Introduction

Rainbow Six Siege (R6Siege) is a competitive 5v5 FPS video game with a simple setting: Attackers siege the Defender's base and complete an objective based on the game mode (ex: Hostage Rescue or Bomb Defusal). Rainbow Six Siege has a competitive ranked 5v5 mode that gives players a matchmaking rating (MMR) based on variables such as games won/lost. Many of the game's players feel that the game's current rating system is flawed. R6Tab is a 3rd party stat tracker website created by hardcore fans of the game. They created a new rating system based on R6's MMR system, but also included other variables into the calculation, such as a kills to deaths ratio. In a video game where victory is possible simply by killing your opponents, K:D ratio is crucial in determining how skilled an individual is.

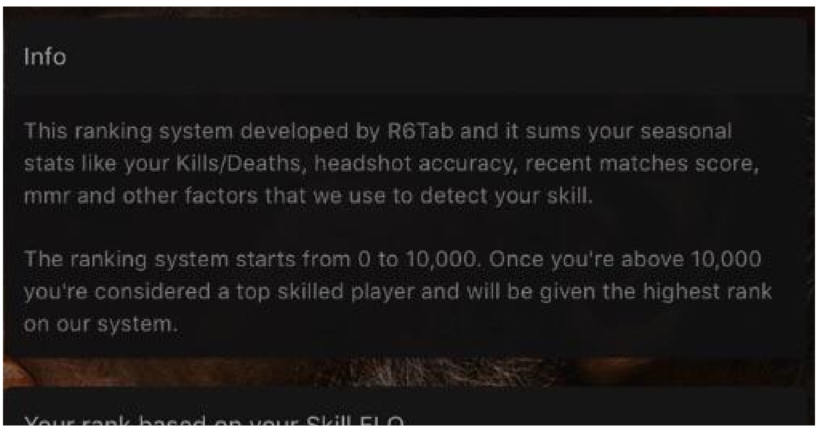
Currently, the developer of R6Siege, Ubisoft, has a ranking system that includes 20 ranks. It is structured as such:

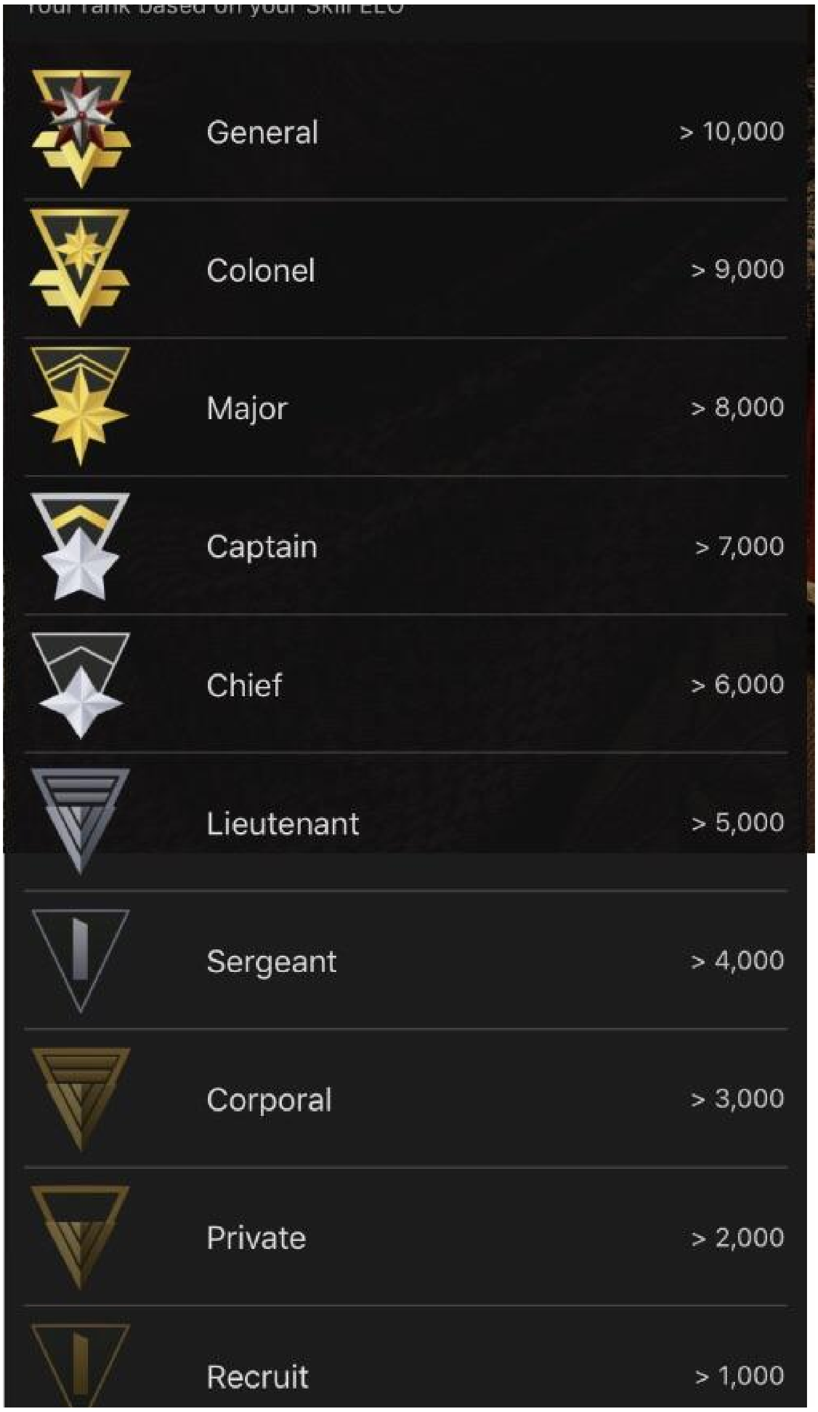
A player's skill rank is first obtained after successfully completing 10 ranked matches. These ranks are derived from numerical scores generated by the TrueSkill algorithm.

From there, a player's skill rank is changed based on:

- The relative skill levels of the players/teams in the game.
- Whether or not the player won the match.
- **Score and Kill/Death ratio do not matter toward ranking.**
- Large skill difference between teams has a dramatic outcome based on who won the match.
  - If a Bronze team loses to a Gold team, neither team's rank will change much.
  - If a Bronze team wins against a Gold team, both team's rank will change dramatically.^{1}

The bolded bullet point is the main purpose of this project. R6Tab attempts to create their own arbitrary ranking system to try to get a better determinant of player skill than Ubisoft's current system that only calculates wins and losses. I investigated R6tab's very own TabRank rating system. This is how R6Tab structures their ranking system:





However, many fans of R6Tab have complained that the website's new skill rating is too heavily influenced by just Kill:Death ratio, and is easily exploited by players whose playstyles are based on getting absurd amounts of kills. Rainbow Six Siege is a very complicated team-based game. There are more variables that lead to victory than just how many kills an individual gets. Many top-tier players find themselves in the top of the leaderboards by being good at the game in other ways. Some examples include being a good captain and calling out important information, or being a good support by setting up a good defense for their teammates.

My hypothesis is that the statistic kill:death ratio (kd_ratio) will be a much stronger predictor than Ubisoft's MMR system (p_current_mmr) in determining R6Tab's skill rating (p_skillrating). I will use linear regression models to test my hypothesis.

There are three stages to this project:

1) Web Scraping of data + SQL upload using python

2) Data Screening using SQL queries and python

3) Data Analysis using SQL queries and python

Special thanks to R6Tab for their unofficial Rainbow Six Siege API

https://github.com/Tabwire/R6Tab-API

Variables

R6Tab's API returns the variables listed here.

The following are variables included in my data analysis:

- ***_pname*** is the player's name
- ***kd_ratio*** is the ratio of kills to deaths a player has
- ***p_headshotacc*** is the percentage of kills that ended with headshots
- ***p_currentmmr*** is Ubisoft's Matchmaking Rating System value. This is an approximate value of the ***p_REGION_rank*** variable. A player's rank(copper-diamond) depends on their mmr (copper=0-1699, diamond=3700+)
- ***p_level*** is the player's overall level. This is separate from the rating system and is more of an indicator of time played
- ***_pskillrating*** is R6Tab's Rating System

Extra variables not important to the discussion:

- ***p_AS_rank*** is the player's Ubisoft rating on Asia's leaderboard (0=Not rated, 10=Silver III, 20=Diamond)
- ***p_EU_rank*** is the player's Ubisoft rating on Europe's leaderboard
- ***p_NA_rank*** is the player's Ubisoft rating on North America's leaderboard
- ***p_current_rank*** is a duplicate column of the player's regional ranking. I did not remove these because it was not imperative for analysis.
- ***p_id*** is the player's unique ID Ubisoft code.
- ***p_platform*** is the platform the player plays on. I stuck with PC (uplay) playerbase only.
- ***p_user*** duplicate of ***p_id***.
- ***p_position*** is the player's position in the leaderboard for ubisoft's MMR. The higher the ***p_currentmmr*** the higher the player is in the leaderboard.

Web Scrape and SQL upload

In [10]:

```
# Import Necessary libraries
import r6tab_API_functions as r6
import pandas as pd
import sqlalchemy
import statsmodels.formula.api as sm
import seaborn as sns
import matplotlib.pyplot as plt
```

(Each leaderboard contains each region's top 100 players)

In [13]:

```
# Scrape leaderboard info from function calls using r6tab API
NA_leaderboard_info = r6.get_leaderboard_info('p_NA_currentmmr')
EU_leaderboard_info = r6.get_leaderboard_info('p_EU_currentmmr')
AS_leaderboard_info = r6.get_leaderboard_info('p_AS_currentmmr')

# Let's take a look at the top player's info in NA. The API returns the data in .JSON format
if NA_leaderboard_info is not None:
    print("Here's a preview: ")
    preview = NA_leaderboard_info[0]
    for k, v in preview.items():
        print("{0}: {1}".format(k, v))
```

```
Here's a preview:
position: 1
p_id: f9eeea28-4c13-48df-b96a-49c726bf546c
p_name: One.TT
p_level: 158
p_platform: uplay
p_user: f9eeea28-4c13-48df-b96a-49c726bf546c
p_currentmmr: 6539
p_currentrank: 20
p_skillrating: 10602
p_NA_rank: 20
p_EU_rank: 20
p_AS_rank: 14
kd: 251
```

```
verified: 0
p_headshotacc: 64590000
p_NA_currentmmr: 6539
```

In [14]:

```
# Store leader boards into pandas data frames to easily upload to mysql server

NA = pd.DataFrame(NA_leaderboard_info)
EU = pd.DataFrame(EU_leaderboard_info)
AS = pd.DataFrame(AS_leaderboard_info)

# Let's see how one data frame looks like (first 6 columns, the dataframe is too wide for JPnotebooks)
print(NA.iloc[:5, :6])
```

```
    kd p_AS_rank p_EU_rank p_NA_currentmmr p_NA_rank p_currentmmr
0  251        14        20            6539        20         6539
1  166        20         0            6486        20         6486
2  187        20        20            6419        20         6419
3  157         0         0            6036        20         6036
4  262         0         0            6025        20         6025
```

Now I want to store my data into a SQL database. This will make data manipulation a bit easier later when working with all three leader boards.

In [2]:

```
# Log in information for mysql server
user = 'root'
passw = 'pw'
host = 'localhost'
database = 'r6_leaderboard_database'

# Establish a connection to the mysql server
engine_stmt = 'mysql+mysqlconnector://%s:%s@%s:3306/%s' % (user, passw, host, database)

engine = sqlalchemy.create_engine(engine_stmt)
```

In [22]:

```
# Work the magic

NA.to_sql(name='na_leaderboard', con=engine,
          if_exists='replace', index=False, chunksize=1000)
EU.to_sql(name='eu_leaderboard', con=engine,
          if_exists='replace', index=False, chunksize=1000)
AS.to_sql(name='as_leaderboard', con=engine,
          if_exists='replace', index=False, chunksize=1000)

test_df = pd.read_sql("SELECT * FROM eu_leaderboard", engine)

print(test_df.iloc[:5, :6])

print('it WORKED.')
```

```
    kd p_AS_rank p_EU_currentmmr p_EU_rank p_NA_rank p_currentmmr
0  175         0           10071        20         0        10071
1  144         0            8089        20         0         8089
2  185         0            7542        20         0         7542
3  227        14            7134        20         0         7134
4  179        18            6392        20         0         6392
it WORKED.
```

Data Screening

We want to increase our sample size, so we'd want to combine all three leaderboards into one. This will be a functioning global leaderboard of the top 300 players.

Issue #1

The different leader board tables contain the same amount of columns and data types. BUT they are in a different order.

To use SQL UNION, they must be in the same order.

Rearrange columns to be uniform across all tables before combining.

Each region's leader board has a separately labeled p_REGION_currentmmr field. In the rainbow six database, this is actually a global mmr. Also, in each region's leaderboard:

- **p_REGION_currentmmr == p_currentmmr.**

So to solve this issue, delete each leader board table's p_REGION_currentmmr

In [32]:

```
# Let's check what's up with these two columns
with engine.connect() as con:
    try:
        check_dup = con.execute('select p_EU_currentmmr, p_currentmmr from r6_leaderboard_database.eu_l
eaderboard LIMIT 10')
        print(check_dup.keys())

        for row in check_dup:
            print(row)
    except:
        print('Already deleted the problem column...')

    con.close()
```

```
['p_EU_currentmmr', 'p_currentmmr']
('10071', '10071')
('8089', '8089')
('7542', '7542')
('7134', '7134')
('6392', '6392')
('6332', '6332')
('6288', '6288')
('6274', '6274')
('6239', '6239')
('6185', '6185')
```

The above output displays two columns that are duplicate of one another. Let's keep the ***p_currentmmr*** column in each table.

In [33]:

```
# Delete the p_REGION_currentmmr columns from each table

# Do a test run first..
with engine.connect() as con:
    try:
        sql_delete_query = """ALTER TABLE %s DROP COLUMN %s"""
        con.execute(sql_delete_query % ('r6_leaderboard_database.na_test', 'p_NA_currentmmr'))

        print('delete done')
    except:
        print("Already Deleted")

    con.close()
```

```
Already Deleted
```

In [34]:

```
# Alright. Luckily, once we delete each p_REGION_mmr column from each table, the order and format of ea
ch table will be the same
with engine.connect() as con:
    try:
```

```python
        sql_delete_query = """ALTER TABLE %s DROP COLUMN %s"""
        con.execute(sql_delete_query % ('r6_leaderboard_database.na_leaderboard', 'p_NA_currentmmr'))
        con.execute(sql_delete_query % ('r6_leaderboard_database.eu_leaderboard', 'p_EU_currentmmr'))
        con.execute(sql_delete_query % ('r6_leaderboard_database.as_leaderboard', 'p_AS_currentmmr'))

        print('delete done')
    except:
        print("Already Deleted")

    con.close()
```

```
delete done
```

In [3]:

```python
# Now we're ready for a SQL UNION statement

with engine.connect() as con:

    union_query = """SELECT * FROM %s UNION SELECT * FROM %s UNION SELECT * FROM %s"""

    union = con.execute(union_query % ('r6_leaderboard_database.na_leaderboard',
                                       'r6_leaderboard_database.eu_leaderboard',
                                       'r6_leaderboard_database.as_leaderboard'))

    # Let's create a new table in the mysql server for this query since it will be our master dataset
    df = pd.DataFrame(union.fetchall())
    df.columns = union.keys()

#     df.to_sql(name='all_leaderboard', con=engine,
#           if_exists='replace', index=False, chunksize=1000)

    con.close()


print('Good to go.')
```

```
Good to go.
```

In [8]:

```python
# Now we got our master dataset!

# First seven columns
print(df.iloc[:29,:7])
```

```
     kd  p_AS_rank  p_EU_rank  p_NA_rank  p_currentmmr  p_currentrank  p_headshotacc
0   251         14         20         20          6539             20       64590000
1   166         20          0         20          6486             20       54950000
2   187         20         20         20          6419             20       44910000
3   157          0          0         20          6036             20       47570000
4   262          0          0         20          6025             20       60080000
5   159         20          0         20          6013             20       43540000
6   160          0         16         20          5921             20       39190000
7   161          0          0         20          5871             20       43220000
8   144          0          0         20          5841             20       46120000
9   119         19          0         20          5749             20       42830000
10  174          0         19         20          5737             20       59300000
11  181          0          0         20          5732             20       45350000
12  106          0          3         20          5718             20       39490000
13  154          0          0         20          5716             20       51030000
14  242          0          0         20          5676             20       49590000
15  141          0         20         20          5640             20       40920000
16  240          0          0         20          5575             20       34580000
17  133          0          0         20          5572             20       46750000
18  119          0         18         20          5550             20       48330000
19  143          0          0         20          5524             20       57500000
20  133          0          0         20          5510             20       41290000
21  126          0          0         20          5510             20       44880000
22  152          0          0         20          5502             20       52180000
23  132          0          0         20          5487             20       47750000
24  161          0          0         20          5487             20       50600000
```

```
24   161          0          0         20          5487            20       59600000
25   152          0          0         20          5473            20       39150000
26   139          0          0         20          5468            20       48950000
27   147          0          0         20          5467            20       53300000
28   151          0          0         20          5464            20       45120000
```

Issue #2

Further Data cleansing is required. The datatypes of the columns are all in TEXT. We need to change some into numeric data types to be able to run analysis on them.

For example, the kd column is actually a ratio column.

- *Player One.TT has a kd of 251, which should be 2.51. So we need to do this calculation (kd / 100)*

Similar situation for p_headshotaccuracy...

- *One.TT has a hs accuracy of 64,590,000. This should be a percentage (64.59%): (p_headshotacc / 1,000,000)*

Other columns such as p_currentmmr should simply be an integer column.

In [75]:

```
# Example of issue #2:

query = """SELECT p_name, kd, p_headshotacc FROM r6_leaderboard_database.all_leaderboard"""
df = pd.read_sql(query, con=engine)

print(df.head(1))
```

```
   p_name   kd p_headshotacc
0  One.TT  251      64590000
```

In [39]:

```
# This can all be fixed with a SQL query.
with engine.connect() as con:

    aggregate_query = """
                      SELECT p_name,
                             cast(kd / 100 as decimal(10,2)) as kd_ratio,
                             cast(p_headshotacc / 1000000 as decimal(10,2)) as p_headshotacc,
                             cast(p_currentmmr as UNSIGNED) as p_currentmmr,
                             cast(p_level as UNSIGNED) as p_level,
                             cast(p_skillrating as UNSIGNED) as p_skillrating
                        FROM all_leaderboard
                      """

    aggregate_exec = con.execute(aggregate_query)

    # Store the aggregated data into a data frame
    df_aggregate = pd.DataFrame(aggregate_exec.fetchall())
    df_aggregate.columns = aggregate_exec.keys()
    print(df_aggregate.head(5))

    con.close()

# Let's create a new table in the mysql server for these variables
df_aggregate.to_sql(name='focus', con=engine,
          if_exists='replace', index=False, chunksize=1000)

print('\nVariables Ready for Analysis.')
```

```
           p_name kd_ratio p_headshotacc  p_currentmmr  p_level  p_skillrating
0          One.TT     2.51         64.59          6539      158          10602
1        Pi3troll     1.66         54.95          6486      340           9940
2          Raclis     1.87         44.91          6419      269          10253
3  geeometrics.EG     1.57         47.57          6036      326           9695
4            hyi.     2.62         60.08          6025      283          10899

Variables Ready for Analysis.
```

Data Analysis

Analysis

To begin, let's make sure there's no null values in our dataset.

In [44]:

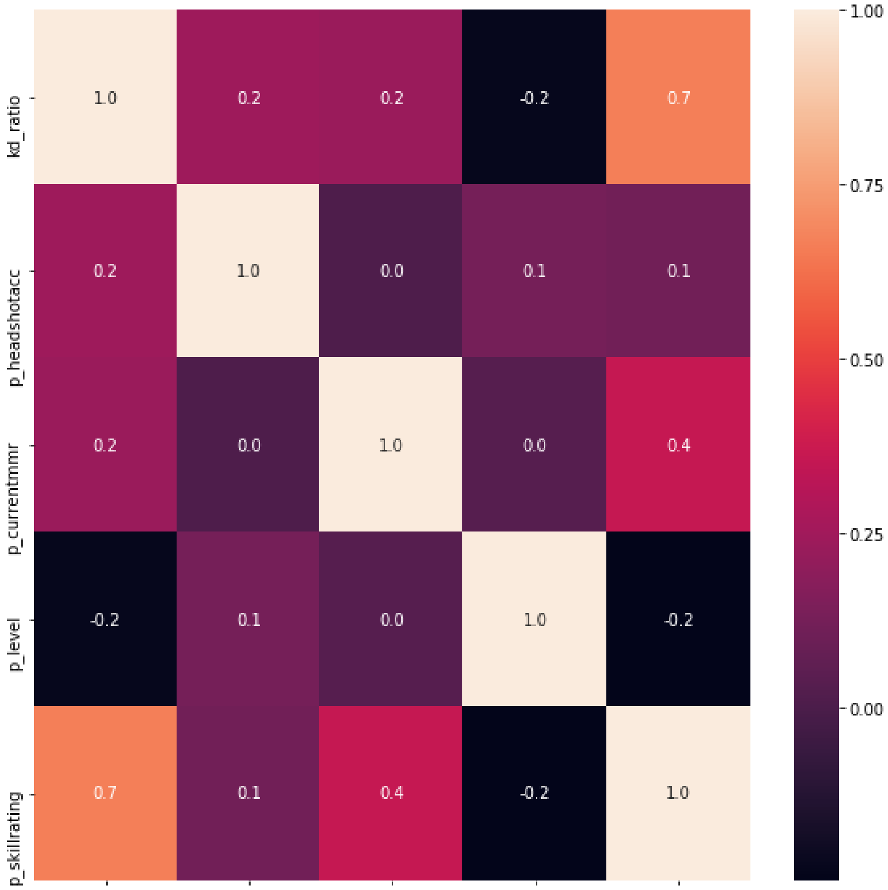
```
query = """
        SELECT kd_ratio,
               p_headshotacc,
               p_currentmmr,
               p_level,
               p_skillrating
          FROM r6_leaderboard_database.focus
        """

df = pd.read_sql(query, con=engine)
print(df.isnull().sum())
```

```
kd_ratio         0
p_headshotacc    0
p_currentmmr     0
p_level          0
p_skillrating    0
dtype: int64
```

Good, no nulls. Now let's check a correlation heatmap of our variables for a bit of forecasting..

In [46]:

```
plt.figure(figsize=(10, 10))
sns.heatmap(df.corr(), annot=True, fmt='.1f')
plt.show()
```



kd_ratio has the highest correlation with ***p_skillrating*** and ***p_currentmmr*** is close behind..

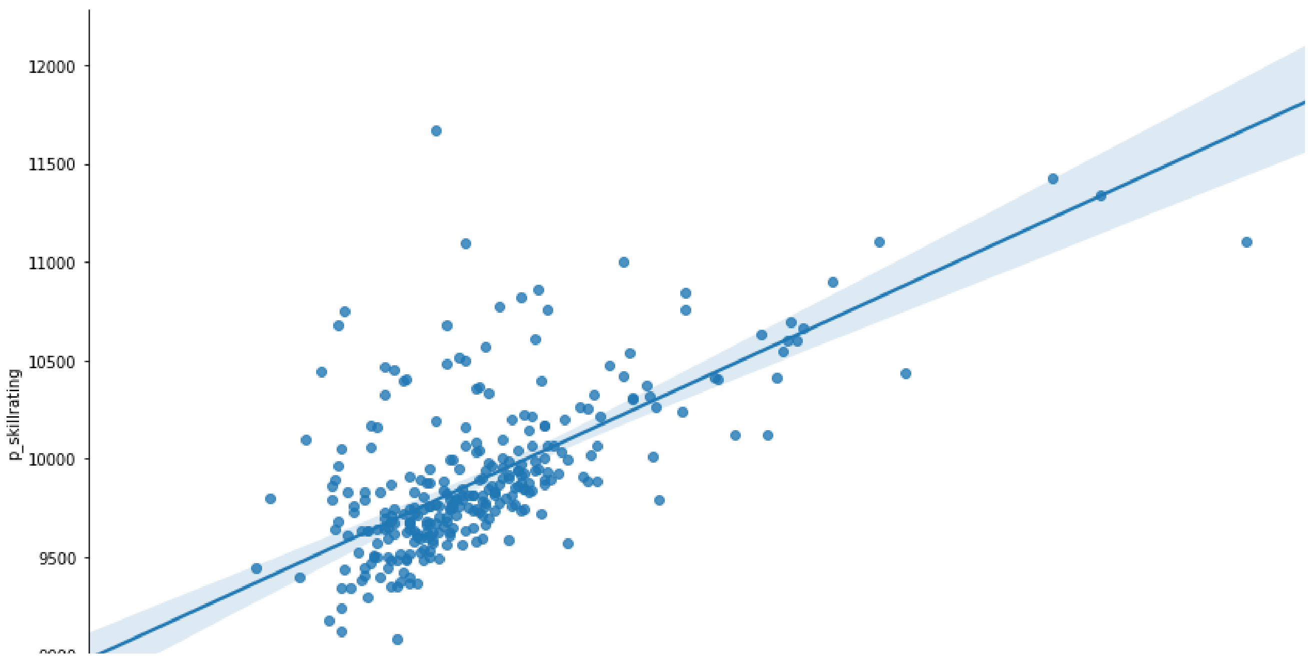
However this is not enough to reject the null hypothesis that kd_ratio is a stronger predictor of skillrating than currentmmr. I also include headshot accuracy into my models as R6tab stated that it is also a variable included in the calculation of their rating system.

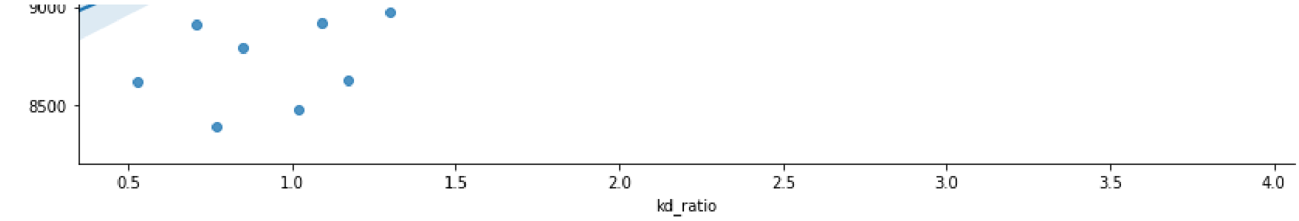
Let's do some simple OLS regression tests

In [49]:

```
# kd_ratio on p_skillrating
query = """SELECT kd_ratio, p_skillrating FROM r6_leaderboard_database.focus"""
df = pd.read_sql(query, con=engine)

result = sm.ols(formula="p_skillrating ~ kd_ratio", data=df).fit()

print(result.summary())

sns.lmplot(x='kd_ratio', y='p_skillrating', data=df, height=8, aspect=1.5)
plt.show()
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:          p_skillrating   R-squared:                       0.446
Model:                            OLS   Adj. R-squared:                  0.444
Method:                 Least Squares   F-statistic:                     240.1
Date:                Wed, 15 May 2019   Prob (F-statistic):           3.98e-40
Time:                        14:15:39   Log-Likelihood:                -2167.5
No. Observations:                 300   AIC:                             4339.
Df Residuals:                     298   BIC:                             4346.
Df Model:                           1
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
Intercept   8714.0342     77.770    112.049      0.000    8560.986    8867.082
kd_ratio     762.5217     49.212     15.495      0.000     665.675     859.368
==============================================================================
Omnibus:                       97.761   Durbin-Watson:                   1.929
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              390.644
Skew:                           1.337   Prob(JB):                     1.49e-85
Kurtosis:                       7.909   Cond. No.                         8.83
==============================================================================

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
```



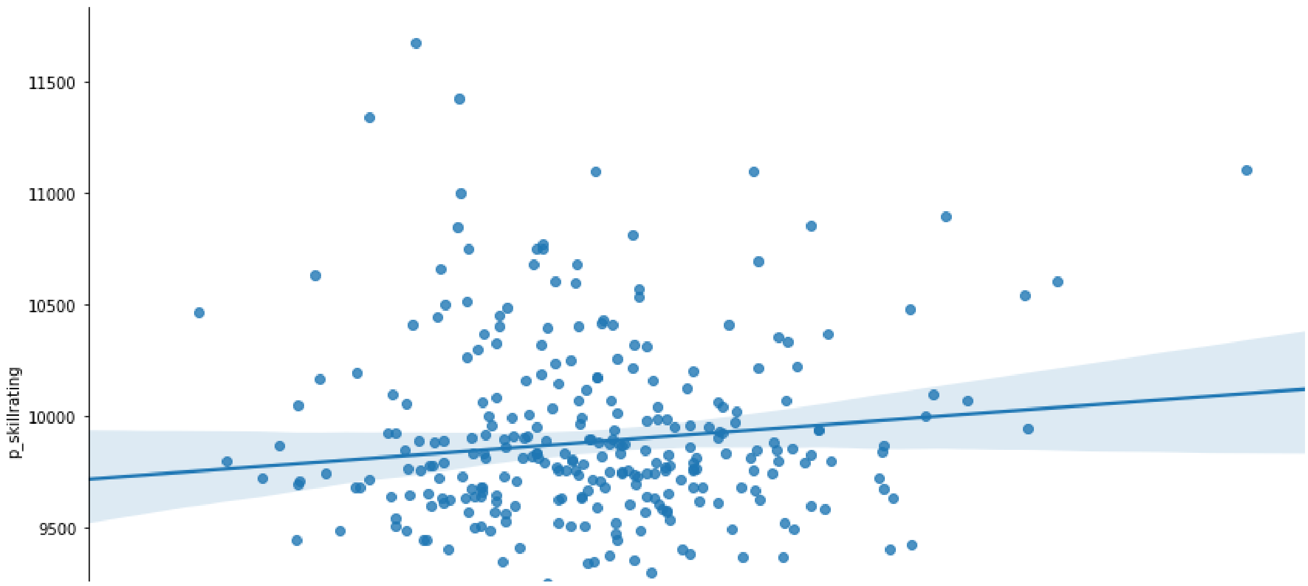


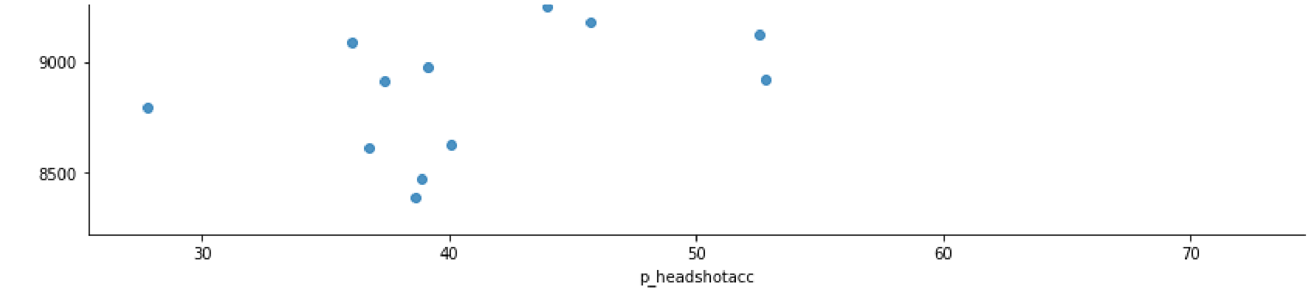
Quick Summary: As predicted, kd_ratio is a significant predictor of p_skillrating. However, the standard error of the predictor is extremely high. Let's keep a note of this moving forward...

In [50]:

```
# p_headshotacc on p_skillrating

query = """SELECT p_headshotacc, p_skillrating FROM r6_leaderboard_database.focus"""
df = pd.read_sql(query, con=engine)

result = sm.ols(formula="p_skillrating ~ p_headshotacc", data=df).fit()

print(result.summary())

sns.lmplot(x='p_headshotacc', y='p_skillrating', data=df, height=8, aspect=1.5)
plt.show()
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:           p_skillrating   R-squared:                       0.014
Model:                             OLS   Adj. R-squared:                  0.010
Method:                  Least Squares   F-statistic:                     4.096
Date:                 Wed, 15 May 2019   Prob (F-statistic):             0.0439
Time:                         14:29:58   Log-Likelihood:                -2254.1
No. Observations:                  300   AIC:                             4512.
Df Residuals:                      298   BIC:                             4520.
Df Model:                            1
Covariance Type:             nonrobust
=================================================================================
                    coef    std err          t      P>|t|      [0.025      0.975]
---------------------------------------------------------------------------------
Intercept      9506.5096    187.081     50.815      0.000    9138.343    9874.676
p_headshotacc     8.2132      4.058      2.024      0.044       0.227      16.199
==============================================================================
Omnibus:                       37.177   Durbin-Watson:                   1.813
Prob(Omnibus):                  0.000   Jarque-Bera (JB):               77.622
Skew:                           0.646   Prob(JB):                     1.39e-17
Kurtosis:                       5.131   Cond. No.                         336.
==============================================================================

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
```



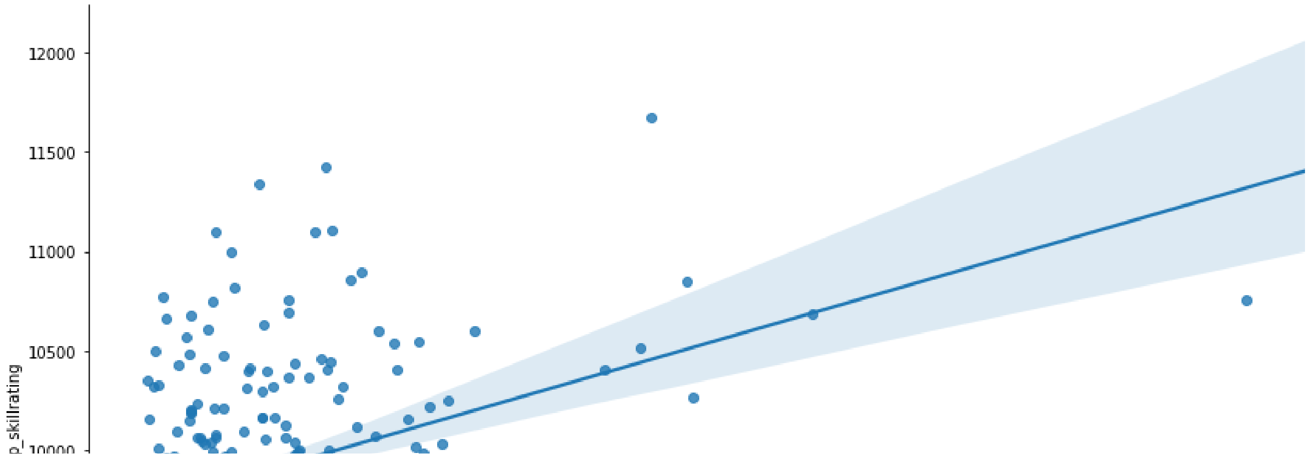


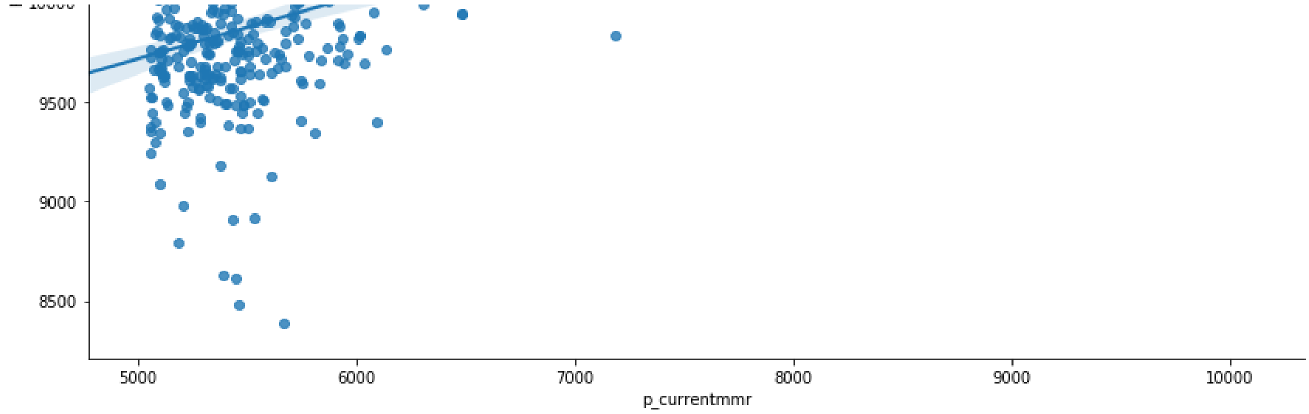
Quick Summary: As expected from R6Tab's explanation of how they calculate their rating system, headshot accuracy is also a significant predictor, but much less so than k:d ratio.

In [53]:

```
# p_currentmmr on p_skillrating

query = """SELECT p_currentmmr, p_skillrating FROM r6_leaderboard_database.focus"""
df = pd.read_sql(query, con=engine)

result = sm.ols(formula="p_skillrating ~ p_currentmmr", data=df).fit()

print(result.summary())

sns.lmplot(x='p_currentmmr', y='p_skillrating', data=df, height=8, aspect=1.5)
plt.show()
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:          p_skillrating   R-squared:                       0.129
Model:                            OLS   Adj. R-squared:                  0.126
Method:                 Least Squares   F-statistic:                     44.18
Date:                Wed, 15 May 2019   Prob (F-statistic):           1.43e-10
Time:                        14:40:35   Log-Likelihood:                -2235.4
No. Observations:                 300   AIC:                             4475.
Df Residuals:                     298   BIC:                             4482.
Df Model:                           1
Covariance Type:            nonrobust
================================================================================
                   coef    std err          t      P>|t|      [0.025      0.975]
--------------------------------------------------------------------------------
Intercept     8135.1532    263.854     30.832      0.000    7615.900    8654.407
p_currentmmr     0.3160      0.048      6.647      0.000       0.222       0.410
==============================================================================
Omnibus:                       26.966   Durbin-Watson:                   2.035
Prob(Omnibus):                  0.000   Jarque-Bera (JB):               67.492
Skew:                           0.402   Prob(JB):                     2.21e-15
Kurtosis:                       5.180   Cond. No.                     6.07e+04
==============================================================================

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 6.07e+04. This might indicate that there are
strong multicollinearity or other numerical problems.
```





Quick Summary: And Ubisoft's MMR system is also a significant predictor, with a very agreeable standard error.

In [63]:

```
# Now for the main model: Multiple OLS Regression with all 3 variables of interest on p_skillrating

query = """SELECT kd_ratio, p_headshotacc, p_currentmmr, p_skillrating FROM r6_leaderboard_database.foc
us"""
df = pd.read_sql(query, con=engine)

result = sm.ols(formula="p_skillrating ~ kd_ratio + p_headshotacc + p_currentmmr", data=df).fit()

print(result.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:          p_skillrating   R-squared:                       0.491
Model:                            OLS   Adj. R-squared:                  0.486
Method:                 Least Squares   F-statistic:                     95.18
Date:                Wed, 15 May 2019   Prob (F-statistic):           3.80e-43
Time:                        15:10:27   Log-Likelihood:                -2154.8
No. Observations:                 300   AIC:                             4318.
Df Residuals:                     296   BIC:                             4333.
Df Model:                           3
Covariance Type:            nonrobust
=================================================================================
                    coef    std err          t      P>|t|      [0.025      0.975]
---------------------------------------------------------------------------------
Intercept      7877.4931    241.417     32.630      0.000    7402.382    8352.604
kd_ratio        716.4235     50.273     14.251      0.000     617.485     815.362
p_headshotacc    -2.7422      3.020     -0.908      0.365      -8.685       3.200
p_currentmmr      0.1868      0.038      4.973      0.000       0.113       0.261
==============================================================================
Omnibus:                       75.303   Durbin-Watson:                   2.042
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              248.239
Skew:                           1.071   Prob(JB):                     1.25e-54
Kurtosis:                       6.908   Cond. No.                     7.24e+04
==============================================================================

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 7.24e+04. This might indicate that there are
strong multicollinearity or other numerical problems.
```

Conclusion of Results

The final regression model proves my hypothesis to be true: kd_ratio (*β=14.25, p*<.001) is a stronger significant predictor of R6Tab's skillrating than Ubisoft's MMR (*β =4.97, p <.001), F*(3, 296) = 95.18, *p*<.001. Headshot accuracy turned out to not be a significant predictor.

There are two points to discuss, as mentioned by the model summary's 'Warning' tags at the end of each analysis. First, the standard errors are extremely high across the models. I expected this would be the case because of how small my sample size is, but also because of what my data is really about. The reason ***p_currentmmr*** has a low and agreeable standard error is because the variable is a calculation of many variables such as games won and player skill differentials. Headshot accuracy and k:d ratio are individual variables and thus contain a larger standard error. Those two variables are not enough to precisely predict skill rating.

Second, multicollinearity might be present in my variables. Further analysis may reveal that there is high multicollinearity between kd_ratio and p_currentmmr

Discussion

From one flawed system to the next, R6Tab's skill rating system may be considered an improvement over Ubisoft's for those that achieve a high amount of kills per death. However, individuals approach the game in a myriad of ways. I applaud R6Tab's attempt to improve an algorithm that attempts to capture a human condition. I personally would benefit from R6tab's system because I fall under the category of achieving a high K:D ratio. To improve R6Tab's formula, they would need to recalculate in a way such that K:D ratio does not have such a significant impact on skill rating, while also including more variables related to support playstyles (gadgets deployed, bombs defused, revives, etc).

There is much more to tell from my analysis. I suggest for future study to pull a large sample size of Rainbow Six's playerbase. I acknowledge that my study had its limitations and biases by working with only the most extreme deviations of Ubisoft's MMR rankings (leaderboard data only). The standard error of the model may be reduced significantly with a larger sample size. Lastly, R6Tab's API only provided me with the variables listed in this report. It may be more feasible to look into other website's API's to get more variables such as games won and points scored.

I would appreciate any advice anyone has for me. Your feedback is very important to me.

References

^{1}: https://rainbowsix.fandom.com/wiki/Ranked