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!

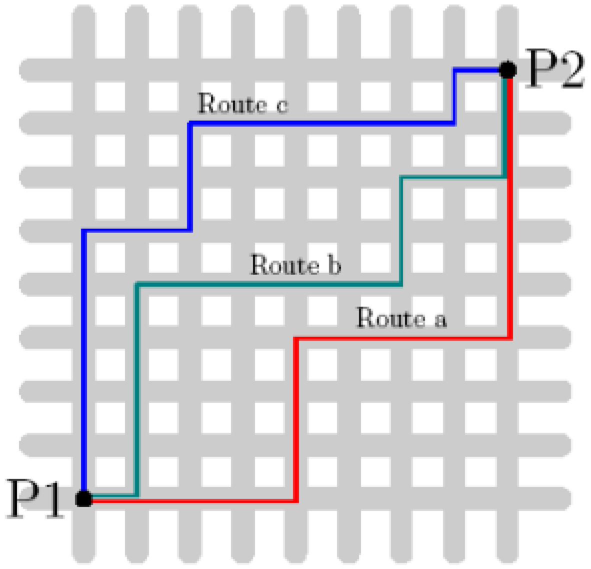
How do we measure distance?

- 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.

Bonus: Include a check to make sure that each vector has the same dimensionality.

Exercise Answer

```python
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
```

OR

```python
def manhattan(p1,p2):
    return np.sum([np.abs(p1[i]-p2[i]) for i in range(len(p1))])
```

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:

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

$$= \sqrt{a^2 + b^2}$$

Calculating Euclidean Distance

Exercise:

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

Exercise Answer

```python
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)
```

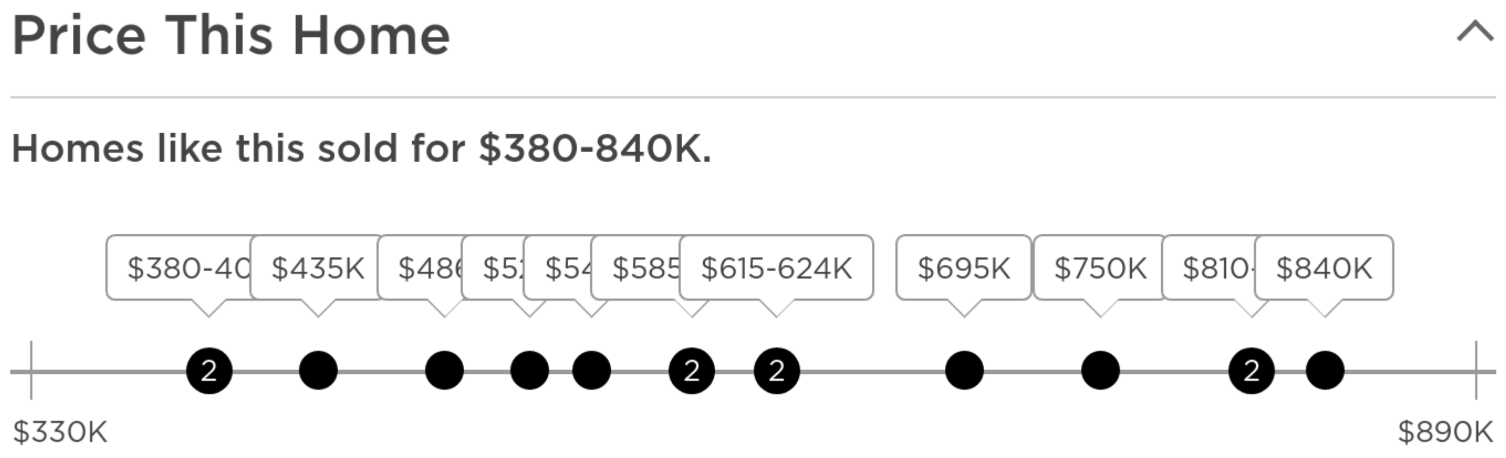
OR

```python
def euclidean(p1,p2):
    return np.sqrt(np.sum([(p1[i] - p2[i])**2 for i in range(len(p1))]))
```

Nearest Neighbor

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

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



Price This Home

Homes like this sold for $380-840K.

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 the 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 the estimation is therefore **"computationally expensive."**

Using k-Nearest Neighbors

Step 4 - Use some sort of average (typically weighted by distance) 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:

- Relatively 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

```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

```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%

Lab Time!