Starcraft Player's Rank Prediction

TOC:

In [ ]:
```
import numpy as np
import pandas as pd

import matplotlib.pyplot as plt
import seaborn as sns

from sklearn.model_selection import GridSearchCV, train_test_split
from sklearn.ensemble import RandomForestClassifier, GradientBoostingClassifier
from sklearn.metrics import confusion_matrix, recall_score

from util_functions import *
```

1. Preprocessing

At first, import dataset and check the fundamental information.

In [ ]:
```
df = pd.read_csv('./data/starcraft_player_data.csv')
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3395 entries, 0 to 3394
Data columns (total 20 columns):
 #   Column                Non-Null Count  Dtype
---  ------                --------------  -----
 0   GameID                3395 non-null   int64
 1   LeagueIndex           3395 non-null   int64
 2   Age                   3395 non-null   object
 3   HoursPerWeek          3395 non-null   object
 4   TotalHours            3395 non-null   object
 5   APM                   3395 non-null   float64
 6   SelectByHotkeys       3395 non-null   float64
 7   AssignToHotkeys       3395 non-null   float64
 8   UniqueHotkeys         3395 non-null   int64
 9   MinimapAttacks        3395 non-null   float64
 10  MinimapRightClicks    3395 non-null   float64
 11  NumberOfPACs          3395 non-null   float64
 12  GapBetweenPACs        3395 non-null   float64
 13  ActionLatency         3395 non-null   float64
 14  ActionsInPAC          3395 non-null   float64
 15  TotalMapExplored      3395 non-null   int64
 16  WorkersMade           3395 non-null   float64
 17  UniqueUnitsMade       3395 non-null   int64
 18  ComplexUnitsMade      3395 non-null   float64
 19  ComplexAbilitiesUsed  3395 non-null   float64
dtypes: float64(12), int64(5), object(3)
memory usage: 530.6+ KB
```

The table above shows that

- there is no null value in the dataset, but
- there might be something wrong in Age, HoursPerWeek and TotalHours columns because their dtypes are object though they should be numerical values.

From here, we use train/test dataset created from original data so that test data is not affected by training process.

In [ ]:
```
df_train, df_test = train_test_split(df, test_size=0.1, random_state=42, stratify=df['LeagueIndex'], shuffle=True)
combine = [df_train, df_test]
df_train.shape, df_test.shape
```

Out[ ]: ((3055, 20), (340, 20))

1.1. Address missing/inappropriate values

Three columns whose dtype are object include non-numerical characters "?", as below.
Besides, almost all "?" are included in the rows of players in the Professional leagues (LeagueIndex=8), and
those three variables for the professional league players are all unknown, at least when it comes to the given dataset.

In [ ]:
```
object_column = df_train.select_dtypes(include='object').columns

for column in object_column:
```

```
    nonnum_train = df_train[column].str.extract(r'([^0-9])').value_counts().rename('count_traindata')
    nonnum_test = df_test[column].str.extract(r'([^0-9])').value_counts().rename('count_testdata')
    nonnum = pd.concat([nonnum_train, nonnum_test], axis=1)
    print('# of rows including non-numerical data in "', column, '":')
    print(nonnum)
    print()
```

```
# of rows including non-numerical data in " Age ":
   count_traindata  count_testdata
0
?               49               6

# of rows including non-numerical data in " HoursPerWeek ":
   count_traindata  count_testdata
0
?               50               6

# of rows including non-numerical data in " TotalHours ":
   count_traindata  count_testdata
0
?               51               6
```

In [ ]:

```
print('Part of rows with TotalHours="?"')
df_train[(df_train['TotalHours']=='?')][['LeagueIndex', 'Age', 'HoursPerWeek', 'TotalHours']].sort_index().head(10)
```

```
Part of rows with TotalHours="?"
```

Out[ ]:

	LeagueIndex	Age	HoursPerWeek	TotalHours
358	5	17	20	?
1841	5	18	?	?
3340	8	?	?	?
3341	8	?	?	?
3342	8	?	?	?
3343	8	?	?	?
3344	8	?	?	?
3345	8	?	?	?
3346	8	?	?	?
3347	8	?	?	?

In [ ]:

```
print('Count of rows for each LeagueIndex with no "?" in the Age column')
df_train[df_train['Age']!='?'].groupby('LeagueIndex').count()['Age']
```

```
Count of rows for each LeagueIndex with no "?" in the Age column
```

Out[ ]:

```
LeagueIndex
1    150
2    312
3    498
4    730
5    725
6    559
7     32
Name: Age, dtype: int64
```

These inappropriate data "?", are explicitly biased in rows with LeagueIndex=8, so I will drop the three columns.
Instead, I will create a new variable "AgeMissing" which is 1 if "Age" equals "?" otherwise 0.

In [ ]:

```
# Add a new column
for data in combine:
    data['AgeMissing'] = np.where(data['Age']=='?', 1, 0)

# Drop three columns
df_train = df_train.drop(object_column, axis=1)
df_test = df_test.drop(object_column, axis=1)
```

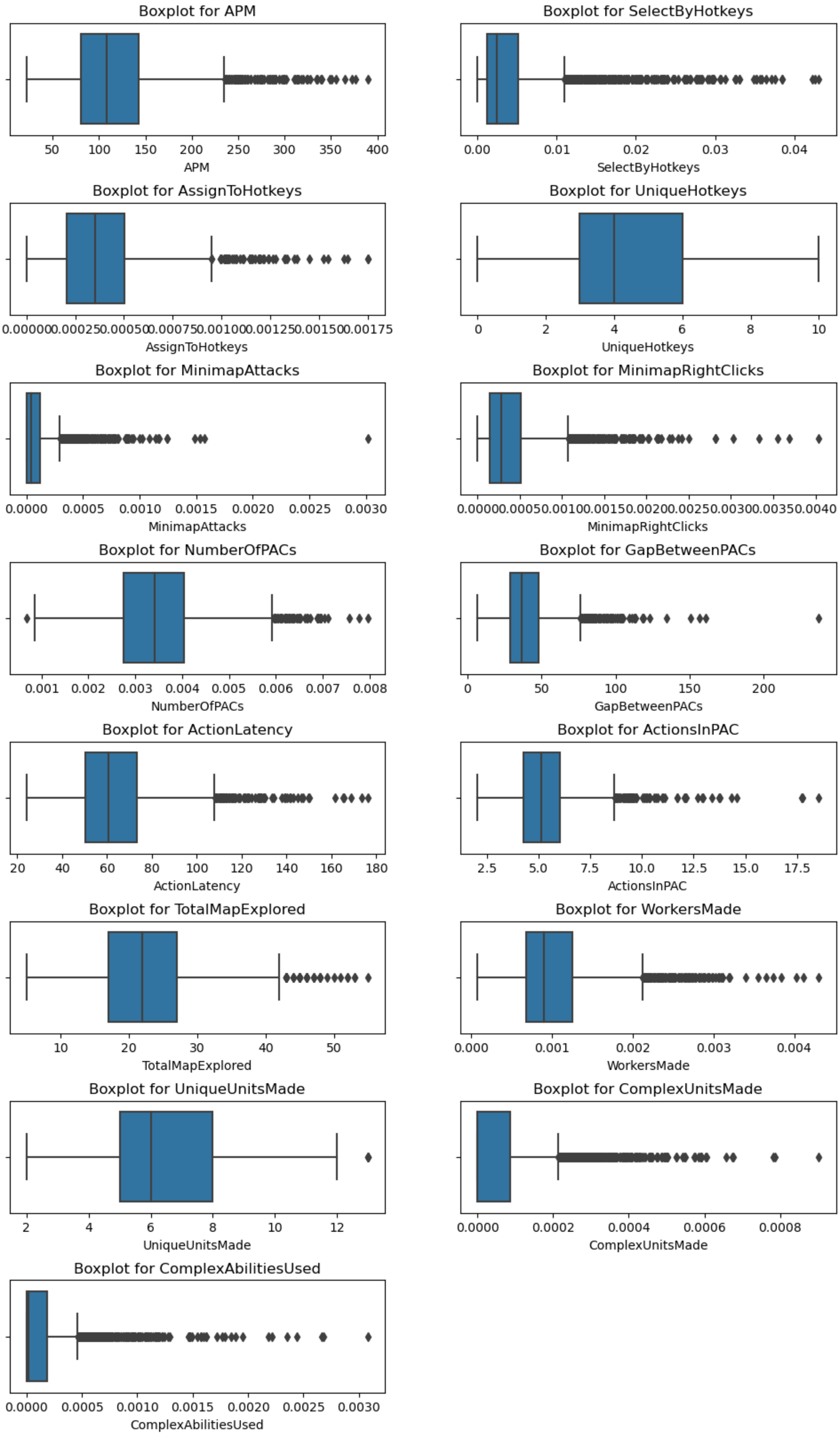
1.2. Address outliers

Next, we checked if each variable had an outlier visually.
In the boxplots below, you can see that some data points exceed the lower/highrer outlier thresholds.

In [ ]:

```
columns = df_train.columns[2:-1]

draw_boxplots(df_train, x=columns, vertical=False, figsize=(12, 20), hspace=0.6)
```


Boxplot for APM
50 100 150 200 250 300 350 400
APM
Boxplot for SelectByHotkeys
0.00 0.01 0.02 0.03 0.04
SelectByHotkeys
Boxplot for AssignToHotkeys
0.00000 0.00025 0.00050 0.00075 0.00100 0.00125 0.00150 0.00175
AssignToHotkeys
Boxplot for UniqueHotkeys
0 2 4 6 8 10
UniqueHotkeys
Boxplot for MinimapAttacks
0.0000 0.0005 0.0010 0.0015 0.0020 0.0025 0.0030
MinimapAttacks
Boxplot for MinimapRightClicks
0.0000 0.0005 0.0010 0.0015 0.0020 0.0025 0.0030 0.0035 0.0040
MinimapRightClicks
Boxplot for NumberOfPACs
0.001 0.002 0.003 0.004 0.005 0.006 0.007 0.008
NumberOfPACs
Boxplot for GapBetweenPACs
0 50 100 150 200
GapBetweenPACs
Boxplot for ActionLatency
20 40 60 80 100 120 140 160 180
ActionLatency
Boxplot for ActionsInPAC
2.5 5.0 7.5 10.0 12.5 15.0 17.5
ActionsInPAC
Boxplot for TotalMapExplored
10 20 30 40 50
TotalMapExplored
Boxplot for WorkersMade
0.000 0.001 0.002 0.003 0.004
WorkersMade
Boxplot for UniqueUnitsMade
2 4 6 8 10 12
UniqueUnitsMade
Boxplot for ComplexUnitsMade
0.0000 0.0002 0.0004 0.0006 0.0008
ComplexUnitsMade
Boxplot for ComplexAbilitiesUsed
0.0000 0.0005 0.0010 0.0015 0.0020 0.0025 0.0030
ComplexAbilitiesUsed

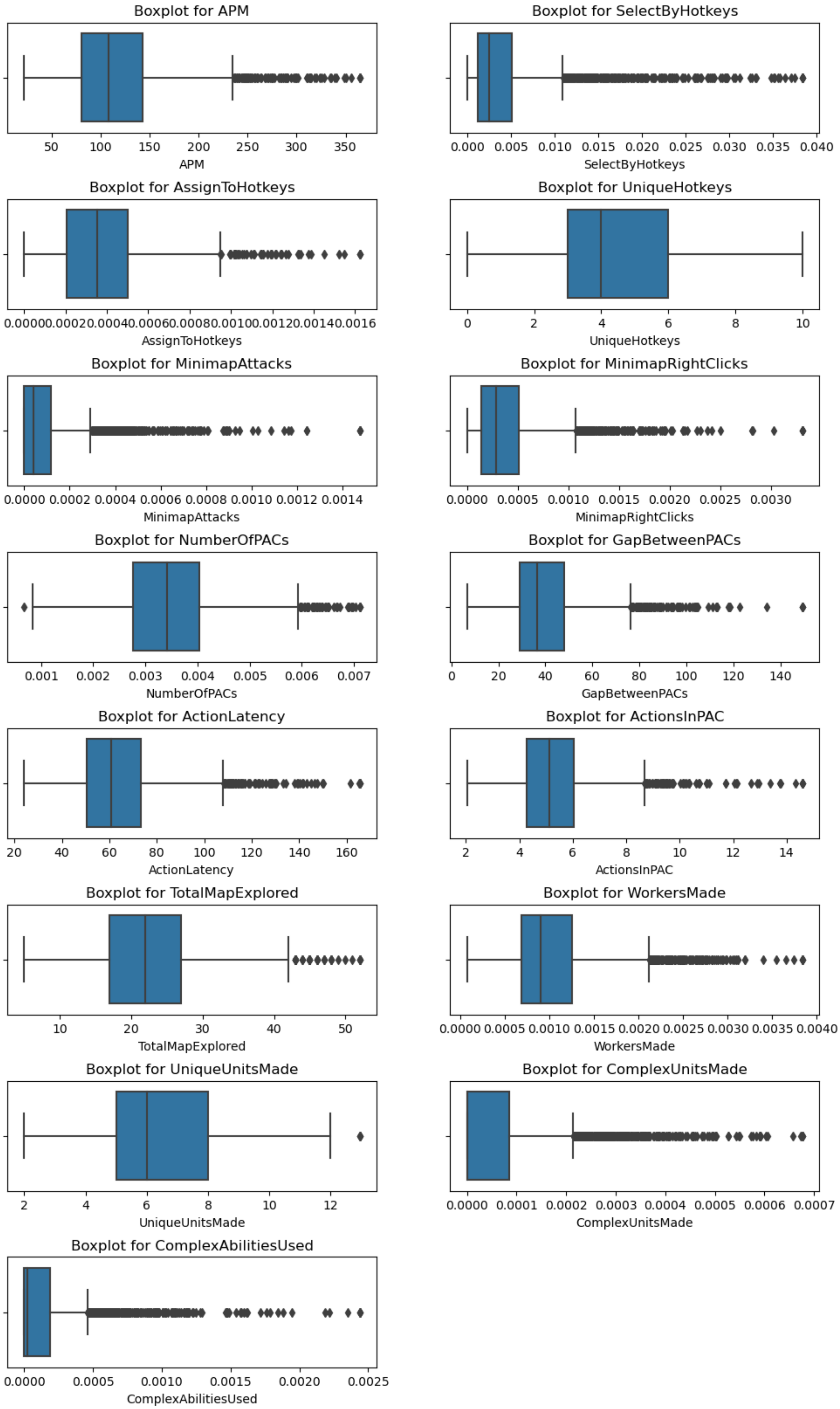
While many data points are regarded as outliers by the boxplots, I will focus only on extreme ones.
To avoid the effect of extreme outliers, I implemented winsorization with upper limit of 0.1%, which will mitigate the outliers.

In [ ]:
```
columns = df_train.columns[2:-1]

# Winsorization: applying train data's limit to test data
for column in columns:
    limit = np.percentile(df_train[column], 99.9)
    df_train[column] = df_train[column].where(df_train[column]<limit, limit)
    df_test[column] = df_test[column].where(df_test[column]<limit, limit)

combine = [df_train, df_test]

draw_boxplots(df_train, x=columns, vertical=False, figsize=(12, 20), hspace=0.6)
```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APM
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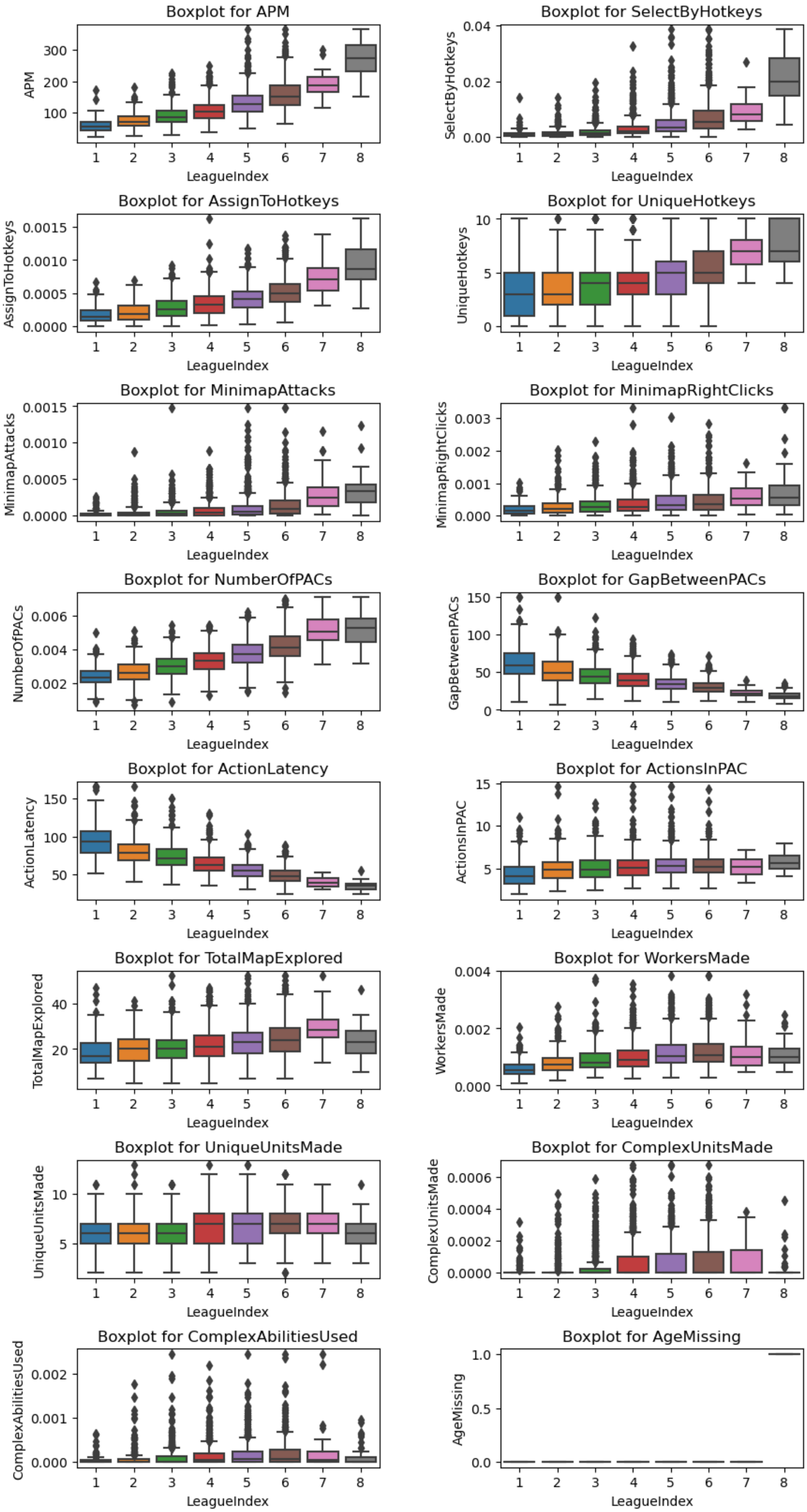
ActionLatency
Boxplot for ActionsInPAC
ActionsInPAC
Boxplot for TotalMapExplored
TotalMapExplored
Boxplot for WorkersMade
WorkersMade
Boxplot for UniqueUnitsMade
UniqueUnitsMade
Boxplot for ComplexUnitsMade
ComplexUnitsMade
Boxplot for ComplexAbilitiesUsed
ComplexAbilitiesUsed

2. Feature Selection

Since we have more than 10 features in the given dataset, we should reduce the number of features to avoid some problems such as overfitting and computational efficiency.
I drew boxplots to see the relationships between LeagueIndex and other features, and I concluded that variables which have an explicit slope of boxes should be included in a classification model.

In [ ]:
```
columns = df_train.columns[2:]

draw_boxplots(df_train, x='LeagueIndex', y=columns, vertical=True, figsize=(10, 20), hspace=0.6, wspace=0.4)
```


Boxplot for APM
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ActionsInPAC
Boxplot for TotalMapExplored
TotalMapExplored
Boxplot for WorkersMade
WorkersMade
Boxplot for UniqueUnitsMade
UniqueUnitsMade
Boxplot for ComplexUnitsMade
ComplexUnitsMade
Boxplot for ComplexAbilitiesUsed
ComplexAbilitiesUsed
Boxplot for AgeMissing
AgeMissing
LeagueIndex

Finally, I chose 9 variables as a feature variable as below. I think the biggest factor that makes players with higer rank differ from those with lower rank is how promptly and efficiently they make actions in a game, with the help of hotkeys and minimap. All variables except for AgeMissing are related to the promptness, that is, we can expect a player to have higher rank as his/her values of those variables are larger(smaller for GapBetweenPACs and ActionLatency).
Therefore, this feature selection seems to be reasonable.

In [ ]:
```
features = ['APM', 'SelectByHotkeys', 'AssignToHotkeys', 'MinimapAttacks', 'MinimapRightClicks', \
            'NumberOfPACs', 'GapBetweenPACs', 'ActionLatency', 'AgeMissing']
```

3. Model Selection

In order to predict player's rank, I applied Random Forest and Gradient Boosting classifier and compared their scores to select a model finally used. Specifically, I figured out the best hyperparameters for each classifier using GridSearchCV, and then chose a model with the best score as the best.

In [ ]:
```
# Assign X and y
X_train = df_train[features]
y_train = df_train['LeagueIndex']
X_test = df_test[features]
y_test = df_test['LeagueIndex']

# Search best hyperparameter/model by GridSearchCV
score_metrics = 'f1_weighted'
param_rf = {
    'n_estimators': [10, 100, 200],
    'max_depth': [3, 6, 9],
    'max_features': ['sqrt', 'log2', None]
}
param_gb = {
    'n_estimators': [10, 100, 200],
    'max_depth': [3, 6, 9],
    'max_features': ['sqrt', 'log2', None],
    'learning_rate': [0.01,0.1,1,10]
}


rf = build_classifier(RandomForestClassifier(random_state=42))
print('Random Forest:')
rf.TuneHParam(X_train, y_train, params=param_rf, cv=3, scoring=score_metrics)
print()

gb = build_classifier(GradientBoostingClassifier(random_state=42))
print('Gradient Boosting:')
gb.TuneHParam(X_train, y_train, params=param_gb, cv=3, scoring=score_metrics)
print()
```

```
Random Forest:
Best Parameters for RandomForestClassifier(random_state=42): {'max_depth': 6, 'max_features': 'sqrt', 'n_estimators': 100}
Best Score RandomForestClassifier(random_state=42): 0.384

Gradient Boosting:
Best Parameters for GradientBoostingClassifier(random_state=42): {'learning_rate': 0.01, 'max_depth': 6, 'max_features': 'sqrt',
'n_estimators': 200}
Best Score GradientBoostingClassifier(random_state=42): 0.381
```

As a result, I selected Random Forest classifier with max_depth=6, max_features='sqrt' and n_estimators=100 as the best model, though there is no big difference between those two classifiers in terms of scores.

In [ ]:
```
best_model = rf.best_model
best_model.fit(X_train, y_train)
```

Out[ ]:
```
RandomForestClassifier(max_depth=6, max_features='sqrt', random_state=42)
```

4. Model Evaluation

Finally, I evaluated the constructed model using scores and confusion matrix. The facts that we can see are:

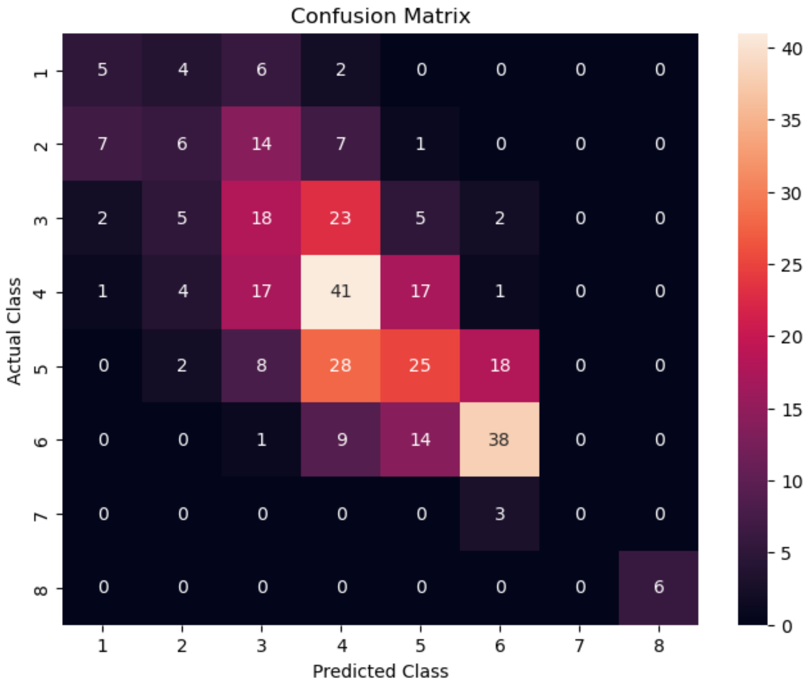
- Accuracy score on test data was 40.9%, that is, this model can predict player's rank correctly with the probability of 40%.
- Confusion Matrix shows that while not few palyers were mistakenly classified, most of them are aligned on/near the diagonal elements.
- LeagueIndex with small sample size tend to have lower recall score.

In [ ]:
```
y_pred = best_model.predict(X_test)
print('Accuracy Score: %.3f' % best_model.score(X_test, y_test))

# Plot Confusion Matrix
cm = confusion_matrix(y_test, y_pred)
cm_df = pd.DataFrame(cm, columns=range(1, 9), index=range(1, 9))

plt.figure(figsize=(8, 6))
sns.heatmap(cm_df, annot=True)
plt.title('Confusion Matrix')
plt.xlabel('Predicted Class')
plt.ylabel('Actual Class')
plt.show()
```

```
Accuracy Score: 0.409
```




```
In [ ]: df_recall = pd.DataFrame({'LeagueIndex': range(1, 9),
                                  'NumSampleInTrain': df_train['LeagueIndex'].value_counts().sort_index().values,
                                  'Recall': recall_score(y_test, y_pred, average=None).round(3)})
        df_recall
```

Out[ ]:

	LeagueIndex	NumSampleInTrain	Recall
0	1	150	0.294
1	2	312	0.171
2	3	498	0.327
3	4	730	0.506
4	5	725	0.309
5	6	559	0.613
6	7	32	0.000
7	8	49	1.000

In conclusion, I think that we can use this model to predict player's rank, but I need to improve it by obtaining additional data.

5. Room for Improvement

If I can ask advice to my collegue and obtain more data, I will ask/confirm:

- why "?" appears in three columns (Age, HoursPerWeek, TotalHours), especially of players with LeagueIndex=8.
- whether I can get more sample so that we will have samples for each LeagueIndex at the same amount.

Once I can clarify them, I will be able to:

- use three columns with confidence to build a model.
- build more accurate model because the variance of each feature variable will decrease as the number of sample increases.