TED Talks
NLP – EDA & Classification

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Objective

To automatically categorize/tag TED Talk videos and **identify key topics/trends based on a series of features provided** in a sample dataset, link below. Once the text data has been cleaned and prepared, a series Classification models will be trained on the sample dataset.

Problem Statement

The data provided, in its raw format, does not make for easy classification and statistical analysis of the various TED Talks. There is no easy way to decipher trends in popular talk topics, categories, or to further explore specific speakers, their occupations, and general talk focus (transcript summary).

Benefit of Analysis

Being able to peel back and examine various layers of details within the dataset to **isolate key trends, categories, or any other features of interest would be beneficial to the analyst/user** in answering a series of questions, often addressed by some of the best and brightest minds in the world and their respective TED talks.

Being able to quickly classify and assign a given TED talk, based on other similar feature patterns, would allow for **improved viewer experiences from accurate user preference alignment as it relates to Tags, Ratings, and Comment popularity (counts)**.

Data Review

Data Collection

There are two datasets, in csv format, pulled from the Kaggle website provided, the main summary for all TED Talks and the respective TED Talk transcripts:

TED Talks: Summary https://www.kaggle.com/rounakbanik/ted-talks?select=ted_main.csv

TED Talks: Transcripts https://www.kaggle.com/rounakbanik/ted-talks?select=transcripts.csv

Data Provided - Summary:

- **Comments:** The number of first level comments made on the talk
- **Description:** A blurb of what the talk is about
- **Duration:** The duration of the talk in seconds
- **Event:** The TED/TEDx event where the talk took place
- **Film_date:** The Unix timestamp of the filming
- **Languages:** The number of languages in which the talk is available
- **Main_speaker:** The first named speaker of the talk
- **Name:** The official name of the TED Talk; includes the title and the speaker
- **Num_speaker:** The number of speakers in the talk
- **Published_date:** The Unix timestamp for the publication of the talk on TED.com
- **Ratings:** Groups of ratings assigned to each talk
- **Related_talks:** Similar talks/links
- **Speaker_occupation:** Primary speaker occupation/focus
- **Tags:** Tags assigned to the talk
- **Title:** Title of TED talk
- **Url:** The URL of the talk
- **Views:** Total views for talk

Data Provided - Transcript:

- **Transcript:** The official English transcript of the talk
- **URL:** The URL of the talk

Data Examination

- The summary file has 2,550 rows of data and 17 columns
- The Transcripts file has slightly less rows (2,467) and only 2 columns
- **Both DataFrames have a URL column**, which can likely serve as the same column for merging both datasets into one overall DataFrame
- There are **no null values** out of the 2,467 entries, however, **Speaker Occupation appears to be missing 6 values** which could be NAs and will require further analysis
- The variables with Object datatypes can be converted to categorical values, saving space and improving EDA presentation

Data Inspection

Top TED Talks by Overall Views

	Main_Speaker	Title	Views
0	Ken Robinson	Do schools kill creativity?	47.23
1268	Amy Cuddy	Your body language may shape who you are	43.16
649	Simon Sinek	How great leaders inspire action	34.31
800	Brené Brown	The power of vulnerability	31.17
444	Mary Roach	10 things you didn't know about orgasm	22.27
1695	Julian Treasure	How to speak so that people want to listen	21.59
198	Jill Bolte Taylor	My stroke of insight	21.19
5	Tony Robbins	Why we do what we do	20.69
2033	James Veitch	This is what happens when you reply to spam email	20.48
1338	Cameron Russell	Looks aren't everything. Believe me, I'm a model.	19.79

The **top 3 TED Talks of all time**, by total views, are:

- **Do Schools Kill Creativity by Ken Robinson (47.2M)**
- Your Body Language May Shape Who You Are by Amy Cuddy (43.2M)
- How Great Leaders Inspire by Simon Sinek (34.3)

We can see a large drop off in overall views after the top 2 Talks, 43.2M to 34.3M, with **an even larger drop off in total views from 4th to 5th**:

- The Power of Vulnerability by Brené Brown (31.2M)
- 10 Things you Didn't Know about Orgasm by Mary Roach (22.3M)

Summary Details by Top Rating %

Rating_Category	Top_Rating	Event	Title	Main_Speaker
Beautiful	0.8332	TED2011	Building a park in the sky	Robert Hammond
Jaw-Dropping	0.7100	TED2007	How PhotoSynth can connect the world's images	Blaise Agüera y Arcas
Funny	0.7021	TED2010	It's time for "The Talk"	Julia Sweeney
Persuasive	0.6428	TEDGlobal 2007	Aid versus trade	Ngozi Okonjo-Iweala
Inspiring	0.6101	INK Conference	Transplant cells, not organs	Susan Lim
Ingenious	0.5693	TEDxBoston 2012	Brilliant designs to fit more people in every city	Kent Larson
Informative	0.4901	TEDMED 2014	The coming crisis in antibiotics	Ramanan Laxminarayan
Unconvincing	0.4542	TED Fellows 2015	The coolest animal you know nothing about ... and how we can save it	Patrícia Medici
Courageous	0.4482	TED2013	How I named, shamed and jailed	Anas Aremeyaw Anas
Fascinating	0.4424	TED2009	Could a Saturn moon harbor life?	Carolyn Porco
Obnoxious	0.3601	TED2009	17 words of architectural inspiration	Daniel Libeskind
OK	0.2671	TED Fellows Retreat 2013	My DNA vending machine	Gabe Barcia-Colombo
Longwinded	0.2532	TED2002	Rethinking the way we sit down	Niels Diffrient
Confusing	0.1741	TED2007	The design genius of Charles + Ray Eames	Eames Demetrios

Top Rated

- The top rated talk (ranked **Beautiful 83%** of the time) was Building a Park in the Sky by Robert Hammond at the TED2011 event
- The funniest talk (ranked **Funny 70%** of the time) was It's Time for the Talk by Julia Sweeney at the TED2010 event

Lowest Rated

- Although The Design Genius of Charles + Ray Eames, by Eames Demetrios at the TED2007 event, was rated as having the highest negative rating for being Confusing, it was **only rated as such 17% of the time which is not a clear indication of overall sentiment**

First 3 TED Talks Filmed

Title	Main_Speaker
5 predictions, from 1984	Nicholas Negroponte
My days as a young rebel	Frank Gehry
Back to the future (of 1994)	Danny Hillis

- The years of: **1984 (first talk)**, 1990, and 1995 each had only 1 TED Talk:
  - **1984: 5 Predictions from 1984 by Nicholas Negroponte**
  - 1990: My days as a young rebel by Frank Gehry
  - 1994: Back to the future (of 1994) by Danny Hillis
  - 1994: Back to the future (of 1994) by Danny Hillis

Talk Duration Information

- The average TED talk was just under 14 minutes long, with the **maximum length being 1 hour and the minimum being just 2.5 minutes long**
  - Min: The Ancestor of Language by Murray Gell-Mann at the TED2007 event (2.5 minutes)
  - Max: Nationalism vs. Globalism: The New Political Divide by Yuval Noah Harari at the TED Dialogues event (60 minutes)
- The most rated TED talk of all time is:
  - Do Schools Kill Creativity? by Ken Robinson (93,850 total reviews)
- The least rated TED talk of all time is:
  - How your pictures can help reclaim lost history by Chance Coughenour (68 total reviews)
- The majority of talks have an overall primary rating of **Funny (850) or Beautiful (712)**, with **63% of the dataset comprised** of those two categories, 34% and 29% respectively

Talk Summary Information

- **Hans Rosling** was the most frequent speaker (9 presentations)
- The most common speaker occupation is Writer (45 occurrences)
- The most frequent date for filming, and subsequently publishing, was **4/24/2017 (64 occurrences)**
- The most frequent event (year) is **TED2014 (84 occurrences)**
- 320 unique events listed
- There 65 unique languages and 555 unique comments tracked indicate **unique counts of languages/comments per event (e.g. 4 different languages and 10 comments for a given TED talk)**
- As expected, the majority of speakers per talk is 1 (2,412), however there were 46 cases of 2 speakers presenting

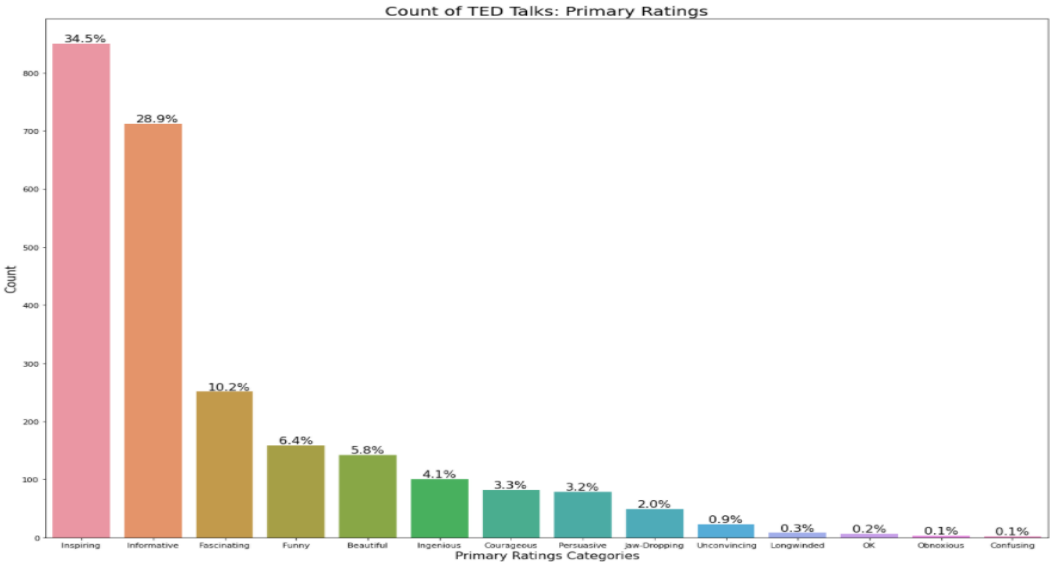
Data Wrangling

- Merged both datasets on URL column into **TED_Combined** DataFrame
- Converted all column names to capitalized first letter, each word
- Replaced 6 missing Speaker Occupations via details found online for each
- Converted Date columns to DateTime format and Object datatypes to Categorical
- Divided total Views by 1M and rounded to 2 decimal places
- Divided Duration by 60 seconds to convert to a minutes total
- Removed Unnecessary Columns:
    - Related Talks
    - URL
    - Number of Speakers (Hardly ever more than 1)
    - Name (redundant - concatenation of Speaker and Title)
- **Created Text Statistics summary columns for each row:**
    - **Sentence Count**
    - **Word Count**
    - **Character Count**
- Unpack Ratings & Tags from List and convert to Dictionaries
- Total Ratings column created
    - Sum of each category count within Ratings dictionary
- Total Ratings % column created
    - **Sum of all individual Ratings always equal 100%**
- Individual Ratings Extracted as Columns (% of Total Ratings)
- Unique Ratings column created
- **Extracted the Following from Ratings dictionary:**
    - **Funny, Beautiful, Ingenious, Courageous, Inspiring, Jaw-Dropping**
    - **Longwinded, Confusing, Unconvincing, Obnoxious**
    - **Informative, Fascinating, Persuasive, OK**
- **Primary Rating column created based on max row value for Individual Ratings**
    - e.g. if Funny is highest % of total, Primary Rating will reflect Funny
    - This column will **serve as the Target for predictive modeling**
- Unique Tags column created
- Film and Published Date converted to simple data format
- **Created Transcript and Tag Corpus** for Word Cloud summaries
- **Primary Rating # column created** as a numerical (non-ordinal) target column for predictive modeling

Exploratory Data Analysis

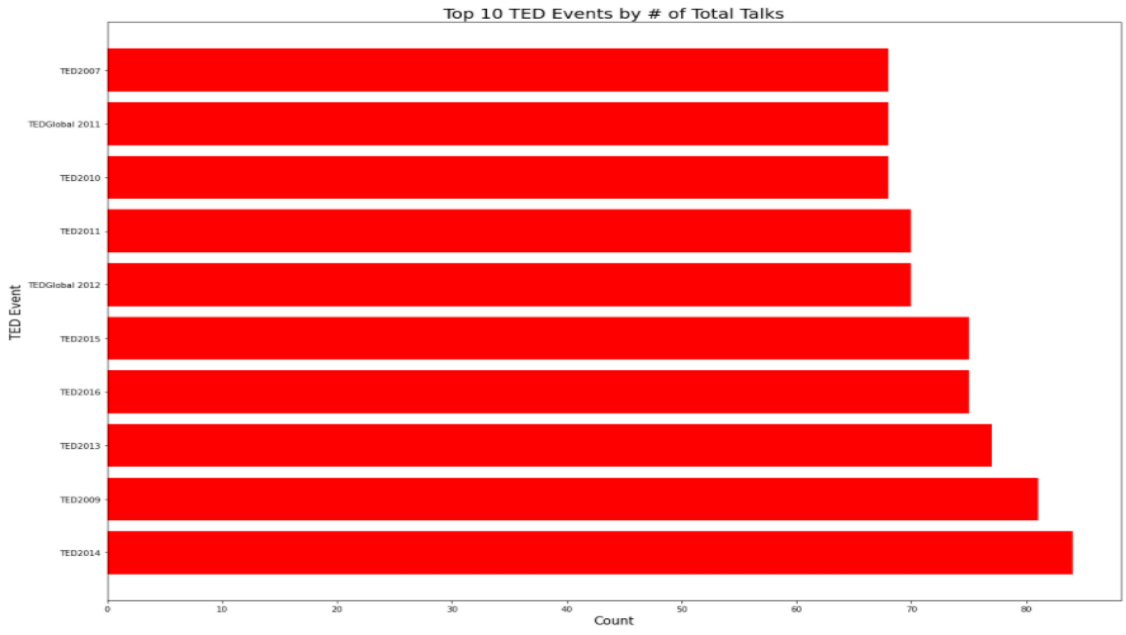
Univariate

Count of Ted Talks by Primary Rating (Target)



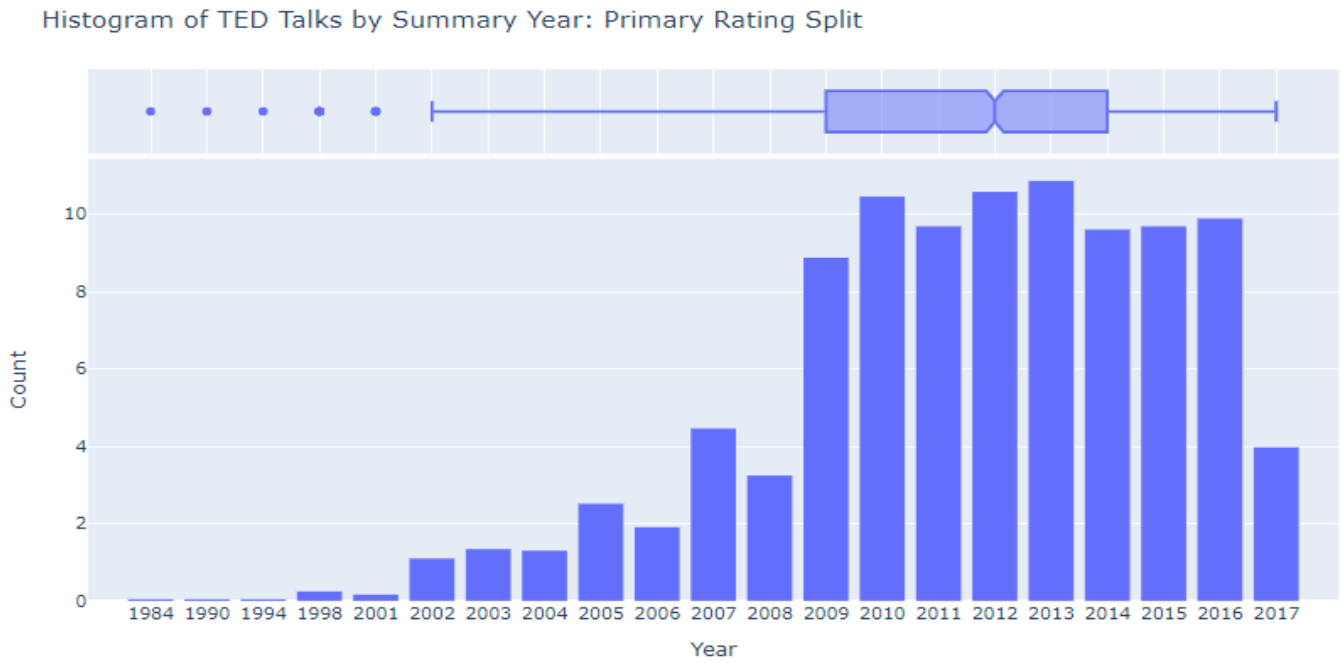
- Over 63% of talks are primarily rated as either **Inspiring (34.5%) or Informative (28.9%)**
- Conversely, **less than 1%** of all talks fall under the following 4 Rating Categories:
  - Longwinded (0.3%)
  - OK (0.2%)
  - Obnoxious (0.1%)
  - Confusing (0.1%)

Count of Ted Talks by Primary Rating (Target)



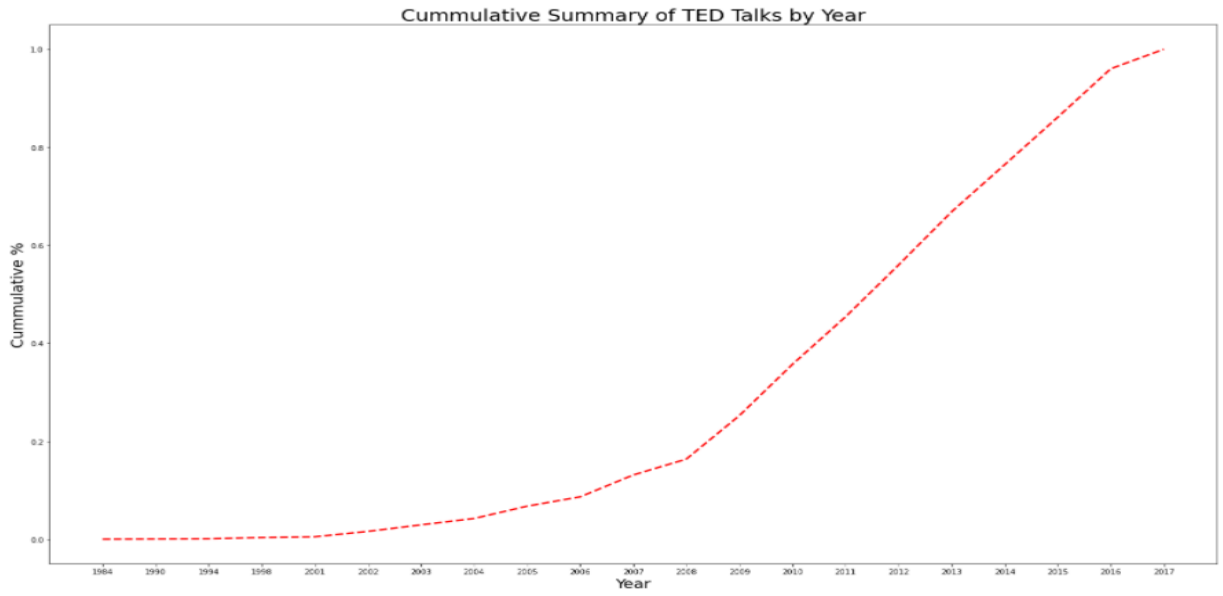
- The most popular event, as it relates to number of talks hosted, was **TED2014, closely followed by TED2009**
- There were numerous TED events with fewer than 10 total talks, some having only 1 unique talk/speaker
    - 1 talk per event - 140
    - 5 or fewer talks per event - 236
    - 10 or fewer talks per event - 276
    - **% of Events with 10 or fewer talks - 11%**

Histogram of Talks by Film Year (by Primary Rating)



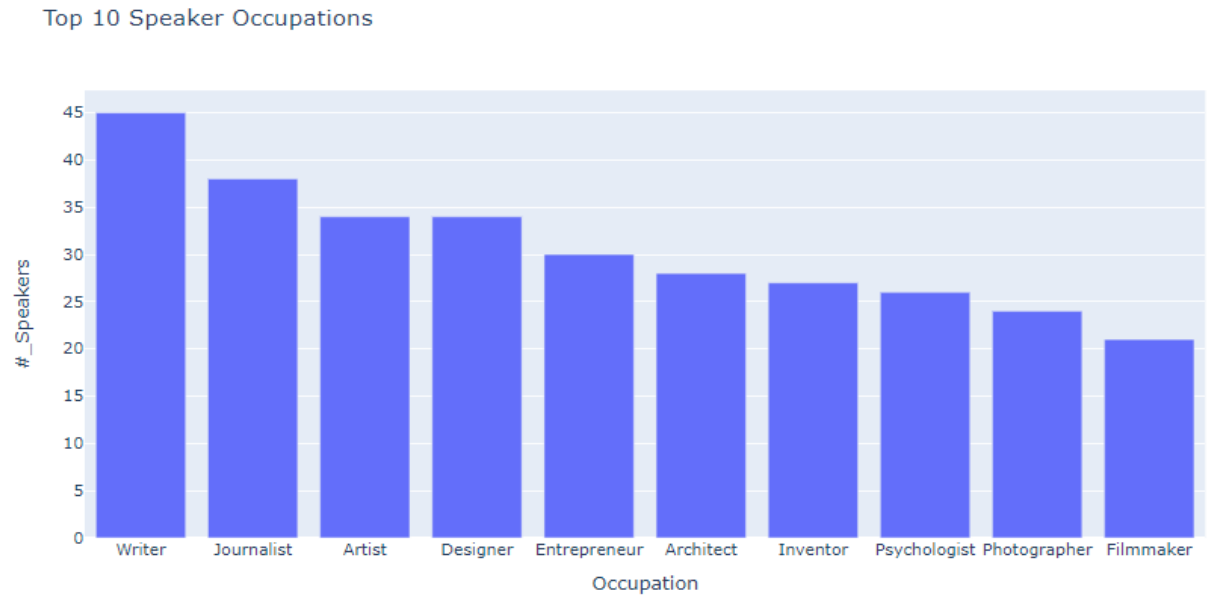
- Over the 33 years of TED talks, **ranging from 1984 to 2017 (partial through 8/27/17)**, the majority of Talks fall in the years of 2013, 2012, and 2010 comprising of 10.9%, 10.6%, and 10.5% respectively
- Outliers exist on the lower end of the data, before 2002, with 1984, 1990, and 1994 only having 1 TED talk each

Cumulative Summary of TED Talks by Year



- 50% of the overall TED talks in the sample dataset occurred from 1984 to between 2011/2012 (roughly 28 years), whereas there is a **strong ramp-up from 2012 through partial 2017 (5 years) for the remaining 50% of TED Talks**

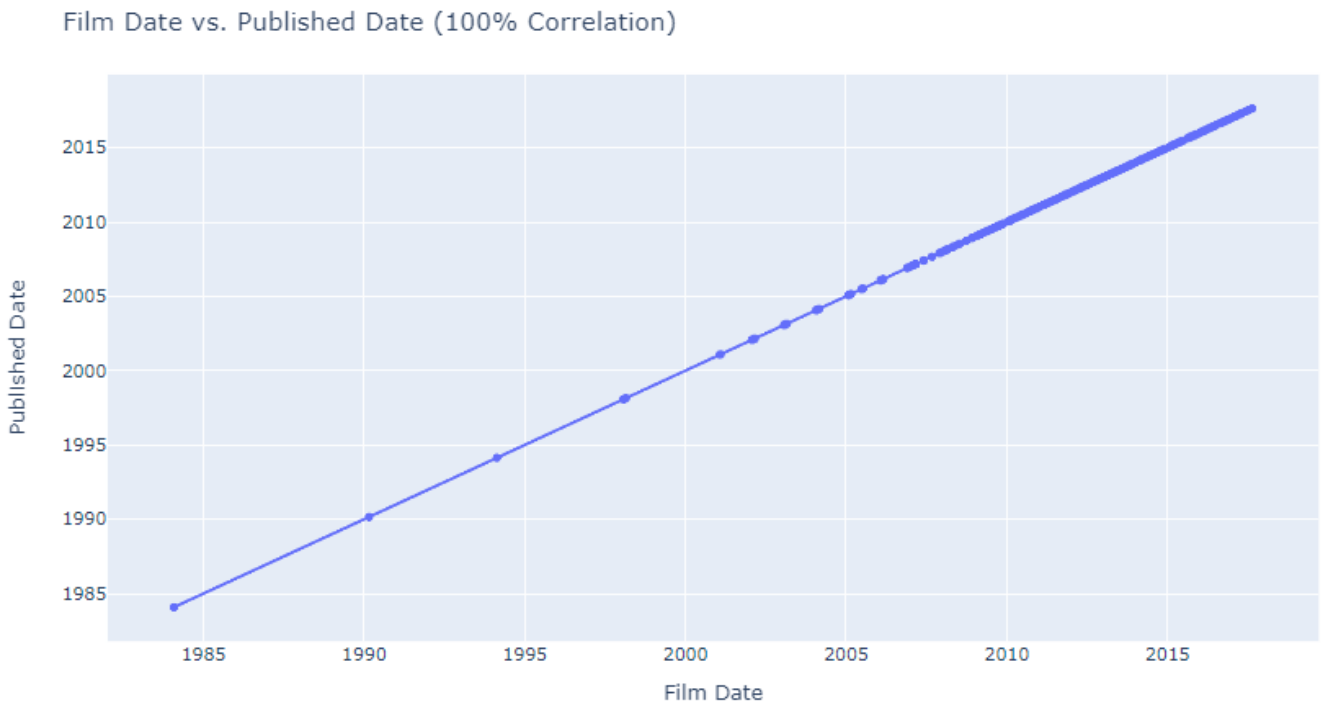
Top 10 Speaker Occupations



Of the top 10 Speaker Occupations sampled, **Writers make up almost 15% of the entire speaker segment**, followed by Journalists (12%) and Artists/Designers (each at 11%)

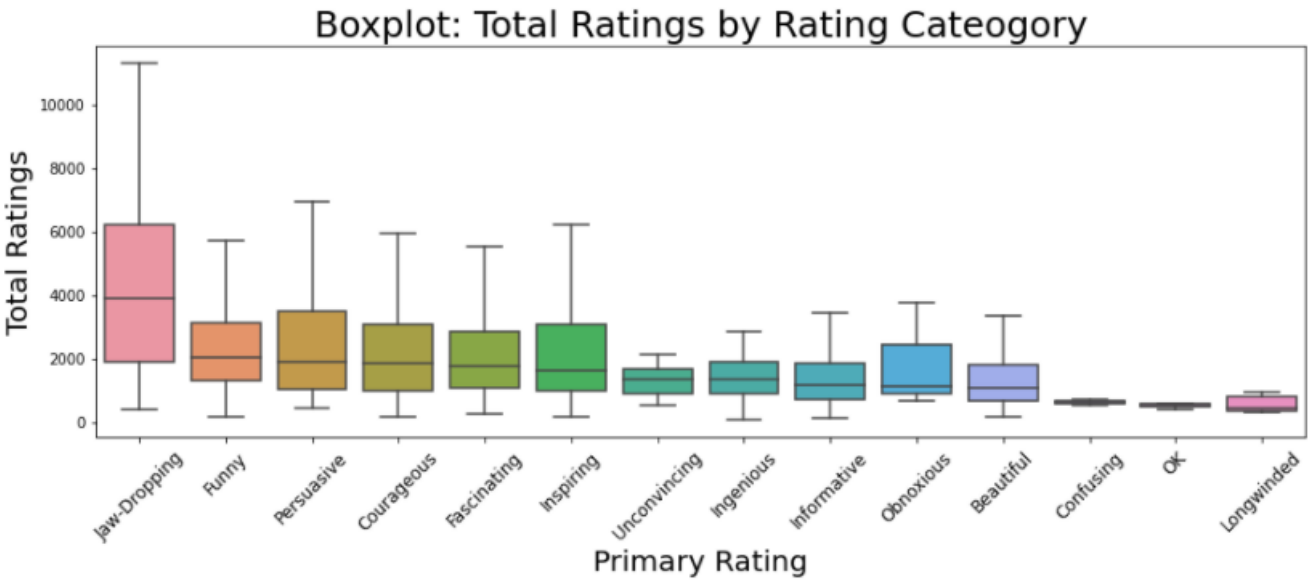
Bivariate

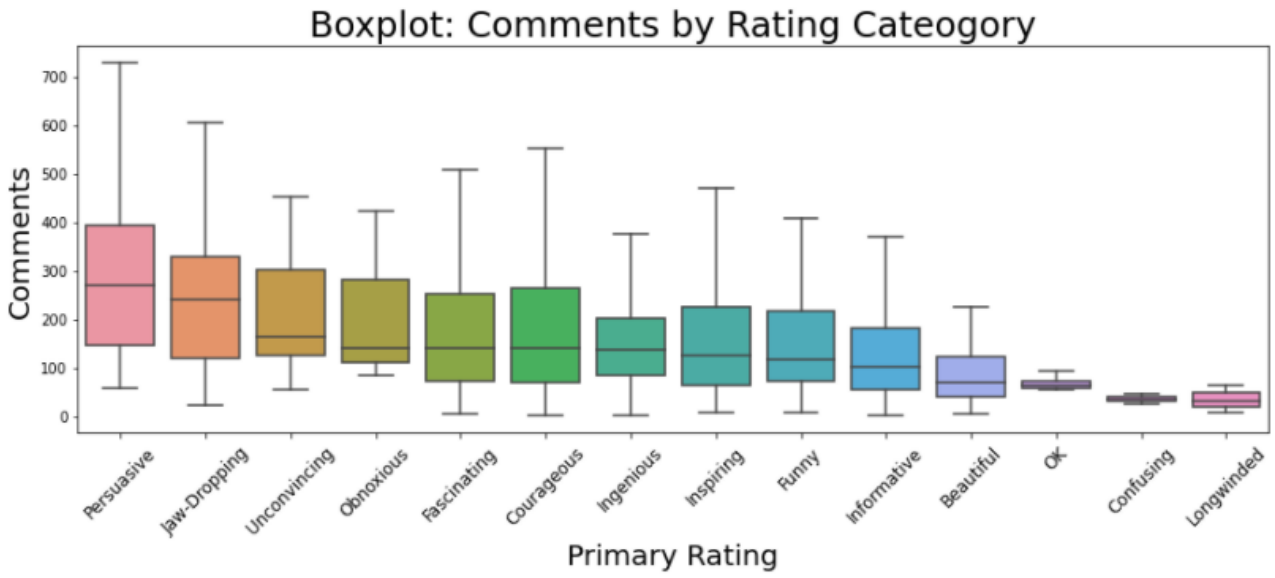
Count of Ted Talks by Primary Rating (Target)

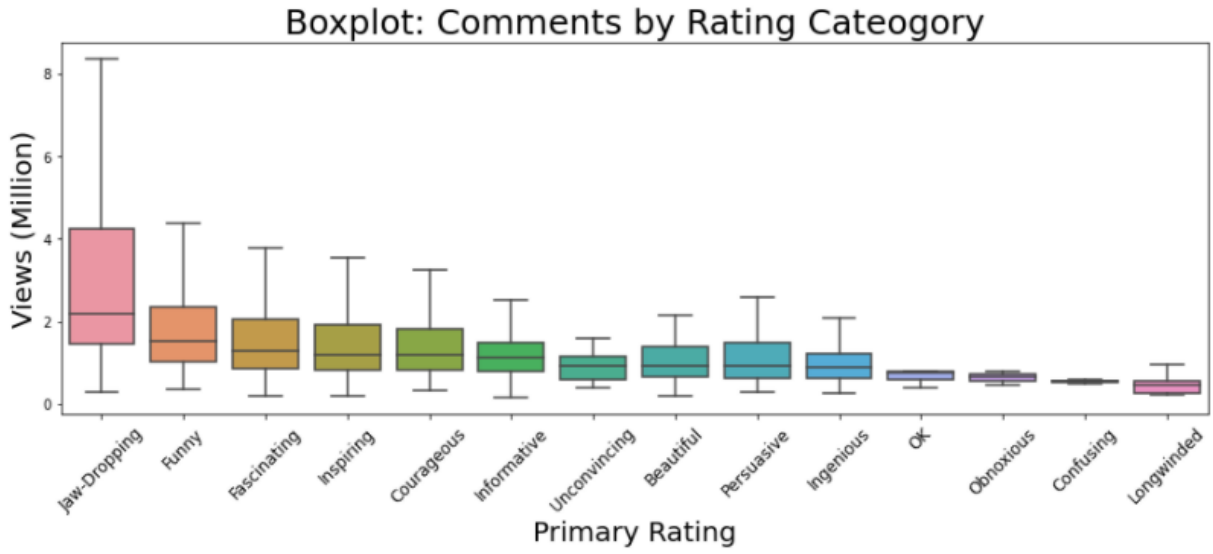


- The plot above confirms that **Film Date and Published Date are equivalent - every TED talk is filmed live and published online that same day** (possibly same time if immediately published after recording)
- There is a **ramp-up in frequency of annual talks hosted per year from around 2008 onwards**

Ted Talks by Primary Rating (Target): Total Ratings, Comments, & Views



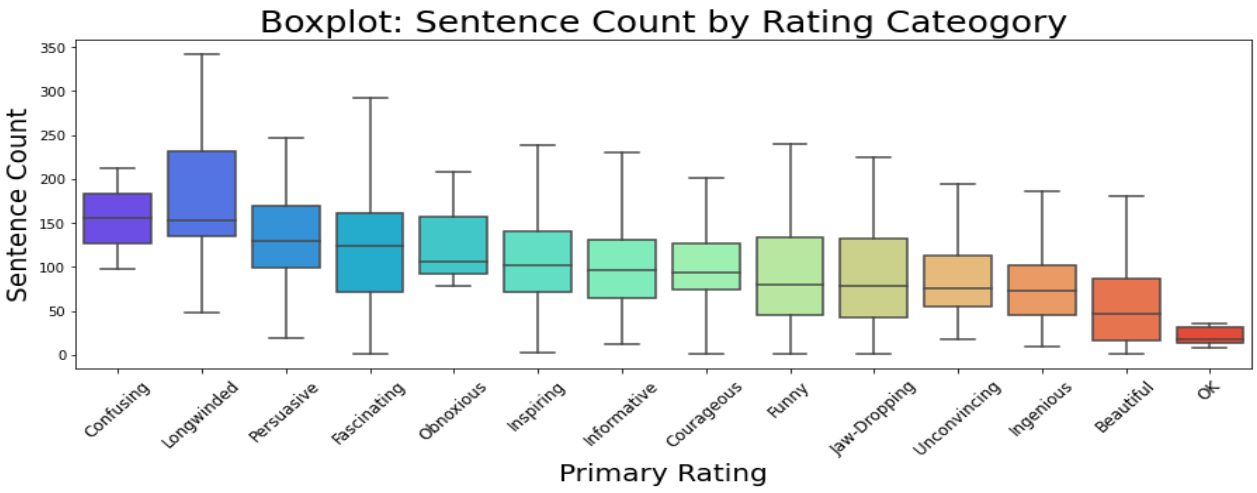


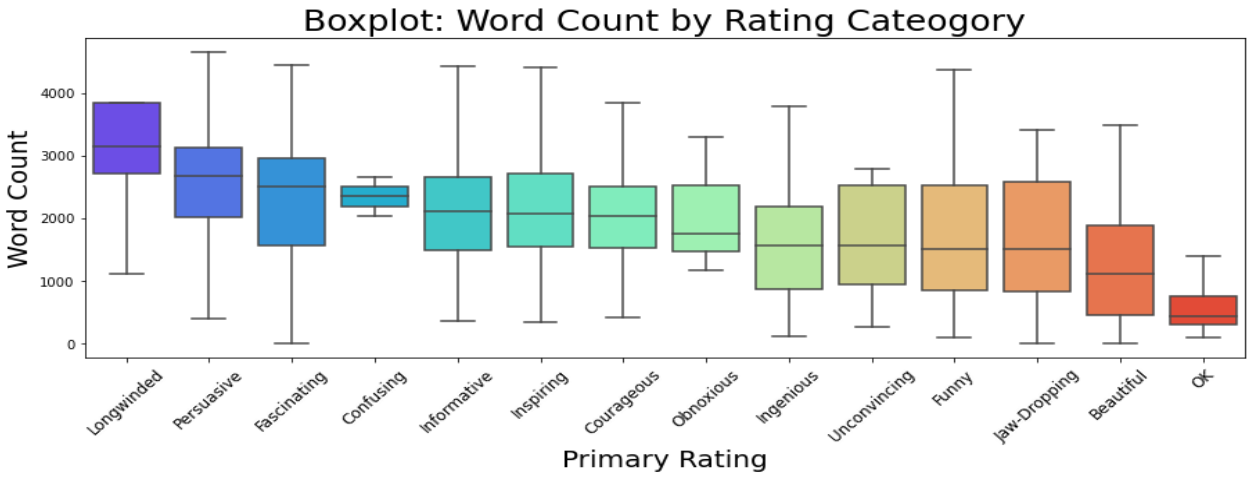


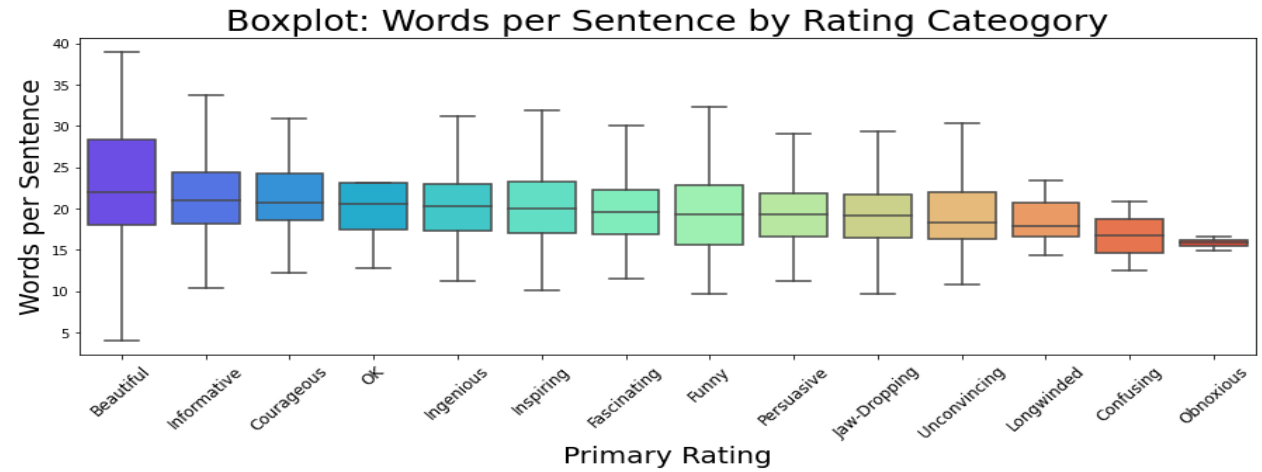
- In general, there are **substantially more positive Rating Categories (9 vs. 5)**
- The majority of Ratings and Comments, particularly outliers are assigned to the **Inspiring** rating category
- Excluding outliers, the **Jaw-Dropping** category has the largest distribution of Ratings, and the **Persuasive** category has the largest distribution of Comments
- The categories for Longwinded, OK, and Confusing, has the lowest distribution of Total Ratings and Comments
    - This, in addition to the large distribution in positive categories, shows that **TED viewers opt to Rate/Comment on a Talk usually do so only usually only when creating a positive reaction for the viewer**
    - **One caveat to this is for talks rated as Obnoxious or Unconvincing**, which do appear to welcome further commentary and ratings form viewers - perhaps invoking stronger feelings and a call to respond

- Talks rated as **Jaw-Dropping have the highest overall views**, substantially higher than all other categories which are relatively similarly distributed
- Talks rated as **Longwinded accounted for the lowest counts for Total Ratings, Comments, and Views**

Sentence/Word Count and Words per Sentence by Primary Rating



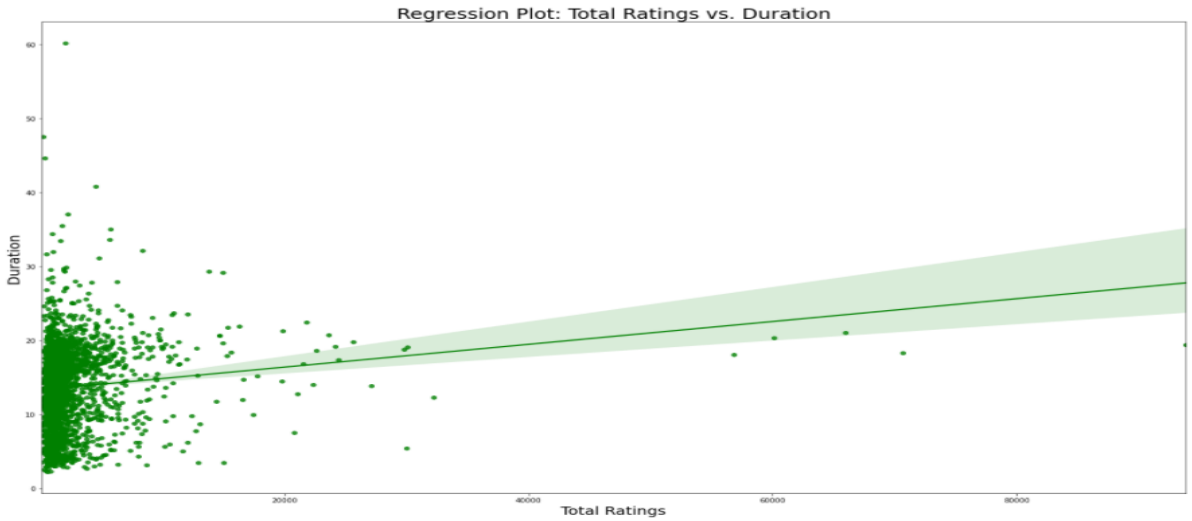


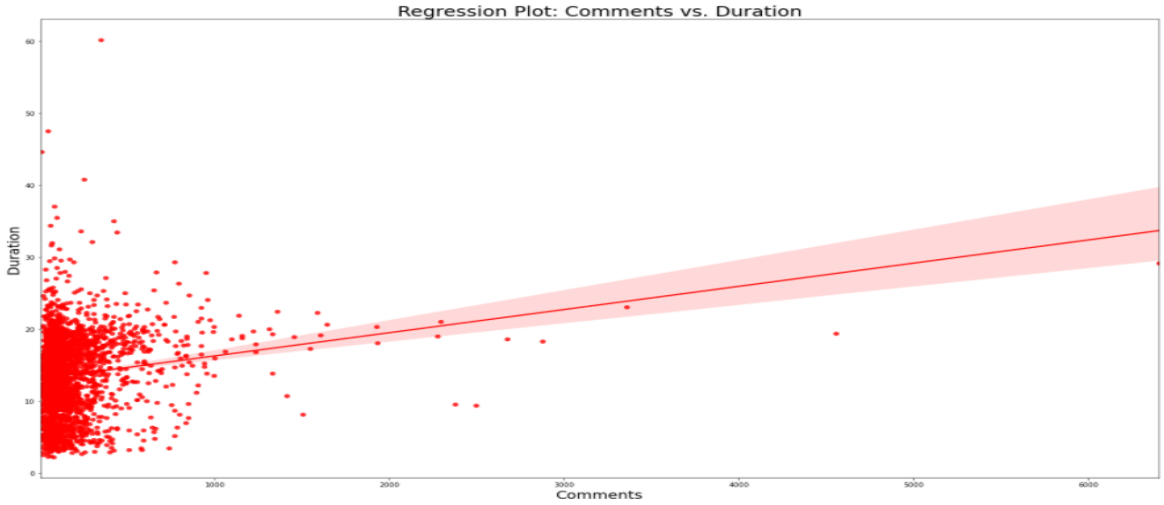


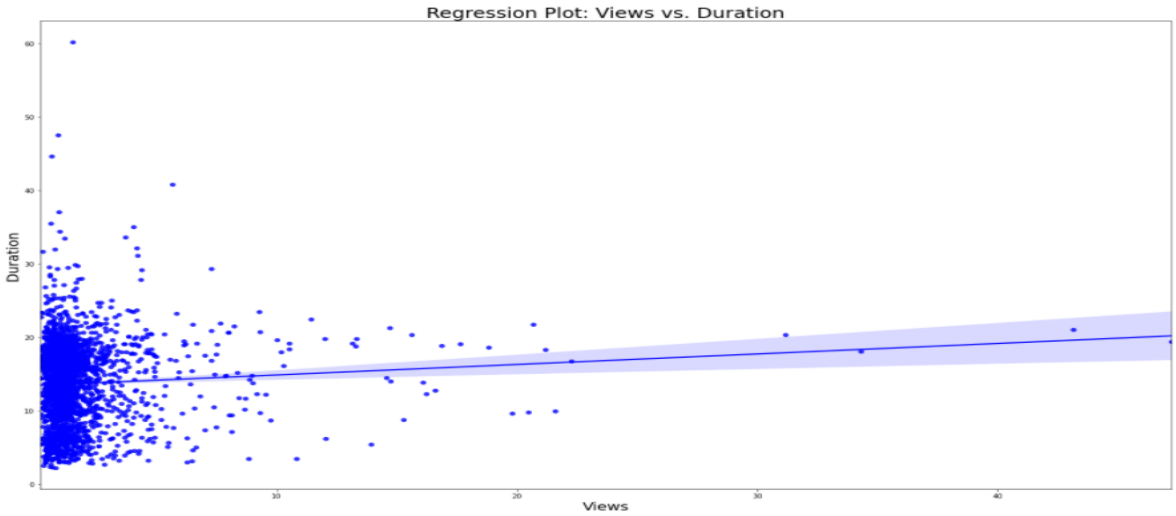
Although **Sentence and Word counts are assumed to be highly correlated for each respective talk**, it is worth further examining the general distribution of each in relation to Primary Rating classifications.

- **Talks classified as OK had the lowest counts for Sentences, Words, and Characters**
  - It seems to show that these talks needed further presentation/delivery in order to impress the audience, but also avoided appearing Longwinded or confusing through being too long
- **Longwinded talks, as the Rating suggests, carried the highest counts for Sentences, Words, and Characters**
  - However, these talks are closely followed by talks rated as Persuasive, Fascinating, and Informative
    - This is perhaps indicative of longer talks, up to a (reasonable) point, showing a greater likelihood of being positively classified
    - There appears to be a **fine line between effective distribution of a message and a Longwinded ramble that could lose audience attention and warrant a negative Primary Rating**

Correlation of Talk Duration vs. Total Ratings, Comments, & Views



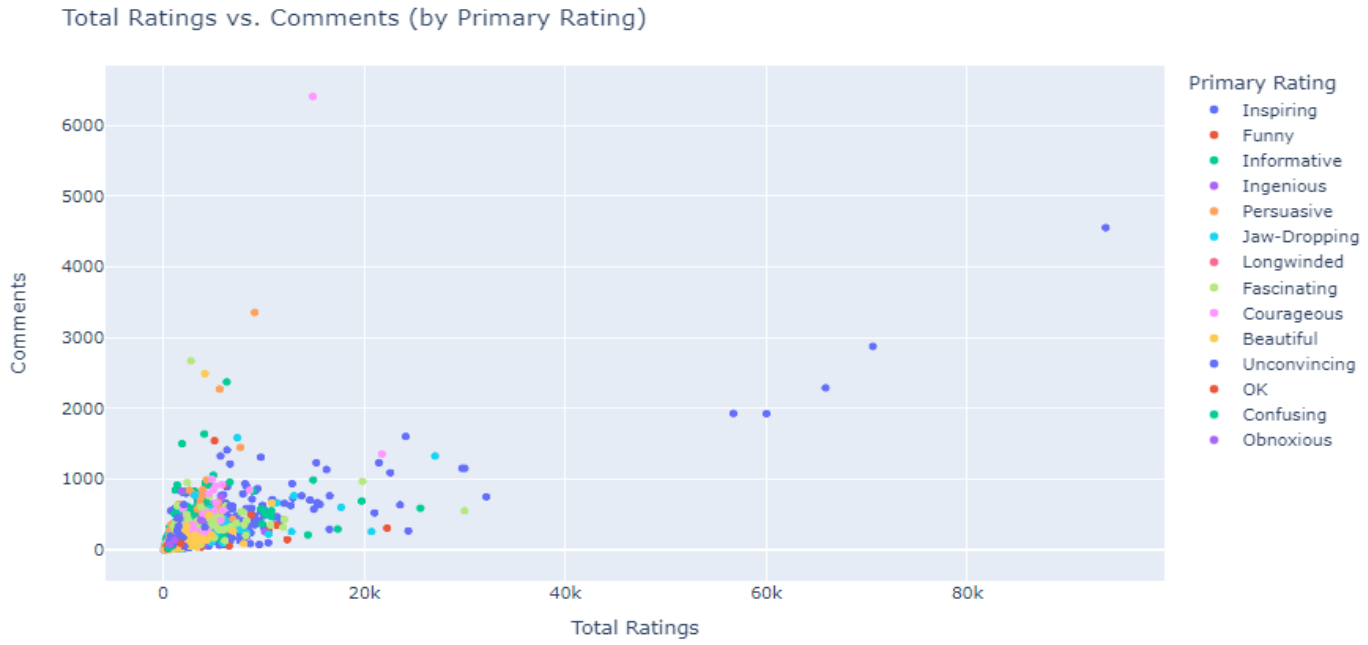


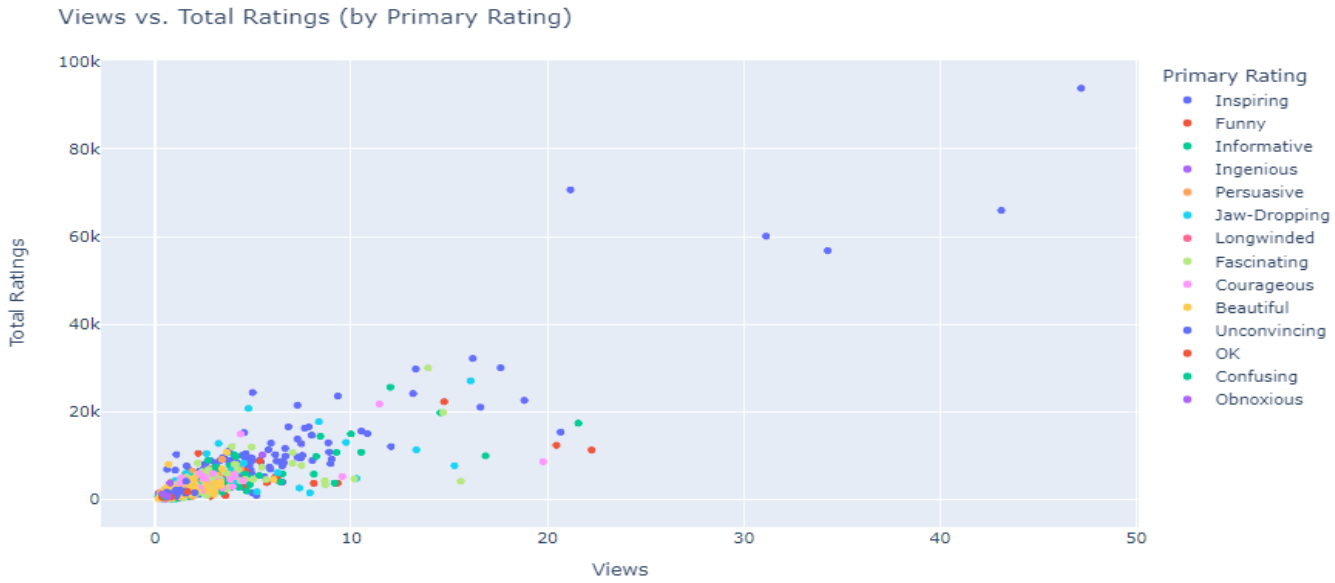


- **Both Comments and Total Ratings have a noticeable positive correlation to Duration**, with Comments have a slightly stronger correlation (higher slope)
    - There is a slight positive correlation between Views and talk Duration with the large majority of talks having a low view count of less than
    - **75% of talks have total views of 1.75M, with the maximum views of 47.2M (Do Schools Kill Creativity by Sir Ken Robinson) largely skewing the dataset**

Multivariate vs. Target

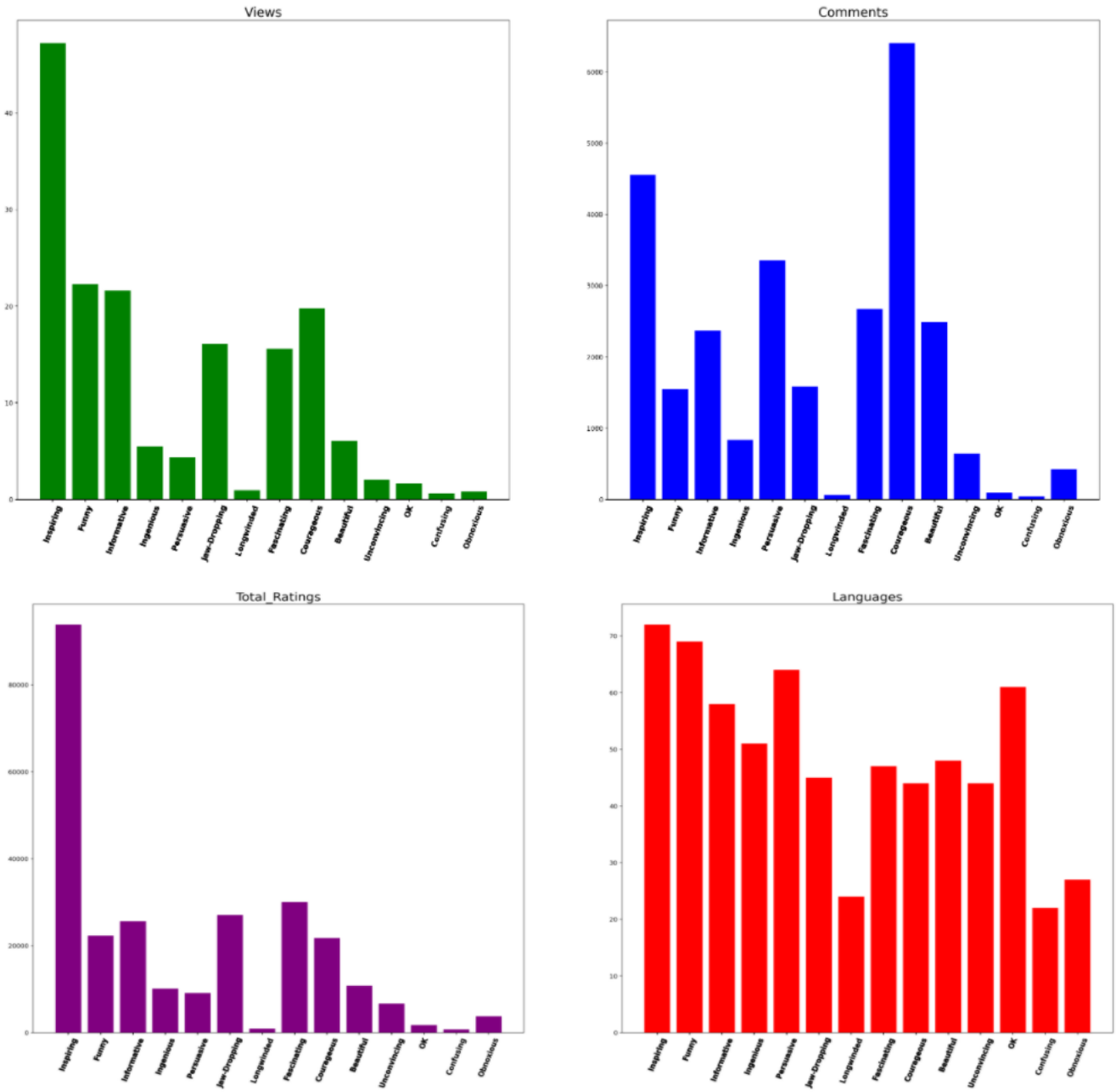
Total Ratings vs. Comments & Vies (by Primary Rating)





- There is a slight correlation between increased Rating counts and the amount of Views and Comments created for a given TED talk
- The top rated (quantity) talks are usually those **individually rated as Inspiring, namely the talk by Ken Robinson, Amy Cuddy, and Simon Sinek**
- One notable outlier having substantially higher comments but lower overall views and ratings, is **Militant Atheism by Richard Dawkins** -This talk which was primarily rated as Courageous

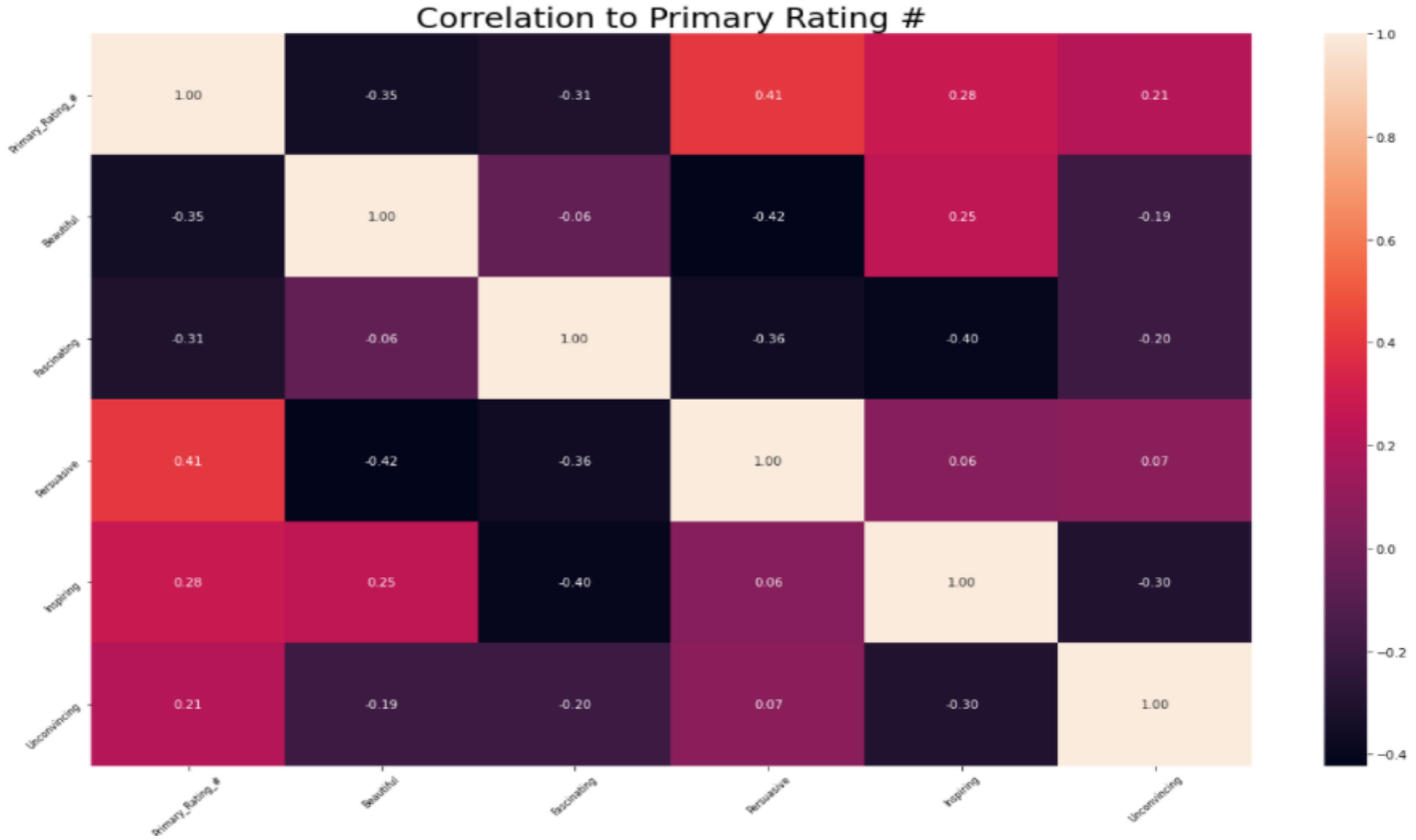
Views/Comments/Total Ratings/Languages vs. Primary Rating



- TED talks classified as **Inspiring show the highest count across almost all metrics, particularly Total Ratings**
    - However, talks classified as Courageous scored the highest Comment counts, followed by talks classified as Inspiring
- Regarding Languages (count), talks classified as: **Confusing, Longwinded, or Obnoxious had substantially lower unique language counts**, with Inspiring, Funny, Persuasive, and OK talks having the highest counts, respectively
- Views and Total Ratings appear to have similar distribution patterns, with Views having more proportionately, as expected since **not everyone who watches a talk will submit a rating**
    - Comments show less of a direct pattern as **certain viewers may be particularly moved by a talk, positively or negatively, and feel compelled to comment, regardless of overall views for that talk**

Correlation Summary

- **Duration, Sentence Count, and Character Count are all highly correlated**, which makes sense since all are somewhat derived from the initial transcripts detail (character < word < sentence)
- **Views, followed by Comments are strongly correlated (+87% and 64% respectively) to the Total Ratings column**, indicating that the higher the amount of views, and respective comments that follow, the higher the likelihood of increased rating counts
- None of the individual ratings are strongly correlated to the target variable
- Regarding **Rating Categories**, there are a few notable correlations:
    - **Positive**
        - Unconvincing and Obnoxious (+57%)
        - Unconvincing and Confusing (+54%)
        - Confusing and Longwinded (+51%)
    - **Negative**
        - Informative and Beautiful (-52%)
        - Fascinating and Courageous (-50%)
        - Persuasive and Beautiful (-42%)
- **Vs. Primary Rating # (Target)**:
    - **Positive**
        - Persuasive (+41%)
        - Inspiring (+28%)
        - Unconvincing (+21%)
    - **Negative**
        - Beautiful (-35%)
        - Fascinating (-31%)



Regression Summary - Top 5 Variables Correlated to Target

OLS Regression Results

Dep. Variable:	Primary_Rating_Num	R-squared:	0.381
Model:	OLS	Adj. R-squared:	0.380
Method:	Least Squares	F-statistic:	303.4
Date:	Thu, 20 Jan 2022	Prob (F-statistic):	1.85e-253
Time:	13:47:59	Log-Likelihood:	-5103.7
No. Observations:	2467	AIC:	1.022e+04
Df Residuals:	2461	BIC:	1.025e+04
Df Model:	5		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
Intercept	3.3097	0.206	16.067	0.000	2.906	3.714
Beautiful	-8.7022	0.518	-16.807	0.000	-9.717	-7.687
Fascinating	-1.1396	0.678	-1.680	0.093	-2.470	0.191
Persuasive	7.8687	0.699	11.255	0.000	6.498	9.240
Inspiring	9.5878	0.453	21.171	0.000	8.700	10.476
Unconvincing	15.9908	1.147	13.937	0.000	13.741	18.241

Omnibus:	161.903	Durbin-Watson:	2.029
Prob(Omnibus):	0.000	Jarque-Bera (JB):	229.508
Skew:	0.559	Prob(JB):	1.46e-50
Kurtosis:	3.991	Cond. No.	32.9

Although the R-Squared score is only around 40% in the above summary, it shows that **nearly 40% of the variance of the target variable (Primary Rating Number) is explained** by just the 5 Categories/Scores:

Positive Correlation

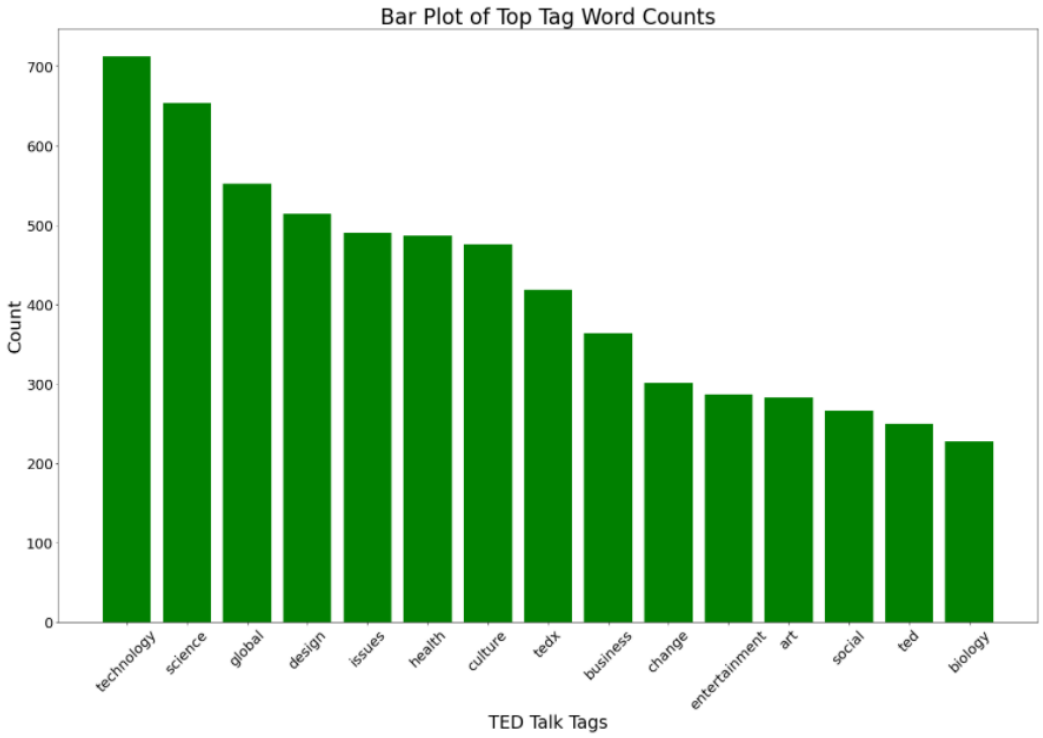
- Unconvincing: Coefficient change of 16 on target for 1 change in variable
- Inspiring: Coefficient change of 9.6 on target for 1 change in variable
- Persuasive: Coefficient change of 7.9 on target for 1 change in variable

Negative Correlation

- Beautiful: Coefficient change of -8.7 on target for 1 change in variable
- Fascinating: Coefficient change of -1.1 on target for 1 change in variable

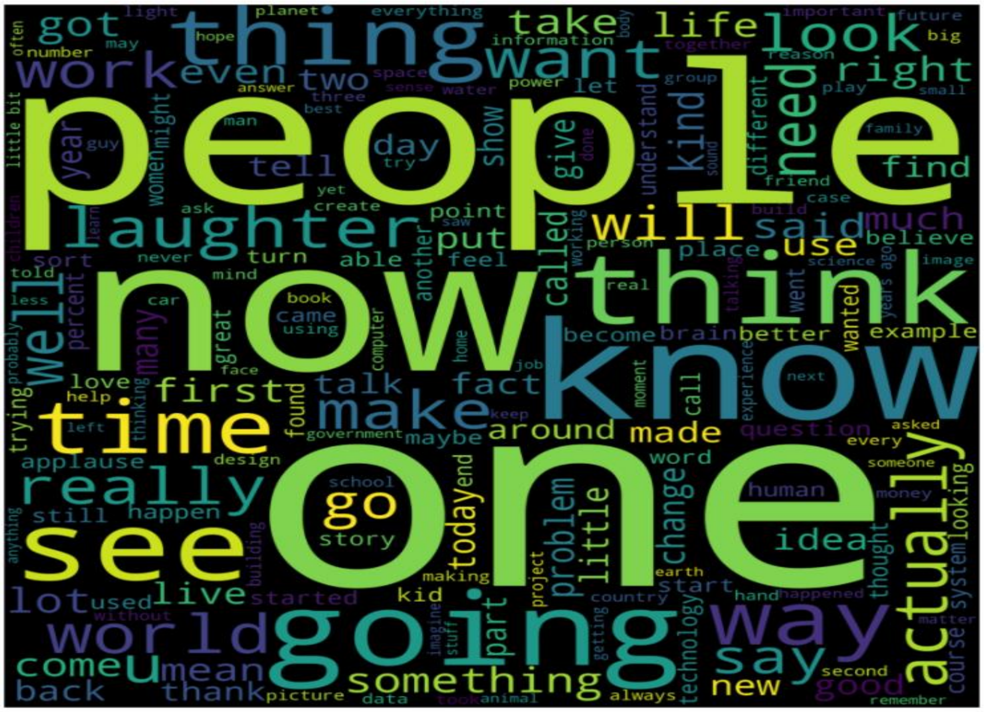
Natural Language Processing

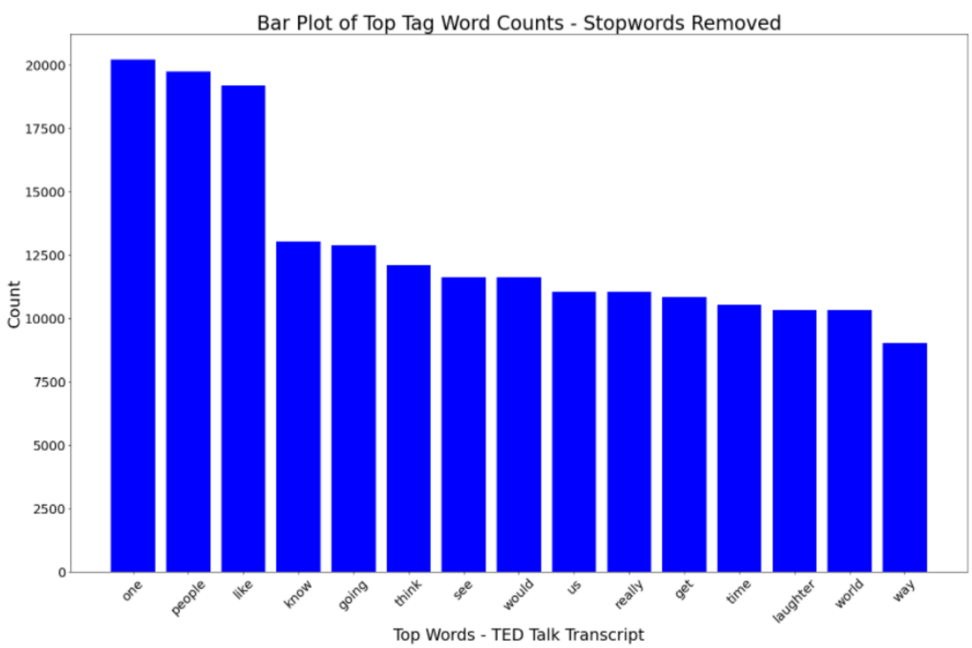
Word Cloud – Tags



- When looking at the most prevalent individual word tags, we can see that Technology, closely followed by Science are the top tags for all TED Talks
- When looking at top two-worded tags, Global Issues are the top tagged TED Talks
    - When browsing both single/double tags, we can **clearly see that Science, Technology, and Global Issues are key focal points for the large majority of TED Talks**

Word Cloud – Transcripts





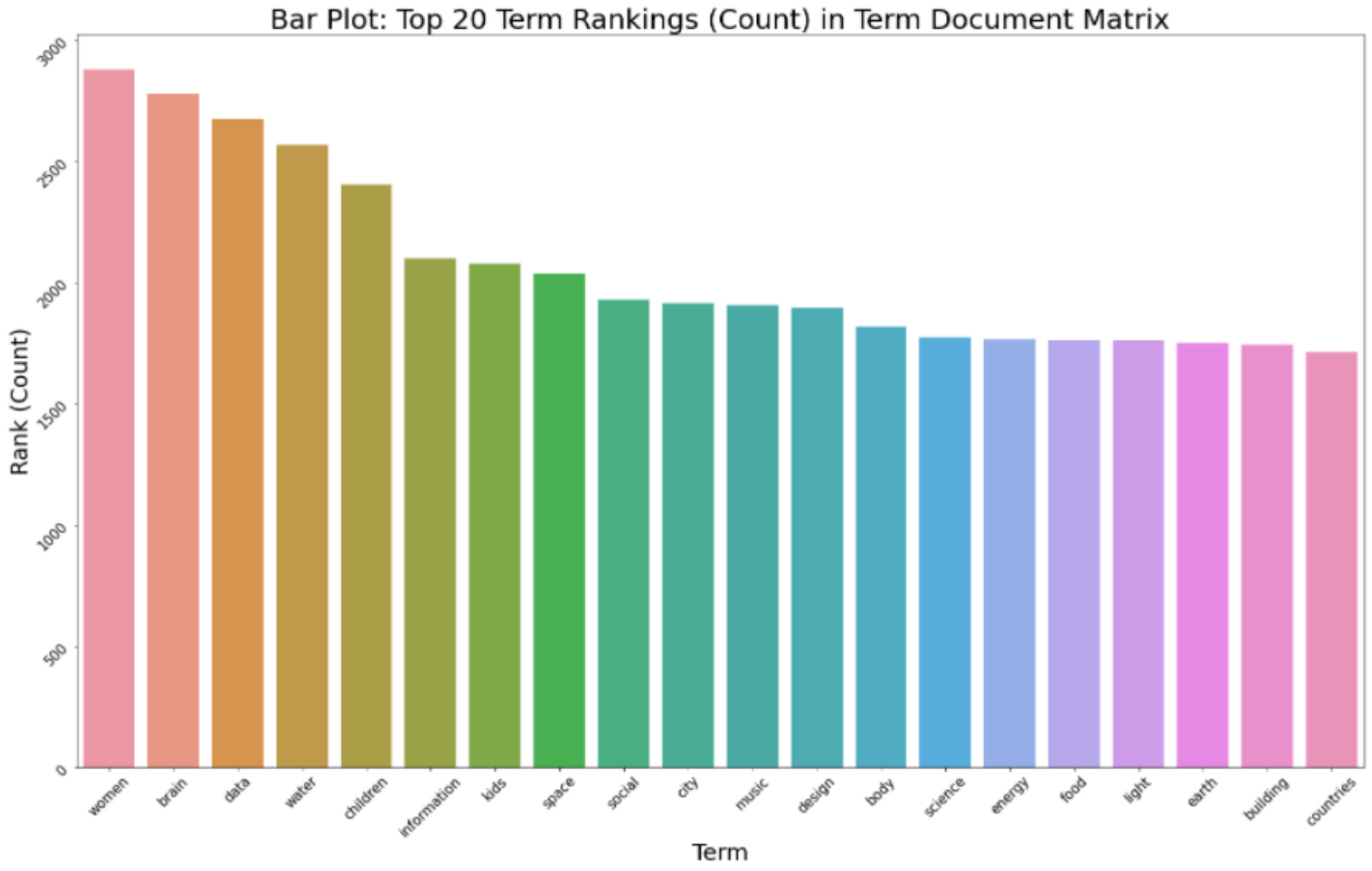
Based on the sizing of key words above, we can see that the following (ordered) are key words/ideas represented within the entire TED dataset:

- Now
- One
- People
- Know
- Going
- Think
- See
- Laughter
- World

These all **encapsulate an overall positive, humanity focused message**, which aligns well with the respective TED Message & Slogan:

- Welcoming People of Every Discipline and Culture who Seek a Deeper Understanding of the World
- Ideas Worth Spreading

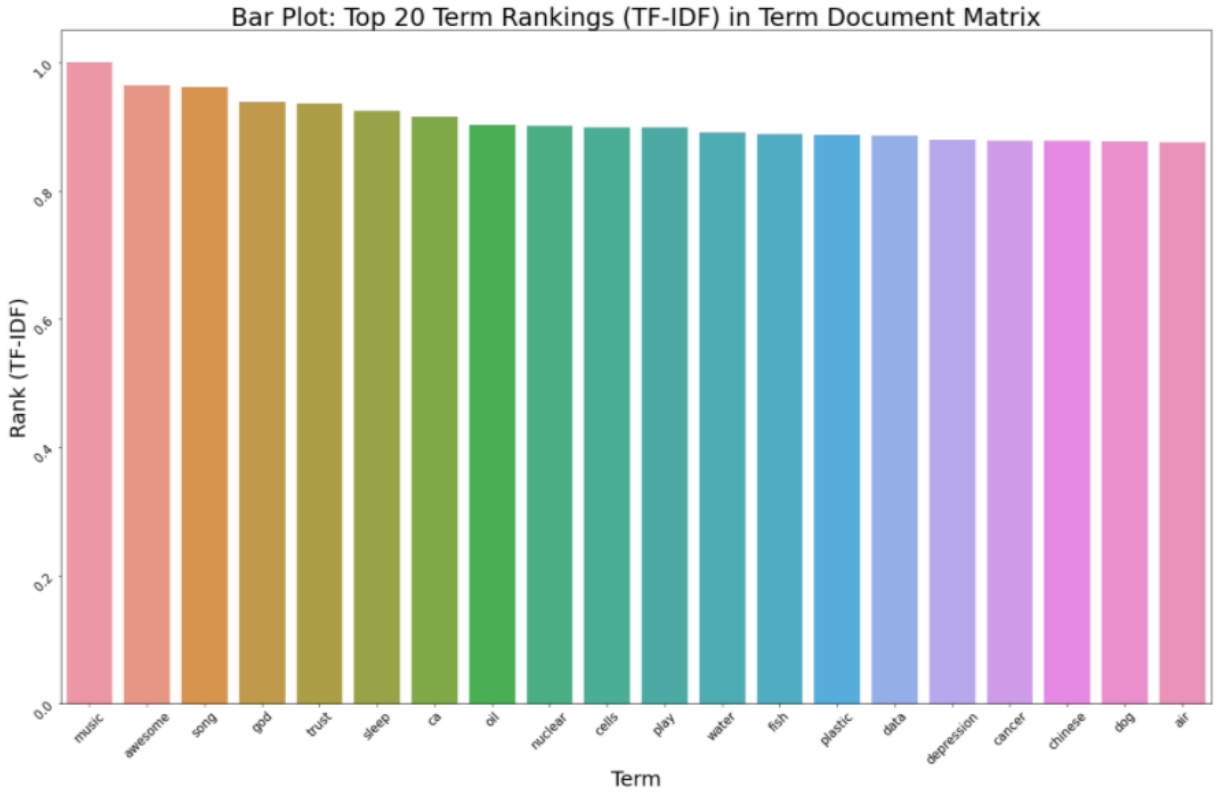
Term Document Matrix – Total Count:



From an Overall Count standpoint, certain keywords/ideas are most prevalent within the total Document Corpus in the Transcript column, including:

- **Humankind/Family**: Women, Children, Kids
- **Science/Learning**: Brain, Data, Information, Science
- **World/Resources**: Water, Space, Energy, Food, Earth, City, Countries
- **Society**: Social, Music, Design, Building

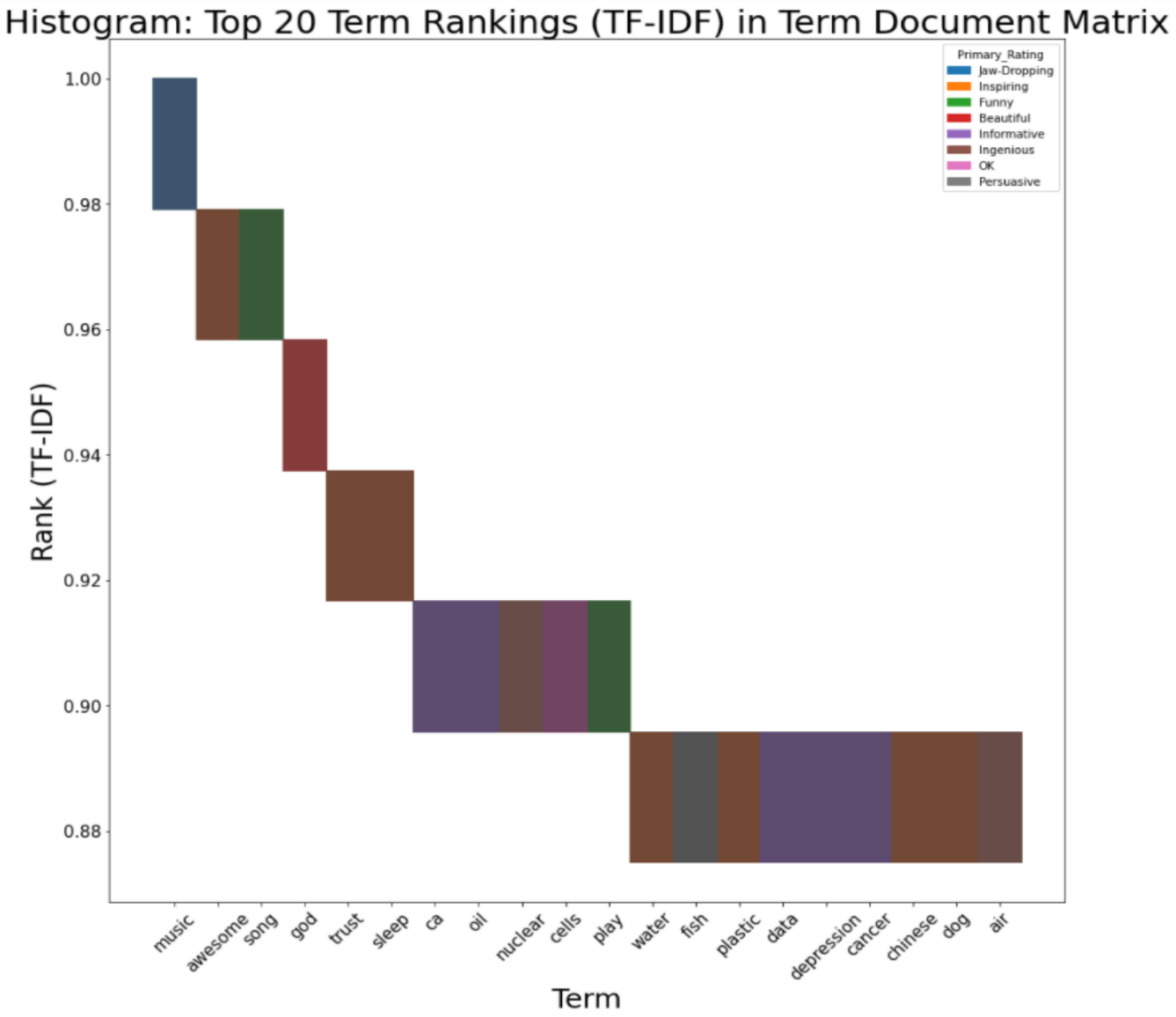
Term Document Matrix – TFIDF Score:



From a maximum TF-IDF score standpoint, certain keywords are most prevalent, however more randomized than when summarizing based on Total Counts, within the total Document Corpus in the Transcript column, including:

- **Musical**: Music, Song
- Awesome (description)
- God
- Trust
- Sleep
- Nuclear
- **Natural Resources**: Water, Fish, Air
- Data
- **Human Issues**: Depression, Cancer
- Chinese
- Dog

Term Document Matrix – TFIDF Score with Primary Rating:



Adding in the respective Primary Rating categories to the Term Document Matrix, we can see that the top predictive words (based on Maximum TF-IDF Scores) and respective Ratings:

- **Music (Jaw-Dropping)**
- Awesome (Ingenious)
- Song (Funny)
- God (Beautiful)
- Trust & Sleep (Ingenious)

Building a Predictive Model on Text Vectors

Since the CountVectorizer will be used first and fitted to the Transcript Corpus, only the TFIDF Transformer will be required for providing IDF values and then computing respective TFIDF scores.

- The **Support Vector Classifier** scored well, with the **Logistic Regression** model scoring slightly better than average on the Training dataset (88% and 69% respectively), and the **Naive Bayes Multinomial** model scoring poorly at slightly above 50%
    - All 3 models scored lower and just over 50% on the Validation dataset, however
- **Both the Decision Tree and Random Forest models scored nearly 100% due to overfitting** on the training set, which is often the case for tree/s based models
    - These models scored substantially lower on Validation data (33% and 52% respectively)
        - **Further Hyperparameter tuning should occur on all models** before determining the top 3

HyperParameter Tuning

Top Model/s Chosen:

- **Naive Bayes - 64% Train/53% Validation**
- Decision Tree - 45% Train/39% Validation

All other models scored very poorly in regards to generalization (strong Training/weak Validation results). The Decision Tree Classifier, although generalized, **scored less than 50% for both datasets**, not worth further consideration as a model.

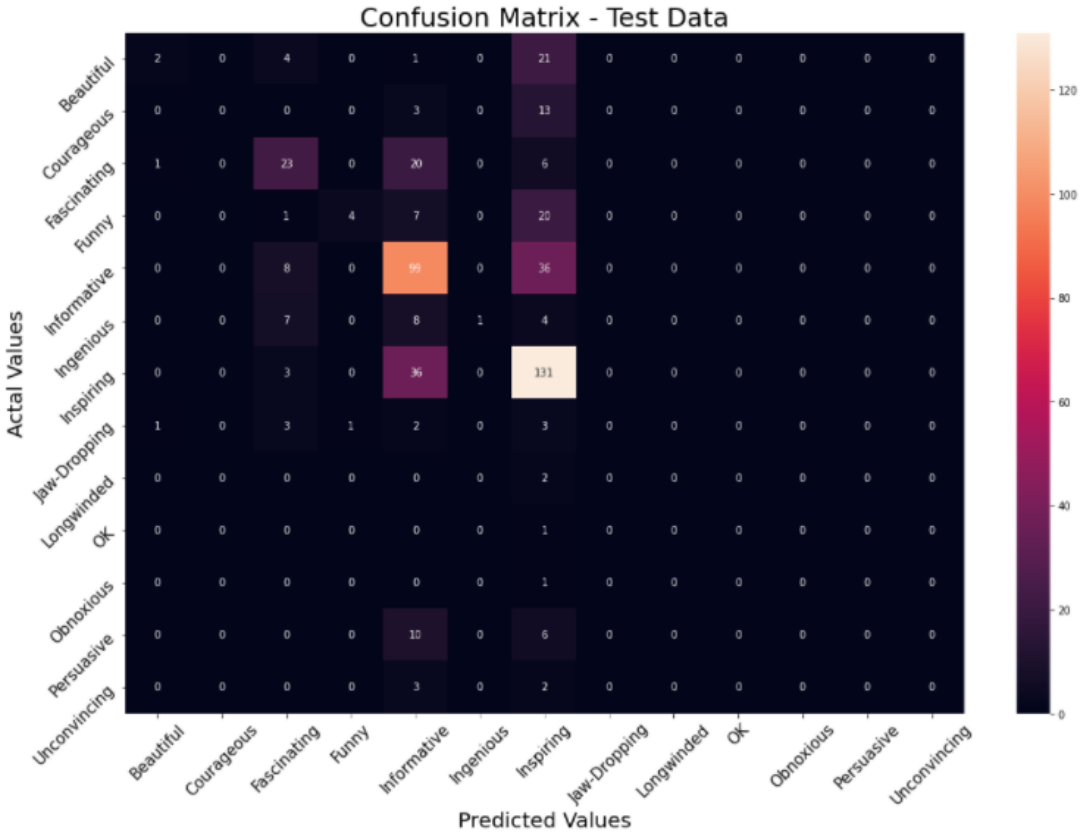
- **Only the Naive Bayes model will be utilized for NLP Classification of the Primary Rating categories**

Confusion Matrix – Test Data

Test Data:

```
Total (Actual) Count by Rating Category:

Inspiring       170
Informative     143
Fascinating      50
Funny            32
Beautiful        28
Ingenious        20
Persuasive       16
Courageous       16
Jaw-Dropping     10
Unconvincing      5
Longwinded        2
Obnoxious         1
OK                1
dtype: int64
```



For the **large majority of Primary Ratings predicted vs. actually assigned**, the correct Primary Rating classification has occurred. The main issues occurred in the following predictions:

- **Predicted Inspiring (36)** vs. Informative Actual Rating
- **Predicted Informative (36)** vs. Inspiring Actual Rating
- **Predicted Inspiring (21)** vs. Beautiful Actual Rating

One caveat to mention is that these **ratings are all somewhat related**, or rather are not opposites.

- Beautiful or informative talks **could all be similarly categorized as inspiring, depending on user preference**

Classification Report – Test Data

	precision	recall	f1-score	support
Beautiful	0.50	0.07	0.12	28
Courageous	0.00	0.00	0.00	16
Fascinating	0.47	0.46	0.46	50
Funny	0.80	0.12	0.22	32
Informative	0.52	0.69	0.60	143
Ingenious	1.00	0.05	0.10	20
Inspiring	0.53	0.77	0.63	170
Jaw-Dropping	0.00	0.00	0.00	10
Longwinded	0.00	0.00	0.00	2
OK	0.00	0.00	0.00	1
Obnoxious	0.00	0.00	0.00	1
Persuasive	0.00	0.00	0.00	16
Unconvincing	0.00	0.00	0.00	5
accuracy			0.53	494
macro avg	0.29	0.17	0.16	494
weighted avg	0.50	0.53	0.46	494

TED Talks rated as **Inspiring or Informative, followed by Fascinating**, scored the highest for Precision and Recall, and appear to be the most prevalent Actual ratings (Support) and easiest to predict for.