STAT 5010 Project - Fashion Recommendations using Neural Networks

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1 Defining problem to solve

Given a dataset of transactions (customer-product pairs that resulted in purchases), I want to find other customer-product pairs that are likely to be purchased. More specifically, I'm trying to figure out what customers will be interested in purchasing next week.

The dataset in use is provided by Kaggle here (https://www.kaggle.com/competitions/h-and-m-personalized-fashion-recommendations/data).

Due to computing power limitations, I have chosen not to use the provided image data in my model, but have instead chosen to use tabular data exclusively.

2 Import libraries

[ ]:
```
!pip install plot_keras_history
from plot_keras_history import plot_history
import matplotlib.pyplot as plt

from datetime import datetime
from scipy import stats
import numpy as np
import pandas as pd
import keras
import numpy as np
import pandas as pd
import os
import random
import tensorflow as tf
import json
import numexpr as ne
from math import sqrt
import time

from keras.layers import Input, Dense, MultiHeadAttention, LayerNormalization,␣
↪Add, Embedding, Dropout, Flatten, LocallyConnected1D, BatchNormalization,␣
↪Dot, Reshape, Concatenate
```

```python
from keras.models import Model, load_model, Sequential
from keras.callbacks import ModelCheckpoint

import os
from sklearn import preprocessing

from google.colab import drive
drive.mount('/content/drive')

# Extracts transactions file from google drive.  Without this extraction,
# for some reason gDrive clips the .csv file so that I lose transactions data.

from zipfile import ZipFile
file = "drive/MyDrive/transactions_train.csv.zip"
with ZipFile(file, 'r') as zip:
    zip.extractall()
```

```
Collecting plot_keras_history
  Downloading plot_keras_history-1.1.35.tar.gz (8.9 kB)
Requirement already satisfied: matplotlib in /usr/local/lib/python3.7/dist-
packages (from plot_keras_history) (3.2.2)
Requirement already satisfied: pandas in /usr/local/lib/python3.7/dist-packages
(from plot_keras_history) (1.3.5)
Requirement already satisfied: scipy in /usr/local/lib/python3.7/dist-packages
(from plot_keras_history) (1.4.1)
Collecting sanitize_ml_labels>=1.0.33
  Downloading sanitize_ml_labels-1.0.33.tar.gz (7.6 kB)
Collecting compress_json
  Downloading compress_json-1.0.5.tar.gz (5.0 kB)
Requirement already satisfied: numpy>=1.11 in /usr/local/lib/python3.7/dist-
packages (from matplotlib->plot_keras_history) (1.21.6)
Requirement already satisfied: pyparsing!=2.0.4,!=2.1.2,!=2.1.6,>=2.0.1 in
/usr/local/lib/python3.7/dist-packages (from matplotlib->plot_keras_history)
(3.0.8)
Requirement already satisfied: python-dateutil>=2.1 in
/usr/local/lib/python3.7/dist-packages (from matplotlib->plot_keras_history)
(2.8.2)
Requirement already satisfied: kiwisolver>=1.0.1 in
/usr/local/lib/python3.7/dist-packages (from matplotlib->plot_keras_history)
(1.4.2)
Requirement already satisfied: cycler>=0.10 in /usr/local/lib/python3.7/dist-
packages (from matplotlib->plot_keras_history) (0.11.0)
Requirement already satisfied: typing-extensions in
/usr/local/lib/python3.7/dist-packages (from
kiwisolver>=1.0.1->matplotlib->plot_keras_history) (4.1.1)
Requirement already satisfied: six>=1.5 in /usr/local/lib/python3.7/dist-
packages (from python-dateutil>=2.1->matplotlib->plot_keras_history) (1.15.0)
```

```
Requirement already satisfied: pytz>=2017.3 in /usr/local/lib/python3.7/dist-
packages (from pandas->plot_keras_history) (2022.1)
Building wheels for collected packages: plot-keras-history, sanitize-ml-labels,
compress-json
  Building wheel for plot-keras-history (setup.py) … done
  Created wheel for plot-keras-history:
filename=plot_keras_history-1.1.35-py3-none-any.whl size=9091
sha256=4dece0ba3f1c42487a0ea5f26a4347e617f5e25e5354bb4054acd8c8446368bf
  Stored in directory: /root/.cache/pip/wheels/40/92/fd/d7d02562f5312ec89748f7ca
7e16d1f1cac44719a551242bf2
  Building wheel for sanitize-ml-labels (setup.py) … done
  Created wheel for sanitize-ml-labels:
filename=sanitize_ml_labels-1.0.33-py3-none-any.whl size=8285
sha256=9efdf8c9e6fbc58a4ccc67b84e56ef784bb4efe0d9df0f2fd78ddbc0fb4967e9
  Stored in directory: /root/.cache/pip/wheels/66/ab/57/d00b27746f59b194d2b311d0
76da744dd3fc1f6ceb8574e9ae
  Building wheel for compress-json (setup.py) … done
  Created wheel for compress-json: filename=compress_json-1.0.5-py3-none-any.whl
size=4899
sha256=359fb099afe999ac42839318b7d43f3f5f818e97340575833534843b759c696d
  Stored in directory: /root/.cache/pip/wheels/9d/c9/7d/7840b772f45f7870c08cb0df
4eefa994af4208bbc046856b41
Successfully built plot-keras-history sanitize-ml-labels compress-json
Installing collected packages: compress-json, sanitize-ml-labels, plot-keras-
history
Successfully installed compress-json-1.0.5 plot-keras-history-1.1.35 sanitize-
ml-labels-1.0.33
Mounted at /content/drive
```

[ ]:
```python
# Number of most popular products to make predictions from.
pred_len = 10000
```

3 Reading in data

[69]:
```python
# Read data into pandas dataframes
transactions = pd.read_csv("transactions_train.csv")
articles = pd.read_csv("drive/MyDrive/articles.csv")
customers = pd.read_csv("drive/MyDrive/customers.csv")
```

4 Performing basic data summarization and preparation

[70]:
```python
articles.nunique()
```

[70]:
```
article_id                        105542
product_code                       47224
```

```
prod_name                       45875
product_type_no                   132
product_type_name                 131
product_group_name                 19
graphical_appearance_no            30
graphical_appearance_name          30
colour_group_code                  50
colour_group_name                  50
perceived_colour_value_id           8
perceived_colour_value_name         8
perceived_colour_master_id         20
perceived_colour_master_name       20
department_no                     299
department_name                   250
index_code                         10
index_name                         10
index_group_no                      5
index_group_name                    5
section_no                         57
section_name                       56
garment_group_no                   21
garment_group_name                 21
detail_desc                     43404
dtype: int64
```

[71]:
```python
customers.nunique()
```

[71]:
```
customer_id               1371980
FN                              1
Active                          1
club_member_status              3
fashion_news_frequency          4
age                            84
postal_code                352899
dtype: int64
```

[72]:
```python
# View basic structure of transactions data
transactions.head()
```

[72]:
```
        t_dat                                        customer_id  article_id  \
0  2018-09-20  000058a12d5b43e67d225668fa1f8d618c13dc232df0ca…   663713001
1  2018-09-20  000058a12d5b43e67d225668fa1f8d618c13dc232df0ca…   541518023
2  2018-09-20  00007d2de826758b65a93dd24ce629ed66842531df6699…   505221004
3  2018-09-20  00007d2de826758b65a93dd24ce629ed66842531df6699…   685687003
4  2018-09-20  00007d2de826758b65a93dd24ce629ed66842531df6699…   685687004

      price  sales_channel_id
```

```
0  0.050831              2
1  0.030492              2
2  0.015237              2
3  0.016932              2
4  0.016932              2
```

[73]:
```
encoders = {}

cust_encoder = preprocessing.LabelEncoder()

cust_encoder = cust_encoder.fit(customers["customer_id"].values)

print(len(cust_encoder.classes_))

encoders["customer_id"] = cust_encoder

transactions["customer_id"] = cust_encoder.
 ↪transform(transactions["customer_id"].values)
customers["customer_id"] = cust_encoder.transform(customers["customer_id"].
 ↪values)
```

```
1371980
```

[74]:
```
counts_dict = transactions["article_id"].value_counts().nlargest(n=pred_len).
 ↪to_dict()
trans_subset = transactions[transactions["article_id"].isin(counts_dict.keys())]
```

[75]:
```
articles_subset = articles[["article_id", "product_type_name",
                            "graphical_appearance_name", "colour_group_name",
                            "perceived_colour_value_name",
                            "perceived_colour_master_name", "department_name",
                            "index_name", "index_group_name", "section_name",
                            "garment_group_name"]]
```

[76]:
```
trans_subset.shape
transactions = pd.merge(articles_subset, trans_subset, on=['article_id'],␣
 ↪how="right")
transactions = pd.merge(transactions, customers[["customer_id", "age",␣
 ↪"postal_code"]], on=["customer_id"], how="left")
```

[77]:
```
transactions.dtypes
```

[77]:
```
article_id                       int64
product_type_name               object
graphical_appearance_name       object
colour_group_name               object
perceived_colour_value_name     object
```

```
perceived_colour_master_name     object
department_name                  object
index_name                       object
index_group_name                 object
section_name                     object
garment_group_name               object
t_dat                            object
customer_id                       int64
price                           float64
sales_channel_id                  int64
age                             float64
postal_code                      object
dtype: object
```

[78]:
```
transactions['t_dat'] =  pd.to_datetime(transactions['t_dat'])
```

[79]:
```
# Get number of unique values in each column for all of our data.
# This will be helpful later.

t_count = transactions.nunique()
transactions.shape

c_count = customers.nunique()
customers.shape

a_count = articles.nunique()
```

[80]:
```
t_count
```

[80]:
```
article_id                        10000
product_type_name                    82
graphical_appearance_name            28
colour_group_name                    49
perceived_colour_value_name           8
perceived_colour_master_name         18
department_name                     119
index_name                            8
index_group_name                      5
section_name                         39
garment_group_name                   19
t_dat                               734
customer_id                     1217586
price                              6633
sales_channel_id                      2
age                                  84
postal_code                      341486
dtype: int64
```

[81]:
```
c_count
```

[81]:
```
customer_id               1371980
FN                              1
Active                          1
club_member_status              3
fashion_news_frequency          4
age                            84
postal_code                352899
dtype: int64
```

[82]:
```
a_count
```

[82]:
```
article_id                      105542
product_code                     47224
prod_name                        45875
product_type_no                    132
product_type_name                  131
product_group_name                  19
graphical_appearance_no             30
graphical_appearance_name           30
colour_group_code                   50
colour_group_name                   50
perceived_colour_value_id            8
perceived_colour_value_name          8
perceived_colour_master_id          20
perceived_colour_master_name        20
department_no                      299
department_name                    250
index_code                          10
index_name                          10
index_group_no                       5
index_group_name                     5
section_no                          57
section_name                        56
garment_group_no                    21
garment_group_name                  21
detail_desc                      43404
dtype: int64
```

5 Create LabelEncoders for each categorical column of interest

A label encoder will convert a categorical string to a number, which I can then feed into the Embedding layers in my transformer-based model severals cells down.

[83]:
```
for column in transactions.columns:

    if column not in ["age", "price", "customer_id", "postal_code", "t_dat"]:
        print(column)

        le = preprocessing.LabelEncoder()
        le = le.fit(transactions[column].values)

        transactions[column] = le.transform(transactions[column].values)

        encoders[column] = le



le = preprocessing.LabelEncoder()
le = le.fit(customers["postal_code"].values)

transactions["postal_code"] = le.transform(transactions["postal_code"].values)
encoders["postal_code"] = le

customers["postal_code"] = encoders["postal_code"].
 ↪transform(customers["postal_code"].values)
```

```
article_id
product_type_name
graphical_appearance_name
colour_group_name
perceived_colour_value_name
perceived_colour_master_name
department_name
index_name
index_group_name
section_name
garment_group_name
sales_channel_id
```

[84]:
```
# Drop all but the 10000 most popular products from our dataset and label␣
 ↪encode what's left.

articles = articles[articles["article_id"].isin(counts_dict.keys())]

articles["article_id"] = encoders["article_id"].
 ↪transform(articles["article_id"].values)

articles.set_index("article_id", inplace=True)
```

```
/usr/local/lib/python3.7/dist-packages/ipykernel_launcher.py:5:
```

```
SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  """
```

[85]:
```
# Print the total number of customers that we need to make predictions for
len(cust_encoder.classes_)
```

[85]: 1371980

[86]:
```
# Find the most common product sold in case we need it later
most_common = transactions["article_id"].value_counts().nlargest(1).index[0]
```

6 Defining model architecture for transformer-based network

This model is based loosely on the encoder half of the transformer network found in "Attention is All You Need" (https://arxiv.org/pdf/1706.03762.pdf).

The biggest difference between this model and their model is that I don't add positional embeddings to each article embedding.

[ ]:
```
embedding_dim = 100

customer_id_dim = c_count["customer_id"]
article_id_dim = t_count["article_id"]
product_type_dim = a_count["product_type_name"]
appearance_dim = a_count["graphical_appearance_name"]
colour_dim = a_count["colour_group_name"]
department_dim = a_count["department_name"]
zip_dim = c_count["postal_code"]
month_dim = 4

max_input_len = 16
num_heads = 8
ffn_units = 1024
dropout_rate = 0.1

# Create model architecture (loosely based on Transformer network encoders)

article_id_inp = Input(shape=(max_input_len,))
product_type_inp = Input(shape=(max_input_len,))
appearance_inp = Input(shape=(max_input_len,))
colour_inp = Input(shape=(max_input_len,))
department_inp = Input(shape=(max_input_len,))
```

```
price_inp = Input(shape=(max_input_len,))
price = Reshape((max_input_len, 1))(price_inp)

age_inp = Input(shape=(1,))
zip_inp = Input(shape=(1,))

article_emb = Embedding(input_dim=article_id_dim,␣
 ↪output_dim=round(sqrt(article_id_dim)))(article_id_inp)
type_emb = Embedding(input_dim=product_type_dim,␣
 ↪output_dim=round(sqrt(product_type_dim)))(product_type_inp)
appearance_emb = Embedding(input_dim=appearance_dim,␣
 ↪output_dim=round(sqrt(appearance_dim)))(appearance_inp)
colour_emb = Embedding(input_dim=colour_dim,␣
 ↪output_dim=round(sqrt(colour_dim)))(colour_inp)
department_emb = Embedding(input_dim=department_dim,␣
 ↪output_dim=round(sqrt(department_dim)))(department_inp)
zip_emb = Embedding(input_dim=zip_dim, output_dim=16)(zip_inp)

zip = Flatten()(zip_emb)

concat = Concatenate()([article_emb, type_emb, appearance_emb, colour_emb,␣
 ↪department_emb, price])

new_emb_dim = (round(sqrt(article_id_dim)) + round(sqrt(product_type_dim))
              + round(sqrt(appearance_dim)) + round(sqrt(colour_dim))
              + round(sqrt(department_dim)) + 1)

att = MultiHeadAttention(num_heads=num_heads, key_dim=new_emb_dim)(concat,␣
 ↪concat)
dropout_1 = Dropout(dropout_rate)(att)
norm_1 = LayerNormalization()(concat + dropout_1)
dense_1 = Dense(ffn_units, activation="relu")(norm_1)
dense_2 = Dense(ffn_units, activation="relu")(dense_1)

norm_2 = BatchNormalization()(dense_2)

dropout_2 = Dropout(dropout_rate)(norm_2)

flat_1 = Flatten()(dropout_2)

concat_2 = Concatenate()([flat_1, age_inp, zip])

dense_3 = Dense(ffn_units, activation="relu")(concat_2)
```

```python
dense_4 = Dense(ffn_units, activation="relu")(dense_3)

dense_5 = Dense(ffn_units, activation="relu")(dense_4)

norm_2 = LayerNormalization()(dense_3 + dense_5)

dense_6 = Dense(ffn_units, activation="relu")(norm_2)

dense_7 = Dense(ffn_units, activation="relu")(dense_6)

dense_8 = Dense(ffn_units, activation="relu")(dense_7)

norm_3 = LayerNormalization()(dense_3 + dense_8)

out = Dense(article_id_dim + 1, activation="softmax")(norm_3)

model = Model([article_id_inp, product_type_inp, appearance_inp, colour_inp,
               department_inp, price_inp, age_inp, zip_inp], out)

model.summary()

model.compile(loss='sparse_categorical_crossentropy', optimizer='adam',
              metrics=["sparse_categorical_accuracy",␣
 ↪"sparse_top_k_categorical_accuracy"])
```

```
Model: "model"
________________________________________________________________________________
__________________
 Layer (type)                   Output Shape         Param #     Connected to
================================================================================
==================
 input_1 (InputLayer)           [(None, 16)]         0           []

 input_2 (InputLayer)           [(None, 16)]         0           []

 input_3 (InputLayer)           [(None, 16)]         0           []

 input_4 (InputLayer)           [(None, 16)]         0           []

 input_5 (InputLayer)           [(None, 16)]         0           []

 input_6 (InputLayer)           [(None, 16)]         0           []

 embedding (Embedding)          (None, 16, 100)      1000000
['input_1[0][0]']

 embedding_1 (Embedding)        (None, 16, 11)       1441
```

```
['input_2[0][0]']

 embedding_2 (Embedding)        (None, 16, 5)        150
['input_3[0][0]']

 embedding_3 (Embedding)        (None, 16, 7)        350
['input_4[0][0]']

 embedding_4 (Embedding)        (None, 16, 16)       4000
['input_5[0][0]']

 reshape (Reshape)              (None, 16, 1)        0
['input_6[0][0]']

 concatenate (Concatenate)      (None, 16, 140)      0
['embedding[0][0]',
'embedding_1[0][0]',
'embedding_2[0][0]',
'embedding_3[0][0]',
'embedding_4[0][0]',
'reshape[0][0]']

 multi_head_attention (MultiHea  (None, 16, 140)     630700
['concatenate[0][0]',
 dAttention)
'concatenate[0][0]']

 dropout (Dropout)              (None, 16, 140)      0
['multi_head_attention[0][0]']

 tf.__operators__.add (TFOpLamb  (None, 16, 140)     0
['concatenate[0][0]',
 da)
'dropout[0][0]']

 layer_normalization (LayerNorm  (None, 16, 140)     280
['tf.__operators__.add[0][0]']
 alization)

 dense (Dense)                  (None, 16, 1024)     144384
['layer_normalization[0][0]']

 dense_1 (Dense)                (None, 16, 1024)     1049600     ['dense[0][0]']

 batch_normalization (BatchNorm  (None, 16, 1024)    4096
['dense_1[0][0]']
 alization)
```

```
 input_8 (InputLayer)           [(None, 1)]          0            []

 dropout_1 (Dropout)            (None, 16, 1024)     0
['batch_normalization[0][0]']

 embedding_5 (Embedding)        (None, 1, 16)        5646384
['input_8[0][0]']

 flatten_1 (Flatten)            (None, 16384)        0
['dropout_1[0][0]']

 input_7 (InputLayer)           [(None, 1)]          0            []

 flatten (Flatten)              (None, 16)           0
['embedding_5[0][0]']

 concatenate_1 (Concatenate)    (None, 16401)        0
['flatten_1[0][0]',
'input_7[0][0]',
'flatten[0][0]']

 dense_2 (Dense)                (None, 1024)         16795648
['concatenate_1[0][0]']

 dense_3 (Dense)                (None, 1024)         1049600
['dense_2[0][0]']

 dense_4 (Dense)                (None, 1024)         1049600
['dense_3[0][0]']

 tf.__operators__.add_1 (TFOpLa  (None, 1024)        0
['dense_2[0][0]',
 mbda)
'dense_4[0][0]']

 layer_normalization_1 (LayerNo  (None, 1024)        2048
['tf.__operators__.add_1[0][0]']
 rmalization)

 dense_5 (Dense)                (None, 1024)         1049600
['layer_normalization_1[0][0]']

 dense_6 (Dense)                (None, 1024)         1049600
['dense_5[0][0]']

 dense_7 (Dense)                (None, 1024)         1049600
['dense_6[0][0]']
```

```
 tf.__operators__.add_2 (TFOpLa  (None, 1024)        0
['dense_2[0][0]',
 mbda)
'dense_7[0][0]']

 layer_normalization_2 (LayerNo  (None, 1024)        2048
['tf.__operators__.add_2[0][0]']
 rmalization)

 dense_8 (Dense)                (None, 10001)        10251025
['layer_normalization_2[0][0]']

================================================================================
==================
Total params: 40,780,154
Trainable params: 40,778,106
Non-trainable params: 2,048
--------------------------------------------------------------------------------
------------------
```

7 Pre-training data processing

My basic training strategy is to feed the model the set of products that each customer has purchased, minus one product. The goal of this model is to guess which product is missing based on the remaining products. I think that makes this a sequence agnostic model, though I'm not certain.

[ ]:
```python
age_dict = pd.Series(customers.age,index=customers.customer_id).to_dict()
zip_dict = pd.Series(customers.postal_code,index=customers.customer_id).
 ↪to_dict()
```

[ ]:
```python
articles_lists = transactions.groupby(['customer_id'])['article_id'].apply(list)
type_lists = transactions.groupby(['customer_id'])['product_type_name'].
 ↪apply(list)
appearance_lists = transactions.
 ↪groupby(['customer_id'])['graphical_appearance_name'].apply(list)
colour_lists = transactions.groupby(['customer_id'])['colour_group_name'].
 ↪apply(list)
department_lists = transactions.groupby(['customer_id'])['department_name'].
 ↪apply(list)
price_lists = transactions.groupby(['customer_id'])['price'].apply(list)
```

[ ]:
```python
art_train = []
type_train = []
app_train = []
colour_train = []
dep_train = []
price_train = []
```

```
age_train = []
zip_train = []
y_train = []
custs = []

count = 0

for cust_num in range(c_count["customer_id"]):
  if (cust_num in articles_lists.index):
    count += 1


    art_set = articles_lists.loc[cust_num]
    type_set = type_lists.loc[cust_num]
    app_set = appearance_lists.loc[cust_num]
    colour_set = colour_lists.loc[cust_num]
    dep_set = department_lists.loc[cust_num]
    price_set = price_lists.loc[cust_num]

    len_set =␣
 ↪set([len(art_set),len(type_set),len(app_set),len(colour_set),len(dep_set),len(price_set)])

    age = age_dict[cust_num]
    zip = zip_dict[cust_num]
    if age is None:
      age = 20

    if len(art_set) != len(type_set):
      print(cust_num)

    for i in range(min(len(art_set), 32)):

        cur_idx = i

        if len(len_set) == 1:
          if list(len_set)[0] <= cur_idx:
            print("ISSUE AT", cust_num)

        else:
          print("BOOOOO")

        art_copy = art_set.copy()
        type_copy = type_set.copy()
        app_copy = app_set.copy()
        colour_copy = colour_set.copy()
        dep_copy = dep_set.copy()
        price_copy = price_set.copy()
```

```
    if cur_idx >= len(art_copy):
      print("AAAAAAAGGGHHHHHHH")

    y = [art_copy.pop(cur_idx)]
    type_copy.pop(cur_idx)
    app_copy.pop(cur_idx)
    colour_copy.pop(cur_idx)
    dep_copy.pop(cur_idx)
    price_copy.pop(cur_idx)

    if y[0] == 10000:
      y = [most_common]

    length = len(art_set)

    if len(art_copy) < max_input_len:
        art_copy = [article_id_dim]*(max_input_len - len(art_copy)) + list(art_copy)
        type_copy = [product_type_dim]*(max_input_len - len(type_copy)) + list(type_copy)
        app_copy = [appearance_dim]*(max_input_len - len(app_copy)) + list(app_copy)
        colour_copy = [colour_dim]*(max_input_len - len(colour_copy)) + list(colour_copy)
        dep_copy = [department_dim]*(max_input_len - len(dep_copy)) + list(dep_copy)
        price_copy = [0]*(max_input_len - len(price_copy)) + list(price_copy)

    elif len(art_copy) > max_input_len:
        idxs = random.sample(range(len(art_copy)), max_input_len)
        art_copy = list(map(art_copy.__getitem__, idxs))
        type_copy = list(map(type_copy.__getitem__, idxs))
        app_copy = list(map(app_copy.__getitem__, idxs))
        colour_copy = list(map(colour_copy.__getitem__, idxs))
        dep_copy = list(map(dep_copy.__getitem__, idxs))
        price_copy = list(map(price_copy.__getitem__, idxs))

    art_train.append(art_copy)
    type_train.append(type_copy)
    app_train.append(app_copy)
    colour_train.append(colour_copy)
    dep_train.append(dep_copy)
    price_train.append(price_copy)
```

```
        age_train.append([age])
        zip_train.append([zip])


        if len(art_copy) != max_input_len:
          print(len(art_copy))
          print("WARNING: INPUT LENGTH INCORRECT 1")

        if len(type_copy) != max_input_len:
          print(len(type_copy))
          print("WARNING: INPUT LENGTH INCORRECT 2")

        if len(app_copy) != max_input_len:
          print(len(app_copy))
          print("WARNING: INPUT LENGTH INCORRECT 3")

        if len(colour_copy) != max_input_len:
          print(len(colour_copy))
          print("WARNING: INPUT LENGTH INCORRECT 4")

        if len(dep_copy) != max_input_len:
          print(len(dep_copy))
          print("WARNING: INPUT LENGTH INCORRECT 5")

        if len(price_copy) != max_input_len:
          print(len(price_copy))
          print("WARNING: INPUT LENGTH INCORRECT 6")

        if len(y) != 1:
          print(len(y))
          print("WARNING: INPUT LENGTH INCORRECT IN Y")

        y_train.append(y)

print(len(art_train))
```

```
14145560
```

[ ]:
```
art_t = tf.convert_to_tensor(art_train)
type_t = tf.convert_to_tensor(type_train)
app_t = tf.convert_to_tensor(app_train)
colour_t = tf.convert_to_tensor(colour_train)
dep_t = tf.convert_to_tensor(dep_train)
price_t = tf.convert_to_tensor(price_train)
age_t = tf.convert_to_tensor(age_train)
zip_t = tf.convert_to_tensor(zip_train)
```

```
y_t = tf.convert_to_tensor(y_train)
```

8 Removing NaN values from age column and replacing with mode

[ ]:
```
mode = stats.mode(age_t)

age_t = np.nan_to_num(age_t, nan=mode[0][0][0])
```

9 Messing around with hyperparameter tuning

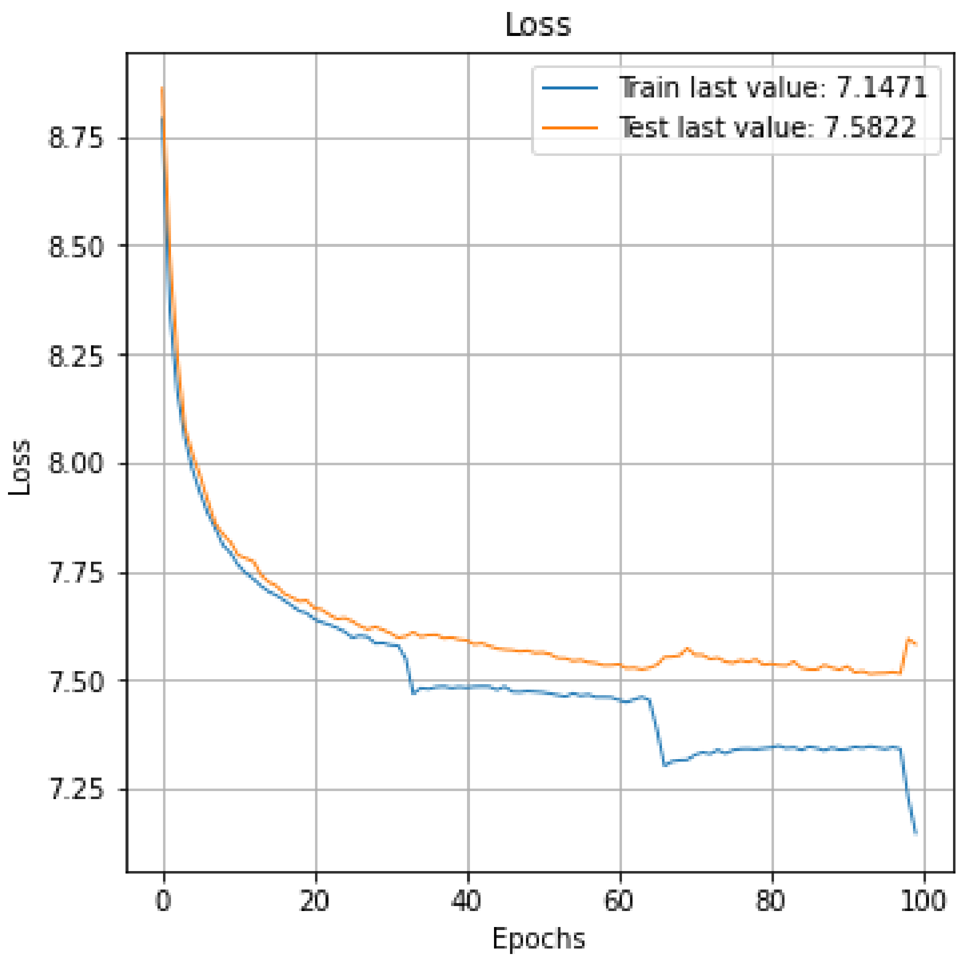
I worked a little bit with keras-tuner to help create an optimized neural network structure, but I simply didn't have the time or computing power for this to be very helpful. I still think it's interesting, so I've included a commented version of what I did here.

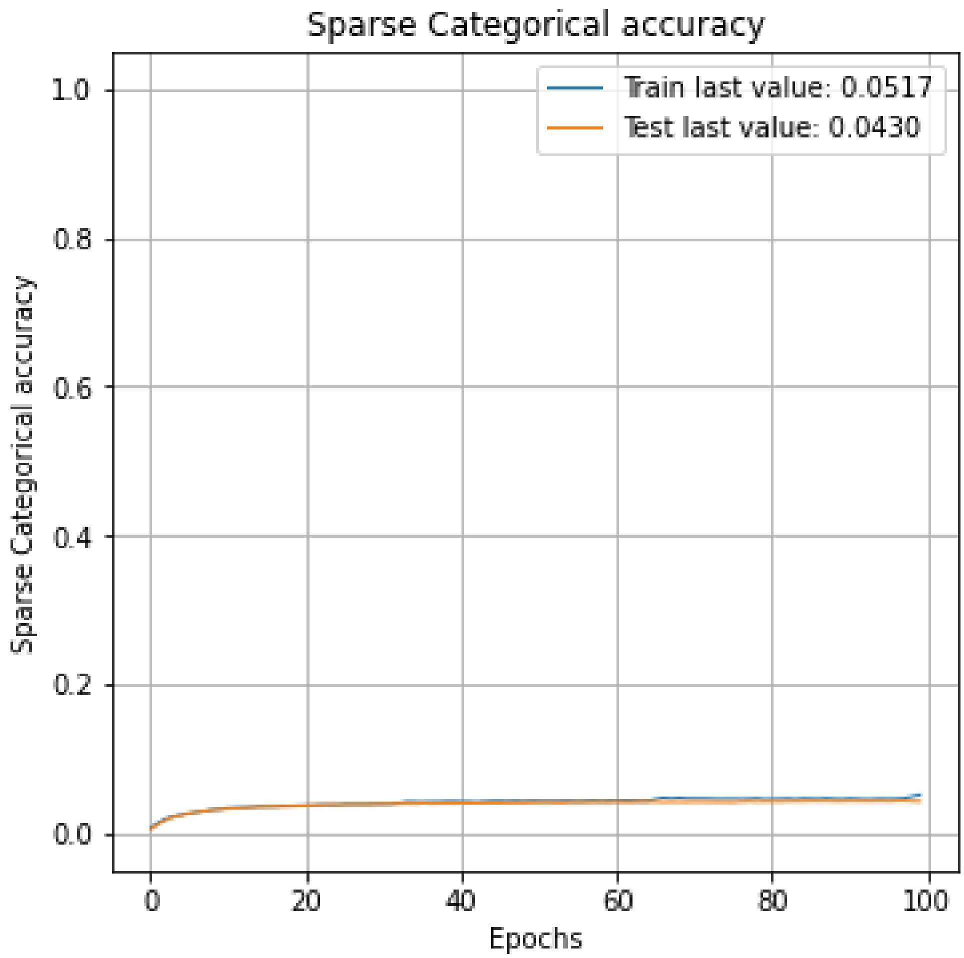
[ ]:
```
# tuner = kt.Hyperband(
#     hypermodel = build_model,
#     objective = "loss",
#     max_epochs=100
# )

# tuner.search(x_t, y_t, epochs=20, batch_size=64, steps_per_epoch=1000)
#best_model = tuner.get_best_models()[0]

# model.compile(loss='mse', optimizer='adam',
#               metrics=["sparse_categorical_accuracy",␣
 ↪"sparse_top_k_categorical_accuracy"])
```

10 Fitting the transformer-based model

[ ]:
```
mcp_save = ModelCheckpoint('drive/MyDrive/model_more_inputs.hdf5',␣
 ↪save_best_only=True, monitor='val_sparse_categorical_accuracy', mode='max')
filename='drive/MyDrive/log_model_more_inputs.csv'
history_logger=tf.keras.callbacks.CSVLogger(filename, separator=",",␣
 ↪append=True)

history = model.fit([art_t, type_t, app_t, colour_t, dep_t, price_t, age_t,␣
 ↪zip_t], y_t, epochs=100,
                    batch_size=4096, steps_per_epoch = 100, verbose=0,
                    callbacks=[mcp_save, history_logger],
                    validation_split=.05, shuffle=True)
```

[ ]:
```
plot_history(history, path="drive/MyDrive/graphs", single_graphs=True)
plt.close()
```


Loss
Train last value: 7.1471
Test last value: 7.5822
8.75
8.50
8.25
8.00
7.75
7.50
7.25
Loss
0
20
40
60
80
100
Epochs



11 Making predictions for each customer

[ ]:
```
ys = []
ids = []
ps = []

id_encoder = encoders["article_id"]
cust_encoder = encoders["customer_id"]
customer_id = []
prediction = []

art_train = []
type_train = []
app_train = []
colour_train = []
dep_train = []
```

```
price_train = []

age_train = []
zip_train = []

y_train = []
custs = []

df = pd.DataFrame()

count = 0
rand_list = np.random.randint(low=0, high=customer_id_dim, size=1)
rand_articles = range(article_id_dim)
articles_list = []
customers = []

for cust_num in range(1371980):

    count += 1

    # if count % 1000 == 0:
    #     print("Count is: ", cust_num)

    if (cust_num in articles_lists.index) and (len(articles_lists.
 ↪loc[cust_num]) != 0):
      art_set = articles_lists.loc[cust_num]
      type_set = type_lists.loc[cust_num]
      app_set = appearance_lists.loc[cust_num]
      colour_set = colour_lists.loc[cust_num]
      dep_set = department_lists.loc[cust_num]
      price_set = price_lists.loc[cust_num]
      age = age_dict[cust_num]
      zip = zip_dict[cust_num]

      if len(set([len(art_set), len(type_set), len(app_set), len(colour_set),␣
 ↪len(dep_set)])) != 1:
        print(cust_num)

    else:
      art_set = [article_id_dim]*max_input_len
      type_set = [product_type_dim]*max_input_len
      app_set = [appearance_dim]*max_input_len
      colour_set = [colour_dim]*max_input_len
      dep_set = [department_dim]*max_input_len
      price_set = [0]*max_input_len
      age = age_dict[cust_num]
      zip = zip_dict[cust_num]
```

```
    art_copy = art_set.copy()
    type_copy = type_set.copy()
    app_copy = app_set.copy()
    colour_copy = colour_set.copy()
    dep_copy = dep_set.copy()
    price_copy = price_set.copy()


    if len(art_copy) < max_input_len:
      art_copy = [article_id_dim]*(max_input_len - len(art_copy)) +␣
↪list(art_copy)
      type_copy = [product_type_dim]*(max_input_len - len(type_copy)) +␣
↪list(type_copy)
      app_copy = [appearance_dim]*(max_input_len - len(app_copy)) +␣
↪list(app_copy)
      colour_copy = [colour_dim]*(max_input_len - len(colour_copy)) +␣
↪list(colour_copy)
      dep_copy = [department_dim]*(max_input_len - len(dep_copy)) +␣
↪list(dep_copy)
      price_copy = [0]*(max_input_len - len(price_copy)) + list(price_copy)
    elif len(art_copy) > max_input_len:
      idxs = random.sample(range(len(art_copy)), max_input_len)
      art_copy = list(map(art_copy.__getitem__, idxs))
      type_copy = list(map(type_copy.__getitem__, idxs))
      app_copy = list(map(app_copy.__getitem__, idxs))
      colour_copy = list(map(colour_copy.__getitem__, idxs))
      dep_copy = list(map(dep_copy.__getitem__, idxs))
      price_copy = list(map(price_copy.__getitem__, idxs))


    art_train.append(art_copy)
    type_train.append(type_copy)
    app_train.append(app_copy)
    colour_train.append(colour_copy)
    dep_train.append(dep_copy)
    price_train.append(price_copy)

    age_train.append([age])
    zip_train.append([zip])
```

[34]:
```
import time

print(np.array(art_train).shape)

art_subsets = np.array_split(np.array(art_train), 200)
type_subsets = np.array_split(np.array(type_train), 200)
```

```
app_subsets = np.array_split(np.array(app_train), 200)
colour_subsets = np.array_split(np.array(colour_train), 200)
dep_subsets = np.array_split(np.array(dep_train), 200)
price_subsets = np.array_split(np.array(price_train), 200)
age_subsets = np.array_split(np.array(age_train), 200)
zip_subsets = np.array_split(np.array(zip_train), 200)

start = time.time()
customers_str = cust_encoder.inverse_transform(range(customer_id_dim))
end = time.time()

customer_id = []
prediction = []

print(end-start)

print(customers_str.shape)
```

```
(1371980, 16)
0.21239519119262695
(1371980,)
```

[37]:
```
def extend(input_string):
  input_string = input_string.ljust(10, "0")
  return input_string
```

[42]:
```
count = 0
row_count = 0

custs_list = []
preds_list = []


for i in range(200):
  cur_art = np.squeeze(tf.convert_to_tensor([art_subsets[i]]))
  cur_type = np.squeeze(tf.convert_to_tensor([type_subsets[i]]))
  cur_app = np.squeeze(tf.convert_to_tensor([app_subsets[i]]))
  cur_colour = np.squeeze(tf.convert_to_tensor([colour_subsets[i]]))
  cur_dep = np.squeeze(tf.convert_to_tensor([dep_subsets[i]]))
  cur_price = np.squeeze(tf.convert_to_tensor([price_subsets[i]]))
  cur_age = np.array([age_subsets[i]]).reshape(age_subsets[i].shape)
  cur_zip = np.array([zip_subsets[i]]).reshape(zip_subsets[i].shape)

  count += 1

  preds = model.predict([cur_art, cur_type, cur_app, cur_colour, cur_dep,␣
↪cur_price, cur_age, cur_zip], verbose=0, batch_size=64)
```

```
  ind = np.argpartition(preds, -12)[:,-12:]
  ind[ind==pred_len] = most_common

  for row in range(ind.shape[0]):
    row_count += 1
    # preds_str = ""

    preds_str = id_encoder.inverse_transform(ind[row,:])
    cust_str = customers_str[row_count-1]
    preds_str = [extend(str(x)) for x in preds_str]
    preds_str = "\n".join(preds_str)

    custs_list.append(cust_str)
    preds_list.append(preds_str)
```

[62]:
```
df = pd.DataFrame()
df["customer_id"] = custs_list
df["prediction"] = preds_list

print(df.shape)
df.to_csv("drive/MyDrive/transformer_preds.csv", index=False)
```

```
(1371980, 2)
```

12 Showing transformer-based model results

Using this metric, my transformer-based model got 0.0034 MAP@12. This isn't great. For perspective, that places me at 2000th out of 2500 places on the current Kaggle competition leaderboard.

[3]:
```
from IPython.display import Image
Image(filename='Screen Shot 2022-04-24 at 11.28.16 AM.png')
```

[3]:

$$MAP@12 = \frac{1}{U}\sum_{u=1}^{U}\frac{1}{min(m,12)}\sum_{k=1}^{min(n,12)} P(k) \times rel(k)$$

13 Transitioning from transformer based model to simple model.

This simpler model is designed just to train embeddings. The embeddings will (hopefully) be some indicator of how likely a customer is to buy a product. This probability will be generated from the trained embeddings by taking the dot product of the customer and article embeddings of interest, and then transforming the number output through a trained linear transformation followed by a sigmoid function.

Dropout is added to this model to help mitigate the risk of model overfitting. I'm not entirely sure if it helped, or if it was even necessary. The idea of embeddings overfitting seems a little bit odd to me.

If, for example, I was creating word embeddings, I essentially want my embeddings to memorize data about my text corpus in a dense way. Given that the goal seems to me to be a form of memorization, I'm not sure that overfitting is actually bad in this case. I think the customer and article embeddings may also not have an issue with overfitting for the same reason, though I'm not positive.

[44]:
```
embed_size = 64
rate = .1

cust_inp = Input(shape=(1, ))
cust_emb = Embedding(customer_id_dim, embed_size,
                         input_length=1)(cust_inp)

dropout_1 = Dropout(rate, seed=1)(cust_emb)

cust_reshaped = Reshape((embed_size, 1))(dropout_1)

article_inp = Input(shape=(1, ))
article_emb = Embedding(article_id_dim, embed_size,
                  input_length=1)(article_inp)

dropout_2 = Dropout(rate, seed=1)(article_emb)

article_reshaped = Reshape((embed_size, 1))(article_emb)

dot = Dot(axes=(1,1))([cust_reshaped, article_reshaped])

dense = Dense(1, activation="sigmoid")(dot)

model = Model([cust_inp, article_inp], dense)
```

[45]:
```
model.compile(loss="binary_crossentropy", optimizer="adam",
              metrics=["binary_accuracy","AUC"])

model.summary()
```

```
Model: "model_1"
________________________________________________________________________________
__________________
 Layer (type)                   Output Shape         Param #     Connected to
================================================================================
==================
```

```
 input_9 (InputLayer)           [(None, 1)]          0            []

 embedding_6 (Embedding)        (None, 1, 64)        87806720
['input_9[0][0]']

 input_10 (InputLayer)          [(None, 1)]          0            []

 dropout_2 (Dropout)            (None, 1, 64)        0
['embedding_6[0][0]']

 embedding_7 (Embedding)        (None, 1, 64)        640000
['input_10[0][0]']

 reshape_1 (Reshape)            (None, 64, 1)        0
['dropout_2[0][0]']

 reshape_2 (Reshape)            (None, 64, 1)        0
['embedding_7[0][0]']

 dot (Dot)                      (None, 1, 1)         0
['reshape_1[0][0]',
'reshape_2[0][0]']

 dense_9 (Dense)                (None, 1, 1)         2            ['dot[0][0]']

================================================================================
==================
Total params: 88,446,722
Trainable params: 88,446,722
Non-trainable params: 0
--------------------------------------------------------------------------------
------------------
```

14 Collecting data for training into one place

The transactions dataset currently has only purchased customer-product pairs. This means that the above model architecture will learn to always predict a positive outcome, given any customer-product pair. Obviously we don't want this.

To help fix this issue, for each customer, I've randomly chosen products that we'll pretend that customer isn't interested in. For example, if the customer has previously purchased eight items, then I'll randomly select eight items that the customer has not purchased from the total set of items, and then pretend that we're certain that the customer is not interested in these items.

That assumption will almost certainly be wrong occasionally, but given that we're randomly choosing a very small subset of the total number of options (10,000) I suspect it is a fine working assumption.

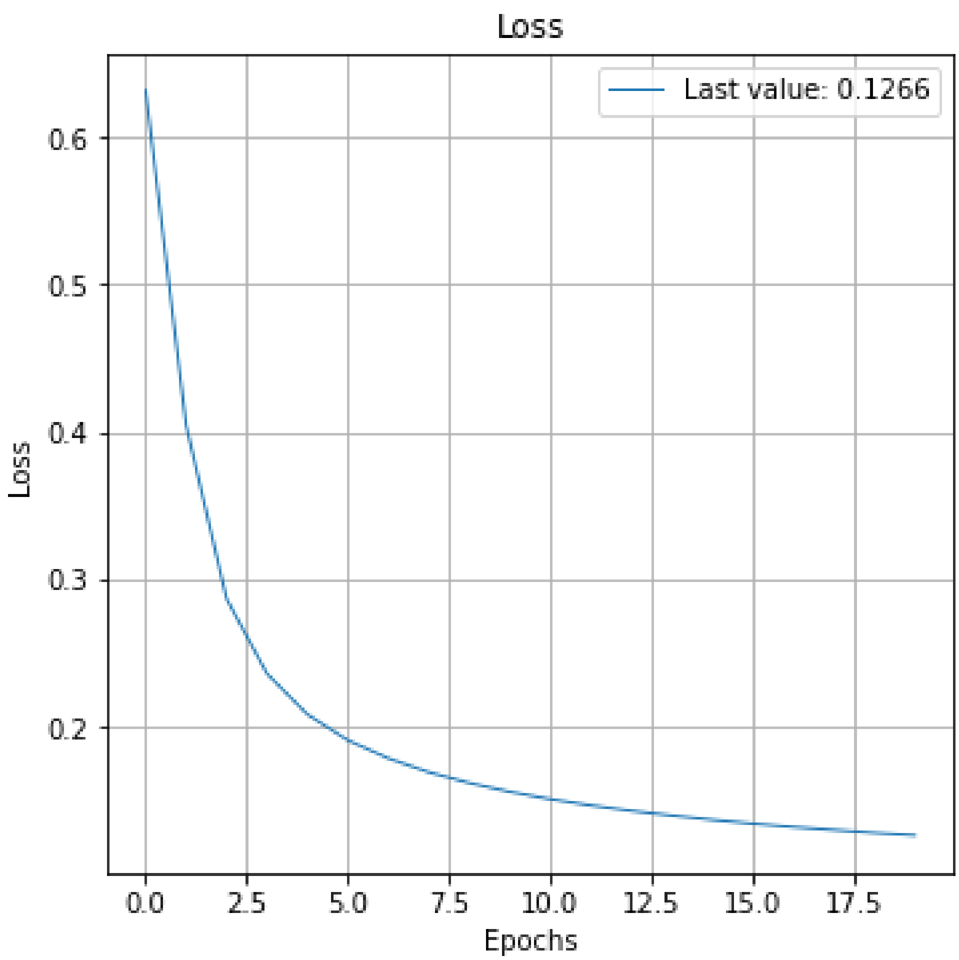
[63]:
```
sample_count = 5
mcp_save = ModelCheckpoint('drive/MyDrive/mdl_wts.hdf5', save_best_only=True,␣
↪monitor='loss', mode='min')

article_train = []
customer_train = []
y_train = []

count = 0
rand_list = np.random.randint(low=0, high=customer_id_dim, size=700000)

for cust_num in range(customer_id_dim):

    count += 1

    # if count % 1000 == 0:
    #     print("Count is: ", count)

    if cust_num in articles_lists.index:
      x = articles_lists.loc[cust_num]
      all_articles = set(range(article_id_dim))
      diff = tuple(all_articles - set(x))
      len_diff = len(diff)

      for i in range(len(x)):

          if len(x) != 0:
              article = [x[i]]
              customer = [cust_num]
              y = [1]

              article_train.append(np.array(article))
              customer_train.append(np.array(customer))
              y_train.append(y)

              article = [diff[int(len_diff * random.random())]]
              customer = [cust_num]
              y = [0]

              article_train.append(np.array(article))
              customer_train.append(np.array(customer))
              y_train.append(y)

          if len(x) == 0:
              print(cust_num)
```

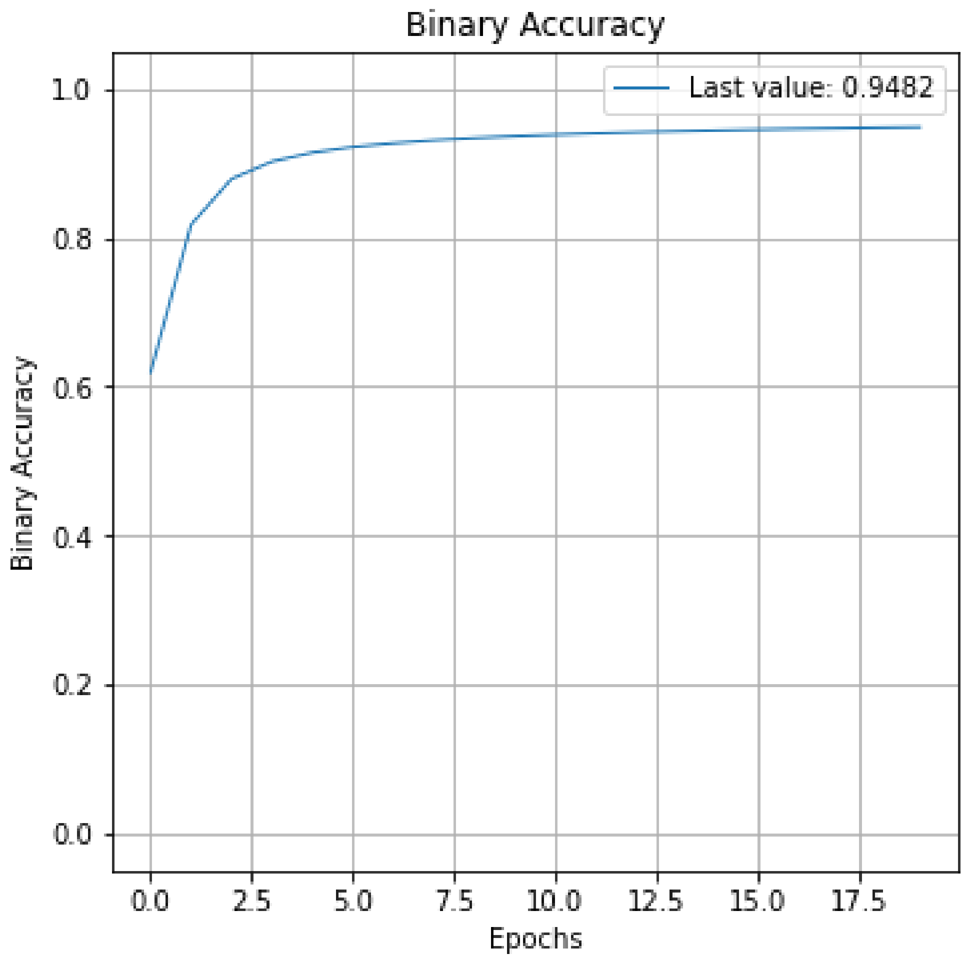
```
article_train = np.array(article_train)
customer_train = np.array(customer_train)
y_train = np.array(y_train)
```

15 Fitting simple embedding model

[64]:
```
history = model.fit([customer_train, article_train], y_train, batch_size=4096,␣
↪epochs=20, verbose=0)
```

[65]:
```
plot_history(history, path="drive/MyDrive/graphs_emb", single_graphs=True)
plt.close()
```





16 Converting embeddings to product predictions

My strategy for converting my trained article embeddings and customer embeddings into predictions is to dot product each customer and article pair, and then transform that dot product using the fitted sigmoid function weights used as the final layer of the simple model.

Then, I'll drop any article_ids that have previously been purchased by that customer, and then I'll select the top n most likely values (see n_values = 60).

Finally, out of those 60 values, I'll group by the department name of each product and select the 12 most likely values (but only one from each department. I'm forcing my model to choose from multiple store departments so that I maximize the variance of my predictions. I'm trying to avoid having all twelve of my predictions be just different colors of one product (t-shirts, for instance).

[66]:
```
cust_embeddings = model.layers[1].get_weights()[0]
art_embeddings = model.layers[4].get_weights()[0]
print(cust_embeddings.shape)
```

```
print(art_embeddings.shape)
```

```
(1371980, 64)
(10000, 64)
```

[67]:
```
cust_subsets = np.array_split(cust_embeddings, 100)
```

[87]:
```
start = time.time()
count = 1
n_values = 60
n_partitions = 12
final_preds = []

inds_list = []
preds_list = []
customer_list = []
department_list = []

weights = model.layers[8].get_weights()[0][0][0]
biases = model.layers[8].get_weights()[1][0]

def sig(x):
  return np.exp(x) / (1+np.exp(x))

def final_layer(x):
  return sig(weights*x + biases)

print(weights, biases)

for array in cust_subsets:

  indices = []

  ids = [x for x in articles_lists.index if (x < array.shape[0]*count) and (x␣
↪>= array.shape[0]*(count-1))]

  for i in ids:
    indices += [[i % array.shape[0], x] for x in list(set(articles_lists.
↪loc[i]))]
    # if i % 10000 == 0:
    #   print(i)

  indices = np.array(indices)

  pred = final_layer(np.matmul(array, art_embeddings.T))
  pred[tuple(indices.T)] = 0
  ind = np.argpartition(pred, -n_values)[:,-n_values:]
```

```python
    preds = np.take_along_axis(pred, ind, axis=1).flatten()

    for cust_id in range((count-1)*array.shape[0], count*array.shape[0]):
        customer_list += n_values*[cust_id]

    inds_list += list(ind.flatten())
    preds_list += list(preds)
    department_list += list(articles.loc[ind.flatten()]["department_no"].values)

    count += 1
```

```
2.4522662 -1.669735
```

[88]:
```python
start = time.time()

df = pd.DataFrame()
df["inds"] = inds_list
df["rank"] = preds_list
df["group"] = department_list
df["id"] = customer_list

end = time.time()

print(end-start)
```

```
120.79200720787048
```

[89]:
```python
chosen = df.sort_values("rank", ascending=False).groupby(["id", "group"],␣
 ↪sort=False, as_index=False).first()
chosen.shape
```

[89]:
```
(27805419, 4)
```

[90]:
```python
chosen_twelve = chosen.groupby(["id"], as_index=False).head(12)
chosen_twelve.shape
```

[90]:
```
(16036357, 4)
```

[91]:
```python
chosen_list = chosen_twelve.groupby(['id'])['inds'].apply(list)
```

[92]:
```python
chosen_list.head()
```

[92]:
```
id
0     [1845, 8236, 5694, 6762, 4675, 5877, 9632, 686…
1     [3073, 5434, 7219, 1, 2211, 4770, 2931, 2346, …
2     [7254, 1688, 8488, 8203, 9553, 2974, 8255, 875…
3        [5794, 5265, 503, 7412, 1794, 5472, 461, 1896]
```

```
4    [4088, 4384, 4635, 5289, 4285, 9597, 4264, 294…
Name: inds, dtype: object
```

17 Formatting customer_id and predictions for submission to Kaggle

[93]:

```
custs = []
preds = []

customers_str = cust_encoder.inverse_transform(range(customer_id_dim))
print(len(customers_str))
indices_set = set(chosen_list.index)

for idx in range(len(customers_str)):
  if idx in indices_set:
    preds_str = encoders["article_id"].inverse_transform(chosen_list.loc[idx])
    cust_str = customers_str[idx]
    preds_str = [extend(str(x)) for x in preds_str]
    preds_str = "\n".join(preds_str)

    custs.append(cust_str)
    preds.append(preds_str)

  else:
    cust_str = customers_str[idx]
    preds.append(preds_str)
    custs.append(cust_str)
```

```
1371980
```

18 Saving predictions from simple model

[94]:

```
df = pd.DataFrame()
df["customer_id"] = custs
df["prediction"] = preds

print(df.shape)

df.to_csv("drive/MyDrive/preds.csv", index=False)
```

```
(1371980, 2)
```

19 Showing simple model results

Using this metric, my simple model got 0.000 MAP@12.

[4]:
```
Image(filename='Screen Shot 2022-04-24 at 11.28.16 AM.png')
```

[4]:

$$MAP@12 = \frac{1}{U}\sum_{u=1}^{U}\frac{1}{min(m,12)}\sum_{k=1}^{min(n,12)} P(k) \times rel(k)$$

20 Attempting to visualize embeddings in 2D using PCA

[95]:
```
from sklearn.decomposition import PCA

col = transactions.groupby(["customer_id"]).first()[transactions["customer_id"].
 ↪isin(set(rand_list))]["product_type_name"]
print(col.shape)

print(art_embeddings.shape)

pca = PCA(n_components=2)
embeddings_pca = pca.fit_transform(art_embeddings)

print(pca.explained_variance_ratio_)

df = pd.DataFrame(embeddings_pca, columns=["emb_1", "emb_2"])
df["product_type"] = col
```

```
/usr/local/lib/python3.7/dist-packages/ipykernel_launcher.py:3: UserWarning:
Boolean Series key will be reindexed to match DataFrame index.
  This is separate from the ipykernel package so we can avoid doing imports
until
```

```
(486421,)
(10000, 64)
[0.03206388 0.02992618]
```

[96]:
```
df.head()
```

[96]:

	emb_1	emb_2	product_type
0	2.291836	-0.177902	6.0
1	1.889428	-0.224657	61.0
2	0.112877	-0.264501	5.0
3	-0.126311	-0.105827	10.0
4	1.067837	0.957382	7.0

20.0.1 As can be seen from the plot below, no clear patterns emerge when compressing 64 dimensions down into 2. This is unsurprising, but also a little dissappointing. If I create 2 dimensional embeddings, a few simple patterns emerge, but given that this is a completely unrealisting embedding dimension I haven't included that plot.

[97]:
```python
sample = df.sample(n=10000)

sample.plot.scatter(x='emb_1',
                    y='emb_2',
                    c='product_type',
                    colormap="Accent_r")
```

[97]: <matplotlib.axes._subplots.AxesSubplot at 0x7fbaed3cf890>