```
#Adapted from the Keras Example https://keras.io/examples/structured_data/collaborative_fi
```

```
#to clean up the code we import warnings
import warnings
warnings.filterwarnings('ignore')

import pandas as pd
import numpy as np
import tensorflow as tf
from tensorflow import keras
from tensorflow.keras import layers
from pathlib import Path
import matplotlib.pyplot as plt
from sklearn.decomposition import PCA
from sklearn.preprocessing import StandardScaler
```

```
df = pd.read_csv("ratings.csv")
```

```
len(df)
```

```
100004
```

```
df.tail(4)
```

	userId	movieId	rating	timestamp
100000	671	6269	4.0	1065149201
100001	671	6365	4.0	1070940363
100002	671	6385	2.5	1070979663
100003	671	6565	3.5	1074784724

```
user_ids = df["userId"].unique().tolist()
movie_ids = df["movieId"].unique().tolist()
```

```
#Make a dictionary mapping ids (keys) to indexes (values)
user_id_to_index = {x: i for i, x in enumerate(user_ids)}
movie_id_to_index = {x: i for i, x in enumerate(movie_ids)}
```

```
#Make a new column in the dataframe which contains the appropriate index for each user and
df["user_index"] = [user_id_to_index[i] for i in df["userId"]]
df["movie_index"] = [movie_id_to_index[i] for i in df["movieId"]]
```

```
df.sample(4)
```

	userId	movieId	rating	timestamp	user_index	movie_index
68286	475	4270	2.5	1447239392	474	1156
15139	99	928	4.0	938587795	98	1950
29974	213	69526	3.0	1462634530	212	1607
43648	311	1099	2.0	897414235	310	4743

```
from sklearn.preprocessing import MinMaxScaler
##Pick the range
df["rating"] = MinMaxScaler().fit_transform(df["rating"].values.reshape(-1, 1))
```

```
df["rating"].describe()
```

```
count    100004.000000
mean          0.676357
std           0.235125
min           0.000000
25%           0.555556
50%           0.777778
75%           0.777778
max           1.000000
Name: rating, dtype: float64
```

```
#Inputs
x = df[["user_index", "movie_index"]]
#Outputs/target
y = df["rating"]
```

```
#scaling the x_train to obtain a better performing trained model and lesser time to train
x['user_index']=x['user_index']/670
x['movie_index']=x['movie_index']/9065
```

```
from sklearn.model_selection import train_test_split
#Get train-test split
# obtain a high test_size (20%) to get better metrics of the model
x_train, x_test, y_train, y_test = train_test_split(x, y, test_size=0.2, random_state=10)
```

```
x_train.sample(5)
```

	user_index	movie_index
99897	1.000000	0.006398
2349	0.020896	0.180916
67254	0.702985	0.046001
28526	0.314925	0.018202
83249	0.840299	0.467512

```
#Define the new class
class RecommenderNet(keras.Model):

    #Override init with new arguments
    def __init__(self, num_users, num_movies, embedding_size, **kwargs):
        super(RecommenderNet, self).__init__(**kwargs)
        #Make an embedding layer for users
        self.user_embedding = layers.Embedding(
            num_users,
            embedding_size,
            embeddings_initializer="he_normal",
            embeddings_regularizer=keras.regularizers.l2(1e-6),
        )
        #Make an embedding layer for user bias
        self.user_bias = layers.Embedding(num_users, 1)
        #Make an embedding layer for movies
        self.movie_embedding = layers.Embedding(
            num_movies,
            embedding_size,
            embeddings_initializer="he_normal",
            embeddings_regularizer=keras.regularizers.l2(1e-6),
        )
        #Make an embedding layer for movie bias
        self.movie_bias = layers.Embedding(num_movies, 1)

    def call(self, inputs):
        #inputs contains [[user,movie],[user,movie],[user,movie]...]
        user_vector = self.user_embedding(inputs[:, 0])
        user_bias = self.user_bias(inputs[:, 0])
        movie_vector = self.movie_embedding(inputs[:, 1])
        movie_bias = self.movie_bias(inputs[:, 1])
        #Dot product
        dot_user_movie = tf.tensordot(user_vector, movie_vector, 2)
        # Add all the components (including bias)
        x = dot_user_movie + user_bias + movie_bias
        # The sigmoid activation forces the rating to between 0 and 1
        return tf.nn.sigmoid(x)
```

```
#Pick Embedding size
EMBEDDING_SIZE = 20
#Make new object (calls __init__())
num_users = len(user_ids)
num_movies = len(movie_ids)
model = RecommenderNet(num_users, num_movies, EMBEDDING_SIZE)
model.compile(
    loss=tf.keras.losses.MeanSquaredError(), optimizer=keras.optimizers.Adam(lr=0.001)
)
```

```
#TRAIN
history = model.fit(
    x=x_train,
    y=y_train,
    batch_size=64,
    epochs=20,
    validation_data=(x_test, y_test)
)
```

```
Epoch 1/20
1251/1251 [==============================] - 16s 11ms/step - loss: 0.0560 - val_loss
Epoch 2/20
1251/1251 [==============================] - 12s 10ms/step - loss: 0.0555 - val_loss
Epoch 3/20
1251/1251 [==============================] - 12s 10ms/step - loss: 0.0554 - val_loss
Epoch 4/20
1251/1251 [==============================] - 7s 6ms/step - loss: 0.0554 - val_loss:
Epoch 5/20
1251/1251 [==============================] - 7s 6ms/step - loss: 0.0554 - val_loss:
Epoch 6/20
1251/1251 [==============================] - 8s 6ms/step - loss: 0.0554 - val_loss:
Epoch 7/20
1251/1251 [==============================] - 7s 6ms/step - loss: 0.0554 - val_loss:
Epoch 8/20
1251/1251 [==============================] - 7s 6ms/step - loss: 0.0553 - val_loss:
Epoch 9/20
1251/1251 [==============================] - 8s 6ms/step - loss: 0.0554 - val_loss:
Epoch 10/20
1251/1251 [==============================] - 7s 6ms/step - loss: 0.0554 - val_loss:
Epoch 11/20
1251/1251 [==============================] - 7s 6ms/step - loss: 0.0554 - val_loss:
Epoch 12/20
1251/1251 [==============================] - 8s 6ms/step - loss: 0.0553 - val_loss:
Epoch 13/20
1251/1251 [==============================] - 9s 8ms/step - loss: 0.0554 - val_loss:
Epoch 14/20
1251/1251 [==============================] - 7s 6ms/step - loss: 0.0553 - val_loss:
Epoch 15/20
1251/1251 [==============================] - 7s 6ms/step - loss: 0.0554 - val_loss:
Epoch 16/20
1251/1251 [==============================] - 7s 6ms/step - loss: 0.0553 - val_loss:
Epoch 17/20
1251/1251 [==============================] - 8s 6ms/step - loss: 0.0553 - val_loss:
Epoch 18/20
1251/1251 [==============================] - 8s 6ms/step - loss: 0.0553 - val_loss:
Epoch 19/20
1251/1251 [==============================] - 7s 6ms/step - loss: 0.0554 - val_loss:
Epoch 20/20
1251/1251 [==============================] - 8s 6ms/step - loss: 0.0553 - val_loss:
```

```
model.user_embedding.trainable_weights[0].numpy()
```

```
array([[-2.3408090e-03,  2.4463711e-03,  9.1342971e-02, ...,
         1.2082976e-03, -9.0303971e-04,  4.0937057e-03],
       [-3.7118573e-02,  2.4850855e-02,  1.7433754e-01, ...,
         1.7154716e-02,  1.7971825e-02,  4.3392878e-02],
       [-4.5668644e-30,  4.5261189e-30,  4.5999291e-30, ...,
        -4.5879296e-30,  4.6935184e-30, -4.6387155e-30],
       ...,
       [-4.5300250e-30, -4.6695815e-30,  4.6122264e-30, ...,
         4.5343339e-30,  4.6241033e-30, -4.5025684e-30],
       [-4.6129152e-30,  4.5623622e-30, -4.5360789e-30, ...,
         4.5302085e-30, -4.6482127e-30, -4.5658646e-30],
       [ 4.6285998e-30,  4.5030379e-30, -4.6468800e-30, ...,
         4.5922927e-30,  4.6586436e-30,  4.6435574e-30]], dtype=float32)
```

```
#Get the movie data so we can map back to names
movie_data = pd.read_csv("movies.csv")
```

Making predictions and `argsort()`

Once we have the predicted ratings for each film, we need to get the **Top N**

Here we use `np.argsort()`, which does the sort based on the **ratings** but returns the **indexes** rather than the **ratings themselves**. We can then use this to look up the `movie_ids` and then the `title`.

```
user = 3
n = 10
#For one user, make a pair with every movie index
x = [[user, i] for i in np.arange(num_movies)]
```

```
#Predict
predicted_ratings = model.predict(x).flatten()
#Get Top-N indexes
top_n_indexes = predicted_ratings.argsort()[-n:]
#Get Movie Names
top_n = [movie_data[movie_data["movieId"]==movie_ids[i]]["title"] for i in top_n_indexes]
```

```
top_n
```

```
[3655    Scenes from the Class Struggle in Beverly Hill...
 Name: title, dtype: object, 4643    This Boy's Life (1993)
 Name: title, dtype: object, 407    Geronimo: An American Legend (1993)
 Name: title, dtype: object, 7901    The Artist (2011)
 Name: title, dtype: object, 8084    Magic Mike (2012)
 Name: title, dtype: object, 4884    Love Actually (2003)
 Name: title, dtype: object, 3919    Mrs. Soffel (1984)
 Name: title, dtype: object, 5901    Sound and Fury (2000)
 Name: title, dtype: object, 2260    Hamlet (1964)
 Name: title, dtype: object, 30    Dangerous Minds (1995)
 Name: title, dtype: object]
```

Practice

Personal note dont forget to comment code

Task 1

We're going to ask you take the trained model and write the code to make two metrics - **Diversity** and **Novelty**. You should end up with **one statistic** for each that tells you something about the recommendations of the trained model based on the **whole dataset**.

Pro Tip

This will take quite a long time to run on the whole dataset, so start off by trying to get the code to work for **one user**, then expand to **two users**, then **every user**.

Diversity

This tells us what the mean diversity (1-similarity, based on movie embeddings) between each film in every users Top 10 films is.

1. Calculate every user's top 10
2. For each top 10, calculate the similarity matrix
3. 1-similarity to get the difference
4. Get mean difference for each top 10
5. Report the mean for whole dataset (every top 10)

Novelty

This tells us what the mean popularity (e.g. mean rating) of the films in every users Top 10 films is

1. Calculate every user's top 10
2. For each top 10, get the mean rating for each film (based on the original **MovieLens Small** dataset (`df = pd.read_csv("ratings.csv")`).
3. Get the mean rating for each top 10.
4. Report the mean for the whole dataset (every top 10).

Task 2

Using a dimensionality reduction approach, plot the top 30 best rated films on a 2-D graph based on their movie embeddings. Label each point with the title.

```
# Specify 'n' to limit movies to top 10 only
n = 10

# Create a list to store indexes of all users top 10 movies.
top_n_indexes = []
```

```
# Loops each user (p) from length of user_ids and predicts their ratings for each movie.
# Sorts in ascending order and takes the last 10 (-n)
for p in range(len(user_ids)):
    x = [[p, i] for i in np.arange(num_movies)]
    predicted_ratings = model.predict(x).flatten()
    indexes = predicted_ratings.argsort()[-n:]
    top_n_indexes.append(indexes)

print(top_n_indexes)
```

```
[array([2943, 4472, 4750, 7738,  370, 2851, 7383, 4425,   16,    0]), array([4750, 7
```

```
# Create variable for accessing movie embedding weights
movie_weights = model.movie_embedding.trainable_weights[0].numpy()
```

```
# Create a list to store embedding weights for each movie (671 users, 10 movies per user,
top_n_weights = []

# Loops each user's top 10 movies (row) from the index list
# Matches movie index with relevant embedding weights
for row in top_n_indexes:
    top_n_weights.append(movie_weights[row])
```

Novelty

```
# Create list to store all ratings for each movie
movie_ratings =[]

# Finds ratings and matches them to their movie based on movie index
for each_movie in df['movie_index']:
    find_rating = df.loc[df['movie_index'] == each_movie, 'rating']
    movie_ratings.append(find_rating)
```

```
movie_ratings_array = np.array(movie_ratings)
```

```
# Create a list to store all the movie ratings from each user's top movies. (671 users, 10
top_n_ratings = []

# Loops each user's top 10 movies (row) from the index list
# Matches movie index with relevant movie rating
for row in top_n_indexes:
    top_n_ratings.append(movie_ratings_array[row])

# Prints all ratings from user0, movie1
print(top_n_ratings[0][1])
```

```
4472     0.333333
18339    0.777778
```

```
41722    0.777778
Name: rating, dtype: float64
```

```
# Create a list to store popularity scores for each user
pop_per_user = []

# Loops each user, then each movie from the list of ratings
# Calculates mean novelty
for each_user in top_n_ratings:
    for each_movie in each_user:
        novelty = each_movie.mean()
        pop_per_user.append(novelty)

# Condense scores from all users into one total mean score
total_pop = np.array(pop_per_user).mean()
print(total_pop)
```

```
0.6764583915776125
```

```
#Task 2
# Remove all movies with only 1 rating
# for loop will take lesser time than a while loop in this aspect
filtered_movie_ratings = []
for i in movie_ratings:
    if len(i) != 1:
        filtered_movie_ratings.append(i)
```

```


# Create a list to store the average rating for each movie
avg_rating = []

for row in filtered_movie_ratings:
    avg = row.mean()
    avg_rating.append(avg)

# Sort the ratings and return indexes
top_30_ratings = np.array(avg_rating).argsort()[-30:]
print(top_30_ratings)
```

```
[14422 32066 79416   804 81929 77875  1348 37536 55524 89825 89355 58840
  8453 52466 37345 77261 40556  4497 23089  5519 86086 14436 73042 45220
 31485 90854 52278 55289 72908 56153]
```

```
#Load movie data
movie_data = pd.read_csv("movies.csv")
```

```
# Convert movie index back to ID
top_30_movies = [df['movie_index'][i] for i in top_30_ratings]

# Map ID to title
movie_names = [movie_data[movie_data["movieId"]==movie_ids[i]]["title"] for i in top_30_mo
```

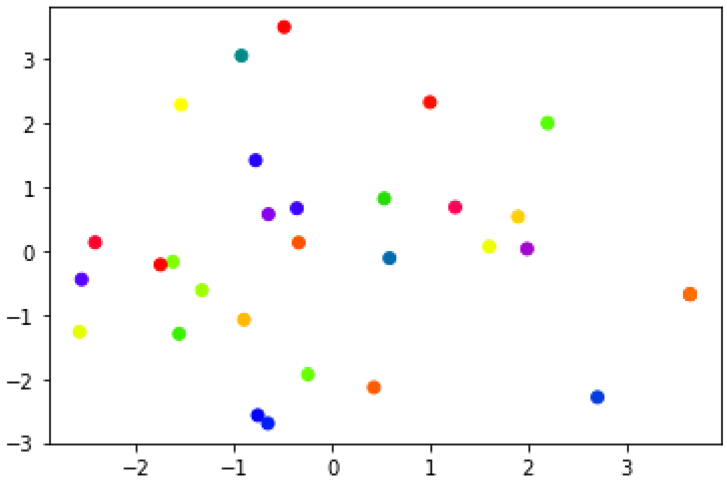
```
# Create a list to store embeding weights for each movie (30 movies, 20 weights per movie
top_30_weights = []

# Loops each movie and matches it to its embedding weight
for i in top_30_movies:
    top_30_weights.append(movie_weights[i])
```

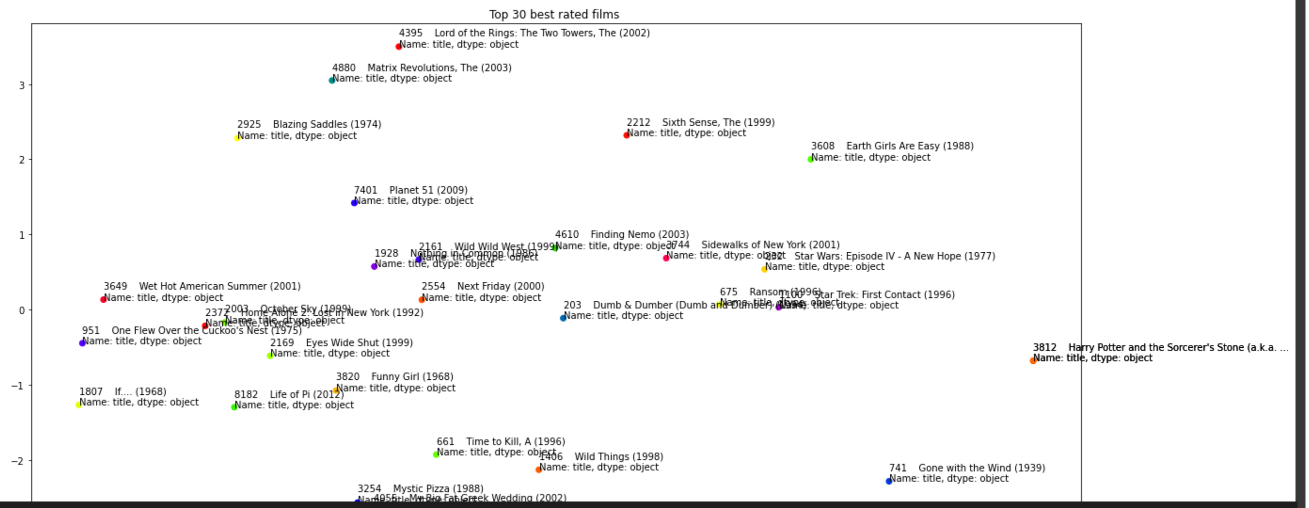
```
# Fit array of weights and condense to 2d
x = StandardScaler().fit_transform(top_30_weights)
pca = PCA(n_components=2)
x_2d = pca.fit_transform(x)

# Plot
x = x_2d[:,0]
y = x_2d[:,1]
plt.scatter(x,y, c=np.arange(0,30), cmap='prism')
```

```
<matplotlib.collections.PathCollection at 0x7f3f7008ff10>
```



```
# Plot with movie names
fig,ax = plt.subplots(figsize = (20,10)) #better visibility
plt.title('Top 30 best rated films ')
ax.scatter(x,y, c=np.arange(0,30), cmap='prism')
annotations = pd.Series(movie_names).astype(str)
for i, label in enumerate(annotations):
    ax.annotate(label, (x[i], y[i]))
```


Top 30 best rated films
4395 Lord of the Rings: The Two Towers, The (2002) Name: title, dtype: object
4880 Matrix Revolutions, The (2003) Name: title, dtype: object
2925 Blazing Saddles (1974) Name: title, dtype: object
2212 Sixth Sense, The (1999) Name: title, dtype: object
3608 Earth Girls Are Easy (1988) Name: title, dtype: object
7401 Planet 51 (2009) Name: title, dtype: object
4610 Finding Nemo (2003) Name: title, dtype: object
2161 Wild Wild West (1999) Name: title, dtype: object
1928 Nothing in Common (1986) Name: title, dtype: object
3744 Sidewalks of New York (2001) Name: title, dtype: object
232 Star Wars: Episode IV - A New Hope (1977) Name: title, dtype: object
3649 Wet Hot American Summer (2001) Name: title, dtype: object
2554 Next Friday (2000) Name: title, dtype: object
675 Ransom (1996) Name: title, dtype: object
1100 Star Trek: First Contact (1996) Name: title, dtype: object
2003 October Sky (1999) Name: title, dtype: object
2372 Home Alone 2: Lost in New York (1992) Name: title, dtype: object
203 Dumb & Dumber (Dumb and Dumber) Name: title, dtype: object
951 One Flew Over the Cuckoo's Nest (1975) Name: title, dtype: object
2169 Eyes Wide Shut (1999) Name: title, dtype: object
3812 Harry Potter and the Sorcerer's Stone (a.k.a. ... Name: title, dtype: object
3820 Funny Girl (1968) Name: title, dtype: object
1807 If.... (1968) Name: title, dtype: object
8182 Life of Pi (2012) Name: title, dtype: object
661 Time to Kill, A (1996) Name: title, dtype: object
1406 Wild Things (1998) Name: title, dtype: object
741 Gone with the Wind (1939) Name: title, dtype: object
3254 Mystic Pizza (1988)
4056 My Big Fat Greek Wedding (2002)
3
2
1
0
−1
−2