eg_ds_interview_nb

May 29, 2023

[90]:
```python
import numpy as np
import matplotlib.pyplot as plt
import pandas as pd
import sklearn
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import train_test_split, RepeatedStratifiedKFold,␣
↪cross_val_score, RandomizedSearchCV
from sklearn.metrics import confusion_matrix, ConfusionMatrixDisplay
from imblearn.over_sampling import SMOTE, SVMSMOTE, BorderlineSMOTE
from imblearn.under_sampling import RandomUnderSampler
from imblearn.pipeline import Pipeline
import threadpoolctl
import lightgbm as lgb

import warnings
import pprint
warnings.filterwarnings('ignore')
```

1 TLDR:

Using Starcraft player data, we are able to create a model that classifies a player's ladder ranking by leveraging a combination of features such as `APM`, `Unique Hotkeys`, `MinimapRightClicks` etc. We tested three different models using cross validation and found that LightGBM performs the best with an accuracy of 0.366 and an f1-score of 0.365, which performs has better accuracy than simply predicting the majority class.

That being said, this accuracy is not good enough for deployment, and we would recommend iterating on this by collecting more data. This means we should collect more samples, especially for ranks that are under-represented in the current dataset, and also collect more features, such as the player's in-game main race and macro-focused features.

[2]:
```python
data = pd.read_csv("starcraft_player_data.csv", na_values = "?")
data.describe()
```

[2]:
```
            GameID  LeagueIndex          Age  HoursPerWeek    TotalHours  \
count  3395.000000  3395.000000  3340.000000   3339.000000   3338.000000
mean   4805.012371     4.184094    21.647904     15.910752    960.421809
std    2719.944851     1.517327     4.206341     11.962912  17318.133922
```

min	52.000000	1.000000	16.000000	0.000000	3.000000
25%	2464.500000	3.000000	19.000000	8.000000	300.000000
50%	4874.000000	4.000000	21.000000	12.000000	500.000000
75%	7108.500000	5.000000	24.000000	20.000000	800.000000
max	10095.000000	8.000000	44.000000	168.000000	1000000.000000

	APM	SelectByHotkeys	AssignToHotkeys	UniqueHotkeys	\
count	3395.000000	3395.000000	3395.000000	3395.000000	
mean	117.046947	0.004299	0.000374	4.364654	
std	51.945291	0.005284	0.000225	2.360333	
min	22.059600	0.000000	0.000000	0.000000	
25%	79.900200	0.001258	0.000204	3.000000	
50%	108.010200	0.002500	0.000353	4.000000	
75%	142.790400	0.005133	0.000499	6.000000	
max	389.831400	0.043088	0.001752	10.000000	

	MinimapAttacks	MinimapRightClicks	NumberOfPACs	GapBetweenPACs	\
count	3395.000000	3395.000000	3395.000000	3395.000000	
mean	0.000098	0.000387	0.003463	40.361562	
std	0.000166	0.000377	0.000992	17.153570	
min	0.000000	0.000000	0.000679	6.666700	
25%	0.000000	0.000140	0.002754	28.957750	
50%	0.000040	0.000281	0.003395	36.723500	
75%	0.000119	0.000514	0.004027	48.290500	
max	0.003019	0.004041	0.007971	237.142900	

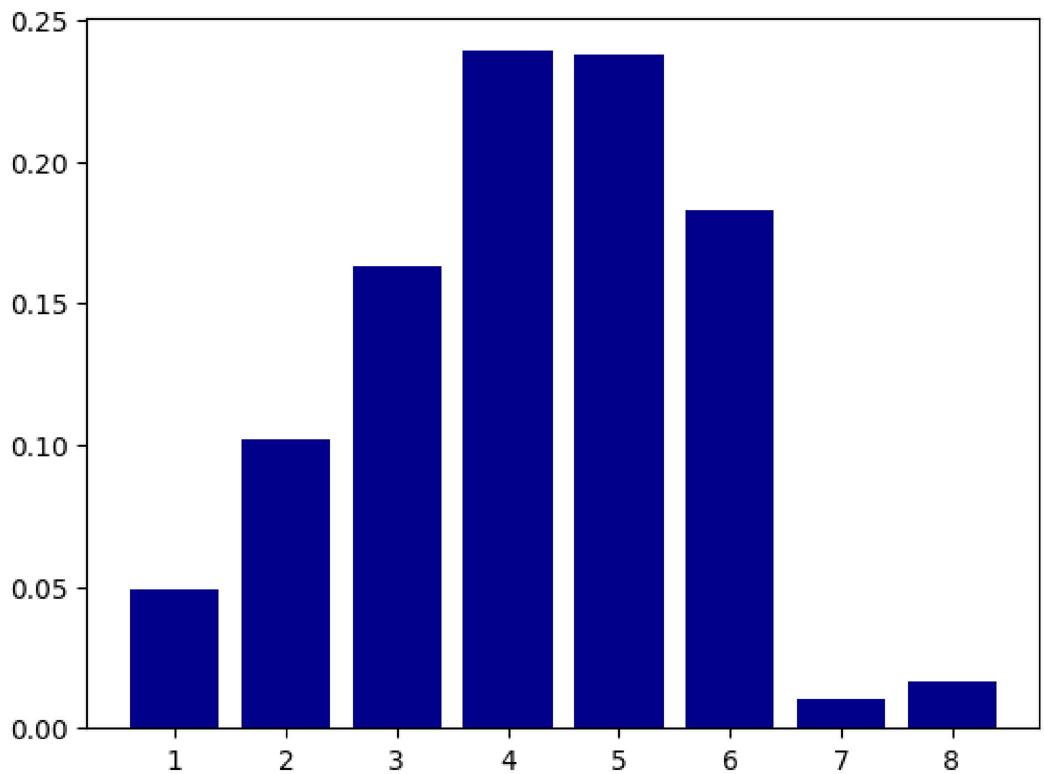
	ActionLatency	ActionsInPAC	TotalMapExplored	WorkersMade	\
count	3395.000000	3395.000000	3395.000000	3395.000000	
mean	63.739403	5.272988	22.131664	0.001032	
std	19.238869	1.494835	7.431719	0.000519	
min	24.093600	2.038900	5.000000	0.000077	
25%	50.446600	4.272850	17.000000	0.000683	
50%	60.931800	5.095500	22.000000	0.000905	
75%	73.681300	6.033600	27.000000	0.001259	
max	176.372100	18.558100	58.000000	0.005149	

	UniqueUnitsMade	ComplexUnitsMade	ComplexAbilitiesUsed
count	3395.000000	3395.000000	3395.000000
mean	6.534021	0.000059	0.000142
std	1.857697	0.000111	0.000265
min	2.000000	0.000000	0.000000
25%	5.000000	0.000000	0.000000
50%	6.000000	0.000000	0.000020
75%	8.000000	0.000086	0.000181
max	13.000000	0.000902	0.003084

2 Exploratory Data Analysis

With any ELO-based ranking system, we can expect that there is reasonable skew in the higher ranks, which the plot shows below. This imbalance requires some additional adjustments to the models, including down/up-sampling and prioritizing F1-score when evaluating on the validation sets.

[3]:
```
# check labels for any imbalances
rank_distribution = data.LeagueIndex.value_counts(normalize = True).sort_index()
plt.bar(rank_distribution.index, rank_distribution.values, color = '#00008B')
plt.show()
```



Moreover, it seems that most of the data is present, except for the age, hours/week and total hours features for professional ranked players.

There is a couple options here. First, if care about all eight ranks, including professionals, then we will have to remove age, hours/week and total hours from the classifier. It is impossible to impute these values correctly due to the features not being missing at random.

Second, if we only care about ranks 1-7 (ex. if we're selling a product that would primarily be used by lower ranked), then it would make sense to remove the professional players from the data set. Even if professional players exist in the real-life test setting, they would likely be classified as 7 and still wouldn't be the target of the product.

We can try to model both versions of the data.

[4]:
```
data[data['LeagueIndex'] == 8].head()
```

[4]:
```
      GameID  LeagueIndex  Age  HoursPerWeek  TotalHours       APM  \
3340   10001            8  NaN           NaN         NaN  189.7404
3341   10005            8  NaN           NaN         NaN  287.8128
3342   10006            8  NaN           NaN         NaN  294.0996
3343   10015            8  NaN           NaN         NaN  274.2552
3344   10016            8  NaN           NaN         NaN  274.3404

      SelectByHotkeys  AssignToHotkeys  UniqueHotkeys  MinimapAttacks  \
3340         0.004582         0.000655              4        0.000073
3341         0.029040         0.001041              9        0.000231
3342         0.029640         0.001076              6        0.000302
3343         0.018121         0.001264              8        0.000053
3344         0.023131         0.000739              8        0.000622

      MinimapRightClicks  NumberOfPACs  GapBetweenPACs  ActionLatency  \
3340            0.000618      0.006291         23.5130        32.5665
3341            0.000656      0.005399         31.6416        36.1143
3342            0.002374      0.006294         16.6393        36.8192
3343            0.000975      0.007111         10.6419        24.3556
3344            0.003552      0.005355         19.1568        36.3098

      ActionsInPAC  TotalMapExplored  WorkersMade  UniqueUnitsMade  \
3340        4.4451                25     0.002218                6
3341        4.5893                34     0.001138                6
3342        4.1850                26     0.000987                6
3343        4.3870                28     0.001106                6
3344        5.2811                28     0.000739                6

      ComplexUnitsMade  ComplexAbilitiesUsed
3340          0.000000                   0.0
3341          0.000058                   0.0
3342          0.000000                   0.0
3343          0.000000                   0.0
3344          0.000000                   0.0
```

[5]:
```
# also a couple errant NaNs from observations whose LeagueIndex = 5
data[(data['LeagueIndex'] != 8) & (data['TotalHours'].isna())]
```

[5]:
```
      GameID  LeagueIndex   Age  HoursPerWeek  TotalHours       APM  \
358     1064            5  17.0          20.0         NaN   94.4724
1841    5255            5  18.0           NaN         NaN  122.2470

      SelectByHotkeys  AssignToHotkeys  UniqueHotkeys  MinimapAttacks  \
358          0.003846         0.000783              3        0.000010
```

```
1841        0.006357        0.000433              3        0.000014

      MinimapRightClicks  NumberOfPACs  GapBetweenPACs  ActionLatency  \
358             0.000135      0.004474         50.5455        54.9287
1841            0.000257      0.003043         30.8929        62.2933

      ActionsInPAC  TotalMapExplored  WorkersMade  UniqueUnitsMade  \
358         3.0972                31     0.000763                7
1841        5.3822                23     0.001055                5

      ComplexUnitsMade  ComplexAbilitiesUsed
358           0.000106              0.000116
1841          0.000000              0.000338
```

Continuing with this investigation into total hours, there are clearly some values that are impossible ex. one observation has total hours being 1,000,000.

Note that HoursPerWeek and TotalHours are the only self-reported features, so presumably the other features should not be impacted by the measurement error. This means that, provided we do not use either of the features, we can retain the observations.

For the version of the dataset that does use totalhours, we can remove some of the observations by using TotalHours and HoursPerWeek to deduce how many years the observation has played. Let's assume that we collect this starcraft data 5 years into the game's lifespan and exclude any observation who indicates they've played for more than 5 years.

[6]:
```
# also a some values that are clearly impossible that can be seen in the
# initial describe above
data[data['TotalHours'] > 5000]
```

[6]:
```
      GameID  LeagueIndex   Age  HoursPerWeek  TotalHours       APM  \
7         72            7  17.0          42.0     10000.0  212.6022
10        83            3  16.0          16.0      6000.0  153.8010
770     2246            5  22.0          16.0     20000.0  248.0490
1793    5140            5  18.0          24.0   1000000.0  281.4246
1978    5610            4  22.0          10.0     18000.0  152.2374
2140    6020            5  22.0          10.0      9000.0  106.0056
2216    6242            3  24.0          20.0     10260.0   76.5852
2324    6518            6  20.0           8.0     25000.0  247.0164
3253    9055            3  19.0          20.0      6000.0  102.0114

      SelectByHotkeys  AssignToHotkeys  UniqueHotkeys  MinimapAttacks  \
7            0.009040         0.000676              6        0.001164
10           0.001677         0.000319              4        0.000000
770          0.023703         0.000391              7        0.000000
1793         0.023428         0.000799              5        0.000041
1978         0.011983         0.000206              1        0.000016
2140         0.003569         0.000635              8        0.000946
2216         0.000780         0.000197              0        0.000063
```

```
2324        0.015794        0.000438              8        0.000308
3253        0.002045        0.000317              5        0.000044

      MinimapRightClicks  NumberOfPACs  GapBetweenPACs  ActionLatency  \
7               0.001253      0.004952         24.6117        41.7671
10              0.000822      0.003772         23.4107        48.0711
770             0.000205      0.004651         37.8795        45.3760
1793            0.000447      0.005136         28.1164        36.1266
1978            0.000364      0.003351         52.1896        63.9811
2140            0.000575      0.003617         28.6645        55.9603
2216            0.000316      0.002438         42.9480        84.6340
2324            0.001339      0.004645         17.6471        37.1837
3253            0.000555      0.003032         62.5423        67.3140

      ActionsInPAC  TotalMapExplored  WorkersMade  UniqueUnitsMade  \
7           6.6104                45     0.002277                9
10          7.0044                24     0.001593                7
770         4.7560                21     0.001526                6
1793        5.8522                29     0.001328                6
1978        4.9575                19     0.000680                5
2140        4.6159                25     0.001018                8
2216        5.9107                27     0.000450               10
2324        6.5944                29     0.001860                6
3253        6.3605                24     0.001410                6

      ComplexUnitsMade  ComplexAbilitiesUsed
7             0.000129              0.000249
10            0.000000              0.000017
770           0.000000              0.000000
1793          0.000000              0.000000
1978          0.000000              0.000000
2140          0.000000              0.000156
2216          0.000246              0.000358
2324          0.000000              0.000012
3253          0.000238              0.001948
```

[7]:
```python
# also people who probably misreporting HoursPerWeek
data[data['HoursPerWeek'] > 84]
```

[7]:
```
      GameID  LeagueIndex   Age  HoursPerWeek  TotalHours       APM  \
237      711            5  17.0          96.0       900.0  145.8060
690     2000            6  16.0         168.0      1260.0  233.3058
1280    3733            6  24.0         112.0      1500.0  139.7598
1299    3768            5  22.0          90.0      1000.0   89.6652
1654    4754            7  18.0          98.0       700.0  236.0316
1677    4817            6  21.0         140.0      1800.0  197.7774
2662    7435            4  34.0          96.0       400.0   56.8584
```

```
      SelectByHotkeys  AssignToHotkeys  UniqueHotkeys  MinimapAttacks  \
237          0.010374         0.000596              4        0.000000
690          0.017521         0.000744             10        0.000178
1280         0.005748         0.000368              4        0.000213
1299         0.001847         0.000360              5        0.000172
1654         0.015664         0.001015             10        0.000366
1677         0.006001         0.000383              4        0.000308
2662         0.000059         0.000029              1        0.000029

      MinimapRightClicks  NumberOfPACs  GapBetweenPACs  ActionLatency  \
237             0.000030      0.003965         43.2906        54.4060
690             0.000235      0.005137         25.5962        38.9165
1280            0.000155      0.005011         24.6822        41.8956
1299            0.000297      0.002551         37.2099        71.6074
1654            0.001632      0.006487         18.7787        29.9871
1677            0.001307      0.004445         29.9962        42.8764
2662            0.000265      0.001530         47.6078       129.8462

      ActionsInPAC  TotalMapExplored  WorkersMade  UniqueUnitsMade  \
237         4.3008                21     0.001014                8
690         5.0961                43     0.001027               10
1280        4.1489                28     0.000756                5
1299        5.8834                13     0.000986                5
1654        4.3371                25     0.001507                8
1677        7.0019                32     0.001365               11
2662        6.9038                11     0.000765                5

      ComplexUnitsMade  ComplexAbilitiesUsed
237           0.000000              0.000104
690           0.000315              0.000502
1280          0.000000              0.000000
1299          0.000094              0.000031
1654          0.000000              0.000000
1677          0.000058              0.000350
2662          0.000000              0.000000
```

The following cell shows the NA removals (either removing rows with NAs or removing columns with NAs) and faulty self-reported `TotalHours` and `HoursPerWeek`

[24]:
```python
# remove age, hoursperweek, totalhours
# so that we can still classify professional players
data_cols_removed = data.dropna(axis = 1)

# remove some observations that have faulty totalhours and hoursperweek
data_rows_removed = data[~((data['HoursPerWeek'] > 84) |
```

```
                ((data['TotalHours']/data["HoursPerWeek"]/52)>5))].dropna(axis =␣
↪0)
```

[25]:
```
data_rows_removed.describe()
```

[25]:
```
             GameID  LeagueIndex          Age  HoursPerWeek    TotalHours  \
count  3302.000000  3302.000000  3302.000000   3302.000000   3302.000000
mean   4716.131738     4.111145    21.656269     15.778922    627.220472
std    2657.468362     1.449149     4.211065     11.026154    522.295281
min      56.000000     1.000000    16.000000      2.000000      3.000000
25%    2418.000000     3.000000    19.000000      8.000000    300.000000
50%    4781.000000     4.000000    21.000000     12.000000    500.000000
75%    6994.750000     5.000000    24.000000     20.000000    800.000000
max    9271.000000     7.000000    44.000000     84.000000  10000.000000

               APM  SelectByHotkeys  AssignToHotkeys  UniqueHotkeys  \
count  3302.000000      3302.000000      3302.000000    3302.000000
mean    114.243658         0.003996         0.000364       4.310721
std      47.943361         0.004702         0.000210       2.334702
min      22.059600         0.000000         0.000000       0.000000
25%      78.992550         0.001240         0.000201       3.000000
50%     106.865100         0.002426         0.000348       4.000000
75%     139.826250         0.004897         0.000493       6.000000
max     389.831400         0.043088         0.001648      10.000000

       MinimapAttacks  MinimapRightClicks  NumberOfPACs  GapBetweenPACs  \
count     3302.000000         3302.000000   3302.000000     3302.000000
mean         0.000093            0.000379      0.003429       40.781669
std          0.000159            0.000358      0.000965       17.097742
min          0.000000            0.000000      0.000679        6.666700
25%          0.000000            0.000138      0.002739       29.345525
50%          0.000039            0.000278      0.003369       37.139950
75%          0.000112            0.000508      0.004000       48.568950
max          0.003019            0.003688      0.007971      237.142900

       ActionLatency  ActionsInPAC  TotalMapExplored  WorkersMade  \
count    3302.000000   3302.000000       3302.000000  3302.000000
mean       64.316671      5.263329         22.104785     0.001031
std        19.027080      1.503526          7.446299     0.000522
min        24.632600      2.038900          5.000000     0.000077
25%        51.092925      4.253750         17.000000     0.000681
50%        61.358600      5.082850         22.000000     0.000903
75%        74.196825      6.026675         27.000000     0.001258
max       176.372100     18.558100         58.000000     0.005149

       UniqueUnitsMade  ComplexUnitsMade  ComplexAbilitiesUsed
count      3302.000000       3302.000000           3302.000000
```

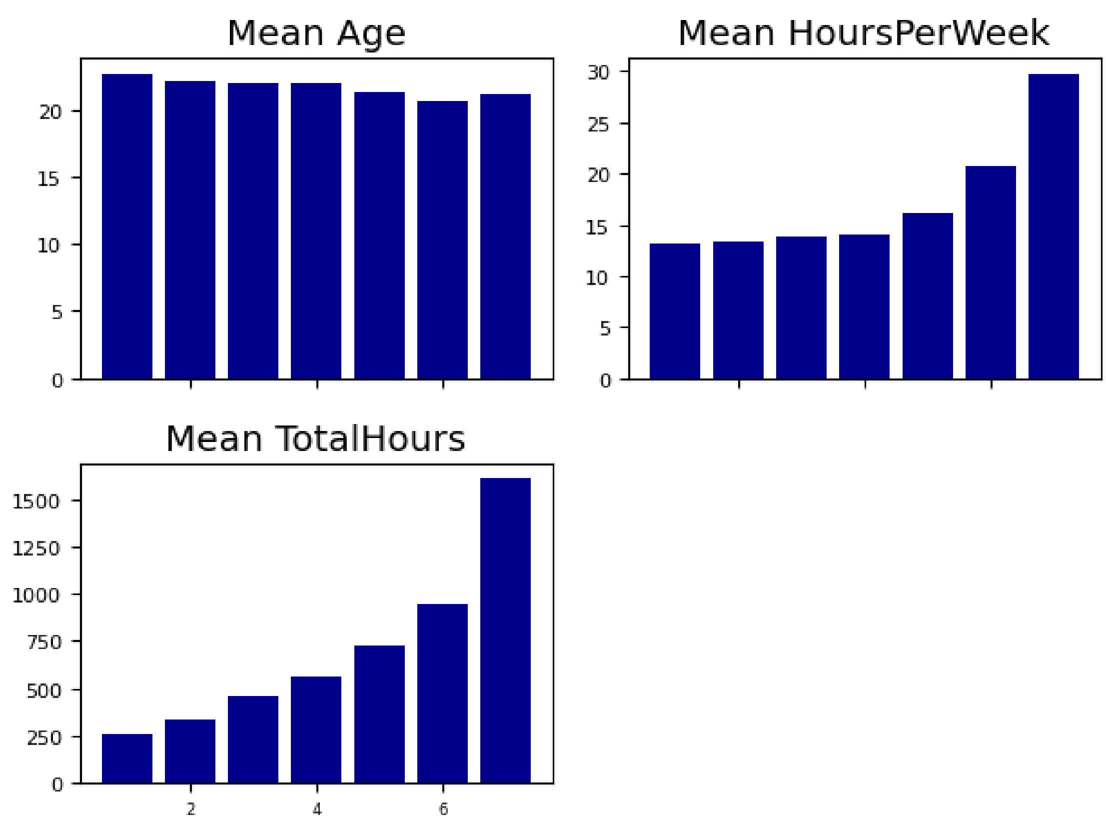
mean	6.536644	0.000060	0.000141
std	1.857468	0.000111	0.000264
min	2.000000	0.000000	0.000000
25%	5.000000	0.000000	0.000000
50%	6.000000	0.000000	0.000020
75%	8.000000	0.000087	0.000180
max	13.000000	0.000902	0.003084

2.1 Checking signals

Now we can do a bit more exploration into the trends. It'll be good to see if we can pick up any signals prior to modeling.

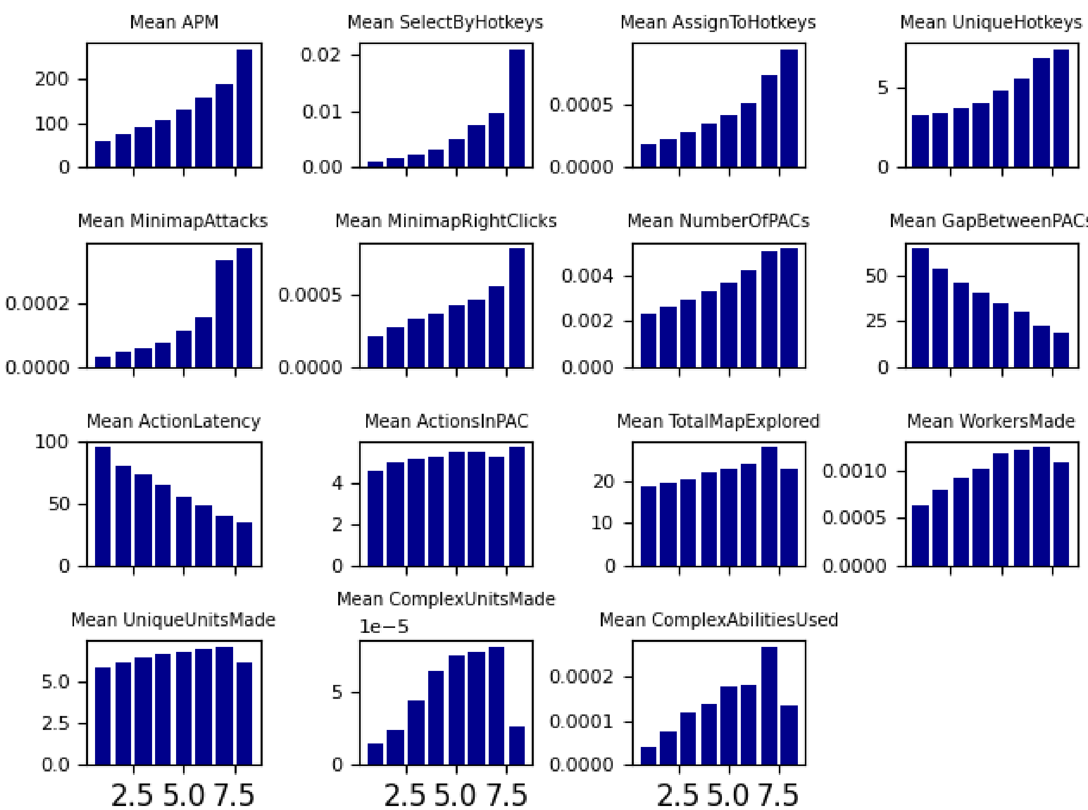
[314]:
```
# check features unique to the data without pros
fig, axs = plt.subplots(2,2, sharex = True)
plt.rc('font', size = 12)
for i, feat in enumerate(['Age', "HoursPerWeek", "TotalHours"]):
    means = data_rows_removed.groupby("LeagueIndex")[feat].mean().sort_index()
    axs[int(i/2), int(i%2)].bar(means.index, means.values, color = '#00008B')
    axs[int(i/2), int(i%2)].set_title("Mean {}".format(feat))

fig.delaxes(axs[1,1])
fig.tight_layout()
plt.show()
```



[315]:

```
other_feats = ['APM', 'SelectByHotkeys', 'AssignToHotkeys',
        'UniqueHotkeys', 'MinimapAttacks', 'MinimapRightClicks', 'NumberOfPACs',
        'GapBetweenPACs', 'ActionLatency', 'ActionsInPAC', 'TotalMapExplored',
        'WorkersMade', 'UniqueUnitsMade', 'ComplexUnitsMade',
        'ComplexAbilitiesUsed']
fig, axs = plt.subplots(4,4, sharex = True)
plt.rc('font', size = 6)
plt.rc('ytick', labelsize =8)
for i, feat in enumerate(other_feats):
    means = data_cols_removed.groupby("LeagueIndex")[feat].mean().sort_index()
    axs[int(i/4), int(i%4)].bar(means.index, means.values, color = '#00008B')
    axs[int(i/4), int(i%4)].set_title("Mean {}".format(feat))
fig.delaxes(axs[3,3])
fig.tight_layout()
plt.show()
```



Clearly, there's a lot of features that are correlated on average with the rankings. Notable ones are the APM and the hotkey related features, which make sense since Starcraft is a mechanically intensive game and the more a player is able to multi-task, the better they are in the ranks. Minimap usage correlation is also positively correlated, which could be some realization of map awareness.

Other variables without clear trends such as `UniqueUnitsMade` can still be used in the modeling, and if there's really no trend then the data-driven, empirical model can hopefully resolve that.

3 Models

We start by splitting the dataset into train/test sets. We will be using stratified k-fold cross-validation to select the best hyperparameters for the models.

[10]:
```
def make_train_test_set(df, test_size, random_state = 100):
    X, y = df.iloc[:, 2:].to_numpy(), df.iloc[:, 1].to_numpy()
    # stratify to keep distribution consistent
    return train_test_split(X, y,
                            test_size = test_size,
                            stratify = y,
                           random_state = random_state)
```

[15]:
```
def create_pipeline(model, smote_val = None, undersample_val = None):
    SMOTE_NUM = smote_val
    UNDERSAMPLE_NUM = undersample_val
    def SMOTE_Distribution(y):
        labels = pd.Series(y).value_counts()
        SMOTE_dict = {}
        for i in labels.index:
            if labels[i] > SMOTE_NUM:
                SMOTE_dict[i] = labels[i]
            else:
                SMOTE_dict[i] = SMOTE_NUM
        return SMOTE_dict
    def UnderSample_Distribution(y):
        labels = pd.Series(y).value_counts()

        Undersample_dict = {}
        for i in labels.index:
            if labels[i] < UNDERSAMPLE_NUM:
                Undersample_dict[i] = labels[i]
            else:
                Undersample_dict[i] = UNDERSAMPLE_NUM
        return Undersample_dict

    seq = []

    if SMOTE_NUM:
        oversample = BorderlineSMOTE(sampling_strategy = SMOTE_Distribution)
        seq.append(('oversample', oversample))
    if UNDERSAMPLE_NUM:
```

```
        undersample = RandomUnderSampler(sampling_strategy =␣
↪UnderSample_Distribution)
        seq.append(('undersample', undersample))
    seq.append(("scaler", StandardScaler()))
    seq.append(("model", model))

    pipeline = Pipeline(steps = seq)
    return pipeline
```

[86]:
```
def display_results(y_true, y_pred):
    acc=sklearn.metrics.accuracy_score(y_true, y_pred)
    balanced_acc=sklearn.metrics.balanced_accuracy_score(y_true, y_pred)
    f1=sklearn.metrics.f1_score(y_true, y_pred, average = 'weighted')
    unagg_f1=sklearn.metrics.f1_score(y_true, y_pred, average = None)


    class_labels = np.sort(np.unique(y_true))
    unagg_f1_dict = {i:k for i, k in zip(class_labels, unagg_f1)}

    results_dict = {
        'acc': acc,
        'balanced acc': balanced_acc,
        'weighted f1': f1,
        'unaggregated f1': unagg_f1_dict
    }
    disp = ConfusionMatrixDisplay(confusion_matrix(y_true, y_pred),
                                  display_labels = [i for i in␣
↪range(1,len(class_labels)+1)])
    disp.plot()
    return results_dict
```

3.1 Linear SVC

To test pipeline concept, we will use a LinearSVC as a baseline. This model has some assumptions, specifically that the class boundaries can be modeled as linear. Otherwise, it's a fairly common model for multi-class classification. The only hyper-parameter we will really test is the penalty term.

[102]:
```
# make the pipeline
X_train, X_test, y_train, y_test = make_train_test_set(data_cols_removed,
                                                       test_size = 0.2)




Cs = np.logspace(-3,3, num = 10)
for C in Cs:
```

```
    model = sklearn.svm.LinearSVC(dual = False, C = C)
    pipeline = create_pipeline(model, smote_val= 70, undersample_val = 500)
    cv = RepeatedStratifiedKFold(n_splits =5, n_repeats = 3,
                                 random_state = 100)
    scores = cross_val_score(pipeline, X_train, y_train,
                             scoring = 'f1_weighted', cv = cv, n_jobs = -1)
    print("C: {}; mean f1: {}".format(C, np.mean(scores)))
```

```
C: 0.001; mean f1: 0.3286482651307633
C: 0.004641588833612777; mean f1: 0.33393867038261327
C: 0.021544346900318832; mean f1: 0.34237526081849823
C: 0.1; mean f1: 0.35036470632988337
C: 0.46415888336127775; mean f1: 0.35306595903440335
C: 2.154434690031882; mean f1: 0.35365813101379767
C: 10.0; mean f1: 0.3538045361205508
C: 46.41588833612773; mean f1: 0.3537896116342694
C: 215.44346900318823; mean f1: 0.35252353836000583
C: 1000.0; mean f1: 0.3530732275958729
```

The baseline so far is at C = 46.415, with an average weighted-f1 of 0.3536

3.2 Shallow Neural Network

Neural networks have less assumptions built into them and can model non-linearities in the data better than the linear svc. The trade-off is NNs are generally data-hungry, especially as the layers grow. In expectation, the neural network may not perform as well (even relative to the linear SVC) due to the small sample size of the dataset.

[78]:
```
import torch
import torch.nn as nn
import torch.nn.functional as F
from torch.utils.data import Dataset, DataLoader
import torch.optim as optim
from tqdm import tqdm

class shallow_nn(nn.Module):
    """
    Inits a shallow NN for multi-class classification
    """

    def __init__(self, num_initial_feat, num_hidden, num_classes = 8, drop_prob␣
 ↪= 0.2):
        super(shallow_nn, self).__init__()
        self.linear_1 = nn.Linear(num_initial_feat, num_hidden)
        self.linear_2 = nn.Linear(num_hidden, num_hidden)
        self.linear_out = nn.Linear(num_hidden, num_classes)

        self.dropout_1 = nn.Dropout(drop_prob)
```

```python
        self.dropout_2 = nn.Dropout(drop_prob)

    def forward(self, x):
        # forward through linear layers
        out = F.relu(self.linear_1(x))
        out = self.dropout_1(out)
        out = F.relu(self.linear_2(out))
        out = self.dropout_2(out)
        out = self.linear_out(out)
        return out
class player_dset(Dataset):
    def __init__(
        self,
        x,
        y
    ):
        self.x = x
        self.y = y
    def __getitem__(self, index):
        x = self.x[index, :]
        y = self.y[index]

        return (x,y)
    def __len__(self):

        return len(self.x)

def acc_score(logits, labels):
    """Returns the mean accuracy of a model's predictions on a set of examples.

    Args:
        logits (torch.Tensor): model predicted logits
            shape (examples, classes)
        labels (torch.Tensor): classification labels from 0 to num_classes - 1
            shape (examples,)
    """

    assert logits.dim() == 2
    assert labels.dim() == 1
    assert logits.shape[0] == labels.shape[0]

    preds = torch.argmax(logits, dim = -1)
    return preds

def evaluate(model, data_loader):
    model.eval()
    preds = []
```

```
    ys = []
    with torch.no_grad(), \
        tqdm(total=len(data_loader.dataset), disable = True) as progress_bar:
        for x,y in data_loader:
            out = model(x.float())
            criterion = nn.CrossEntropyLoss()
            loss = criterion(out, y)

            pred = acc_score(out, y)
            preds.extend(pred)
            ys.extend(y)
    f1 = sklearn.metrics.f1_score(ys, preds, average = 'weighted')
    model.train()
    return f1

batch_size = 64
hidden_size = 15
epochs = 8
lr = 0.01
l2_wd = 0.01

cv = RepeatedStratifiedKFold(n_splits =5, n_repeats = 2,
                                 random_state = 100)
drop_probs = [0.1, 0.2, 0.4, 0.6]
hidden_sizes = [10, 20, 40, 80]
for drop_prob in drop_probs:
    for hidden_size in hidden_sizes:
        f1s = []
        for i, (train_index, val_index) in enumerate(cv.split(X_train,␣
 ↪y_train)):
            scaler = StandardScaler()
            cv_x_train = scaler.fit_transform(X_train[train_index, :])
            cv_y_train = y_train[train_index]-1
            cv_x_val = scaler.transform(X_train[val_index, :])
            cv_y_val = y_train[val_index]-1

            # get datasets
            train_set = player_dset(cv_x_train, cv_y_train)
            val_set = player_dset(cv_x_val, cv_y_val)
            train_loader = DataLoader(train_set,
                                     batch_size = batch_size,
                                     shuffle = True)
            val_loader = DataLoader(val_set,
                                   batch_size = batch_size)

            # init model and optimizer
            model = shallow_nn(num_initial_feat = X_train.shape[1],
```

```
                          num_hidden = hidden_size,
                          num_classes = len(np.unique(y_train)),
                              drop_prob = drop_prob)
            model = model.float()
            optimizer = optim.Adam(model.parameters(),
                                   lr = lr,
                                   betas = (0.9, 0.999),
                                   eps = 1e-7,
                                   weight_decay = l2_wd)

            # define the loss function
            weights = sklearn.utils.class_weight.
↪compute_class_weight(class_weight='balanced',
                                                                     classes=␣
↪np.unique(cv_y_train),
                                                                     y= np.
↪array(cv_y_train))
            criterion = nn.CrossEntropyLoss(weight= torch.from_numpy(weights).
↪type(torch.FloatTensor), reduction = 'mean')

            epoch = 0
            best_f1 = 0
            while epoch != epochs:
                epoch += 1
                with torch.enable_grad(), \
                    tqdm(total=len(train_loader.dataset), disable = True) as␣
↪progress_bar:
                    for x, y in train_loader:
                        optimizer.zero_grad()
                        x = x.float()
                        y = y.type(torch.LongTensor)
                        out = model(x)


                        # calc loss and backprop
                        loss = criterion(out, y)
                        loss.backward()
                        optimizer.step()

                        # update progress bar
                        progress_bar.update(batch_size)
                        progress_bar.set_postfix(epoch = epoch,
                                                 loss = loss)
                f1 = evaluate(model, val_loader)
                if f1 > best_f1:
                    torch.save({
                    'epoch': epoch,
```

```
                    'model_state_dict': model.state_dict(),
                    'optimizer_state_dict': optimizer.state_dict(),
                    'loss': loss,
                    }, 'temp.pt')

            # load back in the best
            checkpoint = torch.load('temp.pt')
            model.load_state_dict(checkpoint['model_state_dict'])
            optimizer.load_state_dict(checkpoint['optimizer_state_dict'])
            epoch = checkpoint['epoch']
            loss = checkpoint['loss']

            # append best f1 to list of f1s for cv splits
            f1s.append(evaluate(model, val_loader))
        print("hidden", hidden_size, "drop_prob", drop_prob, np.mean(f1s))
```

```
hidden 10 drop_prob 0.1 0.33882883277676273
hidden 20 drop_prob 0.1 0.32349953080279237
hidden 40 drop_prob 0.1 0.30714565788394677
hidden 80 drop_prob 0.1 0.3073547616019097
hidden 10 drop_prob 0.2 0.32364599232614666
hidden 20 drop_prob 0.2 0.3028593479880995
hidden 40 drop_prob 0.2 0.31006904575874694
hidden 80 drop_prob 0.2 0.3108510188775661
hidden 10 drop_prob 0.4 0.30415342488009234
hidden 20 drop_prob 0.4 0.28670667392057353
hidden 40 drop_prob 0.4 0.2975643366828393
hidden 80 drop_prob 0.4 0.3026400296027058
hidden 10 drop_prob 0.6 0.289023626571927
hidden 20 drop_prob 0.6 0.3057877590545037
hidden 40 drop_prob 0.6 0.2988206766872925
hidden 80 drop_prob 0.6 0.30647316955699483
```

As we can see above, the weighted f1-score of the best NN model is 0.339, which does not outperform the linear svc.

3.3 LightGBM

Next, we will use a more powerful boosted model to improve on the baseline. Since it is a boosted forest, it should in theory out-perform other tree methods. Since there's a lot of hyper-parameters, we will opt for a random cv search for best hyper-parameters.

[103]:
```
l2_penalty = np.logspace(-3,3,10)
l1_penalty = np.logspace(-3,2,10)
lrs = np.logspace(-2,0,5)
n_estimators = [50, 100, 200, 400]
model = lgb.LGBMClassifier()
distributions = {
```

```
    "model__learning_rate": lrs,
    "model__reg_alpha": l1_penalty,
    "model__reg_lambda" : l2_penalty,
    "model__n_estimators": n_estimators
}
pipeline = create_pipeline(model,
                           smote_val = 70,
                           undersample_val = 500)
cv = RepeatedStratifiedKFold(n_splits =5, n_repeats = 3,
                             random_state = 100)

# random search for hyperparameters
clf = RandomizedSearchCV(pipeline, distributions,
                         n_iter = 50,
                         cv = cv,
                         scoring = 'f1_weighted', random_state=100)
search = clf.fit(X_train, y_train, )
```

[104]:
```
search.best_params_, search.best_score_
```

[104]:
```
({'model__reg_lambda': 1000.0,
  'model__reg_alpha': 0.001,
  'model__n_estimators': 100,
  'model__learning_rate': 1.0},
 0.38400098869349375)
```

[105]:
```
# refit the model using the best parameters
model = lgb.LGBMClassifier(learning_rate = search.
 ↪best_params_['model__learning_rate'],
                           reg_lambda = search.
 ↪best_params_['model__reg_lambda'],
                          reg_alpha = search.best_params_['model__reg_alpha'],
                          n_estimators = search.
 ↪best_params_['model__n_estimators'])
pipeline = create_pipeline(model,
                           smote_val = 70,
                          undersample_val = 500)
pipeline.fit(X_train, y_train)
```

[105]:
```
Pipeline(steps=[('oversample',
                 BorderlineSMOTE(sampling_strategy=<function
create_pipeline.<locals>.SMOTE_Distribution at 0x00000253669443A0>)),
                ('undersample',
                 RandomUnderSampler(sampling_strategy=<function
create_pipeline.<locals>.UnderSample_Distribution at 0x0000025366944550>)),
                ('scaler', StandardScaler()),
                ('model',
```

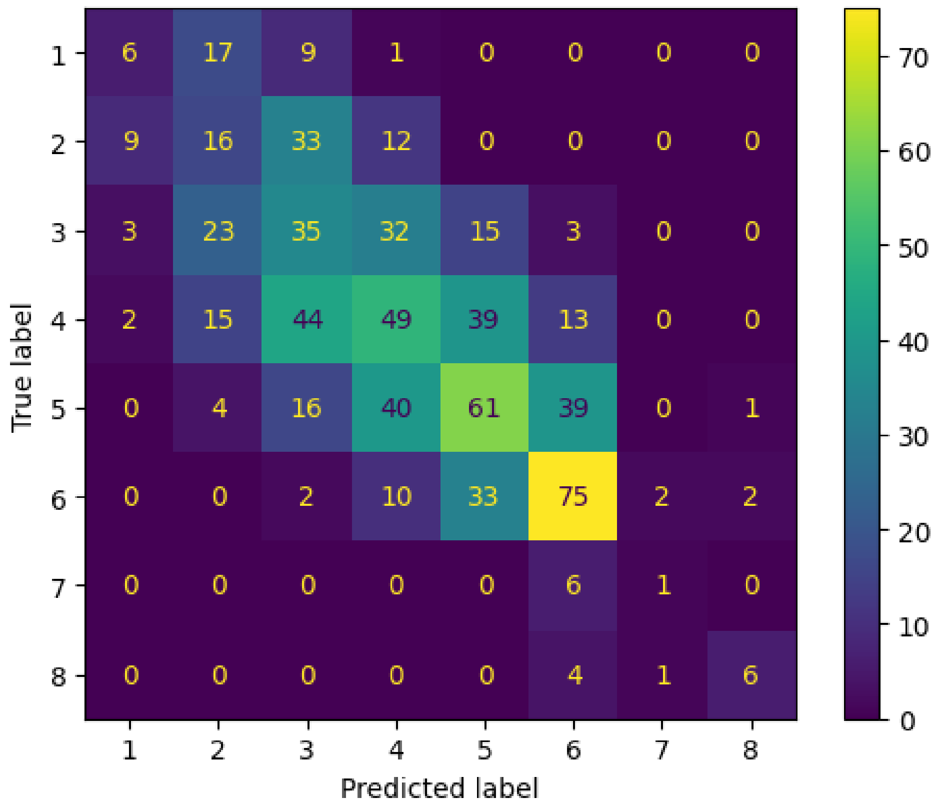
```
                LGBMClassifier(learning_rate=1.0, reg_alpha=0.001,
                               reg_lambda=1000.0))])
```

[106]:
```
# if we were to just guess the majority class
sklearn.metrics.accuracy_score(y_test, [4 for _ in range(len(y_test))])
```

[106]:
```
0.23858615611192932
```

[107]:
```
# use fitted model to predict
y_pred = pipeline.predict(X_test)
results = display_results(y_test, y_pred)
pprint.PrettyPrinter(width = 20).pprint(results)
plt.show()
```

```
{'acc': 0.36671575846833576,
 'balanced acc': 0.3375258058842678,
 'unaggregated f1': {1: 0.22641509433962265,
                     2: 0.2206896551724138,
                     3: 0.28,
                     4: 0.3202614379084967,
                     5: 0.3948220064724919,
                     6: 0.5681818181818182,
                     7: 0.18181818181818182,
                     8: 0.6},
 'weighted f1': 0.3649130231013209}
```



3.4 LightGBM on the no-professional player dataset

This test is to see whether the addition of `Age`, `HoursPerWeek`, and `TotalHours` affects performance to a noticeable degree.

[99]:
```
X_train, X_test, y_train, y_test = make_train_test_set(data_rows_removed,
                                                       test_size = 0.2)


l2_penalty = np.logspace(-3,3,10)
l1_penalty = np.logspace(-3,2,10)
lrs = np.logspace(-2,0,5)
n_estimators = [100, 200, 400]
model = lgb.LGBMClassifier()
distributions = {
    "model__learning_rate": lrs,
    "model__reg_alpha": l1_penalty,
    "model__reg_lambda" : l2_penalty,
    "model__n_estimators": n_estimators
}
smote_val = 50
pipeline = create_pipeline(model,
```

```
                           smote_val = smote_val)
cv = RepeatedStratifiedKFold(n_splits =5, n_repeats = 3,
                                 random_state = 99)

# random search for hyperparameters
clf = RandomizedSearchCV(pipeline, distributions,
                         n_iter = 50,
                         cv = cv,
                         scoring = 'f1_weighted', random_state=100,
                        error_score = 'raise')
search = clf.fit(X_train, y_train )

model = lgb.LGBMClassifier(learning_rate = search.
 ↪best_params_['model__learning_rate'],
                           reg_lambda = search.
 ↪best_params_['model__reg_lambda'],
                          reg_alpha = search.best_params_['model__reg_alpha'],
                          n_estimators = search.
 ↪best_params_['model__n_estimators'])
pipeline = create_pipeline(model, smote_val = smote_val)
pipeline.fit(X_train, y_train)
```

[99]:
```
Pipeline(steps=[('oversample',
                 BorderlineSMOTE(sampling_strategy=<function
create_pipeline.<locals>.SMOTE_Distribution at 0x00000253666298B0>)),
                ('scaler', StandardScaler()),
                ('model',
                 LGBMClassifier(learning_rate=0.03162277660168379,
                                n_estimators=200,
                                reg_alpha=0.046415888336127795,
                                reg_lambda=0.46415888336127775))])
```

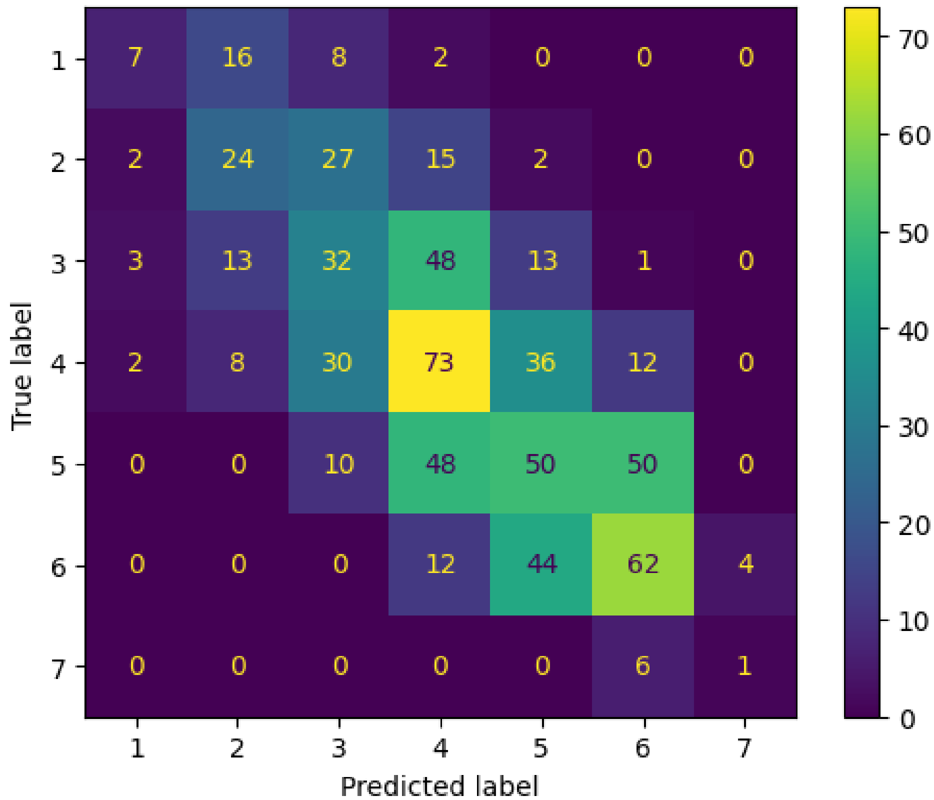
[100]:
```
sklearn.metrics.accuracy_score(y_test, [4 for _ in range(len(y_test))])
```

[100]:
```
0.24357034795763993
```

[101]:
```
y_pred = pipeline.predict(X_test)
results = display_results(y_test, y_pred)
pprint.PrettyPrinter(width = 20).pprint(results)
plt.show()
```

```
{'acc': 0.3767019667170953,
 'balanced acc': 0.32383045076098843,
 'unaggregated f1': {1: 0.2978723404255319,
                     2: 0.366412213740458,
                     3: 0.2949308755760369,
                     4: 0.4066852367688022,
                     5: 0.3300330033003301,
```

```
                     6: 0.4901185770750988,
                     7: 0.16666666666666666},
 'weighted f1': 0.3729254299853203}
```



4 Summary

While we are able to see trends from the data analysis, our model only does a bit better than just predicting the majority class (36.6% accuracy vs. 23.8%), so I would recommend iterating on the data collection and modeling before deploying this. If we break down which ranks our model is relatively good at predicting, it would be Master and Professional players, as evidenced by the larger dis-aggregated f1-scores.

There are a couple areas where our model does poorly. First, the model seems poor at predicting tail classes like bronze and grandmaster ranks. This particular behavior is driven by the data imbalance as noted earlier.

Moreover, the model is not able to distinguish among close ranks, with a lot of false predictions existing on the sub and super-diagonal of the confusion matrix. My theory for this is because there is not a lot of differences between neighboring ranks. For example, a Master and a Grandmaster player probably has a lot of similar behavior from a micro-perspective. If we're not specifically targeting a rank, it might be useful to group ranks together ex. low/medium/high/pro skill buckets.

An interesting thing to note is that Grandmaster players are never classified as professional players by the model, which partly justifies keeping pro as a separate skill bucket above. This could potentially be because of the small sample size of Grandmaster players, or it could also be because Grandmaster and Master players are far more similar than Grandmaster and professional players.

4.0.1 Data Discussion

A model that predicts a player's rank is still possible, but it would require a bit more data and feature collection. Ideally, we would collect data across the board, but we should specifically focus on the tails and get more observations of Grandmaster, Professional and Bronze players (up-sampling/down-sampling can only do so much to improve performance).

It should also be noted that each observation is only a single game from the player, which potentially makes the features we observe inaccurate. To improve on this, we should collect the recent play history of the player and average the performance features across that history to get a more consistent estimate of their performance.

Moreover, we should be more considerate of what kind of data to collect. Some of the features such as `unique units` made might not be that useful of a predictor ex. a Terran player could probably play marine/tank comps into zerg pretty easily throughout ranks, which makes the unique units feature somewhat non-informative. Or the `workers made` feature, which would be much different for Zerg players vs. terran players.

On that note, it is strange that we do not have data about what race the player is using, as that could easily affect APM (ex. mutalisk micro vs. marine stutter-stepping) and other features. It is probably worthwhile to collect that data, since it should be easily retrieved from the gameID.

It is also surprising that almost all the features are micro-focused, especially since Starcraft also has an emphasis on macro gameplay. Data on resource efficiency and management (ex. time supply blocked, production idle time etc.) could be useful additional features.

[ ]:

```
```