













Inspire...Educate...Transform.

#### **Instance Based Learning**

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#### **Instance Based Learning**

- Also known as "Lazy Learning"
- Store the given training data and don't learn any model
- During query time, retrieve a set of "similar" instances from the training data and use them to classify/predict the new instance
- Essentially construct only local approximations to the target function
- There is no global model learnt to perform well across all instances





## K-NN (K-Nearest Neighbours)

- One of the most basic forms of instance learning
- K-NN Algorithm for Classification

Training method:
Save the training examples

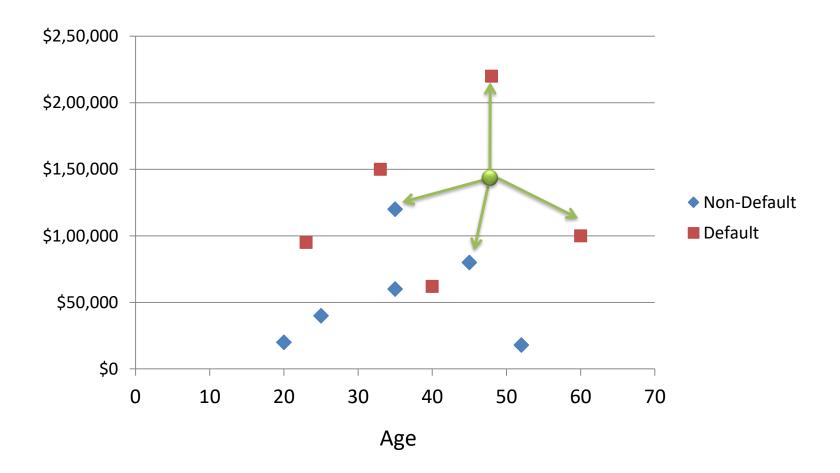
At prediction time:

<u>Find</u> the k training examples  $(x_1, y_1), ...(x_k, y_k)$  that are <u>closest</u> to the test example x Predict the most frequent class among those  $y_i$ 's.





#### K-NN - Classification







## K-NN - Classification (Contd..)

| Age | Loan      | Default | Distance |
|-----|-----------|---------|----------|
| 25  | \$40,000  | N       | 102000   |
| 35  | \$60,000  | N       | 82000    |
| 45  | \$80,000  | N       | 62000    |
| 20  | \$20,000  | N       | 122000   |
| 35  | \$120,000 | N       | 22000    |
| 52  | \$18,000  | N       | 124000   |
| 23  | \$95,000  | Υ       | 47000    |
| 40  | \$62,000  | Υ       | 80000    |
| 60  | \$100,000 | Υ       | 42000    |
| 48  | \$220,000 | Υ       | 78000    |
| 33  | \$150,000 | Υ       | 8000     |
| 40  | 64.42.000 |         |          |
| 48  | \$142,000 | ?       |          |

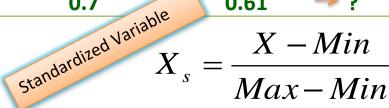
$$D = \sqrt{(x_1 - x_2)^2 + (y_1 - y_2)^2}$$





## K-NN - Classification (Contd..)

| Age   | Loan | Default | Distance |
|-------|------|---------|----------|
| 0.125 | 0.11 | N       | 0.7652   |
| 0.375 | 0.21 | N       | 0.5200   |
| 0.625 | 0.31 | _ N ←   | 0.3160   |
| 0     | 0.01 | N       | 0.9245   |
| 0.375 | 0.50 | N       | 0.3428   |
| 0.8   | 0.00 | N       | 0.6220   |
| 0.075 | 0.38 | Υ       | 0.6669   |
| 0.5   | 0.22 | Y       | 0.4437   |
| 1     | 0.41 | Υ       | 0.3650   |
| 0.7   | 1.00 | Y       | 0.3861   |
| 0.325 | 0.65 | Y       | 0.3771   |
|       |      |         |          |
| 0.7   | 0.61 | , i     |          |







#### **K-NN - Regression**

| Age | Loan      | House Price Index | Distance |
|-----|-----------|-------------------|----------|
| 25  | \$40,000  | 135               | 102000   |
| 35  | \$60,000  | 256               | 82000    |
| 45  | \$80,000  | 231               | 62000    |
| 20  | \$20,000  | 267               | 122000   |
| 35  | \$120,000 | 139               | 22000    |
| 52  | \$18,000  | 150               | 124000   |
| 23  | \$95,000  | 127               | 47000    |
| 40  | \$62,000  | 216               | 80000    |
| 60  | \$100,000 | 139               | 42000    |
| 48  | \$220,000 | 250               | 78000    |
| 33  | \$150,000 | 264               | 8000     |
|     |           |                   |          |
| 48  | \$142,000 | ;                 |          |

$$D = \sqrt{(x_1 - x_2)^2 + (y_1 - y_2)^2}$$





## K-NN Regression (Contd..)

| Age   | Loan | House Price Index | Distance |
|-------|------|-------------------|----------|
| 0.125 | 0.11 | 135               | 0.7652   |
| 0.375 | 0.21 | 256               | 0.5200   |
| 0.625 | 0.31 | 231               | 0.3160   |
| 0     | 0.01 | 267               | 0.9245   |
| 0.375 | 0.50 | 139               | 0.3428   |
| 0.8   | 0.00 | 150               | 0.6220   |
| 0.075 | 0.38 | 127               | 0.6669   |
| 0.5   | 0.22 | 216               | 0.4437   |
| 1     | 0.41 | 139               | 0.3650   |
| 0.7   | 1.00 | 250               | 0.3861   |
| 0.325 | 0.65 | 264               | 0.3771   |
|       |      |                   |          |
| 0.7   | 0.61 | ?                 |          |

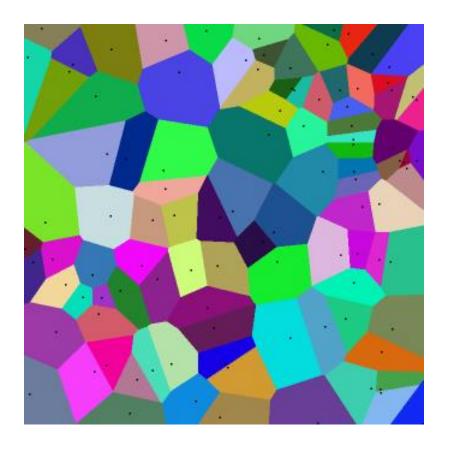
$$X_{s} = \frac{X - Min}{Max - Min}$$





#### **K-NN Decision Boundaries**

#### **Voronoi Diagram**







## Let's play with K-NN

- http://sleepyheads.jp/apps/knn/knn.
   html
- http://scott.fortmannroe.com/docs/BiasVariance.html





# How to determine a good value of "K"?

- Usually tuned using a validation set
- Start with k=1 and test the error rate on validation set
- Repeat with k=k+2
- Choose the value of k which has minimum error rate on validation set
- Note: Odd values of k chosen to avoid ties





## **Improving K-NN**

- Weighting examples from the neighborhood
- Measuring "closeness"
- Finding "close" examples in a large training set quickly





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## **Distance-weighted K-NN**

- Refinement to kNN is to weight the contribution of each k neighbor according to the distance to the query point  $x_q$ 
  - Greater weight to closer neighbors
  - For discrete target functions

$$\hat{f}(x_q) \leftarrow \underset{v \in V}{\operatorname{arg\,max}} \sum_{i=1}^k w_i \delta(v, f(x_i))$$

$$w_{i} = \begin{cases} \frac{1}{d(x_{q}, x_{i})^{2}} & if \quad x_{q} \neq x_{i} \\ 1 & else \end{cases}$$





#### Distance-weighted K-NN (Contd..)

For real valued functions:

$$\hat{f}(x_q) \leftarrow \frac{\sum_{i=1}^k w_i f(x_i)}{\sum_{i=1}^k w_i}$$

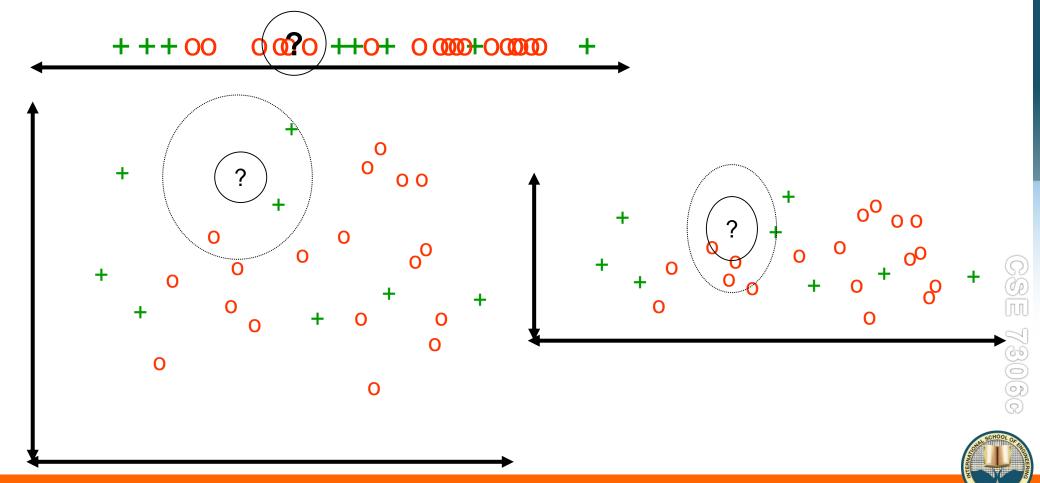
$$w_{i} = \begin{cases} \frac{1}{d(x_{q}, x_{i})^{2}} & if \quad x_{q} \neq x_{i} \\ 1 & else \end{cases}$$





#### **Feature Scaling and Selection**

 K-NN is highly sensitive to the scaling and the subset of features selected as it influences the neighbors



## **Curse of Dimensionality**

- Irrelevant features heavily mislead kNN
- Especially true if the dimensionality of the space is high
- Possible Solutions:
  - -PCA





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## A few ways of rescaling distances

Normalized L1 Distance

$$\Delta(X,Y) = \sum_{i=1}^{n} \delta(x_i, y_i)|$$

where:

$$\delta(x_i, y_i) = \begin{cases} abs(\frac{x_i - y_i}{max_i - min_i}) & \text{if numeric, else} \\ 0 & \text{if } x_i = y_i \\ 1 & \text{if } x_i \neq y_i \end{cases}$$

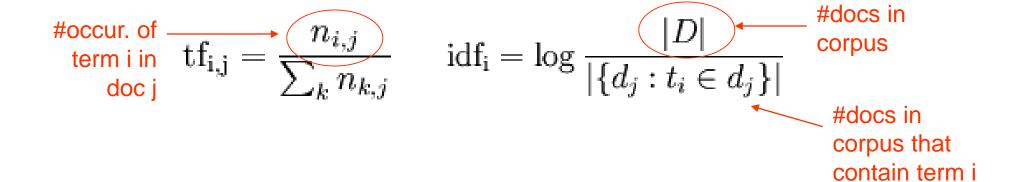
Scale using Information Gain (IG)

$$\Delta(X,Y) = \sum_{i=1}^{n} w_i \, \delta(x_i, y_i) \qquad w_i = H(C) - \sum_{v \in V_i} P(v) \times H(C|v)$$



#### A few ways of rescaling distances

For text, we can use TF-IDF



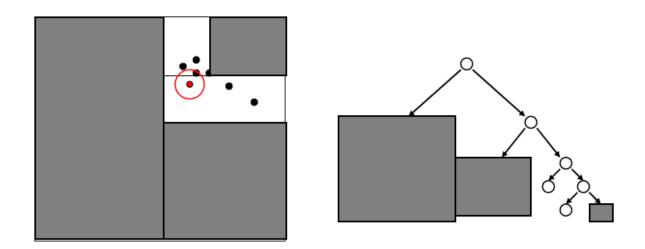




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## Speeding up kNNs

 KD Trees could be used to efficient retrieve closest neighbors for a given query



Using the distance bounds and the bounds of the data below each node, we can prune parts of the tree that could NOT include the nearest neighbor.





#### kNNs - Pros and Cons

- Storage: All training examples are saved in memory
  - A decision tree or linear classifier is much smaller
- Time: To classify x, you need to loop over <u>all</u> training examples (x',y') to compute distance between x and x'.
  - However, you get predictions for every class y
    - kNN is nice when there are many many classes
  - There are some tricks to speed this up...especially when data is sparse





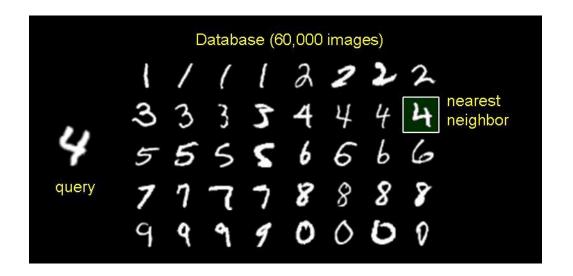
#### **Case Studies - Discussion**

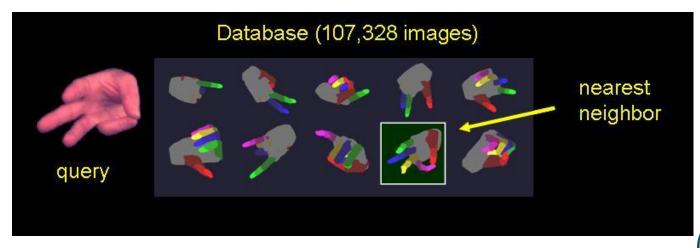
- Handwritten Digit Recognition
- Understanding sign language





#### **Case Studies - Discussion**





#### Summary

- kNN is an example of "Instance Based Learning"
- Conceptually simple, yet able to solve complex problems
- Can work with relatively little information
- Learning is simple (no learning at all!)
- Suffers from the curse of dimensionality
  - Sensitive to representation
  - Feature selection and weighting extremely important
- For practical applications, need to use data structures to speed up retrieval of "close" neighbours





#### References

- Hastie, Tibshirani and Friedman, "Elements of Statistical Learning: Data Mining, Inference and Prediction", Springer
- Duda, Hart and Stork, "Pattern Classification", Wiley Publication
- Tom Mitchell, "Machine Learning", McGraw Hill







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