Recommendation systems with Deep neural network

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Tip> shotcuts for Jupyter Notebook

- Shift + Enter : run cell and select below

Objective> Train deep neural network (autoencoder) to complete movie rating matrix

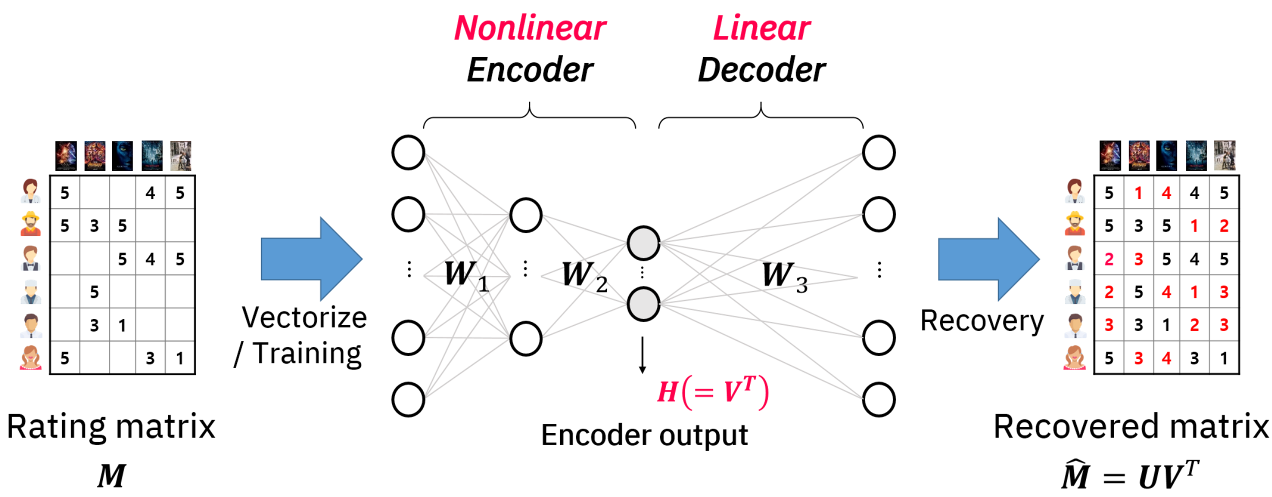


Fig. 1 Item-based autoencoder

- **Loss function**

$$L(M, \hat{M}) = \sum_{(i,j)\in E} (M_{ij} - \hat{M}_{ij})^2 + \lambda \sum_{i=1}^{3} \|W_i\|_2^2$$

- **Update weight and bias**

$$\underset{W,b}{\operatorname{argmin}}\, L(M, \hat{M})$$

```
import numpy as np
import tensorflow as tf
import pandas as pd
import matplotlib.pyplot as plt
%matplotlib inline

import time
```

1. Prepare data

MovieLens Dataset (ref.)

We use "MovieLens Latest Datasets" consisting of 100,000 ratings applied to 9,000 movies by 600 users. Last updated 9/2018.

Fetch MovieLens data

```
rating = pd.read_csv('data/ratings.csv')
rating.head(10)
```

	userId	movieId	rating	timestamp
0	1	1	4.0	964982703
1	1	3	4.0	964981247
2	1	6	4.0	964982224
3	1	47	5.0	964983815
4	1	50	5.0	964982931
5	1	70	3.0	964982400
6	1	101	5.0	964980868
7	1	110	4.0	964982176
8	1	151	5.0	964984041
9	1	157	5.0	964984100

Ratings statistics

Count the number of movies with identical rating.

```
rating.set_index(["userId",
"timestamp","rating"]).count(level="rating").rename({'movieId': 'The number of
movies'}, axis='columns')
```

	The number of movies
rating	
0.5	1370
1.0	2811
1.5	1791
2.0	7551
2.5	5550
3.0	20047
3.5	13136
4.0	26818
4.5	8551
5.0	13211

Count the number of users and movies and check the sparsity

```
n_user = len(rating['userId'].unique())
n_movie = len(rating['movieId'].unique())
n_rating = len(rating['rating'])
print("[*] %d users & %d movies" % (n_user, n_movie))
print("[*] Sparsity: %.2f%%" % (n_rating / (n_user * n_movie) * 100))
```

```
[*] 610 users & 9724 movies
[*] Sparsity: 1.70%
```

Movie list

See the movie list including movies' title and genres.

```
movielist = pd.read_csv('data/movies.csv')
movielist.head(10)
```

	movieId	title	genres
0	1	Toy Story (1995)	Adventure|Animation|Children|Comedy|Fantasy
1	2	Jumanji (1995)	Adventure|Children|Fantasy
2	3	Grumpier Old Men (1995)	Comedy|Romance
3	4	Waiting to Exhale (1995)	Comedy|Drama|Romance
4	5	Father of the Bride Part II (1995)	Comedy
5	6	Heat (1995)	Action|Crime|Thriller
6	7	Sabrina (1995)	Comedy|Romance
7	8	Tom and Huck (1995)	Adventure|Children
8	9	Sudden Death (1995)	Action
9	10	GoldenEye (1995)	Action|Adventure|Thriller

Drop **"timestamp"** which looks useless.

```
rating.drop(['timestamp'], axis=1, inplace=True)
rating.tail()
```

	userId	movieId	rating
100831	610	166534	4.0
100832	610	168248	5.0
100833	610	168250	5.0
100834	610	168252	5.0
100835	610	170875	3.0

Scale **"movieId"** in between 0 and 9741, **"userId"** in between 0 and 609

```
rating['movieId'], _ = pd.factorize(rating['movieId'])
rating['userId'], _ = pd.factorize(rating['userId'])
rating.tail()
```

	userId	movieId	rating
100831	609	3120	4.0
100832	609	2035	5.0
100833	609	3121	5.0
100834	609	1392	5.0
100835	609	2873	3.0

Item-based autoencoder

Transpose the rating matrix

```
rating = rating[['movieId', 'userId', 'rating']]
rating.head()
```

	movieId	userId	rating
0	0	0	4.0
1	1	0	4.0
2	2	0	4.0
3	3	0	5.0
4	4	0	5.0

Split the ratings for training and test

Training : Test = 9 : 1

```
trainIdx = np.random.choice(range(n_rating), int(n_rating * 0.9), replace=False)
dataTrain = rating.iloc[trainIdx]

testIdx = np.setdiff1d(range(n_rating), trainIdx)
dataTest = rating.iloc[testIdx]
```

```
ratingTrain = np.asarray(dataTrain)
ratingTest = np.asarray(dataTest)
d1, d2 = np.max(ratingTrain[:, 0]) + 1, np.max(ratingTrain[:, 1]) + 1
```

2. Build a Graph

We use "tf.sparse_tensor_dense_matmul()" function instead of "tf.layers.dense( )" function, because of the sparse input and regularization.

```
def autoencoder(_X, _units, _l2_lambda, _n_ratings):
    w_init = w_init = tf.contrib.layers.variance_scaling_initializer()
    b_init = tf.constant_initializer(0.)

    ## Encoder
    '1st Hidden layer'
    w1 = tf.get_variable('weight1', [d2, _units[0]], initializer=w_init)
    b1 = tf.get_variable('biases1', [_units[0]], initializer=b_init)
    h1 = tf.sparse_tensor_dense_matmul(_X, w1) + b1
    h1 = tf.nn.relu(h1)

    '2nd Hidden layer'
    w2 = tf.get_variable('weight2', [_units[0], _units[1]], initializer=w_init)
    b2 = tf.get_variable('biases2', [_units[1]], initializer=b_init)
    h2 = tf.matmul(h1, w2) + b2
    h2 = tf.nn.sigmoid(h2)

    ## Decoder
    w3 = tf.get_variable('weight3', [_units[1], d2], initializer=w_init)

    yhat = tf.matmul(h2, w3)
    out = tf.gather_nd(yhat, _X.indices)

    loss = tf.reduce_sum(tf.pow(out - _X.values, 2)) / _n_ratings


    ''' L2 regularization '''
    all_var = [var for var in tf.trainable_variables() ]
    l2_losses = []
    for var in all_var:
        if var.op.name.find('weight') == 0:
            l2_losses.append(tf.nn.l2_loss(var))

    losses = loss + _l2_lambda * tf.reduce_sum(l2_losses)

    return yhat, losses
```

Set hyperparameters

- ***n_epochs*** : The number of epochs
- ***lr*** : Learning rate for gradient descent
- ***l2_lambda*** : regularization parameter
- ***n_units*** : The number of units for each hidden layer

```
"""parameters"""
n_epochs = 1000
lr = 0.1
l2_lambda = 0.003
n_units = [100, 50]
n_ratings = len(ratingTrain)
display_step = n_epochs / 10
```

Placeholder for sparse input data

```
# tf Graph input
X = tf.sparse_placeholder(dtype=tf.float32)
```

Use the GradientDescentOptimizer

```
pred, cost = autoencoder(X, n_units, l2_lambda, n_ratings)
global_step = tf.Variable(0, trainable=False)
optimizer = tf.train.GradientDescentOptimizer(lr).minimize(cost,
global_step=global_step)
```

Create a tensorflow session

Tensorflow operations must be executed in the session. The only one session is activated.

```
sess = tf.Session()
sess.run(tf.global_variables_initializer())
```

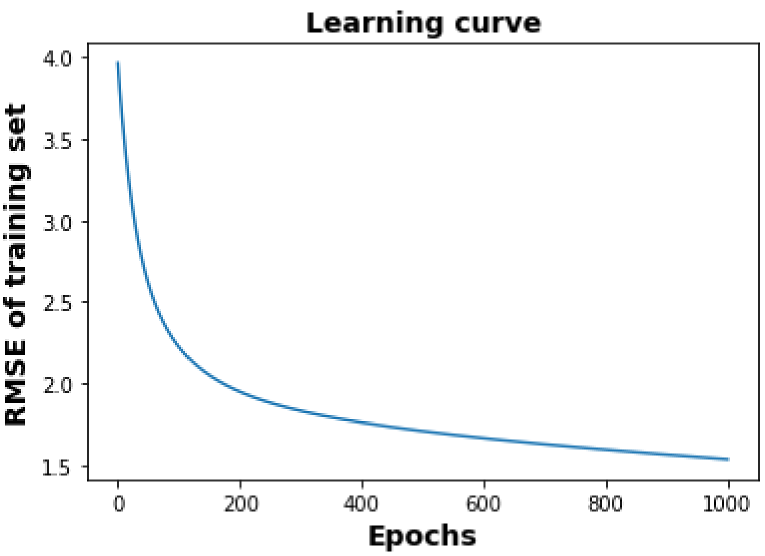
3. Training

```
print("START OPTIMIZATION\n")
start_time = time.time()
losses = []
for epoch in  range(n_epochs + 1):
    feed = {X: (ratingTrain[:, 0:2], ratingTrain[:, 2], [d1, d2])}
    _, avg_cost = sess.run((optimizer, cost), feed_dict = feed)
    losses.append(np.sqrt(avg_cost))

    # DISPLAY
    if epoch % display_step == 0:
        duration = float(time.time() - start_time)
        print(" [*] Epoch: %05d/%05d cost: %2e (duration: %.3fs)" % (epoch, n_epochs,
np.sqrt(avg_cost), duration))
        start_time = time.time()
print("\nOptimization Finished!")
```

```
START OPTIMIZATION
```

```
 [*] Epoch: 00000/01000 cost: 3.966026e+00 (duration: 1.307s)
 [*] Epoch: 00100/01000 cost: 2.224589e+00 (duration: 0.818s)
 [*] Epoch: 00200/01000 cost: 1.948083e+00 (duration: 0.742s)
 [*] Epoch: 00300/01000 cost: 1.831463e+00 (duration: 0.734s)
 [*] Epoch: 00400/01000 cost: 1.760540e+00 (duration: 0.743s)
 [*] Epoch: 00500/01000 cost: 1.708069e+00 (duration: 0.749s)
 [*] Epoch: 00600/01000 cost: 1.665310e+00 (duration: 0.735s)
 [*] Epoch: 00700/01000 cost: 1.628179e+00 (duration: 0.722s)
 [*] Epoch: 00800/01000 cost: 1.594833e+00 (duration: 0.708s)
 [*] Epoch: 00900/01000 cost: 1.564300e+00 (duration: 0.725s)
 [*] Epoch: 01000/01000 cost: 1.535987e+00 (duration: 0.734s)

Optimization Finished!
```

```
plt.plot(losses)
plt.title("Learning curve", fontsize=14, fontweight='bold')
plt.xlabel("Epochs", fontsize=14, fontweight='bold')
plt.ylabel("RMSE of training set", fontsize=14, fontweight='bold')
plt.show()
```



4. Test

```
feed = {X: (ratingTrain[:, 0:2], ratingTrain[:, 2], [d1, d2])}
Pred = sess.run(pred, feed_dict=feed)

idxTest = (ratingTest[:, 0].astype(int), ratingTest[:, 1].astype(int))
idxTrain = (ratingTrain[:, 0].astype(int), ratingTrain[:, 1].astype(int))

RMSE_Test = np.sqrt(np.sum((Pred[idxTest] - ratingTest[:, 2]) ** 2) / len(ratingTest[:,
0]))
RMSE_Train = np.sqrt(np.linalg.norm(Pred[idxTrain] - ratingTrain[:, 2]) ** 2 /
len(ratingTrain[:, 0]))

print("[*] RMSE Test: %.4e" % RMSE_Test)
print("[*] RMSE Train %.4e" % RMSE_Train)
```

```
[*] RMSE Test: 9.3325e-01
[*] RMSE Train 8.9563e-01
```

Report

1. Momentum Optimizer

Use the "MomentumOptimizer( )" instaed of the GradientDescentOptimizer and compare the RMSE learning curves of the two optimizers. When you use MomentumOptimizer, set the momuentum at 0.9 and adjust the learning rate.

2. Batch normalization

Apply "batch normalization" to the 1st and 2nd hidden layers, and compare the resulting RMSE learning curves with those obtained above.
Hint) tf.layers.batch_normalization( )