

# **Capstone Project-2**

# Ted Talk Views Prediction ML Supervised Regression

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#### Problem Statement

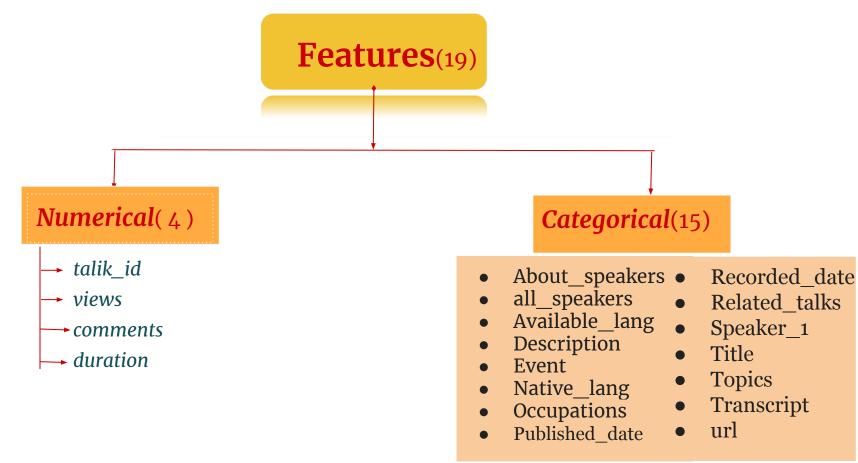


 Prediction of the views of the videos uploaded on the TEDx website.



## Let's see the features'





### Basic Data Exploration

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- This dataset is having 4005 observations & 19 features.
- Most of the features are categorical .
- No duplicate values.

Dataset Shape: (4005, 19)

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 4005 entries, 1 to 62794
Data columns (total 18 columns):
     Column
                     Non-Null Count
                                      Dtype
    title
                     4005 non-null
                                      object
     speaker 1
                     4005 non-null
                                      object
     all speakers
                     4001 non-null
                                      object
     occupations
                     3483 non-null
                                      object
     about speakers
                     3502 non-null
                                      object
 5
    views
                     4005 non-null
                                      int64
     recorded date
                     4004 non-null
                                      object
     published date
                     4005 non-null
                                      object
     event
                     4005 non-null
                                      object
     native lang
                     4005 non-null
                                      object
     available lang
                     4005 non-null
                                      object
     comments
                     3350 non-null
                                      float64
 11
     duration
                     4005 non-null
                                      int64
 13
    topics
                     4005 non-null
                                      object
                                      object
     related talks
                     4005 non-null
 15
                                      object
     url
                     4005 non-null
     description
                     4005 non-null
                                      object
     transcript
                                      object
                     4005 non-null
dtypes: float64(1), int64(2), object(15)
memory usage: 116.5 MB
```

### Data Exploration(NaN values)

0.00



	Feature_Name	Missing	Uniques	%age of missing values
11	comments	655	601	16.35
3	occupations	522	2049	13.03
4	about_speakers	503	2977	12.56
2	all_speakers	4	3306	0.10
6	recorded_date	1	1334	0.02
0	title	0	4005	0.00
16	description	0	4005	0.00
15	url	0	4005	0.00
14	related_talks	0	4005	0.00
13	topics	0	3977	0.00
12	duration	0	1188	0.00
9	native_lang	0	12	0.00
10	available_lang	0	3902	0.00
1	speaker_1	0	3274	0.00
8	event	0	459	0.00
7	published_date	0	2962	0.00
5	views	0	3996	0.00

4005

transcript

#### NaN

- 16% NaN values are present in *comments*
- 13% NaN values are present in *occupations*
- 12.5% NaN values are present in about\_speakers

#### **Unique value**

Most of the columns except **native\_lang**, **event** are containing unique values.

#### Al

# Data Processing

 Initially the datatype of published\_date, recorded\_date was in string format, i have used pandas to\_datetime function to convert the datatype



• Created month, day, year columns based on published\_date column

	published_date	month	year	day
talk_id				
92	2006-06-27	Jun	2006	27
110	2007-04-14	Apr	2007	14

# Data Processing



Created time\_since\_published column based on published\_date & current\_date

	published_date	time_since_published	
talk_id			
64	2006-09-06	4983 days	
45	2006-08-08	5012 days	

• Created daily\_views column based on views & time\_since\_published\_date

2	<pre>published_date</pre>	time_since_published	views	daily_views
talk_id				
820	2010-04-07	3674 days	2248059	611
60	2007-02-09	4827 days	1214012	251
2588	2016-09-26	1310 days	2712894	2069



# Feature removing

• Most of the speakers delivered their talk in english

```
        en
        es
        fr
        hi
        pt
        it
        ko
        ja
        de
        ar
        pt-br
        zh-cn

        native_lang
        3306
        15
        7
        2
        1
        1
        1
        1
        1
        1
        1
        1
        1
```

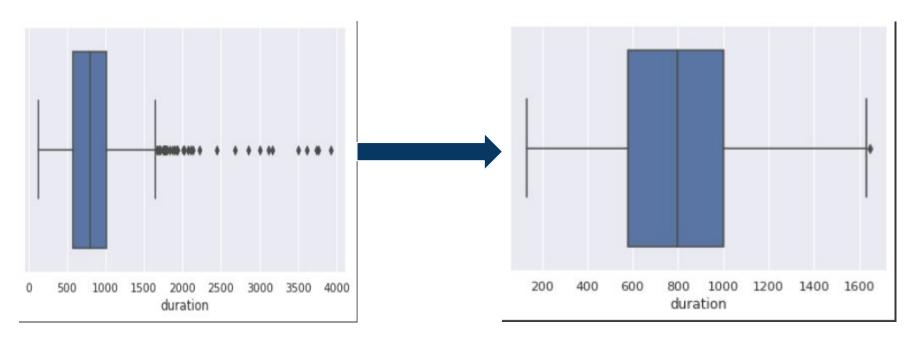
Removed unnecessary features like

'talk_id'	'title'	'speaker_1'	'all_speakers'			
'occupations'	'about_speakers'	'views'	'recorded_date'			
'published_date'	'event'	'native_lang'	'available_lang'			
'topics'	'related_talks'	'url'	'description'			
'transgrint'						

'transcript



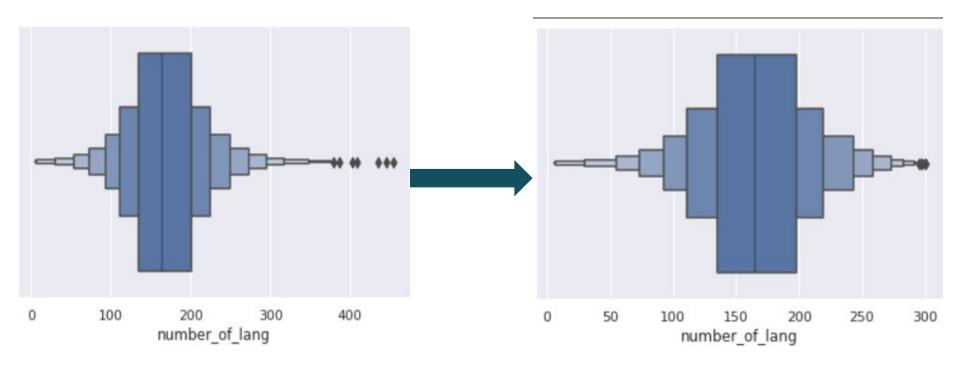
# Removing Outliers



Replaced outliers with mean value of duration

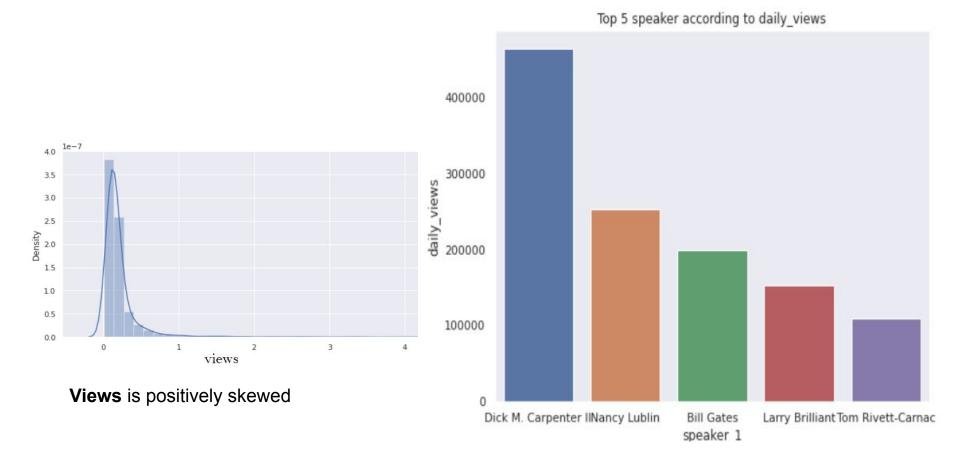


# Removing Outliers



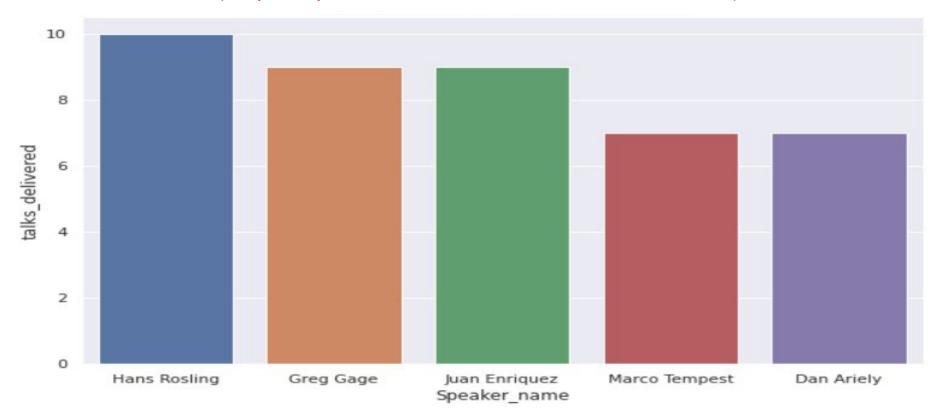
Replaced outliers with mean value of number\_of\_languages





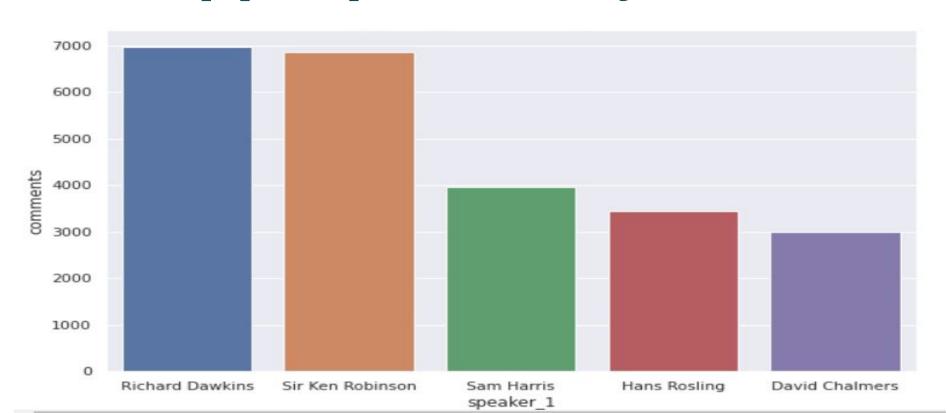


(Top 5 speakers who delivered most talks)



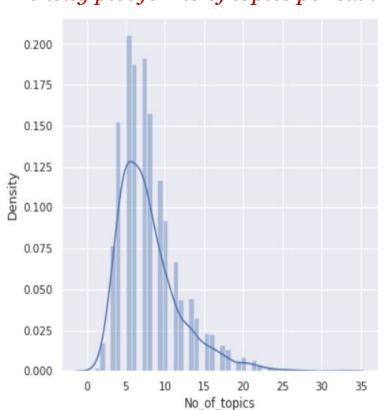


(Most popular speakers according to Comments)

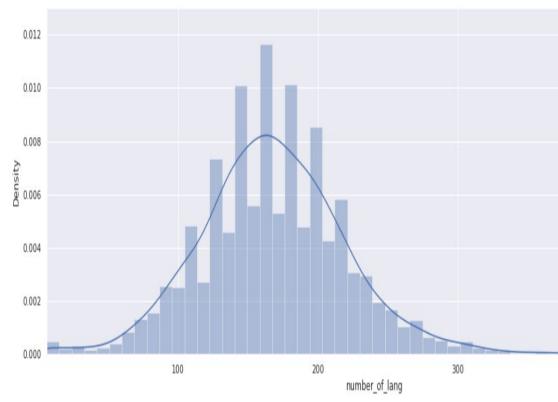




Density plot for no of topics per talk

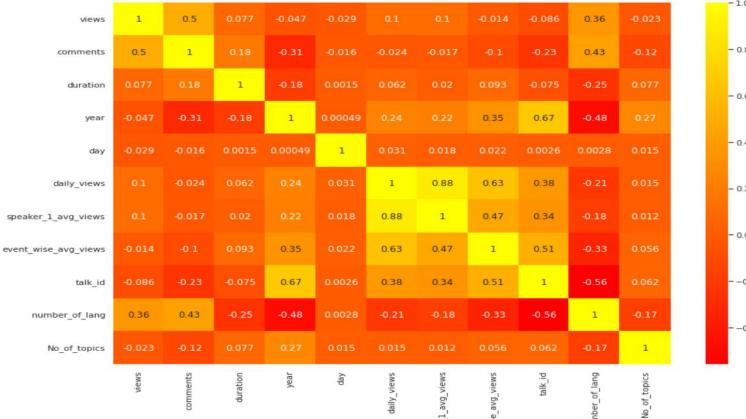


Density plot for no of languages per talk



### Correlation





-1.0 - 0.8 - 0.6 - 0.4 - 0.2 - 0.0 --0.2 -0.4

We can conclude that daily\_views column is highly correlated with Speaker\_1\_avg\_views, event\_wise\_avg\_views,



# Data Preparation

Independent features :-

```
comments, duration, time_since_published, month, year ,day, daily_views, Speaker_1_avg_views , event_wise_avg_views, Number_of_lang , No_of_topics , topics_wise_avg_views
```

- Dependent feature :- daily\_views
- Used **StandScaler**
- Splitted data into 80:20 ratio

# Let's compare those models



	Name	MAE_train	MAE_test	R2_Score_train	R2_Score_test	RMSE_Score_train	RMSE_Score_test
6	GradientBoostingRegressor:	380.283699	759.061577	0.994977	0.399657	857.067785	6248.226254
7	XGBRegressor:	429.726238	680.309046	0.993294	0.766738	990.303692	3894.743516
4	RandomForest	921.695436	839.076255	0.168246	0.335713	11029.234762	6572.562452
3	KNeighborsRegressor:	1031.112739	909.538141	0.541709	0.921037	8186.886733	2266.042923
1	Lasso:	1271.992955	1205.618639	0.859364	0.703730	4535.204569	4389.356547
2	Ridge:	1272.276531	1205.799311	0.859363	0.703867	4535.205410	4388.337808
0	Linear Reg.:	1272.640632	1206.337301	0.859364	0.703543	4535.203672	4390.738157
5	ExtraTreeRegressor:	1528.927152	1371.692837	0.147758	0.305693	11164.243764	6719.433676

We choose MAE and not RMSE as the deciding factor of our model selection because of the following reasons:

- RMSE is heavily influenced by outliers as in the higher the values get the more the RMSE increases.
- MAE doesn't increase with outliers. MAE is linear and RMSE is quadratically increasing.
- The best performing regressor model for this dataset is XGBRegressor on the basis of MAE.

# Hyperparameter Tuning



Name	MAE_train	MAE_test	R2_Score_train	R2_Score_test	RMSE_Score_train	RMSE_Score_test
XGBRegressor_without_hyper	429.888181	680.397815	0.993294	0.766717	990.312172	3894.911052
1 XGBRegressor_with_hyper	102.932939	645.449187	0.999718	0.766717	203.092063	3929.319520

- Used GridSearchCV to do hyperparameter tuning
- Hyperparameters I have used :
  - o gamma
  - Learning rate
  - max\_depth
  - n\_estimators

### **Conclusion**



#### **Models** used

1.Linear Reg.	Linear Reg. 2. Lasso		4. ExtraTreeRegressor		
5. RandomForest	6. KNeighborsRegressor	7. XGBRegressor	8. GradientBoostingRegressor		

#### Notes: -

- Most of the columns are categorical
- After hyper parameter tuning, we have prevented overfitting out of all these models \*\*XGBRegressor\*\* is the best performer in terms of MAE.
- In all the features *speaker\_1\_avg\_views* is most important this implies that speakers are directly impacting the views.
- R2\_score for the final model is 0.99 (train data) & 0.76 (test data)



