Forecasting Popularity of Videos using Social Media

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***Abstract*—This paper presents a systematic online prediction method (Social-Forecast) that is capable to accurately forecast the popularity of videos promoted by social media. Social-Forecast explicitly considers the dynamically changing and evolving propagation patterns of videos in social media when making popularity forecasts, thereby being situation and context aware. Social-Forecast aims to maximize the forecast reward, which is defined as a tradeoff between the popularity prediction accuracy and the timeliness with which a prediction is issued. The forecasting is performed online and requires no training phase or a priori knowledge. We analytically bound the prediction performance loss of Social-Forecast as compared to that obtained by an omniscient oracle and prove that the bound is sublinear in the number of video arrivals, thereby guaranteeing its short-term performance as well as its asymptotic convergence to the optimal performance. In addition, we conduct extensive experiments using real-world data traces collected from the videos shared in RenRen, one of the largest online social networks in China. These experiments show that our proposed method outperforms existing view-based approaches for popularity prediction (which are not context-aware) by more than 30% in terms of prediction rewards.**

***Index Terms*—Situational and contextual awareness, social media, online social networks, popularity prediction, online learning, forecasting algorithm**

I. Introduction

Networked services in the Web 2.0 era focus increasingly on the user participation in producing and interacting with rich media. The role of the Internet itself has evolved from the original use as a communication infrastructure, where users passively receive and consume media content to a social ecosystem, where users equipped with mobile devices constantly generate media data through a variety of sensors (cameras, GPS, accelerometers, etc.) and applications and, subsequently, share this acquired data through social media. Hence, social media is recently being used to provide situational awareness and inform predictions and decisions in a variety of application domains, ranging from live or on-demand event broadcasting, to security and surveillance [1], to health communication [2], to disaster management [3], to economic forecasting [4]. In all these applications, forecasting the popularity of the content shared in a social network is vital due to a variety of reasons. For network and cloud service providers, accurate forecasting facilitates prompt and adequate reservation of computation, storage, and bandwidth resources [5], thereby ensuring smooth and robust content delivery at low costs. For advertisers, accurate and timely popularity prediction provides a good revenue indicator, thereby enabling targeted ads to be composed for specific videos and viewer demographics. For content producers and contributors, attracting a high number of views is paramount for attracting potential revenue through micro-payment mechanisms.

While popularity prediction is a long-lasting research topic [15] [14] [27] [28], understanding how social networks affect the popularity of the media content and using this understanding to make better forecasts poses significant new challenges. Conventional prediction tools have mostly relied on the history of the past view counts, which worked well when the popularity solely depended on the inherent attractiveness of the content and the recipients were generally passive. In contrast, social media users are proactive in terms of the content they watch and are heavily influenced by their social media interactions; for instance, the recipient of a certain media content may further forward it or not, depending on not only its attractiveness, but also the situational and contextual conditions in which this content was generated and propagated through social media [16]. For example, the latest measurement on Twitter's Vine, a highly popular short mobile video sharing service, has suggested that the popularity of a short video indeed depends less on the content itself, but more on the contributor's position in the social network [17]. Hence, being situation-aware, e.g. considering the content initiator's information and the friendship network of the sharers, can clearly improve the accuracy of the popularity forecasts. However, critical new questions need to be answered: which situational information extracted from social media should be used, how to deal with dynamically changing and evolving situational information, and how to use this information efficiently to improve the forecasts?

As social media becomes increasingly more ubiquitous and influential, the video propagation patterns and users' sharing behavior dynamically change and evolve as well. Offline prediction tools [15] [18] [19] [20] depend on specific training datasets, which may be biased or outdated, and hence may not accurately capture the real-world propagation patterns promoted by social media. Moreover, popularity forecasting is a *multi-stage* rather than a single-stage task since each video may be propagated through a cascaded social network for a relatively long time and thus, the forecast can be made at any time while the video is being propagated. A fast prediction

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has important economic and technological benefits; however, too early a prediction may lead to a low accuracy that is less useful or even damaging (e.g. investment in videos that will not actually become popular). The timeliness of the prediction has yet to be considered in existing works [14]-[20] [27] [28] which solely focus on maximizing the accuracy. Hence, we strongly believe that developing a systematic methodology for accurate and timely popularity forecasting is essential.

In this paper, we propose for the first time a systematic methodology and associated online algorithm for forecasting popularity of videos promoted by social media. Our Social-Forecast algorithm is able to make predictions about the popularity of videos while jointly considering the accuracy and the timeliness of the prediction. We explicitly consider the unique situational conditions that affect the video propagated in social media, and demonstrate how this *context information* can be incorporated to improve the accuracy of the forecasts. The unique features of Social-Forecast as well as our key contributions are summarized below:

- We rigorously formulate the online popularity prediction as a multi-stage sequential decision and online learning problem. Our solution, the Social-Forecast algorithm, makes multi-level popularity prediction in an online fashion, requiring no *a priori* training phase or dataset. It exploits the dynamically changing and evolving video propagation patterns through social media to maximize the prediction reward. The algorithm is easily tunable to enable tradeoffs between the accuracy and timeliness of the forecasts as required by various applications, entities and/or deployment scenarios.
- We analytically quantify the regret of Social-Forecast, that is, the performance gap between its expected reward and that of the best prediction policy which can be only obtained by an omniscient oracle having complete knowledge of the video popularity trends. We prove that the regret is sublinear in the number of video arrivals, which implies that the expected prediction reward asymptotically converges to the optimal expected reward. The upper bound on regret also gives a lower bound on the convergence rate to the optimal average reward.
- We validate Social-Forecast's performance through extensive experiments with real-world data traces from RenRen (the largest Facebook-like online social network in China). The results show that significant improvement can be achieved by exploiting the situational and contextual meta-data associated with the video and its propagation through the social media. Specifically, the Social-Forecast algorithm outperforms existing view-based approaches by more than 30% in terms of prediction rewards.

The rest of the paper is organized as follows. Section II discusses related works. In Section III, we describe the system model and rigorously formulate the online popularity prediction problem. Section IV presents a systematic methodology for determining the optimal prediction policy with complete prior knowledge of the video propagation pattern. In Section V, we propose the online learning algorithm for the optimal prediction policy and prove that it achieves sublinear regret bounds. Section VI discusses the experimental results and our findings. Section VII concludes this paper.

II. Related Works

In this section, we review the representative related works from both the application and the theoretical foundation perspectives.

A. Popularity Prediction for Online Content

Popularity prediction of online content has been extensively studied in the literature. Early works have focused on predicting the future popularity of content (e.g. video) on conventional websites such as YouTube. Various solutions are proposed based on time series models like ARIMA (Autoregressive integrated moving average) [6] [7] [8], regression models [9] [10] [11] and classification models [9] [12] [13]. These methods are generally view-based, meaning that the prediction of the future views is solely based on the early views, while disregarding the situational context during propagation. For instance, it was found that a high correlation exists between the number of video views on early days and later days on YouTube [14]. By using the history of views within the past 10 days, the popularity of videos can be predicted up to 30 days ahead [15]. While these predictions methods provide satisfactory performance for YouTube-like accesses, their performance is largely unacceptable [16] when applied to predicting popularity in the social media context. This is because in this case the popularity of videos evolves in a significantly different manner which is highly influenced by the situational and contextual characteristics of the social networks in which the video has propagated [21].

Recently, there have been numerous studies aiming to accurately predicting the popularity of content promoted by social media [2] [3] [23]-[26][43]. For instance, a propagation model is proposed in [18] to predict which users are likely to mention which URLs on Twitter. In [19], the retweets prediction on Twitter is modeled as a classification problem, and a variety of context-aware features are investigated. For predicting the popularity of news in Digg, such aspects as website design have been incorporated [20], and for predicting the popularity of short messages, the structural characteristics of social media have been used [22]. For video sharing in social media, our earlier work [16] has identified a series of context-aware factors which influence the propagation patterns.

Our work in this paper is motivated by these studies, but it is first systematic solution for forecasting the video popularity based on the situational and contextual characteristics of social media. First, existing works are mostly measurement-based and their solutions generally work offline, requiring existing training data sets. Instead, Social-Forecast operates entirely online and does not require any a priori gathered training data set. Second, Social-Forecast is situation-aware and hence it can inherently adapt on-the-fly to the underlying social network structure and user sharing behavior. Last but not least, unlike the early empirical studies which employ only simulations to validate the performance of their predictions, we can rigorously prove performance bounds for Social-Forecast.

Importantly, our Social-Forecast can be easily extended to predict other trends in social media (such as predicting who are the key influencers in social networks, which tweets and news items may become viral, which content may become popular or relevant etc.) by exploiting contextual and situational awareness. For instance, besides popularity, social media has been playing an increasingly important role in predicting present or near future events. Early studies show that the volume and the frequency of Twitter posts can be used to forecast box-office revenues for movies [23] and detect earthquakes [3]. Sentiment detection is investigated in [29] by exploring characteristics of how tweets are written and meta-information of the words that compose these messages. In [2], Google Trends uses search engine data to forecast near-term values of economic indicators, such as automobile sales, unemployment claims, travel destination planning, and consumer confidence. Social-Forecast can be easily adapted for deployment in these applications as well.

Table I provides a comprehensive comparison between existing works on popularity prediction and Social-Forecast, highlighting their differences.

	Situational awareness	Online/offline algorithm	Analytic performance	Multi-stage decision	Timeliness of prediction
Existing works	*No/Partially*	*Offline*	*No*	*No*	*No*
This paper	*Yes*	*Online*	*Yes*	*Yes*	*Yes*

TABLE I
COMPARISON WITH EXISTING WORKS ON POPULARITY PREDICTION FOR ONLINE CONTENT.

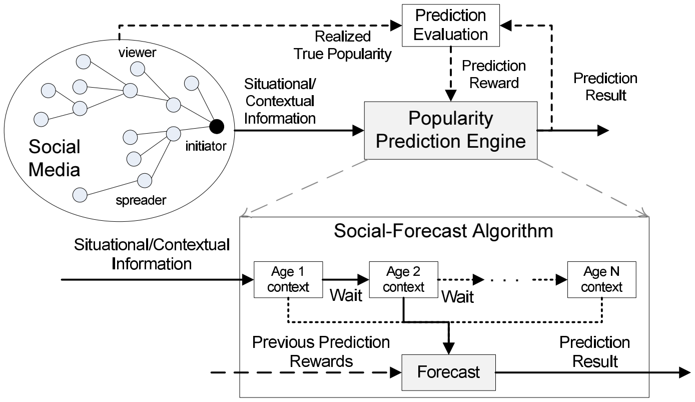

Fig. 1. System diagram.

B. Quickest Detection and Contextual Bandits Learning

In our problem formulation, for each video, the algorithm can choose to make a prediction decision using the currently observed context information or wait to make this prediction until the next period, when more context information arrives. This introduces a tradeoff between accuracy and delay which relates to the literature on quickest detection [30] [31] [32] which is concerned with the problem of detecting the change in the underlying state (which has already occurred in the past). For example, authors in [32] study how to detect the presence of primary users by taking channel sensing samples in cognitive radio systems. In the considered problem, there is no underlying state; in fact, the state is continuously and dynamically changing, and the problem becomes forecasting how it will evolve and which event will occur in the future. Moreover, many quickest detection solutions assume prior knowledge of the hypotheses [32] while this knowledge is unknown a priori in our problem and needs to be discovered over time to make accurate forecasts.

Our forecasting algorithm is based on the contextual bandits framework [33]-[37] but with significant innovations aimed at tackling the unique features of the online prediction problem. First, most of the prior work [34]-[37] on contextual bandits is focused on an agent making a single-stage decision based on the provided context information for each incoming instance. In this paper, for each incoming video instance, the agent needs to make a sequence of decisions at multiple stages. The context information is stage-dependent and is revealed only when that stage takes place. Importantly, the reward obtained by selecting an action at one stage depends on the actions chosen at other stages and thus, rewards and actions at different stages are coupled. Second, in existing works [33]-[37], the estimated rewards of an action can be updated only after the action is selected. In our problem, because the prediction action does not affect the underlying popularity evolution, rewards can be computed and updated even for actions that are not selected. In particular, we update the reward of an action as if it was selected. Therefore, exploration becomes virtual in the sense that explicit explorations are not needed and hence, in each period, actions with the best estimated rewards can always be selected, thereby improving the learning performance.

III. SYSTEM MODEL

A. Sharing Propagation and Popularity Evolution

We consider a generic Web 2.0 information sharing system in which videos are shared by users through social media (see Figure 1 for a system diagram). We assign each video with an index $k \in \{1, 2, ..., K\}$ according to the absolute time t_{init}^k when it is initiated[1]. Once a video is initiated, it will be propagated through the social media for some time duration. We assume a discrete time model where a period can be minutes, hours, days, or any suitable time duration. A video is said to have an age of $n \in \{1, 2, ...\}$ periods if it has been propagated through the social media for n periods. In each period, the video is further shared and viewed by users depending on the sharing and viewing status of the previous period. The propagation characteristics of video k up to age n are captured by a d_n-dimensional vector $\boldsymbol{x}_n^k \in \mathcal{X}_n$ which includes information such as the total number of views and other situational and contextual information such as the characteristics of the social network over which the video was propagated. The specific characteristics that we use in this paper will be discussed in Section VI. In this section, we keep $\boldsymbol{x}_n^k$ in an abstract form and call it succinctly the *context (and situational) information* at age n.

[1] It is easy to assign unique identifiers if multiple videos which are generated/initiated at the same time.

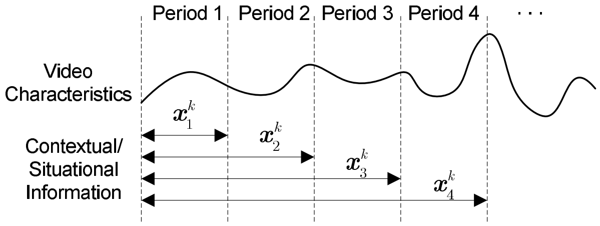

Fig. 2. An illustration of context information taking the history characteristics.

Several points regarding the context information are noteworthy. First, the context space $\mathcal{X}_n$ can be different at different ages n. In particular, $\boldsymbol{x}_n^k$ can include all history information of video k's propagation characteristics up to age n and hence $\boldsymbol{x}_n^k$ includes all information of $\boldsymbol{x}_m^k, \forall m < n$ (See Figure 2). Thus the type of contextual/situational information is also age-dependent. Second, $\boldsymbol{x}_n^k$ can be taken from a large space, e.g. a finite space with a large number of values or even an infinite space. For example, some dimensions of $\boldsymbol{x}_n^k$ (e.g. the Sharing Rate used in Section VI) take values from a continuous value space and $\boldsymbol{x}_n^k$ may include all the past propagation characteristics (e.g. $\boldsymbol{x}_m^k \in \boldsymbol{x}_n^k, \forall m < n$). Third, at age n, $\boldsymbol{x}_m^k, \forall m > n$ are not yet revealed since they represent future situational and contextual information which is yet to be realized. Hence, given the context information $\boldsymbol{x}_n^k$ at age n, the future context information $\boldsymbol{x}_m^k, \forall m > n$ are random variables.

We are interested in predicting the future popularity status of the video by the end of a pre-determined age N, and we aim to make the prediction as soon as possible. The choice of N depends on the specific requirements of the content provider, the advertiser and the web hosts. In this paper, we will treat N as given[2]. Thus, the context information for video k during its lifetime of N periods is collected in $\boldsymbol{x}^k = (\boldsymbol{x}_1^k, \boldsymbol{x}_2^k, ..., \boldsymbol{x}_N^k)$. For expositional simplicity, we also define $\boldsymbol{x}_{n^+} = (\boldsymbol{x}_{n+1}, ..., \boldsymbol{x}_N)$, $\boldsymbol{x}_{n^-} = (\boldsymbol{x}_1, ..., \boldsymbol{x}_{n-1})$ and $\boldsymbol{x}_{-n} = (\boldsymbol{x}_{n^-}, \boldsymbol{x}_{n^+})$.

Let $\mathcal{S}$ be the popularity status space, which is assumed to be finite. For instance, $\mathcal{S}$ can be either a binary space {Popular, Unpopular} or a more refined space containing multiple levels of popularity such as {Low Popularity, Medium Popularity, High Popularity} or any such refinement. We let s^k denote the popularity status of video k by the end of age N. Since s^k is realized only at the end of N periods, it is a random variable at all previous ages. However, the conditional distribution of s^k will vary at different ages since they are conditioned on different context information. In many scenarios, the conditional distribution at a higher age n is more informative for the future popularity status since more contextual information has arrived. Nevertheless, our model does not require this assumption to hold.

B. Prediction Reward

For each video k, at each age $n = 1, ..., N$, we can make a prediction decision $a_n^k \in \mathcal{S} \cup \{\text{Wait}\}$. If $a_n^k \in \mathcal{S}$, we predict a_n^k as the popularity status by age N. If $a_n^k = \text{Wait}$, we choose to wait for the next period context information to decide (i.e. predict a popularity status or wait again). When the prediction is used to make an one-shot decision (e.g. ad investment), introducing a "Wait" option is of significant importance to allow trade-off between accuracy and timeliness. For each video k, at the end of age N, given the decision action vector $\boldsymbol{a}^k$, we define the *age-dependent reward* r_n^k at age n as follows,

$$r_n^k = \begin{cases} U(a_n^k, s^k, n), & \text{if } a_n^k \in \mathcal{S} \\ r_{n+1}^k, & \text{if } a_n^k = \text{Wait} \end{cases} \tag{1}$$

where $U(a_n^k, s^k, n)$ is a reward function depending on the accuracy of the prediction (determined by a_n^k and the realized true popularity status s^k) and the timeliness of the prediction (determined by the age n when the prediction is made).

The specific form of $U(a_n^k, s^k, n)$ depends on how the reward is derived according to the popularity prediction based on various economical and technological factors. For instance, the reward can the ad revenue derived from placing proper ads for potential popular videos or the cost spent for adequately planning computation, storage, and bandwidth resources to ensure the robust operation of the video streaming services. Even though our framework allows any general form of the reward function, in our experiments (Section VI), we will use a reward function that takes the form of $U(a_n^k, s^k, n) = \theta(a_n^k, s^k) + \lambda\psi(n)$ where $\theta(a_n^k, s^k)$ measures the prediction accuracy, $\psi(n)$ accounts for the prediction timeliness and $\lambda > 0$ is a trade-off parameter that controls the relative importance of accuracy and timeliness.

Let n^* be the first age at which the action is not "Wait" (i.e. the first time a forecast is issued). The *overall prediction reward* is defined as the $r^k = r_{n^*}^k$. According to equation (1), when the action is "Wait" at age n, the reward is the same as that at age $n + 1$. Thus $r_1^k = r_2^k = ... = r_{n^*}^k$. This suggests that the overall prediction reward is the same as the age-dependent reward at age 1, i.e. $r^k = r_1^k$. For age $n > n^*$, the action a_k^n and the age-dependent reward r_n^k do not affect the realized overall prediction result since a prediction has already been made. However, we still select actions and compute the age-dependent reward since it helps learning the best action and the best reward for this age n which in turn will help decide whether or not we should wait at an early age. Figure 3 provides an illustration on how the actions at different ages determine the overall prediction reward.

Remark: The prediction action itself does not generate rewards. It is the action (e.g. online ad investment) taken using the prediction results that is rewarding. In many scenarios, this action can only be taken once and cannot be altered afterwards. This motivates the above overall reward function formulation in which the overall prediction reward is determined by the first non-"Wait" action. Nevertheless, our framework can also be easily extended to account for more general overall reward functions which may depend on all non-"Wait" actions. For instance, the action may be revised when a more accurate

[2] This assumption is generally valid given that the video sharing events have daily and weekly patterns, and the active lifespans of most shared videos through social media are quite limited [21].

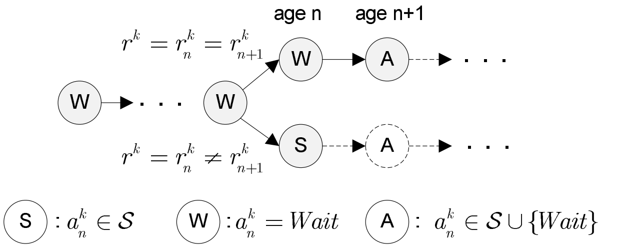
age n
age n+1
$r^k = r^k_n = r^k_{n+1}$
$r^k = r^k_n \neq r^k_{n+1}$
W
W
W
A
S
A
S : $a^k_n \in \mathcal{S}$
W : $a^k_n = Wait$
A : $a^k_n \in \mathcal{S} \cup \{Wait\}$

Fig. 3. An illustration for the multi-stage decision making. The first $n-1$ action is "Wait". If the age-n action is "Wait", then $r^k_n = r^k_{n+1}$ which depends on later actions. If the age-n action is not "Wait", then $r^k_n \neq r^k_{n+1}$ and r^k does not depend on later actions. However, we can still learn the reward of action at age $n+1$ as if all actions before $n+1$ were "Wait".

later prediction is made. In this case, the reward function $U(a^k_n, s^k, n)$ in (1) will depend on not only the current prediction action $a^k_n \in \mathcal{S}$ but also all non-"Wait" actions after age n. We will use the reward function in (1) because of its simplicity for the exposition but our analysis also holds for general reward functions.

C. Prediction Policy

In this paper, we focus on prediction policies that depend on the current contextual information. Let $\pi_n : \mathcal{X}_n \to \mathcal{S} \cup \{\text{Wait}\}$ denote the prediction policy for a video link of age n and $\pi = (\pi_1, ..., \pi_N)$ be the complete prediction policy. Hence, a prediction policy π prescribes actions for all possible context information at all ages. For expositional simplicity, we also define $\pi_{n^+} = (\pi_{n+1}, ..., \pi_N)$ as the policy vector for ages greater than n, $\pi_{n^-} = (\pi_1, ..., \pi_{n-1})$ as the policy vector for ages smaller than n and $\pi_{-n} = (\pi_{n^-}, \pi_{n^+})$. For a video with context information $\boldsymbol{x}^k$, the prediction policy π determines the prediction action at each age and hence the overall prediction reward, denoted by $r(\boldsymbol{x}|\pi)$, as well as the age-dependent rewards $r_n(\boldsymbol{x}|\pi), \forall n = 1, ..., N$. Let $f(\boldsymbol{x})$ be the probability distribution function of the video context information, which also gives information of the popularity evaluation patterns. The expected prediction reward of a policy π is therefore,

$$V(\pi) = \int_{\boldsymbol{x} \in \mathcal{X}} r(\boldsymbol{x}|\pi) f(\boldsymbol{x}) d\boldsymbol{x} \tag{2}$$

Note that the age-n policy π_n will only use the context information $\boldsymbol{x}_n$ rather than $\boldsymbol{x}$ to make predictions since $\boldsymbol{x}_{n^+}$ has not been realized at age n.

Our objective is to determine the optimal policy π^{opt} that maximizes the expected prediction reward, i.e. $\pi^{opt} = \arg\max_{\pi} V(\pi)$. In the following sections, we will propose a systematic methodology and associated algorithms that find the optimal policy for the case when $f(\boldsymbol{x})$ is known or unknown, which are referred to as the complete and incomplete information scenarios, respectively.

IV. Why Online Learning is Important?

In this section, we consider the optimal policy design problem with the complete information of the context distribution $f(\boldsymbol{x})$ and compute the optimal policy π^{opt}. In the next section in which $f(\boldsymbol{x})$ is unknown, we will learn this optimal policy π^{opt} online and hence, the solution that we derive in this section will serve as the benchmark. Even when having the complete information, determining the optimal prediction policy faces great challenges: first, the prediction reward depends on *all* decision actions at *all* ages; and second, when making the decision at age n, the actions for ages larger than n are not known since the corresponding context information has not been realized yet.

Given policies π_{-n}, we define the expected reward when taking action a_n for $\boldsymbol{x}_n$ as follows,

$$\mu_n(\boldsymbol{x}'_n|\pi_{-n}, a_n) = \int_{\boldsymbol{x}} I_{\boldsymbol{x}_n = \boldsymbol{x}'_n} r_n(\boldsymbol{x}|\pi_{-n}, a_n) f(\boldsymbol{x}) d\boldsymbol{x} \tag{3}$$

where $I_{\boldsymbol{x}_n = \boldsymbol{x}'_n}$ is an indicator function which takes value 1 when the age-n context information is $\boldsymbol{x}'_n$ and value 0 otherwise. The optimal $\pi^*(\pi_{-n})$ given π_{-n} thus can be determined by

$$\pi^*_n(\boldsymbol{x}_n|\pi_{-n}) = \arg\max_{a} \mu(\boldsymbol{x}_n|\pi_{-n}, a), \forall \boldsymbol{x}_n \tag{4}$$

and in which we break ties deterministically. Equation (4) defines a best response function from a policy to a new policy $F : \Pi \to \Pi$ where Π is the space of all policies. In order to compute the optimal policy π^{opt}, we iteratively use the best response function in (4) using the output policy computed in the previous iteration as the input for the new iteration. Note that a computation iteration is different from a time period. "Period" is used to describe the time unit of the discrete time model of the video propagation. A period can be a minute, an hour or any suitable time duration. In each period, the sharing and viewing statistics of a *specific* video may change. "Iteration" is used for the (offline) computation method for the optimal policy (which prescribes actions for *all* possible context information in *all* periods). Given the complete statistical information (i.e. the video propagation characteristics distribution $f(\boldsymbol{x})$) of videos, a new policy is computed using best response update in each iteration.

We prove the convergence and optimality of this best response update as follows.

Lemma 1. *$\pi^*_n(\boldsymbol{x}_n|\pi_{-n})$ is independent of $\pi_m, \forall m < n$, i.e. $\pi^*_n(\boldsymbol{x}_n|\pi_{-n}) = \pi^*_n(\boldsymbol{x}_n|\pi_{n^+})$.*

Proof: By the definition of age-dependent reward, the prediction actions before age n does not affect the age-n reward. Hence, the optimal policy depends only on the actions after age n. ■

Lemma 1 shows that the optimal policy π_n at age n is fully determined by the policies for ages larger than n but does not depend on the policies for ages less than n. Using this result, we can show the best response algorithm converges to the optimal policy within a finite number of computation iterations.

Theorem 1. *Starting with any initial policy π^0, the best response update converges to a unique point π^* in N computation iterations. Moreover, $\pi^* = \pi^{opt}$.*

Proof: Given the context distribution $f(\boldsymbol{x})$ which also implies the popularity evolution, the optimal age-N policy can be determined in the first iteration. Since we break ties deterministically when rewards are the same, the policy is unique. Given this, in the second iteration, the optimal age-$(N-1)$ policy can be determined according to (4) and is also unique. By induction, the best response update determines the unique optimal age-n policy after $N+1-n$ iterations. Therefore, the complete policy is found in N iterations and this policy maximizes the overall prediction reward. ■

Theorem 1 proves that we can compute the optimal prediction policy using a simple iterative algorithm as long as we have complete knowledge of the popularity evolution distribution. In practice, this information is unknown and extremely difficult to obtain, if not possible. One way to estimate this information is based on a training set. Since the context space is usually very large (which usually involves infinite number of values), a very large volume of training set is required to obtain a reasonably good estimation. Moreover, existing training sets may be biased and outdated as social media evolves. Hence, prediction policies developed using existing training sets may be highly inefficient [38]. In the following section, we develop learning algorithms to learn the optimal policy in an online fashion, requiring no initial knowledge of the popularity evolution patterns.

V. Learning the Optimal Forecasting Policy with Incomplete Information

In this section, we develop a learning algorithm to determine the optimal prediction policy without any prior knowledge of the underlying context distribution $f(\boldsymbol{x})$. In the considered scenario, videos arrive to the system in sequence[3] and we will make popularity prediction based on past experiences by exploiting the similarity information of videos.

Since we have shown in the last section that we can determine the complete policy π using a simple iterative algorithm, we now focus mainly on learning π_n for one age by fixing the policies π_{-n} for other ages. Importantly, we will provide not only asymptotic convergence results but also prediction performance bounds during the learning process.

A. Learning Regret

In this subsection, we define the performance metric of our learning algorithm. Let σ_n be a learning algorithm of π_n which takes action $\sigma_n^k(\boldsymbol{x}_n^k)$ at instance k. We will use learning regret to evaluate the performance of a learning algorithm. Since we focus on π_n, we will use simplified notations in this section by neglecting π_{-n}. However, keep in mind that the age-n prediction reward depends on actions at all later ages a_{n^+} besides a_n when $a_n = \text{Wait}$. Let $\mu_n(\boldsymbol{x}_n|a_n)$ denote the expected reward when age-n context information is $\boldsymbol{x}_n$ and the algorithm takes the action $a_n \in \mathcal{S} \cup \{\text{Wait}\}$.

The optimal action given a context $\boldsymbol{x}_n$ is therefore, $a^*(\boldsymbol{x}_n) = \arg\max_{a_n} \mu_n(\boldsymbol{x}_n|a_n)$ (with ties broken deterministically) and the optimal expected reward is $\mu_n^*(\boldsymbol{x}_n) = \mu_n(\boldsymbol{x}_n|a_n^*)$. Let $\Delta = \max_{\boldsymbol{x}_n \in \mathcal{X}_n}\{\mu_n^*(\boldsymbol{x}_n) - \mu_n(\boldsymbol{x}_n|a_n \neq a_n^*)\}$ be the maximum reward difference between the optimal action and the non-optimal action over all context $\boldsymbol{x}_n \in \mathcal{X}_n$. Finally, we let $r_n(\boldsymbol{x}_n^k|\sigma_n^k)$ be the realized age-n reward for video k by using the learning algorithm σ. The expected regret by adopting a learning algorithm σ_n is defined as

$$R_n(K) = \mathbb{E}\{\sum_{k=1}^{K} \mu_n^*(\boldsymbol{x}_n^k) - \sum_{k=1}^{K} r_n(\boldsymbol{x}_n^k|\sigma_n^k)\} \quad (5)$$

Our online learning algorithm will estimate the prediction rewards by selecting different actions and then choose the actions with best estimates based on past experience. The reward estimates of $a_n^k \in \mathcal{S}$ implicitly capture the likelihood of different popularity levels. The reward estimate of $a_n^k = \text{Wait}$ captures the reward of the best prediction strategy if the prediction is made at a later age. Thus our algorithm not only decides which prediction is the best at each age but also when to make the best prediction in order to maximize the prediction reward. One way to do this is to record the reward estimates without using the context/situational information. However, this could be very inefficient since for different contexts, the optimal actions can be very different. Another way is to maintain the reward estimates for each individual context $\boldsymbol{x}_n$ and select the action only based on these estimates. However, since the context space $\mathcal{X}_n$ can be very large, for a finite number K of video instances, the number of videos with the same context $\boldsymbol{x}_n$ is very small. Hence it is difficult to select the best action with high confidence. Our learning algorithm will exploit the similarity information of contexts, partition the context space into smaller subspaces and learn the optimal action within each subspace. The key challenge is how and when to partition the subspace in an efficient way. Next, we propose an algorithm that adaptively partitions the context space according the arrival process of contexts.

B. Online Popularity Prediction with Adaptive Partition

In this subsection, we propose the online prediction algorithm with adaptive partition (Adaptive-Partition) that adaptively partitions the context space according to the context arrivals. This will be the key module of the Social-Forecast algorithm. For analysis simplicity, we normalize the context space to be $\mathcal{X}_n = [0,1]^d$. We call a d-dimensional hypercube which has sides of length 2^{-l} a level l hypercube. Denote the partition of $\mathcal{X}_n$ generated by level l hypercubes by $\mathcal{P}_l$. We have $|\mathcal{P}_l| = 2^{ld}$. Let $\mathcal{P} := \cup_{l=0}^{\infty}\mathcal{P}_l$ denote the set of all possible hypercubes. Note that $\mathcal{P}_0$ contains only a single hypercube which is $\mathcal{X}_n$ itself. For each instance arrival, the algorithm keeps a set of hypercubes that cover the context space which are mutually exclusive. We call these hypercubes *active* hypercubes, and denote the set of active hypercubes at instance k by $\mathcal{A}_k$. Clearly, we have $\cup_{C\in\mathcal{A}_k} = \mathcal{X}_n$. Denote the active hypercube that contains $\boldsymbol{x}_n^k$ by C_k. Let $M_{C_k}(k)$ be the number of times context arrives to hypercube C_k by instance k. Once activated, a level l hypercube C will stay active until the first instance k such that $M_{C_k}(k) \geq A2^{pl}$ where $p > 0$ and $A > 0$ are algorithm design parameters. When a hypercube C_k of level l becomes inactive, the hypercubes of level $l+1$ that constitute C_k, denoted by $\mathcal{P}_{l+1}(C_k)$, are then activated.

[3] To simplify our analysis, we will assume that one video arrives at one time. Nevertheless, our framework can be easily extended to scenarios where multiple videos arrive at the same time.

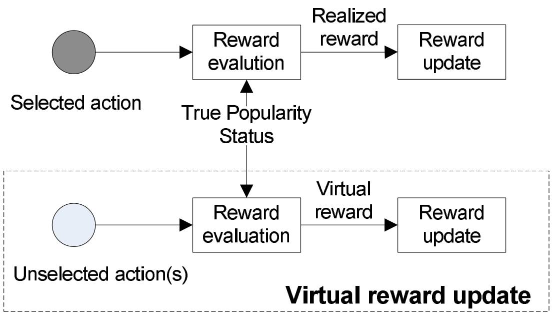

Fig. 4. Illustration for virtual reward update in Adaptive Partition.

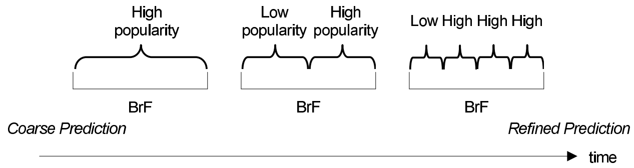

Fig. 5. Learning is refined by context space partitioning.

When a context $\boldsymbol{x}_n^k$ arrives, we first check to which active hypercube $C_k \in \mathcal{A}_k$ it belongs. Then we choose the action with the highest reward estimate $a_n = \arg\max_a \bar{r}_{a,C_k}(k)$, where $\bar{r}_{a,C_k}(k)$ is the sample mean of the rewards collected from action a in C_k which is an activated hypercube at instance k. When the prediction reward is realized for instance k (i.e. at the end of age N), we perform a *virtual update* for the reward estimates for all actions (see Figure 4). The reason why we can perform such a virtual update for actions which are not selected is because the context transition over time is independent of our prediction actions and hence, the reward by choosing any action can still be computed even though it is not realized.

Algorithm 1 provides a formal description for the Adaptive-Partition algorithm. Figure 6 illustrates the adaptive partition process of Adaptive-Partition algorithm. The intuition of our algorithm is as follows. Our algorithm learns the optimal action (whether to make a prediction or wait and which prediction to make) using sample mean reward estimates of different actions. The reward estimates are updated every time a new video instance comes and its popularity evolution pattern is realized. According to the law of large numbers, the reward estimates tend to be accurate as many videos have been seen. However, since there are a large number of different video evolution patterns, it is inefficient to maintain reward estimates for each pattern due to the small number of video instances for each individual pattern. Our algorithm exploits the similarity of video popularity evolution patterns to speed up learning. Specifically, initially we maintain reward estimates for the entire context space (i.e. by treating different patterns equally). These reward estimates are coarse but can be quickly updated since all video instances can be used. As we gather more video instances, the context space is gradually partitioned (i.e. by treating different patterns differently). As the partition becomes more and more refined, the reward estimates for each context subspace (i.e. cluster of patterns) become more and more accurate. Figure 5 illustrates the process of learning refinement assuming that the context only includes the BrF.

Algorithm 1 Adaptive-Partition Algorithm

```
Initialize $\mathcal{A}_1 = P_0$, $M_C(0) = 0$, $\bar{r}_{a,C}(0) = 0, \forall a, \forall C \in \mathcal{P}$.
for each video instance $k$ do
    Determine $C \in \mathcal{A}_k$ such that $\boldsymbol{x}_n^k \in C$.
    Select $a_n = \arg\max_a \bar{r}_{a,C}(k)$.
    After the prediction reward is realized, update $\bar{r}_{a,C}(k+1)$ for all $a$.
    Set $M_C(k) \leftarrow M_C(k-1) + 1$.
    if $M_C(k) \geq A2^{pl}$ then
        Set $\mathcal{A}_{k+1} = (\mathcal{A}_k \backslash C) \cup \mathcal{P}_{l+1}(C)$
    end if
end for
```

Next, we bound the regret by running the Adaptive-Partition algorithm. We make a widely adopted assumption [34] [35] [36] that the expected reward of an action is similar for similar contextual and situational information; we formalize this in terms of (uniform) Lipschitz condition.

Assumption. *(Lipschitz) For each $a_n \in \mathcal{S} \cup \{Wait\}$, there exists $L > 0, \alpha > 0$ such that for all $\boldsymbol{x}_n, \boldsymbol{x}'_n \in \mathcal{X}_n$, we have $|\mu(\boldsymbol{x}_n|a_n) - \mu(\boldsymbol{x}'_n|a_n)| \leq L\|\boldsymbol{x}_n, \boldsymbol{x}'_n\|^\alpha$.*

In order to get the regret bound of the Adaptive-Partition algorithm, we need to consider how many hypercubes of each level is formed by the algorithm up to instance K. The number of such hypercubes explicitly depends on the context arrival process. Therefore, we investigate the regret for different context arrival scenarios.

Definition. *We call the context arrival process* **the worst-case arrival process** *if it is uniformly distributed inside the context space, with minimum distance between any two context samples being $K^{-1/d}$, and* **the best-case arrival process** *if $\boldsymbol{x}^k \in C, \forall k$ for some level $\lceil (\log_2(K)/p \rceil + 1$ hypercube C.*

In Theorem 2, we determine the finite time, uniform regret bound for the Adaptive-Partition algorithm. The complete regret analysis and proofs can be found in the appendix.

Theorem 2.
- *For the worst case arrival process, if $p = \frac{3\alpha+\sqrt{9\alpha^2+8\alpha d}}{2}$, then $R_n(K) = O(K^{\frac{d+\alpha/2+\sqrt{9\alpha^2+8\alpha d}/2}{d+3\alpha/2+\sqrt{9\alpha^2+8\alpha d}/2}})$.*
- *For the best case arrival process, if $p = 3\alpha$, then $R_n(K) = O(K^{2/3})$.*

Proof: See Appendix. ■

The regret bounds proved in Theorem 2 are sublinear in K which guarantee convergence in terms of the average reward, i.e. $\lim_{K\to\infty} \mathbb{E}[R_n(K)]/K = 0$. Thus our online prediction algorithm makes the optimal predictions as sufficiently many videos instances have been seen. More importantly, the regret bound tells how much reward would be lost by running our learning algorithm for any finite number K of videos arrivals. Hence, it provides a rigorous characterization on the learning speed of the algorithm.

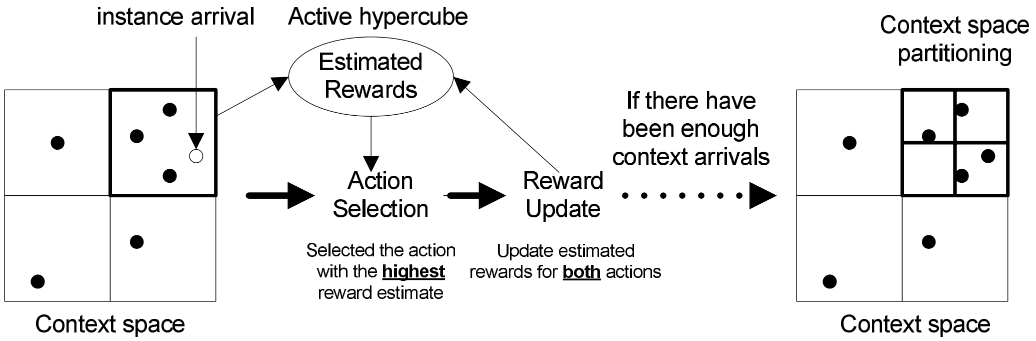
instance arrival
Active hypercube
Estimated Rewards
Action Selection
Reward Update
Selected the action with the highest reward estimate
Update estimated rewards for both actions
If there have been enough context arrivals
Context space partitioning
Context space
Context space

Fig. 6. The context space partitioning of the Adaptive-Partition algorithm.

C. Learning the Complete Policy π

In the previous subsection, we proposed the Adaptive-Partition algorithm to learn the optimal policy $\pi_n^*(\pi_{-n})$ by fixing π_{-n}. We now present in Algorithm 2 the Social-Forecast algorithm that learns the complete policy.

Algorithm 2 Social-Forecast Algorithm

```
for each video instance $k$ do
    for each age $n = 1$ to $N$ do
        Get context information $\boldsymbol{x}_n^k$.
        Select $a_n^k$ according to Adaptive-Partition.
        Perform context partition using Adaptive-Partition.
    end for
    Popularity status $s^k$ is realized.
    for each age $n = 1$ to $N$ do
        Compute the age-dependent reward $r_n^k$.
        Update reward estimates using Adaptive-Partition.
    end for
end for
```

Social-Forecast learns all age-dependent policies $\pi_n, \forall n$ simultaneously. For a given age n, since π_{-n} is not fixed to be the optimal policy π_{-n}^{opt} during the learning process, the learned policy π_n may not be the global optimal π_n^{opt}. However, as we have shown in Section IV, in order to determine π_n^{opt}, only the policies for ages greater than n, i.e. $\pi_{n^+}^{opt}$ need to be determined. Thus even though we are learning $\pi_n, \forall n$ simultaneously, the learning problem of π_N is not affected and hence, π_N^{opt} will be learned with high probability after a sufficient number of video arrivals. Once π_N^{opt} is learned with high probability, π_{N-1}^{opt} can also be learned with high probability after an additional number of video arrivals. By this induction, such a simultaneous learning algorithm can still learn the global optimal complete policy with high probability. In the experiments we will show the performance of this algorithm in practice.

D. Complexity of Social-Forecast

For each age of one video instance arrival, Social-Forecast needs to do one comparison operation and one update operation on the estimated reward of each forecast action. It also needs to update the counting of context arrivals to the current context subspace and perform context space partitioning if necessary. In sum, the time complexity has the order $O(|\mathcal{S}|N)$ for each video instance and $O(|\mathcal{S}|NK)$ for K video arrivals. Since the maximum age N of interest and the popularity status space is given, the time complexity is linear in the number of video arrivals K. The Social-Forecast algorithm maintains for each *active* context subspace reward estimates of all forecast actions. Each partitioning creates $2^d - 1$ more *active* context subspaces and the number of partitioning is at most K/A. Thus the space complexity for K video arrivals is at most $O(2^d NK/A)$. Since the context space dimension d and the algorithm parameter A are given and fixed, the space complexity is at most linear in the number of video arrivals K.

VI. Experiments

In this section we evaluate the performance of the proposed Social-Forecast algorithm. We will first examine the unique propagation characteristics of videos shared through social media. Then we will use these as the context (and situational) information for our proposed online prediction algorithm. Our experiments are based on the dataset that tracks the propagation process of videos shared on RenRen (`www.renren.com`), which is one of the largest Facebook-like online social networks in China. We set one period to be 2 hours and are interested in predicting the video popularity by 100 periods (8.3 days) after its initiation. In most of our experiments, we will consider a binary popularity status space {Popular, Unpopular} where "Popular" is defined for videos whose total number of views exceeds 10000. However, we also conduct experiments on a more refined popularity status space in Section VI(F).

Since our algorithm does not rely on specific assumptions on the selected reward function, we use two different prediction reward functions in our experiment in order to show the generality of our method. The first prediction reward function takes a linear form of accuracy and timeliness, namely $U(a_n^k, s^k, n) = \theta(a_n^k, s^k) + \lambda\psi(n)$ where $\theta(a_n^k, s^k)$ represents the accuracy of the prediction, $\psi(n)$ is the timeliness of the prediction and λ is a trade-off parameter. In particular, ψ is simply taken as $\psi(n) = N - n$. The second prediction reward function takes a discounted form of accuracy, namely $U(a_n^k, s^k, n) = \delta^n\theta(a_n^k, s^k)$ where $\delta \in [0, 1)$ is a discounted factor. For the case of binary popularity status space, the accuracy reward function θ is chosen as follows

$$\theta(a_n^k, s^k) = \begin{cases} 1, & \text{if } a_n^k = s^k = \text{Unpopular} \\ w, & \text{if } a_n^k = s^k = \text{Popular} \\ 0, & \text{if } a_n^k \neq s^k \end{cases} \quad (6)$$

where $w > 0$ is fixed reward for correctly predicting popular videos and hence controls the relative importance of true positive and true negative. Note that we use these specific reward functions in this experiment but other reward functions can easily be adopted in our algorithm.

A. *Video propagation characteristics*

A RenRen user can post a link to a video taken by him/herself or from an external video sharing website such as Youtube. The user, referred to as an *initiators* [16], then starts the sharing process. The friends of these initiators can find this video in their "News Feed". Some of them may watch this video and some may re-share the video to their own friends. We call the users who watched the shared video *viewers* and those who re-shared the video *spreaders*. Since spreaders generally watched the video before re-shared it, most of them are also viewers. In the experiment, we will use two characteristics of videos promoted by social media as the context (and situational) information for our algorithm. The first is the initiator's *Branching Factor (BrF)*, which is the number of users who are directly following the initiator and viewed the video shared by initiator. The second is the *Share Rate (ShR)*, which is the ratio of the viewers that re-share the video after watching it. Figure 7 shows the evolution of the number of views, the BrF and the ShR for three representative videos over 100 periods. Among these three videos, video 1 is an unpopular video while video 2 and video 3 are popular videos, which become popular at age 37 and age 51, respectively. We analyze the differences between popular and unpopular videos as follows.

- *Video 1 vs Video 2*. The ShRs of both videos are similar. The BrF of video 2 is much larger than that of video 1. This indicates that video 2 may be initiated by users with a large number of friends, e.g. celebrities and pubic accounts. Thus, videos with larger BrF potentially will achieve popularity in the future.
- *Video 1 vs Video 3*. The BrFs of both videos are low (at least before video 3 becomes popular). Video 3 has a much larger ShR than video 1. This indicates that video 3 is being shared with high probability and thus, videos with larger ShR will potentially become popular in the future.

The above analysis shows that BrF and ShR are good situational metrics for videos promoted by social media. Therefore we will use these two metrics in addition to the total and per-period numbers of views as the context information for our proposed online prediction algorithms. The RenRen raw dataset records the information of each viewing action on RenRen. In particular, each data entry includes the URL of the video, the viewer id, the sharer id, the two-hop sharer id, the initiator and the time stamp when the view occurs. We pre-processed the raw dataset and extract for each video URL the viewing and sharing behavior over time such as BrF and ShR. Nevertheless, our algorithms are general enough to take other situational metrics to further improve the prediction performance, e.g. the type of the videos, the number of spreaders, other metrics representing the propagation topology etc.

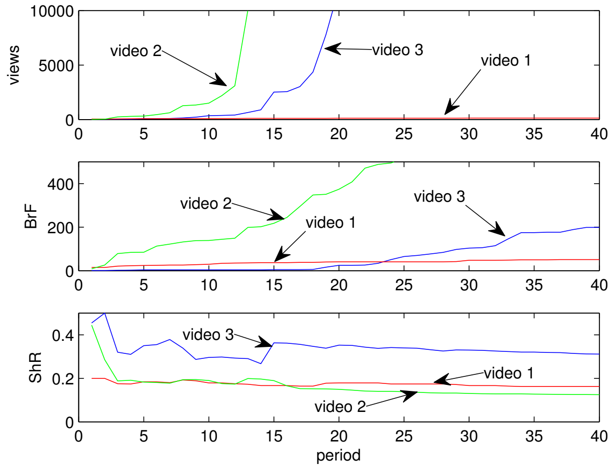

Fig. 7. Popularity evolution of 3 representative videos.

B. *Benchmarks*

We will compare the performance of our online prediction algorithm with three benchmarks.

- **Szabo and Huberman (SH)**. The first benchmark is a conventional view-based prediction algorithm based on [15]. It uses training sets to establish log-linear correlations between the early number of views and the later number of views. Since this algorithm does not explicitly consider timeliness in prediction, we will investigate different versions that make predictions at different ages. Intuitively, the time when the prediction is made has opposite affects on the prediction accuracy and timeliness. A later prediction predicts the video with higher confidence but is less timely.
- **Pinto, Almeida and Goncalves (PAG)**. This benchmark is also a view-based prediction algorithm [28]. Unlike SH which uses only the total view count by a reference time to predict future popularity, PAG incorporates the per-period view counts up to the reference date. Again, since this algorithm does not explicitly consider timeliness in prediction, we will also investigate different versions that make predictions at different ages.
- **Correlation using context information (CC)**. The above two benchmarks do not use siutational/contextual information as our proposed algorithm does. To enable fair comparison, we develop a modified prediction algorithm based on the ideas of SH and PAG by taking into consideration also the situational/contextual information. Specifically, the algorithm establishes (log-)linear correlations between the early number of views together with the context information (i.e. BrF and ShR) and the later number of views.

- **Perfect Prediction**. The last benchmark provides the best prediction results: for each unpopular video, it predicts unpopular at age 1; for each popular video, it predicts popular at age 1. Since this benchmark generates the highest possible prediction reward, we normalize the rewards achieved by other algorithms with respect to this reward.

C. Performance comparison

In this subsection, we compare the prediction performance of our proposed algorithm with the benchmarks. This set of experiments are carried out on a set of 5000 video links. The videos were initiated in sequence and thus, initially we do not have any knowledge of the videos or video popularity evolution patterns. For the SH (or PAG, CC) algorithm, we use three versions, labeled as SH-5 (or PAG-5, CC-5), SH-10 (or PAG-10, CC-10), SH-15 (or PAG-15, CC-15), in which the prediction is made at age 5, 10, 15, respectively.

Table II records the normalized prediction rewards (column 2 to 4) and the prediction accuracy (column 5) obtained by our proposed algorithm and the benchmarks for $\lambda = 0.01$ and $w = 1, 2, 3$ given the reward function $U(a_n^k, s^k, n) = \theta(a_n^k, s^k) + \lambda\psi(n)$. Table III records the normalized prediction rewards obtained by our proposed algorithm and the benchmarks for $w = 1$ and $\lambda = 0.01, 0.015, 0.02$. The trade-off parameter λ for accuracy and timeliness is set to be small because the lifetime N is large. We have the following observations:

- The accuracies of all three benchmarks are increasing in the reference age when the forecast is made. It implies that having more information is helpful for the prediction. The prediction rewards of the benchmarks are relatively insensitive to the time when the forecast is issued. This is because even though accuracy improves when the reference age is large, the prediction timeliness decreases. These two effects almost balance out in our experiments.
- The proposed algorithm Social-Forecast generates significantly higher prediction rewards than all benchmark algorithms. Its performance is not sensitive to the specific value of w which implies that it is able to predict both popular and unpopular videos very accurately and in a timely manner.

Table IV shows the corresponding results for $\delta = 0.99$ given $U(a_n^k, s^k, n) = \delta^n\theta(a_n^k, s^k)$. We obtain similar observations even though a different reward function is used.

We then vary the popularity threshold. Table V reports the prediction rewards and accuracies for different thresholds 10000, 30000, 50000 for SH-10, PAG-10, CC-10 and Social-Forecast by fixing $\lambda = 0.01$ and $w = 1$ given the reward function $U(a_n^k, s^k, n) = \theta(a_n^k, s^k) + \lambda\psi(n)$. As the popularity threshold increases, the rewards and accuracies obtained by the Social-Forecast algorithm and SH-10 and PAG-10 all increase. In particular, the PAG algorithm has a significant increase in the prediction accuracy. This suggests that these benchmark algorithms have better accuracy in videos with a large number of views. However, the proposed Social-Forecast significantly outperforms the benchmarks in all categories.

TABLE II
COMPARISON OF NORMALIZED PREDICTION REWARD WITH VARYING w $(U(a_n^k, s^k, n) = \theta(a_n^k, s^k) + \lambda\psi(n))$

	$w = 1$	$w = 2$	$w = 3$	accuracy
SH-5	0.82	0.82	0.81	0.80
SH-10	0.80	0.80	0.80	0.83
SH-15	0.78	0.80	0.81	0.84
PAG-5	0.71	0.77	0.80	0.64
PAG-10	0.79	0.82	0.84	0.81
PAG-15	0.78	0.82	0.85	0.85
CC-5	0.82	0.81	0.81	0.79
CC-10	0.79	0.80	0.81	0.80
CC-15	0.82	0.83	0.84	0.89
Social-Forecast	0.92	0.93	0.94	0.94

TABLE III
COMPARISON OF NORMALIZED PREDICTION REWARD WITH VARYING λ $(U(a_n^k, s^k, n) = \theta(a_n^k, s^k) + \lambda\psi(n))$

	$\lambda = 0.01$	$\lambda = 0.015$	$\lambda = 0.02$
SH-5	0.82	0.82	0.83
SH-10	0.80	0.79	0.79
SH-15	0.78	0.76	0.75
PAG-5	0.71	0.73	0.74
PAG-10	0.79	0.79	0.78
PAG-15	0.78	0.76	0.75
CC-5	0.82	0.82	0.83
CC-10	0.79	0.79	0.78
CC-15	0.82	0.79	0.78
Social-Forecast	0.92	0.93	0.94

D. Learning performance

Our proposed Social-Forecast algorithm is an online algorithm and does not require any prior knowledge of the video popularity evolution patterns. Hence, it is important to investigate the prediction performance during the learning process. Our analytic results have already provided sublinear bounds on the prediction performance for any given number of video instances which guarantee the convergence to the optimal prediction policy. Now, we show how much prediction

TABLE IV
COMPARISON OF NORMALIZED PREDICTION REWARD WITH VARYING w $(U(a_n^k, s^k, n) = \delta^n\theta(a_n^k, s^k))$

	$w = 1$	$w = 2$	$w = 3$	accuracy
SH-5	0.76	0.76	0.76	0.80
SH-10	0.75	0.74	0.73	0.83
SH-15	0.73	0.74	0.74	0.84
PAG-5	0.61	0.69	0.75	0.64
PAG-10	0.73	0.76	0.77	0.81
PAG-15	0.73	0.76	0.78	0.85
CC-5	0.76	0.76	0.76	0.79
CC-10	0.74	0.74	0.75	0.80
CC-15	0.77	0.77	0.77	0.89
Social-Forecast	0.92	0.91	0.92	0.92

TABLE V
COMPARISON OF NORMALIZED PREDICTION REWARD AND ACCURACY WITH VARYING POPULARITY THRESHOLD (IN EACH ENTRY, THE FIRST NUMBER IS THE REWARD, THE SECOND NUMBER IS THE ACCURACY)

	SH-10	PAG-10	CC-10	Social-Forecast
1e4	0.80, 0.83	0.79, 0.81	0.79, 0.80	0.92, 0.94
3e4	0.81, 0.82	0.86, 0.90	0.83, 0.90	0.94, 0.96
5e4	0.84, 0.87	0.85, 0.89	0.81, 0.88	0.95, 0.96

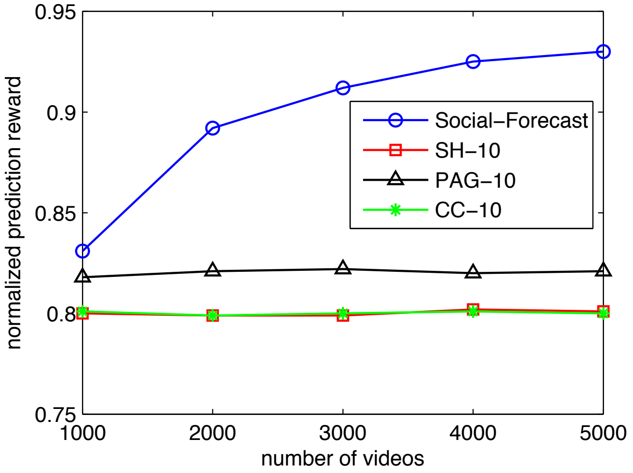

Fig. 8. Prediction performance during the learning process.

reward that we can achieve during the learning process in experiments. Figure 8 shows the normalized prediction reward of Social-Forecast, SH-10, PAG-10 and CC-10 as the number of video instances increases for $\lambda = 0.10$ and $w = 2$. As more video instances arrive, our algorithm learns better the optimal prediction policy and hence, the prediction reward improves with the number of video instances. In particular, the proposed prediction algorithm is able to achieve more than 85% of the best possible reward even with a relatively small number of video instances. On the other hand, the normalized prediction rewards of the benchmark algorithms stay nearly invariant since they are trained offline and do not adapt to the new arriving videos.

E. More refined popularity prediction

In the previous experiments, we considered a binary popularity status space. Nevertheless, our proposed popularity prediction methodology and associated algorithm can also be applied to predict popularity in a more refined space. In this experiment, we consider a refined popularity status space {High Popularity, Medium Popularity, Low Popularity} where "High Popularity" is defined for videos with more than TH_1 views, "Medium Popularity" for videos with views between $TH_2 < TH_1$ and TH_1, and "Low Popularity" for videos with views below TH_2. Table VI illustrates the normalized rewards and accuracy obtained by different algorithms for $\lambda = 0.01, 0.02, 0.03$ and $TH_1 = 10000$, $TH_2 = 5000$. Table VII reports the normalized rewards and accuracy of Social-Forecast, SH-10, PAG-10 and CC-10 by varying the High popularity threshold TH_1 given $\lambda = 0.02, w = 1$. It can been seen that the rewards obtained by all algorithms decrease compared with the binary popularity status case since prediction becomes more difficult. However, the performance improvement of Social-Forecast against the benchmark solutions becomes even larger. This suggests that our algorithm, which explicitly considers the contextual information associated with the social network, is able to achieve a higher performance gain against the benchmark approaches for more refined popularity prediction.

TABLE VI
COMPARISON OF NORMALIZED PREDICTION REWARD FOR TERNARY POPULARITY LEVELS.

	$\lambda = 0.01$	$\lambda = 0.02$	$\lambda = 0.03$	accuracy
SH-5	0.71	0.75	0.78	0.63
SH-10	0.72	0.72	0.74	0.74
SH-15	0.70	0.68	0.68	0.76
PAG-5	0.66	0.71	0.75	0.57
PAG-10	0.74	0.74	0.74	0.73
PAG-15	0.73	0.70	0.69	0.76
CC-5	0.73	0.77	0.79	0.66
CC-10	0.73	0.73	0.74	0.72
CC-15	0.73	0.71	0.70	0.79
Social-Forecast	0.92	0.94	0.86	0.90

TABLE VII
COMPARISON OF NORMALIZED PREDICTION REWARD AND ACCURACY WITH VARYING POPULARITY THRESHOLD (IN EACH ENTRY, THE FIRST NUMBER IS THE REWARD, THE SECOND NUMBER IS THE ACCURACY)

	SH-10	PAG-10	CC-10	Social-Forecast
1e4	0.72, 0.74	0.74, 0.73	0.74, 0.72	0.94, 0.90
3e4	0.75, 0.75	0.79, 0.81	0.79, 0.81	0.91, 0.94
5e4	0.76, 0.74	0.77, 0.78	0.75, 0.75	0.89, 0.92

F. Prediction timeliness

Finally, we investigate at which age the forecast is actually made by our proposed Pop-Forecast algorithm. Figure 9 shows the percentage of the forecasts made at ages between 1 to 10 for the cases of binary and ternary popularity levels. As we can see, most of our forecasts are made at early ages of the video propagation, yet the accuracy is still very high by incorporating the contextual information of the social network in which the video is propagated.

VII. CONCLUSIONS AND FUTURE WORK

In this paper, we have proposed a novel, systematic and highly-efficient online popularity forecasting algorithm for videos promoted by social media. We have shown that by incorporating situational and contextual information, significantly better prediction performance can be achieved than existing approaches which disregard this information and only consider the number of times that videos have been viewed so far. The proposed Social-Forecast algorithm does not require prior knowledge of popularity evolution or a training set and hence can operate easily and successfully in online, dynamically-changing environments such as social

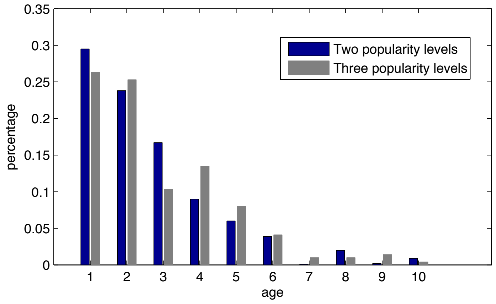

Fig. 9. Distribution of ages at which the forecasts are made.

TABLE VIII
NOTATION TABLE

Notation	Description
$M_C(k)$	number of arrivals to C by k
$D(k)$	deterministic control function, $D(k) = k^z \log k$
$\mathcal{E}_{a,C}(k)$	set of rewards collected from action a by k for C
$a^*(C)$	optimal action for the center context of C
$\bar{\mu}_{a,C}$	maximum expected reward for contexts in C by taking a
$\underline{\mu}_{a,C}$	minimum expected reward for contexts in C by taking a
$\mathcal{L}_{C,l,B}$	suboptimal action set for C with level l given parameter B
A, p	algorithm parameters
L, α	Lipschitz condition parameters
$\mathcal{W}_C(k)$	event that the algorithm virtually exploits in C at k
$\mathcal{V}_{a,C}(k)$	event that a suboptimal action a is chosen in C at k
H_k	a positive number measuring the estimation gap

media. We have systematically proven sublinear regret bounds on the performance loss incurred by our algorithm due to online learning. Thus Social-Forecast guarantees both short-term performance as well as its asymptotic convergence to the optimal performance in the long term.

This paper considered a single learner who observes the propagation patterns of videos promoted by one social media. One important future work direction is to extend to scenarios where there are multiple distributed learners (e.g. multiple advertisers, content producers and web hosts) who have access to multiple different social medias or different sections of one social media. In such scenarios, significant improvement is expected by enabling cooperative learning among the distributed learners [39]. The challenges in these scenarios are how to design efficient cooperative learning algorithms with low communication complexity [40] and, when the distributed learners are self-interested and have conflicting goals, how to incentivize them to participate in the cooperative learning process using, e.g. rating mechanisms [41] [42]. Finally, while this paper has studied the specific problem of online prediction of video popularity based on contextual and situational information, our methodology and associated algorithm can be easily adapted to predict other trends in social media (such as identifying key influencers in social networks, the potential for becoming viral of contents or tweets, identifying popular or relevant content, providing recommendations for social TV etc.).

APPENDIX

In this appendix, we analyze the learning regret of the Adaptive-Partition algorithm. The notations are summarized in Table VIII. To facilitate the analysis, we artificially create two learning steps in the algorithms: for each instance k, it belongs to either a *virtual exploration* step or a *virtual exploitation* step. Let $M_C(k)$ be the number of context arrivals in C by video instance k. Given a context $\boldsymbol{x}_n^k \in C$, which step the instance k belongs to depends on $M_C(k)$ and a deterministic function $D(k)$. If $M_C(k) \leq D(k)$, then it is in a virtual exploration step; otherwise, it is in a virtual exploitation step. Notice that these steps are only used in the analysis; in the implementation of the algorithm, these different steps do not exist and are not needed.

We introduce some notations here. Let $\mathcal{E}_{a,C}(k)$ be the set of rewards collected from action a by instance k for hypercube C. For each hypercube C let $a^*(C)$ be the action which is optimal for the center context of that hypercube, and let $\bar{\mu}_{a,C} := \sup_{\boldsymbol{x} \in C} \mu(\boldsymbol{x}|a)$ and $\underline{\mu}_{a,C} := \inf_{\boldsymbol{x} \in C} \mu(\boldsymbol{x}|a)$. For a level l hypercube C, the set of suboptimal action is given by

$$\mathcal{L}_{C,l,B} := \{a : \underline{\mu}_{a^*,C} - \bar{\mu}_{a,C} > BLd^{\alpha/2}2^{-l\alpha}\} \tag{7}$$

colorwhere $B > 0$ is a constant that will be determined later.

The regret can be written as a sum of three components:

$$R(K) = \mathbb{E}[R_e(K)] + \mathbb{E}[R_s(K)] + \mathbb{E}[R_n(K)] \tag{8}$$

where $R_e(K)$ is the regret due to virtual exploration steps by instance K, $R_s(K)$ is the regret due to sub-optimal action selection in virtual exploitation steps by instance K and $R_n(K)$ is the regret due to near-optimal action selections in virtual exploitation steps by instance K. The following series of lemmas bound each of these terms separately.

We start with a simple lemma which gives an upper bound on the highest level hypercube that is active at any instance k.

Lemma 2. *All the active hypercubes $\mathcal{A}_k$ at instance k have at most a level of* $(\log_2 k)/p + 1$.

Proof: Let $l + 1$ be the level of the highest level active hypercube. Since there are totally k instances, we must have $\sum_{j=1}^{l} A2^{pj} < k$, otherwise the highest level active hypercube will be less than $l + 1$. Summing up the left-hand side, we have for $k/A > 1$,

$$A\frac{2^{p(l+1)-1}}{2^p - 1} < k \Rightarrow 2^{pl} < \frac{k}{A} \Rightarrow l < \frac{\log_2(k)}{p} \tag{9}$$

■

The next three lemmas bound the regrets for any level l hypercube.

Lemma 3. *If $D(k) = k^z \log k$. Then, for any level l hypercube the regret due to virtual explorations by instance k is bounded above by* $k^z \log k + 1$.

Proof: Since the instance k belongs to a virtual exploration step if and only if $M_C(k) \leq D(k)$, up to instance K, there can be at most $\lceil k^z \log k \rceil$ virtual exploration steps for one hypercube. Therefore, the regret is bounded by $k^z \log k + 1$. ■

Lemma 4. *Let $B = \frac{2}{Ld^{\alpha/2}2^{-\alpha}} + 2$. If $p > 0, 2\alpha/p \leq z < 1$, $D(k) = k^z \log k$, then for any level l hypercube C, the regret due to choosing suboptimal actions in virtual exploitation steps, i.e. $\mathbb{E}[R_{C,s}(K)]$, is bounded above by* $2\beta_2$.

Proof: Let Ω denote the space of all possible outcomes, and w be a sample path of the reward realization. The event that the algorithm virtually exploits in C at instance k occurs when exploitation condition holds and the current context falls in an active hypercube C and thus is given by

$$\mathcal{W}_C(k) := \{w : M_C(k) > D(k), \boldsymbol{x}_n^k \in C, C \in \mathcal{A}_k\}$$

We will bound the probability that the algorithm chooses a suboptimal arm in an virtual exploitation step in C, and then bound the expected number of times a suboptimal action is chosen by the algorithm. Recall that loss in every step is at most 1. Let $\mathcal{V}_{a,C}(k)$ be the event that a suboptimal action is chosen. Then

$$\mathbb{E}[R_{C,s}(K)] \leq \sum_{k=1}^{K} \sum_{a\in\mathcal{L}_{C,l,B}} P(\mathcal{V}_{a,C}(k), \mathcal{W}_C(k))$$

For any a, we have

$$\begin{aligned}&\{\mathcal{V}_{a,C}(k), \mathcal{W}_C(k)\}\\ \subset&\{\bar{r}_{a,C}(k) \geq \bar{\mu}_{a,C} + H_k, \mathcal{W}_C(k)\}\\ &\cup \{\bar{r}_{a^*,C}(k) \leq \underline{\mu}_{a^*,C} - H_k, \mathcal{W}_C(k)\}\\ &\cup \{\bar{r}_{a,C}(k) \geq \bar{r}_{a^*,C}(k), \bar{r}_{a,C}(k) < \bar{\mu}_{a,C} + H_k,\\ &\bar{r}_{a^*,C}(k) > \underline{\mu}_{a^*,C} - H_k, \mathcal{W}_C(k)\}\end{aligned}$$

for some positive number $H_k > 0$ that controls the reward estimate gap which will be determined later. This implies

$$\begin{aligned}&P(\mathcal{V}_{a,C}(k), \mathcal{W}_C(k))\\ \leq& P(\bar{r}^{best}_{a,C}(M_C(k)) \geq \bar{\mu}_{a,C} + H_k + Ld^{\alpha/2}2^{-l\alpha}, \mathcal{W}_C(k))\\ +&P(\bar{r}^{worst}_{a^*,C}(M_C(k)) \leq \underline{\mu}_{a^*,C} - H_k - Ld^{\alpha/2}2^{-l\alpha}, \mathcal{W}_C(k))\\ +&P(\bar{r}^{best}_{a,C}(M_C(k)) \geq \bar{r}^{worst}_{a^*,C}(M_C(k)),\\ &\quad \bar{r}^{best}_{a,C}(M_C(k)) < \bar{\mu}_{a,C} + H_k,\\ &\quad \bar{r}^{worst}_{a^*,C}(M_C(k)) > \underline{\mu}_{a^*,C} - H_k, \mathcal{W}_C(k))\end{aligned}$$

Consider the last term in the above equation, we want to make it zero so that we can focus only on the first two terms. If $2H_k \leq (B-2)Ld^{\alpha/2}2^{-l\alpha}$, then the three events in the last term cannot happen simultaneously. Thus, if we let $H_k = k^{-z/2}$, $z \geq 2\alpha/p$ and $B = \frac{2}{Ld^{\alpha/2}2^{-\alpha}} + 2$, then the last probability is 0. For the first two terms, by using a Chernoff-Hoeffding bound, for any $a \in \mathcal{L}_{C,l,B}$, since on the event $\mathcal{W}_C(k)$, $M_C(k) \geq k^z \log k$, we have

$$\begin{aligned}&P(\bar{r}^{best}_{a,C}(M_C(k)) \geq \bar{\mu}_{a,C} + H_k, \mathcal{W}_C(k))\\ \leq& e^{-2(H_k)^2 k^z \log k} \leq e^{-2\log k} \leq \frac{1}{k^2}\end{aligned}$$

and

$$\begin{aligned}&P(\bar{r}^{worst}_{a^*,C}(M_C(k)) \leq \underline{\mu}_{a^*,C} - H_k, \mathcal{W}_C(k))\\ \leq& e^{-2(H_k)^2 k^z \log k} \leq e^{-2\log k} \leq \frac{1}{k^2}\end{aligned}$$

Finally, the regret due to virtual exploitation is bounded by $\sum_{k=1}^{K} \frac{1}{k^2} < \beta_2$. Therefore, $\mathbb{E}[R_{C,s}(K)] \leq 2\beta_2$. ■

Lemma 5. *Let* $B = \frac{2}{Ld^{\alpha/2}2^{-\alpha}} + 2$. *If* $p > 0, 2\alpha/p \leq z < 1$, $D(k) = k^z \log k$, *then for any level* l *hypercube* C, *the regret due to choosing near optimal actions in virtual exploitation steps, i.e.* $\mathbb{E}[R_{C,n}(K)]$, *is bounded above by* $2ABLd^{\alpha/2}2^{(p-\alpha)l}$.

Proof: The one-step regret of any near optimal action a is bounded by $2BLd^{\alpha/2}2^{-l\alpha}$ according to the definition of near optimal actions. Since C remains active for at most $A2^{pl}$ context arrivals, we have

$$\mathbb{E}[R_{C,n}(K)] \leq 2ABLd^{\alpha/2}2^{(p-\alpha)l} \tag{10}$$

■

Now we are ready to prove Theorem 2.

Proof: We let $B = \frac{2}{Ld^{\alpha/2}2^{-\alpha}} + 2$.

Consider the worst-case. It can be shown that in the worst case the highest level hypercube has level at most $1 + \log_{2^{p+d}} K$. The total number of hypercubes is bounded by

$$\sum_{l=0}^{1+\log_{2^{p+d}} K} 2^{dl} \leq 2^{2d} K^{\frac{d}{d+p}} \tag{11}$$

We can calculate the regret from choosing near optimal action as

$$\mathbb{E}[R_n(K)] \leq 2ABLd^{\alpha/2} \sum_{l=0}^{1+\log_{2^{p+d}} K} 2^{(p-\alpha)l} \tag{12}$$

$$\leq 2ABLd^{\alpha/2}2^{2(d+p-\alpha)}K^{\frac{d+p-\alpha}{d+p}} \tag{13}$$

Since the number of hypercubes is $O(K^{\frac{d}{d+p}})$, regret due to virtual explorations is $O(K^{\frac{d}{d+p}+z}\log K)$, while regret due to suboptimal selection is $O(K^{\frac{d}{d+p}+z})$, for $z \geq \frac{2\alpha}{p}$. These three terms are balanced when $z = 2\alpha/p$ and $\frac{d+p-\alpha}{d+p} = \frac{d}{d+p} + z$. Solving for p we get

$$p = \frac{3\alpha + \sqrt{9\alpha^2 + 8\alpha d}}{2} \tag{14}$$

Substituting these parameters and summing up all the terms we get the regret bound.

Consider the best case, the number of activated hypercubes is upper bounded by $\log_2 K/p + 1$, and by the property of context arrivals all the activated hypercubes have different levels. We calculate the regret from choosing near optimal arm as

$$\mathbb{E}[R_n(K)] \leq 2ABLd^{\alpha/2} \sum_{l=0}^{1+\log_2 K/p} 2^{p-\alpha}l \tag{15}$$

$$\leq 2ABLd^{\alpha/2}\frac{2^{2(p-\alpha)}}{2^{p-\alpha}}K^{\frac{p-\alpha}{p}} \tag{16}$$

The terms are balanced by setting $z = 2\alpha/p$, $p = 3\alpha$. ■

References

[1] D. Trottier, "Social media as surveillance," Famham: Ashgate, 2012.

[2] W. Chou, Y. Hung, E. "Social media use in the United States: implications for health communication," Journal of medial Internet research, vol. 11, no. 4, 2009.

[3] T. Sakaki, M. Okazaki, Y. Matsuo, "Earthquake shakes Twitter users: real-time event detection by social sensors," Proc. ACM International Conference on World Wide Web (WWW), 2010.

[4] H. Choi, H. Varian, "Predicting the present with google trends," Economic Record, vol. 88, no. 21, pp. 2-9, 2012.

[5] H. Liu, et al., "Optimizing cost and performance for content multihoming," in Proc. SIGCOMM, 2012.

[6] D. Niu, Z. Liu, and B. Li. "Demand forecast and performance prediction in peer-assisted on-demand streaming systems," In Proc. of INFOCOM, 2011.

[7] G. Glzrsun, M. Crovella, and I. Matta. "Describing and forecasting video access patterns," In Proc. of INFOCOM, 2011.

[8] G. Amodeo, R. Blanco, U. Brefeld, "Hybrid models for future event prediction," Proc. ACM international conference on Information and knowledge management, 2011.

[9] Z. Wang, L. Sun, C. Wu, and S. Yang. "Guiding internet-scale video service deployment using microblog-based prediction," In Proc. of ICWSM, 2012.

[10] J. G. Lee, S. Moon, and K. Salamatian. "An approach to model and predict the popularity of online contents with explanatory factors," In Proc. of Web Intelligence, 2010.

[11] M. Rowe. "Forecasting audience increase on youtube," In Proc. of the International Workshop on User Profile Data on the Social Semantic Web, 2011.

[12] D. A. Shamma, J. Yew, L. Kennedy, and E. F. Churchill. "Viral action: Predicting video view counts using synchronous sharing behaviors," In Proc. of ICWSM, 2011.

[13] S. Siersdorfer, S. Chelaru, and J. S. Pedro. "How useful are your comments? analyzing and predicting youtube comments and comment ratings," In Proc. of WWW, 2010.

[14] M. Cha, H. Kwak, P. Rodriguez, Y. Ahn, and S. B. Moon. "I tube, you tube, everybody tubes: Analyzing the world's largest user generated content video system," In Proc. of IMC, 2007.

[15] G. Szabo and B. A. Huberman. "Predicting the popularity of online content," Commun. ACM, 2010.

[16] H. Li, X. Ma, F. Wang, J. Liu and K. Xu, "On popularity prediction of videos shared in online social networks," CIKM'13, 2013.

[17] L. Zhang, F. Wang, and J. Liu, "Understanding instant video clip sharing on mobile platforms: Twitter Vine as a case study," ACM NOSSDAV'14.

[18] W. Galuba, D. Chakraborty, K. Aberer, Z. Despotovic, and W. Kellerer. "Outtweeting the twitterers - predicting information cascades in microblogs," In Proc. of WOSN, 2010.

[19] L. Hong, O. Dan, and B. D. Davison. "Predicting popular messages in twitter," In Proc. of WWW, 2011.

[20] K. Lerman and T. Hogg. "Using a model of social dynamics to predict popularity of news," In Proc. of WWW, 2010.

[21] H. Li, J. Liu, K. Xu, and S. Wen. "Understanding video propagation in online social networks," In Proc. of IWQoS, 2012.

[22] P. Bao, H. Shen, J. Huang, X. Cheng, "Popularity prediction in microblogging network: a case study on Sina Weibo," Proc. of the 22nd international conference on World Wide Web companion, 2013.

[23] S. Asur, B. A. Huberman, "Predicting the future with social media," IEEE/WIC/ACM International Conference on Web Intelligence and Intelligent Agent Technology (WI-IAT), 2010.

[24] B. Yu, M. Chen, L. Kwok, "Toward predicting popularity of social marketing messages," Social Computing, Behavioral-Cultural Modeling and Prediction. Springer Berlin Heidelberg, pp. 317-324, 2011.

[25] R. Yan, J. Tang, X. Liu, D. Shan, and X. Li. "Citation count prediction: Learning to estimate future citations for literature," In Proc. of CIKM, 2011.

[26] F. Kooti, W. A. Mason, K. P. Gummadi, and M. Cha. "Predicting emerging social conventions in online social networks," In Proc. of CIKM, 2012.

[27] T. Wu, M. Timmers, D. D. Vleeschauwer, and W. V. Leekwijck. "On the use of reservoir computing in popularity prediction," In Proc. of ICCGI, 2010.

[28] H. Pinto, J. Almeida, and M. Goncalves. "Using early view patterns to predict the popularity of youtube videos," In Proc. of WSDM, 2013.

[29] L. Barbosa, J. Feng, "Robust sentiment detection on Twitter from biased and noisy data,", In Proc. of 23rd International Conference on Computational Linguistics: Posters, 2010.

[30] H. V. Poor, O. Hadjiladis. Quickest detection. Vol. 40, Cambridge: Cambridge University Press, 2009.

[31] V. Krishnamurthy, "Quickest detection POMDPs with social learning: Interaction of local and global decision makers," IEEE Trans. Information Theory, vol. 58, no. 8, pp. 5563-5587, 2012.

[32] L. Lai, Y. Fan, H. V. Poor, "Quickest detection in cognitive radio: A sequential change detection framework," IEEE GLOBECOM 2008.

[33] C. Tekin, S. Zhang, and M. van der Schaar, "Distributed online learning in social recommender systems," accepted and to appear in IEEE J. Sel. Topics Sig. Process (JSTSP).

[34] A. Slivkins, "Contextual bandits with similarity information," arXiv preprint arXiv:0907.3986, 2009.

[35] M. Dudik et al. "Efficient optimal learning for contextual bandits," arXiv preprint arXiv: 1106.2369, 2011.

[36] J. Langford and T. Zhang, "The epoch-greedy algorithm for contextual multi-armed bandits," Advances in Neural Information Processing Systems, vol. 20, pp. 1096-1103, 2007.

[37] W. Chu, L. Li, L. Reyzin, R. Schapire, "Contextual bandits with linear payoff functions," in Proc. of the International Conference on Artificial Intelligence and Statistics (AISTATS), 2011.

[38] P. Sollich, D. Barber, "Online learning from finite training sets and robustness to input bias," Neural computations, vol. 10, no. 8, pp. 2201-2217, 1998.

[39] C. Tekin, S. Zhang, and M. van der Schaar, "Distributed online learning in social recommender systems," accepted and to appear in IEEE Journal of Selected Topics in Signal Processing (JSTSP).

[40] J. Xu, C. Tekin, S. Zhang, and M. van der Schaar, "Distributed multi-agent online learning with global feedback," online at http://www.seas.ucla.edu/~jiex/documents/DisCoLearning.

[41] J. Xu, Y. Song and M. van der Schaar, "Incentivizing information sharing in networks," accepted and to appear in ICASSP 2014.

[42] J. Xu and M. van der Schaar, "Incentive design for heterogeneous user-generated content networks," in the joint Workshop on Pricing and Incentives in Networks and Systems (W-Pin + Netecon 2013).

[43] S. D. Roy, T. Mei, W. Zeng, and S. Li, "Towards cross-domain learning for social video popularity prediction," IEEE Trans. Multimedia, vol. 15, no. 6, pp. 1255-1267, May 2013.