Importing Data

In [3]:
```
import numpy as np
import pandas as pd
import seaborn as sns
import json
import matplotlib
import matplotlib.pyplot as plt
import sklearn.metrics as metrics
from sklearn.linear_model import LinearRegression
from sklearn.linear_model import RidgeCV
from sklearn.linear_model import LassoCV
from random import *
from math import log
import json

%matplotlib inline
```

In [4]:
```
with open('dataset/good_reviews.json') as f:
    good_reviews = [json.loads(line) for line in f]
with open('dataset/business.json') as f:
    business_data = [json.loads(line) for line in f]
with open('dataset/user.json') as f:
    user_data = [json.loads(line) for line in f]
```

In [8]:
```
good_reviews = good_reviews[0]
```

In [10]:
```
sorted_user_reviews = sorted(good_reviews, key = lambda x: x['user_id'])
```

Creating the train, valid, and test sets

For matrix factorization, we faced several unique issues:

- Matrix Sparsity: Our data was incredibly sparse. Originally, our matrix had <5% non zero values. However, single-value decomposition doesn't work on sparse matrices. Thus, we had to reduce our set of restaurant reviews significantly, to only include restaurants and user with over 100 reviews. We also used alternating least squares to find the latent factor vectors, as opposed to SVD.
- Runtime: The process of learning the latent was incredibly time intensive. Thus, we limited our model to 4 latent factors.
- Size of model: Our train set included 1252 users and 3484 restaurants, Thus, we only computed latent factors for 1252 users and 3484 items.

We also made sure that the same users were represented in the train, valid, and test sets and in the same proportion.

In [12]:
```
train_set = []
valid_set = []
test_set = []
for i,x in enumerate(sorted_user_reviews[:100000]):
    short = {k: x[k] for k in ['business_id', 'stars', 'user_id']}
    if i % 3 == 0:
        train_set.append(short)
    elif i % 3 == 1:
        valid_set.append(short)
    else:
        test_set.append(short)
```

In [13]:
```
train_df = pd.DataFrame(train_set)
valid_df = pd.DataFrame(valid_set)
test_df = pd.DataFrame(test_set)
```

ALS Matrix Factorization with 4 Factors

Making the dataset more manageable

In [338]:
```
trimmed_train = train_df[:2000]
trimmed_train.shape
train_businesses = [x['business_id'] for x in train_set]
train_users = [x['user_id'] for x in train_set]
c = Counter()
c = Counter(train_businesses)
d = Counter()
d = Counter(train_users)
keep_business = [item for item in c if c[item] > 15 ]
keep_users = [item for item in d if d[item] > 15]
```

In [342]:
```
keep_reviews = [item for item in train_set if item['business_id'] in keep_business
and item['user_id'] in keep_users]
```

In [344]:
```
trimmed_train = pd.DataFrame(keep_reviews)
trimmed_train.head()
```

Out[344]:

	business_id	stars	user_id
0	riFzCvp77DMKDX-5GoTpqA	5	-267Yx8RmdP6io2-qI4UcQ
1	UPIYuRaZvknINOd1w8kqRQ	4	-267Yx8RmdP6io2-qI4UcQ
2	fL-b760btOaGa85OJ9ut3w	3	-50XWnmQGqBgEI-9ANvLlg
3	hIUKufhwR6lfn7bi0-phLA	5	-50XWnmQGqBgEI-9ANvLlg
4	Ec9CBmL3285XkeHaNp-bSQ	4	-50XWnmQGqBgEI-9ANvLlg

Getting the user and item deviations

In [345]:
```
restaurant_data = [x for x in business_data if 'Restaurants' in x['categories']]

good_restaurants_info = [x for x in restaurant_data if x['review_count'] >= 100]
restaurant_dict = {x['business_id']: x['stars'] for x in restaurant_data}
good_user_info = [x for x in user_data if x['review_count'] >= 100]
user_dict = {x['user_id']: x['average_stars'] for x in good_user_info}

global_review_average = sum(trimmed_train['stars'].values)/len(trimmed_train)
user_global_average = sum(user_dict.values())/len(user_dict)
rest_global_average = sum(restaurant_dict.values())/len(restaurant_dict)
user_deviations = {x: user_dict[x] - user_global_average for x in user_dict}
restaurant_deviations = {x: restaurant_dict[x] - rest_global_average for x in rest
aurant_dict}
```

Making the dictionaries

We wanted to create 2 dictionaries:

- ratings_by_restaurant_train_trimmed: This dictionary has key = restaurant and value = all the reviews given to the restaurant
- ratings_by_user_train_trimmed: This dictionary has key = user and value = all the reviews that the user has given

In [346]:
```
ratings_by_restaurant_train_trimmed = {}
ratings_by_user_train_trimmed = {}

for i in range(len(trimmed_train)):
    row = trimmed_train.iloc[i]
    bus_id = row[0]
    stars = row[1]
    user_id = row[2]
    if bus_id not in ratings_by_restaurant_train_trimmed:
        ratings_by_restaurant_train_trimmed[bus_id] = {user_id : stars}
    else:
        ratings_by_restaurant_train_trimmed[bus_id][user_id] = stars

    if user_id not in ratings_by_user_train_trimmed:
        ratings_by_user_train_trimmed[user_id] = {bus_id : stars}
    else:
        ratings_by_user_train_trimmed[user_id][bus_id] = stars
```

In [409]:
```
len(ratings_by_user_train_trimmed), len(ratings_by_restaurant_train_trimmed)
```

Out[409]:
```
(308, 173)
```

Preparing for Alternating Least Squares

We create the random dummy vectors to initial our p and q vectors, set lambda the regularization parameter equal to 0.1, and decided our tuning vectors (quadruplets with values between -0.9 and 0.9).

In [349]:
```
#create dummy vectors for p and q at start
import random
q_item = {}
p_user = {}
#just random
for r in ratings_by_restaurant_train_trimmed:
    q_item[r] = [randrange(-10,10)/10 for _ in range(4)]
for u in ratings_by_user_train_trimmed:
    p_user[u] = [randrange(-10,10)/10 for _ in range(4)]
```

In [351]:
```
tuning_vectors = []
tuning_values = [-0.9, -0.7, -0.5, -0.3, -0.1, 0.1, 0.3, 0.5, 0.7, 0.9]
for a in tuning_values:
    for b in tuning_values:
        for c in tuning_values:
            for d in tuning_values:
                tuning_vectors.append([a, b, c, d])
```

In [353]:
```
lmda = 0.1
```

Defining tuning functions

In [354]:
```
def calculate_sum_user_4(tuning_vector, user):
    user_vector = tuning_vector
    uv_mag = np.linalg.norm(user_vector)
    summation = 0
    #iterate through restaurants that user has rated
    for restaurant in ratings_by_user_train_trimmed[user]:
        #get the restaurants vector
        item_vector = q_item[restaurant]
        rv_mag = np.linalg.norm(item_vector)
        term = np.dot(user_vector, item_vector)
        #get the biases
        user_dev = user_deviations[user]
        item_dev = restaurant_deviations[restaurant]
        #follow the MLE equation
        error = (ratings_by_user_train_trimmed[user][restaurant] - global_review_a
verage - term - user_dev - item_dev) ** 2
        + lmda * (uv_mag **2 + rv_mag ** 2 + user_dev ** 2 + item_dev ** 2)
        summation += error
    return summation


def minimize_user_vectors_4():
    convergence = 0
    #iterate though all the the users
    for user in ratings_by_user_train_trimmed:
        #list of tuples (tuning vector, sum)
        tuning_sums = []
        #iterate though the vectors to find the best one for the user
        for tuning_vector in tuning_vectors:
            tuning_sum = calculate_sum_user_4(tuning_vector, user)
            tuning_sums.append((tuning_vector, tuning_sum))
        #get the vector with the lowest sum
        best = (min(tuning_sums, key = lambda x: x[1])[0])
        #get the difference between the current vector and the best vector
        difference = abs(best[0] - p_user[user][0]) + abs(best[1] - p_user[user][1
])
        + abs(best[2] - p_user[user][2]) + abs(best[3] - p_user[user][3])
        #set vector to best
        p_user[user] = best
        #add the difference to the convergence
        convergence += difference
    return convergence
```

In [329]:
```
def calculate_sum_item_4(tuning_vector, item):
    item_vector = tuning_vector
    rv_mag = np.linalg.norm(item_vector)
    summation = 0
    for user in ratings_by_restaurant_train_trimmed[item]:
        user_vector = p_user[user]
        uv_mag = np.linalg.norm(user_vector)
        term = np.dot(item_vector, user_vector)
        user_dev = user_deviations[user]
        item_dev = restaurant_deviations[item]
        error = (ratings_by_restaurant_train_trimmed[item][user] - global_review_a
verage - user_dev - item_dev - term) ** 2
        + lmda * (uv_mag **2 + rv_mag ** 2 + user_dev ** 2 + item_dev ** 2)
        #print ('error', error)
        summation += error
    return summation


def minimize_item_vectors_4():
    #print ('minimizing item vectors')
    convergence = 0
    #iterate though all the the restaurants
    for item in ratings_by_restaurant_train_trimmed:
        #list with tuple (vector, corresponding sum)
        tuning_sums = []
        #iterate though the vectors to find the best one for the restaurant
        for tuning_vector in tuning_vectors:
            tuning_sum = calculate_sum_item_4(tuning_vector, item)
            tuning_sums.append((tuning_vector, tuning_sum))
        best = (min(tuning_sums, key = lambda x: x[1])[0])
        #print ('best', best)
        #get the difference between the current vector and the best vector
        difference = abs(best[0] - q_item[item][0]) + abs(best[1] - q_item[item][1
])
        + abs(best[2] - q_item[item][2]) + abs(best[3] - q_item[item][3])
        #set vector to best
        #print ('best',best)
        q_item[item] = best
        convergence += difference
        #print ('convergence value', convergence)
    return convergence
```

In [355]:
```
def ALS_4():
    print ('minimizing user vectors')
    conv = minimize_user_vectors_4()
    print (conv)
    #whil vectors have not converged
    while conv > 10:
        for _ in range(1000):
            print ('minimizing item vectors')
            conv = minimize_item_vectors_4()
            print (conv)
            print ('minimizing user vectors')
            conv = minimize_user_vectors_4()
            print (conv)
```

In [356]:
```
ALS_4()
```

```
minimizing user vectors
463.99999999999994
minimizing item vectors
133.7
minimizing user vectors
193.1999999999999
minimizing item vectors
65.80000000000001
minimizing user vectors
110.8000000000002
minimizing item vectors
43.99999999999998
minimizing user vectors
86.00000000000006
minimizing item vectors
24.999999999999982
minimizing user vectors
51.60000000000002
minimizing item vectors
24.199999999999985
minimizing user vectors
37.20000000000001
minimizing item vectors
20.599999999999994
minimizing user vectors
26.199999999999996
minimizing item vectors
17.0
minimizing user vectors
14.399999999999999
minimizing item vectors
5.4
minimizing user vectors
17.999999999999993
minimizing item vectors
5.4
minimizing user vectors
11.0
minimizing item vectors
5.6000000000000005
minimizing user vectors
```

```
ERROR:root:Internal Python error in the inspect module.
Below is the traceback from this internal error.
```

```
Traceback (most recent call last):
  File "/anaconda/lib/python3.6/site-packages/IPython/core/interactiveshell.py",
line 2881, in run_code
    exec(code_obj, self.user_global_ns, self.user_ns)
  File "<ipython-input-356-cf41abbe0d88>", line 1, in <module>
    ALS_4()
  File "<ipython-input-355-d795ed05eb00>", line 12, in ALS_4
    conv = minimize_user_vectors_4()
  File "<ipython-input-354-421af5f37946>", line 29, in minimize_user_vectors_4
    tuning_sum = calculate_sum_user_4(tuning_vector, user)
  File "<ipython-input-354-421af5f37946>", line 10, in calculate_sum_user_4
    term = np.dot(user_vector, item_vector)
KeyboardInterrupt

During handling of the above exception, another exception occurred:

Traceback (most recent call last):
  File "/anaconda/lib/python3.6/site-packages/IPython/core/interactiveshell.py",
line 1821, in showtraceback
    stb = value._render_traceback_()
AttributeError: 'KeyboardInterrupt' object has no attribute '_render_traceback_'

During handling of the above exception, another exception occurred:

Traceback (most recent call last):
  File "/anaconda/lib/python3.6/site-packages/IPython/core/ultratb.py", line 113
2, in get_records
    return _fixed_getinnerframes(etb, number_of_lines_of_context, tb_offset)
  File "/anaconda/lib/python3.6/site-packages/IPython/core/ultratb.py", line 313
, in wrapped
    return f(*args, **kwargs)
  File "/anaconda/lib/python3.6/site-packages/IPython/core/ultratb.py", line 358
, in _fixed_getinnerframes
    records = fix_frame_records_filenames(inspect.getinnerframes(etb, context))
  File "/anaconda/lib/python3.6/inspect.py", line 1453, in getinnerframes
    frameinfo = (tb.tb_frame,) + getframeinfo(tb, context)
  File "/anaconda/lib/python3.6/inspect.py", line 1411, in getframeinfo
    filename = getsourcefile(frame) or getfile(frame)
  File "/anaconda/lib/python3.6/inspect.py", line 666, in getsourcefile
    if getattr(getmodule(object, filename), '__loader__', None) is not None:
  File "/anaconda/lib/python3.6/inspect.py", line 695, in getmodule
    file = getabsfile(object, _filename)
  File "/anaconda/lib/python3.6/inspect.py", line 679, in getabsfile
    return os.path.normcase(os.path.abspath(_filename))
  File "/anaconda/lib/python3.6/posixpath.py", line 374, in abspath
    cwd = os.getcwd()
FileNotFoundError: [Errno 2] No such file or directory

---------------------------------------------------------------------------
```

Here are the first ten final vectors after convergence:

In [357]:
```
list(p_user.items())[:10]
```

Out[357]:
```
[('-267Yx8RmdP6io2-qI4UcQ', [0.5, -0.3, -0.7, 0.9]),
 ('-50XWnmQGqBgEI-9ANvLlg', [-0.3, 0.9, -0.7, -0.7]),
 ('-9WVpTW5LAEo9y6PbW0-cw', [0.9, -0.1, 0.7, -0.3]),
 ('-ARdx8hOcEWlMDjzwLYZ_g', [0.7, -0.7, 0.9, -0.9]),
 ('-C-l8EHSLXtZZVfUAUhsPA', [-0.9, -0.7, -0.9, 0.3]),
 ('-EJorVxe7h2GSxdiRyMmDA', [0.7, -0.7, -0.1, -0.7]),
 ('-Fy91nyOFqPv9M_MaZ4W2g', [-0.1, 0.1, 0.1, 0.9]),
 ('-RhRXVW9z9fs5zzxhFfnHg', [0.9, 0.9, 0.7, 0.3]),
 ('-Vu7L3U7-kxDyY1VHxw3zw', [-0.9, -0.9, 0.9, -0.7]),
 ('-_2h2cJlBOWAYrfplMU-Cg', [0.5, 0.5, -0.1, -0.7])]
```

In [358]:
```
list(q_item.items())[:10]
```

Out[358]:
```
[('riFzCvp77DMKDX-5GoTpqA', [-0.3, 0.9, -0.5, 0.9]),
 ('UPIYuRaZvknINOd1w8kqRQ', [-0.9, 0.3, -0.9, -0.9]),
 ('fL-b760btOaGa85OJ9ut3w', [-0.1, -0.9, 0.9, 0.9]),
 ('hIUKufhwR6Ifn7bi0-phLA', [-0.5, -0.9, -0.7, -0.5]),
 ('Ec9CBmL3285XkeHaNp-bSQ', [-0.1, -0.7, -0.9, 0.9]),
 ('eoHdUeQDNgQ6WYEnP2aiRw', [-0.9, -0.5, 0.9, -0.1]),
 ('D3dAx-QW_uuClz4MambeHA', [-0.7, 0.9, 0.1, -0.7]),
 ('OGRB__fguKfGpPdH7FvBDA', [0.9, 0.3, 0.3, -0.3]),
 ('4JNXUYY8wbaaDmk3BPzlWw', [-0.7, 0.9, 0.9, -0.9]),
 ('umXvdus9LbC6oxtLdXelFQ', [0.9, -0.7, -0.9, -0.9])]
```

Validating to determine the best lambda

In [100]:
```
valid_businesses = [x['business_id'] for x in valid_set]
valid_users = [x['user_id'] for x in valid_set]
```

In [119]:
```
from collections import Counter
c = Counter()
c = Counter(valid_businesses)
d = Counter()
d = Counter(valid_users)
keep_business = [item for item in c if c[item] > 20 ]
keep_users = [item for item in d if d[item] > 20]
```

Validating to determing the regularization parameter

We cut down on our valid set, keeping ~300 data points, in order to expedite the process of validation.

Our code for cross validation is similar to our code above.

In [416]:
```
def calculate_sum_user_CV(tuning_vector, user, LAMBDA, q_item_CV, p_user_CV):
    user_vector = tuning_vector
    uv_mag = np.linalg.norm(user_vector)
    summation = 0
    for restaurant in ratings_by_user_train_trimmed[user]:
        item_vector = q_item_CV[restaurant]
        rv_mag = np.linalg.norm(item_vector)
        term = np.dot(user_vector, item_vector)
        user_dev = user_deviations[user]
        item_dev = restaurant_deviations[restaurant]
        error = (ratings_by_user_train_trimmed[user][restaurant] - global_review_a
verage - term - user_dev - item_dev) ** 2
        + LAMBDA * (uv_mag **2 + rv_mag ** 2 + user_dev ** 2 + item_dev ** 2)
        summation += error
    return summation

def minimize_user_vectors_CV(LAMBDA, q_item_CV, p_user_CV):
    convergence = 0
    for user in ratings_by_user_train_trimmed:
        tuning_sums = []
        for tuning_vector in tuning_vectors:
            tuning_sum = calculate_sum_user_CV(tuning_vector, user, LAMBDA, q_item
_CV, p_user_CV)
            tuning_sums.append((tuning_vector, tuning_sum))
        best = (min(tuning_sums, key = lambda x: x[1])[0])
        difference = abs(best[0] - p_user_CV[user][0]) + abs(best[1] - p_user_CV[u
ser][1])
        + abs(best[2] - p_user_CV[user][2]) + abs(best[3] - p_user_CV[user][3])
        p_user_CV[user] = best
        convergence += difference
    return convergence

def calculate_sum_item_CV(tuning_vector, item, LAMBDA, q_item_CV, p_user_CV):
    item_vector = tuning_vector
    rv_mag = np.linalg.norm(item_vector)
    summation = 0
    for user in ratings_by_restaurant_train_trimmed[item]:
        user_vector = p_user_CV[user]
        uv_mag = np.linalg.norm(user_vector)
        term = np.dot(item_vector, user_vector)
        user_dev = user_deviations[user]
        item_dev = restaurant_deviations[item]
        error = (ratings_by_restaurant_train_trimmed[item][user] - global_review_a
verage - user_dev - item_dev - term) ** 2
        + LAMBDA * (uv_mag **2 + rv_mag ** 2 + user_dev ** 2 + item_dev ** 2)
        summation += error
    return summation


def minimize_item_vectors_CV(LAMBDA, q_item_CV, p_user_CV):
    convergence = 0
    for item in ratings_by_restaurant_train_trimmed:
        tuning_sums = []
        for tuning_vector in tuning_vectors:
            tuning_sum = calculate_sum_item_CV(tuning_vector, item, LAMBDA, q_item
_CV, p_user_CV)
            tuning_sums.append((tuning_vector, tuning_sum))
        best = (min(tuning_sums, key = lambda x: x[1])[0])
        difference = abs(best[0] - q_item_CV[item][0]) + abs(best[1] - q_item_CV[i
tem][1])
        + abs(best[2] - q_item_CV[item][2]) + abs(best[3] - q_item_CV[item][3])
        q_item_CV[item] = best
        convergence += difference
    return convergence
```

In [414]:
```
def ALS_CV(q_item_CV, p_user_CV, LAMBDA):
    print ('optimizing item vectors')
    convergence = minimize_item_vectors_CV(LAMBDA, q_item_CV, p_user_CV)
    print (convergence)
    while convergence > 5:
        print ('optimizing user vectors')
        convergence = minimize_user_vectors_CV(LAMBDA, q_item_CV, p_user_CV)
        print (convergence)
        print ('optimizing item vectors')
        convergence = minimize_item_vectors_CV(LAMBDA, q_item_CV, p_user_CV)
        print (convergence)
    return q_item_CV, p_user_CV

def predict(p_user_CV, q_item_CV, user_id, business_id):
    user_dev = user_deviations[user_id]
    item_dev = restaurant_deviations[business_id]
    latent_term = np.dot(p_user_CV[user_id], q_item_CV[business_id])
    #print (latent_term)
    prediction = global_review_average + user_dev + item_dev + latent_term
    return int(round(prediction))

def score_CV(q_item_CV, p_user_CV, LAMBDA, df):
    predictions = []
    for j in range(len(df)):
        row = df.iloc[j]
        business_id = row[0]
        user_id = row[2]
        pred = predict(p_user_CV, q_item_CV, user_id, business_id)
        #print (pred)
        predictions.append(pred)
    print (predictions)
    actual = df['stars']
    df['validation_{}'.format(LAMBDA)] = predictions
    return metrics.accuracy_score(actual, predictions)

def validate(LAMBDA):
    q_item_CV = {}
    p_user_CV = {}
    for r in ratings_by_restaurant_train_trimmed:
        q_item_CV[r] = [randrange(-10,10)/10 for _ in range(4)]
    for u in ratings_by_user_train_trimmed:
        p_user_CV[u] = [randrange(-10,10)/10 for _ in range(4)]
    best_q_item, best_p_user = ALS_CV(q_item_CV, p_user_CV, LAMBDA)
    score = score_CV(best_q_item, best_p_user, LAMBDA, trimmed_train)
    return score

def run_validation(LAMBDAS):
    validation_scores = {}
    for LAMBDA in LAMBDAS:
        print (LAMBDA)
        score = validate(LAMBDA)
        print ('score', score)
        validation_scores[LAMBDA] = score
    return validation_scores
```

In [ ]:
```
LAMBDAS = [0.01, 1, 10]
run_validation(LAMBDAS)
```

```
0.01
optimizing item vectors
257.39999999999986
optimizing user vectors
336.10000000000014
optimizing item vectors
75.20000000000006
optimizing user vectors
118.40000000000015
optimizing item vectors
57.00000000000001
optimizing user vectors
98.60000000000012
optimizing item vectors
30.199999999999985
optimizing user vectors
```

In [403]:
```
validation_scores
```

Out[403]:
```
{0.001: 0.59477124183,
 0.01: 0.598039215686,
 0.1: 0.598039215686,
 1: 0.598039215686,
 10: 0.601307189542}
```

In [ ]:
```
```

The best lambda according to our validation is 10. However, because ALS is extremely time-intensive, we were unable to retune our latent factors using the lambda.

In [294]:
```
def model_predict(user_id, business_id):
    user_dev = user_deviations[user_id]
    item_dev = restaurant_deviations[business_id]
    latent_term = 0
    if user_id in p_user:
        if business_id in q_item:
            latent_term = np.dot(p_user[user_id], q_item[business_id])
    prediction = global_review_average + user_dev + item_dev
    latent = prediction + latent_term
    #print (prediction)
    return int(round(prediction)), int(round(latent))

def predict_all(df):
    predictions = []
    base_predictions = []
    for j in range(len(df)):
        row = df.iloc[j]
        business_id = row[0]
        user_id = row[2]
        pred, latent = model_predict(user_id, business_id)
        base_predictions.append(pred)
        predictions.append(latent)
    df['pred_base'] = base_predictions
    df['pred_latent'] = predictions
    base_score = metrics.accuracy_score(df['stars'], df['pred_base'])
    latent_score = metrics.accuracy_score(df['stars'], df['pred_latent'])
    return base_score, latent_score
```

Evaluating and comparing the latent factors on the train and test sets

In [363]:
```
train_pred = pd.DataFrame(trimmed_train)
base, latent = predict_all(train_pred)
print ('The accuracy on the train set is {}'.format(base))
print ('The accuracy on the train set using latent factors is {}'.format(latent))
```

```
The accuracy on the train set is 0.39976825028968715
The accuracy on the train set using latent factors is 0.9606025492468134
```

We modified our test set to include (user, restaurant) reviews where both the user and restaurant had a latent factor associated it.

In [367]:
```
test_df_v2.shape
```

Out[367]: (657, 5)

In [404]:
```
test_set_v2 = [x for x in test_set if x['business_id'] in q_item and x['user_id']
in p_user]
test_df_v2 = pd.DataFrame(test_set_v2)
base_test, latent_test = predict_all(test_df_v2)
print ('The accuracy on the test set is {}'.format(base_test))
print ('The accuracy on the test set using latent factors is {}'.format(latent_tes
t))
```

```
The accuracy on the test set is 0.4292237442922374
The accuracy on the test set using latent factors is 0.2861491628614916
```

Our latent factor model is much more fitted to the train set, resulting in a higher train accuracy but equal test accuracy.

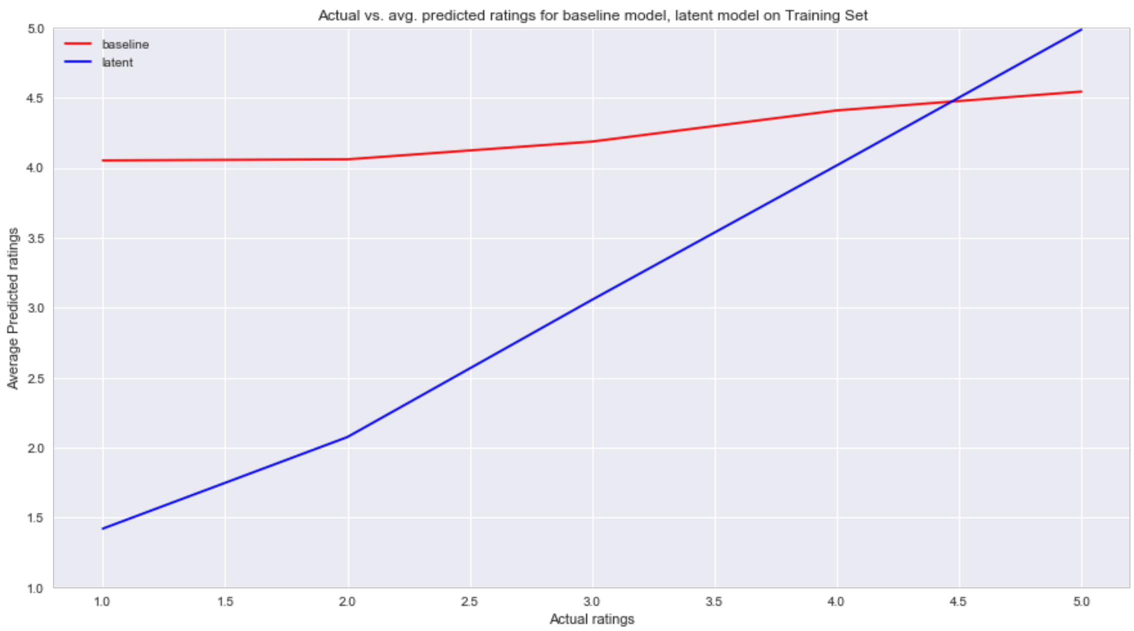
In [298]:
```
train_pred.head()
```

Out[298]:

	business_id	stars	user_id	pred	pred_base	pred_latent
0	sZsJooAzpKqOvDysphkqpQ	5	---1lKK3aKOuomHnwAkAow	4	4	4
1	t6WY1IrohUecqNjd9bG42Q	4	---1lKK3aKOuomHnwAkAow	4	4	4
2	1JgaRBX0oiRsvEhHF3ZMjw	1	---1lKK3aKOuomHnwAkAow	4	4	4
3	2BbFeotL85cIaBjSq1SWiA	1	---1lKK3aKOuomHnwAkAow	3	3	3
4	5cbsjFtrntUAeUx51FaFTg	1	---1lKK3aKOuomHnwAkAow	3	3	3

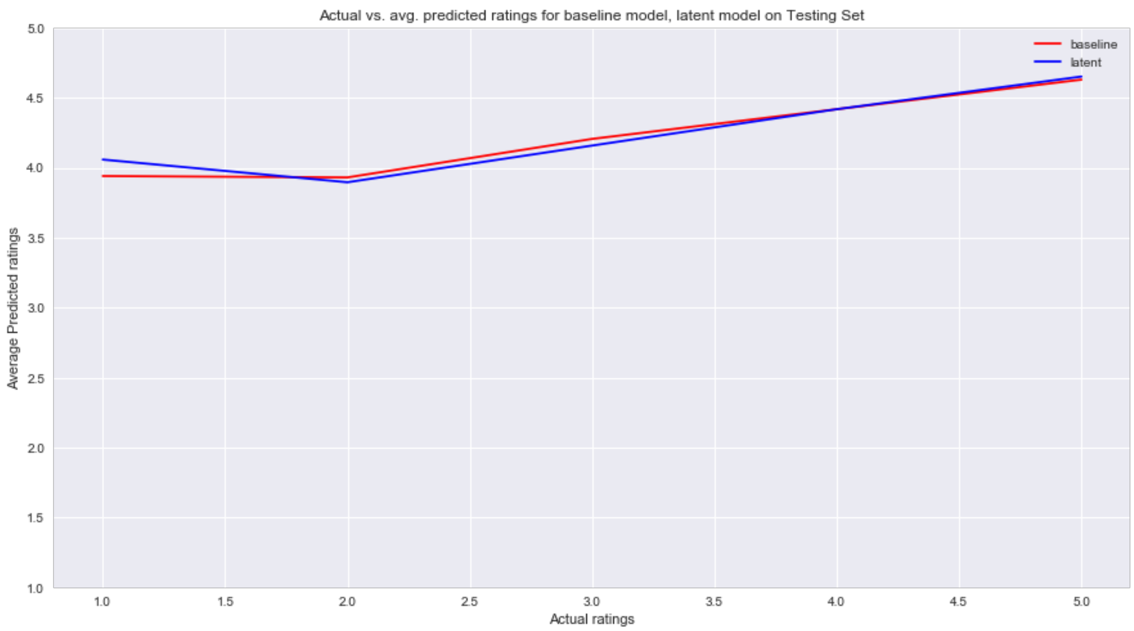
In [405]:
```
pred_avg = []
pred_avg_latent = []
for i in [1, 2, 3, 4, 5]:
    pred_avg.append(train_pred[train_pred['stars'] == i]['pred_base'].mean())
    pred_avg_latent.append(train_pred[train_pred['stars'] == i]['pred_latent'].mea
n())
```

In [406]:
```
fig, ax = plt.subplots(1, 1, figsize=(15, 8))
ax.plot([1, 2, 3, 4, 5], pred_avg, color='red', label = 'baseline')
ax.plot([1, 2, 3, 4, 5], pred_avg_latent, color='blue', label = 'latent')
ax.set_xlabel('Actual ratings')
ax.set_ylabel('Average Predicted ratings')
ax.set_title('Actual vs. avg. predicted ratings for baseline model, latent model o
n Training Set')
ax.set_ylim((1,5))
ax.legend();
```



In [407]:
```
test_pred_avg = []
test_pred_avg_latent = []
for i in [1, 2, 3, 4, 5]:
    test_pred_avg.append(test_df_v2[test_df_v2['stars'] == i]['pred_base'].mean())
    test_pred_avg_latent.append(test_df_v2[test_df_v2['stars'] == i]['pred_latent'
].mean())
```

In [408]:
```
fig, ax = plt.subplots(1, 1, figsize=(15, 8))
ax.plot([1, 2, 3, 4, 5], test_pred_avg, color='red', label = 'baseline')
ax.plot([1, 2, 3, 4, 5], test_pred_avg_latent, color='blue', label = 'latent')
ax.set_xlabel('Actual ratings')
ax.set_ylabel('Average Predicted ratings')
ax.set_title('Actual vs. avg. predicted ratings for baseline model, latent model o
n Testing Set')
ax.set_ylim((1,5))
ax.legend();
```



Latent factors overfit

As you can see, our latent factors vastly overfit on our training set. We have a near perfect accuracy score on our training set while we have baseline level accuracy on our test set using the latent factors. There are several reasons to explain this:

- The size of our training set is very small without only roughly 700 data points. We limited ourselves to this size due to the computational intensity of Alternating Least Squares. Our train set only contained 308 users and 173 restaurants. As a result there were not very many interaction terms that our latent factors had to learn. Thus, the variance in our error was very high, since it was specific to the collection of users and restaurants in our selected data train.
- We only had 4 latent factors. Again, we limited ourselves to four factors due to the time constraints. With an incredibly small inner product space, our model could not capture all the nuances in the interaction terms. We wuld have liked if possible to cross validate in order to tune both the number of factors and lambda.
- We only had one validating set. Cross validating with 4 or 5 folds would have been near impossible.
- Our tuning vectors are very 'rough' in the sense that they are 0.2 points apart from each other. As a result, it was hard to reach a point of convergence in which none of the vectors were changing between iterations. For the future, we would have liked to tune across more granular values.

In [ ]: