Predicting the Outcome of the 2019 Rugby World Cup

On November 2nd, the 2019 Rugby World Cup came to a conclusion in Yokohama, Japan. Twenty teams, six weeks, one champion.

Our goal is to build a model that can accurately predict the winner and score for each Rugby World Cup match-up. The overall outline is as follows:

1. Data Collection
2. Data Preprocessing and Visualization
3. Data Mining and Predictions

To evaluate our model, we will be comparing our predictions to the actual results.

In [455]:
```
import datetime

import psycopg2
import psycopg2.extras

import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import sklearn as sk
```

Data Collection

In order to train our model, we shall require a dataset containing historical statistics from previously held rugby matches.

Fortunately, ESPN Scrum (espnscrum.com) provides data on players, teams, and matches going back to 1896.

Building `rugby_pg.db`

- Using a scrapy spider built by peloyeje (found here (https://github.com/peloyeje/map536-rugby-data-scraper)), it was possible to collect a meaningful sample of matches and results, along with player stats for each match to work with.
- After scraping player, team, and match stats from ESPN Scrum the data was inserted into a SQLite database.
  - Although SQLite format is perfectly fine to work with, we have more experience with PostgreSQL.
  - To make things easier for ourselves, we converted the SQLite into a PostgreSQL database.

Building `rankings.csv`

- The World Rugby rankings were gathered from World Rugby's website (https://www.world.rugby/rankings/mru?lang=en) using Beautiful Soup.
- We were able to gather data points containing `team_name`, `abbreviation`, `num_matches`, `pts`, `pos`, `prev_pts`, `prev_pos`, `data`.
  - Each data point represents a single team's data from the given date.
  - World Rugby began recording this data on November 2003, so unfortunately there are many years of competition that are not represented in the data set.
- The scraping process was done outside of a Jupyter Notebook, due to the heavy memory consumption required to build this large data set
  - Instead, by creating `csv_writer.py` and running this python program on a machine with high-spec hardware, the data set `rankings.csv` was built.

In [456]:
```
'''This is the code from csv_writer.py --- it has been commented out to
 prevent the Jupyter Notebook from building the data set'''


# import json
# import requests
# from bs4 import BeautifulSoup

# from datetime import timedelta, date

# import pandas as pd
# import numpy as np
# import matplotlib.pyplot as plt

# import csv

# def daterange(start_date, end_date):
#     for n in range(int ((end_date - start_date).days)):
#         yield start_date + timedelta(n)

# start_date = date(2003, 10, 13)
# end_date = date(2019, 11, 15)

# csv_data = [['team_name', 'abbreviation', 'num_matches', 'pts', 'pos',
'prev_pts', 'prev_pos', 'date']]

# for single_date in daterange(start_date, end_date):
#     date = single_date.strftime("%Y-%m-%d")

#     ranking_url = "cmsapi.pulselive.com/rugby/rankings/mru?date=%s&cli
ent=pulse" % date
#     r  = requests.get("http://" + ranking_url)

#     soup = BeautifulSoup(r.text)

#     data = json.loads(soup.body.p.text)
#     for entry in data['entries']:
#         csv_data.append(
#             [entry['team']['name'], entry['team']['abbreviation'],
#              entry['matches'], entry['pts'], entry['pos'], entry['prev
iousPts'],
#              entry['previousPos'], date]
#         )

# with open('rankings.csv', 'w') as csv_file:
#     writer = csv.writer(csv_file)
#     writer.writerows(csv_data)
# csv_file.close()
```

Out[456]:
```
'This is the code from csv_writer.py --- it has been commented out to p
revent the Jupyter Notebook from building the data set'
```

Data Visualization -

Preprocessing `rankings.csv`

In [457]:
```
data = pd.read_csv("ranking_data/rankings.csv")

data
```

Out[457]:

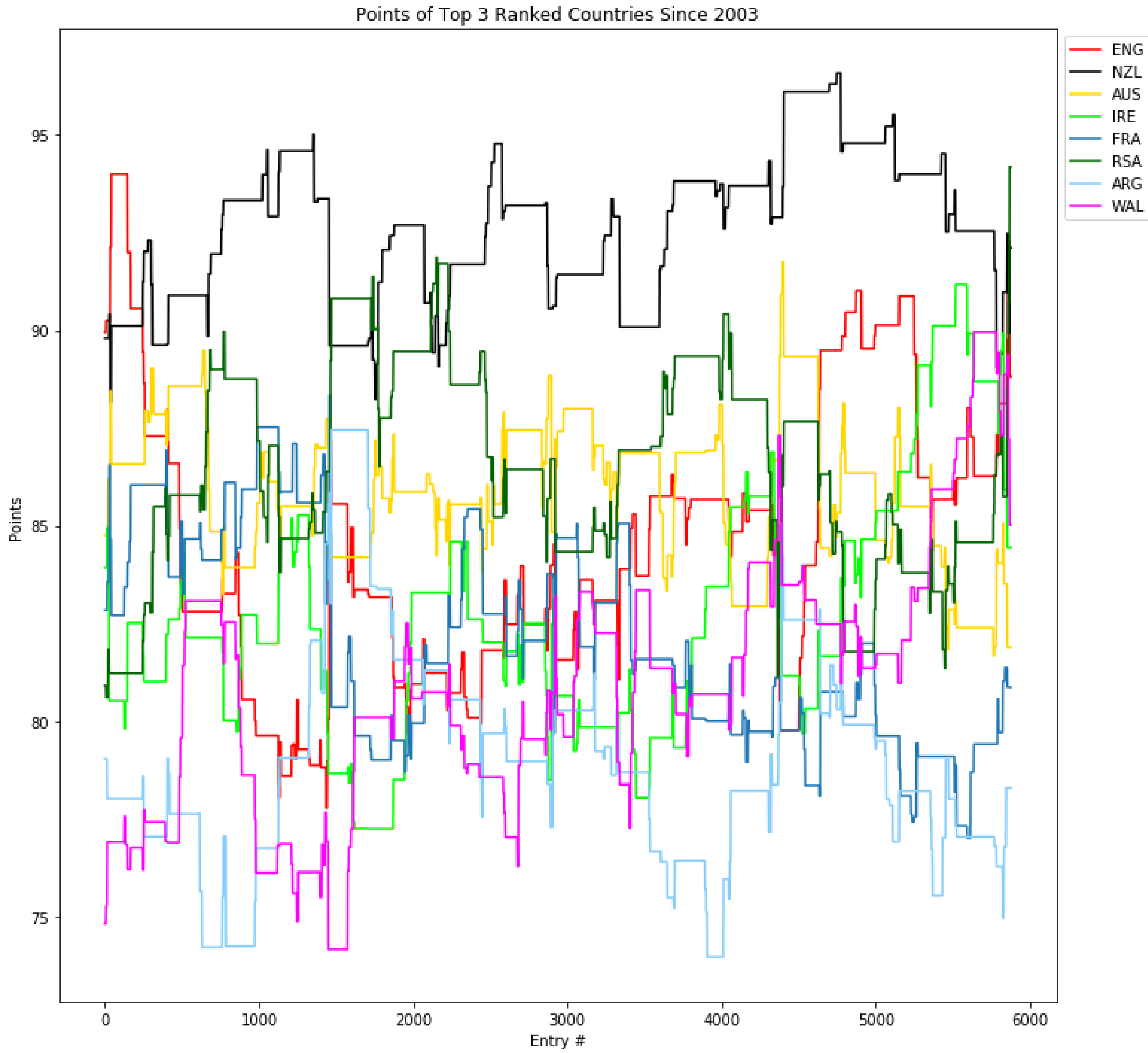
	team_name	abbreviation	num_matches	pts	pos	prev_pts	prev_pos	
0	England	ENG	11	89.948520	1	89.948520	1	2 1
1	New Zealand	NZL	11	89.797710	2	89.797710	2	2 1
2	Australia	AUS	11	84.762690	3	83.805620	4	2 1
3	Ireland	IRE	11	83.924580	4	83.924580	3	2 1
4	France	FRA	11	82.845314	5	82.845314	5	2 1
...	...	...	...	...	...	...	...	..
577110	Monaco	MON	12	23.171558	101	23.171558	101	2 1
577111	Greece	GRE	17	22.546452	102	22.546452	102	2 1
577112	Indonesia	INA	5	21.891422	103	21.891422	103	2 1
577113	Vanuatu	VAN	16	21.453693	104	21.453693	104	2 1
577114	American Samoa	ASA	13	19.532106	105	19.532106	105	2 1

577115 rows × 8 columns

Using the Python library `matplotlib`, we can create several graphs from the `rankings.csv` dataset.

We will mainly explore the dynamics between the top ranking teams.

In [458]:
```
fig = plt.figure(figsize=(12, 12))

for abbr in data.loc[data.pos < 4].abbreviation.unique():
    abbr_pts = data.loc[data.abbreviation == abbr].values[:,[3]]
    if abbr == 'NZL':
        plt.plot(abbr_pts, label = abbr, color = 'black')
    elif abbr == 'ENG':
        plt.plot(abbr_pts, label = abbr, color = 'red')
    elif abbr == 'AUS':
        plt.plot(abbr_pts, label = abbr, color = 'gold')
    elif abbr == 'RSA':
        plt.plot(abbr_pts, label = abbr, color = 'darkgreen')
    elif abbr == 'IRE':
        plt.plot(abbr_pts, label = abbr, color = 'lime')
    elif abbr == 'ARG':
        plt.plot(abbr_pts, label = abbr, color = 'lightskyblue')
    elif abbr == 'WAL':
        plt.plot(abbr_pts, label = abbr, color = 'magenta')
    else:
        plt.plot(abbr_pts, label = abbr)

plt.title("Points of Top 3 Ranked Countries Since 2003")
plt.xlabel("Entry #")
plt.ylabel("Points")
ax = plt.gca()
plt.legend(bbox_to_anchor=(1, 1), bbox_transform=ax.transAxes)
plt.show()
```



Although the graph above presents a ton of valuable information, the data is very noisy and does not allow for easy understanding of the situation that is being represented.

- To improve understanding, we will now calculate the average points per year, rather than the points on each date.

The following table was created directly from `rankings.csv` by first inserting the file into a postgres server and then using the SQL command:

```
SELECT team_name, pos, extract(year FROM date) AS year, AVG(points)
    FROM rankings
    GROUP BY team_name, pos, year
    HAVING pos < 4
    ORDER BY year;
```

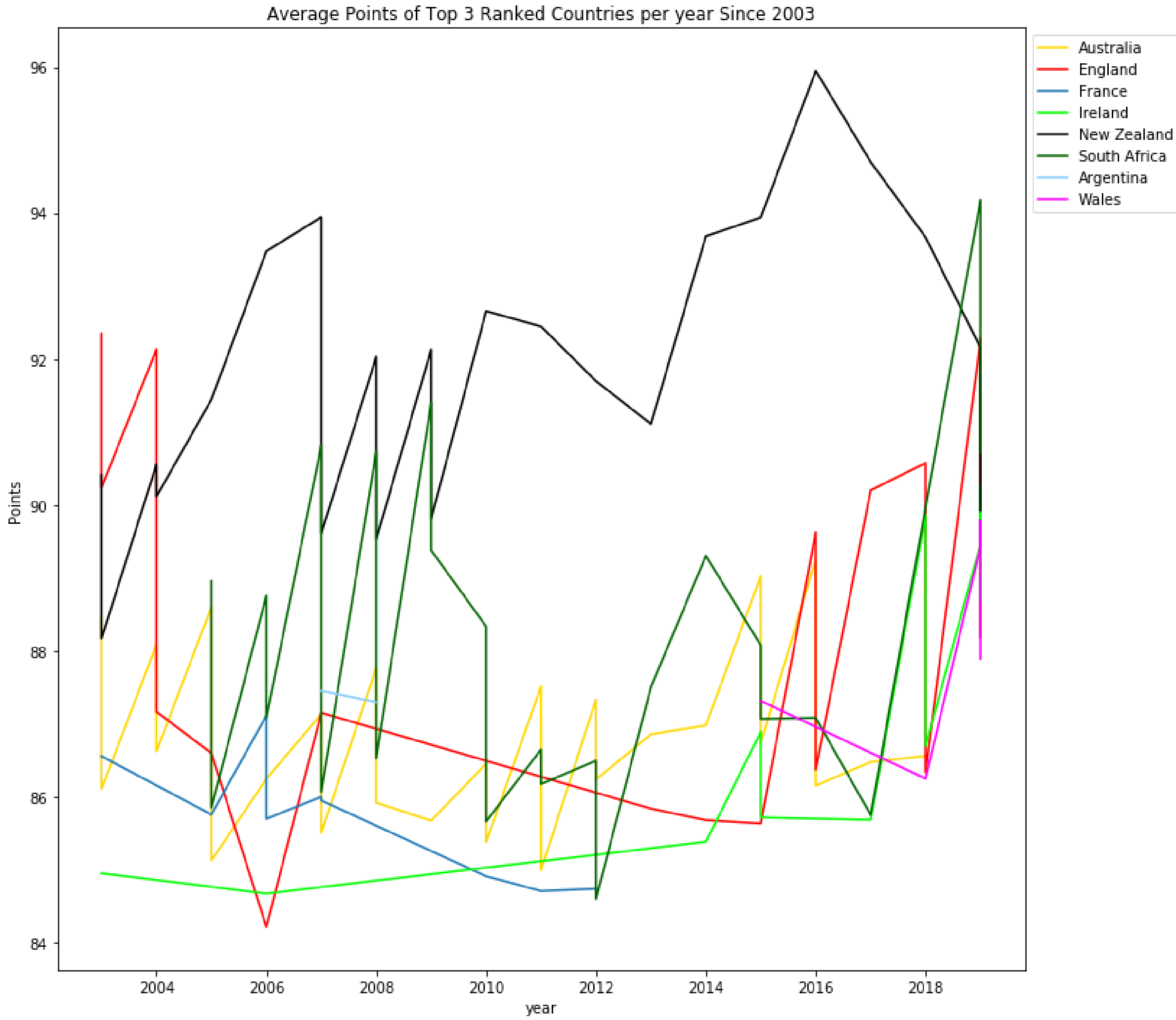
In [459]:
```
data = pd.read_csv("ranking_data/avg_pts_perteam_perpos_peryr.csv")

data
```

Out[459]:

	team_name	pos	year	avg
0	Australia	2	2003	88.441790
1	Australia	3	2003	86.103692
2	England	1	2003	92.347882
3	England	2	2003	90.238914
4	France	3	2003	86.553150
...	...	...	...	...
119	South Africa	1	2019	94.185720
120	South Africa	2	2019	90.712790
121	Wales	1	2019	89.432526
122	Wales	2	2019	89.782635
123	Wales	3	2019	87.887040

124 rows × 4 columns

In [460]:
```
fig = plt.figure(figsize=(12, 12))

for team in data.loc[data.pos < 4].team_name.unique():
    points = data.loc[data.team_name == team].values[:,[3]]
    date = data.loc[data.team_name == team].values[:,[2]]
    if team == 'New Zealand':
        plt.plot(date, points, label = team, color = 'black')
    elif team == 'England':
        plt.plot(date, points, label = team, color = 'red')
    elif team == 'Australia':
        plt.plot(date, points, label = team, color = 'gold')
    elif team == 'South Africa':
        plt.plot(date, points, label = team, color = 'darkgreen')
    elif team == 'Ireland':
        plt.plot(date, points, label = team, color = 'lime')
    elif team == 'Argentina':
        plt.plot(date, points, label = team, color = 'lightskyblue')
    elif team == 'Wales':
        plt.plot(date, points, label = team, color = 'magenta')
    else:
        plt.plot(date, points, label = team)


plt.title("Average Points of Top 3 Ranked Countries per year Since 2003"
)
plt.xlabel("year")
plt.ylabel("Points")
ax = plt.gca()
plt.legend(bbox_to_anchor=(1, 1), bbox_transform=ax.transAxes)
plt.show()
```


Average Points of Top 3 Ranked Countries per year Since 2003
Australia
England
France
Ireland
New Zealand
South Africa
Argentina
Wales
Points
96
94
92
90
88
86
84
year
2004
2006
2008
2010
2012
2014
2016
2018

From the graph above, we notice that there are only eight teams that have ever been ranked in the top 3. We verified this by querying the `rankings.csv` dataset with:

```
SELECT DISTNCT team_name
FROM rankings
WHERE pos < 4;
```

Next, we looked at the average ranking of these eight teams from 2003 to 2019, in order to get a better sense of which teams are consistently ranked at the top. The query follows:

```
SELECT team_name, AVG(pos) AS average_position
FROM rankings
GROUP BY team_name
HAVING team_name = 'New Zealand'
OR team_name = 'Australia'
OR team_name = 'England'
OR team_name = 'South Africa'
OR team_name = 'France'
OR team_name = 'Ireland'
OR team_name = 'Argentina'
OR team_name = 'Wales'
ORDER BY average_position;
```

In [461]:
```
data = pd.read_csv("ranking_data/avg_pos.csv")

data
```

Out[461]:

	team_name	average_position
0	New Zealand	1.119789
1	South Africa	3.254722
2	Australia	3.334354
3	England	4.419772
4	Ireland	5.297771
5	France	5.671941
6	Wales	6.401225
7	Argentina	7.638081

We also looked at the worst ranking of these eight teams during the time period of 2003 to 2019.

Again, the query follows:

```
SELECT team_name, MAX(pos) AS worst_position
FROM rankings
GROUP BY team_name
HAVING team_name = 'New Zealand'
OR team_name = 'Australia'
OR team_name = 'England'
OR team_name = 'South Africa'
OR team_name = 'France'
OR team_name = 'Ireland'
OR team_name = 'Argentina'
OR team_name = 'Wales'
ORDER BY worst_position;
```

In [462]:
```
data = pd.read_csv("ranking_data/worst_pos.csv")

data
```

Out[462]:

	team_name	worst_position
0	New Zealand	3
1	South Africa	7
2	Australia	7
3	England	8
4	Ireland	9
5	Wales	10
6	France	10
7	Argentina	12

Preprocessing `rugby_pg.db`

Using pg_restore on `rugby_pg.db` we created a PostgreSQL database containing all the historical data we previously scraped from ESPN Scrum. We interacted with the database by using the Python library, `pscopg2`.

In [463]:
```
conn = psycopg2.connect(dbname="rugby", user="postgres", password="postg
res")
cur = conn.cursor(cursor_factory = psycopg2.extras.DictCursor)

cur.execute("""
        SELECT *
        FROM
          (SELECT id, date, match_type
           FROM matchs) match_date
        JOIN
          (SELECT *
           FROM matchstats
           JOIN teams ON teams.id = matchstats.team_id) match_team ON ma
tch_date.id = match_team.match_id
        WHERE date > '2003-10-12'::date;
    """)
data = cur.fetchall()

match_data = pd.DataFrame([i.copy() for i in data])
```

By running further queries on the tables we have gathered from ESPN Scrum, we were able to calculate each team's total win percentage over all games they have previously played.

The code to obtain this table is given in the code cell below.

In [464]:

```
cur.execute("""
        SELECT x.name, x.num_matches, y.total_wins, (y.total_wins::NUMER
IC / x.num_matches::NUMERIC * 100.0::NUMERIC)::NUMERIC AS win_percentage
        FROM (SELECT teams.name, COUNT(*) AS num_matches
              FROM teams JOIN matchstats ON teams.id = matchstats.team_i
d
              GROUP BY teams.name) x
              JOIN (SELECT a.name, (a.home_wins + b.away_wins) AS total_
wins
                    FROM (SELECT teams.name, COUNT(matchs.won) AS home_w
ins
                          FROM teams
                          JOIN matchs ON teams.id = matchs.home_team_id
                          GROUP BY teams.name, matchs.won
                          HAVING won = 1) a
                    JOIN (SELECT teams.name, COUNT(matchs.won) AS away_w
ins
                          FROM teams JOIN matchs ON teams.id = matchs.aw
ay_team_id
                          GROUP BY teams.name, matchs.won
                          HAVING won = 2) b
              ON a.name = b.name) y
        ON x.name = y.name
        ORDER BY win_percentage DESC;
    """)
data = cur.fetchall()
win_percentage_data = pd.DataFrame([i.copy() for i in data])
win_percentage_data
```

Out[464]:

	name	num_matches	total_wins	win_percentage
0	Gibraltar	4	4	100.00000000000000000000
1	Qatar	14	12	85.7142857142857142860000
2	New Zealand	311	254	81.6720257234726688100000
3	Armenia	28	20	71.4285714285714285710000
4	Burkina Faso	33	23	69.6969696969696969700000
...	...	...	...	...
132	Uzbekistan	22	5	22.7272727272727272730000
133	El Salvador	18	4	22.2222222222222222220000
134	St Lucia	14	3	21.4285714285714285710000
135	Benin	32	6	18.7500000000000000000000
136	Swaziland	19	3	15.7894736842105263160000

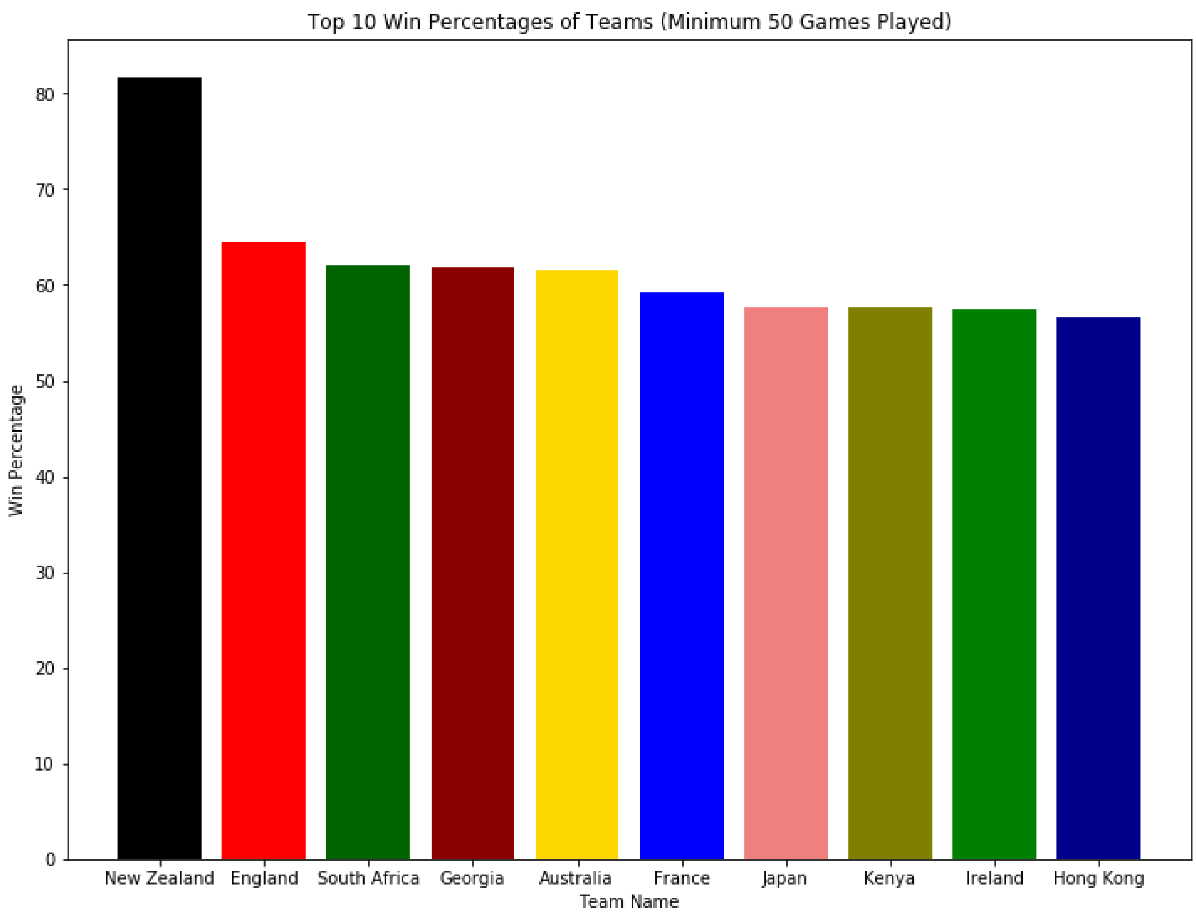
137 rows × 4 columns

However, we notice that there needs to be some cleaning of this dataset as it currently contains teams that have only played a handful of matches.

- These win percentages can be quite misleading, as some teams have not played a meaningful amount of games.
  - To remove the misleading statistics, we set a new criteria of **having at least 50 games played**.
  - After cleaning the data (using the condition that the minimum number of games played be 50) we obtain the processed table below:

In [465]:
```
cur.execute("""
        SELECT x.name, x.num_matches, y.total_wins, (y.total_wins::NUMER
IC / x.num_matches::NUMERIC * 100.0::NUMERIC)::NUMERIC AS win_percentage
        FROM (SELECT teams.name, COUNT(*) AS num_matches
              FROM teams JOIN matchstats ON teams.id = matchstats.team_i
d
              GROUP BY teams.name) x
        JOIN (SELECT a.name, (a.home_wins + b.away_wins) AS total_wins
                    FROM (SELECT teams.name, COUNT(matchs.won) AS home_w
ins
                          FROM teams
                          JOIN matchs ON teams.id = matchs.home_team_id
                          GROUP BY teams.name, matchs.won
                          HAVING won = 1) a
                    JOIN (SELECT teams.name, COUNT(matchs.won) AS away_w
ins
                          FROM teams JOIN matchs ON teams.id = matchs.aw
ay_team_id
                          GROUP BY teams.name, matchs.won
                          HAVING won = 2) b
              ON a.name = b.name) y
        ON x.name = y.name
        WHERE x.num_matches > 49
        ORDER BY win_percentage DESC;
    """)
data = cur.fetchall()

win_percentage_data = pd.DataFrame([i.copy() for i in data])

print(win_percentage_data)

fig = plt.figure(figsize=(12, 9))

win_percentage_data.win_percentage = win_percentage_data.win_percentage.
astype(float)
top_win_percentage_data = win_percentage_data.nlargest(10, 'win_percenta
ge')

plt.bar(top_win_percentage_data.name, top_win_percentage_data.win_percen
tage, color = ['black', 'red', 'darkgreen', 'darkred', 'gold', 'blue',
'lightcoral', 'olive', 'green', 'darkblue'])
plt.title("Top 10 Win Percentages of Teams (Minimum 50 Games Played)")
plt.ylabel("Win Percentage")
plt.xlabel("Team Name")
plt.show()
```

```
            name  num_matches  total_wins          win_percentage
0    New Zealand          311         254  81.6720257234726881000
1        England          292         188  64.3835616438356164380000
2   South Africa          326         202  61.9631901840490797550000
3        Georgia          215         133  61.8604651162790697670000
4      Australia          324         199  61.4197530864197530860000
..           ...          ...         ...                     ...
65         Chile          127          42  33.0708661417322834650000
66       Austria          106          34  32.0754716981132075470000
67         Italy          275          84  30.5454545454545454550000
68       Finland           69          21  30.4347826086956521740000
69        Norway           94          28  29.7872340425531914890000

[70 rows x 4 columns]
```



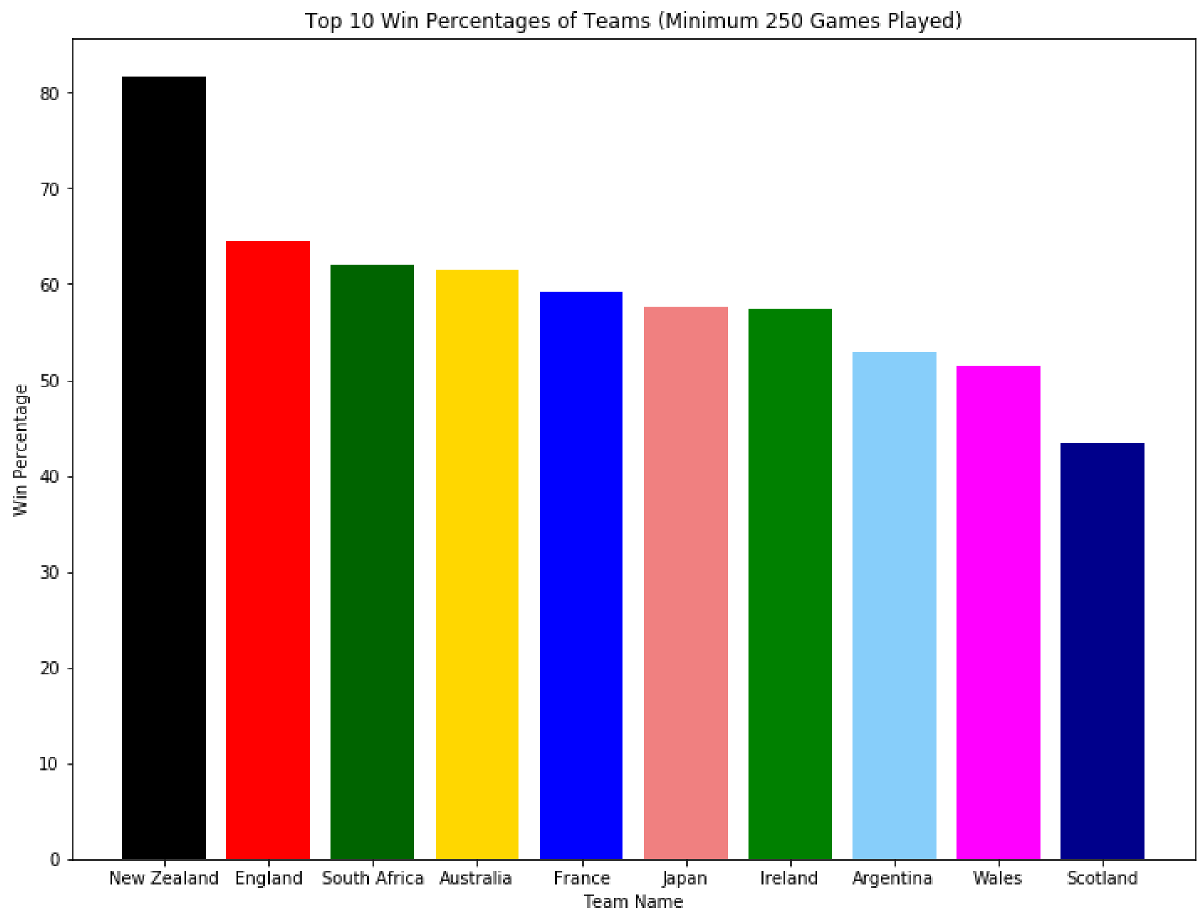
By querying only the teams with a minimum 50 games played, we have been able to remove many teams with unmeaningful records, but the resulting statistics are still quite misleading.

- The main issue being, tier 2 teams such as Kenya and Hong Kong do not play against the same caliber opposition when compared to tier 1 teams like New Zealand and England.
  - To remove these misleading statistics, we set a raise our criteria to **having at least 250 games played**.
  - After cleaning the data (using the condition that the minimum number of games played be 250) we obtain the processed table below:

In [466]:

```
cur.execute("""
        SELECT x.name, x.num_matches, y.total_wins, (y.total_wins::NUMER
IC / x.num_matches::NUMERIC * 100.0::NUMERIC)::NUMERIC AS win_percentage
        FROM (SELECT teams.name, COUNT(*) AS num_matches
              FROM teams JOIN matchstats ON teams.id = matchstats.team_i
d
              GROUP BY teams.name) x
        JOIN (SELECT a.name, (a.home_wins + b.away_wins) AS total_wins
                    FROM (SELECT teams.name, COUNT(matchs.won) AS home_w
ins
                          FROM teams
                          JOIN matchs ON teams.id = matchs.home_team_id
                          GROUP BY teams.name, matchs.won
                          HAVING won = 1) a
                    JOIN (SELECT teams.name, COUNT(matchs.won) AS away_w
ins
                          FROM teams JOIN matchs ON teams.id = matchs.aw
ay_team_id
                          GROUP BY teams.name, matchs.won
                          HAVING won = 2) b
              ON a.name = b.name) y
        ON x.name = y.name
        WHERE x.num_matches > 249
        ORDER BY win_percentage DESC;
    """)
data = cur.fetchall()

win_percentage_data = pd.DataFrame([i.copy() for i in data])

print(win_percentage_data)

fig = plt.figure(figsize=(12, 9))

win_percentage_data.win_percentage = win_percentage_data.win_percentage.
astype(float)
top_win_percentage_data = win_percentage_data.nlargest(10, 'win_percenta
ge')

plt.bar(top_win_percentage_data.name, top_win_percentage_data.win_percen
tage, color = ['black', 'red', 'darkgreen', 'gold', 'blue', 'lightcoral'
, 'green', 'lightskyblue', 'magenta', 'darkblue'])
plt.title("Top 10 Win Percentages of Teams (Minimum 250 Games Played)")
plt.ylabel("Win Percentage")
plt.xlabel("Team Name")
plt.show()
```

	name	num_matches	total_wins	win_percentage
0	New Zealand	311	254	81.672025723472668810000
1	England	292	188	64.383561643835616438000
2	South Africa	326	202	61.963190184049079755000
3	Australia	324	199	61.419753086419753086000
4	France	314	186	59.235668789808917197000
5	Japan	260	150	57.692307692307692308000
6	Ireland	280	161	57.500000000000000000000
7	Argentina	289	153	52.941176470588235294000
8	Wales	316	163	51.582278481012658228000
9	Scotland	276	120	43.478260869565217391000
10	Italy	275	84	30.545454545454545455000



The graph above displays teams that regularly compete against one another. This allows for a more meaningful comparison, as we are not looking at teams who likely never face against echother.

Joining `rankings.csv` and `rugby_pg.db`

By joining the `rankings.csv` data with our match statistics, we can observe how rankings correlate to match outcomes.

- Due to World Rugby rankings first being recorded in 2003, our match data for this section will only cover 2003 onwards.

In [467]:
```
'''This is the code used to gather the ranking position and points for e
ach team on the date of their match --- it has been commented out to pre
vent the Jupyter Notebook from building the data set'''

# rankings_data = pd.read_csv("ranking_data/rankings.csv")

# match_data.date = match_data.date.astype(str)
# rankings_data.date = rankings_data.date.astype(str)

# ordered_pos = []
# ordered_pts = []

# for rec in match_data.itertuples():
#     team_name = rec.name
#     if team_name == 'United States of America':
#         team_name = 'USA'
#     if rankings_data.loc[(rankings_data.team_name == team_name) & (ran
kings_data.date == rec.date)].empty:
#         ordered_pos.append(-1)
#         ordered_pts.append(-1)
#     else:
#         ordered_pos.append(
#             rankings_data.loc[
#                 (rankings_data.team_name == team_name) & (rankings_dat
a.date == rec.date)
#             ].values[:,[4]][0][0])

#         ordered_pts.append(
#             rankings_data.loc[
#                 (rankings_data.team_name == team_name) & (rankings_dat
a.date == rec.date)
#             ].values[:,[3]][0][0])

# match_data['pos'] = ordered_pos
# match_data['pts'] = ordered_pts

# export_csv = match_data.to_csv(r'merged.csv', index = None, header=Tru
e)

# match_rank_data = pd.read_csv('merged.csv')

# opposition_name = []
# opposition_pos = []
# opposition_pts = []

# for match in match_rank_data.itertuples():
#     opposition_name.append(match_rank_data.loc[
#                 (match_rank_data.match_id == match.match_id) & (match_
rank_data.name != match.name)
#             ].values[:,11][0])

#     opposition_pos.append(match_rank_data.loc[
#                 (match_rank_data.match_id == match.match_id) & (match_
rank_data.name != match.name)
#             ].values[:,12][0])
```

```
#     opposition_pts.append(match_rank_data.loc[
#                 (match_rank_data.match_id == match.match_id) & (match_
rank_data.name != match.name)
#             ].values[:,13][0])

# match_rank_data['opp_name'] = opposition_name
# match_rank_data['opp_pos'] = opposition_pos
# match_rank_data['opp_pts'] = opposition_pts

# export_csv = match_rank_data.to_csv(r'merged_with_oppo.csv', index = N
one, header=True)
```

Out[467]:

```
'This is the code used to gather the ranking position and points for ea
ch team on the date of their match --- it has been commented out to pre
vent the Jupyter Notebook from building the data set'
```

Note: If there was no ranking entry for a given team on a certain date, the value `-1` was used for `pos` and `pts`.

In [468]:
```
complete_match_data = pd.read_csv('merged_with_oppo.csv')

complete_match_data
```

Out[468]:

	id	date	match_type	match_id	team_id	scored	conceded	tries	cons	pens	dr
0	8	2019-11-01	3	298261	8	40	17	6.0	2.0	0.0	0.(
1	1	2019-11-02	3	298262	1	12	32	0.0	0.0	2.0	0.(
2	5	2019-11-02	3	298262	5	32	12	2.0	2.0	2.0	0.(
3	5	2019-10-27	3	298260	5	19	16	1.0	1.0	2.0	0.(
4	85	2019-11-02	1	303988	85	38	9	NaN	NaN	NaN	Na
...	...	...	...	...	...	...	...	...	...	...	...
8419	16	2003-10-15	3	24561	16	12	36	2.0	1.0	0.0	0.(
8420	14	2003-10-15	3	24560	14	19	18	1.0	1.0	2.0	0.(
8421	11	2003-10-15	3	24560	11	18	19	2.0	1.0	2.0	0.(
8422	10	2003-10-14	3	24559	10	67	14	9.0	2.0	1.0	0.(
8423	82	2003-10-14	3	24559	82	14	67	2.0	2.0	0.0	0.(

8424 rows × 17 columns

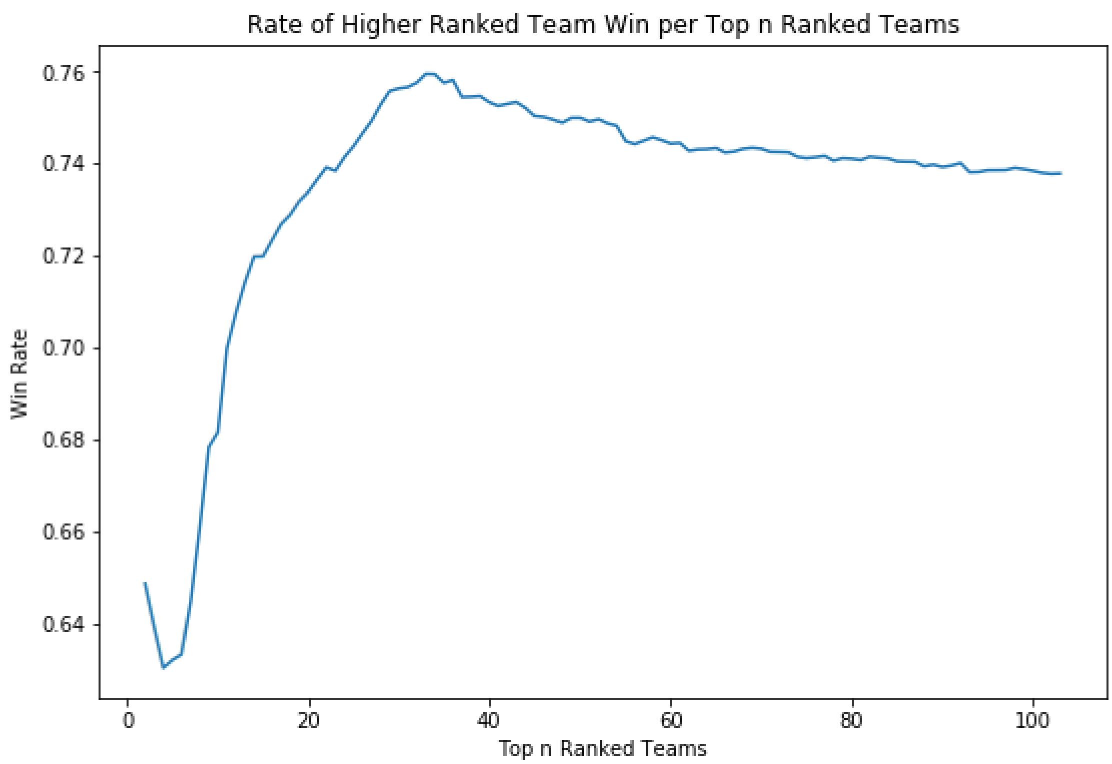
- Now, we shall observe how often the higher ranked team wins for each fixture.
  - We expect a positive rate.

In [469]:
```
data = complete_match_data

high_win = len(data.loc[
        (data.pos < data.opp_pos)
        & (data.scored > data.conceded)
        & (data.pos != -1)
        & (data.opp_pos != -1)
    ])
high_total = len(data.loc[
        (data.pos < data.opp_pos)
        & (data.pos != -1)
        & (data.opp_pos != -1)
    ])

high_win / high_total
```

Out[469]: 0.7376948945276673

Exploring further, how does this rate change when looking at the top n ranked teams?

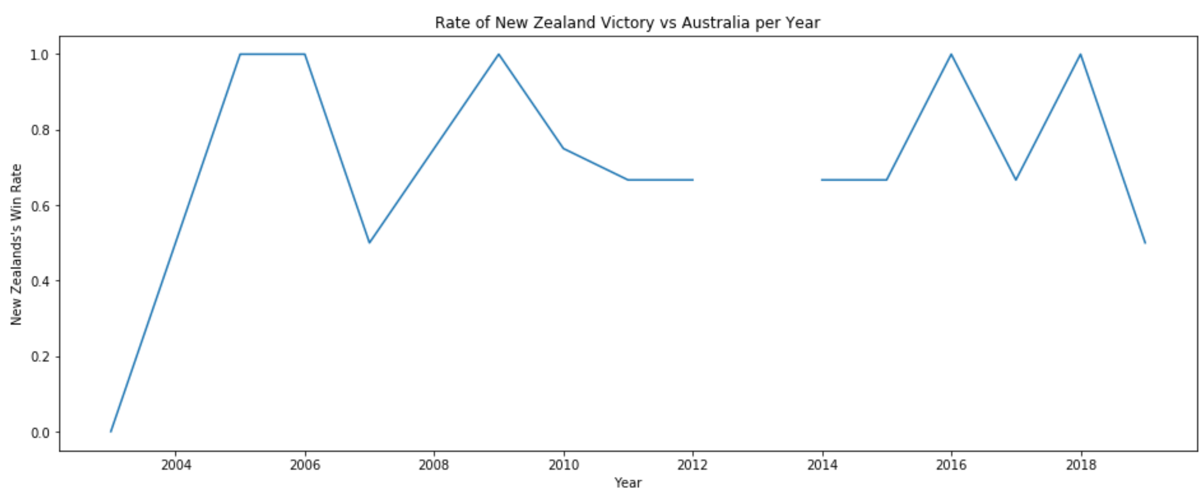
In [470]:
```
win_rate_by_rank = {}

for n in range(2, 104):
    high_win = len(data.loc[
        (data.pos < data.opp_pos)
        & (data.scored > data.conceded)
        & (data.opp_pos < n + 1)
        & (data.pos != -1)
        & (data.opp_pos != -1)
    ])

    high_total = len(data.loc[
        (data.pos < data.opp_pos)
        & (data.opp_pos < n + 1)
        & (data.pos != -1)
        & (data.opp_pos != -1)
    ])

    win_rate_by_rank[n] = high_win / high_total

fig = plt.figure(figsize=(9, 6))

plt.plot(list(win_rate_by_rank.keys()), list(win_rate_by_rank.values()))
plt.title("Rate of Higher Ranked Team Win per Top n Ranked Teams")
plt.xlabel("Top n Ranked Teams")
plt.ylabel("Win Rate")
# plt.gca().invert_xaxis()
plt.show()
```



From the graph above, we can observe that games between high ranking teams (teams who rank > 10) are more competitive than those of lesser ranked teams.

We can also see that as we near the top ranked team, the win rate spikes up. This is likely due to New Zealand's dominance over the years, which can be supported by the overall win rates we looked at earlier.

In [471]:
```
stats = {}

data.date = pd.to_datetime(data['date'])

team_one = 'New Zealand'
team_two = 'Australia'

for n in range(2003, 2020):
    win = len(data.loc[
        (data.name == team_one)
        & (data.opp_name == team_two)
        & (data.scored > data.conceded)
        & (data.date.dt.year == n)
    ])

    total = len(data.loc[
        (data.name == team_one)
        & (data.opp_name == team_two)
        & (data.date.dt.year == n)
    ])

    if total == 0:
        stats[n] = np.nan
    else:
        stats[n] = win / total

fig = plt.figure(figsize=(16, 6))

plt.plot(list(stats.keys()), list(stats.values()))
plt.title("Rate of New Zealand Victory vs Australia per Year")
plt.xlabel("Year")
plt.ylabel("New Zealands's Win Rate")
# plt.gca().invert_xaxis()
plt.show()
```



In a similar fashion, we generalize the data to get the overall win percentage of New Zealand against the top 12 teams in the world. The 12 is chosen due to the fact that the worst position shown in the 'worst_pos.csv' file is 12th.

In [472]:
```
stats = {}

data.date = pd.to_datetime(data['date'])

team_one = 'New Zealand'

for n in range(2003, 2020):
    win = len(data.loc[
        (data.name == team_one)
        & (data.opp_pos < 13)
        & (data.scored > data.conceded)
        & (data.date.dt.year == n)
    ])

    total = len(data.loc[
        (data.name == team_one)
        & (data.opp_pos < 13)
        & (data.date.dt.year == n)
    ])

    if total == 0:
        stats[n] = np.nan
    else:
        stats[n] = win / total

fig = plt.figure(figsize=(16, 6))

plt.plot(list(stats.keys()), list(stats.values()))
plt.title("Rate of New Zealand Victory vs Top 12 teams per Year")
plt.xlabel("Year")
plt.ylabel("New Zealands's Win Rate")
plt.show()
```

Now, we begin to focus more towards team stats on the big stage, the World cup.

There have been many teams qualifying for the world cup and battling it out in the pool stages, but only a handful of teams have progressed to the knockout stages.

We have compiled a list of these teams below with their id and the number of knockout stage appearances.

The data can be found here (https://www.rugbyworldcup.com/) (Note: the time reference is from 2003 to present time, which is equivalent to 5 World Cups):

Id	teams	wc knockout appearances
6	Australia	5
9	France	5
8	New Zealand	5
5	South Africa	5
1	England	4
3	Ireland	4
4	Wales	4
10	Argentina	3
2	Scotland	3
14	Fiji	1
23	Japan	1

Data Mining and Predictions

Now that we have gathered our data and analyzed several interesting statistics, we can build our model for computation.

First, we will need to query our dataset for each `match_id` for the 48 matches that are played at the World Cup.

In [473]:
```
stats = {}

wc_match_ids = data.loc[
        (data.date > datetime.date(2019, 9, 19))
        & (data.pos < 19)
        & (data.pos != -1)
    ].match_id.unique()

wc_match_ids
```

```
/usr/local/Cellar/ipython/7.8.0/libexec/vendor/lib/python3.7/site-packa
ges/ipykernel_launcher.py:6: FutureWarning: Comparing Series of datetim
es with 'datetime.date'.  Currently, the
'datetime.date' is coerced to a datetime. In the future pandas will
not coerce, and a TypeError will be raised. To retain the current
behavior, convert the 'datetime.date' to a datetime with
'pd.Timestamp'.
```

Out[473]:
```
array([298261, 298262, 298260, 298257, 298259, 298256, 298258, 298255,
       298232, 298230, 298229, 298216, 298217, 298218, 298223, 298219,
       298220, 298227, 298221, 298222, 298224, 298231, 298225, 298226,
       298233, 298234, 298235, 298236, 298237, 298238, 298239, 298241,
       298242, 298215, 298243, 298244, 298252, 298245, 298228, 298240,
       298246, 298253, 298254, 298247, 298250])
```

In [474]:
```
wc_matches = []

for match_id in wc_match_ids:
    curr_game = data.loc[data.match_id == match_id].iloc[0]
    wc_matches.append(curr_game)

# for match in wc_matches:
#     print(match['name'] + " vs. " + match['opp_name'])

print(len(wc_matches))
```

```
45
```

- Normally, each Rugby World Cup consists of 48 matches in total.
  - Unfortunately, in 2019 three of the pool games were called off due to a dangerous typhoon. The result of these matches all were counted as ties.
- For the rest of our project, we will be ignoring these games, as it is impossible to predict a typhoon from the data we have collected.

In [475]:
```
wc_match_info = {}

for match in wc_matches:
    team_one = match['name']
    team_two = match['opp_name']

    team_one_pos = match['pos']
    team_two_pos = match['opp_pos']

    past_match_stats = data.loc[
                (data.name == team_one)
            & (data.opp_name == team_two)
            & (data.date < match['date'])
        ]

    score_diff = past_match_stats.sum(axis = 0, skipna = True).scored - 
past_match_stats.sum(axis = 0, skipna = True).conceded

# Use the actual resulting score difference as Y, to compare our predict
ion to the actual result
    team_one_score = match['scored']
    team_two_score = match['conceded']

    resulting_score_diff = team_one_score - team_two_score

    win_count = 0
    draw_count = 0
    loss_count = 0

    for past_match in past_match_stats.values:
        if past_match[4] > past_match[5]:
            win_count += 1
        if past_match[4] == past_match[5]:
            draw_count += 1
        if past_match[4] < past_match[5]:
            loss_count += 1

    if (win_count + draw_count + loss_count) > 0:
        win_percentage = win_count / (win_count + draw_count + loss_coun
t)
    else:
        win_percentage = 0.0

    wc_match_info[match['match_id']] = [1, score_diff, win_percentage, t
eam_one_pos, team_two_pos, resulting_score_diff]

# wc_match_info contains data for each 2019 World Cup match
# -- The format is {match_id : [dummy, score_diff, win_percentage, team_
one_pos, team_two_pos, resulting_score_diff]}
```

The above code builds our **testing** dataset. Each testing instance is one of the 2019 World Cup matches, and consists of the following attributes:

```
[dummy, score_diff, win_percentage, team_one_pos, team_two_pos, resulting_sc
ore_diff]
```

In [476]:
```
pre_wc_match_ids = data.loc[
        (data.date < '2019-09-20')
        & (
            (data.name == 'Argentina')
            | (data.name == 'Australia')
            | (data.name == 'Canada')
            | (data.name == 'England')
            | (data.name == 'Fiji')
            | (data.name == 'France')
            | (data.name == 'Georgia')
            | (data.name == 'Ireland')
            | (data.name == 'Italy')
            | (data.name == 'Japan')
            | (data.name == 'Namibia')
            | (data.name == 'New Zealand')
            | (data.name == 'Russia')
            | (data.name == 'Samoa')
            | (data.name == 'Scotland')
            | (data.name == 'South Africa')
            | (data.name == 'Tonga')
            | (data.name == 'Uruguay')
            | (data.name == 'USA')
            | (data.name == 'Wales')
        )
    ].match_id.unique()

pre_wc_matches = []

for match_id in pre_wc_match_ids:
    curr_game = data.loc[data.match_id == match_id].iloc[0]
    pre_wc_matches.append(curr_game)

pre_wc_match_info = {}
```

The above code builds our **training** dataset. Each testing instance is one of the many matches played by a World Cup team prior to the 2019 World Cup, and consists of the following attributes:

```
[dummy, score_diff, win_percentage, team_one_pos, team_two_pos, resulting_sc
ore_diff]
```

In [477]:
```
wc_teams = [
    'Argentina',
    'Australia',
    'Canada',
    'England',
    'Fiji',
    'France',
    'Georgia',
    'Ireland',
    'Italy',
    'Japan',
    'Namibia',
    'New Zealand',
    'Russia',
    'Samoa',
    'Scotland',
    'South Africa',
    'Tonga',
    'Uruguay',
    'USA',
    'Wales'
]

for match in pre_wc_matches:
    team_one = match['name']
    team_two = match['opp_name']

    if (team_one not in wc_teams) or (team_two not in wc_teams):
        continue

    team_one_pos = match['pos']
    team_two_pos = match['opp_pos']

    past_match_stats = data.loc[
                (data.name == team_one)
            & (data.opp_name == team_two)
            & (data.date < match['date'])
            & (data.date > datetime.date(2003, 1, 1))
        ]
    score_diff = past_match_stats.sum(axis = 0, skipna = True).scored -
past_match_stats.sum(axis = 0, skipna = True).conceded

# Use the actual resulting score difference as Y, to compare our predict
ion to the actual result
    team_one_score = match['scored']
    team_two_score = match['conceded']

    resulting_score_diff = team_one_score - team_two_score

    win_count = 0
    draw_count = 0
    loss_count = 0

    for past_match in past_match_stats.values:
        if past_match[4] > past_match[5]:
            win_count += 1
```

```
        if past_match[4] == past_match[5]:
            draw_count += 1
        if past_match[4] < past_match[5]:
            loss_count += 1

    if (win_count + draw_count + loss_count) > 0:
        win_percentage = win_count / (win_count + draw_count + loss_coun
t)
    else:
        win_percentage = 0.0

    pre_wc_match_info[match['match_id']] = [1, score_diff, win_percentag
e, team_one_pos, team_two_pos, resulting_score_diff]

#     print(match['name'] + " vs. " + match['opp_name'])
#     print(pre_wc_match_info[match['match_id']])

# pre_wc_match_info contains data for all matches prior to the 2019 Worl
d Cup
# -- The format is {match_id : [dummy, score_diff, win_percentage, team_
one_pos, team_two_pos, resulting_score_diff]}
```

```
/usr/local/Cellar/ipython/7.8.0/libexec/vendor/lib/python3.7/site-packa
ges/ipykernel_launcher.py:38: FutureWarning: Comparing Series of dateti
mes with 'datetime.date'.  Currently, the
'datetime.date' is coerced to a datetime. In the future pandas will
not coerce, and a TypeError will be raised. To retain the current
behavior, convert the 'datetime.date' to a datetime with
'pd.Timestamp'.
```

We will now cast our dataset into numpy as an array. This allows for easy use of the many algorithms provided by `sklearn`.

In [478]:

```
training_data = np.asarray(list(pre_wc_match_info.values()), dtype=np.fl
oat32)
print(training_data.shape)

testing_data = np.asarray(list(wc_match_info.values()), dtype=np.float32
)
print(testing_data.shape)
```

```
(1180, 6)
(45, 6)
```

Linear Regression Predictions

As we would like to predict not just the winner of each match, but the resulting score too, linear regression is an incredibly useful tool due to the continuous nature of the outcome value.

Using `sklearn` for computation, the outcome of our linear regression predictions can be see below.

In [479]:

```
from sklearn import linear_model
from sklearn.metrics import mean_squared_error, r2_score

train_X = training_data[:,0:-1]  # [dummy, score_diff, win_percentage, t
eam_one_pos, team_two_pos]
# train_X = training_data[:,[1]]  # [score_diff]
train_Y = training_data[:,-1:]   # [resulting_score_diff]

test_X = testing_data[:,0:-1]    # [dummy, score_diff, win_percentage, t
eam_one_pos, team_two_pos]
# test_X = testing_data[:,[1]]    # [score_diff]
test_Y = testing_data[:,-1:]     # [resulting_score_diff]

regr = sk.linear_model.LinearRegression()
regr.fit(train_X, train_Y)

pred_Y = regr.predict(test_X)
```

In [480]:
```
binary_pred = []
binary_actual = []
correct_count = 0

for val in pred_Y:
    if val > 0:
        binary_pred.append(1)
    else:
        binary_pred.append(0)

accuracy_rating = ""

for indx, val in enumerate(binary_pred, 0):
    correct_outcome_check = (np.sign(pred_Y[indx]) == np.sign(test_Y[ind
x]))

    if (abs(pred_Y[indx] - test_Y[indx]) == 0):
        accuracy_rating = "Spot On!"
    elif (abs(pred_Y[indx] - test_Y[indx]) < 5) and (np.sign(pred_Y[indx
]) == np.sign(test_Y[indx])):
        accuracy_rating = "Good"
    elif (abs(pred_Y[indx] - test_Y[indx]) < 20) and (np.sign(pred_Y[ind
x]) == np.sign(test_Y[indx])):
        accuracy_rating = "Close"
    elif (np.sign(pred_Y[indx]) == np.sign(test_Y[indx])):
        accuracy_rating = "Correct, but score need improvement"
    elif (np.sign(pred_Y[indx]) != np.sign(test_Y[indx])):
        accuracy_rating = "Wrong"

    print(wc_matches[indx]['name'] + " vs. " + wc_matches[indx]['opp_nam
e'] + ":       Predicted: " + str(pred_Y[indx]) + "  |  Actual: "+ str(t
est_Y[indx]) + "    " + accuracy_rating+"\n")
    if correct_outcome_check:
        correct_count += 1

accuracy_rate = correct_count / len(binary_pred)

accuracy_rate
```

```
New Zealand vs. Wales:       Predicted: [7.090617]  |  Actual: [23.]
Close

England vs. South Africa:       Predicted: [6.984626]  |  Actual: [-2
0.]    Wrong

South Africa vs. Wales:       Predicted: [1.6681337]  |  Actual: [3.]
Good

France vs. Wales:       Predicted: [-11.87104]  |  Actual: [-1.]    Clo
se

England vs. New Zealand:       Predicted: [1.6039114]  |  Actual: [12.]
Close

Ireland vs. New Zealand:       Predicted: [-3.8989372]  |  Actual: [-3
2.]    Correct, but score need improvement

Japan vs. South Africa:       Predicted: [-1.6521168]  |  Actual: [-2
3.]    Correct, but score need improvement

Australia vs. England:       Predicted: [-3.685381]  |  Actual: [-24.]
Correct, but score need improvement

Samoa vs. Scotland:       Predicted: [-11.700047]  |  Actual: [-34.]
Correct, but score need improvement

Georgia vs. Uruguay:       Predicted: [23.015724]  |  Actual: [26.]
Good

Namibia vs. South Africa:       Predicted: [-45.6161]  |  Actual: [-5
4.]    Close

Australia vs. Fiji:       Predicted: [12.987925]  |  Actual: [18.]    C
lose

Argentina vs. France:       Predicted: [-3.5838623]  |  Actual: [-2.]
Good

New Zealand vs. South Africa:       Predicted: [9.738501]  |  Actual:
[10.]    Good

Russia vs. Samoa:       Predicted: [-5.1898537]  |  Actual: [-25.]    C
lose

Italy vs. Namibia:       Predicted: [30.5089]  |  Actual: [25.]    Clos
e

Ireland vs. Scotland:       Predicted: [20.903343]  |  Actual: [24.]
Good

Argentina vs. Tonga:       Predicted: [16.28442]  |  Actual: [16.]    G
ood

England vs. Tonga:       Predicted: [37.864876]  |  Actual: [32.]    Cl
ose
```

```
Georgia vs. Wales:       Predicted: [-18.799044]  |  Actual: [-29.]
Close

Fiji vs. Uruguay:       Predicted: [30.111006]  |  Actual: [-3.]    Wro
ng

Australia vs. Wales:       Predicted: [-0.94090843]  |  Actual: [-4.]
Good

Canada vs. Italy:       Predicted: [-17.853878]  |  Actual: [-41.]    C
orrect, but score need improvement

England vs. United States of America:       Predicted: [32.287903]  |
Actual: [38.]    Close

France vs. United States of America:       Predicted: [21.49392]  |  Ac
tual: [24.]    Good

Canada vs. New Zealand:       Predicted: [-54.072353]  |  Actual: [-6
3.]    Close

Fiji vs. Georgia:       Predicted: [1.8629322]  |  Actual: [35.]    Cor
rect, but score need improvement

Ireland vs. Russia:       Predicted: [49.09637]  |  Actual: [35.]    Cl
ose

Italy vs. South Africa:       Predicted: [-21.12493]  |  Actual: [-46.]
Correct, but score need improvement

Australia vs. Uruguay:       Predicted: [38.121872]  |  Actual: [35.]
Good

Argentina vs. England:       Predicted: [-15.019522]  |  Actual: [-29.]
Close

Namibia vs. New Zealand:       Predicted: [-56.81692]  |  Actual: [-6
2.]    Close

France vs. Tonga:       Predicted: [29.852936]  |  Actual: [2.]    Corr
ect, but score need improvement

Japan vs. Russia:       Predicted: [32.889114]  |  Actual: [20.]    Clo
se

Canada vs. South Africa:       Predicted: [-41.253216]  |  Actual: [-5
9.]    Close

Argentina vs. United States of America:       Predicted: [13.415516]  |
Actual: [30.]    Close

Tonga vs. United States of America:       Predicted: [-2.8035507]  |  A
ctual: [12.]    Wrong

Russia vs. Scotland:       Predicted: [-24.706753]  |  Actual: [-61.]
Correct, but score need improvement
```

```
Japan vs. Ireland:      Predicted: [-16.247166]  |  Actual: [7.]    Wr
ong

Japan vs. Samoa:      Predicted: [23.540066]  |  Actual: [19.]    Good

Fiji vs. Wales:      Predicted: [-21.076626]  |  Actual: [-12.]    Clo
se

Uruguay vs. Wales:      Predicted: [-40.54356]  |  Actual: [-22.]    C
lose

Japan vs. Scotland:      Predicted: [5.9878216]  |  Actual: [7.]    Go
od

Australia vs. Georgia:      Predicted: [26.991547]  |  Actual: [19.]
Close

Ireland vs. Samoa:      Predicted: [35.15895]  |  Actual: [42.]    Clo
se
```

```
Out[480]: 0.9111111111111111
```

By classifying the victorious team using the predicted score difference, our model managed to classify 91.11% of the World Cup games correctly. Additionally, the score differences that our model predicted are mostly within 20 points of the actual result.

Though some of the predictions are off, we will look further into these games below in our conclusion.

Conclusion

Using a dataset containing the previous match stats of the 20 qualifying teams, the 2019 Rugby World Cup could have been predicted with a high percentage before it had even begun. Gaining insight into the details such as team rank, World Cup appearances, furthest stage reached, etc. we were able to produce extremely accurate predictions in the mining process of this project.

Some of the incorrect predictions that incurred in our linear regression model were a result of how unpredictable occurences usually happen in reality. With the typhoon hitting Japan during the recent World Cup, the cancelled games may have skewed the results. This problem could not be countered, unless we were to look into weather data and storm patterns (which would be unnecessarily complex for this project). On the other hand, there are some incorrect predictions that might have been correctible upon gathering further information.

With Japan winning all of their group stage games and making it into the quarterfinals, this unbelievable series of events could have been better predicted had we taken location into account as a contributing factor in the performance of a team. In most sports, a team playing in their home city/country can dramatically improve their performance due to less travel time and increased fan support.

To further improve the results of our work, being more tedious towards outside information (such as home advantage) should allow our model to further improve its accuracy.