Applied Analytics and Predictive Modeling Spring 2021

Lecture-12

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Some of the slides adapted from Intro to Data Mining Tan et al. 2nd edition

Today's agenda

- Project details
- K-NN
- Weka demo you can download from https://www.cs.waikato.ac.nz/ml/weka/

K-Nearest Neighbor Algorithm

Adapted from Intro to Data Mining, Tan et al., 2nd edition.

Background

- Situations such as:
 - In Complex decision boundaries
 - If your data is coming in streams
- KNN can address these drawbacks



Nearest Neighbor Classifiers

- Basic idea:
 - If it walks like a duck, quacks like a duck, then it's probably a duck



Nearest-Neighbor Classifiers



- Requires three things
 - The set of labeled records
 - Distance metric to compute distance between records
 - The value of k, the number of nearest neighbors to retrieve
- To classify an unknown record:
 - Compute distance to other training records
 - Identify k nearest neighbors
 - Use class labels of nearest neighbors to determine the class label of unknown record (e.g., by taking majority vote)

- Compute proximity between two points:
 - Example: Euclidean distance

$$d(\mathbf{x}, \mathbf{y}) = \sqrt{\sum_{i} (\mathbf{x}_{i} - \mathbf{y}_{i})^{2}}$$

- Determine the class from nearest neighbor list
 - Take the majority vote of class labels among the k-nearest neighbors
 - Weight the vote according to distance
 - weight factor, $w = 1/d^2$

Example:

• Given this dataset, can you classify this sample data point using *K*-NN where *k*=3 and use Euclidean distance.

To-do:

1. How many classes?

2. To which class does this data point (4,4) belong to?

Can I use this dataset this way without any preprocessing or do I need to do

preprocessing? If so, which operation and if not, why not?

ID	Speed	Agility	Draft
1	400	6	Yes
2	71000	50000	Yes
3	100000	1	No
4	5000	7	Yes
5	1000	200000	No

- (4,4) -> (4,6) = sqrt(4) = 2 -- Yes
- → (7, 5) = sqrt(10) -- Yes
- → (1, 1) = sqrt(18) -- No
- \rightarrow (5, 7) = sqrt((4-5)**2 + (4-7)**2) = sqrt(10) -- Yes
- \rightarrow (1, 2) = sqrt(13) No
- Closest-3 data points: {Yes, Yes, Yes} Yes

- Choosing the value of k:
 - If k is too small, sensitive to noise points
 - If k is too large, neighborhood may include points from other classes



• Choice of proximity measure matters

• For documents, cosine is better than correlation or Euclidean



Euclidean distance = 1.4142 for both pairs

Bag of words model

- Doc1 = "I love ice cream and its cold"
- Doc2 = "I love ice cream"
- Corpus = all the set of documents that you are considering.
- Vocabulary = {I, love, ice, cream, and, its, cold} = 7
- Doc1 = [1, 1, 1, 1, 1, 1, 1]
- Doc2 = [1, 1, 1, 1, 0, 0, 0]

- Doc1 = "my cat likes we fight"
- Doc2 = "my cat fight a lot fight fight"
- Vocabulary = {my, cat, likes, we, fight, a, lot} = 7
- Doc1 = [1, 1, 1, 1, 1, 0, 0]
- Doc2 = [1, 1, 0, 0, 3, 1, 1]

Data preprocessing is often required

- Attributes may have to be scaled to prevent distance measures from being dominated by one of the attributes
 - Example:
 - height of a person may vary from 1.5m to 1.8m
 - weight of a person may vary from 90lb to 300lb
 - income of a person may vary from \$10K to \$1M
- Time series are often standardized to have 0 means a standard deviation of 1

Nearest-neighbor classifiers

- Nearest neighbor classifiers are local classifiers
- They can produce decision boundaries of arbitrary shapes.

1-nn decision boundary is a Voronoi Diagram



• How to handle missing values in training and test sets?

- Proximity computations normally require the presence of all attributes
- Some approaches use the subset of attributes present in two instances
 - This may not produce good results since it effectively uses different proximity measures for each pair of instances
 - Thus, proximities are not comparable

Handling irrelevant and redundant attributes

- Irrelevant attributes add noise to the proximity measure
- Redundant attributes bias the proximity measure towards certain attributes
- Can use variable selection or dimensionality reduction to address irrelevant and redundant attributes

Improving KNN Efficiency

- Avoid having to compute distance to all objects in the training set
 - Multi-dimensional access methods (k-d trees)
 - Fast approximate similarity search
 - Locality Sensitive Hashing (LSH)
- Condensing
 - Determine a smaller set of objects that give the same performance
- Editing
 - Remove objects to improve efficiency

Weka demo..



• Python notebook to follow..