The Spectacular Sailors - Checkpoint 4 Machine Learning

In this Checkpoint

- Can we predict whether an officer is in a crew, a community, or is unaffiliated?
- Can we whether any particular group of officers is a crew or not based on aggregated data about their member officers?

Getting Started

Libraries and tools for this analysis:

- Data Structures: Numpy and Pandas
- Machine Learning: SKLearn
- Data Extraction: DataGrip (PostgreSQL)
- Data Source: CPDB
- Analyzed Data: The Spectacular Sailors/Checkpoint 4/src

In [305]:
```
import numpy as np
import sklearn
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn import linear_model, metrics
from sklearn_pandas import DataFrameMapper
import matplotlib.pyplot as plt
```

In [306]:
```
# read the officer and cohort data into pandas dataframe
url = 'https://raw.githubusercontent.com/Northwestern-Data-Sci-Seminar/Invisible-Institute-Chicago-Rep
orter-Collaboration-Public/master/The%20Spectacular%20Sailors/Checkpoint_4/src/officers_crews_ml_2.cs
v'
df = pd.read_csv(url, header = 0)
df = df._get_numeric_data()
original_headers = list(df.columns.values)
df
```

Out[306]:

	officer_id	avg_coaccusals	avg_years_on_force_at_incident	avg_age_at_incident	gender	avg_complaint_percentile	avg_disciplined_c
0	1	2.166667	5.500000	39.500000	1	61.2357	0.00
1	2	4.250000	4.750000	29.750000	0	72.0378	0.00
2	4	1.714286	27.428571	54.428571	1	49.0044	0.00
3	5	11.000000	37.500000	61.500000	1	74.7611	0.25
4	6	3.000000	8.500000	34.500000	1	45.5641	0.00
...	...	...	...	...	...	...	
22469	33052	1.000000	10.000000	32.000000	0	15.9604	0.00
22470	33055	2.500000	1.666667	29.666667	0	40.9117	0.00
22471	33056	2.800000	13.400000	44.400000	0	45.1645	0.10
22472	33057	1.000000	7.000000	34.000000	0	34.8095	0.85
22473	33062	2.000000	13.000000	48.000000	0	0.0000	0.00

22474 rows × 10 columns

Predicting Officer Membership

Question to answer: Given various attributes of an officer, what group do the belong to? Crew, Community, or Unaffiliated?

Motivation: If we use crew membership as a proxy for elevated risk of misconduct, then predicting whether a police officer is in a crew may help inform intervention; however, what about an officer predicts whether they are in a crew?

The Invisible Institute classified police officers into different groups or cohorts based on a topic modeling analysis, as a result, we have a baseline set of target data for every officer in the dataset.

Based on the data_officercrew table, we selected and aggregated data about officers such as the average number of coaccusals, complaint percentile, and allegation severity to produce a table of approximately 20,000 officers. Given the classification of each officer into a group (1 for crew, 2 for community, and 3 for unaffiliated), we present the potential to identify what features of an officer best predict their membership.

In [307]:
```
# change the datatype in the dataframe
df['cohort_id'] = df['cohort_id'].astype('category',copy=False)
df['gender'] = df['gender'].astype('category',copy=False)
df['officer_id'] = df['officer_id'].astype('category',copy=False)
df.dtypes
```

Out[307]:
```
officer_id                       category
avg_coaccusals                    float64
avg_years_on_force_at_incident    float64
avg_age_at_incident               float64
gender                           category
avg_complaint_percentile          float64
avg_disciplined_count             float64
cohort_id                        category
avg_allegation_severity           float64
max_allegation_severity           float64
dtype: object
```

In [308]:
```
# all minmaxscaler on avg_allegation_severity to scale the data
mapper_features  = DataFrameMapper([
                          (['avg_coaccusals'], sklearn.preprocessing.MinMaxScaler()),
                          (['avg_years_on_force_at_incident'], sklearn.preprocessing.MinMaxScaler()),
                          (['avg_age_at_incident'], sklearn.preprocessing.MinMaxScaler()),
                          ('gender', sklearn.preprocessing.LabelBinarizer()),
                          (['avg_complaint_percentile'], sklearn.preprocessing.MinMaxScaler()),
                          (['avg_disciplined_count'], sklearn.preprocessing.MinMaxScaler()),
                          (['avg_allegation_severity'], sklearn.preprocessing.MinMaxScaler())

])
```

Data Processing

Prior to analyzing the data, we dropped several hundred records where the following calculated fields were null:

- average years on force at incident
- average complaint percentile
- average allegation severity
- maximum allegation severity

After dropping missing data, we mapped feature and target data with SKLearn MinMax Scaler and fit_transform. The results of the mapping process produced a features array and target array. Importantly, the scaled values allow us to scale each of the values to between 0 and 1 which means we can evaluate the value of their coeffients. In other words, we can determine which of the values impact the prediction.

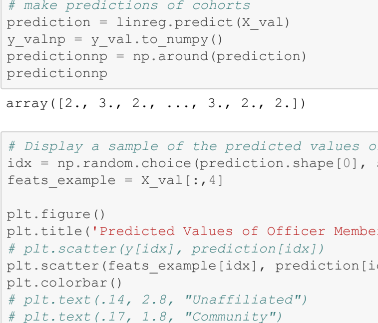
In [309]:
```
# use the mapper to scale the data
features = np.round(mapper_features.fit_transform(df.copy()), 3)
features
```

Out[309]:
```
array([[0.006, 0.436, 0.538, ..., 0.612, 0.   , 0.085],
       [0.017, 0.427, 0.432, ..., 0.72 , 0.   , 0.269],
       [0.004, 0.691, 0.7  , ..., 0.49 , 0.   , 0.213],
       ...,
       [0.009, 0.528, 0.591, ..., 0.452, 0.1  , 0.256],
       [0.   , 0.453, 0.478, ..., 0.348, 0.857, 0.142],
       [0.005, 0.523, 0.63 , ..., 0.   , 0.   , 0.003]])
```

In [310]:
```
# train test validation split
X_train, X_test, y_train, y_test = train_test_split(features, df['cohort_id'], test_size=0.3, shuffle=
True)
```

In [311]:
```
X_val, X_test, y_val, y_test = train_test_split(X_test, y_test, test_size=0.5, shuffle=True)
```

In [312]:
```
# Display a sample of how the features are trained with known classifications
plt.figure()
plt.title('Training Officer Features from Known Labels\nSample of Complaint Percentile Feature')
plt.scatter(X_train[:,4], y_train, c=y_train)
plt.text(.14, 2.8, "Unaffiliated")
plt.text(.17, 1.8, "Community")
plt.text(.23, 1.1, "Crew")
plt.colorbar()
plt.show()
```



In [313]:
```
# train the linear regression model using train data
linreg = linear_model.LinearRegression()
linreg.fit(X_train, y_train)
```

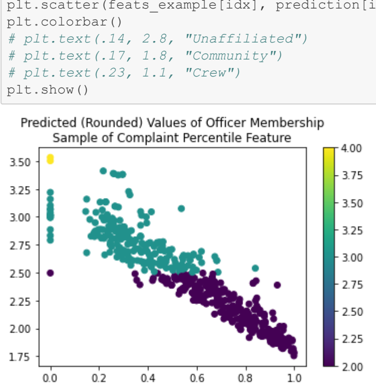
Out[313]:
```
LinearRegression(copy_X=True, fit_intercept=True, n_jobs=None, normalize=False)
```

In [314]:
```
# make predictions of cohorts
prediction = linreg.predict(X_val)
y_valnp = y_val.to_numpy()
predictionnp = np.around(prediction)
predictionnp
```

Out[314]:
```
array([2., 3., 2., ..., 3., 2., 2.])
```

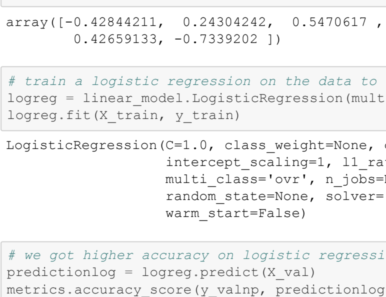
In [315]:
```
# Display a sample of the predicted values of each officer
idx = np.random.choice(prediction.shape[0], size=500)
feats_example = X_val[:,4]

plt.figure()
plt.title('Predicted Values of Officer Membership\nSample of Complaint Percentile Feature')
# plt.scatter(y[idx], prediction[idx])
plt.scatter(feats_example[idx], prediction[idx], c=prediction[idx])
plt.colorbar()
# plt.text(.14, 2.8, "Unaffiliated")
# plt.text(.17, 1.8, "Community")
# plt.text(.23, 1.1, "Crew")
plt.show()
```



In [316]:
```
idx = np.random.choice(prediction.shape[0], size=500)
feats_example = X_val[:,4]

plt.figure()
plt.title('Predicted (Rounded) Values of Officer Membership\nSample of Complaint Percentile Feature')
# plt.scatter(y[idx], prediction[idx])
plt.scatter(feats_example[idx], prediction[idx], c=predictionnp[idx])
plt.colorbar()
# plt.text(.14, 2.8, "Unaffiliated")
# plt.text(.17, 1.8, "Community")
# plt.text(.23, 1.1, "Crew")
plt.show()
```



In [317]:
```
#show accuracy of model 1
metrics.accuracy_score(y_val, predictionnp)
```

Out[317]:
```
0.7279738949866509
```

In [318]:
```
# coefficient of the linear model
linreg.coef_
```

Out[318]:
```
array([-0.42844211,  0.24304242,  0.5470617 , -0.07993756, -1.21990411,
        0.42659133, -0.7339202 ])
```

In [319]:
```
# train a logistic regression on the data to check difference
logreg = linear_model.LogisticRegression(multi_class='ovr')
logreg.fit(X_train, y_train)
```

Out[319]:
```
LogisticRegression(C=1.0, class_weight=None, dual=False, fit_intercept=True,
                   intercept_scaling=1, l1_ratio=None, max_iter=100,
                   multi_class='ovr', n_jobs=None, penalty='l2',
                   random_state=None, solver='lbfgs', tol=0.0001, verbose=0,
                   warm_start=False)
```

In [320]:
```
# we got higher accuracy on logistic regression but generally they are the same
predictionlog = logreg.predict(X_val)
metrics.accuracy_score(y_valnp, predictionlog)
```

Out[320]:
```
0.7356867398398101
```

Data Results - Officer Membership

Based on the scaled values of each feature, we want to train and test predictions whether each row (officer) is in cohort 1, 2, or 3. The array of coefficients indicates which of the features most strongly impacts the prediction. Since we have linear regressions, the value of the coefficient indicates the feature that impacts prediction the most. In this case, the largest negative value is strongest and the largest positive value is weakest.

As show below, the colunm with the strongest coeffiecient is complaint percentile. After considering the meaning, this makes sense - officers that rank highest in complaint percentile are more than likely part of a crew and associated with misocnduct.

On the other hand, the number of years on force and age at incident appeared to have less effect on the prediction. This runs counter to an initial assumption that maturity might have an impact on misconduct.

The current model has an accuracy of about 70%.

In [ ]:
```
# read the officer and cohort data into pandas dataframe
url1 = 'https://raw.githubusercontent.com/Northwestern-Data-Sci-Seminar/Invisible-Institute-Chicago-Rep
orter-Collaboration-Public/master/The%20Spectacular%20Sailors/Checkpoint_4/src/officers_crews_ml_3.csv'
df1 = pd.read_csv(url1, header = 0)
df1 = df1._get_numeric_data()
original_headers = list(df1.columns.values)
df1
```

Out[ ]:

	cohort_id	member_count	years_on_force	percent_black	percent_white	percent_male	percent_female	internal_complaints_per_pers
0	824	7	19.428571	14.285714	28.571429	71.428571	28.571429	4.2857
1	508	11	25.727273	0.000000	63.636364	90.909091	9.090909	3.5454
2	1130	5	22.400000	60.000000	20.000000	100.000000	0.000000	5.8000
3	294	4	22.000000	0.000000	0.000000	100.000000	0.000000	5.0000
4	403	13	26.153846	38.461538	53.846154	100.000000	0.000000	3.2307
...	...	...	...	...	...	...	...	
2329	115	9	22.000000	0.000000	77.777778	44.444444	33.333333	4.1111
2330	883	13	9.500000	7.692308	30.769231	84.615385	7.692308	3.0769
2331	558	12	24.181818	83.333333	0.000000	75.000000	16.666667	4.0833
2332	830	7	30.000000	0.000000	85.714286	100.000000	0.000000	3.2857
2333	1114	7	25.571429	0.000000	14.285714	100.000000	0.000000	3.8571

2334 rows × 9 columns

In [ ]:
```
# change the datatype in the dataframe
df1['detected_crew'] = df1['detected_crew'].astype('category',copy=False)
df1.dtypes
```

Out[ ]:
```
cohort_id                          int64
member_count                       int64
years_on_force                   float64
percent_black                    float64
percent_white                    float64
percent_male                     float64
percent_female                   float64
internal_complaints_per_person   float64
detected_crew                   category
dtype: object
```

In [ ]:
```
# all minmaxscaler on avg_allegation_severity to scale the data
mapper_features1  = DataFrameMapper([
                          (['member_count'], sklearn.preprocessing.MinMaxScaler()),
                          (['years_on_force'], sklearn.preprocessing.MinMaxScaler()),
                          (['percent_black'], sklearn.preprocessing.MinMaxScaler()),
                          (['percent_white'], sklearn.preprocessing.MinMaxScaler()),
                          (['percent_male'], sklearn.preprocessing.MinMaxScaler()),
                          (['internal_complaints_per_person'], sklearn.preprocessing.MinMaxScaler())

])
```

In [ ]:
```
# use the mapper to scale the data
features1 = np.round(mapper_features1.fit_transform(df1.copy()), 3)
features1
```

Out[ ]:
```
array([[0.273, 0.466, 0.143, 0.286, 0.714, 0.245],
       [0.455, 0.617, 0.   , 0.636, 0.909, 0.203],
       [0.182, 0.538, 0.6  , 0.2  , 1.   , 0.331],
       ...,
       [0.5  , 0.58 , 0.833, 0.   , 0.75 , 0.233],
       [0.273, 0.72 , 0.   , 0.857, 1.   , 0.188],
       [0.273, 0.614, 0.   , 0.143, 1.   , 0.22 ]])
```

In [ ]:
```
# train test split
X_train1, X_test1, y_train1, y_test1 = train_test_split(features1, df1['detected_crew'], test_size=0.3,
 shuffle=True)
```

In [ ]:
```
# train the linear regression model1 using train data
linreg1 = linear_model.LinearRegression()
linreg1.fit(X_train1, y_train1)
```

Out[ ]:
```
LinearRegression(copy_X=True, fit_intercept=True, n_jobs=None, normalize=False)
```

In [ ]:
```
# make predictions of cohorts
prediction1 = linreg1.predict(X_test1)
#y_valnp = y_val.to_numpy()
predictionnp1 = np.around(prediction1)
predictionnp1
```

Out[ ]:
```
array([-0.,  0.,  0.,  0.,  0., -0.,  0., -0.,  1., -0.,  0.,  0.,  0.,
       -0.,  0.,  0., -0.,  0.,  0.,  0., -0.,  0.,  1.,  0.,  0.,  0.,
       -0.,  0.,  0.,  0.,  0., -0.,  0.,  0., -0., -0., -0.,  0.,  0.,
        0.,  0.,  0.,  0.,  0., -0., -0., -0.,  0.,  0., -0., -0.,  0.,
        0.,  0.,  0., -0., -0.,  0.,  0., -0.,  0., -0.,  0., -0., -0.,
       -0., -0.,  1., -0., -0., -0., -0., -0.,  0.,  0.,  0., -0.,  0.,
        0.,  0.,  0.,  0., -0.,  0., -0., -0.,  0.,  0.,  0.,  1., -0.,
        1.,  0.,  0.,  0.,  0.,  0.,  0., -0.,  0.,  0.,  0., -0., -0.,
       -0.,  0.,  0.,  0.,  0.,  0.,  0.,  0.,  0.,  0.,  0.,  0., -0.,
        0.,  0.,  0.,  0.,  0., -0., -0., -0., -0., -0.,  0.,  0., -0.,
       -0.,  0.,  0.,  0., -0., -0.,  0.,  0., -0.,  0., -0.,  0.,  1.,
        0.,  0.,  0.,  0.,  0., -0., -0.,  0., -0.,  0., -0.,  0., -0.,
       -0.,  0.,  0.,  0., -0.,  0.,  0.,  0.,  0., -0.,  0.,  0., -0.,
       -0., -0.,  0., -0.,  0.,  0.,  0., -0., -0.,  0., -0., -0.,  0.,
        0.,  0.,  0., -0., -0.,  0.,  0.,  0.,  0., -0.,  0., -0., -0.,
        0.,  0., -0., -0.,  0.,  0.,  0.,  0.,  0.,  1.,  0.,  0.,  0.,
        0.,  0.,  0.,  0.,  0.,  0., -0., -0.,  0., -0.,  0.,  0., -0.,
        0., -0.,  0.,  0., -0., -0.,  0.,  0., -0.,  0.,  0.,  0.,  0.,
        1., -0.,  0.,  0., -0., -0.,  0., -0.,  0., -0.,  0.,  0.,  0.,
        1., -0., -0.,  0., -0.,  0., -0.,  0., -0.,  0.,  0., -0.,  0.,
       -0., -0.,  0.,  0.,  0., -0., -0., -0., -0., -0.,  0.,  0., -0.,
       -0.,  0.,  0., -0.,  0., -0.,  0.,  0., -0.,  0.,  0.,  0.,  1.,
        0., -0.,  0.,  0., -0.,  0., -0.,  0.,  1.,  0.,  0., -0.,  0.,
        0., -0., -0.,  0., -0., -0.,  0., -0., -0.,  0., -0.,  0.,  0.,
        0.,  0., -0., -0., -0.,  0.,  0., -0., -0., -0., -0.,  0.,  0.,
        0.,  0., -0., -0.,  0., -0.,  0., -0.,  0.,  0.,  0.,  0.,  0.,
        0., -0.,  0.,  0.,  0., -0., -0.,  0.,  0.,  1.,  0.,  0.,  0.,
        0., -0., -0.,  0.,  0.,  0.,  0.,  0.,  1.,  0.,  0.,  0.,  0.,
       -0., -0.,  0., -0., -0.,  0.,  0., -0.,  0.,  0.,  0.,  0.,  0.,
        0.,  0.,  0.,  0.,  0., -0.,  0., -0., -0., -0., -0., -0.,  0.,
        0.,  0.,  0., -0., -0.,  0., -0.,  0.,  0.,  0.,  0., -0., -0.,
        0., -0.,  0., -0.,  0.,  0.,  0., -0.,  0.,  0.,  0.,  0., -0.,
        0., -0.,  0., -0., -0.,  0.,  0., -0.,  0.,  0., -0.,  0., -0.,
       -0.,  0., -0., -0., -0.,  0.,  0.,  0., -0.,  0., -0., -0.,  0.,
       -0.,  0., -0., -0.,  0.,  0., -0.,  0.,  0., -0.,  0.,  1.,  0.,
       -0.,  0.,  0.,  0.,  0.,  0., -0., -0.,  0.,  0., -0., -0.,  0.,
       -0.,  0.,  0.,  0., -0., -0., -0., -0.,  0., -0., -0., -0.,  0.,
        0., -0., -0.,  0.,  0., -0.,  0.,  0.,  0.,  0.,  0.,  0., -0.,
        0., -0., -0., -0.,  0.,  0.,  0., -0.,  0.,  0., -0., -0.,  0.,
       -0.,  0.,  0.,  0.,  0.,  0., -0.,  0.,  0.,  0., -0.,  0., -0.,
        0.,  0., -0.,  1., -0., -0.,  0., -0., -0.,  0.,  0., -0.,  0.,
        0.,  0.,  0.,  0., -0.,  0., -0., -0.,  0.,  0.,  0.,  0.,  0.,
        0.,  0.,  0.,  0., -0., -0.,  0.,  0.,  0.,  0.,  0., -0., -0.,
       -0.,  0.,  0.,  0.,  0., -0., -0.,  0.,  0.,  0.,  0., -0., -0.,
       -0.,  0.,  0., -0., -0., -0.,  0.,  0.,  0.,  0.,  0., -0.,  0.,
        0.,  0.,  0.,  0., -0.,  0., -0.,  0.,  0., -0., -0.,  0., -0.,
       -0., -0.,  0.,  0., -0., -0.,  0.,  0.,  0.,  0.,  0.,  0., -0.,
       -0.,  0.,  0.,  0.,  0.,  0., -0., -0.,  0.,  0.,  0.,  0., -0.,
        1.,  0.,  0., -0.,  0.,  0.,  0., -0.,  0., -0.,  1.,  0.,  0.,
        0., -0.,  0.,  0., -0.,  0., -0.,  0.,  0.,  0.,  0., -0.,  0.,
       -0.,  0., -0.,  0.,  0.,  0.,  0.,  0.,  0., -0.,  0.,  0.,  0.,
        0., -0.,  0., -0.,  0.,  0.,  0.,  0., -0., -0., -0.,  0., -0.,
        0.,  0.,  0.,  0., -0.,  0., -0.,  0.,  0., -0.,  0.,  0.,  0.,
        0., -0., -0., -0.,  0.,  1.,  0., -0.,  0.,  0.,  0.,  0.])
```

In [ ]:
```
#show accuracy of model 1
metrics.accuracy_score(y_test1, predictionnp1)
```

Out[ ]:
```
0.9258202567760342
```

In [ ]:
```
# coefficient of the linear model
linreg1.coef_
```

Out[ ]:
```
array([ 0.01854292,  0.03480821,  0.00428483, -0.00797836, -0.00409844,
        1.45437381])
```

In [ ]:
```
# train a logistic regression on the data to check difference
logreg1 = linear_model.LogisticRegression(multi_class='auto')
logreg1.fit(X_train1, y_train1)
```

Out[ ]:
```
LogisticRegression(C=1.0, class_weight=None, dual=False, fit_intercept=True,
                   intercept_scaling=1, l1_ratio=None, max_iter=100,
                   multi_class='auto', n_jobs=None, penalty='l2',
                   random_state=None, solver='lbfgs', tol=0.0001, verbose=0,
                   warm_start=False)
```

In [ ]:
```
predictionlog1 = logreg1.predict(X_test1)
metrics.accuracy_score(y_test1, predictionlog1)
```

Out[ ]:
```
0.9258202567760342
```

Data Results - Group Crew Detection

Earlier, we attempted to predict whether individual officers belonged to a crew, community, or are unaffiliated. In this second model, we attempt to predict whether any grouping of officers is a crew or not.

Similar to the earlier model, we want to know which feature of a group impacts the prediction of crew and whether such a model is accurate. This time, based on the data_crew table, we selected features that average information about the officers in their ranks such as member count, race, and complaints per person.

According to our current model, the internal complaints per person and member count are most heavily weighted when predicting whether a group is classified as a crew or not.

The current group detection model has an accuracy of about 90%.

Conclusion

It is possible to predict and model officer misconduct.

At an indvidual level, officers with high complaint percentiles are most heavily weighted when predicting their cohort.

At a group level, cohorts of officers with many members or with large numbers of complaints indicates there is a crew.

If these metrics are tracked, it may be possible to detect whether individual officers are at higher risk of continued misconduct.