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Modelling View-count Dynamics in YouTube

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Abstract—**The goal of this paper is to study the behaviour of view-count in YouTube. We first propose several bio-inspired models for the evolution of the view-count of YouTube videos. We show, using a large set of empirical data, that the view-count for 90% of videos in YouTube can indeed be associated to at least one of these models, with a Mean Error which does not exceed** 5%**. We derive automatic ways of classifying the view-count curve into one of these models and of extracting the most suitable parameters of the model. We study empirically the impact of videos' popularity and category on the evolution of its view-count. We finally use the above classification along with the automatic parameters extraction in order to predict the evolution of videos' view-count.**

Keywords—YouTube,bio-inspired models, view-count.

I. INTRODUCTION

YouTube has been one of the most successful user-generated video sharing sites since its establishment in early 2005 and constitutes currently the largest share of Internet traffic. The rate of subscription to YouTube as well as the rate of submitted videos has been growing steadily ranking YouTube and none of its competitors has achieved a similar success [1], [2]. An important aspect of videos in YouTube is their popularity, which is defined as the number of view-counts. 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; and on the other hand, popularity has a direct economic impact. A number of researchers have analyzed the popularity characteristics of user-generated video content for understanding the processes governing their popularity dynamics [5], [10], [13], [18], [8], [6], with the aim of developing models for early-stage prediction of future popularity [19]. There has been also interest in understanding what important factors lead some videos to become more popular than others. But few works have studied the temporal aspects of the popularity dynamics using some metrics such as view-counts, ratings and number of comments [5], [9], [17].

In this paper we describe some of the most typical behaviour of the view-count of videos in YouTube. This allows us to provide in-depth analysis and develop models that capture the key properties of the observed popularity dynamics. Our goal is to match observed video view-counts with one of several dynamic models. To select candidates for these models, we turned to bio-inspired dynamics as we believed that the propagation of a content in YouTube has a strong similarity with the temporal behaviour of an infectious disease, which is a classical topic in mathematic biology [3], [16]. Such models

of diseases spread have already been used in order to model the spread of viruses in computer networks [7], [12]. They have been also used in marketing for capturing the life cycle dynamics of a new product [4]. A large number of papers in marketing have shown that product sales life cycle follow an S-curve pattern in which the product sales initially grow at fast rate and it falls off as the limit of the market share is approached [14].

We propose several information diffusion models to classify a dataset of more than 800000 videos randomly extracted from YouTube and aged between 5 and 2500 days. In particular, we exhibit six mathematical models to which we fit videos in our dataset. We then propose automatic ways for associating each video to one of the considered models. The first criterion in selecting the model is related to the size of the population that may be potentially interested by the content. We differentiate between models in which the population potentially interested in the content is nearly constant (we call this the "fixed target population property") and those in which it grows in time (inspired by the branching process terminology, we call this "immigration"). The fixed target population property occurs in some video categories in YouTube as news, sport and movies. Indeed, videos in these categories reach quickly the peak of the popularity and then within a short time the diffusion dies out and the view-count does not further increase.

The second criterion in the classification concerns the structural virality. A model is said to be viral (or to have the viral property) if contaminated nodes (these are the viewers of a video) have a significant role in the propagation of the video through sharing or embedding. It is non-viral if the propagation of the video essentially relies on broadcast of the video from the source (it is then said to have the broadcast property). In that case, a large fraction of potential target population can receive the information directly from the source.

Our contribution can be summarised in the following key points

- We propose six mathematical biology-inspired models and we show that at least 90% of videos in YouTube are associated to one of these six mathematical models with a Mean Error Rate less than 5%. We further show how to extract the model parameters for each video.

- We study the robustness of these models to the different thematic categories of the video in YouTube and to different values of the peak popularity of the video. We show that the fraction of videos withing a given model is quite robust and shows little dependence

on the different thematical categories of the video, except for Education category which has a different behaviour: For this category it seems that the word-of-mouth is the dominate mechanism through which contents are disseminated. The bio-inspired models that we selected are further shown to be robust with respect to the peak popularity of the video but the distribution among them is slightly different between those videos that have acquired less than 1000 views and the rest of the videos.

- In more than 80% of videos in YouTube, the potential population interested in the video increases over time.

- Two of the six models (The modified negative exponential and modified Gompertz models) cover most of videos in our YouTube Dataset (more than 75%). Both models capture the case of immigration process in which the potential population or the ceiling value become dynamic. Further, the modified negative exponential characterizes the dynamic of a non-viral content and it predicts that the accumulated number of view doesn't contribute to the propagation of the content. This model corresponds to the scenario wherein the content has been broadcasted to a pool of users. On the other side, the Gompertz model captures viral videos in which a part of this dynamic is propagated through word-of-mouth.

- We finally use the above classification along with the automatic parameters extraction in order to predict the evolution of videos' view-count. We consider two scenarios: In the first we use half of the view-count curve as a training sequence while in the second one, we take a fixed training sequence that corresponds to the first 50 days in the lifetime of the video. We then compare the predicted curve to the actual one and study the prediction capacity within a given error bound.

II. Setting and data

Since we intend to study different types of dynamic evolution of the view-count in YouTube, we need to collect a huge number of videos which are available to the general public.

In this section we describe how we collected the dataset used in this study. On YouTube, a video is accompanied by a set of valuable data as title, upload time, view-count, related videos. The video web page also provides some statistics which are available if the content's owner allows it.

YouTube provides two APIs which allow to retrieve some of those data : the YouTube Data API for collecting static data (which are available for every user) and the YouTube Analytics API for seeking video statistics such as dynamics of a content (which are only available for content's owner). Since some data cannot be collected through the APIs, we used a tool named YOUStatAnalyzer [20] in order to collect all valuable data.

The collected data are stored in a noSQL database (MongoDB). The noSQL solution has been chosen to allow dynamic insertion of new features for future works. The dataset used for this study contains more than 80000 videos randomly extracted from YouTube and aged between 5 and 2500 days. This dataset 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 of some metrics (shares, subscribers, watch time and views) in a daily form and in a cumulative form, from the upload day till the date of crawling.

III. Popularity growth patterns

We focus the analysis on view-count as the main popularity metric of a video. Previous analyses of YouTube showed a strong correlation between view-count and other metrics as number of comments, favourites and rating. Further, these metrics correlation becomes stronger with popularity [8]. We model the dynamic evolution of view-count some mathematical models from the biology. We classify the evolution of view-count in YouTube using two criteria:

- **Size of the target population:** The target population size is the maximum number of individuals that can be, potentially, interested by the content. A target population belongs to one of these two types: (i) a fixed finite target population or (ii) a potential target population that grows in time which we call **the immigration process**.

- **Virality:** A content is viral if the population that has seen the content participates actively in the dissemination of the content. The content spreads like a virus does in epidemics. Thus the probability that an individual who has not seen the content so far got it by someone who see it, increases in time. On the contrary, a non viral content is one for which former viewers scarcely alter the diffusion process.

In the following we describe the dynamic models in biology and their uses. These dynamic models have been hypothesised to describe the contagion phenomena and each model has its own set of assumptions about how users are infected by others. These models may provide some answers about the behaviour of users in YouTube even if this behaviour remains notoriously difficult to quantify.

A. Fixed target population

1) Viral content: To describe the viral content with fixed target population, we use the logistic model or the Gompertz model. These models have been used in technology forecasting and are referred as "S-shaped" curve. We test these models to capture the evolution of view-count of a video in YouTube since there is a strong similarity between a video posted in YouTube and a new product launched into the marketplace. Indeed, as showed in different problems in marketing, technology product is often growth slowly followed by rapid exponential growth and finally it falls off as limit of market share is approached.

Logistic model: The logistic model is a common sigmoid function which describes the evolution of view-count of a video with fixed target population. This is a first order non-linear differential equation of the form
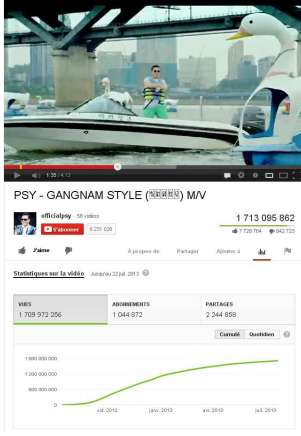
$$\frac{dS}{dt} = \lambda S(M - S) \tag{1}$$

Fig. 1. Example of non symmetric S-shaped behaviour of view-count in YouTube (viral).

where S is the number of view-counts of a video and M is the maximum size of the (potential) population that could access the content. This is a standard equation in epidemiology for describing the evolution of the number of infected individuals under the assumption that all infected nodes have developed an immunity from infection or these infected nodes stay infected and will not be changed to uninfected state. Hence the infection rate is a function of the rate λ and the size of the infected population. For the YouTube case, this model corresponds to the scenario wherein users may watch a video one time and the probability to watch it again is negligible. A solution to equation (1) is given by

$$S(t) = \frac{M}{1 + (\frac{M-S(0)}{S(0)})e^{-\lambda Mt}}$$

This function shows that initial exponential growth is followed by a period in which growth starts to decrease as approaching the maximum size of population.

The S-shape of the sigmoid model curve is symmetric. But in the context of view-count, the convex phase and the concave phase could not always be symmetric. This is shown by the example in Figure 1. For covering these cases we consider the Gompertz model.

Gompertz model: A model which deals with the problem of symmetry of the Logistic model is given by the following dynamic equation:

$$\frac{dS}{dt} = \lambda S \log(\frac{M}{S}), \tag{2}$$

This model is called Gompertz model, and has been also used as diffusion model of product growth. A solution of equation 2 is given by the Gompertz function :

$$S(t) = M \exp(-\log(\frac{M}{S(0)}) \exp(-\lambda t)),$$

Figure 2 shows the effect of varying one of M, λ, $S(0)$ while keeping the others constant.

This model is similar to the logistic curve but it is not symmetric about the inflection. In general the Gompertz's model reaches this point early in the growth trend. This

behaviour seems to fit well for some YouTube view-count evolution dynamics.

2) Non-viral content: A non viral content describes the case where users do not contribute on the propagation of the content. This is the case when the time scale of the content diffusion is very large compared to the size of potential population. 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. Hence we assume that the evolution dynamic of the content follows the linear differential equation:

$$\frac{dS}{dt} = \lambda(M - S) \tag{3}$$

The solution of (3) is given by $S(t) = S(0) + (M - S(0))(1 - e^{-\lambda t})$

B. Growing population

The assumption that the population is fixed, is often a reasonable approximation when the evolution of 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. In this paper we restrict our study on the case where the target population grows with a fixed speed.

1) Non-viral content : The linear growth model $S(t) = S(0) + \lambda t$ describes in a simple way the situation where users do not contribute to propagate the content to other users but the content benefits of the immigration process which gives a linear growth of the view-count.

Another kind of non-viral curves observed are concave curves (given by the negative exponential model) which do not converge to a flat line but become linear at the horizon due to the immigration process influence. Such dynamics could be modelled by modifying solutions of equation 3 where a linear component is added:

$$S(t) = S(0) + (M - S(0))(1 - e^{-\lambda t}) + kt$$

where k is the rate of the target population growth. Note that S no more respects the equation 3 but $(S - kt)$ does.

2) Viral content : Now we consider the case when the immigration process appears in the case of viral contents. In this dynamic the view-count curve first adopts a viral behaviour (in a S-shaped phase) and then grows linearly.

One candidate solution to describe such a behaviour of view-count is to add a linear component to the Gompertz function: $S(t) = M \exp(-\log(\frac{M}{S(0)}) \exp(-\lambda t)) + kt$ This dynamic seems to be relevant according to some examples in the dataset.

3

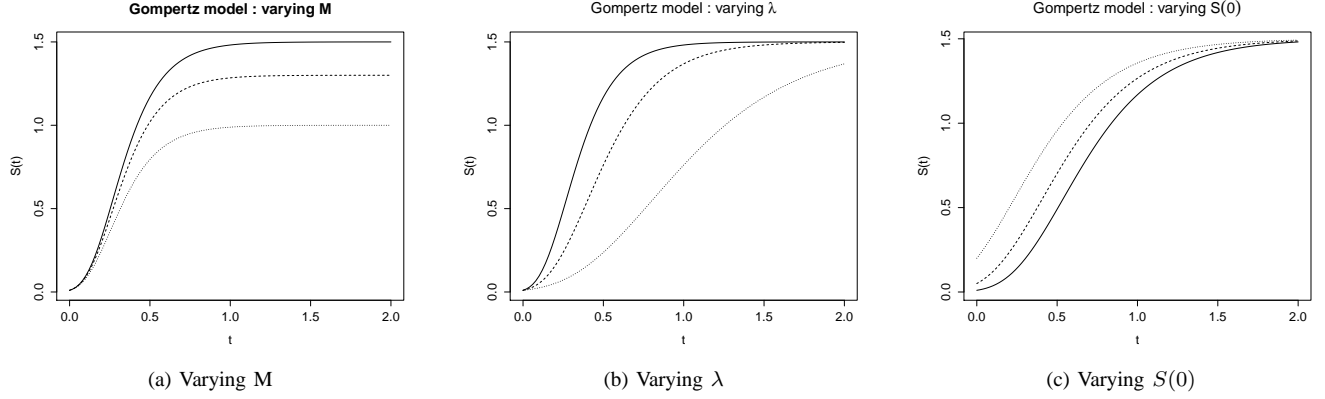| (a) Varying M | (b) Varying λ | (c) Varying $S(0)$ |

Fig. 2. Graphs of Gompertz functions, showing the effect of varying one of M, λ, $S(0)$ while keeping the others constant

IV. DATASET AND DATA FITTING

This section describes how we use the models presented in section III in order to classify the YouTube contents in our dataset.

A. Dataset

As described in section **??**, we collected meta-data of more than 80000 videos in a MongoDB database. In addition of the dynamics of view-count used for modelling, the features we consider for each video are: the age (in number of days), the YouTube category and the popularity (i.e the total number of views at the day of crawling). Table I lists the YouTube categories contained within the dataset and Figure 3a shows their distribution. Table II summarises the values of age and popularity metrics. Figure 3b gives the ages distribution and Figure 3c is about the distribution of popularity (in log values).

TABLE I.   LIST OF ALL YOUTUBE CATEGORIES FOUND INSIDE THE DATASET

1. "Animals"	7. "Games"	13. "Shows"
2. "Autos"	8. "Howto"	14. "Sports"
3. "Comedy"	9. "Music"	15. "Tech"
4. "Education"	10. "News"	16. "Travel"
5. "Entertainment"	11. "Nonprofit"	
6. "Film"	12. "People"	

TABLE II.   SUMMARY OF AGE AND POPULARITY VALUES WITHIN THE YOUTUBE DATASET

Age (in days)	Popularity (number of views)
Min: 5	Min: 1
1st Qu.: 140	1st Qu.: $2,650.10^2$
Median: 393	Median: $2,728.10^3$
Mean: $610,5$	Mean: $6,091.10^5$
3rd Qu.: 923	3rd Qu.: $2,630.10^4$
Max: 2426	Max: $1,746.10^9$

B. Data fitting

a) Observations and normalisation: For the data fitting, we only use the cumulative evolution of view-count. Given the evolution of view-count of a YouTube video as a function of time, we define a set of observations as : $(y_i, t_i)_{1 \leq i \leq n}$ where y_i is the view-count at day t_i and n is the number of observations (this is also its age in number of days). In order to avoid some technical issues due to the estimation algorithms, we use normalised observations :

$$\left(\frac{y_i}{y_{\max}}, \frac{t_i}{t_n} \right)_{1 \leq i \leq n}$$

b) Parameters estimation methods: We estimate the parameters of the models described in section III using regression algorithms both based on the mean squares criterion minimisation. Given a normalised set of observations $(y_i, t_i)_{1 \leq i \leq n}$, let S be the expression for one model. The mean squares criterion (MSC) is then given by: $MSC = \sum_i (S(t_i) - y_i)^2$

We implemented two algorithms in order to automatically classify the dynamics of any video from YouTube in one of the models presented in the III section.

The first method is a simple linear regression. It works for videos where the view-count grows linearly over time t. In that case, the coefficient of determination R gives a measure for the goodness of the fit :

$$R = 1 - \frac{\sum_i (y_i - S(t_i))^2}{\sum_i (y_i - \bar{y})^2}$$

where $\bar{y}$ is the mean of $(y_i)_i$. In our experiments, we consider that a linear model is relevant if the value of R satisfies $|R| \geq 0.985$. In the dataset, there are very few video dynamics that meet the linear case.

The second method is the Levenberg-Marquardt Algorithm [15] which is known to be very efficient for the non-linear case. It is an iterative process for estimating parameters of the model through a minimisation problem of the MSC. Explicit formulation of the models have to be known to use this algorithm because the partial derivatives have to be calculated during the iterative process. One drawback of this method, like all other non-linear regression methods, is that the solution could not be global but only a local one. Nevertheless, the Levenberg-Marquardt Algorithm suits very well for our models.

c) Data fitting for Non viral contents: A non viral behaviour is modelled by the dynamic equation 3. This model, called the negative exponential model, fits for contents which view-count curve goes concave then reaches an asymptote. In Figure 4 we show an example where this model is applied. We observe that the estimated curve (dashed line) admits an asymptote (which limit value is in fact the M parameter of the model). This is typically the case with fixed finite population. But at the horizon, the curve that represents data (plain line) seems to follow a line with a non zero slope. This is what

(a) YouTube categories distribution

(b) Age distribution (in number of days)

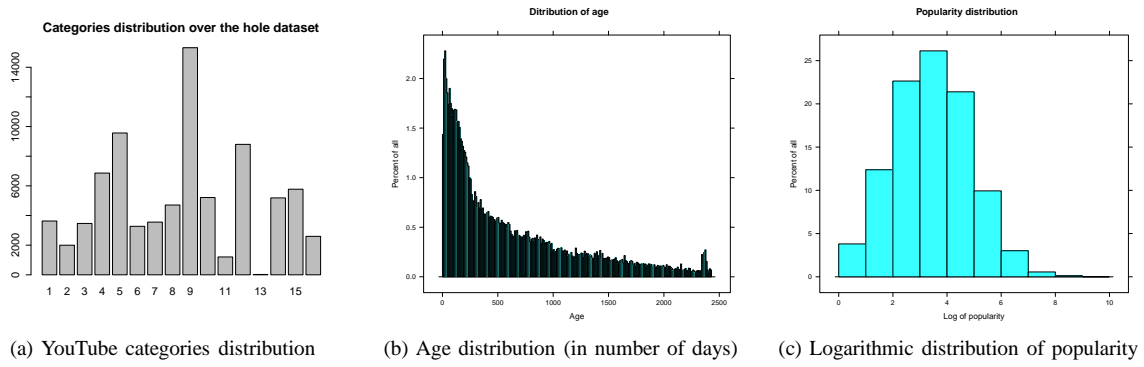(c) Logarithmic distribution of popularity

Fig. 3.   Some features distributions from the YouTube dataset.

we call the immigration phenomena, when the size of target population increases linearly in time. In that case, we model the dynamics by the modified negative exponential functions introduced in subsection III-B1:

$$S(t) = S(0) + (M - S(0))(1 - e^{-\lambda t}) + kt$$

This model fits better as it is shown in Figure 4c. A mixed strategy, which consists in cutting data into two subsets and then applying linear model on one subset and negative exponential model on the other, will be discussed later.

d) Data fitting for Viral contents: Three models have been considered in the case of viral contents: logistic model, Gompertz model and a modified Gompertz model (see section III-B2). The first two models are for the context of fixed finite population and the third one is introduced in the case of immigration.

Figure 5 is an example where we fit these models to one YouTube content (Figure 5a). We observe that the S-shape of the logistic model curve is symmetric due to the symmetrical property of sigmoid function (Figure 5b). However, the convex phase and the concave phase are non symmetric as we can observe in Figure 5a. Hence the Logistic model does not fit well. Then, Gompertz model and modified Gompertz model are fitted to the same YouTube content. The Gompertz model (Figure 5c) fits better than the logistic model, and the modified Gompertz model (Figure 5d) describes better the behaviour of the data at the horizon (immigration phenomena).

e) Mixing linear and non-linear models: An issue that results from the model we use is the changes of the curve dynamics at the horizon. We observe two types of behaviour at the horizon : a flat line showing that the limit of the potential population has been reached or an oblique line highlighting the fact that the population continues to grow.

The first case is coherent with the description of dynamics (then the maximum is one of the parameters of the dynamic equation of the model). However, for the second case we need to add a linear component to the solution function, implying that the initial dynamic equations are not valid anymore. Hence, we propose to adopt a two phases approach for data fitting. Figure 6 gives an example where this method is applied for a YouTube content (Figure 6a).

Given a set of observations $(y_i, t_i)_{1 \leq i \leq n}$, a first phase consists in pointing out a linear behaviour from a time $t = t_k, k \in 1, .., n$. The idea is to find k in an iterative way in order

to have a good regression line for the subset $(y_i, t_i)_{k \leq i \leq n}$. The algorithm is the following : we first fix a threshold ϵ reasonably small. We then apply a linear regression with all the points. The regression line gives the set $(\hat{y}_i)_i$ of the estimated values. Let $\bar{y}$ be the mean of $(y_i)_i$, we consider the coefficient of determination r_1 given by:

$$r_1 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_i (y_i - \bar{y})^2}$$

- if $|1 - r_1| \leq \epsilon$, observations could be considered as linear (the whole view-count curve could be well described by the linear model) and the process ends.

- else, the first element of $(y_i, t_i)_{1 \leq i \leq n}$ is removed from the set and a new linear regression is done for the subset $(y_i, t_i)_{2 \leq i \leq n}$. That gives a new coefficient of determination r_2

The process is repeated until the coefficient of determination r_k satisfies $|1 - r_k| \leq \epsilon$. Doing that, we determine the rank k from which observations $(y_i, t_i)_{k \leq i \leq n}$ can be considered as having a linear behaviour. In Figure 6b, time t_k is represented by a vertical line. From t_k the behaviour can be well described by a linear model (dot-dashed line).

In a second phase, parameter estimation for the non-linear models presented in previous section is done on the subset $(y_i, t_i)_{1 \leq i \leq k}$. Figure 6b illustrates this phase : here, the modified negative exponential model is applied to the subset on the left side of t_k (dashed line).

V. AUTOMATIC CLASSIFICATION

In this section we first investigate the process for an automatic classification of YouTube contents. We then go further in analysing results of our experiment. Finally we give some keys of how to use this classification in order to predict the view-count.

A. Classification issues

The main goal of our work is to provide a system that can automatically classify YouTube contents by associating one model to one content. For each content, two issues have to be managed : First, evaluate each model in order to know which models are good candidates. Then compare candidates to determine which one is the best.

5

(a) YouTube content with a concave shape
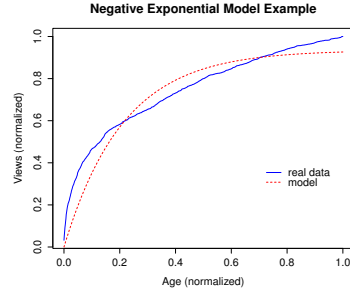
(b) Viewcount curve (plain) is approximated by a negative exponential curve (dashed)
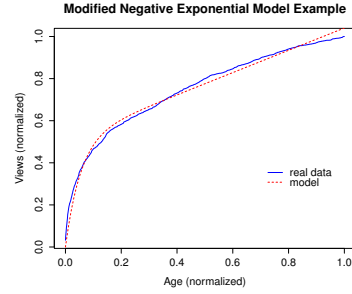
(c) Viewcount curve (plain) is approximated by a modified negative exponential curve (dashed)

Fig. 4. From a YouTube content (on the left side), parameters of the negative exponential model are estimated, then the obtained curve is compared to data (in the centre). The same process is applied to a negative exponential model in which a linear component has been added (on the right side)
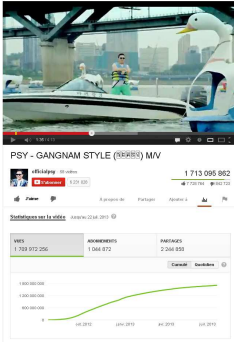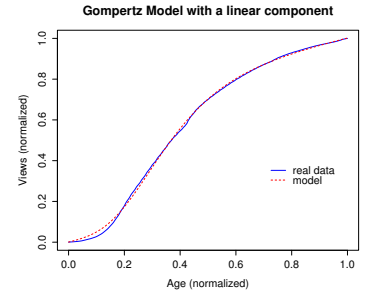

(a) YouTube video
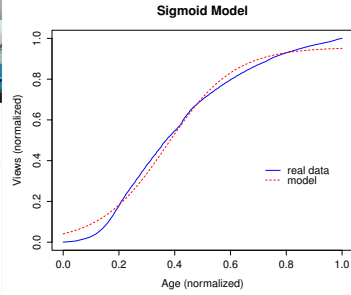
(b) Logistic model fitting
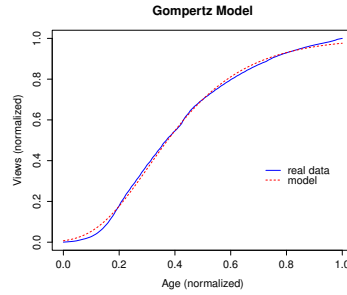
(c) Gompertz model fitting

(d) Modified Gompertz model fitting

Fig. 5. From a YouTube video with a S-shaped view-count curve (5a), we first fit the logistic model in 5b. The estimated curve (dashed) is compared with the actual normalised view-count curve (plain). Then the same is done with the Gompertz model in 5c and finally with the modified Gompertz model in 5d.

(a) YouTube video (Obama about gay marriage)
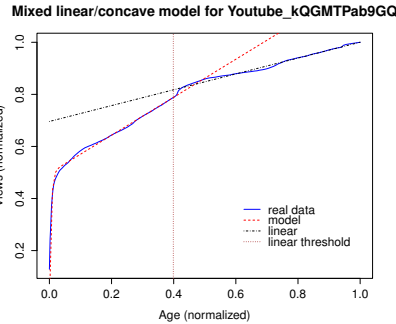
(b) Mixed linear/non linear fitting

Fig. 6. From a YouTube content (Figure 6a), a mixed procedure is made to estimate a linear model and a non linear model on two subset of data (Figure 6b)

Let us consider first the question of evaluating each model. As explained in section IV-B0b, we perform parameters estimation based on the least squares criterion minimisation. Define the mean error rate (MER):

$$MER = \frac{1}{n} \frac{\sum_i |S(t_i) - y_i|}{y_i + 1}$$

MER criterion is the mean error rate done by the model

TABLE III. GOODNESS OF FIT FOR MODELS FROM FIGURE 4

Model	MCS	MER	GoF
Neg. exponential	$3,558$	$0,074$	$0,004$
Modified neg. exponential	0.453	$0,027$	$4,98.10^{-4}$

regarding the observations. For example, if $MER \leq 0,05$, it can be said that on average, the estimation error is under 5% of the observed value. With this criterion we can fix a threshold beyond which one model would be considered as unreliable.

In order to compare models that are under this threshold, we introduce a criterion of quality discussed in [11]. To formulate this criterion we first define the degree of freedom of a model (df). Let p be the number of parameters of the model, the degree of freedom is then defined by: $df = n - p$ The criterion of quality, named "goodness of fit" (GoF) is then given by: $GoF = \frac{1}{(df)} MSC$ The model which have the smallest GoF will be considered as the best one. In other words, it will be the model that fits the data the best. In Table III and Table IV we give values of MSC, MER and GoF for models used respectively in Figure 4 and Figure 5. In the example from Figure 4, with a threshold of MER fixed at $0,075$, both negative exponential model and modified negative exponential model are relevant. With a GoF of value $4,98.10^{-4}$, modified negative exponential model is the one that best fits the data. In the case of YouTube content depicted in Figure 5, if the

TABLE IV. GOODNESS OF FIT FOR MODELS FROM FIGURE 5

Model	MCS	MER	GoF
Sigmoid	$0,480$	0.021	10^{-3}
Gompertz	$0,092$	$0,018$	$1,846.10^{-4}$
Modified Gompertz	$0,033$	$0,008$	$8,831.10^{-5}$

threshold of MER is fixed at the value of $0,02$, sigmoid model is not reliable whereas Gompertz model and modified Gompertz model are under the threshold. According to the value of GoF, modified Gompertz model is the best with $GoF = 8,831.10^{-5}$. Further, the issue of fixing a value for the MER threshold is crucial to rely on an acceptable filter for several videos.

B. Results analysis

Given one video from the dataset, after doing parameters estimation for each model, the system automatically associates one model to the video using MER and GoF criteria. We give results about the distribution of MER values in Figure 7a. It is shown that 89% of videos are associated to a model with a MER under $0,05$. A mean error of 5% seams reasonable to consider a reliable fitting. Hence, if MER is fixed at 0.05, we should conclude that the classification system is efficient in almost 90% of the cases.

(a) Percent of contents by bins of MER values

(b) Models distribution after classification over the whole dataset
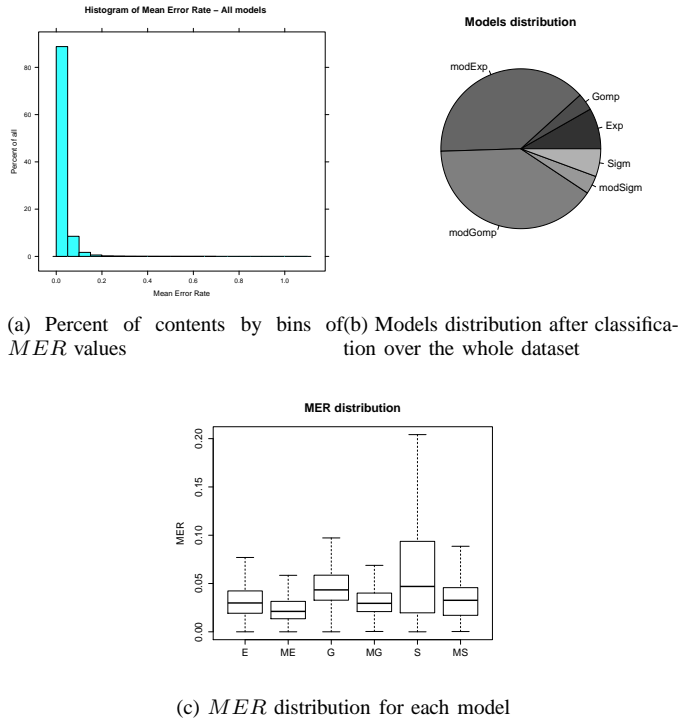

(c) MER distribution for each model

Fig. 7. Sample analysis of an automatic classification for dissemination processes in YouTube

Note that if the threshold of MER is fixed at $0,1$, more than 97% of the videos correspond to one of the models. There is at most 2% of the videos for which the association to one of our models gives a high error rate (let say more than 10%). Figure 8 illustrates one example of such a video. In this case, the system associates the modified Gompertz model to the video, with a MER equal to $0,127$ and a GoF

of value $1,13.10^{-1}$. The association is absolutely unreliable due to the many sharp changes of the behaviour. Indeed, it seems that the models are unable to capture the effect of multiple peaks in view-count evolution. This might be the case of view-count curves that are somehow 'non differentiable'. Further investigation has to be made about this issue, this is one of our direction in future works.
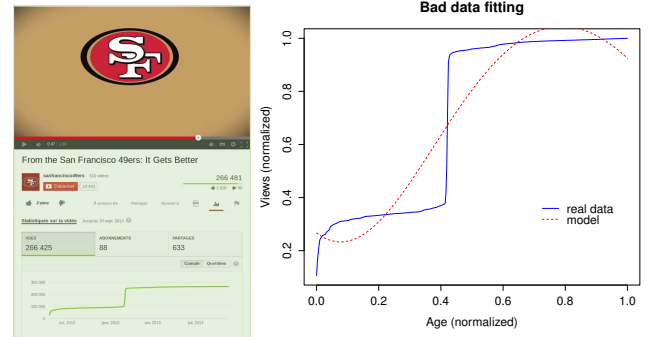

Fig. 8. One bad fitting example.

In Figure 7c we focus on the MER distribution for each model. Note first that we did not used the linear model because it insignificantly appears in the dataset. Secondly we introduce a new model, named modified sigmoid model, given by the logistic model with a linear component added (as done in section III-B2 with the modified Gompertz model).

It appears that modified negative exponential and modified Gompertz models give fitting with less error than the other in most of the cases: they can be referred as the most reliable models for our dataset. We present the models distribution in Figure 7b. The same two models: modified negative exponential and modified Gompertz, almost cover the whole dataset with the same amount of videos for each one. Regarding their reliability, it enforces the classification efficiency. The former is a non viral model whereas the latter is viral, meaning that there is quite a balance between viral and non viral contents. Both highlight an immigration process, leading to the conclusion that a lot of YouTube contents still attracting viewers even after a long period.

We consider the different YouTube categories into the models classification: Four main categories can be highlighted regarding the distribution in Figure 3a. Music (over 14000 videos), Entertainment (over 8500 videos), People (around 7500 videos) and Education (almost 6000 videos). In general, the models distribution in each category is not far from the distribution considering all categories combined. However, Education category is quite different. The models distribution for this category is given in Figure 9. We note that the modified Gompertz model dominates. Furthermore, viral models cover almost 75% of the videos. One might assume that Education is a word-of-mouth category where videos dissemination results mainly from viewers influence and few benefits from advertising processes or internal YouTube mechanisms such as recommendation system.

We analyse the models distribution considering the popularity of videos. Let us introduce the different classes of popularity
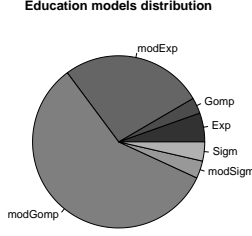
Fig. 9. Models distribution for the Education category

defined for our dataset: According to the distribution depicted in Figure 3c, we define seven classes of popularity listed in Table V. We show the models distribution for each popularity

TABLE V.   POPULARITY CLASSES

Popularity class	Total number of views V
Extremely unpopular (EUP)	$0 \leqslant V < 10$
Very unpopular (VUP)	$10 \leqslant V < 100$
Unpopular (UP)	$100 \leqslant V < 1000$
Not so popular (NSP)	$1000 \leqslant V < 10^4$
Popular (P)	$10^4 \leqslant V < 10^5$
Very popular (VP)	$10^5 \leqslant V < 10^6$
Extremely popular (EP)	$10^6 \leqslant V$

class in Table VI.

We can observe that the distribution varies according to the

TABLE VI.   MODELS DISTRIBUTION BY POPULARITY CLASS (IN %)

Model	EUP	VUP	UP	NSP	P	VP	EP
Exp	11.4	12.2	8.4	8	6.8	6.2	5.7
Gomp	1.6	2.8	1.8	2.5	3.6	3.2	2.1
ModExp	11.6	54.5	48.9	35.2	35.1	42.3	47.5
ModGomp	2.5	19.4	34.7	48.7	49.3	44.3	42.8
ModSigm	1.8	4.3	4.3	3.6	2.9	2.3	0.8
Sigm	70.7	6.6	1.5	1.7	2	1.3	0.8

classes of popularity. First of all, the logistic model (referred as sigmoid in the plots) dominates the extremely unpopular category (constituted by videos of less than 10 views). These results are not reliable due to the few different values of the view-count for these videos. Actually, in our system, all the models should be good for those videos and the first that is tested is the logistic model so that it is the one which is chosen. Popular class and not so popular class can be grouped in terms of models distribution with around 50% for modified Gompertz model and 35% for modified exponential model. We can also group very popular class and extremely popular class for which distribution is slightly equivalent to the whole dataset distribution (see Figure 7b). Very unpopular and unpopular classes exhibit modified exponential model in around 50% of the cases. The modified Gompertz model represents less than 20% in very unpopular class whereas it covers almost 35% of the videos in unpopular class.

C. Tool for prediction

In order to underline directions for future works, we aim at testing how good our models would be for prediction. Our approach is the following:

From the whole dataset, we build a subset as a testing set.

Videos in this subset are at least 50 days old, meaning that we have at least 50 observed values for each video and we consider only videos that admit a model with a MER under 0.05. The given set contains exactly 65093 videos and is referred as $dataModelledAll$.

For each video in this new dataset, we do the fit for the first half of data (half life scenario) and also for the 50 first days of data (50 days scenario). The best case scenario is when we get a model with MER under 0.05 for half life and for 50 days (which is not always the case). However, we refer as $dataHalf$ the subset of videos in $dataModelledAll$ which have a good model (with at most 5% mean error) for its half life time and we refer as $data50d$ the subset of videos in $dataModelledAll$ which have a good model for its 50 first days. $dataHalf$ contains 52134 videos whereas $data50d$ contains 42395 videos.

For each video and for each fixed time (50 days and half life), we determine the maximum size of the prediction window for the given model if it exists. By size of the prediction window, we mean the following : if we denote by T the time at which the modelling is done ($T = halflife$ or $T = 50days$), by S_T the best model designed by the classification system for the time T , by N the age of a video and by $(y_i, t_i)_{i \in 1,...,N}$ the normalised time series defined by the observed values of video, the prediction window size is then given by :

$$\delta T = max\{k \geq T | \frac{1}{k} \sum_{i=0}^{k} \frac{|S_T(t_{T+i}) - y_{T+i}|}{(y_{T+i} + 1)} \leq 0.05\}$$

We then consider the normalised window size defined by : $\Delta T = \frac{\delta T}{N-T}$.

In Table VII and Table VIII we give mean and variance of the prediction window size for each scenario. In Figure 10, E, ME, G, MG, S and MS are respectively for Exponential, Modified Exponential, Gompertz, Modified Gompertz, Sigmoid (logistic) and Modified Sigmoid. Fig. 10a gives an overview of ΔT for the 50 days scenario for each model and Fig. 10b depicts the same for the half life scenario.

TABLE VII.   MEAN AND VARIANCE OF PREDICTION WINDOW SIZE IN THE 50 DAYS SCENARIO

Model	mean	var	number of videos
Exp	0.1240775	0.06050271	3401
modExp	0.6159881	0.1384898	21788
Gomp	0.1861161	0.09028605	687
modGomp	0.2314134	0.09438778	13821
Sigm	0.4750911	0.1083194	1137
modSigm	0.2082774	0.1798454	1561

TABLE VIII.   MEAN AND VARIANCE OF PREDICTION WINDOW SIZE IN THE HALF LIFE SCENARIO

Model	mean	var	number of videos
Exp	0.5833692	0.1504571	4132
modExp	0.576914	0.1415303	25281
Gomp	0.3435265	0.1160928	683
modGomp	0.4596889	0.1360676	19349
Sigm	0.6765688	0.1544357	1030
modSigm	0.4625144	0.1280855	1659

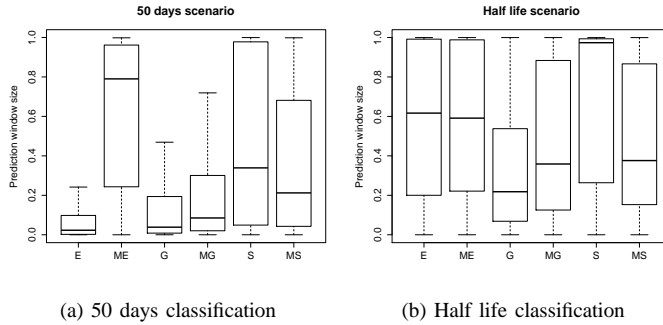| (a) 50 days classification | (b) Half life classification |

Fig. 10. Prediction window size according to models type for 50 days scenario and half life time scenario

VI. CONCLUSION AND FUTURE WORK

In the present work we have focused on a method for classifying view-counts dynamics of videos on YouTube. We presented different models for YouTube view-count evolution which are able to capture virality and potential population growth. Based on these models, we have developed one system for automatic classification of the YouTube videos. It aims at classify each YouTube content within one of the four categories we defined: Viral and fixed population; Viral and growing population; non-viral fixed population; and non-viral growing population. We have tested this automatic classification in a particular dataset -that has been presented and is available upon request-. Results of our experiments reveal that a reasonably small threshold of the MER criterion allows to classify more than 90% of the dataset, meaning that the defined models explain the observed behaviour in most of the cases.

Our future work would focus on the context of the four defined categories. We will analyse how other features influence the dynamic of the view-count evolution.

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