MovieLens Matrix Factorization Residual Learning

Yushuo (Shawn) Han

August 2020

1 Introduction

This notebook seeks to implement a recommender, trained on 25% of the movieLens dataset, to recommend movies to users. The notebook compares the traditional matrix factorization with a residual learning algorithm, to a new, deep learning collaborative filtering architecture described in a new research *Deep Learning Architecture for Collaborative Filtering Recommender Systems* (DOI: 10.3390/app10072441) by J. Bobadilla, S.Alonso and A. Hernando, published in April 2020.

Traditionally, the collaborative filtering (CF) approach can be implemented with residual deep learning as follows: for collaborative filtering/matrix factorization, $MF(x) : r_{ij} = w_i \cdot u_j + b_i + c_j + \mu$. To explore the non-linear patterns, a feedforward neural network can be integrated to model the residual, that is $NN(x) : \hat{r} - MF(x)$.

The deep learning architecture proposed by Bobadilla, Alonso, and Hernando is a Reliability-based Neural Collaborative Filtering (RNCF). In the first stage of the architecture, a traditional matrix factorization (MF) model is first trained on the users, items, and ratings. In the second stage, the mean squared errors (MSE) between the predictions from the MF model and the real ratings in the dataset are used as y-label targets to train a second model – a multi-layer neural network (MNN) model. That is, this MNN is trained to take latent features of the users and items, then predict the MSEs that will be created by the MF model. In the third (last) stage, a third model, also an MNN, is trained to take latent features of users, items and the estimated error predicted by the second model, and output the predicted rating. Mathematically,

- $MF(x) : r_{ij} = w_i \cdot u_j$ (1)
- $MNN(x) : (w_i, u_j) \rightarrow e_{ij} = (\hat{r} - MF(x))^2$ (2), and
- $MNN_2(x) : (w_i, u_j, e_{ij}) \rightarrow r$

The results have shown that the traditional CF/MF model with residual learning achieves a MSE of 0.65, comparing to the deep learning architecture's 1.11. Factors such as the reduced dataset size and the absense of bias and regularization, etc., may be attributed to this observation.

2 Data Preprocessing

[1]:
```
import numpy as np
import pandas as pd
from matplotlib import pyplot as plt
import random
%matplotlib inline
```

[2]:
```
movieDF = pd.read_csv("rating.csv")
movieDF.drop(['timestamp'], axis = 1, inplace = True)
movieDF.head(5)
```

[2]:

	userId	movieId	rating
0	1	2	3.5
1	1	29	3.5
2	1	32	3.5
3	1	47	3.5
4	1	50	3.5

Due to the constraint of time and computing power, only 25% of the entire movieLens dataset is used. The ratio used by train-test-split is 75%-25%.

[3]:
```
from sklearn.utils import shuffle

#Train Test split
ratio = int(0.25*len(movieDF))
movieDF = movieDF.iloc[:ratio]
movieDF = shuffle(movieDF)
trainSize = int(0.75*len(movieDF))
trainDF = movieDF.iloc[:trainSize]
testDF = movieDF.iloc[trainSize:]

# init
userNum = movieDF.userId.max() + 1
movieNum = movieDF.movieId.max() + 1
K = 15
MU = trainDF.rating.mean()
EPOCHS = 15
REGULAR = 0.1
```

3 CF/MF with Residual Learning

3.0.1 Model Definition

[4]:
```
from keras.layers import Input, Embedding, Dense, Flatten, Concatenate, Add,␣
↪Dot, Dropout, BatchNormalization, Activation
from keras.models import Model
from keras.optimizers import Adam, SGD

# input
userInput = Input(shape=(1,))
movieInput = Input(shape=(1,))

# Matrix Factorization
# Since userNum < movieNum, we have userNum = batchsize
userEmbedding = Embedding(userNum, K)(userInput) # bsize x 1 x k
movieEmbedding = Embedding(movieNum, K)(movieInput) # bsize x 1 x k
userBias = Embedding(userNum, 1)(userInput) # bsize x 1 x 1
movieBias = Embedding(movieNum, 1)(movieInput) # bsize x 1 x 1
model = Dot(axes=2)([userEmbedding, movieEmbedding]) # bsize x 1 x 1
model = Add()([model, userBias, movieBias])
model = Flatten()(model) # bsize x 1

# Residual
userEmbeddingFlat = Flatten()(userEmbedding) # bsize x k
movieEmbeddingFlat = Flatten()(movieEmbedding) # bsize x k
residual = Concatenate()([userEmbeddingFlat, movieEmbeddingFlat]) # bsize x 2k
residual = Dense(512)(residual)
residual = Activation('elu')(residual)
residual = Dense(1)(residual)

# Together
model = Add()([model, residual])
model = Model(inputs=[userInput, movieInput], outputs=model)
model.compile(
    loss='mse',
    optimizer=SGD(lr=0.08, momentum=0.9),
    metrics=['mse']
)
```

```
Using TensorFlow backend.
```

```
WARNING:tensorflow:From /Users/yushuohan/opt/anaconda3/lib/python3.7/site-
packages/tensorflow_core/python/ops/resource_variable_ops.py:1630: calling
BaseResourceVariable.__init__ (from tensorflow.python.ops.resource_variable_ops)
with constraint is deprecated and will be removed in a future version.
Instructions for updating:
If using Keras pass *_constraint arguments to layers.
```

3.0.2 Training

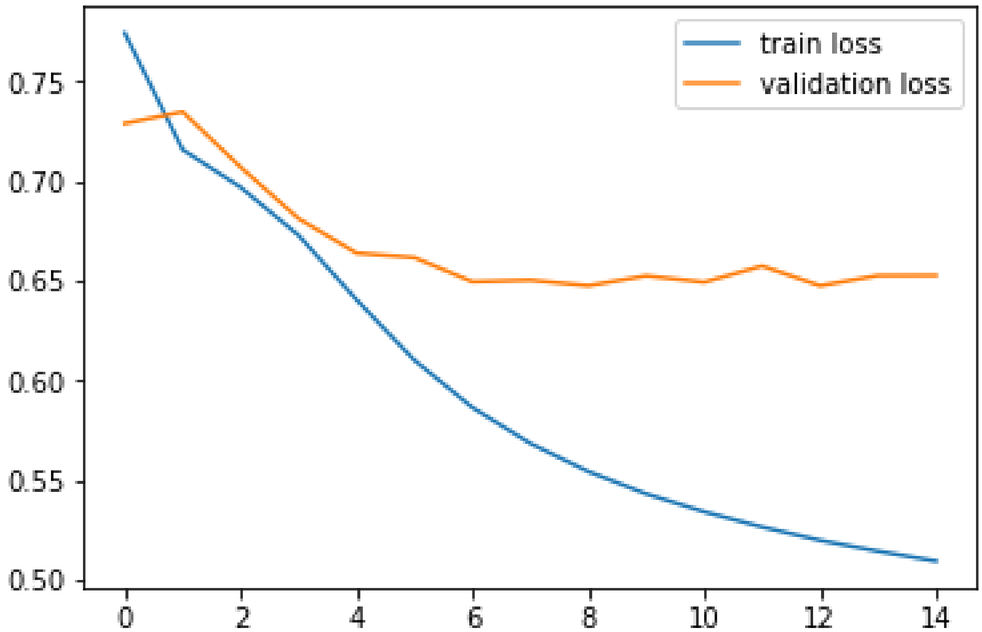
[5]:
```
history = model.fit(
    x=[trainDF.userId.values, trainDF.movieId.values],
    y=trainDF.rating.values - MU,
    epochs=EPOCHS,
    batch_size=128,
    validation_data=(
        [testDF.userId.values, testDF.movieId.values],
        testDF.rating.values - MU
    )
)
```

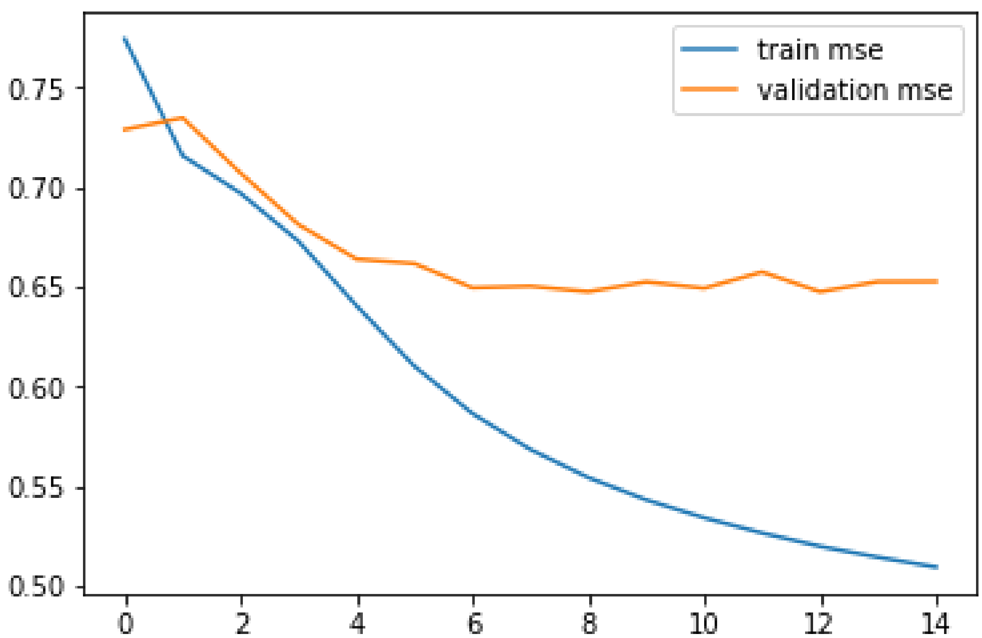
```
WARNING:tensorflow:From /Users/yushuohan/opt/anaconda3/lib/python3.7/site-
packages/keras/backend/tensorflow_backend.py:422: The name tf.global_variables
is deprecated. Please use tf.compat.v1.global_variables instead.

Train on 3750048 samples, validate on 1250017 samples
Epoch 1/15
3750048/3750048 [==============================] - 338s 90us/step - loss: 0.7744
- mse: 0.7744 - val_loss: 0.7291 - val_mse: 0.7291
Epoch 2/15
3750048/3750048 [==============================] - 337s 90us/step - loss: 0.7159
- mse: 0.7159 - val_loss: 0.7350 - val_mse: 0.7350
Epoch 3/15
3750048/3750048 [==============================] - 333s 89us/step - loss: 0.6971
- mse: 0.6971 - val_loss: 0.7072 - val_mse: 0.7072
Epoch 4/15
3750048/3750048 [==============================] - 342s 91us/step - loss: 0.6729
- mse: 0.6729 - val_loss: 0.6814 - val_mse: 0.6814
Epoch 5/15
3750048/3750048 [==============================] - 378s 101us/step - loss:
0.6406 - mse: 0.6406 - val_loss: 0.6640 - val_mse: 0.6640
Epoch 6/15
3750048/3750048 [==============================] - 453s 121us/step - loss:
0.6103 - mse: 0.6103 - val_loss: 0.6618 - val_mse: 0.6618
Epoch 7/15
3750048/3750048 [==============================] - 473s 126us/step - loss:
0.5865 - mse: 0.5865 - val_loss: 0.6496 - val_mse: 0.6496
Epoch 8/15
3750048/3750048 [==============================] - 460s 123us/step - loss:
0.5685 - mse: 0.5685 - val_loss: 0.6504 - val_mse: 0.6504
Epoch 9/15
3750048/3750048 [==============================] - 382s 102us/step - loss:
0.5544 - mse: 0.5544 - val_loss: 0.6476 - val_mse: 0.6476
Epoch 10/15
3750048/3750048 [==============================] - 352s 94us/step - loss: 0.5431
- mse: 0.5431 - val_loss: 0.6526 - val_mse: 0.6526
```

```
Epoch 11/15
3750048/3750048 [==============================] - 349s 93us/step - loss: 0.5342
- mse: 0.5342 - val_loss: 0.6494 - val_mse: 0.6494
Epoch 12/15
3750048/3750048 [==============================] - 350s 93us/step - loss: 0.5265
- mse: 0.5265 - val_loss: 0.6575 - val_mse: 0.6575
Epoch 13/15
3750048/3750048 [==============================] - 353s 94us/step - loss: 0.5198
- mse: 0.5198 - val_loss: 0.6476 - val_mse: 0.6476
Epoch 14/15
3750048/3750048 [==============================] - 351s 94us/step - loss: 0.5144
- mse: 0.5144 - val_loss: 0.6527 - val_mse: 0.6527
Epoch 15/15
3750048/3750048 [==============================] - 350s 93us/step - loss: 0.5095
- mse: 0.5095 - val_loss: 0.6528 - val_mse: 0.6528
```

[6]:

```
model.save("movieLensRecommender_res.h5")

def plot(history):
    plt.plot(history.history['loss'], label="train loss")
    plt.plot(history.history['val_loss'], label="validation loss")
    plt.legend()
    plt.show()

    plt.plot(history.history['mse'], label="train mse")
    plt.plot(history.history['val_mse'], label="validation mse")
    plt.legend()
    plt.show()

plot(history)
```


train loss
validation loss
0.75
0.70
0.65
0.60
0.55
0.50
0
2
4
6
8
10
12
14


train mse
validation mse
0.75
0.70
0.65
0.60
0.55
0.50
0
2
4
6
8
10
12
14

3.0.3 Sample Inference

[7]:
```
def predictRating0(num):
    result = model.predict([[movieDF.iloc[num].userId], [movieDF.iloc[num].
 ↪movieId]])
    result = result[0][0] + MU
    print("(Predicted Rating, Real Rating): ({0}, {1})".format(result, movieDF.
 ↪iloc[num].rating))

def test0(times):
    top = len(movieDF) - 1
    for _ in range(times):
        num = random.randint(0, top)
        predictRating0(num)

test0(20)
```

```
(Predicted Rating, Real Rating): (3.9147259311229496, 4.0)
(Predicted Rating, Real Rating): (3.783999176457575, 3.5)
(Predicted Rating, Real Rating): (4.751980812981776, 5.0)
(Predicted Rating, Real Rating): (3.6924745456725865, 3.5)
(Predicted Rating, Real Rating): (3.7110037223846226, 5.0)
(Predicted Rating, Real Rating): (4.616799505189112, 5.0)
(Predicted Rating, Real Rating): (2.565714390710047, 3.0)
(Predicted Rating, Real Rating): (2.430528910592249, 3.5)
(Predicted Rating, Real Rating): (4.06956151290243, 4.0)
(Predicted Rating, Real Rating): (3.70680299563711, 0.5)
(Predicted Rating, Real Rating): (3.142650456860712, 3.0)
(Predicted Rating, Real Rating): (4.06136956973379, 5.0)
(Predicted Rating, Real Rating): (3.691233725979975, 3.5)
(Predicted Rating, Real Rating): (4.683683784440211, 5.0)
(Predicted Rating, Real Rating): (4.001659901574305, 3.5)
(Predicted Rating, Real Rating): (2.058595807984522, 1.0)
(Predicted Rating, Real Rating): (3.2210759834796696, 4.0)
(Predicted Rating, Real Rating): (3.3304352031499653, 3.0)
(Predicted Rating, Real Rating): (3.424174325302294, 4.0)
(Predicted Rating, Real Rating): (3.1532597856075077, 3.0)
```

4 Deep Learning RNCF

4.1 Model 1: MF

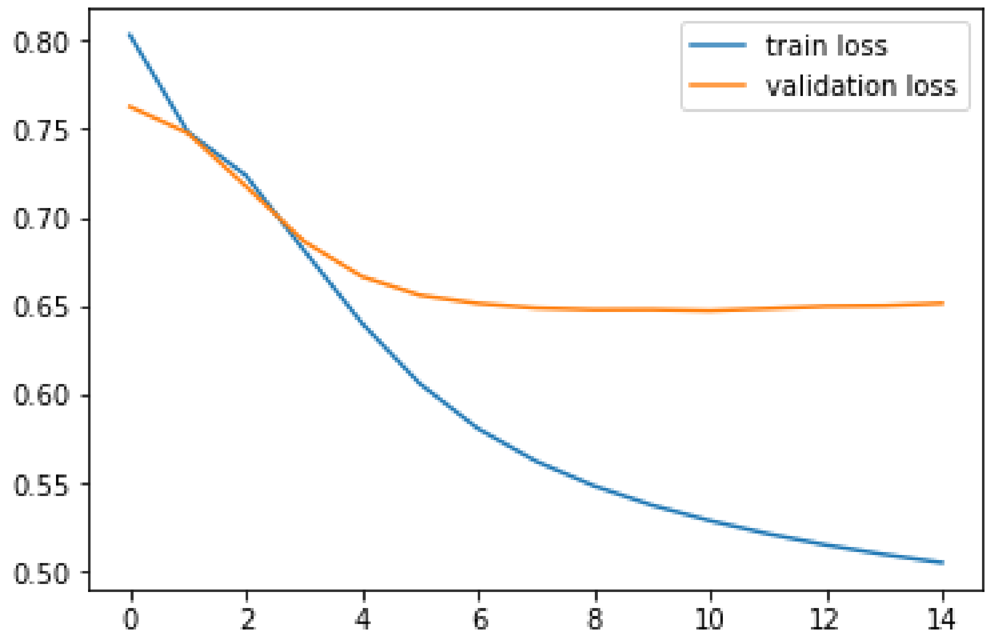
[8]:
```
# input
userInput = Input(shape=(1,))
movieInput = Input(shape=(1,))

# Matrix Factorization
# Since userNum < movieNum, we have userNum = batchsize
userEmbedding = Embedding(userNum, K)(userInput) # bsize x 1 x k
movieEmbedding = Embedding(movieNum, K)(movieInput) # bsize x 1 x k
userBias = Embedding(userNum, 1)(userInput) # bsize x 1 x 1
movieBias = Embedding(movieNum, 1)(movieInput) # bsize x 1 x 1
model1 = Dot(axes=2)([userEmbedding, movieEmbedding]) # bsize x 1 x 1
model1 = Add()([model1, userBias, movieBias])
model1 = Flatten()(model1) # bsize x 1

# Together
model1 = Model(inputs=[userInput, movieInput], outputs=model1)
model1.compile(
    loss='mse',
    optimizer=SGD(lr=0.08, momentum=0.9),
    metrics=['mse']
)
```

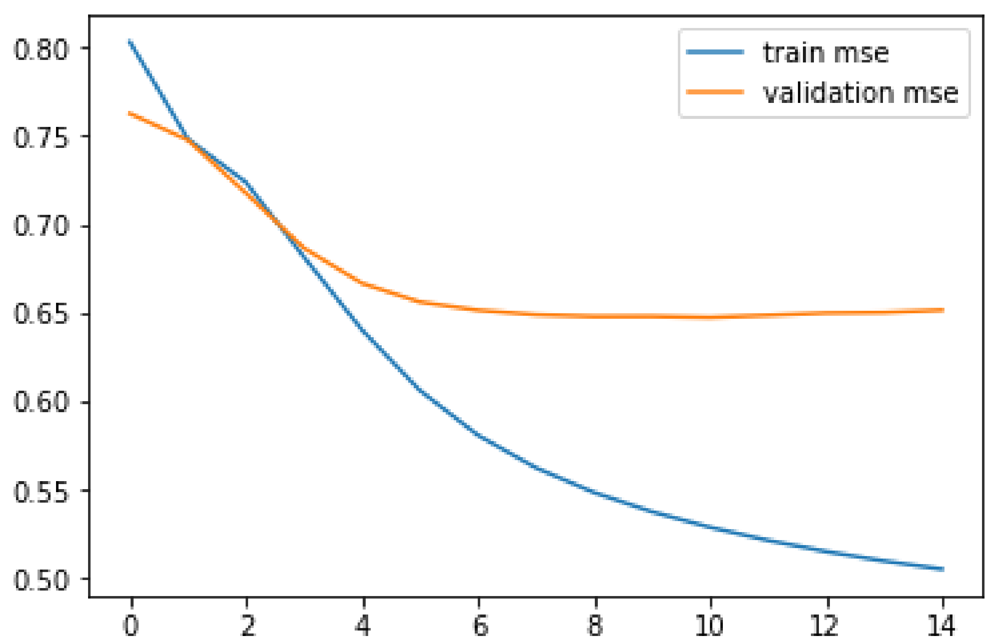
[9]:
```
history1 = model1.fit(
    x=[trainDF.userId.values, trainDF.movieId.values],
    y=trainDF.rating.values - MU,
    epochs=EPOCHS,
    batch_size=128,
    validation_data=(
        [testDF.userId.values, testDF.movieId.values],
        testDF.rating.values - MU
    )
)
```

```
Train on 3750048 samples, validate on 1250017 samples
Epoch 1/15
3750048/3750048 [==============================] - 300s 80us/step - loss: 0.8030
- mse: 0.8030 - val_loss: 0.7627 - val_mse: 0.7627
Epoch 2/15
3750048/3750048 [==============================] - 302s 81us/step - loss: 0.7483
- mse: 0.7483 - val_loss: 0.7477 - val_mse: 0.7477
Epoch 3/15
3750048/3750048 [==============================] - 342s 91us/step - loss: 0.7238
- mse: 0.7238 - val_loss: 0.7177 - val_mse: 0.7177
Epoch 4/15
```

```
3750048/3750048 [==============================] - 303s 81us/step - loss: 0.6816
- mse: 0.6816 - val_loss: 0.6867 - val_mse: 0.6867
Epoch 5/15
3750048/3750048 [==============================] - 345s 92us/step - loss: 0.6405
- mse: 0.6405 - val_loss: 0.6667 - val_mse: 0.6667
Epoch 6/15
3750048/3750048 [==============================] - 339s 90us/step - loss: 0.6063
- mse: 0.6063 - val_loss: 0.6561 - val_mse: 0.6561
Epoch 7/15
3750048/3750048 [==============================] - 346s 92us/step - loss: 0.5810
- mse: 0.5809 - val_loss: 0.6515 - val_mse: 0.6515
Epoch 8/15
3750048/3750048 [==============================] - 339s 90us/step - loss: 0.5625
- mse: 0.5625 - val_loss: 0.6489 - val_mse: 0.6489
Epoch 9/15
3750048/3750048 [==============================] - 345s 92us/step - loss: 0.5486
- mse: 0.5486 - val_loss: 0.6480 - val_mse: 0.6480
Epoch 10/15
3750048/3750048 [==============================] - 338s 90us/step - loss: 0.5377
- mse: 0.5377 - val_loss: 0.6480 - val_mse: 0.6480
Epoch 11/15
3750048/3750048 [==============================] - 345s 92us/step - loss: 0.5289
- mse: 0.5289 - val_loss: 0.6474 - val_mse: 0.6474
Epoch 12/15
3750048/3750048 [==============================] - 337s 90us/step - loss: 0.5215
- mse: 0.5215 - val_loss: 0.6486 - val_mse: 0.6486
Epoch 13/15
3750048/3750048 [==============================] - 332s 88us/step - loss: 0.5153
- mse: 0.5153 - val_loss: 0.6499 - val_mse: 0.6499
Epoch 14/15
3750048/3750048 [==============================] - 337s 90us/step - loss: 0.5099
- mse: 0.5099 - val_loss: 0.6502 - val_mse: 0.6502
Epoch 15/15
3750048/3750048 [==============================] - 347s 92us/step - loss: 0.5053
- mse: 0.5053 - val_loss: 0.6515 - val_mse: 0.6515
```

[10]:
```
model1.save("movieLensRecommender_rncf1.h5")
plot(history1)
```





Inference on all data using model1 to create predicted ratings as the training input for the second model.

[11]:
```
errors = []

for index, row in movieDF.iterrows():
    pred = model1.predict([[row.userId], [row.movieId]])
    pred = pred[0][0]
    mse = (row.rating - pred)**2
    errors.append(mse)
```

[12]:
```
movieDF['error'] = errors
movieDF.head(5)
```

[12]:

	userId	movieId	rating	error
445628	3031	2700	3.5	11.714023
300498	2062	457	4.0	10.846396
1810055	12208	2640	3.0	9.672417
862730	5768	2117	3.5	15.864624
3318896	22688	3825	2.5	12.129237

4.2 Model 2: Reliability MNN

[13]:
```
userInput = Input(shape=(1,))
movieInput = Input(shape=(1,))
userEmbedding = Embedding(userNum, K)(userInput)
movieEmbedding = Embedding(movieNum, K)(movieInput)
userEmbeddingFlat = Flatten()(userEmbedding) # bsize x k
movieEmbeddingFlat = Flatten()(movieEmbedding) # bsize x k
model2 = Concatenate()([userEmbeddingFlat, movieEmbeddingFlat])
model2 = Dense(512)(model2)
model2 = Dense(256)(model2)
model2 = Dense(256)(model2)
model2 = Activation('elu')(model2)
model2 = Dense(1)(model2)

model2 = Model(inputs=[userInput, movieInput], outputs=model2)
model2.compile(
    loss='mse',
    optimizer=Adam(lr=0.01),
    metrics=['mse']
)
```

Re-perform train-test-split using the updated movieLens dataset with the rating error.

[14]:
```
trainSize = int(0.75*len(movieDF))
trainDF = movieDF.iloc[:trainSize]
testDF = movieDF.iloc[trainSize:]
trainDF.head(5)
```

[14]:

	userId	movieId	rating	error
445628	3031	2700	3.5	11.714023
300498	2062	457	4.0	10.846396
1810055	12208	2640	3.0	9.672417
862730	5768	2117	3.5	15.864624
3318896	22688	3825	2.5	12.129237

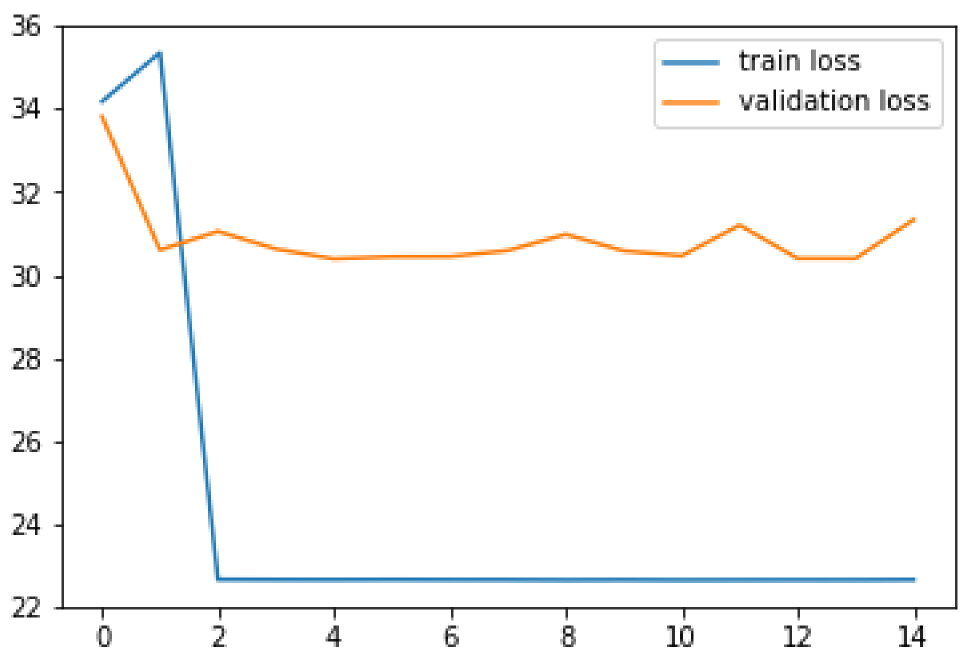
[15]:

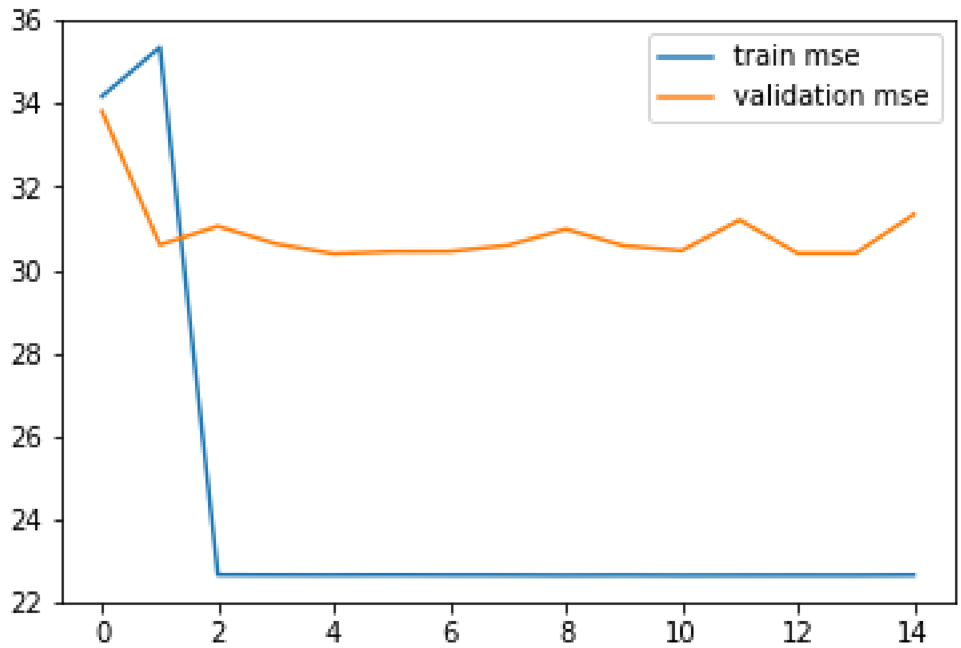
```
history2 = model2.fit(
    x=[trainDF.userId.values, trainDF.movieId.values],
    y=trainDF.error.values,
    epochs=15,
    batch_size=128,
    validation_data=(
        [testDF.userId.values, testDF.movieId.values],
        testDF.error.values
    )
)
```

```
Train on 3750048 samples, validate on 1250017 samples
Epoch 1/15
3750048/3750048 [==============================] - 873s 233us/step - loss:
34.1746 - mse: 34.1746 - val_loss: 33.8165 - val_mse: 33.8165
Epoch 2/15
3750048/3750048 [==============================] - 874s 233us/step - loss:
35.3529 - mse: 35.3531 - val_loss: 30.6076 - val_mse: 30.6076
Epoch 3/15
3750048/3750048 [==============================] - 872s 233us/step - loss:
22.6777 - mse: 22.6776 - val_loss: 31.0549 - val_mse: 31.0549
Epoch 4/15
3750048/3750048 [==============================] - 871s 232us/step - loss:
22.6734 - mse: 22.6733 - val_loss: 30.6317 - val_mse: 30.6317
Epoch 5/15
3750048/3750048 [==============================] - 872s 233us/step - loss:
22.6713 - mse: 22.6713 - val_loss: 30.3925 - val_mse: 30.3924
Epoch 6/15
3750048/3750048 [==============================] - 872s 232us/step - loss:
22.6750 - mse: 22.6750 - val_loss: 30.4452 - val_mse: 30.4452
Epoch 7/15
3750048/3750048 [==============================] - 872s 233us/step - loss:
22.6711 - mse: 22.6710 - val_loss: 30.4486 - val_mse: 30.4486
Epoch 8/15
3750048/3750048 [==============================] - 873s 233us/step - loss:
22.6703 - mse: 22.6702 - val_loss: 30.5937 - val_mse: 30.5937
Epoch 9/15
3750048/3750048 [==============================] - 874s 233us/step - loss:
22.6643 - mse: 22.6643 - val_loss: 30.9838 - val_mse: 30.9839
Epoch 10/15
```

```
3750048/3750048 [==============================] - 872s 233us/step - loss:
22.6685 - mse: 22.6684 - val_loss: 30.5852 - val_mse: 30.5852
Epoch 11/15
3750048/3750048 [==============================] - 874s 233us/step - loss:
22.6631 - mse: 22.6631 - val_loss: 30.4671 - val_mse: 30.4671
Epoch 12/15
3750048/3750048 [==============================] - 873s 233us/step - loss:
22.6650 - mse: 22.6651 - val_loss: 31.2042 - val_mse: 31.2042
Epoch 13/15
3750048/3750048 [==============================] - 873s 233us/step - loss:
22.6663 - mse: 22.6664 - val_loss: 30.4028 - val_mse: 30.4029
Epoch 14/15
3750048/3750048 [==============================] - 874s 233us/step - loss:
22.6656 - mse: 22.6655 - val_loss: 30.4030 - val_mse: 30.4031
Epoch 15/15
3750048/3750048 [==============================] - 876s 233us/step - loss:
22.6719 - mse: 22.6720 - val_loss: 31.3345 - val_mse: 31.3345
```

[16]:
```
model2.save("movieLensRecommender_rncf2.h5")
plot(history2)
```





Again, inference on all data using model2 to create predicted errors as the training input for the third model.

[17]:
```
pred_errors = []

for index, row in movieDF.iterrows():
    pred = model2.predict([[row.userId], [row.movieId]])
    pred = pred[0][0]
    pred_errors.append(pred)
```

[18]:
```
movieDF['pred_error'] = pred_errors
movieDF.head(5)
```

[18]:

	userId	movieId	rating	error	pred_error
445628	3031	2700	3.5	11.714023	12.043268
300498	2062	457	4.0	10.846396	12.043268
1810055	12208	2640	3.0	9.672417	12.043268
862730	5768	2117	3.5	15.864624	12.043268
3318896	22688	3825	2.5	12.129237	12.043268

4.3 Model 3: Inference MNN

[19]:
```
userInput = Input(shape=(1,))
movieInput = Input(shape=(1,))
predErrorInput = Input(shape=(1,)) # bsize x 1
userEmbedding = Embedding(userNum, K)(userInput)
movieEmbedding = Embedding(movieNum, K)(movieInput)
userEmbeddingFlat = Flatten()(userEmbedding) # bsize x k
movieEmbeddingFlat = Flatten()(movieEmbedding) # bsize x k
model3 = Concatenate()([userEmbeddingFlat, movieEmbeddingFlat, predErrorInput])␣
↪# bsize x (2k+1)
model3 = Dense(512)(model3)
model3 = Dense(256)(model3)
model3 = Dense(256)(model3)
model3 = Activation('elu')(model3)
model3 = Dense(1)(model3)

model3 = Model(inputs=[userInput, movieInput, predErrorInput], outputs=model3)
model3.compile(
    loss='mse',
    optimizer=Adam(lr=0.01),
    metrics=['mse']
)
```

Again, re-perform train-test-split using the updated movieLens dataset with the predicted error.

[20]:
```
trainSize = int(0.75*len(movieDF))
trainDF = movieDF.iloc[:trainSize]
testDF = movieDF.iloc[trainSize:]
trainDF.head(5)
```

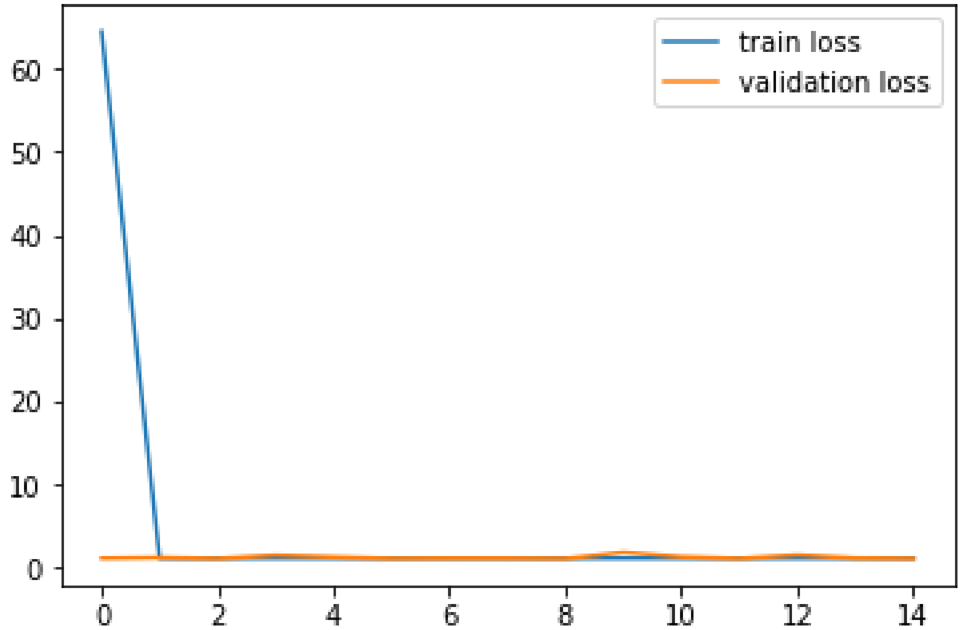
[20]:

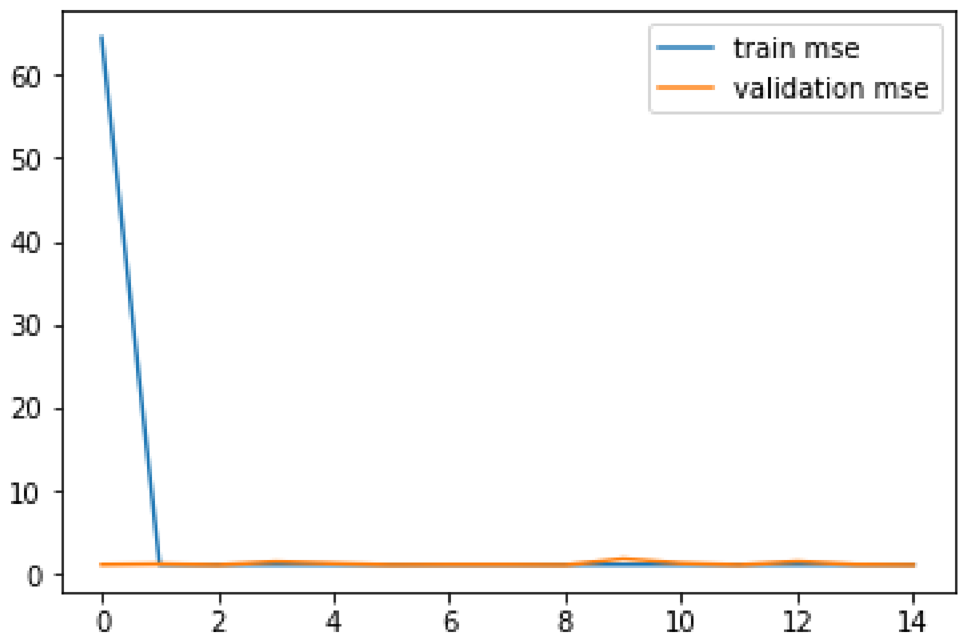
	userId	movieId	rating	error	pred_error
445628	3031	2700	3.5	11.714023	12.043268
300498	2062	457	4.0	10.846396	12.043268
1810055	12208	2640	3.0	9.672417	12.043268
862730	5768	2117	3.5	15.864624	12.043268
3318896	22688	3825	2.5	12.129237	12.043268

[21]:
```
history3 = model3.fit(
    x=[trainDF.userId.values, trainDF.movieId.values, trainDF.pred_error.values],
    y=trainDF.rating.values,
    epochs=15,
    batch_size=128,
    validation_data=(
        [testDF.userId.values, testDF.movieId.values, testDF.pred_error.values],
        testDF.rating.values
    )
)
```

```
Train on 3750048 samples, validate on 1250017 samples
Epoch 1/15
3750048/3750048 [==============================] - 862s 230us/step - loss:
64.4913 - mse: 64.4912 - val_loss: 1.1639 - val_mse: 1.1639
Epoch 2/15
3750048/3750048 [==============================] - 870s 232us/step - loss:
1.1658 - mse: 1.1658 - val_loss: 1.2406 - val_mse: 1.2406
Epoch 3/15
3750048/3750048 [==============================] - 864s 230us/step - loss:
1.1664 - mse: 1.1664 - val_loss: 1.1122 - val_mse: 1.1122
Epoch 4/15
3750048/3750048 [==============================] - 865s 231us/step - loss:
1.1668 - mse: 1.1668 - val_loss: 1.5272 - val_mse: 1.5272
Epoch 5/15
3750048/3750048 [==============================] - 864s 230us/step - loss:
1.1659 - mse: 1.1659 - val_loss: 1.3073 - val_mse: 1.3073
Epoch 6/15
3750048/3750048 [==============================] - 863s 230us/step - loss:
1.1642 - mse: 1.1642 - val_loss: 1.1192 - val_mse: 1.1192
Epoch 7/15
3750048/3750048 [==============================] - 862s 230us/step - loss:
1.1655 - mse: 1.1655 - val_loss: 1.1534 - val_mse: 1.1534
Epoch 8/15
3750048/3750048 [==============================] - 863s 230us/step - loss:
1.1674 - mse: 1.1674 - val_loss: 1.1510 - val_mse: 1.1510
Epoch 9/15
3750048/3750048 [==============================] - 863s 230us/step - loss:
1.1660 - mse: 1.1660 - val_loss: 1.1090 - val_mse: 1.1090
Epoch 10/15
3750048/3750048 [==============================] - 856s 228us/step - loss:
1.1670 - mse: 1.1670 - val_loss: 1.8811 - val_mse: 1.8811
Epoch 11/15
3750048/3750048 [==============================] - 872s 233us/step - loss:
1.1642 - mse: 1.1642 - val_loss: 1.3373 - val_mse: 1.3373
Epoch 12/15
3750048/3750048 [==============================] - 878s 234us/step - loss:
1.1662 - mse: 1.1662 - val_loss: 1.1181 - val_mse: 1.1181
Epoch 13/15
3750048/3750048 [==============================] - 881s 235us/step - loss:
1.1666 - mse: 1.1665 - val_loss: 1.5585 - val_mse: 1.5585
Epoch 14/15
3750048/3750048 [==============================] - 886s 236us/step - loss:
1.1680 - mse: 1.1680 - val_loss: 1.1706 - val_mse: 1.1706
Epoch 15/15
3750048/3750048 [==============================] - 881s 235us/step - loss:
1.1668 - mse: 1.1668 - val_loss: 1.1125 - val_mse: 1.1125
```

[22]:
```
model3.save("movieLensRecommender_rncf3.h5")
plot(history3)
```





4.4 Sample Inference and Metrics

[26]:
```
def predictRating(num):
    pred_error = model2.predict([[movieDF.iloc[num].userId], [movieDF.iloc[num].
 ↪movieId]])
    pred_error = pred_error[0][0]
    result = model3.predict([[movieDF.iloc[num].userId], [movieDF.iloc[num].
 ↪movieId], [pred_error]])
    return [result[0][0], movieDF.iloc[num].rating]

def test(times):
    top = len(movieDF)-1
    for _ in range(times):
        num = random.randint(0, top)
        result = predictRating(num)
        print("(Predicted Rating, Real Rating): ({0}, {1})".format(result[0],␣
 ↪result[1]))

test(10)
```

```
(Predicted Rating, Real Rating): (4.054775714874268, 5.0)
(Predicted Rating, Real Rating): (4.996739387512207, 5.0)
(Predicted Rating, Real Rating): (3.8663785457611084, 4.0)
(Predicted Rating, Real Rating): (3.9270434379577637, 4.0)
(Predicted Rating, Real Rating): (3.9943039417266846, 4.5)
(Predicted Rating, Real Rating): (2.8923263549804688, 3.5)
(Predicted Rating, Real Rating): (3.4835503101348877, 4.0)
(Predicted Rating, Real Rating): (3.1241343021392822, 3.0)
(Predicted Rating, Real Rating): (3.3643698692321777, 3.5)
(Predicted Rating, Real Rating): (3.432689666748047, 4.0)
```

[24]:
```
from sklearn.metrics import mean_squared_error

predictions = np.empty((0))

for index, _ in enumerate(testDF.iterrows()):
    pred = predictRating(index)
    pred = pred[0]
    predictions = np.append(predictions, pred)

print('Validation MSE:', mean_squared_error(testDF.rating.values, predictions))
```

```
Validation MSE: 1.1125286187700671
```

5 Conclusion

This notebook implements a recommender system using the traditional collaborative filtering matrix factorization technique with residual learning, and compared it with the implementation of a new residual learning technique using a deep learning architecture, proposed by Bobadilla, Alonso, and Hernando, using matrix factorization, residual learning and deep feedforward neural nets. It is observed that the newly-proposed deep learning architecture has greater error than the traditional approach, which may be attributed to the reduced dataset size, lack of bias terms and regularizations in the matrix factorization stage, etc.