vdots \\ P(y = K|x;\theta) \end{bmatrix} = \frac{1}{\sum_{j=1}^{K} \exp(\theta^{(j)\top} x)} \begin{bmatrix} \exp(\theta^{(1)\top} x) \\ \exp(\theta^{(2)\top} x) \\ \vdots \\ \exp(\theta^{(K)\top} x) \end{bmatrix}$$

Decision tree classifier

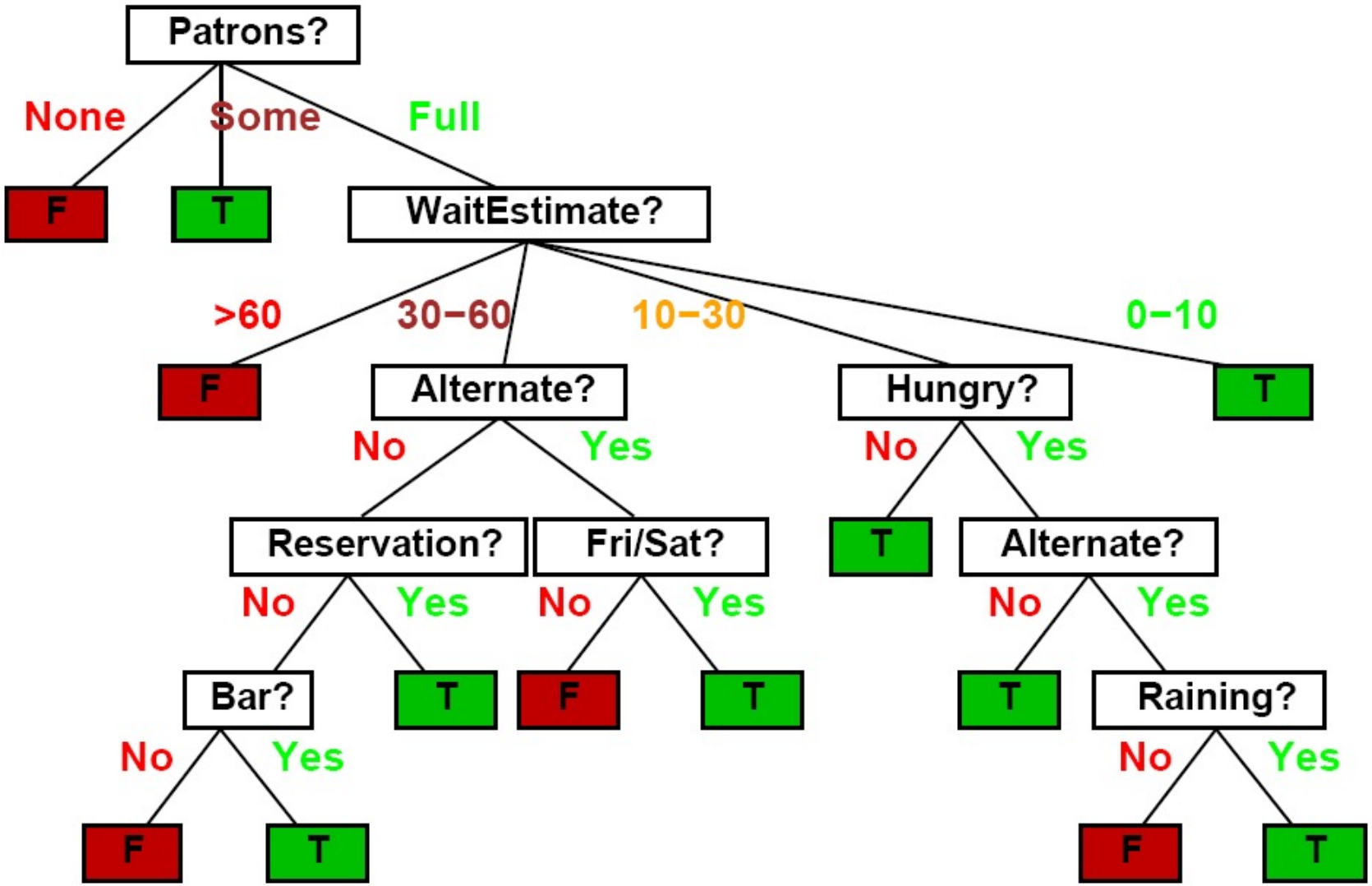
Example problem: decide whether to wait for a table at a restaurant, based on the following attributes:

1. **Alternate:** is there an alternative restaurant nearby?
2. **Bar:** is there a comfortable bar area to wait in?
3. **Fri/Sat:** is today Friday or Saturday?
4. **Hungry:** are we hungry?
5. **Patrons:** number of people in the restaurant (None, Some, Full)
6. **Price:** price range ($, $$, $$$)
7. **Raining:** is it raining outside?
8. **Reservation:** have we made a reservation?
9. **Type:** kind of restaurant (French, Italian, Thai, Burger)
10. **WaitEstimate:** estimated waiting time (0-10, 10-30, 30-60, >60)

Decision tree classifier

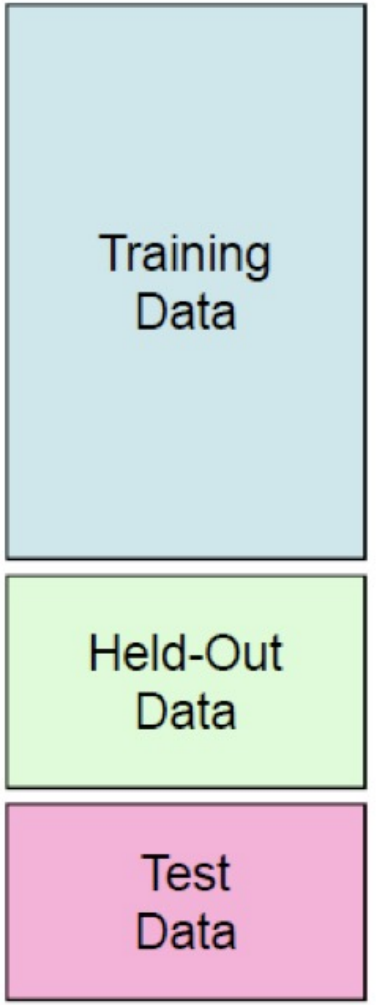
Example	Attributes										Target
	Alt	*Bar*	*Fri*	*Hun*	*Pat*	*Price*	*Rain*	*Res*	*Type*	*Est*	*Wait*
X_1	T	F	F	T	Some	$$$	F	T	French	0–10	T
X_2	T	F	F	T	Full	$	F	F	Thai	30–60	F
X_3	F	T	F	F	Some	$	F	F	Burger	0–10	T
X_4	T	F	T	T	Full	$	F	F	Thai	10–30	T
X_5	T	F	T	F	Full	$$$	F	T	French	>60	F
X_6	F	T	F	T	Some	$$	T	T	Italian	0–10	T
X_7	F	T	F	F	None	$	T	F	Burger	0–10	F
X_8	F	F	F	T	Some	$$	T	T	Thai	0–10	T
X_9	F	T	T	F	Full	$	T	F	Burger	>60	F
X_{10}	T	T	T	T	Full	$$$	F	T	Italian	10–30	F
X_{11}	F	F	F	F	None	$	F	F	Thai	0–10	F
X_{12}	T	T	T	T	Full	$	F	F	Burger	30–60	T

Decision tree classifier



Experimentation cycle

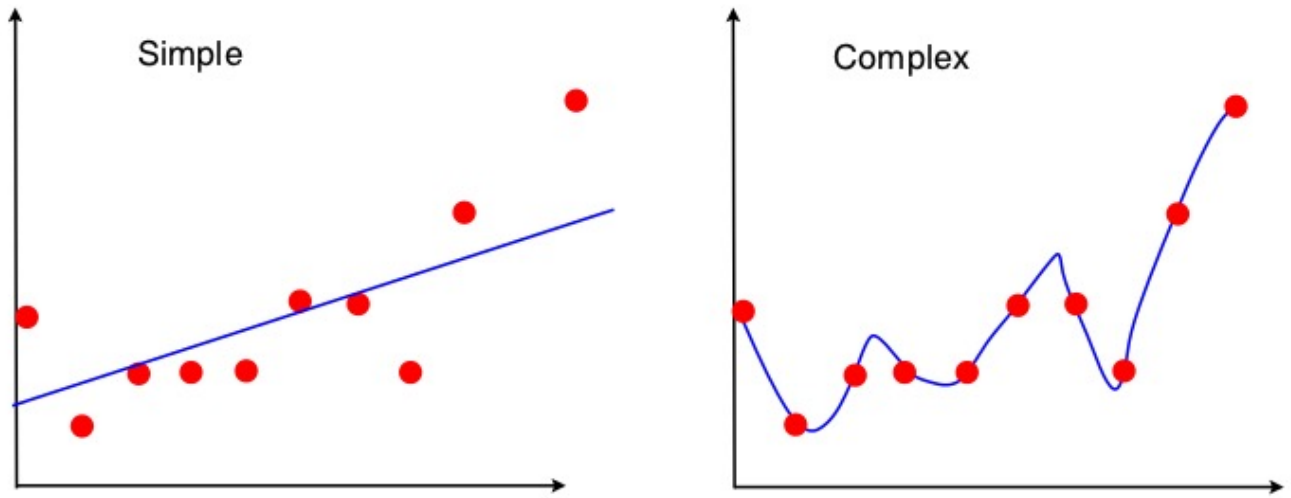
- Learn *parameters* on the *training set*
- Tune *hyperparameters* (implementation choices) on the *held out validation set*
- Evaluate performance on the *test set*
- Do not peek at the test set!
- *Generalization* and *overfitting*
  - Want classifier that does well on never before seen data
  - Overfitting: good performance on the training/validation set, poor performance on test set

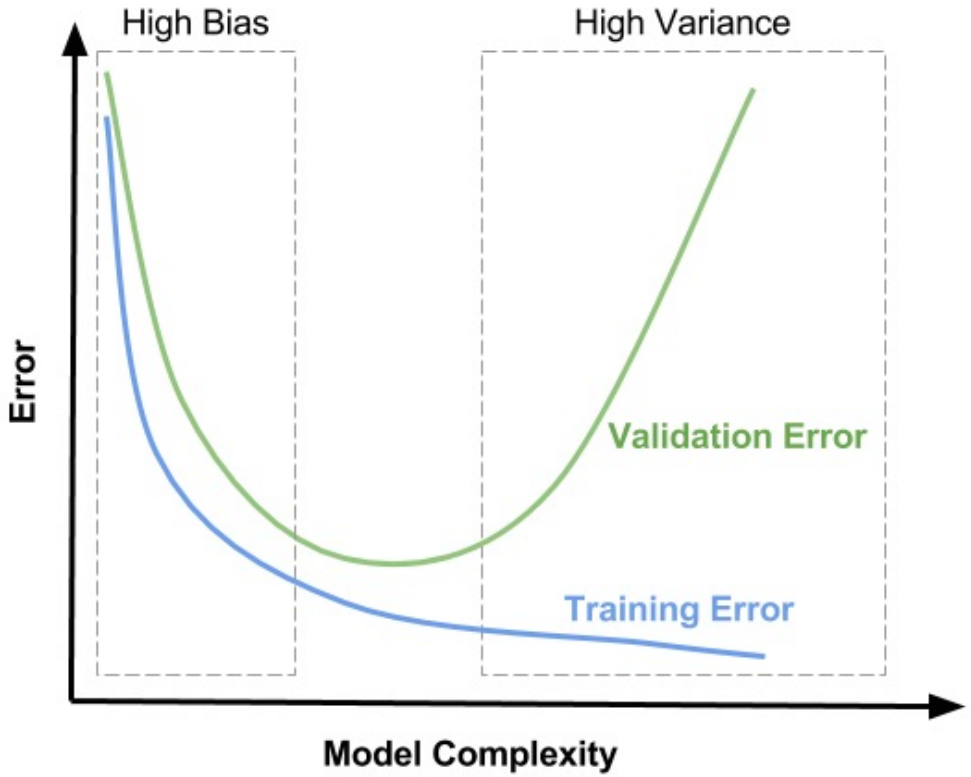


Bias-Variance Tradeoff

- The bias–variance tradeoff is the fundamental dilemma of minimizing between two sources of errors that prevent ML algorithms from generalizing beyond their training set:
  - The bias is error from erroneous assumptions in the learning algorithm. High bias can cause an algorithm to miss the relevant relations between features and target outputs (e.g., model is too simple -> **underfitting**).
  - The variance is error from sensitivity to small fluctuations in the training set. High variance can cause an algorithm to model the random noise in the training data, rather than the intended outputs (e.g., model is too complicated -> **overfitting**).

Bias-Variance Tradeoff





Cross Validation

- Give available data in practice, how can we try to find the best-trained algorithm, that will generalize well on unseen testing data?

- Most common approach is K-**fold cross validation**:
  - Partition the training data $\mathcal{D}$ into K separate sets of equal size
    - Suppose $\mathcal{D} = (\mathcal{D}_1, \mathcal{D}_2, ..., \mathcal{D}_K)$
    - Commonly chosen Ks are $K = 5$ and $K = 10$
  - For each $k = 1, 2, ..., K$, fit the model $\hat{f}_{-k}^{(\lambda)}(\mathbf{x})$ to the training set excluding the kth-fold $\mathcal{D}_k$
  - Compute the fitted values for the observations in $\mathcal{D}_k$, based on the training data that excluded this fold
  - Compute the cross-validation (CV) error for the k-th fold:

$$(\text{CV Error})_k^{(\lambda)} = |\mathcal{D}_k|^{-1} \sum_{(\mathbf{x},y)\in\mathcal{D}_k} (y - \hat{f}_{-k}^{(\lambda)}(\mathbf{x}))^2$$

- The model then has overall cross-validation error:

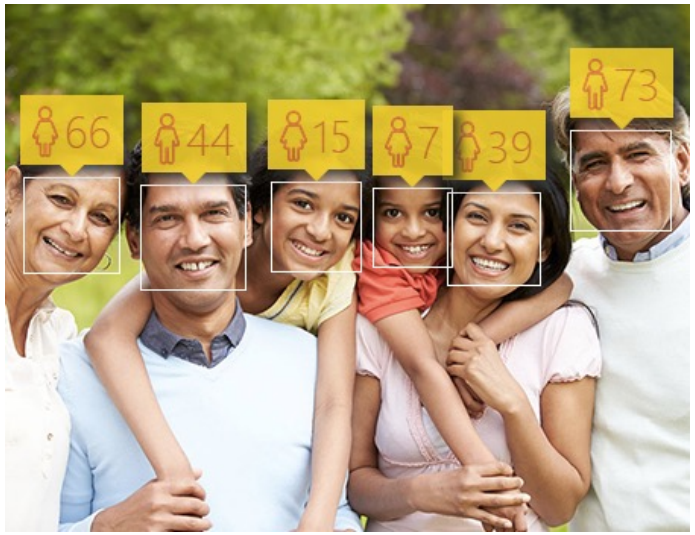
$$(\text{CV Error})^{(\lambda)} = K^{-1} \sum_{k=1}^{K} (\text{CV Error})_k^{(\lambda)}$$

- Select λ^* as the one with minimum $(\text{CV Error})^{(\lambda)}$
- Compute the chosen model $\hat{f}_{-k}^{(\lambda^*)}(\mathbf{x})$ on the entire training set $T = (\mathcal{D}_1, \mathcal{D}_2, \ldots, \mathcal{D}_k)$
- Apply $\hat{f}_{-k}^{(\lambda^*)}(\mathbf{x})$ to the test set to assess test error

Beyond supervised classification

- Other prediction scenarios
  - Regression
  - Structured prediction
- Other supervision scenarios
  - Unsupervised learning
  - Self-supervised or predictive learning
  - Active learning
  - Lifelong learning

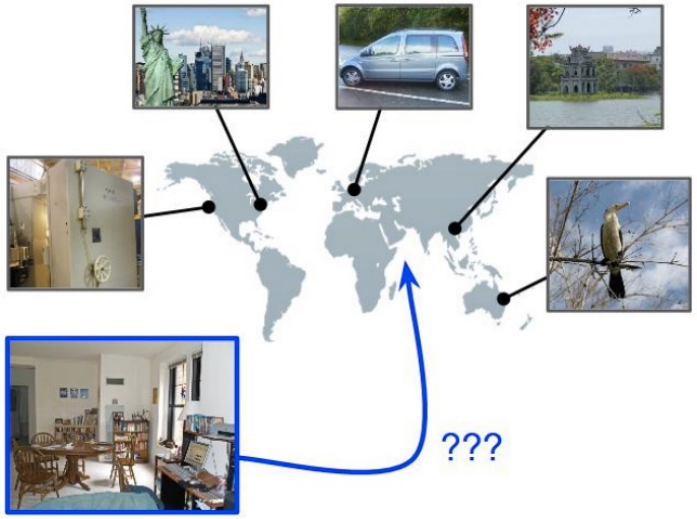
Beyond classification: Regression



Age estimation

When was that made?

IM2GPS



Beyond classification: Structured prediction

Image

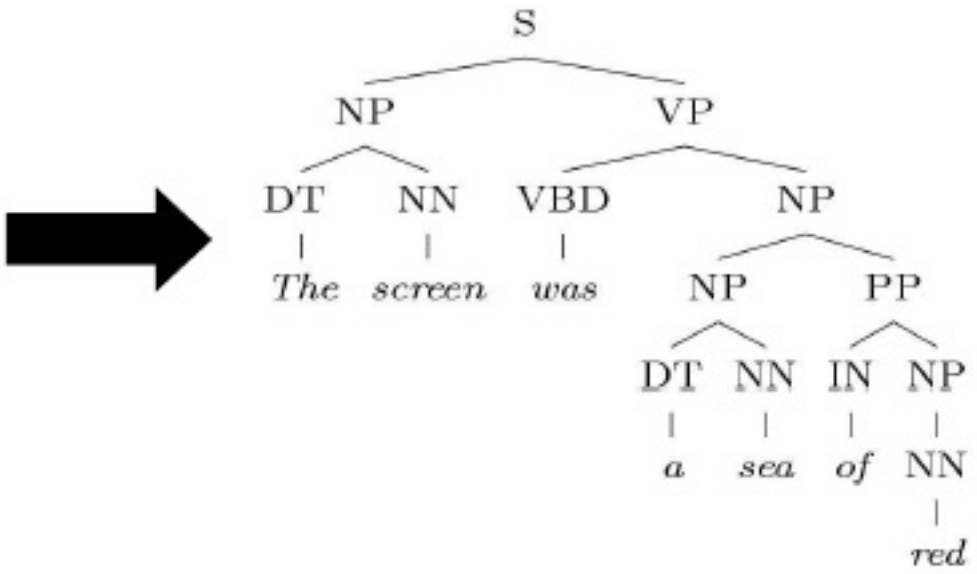
brace

Word

Source: B. Taskar

Structured Prediction

The screen was
a sea of red



Sentence

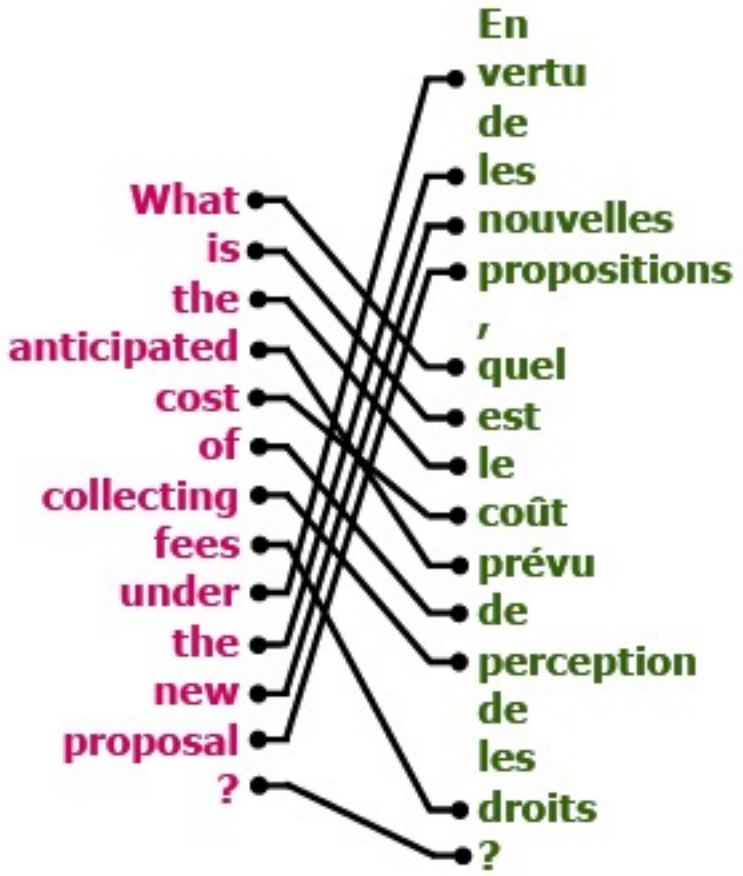
Parse tree

Source: B. Taskar

Structured Prediction

What is the anticipated cost of collecting fees under the new proposal?

En vertu des nouvelles propositions, quel est le coût prévu de perception des droits?

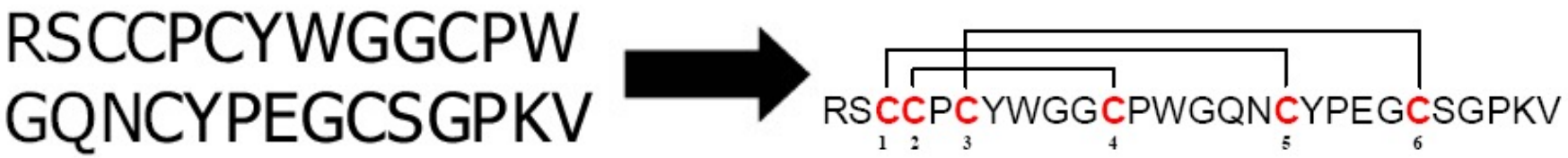


Sentence in two languages

Word alignment

Source: B. Taskar

Structured Prediction



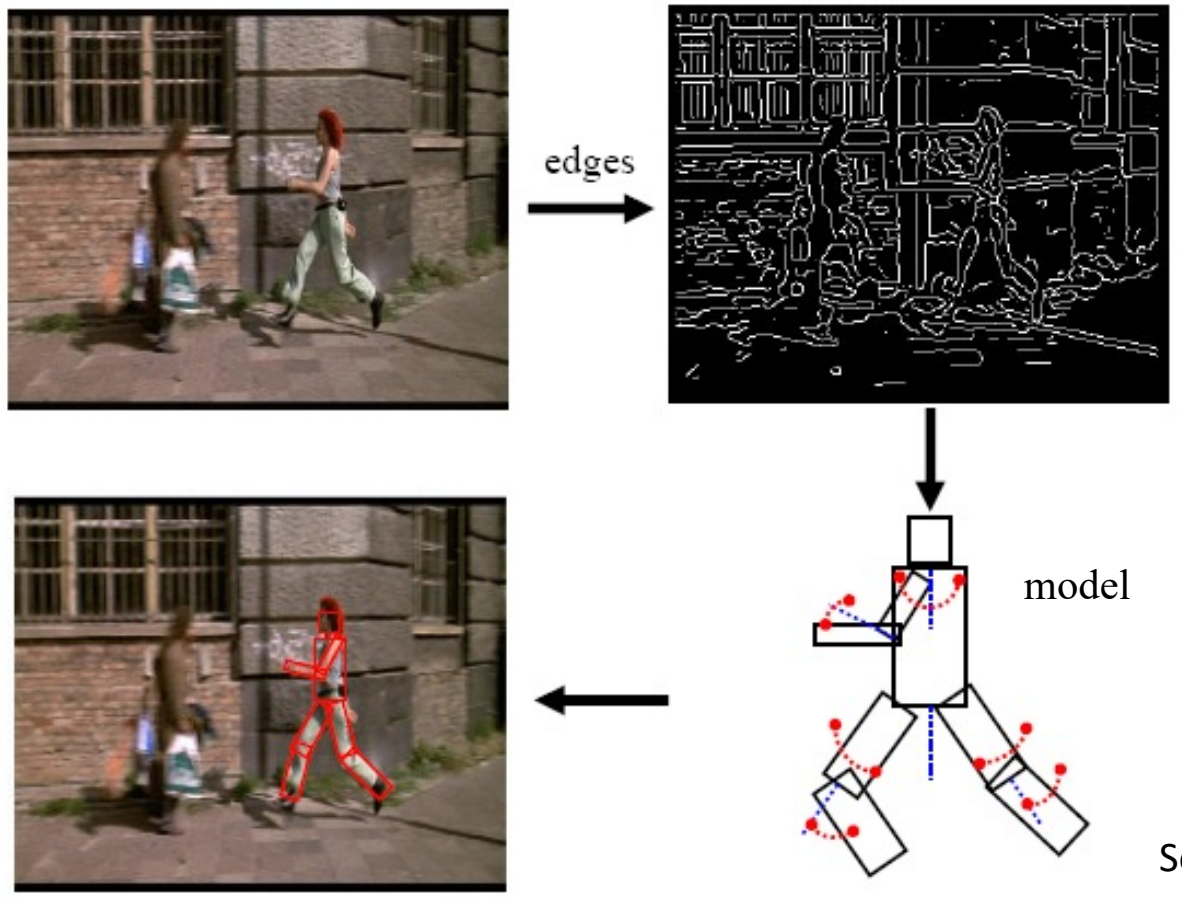
Amino-acid sequence

Bond structure

Source: B. Taskar

Structured Prediction

- Many image-based inference tasks can loosely be thought of as "structured prediction"



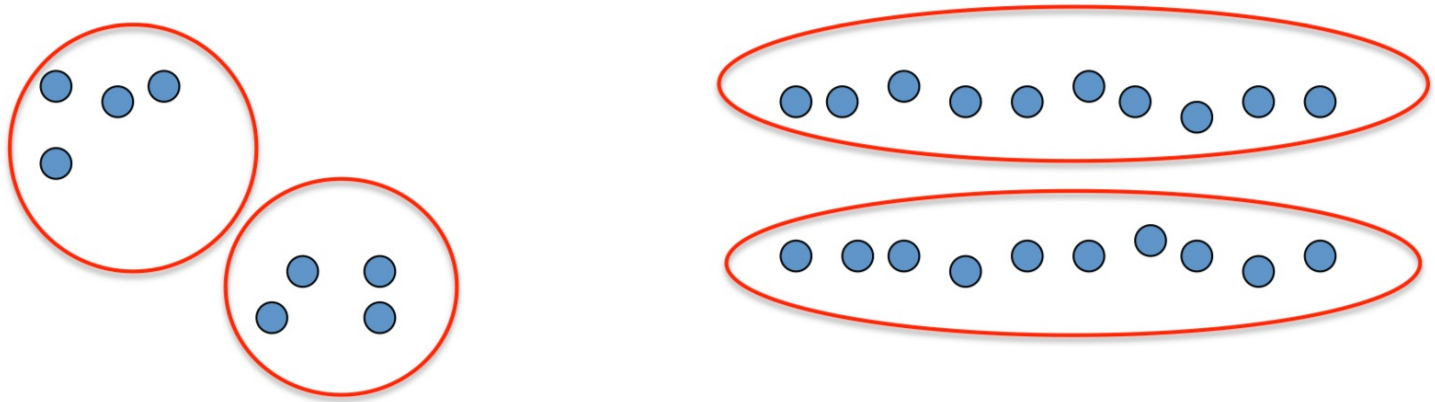
Source: D. Ramanan

Unsupervised Learning

- Idea: Given only *unlabeled* data as input, learn some sort of structure
- The objective is often more vague or subjective than in supervised learning
- This is more of an exploratory/descriptive data analysis

Clustering

- Basic idea: group together similar instances
- Example: 2D point patterns



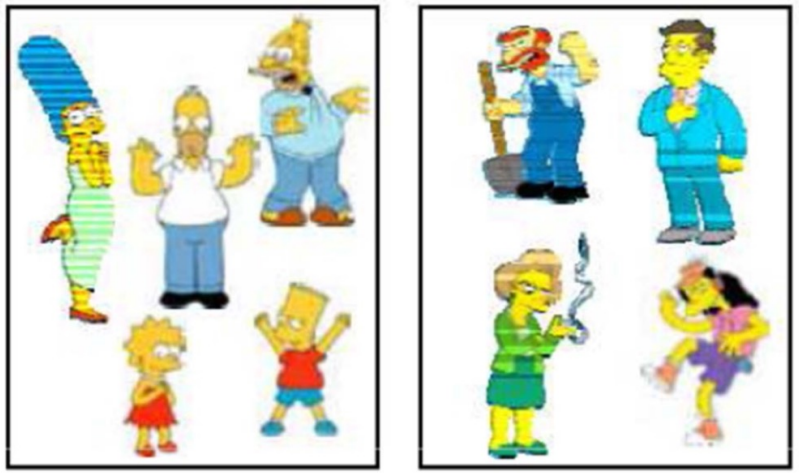
- What could "similar" mean?
  - One option: small Euclidean distance (squared)

$$\text{dist}(\vec{x}, \vec{y}) = ||\vec{x} - \vec{y}||_2^2$$

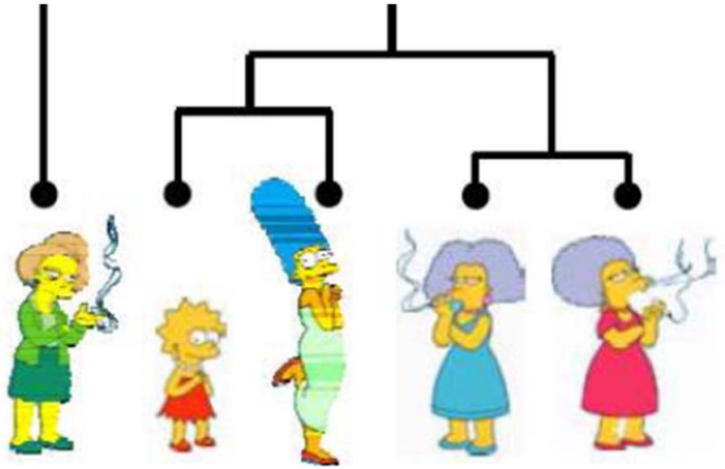
  - Clustering results are crucially dependent on the measure of similarity (or distance) between "points" to be clustered

Clustering Algorithms

- Partition algorithms (Flat)
  - K-means
  - Mixture of Gaussian
  - Spectral Clustering

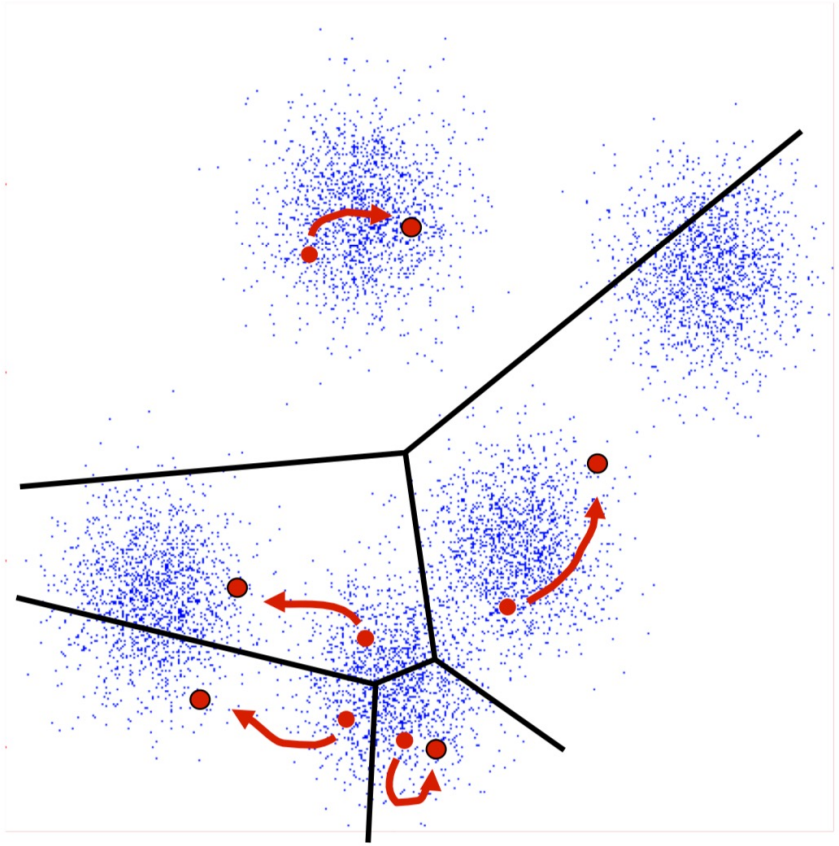


- Hierarchical algorithms
  - Bottom up – agglomerative
  - Top down – divisive



K-Means

- An iterative clustering algorithm
  - Initialize: Pick *K* random points as cluster centers
  - Alternate:
    1. Assign data points to closest cluster center
    2. Change the cluster center to the average of its assigned points
  - Stop when no points' assignments change



K-Means: Local Convergence

Objective

$$\min_{\mu}\min_{C} \sum_{i=1}^{k} \sum_{x \in C_i} |x - \mu_i|^2$$

1. Fix μ, optimize *C:*

$$\min_{C} \sum_{i=1}^{k} \sum_{x \in C_i} |x - \mu_i|^2 = \min_{c} \sum_{i}^{n} \left|x_i - \mu_{x_i}\right|^2$$

Step 1 of kmeans

2. Fix *C,* optimize μ:

$$\min_{\mu} \sum_{i=1}^{k} \sum_{x \in C_i} |x - \mu_i|^2$$

   – Take partial derivative of μ_i and set to zero, we have

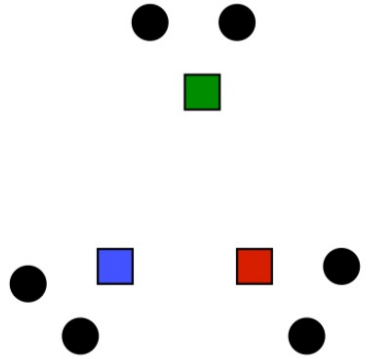
$$\mu_i = \frac{1}{|C_i|} \sum_{x \in C_i} x$$

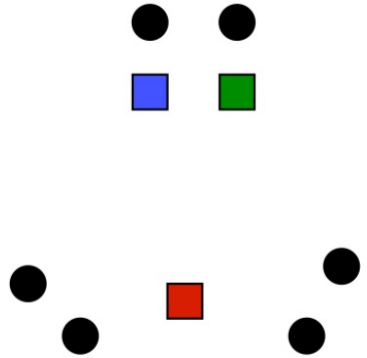
Step 2 of kmeans

Kmeans takes an alternating optimization approach, each step is guaranteed to decrease the objective – thus guaranteed to converge

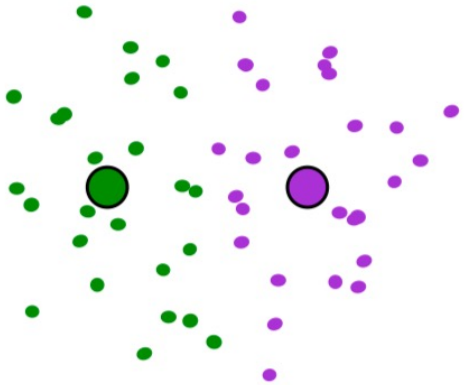
K-Means is Fragile

- K-means **algorithm** is a heuristic
  - Requires initial means
  - It does matter what you pick!
  - What can go wrong?
  - Various schemes for preventing this kind of thing: variance-based split / merge, initialization heuristics

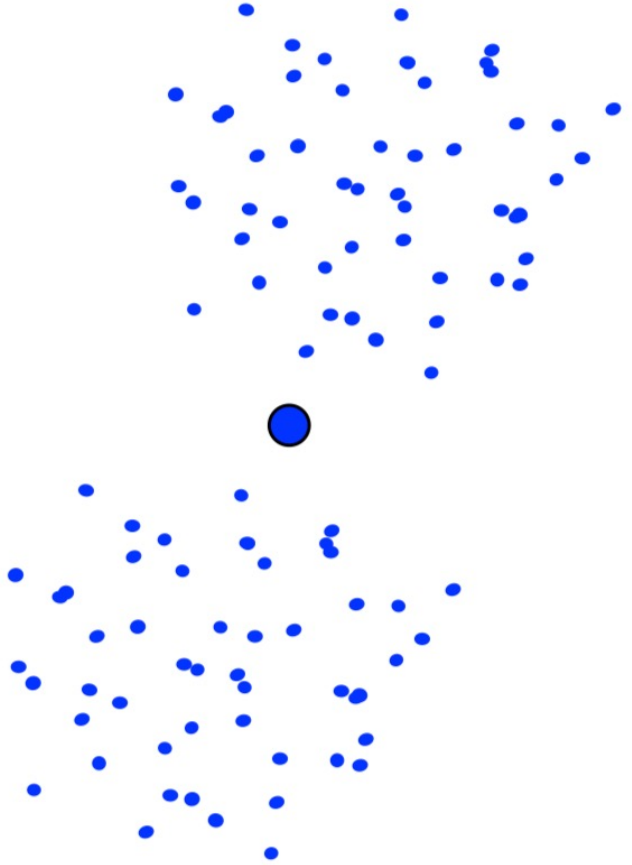




Stuck at Poor Local Minimum

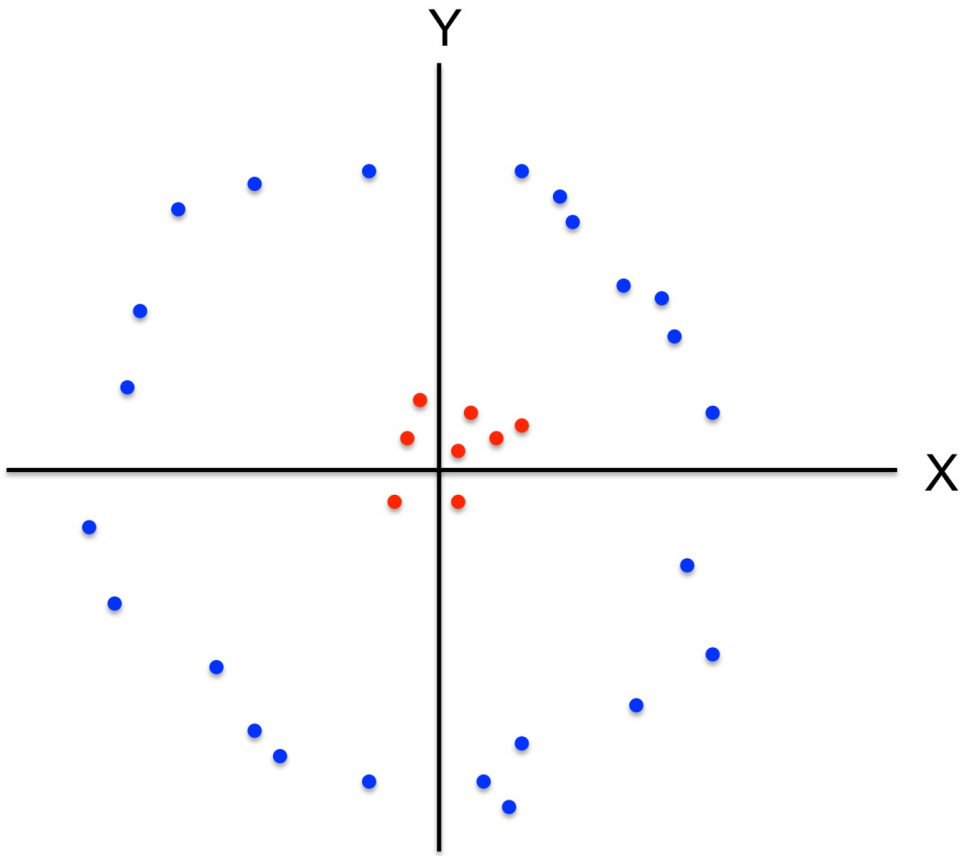


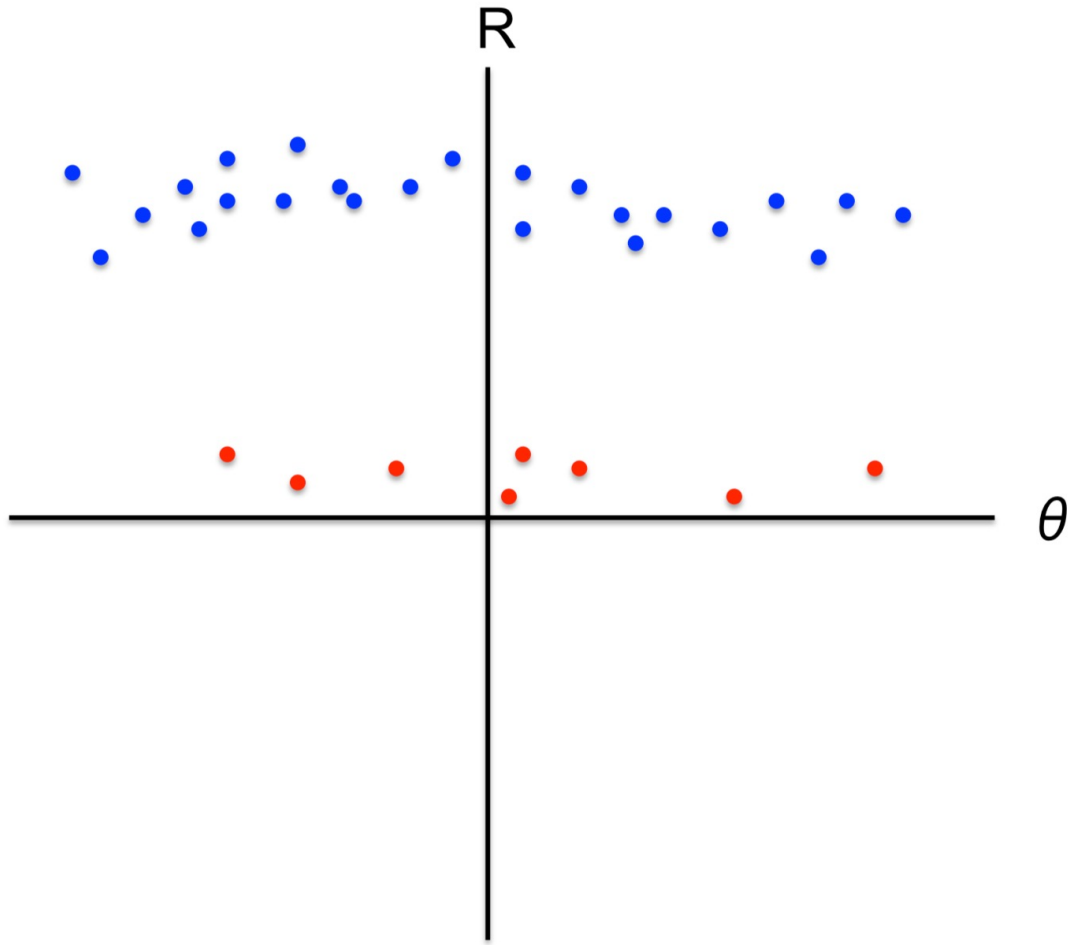
Would be better to have
one cluster here



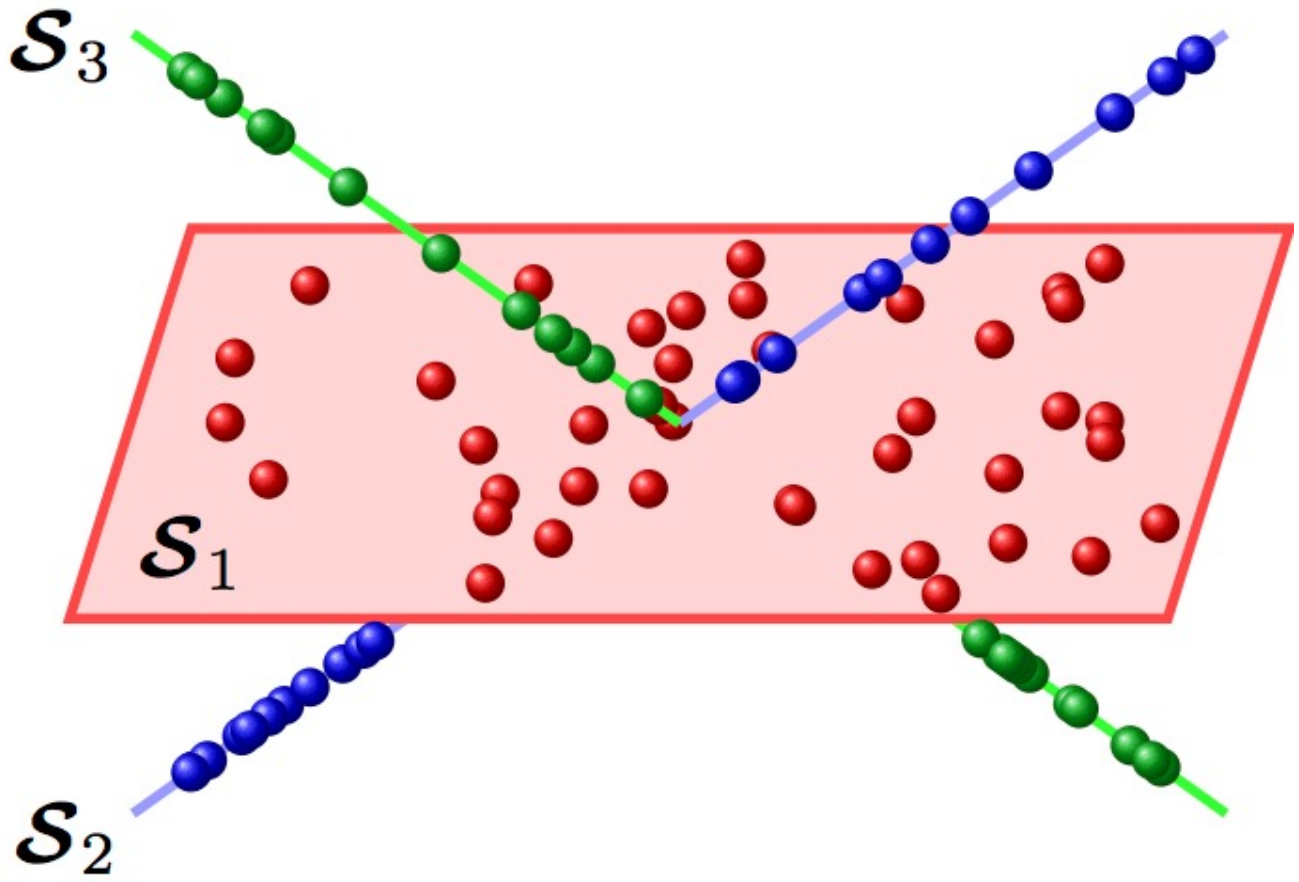
… and two clusters here

Euclidean Distance Might Not be Proper





Do not underestimate clustering!!



cute rabbit bunny animal baby adorable pet funny animals

cheerleader football girls basketball girls dance university sports college

bird birds nature wildlife animal booby eagle hawk flight

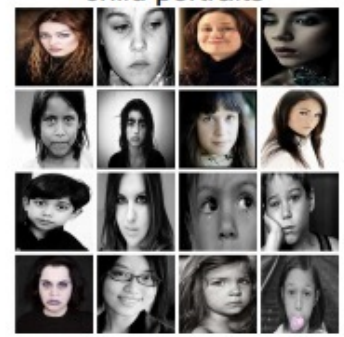
nature macro flower closeup green insect bravo red yellow

music concert rock live festival band scientists dance drum

city urban manhattan new building downtown night architecture buildings

home design office house interior kitchen fashion work room

portrait face self girl woman eyes smile child portraits



abandoned decay old urban rust industrial factory jail rusty

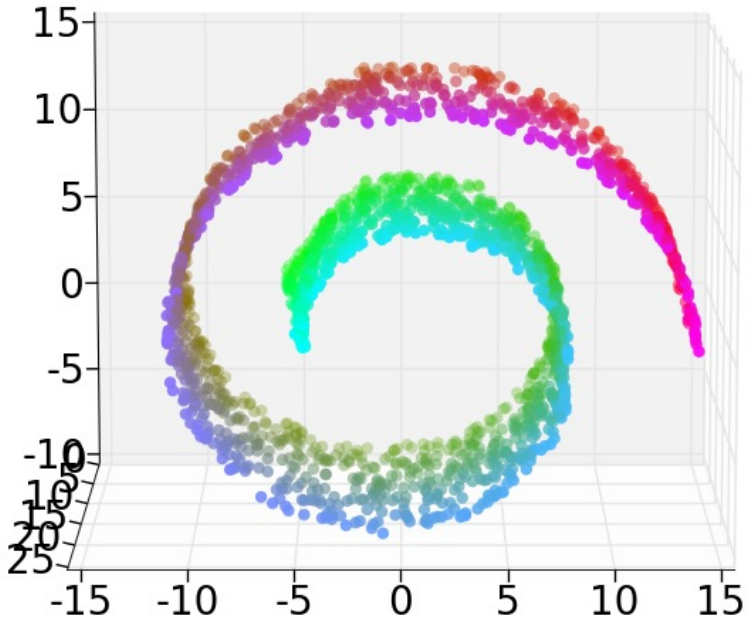
underwater fish diving scuba coral sea ocean reef dive

autumn trees tree park fall leaves forest fog mist

snow winter ice cold nature trees mountains white mountain

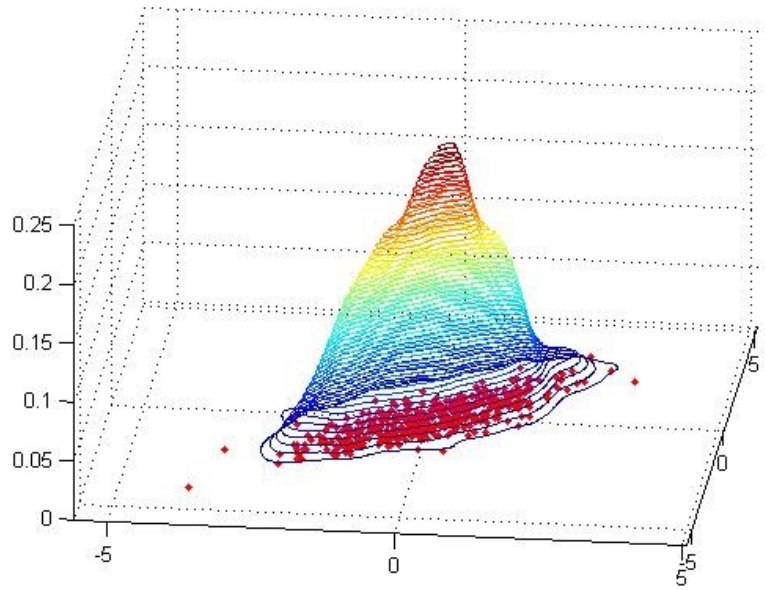
Unsupervised Learning

- **Dimensionality reduction, manifold learning**
  - Discover a lower-dimensional surface on which the data lives



Unsupervised Learning

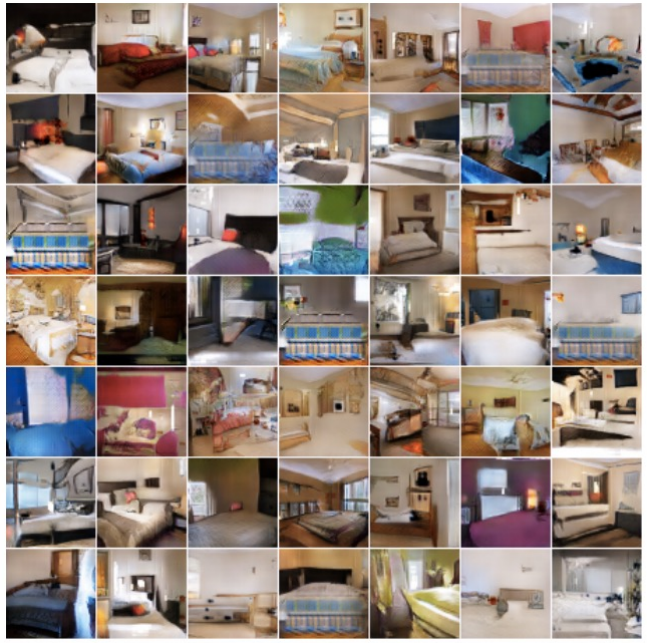
- **Density estimation**
  - Find a function that approximates the probability density of the data (i.e., value of the function is high for “typical” points and low for “atypical” points)
  - Can be used for **anomaly detection**



Unsupervised Learning

- **Density estimation**
  - Produce samples from a data distribution that mimics the training set

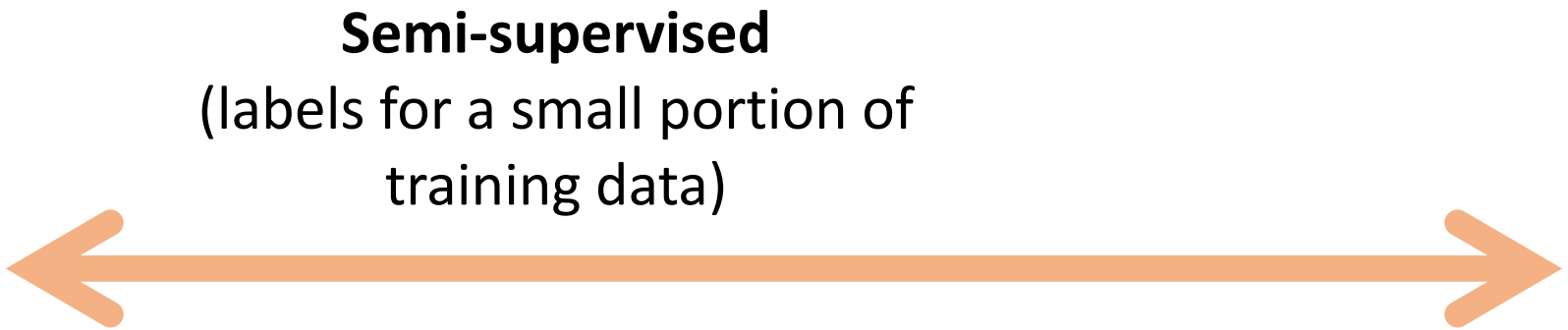
"Bedroom"



"Face"

Generative adversarial networks

Continuum of supervision



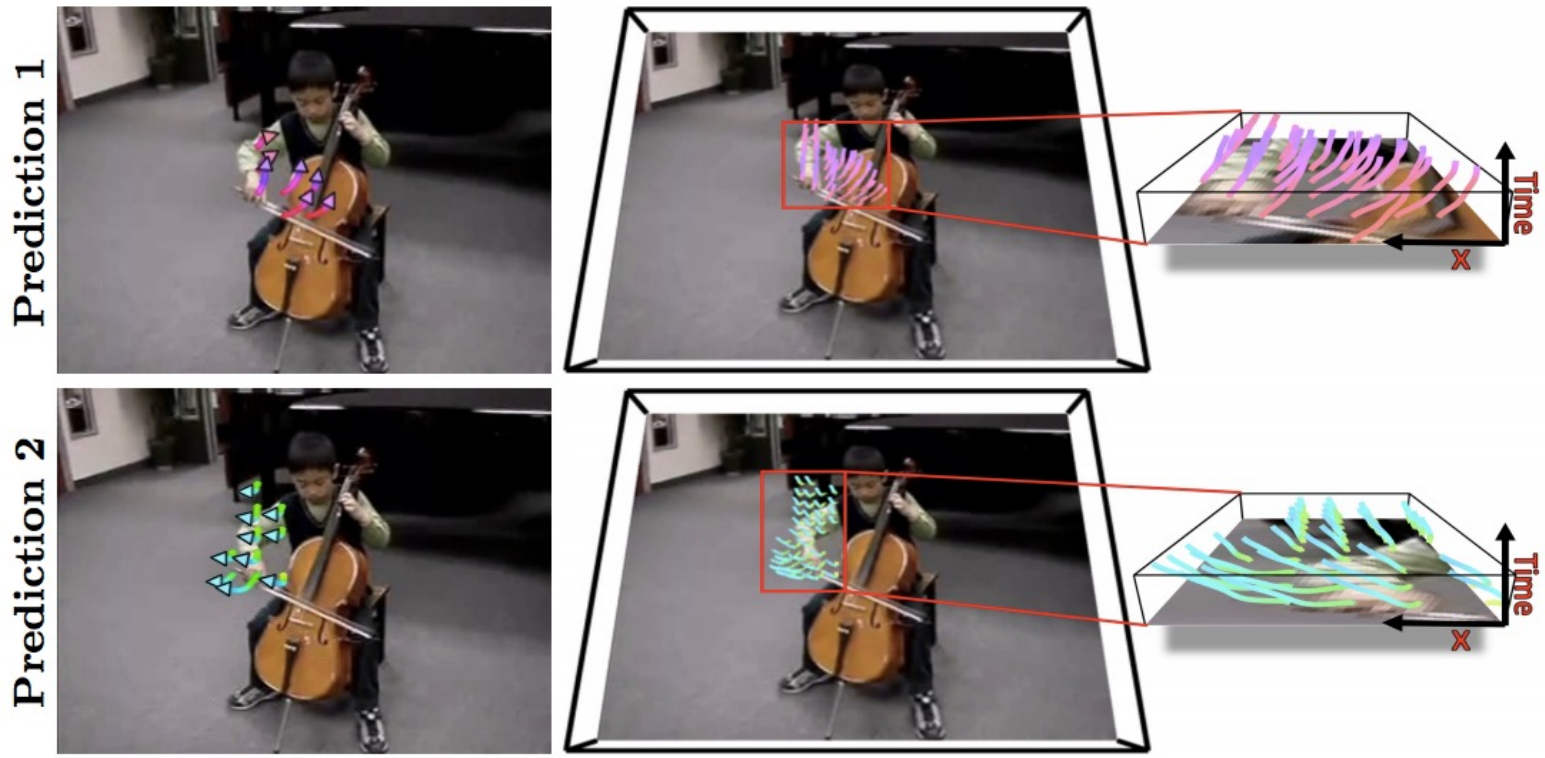
Self-supervised or predictive learning

- Use part of the data to predict other parts of the data
  - Image colorization

R. Zhang et al., Colorful Image Colorization, ECCV 2016

Self-supervised or predictive learning

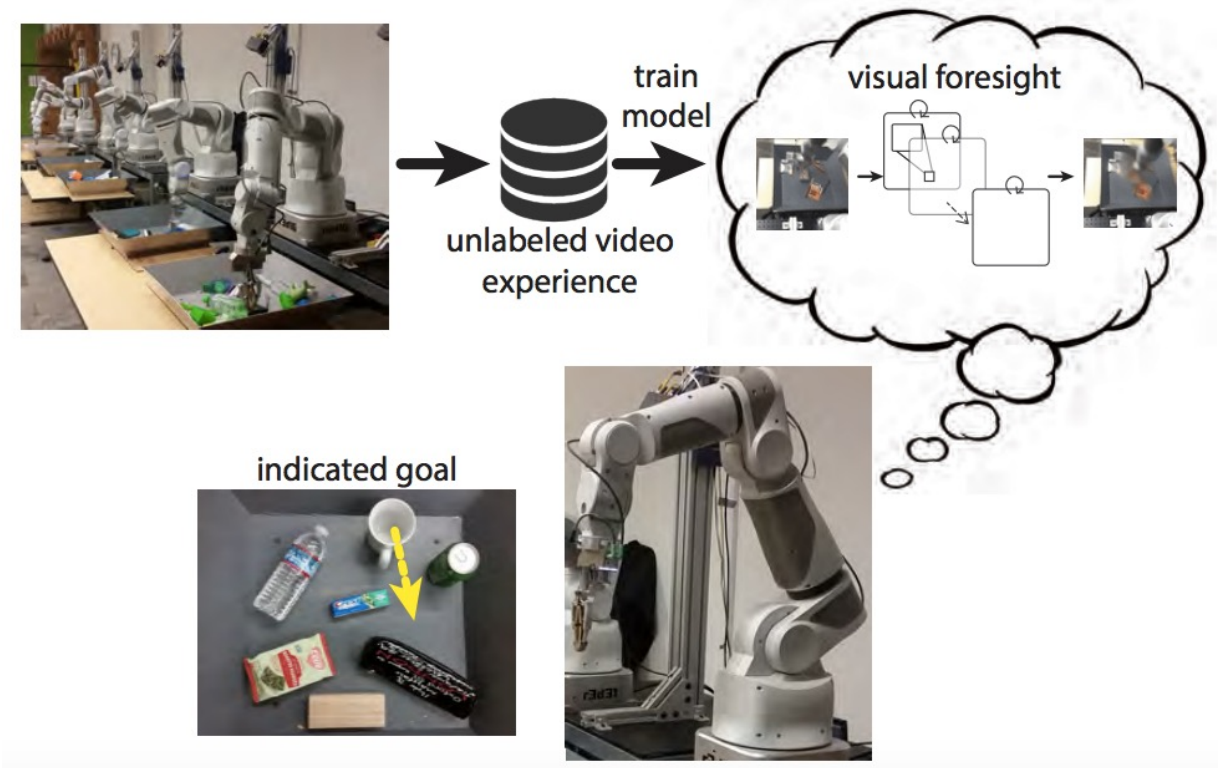
- Use part of the data to predict other parts of the data
  - Future prediction



J. Walker et al. An Uncertain Future: Forecasting from Static Images Using Variational Autoencoders. ECCV 2016.

Self-supervised or predictive learning

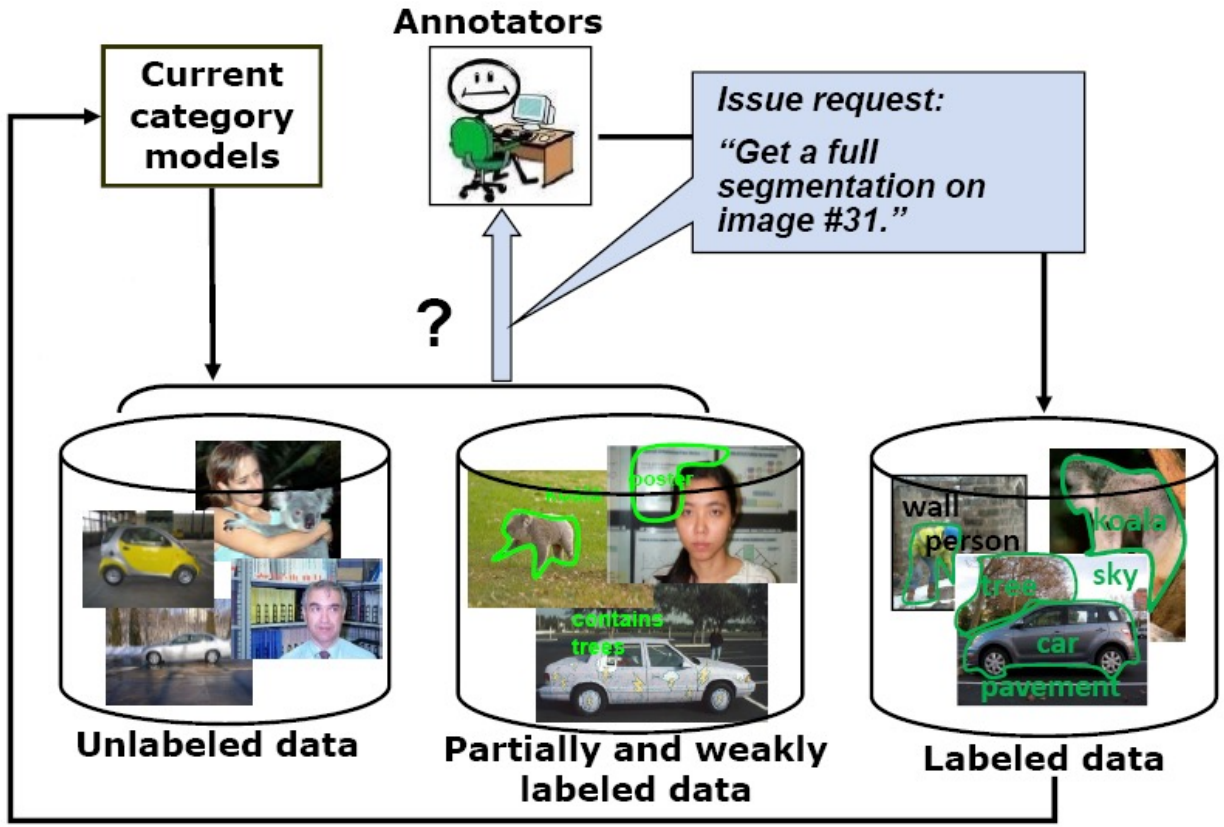
- Use part of the data to predict other parts of the data
  - Future prediction



C. Finn and S. Levine. Deep Visual Foresight for Planning Robot Motion. ICRA 2017. YouTube video

Active learning

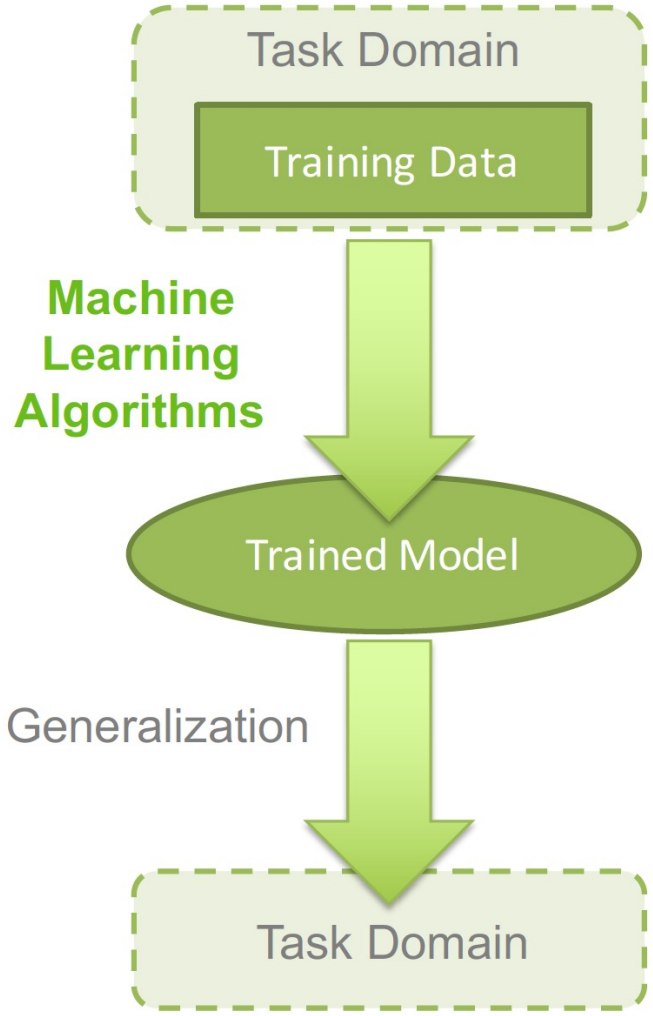
- The learning algorithm can choose its own training examples, or ask a "teacher" for an answer on selected inputs



S. Vijayanarasimhan and K. Grauman, "Cost-Sensitive Active Visual Category Learning," 2009

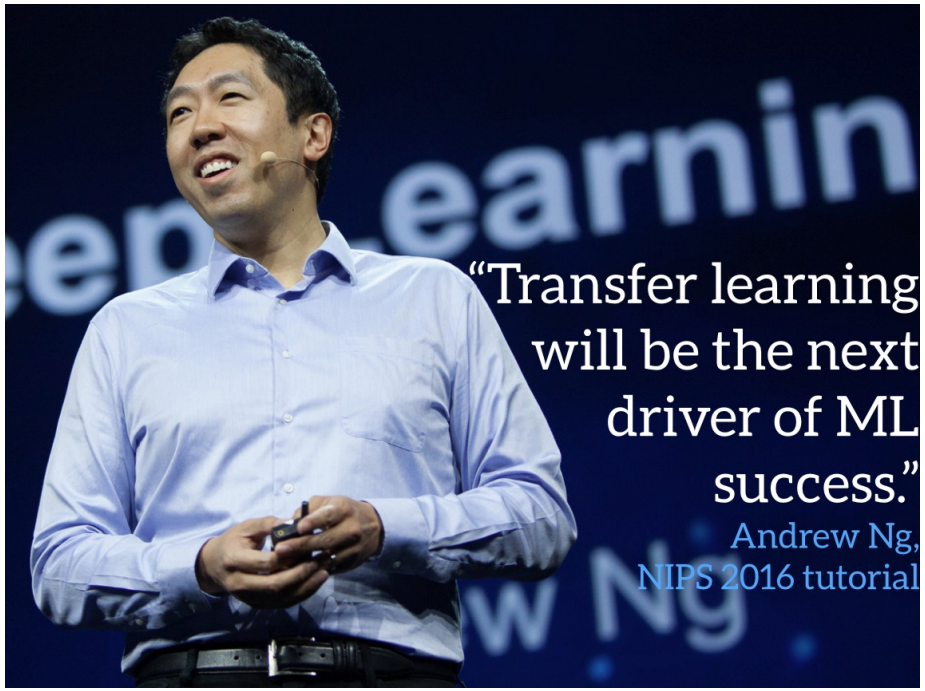
Machine Learning for Single Task

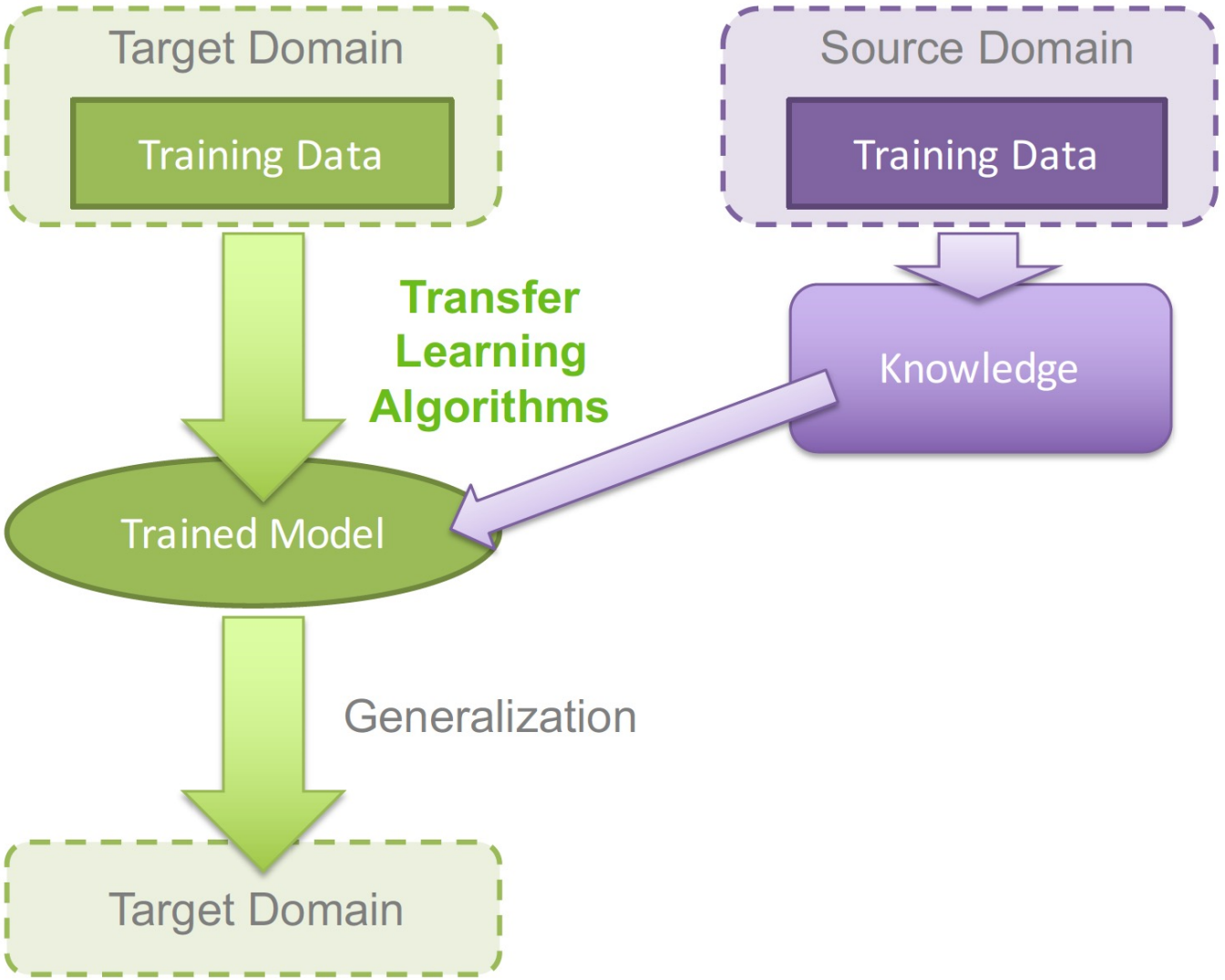
- Elements of machine learning on single task
  - The problem (task/domain)
  - Training data
  - Learning algorithms
  - Trained model
  - Applying model on unseen data (generalization)



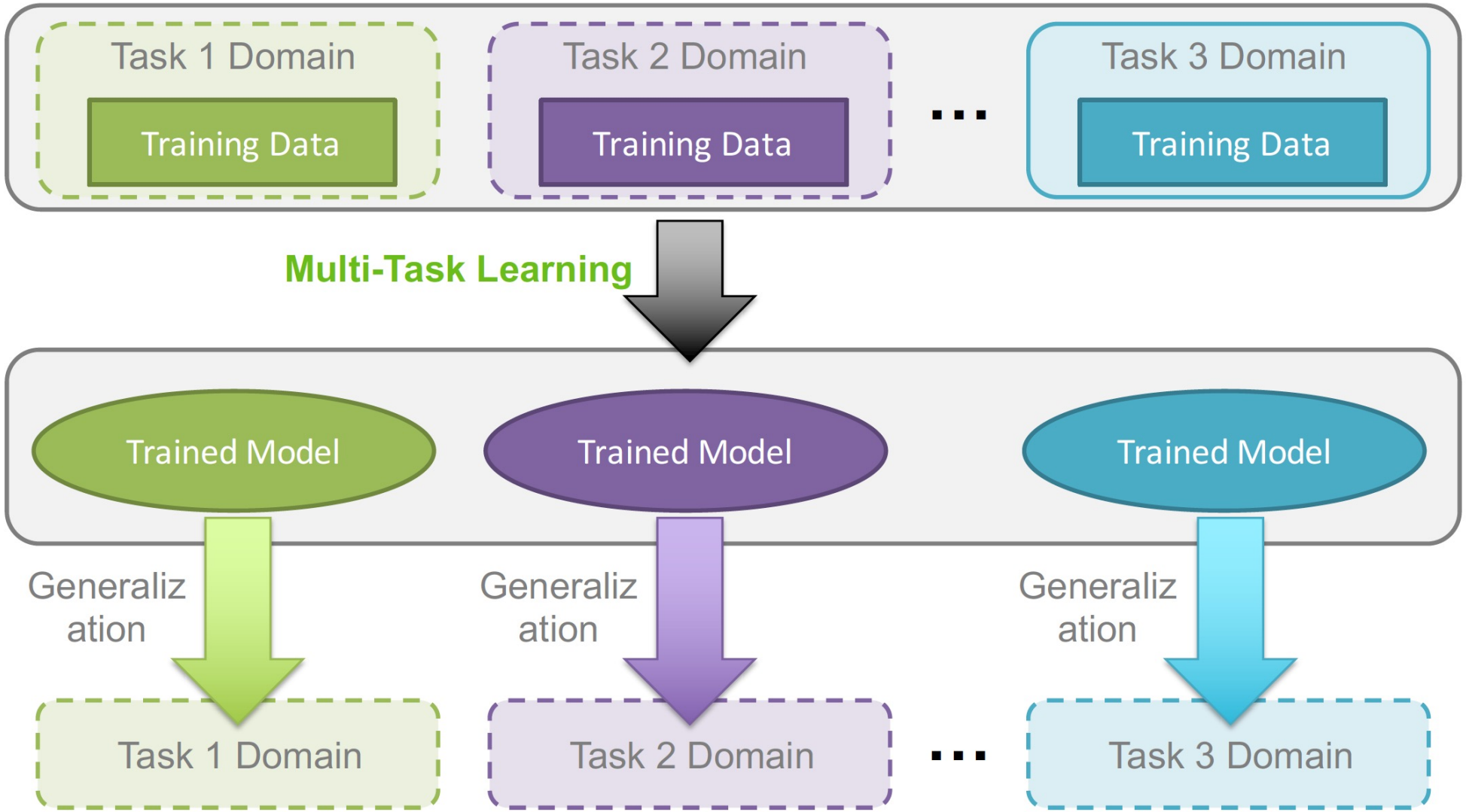
Transfer Learning

Improve Learning New Task
by Learned Task

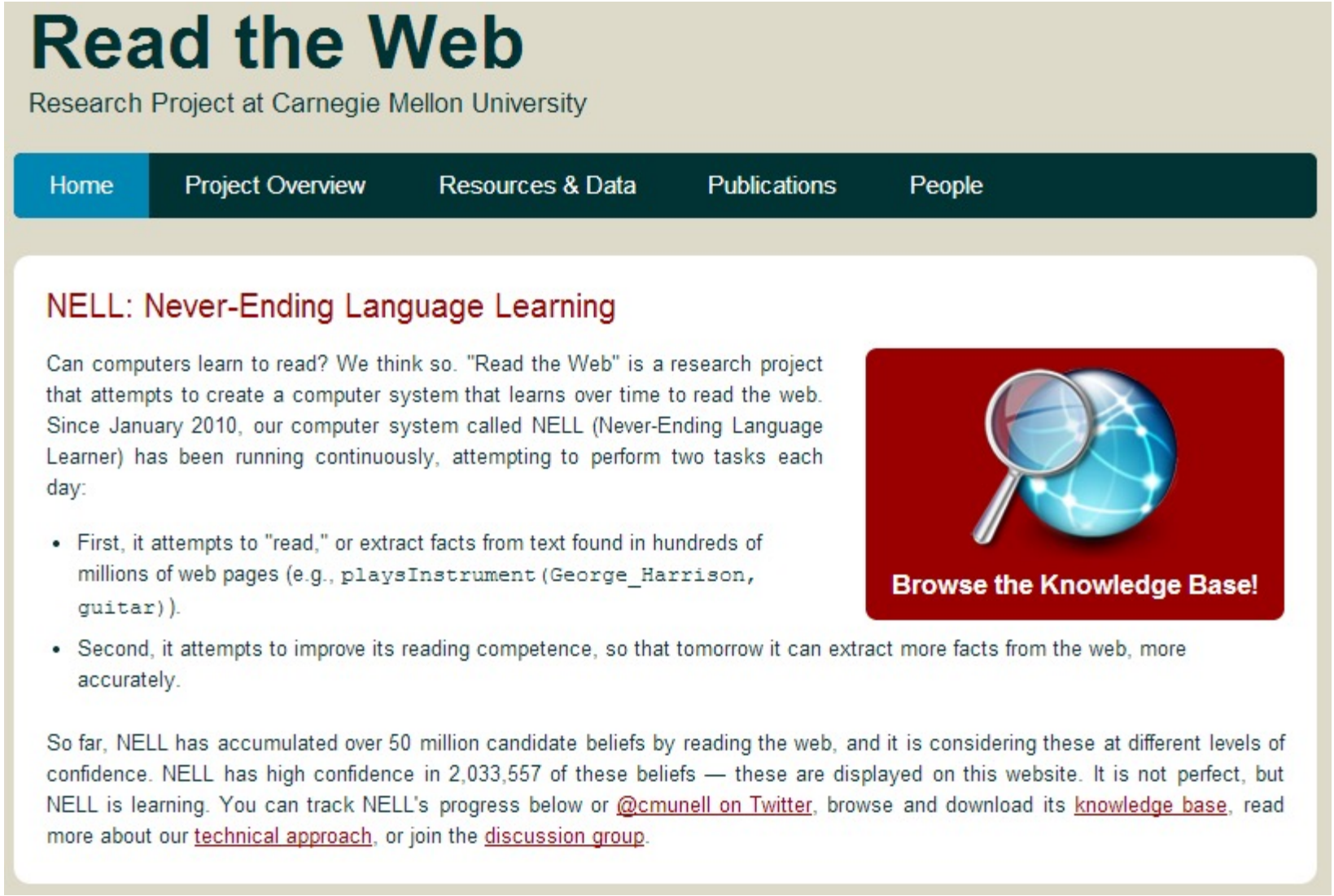




Multi-Task Learning

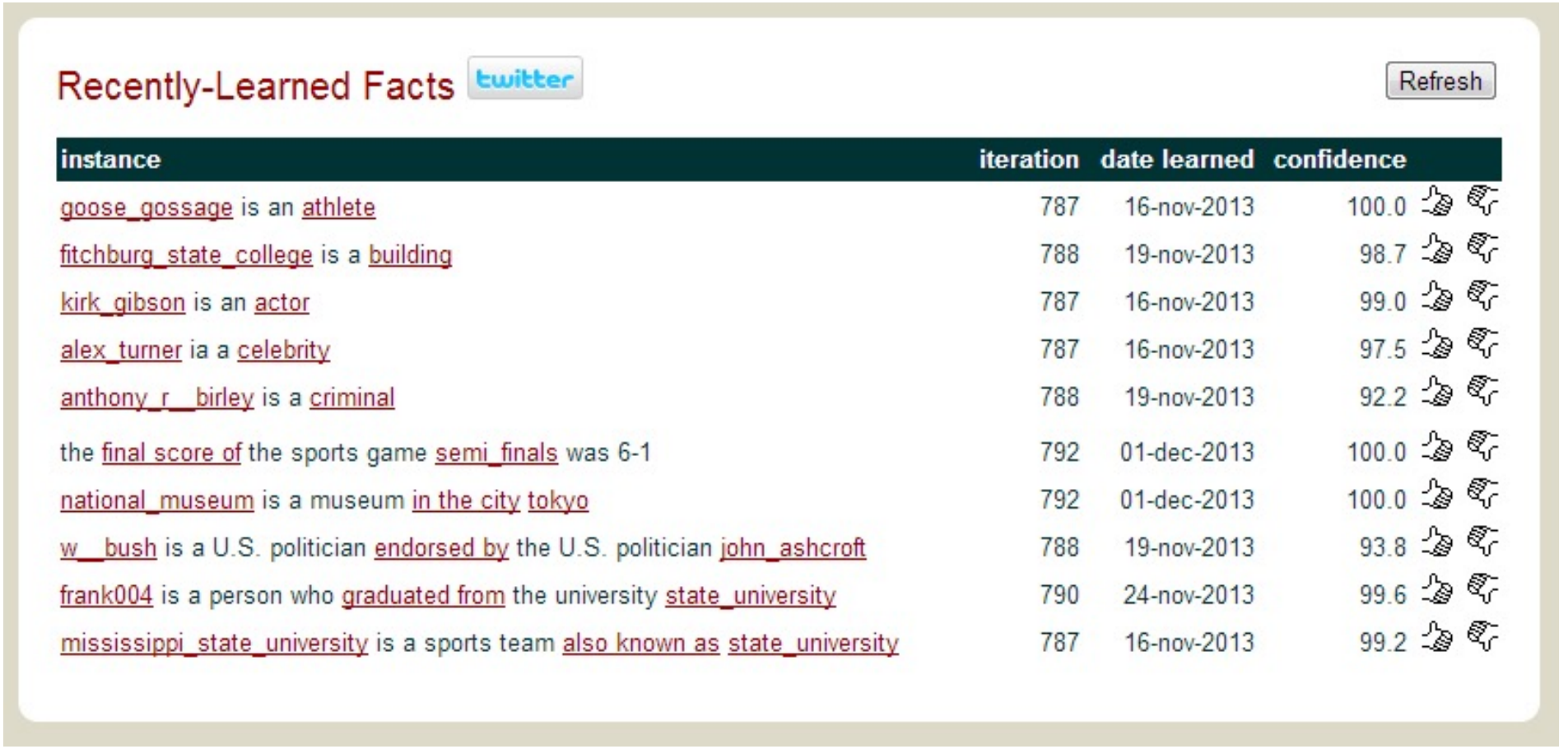


Lifelong learning



http://rtw.ml.cmu.edu/rtw/

Lifelong learning



Recently-Learned Facts twitter Refresh

instance	iteration	date learned	confidence
goose_gossage is an athlete	787	16-nov-2013	100.0
fitchburg_state_college is a building	788	19-nov-2013	98.7
kirk_gibson is an actor	787	16-nov-2013	99.0
alex_turner ia a celebrity	787	16-nov-2013	97.5
anthony_r__birley is a criminal	788	19-nov-2013	92.2
the final score of the sports game semi_finals was 6-1	792	01-dec-2013	100.0
national_museum is a museum in the city tokyo	792	01-dec-2013	100.0
w__bush is a U.S. politician endorsed by the U.S. politician john_ashcroft	788	19-nov-2013	93.8
frank004 is a person who graduated from the university state_university	790	24-nov-2013	99.6
mississippi_state_university is a sports team also known as state_university	787	16-nov-2013	99.2

http://rtw.ml.cmu.edu/rtw/

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Electrical and Computer Engineering
Cockrell School of Engineering