# CS167: Machine Learning

#### Notebook#1 questions k-Nearest Neighbor (k-NN)

Tuesday, February 13th, 2024



#### Announcements

- Notebook #1, is due tonight by 11:59 pm
  - to submit, download the ipynb file from Colab
  - directly upload to CodePost
- <u>Notebook #2: kNN and Normalization</u> will be released soon
  - due a week after the release
- Heads up that Quiz #1
  - will be released on Tuesday 02/20 after class
  - will be due Tuesday 02/27 by 11:59pm

# Today's Agenda

- Topics:
  - Notebook # 1 Help
  - Quick Overview about ML
  - k-Nearest Neighbor (k-NN)
  - Distances
  - kNN Implementation using Pandas

Before we get started, let's load in our datasets:

- Make sure you change the path to match your Google Drive.
  - Also, go ahead and download the vehicles.csv file from Blackboard and put it in your Google Drive

[2] #run this cell if you're using Colab: from google.colab import drive drive.mount('/content/drive')

```
#import the data:
#make sure the path on the line below corresponds to the path where you put your
import pandas as pd
path1 = '/content/drive/MyDrive/cs167_fall23/datasets/titanic.csv'
titanic = pd.read_csv(path1)
```

```
path2 = '/content/drive/MyDrive/cs167_fall23/datasets/irisData.csv'
iris= pd.read_csv(path2)
iris.head()
```

path3 = '/content/drive/MyDrive/cs167\_fall23/datasets/vehicles.csv'
vehicles= pd.read\_csv(path3)
vehicles.head()

# Notebook #1 Help

- A few helpful functions for Notebook #1:
  - max() will return the maximum value in a Series
  - idxmax() will return the index of the maximum value

[ ] #find the deck of the passenger who was the oldest on the titanic titanic.age.max()

80.0

[10] ndx = titanic.age.idxmax() ## returns the name of the 'row' and NOT integer index of the row
 print(ndx)
 titanic.loc[ndx].embark\_town

630 'Southampton'

# Notebook #1 Help

- Other functions worth mentioning:
  - min() will return the minimum value in a Series
  - mode() will return the mode the most common value of the dataset



# Notebook #1 Help

- Pandas Exercises Solutions (Day03 Solutions)
  - Posted the solution on Blackboard

# Today's Agenda

- Topics:
  - Notebook # 1 help
  - Quick Overview about ML
  - k-Nearest Neighbor (k-NN)

- Distances
- kNN Implementation using Pandas

# **Quick Overview**

- So far, we've talked about:
  - Introduction to ML
  - Python review
  - Introduction to Pandas

# **Quick Overview**

- Quick simple statistics review:
  - mean: the average, take the sum of elements, and divide by the number of total elements
  - median: The middle number; found by ordering all data points and picking out the one in the middle (or if there are two numbers in the middle, taking the mean of those two numbers)
  - mode: The most frequent number; the number that occurs the highest number of times

## Poll

- Participate in the following poll:
  - https://forms.gle/XxVom9ezek9s5u8b9

# Machine Learning Variations

- We are going to learn about a lot of different types of machine learning in CS167. Here are a few categories to look out for:
  - **classification:** identify which category it goes in. Examples: Spam or ham? Reza or Eric? Fish, amphibian, reptile, bird, or mammal
  - **regression**: real-valued labels. Examples: price of Bitcoin, tomorrow's temperature, etc
  - **supervised learning:** data has labels, goal is to predict the labels of new instance
  - **unsupervised learning:** data does not have a label, the goal is to analyze/cluster the examples
  - **other issues:** missing data, sequential data, outlier anomaly detetion, and many more

# Terminology Alert!

- Load the "Iris" Dataset (which we already did on the 4th slide)
- Let's take a look at a couple rows of the "Iris" Dataset:

iris.head(2)								
	sepal length	sepal width	petal length	petal width	species			
0	5.1	3.5	1.4	0.2	Iris-setosa	11.		
1	4.9	3.0	1.4	0.2	Iris-setosa			

# Terminology Alert!

iris.head(2)								
	sepal length	sepal width	petal length	petal width	species	Ħ		
0	5.1	3.5	1.4	0.2	Iris-setosa	11.		
1	4.9	3.0	1.4	0.2	Iris-setosa			

- Each row in the table represents a training example, a previously-seen, known instance of the thing we are trying to model
- Each column in the table represents a **feature**, some attribute or variable that each training example has a value for
- Target variable: the 'feature' we will try to predict (species in this case) it's value is unknown for any new cases not in the training data
- Predictor variables: (or just predictors), the features that will be used to make predictions of the target variable e.g., sepal length, petal length, sepal width, petal width

# Terminology Alert!

• Remember this question from Day01?



Imagine you found this beautiful flower while on a walk and took the following measurements:

5.1 cm petal length 7.2 cm sepal length

What species do you think it is?



CS 167: Machine Learning

# Today's Agenda

- Topics:
  - Notebook # 1 help
  - Quick Overview about ML
  - k-Nearest Neighbor (k-NN)

- Distances
- kNN Implementation using Pandas

# Our First Machine Learning Model: kNN

- We are starting with a relatively simple, but foundational, machine learning model, the k-Nearest Neighbors (kNN) algorithm.
  - 1-Nearest-Neighbor Algorithm: predict the most commonly appearing class among the 1 closest training examples
  - **3-Nearest-Neighbor Algorithm:** predict the *most commonly appearing* class among the 3 closest training examples

• k-Nearest-Neighbor Algorithm: predict the most commonly appearing class among the k closest training examples

...

# 1-Nearest Neighbor (1-NN)

- 1-Nearest-Neighbor Algorithm: predict the most commonly appearing class among the 1 closest training examples
  - In other words, k=1
- Let's assume this subset of Iris has only 2 classes (even number):

Iris-versicolor Iris-virginica

• What class will a 1NN algorithm predict?



# 3-Nearest Neighbor (3-NN)

- 3-Nearest-Neighbor Algorithm: predict the most commonly appearing class among the 3 closest training examples
  - In other words, k=3
- Let's assume this subset of Iris has only 2 classes (even number): Iris-versicolor

Iris-virginica

• What class will a **3NN** algorithm predict?



# k-Nearest Neighbor (k-NN)

- k-Nearest-Neighbor Algorithm: predict the *most commonly appearing* class among the k closest training examples
- The full Iris Dataset has 3 classes (odd number):

Iris-versicolor Iris-virginica Iris-setosa

What value of k we should use for k-NN algorithm to predict correctly?



# k-Nearest Neighbor (k-NN)

- k-Nearest-Neighbor Algorithm: predict the most commonly appearing class among the k closest training examples
- What value of k we should use for k-NN algorithm to predict correctly?
  - In general, try out various values of k=1, k=2, ..., k=100 etc
  - Find out the accuracies on validation set (NOT ON TRAINING SET)
  - Pick the k-value for which you get the highest accuracy on validation set (NOT ON TRAINING SET)

# What do you mean by "closest"?

• **k-Nearest-Neighbor Algorithm:** Predict the *most commonly appearing* class among the **k** closest training examples.

• Alright ... but how do we determine which training examples are the 'closest'?

- **defining 'nearness':** as the machine learning engineer, we get to choose how we define *close*.
  - What ways can you think of to determine a distance between any two training examples?

# Today's Agenda

- Topics:
  - Notebook # 1 help
  - Quick Overview about ML
  - k-Nearest Neighbor (k-NN)

- Distances
- kNN Implementation using Pandas

• Euclidean distance: example in 2D space the distance between two points (x1, y1) and (x2, y2) is:

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

• **2D Euclidean distance:** example in 2D space the distance between two points (1, 2) and (4, 6):

$$\sqrt{(1-4)^2 + (2-6)^2}$$

$$\sqrt{(-3)^2 + (-4)^2}$$

$$\sqrt{9+16}$$

$$\sqrt{25}$$
5

• Euclidean distance in n-Dimensional Space:

Suppose features of an example:

$$\langle a_1(x), a_2(x), \ldots, a_n(x) \rangle$$

• where *n* is the number of features.

Then the Euclidean Distance:

$$d(x_i, x_j) = \sqrt{\sum_{r=1}^n (a_r(x_i) - a_r(x_j))^2}$$

• Example for Euclidean distance in n-Dimensional Space:

$$d(x_i, x_j) = \sqrt{\sum_{r=1}^n (a_r(x_i) - a_r(x_j))^2}$$

Suppose we find a new iris with:

• 7.2 cm sepal length, 2.5 cm sepal width, 5.1 cm petal length, and 1.5 cm petal width

Here are some rows from the training data:

sepal length	sepal width	petal length	petal width	species
4.6	3.2	1.4	0.2	Iris-setosa
6.2	2.8	4.8	1.8	Iris-virginica

• Example for Euclidean distance in n-Dimensional Space:

$$d(x_i, x_j) = \sqrt{\sum_{r=1}^n (a_r(x_i) - a_r(x_j))^2}$$



Distance from this new iris sample to training data:

## **Group Exercise: Distances**

• Example for Euclidean distance in n-Dimensional Space:

$$d(x_i, x_j) = \sqrt{\sum_{r=1}^n (a_r(x_i) - a_r(x_j))^2}$$

Distance from this new iris sample to following training data samples:

• <7.2 cm, 2.5 cm, 5.1 cm, and 1.5 cm>

sepal length	sepal width	petal length	petal width	species
4.6	3.2	1.4	0.2	lris-setosa
6.2	2.8	4.8	1.8	Iris-virginica
6.2	2.2	4.5	1.5	Iris-versicolor
6.3	2.7	4.9	1.8	Iris-virginica

• What would the 1-NN version predict? 2-NN? 3-NN? 4-NN?

# **Other Distance Functions**

• You can use any distance function you want. Other common distances include:

Manhattan Distance:

$$d(x_i, x_j) = \sum_{r=1}^n |a_r(x_i) - a_r(x_j)|$$

• Minkowski distance:

$$d(x_i, x_j) = (\sum_{r=1}^n |a_r(x_i) - a_r(x_j)|^p)^{1/p}$$

#### • Or you can make your own:

- Online dating use distance scores to predict who you will swipe left/right on
- Baseball similarity matrix
- etc.

# **Discussion Question**

- What do we do if the features aren't numbers?
  - like Titanic embark\_town... how can we calculate a distance between Southampton and Queenstown?

pd.get\_dummies(titanic.embark\_town)

	C→		Cherbourg	Queenstown	Southampton
<pre>[ ] titanic.embark_town.unique()</pre>		0	0	0	1
array(['Southampton', 'Cherbourg', 'Queenstown', nan]		1	1	0	0
		2	0	0	1
		3	0	0	1
		4	0	0	1
		886	0	0	1
		887	0	0	1
		888	0	0	1
		889	1	0	0
		890	0	1	0
		891 ro	ows × 3 columr	IS	

CS 167: Machine Learning

# **Discussion Question**

- What if our **target variable** is continuous rather than categorical? How would we make a prediction using kNN?
  - Can we do regression with kNN? If so, how?

- Example of Regression problems
  - predict tomorrow's temperature
  - predict the fuel efficiency of a vehicle
  - predict how much someone will like a show on Netflix

# Today's Agenda

- Topics:
  - Notebook # 1 help
  - Quick Overview about ML
  - k-Nearest Neighbor (k-NN)

- Distances
- kNN Implementation using Pandas

# k-NN Implementation in Python/Pandas

- Let's build a 5-Nearest-Neighbor Iris classifier from scratch using our Pandas/Python skills:
- To implement this 5NN, we need to do 3 things:
  - 1. Calculate the distances from each of the rows to the new instance
  - 3. Sort the data by these distances
  - 5. Select the k closest training examples and use them to predict the most commonly occurring class of the closest neighbors.

# Step 1: Calculate the Distances

- Let's start by adding a new column to our iris DataFrame that is the distance from each existing row to the new instance with:
  - 5.1 petal length, 7.2 sepal length, 1.5 petal width, and 2.5 sepal width
  - The syntax for adding a new column is as follows:

```
• df['new col name'] = _____
```

# Step 2: Sort the data by the Distances

- Let's now sort our data using the built in sort\_values() function.
   [documentation]
- We want to find the nearest k neighbors, so sorting them in ascending order (which is the default setting for sort\_values() will work nicely.

```
[10] k=15
     sorted_data = iris.sort_values(['distance_to_new'])
     sorted data.head() #shortest distances first
                                                                                                           Ħ
           sepal length sepal width petal length petal width
                                                                            species distance to new
      76
                       6.8
                                     2.8
                                                     4.8
                                                                    1.4 Iris-versicolor
                                                                                                0.591608
                                                                                                           ıl.
       52
                       6.9
                                     3.1
                                                                        Iris-versicolor
                                                     4.9
                                                                    1.5
                                                                                                0.700000
                       6.7
                                                                    1.7 Iris-versicolor
      77
                                     3.0
                                                     5.0
                                                                                                0.741620
       50
                      7.0
                                     3.2
                                                     4.7
                                                                    1.4 Iris-versicolor
                                                                                                0.836660
      129
                      7.2
                                     3.0
                                                     5.8
                                                                    1.6
                                                                          Iris-virginica
                                                                                                0.866025
```

# Step 3: Display the most common species among these 5



• And Viola! We have successfully implemented our first machine learning model from scratch.

# **Programming Exercise:**

- Rewrite k-NN code so that it's a function.
- Pass the iris measurements (specimen), DataFrame, and k as parameters and return the predicted class.

```
def kNN(specimen, data, k):
    # write your code in here to make this function work
    # 1. calculate distances

    # 2. sort
    # 3. predict
    return prediction
```

# Group Programming Exercise:

- Rewrite k-NN code so that it's a function.
- Pass the iris measurements (specimen), DataFrame, and k as parameters and return the predicted class.

```
new_iris = {}
new_iris['petal length'] = 5.1
new_iris['sepal length'] = 7.2
new_iris['petal width'] = 1.5
new_iris['sepal width'] = 2.5
# call the function you just wrote
kNN(new_iris, iris, 15)
```