Ruiting Yang. Predicting the Popularity of TED Talks. A Master's Paper for the M.S. in I.S degree. May, 2020. 63 pages. Advisor: Yue Wang

In this paper, we explore how to predict a TED talk's popularity by its inherent features via machine learning techniques. We quantify a TED talk's popularity as logarithmic transformation of its daily views and daily comments and include 43 features as predictors. We find that the ordinary least squares regression, ridge regression, and LASSO regression models perform well, and predictors such as a talk's number of language translations, average Internet development environment when published, duration, main speaker's occupation, as well as the timing it being uploaded have essential effects on its popularity. In the end, we also provide our suggestion on how to improve TED talks' popularity within and beyond the scope of machine learning.

Headings:

TED talks popularity

Machine learning

Linear regression

Ordinary least squares (OLS)

Best feature subset

Ridge regression

LASSO regression

Random forest

PREDICTING THE POPULARITY OF TED TALKS

by
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Approved by

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Introduction

Founded by Richard Saul Wurman in 1984 as a conference and under the slogan "ideas worth spreading" ("TED (conference)"[2], 2020), TED is one of the most well-known non-profit organizations in the world for its powerful impact on education. Based on the data from TED talks[3], since June 2006, when TED released its first talk for free viewing online, TED has offered more than 3,300 talks covering various topics from science to humanities to daily lives in over 110 languages as of March 2020. According to TED Blog[4], TED surpassed a billion video views in total back to November 2012. Also based on the data from TED talks[5], until March 2020, the most popular talk on TED has gained over 64 million views, and the median views of all the talks have also reached 1.2 million.

It is not surprising to acknowledge that TED Talk, an online educational platform devoted to spreading ideas, has valued and will be valuing the popularity of its content (web-based talks) all the time. As Pinto, Almeida, & Gonçalves (2013) points out, "web content popularity is of great importance to support and drive the design and management of various services." In TED's case, "various services" are reflected on its slogan "ideas worth spreading" including producing high-quality videos, finding sponsorship from partnerships, establishing TED Fellows programs to support new voices, etc. (How TED Works[6], 2020).

Additionally, from the audience's perspective, a higher level of video popularity means more chances to be exposed to TED talks, especially for people who are willing to learn via online platforms at the age of social media. More chances of being exposed to cutting-edge and high-quality ideas like TED provides, more times of educational inspiration could be expected to happen.

What is more, given educational communities, TED's success in collecting brilliant ideas from all over the world and spreading them further and further could function as a prototype model for people in the field of education generating and spreading high-quality content. Wingrove (2017)'s research also reveals that "TED talk variation enables a range of academic listening applications." To learn from TED's successful experiences in education, the reasons for the TED talk's popularity is also worth exploring.

Then, how can we approach the myth behind TED talks' popularity from the aspect of information science? Machine learning is an ideal solution. Murphy (2012) defines machine learning as "a set of methods that can automatically detect patterns in data, and then use the uncovered patterns to predict future data, or to perform other kinds of decision making under uncertainty."

In this paper, we will "detect patterns," "predict future data," and "perform decision making" (Murphy, 2012) via machine learning methods of linear regression and random forest in terms of the data related to TED talks' popularity. Relying on the dataset retrieved from Kaggle.com[7] (Banik, 2017), which was originally obtained based on

Pappas and Popescu-Belis (2013)'s work, we quantify a TED talk's popularity as log of its daily views and log of daily comments and include 43 TED inherent features as predictors for a talk's popularity. We find that OLS, Ridge, and LASSO models perform well in our prediction, and features such as the number of language translations, average Internet connection speed, duration, posting gap between the date of being filmed and the date of being published, main speaker's occupation as writer or psychologist, being themed on "culture" or "design", being published on Friday, Saturday or March are all powerful predictors.

In summary, this paper focuses on predicting a TED talk's popularity by its features using machine learning techniques. Given the historical data retrieved and the machine learning models such as linear regression and random forest, this research is promising in practice. Also, it is worth-pursuing in theory since figuring out what makes a TED talk popular is of great value for TED, TED's audience, the general public who are willing to learn through video-hosting platforms, existing and potential educators, educational communities, and even the social literacy environment.

The paper proceeds as follows. The literature review section focuses on having an overview of the research background. The problem statement and data description section states our research goal and how we process the raw data to generate dependent and independent variables. The method section introduces our rationale for using linear regression and random forest models. The result section displays different models' performance and the learned parameter importance. The discussion section covers our findings based on as well as beyond the scope of machine learning prediction. Finally, the conclusion section summarizes all the work we have done in this research and looks into possible exploration in the future.

Literature Review

We will review relevant literature of our research to have an overview of the research background from four perspectives: how to quantify "popularity," possible predictors for "popularity," applicable machine learning methods, and evaluation metrics.

How to Quantify "Popularity"

Since the dataset on Kaggle[8] has been as open source for anyone since published in 2017 September, there have been many practices with the same topic of mine, and they offer me a robust and practical platform to quantify a TED talk's popularity. Based on the same dataset that I intend to use, explored indicators that can represent a TED talk's popularity include and don't limit to:

1. the number of views (Alvarez, 2017; Banik, 2017; Eldor, 2018; Kumar, 2017);
2. the number of comments, which is assumed as a reflection of "constructive criticism" and online community involvement (Banik, 2017);
3. the ratio of positive to negative ratings (Yuen, 2018).

These three indicators have also been further discussed. For instance, similar to the concept of "popularity," Moser (2017) defined how "powerful" a TED talk's idea is by combining three features: the number of views, the number of positive ratings, and the number of comments. Ray, Yadav & Garg (2018) found out that "the number of views and the number of comments were correlated." Tanveer et al. (2019)'s research mentioned that "the longer a TED talk remains on the web, the more views it gets," which means the "age" of a talk should be considered into the change of its number of views.

Not limited to the existing dataset, the general idea behind our research topic is based on what evidence can we reveal a underlying web-based content's attribute, which, in my case, is "popularity." Therefore, we also broaden our horizon for reviewing outside research regarding different types of web-contents' popularity. Some good examples in point are Liu et al. (2017) used audience's applause as an indicator of user engagement based on analyzing TED talks' transcripts; Chen and Lee (2017) predicted humorous utterances using audience's laughter based on TED talks; Chen et al. (2016) focused on predicting the popularity of micro-videos on Vine using four indicators: the number of comments, the number of likes, the number of reposts and the number of views; Hong et al. (2011) targeted on Twitter and measured a tweet's popularity by the number of its future retweets; Cappallo et al. (2015) defined an image's popularity by its view count and the number of comments, etc. Besides, not surprisingly, on top of common popularity prediction for videos, social media, and images, almost every kind of web content's popularity has been measured for exploration, such as online news (Fernandes et al., 2015), even for Github repositories (Borges, 2016).

To sum up, based on prior experience, we have learned that almost every type of web content's popularity can be measured by the frequency of certain kinds of human interaction with it, which in the TED talk's case could be the number of views or the number of comments. At the same time, we take the "accumulating effect" into account, given a longer time of an item remaining online naturally triggers more human interactions with it. Therefore, we think it would be more reasonable to use the number of averaged views or comments of each TED talk in a certain period as the indicator of their popularity.

Possible Predictors for "Popularity"

Given "popularity," what are the possible predictors for it? In other words, what features/attributes/characteristics of a TED talk can we use to predict its popularity? In this sense, explored features in the previous work that can be applied to our research are a TED talk's:

1. marked theme(s) (Alvarez, 2017; Banik, 2017; Yuen, 2018)
2. number of the marked tag(s) (Eldor, 2018)
3. year of the published date (Alvarez, 2017; Banik, 2017; Kumar, 2017)
4. duration of the talk (Alvarez, 2017; Banik, 2017; Kumar, 2017)
5. days between video creation and publishing (Alvarez, 2017)
6. days between publishing and dataset collection (Alvarez, 2017)
7. translations in languages (Eldor, 2018; Banik, 2017)
8. being published on what day of a week (Eldor, 2018; Banik, 2017; Yuen, 2018)
9. being published on which month of a year (Banik, 2017; Kumar, 2017)
10. speaker's occupation(s) (Eldor, 2018; Banik, 2017; Kumar, 2017; Yuen, 2018)
11. number of speakers (Banik, 2017)

12. word count (Banik, 2017)
13. voted count of “variety of metrics” like “funny,” “inspiring”… (Banik, 2017)
14. length of video description (Kumar, 2017)
15. belonging to which TED event (e.g., TEDx) (Banik, 2017; Kumar, 2017)
16. whether occurring in the popular words’ cloud created by all talks’ titles or description (Banik, 2017; Yuen, 2018)

Our research will rely on these features to find the most successful predictors combination among them, which achieves the best performance on predicting a TED talk’s popularity.

Applicable Machine Learning Methods

Based on the summary of machine learning by Ray (2017), one type is called supervised learning which refers to “algorithm consisting of a target/outcome variable (or dependent variable) which is to be predicted from a given set of predictors (independent variables).” (Ray, 2017); and the other type is called unsupervised learning which means “in this algorithm, we do not have any target or outcome variable to predict or estimate.” (Ray, 2017). In our case, since we do have a target variable, which is a TED talk’s popularity, we will be using supervised machine learning models.

In terms of supervised machine learning models, Provost & Fawcett (2013) and Ray (2017) both bring up linear regression, logistic regression, decision trees, support vector machines (SVM), naive Bayes, k-nearest neighbor algorithm (KNN), random forest, as well as neural networks. And most of these machine learning models have been tried, and therefore, they can be regarded as applicable. The detailed applications are as follows:

From the perspective of linear regression, it has been used to predict YouTube video's popularity (Ma, Yan, & Chen, 2017; Pinto, Almeida, & Gonçalves, 2013), TED talk's applause, another indicator of TED popularity as mentioned (Liu et al., 2017), how suitable TED talks are for academic listening (Wingrove, 2017), the popularity of GitHub repositories (Borges, Hora, & Valente, 2016). In terms of logistic regression and decision trees, Ray, Yadav, & Garg (2018) 's work used both to conduct a predictive analysis using classification algorithms on TED Talks. For support vector machines (SVM), successful applications are predicting the popularity of online videos (Trzciński and Rokita, 2017), the popularity of social media (Hidayati et al., 2017), the popularity of social image (Huang et al., 2017). Given naive Bayes, there are social content popularity prediction conducted by Wu et al. (2018). In the case of k-nearest neighbor algorithm (KNN) and random forest, Ray, Yadav & Garg's work (2018) again employed both techniques. Besides, the random forest model has been applied to predicting the popularity of TED talks by Dochev (2019) as well as online news by Fernandes, Vinagre, & Cortez (2015). Last but not least, concerning neural networks, TED Talk ratings have been predicted from language and prosody through this method by Tanveer et al. (2019). So has the audience's laughter via Convolutional Neural Network (CNN) by Chen & Lee (2017). Plus, also based on the popularity prediction of streaming service, Jeon et al. (2019) focused on the newly released contents for online video using neural networks.

We decide to employ both linear regression and random forest models for our research since they are classical in practical experiments so that they can further compare and mutually prove each other's findings.

Evaluation Metrics

An integral part of machine learning is doing the evaluation. In our research's case, the evaluation question would be, how can we decide whether a model with certain features outperform the other one? Provost & Fawcett (2013) have mentioned various evaluation metrics for machine learning models under various assumptions, such as "mean squared error", "accuracy", "precision", "recall", "F1 score", "ROC curve", "confusion matrix"... It is never easy to choose from them, while with the help of relevant literature, things could also get a little easier since there are successful cases to learn from. Specifically speaking, a fit evaluation metric is mainly determined by the dependent variable. If the dependent variable is "number of views" or "number of comments," then it's a numerical prediction task. In that case, "mean squared error" or "mean absolute error" can be used (e.g., Dochev, 2019, etc.). If the dependent variable is "whether the number of views is above 100k" (true or false, binary classification), or "the number of reviews is 0-100k, 100k-1M, or 1M" (three-way classification), then we will need to use an evaluation metric for classification, in which case (e.g., Yuen, 2018, etc.), "accuracy", "precision", "recall", "F1 score", "ROC curve", "confusion matrix" can be used.

Given our dataset supports us in conducting predictions on a numerical dependent variable, mean squared error (MSE) or mean absolute error (MAE) will be the primary metric for us to evaluate a model's performance.

Problem Statement and Data Description

In this section, we will start by stating the research problem. Then, based on the research problem, we will describe the original dataset, illustrate how we preprocessed it for further data exploration, and show the preprocessed data statistics.

Problem Statement

Our research problem is to predict the popularity of a TED talk given its inherent attributes using machine learning techniques.

Given "popularity", we will find numerical indicators such as a TED talk's daily views and daily comments to represent this information.

In terms of "inherent attributes", we mean the attributes that are generated on or before the time when a TED talk is uploaded online. For example, a TED talk's title length, duration, published on what day of a week, speaker(s)' occupation(s), related tags, number of translated languages, etc. We decide to only focus on these "inherent attributes" since we would like to carry out our prediction as soon as a TED talk is published. In other words, we will not consider the features that will emerge only after a talk being released for a certain period, for instance, the audience's sentiments.

For “machine learning techniques”, we will focus on linear regressions and random forest.

The Original Dataset

The original dataset on Kaggle[9] contains all 2,550 TED talks published on the official TED.com website from February 24th, 2006 to September 22nd, 2017.

For each TED talk in the original dataset, captured features include a talk’s title, description (a summary of what the talk is about), main speaker (the first-named speaker of the talk), main speaker’s occupation, number of speakers, the duration of the talk in seconds, in which event the talk took place, the Unix timestamp of the filming date, the Unix timestamp for the publication date, the tags/themes associated with the talk, the number of language translations, ratings (e.g., a talk can be rated by voting from various dimensions and stored as {'name': 'Funny', 'count': 19645}, {"name': 'Beautiful', 'count': 4573}…), a list of talks recommended for continuing to watch, the URL link, number of comments, and number of views.

To conduct further data exploration for our research, figuring out the original data’s data types matters as they determine how the data preprocessing would be. Generally speaking, there are four data types: categorical, ordinal, interval, and ratio/proportional. The above data’s types are as follows:

According to O'Sullivan, et al. (2016), “categorical variables are measured with nominal scales—identifying and labeling categories...do not have a relative value.” In the case of data from the original dataset, categorical data include a talk’s title, description, main speaker’s occupation, in which event the talk took place, the tags/themes associated with the talk, ratings, a list of talks recommended for continuing to watch, and the URL link.

Ordinal variables “identify and categorize values of a variable and put them in rank order according to those values… without regard to the distance between values” (O'Sulliva, et al., 2016). Given this dataset, there are no ordinal data.

“Interval and ratio scales measure characteristics by ranking their values on a scale and determining the numerical differences between them” (O'Sulliva, et al., 2016). And “a ratio scale has an absolute zero; an interval scale does not” (O'Sulliva, et al., 2016). Therefore, the interval data include a talk’s Unix timestamp of the filming date, Unix timestamp for the publication date. And the ratio data include the number of speakers, the duration of the talk in seconds, the number of language translations, number of comments, and number of views.

How the Original Dataset is Preprocessed

As we are attempting to figure out the effect of various TED talk attributes on a TED talk’s popularity, the dependent variable is TED talk’s popularity, and the independent variables can be selected or generated from various TED talk features mentioned. We will further demonstrate how the original dataset is preprocessed from the perspectives of these two types of variables.

Dependent Variables

In terms of the dependent variable, “popularity,” we decide to use: daily views of a TED talk, as well as daily comments of a TED talk as two separate indicators. In other words, we will run the same models with the same set of independent variables twice based on two different dependent variables.

Both dependent variables can be calculated by the total number of views or comments divided by the number of days gap between the date when a talk was published and the date when the dataset was collected (September 25th, 2017).

The reason for making this decision is aligned with the findings from the literature review. In essence, we believe the natural time effect on accumulating a TED talk’s views or comments so that we are averaging it out. Also, we deem “views” and “comments” could reflect different aspects of “popularity” so that we should separate them, for instance, more views can be regarded as more times of a video being clicked, while more comments usually mean more discussion is inspired.

Also, we plotted these two variables (as shown in Figure 1 and Figure 2) given all 2,550 talks’ distribution frequency, and we found that both of their patterns are highly right-skewed. Inspired by Russell and Dean (2000)’s work on how to deal with skewed dependent variables, we conducted natural logarithmic transformations on both of them and found that their log-transformed values' patterns both approximate the normal distribution (as shown in Figure 3 and Figure 4) and are more suitable given machine learning model construction. Therefore, we decide to use the logarithm of both variables as our two dependent variables:

1. log of daily views
2. log of daily comments

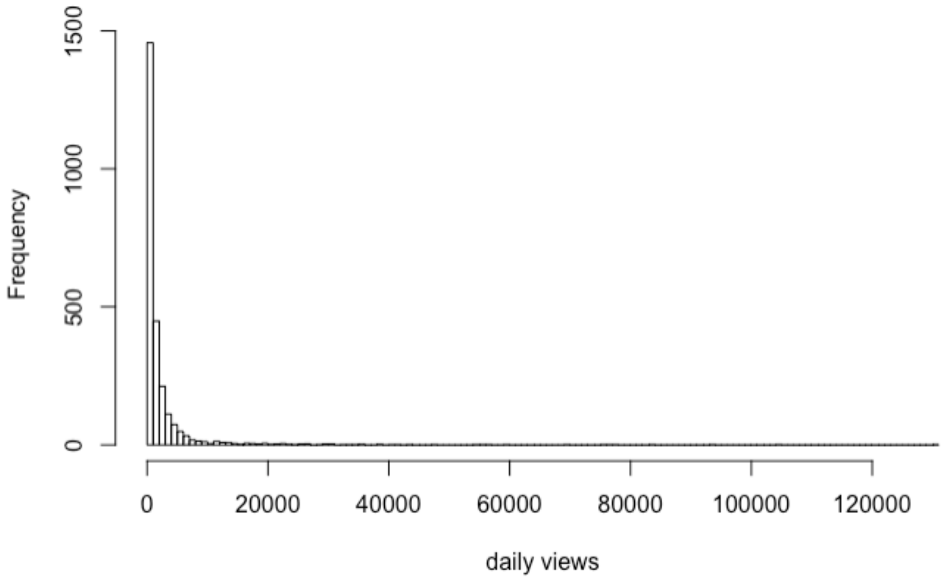


Figure 1. Distribution of daily views for all 2,550 talks

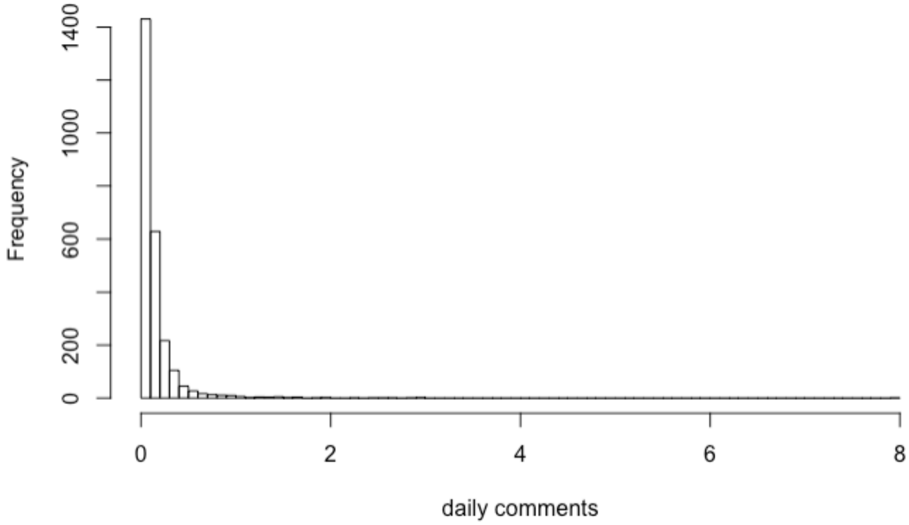


Figure 2. Distribution of daily comments for all 2,550 talks

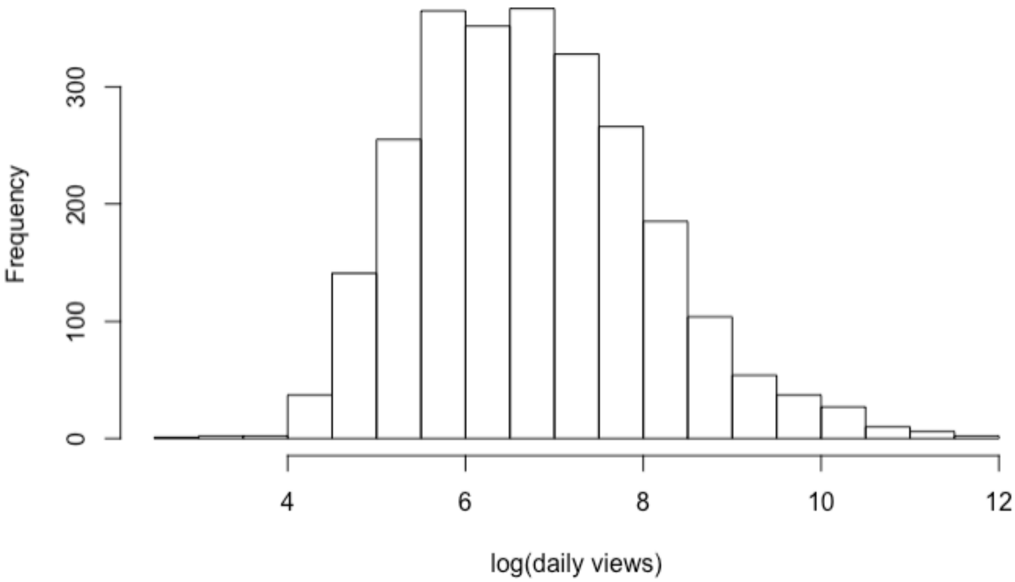


Figure 3. Distribution of log(daily views) for all 2,550 talks

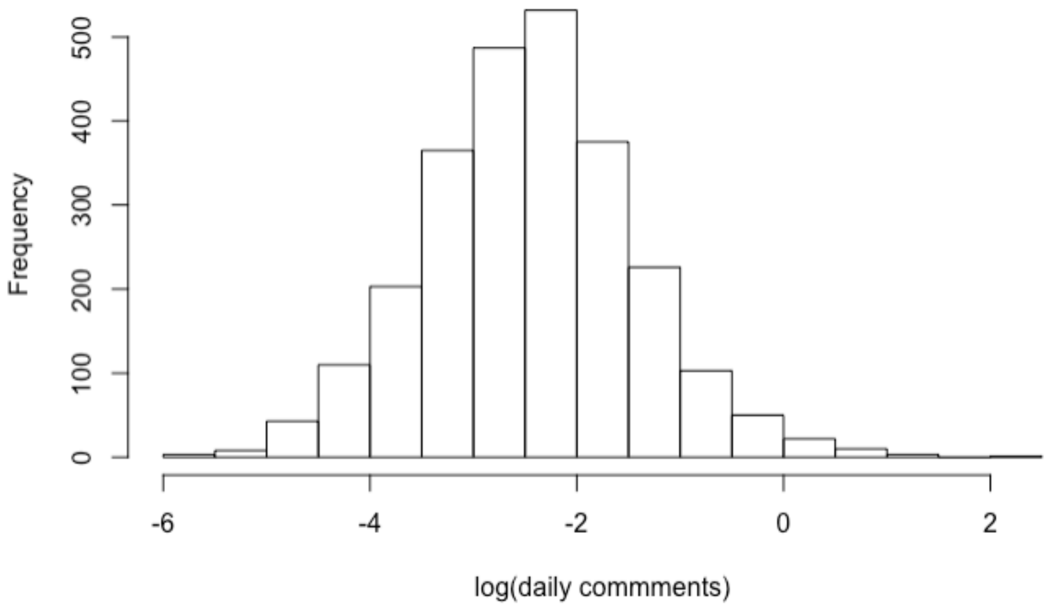


Figure 4. Distribution of log(daily comments) for all 2,550 talks

Independent Variables

Concerning independent variables, also based on the literature review, almost every captured feature mentioned can be deemed as an independent variable, while the variables that can be directly used are only:

1. number of language translations;
2. number of speakers;

Other ones are all in need of being further engineered more or less. For example, the published date and filmed date need to be converted to standard date format so that we could calculate the number of days difference between them as a variable:

3. posting gap;

Given the posting gap, we found 9 abnormal talks – each of them shows a negative value. We tracked them back on the TED website and we believe it is because their published dates are wrongly recorded on the website. Therefore, we removed these 9 talks, and the full size of our dataset drops to 2,541.

For easier interpretation, we also convert duration in seconds to:

4. duration in minutes;

Besides, to measure the length of a talk's title by how many characters it owns, we create a variable:

5. title length;

Additionally, we introduce an outside-sourced feature:

6. mbp;

This feature, "mbp," represents U.S. average internet connection speed in Mbps (million bits transferred per second). This data is originally collected by Akamai Technologies[10] every quarter (Q) from 2007 Q3 to 2017 Q1 and further organized by Statista[11]. We intentionally add this feature to the model building, since we believe the development of the Internet in recent years has an essential effect on making TED talks more and more popular, and this feature can be a good indicator for the blurred concept, “Internet development”. Additionally, since the original data source only captured “mbp” from 2007 Q3 to 2017 Q1, while the published date of all 2,541 talks ranges from 2006 Q2 to 2017 Q3, we approximated and filled 7 missing “mbp” values holding the assumption that the increasing rate of “mbp” between two quarters is same as the averaged increasing rate of “mbp” among their closest five quarters with known values.

Plus, to capture the information of what day on a week might affect a talk’s popularity, we create many dummy variables, for instance:

7. Mon (using 1 or 0 to represent a talk is published on Monday or not);

8. Tue (using 1 or 0 to represent a talk is published on Tuesday or not);

9. Wed (using 1 or 0 to represent a talk is published on Wednesday not);

10.Thur (using 1 or 0 to represent a talk is published on Thursday or not);

11. Fri (using 1 or 0 to represent a talk is published on Friday or not);

12. Sat (using 1 or 0 to represent a talk is published on Saturday or not);

We don’t need “Sun” as “Sun” can be represented when all 7.~12. variables equal to 0.

Similarly, to explore which month in a year affects a talk’s popularity, we have:

13. Jan (using 1 or 0 to represent a talk is published in January or not);

14. Feb (using 1 or 0 to represent a talk is published in February or not);

15. Mar (using 1 or 0 to represent a talk is published in March or not);

16. Apr (using 1 or 0 to represent a talk is published in April or not);

17. May (using 1 or 0 to represent a talk is published in May or not);

18. June (using 1 or 0 to represent a talk is published in June or not);

19. July (using 1 or 0 to represent a talk is published in July or not);

20. Aug (using 1 or 0 to represent a talk is published in August or not);

21. Sept (using 1 or 0 to represent a talk is published in September or not);

22. Oct (using 1 or 0 to represent a talk is published in October or not);

23. Nov (using 1 or 0 to represent a talk is published in November or not);

Likewise, we don't need "Dec" as "Dec" can be represented when all 13.~24. variables equal to 0.

Based on the same idea of generating dummy variables, we record the information of TED talks' top 10 frequent tags and top 10 frequent main speaker's occupations via another 20 variables, and they are:

24. technology (using 1 or 0 to represent a talk is themed on technology or not);

25. science (using 1 or 0 to represent a talk is themed on science or not);

26. global_issue (using 1 or 0 to represent a talk is themed on a global issue or not);

27. culture (using 1 or 0 to represent a talk is themed on culture or not);

28. TEDx (using 1 or 0 to represent a talk is themed on TEDx or not — According to Fidelman (2012), the difference between TED and TEDx is the former takes a global approach while the latter focuses on local communities and voices.);

29. design (using 1 or 0 to represent a talk is themed on design or not);

30. business (using 1 or 0 to represent a talk is themed on business or not);

31. entertainment (using 1 or 0 to represent a talk is themed on entertainment or not);
32. health (using 1 or 0 to represent a talk is themed on health or not);
33. innovation (using 1 or 0 to represent a talk is themed on innovation or not);
34. writer (using 1 or 0 to represent a talk's main speaker is a writer/author or not);
35. artist (using 1 or 0 to represent a talk's main speaker is an artist or not);
36. designer (using 1 or 0 to represent a talk's main speaker is a designer or not);
37. journalist (using 1 or 0 to represent a talk's main speaker is a journalist or not);
38. entrepreneur (using 1 or 0 to represent a talk's main speaker is an entrepreneur or not);
39. inventor (using 1 or 0 to represent a talk's main speaker is an inventor or not);
40. architect (using 1 or 0 to represent a talk's main speaker is an architect or not);
41.psychologist (using 1 or 0 to represent a talk's main speaker is a psychologist or not);
42. neuroscientist (using 1 or 0 to represent a talk's main speaker is a neuroscientist or not);
43. photographer (using 1 or 0 to represent a talk's main speaker is a photographer or not);

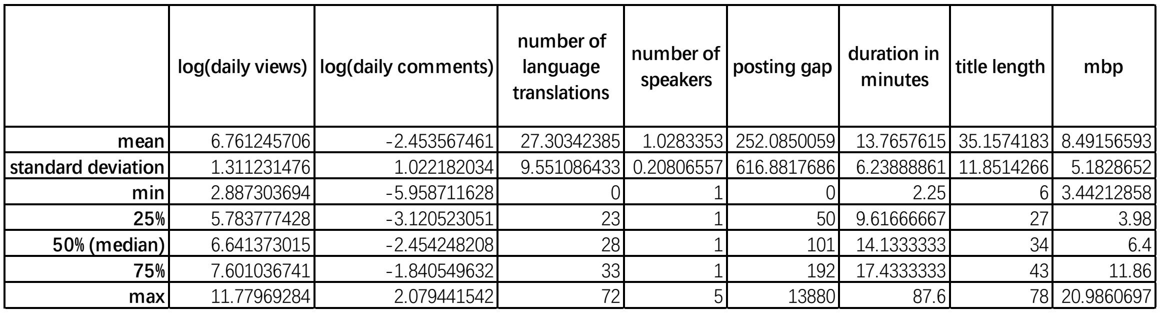
One thing that needs to be pointed out is a TED talk could have one or more themed tags, and the number of its main speaker's occupations could also be more than one.

In total, we have 2,541 talks with 43 independent variables for 2 dependent variables individually.

An important note is that we did consider but ended up giving up sentiment-related independent variables such as how many sentiment-related votes (TED has such a voting function for each talk) are generated after a talk is uploaded, what proportion of these sentiments is positive or negative, etc. This decision is made since we realize that this kind of information can only be retrieved after a talk being uploaded so that we think it could not provide us with a time-efficient prediction. More importantly, the volume of sentiments, as well as the number of comments are both highly related to the concept of "popularity", therefore, we should have known the number of views if we knew the volume of sentiments or the number of comments, which makes such a prediction completely unnecessary. To this point, a piece of previous work we would criticize is Eldor (2018)'s in which he took the number of comments as a predictor for the number of views.

Preprocessed Data's Statistics

Both dependent variables and 1.~6. independent variables are continuous variables, and their statistics are shown in table 1.

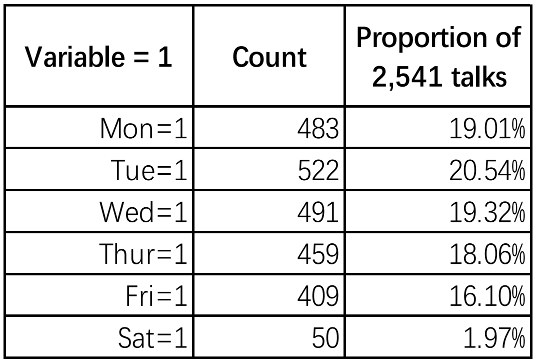


	log(daily views)	log(daily comments)	number of language translations	number of speakers	posting gap	duration in minutes	title length	mbp
mean	6.761245706	-2.453567461	27.30342385	1.0283353	252.0850059	13.7657615	35.1574183	8.49156593
standard deviation	1.311231476	1.022182034	9.551086433	0.20806557	616.8817686	6.23888861	11.8514266	5.1828652
min	2.887303694	-5.958711628	0	1	0	2.25	6	3.44212858
25%	5.783777428	-3.120523051	23	1	50	9.61666667	27	3.98
50% (median)	6.641373015	-2.454248208	28	1	101	14.1333333	34	6.4
75%	7.601036741	-1.840549632	33	1	192	17.4333333	43	11.86
max	11.77969284	2.079441542	72	5	13880	87.6	78	20.9860697

Table 1. Continuous variables' statistics

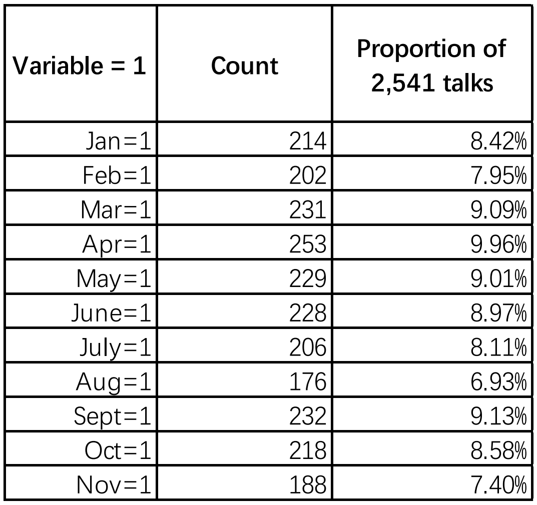
All of the rest 37 variables (7.~ 43. independent variables) are binary. Therefore, we only need to calculate counts when their values = 1 to show their statistics.

For example, the statistics of 7.~ 12. independent variables representing what day of a week a given talk is published are shown in Table 2; And statistics of 13.~ 23. independent variables representing which month of a year a given talk is published are also shown in Table 3.



Variable = 1	Count	Proportion of 2,541 talks
Mon=1	483	19.01%
Tue=1	522	20.54%
Wed=1	491	19.32%
Thur=1	459	18.06%
Fri=1	409	16.10%
Sat=1	50	1.97%

Table 2. Different weekdays' statistics



Variable = 1	Count	Proportion of 2,541 talks
Jan=1	214	8.42%
Feb=1	202	7.95%
Mar=1	231	9.09%
Apr=1	253	9.96%
May=1	229	9.01%
June=1	228	8.97%
July=1	206	8.11%
Aug=1	176	6.93%
Sept=1	232	9.13%
Oct=1	218	8.58%
Nov=1	188	7.40%

Table 3. Different months' statistics

For 24.~ 33. independent variables reflecting a given talk's themed tag(s) and 34.~ 43. independent variables reflecting a given talk's main speaker's occupations(s), similarly we use table 4 and table 5 to display their statistics.

Variable = 1	Count	Proportion of 2,541 talks
technology=1	726	28.57%
science=1	603	23.73%
global_issue=1	494	19.44%
culture=1	561	22.08%
TEDx=1	449	17.67%
design=1	449	17.67%
business=1	354	13.93%
entertainment=1	299	11.77%
health=1	320	12.59%
innovation=1	229	9.01%

Table 4. Different themed tags' statistics

Variable = 1	Count	Proportion of 2,541 talks
writer=1	216	8.50%
artist=1	107	4.21%
designer=1	115	4.53%
journalist=1	72	2.83%
entrepreneur=1	100	3.94%
inventor=1	58	2.28%
architect=1	50	1.97%
psychologist=1	58	2.28%
neuroscientist=1	42	1.65%
photographer=1	45	1.77%

Table 5. Different occupations' statistics

Method

In this section, we will focus on how to split our preprocessed data into training, validation, and test datasets, as well as the machine learning models and methods we intend to use.

Training, Validation and Test Datasets

Since we are going to use various machine learning models with differing hyperparameters, we need to split our preprocessed data into training, validation, and test datasets. Specifically speaking, we will use training and validation datasets to train our models and select the best one from them based on their different levels of prediction performances, which can be reflected by mean squared error (MSE). Also, once we have decided on a certain model, we need the test dataset to report how the selected model can generally perform on the data outside our model building. Therefore, the test dataset should not be overlapped with training or validation datasets at any degree.

Also, since we are interested in predicting a TED talk's popularity, we would like to build the prediction model in a way of being able to "foresee" the future. Therefore, we reordered our original dataset by these talks' published date and picked the most recent 30% talks (762 observations) into our test dataset.

For the 70% talks (1779 observations) left, we will conduct 5-fold cross-validation for model training and selection.

Machine Learning Models

Corresponding to what has been discussed in the literature review section, we intend to use two main machine models: linear regression and random forest for our prediction.

Linear Regression

Linear regression assumes linear functional dependency between the independent variables and the dependent variables. Under this assumption, we will approach our prediction from the following four methods:

Ordinary least squares (OLS)

OLS is the simplest type of linear regression without regularization or feature selection. In other words, we will put all 43 independent variables to fit the linear model by the principle of least squares, which refers to “choosing the regression coefficients so that the estimated regression line is as close as possible to the observed data, where closeness is measured by the sum of the squared mistakes made in predicting Y given X.” (Stock and Watson, 2015).

OLS has its advantages for it is efficient to operate the model building process with reasonable computation and the results are easy to interpret. However, its disadvantages are also evident, for example, without regularization or feature selection, we can include some useless variables in the model since we have no ideas on how to distinguish which of these 43 predictors are useful for the model building and this will lead to an overly complex model or overfitting issues.

After all, OLS could function as the baseline method for others to compare with.

Best feature subset

Best feature subset is a method on top of OLS conducting discrete feature selection. Best feature subset will allow us to fit separate OLS models for every possible combination of all independent variables (James et al., 2013). We will use 5-fold cross-validation approach to determine which of these combinations reaches the best performance with the smallest training MSE.

Best feature subset can effectively address OLS's overfitting issues while it usually involves a much higher level of computation.

Ridge regression

Ridge regression is also invented for controlling model complexity based on OLS. Instead of directly minimizing OLS's least squares, ridge regression adds the regularization/ penalty term $\lambda \sum_{j=1}^{p} \beta j^2$ (where $\lambda \geq 0$ is a tuning hyperparameter and βj refers to any coefficient given p-dimensional model, which in our case p = 43) to shrink the regression coefficients (James et al., 2013). We will use cv.glmnet[12]'s defaulted values of λ and cross-validate them to find the most reasonable hyperparameter.

Although ridge regression helps us control model complexity via λ, it suffers from the problem of interpretability from the shrunken coefficients. Plus, it will include all 43 variables without doing any feature selection so that it won't apply well to the cases when many of the independent variables are useless, which we will never know before running any models.

LASSO regression

With a similar idea of shrinking coefficients, LASSO regression can be regarded as a transformation from ridge regression. According to James et al. (2013), the only difference between these two is LASSO regression adds the term $\lambda \sum_{j=1}^{p} |\beta j\,|$ (where $\lambda \geq 0$ is a tuning hyperparameter, and βj refers to any coefficient given p-dimensional model, which in our case p = 43) instead of $\lambda \sum_{j=1}^{p} \beta j^2$. We will also use cv.glmnet[13]'s defaulted values of λ and cross-validate them for the optimal hyperparameter.

LASSO regression also controls model complexity via λ like ridge regression does, while not like ridge, it does feature selection by yielding zero coefficients for some variables. Therefore, LASSO regression usually outperforms ridge regression if the case is many of the independent variables are useless. However, as mentioned, we will never know how many of our independent variables are useful before running any models. Therefore, it is better to experiment with both ridge and LASSO.

Random Forest

The underlying assumption of random forest is the functional dependency between the independent variables and the dependent variables is non-linear and can be reached by a collection of decision trees. Random Forest is famous for “decorrelating the trees” by “not even allowing to consider a majority of the available predictors” at each tree split (James et al., 2013). For instance, given a total number of independent variables, p, which is 43 in our case, random forest might only randomly take m = $\sqrt{p} = \sqrt{43} \approx 6$ of them for each split in the tree (where m is a hyperparameter deciding how the subset size of predictors is in each split). Our model building will be based on randomForest[14] and rfcv[15]’s defaulted number of trees grown and cross-validate the common choices of m, such as $\sqrt{p}, \frac{p}{2}$, and $\frac{p}{3}$, etc.

Random forest is a good complement for linear regression due to it holds a completely different model building assumption, and it is computationally attractive as well. Nevertheless, its result cannot be easily interpreted, and the common way to gain insights from a random forest model is to look at a variable importance plot which only shows the percentage of model performance’s improvement from splitting a given variable.

Result

In this section, we will focus on different models' prediction performance and the learned parameter importance from them.

Prediction Performance

For each model, MSE in the raining-validation set will be used to select independent variables or hyperparameters, and prediction performance will be reflected on each model's MSE in the test dataset.

Linear Regression

We will start with illustrating linear regressions' predication performance.

OLS

Since there is no feature selection or regularization in OLS, we don't need to do cross validation in this case. And we can directly apply the OLS model trained from the 70% training-validation data to the 30% test data for calculating test MSE.

Given the dependent variable is log(daily view), test MSE is 0.7606548; while given the dependent variable is log(daily comment), test MSE is 0.8634327.

Best feature subset

We use 5-fold cross-validation (5-fold CV) for selecting how many variables should be included in the model to reach the smallest training MSE.

Given the dependent variable is log(daily views), as shown in figure 5, the model including 19 variables reaches the smallest training MSE (0.37068) and therefore it is selected. When applied to test data, this model's corresponding test MSE is 0.8418204.

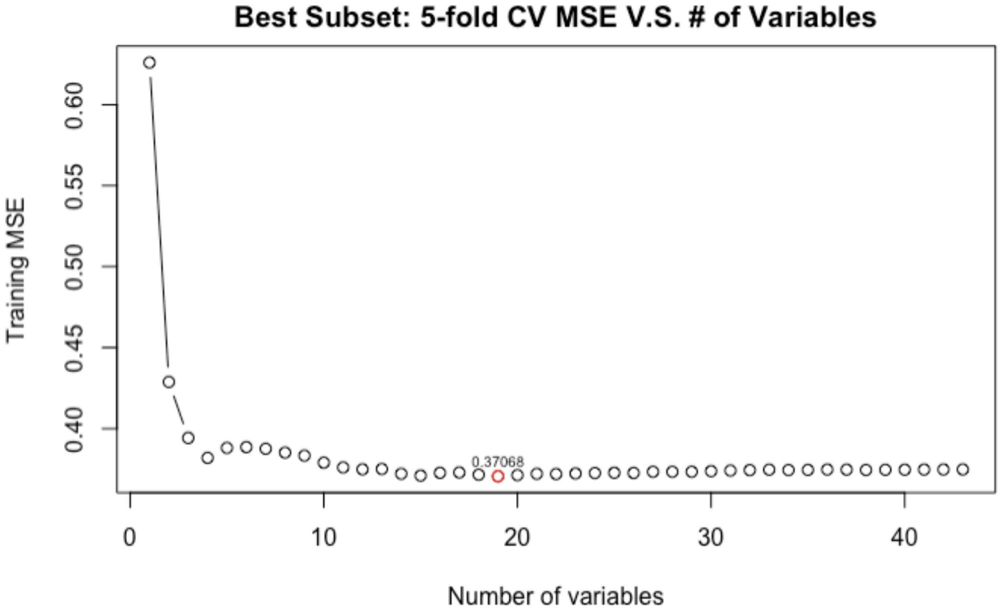


Figure 5. Best subset's training MSE, Y = log(daily views)

Given the dependent variable is log(daily comments), as shown in figure 6, the model including 28 features is selected for reaching the smallest training MSE (0.5822), and this model's corresponding test MSE is 0.881414.

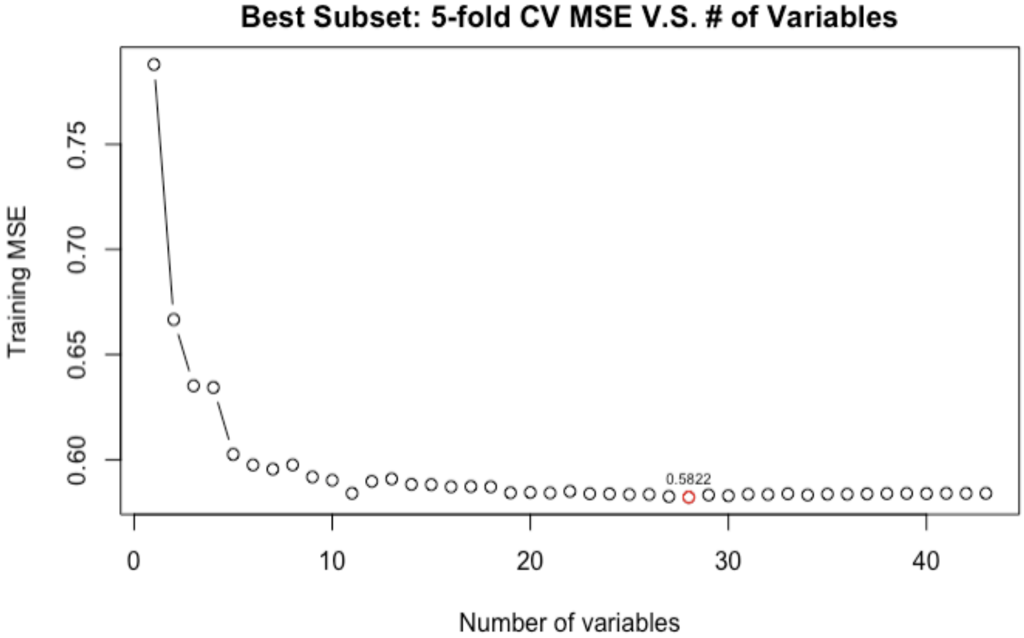


Figure 6. Best subset's training MSE, Y = log(daily comments)

Ridge

We also use 5-fold CV for selecting which λ should be applied to the model. Inspired by Hastie and Qian (2014), in instead of using the value of λ that gives minimum cross-validated training MSE, we choose the largest value of λ within one standard error of the minimum λ ("lambda.1se"[16], a value saved by cv.glmnet[17]) to address possible overfitting issues (as shown in figure 7 and figure 8).

Given the dependent variable is log(daily views), the selected λ (marked in figure 7)'s corresponding model's test MSE is 1.094431.

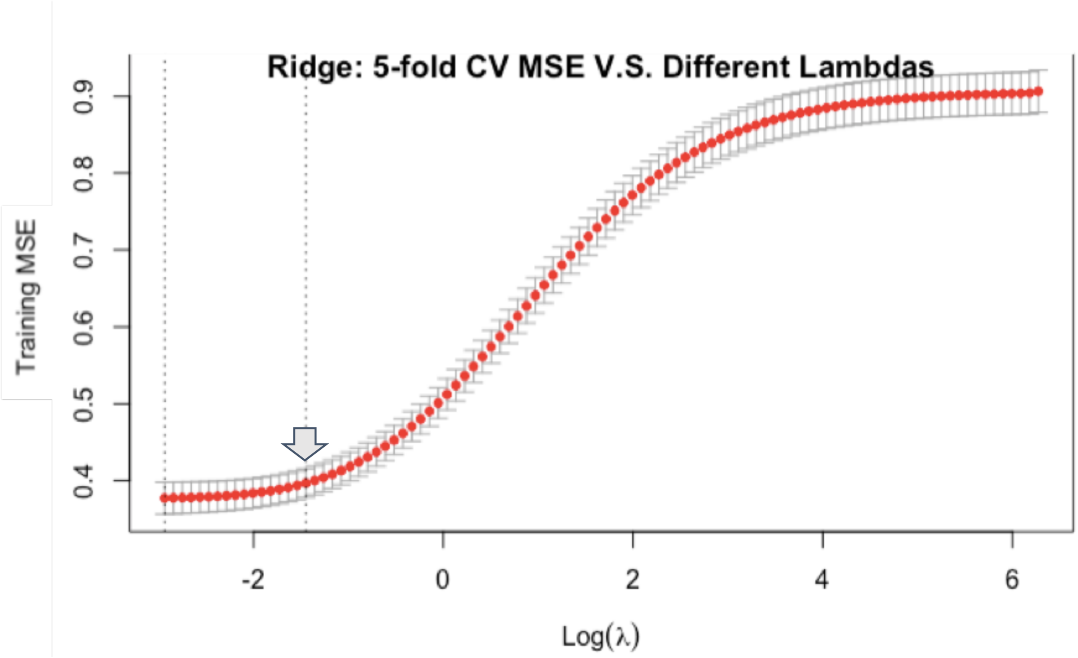


Figure 7. Ridge's training MSE, Y = log(daily views)

Given the dependent variable is log(daily comments), the selected λ (marked in figure 8)'s corresponding model's test MSE is 0.782524.

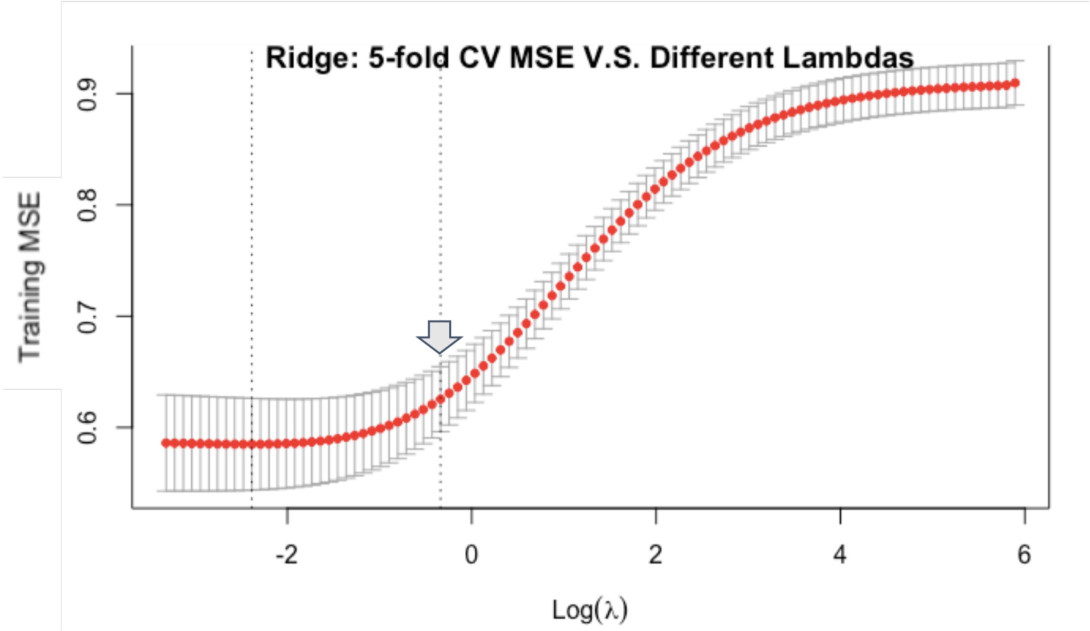


Figure 8. Ridge's training MSE, Y = log(daily comments)

LASSO

We still use 5-fold CV for selecting which λ should be applied to the model. As what we have done in Ridge, still inspired by Hastie and Qian (2014), in instead of using the value of λ that yields minimum cross-validated training MSE, we still choose "lambda.1se"[18] as mentioned for generating a more regularized model (as shown in figure 9 and 10).

Given the dependent variable is log(daily views), the selected λ (marked in figure 9)'s corresponding model only includes 12 features (31 features' coefficients are assigned as 0), and its corresponding test MSE is 0.8599129.

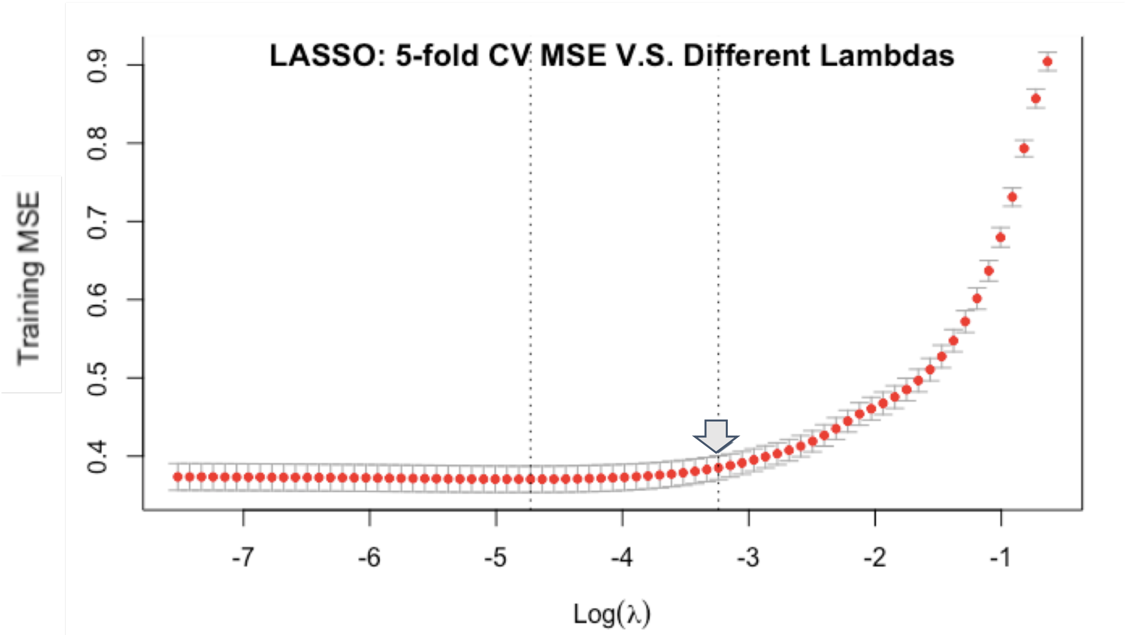


Figure 9. LASSO's training MSE, Y = log(daily views)

Given the dependent variable is log(daily comments), the selected λ (marked in figure 10)'s corresponding model only includes 11 features (32 features' coefficients are assigned as 0), and its corresponding test MSE is 0.7828465.

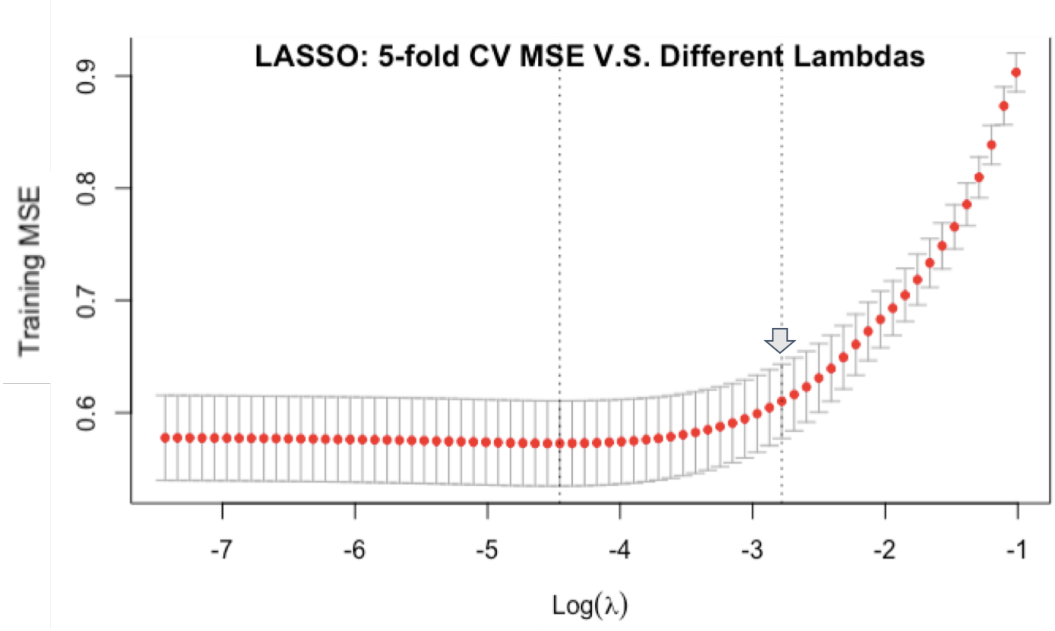


Figure 10. LASSO's training MSE, Y = log(daily comments)

Random Forest

We also apply 5-fold CV to our selection of which "m" should be optimal for the model building based on the assumption of random forest.

In the case that the dependent variable is log(daily views), the smallest training MSE is reached when m = 5, and its corresponding test MSE is 3.19092.

In the case that the dependent variable is log(daily comments), the smallest training MSE is reached when m = 11, and its corresponding test MSE is 1.13386.

In summary, we create table 6 to display different models' test MSE. Given the dependent variable is log(daily views), OLS outperforms other models on the list of our choices with the smallest test MSE (0.7606548). Meanwhile, given the dependent variable is log(daily comments), Ridge has the lowest test MSE (0.782524). However, it is also worth noting that Ridge's test MSE difference from LASSO's is fairly small, and LASSO has a much lower level of model complexity than Ridge, therefore we lean to say LASSO also performs better the others in the case of log(daily views).

Model	OLS	Best Subset	Ridge	LASSO	Random Forest
Test MSE given Y = log(daily views)	0.761	0.842	1.094	0.860	3.191
Test MSE given Y = log(daily comments)	0.863	0.881	0.783	0.783	1.134

Table 6. Different models' test MSE

Since our dependent variables are both log-based, we need to transform them back to the original unit to better interpret these outperforming test MSEs. With the helpful instruction from Wang (2020), we have the statements as follows:

Given the dependent variable is log (daily views), test MSE (0.7606548) from OLS means on average, the prediction deviates from the truth by exp(sqrt(0.7606548))-1 = 139.2061% higher or lower than the original count of daily views.

Given the dependent variable is log (daily comments), test MSE (0.782524) from Ridge means on average, the prediction deviates from the truth by exp(sqrt(0. 782524))-1=

142.2025% higher or lower than the original count of daily comments, while test MSE (0.7828465) from LASSO means on average, the prediction deviates from the truth by exp(sqrt(0. 7828465))-1= 142.2466%, which is also not far away from Ridge's performance.

Learned Parameter Importance

Not only do we care about different models' test MSEs indicating different levels of model performance, but we also would like to explore the learned parameter importance from them, if possible. In other words, we are eager to learn what variables are powerful/useless for our prediction to hone our model interpretation.

Linear Regression

In terms of OLS models:

For predicting log(daily views), statistically significant variables (p-value<.05) are number of language translations (+0.05736), posting gap (-0.00007247), duration in minutes (+0.03219), mbp (+0.1912), writer (+0.1781), psychologist (+0.3911), global_issue (-0.3042), culture (+0.09236), design (-0.09074), business (+0.1211), Fri (+0.2153), Sat (+0.2633), Mar (+0.2108), as well as intercept (3.178). What is in () is each variable or intercept's learned coefficient: (+)/ (-) stands for positive/negative effect on log(daily views), and the following number reflects the effect magnitude.

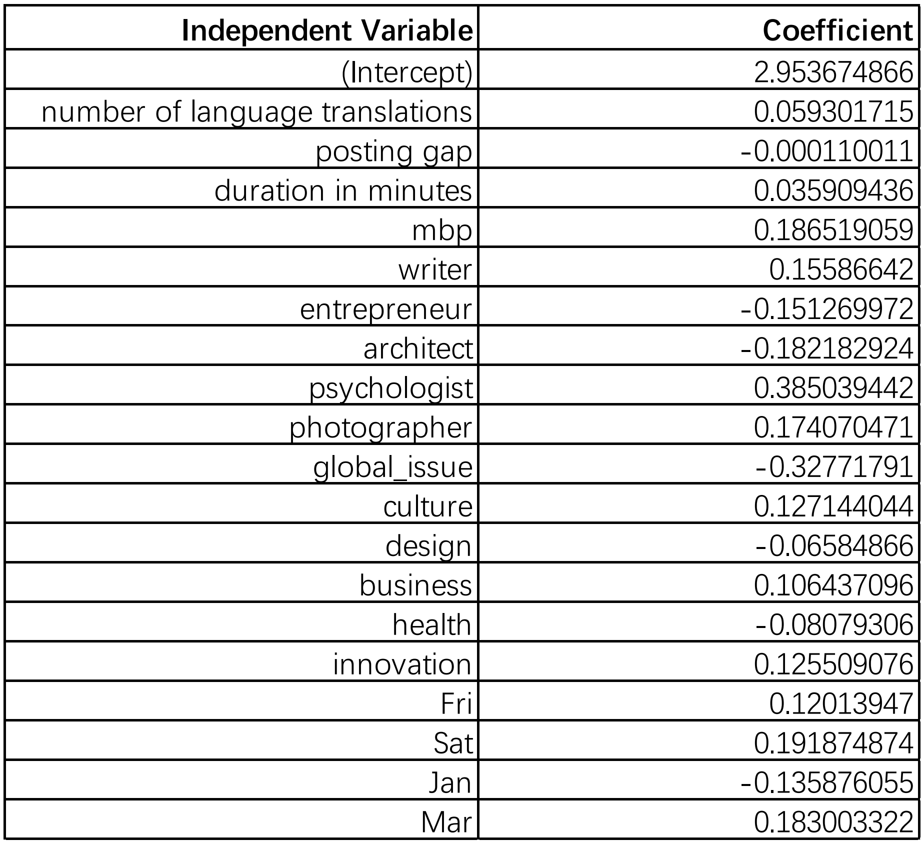
Referred to UCLA Statistical Consulting Group[19], the intercept, 3.178, is the unconditional expected mean of log(daily views), and the exponentiated value, exp(3.178) = 23.99871, is the geometric mean of daily comments. Plus, number of language translations (+0.05736) means when holding other variables constant, if a TED talk's translated languages increase 1 type, the OLS model predicts that its daily views will increase exp(0.05736)-1= 5.9037%. Also, psychologist (+0.3911) shows that when holding other variables constant, we expect to see a TED talk delivered by a psychologist generates exp(0.3911)-1=47.86% more daily views than those which are not. To our surprise, duration in minutes has an exp(0.03219)-1 = 3.27% positive effect which means when holding other variables constant, if the talk increases 1 minute, we could expect its daily views to increase 3.27%. The only explanation we could make is TED talks are so high-quality that the TED community tends to be immersed watching them, therefore extending a talk's duration could trigger more attraction. In other words, in TED community, a talk is not as engaging or popular if its time duration is too short.

For predicting log(daily comments), statistically significant variables (p-value<.05) are number of language translations (+0.03944), posting gap (-0.0002041), duration in minutes (+0.03015), mbp (+0.1295), writer (+0.1629), architect (-0.04516), psychologist (+0.4010), neuroscientist (+0.3452), culture (+0.1076), TEDx (+0.2035), design (-0.2558), entertainment (-0.2324), innovation (+0.1961), Sat (+0.5282), Mar (+0.2447), as well as intercept (-4.662). What is in () is still each variable or intercept's coefficient: (+)/(-) stands for positive/negative effect on log(daily comments), and the following number still reflects the effect magnitude.

Still referred to UCLA Statistical Consulting Group[20], the intercept, -4.662, is the unconditional expected mean of log(daily comments), and the exponentiated value, exp(-4.662) = 0.009447548, is the geometric mean of daily comments. Plus, mbp (+0.1295) means when holding other variables constant, if U.S. average internet connection speed increases 1 Mbp, the OLS model predicts that a TED talk's daily comments will increase exp(0.1295)-1=13.83%. In addition, Sat (+0.5282) shows that when holding other variables constant, we expect to see a TED talk published on Saturday generates exp(0.5282)-1=69.58% more daily comments than those which are not. This makes sense to us as people are usually more relaxed and more willing to be exposed to Internet-based contents during the weekend. Mar (+0.2447) means that when holding other variables constant, we expect to see a TED talk published in March generates exp(0.2447)-1=27.72% more daily comments than those which are not, and we think this is because most annual TED conferences hold around March (TED Conference, 2020).

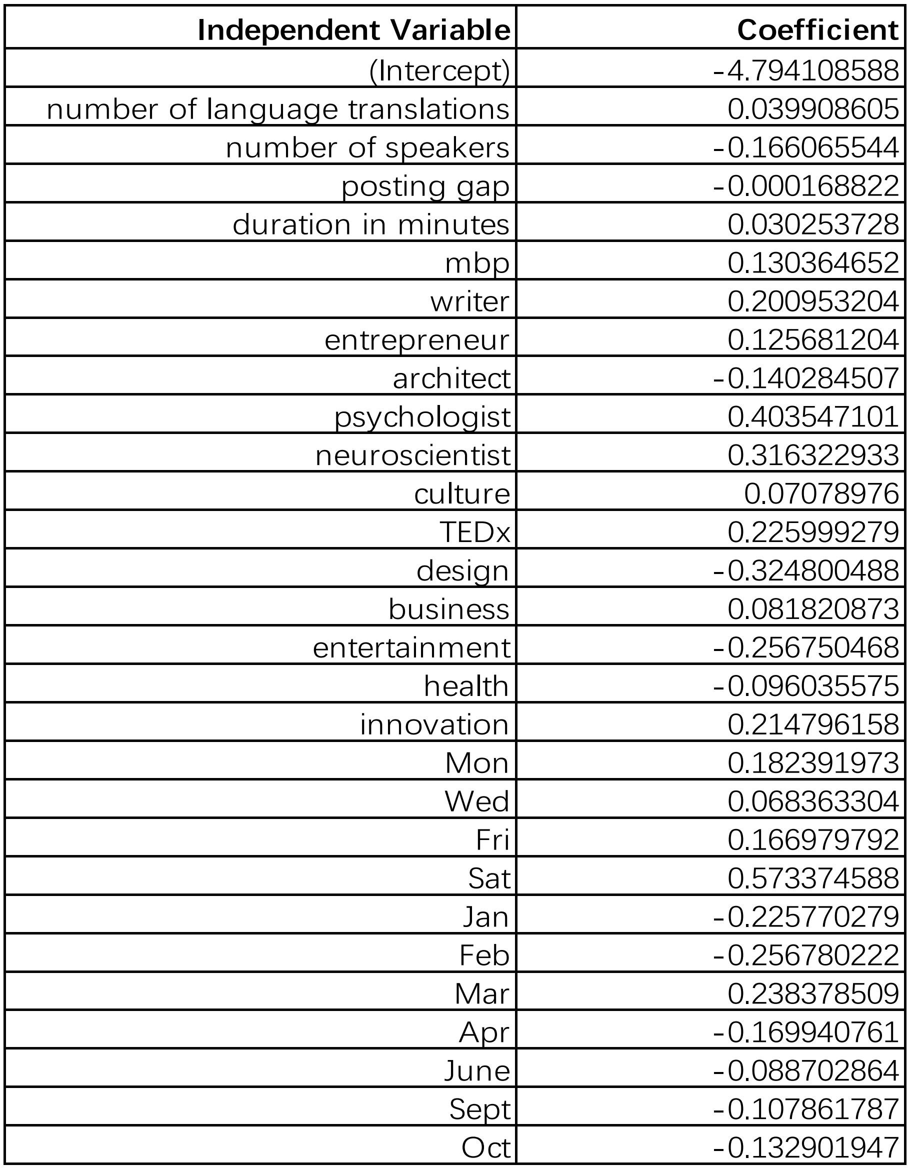
With respect to Best subset models:

Similar variables as OLS's statistically significant ones are reserved for both dependent variables and their coefficients are shown in table 7 and table 8.



Independent Variable	Coefficient
(Intercept)	2.953674866
number of language translations	0.059301715
posting gap	-0.000110011
duration in minutes	0.035909436
mbp	0.186519059
writer	0.15586642
entrepreneur	-0.151269972
architect	-0.182182924
psychologist	0.385039442
photographer	0.174070471
global_issue	-0.32771791
culture	0.127144044
design	-0.06584866
business	0.106437096
health	-0.08079306
innovation	0.125509076
Fri	0.12013947
Sat	0.191874874
Jan	-0.135876055
Mar	0.183003322

Table 7. Best subset selected variables and their coefficients, Y = log(daily views)



Independent Variable	Coefficient
(Intercept)	-4.794108588
number of language translations	0.039908605
number of speakers	-0.166065544
posting gap	-0.000168822
duration in minutes	0.030253728
mbp	0.130364652
writer	0.200953204
entrepreneur	0.125681204
architect	-0.140284507
psychologist	0.403547101
neuroscientist	0.316322933
culture	0.07078976
TEDx	0.225999279
design	-0.324800488
business	0.081820873
entertainment	-0.256750468
health	-0.096035575
innovation	0.214796158
Mon	0.182391973
Wed	0.068363304
Fri	0.166979792
Sat	0.573374588
Jan	-0.225770279
Feb	-0.256780222
Mar	0.238378509
Apr	-0.169940761
June	-0.088702864
Sept	-0.107861787
Oct	-0.132901947

Table 8. Best subset selected variables and their coefficients, Y = log(daily comments)

Given Ridge and LASSO models:

Their introduction of λ makes it hard to interpret independent variables' effect magnitude in their practical meanings. However, LASSO does feature selection by assigning coefficient = 0 to the variables it regards as useless. Therefore, variables with non-zero coefficients can be deemed as of importance for our prediction.

For predicting log(daily views), LASSO assigned non-zero coefficients to 12 variables, and they are number of language translations (+), posting gap (-), duration in minutes (+), mbp (+), writer (+), psychologist (+), global_issue (-), culture (+), design (-), Fri (+), Jan (-) and March (+), where (+)/ (-) stands for positive/negative effect on log(daily views).

For predicting log(daily comments), LASSO assigned non-zero coefficients to 11 variables, and they are number of language translations (+), posting gap (-), duration in minutes (+), mbp (+), psychologist (+), culture (+), TEDx (+), design (-), entertainment (-), Sat (+), and March (+), where (+)/ (-) stands for positive/negative effect on log(daily comments).

Random Forest

Concerning random forest models:

Even though random forest models do not perform well in the sense of test MSE, and they are not good at interpretation, these models are still good references to learn parameter importance because we can generate variable importance plots from them directly as shown in figure 11 and figure 12.

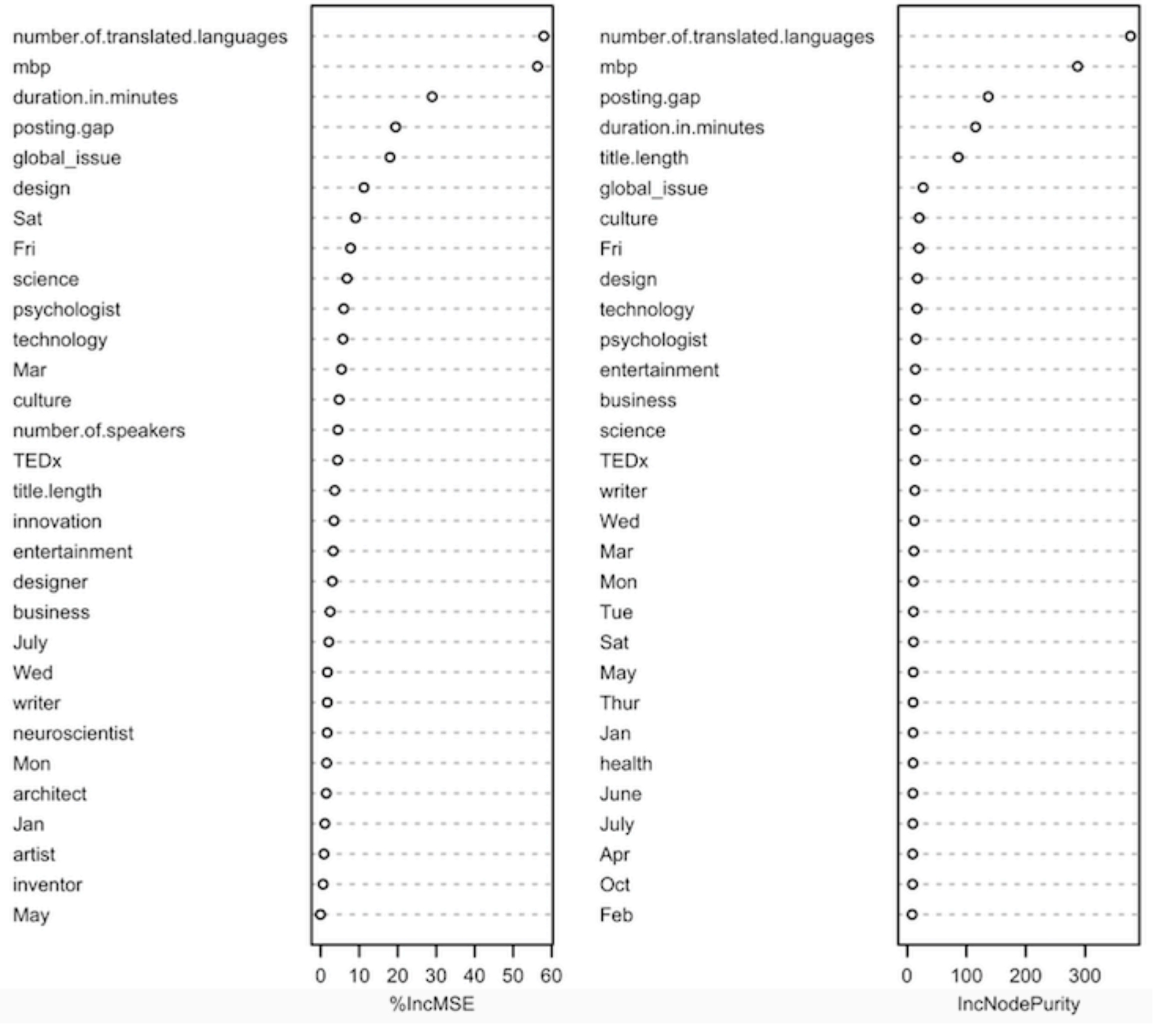


Figure 11. Variance importance plot, random forest, m = 5, Y = log(daily views)

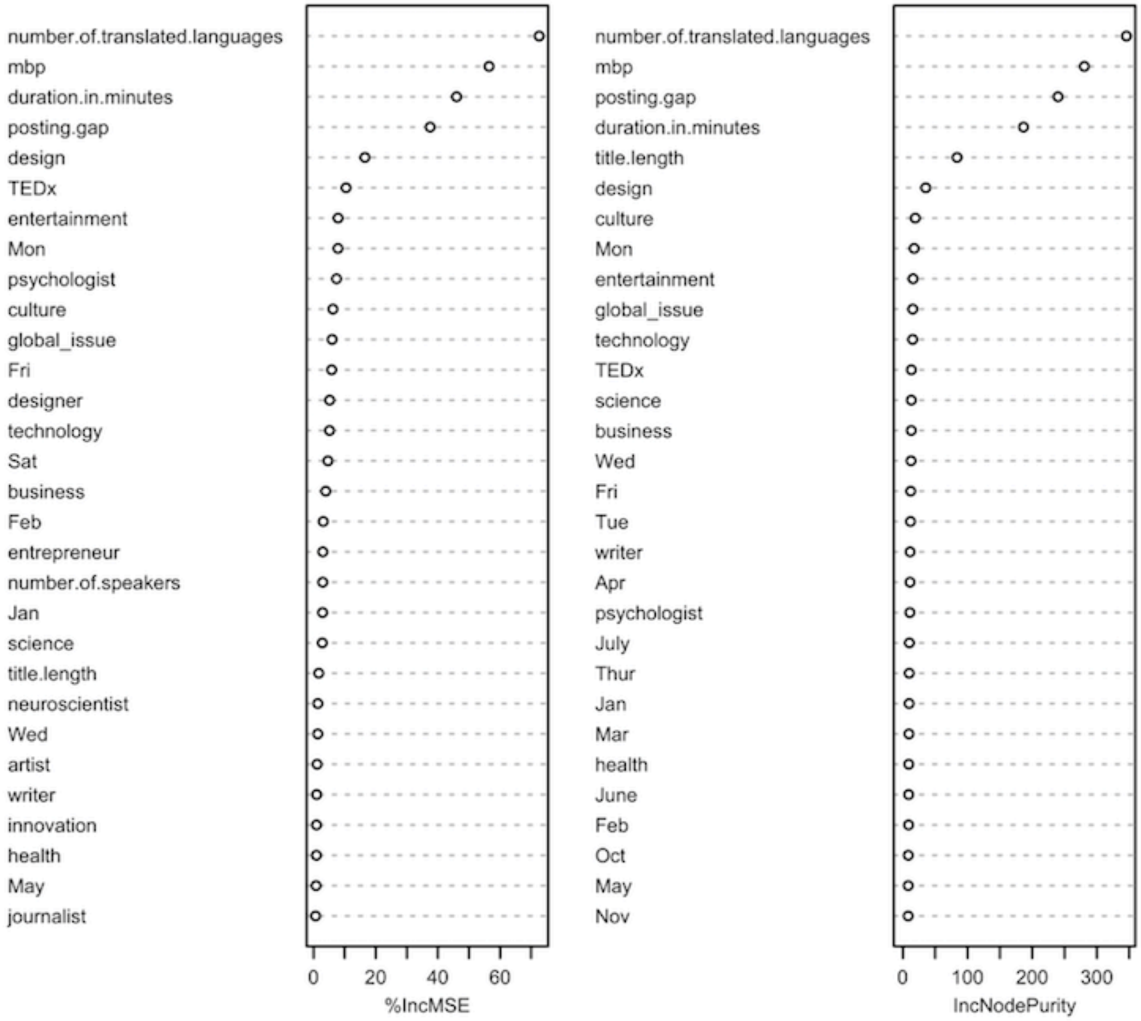


Figure 12. Variance importance plot, random forest, m = 11, Y = log(daily comments)

To sum up, for both dependent variables, the important predictors are very similar, and the overlapped ones are the number of language translations, mbp, duration in minutes, and posting gap. Given the main speaker's occupation, writer and psychologist have the most noticeably positive effects on a TED talk's popularity. As for the themed tags, "culture" stands out for its significant positive influence, while "design" is found to hurt a talk's popularity. Besides, Friday, Saturday, and March are good timings for a TED talk being published as it is highly likely to receive a plus on its popularity.

Discussion

This section will discuss our thinking from two aspects: what machine learning prediction can tell us, and what machine learning prediction cannot tell us.

What Machine Learning Prediction Can Tell us

What machine learning prediction can tell us is how to "detect patterns," "predict future data," and "perform decision making" (Murphy, 2012) based on the prediction model's performance and learned parameter importance.

The most evident pattern we have detected is either daily views or daily comments can function well as the indicator for a TED talk's popularity, and the important predictors for them are nearly the same regardless of their different numerical scales. This finding is also consistent with the previous work (e.g. Ray, Yadav & Garg, 2018) which states a TED talk's views and comments are highly related. Therefore, we don't recommend predicting a TED talk's views via comments or vice versa like some work (e.g. Eldor (2018)'s) did as it would be meaningless like using a feature to predict itself.

Outperforming models can help us "predict future data" (Murphy, 2012). For instance, once a new TED talk is uploaded online, we could apply the coefficients from OLS to its 43 independent variables to calculate its daily views or daily comments in the future since all the predictors we use can be known before or as soon as the talk is published. Relying on the OLS's test MSE, we would also expect our prediction deviating from the true values around 140%, which is fairly acceptable given the unit is so small as a talks' daily views or comments.

Plus, we can make decisions based on learned parameter importance. For example, the OLS model predicting log(daily views) tells us that if we increase a talk's number of language translations, duration in minutes, or accelerate the U.S. average Internet connection speed when the talk is published, we could expect more daily views gained. The OLS model also tells us that if we let a writer/ psychologist be a talk's main speaker, or theme the talk on culture/ business instead of design or global issue, or publish it on a Friday, Saturday or in March, we could also give a plus on the talk's popularity.

What Machine Learning Prediction Cannot Tell us

What machine learning prediction cannot tell us is strategically speaking, what actions should TED take in the long term beyond these models and predictors?

Taking the predictor, duration in minutes, as an example, the machine learning prediction suggests we extend every talk's duration to gain a higher level of popularity. However, this won't make sense in practice. If we only focus on extending a talk's duration while ignoring its quality, it might generate more attraction in the short run, however, it will harm TED's reputation in the long term. Plus, even if we could maintain each talk's quality as high as theirs now, duration extension should still hold within a certain degree as we all know a too-long video could scare people away. The positive effect of duration in minutes on current TED talks could be a reflection that TED has experience in its domain, spreading ideas of worth by balancing talks' duration and attraction. Such domain knowledge cannot be produced by machine learning prediction while it is of importance for TED to map out their strategy.

What's more, machine learning prediction also tells us that if we invite more writers/ psychologists to be TED talks' main speakers, or theme the talks only on the topics of culture/ business and avoid topics such as design/ global issue, we could leverage TED talks' popularity. Nevertheless, such action goes against the mission TED stands for. We assume that TED would like to encourage more voices to be heard instead of pursuing a higher level of popularity by sacrificing its diversity. Therefore, our suggestion is TED talks' speakers with different occupations or themed topics could build the communication bridge among each other and learn the successful experience from writers/ psychologists or culture/ business topics to improve every talk's attraction as a whole community.

Conclusion

In a nutshell, a TED talk’s popularity can be predicted by its inherent features via machine learning techniques. We found that the OLS, Ridge, and LASSO models performed well in the prediction, and we also learned several powerful predictors such as a talk’s number of language translations, average Internet connection speed, duration, main speaker’s occupation, as well as its being published timing. With the support of our experimented models and their corresponding predictors, we detected that a TED talk’s views or comments are highly related and can either function well as the indicator of “popularity.” Furthermore, we also looked into how to predict future data and make sound decisions based on our trained models. In the end, we discussed our suggestion on how to improve TED talks’ popularity beyond the perspective of machine learning and emphasized on the importance of domain knowledge in mapping out TED’s long-term strategies.

Note

[1] https://creativecommons.org/licenses/by-nc-nd/3.0/

[2] https://en.wikipedia.org/w/index.php?title=TED_(conference)&oldid=955207602

[3] https://www.ted.com/talks

[4] https://blog.ted.com/ted-reaches-its-billionth-video-view/

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[19] https://stats.idre.ucla.edu/other/mult-pkg/faq/general/faqhow-do-i-interpret-a-regression-model-when-some-variables-are-log-transformed/

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