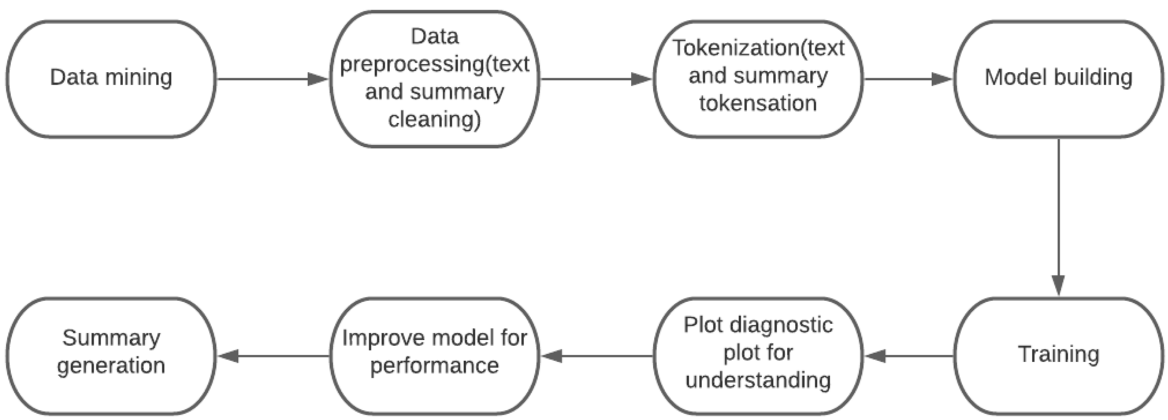
Customer Review Summarizer

Introduction:

Websites such as Amazon and Yelp allow customers to leave reviews for various products. There are usually hundreds of reviews for a single product; each review could be lengthy and repetitive. Therefore automatic review summarization has a huge potential in that it could help customers to make quick decisions on certain products. Summarization is an important challenge of natural language understanding. The aim is to produce a condensed representation of an input text that captures the core meaning of the original.

Conceptual Design:



1. Dataset Mining:
   The dataset used consists of reviews of fine foods from Amazon. The data spans a period of more than 10 years, including all ~500,000 reviews up to October 2012. These reviews include product and user information, ratings, plain text review, and summary. It also includes reviews from all other Amazon categories.

2. Data Preprocessing:
   Performing basic preprocessing steps is very important before we get to the model building part. Using messy and unclean text data is a potentially disastrous move. So in this step, we will drop all the unwanted symbols, characters, etc. from the text that do not affect the objective of our problem. We'll look at the first 10 rows of the reviews and dataset to get an idea of the preprocessing steps for the summary column.
3. Tokenization:
   A tokenizer builds the vocabulary and converts a word sequence to an integer sequence.

4. Model building:

During the model building part, we need to split our dataset into a training and validation set. We'll use 90% of the dataset as the training data and evaluate the performance on the remaining 10% (holdout set). In this step we need to be familiar with the terms such as return sequence, return state, initial state and stacked LSTM.

5. Training:
   In the training phase, we will first set up the encoder and decoder. We will then train the model to predict the target sequence offset by one timestep. Let us see in detail on how to set up the encoder and decoder. An Encoder Long Short Term Memory model (LSTM) reads the entire input sequence wherein, at each timestep, one word is fed into the encoder. It then processes the information at every timestep and captures the contextual information present in the input sequence.The decoder is also an LSTM network which reads the entire target sequence word-by-word and predicts the same sequence offset by one timestep. The decoder is trained to predict the next word in the sequence given the previous word.

6. Plot diagnostic:
   We will plot a few diagnostic plots to understand the behavior of the model over time.After training, the model is tested on new source sequences for which the target sequence is unknown.

7. Improve model performance:
   We will try to increase the training dataset size and build the model. The generalization capability of a deep learning model enhances with an increase in the training dataset size. We can try implementing Bi-Directional LSTM which is capable of capturing the context from both the directions and results in a better context vector

8. Summary generation:
   After all the steps are completed we will have the abstractive summary generated. Even though the actual summary and the summary generated by our model do not match in terms of words, both of them are conveying the same meaning. Our model will be able to generate a legible summary based on the context present in the text.

Implementation and Evaluation:

Implementation code :

```
from attention import AttentionLayer
from google.colab import drive
drive.mount('--/content/drive')
```

```
import numpy as np
import pandas as pd
import re
from bs4 import BeautifulSoup
from keras.preprocessing.text import Tokenizer
from keras.preprocessing.sequence import pad_sequences
from nltk.corpus import stopwords
from tensorflow.keras.layers import Input, LSTM, Embedding, Dense, Concatenate,
TimeDistributed
from tensorflow.keras.models import Model
from tensorflow.keras.callbacks import EarlyStopping
import warnings
pd.set_option("display.max_colwidth", 200)
warnings.filterwarnings("ignore")
data=pd.read_csv("/content/drive/MyDrive/NLP//Reviews.csv",nrows=100000)
data.drop_duplicates(subset=['Text'],inplace=True)#dropping duplicates
data.dropna(axis=0,inplace=True)#dropping na
data.info()
<class 'pandas.core.frame.DataFrame'>
Int64Index: 88421 entries, 0 to 99999
Data columns (total 10 columns):
 #   Column                  Non-Null Count  Dtype
---  ------                  --------------  -----
 0   Id                      88421 non-null  int64
 1   ProductId               88421 non-null  object
 2   UserId                  88421 non-null  object
 3   ProfileName             88421 non-null  object
 4   HelpfulnessNumerator    88421 non-null  int64
 5   HelpfulnessDenominator  88421 non-null  int64
 6   Score                   88421 non-null  int64
 7   Time                    88421 non-null  int64
 8   Summary                 88421 non-null  object
 9   Text                    88421 non-null  object
dtypes: int64(5), object(5)
memory usage: 7.4+ MB
contraction_mapping = {"ain't": "is not", "aren't": "are not","can't": "cannot", "'cause":
"because", "could've": "could have", "couldn't": "could not",
                           "didn't": "did not",  "doesn't": "does not", "don't": "do not", "hadn't": "had not",
"hasn't": "has not", "haven't": "have not",
```

"he'd": "he would","he'll": "he will", "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", "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 as",

"this's": "this 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", "here's": "here 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", "to've": "to 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"}
import nltk
nltk.download('stopwords')
stop_words = set(stopwords.words('english'))

def text_cleaner(text,num):
    newString = text.lower()
    newString = BeautifulSoup(newString, "lxml").text
    newString = re.sub(r'\([^)]*\)', '', newString)
    newString = re.sub('"','', newString)
    newString = ' '.join([contraction_mapping[t] if t in contraction_mapping else t for t in
newString.split(" ")])
    newString = re.sub(r"'s\b","",newString)
    newString = re.sub("[^a-zA-Z]", " ", newString)
    newString = re.sub('[m]{2,}', 'mm', newString)
    if(num==0):
        tokens = [w for w in newString.split() if not w in stop_words]
    else:
        tokens=newString.split()
    long_words=[]
    for i in tokens:
        if len(i)>1:                                    #removing short word
            long_words.append(i)
    return (" ".join(long_words)).strip()
[nltk_data] Downloading package stopwords to /root/nltk_data...
[nltk_data]   Unzipping corpora/stopwords.zip.
#call the function
cleaned_text = []
for t in data['Text']:
    cleaned_text.append(text_cleaner(t,0))
#call the function
cleaned_summary = []
for t in data['Summary']:
    cleaned_summary.append(text_cleaner(t,1))
data['cleaned_text']=cleaned_text
data['cleaned_summary']=cleaned_summary
data.replace('', np.nan, inplace=True)
data.dropna(axis=0,inplace=True)
import matplotlib.pyplot as plt
```

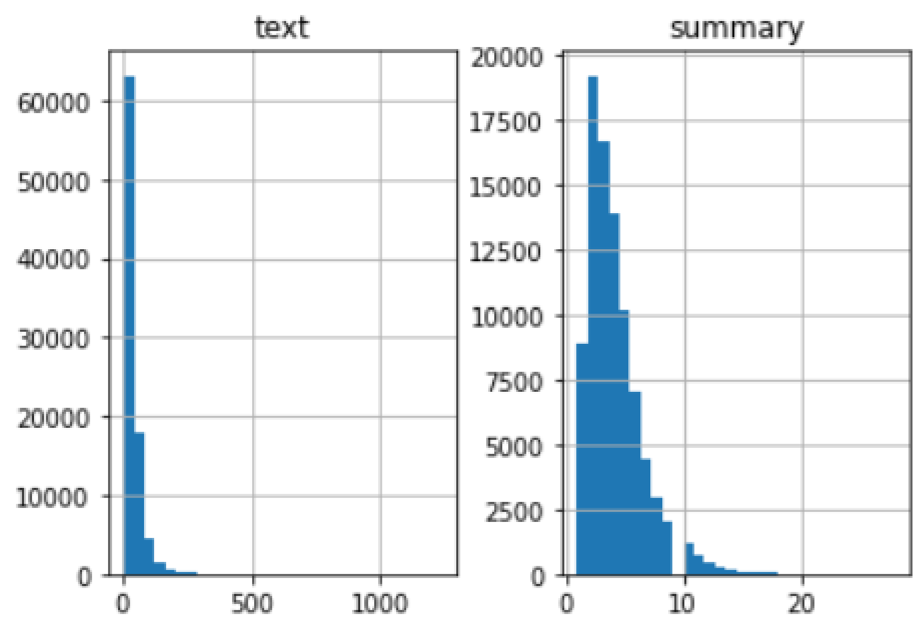
```
text_word_count = []
summary_word_count = []

# populate the lists with sentence lengths
for i in data['cleaned_text']:
      text_word_count.append(len(i.split()))

for i in data['cleaned_summary']:
      summary_word_count.append(len(i.split()))

length_df = pd.DataFrame({'text':text_word_count, 'summary':summary_word_count})

length_df.hist(bins = 30)
plt.show()
```




```
cnt=0
for i in data['cleaned_summary']:
    if(len(i.split())<=8):
        cnt=cnt+1
print(cnt/len(data['cleaned_summary']))
0.9424907471335922
max_text_len=30
max_summary_len=8
cleaned_text =np.array(data['cleaned_text'])
cleaned_summary=np.array(data['cleaned_summary'])
```

```
short_text=[]
short_summary=[]

for i in range(len(cleaned_text)):
    if(len(cleaned_summary[i].split())<=max_summary_len and
len(cleaned_text[i].split())<=max_text_len):
        short_text.append(cleaned_text[i])
        short_summary.append(cleaned_summary[i])

df=pd.DataFrame({'text':short_text,'summary':short_summary})
df['summary'] = df['summary'].apply(lambda x : 'sostok '+ x + ' eostok')
from sklearn.model_selection import train_test_split
x_tr,x_val,y_tr,y_val=train_test_split(np.array(df['text']),np.array(df['summary']),test_size=0.1,ra
ndom_state=0,shuffle=True)
from keras.preprocessing.text import Tokenizer
from keras.preprocessing.sequence import pad_sequences

#prepare a tokenizer for reviews on training data
x_tokenizer = Tokenizer()
x_tokenizer.fit_on_texts(list(x_tr))
thresh=4

cnt=0
tot_cnt=0
freq=0
tot_freq=0

for key,value in x_tokenizer.word_counts.items():
    tot_cnt=tot_cnt+1
    tot_freq=tot_freq+value
    if(value<thresh):
        cnt=cnt+1
        freq=freq+value

print("% of rare words in vocabulary:",(cnt/tot_cnt)*100)
print("Total Coverage of rare words:",(freq/tot_freq)*100)
% of rare words in vocabulary: 66.12339930151339
Total Coverage of rare words: 2.953684513790566
#prepare a tokenizer for reviews on training data
x_tokenizer = Tokenizer(num_words=tot_cnt-cnt)
```

```
x_tokenizer.fit_on_texts(list(x_tr))

#convert text sequences into integer sequences
x_tr_seq    =   x_tokenizer.texts_to_sequences(x_tr)
x_val_seq   =   x_tokenizer.texts_to_sequences(x_val)

#padding zero upto maximum length
x_tr    =   pad_sequences(x_tr_seq,  maxlen=max_text_len, padding='post')
x_val   =   pad_sequences(x_val_seq, maxlen=max_text_len, padding='post')

#size of vocabulary ( +1 for padding token)
x_voc   =  x_tokenizer.num_words + 1
x_voc
8440
#prepare a tokenizer for reviews on training data
y_tokenizer = Tokenizer()
y_tokenizer.fit_on_texts(list(y_tr))
thresh=6

cnt=0
tot_cnt=0
freq=0
tot_freq=0

for key,value in y_tokenizer.word_counts.items():
    tot_cnt=tot_cnt+1
    tot_freq=tot_freq+value
    if(value<thresh):
        cnt=cnt+1
        freq=freq+value

print("% of rare words in vocabulary:",(cnt/tot_cnt)*100)
print("Total Coverage of rare words:",(freq/tot_freq)*100)
% of rare words in vocabulary: 78.12740675541863
Total Coverage of rare words: 5.3921899389571895
#prepare a tokenizer for reviews on training data
y_tokenizer = Tokenizer(num_words=tot_cnt-cnt)
y_tokenizer.fit_on_texts(list(y_tr))

#convert text sequences into integer sequences
```

```
y_tr_seq    =   y_tokenizer.texts_to_sequences(y_tr)
y_val_seq   =   y_tokenizer.texts_to_sequences(y_val)

#padding zero upto maximum length
y_tr    =   pad_sequences(y_tr_seq, maxlen=max_summary_len, padding='post')
y_val   =   pad_sequences(y_val_seq, maxlen=max_summary_len, padding='post')

#size of vocabulary
y_voc  =   y_tokenizer.num_words +1
ind=[]
for i in range(len(y_tr)):
    cnt=0
    for j in y_tr[i]:
        if j!=0:
            cnt=cnt+1
    if(cnt==2):
        ind.append(i)

y_tr=np.delete(y_tr,ind, axis=0)
x_tr=np.delete(x_tr,ind, axis=0)
ind=[]
for i in range(len(y_val)):
    cnt=0
    for j in y_val[i]:
        if j!=0:
            cnt=cnt+1
    if(cnt==2):
        ind.append(i)

y_val=np.delete(y_val,ind, axis=0)
x_val=np.delete(x_val,ind, axis=0)
from keras import backend as K
K.clear_session()

latent_dim = 300
embedding_dim=100

# Encoder
encoder_inputs = Input(shape=(max_text_len,))
```

```
#embedding layer
enc_emb =  Embedding(x_voc, embedding_dim,trainable=True)(encoder_inputs)

#encoder lstm 1
encoder_lstm1 =
LSTM(latent_dim,return_sequences=True,return_state=True,dropout=0.4,recurrent_dropout=0.4
)
encoder_output1, state_h1, state_c1 = encoder_lstm1(enc_emb)

#encoder lstm 2
encoder_lstm2 =
LSTM(latent_dim,return_sequences=True,return_state=True,dropout=0.4,recurrent_dropout=0.4
)
encoder_output2, state_h2, state_c2 = encoder_lstm2(encoder_output1)

#encoder lstm 3
encoder_lstm3=LSTM(latent_dim, return_state=True,
return_sequences=True,dropout=0.4,recurrent_dropout=0.4)
encoder_outputs, state_h, state_c= encoder_lstm3(encoder_output2)

# Set up the decoder, using `encoder_states` as initial state.
decoder_inputs = Input(shape=(None,))

#embedding layer
dec_emb_layer = Embedding(y_voc, embedding_dim,trainable=True)
dec_emb = dec_emb_layer(decoder_inputs)

decoder_lstm = LSTM(latent_dim, return_sequences=True,
return_state=True,dropout=0.4,recurrent_dropout=0.2)
decoder_outputs,decoder_fwd_state, decoder_back_state =
decoder_lstm(dec_emb,initial_state=[state_h, state_c])

# Attention layer
attn_layer = AttentionLayer(name='attention_layer')
attn_out, attn_states = attn_layer([encoder_outputs, decoder_outputs])

# Concat attention input and decoder LSTM output
decoder_concat_input = Concatenate(axis=-1, name='concat_layer')([decoder_outputs, attn_out])

#dense layer
```

```
decoder_dense =  TimeDistributed(Dense(y_voc, activation='softmax'))
decoder_outputs = decoder_dense(decoder_concat_input)

# Define the model
model = Model([encoder_inputs, decoder_inputs], decoder_outputs)

model.summary()
```

WARNING:tensorflow:Layer lstm will not use cuDNN kernel since it doesn't meet the cuDNN kernel criteria. It will use generic GPU kernel as fallback when running on GPU
WARNING:tensorflow:Layer lstm_1 will not use cuDNN kernel since it doesn't meet the cuDNN kernel criteria. It will use generic GPU kernel as fallback when running on GPU
WARNING:tensorflow:Layer lstm_2 will not use cuDNN kernel since it doesn't meet the cuDNN kernel criteria. It will use generic GPU kernel as fallback when running on GPU
WARNING:tensorflow:Layer lstm_3 will not use cuDNN kernel since it doesn't meet the cuDNN kernel criteria. It will use generic GPU kernel as fallback when running on GPU
Model: "model"

```
__________________________________________________________________________________________________
Layer (type)                    Output Shape         Param #     Connected to
==================================================================================================
input_1 (InputLayer)            [(None, 30)]         0
__________________________________________________________________________________________________
embedding (Embedding)           (None, 30, 100)      844000      input_1[0][0]
__________________________________________________________________________________________________
lstm (LSTM)                     [(None, 30, 300), (N 481200      embedding[0][0]
__________________________________________________________________________________________________
input_2 (InputLayer)            [(None, None)]       0
__________________________________________________________________________________________________
lstm_1 (LSTM)                   [(None, 30, 300), (N 721200      lstm[0][0]
__________________________________________________________________________________________________
embedding_1 (Embedding)         (None, None, 100)    198900      input_2[0][0]
__________________________________________________________________________________________________
lstm_2 (LSTM)                   [(None, 30, 300), (N 721200      lstm_1[0][0]
```

```
__________________________________________________________________________________________________
lstm_3 (LSTM)                   [(None, None, 300),  481200      embedding_1[0][0]
                                                                 lstm_2[0][1]
                                                                 lstm_2[0][2]
__________________________________________________________________________________________________
attention_layer (AttentionLayer ((None, None, 300),  180300      lstm_2[0][0]
                                                                 lstm_3[0][0]
__________________________________________________________________________________________________
concat_layer (Concatenate)      (None, None, 600)    0           lstm_3[0][0]
                                                                 attention_layer[0][0]
__________________________________________________________________________________________________
time_distributed (TimeDistribut (None, None, 1989)   1195389     concat_layer[0][0]
==================================================================================================
Total params: 4,823,389
Trainable params: 4,823,389
Non-trainable params: 0
model.compile(optimizer='rmsprop', loss='sparse_categorical_crossentropy')
es = EarlyStopping(monitor='val_loss', mode='min', verbose=1,patience=2)
history=model.fit([x_tr,y_tr[:,:-1]], y_tr.reshape(y_tr.shape[0],y_tr.shape[1], 1)[:,1:]
,epochs=50,callbacks=[es],batch_size=128, validation_data=([x_val,y_val[:,:-1]],
y_val.reshape(y_val.shape[0],y_val.shape[1], 1)[:,1:]))

# Encode the input sequence to get the feature vector
encoder_model = Model(inputs=encoder_inputs,outputs=[encoder_outputs, state_h, state_c])

# Decoder setup
# Below tensors will hold the states of the previous time step
decoder_state_input_h = Input(shape=(latent_dim,))
decoder_state_input_c = Input(shape=(latent_dim,))
decoder_hidden_state_input = Input(shape=(max_text_len,latent_dim))

# Get the embeddings of the decoder sequence
dec_emb2= dec_emb_layer(decoder_inputs)
# To predict the next word in the sequence, set the initial states to the states from the previous
time step
```

```
decoder_outputs2, state_h2, state_c2 = decoder_lstm(dec_emb2,
initial_state=[decoder_state_input_h, decoder_state_input_c])

#attention inference
attn_out_inf, attn_states_inf = attn_layer([decoder_hidden_state_input, decoder_outputs2])
decoder_inf_concat = Concatenate(axis=-1, name='concat')([decoder_outputs2, attn_out_inf])

# A dense softmax layer to generate prob dist. over the target vocabulary
decoder_outputs2 = decoder_dense(decoder_inf_concat)

# Final decoder model
decoder_model = Model(
   [decoder_inputs] + [decoder_hidden_state_input,decoder_state_input_h,
decoder_state_input_c],
   [decoder_outputs2] + [state_h2, state_c2])
def decode_sequence(input_seq):
   # Encode the input as state vectors.
   e_out, e_h, e_c = encoder_model.predict(input_seq)

   # Generate empty target sequence of length 1.
   target_seq = np.zeros((1,1))

   # Populate the first word of target sequence with the start word.
   target_seq[0, 0] = target_word_index['sostok']

   stop_condition = False
   decoded_sentence = ''
   while not stop_condition:

      output_tokens, h, c = decoder_model.predict([target_seq] + [e_out, e_h, e_c])

      # Sample a token
      sampled_token_index = np.argmax(output_tokens[0, -1, :])
      sampled_token = reverse_target_word_index[sampled_token_index]

      if(sampled_token!='eostok'):
         decoded_sentence += ' '+sampled_token

      # Exit condition: either hit max length or find stop word.
      if (sampled_token == 'eostok'  or len(decoded_sentence.split()) >= (max_summary_len-1)):
```

```python
            stop_condition = True

        # Update the target sequence (of length 1).
        target_seq = np.zeros((1,1))
        target_seq[0, 0] = sampled_token_index

        # Update internal states
        e_h, e_c = h, c

    return decoded_sentence
def seq2summary(input_seq):
    newString=''
    for i in input_seq:
        if((i!=0 and i!=target_word_index['sostok']) and i!=target_word_index['eostok']):
            newString=newString+reverse_target_word_index[i]+' '
    return newString

def seq2text(input_seq):
    newString=''
    for i in input_seq:
        if(i!=0):
            newString=newString+reverse_source_word_index[i]+' '
    return newString
for i in range(0,5):
    print("Review:",seq2text(x_tr[i]))
    print("Original summary:",seq2summary(y_tr[i]))
    print("Predicted summary:",decode_sequence(x_tr[i].reshape(1,max_text_len)))
    print("\n")
```

Review: gave caffeine shakes heart anxiety attack plus tastes unbelievably bad stick coffee tea soda thanks
Original summary: hour
Predicted summary: green tea

Review: got great course good belgian chocolates better
Original summary: would like to give it stars but
Predicted summary: delicious

Review: one best flavored coffees tried usually like flavored coffees one great serve company love
Original summary: delicious
Predicted summary: great coffee

Review: salt separate area pain makes hard regulate salt putting like salt go ahead get product
Original summary: tastes ok packaging
Predicted summary: salt

Review: really like product super easy order online delivered much cheaper buying gas station stocking good long drives
Original summary: turkey jerky is great
Predicted summary: great