Task 3

Sentiment Analysis

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Data Source

https://github.com/mulhod/steam_reviews (https://github.com/mulhod/steam_reviews)

Task Description

Sentiment analysis merupakan sebuah task untuk menentukan sebuah teks yang bersifat subjektif (karena merupakan pendapat dari seseorang). Sentiment dari seseorang dapat bernilai positif, negatif, atau netral.
Pada sentiment analysis di task ini, nilai sentiment dari seseorang hanya bernilai 2, yaitu positif atau negatif. Dataset berisi review dari **Steam** mengenai sebuah game dan nilai targetnya merupakan apakah game tersebut *recommended* atau *not recommended*. Akurasi yang dihitung merupakan berapa dari review steam tersebut yang diprediksi benar.

Latar Belakang

Game **Steam** sudah memiliki banyak review dari setiap orang. Kita juga dapat menilai apakah orang tersebut menilai apakah game tersebut direkomendasikan atau tidak. Jumlah data yang banyak tersebut mendorong kami untuk membuat sebuah sentiment analysis untuk review-review yang terdapat dalam **Steam**. Dari data tersebut, kami berharap setidaknya dapat memprediksi dari sebuah review game yang diberikan, apakah orang tersebut merekomendasikan *game* tersebut atau tidak.
Sebenarnya, sudah terdapat penelitian yang lebih *advanced* berupa *Aspect Based Sentiment Analysis*. Pada penelitian tersebut, ditentukan aspek-aspek yang dideteksi dari sebuah review dan ditentukan nilai sentimen dari aspek tersebut. Namun, kami tidak membuat *entity linkning* untuk menghubungkan sebuah entitas aspek dan sentimennya. Maka dari itu, kami membuat *sentiment analysis* biasa saja.

Related Works

- Zuo, Z. (n.d.). Sentiment Analysis of Steam Review Datasets using Naive Bayes and Decision Tree Classifier. Retrieved November 9, 2020, from https://analytics.twitter.com (https://analytics.twitter.com)
- Sobkowicza, A., & Stokowiec, W. (2016). Steam Review Dataset - new, large scale sentiment dataset. Emotion and Sentiment Analysis PROCEEDINGS, May, 55–58. http://gsi.dit.upm.es/esa2016/Proceedings-ESA2016.pdf (http://gsi.dit.upm.es/esa2016/Proceedings-ESA2016.pdf)

Kedua penelitian di atas merupakan penelitian yang mencari sentiment analysis menggunakan dataset dari **Steam**. Pada penelitian pertama, Zuo dkk. menggunakan klasifikasi Naive Bayes dan Decision Tree Classifier untuk menentukan nilai sentimen pada review di steam. Sementara itu, pada penelitian kedua, Sobkowiczka dan Stokowiec menggunakan algoritma-algoritma machine learning yang terdapat pada scikit-learn untuk mendapatkan nilai sentimen dari data-data steam.

Flow Modul

Flow modul yang kami miliki adalah sebagai berikut:

1. Load dataset
2. Ubah nilai target dari dataset ('recommended' dan 'not recommended') menjadi tipe numerik (1 dan 0)
3. Lakukan preprocessing berupa tokenization, stemming, dan stopword removal.
4. Lakukan POS Tagging menggunakan modul POS Tag kami (dibuat oleh Nixon / 13517059). Hasil dari POS Tagging ini akan dicoba dibandingkan untuk SVM.
5. Melakukan TF-IDF untuk mendapatkan nilai term dari setiap kata dalam kalimat.
6. Lakukan prediksi menggunakan SVM dengan data tanpa POS Tagging.
7. Lakukan prediksi menggunakan SVM dengan data dengan POS Tagging.
8. Lakukan prediksi menggunakan DNN (Fully connected Dense layer).
9. Lakukan pemrosesan word2vec sehingga mendapatkan vektor dari sebuah instance kata.
10. Lakukan prediksi menggunakan DNN (Dengan LSTM (Long Short Term Memory).

Modul: Sentiment Analysis

Teknik yang Digunakan

1. Preprocessing: Tokenization, stemming, stopword removal, dan POS Tagging.
2. Feature Extraction: Word2Vec (untuk LSTM) dan TF-IDF (non-LSTM).

2. Feature Extraction: Word2Vec (untuk LSTM) dan TF-IDF (non LSTM).
3. Pembelajaran mesin: SVM, DNN (linear), dan DNN (LSTM).

Data

Berupa 2 jenis kolom yang ingin diambil, yaitu kolom Review (berisi kata-kata review) dan kolom Rating (berisi nilai *recommended* atau *not recommended*. Jumlah data yang digunakan untuk training sebanyak 50000 data, untuk validasi sebanyak 5000 data, dan untuk testing sebanyak 13477 data. Aslinya data training dapat berjumlah 103099 dan data validasi dapat berjumlah 18194. Namun, untuk mempersingkat proses *training*, kami memotongnya.

Eksperimen

Hasil

Hasil yang didapatkan, kami mendapatkan bahwa POS Tagging tidak memiliki pengaruh yang begitu besar pada penelitian kami. Di satu waktu akurasi meningkat, namun di waktu lain akurasinya berkurang. Untuk percobaan ini, akurasi yang didapatkan adalah seperti di bawah segmen ini.

Analisis

Analisis yang kami simpulkan adalah sebagai berikut:

1. POS Tag tidak terlalu mempengaruhi hasil dari Sentiment Analysis
2. SVM menghasilkan hasil yang lebih baik. Namun, untuk jumlah data yang besar, waktu training SVM menjadi lebih lama dari DNN biasa (nyaris 30 menit).
3. Dari segi waktu dan akurasi, DNN biasa menang karena merupakan model yang lebih cepat dalam memeberikan hasil (sekitar 5 menit untuk 50 epoch) dan akurasinya tidak terlalu beda jauh dengan SVM Tanpa POS Tag
4. DNN LSTM secara teori seharusnya memberikan hasil yang lebih baik. Dengan demikian, ada kemungkinan 2 permaslaahan, yaitu:
   - Feature extraction Word2Vec tidak sefektif TF/IDF
   - Model LSTM yang dibuat masih belum terlalu bagus

Method	SVM Tanpa POS Tag	SVM POS Tag	DNN biasa	DNN LSTM
Akurasi	90,48%	89,68%	89,90%	83,58%

Imports

In [1]:

```python
import matplotlib.pyplot as plt
import nltk
import pandas as pd
import string
import tensorflow as tf
import numpy as np
import re

from sklearn import svm
from sklearn.feature_extraction.text import TfidfVectorizer, CountVectorizer
from sklearn.metrics import accuracy_score, mean_squared_error
from sklearn.model_selection import train_test_split
from sklearn.model_selection import StratifiedShuffleSplit

from tensorflow import keras
from tensorflow.keras.callbacks import EarlyStopping
from tensorflow.keras.layers import Embedding, LSTM, Dense, Dropout
from tensorflow.keras.models import Sequential, Model, load_model
from tensorflow.keras.optimizers import Adam
from tensorflow.keras.preprocessing.text import Tokenizer
from tensorflow.keras.preprocessing.sequence import pad_sequences
from tensorflow.keras.utils import to_categorical

# NLTK
from nltk.corpus import stopwords
from nltk.tokenize import word_tokenize
from nltk.stem.snowball import SnowballStemmer
nltk.download('punkt')
nltk.download('wordnet')
nltk.download('stopwords')

import pickle
from pattern.en import spelling
```

```
[nltk_data] Downloading package punkt to
[nltk_data]     C:\Users\Meyjan\AppData\Roaming\nltk_data...
[nltk_data]   Package punkt is already up-to-date!
[nltk_data] Downloading package wordnet to
[nltk_data]     C:\Users\Meyjan\AppData\Roaming\nltk_data...
[nltk_data]   Package wordnet is already up-to-date!
[nltk_data] Downloading package stopwords to
```

```
[nltk_data]     C:\Users\Meyjan\AppData\Roaming\nltk_data...
[nltk_data]   Package stopwords is already up-to-date!
```

Constants

In [2]:
```
sentence_len = 50
unique_word_len = 500
test_size = 0.1
val_size = 0.15
embedding_size = 256
dropout = 0.2
epoch_count_dnn_1 = 50
epoch_count_dnn_2 = 10

pos_tag_file = 'model/bi_lstm_model.h5'
svm_file = 'model/svm_1.h5'
svm_pos_file = 'model/svm_pos_1.h5'
dnn_file = 'model/dnn.h5'
lstm_file = 'model/lstm.h5'
```

Helper Functions

In [3]:
```
def save_prep_data():
    pickle.dump(x_train_prep, open('data/x_train_prep.h5', 'wb'))
    pickle.dump(x_val_prep, open('data/x_val_prep.h5', 'wb'))
    pickle.dump(x_test_prep, open('data/x_test_prep.h5', 'wb'))
    pickle.dump(y_train, open('data/y_train.h5', 'wb'))
    pickle.dump(y_val, open('data/y_val.h5', 'wb'))
    pickle.dump(y_test, open('data/y_test.h5', 'wb'))

def load_prep_data():
    x_train_prep = pickle.load(open('data/x_train_prep.h5', 'rb'))
    x_val_prep = pickle.load(open('data/x_val_prep.h5', 'rb'))
    x_test_prep = pickle.load(open('data/x_test_prep.h5', 'rb'))
    y_train = pickle.load(open('data/y_train.h5', 'rb'))
    y_val = pickle.load(open('data/y_val.h5', 'rb'))
    y_test = pickle.load(open('data/y_test.h5', 'rb'))
    return x_train_prep, x_val_prep, x_test_prep, y_train, y_val, y_test

def save_tagged_data():
    pickle.dump(x_train_tagged, open('data/x_train_tagged.h5', 'wb'))
    pickle.dump(x_val_tagged, open('data/x_val_tagged.h5', 'wb'))
    pickle.dump(x_test_tagged, open('data/x_test_tagged.h5', 'wb'))
    pickle.dump(y_train, open('data/y_train.h5', 'wb'))
    pickle.dump(y_val, open('data/y_val.h5', 'wb'))
    pickle.dump(y_test, open('data/y_test.h5', 'wb'))

def load_tagged_data():
    x_train_tagged = pickle.load(open('data/x_train_tagged.h5', 'rb'))
    x_val_tagged = pickle.load(open('data/x_val_tagged.h5', 'rb'))
    x_test_tagged = pickle.load(open('data/x_test_tagged.h5', 'rb'))
    y_train = pickle.load(open('data/y_train.h5', 'rb'))
    y_val = pickle.load(open('data/y_val.h5', 'rb'))
    y_test = pickle.load(open('data/y_test.h5', 'rb'))
    return x_train_tagged, x_val_tagged, x_test_tagged, y_train, y_val, y_test

def save_tfidf_data():
    pickle.dump(x_train_tfidf, open('data/x_train_tfidf.h5', 'wb'))
    pickle.dump(x_val_tfidf, open('data/x_val_tfidf.h5', 'wb'))
    pickle.dump(x_test_tfidf, open('data/x_test_tfidf.h5', 'wb'))
    pickle.dump(y_train, open('data/y_train.h5', 'wb'))
    pickle.dump(y_val, open('data/y_val.h5', 'wb'))
    pickle.dump(y_test, open('data/y_test.h5', 'wb'))
```

```
def load_tfidf_data():
    x_train_tfidf = pickle.load(open('data/x_train_tfidf.h5', 'rb'))
    x_val_tfidf = pickle.load(open('data/x_val_tfidf.h5', 'rb'))
    x_test_tfidf = pickle.load(open('data/x_test_tfidf.h5', 'rb'))
    y_train = pickle.load(open('data/y_train.h5', 'rb'))
    y_val = pickle.load(open('data/y_val.h5', 'rb'))
    y_test = pickle.load(open('data/y_test.h5', 'rb'))
    return x_train_tfidf, x_val_tfidf, x_test_tfidf, y_train, y_val, y_test

def save_tfidf_tagged_data():
    pickle.dump(x_train_tfidf_tagged, open('data/x_train_tfidf_tagged.h5', 'wb'))
    pickle.dump(x_val_tfidf_tagged, open('data/x_val_tfidf_tagged.h5', 'wb'))
    pickle.dump(x_test_tfidf_tagged, open('data/x_test_tfidf_tagged.h5', 'wb'))
    pickle.dump(y_train, open('data/y_train.h5', 'wb'))
    pickle.dump(y_val, open('data/y_val.h5', 'wb'))
    pickle.dump(y_test, open('data/y_test.h5', 'wb'))

def load_tfidf_tagged_data():
    x_train_tfidf_tagged = pickle.load(open('data/x_train_tfidf_tagged.h5', 'rb'))
    x_val_tfidf_tagged = pickle.load(open('data/x_val_tfidf_tagged.h5', 'rb'))
    x_test_tfidf_tagged = pickle.load(open('data/x_test_tfidf_tagged.h5', 'rb'))
    y_train = pickle.load(open('data/y_train.h5', 'rb'))
    y_val = pickle.load(open('data/y_val.h5', 'rb'))
    y_test = pickle.load(open('data/y_test.h5', 'rb'))
    return x_train_tfidf_tagged, x_val_tfidf_tagged, x_test_tfidf_tagged, y_train, y_val, y_test

def save_model_pickle(model, filename):
    pickle.dump(model, open(svm_file, 'wb'))

def load_model_pickle(filename):
    model = pickle.load(open(filename, 'rb'))
    return model
```

Preprocessing

Read Data

In [4]:
```
# Read CSV
df = pd.read_csv('./data/data_3.csv')
```

In [5]:
```
# Handle columns
df = df[['review', 'rating']]
```

In [6]:
```
# Drop NaNs
df.dropna(inplace = True)
```

In [7]:
```
df['rating'] = df['rating'].replace({ 'Recommended':1, 'Not Recommended': 0})
df
```

Out[7]:

	review	rating
0	My first game on A3 brought me the most horrif...	1
1	This is not a game for people who want fast ac...	1
2	Oh man. Where to even begin with this one. It ...	1
3	This is quite possibly the most emotional shoo...	1
4	If you have friends, this is a great game to p...	1
...	...	...
79432	This is my life!. MY GAME!	1
79433	Even with all unusual style and gameplay this ...	0
79434	i more of a fan of first person shooter and al...	0
79435	My friends have been going on and on about thi...	0
79436	great game lots of fun. To bad it comes with t...	0

79437 rows × 2 columns

Balancing Data

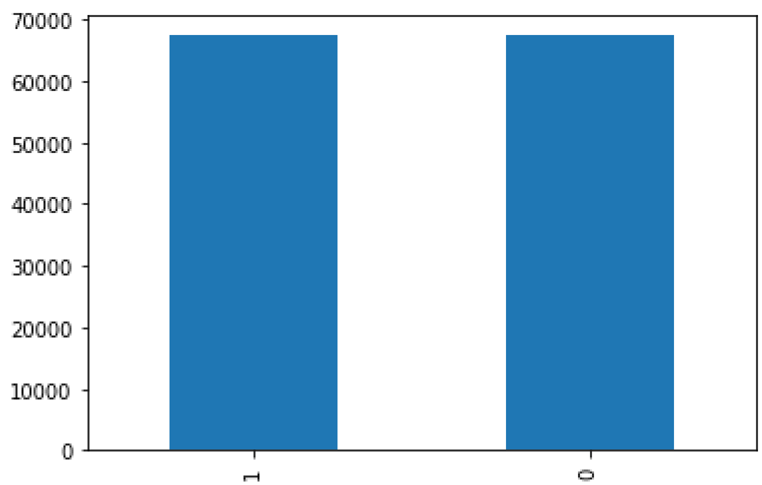
In [8]:
```
# Oversampling
max_size = df['rating'].value_counts().max()
lst = [df]
for class_index, group in df.groupby('rating'):
    lst.append(group.sample(max_size-len(group), replace=True))
df = pd.concat(lst)
```

In [9]:
```
# Reset index, shuffle
df = df.sample(frac=1).reset_index(drop=True)
```

Check Data Balance

In [10]:
```
df['rating'].value_counts().plot.bar()
```

Out[10]: <AxesSubplot:>



Train Test Validation Split

Get Train Data

In [11]:
```
sss = StratifiedShuffleSplit(n_splits = 1, test_size=0.1, random_state=3)
for train_idx, test_idx in sss.split(df['review'], df['rating']):
    x_train, x_test = df['review'][train_idx], df['review'][test_idx]
    y_train, y_test = df['rating'][train_idx], df['rating'][test_idx]

x_train = x_train.reset_index(drop=True)
x_test = x_test.reset_index(drop=True)
y_train = y_train.reset_index(drop=True)
y_test = y_test.reset_index(drop=True)
```

Get Test Data

In [12]:
```
sss = StratifiedShuffleSplit(n_splits = 1, test_size=0.15, random_state=3)
for train_idx, val_idx in sss.split(x_train, y_train):
    idx_train = train_idx
    idx_val = val_idx

y_val = y_train[idx_val]
x_val = x_train[idx_val]
x_train_train = x_train[idx_train]
y_train_train = y_train[idx_train]
x_train = x_train_train
y_train = y_train_train

x_train = x_train.reset_index(drop=True)
x_val = x_val.reset_index(drop=True)
y_train = y_train.reset_index(drop=True)
y_val = y_val.reset_index(drop=True)

x_train
```

Out[12]:
```
0          I met a lot of people who slept with my mother...
1          This is one of those games that clearly should...
2                           much funz. 10/10 would buy again
3          Got Franklin and Trevor spooked. They noclippe...
4          Less content than either Morrowind or Oblivion...
                                 ...
103094     It suck that I can't remove this crepe from my...
103095     Pay for mods is something that EA would come u...
103096     Changed price to $79 right before summer sale,...
103097                     Great game to uninstall, 4/20 IGN
103098     why you no work?? Bought the disk, not the ste...
Name: review, Length: 103099, dtype: object
```

NLP Preprocessing

Tokenization and Removing Unnecessary Information

In [13]:

```python
# Eksekusi preprocess untuk satu row data
def execute_preprocess(value):
    # Mendapatkan token seperti kata, tanda baca dari kalimat
    tokenList = word_tokenize(value)
    tokenList = [w.lower() for w in tokenList]

    # Menghilangkan stopwords dalam bahasa Inggris untuk mengurangi jumlah token yang diproses
    stop_words = set(stopwords.words('english'))
    tokenList = [word for word in tokenList if not word in stop_words]

    # Menggabungkan semua token menjadi 1 kalimat panjang dengan setiap token dipisahkan oleh spasi
    result = ""
    for token in tokenList:
        if token != "":
            result += token + ' '
    result = result[:-1]

    # Remove multiple space and tokens
    result = re.sub(r'[?=.*\!-_,\.]','',result)
    result = re.sub(' +', ' ', result)

    return result

# Preprocess setiap baris untuk setiap row dalam data
def preprocess_data(raw_data):
    tokens = []
    for raw in raw_data:
        tokenList = execute_preprocess(raw)
        tokens.append(tokenList)
    return tokens
```

In [14]:
```
x_train_prep = preprocess_data(x_train)
x_val_prep = preprocess_data(x_val)
x_test_prep = preprocess_data(x_test)

x_train_prep
```

```
loss death vs buyback availability good essentially dota greedy woman love time would play',
 'story single player freeroam story mature quite long hours put middle heist learn basics game walking runn
ing shooting mission tutorial backstory protagonists trevor michael finish put control franklin unlock first
michael trevor unlock new character switch given time missions story face lot modern problems told honeststy
le top lot swearing blood even torture scene sometime need switch specific character continue story need kil
l sometime waiting next story mission waiting called wait side missions character could use work lot side ch
aracters meet one got missions want take break missions drive around join side activities like race golf yog
a tennis overall single player keep occupied quite sometime gameplay rpg elements standard gta gameplay cove
rbased shooting driving cars like mad clunky flying controls cover sticky weird times near walls may always
cover behind one want also may always covered head might open wall behind might cardboard something careful
die pretty fast hits armor hits armor experience driving feels arcadish realistic never drove kmh irl still
physics crashing feel weird sometimes fly windshield reason higher speed nothing happens flying still crap o
ne missclick turn meteorite gta v improve stats single player stamina important shooting doesnt make differe

nce strength goes gunfight fists stealth rarely used flying yet try driving doesnt make difference lung capa
city important gon na sleep fishes special single player furthermore modify weapons quite limited add extend
ed clip scope suppressor flashlight grip apply different skin something hoping something spoiled alpha proto
col online microtransactions think make gta online pw okay consider thanks people buy shark cards everybody
gtao able enjoy free patches also imo microtransactions dont make online mode pw still upgrades cars locked
behind heists rank yeah would like earn money fair square option get real money get free dlcs earn money fai
```

Save and Load Prep File

In [15]:
```
save_prep_data()
x_train_prep, x_val_prep, x_test_prep, y_train, y_val, y_test = load_prep_data()
y_train
```

Out[15]:
```
0         1
1         0
2         1
3         1
4         0
         ..
103094    0
103095    0
103096    0
103097    0
103098    0
Name: rating, Length: 103099, dtype: int64
```

POS Tagging

In [16]:
```
from posTagger import posTagger

def split_string_to_list(string_list):
    splitted_strings = []
    for string_comp in string_list:
        splitted_strings.append(string_comp.split())
    return splitted_strings

def append_pos_tag(pos_tag_list):
    merge_pos_tag = []
    for i in range(len(pos_tag_list)):
        string_total = ""
        for j in range(len(pos_tag_list[i])):
            string_total += ' '
            string_total += pos_tag_list[i][j][0] + '_' + pos_tag_list[i][j][1].lower()
        merge_pos_tag.append(string_total[1:])
    return merge_pos_tag
```

In [17]:
```
x_train_prep_split =split_string_to_list(x_train_prep)
x_val_prep_split =split_string_to_list(x_val_prep)
x_test_prep_split =split_string_to_list(x_test_prep)

posTag = posTagger()
x_train_pos = posTag.pos_tag(x_train_prep_split)
x_val_pos = posTag.pos_tag(x_val_prep_split)
x_test_pos = posTag.pos_tag(x_test_prep_split)

print(len(x_train_pos), len(x_val_pos), len(x_test_pos))
```

```
103099 18194 13477
```

In [18]:
```
x_train_tagged = append_pos_tag(x_train_pos)
x_val_tagged = append_pos_tag(x_val_pos)
x_test_tagged = append_pos_tag(x_test_pos)
save_tagged_data()
```

In [19]:
```
x_train_tagged, x_val_tagged, x_test_tagged, y_train, y_val, y_test = load_tagged_data()
x_train_tagged
```

```
f_noun deathmatch_noun last_adj man_noun standing_verb includes_verb team_noun version_noun modes_noun im_no
un yet_conj test_noun host_noun decide_verb able_adj use_noun custom_noun carsweapons_noun coop_noun apart_a
dv competitive_adj big_adj variety_noun coop_noun jobs_noun different_adj missions_noun like_adp stealing_no
un carstrucksdrugs_noun assassination_noun targets_noun like_adp look_noun big_adj picture_noun setup_noun h
eists_noun jobs_noun played_verb players_noun heists_adj requirement_noun players_noun setup_noun missions_n
oun heists_noun finale_noun heists_noun got_verb certain_adj payout_noun jobs_noun payment_noun depends_verb
much_adj time_noun spend_verb mission_noun time_noun waste_noun higher_adj payout_noun often_adv would_verb
like_adp finish_noun mission_noun asap_noun start_verb another_det start_noun repeating_verb overall_adj gon
_noun na_noun get_verb money_noun worth_adj regardless_adv gon_adj na_noun play_noun sponline_noun',
 'cant_noun play_verb first_adj person_noun without_adp getting_verb motion_noun sick_adj get_verb banned_ve
rb fix_noun mod_noun rockstar_noun wont_adj fix_noun themselfs_noun go_verb shatter_verb lightbulb_noun rock
star_noun',
 'got_verb ``_. communicate_verb people_noun around_adp globe_noun fb_noun',
 'loved_verb game_noun every_det minute_noun start_noun finish_noun purchased_verb soon_adv came_verb well_a
dv dlc_noun came_verb ps_noun owner_noun little_adj upset_verb length_noun time_noun took_verb get_verb dlc_
noun nt_noun fazed_noun slightest_adj loved_verb dawnguard_noun loved_verb heartfire_noun loved_verb dragonb
orn_noun nt_noun mind_noun paying_verb quality_noun content_noun fit_noun well_adv lore_noun story_noun pay_
verb mods_noun nt_noun even_adv canon_noun nt_noun complete_adj story_noun nt_noun add_verb anything_noun ne
w_adj adventure_noun means_noun nothing_noun rest_noun elder_adj scrolls_noun games_noun wo_verb nt_noun pla
```

Feature Extraction (TF-IDF)

Fitting

In [20]:
```
tfidf = TfidfVectorizer(binary=True, use_idf = True, max_features=256)
tfidf = tfidf.fit(x_train_prep)
tfidf
```

Out[20]:
```
TfidfVectorizer(binary=True, max_features=256)
```

Extracting

In [21]:
```python
x_train_tfidf = pd.DataFrame(tfidf.transform(x_train_prep).toarray(), columns=[tfidf.get_feature_names()])
x_val_tfidf = pd.DataFrame(tfidf.transform(x_val_prep).toarray(), columns=[tfidf.get_feature_names()])
x_test_tfidf = pd.DataFrame(tfidf.transform(x_test_prep).toarray(), columns=[tfidf.get_feature_names()])

save_tfidf_data()

x_train_tfidf
```

Out[21]:

	able	actually	add	almost	already	also	always	amazing	amount	another	...	workshop	world	worst	worth	wou
0	0.000000	0.0	0.0	0.0	0.0	0.0	0.0	0.000000	0.0	0.000000	...	0.0	0.000000	0.0	0.0	0.00
1	0.000000	0.0	0.0	0.0	0.0	0.0	0.0	0.000000	0.0	0.196611	...	0.0	0.193062	0.0	0.0	0.00
2	0.000000	0.0	0.0	0.0	0.0	0.0	0.0	0.000000	0.0	0.000000	...	0.0	0.000000	0.0	0.0	0.54
3	0.000000	0.0	0.0	0.0	0.0	0.0	0.0	0.000000	0.0	0.000000	...	0.0	0.000000	0.0	0.0	0.00
4	0.406341	0.0	0.0	0.0	0.0	0.0	0.0	0.000000	0.0	0.000000	...	0.0	0.000000	0.0	0.0	0.00
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	
103094	0.000000	0.0	0.0	0.0	0.0	0.0	0.0	0.000000	0.0	0.000000	...	0.0	0.000000	0.0	0.0	0.00
103095	0.000000	0.0	0.0	0.0	0.0	0.0	0.0	0.000000	0.0	0.000000	...	0.0	0.000000	0.0	0.0	0.28
103096	0.000000	0.0	0.0	0.0	0.0	0.0	0.0	0.413857	0.0	0.000000	...	0.0	0.000000	0.0	0.0	0.00
103097	0.000000	0.0	0.0	0.0	0.0	0.0	0.0	0.000000	0.0	0.000000	...	0.0	0.000000	0.0	0.0	0.00
103098	0.000000	0.0	0.0	0.0	0.0	0.0	0.0	0.000000	0.0	0.000000	...	0.0	0.000000	0.0	0.0	0.00

103099 rows × 256 columns

Fitting Tagged

In [22]:
```python
tfidf_tagged = TfidfVectorizer(binary=True, use_idf = True, max_features=256)
tfidf_tagged = tfidf_tagged.fit(x_train_tagged)
tfidf_tagged
```

Out[22]:
```
TfidfVectorizer(binary=True, max_features=256)
```

Extracting Tagged

In [23]:
```python
x_train_tfidf_tagged = pd.DataFrame(tfidf_tagged.transform(x_train_tagged).toarray(), columns=[tfidf_tagged.get_
x_val_tfidf_tagged = pd.DataFrame(tfidf_tagged.transform(x_val_tagged).toarray(), columns=[tfidf_tagged.get_feat
x_test_tfidf_tagged = pd.DataFrame(tfidf_tagged.transform(x_test_tagged).toarray(), columns=[tfidf_tagged.get_fe

save_tfidf_tagged_data()

x_train_tfidf_tagged
```

Out[23]:

	able_adj	actually_adv	almost_adv	already_adv	also_adv	always_adv	amazing_adj	amount_noun	another_det	anyone_noun
0	0.000000	0.0	0.0	0.0	0.0	0.0	0.000000	0.0	0.000000	0.0
1	0.000000	0.0	0.0	0.0	0.0	0.0	0.000000	0.0	0.212606	0.0
2	0.000000	0.0	0.0	0.0	0.0	0.0	0.000000	0.0	0.000000	0.0
3	0.000000	0.0	0.0	0.0	0.0	0.0	0.000000	0.0	0.000000	0.0
4	0.402425	0.0	0.0	0.0	0.0	0.0	0.000000	0.0	0.000000	0.0
...	...	...	...	...	...	...	...	...	...	...
103094	0.000000	0.0	0.0	0.0	0.0	0.0	0.000000	0.0	0.000000	0.0
103095	0.000000	0.0	0.0	0.0	0.0	0.0	0.000000	0.0	0.000000	0.0
103096	0.000000	0.0	0.0	0.0	0.0	0.0	0.405788	0.0	0.000000	0.0
103097	0.000000	0.0	0.0	0.0	0.0	0.0	0.000000	0.0	0.000000	0.0
103098	0.000000	0.0	0.0	0.0	0.0	0.0	0.000000	0.0	0.000000	0.0

103099 rows × 256 columns

Classification 1: Support Vector Machine (SVM)

Tanpa POS Tag

Training

In [24]:
```
from sklearn import svm
clf = svm.SVC()
clf.fit(x_train_tfidf[:50000], y_train[:50000])
```

Out[24]:
```
SVC()
```

Testing

In [25]:
```
y_test_predict = clf.predict(x_test_tfidf)
y_test_predict
```

Out[25]:
```
array([0, 0, 0, ..., 1, 0, 0], dtype=int64)
```

In [26]:
```
untagged_accuracy = accuracy_score(y_test, y_test_predict)
untagged_accuracy
```

Out[26]:
```
0.9048007716850931
```

Save Model

In [27]:
```
pickle.dump(clf, open(svm_file, 'wb'))
```

Dengan POS Tag

Training

In [28]:
```
from sklearn import svm
clf = svm.SVC()
clf.fit(x_train_tfidf_tagged[:50000], y_train[:50000])
```

Out[28]:
```
SVC()
```

Testing

In [29]:
```
y_test_predict = clf.predict(x_test_tfidf_tagged)
y_test_predict
```

Out[29]:
```
array([0, 0, 0, ..., 1, 0, 0], dtype=int64)
```

In [30]:
```
tagged_accuracy = accuracy_score(y_test, y_test_predict)
tagged_accuracy
```

Out[30]:
```
0.8967871187949841
```

Save Model

In [31]:
```
pickle.dump(clf, open(svm_pos_file, 'wb'))
```

Classification 2: Deep Neural Network (DNN)

In [32]:
```
y_train_sigm = []
for y in y_train:
    if y == 1:
        y_train_sigm.append([0, 1])
    else:
        y_train_sigm.append([1, 0])

y_val_sigm = []
for y in y_val:
    if y == 1:
        y_val_sigm.append([0, 1])
    else:
        y_val_sigm.append([1, 0])

y_test_sigm = []
for y in y_test:
    if y == 1:
        y_test_sigm.append([0, 1])
    else:
        y_test_sigm.append([1, 0])

y_train_sigm = pd.DataFrame(y_train_sigm)
y_val_sigm = pd.DataFrame(y_val_sigm)
y_test_sigm = pd.DataFrame(y_test_sigm)

y_test_sigm
```

Out[32]:

	0	1
0	1	0
1	1	0
2	1	0
3	0	1
4	0	1
...	...	...
13472	1	0
13473	1	0

	0	1
13474	0	1
13475	1	0
13476	1	0

13477 rows × 2 columns

```
In [33]: x_test_tfidf_tagged
```

Out[33]:

	able_adj	actually_adv	almost_adv	already_adv	also_adv	always_adv	amazing_adj	amount_noun	another_det	anyone_noun	...
0	0.0	0.000000	0.0	0.000000	0.000000	0.000000	0.000000	0.0	0.0	0.0	..
1	0.0	0.000000	0.0	0.000000	0.000000	0.000000	0.000000	0.0	0.0	0.0	..
2	0.0	0.000000	0.0	0.000000	0.000000	0.000000	0.000000	0.0	0.0	0.0	..
3	0.0	0.298208	0.0	0.000000	0.000000	0.300625	0.000000	0.0	0.0	0.0	..
4	0.0	0.000000	0.0	0.000000	0.000000	0.000000	0.000000	0.0	0.0	0.0	..
...	...	...	...	...	...	...	...	...	...	...	..
13472	0.0	0.000000	0.0	0.000000	0.000000	0.000000	0.000000	0.0	0.0	0.0	..
13473	0.0	0.000000	0.0	0.294957	0.239663	0.000000	0.000000	0.0	0.0	0.0	..
13474	0.0	0.000000	0.0	0.000000	0.000000	0.000000	0.000000	0.0	0.0	0.0	..
13475	0.0	0.000000	0.0	0.000000	0.000000	0.000000	0.000000	0.0	0.0	0.0	..
13476	0.0	0.000000	0.0	0.000000	0.000000	0.000000	0.225051	0.0	0.0	0.0	..

13477 rows × 256 columns

Model Building

In [34]:
```
dnn_model = Sequential()
dnn_model.add(keras.Input(shape=(256)))
dnn_model.add(Dense(64,activation='relu'))
dnn_model.add(Dropout(0.2))
dnn_model.add(Dense(8,activation='relu'))
dnn_model.add(Dropout(0.1))
dnn_model.add(Dense(1,activation='sigmoid'))
dnn_model.compile(loss='mean_squared_error',optimizer=Adam(lr=0.01),metrics=['accuracy'])
dnn_model.summary()
```

```
Model: "sequential"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
dense (Dense)                (None, 64)                16448
_________________________________________________________________
dropout (Dropout)            (None, 64)                0
_________________________________________________________________
dense_1 (Dense)              (None, 8)                 520
_________________________________________________________________
dropout_1 (Dropout)          (None, 8)                 0
_________________________________________________________________
dense_2 (Dense)              (None, 1)                 9
=================================================================
Total params: 16,977
Trainable params: 16,977
Non-trainable params: 0
_________________________________________________________________
```

Training

In [35]:
```
history = dnn_model.fit(x_train_tfidf_tagged[:50000], y_train[:50000], validation_data=(x_val_tfidf_tagged[:5000
                    epochs = epoch_count_dnn_1, batch_size = 64)
```

```
- val_accuracy: 0.8824
Epoch 9/50
782/782 [==============================] - 1s 2ms/step - loss: 0.0746 - accuracy: 0.9008 - val_loss: 0.0990
- val_accuracy: 0.8744
Epoch 10/50
782/782 [==============================] - 1s 2ms/step - loss: 0.0725 - accuracy: 0.9035 - val_loss: 0.0967
- val_accuracy: 0.8790
Epoch 11/50
782/782 [==============================] - 1s 2ms/step - loss: 0.0714 - accuracy: 0.9048 - val_loss: 0.0957
- val_accuracy: 0.8800
Epoch 12/50
782/782 [==============================] - 1s 2ms/step - loss: 0.0702 - accuracy: 0.9072 - val_loss: 0.0923
- val_accuracy: 0.8824
Epoch 13/50
782/782 [==============================] - 1s 2ms/step - loss: 0.0684 - accuracy: 0.9097 - val_loss: 0.0919

- val_accuracy: 0.8854
Epoch 14/50
782/782 [==============================] - 1s 2ms/step - loss: 0.0672 - accuracy: 0.9112 - val_loss: 0.0889
- val_accuracy: 0.8892
```

Testing

In [36]:
```
y_pred=(dnn_model.predict(x_test_tfidf_tagged))
for y in y_pred:
    y[0] = round(y[0])
y_pred = y_pred.astype("int32")
y_pred
```

Out[36]:
```
array([[0],
       [0],
       [0],
       ...,
       [1],
       [0],
       [0]])
```

Accuracy

In [37]:
```
dnn_accuracy = accuracy_score(y_test, y_pred)
dnn_accuracy
```

Out[37]:
```
0.899013133486681
```

Save Model

In [38]:
```
dnn_model.save(dnn_file)
```

Classification 3: Long-Short Term Memory (LSTM)

Word To Vec

In [39]:
```
tokenizer = Tokenizer(num_words = unique_word_len, filters='!"#$%&()*+,-./:;<=>?@[\\]^_`{|}~\t\n', lower=True, c
tokenizer.fit_on_texts(x_train_tagged)

x_train_lstm = tokenizer.texts_to_sequences(x_train_tagged)
x_val_lstm = tokenizer.texts_to_sequences(x_val_tagged)
x_test_lstm = tokenizer.texts_to_sequences(x_test_tagged)

x_train_lstm
```

Out[39]:
```
[[1, 3, 88, 2, 22, 2, 1, 3, 1, 2],
 [16,
  15,
  25,
  2,
  1,
  5,
  1,
  2,
  292,
  5,
  1,
  2,
  1,
  2,
  55,
  3,
  136,
  4,
```

Padding

In [40]:
```
x_train_padded = pad_sequences(x_train_lstm, maxlen = sentence_len, padding="pre", truncating="post")
x_val_padded = pad_sequences(x_val_lstm, maxlen = sentence_len, padding="pre", truncating="post")
x_test_padded = pad_sequences(x_test_lstm, maxlen = sentence_len, padding="pre", truncating="post")

x_train_padded
```

Out[40]:
```
array([[  0,   0,   0, ...,   3,   1,   2],
       [ 16,  15,  25, ...,   3,   1,   2],
       [  0,   0,   0, ...,   3,  24,   3],
       ...,
       [  0,   0,   0, ...,   3, 100,   4],
       [  0,   0,   0, ...,   2,   1,   2],
       [  0,   0,   0, ...,   7, 120,   4]])
```

Building Model

In [41]:
```
model = Sequential()
model.add(Embedding(input_dim = unique_word_len, output_dim = embedding_size, input_length = sentence_len))
model.add(LSTM(128, dropout = dropout, recurrent_dropout = dropout))
model.add(Dense(1,activation='sigmoid'))
model.compile(loss='mean_squared_error',optimizer=Adam(lr=0.01),metrics=['accuracy'])
model.summary()
```

```
WARNING:tensorflow:Layer lstm will not use cuDNN kernel since it doesn't meet the cuDNN kernel criteria. It wi
ll use generic GPU kernel as fallback when running on GPU
Model: "sequential_1"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
embedding (Embedding)        (None, 50, 256)           128000
_________________________________________________________________
lstm (LSTM)                  (None, 128)               197120
_________________________________________________________________
dense_3 (Dense)              (None, 1)                 129
=================================================================
Total params: 325,249
Trainable params: 325,249
Non-trainable params: 0
_________________________________________________________________
```

Training

In [42]:
```python
history = model.fit(x_train_padded[:50000], y_train[:50000], validation_data=(x_val_padded[:5000], y_val[:5000]),
                    epochs = epoch_count_dnn_2, batch_size = 64)
```

```
Epoch 1/10
782/782 [==============================] - 159s 204ms/step - loss: 0.1331 - accuracy: 0.8101 - val_loss: 0.120
9 - val_accuracy: 0.8320
Epoch 2/10
782/782 [==============================] - 159s 203ms/step - loss: 0.1164 - accuracy: 0.8352 - val_loss: 0.115
4 - val_accuracy: 0.8408
Epoch 3/10
782/782 [==============================] - 159s 203ms/step - loss: 0.1168 - accuracy: 0.8360 - val_loss: 0.123
6 - val_accuracy: 0.8272
Epoch 4/10
782/782 [==============================] - 158s 202ms/step - loss: 0.1170 - accuracy: 0.8361 - val_loss: 0.120
9 - val_accuracy: 0.8290
Epoch 5/10
782/782 [==============================] - 157s 201ms/step - loss: 0.1166 - accuracy: 0.8371 - val_loss: 0.119
7 - val_accuracy: 0.8328
Epoch 6/10
782/782 [==============================] - 157s 201ms/step - loss: 0.1165 - accuracy: 0.8376 - val_loss: 0.120
0 - val_accuracy: 0.8400
Epoch 7/10
782/782 [==============================] - 156s 200ms/step - loss: 0.1175 - accuracy: 0.8360 - val_loss: 0.120
9 - val_accuracy: 0.8322
Epoch 8/10
782/782 [==============================] - 157s 201ms/step - loss: 0.1159 - accuracy: 0.8381 - val_loss: 0.121
7 - val_accuracy: 0.8312
Epoch 9/10
782/782 [==============================] - 159s 203ms/step - loss: 0.1161 - accuracy: 0.8394 - val_loss: 0.121
9 - val_accuracy: 0.8288
Epoch 10/10
782/782 [==============================] - 158s 202ms/step - loss: 0.1162 - accuracy: 0.8392 - val_loss: 0.120
9 - val_accuracy: 0.8300
```

Testing

In [43]:
```
y_pred=(model.predict(x_test_padded))
for y in y_pred:
    y[0] = round(y[0])
y_pred = y_pred.astype("int32")
y_pred
```

Out[43]:
```
array([[0],
       [0],
       [0],
       ...,
       [1],
       [0],
       [1]])
```

Accuracy

In [44]:
```
lstm_accuracy = accuracy_score(y_test, y_pred)
lstm_accuracy
```

Out[44]:
```
0.8357943162424872
```

Save Model

In [45]:
```
model.save(lstm_file)
```