## Data 102 Fall 2022 Lecture 3

```
In [1]: import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

%matplotlib inline

sns.set() # This helps make our plots look nicer

# These make our figures bigger
plt.rcParams['figure.figsize'] = (6, 4.5)
plt.rcParams['figure.dpi'] = 100
```

## Comparing row-wise and column-wise rates

The FDP is the column-wise error rate for when our decision is 1. It asks: how many of the discoveries we made (i.e., our decision was 1) were false (wrong)?

We can relate this to row-wise rates using Bayes' rule. To simplify notation, we'll use  $\pi_0 = P(R=0)$ .

$$FDP = P(R = 0|D = 1)$$

$$(using Bayes' rule) = \frac{P(D = 1|R = 0)P(R = 0)}{P(D = 1)}$$

$$(Law of total probability) = \frac{P(D = 1|R = 0)P(R = 0)}{P(D = 1|R = 0)P(R = 0) + P(D = 1|R = 1)P(R = 1)}$$

$$(dividing by the numerator) = \frac{1}{1 + \frac{P(D = 1|R = 1)}{P(D = 1|R = 0)} \frac{P(R = 1)}{P(R = 0)}}$$

$$(applying definitions) = \frac{1}{1 + \frac{TPR}{FPR} \frac{1 - \pi_0}{\pi_0}}$$

```
In [2]: def compute_fdp(tpr, fpr, prevalence):
    return 1 / (1 + (tpr/fpr) * (prevalence/(1-prevalence)))
```

Suppose we have an algorithm that predicts whether or not it'll rain. We apply our algorithm in Berkeley (where it almost never rains in the summer) and in Miami, FL (where it rains about half the time in the summer).

```
In [3]: # Summer in Miami, good test
    compute_fdp(tpr=0.99, fpr=0.01, prevalence=0.5)

Out[3]: 0.01

In [4]: # Summer in Berkeley, good test
    compute_fdp(tpr=0.99, fpr=0.01, prevalence=0.01)

Out[4]: 0.5
```

```
In [5]: # Summer in Miami, bad test
    compute_fdp(tpr=0.6, fpr=0.4, prevalence=0.5)

Out[5]: 0.4

In [6]: # Summer in Berkeley, bad test
    compute_fdp(tpr=0.6, fpr=0.4, prevalence=0.01)

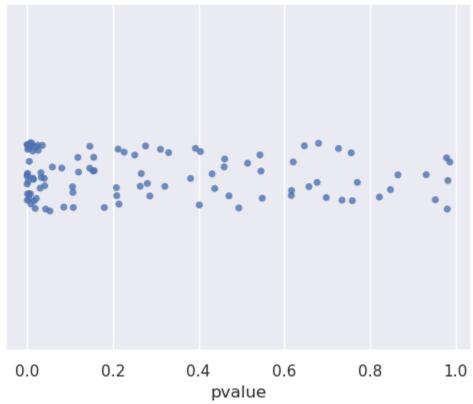
Out[6]: 0.9850746268656717
```

## Multiple hypothesis testing and error control

Suppose we have a collection of p-values, with ground truth labels.

```
In [8]: sns.stripplot(
    data=p_values, x='pvalue',
    alpha = 0.8, order = [0, 1], orient = "h",
    #ax=ax
)
plt.title("P-values (as we'd actually see them, without labels)");
```

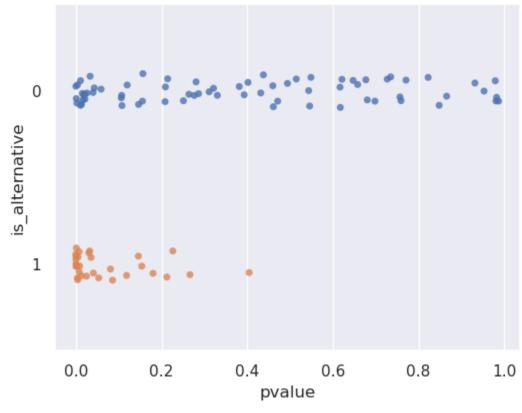
P-values (as we'd actually see them, without labels)



```
In [9]: sns.stripplot(
    data=p_values, x='pvalue', y='is_alternative',
    alpha = 0.8, order = [0, 1], orient = "h",
)
plt.title('P-values, with ground truth labels')
```

Out[9]: Text(0.5, 1.0, 'P-values, with ground truth labels')

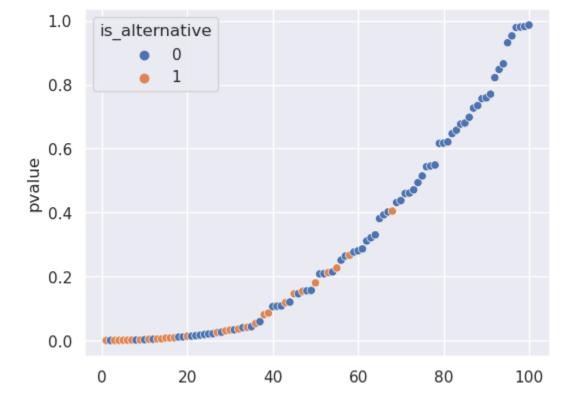
## P-values, with ground truth labels



```
0 0.226410
                                1
           1 0.053205
                                1
                                1
           2 0.001128
           3 0.404488
                                1
                                0
           4 0.401786
          95 0.146346
                                0
          96 0.003678
          97 0.013303
                                0
                                0
          98 0.493987
          99 0.000219
                                1
         100 rows × 2 columns
In [11]:
          p_sorted = p_values.sort_values('pvalue')
In [19]: m = len(p sorted) # number of tests
          k = np.arange(1, m+1) # index of each test in sorted order
          p_sorted['k'] = k
          p_sorted
               pvalue is_alternative
                                     k
Out[19]:
          94 0.000008
                                     1
          10 0.000109
                                     2
                                0
          86 0.000162
                                     3
                                1
          99 0.000219
                                     4
          42 0.000436
                                1
                                    5
          45 0.952674
                                0
                                   96
           9 0.978843
                                    97
          22 0.980498
                                    98
          76 0.982076
                                    99
          20 0.986542
                                0 100
         100 rows × 3 columns
In [20]: alpha = .05
In [21]: sns.scatterplot(x=k, y=p_sorted['pvalue'], hue=p_sorted['is_alternative']);
```

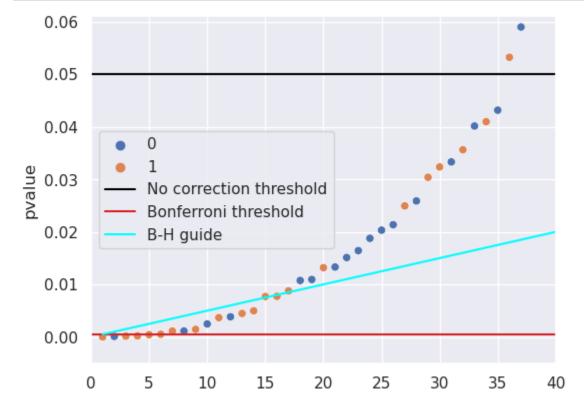
pvalue is\_alternative

Out[10]:

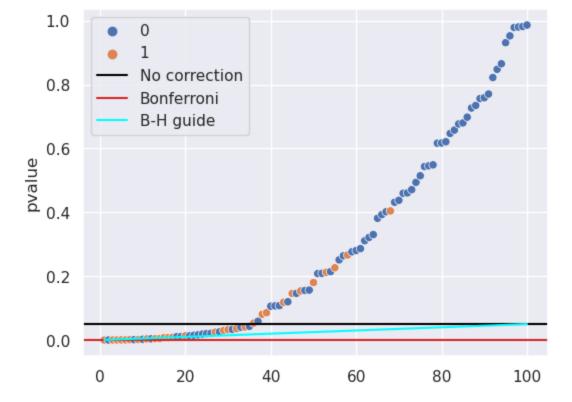


```
In [22]: sns.scatterplot(x=k, y=p_sorted['pvalue'], hue=p_sorted['is_alternative'])
    plt.axhline(alpha, label='No correction threshold', color='black')
    plt.axhline(alpha / len(p_sorted), label='Bonferroni threshold', color='tab:red')
    plt.plot(k, k/len(p_sorted)* alpha, label='B-H guide', color='cyan')
    plt.legend()

plt.axis([-0.01, 40, -0.005, .061]);
```



```
In [23]: sns.scatterplot(x=k, y=p_sorted['pvalue'], hue=p_sorted['is_alternative']);
plt.axhline(alpha, label='No correction', color='black')
plt.axhline(alpha / m, label='Bonferroni', color='tab:red')
plt.plot(k, k/m * alpha, label='B-H guide', color='cyan')
plt.legend();
```



```
In [24]: sns.scatterplot(x=k, y=p_sorted['pvalue'], hue=p_sorted['is_alternative']);
plt.axhline(alpha, label='No correction', color='black')
plt.axhline(alpha / m, label='Bonferroni', color='tab:red')
plt.plot(k, k/m * alpha, label='B-H guide', color='cyan')

plt.axis([-0.05, 40, -0.0005, 0.0605])
plt.legend();
```

