```
# Code to read csv file into Colaboratory:
!pip install -U -q PyDrive
from pydrive.auth import GoogleAuth
from pydrive.drive import GoogleDrive
from google.colab import auth
from oauth2client.client import GoogleCredentials
# Authenticate and create the PyDrive client.
auth.authenticate_user()
gauth = GoogleAuth()
gauth.credentials = GoogleCredentials.get_application_default()
drive = GoogleDrive(gauth)
```

Load data

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt

fileURL = "https://drive.google.com/open?id=1DdYNXjLQZEp9NBvg8y20eBZCyLL5ljWl"
csvHeaders = ["match_id", "account_id", "player_slot", "hero_id", "item_0", "item_1",
              "item_2", "item_3", "item_4", "item_5", "backpack_0", "backpack_1", "bac
              "kills", "deaths", "assists", "leaver_status", "gold", "last_hits", "den
              "gold_per_min", "xp_per_min", "gold_spent", "hero_damage", "tower_damage
              "hero_healing", "level", "stuns", "obs_placed", "sen_placed", "creeps_st
              "camps_stacked", "rune_pickups", "party_id", "lane", "lane_role", "is_ro
              "firstblood_claimed", "teamfight_participation", "towers_killed", "rosha
              "observers_placed", "party_size", "match_seq_num", "radiant_win", "start
              "duration", "tower_status_radiant", "tower_status_dire", "barracks_statu
              "barracks_status_dire", "cluster", "first_blood_time", "lobby_type", "hu
              "leagueid", "positive_votes", "negative_votes", "game_mode", "engine", "
              "dire_score", "radiant_team_id", "dire_team_id", "radiant_team_name", "d
              "radiant_team_complete", "dire_team_complete", "radiant_captain", "dire_
              "version"]
fluff, id = fileURL.split('=')
downloaded = drive.CreateFile({'id':id})
downloaded.GetContentFile('matches_join_player_matches.csv')
df = pd.read_csv('matches_join_player_matches.csv', names=csvHeaders, header=None)
```

```
/usr/local/lib/python3.6/dist-packages/IPython/core/interactiveshell.py:2718: Dty
  interactivity=interactivity, compiler=compiler, result=result)
```

```
df.head(5)
```

	match_id	account_id	player_slot	hero_id	item_0	item_1	item_2	item_3	it
0	1000018815	98134803	2	15	119	110	46	108	
1	1000018815	182993582	130	86	214	60	1	46	
2	1000018815	87219396	129	78	1	0	108	119	
3	1000018815	191422410	1	30	36	214	108	116	
4	1000018815	87201671	131	67	185	127	174	147	

Hero Clustering

Pick interested columns

```
data = df[["hero_id", "kills", "deaths", "assists", "gold", "last_hits", "denies",
           "gold_per_min", "xp_per_min", "gold_spent", "hero_damage", "tower_damage",
           "hero_healing", "level"]]
# get rid of NaN gold rows
data = data[np.isfinite(data['gold'])]
```

```
# check any NaN value
data.isnull().values.any()
```

```
False
```

```
data.head(5)
```

	hero_id	kills	deaths	assists	gold	last_hits	denies	gold_per_min	xp_
69130	46	1	6	4	1.0	166	25	443	
69131	65	3	4	3	1124.0	90	2	321	
69132	8	5	5	1	1.0	244	22	556	
69133	17	11	3	8	4393.0	136	7	565	
69134	20	1	3	11	1936.0	27	2	266	

Aggregate heroes by ID

```
hero_data = data.groupby('hero_id').agg({"kills": ["mean"], "deaths": ["mean"],
                                        "assists": ["mean"], "last_hits": ["mean"],
                                       "denies": ["mean"], "gold_per_min": ["mean"],
```

```
                                        "xp_per_min": ["mean"], "gold_spent": ["mean"]
                                        "hero_damage": ["mean"], "tower_damage": ["mea
                                        "tower_damage": ["mean"], "level": ["mean"]})
# how many heroes
len(hero_data)
```

```
116
```

```
hero_data.head()
```

	kills	deaths	assists	last_hits	denies	gold_per_min	xp_per_min
	mean	mean	mean	mean	mean	mean	mean
hero_id							
1	6.823423	2.962883	5.501261	374.985225	16.980541	652.436757	657.051892
2	6.532593	6.262192	8.362144	144.345727	2.922743	393.459440	436.087880
3	2.949980	6.332933	11.152461	25.117047	3.522209	247.899760	308.888956
4	8.385020	5.354008	9.347572	236.993563	16.308953	506.483909	529.891750
5	2.803379	6.296534	12.744538	59.079231	1.074862	291.036411	333.853772

Apply k-means clustering

```
# (c) 2014 Reid Johnson
#
# Modified from:
# (c) 2013 Mikael Vejdemo-Johansson
# BSD License
#
# SciPy function to compute the gap statistic for evaluating k-means clustering.
#
# The gap statistic is defined by Tibshirani, Walther, Hastie in:
#  Estimating the number of clusters in a data set via the gap statistic
#  J. R. Statist. Soc. B (2001) 63, Part 2, pp 411-423

import scipy as sp
import scipy as sp
import scipy.cluster.vq
import scipy.spatial.distance
import scipy.stats
import sklearn.cluster

import pylab as pl

dst = sp.spatial.distance.euclidean

def gap_statistics(data, refs=None, nrefs=20, ks=range(1,11)):
```

```
"""Computes the gap statistics for an nxm dataset.

The gap statistic measures the difference between within-cluster dispersion on an
dataset and that expected under an appropriate reference null distribution.

Computation of the gap statistic, then, requires a series of reference (null) dist
One may either input a precomputed set of reference distributions (via the paramet
or specify the number of reference distributions (via the parameter nrefs) for aut
generation of uniform distributions within the bounding box of the dataset (data).

Each computation of the gap statistic requires the clustering of the input dataset
several reference distributions. To identify the optimal number of clusters k, the
statistic is computed over a range of possible values of k (via the parameter ks).

For each value of k, within-cluster dispersion is calculated for the input dataset
reference distribution. The calculation of the within-cluster dispersion for the r
distributions will have a degree of variation, which we measure by standard deviat
standard error.

The estimated optimal number of clusters, then, is defined as the smallest value k
gap_k is greater than or equal to the sum of gap_k+1 minus the expected error err_

Args:
  data ((n,m) SciPy array): The dataset on which to compute the gap statistics.
  refs ((n,m,k) SciPy array, optional): A precomputed set of reference distributio
    Defaults to None.
  nrefs (int, optional): The number of reference distributions for automatic gener
    Defaults to 20.
  ks (list, optional): The list of values k for which to compute the gap statistic
    Defaults to range(1,11), which creates a list of values from 1 to 10.

Returns:
  gaps: an array of gap statistics computed for each k.
  errs: an array of standard errors (se), with one corresponding to each gap compu
  difs: an array of differences between each gap_k and the sum of gap_k+1 minus er

"""
shape = data.shape

if refs==None:
    tops = data.max(axis=0) # maxima along the first axis (rows)
    bots = data.min(axis=0) # minima along the first axis (rows)
    dists = sp.matrix(sp.diag(tops-bots)) # the bounding box of the input dataset

    # Generate nrefs uniform distributions each in the half-open interval [0.0, 1.
    rands = sp.random.random_sample(size=(shape[0],shape[1], nrefs))

    # Adjust each of the uniform distributions to the bounding box of the input da
    for i in range(nrefs):
        rands[:,:,i] = rands[:,:,i]*dists+bots
else:
    rands = refs
```

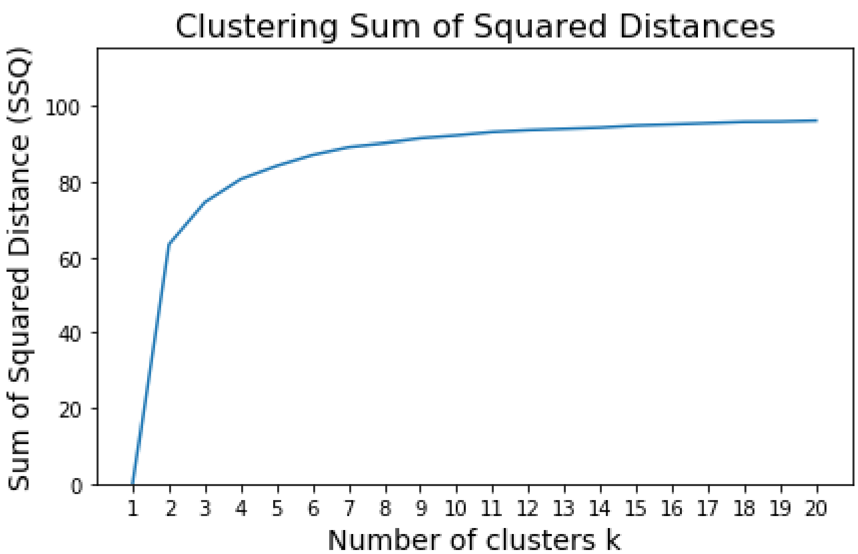
```
    rands = refs

    gaps = sp.zeros((len(ks),))   # array for gap statistics (lenth ks)
    errs = sp.zeros((len(ks),))   # array for model standard errors (length ks)
    difs = sp.zeros((len(ks)-1,)) # array for differences between gaps (length ks-1)

    for (i,k) in enumerate(ks): # iterate over the range of k values
        # Cluster the input dataset via k-means clustering using the current value of
        try:
            (kmc,kml) = sp.cluster.vq.kmeans2(data, k)
        except LinAlgError:
            kmeans = sklearn.cluster.KMeans(n_clusters=k).fit(data)
            (kmc, kml) = kmeans.cluster_centers_, kmeans.labels_

        # Generate within-dispersion measure for the clustering of the input dataset
        disp = sum([dst(data[m,:],kmc[kml[m],:]) for m in range(shape[0])])

        # Generate within-dispersion measures for the clusterings of the reference dat
        refdisps = sp.zeros((rands.shape[2],))
        for j in range(rands.shape[2]):
            # Cluster the reference dataset via k-means clustering using the current v
            try:
                (kmc,kml) = sp.cluster.vq.kmeans2(rands[:,:,j], k)
            except LinAlgError:
                kmeans = sklearn.cluster.KMeans(n_clusters=k).fit(rands[:,:,j])
                (kmc, kml) = kmeans.cluster_centers_, kmeans.labels_

            refdisps[j] = sum([dst(rands[m,:,j],kmc[kml[m],:]) for m in range(shape[0]

        # Compute the (estimated) gap statistic for k
        gaps[i] = sp.mean(sp.log(refdisps) - sp.log(disp))

        # Compute the expected error for k
        errs[i] = sp.sqrt(sum(((sp.log(refdisp)-sp.mean(sp.log(refdisps)))**2) \
                              for refdisp in refdisps)/float(nrefs)) * sp.sqrt(1+1/nre

    # Compute the difference between gap_k and the sum of gap_k+1 minus err_k+1
    difs = sp.array([gaps[k] - (gaps[k+1]-errs[k+1]) for k in range(len(gaps)-1)])

    #print "Gaps: " + str(gaps)
    #print "Errs: " + str(errs)
    #print "Difs: " + str(difs)

    return gaps, errs, difs

def plot_gap_statistics(gaps, errs, difs):
    """Generates and shows plots for the gap statistics.

    A figure with two subplots is generated. The first subplot is an errorbar plot of
    estimated gap statistics computed for each value of k. The second subplot is a bar
    of the differences in the computed gap statistics.
```

```
    Args:
      gaps (SciPy array): An array of gap statistics, one computed for each k.
      errs (SciPy array): An array of standard errors (se), with one corresponding to
        computation.
      difs (SciPy array): An array of differences between each gap_k and the sum of ga
        minus err_k+1.

    """
    # Create a figure
    fig = pl.figure(figsize=(16, 4))

    pl.subplots_adjust(wspace=0.35) # adjust the distance between figures

    # Subplot 1
    ax = fig.add_subplot(121)
    ind = range(1,len(gaps)+1) # the x values for the gaps

    # Create an errorbar plot
    rects = ax.errorbar(ind, gaps, yerr=errs, xerr=None, linewidth=1.0)

    # Add figure labels and ticks
    ax.set_title('Clustering Gap Statistics', fontsize=16)
    ax.set_xlabel('Number of clusters k', fontsize=14)
    ax.set_ylabel('Gap Statistic', fontsize=14)
    ax.set_xticks(ind)

    # Add figure bounds
    ax.set_ylim(0, max(gaps+errs)*1.1)
    ax.set_xlim(0, len(gaps)+1.0)

    # Subplot 2
    ax = fig.add_subplot(122)
    ind = range(1,len(difs)+1) # the x values for the difs

    max_gap = None
    if len(np.where(difs > 0)[0]) > 0:
        max_gap = np.where(difs > 0)[0][0] + 1 # the k with the first positive dif

    # Create a bar plot
    ax.bar(ind, difs, alpha=0.5, color='g', align='center')

    # Add figure labels and ticks
    if max_gap:
        ax.set_title('Clustering Gap Differences\n(k=%d Estimated as Optimal)' % (max_
                     fontsize=16)
    else:
        ax.set_title('Clustering Gap Differences\n', fontsize=16)
    ax.set_xlabel('Number of clusters k', fontsize=14)
    ax.set_ylabel('Gap Difference', fontsize=14)
    ax.xaxis.set_ticks(range(1,len(difs)+1))

    # Add figure bounds
```

```
        ax.set_ylim(min(difs)*1.2, max(difs)*1.2)
        ax.set_xlim(0, len(difs)+1.0)

        # Show the figure
        pl.show()

# (c) 2014 Reid Johnson
# BSD License
#
# Function to compute the sum of squared distance (SSQ) for evaluating k-means cluster

import numpy as np
import scipy as sp
import sklearn.cluster
from scipy.spatial.distance import cdist, pdist

import pylab as pl

def ssq_statistics(data, ks=range(1,11), ssq_norm=True):
    """Computes the sum of squares for an nxm dataset.

    The sum of squares (SSQ) is a measure of within-cluster variation that measures th
    squared distances from cluster prototypes.

    Each computation of the SSQ requires the clustering of the input dataset. To ident
    optimal number of clusters k, the SSQ is computed over a range of possible values
    (via the parameter ks). For each value of k, within-cluster dispersion is calculat
    input dataset.

    The estimated optimal number of clusters, then, is defined as the value of k prior
    "elbow" point in the plot of SSQ values.

    Args:
      data ((n,m) SciPy array): The dataset on which to compute the gap statistics.
      ks (list, optional): The list of values k for which to compute the gap statistic
        Defaults to range(1,11), which creates a list of values from 1 to 10.

    Returns:
      ssqs: an array of SSQs, one computed for each k.

    """
    ssqs = sp.zeros((len(ks),)) # array for SSQs (lenth ks)

    #n_samples, n_features = data.shape # the number of rows (samples) and columns (fe
    #if n_samples >= 2500:
    #    # Generate a small sub-sample of the data
    #    data_sample = shuffle(data, random_state=0)[:1000]
    #else:
    #    data_sample = data

    for (i,k) in enumerate(ks): # iterate over the range of k values
```

```
        # Fit the model on the data
        kmeans = sklearn.cluster.KMeans(n_clusters=k, random_state=0).fit(data)

        # Predict on the data (k-means) and get labels
        #labels = kmeans.predict(data)

        if ssq_norm:
            dist = np.min(cdist(data, kmeans.cluster_centers_, 'euclidean'), axis=1)

            tot_withinss = sum(dist**2) # Total within-cluster sum of squares
            totss = sum(pdist(data)**2) / data.shape[0] # The total sum of squares
            betweenss = totss - tot_withinss # The between-cluster sum of squares
            ssqs[i] = betweenss/totss*100
        else:
            # The sum of squared error (SSQ) for k
            ssqs[i] = kmeans.inertia_

    return ssqs

def plot_ssq_statistics(ssqs):
    """Generates and shows plots for the sum of squares (SSQ).

    A figure with one plot is generated. The plot is a bar plot of the SSQ computed fo
    value of k.

    Args:
      ssqs (SciPy array): An array of SSQs, one computed for each k.

    """
    # Create a figure
    fig = pl.figure(figsize=(6.75, 4))

    ind = range(1,len(ssqs)+1) # the x values for the ssqs
    width = 0.5 # the width of the bars

    # Create a bar plot
    #rects = pl.bar(ind, ssqs, width)
    pl.plot(ind, ssqs)

    # Add figure labels and ticks
    pl.title('Clustering Sum of Squared Distances', fontsize=16)
    pl.xlabel('Number of clusters k', fontsize=14)
    pl.ylabel('Sum of Squared Distance (SSQ)', fontsize=14)
    pl.xticks(ind)

    # Add text labels
    #for rect in rects:
    #    height = rect.get_height()
    #    pl.text(rect.get_x()+rect.get_width()/2., 1.05*height, '%d' % int(height), \
    #            ha='center', va='bottom')

    # Add figure bounds
```

```
    pl.ylim(0, max(ssqs)*1.2)
    pl.xlim(0, len(ssqs)+1.0)

    pl.show()

# Generate and plot the SSQ statistics
ssqs = ssq_statistics(hero_data, ks=range(1,20+1))
plot_ssq_statistics(ssqs)
```



Fit and group heroes into 8 clusters

```
from sklearn.cluster import KMeans
kmeans = KMeans(n_clusters=8).fit(hero_data)
labels = kmeans.labels_
```

```
len(labels)
```

```
116
```

```
labels
```

```
array([5, 2, 0, 1, 6, 4, 6, 5, 1, 5, 5, 5, 1, 2, 1, 2, 1, 4, 1, 0, 4, 7,
       2, 1, 0, 6, 0, 6, 0, 6, 6, 4, 3, 7, 1, 6, 6, 1, 7, 4, 4, 1, 1, 7,
       5, 1, 5, 4, 0, 2, 1, 4, 1, 2, 1, 0, 2, 1, 6, 4, 6, 1, 6, 2, 0, 7,
       6, 2, 1, 0, 1, 5, 1, 6, 1, 4, 2, 6, 5, 4, 5, 0, 0, 0, 6, 0, 6, 4,
       6, 0, 2, 4, 5, 5, 2, 6, 1, 1, 6, 2, 2, 6, 2, 2, 1, 6, 2, 5, 2, 0,
       6, 3, 1, 2, 1, 6], dtype=int32)
```

```
# add cluster column to hero data
hero_data['cluster'] = labels
```

```
hero_data.head()
```

	kills	deaths	assists	last_hits	denies	gold_per_min	xp_per_min
	mean	mean	mean	mean	mean	mean	mean
hero_id							
1	6.823423	2.962883	5.501261	374.985225	16.980541	652.436757	657.051892
2	6.532593	6.262192	8.362144	144.345727	2.922743	393.459440	436.087880
3	2.949980	6.332933	11.152461	25.117047	3.522209	247.899760	308.888956
4	8.385020	5.354008	9.347572	236.993563	16.308953	506.483909	529.891750
5	2.803379	6.296534	12.744538	59.079231	1.074862	291.036411	333.853772

```
# create index id
ind = list(range(0, 116))

hero_clusters = hero_data[['cluster']]
hero_clusters['hero_id'] = hero_clusters.index
hero_clusters.insert(0, 'id', ind)
# hero_clusters.index.names = ['id']
hero_clusters.set_index(['id'], inplace = True)
hero_clusters.head()
```

```
/usr/local/lib/python3.6/dist-packages/ipykernel_launcher.py:2: SettingWithCopyWa
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: http://pandas.pydata.org/pandas-docs/stable
```

	cluster	hero_id
id		
0	5	1
1	2	2
2	0	3
3	1	4
4	6	5

```
# summarize clustering labels
g = hero_clusters.groupby('cluster').agg({'hero_id': lambda x: list(x)})

g.head(9)
```

```
/usr/local/lib/python3.6/dist-packages/pandas/core/groupby/generic.py:1455: Futur
in a future version.

For column-specific groupby renaming, use named aggregation

    >>> df.groupby(...).agg(name=('column', aggfunc))

  return super().aggregate(arg, *args, **kwargs)
```

cluster	hero_id
0	[3, 20, 26, 28, 30, 50, 57, 66, 71, 83, 84, 85...
1	[4, 9, 13, 15, 17, 19, 25, 36, 39, 43, 44, 47,...
2	[2, 14, 16, 23, 51, 55, 58, 65, 69, 78, 92, 96...
3	[34, 113]
4	[6, 18, 21, 33, 41, 42, 49, 53, 61, 77, 81, 89...
5	[1, 8, 10, 11, 12, 46, 48, 73, 80, 82, 94, 95,...
6	[5, 7, 27, 29, 31, 32, 37, 38, 60, 62, 64, 68,...
7	[22, 35, 40, 45, 67]

Win probability prediction based on team drafts

```
player_data = df[["match_id", "player_slot", "kills", "deaths", "assists", "gold", "la
# get rid of NaN gold rows
player_data = player_data[np.isfinite(player_data['gold'])]

# add column to check win/lose
player_data["is_radiant"] = pd.to_numeric(player_data["player_slot"]) <= 4
player_data["is_win"] = (player_data["is_radiant"] == player_data["radiant_win"])


# check any NaN value
player_data.isnull().values.any()
```

```
False
```

```
player_data.head()
```

	match_id	player_slot	kills	deaths	assists	gold	last_hits	denies	le
69130	1384504402	2	1	6	4	1.0	166	25	
69131	1384504402	3	3	4	3	1124.0	90	2	
69132	1384504402	4	5	5	1	1.0	244	22	
69133	1384504402	128	11	3	8	4393.0	136	7	
69134	1384504402	129	1	3	11	1936.0	27	2	

```
team_data = player_data.groupby(['match_id', 'is_radiant']).agg({"kills": ["sum"], "de
                                                                  "assists": ["sum"],
                                                                  "denies": ["sum"], '
# how many teams
len(team_data)
```

```
83878
```

```
team_data.head()
```

		kills	deaths	assists	gold	last_hits	denies	level	i
		sum	sum	sum	sum	sum	sum	sum	<
match_id	**is_radiant**								
1384504402	**False**	23	12	50	14721.0	659	33	85	
	True	12	24	18	2480.0	565	53	68	
1384528617	**False**	3	17	12	1326.0	407	24	53	
	True	16	4	31	9162.0	474	47	65	
1384560471	**False**	29	14	40	13196.0	765	48	90	

```
# Create training and testing datasets
from sklearn.model_selection import train_test_split
dt_data = team_data.iloc[:, :-1]
dt_data = dt_data.as_matrix()
dt_label = team_data['is_win']
dt_label = dt_label.as_matrix()
x_train, x_test, y_train, y_test = train_test_split(dt_data, dt_label, test_size=0.3)
```

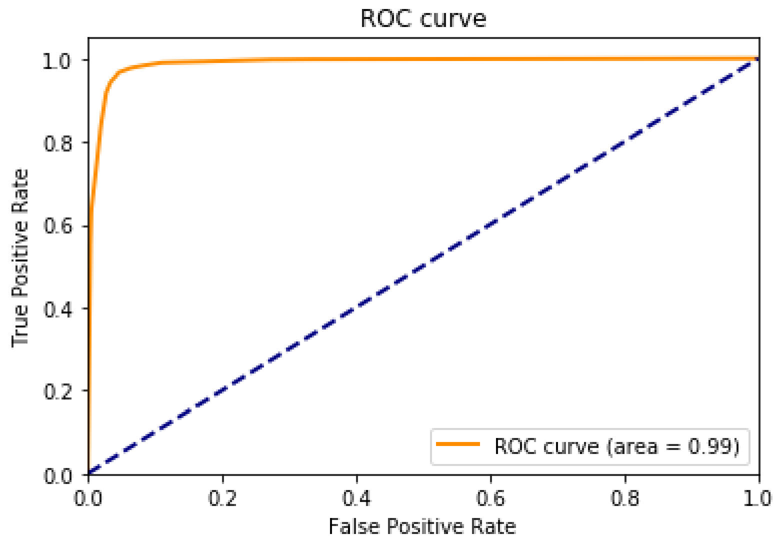
```
/usr/local/lib/python3.6/dist-packages/ipykernel_launcher.py:3: FutureWarning: Me
  This is separate from the ipykernel package so we can avoid doing imports until
/usr/local/lib/python3.6/dist-packages/ipykernel_launcher.py:5: FutureWarning: Me
  """
```

```
# Use decision tree model to train the datasets
from sklearn import tree
from sklearn.metrics import accuracy_score, precision_score, recall_score, confusion_r

clf = tree.DecisionTreeClassifier(max_depth=5)
clf = clf.fit(x_train, y_train)
y_pred = clf.predict(x_test)

print("Accuracy score is: ", accuracy_score(y_test, y_pred))
print("Precision score is: ", precision_score(y_test, y_pred))
print("Recall score is: ", recall_score(y_test, y_pred))
print("Confusion matrix is: \n", confusion_matrix(y_test, y_pred))
```

```
Accuracy score is:  0.9597838181529169
Precision score is:  0.9550544201706992
Recall score is:  0.9653343886030866
Confusion matrix is: 
 [[11955   574]
 [  438 12197]]
```

Decision Tree Model

```
# Plot ROC curve
from sklearn.metrics import roc_curve, auc

y_score = clf.predict_proba(x_test)[:,1]
fpr, tpr, threshold = roc_curve(y_test, y_score)
roc_auc = auc(fpr, tpr)
plt.figure()
lw = 2
plt.plot(fpr, tpr, color='darkorange',
lw=lw, label='ROC curve (area = %0.2f)' % roc_auc)
plt.plot([0, 1], [0, 1], color='navy', lw=lw, linestyle='--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('ROC curve')
plt.legend(loc="lower right")
plt.show()
```



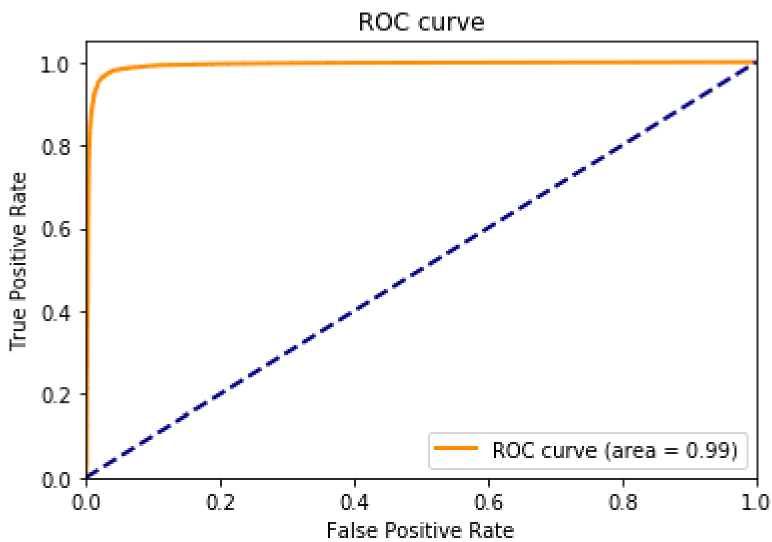
Logistic Regression Model

```
# Use logistic regression model to train the datasets
from sklearn.linear_model import LogisticRegression

clf = LogisticRegression()
clf = clf.fit(x_train, y_train)
y_pred = clf.predict(x_test)

print("Accuracy score is: ", accuracy_score(y_test, y_pred))
print("Precision score is: ", precision_score(y_test, y_pred))
print("Recall score is: ", recall_score(y_test, y_pred))
print("Confusion matrix is: \n", confusion_matrix(y_test, y_pred))
```

```
/usr/local/lib/python3.6/dist-packages/sklearn/linear_model/logistic.py:432: Futu
  FutureWarning)
/usr/local/lib/python3.6/dist-packages/sklearn/utils/validation.py:724: DataConve
  y = column_or_1d(y, warn=True)
Accuracy score is:  0.9695596884438086
Precision score is:  0.9690933523041657
Recall score is:  0.9703205381875742
Confusion matrix is: 
 [[12138   391]
 [  375 12260]]
```

```
# Plot ROC curve
y_score = clf.predict_proba(x_test)[:,1]
fpr, tpr, threshold = roc_curve(y_test, y_score)
roc_auc = auc(fpr, tpr)
plt.figure()
lw = 2
plt.plot(fpr, tpr, color='darkorange',
```

```
    lw=lw, label='ROC curve (area = %0.2f)' % roc_auc)
plt.plot([0, 1], [0, 1], color='navy', lw=lw, linestyle='--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('ROC curve')
plt.legend(loc="lower right")
plt.show()
```



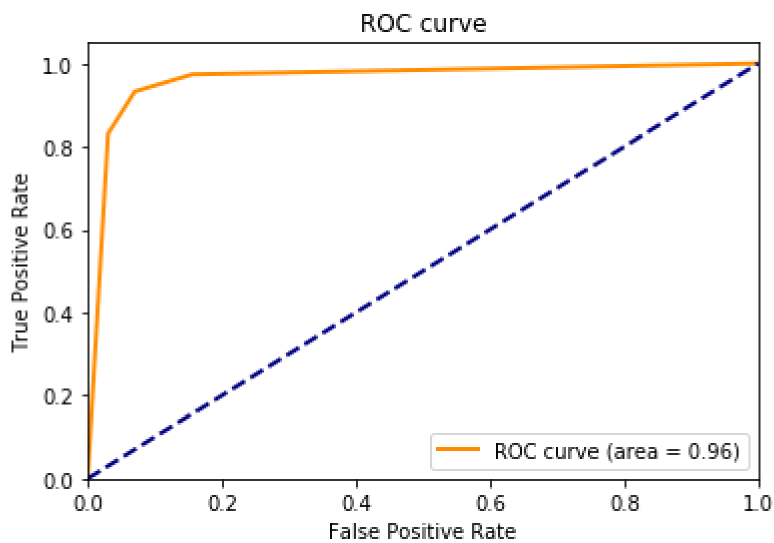
K-Nearest Neighbor Model

```
from sklearn.neighbors import KNeighborsClassifier

clf = KNeighborsClassifier(n_neighbors=3)
clf = clf.fit(x_train, y_train)
y_pred = clf.predict(x_test)

print("Accuracy score is: ", accuracy_score(y_test, y_pred))
print("Precision score is: ", precision_score(y_test, y_pred))
print("Recall score is: ", recall_score(y_test, y_pred))
print("Confusion matrix is: \n", confusion_matrix(y_test, y_pred))
```

```
/usr/local/lib/python3.6/dist-packages/ipykernel_launcher.py:4: DataConversionWar
  after removing the cwd from sys.path.
Accuracy score is:  0.9308933396916229
Precision score is:  0.9303997471954495
Recall score is:  0.9320933913731698
Confusion matrix is: 
 [[11648   881]
 [  858 11777]]
```

```
# Plot ROC curve
```

```
y_score = clf.predict_proba(x_test)[:,1]
fpr, tpr, threshold = roc_curve(y_test, y_score)
roc_auc = auc(fpr, tpr)
plt.figure()
lw = 2
plt.plot(fpr, tpr, color='darkorange',
lw=lw, label='ROC curve (area = %0.2f)' % roc_auc)
plt.plot([0, 1], [0, 1], color='navy', lw=lw, linestyle='--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('ROC curve')
plt.legend(loc="lower right")
plt.show()
```



Hero pick rate with win rate

```
# number of heros
print(max(df['hero_id']))
```

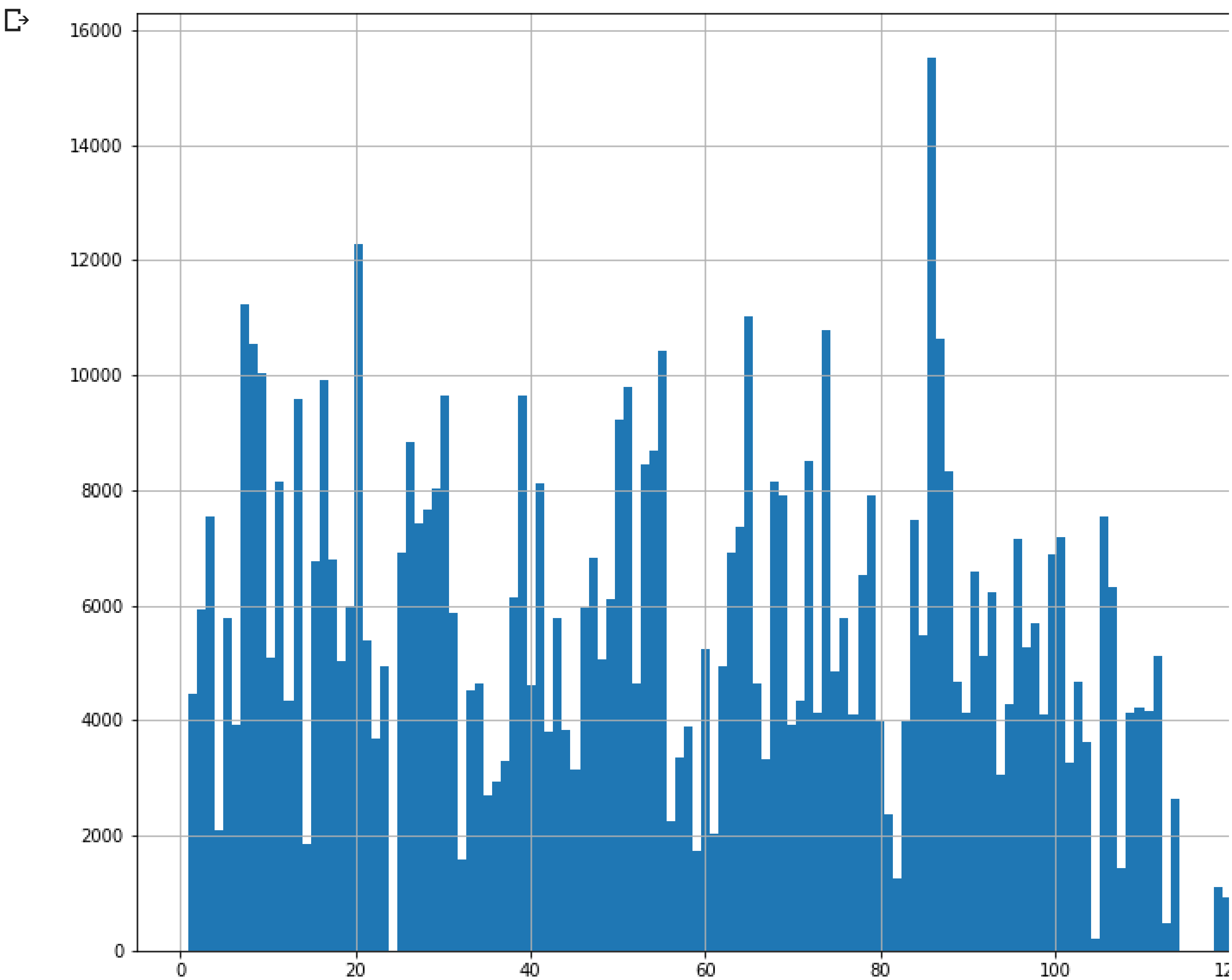
```
121
```

```
heros = df['hero_id']
heros.value_counts()
```

```
86     15518
20     12279
7      11248
65     11036
74     10797
       ...
82      1245
119     1112
120      931
113      467
105      206
Name: hero_id, Length: 116, dtype: int64
```

We can see from the value count, the most frequent used hero is number 86 and least frequent used h

```
out = df.iloc[:, 3].hist(bins=121,figsize=(12, 10))
```




```
radiant_win = df[(df['radiant_win'] == True) & (df['player_slot'] < 5)]
radiant_win.head()
```

```
# match_radiant_win = df[((df['radiant_win'] == True) & (df['player_slot'] < 5)) & ((c
```

	match_id	account_id	player_slot	hero_id	item_0	item_1	item_2	item_3	it
0	1000018815	98134803	2	15	119	110	46	108	
3	1000018815	191422410	1	30	36	214	108	116	
5	1000018815	86785083	4	88	41	46	1	104	
8	1000018815	123051238	3	93	110	1	160	208	
9	1000018815	93552791	0	84	92	102	23	214	

```
heros_radiant_win = radiant_win['hero_id']
heros_radiant_win.value_counts()
```

```
86     4018
20     3154
7      2927
65     2899
9      2806
       ...
82      348
120     281
119     270
113     117
105      53
Name: hero_id, Length: 116, dtype: int64
```

```
dire_win = df[(df['radiant_win'] == False) & (df['player_slot'] > 5)]
dire_win.head()
```

	match_id	account_id	player_slot	hero_id	item_0	item_1	item_2	item_3	i
11	1000020264	97073485	128	42	36	63	170	151	
12	1000020264	86748852	130	59	50	151	1	172	
13	1000020264	49842719	132	64	48	151	172	0	
17	1000020264	91480675	131	104	63	1	151	116	
19	1000020264	96191708	129	9	63	151	42	0	

```
heros_dire_win = dire_win['hero_id']
heros_dire_win.value_counts()
```

```
86      3812
20      3194
65      2727
8       2654
74      2635
        ...
82       271
119      263
120      207
113      111
105       48
Name: hero_id, Length: 116, dtype: int64
```

```
df_win_match = pd.concat([radiant_win, dire_win], ignore_index=True)
df_win_match.head()
```

	match_id	account_id	player_slot	hero_id	item_0	item_1	item_2	item_3	it
0	1000018815	98134803	2	15	119	110	46	108	
1	1000018815	191422410	1	30	36	214	108	116	
2	1000018815	86785083	4	88	41	46	1	104	
3	1000018815	123051238	3	93	110	1	160	208	
4	1000018815	93552791	0	84	92	102	23	214	

```
heros_win = df_win_match['hero_id']
heros_win.value_counts()
```

```
86      7830
20      6348
65      5626
7       5508
8       5434
        ...
82       619
119      533
120      488
113      228
105      101
Name: hero_id, Length: 116, dtype: int64
```

```
# Hero pick rate and win rate table
group_by_match = df.groupby('match_id').size()
print(group_by_match.shape)
```

```
(66009,)
```

```
hero_data = df[["match_id", "hero_id", "player_slot", "radiant_win"]]
```

```
number_of_matches = 66009
# add column to check win/lose
hero_data["is_radiant"] = pd.to_numeric(hero_data["player_slot"]) <= 4
hero_data["is_win"] = (hero_data["is_radiant"] == hero_data["radiant_win"])
hero_data.head()
# hero_aggregation_data = hero_data.groupby(['hero_id']).agg({"hero_pick", "is_win"})
```

```
/usr/local/lib/python3.6/dist-packages/ipykernel_launcher.py:4: SettingWithCopyWa
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: http://pandas.pydata.org/pandas-docs/stable
  after removing the cwd from sys.path.
/usr/local/lib/python3.6/dist-packages/ipykernel_launcher.py:5: SettingWithCopyWa
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: http://pandas.pydata.org/pandas-docs/stable
  """
```

	match_id	hero_id	player_slot	radiant_win	is_radiant	is_win
0	1000018815	15	2	True	True	True
1	1000018815	86	130	True	False	False
2	1000018815	78	129	True	False	False
3	1000018815	30	1	True	True	True
4	1000018815	67	131	True	False	False

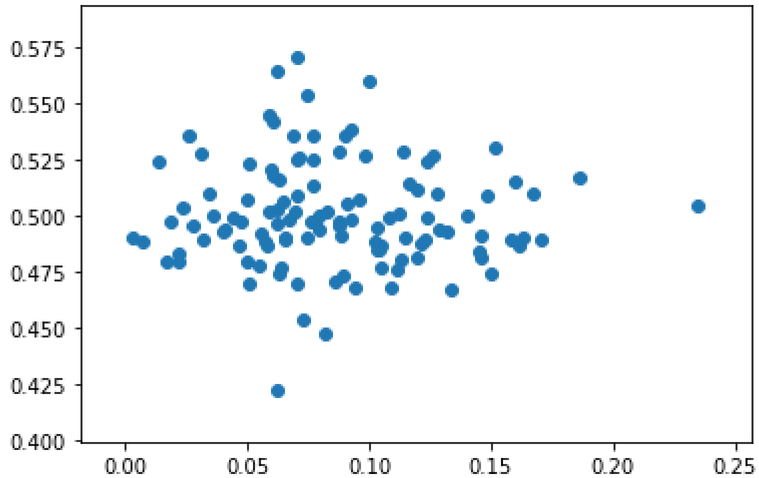
```
# Prepare data with hero pick rate and win rate
mid_table = hero_data.groupby('hero_id').agg({"is_radiant": [lambda x: float((x.sum()
                                              "is_win": [lambda x: float(x.sum() / (x.sum(
pick_win_rate = mid_table.rename(columns={'is_radiant': 'pick_rate', 'is_win': 'win_ra
pick_win_rate.head(5)
```

	pick_rate	win_rate
	<lambda>	<lambda>
hero_id		
1	0.067370	0.498313
2	0.089609	0.473035
3	0.114378	0.528609
4	0.031708	0.489250
5	0.087730	0.528579

```
# Plot between pick rate and win rate
import matplotlib.pyplot as plt
```

```
import matplotlib.pyplot as plt
xs=pick_win_rate['pick_rate']
ys=pick_win_rate['win_rate']
plt.scatter(xs,ys)
```

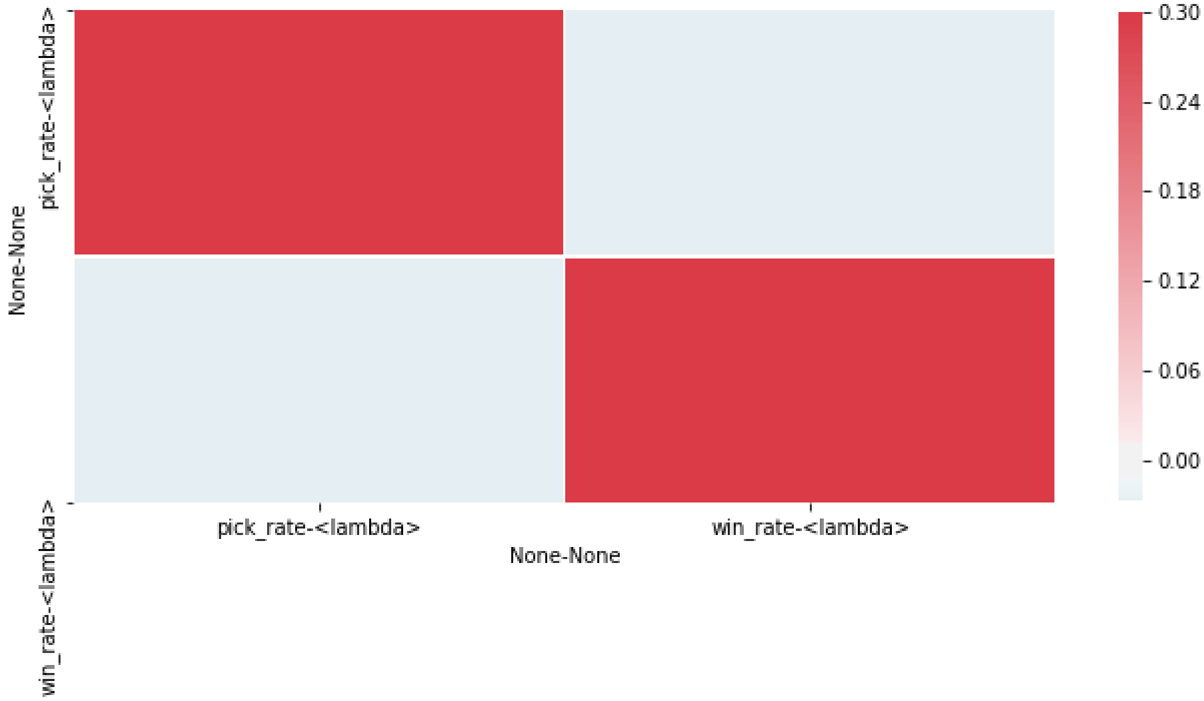
```
<matplotlib.collections.PathCollection at 0x7f714a655390>
```




```
# Pearson's r
corr=pick_win_rate.corr()
print(corr)
```

```
                      pick_rate  win_rate
                       <lambda>  <lambda>
pick_rate <lambda>     1.000000 -0.026916
win_rate  <lambda>    -0.026916  1.000000
```

```
import seaborn as sns
import matplotlib.pyplot as plt
f, ax = plt.subplots(figsize=(11, 9))
# Generate a custom diverging colormap
cmap = sns.diverging_palette(220, 10, as_cmap=True)

# Draw the heatmap with the mask and correct aspect ratio
sns.heatmap(corr, cmap=cmap, vmax=.3, center=0,
            square=True, linewidths=.5, cbar_kws={"shrink": .5})
plt.show()
```



Relationship between first blood and match outcome

```
player_data = df[["firstblood_claimed", "first_blood_time", "match_id", "player_slot",
# get rid of NaN firstblood_claimed rows
player_data = player_data[np.isfinite(player_data['firstblood_claimed'])]
# add column to check win/lose
player_data["is_radiant"] = pd.to_numeric(player_data["player_slot"]) <= 4
player_data["is_win"] = (player_data["is_radiant"] == player_data["radiant_win"])
team_data = player_data.groupby(['match_id', 'is_radiant']).agg({"firstblood_claimed":
                                                                  "is_win":[lambda x:
```

```
player_data.head()
```

	firstblood_claimed	first_blood_time	match_id	player_slot	radiant_win	is_
9	0.0	38	1000018815	0	True	
16	0.0	74	1000020264	0	False	
25	0.0	165	1000025803	0	False	
36	0.0	64	1000026645	0	True	
49	0.0	222	1000038577	0	True	

```
team_data.head()
```

		firstblood_claimed	first_blood_time	is_win
		max	mean	<lambda>
match_id	is_radiant			
18355350	**True**	0.0	139	True
19009163	**True**	0.0	206	False
19249598	**True**	0.0	403	False
19254348	**True**	0.0	54	True
19266829	**True**	0.0	62	False

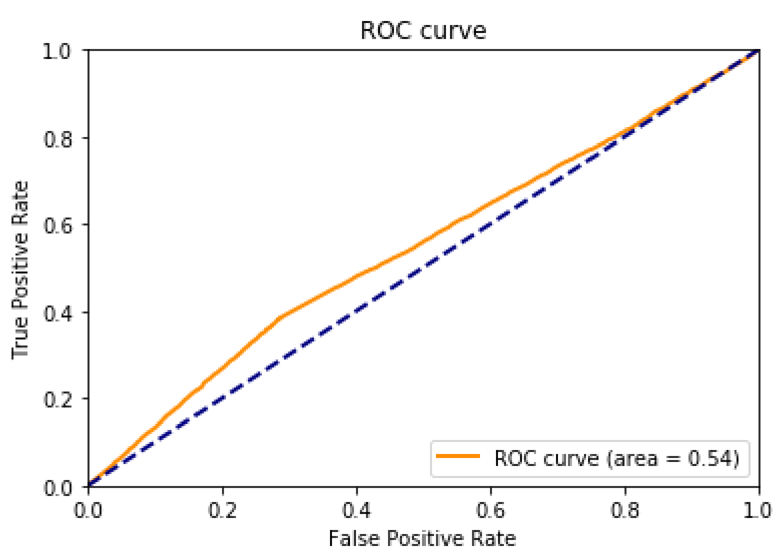
```
# Create training and testing datasets
from sklearn.model_selection import train_test_split
dt_data = team_data.iloc[:, :-1]
dt_data = dt_data.as_matrix()
dt_label = team_data['is_win']
dt_label = dt_label.as_matrix()
x_train, x_test, y_train, y_test = train_test_split(dt_data, dt_label, test_size=0.2)
```

```
/usr/local/lib/python3.6/dist-packages/ipykernel_launcher.py:3: FutureWarning: Me
  This is separate from the ipykernel package so we can avoid doing imports until
/usr/local/lib/python3.6/dist-packages/ipykernel_launcher.py:5: FutureWarning: Me
  """
```

```
from sklearn import tree
from sklearn.metrics import accuracy_score, precision_score, recall_score, confusion_r
import matplotlib.pyplot as plt
from sklearn.linear_model import LogisticRegression

clf = LogisticRegression()
clf = clf.fit(x_train, y_train)
y_pred = clf.predict(x_test)

print("Accuracy score is: ", accuracy_score(y_test, y_pred))
print("Precision score is: ", precision_score(y_test, y_pred))
print("Recall score is: ", recall_score(y_test, y_pred))
print("Confusion matrix is: \n", confusion_matrix(y_test, y_pred))
```

```
Accuracy score is:  0.5468085106382978
Precision score is:  0.5787131466716113
Recall score is:  0.385737238907428
Confusion matrix is:
 [[5617 2272]
 [4970 3121]]
/usr/local/lib/python3.6/dist-packages/sklearn/linear_model/logistic.py:432: Futu
  FutureWarning)
/usr/local/lib/python3.6/dist-packages/sklearn/utils/validation.py:724: DataConve
  y = column_or_1d(y, warn=True)
```

```
from sklearn.metrics import roc_curve, auc

y_score = clf.predict_proba(x_test)[:,1]
fpr, tpr, threshold = roc_curve(y_test, y_score)
roc_auc = auc(fpr, tpr)
plt.figure()
lw = 2
plt.plot(fpr, tpr, color='darkorange',
lw=lw, label='ROC curve (area = %0.2f)' % roc_auc)
plt.plot([0, 1], [0, 1], color='navy', lw=lw, linestyle='--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.0])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('ROC curve')
plt.legend(loc="lower right")
plt.show()
```



We can see from the metric and ROC curve above, the relationship between first blood (`firstblood_` match result is fairly weak. It is not reliable to predict the match result

Double-click (or enter) to edit