

Multi-task recommenders

In [1]:

```
import os
import pprint
import tempfile

from typing import Dict, Text

import numpy as np
import tensorflow as tf
import tensorflow_recommenders as tfrcs
import pandas as pd
from firebase import firebase
import matplotlib.pyplot as plt
```

Preparing the dataset

In [2]:

```
firebase = firebase.FirebaseApplication('https://thesis-bd8c8-default-rtdb.europe-west1.firebaseio.com')
firebase_ratings = firebase.get('/User_Book', None)
firebase_books = firebase.get('/Books', None)
```

In [3]:

```
ratings_df = pd.DataFrame.from_dict(firebase_ratings, orient='index')
books_df = pd.DataFrame.from_dict(firebase_books, orient='index')
```

In [4]:

```
ratings_df.head()
```

Out[4]:

| | bookId | isbn | myRate |
|----------------------|----------------------|----------------|--------|
| -NWcEFgMwmdaYc-4ndml | -NWcEFeoVaEgjMwiboCA | 09781565841000 | 5.0 |
| NWcEGniRUJ0hRQmvlc0 | NWcEGmQeH3eiHRZ0w7G | 09781929610259 | 4.5 |
| NWcEHtzsgGbN7rpUZ6V | -NWcEHsFfJ3yqXud1NGo | 09780814326114 | 4.0 |
| -NWcEJunG4PfX-aAVxiF | -NWcEJqjxlyMQv5izHrS | 09780312010447 | 4.5 |
| -NWcELFol68JZpsfvkyF | -NWcELEEV0QR6EHobxle | 09780143036357 | 3.5 |

In [5]:

```
len(set(books_df["isbn"]))
```

Out[5]:

704

In [6]:

```
len(books_df)
```

Out[6]:

1011

In [7]:

```
books_df = pd.DataFrame(set(books_df["isbn"]), columns=["isbn"])
```

In [8]:

```
len(books_df)
```

Out[8]:

704

In [9]:

```
ratings_dataset = tf.data.Dataset.from_tensor_slices(dict(ratings_df))  
books_dataset = tf.data.Dataset.from_tensor_slices(dict(books_df))
```

In [10]:

```
ratings = ratings_dataset.map(lambda x: {  
    "book_isbn": x["isbn"],  
    "user_id": x["userId"],  
    "user_rating": x["myRate"],  
})  
books = books_dataset.map(lambda x: x["isbn"])
```

In [11]:

```
len(books)
```

Out[11]:

704

In [12]:

```
len(ratings)
```

Out[12]:

1011

In [13]:

```
# Randomly shuffle data and split between train and test.
tf.random.set_seed(42)
shuffled = ratings.shuffle(len(ratings_df), seed=42, reshuffle_each_iteration=False)

train = shuffled.take(800)
test = shuffled.skip(800).take(210)

book_isbns = books.batch(25) #100 50
user_ids = ratings.batch(10_000).map(lambda x: x["user_id"])

unique_book_isbns = np.unique(np.concatenate(list(book_isbns)))
unique_user_ids = np.unique(np.concatenate(list(user_ids)))
```

A multi-task model

In [14]:

```

class BookModel(tf.keras.models.Model):

    def __init__(self, rating_weight: float, retrieval_weight: float) -> None:
        # We take the loss weights in the constructor: this allows us to instantiate
        # several model objects with different loss weights.

        super().__init__()

        embedding_dimension = 64 #32

        # User and book models.
        self.book_model: tf.keras.layers.Layer = tf.keras.Sequential([
            tf.keras.layers.StringLookup(
                vocabulary=unique_book_isbns, mask_token=None),
            tf.keras.layers.Embedding(len(unique_book_isbns) + 1, embedding_dimension)
        ])
        self.user_model: tf.keras.layers.Layer = tf.keras.Sequential([
            tf.keras.layers.StringLookup(
                vocabulary=unique_user_ids, mask_token=None),
            tf.keras.layers.Embedding(len(unique_user_ids) + 1, embedding_dimension)
        ])

        # A small model to take in user and book embeddings and predict ratings.
        # We can make this as complicated as we want as long as we output a scalar
        # as our prediction.
        self.rating_model = tf.keras.Sequential([
            tf.keras.layers.Dense(512, activation="relu"),
            tf.keras.layers.Dropout(0.3),
            tf.keras.layers.Dense(256, activation="relu"),
            tf.keras.layers.Dropout(0.2),
            tf.keras.layers.Dense(128, activation="relu"),
            tf.keras.layers.Dropout(0.2),
            tf.keras.layers.Dense(32, activation="relu"),
            tf.keras.layers.Dense(1),
        ])

        # The tasks.
        self.rating_task: tf.keras.layers.Layer = tf.keras.layers.Ranking(
            loss=tf.keras.losses.MeanSquaredError(),
            metrics=[tf.keras.metrics.RootMeanSquaredError()],
        )
        self.retrieval_task: tf.keras.layers.Layer = tf.keras.layers.Retrieval(
            metrics=tf.keras.metrics.FactorizedTopK(
                candidates=books.batch(16).map(self.book_model) #128 32
            )
        )

        # The loss weights.
        self.rating_weight = rating_weight
        self.retrieval_weight = retrieval_weight

    def call(self, features: Dict[Text, tf.Tensor]) -> tf.Tensor:
        # We pick out the user features and pass them into the user model.
        user_embeddings = self.user_model(features["user_id"])
        # And pick out the book features and pass them into the book model.
        book_embeddings = self.book_model(features["book_isbn"])

        return (
            user_embeddings,

```

```

        book_embeddings,
        # We apply the multi-layered rating model to a concatenation of
        # user and book embeddings.
        self.rating_model(
            tf.concat([user_embeddings, book_embeddings], axis=1)
        ),
    )

def compute_loss(self, features: Dict[Text, tf.Tensor], training=False) -> tf.Tensor

    ratings = features.pop("user_rating")

    user_embeddings, book_embeddings, rating_predictions = self(features)

    # We compute the loss for each task.
    rating_loss = self.rating_task(
        labels=ratings,
        predictions=rating_predictions,
    )
    retrieval_loss = self.retrieval_task(user_embeddings, book_embeddings)
    # And combine them using the loss weights.
    return (self.rating_weight * rating_loss
            + self.retrieval_weight * retrieval_loss)

```

Rating-specialized model

In [15]:

```

model = BookModel(rating_weight=1.0, retrieval_weight=0.0)
model.compile(optimizer=tf.keras.optimizers.AdamW(0.001))

```

In [16]:

```

cached_train = train.shuffle(800).batch(32).cache() #128 64
cached_test = test.batch(16).cache() #64 32

```

In [17]:

```

history_rating_model = model.fit(cached_train, epochs= 100)
metrics = model.evaluate(cached_test, return_dict=True)

print(f"Retrieval top-100 accuracy: {metrics['factorized_top_k/top_100_categorical_accu
print(f"Ranking RMSE: {metrics['root_mean_squared_error']:.3f}.")

ed_error: 0.8434 - factorized_top_k/top_1_categorical_accuracy: 0.0000e
+00 - factorized_top_k/top_5_categorical_accuracy: 0.0063 - factorized_
top_k/top_10_categorical_accuracy: 0.0100 - factorized_top_k/top_50_cat
egorical_accuracy: 0.0725 - factorized_top_k/top_100_categorical_accura
cy: 0.1488 - loss: 0.7023 - regularization_loss: 0.0000e+00 - total_los
s: 0.7023
Epoch 5/100
25/25 [=====] - 2s 77ms/step - root_mean_squar
ed_error: 0.9139 - factorized_top_k/top_1_categorical_accuracy: 0.0000e
+00 - factorized_top_k/top_5_categorical_accuracy: 0.0075 - factorized_
top_k/top_10_categorical_accuracy: 0.0125 - factorized_top_k/top_50_cat
egorical_accuracy: 0.0700 - factorized_top_k/top_100_categorical_accura
cy: 0.1525 - loss: 0.8181 - regularization_loss: 0.0000e+00 - total_los
s: 0.8181
Epoch 6/100
25/25 [=====] - 2s 82ms/step - root_mean_squar
ed_error: 1.3795 - factorized_top_k/top_1_categorical_accuracy: 0.0000e
+00 - factorized_top_k/top_5_categorical_accuracy: 0.0075 - factorized_
top_k/top_10_categorical_accuracy: 0.0162 - factorized_top_k/top_50_cat
egorical_accuracy: 0.0700 - factorized_top_k/top_100_categorical_accura

```

Retrieval-specialized model

In [18]:

```

model = BookModel(rating_weight=0.0, retrieval_weight=1.0)
model.compile(optimizer=tf.keras.optimizers.AdamW(0.001))

```

In [19]:

```

history_retrieval_model = model.fit(cached_train, epochs= 100)
metrics = model.evaluate(cached_test, return_dict=True)

print(f"Retrieval top-100 accuracy: {metrics['factorized_top_k/top_100_categorical_accu
print(f"Ranking RMSE: {metrics['root_mean_squared_error']:.3f}.")
25/25 [=====] - 3s 105ms/step - root_mean_squa
red_error: 3.7425 - factorized_top_k/top_1_categorical_accuracy: 0.0000
e+00 - factorized_top_k/top_5_categorical_accuracy: 0.3338 - factorized
_top_k/top_10_categorical_accuracy: 0.5738 - factorized_top_k/top_50_ca
tegorical_accuracy: 0.8775 - factorized_top_k/top_100_categorical_accu
acy: 0.9450 - loss: 110.2019 - regularization_loss: 0.0000e+00 - total_
loss: 110.2019
Epoch 4/100
25/25 [=====] - 2s 71ms/step - root_mean_squa
ed_error: 3.7429 - factorized_top_k/top_1_categorical_accuracy: 0.0000e
+00 - factorized_top_k/top_5_categorical_accuracy: 0.4125 - factorized_
top_k/top_10_categorical_accuracy: 0.8300 - factorized_top_k/top_50_cat
egorical_accuracy: 0.9775 - factorized_top_k/top_100_categorical_accu
cy: 0.9912 - loss: 109.7138 - regularization_loss: 0.0000e+00 - total_l
oss: 109.7138
Epoch 5/100
25/25 [=====] - 2s 67ms/step - root_mean_squa
ed_error: 3.7435 - factorized_top_k/top_1_categorical_accuracy: 0.0000e
+00 - factorized_top_k/top_5_categorical_accuracy: 0.4250 - factorized_
top_k/top_10_categorical_accuracy: 0.9312 - factorized_top_k/top_50_cat

```

Joint model

In [20]:

```

model = BookModel(rating_weight=1.0, retrieval_weight=1.0)
model.compile(optimizer=tf.keras.optimizers.AdamW(0.001))

```


In [21]:

```

history_joint_model = model.fit(cached_train, epochs= 100)
metrics = model.evaluate(cached_test, return_dict=True)

print(f"Retrieval top-100 accuracy: {metrics['factorized_top_k/top_100_categorical_accu
print(f"Ranking RMSE: {metrics['root_mean_squared_error']:.3f}.")
112.0851
Epoch 3/100
25/25 [=====] - 2s 69ms/step - root_mean_squar
ed_error: 0.9977 - factorized_top_k/top_1_categorical_accuracy: 0.0025
- factorized_top_k/top_5_categorical_accuracy: 0.1925 - factorized_top_
k/top_10_categorical_accuracy: 0.3187 - factorized_top_k/top_50_categor
ical_accuracy: 0.6087 - factorized_top_k/top_100_categorical_accuracy:
0.7450 - loss: 111.4211 - regularization_loss: 0.0000e+00 - total_loss:
111.4211
Epoch 4/100
25/25 [=====] - 2s 67ms/step - root_mean_squar
ed_error: 0.8334 - factorized_top_k/top_1_categorical_accuracy: 0.0012
- factorized_top_k/top_5_categorical_accuracy: 0.3225 - factorized_top_
k/top_10_categorical_accuracy: 0.4950 - factorized_top_k/top_50_categor
ical_accuracy: 0.7812 - factorized_top_k/top_100_categorical_accuracy:
0.8737 - loss: 110.8924 - regularization_loss: 0.0000e+00 - total_loss:
110.8924
Epoch 5/100
25/25 [=====] - 2s 80ms/step - root_mean_squar
ed_error: 0.8952 - factorized_top_k/top_1_categorical_accuracy: 0.0037

```

DATA

In [49]:

```

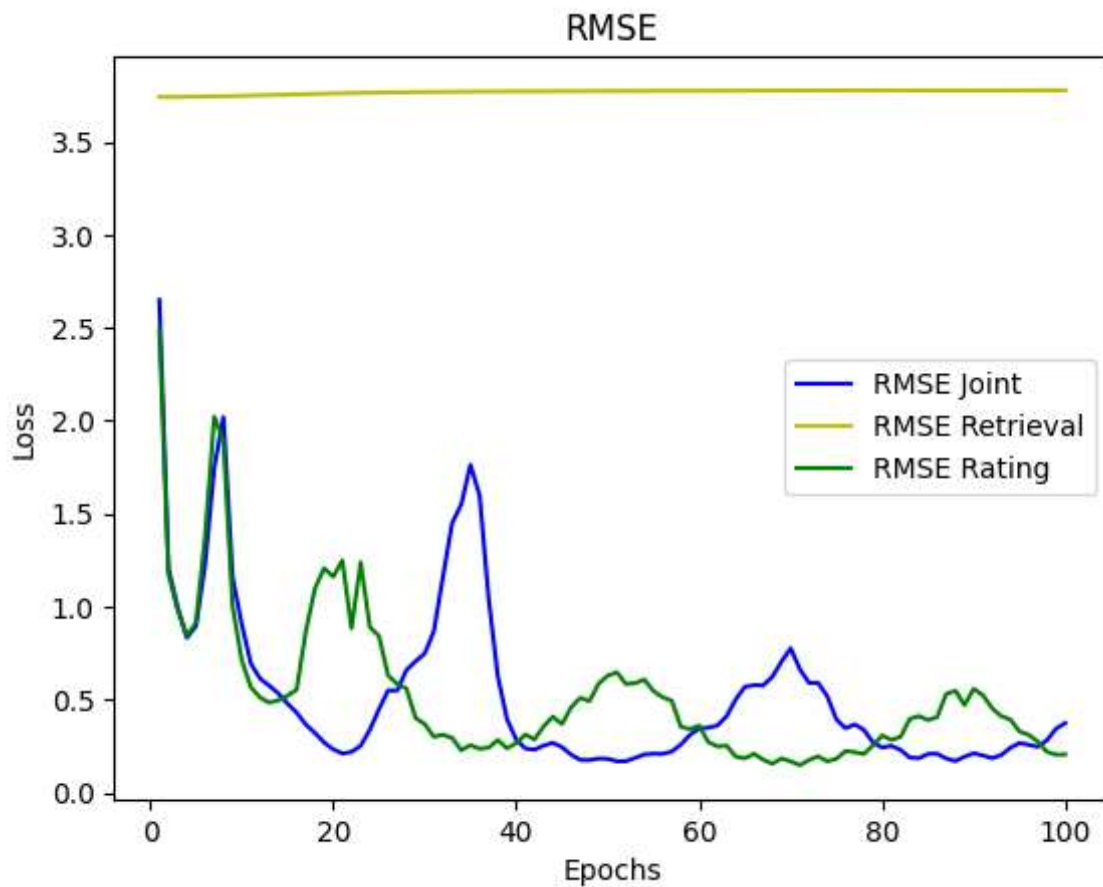
def draw_plot(name, joint, retrieval, rating):
    epochs = range(1, len(joint) + 1)

    plt.plot(epochs, joint, 'b', label= name + ' Joint')
    plt.plot(epochs, retrieval, 'y', label=name + ' Retrieval')
    plt.plot(epochs, rating, 'g', label=name + ' Rating')
    plt.title(name)
    plt.xlabel('Epochs')
    plt.ylabel('Loss')
    plt.legend()
    plt.show()

```

In [50]:

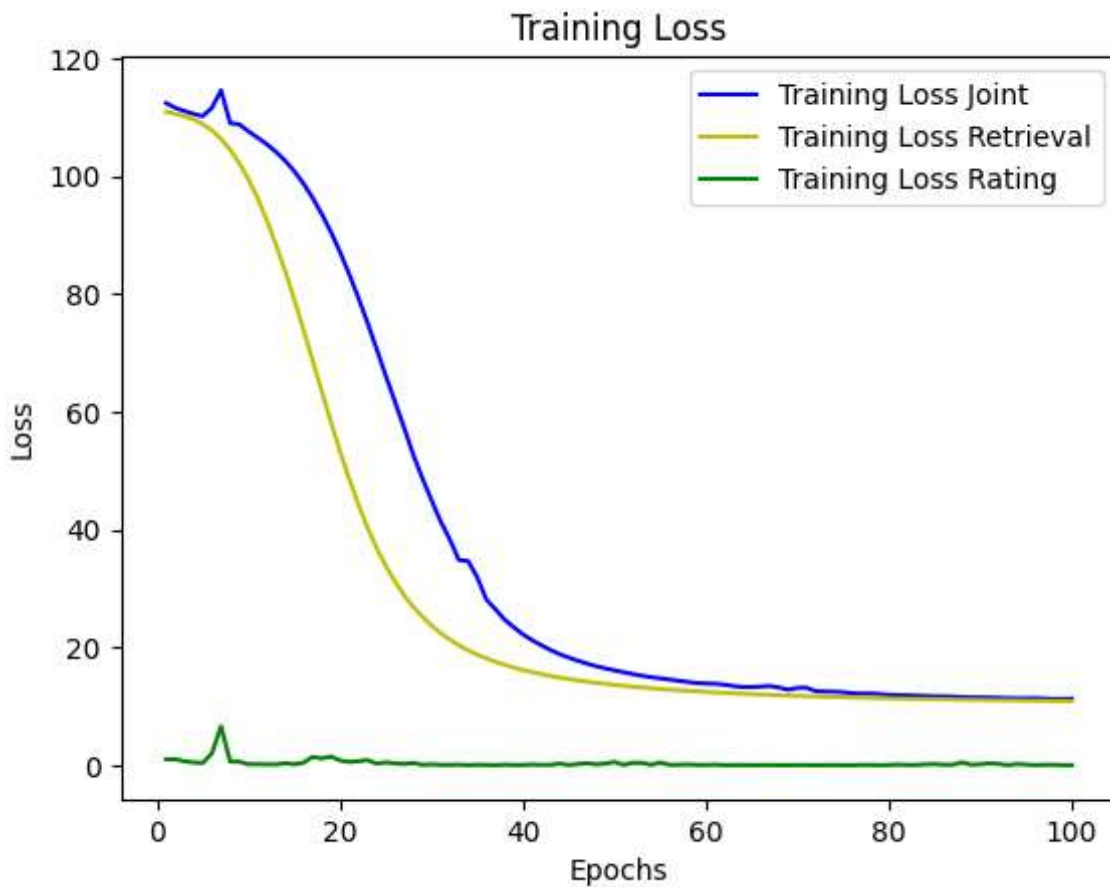
```
RMSE_joint = history_joint_model.history['root_mean_squared_error']  
RMSE_retrieval = history_retrieval_model.history['root_mean_squared_error']  
RMSE_rating = history_rating_model.history['root_mean_squared_error']  
  
draw_plot('RMSE', RMSE_joint, RMSE_retrieval, RMSE_rating)
```



In [51]:

```
total_loss_values_joint = history_joint_model.history['total_loss']
total_loss_values_retrieval = history_retrieval_model.history['total_loss']
total_loss_values_rating = history_rating_model.history['total_loss']

draw_plot('Training Loss', total_loss_values_joint, total_loss_values_retrieval, total_loss_values_rating)
```



Making predictions

In [52]:

```
trained_movie_embeddings, trained_user_embeddings, predicted_rating = model({
    "user_id": np.array(["3avc3TUJioP8XGD0bLK9xtV7uIG3"]),
    "book_isbn": np.array(["09781880685358"])
})
print("Predicted rating:")
print(predicted_rating)
```

Predicted rating:
 tf.Tensor([[3.6408298]], shape=(1, 1), dtype=float32)

In [53]:

```

user_id = ["3avc3TUJioP8XGD0bLK9xtV7uIG3"]
isbn_list = set(books_df["isbn"])
for isbn in isbn_list:
    trained_movie_embeddings, trained_user_embeddings, predicted_rating = model({
        "user_id": np.array(user_id),
        "book_isbn": np.array([isbn])
    })
    print(predicted_rating)

```

```

tf.Tensor([[2.7636173]], shape=(1, 1), dtype=float32)
tf.Tensor([[1.7629036]], shape=(1, 1), dtype=float32)
tf.Tensor([[2.688934]], shape=(1, 1), dtype=float32)
tf.Tensor([[2.988138]], shape=(1, 1), dtype=float32)
tf.Tensor([[3.3087287]], shape=(1, 1), dtype=float32)
tf.Tensor([[2.0517175]], shape=(1, 1), dtype=float32)
tf.Tensor([[2.948065]], shape=(1, 1), dtype=float32)
tf.Tensor([[2.952101]], shape=(1, 1), dtype=float32)
tf.Tensor([[4.722532]], shape=(1, 1), dtype=float32)
tf.Tensor([[5.054215]], shape=(1, 1), dtype=float32)
tf.Tensor([[2.791417]], shape=(1, 1), dtype=float32)
tf.Tensor([[3.4679494]], shape=(1, 1), dtype=float32)
tf.Tensor([[4.9191465]], shape=(1, 1), dtype=float32)
tf.Tensor([[5.2447853]], shape=(1, 1), dtype=float32)
tf.Tensor([[3.2389157]], shape=(1, 1), dtype=float32)
tf.Tensor([[3.0862436]], shape=(1, 1), dtype=float32)
tf.Tensor([[3.6737854]], shape=(1, 1), dtype=float32)
tf.Tensor([[2.7541964]], shape=(1, 1), dtype=float32)
tf.Tensor([[3.1186855]], shape=(1, 1), dtype=float32)
tf.Tensor([[3.3595603]], shape=(1, 1), dtype=float32)

```

Save the model

In [54]:

```

model.retrieval_task = tf.keras.tasks.Retrieval() # Removes the metrics.
model.compile()
model.save("multi_recc3")

```

WARNING:tensorflow:Skipping full serialization of Keras layer <tensorflow_recommenders.tasks.retrieval.Retrieval object at 0x0000014B9F184C10>, because it is not built.

WARNING:tensorflow:Skipping full serialization of Keras layer <tensorflow_recommenders.tasks.retrieval.Retrieval object at 0x0000014B9F184C10>, because it is not built.

INFO:tensorflow:Assets written to: multi_recc3\assets

INFO:tensorflow:Assets written to: multi_recc3\assets

In [55]:

```

# Load model
model = tf.keras.models.load_model("multi_recc3")

```

In [56]:

```
# Convert the model
converter = tf.lite.TFLiteConverter.from_saved_model("multi_recc3") # path to the SavedM
tflite_model = converter.convert()

# Save the model.
with open('model3.tflite', 'wb') as f:
    f.write(tflite_model)
```

Tf Lite

In [57]:

```
interpreter = tf.lite.Interpreter(model_path="model3.tflite")
interpreter.allocate_tensors()

#Get input details
input_details = interpreter.get_input_details()
for input_tensor in input_details:
    print("Input name:", input_tensor["name"])
    print("Input shape:", input_tensor["shape"])
    print("Input data type:", input_tensor["dtype"])
    print()
#Get output details
output_details = interpreter.get_output_details()
for output_tensor in output_details:
    print("Output name:", output_tensor["name"])
    print("Output shape:", output_tensor["shape"])
    print("Output data type:", output_tensor["dtype"])
    print()
```

```
Input name: serving_default_args_0:0
Input shape: [1]
Input data type: <class 'numpy.bytes_'>
```

```
Input name: serving_default_args_0_1:0
Input shape: [1]
Input data type: <class 'numpy.bytes_'>
```

```
Output name: StatefulPartitionedCall_2:0
Output shape: []
Output data type: <class 'numpy.float32'>
```

```
Output name: StatefulPartitionedCall_2:2
Output shape: [1 1]
Output data type: <class 'numpy.float32'>
```

```
Output name: StatefulPartitionedCall_2:1
Output shape: []
Output data type: <class 'numpy.float32'>
```

In [58]:

```

# Prepare the input data
input_data_isbn = np.array([b'09780143036357'], dtype=np.bytes_)
input_data_user_id = np.array([b'3avc3TUJioP8XGD0bLK9xtV7uIG3'], dtype=np.bytes_)

input_details = interpreter.get_input_details()
interpreter.set_tensor(input_details[0]['index'], input_data_isbn)
interpreter.set_tensor(input_details[1]['index'], input_data_user_id)

# Run the inference
interpreter.invoke()

# Retrieve the output results
output_details = interpreter.get_output_details()

output_data_prediction = interpreter.get_tensor(output_details[0]['index'])
output_data_probabilities = interpreter.get_tensor(output_details[1]['index'])
output_data_score = interpreter.get_tensor(output_details[2]['index'])

# Process the output
#prediction = output_data_prediction.squeeze()
probabilities = output_data_probabilities.squeeze()
#score = output_data_score.squeeze()

# Print the results
#print("Prediction:", prediction)
print("Probability:", probabilities)
#print("Score:", score)

```

Probability: 3.2864304

Tensorflow recommenders

Brute Force

In [59]:

```

# Create a model that takes in raw query features, and
index = tf.rs.layers.factorized_top_k.BruteForce(model.user_model)
# recommends books out of the entire books dataset.
index.index_from_dataset(
    tf.data.Dataset.zip((books.batch(100), books.batch(100).map(model.book_model)))
)

# Get recommendations.
_, isbns = index(np.array([b'Pgzb07La4DUN0hYPzYXHA7CdFni1']))
print(f"Recommendations for user: {isbns[0, :10]}")

```

Recommendations for user: [b'09780140286014' b'09780618257768' b'09781857024074' b'09780465014903' b'09781592289806' b'09780590428880' b'09781859843406' b'09780321209184' b'09780195117950' b'09780140448948']

Save the brute force model

In [60]:

```
index.save("brute_force_model3")
```

WARNING:tensorflow:Model's `__init__()` arguments contain non-serializable objects. Please implement a `get_config()` method in the subclassed Model for proper saving and loading. Defaulting to empty config.

WARNING:tensorflow:Model's `__init__()` arguments contain non-serializable objects. Please implement a `get_config()` method in the subclassed Model for proper saving and loading. Defaulting to empty config.

WARNING:tensorflow:Model's `__init__()` arguments contain non-serializable objects. Please implement a `get_config()` method in the subclassed Model for proper saving and loading. Defaulting to empty config.

INFO:tensorflow:Assets written to: brute_force_model3\assets

INFO:tensorflow:Assets written to: brute_force_model3\assets

WARNING:tensorflow:Model's `__init__()` arguments contain non-serializable objects. Please implement a `get_config()` method in the subclassed Model for proper saving and loading. Defaulting to empty config.

WARNING:tensorflow:Model's `__init__()` arguments contain non-serializable objects. Please implement a `get_config()` method in the subclassed Model for proper saving and loading. Defaulting to empty config.

In [61]:

```
# test loading
```

```
loaded = tf.saved_model.load("brute_force_model3")
```

```
# Pass a user id in, get top predicted movie titles back.
scores, isbns = loaded(["Pgzb07La4DUNOhYPzYXHA7CdFni1"])
```

```
print(f"Recommendations: {isbns[0][:5]}")
```

```
Recommendations: [b'09780140286014' b'09780618257768' b'09781857024074'
b'09780465014903'
b'09781592289806']
```

TFLite for the model

In [62]:

```
# Convert the model
```

```
converter = tf.lite.TFLiteConverter.from_saved_model("brute_force_model3") # path to the
tflite_model = converter.convert()
```

```
# Save the model.
```

```
with open('brute_force_model3.tflite', 'wb') as f:
    f.write(tflite_model)
```

Tf lite testing

In [63]:

```
interpreter = tf.lite.Interpreter(model_path="brute_force_model3.tflite")
interpreter.allocate_tensors()
```

#Get input details

```
input_details = interpreter.get_input_details()
```

```
for input_tensor in input_details:
    print("Input name:", input_tensor["name"])
    print("Input shape:", input_tensor["shape"])
    print("Input data type:", input_tensor["dtype"])
    print()
```

#Get output details

```
output_details = interpreter.get_output_details()
```

```
for output_tensor in output_details:
    print("Output name:", output_tensor["name"])
    print("Output shape:", output_tensor["shape"])
    print("Output data type:", output_tensor["dtype"])
    print()
```

Input name: serving_default_input_1:0

Input shape: [1]

Input data type: <class 'numpy.bytes_'>

Output name: StatefulPartitionedCall_1:0

Output shape: [1 10]

Output data type: <class 'numpy.float32'>

Output name: StatefulPartitionedCall_1:1

Output shape: [1 10]

Output data type: <class 'numpy.bytes_'>

In [66]:

```
# Prepare the input data
input_data = np.array(["zwVJUfdC0oa9hWWp9uK0hRTM71j1"], dtype=np.bytes_)

input_details = interpreter.get_input_details()
interpreter.set_tensor(input_details[0]['index'], input_data)

# Run the inference
interpreter.invoke()

# Retrieve the output results
output_details = interpreter.get_output_details()

output_data_prediction = interpreter.get_tensor(output_details[0]['index'])
output_data_classes = interpreter.get_tensor(output_details[1]['index'])

# Process the output
#prediction = output_data_prediction.squeeze()
classes = output_data_classes.squeeze().astype(str)

# Print the results
#print("Prediction:", prediction)
print("Classes:", classes)
```

```
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