Capstone Project
Ted talk view prediction

By-

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Point of discussion

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INTRODUCTION

TED talk is a nonprofit organisation that aimed at bringing experts from the fields of Technology, Entertainment, and Design together.TED talks have been given for many years with the platform of "Ideas Worth Spreading". In the digital world we live in today, TED is a great platform to get your idea out there. But how do you know if your idea will be heard or appreciated? We aim to perform a comprehensive analysis of TED talks to determine what it is that makes an idea powerful.

These datasets contain over 4,000 TED talks including transcripts in many languages

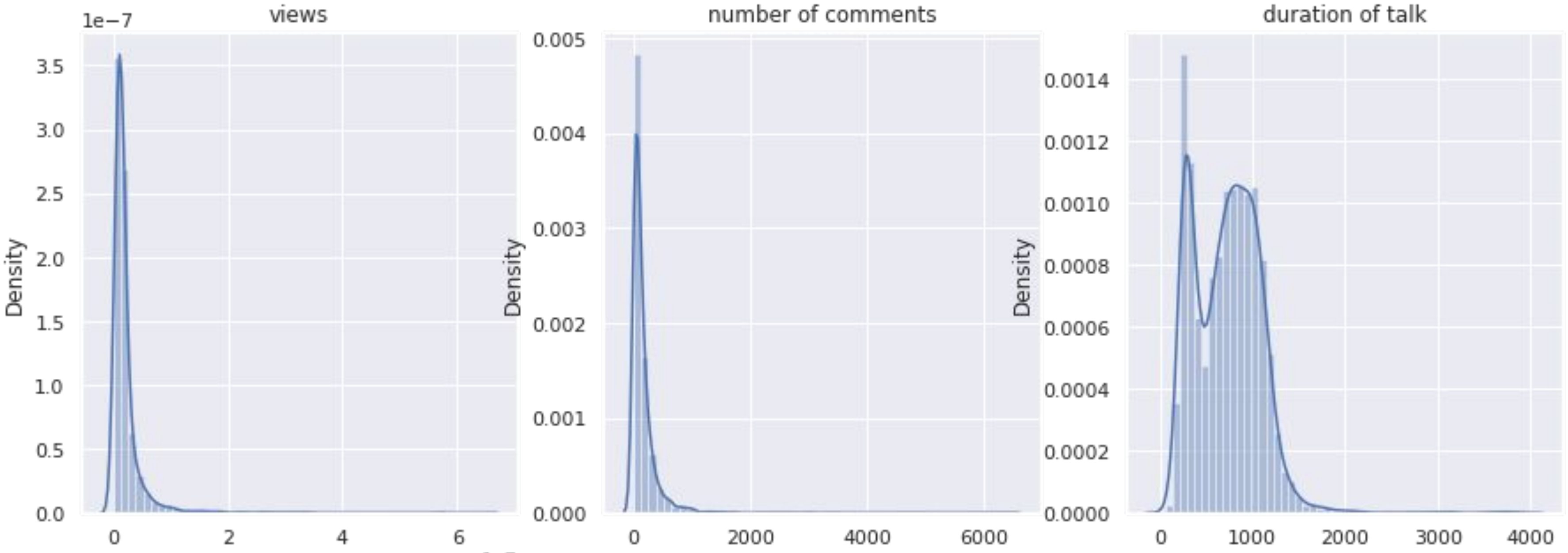
PROBLEM STATEMENT

The main objective is to build a predictive model, which could help in predicting the views of the videos uploaded on the TEDx website.

Exploratory Data Analysis

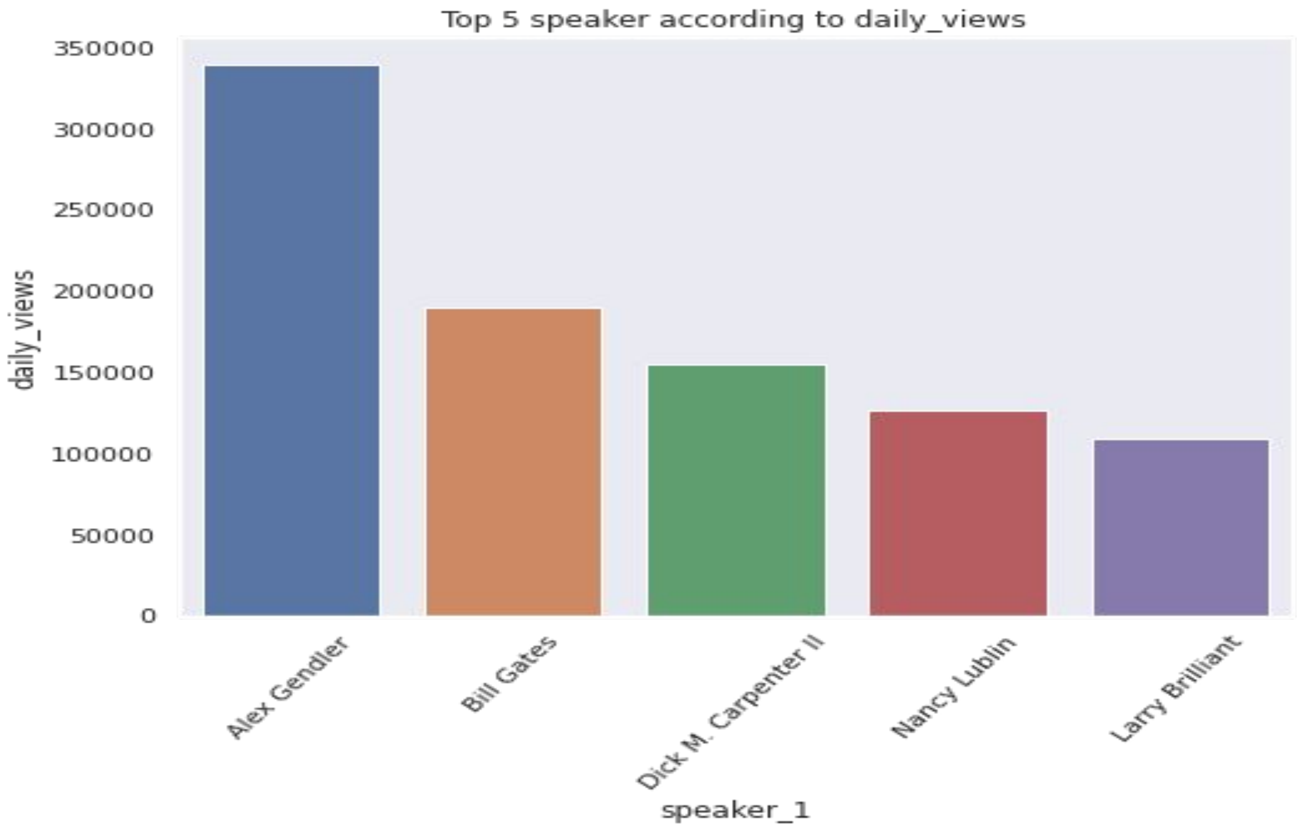
Univariate analysis

Univariate analysis is the simplest form of analyzing data.



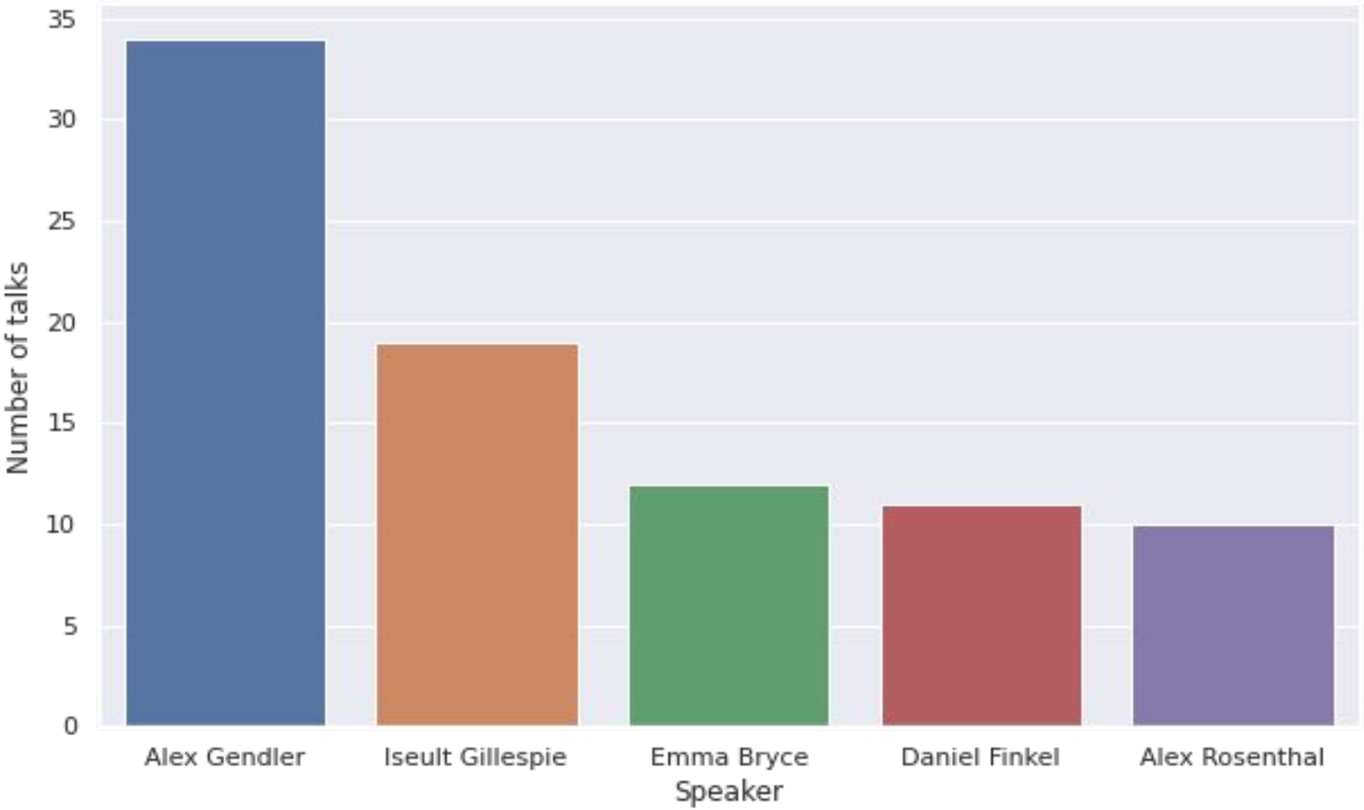
Bivariate analysis with dependent variable

speaker_1 vs daily_views



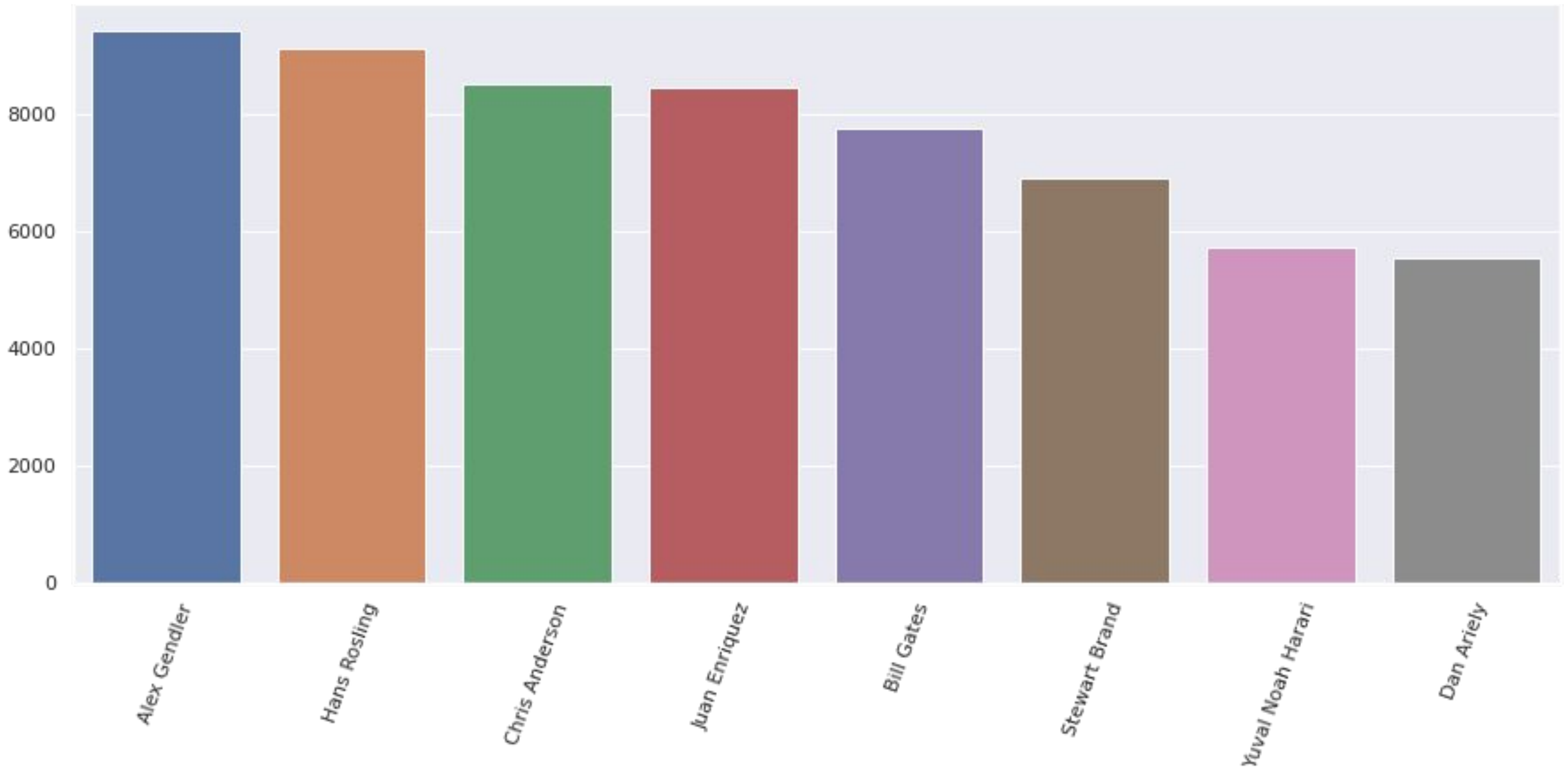
- **Ted Talk by Alex Gendler has the highest daily views followed by Bill Gates.**
- **Here it seems the daily views does depend on the first speaker.**

Speaker Vs Number of talks delivered

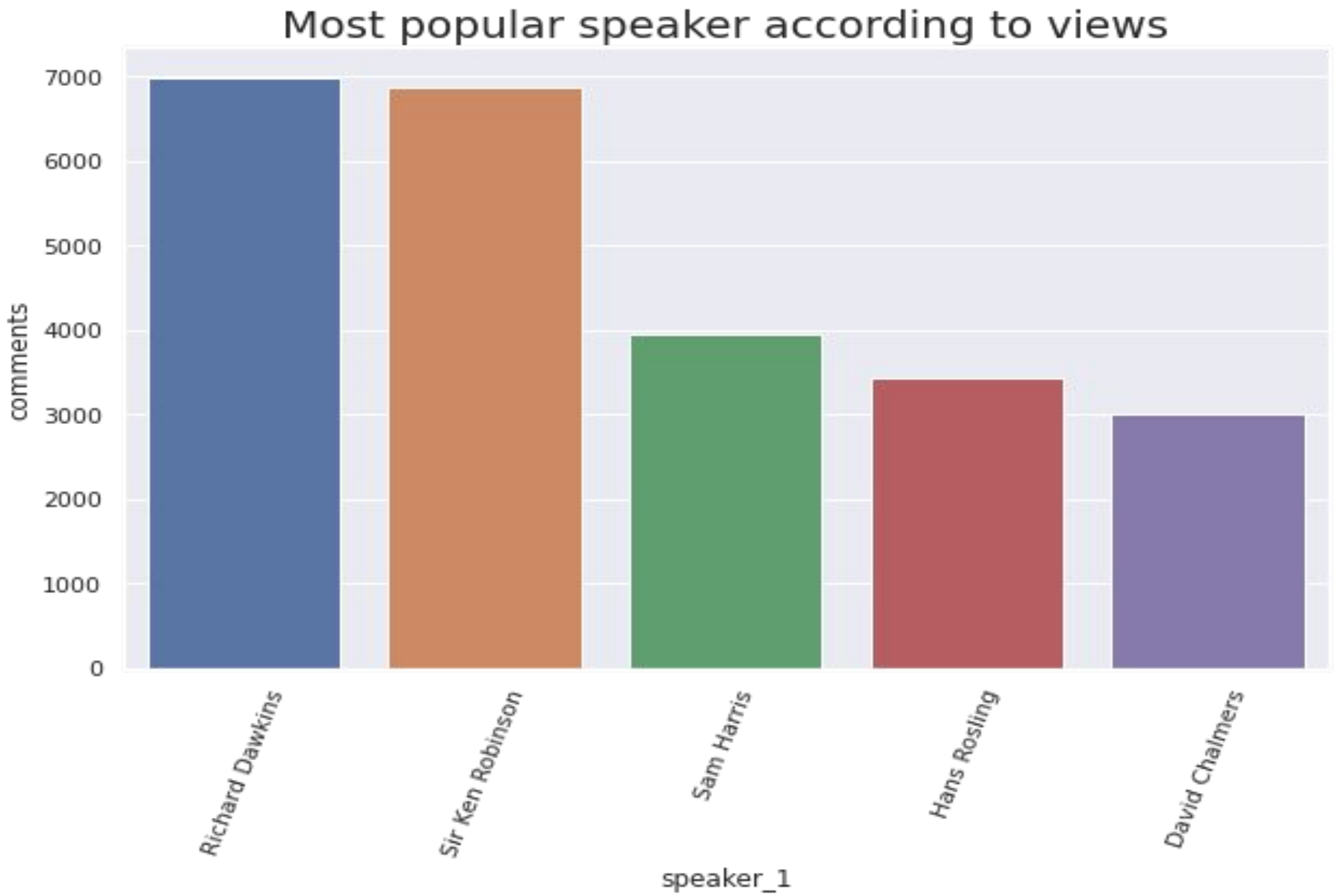


- **Alex Gendler also has highest number of talks that could explain such high overall views.**

speaker vs duration

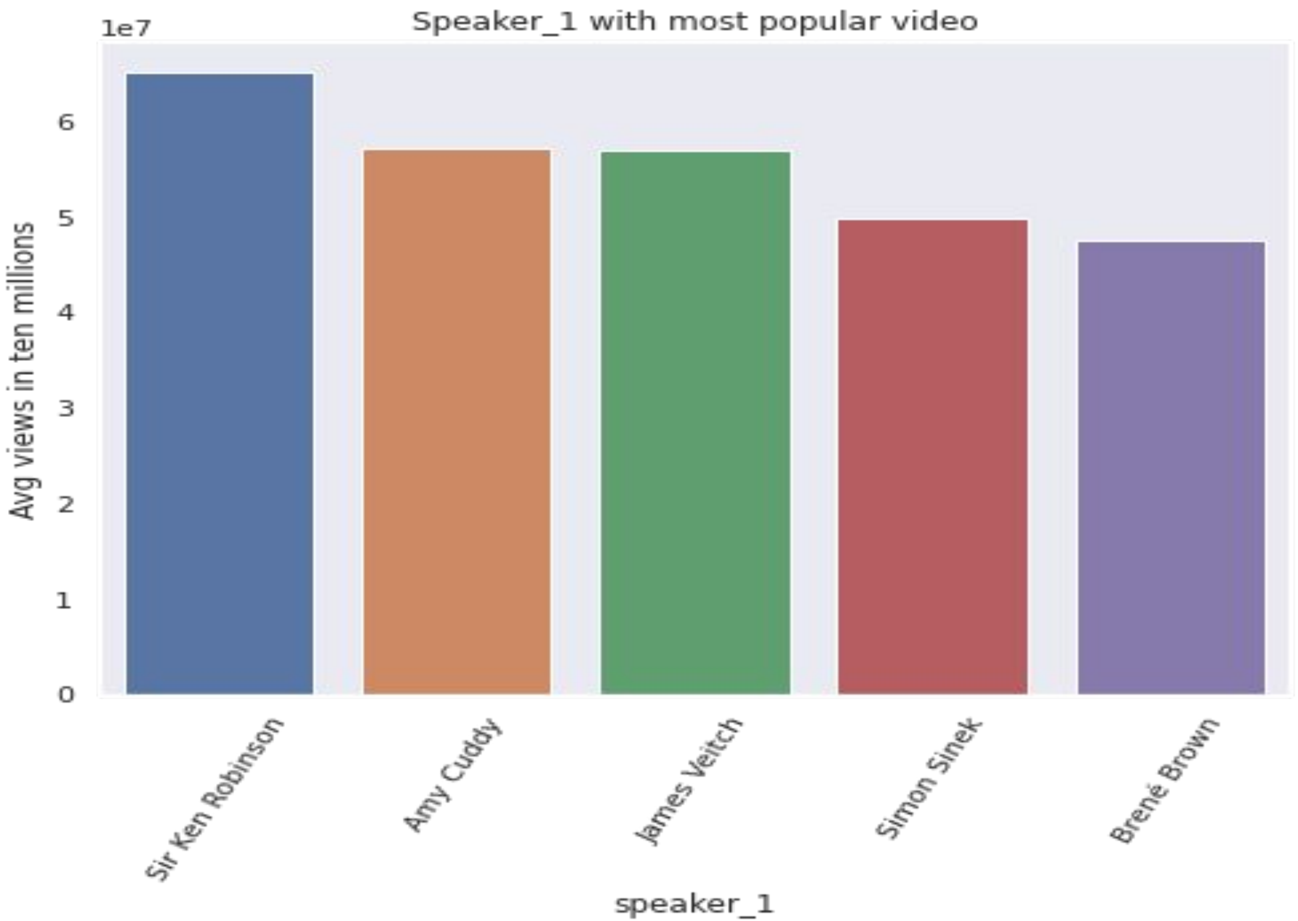


Speaker vs comments



- **Richard Dawkins has highest number of comments followed by Sir Ken Robinson**

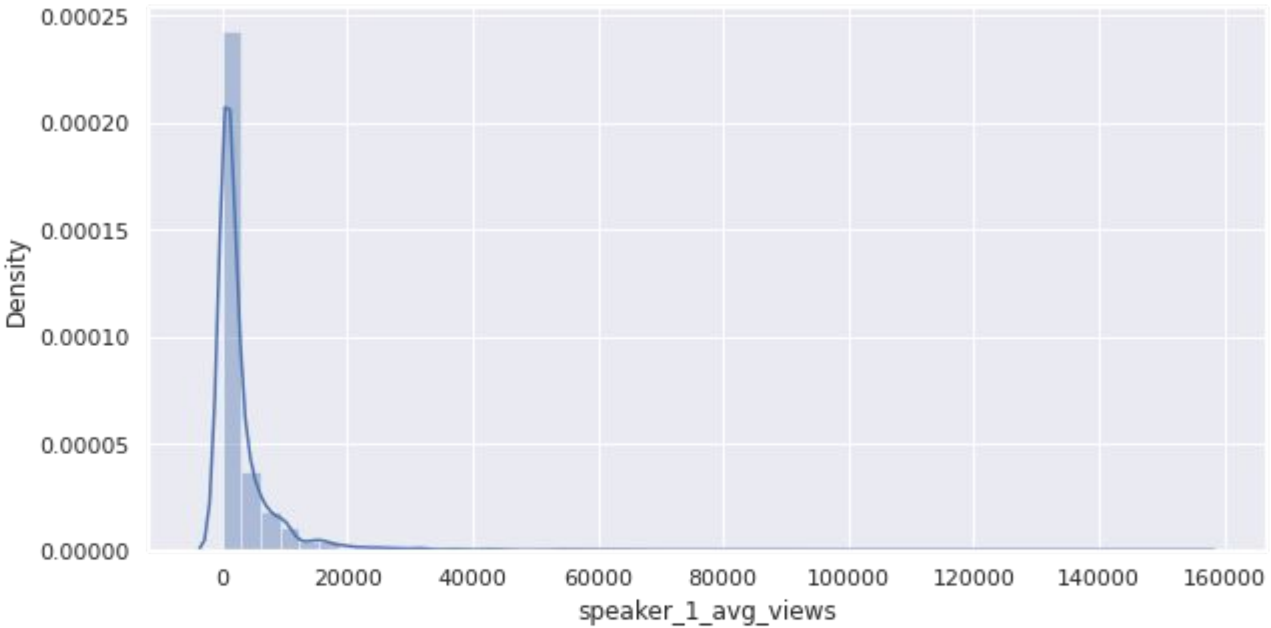
Speaker vs Average Views



Target Encoding

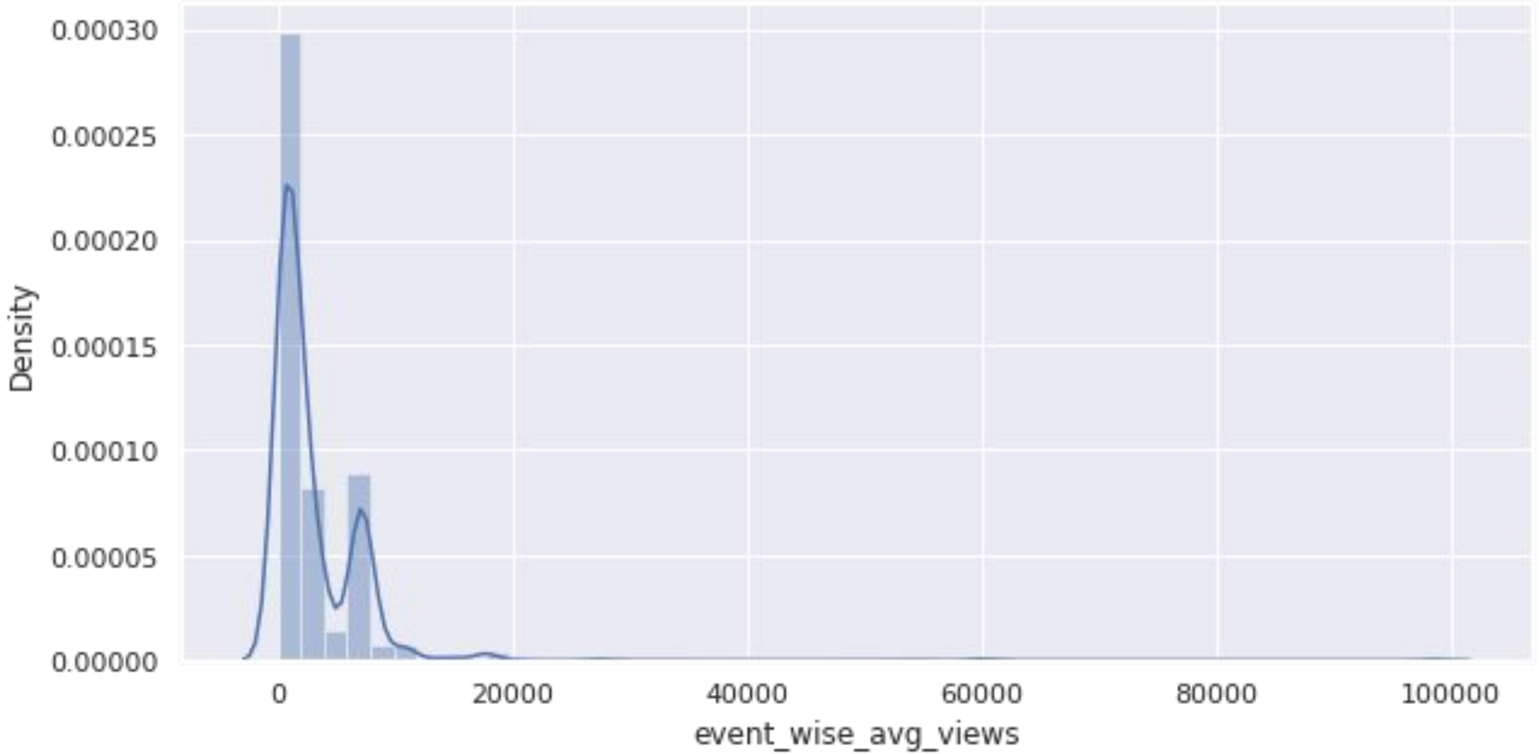
Target encoding is the process of replacing a categorical variable values with the mean of the target (dependent variable) variable

Applying Target encoding on speaker_1

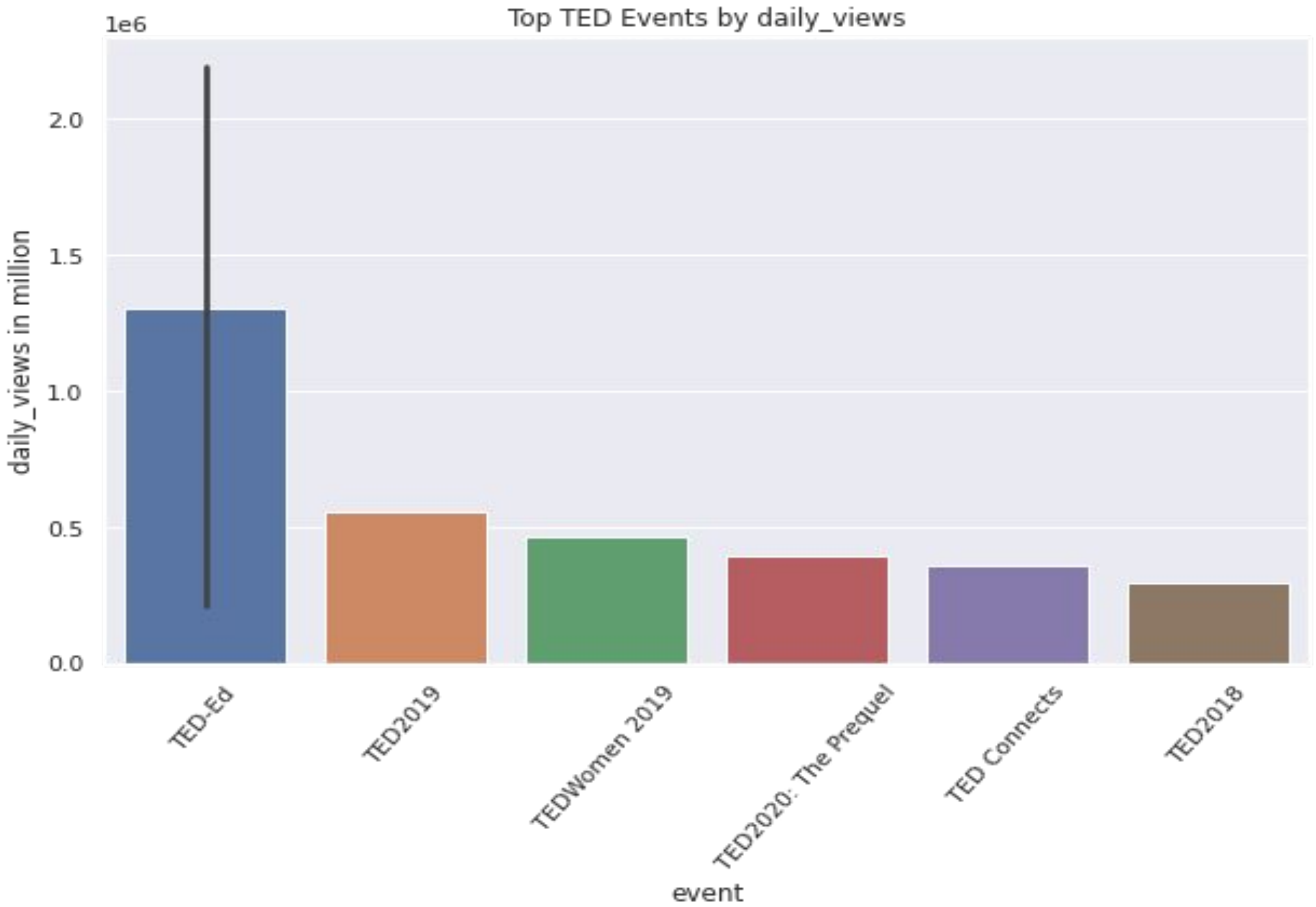


Event

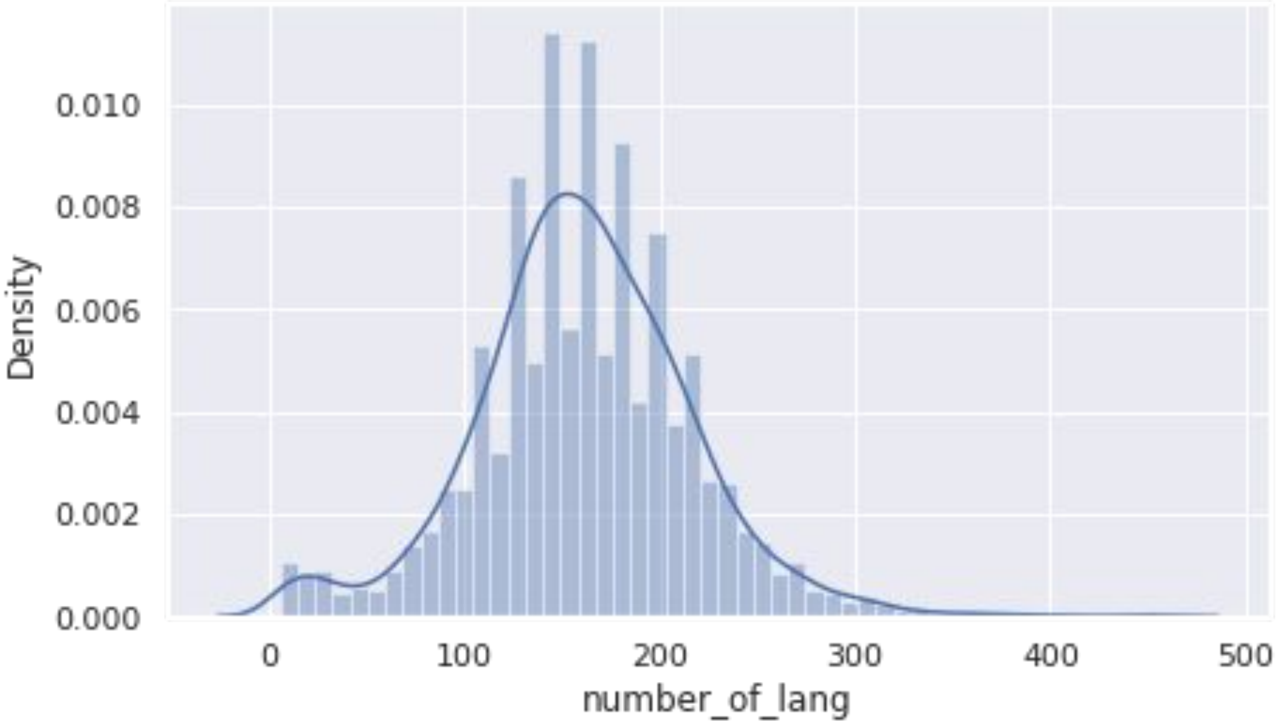
Event is also a categorical variable, therefore we also apply target encoding on it



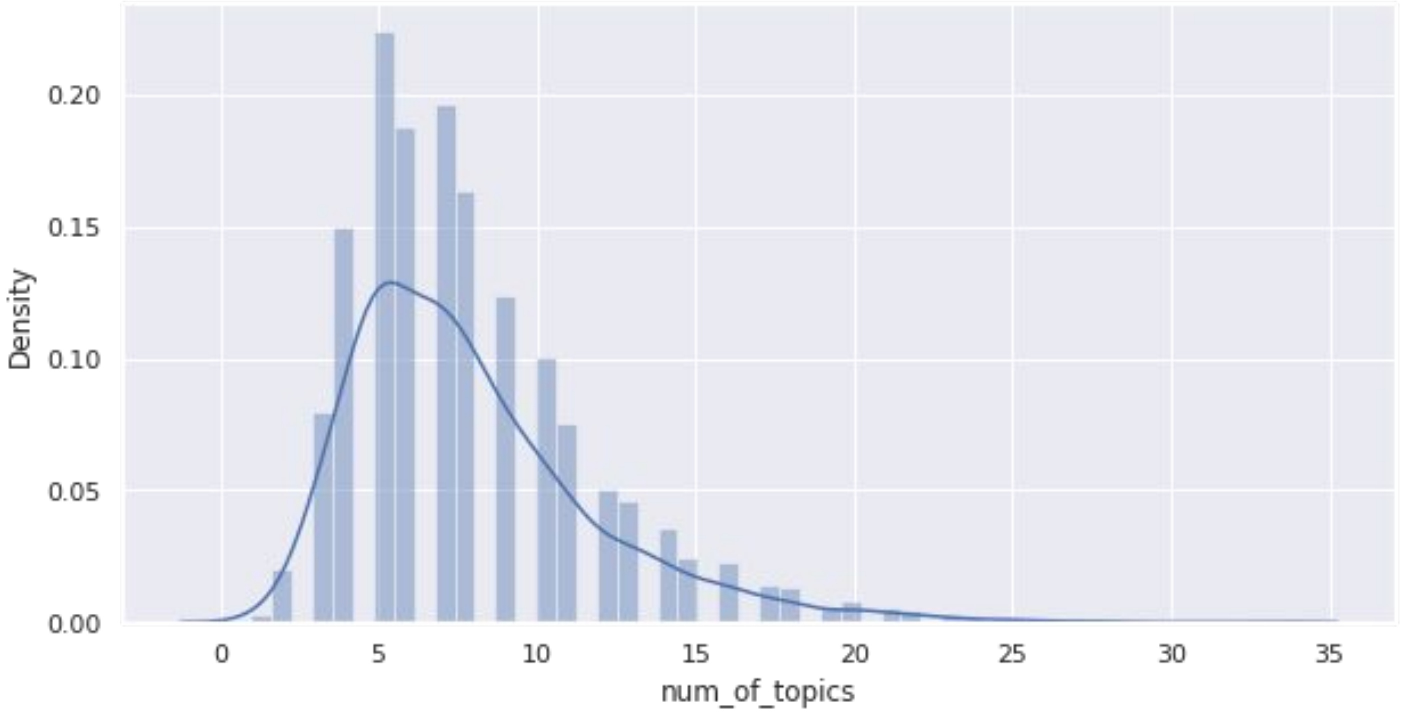
Top ted talk event



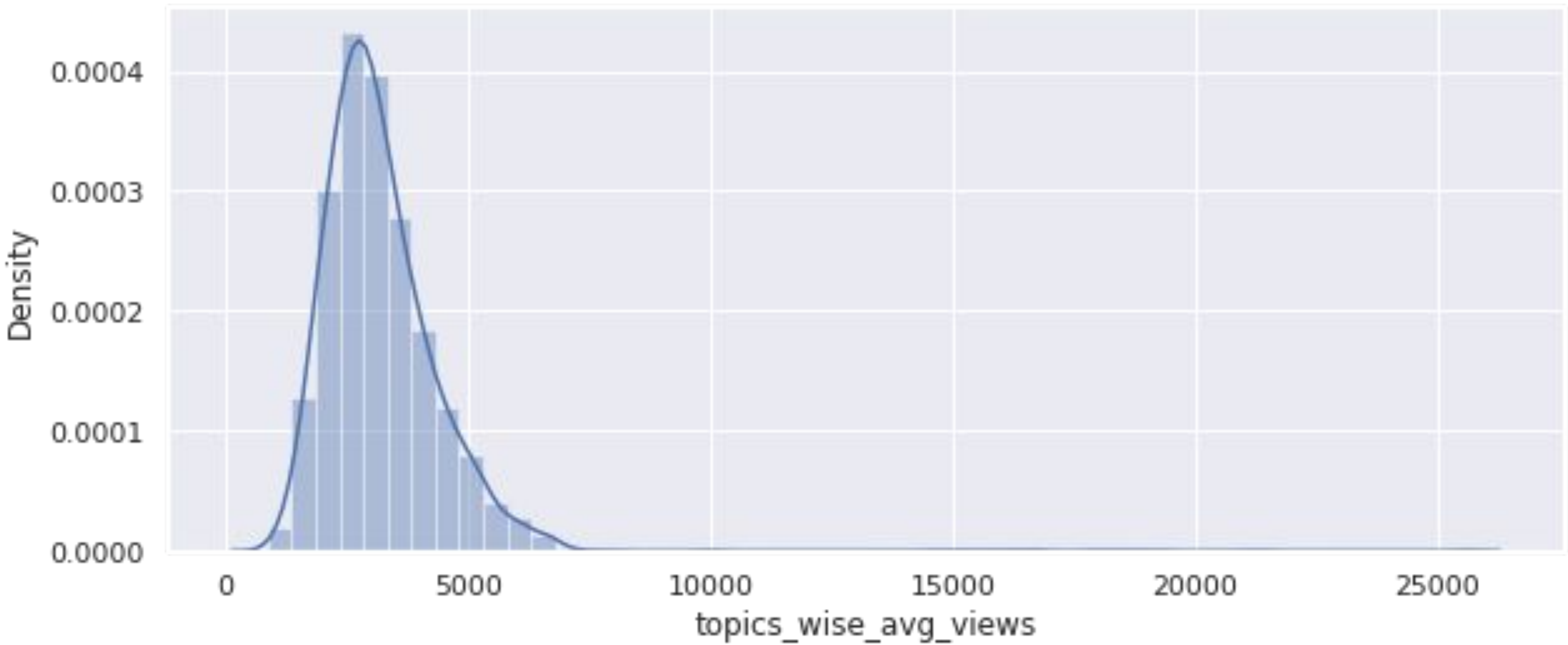
available_language variable



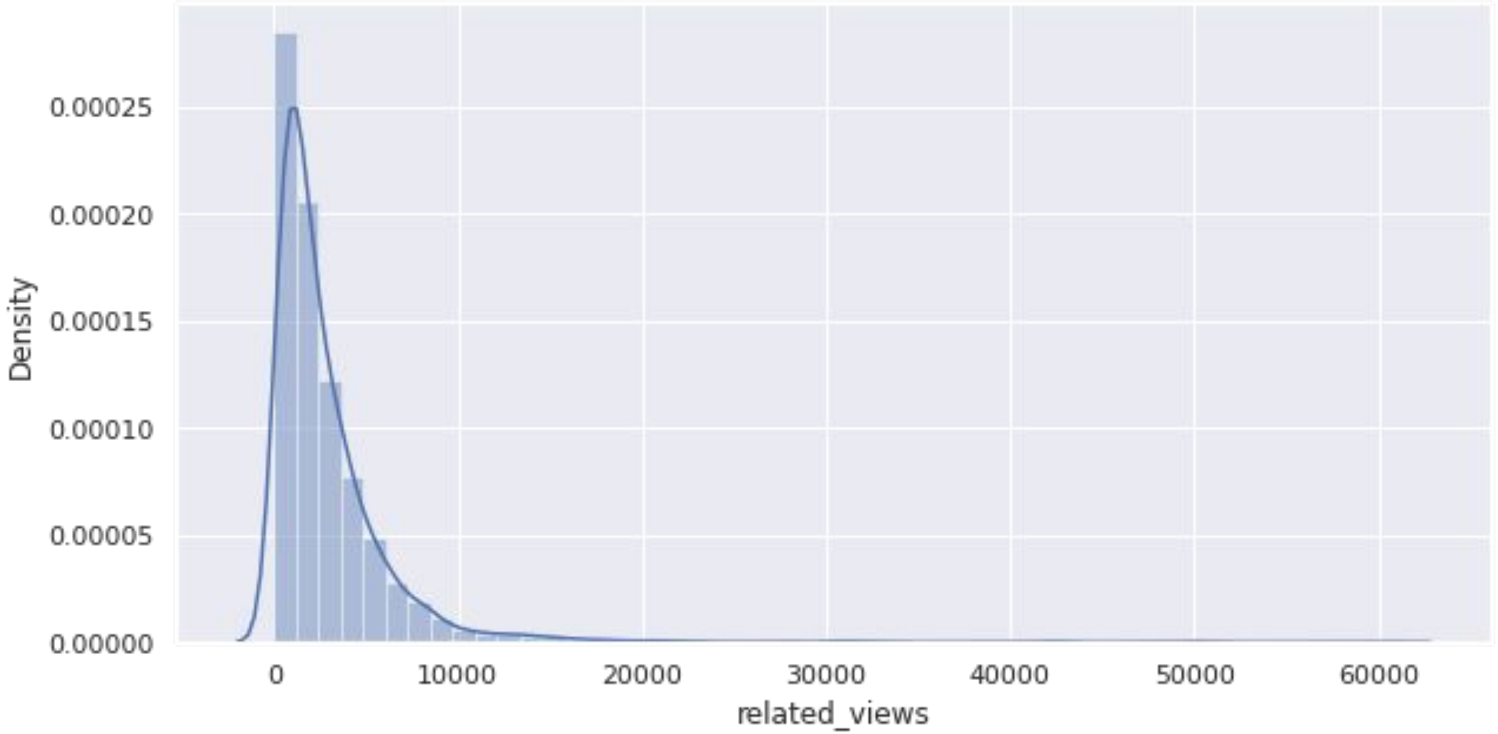
num_of_topic variable from topic variable



Target coding on unique topics

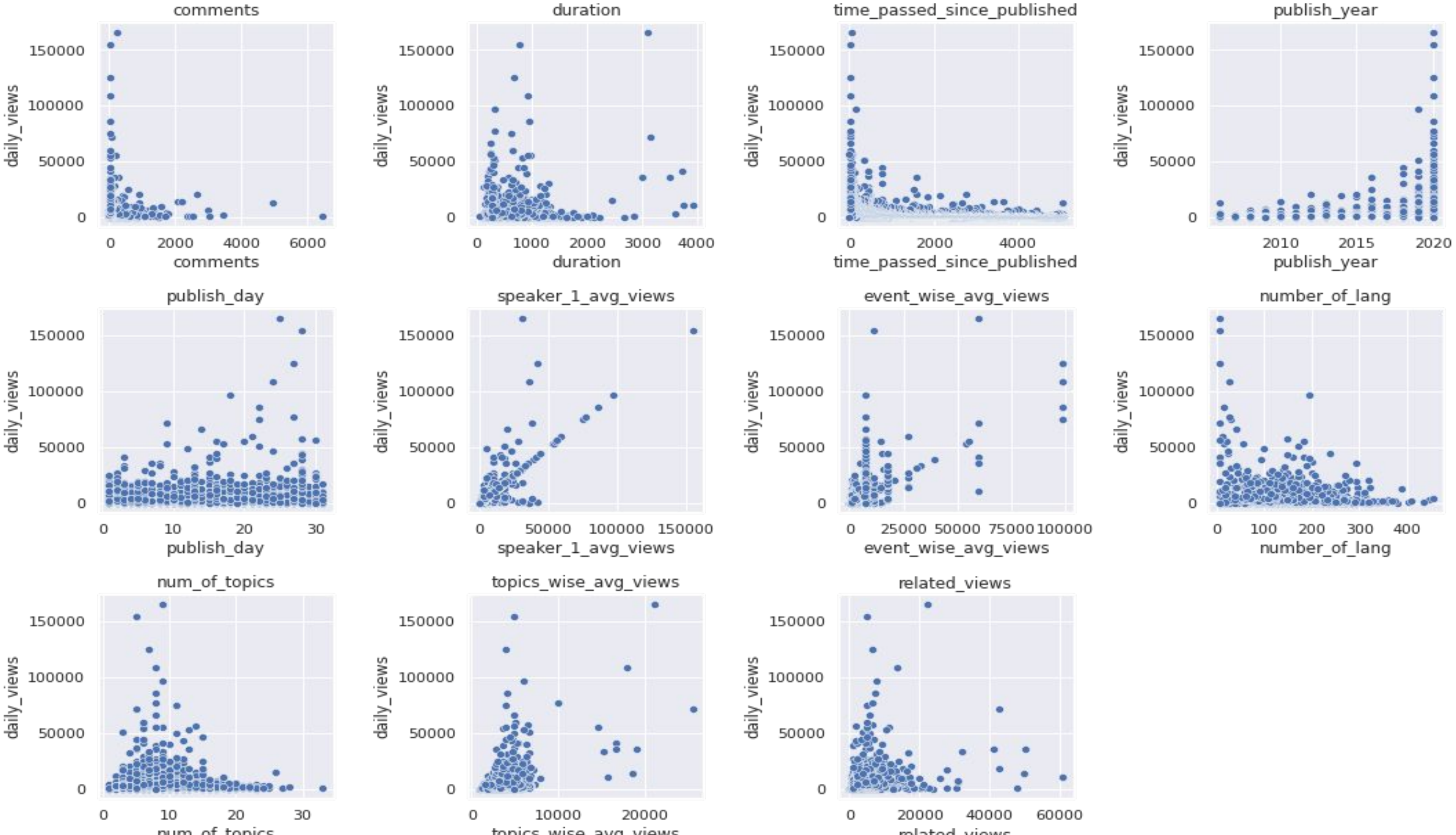


Related talk variable

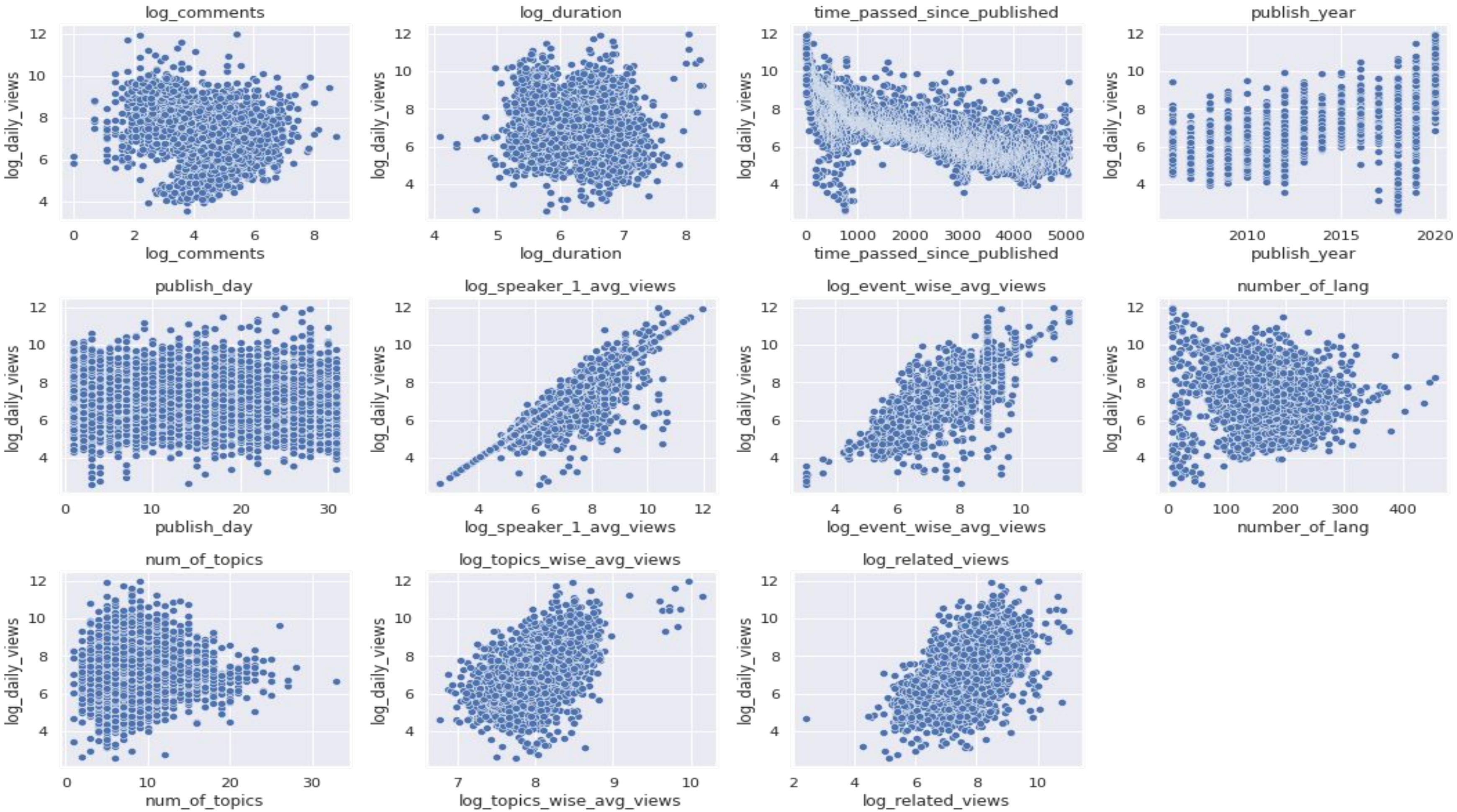


Feature Engineering and Data Preprocessing

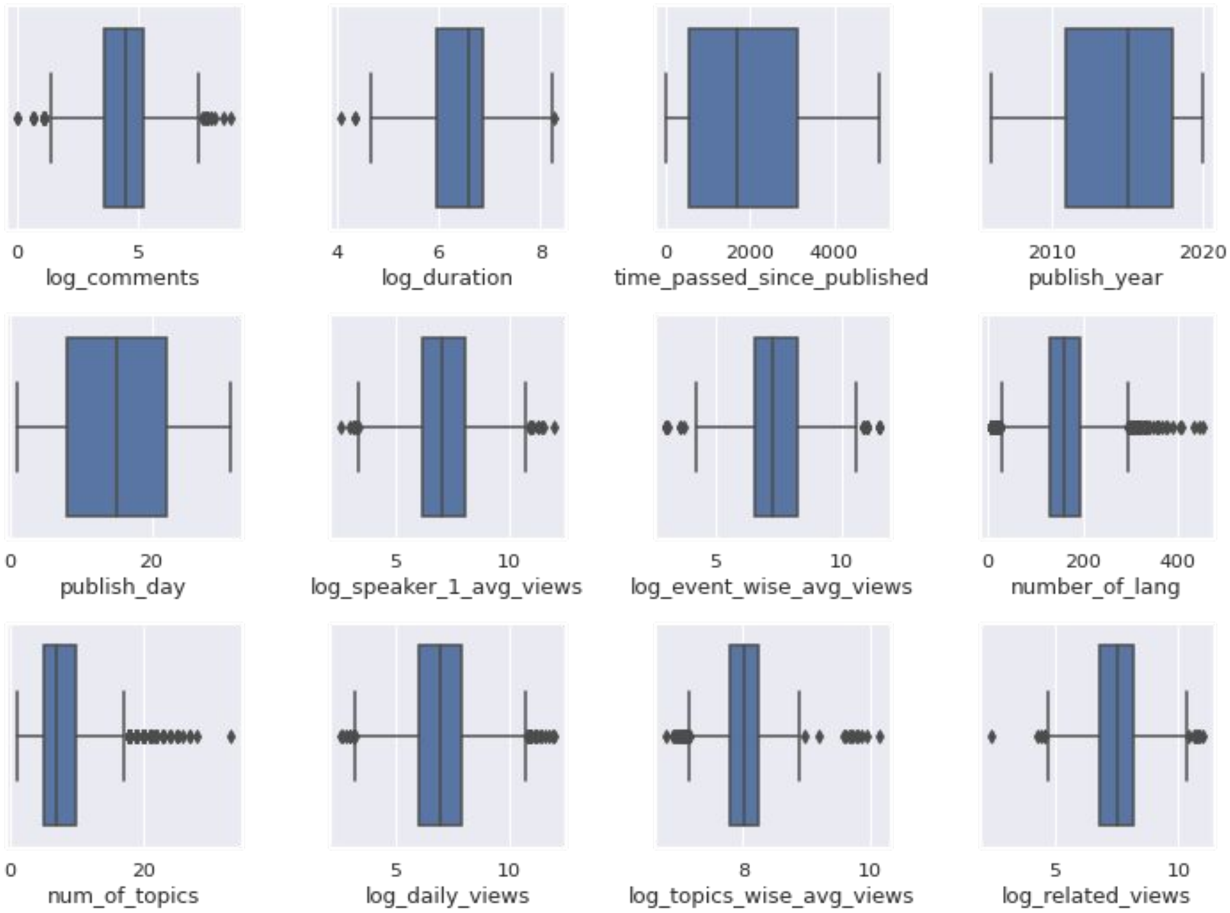
Verifying OLS assumptions Linearity



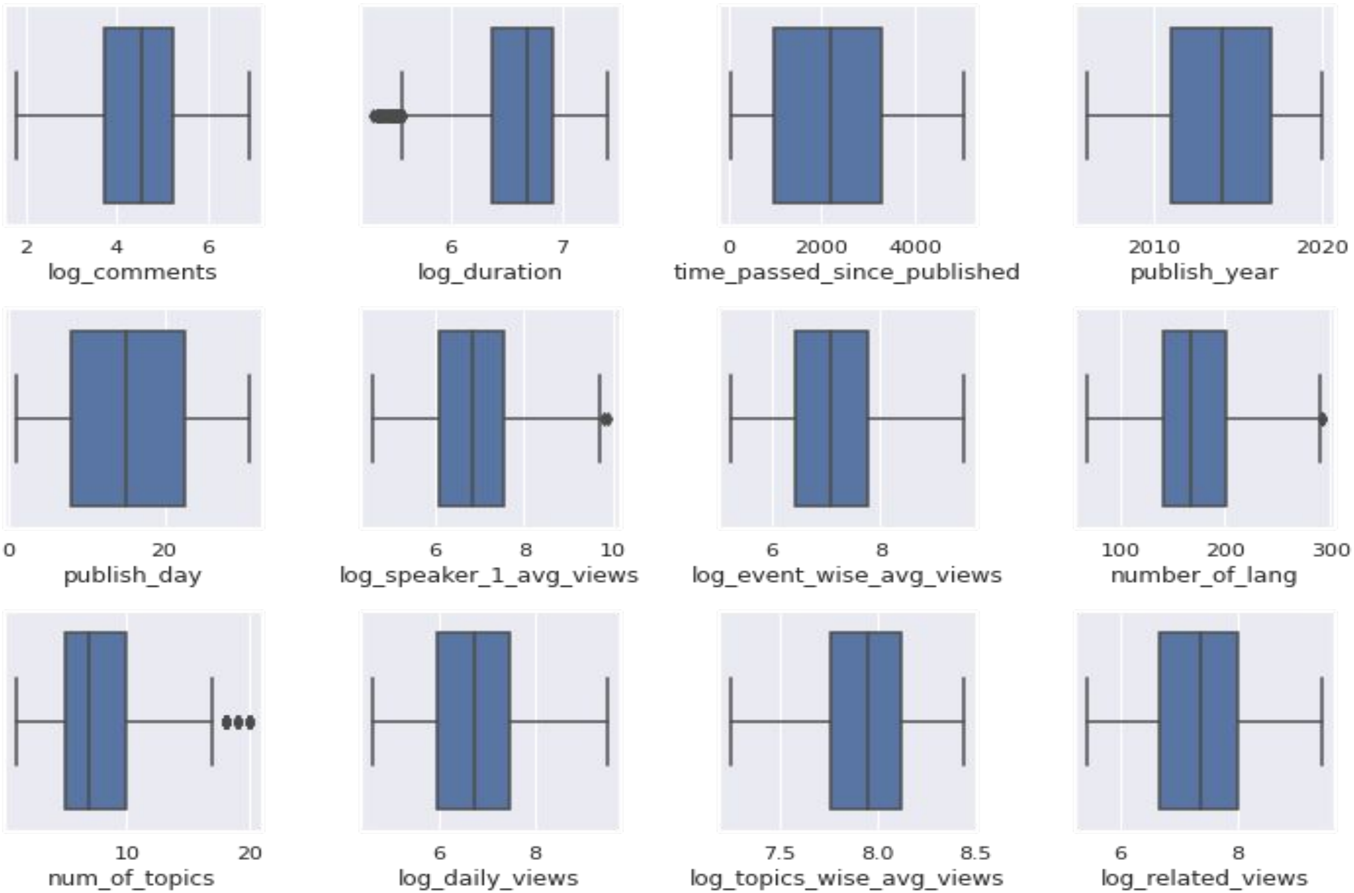
Transformation for Linearity



Outliers Detection (Before)



Outliers Detection (After)

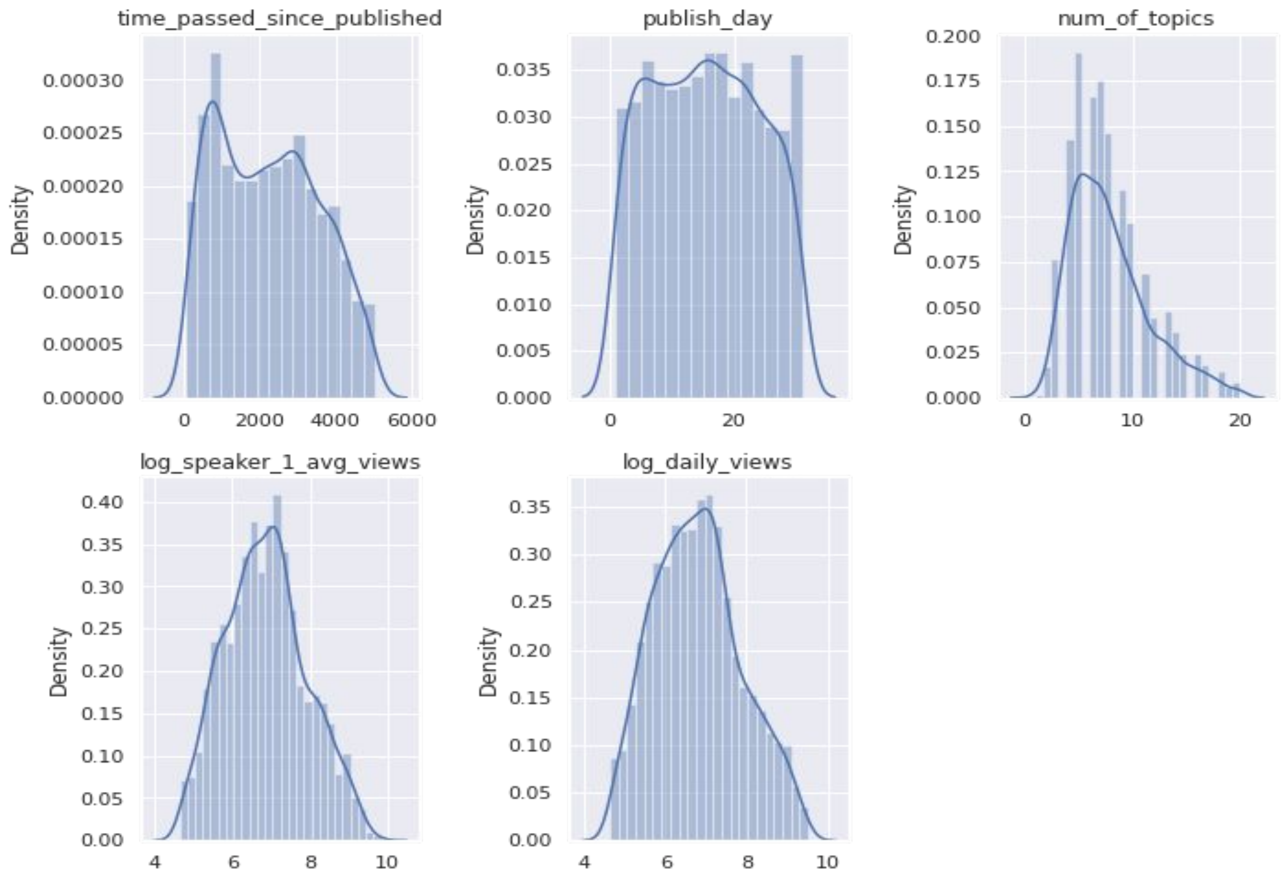


Removing collinearity

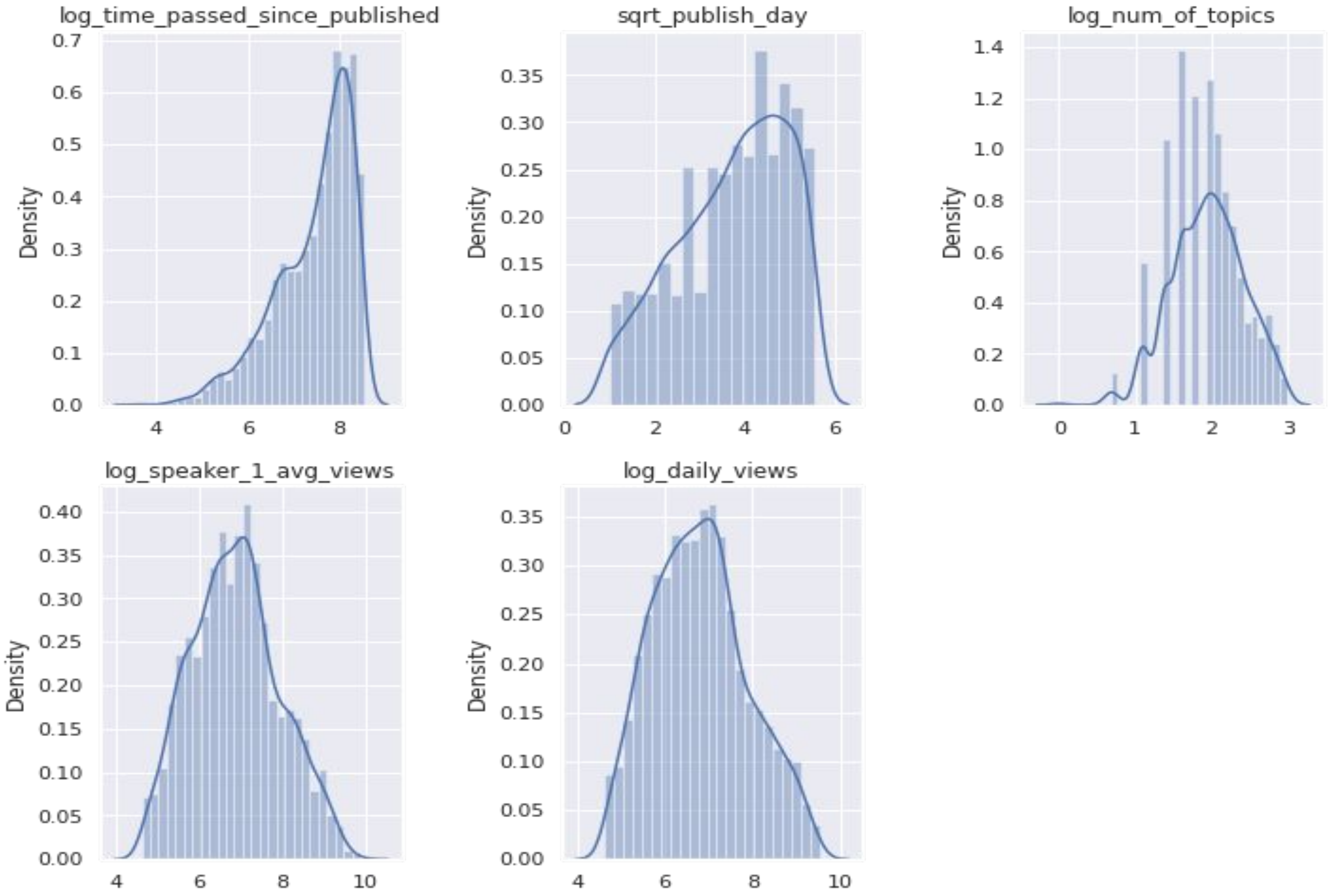
After removing collinearity from the features we were left with features:

- **time_passed_since_published**
- **publish_day**
- **num_of_topics**
- **log_speaker_1_avg_views**

Normal distribution of features in data



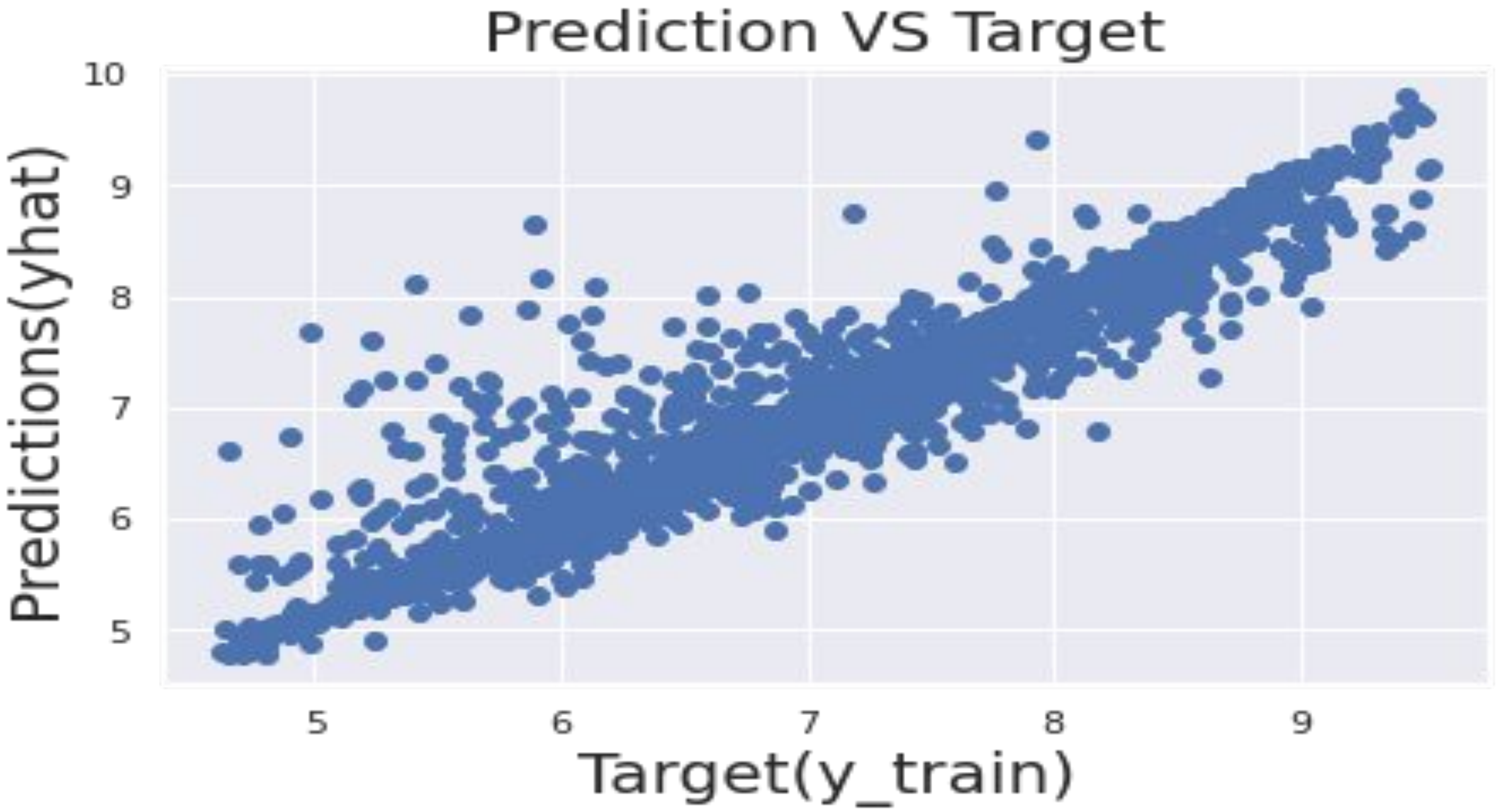
Transformation



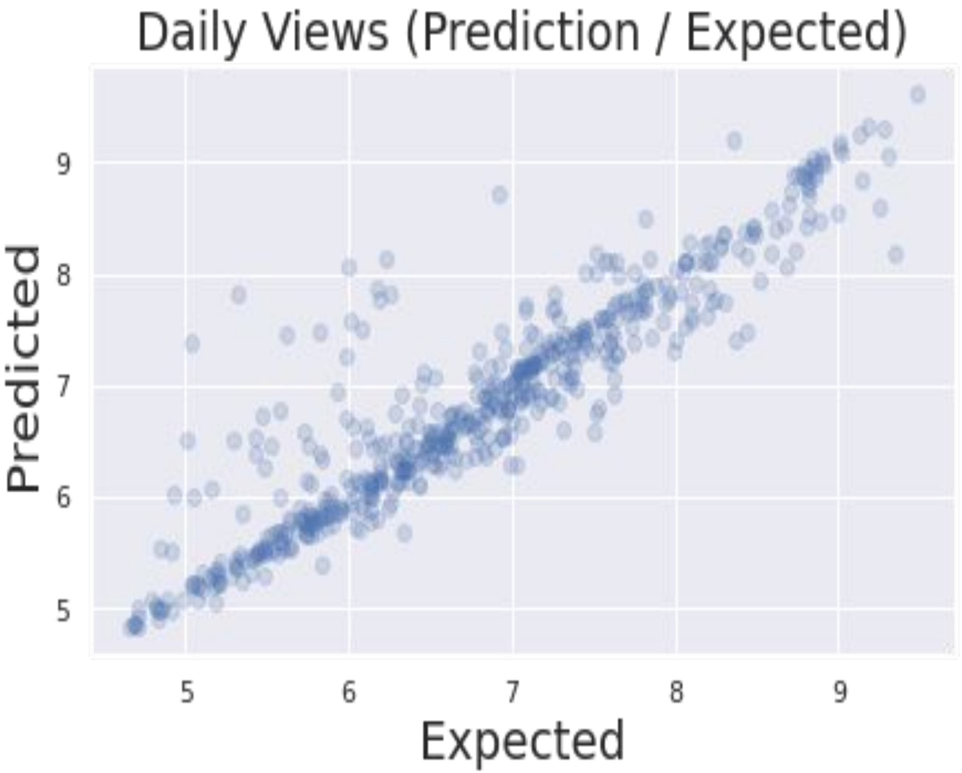
Model preparation.

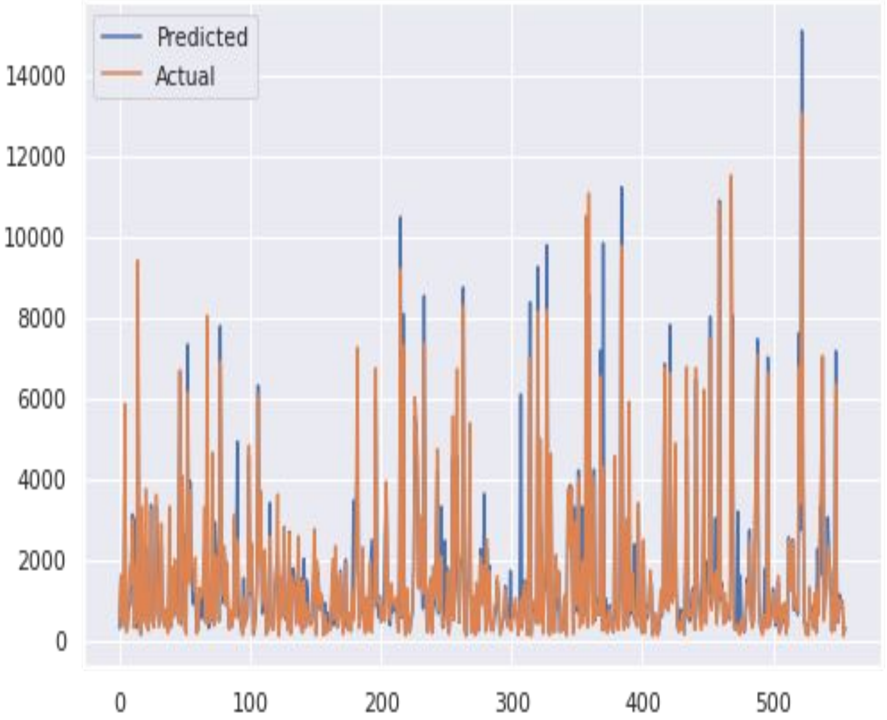
- Removing null values from dataset
- Introducing dummy variables for Categorical features
- Defining dependent and independent features
- Next we will standardize the features
- Splitting the data into training and testing
- Implementing Linear Regression Training Models
- Model Accuracy on test data

Model Accuracy on train data



Model Accuracy on test data (Base LR Model)





Error metrics on Base LR Model

Values

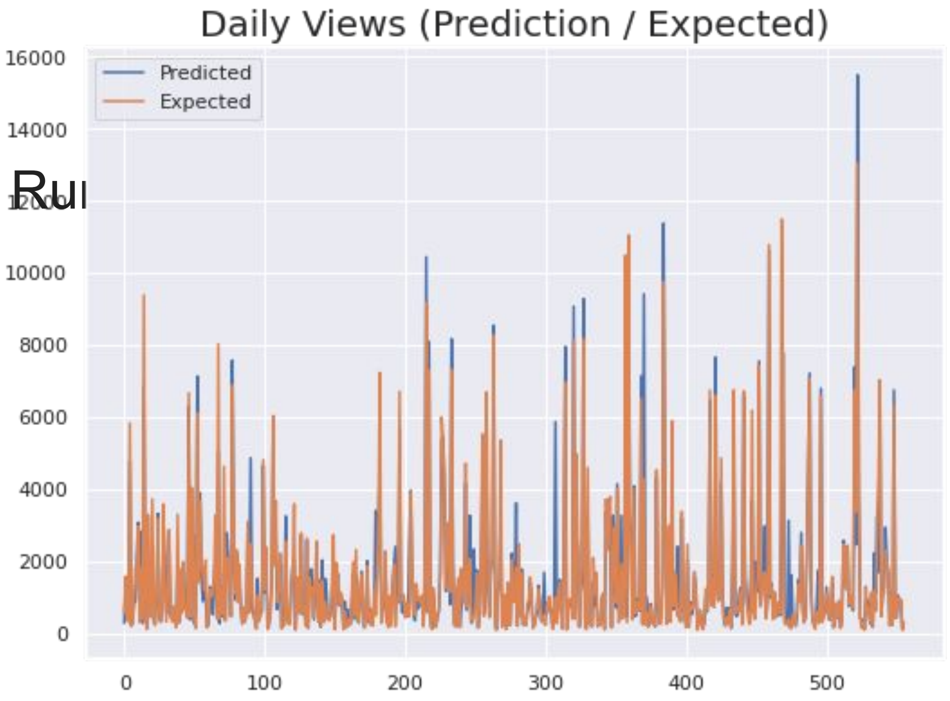
R-Square-	0.83691
Adj.R-Square-	0.830500
MSE-	651492.850559
RMSE-	807.151070
MAE-	368.333887
MAPE-	0.344262

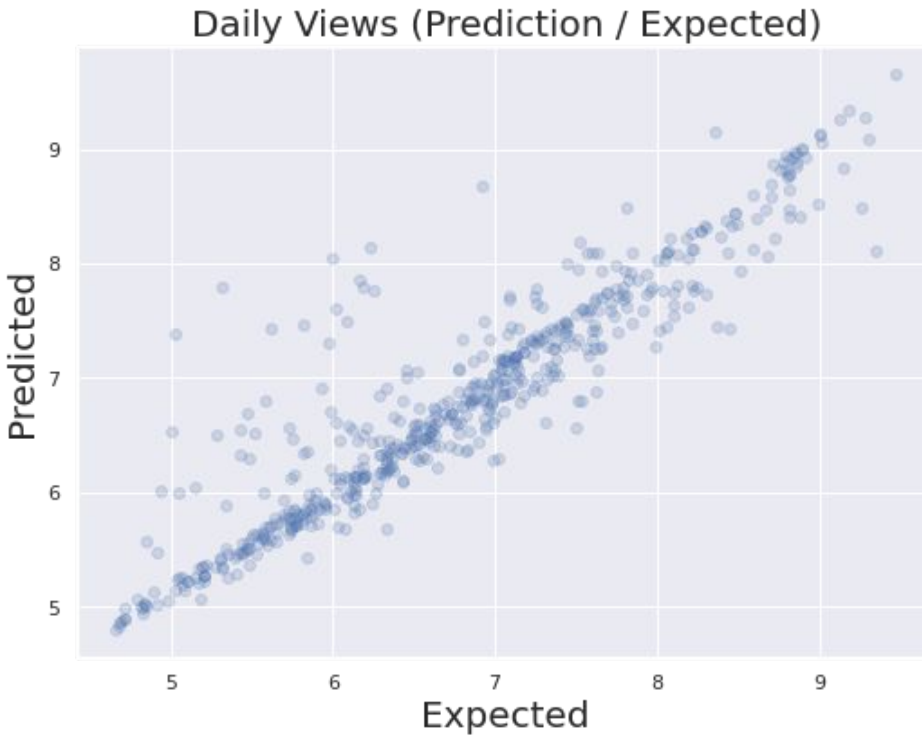
Hyperparameter Tuning through Grid Search

Grid Search combines a selection of hyperparameters established by the scientist and runs through all of them to evaluate the model’s performance. Its advantage is that it is a simple technique that will go through all the programmed combinations. The biggest disadvantage is that it traverses a specific region of the parameter space and cannot understand which movement or which region of the space is important to optimize the model.

Model Accuracy on test data (Lasso Regression Model)

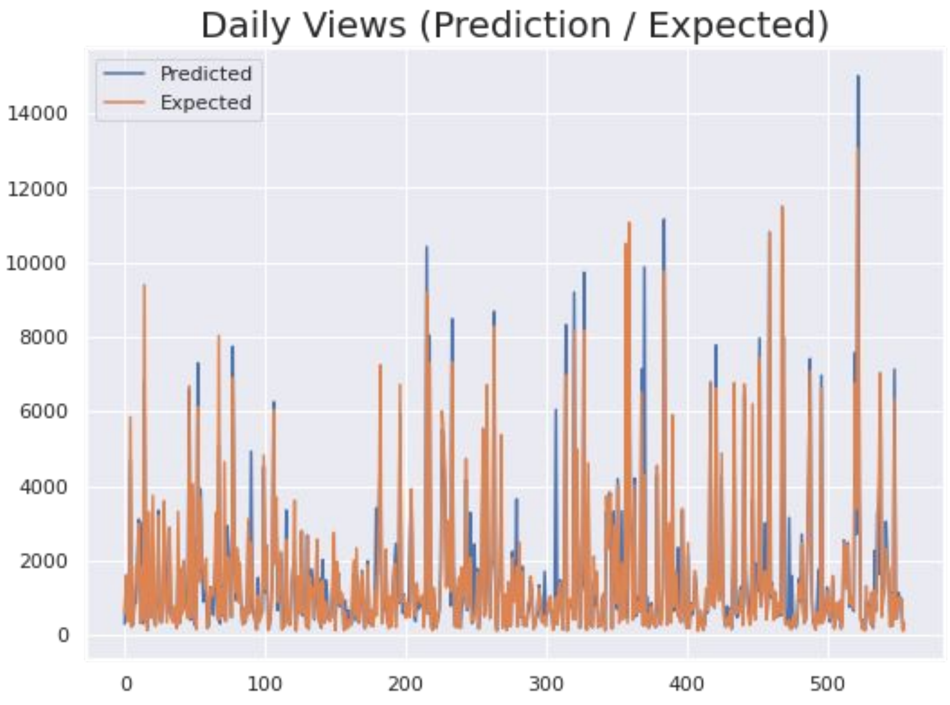
Ru

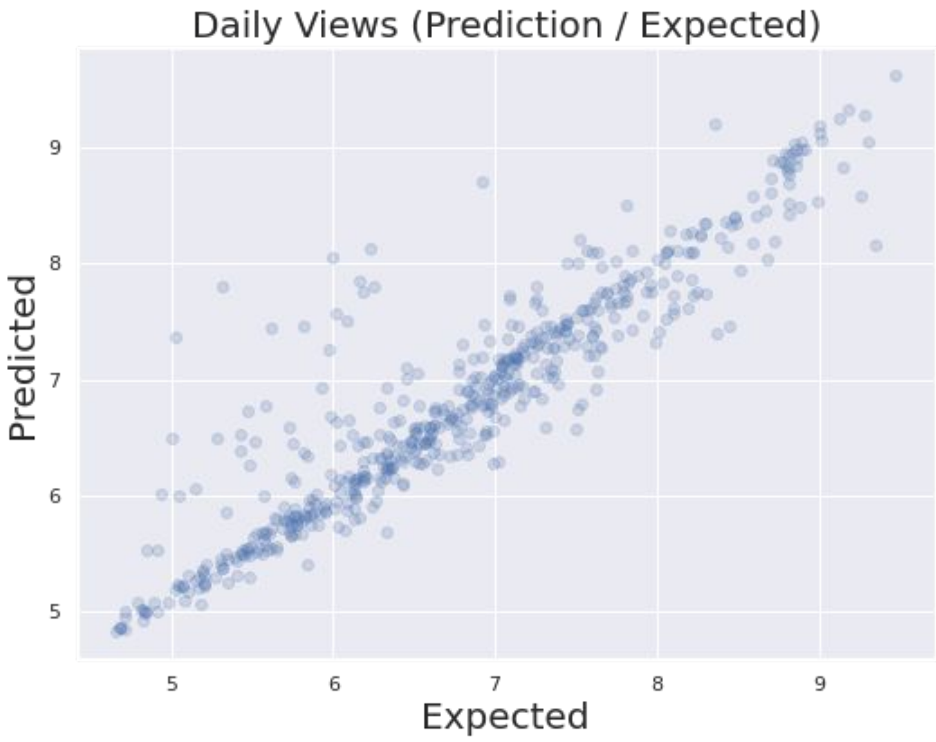




Ridge regression model

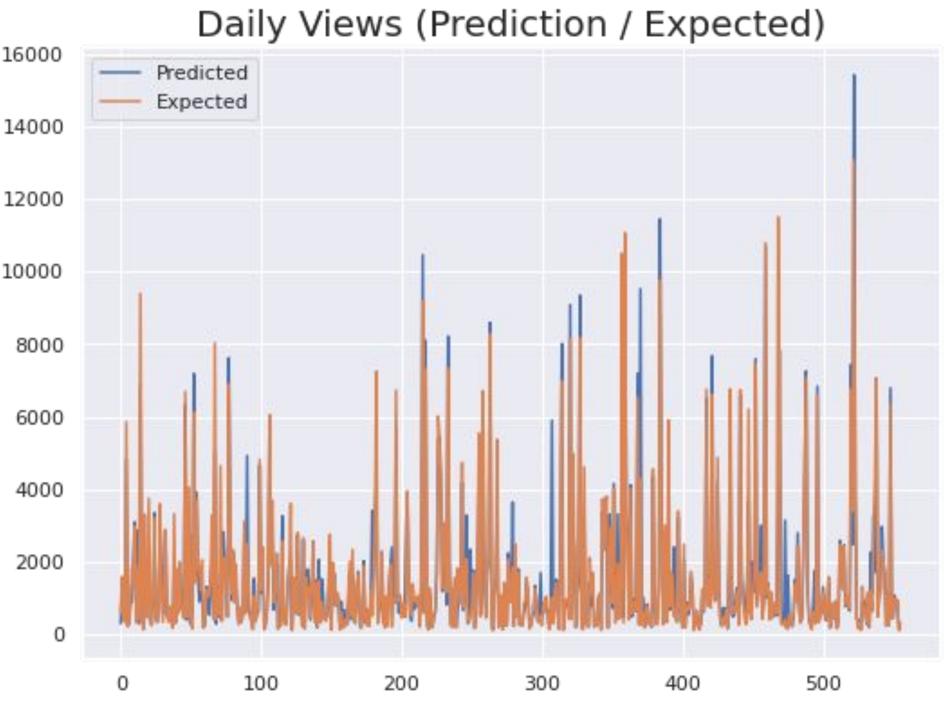
Running Grid Search Cross Validation

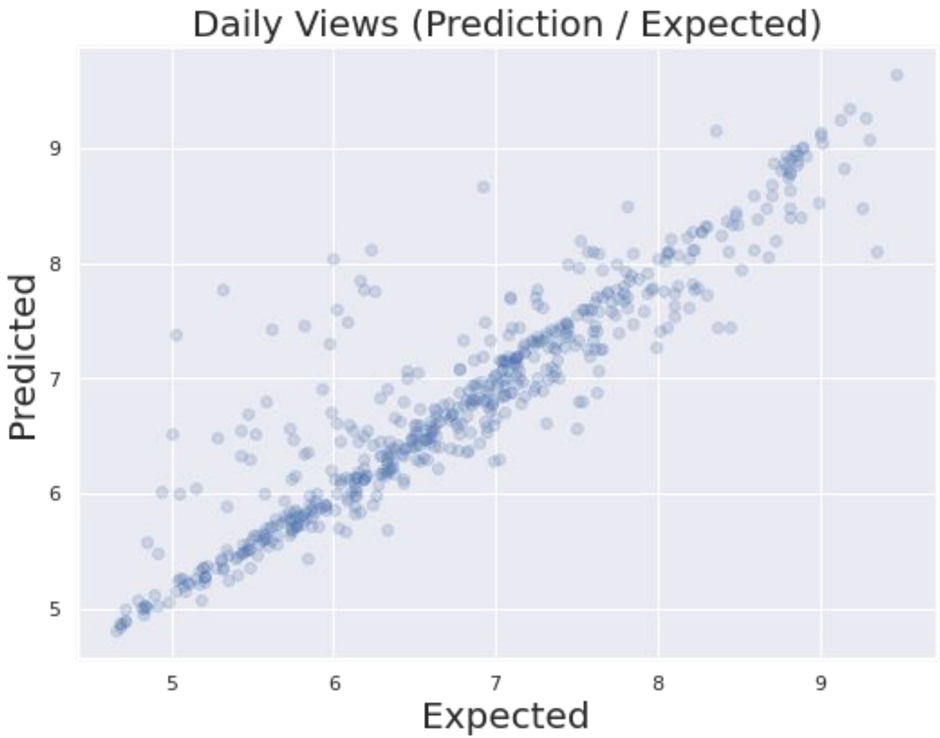




Elastic regression model

Running Grid Search Cross Validation





Observation

On comparing all the models our base linear regression model is still is performing better followed by Lasso, Ridge and ElasticNet Regression model on the basis of RMSE. But our model contains large number of outliers and the value of RMSE is affected by outliers therefore we will use MAE as our evaluation matrix according to which *Lasso Regression* has the best performance

Conclusion

- We performed EDA, feature engineering, data cleaning, target encoding and one hot encoding of categorical columns, feature selection and then model building.
- Then we checked our model for overfitting by comparing it with Lasso Regression model, Ridge Regression model, ElasticNet Regression model.
- We found that our original base model was overfit and Lasso Regressor has the best accuracy.
- In all of these models our mean errors is 13 %. That implies we have been able to correctly predict views 87 % of the time.
- In all the features speaker_1_avg_views is most important this implies that speakers are directly impacting the views.

Future Work

- Training our data on other models (XGB, Random Forest, etc)
- More efficient Hyperparameter Tuning through techniques like Random Search

Q/A