ChessData

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1 DATA EXPLORATION AND VISUALIZATION

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We will explore the data and try to answer the following questions:

What were the most common first 8 moves for white and black each year? How have these opening moves changed over time?

For each year in the data set, how many unique moves were made at each part of the game (opening, early, midgame and endgame)?

[1]:
```
import pandas as pd
import numpy as np
import seaborn as sns
import random
from matplotlib import rcParams
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.neighbors import KNeighborsClassifier

# allow output to span multiple output lines in the console
pd.set_option('display.max_columns', 500)

# switch to seaborn default stylistic parameters
# see the useful https://seaborn.pydata.org/tutorial/aesthetics.html

sns.set()
sns.set_context('paper') # 'talk' for slightly larger

# change default plot size
rcParams['figure.figsize'] = 9,7
```

Get PKL file with chess data from this link, https://github.com/abecsumb/DataScienceProject/blob/main/chess_

If PKL will not load or some other issues, try this link and use the read_csv method. https://archive.org/download/chess_data_202206/chess_data.csv

[2]:
```
# conda install pandas = 1.4.2
print(pd.__version__)
```

```
1.4.2
```

[3]:
```
# read pkl file from local folder. The file contains the dataframe.
chess_data = pd.read_pickle('https://github.com/abecsumb/DataScienceProject/
 ↪blob/main/chess_data.pkl?raw=true', compression = 'zip')
```

[4]:
```
chess_data.head()
```

[4]:

	Date	Game Result	W-ELO	B-ELO	Num Moves	W1	B1	W2	B2	W3	B3	\
Game1	2000	1-0	2851	2555	147	d4	d5	c4	e6	Nc3	Nf6	
Game2	2000	1-0	2851	2544	45	e4	c5	Nf3	Nc6	Bb5	d6	
Game3	2000	1-0	2851	2748	90	d4	d5	c4	c6	Nc3	Nf6	
Game4	2000	1-0	2851	2637	51	e4	e5	Nf3	Nf6	Nxe5	d6	
Game5	2000	1-0	2851	2751	69	e4	e6	d4	d5	Nc3	Nf6	

	W4	B4	W5	B5	W6	B6	W7	B7	W8	B8	W9	B9	\
Game1	cxd5	exd5	Bg5	c6	Qc2	Be7	e3	Nbd7	Bd3	O-O	Nge2	Re8	
Game2	c3	Nf6	Qe2	e5	d4	exd4	cxd4	a6	e5	Nd5	exd6+	Be6	
Game3	Nf3	dxc4	a4	Bf5	Ne5	Nbd7	Nxc4	Qc7	g3	e5	dxe5	Nxe5	
Game4	Nf3	Nxe4	d4	d5	Bd3	Be7	O-O	Nc6	c4	Nb4	Be2	O-O	
Game5	Bg5	dxe4	Nxe4	Nbd7	Nf3	Be7	Nxf6+	Bxf6	h4	O-O	Bd3	c5	

	W10	B10	W11	B11	W12	B12	W13	B13	W14	B14	W15	\
Game1	O-O	Nf8	f3	Ng6	Rad1	h6	Bxf6	Bxf6	Bxg6	fxg6	e4	
Game2	Bxc6+	bxc6	dxc5	Qa5+	Bd2	Qxc5	O-O	Kd7	Na3	Bxd6	Rab1	
Game3	Bf4	Nfd7	Bg2	g5	Ne3	gxf4	Nxf5	O-O-O	Qc2	Ng4	a5	
Game4	Nc3	Bf5	a3	Nxc3	bxc3	Nc6	Re1	Bf6	Bf4	Ne7	Qb3	
Game5	Qe2	cxd4	Qe4	g6	O-O-O	Qa5	Bxf6	Nxf6	Qxd4	Nh5	a3	

	B15	W16	B16	W17	B17	W18	B18	W19	B19	W20	B20	W21	\
Game1	g5	e5	Be7	f4	gxf4	Nxf4	Rf8	Ng6	Rxf1+	Rxf1	Be6	Ne2	
Game2	Bf5	Rbc1	Rhe8	Qd1	Qa7	Nc4	Bc7	Bc3	f6	Nd4	Be6	Nxc6	
Game3	fxg3	hxg3	a6	Ra4	Ndf6	Ne4	Nxe4	Bxe4	h5	Kf1	Kb8	Kg2	
Game4	b6	cxd5	Nxd5	Be5	Bg4	Rad1	Be7	h3	Bh5	g4	Bg6	Bg3	
Game5	Rd8	Qe3	Bd7	g4	Nf6	Qf4	Nd5	Qh6	Nf6	Ng5	Bc6	Bxg6	

	B21	W22	B22	W23	B23	W24	B24	W25	B25	W26	B26	\
Game1	Qd7	h4	Re8	Ng3	Bf7	Nxe7+	Rxe7	Nf5	Re6	Nd6	Bg6	
Game2	Kxc6	Bd4	Qb8	Qa4+	<NA>	<NA>	<NA>	<NA>	<NA>	<NA>	<NA>	
Game3	Be7	Nxe7	Qxe7	Bf3	Ne5	Bxh5	Qe6	Qc3	f6	Rah4	Qf5	
Game4	Nf6	Ne5	Ne4	Bf3	Nxg3	Nc6	Qd6	Nxe7+	Kh8	Bxa8	<NA>	
Game5	hxg6	Nxe6	fxe6	Qxg6+	Kh8	Qxf6+	Kh7	Rhe1	Rxd1+	Rxd1	Qc5	

	W27	B27	W28	B28	W29	B29	W30	B30	W31	B31	W32	\

Game1	Qc3	Rxd6	exd6	Qxd6	Qa3	Qb8	Qe7	Qg3	Rf3	Qg4	Qf8+	
Game2	<NA>	<NA>	<NA>	<NA>	<NA>	<NA>	<NA>	<NA>	<NA>	<NA>	<NA>	
Game3	Bf3	Rxh4	Rxh4	Qb1	Rh1	Rd1	Rxd1	Qxd1	b4	Kc7	Qc5	
Game4	<NA>	<NA>	<NA>	<NA>	<NA>	<NA>	<NA>	<NA>	<NA>	<NA>	<NA>	
Game5	g5	Rf8	Qh6+	Kg8	Qxe6+	Kg7	Qh6+	Kg8	Qg6+	Kh8	Qh6+	

	B32	W33	B33	W34	B34	W35	B35	W36	B36	W37	B37	\
Game1	Kh7	Qf4	Qd7	Rg3	Be4	Qe5	Qf7	h5	Qd7	b4	a6	
Game2	<NA>	<NA>	<NA>	<NA>	<NA>	<NA>	<NA>	<NA>	<NA>	<NA>	<NA>	
Game3	Qd6	Qxd6+	Kxd6	Be4	Nc4	Bd3	Nb2	f4	Nd1	g4	Ne3+	
Game4	<NA>	<NA>	<NA>	<NA>	<NA>	<NA>	<NA>	<NA>	<NA>	<NA>	<NA>	
Game5	Kg8	Qe6+	Kg7	Rd6	Be8	Qe7+	<NA>	<NA>	<NA>	<NA>	<NA>	

	W38	B38	W39	B39	W40	B40	W41	B41	W42	B42	W43	B43	\
Game1	a4	Kg8	a5	Kh7	Kf2	Kg8	Qb8+	Kh7	Qf8	Bc2	Qf4	Be4	
Game2	<NA>	<NA>	<NA>	<NA>	<NA>	<NA>	<NA>	<NA>	<NA>	<NA>	<NA>	<NA>	
Game3	Kf3	Nd5	Ke4	Nxb4	Bc4	c5	g5	fxg5	fxg5	Ke7	Kf5	Nc2	
Game4	<NA>	<NA>	<NA>	<NA>	<NA>	<NA>	<NA>	<NA>	<NA>	<NA>	<NA>	<NA>	
Game5	<NA>	<NA>	<NA>	<NA>	<NA>	<NA>	<NA>	<NA>	<NA>	<NA>	<NA>	<NA>	

	W44	B44	W45	B45	W46	B46	W47	B47	W48	B48	W49	B49	\
Game1	Qe5	Kg8	Ke3	Kh7	Ke2	Kg8	Qb8+	Kh7	Qf8	Bc2	Kd2	Be4	
Game2	<NA>	<NA>	<NA>	<NA>	<NA>	<NA>	<NA>	<NA>	<NA>	<NA>	<NA>	<NA>	
Game3	Ke5	Ne3	Be6	c4	<NA>	<NA>	<NA>	<NA>	<NA>	<NA>	<NA>	<NA>	
Game4	<NA>	<NA>	<NA>	<NA>	<NA>	<NA>	<NA>	<NA>	<NA>	<NA>	<NA>	<NA>	
Game5	<NA>	<NA>	<NA>	<NA>	<NA>	<NA>	<NA>	<NA>	<NA>	<NA>	<NA>	<NA>	

	W50	B50	W51	B51	W52	B52	W53	B53	W54	B54	W55	B55	\
Game1	Kc1	Qc7	Rg4	Qd7	Rf4	Bxg2	Qf5+	Qxf5	Rxf5	Kg8	d2	h3	
Game2	<NA>	<NA>	<NA>	<NA>	<NA>	<NA>	<NA>	<NA>	<NA>	<NA>	<NA>	<NA>	
Game3	<NA>	<NA>	<NA>	<NA>	<NA>	<NA>	<NA>	<NA>	<NA>	<NA>	<NA>	<NA>	
Game4	<NA>	<NA>	<NA>	<NA>	<NA>	<NA>	<NA>	<NA>	<NA>	<NA>	<NA>	<NA>	
Game5	<NA>	<NA>	<NA>	<NA>	<NA>	<NA>	<NA>	<NA>	<NA>	<NA>	<NA>	<NA>	

	W56	B56	W57	B57	W58	B58	W59	B59	W60	B60	W61	B61	\
Game1	f4	e6	e3	f7	f5	f8	e5	e8	f4	f7	g4	e8	
Game2	<NA>	<NA>	<NA>	<NA>	<NA>	<NA>	<NA>	<NA>	<NA>	<NA>	<NA>	<NA>	
Game3	<NA>	<NA>	<NA>	<NA>	<NA>	<NA>	<NA>	<NA>	<NA>	<NA>	<NA>	<NA>	
Game4	<NA>	<NA>	<NA>	<NA>	<NA>	<NA>	<NA>	<NA>	<NA>	<NA>	<NA>	<NA>	
Game5	<NA>	<NA>	<NA>	<NA>	<NA>	<NA>	<NA>	<NA>	<NA>	<NA>	<NA>	<NA>	

	W62	B62	W63	B63	W64	B64	W65	B65	W66	B66	W67	B67	\
Game1	g3	f7	f4	e8	f5	xh5	e6	g6	e3	c2	f3+	g8	
Game2	<NA>	<NA>	<NA>	<NA>	<NA>	<NA>	<NA>	<NA>	<NA>	<NA>	<NA>	<NA>	
Game3	<NA>	<NA>	<NA>	<NA>	<NA>	<NA>	<NA>	<NA>	<NA>	<NA>	<NA>	<NA>	
Game4	<NA>	<NA>	<NA>	<NA>	<NA>	<NA>	<NA>	<NA>	<NA>	<NA>	<NA>	<NA>	
Game5	<NA>	<NA>	<NA>	<NA>	<NA>	<NA>	<NA>	<NA>	<NA>	<NA>	<NA>	<NA>	

```
        W68   B68   W69   B69   W70   B70   W71   B71   W72   B72   W73   B73  \
Game1     5   xb5   xd5     4    c4     3    c3     5     5     4    f4     5
Game2  <NA>  <NA>  <NA>  <NA>  <NA>  <NA>  <NA>  <NA>  <NA>  <NA>  <NA>  <NA>
Game3  <NA>  <NA>  <NA>  <NA>  <NA>  <NA>  <NA>  <NA>  <NA>  <NA>  <NA>  <NA>
Game4  <NA>  <NA>  <NA>  <NA>  <NA>  <NA>  <NA>  <NA>  <NA>  <NA>  <NA>  <NA>
Game5  <NA>  <NA>  <NA>  <NA>  <NA>  <NA>  <NA>  <NA>  <NA>  <NA>  <NA>  <NA>

        W74   B74   W75   B75
Game1     6  <NA>  <NA>  <NA>
Game2  <NA>  <NA>  <NA>  <NA>
Game3  <NA>  <NA>  <NA>  <NA>
Game4  <NA>  <NA>  <NA>  <NA>
Game5  <NA>  <NA>  <NA>  <NA>
```

Let's explore how many games were played in each year. We see that we can probably remove games that were played 1970 and earlier since there are so few of them.

[5]:
```
chess_data[['Date']].value_counts()
```

[5]:
```
Date
2004    14738
2005    13852
2003    13185
2002    12167
2006    11229
2001    10411
2000     9783
1999     8473
1998     7820
1997     6876
1996     6647
1995     5598
1994     4816
1993     4046
2007     3365
1992     3350
1991     2857
1990     2391
1989     2076
1988     1865
1987     1195
1986      994
1984      900
1985      892
1981      855
1982      831
```

```
1983      722
1980      717
1978      693
1979      597
1977      453
1976      439
1972      404
1975      375
1974      287
1973      269
1971      168
1970       26
1968       18
1966       11
1906        8
1964        7
1905        5
1958        3
1956        2
1952        1
dtype: int64
```

[6]:
```
# Let's take out any games on or before 1970 since there are so few of them
chess_data = chess_data[chess_data['Date'] > 1970]
```

[7]:
```
chess_data[['Date']].value_counts()
```

[7]:
```
Date
2004    14738
2005    13852
2003    13185
2002    12167
2006    11229
2001    10411
2000     9783
1999     8473
1998     7820
1997     6876
1996     6647
1995     5598
1994     4816
1993     4046
2007     3365
1992     3350
1991     2857
1990     2391
1989     2076
```

```
1988     1865
1987     1195
1986      994
1984      900
1985      892
1981      855
1982      831
1983      722
1980      717
1978      693
1979      597
1977      453
1976      439
1972      404
1975      375
1974      287
1973      269
1971      168
dtype: int64
```

In our current data set we observe that White has slightly more wins than Black. White is expected to win more than Black on average because it is generally accepted that White has an advantage. Chess.com compiles and analyzes their own database of chess games. White consistently wins more often than Black in their data set.

[8]:
```
chess_data[['Game Result']].value_counts()
```

[8]:
```
Game Result
1-0            88204
0-1            68132
dtype: int64
```

Knowing the typical percentage win for white will become useful later when we compare it to the predicted wins using our model.

[9]:
```
# find percentage wins for white
(chess_data[['Game Result']].value_counts()[0]) / chess_data.shape[0]
```

[9]:
```
0.5641950670351039
```

Digging deeper we observe that there are mostly games in which White had a higher ELO rating than Black. This fact indicates that there could be a strong correlation between the ELO rating of a player and how often they beat the player with a weaker ELO rating.

[10]:
```
# number of games where white had higher ELO rating
chess_data[chess_data['W-ELO'] > chess_data['B-ELO']].shape[0]
```

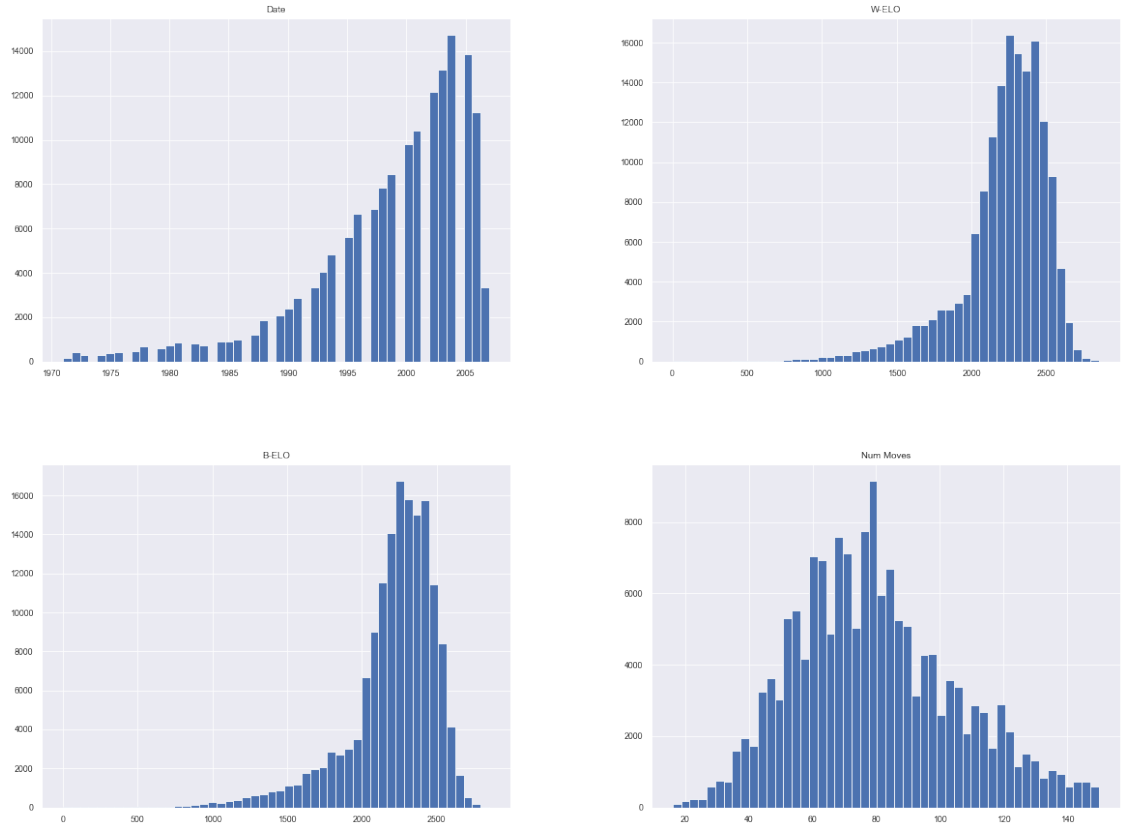
[10]:
```
81061
```

[11]:
```
# number of games where black had higher elo rating.
chess_data[chess_data['B-ELO'] > chess_data['W-ELO']].shape[0]
```

[11]: 73582

Further analysis reveals that the White and Black ELO in this dataset is almost identical. But white wins more games. One explanation for this fact is that White has an inherent advantage over Black since White moves first.

[12]:
```
chess_data.hist(bins = 50, figsize = (20, 15));
```



Most of the games in this data set are from 1970 and on. This is mostly due to the fact that Chess became hugely popular in the U.S. and elsewhere during the Cold War (https://www.quora.com/How-did-chess-get-so-popular-during-the-Cold-War). The histogram tells us that most games last between 30 and 50 moves per player. Also White has a higher ELO on average than Black. We will calculate this mean again after the data has been further cleaned up.

[13]:
```
chess_data['B-ELO'].mean()
```

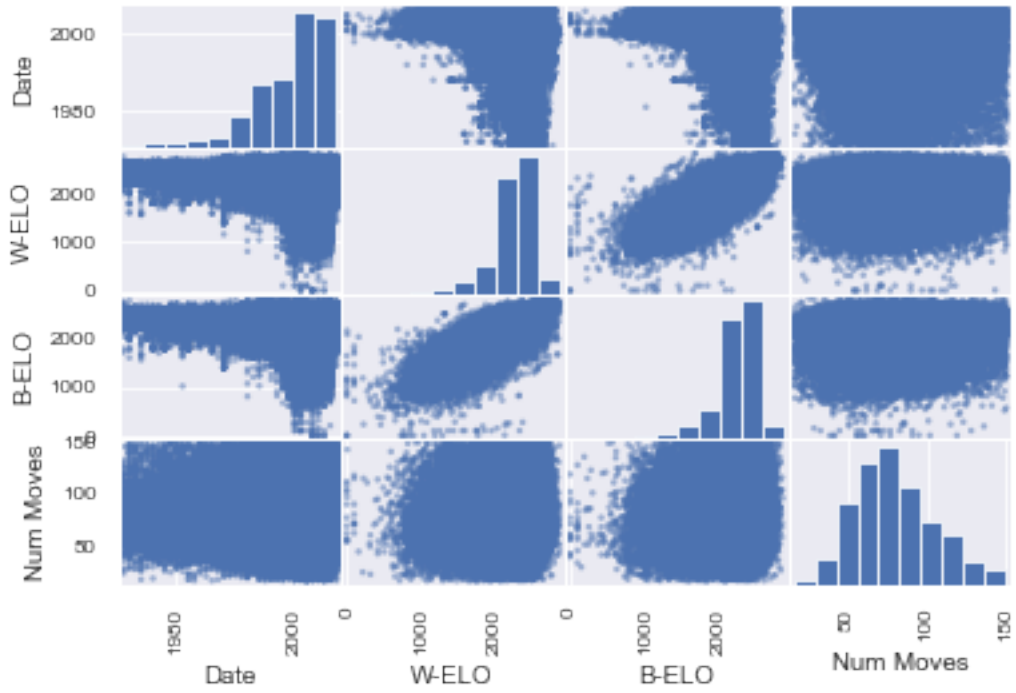
[13]: 2206.689905076246

[14]:
```
chess_data['W-ELO'].mean()
```

[14]: 2215.2228597380004

In the scatter matrix we can se that there is a strong correlation between W-ELO and B-ELO. This makes a lot of sense, because as White gets better, so does Black in order to stay competitive. We also observe that this data set has a nice mix of amateur games and also top player games by looking at the spread of ELO ratings versus date. We also note that the number of moves per game is evenly spread between few and many. That is interesting because the team assumed that there would be many more long games as the ELO ratings went up, but that is not the case.

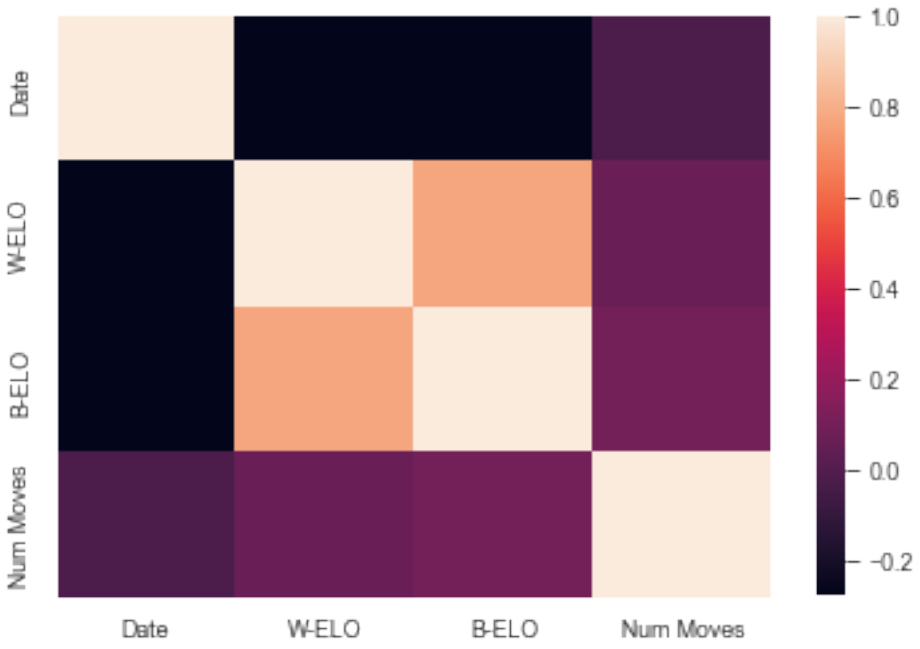
[15]:
```
pd.plotting.scatter_matrix(chess_data[['Date', 'W-ELO', 'B-ELO', 'Num Moves']]);
```



The heatmap below confirms first impressions about the correlation between the ELO ratings. We will come back to this heatmap later when we analyze the openings.

[16]:
```
corr = chess_data.corr()
sns.heatmap(corr, xticklabels=corr.columns, yticklabels=corr.columns)
```

[16]: <AxesSubplot:>



Next, let's explore the common openings for White and Black. we make a few more dataframes that are views into chess_data. This will make it a little easier to do analysis.

[17]:
```
# consider the opening as the first 8 moves (each side).
openings_white = chess_data.loc[:, 'W1': 'W8': 2]
openings_black = chess_data.loc[:, 'B1': 'B8': 2]
```

[18]:
```
openings_white.head()
```

[18]:

	W1	W2	W3	W4	W5	W6	W7	W8
Game1	d4	c4	Nc3	cxd5	Bg5	Qc2	e3	Bd3
Game2	e4	Nf3	Bb5	c3	Qe2	d4	cxd4	e5
Game3	d4	c4	Nc3	Nf3	a4	Ne5	Nxc4	g3
Game4	e4	Nf3	Nxe5	Nf3	d4	Bd3	O-O	c4
Game5	e4	d4	Nc3	Bg5	Nxe4	Nf3	Nxf6+	h4

[19]:
```
openings_black.head()
```

[19]:

	B1	B2	B3	B4	B5	B6	B7	B8
Game1	d5	e6	Nf6	exd5	c6	Be7	Nbd7	O-O
Game2	c5	Nc6	d6	Nf6	e5	exd4	a6	Nd5
Game3	d5	c6	Nf6	dxc4	Bf5	Nbd7	Qc7	e5
Game4	e5	Nf6	d6	Nxe4	d5	Be7	Nc6	Nb4
Game5	e6	d5	Nf6	dxe4	Nbd7	Be7	Bxf6	O-O

We observe that there are well established common openings represented in the dataset for both

players. Some of these openings include the Scott opening, King' Indian defense and the Sicilian Defence, Najdorf Variation.

[20]:
```
openings_white.value_counts().head(10)
```

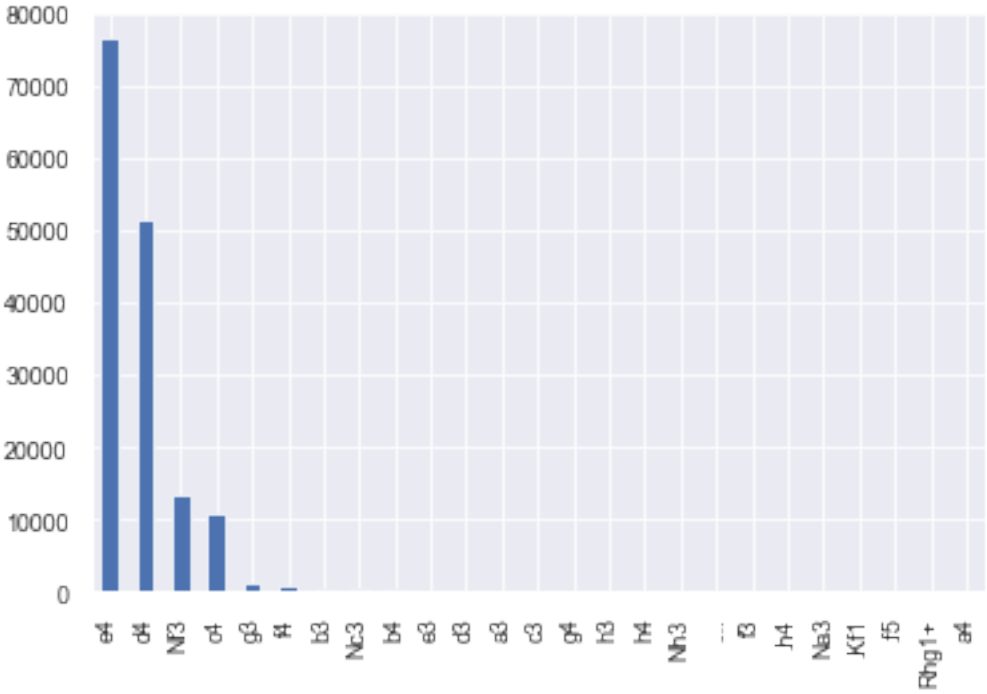
[20]:
```
W1  W2   W3   W4    W5   W6    W7   W8
e4  Nf3  d4   Nxd4  Nc3  Be3   f3   Qd2      1012
                        Ndb5  Bg5  Na3       916
         Bb5  Ba4   O-O  Re1   Bb3  c3        895
         d4   Nxd4  Nc3  Bg5   Qd2  O-O-O     855
d4  c4   Nc3  e4    Nf3  Be2   O-O  d5        485
e4  Nf3  d4   Nxd4  Nc3  Be2   O-O  Be3       444
                        Bg5   f4   Qf3       393
                        g3    Bg2  O-O       345
    d4   Nd2  e5    Bd3  c3    Ne2  cxd4      329
    Nf3  d4   Nxd4  Nc3  Be2   Nb3  O-O       318
dtype: int64
```

[21]:
```
openings_black.value_counts().head(10)
```

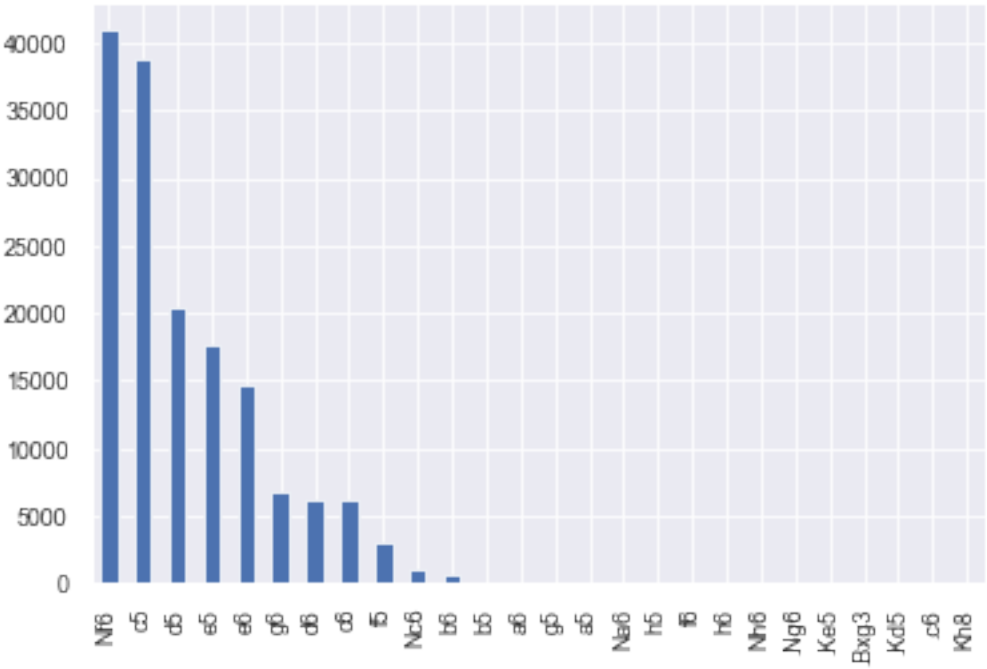
[21]:
```
B1   B2   B3   B4    B5   B6   B7   B8
c5   Nc6  cxd4 Nf6   e5   d6   a6   b5     866
     d6   cxd4 Nf6   g6   Bg7  O-O  Nc6    861
e5   Nc6  a6   Nf6   Be7  b5   d6   O-O    725
Nf6  g6   Bg7  d6    O-O  e5   Nc6  Ne7    697
e6   d5   Nf6  Nfd7  c5   Nc6  cxd4 f6     377
c5   d6   cxd4 Nf6   a6   e6   Be7  Qc7    352
                    g6   Bg7  Nc6  O-O    345
Nf6  c5   e6   exd5  d6   g6   Bg7  O-O    334
c5   d6   cxd4 Nf6   a6   e6   Be7  O-O    282
                         e5   Be7  O-O    267
dtype: int64
```

It's interesting to note that Black's opening move list is more diverse than White's. This is most likely due to the reactionary nature of the game for Black. We can see that the most common opening is the Alekhine's defence (White e4, Black Nf6)

[22]:
```
openings_white['W1'].value_counts().plot.bar();
```

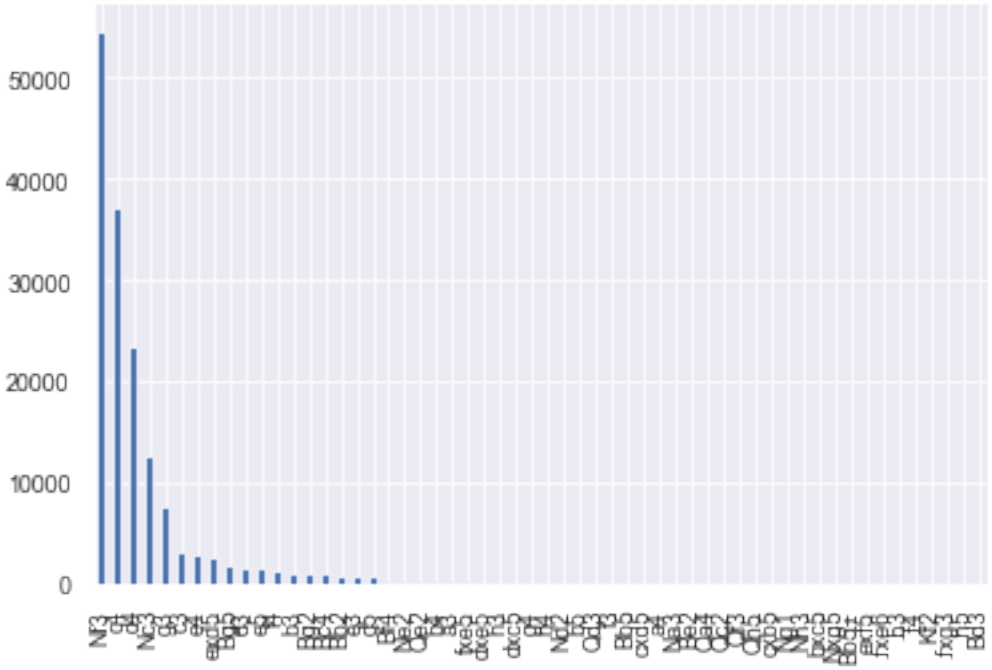


[23]:
```
openings_black['B1'].value_counts().plot.bar();
```

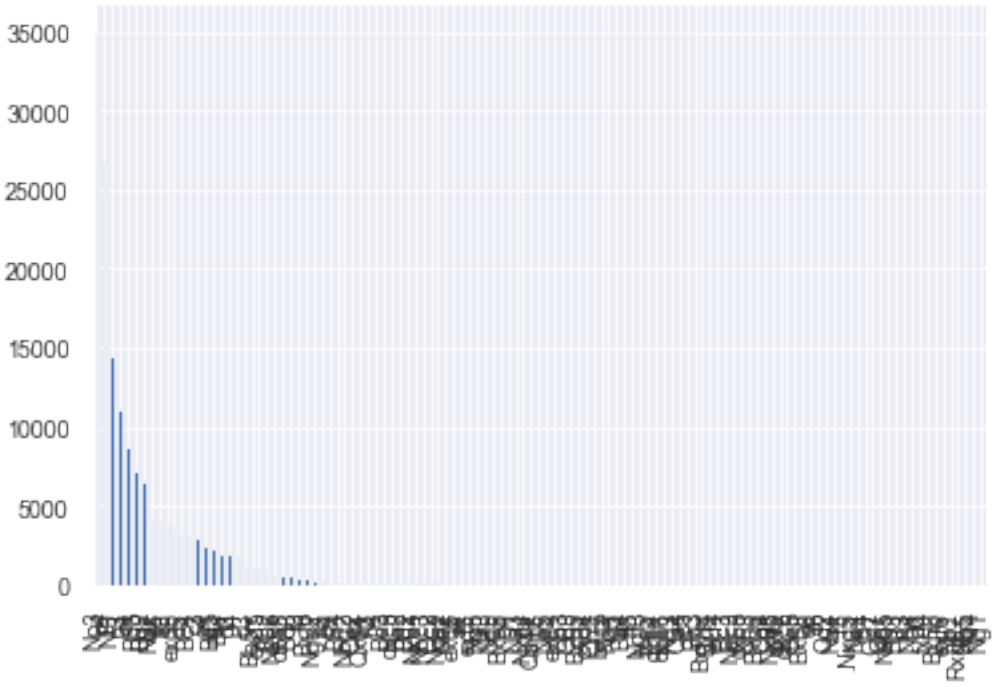


One interesting thing to note here is how quickly there will be different chess games developing. Observe how many more moves are played at move 2 and 3. However, we can still observe that most games play out very similarly at the beginning.

[24]:
```
openings_white['W2'].value_counts().plot.bar();
```

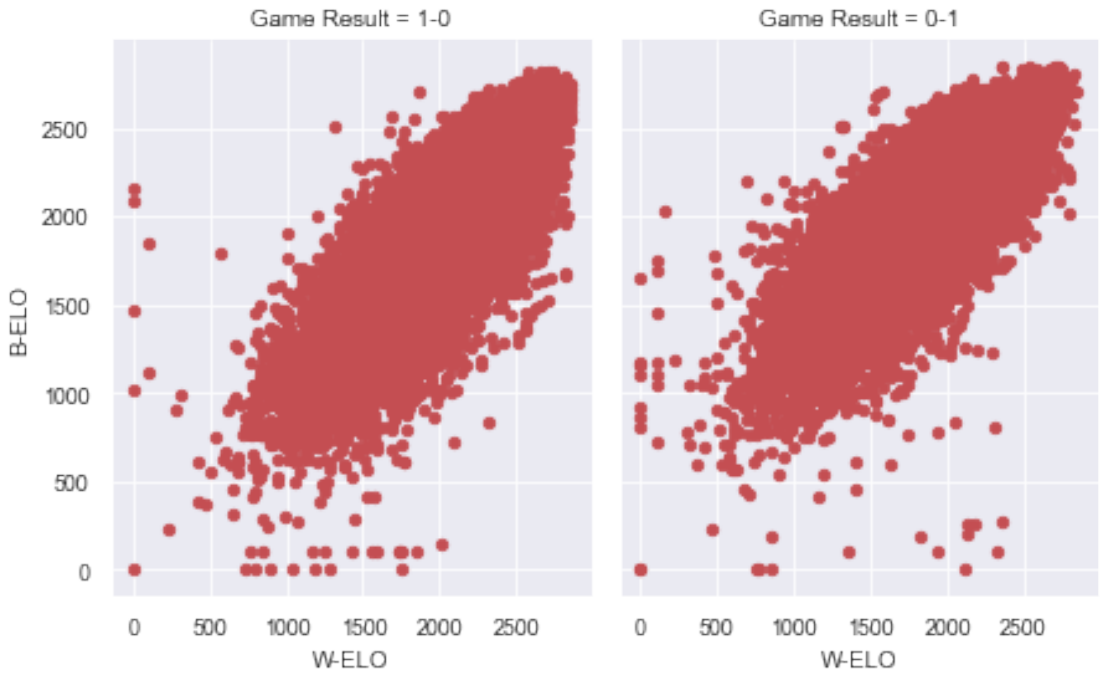


[25]:
```
openings_white['W3'].value_counts().plot.bar();
```



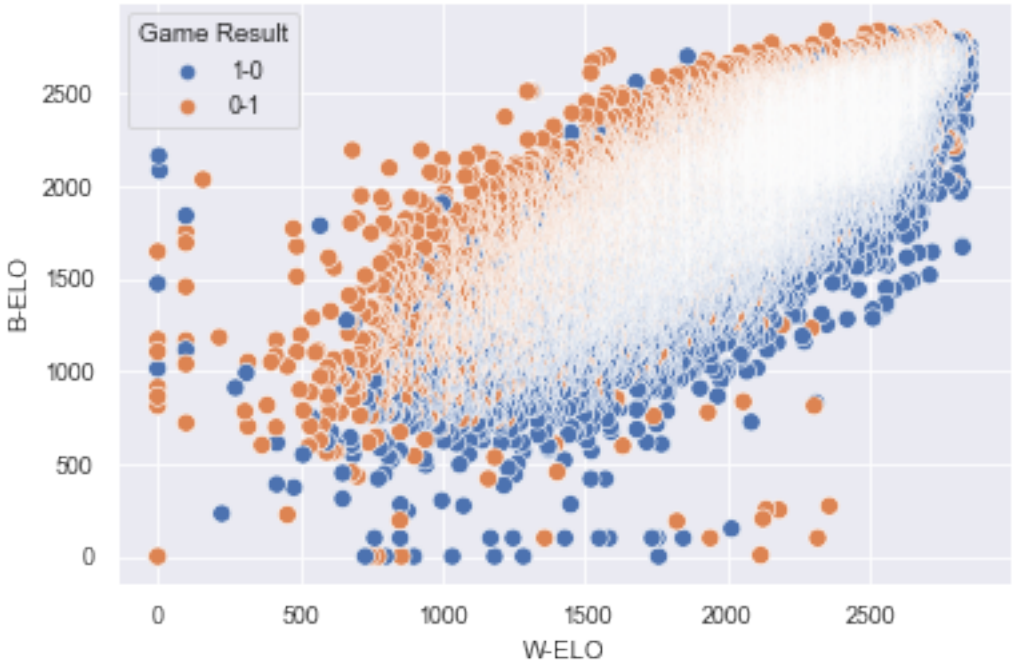
In the facet grid below we can see an interesting feature. There are many outliers.

[26]:
```
g = sns.FacetGrid(chess_data, col = 'Game Result', height = 4, aspect = 0.8)
g.map(plt.scatter, 'W-ELO', 'B-ELO', s = 20, color = "r");
```



From the plot below we see that we can take out some of those outliers by further cleaning the data to include only ELO ratings above 500.

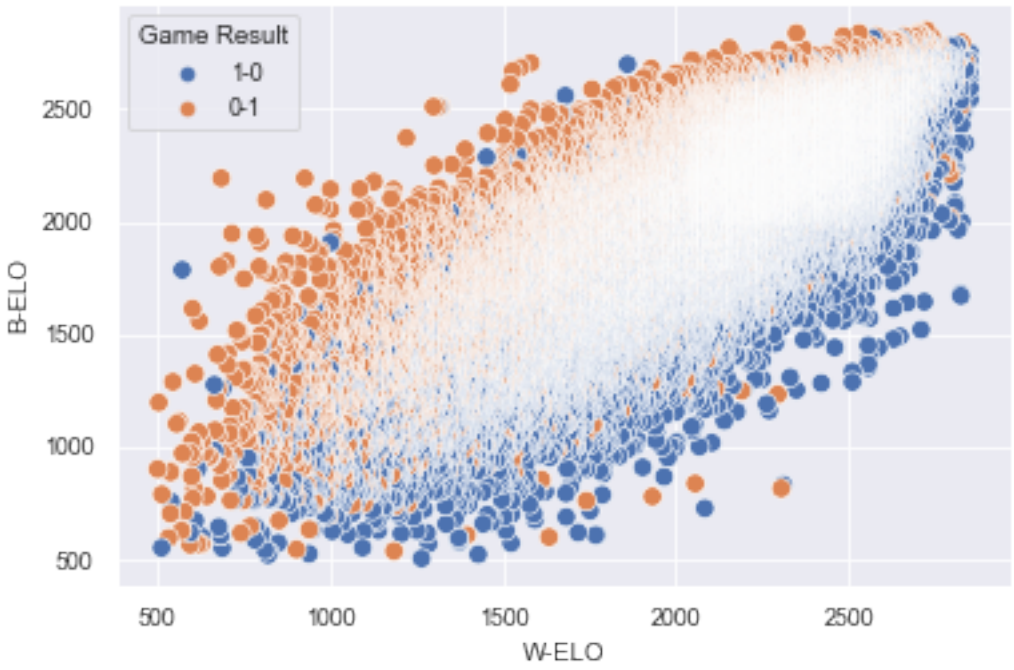
[27]:
```
sns.scatterplot(x = 'W-ELO', y = 'B-ELO', hue = 'Game Result', data =␣
↪chess_data, s = 50);
```



[28]:
```
# trim low ELO ratings and reassign openings dataframes.
chess_data = chess_data[chess_data['W-ELO'] >= 500]
chess_data = chess_data[chess_data['B-ELO'] >= 500]

openings_white = chess_data.loc[:, 'W1': 'W8': 2]
openings_black = chess_data.loc[:, 'B1': 'B8': 2]
```

[29]:
```
sns.scatterplot(x = 'W-ELO', y = 'B-ELO', hue = 'Game Result', data =␣
↪chess_data, s = 55);
```



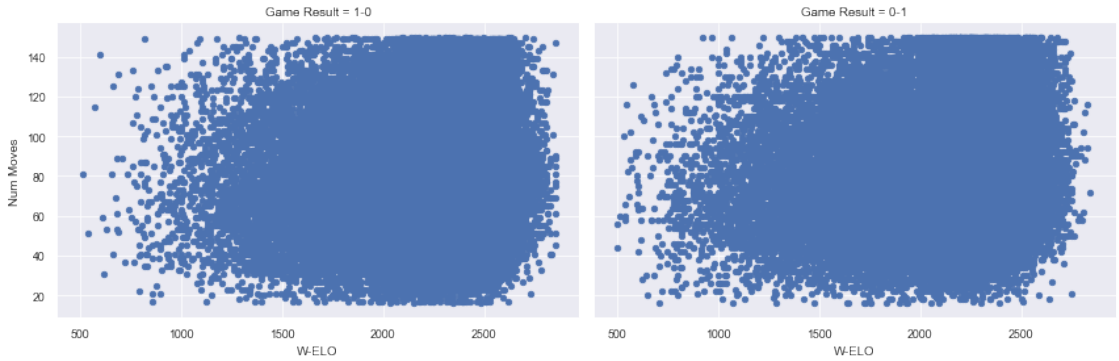
That looks much better but this plot shows something strange. Why are there so many games where the better player loses to the vastly worse player? For example, there are games where White is above 2000 ELO and loses to players below 1000. Perhaps this is an indication of match fixing, https://nextlevelchess.blog/pre-arranged/ ?

Another thing we observe is that the very best players win or lose at about the same rate (the end of the scatter plot is pointy).

There are no recorded games with W-ELO below 1500 until the 1980s. That's probably due to better record keeping as the years went by. Also, since chess popularity increased greatly during the late 70s and on, there would be more amateurs playing.

The plot below seems to show that white loses more often when the game is shorter.

[30]:
```
g = sns.FacetGrid(chess_data, col = 'Game Result', height = 4, aspect = 1.5)
g.map(plt.scatter, 'W-ELO', 'Num Moves', s = 20, color = "b");
```



We can do more analysis if we convert the Game Results column to int. 1 represents a win for White, 0 repesents loss for White

[31]:
```
def GetResults(x):
  if x[0] == '0':
    return 0
  else:
    return 1
new_col = chess_data['Game Result'].apply(GetResults)
chess_data['Game Result'] = new_col
```

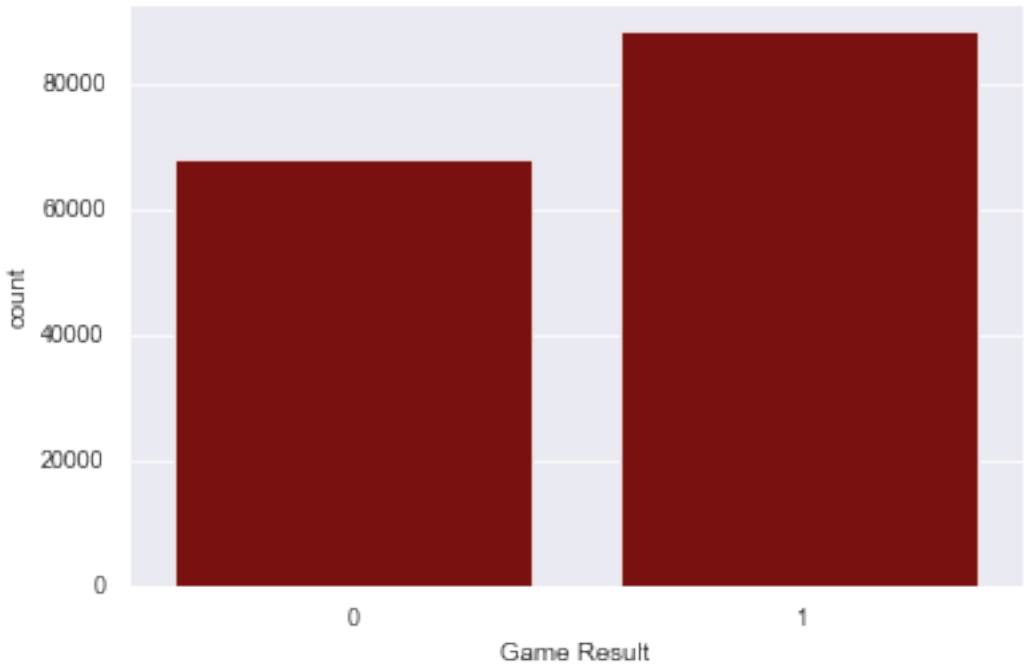
[32]:
```
chess_data.dtypes
```

[32]:
```
Date            int32
Game Result     int64
W-ELO           int32
B-ELO           int32
Num Moves       int32
                ...
B73            string
W74            string
B74            string
W75            string
B75            string
Length: 155, dtype: object
```

The bar plot confirms what we already know, which is that white wins more games (1)

[33]:
```
sns.countplot(chess_data['Game Result'], color = 'darkred');
```

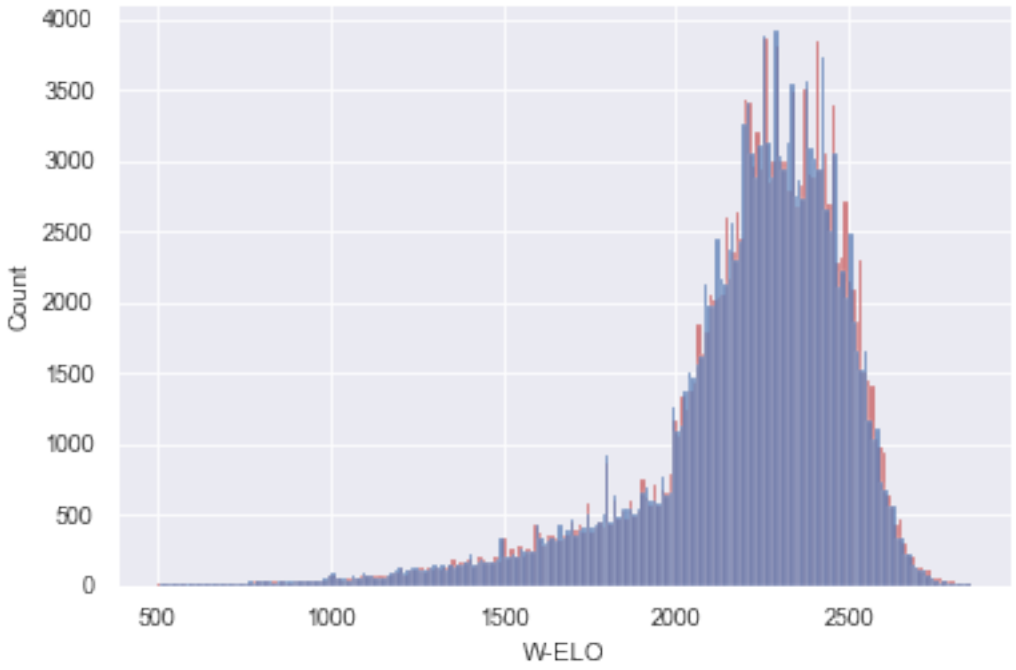
```
C:\Users\Abrah\anaconda3\lib\site-packages\seaborn\_decorators.py:36:
FutureWarning: Pass the following variable as a keyword arg: x. From version
0.12, the only valid positional argument will be `data`, and passing other
arguments without an explicit keyword will result in an error or
misinterpretation.
  warnings.warn(
```



The histogram further illustrates how closely matched White and Black players are in this data set.

[34]:
```
sns.histplot(chess_data['W-ELO'], color = 'r')
sns.histplot(chess_data['B-ELO'], color = 'b')
```

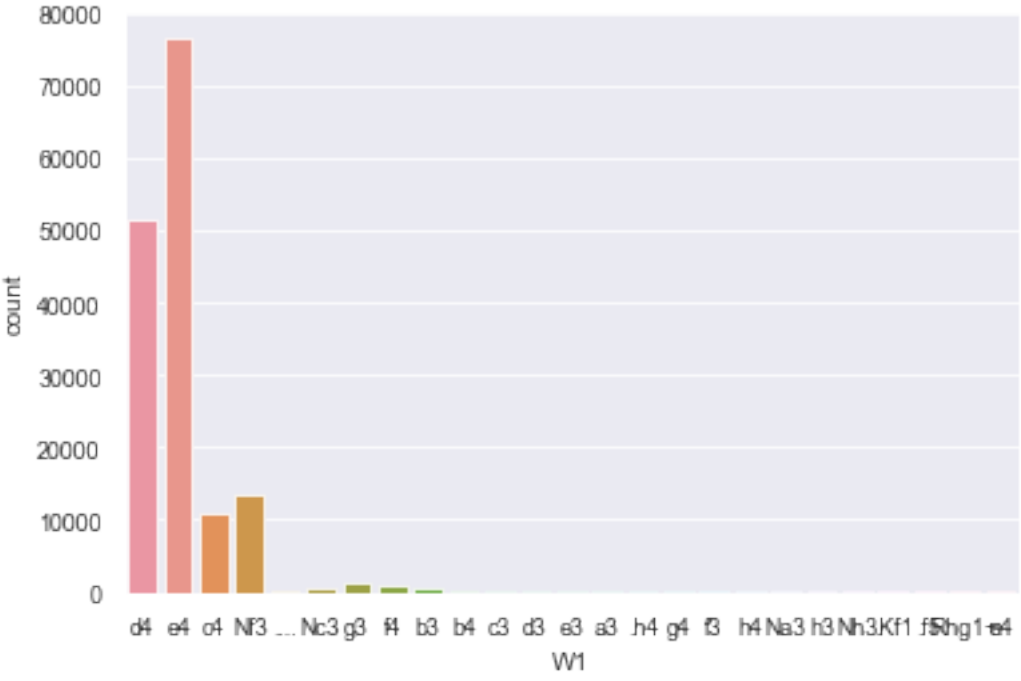
[34]:
```
<AxesSubplot:xlabel='W-ELO', ylabel='Count'>
```



The following count plots better illustrate the most common first move for both players.

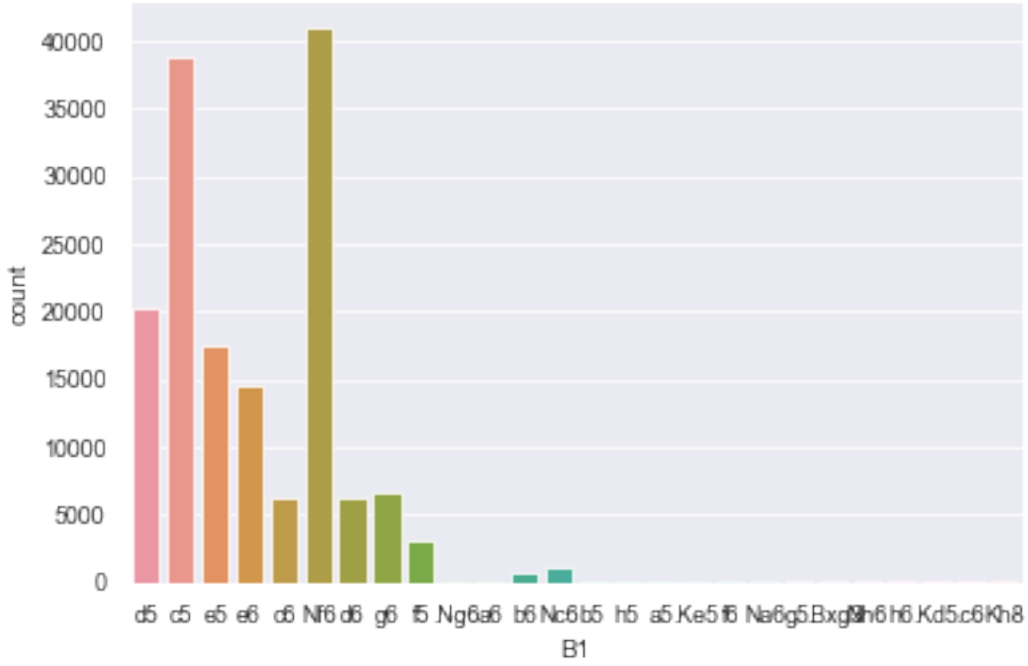
[35]:
```
sns.countplot(x = openings_white['W1'])
```

[35]:
```
<AxesSubplot:xlabel='W1', ylabel='count'>
```



[36]:
```
sns.countplot(x = openings_black['B1'])
```

[36]:
```
<AxesSubplot:xlabel='B1', ylabel='count'>
```



CONVERT OPENINGS INTO NUM VALUES It would be better to analyze the opening moves by treating them as integers.

[37]:
```
# add columns to anaylize openings.
openings_white['W1-Numeric'] = openings_white['W1'].astype('category').cat.codes
openings_white['W2-Numeric'] = openings_white['W2'].astype('category').cat.codes
openings_white['W3-Numeric'] = openings_white['W3'].astype('category').cat.codes
openings_white['W4-Numeric'] = openings_white['W4'].astype('category').cat.codes
openings_white['W5-Numeric'] = openings_white['W5'].astype('category').cat.codes
openings_white['W6-Numeric'] = openings_white['W6'].astype('category').cat.codes
openings_white['W7-Numeric'] = openings_white['W7'].astype('category').cat.codes
openings_white['W8-Numeric'] = openings_white['W8'].astype('category').cat.codes
```

[42]:
```
openings_black['B1-Numeric'] = openings_black['B1'].astype('category').cat.codes
openings_black['B2-Numeric'] = openings_black['B2'].astype('category').cat.codes
openings_black['B3-Numeric'] = openings_black['B3'].astype('category').cat.codes
openings_black['B4-Numeric'] = openings_black['B4'].astype('category').cat.codes
openings_black['B5-Numeric'] = openings_black['B5'].astype('category').cat.codes
```

```
openings_black['B6-Numeric'] = openings_black['B6'].astype('category').cat.codes
openings_black['B7-Numeric'] = openings_black['B7'].astype('category').cat.codes
openings_black['B8-Numeric'] = openings_black['B8'].astype('category').cat.codes
```

[43]:
```
openings_white.head(10)
```

[43]:

	W1	W2	W3	W4	W5	W6	W7	W8	W1-Numeric	W2-Numeric	\
Game1	d4	c4	Nc3	cxd5	Bg5	Qc2	e3	Bd3	16	35	
Game2	e4	Nf3	Bb5	c3	Qe2	d4	cxd4	e5	18	18	
Game3	d4	c4	Nc3	Nf3	a4	Ne5	Nxc4	g3	16	35	
Game4	e4	Nf3	Nxe5	Nf3	d4	Bd3	O-O	c4	18	18	
Game5	e4	d4	Nc3	Bg5	Nxe4	Nf3	Nxf6+	h4	18	39	
Game6	e4	Nf3	d4	Nxd4	Nxc6	e5	Qe2	c4	18	18	
Game7	e4	d4	Nc3	Bg5	Nxe4	Bxf6	Nf3	Qd2	18	39	
Game8	e4	Nf3	Bb5	Ba4	O-O	d4	Bb3	dxe5	18	18	
Game9	e4	d4	e5	Nc3	g4	Nge2	Nf4	dxc5	18	39	
Game10	e4	Nf3	Bb5	Ba4	O-O	Re1	Bb3	c3	18	18	

	W3-Numeric	W4-Numeric	W5-Numeric	W6-Numeric	W7-Numeric	W8-Numeric
Game1	36	157	30	225	440	28
Game2	8	151	168	350	422	557
Game3	36	72	215	145	226	585
Game4	57	72	241	18	264	526
Game5	36	23	139	155	252	602
Game6	86	89	131	364	293	526
Game7	36	23	139	74	192	356
Game8	8	6	152	350	13	552
Game9	96	59	276	167	193	547
Game10	8	6	152	303	13	525

[44]:
```
openings_black.head(10)
```

[44]:

	B1	B2	B3	B4	B5	B6	B7	B8	B1-Numeric	B2-Numeric	\
Game1	d5	e6	Nf6	exd5	c6	Be7	Nbd7	O-O	16	64	
Game2	c5	Nc6	d6	Nf6	e5	exd4	a6	Nd5	14	23	
Game3	d5	c6	Nf6	dxc4	Bf5	Nbd7	Qc7	e5	16	54	
Game4	e5	Nf6	d6	Nxe4	d5	Be7	Nc6	Nb4	18	30	
Game5	e6	d5	Nf6	dxe4	Nbd7	Be7	Bxf6	O-O	19	58	
Game6	e5	Nc6	exd4	Nf6	bxc6	Qe7	Nd5	Ba6	18	23	
Game7	e6	d5	Nf6	dxe4	Be7	Bxf6	Nd7	O-O	19	58	
Game8	e5	Nc6	a6	Nf6	Nxe4	b5	d5	Be6	18	23	
Game9	c6	d5	Bf5	e6	Bg6	Ne7	c5	Nd7	15	58	
Game10	e5	Nc6	a6	Nf6	Be7	b5	d6	O-O	18	23	

	B3-Numeric	B4-Numeric	B5-Numeric	B6-Numeric	B7-Numeric	B8-Numeric
Game1	55	214	280	30	159	327
Game2	122	91	306	406	427	205

```
Game3          55         200          25         132         304         562
Game4         122         112         293          30         168         169
Game5          55         204         103          30          97         327
Game6         134          91         275         266         184           9
Game7          55         204          24          85         186         327
Game8         102          91         167         365         462          33
Game9          16         211          32         164         448         207
Game10        102          91          24         365         463         327
```

[45]:
```
# keep numeric opening data, remove the nonnumeric data
openings_white = openings_white.loc[:, 'W1-Numeric':]
```

[46]:
```
openings_white.head()
```

[46]:
```
       W1-Numeric  W2-Numeric  W3-Numeric  W4-Numeric  W5-Numeric  W6-Numeric  \
Game1          16          35          36         157          30         225
Game2          18          18           8         151         168         350
Game3          16          35          36          72         215         145
Game4          18          18          57          72         241          18
Game5          18          39          36          23         139         155

       W7-Numeric  W8-Numeric
Game1         440          28
Game2         422         557
Game3         226         585
Game4         264         526
Game5         252         602
```

[47]:
```
# keep numeric opening data, remove the nonnumeric data
openings_black = openings_black.loc[:, 'B1-Numeric':]
```

[48]:
```
openings_black.head()
```

[48]:
```
       B1-Numeric  B2-Numeric  B3-Numeric  B4-Numeric  B5-Numeric  B6-Numeric  \
Game1          16          64          55         214         280          30
Game2          14          23         122          91         306         406
Game3          16          54          55         200          25         132
Game4          18          30         122         112         293          30
Game5          19          58          55         204         103          30

       B7-Numeric  B8-Numeric
Game1         159         327
Game2         427         205
Game3         304         562
Game4         168         169
Game5          97         327
```

We can use this numerical representation of the openings in heatmap to see how each game plays out in the beginning. The darker colors signify a lack or diversity of play. We see the same moves are consistently used in the first 1-3 moves and then starts to deviate.

[49]:
```
# Draw a heatmap with the numeric values in each cell
f, ax = plt.subplots(figsize=(12, 10))
sns.heatmap(openings_white.iloc[:10, :], annot = True, fmt = "d", linewidths =␣
↪0.5, ax = ax)
```

[49]: <AxesSubplot:>

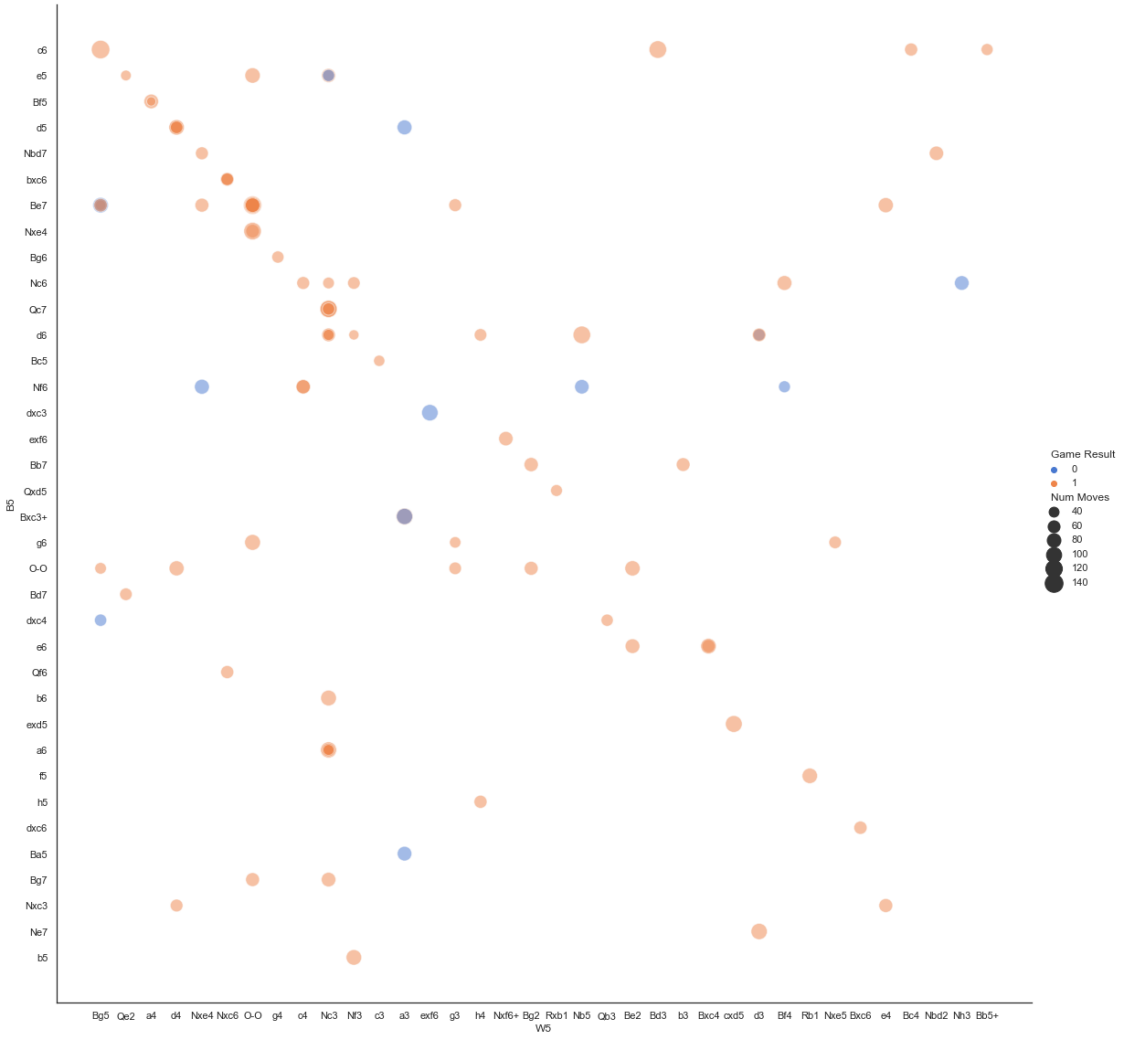
[50]:
```
# Draw a heatmap with the numeric values in each cell
f, ax = plt.subplots(figsize=(12, 10))
sns.heatmap(openings_black.iloc[:10, :], annot = True, fmt = "d", linewidths =␣
↪0.5, ax = ax)
```

[50]: <AxesSubplot:>

One more observation about the openings. We see from the heatmap that the games really start to diversify after the 4th or 5th moves. If we plot some games and the moves after that, we see an interesting trend. White wins at key points consistently. For example, for the first 100 games analyzed, if Black plays c6 after White's Bg5, white wins, especially if the game goes on for more than 100 moves. But if Black responds to Bg5 with dxc4, then Black wins.

[96]:
```
sns.set_theme(style = "white")
sns.relplot(x = 'W5', y = 'B5', hue = "Game Result", size = "Num Moves",
            sizes=(100, 400), alpha = 0.5, palette = "muted",
            height = 16, data = chess_data[:'Game100'])
```

[96]: <seaborn.axisgrid.FacetGrid at 0x266b046e3d0>



Below we can see that the number of unique moves for each player is very similar. This means that each player has an established response to their opponents move. It would be strange, but also very interesting for Black to have 5000 unique moves at B50 instead of 1487.

[97]:
```
openings_white.apply(lambda x: len(x.unique()))
```

[97]:
```
W1-Numeric     25
W2-Numeric     55
W3-Numeric    115
W4-Numeric    198
W5-Numeric    292
W6-Numeric    403
W7-Numeric    487
W8-Numeric    609
dtype: int64
```

[98]:
```
openings_black.apply(lambda x: len(x.unique()))
```

[98]:
```
B1-Numeric     26
B2-Numeric     77
B3-Numeric    155
B4-Numeric    240
B5-Numeric    342
B6-Numeric    446
B7-Numeric    523
B8-Numeric    604
dtype: int64
```

[99]:
```
# early game
chess_data.loc[:, 'W9': 'B20'].apply(lambda x: len(x.unique()))
```

[99]:
```
W9      689
B9      710
W10     788
B10     796
W11     890
B11     877
W12     959
B12     968
W13    1073
B13    1064
W14    1163
B14    1154
W15    1217
B15    1224
W16    1321
B16    1277
W17    1413
B17    1359
W18    1506
B18    1452
W19    1591
B19    1523
W20    1653
B20    1606
dtype: int64
```

[100]:
```
# middle game
chess_data.loc[:, 'W21': 'B40'].apply(lambda x: len(x.unique()))
```

[100]:
```
W21    1750
B21    1678
W22    1832
```

```
B22    1754
W23    1898
B23    1807
W24    1935
B24    1892
W25    2003
B25    1913
W26    2056
B26    1953
W27    2060
B27    2028
W28    2101
B28    2030
W29    2132
B29    2070
W30    2151
B30    2086
W31    2149
B31    2116
W32    2146
B32    2120
W33    2148
B33    2080
W34    2147
B34    2091
W35    2146
B35    2104
W36    2129
B36    2069
W37    2092
B37    2032
W38    2084
B38    2037
W39    2056
B39    1959
W40    1948
B40    1938
dtype: int64
```

It's also notable that there are many less unique moves at the end game. This makes a lot of sense because there are fewer pieces.

[101]:
```
# end game
chess_data.loc[:, 'W41': 'B75'].apply(lambda x: len(x.unique()))
```

[101]:
```
W41    1930
B41    1849
```

```
W42    1874
B42    1800
W43    1794
       …
B73     196
W74     185
B74     160
W75     140
B75     101
Length: 70, dtype: int64
```

Is there a mathematical limit to how many unique moves there are at each phase of the game? One interesting question is if the number of unique moves goes up or down as players get better.

We can find that out by analyzing it year by year. This is assuming that players are getting better each year. Let's also limit the ELO to 2000 or more.

[106]:
```
# EARLY GAME, 1970S
chess_data[(chess_data['Date'] >= 1971) & (chess_data['Date'] < 1980) &␣
↪(chess_data['W-ELO'] >= 2000) & (chess_data['B-ELO'] >= 2000)].loc[:, 'W9':␣
↪'B20'].apply(lambda x: len(x.unique()))
```

[106]:
```
W9     274
B9     275
W10    314
B10    313
W11    334
B11    358
W12    389
B12    401
W13    410
B13    436
W14    476
B14    465
W15    501
B15    502
W16    531
B16    521
W17    556
B17    545
W18    574
B18    578
W19    631
B19    598
W20    640
B20    623
dtype: int64
```

[108]:
```
# EARLY GAME, 1980S
chess_data[(chess_data['Date'] >= 1980) & (chess_data['Date'] < 1990) &␣
 ↪(chess_data['W-ELO'] >= 2000) & (chess_data['B-ELO'] >= 2000)].loc[:, 'W9':␣
 ↪'B20'].apply(lambda x: len(x.unique()))
```

[108]:
```
W9     356
B9     369
W10    414
B10    434
W11    479
B11    511
W12    526
B12    558
W13    608
B13    602
W14    647
B14    641
W15    674
B15    698
W16    716
B16    735
W17    748
B17    768
W18    800
B18    794
W19    845
B19    815
W20    866
B20    838
dtype: int64
```

[109]:
```
# EARLY GAME, 1990S
chess_data[(chess_data['Date'] >= 1990) & (chess_data['Date'] < 2000) &␣
 ↪(chess_data['W-ELO'] >= 2000) & (chess_data['B-ELO'] >= 2000)].loc[:, 'W9':␣
 ↪'B20'].apply(lambda x: len(x.unique()))
```

[109]:
```
W9      533
B9      556
W10     608
B10     631
W11     700
B11     705
W12     763
B12     761
W13     853
B13     841
W14     921
```

```
B14     891
W15     954
B15     962
W16    1024
B16     993
W17    1094
B17    1061
W18    1153
B18    1128
W19    1196
B19    1159
W20    1273
B20    1220
dtype: int64
```

How fascinating! The number of unique moves is going UP. That means the richness of the game is increasing with time. We can check the middle game meta from the 70s and compare that with the 90s

[110]:
```
# MIDDLE GAME, 1970s
chess_data[(chess_data['Date'] >= 1971) & (chess_data['Date'] < 1980) &␣
↪(chess_data['W-ELO'] >= 2000) & (chess_data['B-ELO'] >= 2000)].loc[:, 'W21':␣
↪'B40'].apply(lambda x: len(x.unique()))
```

[110]:
```
W21    652
B21    631
W22    691
B22    658
W23    712
B23    647
W24    685
B24    675
W25    701
B25    684
W26    718
B26    687
W27    713
B27    693
W28    736
B28    709
W29    747
B29    721
W30    763
B30    711
W31    754
B31    717
W32    727
```

```
B32    731
W33    734
B33    700
W34    704
B34    682
W35    739
B35    714
W36    712
B36    700
W37    697
B37    705
W38    681
B38    664
W39    678
B39    618
W40    637
B40    633
dtype: int64
```

[111]:
```
# MIDDLE GAME, 1990S
chess_data[(chess_data['Date'] >= 1990) & (chess_data['Date'] < 2000) &␣
 ↪(chess_data['W-ELO'] >= 2000) & (chess_data['B-ELO'] >= 2000)].loc[:, 'W21':␣
 ↪'B40'].apply(lambda x: len(x.unique()))
```

[111]:
```
W21    1323
B21    1297
W22    1381
B22    1332
W23    1451
B23    1358
W24    1434
B24    1411
W25    1508
B25    1430
W26    1519
B26    1484
W27    1507
B27    1485
W28    1540
B28    1516
W29    1550
B29    1522
W30    1594
B30    1556
W31    1599
B31    1527
W32    1580
```

```
B32    1557
W33    1573
B33    1534
W34    1563
B34    1516
W35    1592
B35    1558
W36    1552
B36    1526
W37    1535
B37    1498
W38    1534
B38    1492
W39    1505
B39    1460
W40    1430
B40    1425
dtype: int64
```

Wow… It's not even close. The diversity of the middle game meta increased dramatically between the 70s and 90s.

Finally, we investigate how the endgame meta has changed. We assumed that it would not have changed much because there are so few pieces at the endgame.

[112]:
```
# ENDGAME, 1970S
chess_data[(chess_data['Date'] >= 1971) & (chess_data['Date'] < 1980) &␣
 ↪(chess_data['W-ELO'] >= 2000) & (chess_data['B-ELO'] >= 2000)].loc[:, 'W41':␣
 ↪'B75'].apply(lambda x: len(x.unique()))
```

[112]:
```
W41    578
B41    568
W42    585
B42    527
W43    508
      …
B73     27
W74     24
B74     15
W75     13
B75      8
Length: 70, dtype: int64
```

[113]:
```
# ENDGAME, 1990S
chess_data[(chess_data['Date'] >= 1990) & (chess_data['Date'] < 2000) &␣
 ↪(chess_data['W-ELO'] >= 2000) & (chess_data['B-ELO'] >= 2000)].loc[:, 'W41':␣
 ↪'B75'].apply(lambda x: len(x.unique()))
```

[113]:
```
W41    1436
B41    1373
W42    1364
B42    1333
W43    1326
       …
B73     113
W74     104
B74      80
W75      65
B75      47
Length: 70, dtype: int64
```

The diversity of the endgame meta also greatly increased between 1970 and 1990s.

[ ]:
```
chess_data.to_pickle("./chess_data_ML.pkl", compression = 'zip')
```

[ ]:
```
openings_white.to_pickle("./openings_white.pkl", compression = 'zip')
```

[ ]:
```
openings_black.to_pickle("./openings_black.pkl", compression = 'zip')
```

[ ]:
```
chess_data.to_csv('./chess_data_ML.csv')
```

[ ]:
```
openings_white.to_csv('./openings_white.csv')
```

[ ]:
```
openings_black.to_csv('./openings_black.csv')
```