Predicting the Winning Football Team

Can we design a predictive model capable of accurately predicting if the home team will win a football match?

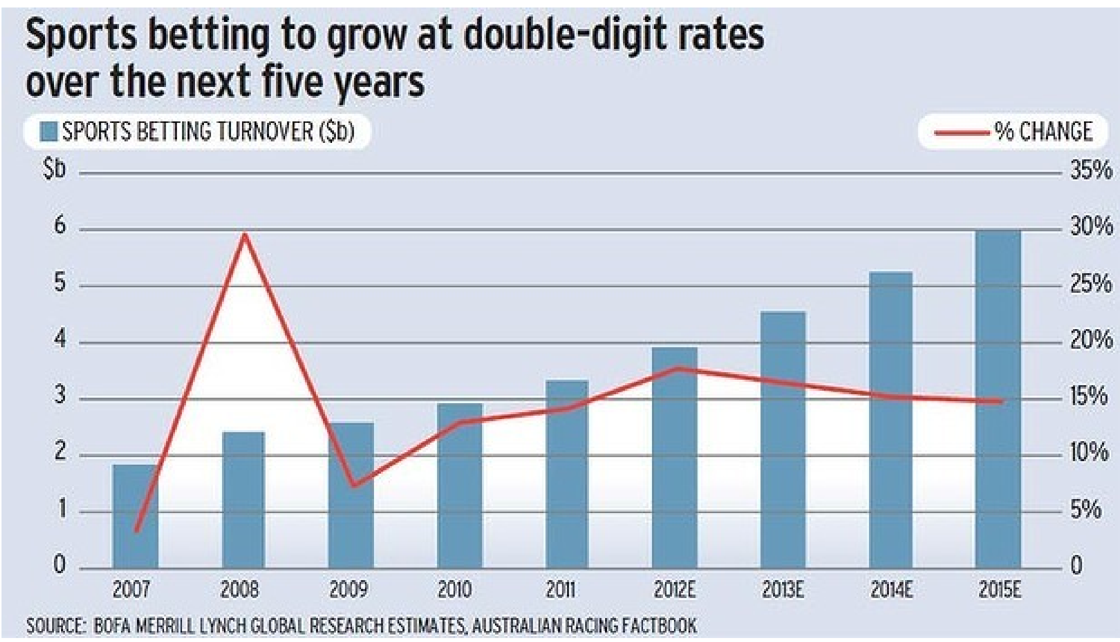
alt text

Steps

1. We will clean our dataset
2. Split it into training and testing data (12 features & 1 target (winning team (Home/Away/Draw))
3. Train 3 different classifiers on the data -Logistic Regression -Support Vector Machine -XGBoost
4. Use the best Classifer to predict who will win given an away team and a home team

History

Sports betting is a 500 billion dollar market (Sydney Herald)



Kaggle hosts a yearly competiton called March Madness

https://www.kaggle.com/c/march-machine-learning-mania-2017/kernels

Several Papers on this

https://arxiv.org/pdf/1511.05837.pdf

"It is possible to predict the winner of English county twenty twenty cricket games in almost two thirds of instances."

https://arxiv.org/pdf/1411.1243.pdf

"Something that becomes clear from the results is that Twitter contains enough information to be useful for predicting outcomes in the Premier League"

https://qz.com/233830/world-cup-germany-argentina-predictions-microsoft/

For the 2014 World Cup, Bing correctly predicted the outcomes for all of the 15 games in the knockout round.

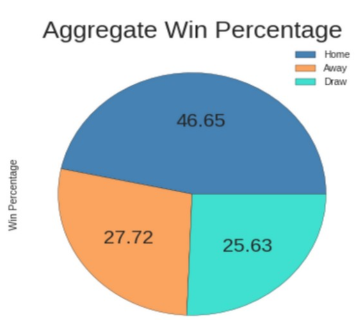
So the right questions to ask are

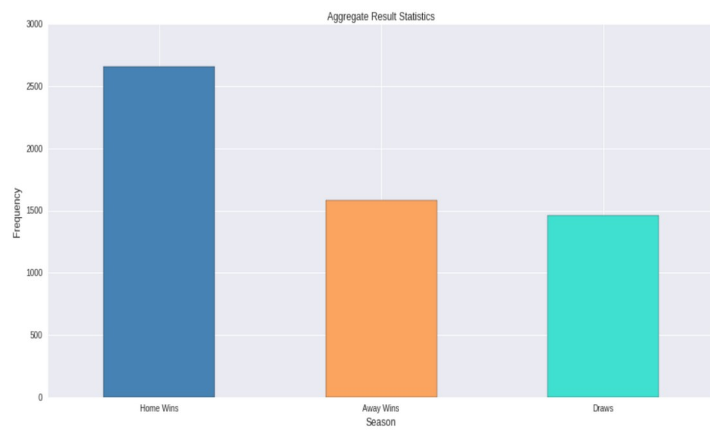
-What model should we use? -What are the features (the aspects of a game) that matter the most to predicting a team win? Does being the home team give a team the advantage?

Dataset

- Football is played by 250 million players in over 200 countries (most popular sport globally)
- The English Premier League is the most popular domestic team in the world
- Retrived dataset from http://football-data.co.uk/data.php

	Home Wins	Away Wins	Draws	Total
Overall	2659	1580	1461	5700





- Football is a team sport, a cheering crowd helps morale
- Familarity with pitch and weather conditions helps
- No need to travel (less fatigue)

Acrononyms-
https://rstudio-pubs-static.s3.amazonaws.com/179121_70eb412bbe6c4a55837f2439e5ae6d4e.html

Other repositories

- https://github.com/rsibi/epl-prediction-2017 (EPL prediction)
- https://github.com/adeshpande3/March-Madness-2017 (NCAA prediction)

Import Dependencies

```
#data preprocessing
import pandas as pd
#produces a prediction model in the form of an ensemble of weak
prediction models, typically decision tree
import xgboost as xgb
#the outcome (dependent variable) has only a limited number of
possible values.
#Logistic Regression is used when response variable is categorical in
nature.
from sklearn.linear_model import LogisticRegression
#A random forest is a meta estimator that fits a number of decision
tree classifiers
#on various sub-samples of the dataset and use averaging to improve
the predictive
#accuracy and control over-fitting.
from sklearn.ensemble import RandomForestClassifier
#a discriminative classifier formally defined by a separating
hyperplane.
from sklearn.svm import SVC
#displayd data
from IPython.display import display
%matplotlib inline

# Read data and drop redundant column.
data = pd.read_csv('final_dataset.csv')

# Preview data.
display(data.head())


#Full Time Result (H=Home Win, D=Draw, A=Away Win)
#HTGD - Home team goal difference
#ATGD - away team goal difference
#HTP - Home team points
#ATP - Away team points
#DiffFormPts Diff in points
#DiffLP - Differnece in last years prediction

#Input - 12 other features (fouls, shots, goals, misses,corners, red
card, yellow cards)
#Output - Full Time Result (H=Home Win, D=Draw, A=Away Win)
```

```
   FTR   HTP   ATP HM1 HM2 HM3 AM1 AM2 AM3  HTGD  ATGD  DiffFormPts
DiffLP
30   H  1.25  1.00   D   D   W   D   W   L  0.50  0.25         0.25
-16.0
31  NH  0.75  0.25   L   L   W   D   L   L -0.50 -0.75         0.50
-2.0
32   H  1.00  1.00   L   D   W   D   W   L  0.00  0.25         0.00
```

```
-3.0
33  NH  0.75  0.50   L   L   W   D   L   D -0.25 -0.25         0.25
3.0
34  NH  1.00  1.50   D   L   W   W   W   L  0.00  0.75        -0.50
3.0
```

Data Exploration

```
#what is the win rate for the home team?

# Total number of matches.
n_matches = data.shape[0]

# Calculate number of features. -1 because we are saving one as the
target variable (win/lose/draw)
n_features = data.shape[1] - 1

# Calculate matches won by home team.
n_homewins = len(data[data.FTR == 'H'])

# Calculate win rate for home team.
win_rate = (float(n_homewins) / (n_matches)) * 100

# Print the results
print "Total number of matches: {}".format(n_matches)
print "Number of features: {}".format(n_features)
print "Number of matches won by home team: {}".format(n_homewins)
print "Win rate of home team: {:.2f}%".format(win_rate)
```

```
Total number of matches: 5600
Number of features: 12
Number of matches won by home team: 2603
Win rate of home team: 46.48%
```

```
# Visualising distribution of data
from pandas.tools.plotting import scatter_matrix

#the scatter matrix is plotting each of the columns specified against
each other column.
#You would have observed that the diagonal graph is defined as a
histogram, which means that in the
#section of the plot matrix where the variable is against itself, a
histogram is plotted.

#Scatter plots show how much one variable is affected by another.
#The relationship between two variables is called their correlation
#negative vs positive correlation

#HTGD - Home team goal difference
#ATGD - away team goal difference
#HTP - Home team points
```

```
#ATP - Away team points
#DiffFormPts Diff in points
#DiffLP - Differnece in last years prediction

scatter_matrix(data[['HTGD','ATGD','HTP','ATP','DiffFormPts','DiffLP']
], figsize=(10,10))
```

```
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```
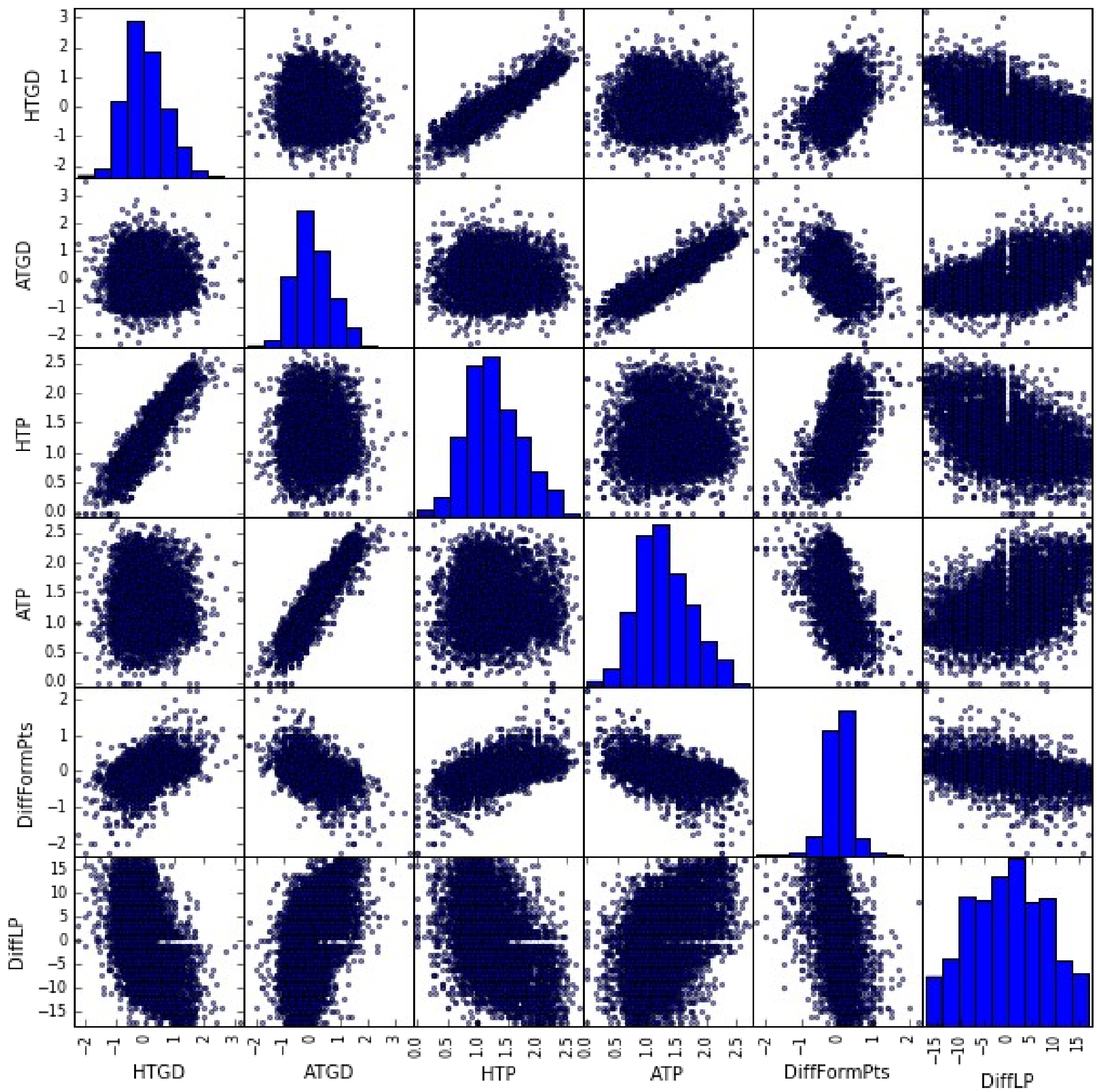



Preparing the Data

```
# Separate into feature set and target variable
#FTR = Full Time Result (H=Home Win, D=Draw, A=Away Win)
X_all = data.drop(['FTR'],1)
y_all = data['FTR']

# Standardising the data.
from sklearn.preprocessing import scale

#Center to the mean and component wise scale to unit variance.
cols = [['HTGD','ATGD','HTP','ATP','DiffLP']]
for col in cols:
    X_all[col] = scale(X_all[col])
```

```
#last 3 wins for both sides
X_all.HM1 = X_all.HM1.astype('str')
X_all.HM2 = X_all.HM2.astype('str')
X_all.HM3 = X_all.HM3.astype('str')
X_all.AM1 = X_all.AM1.astype('str')
X_all.AM2 = X_all.AM2.astype('str')
X_all.AM3 = X_all.AM3.astype('str')

#we want continous vars that are integers for our input data, so lets
remove any categorical vars
def preprocess_features(X):
    ''' Preprocesses the football data and converts catagorical
variables into dummy variables. '''

    # Initialize new output DataFrame
    output = pd.DataFrame(index = X.index)

    # Investigate each feature column for the data
    for col, col_data in X.iteritems():

        # If data type is categorical, convert to dummy variables
        if col_data.dtype == object:
            col_data = pd.get_dummies(col_data, prefix = col)

        # Collect the revised columns
        output = output.join(col_data)

    return output

X_all = preprocess_features(X_all)
print "Processed feature columns ({} total features):\
n{}".format(len(X_all.columns), list(X_all.columns))
```

```
Processed feature columns (24 total features):
['HTP', 'ATP', 'HM1_D', 'HM1_L', 'HM1_W', 'HM2_D', 'HM2_L', 'HM2_W',
'HM3_D', 'HM3_L', 'HM3_W', 'AM1_D', 'AM1_L', 'AM1_W', 'AM2_D',
'AM2_L', 'AM2_W', 'AM3_D', 'AM3_L', 'AM3_W', 'HTGD', 'ATGD',
'DiffFormPts', 'DiffLP']
```

```
# Show the feature information by printing the first five rows
print "\nFeature values:"
display(X_all.head())
```

```
Feature values:

         HTP       ATP  HM1_D  HM1_L  HM1_W  HM2_D  HM2_L  HM2_W
HM3_D  \
30 -0.043829 -0.611968    1.0    0.0    0.0    1.0    0.0    0.0
0.0
31 -1.120644 -2.238746    0.0    1.0    0.0    0.0    1.0    0.0
```

```
0.0
32 -0.582236 -0.611968    0.0    1.0    0.0    1.0    0.0    0.0
0.0
33 -1.120644 -1.696487    0.0    1.0    0.0    0.0    1.0    0.0
0.0
34 -0.582236  0.472551    1.0    0.0    0.0    0.0    1.0    0.0
0.0

    HM3_L    ...     AM2_D  AM2_L  AM2_W  AM3_D  AM3_L  AM3_W
HTGD  \
30    0.0    ...       0.0    0.0    1.0    0.0    1.0    0.0
0.753719
31    0.0    ...       0.0    1.0    0.0    0.0    1.0    0.0 -
0.737082
32    0.0    ...       0.0    0.0    1.0    0.0    1.0    0.0
0.008318
33    0.0    ...       0.0    1.0    0.0    1.0    0.0    0.0 -
0.364382
34    0.0    ...       0.0    0.0    1.0    0.0    1.0    0.0
0.008318

        ATGD  DiffFormPts    DiffLP
30  0.355995         0.25 -1.989216
31 -1.138834         0.50 -0.248963
32  0.355995         0.00 -0.373267
33 -0.391419         0.25  0.372556
34  1.103409        -0.50  0.372556

[5 rows x 24 columns]
```

```
from sklearn.cross_validation import train_test_split

# Shuffle and split the dataset into training and testing set.
X_train, X_test, y_train, y_test = train_test_split(X_all, y_all,
                                                    test_size = 50,
                                                    random_state = 2,
                                                    stratify = y_all)
```

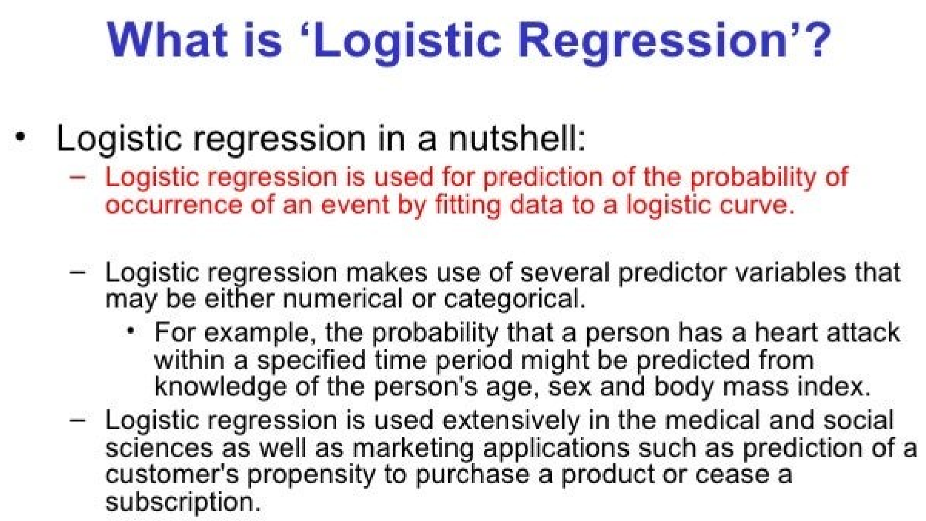
Training and Evaluating Models

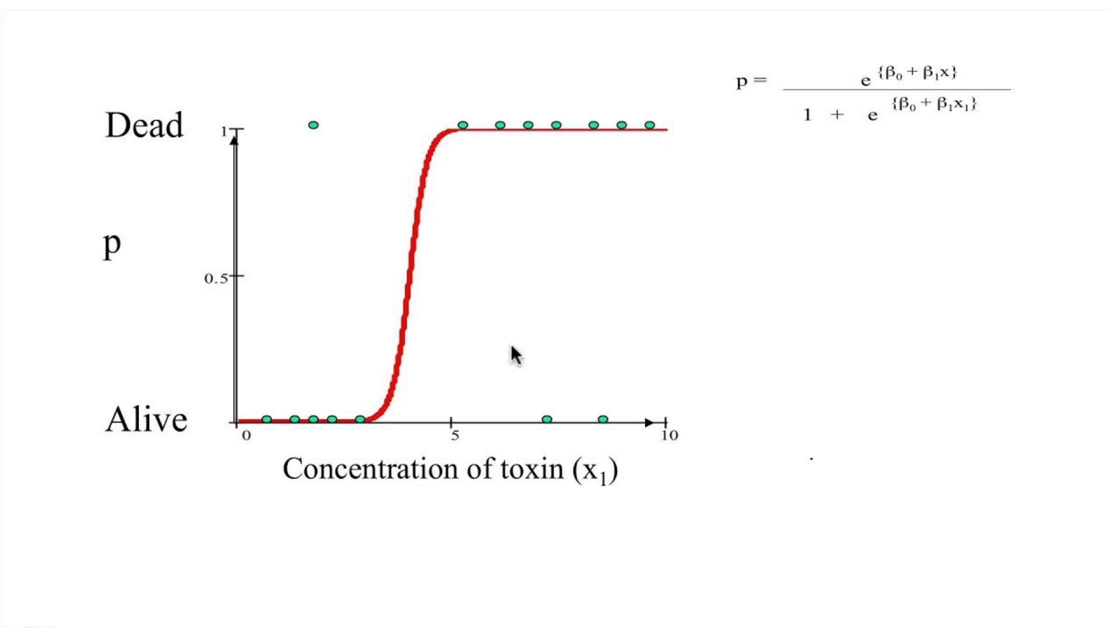
```
#for measuring training time
from time import time
# F1 score (also F-score or F-measure) is a measure of a test's
accuracy.
#It considers both the precision p and the recall r of the test to
compute
#the score: p is the number of correct positive results divided by the
number of
#all positive results, and r is the number of correct positive results
divided by
#the number of positive results that should have been returned. The F1
```

```
score can be
#interpreted as a weighted average of the precision and recall, where
an F1 score
#reaches its best value at 1 and worst at 0.
from sklearn.metrics import f1_score

def train_classifier(clf, X_train, y_train):
    ''' Fits a classifier to the training data. '''

    # Start the clock, train the classifier, then stop the clock
    start = time()
    clf.fit(X_train, y_train)
    end = time()

    # Print the results
    print "Trained model in {:.4f} seconds".format(end - start)


def predict_labels(clf, features, target):
    ''' Makes predictions using a fit classifier based on F1 score.
'''

    # Start the clock, make predictions, then stop the clock
    start = time()
    y_pred = clf.predict(features)

    end = time()
    # Print and return results
    print "Made predictions in {:.4f} seconds.".format(end - start)

    return f1_score(target, y_pred, pos_label='H'), sum(target ==
y_pred) / float(len(y_pred))


def train_predict(clf, X_train, y_train, X_test, y_test):
    ''' Train and predict using a classifer based on F1 score. '''

    # Indicate the classifier and the training set size
    print "Training a {} using a training set size of
{}. . .".format(clf.__class__.__name__, len(X_train))

    # Train the classifier
    train_classifier(clf, X_train, y_train)

    # Print the results of prediction for both training and testing
    f1, acc = predict_labels(clf, X_train, y_train)
    print f1, acc
    print "F1 score and accuracy score for training set: {:.4f} ,
{:.4f}.".format(f1 , acc)
```

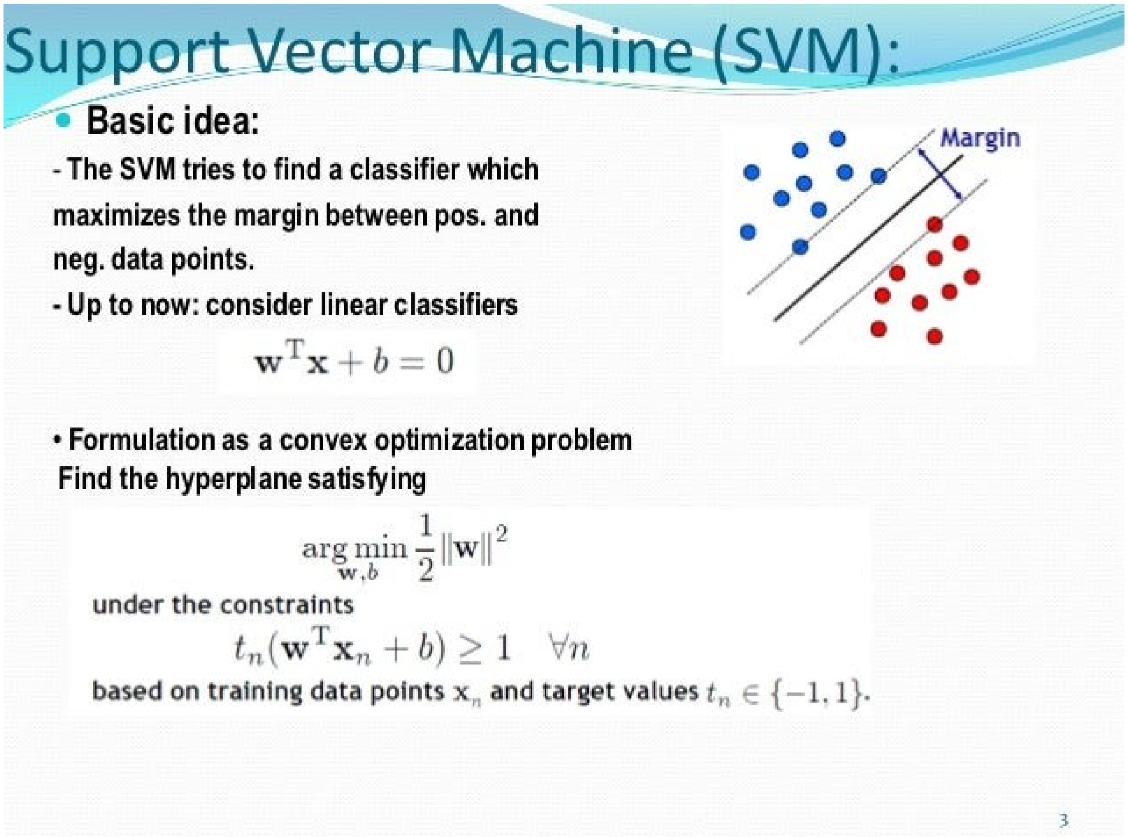
```
    f1, acc = predict_labels(clf, X_test, y_test)
    print "F1 score and accuracy score for test set: {:.4f} ,
{:.4f}.".format(f1 , acc)
```

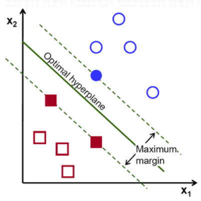
Logistic Regression



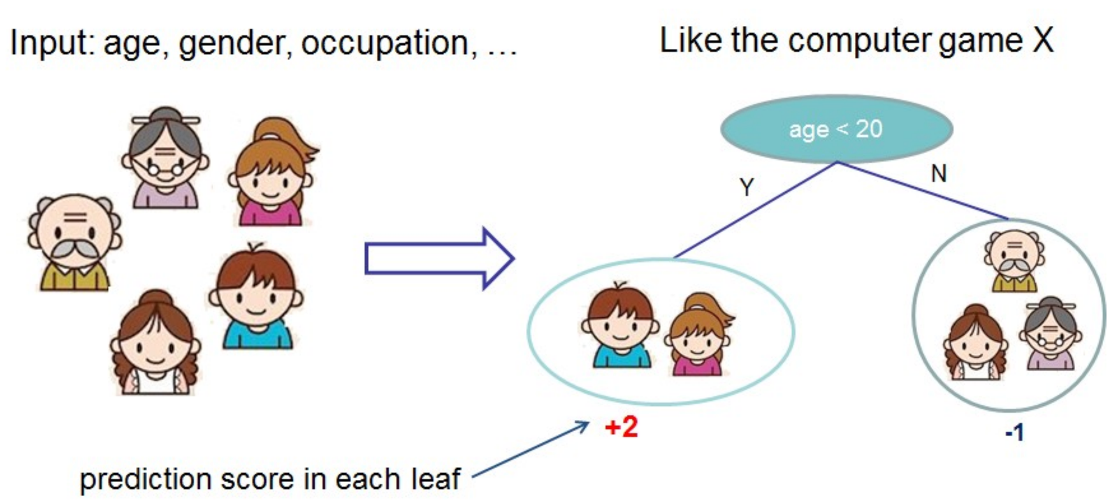


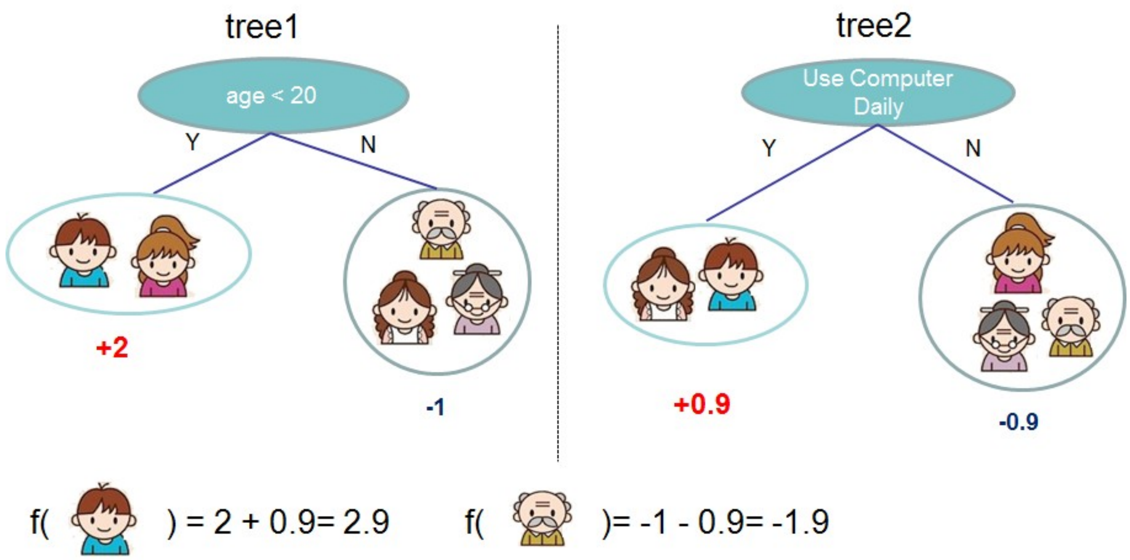
Support Vector Machine

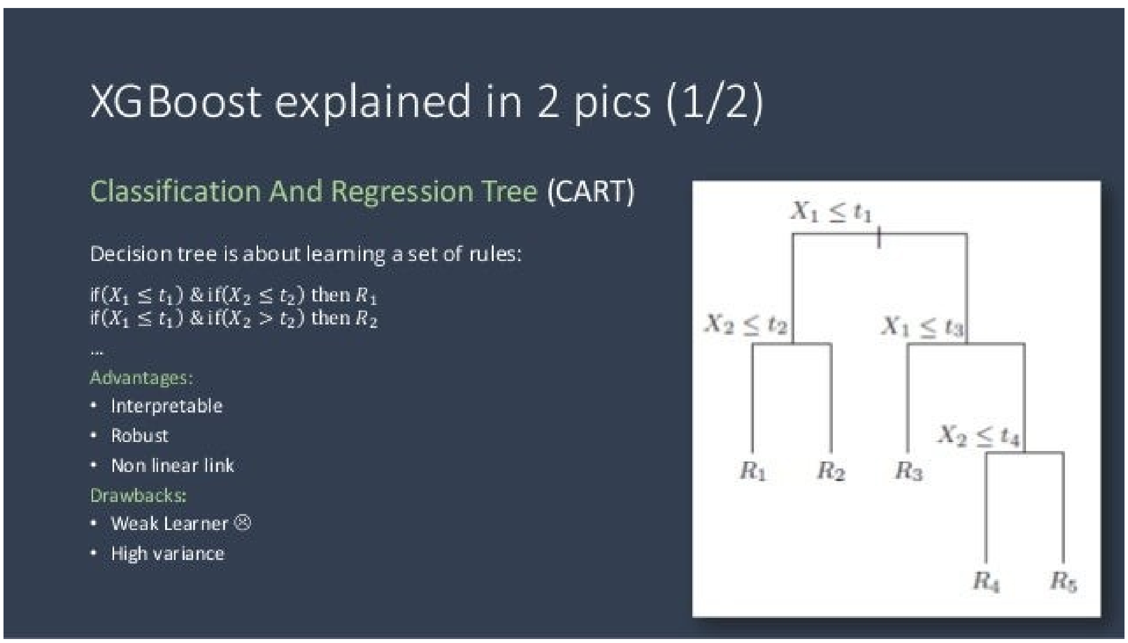


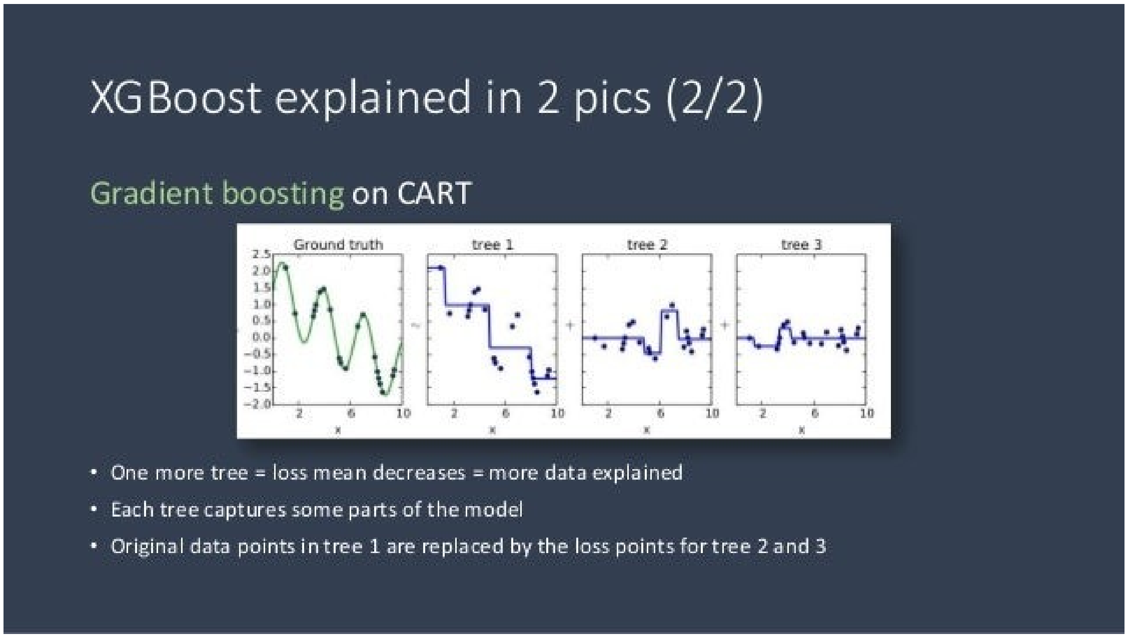


XGBoost




tree1
age < 20
Y
N
+2
-1
tree2
Use Computer Daily
Y
N
+0.9
-0.9
f( ) = 2 + 0.9= 2.9
f( )= -1 - 0.9= -1.9


XGBoost explained in 2 pics (1/2)
Classification And Regression Tree (CART)
Decision tree is about learning a set of rules:
if($X_1 \leq t_1$) & if($X_2 \leq t_2$) then R_1
if($X_1 \leq t_1$) & if($X_2 > t_2$) then R_2
...
Advantages:
• Interpretable
• Robust
• Non linear link
Drawbacks:
• Weak Learner ☹
• High variance
$X_1 \leq t_1$
$X_2 \leq t_2$
$X_1 \leq t_3$
$X_2 \leq t_4$
R_1
R_2
R_3
R_4
R_5




```
# Initialize the three models (XGBoost is initialized later)
clf_A = LogisticRegression(random_state = 42)
clf_B = SVC(random_state = 912, kernel='rbf')
#Boosting refers to this general problem of producing a very accurate
prediction rule
#by combining rough and moderately inaccurate rules-of-thumb
clf_C = xgb.XGBClassifier(seed = 82)

train_predict(clf_A, X_train, y_train, X_test, y_test)
print ''
train_predict(clf_B, X_train, y_train, X_test, y_test)
print ''
train_predict(clf_C, X_train, y_train, X_test, y_test)
print ''

Training a LogisticRegression using a training set size of 5550. . .
Trained model in 0.2450 seconds
Made predictions in 0.0380 seconds.
0.621561035256 0.665405405405
F1 score and accuracy score for training set: 0.6216 , 0.6654.
Made predictions in 0.0000 seconds.
F1 score and accuracy score for test set: 0.6957 , 0.7200.

Training a SVC using a training set size of 5550. . .
Trained model in 2.5040 seconds
Made predictions in 1.2430 seconds.
0.620453572957 0.68036036036
F1 score and accuracy score for training set: 0.6205 , 0.6804.
Made predictions in 0.0250 seconds.
F1 score and accuracy score for test set: 0.6818 , 0.7200.
```

```
Training a XGBClassifier using a training set size of 5550. . .
Trained model in 0.4470 seconds
Made predictions in 0.0160 seconds.
0.652147113211 0.694954954955
F1 score and accuracy score for training set: 0.6521 , 0.6950.
Made predictions in 0.0020 seconds.
F1 score and accuracy score for test set: 0.7451 , 0.7400.
```

Clearly XGBoost seems like the best model as it has the highest F1 score and accuracy score on the test set.

Tuning the parameters of XGBoost.

GBDT Hyper Parameter Tuning

Hyper Parameter	Tuning Approach	Range	Note
# of Trees	Fixed value	100-1000	Depending on datasize
Learning Rate	Fixed => Fine Tune	[2 - 10] / # of Trees	Depending on # trees
Row Sampling	Grid Search	[.5, .75, 1.0]	
Column Sampling	Grid Search	[.4, .6, .8, 1.0]	
Min Leaf Weight	Fixed => Fine Tune	3/(% of rare events)	Rule of thumb
Max Tree Depth	Grid Search	[4, 6, 8, 10]	
Min Split Gain	Fixed	0	Keep it 0

Best GBDT implementation today: https://github.com/tqchen/xgboost
by **Tianqi Chen** (U of Washington)

DataRobot

```
# TODO: Import 'GridSearchCV' and 'make_scorer'
from sklearn.grid_search import GridSearchCV
from sklearn.metrics import make_scorer


# TODO: Create the parameters list you wish to tune
parameters = { 'learning_rate' : [0.1],
               'n_estimators' : [40],
               'max_depth': [3],
               'min_child_weight': [3],
               'gamma':[0.4],
               'subsample' : [0.8],
               'colsample_bytree' : [0.8],
               'scale_pos_weight' : [1],
               'reg_alpha':[1e-5]
             }

# TODO: Initialize the classifier
```

```
clf = xgb.XGBClassifier(seed=2)

# TODO: Make an f1 scoring function using 'make_scorer'
f1_scorer = make_scorer(f1_score,pos_label='H')

# TODO: Perform grid search on the classifier using the f1_scorer as
the scoring method
grid_obj = GridSearchCV(clf,
                        scoring=f1_scorer,
                        param_grid=parameters,
                        cv=5)

# TODO: Fit the grid search object to the training data and find the
optimal parameters
grid_obj = grid_obj.fit(X_train,y_train)

# Get the estimator
clf = grid_obj.best_estimator_
print clf

# Report the final F1 score for training and testing after parameter
tuning
f1, acc = predict_labels(clf, X_train, y_train)
print "F1 score and accuracy score for training set: {:.4f} ,
{:.4f}.".format(f1 , acc)

f1, acc = predict_labels(clf, X_test, y_test)
print "F1 score and accuracy score for test set: {:.4f} ,
{:.4f}.".format(f1 , acc)

XGBClassifier(base_score=0.5, colsample_bylevel=1,
colsample_bytree=0.8,
       gamma=0.4, learning_rate=0.1, max_delta_step=0, max_depth=3,
       min_child_weight=3, missing=None, n_estimators=40, nthread=-1,
       objective='binary:logistic', reg_alpha=1e-05, reg_lambda=1,
       scale_pos_weight=1, seed=2, silent=True, subsample=0.8)
Made predictions in 0.0150 seconds.
F1 score and accuracy score for training set: 0.6365 , 0.6827.
Made predictions in 0.0000 seconds.
F1 score and accuracy score for test set: 0.7826 , 0.8000.

#prediction
```

Possible Improvements?

-Adding Sentiment from Twitter, News Articles -More features from other data sources (how much did others bet, player specific health stats)