nypd

December 13, 2021

1 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.

1.0.1 Getting the Data

The data and its corresponding data dictionary is downloadable here.

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

1.0.2 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.

1.0.3 Assessment of Missingness

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

1.0.4 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.

2 Summary of Findings

2.0.1 Introduction

In this case study, we will be studying 12,000 civilian complaints filed against New York City police officers, out main goal is to know whether there is a relationship between the gender of the police officer and their age to the allegation incident that they were involved in. The dataset contains 33358 observations including incident details, complainant details, and well as the police officer's information, and 30 variables including categorical and numerical values. We will be access the dataset using these values. We're going to be performing a hypothesis test for the research.

2.0.2 Cleaning and EDA

To more accuratly perform statistical analysis on the dataset, we will need to perform data cleaning to reduce dimension. We will also utilize bar charts, scatter plots, etc. to perform EDA(Explainatory Data Analysis)

- **Cleaning the data**

1. For conditions that were unable to record from the dataset, we decided to replace those values with `NaNs`.
    - The following keyword in the dataset columns values will be converted: `'Unknown'`, `'Refused'`,`'non-conforming'`, `'Not described'`
2. We also observed categorical data such as `Transman (FTM)'`,`'Transwoman (MTF)'` in the `'complainant_gender'` column of the dataset that could be categorized into `'Male'` and `'Female'`, accordingly.
3. Transform `'mos_gender'` column values into `'Male'` and `'Female'`
4. Combine the `'month_received'` and `'year_received'` column into `'complaint_receive_date'` and convert it to a **datatime** object.
5. Combine the `'month_closed'` and `'year_closed'` column into `'complaint_closed_date'` and convert it to a **datatime** object.
6. Combine the `'first_name'` and `'last_name'` column into `'mos_name'` and convert it to a **string** object.

- **Univariate Analysis:** We plotted a histrgram distribution on `'year_received'` and `'year_closed'` column, and we discovered that the allegation incidents are increasing in a exponential growth on averate, we do see a pike in 2006 and 2013, it might implies to certain movements occuring in the society at the moment. Also, the two distribution are sharing a similar shape, which we can also say that the government is working on the incidents at a good pace so that the cases are being handled in time.
- **Bivariate Analysis:** We conducted a multiple box plot on `'mos_age_incident'` and `'mos_ethnicity'` to observe the range and mean of the officer that was being reported, as well as `'complainant_age_incident'` and `'complainant_ethnicity'`. From officer box plot, we observed that most of the officers that was being acused of allegation are around 33 years old and the distribution of officer's ethinicity are about the same except for American Indian, American Indian has the least amount of cases across all the other races. On the other hand, the complainant ages range and mean shares across all the ethnicity and

in around 30-35 years old, which are also at a similar age like as the officers that we being reported.

- **Interesting Aggregates:** In this case, we aggreated the `'contact_reason'` column and `'complainant_ethnicity'` with `'allegation'`, to get the most-frequent happened allegation. By knowing the different behavior, we can observed the allegations were being charged to the officer based on complainant's ethnicity along with the contact reason.

2.0.3 Assessment of Missingness

We observed the majority of the missing value of the dataset comes from the complainant information such as age and gender. We decided to assess the missingness by using complainant ethnicity and police officer's gender for comparison. Empirical distribution and permutation were being used in the assessment. Both complainant ethnicity and gender shared a similar distribution of whether or not having the null values. Tvd was also being used as test statistics and by looking at the distribution, we confirm that the two variable `'mos_gender'` and `'complainant_gender'` are dependent to each other and the missingness in this case is MAR.

On the other hand, we applied the same technique to the columns `'complainant_ethnicity'` and `'month_received'`, and we obtained a test statistic lies within the empirical distribution. We can conclude that it is possible to get such value under the null hypothesis. Thus, `'complainant_ethnicity'` is MCAR and dependent from `'month_received'`.

In addition, the missing data (column) could be ignoarable as the data is MCAR, we will remove all the null values in the dataset for a more accurate assessment of the case study.

2.0.4 Hypothesis Test

In the hypothesis test, we will be looking at the `'mos_age_incident'` and the `'mos_gender'`column to trying to determine whether there is a relationship between the gender of the police officer and their age to the allegation incident that they were involved in. More specifically, we wanted to know if male tends to have a higher age in allegations. Therefore, we will be conducting the test based on the following hypothesis: - **Null hypothesis**: In the population, age of male and female has the same distribution.

- **Alternative hypothesis**: In the population, male tends to have a higher age in allegations.

Process

We shuffled the age column `'mos_age_incident'` and assessed the difference in `'mos_gender'` and appended the test statistic in the a result list. We repeated the test for 1000 time to get the simulated distribution under the null hypothesis.

Result - After conducting the results, we observed the observed value lies outside of the emprical distribution under the null hypothesis - Therefore, we reject the null hypothesis: the two groups do not come from the same distribution. That is, officer's gender and age do not come from the same distribution, the result seems to favor the alternative hypothesis, but we cannot conclude that male has a higher age at the incident time frame. - To improve the test result, we can introduce machine learning techniques such as logistic regression to find a better predictor to further investigate the relationship between the police officer gender and age.

3 Code

[2]:
```
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
```

3.0.1 Cleaning and EDA

[3]:
```
# Data Loading
df = pd.read_csv('allegations_202007271729.csv')
```

```
        ␣
↪---------------------------------------------------------------------------

        FileNotFoundError                         Traceback (most recent call␣
↪last)

        /tmp/ipykernel_98/1074675436.py in <module>
          1 # Data Loading
    ----> 2 df = pd.read_csv('allegations_202007271729.csv')


        /opt/conda/lib/python3.9/site-packages/pandas/util/_decorators.py in␣
↪wrapper(*args, **kwargs)
        309                     stacklevel=stacklevel,
        310                 )
    --> 311             return func(*args, **kwargs)
        312
        313         return wrapper


        /opt/conda/lib/python3.9/site-packages/pandas/io/parsers/readers.py in␣
↪read_csv(filepath_or_buffer, sep, delimiter, header, names, index_col,␣
↪usecols, squeeze, prefix, mangle_dupe_cols, dtype, engine, converters,␣
↪true_values, false_values, skipinitialspace, skiprows, skipfooter, nrows,␣
↪na_values, keep_default_na, na_filter, verbose, skip_blank_lines, parse_dates,␣
↪infer_datetime_format, keep_date_col, date_parser, dayfirst, cache_dates,␣
↪iterator, chunksize, compression, thousands, decimal, lineterminator,␣
↪quotechar, quoting, doublequote, escapechar, comment, encoding,␣
↪encoding_errors, dialect, error_bad_lines, warn_bad_lines, on_bad_lines,␣
↪delim_whitespace, low_memory, memory_map, float_precision, storage_options)
        584     kwds.update(kwds_defaults)
```

```
    585
--> 586     return _read(filepath_or_buffer, kwds)
    587
    588


    /opt/conda/lib/python3.9/site-packages/pandas/io/parsers/readers.py in␣
↪_read(filepath_or_buffer, kwds)
    480
    481     # Create the parser.
--> 482     parser = TextFileReader(filepath_or_buffer, **kwds)
    483
    484     if chunksize or iterator:


    /opt/conda/lib/python3.9/site-packages/pandas/io/parsers/readers.py in␣
↪__init__(self, f, engine, **kwds)
    809             self.options["has_index_names"] = kwds["has_index_names"]
    810
--> 811         self._engine = self._make_engine(self.engine)
    812
    813     def close(self):


    /opt/conda/lib/python3.9/site-packages/pandas/io/parsers/readers.py in␣
↪_make_engine(self, engine)
   1038             )
   1039         # error: Too many arguments for "ParserBase"
-> 1040         return mapping[engine](self.f, **self.options)  # type:␣
↪ignore[call-arg]
   1041
   1042     def _failover_to_python(self):


    /opt/conda/lib/python3.9/site-packages/pandas/io/parsers/
↪c_parser_wrapper.py in __init__(self, src, **kwds)
     49
     50         # open handles
---> 51         self._open_handles(src, kwds)
     52         assert self.handles is not None
     53


    /opt/conda/lib/python3.9/site-packages/pandas/io/parsers/base_parser.py␣
↪in _open_handles(self, src, kwds)
    220         Let the readers open IOHandles after they are done with␣
↪their potential raises.
```

```
    221         """
--> 222         self.handles = get_handle(
    223             src,
    224             "r",


    /opt/conda/lib/python3.9/site-packages/pandas/io/common.py in␣
↪get_handle(path_or_buf, mode, encoding, compression, memory_map, is_text,␣
↪errors, storage_options)
    700         if ioargs.encoding and "b" not in ioargs.mode:
    701             # Encoding
--> 702             handle = open(
    703                 handle,
    704                 ioargs.mode,


    FileNotFoundError: [Errno 2] No such file or directory:␣
↪'allegations_202007271729.csv'
```

[4]:
```python
# Create a copy of the original data
data = df.copy()
```

```
    ␣
↪---------------------------------------------------------------------------

    NameError                                 Traceback (most recent call␣
↪last)

    /tmp/ipykernel_98/2213038813.py in <module>
      1 # Create a copy of the original data
----> 2 data = df.copy()


    NameError: name 'df' is not defined
```

[5]:
```python
# Display the first 5 entries of the dataset
data.head()
```

```
    ␣
↪---------------------------------------------------------------------------

    NameError                                 Traceback (most recent call␣
↪last)
```

```
/tmp/ipykernel_98/3622289625.py in <module>
      1 # Display the first 5 entries of the dataset
----> 2 data.head()


NameError: name 'data' is not defined
```

[1]:
```
data.info().head()
```

```
       ␣
↪---------------------------------------------------------------------------

       NameError                                 Traceback (most recent call␣
↪last)

       /tmp/ipykernel_98/4011724427.py in <module>
   ----> 1 data.info().head()


       NameError: name 'data' is not defined
```

[33]:
```
# data Cleaning

data['complainant_ethnicity'] = data['complainant_ethnicity'].
 ↪replace({'Unknown':np.NaN, 'Refused':np.NaN})
data['complainant_gender'] = data['complainant_gender'].replace({'Gender␣
 ↪non-conforming':np.NaN, 'Not described':np.NaN,'Transman (FTM)':'Male',␣
 ↪'Transwoman (MTF)':'Female'})
data['complaint_receive_date'] = (
    df['year_received'].astype(str) + '-' +
    df['month_received'].astype(str).str.zfill(2)
)
data['complaint_closed_date'] = (
    df['year_closed'].astype(str) + '-' +
    df['month_closed'].astype(str).str.zfill(2)
)
data['mos_name'] = (
    df['first_name'].astype(str) + ' ' +
    df['last_name'].astype(str)
)
data['mos_gender'] = data['mos_gender'].replace({'M':'Male', 'F':'Female'})

data.drop_duplicates()
```

```
data = data.sort_values(by = ['month_received','year_received','month_closed',
    'year_closed'])
data
```

[33]:

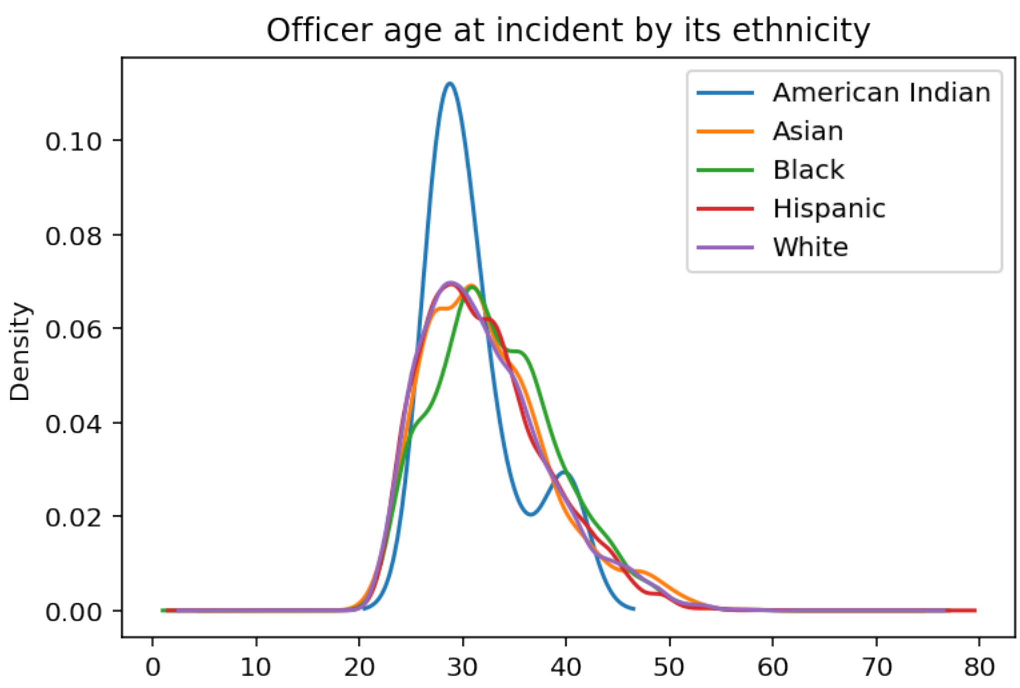
```
       unique_mos_id first_name  last_name command_now  shield_no  \
10893          20619       Troy  Patterson     FAM SEC       2609
10898          20619       Troy  Patterson     FAM SEC       2609
10899          20619       Troy  Patterson     FAM SEC       2609
7968           18770       Paul  Digiacomo      DB CID       3505
25078          34710       John      Caban     TB DT30          0
…                …          …          …          …          …
29194           5752      David    Ramirez     048 PCT      25053
31480             83      Miles     Holman     001 PCT      31489
31481             83      Miles     Holman     001 PCT      31489
31482             83      Miles     Holman     001 PCT      31489
11178           2082    Timothy    Sprague     024 PCT       5620

       complaint_id  month_received  year_received  month_closed  year_closed  \
10893           622               1           1987             1         1987
10898           624               1           1987             1         1987
10899           624               1           1987             1         1987
7968            718               1           1988             1         1988
25078           716               1           1988             1         1988
…               …             …            …          …           …
29194         43605              12           2019             5         2020
31480         43620              12           2019             5         2020
31481         43620              12           2019             5         2020
31482         43620              12           2019             5         2020
11178         43673              12           2019             6         2020

       … complainant_age_incident           fado_type  \
10893  …                      NaN  Offensive Language
10898  …                      NaN  Abuse of Authority
10899  …                      NaN  Offensive Language
7968   …                      NaN         Discourtesy
25078  …                      NaN               Force
…    …                      …                 …
29194  …                     43.0  Abuse of Authority
31480  …                     32.0  Abuse of Authority
31481  …                     32.0  Abuse of Authority
31482  …                     32.0  Abuse of Authority
11178  …                     42.0  Abuse of Authority

                            allegation precinct  \
10893                            White     71.0
10898                  Threat of force     71.0
10899                           Jewish     71.0
```

```
7968                            Curse    67.0
25078                            Slap    90.0
…                                   …      …
29194   Threat to damage/seize property    48.0
31480      Failure to provide RTKA card     1.0
31481  Refusal to provide shield number     1.0
31482           Refusal to provide name     1.0
11178                  Threat of arrest    24.0

                                 contact_reason  \
10893              Report of Crime Past/Present
10898                                    Others
10899                                    Others
7968   Traffic Incidents/Accident/Prk Violation
25078                       Summons/Complainant
…                                             …
29194                     Report of other crime
31480                         Parking violation
31481                         Parking violation
31482                         Parking violation
11178                     Report of other crime

                    outcome_description  \
10893  No arrest made or summons issued
10898         Resisting Arrest/Arrested
10899         Resisting Arrest/Arrested
7968   No arrest made or summons issued
25078     Disorderly-Conduct/Arr/Summons
…                                     …
29194  No arrest made or summons issued
31480            Parking summons issued
31481            Parking summons issued
31482            Parking summons issued
11178     Arrest - other violation/crime

                              board_disposition  complaint_receive_date  \
10893                           Unsubstantiated                 1987-01
10898                           Unsubstantiated                 1987-01
10899                           Unsubstantiated                 1987-01
7968                            Unsubstantiated                 1988-01
25078                           Unsubstantiated                 1988-01
…                                             …                       …
29194                           Unsubstantiated                 2019-12
31480                           Unsubstantiated                 2019-12
31481                           Unsubstantiated                 2019-12
31482  Substantiated (Command Lvl Instructions)                 2019-12
11178                                Exonerated                 2019-12
```

```
      complaint_closed_date          mos_name
10893               1987-01    Troy Patterson
10898               1987-01    Troy Patterson
10899               1987-01    Troy Patterson
7968                1988-01    Paul Digiacomo
25078               1988-01        John Caban
…                      …                 …
29194               2020-05     David Ramirez
31480               2020-05      Miles Holman
31481               2020-05      Miles Holman
31482               2020-05      Miles Holman
11178               2020-06   Timothy Sprague

[33358 rows x 30 columns]
```

[34]:

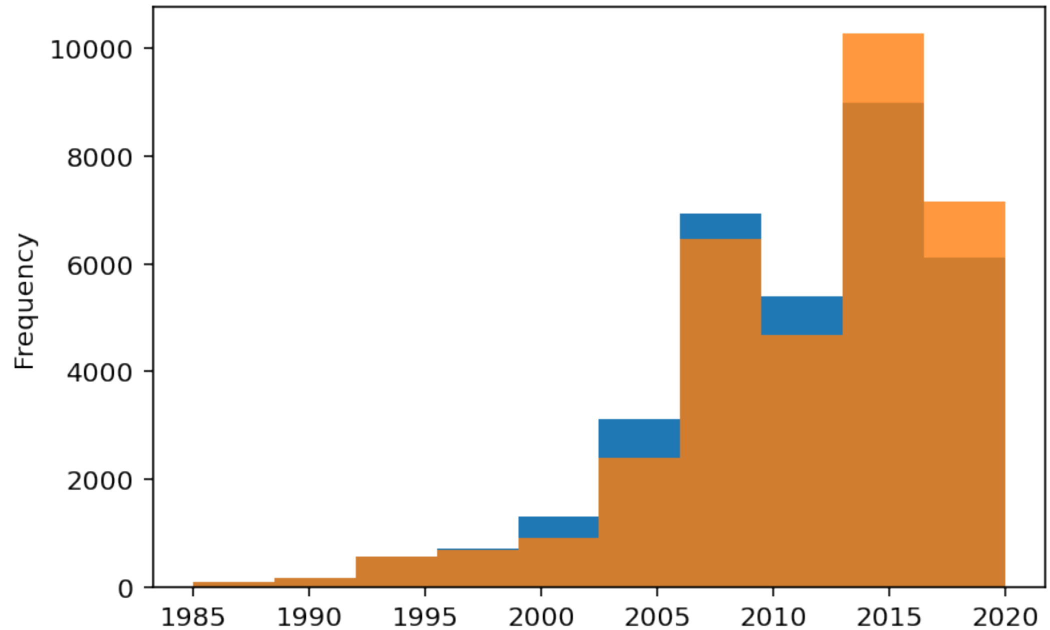
```
title='Officer age at incident by its ethnicity'
(
    data
    .groupby('mos_ethnicity')['mos_age_incident']
    .plot(kind='kde', legend=True, subplots=False, title=title)
);
```



We can see that age around 35 occured the most-often, across of all the ethnicity of the police officers.

[35]:
```
data['year_received'].plot(kind='hist')
data['year_closed'].plot(kind='hist',alpha=.8)
```

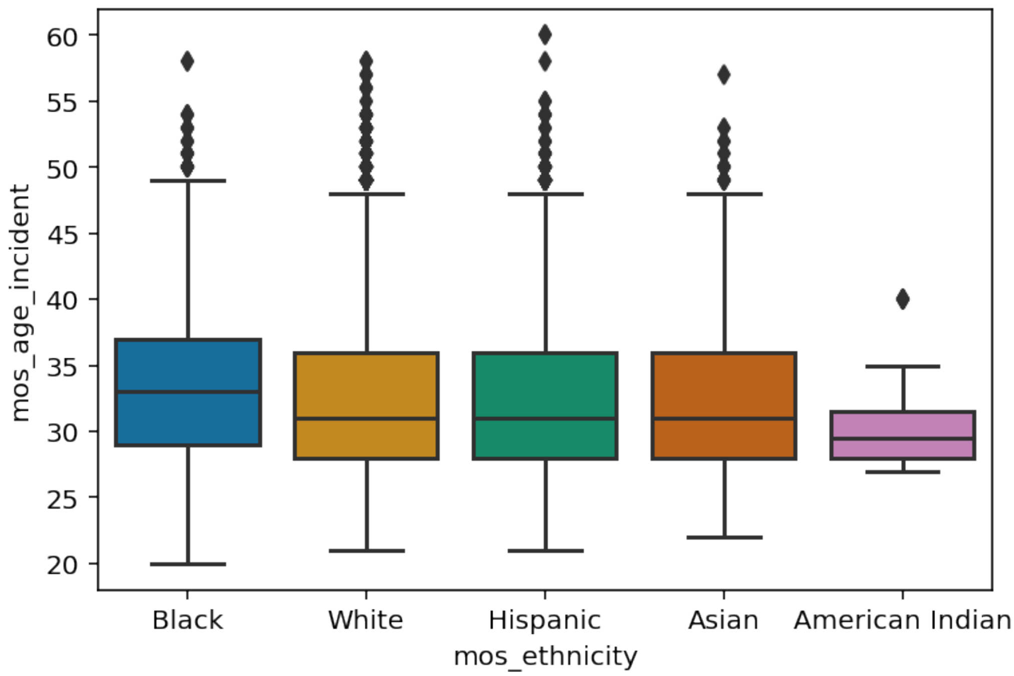
[35]: <AxesSubplot:ylabel='Frequency'>



The two columns are roughly having the same distribution

[36]:
```
#multiple box plot for officer age and race

sns.boxplot(y='mos_age_incident', x = 'mos_ethnicity',
                 data=data,
                 palette="colorblind")
```

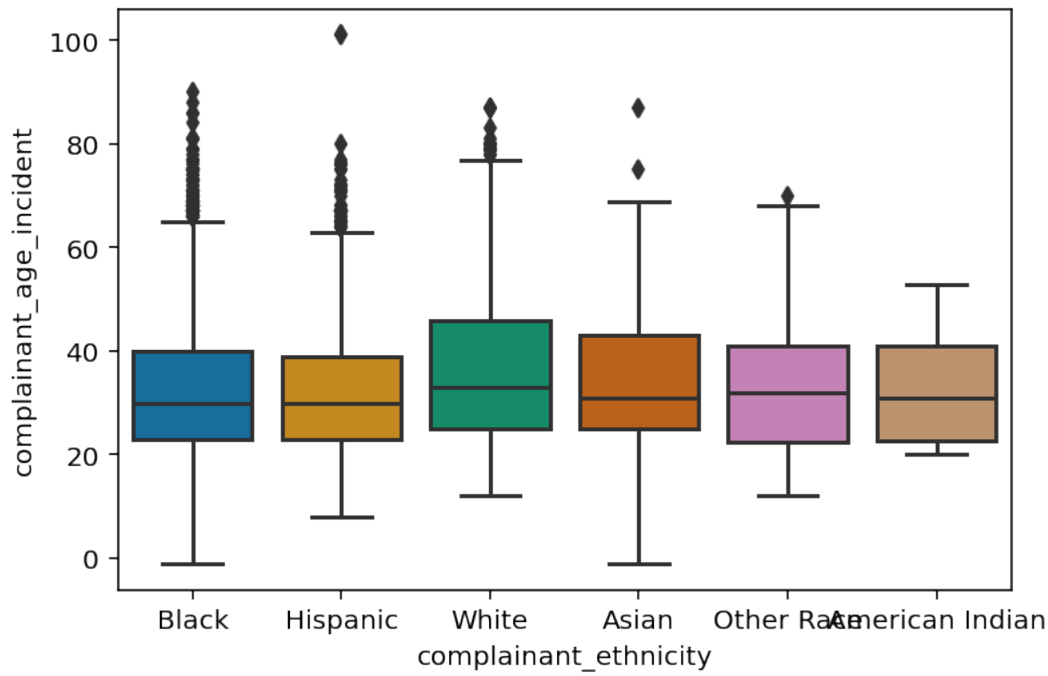
[36]: <AxesSubplot:xlabel='mos_ethnicity', ylabel='mos_age_incident'>



American Indian police officers seems to have the least allegation cases, and all of the officers seems to have an average age of 30-35 at the incident time. Races except American Indian roughly shares the same porportion and ra.nges

[37]:
```
#multiple box plot for comlainant age and race

sns.boxplot(y='complainant_age_incident', x = 'complainant_ethnicity',
                 data=data,
                 palette="colorblind")
```

[37]: <AxesSubplot:xlabel='complainant_ethnicity', ylabel='complainant_age_incident'>



The age range were similar across all the ethinicities among the complainant, Hispanic seems to report least of the police allegation, and White people seems to take the greatest amount

[38]:
```
data.groupby(by=["contact_reason",'complainant_ethnicity']).
    ↪aggregate({"allegation":"max"})
```

[38]:
```
                                                                allegation
contact_reason      complainant_ethnicity
Aided case          Asian                         Refusal to provide name
                    Black                                            Word
                    Hispanic                                         Word
                    Other Race                Threat re: removal to hospital
                    White                                            Word
…                                                                       …
Traffic accident    White                                            Word
Transit checkpoint  Asian                                            Word
                    Black                                            Stop
                    Hispanic                              Search (of person)
                    White                                            Word

[175 rows x 1 columns]
```

3.0.2 Assessment of Missingness

We will be assessing data on complainant details(age, gender, ethnicity, etc.) in this dataset. Moreover, we will be looking at the distributions of ethnicity similar when gender is null vs not null, and later use a permutation test with a 0.05 significance value to determine whether the test statistics are valid to use.

Verify that complaint ethnicities are MCAR in `data`

- Check the data look the 'same' when `complainant_gender` is null vs not-null
  - Is the empirical distribution of officer's gender similar for null/not-null?
  - Is the empirical distribution of complainant ethnicity similar for null/not-null?

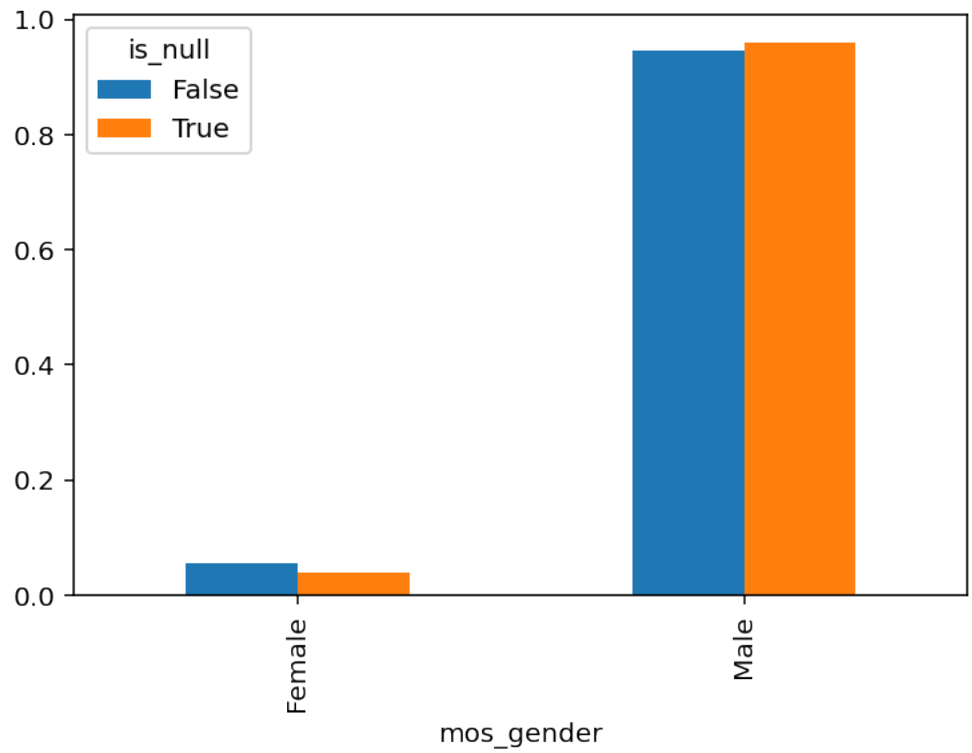
[39]:
```
# conditinal empirical distribution of complainant ethnicity by null and␣
↪not-null
distr = (
    data
    .assign(is_null=data.complainant_gender.isnull())
    .pivot_table(index='is_null', columns='mos_gender', aggfunc='size')
)
distr = (distr.T / distr.sum(axis=1)).T
distr
```

[39]:

mos_gender	Female	Male
is_null		
False	0.054700	0.945300
True	0.039492	0.960508

[40]:
```
distr.T.plot(kind = 'bar')
```

[40]: <AxesSubplot:xlabel='mos_gender'>



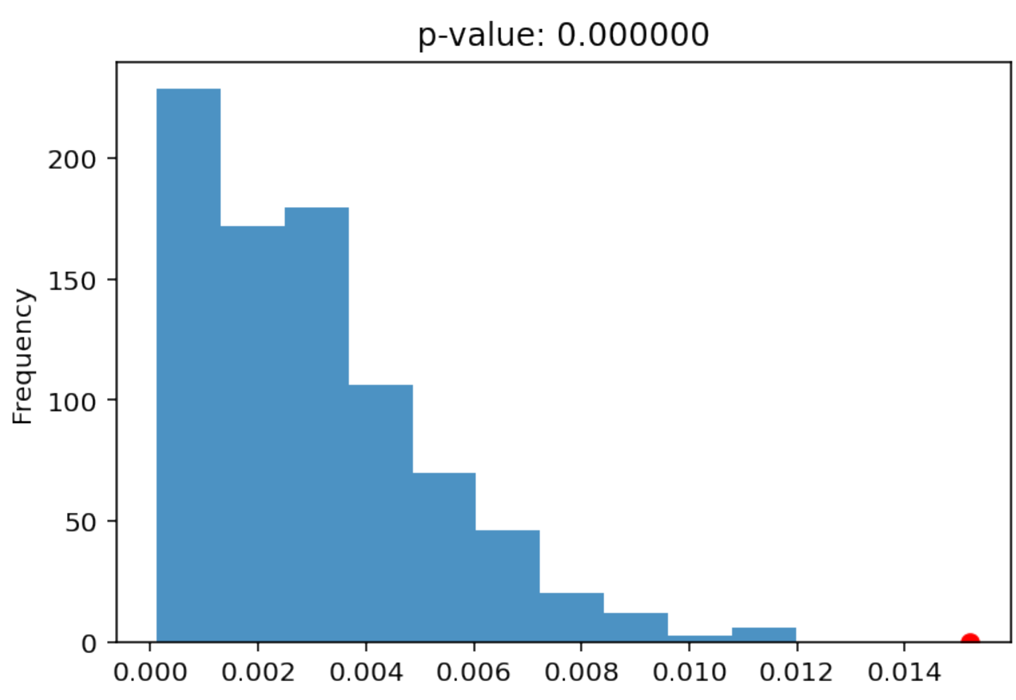
Although we see that the two distribution are similar to each other, which implies that the null values are missing NMAR. But we need to perform a permutation test to validate our assumptions * Tvd will be used as a staticial mesurman as we are having categorical variables (Complainant gender, ethnicity)

[41]:
```
n_repetitions = 1000

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

    # shuffle the gender column
    shuffled_col = (
        data['mos_gender']
        .sample(replace=False, frac=1)
        .reset_index(drop=True)
    )

    # put them in a table
    shuffled = (
        data
        .assign(**{
            'mos_gender': shuffled_col,
            'is_null': data['complainant_gender'].isnull()
```

```
        })
    )

    # compute the tvd
    shuffled = (
        shuffled
        .pivot_table(index='is_null', columns='mos_gender', aggfunc='size')
        .apply(lambda x:x / x.sum(), axis=1)
    )

    tvd = shuffled.diff().iloc[-1].abs().sum() / 2
    # add it to the list of results

    tvds.append(tvd)
```

[42]:
```
# Observed Statistic
obs = distr.diff().iloc[-1].abs().sum() / 2
```

[43]:
```
# The similarity is very high
pval = np.mean(tvds > obs)
pd.Series(tvds).plot(kind='hist', density=True, alpha=0.8, title='p-value: %f'␣
 ↪% pval)
plt.scatter(obs, 0, color='red', s=40);
```

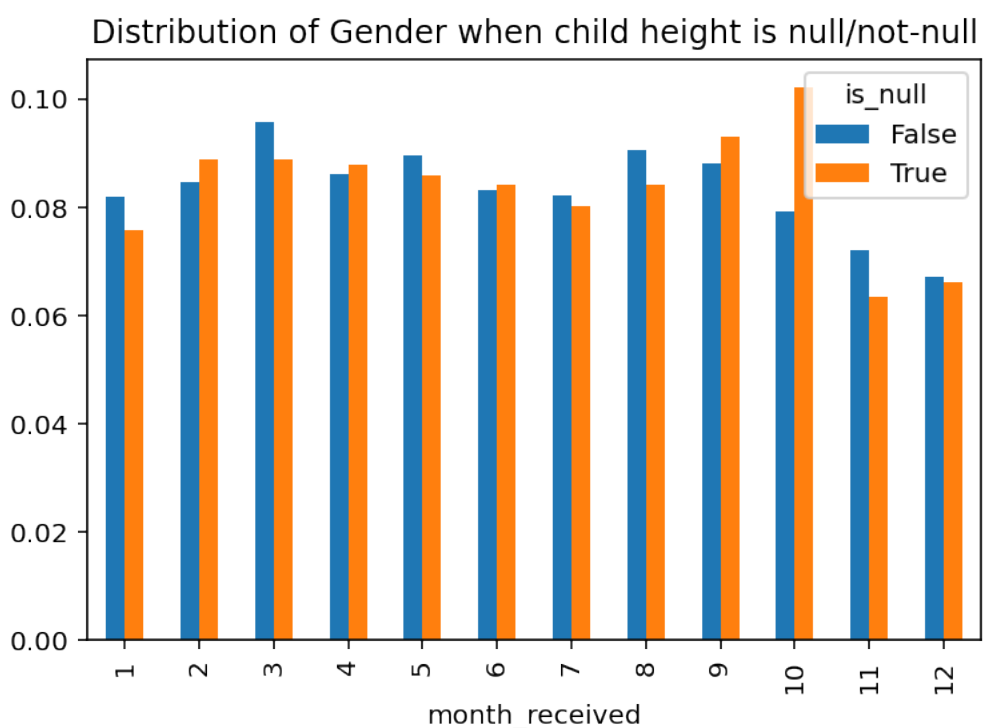


We can see that the observed value is not consistent with the distribution becuase it is at a extreme point, therefore we can reject the null hypothesis and conclude that they are MAR.

[44]:
```
distr = (
    data
    .assign(is_null=data.complainant_ethnicity.isnull())
    .pivot_table(index='is_null', columns='month_received', aggfunc='size')
    .apply(lambda x:x / x.sum(), axis=1)
)
distr
```

[44]:
```
month_received         1         2         3         4         5         6   \
is_null
False           0.081938  0.084511  0.095745  0.086069  0.089621  0.083170
True            0.075642  0.088827  0.088827  0.087786  0.085878  0.084143

month_received         7         8         9        10        11        12
is_null
False           0.082083  0.090418  0.088063  0.079256  0.072045  0.06708
True            0.080153  0.084143  0.092991  0.102186  0.063324  0.06610
```

[45]:
```
distr.T.plot(kind='bar', title='Distribution of Gender when child height is␣
↪null/not-null');
```



[46]:

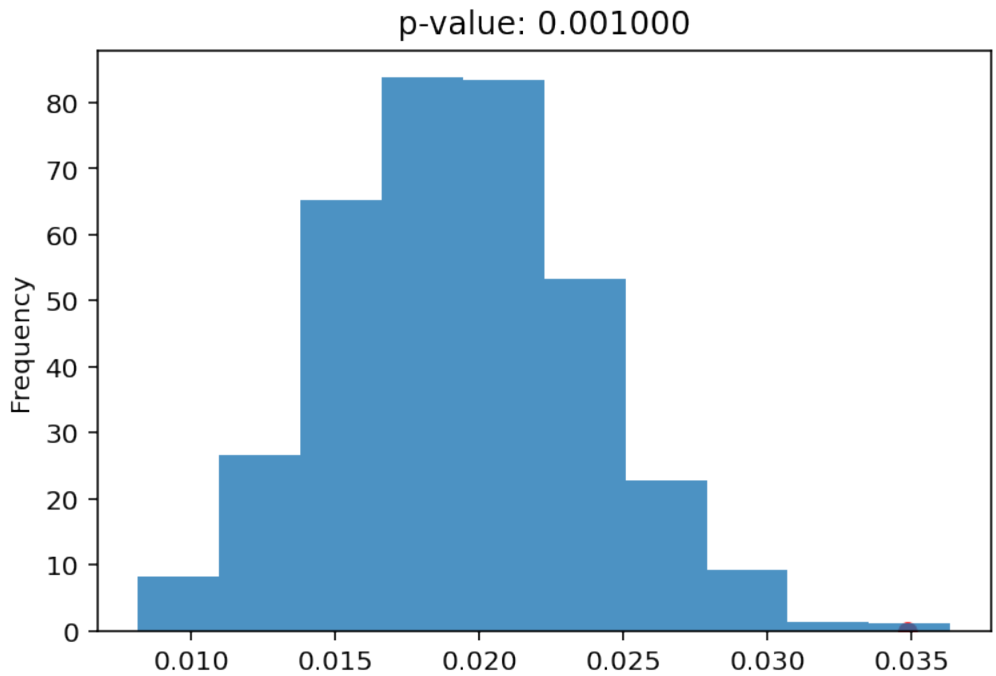
```
n_repetitions = 1000

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

    # shuffle the gender column
    shuffled_col = (
        data['month_received']
        .sample(replace=False, frac=1)
        .reset_index(drop=True)
    )

    # put them in a table
    shuffled = (
        data
        .assign(**{
            'month_received': shuffled_col,
            'is_null': data['complainant_ethnicity'].isnull()
        })
    )

    # compute the tvd
    shuffled = (
        shuffled
        .pivot_table(index='is_null', columns='month_received', aggfunc='size')
        .apply(lambda x:x / x.sum(), axis=1)
    )

    tvd = shuffled.diff().iloc[-1].abs().sum() / 2
    # add it to the list of results

    tvds.append(tvd)
```

[47]:

```
# Observed Statistic
obs = distr.diff().iloc[-1].abs().sum() / 2
```

[48]:

```
# The similarity is very high
pval = np.mean(tvds > obs)
pd.Series(tvds).plot(kind='hist', density=True, alpha=0.8, title='p-value: %f'␣
 ↪% pval)
plt.scatter(obs, 0, color='red', s=40);
```



We can see that it is possible to get such value in the distribution as the test statistic lies within the empirical distribution. Therefore, `'complainant_ethnicity'` is MCAR and dependent from `'month_received'`.

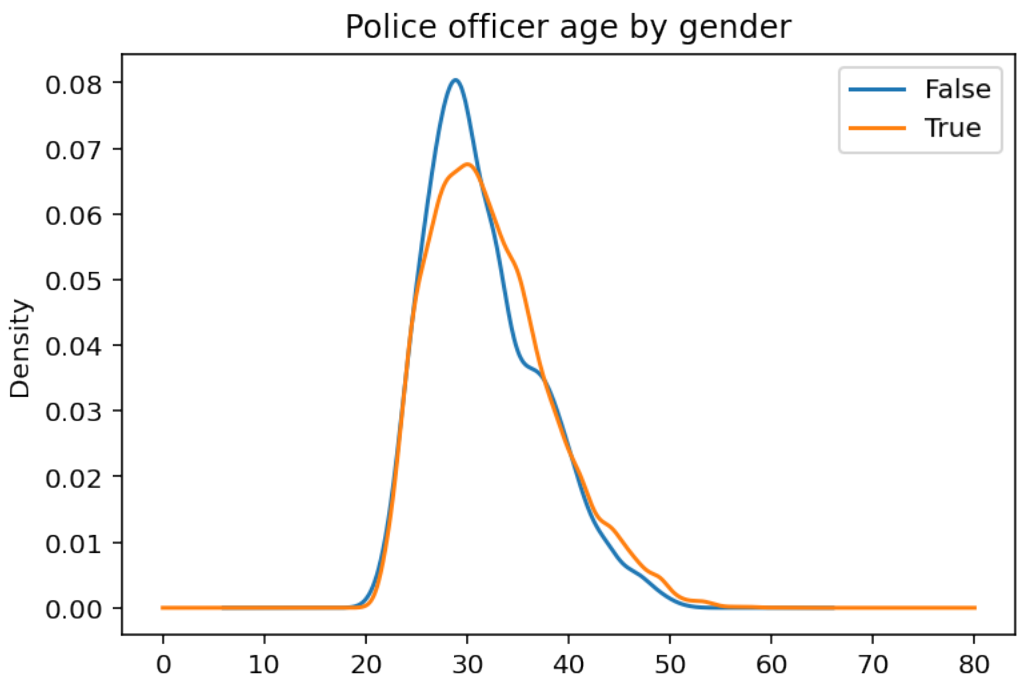
3.0.3 Hypothesis Test

[49]:
```
data['mos_gender'] = data['mos_gender'].replace({'Male': True, 'Female': False})

means_table = data.groupby('mos_gender').mean()

# Mean age for each ranking of the allegations
mean_age = means_table['mos_age_incident']
mean_age
```

[49]:
```
mos_gender
False    31.652841
True     32.385531
Name: mos_age_incident, dtype: float64
```

[50]:
```
# Visualizing the distribution of each group

title='Police officer age by gender'

(
    data
```

```
    .groupby('mos_gender')['mos_age_incident']
    .plot(kind='kde', legend=True, subplots=False, title=title)
);
```



Recall: - **Null hypothesis**: In the population, age of male and female has the same distribution. - I.e., what we saw is due to random chance. - **Alternative hypothesis**: In the population, male tends to have a higher age in allegations.

[51]:
```
means_table = data.groupby('mos_gender').mean()
means_table
```

[51]:

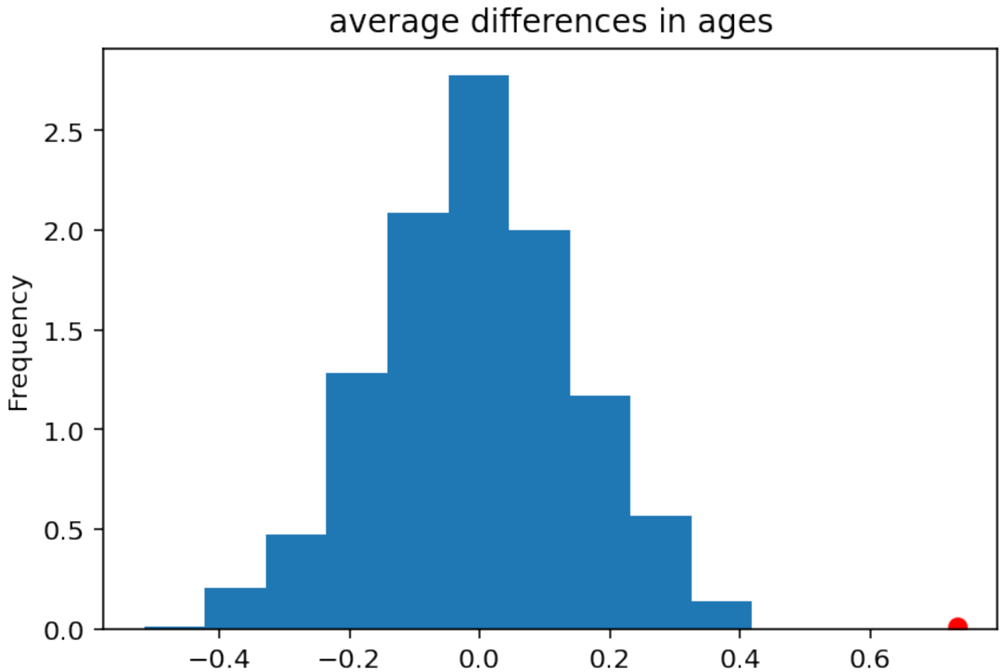
```
            unique_mos_id    shield_no  complaint_id  month_received  \
mos_gender
False        16525.276136  8241.657386  25043.762500        6.123864
True         18261.518292  6351.903601  23841.632698        6.334673

            year_received  month_closed  year_closed  mos_age_incident  \
mos_gender
False         2011.442045      6.660227  2012.201136         31.652841
True          2010.686942      6.460219  2011.488037         32.385531

            complainant_age_incident   precinct
mos_gender
False                      34.778133  58.797612
True                       32.351234  64.675376
```

[52]:
```
obs = means_table.loc[True, 'mos_age_incident'] - means_table.loc[False,␣
↪'mos_age_incident']
obs
```

[52]: 0.7326898207021166

[53]:
```
n_repetitions = 1000

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

    # shuffle the weights
    shuffled_age = (
        data['mos_age_incident']
        .sample(replace=False, frac=1)
        .reset_index(drop=True) # be sure to reset the index! (why?)
    )

    # put them in a table
    shuffled = (
        data
        .assign(**{'Shuffled_age': shuffled_age})
    )

    # compute the group differences (test statistic!)
    group_means = (
        shuffled
        .groupby('mos_gender')
        .mean()
        .loc[:, 'Shuffled_age']
    )
    difference = group_means.diff().iloc[-1]

    # add it to the list of results
    differences.append(difference)
```

[54]:
```
title = 'average differences in ages'
pd.Series(differences).plot(kind='hist', density=True, title=title)
plt.scatter(obs, 0.01, color='red', s=40);
```



We do not observed the observed value lies under the null hypothesis assumptioned distribution