project

March 27, 2025

1 Research Project

COMP 435 Introduction to Machine Learning, Spring 2025

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- Author: Ina Tang
- Dataset: Sentiment140 on Kaggle
- Citation: Go, A., Bhayani, R. and Huang, L., 2009. Twitter sentiment classification using distant supervision. CS224N Project Report, Stanford, 1(2009), p.12.

  Just 75% accuracy would be good… – Dr. Hutchins

1.0.1 Schema

- target: the polarity of the tweet (0 = negative, 4 = positive)
- ids: The id of the tweet (2087)
- date: the date of the tweet (Sat May 16 23:58:44 UTC 2009)
- flag: The query (lyx). If there is no query, then this value is NO_QUERY.
- user: the user that tweeted (robotickilldozr)
- text: the text of the tweet (Lyx is cool)

1.0.2 Ideas

- [ ] Proportions of + and -
- [ ] Total frequency of word
  - [ ] remove pronouns, prepositions, conjunctions, article adjectives, etc. ?
  - [ ] cutoff for words with (say) less than 1% frequency
- [ ] Correlation between word and each label (porportions)
- [ ] Affect of capitalization and punctuations on prediction
- [ ] Use deep neural network(s) to identify strong FPs and FNs (weird data points)
- [ ] (Synthesized feature) Certain collection(s) of words that strongly correlates with one of the labels

1.0.3 Previous labs

- Linear Regression with a Real Dataset
- Linear Regression with Synthetic Data
- Logistic Regression

1.1 Setup

[ ]:
```
# pip install numpy pandas matplotlib seaborn  # torch
```

[48]:
```
import numpy as np
import pandas as pd
# import torch
import matplotlib.pyplot as plt
import seaborn as sns  # sns.pairplot

from typing import Dict, List
```

[49]:
```
# generated by GitHub Copilot with minor edits

# Load & setup
# runtime: 5s
df = pd.read_csv('data.csv', encoding='latin-1', header=None)
df.columns = ['target', 'id', 'date', 'flag', 'user', 'text']  # target: 0 =␣
↪negative, 4 = positive
df['target'] = df['target'].replace({4: 1})  # Replace 4s (positives) with 1s␣
↪in the 'target' column
print(df.head())
```

```
   target          id                          date     flag  \
0       0  1467810369  Mon Apr 06 22:19:45 PDT 2009  NO_QUERY
1       0  1467810672  Mon Apr 06 22:19:49 PDT 2009  NO_QUERY
2       0  1467810917  Mon Apr 06 22:19:53 PDT 2009  NO_QUERY
3       0  1467811184  Mon Apr 06 22:19:57 PDT 2009  NO_QUERY
4       0  1467811193  Mon Apr 06 22:19:57 PDT 2009  NO_QUERY

              user                                               text
0  _TheSpecialOne_  @switchfoot http://twitpic.com/2y1zl - Awww, t…
1    scotthamilton  is upset that he can't update his Facebook by …
2         mattycus  @Kenichan I dived many times for the ball. Man…
3          ElleCTF    my whole body feels itchy and like its on fire
4           Karoli  @nationwideclass no, it's not behaving at all…
```

[52]:
```
print(f"Total number of examples: {df['target'].value_counts().sum()}")
```

```
Total number of examples: 1600000
```

[50]:
```
# Helpful constants

NUMBER_OF_TARGET_VALUES = 2
TOTAL_NUMBER_OF_EXAMPLES = 16000000
```

[ ]:
```
# Apply seaborn style to all matplotlib plots!
sns.set_theme(style="whitegrid", palette="pastel")
```

[ ]:

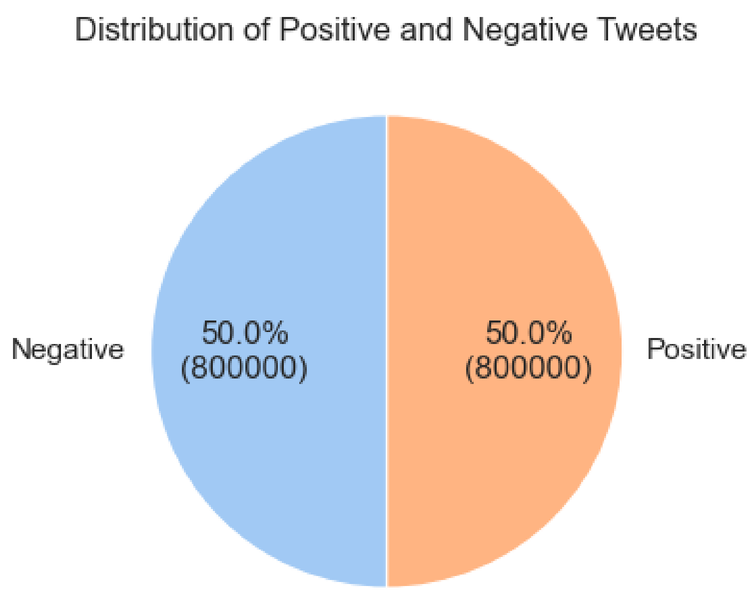
```python
# generated by GitHub Copilot with minor edits

# Plot ratio of positive and negative tweets
# runtime: 0s

def func(pct, allvals):
    absolute = int(np.round(pct / 100. * np.sum(allvals)))
    return f"{pct:.1f}%\n({absolute:d})"

# Data for the pie chart
data = df['target'].value_counts()

# Create the pie chart
plt.figure(figsize=(4, 4))
plt.pie(
    data,
    labels=['Negative', 'Positive'],  # Adjust labels as needed
    autopct=lambda pct: func(pct, data),
    startangle=90
)
plt.title('Distribution of Positive and Negative Tweets')
plt.show()
```



1.2 "Unigram" / Inidivdual Words

[54]:
```python
# generated by GitHub Copilot with minor edits
# runtime: 45s

print("Counting words...")
word_counts: Dict[str, Dict[int, int]] = {}  # word -> target -> frequency

for i, row in df.iterrows():
    words: List[str] = list(set(row['text'].split()))
    target: int = row['target']
    for word in words:
        if word in word_counts:
            word_counts[word][target] += 1
        else:
            word_counts[word] = {0: 0, 1: 0}  # initialize
            word_counts[word][target] = 1

print("Sorting words by total frequency...")  # runtime: 1s
word_counts = {k: v for k, v in sorted(word_counts.items(), key=lambda item:␣
 ↪sum(item[1].values()), reverse=True)}  # sort by counts
```

```
Counting words…
Sorting words by total frequency…
```

[55]:
```python
# print(word_counts)
```

[56]:
```python
# generated by GitHub Copilot with minor edits
# runtime: 15s
word_counts_df = pd.DataFrame(word_counts).T.reset_index()
word_counts_df.columns = ['word', 'neg', 'pos']
# pos: number of positive examples which contains the word
word_counts_df['total'] = word_counts_df['neg'] + word_counts_df['pos']
word_counts_df.head()
```

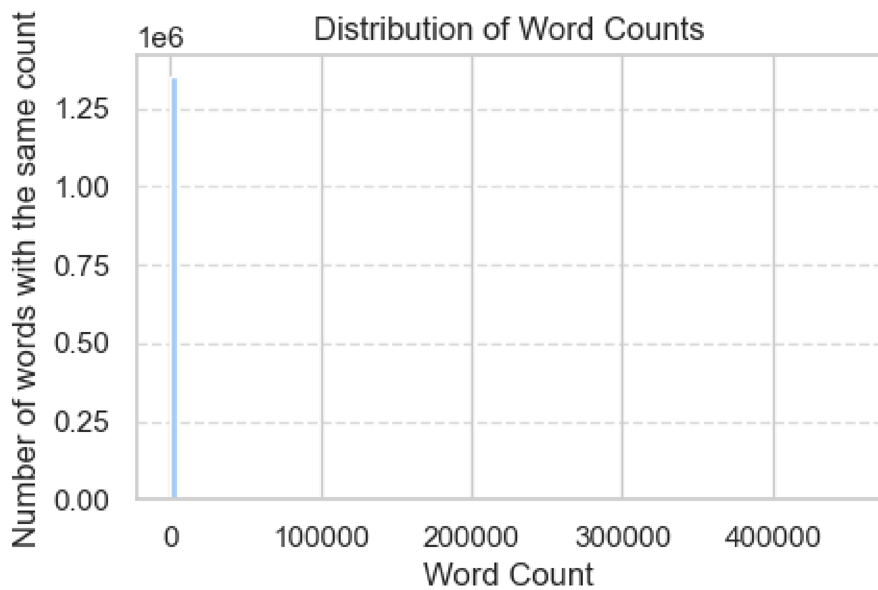
[56]:

	word	neg	pos	total
0	to	243891	205548	449439
1	the	198554	204706	403260
2	I	225262	157744	383006
3	a	154666	166868	321534
4	my	148772	103172	251944

[67]:
```python
# generated by GitHub Copilot with minor edits

# Plot the distribution of the words
plt.figure(figsize=(5, 3))
# sns.kdeplot(word_counts_df['total'], fill=True, color=sns.
 ↪color_palette("pastel")[0], alpha=0.7)
```

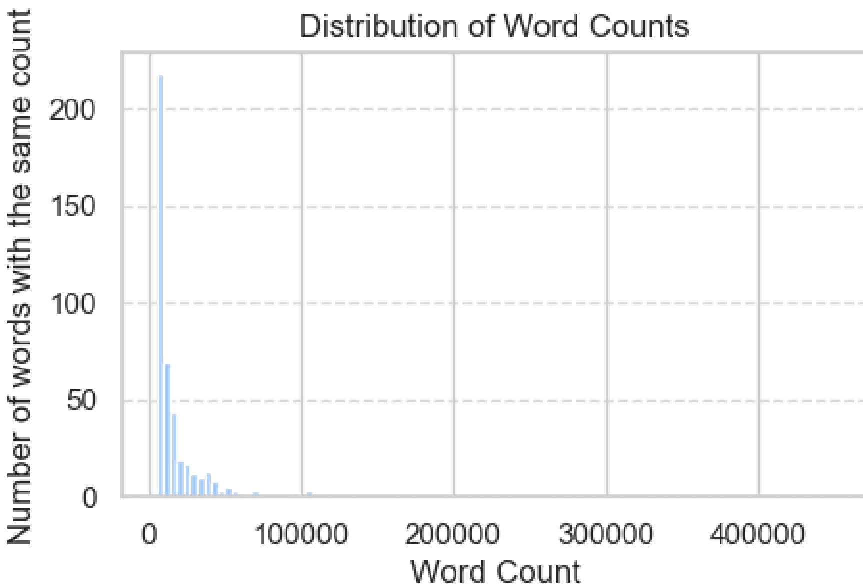
```
plt.hist(word_counts_df['total'], bins=100)
# TODO: Fix the following line
# plt.stairs(word_counts_df['total'], color=sns.color_palette("pastel")[0])
plt.title('Distribution of Word Counts')
plt.xlabel('Word Count')
plt.ylabel('Number of words with the same count')
plt.grid(axis='y', linestyle='--', alpha=0.7)
plt.show()
```



Since most words appears only a few times in the entire dataset, the plot is strongly right-skewed. We can verify that the plot is not just one bar but is in fact right-skewed with the following operation:

[68]:
```
# remove words that appear only a certain number of times in the dataset to␣
↪visualize the distribution better
word_counts_trimmed_df = word_counts_df[word_counts_df['total'] > 5000]

# plot the distribution of the words again
plt.figure(figsize=(5, 3))
plt.hist(word_counts_trimmed_df['total'], bins=100)
plt.title('Distribution of Word Counts')
plt.xlabel('Word Count')
plt.ylabel('Number of words with the same count')
plt.grid(axis='y', linestyle='--', alpha=0.7)
plt.show()
```



We can remove article adjectives, conjunctions, prepositions, etc. to see better if there are particular words that or collections of words are correlated to positive or negative emotion.

[59]:
```
# generated by GitHub Copilot with minor edits
pronouns: List[str] = ['i', 'me', 'my', 'mine', 'myself', 'we', 'us', 'our',␣
↪'ours', 'ourselves', 'you', 'your', 'yours', 'yourself', 'yourselves', 'he',␣
↪'him', 'his', 'himself', 'she', 'her', 'hers', 'herself', 'it', 'its',␣
↪'itself', 'they', 'them', 'their', 'theirs', 'themselves', 'what', 'which',␣
↪'who', 'whom', 'whose', 'this', 'that', 'these', 'those']
helping_verbs: List[str] = ['am', 'is', 'are', 'was', 'were', 'be', 'been',␣
↪'being', 'have', 'has', 'had', 'do', 'does', 'did', 'shall', 'will',␣
↪'should', 'would', 'may', 'might', 'must', 'can', 'could']
article_adj: List[str] = ['a', 'an', 'the']
conjunctions: List[str] = ['and', 'but', 'or', 'nor', 'for', 'yet', 'so']
prepositions: List[str] = ['aboard', 'about', 'above', 'across', 'after',␣
↪'against', 'along', 'among', 'around', 'at', 'before', 'behind', 'below',␣
↪'beneath', 'beside', 'between', 'beyond', 'by', 'down', 'during', 'except',␣
↪'for', 'from', 'in', 'inside', 'into', 'like', 'near', 'of', 'off', 'on',␣
↪'onto', 'out', 'outside', 'over', 'past', 'since', 'through', 'throughout',␣
↪'to', 'toward', 'under', 'underneath', 'until', 'up', 'upon', 'with',␣
↪'within', 'without']
neutral_words: List[str] = pronouns + helping_verbs + article_adj +␣
↪conjunctions + prepositions

word_counts_filtered_df = word_counts_df[~word_counts_df['word'].str.lower().
↪isin(neutral_words)]
word_counts_filtered_df.head()
```

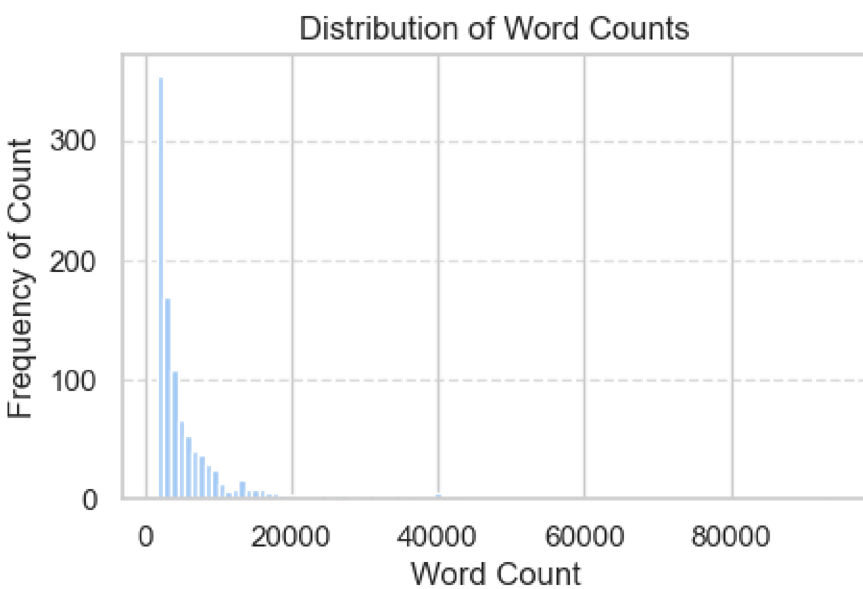
[59]:

	word	neg	pos	total
22	just	48767	45315	94082
23	I'm	52391	40770	93161
25	not	59359	25921	85280
27	get	42487	31566	74053
31	all	33968	31831	65799

[69]:

```
# Plot again
plt.figure(figsize=(5, 3))
plt.hist(word_counts_filtered_df['total'], bins=100)
plt.title('Distribution of Word Counts')
plt.xlabel('Word Count')
plt.ylabel('Frequency of Count')
plt.grid(axis='y', linestyle='--', alpha=0.7)
plt.show()

# OK I need to do another plot
```



Now we can actually see somethings from the data…We can create a another column representing the relative frequency of positive tweets associated with the word.

[70]:

```
# generated by GitHub Copilot with minor edits

word_counts_filtered_df['pos_ratio'] = word_counts_filtered_df['pos'] /␣
↪word_counts_filtered_df['total']
```

```
word_counts_filtered_df.loc[:, 'intensity'] =
↪abs(word_counts_filtered_df['pos_ratio'] - 0.5) / 0.5  # [0, 1], how
↪strongly the word is correlated with either positive or negative
word_counts_filtered_df = word_counts_filtered_df.sort_values(by='intensity',
↪ascending=False)

word_counts_filtered_df.head()
```

[70]:

```
                word    neg   pos  total  pos_ratio  intensity  \
961              Sad   1937    80   2017   0.039663   0.920674
675             sad.   2946   138   3084   0.044747   0.910506
1064  #followfriday      86  1733   1819   0.952721   0.905443
121              sad  18033   936  18969   0.049344   0.901313
428            hurts   5168   278   5446   0.051047   0.897907

      total x intensity
961              1857.0
675              2808.0
1064             1647.0
121             17097.0
428              4890.0
```

- `pos_ratio` is the proportion of positive examples wrt all examples
- `intensity` is a measurement of strength of the word's correlation with either a positive or negative emotion, i.e., the distance between `pos_ratio` and `0.5`.
  - 0.5 means the word occurs equally frequently in positive and negative tweets
  - i.e, the word is not directly correlated with either emotion

Notice the examples that might cause overfitting :) While some words are very strongly correlated with emotions (i.e., they only appear in positive/negative tweets), their relative frequency in the dataset is negligible. We might as well remove words with negligible frequency…

[62]:

```
threshhold: float = 0.0001  # minimum relative frequency; play with this

word_counts_filtered_df =
↪word_counts_filtered_df[word_counts_filtered_df['total'] > threshhold *
↪TOTAL_NUMBER_OF_EXAMPLES]
word_counts_filtered_df.head()
```

[62]:

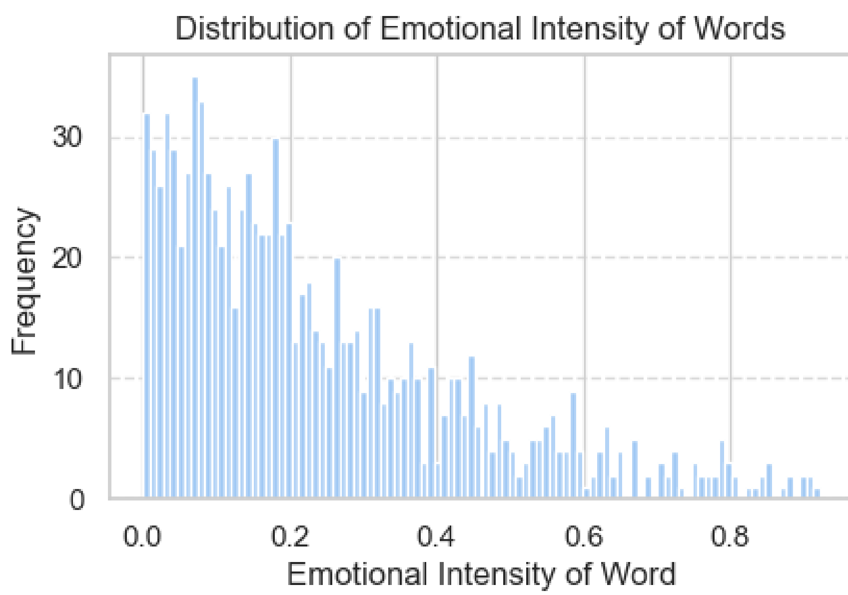
```
                word    neg   pos  total  pos_ratio  intensity
961              Sad   1937    80   2017   0.039663   0.920674
675             sad.   2946   138   3084   0.044747   0.910506
1064  #followfriday      86  1733   1819   0.952721   0.905443
121              sad  18033   936  18969   0.049344   0.901313
428            hurts   5168   278   5446   0.051047   0.897907
```

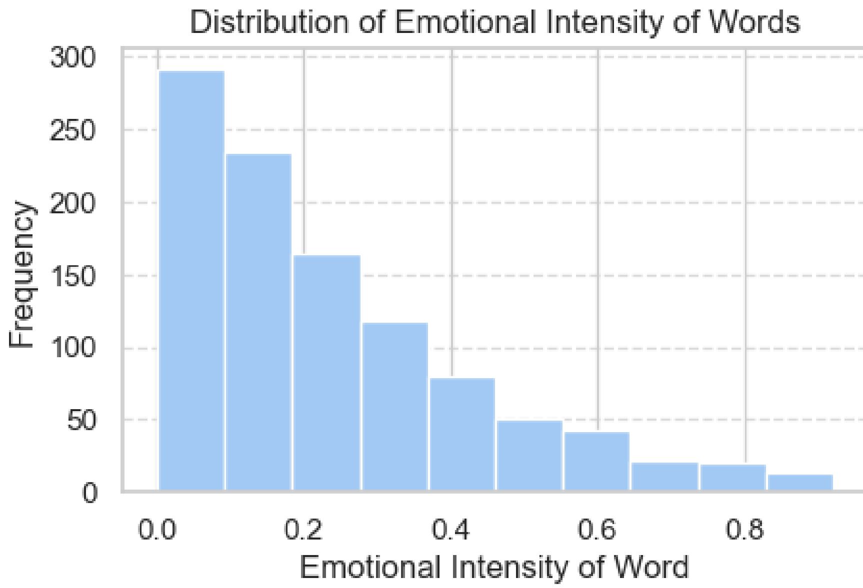
[ ]:

```
# Plot the distribution of intensity
```

```
# bin = 100
plt.figure(figsize=(5, 3))
plt.hist(word_counts_filtered_df['intensity'], bins=100)
plt.title('Distribution of Emotional Intensity of Words')
plt.xlabel('Emotional Intensity of Word')
plt.ylabel('Frequency')
plt.grid(axis='y', linestyle='--', alpha=0.7)
plt.show()

# bin = 10
plt.figure(figsize=(5, 3))
plt.hist(word_counts_filtered_df['intensity'], bins=10)
plt.title('Distribution of Emotional Intensity of Words')
plt.xlabel('Emotional Intensity of Word')
plt.ylabel('Frequency')
plt.grid(axis='y', linestyle='--', alpha=0.7)
plt.show()
```





A beautiful atypical right-skewed distribution! i.e., most words are not emotionally intense.

A synthetic feature multiplying total and intensity would reveal the most commons words with a considerable emotional intensity.

[64]:
```
# modify intensity to account for trustworthiness / quantity / total
word_counts_filtered_df['total x intensity'] =␣
↪(word_counts_filtered_df['intensity'] * word_counts_filtered_df['total'])
word_counts_filtered_df = word_counts_filtered_df.sort_values(by='total x␣
↪intensity', ascending=False)
word_counts_filtered_df.head()
```

[64]:

	word	neg	pos	total	pos_ratio	intensity	total x intensity
25	not	59359	25921	85280	0.303952	0.392097	33438.0
76	miss	27753	4658	32411	0.143717	0.712567	23095.0
43	love	12800	35220	48020	0.733444	0.466889	22420.0
44	no	34460	13148	47608	0.276172	0.447656	21312.0
46	work	32027	12681	44708	0.283641	0.432719	19346.0

The topmost examples in `word_counts_filtered` now are the words that are most correlated with a strong emotion either positive or negative.

1.3 Bigrams