## CSE258\_HW3\_lu

November 13, 2019

### 1 Task 1: Read Prediction

# 1.1 1: Evaluate the performance (accuracy) of the baseline model on the validation set you have built

```
[79]: import gzip
     from collections import defaultdict
     import random
     def readGz(path):
       for l in gzip.open(path, 'rt'):
         yield eval(1)
     def readCSV(path):
      f = gzip.open(path, 'rt')
      f.readline()
      for l in f:
         yield l.strip().split(',')
     ### Rating baseline: compute averages for each user, or return the globalu
      →average if we've never seen the user before
     allRatings = []
     allReview = []
     userRatings = defaultdict(list)
     allBooks = []
     for user,book,r in readCSV("train_Interactions.csv.gz"):
       r = int(r)
      allRatings.append(r)
      userRatings[user].append(r)
      allReview.append([user,book,r])
       if book not in allBooks: allBooks.append(book)
     globalAverage = sum(allRatings) / len(allRatings)
     userAverage = {}
     for u in userRatings:
       userAverage[u] = sum(userRatings[u]) / len(userRatings[u])
```

#### 1.1.1 Separate our data into Train and Validation

```
[80]: reviewTrain = allReview[:190000] reviewVal = allReview[190000:]
```

#### 1.1.2 Modify the baseline so it depends on the training set we have

```
[81]: ### Would-read baseline: just rank which books are popular and which are not,
     →and return '1' if a book is among the top-ranked
     bookCount = defaultdict(int)
     totalRead = 0
     for user,book,_ in reviewTrain:
       bookCount[book] += 1
       totalRead += 1
    mostPopular = [(bookCount[x], x) for x in bookCount]
     mostPopular.sort()
     mostPopular.reverse()
     return1 = set()
     count = 0
     for ic, i in mostPopular:
       count += ic
       return1.add(i)
       if count > totalRead/2: break
```

#### 1.1.3 Prepare a negative-entry for our validation set

```
[82]: ## build the dictionary where we could find the read book and hasnt read book
     userRatingsTrain = defaultdict(set)
     for (user,book,r) in reviewTrain:
         userRatingsTrain[user].add(book)
     print(len(userRatingsTrain))
     print(userRatingsTrain['u79354815'])
     userRatingsVal = defaultdict(set)
     for (user,book,r) in reviewVal:
         userRatingsVal[user].add(book)
     print(len(reviewVal))
     print(len(userRatingsVal))
    11357
    {'b50552757', 'b56923147', 'b14275065', 'b66134745', 'b03661054', 'b10241989',
    'b19841474', 'b73351796', 'b37649900', 'b78541130', 'b28542052'}
    10000
    6288
```

20000

## 1.1.4 Test the accuracy on our validation set with random book users haven't read

```
[84]: predictions = open("predictions_Read.txt", 'w')
     tpredict = 0
     totalpredict = 0
     for (u,b,r) in readPredictVal:
         totalpredict += 1
         if r >= 0:
             if b in return1:
                 predictions.write(u + '-' + b + ",1 \n")
                 tpredict += 1
             else:
                 predictions.write(u + '-' + b + ",0\n")
         else:
             if b in return1:
                 predictions.write(u + '-' + b + ",1\n")
             else:
                 predictions.write(u + '-' + b + ",0 n")
                 tpredict += 1
     predictions.close()
     accVal = tpredict/totalpredict
     print('Accuracy of read prediction on the validation set',accVal)
     print('Total books predicted',totalpredict)
```

Accuracy of read prediction on the validation set 0.64405 Total books predicted 20000

- 1.2 2: See if you can find a better threshold and report its performance on your validatin set
- 1.2.1 Modify our baseline model to become a function that we could modify the percentage of popular standard

```
[85]: # input: the percentage of popular standard percentage
# output: the book set that are the most p% popular
def wouldRead(p):
    return1 = set()
    count = 0
    for ic, i in mostPopular:
        count += ic
        return1.add(i)
        if count > totalRead*(p): break
    return return1
```

#### 1.2.2 Define a function for predicting accuracy calculate

```
[86]: # input: the percentage of popular standard percentage
     # output: the book set that are the most p% popular
     def accCalculator(p):
         bookset = wouldRead(p)
         tpredict = 0
         totalpredict = 0
         for (u,b,r) in readPredictVal:
             totalpredict += 1
             if r > 0:
                 if b in bookset:
                     tpredict += 1
             else:
                 if b not in bookset:
                     tpredict += 1
         accVal = tpredict/totalpredict
         return accVal
     accCalculator(0.5)
```

[86]: 0.6492

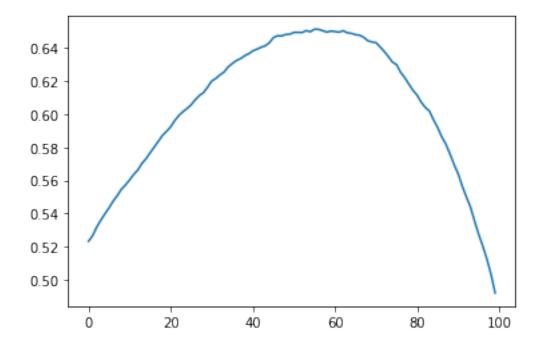
#### 1.2.3 Plot a graph for our predicting accuracy result

```
[87]: plodata = []
for i in range(100):
    plodata.append(accCalculator(i*0.01))

from matplotlib import pyplot as plt
plt.plot(plodata)
```

```
plt.show
print('most popular of',plodata.index(max(plodata)),'percent, with an accuracy
→of',max(plodata))
```

most popular of 55 percent, with an accuracy of 0.65115



### 1.3 3: Use Jaccard similarity to conduct a read prediction

```
[88]: ### build our dictionary for each book in the training set
bookReadbyTrain = defaultdict(set)
for (user,book,r) in reviewTrain:
bookReadbyTrain[book].add(user)
```

## 1.3.1 Define a function for calculate the similartiy over two books

```
[89]: def jaccardSim(b1,b2):
    usersforb1 = bookReadbyTrain[b1]
    usersforb2 = bookReadbyTrain[b2]
    if len(usersforb1) == 0 and len(usersforb2) == 0:
        return 0
    else:
        numer = len(set(usersforb1).intersection(set(usersforb2)))
        denom = len(set(usersforb1).union(set(usersforb2)))
```

```
return numer/denom
```

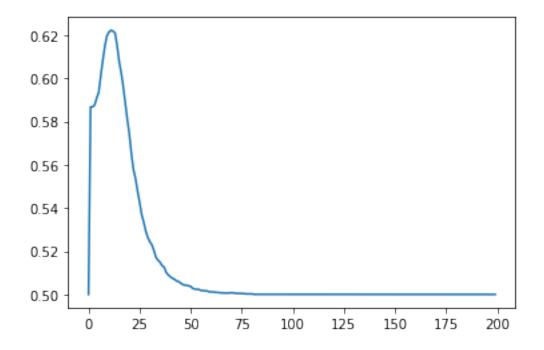
1.3.2 Define a function for predict the read status for a single pair of (user, book)

```
[91]: def simJaccard(user,book):
         if user not in userRatingsTrain:
             return 0
         if book not in bookReadbyTrain:
             return 0
         simmax = 0
         for b in userRatingsTrain[user]:
             if b == book: continue
             simmax = max(jaccardSim(b,book),simmax)
         return simmax
[92]: totalpred = len(readPredictVal)
     simmax = []
     readPredictVal1 = []
     for u, b, r in readPredictVal:
         simmax.append(simJaccard(u,b))
         if r >= 0:
             readPredictVal1.append(1)
         else:
             readPredictVal1.append(0)
```

1.3.3 Plot a graph for our prediction result with different threshold from 0 to 99 with Jaccard sim on validation set

after I tried with p from 0 to 100%, I noticed that when the threshold goes upper than 15%, the Jaccard Similarity stays the same. So we are only going to try in a more specific way

max similarity of 0.011 percent similarity, with an accuracy of 0.62225



## 1.4 4. Incorporate two of our features to become a better model

```
[94]: import numpy as np
[95]: from sklearn import linear_model
[96]: model = linear_model.LogisticRegression()
```

# 1.4.1 Use our validation set to select the best parameters for the classifier based on previous two models

```
[420]: ## data set we are going to use:
import warnings
warnings.filterwarnings('ignore')
def dataPrep(pop,per):
    predPop = [1 if b in wouldRead(pop) else 0 for u,b,r in readPredictVal]
    predjaccard = [1 if simmax[j] >= per else 0 for j in range(len(simmax))]
    return (predPop,predjaccard)

y = readPredictVal1
colOf1 = [1]*len(readPredictVal1)
accIncorModel = []
for pop in range(53,57):
    for per in range(9,12):
        #print(pop,per)
        predPop = dataPrep(0.01*pop,0.001*per)[0]
```

```
predjaccard = dataPrep(0.01*pop,0.001*per)[1]
                                                       X = np.column_stack((colOf1,predPop,predjaccard))
                                                       model.fit(X, y)
                                                      predictions = model.predict(X)
                                                       correctPredictions = predictions == y
                                                       accIncorModel.append((pop,per,sum(correctPredictions)/
                            →len(correctPredictions)))
[421]: print(accIncorModel)
                     [(53, 9, 0.6482), (53, 10, 0.64635), (53, 11, 0.64635), (54, 9, 0.64955), (54, 9, 0.64955), (54, 9, 0.64955), (54, 9, 0.64955), (54, 9, 0.64955), (54, 9, 0.64955), (55, 11, 0.64635), (56, 9, 0.64955), (56, 9, 0.64955), (56, 9, 0.64955), (56, 9, 0.64955), (56, 9, 0.64955), (56, 9, 0.64955), (56, 9, 0.64955), (56, 9, 0.64955), (56, 9, 0.64955), (56, 9, 0.64955), (56, 9, 0.64955), (56, 9, 0.64955), (56, 9, 0.64955), (56, 9, 0.64955), (56, 9, 0.64955), (56, 9, 0.64955), (56, 9, 0.64955), (56, 9, 0.64955), (56, 9, 0.64955), (56, 9, 0.64955), (56, 9, 0.64955), (56, 9, 0.64955), (56, 9, 0.64955), (56, 9, 0.64955), (56, 9, 0.64955), (56, 9, 0.64955), (56, 9, 0.64955), (56, 9, 0.64955), (56, 9, 0.64955), (56, 9, 0.64955), (56, 9, 0.64955), (56, 9, 0.64955), (56, 9, 0.64955), (56, 9, 0.64955), (56, 9, 0.64955), (56, 9, 0.64955), (56, 9, 0.64955), (56, 9, 0.64955), (56, 9, 0.64955), (56, 9, 0.64955), (56, 9, 0.64955), (56, 9, 0.64955), (56, 9, 0.64955), (56, 9, 0.64955), (56, 9, 0.64955), (56, 9, 0.64955), (56, 9, 0.64955), (56, 9, 0.64955), (56, 9, 0.64955), (56, 9, 0.64955), (56, 9, 0.64955), (56, 9, 0.64955), (56, 9, 0.64955), (56, 9, 0.64955), (56, 9, 0.64955), (56, 9, 0.64955), (56, 9, 0.64955), (56, 9, 0.64955), (56, 9, 0.64955), (56, 9, 0.64955), (56, 9, 0.64955), (56, 9, 0.64955), (56, 9, 0.64955), (56, 9, 0.64955), (56, 9, 0.64955), (56, 9, 0.64955), (56, 9, 0.64955), (56, 9, 0.64955), (56, 9, 0.64955), (56, 9, 0.64955), (56, 9, 0.64955), (56, 9, 0.64955), (56, 9, 0.64955), (56, 9, 0.64955), (56, 9, 0.64955), (56, 9, 0.64955), (56, 9, 0.64955), (56, 9, 0.64955), (56, 9, 0.64955), (56, 9, 0.64955), (56, 9, 0.64955), (56, 9, 0.64955), (56, 9, 0.64955), (56, 9, 0.64955), (56, 9, 0.64955), (56, 9, 0.64955), (56, 9, 0.64955), (56, 9, 0.64955), (56, 9, 0.64955), (56, 9, 0.64955), (56, 9, 0.64955), (56, 9, 0.64955), (56, 9, 0.64955), (56, 9, 0.64955), (56, 9, 0.64955), (56, 9, 0.64955), (56, 9, 0.64955), (56, 9, 0.64955), (56, 9, 0.64955), (56, 9, 0.64955), (56, 9, 0.64955), (56, 9, 0.64955), (56, 9, 0.64955), (56, 9,
                     10, 0.64655), (54, 11, 0.64655), (55, 9, 0.65265), (55, 10, 0.6487), (55, 11,
                     0.6487), (56, 9, 0.6537), (56, 10, 0.649), (56, 11, 0.649)]
[422]: accTn = [k for (p,q,k) in accIncorModel]
                       indexMax = accTn.index(max(accTn))
                       print('the parameters we choose',
                                               accIncorModel[indexMax],
                                                 'with an accuracy of',max(accTn))
```

the parameters we choose (56, 9, 0.6537) with an accuracy of 0.6537

I tried several ways to incorporate two models, including have their union/intersection, with several paramaters input. This is after modifed since I tried different way to predict and try them on Kaggle

```
[431]: predictionsLu = open("predictions_Read_Lu.txt", 'w')
for l in open("pairs_Read.txt"):
    if l.startswith("userID"):
        #header
        predictionsLu.write(l)
        continue
        u,b = l.strip().split('-')
        poppred = 1 if b in wouldRead(0.56) else 0
        Japred = 1 if simJaccard(u,b) >= 0.011 else 0
        out = str(1 if Japred == 1 else 0)
        predictionsLu.write(u + '-' + b + ","+ out +"\n")
        predictionsLu.close()

[425]: print('My Kaggle team name for this rating contest is PSG.LGD.LuNova with my⊔
        →name Lu0321')
```

My Kaggle team name for this rating contest is PSG.LGD.LuNova with my name  ${\rm Lu}0321$ 

## 2 Task 2: Rating prediction

2.1 9. Fit a predictor of given form and use a regularization parameter of = 1. Report the MSE on the validation set (1 mark).

#### 2.1.1 Prepare our data

```
[418]: # as we used before, the traingin set contains 1-190,000 reviews, with the
       →validation set contains 190,001-200,000
      reviewTrain
      reviewVal
      print(len(reviewTrain))
      print(len(reviewVal))
     190000
     10000
[366]: Usersreadi = defaultdict(set)
      ItemRatebyu = defaultdict(set)
      Usersreadi_count = defaultdict(list)
      ItemRatebyu_count = defaultdict(list)
      for u,b,r in reviewTrain:
          Usersreadi[b].add(u)
          ItemRatebyu[u].add(b)
      book_list = list(Usersreadi.keys())
      user_list = list(ItemRatebyu.keys())
[367]: UsersreadiAvg = defaultdict(list)
      ItemRatebyuAvg = defaultdict(list)
      rateAfterReadi = defaultdict(list)
      ratebyUser = defaultdict(list)
      for u,b,r in reviewTrain:
          rateAfterReadi[b].append(r)
          ratebyUser[u].append(r)
      for b in rateAfterReadi:
          UsersreadiAvg[b] = mean(rateAfterReadi[b])
      for u in ratebyUser:
          ItemRatebyuAvg[u] = mean(ratebyUser[u])
      globalAvgTrain = mean([r for u,b,r in reviewTrain])
[368]: globalAvgTrain
```

```
[368]: 3.897121052631579
[369]: # set up two dictionaries for count the amount of books for each user and each
       \rightarrowbook
      Usersreadi_count = defaultdict(list)
      ItemRatebyu_count = defaultdict(list)
[370]: for b in Usersreadi:
          Usersreadi_count[b] = len(Usersreadi[b])
      for u in ItemRatebyu:
          ItemRatebyu_count[u] = len(ItemRatebyu[u])
[371]: print(len(Usersreadi))
      print(len(ItemRatebyu))
     7169
     11357
[372]: # set up our staring dictionary for betas
      beta_i = defaultdict(float)
      beta_u = defaultdict(float)
[373]: for b in Usersreadi:
          beta_i[b] = 2
      for u in ItemRatebyu:
          beta_u[u] = 2
      print(len(beta_i))
      print(len(beta_u))
     7169
     11357
[374]: TrainFrame = pd.DataFrame(reviewTrain,columns=['user','book','rate'])
      s = 0
      s_ItemRatebyu = defaultdict(int)
      s Usersreadi = defaultdict(int)
      for i in range(len(TrainFrame)):
          r = TrainFrame.iloc[i]
          if r[1] not in s_Usersreadi:
              s_Usersreadi[r[1]] = int(r[2])
          else:
              s_Usersreadi[r[1]] = s_Usersreadi[r[1]] + int(r[2])
          if r[0] not in s_ItemRatebyu:
              s_{t} = \inf(r[0]) = \inf(r[2])
              s_ItemRatebyu[r[0]] = s_ItemRatebyu[r[0]] + int(r[2])
          s = s + int(r[2])
```

```
[375]: def ratePredicting(a,betai,betau,lamda,times):
          for k in range(times):
              temp = 0
              for i in ItemRatebyu:
                  temp = temp + betau[i]*ItemRatebyu_count[i]
              temp1 = 0
              for i in Usersreadi:
                  temp1 = temp1 + betai[i]*Usersreadi_count[i]
              a = (total - temp - temp1)/len(TrainFrame)
              for i in ItemRatebyu:
                  temp2 = 0
                  for j in list(ItemRatebyu[i]):
                      temp2 = temp2 + betai[j]
                  betau[i] = (total_ItemRatebyu[i] - a*ItemRatebyu_count[i] - temp2)/
       →(lamda + ItemRatebyu_count[i])
              for i in Usersreadi:
                  temp3 = 0
                  for j in list(Usersreadi[i]):
                      temp3 = temp3 + betau[j]
                  betai[i] = (total_Usersreadi[i] - a*Usersreadi_count[i] - temp3)/
       →(lamda + Usersreadi_count[i])
          return a, betai, betau
[376]: a,beta_i,beta_u = ratePredicting(2,beta_i,beta_u,1,400)
[378]: a
[378]: 3.804997206562257
[379]: beta_i['b14275065']
[379]: 0.07982214232076082
[380]: beta_u['u79354815']
[380]: 0.007200183261631539
[381]: def predRating(user, item):
          if item in beta_i and user in beta_u:
              y = a + beta_i[item] + beta_u[user]
          elif item not in beta_i and user in beta_u:
              y = ItemRatebyuAvg[user]
          elif item in beta_i and user not in beta_u:
              y = UsersreadiAvg[item]
          else:
              y = globalAvgTrain
          return y
```

```
for books
[388]: key_list = list(beta_i.keys())
      val list = list(beta i.values())
[389]: max(val_list)
[389]: 1.4291517056125491
[390]: booknamemx = key_list[val_list.index(max(val_list))]
[391]: print('max of beta i attained by book', booknamemx, with max
       →beta_i',max(val_list))
     max of beta_i attained by book b19925500 with max beta_i 1.4291517056125491
[392]: booknamemx1 = key_list[val_list.index(min(val_list))]
[393]: print('min of beta_i attained by book', booknamemx1,'with min_
       ⇔beta_i',min(val_list))
     min of beta_i attained by book b84091840 with min beta_i -1.7548572177626496
     for users
[394]: key_listu = list(beta_u.keys())
      val_listu = list(beta_u.values())
[395]: max(val_listu)
[395]: 1.3234209748117745
[396]: username = key_listu[val_listu.index(max(val_listu))]
[397]: print('max of beta_u attained by', username, 'with max beta_u', max(val_listu))
```

max of beta\_u attained by u32162993 with max beta\_u 1.3234209748117745

```
[398]: username1 = key_listu[val_listu.index(min(val_listu))]
[399]: print('min of beta_u attained by', username1,'with min beta_u',min(val_listu))
```

min of beta\_u attained by u48313610 with min beta\_u -3.746716329066186

2.3 11. Find a better value of using your validation set. Report the value you chose, its MSE, and upload your solution to Kaggle by running it on the test data (1 mark).

```
[413]: MSElist = []
      for lamda in range(20,40):
          a,beta_i,beta_u = ratePredicting(2,beta_i,beta_u,lamda*0.1,400)
          preR = [predRating(u,b) for u,b in xVal]
          MSElist.append(MSE(preR,yVal))
[414]: MSElist
[414]: [1.1099433236415106,
       1.1096049794606406,
       1.1093051163327652,
       1.1090418676304843,
       1.1088134767042521,
       1.1086182886118003,
       1.108454742633723,
       1.1083213654823691,
       1.1082167651247945,
       1.1081396251512856,
       1.1080886996304216,
       1.108062808399123,
       1.1080608327427375,
       1.1080817114258992,
       1.1081244370395802,
       1.1081880526336327,
       1.108271648607965,
       1.1083743598383722,
       1.1084953630155325,
       1.1086338741782735]
[419]: from matplotlib import pyplot as plt
      plt.plot(MSElist)
      plt.show
      print('min MSE attained at',
            0.1*(20+MSElist.index(min(MSElist))),
            'with a minimum MSE of',min(MSElist))
```

min MSE attained at 3.2 with a minimum MSE of 1.1080608327427375

