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Predicting_Winning_Teams / Prediction.ipynb

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0d89b83 on Aug 23, 2017

1 contributor

Raw Blame History

965 lines (965 sloc) 474 KB

# Predicting the Winning Football Team

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

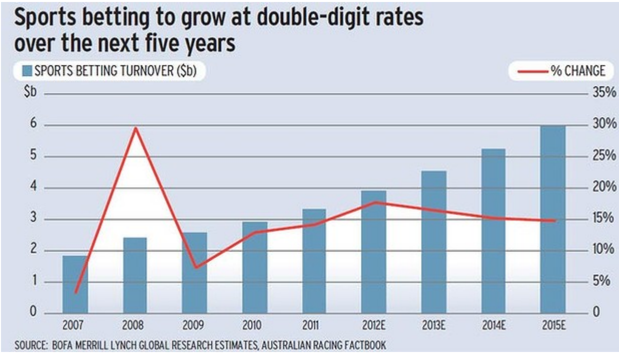
alt text

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

Several Papers on this

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

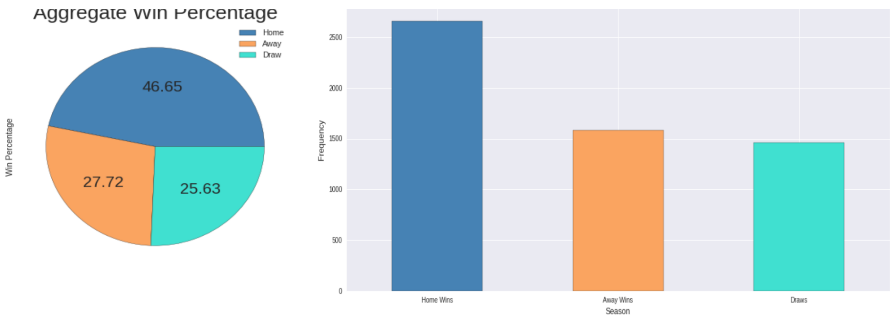
So the right questions to ask are

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

## Other repositories

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

## Import Dependencies

In [ ]:
```
#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
```

In [2]:
```
# 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 |

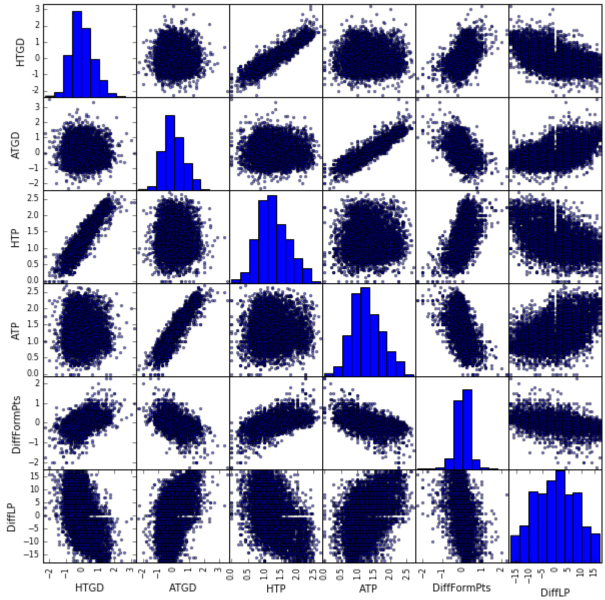
## Data Exploration

In [3]:
```
#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%
```

In [4]:
```
# 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))
```

Out[4]:
```
array([[<matplotlib.axes._subplots.AxesSubplot object at 0x0000000003A7BA90>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x000000000A28B908>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x000000000A1481D0>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x000000000A1E9BA8>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x000000000A0B3470>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x000000000AA29470>],
       [<matplotlib.axes._subplots.AxesSubplot object at 0x000000000AAE5DD8>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x000000000AA38208>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x000000000ACE4400>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x000000000AD5EC88>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x000000000AE9B5F8>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x000000000AF56F60>],
       [<matplotlib.axes._subplots.AxesSubplot object at 0x000000000AFF3EB8>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x000000000B159860>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x000000000B18DE80>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x000000000B2CAE48>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x000000000B3D5710>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x000000000B4BA978>],
       [<matplotlib.axes._subplots.AxesSubplot object at 0x000000000B544240>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x000000000B625D68>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x000000000B744860>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x000000000B813128>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x000000000B8B5A20>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x000000000B9E82E8>],
       [<matplotlib.axes._subplots.AxesSubplot object at 0x000000000BA4E320>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x000000000BB48C88>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x000000000BC0D2E8>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x000000000BCEB8D0>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x000000000BDF9198>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x000000000BE9E128>],
       [<matplotlib.axes._subplots.AxesSubplot object at 0x000000000BF989B0>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x000000000BFCEE80>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x000000000C18BFD0>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x000000000C253898>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x000000000C2F8B00>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x000000000C4053C8>]], dtype=object)
```




## Preparing the Data

In [5]:
```
# 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])
```

In [6]:
```
#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):

```
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', 'Di
ffLP']
```

In [7]:

```
# 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 | HM3_L | ... | AM2_D | AM2_L | AM2_W |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **30** | -0.043829 | -0.611968 | 1.0 | 0.0 | 0.0 | 1.0 | 0.0 | 0.0 | 0.0 | 0.0 | ... | 0.0 | 0.0 | 1.0 |
| **31** | -1.120644 | -2.238746 | 0.0 | 1.0 | 0.0 | 0.0 | 1.0 | 0.0 | 0.0 | 0.0 | ... | 0.0 | 1.0 | 0.0 |
| **32** | -0.582236 | -0.611968 | 0.0 | 1.0 | 0.0 | 1.0 | 0.0 | 0.0 | 0.0 | 0.0 | ... | 0.0 | 0.0 | 1.0 |
| **33** | -1.120644 | -1.696487 | 0.0 | 1.0 | 0.0 | 0.0 | 1.0 | 0.0 | 0.0 | 0.0 | ... | 0.0 | 1.0 | 0.0 |
| **34** | -0.582236 | 0.472551 | 1.0 | 0.0 | 0.0 | 0.0 | 1.0 | 0.0 | 0.0 | 0.0 | ... | 0.0 | 0.0 | 1.0 |

5 rows × 24 columns

In [8]:

```
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)
```

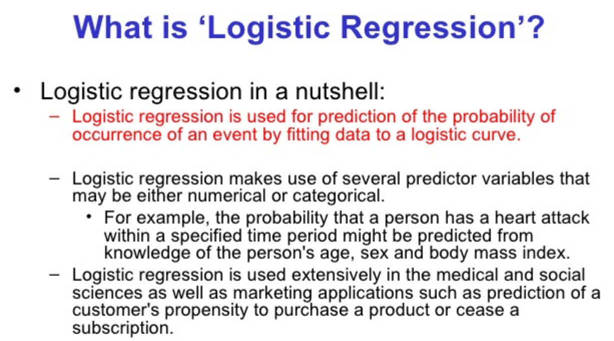
## Training and Evaluating Models

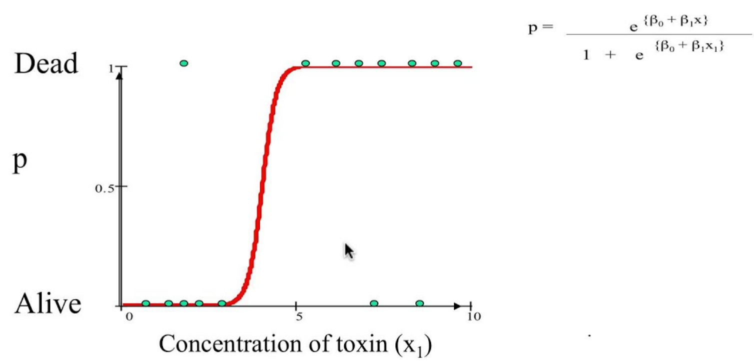
In [9]:

```
#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
```

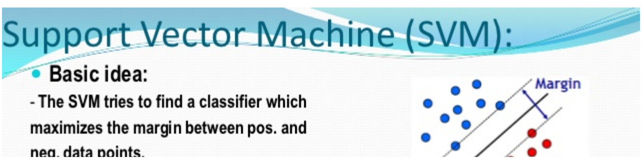
```
f1, acc = predict_labels(clf, X_train, y_train)
print f1, acc
print "F1 score and accuracy score for training set: {:.4f} , {:.4f}.".format(f1 , acc)

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

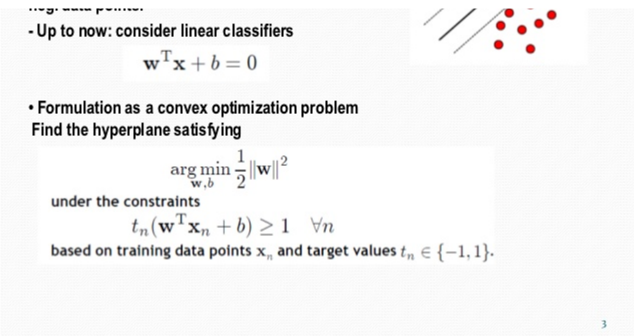
Logistic Regression

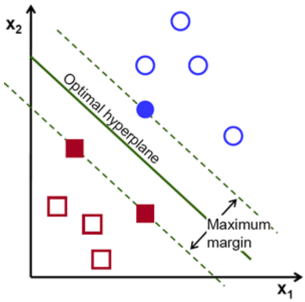


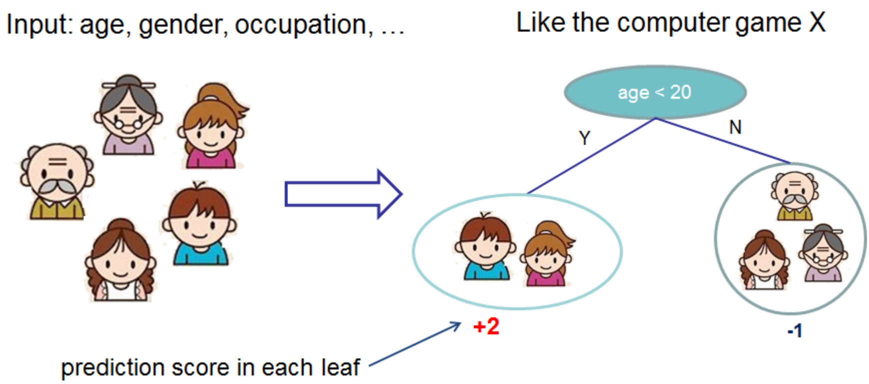

Support Vector Machine

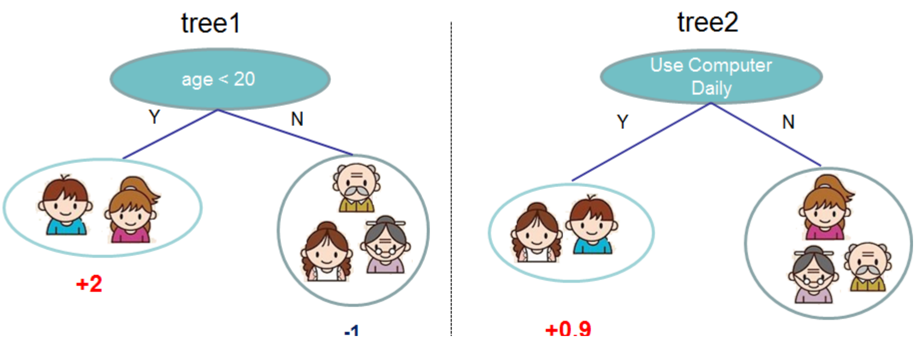


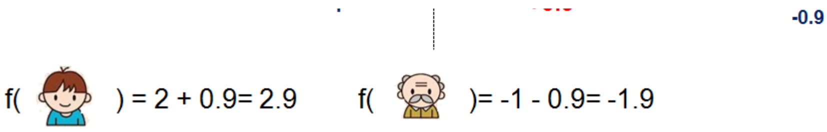

- Up to now: consider linear classifiers
$\mathbf{w}^{\mathrm{T}}\mathbf{x} + b = 0$
• Formulation as a convex optimization problem
Find the hyperplane satisfying
$\arg\min_{\mathbf{w},b} \frac{1}{2}\|\mathbf{w}\|^2$
under the constraints
$t_n(\mathbf{w}^{\mathrm{T}}\mathbf{x}_n + b) \geq 1 \quad \forall n$
based on training data points $\mathbf{x}_n$ and target values $t_n \in \{-1, 1\}$.
3

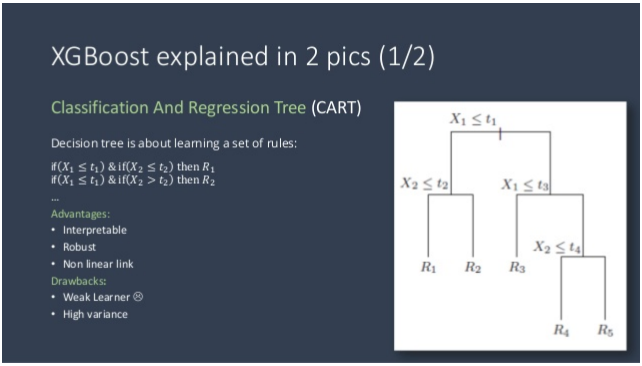

$x_2$
Optimal hyperplane
Maximum margin
$x_1$

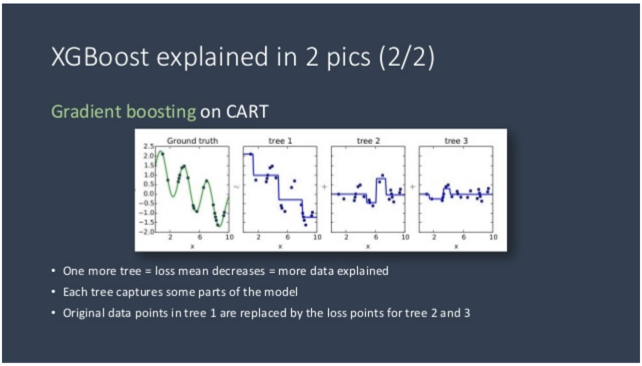
XGBoost


Input: age, gender, occupation, …
Like the computer game X
age < 20
Y
N
+2
-1
prediction score in each leaf


tree1
age < 20
Y
N
+2
-1
tree2
Use Computer Daily
Y
N
+0.9




In [10]:

```
# 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.
```

```
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)

In [39]:

```
# 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,
```