NYPD Civilian Complaints

This project contains data on 12,000 civilian complaints filed against New York City police officers. Interesting questions to consider include:

- Does the length that the complaint is open depend on ethnicity/age/gender?
- Are white-officer vs non-white complaintant cases more likely to go against the complainant?
- Are allegations more severe for cases in which the officer and complaintant are not the same ethnicity?
- Are the complaints of women more succesful than men (for the same allegations?)

There are a lot of questions that can be asked from this data, so be creative! You are not limited to the sample questions above.

Getting the Data

The data and its corresponding data dictionary is downloadable [here (https://www.propublica.org/datastore/dataset/civilian-complaints-against-new-york-city-police-officers)](https://www.propublica.org/datastore/dataset/civilian-complaints-against-new-york-city-police-officers). The data dictionary is in the project03 folder.

Note: you don't need to provide any information to obtain the data. Just agree to the terms of use and click "submit."

Cleaning and EDA

- Clean the data.
  - Certain fields have "missing" data that isn't labeled as missing. For example, there are fields with the value "Unknown." Do some exploration to find those values and convert them to null values.
  - You may also want to combine the date columns to create a `datetime` column for time-series exploration.
- Understand the data in ways relevant to your question using univariate and bivariate analysis of the data as well as aggregations.

Assessment of Missingness

- Assess the missingness per the requirements in `project03.ipynb`

Hypothesis Test / Permutation Test

Find a hypothesis test or permutation test to perform. You can use the questions at the top of the notebook for inspiration.

Summary of Findings

Introduction

Question:

Are the complaints of women more succesful than men (for the same allegations?)

Dataset:

command_at_incident: 1544 null values
complainant_ethnicity: 4464 null values 1041 'Unknown'
complainant_gender: 4195 null values and some 'Not described'
complainant_age_incident: 4812 null values
allegation: 1 null value
precinct: 24 null values
contact_reason: 199 null values and some 'No contact'

33358 rows x 29 columns

Each row in the dataset is an allegation filed against the police. Each column gives some kind of information about the allegation and if it was successful or not.

Cleaning and EDA

cleaning:

First we replaced all values that are "missing" to np.NaN. Such as "Unknown" in complainant_ethnicity, "Not described" in complainant_gender, and "No contact" in contact_reason. We did this because these values are equal to np.NaN values and contribute to missingness.

Second we removed anyone that was below the age of 0. There should not exist anyone below the age of 0 in this dataset.

Third we chose columns that we deemed relevant to our question.

Fourth we located allegations that only came specifically from a "male" or "female". We decided not to include non-binary genders because they are not part of the population that our question is focused on.

Fifth we created a success column that quantified if an allegation was a success or not based on the board_disposition. We did this to quantify what success meant for each allegation.

*note: in the pre cleaning before we started analyzing, we removed non-binary genders bc we're only focused on males and females and that it doesn't affect our analysis because they constituted a very small minority of the total population

analysis:

From just looking at the complainant_gender column, we can see that an overwhelming majority of complaints are filed by men.

From the success column, we can see that only around 25% of cases are won against the police. Any substantiated value in 'board_disposition' constitutes a win for the complainant.

Men seem to have a higher win rate for cases than women.

Assessment of Missingness

We believe that the data is NMAR because the site that we got the data from says that every complaint in the database was heavily investigated and thus the authorities should have identifying information on both the complaining party and the officer(s). The complainants have to provide a sworn statement, so it's hard to assume that the authorities don't know the ethnicity of a complainant when knowing their name gives them access to other avenues to identify them through and thus figure out personal information such as gender and ethnicity. A plausible reason as to why it's missing could be that either the officers or the complainant's would rather not disclose that information

We chose to provide a possible explanation for the missingness through the column success. If a case was unsuccessful for the complainant, then the police may choose to withhold putting his or her race down because if he or she is a minority, it could look bad for them if so many cases made by minorities are won in favor of the police.

We chose complainant_gender to be the column where we expected complainant_ethnicity to not be dependent on it because we don't believe gender to be a reason as to why a complainant's ethnicity cannot be identified.

sig fig:

0.05 to insure accuracy

test statistic:

we used tvd (total variation distance) to compare distributions of missingness. We chose tvd because we are dealing with categorical data (complainant_ethnicity).

setup:

We did not have a setup for the first and last test, but the second test we isolated race allegations from the dataset.

results:

pval: 0.009
We reject our null hypothesis therefore complaiant_ethnicity's missingness is dependent on success

pval: 0.018
We reject our null hypothesis, so complainant_ethnicity's missingness is also dependent on success when allegations are about race

pval: 0.311
We do not reject the null hypothesis, so complainant_ethnicity's missingness is not dependent on complainant_gender.

Hypothesis Test

null hypothesis:

In our population, for the same allegations, the successes of men and women have the same distribution.

alt hypothesis:

In our population, for the same allegations, women are more likely to be successful in their cases than men.

sig fig:

0.01 to insure accuracy

test statistic:

we used diff of means between the proportions of females that win and the proportions of males that win for each individual allegation. Despite gender being categorical we wanted to compare the proportion of the male population vs the female population.

setup:

To choose the allegations that we would like to compare the successes between males and females, we eliminated the allegations where charges were made exclusively by either males or females. Then, we selected the top 10 allegations with the most sample size and among them, we chose the ones that had as close to the same proportion of female representation as in the entire population of males and females. Since alternate hypothesis concerns women, we wanted the proportion of women in each allegation to be as representative of all of the women in the population as possible. We selected "Physical force," "Word," 'Vehicle stop," and "Threat of force (verbal of physical)."

results:

pval:
Physical force: 0.002
Therefore for 'Physical force' we reject our null hypothesis meaning that for when allegation type is of 'Physical force' women are more likely to be successful in their case than men

Word: 0.052
Therefore for word we do not reject our null hypothesis meaning that when allegation type is 'word' women and men are equally likely to be successful in their case.

Vehicle stop: 0.082
Therefore for 'Vehicle stop' we do not reject our null hypothesis meaning that when allegation type is 'Vehicle stop' women and men are equally likely to be successful in their case.

Threat of force (verbal or physical): 0.789
Therefore for 'Threat of force (verbal or physical)' we do not reject our null hypothesis meaning that when allegation type is 'Threat of force (verbal or physical)' women and men are equally likely to

be successful in their case.

conclusion:

We conclude that when allegations are about 'physical force' women are more likely to have a successful case than men, but for the other three allegations we found that women and men are equally likely to have a successful case. This could be because women are seen to be "weaker" than men, so then when they allege 'physical force' they are more likely to be believed than men. Otherwise most allegations seem to be very generally categorized into direct physical contact between the officer and complainant, and non-direct physical (coming into contact with a complainant's belongings, etc.) or verbal actions. "Word", "vehicle stop," and "threat of force (verbal of physical)" do not involve the police coming into direct physical contact with the complainant (physical threat of force is probably like posturing or brandishing a baton but not actually assaulting the complainant) and thus it seems that women and men are both equally likely to win a case for those allegations. With those allegations, neither men or women seem more "susceptible."

Code

In [1]:
```
import matplotlib.pyplot as plt
import numpy as np
import os
import pandas as pd
import seaborn as sns
%matplotlib inline
%config InlineBackend.figure_format = 'retina'  # Higher resolution figures
```

Cleaning and EDA

Cleaning

In [2]:
```
nypd = pd.read_csv('allegations_202007271729.csv')
df = nypd.copy()
```

replaces "unknown" in complainant_ethnicity with NaN and replaces "not described" in complainant_gender with NaN and replaces 'No contact" in contact_reason

In [3]:
```
df['complainant_ethnicity'] = df ['complainant_ethnicity'].replace('Unknown', np.
df['complainant_gender'] = df['complainant_gender'].replace('Not described', np.N
df['contact_reason'] = df['contact_reason'].replace('No contact', np.NaN)
```

if anyone is under the age of 0 then the row is removed

In [4]:
```
df['complainant_age_incident'] = df['complainant_age_incident'].apply(lambda x: r
```

Revelant columns to our question

In [5]:
```
useful_cols = ['complainant_ethnicity',
            'complainant_gender',
            'complainant_age_incident',
            'allegation',
            'contact_reason',
           'outcome_description',
           'board_disposition',
              ]
```

Locates allegations that are only by a "Male" or "Female"

In [6]:
```
only_binary = df[(df['complainant_gender'] == 'Male') | (df['complainant_gender']
q_data = only_binary.loc[:, useful_cols]
```

creates the success column which quantifies if an allegation was a success or not based on if the board_disposition was unsubstantiated/exonerated for unsuccessful and substantiated for successful

In [7]:
```
q_data['success'] = only_binary['board_disposition'].apply(lambda x: 0 if x in ['
```

Cleaned data set

In [8]:
```
q_data = q_data.reset_index(drop=True)
q_data.head()
```

Out[8]:

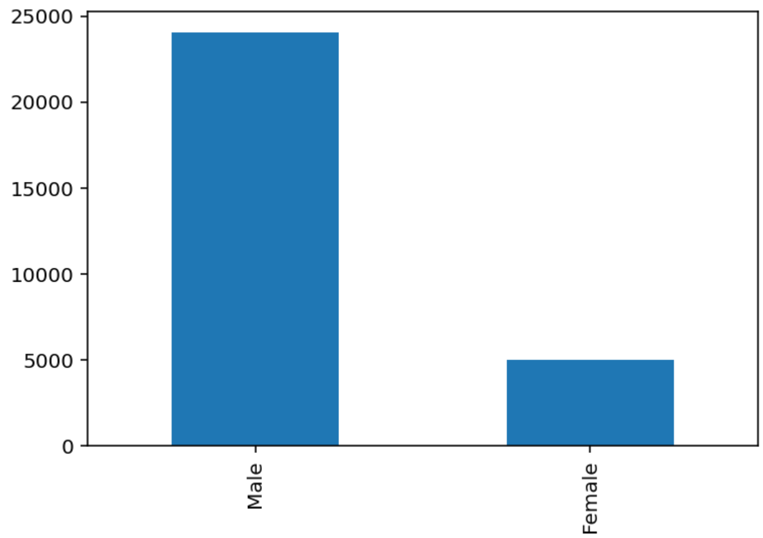
	complainant_ethnicity	complainant_gender	complainant_age_incident	allegation	contact_reason
0	Black	Female	38.0	Failure to provide RTKA card	Report-domestic dispute
1	Black	Male	26.0	Action	Moving violation
2	Black	Male	26.0	Race	Moving violation
3	Black	Male	45.0	Question	PD suspected C/V of violation/crime - street
4	White	Male	31.0	Refusal to process civilian complaint	C/V telephoned PCT

Univariate analysis

We plotted complainant_gender to calculate the distribution of males and females

In [9]:
```
q_data['complainant_gender'].value_counts().plot(kind='bar')
```

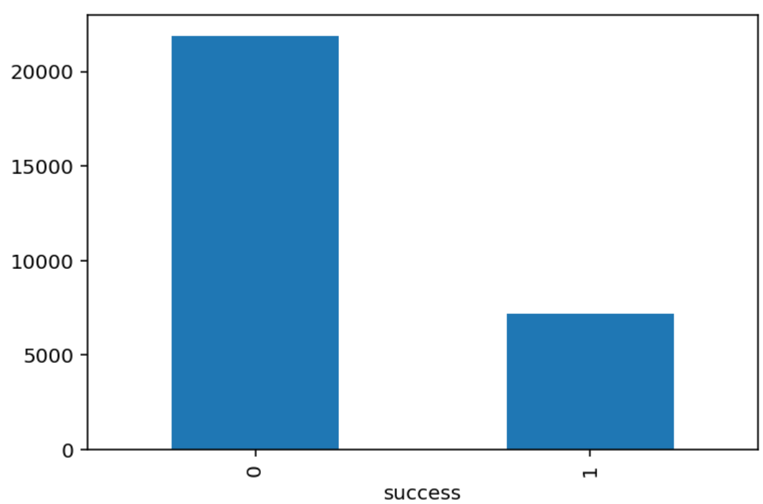
Out[9]: <matplotlib.axes._subplots.AxesSubplot at 0x1e7d4233be0>



Here we plotted the size of successes compared to failures

In [10]:
```
q_data.pivot_table(index='success', aggfunc='size').plot(kind='bar')
```

Out[10]: <matplotlib.axes._subplots.AxesSubplot at 0x1e7d48a26d0>

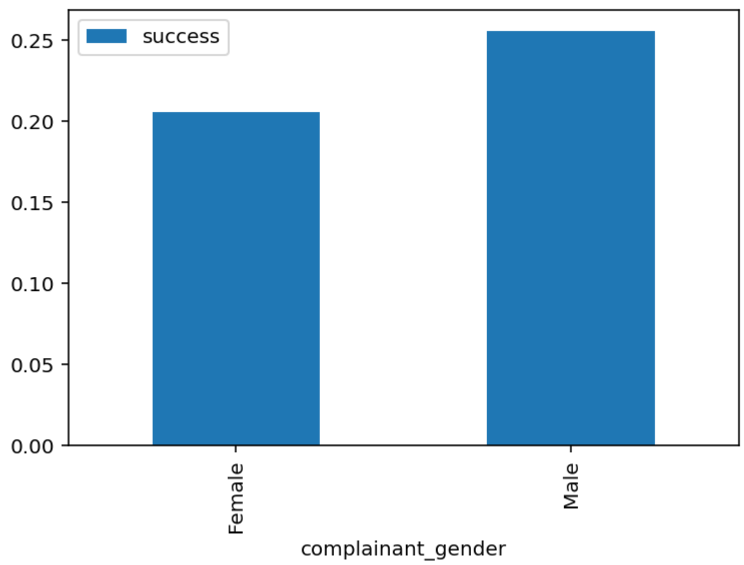


Bivariate Analysis

Here we plotted successes grouped by gender.

In [11]:
```
q_data.pivot_table(index='complainant_gender', values=['success'], aggfunc='mean'
```

Out[11]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x1e7d49095e0>
```



Interesting Aggregates

All allegation types that have both "male" and "female" complainants

In [12]:
```
q_data = q_data.assign(gender = q_data['complainant_gender'].replace({'Male':1,'F
out = q_data.groupby(['allegation'])['gender'].mean()
out2 = (out == 2) | (out==1)
alle = out2[out2].index
new_data = q_data[~q_data['allegation'].isin(alle)]
new_data.allegation.unique()
```

Out[12]:
```
array(['Failure to provide RTKA card', 'Action', 'Race', 'Question',
       'Refusal to process civilian complaint', 'Sexual orientation',
       'Word', 'Refusal to provide shield number', 'Retaliatory summons',
       'Refusal to provide name/shield number', 'Search (of person)',
       'Pepper spray', 'Physical force', 'Handcuffs too tight', 'Frisk',
       'Vehicle stop', 'Vehicle search', 'Strip-searched',
       'Threat of arrest', 'Threat of force (verbal or physical)', 'Stop',
       'Refusal to obtain medical treatment',
       'Hit against inanimate object', 'Frisk and/or search', 'Other',
       'Question and/or stop', 'Nonlethal restraining device',
       'Retaliatory arrest', 'Seizure of property', 'Chokehold', 'Gender',
       'Nightstick as club (incl asp & baton)', 'Refusal to provide name',
       'Gun Pointed', 'Other blunt instrument as a club',
       'Property damaged', 'Interference with recording',
       'Refusal to show search warrant',
       'Threat to damage/seize property', 'Gesture',
       'Sex Miscon (Sexual Harassment, Verbal)',
       'Sex Miscon (Sexual Harassment, Gesture)',
       'Forcible Removal to Hospital', 'Entry of Premises', 'Ethnicity',
       'Threat of summons', 'Threat re: removal to hospital',
       'Photography/Videography', 'Demeanor/tone', 'Restricted Breathing',
       'Flashlight as club', 'Electronic device information deletion',
       'Search of recording device', 'Gun as club', 'Religion',
       'Gun fired', 'Sexual Misconduct (Sexual Humiliation)',
       'Radio as club', 'Search of Premises', 'Physical disability',
       'Failed to Obtain Language Interpretation',
       'Premises entered and/or searched', 'Police shield',
       'Refusal to show arrest warrant', 'Threat to notify ACS',
       'Gender Identity'], dtype=object)
```

Here are the success rates of allegations grouped by allegation type and gender

In [13]:
```
data = new_data.groupby(['allegation','complainant_gender']).aggregate({'success'
data.head()
```

Out[13]:

	allegation	complainant_gender	success
0	Action	Female	0.261538
1	Action	Male	0.323651
2	Chokehold	Female	0.166667
3	Chokehold	Male	0.181818
4	Demeanor/tone	Female	0.150000

There are 16 allegation types grouped by gender that have a 0% success rate

In [14]:
```
c = data.sort_values(by=['success'])
c.head(16)
```

Out[14]:

	allegation	complainant_gender	success
82	Refusal to show arrest warrant	Female	0.0
32	Gun as club	Female	0.0
34	Gun fired	Female	0.0
36	Handcuffs too tight	Female	0.0
108	Sexual orientation	Female	0.0
16	Flashlight as club	Female	0.0
103	Sex Miscon (Sexual Harassment, Gesture)	Male	0.0
26	Gender Identity	Female	0.0
102	Sex Miscon (Sexual Harassment, Gesture)	Female	0.0
54	Physical disability	Female	0.0
125	Threat to notify ACS	Male	0.0
58	Police shield	Female	0.0
59	Police shield	Male	0.0
83	Refusal to show arrest warrant	Male	0.0
70	Radio as club	Female	0.0
88	Restricted Breathing	Female	0.0

There are 5 allegation types grouped by gender that have a 100% success rate

In [15]:
```
d = data.sort_values(by=['success'],ascending=False)
d.head(5)
```

Out[15]:

	allegation	complainant_gender	success
48	Other blunt instrument as a club	Female	1.0
27	Gender Identity	Male	1.0
98	Search of recording device	Female	1.0
13	Failed to Obtain Language Interpretation	Male	1.0
12	Failed to Obtain Language Interpretation	Female	1.0

Assessment of Missingness

Here we check if complaiant_ethnicity's missingness is dependent on success

First we calculate the empirical distribution of success by null and not-null

In [16]:
```
distr = (
    q_data
    .assign(is_null=q_data.complainant_ethnicity.isnull())
    .pivot_table(index='is_null', columns='success', aggfunc='size')
    .apply(lambda x:x / x.sum(), axis=1)
)
distr
```

Out[16]:

success	0	1
is_null		
False	0.754301	0.245699
True	0.724671	0.275329

Then we shuffle success and calculate its tvd for 1000 repetitions

In [17]:
```
n_repetitions = 1000

tvds = []
for _ in range(n_repetitions):


    shuffled_col = (
        q_data['success']
        .sample(replace=False, frac=1)
        .reset_index(drop=True)
    )


    shuffled = (
        q_data
        .assign(**{
            'success': shuffled_col,
            'is_null': q_data['complainant_ethnicity'].isnull()
        })
    )


    shuffled = (
        shuffled
        .pivot_table(index='is_null', columns='success', aggfunc='size')
        .apply(lambda x:x / x.sum(), axis=1)
    )

    tvd = shuffled.diff().iloc[-1].abs().sum() / 2


    tvds.append(tvd)
```

We calculate our observed value

In [18]:
```
obs = distr.diff().iloc[-1].abs().sum() / 2
obs
```

Out[18]: 0.029629419946916147

Finally we calculate our pvalue

In [19]:
```
pval = np.mean(tvds > obs)
pval
```

Out[19]: 0.009

We reject our null hypothesis therefore complaiant_ethnicity's missingness is dependent on success

Here we check if complaiant_ethnicity's missingness is dependent on allegations about race

Here we create a dataframe that only has allegations about race

In [20]:
```
race = q_data[q_data['allegation'] == 'Race'].reset_index(drop=True)
race.head()
```

Out[20]:

	complainant_ethnicity	complainant_gender	complainant_age_incident	allegation	contact_reason
0	Black	Male	26.0	Race	Moving violation
1	Black	Female	42.0	Race	Regulatory inspection
2	Black	Male	27.0	Race	PD suspected C/V of violation/crime - street
3	Black	Male	28.0	Race	Execution of search warrant
4	Black	Female	25.0	Race	PD suspected C/V of violation/crime - street

Here we calculate the empirical distribution of success by null and not-null

In [21]:
```
distr = (
    race
    .assign(is_null=race.complainant_ethnicity.isnull())
    .pivot_table(index='is_null', columns='success', aggfunc='size')
    .apply(lambda x:x / x.sum(), axis=1)
)
distr
```

Out[21]:

success	0	1
is_null		
False	0.905085	0.094915
True	0.714286	0.285714

Then we shuffle success and calculate its tvd for 1000 repetitions

In [22]:
```
n_repetitions = 1000

tvds = []
for _ in range(n_repetitions):


    shuffled_col = (
        race['success']
        .sample(replace=False, frac=1)
        .reset_index(drop=True)
    )


    shuffled = (
        race
        .assign(**{
            'success': shuffled_col,
            'is_null': race['complainant_ethnicity'].isnull()
        })
    )


    shuffled = (
        shuffled
        .pivot_table(index='is_null', columns='success', aggfunc='size')
        .apply(lambda x:x / x.sum(), axis=1)
    )

    tvd = shuffled.diff().iloc[-1].abs().sum() / 2


    tvds.append(tvd)
```

We calculate the observed value

In [23]:
```
obs = distr.diff().iloc[-1].abs().sum() / 2
obs
```

Out[23]: 0.1907990314769976

Finally we calculate the pvalue

In [24]:
```
pval = np.mean(tvds > obs)
pval
```

Out[24]: 0.018

We reject our null hypothesis, so complainant_ethnicity's missingness is also dependent on success when allegations are about race

Here we check if complainant_ethnicity's missingness is dependent on complainant_gender

First we calculate the empirical distribution of complainant_gender by null and not-null

In [25]:
```
distr = (
    q_data
    .assign(is_null=q_data.complainant_ethnicity.isnull())
    .pivot_table(index='is_null', columns='complainant_gender', aggfunc='size')
    .apply(lambda x:x / x.sum(), axis=1)
)
distr
```

Out[25]:

complainant_gender	Female	Male
is_null		
False	0.172209	0.827791
True	0.182521	0.817479

Then we shuffle complainant_gender and calculate its tvd for 1000 repetitions

In [33]:
```
n_repetitions = 1000

tvds = []
for _ in range(n_repetitions):


    shuffled_col = (
        q_data['complainant_gender']
        .sample(replace=False, frac=1)
        .reset_index(drop=True)
    )


    shuffled = (
        q_data
        .assign(**{
            'complainant_gender': shuffled_col,
            'is_null': q_data['complainant_ethnicity'].isnull()
        })
    )


    shuffled = (
        shuffled
        .pivot_table(index='is_null', columns='complainant_gender', aggfunc='size
        .apply(lambda x:x / x.sum(), axis=1)
    )

    tvd = shuffled.diff().iloc[-1].abs().sum() / 2


    tvds.append(tvd)
```

Here we calculate the observed value

In [27]:
```
obs = distr.diff().iloc[-1].abs().sum() / 2
obs
```

Out[27]: 0.010312242239870067

Finally we calculate the pvalue

In [28]:
```
pval = np.mean(tvds > obs)
pval
```

Out[28]: 0.311

We do not reject the null hypothesis, so complainant_ethnicity's missingness is not dependent on complainant_gender.

Hypothesis Test

null hypothesis:

In our population, for the same allegations, the successes of men and women have the same distribution.

alt hypothesis:

In our population, for the same allegations, women are more likely to be successful in their cases than men.

sig fig:

0.01

To choose the allegations that we would like to compare the successes between males and females, we eliminated the allegations where charges were made exclusively by either males or females. Then, we selected the top 10 allegations with the most sample size and among them, we chose the ones that had as close to the same proportion of female representation as in the entire population of males and females. Since alternate hypothesis concerns women, we wanted the proportion of women in each allegation to be as representative of all of the women in the population as possible. We selected "Physical force," "Word," 'Vehicle stop," and "Threat of force (verbal of physical)."

In [29]:
```
# proportion of females in the data set
fem_only= q_data.groupby('complainant_gender').size()
prop_fem = fem_only[0] / fem_only.sum()

# proportion of women who filed against the police for physical force
pf = q_data[q_data['allegation'] == 'Physical force'].groupby('complainant_gender
prop_pf = pf[0] / pf.sum()

# proportion of women who filed against the police for word
w = q_data[q_data['allegation'] == 'Word'].groupby('complainant_gender').size()
prop_w = w[0] / w.sum()

# proportion of women who filed against the police for vehicle stop
vst = q_data[q_data['allegation'] == 'Vehicle stop'].groupby('complainant_gender'
prop_vst = vst[0] / vst.sum()

# proportion of women who filed against the police for threat of force
tof = q_data[q_data['allegation'] == 'Threat of force (verbal or physical)'].grou
prop_tof = tof[0] / tof.sum()

alleg = ['Physical force', 'Word', 'Vehicle stop', 'Threat of force (verbal or ph

{'Whole population': prop_fem, 'Physical force': prop_pf, 'Word': prop_w, \
    'Vehicle stop': prop_vst, 'Threat of force (verbal or physical)': prop_tof}
```

Out[29]:
```
{'Whole population': 0.1726675607826954,
 'Physical force': 0.1672940192388122,
 'Word': 0.2368558042686101,
 'Vehicle stop': 0.10487580496780129,
 'Threat of force (verbal or physical)': 0.12288613303269448}
```

In our hypothesis test, we're doing a test for each allegation individually. We run 1000 simulations for each allegation and we shuffle the success column in each simulation. We find the difference of means between both genders after shuffling and add it to the nested list of results.

In [30]:
```
nrepetitions = 1000

alleg = ['Physical force', 'Word', 'Vehicle stop', 'Threat of force (verbal or ph

differences = []
for i in alleg:
    lst = []
    for j in range(n_repetitions):
        filt = q_data[q_data['allegation'] == i].reset_index(drop=True)

        shuffled_successes = (
            filt['success']
            .sample(replace=False, frac=1)
            .reset_index(drop=True)
        )


        shuffled = (
            filt
            .assign(**{'shuffled success': shuffled_successes})
        )


        group_means = (
            shuffled
            .groupby('complainant_gender')
            .mean()
            .loc[:, 'shuffled success']
        )
        difference = group_means.diff().iloc[-1]


        lst.append(abs(difference))
    differences.append(lst)
```

Here we get the observed values for each allegation type

In [31]:
```
alleg = ['Physical force', 'Word', 'Vehicle stop', 'Threat of force (verbal or ph
obs_diff = []
for i in alleg:
    filt = q_data[q_data['allegation'] == i].reset_index(drop=True)
    observed_difference = (
        filt
        .groupby('complainant_gender')['success']
        .mean()
        .diff()
        .iloc[-1]
    )
    obs_diff.append(observed_difference)
obs_diff
```

Out[31]:
```
[0.03624497739829231,
 0.03093713925910377,
 0.06068228124267505,
 0.009669583264545645]
```

Finally we calculate the pvalue for each allegation type

In [32]:
```
pval = []
for i in range(4):
    pval.append(np.mean(differences[i] > obs_diff[i]))
pd.Series(pval,index=alleg)
```

Out[32]:
```
Physical force                            0.002
Word                                      0.052
Vehicle stop                              0.082
Threat of force (verbal or physical)      0.789
dtype: float64
```

For 'Physical force' we reject our null hypothesis

For 'word' we do not reject our null hypothesis

For 'Vehicle stop' we do not reject our null hypothesis

For 'Threat of force (verbal or physical)' we do not reject our null hypothesis