

Final_version

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1 CS 109a Recommendations

1.1 PROJECT INFO

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```
In [5]: import matplotlib.pyplot as plt
import datetime as dt
import pandas as pd
import numpy as np
import json
from sklearn.linear_model import Ridge
from sklearn.linear_model import LassoCV
from sklearn.model_selection import KFold
from sklearn.model_selection import GridSearchCV
from sklearn.linear_model import Lasso
```

2 LOAD DATA

*** Only for the first time. For later uses skip to the "RELOAD DATA" part. Make sure to download smaller (preprocessed) datasets before running it ***

```
In [ ]: # LOAD USER
df_user = pd.read_json("user.json", lines = True)
```

```
In [ ]: # LOAD BUSINESS
df_business = pd.read_json("business.json", lines = True)
```

```
In [ ]: # LOAD REVIEWS
with open('review.json', encoding="utf8") as json_file:
    data_review = json_file.readlines()
    # this line below may take at least 8-10 minutes of processing for 4-5 million rows.
    data_review = list(map(json.loads, data_review))

df_review = pd.DataFrame(data_review)
```

3 PROCESS

3.0.1 Select restaurants with more than 30 reviews

```
In [ ]: df_business.shape
```

```
In [ ]: df_business = df_business.drop(["hours", "is_open", "latitude", "longitude", "postal_cod
```

```
In [ ]: df_business_350 = df_business[df_business["review_count"] > 350]
```

```
In [ ]: df_business_350.shape
```

3.0.2 Select users who gave more than 100 reviews

```
In [ ]: df_users.shape
```

```
In [ ]: df_user = df_user[["user_id", "review_count"]]
```

```
In [ ]: df_users_150 = df_user[df_user["review_count"] > 150]
```

```
In [ ]: df_users_150.shape
```

3.0.3 Filter out reviews to those corresponding to selected users and restaurants

```
In [ ]: df_review.shape
```

```
In [ ]: df_review = df_review.drop(["cool", "date", "funny", "review_id", "text", "useful"], axi
```

```
In [24]: df_review_350_150 = df_review[df_review["user_id"].isin(df_users_150["user_id"])]
```

```
In [27]: df_review_350_150 = df_review_350_150[df_review_350_150["business_id"].isin(df_business
```

3.0.4 Save data for future reference so we deal with smaller files

```
In [ ]: df_users_150.to_json("df_user_150.json")
```

```
In [ ]: df_business_350.to_json("df_business_350.json")
```

```
In [30]: df_review_350_150.to_json("df_review_350_150.json")
```

4 RELOAD DATA

```
In [82]: df_user = pd.read_json("df_user_100.json")
```

```
In [81]: df_business = pd.read_json("df_business_30.json")
```

```
In [6]: df_review = pd.read_json("df_review_350_150.json")
```

4.0.1 Sample from the data frame because the dataset is still too big

```
In [7]: np.random.seed(9001)
        fraction_of_df = 0.15
```

```
In [8]: df_review_smaller = df_review.sample(frac=fraction_of_df)
```

```
In [9]: df_review_smaller.shape
```

```
Out[9]: (38198, 3)
```

```
In [10]: df_review_smaller.to_json("df_review_smaller.json")
```

```
In [2]: df_review_smaller = pd.read_json("df_review_smaller.json")
```

4.0.2 Create latent matrix

```
In [11]: r_df = df_review_smaller.pivot(index = 'user_id', columns = 'business_id', values = 'stars')
        r_df.head()
```

```
Out[11]: business_id      --9e10NYQuAa-CB_Rrw7Tw  -050d_XIor1NpCuWkbIVaQ  \
        user_id
        ---1lKK3aK0uomHnwAkAow                    NaN                    NaN
        --2vR0DIsmQ6WfcSzKWigw                    NaN                    NaN
        --4q8EyqThydQm-eKZpS-A                    NaN                    NaN
        --56mD0sm1e0ogphi2FFLw                    NaN                    NaN
        --CIuK7sUpaNzalLA1HJKA                    NaN                    NaN

        business_id      -1xuC540Nycht_iWFeJ-dw  -2ToCaDFpTNmmg3QFzxcWg  \
        user_id
        ---1lKK3aK0uomHnwAkAow                    NaN                    NaN
        --2vR0DIsmQ6WfcSzKWigw                    NaN                    NaN
        --4q8EyqThydQm-eKZpS-A                    NaN                    NaN
        --56mD0sm1e0ogphi2FFLw                    NaN                    NaN
        --CIuK7sUpaNzalLA1HJKA                    NaN                    NaN

        business_id      -3zffZUHoY8bQjGfPSoBKQ  -6h3K1hj0d4DRcZNUtHDuw  \
        user_id
        ---1lKK3aK0uomHnwAkAow                    NaN                    NaN
        --2vR0DIsmQ6WfcSzKWigw                    NaN                    NaN
        --4q8EyqThydQm-eKZpS-A                    NaN                    NaN
        --56mD0sm1e0ogphi2FFLw                    NaN                    NaN
        --CIuK7sUpaNzalLA1HJKA                    NaN                    NaN

        business_id      -6tvduBzjLI1ISfs3F_qTg  -7H-oXvCxJzuT42ky6Db0g  \
        user_id
        ---1lKK3aK0uomHnwAkAow                    NaN                    NaN
        --2vR0DIsmQ6WfcSzKWigw                    NaN                    NaN
        --4q8EyqThydQm-eKZpS-A                    NaN                    NaN
```

--56mD0sm1e0ogphi2FFLw	NaN	NaN
--CIuK7sUpaNzalLA1HJKA	NaN	NaN
business_id	-95mbLJsa0CxXhpaNL4LvA	-9dmhyBvepc08KPEH1EM0w \
user_id		
---1lKK3aK0uomHnwAkAow	NaN	NaN
--2vR0DIsmQ6WfcSzKWigw	NaN	NaN
--4q8EyqThydQm-eKZpS-A	NaN	NaN
--56mD0sm1e0ogphi2FFLw	NaN	NaN
--CIuK7sUpaNzalLA1HJKA	NaN	NaN
business_id	...	zcScEL0WEdFkR0cnz5379g \
user_id	...	
---1lKK3aK0uomHnwAkAow	...	NaN
--2vR0DIsmQ6WfcSzKWigw	...	NaN
--4q8EyqThydQm-eKZpS-A	...	NaN
--56mD0sm1e0ogphi2FFLw	...	NaN
--CIuK7sUpaNzalLA1HJKA	...	NaN
business_id	zdE82PiD6wquvjYLyh0JNA	zgQHtqX0gqMw1n1BZ12VnQ \
user_id		
---1lKK3aK0uomHnwAkAow	NaN	NaN
--2vR0DIsmQ6WfcSzKWigw	NaN	NaN
--4q8EyqThydQm-eKZpS-A	NaN	NaN
--56mD0sm1e0ogphi2FFLw	NaN	NaN
--CIuK7sUpaNzalLA1HJKA	NaN	NaN
business_id	zlpLjbwrKuNs8zR0gB_qUQ	znWHLW1pt19HzW1VY6KfCA \
user_id		
---1lKK3aK0uomHnwAkAow	NaN	NaN
--2vR0DIsmQ6WfcSzKWigw	NaN	NaN
--4q8EyqThydQm-eKZpS-A	NaN	NaN
--56mD0sm1e0ogphi2FFLw	NaN	NaN
--CIuK7sUpaNzalLA1HJKA	NaN	NaN
business_id	zoOD1H40edpJYLPLkHilNA	zpoZ6WyQUYff18-z4ZU1mA \
user_id		
---1lKK3aK0uomHnwAkAow	NaN	NaN
--2vR0DIsmQ6WfcSzKWigw	NaN	NaN
--4q8EyqThydQm-eKZpS-A	NaN	NaN
--56mD0sm1e0ogphi2FFLw	NaN	NaN
--CIuK7sUpaNzalLA1HJKA	NaN	NaN
business_id	zrDi4gEaUi64lAMfJU51dw	zrTGcb83AsfyVTMrsCa65A \
user_id		
---1lKK3aK0uomHnwAkAow	NaN	NaN
--2vR0DIsmQ6WfcSzKWigw	NaN	NaN
--4q8EyqThydQm-eKZpS-A	NaN	NaN

--56mD0sm1e0ogphi2FFLw	NaN	NaN
--CIuK7sUpaNzalLA1HJKA	NaN	NaN

business_id	zwNC-0w4eIMan2__bS9-rg
user_id	
---1lKK3aK0uomHnwAkAow	NaN
--2vR0DIsmQ6WfcSzKWigw	NaN
--4q8EyqThydQm-eKZpS-A	NaN
--56mD0sm1e0ogphi2FFLw	NaN
--CIuK7sUpaNzalLA1HJKA	NaN

[5 rows x 1523 columns]

In [12]: r_df.shape

Out[12]: (15455, 1523)

In [13]: fill_zero_rf = r_df.fillna(0)

In [14]: fill_zero_rf.shape

Out[14]: (15455, 1523)

In [15]: fill_zero_rf.head()

business_id	--9e10NYQuAa-CB_Rrw7Tw	-050d_XIor1NpCuWkbIVaQ	\
user_id			
---1lKK3aK0uomHnwAkAow	0.0	0.0	
--2vR0DIsmQ6WfcSzKWigw	0.0	0.0	
--4q8EyqThydQm-eKZpS-A	0.0	0.0	
--56mD0sm1e0ogphi2FFLw	0.0	0.0	
--CIuK7sUpaNzalLA1HJKA	0.0	0.0	

business_id	-1xuC540Nycht_iWFeJ-dw	-2ToCaDFpTNmmg3QFzxcWg	\
user_id			
---1lKK3aK0uomHnwAkAow	0.0	0.0	
--2vR0DIsmQ6WfcSzKWigw	0.0	0.0	
--4q8EyqThydQm-eKZpS-A	0.0	0.0	
--56mD0sm1e0ogphi2FFLw	0.0	0.0	
--CIuK7sUpaNzalLA1HJKA	0.0	0.0	

business_id	-3zffZUHoY8bQjGfPSoBKQ	-6h3K1hj0d4DRcZNUtHDuw	\
user_id			
---1lKK3aK0uomHnwAkAow	0.0	0.0	
--2vR0DIsmQ6WfcSzKWigw	0.0	0.0	
--4q8EyqThydQm-eKZpS-A	0.0	0.0	
--56mD0sm1e0ogphi2FFLw	0.0	0.0	
--CIuK7sUpaNzalLA1HJKA	0.0	0.0	

business_id	-6tvduBzjLI1ISfs3F_qTg	-7H-oXvCxJzuT42ky6Db0g	\
user_id			
---1lKK3aK0uomHnwAkAow	0.0	0.0	
--2vR0DIsmQ6WfcSzKWigw	0.0	0.0	
--4q8EyqThydQm-eKZpS-A	0.0	0.0	
--56mD0sm1e0ogphi2FFLw	0.0	0.0	
--CIuK7sUpaNzalLA1HJKA	0.0	0.0	

business_id	-95mbLJsa0CxXhpaNL4LvA	-9dmhyBvepc08KPEH1EM0w	\
user_id			
---1lKK3aK0uomHnwAkAow	0.0	0.0	
--2vR0DIsmQ6WfcSzKWigw	0.0	0.0	
--4q8EyqThydQm-eKZpS-A	0.0	0.0	
--56mD0sm1e0ogphi2FFLw	0.0	0.0	
--CIuK7sUpaNzalLA1HJKA	0.0	0.0	

business_id	...	zcScEL0WEdFkR0cnz5379g	\
user_id	...		
---1lKK3aK0uomHnwAkAow	...	0.0	
--2vR0DIsmQ6WfcSzKWigw	...	0.0	
--4q8EyqThydQm-eKZpS-A	...	0.0	
--56mD0sm1e0ogphi2FFLw	...	0.0	
--CIuK7sUpaNzalLA1HJKA	...	0.0	

business_id	zdE82PiD6wquvjYLyh0JNA	zgQHtqX0gqMw1n1BZ12VnQ	\
user_id			
---1lKK3aK0uomHnwAkAow	0.0	0.0	
--2vR0DIsmQ6WfcSzKWigw	0.0	0.0	
--4q8EyqThydQm-eKZpS-A	0.0	0.0	
--56mD0sm1e0ogphi2FFLw	0.0	0.0	
--CIuK7sUpaNzalLA1HJKA	0.0	0.0	

business_id	zlpLjbwrKuNs8zR0gB_qUQ	znWHLW1pt19HzW1VY6KfCA	\
user_id			
---1lKK3aK0uomHnwAkAow	0.0	0.0	
--2vR0DIsmQ6WfcSzKWigw	0.0	0.0	
--4q8EyqThydQm-eKZpS-A	0.0	0.0	
--56mD0sm1e0ogphi2FFLw	0.0	0.0	
--CIuK7sUpaNzalLA1HJKA	0.0	0.0	

business_id	zoOD1H40edpJYLPLkHilNA	zpoZ6WyQUYff18-z4ZU1mA	\
user_id			
---1lKK3aK0uomHnwAkAow	0.0	0.0	
--2vR0DIsmQ6WfcSzKWigw	0.0	0.0	
--4q8EyqThydQm-eKZpS-A	0.0	0.0	
--56mD0sm1e0ogphi2FFLw	0.0	0.0	
--CIuK7sUpaNzalLA1HJKA	0.0	0.0	

```

business_id      zrDi4gEaUi64lAMfJU51dw  zrTGcb83AsfyVTMrsCa65A  \
user_id
---1lKK3aK0uomHnwAkAow                    0.0                    0.0
--2vR0DIsmQ6WfcSzKWigw                    0.0                    0.0
--4q8EyqThydQm-eKZpS-A                    0.0                    0.0
--56mD0sm1e0ogphi2FFLw                    0.0                    0.0
--CIuK7sUpaNzalLA1HJKA                    0.0                    0.0

business_id      zwNC-0w4eIMan2__bS9-rg
user_id
---1lKK3aK0uomHnwAkAow                    0.0
--2vR0DIsmQ6WfcSzKWigw                    0.0
--4q8EyqThydQm-eKZpS-A                    0.0
--56mD0sm1e0ogphi2FFLw                    0.0
--CIuK7sUpaNzalLA1HJKA                    0.0

[5 rows x 1523 columns]

```

5 MODELS

5.0.1 Define RMSE error functions

```

In [16]: def rmse(predictions, targets):
          return np.sqrt(((predictions - targets) ** 2).mean())

In [17]: def rmse2(model, x, y):
          predict = model.predict(x)
          mse2 = rmse(y, predict)
          return mse2

```

5.0.2 Baseline Averages

```

In [18]: avg_mean = r_df.mean().mean()
          avg_mean

Out[18]: 3.8393172911341806

In [19]: rows_length = r_df.shape[0]
          cols_length = r_df.shape[1]

In [20]: cols_means = r_df.mean(axis = 0)
          rows_means = r_df.mean(axis = 1)

In [21]: cols_means.head()

Out[21]: business_id
          --9e10NYQuAa-CB_Rrw7Tw      4.060606
          -050d_XIor1NpCuWkbIVaQ      3.771429
          -1xuC540Nycht_iWFeJ-dw      4.333333

```

```
-2ToCaDFpTNmmg3QFzxcWg    1.625000
-3zffZUHoY8bQjGfPSoBKQ    4.027778
dtype: float64
```

```
In [22]: rows_means.head()
```

```
Out [22]: user_id
---1lKK3aK0uomHnwAkAow    4.5
--2vR0DIsmQ6WfcSzKWigw    4.5
--4q8EyqThydQm-eKZpS-A    3.0
--56mD0sm1e0ogphi2FFLw    4.0
--CIuK7sUpaNzalLA1HJKA    3.0
dtype: float64
```

```
In [23]: preds_array_avg = np.fromfunction(lambda i, j: rows_means[i] + cols_means[j] - avg_mean,
```

```
In [24]: preds_array_avg
```

```
Out [24]: array([[ 4.72128877,  4.43211128,  4.99401604, ...,  4.52734938,
                   4.31782557,  4.89145194],
 [ 4.72128877,  4.43211128,  4.99401604, ...,  4.52734938,
                   4.31782557,  4.89145194],
 [ 3.22128877,  2.93211128,  3.49401604, ...,  3.02734938,
                   2.81782557,  3.39145194],
 ...,
 [ 2.72128877,  2.43211128,  2.99401604, ...,  2.52734938,
                   2.31782557,  2.89145194],
 [ 2.22128877,  1.93211128,  2.49401604, ...,  2.02734938,
                   1.81782557,  2.39145194],
 [ 4.22128877,  3.93211128,  4.49401604, ...,  4.02734938,
                   3.81782557,  4.39145194]])
```

```
In [25]: avg_preds_df = pd.DataFrame(preds_array_avg, columns = r_df.columns, index = r_df.index)
```

```
In [26]: avg_preds_df.head()
```

```
Out [26]: business_id    --9e10NYQuAa-CB_Rrw7Tw    -050d_XIor1NpCuWkbIVaQ  \
user_id
---1lKK3aK0uomHnwAkAow    4.721289    4.432111
--2vR0DIsmQ6WfcSzKWigw    4.721289    4.432111
--4q8EyqThydQm-eKZpS-A    3.221289    2.932111
--56mD0sm1e0ogphi2FFLw    4.221289    3.932111
--CIuK7sUpaNzalLA1HJKA    3.221289    2.932111

business_id    -1xuC540Nycht_iWFeJ-dw    -2ToCaDFpTNmmg3QFzxcWg  \
user_id
---1lKK3aK0uomHnwAkAow    4.994016    2.285683
--2vR0DIsmQ6WfcSzKWigw    4.994016    2.285683
--4q8EyqThydQm-eKZpS-A    3.494016    0.785683
```


--56mD0sm1e0ogphi2FFLw	4.494016	1.785683
--CIuK7sUpaNzalLA1HJKA	3.494016	0.785683
business_id	-3zffZUHoY8bQjGfPSoBKQ	-6h3K1hj0d4DRcZNUtHDuw \
user_id		
---1lKK3aK0uomHnwAkAow	4.68846	3.771794
--2vR0DIsmQ6WfcSzKWigw	4.68846	3.771794
--4q8EyqThydQm-eKZpS-A	3.18846	2.271794
--56mD0sm1e0ogphi2FFLw	4.18846	3.271794
--CIuK7sUpaNzalLA1HJKA	3.18846	2.271794
business_id	-6tvduBzjLI1ISfs3F_qTg	-7H-oXvCxJzuT42ky6Db0g \
user_id		
---1lKK3aK0uomHnwAkAow	4.271794	4.478865
--2vR0DIsmQ6WfcSzKWigw	4.271794	4.478865
--4q8EyqThydQm-eKZpS-A	2.771794	2.978865
--56mD0sm1e0ogphi2FFLw	3.771794	3.978865
--CIuK7sUpaNzalLA1HJKA	2.771794	2.978865
business_id	-95mbLJsa0CxXhpaNL4LvA	-9dmhyBvepc08KPEH1EM0w \
user_id		
---1lKK3aK0uomHnwAkAow	4.115228	4.535683
--2vR0DIsmQ6WfcSzKWigw	4.115228	4.535683
--4q8EyqThydQm-eKZpS-A	2.615228	3.035683
--56mD0sm1e0ogphi2FFLw	3.615228	4.035683
--CIuK7sUpaNzalLA1HJKA	2.615228	3.035683
business_id	...	zcScEL0WEdFkR0cnz5379g \
user_id	...	
---1lKK3aK0uomHnwAkAow	...	4.374968
--2vR0DIsmQ6WfcSzKWigw	...	4.374968
--4q8EyqThydQm-eKZpS-A	...	2.874968
--56mD0sm1e0ogphi2FFLw	...	3.874968
--CIuK7sUpaNzalLA1HJKA	...	2.874968
business_id	zdE82PiD6wquvjYLyh0JNA	zgQHtqX0gqMw1nlBZL2VnQ \
user_id		
---1lKK3aK0uomHnwAkAow	4.732111	3.860683
--2vR0DIsmQ6WfcSzKWigw	4.732111	3.860683
--4q8EyqThydQm-eKZpS-A	3.232111	2.360683
--56mD0sm1e0ogphi2FFLw	4.232111	3.360683
--CIuK7sUpaNzalLA1HJKA	3.232111	2.360683
business_id	zlpLjbwrKuNs8zR0gB_qUQ	znWHLW1pt19HzW1VY6KfCA \
user_id		
---1lKK3aK0uomHnwAkAow	3.73963	4.131271
--2vR0DIsmQ6WfcSzKWigw	3.73963	4.131271
--4q8EyqThydQm-eKZpS-A	2.23963	2.631271

```

--56mD0sm1e0ogphi2FFLw          3.23963          3.631271
--CIuK7sUpaNzalLAlHJKA          2.23963          2.631271

business_id          zoOD1H40edpJYLPLkHilNA  zpoZ6WyQUYff18-z4ZU1mA  \
user_id
---1lKK3aK0uomHnwAkAow          5.182422          4.994016
--2vR0DIsmQ6WfcSzKWigw          5.182422          4.994016
--4q8EyqThydQm-eKZpS-A          3.682422          3.494016
--56mD0sm1e0ogphi2FFLw          4.682422          4.494016
--CIuK7sUpaNzalLAlHJKA          3.682422          3.494016

business_id          zrDi4gEaUi64lAMfJU51dw  zrTGcb83AsfyVTMrsCa65A  \
user_id
---1lKK3aK0uomHnwAkAow          4.527349          4.317826
--2vR0DIsmQ6WfcSzKWigw          4.527349          4.317826
--4q8EyqThydQm-eKZpS-A          3.027349          2.817826
--56mD0sm1e0ogphi2FFLw          4.027349          3.817826
--CIuK7sUpaNzalLAlHJKA          3.027349          2.817826

business_id          zwNC-0w4eIMan2__bS9-rg
user_id
---1lKK3aK0uomHnwAkAow          4.891452
--2vR0DIsmQ6WfcSzKWigw          4.891452
--4q8EyqThydQm-eKZpS-A          3.391452
--56mD0sm1e0ogphi2FFLw          4.391452
--CIuK7sUpaNzalLAlHJKA          3.391452

[5 rows x 1523 columns]

```

```
In [28]: # avg_preds_df.to_json("avg_preds_df_0.15.json")
```

5.0.3 Baseline Regression

```
In [29]: categorical_columns = ['business_id', 'user_id']
```

```
In [30]: unique_business = df_review_smaller.business_id.nunique()
         unique_business
```

```
Out[30]: 1523
```

```
In [31]: unique_user = df_review_smaller.user_id.nunique()
         unique_user
```

```
Out[31]: 15455
```

```
In [32]: df_review_dummies = pd.get_dummies(df_review_smaller, columns=categorical_columns, drop
```

```
In [33]: df_review_dummies.shape
```

```
Out[33]: (38198, 16979)
```

```

In [34]: # df_review_dummies.to_json("df_review_dummies.json")

In [35]: # df_review_smaller = pd.read_json("df_review_smaller.json")

In [36]: np.random.seed(9001)
         msk = np.random.rand(len(df_review_dummies)) < 0.5

         # data_train = df_subset[msk]
         # data_test = df_subset[~msk]

         x_train = df_review_dummies[msk].drop(['stars'], axis=1) # DataFrame
         x_test = df_review_dummies[~msk].drop(['stars'], axis=1) # DataFrame

         y_train = df_review_dummies[msk].stars #series

         y_test = df_review_dummies[~msk].stars # series

In [37]: ols_lasso = Lasso(alpha=0.0001)
         ols_lasso.fit(x_train,y_train)

Out[37]: Lasso(alpha=0.0001, copy_X=True, fit_intercept=True, max_iter=1000,
              normalize=False, positive=False, precompute=False, random_state=None,
              selection='cyclic', tol=0.0001, warm_start=False)

In [38]: rmse2(ols_lasso, x_train, y_train)

Out[38]: 0.86079140172462165

In [39]: rmse2(ols_lasso, x_test, y_test)

Out[39]: 0.97445307396512448

In [40]: y_preds = ols_lasso.predict(x_train)

In [41]: ols_lasso.coef_

Out[41]: array([ 0.29526438,  0.          ,  0.08687282, ..., -0.31021108,
                -0.          , -0.          ])

In [42]: busienss_coeffs = ols_lasso.coef_[unique_business]

In [43]: user_coeffs = ols_lasso.coef_[unique_business:]

In [44]: user_coeffs.shape, busienss_coeffs.shape

Out[44]: ((15455,), (1523,))

In [18]: # train_residuals = y_train - y_preds

In [20]: # train_residuals.head()

```

```
Out[20]: 1000283    -0.850750
         100126    -0.429319
         1001936   -0.850750
         1002945   -0.850750
         1002957    0.149250
         Name: stars, dtype: float64
```

```
In [45]: preds_array_reg = np.fromfunction(lambda i, j: user_coeffs[i] + busienss_coeffs[j] + av
```

```
In [46]: preds_array_reg
```

```
Out[46]: array([[ 4.13458167,  3.83931729,  3.92619012, ...,  3.83931729,
                  3.71403969,  3.83931729],
                [ 4.13458167,  3.83931729,  3.92619012, ...,  3.83931729,
                  3.71403969,  3.83931729],
                [ 4.13458167,  3.83931729,  3.92619012, ...,  3.83931729,
                  3.71403969,  3.83931729],
                ...,
                [ 3.82437059,  3.52910621,  3.61597903, ...,  3.52910621,
                  3.40382861,  3.52910621],
                [ 4.13458167,  3.83931729,  3.92619012, ...,  3.83931729,
                  3.71403969,  3.83931729],
                [ 4.13458167,  3.83931729,  3.92619012, ...,  3.83931729,
                  3.71403969,  3.83931729]])
```

```
In [47]: preds_array_reg_df = pd.DataFrame(preds_array_reg, columns = r_df.columns, index = r_df
```

```
In [48]: preds_array_reg_df.head()
```

```
Out[48]: business_id      --9e1ONYQuAa-CB_Rrw7Tw  -050d_XIor1NpCuWkbIVaQ  \
         user_id
         ---1lKK3aK0uomHnwAkAow                4.134582                3.839317
         --2vR0DIsmQ6WfcSzKWigw                4.134582                3.839317
         --4q8EyqThydQm-eKZpS-A                4.134582                3.839317
         --56mD0sm1eOogphi2FFLw                4.134582                3.839317
         --CIuK7sUpaNzalLA1HJKA                4.134582                3.839317

         business_id      -1xuC540Nycht_iWFeJ-dw  -2ToCaDFpTNmmg3QFzxcWg  \
         user_id
         ---1lKK3aK0uomHnwAkAow                3.92619                1.540696
         --2vR0DIsmQ6WfcSzKWigw                3.92619                1.540696
         --4q8EyqThydQm-eKZpS-A                3.92619                1.540696
         --56mD0sm1eOogphi2FFLw                3.92619                1.540696
         --CIuK7sUpaNzalLA1HJKA                3.92619                1.540696

         business_id      -3zffZUHoY8bQjGfPSoBKQ  -6h3K1hj0d4DRcZNUtHDuw  \
         user_id
         ---1lKK3aK0uomHnwAkAow                3.928585                2.874029
         --2vR0DIsmQ6WfcSzKWigw                3.928585                2.874029
```

--4q8EyqThydQm-eKZpS-A	3.928585	2.874029
--56mD0sm1e0ogphi2FFLw	3.928585	2.874029
--CIuK7sUpaNzalLA1HJKA	3.928585	2.874029
business_id	-6tvduBzjLI1ISfs3F_qTg	-7H-oXvCxJzuT42ky6Db0g \
user_id		
---1lKK3aK0uomHnwAkAow	3.839317	3.839317
--2vR0DIsmQ6WfcSzKWigw	3.839317	3.839317
--4q8EyqThydQm-eKZpS-A	3.839317	3.839317
--56mD0sm1e0ogphi2FFLw	3.839317	3.839317
--CIuK7sUpaNzalLA1HJKA	3.839317	3.839317
business_id	-95mbLJsa0CxXhpaNL4LvA	-9dmhyBvepc08KPEH1EM0w \
user_id		
---1lKK3aK0uomHnwAkAow	3.839317	3.760319
--2vR0DIsmQ6WfcSzKWigw	3.839317	3.760319
--4q8EyqThydQm-eKZpS-A	3.839317	3.760319
--56mD0sm1e0ogphi2FFLw	3.839317	3.760319
--CIuK7sUpaNzalLA1HJKA	3.839317	3.760319
business_id	...	zcScEL0WEdFkR0cnz5379g \
user_id	...	
---1lKK3aK0uomHnwAkAow	...	3.574515
--2vR0DIsmQ6WfcSzKWigw	...	3.574515
--4q8EyqThydQm-eKZpS-A	...	3.574515
--56mD0sm1e0ogphi2FFLw	...	3.574515
--CIuK7sUpaNzalLA1HJKA	...	3.574515
business_id	zdE82PiD6wquvjYLyh0JNA	zgQHtqX0gqMw1n1BZ12VnQ \
user_id		
---1lKK3aK0uomHnwAkAow	3.904549	3.254626
--2vR0DIsmQ6WfcSzKWigw	3.904549	3.254626
--4q8EyqThydQm-eKZpS-A	3.904549	3.254626
--56mD0sm1e0ogphi2FFLw	3.904549	3.254626
--CIuK7sUpaNzalLA1HJKA	3.904549	3.254626
business_id	zlpLjbwrKuNs8zROgB_qUQ	znWHLW1pt19HzW1VY6KfCA \
user_id		
---1lKK3aK0uomHnwAkAow	2.938128	3.766569
--2vR0DIsmQ6WfcSzKWigw	2.938128	3.766569
--4q8EyqThydQm-eKZpS-A	2.938128	3.766569
--56mD0sm1e0ogphi2FFLw	2.938128	3.766569
--CIuK7sUpaNzalLA1HJKA	2.938128	3.766569
business_id	zoOD1H40edpJYLPLkHilNA	zpoZ6WyQUYff18-z4ZU1mA \
user_id		
---1lKK3aK0uomHnwAkAow	3.977102	3.925678
--2vR0DIsmQ6WfcSzKWigw	3.977102	3.925678

--4q8EyqThydQm-eKZpS-A	3.977102	3.925678
--56mD0sm1e0ogphi2FFLw	3.977102	3.925678
--CIuK7sUpaNzalLA1HJKA	3.977102	3.925678

business_id	zrDi4gEaUi64lAMfJU51dw	zrTGcb83AsfyVTMrsCa65A	\
user_id			
---1lKK3aK0uomHnwAkAow	3.839317	3.71404	
--2vR0DIsmQ6WfcSzKWigw	3.839317	3.71404	
--4q8EyqThydQm-eKZpS-A	3.839317	3.71404	
--56mD0sm1e0ogphi2FFLw	3.839317	3.71404	
--CIuK7sUpaNzalLA1HJKA	3.839317	3.71404	

business_id	zwNC-0w4eIMan2__bS9-rg	
user_id		
---1lKK3aK0uomHnwAkAow	3.839317	
--2vR0DIsmQ6WfcSzKWigw	3.839317	
--4q8EyqThydQm-eKZpS-A	3.839317	
--56mD0sm1e0ogphi2FFLw	3.839317	
--CIuK7sUpaNzalLA1HJKA	3.839317	

[5 rows x 1523 columns]

In [53]: `resids_array = np.subtract(r_df, preds_array_reg)`

In [58]: `resids_df = resids_array.fillna(0)`

In [59]: `resids_df.head()`

Out [59]:

business_id	--9e10NYQuAa-CB_Rrw7Tw	-050d_XIor1NpCuWkbIVaQ	\
user_id			
---1lKK3aK0uomHnwAkAow	0.0	0.0	
--2vR0DIsmQ6WfcSzKWigw	0.0	0.0	
--4q8EyqThydQm-eKZpS-A	0.0	0.0	
--56mD0sm1e0ogphi2FFLw	0.0	0.0	
--CIuK7sUpaNzalLA1HJKA	0.0	0.0	

business_id	-1xuC540Nycht_iWFeJ-dw	-2ToCaDFpTNmmg3QFzxcWg	\
user_id			
---1lKK3aK0uomHnwAkAow	0.0	0.0	
--2vR0DIsmQ6WfcSzKWigw	0.0	0.0	
--4q8EyqThydQm-eKZpS-A	0.0	0.0	
--56mD0sm1e0ogphi2FFLw	0.0	0.0	
--CIuK7sUpaNzalLA1HJKA	0.0	0.0	

business_id	-3zffZUHoY8bQjGfPSoBKQ	-6h3K1hj0d4DRcZNUtHDuw	\
user_id			
---1lKK3aK0uomHnwAkAow	0.0	0.0	
--2vR0DIsmQ6WfcSzKWigw	0.0	0.0	
--4q8EyqThydQm-eKZpS-A	0.0	0.0	

--56mD0sm1e0ogphi2FFLw	0.0	0.0
--CIuK7sUpaNzalLA1HJKA	0.0	0.0
business_id	-6tvduBzjLI1ISfs3F_qTg	-7H-oXvCxJzuT42ky6Db0g \
user_id		
---1lKK3aK0uomHnwAkAow	0.0	0.0
--2vR0DIsmQ6WfcSzKWigw	0.0	0.0
--4q8EyqThydQm-eKZpS-A	0.0	0.0
--56mD0sm1e0ogphi2FFLw	0.0	0.0
--CIuK7sUpaNzalLA1HJKA	0.0	0.0
business_id	-95mbLJsa0CxXhpaNL4LvA	-9dmhyBvepc08KPEH1EM0w \
user_id		
---1lKK3aK0uomHnwAkAow	0.0	0.0
--2vR0DIsmQ6WfcSzKWigw	0.0	0.0
--4q8EyqThydQm-eKZpS-A	0.0	0.0
--56mD0sm1e0ogphi2FFLw	0.0	0.0
--CIuK7sUpaNzalLA1HJKA	0.0	0.0
business_id	...	zcScEL0WEdFkR0cnz5379g \
user_id	...	
---1lKK3aK0uomHnwAkAow	...	0.0
--2vR0DIsmQ6WfcSzKWigw	...	0.0
--4q8EyqThydQm-eKZpS-A	...	0.0
--56mD0sm1e0ogphi2FFLw	...	0.0
--CIuK7sUpaNzalLA1HJKA	...	0.0
business_id	zdE82PiD6wquvjYLyh0JNA	zgQHtqX0gqMw1n1BZ12VnQ \
user_id		
---1lKK3aK0uomHnwAkAow	0.0	0.0
--2vR0DIsmQ6WfcSzKWigw	0.0	0.0
--4q8EyqThydQm-eKZpS-A	0.0	0.0
--56mD0sm1e0ogphi2FFLw	0.0	0.0
--CIuK7sUpaNzalLA1HJKA	0.0	0.0
business_id	zlpLjbwrKuNs8zR0gB_qUQ	znWHLW1pt19HzW1VY6KfCA \
user_id		
---1lKK3aK0uomHnwAkAow	0.0	0.0
--2vR0DIsmQ6WfcSzKWigw	0.0	0.0
--4q8EyqThydQm-eKZpS-A	0.0	0.0
--56mD0sm1e0ogphi2FFLw	0.0	0.0
--CIuK7sUpaNzalLA1HJKA	0.0	0.0
business_id	zoOD1H40edpJYLPLkHilNA	zpoZ6WyQUYff18-z4ZU1mA \
user_id		
---1lKK3aK0uomHnwAkAow	0.0	0.0
--2vR0DIsmQ6WfcSzKWigw	0.0	0.0
--4q8EyqThydQm-eKZpS-A	0.0	0.0

```

--56mD0sm1e0ogphi2FFLw          0.0          0.0
--CIuK7sUpaNzalLAlHJKA          0.0          0.0

business_id      zrDi4gEaUi64lAMfJU51dw  zrTGcb83AsfyVTMrsCa65A  \
user_id
---1lKK3aK0uomHnwAkAow          0.0          0.0
--2vR0DIsmQ6WfcSzKWigw          0.0          0.0
--4q8EyqThydQm-eKZpS-A          0.0          0.0
--56mD0sm1e0ogphi2FFLw          0.0          0.0
--CIuK7sUpaNzalLAlHJKA          0.0          0.0

business_id      zwNC-0w4eIMan2__bS9-rg
user_id
---1lKK3aK0uomHnwAkAow          0.0
--2vR0DIsmQ6WfcSzKWigw          0.0
--4q8EyqThydQm-eKZpS-A          0.0
--56mD0sm1e0ogphi2FFLw          0.0
--CIuK7sUpaNzalLAlHJKA          0.0

[5 rows x 1523 columns]

```

5.0.4 Matrix Factorization

Code taken from <https://bugra.github.io/work/notes/2014-04-19/alternating-least-squares-method-for-collaborative-filtering/>

```
In [61]: Q = resids_df.values
```

```
In [62]: W = Q>0.5
         W[W == True] = 1
         W[W == False] = 0
         # To be consistent with our Q matrix
         W = W.astype(np.float64, copy=False)
```

```
In [63]: W.shape
```

```
Out[63]: (15455, 1523)
```

```
In [72]: lambda_ = 0.1
         n_factors = 20
         m, n = Q.shape
         n_iterations = 10
```

```
In [73]: X = 5 * np.random.rand(m, n_factors)
         Y = 5 * np.random.rand(n_factors, n)
```

```
In [74]: def get_error(Q, X, Y, W):
         return np.sum((W * (Q - np.dot(X, Y)))*2)
```



```
In [75]: errors = []
        for ii in range(n_iterations):
            X = np.linalg.solve(np.dot(Y, Y.T) + lambda_ * np.eye(n_factors),
                                np.dot(Y, Q.T)).T
            Y = np.linalg.solve(np.dot(X.T, X) + lambda_ * np.eye(n_factors),
                                np.dot(X.T, Q))
            errors.append(get_error(Q, X, Y, W))
        Q_hat = np.dot(X, Y)
        print('Error of rated movies: {}'.format(get_error(Q, X, Y, W)))
```

Error of rated movies: 12955.384191909738

```
In [77]: fac_preds_df = pd.DataFrame(Q_hat, columns = r_df.columns, index = r_df.index)
```

```
In [78]: fac_preds_df.head()
```

```
Out[78]: business_id      --9e10NYQuAa-CB_Rrw7Tw  -050d_XIor1NpCuWkbIVaQ  \
user_id
---1lKK3aK0uomHnwAkAow      -0.001057          0.001861
--2vR0DIsmQ6WfcSzKWigw      -0.004634          -0.000084
--4q8EyqThydQm-eKZpS-A       0.015085          -0.000305
--56mD0sm1e0ogphi2FFLw       0.000005          -0.000002
--CIuK7sUpaNzalLA1HJKA      -0.000144          -0.000058

business_id      -1xuC540Nycht_iWFeJ-dw  -2ToCaDFpTNmmg3QFzxcWg  \
user_id
---1lKK3aK0uomHnwAkAow      -4.930082e-04      -4.918077e-04
--2vR0DIsmQ6WfcSzKWigw      -2.785871e-04      1.090502e-04
--4q8EyqThydQm-eKZpS-A       2.351535e-04      -3.563541e-05
--56mD0sm1e0ogphi2FFLw      -3.324232e-07      7.451144e-07
--CIuK7sUpaNzalLA1HJKA       3.799868e-04      -2.089563e-05

business_id      -3zffZUHoY8bQjGfPSoBKQ  -6h3K1hj0d4DRcZNUtHDuw  \
user_id
---1lKK3aK0uomHnwAkAow      -0.007930          -0.002952
--2vR0DIsmQ6WfcSzKWigw       0.007119          -0.000503
--4q8EyqThydQm-eKZpS-A      -0.000531          -0.000158
--56mD0sm1e0ogphi2FFLw       0.000004          -0.000001
--CIuK7sUpaNzalLA1HJKA       0.000032          0.000053

business_id      -6tvduBzjLI1ISfs3F_qTg  -7H-oXvCxJzuT42ky6Db0g  \
user_id
---1lKK3aK0uomHnwAkAow       0.000315          -0.000522
--2vR0DIsmQ6WfcSzKWigw      -0.000032          -0.000023
--4q8EyqThydQm-eKZpS-A      -0.000294          0.000067
--56mD0sm1e0ogphi2FFLw       0.000002          0.000001
--CIuK7sUpaNzalLA1HJKA      -0.000015          0.000008
```

business_id	-95mbLJsa0CxXhpaNL4LvA	-9dmhyBvepc08KPEHlEM0w	\
user_id			
---1lKK3aK0uomHnwAkAow	-0.000073	0.000288	
--2vR0DIsmQ6WfcSzKWigw	-0.000135	-0.000097	
--4q8EyqThydQm-eKZpS-A	-0.000652	0.000113	
--56mD0sm1e0ogphi2FFLw	-0.000002	0.000001	
--CIuK7sUpaNzalLA1HJKA	-0.000035	0.000017	
business_id	...	zcScEL0WEdFkR0cnz5379g	\
user_id	...		
---1lKK3aK0uomHnwAkAow	...	0.002016	
--2vR0DIsmQ6WfcSzKWigw	...	0.000377	
--4q8EyqThydQm-eKZpS-A	...	-0.000833	
--56mD0sm1e0ogphi2FFLw	...	0.000011	
--CIuK7sUpaNzalLA1HJKA	...	-0.000534	
business_id	zdE82PiD6wquvjYLyh0JNA	zgQHtqX0gqMw1nlBZL2VnQ	\
user_id			
---1lKK3aK0uomHnwAkAow	0.009009	-0.000488	
--2vR0DIsmQ6WfcSzKWigw	0.000877	0.000114	
--4q8EyqThydQm-eKZpS-A	-0.000261	-0.000050	
--56mD0sm1e0ogphi2FFLw	0.000030	0.000002	
--CIuK7sUpaNzalLA1HJKA	-0.000084	-0.000015	
business_id	zlpLjbwrKuNs8zR0gB_qUQ	znWHLW1pt19HzW1VY6KfCA	\
user_id			
---1lKK3aK0uomHnwAkAow	-0.001545	0.000669	
--2vR0DIsmQ6WfcSzKWigw	0.000052	-0.000063	
--4q8EyqThydQm-eKZpS-A	-0.001531	-0.004251	
--56mD0sm1e0ogphi2FFLw	-0.000025	0.000007	
--CIuK7sUpaNzalLA1HJKA	-0.000206	0.000069	
business_id	zoOD1H40edpJYLPLkHilNA	zpoZ6WyQUYff18-z4ZU1mA	\
user_id			
---1lKK3aK0uomHnwAkAow	0.004804	0.000167	
--2vR0DIsmQ6WfcSzKWigw	0.000586	-0.005376	
--4q8EyqThydQm-eKZpS-A	-0.000271	-0.000081	
--56mD0sm1e0ogphi2FFLw	-0.000008	0.000003	
--CIuK7sUpaNzalLA1HJKA	-0.000407	-0.000018	
business_id	zrDi4gEaUi64lAMfJU51dw	zrTGcb83AsfyVTMrsCa65A	\
user_id			
---1lKK3aK0uomHnwAkAow	0.005785	-0.001261	
--2vR0DIsmQ6WfcSzKWigw	-0.001118	0.000532	
--4q8EyqThydQm-eKZpS-A	-0.000432	0.000208	
--56mD0sm1e0ogphi2FFLw	0.000006	0.000004	
--CIuK7sUpaNzalLA1HJKA	0.000072	0.000072	

```

business_id          zwNC-0w4eIMan2__bS9-rg
user_id
---1lKK3aKOuomHnwAkAow          -0.006878
--2vR0DIsmQ6WfcSzKWigw          -0.000522
--4q8EyqThydQm-eKZpS-A          0.000258
--56mD0sm1eOogphi2FFLw          -0.000003
--CIuK7sUpaNzalLA1HJKA          0.000082

[5 rows x 1523 columns]

```

6 PREDICT

```

In [83]: def get_reccomendations(user, number_rec,df):
          top_preds = df.loc[user][fill_zero_rf.loc[user] == 0].sort_values(ascending = False)
          top_preds_df = pd.DataFrame(top_preds).rename(columns={user:"predicted rating"})
          predictions = pd.merge(left = top_preds_df, right = df_business, left_index = True,
          #   top_preds_df.join(df_business, on="business_id")
          return predictions
          #   return top_preds_df

```

Let's predict for user ---1lKK3aKOuomHnwAkAow. Let's check what are his top choices:

```

In [105]: top_ratings_user_x = df_review[df_review["user_id"] == "---1lKK3aKOuomHnwAkAow"].sort_

In [106]: df_business[df_business["business_id"].isin(top_ratings_user_x)]

```

```

Out[106]:
          address \
104700          750 S Rampart Blvd, Ste 7
110934          113 N 4th St
142630          3555 S Town Center Dr, Ste 105
14551          750 S Rampart Blvd, Ste 9
32230          440 S Rampart Blvd
40479          10100 W Charleston Blvd, Ste 150
78134          8975 S Eastern Ave
84520  The Mirage Hotel Casino, 3400 Las Vegas Blvd S
92918          953 E Sahara Ave, Ste A5
93528          8751 W Charleston Blvd, Ste 110

          business_id \
104700  RRw9I8pHt5PzgYGT2QeODw
110934  eJKnymd0BywNPrJw1IuXVw
142630  bPcqucuuClxYrIM8xWoArg
14551   rq5dgoksPHkJwJNQKlGQ7w
32230   igHYkXZMLAc9UdV5VnR_AA
40479   qmymSqVwHYRqdwfcBatzpQ
78134   p5rpYtxS5xPQjt3MXYVEwA
84520   mz9ltimeAIy2c2qf5ctljw
92918   KskYqH1Bi7Z_61pH60m8pg

```

93528 A0X1baHPgw9IiBRivu0G9g

	categories	city \
104700	[Pizza, Restaurants]	Las Vegas
110934	[Breakfast & Brunch, Mexican, Restaurants, Ame...	Las Vegas
142630	[Italian, Wine Bars, Restaurants, Nightlife, B...	Las Vegas
14551	[Food, Coffee & Tea, Breakfast & Brunch, Cafes...	Las Vegas
32230	[Steakhouses, Restaurants]	Las Vegas
40479	[American (New), Restaurants, Sandwiches, Bars...	Las Vegas
78134	[Vegetarian, Restaurants, Burgers, Vegan, Amer...	Las Vegas
84520	[Arts & Entertainment, Performing Arts]	Las Vegas
92918	[Automotive, Car Dealers, Restaurants, Thai, N...	Las Vegas
93528	[Bakeries, French, Restaurants, Food]	Las Vegas

	name	review_count	stars	state
104700	Grimaldi's Pizzeria	431	4.0	NV
110934	Nacho Daddy Downtown	723	4.0	NV
142630	Due Forni	446	4.0	NV
14551	Sambalatte Torrefazione	752	4.0	NV
32230	Echo & Rig	1665	4.5	NV
40479	Vintner Grill	571	4.0	NV
78134	Greens and Proteins	600	4.0	NV
84520	Cirque du Soleil - The Beatles LOVE	1766	4.5	NV
92918	Lotus of Siam	3838	4.0	NV
93528	Patisserie Manon	598	4.0	NV

We see that this user really likes American Restaurants, Pizza, etc. He probably lives in Las vegas

Predict using basic averages

In [86]: `get_reccomendations("---11KK3aKQuomHnwAkAow",5,avg_preds_df)`

Out [86]:

	predicted rating	address \
135187	5.660683	4627 E Ivy St, Ste 1
100304	5.660683	2960 S Durango Dr, Ste 112
107956	5.660683	7910 S Rainbow Blvd, Ste 110
87518	5.660683	10520 S Eastern Ave
143283	5.660683	7608 W Cactus Rd

	business_id \
135187	1H0Ph4DiYSqj9UJBXAq8hQ
100304	56_j_1cGj5X9SpM2KzLm4A
107956	Hp8k_RpSIWSeJguyaQpfIw
87518	Wcuo6YmYj3xhCso5sMQcOw
143283	ZKsVCA89iXMccf3fEhS3iw

categories	city \
------------	--------

135187	[Home Services, Local Services, Self Storage, ...	Mesa
100304	[Laser Hair Removal, Beauty & Spas, Skin Care,...	Las Vegas
107956	[Gelato, Food, Desserts, Ice Cream & Frozen Yo...	Las Vegas
87518	[Pizza, Gluten-Free, Restaurants, Fast Food, S...	Henderson
143283	[Restaurants, Seafood, Cajun/Creole, American ...	Peoria

	name	review_count	stars	state
135187	Just-In Time Moving and Delivery	374	5.0	AZ
100304	Fabulous Eyebrow Threading	453	5.0	NV
107956	Gelatology	473	5.0	NV
87518	Blaze Fast-Fire'd Pizza	364	4.5	NV
143283	Angry Crab Peoria	365	4.5	AZ

Our baseline model recommends only one restaurant with American food and a few places with weird categories.

Predict using lasso regression

```
In [88]: get_recommendaions("---11KK3aK0uomHnwAkAow",5,preds_array_reg_df)
```

```
Out[88]:
```

	predicted rating	address	business_id \
36525	4.719550	3799 Las Vegas Blvd S	XnJeadLrlj9AZB8qSdIR2Q
89310	4.710545	115 Federal St	X-b4-QvZLENnf3yFwhpSXQ
15676	4.675836	Flamingo Rd	ty5KQYqYRxxWDG_e4pz-4w
95839	4.672092	3600 S Las Vegas Blvd	NCFwm2-TDb-oBQ2medmYDg
87314	4.649546		jeTvVMOR8W_04xFsPjzOEq

	categories	city \
36525	[Restaurants, French]	Las Vegas
89310	[Baseball Fields, Stadiums & Arenas, Active Li...	Pittsburgh
15676	[Arts & Entertainment, Performing Arts]	Las Vegas
95839	[Street Art, Performing Arts, Public Services ...	Las Vegas
87314	[Local Services, Movers, Home Services, Self S...	Phoenix

	name	review_count	stars	state
36525	Joël Robuchon	831	4.5	NV
89310	PNC Park	426	4.5	PA
15676	Absinthe	1452	4.5	NV
95839	Fountains of Bellagio	1083	4.5	NV
87314	Camelback Moving	394	5.0	AZ

Our baseline model based on lasso predicts restaurants completely unrelated to users preferences. Bad... At least it's mostly in Las Vegas

Predict using matrix factorization

```
In [87]: get_recommendaions("---11KK3aK0uomHnwAkAow",5,fac_preds_df)
```

```

Out[87]:
      predicted rating      address \
43284      0.202872  3400 E Sky Harbor Blvd, Ste 3300
36211      0.122170      3950 S Las Vegas Blvd
155316      0.091723      3355 South Las Vegas Boulevard
115819      0.068040      3131 Las Vegas Blvd S
106982      0.056872      3799 Las Vegas Blvd S

      business_id \
43284  JmI9nslLD7KZqRr__Bg6NQ
36211  Cni2l-VKG_pdospJ6xliXQ
155316  Wxxvi3LZbHNIDwJ-ZimtnA
115819  MpmFFw0GE_2iRFPdsRpJbA
106982  El4FC8jcawUVgw_0EIcbaQ

      categories      city \
43284      [Hotels & Travel, Airports]      Phoenix
36211  [Bars, Nightlife, Burgers, American (New), Res...  Las Vegas
155316  [Resorts, Arts & Entertainment, Event Planning...  Las Vegas
115819      [Nightlife, Dance Clubs]  Las Vegas
106982  [Restaurants, Casinos, Hotels & Travel, Event ...  Las Vegas

      name      review_count      stars      state
43284  Phoenix Sky Harbor International Airport      2103      3.0      AZ
36211      Burger Bar      2396      4.0      NV
155316      The Venetian Las Vegas      2951      4.0      NV
115819      XS Nightclub      2848      4.0      NV
106982      MGM Grand Hotel      3285      3.0      NV

```

Our Matrix Factorization model predicts places in Las Vegas related to nightlife and party, including restaurants with American Food. Not bad :)