Practice lab: Deep Learning for Content-Based Filtering

In this exercise, you will implement content-based filtering using a neural network to build a recommender system for movies.

Outline

***NOTE:** To prevent errors from the autograder, you are not allowed to edit or delete non-graded cells in this lab. Please also refrain from adding any new cells. **Once you have passed this assignment** and want to experiment with any of the non-graded code, you may follow the instructions at the bottom of this notebook.*

1 - Packages

We will use familiar packages, NumPy, TensorFlow and helpful routines from scikit-learn (https://scikit-learn.org/stable/). We will also use tabulate (https://pypi.org/project/tabulate/) to neatly print tables and Pandas (https://pandas.pydata.org/) to organize tabular data.

In [1]:

```
import numpy as np
import numpy.ma as ma
import pandas as pd
import tensorflow as tf
from tensorflow import keras
from sklearn.preprocessing import StandardScaler, MinMaxScaler
from sklearn.model_selection import train_test_split
import tabulate
from recsysNN_utils import *
pd.set_option("display.precision", 1)
```

2 - Movie ratings dataset

The data set is derived from the MovieLens ml-latest-small (https://grouplens.org/datasets/movielens/latest/) dataset.

[F. Maxwell Harper and Joseph A. Konstan. 2015. The MovieLens Datasets: History and Context. ACM Transactions on Interactive Intelligent Systems (TiiS) 5, 4: 19:1–19:19. https://doi.org/10.1145/2827872 (https://doi.org/10.1145/2827872)]

The original dataset has roughly 9000 movies rated by 600 users with ratings on a scale of 0.5 to 5 in 0.5 step increments. The dataset has been reduced in size to focus on movies from the years since 2000 and popular genres. The reduced dataset has $n_u = 397$ users, $n_m = 847$ movies and 25521 ratings. For each movie, the dataset provides a movie title, release date, and one or more genres. For example "Toy Story 3" was released in 2010 and has several genres: "Adventure|Animation|Children|Comedy|Fantasy". This dataset contains little information about users other than their ratings. This dataset is used to create training vectors for the neural networks described below. Let's learn a bit more about this data set. The table below shows the top 10 movies ranked by the number of ratings. These movies also happen to have high average ratings. How many of these movies have you watched?

In [2]:

```
top10_df = pd.read_csv("./data/content_top10_df.csv")
bygenre_df = pd.read_csv("./data/content_bygenre_df.csv")
top10_df
```

Out[2]:

	movie id	num ratings	ave rating	title	genres
0	4993	198	4.1	Lord of the Rings: The Fellowship of the Ring,...	Adventure|Fantasy
1	5952	188	4.0	Lord of the Rings: The Two Towers, The	Adventure|Fantasy
2	7153	185	4.1	Lord of the Rings: The Return of the King, The	Action|Adventure|Drama|Fantasy
3	4306	170	3.9	Shrek	Adventure|Animation|Children|Comedy|Fantasy|Ro...
4	58559	149	4.2	Dark Knight, The	Action|Crime|Drama
5	6539	149	3.8	Pirates of the Caribbean: The Curse of the Bla...	Action|Adventure|Comedy|Fantasy
6	79132	143	4.1	Inception	Action|Crime|Drama|Mystery|Sci-Fi|Thriller
7	6377	141	4.0	Finding Nemo	Adventure|Animation|Children|Comedy
8	4886	132	3.9	Monsters, Inc.	Adventure|Animation|Children|Comedy|Fantasy
9	7361	131	4.2	Eternal Sunshine of the Spotless Mind	Drama|Romance|Sci-Fi

The next table shows information sorted by genre. The number of ratings per genre vary substantially. Note that a movie may have multiple genre's so the sum of the ratings below is larger than the number of original ratings.

In [3]:

```
bygenre_df
```

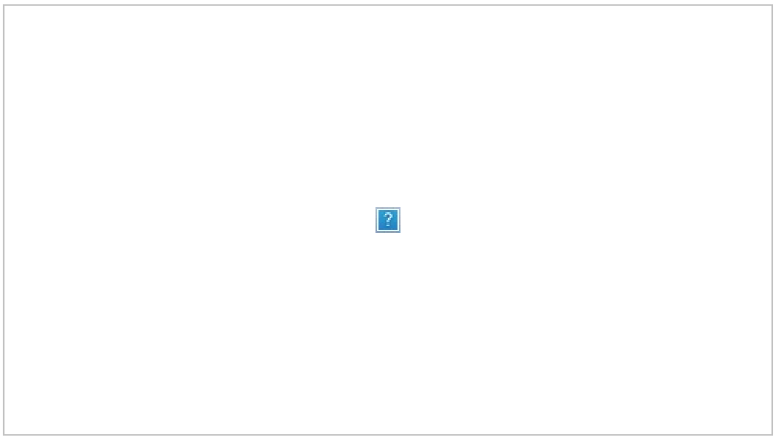
Out[3]:

	genre	num movies	ave rating/genre	ratings per genre
0	Action	321	3.4	10377
1	Adventure	234	3.4	8785
2	Animation	76	3.6	2588
3	Children	69	3.4	2472
4	Comedy	326	3.4	8911
5	Crime	139	3.5	4671
6	Documentary	13	3.8	280
7	Drama	342	3.6	10201
8	Fantasy	124	3.4	4468
9	Horror	56	3.2	1345
10	Mystery	68	3.6	2497
11	Romance	151	3.4	4468
12	Sci-Fi	174	3.4	5894
13	Thriller	245	3.4	7659

3 - Content-based filtering with a neural network

In the collaborative filtering lab, you generated two vectors, a user vector and an item/movie vector whose dot product would predict a rating. The vectors were derived solely from the ratings.

Content-based filtering also generates a user and movie feature vector but recognizes there may be other information available about the user and/or movie that may improve the prediction. The additional information is provided to a neural network which then generates the user and movie vector as shown below.



3.1 Training Data

The movie content provided to the network is a combination of the original data and some 'engineered features'. Recall the feature engineering discussion and lab from Course 1, Week 2, lab 4. The original features are the year the movie was released and the movie's genre's presented as a one-hot vector. There are 14 genres. The engineered feature is an average rating derived from the user ratings.

The user content is composed of engineered features. A per genre average rating is computed per user. Additionally, a user id, rating count and rating average are available but not included in the training or prediction content. They are carried with the data set because they are useful in interpreting data.

The training set consists of all the ratings made by the users in the data set. Some ratings are repeated to boost the number of training examples of underrepresented genre's. The training set is split into two arrays with the same number of entries, a user array and a movie/item array.

Below, let's load and display some of the data.

In [4]:

```
# Load Data, set configuration variables
item_train, user_train, y_train, item_features, user_features, item_vecs, movie_dict, user_to_genre = load_data()

num_user_features = user_train.shape[1] - 3  # remove userid, rating count and ave rating during training
num_item_features = item_train.shape[1] - 1  # remove movie id at train time
uvs = 3  # user genre vector start
ivs = 3  # item genre vector start
u_s = 3  # start of columns to use in training, user
i_s = 1  # start of columns to use in training, items
print(f"Number of training vectors: {len(item_train)}")
```

```
Number of training vectors: 50884
```

Let's look at the first few entries in the user training array.

In [5]:

```
pprint_train(user_train, user_features, uvs,  u_s, maxcount=5)
```

Out[5]:

[user id]	[rating count]	[rating ave]	Act ion	Adve nture	Anim ation	Chil dren	Com edy	Crime	Docum entary	Drama	Fan tasy	Hor ror	Mys tery	Rom ance	Sci -Fi	Thri ller
2	22	4.0	4.0	4.2	0.0	0.0	4.0	4.1	4.0	4.0	0.0	3.0	4.0	0.0	3.9	3.9
2	22	4.0	4.0	4.2	0.0	0.0	4.0	4.1	4.0	4.0	0.0	3.0	4.0	0.0	3.9	3.9
2	22	4.0	4.0	4.2	0.0	0.0	4.0	4.1	4.0	4.0	0.0	3.0	4.0	0.0	3.9	3.9
2	22	4.0	4.0	4.2	0.0	0.0	4.0	4.1	4.0	4.0	0.0	3.0	4.0	0.0	3.9	3.9
2	22	4.0	4.0	4.2	0.0	0.0	4.0	4.1	4.0	4.0	0.0	3.0	4.0	0.0	3.9	3.9

Some of the user and item/movie features are not used in training. In the table above, the features in brackets "[]" such as the "user id", "rating count" and "rating ave" are not included when the model is trained and used. Above you can see the per genre rating average for user 2. Zero entries are genre's which the user had not rated. The user vector is the same for all the movies rated by a user.
Let's look at the first few entries of the movie/item array.

In [6]:

```
pprint_train(item_train, item_features, ivs, i_s, maxcount=5, user=False)
```

Out[6]:

[movie id]	year	ave rating	Act ion	Adve nture	Anim ation	Chil dren	Com edy	Crime	Docum entary	Drama	Fan tasy	Hor ror	Mys tery	Rom ance	Sci -Fi	Thri ller
6874	2003	4.0	1	0	0	0	0	1	0	0	0	0	0	0	0	1
8798	2004	3.8	1	0	0	0	0	1	0	1	0	0	0	0	0	1
46970	2006	3.2	1	0	0	0	1	0	0	0	0	0	0	0	0	0
48516	2006	4.3	0	0	0	0	0	1	0	1	0	0	0	0	0	1
58559	2008	4.2	1	0	0	0	0	1	0	1	0	0	0	0	0	0

Above, the movie array contains the year the film was released, the average rating and an indicator for each potential genre. The indicator is one for each genre that applies to the movie. The movie id is not used in training but is useful when interpreting the data.

In [7]:

```
print(f"y_train[:5]: {y_train[:5]}")
```

```
y_train[:5]: [4.  3.5 4.  4.  4.5]
```

The target, y, is the movie rating given by the user.

Above, we can see that movie 6874 is an Action/Crime/Thriller movie released in 2003. User 2 rates action movies as 3.9 on average. MovieLens users gave the movie an average rating of 4. 'y' is 4 indicating user 2 rated movie 6874 as a 4 as well. A single training example consists of a row from both the user and item arrays and a rating from y_train.

3.2 Preparing the training data

Recall in Course 1, Week 2, you explored feature scaling as a means of improving convergence. We'll scale the input features using the scikit learn StandardScaler (https://scikit-learn.org/stable/modules/generated/sklearn.preprocessing.StandardScaler.html). This was used in Course 1, Week 2, Lab 5. Below, the inverse_transform is also shown to produce the original inputs. We'll scale the target ratings using a Min Max Scaler which scales the target to be between -1 and 1. scikit learn MinMaxScaler (https://scikit-learn.org/stable/modules/generated/sklearn.preprocessing.MinMaxScaler.html)

In [8]:

```
# scale training data
item_train_unscaled = item_train
user_train_unscaled = user_train
y_train_unscaled    = y_train

scalerItem = StandardScaler()
scalerItem.fit(item_train)
item_train = scalerItem.transform(item_train)

scalerUser = StandardScaler()
scalerUser.fit(user_train)
user_train = scalerUser.transform(user_train)

scalerTarget = MinMaxScaler((-1, 1))
scalerTarget.fit(y_train.reshape(-1, 1))
y_train = scalerTarget.transform(y_train.reshape(-1, 1))
#ynorm_test = scalerTarget.transform(y_test.reshape(-1, 1))

print(np.allclose(item_train_unscaled, scalerItem.inverse_transform(item_train)))
print(np.allclose(user_train_unscaled, scalerUser.inverse_transform(user_train)))
```

```
True
True
```

To allow us to evaluate the results, we will split the data into training and test sets as was discussed in Course 2, Week 3. Here we will use sklean train_test_split (https://scikit-learn.org/stable/modules/generated/sklearn.model_selection.train_test_split.html) to split and shuffle the data. Note that setting the initial random state to the same value ensures item, user, and y are shuffled identically.

In [9]:

```
item_train, item_test = train_test_split(item_train, train_size=0.80, shuffle=True, random_state=1)
user_train, user_test = train_test_split(user_train, train_size=0.80, shuffle=True, random_state=1)
y_train, y_test       = train_test_split(y_train,    train_size=0.80, shuffle=True, random_state=1)
print(f"movie/item training data shape: {item_train.shape}")
print(f"movie/item test data shape: {item_test.shape}")
```

```
movie/item training data shape: (40707, 17)
movie/item test data shape: (10177, 17)
```

The scaled, shuffled data now has a mean of zero.

In [10]:

```
pprint_train(user_train, user_features, uvs, u_s, maxcount=5)
```

Out[10]:

[user id]	[rating count]	[rating ave]	Action	Adventure	Animation	Children	Comedy	Crime	Documentary	Drama	Fantasy	Horror	Mystery	Romance	Sci-Fi	Thriller
1	0	-1.0	-0.8	-0.7	0.1	-0.0	-1.2	-0.4	0.6	-0.5	-0.5	-0.1	-0.6	-0.6	-0.7	-0.7
0	1	-0.7	-0.5	-0.7	-0.1	-0.2	-0.6	-0.2	0.7	-0.5	-0.8	0.1	-0.0	-0.6	-0.5	-0.4
-1	-1	-0.2	0.3	-0.4	0.4	0.5	1.0	0.6	-1.2	-0.3	-0.6	-2.3	-0.1	0.0	0.4	-0.0
0	-1	0.6	0.5	0.5	0.2	0.6	-0.1	0.5	-1.2	0.9	1.2	-2.3	-0.1	0.0	0.2	0.3
-1	0	0.7	0.6	0.5	0.3	0.5	0.4	0.6	1.0	0.6	0.3	0.8	0.8	0.4	0.7	0.7

4 - Neural Network for content-based filtering

Now, let's construct a neural network as described in the figure above. It will have two networks that are combined by a dot product. You will construct the two networks. In this example, they will be identical. Note that these networks do not need to be the same. If the user content was substantially larger than the movie content, you might elect to increase the complexity of the user network relative to the movie network. In this case, the content is similar, so the networks are the same.

Exercise 1

- Use a Keras sequential model
  - The first layer is a dense layer with 256 units and a relu activation.
  - The second layer is a dense layer with 128 units and a relu activation.
  - The third layer is a dense layer with `num_outputs` units and a linear or no activation.

The remainder of the network will be provided. The provided code does not use the Keras sequential model but instead uses the Keras [functional api (https://keras.io/guides/functional_api/)](https://keras.io/guides/functional_api/). This format allows for more flexibility in how components are interconnected.

In [12]:

```
# GRADED_CELL
# UNQ_C1

num_outputs = 32
tf.random.set_seed(1)
user_NN = tf.keras.models.Sequential([
    ### START CODE HERE ###
    tf.keras.layers.Dense(256, activation='relu'),
    tf.keras.layers.Dense(128, activation='relu'),
    tf.keras.layers.Dense(num_outputs),
    ### END CODE HERE ###
])

item_NN = tf.keras.models.Sequential([
    ### START CODE HERE ###
    tf.keras.layers.Dense(256, activation='relu'),
    tf.keras.layers.Dense(128, activation='relu'),
    tf.keras.layers.Dense(num_outputs),
    ### END CODE HERE ###
])

# create the user input and point to the base network
input_user = tf.keras.layers.Input(shape=(num_user_features))
vu = user_NN(input_user)
vu = tf.linalg.l2_normalize(vu, axis=1)

# create the item input and point to the base network
input_item = tf.keras.layers.Input(shape=(num_item_features))
vm = item_NN(input_item)
vm = tf.linalg.l2_normalize(vm, axis=1)

# compute the dot product of the two vectors vu and vm
output = tf.keras.layers.Dot(axes=1)([vu, vm])

# specify the inputs and output of the model
model = tf.keras.Model([input_user, input_item], output)

model.summary()
```

```
Model: "model"
__________________________________________________________________________________________________
Layer (type)                    Output Shape         Param #     Connected to                     
==================================================================================================
input_3 (InputLayer)            [(None, 14)]         0                                            
__________________________________________________________________________________________________
input_4 (InputLayer)            [(None, 16)]         0                                            
__________________________________________________________________________________________________
sequential_2 (Sequential)       (None, 32)           40864       input_3[0][0]                    
__________________________________________________________________________________________________
sequential_3 (Sequential)       (None, 32)           41376       input_4[0][0]                    
__________________________________________________________________________________________________
tf_op_layer_l2_normalize_2/Squa [(None, 32)]         0           sequential_2[0][0]               
__________________________________________________________________________________________________
tf_op_layer_l2_normalize_3/Squa [(None, 32)]         0           sequential_3[0][0]               
__________________________________________________________________________________________________
tf_op_layer_l2_normalize_2/Sum  [(None, 1)]          0           tf_op_layer_l2_normalize_2/Square
__________________________________________________________________________________________________
tf_op_layer_l2_normalize_3/Sum  [(None, 1)]          0           tf_op_layer_l2_normalize_3/Square
__________________________________________________________________________________________________
tf_op_layer_l2_normalize_2/Maxi [(None, 1)]          0           tf_op_layer_l2_normalize_2/Sum[0]
__________________________________________________________________________________________________
tf_op_layer_l2_normalize_3/Maxi [(None, 1)]          0           tf_op_layer_l2_normalize_3/Sum[0]
__________________________________________________________________________________________________
tf_op_layer_l2_normalize_2/Rsqr [(None, 1)]          0           tf_op_layer_l2_normalize_2/Maximu
__________________________________________________________________________________________________
tf_op_layer_l2_normalize_3/Rsqr [(None, 1)]          0           tf_op_layer_l2_normalize_3/Maximu
__________________________________________________________________________________________________
tf_op_layer_l2_normalize_2 (Ten [(None, 32)]         0           sequential_2[0][0]               
                                                                 tf_op_layer_l2_normalize_2/Rsqrt[
__________________________________________________________________________________________________
tf_op_layer_l2_normalize_3 (Ten [(None, 32)]         0           sequential_3[0][0]               
                                                                 tf_op_layer_l2_normalize_3/Rsqrt[
__________________________________________________________________________________________________
dot_1 (Dot)                     (None, 1)            0           tf_op_layer_l2_normalize_2[0][0] 
                                                                 tf_op_layer_l2_normalize_3[0][0] 
==================================================================================================
Total params: 82,240
Trainable params: 82,240
Non-trainable params: 0
__________________________________________________________________________________________________
```

In [13]:

```
# Public tests
from public_tests import *
test_tower(user_NN)
test_tower(item_NN)
```

```
All tests passed!
All tests passed!
```

▶ **Click for hints**

We will use a mean squared error loss and an Adam optimizer.

In [14]:

```
tf.random.set_seed(1)
cost_fn = tf.keras.losses.MeanSquaredError()
opt = keras.optimizers.Adam(learning_rate=0.01)
model.compile(optimizer=opt,
              loss=cost_fn)
```

In [15]:

```
tf.random.set_seed(1)
model.fit([user_train[:, u_s:], item_train[:, i_s:]], y_train, epochs=30)
```

```
Train on 40707 samples
Epoch 1/30
40707/40707 [==============================] - 5s 130us/sample - loss: 0.1232
Epoch 2/30
40707/40707 [==============================] - 5s 118us/sample - loss: 0.1146
Epoch 3/30
40707/40707 [==============================] - 5s 122us/sample - loss: 0.1089
Epoch 4/30
40707/40707 [==============================] - 5s 114us/sample - loss: 0.1039
Epoch 5/30
40707/40707 [==============================] - 5s 115us/sample - loss: 0.1001
Epoch 6/30
40707/40707 [==============================] - 5s 121us/sample - loss: 0.0973
Epoch 7/30
40707/40707 [==============================] - 5s 120us/sample - loss: 0.0956
Epoch 8/30
40707/40707 [==============================] - 5s 119us/sample - loss: 0.0935
Epoch 9/30
40707/40707 [==============================] - 5s 119us/sample - loss: 0.0916
Epoch 10/30
40707/40707 [==============================] - 5s 117us/sample - loss: 0.0897
Epoch 11/30
40707/40707 [==============================] - 5s 120us/sample - loss: 0.0880
Epoch 12/30
40707/40707 [==============================] - 5s 120us/sample - loss: 0.0865
Epoch 13/30
40707/40707 [==============================] - 5s 119us/sample - loss: 0.0852s -
Epoch 14/30
40707/40707 [==============================] - 5s 117us/sample - loss: 0.0839
Epoch 15/30
40707/40707 [==============================] - 5s 118us/sample - loss: 0.0830
Epoch 16/30
40707/40707 [==============================] - 5s 115us/sample - loss: 0.0815
Epoch 17/30
40707/40707 [==============================] - 5s 116us/sample - loss: 0.0807
Epoch 18/30
40707/40707 [==============================] - 5s 119us/sample - loss: 0.0796
Epoch 19/30
40707/40707 [==============================] - 5s 116us/sample - loss: 0.0786
Epoch 20/30
40707/40707 [==============================] - 5s 120us/sample - loss: 0.0776
Epoch 21/30
40707/40707 [==============================] - 5s 122us/sample - loss: 0.0769
Epoch 22/30
40707/40707 [==============================] - 5s 118us/sample - loss: 0.0761
Epoch 23/30
40707/40707 [==============================] - 5s 119us/sample - loss: 0.0755
Epoch 24/30
40707/40707 [==============================] - 5s 119us/sample - loss: 0.0746
Epoch 25/30
40707/40707 [==============================] - 5s 117us/sample - loss: 0.0741
Epoch 26/30
40707/40707 [==============================] - 5s 118us/sample - loss: 0.0733
Epoch 27/30
40707/40707 [==============================] - 5s 118us/sample - loss: 0.0728
Epoch 28/30
40707/40707 [==============================] - 5s 118us/sample - loss: 0.0723
Epoch 29/30
40707/40707 [==============================] - 5s 119us/sample - loss: 0.0717
Epoch 30/30
40707/40707 [==============================] - 5s 119us/sample - loss: 0.0713
```

Out[15]:

```
<tensorflow.python.keras.callbacks.History at 0x7f36b5796310>
```

Evaluate the model to determine loss on the test data.

In [16]:

```
model.evaluate([user_test[:, u_s:], item_test[:, i_s:]], y_test)
```

```
10177/10177 [==============================] - 0s 39us/sample - loss: 0.0815
```

Out[16]:

```
0.08146006993124337
```

It is comparable to the training loss indicating the model has not substantially overfit the training data.

5 - Predictions

Below, you'll use your model to make predictions in a number of circumstances.

5.1 - Predictions for a new user

First, we'll create a new user and have the model suggest movies for that user. After you have tried this on the example user content, feel free to change the user content to match your own preferences and see what the model suggests. Note that ratings are between 0.5 and 5.0, inclusive, in half-step increments.

In [17]:

```
new_user_id = 5000
new_rating_ave = 0.0
new_action = 0.0
new_adventure = 5.0
new_animation = 0.0
new_childrens = 0.0
new_comedy = 0.0
new_crime = 0.0
new_documentary = 0.0
new_drama = 0.0
new_fantasy = 5.0
new_horror = 0.0
new_mystery = 0.0
new_romance = 0.0
new_scifi = 0.0
new_thriller = 0.0
new_rating_count = 3

user_vec = np.array([[new_user_id, new_rating_count, new_rating_ave,
                      new_action, new_adventure, new_animation, new_childrens,
                      new_comedy, new_crime, new_documentary,
                      new_drama, new_fantasy, new_horror, new_mystery,
                      new_romance, new_scifi, new_thriller]])
```

The new user enjoys movies from the adventure, fantasy genres. Let's find the top-rated movies for the new user.
Below, we'll use a set of movie/item vectors, `item_vecs` that have a vector for each movie in the training/test set. This is matched with the new user vector above and the scaled vectors are used to predict ratings for all the movies.

In [18]:

```
# generate and replicate the user vector to match the number movies in the data set.
user_vecs = gen_user_vecs(user_vec,len(item_vecs))

# scale our user and item vectors
suser_vecs = scalerUser.transform(user_vecs)
sitem_vecs = scalerItem.transform(item_vecs)

# make a prediction
y_p = model.predict([suser_vecs[:, u_s:], sitem_vecs[:, i_s:]])

# unscale y prediction
y_pu = scalerTarget.inverse_transform(y_p)

# sort the results, highest prediction first
sorted_index = np.argsort(-y_pu,axis=0).reshape(-1).tolist()  #negate to get largest rating first
sorted_ypu   = y_pu[sorted_index]
sorted_items = item_vecs[sorted_index]  #using unscaled vectors for display

print_pred_movies(sorted_ypu, sorted_items, movie_dict, maxcount = 10)
```

Out[18]:

y_p	movie id	rating ave	title	genres
4.5	98809	3.8	Hobbit: An Unexpected Journey, The (2012)	Adventure|Fantasy
4.4	8368	3.9	Harry Potter and the Prisoner of Azkaban (2004)	Adventure|Fantasy
4.4	54001	3.9	Harry Potter and the Order of the Phoenix (2007)	Adventure|Drama|Fantasy
4.3	40815	3.8	Harry Potter and the Goblet of Fire (2005)	Adventure|Fantasy|Thriller
4.3	106489	3.6	Hobbit: The Desolation of Smaug, The (2013)	Adventure|Fantasy
4.3	81834	4	Harry Potter and the Deathly Hallows: Part 1 (2010)	Action|Adventure|Fantasy
4.3	59387	4	Fall, The (2006)	Adventure|Drama|Fantasy
4.3	5952	4	Lord of the Rings: The Two Towers, The (2002)	Adventure|Fantasy
4.3	5816	3.6	Harry Potter and the Chamber of Secrets (2002)	Adventure|Fantasy
4.3	54259	3.6	Stardust (2007)	Adventure|Comedy|Fantasy|Romance

5.2 - Predictions for an existing user.

Let's look at the predictions for "user 2", one of the users in the data set. We can compare the predicted ratings with the model's ratings.

In [19]:

```
uid = 2
# form a set of user vectors. This is the same vector, transformed and repeated.
user_vecs, y_vecs = get_user_vecs(uid, user_train_unscaled, item_vecs, user_to_genre)

# scale our user and item vectors
suser_vecs = scalerUser.transform(user_vecs)
sitem_vecs = scalerItem.transform(item_vecs)

# make a prediction
y_p = model.predict([suser_vecs[:, u_s:], sitem_vecs[:, i_s:]])

# unscale y prediction
y_pu = scalerTarget.inverse_transform(y_p)

# sort the results, highest prediction first
sorted_index = np.argsort(-y_pu,axis=0).reshape(-1).tolist()  #negate to get largest rating first
sorted_ypu   = y_pu[sorted_index]
sorted_items = item_vecs[sorted_index]  #using unscaled vectors for display
sorted_user  = user_vecs[sorted_index]
sorted_y     = y_vecs[sorted_index]

#print sorted predictions for movies rated by the user
print_existing_user(sorted_ypu, sorted_y.reshape(-1,1), sorted_user, sorted_items, ivs, uvs, movie_dict, maxcount
= 50)
```

Out[19]:

y_p	y	user	user genre ave	movie rating ave	movie id	title	genres
4.5	5.0	2	[4.0]	4.3	80906	Inside Job (2010)	Documentary
4.2	3.5	2	[4.0,4.0]	3.9	99114	Django Unchained (2012)	Action|Drama
4.1	4.5	2	[4.0,4.0]	4.1	68157	Inglourious Basterds (2009)	Action|Drama
4.1	3.5	2	[4.0,3.9,3.9]	3.9	115713	Ex Machina (2015)	Drama|Sci-Fi|Thriller
4.0	4.0	2	[4.0,4.1,4.0,4.0,3.9,3.9]	4.1	79132	Inception (2010)	Action|Crime|Drama|Mystery|Sci-Fi|Thriller
4.0	4.0	2	[4.1,4.0,3.9]	4.3	48516	Departed, The (2006)	Crime|Drama|Thriller
4.0	4.5	2	[4.0,4.1,4.0]	4.2	58559	Dark Knight, The (2008)	Action|Crime|Drama
4.0	4.0	2	[4.0,4.1,3.9]	4.0	6874	Kill Bill: Vol. 1 (2003)	Action|Crime|Thriller
4.0	3.5	2	[4.0,4.1,4.0,3.9]	3.8	8798	Collateral (2004)	Action|Crime|Drama|Thriller
3.9	5.0	2	[4.0,4.1,4.0]	3.9	106782	Wolf of Wall Street, The (2013)	Comedy|Crime|Drama
3.9	3.5	2	[4.0,4.2,4.1]	4.0	91529	Dark Knight Rises, The (2012)	Action|Adventure|Crime
3.9	4.0	2	[4.0,4.0,3.9]	4.0	74458	Shutter Island (2010)	Drama|Mystery|Thriller
3.9	4.5	2	[4.1,4.0,3.9]	4.0	80489	Town, The (2010)	Crime|Drama|Thriller
3.8	4.0	2	[4.0]	4.0	112552	Whiplash (2014)	Drama
3.8	3.0	2	[3.9]	4.0	109487	Interstellar (2014)	Sci-Fi
3.8	5.0	2	[4.0]	3.7	89774	Warrior (2011)	Drama
3.7	3.0	2	[4.0,4.0,3.0]	3.9	71535	Zombieland (2009)	Action|Comedy|Horror
3.7	5.0	2	[4.0,4.2,3.9,3.9]	3.8	122882	Mad Max: Fury Road (2015)	Action|Adventure|Sci-Fi|Thriller
3.5	5.0	2	[4.0]	3.6	60756	Step Brothers (2008)	Comedy
3.5	2.5	2	[4.0,3.9]	3.5	91658	Girl with the Dragon Tattoo, The (2011)	Drama|Thriller
3.1	3.0	2	[4.0,4.0]	4.0	77455	Exit Through the Gift Shop (2010)	Comedy|Documentary
3.1	4.0	2	[4.0,4.0]	3.2	46970	Talladega Nights: The Ballad of Ricky Bobby (2006)	Action|Comedy

The model prediction is generally within 1 of the actual rating though it is not a very accurate predictor of how a user rates specific movies. This is especially true if the user rating is significantly different than the user's genre average. You can vary the user id above to try different users. Not all user id's were used in the training set.

5.3 - Finding Similar Items

The neural network above produces two feature vectors, a user feature vector v_u, and a movie feature vector, v_m. These are 32 entry vectors whose values are difficult to interpret. However, similar items will have similar vectors. This information can be used to make recommendations. For example, if a user has rated "Toy Story 3" highly, one could recommend similar movies by selecting movies with similar movie feature vectors.

A similarity measure is the squared distance between the two vectors $\mathbf{v_m^{(k)}}$ and $\mathbf{v_m^{(i)}}$:

$$\left\Vert \mathbf{v_m^{(k)}} - \mathbf{v_m^{(i)}} \right\Vert^2 = \sum_{l=1}^{n}(v_{m_l}^{(k)} - v_{m_l}^{(i)})^2 \tag{1}$$

Exercise 2

Write a function to compute the square distance.

In [20]:

```
# GRADED_FUNCTION: sq_dist
# UNQ_C2
def sq_dist(a,b):
    """
    Returns the squared distance between two vectors
    Args:
      a (ndarray (n,)): vector with n features
      b (ndarray (n,)): vector with n features
    Returns:
      d (float) : distance
    """
    ### START CODE HERE ###
    d = 0.
    for i in range(len(a)):
        d += (a[i]-b[i])**2
    ### END CODE HERE ###
    return d
```

In [21]:

```
a1 = np.array([1.0, 2.0, 3.0]); b1 = np.array([1.0, 2.0, 3.0])
a2 = np.array([1.1, 2.1, 3.1]); b2 = np.array([1.0, 2.0, 3.0])
a3 = np.array([0, 1, 0]);       b3 = np.array([1, 0, 0])
print(f"squared distance between a1 and b1: {sq_dist(a1, b1):0.3f}")
print(f"squared distance between a2 and b2: {sq_dist(a2, b2):0.3f}")
print(f"squared distance between a3 and b3: {sq_dist(a3, b3):0.3f}")
```

```
squared distance between a1 and b1: 0.000
squared distance between a2 and b2: 0.030
squared distance between a3 and b3: 2.000
```

Expected Output:

squared distance between a1 and b1: 0.000
squared distance between a2 and b2: 0.030
squared distance between a3 and b3: 2.000

In [22]:

```
# Public tests
test_sq_dist(sq_dist)
```

```
All tests passed!
```

▶ **Click for hints**

A matrix of distances between movies can be computed once when the model is trained and then reused for new recommendations without retraining. The first step, once a model is trained, is to obtain the movie feature vector, v_m, for each of the movies. To do this, we will use the trained `item_NN` and build a small model to allow us to run the movie vectors through it to generate v_m.

In [23]:

```
input_item_m = tf.keras.layers.Input(shape=(num_item_features))    # input layer
vm_m = item_NN(input_item_m)                                       # use the trained item_NN
vm_m = tf.linalg.l2_normalize(vm_m, axis=1)                        # incorporate normalization as was done in the original model
model_m = tf.keras.Model(input_item_m, vm_m)
model_m.summary()
```

```
Model: "model_1"
__________________________________________________________________________________________________
Layer (type)                    Output Shape         Param #     Connected to
==================================================================================================
input_5 (InputLayer)            [(None, 16)]         0
__________________________________________________________________________________________________
sequential_3 (Sequential)       (None, 32)           41376       input_5[0][0]
__________________________________________________________________________________________________
tf_op_layer_l2_normalize_4/Squa [(None, 32)]         0           sequential_3[1][0]
__________________________________________________________________________________________________
tf_op_layer_l2_normalize_4/Sum  [(None, 1)]          0           tf_op_layer_l2_normalize_4/Square
__________________________________________________________________________________________________
tf_op_layer_l2_normalize_4/Maxi [(None, 1)]          0           tf_op_layer_l2_normalize_4/Sum[0]
__________________________________________________________________________________________________
tf_op_layer_l2_normalize_4/Rsqr [(None, 1)]          0           tf_op_layer_l2_normalize_4/Maximu
__________________________________________________________________________________________________
tf_op_layer_l2_normalize_4 (Ten [(None, 32)]         0           sequential_3[1][0]
                                                                 tf_op_layer_l2_normalize_4/Rsqrt[
==================================================================================================
Total params: 41,376
Trainable params: 41,376
Non-trainable params: 0
__________________________________________________________________________________________________
```

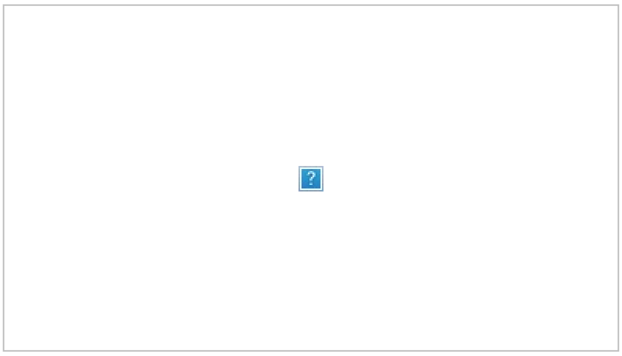
Once you have a movie model, you can create a set of movie feature vectors by using the model to predict using a set of item/movie vectors as input. `item_vecs` is a set of all of the movie vectors. It must be scaled to use with the trained model. The result of the prediction is a 32 entry feature vector for each movie.

In [24]:

```
scaled_item_vecs = scalerItem.transform(item_vecs)
vms = model_m.predict(scaled_item_vecs[:,i_s:])
print(f"size of all predicted movie feature vectors: {vms.shape}")
```

```
size of all predicted movie feature vectors: (847, 32)
```

Let's now compute a matrix of the squared distance between each movie feature vector and all other movie feature vectors:



We can then find the closest movie by finding the minimum along each row. We will make use of [numpy masked arrays (https://numpy.org/doc/1.21/user/tutorial-ma.html)](https://numpy.org/doc/1.21/user/tutorial-ma.html) to avoid selecting the same movie. The masked values along the diagonal won't be included in the computation.

In [26]:

```
count = 50  # number of movies to display
dim = len(vms)
dist = np.zeros((dim,dim))

for i in range(dim):
    for j in range(dim):
        dist[i,j] = sq_dist(vms[i, :], vms[j, :])

m_dist = ma.masked_array(dist, mask=np.identity(dist.shape[0]))  # mask the diagonal

disp = [["movie1", "genres", "movie2", "genres"]]
for i in range(count):
    min_idx = np.argmin(m_dist[i])
    movie1_id = int(item_vecs[i,0])
    movie2_id = int(item_vecs[min_idx,0])
    disp.append( [movie_dict[movie1_id]['title'], movie_dict[movie1_id]['genres'],
                  movie_dict[movie2_id]['title'], movie_dict[movie1_id]['genres']]
               )
table = tabulate.tabulate(disp, tablefmt='html', headers="firstrow")
table
```

Out[26]:

movie1	genres	movie2	genres
Save the Last Dance (2001)	Drama|Romance	Mona Lisa Smile (2003)	Drama|Romance
Wedding Planner, The (2001)	Comedy|Romance	Mr. Deeds (2002)	Comedy|Romance
Hannibal (2001)	Horror|Thriller	Final Destination 2 (2003)	Horror|Thriller
Saving Silverman (Evil Woman) (2001)	Comedy|Romance	Down with Love (2003)	Comedy|Romance
Down to Earth (2001)	Comedy|Fantasy|Romance	Bewitched (2005)	Comedy|Fantasy|Romance
Mexican, The (2001)	Action|Comedy	Rush Hour 2 (2001)	Action|Comedy
15 Minutes (2001)	Thriller	Panic Room (2002)	Thriller
Enemy at the Gates (2001)	Drama	Kung Fu Hustle (Gong fu) (2004)	Drama
Heartbreakers (2001)	Comedy|Crime|Romance	Fun with Dick and Jane (2005)	Comedy|Crime|Romance
Spy Kids (2001)	Action|Adventure|Children|Comedy	Tuxedo, The (2002)	Action|Adventure|Children|Comedy
Along Came a Spider (2001)	Action|Crime|Mystery|Thriller	Insomnia (2002)	Action|Crime|Mystery|Thriller
Blow (2001)	Crime|Drama	25th Hour (2002)	Crime|Drama
Bridget Jones's Diary (2001)	Comedy|Drama|Romance	Punch-Drunk Love (2002)	Comedy|Drama|Romance
Joe Dirt (2001)	Adventure|Comedy|Mystery|Romance	Polar Express, The (2004)	Adventure|Comedy|Mystery|Romance
Crocodile Dundee in Los Angeles (2001)	Comedy|Drama	Bewitched (2005)	Comedy|Drama
Mummy Returns, The (2001)	Action|Adventure|Comedy|Thriller	Rundown, The (2003)	Action|Adventure|Comedy|Thriller
Knight's Tale, A (2001)	Action|Comedy|Romance	Legally Blonde (2001)	Action|Comedy|Romance
Shrek (2001)	Adventure|Animation|Children|Comedy|Fantasy|Romance	Tangled (2010)	Adventure|Animation|Children|Comedy|Fantasy|Romance
Moulin Rouge (2001)	Drama|Romance	Notebook, The (2004)	Drama|Romance
Pearl Harbor (2001)	Action|Drama|Romance	Bridget Jones: The Edge of Reason (2004)	Action|Drama|Romance
Animal, The (2001)	Comedy	Dumb and Dumberer: When Harry Met Lloyd (2003)	Comedy
Evolution (2001)	Comedy|Sci-Fi	Behind Enemy Lines (2001)	Comedy|Sci-Fi
		We Were	

Swordfish (2001)	Action|Crime|Drama	Soldiers (2002)	Action|Crime|Drama
Atlantis: The Lost Empire (2001)	Adventure|Animation|Children|Fantasy	Cloudy with a Chance of Meatballs (2009)	Adventure|Animation|Children|Fantasy
Lara Croft: Tomb Raider (2001)	Action|Adventure	National Treasure: Book of Secrets (2007)	Action|Adventure
Dr. Dolittle 2 (2001)	Comedy	Legally Blonde 2: Red, White & Blonde (2003)	Comedy
Fast and the Furious, The (2001)	Action|Crime|Thriller	xXx (2002)	Action|Crime|Thriller
A.I. Artificial Intelligence (2001)	Adventure|Drama|Sci-Fi	Bubba Ho-tep (2002)	Adventure|Drama|Sci-Fi
Cats & Dogs (2001)	Children|Comedy	Robots (2005)	Children|Comedy
Scary Movie 2 (2001)	Comedy	Orange County (2002)	Comedy
Final Fantasy: The Spirits Within (2001)	Adventure|Animation|Fantasy|Sci-Fi	Madagascar: Escape 2 Africa (2008)	Adventure|Animation|Fantasy|Sci-Fi
Legally Blonde (2001)	Comedy|Romance	Serendipity (2001)	Comedy|Romance
Score, The (2001)	Action|Drama	Punisher, The (2004)	Action|Drama
Jurassic Park III (2001)	Action|Adventure|Sci-Fi|Thriller	Men in Black II (a.k.a. MIIB) (a.k.a. MIB 2) (2002)	Action|Adventure|Sci-Fi|Thriller
America's Sweethearts (2001)	Comedy|Romance	Maid in Manhattan (2002)	Comedy|Romance
Ghost World (2001)	Comedy|Drama	Station Agent, The (2003)	Comedy|Drama
Planet of the Apes (2001)	Action|Adventure|Drama|Sci-Fi	Day After Tomorrow, The (2004)	Action|Adventure|Drama|Sci-Fi
Princess Diaries, The (2001)	Children|Comedy|Romance	Lake House, The (2006)	Children|Comedy|Romance
Rush Hour 2 (2001)	Action|Comedy	Mexican, The (2001)	Action|Comedy
American Pie 2 (2001)	Comedy	Rat Race (2001)	Comedy
Others, The (2001)	Drama|Horror|Mystery|Thriller	The Machinist (2004)	Drama|Horror|Mystery|Thriller
Rat Race (2001)	Comedy	American Pie 2 (2001)	Comedy
Jay and Silent Bob Strike Back (2001)	Adventure|Comedy	Mexican, The (2001)	Adventure|Comedy
Training Day (2001)	Crime|Drama|Thriller	Frailty (2001)	Crime|Drama|Thriller
Zoolander (2001)	Comedy	Old School (2003)	Comedy
Serendipity (2001)	Comedy|Romance	Legally Blonde (2001)	Comedy|Romance
Mulholland Drive (2001)	Crime|Drama|Mystery|Thriller	Prisoners (2013)	Crime|Drama|Mystery|Thriller
From Hell (2001)	Crime|Horror|Mystery|Thriller	Identity (2003)	Crime|Horror|Mystery|Thriller
Waking Life (2001)	Animation|Drama|Fantasy	Warm Bodies (2013)	Animation|Drama|Fantasy
K-PAX (2001)	Drama|Fantasy|Mystery|Sci-Fi	Gosford Park (2001)	Drama|Fantasy|Mystery|Sci-Fi

The results show the model will generally suggest a movie with similar genre's.

6 - Congratulations!

You have completed a content-based recommender system.

This structure is the basis of many commercial recommender systems. The user content can be greatly expanded to incorporate more information about the user if it is available. Items are not limited to movies. This can be used to recommend any item, books, cars or items that are similar to an item in your 'shopping cart'.

▶ **Please click here if you want to experiment with any of the non-graded code.**