Final Project: CSCI S-109A: Introduction to Data Science

S-109A Introduction to Data Science
Harvard University
Summer 2018
Instructors: Pavlos Protopapas, Kevin Rader

Project: FIFA World Cup 2018 - Predictions

Goal: To be able to predict outcome of FIFA World Cup 2018 for: Round-16, Quater Finals, Semi Finals, and Final match(es)

Sections

- **Exploratory Data Analysis (EDA)**
    - *Visualize: Game & Game Results Distributions*
    - *Visualize: Top 20 Winners & Loosers (All Time)*
    - *Visualize: Top 20 Winners & Loosers (Last 10 years)*
    - *Visualize: Distribution of Team Rankings, and Rank Difference, grouped by Game Results*
- **Data Transformation**
    - *Add Feature: FIFA Team Ranks*
    - *Add Feature: Year Weight*
    - *Add Feature: FIFA World Cup Points*
    - *Add Feature: FIFA World Cup Participations*
    - *Add Feature: Team's overall player strength*
    - *Add Quadratic Terms*
    - *Normalize Predictors*
    - *Build Train & Test Datasets*
- **Building Models**
    - *Logistic Regression*
    - *Linear Discriminant Analysis*
    - *Quadratic Discriminant Analysis*
    - *K-Nearest Neighbors*
    - *Decision Tree Classifier*
    - *Random Forest Classifier*
    - *AdaBoost Classifier*
    - *Neural Network*
    - *Stacking - Baged Models (Bootstrapped n=25)*
- **Model Comparision**
- **Final Predictions**

Note: Webscrapping process and methods are included in the supplemental notebook: nb_webscrape.ipynb

Exploratory Data Analysis (EDA)

In this section we will load and analyze two datasets - international match results: `international_results.csv`, and players data: `PlayerAttributeData.csv`, `PlayerPersonalData.csv`, `PlayerPlayingPositionData.csv`, `CompleteDataset.csv`. We will also add new features to these datasource from additonal datasets build via web-scraping (detailed in supplemental notebook).

In [7]:

```
# import the necessary libraries
%matplotlib inline
import numpy as np
import scipy as sp
import matplotlib as mpl
import matplotlib.cm as cm
import matplotlib.pyplot as plt
from matplotlib.lines import Line2D
import pandas as pd
from pandas import Series
import random
import time
from sklearn.preprocessing import MinMaxScaler
from sklearn.linear_model import LogisticRegression
from sklearn.linear_model import LogisticRegressionCV
from sklearn.discriminant_analysis import LinearDiscriminantAnalysis
from sklearn.discriminant_analysis import QuadraticDiscriminantAnalysi
s
from sklearn.preprocessing import PolynomialFeatures
from sklearn.neighbors import KNeighborsClassifier
from sklearn.model_selection import cross_val_score
from sklearn.metrics import accuracy_score
from sklearn.metrics import r2_score
from sklearn.model_selection import KFold
from sklearn.model_selection import GridSearchCV
from sklearn.model_selection import train_test_split
from sklearn.decomposition import PCA
from sklearn.utils import resample
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.ensemble import AdaBoostClassifier
from sklearn.linear_model import LogisticRegressionCV
from sklearn.model_selection import StratifiedKFold
from keras.models import Sequential
from keras.layers import Dense
from keras.layers import regularizers
from PIL import Image
from PIL import ImageFont
from PIL import ImageDraw
from matplotlib.pyplot import imshow
```

Loading and analyzing datasets.

In [8]:

```
df_matches = pd.read_csv("datasets/fifa/international_results.csv")
print("df_matches: ", df_matches.shape)
print(df_matches.dtypes)
df_matches.head(10)
```

```
df_matches:  (39654, 9)
date          object
home_team     object
away_team     object
home_score     int64
away_score     int64
tournament    object
city          object
country       object
neutral         bool
dtype: object
```

Out[8]:

	date	home_team	away_team	home_score	away_score	tournament	city	c
0	1872-11-30	Scotland	England	0	0	Friendly	Glasgow	Sc
1	1873-03-08	England	Scotland	4	2	Friendly	London	En
2	1874-03-07	Scotland	England	2	1	Friendly	Glasgow	Sc
3	1875-03-06	England	Scotland	2	2	Friendly	London	En
4	1876-03-04	Scotland	England	3	0	Friendly	Glasgow	Sc
5	1876-03-25	Scotland	Wales	4	0	Friendly	Glasgow	Sc
6	1877-03-03	England	Scotland	1	3	Friendly	London	En
7	1877-03-05	Wales	Scotland	0	2	Friendly	Wrexham	W
8	1878-03-02	Scotland	England	7	2	Friendly	Glasgow	Sc
9	1878-03-23	Scotland	Wales	9	0	Friendly	Glasgow	Sc

The `international_results.csv` dataset has $39,654$ observations, and 9 variables —

- `date`: when the match is held
- `home_team`: name of the home team
- `away_team`: name of the away team
- `home_score`: number of goals made by the home_team
- `away_score`: number of goals made by the away_team
- `tournament`: name of the tournament, ex: FIFA World Cup
- `city`: where the game is held
- `country`: where the game is held.
- `neutral`: False, if game venue is not in home_team's city/ country. True, otherwise.

Add Feature: Year, Net Score, and Game Result

In the section below, we are adding few additional variables —

- `neutral`: changed datatype to numeric binary (from boolean binary).
- `year`: when the game is held.
- `net_score`: home_score minus the away_score
- `result`: of the game from home_team prespective.
  - 0: Lost,
  - 1: Won,
  - 2: Draw

In [9]:
```python
def get_game_result(data_row):
    """A function which returns the result of the match
    for a given match observation

    Inputs: data row of international_results.csv dataset

    Returns:
        0: home_team lost the match
        1: home_team won the match
        2: match is a draw
    """
    if data_row["home_score"] > data_row["away_score"]:
        return 1
    elif data_row["home_score"] < data_row["away_score"]:
        return 0
    else:
        return 2

def get_net_score(data_row):
    """A function which returns the net score of the game,
    given as: home_score - away_score

    Inputs: data row of international_results.csv dataset

    Returns: net_score = home_score - away_score
    """
    return data_row["home_score"] - data_row["away_score"]

df_matches.neutral = df_matches.neutral.astype(int)
df_matches['year'] = pd.to_datetime(df_matches['date']).dt.year
df_matches['net_score'] = df_matches.apply(get_net_score, axis=1)
df_matches['result'] = df_matches.apply(get_game_result, axis=1)
```

In [10]:
```
# rearranging columns
colnames = ["date","year","home_team","away_team","home_score","away_s
core",
            "net_score","result","tournament","city","country","neutra
l"]
df_matches = df_matches[colnames]
df_matches.sample(10)
```

Out[10]:

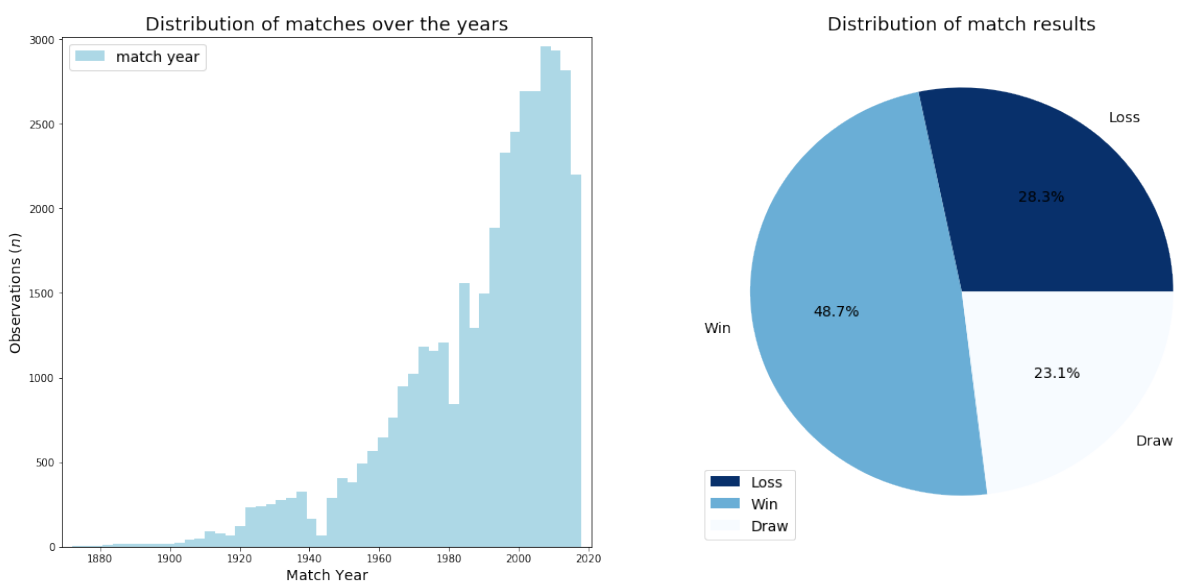
	date	year	home_team	away_team	home_score	away_score	net_score	res
30188	2008-06-14	2008	Puerto Rico	Honduras	2	2	0	2
22354	2000-01-20	2000	Malta	Qatar	2	0	2	1
9153	1975-01-31	1975	Malawi	Mauritius	1	1	0	2
27481	2005-06-21	2005	Australia	Tunisia	0	2	-2	0
24328	2001-11-21	2001	Ethiopia	Zambia	1	2	-1	0
25169	2003-02-12	2003	Israel	Armenia	2	0	2	1
31288	2009-07-23	2009	USA	Honduras	2	0	2	1
1309	1930-09-21	1930	Norway	Denmark	1	0	1	1
27295	2005-03-29	2005	Ireland	China	1	0	1	1
14157	1986-06-28	1986	France	Belgium	4	2	2	1

Visualize: Game & Game Results Distributions

In [11]:
```
fig, ax = plt.subplots(1,2, figsize=(20,9))
ax[0].set_title("Distribution of matches over the years", fontsize=18)
ax[0].margins(0.02)
ax[0].hist(df_matches["year"], bins=50, color="lightblue", label="matc
h year")
ax[0].set_xlabel("Match Year", fontsize=14)
ax[0].set_ylabel("Observations ($n$)", fontsize=14)
ax[0].legend(loc=2, fontsize=14)

results = list(df_matches.groupby("result").agg({
    'date': 'count'
})["date"])
lbl_results = ["Loss", "Win", "Draw"] # 0: loose, 1: win, 2: draw
colors = plt.cm.Blues(np.linspace(1, 0, 3))
ax[1].set_title("Distribution of match results", fontsize=18)
ax[1].margins(0.02)
ax[1].pie(results, labels=lbl_results, colors=colors, autopct='%.1f%%'
, textprops={'fontsize': 14})
ax[1].legend(loc=3, fontsize=14)
```

Out[11]: <matplotlib.legend.Legend at 0x1a4622a7f0>



From the plots above we can see that —

- data is significantly skewed over the year variable. The volume of data available between 1990 - 2018 (18 years) is far greater than the volume of data available between 1880 - 1990 (110 years). This trend could be for many reasons — (1) more games being played in recent years, (2) more data being captured & recorded for the games being played. We'll keep this trend in mind, while working with this dataset to build our learning models.
- data is also skewed over the result variable. There are far more observations with result=win, compared to combined observations of result=loss, and result=draw. As result variable will be our outcome variable, we would have preferred if the volume of data was balanced between these three levels of result variable. We'll have to keep this trend in mind, while working with this dataset to build our learning models.

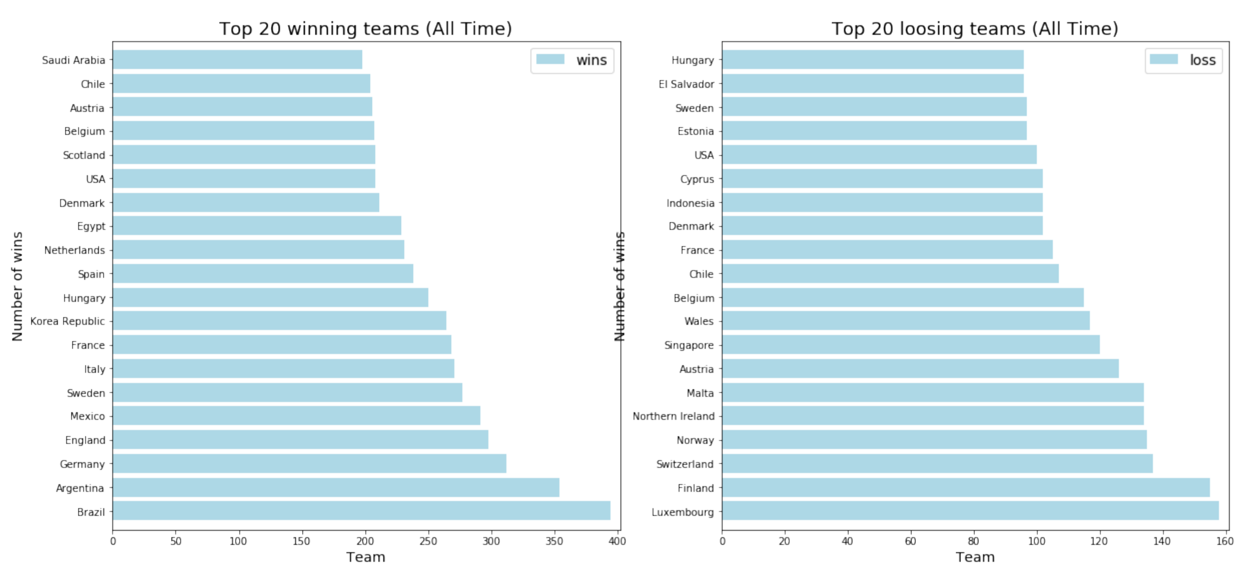
Visualize: Top 20 Winners & Loosers (All Time)

In [12]:
```
fig, ax = plt.subplots(1,2, figsize=(20,9))

# 0: loose, 1: win, 2: draw
df_winners = df_matches[df_matches.result==1].groupby(["home_team"]).a
gg({
    'date':'count'
}).copy()
df_winners.columns = ["count"]
df_winners = df_winners.reset_index()
df_winners = df_winners.sort_values(by="count", ascending=False).copy(
)
ax[0].set_title("Top 20 winning teams (All Time)", fontsize=18)
ax[0].margins(0.02)
ax[0].barh(df_winners[:20]["home_team"], df_winners[:20]["count"], col
or="#add8e6", label="wins")
ax[0].set_xlabel("Team", fontsize=14)
ax[0].set_ylabel("Number of wins", fontsize=14)
ax[0].legend(loc=1, fontsize=14)

df_looser = df_matches[df_matches.result==0].groupby(["home_team"]).ag
g({
    'date':'count'
}).copy()
df_looser.columns = ["count"]
df_looser = df_looser.reset_index()
df_looser = df_looser.sort_values(by="count", ascending=False).copy()
ax[1].set_title("Top 20 loosing teams (All Time)", fontsize=18)
ax[1].margins(0.02)
ax[1].barh(df_looser[:20]["home_team"], df_looser[:20]["count"], color
="#add8e6", label="loss")
ax[1].set_xlabel("Team", fontsize=14)
ax[1].set_ylabel("Number of wins", fontsize=14)
ax[1].legend(loc=1, fontsize=14)
```

Out[12]: <matplotlib.legend.Legend at 0x1a53fd6860>



The plot above shows the —

- top-20 teams (left-plot) of all time: Brazil, Argentina, Germany, England, Mexico, ...
- bottom-20 teams (right-plot) of all time: Luxembourg, Finland, Switzerland, Norway, Malta, ...

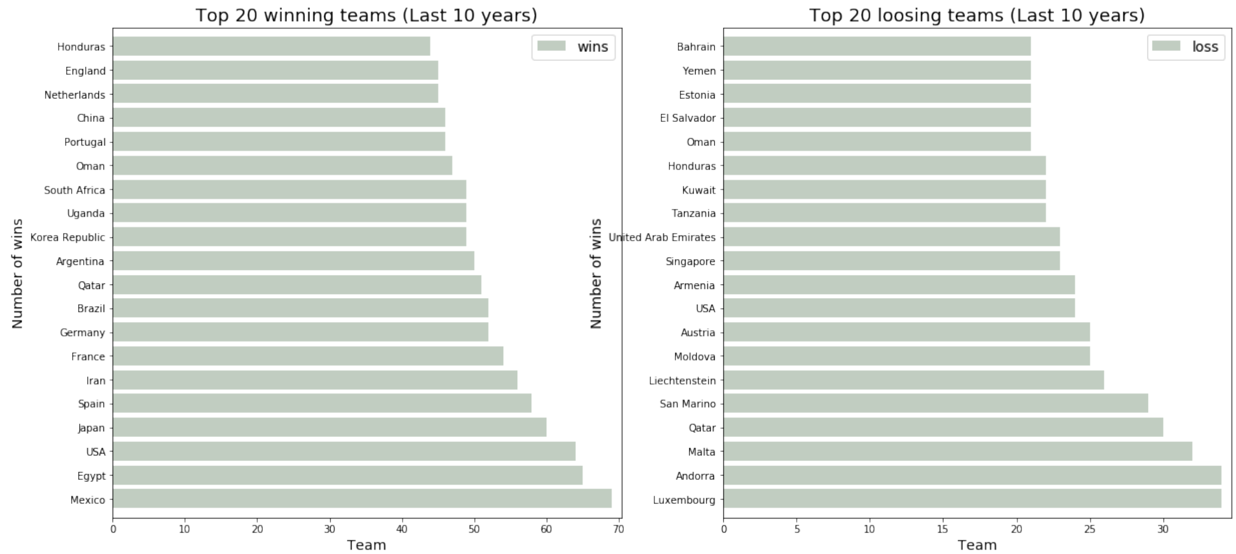
Visualize: Top 20 Winners & Loosers (Last 10 years)

In [13]:
```python
fig, ax = plt.subplots(1,2, figsize=(20,9))

# 0: loose, 1: win, 2: draw
df_winners = df_matches[(df_matches.result==1) & (df_matches.year>=2008)].groupby(["home_team"]).agg({
    'date':'count'
}).copy()
df_winners.columns = ["count"]
df_winners = df_winners.reset_index()
df_winners = df_winners.sort_values(by="count", ascending=False).copy()
ax[0].set_title("Top 20 winning teams (Last 10 years)", fontsize=18)
ax[0].margins(0.02)
ax[0].barh(df_winners[:20]["home_team"], df_winners[:20]["count"], color="#c1cdc1", label="wins")
ax[0].set_xlabel("Team", fontsize=14)
ax[0].set_ylabel("Number of wins", fontsize=14)
ax[0].legend(loc=1, fontsize=14)

df_looser = df_matches[(df_matches.result==0) & (df_matches.year>=2008)].groupby(["home_team"]).agg({
    'date':'count'
}).copy()
df_looser.columns = ["count"]
df_looser = df_looser.reset_index()
df_looser = df_looser.sort_values(by="count", ascending=False).copy()
ax[1].set_title("Top 20 loosing teams (Last 10 years)", fontsize=18)
ax[1].margins(0.02)
ax[1].barh(df_looser[:20]["home_team"], df_looser[:20]["count"], color="#c1cdc1", label="loss")
ax[1].set_xlabel("Team", fontsize=14)
ax[1].set_ylabel("Number of wins", fontsize=14)
ax[1].legend(loc=1, fontsize=14)
```

```
Out[13]: <matplotlib.legend.Legend at 0x1a83cd7a20>
```



The plot above shows the —

- top-20 teams (left-plot) for last 10 years: Mexico, Egypt, USA, Japan, Spain, ...
- bottom-20 teams (right-plot) for last 10 years: Luxembourg, Andorra, Malta, Qatar, San Marino, ...

From the data above we can see that there is a significant change in both top & bottom team orders within last 10 years. We see the top 4 teams of all time: Brazil, Argentina, Germany, England, do not show up in top 5 teams for last 10 years. What could be the reason for this?

Data Transformation - adding new features

Add Feature: FIFA Team Ranks

Let's add FIFA team ranking to our dataset —

- `ranking`: data scraped from FIFA website.
  - `home_rank`: ranking of the home_team in the given year
  - `away_rank`: ranking of the away_team in the given year
  - `Note`: If no data available for given team for a given year, average rank (over the years) for that team will be applied

In [15]:
```
df_ranking = pd.read_pickle("datasets/ranking_data.pkl")
df_ranking.sample(10)
```

Out[15]:

	date	year	team	rank
53970	2016-12-22	2016	Bermuda	187
14443	2000-10-11	2000	Sri Lanka	150
17477	2002-01-16	2002	Korea DPR	139
1396	1994-05-17	1994	Senegal	55
9063	1998-07-15	1998	Brunei Darussalam	176
1821	1994-07-21	1994	Liberia	136
18698	2002-08-14	2002	Sri Lanka	142
36433	2009-11-20	2009	British Virgin Islands	192
15148	2001-02-14	2001	Greece	43
42603	2012-06-06	2012	Kazakhstan	141

In [16]:
```
df_grouped_ranking = df_ranking.groupby(["year","team"]).agg({
    "rank": 'max'
}).copy()
df_grouped_ranking = df_grouped_ranking.reset_index()
df_grouped_ranking['year'] = pd.to_numeric(df_grouped_ranking['year'])
df_grouped_ranking['rank'] = pd.to_numeric(df_grouped_ranking['rank'])
df_grouped_ranking.sample(10)
```

Out[16]:

	year	team	rank
3079	2008	Moldova	97
4450	2015	Cayman Islands	205
4087	2013	Iraq	98
2800	2007	Cyprus	82
2196	2004	Faroe Islands	137
717	1996	Wales	82
1731	2002	Aruba	189
31	1993	Chinese Taipei	161
4279	2014	Germany	2
3640	2011	England	8

In [17]:
```
def get_home_rank(data_row):
```

```
In [17]: def get_home_rank(data_row):
    """A function which returns the rank of the home_team
    for the given year

    Inputs: data row of international_results.csv dataset

    Returns: rank
    """
    rank = df_grouped_ranking[(df_grouped_ranking["year"]==data_row["y
ear"]) & (df_grouped_ranking["team"]==data_row["home_team"])]["rank"]
    if len(rank) > 0:
        # apply exact rank
        return list(rank)[0]
    else:
        # apply average rank
        ranks=list(df_grouped_ranking[(df_grouped_ranking["team"]==dat
a_row["home_team"])]["rank"])
        if len(ranks) > 0:
            return int(round(np.mean(ranks)))
        else:
            return df_grouped_ranking["rank"].max()

def get_away_rank(data_row):
    """A function which returns the rank of the away_team
    for the given year

    Inputs: data row of international_results.csv dataset

    Returns: rank
    """
    rank = df_grouped_ranking[(df_grouped_ranking["year"]==data_row["y
ear"]) & (df_grouped_ranking["team"]==data_row["away_team"])]["rank"]
    if len(rank) > 0:
        # apply exact rank
        return list(rank)[0]
    else:
        # apply average rank
        ranks=list(df_grouped_ranking[(df_grouped_ranking["team"]==dat
a_row["away_team"])]["rank"])
        if len(ranks) > 0:
            return int(round(np.mean(ranks)))
        else:
            return df_grouped_ranking["rank"].max()

def get_rank_diff(data_row):
    """A function which returns the difference in home_team and
    away_team rankings

    Inputs: data row of international_results.csv dataset

    Returns: rank difference (home_rank - away_rank)
    """
    return data_row["home_rank"] - data_row["away_rank"]
```

```
df_matches['home_rank'] = df_matches.apply(get_home_rank, axis=1)
df_matches['away_rank'] = df_matches.apply(get_away_rank, axis=1)
df_matches['rank_diff'] = df_matches.apply(get_rank_diff, axis=1)
```

In [18]:
```
# rearranging columns
colnames = ["date","year","home_team","away_team","home_rank","away_ra
nk","rank_diff","home_score",
            "away_score","net_score","result","tournament","city","cou
ntry","neutral"]
df_matches = df_matches[colnames]

print("df_matches: ", df_matches.shape)
print(df_matches.dtypes)
df_matches.iloc[:,1:15].sample(10)
```

```
df_matches:  (39654, 15)
date          object
year           int64
home_team     object
away_team     object
home_rank      int64
away_rank      int64
rank_diff      int64
home_score     int64
away_score     int64
net_score      int64
result         int64
tournament    object
city          object
country       object
neutral        int64
dtype: object
```

Out[18]:

	year	home_team	away_team	home_rank	away_rank	rank_diff	home_score
10078	1977	Peru	Poland	64	44	20	1
10554	1978	Botswana	Mozambique	128	106	22	0
32495	2010	Guadeloupe	Antigua and Barbuda	209	131	78	1
39220	2017	Kenya	Rwanda	88	93	-5	2
23329	2000	Vietnam	Indonesia	99	99	0	2
30477	2008	United Arab Emirates	Korea DPR	99	94	5	1
20058	1997	Congo DR	Congo	82	98	-16	1
6804	1968	Suriname	French Guyana	146	209	-63	2
13001	1984	Morocco	Senegal	51	64	-13	2
13705	1985	Saudi Arabia	Qatar	61	89	-28	1

Visualize: Distribution of Team Rankings, and Rank Difference, grouped by Game Results

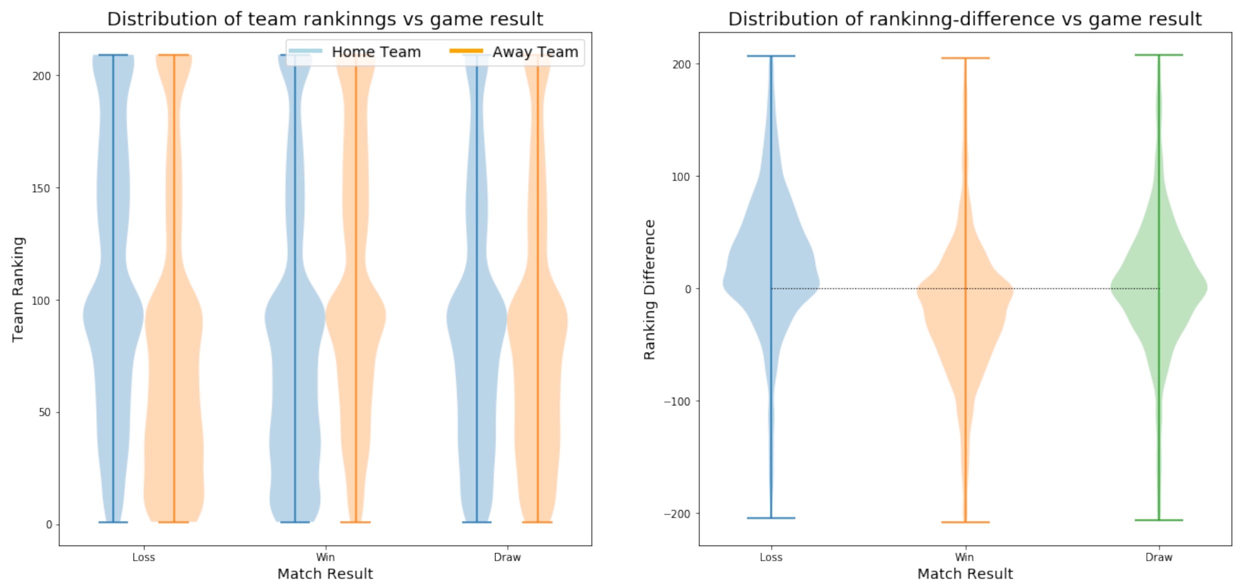
In [19]:
```
fig, ax = plt.subplots(1,2, figsize=(20,9))

home_team = []
away_team = []
for cur_pos, cur_df in df_matches.groupby("result"):
    home_team.append(cur_df[cur_df["year"]>=1993]["home_rank"].values)
    away_team.append(cur_df[cur_df["year"]>=1993]["away_rank"].values)

# 0: loose, 1: win, 2: draw
ax[0].set_title("Distribution of team rankinngs vs game result", fonts
ize=18)
ax[0].violinplot(home_team, positions=[1,2.5,4.0])
ax[0].violinplot(away_team, positions=[1.5,3.0,4.5])
ax[0].set_xticks([1.25, 2.75, 4.25])
ax[0].set_xticklabels(["Loss","Win","Draw"])
ax[0].set_xlabel("Match Result", fontsize=14)
ax[0].set_ylabel("Team Ranking", fontsize=14)
custom_lines = [Line2D([0], [0], color="lightblue", lw=4), Line2D([0],
[0], color="orange", lw=4)]
ax[0].legend(custom_lines, ['Home Team', 'Away Team'], loc=1, ncol=2,
fontsize=14)

diff0 = list(df_matches[df_matches.result==0]["rank_diff"])
diff1 = list(df_matches[df_matches.result==1]["rank_diff"])
diff2 = list(df_matches[df_matches.result==2]["rank_diff"])
ax[1].set_title("Distribution of rankinng-difference vs game result",
fontsize=18)
ax[1].violinplot(diff0, positions=[1])
ax[1].violinplot(diff1, positions=[2])
ax[1].violinplot(diff2, positions=[3])
ax[1].set_xticks([1,2,3])
ax[1].set_xticklabels(["Loss","Win","Draw"])
ax[1].plot([1,3],[0,0], lw=1, ls="dotted", c="black")
ax[1].set_xlabel("Match Result", fontsize=14)
ax[1].set_ylabel("Ranking Difference", fontsize=14)
```

Out[19]: Text(0,0.5,'Ranking Difference')



Add Feature: Year Weight

`year_wt`: higher weightage to recent data, lower weightage to older data (on the scale of 0 to 2)

In [20]:
```
# apply weight to year when match was played.
# recent year(s) performance should be treated as more relevant (higher weight)
# compared to older year(s) performance (lower weight)

df_matches['year_wt'] = df_matches['year']
min_year = min(df_matches["year"])
max_year = max(df_matches["year"])
range_year = max_year - min_year
weights = list(np.linspace(0,1,range_year+2))

for count, year in enumerate(range(min_year-1, max_year+1)):
    df_matches["year_wt"] = df_matches["year_wt"].replace(year, weights[count])

# rearranging columns
colnames = ["date","year","year_wt","home_team","away_team","home_rank","away_rank","rank_diff","home_score",
            "away_score","net_score","result","tournament","city","country","neutral"]
df_matches = df_matches[colnames]

print("df_matches: ", df_matches.shape)
print(df_matches.dtypes)
df_matches.sample(10)
```

```
df_matches:  (39654, 16)
date            object
year             int64
year_wt        float64
home_team       object
away_team       object
home_rank        int64
away_rank        int64
rank_diff        int64
home_score       int64
away_score       int64
net_score        int64
result           int64
tournament      object
city            object
country         object
neutral          int64
dtype: object
```

Out[20]:

	date	year	year_wt	home_team	away_team	home_rank	away_rank	ran
2269	1940-10-20	1940	0.469388	Germany	Bulgaria	6	52	-46
4748	1960-10-14	1960	0.605442	Korea Republic	Vietnam Republic	49	209	-16
3278	1952-05-11	1952	0.551020	Romania	Czechoslovakia	28	209	-18
16727	1992-02-02	1992	0.823129	USA	Russia	25	27	-2
31896	2010-05-26	2010	0.945578	Northern Ireland	Turkey	59	42	17
28676	2006-11-20	2006	0.918367	Northern Cyprus	Tajikistan	209	141	68
2149	1939-02-12	1939	0.462585	Portugal	Switzerland	12	35	-23
19732	1996-09-01	1996	0.850340	Colombia	Chile	9	39	-30
32303	2010-10-09	2010	0.945578	Rwanda	Benin	132	72	60
8977	1974-07-03	1974	0.700680	Sweden	Yugoslavia	27	46	-19

Add Feature: FIFA World Cup Points

- `home_wc_points`: home_team's all time points for world cup games
- `away_wc_points`: away_team's all time points for world cup games

In [21]:
```
df_fifa_wc_ranking = pd.read_pickle("datasets/fifa_wc_ranking.pkl")
df_fifa_wc_ranking.head()
```

Out[21]:

	rank	team	points	matches	win	draw	lost	goal_for	goal_against	points_avg
0	1	Brazil	227	104	70	17	17	221	102	2.2
1	2	Germany	218	106	66	20	20	224	121	2.1
2	3	Italy	156	83	45	21	17	128	77	1.9
3	4	Argentina	140	77	42	14	21	131	84	1.8
4	5	Spain	99	59	29	12	18	92	66	1.7

In [22]:
```
def get_home_wc_points(data_row):
    wc_points = df_fifa_wc_ranking[df_fifa_wc_ranking.team == data_row
["home_team"]]["points"]
    if len(wc_points) > 0:
        return list(wc_points)[0]
    else:
        return 0

def get_away_wc_points(data_row):
    wc_points = df_fifa_wc_ranking[df_fifa_wc_ranking.team == data_row
["away_team"]]["points"]
    if len(wc_points) > 0:
        return list(wc_points)[0]
    else:
        return 0

df_matches['home_wc_pts'] = df_matches.apply(get_home_wc_points, axis=
1)
df_matches['away_wc_pts'] = df_matches.apply(get_away_wc_points, axis=
1)
df_matches.sample(5)
```

Out[22]:

	date	year	year_wt	home_team	away_team	home_rank	away_rank	rank_d
17905	1993-10-05	1993	0.829932	Cyprus	Israel	75	71	4
15416	1989-05-18	1989	0.802721	Peru	Venezuela	64	84	-20
34324	2012-10-05	2012	0.959184	Burma	Brunei	209	209	0
33727	2012-02-29	2012	0.959184	Guinea-Bissau	Cameroon	175	71	104
26261	2004-03-31	2004	0.904762	Scotland	Romania	86	35	51

Add Feature: FIFA World Cup Participations

- `home_wc_plays`: home_team's world cup participations
- `away_wc_plays`: away_team's world cup participations

In [23]:

```
df_fifa_participations = pd.read_pickle("datasets/fifa_participations.
pkl")
df_fifa_participations.head()
```

Out[23]:

	team	participations	years
0	Brazil	20	1930, 1934, 1938, 1950, 1954, 1958, 1962, 1966...
1	Germany	18	1934, 1938, 1954, 1958, 1962, 1966, 1970, 1974...
2	Italy	18	1934, 1938, 1950, 1954, 1962, 1966, 1970, 1974...
3	Argentina	16	1930, 1934, 1958, 1962, 1966, 1974, 1978, 1982...
4	Mexico	15	1930, 1950, 1954, 1958, 1962, 1966, 1970, 1978...

In [24]:

```
def get_home_wc_plays(data_row):
    wc_plays = df_fifa_participations[df_fifa_participations.team == d
ata_row["home_team"]]["participations"]
    if len(wc_plays) > 0:
        return list(wc_plays)[0]
    else:
        return 0

def get_away_wc_plays(data_row):
    wc_plays = df_fifa_participations[df_fifa_participations.team == d
ata_row["away_team"]]["participations"]
    if len(wc_plays) > 0:
        return list(wc_plays)[0]
    else:
        return 0

df_matches['home_wc_plays'] = df_matches.apply(get_home_wc_plays, axis
=1)
df_matches['away_wc_plays'] = df_matches.apply(get_away_wc_plays, axis
=1)
df_matches.sample(5)
```

Out[24]:

	date	year	year_wt	home_team	away_team	home_rank	away_rank	rank_d
10731	1979-05-09	1979	0.734694	Denmark	Sweden	24	27	-3
20254	1997-04-02	1997	0.857143	Scotland	Austria	37	47	-10
5017	1962-03-28	1962	0.619048	Argentina	Mexico	7	16	-9
38447	2017-03-22	2017	0.993197	Curaçao	El Salvador	209	99	110
18390	1994-09-07	1994	0.836735	Georgia	Moldova	93	149	-56

In [25]:
```
df_matches.to_pickle("datasets/matches_data.pkl")
```

Add Feature: Team's overall player strength

In [26]:
```
df_players = pd.read_pickle("datasets/sofifa_players.pkl")
df_players_grouped = df_players.groupby(["year","team"]).agg({"age":np
.mean,"overall":np.mean}).copy()
df_players_grouped = df_players_grouped.reset_index()
df_players_grouped.columns = ["year","team","age_mean","overall_mean"]
df_players_grouped["age_wt"] = df_players_grouped["age_mean"] - df_pla
yers_grouped["age_mean"].mean()
df_players_grouped["perf_wt"] = df_players_grouped["overall_mean"] - d
f_players_grouped["overall_mean"].mean()
df_matches.to_pickle("datasets/df_players_grouped.pkl")

def get_home_player_agewt(data_row):
    age_wt = list(df_players_grouped[(df_players_grouped.year==data_ro
w["year"])&(df_players_grouped.team==data_row["home_team"])]["age_wt"]
)
    if len(age_wt) > 0:
        return age_wt[0]
    else:
        return 0

def get_away_player_agewt(data_row):
    age_wt = list(df_players_grouped[(df_players_grouped.year==data_ro
w["year"])&(df_players_grouped.team==data_row["away_team"])]["age_wt"]
)
    if len(age_wt) > 0:
        return age_wt[0]
    else:
```

```
        return 0

def get_home_player_prfwt(data_row):
    prf_wt = list(df_players_grouped[(df_players_grouped.year==data_ro
w["year"])&(df_players_grouped.team==data_row["home_team"])]["perf_wt"
])
    if len(prf_wt) > 0:
        return prf_wt[0]
    else:
        return 0

def get_away_player_prfwt(data_row):
    prf_wt = list(df_players_grouped[(df_players_grouped.year==data_ro
w["year"])&(df_players_grouped.team==data_row["away_team"])]["perf_wt"
])
    if len(prf_wt) > 0:
        return prf_wt[0]
    else:
        return 0

df_matches['home_p_age_wt'] = df_matches.apply(get_home_player_agewt,
axis=1)
df_matches['away_p_age_wt'] = df_matches.apply(get_away_player_agewt,
axis=1)
df_matches['home_p_prf_wt'] = df_matches.apply(get_home_player_prfwt,
axis=1)
df_matches['away_p_prf_wt'] = df_matches.apply(get_away_player_prfwt,
axis=1)

df_matches.sample(20)
```

Out[26]:

	date	year	year_wt	home_team	away_team	home_rank	away_rank	rank_d
34018	2012-06-12	2012	0.959184	Bahrain	Kuwait	97	96	1
27083	2004-12-17	2004	0.904762	Bahrain	Saudi Arabia	64	30	34
10103	1977-07-03	1977	0.721088	Argentina	Yugoslavia	7	46	-39
13721	1985-07-14	1985	0.775510	Fiji	Tahiti	155	163	-8
14095	1986-05-28	1986	0.782313	China	Iran	209	209	0
14103	1986-06-02	1986	0.782313	Russia	Hungary	27	62	-35
28883	2007-03-24	2007	0.925170	Austria	Ghana	94	47	47

3543	1954-03-21	1954	0.564626	Israel	Yugoslavia	60	46	14
30184	2008-06-14	2008	0.931973	Malawi	Egypt	138	35	103
17474	1993-04-13	1993	0.829932	Vietnam	Singapore	135	75	60
11854	1981-09-23	1981	0.748299	Portugal	Poland	12	44	-32
36776	2015-06-11	2015	0.979592	Spain	Costa Rica	9	42	-33
21007	1998-02-16	1998	0.863946	South Africa	Namibia	36	81	-45
31985	2010-06-16	2010	0.945578	Spain	Switzerland	2	26	-24
31474	2009-10-10	2009	0.938776	France	Faroe Islands	9	185	-176
22786	2000-05-23	2000	0.877551	Lebanon	Iraq	114	89	25
16260	1991-02-20	1991	0.816327	France	Spain	9	6	3
24636	2002-05-18	2002	0.891156	Czech Republic	Italy	21	9	12
33137	2011-08-25	2011	0.952381	United Arab Emirates	Qatar	130	95	35
7154	1969-09-24	1969	0.666667	Turkey	Switzerland	38	35	3

20 rows × 24 columns

Add Quadratic Terms, Normalize Predictors, Build Train & Test Datasets

In [27]:

```
df_matches.to_pickle("datasets/matches_data.pkl")
df_matches = pd.read_pickle("datasets/matches_data.pkl")
df_matches["result"] = df_matches["result"].replace(2,0)
```

```
all_features = ['date', 'year', 'year_wt', 'home_team', 'away_team', '
home_rank',
                'away_rank', 'rank_diff', 'home_score', 'away_score',
'net_score',
                'result', 'tournament', 'city', 'country', 'neutral',
'home_wc_pts',
                'away_wc_pts', 'home_wc_plays', 'away_wc_plays', 'home
_p_age_wt',
                'away_p_age_wt', 'home_p_prf_wt', 'away_p_prf_wt']

final_features = ["year_wt","home_team","away_team","home_rank","away_
rank",
                    "neutral","home_wc_pts","away_wc_pts","home_wc_pla
ys",
                    "away_wc_plays","home_p_age_wt","away_p_age_wt",
                    "home_p_prf_wt","away_p_prf_wt","result"]

df_final =  df_matches[df_matches.year >= 2006][final_features]

scaler = MinMaxScaler(copy=True, feature_range=(0, 1)).fit(df_final["h
ome_rank"].values.reshape(-1,1))
df_final["home_rank"] = scaler.transform(df_final["home_rank"].values.
reshape(-1,1))
df_final["home_rank"] = abs(df_final["home_rank"]-1)

scaler = MinMaxScaler(copy=True, feature_range=(0, 1)).fit(df_final["a
way_rank"].values.reshape(-1,1))
df_final["away_rank"] = scaler.transform(df_final["away_rank"].values.
reshape(-1,1))
df_final["away_rank"] = abs(df_final["away_rank"]-1)

scaler = MinMaxScaler(copy=True, feature_range=(0, 1)).fit(df_final["h
ome_wc_pts"].values.reshape(-1,1))
df_final["home_wc_pts"] = scaler.transform(df_final["home_wc_pts"].val
ues.reshape(-1,1))

scaler = MinMaxScaler(copy=True, feature_range=(0, 1)).fit(df_final["a
way_wc_pts"].values.reshape(-1,1))
df_final["away_wc_pts"] = scaler.transform(df_final["away_wc_pts"].val
ues.reshape(-1,1))

scaler = MinMaxScaler(copy=True, feature_range=(0, 1)).fit(df_final["h
ome_wc_plays"].values.reshape(-1,1))
df_final["home_wc_plays"] = scaler.transform(df_final["home_wc_plays"]
.values.reshape(-1,1))

scaler = MinMaxScaler(copy=True, feature_range=(0, 1)).fit(df_final["a
way_wc_plays"].values.reshape(-1,1))
df_final["away_wc_plays"] = scaler.transform(df_final["away_wc_plays"]
.values.reshape(-1,1))

scaler = MinMaxScaler(copy=True, feature_range=(-1, 1)).fit(df_final["
home_p_age_wt"].values.reshape(-1,1))
```

```
df_final["home_p_age_wt"] = scaler.transform(df_final["home_p_age_wt"]
.values.reshape(-1,1))

scaler = MinMaxScaler(copy=True, feature_range=(-1, 1)).fit(df_final["
away_p_age_wt"].values.reshape(-1,1))
df_final["away_p_age_wt"] = scaler.transform(df_final["away_p_age_wt"]
.values.reshape(-1,1))

scaler = MinMaxScaler(copy=True, feature_range=(-1, 1)).fit(df_final["
home_p_prf_wt"].values.reshape(-1,1))
df_final["home_p_prf_wt"] = scaler.transform(df_final["home_p_prf_wt"]
.values.reshape(-1,1))

scaler = MinMaxScaler(copy=True, feature_range=(-1, 1)).fit(df_final["
away_p_prf_wt"].values.reshape(-1,1))
df_final["away_p_prf_wt"] = scaler.transform(df_final["away_p_prf_wt"]
.values.reshape(-1,1))

df_final["home_p_age_wt_2"] = df_final["home_p_age_wt"]**2
df_final["away_p_age_wt_2"] = df_final["away_p_age_wt"]**2
df_final["home_p_prf_wt_2"] = df_final["home_p_prf_wt"]**2
df_final["away_p_prf_wt_2"] = df_final["away_p_prf_wt"]**2

df_final["home_p_age_wt_3"] = df_final["home_p_age_wt"]**3
df_final["away_p_age_wt_3"] = df_final["away_p_age_wt"]**3
df_final["home_p_prf_wt_3"] = df_final["home_p_prf_wt"]**3
df_final["away_p_prf_wt_3"] = df_final["away_p_prf_wt"]**3

df_final["home_p_age_perf_wt"] = df_final["home_p_age_wt"] * df_final[
"home_p_prf_wt"]
df_final["away_p_age_perf_wt"] = df_final["away_p_age_wt"] * df_final[
"away_p_prf_wt"]

df_final = pd.get_dummies(df_final)
x_df_final = df_final.drop(["result"], axis=1).copy()
y_df_final = df_final["result"].copy()

X_train, X_test, y_train, y_test = train_test_split(x_df_final, y_df_f
inal, test_size=0.1, random_state=42)

print(X_train.shape, X_test.shape, y_train.shape, y_test.shape)
```

```
(10571, 576) (1175, 576) (10571,) (1175,)
```

```
/Volumes/Data/ramandeepharjai/anaconda3/envs/ds/lib/python3.6/site-p
ackages/sklearn/utils/validation.py:475: DataConversionWarning: Data
with input dtype int64 was converted to float64 by MinMaxScaler.
  warnings.warn(msg, DataConversionWarning)
```

Building Models

- ### Single Models
  - *Logistic Regression*
  - *Linear Discriminant Analysis*
  - *Quadratic Discriminant Analysis*
  - *K-Nearest Neighbors*
  - *Decision Tree Classifier*
- ### Ensemble Models
  - *Random Forest Classifier*
  - *AdaBoost Classifier*
  - *Stacking*
- ### Neural Network

In [28]:
```
# defining dictionary objects to store -
#     * tuned models
#     * predictions obtained from tuned models
#     * probabilities obtained from tuned models
#     * execution time to train the model

# uncomment below lines to build the dictionaries again
# models = {}
# probs = {}
# scores = {}
# exeTime = {}
```

Logistic Regression

In [32]:
```
modelName = "logistic"

# build parameters list to find best parameter values
parameters = {
    'C':[.01, 1, 10, 100, 1000],
    'solver':['newton-cg', 'lbfgs', 'sag'],
    'fit_intercept':[True,False]
}

# build base estimator model, and run GridSearchCV to find best model
start_time = time.time()
model = LogisticRegression(penalty="l2", max_iter=1000)
gs = GridSearchCV(estimator=model, param_grid=parameters, cv=5, n_jobs
=4, verbose=1).fit(X_train, y_train)
exe_time = round((time.time() - start_time)/60, 2)

# compute scores, and probabilities
train_score = round(accuracy_score(y_train, gs.predict(X_train)),4)
test_score = round(accuracy_score(y_test, gs.predict(X_test)),4)
train_prob = gs.predict_proba(X_train)
test_prob = gs.predict_proba(X_test)

# store model, score, and probabilities in a dictionary
exeTime.update({modelName:exe_time})
scores.update({modelName:[train_score,test_score]})
probs.update({modelName:[train_prob,test_prob]})
models.update({modelName:gs.best_estimator_})

# display scores and best model
print("[Logistic Regression]")
print("Execution time : {} minutes".format(exe_time))
print("Train Accuracy : {:>0.4f}".format(train_score))
print("Test Accuracy  : {:>0.4f}".format(test_score))
print("\nBest Model:\n", gs.best_estimator_)
```

```
[Logistic Regression]
Execution time : 4.32 minutes
Train Accuracy : 0.7409
Test Accuracy  : 0.7106

Best Model:
 LogisticRegression(C=1, class_weight=None, dual=False, fit_intercep
t=False,
          intercept_scaling=1, max_iter=1000, multi_class='ovr', n_j
obs=1,
          penalty='l2', random_state=None, solver='lbfgs', tol=0.000
1,
          verbose=0, warm_start=False)
```

Linear Discriminant Analysis

In [33]:
```
modelName = "lda"

# build parameters list to find best parameter values
parameters = {
    'shrinkage':[.001, .01, .1, 1],
    'solver':['lsqr', 'eigen']
}

# build base estimator model, and run GridSearchCV to find best model
start_time = time.time()
model = LinearDiscriminantAnalysis()
gs = GridSearchCV(estimator=model, param_grid=parameters, cv=5, n_jobs
=4, verbose=1).fit(X_train, y_train)
exe_time = round((time.time() - start_time)/60, 2)

# compute scores, and probabilities
train_score = round(accuracy_score(y_train, gs.predict(X_train)),4)
test_score = round(accuracy_score(y_test, gs.predict(X_test)),4)
train_prob = gs.predict_proba(X_train)
test_prob = gs.predict_proba(X_test)

# store model, score, and probabilities in a dictionary
exeTime.update({modelName:exe_time})
scores.update({modelName:[train_score,test_score]})
probs.update({modelName:[train_prob,test_prob]})
models.update({modelName:gs.best_estimator_})

# display scores and best model
print("[Linear Discriminant Analysis]")
print("Execution time : {} minutes".format(exe_time))
print("Train Accuracy : {:>0.4f}".format(train_score))
print("Test Accuracy  : {:>0.4f}".format(test_score))
print("\nBest Model:\n", gs.best_estimator_)

# save dictionaries to disk
np.save("datasets/dict_models.npy", models)
np.save("datasets/dict_scores.npy", scores)
np.save("datasets/dict_probs.npy", probs)
np.save("datasets/dict_exeTime.npy", exeTime)
```

```
Fitting 5 folds for each of 8 candidates, totalling 40 fits

[Parallel(n_jobs=4)]: Done  40 out of  40 | elapsed:    4.1s finishe
d

[Linear Discriminant Analysis]
Execution time : 0.07 minutes
Train Accuracy : 0.7405
Test Accuracy  : 0.7140

Best Model:
 LinearDiscriminantAnalysis(n_components=None, priors=None, shrinkag
e=0.1,
              solver='lsqr', store_covariance=False, tol=0.0001)
```

Quadratic Discriminant Analysis

In [36]:
```
modelName = "qda"

# build parameters list to find best parameter values
parameters = {
    'reg_param':[.001, .01, .1, 1]
}

# build base estimator model, and run GridSearchCV to find best model
start_time = time.time()
model = QuadraticDiscriminantAnalysis()
gs = GridSearchCV(estimator=model, param_grid=parameters, cv=5, n_jobs
=4, verbose=1).fit(X_train, y_train)
exe_time = round((time.time() - start_time)/60, 2)

# compute scores, and probabilities
train_score = round(accuracy_score(y_train, gs.predict(X_train)),4)
test_score = round(accuracy_score(y_test, gs.predict(X_test)),4)
train_prob = gs.predict_proba(X_train)
test_prob = gs.predict_proba(X_test)

# store model, score, and probabilities in a dictionary
exeTime.update({modelName:exe_time})
scores.update({modelName:[train_score,test_score]})
probs.update({modelName:[train_prob,test_prob]})
models.update({modelName:gs.best_estimator_})

# display scores and best model
print("[Quadratic Discriminant Analysis]")
print("Execution time : {} minutes".format(exe_time))
print("Train Accuracy : {:>0.4f}".format(train_score))
print("Test Accuracy  : {:>0.4f}".format(test_score))
print("\nBest Model:\n", gs.best_estimator_)

# save dictionaries to disk
np.save("datasets/dict_models.npy", models)
np.save("datasets/dict_scores.npy", scores)
np.save("datasets/dict_probs.npy", probs)
np.save("datasets/dict_exeTime.npy", exeTime)
```

```
[Quadratic Discriminant Analysis]
Execution time : 0.15 minutes
Train Accuracy : 0.7086
Test Accuracy  : 0.6868

Best Model:
 QuadraticDiscriminantAnalysis(priors=None, reg_param=0.1,
               store_covariance=False, store_covariances=None, tol=0
.0001)
```

K-Nearest Neighbors

In [37]:
```
modelName = "knn"

# build parameters list to find best parameter values
parameters = {
    'n_neighbors':[10, 20, 40, 60],
    'weights':['uniform','distance'],
    'algorithm':['ball_tree','kd_tree']
}

# build base estimator model, and run GridSearchCV to find best model
start_time = time.time()
model = KNeighborsClassifier()
gs = GridSearchCV(estimator=model, param_grid=parameters, cv=5, n_jobs
=4, verbose=1).fit(X_train, y_train)
exe_time = round((time.time() - start_time)/60, 2)

# compute scores, and probabilities
train_score = round(accuracy_score(y_train, gs.predict(X_train)),4)
test_score = round(accuracy_score(y_test, gs.predict(X_test)),4)
train_prob = gs.predict_proba(X_train)
test_prob = gs.predict_proba(X_test)

# store model, score, and probabilities in a dictionary
exeTime.update({modelName:exe_time})
scores.update({modelName:[train_score,test_score]})
probs.update({modelName:[train_prob,test_prob]})
models.update({modelName:gs.best_estimator_})

# display scores and best model
print("[K-Nearest Neighbors]")
print("Execution time : {} minutes".format(exe_time))
print("Train Accuracy : {:>0.4f}".format(train_score))
print("Test Accuracy  : {:>0.4f}".format(test_score))
print("\nBest Model:\n", gs.best_estimator_)

# save dictionaries to disk
np.save("datasets/dict_models.npy", models)
np.save("datasets/dict_scores.npy", scores)
np.save("datasets/dict_probs.npy", probs)
np.save("datasets/dict_exeTime.npy", exeTime)
```

```
Fitting 5 folds for each of 16 candidates, totalling 80 fits

[Parallel(n_jobs=4)]: Done  42 tasks      | elapsed: 16.1min
[Parallel(n_jobs=4)]: Done  80 out of  80 | elapsed: 29.1min finishe
d

[K-Nearest Neighbors]
Execution time : 29.1 minutes
Train Accuracy : 0.9886
Test Accuracy  : 0.6528

Best Model:
 KNeighborsClassifier(algorithm='kd_tree', leaf_size=30, metric='min
kowski',
           metric_params=None, n_jobs=1, n_neighbors=20, p=2,
           weights='distance')
```

Decision Tree Classifier

In [38]:

```
modelName = "dtc"

# build parameters list to find best parameter values
parameters = {
    'criterion':['gini','entropy'],
    'splitter':['best','random'],
    'max_depth':[5,10,50,30,60]
}

# build base estimator model, and run GridSearchCV to find best model
start_time = time.time()
model = DecisionTreeClassifier()
gs = GridSearchCV(estimator=model, param_grid=parameters, cv=5, n_jobs
=4, verbose=1).fit(X_train, y_train)
exe_time = round((time.time() - start_time)/60, 2)

# compute scores, and probabilities
train_score = round(accuracy_score(y_train, gs.predict(X_train)),4)
test_score = round(accuracy_score(y_test, gs.predict(X_test)),4)
train_prob = gs.predict_proba(X_train)
test_prob = gs.predict_proba(X_test)

# store model, score, and probabilities in a dictionary
exeTime.update({modelName:exe_time})
scores.update({modelName:[train_score,test_score]})
probs.update({modelName:[train_prob,test_prob]})
models.update({modelName:gs.best_estimator_})

# display scores and best model
print("[Decision Tree Classifier]")
print("Execution time : {} minutes".format(exe_time))
print("Train Accuracy : {:>0.4f}".format(train_score))
print("Test Accuracy  : {:>0.4f}".format(test_score))
print("\nBest Model:\n", gs.best_estimator_)

# save dictionaries to disk
np.save("datasets/dict_models.npy", models)
np.save("datasets/dict_scores.npy", scores)
np.save("datasets/dict_probs.npy", probs)
np.save("datasets/dict_exeTime.npy", exeTime)
```

```
Fitting 5 folds for each of 20 candidates, totalling 100 fits

[Parallel(n_jobs=4)]: Done  42 tasks      | elapsed:    3.0s
[Parallel(n_jobs=4)]: Done 100 out of 100 | elapsed:    7.0s finishe
d

[Decision Tree Classifier]
Execution time : 0.12 minutes
Train Accuracy : 0.7034
Test Accuracy  : 0.6689

Best Model:
 DecisionTreeClassifier(class_weight=None, criterion='entropy', max_
depth=10,
            max_features=None, max_leaf_nodes=None,
            min_impurity_decrease=0.0, min_impurity_split=None,
            min_samples_leaf=1, min_samples_split=2,
            min_weight_fraction_leaf=0.0, presort=False, random_stat
e=None,
            splitter='random')
```

Ensemble Methods

Random Forest Classifier

In [39]:

```
modelName = "rfc"

# build parameters list to find best parameter values
parameters = {
    'n_estimators':[20,40,80,100,200],
    'criterion':['gini','entropy'],
    'max_depth':[5,10,50,30,60]
}

# build base estimator model, and run GridSearchCV to find best model
start_time = time.time()
model = RandomForestClassifier(bootstrap=True)
gs = GridSearchCV(estimator=model, param_grid=parameters, cv=5, n_jobs
=4, verbose=1).fit(X_train, y_train)
exe_time = round((time.time() - start_time)/60, 2)

# compute scores, and probabilities
train_score = round(accuracy_score(y_train, gs.predict(X_train)),4)
test_score = round(accuracy_score(y_test, gs.predict(X_test)),4)
train_prob = gs.predict_proba(X_train)
test_prob = gs.predict_proba(X_test)

# store model, score, and probabilities in a dictionary
exeTime.update({modelName:exe_time})
scores.update({modelName:[train_score,test_score]})
probs.update({modelName:[train_prob,test_prob]})
models.update({modelName:gs.best_estimator_})

# display scores and best model
print("[Random Forest Classifier]")
print("Execution time : {} minutes".format(exe_time))
print("Train Accuracy : {:>0.4f}".format(train_score))
print("Test Accuracy  : {:>0.4f}".format(test_score))
print("\nBest Model:\n", gs.best_estimator_)

# save dictionaries to disk
np.save("datasets/dict_models.npy", models)
np.save("datasets/dict_scores.npy", scores)
np.save("datasets/dict_probs.npy", probs)
np.save("datasets/dict_exeTime.npy", exeTime)
```

```
Fitting 5 folds for each of 50 candidates, totalling 250 fits

[Parallel(n_jobs=4)]: Done  42 tasks      | elapsed:    6.4s
[Parallel(n_jobs=4)]: Done 192 tasks      | elapsed:  1.5min
[Parallel(n_jobs=4)]: Done 250 out of 250 | elapsed:  2.4min finishe
d

[Random Forest Classifier]
Execution time : 2.49 minutes
Train Accuracy : 0.9501
Test Accuracy  : 0.6868

Best Model:
 RandomForestClassifier(bootstrap=True, class_weight=None, criterion
='entropy',
            max_depth=30, max_features='auto', max_leaf_nodes=None,
            min_impurity_decrease=0.0, min_impurity_split=None,
            min_samples_leaf=1, min_samples_split=2,
            min_weight_fraction_leaf=0.0, n_estimators=100, n_jobs=1
,
            oob_score=False, random_state=None, verbose=0,
            warm_start=False)
```

AdaBoost Classifier

In [41]:
```
modelName = "ada"

# build parameters list to find best parameter values
parameters = {
    'learning_rate':[0.001, 0.01, 0.1, 1],
    'n_estimators':[10,20,40,80,100]
}

# build base estimator model, and run GridSearchCV to find best model
start_time = time.time()
rf_model = RandomForestClassifier(bootstrap=True)
model = AdaBoostClassifier(base_estimator=rf_model)
gs = GridSearchCV(estimator=model, param_grid=parameters, cv=5, n_jobs
=4, verbose=1).fit(X_train, y_train)
exe_time = round((time.time() - start_time)/60, 2)

# compute scores, and probabilities
train_score = round(accuracy_score(y_train, gs.predict(X_train)),4)
test_score = round(accuracy_score(y_test, gs.predict(X_test)),4)
train_prob = gs.predict_proba(X_train)
test_prob = gs.predict_proba(X_test)

# store model, score, and probabilities in a dictionary
exeTime.update({modelName:exe_time})
scores.update({modelName:[train_score,test_score]})
probs.update({modelName:[train_prob,test_prob]})
models.update({modelName:gs.best_estimator_})

# display scores and best model
print("[Random Forest Classifier]")
print("Execution time : {} minutes".format(exe_time))
print("Train Accuracy : {:>0.4f}".format(train_score))
print("Test Accuracy  : {:>0.4f}".format(test_score))
print("\nBest Model:\n", gs.best_estimator_)

# save dictionaries to disk
np.save("datasets/dict_models.npy", models)
np.save("datasets/dict_scores.npy", scores)
np.save("datasets/dict_probs.npy", probs)
np.save("datasets/dict_exeTime.npy", exeTime)
```

```
Fitting 5 folds for each of 20 candidates, totalling 100 fits

[Parallel(n_jobs=4)]: Done  42 tasks      | elapsed:  3.5min
[Parallel(n_jobs=4)]: Done 100 out of 100 | elapsed:  9.0min finishe
d

[Random Forest Classifier]
Execution time : 9.61 minutes
Train Accuracy : 0.9886
Test Accuracy  : 0.6621

Best Model:
 AdaBoostClassifier(algorithm='SAMME.R',
          base_estimator=RandomForestClassifier(bootstrap=True, clas
s_weight=None, criterion='gini',
            max_depth=None, max_features='auto', max_leaf_nodes=None
,
            min_impurity_decrease=0.0, min_impurity_split=None,
            min_samples_leaf=1, min_samples_split=2,
            min_weight_fraction_leaf=0.0, n_estimators=10, n_jobs=1,
            oob_score=False, random_state=None, verbose=0,
            warm_start=False),
          learning_rate=0.001, n_estimators=100, random_state=None)
```

Neural Network

In [48]:

```
X = X_train.copy(deep=True).reset_index(drop=True)
Y = y_train.copy().values.reshape(-1,1)

counter=1
nn_cvscores=[]
kfold = StratifiedKFold(n_splits=10, shuffle=True, random_state=42)
start_time = time.time()
for train, test in kfold.split(X, Y):
    print("KFold: {}".format(counter), end="\r")
    nn_model = Sequential([
        Dense(576, input_shape=(576,), kernel_initializer='normal', ac
tivation='relu'),
        Dense(144, kernel_initializer='normal', activation='relu'),
        Dense(36, kernel_initializer='normal', activation='relu'),
        Dense(9, kernel_initializer='normal', activation='relu'),
        Dense(1, kernel_initializer='normal', activation='sigmoid')
    ])
    nn_model.compile(loss='binary_crossentropy', optimizer='adam', met
rics=['accuracy'])
    mfit = nn_model.fit(X.iloc[train], Y[train], epochs=50, validation
_split=0.2, shuffle=True, verbose=0)
    nn_scores = nn_model.evaluate(X.iloc[test], Y[test], verbose=0)
    nn_score = round(nn_scores[1],4)
    nn_cvscores.append(nn_score)
    counter+=1
end_time = time.time()
exe_time = round((end_time - start_time)/60, 2)

# compute scores, and probabilities
nn_train_score = round(accuracy_score(y_train, nn_model.predict_classe
s(X_train)),4)
nn_test_score = round(accuracy_score(y_test, nn_model.predict_classes(
X_test)),4)

# store model, score, and probabilities in a dictionary
exeTime.update({'nn':exe_time})
scores.update({'nn':[train_score,test_score]})

# display scores and best model
print("[Neural Network]")
print("Execution time : {} minutes".format(exe_time))
print("Train Accuracy : {:>0.4f}".format(nn_train_score))
print("Test Accuracy  : {:>0.4f}".format(nn_test_score))
print(nn_model.summary())
```

```
[Neural Network]
Execution time : 9.49 minutes
Train Accuracy : 0.8821
Test Accuracy  : 0.6638
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
dense_96 (Dense)             (None, 576)               332352    
_________________________________________________________________
dense_97 (Dense)             (None, 144)               83088     
_________________________________________________________________
dense_98 (Dense)             (None, 36)                5220      
_________________________________________________________________
dense_99 (Dense)             (None, 9)                 333       
_________________________________________________________________
dense_100 (Dense)            (None, 1)                 10        
=================================================================
Total params: 421,003
Trainable params: 421,003
Non-trainable params: 0
_________________________________________________________________
None
```

Stacking - Baged Models (Bootstrapped n=25)

Stacking 25-bagged (Logistic, LDA, QDA, KNN, Decision Tree, Random Forest, and ADABoost) models, and taking a popular vote

In [43]:
```
stacked_results = pd.DataFrame()

N=25
all_results = {}
for model in models.keys():
    counter = 1
    print("[{}]: computing bootstraped results...".format(model))
    train_results=[]
    test_results=[]
    for i in range(N):
        X, y = resample(X_train, y_train)
        fit = models[model].fit(X, y)
        train_results.append(round(accuracy_score(y, fit.predict(X)),4
))
        test_results.append(round(accuracy_score(y_test, fit.predict(X
_test)),4))
        colname = model + "." + str(counter)
        stacked_results[colname] = fit.predict(X_test)
        counter+=1
    all_results.update({model:[train_results, test_results]})

def popular_vote(row):
    if row.mean() >= 0.5:
        return 1
    else:
        return 0

stacked_results["results"] = stacked_results.apply(popular_vote, axis=
1)
st_train_score = round(np.mean(train_results),4)
st_test_score = round(accuracy_score(y_test, stacked_results["results"
]),4)
print("Train Accuracy  : {:>0.4f}".format(st_train_score))
print("Test Accuracy  : {:>0.4f}".format(st_test_score))
stacked_results.sample(10)
```

```
[logistic]: computing bootstraped results...
[lda]: computing bootstraped results...
[qda]: computing bootstraped results...
```

```
/Volumes/Data/ramandeepharjai/anaconda3/envs/ds/lib/python3.6/site-p
ackages/sklearn/discriminant_analysis.py:682: UserWarning: Variables
are collinear
  warnings.warn("Variables are collinear")
```

```
[knn]: computing bootstraped results...
[dtc]: computing bootstraped results...
[rfc]: computing bootstraped results...
[ada]: computing bootstraped results...
Train Accuracy  : 0.9944
Test Accuracy  : 0.7013
```

Out[43]:

	logistic.1	logistic.2	logistic.3	logistic.4	logistic.5	logistic.6	logistic.7	logistic.8
884	0	0	0	0	0	0	0	0
1137	0	0	0	0	0	0	0	0
407	0	0	0	0	0	0	0	0
676	0	0	0	0	0	0	0	0
48	0	0	0	0	0	0	0	0
1043	0	0	0	0	0	0	0	0
892	0	0	0	0	0	0	0	0
858	1	1	1	1	1	1	1	1
531	1	1	1	1	1	1	1	1
793	1	1	1	1	1	1	1	1

10 rows × 176 columns

In [ ]:

```
# save dataframe, and dictionaries to disk
# which are used for final predictions
np.save("datasets/dict_models_final.npy", models)
X_test.to_pickle("datasets/X_test_final.pkl")
df_matches.to_pickle("datasets/matches_data_final.pkl")
```

Model Comparision

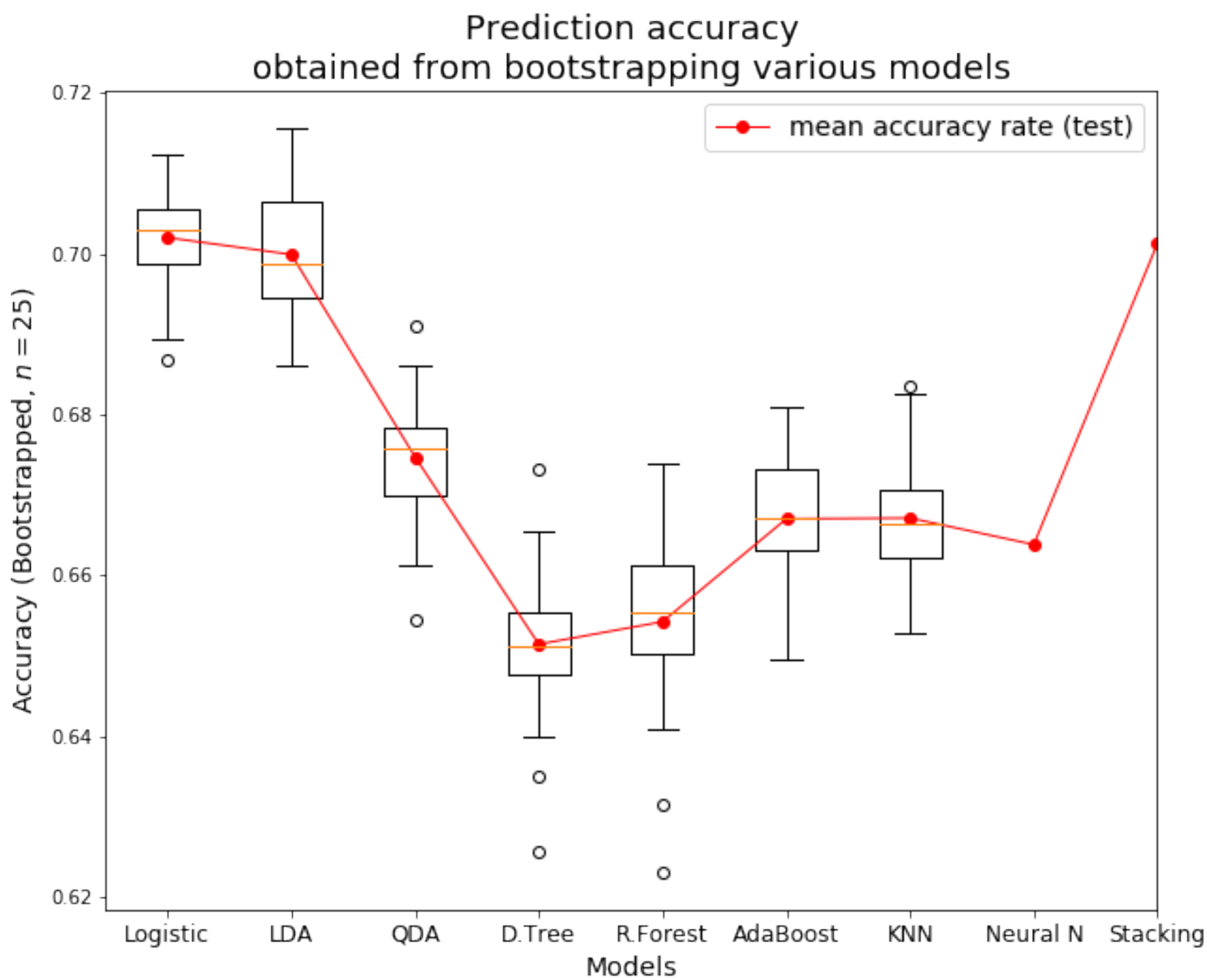
In [65]:
```
all_test_results=[]
test_means=[]
train_means=[]

print("|-----------------------------------------|")
print("| {:<9} | {:>12} | {:>12} |".format("model", "train (mean)", "t
est (mean)"))
print("|-----------------------------------------|")
print("| {:<9} | {:>12} | {:>12} |".format("stacking", st_train_score,
st_test_score))
print("| {:<9} | {:>12} | {:>12} |".format("neural n.", nn_train_score
, nn_test_score))
for key in all_results.keys():
    all_test_results.append(all_results[key][1])
    trainmean = round(np.mean(all_results[key][0]),4)
    testmean = round(np.mean(all_results[key][1]),4)
    test_means.append(testmean)
    train_means.append(trainmean)
    print("| {:<9} | {:>12} | {:>12} |".format(key, trainmean, testmea
n))
print("|-----------------------------------------|")

test_means.append(nn_test_score)
test_means.append(st_test_score)
fig, ax = plt.subplots(1,1, figsize=(10,8))
ax.set_title("Prediction accuracy\nobtained from bootstrapping various
models", fontsize=18)
ax.boxplot(all_test_results)
ax.plot(range(1,10), test_means, marker="o", lw=1, ls="solid", c="red"
, label="mean accuracy rate (test)")
ax.set_xlabel("Models", fontsize=14)
ax.set_ylabel("Accuracy (Bootstrapped, $n=25$)", fontsize=14)
ax.set_xticks(range(1,10))
ax.set_xticklabels(['Logistic', 'LDA', 'QDA', 'D.Tree', 'R.Forest', 'A
daBoost', 'KNN', 'Neural N', 'Stacking'], fontsize=12)
ax.legend(loc=1, fontsize=14)
```

```
|--------------------------------------------|
| model       | train (mean) |  test (mean) |
|--------------------------------------------|
| stacking    |       0.9944 |       0.7013 |
| neural n.   |       0.8821 |       0.6638 |
| logistic    |       0.7578 |        0.702 |
| lda         |       0.7538 |       0.6999 |
| qda         |       0.7343 |       0.6747 |
| knn         |       0.9941 |       0.6514 |
| dtc         |        0.725 |       0.6542 |
| rfc         |       0.9685 |        0.667 |
| ada         |       0.9944 |       0.6671 |
|--------------------------------------------|
```

```
Out[65]: <matplotlib.legend.Legend at 0x1a5f3b7358>
```



Final Predictions

FIFA World-Cup 2018 - Round-16, Quater Final, Semi Final, and Final matches

In [66]:
```
# load final dataset and tuned models
models = np.load("datasets/dict_models_final.npy").item()
df_matches = pd.read_pickle("datasets/matches_data_final.pkl")
X_test = pd.read_pickle("datasets/X_test.pkl")

def design_match_data(teams):
        home_team = teams[0]
        away_team = teams[1]
        X = pd.DataFrame(list(np.zeros((1,576))), columns=X_test.colum
ns)

        # set predictors
        X["year_wt"]=1
        X["home_rank"]=df_matches[(df_matches.home_team==home_team)&(d
f_matches.year==2018)].iloc[0]["home_rank"]
        X["away_rank"]=df_matches[(df_matches.home_team==away_team)&(d
f_matches.year==2018)].iloc[0]["home_rank"]

        if home_team != "Russia":
            X["neutral"]=0
        else:
            X["neutral"]=1

        X["home_wc_pts"]=df_matches[(df_matches.home_team==home_team)&
(df_matches.year==2018)].iloc[0]["home_wc_pts"]
        X["away_wc_pts"]=df_matches[(df_matches.home_team==away_team)&
(df_matches.year==2018)].iloc[0]["away_wc_pts"]
        X["home_wc_plays"]=df_matches[(df_matches.home_team==home_team
)&(df_matches.year==2018)].iloc[0]["home_wc_plays"]
        X["away_wc_plays"]=df_matches[(df_matches.home_team==away_team
)&(df_matches.year==2018)].iloc[0]["away_rank"]

        home_p_age_wt = df_matches[(df_matches.home_team==home_team)&(
df_matches.year==2018)].iloc[0]["home_p_age_wt"]
        home_p_prf_wt = df_matches[(df_matches.home_team==home_team)&(
df_matches.year==2018)].iloc[0]["home_p_prf_wt"]
        away_p_age_wt = df_matches[(df_matches.home_team==away_team)&(
df_matches.year==2018)].iloc[0]["away_p_age_wt"]
        away_p_prf_wt = df_matches[(df_matches.home_team==away_team)&(
df_matches.year==2018)].iloc[0]["away_p_prf_wt"]
        X["home_p_age_wt"]=home_p_age_wt
        X["away_p_age_wt"]=away_p_age_wt
```

```
        X["home_p_prf_wt"]=home_p_prf_wt
        X["away_p_prf_wt"]=away_p_prf_wt
        X["home_p_age_wt_2"]=home_p_age_wt**2
        X["away_p_age_wt_2"]=away_p_age_wt**2
        X["home_p_prf_wt_2"]=home_p_prf_wt**2
        X["away_p_prf_wt_2"]=away_p_prf_wt**2
        X["home_p_age_wt_3"]=home_p_age_wt**3
        X["away_p_age_wt_3"]=away_p_age_wt**3
        X["home_p_prf_wt_3"]=home_p_prf_wt**3
        X["away_p_prf_wt_3"]=away_p_prf_wt**3
        X["home_p_age_perf_wt"]=home_p_age_wt*home_p_prf_wt
        X["away_p_age_perf_wt"]=away_p_age_wt*away_p_prf_wt

        # set dummy variables for home & away teams
        home_col = "home_team_" + home_team
        away_col = "away_team_" + away_team
        X[home_col] = 1
        X[away_col] = 1

        # return dataset
        return X

def predict_outcome(match):
    X = design_match_data(match)
    p_results = []
    for key in models.keys():
        p_results.append(models[key].predict(X)[0])
    return p_results

def popular_win(arr,boundry):
    if boundry==0: decision = 0.4
    if boundry==1: decision = 0.5
    if boundry==2: decision = 0.6
    if np.mean(arr) >= decision: return 0
    else: return 1

# FIFA World Cup 2018 - Round-16 Match line-up
round16_matches = [['Uruguay','Portugal'], ['France','Argentina'], ['B
razil','Mexico'], ['Japan','Belgium'],
                   ['Spain','Russia'], ['Denmark','Croatia'], ['Sweden
','Switzerland'], ['Colombia','England']]
round16_results = []
qfinal_matches = []
qfinal_results = []
sfinal_matches=[]
sfinal_results=[]
final_match=[]
final_result=[]
msg="{:<12}  :  {:<8}  -vs-  {:<11}  :  {:<10} wins"

print("\nFINAL PREDICTIONS")
print("-----------------\n")
```

```python
# predict Round-16 outcome
for match in round16_matches:
    winner = match[popular_win(predict_outcome(match),0)]
    round16_results.append(winner)
    print(msg.format("Round 16", match[0], match[1], winner))

# predict Quater-Final outcome
print("\n")
qfinal_matches = [[round16_results[0],round16_results[1]], [round16_re
sults[2],round16_results[3]],
                  [round16_results[4],round16_results[5]], [round16_re
sults[6],round16_results[7]]]
for match in qfinal_matches:
    winner = match[popular_win(predict_outcome(match),2)]
    qfinal_results.append(winner)
    print(msg.format("Quater Final", match[0], match[1], winner))

# predict Semi-Final outcome
print("\n")
sfinal_matches = [[qfinal_results[0],qfinal_results[1]], [qfinal_resul
ts[3],qfinal_results[2]]]
for match in sfinal_matches:
    winner = match[popular_win(predict_outcome(match),0)]
    sfinal_results.append(winner)
    print(msg.format("Semi Final", match[0], match[1], winner))

# predict Final outcome
print("\n")
final_match = [[sfinal_results[0],sfinal_results[1]]]
for match in final_match:
    winner = match[popular_win(predict_outcome(match),0)]
    final_result.append(winner)
    print(msg.format("Final", match[0], match[1], winner))



# draw results graph
img = Image.open("fig/ALPEOs0.jpg")
draw = ImageDraw.Draw(img)
font = ImageFont.truetype("fig/Roboto-Regular.ttf", 20)
draw.text((150, 200),round16_results[0],(139,0,0),font=font)
draw.text((150, 365),round16_results[1],(139,0,0),font=font)
draw.text((150, 530),round16_results[2],(139,0,0),font=font)
draw.text((150, 700),round16_results[3],(139,0,0),font=font)
draw.text((770, 200),round16_results[4],(139,0,0),font=font)
draw.text((770, 365),round16_results[5],(139,0,0),font=font)
draw.text((770, 530),round16_results[6],(139,0,0),font=font)
draw.text((770, 700),round16_results[7],(139,0,0),font=font)
draw.text((280, 282),qfinal_results[0],(139,0,0),font=font)
draw.text((280, 642),qfinal_results[1],(139,0,0),font=font)
draw.text((630, 282),qfinal_results[2],(139,0,0),font=font)
draw.text((630, 642),qfinal_results[3],(139,0,0),font=font)
draw.text((220, 465),sfinal_results[0],(139,0,0),font=font)
draw.text((680, 465),sfinal_results[1],(139,0,0),font=font)
```

```
draw.text((460, 465),final_result[0],(139,0,0),font=font)
img.save('fig/output.jpg')
img.show()
```

```
FINAL PREDICTIONS
-----------------

Round 16      :  Uruguay   -vs-  Portugal     :  Uruguay    wins
Round 16      :  France    -vs-  Argentina    :  France     wins
Round 16      :  Brazil    -vs-  Mexico       :  Brazil     wins
Round 16      :  Japan     -vs-  Belgium      :  Belgium    wins
Round 16      :  Spain     -vs-  Russia       :  Russia     wins
Round 16      :  Denmark   -vs-  Croatia      :  Croatia    wins
Round 16      :  Sweden    -vs-  Switzerland  :  Sweden     wins
Round 16      :  Colombia  -vs-  England      :  England    wins


Quater Final  :  Uruguay   -vs-  France       :  France     wins
Quater Final  :  Brazil    -vs-  Belgium      :  Belgium    wins
Quater Final  :  Russia    -vs-  Croatia      :  Croatia    wins
Quater Final  :  Sweden    -vs-  England      :  England    wins


Semi Final    :  France    -vs-  Belgium      :  France     wins
Semi Final    :  England   -vs-  Croatia      :  Croatia    wins


Final         :  France    -vs-  Croatia      :  France     wins
```


CBS SPORTS
2018 WORLD CUP BRACKET
ROUND 16
QUARTER FINALS
SEMI FINALS
FIFA WORLD CUP
RUSSIA 2018
SEMI FINALS
QUARTER FINALS
ROUND 16
URUGUAY
PORTUGAL
Uruguay
FRANCE
ARGENTINA
France
France
France
BRAZIL
MEXICO
Brazil
BELGIUM
JAPAN
Belgium
Belgium
France
CHAMPION
SPAIN
RUSSIA
Russia
CROATIA
DENMARK
Croatia
Croatia
Croatia
SWEDEN
SWITZERLAND
Sweden
COLOMBIA
ENGLAND
England
England