Dota Hero Picks

April 24, 2022

[1]:
```
# Import libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import json
from scipy import stats
```

[2]:
```
# Load dataset and hero key file
df = pd.read_csv("datasets/picks_data.csv")
heros = {}

with open("datasets/heros.json") as hero_ids:
    heros_json = json.load(hero_ids)

for hero in heros_json:
    heros[hero['id']] = hero['name']

df.head()
```

[2]:
```
   loosing_hero_id_1  loosing_hero_id_2  loosing_hero_id_3  loosing_hero_id_4  \
0                 18                 28                 43                 75
1                 47                 72                 78                 86
2                 21                 51                 65                 71
3                 11                 26                 83                 93
4                 15                 16                 21                 26

   loosing_hero_id_5  winning_hero_id_1  winning_hero_id_2  winning_hero_id_3  \
0                 84                 60                 71                 74
1                107                 11                 12                 30
2                 73                 13                 63                 66
3                110                  8                 22                 33
4                 99                  7                 11                 47

   winning_hero_id_4  winning_hero_id_5
0                 87                 93
1                 38                 51
2                 80                 89
```

```
3                  90                  97
4                  93                 102
```

[3]:
```python
# Separate winning and losing teams' heros
losers = df.iloc[:,:5]
winners = df.iloc[:,5:]

# Count all unique winning and losing heros
unique_losers, count_losers = np.unique(losers.to_numpy().flatten(),␣
 ↪return_counts=True)
unique_winners, count_winners = np.unique(winners.to_numpy().flatten(),␣
 ↪return_counts=True)
```

[4]:
```python
# Create dataframe for each hero with its win and pick rate
data = pd.DataFrame()
data['id'] = unique_losers
data['hero'] = [heros[i] for i in unique_losers]
data['wins'] = count_winners
data['losses'] = count_losers
data['total games'] = data['wins'] + data['losses']
data['popularity'] = data['total games']/df.shape[0]
data['win rate'] = data['wins']/data['total games']
data
```

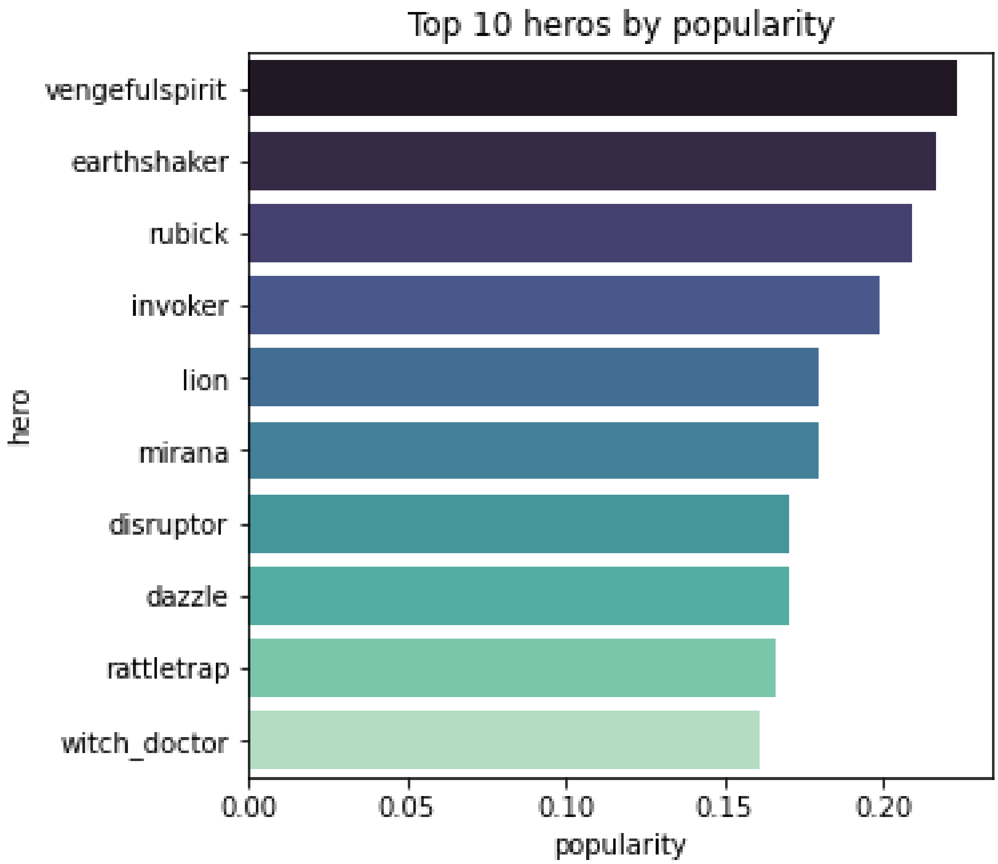
[4]:
```
      id            hero  wins  losses  total games  popularity  win rate
0      1        antimage  2485    2574         5059    0.070820  0.491204
1      2             axe  3094    3375         6469    0.090558  0.478281
2      3            bane  3086    3070         6156    0.086176  0.501300
3      4     bloodseeker  1290    1388         2678    0.037489  0.481703
4      5  crystal_maiden  3784    3616         7400    0.103591  0.511351
..   …             …     …      …           …         …         …
108  110         phoenix  1882    1924         3806    0.053279  0.494482
109  111          oracle  1331    1417         2748    0.038469  0.484352
110  112   winter_wyvern  2374    2369         4743    0.066396  0.500527
111  113      arc_warden   125     127          252    0.003528  0.496032
112  114     monkey_king   560     493         1053    0.014741  0.531814

[113 rows x 7 columns]
```

Getting the most picked heros gives an insight into the perceived strength of the hero

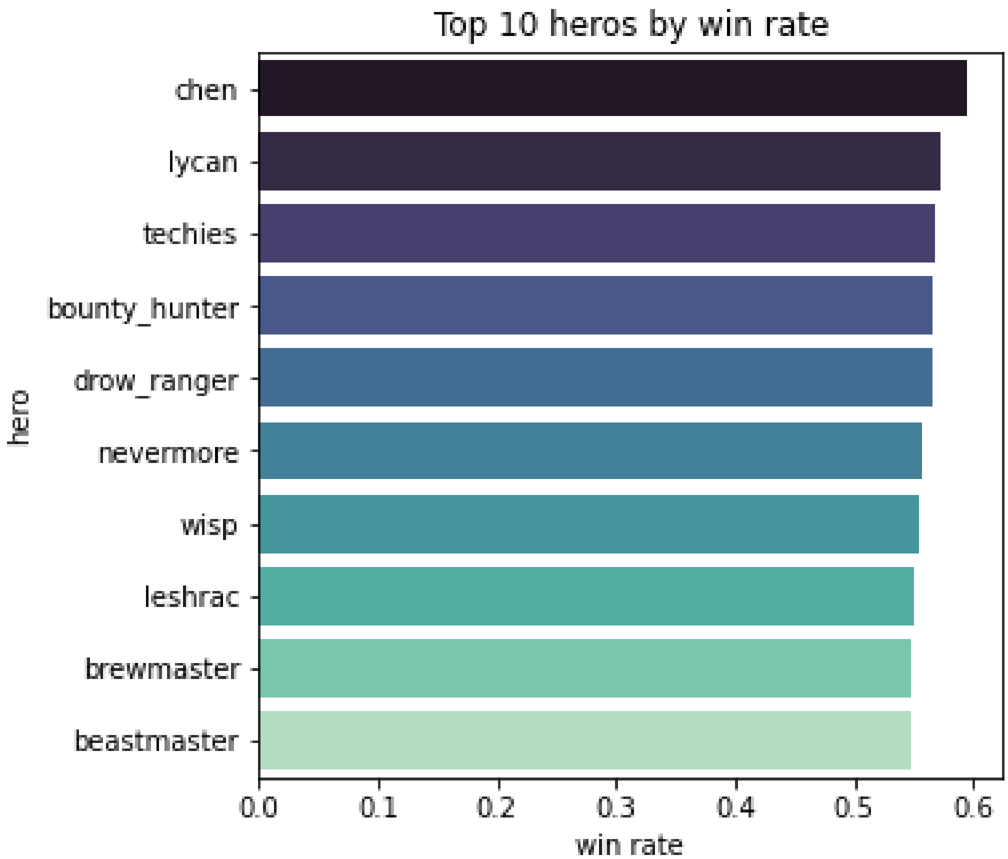
[17]:
```python
plt.figure(figsize=(5,5))
plt.title("Top 10 heros by popularity")
sns.barplot(x='popularity', y='hero', palette='mako', data=data.
 ↪sort_values(by=['popularity'], ascending=False).iloc[0:10])
```

[17]:
```
<AxesSubplot:title={'center':'Top 10 heros by popularity'}, xlabel='popularity',
ylabel='hero'>
```



[19]:
```
plt.figure(figsize=(5,5))
plt.title("Top 10 heros by win rate")
sns.barplot(x='win rate', y='hero', palette='mako', data=data.
 ↪sort_values(by=['win rate'], ascending=False).iloc[0:10])
```

[19]:
```
<AxesSubplot:title={'center':'Top 10 heros by win rate'}, xlabel='win rate',
ylabel='hero'>
```



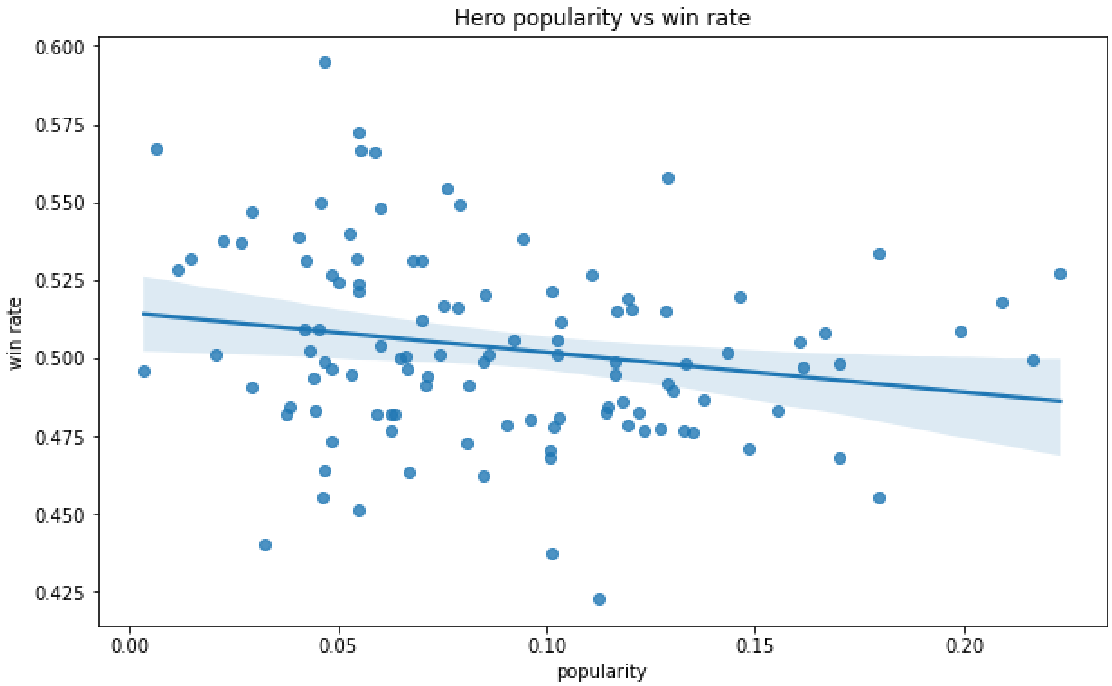
[7]:
```
# Calculate the Pearson's r correlation coefficient between player
# popularity and win rate
stats.pearsonr(data['popularity'], data['win rate'])
```

[7]:
```
(-0.20070485321770554, 0.03304469711580285)
```

Based on the Pearson correlation coefficient, we can see that there is a small negative correlation between the hero pick rates (popularity) and the win rate of the hero. This leads us to believe that picking the most popular heros doesn't necessarily add to the win probability. Win rate depends more on the skill of the player and picking the correct counter for the opponent's roster.

[8]:
```
plt.figure(figsize=(10,6))
plt.title("Hero popularity vs win rate")
sns.regplot(x="popularity", y="win rate", data=data)
```

[8]:
```
<AxesSubplot:title={'center':'Hero popularity vs win rate'},
xlabel='popularity', ylabel='win rate'>
```



Getting teams that won the most rounds

[9]:
```
# Restructure dataset and add a win status for each team composition
winners_team = winners.rename(columns = {'winning_hero_id_1': 'hero_1',
 ↪'winning_hero_id_2': 'hero_2', 'winning_hero_id_3': 'hero_3',
 ↪'winning_hero_id_4': 'hero_4', 'winning_hero_id_5': 'hero_5'})
winners_team['win'] = 1
losers_team = losers.rename(columns = {'loosing_hero_id_1': 'hero_1',
 ↪'loosing_hero_id_2': 'hero_2', 'loosing_hero_id_3': 'hero_3',
 ↪'loosing_hero_id_4': 'hero_4', 'loosing_hero_id_5': 'hero_5'})
losers_team['win'] = 0
teams = pd.DataFrame(columns=['hero_1', 'hero_2', 'hero_3', 'hero_4', 'hero_5',
 ↪'win'])
teams = pd.concat([teams, winners_team, losers_team])
teams = teams.astype('int32')
teams
```

[9]:

	hero_1	hero_2	hero_3	hero_4	hero_5	win
0	60	71	74	87	93	1
1	11	12	30	38	51	1
2	13	63	66	80	89	1
3	8	22	33	90	97	1
4	7	11	47	93	102	1
…	…	…	…	…	…	…
71430	11	20	36	68	69	0

```
71431       42      85      89      99     111    0
71432        7      12      21      25      75    0
71433       44      53      64      71      74    0
71434       23      30      44      83      88    0

[142870 rows x 6 columns]
```

[10]:
```
# Get the most winning composition of teams
teams_cumulative = teams.groupby(teams.columns.to_list(), as_index=False).size()
winners_cumulative = teams_cumulative[(teams_cumulative['size'] > 1) &␣
↪(teams_cumulative['win'] == 1)].rename(columns={'size':'wins'})
top_10_teams = winners_cumulative.sort_values(by='wins', ascending=False)[:10].
↪drop(['win'], axis=1)
```

[11]:
```
winners_cumulative
```

[11]:
```
        hero_1  hero_2  hero_3  hero_4  hero_5  win  wins
299          1       3      28      47      50    1     2
710          1       7      11      50      55    1     2
714          1       7      11      50      71    1     3
728          1       7      11      71     112    1     2
781          1       7      15      20      51    1     2
…          …     …     …     …     …    …  …
139601      63      68      88      89      96    1     2
140349      68      74      80      84      93    1     2
140673      72      74      85     100     112    1     2
140674      72      74      86      92      98    1     2
140866      74      83      86      93      99    1     2

[921 rows x 7 columns]
```

Top 10 team compositions based on wins

[12]:
```
top_10_teams_names = top_10_teams.replace({"hero_1": heros, "hero_2": heros,␣
↪"hero_3": heros, "hero_4": heros ,"hero_5": heros})
top_10_teams_names
```

[12]:
```
                hero_1            hero_2             hero_3      hero_4  \
94155   vengefulspirit      witch_doctor        beastmaster        luna
66195        nevermore         dark_seer     spirit_breaker  gyrocopter
129420   faceless_void        rattletrap  ancient_apparition     invoker
24870    crystal_maiden            pugna       dragon_knight      furion
53112           mirana              tiny           batrider      treant
114654         slardar            dazzle      night_stalker     abaddon
46716       juggernaut              lion         tidehunter      tinker
122513          enigma  templar_assassin               luna   dark_seer
32632      earthshaker         nevermore         rattletrap  gyrocopter
61832        nevermore              puck      night_stalker      jakiro
```

```
                hero_5  wins
94155            lycan     6
66195    winter_wyvern     4
129420     nyx_assassin    4
24870          abaddon     4
53112             wisp     4
114654     elder_titan     4
46716    skywrath_mage     3
122513          rubick     3
32632        disruptor     3
61832    troll_warlord     3
```

Fitting a linear and KNN classifier to predict win/loss based on team composition

[13]:
```python
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegressionCV
from sklearn.preprocessing import StandardScaler

scaler = StandardScaler()

X = teams.drop('win', axis=1)
y = teams['win']

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3,␣
 ↪stratify=y)
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)

clf = LogisticRegressionCV(solver='lbfgs', random_state=6220).fit(X_train,␣
 ↪y_train)
clf.score(X_test, y_test)
```

[13]: 0.505681155362684

[14]:
```python
from sklearn.neighbors import KNeighborsClassifier

knn_clf = KNeighborsClassifier(n_neighbors=3)
knn_clf.fit(X_train, y_train)
knn_clf.score(X_test, y_test)
```

[14]: 0.5081775973495719

We can see that the dataset isn't really structured to help classification.