World Cup 2014 Predictions

There are four python files that are used by this notebook. They must be in the path. These are:

`match_stats`: Reads the match statistics from BigQuery. Because we are using the pre-aggregated data, most of the code here is disabled, but it is kept in order to show the data transformations that are done from the raw data in order to build the stats.

`features`: Turns raw statistics into features that get fed into the machine learning model. These features combine statistics from the trailing N games to predict the next game.

`world_cup`: Helper methods for cleaning the data and building and running the logistic regression model.

`power`: Computes a "power" statistic over a number of teams who have played against eachother, attempting to come up with a ranking.

Building features

This will return a pandas dataframe that contains the features that will be used to build a model.

The features query will read from the game summary table that has prepared per-game statistics that will be used to predict outcomes. The data has been aggregated from touch-by-touch data from Opta. However, since that data is not public, we use these prepared statistics instead of the raw data.

In order to predict a game, we look at the previous N games of history for each team, where N is defined here as `history_size`.

```
import world_cup
import features
import match_stats
import world_cup
import pandas as pd
history_size = 3

game_summaries = features.get_game_summaries()
data = features.get_features(history_size)
```

The features include rollups from the last K games. Most of them are averages that are computed per-minute of game time. Per-minute stats are used in order to be able to normalize for games in the world cup that go into overtime. Feature columns:

The following columns are the features that will be used to build the prediction model:

`is_home`: Whether a team is playing at home or away. This turns out to be a big deal in soccer.

avg_points: Average number of points (3 for a win, 1 for a draw, 0 for a loss) earned in the last K games.

avg_goals: Average number of goals scored in the last K games.

op_average_goals: Average number of goals scored by the opponent in the last K games.

pass_70/80: Number of completed passes per minute in the attacking 30%-20% of the field.

op_pass70/80: Number of completed passes by the opponent in their attacking 30%-20% of the field.

expected_goals: Average number of expected goals in the last K games, where expected goals is computed based on the number of shots taken and their distance from the goal.

passes: Number of passes completed per minute.

bad_passes: Number of passes that didn't complete successfully per minute.

pass_ratio: Percentage of completed passes.

corners: Number of corner kicks awareded per minute.

fouls: Number of fouls committed per minute.

cards: Number of cards recieved (red or yellow) per game.

shots: Number of shots taken per minute.

op_*: Statistics about the opponent in the historical games. This is not the opponent shown in op_team_name; instead, these stats show how the primary team's opponents have fared against them. For example, op_corners is how many corners the teams opponents have been awarded per minute.

*_op_ratio: Ratio of a team's statistics to their opponents.

Non-feature columns:

The following columns are included as metadata about the match:

matchid: Unique id for the match

teamid: Unique id for the team whose historical statistics we're looking at.

op_teamid: Unique id for the opposing team. None of these statistics reflect this opponent.

team_name: Name of the team whose historical statistics we're looking at.

op_team_name: Name of the opposing team.

timestamp: Time at which the game was played.

`competitionid`: Unique id for the competition (separates MLS from FIFA World CUP from EPL).

Target columns:

The following columns are target variables that we will be attempting to predict. These columns must be dropped before any prediction is done, but are useful when building a model. The models that we will build below will just try to predict outcome (points) but other models may choose to predict goals, which is why they are also included here.

`points`: The outcome of the game. 3 points for a win, 1 point for a draw, 0 for a loss. (Points are not goals!)

`goals`: The number of goals the team referenced by `teamid` scored.

`op_goals`: The number of goals the team referenced by `op_teamid` scored.

```
club_data = data[data['competitionid'] <> 4]
# Show the features latest game in competition id 4, which is the world cup.
print data[data['competitionid'] == 4].iloc[0]
```

```
matchid                                731828
teamid                                    366
op_teamid                                 632
competitionid                               4
seasonid                                 2013
is_home                                     0
team_name                         Netherlands
op_team_name                        Argentina
timestamp          2014-07-09 21:00:00.000000
goals                                       0
op_goals                                    0
points                                      1
avg_points                           2.333333
avg_goals                            1.333333
op_avg_goals                        0.3333333
pass_70                             0.4720355
pass_80                             0.1506976
op_pass_70                          0.2647796
op_pass_80                         0.07850102
expected_goals                       1.444374
op_expected_goals                   0.4114247
passes                               3.834864
bad_passes                           1.013622
pass_ratio                          0.7655947
corners                            0.07099121
fouls                               0.1262374
cards                                       1
shots                               0.1552259
op_passes                             3.38986
op_bad_passes                        1.024551
op_corners                         0.03467955
op_fouls                            0.1570661
op_cards                             2.666667
```

```
op_shots                                    0.09249659
goals_op_ratio                                1.333333
shots_op_ratio                                1.702273
pass_op_ratio                                 1.025426
Name: 0, dtype: object
```

Compute the crosstabs for goals scored vs outcomes. Scoring more than 5 goals means you're guaranteed to win, and scoring no goals means you lose about 75% of the time (sometimes you tie!).

```
import pandas as pd
print pd.crosstab(
    club_data['goals'],
    club_data.replace(
        {'points': {
            0: 'lose', 1: 'tie', 3: 'win'}})['points'])
```

```
points  lose  tie  win
goals
0        768  279    0
1        508  416  334
2        134  218  531
3         23   42  325
4          2    6  158
5          0    2   67
6          0    0   13
7          0    0    6
8          0    0    1
```

Note: How come as goals go beyond 4, the wins do not increase automatically? These are goals from penalty shots at the end of games, hence both teams might score a lot, but one of them ends up losing. See [1] for more details.

Training the model

We're going to train a logistic regression model based on the club data only. This will use an external code file `world_cup.py` to build the model.

The output of this cell this will be a logistic regression model and a test set that we can use to test how good we are at predicting outcomes. The cell will also print out the Rsquared value for the regression. This is a measaure of how good the fit was to the model (higher is better).

```
import world_cup
reload(world_cup)
import match_stats
pd.set_option('display.max_rows', 5000)
pd.set_option('display.max_columns', 500)
pd.set_option('display.width', 1000)

# Don't train on games that ended in a draw, since they have less signal.
train = club_data.loc[club_data['points'] <> 1]
# train = club_data
```

```
(model, test) = world_cup.train_model(
    train, match_stats.get_non_feature_columns())
print "Rsquared: %0.03g" % model.prsquared
```

```
Rsquared: 0.149
```

Picking important features

The logistic regression model is built using regularization; this means that it penalizes complex models. It has the side effect of helping us with feature selection. Features that are not important will be dropped out of the model completely.

We can divide the features into three buckets:

Positive features: These features mean that a team is more likely to win.

Negative features: These features mean that a team is less likely to win.

Dropped features: These features aren't important, and if we included them in the model, we'd probably be overfitting.

```
def print_params(model, limit=None):
    params = model.params.copy()
    params.sort(ascending=False)
    del params['intercept']

    if not limit:
        limit = len(params)

    print("Positive features")
    params.sort(ascending=False)
    print np.exp(params[[param > 0.001 for param in params]]).sub(1)[:limit]

    print("\nDropped features")
    print params[[param  == 0.0 for param in params]][:limit]

    print("\nNegative features")
    params.sort(ascending=True)
    print np.exp(params[[param < -0.001 for param in params]]).sub(1)[:limit]

print_params(model, 10)
```

```
Positive features
is_home             0.848337
pass_70             0.254729
expected_goals      0.169235
opp_op_corners      0.159163
op_passes           0.120319
opp_op_pass_80      0.095970
avg_goals           0.092000
opp_bad_passes      0.075657
opp_cards           0.068903
fouls               0.062809
dtype: float64

Dropped features
```

```
op_pass_70            0
opp_op_cards          0
op_bad_passes         0
opp_op_bad_passes     0
opp_op_fouls          0
corners               0
pass_ratio            0
opp_corners           0
op_fouls              0
opp_goals_op_ratio    0
dtype: float64

Negative features
opp_pass_70          -0.203015
opp_expected_goals   -0.144740
op_corners           -0.137309
opp_op_passes        -0.107397
op_pass_80           -0.087566
opp_avg_goals        -0.084249
bad_passes           -0.070335
cards                -0.064461
opp_fouls            -0.059097
opp_passes           -0.049240
dtype: float64
```

Predicting wins in club data

This cell uses the test set (which was not used during the creation of the model) to predict outcomes. We can a few of the predictions to see how well we did. We'll show 5 each from two buckets: cases where we got it right, and cases where we got it wrong. We can see if these make sense. When we display these, the home team is always on the left.

For example, it might show that we predicted Manchester United playing at home beating Sunderland. This is completely reasonable and we'd expect that the outcome would be 3 points (a victory).

The columns of the output are:

`team_name`: Home team

`op_team_name`: Away team

`predicted`: The percentage chance that we believe the home team will win.

`points`: What actually happenned. 3 points for a win, 1 point for a draw, 0 points for a loss.

```
reload(world_cup)
results = world_cup.predict_model(model, test,
    match_stats.get_non_feature_columns())

predictions = world_cup.extract_predictions(
    results.copy(), results['predicted'])
```

```
print 'Correct predictions:'
print predictions[(predictions['predicted'] > 50) & (predictions['points'] == 3)][:5]
```

```
Correct predictions:
               team_name          op_team_name  predicted            expected
8     Portland Timbers       Real Salt Lake  52.418756     Portland Timbers     Portland
42      Rayo Vallecano           Granada CF  60.862465      Rayo Vallecano        Rayo V
49  AtlÃ©tico de Madrid                Getafe  64.383541 AtlÃ©tico de Madrid  AtlÃ©t
57     Colorado Rapids  Vancouver Whitecaps  51.836366     Colorado Rapids     Colorad
58         Real Madrid        Real Sociedad  64.100904         Real Madrid          Rea
```

```
print 'Incorrect predictions:'
print predictions[(predictions['predicted'] > 50) & (predictions['points'] < 3)][:5]
```

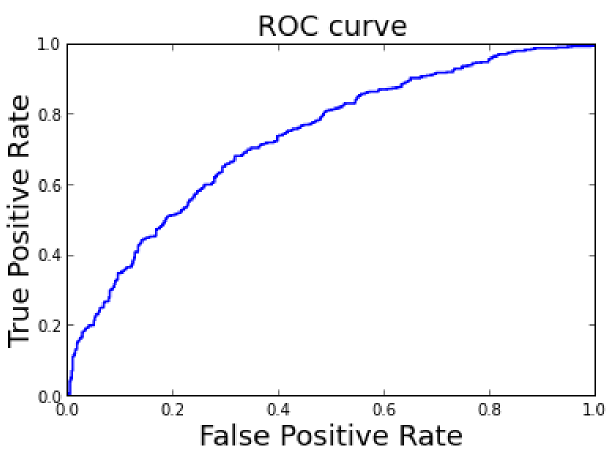
```
Incorrect predictions:
                   team_name          op_team_name  predicted                 expected
1      Seattle Sounders FC  Vancouver Whitecaps  51.544963      Seattle Sounders FC  Va
2   New England Revolution       Real Salt Lake  63.950714   New England Revolution
3       Philadelphia Union            FC Dallas  54.213693       Philadelphia Union
14  New England Revolution       Montreal Impact  52.762065   New England Revolution
20       New York Red Bulls           Toronto FC  55.533969       New York Red Bulls
```

Validating our predictions

Next, we want to actually quantify how good our predictions are. We can compute the lift ("How much better are we doing than random chance?"), AUC (the area under the ROC curve) and plot the ROC curve. AUC is arguable the most interesting number, it ranges between 0.5 (your model is no better than dumb luck) and 1.0 (perfect prediction).

```
# Compute a baseline, which is the percentage of overall outcomes are actually wins.
# (remember in soccer we can have draws too).
baseline = (sum([yval == 3 for yval in club_data['points']])
            * 1.0 / len(club_data))
y = [yval == 3 for yval in test['points']]
world_cup.validate(3, y, results['predicted'], baseline,
                   compute_auc=True)
plt.savefig('doc_en_01.png')
```

```
(3) Lift: 1.42 Auc: 0.738
```



Need.... more .... power!

One thing that is missing, if you're predicting the next game based on the previous few games, is that some teams may have just played a really tough schedule, while other teams have played against much weaker competition.

We can solve for schedule difficulty by running another regression; this one computes a power ranking, similar to the FIFA/CocaCola power ranking for international soccer teams (there are power rankings for other sports like college (american) football that may be familiar.)

Once we compute the power ranking (which creates a stack ranking of all of the teams), we can add that power ranking as a feature to our model, then rebuild it and re-validate it. The regression essentailly automated the process of looking at relationships like "Well, team A beat team B and team B beat team C, so A is probably better than C".

The output here will show the power ranking for various teams. This can be useful to spot check the ranking, since if we rank Wiggan at 1.0 and Chelsea at 0.0, something is likely wrong.

Note that because there isn't a strict ordering to the data (if team A beats team B and team B beats team C, sometimes team C will then beat team A) we sometimes fail to assign ordering to all of the teams (especially where the data is sparse). For teams that we can't rank, we put them in the middle (0.5).

Additionally, because the rankings for international teams are noisy and sparse, we chunk the rankings into quartiles. So teams that have been ranked will show up as 0, .33, .66, or 1.0.

Once we add this to the model, the performance generally improves significantly.

```
import power
reload(power)
reload(world_cup)
def points_to_sgn(p):
  if p > 0.1: return 1.0
  elif p < -0.1: return -1.0
  else: return 0.0
power_cols = [
  ('points', points_to_sgn, 'points'),
]

power_data = power.add_power(club_data, game_summaries, power_cols)
power_train = power_data.loc[power_data['points'] <> 1]

# power_train = power_data
(power_model, power_test) = world_cup.train_model(
    power_train, match_stats.get_non_feature_columns())
print "\nRsquared: %0.03g, Power Coef %0.03g" % (
    power_model.prsquared,
    math.exp(power_model.params['power_points']))
```

```
power_results = world_cup.predict_model(power_model, power_test,
    match_stats.get_non_feature_columns())
power_y = [yval == 3 for yval in power_test['points']]
world_cup.validate(3, power_y, power_results['predicted'], baseline,
                   compute_auc=True, quiet=False)

print_params(power_model, 8)

plt.plot([0, 1], [0, 1], '--', color=(0.6, 0.6, 0.6), label='Luck')
# Add the old model to the graph
world_cup.validate('old', y, results['predicted'], baseline,
                   compute_auc=True, quiet=True)
plt.legend(loc="lower right")
plt.savefig('doc_en_02.png')
```

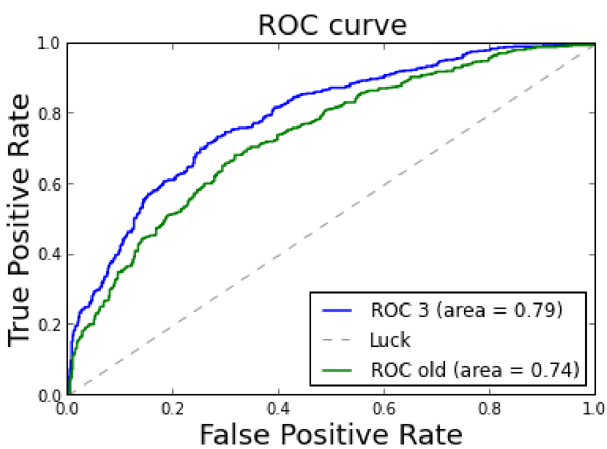
```
New season 2014
New season 2013
QC check did not pass for 19 out of 20 parameters
Try increasing solver accuracy or number of iterations, decreasing alpha, or switch so
Could not trim params automatically due to failed QC check.  Trimming using trim_mode
New season 2013
New season 2012
QC check did not pass for 24 out of 24 parameters
Try increasing solver accuracy or number of iterations, decreasing alpha, or switch so
Could not trim params automatically due to failed QC check.  Trimming using trim_mode
New season 2012
New season 2011
QC check did not pass for 24 out of 24 parameters
Try increasing solver accuracy or number of iterations, decreasing alpha, or switch so
Could not trim params automatically due to failed QC check.  Trimming using trim_mode
['Blackburn Rovers: 0.000', 'Real Betis: 0.000', 'D.C. United: 0.000',
'Celta de Vigo: 0.004', 'Deportivo de La Coru\xc3\xb1a: 0.009',
'Wolverhampton Wanderers: 0.021', 'Reading: 0.022', 'Real Zaragoza: 0.026',
'Real Valladolid: 0.044', 'Granada CF: 0.062', 'Queens Park Rangers:
0.073', 'Mallorca: 0.089', 'Aston Villa: 0.092', 'Bolton Wanderers: 0.102',
'Osasuna: 0.109', 'Espanyol: 0.112', 'Wigan Athletic: 0.124', 'Sunderland:
0.130', 'Rayo Vallecano: 0.138', 'Almer\xc3\xada: 0.145', 'Levante: 0.148',
'Elche: 0.154', 'Getafe: 0.170', 'Swansea City: 0.192', 'Southampton:
0.197', 'Norwich City: 0.206', 'Toronto FC: 0.211', 'Chivas USA: 0.218',
'West Ham United: 0.220', 'West Bromwich Albion: 0.224', 'Villarreal:
0.231', 'Stoke City: 0.255', 'Fulham: 0.274', 'Valencia: 0.296', 'Valencia
CF: 0.296', 'M\xc3\xa1laga: 0.305', 'Newcastle United: 0.342', 'Sevilla:
0.365', 'Columbus Crew: 0.366', 'Athletic Club: 0.386', 'Liverpool: 0.397',
'Everton: 0.417', 'Philadelphia Union: 0.466', 'Montreal Impact: 0.470',
'Chelsea: 0.530', 'Real Sociedad: 0.535', 'Tottenham Hotspur: 0.551',
'Arsenal: 0.592', 'Houston Dynamo: 0.593', 'FC Dallas: 0.612', 'Chicago
Fire: 0.612', 'Vancouver Whitecaps: 0.615', 'San Jose Earthquakes: 0.632',
'New England Revolution: 0.634', 'Atl\xc3\xa9tico de Madrid: 0.672',
'Colorado Rapids: 0.743', 'Barcelona: 0.759', 'Seattle Sounders FC: 0.781',
'New York Red Bulls: 0.814', 'Sporting Kansas City: 0.854', 'LA Galaxy:
0.882', 'Real Salt Lake: 0.922', 'Manchester City: 0.928', 'Real Madrid:
1.000', 'Manchester United: 1.000', 'Portland Timbers: 1.000']

Rsquared: 0.22, Power Coef 2.18
(3)  Lift: 1.56 Auc: 0.791
    Base: 0.374 Acc: 0.708 P(1|t): 0.778 P(0|f): 0.667
```

```
    Fp/Fn/Tp/Tn p/n/c: 99/248/347/496 595/595/1190
Positive features
power_points       1.177169
is_home            0.787110
opp_op_corners     0.170848
expected_goals     0.058597
opp_cards          0.045538
pass_70            0.036267
avg_goals          0.035456
opp_avg_points     0.033857
dtype: float64

Dropped features
passes                 0
op_pass_80             0
op_expected_goals      0
opp_shots_op_ratio     0
bad_passes             0
pass_ratio             0
opp_pass_op_ratio      0
shots                  0
dtype: float64

Negative features
opp_power_points      -0.540688
op_corners            -0.145918
opp_expected_goals    -0.055353
cards                 -0.043555
opp_pass_70           -0.034997
opp_avg_goals         -0.034242
avg_points            -0.032748
opp_fouls             -0.022867
dtype: float64
(old) Lift: 1.42 Auc: 0.738
```



On to the world cup!

Now that we've got a model that we like, let's look at predicting the world cup. We can build the same statistics (features) for the world cup games that we did for the club games. In this case, however, we don't have the targets; that is, we don't know who won (for some of the previous games, we do know who won, but let's predict them all equally as if we didn't know).

`features.get_wc_features()` will return build features from the world cup games.

```
import world_cup
import features
reload(match_stats)
reload(features)
reload(world_cup)
wc_data = world_cup.prepare_data(features.get_wc_features(history_size))
wc_labeled = world_cup.prepare_data(features.get_features(history_size))
wc_labeled = wc_labeled[wc_labeled['competitionid'] == 4]
wc_power_train = game_summaries[game_summaries['competitionid'] == 4].copy()
```

Predicting the world cup

Once we have the model and the features, we can start predicting.

Home Team Advantage

There are a couple of differences between the world cup and club data. For one, while home team advantage is important in club games, who is really at home? Is it only Brazil? What about other south american teams? Some models give the 'is home' status to only Brazil, others give partial status to other teams from the same continent, since historical data shows that teams from the same continent tend to outperform.

We use a slightly modified model that is, however, somewhat subjective. We assing a value to `is_home` between 0.0 to 1.0 depending on the fan support (both numbers and enthusiasm) that a team enjoys. This is a result of noticing, in the early rounds, that the teams that had the more entusiastic supporters did better. For example, Chile's fans were deafining in support of their team, but Spain's fans barely showed up (Chile upset spain 2-0). There were a number of other cases like this; many involving south american sides, but many involving other teams that had sent a lot of supporters (Mexico, for example). Some teams, like the USA, had a lot of fans, but they were more reserved... they got a lower score. This factor was set based on first-hand reports from the group games.

```
import pandas as pd
wc_home = pd.read_csv('wc_home.csv')

def add_home_override(df, home_map):
  for ii in xrange(len(df)):
    team = df.iloc[ii]['teamid']
    if team in home_map:
        df['is_home'].iloc[ii] = home_map[team]
    else:
        # If we don't know, assume not at home.
        df['is_home'].iloc[ii] = 0.0

home_override = {}
```

```
for ii in xrange(len(wc_home)):
    row = wc_home.iloc[ii]
    home_override[row['teamid']] = row['is_home']

# Add home team overrides.
add_home_override(wc_data, home_override)
```

World Cup Power Rankings

The lattice of teams playing eachother in the world cup is pretty sparse. Many teams haven't played eachother for decades. Many European teams rarely play South American ones, and even more rarely play Asian ones. We can use the same technique as we did for the club games, but we have to be prepared for failure.

We'll output the power rankings from the previous games. We should eyeball them to make sure they make sense.

```
# When training power data, since the games span multiple competitions,
# just set is_home to 0.5
#
# Otherwise when we looked at games from the 2010 world cup, we'd think
# Brazil was still at home instead of South Africa.

wc_power_train['is_home'] = 0.5
wc_power_data = power.add_power(wc_data, wc_power_train, power_cols)

wc_results = world_cup.predict_model(power_model, wc_power_data,
    match_stats.get_non_feature_columns())
```

```
New season 2013
New season 2009
New season 6
QC check did not pass for 45 out of 50 parameters
Try increasing solver accuracy or number of iterations, decreasing alpha, or switch sc
Could not trim params automatically due to failed QC check.  Trimming using trim_mode
['Australia: 0.000', 'Serbia: 0.016', 'USA: 0.017', 'Cameroon: 0.035',
'Iran: 0.081', 'Croatia: 0.180', 'Nigeria: 0.204', "C\xc3\xb4te d'Ivoire:
0.244", 'Costa Rica: 0.254', 'Algeria: 0.267', 'Paraguay: 0.277',
'Honduras: 0.279', 'Slovakia: 0.281', 'Greece: 0.284', 'Switzerland:
0.291', 'Ecuador: 0.342', 'Uruguay: 0.367', 'Sweden: 0.386', 'Japan:
0.406', 'Mexico: 0.409', 'Chile: 0.413', 'Colombia: 0.438', 'England:
0.460', 'Belgium: 0.467', 'Ukraine: 0.470', 'Portugal: 0.487', 'Ghana:
0.519', 'South Korea: 0.532', 'France: 0.648', 'Spain: 0.736', 'Argentina:
0.793', 'Italy: 0.798', 'Brazil: 0.898', 'Netherlands: 0.918', 'Germany:
1.000']
```

Predicting games

Now's the moment we've been waiting for. Let's predict some world cup games. Let's start with predicting the ones that have already happenned.

We will output 4 columns:

`team_name`: Team we're predicting

`op_team_name`: Team that the team we're predicting is playing against

`predicted`: Precentage chance (we believe) that the team will win.

`points`: If the game has been played, what actually happenned. (if the game hasn't been played, we'll show a `NaN` here). 3 points is a win, 1 point is a draw, 0 points is a loss. Note that for games in the knockout phase that went into penalty kicks, we'll mark that as a draw.

But wait! These predictions are different from the ones you published!

There are three reasons why the prediction numbers might be different from the numbers you may have seen as published predictions:

We've updated our code several times to fix bugs and improve accuracy. Our original model, for example, didn't account for extra time causing inflated statistics.

Model building is non-deterministic. Since we pick a random subset of the data to use as our training set, the results will change from run to run. Sometimes fairly significantly.

When we predicted the round of 16, we used the trailing 3 games to predict (since each team had played 3 games in the current world cup). For the quarterfinals, we used the trailing 4 games; for the semis, 5, and for the finals, we used all 6 [in this notebook, we use different ones at times, please check]. The code below will predict based on the last 6 games; for many teams, we don't have 6 games of history, and even if we do, that history will be from previous world cups. To see a more apples-to-apples comparison, set the `history_size` variable to 3 and rerun the notebook.

```
pd.set_option('display.max_rows', 5000)
pd.set_option('display.max_columns', 500)
pd.set_option('display.width', 1000)

wc_with_points = wc_power_data.copy()
wc_with_points.index = pd.Index(
    zip(wc_with_points['matchid'], wc_with_points['teamid']))
wc_labeled.index = pd.Index(
    zip(wc_labeled['matchid'], wc_labeled['teamid']))
wc_with_points['points'] = wc_labeled['points']

wc_pred = world_cup.extract_predictions(wc_with_points,
                                        wc_results['predicted'])

# Reverse our predictions to show the most recent first.
wc_pred.reindex(index=wc_pred.index[::-1])
# Show our predictions for the games that have already happenned.
print wc_pred
```

```
        team_name   op_team_name   predicted        expected          winner   points
0       Argentina        Germany   46.070814         Germany              NA      NaN
1     Netherlands         Brazil   42.833863          Brazil              NA      NaN
```

2	Netherlands	Argentina	48.641542	Argentina	draw	1
3	Germany	Brazil	44.011593	Brazil	Germany	3
4	Costa Rica	Netherlands	14.442625	Netherlands	draw	1
5	Belgium	Argentina	18.596031	Argentina	Argentina	0
6	Colombia	Brazil	23.890421	Brazil	Brazil	0
7	Germany	France	75.116349	Germany	Germany	3
8	USA	Belgium	32.400646	Belgium	Belgium	0
9	Switzerland	Argentina	19.272768	Argentina	Argentina	0
10	Algeria	Germany	5.926496	Germany	Germany	0
11	Nigeria	France	8.694729	France	France	0
12	Greece	Costa Rica	40.448104	Costa Rica	draw	1
13	Mexico	Netherlands	20.402491	Netherlands	Netherlands	0
14	Uruguay	Colombia	46.480264	Colombia	Colombia	0
15	Chile	Brazil	26.574916	Brazil	draw	1
16	Germany	USA	91.980986	Germany	Germany	3
17	Ghana	Portugal	49.051707	Portugal	Portugal	0
18	Switzerland	Honduras	60.223070	Switzerland	Switzerland	3
19	France	Ecuador	84.538857	France	draw	1
20	Argentina	Nigeria	88.491450	Argentina	Argentina	3
21	CÃ´te d'Ivoire	Greece	61.074502	CÃ´te d'Ivoire	Greece	0
22	Uruguay	Italy	32.685428	Italy	Uruguay	3
23	England	Costa Rica	63.457326	England	draw	1
24	Brazil	Cameroon	94.788074	Brazil	Brazil	3
25	Mexico	Croatia	78.020214	Mexico	Mexico	3
26	Spain	Australia	90.521542	Spain	Spain	3
27	Chile	Netherlands	28.342133	Netherlands	Netherlands	0
28	Portugal	USA	65.457259	Portugal	draw	1
29	Algeria	South Korea	17.376285	South Korea	Algeria	3
30	Ghana	Germany	14.588539	Germany	draw	1
31	Iran	Argentina	5.193843	Argentina	Argentina	0
32	Ecuador	Honduras	53.848926	Ecuador	Ecuador	3
33	France	Switzerland	78.659381	France	France	3
34	Costa Rica	Italy	24.836756	Italy	Costa Rica	3
35	Greece	Japan	44.355013	Japan	draw	1
36	England	Uruguay	61.012694	England	Uruguay	0
37	Croatia	Cameroon	40.212875	Cameroon	Croatia	3
38	Chile	Spain	42.624474	Spain	Chile	3
39	Netherlands	Australia	93.535889	Netherlands	Netherlands	3
40	Mexico	Brazil	20.372064	Brazil	draw	1
41	USA	Ghana	39.500993	Ghana	USA	3
42	Nigeria	Iran	53.813244	Nigeria	draw	1
43	Portugal	Germany	15.337884	Germany	Germany	0
44	Honduras	France	22.953848	France	France	0
45	Ecuador	Switzerland	59.987076	Ecuador	Switzerland	0
46	Japan	CÃ´te d'Ivoire	51.528885	Japan	CÃ´te d'Ivoire	0
47	Italy	England	68.767968	Italy	Italy	3
48	Costa Rica	Uruguay	45.347946	Uruguay	Costa Rica	3
49	Australia	Chile	19.487987	Chile	Chile	0
50	Netherlands	Spain	60.493928	Netherlands	Netherlands	3
51	Cameroon	Mexico	30.018950	Mexico	Mexico	0
52	Croatia	Brazil	6.268704	Brazil	Brazil	0
53	Spain	Netherlands	35.602227	Netherlands	Spain	3
54	Germany	Uruguay	76.467450	Germany	Germany	3
55	Spain	Germany	29.438134	Germany	Spain	3
56	Netherlands	Uruguay	71.342186	Netherlands	Netherlands	3

57	Spain	Paraguay	83.007655	Spain	Spain	3
58	Germany	Argentina	42.635127	Argentina	Germany	3
59	Ghana	Uruguay	41.784682	Uruguay	draw	1
60	Brazil	Netherlands	60.821972	Brazil	Netherlands	0
61	Portugal	Spain	23.464891	Spain	Spain	0
62	Japan	Paraguay	61.278000	Japan	draw	1
63	Chile	Brazil	24.459600	Brazil	Brazil	0
64	Slovakia	Netherlands	12.082967	Netherlands	Netherlands	0
65	Mexico	Argentina	17.626748	Argentina	Argentina	0
66	England	Germany	20.763176	Germany	Germany	0
67	Ghana	USA	71.310871	Ghana	Ghana	3
68	South Korea	Uruguay	45.148588	Uruguay	Uruguay	0
69	Brazil	Portugal	81.610878	Brazil	draw	1
70	Germany	Ghana	81.621494	Germany	Germany	3
71	Serbia	Australia	38.204905	Australia	Australia	0
72	CÃ´te d’Ivoire	Brazil	10.186423	Brazil	Brazil	0
73	Australia	Ghana	23.702414	Ghana	draw	1
74	Japan	Netherlands	10.773998	Netherlands	Netherlands	0
75	Serbia	Germany	4.731113	Germany	Serbia	3
76	Mexico	France	42.801515	France	Mexico	3
77	South Korea	Argentina	15.255040	Argentina	Argentina	0
78	Switzerland	Spain	18.747704	Spain	Switzerland	3
79	Portugal	CÃ´te d’Ivoire	65.031075	Portugal	draw	1
80	Paraguay	Italy	12.288896	Italy	draw	1
81	Australia	Germany	7.395354	Germany	Germany	0
82	Ghana	Serbia	83.682899	Ghana	Ghana	3
83	USA	England	34.763699	England	draw	1
84	France	Italy	28.651132	Italy	draw	1
85	Portugal	Germany	14.833907	Germany	Germany	0
86	France	Portugal	72.141913	France	France	3
87	Italy	Germany	33.364112	Germany	Italy	3
88	France	Brazil	22.742882	Brazil	France	3
89	Portugal	England	49.550454	England	draw	1
90	Ukraine	Italy	28.378865	Italy	Italy	0
91	Argentina	Germany	46.801014	Germany	draw	1
92	France	Spain	47.126654	Spain	France	3
93	Ghana	Brazil	9.144470	Brazil	Brazil	0
94	Ukraine	Switzerland	62.637340	Ukraine	draw	1
95	Australia	Italy	8.365416	Italy	Italy	0
96	Netherlands	Portugal	70.231295	Netherlands	Portugal	0
97	Ecuador	England	34.379086	England	England	0
98	Mexico	Argentina	29.233199	Argentina	Argentina	0
99	Sweden	Germany	10.914079	Germany	Germany	0

References

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