Implicit Feedback

In [1]:
```
import numpy as np
import pandas as pd
```

In [2]:
```
ratings = pd.read_csv("/tf/notebooks/data/data/ratings.csv")
users = pd.read_csv("/tf/notebooks/data/data/users.csv")
items = pd.read_csv("/tf/notebooks/data/data/items.csv")
```

In [3]:
```
from recoflow.utils import NegativeSamples
```

In [24]:
```
NegativeSamples??
```

```
Signature: NegativeSamples(df, rating_threshold, ratio_neg_per_user=1)
Source:
def NegativeSamples(df, rating_threshold, ratio_neg_per_user=1):
    """ function to sample negative feedback from user-item interaction dataset.

    This negative sampling function will take the user-item interaction data to create
    binarized feedback, i.e., 1 and 0 indicate positive and negative feedback,
    respectively.

    Args:
        df (pandas.DataFrame): input data that contains user-item tuples.
        rating_threshold (int): value below which feedback is set to 0 and above which feedback is set to 1
        ratio_neg_per_user (int): ratio of negative feedback w.r.t to the number of positive feedback for ea
ch user.

    Returns:
        pandas.DataFrame: data with negative feedback
    """

    df.columns = ["USER", "ITEM", "RATING", "unix_timestamp"]

    seed = 42

    df_pos = df.copy()
    df_pos["RATING"] = df_pos["RATING"].apply(lambda x: 1 if x >= rating_threshold else 0)
    df_pos = df_pos[df_pos.RATING>0]


    # Create a dataframe for all user-item pairs
    df_neg = _UserItemCrossJoin(df)

    #remove positive samples from the cross-join dataframe
    df_neg = _FilterBy(df_neg, df_pos, ["USER", "ITEM"])

    #Add a column for rating - setting it to 0
    df_neg["RATING"] = 0

    # Combine positive and negative samples into a single dataframe
    df_all = pd.concat([df_pos, df_neg], ignore_index=True, sort=True)
    df_all = df_all[["USER", "ITEM", "RATING"]]


    # Sample negative feedback from the combined dataframe.
    df_sample = (
        df_all.groupby("USER")
        .apply(
            lambda x: pd.concat(
```

```
                    [
                        x[x["RATING"] == 1],
                        x[x["RATING"] == 0].sample(
                            min(
                                max(
                                    round(len(x[x["RATING"] == 1]) * ratio_neg_per_user), 1
                                ),
                                len(x[x["RATING"] == 0]),
                            ),
                            random_state=seed,
                            replace=False,
                        )
                        if len(x[x["RATING"] == 0] > 0)
                        else pd.DataFrame({}, columns=["USER", "ITEM", "RATING"]),
                    ],
                    ignore_index=True,
                    sort=True,
                )
            )
            .reset_index(drop=True)
            .sort_values("USER")
        )

        df_sample.columns = ["movie_id", "rating", "user_id"]
        return df_sample[["user_id", "movie_id", "rating"]]
File:      /usr/local/lib/python3.6/dist-packages/recoflow/utils.py
Type:      function
```

In [4]:
```
df_implicit = NegativeSamples(ratings, rating_threshold=3, ratio_neg_per_user=1)
```

In [5]:
```
ratings.shape, df_implicit.shape
```

Out[5]:
```
((100000, 4), (165040, 3))
```

In [6]:
```
df_implicit.head()
```

Out[6]:

	user_id	movie_id	rating
0	1	61	1
298	1	866	0
297	1	510	0
296	1	102	0
295	1	886	0

In [7]:
```
df_implicit["unix_timestamp"] = 1
```

In [8]:
```
from recoflow. preprocessing import EncodeUserItem
```

In [10]:
```
# Data encoding

interaction, n_users, n_items, user_encoder, item_encoder = EncodeUserItem(df_implicit, "user_id", "movie_id",
"rating", "unix_timestamp")
```

```
Number of users:  943
Number of items:  1682
```

In [21]:
```
from recoflow.preprocessing import RandomSplit
```

In [22]:
```
train, test = RandomSplit(interaction, [0.8, 0.2])
```

In [11]:
```
max_rating = interaction.RATING.max()
min_rating = interaction.RATING.min()
min_rating, max_rating
```

Out[11]:
```
(0, 1)
```

Implicit Matrix Factorization

In [13]:
```
from keras.models import Model
from keras.layers import Input, Embedding, Flatten, Dot, Add, Lambda, Activation, Reshape
from keras.regularizers import l2
from keras.utils import plot_model
```

In [14]:
```
from recoflow.models import ExplicitMatrixFactorisationBias
```

In [15]:
```
ExplicitMatrixFactorisationBias??
```

```
Signature:
ExplicitMatrixFactorisationBias(
    n_users,
    n_items,
    n_factors,
    min_rating,
    max_rating,
)
Docstring: <no docstring>
Source:
def ExplicitMatrixFactorisationBias(n_users, n_items, n_factors, min_rating, max_rating):

    # Item Layer
    item_input = Input(shape=[1], name='Item')
    item_embedding = Embedding(n_items, n_factors, embeddings_regularizer=l2(1e-6), name='ItemEmbedding')(it
em_input)
    item_vec = Flatten(name='FlattenItemE')(item_embedding)

    # Item Bias
    item_bias = Embedding(n_items, 1, embeddings_regularizer=l2(1e-6), name='ItemBias')(item_input)
    item_bias_vec = Flatten(name='FlattenItemBiasE')(item_bias)

    # User Layer
    user_input = Input(shape=[1], name='User')
    user_embedding = Embedding(n_users, n_factors, embeddings_regularizer=l2(1e-6), name='UserEmbedding')(us
er_input)
    user_vec = Flatten(name='FlattenUserE')(user_embedding)

    # User Bias
    user_bias = Embedding(n_users, 1, embeddings_regularizer=l2(1e-6), name='UserBias')(user_input)
    user_bias_vec = Flatten(name='FlattenUserBiasE')(user_bias)

    # Dot Product of Item and User & then Add Bias
    DotProduct = Dot(axes=1, name='DotProduct')([item_vec, user_vec])
    AddBias = Add(name="AddBias")([DotProduct, item_bias_vec, user_bias_vec])

    # Scaling for each user
    y = Activation('sigmoid')(AddBias)
    rating_output = Lambda(lambda x: x * (max_rating - min_rating) + min_rating)(y)

    # Model Creation
    model = Model([user_input, item_input], rating_output, name="ExplicitMatrixFactorisationBias")

    # Compile Model
    model.compile(loss='mean_squared_error', optimizer=Adam(lr=0.001))

    return model
```

```
File:      /usr/local/lib/python3.6/dist-packages/recoflow/models.py
Type:      function
```

In [16]:
```
def ImplicitMatrixFactorisationBias(n_users, n_items, n_factors, min_rating, max_rating):

    # Item Layer
    item_input = Input(shape=[1], name='Item')
    item_embedding = Embedding(n_items, n_factors, embeddings_regularizer=l2(1e-6), name='ItemEmbedding')(item
_input)
    item_vec = Flatten(name='FlattenItemE')(item_embedding)

    # Item Bias
    item_bias = Embedding(n_items, 1, embeddings_regularizer=l2(1e-6), name='ItemBias')(item_input)
    item_bias_vec = Flatten(name='FlattenItemBiasE')(item_bias)

    # User Layer
    user_input = Input(shape=[1], name='User')
    user_embedding = Embedding(n_users, n_factors, embeddings_regularizer=l2(1e-6), name='UserEmbedding')(user
_input)
    user_vec = Flatten(name='FlattenUserE')(user_embedding)

    # User Bias
    user_bias = Embedding(n_users, 1, embeddings_regularizer=l2(1e-6), name='UserBias')(user_input)
    user_bias_vec = Flatten(name='FlattenUserBiasE')(user_bias)

    # Dot Product of Item and User & then Add Bias
    DotProduct = Dot(axes=1, name='DotProduct')([item_vec, user_vec])
    AddBias = Add(name="AddBias")([DotProduct, item_bias_vec, user_bias_vec])

    # Scaling for each user
    y = Activation('sigmoid')(AddBias)
    rating_output = Lambda(lambda x: x * (max_rating - min_rating) + min_rating)(y)

    # Model Creation
    model = Model([user_input, item_input], rating_output, name="ImplicitMatrixFactorisationBias")

    # Compile Model
    model.compile(loss='binary_crossentropy', optimizer="sgd")

    return model
```

In [18]:
```
n_factors = 40
model = ImplicitMatrixFactorisationBias(n_users, n_items, n_factors, min_rating, max_rating)
```

In [19]:
```
model.summary()
```

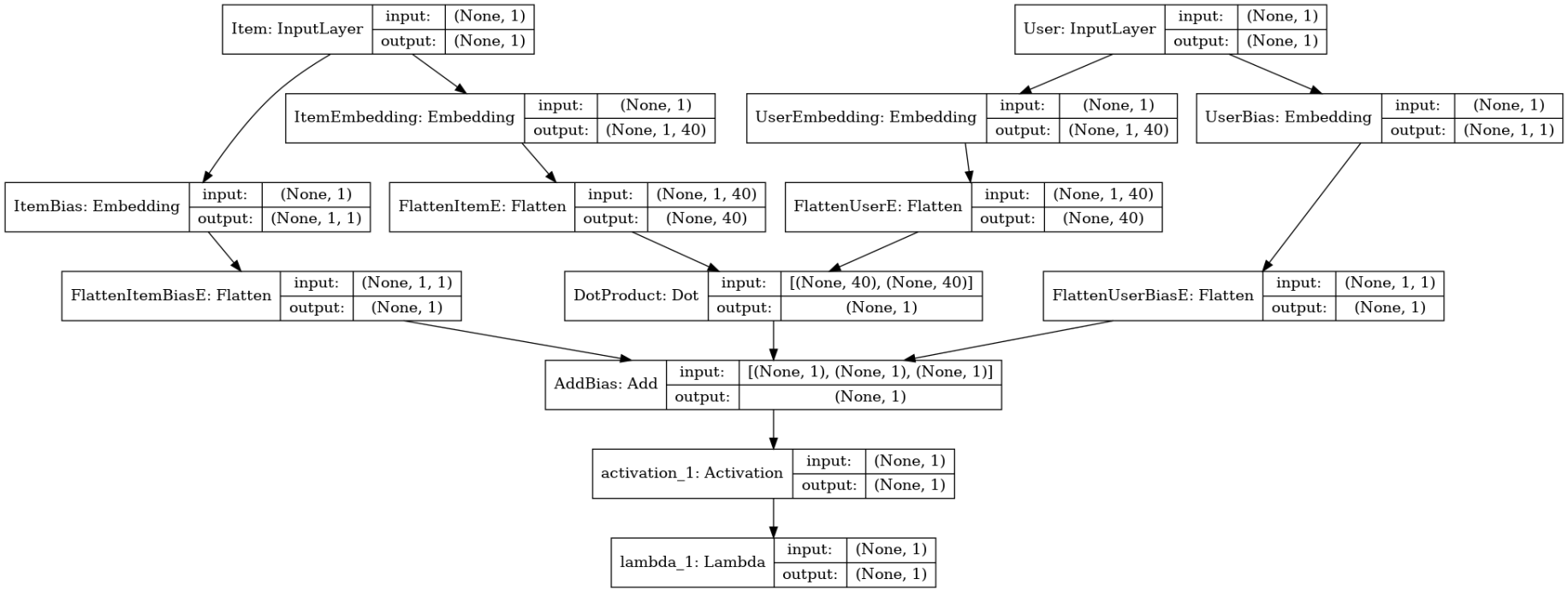
```
Model: "ImplicitMatrixFactorisationBias"
```

Layer (type)	Output Shape	Param #	Connected to
Item (InputLayer)	(None, 1)	0	
User (InputLayer)	(None, 1)	0	
ItemEmbedding (Embedding)	(None, 1, 40)	67280	Item[0][0]
UserEmbedding (Embedding)	(None, 1, 40)	37720	User[0][0]
FlattenItemE (Flatten)	(None, 40)	0	ItemEmbedding[0][0]
FlattenUserE (Flatten)	(None, 40)	0	UserEmbedding[0][0]
ItemBias (Embedding)	(None, 1, 1)	1682	Item[0][0]
UserBias (Embedding)	(None, 1, 1)	943	User[0][0]
DotProduct (Dot)	(None, 1)	0	FlattenItemE[0][0] FlattenUserE[0][0]
FlattenItemBiasE (Flatten)	(None, 1)	0	ItemBias[0][0]
FlattenUserBiasE (Flatten)	(None, 1)	0	UserBias[0][0]
AddBias (Add)	(None, 1)	0	DotProduct[0][0] FlattenItemBiasE[0][0] FlattenUserBiasE[0][0]
activation_1 (Activation)	(None, 1)	0	AddBias[0][0]
lambda_1 (Lambda)	(None, 1)	0	activation_1[0][0]

```
Total params: 107,625
Trainable params: 107,625
Non-trainable params: 0
```

In [20]:
```
plot_model(model, show_layer_names=True, show_shapes=True)
```

Out[20]:



Train the model

In [23]:
```
%%time
output = model.fit([train.USER, train.ITEM], train.RATING,
                   batch_size=128, epochs=5, verbose=1,
                   validation_data=([test.USER, test.ITEM], test.RATING))
```

```
WARNING:tensorflow:From /usr/local/lib/python3.6/dist-packages/tensorflow/python/ops/math_grad.py:1250: add_
dispatch_support.<locals>.wrapper (from tensorflow.python.ops.array_ops) is deprecated and will be removed i
n a future version.
Instructions for updating:
Use tf.where in 2.0, which has the same broadcast rule as np.where
WARNING:tensorflow:From /usr/local/lib/python3.6/dist-packages/keras/backend/tensorflow_backend.py:422: The
name tf.global_variables is deprecated. Please use tf.compat.v1.global_variables instead.

Train on 132032 samples, validate on 33008 samples
Epoch 1/5
132032/132032 [==============================] - 2s 14us/step - loss: 0.6933 - val_loss: 0.6929
Epoch 2/5
132032/132032 [==============================] - 2s 13us/step - loss: 0.6922 - val_loss: 0.6918
Epoch 3/5
132032/132032 [==============================] - 2s 12us/step - loss: 0.6912 - val_loss: 0.6908
Epoch 4/5
132032/132032 [==============================] - 2s 12us/step - loss: 0.6901 - val_loss: 0.6898
Epoch 5/5
132032/132032 [==============================] - 2s 12us/step - loss: 0.6891 - val_loss: 0.6887
CPU times: user 16.6 s, sys: 1.31 s, total: 17.9 s
Wall time: 8.68 s
```

Evaluate the Model

In [25]:
```
from recoflow.recommend import GetPredictions
```

In [26]:
```
%%time
predictions = GetPredictions(model, interaction)
```

```
CPU times: user 23.8 s, sys: 3.17 s, total: 26.9 s
Wall time: 17.1 s
```

In [27]:
```
predictions.head()
```

Out[27]:

	USER	ITEM	RATING
0	0	60	0.494863
1	0	865	0.497352
2	0	509	0.502310
3	0	101	0.500138
4	0	885	0.486868

In [51]:
```
from recoflow.recommend import GetRankingTopK
```

In [54]:
```
rankeditems = GetRankingTopK(model, interaction, train, k=3)
```

In [55]:
```
rankeditems.head()
```

Out[55]:

	USER	ITEM	RATING	rank
0	0	327	0.515287	1
1	0	470	0.515200	2
2	0	285	0.515196	3
3	0	654	0.514628	4
4	0	317	0.514491	5

In [28]:
```
from recoflow.metrics import RankingMetrics
```

In [29]:
```
RankingMetrics(test, predictions, k=10)
```

Out[29]:

	k	Precision@k	Recall@k	MAP@k	MRR@k	NDCG@k
0	10	0.3722	0.03	0.0167	0.2472	0.3836

In [30]:
```
from recoflow.datasets import SampleEvaluate
```

In [31]:
```
rating_test, rating_pred = SampleEvaluate()
```

In [50]:
```
RankingMetrics(rating_test, rating_pred, k=3)
```

Out[50]:

	k	Precision@k	Recall@k	MAP@k	MRR@k	NDCG@k
0	3	0.2222	0.1444	0.1278	0.1667	0.2551

In [47]:
```
rating_test[rating_test.USER == 2]
```

Out[47]:

	USER	ITEM	RATING
3	2	1	5
4	2	4	5
5	2	5	3
6	2	6	3
7	2	7	1

In [48]:
```
rating_pred[rating_pred.USER == 2]
```

Out[48]:

	USER	ITEM	RATING
3	2	10	14
4	2	3	13
5	2	11	12
6	2	5	11
7	2	13	10

In [36]:
```
from recoflow.metrics import PrecisionK, RecallK,
```

In [45]:
```
PrecisionK(rating_test, rating_pred, k=3 )
```

Out[45]: 0.2222222222222222

In [46]:
```
RecallK(rating_test, rating_pred, k=3 )
```

Out[46]: 0.14444444444444446

In [ ]:
```

```