L08-18-10-31-Supervised-ML

November 12, 2018

0.1 Supervised Learning

Machine learning has a few flavors of problems. We can think of it as ways to THINK about a problem. If we can think about a problem in this way, it gives us a framework to solve it. Suppose we have a random variable we can observe like height H, and a variable we want to predict like gender G. We know that *height* doesn't determine gender, there are tall women and short men. Lets say we measure somebodies hight as 67 inches and we want a predictor to estimate gender. Suppose we can compute a probability $P(G|H)$. Then if we plug in what we know (and assume men and women are equal in the population) ... we have numbers A and B.

$$A = P(G = \text{Male}|H = 67), B = P(G = \text{Female}|H = 67)$$

Then if $A > B$ then it is more probable that the person is male and if $B > A$ then it is more likely it is a women. We can say this as

$$G^* = \text{argmax}_G P(G|H = 67)$$

So G^* is formally our best guess. We don't have lots of data on people who are exactly 67 inches tall so we need to flip this a bit using Bayes formula. It follows from $P(G, H) = P(G|H) * P(H) = P(H|G) * P(G)$

$$P(G|H) = P(H|G) * P(G)/P(H)$$

Now we are going to be told that $H = 171$ so when we compare $G =$Male and $G =$Female, it doesn't matter what $P(H)$ is in terms of if $A > B$ or $B > A$. Also we are going to assume $P(G)$ is equal so again, since it is the same for both sides, it doesn't matter. So all we need to do is compute $P(H|G)$ which is easier. Why? Because this is the distribution of Men's heights and separately the distribution of Women's heights. We can estimate that somehow (assume normal ... whatever).

```
In [1]: %matplotlib inline
        import numpy as np
        import pandas as pd
        from matplotlib import pyplot as plt
        import sklearn
```

```
In [35]: df = pd.read_csv('weight-height.csv')
         df.head()
```

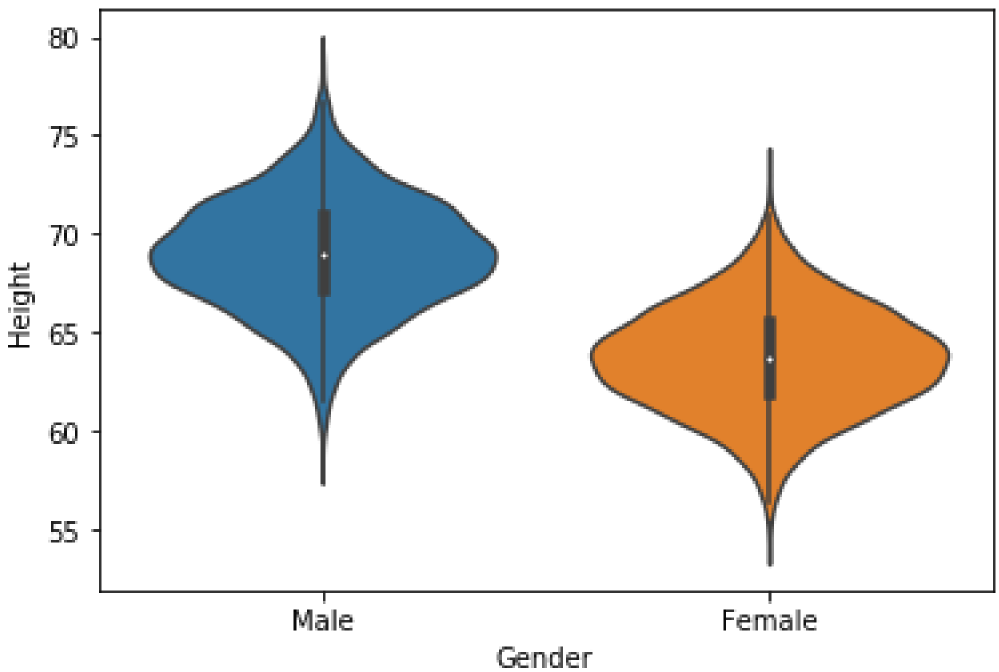
```
Out[35]:   Gender     Height      Weight
        0   Male  73.847017  241.893563
        1   Male  68.781904  162.310473
        2   Male  74.110105  212.740856
        3   Male  71.730978  220.042470
        4   Male  69.881796  206.349801
```

```
In [40]: import seaborn as sns
```

```
In [41]: sns.violinplot(x='Gender', y='Height', data=df[['Gender', 'Height']])
```

```
/opt/tljh/user/lib/python3.6/site-packages/scipy/stats/stats.py:1713: FutureWarning: Using a no
  return np.add.reduce(sorted[indexer] * weights, axis=axis) / sumval
```

```
Out[41]: <matplotlib.axes._subplots.AxesSubplot at 0x7f7301d86a20>
```




```
In [42]: df[['Height',"Gender"]].groupby("Gender").describe()
```

```
Out[42]:        Height                                                          \
                 count       mean       std        min        25%        50%
        Gender
        Female  5000.0  63.708774  2.696284  54.263133  61.894441  63.730924
        Male    5000.0  69.026346  2.863362  58.406905  67.174679  69.027709
```

```
                 75%        max
Gender
Female  65.563565  73.389586
Male    70.988744  78.998742
```

In [43]:
```
male_heights = (df[df['Gender']=='Male']['Height']).values
female_heights = (df[df['Gender']=='Female']['Height']).values
```

In [45]:
```
print(male_heights.mean(),male_heights.std())
print(female_heights.mean(),female_heights.std())
```

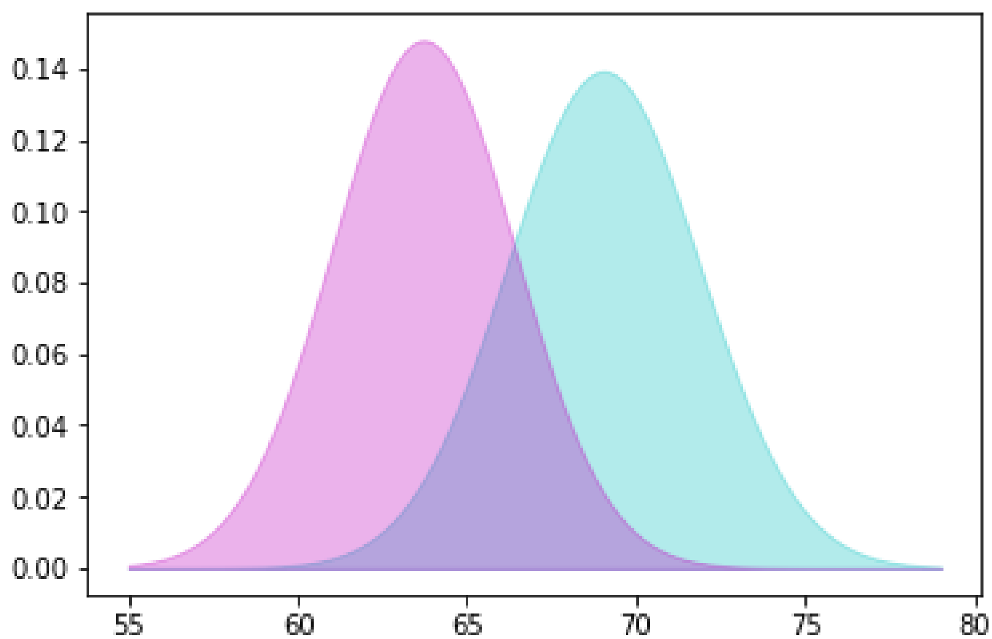
```
69.02634590621741 2.863075878119538
63.70877360342507 2.696014373880709
```

In [47]:
```
from scipy import stats
rv_male = stats.norm(loc=male_heights.mean(), scale=male_heights.std())
rv_female = stats.norm(loc=female_heights.mean(), scale=female_heights.std())
```

In [52]:
```
heights = np.linspace(55,79,1000)
male_probs = rv_male.pdf(heights)
female_probs = rv_female.pdf(heights)
```

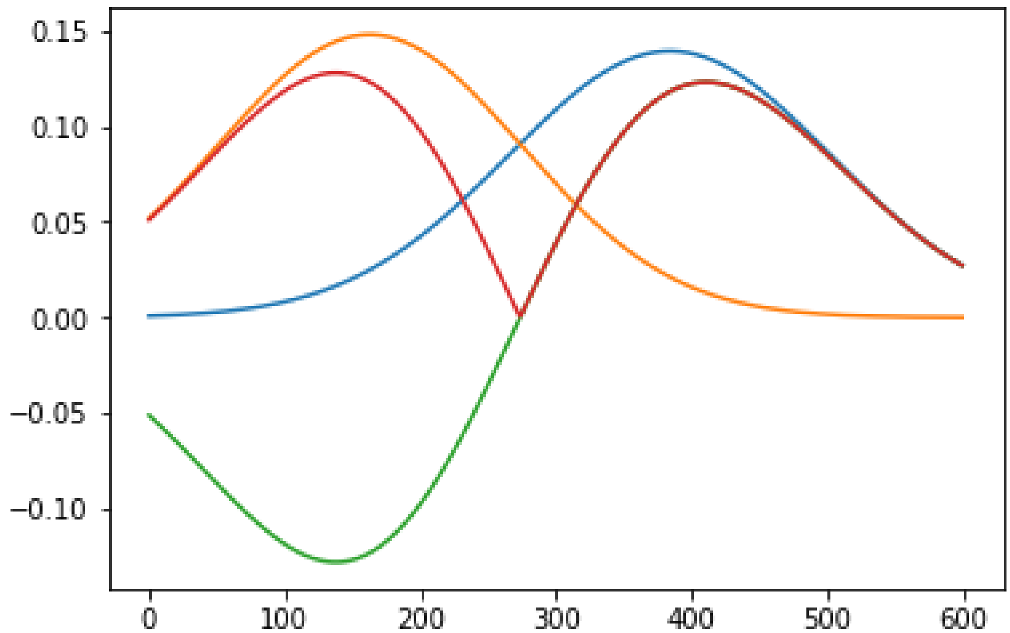
In [59]:
```
plt.fill_between(heights, male_probs, color='c', alpha=0.3)
plt.fill_between(heights, female_probs, color='m', alpha=0.3)
```

Out[59]:
```
<matplotlib.collections.PolyCollection at 0x7f7301b17eb8>
```



```
In [72]: plt.plot(male_probs[200:-200])
         plt.plot(female_probs[200:-200])
         plt.plot(male_probs[200:-200]-female_probs[200:-200])
         plt.plot(np.abs(male_probs[200:-200]-female_probs[200:-200]))

Out[72]: [<matplotlib.lines.Line2D at 0x7f7301810e80>]
```

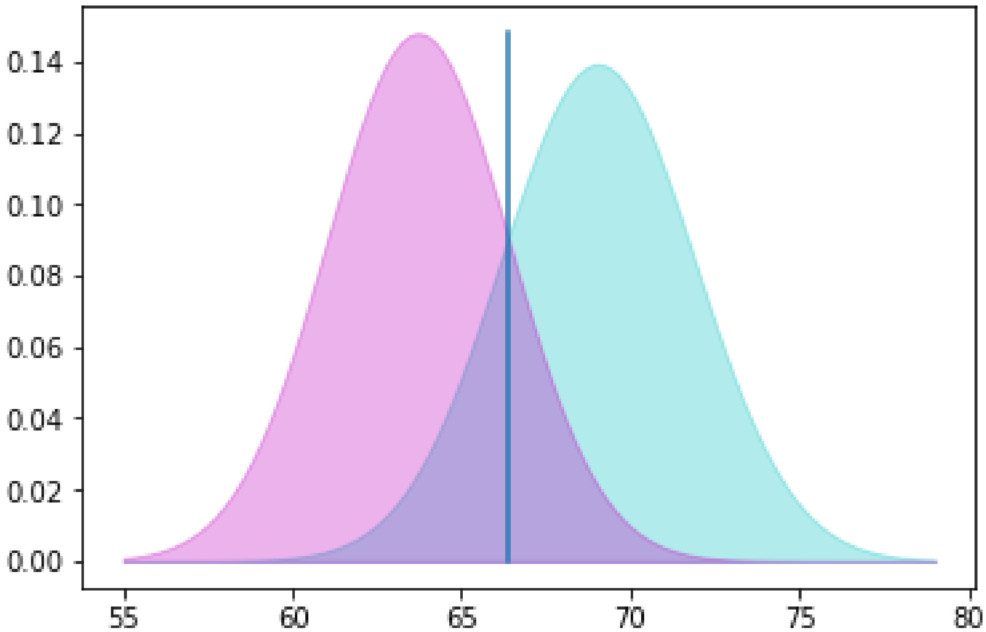



```
In [74]: threshold = heights[200:-200][np.argmin(np.abs(male_probs[200:-200]-female_probs[200:
         threshold

Out[74]: 66.36336336336336

In [75]: plt.fill_between(heights, male_probs, color='c', alpha=0.3)
         plt.fill_between(heights, female_probs, color='m', alpha=0.3)
         plt.plot([threshold,threshold],[0,max([male_probs.max(),female_probs.max()])])

Out[75]: [<matplotlib.lines.Line2D at 0x7f73017f2860>]
```



This is called the generative approach because we have to model our data well enough to build a probability for it. What if we have multi-dimensional data. This seems extra hard. All we really want to do is fit a function that tells us given an input in inches whether it is male or female. That is a discriminative approach.

0.2 Iris Data Sets

Lets think about the Iris data set. Lets say we measure 4 variables of different iris flowers. Lets say there are 3 species (Iris setosa, Iris virginica and Iris versicolor) of this data and we want to classify which species we are looking at. Lets say the species is a random variable S, and the four attributes are W, X, Y, Z. Assume we measure W, X, Y, Z for a particular flower F. It is not clear that those properties will with 100% certainty. Lets use conditional probability to express our knowledge.

$$P(S|W, X, Y, X)$$

is the probability of a species S given we measured the other variables. We want to figure out which species it is given the four attributes.

```
In [76]: from sklearn import datasets
         iris = datasets.load_iris()
```

```
In [77]: iris_df = pd.DataFrame(data= np.c_[iris['data'], iris['target']],
                              columns= iris['feature_names'] + ['target'])
```

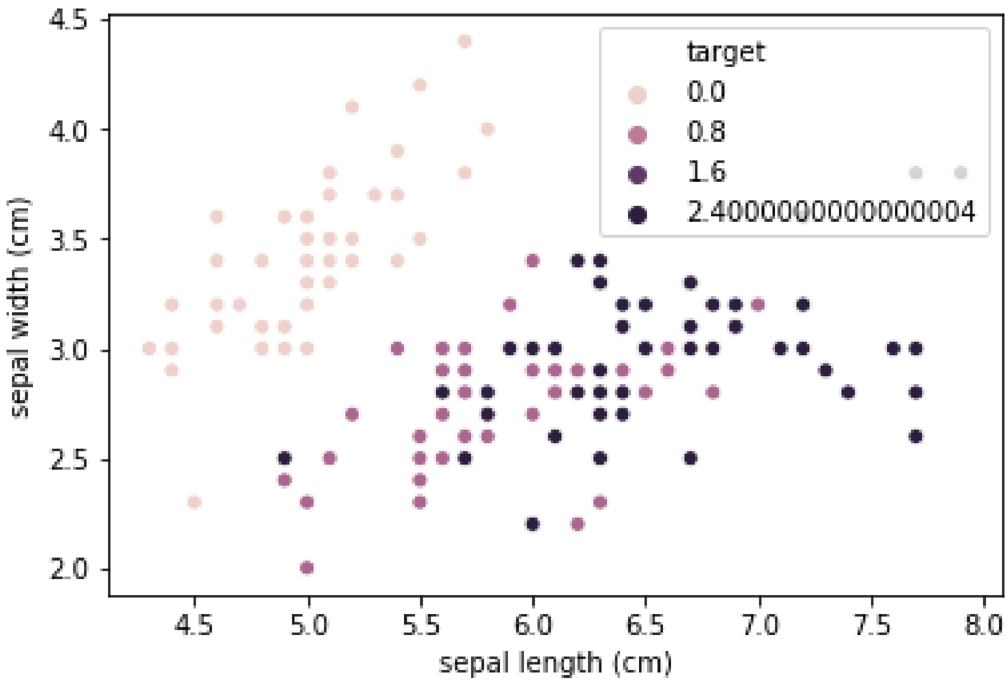
```
In [78]: iris_df.head()
```

```
Out[78]:    sepal length (cm)  sepal width (cm)  petal length (cm)  petal width (cm)  \
         0                5.1               3.5                1.4               0.2
```

```
1                 4.9              3.0              1.4              0.2
2                 4.7              3.2              1.3              0.2
3                 4.6              3.1              1.5              0.2
4                 5.0              3.6              1.4              0.2

   target
0     0.0
1     0.0
2     0.0
3     0.0
4     0.0
```

In [81]:
```
ax = sns.scatterplot(x="sepal length (cm)", y="sepal width (cm)", hue="target", data=
```



In [82]:
```
from sklearn import neighbors
```

In [ ]:
```
n_neighbors = 3
clf = neighbors.KNeighborsClassifier(n)
```