```
In [1]: # Install TensorFlow
        # !pip install -q tensorflow-gpu==2.0.0-rc0
          %tensorflow_version 2.x # Colab only.
        except Exception:
          pass
        import tensorflow as tf
        print(tf.__version__)
        Colab only includes TensorFlow 2.x; %tensorflow version has no effect.
        2.12.0
In [2]: # More imports
        from tensorflow.keras.layers import Input, Dense, Embedding, Flatten, \
          Concatenate
        from tensorflow.keras.models import Model
        from tensorflow.keras.optimizers import SGD, Adam
        from sklearn.utils import shuffle
        import numpy as np
        import pandas as pd
        import matplotlib.pyplot as plt
In [3]: # data is from: https://grouplens.org/datasets/movielens/
        # in case the link changes in the future
        !wget -nc http://files.grouplens.org/datasets/movielens/ml-20m.zip
        --2023-05-21 03:46:19-- http://files.grouplens.org/datasets/movielens/ml-20m.zip
        Resolving files.grouplens.org (files.grouplens.org)... 128.101.65.152
        Connecting to files.grouplens.org (files.grouplens.org) | 128.101.65.152 | :80... conn
        ected.
        HTTP request sent, awaiting response... 200 OK
        Length: 198702078 (189M) [application/zip]
        Saving to: 'ml-20m.zip'
        ml-20m.zip
                           in 1.8s
        2023-05-21 03:46:21 (102 MB/s) - 'ml-20m.zip' saved [198702078/198702078]
In [4]: !unzip -n ml-20m.zip
        Archive: ml-20m.zip
           creating: ml-20m/
          inflating: ml-20m/genome-scores.csv
          inflating: ml-20m/genome-tags.csv
          inflating: ml-20m/links.csv
          inflating: ml-20m/movies.csv
          inflating: ml-20m/ratings.csv
          inflating: ml-20m/README.txt
          inflating: ml-20m/tags.csv
```

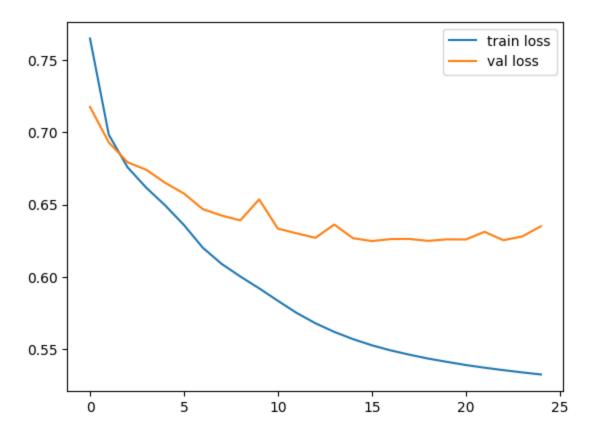
```
In [5]:
        !1s
        ml-20m ml-20m.zip sample_data
In [6]: df = pd.read_csv('ml-20m/ratings.csv')
        df.head()
           userld movield rating
Out[6]:
                                timestamp
        0
               1
                       2
                             3.5 1112486027
               1
                      29
                            3.5 1112484676
        2
               1
                      32
                            3.5 1112484819
        3
                             3.5 1112484727
        4
               1
                      50
                            3.5 1112484580
In [7]: # We can't trust the userId and movieId to be numbered 0...N-1
        # Let's just set our own ids
        # current user id = 0
        # custom_user_map = {} # old user id > new user id
        # def map_user_id(row):
        # global current_user_id, custom_user_map
        # old_user_id = row['userId']
           if old_user_id not in custom_user_map:
             custom_user_map[old_user_id] = current_user id
              current_user_id += 1
           return custom_user_map[old_user_id]
        # df['new_user_id'] = df.apply(map_user_id, axis=1)
        df.userId = pd.Categorical(df.userId)
        df['new_user_id'] = df.userId.cat.codes
In [8]: # Now do the same thing for movie ids
        # current movie id = 0
        # custom_movie_map = {} # old movie id > new movie id
        # def map_movie_id(row):
        # global current movie id, custom movie map
           old_movie_id = row['movieId']
           if old_movie_id not in custom_movie_map:
             custom_movie_map[old_movie_id] = current_movie_id
              current_movie_id += 1
           return custom_movie_map[old_movie_id]
        # df['new_movie_id'] = df.apply(map_movie_id, axis=1)
        df.movieId = pd.Categorical(df.movieId)
        df['new_movie_id'] = df.movieId.cat.codes
In [9]: # Get user IDs, movie IDs, and ratings as separate arrays
        user_ids = df['new_user_id'].values
```

```
movie_ids = df['new_movie_id'].values
         ratings = df['rating'].values
In [10]: # Get number of users and number of movies
         N = len(set(user ids))
         M = len(set(movie_ids))
         # Set embedding dimension
         K = 10
In [11]: # Make a neural network
         # User input
         u = Input(shape=(1,))
         # Movie input
         m = Input(shape=(1,))
         # User embedding
         u_emb = Embedding(N, K)(u) # output is (num_samples, 1, K)
         # Movie embedding
         m_emb = Embedding(M, K)(m) # output is (num_samples, 1, K)
         # Flatten both embeddings
         u_emb = Flatten()(u_emb) # now it's (num_samples, K)
         m_emb = Flatten()(m_emb) # now it's (num_samples, K)
         # Concatenate user-movie embeddings into a feature vector
         x = Concatenate()([u_emb, m_emb]) # now it's (num_samples, 2K)
         # Now that we have a feature vector, it's just a regular ANN
         x = Dense(1024, activation='relu')(x)
         \# x = Dense(400, activation='relu')(x)
         \# x = Dense(400, activation='relu')(x)
         x = Dense(1)(x)
In [12]: # Build the model and compile
         model = Model(inputs=[u, m], outputs=x)
         model.compile(
           loss='mse',
           optimizer=SGD(learning_rate=0.08, momentum=0.9),
In [13]: # split the data
         user_ids, movie_ids, ratings = shuffle(user_ids, movie_ids, ratings)
         Ntrain = int(0.8 * len(ratings))
         train user = user ids[:Ntrain]
         train_movie = movie_ids[:Ntrain]
         train_ratings = ratings[:Ntrain]
         test_user = user_ids[Ntrain:]
         test_movie = movie_ids[Ntrain:]
         test_ratings = ratings[Ntrain:]
```

```
# center the ratings
avg_rating = train_ratings.mean()
train_ratings = train_ratings - avg_rating
test_ratings = test_ratings - avg_rating
]: r = model.fit(
```

```
In [14]: r = model.fit(
    x=[train_user, train_movie],
    y=train_ratings,
    epochs=25,
    batch_size=1024,
    verbose=2, # goes a little faster when you don't print the progress bar
    validation_data=([test_user, test_movie], test_ratings),
)
```

```
Epoch 1/25
         15626/15626 - 81s - loss: 0.7649 - val_loss: 0.7175 - 81s/epoch - 5ms/step
         Epoch 2/25
         15626/15626 - 60s - loss: 0.6983 - val_loss: 0.6930 - 60s/epoch - 4ms/step
         Epoch 3/25
         15626/15626 - 60s - loss: 0.6758 - val_loss: 0.6793 - 60s/epoch - 4ms/step
         Epoch 4/25
         15626/15626 - 63s - loss: 0.6616 - val_loss: 0.6740 - 63s/epoch - 4ms/step
         Epoch 5/25
         15626/15626 - 60s - loss: 0.6494 - val_loss: 0.6650 - 60s/epoch - 4ms/step
         Epoch 6/25
         15626/15626 - 64s - loss: 0.6358 - val_loss: 0.6576 - 64s/epoch - 4ms/step
         Epoch 7/25
         15626/15626 - 59s - loss: 0.6202 - val_loss: 0.6469 - 59s/epoch - 4ms/step
         Epoch 8/25
         15626/15626 - 59s - loss: 0.6090 - val_loss: 0.6424 - 59s/epoch - 4ms/step
         Epoch 9/25
         15626/15626 - 63s - loss: 0.6002 - val_loss: 0.6390 - 63s/epoch - 4ms/step
         Epoch 10/25
         15626/15626 - 60s - loss: 0.5920 - val_loss: 0.6536 - 60s/epoch - 4ms/step
         Epoch 11/25
         15626/15626 - 63s - loss: 0.5834 - val_loss: 0.6333 - 63s/epoch - 4ms/step
         Epoch 12/25
         15626/15626 - 62s - loss: 0.5750 - val_loss: 0.6301 - 62s/epoch - 4ms/step
         Epoch 13/25
         15626/15626 - 63s - loss: 0.5679 - val_loss: 0.6270 - 63s/epoch - 4ms/step
         Epoch 14/25
         15626/15626 - 60s - loss: 0.5619 - val_loss: 0.6362 - 60s/epoch - 4ms/step
         Epoch 15/25
         15626/15626 - 60s - loss: 0.5569 - val_loss: 0.6267 - 60s/epoch - 4ms/step
         Epoch 16/25
         15626/15626 - 63s - loss: 0.5526 - val_loss: 0.6247 - 63s/epoch - 4ms/step
         Epoch 17/25
         15626/15626 - 63s - loss: 0.5491 - val_loss: 0.6261 - 63s/epoch - 4ms/step
         Epoch 18/25
         15626/15626 - 60s - loss: 0.5461 - val_loss: 0.6262 - 60s/epoch - 4ms/step
         Epoch 19/25
         15626/15626 - 60s - loss: 0.5434 - val_loss: 0.6249 - 60s/epoch - 4ms/step
         Epoch 20/25
         15626/15626 - 60s - loss: 0.5412 - val_loss: 0.6259 - 60s/epoch - 4ms/step
         Epoch 21/25
         15626/15626 - 60s - loss: 0.5390 - val_loss: 0.6258 - 60s/epoch - 4ms/step
         Epoch 22/25
         15626/15626 - 59s - loss: 0.5371 - val_loss: 0.6311 - 59s/epoch - 4ms/step
         Epoch 23/25
         15626/15626 - 59s - loss: 0.5354 - val_loss: 0.6253 - 59s/epoch - 4ms/step
         Epoch 24/25
         15626/15626 - 59s - loss: 0.5339 - val_loss: 0.6279 - 59s/epoch - 4ms/step
         Epoch 25/25
         15626/15626 - 59s - loss: 0.5324 - val_loss: 0.6350 - 59s/epoch - 4ms/step
In [15]: # plot losses
         plt.plot(r.history['loss'], label="train loss")
         plt.plot(r.history['val_loss'], label="val loss")
         plt.legend()
         plt.show()
```



In [16]: # is this on par with other approaches?
# https://datascience.stackexchange.com/questions/29740/benchmark-result-for-moviel
np.sqrt(0.6259)

Out[16]: 0.7911384202527394