SteamRecSys

December 29, 2020

[1]:
```python
import gzip
import sklearn
from sklearn import linear_model
from collections import defaultdict
import random
import math
import numpy as np
from sklearn.metrics import jaccard_score as jaccard
import pandas as pd
import os
import matplotlib.pyplot as plt
```

1 * RecSys.pdf contains write up for assignment

2 Tasks (Play prediction)

2.0.1 Play prediction (both classes)

Predict given a (user,game) pair from 'pairs Played.txt' whether the user would play the game (0 or 1). Accuracy will be measured in terms of the categorization accuracy (fraction of correct predictions). The test set has been constructed such that exactly 50% of the pairs correspond to played games and the other 50% do not.

[2]:
```python
def parse(f):
    for l in gzip.open(f):
        yield eval(l)
```

[3]:
```python
train_json = list(parse("data/train.json.gz"))
```

[4]:
```python
train_json[1]
```

[4]:
```
{'userID': 'u88836191',
 'early_access': False,
 'hours': 63.5,
 'hours_transformed': 6.011227255423254,
 'found_funny': 1,
 'text': 'If you want to sit in queue for 10-20min and have 140 ping then this
game is perfect for you :)',
```

```
 'gameID': 'b19457938',
 'user_id': '76561198030408772',
 'date': '2017-05-20'}
```

[5]:
```python
df = pd.DataFrame(train_json)
```

[ ]:

[6]:
```python
df['date'] = pd.to_datetime(df['date'])
```

[ ]:

[7]:
```python
df['year'] = df['date'].dt.year
```

[8]:
```python
df['month'] = df['date'].dt.month
```

[9]:
```python
df['year'].value_counts()
```

[9]:
```
2017    49848
2016    43667
2015    37646
2014    27357
2013     8910
2012     3376
2011     2659
2018     1034
2010      503
Name: year, dtype: int64
```

[ ]:

[10]:
```python
data = [[d['userID'],d['gameID'],1] for d in train_json]

split = 165000
train = train_json[:split]
ug_train = [[d['userID'],d['gameID'],1] for d in train]
validation = train_json[split:]
ug_valid = [[d['userID'],d['gameID'],1] for d in validation]
```

[11]:
```python
def readJSON(path):
  for l in gzip.open(path, 'rt'):
    d = eval(l)
    u = d['userID']
    try:
      g = d['gameID']
    except Exception as e:
      g = None
```

```
        yield u,g,d
```

Cells below for Kaggle comptetition

[12]:
```
### Time-played baseline: compute averages for each user, or return the global␣
↪average if we've never seen the user before

# allHours = []
# userHours = defaultdict(list)

# for user,game,d in readJSON("data/train.json.gz"):
#   h = d['hours_transformed']
#   allHours.append(h)
#   userHours[user].append(h)

# globalAverage = sum(allHours) / len(allHours)
# userAverage = {}
# for u in userHours:
#   userAverage[u] = sum(userHours[u]) / len(userHours[u])
```

[13]:
```
# predictions = open("predictions_Hours.txt", 'w')
# for l in open("data/pairs_Hours.txt"):
#   if l.startswith("userID"):
#     #header
#     predictions.write(l)
#     continue
#   u,g = l.strip().split('-')
#   if u in userAverage:
#     predictions.write(u + '-' + g + ',' + str(userAverage[u]) + '\n')
#   else:
#     predictions.write(u + '-' + g + ',' + str(globalAverage) + '\n')

# predictions.close()
```

[14]:
```
### Would-play baseline: just rank which games are popular and which are not,␣
↪and return '1' if a game is among the top-ranked

# gameCount = defaultdict(int)
# totalPlayed = 0

# for user,game,_ in readJSON("data/train.json.gz"):
#   gameCount[game] += 1
#   totalPlayed += 1

# mostPopular = [(gameCount[x], x) for x in gameCount]
# mostPopular.sort()
# mostPopular.reverse()
```

```
# return1 = set()
# count = 0
# for ic, i in mostPopular:
#   count += ic
#   return1.add(i)
#   if count > totalPlayed/2: break
```

[15]:
```
# predictions = open("predictions_Played.txt", 'w')
# for l in open("data/pairs_Played.txt"):
#   if l.startswith("userID"):
#     #header
#     predictions.write(l)
#     continue
#   u,g = l.strip().split('-')
#   if g in return1:
#     predictions.write(u + '-' + g + ",1\n")
#   else:
#     predictions.write(u + '-' + g + ",0\n")

# predictions.close()
```

[16]:
```
# ### Category prediction baseline: Just consider some of the most common words from each category

# catDict = {
#   "Action": 0,
#   "Strategy": 1,
#   "RPG": 2,
#   "Adventure": 3,
#   "Sport": 4
# }

# predictions = open("predictions_Category.txt", 'w')
# predictions.write("userID-reviewID,prediction\n")
# for u,_,d in readJSON("data/test_Category.json.gz"):
#   cat = catDict['Action'] # If there's no evidence, just choose the most common category in the dataset
#   words = d['text'].lower()
#   if 'strategy' in words:
#     cat = catDict['Strategy']
#   if 'rpg' in words:
#     cat = catDict['RPG']
#   if 'adventure' in words:
#     cat = catDict['Adventure']
#   if 'sport' in words:
#     cat = catDict['Sport']
```

```
#   predictions.write(u + '-' + d['reviewID'] + "," + str(cat) + "\n")

# predictions.close()
```

Task 1 - generate *negative entries* to build training and test set

[ ]:

```

```

[17]:

```
#gets users per game and games per user from entire dataset
usersPerGame = defaultdict(set)
gamesPerUser = defaultdict(set)
#collects all unique games in the dataset
uniqueGames = set()

for d in data:
    u, g = d[0], d[1]
    usersPerGame[g].add(u)
    gamesPerUser[u].add(g)
    uniqueGames.add(g)
```

[18]:

```
users_valid = [d[0] for d in ug_valid]
users_train = [d[0] for d in ug_train]
```

[19]:

```
ug_valid_neg= []
for u in users_valid:
    gamesNotPlayed = uniqueGames - gamesPerUser[u]
    randomGame = random.choice(list(gamesNotPlayed))
    ug_valid_neg.append([u, randomGame,0])


ug_train_neg= []
for u in users_train:
    gamesNotPlayed = uniqueGames - gamesPerUser[u]
    randomGame = random.choice(list(gamesNotPlayed))
    ug_train_neg.append([u, randomGame,0])
```

[20]:

```
ug_valid_build = ug_valid + ug_valid_neg
ug_train_build = ug_train + ug_train_neg
```

[21]:

```
ug_valid_build[9995:10005]
```

[21]:

```
[['u90835702', 'b62891570', 1],
 ['u40505592', 'b75563467', 1],
 ['u67709233', 'b14676161', 1],
 ['u79727950', 'b36105300', 1],
 ['u25903175', 'b50879604', 1],
```

```
 ['u49969792', 'b03148978', 0],
 ['u33147591', 'b27897741', 0],
 ['u00954406', 'b36463329', 0],
 ['u40416473', 'b30552994', 0],
 ['u08125051', 'b58508951', 0]]
```

[22]:
```
len(ug_valid_build)
```

[22]: 20000

[23]:
```
Xvalid = [[d[0],d[1]] for d in ug_valid_build]
yvalid = [d[2] for d in ug_valid_build]

Xtrain = [[d[0], d[1]] for d in ug_train_build]
ytrain = [d[2] for d in ug_train_build]
```

[24]:
```
### Would-play baseline: just rank which games are popular and which are not,␣
↪and return '1' if a game is among the top-ranked
##task 1 baseline
def baselinePreds(Xvalid, threshold):
    gameCount = defaultdict(int)
    totalPlayed = 0

    for user,game,_ in readJSON("data/train.json.gz"):
      gameCount[game] += 1
      totalPlayed += 1



    mostPopular = [(gameCount[x], x) for x in gameCount]
    mostPopular.sort()
    mostPopular.reverse()

    return1 = set()
    count = 0
    for ic, i in mostPopular:
      count += ic
      return1.add(i)
      if count > totalPlayed/threshold: break


    #task 1 predictions
    predictions = []
    for user, game in Xvalid:
        if game in return1:
            predictions.append(1)
        else:
```

```
            predictions.append(0)

    return predictions
```

[25]:
```
def computeAccuracy(preds, true):
    correct = np.array(preds) == np.array(true)
    return sum(correct) / len(correct)
```

[26]:
```
preds = baselinePreds(Xvalid,2)
```

baseline accuracy

[27]:
```
#accuracy of baseline model on validation set
th2_acc = computeAccuracy(preds, yvalid)
print(computeAccuracy(preds, yvalid))
```

```
0.68055
```

Task 2 - find an optimal popularity threshold

my choice for thresholds was to keep it low, and see if being more selective in terms of popularity percentile would yield a better model, as you can see it performed slightly better in terms of accuracy

[28]:
```
# my choice for thresholds was to keep it low, and see if being more selective
#in terms of popularity percentile would yield a better model

def bestThreshold():
    best_th = 2
    best_acc = th2_acc
    for i in np.arange(1,2.05,.01):
        acc = computeAccuracy(baselinePreds(Xvalid,i), yvalid)
        if acc > best_acc:
            best_th = i
            best_acc = acc
    return best_th, best_acc

x = bestThreshold()
print(x)
```

```
(1.5200000000000005, 0.7011)
```

[29]:
```
best_popth = x[0]
print(best_popth)
```

```
1.5200000000000005
```

Task 3 - build Jaccard similarity based recommender system

[30]:
```python
from sklearn.metrics.pairwise import cosine_similarity
```

[31]:
```python
def Jaccard(s1, s2):
    numer = len(s1.intersection(s2))
    denom = len(s1.union(s2))
    if denom == 0:
        return 0
    return numer / denom
```

[ ]:
```python

```

[32]:
```python
#all users for a specific game in training data
#all games for a specific user in training data
usersPerGame = defaultdict(set)
gamesPerUser = defaultdict(set)
for u,g in Xtrain:
    usersPerGame[g].add(u)
    gamesPerUser[u].add(g)
```

[33]:
```python
#testing different implementation
def mostSimilar(u, g):
    similarities = []
    games = gamesPerUser[u]
    for g2 in games:
        if g2 == g:continue
        sim = Jaccard(usersPerGame[g], usersPerGame[g2])
        similarities.append(sim)
    similarities.sort(reverse=True)
    return similarities[:10]
```

[ ]:
```python

```

[34]:
```python
def similarityScores(user, game):
    #consider g' in training set that a user has played
    g_primes = gamesPerUser[user]
    similarities = []

    if len(g_primes) == 0:
        similarities.append(0)
        return similarities

    for g_prime in g_primes:
        if g_prime == game:
            continue
        #users in training data who have played g
        ugTrain = usersPerGame[game]
        #users who have played g'
```

```
        ugPrime = usersPerGame[g_prime]
        if len(ugPrime) == 0:
            similarities.append(0)
        if len(ugTrain) == 0:
            similarities.append(0)
        else:
            similarities.append(Jaccard(ugTrain,ugPrime))



    similarities.sort(reverse= True)
    return similarities[:10]
```

[35]:
```
#item-item similarity implementation
def i_similarityScores(user, game):
    #consider g' in training set that a user has played
    u_primes = usersPerGame[game]
    similarities = []

    #item to titem
    if len(u_primes) == 0:
        similarities.append(0)
        return similarities

    for u_prime in u_primes:
        if u_prime == user:
            continue
        #users in training data who have played g
        ugTrain = gamesPerUser[user]
        #users who have played g'
        ugPrime = gamesPerUser[u_prime]
        if len(ugPrime) == 0:
            similarities.append(0)
        else:
            similarities.append(Jaccard(ugTrain,ugPrime))


    similarities.sort(reverse= True)

    return similarities[:10]
```

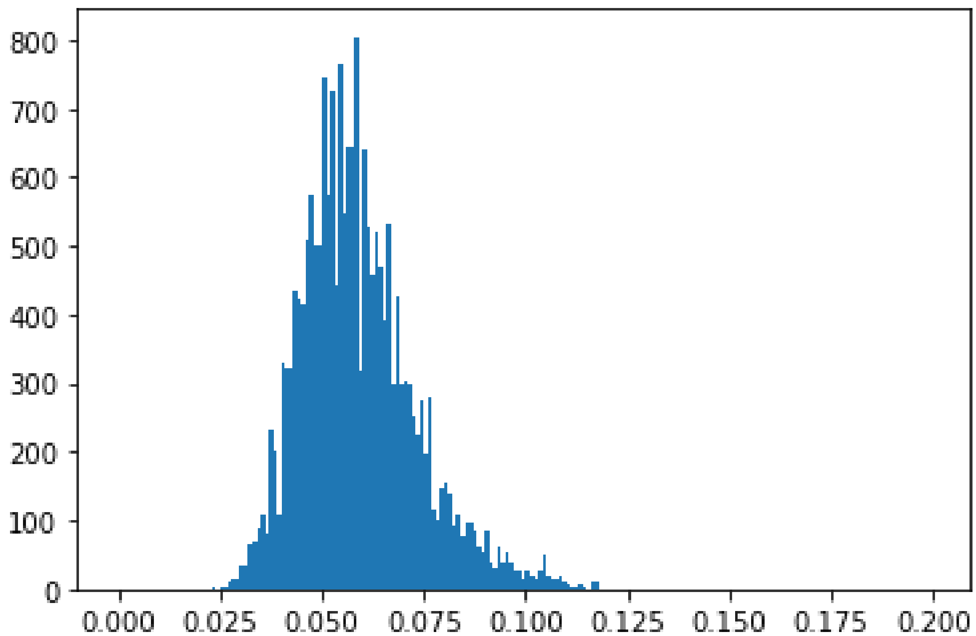
[36]:
```
max_scores = []
for user, game in Xvalid:
    max_scores.append(np.max(similarityScores(user, game)))
```

[37]:
```
# max_scores_fast = []
# for user, game in Xvalid:
```

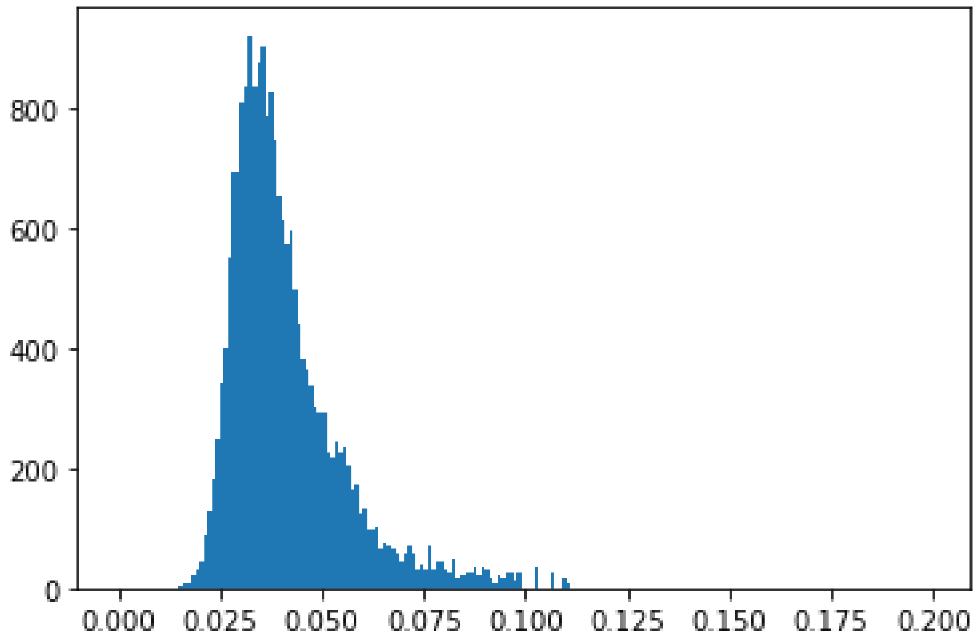
```
#     msf = mostSimilarFast(game)
#     max_scores_fast.append(np.max(msf))
```

[38]:
```
i_max_scores = []
for user, game in Xvalid:
    i_max_scores.append(np.max(i_similarityScores(user, game)))
```

[39]:
```
plt.hist(i_max_scores, bins = np.arange(0,.2,.001))
plt.show()
```



[40]:
```
plt.hist(max_scores, bins = np.arange(0,.2,.001))
plt.show()
```



[ ]:

[41]:
```
def jaccard_preds(max_scores,th):
    predictions = []
    for sim in max_scores:
        if sim > th:
            predictions.append(1)
        else:
            predictions.append(0)
    return predictions
```

[42]:
```
def bestThreshold():
    best_th = 0
    best_acc = 0
    for th in np.arange(0,.1,.001):
        preds = jaccard_preds(max_scores,th)
        acc = computeAccuracy(preds, yvalid)
        if acc > best_acc:
            best_th = th
            best_acc = acc

    return (best_th, best_acc)
best_jacc = bestThreshold()
```

[43]:
```
best_jacc
```

[43]: (0.041, 0.66515)

[44]:
```
best_jth = best_jacc[0]
best_jth
```

[44]: 0.041

[45]:
```
def i_bestThreshold():
    best_th = 0
    best_acc = 0
    for th in np.arange(0,.125,.001):
        preds = jaccard_preds(i_max_scores,th)
        acc = computeAccuracy(preds, yvalid)
        if acc > best_acc:
            best_th = th
            best_acc = acc

    return (best_th, best_acc)
#item to item results
x = i_bestThreshold()
print(x)
```

(0.055, 0.56925)

[46]:
```
best_ijth = x[0]
print(best_ijth)
```

0.055

[47]:
```
# #using mostSimilarFast implementation
# def bestThreshold():
#     best_th = 0
#     best_acc = 0
#     for th in np.arange(0.025,.175,.001):
#         preds = jaccard_preds(max_scores_fast,th)
#         acc = computeAccuracy(preds, yvalid)
#         if acc > best_acc:
#             best_th = th
#             best_acc = acc

#     return (best_th, best_acc)
# x = bestThreshold()
```

Task 4 - Improve the above predictor by incorporating both a Jaccard-based threshold and a popularity based threshold.

[48]:
```
def baselinePreds4(ug_valid_build, j_th,pop_th):
    gameCount = defaultdict(int)
    totalPlayed = 0

    for user,game,_ in readJSON("data/train.json.gz"):
        gameCount[game] += 1
        totalPlayed += 1

    mostPopular = [(gameCount[x], x) for x in gameCount]
    mostPopular.sort()
    mostPopular.reverse()

    return1 = set()
    count = 0
    for ic, i in mostPopular:
        count += ic
        return1.add(i)
        if count > totalPlayed/pop_th: break


    predictions_or = []
    for user, game, _ in ug_valid_build:
        mostSim = similarityScores(user, game)
        if (game in return1) or (max(mostSim) >= j_th):
            predictions_or.append(1)
        else:
            predictions_or.append(0)

    predictions_and = []
    for user, game, _ in ug_valid_build:
        mostSim = similarityScores(user, game)
        if (game in return1) and (max(mostSim) >= j_th):
            predictions_and.append(1)
        else:
            predictions_and.append(0)
    return predictions_and, predictions_or
```

[49]:
```
preds_and,preds_or = baselinePreds4(ug_valid_build,best_jth,best_popth)
and_acc = computeAccuracy(preds_and, yvalid)
or_acc = computeAccuracy(preds_or, yvalid)
print(and_acc)
print(or_acc)
```

```
0.677
0.68925
```

[50]:
```
preds_and,preds_or = baselinePreds4(ug_valid_build,.031,1.52)
and_acc = computeAccuracy(preds_and, yvalid)
or_acc = computeAccuracy(preds_or, yvalid)
print(and_acc)
print(or_acc)
```

```
0.7009
0.59255
```

[51]:
```
preds_and,preds_or = baselinePreds4(ug_valid_build,.030,1.5)
and_acc = computeAccuracy(preds_and, yvalid)
or_acc = computeAccuracy(preds_or, yvalid)
print(and_acc)
print(or_acc)
```

```
0.7004
0.57995
```

[52]:
```
# best_jth = .031
# best_popth = 1.52
```

redesign model

when passing the best threshold from q2 and q3 into the function above i mistyped one of the thresholds and managed to get an unexpected accuracy, so I ran a script to see if combining different jaccard-based thresholds and popularity thresholds would give better accuracy, or if the optimal thresholds from q2 and q3 were still the best, unfortunately the run time was a couple of hours because I was testing a large range of every possible combination for jaccard/popularity thresholds, i also redid some of the conditional statements for a more lenient predictor

the pseudo code for finding a better threshold combo is having two for loops, one outer and one nested, one loops through a range in jaccard thresholds and the other loops through some popularity threshold, then i run baselinePreds4 passing in those thresholds, compute accuracies and print out the accuracies with the thresholds to see which combo gives the best result in the redesigned baseline predictor

[53]:
```
from tqdm import tqdm
```

[54]:
```
def baselinePreds4(ug_valid_build, j_th,pop_th):
    gameCount = defaultdict(int)
    totalPlayed = 0

    usersPerGame = defaultdict(set)
    gamesPerUser = defaultdict(set)
```

```python
    for user,game,_ in readJSON("data/train.json.gz"):
        gameCount[game] += 1
        totalPlayed += 1
        usersPerGame[g].add(u)
        gamesPerUser[u].add(g)

    mostPopular = [(gameCount[x], x) for x in gameCount]
    mostPopular.sort()
    mostPopular.reverse()

    return1 = set()
    count = 0
    for ic, i in mostPopular:
        count += ic
        return1.add(i)
        if count > totalPlayed/pop_th: break


    predictions_and = []
    for user, game, _ in ug_valid_build:
        mostSim = similarityScores(user, game)
        if (game in return1):
            predictions_and.append(1)
        elif game in gamesPerUser[user]:
            predictions_and.append(1)
        else:
            if (game not in return1) and (max(mostSim) >= j_th):
                predictions_and.append(1)
            else:
                predictions_and.append(0)
    return predictions_and
```

[55]:

```python
preds_and = baselinePreds4(ug_valid_build,best_jth,best_popth)
and_acc = computeAccuracy(preds_and, yvalid)
print(and_acc)
```

0.68925

[56]:

```python
preds_and = baselinePreds4(ug_valid_build,.048,1.55)
and_acc = computeAccuracy(preds_and, yvalid)
print(and_acc)
```

0.6991

[57]:

```python
preds_and = baselinePreds4(ug_valid_build,.04,1.52)
and_acc = computeAccuracy(preds_and, yvalid)
print(and_acc)
```

0.6843

[58]:
```
#>=
preds_and = baselinePreds4(ug_valid_build,.048,1.52)
and_acc = computeAccuracy(preds_and, yvalid)
print(and_acc)
```

0.6994

[59]:
```
preds_and = baselinePreds4(ug_valid_build,.048,1.51)
and_acc = computeAccuracy(preds_and, yvalid)
print(and_acc)
```

0.69865

[60]:
```
best_jth = .031
best_popth =1.52

def baselinePreds4(ug_valid_build, j_th,pop_th):
    gameCount = defaultdict(int)
    totalPlayed = 0

    for user,game,_ in readJSON("data/train.json.gz"):
        gameCount[game] += 1
        totalPlayed += 1

    mostPopular = [(gameCount[x], x) for x in gameCount]
    mostPopular.sort()
    mostPopular.reverse()

    return1 = set()
    count = 0
    game_pop = defaultdict(float)
    for ic, i in mostPopular:
        count += ic
        game_pop[i] = 1 - (count/totalPlayed)
        return1.add(i)
        if count > totalPlayed/pop_th: break


#     predictions_or = []
#     for user, game, _ in ug_valid_build:
#         mostSim = similarityScores(user, game)
#         if (game in return1) or (max(mostSim) >= j_th):
#             predictions_or.append(1)
#         else:
#             predictions_or.append(0)
```

```
    predictions_and = []
    for user, game, _ in ug_valid_build:
        mostSim = similarityScores(user, game)
        if (game in return1) and (max(mostSim) >= j_th):
            predictions_and.append(1)
        else:
            predictions_and.append(0)
    return predictions_and
```

[61]:
```
#user-user similarity
def similarityScores(user, game):
    #consider g' in training set that a user has played
    g_primes = gamesPerUser[user]
    similarities = []

    if len(g_primes) == 0:
        similarities.append(0)
        return similarities

    for g_prime in g_primes:
        if g_prime == game:
            continue
        #users in training data who have played g
        ugTrain = usersPerGame[game]
        #users who have played g'
        ugPrime = usersPerGame[g_prime]
        if len(ugPrime) == 0:
            similarities.append(0)
        if len(ugTrain) == 0:
            similarities.append(0)
        else:
            similarities.append(Jaccard(ugTrain,ugPrime))

    similarities.sort(reverse= True)

    return similarities[:10]
```

[62]:
```
#item-item similarity
def i_similarityScores(user, game):
    #consider all u' in training set that have played game
    u_primes = usersPerGame[game]
    similarities = []

    #item to titem
    if len(u_primes) == 0:
        similarities.append(0)
        return similarities
```

```
    #for user' in u'
    for u_prime in u_primes:
        if u_prime == user:
            continue
        #games in training data played by user
        ugTrain = gamesPerUser[user]
        #games played by user'
        ugPrime = gamesPerUser[u_prime]
        if len(ugPrime) == 0:
            similarities.append(0)
        if len(ugTrain) == 0:
            similarities.append(0)
        else:
            similarities.append(Jaccard(ugTrain,ugPrime))


    similarities.sort(reverse= True)

    return similarities[:10]
```

[63]:
```
from sklearn.linear_model import LogisticRegression
```

[64]:
```
train_json[0]
```

[64]:
```
{'hours': 0.3,
 'gameID': 'b96045472',
 'hours_transformed': 0.37851162325372983,
 'early_access': False,
 'date': '2015-04-08',
 'text': '+1',
 'userID': 'u01561183'}
```

[65]:
```
# split = 165000
# data = [[d['userID'],d['gameID'],1] for d in train_json]
# train = train_json[:split]
# ug_train = [[d['userID'],d['gameID'],d['hours_transformed'],1] for d in train]
# validation = train_json[split:]
# ug_valid = [[d['userID'],d['gameID'],d['hours_transformed'],1] for d in␣
 ↪validation]
```

[66]:
```
# users_valid = [d[0] for d in ug_valid]
# users_train = [d[0] for d in ug_train]
```

[67]:
```
# #gets users per game and games per user from entire dataset
# usersPerGame = defaultdict(set)
# gamesPerUser = defaultdict(set)
# #collects all unique games in the dataset
```

```
# uniqueGames = set()

# for d in data:
#     u, g = d[0], d[1]
#     usersPerGame[g].add(u)
#     gamesPerUser[u].add(g)
#     uniqueGames.add(g)
```

[68]:
```
# ug_valid_neg= []
# for u in users_valid:
#     gamesNotPlayed = uniqueGames - gamesPerUser[u]
#     randomGame = random.choice(list(gamesNotPlayed))
#     ug_valid_neg.append([u, randomGame,0,0])


# ug_train_neg= []
# for u in users_train:
#     gamesNotPlayed = uniqueGames - gamesPerUser[u]
#     randomGame = random.choice(list(gamesNotPlayed))
#     ug_train_neg.append([u, randomGame,0,0])
```

[69]:
```
# ug_valid_build = ug_valid + ug_valid_neg
# ug_train_build = ug_train + ug_train_neg
```

[70]:
```
# #hour dict
# user_game_hrs = defaultdict(dict)
# for u,g,h,_ in ug_train_build:
#     user_game_hrs[str(u)+"-"+str(g)] = h
```

[71]:
```
# yvalid = [d[3] for d in ug_valid_build]
# ytrain = [d[3] for d in ug_train_build]
```

try a logistic regression model

[72]:
```
Xy = list(zip(ug_train_build,ytrain))
random.shuffle(Xy)
Xtrain = [d[0] for d in Xy]
ytrain = [d[1] for d in Xy]
```

[73]:
```
Xy = list(zip(ug_valid_build,yvalid))
random.shuffle(Xy)
Xvalid = [d[0] for d in Xy]
yvalid = [d[1] for d in Xy]
```

[74]:
```
#user-user similarity feature vector
X_valid = [[np.max(similarityScores(user,game))] for user, game,_ in Xvalid]
```

[75]:
```
X_train = [[np.max(similarityScores(user,game))] for user, game,_ in Xtrain]
```

[76]:
```
clf = LogisticRegression(max_iter = 2000, fit_intercept = True)
clf.fit(X_train,ytrain)
pred = clf.predict(X_valid)
correct = pred == yvalid
print("accuracy: ", sum(correct) / len(correct))
```

```
accuracy:  0.6584
```

[77]:
```
C = [.1,1,10,100,1000]
acc_list =[]
for c in C:
    clf = LogisticRegression(max_iter = 8000, C = c,fit_intercept = True)
    clf.fit(X_train,ytrain)
    pred = clf.predict(X_valid)
    correct = pred == yvalid
    acc = sum(correct) / len(correct)
    acc_list.append(acc)
```

[78]:
```
acc_list
```

[78]:
```
[0.65575, 0.6584, 0.65885, 0.65905, 0.65905]
```

[79]:
```
clf = LogisticRegression(max_iter = 2000, C = 100, fit_intercept = True)
clf.fit(X_train,ytrain)
pred = clf.predict(X_valid)
correct = pred == yvalid
print("accuracy: ", sum(correct) / len(correct))
```

```
accuracy:  0.65905
```

[80]:
```
#0.66555 user-user sim accuracy
#0.66255 user-user sim acc with class_weight balanced
#0.6638 user-user and item-item sim
#0.6605 user-user, item-item, class_weight balanced
#0.99955 user-user similarity with hours_transformed, unshuffled, overfitting
#0.99955 user-user similarity with hours_transformed, shuffled, overfitting
```

[81]:
```
# test = pd.read_csv("data/pairs_Played.txt", sep="-|,", engine='python')
```

[82]:
```
# test
```

[83]:
```
# test['pairs'] = test[['userID', 'gameID']].apply(lambda x: '-'.join(x),␣
↪axis=1)
```

[84]:
```
# hrs_arr = [user_game_hrs[i] for i in test['pairs'].values]
```

[85]:
```
# test['hours_transformed'] = hrs_arr
```

[86]:
```
## Would-play baseline: just rank which games are popular and which are not,␣
↪and return '1' if a game is among the top-ranked

# j_th = .031
# pop_th =1.52

# gameCount = defaultdict(int)
# totalPlayed = 0

# for user,game,_ in readJSON("data/train.json.gz"):
#   gameCount[game] += 1
#   totalPlayed += 1

# mostPopular = [(gameCount[x], x) for x in gameCount]
# mostPopular.sort()
# mostPopular.reverse()

# return1 = set()
# count = 0
# for ic, i in mostPopular:
#   count += ic
#   return1.add(i)
#   if count > totalPlayed/pop_th: break

# predictions = open("predictions_Played.txt", 'w')
# for l in open("data/pairs_Played.txt"):
#   if l.startswith("userID"):
#     #header
#     predictions.write(l)
#     continue
#   u,g = l.strip().split('-')
#   mostSim = similarityScores(u,g)

#   if g in return1 and (max(mostSim) >= j_th):
#     predictions.write(u + '-' + g + ",1\n")
#   else:
#     predictions.write(u + '-' + g + ",0\n")

# predictions.close()
```

incorporating item-item similarity hurts model performance

[87]:
```
#item to item th and acc (0.066, 0.64115)

def baselinePreds5(ug_valid_build, j_th,pop_th):
```

```
    gameCount = defaultdict(int)
    totalPlayed = 0

    for user,game,_ in readJSON("data/train.json.gz"):
        gameCount[game] += 1
        totalPlayed += 1

    mostPopular = [(gameCount[x], x) for x in gameCount]
    mostPopular.sort()
    mostPopular.reverse()

    return1 = set()
    count = 0
    for ic, i in mostPopular:
        count += ic
        return1.add(i)
        if count > totalPlayed/pop_th: break


#     #task 1 predictions
#     predictions = []
#     for user, game, _ in ug_valid_build:
#         if game in return1:
#             predictions.append(1)
#         else:
#             predictions.append(0)


#     predictions_or = []
#     for user, game, _ in ug_valid_build:
#         mostSim = similarityScores(user, game)
#         if (game in return1) or (max(mostSim) >= j_th):
#             predictions_or.append(1)
#         else:
#             predictions_or.append(0)

    predictions_and = []
    for user, game, _ in ug_valid_build:
        mostSim = similarityScores(user, game)
        i_mostSim = i_similarityScores(user, game)
        if (game in return1):
            predictions_and.append(1)
        else:
            if (game not in return1) and (max(mostSim) >= j_th)␣
↪and(max(i_mostSim)) > .066:
                predictions_and.append(1)
            else:
```

```
                predictions_and.append(0)
    return predictions_and
```

[88]:
```
#>=
preds_and = baselinePreds5(ug_valid_build,.048,1.51)
and_acc = computeAccuracy(preds_and, yvalid)
print(and_acc)
```

0.49955

[89]:
```
#with item-item similarity
def baselinePreds5(ug_valid_build, j_th,pop_th):
    gameCount = defaultdict(int)
    totalPlayed = 0

    for user,game,_ in readJSON("data/train.json.gz"):
        gameCount[game] += 1
        totalPlayed += 1

    mostPopular = [(gameCount[x], x) for x in gameCount]
    mostPopular.sort()
    mostPopular.reverse()

    return1 = set()
    count = 0
    for ic, i in mostPopular:
        count += ic
        return1.add(i)
        if count > totalPlayed/pop_th: break

    predictions_and = []
    for user, game, _ in ug_valid_build:
        mostSim = similarityScores(user, game)
        i_mostSim = i_similarityScores(user, game)
        if (game in return1) and (max(mostSim) >= j_th):
            predictions_and.append(1)
        elif (max(i_mostSim) >= .068):
            predictions_and.append(1)
        else:
            predictions_and.append(0)

    return predictions_and
```

[90]:
```
#>= .066
preds_and = baselinePreds5(ug_valid_build,.048,1.51)
and_acc = computeAccuracy(preds_and, yvalid)
print(and_acc)
```

0.496

[91]:
```
# mix1Result = []
# mix2Result = []

# for thresJac in tqdm(np.arange(0, 0.052, 0.002)):
#     jacPredBookDataYValid = jaccard_preds(max_scores,thresJac)

#     for thresBase in np.arange(1, 2, 0.05):
#         basePredBookDataYValid = baselinePreds4(ug_valid_build, thresJac,␣
↪thresBase)

#         mix1PredBookDataYValid = []
#         mix2PredBookDataYValid = []

#         for jacPred, basePred in zip(jacPredBookDataYValid,␣
↪basePredBookDataYValid):
#             if jacPred == basePred:
#                 mix1PredBookDataYValid.append(jacPred)
#                 mix2PredBookDataYValid.append(jacPred)
#             elif jacPred > basePred:
#                 mix1PredBookDataYValid.append(jacPred)
#                 mix2PredBookDataYValid.append(basePred)
#             elif basePred > jacPred:
#                 mix1PredBookDataYValid.append(basePred)
#                 mix2PredBookDataYValid.append(jacPred)
#         acc = computeAccuracy(mix1PredBookDataYValid, yvalid)
#         #print("Validataion Mix1: tJaccard=%f, tBaseline=%f, acc=%f, TPR=%f,␣
↪TNR=%f" % (thresJac, thresBase, acc, TPR, TNR) )
#         mix1Result.append((acc,thresJac,thresBase))

#         acc = computeAccuracy(mix2PredBookDataYValid, yvalid)
#         #print("Validataion Mix2: tJaccard=%f, tBaseline=%f, acc=%f, TPR=%f,␣
↪TNR=%f" % (thresJac, thresBase, acc, TPR, TNR) )
#         mix2Result.append((acc,thresJac,thresBase))
```

[92]:
```
# mix1Result.sort(reverse=True)
# mix2Result.sort(reverse=True)
```

[93]:
```
# mix1Result[:10]
```

[94]:
```
# mix2Result[:10]
```

[95]:
```
# usersPerGame = defaultdict(set)
# gamesPerUser = defaultdict(set)
# for u,g in Xtrain:
#     usersPerGame[g].add(u)
```

```
#     gamesPerUser[u].add(g)

# def Pearson(s1,s2):

#     g1rList = []
#     g2rList = []
#     uavg = []
#     for u in (s1& s2):
#         g1rList.append(gamesPerUser[s1][u])
#         g2rList.append(gamesPerUser[s2][u])
#         uavg.append(userAvg[u])

#     if len(s1 & s2) != 0:
#         cov = np.sum([(b1rList[i]-uavg[i])*(b2rList[i]-uavg[i]) for i in␣
↪range(len(b1rList))])
#         std = math.sqrt(np.sum([(r-a)**2 for r,a in zip(b1rList, uavg)]) * np.
↪sum(([(r-a)**2 for r,a in zip(b2rList, uavg)])))
#         return (cov*1.0)/std if std != 0 else 0
#     else:
#         return 0
```

[96]:

```
# def psimilarityScores(user, game):
#     #consider g' in training set that a user has played
#     g_primes = gamesPerUser[user]
#     similarities = []

#     if len(g_primes) == 0:
#         similarities.append(0)
#         return similarities

#     for g_prime in g_primes:
#         if g_prime == game:
#             continue
#         #users in training data who have played g
#         ugTrain = usersPerGame[game]
#         #users who have played g'
#         ugPrime = usersPerGame[g_prime]
#         if len(ugPrime) == 0:
#             similarities.append(0)
#         else:
#             similarities.append(Pearson(ugTrain,ugPrime))



#     similarities.sort(reverse= True)
```

```
#     return similarities[:10]
```

[97]:

```
# gamesPerUser['u24470137']
```

Task 5 - run model on test set

Kaggle Username: anthonylimon

[99]:

```
j_th = .031
pop_th = 1.52

gameCount = defaultdict(int)
totalPlayed = 0

usersPerGame = defaultdict(set)
gamesPerUser = defaultdict(set)
for user,game,_ in readJSON("data/train.json.gz"):
    gameCount[game] += 1
    totalPlayed += 1
    usersPerGame[g].add(u)
    gamesPerUser[u].add(g)

mostPopular = [(gameCount[x], x) for x in gameCount]
mostPopular.sort()
mostPopular.reverse()

return1 = set()
count = 0
for ic, i in mostPopular:
    count += ic
    return1.add(i)
    if count > totalPlayed/pop_th: break



predictions = open("predictions_Played.txt", 'w')
for l in open("data/pairs_Played.txt"):
    if l.startswith("userID"):
    #header
        predictions.write(l)
        continue
    u,g = l.strip().split('-')
    mostSim = similarityScores(u,g)
    if g in return1 and (max(mostSim) >= j_th):
        predictions.write(u + '-' + g + ",1\n")
    else:
        predictions.write(u + '-' + g + ",0\n")
```

```
predictions.close()
```

3 Tasks (Category prediction)

3.0.1 For these experiments, you may want to select a smaller dictionary size (i.e., fewer words), or a smaller training set size, if the experiments are taking too long to run.

Predict the category of a game from a review. Five categories are used for this task, which can be seen in the baseline program, namely Action, Strategy, RPG, Adventure, and Sport. Performance will be measured in terms of the fraction of correct classifications.

[100]:
```
import string
import nltk
from nltk.stem.porter import *
from nltk.stem.porter import PorterStemmer
from nltk.stem.snowball import SnowballStemmer
from scipy.sparse import lil_matrix
```

[101]:
```
train_cat_json = list(parse("data/train_Category.json.gz"))
```

[102]:
```
train_cat_json[165000:170000][0]
```

[102]:
```
{'userID': 'u24470137',
 'genre': 'Strategy',
 'early_access': False,
 'reviewID': 'r85460939',
 'hours': 4.2,
 'text': 'THIS GAME\nTHIS   ING GAME',
 'genreID': 1,
 'date': '2014-01-03'}
```

[103]:
```
#review data

data = [[d['genreID'],d['text']] for d in train_cat_json]

split = 165000

train = train_cat_json[:split]
Xtrain = [[d['text']] for d in train]
ytrain = [[d['genreID']] for d in train]

validation = train_cat_json[split:]
Xvalid = [[d['text']] for d in validation]
yvalid = [d['genreID'] for d in validation]
```

[ ]:

```

```

[104]:

```
### Ignore capitalization and remove punctuation

wordCount = defaultdict(int)
punctuation = set(string.punctuation)
totalCount = 0
for d in Xtrain:
    r = ''.join([c for c in d[0].lower() if not c in punctuation])
    for w in r.split():
        wordCount[w] += 1
        totalCount +=1

print(len(wordCount))
```

```
154889
```

Task 6 - We'll start by building features to represent common words. Start by removing punctuation and capitalization, and finding the 1,000 most common words across all reviews ('text' field) in the training set.

1000 most common words

[105]:

```
#top 1000 most frequent words in training set
sorted(wordCount.items(),key=lambda v: v[1],reverse=True)[:1000]
```

[105]:

```
[('the', 544597),
 ('and', 317620),
 ('a', 305414),
 ('to', 291882),
 ('game', 245359),
 ('of', 227234),
 ('is', 208417),
 ('you', 200633),
 ('i', 195953),
 ('it', 190966),
 ('this', 158622),
 ('in', 132348),
 ('that', 115044),
 ('for', 105210),
 ('but', 100985),
 ('with', 91007),
 ('its', 83631),
 ('are', 77355),
 ('on', 72366),
 ('as', 69754),
 ('not', 65475),
 ('have', 63625),
```

```
('if', 58019),
('like', 57252),
('be', 56116),
('can', 50151),
('so', 48201),
('your', 47720),
('was', 46825),
('just', 45696),
('or', 45686),
('all', 45297),
('good', 45152),
('more', 42838),
('one', 42197),
('at', 41525),
('play', 40611),
('get', 39537),
('my', 38847),
('games', 37677),
('there', 37202),
('fun', 36986),
('really', 36441),
('some', 35836),
('an', 35701),
('very', 35477),
('from', 34854),
('time', 32421),
('will', 32065),
('they', 31200),
('me', 30495),
('has', 30323),
('great', 30314),
('out', 29522),
('up', 29314),
('story', 29273),
('no', 28975),
('even', 27341),
('only', 25972),
('what', 25911),
('dont', 25675),
('do', 25627),
('which', 25568),
('when', 25293),
('about', 24393),
('much', 23984),
('would', 23780),
('by', 22763),
('still', 21979),
```

```
('well', 21797),
('than', 21644),
('also', 21088),
('first', 21085),
('them', 19560),
('because', 19217),
('other', 18936),
('played', 18878),
('then', 18826),
('gameplay', 18395),
('into', 18069),
('best', 17463),
('playing', 17196),
('too', 17176),
('make', 17134),
('way', 16600),
('how', 16345),
('most', 16149),
('better', 15721),
('had', 15622),
('pretty', 15607),
('new', 15544),
('2', 15473),
('people', 15043),
('any', 14772),
('lot', 14727),
('now', 14662),
('after', 14539),
('while', 14286),
('where', 14277),
('want', 14166),
('im', 13751),
('hours', 13709),
('graphics', 13660),
('many', 13608),
('who', 13512),
('go', 13410),
('bad', 13345),
('recommend', 13094),
('over', 13058),
('through', 13043),
('worth', 13035),
('little', 12738),
('buy', 12665),
('love', 12408),
('feel', 12330),
('1', 12150),
```

```
('youre', 12097),
('though', 12060),
('every', 11982),
('cant', 11955),
('their', 11948),
('being', 11870),
('few', 11800),
('think', 11689),
('could', 11667),
('been', 11620),
('say', 11619),
('see', 11576),
('ever', 11569),
('level', 11568),
('got', 11488),
('characters', 11297),
('things', 11179),
('3', 11128),
('back', 11074),
('bit', 11049),
('same', 10955),
('ive', 10838),
('nice', 10771),
('around', 10763),
('find', 10757),
('made', 10735),
('different', 10679),
('were', 10566),
('know', 10420),
('again', 10377),
('never', 10129),
('something', 9820),
('should', 9745),
('off', 9617),
('theres', 9558),
('need', 9466),
('thing', 9336),
('each', 9266),
('hard', 9225),
('experience', 9224),
('amazing', 9160),
('thats', 9141),
('end', 9118),
('actually', 9083),
('doesnt', 9064),
('down', 9048),
('world', 9039),
```

```
('enough', 8937),
('take', 8884),
('short', 8868),
('those', 8767),
('before', 8740),
('give', 8708),
('interesting', 8638),
('going', 8623),
('makes', 8612),
('use', 8609),
('does', 8607),
('free', 8589),
('quite', 8579),
('right', 8565),
('character', 8510),
('work', 8461),
('times', 8459),
('long', 8298),
('these', 8288),
('system', 8280),
('levels', 8224),
('player', 8162),
('did', 8122),
('since', 8121),
('enemies', 8094),
('however', 8077),
('far', 8053),
('isnt', 8052),
('try', 7997),
('everything', 7987),
('point', 7934),
('music', 7872),
('here', 7822),
('old', 7791),
('look', 7763),
('kill', 7715),
('combat', 7687),
('steam', 7610),
('weapons', 7474),
('two', 7467),
('didnt', 7446),
('overall', 7439),
('without', 7407),
('series', 7379),
('why', 7327),
('easy', 7326),
('multiplayer', 7324),
```

```
('1010', 7304),
('own', 7247),
('players', 7235),
('start', 7190),
('nothing', 7178),
('money', 7150),
('youll', 6994),
('review', 6979),
('enjoy', 6905),
('awesome', 6869),
('mode', 6833),
('another', 6700),
('once', 6675),
('feels', 6647),
('such', 6629),
('puzzles', 6528),
('original', 6488),
('we', 6457),
('may', 6396),
('price', 6384),
('simple', 6333),
('4', 6315),
('sure', 6265),
('probably', 6229),
('run', 6222),
('real', 6168),
('always', 6156),
('might', 6150),
('getting', 6117),
('style', 6091),
('part', 6077),
('keep', 6046),
('5', 5984),
('fps', 5956),
('friends', 5875),
('full', 5830),
('sale', 5813),
('looking', 5807),
('anything', 5760),
('yes', 5743),
('10', 5716),
('controls', 5680),
('he', 5628),
('years', 5621),
('am', 5618),
('having', 5538),
('design', 5481),
```

```
('life', 5476),
('mechanics', 5472),
('done', 5433),
('cool', 5417),
('almost', 5384),
('his', 5327),
('pc', 5321),
('super', 5281),
('yet', 5276),
('shooter', 5186),
('kind', 5173),
('least', 5152),
('definitely', 5107),
('main', 5096),
('enemy', 5094),
('last', 5087),
('ai', 5074),
('put', 5070),
('version', 5065),
('less', 5064),
('come', 5059),
('id', 5041),
('gets', 5038),
('found', 5026),
('until', 5004),
('action', 4974),
('dead', 4943),
('boring', 4942),
('sometimes', 4908),
('big', 4901),
('single', 4874),
('trying', 4861),
('both', 4792),
('maybe', 4791),
('making', 4778),
('unique', 4771),
('instead', 4744),
('must', 4742),
('stuff', 4738),
('difficulty', 4706),
('seems', 4702),
('content', 4655),
('rather', 4622),
('art', 4603),
('looks', 4568),
('map', 4564),
('day', 4563),
```

```
('whole', 4550),
('especially', 4505),
('fan', 4502),
('used', 4495),
('next', 4493),
('said', 4441),
('either', 4440),
('able', 4440),
('campaign', 4438),
('between', 4423),
('away', 4417),
('puzzle', 4402),
('voice', 4289),
('sound', 4282),
('wont', 4256),
('already', 4251),
('fast', 4240),
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('heard', 1190),
('planet', 1188),
('stick', 1187),
('heavy', 1187),
('positive', 1186)]
```

top 10 words and their frequencies

[106]:
```
#top 10 words and frequencies
wordFreq = {k : v /totalCount for k,v in wordCount.items()}
mostCommon1000_wf = sorted(wordFreq.items(),key=lambda v: v[1] /␣
↪totalCount,reverse=True)[:1000]
```

```
top10 = mostCommon1000_wf[:10]
top10
```

[106]:
```
[('the', 0.047446967093177694),
 ('and', 0.02767203214144606),
 ('a', 0.02660860784726279),
 ('to', 0.025429658351204455),
 ('game', 0.021376431377725155),
 ('of', 0.019797325582864286),
 ('is', 0.018157930617794103),
 ('you', 0.017479764576017718),
 ('i', 0.01707202856939985),
 ('it', 0.016637545777732472)]
```

[107]:
```
mostCommon1000words = [w for w,f in mostCommon1000_wf]
```

[108]:
```
len(mostCommon1000words)
```

[108]:
```
1000
```

Task 7 - Build bag-of-words feature vectors by counting the instances of these 1,000 words in each review. Use LogisticRegression model, which will automatically perform multiclass classification.

[109]:
```
wordId = dict(zip(mostCommon1000words, range(len(mostCommon1000words))))
wordSet = set(mostCommon1000words)


stemmer = SnowballStemmer("english")
def feature(d):
    feat = [0]*len(mostCommon1000words)
    r = ''.join([c for c in d['text'].lower() if not c in punctuation])
    for w in r.split():
        w = stemmer.stem(w)
        if w in mostCommon1000words:
            feat[wordId[w]] += 1
    feat.append(1) #offset
    return feat
```

[110]:
```
#(for reference) almost two minutes to run
Xtrain = [feature(d) for d in train]
Xlil = lil_matrix(Xtrain)
ytrain =  [d['genreID'] for d in train]
```

[ ]:
```

```

[111]:
```
from sklearn.linear_model import LogisticRegression
```

[112]:
```
#snowball stemmer 3000 max iter, 2000 for others/non stemming model
clf = LogisticRegression(max_iter = 3000)
clf.fit(Xlil,ytrain)
```

[112]:
```
LogisticRegression(max_iter=3000)
```

[113]:
```
Xvalid = [feature(d) for d in validation]
```

[114]:
```
pred = clf.predict(Xvalid)
```

[115]:
```
#.6723 without stemming
correct = pred == yvalid
print("accuracy: ", sum(correct) / len(correct))
```

```
accuracy:  0.6489
```

[116]:
```
#porterstemmer
correct = pred == yvalid
print("accuracy: ", sum(correct) / len(correct))
```

```
accuracy:  0.6489
```

[117]:
```
#snowball stemmer
correct = pred == yvalid
print("accuracy: ", sum(correct) / len(correct))
```

```
accuracy:  0.6489
```

Task 8 - Try to improve upon the performance of the above classifier by using different dictionary sizes, or changing the regularization constant C passed to the logistic regression model.

observation: as dict size increases so does accuracy, the classifier ending up improving by .05% accuracy

unfortunately due to time concerns and nearing the homework deadline I didn't get to test dictionary sizes > 5000

I only tested sizes 500, 800, 1000, 2000, 3000, 4000, and 5000 for c values [10-2, .1,1,10,100], and found that a c value of 1 usually results in the highest accuracy**

i will use a dictionary size of 5000 and C value of 1 in the improved classifier

[118]:
```
mostCommon15000_wf = sorted(wordFreq.items(),key=lambda v: v[1] /␣
 ↪totalCount,reverse=True)[:15000]
mostCommon15000words = [w for w,f in mostCommon15000_wf]
wordId = dict(zip(mostCommon15000words, range(len(mostCommon15000words))))
wordSet = set(mostCommon15000words)
```

[119]:
```
def feature(d):
    feat = [0]*len(mostCommon15000words)
    r = ''.join([c for c in d['text'].lower() if not c in punctuation])
    for w in r.split():
        if w in mostCommon15000words:
            feat[wordId[w]] += 1
    feat.append(1) #offset
    return feat
```

[120]:
```
Xtrain = [feature(d) for d in train]
Xlil = lil_matrix(Xtrain)
ytrain =  [d['genreID'] for d in train]
Xvalid = [feature(d) for d in validation]
```

[121]:
```
clf = LogisticRegression(max_iter = 8000)
clf.fit(Xlil,ytrain)
pred = clf.predict(Xvalid)
```

[122]:
```
#acc for 5000 top words
correct = pred == yvalid
print("accuracy: ", sum(correct) / len(correct))
```

```
accuracy:  0.7437
```

[123]:
```
#acc for 10000 words
correct = pred == yvalid
print("accuracy: ", sum(correct) / len(correct))
```

```
accuracy:  0.7437
```

[124]:
```
#acc for 15000 words
correct = pred == yvalid
print("accuracy: ", sum(correct) / len(correct))
```

```
accuracy:  0.7437
```

[125]:
```
## Category prediction baseline: Just consider some of the most common words␣
↪from each category

catDict = {
  "Action": 0,
  "Strategy": 1,
  "RPG": 2,
  "Adventure": 3,
  "Sport": 4
}
```

```python
predictions = open("predictions_Category.txt", 'w')
predictions.write("userID-reviewID,prediction\n")
for u,_,d in readJSON("data/test_Category.json.gz"):
    cat = clf.predict([feature(d)])
    predictions.write(u + '-' + d['reviewID'] + "," + str(cat[0]) + "\n")

predictions.close()
```

[126]:
```python
# C = [.1,1,10,100]
# ps =[]
# for c in C:
#     clf = LogisticRegression(max_iter = 8000, C = c)
#     clf.fit(Xlil,ytrain)
#     pred = clf.predict(Xvalid)
#     ps.append(pred)
```

[127]:
```python
# correct = pred == yvalid
# print("accuracy: ", sum(correct) / len(correct))
```

[128]:
```python
# acc_list =[]
# for p in ps:
#     correct = p == yvalid
#     acc_list.append(sum(correct)/len(correct))
```

[129]:
```python
#dict size 2000
#max_iter = 6000
#C = [10**-2,.1,1,10,100]
# acc_list  = [0.6886, 0.7003, 0.7017, 0.7015, 0.7011]
```

[130]:
```python
#dict size 3000
#max_iter = 6000
#C = [.1,1,10,100]
# acc_list = [0.7116, 0.7146, 0.713, 0.7128]
```

[131]:
```python
#dict size 5000
#max_iter = 6000
#C = [.1,1,10,100]
# acc_list = [0.7277, 0.7294, 0.7282, 0.7274]
```

[ ]:
```python

```