Datalab Cup 4: Recommender Systems

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Overview

In this competition, you should design a recommender system that recommends movies to users. When a user queries your system with $(UserID, Timestamp)$, your system should **return a list of 10 movies in their MovieIDs** $(MovieID_1, MovieID_2, \cdots, MovieID_{10})$ which the user might be interested in.

Dataset

Please download the dataset here.

The dataset used in this competition is a modified version of the MovieLens Dataset. **However, training your model with the original MovieLens Dataset is prohibited. You should use the one provided by us**.

The provided dataset consists of three files: `ratings_train.csv`, `users.csv`, and `movies.csv`.

`ratings_train.csv`:

Interactions between users and movies in format $(UserID, MovieID, Rating, Timestamp)$. For each user, all interactions in this training set occur earlier than all the interactions corresponding to the same user in the testing set which we will use to evaluate your model.

- $UserID$: ID of the user.
- $MovieID$: ID of the movie.
- $Rating$: Rating score that the user gives to the movie.
- $Timestamp$: Timestamp of when the user rated the movie.

`users.csv`:

Features of all users in format $(UserID, Gender, Age, Occupation, ZipCode)$. Includes all users in the training and the testing set.

- $UserID$: ID of the user.
- $Gender$: Gender of the user.
- Age: Age interval to which the user belongs. The number represents the starting age of the interval.
- $Occupation$: Occupation class number of the user.
- $ZipCode$: ZIP code string of the user.

`movies.csv`:

Features of all movies in format $(MovieID, Title, Genres)$. Includes all movies in the training and the testing set.

- $MovieID$: ID of the movie.
- $Title$: Title of the movie.
- $Genres$: Genres of the movie. Multiple genres are separated by `|`.

In this competition, you can implement any recommender system. Here we provide an example model which implements the simplified version of Funk-SVD mentioned in class.

In [ ]:
```
import os
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import tensorflow as tf
from tqdm import tqdm
```

In [ ]:
```
gpus = tf.config.experimental.list_physical_devices('GPU')
if gpus:
    try:
        # Currently, memory growth needs to be the same across GPUs
        for gpu in gpus:
            tf.config.experimental.set_memory_growth(gpu, True)
        # Select GPU number 1
        tf.config.experimental.set_visible_devices(gpus[0], 'GPU')
        logical_gpus = tf.config.experimental.list_logical_devices('GPU')
        print(len(gpus), "Physical GPUs,", len(logical_gpus), "Logical GPUs")
    except RuntimeError as e:
        # Memory growth must be set before GPUs have been initialized
        print(e)
```

```
1 Physical GPUs, 1 Logical GPUs
```

Inspect the dataset

Let's load and inspect the three files `ratings_train.csv`, `users.csv`, and `movies.csv` in the dataset.

In [ ]:
```
DATASET_PATH = 'dataset'
USERS_PATH = os.path.join(DATASET_PATH, 'users.csv')
MOVIES_PATH = os.path.join(DATASET_PATH, 'movies.csv')
RATINGS_PATH = os.path.join(DATASET_PATH, 'ratings_train.csv')
```

In [ ]:
```
df_users = pd.read_csv(USERS_PATH)
df_users
```

Out[ ]:

	UserID	Gender	Age	Occupation	ZipCode
0	0	F	1	10	48067
1	1	M	56	16	70072
2	2	M	25	15	55117
3	3	M	45	7	02460
4	4	M	25	20	55455
...	...	...	...	...	...
6035	6035	F	25	15	32603
6036	6036	F	45	1	76006
6037	6037	F	56	1	14706
6038	6038	F	45	0	01060
6039	6039	M	25	6	11106

6040 rows × 5 columns

In [ ]:
```
df_movies = pd.read_csv(MOVIES_PATH)
df_movies
```

Out[ ]:

	MovieID	Title	Genres
0	0	Toy Story (1995)	Animation|Children's|Comedy
1	1	Jumanji (1995)	Adventure|Children's|Fantasy
2	2	Grumpier Old Men (1995)	Comedy|Romance
3	3	Waiting to Exhale (1995)	Comedy|Drama
4	4	Father of the Bride Part II (1995)	Comedy
...	...	...	...
3878	3947	Meet the Parents (2000)	Comedy
3879	3948	Requiem for a Dream (2000)	Drama
3880	3949	Tigerland (2000)	Drama
3881	3950	Two Family House (2000)	Drama
3882	3951	Contender, The (2000)	Drama|Thriller

3883 rows × 3 columns

In [ ]:
```
df_ratings = pd.read_csv(RATINGS_PATH)
df_ratings
```

Out[ ]:

	UserID	MovieID	Rating	Timestamp
0	6039	857	4	956703932
1	6039	2383	4	956703954
2	6039	592	5	956703954
3	6039	1960	4	956703977
4	6039	2018	5	956703977
...	...	...	...	...
939757	5949	1996	3	1046368734
939758	5949	1260	4	1046368750
939759	5949	3151	3	1046368831
939760	5949	3910	4	1046369026
939761	4957	2452	4	1046454260

939762 rows × 4 columns

Let's calculate how many users and movies are in the dataset. Note that `users.csv` and `movies.csv` contain features for all users and movies in **both the training set and the testing set** respectively. Thus, the calculated number of users and movies covers both the training set and the testing set. Also, there are some $MovieIDs$ that do not correspond to any movie, however, we will just ignore this fact.

In [ ]:
```
M_USERS = max(len(df_users['UserID'].unique()), df_users['UserID'].max() + 1)
N_ITEMS = max(len(df_movies['MovieID'].unique()), df_movies['MovieID'].max() + 1)
print(f'# of users: {M_USERS}, # of movies: {N_ITEMS}')
```

```
# of users: 6040, # of movies: 3952
```

Model Template

In this competition, to simulate the situation of an operating online recommender system, **we will sequentially feed the test input in ascending order of the timestamp to test your model, and we also allow you to update your model during testing**. This means your model will receive ground truth data from the testing set. To prevent disputes, we will ask you to upload your saved model to your Google Drive and submit the share link to the eeclass system, and we will then download and evaluate your model with an evaluation script. To make sure the evaluation process can be successfully executed, your model should follow the template below. Your model should inherit the `tf.keras.Model` class and at least implement the three methods: `call()`, `eval_predict_onestep()`, and `eval_update_onestep()`. Note that the `@tf.function` decorators on these methods are necessary for `model.save()` to record and save these methods.

In [ ]:
```
class RecommenderTemplate(tf.keras.Model):
    '''
    Template model class for competition 4
    '''

    @tf.function
    def call(self, data: tf.Tensor) -> tf.Tensor:
        '''
        Please remember to implement this method and use it by calling self() or your_model_name() at least once during training
        This method is crucial for model.save() to successfully save your model
```

```
        '''
        pass

    @tf.function
    def eval_predict_onestep(self, query: tf.Tensor) -> tf.Tensor:
        '''
        Retrieve and return the MovieIDs of the 10 recommended movies given a query
        You should return a tf.Tensor with shape=(10,)
        query will be a tf.Tensor with shape=(2,) and dtype=tf.int64
        query[0] is the UserID of the query
        query[1] is the Timestamp of the query
        Please make sure you have called this method at least once before calling model.save()
        '''
        pass

    @tf.function
    def eval_update_onestep(self, data: tf.Tensor) -> None:
        '''
        Update your model with the ground truth data of the last query
        If your model does not require test-time updating, you should still define this method and leave it empty
        data will be a tf.Tensor with shape=(4,) and dtype=tf.int64
        data[0] is the UserID
        data[1] is the MovieID
        data[2] is the Rating
        data[3] is the Timestamp
        Please make sure you have called this method at least once before calling model.save()
        '''
        pass
```

Model

Here we provide an implementation of a simplified version of the Funk-SVD model.

In [ ]:
```
class FunkSVDRecommender(tf.keras.Model):
    '''
    Simplified Funk-SVD recommender model
    '''

    def __init__(self, m_users: int, n_items: int, embedding_size: int, learning_rate: float):
        '''
        Constructor of the model
        '''
        super().__init__()
        self.m = m_users
        self.n = n_items
        self.k = embedding_size
        self.lr = learning_rate

        # user embeddings P
        self.P = tf.Variable(tf.keras.initializers.RandomNormal()(shape=(self.m, self.k)))

        # item embeddings Q
        self.Q = tf.Variable(tf.keras.initializers.RandomNormal()(shape=(self.n, self.k)))

        # optimizer
        self.optimizer = tf.optimizers.Adam(learning_rate=self.lr)

    @tf.function
    def call(self, user_ids: tf.Tensor, item_ids: tf.Tensor) -> tf.Tensor:
        '''
        Forward pass used in training and validating
        '''
        # dot product the user and item embeddings corresponding to the observed interaction pairs to produce predictions
        y_pred = tf.reduce_sum(tf.gather(self.P, indices=user_ids) * tf.gather(self.Q, indices=item_ids), axis=1)

        return y_pred

    @tf.function
    def compute_loss(self, y_true: tf.Tensor, y_pred: tf.Tensor) -> tf.Tensor:
        '''
        Compute the MSE loss of the model
        '''
        loss = tf.losses.mean_squared_error(y_true, y_pred)

        return loss

    @tf.function
    def train_step(self, data: tf.Tensor) -> tf.Tensor:
        '''
        Train the model with one batch
        data: batched user-item interactions
        each record in data is in the format [UserID, MovieID, Rating, Timestamp]
        '''
        user_ids = tf.cast(data[:, 0], dtype=tf.int32)
        item_ids = tf.cast(data[:, 1], dtype=tf.int32)
        y_true = tf.cast(data[:, 2], dtype=tf.float32)

        # compute loss
        with tf.GradientTape() as tape:
            y_pred = self(user_ids, item_ids)
            loss = self.compute_loss(y_true, y_pred)

        # compute gradients
        gradients = tape.gradient(loss, self.trainable_variables)

        # update weights
        self.optimizer.apply_gradients(zip(gradients, self.trainable_variables))

        return loss

    @tf.function
    def val_step(self, data: tf.Tensor) -> tf.Tensor:
        '''
        Validate the model with one batch
        data: batched user-item interactions
        each record in data is in the format [UserID, MovieID, Rating, Timestamp]
        '''
```

```
        user_ids = tf.cast(data[:, 0], dtype=tf.int32)
        item_ids = tf.cast(data[:, 1], dtype=tf.int32)
        y_true = tf.cast(data[:, 2], dtype=tf.float32)

        # compute loss
        y_pred = self(user_ids, item_ids)
        loss = self.compute_loss(y_true, y_pred)

        return loss

    @tf.function
    def eval_predict_onestep(self, query: tf.Tensor) -> tf.Tensor:
        '''
        Retrieve and return the MovieIDs of the 10 recommended movies given a query
        You should return a tf.Tensor with shape=(10,)
        query will be a tf.Tensor with shape=(2,) and dtype=tf.int64
        query[0] is the UserID of the query
        query[1] is the Timestamp of the query
        Please make sure you have called this method at least once before calling model.save()
        '''
        # dot product the selected user and all item embeddings to produce predictions
        user_id = tf.cast(query[0], tf.int32)
        y_pred = tf.reduce_sum(tf.gather(self.P, user_id) * self.Q, axis=1)

        # select the top 10 items with highest scores in y_pred
        y_top_10 = tf.math.top_k(y_pred, k=10).indices

        return y_top_10

    @tf.function
    def eval_update_onestep(self, data: tf.Tensor) -> None:
        '''
        Update your model with the ground truth data of the last query
        If your model does not require test-time updating, you should still define this method and leave it empty
        data will be a tf.Tensor with shape=(4,) and dtype=tf.int64
        data[0] is the UserID
        data[1] is the MovieID
        data[2] is the Rating
        data[3] is the Timestamp
        Please make sure you have called this method at least once before calling model.save()
        '''
        pass
```

Split datasets

Since the testing set is not provided, splitting a validation set is highly recommended. We recommend first creating per-user validation sets with the latest interactions of each user (should also contain sufficient positive interactions), then joining all small validation sets to form a complete validation set since this is the exact way the testing set is created.

In [ ]:

```
# interactions with rating >= 4 are positive interactions
POSITIVE_THRESHOLD = 4

# each per-user validation set should contain at least 5 positive interactions
POSITIVE_PER_USER = 5

train_dataframes = []
val_dataframes = []

for i in tqdm(range(M_USERS)):
    user_all = df_ratings[df_ratings['UserID'] == i]
    user_positive = user_all[user_all['Rating'] >= POSITIVE_THRESHOLD]

    # check if there are enough positive interactions to build a validation set for this user
    if len(user_positive) >= POSITIVE_PER_USER:
        split_idx = user_positive.iloc[-POSITIVE_PER_USER].name
        user_train = user_all.loc[:split_idx]
        user_test = user_all.loc[split_idx:]
        assert user_train['Timestamp'].max() <= user_test['Timestamp'].min()
        train_dataframes.append(user_train)
        val_dataframes.append(user_test)
    else:
        train_dataframes.append(user_all)

# concat all per-user training sets
df_train = pd.concat(train_dataframes).sort_values(by='Timestamp', ascending=True, ignore_index=True)

# normalize the ratings (may be beneficial to some models)
df_train_norm = df_train
df_train_norm['Rating'] -= 3
df_train_norm['Rating'] /= 2

# concat all per-user validation sets
df_val = pd.concat(val_dataframes).sort_values(by='Timestamp', ascending=True, ignore_index=True)

# normalize the ratings (may be beneficial to some models)
# here we make a copy of the un-normalized validation set for evaluation
df_val_norm = df_val.copy(deep=True)
df_val_norm['Rating'] -= 3
df_val_norm['Rating'] /= 2
```

```
100%|██████████| 6040/6040 [00:08<00:00, 696.21it/s]
```

In [ ]:

```
df_train_norm
```

Out[ ]:

	UserID	MovieID	Rating	Timestamp
0	6039	857	0.5	956703932
1	6039	592	1.0	956703954
2	6039	2383	0.5	956703954
3	6039	2018	1.0	956703977
4	6039	1960	0.5	956703977
...	...	...	...	...
893652	5949	2857	0.0	1046368290
893653	5949	2663	0.0	1046368398
893654	5949	1299	0.5	1046368398
893655	5949	1195	0.5	1046368417
893656	5949	1357	0.5	1046368429

893657 rows × 4 columns

In [ ]:

```
df_val_norm
```

Out[ ]:

	UserID	MovieID	Rating	Timestamp
0	6038	2018	0.5	956706538
1	6038	1251	0.5	956706538
2	6038	922	0.5	956706538
3	6037	2715	0.0	956707604
4	6037	3547	0.5	956707604
...	...	...	...	...
52084	5949	1996	0.0	1046368734
52085	5949	1260	0.5	1046368750
52086	5949	3151	0.0	1046368831
52087	5949	3910	0.5	1046369026
52088	4957	2452	0.5	1046454260

52089 rows × 4 columns

Evaluation metric

For the evaluation metric, we will use a modified version of $NDCG@10$ specifically for this task to evaluate the performance of your model.

$$NDCG@10 = \begin{cases} \frac{1}{log2(i_A+1)}, & \text{if } A \in \mathbf{Y}, \text{ where } A \text{ is the ground truth item, } \mathbf{Y} \text{ is the predicted items, and } i_A \text{ is the index of } A \text{ in } \mathbf{Y} \\ 0, & \text{otherwise} \end{cases}$$

Also, $Recall@10$ (same as $HitRate@10$ in this task) will be calculated. However, it is just for your reference and does not account for the performance score.

While evaluating your test performance, we will use an evaluation procedure very similar to the `evaluate()` function below. However, the `evaluate()` function provided here is just for validating your training performance.

For all evaluation rounds, we will ask you to upload your saved model to your Google Drive and submit the share link to the eeclass system, and we will then download and evaluate your model with an evaluation script. A download link to a sample evaluation script that uses part of the training set is provided here. Please make sure your saved model can be loaded and evaluated by the sample evaluation script. Note that the evaluation procedure will not provide any features of the users and the movies. If you want to use them during evaluation, you should store them in your model while training.

Note that we define an interaction as positive if its rating is >= 4. For score calculating, e.g., $NDCG@10$, we will only invoke your model to make recommendations for queries that the ground truth interaction is positive. However, since neutral or negative interactions may still aid your model, we will invoke your model to perform the evaluation-stage update regardless of the ratings of the data points.

In [ ]:

```
@tf.function
def log2(x: tf.Tensor) -> tf.Tensor:
    return tf.math.log(tf.cast(x, tf.float32)) / tf.math.log(2.)

@tf.function
def ndcg_at_10(y_true: tf.Tensor, y_pred: tf.Tensor) -> tf.Tensor:
    y_pred = y_pred[:10]
    idx = tf.equal(tf.cast(y_pred, tf.int32), tf.cast(y_true, tf.int32))
    if tf.reduce_sum(tf.cast(idx, tf.int32)) > 0:
        return 1. / log2(2 + tf.argmax(idx))
    else:
        return tf.constant(0.)

@tf.function
def recall_at_10(y_true: tf.Tensor, y_pred: tf.Tensor) -> tf.Tensor:
    y_pred = y_pred[:10]
    idx = tf.equal(tf.cast(y_pred, tf.int32), tf.cast(y_true, tf.int32))
    if tf.reduce_sum(tf.cast(idx, tf.int32)) > 0:
        return tf.constant(1.)
    else:
        return tf.constant(0.)

def evaluate(model: tf.keras.Model, dataset: tf.data.Dataset) -> tuple:
    '''
    For each data point in the dataset:
    data[0] is the UserID
    data[1] is the MovieID
    data[2] is the Rating
    data[3] is the Timestamp
    '''
    ndcg_scores = []
    recall_scores = []

    for data in tqdm(dataset, desc='Evaluating'):
        # query the model to make predictions if the observed event is a positive interaction (ratings >= 4)
```

```python
        if data[2] >= 4:
            y_pred = model.eval_predict_onestep(tf.gather(data, (0, 3)))
            y_true = tf.gather(data, 1)
            ndcg = ndcg_at_10(y_true, y_pred)
            recall = recall_at_10(y_true, y_pred)
            ndcg_scores.append(ndcg)
            recall_scores.append(recall)

        # update the model with the observerd event
        model.eval_update_onestep(data)

    ndcg_result = tf.reduce_mean(ndcg_scores).numpy()
    recall_result = tf.reduce_mean(recall_scores).numpy()

    return ndcg_result, recall_result
```

Train the model

In [ ]:

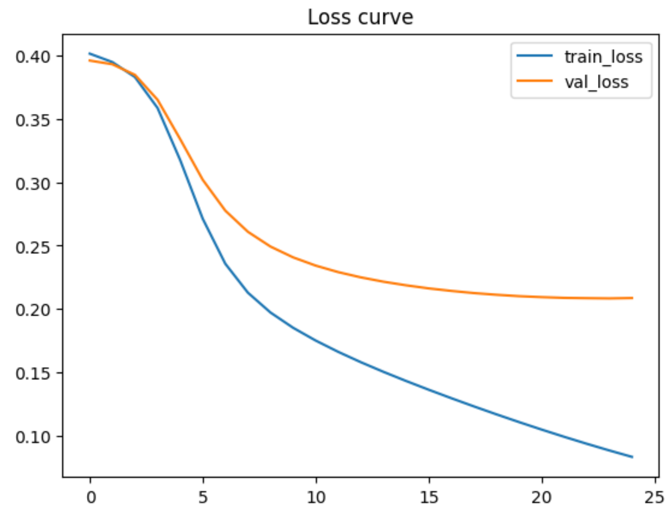
```python
# hyperparameters
EMBEDDING_SIZE = 256
BATCH_SIZE = 512
N_EPOCHS = 25
LEARNING_RATE = 1e-4
```

In [ ]:

```python
# prepare datasets
dataset_train = tf.data.Dataset.from_tensor_slices(df_train_norm)
dataset_train = dataset_train.batch(batch_size=BATCH_SIZE, num_parallel_calls=tf.data.AUTOTUNE).prefetch(buffer_size=tf.data.AUTOTUNE)

dataset_val = tf.data.Dataset.from_tensor_slices(df_val_norm)
dataset_val = dataset_val.batch(batch_size=BATCH_SIZE, num_parallel_calls=tf.data.AUTOTUNE).prefetch(buffer_size=tf.data.AUTOTUNE)

# build the model
model = FunkSVDRecommender(m_users=M_USERS, n_items=N_ITEMS, embedding_size=EMBEDDING_SIZE, learning_rate=LEARNING_RATE)

# train the model
train_losses = []
val_losses = []

for epoch in range(1, N_EPOCHS + 1):
    train_loss = []
    val_loss = []
    print(f'Epoch {epoch}:')

    # training
    for data in tqdm(dataset_train, desc='Training'):
        loss = model.train_step(data)
        train_loss.append(loss.numpy())

    # validating
    for data in tqdm(dataset_val, desc='Validating'):
        loss = model.val_step(data)
        val_loss.append(loss.numpy())

    # record losses
    avg_train_loss = np.mean(train_loss)
    avg_val_loss = np.mean(val_loss)
    train_losses.append(avg_train_loss)
    val_losses.append(avg_val_loss)

    # print losses
    print(f'Epoch {epoch} train_loss: {avg_train_loss:.4f}, val_loss: {avg_val_loss:.4f}\n')

# plot the training curve
plt.plot(train_losses, label='train_loss')
plt.plot(val_losses, label='val_loss')
plt.legend(loc='upper right')
plt.title('Loss curve')
plt.show()
```

```
Epoch 1:
Training: 100%|██████████| 1746/1746 [00:05<00:00, 337.51it/s]
Validating: 100%|██████████| 102/102 [00:00<00:00, 524.48it/s]
Epoch 1 train_loss: 0.4015, val_loss: 0.3960

Epoch 2:
Training: 100%|██████████| 1746/1746 [00:04<00:00, 367.21it/s]
Validating: 100%|██████████| 102/102 [00:00<00:00, 1262.62it/s]
Epoch 2 train_loss: 0.3948, val_loss: 0.3931

Epoch 3:
Training: 100%|██████████| 1746/1746 [00:04<00:00, 385.18it/s]
Validating: 100%|██████████| 102/102 [00:00<00:00, 1262.64it/s]
Epoch 3 train_loss: 0.3830, val_loss: 0.3847

Epoch 4:
Training: 100%|██████████| 1746/1746 [00:04<00:00, 401.76it/s]
Validating: 100%|██████████| 102/102 [00:00<00:00, 1232.22it/s]
Epoch 4 train_loss: 0.3586, val_loss: 0.3651

Epoch 5:
Training: 100%|██████████| 1746/1746 [00:04<00:00, 392.67it/s]
Validating: 100%|██████████| 102/102 [00:00<00:00, 1278.40it/s]
Epoch 5 train_loss: 0.3176, val_loss: 0.3341

Epoch 6:
Training: 100%|██████████| 1746/1746 [00:04<00:00, 395.57it/s]
Validating: 100%|██████████| 102/102 [00:00<00:00, 1217.53it/s]
Epoch 6 train_loss: 0.2712, val_loss: 0.3020

Epoch 7:
Training: 100%|██████████| 1746/1746 [00:04<00:00, 379.49it/s]
Validating: 100%|██████████| 102/102 [00:00<00:00, 1247.24it/s]
Epoch 7 train_loss: 0.2357, val_loss: 0.2776

Epoch 8:
```

```
Training: 100%|██████████| 1746/1746 [00:04<00:00, 395.21it/s]
Validating: 100%|██████████| 102/102 [00:00<00:00, 1262.63it/s]
Epoch 8 train_loss: 0.2129, val_loss: 0.2609

Epoch 9:
Training: 100%|██████████| 1746/1746 [00:04<00:00, 396.38it/s]
Validating: 100%|██████████| 102/102 [00:00<00:00, 1247.24it/s]
Epoch 9 train_loss: 0.1972, val_loss: 0.2493

Epoch 10:
Training: 100%|██████████| 1746/1746 [00:04<00:00, 400.41it/s]
Validating: 100%|██████████| 102/102 [00:00<00:00, 1222.92it/s]
Epoch 10 train_loss: 0.1852, val_loss: 0.2408

Epoch 11:
Training: 100%|██████████| 1746/1746 [00:04<00:00, 387.81it/s]
Validating: 100%|██████████| 102/102 [00:00<00:00, 1232.20it/s]
Epoch 11 train_loss: 0.1751, val_loss: 0.2342

Epoch 12:
Training: 100%|██████████| 1746/1746 [00:04<00:00, 390.69it/s]
Validating: 100%|██████████| 102/102 [00:00<00:00, 1247.23it/s]
Epoch 12 train_loss: 0.1662, val_loss: 0.2291

Epoch 13:
Training: 100%|██████████| 1746/1746 [00:04<00:00, 368.12it/s]
Validating: 100%|██████████| 102/102 [00:00<00:00, 1111.65it/s]
Epoch 13 train_loss: 0.1580, val_loss: 0.2250

Epoch 14:
Training: 100%|██████████| 1746/1746 [00:04<00:00, 360.70it/s]
Validating: 100%|██████████| 102/102 [00:00<00:00, 1123.86it/s]
Epoch 14 train_loss: 0.1504, val_loss: 0.2215

Epoch 15:
Training: 100%|██████████| 1746/1746 [00:04<00:00, 363.75it/s]
Validating: 100%|██████████| 102/102 [00:00<00:00, 1111.67it/s]
Epoch 15 train_loss: 0.1432, val_loss: 0.2187

Epoch 16:
Training: 100%|██████████| 1746/1746 [00:04<00:00, 366.34it/s]
Validating: 100%|██████████| 102/102 [00:00<00:00, 1123.88it/s]
Epoch 16 train_loss: 0.1363, val_loss: 0.2163

Epoch 17:
Training: 100%|██████████| 1746/1746 [00:04<00:00, 366.08it/s]
Validating: 100%|██████████| 102/102 [00:00<00:00, 1081.72it/s]
Epoch 17 train_loss: 0.1297, val_loss: 0.2143

Epoch 18:
Training: 100%|██████████| 1746/1746 [00:04<00:00, 370.40it/s]
Validating: 100%|██████████| 102/102 [00:00<00:00, 1136.37it/s]
Epoch 18 train_loss: 0.1232, val_loss: 0.2126

Epoch 19:
Training: 100%|██████████| 1746/1746 [00:04<00:00, 373.74it/s]
Validating: 100%|██████████| 102/102 [00:00<00:00, 1162.20it/s]
Epoch 19 train_loss: 0.1169, val_loss: 0.2112

Epoch 20:
Training: 100%|██████████| 1746/1746 [00:04<00:00, 370.71it/s]
Validating: 100%|██████████| 102/102 [00:00<00:00, 1149.13it/s]
Epoch 20 train_loss: 0.1108, val_loss: 0.2101

Epoch 21:
Training: 100%|██████████| 1746/1746 [00:04<00:00, 365.57it/s]
Validating: 100%|██████████| 102/102 [00:00<00:00, 1111.66it/s]
Epoch 21 train_loss: 0.1049, val_loss: 0.2094

Epoch 22:
Training: 100%|██████████| 1746/1746 [00:04<00:00, 366.24it/s]
Validating: 100%|██████████| 102/102 [00:00<00:00, 1123.88it/s]
Epoch 22 train_loss: 0.0992, val_loss: 0.2088

Epoch 23:
Training: 100%|██████████| 1746/1746 [00:04<00:00, 363.96it/s]
Validating: 100%|██████████| 102/102 [00:00<00:00, 1149.11it/s]
Epoch 23 train_loss: 0.0937, val_loss: 0.2085

Epoch 24:
Training: 100%|██████████| 1746/1746 [00:04<00:00, 376.63it/s]
Validating: 100%|██████████| 102/102 [00:00<00:00, 1142.49it/s]
Epoch 24 train_loss: 0.0884, val_loss: 0.2084

Epoch 25:
Training: 100%|██████████| 1746/1746 [00:04<00:00, 378.08it/s]
Validating: 100%|██████████| 102/102 [00:00<00:00, 1141.70it/s]
Epoch 25 train_loss: 0.0833, val_loss: 0.2087
```



Evaluate the model with the validation set

This part is just for you to check the validation performance. We will use a private testing set to evaluate the performance of your model.

In [ ]:
```
dataset_eval = tf.data.Dataset.from_tensor_slices(df_val)
dataset_eval = dataset_eval.prefetch(buffer_size=tf.data.AUTOTUNE)
ndcg_result, recall_result = evaluate(model, dataset_eval)
print(f'Evaluation result: [NDCG@10: {ndcg_result:.6f}, Recall@10: {recall_result:.6f}]')
```

```
Evaluating: 100%|██████████| 52089/52089 [01:51<00:00, 468.22it/s]
Evaluation result: [NDCG@10: 0.021212, Recall@10: 0.041644]
```

Save the model

Please remember to save your model and make sure the saved model can be loaded and evaluated by the sample evaluation script provided here.

We recommend you first evaluate your model with the `evaluate()` function defined above, then save your model. This ensures the custom methods `eval_predict_onestep()` and `eval_update_onestep()` are both called and tracked.

In [ ]:
```
# save the model
model.save('funksvd_model')
```

```
INFO:tensorflow:Assets written to: funksvd_model\assets
```

Precautions

What you should do in this competition

0. Design a recommender system that recommends movies to users.

When a user queries your system with $(UserID, Timestamp)$, your system should **return a list of 10 movies in their MovieIDs** $(MovieID_1, MovieID_2, \cdots, MovieID_{10})$ which the user might be interested in.

1. Download the dataset here and the sample evaluation script here.

Please refer to the previous part of the notebook for more detail about the dataset.

2. Implement and train a recommender system with the provided dataset. Your model should follow the template below.

In this competition, to simulate the situation of an operating online recommender system, **we will sequentially feed the test input in ascending order of the timestamp to test your model, and we also allow you to update your model during testing**. This means your model will receive ground truth data from the testing set. To prevent disputes, we will ask you to upload your saved model to your Google Drive and submit the share link to the eeclass system, and we will then download and evaluate your model with an evaluation script. To make sure the evaluation process can be successfully executed, your model should follow the template below. Your model should inherit the `tf.keras.Model` class and at least implement the three methods: `call()`, `eval_predict_onestep()`, and `eval_update_onestep()`. Note that the `@tf.function` decorators on these methods are necessary for `model.save()` to record and save these methods.

Note: Since the evaluation script will not provide user and movie features while testing your model, you should save these features in your model during training if you utilize them in `eval_predict_onestep()` or `eval_update_onestep()`.

In [ ]:
```
class RecommenderTemplate(tf.keras.Model):
    '''
    Template model class for competition 4
    '''

    @tf.function
    def call(self, data: tf.Tensor) -> tf.Tensor:
        '''
        Please remember to implement this method and use it by calling self() or your_model_name() at least once during training
        This method is crucial for model.save() to successfully save your model
        '''
        pass

    @tf.function
    def eval_predict_onestep(self, query: tf.Tensor) -> tf.Tensor:
        '''
        Retrieve and return the MovieIDs of the 10 recommended movies given a query
        You should return a tf.Tensor with shape=(10,)
        query will be a tf.Tensor with shape=(2,) and dtype=tf.int64
        query[0] is the UserID of the query
        query[1] is the Timestamp of the query
        Please make sure you have called this method at least once before calling model.save()
```

```
        '''
        pass

    @tf.function
    def eval_update_onestep(self, data: tf.Tensor) -> None:
        '''
        Update your model with the ground truth data of the last query
        If your model does not require test-time updating, you should still define this method and leave it empty
        data will be a tf.Tensor with shape=(4,) and dtype=tf.int64
        data[0] is the UserID
        data[1] is the MovieID
        data[2] is the Rating
        data[3] is the Timestamp
        Please make sure you have called this method at least once before calling model.save()
        '''
        pass
```

3. Save your entire model with `model.save()` and verify if it can be loaded and evaluated by the sample evaluation script.

To execute the sample evaluation script, type the command below (please replace the paths with actual values):

```
python evaluate_sample.py [path to ratings_train.csv] [path to your saved model]
```

If you have tried your best debugging but still failed to make the evaluation script evaluate your model successfully, please contact the TAs with the eeclass discussion forum.

4. Participate in evaluation rounds **(One submission per group in each round)**.

To evaluate your model, we will use a private testing set and an evaluation script similar to the provided sample evaluation script to test your model. There will be three evaluation rounds, and **we will use the same testing set in all rounds**.

For each evaluation round, we will open an eeclass assignment for submission. You should upload your model to your Google Drive and submit the share link to the corresponding assignment. The first two evaluation rounds are optional. However, **all groups should submit your model in the final evaluation round. Only the model performance in the final evaluation round will account for your score.**

The deadline for model submission in the final evaluation round is 2023/01/13 (Fri) 23:59 (UTC+8).

5. Write a report after the final evaluation (One report per group).

Your report should contain:

- Models you have tried during the competition. Please briefly describe the main idea of the model and the reason why you chose that model.
- List the experiments you have done. For instance, data preprocessing, hyperparameters tuning, architecture tuning, optimizer tuning, and so on.
- Discussions, lessons learned, or anything else worth mentioning.

The deadline for report submission is 2023/01/15 (Sun) 23:59 (UTC+8).

What you can do

- Implement any recommender model with any packages in TensorFlow 2.
- **Train your recommender model with the provided dataset from scratch**.
- Update your model during evaluation by implementing `eval_update_onestep()`.
- Save the user and movie features in your model since we will not provide them during evaluation.
- You can use a pretrained text encoder if you need text embeddings. **(This is the only place you can use a pretrained model in this competition)**

What you CAN NOT do

- **Use any dataset other than the provided one. Using any official MovieLens datasets is also prohibited.**
- **Use any pretrained recommender models.**
- Plagiarize other teams' work.
- Hack or crash our evaluation platform with your submitted saved models.

Scoring

- $NDCG@10$ ranking of the **final evaluation round** (80%)
- Report (20%)

Important dates

- 2022/12/29 (Thur): Competition starts
- 2023/01/03 (Tue): First round of evaluation (optional)
- 2023/01/08 (Sun): Second round of evaluation (optional)
- 2023/01/13 (Fri): Final round of evaluation **(mandatory)**
- 2023/01/15 (Sun): Report submission
- 2023/01/17 (Tue): Competition 4 showoff