Bachelor_Thesis_Text_Generation

May 3, 2020

Bachelor Thesis

IT-based Automatic Text Summarization with the use of Text Generation methods

State of the art and design of a prototype

from Tim Löhr

1 1.0 Importing the Dependcies

[1]:
```
from attention import AttentionLayer

import numpy as np
import pandas as pd
import re
from bs4 import BeautifulSoup

from nltk.corpus import stopwords
from nltk.tokenize import word_tokenize
from nltk.tokenize import RegexpTokenizer

from keras.preprocessing.sequence import pad_sequences
from keras.preprocessing.text import Tokenizer
from keras import backend as K

from tensorflow.keras.layers import Input, LSTM, Embedding, Dense, Concatenate,␣
 ↪TimeDistributed, Bidirectional
from tensorflow.keras.models import Model
from tensorflow.keras.callbacks import EarlyStopping
from tensorflow.keras.models import load_model, model_from_json

from sklearn.model_selection import train_test_split

import nltk
```

```
nltk.download('stopwords')
import matplotlib.pyplot as plt

import spacy
spacy.load("en")

from sumeval.metrics.rouge import RougeCalculator
from sumeval.metrics.bleu import BLEUCalculator
from nltk.translate.bleu_score import sentence_bleu

import warnings
pd.set_option("display.max_colwidth", 200)
warnings.filterwarnings("ignore")
```

```
Using TensorFlow backend.
[nltk_data] Downloading package stopwords to
[nltk_data]     /Users/timloehr/nltk_data…
[nltk_data]   Package stopwords is already up-to-date!
```

2 2.0 Loading the Data

[4]:
```
data = pd.read_csv('amazon-fine-food-reviews/Reviews.csv', nrows=250000)
data.head(1)
```

[4]:
```
   Id   ProductId          UserId ProfileName  HelpfulnessNumerator  \
0   1  B001E4KFG0  A3SGXH7AUHU8GW  delmartian                     1

   HelpfulnessDenominator  Score        Time                Summary  \
0                       1      5  1303862400  Good Quality Dog Food

                                        Text
0  I have bought several of the Vitality canned dog food products and have found
them all to be of good quality. The product looks more like a stew than a
processed meat and it smells better. My Labr…
```

[4]:
```
data.shape
```

[4]:
```
(250000, 10)
```

3 3.0 Data Preprocessing

[5]:
```
data = data[['Summary', 'Text']]
```

[6]:
```
data.drop_duplicates(subset='Text')
data.dropna(axis=0, inplace=True)
```

[7]:
```
data.shape
```

[7]: (249990, 2)

3.0.1 Contraction Mapping

[8]:
```
from contraction_mapping import contraction_mapping

contraction_mapping = contraction_mapping()
```

3.1 Cleaning

3.1.1 Text Cleaning

[9]:
```
stop_words = stopwords.words('english')
tokenizer = RegexpTokenizer(r'\w+')

def text_cleaner(text):
    newString = text.lower()
    #newString = BeautifulSoup(newString, "lxml").text
    tags = re.compile('<.*?>|&([a-z0-9]+|#[0-9]{1,6}|#x[0-9a-f]{1,6});')
    newString = tags.sub('', newString)
    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)
    tokens = [w for w in newString.split() if not w in stop_words]
    long_words=[]
    for i in tokens:
        if len(i)>=3:                  #removing short word
            long_words.append(i)
    return (" ".join(long_words)).strip()
```

Cleaned text concatenate with DataFrame

[10]:
```
cleaned_text = []
for t in data['Text']:
    cleaned_text.append(text_cleaner(t))
```

3.1.2 Summary Cleaning

[11]:
```
data['Summary'][:10]
```

[11]:
```
0                             Good Quality Dog Food
1                                 Not as Advertised
```

```
2                            "Delight" says it all
3                                   Cough Medicine
4                                      Great taffy
5                                       Nice Taffy
6     Great!  Just as good as the expensive brands!
7                           Wonderful, tasty taffy
8                                       Yay Barley
9                                 Healthy Dog Food
Name: Summary, dtype: object
```

[12]:

```
def summary_cleaner(text):
    newString = re.sub('"','', text)
    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 = newString.lower()
    tokens=newString.split()
    newString=''
    for i in tokens:
        if len(i)>1:
            newString=newString+i+' '
    return newString
```

[13]:

```
cleaned_summary = []
for t in data['Summary']:
    cleaned_summary.append(summary_cleaner(t))

data['cleaned_text']=cleaned_text
data['cleaned_summary']=cleaned_summary

data['cleaned_summary'].replace('', np.nan, inplace=True)
data.dropna(axis=0,inplace=True)

data['cleaned_summary'] = data['cleaned_summary'].apply(lambda x: '_START_ ' +␣
 ↪x + ' _END_')
```

[14]:

```
data.head()
```

[14]:

```
                  Summary  \
0  Good Quality Dog Food
1      Not as Advertised
2  "Delight" says it all
3         Cough Medicine
4            Great taffy

                                                Text  \
```

```
0  I have bought several of the Vitality canned dog food products and have found
them all to be of good quality. The product looks more like a stew than a
processed meat and it smells better. My Labr…
1            Product arrived labeled as Jumbo Salted Peanuts…the peanuts were
actually small sized unsalted. Not sure if this was an error or if the vendor
intended to represent the product as "Jumbo".
2  This is a confection that has been around a few centuries.  It is a light,
pillowy citrus gelatin with nuts - in this case Filberts. And it is cut into
tiny squares and then liberally coated with …
3  If you are looking for the secret ingredient in Robitussin I believe I have
found it.  I got this in addition to the Root Beer Extract I ordered (which was
good) and made some cherry soda.  The fl…
4                                                              Great taffy at a
great price.  There was a wide assortment of yummy taffy.  Delivery was very
quick.  If your a taffy lover, this is a deal.

                              cleaned_text  \
0                                      bought several vitality canned dog food
products found good quality product looks like stew processed meat smells better
labrador finicky appreciates product better
1                                                                     product
arrived labeled jumbo salted peanuts peanuts actually small sized unsalted sure
error vendor intended represent product jumbo
2  confection around centuries light pillowy citrus gelatin nuts case filberts
cut tiny squares liberally coated powdered sugar tiny mouthful heaven chewy
flavorful highly recommend yummy treat famil…
3
looking secret ingredient robitussin believe found got addition root beer
extract ordered made cherry soda flavor medicinal
4
great taffy great price wide assortment yummy taffy delivery quick taffy lover
deal

                        cleaned_summary
0  _START_ good quality dog food  _END_
1      _START_ not as advertised  _END_
2    _START_ delight says it all  _END_
3         _START_ cough medicine  _END_
4            _START_ great taffy  _END_
```

3.1.3 Distribution of the sequences

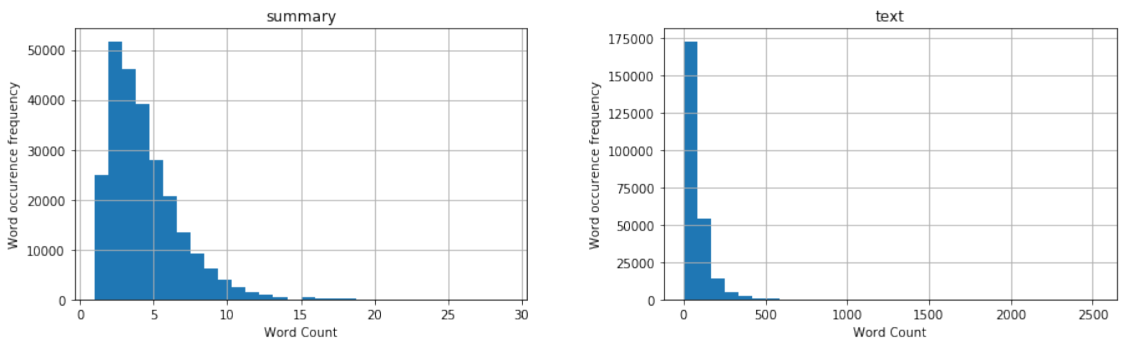
[22]:
```
text_word_count = []
summary_word_count = []

# populate the lists with sentence lengths
for i in data['Text']:
```

```
        text_word_count.append(len(i.split()))

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

length_df = pd.DataFrame({'text':text_word_count, 'summary':summary_word_count})
axarr = length_df.hist(bins = 30, figsize=(15,4))
for ax in axarr.flatten():
    ax.set_xlabel("Word Count")
    ax.set_ylabel("Word occurence frequency")
plt.show()
```



[101]:
```
max_len_text=80
max_len_summary=10
```

3.1.4 Preparing Tokenizer

[102]:
```
X_train , X_test , y_train , y_test = train_test_split(data['cleaned_text'],␣
↪data['cleaned_summary'], test_size=0.1, random_state=0, shuffle=True)

print(X_train.shape)
print(X_test.shape)
print(y_train.shape)
print(y_test.shape)
```

```
(224814,)
(24980,)
(224814,)
(24980,)
```

Text Tokenizer

[103]:
```
#prepare a tokenizer for reviews on training data
x_tokenizer = Tokenizer()
x_tokenizer.fit_on_texts(list(X_train))
```

```python
#convert text sequences into integer sequences
X_train = x_tokenizer.texts_to_sequences(X_train)
X_test = x_tokenizer.texts_to_sequences(X_test)

#padding zero upto maximum length
X_train = pad_sequences(X_train,  maxlen=max_len_text, padding='post')
X_test = pad_sequences(X_test, maxlen=max_len_text, padding='post')

x_voc_size = len(x_tokenizer.word_index) +1
```

Summary Tokenizer

[104]:
```python
#preparing a tokenizer for summary on training data
y_tokenizer = Tokenizer()
y_tokenizer.fit_on_texts(list(y_train))

#convert summary sequences into integer sequences
y_train = y_tokenizer.texts_to_sequences(y_train)
y_test = y_tokenizer.texts_to_sequences(y_test)

#padding zero upto maximum length
y_train = pad_sequences(y_train, maxlen=max_len_summary, padding='post')
y_test = pad_sequences(y_test, maxlen=max_len_summary, padding='post')

y_voc_size = len(y_tokenizer.word_index) +1
```

[105]:
```python
print(X_train.shape)
print(X_test.shape)
print(y_train.shape)
print(y_test.shape)
```

```
(224814, 80)
(24980, 80)
(224814, 10)
(24980, 10)
```

4 4.0 Model

[106]:
```python
K.clear_session()
latent_dim = 500

# Encoder
encoder_inputs = Input(shape=(max_len_text,))
enc_emb = Embedding(x_voc_size, latent_dim, trainable=True)(encoder_inputs)

#LSTM 1
```

```
encoder_lstm1 = LSTM(latent_dim, return_sequences=True, return_state=True)
encoder_output1, state_h1, state_c1 = encoder_lstm1(enc_emb)

#LSTM 2
encoder_lstm2 = LSTM(latent_dim, return_sequences=True, return_state=True)
encoder_output2, state_h2, state_c2 = encoder_lstm2(encoder_output1)

#LSTM 3
encoder_lstm3=LSTM(latent_dim, return_sequences=True, return_state=True)
encoder_outputs, state_h, state_c= encoder_lstm3(encoder_output2)

# Set up the decoder.
decoder_inputs = Input(shape=(None,))
dec_emb_layer = Embedding(y_voc_size, latent_dim, trainable=True)
dec_emb = dec_emb_layer(decoder_inputs)

#LSTM using encoder_states as initial state
decoder_lstm = LSTM(latent_dim, return_sequences=True, return_state=True)
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 output 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_size, activation='softmax'))
decoder_outputs = decoder_dense(decoder_concat_input)

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

[107]:
```
model.summary()
```

```
Model: "model"
________________________________________________________________________________
__________________
Layer (type)                    Output Shape         Param #     Connected to
================================================================================
==================
input_1 (InputLayer)            [(None, 80)]         0

________________________________________________________________________________
__________________
```

```
embedding (Embedding)           (None, 80, 500)      40049500    input_1[0][0]
________________________________________________________________________________
__________________
lstm (LSTM)                     [(None, 80, 500), (N 2002000     embedding[0][0]
________________________________________________________________________________
__________________
input_2 (InputLayer)            [(None, None)]       0
________________________________________________________________________________
__________________
lstm_1 (LSTM)                   [(None, 80, 500), (N 2002000     lstm[0][0]
________________________________________________________________________________
__________________
embedding_1 (Embedding)         (None, None, 500)    10933500    input_2[0][0]
________________________________________________________________________________
__________________
lstm_2 (LSTM)                   [(None, 80, 500), (N 2002000     lstm_1[0][0]
________________________________________________________________________________
__________________
lstm_3 (LSTM)                   [(None, None, 500),  2002000
embedding_1[0][0]
                                                                 lstm_2[0][1]
                                                                 lstm_2[0][2]
________________________________________________________________________________
__________________
attention_layer (AttentionLayer ((None, None, 500),  500500      lstm_2[0][0]
                                                                 lstm_3[0][0]
________________________________________________________________________________
__________________
concat_layer (Concatenate)      (None, None, 1000)   0           lstm_3[0][0]
attention_layer[0][0]
________________________________________________________________________________
__________________
time_distributed (TimeDistribut (None, None, 21867)  21888867
concat_layer[0][0]
================================================================================
==================
Total params: 81,380,367
Trainable params: 81,380,367
Non-trainable params: 0
________________________________________________________________________________
__________________
```

Model optimization

[108]:
```
model.compile(optimizer='rmsprop', loss='sparse_categorical_crossentropy')

es = EarlyStopping(monitor='val_loss', mode='min', verbose=1)
```

Model fitting

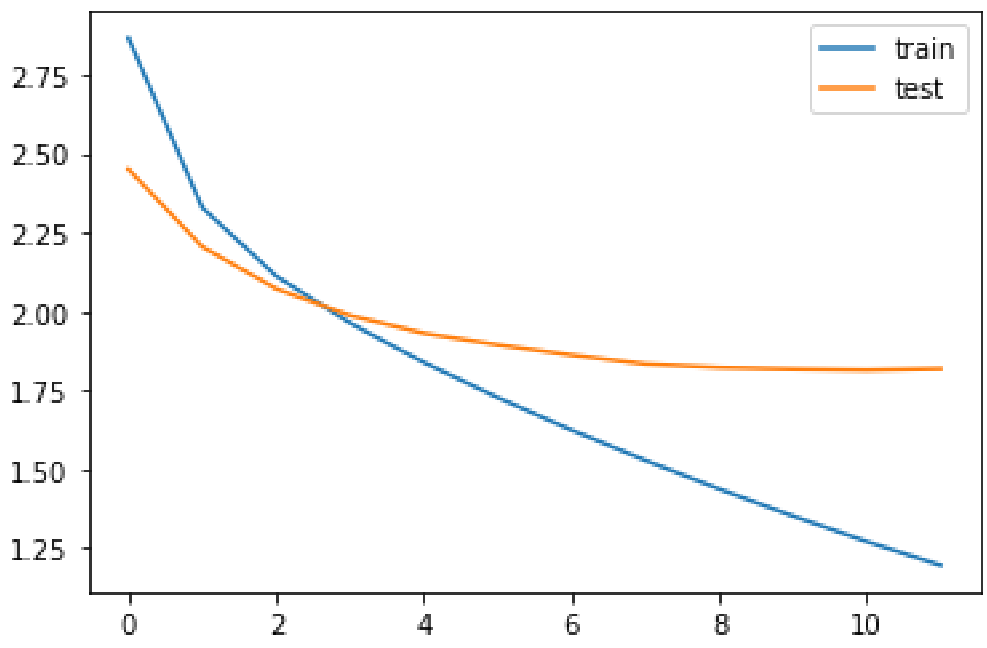
[109]:
```
try:
    model = load_model('model.h5', custom_objects={'AttentionLayer':␣
↪AttentionLayer})
    print("Model successfully loaded.")
except:
    print("Train Model...")
    history = model.fit([X_train, y_train[:,:-1]],
                    y_train.reshape(y_train.shape[0], y_train.shape[1], 1)[:,1:
↪],
                    epochs=30,
                    callbacks=[es],
                    batch_size=512,
                    validation_data=([X_test,y_test[:,:-1]],
                                    y_test.reshape(y_test.shape[0],y_test.
↪shape[1], 1)[:,1:])
                   )
    model.save('model.h5')
    print("Model saved")
```

```
Train Model…
Train on 224814 samples, validate on 24980 samples
Epoch 1/30
224814/224814 [==============================] - 982s 4ms/sample - loss: 2.8669
- val_loss: 2.4505
Epoch 2/30
224814/224814 [==============================] - 980s 4ms/sample - loss: 2.3291
- val_loss: 2.2047
Epoch 3/30
224814/224814 [==============================] - 979s 4ms/sample - loss: 2.1111
- val_loss: 2.0710
Epoch 4/30
224814/224814 [==============================] - 979s 4ms/sample - loss: 1.9626
- val_loss: 1.9864
Epoch 5/30
224814/224814 [==============================] - 977s 4ms/sample - loss: 1.8385
- val_loss: 1.9306
Epoch 6/30
224814/224814 [==============================] - 976s 4ms/sample - loss: 1.7271
- val_loss: 1.8944
Epoch 7/30
224814/224814 [==============================] - 978s 4ms/sample - loss: 1.6239
- val_loss: 1.8619
Epoch 8/30
224814/224814 [==============================] - 979s 4ms/sample - loss: 1.5275
- val_loss: 1.8335
Epoch 9/30
```

```
224814/224814 [==============================] - 977s 4ms/sample - loss: 1.4366
- val_loss: 1.8225
Epoch 10/30
224814/224814 [==============================] - 975s 4ms/sample - loss: 1.3509
- val_loss: 1.8176
Epoch 11/30
224814/224814 [==============================] - 977s 4ms/sample - loss: 1.2701
- val_loss: 1.8145
Epoch 12/30
224814/224814 [==============================] - 976s 4ms/sample - loss: 1.1944
- val_loss: 1.8190
Epoch 00012: early stopping
Model saved
```

5 5.0 Prediction

[110]:
```
plt.plot(history.history['loss'], label='train')
plt.plot(history.history['val_loss'], label='test')
plt.legend()
plt.show()
```



[111]:
```
reverse_target_word_index = y_tokenizer.index_word
reverse_source_word_index = x_tokenizer.index_word
target_word_index = y_tokenizer.word_index
```

Inference

[112]:
```
# encoder inference
encoder_model = Model(inputs=encoder_inputs, outputs=[encoder_outputs, state_h,␣
↪state_c])

# decoder inference
# 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_len_text,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]
)
```

Inference Process

[123]:
```
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))

    # Chose the 'start' word as the first word of the target sequence
    target_seq[0, 0] = target_word_index['start']
```

```
    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 != 'end'):
            decoded_sentence += ' ' + sampled_token

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

[124]:
```
def seq2summary(input_seq):
    newString = ''

    for i in input_seq:
        if((i!=0 and i!= target_word_index['start']) and i !=␣
 ↪target_word_index['end']):
            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
```

[125]:

```
for i in range(10):
    print("Review:", seq2text(X_test[i]))
    print("Original summary:", seq2summary(y_test[i]))
    print("Predicted summary:", decode_sequence(X_test[i].
↪reshape(1,max_len_text)))
    print("\n")
```

```
Review: already big fan popchips salt vinegar flavor saw coming chili lime
flavor excited try flavor disappoint tangy spicy dash sweet new favorite chip
never tried popchips aware texture different regular potato chips somewhere
traditional chip rice cake throw die hard potato chip fans want something
crunchy awesome tasting without many calories fat going new favorite snack
Original summary: excellent
Predicted summary:  delicious


Review: ordered chips found salty dry huge amount spices ball one bags opened
Original summary: too salty and dry
Predicted summary:  too salty


Review: found tea favorite movie theater found perfect tea guests everyone loves
makes love
Original summary: at the movies and home
Predicted summary:  love it


Review: dogs special diet treats feed favorites cause problems
Original summary: must be good
Predicted summary:  my dogs love these


Review: active lab loves chew really enjoys treats ration gags time usually give
treat sitting back porch relaxing chewing tennis ball really seem improve breath
inevitably pushes far back mouth gags throws seen real difference teeth
reduction plaque tartar keep hoping
Original summary: makes breath smell better dog always gags on them
Predicted summary:  great for puppy teeth


Review: want chocolate bar probably buy one want chocolate chip cookie ice cream
buy suggest want chocolate chip cookies try another kind cookie sort half baked
cookie effect makes although tasting good something eat many fast healthy
desirable
Original summary: cookie coated chocolate bars
Predicted summary:  good but not great
```

```
Review: delicious sherry flavor salad dressing great used marinade give try
sweet balsamic tart red wine vinegar
Original summary: yummy sweet sherry vinegar
Predicted summary:  love these


Review: cats loved treats think really help releasing hairballs noticed changes
litterbox prove treats help hairballs issues going buy treats cats finish
Original summary: my cats love temptations
Predicted summary:  my cats love these treats


Review: received medium roast receive correct coffee shown picture disappointed
suppose ill try lot trouble return
Original summary: wrong coffee received
Predicted summary:  coffee received


Review: kids love happybaby tots tried every flavor eat love getting good
organic nutrition ingredients wholesome convenient throw diaper bag purse stick
lunch box snack use spoon sometimes bowl home self feeding little one also give
pouch eat directly squeeze pouch thank happybaby great products
Original summary: love all happybaby tots
Predicted summary:  love all happybaby tots
```

6 6.0 Evaluation

6.1 6.1 Rouge Score

[78]:
```python
rouge = RougeCalculator(stopwords=True, lang="en")

original_summary = ["too salty and dry", "at the movies and home", "must be␣
↪good", "yummy sweet sherry vinegar", "wrong coffee received"]
predicted_summary = ["too salty", "love it", "my dogs love these", "love␣
↪these", "coffee received"]
```

[109]:
```python
for orig, pred in zip(original_summary, predicted_summary):
    rouge_1 = rouge.rouge_n(summary=orig, references=pred,n=1)

    rouge_2 = rouge.rouge_n(summary=orig, references=pred, n=2)

    rouge_l = rouge.rouge_l(summary=orig, references=pred)

    rouge_be = rouge.rouge_be(summary=orig, references=pred)
```

```
    print(40*"=")
    print("Original: " + orig)
    print("Predicted: " + pred)
    print("ROUGE-1: {}, ROUGE-2: {}, ROUGE-L: {}, ROUGE-BE: {}".format(rouge_1,␣
↪rouge_2, rouge_l, rouge_be).replace(", ", "\n"))
    print(40*"=")
    print("\n")
```

```
========================================
Original: too salty and dry
Predicted: too salty
ROUGE-1: 0.6666666666666666
ROUGE-2: 0
ROUGE-L: 0.6666666666666666
ROUGE-BE: 0
========================================


========================================
Original: at the movies and home
Predicted: love it
ROUGE-1: 0
ROUGE-2: 0
ROUGE-L: 0
ROUGE-BE: 0
========================================


a.dogs=(nsubj)=>love
<BasicElement: dogs-[nsubj]->love>
========================================
Original: must be good
Predicted: my dogs love these
ROUGE-1: 0
ROUGE-2: 0
ROUGE-L: 0
ROUGE-BE: 0
========================================


========================================
Original: yummy sweet sherry vinegar
Predicted: love these
ROUGE-1: 0
ROUGE-2: 0
ROUGE-L: 0
```

```
ROUGE-BE: 0
========================================


b.wrong=(amod)=>coffee
a.coffee=(nsubj)=>received
<BasicElement: coffee-[nsubj]->receive>
a.coffee=(nsubj)=>received
<BasicElement: coffee-[nsubj]->receive>
========================================
Original: wrong coffee received
Predicted: coffee received
ROUGE-1: 0.8
ROUGE-2: 0.6666666666666666
ROUGE-L: 0.8
ROUGE-BE: 0.6666666666666666
========================================
```

6.2 6.2 BLEU Score

[110]:

```
for reference, candidate in zip(original_summary, predicted_summary):

    reference_s = [reference.split()]
    candidate_s = candidate.split()

    print(40*"=")
    print("Original: " + reference)
    print("Prediction: " + candidate)
    print('Individual 1-gram: %f' % sentence_bleu(reference_s, candidate_s,␣
↪weights=(1, 0, 0, 0)))
    print('Individual 2-gram: %f' % sentence_bleu(reference_s, candidate_s,␣
↪weights=(0, 1, 0, 0)))
    print('Individual 3-gram: %f' % sentence_bleu(reference_s, candidate_s,␣
↪weights=(0, 0, 1, 0)))
    print('Individual 4-gram: %f' % sentence_bleu(reference_s, candidate_s,␣
↪weights=(0, 0, 0, 1)))
    print(40*"=")
    print("\n")
```

```
========================================
Original: too salty and dry
Prediction: too salty
Individual 1-gram: 0.367879
Individual 2-gram: 0.367879
Individual 3-gram: 0.000000
Individual 4-gram: 0.000000
```

```
========================================


========================================
Original: at the movies and home
Prediction: love it
Individual 1-gram: 0.000000
Individual 2-gram: 0.000000
Individual 3-gram: 0.000000
Individual 4-gram: 0.000000
========================================


========================================
Original: must be good
Prediction: my dogs love these
Individual 1-gram: 0.000000
Individual 2-gram: 0.000000
Individual 3-gram: 0.000000
Individual 4-gram: 0.000000
========================================


========================================
Original: yummy sweet sherry vinegar
Prediction: love these
Individual 1-gram: 0.000000
Individual 2-gram: 0.000000
Individual 3-gram: 0.000000
Individual 4-gram: 0.000000
========================================


========================================
Original: wrong coffee received
Prediction: coffee received
Individual 1-gram: 0.606531
Individual 2-gram: 0.606531
Individual 3-gram: 0.000000
Individual 4-gram: 0.000000
========================================
```