Analysing the effect of content of speech on viewership results

Text Mining Course Project

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Abstract

With the full expansion of the Internet worldwide and the appearence of massive social networks and social media, the amount of informational content quickly available to any human user has increased exponentially in the recent years. Because of that, in order to do a good selection of consumption of such content, users must dedicate their scarce time resources in a disciplined manner in order to maximise their utility given obvious constraints. In this project, we intend to analyse if the composition of the content is relevant for consumption, using content of the multimedia website TED Talks, by applying a few text mining techniques to extract information on what topics attract more or less viewership online. Results seem to point towards the relevance of the topic, emphasising this effect over the effect of less influential characteristics, such as duration or sentiment, among others.

Keywords: Speech popularity, Latent Dirichlet Allocation, TED Talks.

Framework

During the 21st century, with the expansion of the Internet, the amount of media content available to an average consumer has increased exponentially. Online media offer a varied, plural and sizeable range of content compared to traditional sources of general information. To that, we should pair the fact that current users of such content have increased their education and expanded the limits of their interests. Nowadays, it is not strange to see considerable social interest in content related to subjects on which the generic user may have superficial knowledge, e.g. interest in mass divulgation of science or technology. At the same time, the communication tools and skills of experts on these fields have evolved enough to make them attractive to the general public. It is not rare to see semi-technical

content in magazines, newspapers and online media of generalist nature, which may have not been equally common some years ago.

Simultaneously, the bloom of content has forced consumers to be more selective, since the time available for consumption has not increased at the path of the available content. With that, the importance of quality over quantity has become more relevant, and thus with a wide range of choice, the composition of the content stands out as an important factor of decision. More options imply being more restrictive in the consumption choice, and the topic of this content may very well have an effect on this selection.

In this project, we intend to investigate towards this direction, by examining what features of the content of a speech are boosting the amount of attention that consumers pay to it. As a proxy to do so, we analyse the content of the speeches published online at the popular multimedia website TED Talks. We will measure how the composition of the talks is explaining the number of visits that they are receiving online. Since the website is free and open to anyone, and it contains content related to any sort of topic, it is of especial interest to understand wether the topic of the content can have an effect on the final consumption aggregates. This may be able to tell us how sensitive the same consumer is to content of very different nature.

This is a fundamental question in the media industry, since the atomization of content among all suppliers is forcing producers to put a strong emphasis on what content is actually published. Understanding which topics and what characteristics of it will partially determine the attractiveness of publications is an issue relevant from a sociologic, economic and entrepreneurial point of view, with lasting consequences in the media or education business, among many other marketing-based sectors.

Data

The data used for this project consist of the transcripts of all talks posted on the popular website of TED Talks, at `http://www.ted.com`. The information retrieved includes the transcripts themselves, as well as some additional metadata on each talk. We summarise the main features extracted in the following list:

- Transcript of the talk, i.e. raw text of all statements said during the speech.
- Title of the talk.
- Full name of the speaker performing.
- Date in which the talk was posted online, in monthly format.
- Date in which the talk was filmed, in monthly format.
- Number of visualisations of the talk online at the moment of retrieval.
- Duration of the talk, in seconds.
- Set of qualitative tags assigned to the talk, which are adjectives that are suitable in each case, e.g. "inspiring", "ingenious", "beautiful", among others. These are voted by users from a set of adjectives made available by the website. Then, the website tags the speeches with the two highest voted options.

- Set of topics assigned to the talk, e.g. "communications", "future", "parenting", among others. This set of topics is more diverse and is assigned by the website, without user interaction.

All data collected date as of June 1, 2016. The scrapper was launched at 9.00 AM GMT and the information retrieval lasted for about two hours. It was performed backward in time, which means that older talks were retrieved later, thus there might be a small difference to what would be considered a snapshot of the website. No other source was used as input for the project.

The data retrieved comprise a period of ten years of posted material, between June 2006 and May 2016. Nevertheless, the content posted may have been filmed prior to the uploading date, which means that a few talks were actually filmed in the early 2000s, or even before.

In the end, a total of 2,130 talks were successfully collected from the website. A small additional percentage of talks —between 1% and 2%— was not available in transcript mode or had no metadata available, and thus was not regarded. These are mainly concentrated within older talks. A handful of them were also disregarded because they were purely performance shows, such as music or dancing, which had no textual content to be analysed.

Methodology

We will try to build a model that explains how the number of visualisations online of the speech is affected by the textual content of the talk. For that, we will exploit dictionary methods on the speeches, as well as a Latent Dirichlet Allocation (LDA) model that will provide probabilities of the talks belonging to a number of topics —see [1]—.

The entire material and the code for this project can be found in the following Github repository:

- `https://github.com/mtorrens/tm/tree/master/project`

We divide this section in two parts: first, the text mining and analysis and, second, the viewership statistical model.

Text analysis

As a first step, cleaning the raw text requires some effort and discussion. The steps taken can be summarised as follows:

1. Tokenisation: this implies eiliminating all punctuation, rebuilding the set of contractions and stripping the text down to the set of words involved. This way, the entire text of the speech is reduced to a bag of lower-cased words without diacritics or unrecognisable characters.

2. Cleaning the set of tokens: only those tokens that are not numbers or years are kept, i.e. a string such as "1950" is suppressed. In this context, it is helpful as this sort of tokens are not useful in topic detection, given that the plurality of topics is wide enough.
3. Removing stopwords: all tokens that include little meaning or that are too abundant are kept out of the model. These include pronouns, frequent connectors, modal verbs, articles and highly-frequent verbs, e.g. "this", "which", "me", "not", "thing", "go", among many others. The full list of stopwords used for this corpus can be found in the aforementioned Github repository.
4. Removing rare words: words that once stemmed appear only once in the whole corpus are considered rare, and they are removed from the documents. In our varied set of documents, this is a relevant fraction of the unique words observed, although they are by definition a small fraction of the actual words used. This step has been quite helpful in the dimensionality reduction of the document term matrix, with its subsequent computations.
5. Stemming: to stem the words, the Porter stemming algorithm has been employed.

After all these operations, the final set of tokens is reduced to 21,944 unique terms.

Once the set of tokens is established, the document term matrix (DTM) is built and we make use of dictionary methods to score all documents. For completeness, both the DTM and the TF-IDF scores were computed. The dictionary used for scoring the documents is the Harvard IV set. These scores will be used afterwards in the viewership model.

For the sentiment score, the AFINN-111 set of rated words has been employed. Both the cumulative and the relative sentiment scores have been computed for all documents, which will be another ingredient for the viewership model.

The main text mining technique used for the model, however, will be the exploration of topics of the talks, through an LDA on the documents. The Gibbs sampler is run for 3,000 iterations over the 2,130 documents and a size of the voabularyof 21,944 unique terms. The total number of words is of 1,729,588 words. After trying a set of different number of topics, ranging from 5 to 20, the final choice has been $K = 12$. The reason for this value is the clarity of the resulting top words used for each topic, which appear to naturally cluster in a clear set of topics, without merging dissimilar ones. Also, the visualisation of the most-likely topic allocation on the titles of the talks seem appropriate in the vast majority of manually checked cases. The choice of number of iterations run responds to the long stabilisation of the log-likelihood after each iteration of the Gibbs sampler is run.

The twelve resulting topics have as most used words the following list:

```
Topic 0: life, year, women, live, stori, day, time, peopl, school, love
Topic 1: design, citi, build, work, creat, space, project, art, place, kind
Topic 2: cell, diseas, patient, cancer, drug, health, year, actual, gene, doctor
Topic 3: energi, year, earth, univers, planet, light, space, time, life, actual
Topic 4: water, year, anim, food, ocean, speci, fish, plant, world, live
Topic 5: peopl, war, countri, state, govern, polit, world, power, nation, american
```

```
Topic 6: peopl, world, year, countri, percent, need, dollar, problem, work, money
Topic 7: know, laughter, think, peopl, littl, time, work, come, actual, start
Topic 8: brain, robot, bodi, move, human, control, time, show, video, differ
Topic 9: think, peopl, differ, know, human, mean, question, time, kind, much
Topic 10: music, play, laughter, applaus, sound, game, word, languag, hear, thank
Topic 11: comput, data, technolog, actual, inform, peopl, internet, world, start, year
```

From now on, we will name the topics as follows:

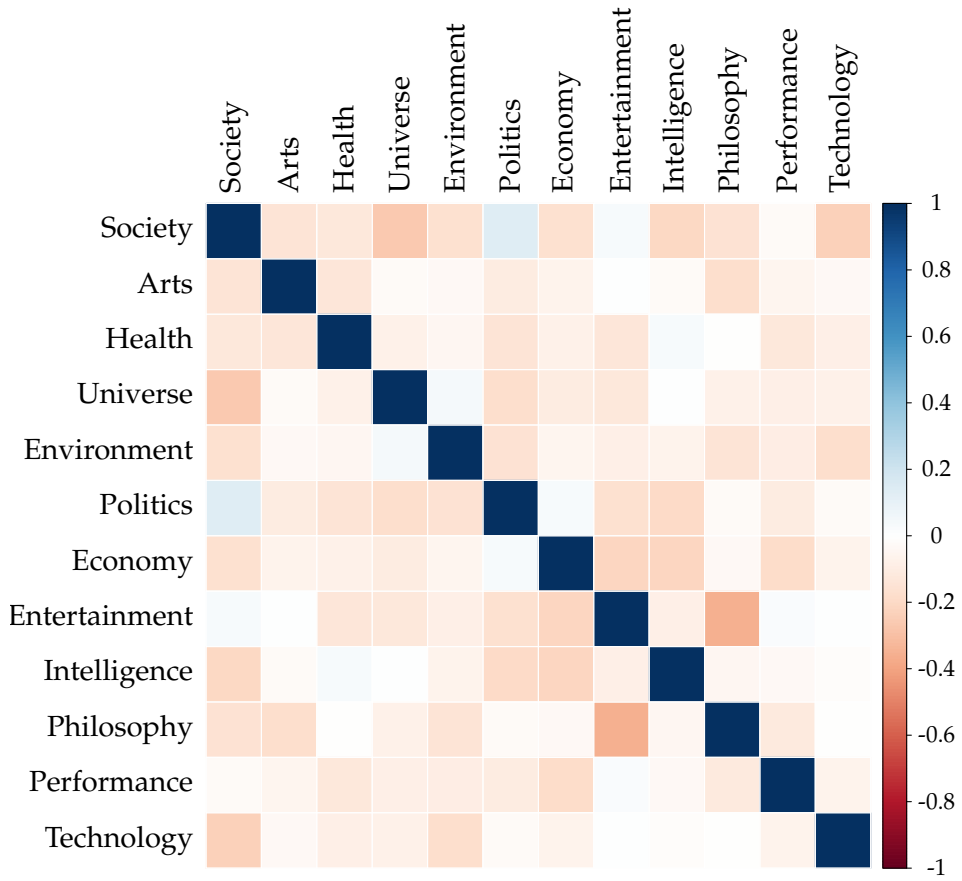
- Topic 0 (15.3%): Society
- Topic 1 (5.7%): Arts
- Topic 2 (5.8%): Health
- Topic 3 (5.4%): Universe
- Topic 4 (7.3%): Environment
- Topic 5 (5.3%): Politics
- Topic 6 (9.6%): Economy
- Topic 7 (15.9%): Entertainment
- Topic 8 (5.1%): Intelligence
- Topic 9 (16.7%): Philosophy
- Topic 10 (3.4%): Performance
- Topic 11 (4.7%): Technology

In parenthesis we have shown in what percentage of the documents, the topic is assigned with highest probability. We report what is the topic with maximum likelihood for the first ten documents, together with the title of the talk:

```
A smarter, more precise way to think about public health (top topic: 2)
Why I bring theater to the military (top topic: 7)
How barbershops can keep men healthy (top topic: 2)
Drawings that show the beauty and fragility of Earth (top topic: 4)
Your words may predict your future mental health (top topic: 9)
The beauty of being a misfit (top topic: 0)
How free is our freedom of the press? (top topic: 5)
The laws that sex workers really want (top topic: 5)
Our lonely society makes it hard to come home from war (top topic: 5)
Good news in the fight against pancreatic cancer (top topic: 2)
```

We also report what is the correlation matrix between the resulting probabilities:

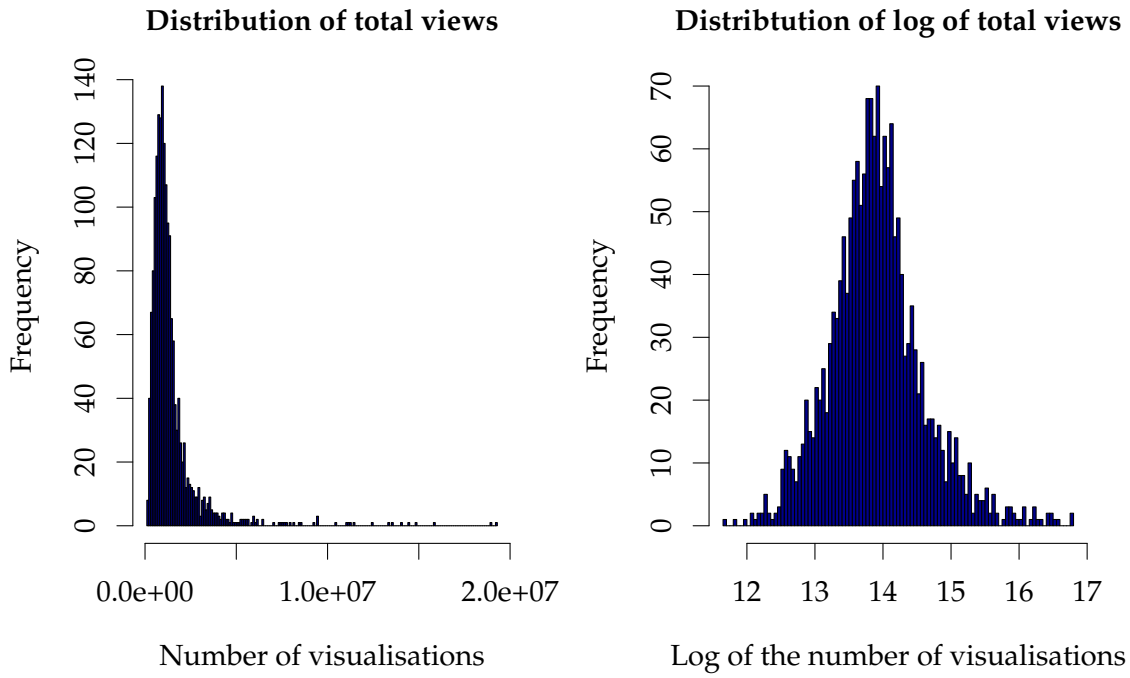
Correlation plot of the probabilities of LDA Topics (document level)



We can observe that most topic probabilities are moderately negatively correlated with the probabilities of being other topics, which is logical given that the probability space is represented by a simplex of degree $K - 1$. Therefore, two topics with stronger negative correlation suggest that their dissimilarity is also strong.

Viewership model

To build the model to explain the number of visits a certain talk has received on the website, we will use several features of the text. The explained variable will be the natural logarithm of the number of visualisations. Given that the original variable is a count with high skewness, it seems appropriate to apply a logarithm to recover a more symmetric well-behaved empirical distribution. We can observe the shape of the observations prior and after the transformation:



After this, we will choose the dimensionality of the design matrix as follows. First of all, we make a selection of the observations that will be part of the model. We discard a set of them for different reasons:

- Documents that are too recent or too old. Those talks prior to January 2008 are discarded because we want to restrict the model to the period where the website had already sizeable market penetration. We also discard those documents from the month of May 2015, due to the fact that their visualisation counts were still immature at the date of retrieval. These filters combined suppress a total of 204 talks.
- Documents with extreme values on the number of visualisations. These are three outliers with an exceptionally high amount of views.
- Talks that last for less than three minutes, or over 20 minutes. The content of talks that are too short may have small significance on the number of views, as well as talks that are too long, which can affect the number of views negatively. Together, we disregard 167 talks with this filter.
- Talks that contain less than 100 words, as their textual content may have no effect on the number of visualisations, and which probably contain other determinant activities besides the speech. We eliminate 7 observations with this filter.

Once we have applied this set of filters, the total number of documents that remain to be part of the model is 1,749.

With respect to the predictors, the model works with features exclusively extracted from the text analysis, with three exceptions that act as control variables. These are, first, the natural logarithm of the amount of days during which the talk has been posted online, second, the natural logarithm of the duration of the the video in seconds and, third, a dummy variable indicating if the speaker is a recurrent speaker (1) or a new one (0). In addition to these three, the rest of variables included in the model are:

- The natural logarithm of the DTM score.
- The natural logarithm of the TF-IDF score.
- The natural logarithm of the number of words that the speech consists of. A variation was introduced using the number of unique words, which yielded identical results, as the correlation between the two is virtually 1. The case is the same with the number of charachters.
- The cumulative sentiment score computed with the AFINN-111 sentiment dictionary.
- The topic probabilities obtained through the LDA analysis. Given that row-wise they sum to one, it is necessary to hold one of the features out. The reference topic of choice is "universe".
- Dummy variables that express if the document has been tagged as each of the qualitative tags explained in the data section. The set of tags is of length nine, which implies eight dummy variables, as row-wise these variables sum to two —each talk is tagged with the top-two tags—. Thus, the reference category will be the tag "informative".
- Dummy variables that express if the document has been tagged as each of the topics explained in the data section. Given that this set is large, we consider only those topics assigned to at least 5% of the talks, also to make the estimations more consistent. The table of results includes the model with significant topics, since many of the topics are far from significance even if present in a non-negligible fraction of talks.

With these, the full design matrix for the model consists of 1,749 speeches with 37 explanatory features each.

Results

We build two OLS models. The first one is a preliminary model that regresses the outcome of the LDA probabilities on the logarithm of the number of views. The second one includes the control variables, as well as the rest of text features aforementioned.

The results can be examnined in the following Table 1:

Table 1: OLS Regression results

	Dependent variable:	
	Logarithm of the number of visualisations	
	(1)	(2)
Log of time posted (days)		-0.208^{***} (0.019)
Log duration of talk (seconds)		0.124 (0.080)
Recurrent speaker		0.106^{***} (0.035)
Log of DTM score		-0.005 (0.020)
Log of TF-IDF score		0.016 (0.022)
Log of number of words		-0.105 (0.070)
Cumulative sentiment score		-0.001^{*} (0.0004)
LDA topic prob.: Society	0.510^{***} (0.151)	0.188 (0.168)
LDA topic prob.: Arts	-0.716^{***} (0.200)	-0.524^{**} (0.214)
LDA topic prob.: Health	-0.546^{***} (0.185)	-0.607^{***} (0.178)
LDA topic prob.: Environment	-0.656^{***} (0.187)	-0.699^{***} (0.178)
LDA topic prob.: Politics	-1.043^{***} (0.192)	-0.807^{***} (0.225)
LDA topic prob.: Economy	-0.349^{**} (0.165)	-0.318^{*} (0.185)
LDA topic prob.: Entertainment	0.672^{***} (0.172)	0.450^{**} (0.182)
LDA topic prob.: Intelligence	0.348^{*} (0.191)	0.107 (0.186)
LDA topic prob.: Philosophy	0.609^{***} (0.169)	0.405^{**} (0.172)
LDA topic prob.: Performance	0.178 (0.215)	-0.031 (0.260)
LDA topic prob.: Technology	-0.159 (0.198)	-0.176 (0.198)
Tagged as: fascinating		0.150^{***} (0.042)
Tagged as: funny		0.253^{***} (0.058)
Tagged as: inspiring		0.113^{***} (0.038)
Tagged as: jaw-dropping		0.594^{***} (0.078)
Tagged as topic: AI		-0.088^{**} (0.043)
Tagged as topic: art		-0.175^{***} (0.047)
Tagged as topic: brain		0.264^{***} (0.074)
Tagged as topic: business		0.120^{**} (0.047)
Tagged as topic: change		-0.205^{***} (0.060)
Tagged as topic: conference		0.113^{***} (0.035)
Tagged as topic: culture		0.194^{***} (0.039)
Tagged as topic: design		-0.112^{**} (0.046)
Tagged as topic: global issues		-0.127^{***} (0.044)
Tagged as topic: music		-0.158^{*} (0.093)
Tagged as topic: politics		-0.145^{**} (0.063)
Tagged as topic: science		-0.090^{**} (0.044)
Tagged as topic: technology		-0.119^{***} (0.040)
Tagged as topic: war		-0.137^{**} (0.070)
Constant	13.795^{***} (0.124)	15.192^{***} (0.327)
Observations	1,749	1,749
R^2	0.112	0.263
Adjusted R^2	0.106	0.248
Residual Std. Error	0.653 (df = 1737)	0.599 (df = 1712)
F Statistic	19.850^{***} (df = 11; 1737)	16.995^{***} (df = 36; 1712)
Note:		$^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$

As we can see, the general explanatory power of the models is satisfactory. LDA probabilities alone already achieve an adjusted $R^2 = 0.106$, which is boosted up to $R^2 = 0.248$ when all the features are taken into account.

The first model is an initial approximation to spot if the topic allocation is significant, regardless of the rest of the features. Some of the additional features will encode the topic allocation partly, via the tags, and thus it is relevant to see the LDA result cleanly. We should bear in mind that some dummy variables explicitely include the name of the topic we have assigned. Then, in the basic model, most of the topics show significance at some tight level, with the exception of performance and technology. Arts, health, environment, politics and economy raise significantly less interest than the topic of reference, Universe. Contrarily, entertainment and philosophy exhibit higher interest, and with 10% significance we could also add intelligence to the group.

In the second model, the full model, all signs for LDA probabilities among significant predictors are maintained, however significance of topic economy drops to the 5%-10% level, and society and intelligence lose their significance at any level. In this model, the control variables make their way in, and we observe that the duration of the post affects negatively the number of views. This can be caused by the fact that the increasing popularity of TED affects positively more recently posted talks. Also, recurrent speakers seem to attract more attention, which is logical —although the causality is not clear at all—. The duration of the talk is not significant, which leads us to believe that the length of the speech has less effect on viewership than one could especulate *a priori*. This is not masked by the coefficient of number of words, as despite being correlated, excluding either of them from the model does not affect their separate lack of significance.

With respect to text features, the results show no significance of either the DTM or the TF-IDF scores. Their rank was also used as variation without better results. This is somewhat expected given the plurality of topics and the dissimilarity of the set of speeches. The sentiment score, on the other hand, shows significance only at the 10% level and indicates, if we relied on its sign, that negativity on the sentiment can benefit the number of views.

As for the qualitative tags, we observe that those talks voted as "fascinating", "funny", "inspiring" and "jaw-dropping" have more visits than the rest. The other tags showed no significance in the intermediate models and were dropped in the final model. These results seem plausible, as stronger adjectives as the ones mentioned encourage visualisation in comparison to softer –non-significant— adjectives such as "beautiful", "courageous" or "persuasive".

In the case of topics, we observed strong significance for some of them. The set of topic tags that exhibit a positive effect on the number of views are "brain", "culture", "business" and "conference", whereas "change", "art", "politics", "war", "global issues", "technology", "design", "science" and "AI" show a negative effect, both presented in order of decreasing magnitude. "Music" also shows a negative effect, but only at 10% level of significance. Although individually these topics appear to be significant, there is no clear pattern to distinct on a higher topic-level what topics help boosting visualisation counts.

Conclusions

The determinants affecting the popularity of online content are varied and complex. In this project, we have tried to simplify this popularity by pure raw text characteristics of the composition of such content using the set of available TED talks. After performing the aforementioned text mining techniques, we have built an explanatory model to analyse to what extend these textual features can explain the variations in number of online views of each talk. Our model has good explanatory power, taking into account the nature and amount of information we can gather from the website.

Results seem to suggest that the topic of the content has strongly significant importance on the view counts, as well as the user-tagged impressions that the content has on viewers. We have spotted a set of topics that draw relatively more attention than others, both using non-supervised methods and user-tagged topics. This outcome, however, does not clearly separate sets of topics that one could hierarchically cluster, that is, meta-topics that can draw more or less attention. A possible explanation for that is that the wide variety of content available allows for different user profiles to consume content separately different meta-topics. On the other hand, other predictors that one might consider relevant, such as length or sentiment of the content, do not show strong significance on the outcome results, and so do not seem to be related to popularity after all.

All in all, this is simple but insightful information on understanding how the text features of content can explain its popularity, and an example on how many media and content-based businesses can easily extract information from their text data in order to answer basic but fundamental questions of their industry. One must be careful, however, on applying the Lucas critique to these results. The fact that we may understand to some extent what drives popularity does not mean that adapting our content will boost it. As soon as the suppliers adapt their behavior to meet such demand, the validity of these results may be invalidated and the dynamics of the current drivers of content popularity could be alter irreversibly. Therefore, even if the outcome can be insightful, the line of action is beyond the scopre these results and remains open question to this point.

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