Forecasting popularity of videos in YouTube

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Abstract—This paper proposes a new prediction process to explain and predict popularity evolution of YouTube videos. We exploit our recent study on the classification of YouTube videos in order to predict the evolution of videos’ view-count. This classification allows to identify important factors of the observed popularity dynamics. Our experimental results show that our prediction process is able to reduce the average prediction errors compared to a state-of-the-art baseline model. We also evaluate the impact of adding popularity criteria in our classification.

I. INTRODUCTION

Multimedia traffic over the Internet has boosted in the recent years and more media is watched and shared online. Some platforms such as YouTube have been established as a key international website for user generated content. This platform allows not only to share videos, but also to create interaction between users. YouTube has become the most attractive and popular media diffusion with a huge quantity of user generated content and none of its competitors have achieved the same success [1].

Predicting content popularity is a challenging task. Understanding and predicting the popularity is useful from a twofold perspective: on one hand, more popular content generates more traffic, so understanding popularity has a direct impact on caching and replication strategy that the provider should adopt; on the other hand, popularity has a direct economic impact. For example, in online marketing, popularity and view-count are often directly related to click-through rates of linked advertisements, which constitute the basis of YouTube’s business model. Moreover popularity prediction can be useful for allocating resources according to the popularity of contents, in a proactive way. The effect of content popularity dynamics on cache performance becomes an important factor when the time scale of cache dynamics becomes comparable to the popularity dynamics of contents. Since the storage capacity becomes more voluminous and cheaper, this assumption is often observed in many storage systems [2]. For instance, the Internet Service Providers (ISP) could exploit the popularity growth to develop more effective strategies on caching. A recent paper [2] has developed an efficient caching strategy under dynamic content popularity.

Recently, several researchers have analysed the popularity evolution of online media content [3]−[7], to develop models for early-stage prediction of future popularity [8]. A wide overview of content popularity prediction is described in [9]. These studies showed that the interest generated by an online content is heterogeneous and often unpredictable. But we found little effort towards predicting popularity evolution related to a mixture of endogenous and exogenous factors. There has been also interest in understanding what important factors lead videos to become popular. But few works studied the temporal aspects of the popularity dynamics using metrics such as view-count, ratings and number of comments [9], [10]. Understanding the most typical behaviour of popularity growth and identifying the factors responsible for this evolution can be exploited to predict the popularity trend of individual content.

This paper exploits our recent study in [11] on the behaviour of the view-count of YouTube videos. Through six mathematical biology-inspired models we showed that at least 90% of videos in YouTube are associated to one of the six mathematical models with a Mean Error Rate lower than 5%. Furthermore, these models cover 98% of videos with a Mean Error Rate lower than 10%. Our classification allows us to identify key properties of the observed popularity dynamics such as virality and the growth rate of number of users potentially interested in the video. We differentiate between models in which the population potentially interested in the content is nearly constant or fixed and those in which it grows in time (inspired by the modelling of immigration in branching processes). Virality is also an important factor which indicates if contaminated users (the viewers of a video) have a significant role in the propagation of the video through sharing or embedding links. These models can be seen as a simplified representation of some real-world dynamics and they intend to mimic essential features of the study while leaving out inessentials. In our previous study, we considered the view-count as the main metric of the popularity since there is a strong correlation between view-count and other metrics as number of comments, favourites and rating. Further, these metrics for measuring popularity of videos became more correlated among each other [12].

The prediction methods developed in this paper are based on the study performed by Szabo and Huberman [8] and Pinto et al. [13]. They found strong linear correlation between view-count received till the 7th day and view-count received 30 days after uploading video. Based on this observation, Szabo and Huberman developed a simple model (referred to as S-H model) that predicts the view-count of a video at a target date \( t_r \), based on the view-count at a reference time \( t_r < t_l \). Pinto et al. used multivariate linear regression (referred to as ML model) on the shape of the popularity from the first day till some reference time to improve prediction. These simple prediction approaches gave accurate results even though they do not exploit the various patterns that the time evolution of the view-count is likely to have. Thus we investigate here whether the automatic classification of YouTube video view-count, developed in our earlier work [11], leads to improve the prediction model by embedding the dynamic evolution of view-
count through a mathematical model among six mathematical models. We compare our prediction process against the S-H model and ML model. We find that our models improve the prediction accuracy over S-H model and ML model. Further this improvement increases when the target time increases. We also propose other prediction methods which try to exploit the popularity observed before reference time. To address this aim, we evaluate whether adding popularity criteria in our classification leads to more accurate popularity predictions. However, we found that these prediction methods reduce the prediction error but show some issues in terms of variance. This indicates that the mathematical models still more robust compared to all other filtering methods.

II. CLASSIFICATION MODELS

In this section we describe the classification models for identifying temporal patterns that are significant for characterising and predicting the popularity evolution of online media. In [11] we built an automatic way to classify the view-count curve into one of six mathematical models. We also introduce here an additional linear model. These mathematical models have been considered to describe the contagion phenomena and each model has its own set of assumptions about how users are infected by others. These models provide some answers about the behaviour of users in YouTube even if this behaviour remains notoriously difficult to quantify. They also provide many internal features allowing to cover a richer variety of user interactions, which can influence the popularity of content in YouTube. Here we describe briefly our classification of YouTube content by embedding two criteria: the target population size and virality.

Fixed target population and viral content This class contains models in which users participate actively in the dissemination of the content through YouTube or other social networks. These models have been used in technology forecasting and we test them since there is a strong similarity between a video posted in YouTube and a new product launched into the marketplace. To describe the viral content with fixed target population, we use the Logistic model (referred to as Sigmoid model) or the Gompertz model (see [11] for more details).

Fixed target population and non-viral content One model, named negative exponential model (referred to as exponential model), falls into this class. It allows us to cover some behaviour of dynamic popularity where participation of viewers has insignificant effect on the diffusion process and where contents no longer attract users after a while. Hence this dynamic can model the case where contents gain popularity through advertisement and other marketing tools; examples are when advertisement is broadcasted to a very large pool of users of a social network and people access the content at random thereafter.

Growing population The assumption that the population is fixed is often a reasonable approximation when the popularity of a content increases quickly and dies out within a short time. But for many cases, this assumption becomes inappropriate when the time before reaching the saturation region is longer. Here we consider the case of immigration process in which the potential population growth and the dynamic of view-count of a content are intricacy linked. To capture such dependence we consider different growth scenarios that model the viral case and non viral case. For non viral content we consider a linear model as well as a modified negative exponential model (modified exponential model). Both models describe the situation where users do not contribute to propagate the content to other users but the content benefits of the immigration process with linear growth. This scenario is often observed in many categories of content such as news and music. For viral content, we consider the Gompertz model, as well as the Sigmoid model, by adding a linear component. These dynamics, called modified Gompertz model and modified Sigmoid model respectively, seem to be relevant according to some examples in the dataset.

III. DATASET

One strong aspect of this work is our YouTube database which provides valuable meta data about a huge number of videos (around one million). In the Youtube platform, a video is accompanied by a set of valuable data as title, upload time, view-count and related videos. The video web page also provides some statistics which are available if the content’s owner allows it. Since some data cannot be collected through the APIs, we used a tool named YOUStatAnalyzer [14] in order to collect all valuable data. The collected data was stored in a NoSQL data base (MongoDB). It contains some static information for each video such as YouTube id, title of the video, name of the author, duration and list of related videos. It also provides the evolution in time of some metrics (shares, subscribers, watch time and views) in a daily form and in a cumulative form. We focus the analysis on view-count as the main popularity metric of a video. From the database, we build a dataset of videos that have at least 100 days in the system. This set contains 34060 videos.

In Fig. [1a] we compute models distribution after classification over the whole dataset based on the observation of the dynamic popularity during the first week. To highlight the temporal transitions between dynamic models followed by videos, Fig. [1b] depicts the same distribution during 100 days after uploading videos. Models’ names with their labels are listed in Table I. Once the set was built, we randomly subdivided it into two separated sets such that both sets show the same characteristics: a training set with 22704 videos and a test set with 11356 videos. The training set is used to compute prediction models’ parameters while the test set is used to evaluate our prediction process.

| E : Exponential | G : Gompertz |
| L : Linear | ME : Modified Exponential |
| MG : Modified Gompertz | MS : Modified Sigmoid |
| S : Sigmoid |

IV. POPULARITY PREDICTION METHODS

In this section we propose a new method to predict popularity evolution of YouTube contents. The main goal is to estimate the dynamic of view-count of a video until a certain target date \( t_r \), knowing its dynamic of view-count till a reference time \( t_p \) with \( t_p < t_r \). Our approach can be applied to any prediction method using a training dataset. Fig. [2] describes an overview of the whole process of the prediction. The main idea relies on selecting a specific subset from the training dataset for each single video that we want to predict its future popularity.
Using \( n \) mathematical models, we build a partition \( M(t) = \{ M_1(t), M_2(t), ..., M_n(t) \} \) of the training set where \( M_l(t) \) is the subset that contains videos associated to the mathematical model \( l \) based on the dynamic of view-count till time \( t \) after uploading. Note that if \( t \) increases, the mathematical model assigned to a video may change depending on the size of the observed sequence.

**Filtering method based on Popularity** Our second intuitive filter is based on slices of popularity, referred to as popularity method. From the training set, we build a partition \( P(t) = \{ P_1(t), P_2(t), ..., P_K(t) \} \) where \( P_l(t) \) is the subset of videos with view-count at time \( t \) belonging to a region of popularity, i.e., \( v \in P_l(t) \) if \( N(v,t) \in [p_{i-1}, p_i] \) with \( p_0 = 0 < p_1 < p_2 < ... < p_K \).

**Coupling filters** For the third filtering method, we apply both filters: mathematical models and popularity. For that we use intersections between \( M_k(t) \) and \( P_l(t) \) as training subset that incorporate the mathematical model and the popularity region. We believe that coupling filters would benefit from each of both filters since enough data in each intersection are available.

Using knowledge of some patterns from the future: We have described three methods where filters are used to refine our prediction model. Here we assume that there are some additional exogenous information that can be used for classification task at the target time instead reference time. This knowledge could be derived from uploader characteristics (e.g uploader network, followers, audience of previous videos, etc).

**B. Evaluation metric**

We use the Relative Squared Error (RSE) to evaluate the performance of our prediction methods. The RSE for video \( v \) at target date \( t_r \), knowing its historic until reference date \( t_s \) is given by:

\[
RSE = \left( \frac{\hat{N}(v,t_r,t_s) - N(v,t_s)}{N(v,t_s)} \right)^2 = \left( \frac{\hat{N}(v,t_r,t_s)}{N(v,t_s)} - 1 \right)^2
\]

For a set of videos \( S \) the mean Relative Squared Error (mRSE) is defined as the arithmetic mean of RSE for all videos in \( S \):

\[
mRSE = \frac{1}{|S|} \sum_{v \in S} \left( \frac{\hat{N}(v,t_r,t_s)}{N(v,t_s)} - 1 \right)^2
\]

Note here that RSE is a relative error and tends to be more relevant than the absolute quadratic error due to large variability in popularity of contents.

**C. Prediction models**

In this paper we use two prediction models in our prediction process described in section II.

- **Szabo and Huberman (S-H) model** This model exploited the correlation between early and late story popularity to make the prediction. They provide the constant scaling model (referred as linear model) to predict future popularity:

\[
\hat{N}(v,t_r,t_s) = \alpha(t_r,t_s)N(v,t_s)
\]

The value \( \alpha \) is computed through the training dataset of videos for which the view-count is known at every stage from the first
day to any target date \( t_t \). The method used to calculate \( \alpha \) aims at minimising mRSE for given dates \( t_r \) and \( t_t \).

**Multivariate Linear (ML) model** This model is an extension of S-H model since the ML model uses as input the view-count of a video up to day \( t_r \) and assigns different weights to each monitored day. This approach hopes to benefit from the historical information given by early popularity behaviour.

### V. EXPERIMENTAL RESULTS

As described in section [II] we run our prediction experiments using a training set of 22704 videos and a test set containing 11356 videos. For all experimental results, we set reference time \( t_r = 7 \) days and the target time \( t_t \) is varying from the 8th day to the 70th day after uploading video. The whole daily information (view-count, class of mathematical model and class of popularity) are known from upload up to the 10th day (resp. the 7th day) for videos in training set (resp. in test set). We compute, for each video from the test set and for each value of \( t_t \), the predictions obtained by the various methods presented in section [IV]. Note that the S-H model derived from [8] is used as a reference. Since the ML model gives best performance ([13]), it sets our baseline. However, our prediction process will use the ML model as prediction model trained on filtered training subsets. Finally, the mRSE and variance are calculated over all videos for each value of \( t_t \). Concerning the popularity filter method, we define \( K = 7 \) classes of popularity. Each class corresponds to a range of popularity with \( p_0 = 0 \), \( p_i = 10^i \) for \( i = 1..6 \) and \( p_7 = \infty \). When knowledge about the future is used, the classification tasks are processed using information until the 10th day after uploading video. Though, the prediction model is still applied using historic up to the 7th day.

An overview of the results are presented in Fig. [3] Prediction errors (mRSE) as well as variance in function of \( t_t \) are compared between the different methods for various experimental settings. In Table [II] we focus on some values of the target date. Here are reported the mRSE results along with corresponding 95% confidence intervals for the whole test set (whether future information is used or not) as well as for popular videos with views between \( 10^5 \) and \( 10^6 \) after one week from upload. In each case, results for the most accurate method are shown in bold. In Fig. [4] the relative gain compared to the ML baseline in terms of mRSE are given as a function of the target date \( t_t \) for each method over all the test set. Blue curves are for the mathematical models filter, green ones are for the popularity filter and red curves are for the coupled filters method. Dashed lines depict methods where future information are used whereas solid lines give results without using these information.

For results over all the test set, we observe In Fig. [5] that the filters by model as well as by popularity reduce the mRSE in a similar way (1% less than the ML baseline for
Fig. 4. Relative gains compared to the ML baseline for different methods, as functions of target time $t_t$.

$t_t = 30$ days, which represents a relative gain of 6.5%). This reduction gets more important for longer term prediction with a maximum improvement of around 7.5% for the models filter when $t_t$ varies from 10 to 20 days after uploading. When coupling both filters we reduce the mRSE for $t_t \geq 10$ days (from 2% to 3% lesser than ML for $t_t \geq 30$ days). This method improves the ML baseline by 10%–15% when $t_t$ varies from 10 to 20 days after uploading. From Fig. 3b we note that the variance is smaller for the models filter than for the ML baseline. The variance is quite small in all the cases when predicting up to the 20th day after uploading. Note that for $t_t \geq 40$ days, coupling filters by models and popularity together gives the worst variance results. However, regarding confidence intervals, the gain in mRSE compared to the baseline is still good. The nuanced variance results can be explained by the fact that when filtering with coupled filters, there are some training subsets with a very small number of videos, thus the corresponding parameters of the prediction model might be inaccurate. For longer term prediction (1 month after upload and more), we observe that our method of filtering by models improves the results of the ML model in terms of mRSE and variance. This method seems to be a powerful compromise between all our approaches.

Fig. 3c illustrates mRSE results for videos in test set with views between $10^2$ and $10^4$ one week after uploading (5511 videos). We observe that the mRSE is lesser than 8% for $t_t \geq 30$ days. Filtering by popularity provides almost the same results than the ML baseline, but using the filter by models or combining both filters produce a gain of at least 1% when $t_t \geq 20$ days. For long term prediction (1 month or more after uploading), filtering by both models and popularity outperform by 2% the ML baseline in terms of mRSE and variance, giving an improvement of 12%–13.5%.

Fig. 3d shows the results over all the test set where we use information up to the 100th day after uploading while doing the classification (in mathematical models as well as in classes of popularity). Compared to Fig. 3a, the popularity filter does not gain with this additional information, but the filter by models does. Using both filters at the same time performs much better in this case. For long term prediction, the results are 1% better than without using additional patterns from the future. This is because we take advantage of the gain on the mathematical models filter. Best improvements are achieved in this case with a relative gain of more than 20% compared to the ML baseline when $t_t$ varies from 20 to 40 days after upload. From Fig. 4 we observe that using future information gives by far the best improvement compared to the ML baseline in terms of mRSE when applying the coupled filters method. The relative gain in this case varies from 10% to more than 20% when $t_t$ varies. However, it is also observed that the coupled filters method without using these future information gives best improvements (most of the time greater than 10%) than each single filter with the use of future knowledge as soon as $t_t$ is greater than 14 days after uploading. Despite the loss in variance, this remains a good result when considering 95% confidence intervals showed in Table II.

Doubtful variance results for popularity and coupled filters in Fig. 3b might be explained by unbalanced classes of popularity in terms of number of videos in the training set. In order to address this issue, we divide the training set into five 20% quantiles (calculated from the views received during one week after uploading). Each quantile has around 450 videos and defines a class of popularity. We use these classes for the popularity filter method and for the coupled filters method.
Each class has around 2250 corresponding videos in the test set. In Fig. 3e we compare the mRSE for the second quantile (in this quantile videos have between 37 and 10460 views at $t_r = 7$ days). We observe that the three filter methods are better than the ML baseline. Fig. 3f shows the fourth quantile (videos with between 172300 and 411900 views at $t_r = 7$ days). For this quantile the popularity filter behaves better than the models one. The mRSE when filtering by models is almost the same as the ML baseline. The filter by popularity improves a little both the mRSE as well as the variance. Using the two filters together is slightly better for the mRSE but not for variance.

Results obtained by our methods are quite promising. Using popularity filter should perform better with a well balanced training set. Our mathematical models filtering approach shows some robustness and always improves the ML baseline in variance as well as in average prediction errors.

VI. CONCLUSION AND FUTURE WORK

We proposed a novel prediction process used in predicting future popularity of YouTube videos. Our goal is to investigate how our classification of the dynamic evolution of view-count of videos into several mathematical models, can be exploited for predicting popularity. These models are able to better distinguish between videos with different popularity evolution patterns in a more explicit form. The next step in this work is to investigate how data from Google Trends related to some videos, affect our classification as well as the prediction process.

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