NLP_project1_4_siyu_xiao

June 24, 2024

0.1 Task 1: Extract Insights from Data

[1]:
```
import pandas as pd
import numpy as np
import json
from pathlib import Path
from collections import Counter, defaultdict
import matplotlib.pyplot as plt
import seaborn as sns
from wordcloud import WordCloud
# pd.set_option('display.max_colwidth', 11)
```

[2]:
```
data_name = Path('Oppositional_thinking_analysis_dataset')
data_path = Path('data_ota') / data_name.with_suffix(".json")
assert data_path.exists, "File doesn't exist!"
```

[3]:
```
"""
read file
----------
use data frame in pandas to observe the structure of data
total 4000 texts:
+ unique id
+ unique text
+ 2 categories: conspiracy, critical,
+ annotations: sub-features, contain 5 categories
+ spacy_tokens: tokenized text
"""
with open(data_path, 'r', encoding='utf-8') as file:
    data = json.load(file)
df = pd.json_normalize(data)
df.shape
```

[3]:
```
(4000, 5)
```

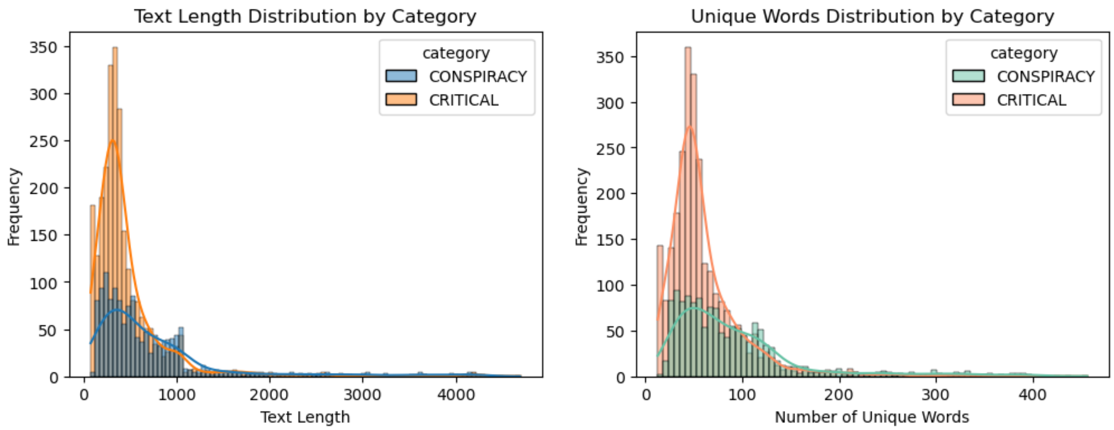
0.1.1 1. General view of categories

[4]:
```python
"""
add 2 new columns in data frame, for further visualizaiton:
text length
unique words
"""
df['text_length'] = df['text'].apply(len)
df['unique_words'] = df['text'].apply(lambda x: len(set(x.split())))
display(df.head())
```

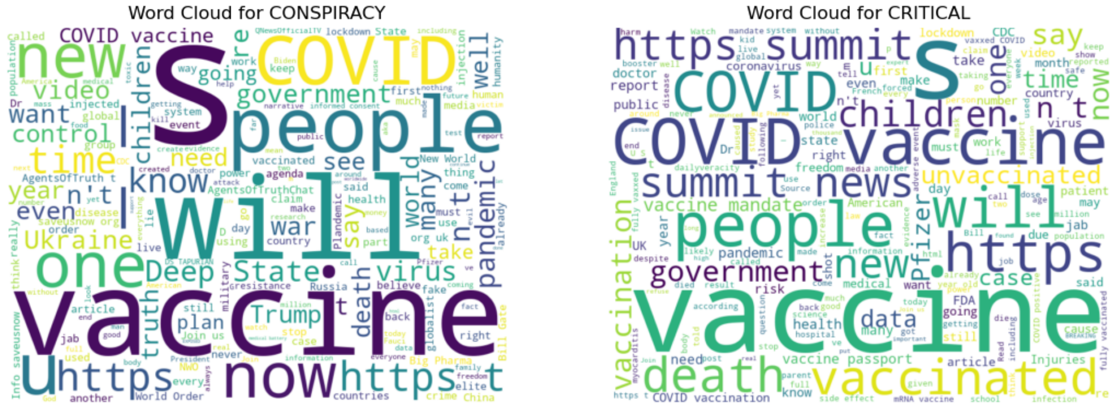
```
      id                                               text    category  \
0   5206  THIS IS MASSIVE Australian Senator Malcolm Rob…  CONSPIRACY
1   1387  " I ’m deeply concerned that the push to vacci…    CRITICAL
2  13116  2021 : They wanted to know your vaccination st…    CRITICAL
3  11439  Anthony Fauci once again defended brutal Chine…    CRITICAL
4     98  Proof has emerged showing that death from Wuha…    CRITICAL

                                         annotations  \
0  [{'span_text': 'Australian Senator Malcolm Rob…
1  [{'span_text': 'I ’m deeply concerned that the…
2  [{'span_text': 'someone who died suddenly', 'c…
3  [{'span_text': 'brutal Chinese lockdowns', 'ca…
4  [{'span_text': 'death from Wuhan coronavirus (…

                                        spacy_tokens  text_length  \
0  WyJUSElTIiwgIklTIiwgIk1BU1NJVkUiLCAiQXVzdHJhbG…          218
1  WyJcdTIwMWMiLCAiSSIsICJcdTIwMTltIiwgImRlZXBseS…          294
2  WyIyMDIxIiwgIjoiLCAiVGhleSIsICJ3YW50ZWQiLCAidG…          198
3  WyJBbnRob255IiwgIkZhdWNpIiwgIm9uY2UiLCAiYWdhaW…          326
4  WyJQcm9vZiIsICJoYXMiLCAiZW1lcmdlZCIsICJzaG93aW…          698

   unique_words
0            37
1            48
2            28
3            47
4           105
```

[5]:
```python
"""
plot the distribution of 'text length' and 'unique words'
"""
plt.figure(figsize=(12, 4))
plt.subplot(1,2,1)
sns.histplot(data=df, x='text_length', hue='category', kde=True)
plt.title('Text Length Distribution by Category')
plt.xlabel('Text Length')
plt.ylabel('Frequency')
```

```python
plt.subplot(1,2,2)
sns.histplot(data=df, x='unique_words', hue='category', kde=True,␣
 ↪palette='Set2')
plt.title('Unique Words Distribution by Category')
plt.xlabel('Number of Unique Words')
plt.ylabel('Frequency')

plt.show()
```



[6]:
```python
"""
use Word Cloud to visualize each category
"""
plt.figure(figsize=(13, 8))
for category, i in zip(df['category'].unique(), range(2)):
    text = " ".join(df[df['category'] == category]['text'])
    wordcloud = WordCloud(width=800, height=600, background_color='white').
 ↪generate(text)
    plt.subplot(1, 2, i+1)
    plt.imshow(wordcloud, interpolation='bilinear')
    plt.title(f'Word Cloud for {category}')
    plt.axis('off')
plt.show()
```



0.1.2 2. Look into the annotations

[7]:
```python
"""
extract information of annotations and tokens
----------
+ span text
+ 5 annotation categories:  CAMPAIGNER, AGENT, NEGATIVE_EFFECT, VICTIM,␣
↪FACILITATOR, OBJECTIVE, X
"""
annotations_expanded = df.explode('annotations')[['id', 'annotations']]
annotations_df = pd.json_normalize(annotations_expanded['annotations'])
annotations_df['id'] = annotations_expanded['id'].values
display(annotations_df.head())

category_counts = annotations_df['category'].value_counts().reset_index()
category_counts.columns = ['category', 'count']
display(category_counts.transpose())
```

```
                                          span_text         category  \
0                     Australian Senator Malcolm Roberts       CAMPAIGNER
1                                  the first politician       CAMPAIGNER
2  I ’m deeply concerned that the push to vaccina…  NEGATIVE_EFFECT
3                           to vaccinate these children        OBJECTIVE
4                                        these children           VICTIM

    annotator  start_char  end_char  start_spacy_token  end_spacy_token    id
0  gold_label          16        50                  3                7  5206
1  gold_label         135       155                 24               27  5206
2  gold_label           2       135                  1               22  1387
3  gold_label          38        65                  8               12  1387
4  gold_label          51        65                 10               12  1387

                   0        1                 2         3             4            5  \
```

```
category  CAMPAIGNER  AGENT  NEGATIVE_EFFECT  VICTIM  FACILITATOR  OBJECTIVE
count           5096   5082             4387    3517         2763       1602

            6
category    X
count     206
```

[8]:
```
"""
merge annotation categories into df
"""
df = df.merge(annotations_df.groupby('id')['category'].apply(list).
↪reset_index(), on='id', how='left', suffixes=('', '_annotations'))
df.head(2)
```

[8]:
```
     id                                               text    category  \
0  5206  THIS IS MASSIVE Australian Senator Malcolm Rob…  CONSPIRACY
1  1387  " I ’m deeply concerned that the push to vacci…    CRITICAL

                                     annotations  \
0  [{'span_text': 'Australian Senator Malcolm Rob…
1  [{'span_text': 'I ’m deeply concerned that the…

                                    spacy_tokens  text_length  \
0  WyJUSElTIiwgIklTIiwgIk1BU1NJVkUiLCAiQXVzdHJhbG…          218
1  WyJcdTIwMWMiLCAiSSIsICJcdTIwMTltIiwgImRlZXBseS…          294

   unique_words                          category_annotations
0            37                      [CAMPAIGNER, CAMPAIGNER]
1            48  [NEGATIVE_EFFECT, OBJECTIVE, VICTIM, CAMPAIGNE…
```

0.2 Task 2: Pre-processing

[9]:
```
import nltk
from nltk.stem import PorterStemmer
from nltk.corpus import stopwords
import re
from tqdm import tqdm
import time
import base64
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.manifold import TSNE
import plotly
import plotly.express as px
```

[10]:
```
"""
use nltk for normalization
"""
```

```
def download_with_progress(resource):
    print(f"Downloading {resource}...")
    for _ in tqdm(range(100), desc=f"Downloading {resource}", unit="B",␣
↪unit_scale=True, ncols=100):
        time.sleep(0.01)
    nltk.download(resource)

download_with_progress('stopwords')
stop_words = set(stopwords.words('english'))
stemmer = PorterStemmer() # initialize nltk stemmer
```

```
Downloading stopwords…

Downloading stopwords: 100%|                         | 100/100
[00:01<00:00, 95.0B/s]
[nltk_data] Downloading package stopwords to
[nltk_data]     C:\Users\siyux\AppData\Roaming\nltk_data…
[nltk_data]   Package stopwords is already up-to-date!
```

[11]:
```
def decode_tokens(tokens):
    """
    decode spaCy tokens from base64
    add to column -> decoded_tokens
    """
    decoded_bytes = base64.b64decode(tokens)
    decoded_str = decoded_bytes.decode('utf-8')
    return json.loads(decoded_str)

def preprocess_stpw(tokens):
    """
    normalization: remove punctuation and stop words
    add to column -> process_stpw
    """
    tokens = [token.lower() for token in tokens if token.isalnum() and token␣
↪not in stop_words]
    return ' '.join(tokens)

def preprocess_stpw_stem(tokens):
    """
    normalization: stop words removal and stemming
    add to column -> process_stpw_stem
    """
    tokens = [stemmer.stem(token.lower()) for token in tokens if token.
↪isalnum() and token not in stop_words]
    return ' '.join(tokens)

df['decoded_tokens'] = df['spacy_tokens'].apply(decode_tokens)
df['process_stpw_stem'] = df['decoded_tokens'].apply(preprocess_stpw_stem)
```

```
df['process_stpw'] = df['decoded_tokens'].apply(preprocess_stpw)
```

[12]:
```
df.head(2)
```

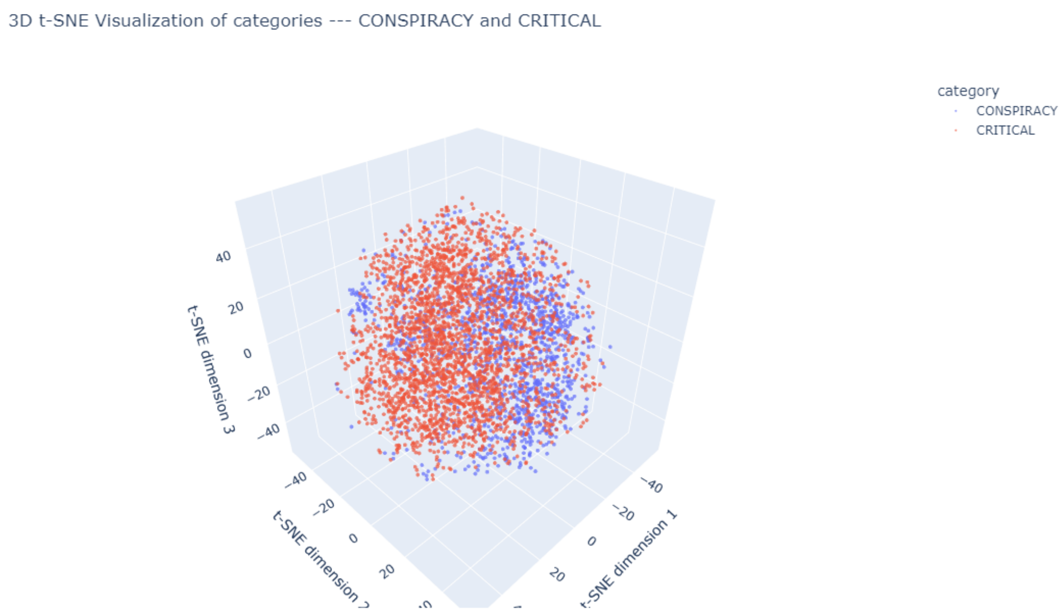
[12]:
```
     id                                               text    category  \
0  5206  THIS IS MASSIVE Australian Senator Malcolm Rob…  CONSPIRACY
1  1387  " I ’m deeply concerned that the push to vacci…    CRITICAL

                                         annotations  \
0  [{'span_text': 'Australian Senator Malcolm Rob…
1  [{'span_text': 'I ’m deeply concerned that the…

                                        spacy_tokens  text_length  \
0  WyJUSElTIiwgIklTIiwgIk1BU1NJVkUiLCAiQXVzdHJhbG…          218
1  WyJcdTIwMWMiLCAiSSIsICJcdTIwMTltIiwgImRlZXBseS…          294

   unique_words                            category_annotations  \
0            37                            [CAMPAIGNER, CAMPAIGNER]
1            48  [NEGATIVE_EFFECT, OBJECTIVE, VICTIM, CAMPAIGNE…

                                      decoded_tokens  \
0  [THIS, IS, MASSIVE, Australian, Senator, Malco…
1  [", I, ’m, deeply, concerned, that, the, push,…

                                   process_stpw_stem  \
0  thi is massiv australian senat malcolm robert …
1  i deepli concern push vaccin children noth dys…

                                        process_stpw
0  this is massive australian senator malcolm rob…
1  i deeply concerned push vaccinate children not…
```

*** **Visualization after Preprocessing**

[13]:
```
# vectorization using tf-idf
vectorizer = TfidfVectorizer()
X = vectorizer.fit_transform(df['process_stpw'])
# dimision reduction using tsne
tsne = TSNE(n_components=3, random_state=42)
X_tsne = tsne.fit_transform(X.toarray())

df_tsne = pd.DataFrame(X_tsne, columns=['x', 'y', 'z'])
df_tsne['category'] = df['category']
df_tsne = df_tsne[df_tsne['category'].isin(['CONSPIRACY', 'CRITICAL'])]
```

[14]:
```
fig = px.scatter_3d(df_tsne, x='x', y='y', z='z', color='category',
                    title='3D t-SNE Visualization of categories --- CONSPIRACY␣
 ↪and CRITICAL',
```

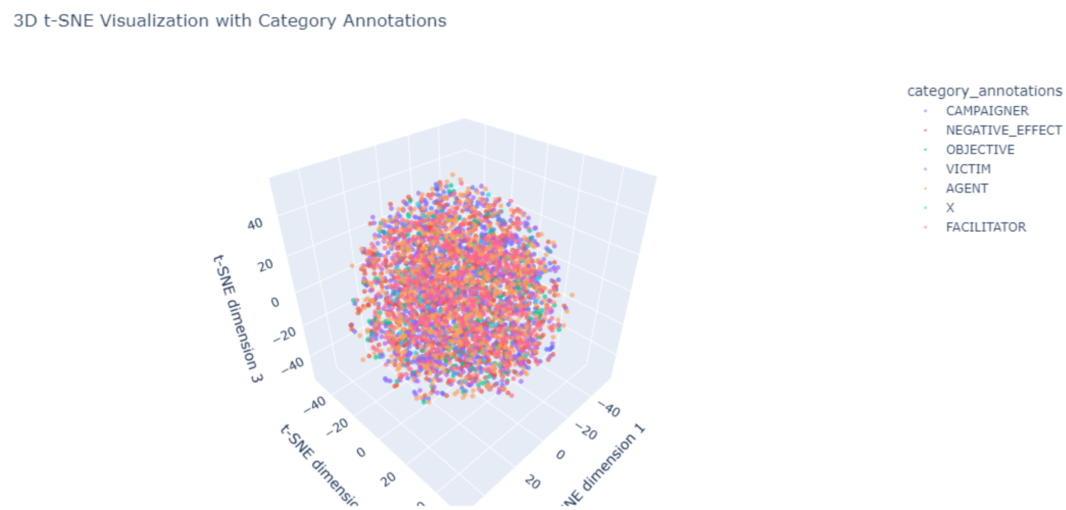
```
                    labels={'x': 't-SNE dimension 1', 'y': 't-SNE dimension 2', 'z': 't-SNE dimension 3'},
                    opacity=0.7,
                    width=800, height=700)
fig.update_traces(marker=dict(size=2))
fig.show()
```



[15]:
```
# vectorization using tf-idf
vectorizer = TfidfVectorizer()
X = vectorizer.fit_transform(df['process_stpw'])
# dimision reduction using tsne
tsne = TSNE(n_components=3, random_state=42)
X_tsne = tsne.fit_transform(X.toarray())
# flatten the annotation categories
df_expanded = df.explode('category_annotations')
df_expanded = df_expanded.reset_index(drop=True)
df_tsne = pd.DataFrame(X_tsne, columns=['x', 'y', 'z'])
df_tsne['category_annotations'] = df_expanded['category_annotations']
```

[16]:
```
# might not be useful and perceptive, but really amusing
fig = px.scatter_3d(df_tsne, x='x', y='y', z='z', color='category_annotations',
                    title='3D t-SNE Visualization with Category Annotations',
                    labels={'x': 't-SNE dimension 1', 'y': 't-SNE dimension 2', 'z': 't-SNE dimension 3'},
```

```
                    opacity=0.7,
                    width=800, height=600)

fig.update_traces(marker=dict(size=2.5))
fig.show()
```



0.3 Task 3: Text classification

[17]:
```
# dependencies for naive bayes
from sklearn.feature_extraction.text import CountVectorizer
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.model_selection import train_test_split
from sklearn.naive_bayes import MultinomialNB
from sklearn.metrics import classification_report, confusion_matrix,␣
 ↪accuracy_score
from scipy.sparse import hstack
```

[18]:
```
# dependencies for feed forward neural network
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense, Dropout
from tensorflow.keras.utils import to_categorical
import tensorflow as tf
```

0.3.1 Sub-task 1

- Split data into train and test sets. Use 20% of the data as the test set. Make sure to under or over-sample in case of imbalance in classes.

- Train a naïve Bayes model on the training part and test it, using the test set.
  - Compare the impact of different vectorization models (e.g., count vectorizer, TF-IDF, and …) on the final performance of your naïve Bayes model.
  - Compare the impact of different pre-processing pipelines (e.g., with and without stop words, stemming, and …) on the final performance of your naïve Bayes model.
  - Perform error analysis on the model's prediction. In other words, analyze errors that have been made by the model and describe why your model couldn't work well in case of these errors.

[19]:
```
class ModelComparison:
    """
    Compare between: different classifiers, normalization methods,␣
↪vectorization methods
    ----------
    parameters:
    + X: text data only normalized with stpw removal or also with stemming, can␣
↪be set from outside
    + y: categories, need to be preprocessed in FNN
    + evaluation: dict, use for visualizing comparison
    + history: training dynamics along epochs
    + model: classifier type
    """
    def __init__(self, X, y):
        self.X = X
        self.y = y
        self.X_train, self.X_test, self.y_train, self.y_test, self.y_pred =␣
↪None, None, None, None, None
        self.history = None
        self.evaluation = {
            'model': [],
            'vectorizer': [],
            'accuracy': []
        }
        self.accuracy = None
        self.model = None

    def set_X(self, X):
        """
        either stpw or stpw&stem
        """
        self.X = X

    def set_vectorizer(self, vectorizer):
        """
        Vectorize the text or text&annotations into feature vectors.
        """
        if vectorizer == 'bow':
```

```
            return CountVectorizer()
        elif vectorizer == 'tfidf':
            return TfidfVectorizer()

    def set_model(self, model):
        """
        set classifier type from outside, take care the format of y
        """
        self.model = model
        if model == 'fnn':
            self.y = to_categorical(pd.factorize(df['category'])[0])

    def predict(self, vectorizer='bow', model='nb'):
        """
        training entry, data splitting
        """
        V = self.set_vectorizer(vectorizer)
        X_vectorized = V.fit_transform(self.X)
        self.X_train, self.X_test, self.y_train, self.y_test = 
 ↪train_test_split(X_vectorized, self.y, test_size=0.2, random_state=42)

        if self.model == 'nb':
            M = MultinomialNB()
            M.fit(self.X_train, self.y_train)
            self.y_pred = M.predict(self.X_test)
            self.evaluation_nb()

        elif model == 'fnn':
            input_dim = self.X_train.shape[1]
            output_dim = len(np.unique(self.y))
            self.fit_fnn(input_dim, output_dim)
            self.evaluation_fnn()
        self.update_eval(vectorizer, model)

    def fit_fnn(self, input_dim, output_dim):
        """
        3-layer fnn;
        optimizer: adam;
        regularization: dropout;
        loss function: cross entropy;
        evaluation score: f1, accuracy
        best epoch arount 6th
        ----------
        | layer | size | activation |
        |-------|------|------------|
        | 1 fully connected | 128 | ReLU |
        | 2 fully connected | 64 | ReLU |
```

```
        | 3 output  | 2 | SoftMax |
        """
        model = Sequential()
        model.add(Dense(128, input_dim=input_dim, activation='relu'))
        model.add(Dropout(0.5))
        model.add(Dense(64, activation='relu'))
        model.add(Dense(output_dim, activation='softmax'))
        # train
        model.compile(loss='categorical_crossentropy', optimizer='adam',␣
↪metrics=['accuracy', ModelComparison.f1_score])
        # store metrics
        self.history = model.fit(self.X_train.toarray(), self.y_train,␣
↪epochs=7, batch_size=32, verbose=1)
        self.y_pred = np.argmax(model.predict(self.X_test.toarray()), axis=1)
        self.accuracy = max(self.history.history['accuracy'])

    def evaluation_nb(self):
        """
        print and plot report for nb model
        """
        accuracy = accuracy_score(self.y_test, self.y_pred)
        self.accuracy = accuracy
        report = classification_report(self.y_test, self.y_pred,␣
↪output_dict=True)
        confusion = confusion_matrix(self.y_test, self.y_pred)

        report_df = pd.DataFrame(report).transpose().iloc[:2]
        confusion = confusion[:2, :2]
        print(f"Accuracy: {accuracy:.4f}\n")
        print("Classification Report:\n", report_df)

        plt.figure(figsize=(6, 2.5))
        plt.subplot(1,2,1)
        sns.heatmap(confusion, annot=True, fmt="d", cmap="Blues")
        plt.title('Condusion Matix')
        plt.xlabel('Predicted')
        plt.ylabel('Actual')

        plt.subplot(1, 2, 2)
        report_df.drop(['support'], axis=1, inplace=True)
        report_df.plot(kind='bar', ax=plt.gca())
        plt.title('Scores')
        plt.xlabel('Classes')
        plt.ylabel('Scores')
        plt.xticks(rotation=0)
        plt.legend(loc='lower right')
```

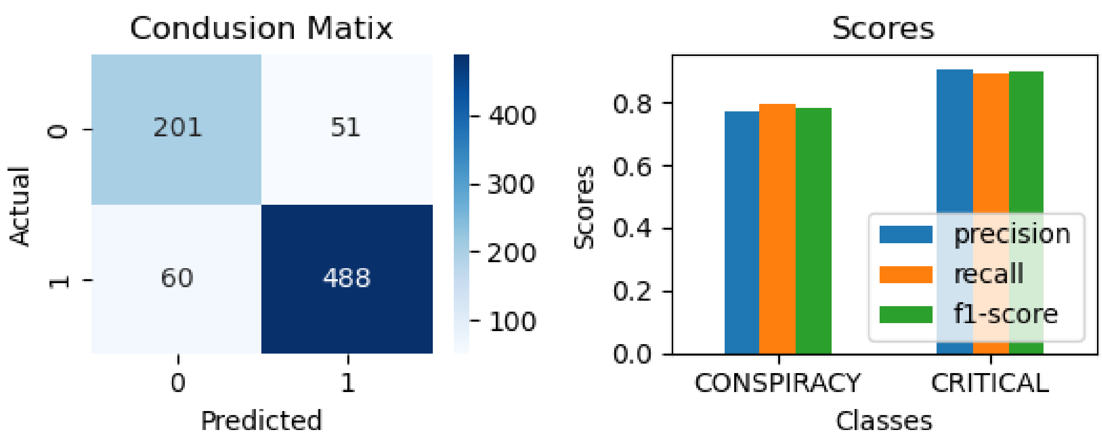
```
        plt.tight_layout()
        plt.show()

    def evaluation_fnn(self):
        """
        plot  learned accuracy, loss, f1
        """
        plt.figure(figsize=(5, 3))
        metrics = ['accuracy', 'loss', 'f1_score']
        colors = ['purple', 'gray', 'orange']
        labels = ['Accuracy', 'Loss', 'F1 Score']

        for metric, color, label in zip(metrics, colors, labels):
            plt.plot(self.history.history[metric], color=color, label=label)
            plt.fill_between(range(len(self.history.history[metric])),
                             self.history.history[metric], color=color, alpha=0.
↪1)
        plt.xlabel('Epochs')
        plt.ylabel('Value')
        plt.title('Metrics over Epochs')
        plt.legend()
        plt.show()

    def update_eval(self, vectorizer, model):
        self.evaluation['model'].append(model)
        self.evaluation['vectorizer'].append(vectorizer)
        self.evaluation['accuracy'].append(self.accuracy)

    @staticmethod
    def f1_score(y_true, y_pred):
        """
        for f1 score in fnn
        """
        y_pred = tf.argmax(y_pred, axis=1)
        y_true = tf.argmax(y_true, axis=1)
        precision = tf.reduce_sum(tf.cast(y_true * y_pred, tf.float32)) / (tf.
↪reduce_sum(tf.cast(y_pred, tf.float32)) + tf.keras.backend.epsilon())
        recall = tf.reduce_sum(tf.cast(y_true * y_pred, tf.float32)) / (tf.
↪reduce_sum(tf.cast(y_true, tf.float32)) + tf.keras.backend.epsilon())
        return 2 * (precision * recall) / (precision + recall + tf.keras.
↪backend.epsilon())
```

[20]:
```
# initialize MC (only once, later set other parameters)
MC = ModelComparison(df['process_stpw'], df['category'])
MC.set_model('nb')
```

[21]:

```
"""
| Nr. | preprocessing | vectorizer | model |
|  01 |  stop words   |     BoW    |  NB   |
"""
MC.predict()
```

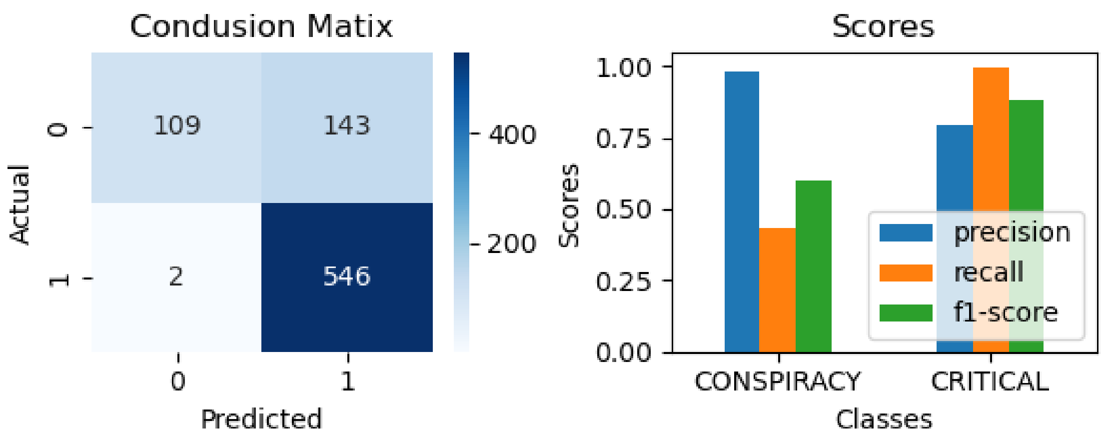
```
Accuracy: 0.8612

Classification Report:
            precision    recall  f1-score   support
CONSPIRACY   0.770115  0.797619  0.783626     252.0
CRITICAL     0.905380  0.890511  0.897884     548.0
```



[22]:

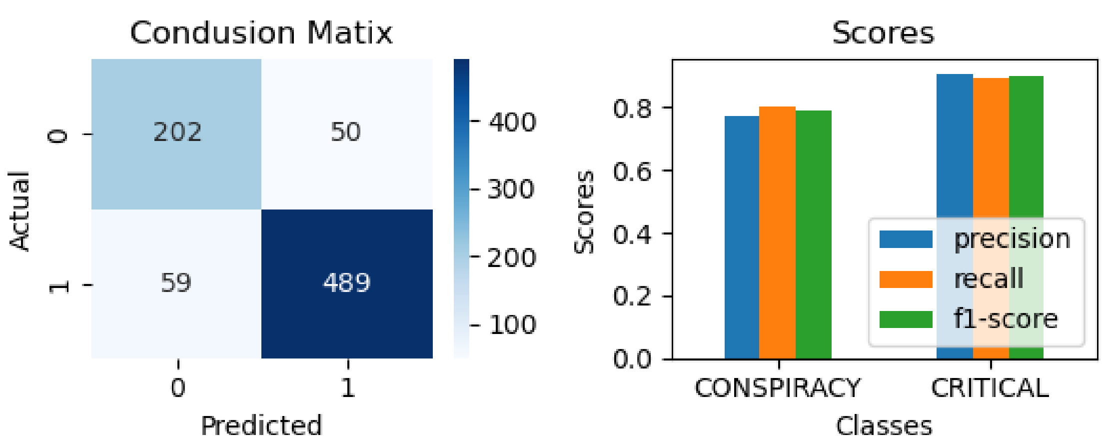
```
"""
| Nr. | preprocessing | vectorizer | model |
|  02 |  stop words   |   TFI-DF   |  NB   |
"""
MC.predict('tfidf', 'nb')
```

```
Accuracy: 0.8187

Classification Report:
            precision   recall  f1-score   support
CONSPIRACY   0.981982  0.43254  0.600551     252.0
CRITICAL     0.792453  0.99635  0.882781     548.0
```



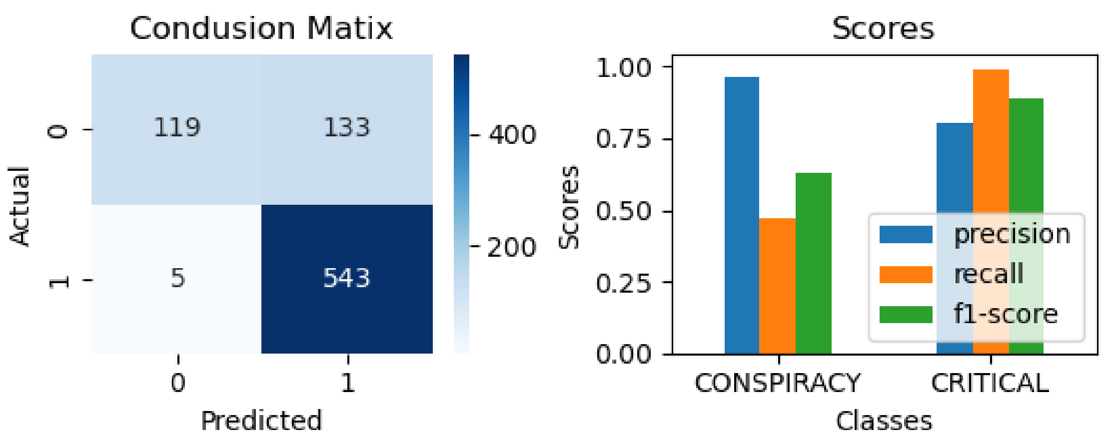
[23]:
```python
"""
| Nr. | preprocessing              | vectorizer | model |
|  04 |  stop words & stemming     |     BoW    |  NB   |
"""
MC.set_X(df['process_stpw_stem'])
MC.predict('bow', 'nb')
```

```
Accuracy: 0.8638

Classification Report:
             precision    recall  f1-score   support
CONSPIRACY    0.773946  0.801587  0.787524     252.0
CRITICAL      0.907236  0.892336  0.899724     548.0
```



[24]:
```
"""
| Nr.  | preprocessing            | vectorizer | model |
|  04  |  stop words & stemming   |    TFI-DF  |  NB   |
"""
MC.predict('tfidf', 'nb')
```

```
Accuracy: 0.8275

Classification Report:
              precision    recall  f1-score   support
CONSPIRACY    0.959677  0.472222  0.632979     252.0
CRITICAL      0.803254  0.990876  0.887255     548.0
```



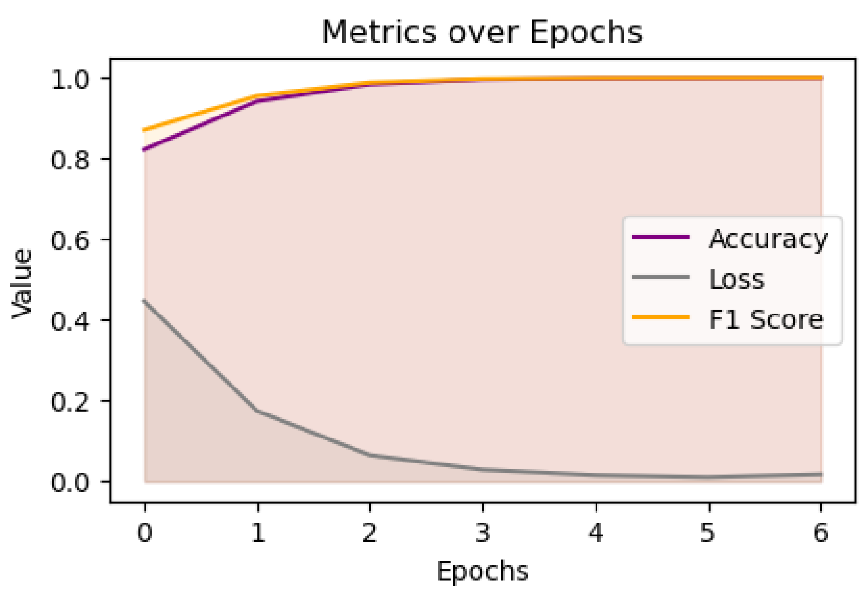
0.3.2 Sub-task 2

- Train a feed-forward neural network model and report its performance (F1 score) on test data.
  - Again, compare the impact of different vectorization approaches on the final performance of your model.
  - Again, Compare the impact of different pre-processing pipelines (e.g., with and without stop words, stemming, and …) on the final performance of your model.
  - Perform error analysis on the model's prediction.

[25]:
```
"""
| Nr.  | preprocessing | vectorizer | model |
|  05  |  stop words   |    BoW     |  FNN  |
"""
MC.set_model('fnn')
MC.set_X(df['process_stpw'])
MC.predict('bow', 'fnn')
```

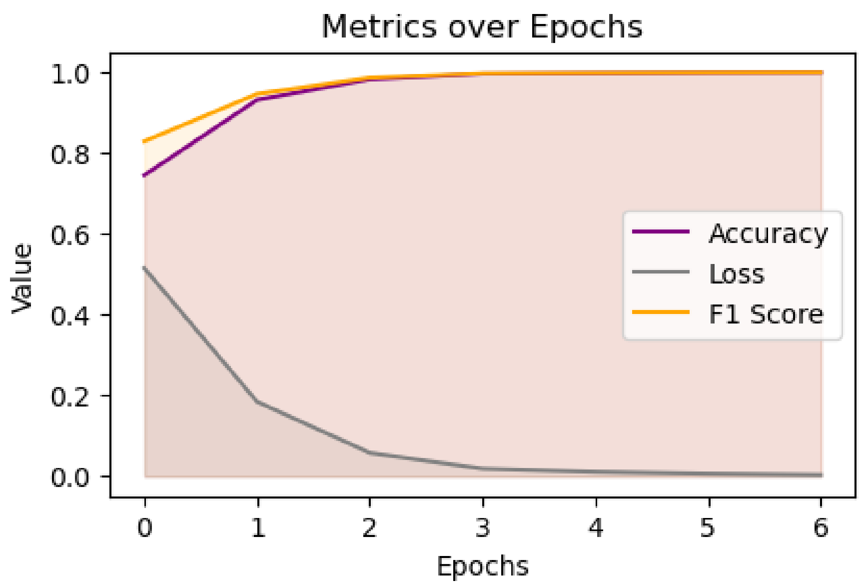
```
C:\Users\siyux\.conda\envs\mydata\Lib\site-
packages\keras\src\layers\core\dense.py:87: UserWarning:
```

```
Do not pass an `input_shape`/`input_dim` argument to a layer. When using
Sequential models, prefer using an `Input(shape)` object as the first layer in
the model instead.


Epoch 1/7
100/100              5s 36ms/step -
accuracy: 0.7558 - f1_score: 0.8288 - loss: 0.5425
Epoch 2/7
100/100              4s 36ms/step -
accuracy: 0.9405 - f1_score: 0.9531 - loss: 0.1768
Epoch 3/7
100/100              4s 37ms/step -
accuracy: 0.9853 - f1_score: 0.9885 - loss: 0.0584
Epoch 4/7
100/100              4s 36ms/step -
accuracy: 0.9944 - f1_score: 0.9953 - loss: 0.0292
Epoch 5/7
100/100              4s 36ms/step -
accuracy: 0.9951 - f1_score: 0.9962 - loss: 0.0148
Epoch 6/7
100/100              4s 37ms/step -
accuracy: 0.9955 - f1_score: 0.9962 - loss: 0.0105
Epoch 7/7
100/100              4s 35ms/step -
accuracy: 0.9984 - f1_score: 0.9986 - loss: 0.0094
25/25              0s 4ms/step
```



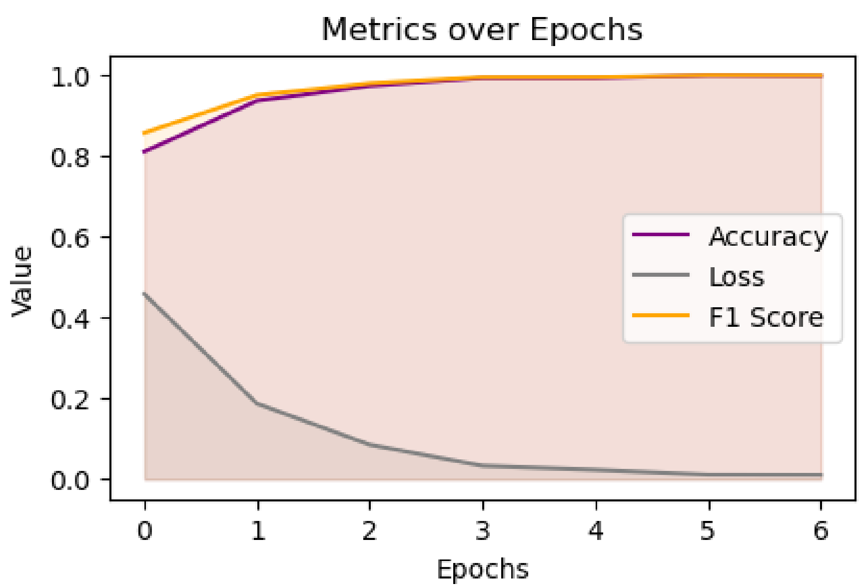
[26]:
```
"""
| Nr. | preprocessing | vectorizer | model |
|  06 |  stop words   |    TFI-DF  |  FNN  |
"""
MC.predict('tfidf', 'fnn')
```

```
Epoch 1/7
100/100              5s 34ms/step -
accuracy: 0.6774 - f1_score: 0.7824 - loss: 0.6095
Epoch 2/7
100/100              3s 34ms/step -
accuracy: 0.9370 - f1_score: 0.9499 - loss: 0.1914
Epoch 3/7
100/100              3s 35ms/step -
accuracy: 0.9821 - f1_score: 0.9864 - loss: 0.0583
Epoch 4/7
100/100              3s 34ms/step -
accuracy: 0.9956 - f1_score: 0.9966 - loss: 0.0199
Epoch 5/7
100/100              4s 35ms/step -
accuracy: 0.9985 - f1_score: 0.9989 - loss: 0.0087
Epoch 6/7
100/100              4s 35ms/step -
accuracy: 0.9993 - f1_score: 0.9995 - loss: 0.0052
Epoch 7/7
100/100              4s 35ms/step -
accuracy: 0.9996 - f1_score: 0.9997 - loss: 0.0027
25/25              0s 3ms/step
```



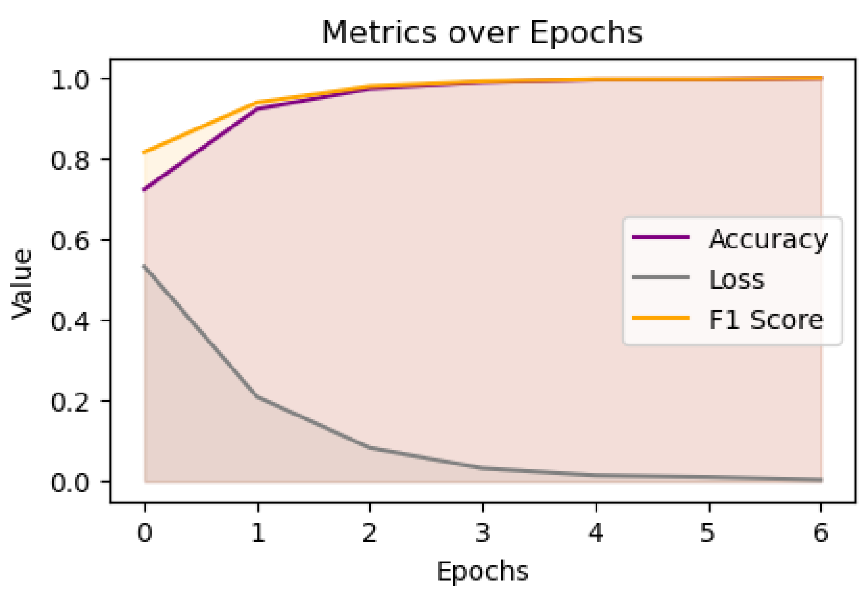
[27]:
```
"""
| Nr. | preprocessing           | vectorizer | model |
|  07 |  stop words & stemming  |    BoW     |  FNN  |
"""
MC.set_X(df['process_stpw_stem'])
MC.predict('bow', 'fnn')
```

```
Epoch 1/7
100/100              4s 25ms/step -
accuracy: 0.7534 - f1_score: 0.8123 - loss: 0.5394
Epoch 2/7
100/100              3s 26ms/step -
accuracy: 0.9325 - f1_score: 0.9491 - loss: 0.1986
Epoch 3/7
100/100              3s 25ms/step -
accuracy: 0.9765 - f1_score: 0.9820 - loss: 0.0775
Epoch 4/7
100/100              3s 25ms/step -
accuracy: 0.9915 - f1_score: 0.9930 - loss: 0.0357
Epoch 5/7
100/100              3s 25ms/step -
accuracy: 0.9902 - f1_score: 0.9922 - loss: 0.0225
Epoch 6/7
100/100              3s 26ms/step -
accuracy: 0.9988 - f1_score: 0.9990 - loss: 0.0098
Epoch 7/7
100/100              3s 25ms/step -
accuracy: 0.9974 - f1_score: 0.9979 - loss: 0.0097
25/25              0s 3ms/step
```



[28]:
```
"""
| Nr. | preprocessing            | vectorizer | model |
|  08 |  stop words & stemming   |    TFI-DF  |  FNN  |
"""
MC.predict('tfidf', 'fnn')
```

```
Epoch 1/7
100/100              3s 24ms/step -
accuracy: 0.6532 - f1_score: 0.7624 - loss: 0.6231
Epoch 2/7
100/100              3s 28ms/step -
accuracy: 0.9225 - f1_score: 0.9394 - loss: 0.2068
Epoch 3/7
100/100              2s 24ms/step -
accuracy: 0.9822 - f1_score: 0.9857 - loss: 0.0740
Epoch 4/7
100/100              2s 24ms/step -
accuracy: 0.9923 - f1_score: 0.9938 - loss: 0.0265
Epoch 5/7
100/100              2s 24ms/step -
accuracy: 0.9981 - f1_score: 0.9985 - loss: 0.0120
Epoch 6/7
100/100              2s 24ms/step -
accuracy: 0.9963 - f1_score: 0.9971 - loss: 0.0103
Epoch 7/7
100/100              3s 25ms/step -
accuracy: 0.9996 - f1_score: 0.9996 - loss: 0.0037
25/25              0s 3ms/step
```



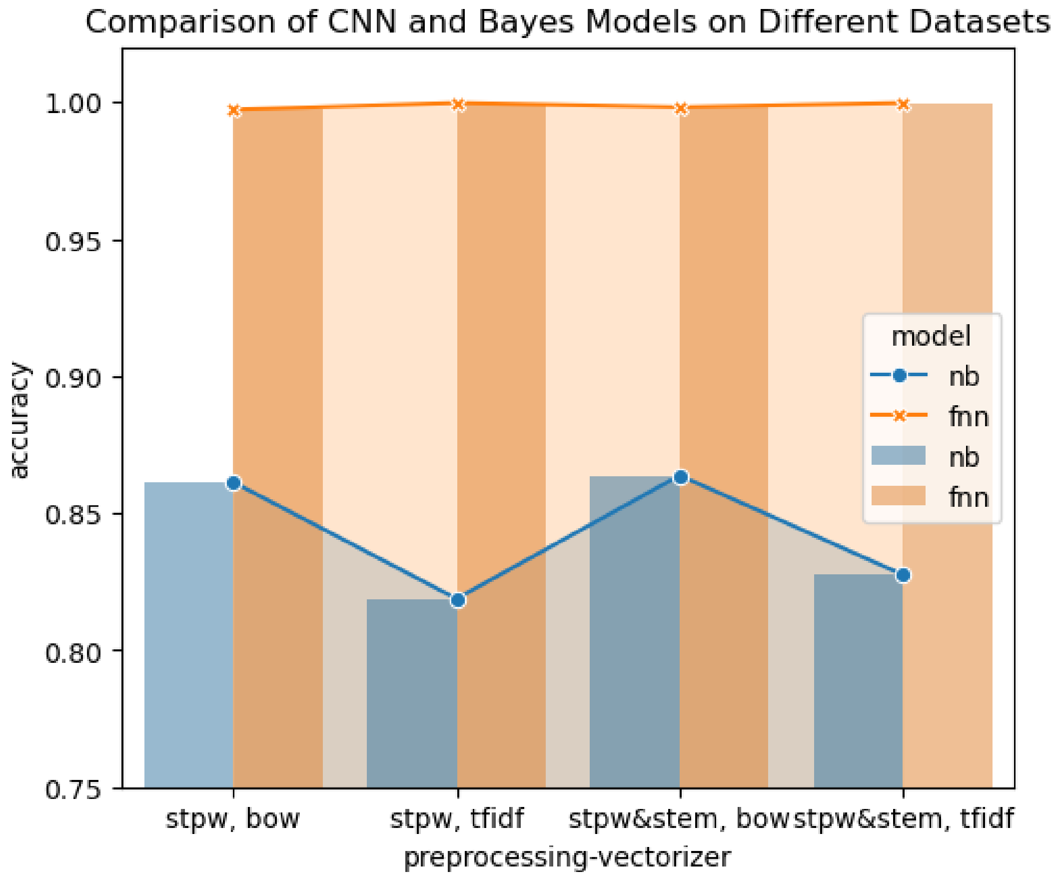
0.3.3 Sub-task 3

- Compare the performance of your naïve Bayes model with the achieved results from the feed-forward model. What can you conclude from the differences between the performance of the two models?
  ANSWER
  - Using counter vectorizer/BoW improve the accuracy significantly for naive bayes classifier, while not necessary for FNN, since FNN is apparently reaching close-to-optimal result.

[29]:
```
"""
synthetic comparison
"""
def plot_compar(data):
    """
    add normalization, plot info stored in MC.evaluation
    """
    df = pd.DataFrame(data)
    plt.figure(figsize=(6,5))
    df['process'] =␣
 ↪['stpw','stpw','stpw&stem','stpw&stem','stpw','stpw','stpw&stem','stpw&stem']
    display(df.transpose())
    df['pv'] = df['process'] + ', ' + df['vectorizer']
    sns.lineplot(x='pv', y='accuracy', hue='model', style='model', data=df,␣
 ↪markers=True, dashes=False)
    models = df['model'].unique()
    for model in models:
        subset = df[df['model'] == model]
        plt.fill_between(subset['pv'], subset['accuracy'], alpha=0.2)
    sns.barplot(x='pv', y='accuracy', hue='model', data=df, alpha=0.5)

    plt.ylim(0.75, 1.02)
    plt.title('Comparison of CNN and Bayes Models on Different Datasets')
    plt.xlabel('preprocessing-vectorizer')
    plt.ylabel('accuracy')
    plt.show()

plot_compar(MC.evaluation)
```

```
                  0        1          2          3         4         5  \
model            nb       nb         nb         nb       fnn       fnn
vectorizer      bow    tfidf        bow      tfidf       bow     tfidf
accuracy    0.86125  0.81875    0.86375     0.8275  0.997187  0.999687
process        stpw     stpw  stpw&stem  stpw&stem      stpw      stpw
```

```
                       6          7
model                fnn        fnn
vectorizer           bow      tfidf
accuracy        0.998125   0.999687
process        stpw&stem  stpw&stem
```



0.4 Task 4: PMI based word similarity

[30]:
```python
import random
```

[36]:
```python
def cooccurrence_matrix(tokenized_texts, window_size=2):
    """
    window_size: the range of context words to consider, fixed -> 2
    cooccurrence matrix: the co-occurrence counts of each word with its context␣
 ↪words
    """
    cooccu = defaultdict(Counter)
    for text in tokenized_texts:
        for idx, word in enumerate(text):
```

```python
            start = max(0, idx - window_size)
            end = min(len(text), idx + window_size + 1)
            for idx2 in range(start, end):
                if idx2 != idx:
                    cooccu[word][text[idx2]] += 1
    return cooccu

def pmi_matrix(cooccu, total_words, min_count=2):
    """
    total_words: total number of words in corpus
    min_count: minimum co-occurrence count threshold, best at 2 (avoiding None)
    PMI matrix: PMI values of each word with its context words
    """
    pmi_matrix = defaultdict(dict)
    word_counts = Counter()
    for word, neighbors in cooccu.items():
        word_counts[word] += sum(neighbors.values())

    total_count = sum(word_counts.values())
    for word, neighbors in cooccu.items():
        for neighbor, count in neighbors.items():
            if count >= min_count:
                p_w = word_counts[word] / total_count
                p_n = word_counts[neighbor] / total_count
                p_wn = count / total_count
                pmi = np.log2(p_wn / (p_w * p_n))
                if pmi > 0:
                    pmi_matrix[word][neighbor] = pmi
    return pmi_matrix

def most_similar_words(pmi_mat, word, n=5):
    if word in pmi_mat:
        similar_words = sorted(pmi_mat[word].items(), key=lambda x: x[1],␣
↪reverse=True)[:n]
        return [w for w, _ in similar_words]
    else:
        return [None] * n      # if the target word is not in the PMI matrix,␣
↪return n None values
```

[32]:
```python
df['tokenized_text'] = df['process_stpw_stem'].apply(lambda x: x.split())
cooccu_mat = cooccurrence_matrix(df['tokenized_text'].tolist())
```

[33]:
```python
total_words = sum([len(text) for text in df['tokenized_text']])
pmi_mat = pmi_matrix(cooccu_mat, total_words)
```

[34]:
```python
random_words = random.sample(list(pmi_mat.keys()), 10)
```

```
similar_words = {word: most_similar_words(pmi_mat, word) for word in␣
↪random_words}
```

[35]:
```
report_df = pd.DataFrame.from_dict(similar_words, orient='index',␣
↪columns=[f'Similar Word {i+1}' for i in range(5)])
report_df.index.name = 'Random Word'
report_df.reset_index(inplace=True)
report_df
```

[35]:
```
          Random Word  Similar Word 1 Similar Word 2 Similar Word 3  \
0              tragic         cofound           japl         currow
1           hindemith          studio         rudolf    kammermusik
2  106250802779281805  americanoffici        annaeva            gab
3                leed          owlcot    stanningley         pudsey
4           boomerang         inbound          color        revolut
5                  95   thierrybaudet   storeconnect           bode
6                  88   iduskbn29413i            122            arr
7               damag        anterior         sheath          wrist
8              decern            amaz          spend         factor
9           pakistani     superintend          walid          mumta

  Similar Word 4 Similar Word 5
0        deepest         coloss
1          cello       concerto
2           post            com
3           ls28            6ar
4         unfold         realiz
5         procur           5890
6             64          swiss
7         myelin     endothelia
8            did        content
9        mahmood          polic
```

[ ]: