Prediction of Officer's Rank

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Summary of Findings

Introduction

- This dataset in this project contains filled civilian complaints against the New York City police officers. For police officers, their ranking have effects on their authority and responsibility and implies the police culture they usually engage during work. Hence, it is useful predict the ranking of a police officer as it may reflect some about that officer.
- We plan to predict, as of July 2020, the rank of an officer that got filed with a complaint. The relavent data stored in the `'rank_now'` column. Since there are several ranking and the ranking is a categorical variable, we decided to use multiclass classification for our prediction.
- We choose balanced accuracy for our metric. It's most important for our model to correctly predict the ranking of an officer. False positives and false negatives does not have much of a concern for us.
- Since we are planning to predict the officer's latest rank, we are going to only use data that can be obtained during the time of the incident to form our features.

Baseline Model

- We are using 2 categorical features (`'mos_gender'` and `'mos_ethnicity'`) for prediction:
  - Both features are encoded using `OneHotEncoder`
- We chose `DecisionTreeClassifier` as our classifier
  - Our performance metric is around 0.13 for both the training and testing dataset.
- This current model is not ideal since its performance metric is poor. However, it's performance between the training and testing set is similar, meaning that the classifier did not overfit the data.

Final Model

- We added 4 new features for prediction:
  - Categorical columns: `'complainant_gender'` , `'complainant_ethnicity'` , and `'rank_incident'` .
    - We use `FunctionTransformer` to derive new features `'same_gender'` and `'same_ethnicity'` that show whether or not the police and the complainant have the same gender or same ethnicity.
    - Then we one-hot encode these two new features and the `'rank_incident'` feature.
  - Quantitative column: `'mos_age_incident'` .
    - We use `'StandardScaler'` to standardize the `'mos_age_incident'` column.
- We chose `DecisionTreeClassifier` as our classifier. By using `GridSearchCV` , the best hyperparameters obtained are `'gini'` and 14 for criterion and max_depth, respectively.
- This model is still not a good fit since it has low `balanced_accuracy_score` . However, our model improved from 0.13 to 0.34 on both the training and testing dataset, showing that the added features help improve the model.

Fairness Analysis

> **Null Hypothesis**: Our model is fair. Its balanced accuracy for female and male officers are roughly the same, and any differences are due to random chance.
> **Alternative Hypothesis**: Our model is unfair. Its balanced accuracy for male officers is higher than its balanced accuracy for female officers.
> **Test Statistic**: `balanced_accuray_male - balanced_accuray_female`

Since our p-value from our permutation test is smaller than 0.05, we reject the null hypothesis. It seems like the difference we've observed is not due to random chance and our model maybe unfair performance between male and female officers.

Code

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

In [2]:
```
# Load the data of NYPD Civilian Complaints
data = os.path.join('data', 'allegations_202007271729.csv')
police_data = pd.read_csv(data)
print(police_data.shape)
police_data.head()
```

```
(33358, 27)
```

Out[2]:

	unique_mos_id	first_name	last_name	command_now	shield_no	complaint_id	month_received	year_receive
0	10004	Jonathan	Ruiz	078 PCT	8409	42835	7	201
1	10007	John	Sears	078 PCT	5952	24601	11	201
2	10007	John	Sears	078 PCT	5952	24601	11	201
3	10007	John	Sears	078 PCT	5952	26146	7	201
4	10009	Noemi	Sierra	078 PCT	24058	40253	8	201

5 rows × 27 columns

Checking for missingness and data types in `police_data`

In [3]:
```
police_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 33358 entries, 0 to 33357
Data columns (total 27 columns):
 #   Column                     Non-Null Count  Dtype  
---  ------                     --------------  -----  
 0   unique_mos_id              33358 non-null  int64  
 1   first_name                 33358 non-null  object 
 2   last_name                  33358 non-null  object 
 3   command_now                33358 non-null  object 
 4   shield_no                  33358 non-null  int64  
 5   complaint_id               33358 non-null  int64  
 6   month_received             33358 non-null  int64  
 7   year_received              33358 non-null  int64  
 8   month_closed               33358 non-null  int64  
 9   year_closed                33358 non-null  int64  
 10  command_at_incident        31814 non-null  object 
 11  rank_abbrev_incident       33358 non-null  object 
 12  rank_abbrev_now            33358 non-null  object 
 13  rank_now                   33358 non-null  object 
 14  rank_incident              33358 non-null  object 
 15  mos_ethnicity              33358 non-null  object 
 16  mos_gender                 33358 non-null  object 
 17  mos_age_incident           33358 non-null  int64  
 18  complainant_ethnicity      28894 non-null  object 
 19  complainant_gender         29163 non-null  object 
 20  complainant_age_incident   28546 non-null  float64
 21  fado_type                  33358 non-null  object 
 22  allegation                 33357 non-null  object 
 23  precinct                   33334 non-null  float64
 24  contact_reason             33159 non-null  object 
 25  outcome_description        33302 non-null  object 
 26  board_disposition          33358 non-null  object 
dtypes: float64(2), int64(8), object(17)
memory usage: 6.9+ MB
```

Column `'rank_now'` does not have any missing values. Therefore we shall leave the dataframe as it is for now and will do permutation later if we decided to create features from columns.

Now we anaylze the type of data in `'rank_now'`

In [4]:
```
police_data['rank_now'].value_counts()
```

Out[4]:
```
Police Officer            10298
Detective                  9917
Sergeant                   7751
Lieutenant                 3696
Captain                     735
Deputy Inspector            435
Chiefs and other ranks      312
Inspector                   214
Name: rank_now, dtype: int64
```

`'rank_now'` has categorical values with 8 different types. Therefore we will perform a multiclass classification for our prediction.

Baseline Model

In [5]:
```
# Import packages needed for model predictions
from sklearn.model_selection import train_test_split, GridSearchCV
from sklearn.tree import DecisionTreeClassifier
from sklearn.pipeline import Pipeline
from sklearn.preprocessing import (OneHotEncoder, StandardScaler,
                                   FunctionTransformer)
from sklearn.compose import ColumnTransformer
from sklearn import metrics
import warnings
warnings.filterwarnings('ignore')
```

We believe that the gender of the ethnicity may have an influence on an officer's ranking and so we decided to use `'mos_gender'` and `'mos_ethnicity'` to predict the lastest ranking of the officer for our baseline model.

First, we split our dataset into a training group and a testing group:

In [6]:
```
# Split dataframe into training and testing set
X = police_data[['mos_gender', 'mos_ethnicity']]
y = police_data['rank_now']
X_train, X_test, y_train, y_test = train_test_split(X, y)
```

In [7]:
```
police_data[['mos_gender', 'mos_ethnicity']].head()
```

Out[7]:

	mos_gender	mos_ethnicity
0	M	Hispanic
1	M	White
2	M	White
3	M	White
4	F	Hispanic

Since both `'mos_gender'` and `'mos_ethnicity'` are categorical variables, we shall use `OneHotEncoder` to transform them. We will use `DecisionTreeClassifier` as our model for multiclass prediction.

In [8]:
```python
# Create a Pipeline to perform feature transformation and model training
pl = Pipeline([
    ('preproc', ColumnTransformer(
        transformers = [
            ('ohe', OneHotEncoder(handle_unknown='ignore', drop='first'),
             ['mos_ethnicity', 'mos_gender'])
        ])
    ),
    ('clf', DecisionTreeClassifier())
])

# Fit our pipeline with the training dataset
pl.fit(X_train, y_train)
```

Out[8]:
```
▾ Pipeline

Pipeline(steps=[('preproc',
                 ColumnTransformer(transformers=[('ohe',
                                                  OneHotEncoder(drop='first',
                                                                handle_unknown
='ignore'),
                                                  ['mos_ethnicity',
                                                   'mos_gender'])])),
                ('clf', DecisionTreeClassifier())])

▸ preproc: ColumnTransformer
    ▸ ohe
    ▸ OneHotEncoder
▸ DecisionTreeClassifier
```

In [9]:
```python
# Obtain our performance metric on training data
metrics.balanced_accuracy_score(y_train, pl.predict(X_train))
```

Out[9]: 0.1351067464301651

In [10]:
```python
# Obtain our performance metric on testing data
metrics.balanced_accuracy_score(y_test, pl.predict(X_test))
```

Out[10]: 0.13594151604823201

Final Model

In [11]:
```python
# Split dataframe into training and testing set
X2 = police_data[['mos_gender', 'complainant_gender', 'mos_ethnicity',
                  'complainant_ethnicity', 'mos_age_incident', 'rank_incident']]
y2 = police_data['rank_now']
X_train2, X_test2, y_train2, y_test2 = train_test_split(X2, y2)
```

In [12]:
```python
def modify(df):
    res = pd.DataFrame()
    res['same_gender'] = df['mos_gender'] == df['complainant_gender']
    res['same_ethnicity'] = df['mos_ethnicity'] == df['complainant_ethnicity']
    return res

# Pipeline for transforming the gender and ethnicity columns of police and
# complainants and performing one-hot encoding
p = Pipeline([
    ('modify', FunctionTransformer(modify)),
    ('ohe', OneHotEncoder(handle_unknown='ignore', drop='first')),
])


# Create a Pipeline to perform feature transformation and model training
pl2 = Pipeline([
    ('preproc', ColumnTransformer(
        transformers = [
            ('modify', p, ['mos_gender', 'complainant_gender',
                           'mos_ethnicity', 'complainant_ethnicity']),
            ('ohe', OneHotEncoder(handle_unknown = 'ignore', drop='first'),
             ['rank_incident']),
            ('std', StandardScaler(), ['mos_age_incident'])
        ])
    ),
    ('clf', DecisionTreeClassifier())
])
```

In [13]:
```python
hyperparameters = {
    'clf__max_depth': np.arange(2, 50),
    'clf__criterion': ['gini', 'entropy']
}

# Get the best hyperparameters using GridSearchCV
searcher = GridSearchCV(pl2, hyperparameters, cv=5, scoring = 'balanced_accuracy')

# Fit our searcher with the training dataset
searcher.fit(X_train2, y_train2)
searcher.best_params_
```

Out[13]:
```
{'clf__criterion': 'gini', 'clf__max_depth': 14}
```

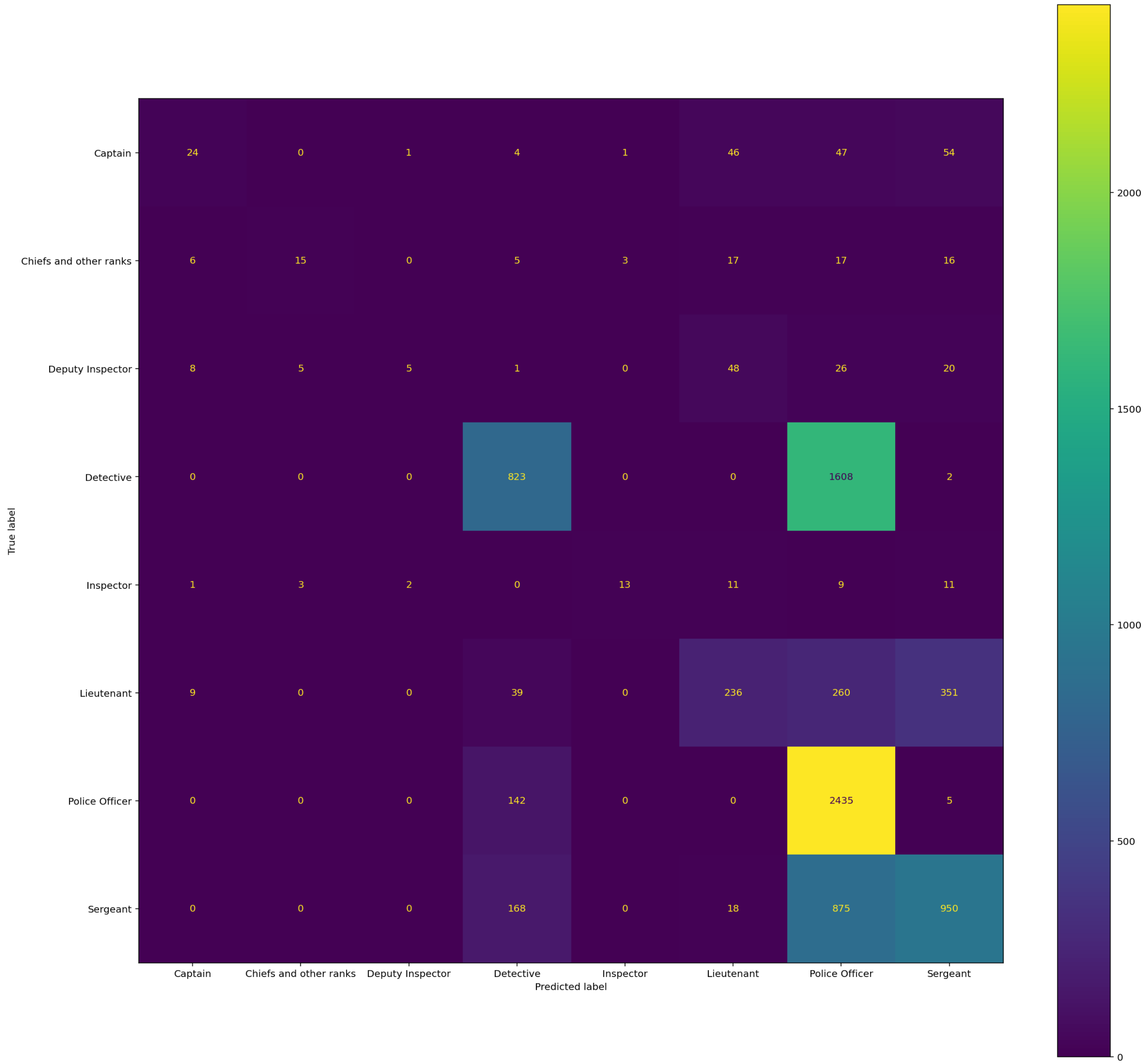
In [14]:
```python
# Obtain our performance metric on training data
metrics.balanced_accuracy_score(y_train2, searcher.predict(X_train2))
```

Out[14]:
```
0.35156724991439636
```

In [15]:
```python
# Obtain our performance metric on testing data
metrics.balanced_accuracy_score(y_test2, searcher.predict(X_test2))
```

Out[15]:
```
0.33089203401347467
```

In [16]:
```python
# Plot the confusion matrix
fig, ax = plt.subplots(figsize=(20, 20))
metrics.plot_confusion_matrix(searcher, X_test2, y_test2, ax=ax)
plt.show()
```



Fairness Analysis

In this section, we want to see if our model gives similar performance between officers of different genders.

In [17]:
```python
police_data['mos_gender'].unique()
```

Out[17]:
```
array(['M', 'F'], dtype=object)
```

Since there are only two genders in the `'mos_gender'` , we can carry on our analysis and form our hypotheses:

> **Null Hypothesis**: Our model is fair. Its balanced accuracy for female and male officers are roughly the same, and any differences are due to random chance.
> **Alternative Hypothesis**: Our model is unfair. Its balanced accuracy for male officers is higher than its balanced accuracy for female officers.
> **Test Statistic**: `balanced_accuray_male - balanced_accuray_female`

First we assign a new column `'mos_is_male'` to the dataframe. The value will be `True` if the gender of the officer is male, otherwise `False` .

In [18]:
```
# Add new column to the dataframe
police_data['mos_is_male'] = police_data['mos_gender'] == 'M'
```

Now we create a function that helps us calculate the test statistic:

In [19]:
```
# define function that calculates the difference between the model metrics of
# male and female officers
def f1_diff(m_df,f_df):
    m_accuracy = metrics.balanced_accuracy_score(m_df['rank_now'],
                                                  searcher.predict(m_df))
    f_accuracy = metrics.balanced_accuracy_score(f_df['rank_now'],
                                                  searcher.predict(f_df))

    return m_accuracy - f_accuracy
```

In [20]:
```
# Obtain the metric difference between male and female officers
male = police_data[police_data['mos_is_male']]
female = police_data[~police_data['mos_is_male']]
obs_diff = f1_diff(male,female)
print('difference:', obs_diff)
```

```
difference: 0.056551016855769076
```

Now we run a permutation test with 500 trials and store the test statistic for all trials in `perm_diffs`

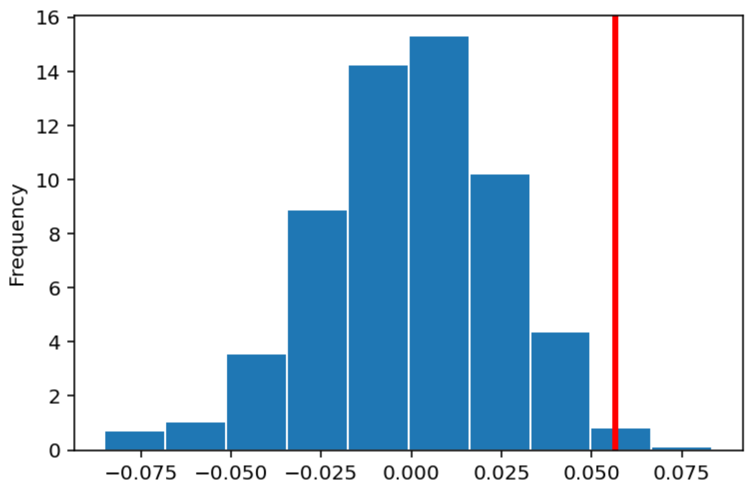
In [21]:
```
# Run a permutation test
perm_diffs = []
for _ in range(500):
    police_data['gender_perm'] = np.random.permutation(
        police_data['mos_is_male'].values
    )
    male = police_data[police_data['gender_perm']]
    female = police_data[~police_data['gender_perm']]

    perm_diffs.append(f1_diff(male,female))
```

In [22]:
```
# Obtain p-value
(perm_diffs > obs_diff).mean()
```

Out[22]: 0.006

In [23]:
```
# Visualize the distribution of the permutation set reuslts
pd.Series(perm_diffs).plot(kind='hist', density=True, ec='w')
plt.axvline(x=obs_diff, color='red', linewidth=3);
```



- Our p-value is around 0.006, which is smaller than our threshold of 0.05. Therefore, we reject the null hypothesis in favor of the alternative hypothesis. It seems like our model maybe biased towards giving higher balanced accuracy scores for male officers.

In [ ]: