

Matrix Factorisation

Classical Matrix Factorisation model used for Collaborative Filtering - Popularised by Netflix Competition

```
In [2]: import sys
sys.path.append("../")
```

```
In [3]: import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
```

```
In [4]: %matplotlib inline
```

Step 1: Load & Prepare the Data

Dataset from <https://grouplens.org/datasets/movielens/100k/> (<https://grouplens.org/datasets/movielens/100k/>)

```
In [5]: df_ratings = pd.read_csv("/tf/notebooks/data/data/ratings.csv")
```

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

```
Out[6]:
```

	user_id	movie_id	rating	unix_timestamp
0	196	242	3	881250949
1	186	302	3	891717742
2	22	377	1	878887116
3	244	51	2	880606923
4	166	346	1	886397596

```
In [7]: df_ratings.shape
```

```
Out[7]: (100000, 4)
```

```
In [8]: #Sparsity
df_ratings.shape[0]/ (df_ratings.user_id.nunique() * df_ratings.movie_id.nunique())
```

Out[8]: 0.06304669364224531

Data Transformation

- Encoding: Create User and Item Labels (Index) => Label Encoding
- Splitting: How do we split the data in train and test
- Ratings: Explicit or transform them into something else??

```
In [9]: from reco.preprocess import encode_user_item
```

```
In [10]: #encode_user_item??
```

```
In [11]: DATA, user_encoder, item_encoder = encode_user_item(df_ratings, "user_id", "movie_id",
                                                             "rating", "unix_timestamp")
```

Number of users: 943
Number of items: 1682

```
In [12]: DATA.head()
```

Out[12]:

	user_id	movie_id	RATING	TIMESTAMP	USER	ITEM
0	196	242	3	881250949	195	241
1	186	302	3	891717742	185	301
2	22	377	1	878887116	21	376
3	244	51	2	880606923	243	50
4	166	346	1	886397596	165	345

Data Splitting Strategy

- Random
- Stratified: For each user, split it by train and test
- Chronological: For each user, split it by train and test in chronological order

```
In [13]: from reco.preprocess import user_split, random_split
```

```
In [14]: #user_split??
```

```
In [15]: #train, val, test = user_split(DATA, [0.6, 0.2, 0.2])  
train, test = random_split(DATA, [0.8, 0.2])
```

Step 2: Build Model - Explicit Matrix Factorisation

```
In [16]: from keras.models import Model  
from keras.layers import Input, Embedding, Flatten, Add, Dot, Activation  
from keras.regularizers import l2  
from keras.utils import plot_model
```

Using TensorFlow backend.

```
In [17]: def ExplicitMF(n_users, n_items, n_factors):

    # 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)

    # 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)

    # Dot Product
    rating = Dot(axes=1, name="DotProduct")([item_vec, user_vec])

    # Model Creation
    model = Model([user_input, item_input], rating)

    # Compile
    model.compile(loss="mean_squared_error", optimizer="adam")

    return model
```

```
In [18]: n_users = DATA.USER.nunique()
n_items = DATA.ITEM.nunique()
```

```
In [19]: n_factors = 40
model = ExplicitMF(n_users, n_items, n_factors)
```

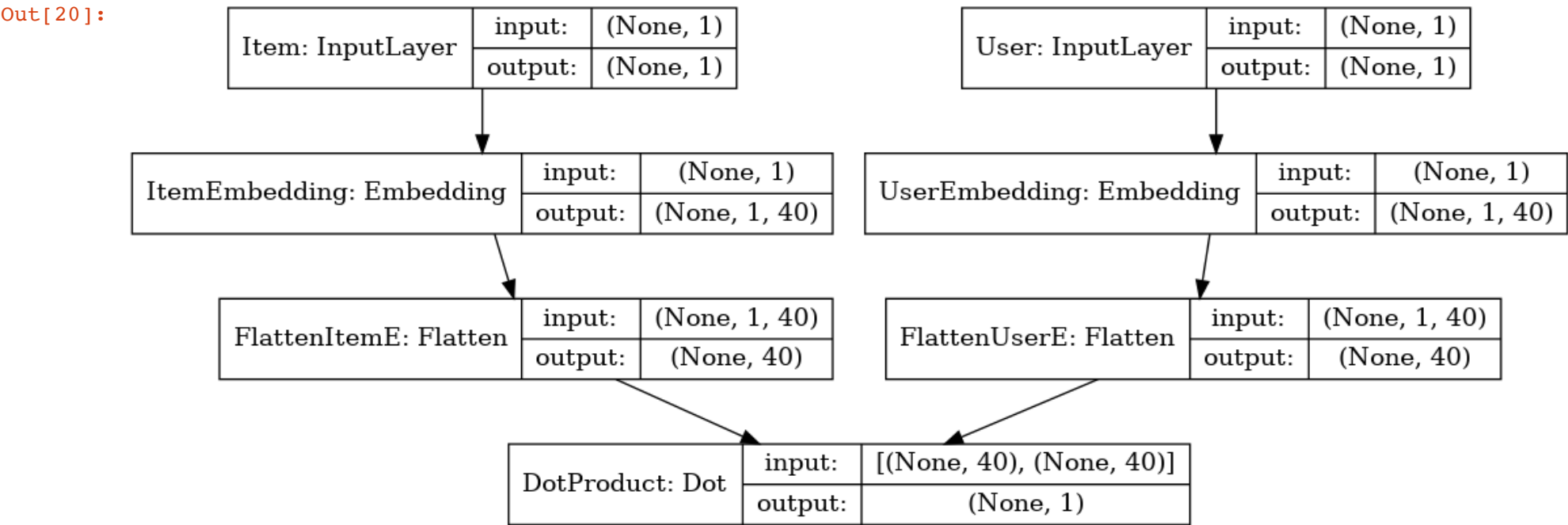
WARNING:tensorflow:From /usr/local/lib/python3.6/dist-packages/keras/backend/tensorflow_backend.py:541: The name tf.placeholder is deprecated. Please use tf.compat.v1.placeholder instead.

WARNING:tensorflow:From /usr/local/lib/python3.6/dist-packages/keras/backend/tensorflow_backend.py:4432: The name tf.random_uniform is deprecated. Please use tf.random.uniform instead.

WARNING:tensorflow:From /usr/local/lib/python3.6/dist-packages/keras/backend/tensorflow_backend.py:66: The name tf.get_default_graph is deprecated. Please use tf.compat.v1.get_default_graph instead.

WARNING:tensorflow:From /usr/local/lib/python3.6/dist-packages/keras/optimizers.py:793: The name tf.train.Optimizer is deprecated. Please use tf.compat.v1.train.Optimizer instead.

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



In [21]:

model.summary()

Model: "model_1"

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/>			
DotProduct (Dot)	(None, 1)	0	FlattenItemE[0][0] FlattenUserE[0][0]
=====			
Total params: 105,000			
Trainable params: 105,000			
Non-trainable params: 0			
<hr/>			

In [22]:

n_users * 40, n_items * 40

Out[22]: (37720, 67280)

Step: Train the Model

```
In [23]: %%time
output = model.fit([train.USER, train.ITEM], train.RATING,
                    batch_size=64, epochs=10, verbose=1, validation_split=0.2)
```

WARNING:tensorflow:From /usr/local/lib/python3.6/dist-packages/keras/backend/tensorflow_backend.py:1033: The name tf.assign_add is deprecated. Please use tf.compat.v1.assign_add instead.

WARNING:tensorflow:From /usr/local/lib/python3.6/dist-packages/keras/backend/tensorflow_backend.py:1020: The name tf.assign is deprecated. Please use tf.compat.v1.assign instead.

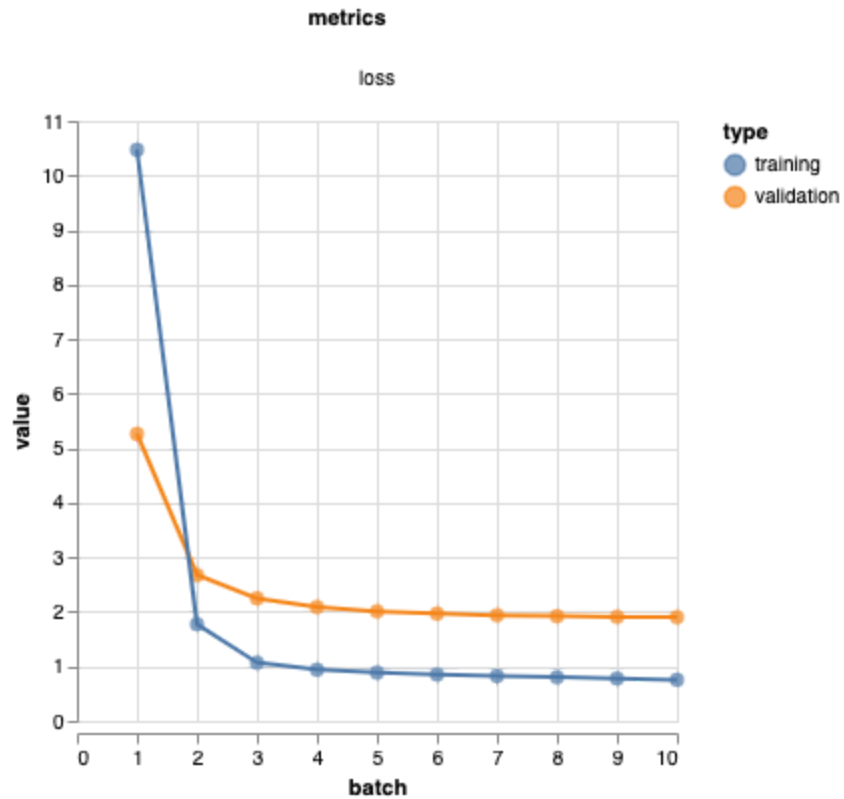
Train on 64000 samples, validate on 16000 samples

```
Epoch 1/10
64000/64000 [=====] - 2s 27us/step - loss: 10.4725 - val_loss: 5.2628
Epoch 2/10
64000/64000 [=====] - 1s 23us/step - loss: 1.7734 - val_loss: 2.6748
Epoch 3/10
64000/64000 [=====] - 1s 23us/step - loss: 1.0691 - val_loss: 2.2491
Epoch 4/10
64000/64000 [=====] - 1s 23us/step - loss: 0.9400 - val_loss: 2.0893
Epoch 5/10
64000/64000 [=====] - 1s 23us/step - loss: 0.8859 - val_loss: 2.0105
Epoch 6/10
64000/64000 [=====] - 1s 23us/step - loss: 0.8522 - val_loss: 1.9679
Epoch 7/10
64000/64000 [=====] - 1s 23us/step - loss: 0.8262 - val_loss: 1.9385
Epoch 8/10
64000/64000 [=====] - 1s 23us/step - loss: 0.8024 - val_loss: 1.9208
Epoch 9/10
64000/64000 [=====] - 1s 23us/step - loss: 0.7797 - val_loss: 1.9095
Epoch 10/10
64000/64000 [=====] - 1s 23us/step - loss: 0.7548 - val_loss: 1.9026
CPU times: user 30 s, sys: 2.2 s, total: 32.2 s
Wall time: 15.1 s
```

```
In [24]: from reco.vis import metrics
```

```
In [25]: metrics(output.history)
```

Out[25]:



Getting Simple Recommendation

```
In [26]: from reco.evaluate import get_embedding
```

```
In [27]: item_embedding = model.get_layer("ItemEmbedding").get_weights()[0]
```

```
In [28]: item_embedding.shape
```

Out[28]: (1682, 40)

Get Similiar Items

```
In [29]: from reco.recommend import get_similar, show_similar
```



```
In [30]: from sklearn.neighbors import NearestNeighbors
```

```
In [31]: def get_similar(embedding, k):  
    model_similar_items = NearestNeighbors(n_neighbors=k, algorithm="ball_tree").fit(embedding)  
    distances, indices = model_similar_items.kneighbors(embedding)  
  
    return distances, indices
```

```
In [32]: item_distance, item_similar_indices = get_similar(item_embedding, 5)
```

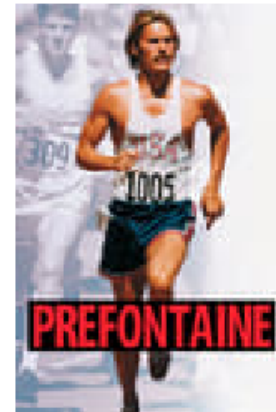
```
In [33]: item_similar_indices
```

```
Out[33]: array([[ 0, 1482,  499, 1188, 1472],  
               [ 1,  722, 1034,  619, 1031],  
               [ 2, 1237,  722,  591, 1439],  
               ...,  
               [1679, 1680, 1639, 1543, 1630],  
               [1680, 1666, 1679, 1678, 1669],  
               [1681, 1626, 1674, 1639, 1603]])
```

```
In [34]: import matplotlib.image as mpimage
```

```
In [35]: def show_similar(item_index, item_similar_indices, item_encoder):  
  
    s = item_similar_indices[item_index]  
    movie_ids = item_encoder.inverse_transform(s)  
  
    images = []  
    for movie_id in movie_ids:  
        img_path = '/tf/notebooks/data/data/posters/' + str(movie_id) + '.jpg'  
        images.append(mpimage.imread(img_path))  
  
    plt.figure(figsize=(20,10))  
    columns = 5  
    for i, image in enumerate(images):  
        plt.subplot(len(images) / columns + 1, columns, i + 1)  
        plt.axis('off')  
        plt.imshow(image)
```

```
In [36]: show_similar(0, item_similar_indices, item_encoder)
```



For Non-Negative Matrix Factorisation

Embedding: add Non negative constraints to the embedding layer

Explicit MF with bias -> FastAI Model

- Embedding Dot Product with Bias
- Sigmoid Layer adjustment

```
In [37]: from keras.layers import Lambda
```

```
In [38]: max_rating = DATA.RATING.max()  
min_rating = DATA.RATING.min()  
max_rating, min_rating
```

```
Out[38]: (5, 1)
```

```
In [39]: def ExplicitMF_bias (n_users, n_items, n_factors):

    # 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)

    # 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)

    # 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)

    # Dot Product
    DotProduct = Dot(axes=1, name="DotProduct")([item_vec, user_vec])
    # Add Bias
    AddBias = Add(name="AddBias")([DotProduct, user_bias_vec, item_bias_vec])

    # Scaling trick
    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)

    # Compile
    model.compile(loss="mean_squared_error", optimizer="adam")

    return model
```

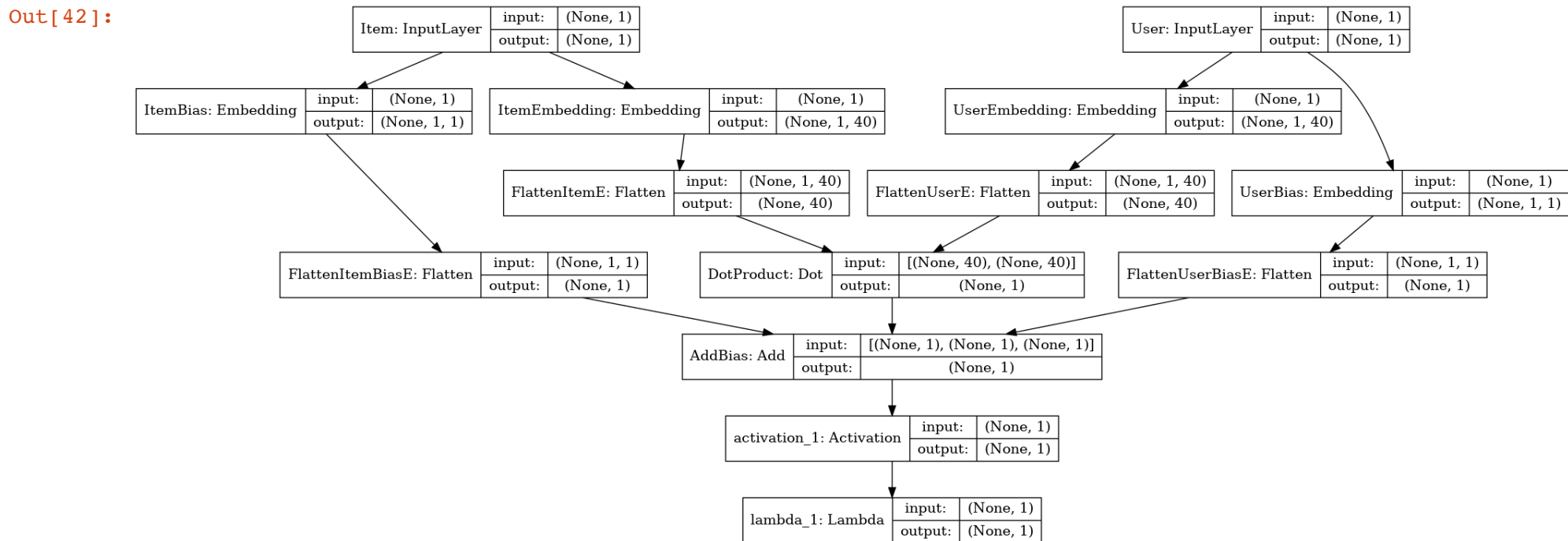
```
In [40]: n_factors = 40
model_bias = ExplicitMF_bias(n_users, n_items, n_factors)
```

```
In [41]: model_bias.summary()
```

Model: "model_2"

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]
UserBias (Embedding)	(None, 1, 1)	943	User[0][0]
ItemBias (Embedding)	(None, 1, 1)	1682	Item[0][0]
DotProduct (Dot)	(None, 1)	0	FlattenItemE[0][0] FlattenUserE[0][0]
FlattenUserBiasE (Flatten)	(None, 1)	0	UserBias[0][0]
FlattenItemBiasE (Flatten)	(None, 1)	0	ItemBias[0][0]
AddBias (Add)	(None, 1)	0	DotProduct[0][0] FlattenUserBiasE[0][0] FlattenItemBiasE[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 [42]: `plot_model(model_bias, show_layer_names=True, show_shapes=True)`



In [43]: `%%time
output_bias = model_bias.fit([train.USER, train.ITEM], train.RATING,
 batch_size=128, epochs=5, verbose=1, validation_split=0.2)`

Train on 64000 samples, validate on 16000 samples

Epoch 1/5

64000/64000 [=====] - 1s 18us/step - loss: 1.4060 - val_loss: 1.2313

Epoch 2/5

64000/64000 [=====] - 1s 13us/step - loss: 1.0302 - val_loss: 0.9930

Epoch 3/5

64000/64000 [=====] - 1s 13us/step - loss: 0.8549 - val_loss: 0.9347

Epoch 4/5

64000/64000 [=====] - 1s 13us/step - loss: 0.7629 - val_loss: 0.9055

Epoch 5/5

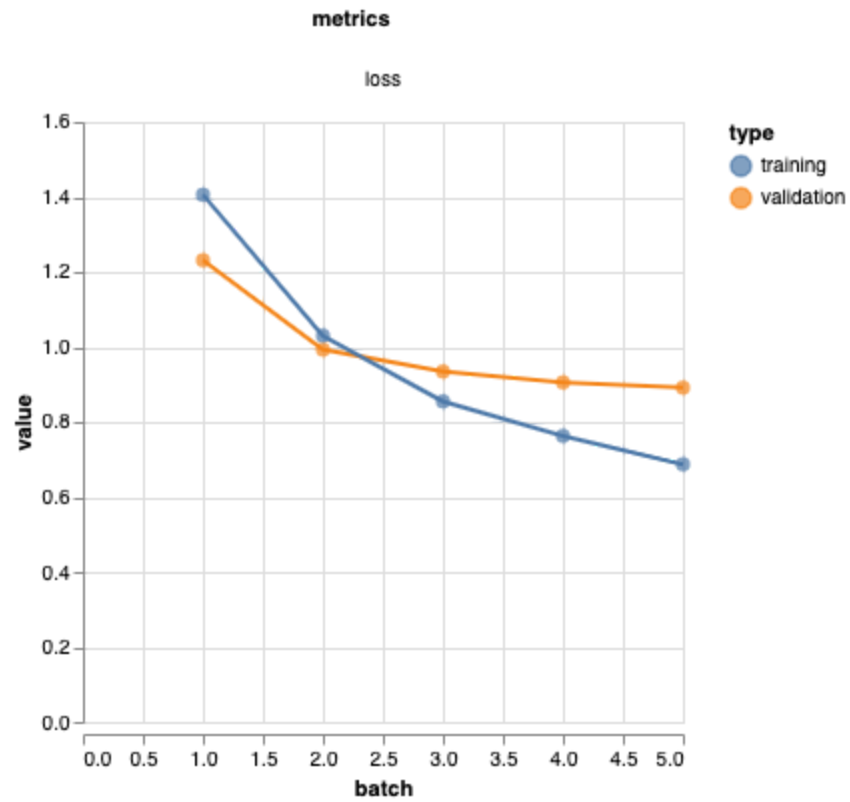
64000/64000 [=====] - 1s 14us/step - loss: 0.6872 - val_loss: 0.8917

CPU times: user 9.86 s, sys: 742 ms, total: 10.6 s

Wall time: 4.87 s

```
In [44]: metrics(output_bias.history)
```

Out[44]:



Concat Explicit Bias

```
In [48]: from keras.layers import Concatenate, Dense, Dropout
```

```

In [52]: def ExplicitMF_bias_concat (n_users, n_items, n_factors):

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

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

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

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

    # Concatenate
    concat = Concatenate(name="Concat")([item_vec, user_vec])
    concatD = Dropout(0.5)(concat)

    # Use Dense
    dense_1 = Dense(32, kernel_initializer="he_normal")(concatD)
    dense_1_drop = Dropout(0.5)(dense_1)
    dense_2 = Dense(1, kernel_initializer="he_normal")(dense_1_drop)

    # Dot Product
    #DotProduct = Dot(axes=1, name="DotProduct")([item_vec, user_vec])
    # Add Bias
    AddBias = Add(name="AddBias")([dense_2, user_bias_vec, item_bias_vec])

    # Scaling trick

```

```
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)

# Compile
model.compile(loss="mean_squared_error", optimizer="adam")

return model
```

```
In [64]: n_factors = 2
model_concat = ExplicitMF_bias_concat(n_users, n_items, n_factors)
```



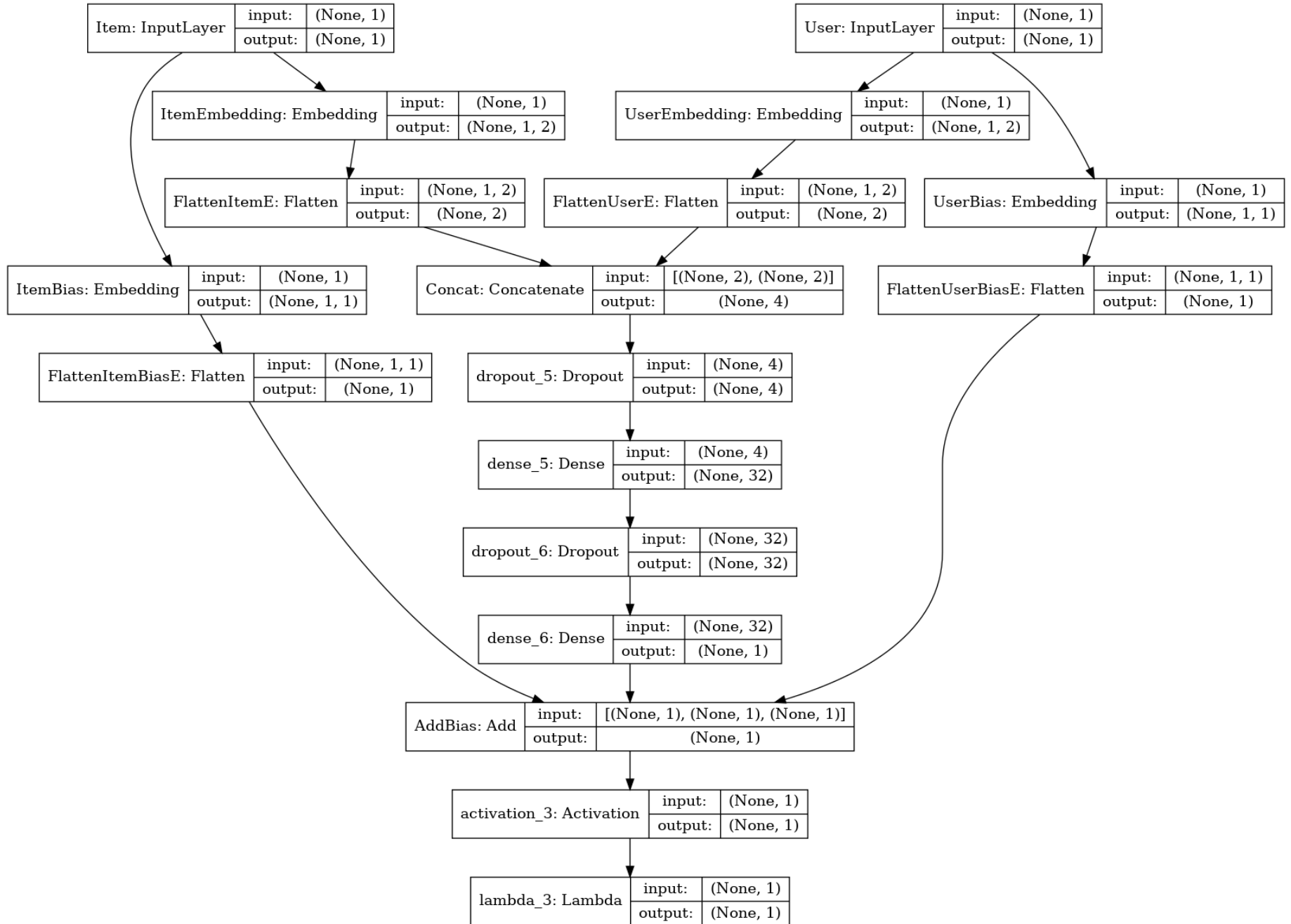
```
In [65]: model_concat.summary()
```

Model: "model_4"

Layer (type)	Output Shape	Param #	Connected to
=====			
Item (InputLayer)	(None, 1)	0	
User (InputLayer)	(None, 1)	0	
ItemEmbedding (Embedding)	(None, 1, 2)	3364	Item[0][0]
UserEmbedding (Embedding)	(None, 1, 2)	1886	User[0][0]
FlattenItemE (Flatten)	(None, 2)	0	ItemEmbedding[0][0]
FlattenUserE (Flatten)	(None, 2)	0	UserEmbedding[0][0]
Concat (Concatenate)	(None, 4)	0	FlattenItemE[0][0] FlattenUserE[0][0]
dropout_5 (Dropout)	(None, 4)	0	Concat[0][0]
dense_5 (Dense)	(None, 32)	160	dropout_5[0][0]
dropout_6 (Dropout)	(None, 32)	0	dense_5[0][0]
UserBias (Embedding)	(None, 1, 1)	943	User[0][0]
ItemBias (Embedding)	(None, 1, 1)	1682	Item[0][0]
dense_6 (Dense)	(None, 1)	33	dropout_6[0][0]
FlattenUserBiasE (Flatten)	(None, 1)	0	UserBias[0][0]
FlattenItemBiasE (Flatten)	(None, 1)	0	ItemBias[0][0]
AddBias (Add)	(None, 1)	0	dense_6[0][0] FlattenUserBiasE[0][0] FlattenItemBiasE[0][0]
activation_3 (Activation)	(None, 1)	0	AddBias[0][0]
lambda_3 (Lambda)	(None, 1)	0	activation_3[0][0]
=====			
Total params: 8,068			
Trainable params: 8,068			
Non-trainable params: 0			

```
In [66]: plot_model(model_concat, show_layer_names=True, show_shapes=True)
```

Out[66]:



```
In [67]: trainU, testU = user_split(DATA, [0.8, 0.2])
```

In [68]:

```
%%time
output_concat = model.fit([trainU.USER, trainU.ITEM], trainU.RATING,
                           batch_size=128, verbose=1, epochs=3,
                           validation_data=([testU.USER, testU.ITEM], testU.RATING))
```

Train on 80000 samples, validate on 20000 samples

Epoch 1/3

80000/80000 [=====] - 1s 14us/step - loss: 0.5930 - val_loss: 0.8492

Epoch 2/3

80000/80000 [=====] - 1s 12us/step - loss: 0.5645 - val_loss: 0.8520

Epoch 3/3

80000/80000 [=====] - 1s 12us/step - loss: 0.5358 - val_loss: 0.8572

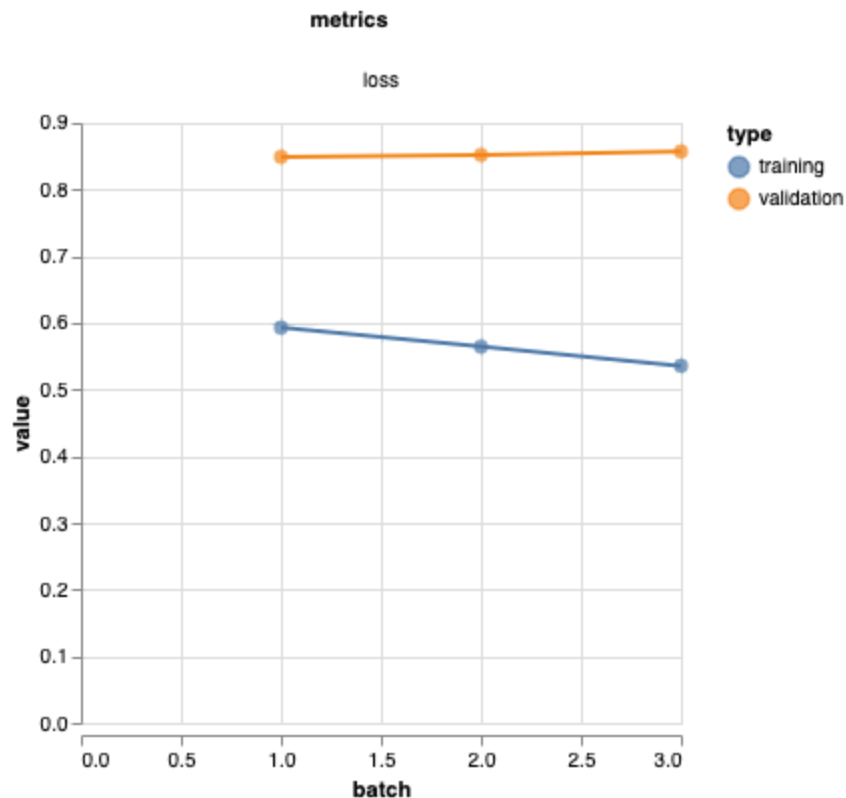
CPU times: user 6.09 s, sys: 434 ms, total: 6.53 s

Wall time: 3.13 s

In [69]:

```
metrics(output_concat.history)
```

Out[69]:



In []: