Sentiment Analysis dari Review terhadap Barang yang dibeli melalui Online Shop di Lazada

Persiapan

Menghilangkan notifikasi warning yang mungkin muncul saat run kode dan mencari lokasi untuk meletakkan file

In [ ]:

```
import warnings
warnings.filterwarnings('ignore')
import os
os.getcwd()
```

Out[1]:

```
'/content'
```

Membuka data dari file yg telah di download

In [ ]:

```
import pandas as pd
df = pd.read_csv('20191002-reviews.csv')
df.head()
```

Out[2]:

	itemId	category	name	rating	originalRating	reviewTitle	reviewContent	likeCount	upVotes	downVotes	helpful	relevanceScor
0	100002528	beli-harddisk-eksternal	Kamal U.	5	NaN	NaN	bagus mantap dah sesui pesanan	0	0	0	True	26.5
1	100002528	beli-harddisk-eksternal	yofanca m.	4	NaN	NaN	Bagus, sesuai foto	0	0	0	True	22.4
2	100002528	beli-harddisk-eksternal	Lazada Customer	5	NaN	ok mantaaapppp barang sesuai pesanan.. good	okkkkk mantaaaaaaapppp ... goood	0	0	0	True	21.5
3	100002528	beli-harddisk-eksternal	Lazada Customer	4	NaN	NaN	bagus sesuai	0	0	0	True	20.5
4	100002528	beli-harddisk-eksternal	Yosep M.	5	NaN	NaN	NaN	0	0	0	True	16.0

Melihat info data yang meliputi banyaknya data tak kosong pada tiap kolom

In [ ]:

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 203787 entries, 0 to 203786
Data columns (total 15 columns):
 #   Column          Non-Null Count   Dtype  
---  ------          --------------   -----  
 0   itemId          203787 non-null  int64  
 1   category        203787 non-null  object 
 2   name            203787 non-null  object 
 3   rating          203787 non-null  int64  
 4   originalRating  8 non-null       float64
 5   reviewTitle     23404 non-null   object 
 6   reviewContent   107029 non-null  object 
 7   likeCount       203787 non-null  int64  
 8   upVotes         203787 non-null  int64  
 9   downVotes       203787 non-null  int64  
 10  helpful         203787 non-null  bool   
 11  relevanceScore  203787 non-null  float64
 12  boughtDate      196680 non-null  object 
 13  clientType      203787 non-null  object 
 14  retrievedDate   203787 non-null  object 
dtypes: bool(1), float64(2), int64(5), object(7)
memory usage: 22.0+ MB
```

Mengambil data dari kolom yang dibutuhkan dan menjadikannya data baru

In [ ]:

```
df_baru=df.copy()
df_baru.drop(df_baru.columns[[0,1,2,4,5,7,8,9,10,11,12,13,14]],axis=1,inplace=True)
df_baru.head()
```

Out[4]:

	rating	reviewContent
0	5	bagus mantap dah sesui pesanan
1	4	Bagus, sesuai foto
2	5	okkkkk mantaaaaaaapppp ... goood
3	4	bagus sesuai
4	5	NaN

Data Preprocessing

Menghapus data kosong pada kolom review

In [ ]:

```
df_baru.dropna(subset=['reviewContent'],inplace=True)
df_baru.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 107029 entries, 0 to 203786
Data columns (total 2 columns):
 #   Column         Non-Null Count   Dtype 
---  ------         --------------   ----- 
 0   rating         107029 non-null  int64 
 1   reviewContent  107029 non-null  object
dtypes: int64(1), object(1)
memory usage: 2.4+ MB
```

Mengecek data review yang terduplikasi

In [ ]:

```
df_baru.duplicated().sum()
```

Out[6]:

```
68688
```

Menghapus data review yang terduplikasi

In [ ]:

```
df_baru.drop_duplicates(inplace=True)
df_baru.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 38341 entries, 0 to 199781
Data columns (total 2 columns):
 #   Column         Non-Null Count  Dtype 
---  ------         --------------  ----- 
 0   rating         38341 non-null  int64 
 1   reviewContent  38341 non-null  object
dtypes: int64(1), object(1)
memory usage: 898.6+ KB
```

Mengecek data reiew yang kosong

In [ ]:

```
df_baru.isnull().sum()
```

Out[8]:

```
rating           0
reviewContent    0
dtype: int64
```

Membersihkan data review meliputi:

1. Menghilangkan emoji
2. Menghilangkan whitespace (ruang kosong)

3. Menghilangkan emoji
4. Menghilangkan tag html
5. Menghilangkan url
6. Menghilangkan angka
7. Menghilangkan tanda baca
8. Menghilangkan stopword
9. Mengganti kata yang mengandung pemanjangan
10. Mengganti kata slang

In [ ]:

```
import re
import string
import unicodedata
from tqdm.notebook import tqdm
from indoNLP.preprocessing import *
from Sastrawi.Stemmer.StemmerFactory import StemmerFactory
STEMMER = StemmerFactory().create_stemmer()
def preprocessing(text):
    text = text.lower()
    text = re.sub(r"\s+", " ", text, flags=re.UNICODE)  # menghilangkan whitespace (ruang kosong)
    text = emoji_to_words(text)  # menghilangkan emoji
    text = unicodedata.normalize("NFD", text).encode("ascii", "ignore").decode("ascii")
    text = remove_html(text)  # menghilangkan tag html
    text = remove_url(text)  # menghilangkan url
    text = text.translate(str.maketrans(string.digits, " " * len(string.digits)))  # menghilangkan angka
    text = text.translate(str.maketrans(string.punctuation, " " * len(string.punctuation)))  # menghilangkan tanda baca
    text = remove_stopwords(text)  # menghapus stopwords
    text = replace_word_elongation(text)  # mengganti kata yg mengandung pemanjangan
    text = replace_slang(text)  # mengganti kata slang
    text = " ".join(text.split())
    text = STEMMER.stem(text)
    return " ".join(text.split())
df_baru["reviewClean"] = [preprocessing(x) for x in tqdm(df_baru["reviewContent"].values)]
df_baru.reviewClean.head()
```

```
  0%|          | 0/38341 [00:00<?, ?it/s]
```

Out[9]:

```
0    bagus mantap deh sesui pesan
1               bagus sesuai foto
2           ok mantaaaaaaap goood
3                    bagus sesuai
7                            bima
Name: reviewClean, dtype: object
```

Mendefinisikan review dengan rating 5 sebagai sentimen positif dan selainnya sebagai sentimen negatif

In [ ]:

```
def sentiment(int):
    if (int == 5):
        return 1
    else:
        return 0
df_baru["sentiment"] = df_baru.rating.apply(lambda x:sentiment(x))
df_baru.head()
```

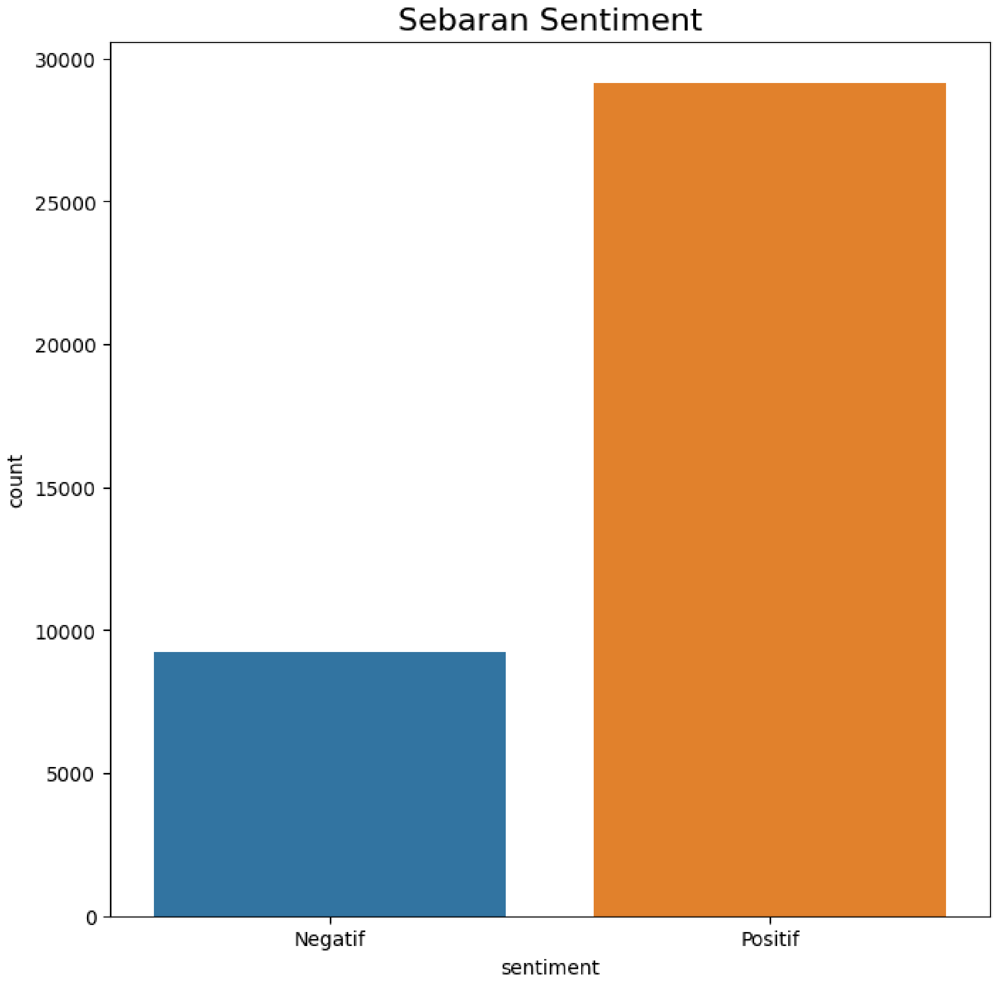
Out[10]:

	rating	reviewContent	reviewClean	sentiment
0	5	bagus mantap dah sesui pesanan	bagus mantap deh sesui pesan	1
1	4	Bagus, sesuai foto	bagus sesuai foto	0
2	5	okkkkk mantaaaaaaapppp ... goood	ok mantaaaaaaap goood	1
3	4	bagus sesuai	bagus sesuai	0
7	1	bima	bima	0

Mengecek sebaran setiment positif dan negatif

In [ ]:

```
import matplotlib.pyplot as plt
import seaborn as sns
plt.figure(figsize=(8, 8))
sns.countplot(data=df_baru, x="sentiment")
plt.title("Sebaran Sentiment", fontsize=16)
plt.xticks([0, 1], ["Negatif", "Positif"])
plt.show()
```



Membuat word cloud dari review dengan sentiment positif

In [ ]:

```python
from PIL import Image
from wordcloud import WordCloud,STOPWORDS,ImageColorGenerator
import numpy as np
lazada_mask=np.array(Image.open('lazada.png'))
colormap=ImageColorGenerator(lazada_mask)
wc=WordCloud(
    stopwords=STOPWORDS,
    background_color='white',
    max_words=1000,
    mask=lazada_mask,
)
wc.generate(' '.join(text for text in df_baru.loc[df_baru.sentiment == 1, 'reviewClean']))
wc.recolor(color_func=colormap)
plt.figure(figsize=(10,10))
plt.title('Kata Review Lazada yang Sering Muncul dengan Rating Positif',
          fontdict={'size':22,'verticalalignment':'bottom'})
plt.imshow(wc)
plt.axis("off")
plt.show()
```

Kata Review Lazada yang Sering Muncul dengan Rating Positif

Membuat word cloud dari review dengan sentiment negatif

In [ ]:

```python
wc.generate(' '.join(text for text in df_baru.loc[df_baru.sentiment == 0, 'reviewClean']))
wc.recolor(color_func=colormap)
plt.figure(figsize=(11,11))
plt.title('Kata Review Lazada yang Sering Muncul dengan Rating Negatif',
          fontdict={'size':22,'verticalalignment':'bottom'})
plt.imshow(wc)
plt.axis("off")
plt.show()
```

Kata Review Lazada yang Sering Muncul dengan Rating Negatif

Deep Learning

Mempelajari dan memodelkan untuk mengetahui keakuratan data

In [ ]:

```python
from sklearn.feature_extraction.text import CountVectorizer
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.model_selection import train_test_split
```

In [ ]:

```python
x_train,x_test,y_train,y_test = train_test_split(df_baru.reviewClean,df_baru.sentiment,test_size = 0.2 , random_state = 0)
```

In [ ]:

```python
positif = x_train[y_train[y_train == 1].index]
negatif = x_train[y_train[y_train == 0].index]
x_train.shape,positif.shape,negatif.shape
```

Out[16]:

```
((30672,), (23279,), (7393,))
```

In [ ]:

```
cv=CountVectorizer(min_df=0,max_df=1)
cv_train_reviews=cv.fit_transform(x_train).toarray()
cv_test_reviews=cv.transform(x_test).toarray()

print('BOW_cv_train:',cv_train_reviews.shape)
print('BOW_cv_test:',cv_test_reviews.shape)
```

```
BOW_cv_train: (30672, 7340)
BOW_cv_test: (7669, 7340)
```

In [ ]:

```
tv=TfidfVectorizer(min_df=0,max_df=1,use_idf=True)
tv_train_reviews=tv.fit_transform(x_train).toarray()
tv_test_reviews=tv.transform(x_test).toarray()
print('Tfidf_train:',tv_train_reviews.shape)
print('Tfidf_test:',tv_test_reviews.shape)
```

```
Tfidf_train: (30672, 7340)
Tfidf_test: (7669, 7340)
```

Mengecek akurasi rata-rata pada masing-masing metode untuk menentukan metode yang akan digunakan untuk menganalisa

In [ ]:

```
from sklearn.model_selection import cross_val_score
from sklearn.model_selection import GridSearchCV, StratifiedKFold
from sklearn.pipeline import Pipeline
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn.svm import SVC
from sklearn.metrics import *
CV = StratifiedKFold(shuffle=True,random_state=0)

classifiers = {
    "Decision Tree Classifier ": DecisionTreeClassifier(random_state=0),
    "Logistic Regression      ": LogisticRegression(random_state=0),
    "Random Forest Classifier ": RandomForestClassifier(random_state=0),
    "SVM                      ": SVC(kernel="linear", probability=True,random_state=0),
}

for name, clf in classifiers.items():
    pipe = Pipeline([("tf-idf", TfidfVectorizer()), ("clf", clf)])
    scores = cross_val_score(pipe, df_baru["reviewClean"].values, df_baru["sentiment"].values, cv=CV)
    print(f"Rata - rata akurasi dari {name} : {scores.mean():.4f} - std : {scores.std():.4f}")
```

```
Rata - rata akurasi dari Decision Tree Classifier  : 0.7441 - std : 0.0030
Rata - rata akurasi dari Logistic Regression       : 0.8171 - std : 0.0037
Rata - rata akurasi dari Random Forest Classifier  : 0.8109 - std : 0.0036
Rata - rata akurasi dari SVM                       : 0.8125 - std : 0.0042
```

Melakukan hyperparameter tuning untuk menentukan kombinasi analisa terbaik

In [ ]:

```python
import numpy as np

param_grid = {
    'penalty' : ['l1','l2'],
    'C'       : np.arange(0.1,1.5,0.1),
    'solver'  : ['liblinear','saga'],
    'max_iter': [100,500,1000,2000]
}

search = GridSearchCV(LogisticRegression(random_state=0), param_grid, cv=5)
search.fit(tv.fit_transform(x_train), y_train)
search_df = pd.DataFrame(search.cv_results_)

(
    search_df.sort_values(["rank_test_score", "std_test_score"])
    .drop(
        [
            "mean_fit_time",
            "std_fit_time",
            "mean_score_time",
            "std_score_time",
            "split0_test_score",
            "split1_test_score",
            "split2_test_score",
            "split3_test_score",
            "split4_test_score",
        ],
        axis=1,
    )
    .head(20)
)
```

Out[20]:

	param_C	param_max_iter	param_penalty	param_solver	params	mean_test_score	std_test_score	rank_test_score
0	0.1	100	l1	liblinear	{'C': 0.1, 'max_iter': 100, 'penalty': 'l1', '...	0.758966	0.000069	1
1	0.1	100	l1	saga	{'C': 0.1, 'max_iter': 100, 'penalty': 'l1', '...	0.758966	0.000069	1
2	0.1	100	l2	liblinear	{'C': 0.1, 'max_iter': 100, 'penalty': 'l2', '...	0.758966	0.000069	1
3	0.1	100	l2	saga	{'C': 0.1, 'max_iter': 100, 'penalty': 'l2', '...	0.758966	0.000069	1
4	0.1	500	l1	liblinear	{'C': 0.1, 'max_iter': 500, 'penalty': 'l1', '...	0.758966	0.000069	1
5	0.1	500	l1	saga	{'C': 0.1, 'max_iter': 500, 'penalty': 'l1', '...	0.758966	0.000069	1
6	0.1	500	l2	liblinear	{'C': 0.1, 'max_iter': 500, 'penalty': 'l2', '...	0.758966	0.000069	1
7	0.1	500	l2	saga	{'C': 0.1, 'max_iter': 500, 'penalty': 'l2', '...	0.758966	0.000069	1
8	0.1	1000	l1	liblinear	{'C': 0.1, 'max_iter': 1000, 'penalty': 'l1', ...	0.758966	0.000069	1
9	0.1	1000	l1	saga	{'C': 0.1, 'max_iter': 1000, 'penalty': 'l1', ...	0.758966	0.000069	1
10	0.1	1000	l2	liblinear	{'C': 0.1, 'max_iter': 1000, 'penalty': 'l2', ...	0.758966	0.000069	1
11	0.1	1000	l2	saga	{'C': 0.1, 'max_iter': 1000, 'penalty': 'l2', ...	0.758966	0.000069	1
12	0.1	2000	l1	liblinear	{'C': 0.1, 'max_iter': 2000, 'penalty': 'l1', ...	0.758966	0.000069	1
13	0.1	2000	l1	saga	{'C': 0.1, 'max_iter': 2000, 'penalty': 'l1', ...	0.758966	0.000069	1
14	0.1	2000	l2	liblinear	{'C': 0.1, 'max_iter': 2000, 'penalty': 'l2', ...	0.758966	0.000069	1
15	0.1	2000	l2	saga	{'C': 0.1, 'max_iter': 2000, 'penalty': 'l2', ...	0.758966	0.000069	1
16	0.2	100	l1	liblinear	{'C': 0.2, 'max_iter': 100, 'penalty': 'l1', '...	0.758966	0.000069	1
17	0.2	100	l1	saga	{'C': 0.2, 'max_iter': 100, 'penalty': 'l1', '...	0.758966	0.000069	1
18	0.2	100	l2	liblinear	{'C': 0.2, 'max_iter': 100, 'penalty': 'l2', '...	0.758966	0.000069	1
19	0.2	100	l2	saga	{'C': 0.2, 'max_iter': 100, 'penalty': 'l2', '...	0.758966	0.000069	1

In [ ]:

```
lr=LogisticRegression(penalty='l1',max_iter=100,C=0.1,solver='liblinear',random_state=0)
#Fitting model untuk bag of word
lr_bow=lr.fit(cv_train_reviews,y_train)
print(lr_bow)
#Fitting model untuk tfidf
lr_tfidf=lr.fit(tv_train_reviews,y_train)
print(lr_tfidf)
```

```
LogisticRegression(C=0.1, penalty='l1', random_state=0, solver='liblinear')
LogisticRegression(C=0.1, penalty='l1', random_state=0, solver='liblinear')
```

In [ ]:

```
#Memprediksi model untuk bag of words
lr_bow_predict=lr.predict(cv_test_reviews)
##Memprediksi model untuk tfidf
lr_tfidf_predict=lr.predict(tv_test_reviews)
```

In [ ]:

```
#Skor akurasi untuk bag of words
lr_bow_score=accuracy_score(y_test,lr_bow_predict)
print("lr_bow_score :",lr_bow_score)
#Skor akurasi untuk tfidf
lr_tfidf_score=accuracy_score(y_test,lr_tfidf_predict)
print("lr_tfidf_score :",lr_tfidf_score)
```

```
lr_bow_score : 0.76424566436302
lr_tfidf_score : 0.76424566436302
```

In [ ]:

```
#Report klasifikasi untuk bag of words
lr_bow_report=classification_report(y_test,lr_bow_predict,target_names=['0','1'])
print(lr_bow_report)

#Report klasifikasi untuk tfidf
lr_tfidf_report=classification_report(y_test,lr_tfidf_predict,target_names=['0','1'])
print(lr_tfidf_report)
```

```
              precision    recall  f1-score   support

           0       0.00      0.00      0.00      1808
           1       0.76      1.00      0.87      5861

    accuracy                           0.76      7669
   macro avg       0.38      0.50      0.43      7669
weighted avg       0.58      0.76      0.66      7669

              precision    recall  f1-score   support

           0       0.00      0.00      0.00      1808
           1       0.76      1.00      0.87      5861

    accuracy                           0.76      7669
   macro avg       0.38      0.50      0.43      7669
weighted avg       0.58      0.76      0.66      7669
```

In [ ]:

```
import keras
from keras.layers import Dense,LSTM
from keras.models import Sequential
model = Sequential()
model.add(Dense(units = 75 , activation = 'relu' , input_dim = cv_train_reviews.shape[1]))
model.add(Dense(units = 50 , activation = 'relu'))
model.add(Dense(units = 25 , activation = 'relu'))
model.add(Dense(units = 10 , activation = 'relu'))
model.add(Dense(units = 1 , activation = 'sigmoid'))
model.compile(optimizer = 'adam' , loss = 'binary_crossentropy' , metrics = ['accuracy'])
```

In [ ]:

```
model.summary()
```

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 dense (Dense)               (None, 75)                550575

 dense_1 (Dense)             (None, 50)                3800

 dense_2 (Dense)             (None, 25)                1275

 dense_3 (Dense)             (None, 10)                260

 dense_4 (Dense)             (None, 1)                 11

=================================================================
Total params: 555,921
Trainable params: 555,921
Non-trainable params: 0
_________________________________________________________________
```

In [ ]:

```
model.fit(cv_train_reviews,y_train, epochs = 10)
```

```
Epoch 1/10
959/959 [==============================] - 22s 19ms/step - loss: 0.5571 - accuracy: 0.7585
Epoch 2/10
959/959 [==============================] - 11s 12ms/step - loss: 0.4640 - accuracy: 0.8098
Epoch 3/10
959/959 [==============================] - 10s 10ms/step - loss: 0.4455 - accuracy: 0.8136
Epoch 4/10
959/959 [==============================] - 10s 10ms/step - loss: 0.4440 - accuracy: 0.8136
Epoch 5/10
959/959 [==============================] - 10s 11ms/step - loss: 0.4434 - accuracy: 0.8136
Epoch 6/10
959/959 [==============================] - 10s 11ms/step - loss: 0.4429 - accuracy: 0.8136
Epoch 7/10
959/959 [==============================] - 10s 11ms/step - loss: 0.4432 - accuracy: 0.8136
Epoch 8/10
959/959 [==============================] - 9s 10ms/step - loss: 0.4429 - accuracy: 0.8136
Epoch 9/10
959/959 [==============================] - 11s 11ms/step - loss: 0.4427 - accuracy: 0.8136
Epoch 10/10
959/959 [==============================] - 10s 11ms/step - loss: 0.4427 - accuracy: 0.8136
```

Out[29]:

```
<keras.callbacks.History at 0x7f257840d4b0>
```

In [ ]:

```
model.evaluate(cv_train_reviews,y_train)[1]
```

```
959/959 [==============================] - 5s 5ms/step - loss: 0.4421 - accuracy: 0.8136
```

Out[30]:

```
0.8135759234428406
```

In [ ]:

```
model.add(Dense(units = 75, activation = 'relu', input_dim = tv_train_reviews.shape[1]))
model.add(Dense(units = 50, activation = 'relu'))
model.add(Dense(units = 25, activation = 'relu'))
model.add(Dense(units = 10, activation = 'relu'))
model.add(Dense(units = 1, activation = 'sigmoid'))
model.compile(optimizer = 'adam', loss = 'binary_crossentropy', metrics = ['accuracy'])
```

In [ ]:

```
model.summary()
```

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #   
=================================================================
 dense (Dense)               (None, 75)                550575    
                                                                 
 dense_1 (Dense)             (None, 50)                3800      
                                                                 
 dense_2 (Dense)             (None, 25)                1275      
                                                                 
 dense_3 (Dense)             (None, 10)                260       
                                                                 
 dense_4 (Dense)             (None, 1)                 11        
                                                                 
 dense_5 (Dense)             (None, 75)                150       
                                                                 
 dense_6 (Dense)             (None, 50)                3800      
                                                                 
 dense_7 (Dense)             (None, 25)                1275      
                                                                 
 dense_8 (Dense)             (None, 10)                260       
                                                                 
 dense_9 (Dense)             (None, 1)                 11        
                                                                 
=================================================================
Total params: 561,417
Trainable params: 561,417
Non-trainable params: 0
_________________________________________________________________
```

In [ ]:

```
model.fit(tv_train_reviews, y_train, epochs = 10)
```

```
Epoch 1/10
959/959 [==============================] - 13s 12ms/step - loss: 0.4893 - accuracy: 0.8039
Epoch 2/10
959/959 [==============================] - 13s 14ms/step - loss: 0.4706 - accuracy: 0.8134
Epoch 3/10
959/959 [==============================] - 16s 16ms/step - loss: 0.4703 - accuracy: 0.8136
Epoch 4/10
959/959 [==============================] - 17s 18ms/step - loss: 0.4700 - accuracy: 0.8136
Epoch 5/10
959/959 [==============================] - 12s 13ms/step - loss: 0.4703 - accuracy: 0.8136
Epoch 6/10
959/959 [==============================] - 11s 12ms/step - loss: 0.4701 - accuracy: 0.8136
Epoch 7/10
959/959 [==============================] - 12s 12ms/step - loss: 0.4702 - accuracy: 0.8136
Epoch 8/10
959/959 [==============================] - 10s 11ms/step - loss: 0.4701 - accuracy: 0.8135
Epoch 9/10
959/959 [==============================] - 9s 9ms/step - loss: 0.4699 - accuracy: 0.8136
Epoch 10/10
959/959 [==============================] - 10s 11ms/step - loss: 0.4555 - accuracy: 0.8136
```

Out[33]:

```
<keras.callbacks.History at 0x7f25002051e0>
```

In [ ]:

```
model.evaluate(tv_train_reviews, y_train)[1]
```

```
959/959 [==============================] - 4s 4ms/step - loss: 0.4448 - accuracy: 0.8136
```

Out[34]:

```
0.8135759234428406
```