Day 14: k-Nearest Neighbors

How are homes appraised?

When a house is bought or sold, an appraiser typically evaluates the expected value of the home.

- Number of bedrooms
- House amenities
- Square footage
- Many other features...

The features of the marketed home are then compared to similar homes that have sold recently.

What do we mean by similar?

How do we measure similarity?

We can measure it as a distance!

How far is it?

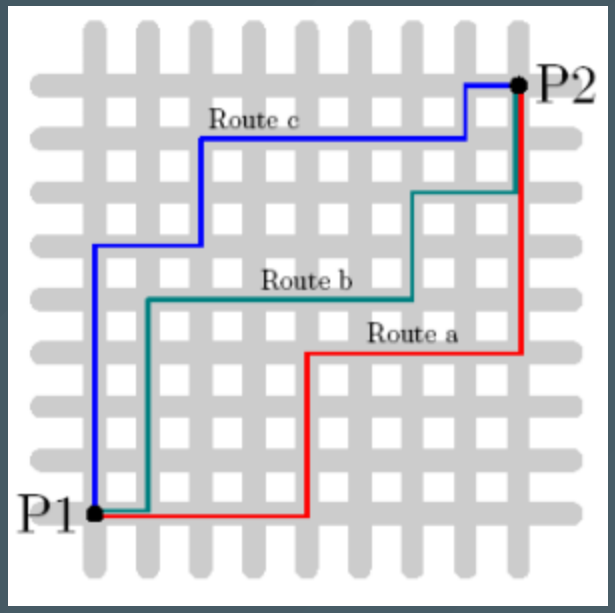
How do we measure distance?

- City blocks
- "As the crow flies" (shortest line)
- Distance on a sphere (ie - shortest flight path)
- Travel time

City Blocks

The measurement of distance by city blocks is frequently referred to as **manhattan distance**.

$$\text{Manhattan Distance} = \text{X Blocks} + \text{Y Blocks}$$



Calculating Manhattan Distance

Exercise:

Given two points with n-dimensional coordinates, generate a function that will return the manhattan distance between those two points.

Feel free to work with your group.

Bonus: Check to make sure that each vector representing a point has the same dimensionality.

Exercise Answer

```
import numpy as np

def manhattan(p1, p2):
    d = 0
    for i in range(len(p1)):
        d+=np.abs(p1[i]-p2[i])
    return d
```

Note that we need to use the absolute value, since negative distances in a given dimension must still be travelled in the same way as positive distances (no wormholes here).

As the crow flies

This is the measurement that we most often think of as distance. It is referred to as **Euclidean distance**, and is calculated with the Pythagorean Equation.

$$\text{Euclidean Distance} = \sqrt{\sum_{i=1}^{N}(x_{i1} - x_{i2})^2}$$

In two dimensions:

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

Calculating Euclidean Distance

Exercise:

Given two points with n-dimensional coordinates, generate a function that will return the euclidean distance between those two points.

Feel free to work with your group.

Exercise Answer

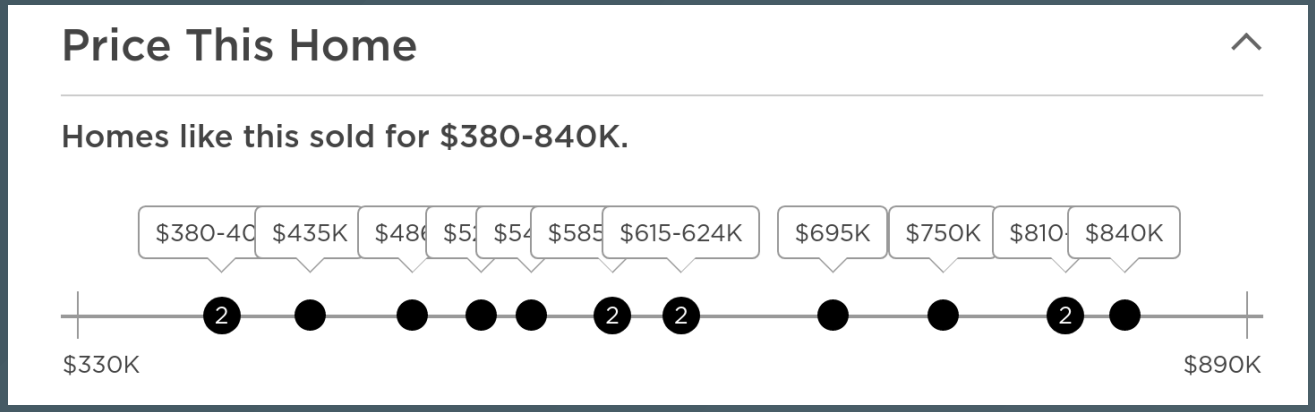
```
import numpy as np

def euclidean(p1, p2):
    d = 0
    for i in range(len(p1)):
        d+=(p1[i]-p2[i])**2
    return np.sqrt(d)
```

Nearest Neighbor

One way to make inference about a new, **unlabeled** observation is to compare it to the most similar (and labeled) observation.

- Do this using distance metrics!
- Find the observation with the smallest **distance**, and make inference about our new point



k-Nearest Neighbors

What if there are a lot of similar observations? We can choose a number of comparisons to make! This algorithm is called **k-Nearest Neighbors**. If $k = 1$, then we simply compare the single nearest observation.

- Increasing k will decrease variance (overfitting), but may also increase bias

Using k-Nearest Neighbors

Step 1 - Collect all labeled data and store as "coordinates" of observations, with each label as the value at a given coordinate.

- We don't have to do ANY up-front calculations or modeling when we use k-Nearest Neighbors
- We have no way of knowing which stored observations will matter until we see the coordinates of the test observation

Using k-Nearest Neighbors

Step 2 - When you receive a test observation (or many), calculate the distance from **each** new observation to **every** stored observation.

Step 3 - Sort the distances, and select the k observations with the lowest distance value.

Note: The calculations that must be performed for every test observation are the same, and that the estimation is "computationally expensive."

Using k-Nearest Neighbors

Step 4 - Use some sort of (possibly weighted) average of the outcomes for the k nearest neighbors of the new observation to determine the predicted label of the new observation.

Using k-Nearest Neighbors

Positives:

- No up-front training necessary!
- Have control over how many observations affect prediction

Negatives:

- Very slow to generate a label, since all training must be done *after* observing test data
- Fitting must be done for **every** new observation

kNN in Python

```
# Import our typical libraries, and the kNN Classifier
import pandas as pd
import numpy as np
from sklearn.model_selection import train_test_split
from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import accuracy_score

# Import our data, and separate our dependent variable
data = pd.read_csv("passFailTrain.csv")
y = data['G3']
x = data.drop(['Unnamed: 0','G3'], axis=1)
```

kNN in Python

```
# Create train and testing data
x, xt, y, yt = train_test_split(x, y,
        test_size=0.1, random_state=42)
# Declare our classifier and its parameters
model = KNeighborsClassifier(n_neighbors=10,
        metric='euclidean')
# 'Fit' the model to the data
reg = model.fit(x, y)
# Generate predicted labels for our test data
pred = reg.predict(xt)
# Calculate accuracy score
accuracy_score(pred, yt)
```

Produces an accuracy of 83.3%

For Lab Today

With your team, use the poisonous mushrooms data to create a kNN model that will allow an avid mushroom picker to determine whether or not the mushroom they have picked is edible or poisonous.

- How does your model perform out-of-sample?
- How does it perform relative to other algorithms we have used? (Try a few to find out!)
- Is accuracy score the best measure on this data? (Might one kind of inaccuracy matter more than another?)