

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 each 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')(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="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)
```

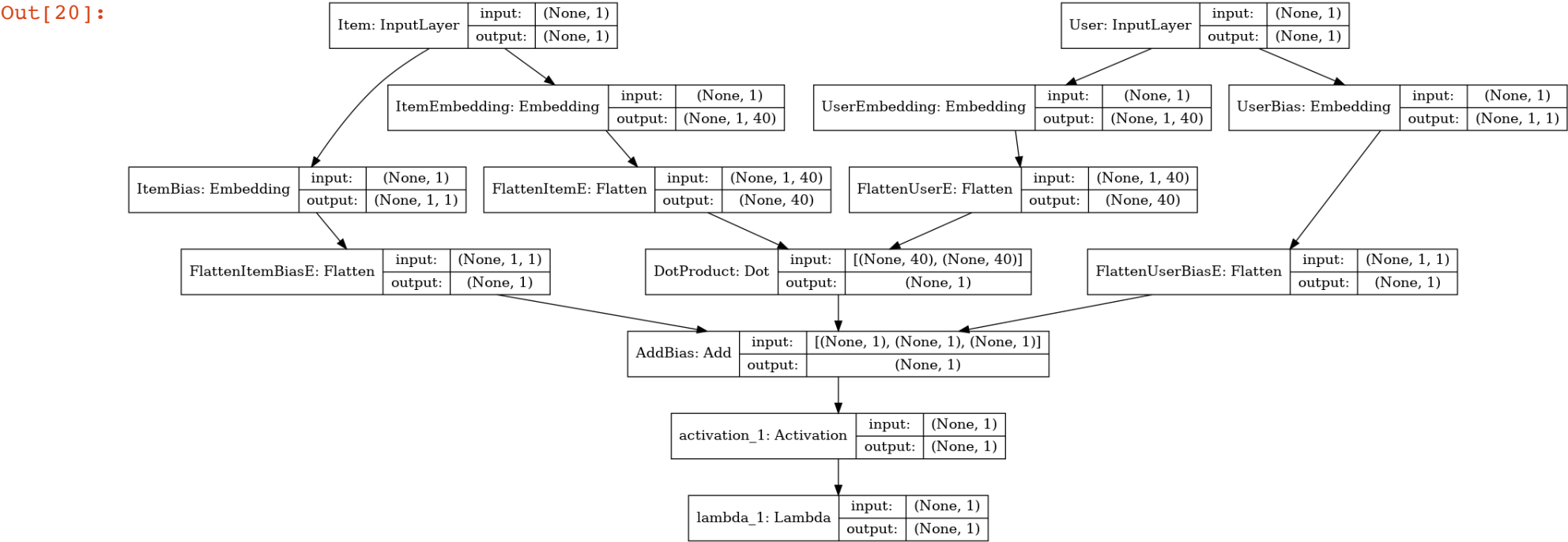


```
In [19]: model.summary()
```

Model: "ImplicitMatrixFactorisationBias"

Layer (type)	Output Shape	Param #	Connected to
=====			
Item (InputLayer)	(None, 1)	0	
<hr/>			
User (InputLayer)	(None, 1)	0	
<hr/>			
ItemEmbedding (Embedding)	(None, 1, 40)	67280	Item[0][0]
<hr/>			
UserEmbedding (Embedding)	(None, 1, 40)	37720	User[0][0]
<hr/>			
FlattenItemE (Flatten)	(None, 40)	0	ItemEmbedding[0][0]
<hr/>			
FlattenUserE (Flatten)	(None, 40)	0	UserEmbedding[0][0]
<hr/>			
ItemBias (Embedding)	(None, 1, 1)	1682	Item[0][0]
<hr/>			
UserBias (Embedding)	(None, 1, 1)	943	User[0][0]
<hr/>			
DotProduct (Dot)	(None, 1)	0	FlattenItemE[0][0] FlattenUserE[0][0]
<hr/>			
FlattenItemBiasE (Flatten)	(None, 1)	0	ItemBias[0][0]
<hr/>			
FlattenUserBiasE (Flatten)	(None, 1)	0	UserBias[0][0]
<hr/>			
AddBias (Add)	(None, 1)	0	DotProduct[0][0] FlattenItemBiasE[0][0] FlattenUserBiasE[0][0]
<hr/>			
activation_1 (Activation)	(None, 1)	0	AddBias[0][0]
<hr/>			
lambda_1 (Lambda)	(None, 1)	0	activation_1[0][0]
=====			
Total params: 107,625			
Trainable params: 107,625			
Non-trainable params: 0			
<hr/>			

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



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 [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 [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]: 0.144444444444444446
```

```
In [ ]:
```