data report

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# 1 Silent Signals Dataset - Combined Data Report

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#### 1.1 1. Introduction

This notebook provides a data report on the combined data from the Silent Signals dataset. - Data inspection and label distribution. - Key observations regarding root words in the dogwhistle class. - The impact of manual label review on dataset quality.

## 1.2 2. Data Import and Preprocessing

```
[]: from datasets import load_dataset
     import matplotlib.pyplot as plt
     import numpy as np
     import pandas as pd
     import seaborn as sns
     dataset = load_dataset("SALT-NLP/silent_signals")
     print(dataset)
     dataset = dataset["train"]
     # as pandas dataframe
     df = pd.DataFrame(dataset)
     # function that drops duplicates but saves those dropped instances in a_{\sqcup}
      ⇔separate data frame
     def drop duplicates save(df):
         duplicates = df[df.duplicated(subset=["content"], keep=False)]
         df = df.drop_duplicates(subset=["content"])
         # drop missing values in lable and content
         df = df.dropna(subset=["content"])
         if "lable" in df.columns:
             df = df.dropna(subset=["lable"])
         return df, duplicates
```

/Users/linozurmuhl/miniforge3/envs/NLP/lib/python3.11/site-packages/tqdm/auto.py:21: TqdmWarning: IProgress not found. Please update

```
jupyter and ipywidgets. See
     https://ipywidgets.readthedocs.io/en/stable/user_install.html
       from .autonotebook import tqdm as notebook_tqdm
     MPS is available on this device
     DatasetDict({
         train: Dataset({
             features: ['dog_whistle', 'dog_whistle_root', 'ingroup', 'content',
     'date', 'speaker', 'chamber', 'subreddit', 'source', 'definition', 'type',
     'party'],
             num_rows: 16258
         })
     })
 [2]: # filter out the informal and formal sentences
      df informal = df[df["type"] == "Informal"]
      df_formal = df[df["type"] == "Formal"]
      print('With duplicates:', df_informal.shape, df_formal.shape)
      # drop duplicates
      df_informal, duplicates_if_1 = drop_duplicates_save(df_informal)
      df_formal, duplicates_f_1 = drop_duplicates_save(df_formal)
      print('Without duplicates:', df_informal.shape, df_formal.shape)
     With duplicates: (12923, 12) (3335, 12)
     Without duplicates: (12901, 12) (3298, 12)
 [3]: # load csv 0 Instances
      null_dataset_formal = pd.read_csv("0_data/formal_neg_predictions.csv")
     null_dataset_informal = pd.read_csv("0_data/informal_neg_predictions.csv")
     /var/folders/vx/1wqkklmd4qzbv02gbc6344wc0000gn/T/ipykernel_61961/3542576506.py:2
     : DtypeWarning: Columns (9,10) have mixed types. Specify dtype option on import
     or set low_memory=False.
       null_dataset_formal = pd.read_csv("0_data/formal_neg_predictions.csv")
[10]: # join null informal data and original informal data
      df_informal = pd.concat([df_informal, null_dataset_informal])
      # label missing values as 1 in label column
      df_informal['lable'] = df_informal['lable'].fillna(1)
      # join null formal data and original formal data
      df_formal = pd.concat([df_formal, null_dataset_formal])
      # label missing values as 0 in label column
      df_formal['lable'] = df_formal['lable'].fillna(1)
      # drop duplicates
      df_informal, duplicates_if_2 = drop_duplicates_save(df_informal)
```

# 1.3 3. Exploratory Data Analysis

### 1.3.1 3.1 Label Distribution of Combined Data

We have 14 columns of which the label and content columns are the most important for our analysis. The label column contains the target variable and the content contains the text data from reddit. The target variable is a binary variable with 0 representing the dogwhistle class and 1 representing the non-dogwhistle class.

We have 47,111 rows in the dataset. The dataset is imbalanced with 27.38% in the dogwhistle class and 72.62% in the non-dogwhistle class.

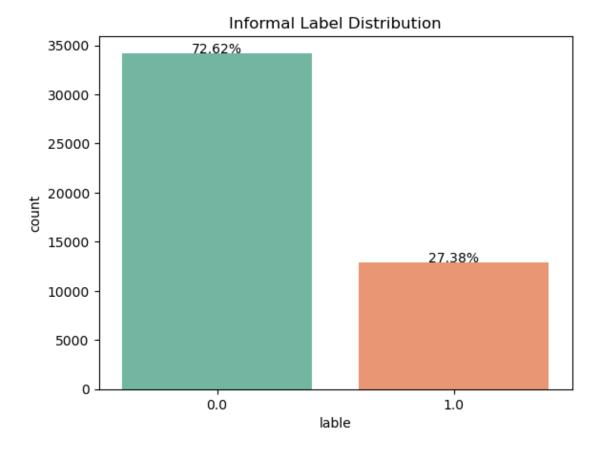
```
[11]: print(df_informal.info())
     <class 'pandas.core.frame.DataFrame'>
     Index: 47111 entries, 0 to 34359
     Data columns (total 15 columns):
      #
          Column
                            Non-Null Count
                                            Dtype
          _____
                            _____
      0
          dog_whistle
                            47111 non-null object
      1
          dog_whistle_root 47111 non-null
                                            object
      2
          ingroup
                            47111 non-null object
      3
          content
                                            object
                            47111 non-null
      4
          date
                            47111 non-null object
      5
          speaker
                            0 non-null
                                            object
      6
          chamber
                            0 non-null
                                            object
      7
          subreddit
                            47095 non-null object
      8
          source
                            47095 non-null object
      9
          definition
                            47111 non-null object
                            47111 non-null
                                            object
      10
         type
      11
         party
                            0 non-null
                                            object
         community
                            16 non-null
                                            object
      13
         in_group
                            34194 non-null object
      14 lable
                            47111 non-null float64
     dtypes: float64(1), object(14)
     memory usage: 5.8+ MB
     None
[29]: | ax = sns.countplot(x='lable', data=df_informal, palette='Set2')
      # add percentage of each class
      total = len(df_informal)
      for p in ax.patches:
          height = p.get_height()
          ax.text(p.get_x() + p.get_width() / 2, height + 3, f'{height/total:.2%}',__
       ⇔ha="center")
      plt.title('Informal Label Distribution')
      plt.show()
```

/var/folders/vx/1wqkklmd4qzbv02gbc6344wc0000gn/T/ipykernel\_61961/3980190155.py:1

### : FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14.0. Assign the `x` variable to `hue` and set `legend=False` for the same effect.

ax = sns.countplot(x='lable', data=df\_informal, palette='Set2')

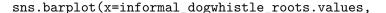


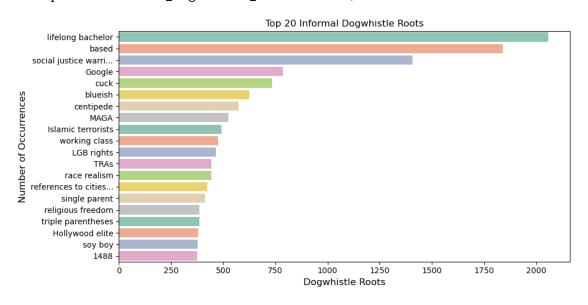
**Key Observation:** This class imbalance will need to be addressed during model training with techniques like SMOTE or class weights.

# 1.3.2 3.2 Dogwhistle Root Analysis

/var/folders/vx/1wqkklmd4qzbv02gbc6344wc0000gn/T/ipykernel\_61961/2523524849.py:1
1: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14.0. Assign the `y` variable to `hue` and set `legend=False` for the same effect.





The most common root words in the dogwhistle data set is the 'lifelong bachelor' root word. This root word is a dogwhistle term used mainly used by homophobes, pointing out that the opposing political candidate is "single," "never married", "a lifelong bachelor," "limp-wristed", "has no children" if they are married, or "flounced" from a debate, is a dog whistle term intended to send a signal to homophobes that others will miss. The word "single" is the important one here since it used commonly in normal conversations and non political discussion. This over-representation will

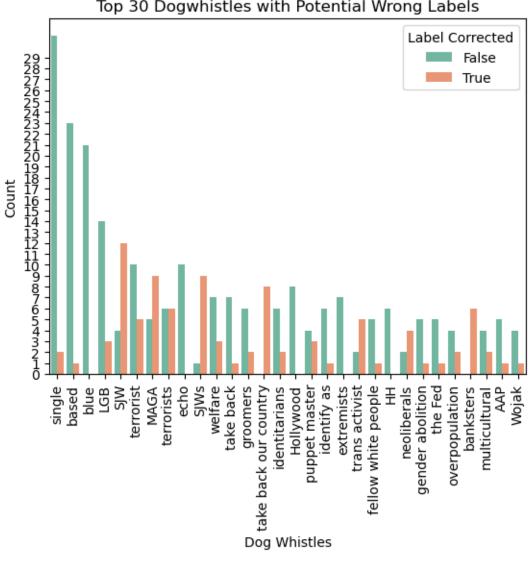
need to be addressed when cleaning the data.

#### 1.4 3.3 Manual Label Review

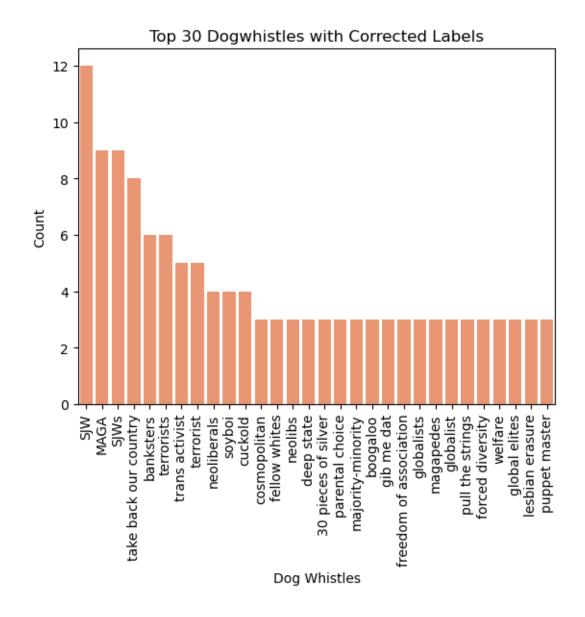
```
[25]: reviewed_labels = pd.read_csv('vetting_instances/reviewed_labels.csv')
```

After the first manual review of potential mislabeled data, I found that 36.16% of the 1000 reviewed labels were mislabeled. Showing the need for the manual review process to improve the quality of the dataset.

```
[33]: # get the split by updated column
      sns.countplot(x='dog_whistles', data=reviewed_labels, hue='updated', u
       order=reviewed_labels['dog_whistles'].value_counts().iloc[:30].index, ___
       ⇒palette='Set2')
      # rotate x-axis labels
      plt.xticks(rotation=90)
      # y axis ticks only integers
      plt.yticks(np.arange(0, 30, 1))
      plt.xlabel('Dog Whistles')
      # y axis label
      plt.ylabel('Count')
      # set legend title
      plt.legend(title='Label Corrected')
      plt.title('Top 30 Dogwhistles with Potential Wrong Labels')
      # save the plot so it does not get cut off
      plt.savefig('top_20_labels_with_potential_wrong_labels.png',u
       ⇔bbox_inches='tight')
      plt.show()
      # most updated dog_whistles in reviewed_labels
      updated dog whistles = reviewed labels[reviewed labels['updated'] == True]
      sns.countplot(x='dog_whistles', data=updated_dog_whistles,_
       order=updated_dog_whistles['dog_whistles'].value_counts().iloc[:30].index,__
       ⇔color='#fc8d62')
      # rotate x-axis labels
      plt.xticks(rotation=90)
      plt.xlabel('Dog Whistles')
      plt.ylabel('Count')
      plt.title('Top 30 Dogwhistles with Corrected Labels')
      plt.show()
```



Top 30 Dogwhistles with Potential Wrong Labels



Out of the manual reviewed cases expectedly most had the keyword single in them. But here only a small portion was actually mislabeled. When looking at the dogwhistles that were manually changed the most SWJ MAGA and TBOC were the most common. Here There seems to be a bias towards there dogwhistles in the LLms used by Kruk et al.