# Nearest Neighbor Methods

Shusen Wang

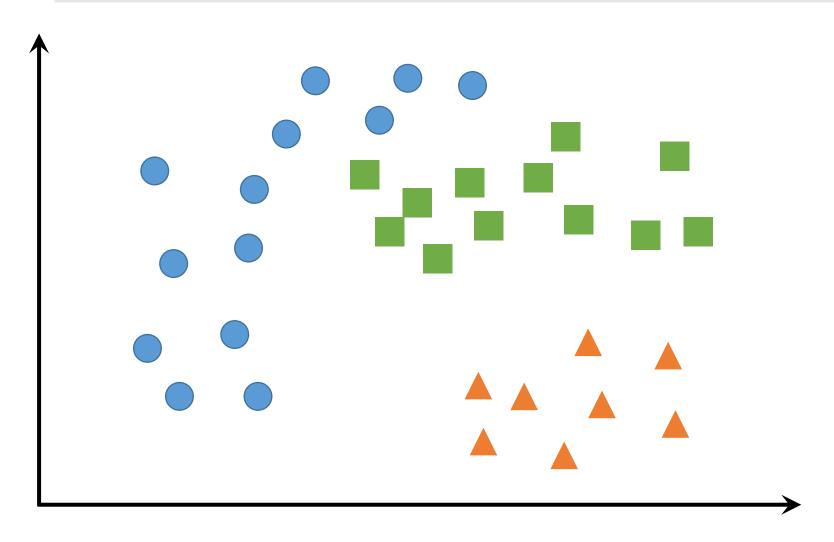
### K-Nearest Neighbor (KNN)

Tasks

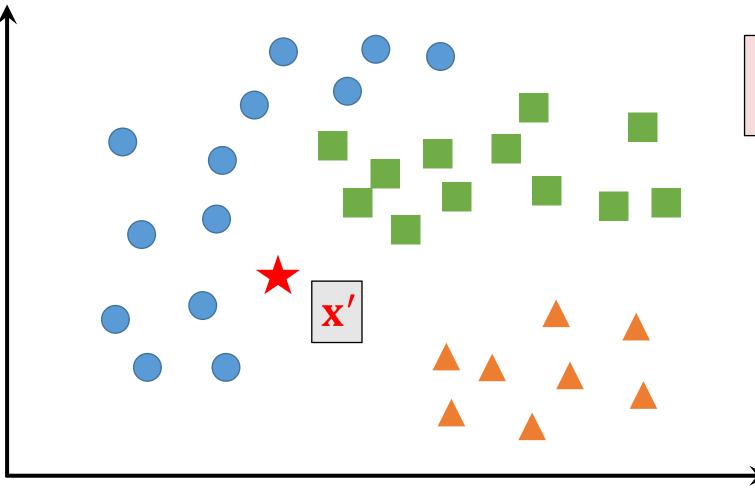
Methods

Algorithms

**Input:** feature vectors  $\mathbf{x}_1, \dots, \mathbf{x}_n \in \mathbb{R}^d$  and labels  $y_1, \dots, y_n \in \mathbb{N}$ .

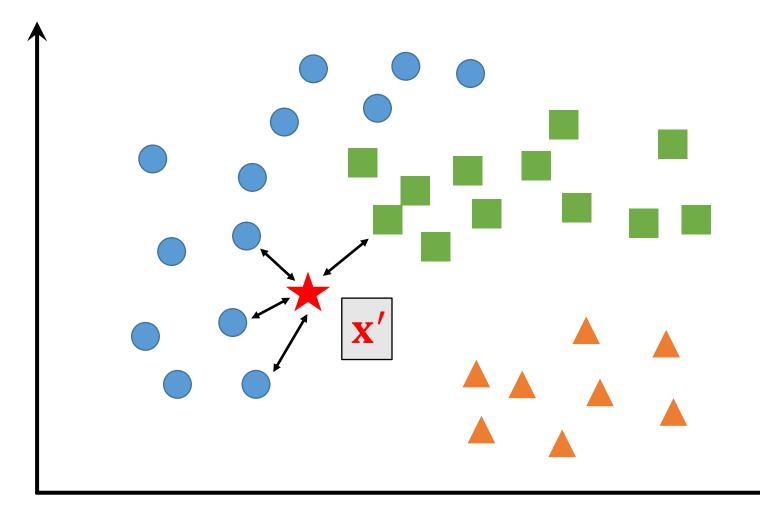


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How to classify an test feature vector **x**'?

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How to classify an test feature vector **x**'?

### k-Nearest Neighbor (KNN):

- Find the k nearest neighbors (NN) of  $\mathbf{x}'$ .
- Let the *k* NNs vote.

**Input:** feature vectors  $\mathbf{x}_1, \dots, \mathbf{x}_n \in \mathbb{R}^d$  and labels  $y_1, \dots, y_n \in \mathbb{N}$ .

### **k**-Nearest Neighbor (KNN) classifier:

- Find the k nearest neighbors of x'.
- Let the NNs vote.

**Question:** How to set *k*?

- Treat k as hyper-parameter.
- Tune k using cross-validation.

**Input:** feature vectors  $\mathbf{x}_1, \dots, \mathbf{x}_n \in \mathbb{R}^d$  and labels  $y_1, \dots, y_n \in \mathbb{N}$ .

### k-Nearest Neighbor (KNN) classifier:

- Find the k nearest neighbors of  $\mathbf{x}'$ .
- Let the NNs vote.

#### **Question:** How to measure similarity?

- Cosine similarity:  $sim(\mathbf{x}, \mathbf{x}') = \frac{\mathbf{x}^T \mathbf{x}'}{||\mathbf{x}||_2 ||\mathbf{x}'||_2}$ .
- Gaussian kernel:  $sim(\mathbf{x}, \mathbf{x}') = exp\left(-\frac{1}{\sigma^2} ||\mathbf{x} \mathbf{x}'||_2^2\right)$ .
- Laplacian kernel:  $sim(\mathbf{x}, \mathbf{x}') = exp\left(-\frac{1}{\sigma}||\mathbf{x} \mathbf{x}'||_{1}\right)$ .

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### k-Nearest Neighbor (KNN) classifier:

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Nearest neighbor of x':

$$\mathbf{x}_{\text{nearest}} = \underset{\mathbf{x} \in \{\mathbf{x}_1, \dots, \mathbf{x}_n\}}{\operatorname{argmax}} \sin(\mathbf{x}, \mathbf{x}').$$

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### k-Nearest Neighbor (KNN) classifier:

- Find the k nearest neighbors of  $\mathbf{x}'$ .
- Let the NNs vote.

**Question:** How to find the k nearest neighbors?

- Naïve algorithm
  - compute all the similarities  $sim(\mathbf{x}_1, \mathbf{x}'), \dots, sim(\mathbf{x}_n, \mathbf{x}')$
  - Sort the scores and find the top k.
  - O(nd) time complexity (n: #samples, d: # features).
- Efficient algorithms (to be discussed later).

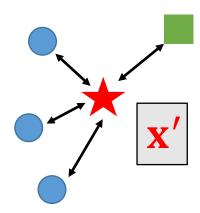
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### k-Nearest Neighbor (KNN) classifier:

- Find the k nearest neighbors of  $\mathbf{x}'$ .
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**Question:** How to vote?

Option 1: Every neighbor has the same weight.



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### k-Nearest Neighbor (KNN) classifier:

- Find the k nearest neighbors of  $\mathbf{x}'$ .
- Let the NNs vote.

Question: How to vote?

- Option 1: Every neighbor has the same weight.
- Option 2: Nearer neighbor has higher weight.
  - E.g., weight<sub>i</sub> =  $sim(\mathbf{x}_i, \mathbf{x}')$

Tasks

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**Algorithms** 

## KNN: Naïve Algorithm

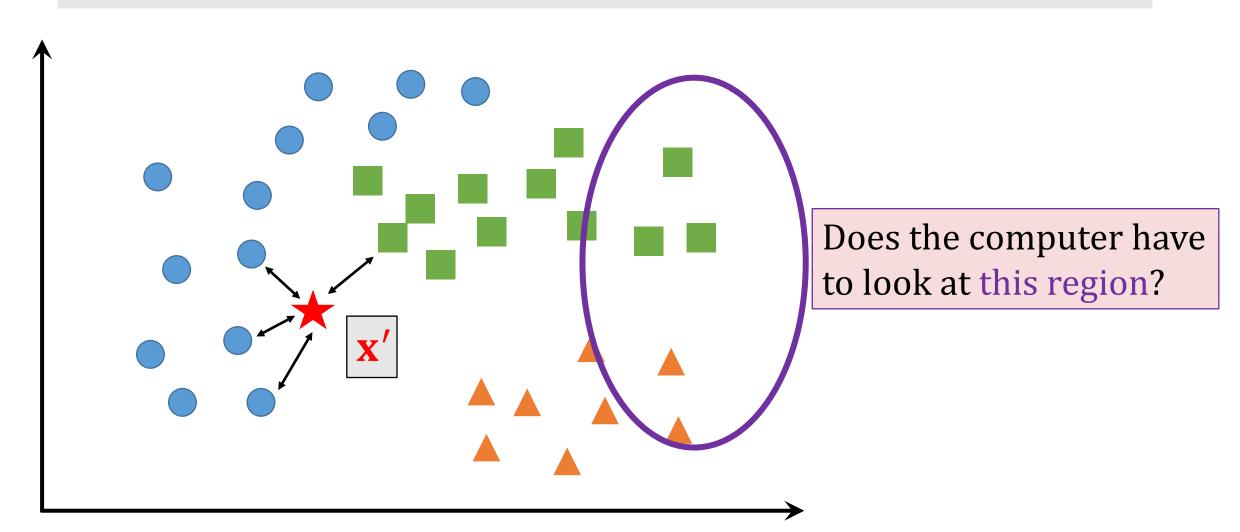
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**Algorithm**: find the k nearest neighbors to  $\mathbf{x}'$ .

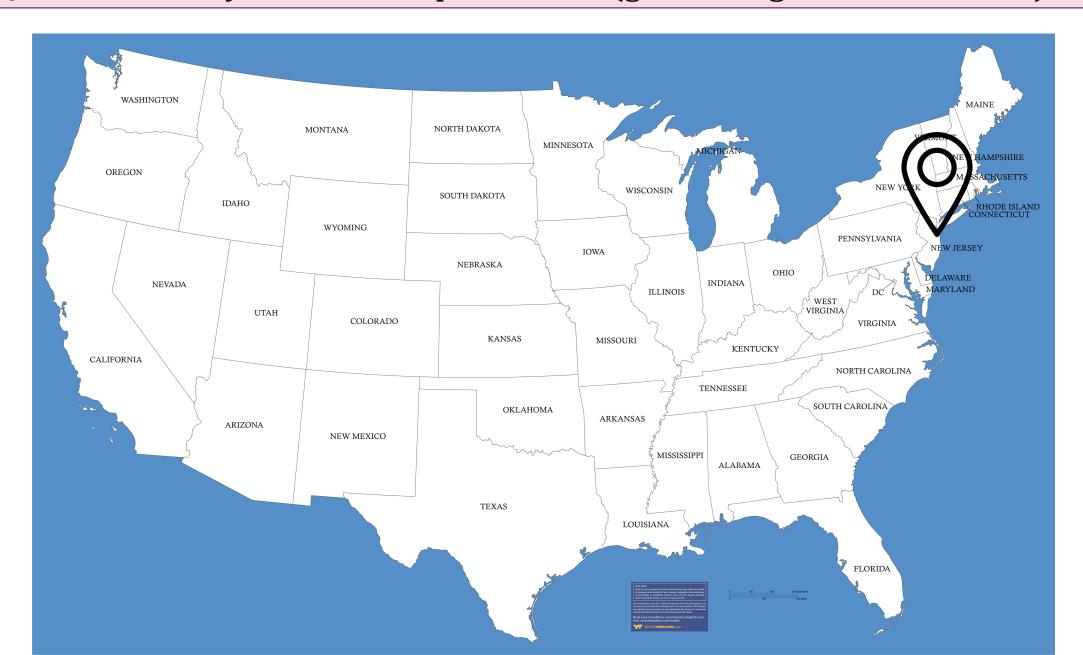
- Naïve algorithm
  - compute all the similarities  $sim(\mathbf{x}_1, \mathbf{x}'), \dots, sim(\mathbf{x}_n, \mathbf{x}')$  and find the top k.
- Training: no training at all.
- Test: for each query, O(nd) time complexity

# **KNN: Efficient Algorithm**

**Input:** feature vectors  $\mathbf{x}_1, \dots, \mathbf{x}_n \in \mathbb{R}^d$  and labels  $y_1, \dots, y_n \in \mathbb{N}$ .



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**Data:** n = 30,000 post offices' latitude and longitude:

- Post office 1: (lat<sub>1</sub>, lon<sub>1</sub>)
- Post office 2: (lat<sub>2</sub>, lon<sub>2</sub>)
- Post office 3: (lat<sub>3</sub>, lon<sub>3</sub>)
- Post office 4: (lat<sub>4</sub>, lon<sub>4</sub>)

•

• Post office n: (lat<sub>n</sub>, lon<sub>n</sub>)

**Query:** your own latitude and longitude:

• (40.74627, -74.02431)

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**Query:** your own latitude and longitude:

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Question: Which is your nearest post office?

• Post office n: (lat<sub>n</sub>, lon<sub>n</sub>)



#### Training:

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#### **Test**

 Compare your location with all the landmarks and find the nearest landmarks.

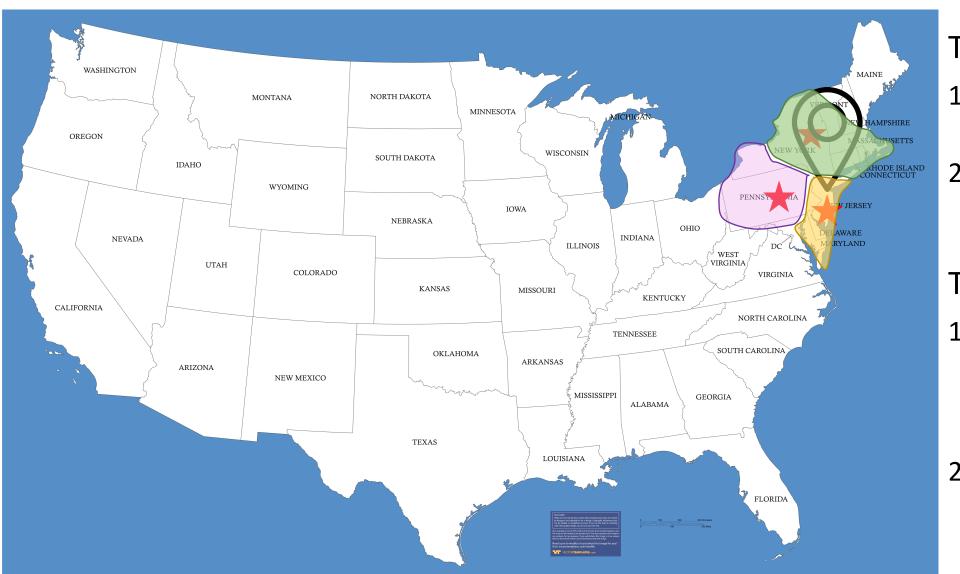


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#### Training:

- Vector quantization (build landmarks)
- Assign each post office to its nearest landmarks.

#### **Test**

- Compare your location with all the landmarks and find the nearest landmarks.
- Compare with the postal offices assigned to the landmarks.

# **KNN: Efficient Algorithms**

- Fast algorithms
  - Vector Quantization
  - KD-tree
  - Locality sensitive hashing

- More resources:
  - KNN Search (Wikipedia)

### Summary

KNN method for multi-class classification.

- KNN's advantage over Softmax classifier:
  - When #class is huge, Softmax classifier is expensive.
  - E.g., in the face recognition problem, #class can be millions.

## Summary

- Training: partition the feature space to regions.
- Prediction (for a test feature vector x'):
  - 1. Find the nearest regions.
  - 2. Retrieve all the training feature vectors in the regions.
  - 3. Compare  $\mathbf{x}'$  with the retrieved feature vectors (using similarity score) and return the k nearest.
  - 4. Weighted/unweighted votes by the k nearest neighbors.