

```
In [2]: import database_connection as db
import argparse
import pandas as pd
from os import path
import text_preprocess
from textblob import TextBlob
from vaderSentiment.vaderSentiment import SentimentIntensityAnalyzer
import nltk
from nltk.stem import WordNetLemmatizer
from transformers import AutoModelForSequenceClassification
from transformers import AutoTokenizer
import numpy as np
from scipy.special import softmax
from evaluator import evaluate
from datetime import datetime
import sentiment_analysis
```

```
In [3]: in_file = 'sentiment_annotations.csv'
data_in_file = pd.read_csv(in_file, sep=',', keep_default_na=False)
```

```
In [4]: data = sentiment_analysis.getDataFromDB()
```

```
In [5]: # For now, combine title and entry as 1 feature.
# TODO: evaluate perf of each.
concatenation = data['title'] + ' ' + data['entry']
```

```
In [6]: # Original Results from .csv File
start_time = datetime.now()
print(f'{datetime.now().strftime("%H:%M:%S.%f")}: Evaluating the accuracy metrics')
og_metrics = evaluate(data_in_file['annotated_sentiment'], data_in_file['sentiment'])
end_time = datetime.now()
print(f'{datetime.now().strftime("%H:%M:%S.%f")}: Total runtime: {end_time - start_time}')
```

19:18:50.890396: Evaluating the accuracy metrics.

Confusion Matrix:

```
[[105  28   0]
 [ 51  49  10]
 [  2   2  53]]
```

Classification Report:

*Ignore F1-Score since this is multiclass.

	precision	recall	f1-score	support
NEGATIVE	0.665	0.789	0.722	133
NEUTRAL	0.620	0.445	0.519	110
POSITIVE	0.841	0.930	0.883	57
accuracy			0.690	300
macro avg	0.709	0.722	0.708	300
weighted avg	0.682	0.690	0.678	300

Individualized metrics:

accuracy: 0.69

precision: [0.66455696 0.62025316 0.84126984]

recall: [0.78947368 0.44545455 0.92982456]

19:18:50.907018: Total runtime: 0:00:00.016619

```
In [7]: # Method: TextBlob, concatenating title and entry
start_time = datetime.now()
# PreProcess the text
print(f'{datetime.now().strftime("%H:%M:%S.%f")}: Preprocessing the data.')
processed = concatenation.apply(text_preprocess.preprocessText)
print(f'{datetime.now().strftime("%H:%M:%S.%f")}: Finished preprocessing the data.')
print(f'{datetime.now().strftime("%H:%M:%S.%f")}: Calculating predictions with the TextBlob statistical method.')
polarity = processed.apply(sentiment_analysis.getPolarity)
print(f'{datetime.now().strftime("%H:%M:%S.%f")}: Finished calculating predictions.')
print(f'{datetime.now().strftime("%H:%M:%S.%f")}: Analyzing the scores.')
sentiment_output = polarity.apply(sentiment_analysis.lowThresholdAnalysis)
print(f'{datetime.now().strftime("%H:%M:%S.%f")}: Finished analyzing the scores.')
print(f'{datetime.now().strftime("%H:%M:%S.%f")}: Evaluating the accuracy metrics.')
textblob_metrics = evaluate(data['annotated_sentiment'], sentiment_output)
end_time = datetime.now()
print(f'{datetime.now().strftime("%H:%M:%S.%f")}: Total runtime: {end_time - start_time}')
```

```
19:18:50.913480: Preprocessing the data.
19:18:53.266147: Finished preprocessing the data.
19:18:53.266252: Calculating predictions with the TextBlob statistical method.
19:18:53.332936: Finished calculating predictions.
19:18:53.332975: Analyzing the scores.
19:18:53.333152: Finished analyzing the scores.
19:18:53.333172: Evaluating the accuracy metrics.
Confusion Matrix:
[[ 11 134  13]
 [  2  68  9]
 [  0  18 45]]
```

Classification Report:

*Ignore F1-Score since this is multiclass.

	precision	recall	f1-score	support
NEGATIVE	0.846	0.070	0.129	158
NEUTRAL	0.309	0.861	0.455	79
POSITIVE	0.672	0.714	0.692	63
accuracy			0.413	300
macro avg	0.609	0.548	0.425	300
weighted avg	0.668	0.413	0.333	300

Individualized metrics:

```
accuracy: 0.4133333333333333
precision: [0.84615385 0.30909091 0.67164179]
recall: [0.06962025 0.86075949 0.71428571]
19:18:53.339999: Total runtime: 0:00:02.426535
```

```
In [8]: # Vader: Valence Aware Dictionary and Sentiment Reasoner
start_time = datetime.now()
print(f'{datetime.now().strftime("%H:%M:%S.%f")}: Preprocessing the data.')
processed = concatenation.apply(text_preprocess.preprocessText)
print(f'{datetime.now().strftime("%H:%M:%S.%f")}: Finished preprocessing the data.')
print(f'{datetime.now().strftime("%H:%M:%S.%f")}: Calculating predictions with the Vader statistical method.')
scores = processed.apply(sentiment_analysis.getVaderSentiment)
print(f'{datetime.now().strftime("%H:%M:%S.%f")}: Finished calculating predictions.')
print(f'{datetime.now().strftime("%H:%M:%S.%f")}: Analyzing the scores.')
sentiment_output = scores.apply(sentiment_analysis.highThresholdAnalysis)
print(f'{datetime.now().strftime("%H:%M:%S.%f")}: Finished analyzing the scores.')
print(f'{datetime.now().strftime("%H:%M:%S.%f")}: Evaluating the accuracy metrics.')
vader_metrics = evaluate(data['annotated_sentiment'], sentiment_output)
end_time = datetime.now()
print(f'{datetime.now().strftime("%H:%M:%S.%f")}: Total runtime: {end_time - start_time}')
```

```
19:18:53.343772: Preprocessing the data.
19:18:54.971345: Finished preprocessing the data.
19:18:54.971450: Calculating predictions with the Vader statistical method.
19:18:56.409766: Finished calculating predictions.
19:18:56.409871: Analyzing the scores.
19:18:56.410077: Finished analyzing the scores.
19:18:56.410098: Evaluating the accuracy metrics.
```

Confusion Matrix:

```
[[37 79 42]
 [ 8 37 34]
 [ 0 16 47]]
```

Classification Report:

*Ignore F1-Score since this is multiclass.

	precision	recall	f1-score	support
NEGATIVE	0.822	0.234	0.365	158
NEUTRAL	0.280	0.468	0.351	79
POSITIVE	0.382	0.746	0.505	63
accuracy			0.403	300
macro avg	0.495	0.483	0.407	300
weighted avg	0.587	0.403	0.390	300

Individualized metrics:

```
accuracy: 0.4033333333333333
precision: [0.82222222 0.28030303 0.38211382]
recall: [0.23417722 0.46835443 0.74603175]
19:18:56.417536: Total runtime: 0:00:03.073756
```

```

In [11]: # HuggingFace sentiment analysis pipeline with RoBERTa twitter model
start_time = datetime.now()

print(f'{datetime.now().strftime("%H:%M:%S.%f")}: Preprocessing the data.')
preprocessed = concatenation.apply(sentiment_analysis.preprocess)
print(f'{datetime.now().strftime("%H:%M:%S.%f")}: Finished preprocessing the data.')
print(f'{datetime.now().strftime("%H:%M:%S.%f")}: Calculating predictions with the model.')

# using autotokenizer pretrained on same model as used instead of my custom preprocessor
# processed = concatenation.apply(text_preprocess.preprocessText)

# Use tokenizer from base model, not task model.
# RoBERTa's max token length is 512.
tokenizer = AutoTokenizer.from_pretrained('cardiffnlp/twitter-roberta-base')

# PyTorch
# TODO: consider tuning classifier model hyperparams: hidden_states, attentions
model='cardiffnlp/twitter-roberta-base-sentiment'
task='sentiment'
"""
# Valid tasks for this model:
# emoji, emotion, hate, irony, offensive, sentiment
# stance/abortion, stance/atheism, stance/climate, stance/feminist, stance/hillary
"""

classifier = AutoModelForSequenceClassification.from_pretrained(model)

scores_series = preprocessed.apply(sentiment_analysis.getRobertaScore, args=(model, tokenizer))
print(f'{datetime.now().strftime("%H:%M:%S.%f")}: Finished calculating predictions.')
print(f'{datetime.now().strftime("%H:%M:%S.%f")}: Analyzing the scores.')
sentiment_output = scores_series.apply(sentiment_analysis.robertaScoresAnalysis)
print(f'{datetime.now().strftime("%H:%M:%S.%f")}: Finished analyzing the scores.')

print(f'{datetime.now().strftime("%H:%M:%S.%f")}: Evaluating the accuracy metrics.')
hf_roberta_metrics = evaluate(data['annotated_sentiment'], sentiment_output)
end_time = datetime.now()
print(f'{datetime.now().strftime("%H:%M:%S.%f")}: Total runtime: {end_time - start_time}')

```

```

17:26:35.209837: Preprocessing the data.
17:26:35.223722: Finished preprocessing the data.
17:26:35.223813: Calculating predictions with the Roberta Twitter model.
17:29:11.852828: Finished calculating predictions.
17:29:11.852951: Analyzing the scores.
17:29:11.853725: Finished analyzing the scores.
17:29:11.853747: Evaluating the accuracy metrics.

```

Confusion Matrix:

```

[[113  40   5]
 [ 26  42  11]
 [   0   5  58]]

```

Classification Report:

*Ignore F1-Score since this is multiclass.

	precision	recall	f1-score	support
NEGATIVE	0.813	0.715	0.761	158
NEUTRAL	0.483	0.532	0.506	79
POSITIVE	0.784	0.921	0.847	63
accuracy			0.710	300
macro avg	0.693	0.722	0.705	300
weighted avg	0.720	0.710	0.712	300

Individualized metrics:
accuracy: 0.71
precision: [0.81294964 0.48275862 0.78378378]
recall: [0.71518987 0.53164557 0.92063492]
Confusion Matrix:
[[113 40 5]
 [26 42 11]
 [0 5 58]]

Classification Report:
*Ignore F1-Score since this is multiclass.

	precision	recall	f1-score	support
NEGATIVE	0.813	0.715	0.761	158
NEUTRAL	0.483	0.532	0.506	79
POSITIVE	0.784	0.921	0.847	63
accuracy			0.710	300
macro avg	0.693	0.722	0.705	300
weighted avg	0.720	0.710	0.712	300

Individualized metrics:
accuracy: 0.71
precision: [0.81294964 0.48275862 0.78378378]
recall: [0.71518987 0.53164557 0.92063492]
17:29:11.867042: Total runtime: 0:02:36.657257

```
In [44]: # HuggingFace sentiment analysis pipeline with RoBERTa twitter model
# There is a difference in evaluation between the database and the CSV file.
# These are results against the CSV file.
start_time = datetime.now()
concatenation = data_in_file['title'] + ' ' + data_in_file['entry']

print(f'{datetime.now().strftime("%H:%M:%S.%f")}: Preprocessing the data.')
preprocessed = concatenation.apply(sentiment_analysis.preprocess)
print(f'{datetime.now().strftime("%H:%M:%S.%f")}: Finished preprocessing the data.')
print(f'{datetime.now().strftime("%H:%M:%S.%f")}: Calculating predictions with the model.')

# using autotokenizer pretrained on same model as used instead of my custom preprocessor
# processed = concatenation.apply(text_preprocess.preprocessText)

# Use tokenizer from base model, not task model.
# RoBERTa's max token length is 512.
tokenizer = AutoTokenizer.from_pretrained('cardiffnlp/twitter-roberta-base')

# PyTorch
# TODO: consider tuning classifier model hyperparams: hidden_states, attentions
model='cardiffnlp/twitter-roberta-base-sentiment'
task='sentiment'
"""
# Valid tasks for this model:
# emoji, emotion, hate, irony, offensive, sentiment
# stance/abortion, stance/atheism, stance/climate, stance/feminist, stance/hillary
"""

classifier = AutoModelForSequenceClassification.from_pretrained(model)

scores_series = preprocessed.apply(sentiment_analysis.getRobertaScore, args=(model, tokenizer))
print(f'{datetime.now().strftime("%H:%M:%S.%f")}: Finished calculating predictions.')
print(f'{datetime.now().strftime("%H:%M:%S.%f")}: Analyzing the scores.')
sentiment_output = scores_series.apply(sentiment_analysis.robertaScoresAnalysis)
print(f'{datetime.now().strftime("%H:%M:%S.%f")}: Finished analyzing the scores.')

print(f'{datetime.now().strftime("%H:%M:%S.%f")}: Evaluating the accuracy metrics.')
hf_roberta_metrics = evaluate(data_in_file['annotated_sentiment'], sentiment_output)
end_time = datetime.now()
print(f'{datetime.now().strftime("%H:%M:%S.%f")}: Total runtime: {end_time - start_time}')
```

```
18:34:47.195394: Preprocessing the data.
18:34:47.205984: Finished preprocessing the data.
18:34:47.206051: Calculating predictions with the Roberta Twitter model against the .csv file.
18:37:21.464121: Finished calculating predictions.
18:37:21.464321: Analyzing the scores.
18:37:21.465230: Finished analyzing the scores.
18:37:21.465273: Evaluating the accuracy metrics.
```

Confusion Matrix:

```
[[104  26   3]
 [ 35  58  17]
 [  0   3  54]]
```

Classification Report:

*Ignore F1-Score since this is multiclass.

	precision	recall	f1-score	support
NEGATIVE	0.748	0.782	0.765	133
NEUTRAL	0.667	0.527	0.589	110
POSITIVE	0.730	0.947	0.824	57

accuracy			0.720	300
macro avg	0.715	0.752	0.726	300
weighted avg	0.715	0.720	0.712	300

Individualized metrics:

accuracy: 0.72

precision: [0.74820144 0.66666667 0.72972973]

recall: [0.78195489 0.52727273 0.94736842]

18:37:21.471527: Total runtime: 0:02:34.277609

```
In [41]: import matplotlib.pyplot as plt
%matplotlib inline

gold_class_counts = data_in_file['annotated_sentiment'].value_counts()

plt.figure(figsize=(15,7))

plt.subplot(1,5,1)
plt.title("Gold class division")
plt.pie(gold_class_counts.values, labels = gold_class_counts.index, explode = (0, 0, 0.1))

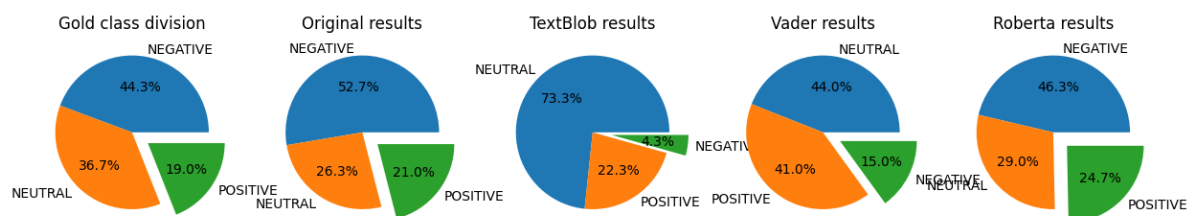
plt.subplot(1,5,2)
plt.title("Original results")
plt.pie(og_metrics[3].values, labels = og_metrics[3].index, explode = (0, 0, 0.1))

plt.subplot(1,5,3)
plt.title("TextBlob results")
plt.pie(textblob_metrics[3].values, labels = textblob_metrics[3].index, explode = (0, 0, 0.1))

plt.subplot(1,5,4)
plt.title("Vader results")
plt.pie(vader_metrics[3].values, labels = vader_metrics[3].index, explode = (0, 0, 0.1))

plt.subplot(1,5,5)
plt.title("Roberta results")
plt.pie(hf_roberta_metrics[3].values, labels = hf_roberta_metrics[3].index, explode = (0, 0, 0.1))

print()
```



```

In [42]: # Abbreviation
og = og_metrics
tb = textblob_metrics
vd = vader_metrics
hf = hf_roberta_metrics

# set width of bar
barWidth = 0.25
fig = plt.subplots(figsize =(12, 8))

# set height of grouped metrics per class
accuracy = [og[0], tb[0], vd[0], hf[0]]
precision = [np.average(og[1]), np.average(tb[1]), np.average(vd[1]), np.average(hf[1])]
recall = [np.average(og[2]), np.average(tb[2]), np.average(vd[2]), np.average(hf[2])]

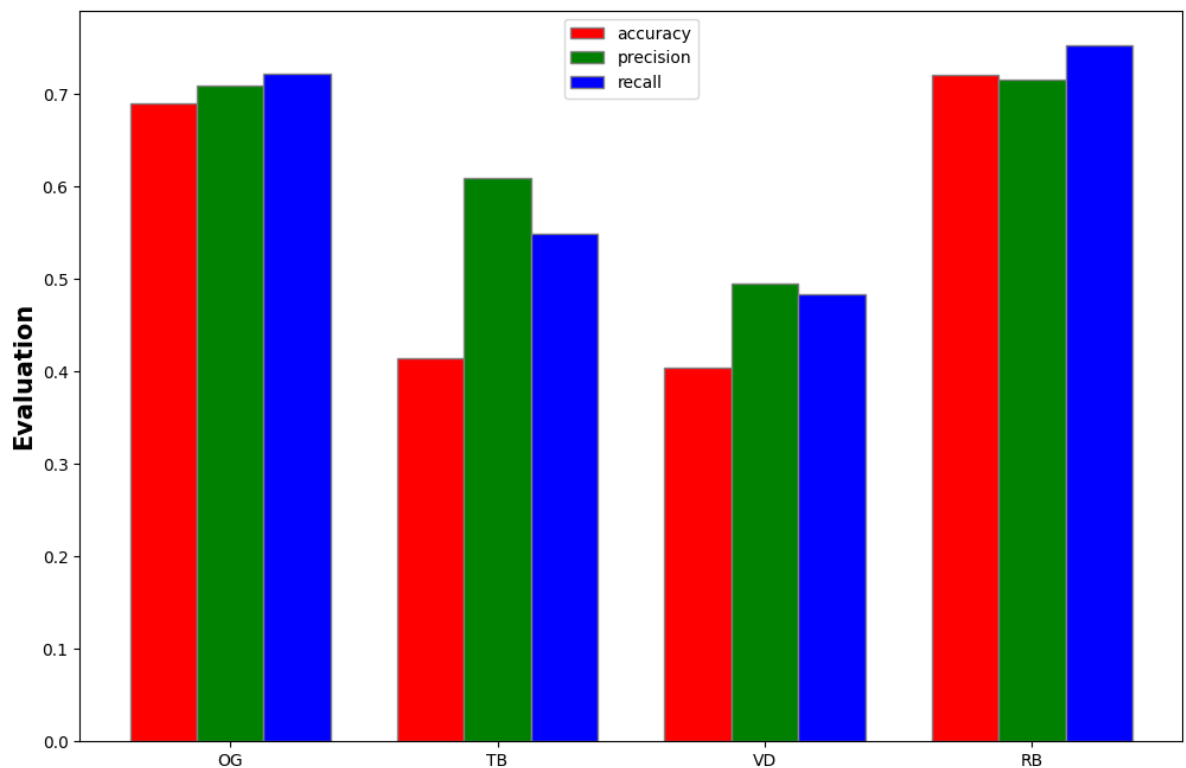
# Set position of bar on X axis
br1 = np.arange(len(accuracy))
br2 = [x + barWidth for x in br1]
br3 = [x + barWidth for x in br2]

# Make the plot
plt.bar(br1, accuracy, color ='r', width = barWidth,
        edgecolor ='grey', label ='accuracy')
plt.bar(br2, precision, color ='g', width = barWidth,
        edgecolor ='grey', label ='precision')
plt.bar(br3, recall, color ='b', width = barWidth,
        edgecolor ='grey', label ='recall')

# Adding Xticks
plt.xlabel('Models', fontweight ='bold', fontsize = 15)
plt.ylabel('Evaluation', fontweight ='bold', fontsize = 15)
plt.xticks([r + barWidth for r in range(len(acc))],
           ['OG', 'TB', 'VD', 'RB'])

plt.legend()
plt.show()

```



Models

```
In [43]: og = og_metrics
rb = hf_roberta_metrics

metrics = ("accuracy", "precision", "recall")

metrics_dict = {
    'original': (og[0], round(np.average(og[1]), 2), round(np.average(og[2]
    'RoBERTa': (rb[0], round(np.average(rb[1]), 2), round(np.average(rb[2])
})

x = np.arange(len(metrics)) # the label locations
width = 0.25 # the width of the bars
multiplier = 0

fig, ax = plt.subplots(constrained_layout=True)

for attribute, measurement in metrics_dict.items():
    offset = width * multiplier
    rects = ax.bar(x + offset, measurement, width, label=attribute)
    ax.bar_label(rects, padding=3)
    multiplier += 1

# Add some text for labels, title and custom x-axis tick labels, etc.
ax.set_ylabel('Length (mm)')
ax.set_title('Evaluation of models')
ax.set_xticks(x + width, metrics)
ax.legend(loc='upper left', ncols=3)
ax.set_ylim(0, 1)

plt.show()
```

