kobe

May 21, 2016

1 Definition

1.1 Project Overview

This is a competition from Kaggle, Kobe Bryant Shot Selection. The description of this problem from Kaggle is as follows. > Kobe Bryant marked his retirement from the NBA by scoring 60 points in his final game as a Los Angeles Laker on Wednesday, April 12, 2016. Drafted into the NBA at the age of 17, Kobe earned the sport's highest accolades throughout his long career. Using 20 years of data on Kobe's swishes and misses, can you predict which shots will find the bottom of the net?

1.2 Problem Statement

> Given location and circumstances of every field goal attempted by Kobe Bryant took during his 20-year career, the task is to predict the probability that Kobe made the field goal.

This is a classification problem, but the classification algorithm should be able to give the probability for each class. To solve this problem, first I will do some data exploration, we all know that the shot percentage depends on all kinds of features, such as shot type, shot distance, the state of the athlete and so on, some statistics will be made to understand the importance of each feature. Then I will try different kinds of supervised learning classification algorithms, and tune the model using cross validation, then choose the best model, and train it on the whole data sets, finally use this model to generate the precdictions on test data. And try to rank as high as possible in the competion.

1.3 Metrics

The metrics I use will follow the competition metrics, log loss > The logarithm of the likelihood function for a Bernouli random distribution. In plain English, this error metric is used where contestants have to predict that something is true or false with a probability (likelihood) ranging from definitely true (1) to equally true (0.5) to definitely false(0). > The use of log on the error provides extreme punishments for being both confident and wrong. In the worst possible case, a single prediction that something is definitely true (1) when it is actually false will add infinite to your error score and make every other entry pointless. In Kaggle competitions, predictions are bounded away from the extremes by a small value in order to prevent this.

2 Analysis

2.1 Data Exploration

```
In [1]: import csv
        import pandas as pd
```

```
In [39]: all_data = pd.read_csv('data.csv')
         all_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 30697 entries, 0 to 30696
Data columns (total 25 columns):
action_type           30697 non-null object
combined_shot_type    30697 non-null object
game_event_id         30697 non-null int64
game_id               30697 non-null int64
lat                   30697 non-null float64
loc_x                 30697 non-null int64
loc_y                 30697 non-null int64
lon                   30697 non-null float64
minutes_remaining     30697 non-null int64
period                30697 non-null int64
playoffs              30697 non-null int64
season                30697 non-null object
seconds_remaining     30697 non-null int64
shot_distance         30697 non-null int64
shot_made_flag        25697 non-null float64
shot_type             30697 non-null object
shot_zone_area        30697 non-null object
shot_zone_basic       30697 non-null object
shot_zone_range       30697 non-null object
team_id               30697 non-null int64
team_name             30697 non-null object
game_date             30697 non-null object
matchup               30697 non-null object
opponent              30697 non-null object
shot_id               30697 non-null int64
dtypes: float64(3), int64(11), object(11)
memory usage: 5.9+ MB
```

There are 24 features whose name are self explanatory, and shot_made_flag is our prediction target. There are 30697 entries, and 5000 entries don't have label, which means the size of training data is 25697, and size of test data is 5000. There is no missing value, so we don't have to worry about this.

```
In [28]: all_data.head()
```

```
Out[28]:          action_type combined_shot_type  game_event_id   game_id      lat
         0          Jump Shot          Jump Shot             10  20000012  33.9723
         1          Jump Shot          Jump Shot             12  20000012  34.0443
         2          Jump Shot          Jump Shot             35  20000012  33.9093
         3          Jump Shot          Jump Shot             43  20000012  33.8693
         4  Driving Dunk Shot               Dunk            155  20000012  34.0443

            loc_x  loc_y       lon  minutes_remaining  period   ...          shot_t
         0    167     72 -118.1028                 10       1   ...     2PT Field G
         1   -157      0 -118.4268                 10       1   ...     2PT Field G
         2   -101    135 -118.3708                  7       1   ...     2PT Field G
         3    138    175 -118.1318                  6       1   ...     2PT Field G
         4      0      0 -118.2698                  6       2   ...     2PT Field G

                   shot_zone_area  shot_zone_basic  shot_zone_range     team_id  \
         0          Right Side(R)        Mid-Range        16-24 ft.  1610612747
         1           Left Side(L)        Mid-Range         8-16 ft.  1610612747
         2   Left Side Center(LC)        Mid-Range        16-24 ft.  1610612747
         3  Right Side Center(RC)        Mid-Range        16-24 ft.  1610612747
         4              Center(C)  Restricted Area  Less Than 8 ft.  1610612747

                     team_name   game_date    matchup opponent  shot_id
         0  Los Angeles Lakers  2000-10-31  LAL @ POR      POR        1
         1  Los Angeles Lakers  2000-10-31  LAL @ POR      POR        2
         2  Los Angeles Lakers  2000-10-31  LAL @ POR      POR        3
         3  Los Angeles Lakers  2000-10-31  LAL @ POR      POR        4
         4  Los Angeles Lakers  2000-10-31  LAL @ POR      POR        5

         [5 rows x 25 columns]
```

action_type, combined_shot_type, season, shot_type, shot_zone_area, shot_zone_basic, shot_zone_range, team_name, game_date, matchup, opponent, these categorical variables need to be transformed using one hot encoding. team_name and team_id is always "Los Angeles Lakers", so it can be droped. game_date is time series, so it can be change to ordered number. matchup should be transformed to a new feature, whether the competion is held home. game_event_id is global, it should be localised for kobe. game_id is useless, because we have game_date, and there is only one game a day. lat , lon, shot_id are useless, can be droped.

```
In [29]: all_data.describe()
```

```
Out[29]:       game_event_id       game_id           lat          loc_x          loc
         count  30697.000000  3.069700e+04  30697.000000  30697.000000  30697.0000
         mean     249.190800  2.476407e+07     33.953192       7.110499     91.1075
         std      150.003712  7.755175e+06      0.087791     110.124578     87.7913
         min        2.000000  2.000001e+07     33.253300    -250.000000    -44.0000
         25%      110.000000  2.050008e+07     33.884300     -68.000000      4.0000
         50%      253.000000  2.090035e+07     33.970300       0.000000     74.0000
         75%      368.000000  2.960047e+07     34.040300      95.000000    160.0000
```

```
max       659.000000   4.990009e+07     34.088300    248.000000    791.0000

                  lon  minutes_remaining        period     playoffs  \
count  30697.000000       30697.000000  30697.000000 30697.000000
mean    -118.262690           4.885624      2.519432     0.146562
std        0.110125           3.449897      1.153665     0.353674
min     -118.519800           0.000000      1.000000     0.000000
25%     -118.337800           2.000000      1.000000     0.000000
50%     -118.269800           5.000000      3.000000     0.000000
75%     -118.174800           8.000000      3.000000     0.000000
max     -118.021800          11.000000      7.000000     1.000000

       seconds_remaining  shot_distance  shot_made_flag       team_id  \
count       30697.000000   30697.000000    25697.000000  3.069700e+04
mean           28.365085      13.437437        0.446161  1.610613e+09
std            17.478949       9.374189        0.497103  0.000000e+00
min             0.000000       0.000000        0.000000  1.610613e+09
25%            13.000000       5.000000        0.000000  1.610613e+09
50%            28.000000      15.000000        0.000000  1.610613e+09
75%            43.000000      21.000000        1.000000  1.610613e+09
max            59.000000      79.000000        1.000000  1.610613e+09

            shot_id
count  30697.000000
mean   15349.000000
std     8861.604943
min        1.000000
25%     7675.000000
50%    15349.000000
75%    23023.000000
max    30697.000000
```

From shot_distance we can see kobe likes to make close range shot, other statistic results don't have much meaning.

2.2 Exploratory Visualization

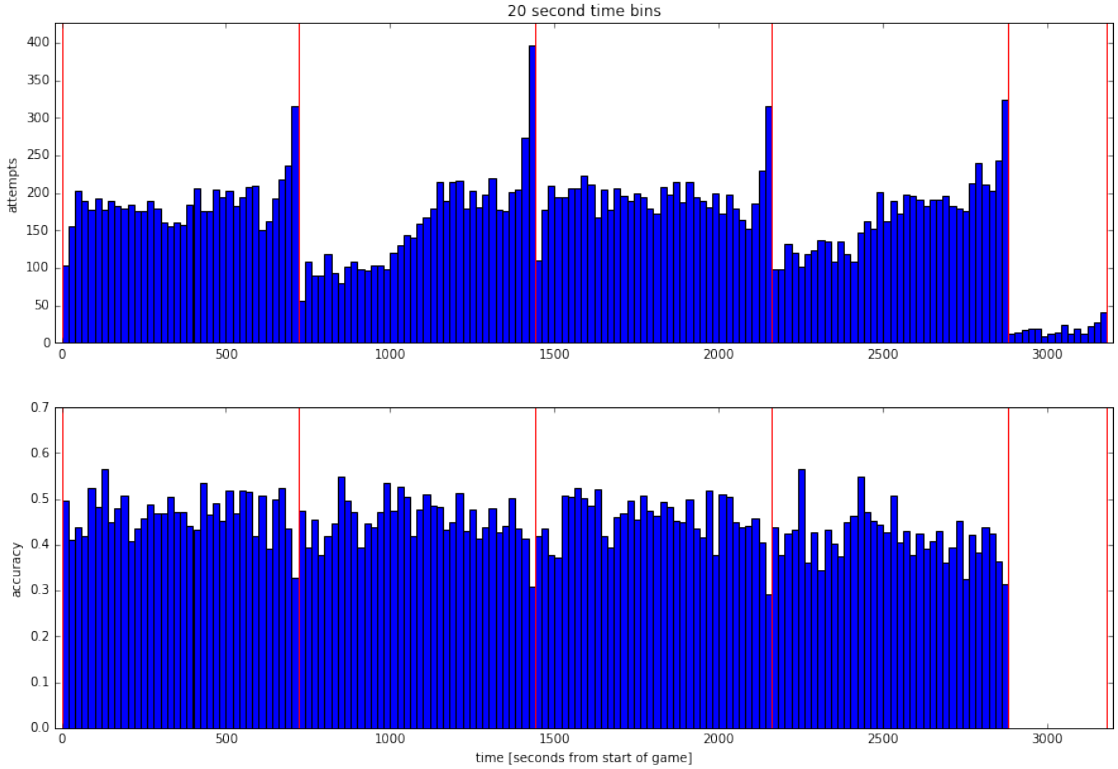
The visualization scrip is borrowed from a kaggle scrip.First, let's examine the temporal aspect of Kobe's shots.

In [54]:
```
import matplotlib.pyplot as plt
import numpy as np
import matplotlib as mpl
from sklearn import mixture
from matplotlib.patches import Circle, Rectangle, Arc
%matplotlib inline

data = all_data[all_data['shot_made_flag'].notnull()].reset_index()
```

```
#%% add some temporal columns to the data

data['game_date_DT'] = pd.to_datetime(data['game_date'])
data['dayOfWeek'] = data['game_date_DT'].dt.dayofweek
data['dayOfYear'] = data['game_date_DT'].dt.dayofyear

data['secondsFromPeriodEnd'] = 60*data['minutes_remaining']+data['seconds_
data['secondsFromPeriodStart'] = 60*(11-data['minutes_remaining'])+(60-dat
data['secondsFromGameStart'] = (data['period'] <= 4).astype(int)*(data['pe
    4).astype(int)*((data['period']-4)*5*60 + 3*12*60) + data['secondsFrom
```

In [55]:
```
#%% plot the accuracy as a function of time
plt.rcParams['figure.figsize'] = (15, 10)

binSizeInSeconds = 20
timeBins = np.arange(0,60*(4*12+3*5),binSizeInSeconds)+0.01
attemptsAsFunctionOfTime, b = np.histogram(data['secondsFromGameStart'], b
madeAttemptsAsFunctionOfTime, b = np.histogram(data.ix[data['shot_made_fla
accuracyAsFunctionOfTime = madeAttemptsAsFunctionOfTime.astype(float)/atte
accuracyAsFunctionOfTime[attemptsAsFunctionOfTime <= 50] = 0 # zero accura

maxHeight = max(attemptsAsFunctionOfTime) + 30
barWidth = 0.999*(timeBins[1]-timeBins[0])

plt.figure();
plt.subplot(2,1,1); plt.bar(timeBins[:-1],attemptsAsFunctionOfTime, align=
plt.xlim((-20,3200)); plt.ylim((0,maxHeight)); plt.ylabel('attempts'); plt
plt.vlines(x=[0,12*60,2*12*60,3*12*60,4*12*60,4*12*60+5*60,4*12*60+2*5*60,
plt.subplot(2,1,2); plt.bar(timeBins[:-1],accuracyAsFunctionOfTime, align=
plt.xlim((-20,3200)); plt.ylabel('accuracy'); plt.xlabel('time [seconds fr
plt.vlines(x=[0,12*60,2*12*60,3*12*60,4*12*60,4*12*60+5*60,4*12*60+2*5*60,
```

Out[55]:
```
<matplotlib.collections.LineCollection at 0x19fc7c50>
```



From shot attempts figure, it looks like Kobe is entrusted to take the last shot of every period, and he's usually on the bench at the start of 2nd and 4th periods. As the accuracy graph shows, these "last second shots" is consisently lower than usual, this is probably due to the fact that a large amonut of these shots are from very far away and in a hurry.

Now let's examine the spatial location aspect of kobe's shots. we'll do this by building a gaussian mixture model that tries to explain Kobe's shot locations

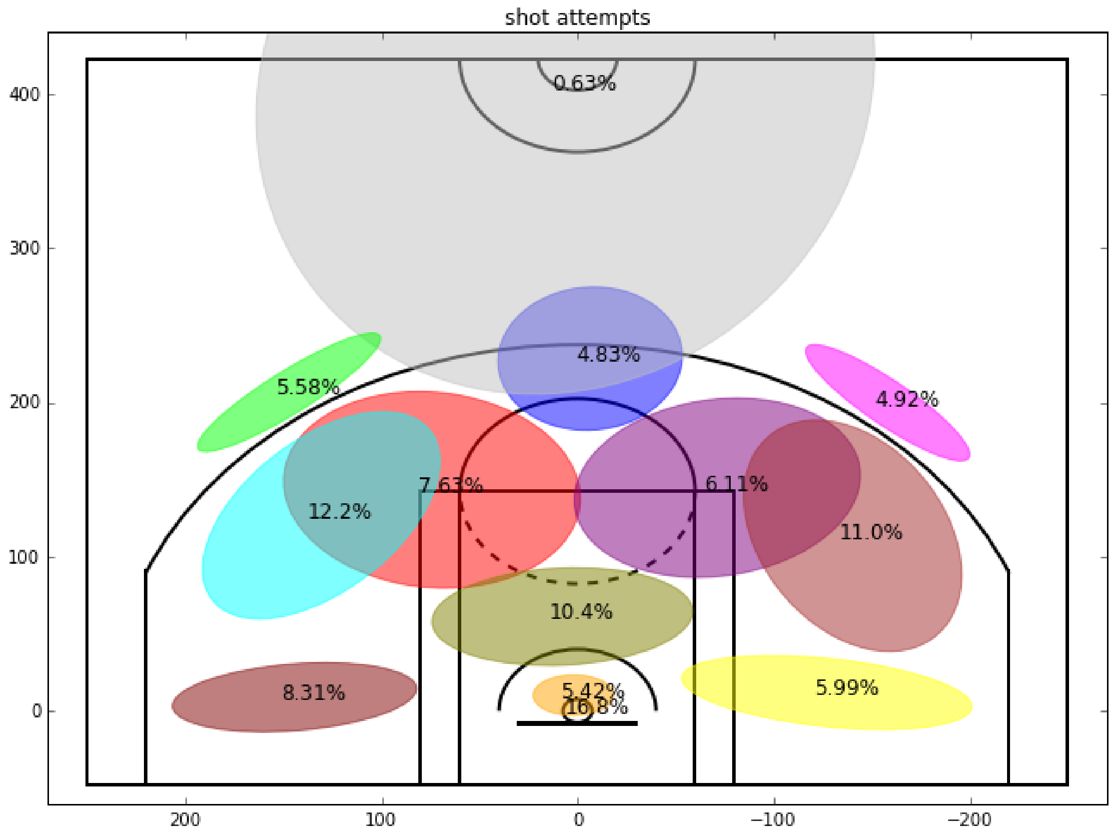
```
In [58]: #%% cluster the shot attempts of kobe using GMM on their location

         numGaussians = 13
         gaussianMixtureModel = mixture.GMM(n_components=numGaussians, covariance_t
                                            params='wmc', init_params='wmc',
                                            random_state=1, n_init=3,  verbose=0)
         gaussianMixtureModel.fit(data.ix[:,['loc_x','loc_y']])

         data['shotLocationCluster'] = gaussianMixtureModel.predict(data.ix[:,['loc

In [59]: #%% define draw functions (stealing shamelessly the draw_court() function

         def draw_court(ax=None, color='black', lw=2, outer_lines=False):
             # If an axes object isn't provided to plot onto, just get current one
             if ax is None:
                 ax = plt.gca()
```

```
# Create the various parts of an NBA basketball court

# Create the basketball hoop
# Diameter of a hoop is 18" so it has a radius of 9", which is a value
# 7.5 in our coordinate system
hoop = Circle((0, 0), radius=7.5, linewidth=lw, color=color, fill=Fals

# Create backboard
backboard = Rectangle((-30, -7.5), 60, -1, linewidth=lw, color=color)

# The paint
# Create the outer box 0f the paint, width=16ft, height=19ft
outer_box = Rectangle((-80, -47.5), 160, 190, linewidth=lw, color=colo
                      fill=False)
# Create the inner box of the paint, widt=12ft, height=19ft
inner_box = Rectangle((-60, -47.5), 120, 190, linewidth=lw, color=colo
                      fill=False)

# Create free throw top arc
top_free_throw = Arc((0, 142.5), 120, 120, theta1=0, theta2=180,
                     linewidth=lw, color=color, fill=False)
# Create free throw bottom arc
bottom_free_throw = Arc((0, 142.5), 120, 120, theta1=180, theta2=0,
                        linewidth=lw, color=color, linestyle='dashed')
# Restricted Zone, it is an arc with 4ft radius from center of the hoo
restricted = Arc((0, 0), 80, 80, theta1=0, theta2=180, linewidth=lw,
                 color=color)

# Three point line
# Create the side 3pt lines, they are 14ft long before they begin to a
corner_three_a = Rectangle((-220, -47.5), 0, 140, linewidth=lw,
                           color=color)
corner_three_b = Rectangle((220, -47.5), 0, 140, linewidth=lw, color=c
# 3pt arc - center of arc will be the hoop, arc is 23'9" away from hoo
# I just played around with the theta values until they lined up with
# threes
three_arc = Arc((0, 0), 475, 475, theta1=22, theta2=158, linewidth=lw,
                color=color)

# Center Court
center_outer_arc = Arc((0, 422.5), 120, 120, theta1=180, theta2=0,
                       linewidth=lw, color=color)
center_inner_arc = Arc((0, 422.5), 40, 40, theta1=180, theta2=0,
                       linewidth=lw, color=color)

# List of the court elements to be plotted onto the axes
court_elements = [hoop, backboard, outer_box, inner_box, top_free_thro
                  bottom_free_throw, restricted, corner_three_a,
```

```
                        corner_three_b, three_arc, center_outer_arc,
                        center_inner_arc]

    if outer_lines:
        # Draw the half court line, baseline and side out bound lines
        outer_lines = Rectangle((-250, -47.5), 500, 470, linewidth=lw,
                               color=color, fill=False)
        court_elements.append(outer_lines)

    # Add the court elements onto the axes
    for element in court_elements:
        ax.add_patch(element)

    return ax

def Draw2DGaussians(gaussianMixtureModel, ellipseColors, ellipseTextMessag

    fig, h = plt.subplots();
    for i, (mean, covarianceMatrix) in enumerate(zip(gaussianMixtureModel.
        # get the eigen vectors and eigen values of the covariance matrix
        v, w = np.linalg.eigh(covarianceMatrix)
        v = 2.5*np.sqrt(v) # go to units of standard deviation instead of

        # calculate the ellipse angle and two axis length and draw it
        u = w[0] / np.linalg.norm(w[0])
        angle = np.arctan(u[1] / u[0])
        angle = 180 * angle / np.pi  # convert to degrees
        currEllipse = mpl.patches.Ellipse(mean, v[0], v[1], 180 + angle, c
        currEllipse.set_alpha(0.5)
        h.add_artist(currEllipse)
        h.text(mean[0]+7, mean[1]-1, ellipseTextMessages[i], fontsize=12)
```

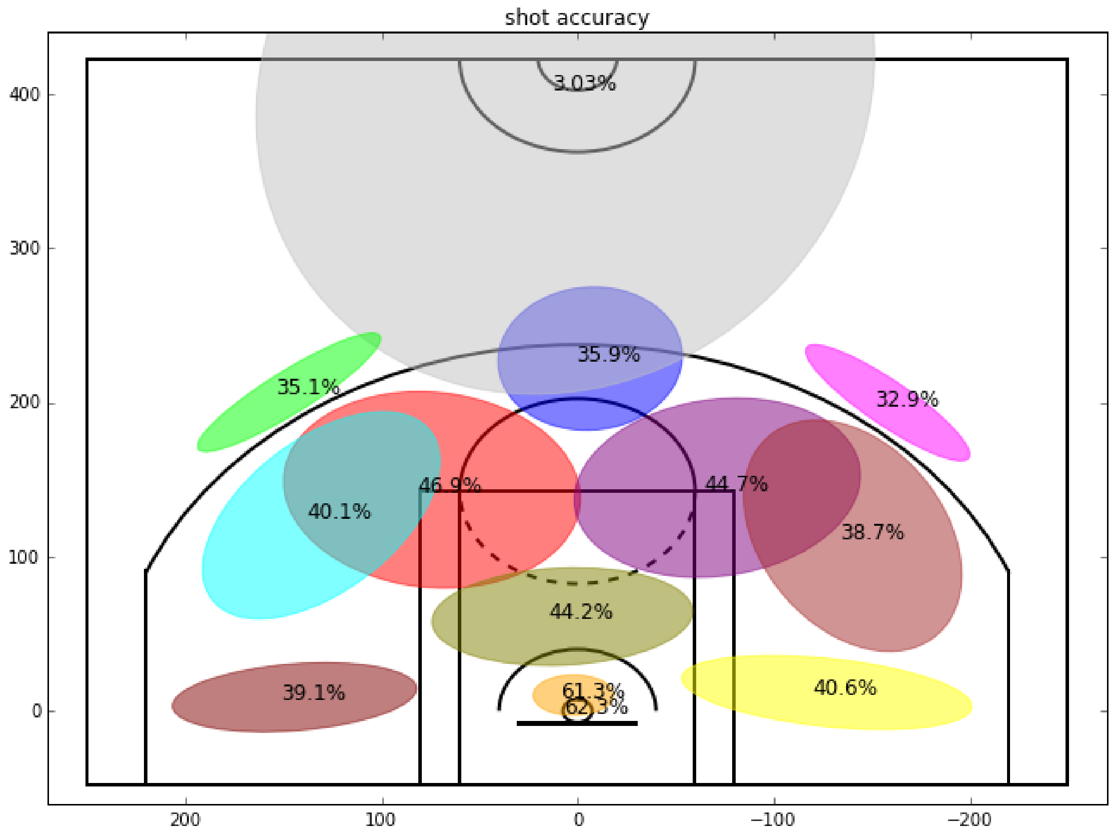
In [60]:
```
#%% show gaussian mixture elipses of shot attempts
plt.rcParams['figure.figsize'] = (11, 8)

ellipseTextMessages = [str(100*gaussianMixtureModel.weights_[x])[:4]+'%' f
ellipseColors = ['red','green','purple','cyan','magenta','yellow','blue','
Draw2DGaussians(gaussianMixtureModel, ellipseColors, ellipseTextMessages)
draw_court(outer_lines=True); plt.ylim(-60,440); plt.xlim(270,-270); plt.t
```

Out[60]: <matplotlib.text.Text at 0x1a8d3cc0>



We can see that Kobe shots more on his right side, which is a strong side for a right hand player. Comparing to 3 point shot, Kobe prefers to shot close to basket.

```
In [61]: #%% for each cluster, calculate it's individual accuracy and plot it

         plt.rcParams['figure.figsize'] = (11, 8)

         variableCategories = data['shotLocationCluster'].value_counts().index.toli

         clusterAccuracy = {}
         for category in variableCategories:
             shotsAttempted = np.array(data['shotLocationCluster'] == category).sum
             shotsMade = np.array(data.ix[data['shotLocationCluster'] == category,'
             clusterAccuracy[category] = float(shotsMade)/shotsAttempted

         ellipseTextMessages = [str(100*clusterAccuracy[x])[:4]+'%' for x in range
         Draw2DGaussians(gaussianMixtureModel, ellipseColors, ellipseTextMessages)
         draw_court(outer_lines=True); plt.ylim(-60,440); plt.xlim(270,-270); plt.t

Out[61]: <matplotlib.text.Text at 0x1b02dcc0>
```



As it shows that, Kobe is not really good at 3 point shot, but he is strong under the basket, more than 60 percent shot accuracy. He has higher accuracy from his right side, 45 degeee shot is also his strong point.

2.3 Algorithms and Techniques

I'm going to try different kinds of supervised learninig classification algotithms, from simple to complex, linear model such as logistic regression, nonlinear model like decision tree, and ensemble method like random forest. All the default parameters in the algorithms are the same with sklean's Logistic Regression,DecisionTreeClassifier and RandomForestClassifier. The data will be split into train and test set, train data set's label is shot_made_flag, data without this label is going to be in test data sets. And all the values in the data should be converted into numerical values. Then just train the algorithm on these data sets.

2.4 Benchmark

The benchmark value is 0.69315. It's easy to think about this hypothesis, every shot has 50-50 chance miss, so just predict 0.5 for all the data, and that will get 0.69315 score.

3 Methodology

3.1 Data Preprocessing

```
In [478]: all_data = pd.read_csv('data.csv')
          # drop the useless features
          drop_names = ['team_name', 'team_id', 'game_id', 'lat', 'lon', 'shot_id']
          all_data.drop(drop_names, axis=1, inplace=True)
          # convert object features using one hot encode
          convert_names = ['action_type', 'combined_shot_type', 'season', 'shot_typ
          for name in convert_names:
              dummies = pd.get_dummies(all_data[name]).rename(columns=lambda x: nam
              all_data = pd.concat([all_data, dummies], axis=1)
              all_data.drop(name, axis=1, inplace=True)
          # convert game_date to year, month, day
          col_names = ['year', 'month', 'day']
          for i in range(3):
              val = all_data['game_date'].apply(lambda x:x.split('-')[i]).rename(co
              all_data = pd.concat([all_data, val], axis=1)
          # extract the information whether the game is held home from matchup
          all_data = pd.concat([all_data, all_data['matchup'].apply(lambda x:1 if '
          all_data.drop('matchup', axis=1, inplace=True)
          # convert game_event_id to shot id for kobe in that game
          cnt = 1
          last = -1
          re_id = []
          for i in range(all_data.shape[0]):
              date = all_data['game_date'][i]
              idx = all_data['game_event_id'][i]
              if date != last:
                  cnt = 1
              re_id.append(cnt)
              cnt += 1
              last = date
          all_data['game_event_id'].update(pd.Series(re_id))
          # consider the time series features
          # add a new feature, last_shot_made, whether kobe has made last shot,
          # 0.446( kobe's average shot accuracy) if it's none, 0 if it's the first
          last = 0
          last_shot_made = []
          for i in range(all_data.shape[0]):
              idx = all_data['game_event_id'][i]
              if idx == 1:
                  last = 0
              last_shot_made.append(last)
              last = 0.446 if np.isnan(all_data['shot_made_flag'][i]) else all_data
          all_data = pd.concat([all_data, pd.Series(last_shot_made,name='last_shot_
          # last shot distance: Euclid distance between this shot and last shot's p
```

```
last_pos = np.array((0, 0))
last_shot_dis = []
for i in range(all_data.shape[0]):
    x = all_data['loc_x'][i]
    y = all_data['loc_y'][i]
    idx = all_data['game_event_id'][i]
    pos = np.array((x, y))
    dis = np.linalg.norm(pos-last_pos)
    if idx == 1:
        dis = 0
    last_shot_dis.append(dis)
    last_pos = pos
all_data = pd.concat([all_data, pd.Series(last_shot_dis,name='last_shot_d
# last_shot_gap_time: the time gap between this shot and last shot measur
last_shot_gap_time = []
la_minute = 0
la_period = 0
la_second = 0
for i in range(all_data.shape[0]):
    minute = all_data['minutes_remaining'][i]
    period = all_data['period'][i]
    second = all_data['seconds_remaining'][i]
    idx = all_data['game_event_id'][i]
    gap = (period-la_period)*12*60 + -(minute-la_minute)*60 + -(second-la
    if idx == 1 or gap<0: # there are some mistakes in the data
        gap = 0
    last_shot_gap_time.append(gap)
    la_minute, la_period, la_second = minute, period, second
all_data = pd.concat([all_data, pd.Series(last_shot_gap_time,name='last_s
# back_to_back: whether the game is held in two successive days
back_to_back = [0]
for i in range(1, all_data.shape[0]):
    tag = 0
    if (pd.to_datetime(all_data['game_date'][i])-pd.to_datetime(all_data[
        tag = 1
    if (pd.to_datetime(all_data['game_date'][i])-pd.to_datetime(all_data[
        tag = back_to_back[-1]
    back_to_back.append(tag)
all_data = pd.concat([all_data, pd.Series(back_to_back,name='back_to_back
# convert game date to ordered number, start from 0
order_date = sorted(all_data['game_date'])
all_data['game_date'] = all_data['game_date'].apply(lambda x:order_date.i
```

3.2 Implementation

In [480]:
```
from sklearn.cross_validation import train_test_split, ShuffleSplit
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
```

```
from sklearn.ensemble import RandomForestClassifier, GradientBoostingClas
from sklearn.metrics import log_loss
from sklearn.grid_search import GridSearchCV
import numpy as np

train_data = all_data[all_data['shot_made_flag'].notnull()]
pred_data = all_data[all_data['shot_made_flag'].isnull()].drop('shot_made
X = train_data.drop('shot_made_flag', axis=1).values
y = train_data['shot_made_flag'].values

clfs = [LogisticRegression(), DecisionTreeClassifier(), RandomForestClass
clf_names = ['LogisticRegression', 'DecisionTree', 'RandomForest', 'Gradi
train_loss = []
val_loss = []
rs = ShuffleSplit(X.shape[0], n_iter=10, test_size=0.1, random_state=0)
for clf in clfs:
    train_tem = []
    val_tem = []
    for train_index, test_index in rs:
        X_train, X_test, y_train, y_test = X[train_index], X[test_index],
        clf.fit(X_train, y_train)
        train_tem.append(log_loss(y_train, clf.predict_proba(X_train)))
        val_tem.append(log_loss(y_test, clf.predict_proba(X_test)))
    train_loss.append(np.mean(train_tem))
    val_loss.append(np.mean(val_tem))
```

3.3 Refinement

```
In [481]: pd.DataFrame({'clf':clf_names, 'train_loss':train_loss, 'val_loss':val_lo
```

Out[481]:

	clf	train_loss	val_loss
0	LogisticRegression	6.112325e-01	0.611777
1	DecisionTree	9.992007e-16	14.310074
2	RandomForest	1.826032e-01	0.897065
3	GradientBoosting	5.936789e-01	0.603428
4	AdaBoost	6.883323e-01	0.688488

The initial solution result is shown above. As we can see, GradientBoosting has the best validation loss, LogisticRegression is good too, but they are underfitting, while Decision Tree and RandomForest is suffering from overfitting issues. So, I'm going to use GridSearch to find the best parameters for each model.

After a long time GridSearch, I just found that the model using default parameters has the best performance. And it seems that GradientBoostingClassifier is the best choice in this problem, but the overfitting issue is still heavy, I think maybe the features are not good enough, so I add some features, but the performance doesn't get better.

4 Results

4.1 Model Evaluation and Validation

```
In [509]: clf = GradientBoostingClassifier().fit(X, y)
          print 'Log loss:', log_loss(y, clf.predict_proba(X))
          print 'Accuracy:', clf.score(X, y)
```

```
Log loss: 0.594415594472
Accuracy: 0.68556640853
```

```
In [502]: predictions = clf.predict_proba(pred_data)
          out = pd.DataFrame({'shot_id':pred_data.index+1, 'shot_made_flag':[i[1] f
          out.to_csv('first_submission.csv', index=False)
```

I choose GradientBoostingClassifier as the final model, and use the default parameters. My submission in the competitin get 0.60593 score, it's way much than the benchmark 0.69315, the best score in the leader board is 0.59509, So I think this result is acceptable.

4.2 Justification

The final result is much better than the benchmark result. But as we can see, the prediction accuracy is still not good enouch, maybe the problem target is impossible to predict well just use these features, more data should be added, something like whether kobe is guarded when he shot. Anyway, I rank 90th, and this result meet the expectation.

5 Conclusion

5.1 Free-Form Visualization

The most important thing is the data I think, and the visualization result can be seen from Exploratory Visualization part, please check.

5.2 Reflection

In this project, I first explore the data using some data visualization to get a sense of the data, then preproces the data and do some feature engineering, then train the model using different algorithms, and tune the model parameters using gridsearch to get the final model. I think the most interesting part in this project is the data visualization part, I can get a feel of kobe's shot ability in all kinds of aspects. And the prediction part is the most difficult part for me, the model is really hard to train, it's always suffering from underfitting or overfitting issues. The prediction accuracy is not good enough to use in reality, although it's a little better than random guess.

5.3 Improvement

I think there are some features I'm not using really well, that is the time series features. I just only considered the last one shot, but that's not enough. In fact, recurrent neural network is a great method to model time series data, I will try this method in future work to see if I can get better result. I think my result is still not good enough, RNN method will beat this!