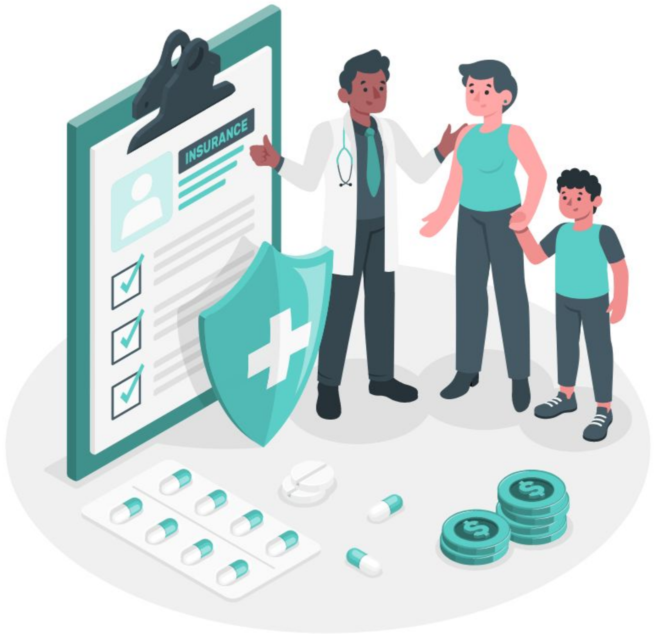
# UN Sustainable Development Goal Text Classification

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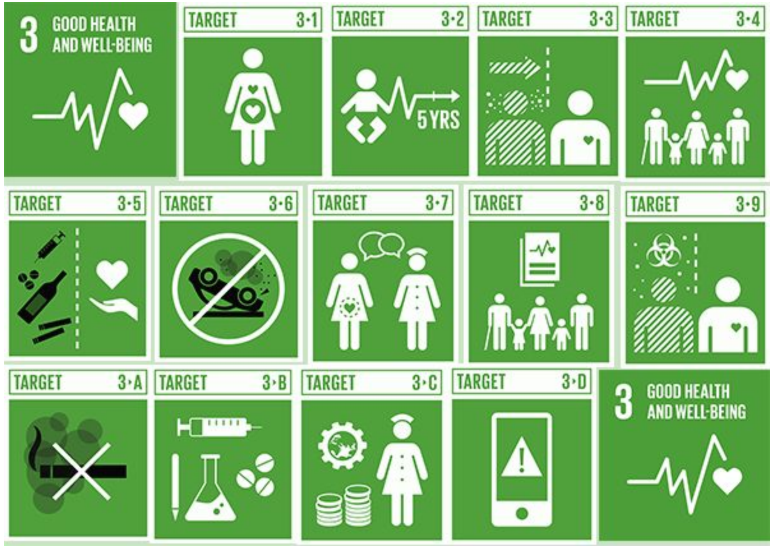
# Getting to Know the United Nation

The Sustainable Development Goals

# What are the Sustainable Goals?

The United Nation created 17 measurable indication for development refer to as Sustainable Development Goals or refer to as SDG that they hope to achieve by 2030.

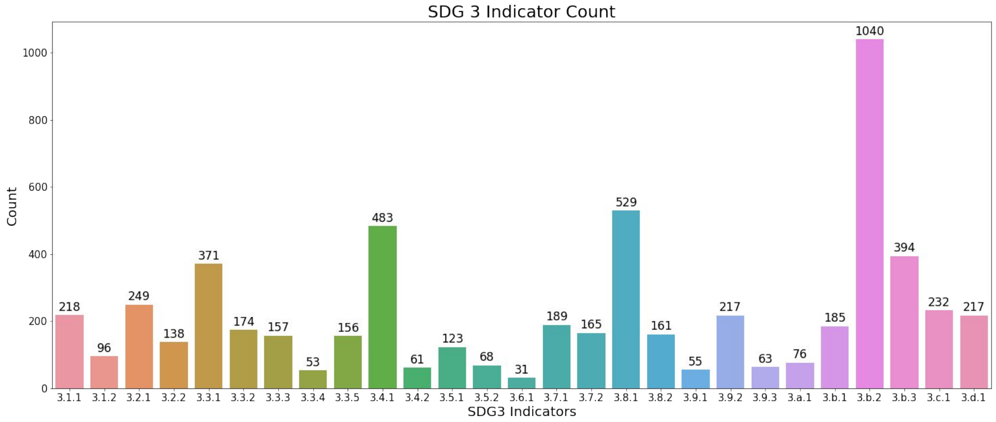
# Our Focus




## Goal 3: Good Health and Well Being

- 27 categories that provide quantitative measurement for Goal 3, example:
  - Maternal mortality ratio
  - Number of new HIV infections
  - Suicide mortality rate
  - Malaria incidence
- The categories are used as a judge to  see whether the SDG has been achieved in 2030 or not

# Understanding the Categories




## 27 Categories:

- Most common categories:
  - 3.b.2 - International Health Regulation
- Least common categories:
  - 3.6.1 - Death rate due to road traffic injuries

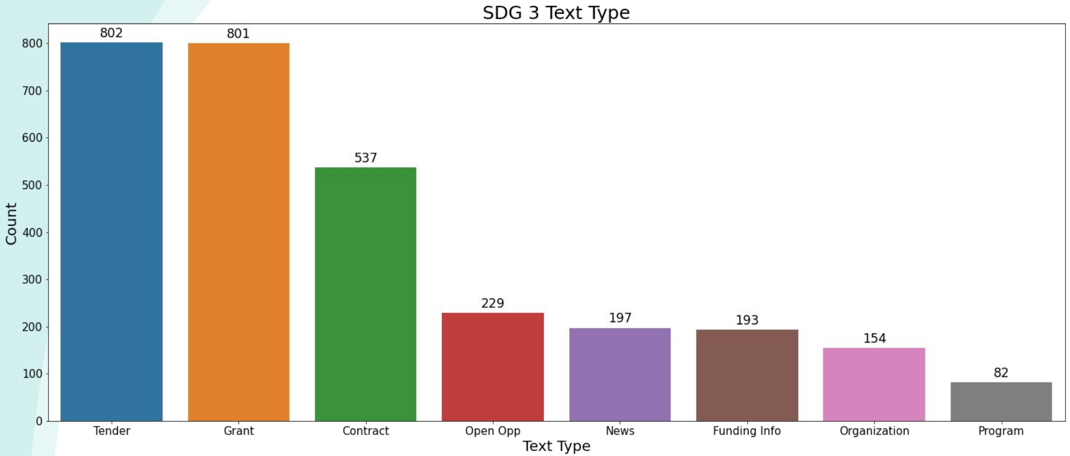
Since there are many categories, the UN needs to find contenders that can help aid each categories...

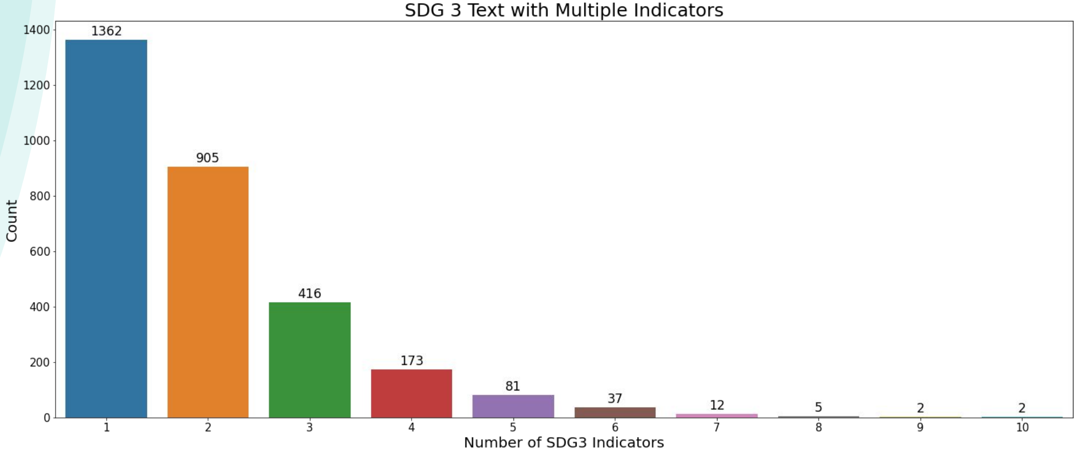
# The Contenders

There are many contenders and international agencies that contributes to the sustainable development goals. These contenders can be in the form of organizations, funding, contracts, programs and other forms. Some notable examples are:

- World Health Organization (Organization)
- Cambodia Aid investment (Program)
- The Tropical Agriculture Association (Funding)

# Our Contenders




8 Types of Contender:

- Grant
- Organization
- Tender
- Funding Information
- Open Opportunity
- Program
- Contract
- News

One contenders can be relevant to more than one categories:

- Most are related to 1 to 3 categories

# The Problem

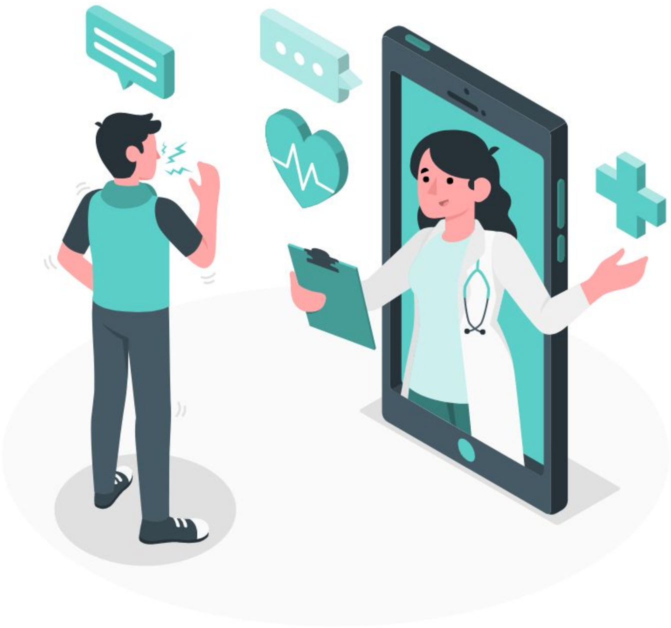
Since there are many contenders and categories within the goal of Good Health and Well Being, the UN struggles to identify which contenders are reports ot related to which of the 27 categories.

**Our Goal: Develope a text classifier to identify which contenders, using their text description, are most relevant to which categories**

To predict which categories are relevant to the individual contenders

# The Data

What are we exploring



# The Data

## The Train Data

Includes **2995 web-scrapped** text with:

- **Unique ID:** IDs of text to be classified
- **Type:** Type of contenders
    - Grants
    - Tenders
    - Contract
    - News
    - Program
    - Organization
    - Open opportunity
    - Funding information
- **Text:** text to be classified
- **Labels:** Categories for each text (ie 3.1.1)

## The Test Data

Includes **998 web-scrapped** text with:

- **Unique ID:** IDs of text to be classified
- **Type:** Type of contenders
    - Grants
    - Tenders
    - Contract
    - News
    - Program
    - Organization
    - Open opportunity
    - Funding information
- **Text:** text to be classified

# Text Example - Description

```
grant_text.Text[50]
```

```
'Evaluating Policies for Impacts on Multiple Forms of Violence <p><strong>Background: </strong></p>    <p>Violence is a significant publi
c health problem in the United States. In 2015, more than 62,000 people in the United States died because of violence and more than 2,16
5,000 were treated in emergency departments for a violence-related injury (CDC, 2016a). Exposure to violence in childhood and adolescence
can increase risk for later violent experiences, such as intimate partner violence, sexual violence, and suicide, which can have a cumula
tive and compounding impact on health and well-being. This is alarming given the prevalence of violence among children and youth. In 201
5, approximately 1,670 children died in the United States from child abuse and neglect, and approximately 683,000 children were victims o
f child abuse and neglect per Child Protective Services (U.S. Department of Health &amp; Human Services, 2017). Youth violence is also pr
evalent among persons aged 10 to 24 years; each day approximately 13 young people are victims of homicide and more than 1,300 are treated
in emergency departments for nonfatal physical assault-related injuries (CDC, 2016a). Additionally, 1 in 5 high school students reported
being bullied at school or getting in a physical fight in the past year (CDC, 2016b). Among high school students who reported dating duri
ng the 12 months before the survey, approximately 10% experienced physical dating violence and approximately 11% experienced sexual datin
g violence one or more times during the 12 months before the survey (CDC, 2016b). These forms of violence are common across the lifespan,
with approximately 37% of U.S. women and 31% of U.S. men experiencing sexual violence, physical violence, and/or stalking by an intimate
partner in their lifetime (Smith et al., 2017). In the U.S., approximately 1 in 3 women and nearly 1 in 6 men experience some form of con
tact sexual violence in their lifetime (Smith et al., 2017). In 2015, 44,193 individuals died by suicide, and between 1999 and 2015 suici
de rates increased 27% (CDC, 2016a). According to self-report survey data, 1.4 million adults attempted suicide, 2.7 million made plans f
or suicide, and 9.8 million adults seriously considered suicide in 2015 (Center for Behavioral Health Statistics and Quality, 2016).</p>'
```

```
org_text.Text[110]
```

```
"TAA Agribusiness Group: <p><strong>The Tropical Agriculture Association (TAA)</strong> is a professional association of individuals and
corporate bodies concerned with the role of agriculture for development throughout the world. TAA brings together individuals and organis
ations from both developed and less developed countries to enable them to contribute to international policies and actions aimed at reduc
ing poverty and improving livelihoods.</p>    <p> </p>    <p>The Association was formed in the late 1970's and stemmed largely from
the alumni of the Imperial College of Tropical Agriculture, Trinidad. Over the years its membership has broadened to include all those in
terested in the various aspects of agricultural development worldwide. It has produced a quarterly Newsletter since 1981 that is now call
ed 'Agriculture for Development'.</p>    <p> </p>    <p><strong>Mission</strong></p>    <p>To advance education, research and practi
ce in agriculture* for development</p>    <p> </p>    <p><strong>Association&rsquo;s Primary Objective</strong></p>    <ul>    <li>C
ontribute to international policies aimed at reducing poverty and improving livelihoods in rural areas in the tropics, sub-tropics and co
untries with less developed economies in temperate areas.</li>    <li>Encourage efficient and sustainable use of local resources and tech
nologies, to arrest and reverse the degradation of the natural resources base on which agriculture depends, and to raise productivity of
both agriculture and related enterprises to increase family incomes and commercial investment in the rural sector.</li>    </ul>    <p>&n
bsp;</p>    <p>Particular emphasis is given to rural areas in the tropics and subtropics and to countries with less-developed economies i
n temperate areas. TAA recognizes the interrelated roles of farmers and other stakeholders living in rural areas, scientists (agriculturi
sts, economists, sociologists, etc.), government and the private sector in achieving a convergent approach to rural development. This inc
ludes recognition of the importance of the role of women, the effect of AIDS and other social and cultural issues on the rural economy an
d livelihoods.</p>    <p> </p>    <p><strong>Services</strong></p>    <ul>    <li>Seminars/meetings on key issues in agriculture and
development.</li>    <li>Visits to organisations, companies and other interesting venues.</li>    <li>Social events. </li>    </ul>"
```

Text from:

- Grants
- Organizations
- Tenders
- Funding Information
- Open Opportunity
- Programs

These text consist of full description with an average of 700 to 1200 words

# Text Example - Titles

```
news_text[['word_count','unique_
```

| | word_count | unique_word |
|---|---|---|
| **count** | 197.000000 | 197.000000 |
| **mean** | 10.598985 | 10.487310 |
| **std** | 2.481893 | 2.391757 |
| **min** | 5.000000 | 5.000000 |
| **25%** | 9.000000 | 9.000000 |
| **50%** | 10.000000 | 10.000000 |
| **75%** | 12.000000 | 12.000000 |
| **max** | 18.000000 | 18.000000 |

```
contract_text[['word_count','uni
```

| | word_count | unique_word |
|---|---|---|
| **count** | 537.000000 | 537.000000 |
| **mean** | 9.538175 | 9.067039 |
| **std** | 5.306548 | 4.599154 |
| **min** | 2.000000 | 2.000000 |
| **25%** | 5.000000 | 5.000000 |
| **50%** | 9.000000 | 8.000000 |
| **75%** | 13.000000 | 12.000000 |
| **max** | 36.000000 | 27.000000 |

```
contract_text.Text[2976]
```

```
'Equitable Access to Diabetes Care'
```

```
news_text.Text[21]
```

```
'Applying a workplace model to family planning outreach in the Philippines:'
```

Text from:

- News
- Contract

These text consist of titles and headlines with an average of 10 words

# Text Preprocessing

To identify which categories the contenders are relevant in, we will be exploring their descriptions of who they are and what they do. First we have to clean the texts:

**Removing HTML Marking**

Anything behind https://

**Removing Empty Spaces**

Anything with  

**Removing Non-letters**

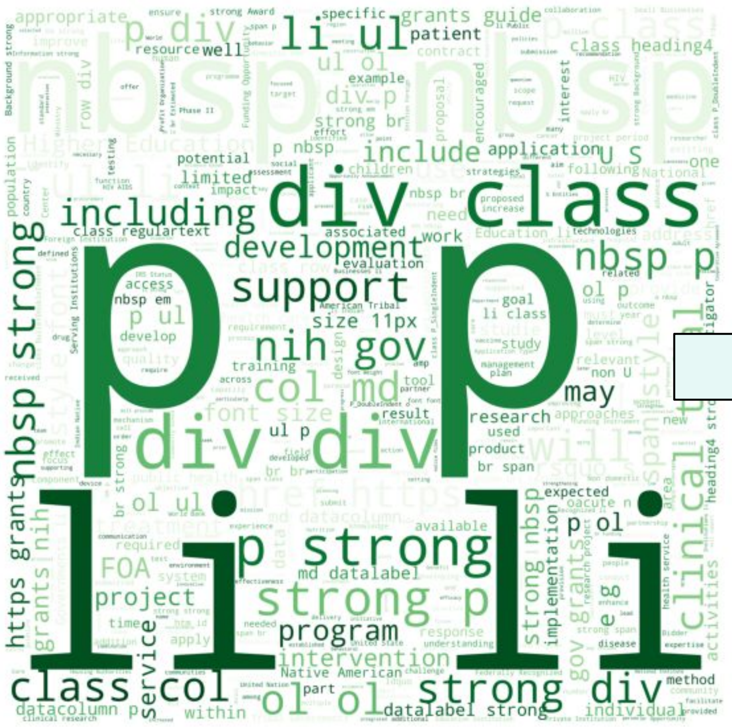
Anything with numbers, symbols

**Removing Stopwords**

Any repeating and stopwords

# Text Data at a Glance

Original Data

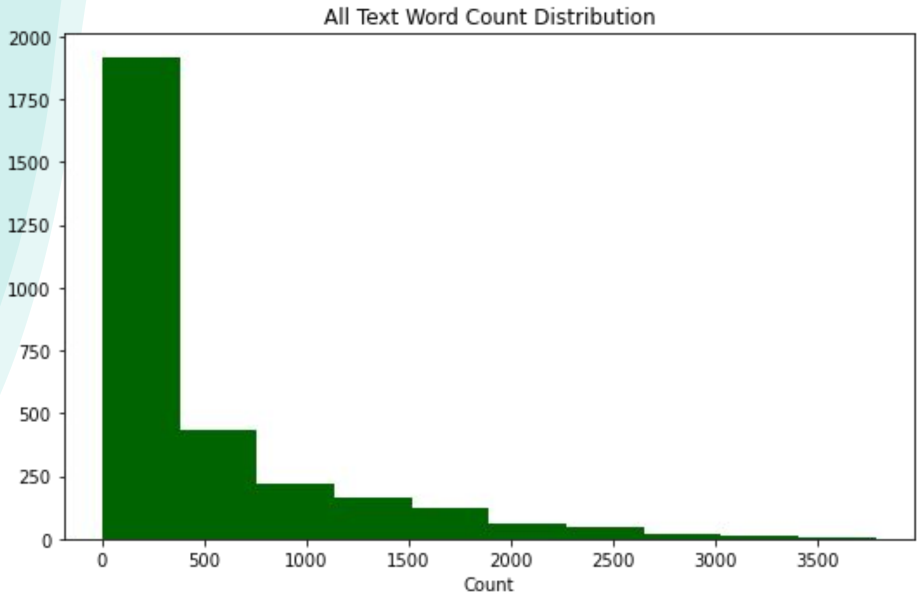



Cleaned Data

# Features Engineering

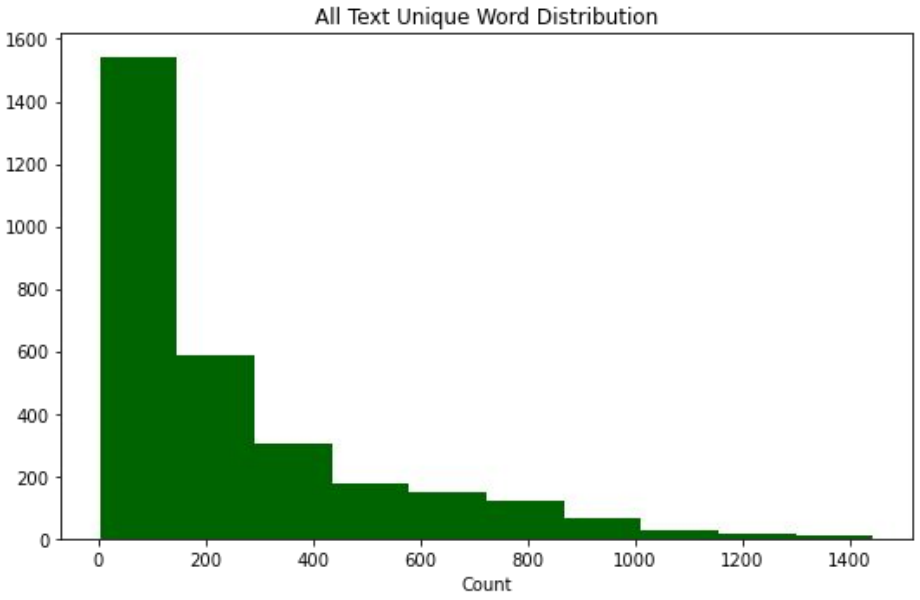
## Word Count

Count number of words in the contender description text



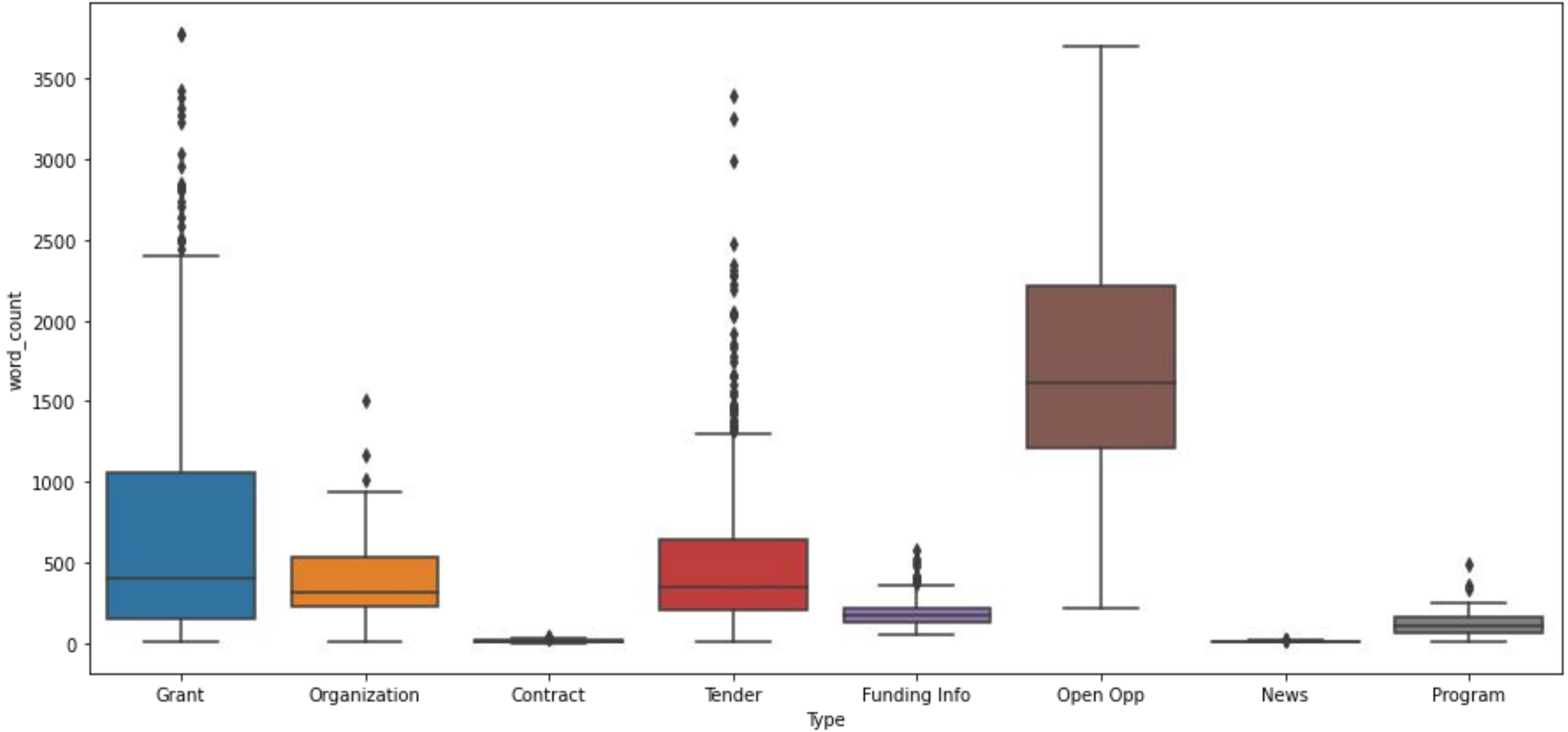

## Unique Word Count

Count number of unique words in the contender description text



# The Word Count by Text Type

Most of the text are longer as they are full descriptions of who the contenders are and what they do



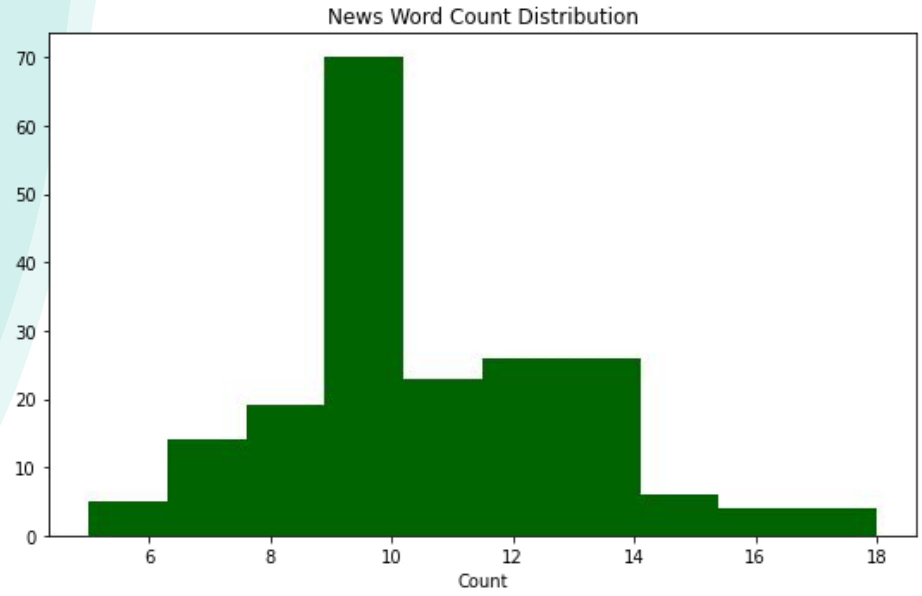
# Taking a Closer Look

Exploring Text Type and Categories

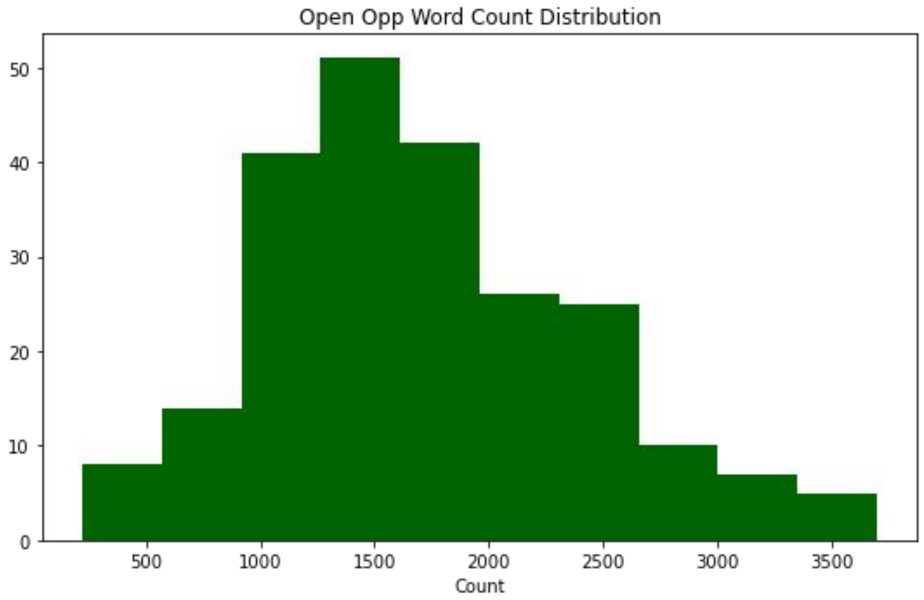
# Looking Closer at the Text Type

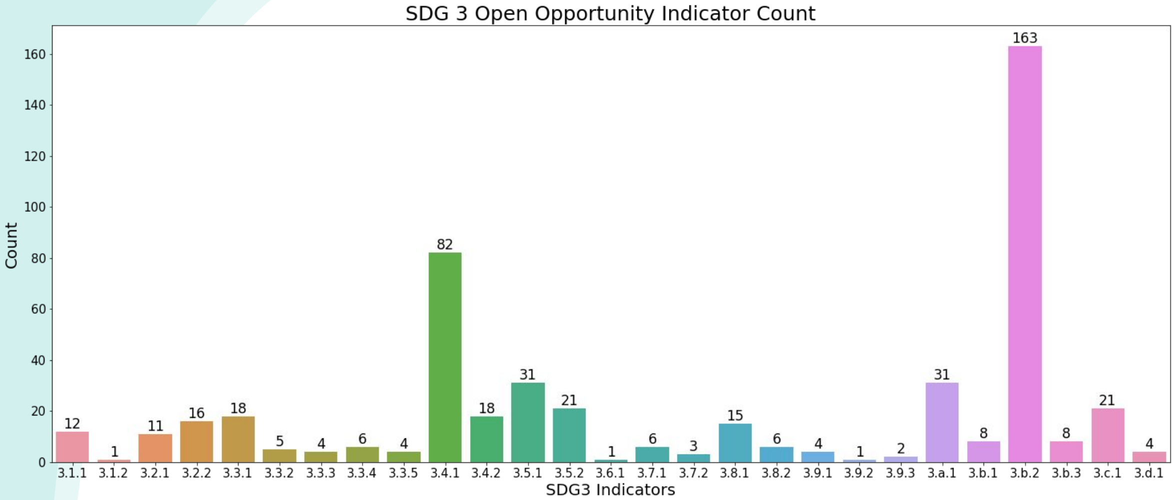
Different text type have different spread in word count:

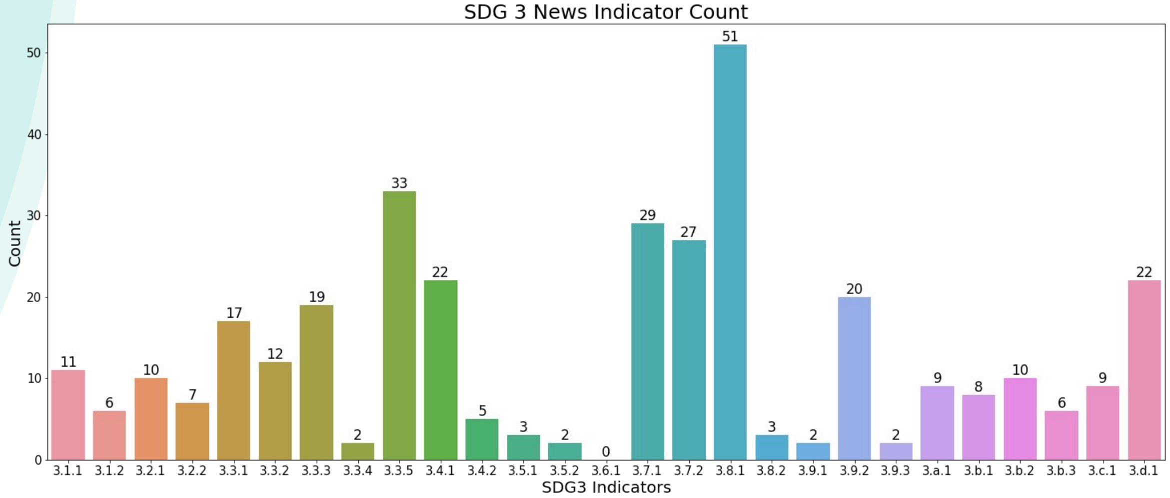
News Contender




Open Opportunity Contender





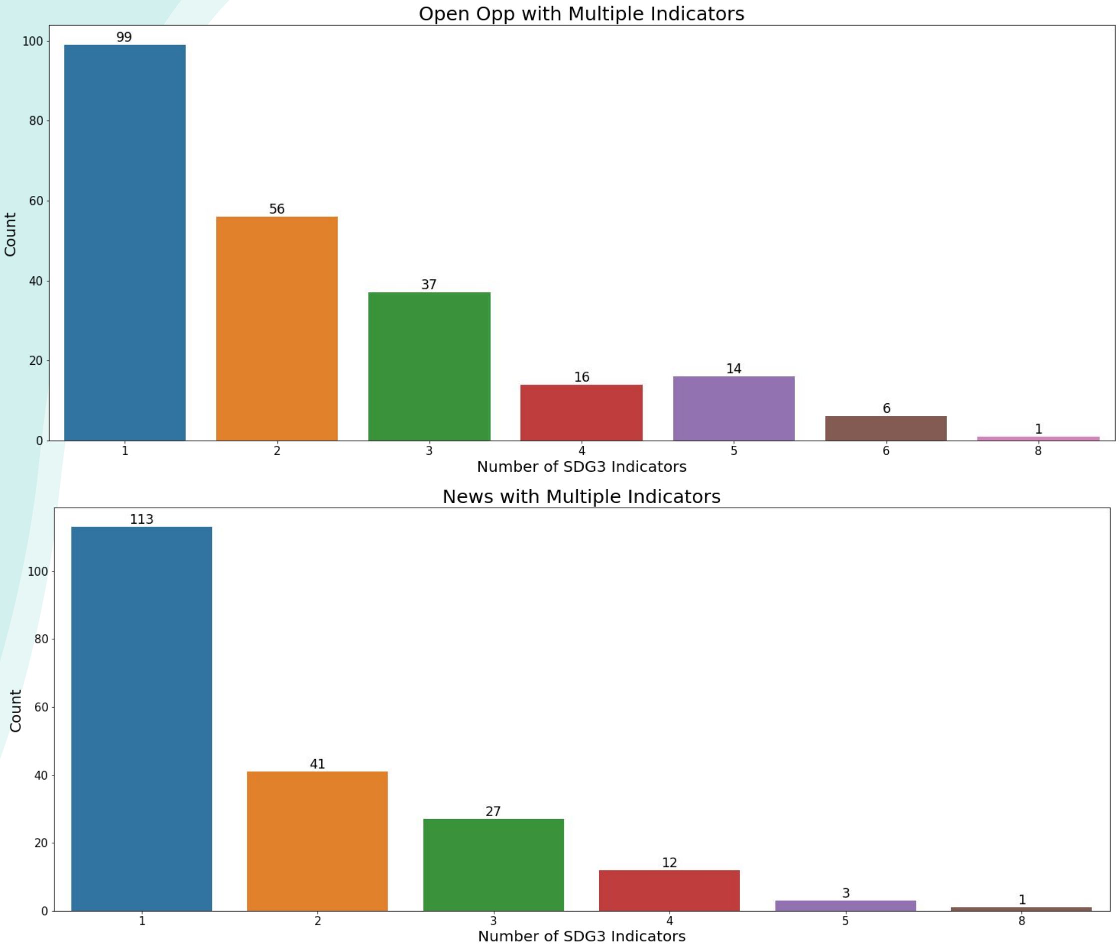

# Category Count by Text Type

Open Opportunity

- Top Category: 3.b.1
- Low Category: 3.1.2, 3.6.1

News

- Top Category: 3.8.1
- Low Category: 3.6.1, 3.3.4




# Number of Category by Text Type

## Funding Information

- Most relevant between 1 to 3 categories
- Range from 1 to 8 relevant categories

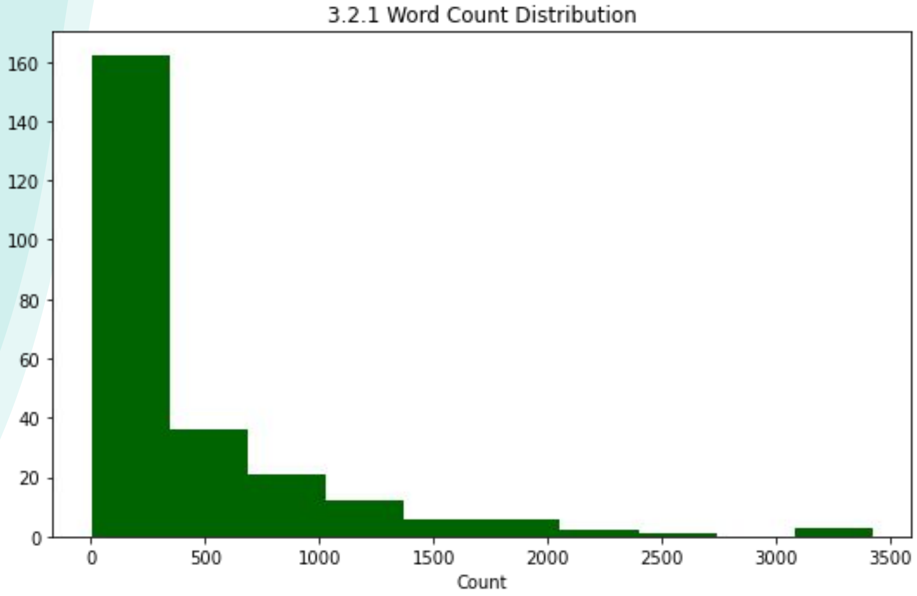
## News

- Most relevant to 1 categories
- Range from 1 to 5

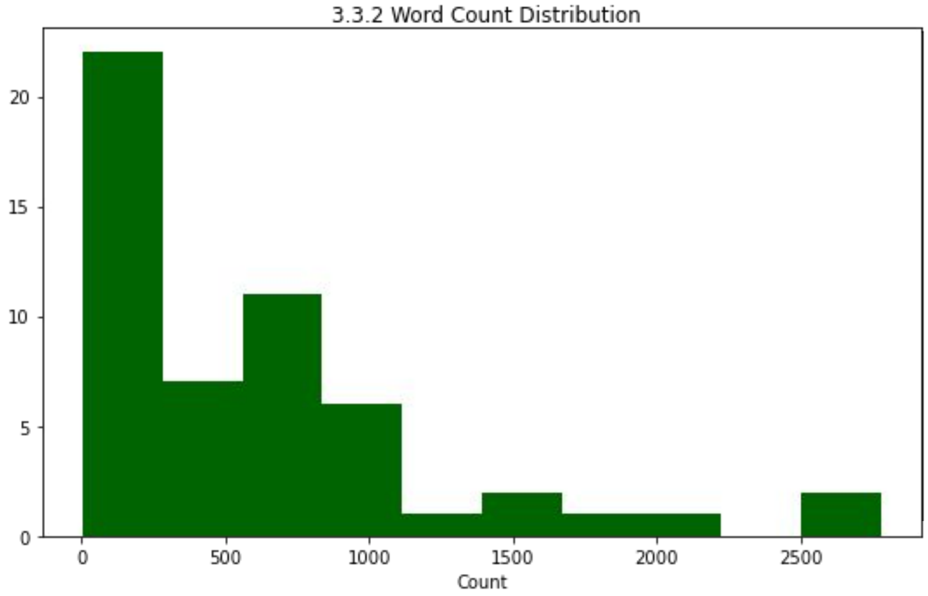
# Looking Closer at the Categories

Different Categories have different spread in word count:

Category 3.2.1: Under-5 mortality rate



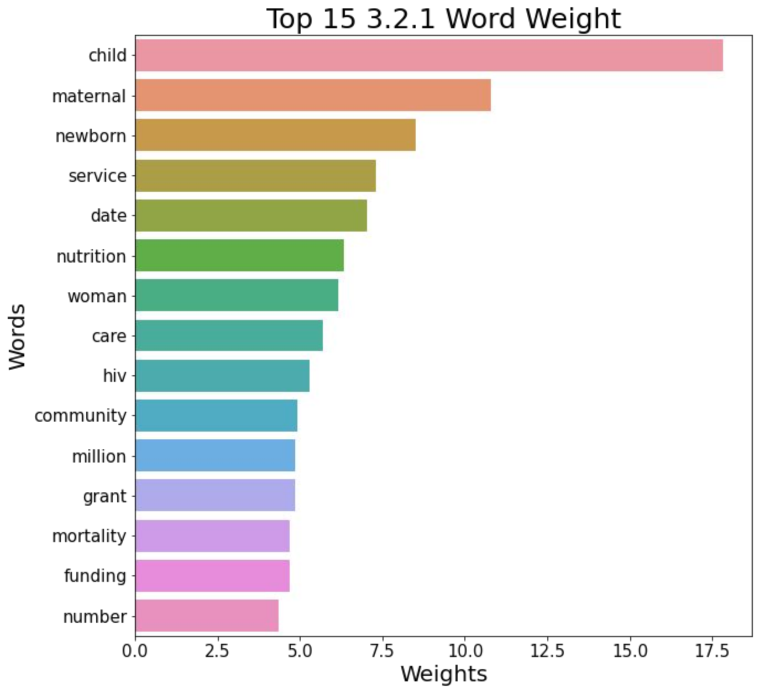

Category 3.3.2: Tuberculosis incidence



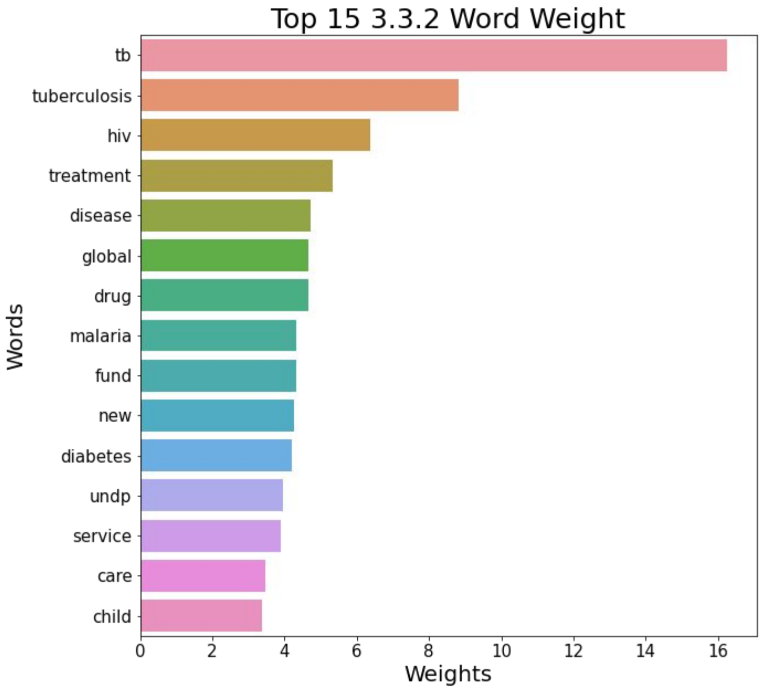
# Text from Categories

Each categories contender text description emphasis on different things according to the categories example:

Category 3.2.1: Under-5 mortality rate



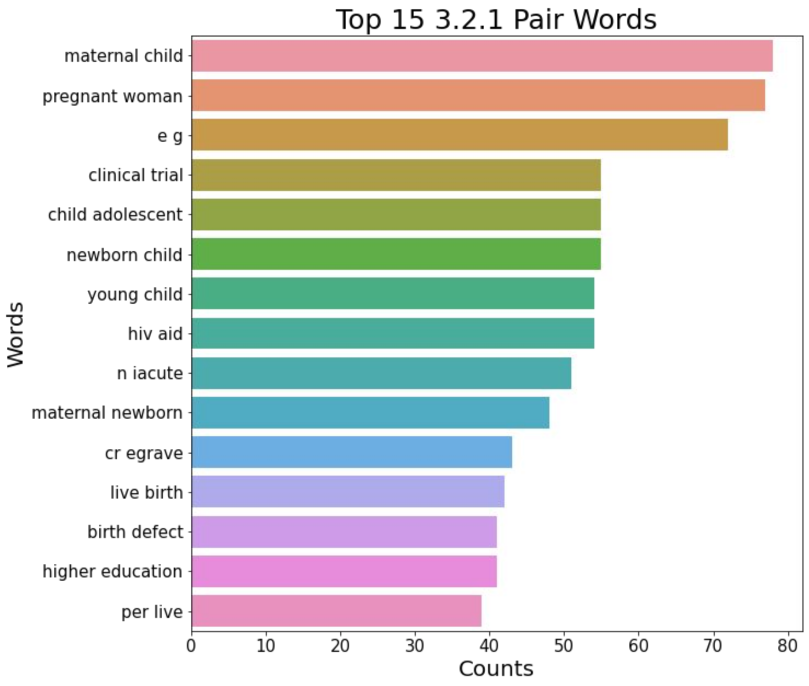

Category 3.3.2: Tuberculosis incidence



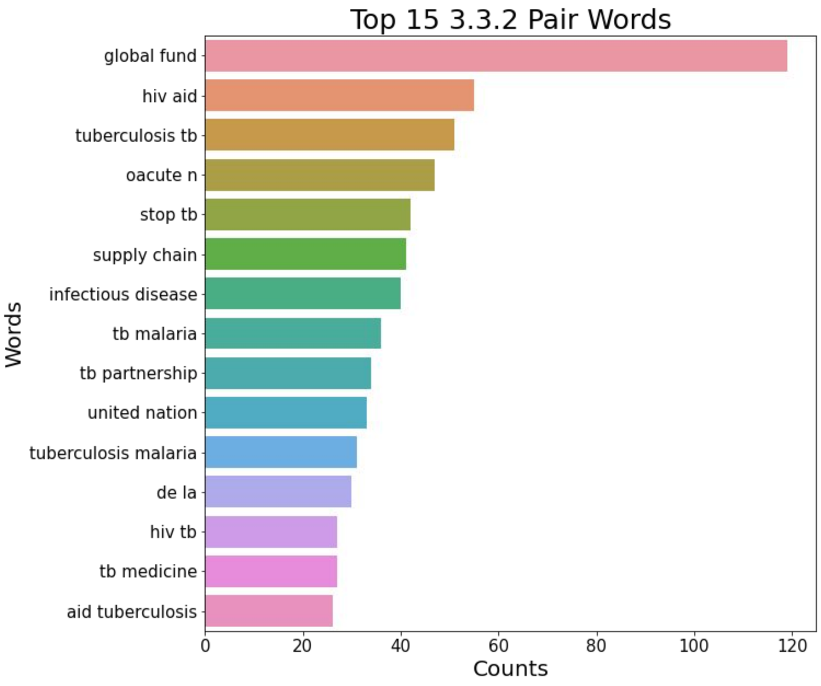
# Pair Words from Categories

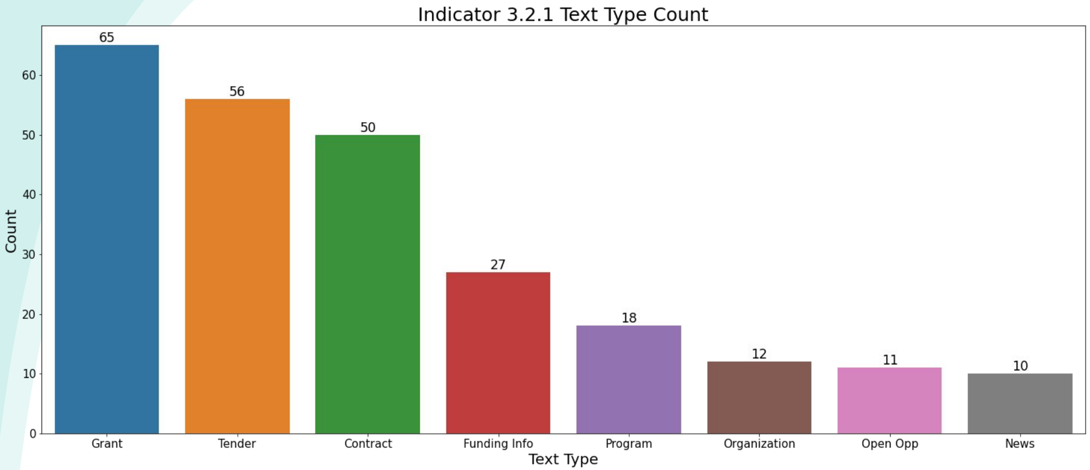
Each categories contender text description emphasis on different things according to the categories example:

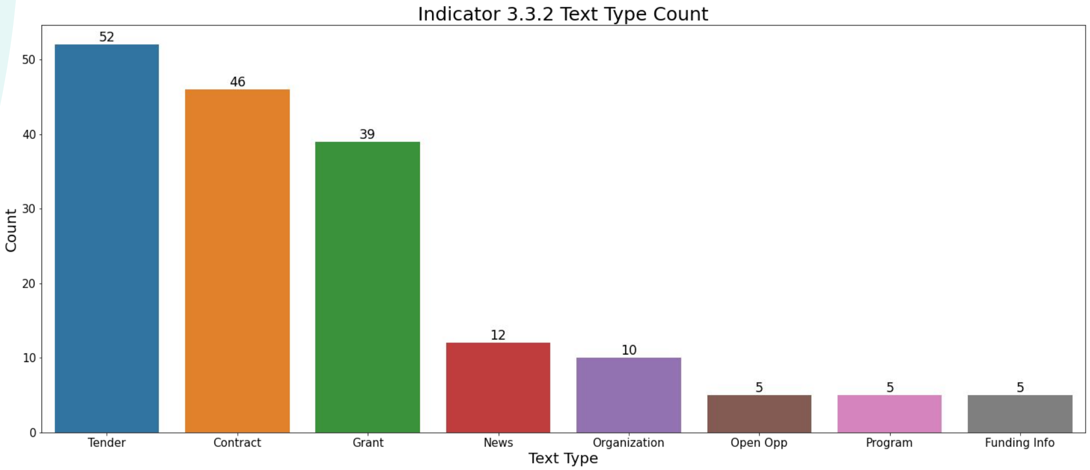
Category 3.2.1: Under-5 mortality rate




Category 3.3.2: Tuberculosis incidence






# Text Type from Categories

Category 3.2.1: Under-5 mortality rate

- Grant (65)
- Tender (56)
- Contract (50)

Category 3.3.2: Tuberculosis incidence

- Tender (52)
- Contract (46)
- Grant (39)

# Correlation?

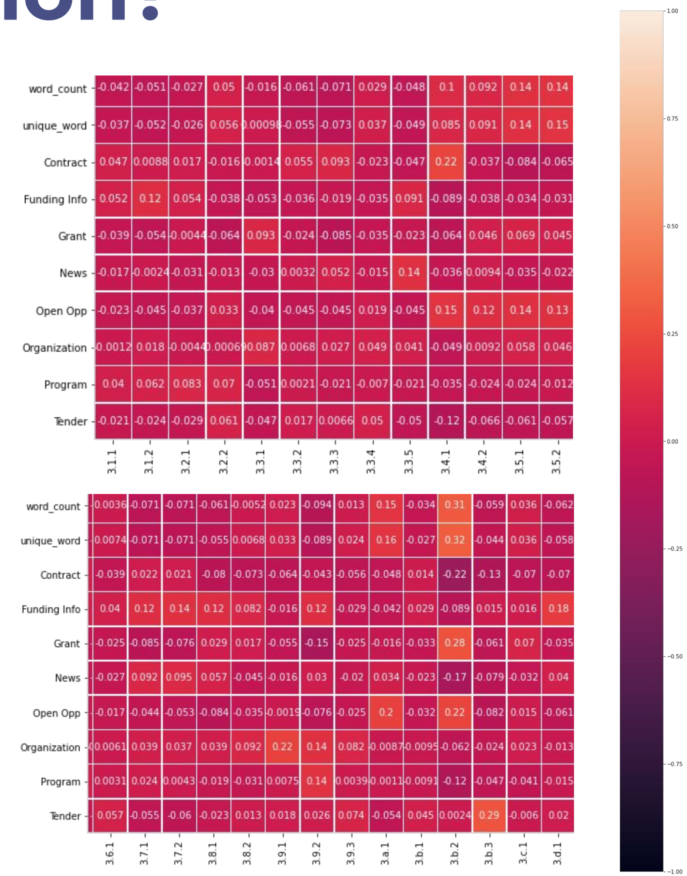
Overall, there is **no correlations** between...

- Type of contenders or word counts of the contenders description

VS

- Any of the categories

Shown by the colour heat map →



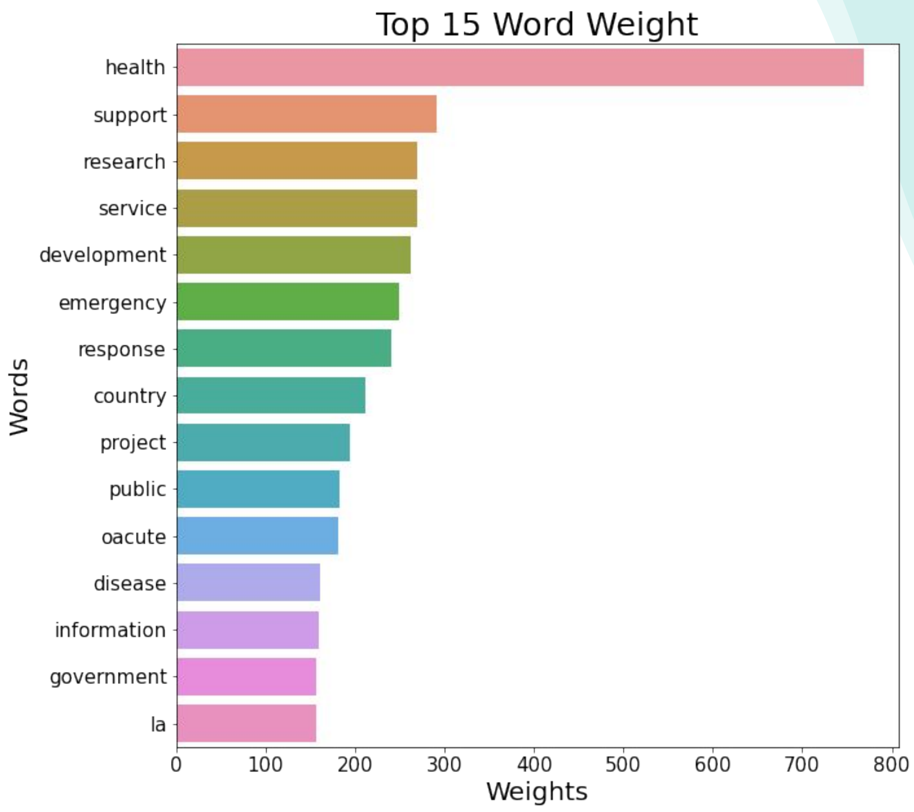
# Modeling and Prediction

Putting our data to use

# The Top Three Model

## KNN, Random Forest and Ridge Classifier

- Using only the text data as the input
- TF-IDF Vectorizer to determined the value and weight of each words
- From the fitted parameter, an optimized model is created with high accuracy



# From the Top Three

Evaluating the models by:

**Hamming Loss Score** which is the fraction of labels that are incorrectly predicted

**Accuracy** or the **Exact Match Ratio**  which is the most strict metrics, indicating the percentage of samples that have all their labels classified correctly.

### KNN Classifier

- Hamming Loss: 0.0553
- Accuracy: 0.2921

### Random Forest

- Hamming Loss: 0.0555
- Accuracy: 0.2604

### Ridge Classifier

- Hamming Loss: 0.0472
- Accuracy: 0.327

# Product Model

## Ridge Classifier CV

- Based on Ridge regression method, use with MultiOutputClassifer function
- Use TF-IDF Vectorizer and ridge classifier default parameters
- Hamming Loss Score of 0.04

# Product Model Evaluation

| | precision | recall | f1-score | support |
|---|---|---|---|---|
| '3.1.1' | 1.00 | 0.43 | 0.60 | 30 |
| '3.1.2' | 0.00 | 0.00 | 0.00 | 18 |
| '3.2.1' | 0.86 | 0.40 | 0.55 | 45 |
| '3.2.2' | 0.67 | 0.11 | 0.18 | 19 |
| '3.3.1' | 0.96 | 0.63 | 0.76 | 78 |
| '3.3.2' | 0.96 | 0.49 | 0.65 | 47 |
| '3.3.3' | 0.96 | 0.53 | 0.69 | 45 |
| '3.3.4' | 1.00 | 0.24 | 0.38 | 17 |
| '3.3.5' | 0.72 | 0.38 | 0.50 | 34 |
| '3.4.1' | 0.93 | 0.56 | 0.70 | 93 |
| '3.4.2' | 0.75 | 0.27 | 0.40 | 11 |
| '3.5.1' | 0.78 | 0.44 | 0.56 | 16 |
| '3.5.2' | 0.83 | 0.33 | 0.48 | 15 |
| '3.6.1' | 1.00 | 0.67 | 0.80 | 3 |
| '3.7.1' | 1.00 | 0.51 | 0.68 | 35 |
| '3.7.2' | 1.00 | 0.50 | 0.67 | 32 |
| '3.8.1' | 0.75 | 0.32 | 0.45 | 102 |
| '3.8.2' | 1.00 | 0.15 | 0.26 | 33 |
| '3.9.1' | 1.00 | 0.11 | 0.20 | 9 |
| '3.9.2' | 0.88 | 0.42 | 0.57 | 36 |
| '3.9.3' | 0.00 | 0.00 | 0.00 | 13 |
| '3.a.1' | 0.86 | 0.38 | 0.52 | 16 |
| '3.b.1' | 0.92 | 0.28 | 0.43 | 39 |
| '3.b.2' | 0.75 | 0.64 | 0.69 | 215 |
| '3.b.3' | 0.57 | 0.22 | 0.31 | 79 |
| '3.c.1' | 0.88 | 0.32 | 0.47 | 47 |
| '3.d.1' | 0.93 | 0.33 | 0.49 | 42 |

- The model is best use for some of the categories:
  - 3.3.1
  - 3.6.1
- Categories that might need other model:
  - 3.1.2
  - 3.9.3
- The model might need to be more tuned for categories:
  - 3.4.1
  - 3.b.2

# Alternative Models

## KNN Classifier

| | precision | recall | f1-score |
|---|---|---|---|
| '3.1.1' | 0.57 | 0.27 | 0.36 |
| '3.1.2' | 0.33 | 0.17 | 0.22 |
| '3.2.1' | 0.53 | 0.22 | 0.31 |
| '3.2.2' | 0.29 | 0.11 | 0.15 |
| '3.3.1' | 0.86 | 0.55 | 0.67 |
| '3.3.2' | 0.83 | 0.53 | 0.65 |
| '3.3.3' | 0.81 | 0.49 | 0.61 |
| '3.3.4' | 1.00 | 0.12 | 0.21 |
| '3.3.5' | 0.71 | 0.35 | 0.47 |
| '3.4.1' | 0.76 | 0.57 | 0.65 |
| '3.4.2' | 0.50 | 0.36 | 0.42 |
| '3.5.1' | 0.69 | 0.56 | 0.62 |
| '3.5.2' | 0.75 | 0.40 | 0.52 |
| '3.6.1' | 0.00 | 0.00 | 0.00 |
| '3.7.1' | 0.90 | 0.54 | 0.68 |
| '3.7.2' | 0.90 | 0.56 | 0.69 |
| '3.8.1' | 0.54 | 0.28 | 0.37 |
| '3.8.2' | 0.60 | 0.18 | 0.28 |
| '3.9.1' | 1.00 | 0.33 | 0.50 |
| '3.9.2' | 0.82 | 0.50 | 0.62 |
| '3.9.3' | 0.40 | 0.15 | 0.22 |
| '3.a.1' | 0.82 | 0.56 | 0.67 |
| '3.b.1' | 0.69 | 0.28 | 0.40 |
| '3.b.2' | 0.68 | 0.63 | 0.66 |
| '3.b.3' | 0.44 | 0.29 | 0.35 |
| '3.c.1' | 0.61 | 0.30 | 0.40 |
| '3.d.1' | 0.73 | 0.38 | 0.50 |

- KNN Classifier is best for
  - 3.3.4
  - 3.9.1
- Random Forest is best for:
  - 3.1.1
  - 3.4.1
- Both models still need tuning for other categories as well:
  - KNN have high precision but mid range recall
  - Random Forest have high precision but low recall

Both models show promised for categories that were low in the product (ridge) model evaluation score

## Random Forest

| | precision | recall | f1-score |
|---|---|---|---|
| '3.1.1' | 1.00 | 0.23 | 0.38 |
| '3.1.2' | 0.00 | 0.00 | 0.00 |
| '3.2.1' | 1.00 | 0.11 | 0.20 |
| '3.2.2' | 0.50 | 0.05 | 0.10 |
| '3.3.1' | 0.97 | 0.38 | 0.55 |
| '3.3.2' | 1.00 | 0.26 | 0.41 |
| '3.3.3' | 0.94 | 0.38 | 0.54 |
| '3.3.4' | 0.00 | 0.00 | 0.00 |
| '3.3.5' | 0.67 | 0.06 | 0.11 |
| '3.4.1' | 1.00 | 0.43 | 0.60 |
| '3.4.2' | 0.00 | 0.00 | 0.00 |
| '3.5.1' | 0.67 | 0.12 | 0.21 |
| '3.5.2' | 1.00 | 0.13 | 0.24 |
| '3.6.1' | 1.00 | 0.33 | 0.50 |
| '3.7.1' | 0.90 | 0.26 | 0.40 |
| '3.7.2' | 1.00 | 0.25 | 0.40 |
| '3.8.1' | 0.88 | 0.14 | 0.24 |
| '3.8.2' | 0.83 | 0.15 | 0.26 |
| '3.9.1' | 0.00 | 0.00 | 0.00 |
| '3.9.2' | 0.78 | 0.19 | 0.31 |
| '3.9.3' | 0.00 | 0.00 | 0.00 |
| '3.a.1' | 1.00 | 0.19 | 0.32 |
| '3.b.1' | 1.00 | 0.18 | 0.30 |
| '3.b.2' | 0.79 | 0.60 | 0.68 |
| '3.b.3' | 0.58 | 0.14 | 0.22 |
| '3.c.1' | 0.90 | 0.19 | 0.32 |
| '3.d.1' | 0.71 | 0.12 | 0.20 |

# Recommendation and the Future

Improve by:

## Unique Models

Optimized unique models for each individual categories

The best text classifier to use:

## Ridge Classifier

to help the UN to classify which contender is relevant to which of the 27 categories

# Thank you

Appreciate your time

# Appendix

## The Categories

- The code and what it is

# 27 Categories

There are 27 possible SDG 3 categories, in the dataset each indicator will be refer using code:

- 3.1.1 - Maternal mortality ratio
- 3.1.2 - Proportion of births attended by skilled health personnel
- 3.2.1 - Under-5 mortality rate
- 3.2.2 - Neonatal mortality rate
- 3.3.1 - Number of new HIV infections per 1 000 uninfected population, by sex, age and key populations
- 3.3.2 - Tuberculosis incidence per 100 000 population
- 3.3.3 - Malaria incidence per 1 000 population
- 3.3.4 - Hepatitis B incidence per 100 000 population
- 3.3.5 - Number of people requiring interventions against neglected tropical diseases

# 27 Categories

- 3.4.1 - Mortality rate attributed to cardiovascular disease, cancer, diabetes or chronic respiratory disease
- 3.4.2 - Suicide mortality rate
- 3.5.1 - Coverage of treatment interventions (pharmacological, psychosocial and rehabilitation and aftercare services) for substance use disorders
- 3.5.2 - Harmful use of alcohol, defined according to the national context as alcohol per capita consumption (aged 15 years and older) within a calendar year in litres of pure alcohol
- 3.6.1 - Death rate due to road traffic injuries
- 3.7.1 - Proportion of women of reproductive age (aged 15–49 years) who have their need for family planning satisfied with modern methods
- 3.7.2 - Adolescent birth rate (aged 10–14 years; aged 15–19 years) per 1 000 women in that age group

# 27 Categories

- 3.8.1 - Coverage of essential health services (defined as the average coverage of essential services based on tracer interventions that include reproductive, maternal, newborn and child health, infectious diseases, non-communicable diseases and service capacity and access, among the general and the most disadvantaged population)
- 3.8.2 - Proportion of population with large household expenditures on health as a share of total household expenditure or income
- 3.9.1 - Mortality rate attributed to household and ambient air pollution
- 3.9.2 - Mortality rate attributed to unsafe water, unsafe sanitation and lack of hygiene (exposure to unsafe Water, Sanitation and Hygiene for All (WASH) services)
- 3.9.3 - Mortality rate attributed to unintentional poisoning

# 27 Categories

- 3.b.2 - Total net official development assistance to medical research and basic health sector
- 3.b.3 - Proportion of health facilities that have a core set of relevant essential medicines available and affordable on a sustainable basis
- 3.c.1 - Health worker density and distribution
- 3.d.1 - International Health Regulations (IHR) capacity and health emergency preparedness
- 3.a.1 - Age-standardized prevalence of current tobacco use among persons aged 15 years and older
- 3.b.1 - Proportion of the target population covered by all vaccines included in their national programme