ms2

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1 Data Science 2: Advanced Topics in Data Science

1.1 Final Project Milestone 2

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1.1.1 The Dataset

We are using the unprocessed version of the Jigsaw Unintended Bias in Toxicity Classification dataset (jigsaw-unintended-bias-train.csv) that we obtained from Kaggle.

This dataset contains approximately 3 million user comments posted on the Civil Comments platform or Wikipedia talk page talk page edits. Each comment is annotated with toxicity scores across multiple categories, including *toxic, severe_toxicity, obscene, insult, identity_attack,* and *threat.*

The dataset also includes demographic annotations, which demonstrate how much of each comment refers to a specific identity (*female, black, muslim*, etc). The total dataset size is around 820 MB

While the original dataset includes both raw and preprocessed versions, we are working with the raw data so that we can have full control over preprocessing: text cleaning, tokenization, truncation, and formatting. This approach will provide us more flexibility to optimize our model performance.

[ ]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import matplotlib.cm as cm  # For optional color mapping
from sklearn.cluster import KMeans
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import silhouette_score, silhouette_samples
from sklearn.decomposition import PCA
import csv
import os
%matplotlib inline
```

1.1.2 Loading Data

[ ]:
```
df = pd.read_csv("data/ms2_data.csv")
df.info()
df.describe(include='all')
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1902194 entries, 0 to 1902193
Data columns (total 45 columns):
 #   Column                               Dtype
---  ------                               -----
 0   id                                   int64
 1   comment_text                         object
 2   toxic                                float64
 3   severe_toxicity                      float64
 4   obscene                              float64
 5   identity_attack                      float64
 6   insult                               float64
 7   threat                               float64
 8   asian                                float64
 9   atheist                              float64
 10  bisexual                             float64
 11  black                                float64
 12  buddhist                             float64
 13  christian                            float64
 14  female                               float64
 15  heterosexual                         float64
 16  hindu                                float64
 17  homosexual_gay_or_lesbian            float64
 18  intellectual_or_learning_disability  float64
 19  jewish                               float64
 20  latino                               float64
 21  male                                 float64
 22  muslim                               float64
 23  other_disability                     float64
 24  other_gender                         float64
 25  other_race_or_ethnicity              float64
 26  other_religion                       float64
 27  other_sexual_orientation             float64
 28  physical_disability                  float64
 29  psychiatric_or_mental_illness        float64
 30  transgender                          float64
 31  white                                float64
 32  created_date                         object
 33  publication_id                       int64
 34  parent_id                            float64
 35  article_id                           int64
 36  rating                               object
```

```
 37  funny                              int64
 38  wow                                int64
 39  sad                                int64
 40  likes                              int64
 41  disagree                           int64
 42  sexual_explicit                    float64
 43  identity_annotator_count           int64
 44  toxicity_annotator_count           int64
dtypes: float64(32), int64(10), object(3)
memory usage: 653.1+ MB
```

[ ]:

```
                  id comment_text         toxic  severe_toxicity  \
count   1.902194e+06      1902191  1.902194e+06     1.902194e+06
unique           NaN      1876467           NaN              NaN
top              NaN   Well said.           NaN              NaN
freq             NaN          196           NaN              NaN
mean    3.912771e+06          NaN  1.030068e-01     4.585531e-03
std     2.497349e+06          NaN  1.970813e-01     2.286902e-02
min     5.984800e+04          NaN  0.000000e+00     0.000000e+00
25%     8.273542e+05          NaN  0.000000e+00     0.000000e+00
50%     5.282205e+06          NaN  0.000000e+00     0.000000e+00
75%     5.862735e+06          NaN  1.666667e-01     0.000000e+00
max     7.194639e+06          NaN  1.000000e+00     1.000000e+00

             obscene  identity_attack        insult        threat  \
count   1.902194e+06     1.902194e+06  1.902194e+06  1.902194e+06
unique           NaN              NaN           NaN           NaN
top              NaN              NaN           NaN           NaN
freq             NaN              NaN           NaN           NaN
mean    1.388516e-02     2.259572e-02  8.117227e-02  9.298498e-03
std     6.465998e-02     7.863447e-02  1.760987e-01  4.939469e-02
min     0.000000e+00     0.000000e+00  0.000000e+00  0.000000e+00
25%     0.000000e+00     0.000000e+00  0.000000e+00  0.000000e+00
50%     0.000000e+00     0.000000e+00  0.000000e+00  0.000000e+00
75%     0.000000e+00     0.000000e+00  9.090909e-02  0.000000e+00
max     1.000000e+00     1.000000e+00  1.000000e+00  1.000000e+00

                asian        atheist  …    article_id    rating  \
count   426707.000000  426707.000000  …  1.902194e+06   1902194
unique            NaN            NaN  …           NaN         2
top               NaN            NaN  …           NaN  approved
freq              NaN            NaN  …           NaN   1775959
mean         0.011905       0.003362  …  2.811915e+05       NaN
std          0.086914       0.051648  …  1.040056e+05       NaN
min          0.000000       0.000000  …  2.006000e+03       NaN
25%          0.000000       0.000000  …  1.600630e+05       NaN
50%          0.000000       0.000000  …  3.320280e+05       NaN
```

```
75%           0.000000        0.000000  …  3.662350e+05       NaN
max           1.000000        1.000000  …  3.995440e+05       NaN

               funny           wow           sad         likes      disagree  \
count   1.902194e+06  1.902194e+06  1.902194e+06  1.902194e+06  1.902194e+06
unique           NaN           NaN           NaN           NaN           NaN
top              NaN           NaN           NaN           NaN           NaN
freq             NaN           NaN           NaN           NaN           NaN
mean    2.777982e-01  4.429990e-02  1.090688e-01  2.443550e+00  5.824227e-01
std     1.054929e+00  2.457508e-01  4.563106e-01  4.720064e+00  1.861857e+00
min     0.000000e+00  0.000000e+00  0.000000e+00  0.000000e+00  0.000000e+00
25%     0.000000e+00  0.000000e+00  0.000000e+00  0.000000e+00  0.000000e+00
50%     0.000000e+00  0.000000e+00  0.000000e+00  1.000000e+00  0.000000e+00
75%     0.000000e+00  0.000000e+00  0.000000e+00  3.000000e+00  0.000000e+00
max     1.020000e+02  2.100000e+01  3.100000e+01  3.000000e+02  1.870000e+02

        sexual_explicit  identity_annotator_count  toxicity_annotator_count
count      1.902194e+06              1.902194e+06              1.902194e+06
unique              NaN                       NaN                       NaN
top                 NaN                       NaN                       NaN
freq                NaN                       NaN                       NaN
mean       6.595598e-03              1.435714e+00              8.782232e+00
std        4.525432e-02              1.774053e+01              4.338458e+01
min        0.000000e+00              0.000000e+00              3.000000e+00
25%        0.000000e+00              0.000000e+00              4.000000e+00
50%        0.000000e+00              0.000000e+00              4.000000e+00
75%        0.000000e+00              0.000000e+00              6.000000e+00
max        1.000000e+00              1.866000e+03              4.936000e+03

[11 rows x 45 columns]
```

[ ]:
```
df.columns.tolist()
```

[ ]:
```
['id',
 'comment_text',
 'toxic',
 'severe_toxicity',
 'obscene',
 'identity_attack',
 'insult',
 'threat',
 'asian',
 'atheist',
 'bisexual',
 'black',
 'buddhist',
 'christian',
```

```
 'female',
 'heterosexual',
 'hindu',
 'homosexual_gay_or_lesbian',
 'intellectual_or_learning_disability',
 'jewish',
 'latino',
 'male',
 'muslim',
 'other_disability',
 'other_gender',
 'other_race_or_ethnicity',
 'other_religion',
 'other_sexual_orientation',
 'physical_disability',
 'psychiatric_or_mental_illness',
 'transgender',
 'white',
 'created_date',
 'publication_id',
 'parent_id',
 'article_id',
 'rating',
 'funny',
 'wow',
 'sad',
 'likes',
 'disagree',
 'sexual_explicit',
 'identity_annotator_count',
 'toxicity_annotator_count']
```

[ ]:
```
print("Shape:", df.shape)
```

```
Shape: (1902194, 45)
```

1.1.3 EDA

To understand our data better, we do an initial missingness analysis of all columns.

[ ]:
```
file_path = "data/ms2_data.csv"
size_bytes = os.path.getsize(file_path)

size_mb = size_bytes / (1024 * 1024)
size_gb = size_bytes / (1024 * 1024 * 1024)

print(f"File size: {size_mb:.2f} MB ({size_gb:.4f} GB)")
```

```
File size: 820.46 MB (0.8012 GB)
```

[ ]:
```
missing_summary = df.isnull().sum()
missing_percent = (df.isnull().sum() / len(df)) * 100

missing_df = pd.DataFrame({'Missing Count': missing_summary, 'Missing %':␣
 ↪missing_percent})
missing_df = missing_df[missing_df['Missing Count'] > 0].
 ↪sort_values(by='Missing %', ascending=False)
missing_df
```

[ ]:

	Missing Count	Missing %
latino	1475487	77.567640
white	1475487	77.567640
psychiatric_or_mental_illness	1475487	77.567640
physical_disability	1475487	77.567640
other_sexual_orientation	1475487	77.567640
other_religion	1475487	77.567640
other_race_or_ethnicity	1475487	77.567640
other_gender	1475487	77.567640
other_disability	1475487	77.567640
muslim	1475487	77.567640
male	1475487	77.567640
asian	1475487	77.567640
jewish	1475487	77.567640
intellectual_or_learning_disability	1475487	77.567640
homosexual_gay_or_lesbian	1475487	77.567640
hindu	1475487	77.567640
heterosexual	1475487	77.567640
female	1475487	77.567640
christian	1475487	77.567640
buddhist	1475487	77.567640
black	1475487	77.567640
bisexual	1475487	77.567640
atheist	1475487	77.567640
transgender	1475487	77.567640
parent_id	821840	43.204847
comment_text	3	0.000158

We notice that the missinginess is most present in the identity columns. This is because only a subset of the comments have been labeled with identity attributes.

These identity columns will be used only to evaluate the fairness of the model after training, not to train the model itself. In other words, we can train the model on the non-identity inputs and evaluate the bias of the model later using the identity columns.

Before addressing the missingness of the variables we plan to include, we'll subset the data to include only what we will input to our model.

1.1.4 Subsetting Dataset

Here, we subset to only include relevant columns. We remove identity columns, as mentioned above, and we also remove columns related to metadata (such as *id, publication_id, article_id,* etc) because they are not useful for toxicity prediction.

Other columns (*likes, funny, sad, wow*) may tell us about user sentiment but are not immediately useful for toxicity prediction.

We subset to a dataset with just the input and outputs. The input to our model is *comment_text*, and the outputs we will predict are *toxic, severe_toxicity, obscene, identity_attack, insult, threat, sexual_explicit*

[ ]:
```
cols = ['id', 'comment_text', 'toxic', 'severe_toxicity', 'obscene',␣
↪'identity_attack', 'insult', 'threat', 'sexual_explicit']
df_subset = df[cols]
```

1.1.5 Missingness

We now examine the missingness of the subsetted dataset

[ ]:
```
missing_summary = df_subset.isnull().sum()
missing_percent = (df_subset.isnull().sum() / len(df_subset)) * 100

missing_df = pd.DataFrame({'Missing Count': missing_summary, 'Missing %':␣
↪missing_percent})
missing_df = missing_df[missing_df['Missing Count'] > 0].
↪sort_values(by='Missing %', ascending=False)
missing_df
```

[ ]:
```
              Missing Count  Missing %
comment_text              3   0.000158
```

[ ]:
```
df_missing_comment_text = df[df['comment_text'].isna()]
df_missing_comment_text.head()
```

[ ]:
```
              id comment_text  toxic  severe_toxicity  obscene  \
513346    872115          NaN    0.0              0.0      0.0
1010795  5353666          NaN    0.0              0.0      0.0
1512317  5971919          NaN    0.0              0.0      0.0

         identity_attack  insult  threat  asian  atheist  …  article_id  \
513346               0.0     0.0     0.0    NaN      NaN  …      163140
1010795              0.0     0.0     0.0    0.0      0.0  …      340316
1512317              0.0     0.0     0.0    0.0      0.0  …      378393

           rating  funny  wow  sad  likes  disagree  sexual_explicit  \
513346   approved      5    0    0      9         1              0.0
1010795  approved      0    0    0      0         0              0.0
```

```
1512317  approved      0     0     0      1          0               0.0

         identity_annotator_count  toxicity_annotator_count
513346                          0                         4
1010795                         4                         4
1512317                         4                         4

[3 rows x 45 columns]
```

It looks like there is no missing data outside of 3 observations where there is no comment_text. Since the dataset is so large, we can drop these three observations.

[ ]:
```
len(df_subset)
```

[ ]:
```
1902194
```

[ ]:
```
df_cleaned = df_subset.dropna(subset=['comment_text'])
```

[ ]:
```
len(df_cleaned)
```

[ ]:
```
1902191
```

1.1.6 Examining Imbalance

[ ]:
```
label_cols = ['toxic', 'severe_toxicity', 'obscene', 'identity_attack',␣
↪'insult', 'threat', 'sexual_explicit']

# Convert all to numeric
for col in label_cols:
    df_cleaned[col] = pd.to_numeric(df_cleaned[col], errors='coerce')

# From *Kaggle*: If >0.5 --> 1; If <0.5 --> 0
for col in label_cols:
    df_cleaned[col] = df_cleaned[col].apply(lambda x: 1 if x >= 0.5 else 0)

# Print
for col in label_cols:
    print(f"\n{col.upper()} distribution:")
    print(df_cleaned[col].value_counts())
```

```
/var/folders/6r/ywxm_hr95d3_b__w0dw6q_7r0000gn/T/ipykernel_20963/2954108152.py:5
: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  df_cleaned[col] = pd.to_numeric(df_cleaned[col], errors='coerce')
```

```
/var/folders/6r/ywxm_hr95d3_b__w0dw6q_7r0000gn/T/ipykernel_20963/2954108152.py:9
: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  df_cleaned[col] = df_cleaned[col].apply(lambda x: 1 if x >= 0.5 else 0)


TOXIC distribution:
toxic
0    1750080
1     152111
Name: count, dtype: int64

SEVERE_TOXICITY distribution:
severe_toxicity
0    1902178
1         13
Name: count, dtype: int64

OBSCENE distribution:
obscene
0    1892045
1      10146
Name: count, dtype: int64

IDENTITY_ATTACK distribution:
identity_attack
0    1888094
1      14097
Name: count, dtype: int64

INSULT distribution:
insult
0    1789881
1     112310
Name: count, dtype: int64

THREAT distribution:
threat
0    1897690
1       4501
Name: count, dtype: int64

SEXUAL_EXPLICIT distribution:
sexual_explicit
```

```
0    1897265
1       4926
Name: count, dtype: int64
```

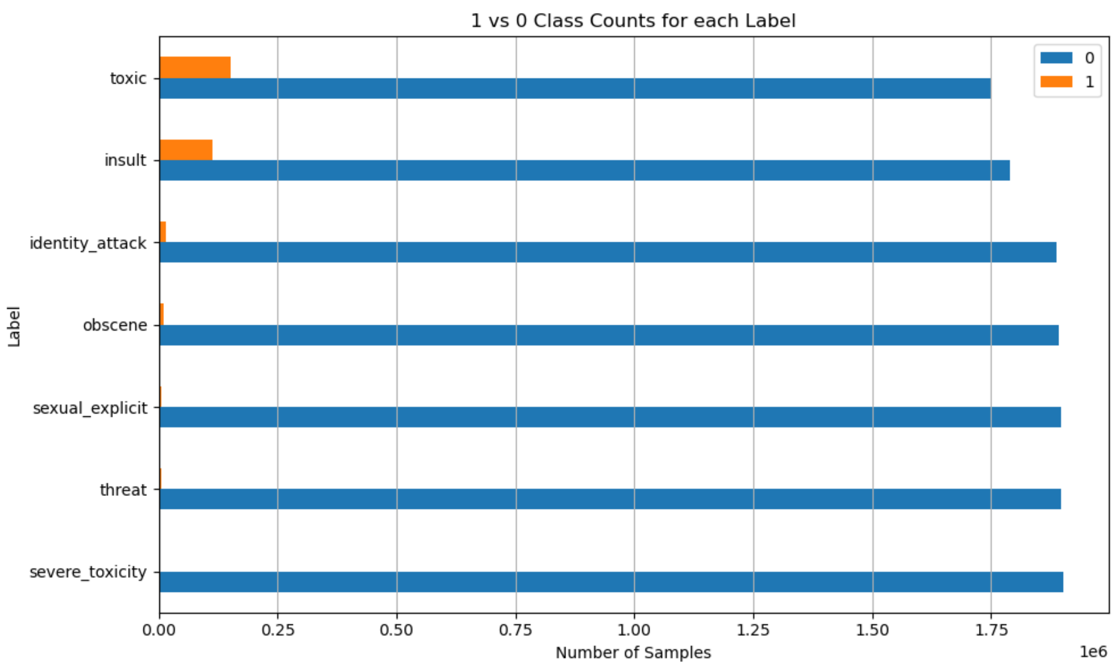
[ ]:
```
## AI Assistance for graphing here - ChatGPT showed us to make a dataframe and
↪transpose it
labels_for_graphing = ['toxic', 'severe_toxicity', 'obscene',
↪'identity_attack', 'insult', 'threat', 'sexual_explicit']

label_distributions = {
    col: df_cleaned[col].value_counts() for col in labels_for_graphing
}

dist_df = pd.DataFrame(label_distributions).T
dist_df.columns = ['0', '1']
dist_df = dist_df.sort_values('1')

# plot
dist_df.plot(kind='barh', stacked=False, figsize=(10, 6))
plt.title("1 vs 0 Class Counts for each Label")
plt.xlabel("Number of Samples")
plt.grid(axis='x')
plt.ylabel("Label")
plt.tight_layout()


plt.show()
```



Here, we see very high levels of imbalance in our cleaned dataframe. This isn't great because that means a model could just predict '0' and be correct 97% of the time in most cases.

We aim to address these imbalances using resampling methods:

One resampling method we might consider is oversampling the minority class. While this may work for *toxic* and *insult*, it is unlikely to be a good method for the more extreme cases of imbalances seen in other output variables.

We could also undersample the majority class; however, this would significantly reduce the training data we have. We are unlikely to use this approach.

We will not use SMOTE because we are dealing with text data.

(AI Assitance for this part:)

We can also use class weights, which basically tells the model to pay more attention to the minority class because it's underrepresented.

One last strategy we will consider is combining the some of the outputs. For example, there are only 13 observations that are observed as *severe_toxicity*. We could combine all toxicity metrics into one binary variable.

1.1.7 Feature Scaling

Feature scaling is not required for our dataset since we are dealing with raw text data and using BERT/GPT models. Furthermore, our target labels are all float values between 0 and 1 and do not require scaling either.

1.1.8 Final Dataset

[ ]:
```
df_cleaned.head()
```

[ ]:
```
      id                                       comment_text  toxic  \
0  59848  This is so cool. It's like, 'would you want yo…      0
1  59849  Thank you!! This would make my life a lot less…      0
2  59852  This is such an urgent design problem; kudos t…      0
3  59855  Is this something I'll be able to install on m…      0
4  59856                haha you guys are a bunch of losers.      1

   severe_toxicity  obscene  identity_attack  insult  threat  sexual_explicit
0                0        0                0       0       0                0
1                0        0                0       0       0                0
2                0        0                0       0       0                0
3                0        0                0       0       0                0
4                0        0                0       1       0                0
```

Here are the first 5 observations of our cleaned dataset, which includes the input *comment_text* and several output features all between 0 and 1.

In this milestone, we focused on understanding our data and subsetting our dataset to only include useful variables for model training. We discovered extreme levels of imbalance and discussed several ways to address them. In our next milestone, we will experiment with various methods to address this imbalance.