Initial considerations

To run this notebook I had to rely on my laptop, since colab runs out of memory in all the stages (word2vec training and reviews rating prediction model training).

I performed the word2vec training on the raw text of the reviews, trying to capture the dependencies and correlation of the words in this specific context.

I also tried a model using keras embedding, so giving the model the raw text as array of integers, to see if my word2vec improves performances or not.

Importings & uploads

```
import pandas as pd
import os
import shutil
import io
import re
import string
import tqdm
import numpy as np
import tensorflow as tf
from tensorflow.keras import layers
from tensorflow import keras
from sklearn.model_selection import train_test_split
from keras.models import Sequential, load_model
from keras.layers import LSTM, GRU, Dense, Input, Bidirectional, Dropout
from keras.layers.core import  Activation
import tensorflow as tf
from matplotlib import pyplot
from imblearn.under_sampling import RandomUnderSampler
import matplotlib.pyplot as plt
from sklearn.datasets import make_classification
from sklearn.metrics import confusion_matrix, ConfusionMatrixDisplay
from sklearn.svm import SVC
from urllib.request import urlopen
from io import BytesIO
from zipfile import ZipFile
```

```
url = 'https://raw.githubusercontent.com/Beshoy22/park_rev/main/parkReviews.csv'
reviews = pd.read_csv(url, encoding_errors='ignore')
```

```
reviews.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 42656 entries, 0 to 42655
Data columns (total 6 columns):
 #   Column             Non-Null Count  Dtype 
---  ------             --------------  ----- 
 0   Review_ID          42656 non-null  int64 
 1   Rating             42656 non-null  int64 
 2   Year_Month         42656 non-null  object
 3   Reviewer_Location  42656 non-null  object
 4   Review_Text        42656 non-null  object
 5   Branch             42656 non-null  object
dtypes: int64(2), object(4)
memory usage: 2.0+ MB
```

Text tokenization

In this section I pre-processed the raw text of the reviews, by eliminating punctuation, lowercasing all the words and handling the contractions to have a standard format.

After that I made a vocabolary with all the unique words (which went from about 100K to 42K); this is necessary to transorm my raw text into an integer vector that can be processed through skip gram to generate my embedding.

At any step I check that I didn't made any error (ex. after int trasformation I printed the trasformed vector and checked its consistency).

```
# Load the TensorBoard notebook extension
%load_ext tensorboard
```

```
SEED = 42
AUTOTUNE = tf.data.AUTOTUNE
```

```
contraction_mapping = {
    "ain't": "is not",
    "aren't": "are not",
    "can't": "cannot",
    "can't've": "cannot have",
    "'cause": "because",
    "could've": "could have",
    "couldn't": "could not",
    "couldn't've": "could not have",
    "didn't": "did not",
    "doesn't": "does not",
    "don't": "do not",
```

```
    "hadn't": "had not",
    "hadn't've": "had not have",
    "hasn't": "has not",
    "haven't": "have not",
    "he'd": "he would",
    "he'd've": "he would have",
    "he'll": "he will",
    "he'll've": "he will have",
    "he's": "he is",
    "how'd": "how did",
    "how'd'y": "how do you",
    "how'll": "how will",
    "how's": "how is",
    "I'd": "I would",
    "I'd've": "I would have",
    "I'll": "I will",
    "I'll've": "I will have",
    "I'm": "I am",
    "I've": "I have",
    "isn't": "is not",
    "it'd": "it would",
    "it'd've": "it would have",
    "it'll": "it will",
    "it'll've": "it will have",
    "it's": "it is",
    "let's": "let us",
    "ma'am": "madam",
    "mayn't": "may not",
    "might've": "might have",
    "mightn't": "might not",
    "mightn't've": "might not have",
    "must've": "must have",
    "mustn't": "must not",
    "mustn't've": "must not have",
    "needn't": "need not",
    "needn't've": "need not have",
    "o'clock": "of the clock",
    "oughtn't": "ought not",
    "oughtn't've": "ought not have",
    "shan't": "shall not",
    "sha'n't": "shall not",
    "shan't've": "shall not have",
    "she'd": "she would",
    "she'd've": "she would have",
    "she'll": "she will",
    "she'll've": "she will have",
    "she's": "she is",
    "should've": "should have",
    "shouldn't": "should not",
    "shouldn't've": "should not have",
    "so've": "so have",
    "so's": "so is",
    "that'd": "that would",
    "that'd've": "that would have",
```

```
    "that's": "that is",
    "there'd": "there would",
    "there'd've": "there would have",
    "there's": "there is",
    "they'd": "they would",
    "they'd've": "they would have",
    "they'll": "they will",
    "they'll've": "they will have",
    "they're": "they are",
    "they've": "they have",
    "wasn't": "was not",
    "we'd": "we would",
    "we'd've": "we would have",
    "we'll": "we will",
    "we'll've": "we will have",
    "we're": "we are",
    "we've": "we have",
    "weren't": "were not",
    "what'll": "what will",
    "what'll've": "what will have",
    "what're": "what are",
    "what's": "what is",
    "what've": "what have",
    "when's": "when is",
    "when've": "when have",
    "where'd": "where did",
    "where's": "where is",
    "where've": "where have",
    "who'll": "who will",
    "who'll've": "who will have",
    "who's": "who is",
    "who've": "who have",
    "why's": "why is",
    "why've": "why have",
    "will've": "will have",
    "won't": "will not",
    "won't've": "will not have",
    "would've": "would have",
    "wouldn't": "would not",
    "wouldn't've": "would not have",
    "y'all": "you all",
    "y'all'd": "you all would",
    "y'all'd've": "you all would have",
    "y'all're": "you all are",
    "y'all've": "you all have",
    "you'd": "you would",
    "you'd've": "you would have",
    "you'll": "you will",
    "you'll've": "you will have",
    "you're": "you are",
    "you've": "you have"
}

def handle_contractions(text): #in this function I perform the mapping of the contractions an
```

```
  translator = str.maketrans(string.punctuation, ' ' * len(string.punctuation))
  words = text.split()
  processed_words = []

  for word in words:
    if word.lower() in contraction_mapping:
      processed_words.extend(contraction_mapping[word.lower()].split())
    else:
      word = word.translate(translator)
      if len(word.lower().split()) > 1:
        processed_words.extend(word.lower().split())
      else:
        processed_words.append(word.replace(" ", "").lower())

  return processed_words


vocab, index = {}, 1  # start indexing from 1
vocab['<pad>'] = 0  # add a padding token

#here I create the vocab to map integers with unique words after handling contractions and pu
for k in range(0, len(reviews)):
  sentence = handle_contractions(reviews.loc[k].Review_Text)
  for token in sentence:
    if token not in vocab:
      vocab[token] = index
      index += 1

vocab_size = len(vocab)
print(vocab)
```

```
{'<pad>': 0, 'if': 1, 'you': 2, 'have': 3, 'ever': 4, 'been': 5, 'to': 6, '
```

```
print(vocab_size)
```

```
42591
```

```
inverse_vocab = {index: token for token, index in vocab.items()}
print(inverse_vocab) #the inverse vocab will be useful to verify the correctness of the mappi
```

```
{0: '<pad>', 1: 'if', 2: 'you', 3: 'have', 4: 'ever', 5: 'been', 6: 'to', 7
```

```
#here I replace the words with their correspondent int value
for p in range(0, len(reviews)):
  sentence = handle_contractions(reviews.loc[p].Review_Text)
  new_mapping = []
  for token in sentence:
    new_mapping.append(vocab[token])
  reviews.at[p, "Review_Text"] = new_mapping
```

```
#here I verify the consistency of my operations by looking if the first review was correctly r
print(reviews.loc[0].Review_Text)
print(reviews.loc[0].Review_ID)

for token in reviews.loc[0].Review_Text:
  print(inverse_vocab[token], end = " ")
```

```
[1, 2, 3, 4, 5, 6, 7, 8, 2, 9, 10, 7, 11, 12, 13, 14, 15, 16, 17, 18, 2, 19
670772142
if you have ever been to disneyland anywhere you will find disneyland hong
```

Word embedding (word2vec)

I ran this section on my laptop since colab run out of memory any time I tried, then I uploaded the weights of the hidden layer (my word2vec embedding) on github and I imported it in the pre-processing section.

I used the skip gram approach, which consists in training a network to predict context words given the target word, this allows to have a hidden layer that represents the target word based on its contexts.

I got accuracy of about 0.80 in the skip gram, and my embedding consists of 256 dimesions.

Afer retriving the hidden layer weights I downloaded them with the meta data and I plotted them on [this site](), that uses the PCA to reduce the 256 dimesions to 3, to verify the closure between similar words.

In this section I followed the tutorial provided by tensorflow, increasing the embedding dimension from 128 to 256, the positive samples from 2 to 3 and the negative samples from 4 to 6.

```
# Generates skip-gram pairs with negative sampling for a list of sequences
# (int-encoded sentences) based on window size, number of negative samples
# and vocabulary size.
def generate_training_data(sequences, window_size, num_ns, vocab_size, seed):
  # Elements of each training example are appended to these lists.
  targets, contexts, labels = [], [], []

  # Build the sampling table for `vocab_size` tokens.
  sampling_table = tf.keras.preprocessing.sequence.make_sampling_table(vocab_size)

  # Iterate over all sequences (sentences) in the dataset.
  for sequence in tqdm.tqdm(sequences):

    # Generate positive skip-gram pairs for a sequence (sentence).
    positive_skip_grams, _ = tf.keras.preprocessing.sequence.skipgrams(
          sequence,
          vocabulary_size=vocab_size,
          sampling_table=sampling_table,
          window_size=window_size,
          negative_samples=0)

    # Iterate over each positive skip-gram pair to produce training examples
    # with a positive context word and negative samples.
    for target_word, context_word in positive_skip_grams:
      context_class = tf.expand_dims(
          tf.constant([context_word], dtype="int64"), 1)
      negative_sampling_candidates, _, _ = tf.random.log_uniform_candidate_sampler(
          true_classes=context_class,
          num_true=1,
          num_sampled=num_ns,
          unique=True,
          range_max=vocab_size,
          seed=SEED,
          name="negative_sampling")

      # Build context and label vectors (for one target word)
      negative_sampling_candidates = tf.expand_dims(
          negative_sampling_candidates, 1)

      context = tf.concat([context_class, negative_sampling_candidates], 0)
      label = tf.constant([1] + [0]*num_ns, dtype="int64")

      # Append each element from the training example to global lists.
      targets.append(target_word)
      contexts.append(context)
      labels.append(label)

  return targets, contexts, labels
```

```
sentences = []

for c in range(0, len(reviews)):
  sentences.append(reviews.loc[c].Review_Text)


targets, contexts, labels = generate_training_data(sentences, 3, 6, vocab_size, 1234)
```

```
100%|██████████| 42656/42656 [06:40<00:00, 106.63it/s]
```

```
targets, contexts, labels = generate_training_data(
    sequences=sentences,
    window_size=3,
    num_ns=6,
    vocab_size=vocab_size,
    seed=1234)

targets = np.array(targets)
contexts = np.array(contexts)[:,:,0]
labels = np.array(labels)

print('\n')
print(f"targets.shape: {targets.shape}")
print(f"contexts.shape: {contexts.shape}")
print(f"labels.shape: {labels.shape}")
```

```
100%|██████████| 42656/42656 [06:50<00:00, 103.79it/s]


targets.shape: (5888394,)
contexts.shape: (5888394, 7)
labels.shape: (5888394, 7)
```

```
print(targets[0:5])
print(contexts[0:5])
print(labels[100:120])
print(sentences[0:10])
```

```
[42 42 42 42 42]
[[   43 13343   279  6081 34236    42    10]
 [   40   786  2556   140     2     0    94]
 [   16    77 15692  1011     6   205     0]
 [   44  3900    89    12     0   119 14278]
 [   41    12   131     1     9 23236   779]]
[[1 0 0 0 0 0 0]
 [1 0 0 0 0 0 0]
 [1 0 0 0 0 0 0]
 [1 0 0 0 0 0 0]
 [1 0 0 0 0 0 0]
 [1 0 0 0 0 0 0]
 [1 0 0 0 0 0 0]
 [1 0 0 0 0 0 0]
 [1 0 0 0 0 0 0]
 [1 0 0 0 0 0 0]
 [1 0 0 0 0 0 0]
 [1 0 0 0 0 0 0]
 [1 0 0 0 0 0 0]
 [1 0 0 0 0 0 0]
 [1 0 0 0 0 0 0]
 [1 0 0 0 0 0 0]
 [1 0 0 0 0 0 0]
 [1 0 0 0 0 0 0]
 [1 0 0 0 0 0 0]
 [1 0 0 0 0 0 0]]
[[1, 2, 3, 4, 5, 6, 7, 8, 2, 9, 10, 7, 11, 12, 13, 14, 15, 16, 17, 18, 2, 1
```

```
class Word2Vec(tf.keras.Model):
  def __init__(self, vocab_size, embedding_dim):
    super(Word2Vec, self).__init__()
    self.target_embedding = layers.Embedding(vocab_size,
                                      embedding_dim,
                                      input_length=1,
                                      name="w2v_embedding")
    self.context_embedding = layers.Embedding(vocab_size,
                                       embedding_dim,
                                       input_length=5+1)

  def call(self, pair):
    target, context = pair
    # target: (batch, dummy?)  # The dummy axis doesn't exist in TF2.7+
    # context: (batch, context)
    if len(target.shape) == 2:
      target = tf.squeeze(target, axis=1)
    # target: (batch,)
    word_emb = self.target_embedding(target)
    # word_emb: (batch, embed)
    context_emb = self.context_embedding(context)
    # context_emb: (batch, context, embed)
    dots = tf.einsum('be,bce->bc', word_emb, context_emb)
    # dots: (batch, context)
    return dots


def custom_loss(x_logit, y_true):
      return tf.nn.sigmoid_cross_entropy_with_logits(logits=x_logit, labels=y_true)


embedding_dim = 256
word2vec = Word2Vec(vocab_size, embedding_dim)
word2vec.compile(optimizer='adam',
                 loss=tf.keras.losses.CategoricalCrossentropy(from_logits=True),
                 metrics=['accuracy'])


tensorboard_callback = tf.keras.callbacks.TensorBoard(log_dir="logs")


BATCH_SIZE = 1024
BUFFER_SIZE = 10000
dataset = tf.data.Dataset.from_tensor_slices(((targets, contexts), labels))
dataset = dataset.shuffle(BUFFER_SIZE).batch(BATCH_SIZE, drop_remainder=True)
print(dataset)
```

```
<BatchDataset element_spec=((TensorSpec(shape=(1024,), dtype=tf.int64, name
```

```
dataset = dataset.cache().prefetch(buffer_size=AUTOTUNE)
print(dataset)
```

```
<PrefetchDataset element_spec=((TensorSpec(shape=(1024,), dtype=tf.int64, n
```

```
word2vec.fit(dataset, epochs=8, callbacks=[tensorboard_callback])
```

```
Epoch 1/8
2023-07-03 14:25:02.822784: W tensorflow/tsl/platform/profile_utils/cpu_uti

<keras.callbacks.History at 0x2cf7569a0>
```

Below I uploaded the screenshot of the epochs (this output went lost uploading the notebook on colab).

```
word2vec.fit(dataset, epochs=8, callbacks=[tensorboard_callback])
```

```
Epoch 1/8
   2/5750 [..............................] - ETA: 7:20 - loss: 1.9461 - accuracy: 0.1406
2023-07-03 14:25:02.822784: W tensorflow/tsl/platform/profile_utils/cpu_utils.cc:128] Failed to get CPU frequency: 0 Hz
5750/5750 [==============================] - 450s 78ms/step - loss: 0.9943 - accuracy: 0.646
Epoch 2/8
5750/5750 [==============================] - 514s 89ms/step - loss: 0.8316 - accuracy: 0.699
Epoch 3/8
5750/5750 [==============================] - 545s 95ms/step - loss: 0.7477 - accuracy: 0.729
Epoch 4/8
5750/5750 [==============================] - 554s 96ms/step - loss: 0.6804 - accuracy: 0.75
Epoch 5/8
5750/5750 [==============================] - 556s 97ms/step - loss: 0.6288 - accuracy: 0.772
Epoch 6/8
5750/5750 [==============================] - 553s 96ms/step - loss: 0.5911 - accuracy: 0.785
Epoch 7/8
5750/5750 [==============================] - 546s 95ms/step - loss: 0.5640 - accuracy: 0.794
Epoch 8/8
5750/5750 [==============================] - 559s 97ms/step - loss: 0.5443 - accuracy: 0.801

<keras.callbacks.History at 0x2cf7569a0>
```

```
weights = word2vec.get_layer('embedding').get_weights()[0]
vocab = inverse_vocab
```

```
out_v = io.open('./vectors_new.tsv', 'w', encoding='utf-8')
out_m = io.open('./metadata_new.tsv', 'w', encoding='utf-8')

for index, word in enumerate(vocab):
  if index == 0:
    continue  # skip 0, it's padding.
  vec = weights[index]
  out_v.write('\t'.join([str(x) for x in vec]) + "\n")
  out_m.write(str(inverse_vocab[word]) + "\n")
out_v.close()
out_m.close()
```

Pre-processing

In this section the final objective is to create a 3d tensor processable by an RNN architecture.

First thing I did was **deleting all the rows with missing values** (it reguards only year_month column), I didn't rely on an imputer since the "most frequent" strategy would only cause unnecessary "noise" in the data, while a KNN imputer is not so representative without processing the raw text; anyways there are about 2K rows with missing values, so on 42K total rows is not a problem to drop them.

After that I transformed the year_month feature in 2 separate columns and I normalized them.

Then I managed the reviewer_location and branch by transforming them in integers values.

I then dropped the review_id column that is obviously useless in the training.

I performed an **undersampling** because the first times I ran the model (before undersampling) I realized that the model had an accuracy of about 0.6 but only because having umbalanced classed (about 60% of reviews are 5 stars) it was just predicting all 5.

Then I transofrmed the integer vectors of the raw texts by substituting all the values with the correspondent embedding vectors, deleting all the reviews with more than 300 words. In this stage I created an 2d tensor for any review and I added the year, month, rev_loc and branch as elements in the first dimesion (so the RNN will process all the words and also these features).

Last thing I did was the train test splitting keeping the same ratio between classes presence in the train and test.

```
model_reviews = reviews
```

```
#here I handle the year_month feature as specified above

Year = []
Month = []
q = 0
count = 0

for t in range(0, len(model_reviews)):
  try:
    year_month = model_reviews.loc[t].Year_Month.replace("-", " ").split()
    Year.append((int(year_month[0])-2010)/9) #since years are from 2010 to 2019, I will norma
    Month.append((int(year_month[1])-1)/12) #since months are from 1 to 12, I will normalize w
  except: #missing values, since my dataset is pretty large is not a problem to drop them
    model_reviews = model_reviews.drop(index = t)
    count += 1

print(count)
print(len(model_reviews))
```

```
2613
40043
```

```
model_reviews = model_reviews.reset_index(drop = True) #after dropping rows I perform the rese
```

```
#separate year and month features

model_reviews['Year'] = Year
model_reviews['Month'] = Month
model_reviews = model_reviews.drop('Year_Month', axis=1)
```

```
#handling reviewer_location and branch mapping to integers

t = 0
Locations = dict()
Branch = dict()
count_br = 0
count_loc = 0

for t in range(0, len(model_reviews)):
  br = model_reviews.loc[t].Branch
  loc = model_reviews.loc[t].Reviewer_Location
  if br in Branch:
    model_reviews.at[t, "Branch"] = Branch[br]
  else:
    Branch[br] = count_br
    count_br += 1
    model_reviews.at[t, "Branch"] = Branch[br]
  if loc in Locations:
    model_reviews.at[t, "Reviewer_Location"] = Locations[loc]
  else:
    Locations[loc] = count_loc
    count_loc += 1
    model_reviews.at[t, "Reviewer_Location"] = Locations[loc]
```

```
model_reviews
```

	Review_ID	Rating	Reviewer_Location	Review_Text	Branch	Year	
0	670772142	4	0	[1, 2, 3, 4, 5, 6, 7, 8, 2, 9, 10, 7, 11, 12, ...	0	1.000000	0.2
1	670682799	4	1	[31, 5, 25, 52, 53, 54, 55, 56, 41, 57, 58, 7,...	0	1.000000	0.3
2	670623270	4	2	[164, 165, 23, 166, 167, 168, 45, 96, 168, 169...	0	1.000000	0.2
3	670607911	4	0	[58, 7, 34, 25, 79, 239, 131, 186, 175, 34, 22...	0	1.000000	0.2
4	670607296	4	3	[16, 275, 34, 176, 15, 16, 276, 277, 180	0	1.000000	0.2

```
model_reviews_t = model_reviews.drop('Review_ID', axis=1)
```

Checking the class distribution to perform a custom undersampling, since the default one will give only 6K (less frequent class counting * num of classes) rows.

```
class_distr = {1: 0, 2: 0, 3: 0, 4: 0, 5:0}
rating_t = model_reviews.pop('Rating')


for rat in rating_t:
    class_distr[int(rat)] += 1


class_distr
```

```
{1: 1338, 2: 1929, 3: 4782, 4: 10086, 5: 21908}
```

After many tries, the best undersampling I found is the one in this mapping, previously I tried the deafult one and I tried with {1:1338, 2:1929, 3:4782, 4:10086, 5:10086} but I run in underfitting and the models were only giving 4 and 5 as predictions.

```
sampling_strategy = {1:1338, 2:1929, 3:4782, 4:5000, 5:5000}

rand_und_samp = RandomUnderSampler(sampling_strategy=sampling_strategy, random_state=22)

model_reviews, rating = rand_und_samp.fit_resample(model_reviews_t, rating_t)


#here I count how many reviews I have with more than 300 words, to then determine my 3d tenso

k = 0
count_l300 = 0

for k in range(0, len(model_reviews)):
  if len(model_reviews.loc[k].Review_Text) > 300:
    count_l300 += 1

print(count_l300)
```

```
1895
```

```
#here i retrieve the word2vec embedding

url_vec = 'https://github.com/Beshoy22/park_rev/raw/main/vectors_new.tsv.zip'

http_response = urlopen(url_vec)
zipfile = ZipFile(BytesIO(http_response.read()))
zipfile.extractall(path='./')

word_embedding = pd.read_csv('./vectors_new.tsv', sep = '\t')
```

```
word_embedding #first row taken as column labels is not a problem given that it's the <pad> er
```

	-0.06352582	-0.30229187	-0.054907408	-0.14134605	-0.28957686	-0.1
0	-0.375374	-0.025237	-0.121046	-0.030608	-0.103377	
1	-0.140034	-0.016912	-0.235089	0.108179	-0.266811	
2	-0.413697	0.042012	-0.196076	-0.149451	-0.418595	
3	-0.776379	-0.211969	0.353324	0.456524	-0.545730	
4	0.049112	-0.073238	-0.025378	0.069521	0.038491	
...	...	...	...	...	...	
42584	-0.167121	0.605535	0.354194	-0.198207	-0.486989	
42585	-0.211664	0.193998	0.369679	-0.224391	-0.153037	
42586	-0.164826	0.752815	0.506144	-0.635669	-0.608435	
42587	-0.544367	0.435817	0.144380	-0.372321	-0.409313	
42588	-0.042978	0.062498	-0.052398	-0.203922	-0.209014	

42589 rows × 256 columns

```
#rename the column labels lossing the useless <pad> encoding

i = 0
we = []

for i in range(0, 256):
  we.append(str(i))

word_embedding.columns = we

word_embedding
```

	0	1	2	3	4	5	6	
0	-0.375374	-0.025237	-0.121046	-0.030608	-0.103377	0.178554	-0.178581	-0.18
1	-0.140034	-0.016912	-0.235089	0.108179	-0.266811	-0.017369	-0.444216	0.01
2	-0.413697	0.042012	-0.196076	-0.149451	-0.418595	0.269462	-0.165335	-0.62
3	-0.776379	-0.211969	0.353324	0.456524	-0.545730	0.093131	-0.219958	0.14
4	0.049112	-0.073238	-0.025378	0.069521	0.038491	-0.115676	-0.032902	0.11
...	...	...	...	...	...	...	...	
42584	-0.167121	0.605535	0.354194	-0.198207	-0.486989	0.377161	-0.136884	-0.39
42585	-0.211664	0.193998	0.369679	-0.224391	-0.153037	0.668806	-0.162833	-0.52
42586	-0.164826	0.752815	0.506144	-0.635669	-0.608435	0.367470	-0.184772	-0.10
42587	-0.544367	0.435817	0.144380	-0.372321	-0.409313	0.471819	-0.236582	-0.02
42588	-0.042978	0.062498	-0.052398	-0.203922	-0.209014	0.211914	-0.089485	0.14

42589 rows × 256 columns

```
#here I create the 3d tensor that I will use as input for my first model (the one to which I g

j = 0
i = 0
model_reviews_arr = np.zeros((len(model_reviews)-count_l300, 304, 256), dtype=float)
rating_arr = []
count = 0

for j in range(0, len(model_reviews)):
  k = 0
  if len(model_reviews.loc[j].Review_Text) <= 300:
    for k in range(0, len(model_reviews.loc[j].Review_Text)):
      model_reviews_arr[count][k][0:256] = word_embedding.loc[int(model_reviews.loc[j].Review_

    model_reviews_arr[count][300] = float(model_reviews.loc[j].Reviewer_Location)
    model_reviews_arr[count][301] = float(model_reviews.loc[j].Branch)
    model_reviews_arr[count][302] = float(model_reviews.loc[j].Year)
    model_reviews_arr[count][303] = float(model_reviews.loc[j].Month)
    rating_arr.append(rating[j])
    count += 1
  if j%1000 == 0:
      print(j/1000, end = " ")
```

```
0.0 1.0 2.0 3.0 4.0 5.0 6.0 7.0 8.0 9.0 10.0 11.0 12.0 13.0 14.0 15.0 16.0
```

```
#since my model wants the integer label from 0 to 4 and not from 1 to 5, and map them

i = 0

for i in range(0, len(rating_arr)):
    rating_arr[i] = rating_arr[i] - 1

rating_arr_np = np.array(rating_arr, dtype=int)
```

```
#to perform the train test split keeping the same percentage of each class in both the sets I

X = model_reviews_arr
y = rating_arr_np
# Reshape the 3D tensor into a 2D matrix
X_2D = X.reshape(X.shape[0], -1)

# Split the dataset while maintaining class balance
X_train, X_test, Y_train, Y_test = train_test_split(X_2D, y, test_size=0.2, stratify=y)

# Reshape the training and testing subsets back to 3D tensors
X_train = X_train.reshape(X_train.shape[0], X.shape[1], X.shape[2])
X_test = X_test.reshape(X_test.shape[0], X.shape[1], X.shape[2])
```

```
#here I check that after all this processes I didn't make any error, by printing a review and

first_review = X_train[0][0:304][0:256]
i = 0
j = 0
k = 0
zr = np.zeros((256), dtype=float)

for i in range(0, 20):
    for k in range(0, len(word_embedding)):
        if (word_embedding.loc[k][0:256] != zr).all() and (word_embedding.loc[k][0:256] == fi
            print(inverse_vocab[k], end = " ")
```

```
my 8 yo daughter and i visited disneyland hkg this aug given the weather in
```

Model

I trained **2 models**, one using the word2vec embedding that I performed above, an the other using the keras embedding layer.

I didn't perform a Random or Grid search over the hyperparameters because it would have taken several hours/days to run; a solution could have been to run a random search over a small dataset, but since the most informative feature is the raw text it may not capture the patterns with a little amount of reviews (since the words live in a 256 dim space and they're about 18K, so to capture the patterns we require a lot of samples).

Instead I manually tuned them while looking at the first epochs performances (clearly it's a rudimental solution, but without enough computational power it's the only way to go).

In particular I played with the leanrning rate, the batch size, the numer of recurrent units and of neurons in dense layers, the dropout rate (that turned to be foundamental to prevent overfitting in the second model) and the activation functions of the dense layers.

Then I compared the performances between LSTM and GRU, and since they were pretty similar I decided to **rely on the GRU** since it's more efficient and it takes about half the time to run.

I tried with many configurations, initially I used 2 bidirectional recurrent layers, and I was using 128 and 64 units, then I realized that the best configuration was with a single bidirectional recurrent layer with 32 units (I also tried 64 and 128).

I also tried many configurations of the dense layers with more dropouts and increasing the dropout rate.

Looking to the 2 models we can see that the first one doesn't suffer of over/under fitting but it has a relative low accuracy (about 0.5), going on with the epochs it starts to overfit (since accuracy, val_accuracy and loss, val_loss are increasing in difference); the second model instead overfits from the 3/4 epoch (the 2 models are equal except for the embedding).

Concluding, the word2vec I trained resulted in a better model that doesn't overfit with the same configuration; clearly doing a grid search over many hyperparameters could give different results (especially working on the dropout rate, the number of units and the learning rate).

```
model = keras.Sequential(
    [
        Input(shape=(304, 256)),
        #Bidirectional(GRU(128, return_sequences=True, dropout = 0.2, recurrent_dropout = 0.2
        #GRU(64, dropout = 0.1, recurrent_dropout = 0.1),
        Bidirectional(GRU(32, dropout = 0.2, recurrent_dropout = 0.2)),
        Dropout(0.15),
        Dense(256, activation="sigmoid", kernel_initializer="glorot_uniform"),
        Dense(128, activation="sigmoid", kernel_initializer="glorot_uniform"),
        Dense(5, activation="softmax"),
    ]
)


model.compile(optimizer=tf.keras.optimizers.Adam(learning_rate=10**-3),
                loss='sparse_categorical_crossentropy',
                metrics=['accuracy'])

print(model.summary())
```

```
Model: "sequential_3"
_________________________________________________________________
 Layer (type)                Output Shape              Param #   
=================================================================
 bidirectional_3 (Bidirectio  (None, 64)               55680     
 nal)                                                            
                                                                 
 dropout_3 (Dropout)         (None, 64)                0         
                                                                 
 dense_9 (Dense)             (None, 256)               16640     
                                                                 
 dense_10 (Dense)            (None, 128)               32896     
                                                                 
 dense_11 (Dense)            (None, 5)                 645       
                                                                 
=================================================================
Total params: 105,861
Trainable params: 105,861
Non-trainable params: 0
_________________________________________________________________
None
```

```
batch_size = 16
epochs = 16
history = model.fit(x=X_train,y=Y_train,
        epochs=epochs,
        batch_size = batch_size,
        shuffle=True,
        validation_data=(X_test, Y_test))
```

```
Epoch 1/16
808/808 [==============================] - 168s 205ms/step - loss: 1.4548 -
Epoch 2/16
808/808 [==============================] - 170s 210ms/step - loss: 1.3196 -
Epoch 3/16
808/808 [==============================] - 170s 211ms/step - loss: 1.2260 -
Epoch 4/16
808/808 [==============================] - 173s 214ms/step - loss: 1.1619 -
Epoch 5/16
808/808 [==============================] - 171s 211ms/step - loss: 1.1166 -
Epoch 6/16
808/808 [==============================] - 171s 212ms/step - loss: 1.0847 -
Epoch 7/16
808/808 [==============================] - 169s 209ms/step - loss: 1.0670 -
Epoch 8/16
808/808 [==============================] - 172s 212ms/step - loss: 1.0665 -
Epoch 9/16
808/808 [==============================] - 170s 211ms/step - loss: 1.0371 -
Epoch 10/16
808/808 [==============================] - 169s 209ms/step - loss: 1.0203 -
Epoch 11/16
808/808 [==============================] - 169s 209ms/step - loss: 1.0016 -
Epoch 12/16
808/808 [==============================] - 169s 210ms/step - loss: 0.9914 -
Epoch 13/16
808/808 [==============================] - 171s 212ms/step - loss: 0.9815 -
Epoch 14/16
808/808 [==============================] - 171s 212ms/step - loss: 0.9751 -
Epoch 15/16
808/808 [==============================] - 174s 215ms/step - loss: 0.9645 -
Epoch 16/16
808/808 [==============================] - 181s 224ms/step - loss: 0.9624 -
```

```
model.save_weights('./model_weights_new.h5')
```

```
pyplot.plot(history.history['val_loss'])
pyplot.plot(history.history['val_accuracy'])
pyplot.title('model loss vs accuracy')
pyplot.xlabel('epoch')
pyplot.legend(['loss', 'accuracy'], loc='upper right')
pyplot.show()
```

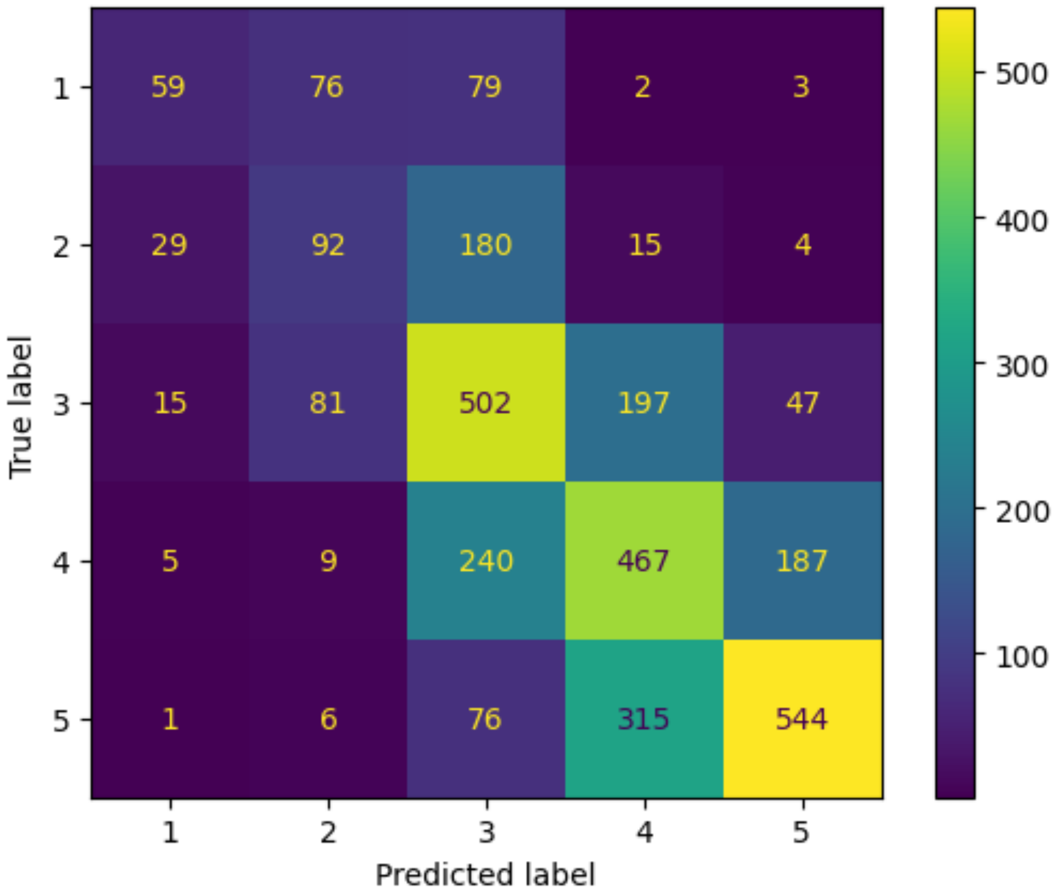
```
predictions = model.predict(X_test)
predictions
```

```
101/101 [==============================] - 3s 28ms/step
array([[6.0763615e-03, 8.9917462e-03, 7.6590389e-02, 3.6561817e-01,
        5.4272336e-01],
       [2.1253293e-02, 1.7067678e-01, 5.8581609e-01, 1.9727905e-01,
        2.4974789e-02],
       [2.5500623e-03, 1.5481868e-02, 2.0604737e-01, 5.3528887e-01,
        2.4063183e-01],
       ...,
       [7.2819093e-04, 3.8339423e-03, 9.4944589e-02, 6.0011083e-01,
        3.0038255e-01],
       [2.3342501e-03, 5.1446055e-04, 3.5608481e-03, 9.3453750e-02,
        9.0013671e-01],
       [9.7714690e-04, 6.0322543e-04, 1.3912452e-02, 3.2939139e-01,
        6.5511578e-01]], dtype=float32)
```

```
predicted_classes = []
for softmax_probabilities in predictions:
    predicted_class = np.argmax(softmax_probabilities)+1
    predicted_classes.append(predicted_class)
```

```
i = 0

for i in range(0, len(Y_test)):
    Y_test[i] = Y_test[i] + 1
```

```
cm = confusion_matrix(Y_test, predicted_classes, labels=[1,2,3,4,5])
disp = ConfusionMatrixDisplay(confusion_matrix=cm, display_labels=[1,2,3,4,5])
disp.plot()
plt.show()
```



```
#here I create a 3d tensor with integer encoding for the model with the keras embedding layer

j = 0
i = 0
rev_l300 = np.zeros((len(model_reviews)-count_l300, 304, 1), dtype=float)
count = 0

for j in range(0, len(model_reviews)):
  k = 0
  if len(model_reviews.loc[j].Review_Text) <= 300:
    for k in range(0, len(model_reviews.loc[j].Review_Text)):
      rev_l300[count][k][0:256] = int(model_reviews.loc[j].Review_Text[k])

    rev_l300[count][300] = float(model_reviews.loc[j].Reviewer_Location)
    rev_l300[count][301] = float(model_reviews.loc[j].Branch)
    rev_l300[count][302] = float(model_reviews.loc[j].Year)
    rev_l300[count][303] = float(model_reviews.loc[j].Month)
    count += 1
  if j%1000 == 0:
      print(j/1000, end = " ")
```

```
0.0 1.0 2.0 3.0 4.0 5.0 6.0 7.0 8.0 9.0 10.0 11.0 12.0 13.0 14.0 15.0 16.0
```

```
X = rev_l300
y = rating_arr_np
# Reshape the 3D tensor into a 2D matrix
X_2D = X.reshape(X.shape[0], -1)

# Split the dataset while maintaining class balance
X_train_n, X_test_n, Y_train_n, Y_test_n = train_test_split(X_2D, y, test_size=0.2, stratify=y

# Reshape the training and testing subsets back to 3D tensors
X_train_n = X_train_n.reshape(X_train_n.shape[0], X.shape[1], X.shape[2])
X_test_n = X_test_n.reshape(X_test_n.shape[0], X.shape[1], X.shape[2])
```

```
from keras.layers import Embedding

model_n = keras.Sequential(
    [
        Embedding(42591, 256, input_length=304),
        #Bidirectional(GRU(64, return_sequences=True, dropout = 0.2, recurrent_dropout = 0.2)
        #GRU(32, dropout = 0.2, recurrent_dropout = 0.2),
        Bidirectional(GRU(32, dropout = 0.2, recurrent_dropout = 0.2)),
        Dropout(0.15),
        Dense(256, activation="sigmoid", kernel_initializer="glorot_uniform"),
        Dense(128, activation="sigmoid", kernel_initializer="glorot_uniform"),
        Dense(5, activation="softmax"),
    ]
)


model_n.compile(optimizer=tf.keras.optimizers.Adam(learning_rate=10**-3),
                loss='sparse_categorical_crossentropy',
                metrics=['accuracy'])

print(model_n.summary())
```

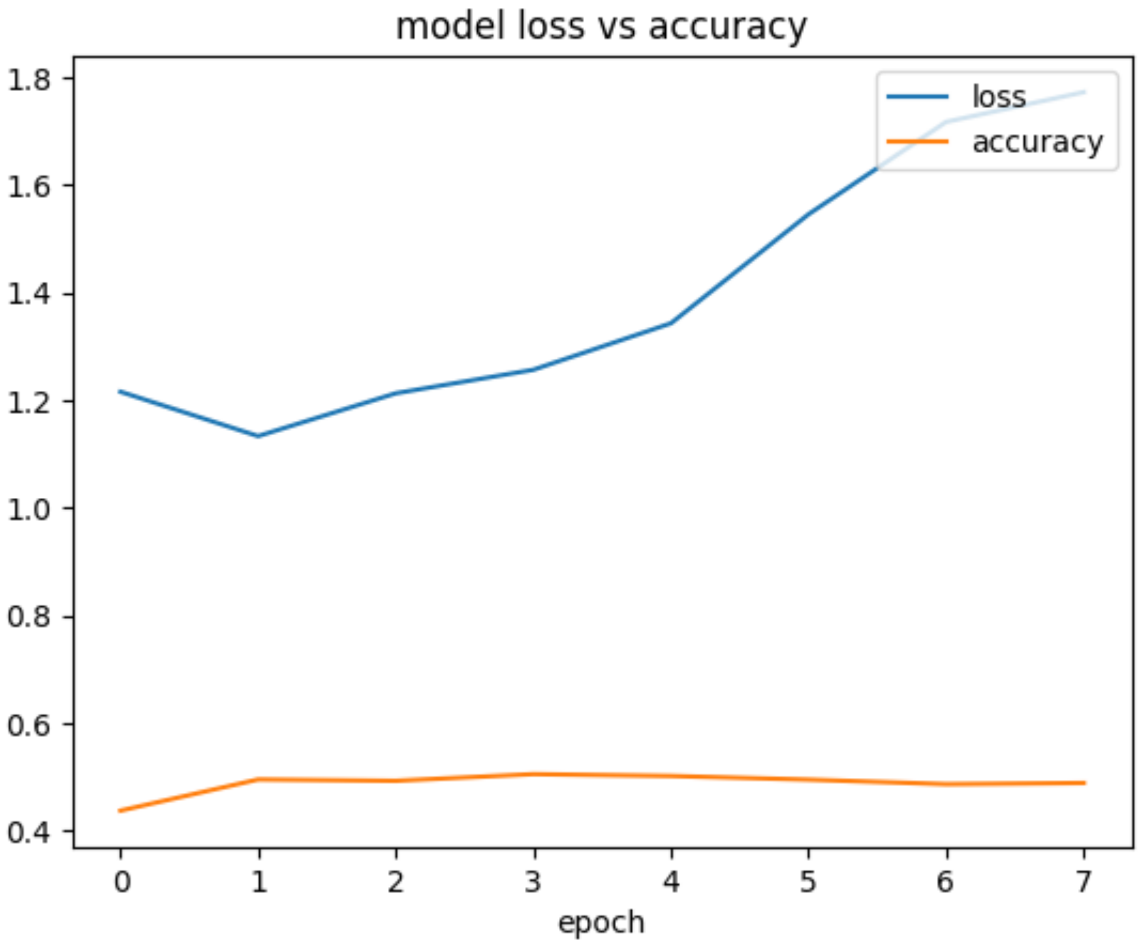
```
Model: "sequential_4"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 embedding (Embedding)       (None, 304, 256)          10903296

 bidirectional_4 (Bidirectio  (None, 64)               55680
 nal)

 dropout_4 (Dropout)         (None, 64)                0

 dense_12 (Dense)            (None, 256)               16640

 dense_13 (Dense)            (None, 128)               32896

 dense_14 (Dense)            (None, 5)                 645

=================================================================
Total params: 11,009,157
Trainable params: 11,009,157
Non-trainable params: 0
_________________________________________________________________
None
```

```
batch_size = 16
epochs = 8
history_n = model_n.fit(x=X_train_n,y=Y_train_n,
        epochs=epochs,
        batch_size = batch_size,
        shuffle=True,
        validation_data=(X_test_n, Y_test_n))
```

```
Epoch 1/8
808/808 [==============================] - 236s 289ms/step - loss: 1.3264 -
Epoch 2/8
808/808 [==============================] - 278s 344ms/step - loss: 1.0955 -
Epoch 3/8
808/808 [==============================] - 265s 328ms/step - loss: 0.9362 -
Epoch 4/8
808/808 [==============================] - 261s 323ms/step - loss: 0.7951 -
Epoch 5/8
808/808 [==============================] - 246s 305ms/step - loss: 0.6603 -
Epoch 6/8
808/808 [==============================] - 231s 286ms/step - loss: 0.5382 -
Epoch 7/8
808/808 [==============================] - 229s 283ms/step - loss: 0.4407 -
Epoch 8/8
808/808 [==============================] - 225s 278ms/step - loss: 0.3688 -
```

```
model_n.save_weights('./model_weights_new_2.h5')
```

```
pyplot.plot(history_n.history['val_loss'])
pyplot.plot(history_n.history['val_accuracy'])
pyplot.title('model loss vs accuracy')
pyplot.xlabel('epoch')
pyplot.legend(['loss', 'accuracy'], loc='upper right')
pyplot.show()
```



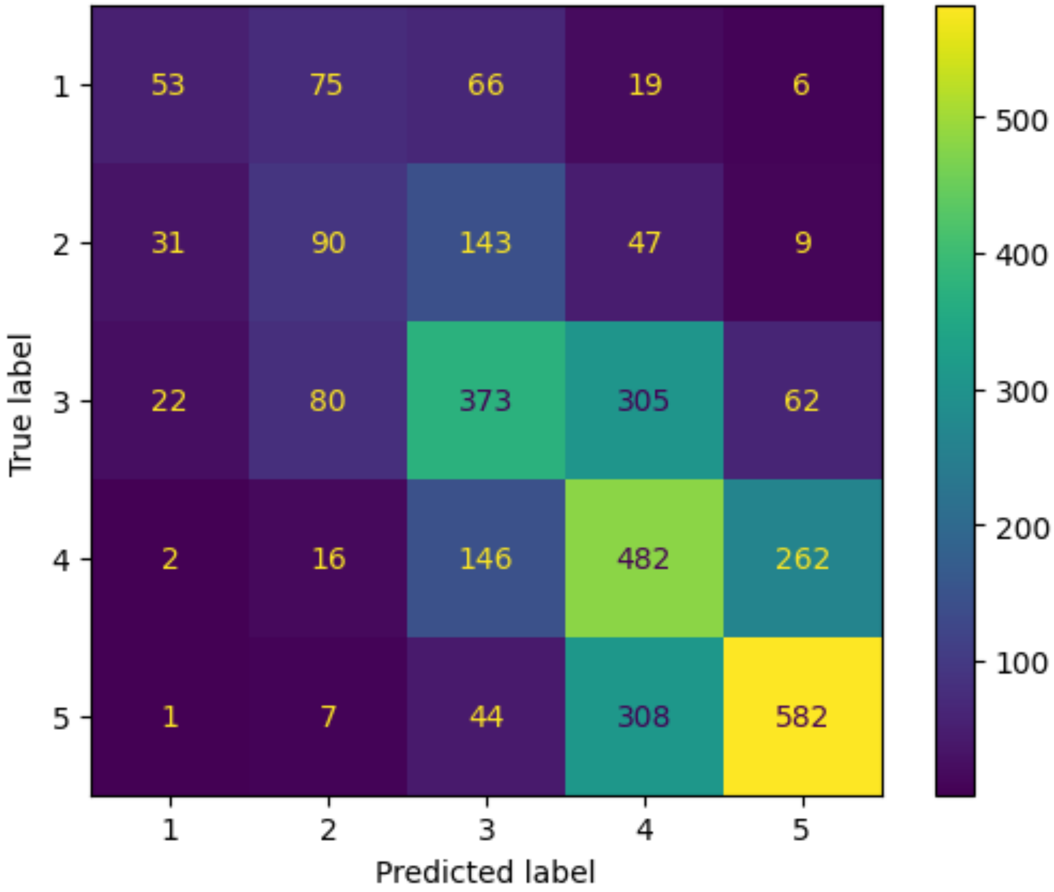
```
predictions_n = model_n.predict(X_test_n)
predictions_n
```

```
101/101 [==============================] - 3s 24ms/step
array([[6.3422980e-05, 2.4922675e-04, 2.1380682e-03, 1.0628968e-01,
        8.9125955e-01],
       [6.4810715e-04, 3.3221699e-03, 2.2994791e-01, 7.4643970e-01,
        1.9642092e-02],
       [2.1254239e-04, 9.4975054e-04, 1.3417753e-02, 5.4089540e-01,
        4.4452453e-01],
       ...,
       [2.1372335e-04, 9.6163870e-04, 1.3117921e-02, 5.2548426e-01,
        4.6022245e-01],
       [4.4868761e-05, 1.7112371e-04, 1.3692724e-03, 7.0374168e-02,
        9.2804056e-01],
       [7.5085508e-04, 1.1400322e-02, 9.5315558e-01, 3.3335544e-02,
        1.3577265e-03]], dtype=float32)
```

```
predicted_classes_n = []
for softmax_probabilities in predictions_n:
    predicted_class = np.argmax(softmax_probabilities)+1
    predicted_classes_n.append(predicted_class)
```

```
i = 0

for i in range(0, len(Y_test_n)):
    Y_test_n[i] = Y_test_n[i] + 1
```

```
cm = confusion_matrix(Y_test_n, predicted_classes_n, labels=[1,2,3,4,5])
disp = ConfusionMatrixDisplay(confusion_matrix=cm, display_labels=[1,2,3,4,5])
disp.plot()
plt.show()
```



0 s data/ora di completamento: 16:29