# Strategic Timing of Content in Online Social Networks

Tauhid Zaman, Sina Modaresi, Juan Pablo Vielma

# Strategic Timing of Content in Online Social Networks

## Introduction

In online social networks users generate content for which they wish to maximize engagement by other users. Engagement consists of the users interacting with the content through various mechanisms. For instance, in Twitter where the content is a 140 character message known as a tweet, engagement can be a user replying to the tweet. Engagement can only occur if a user actually sees the content, which is referred to as an impression. Therefore, if one can increase the number of impressions their content receives, this should also increase engagement. While many studies have looked at how to engineer the content to maximize engagement [1, 2], to the best of our knowledge there has been no work done on how to maximize the number of impressions. In this paper we show that through strategic timing of content in social networks such as Twitter or Instagram, one can increase the number of impressions it receives by as much as 80%. This is of importance not only for normal users of social networks, but also for many firms which manage social media accounts for high profile clients. Our work transforms the timing of content into an operational lever that can be used to optimize social media campaigns for essentially no cost.

## Model

We present a model of how an impression is created in a social network such as Twitter or Instagram. There are three main components to the model: the user arrival process, the timeline process, and the user interface. The user arrival process models the times when the user checks for new content posted on the social network. We will refer to the content as a post. In a social network a user can choose to follow other people. When the user checks the social network, he will look at his timeline, which contains posts from all people he follows. The timeline process models the arrivals of posts to a user's timeline. The user interface characterizes how the user views the content. The timeline posts are arranged in chronological order, with the most recent post located at the top of the timeline. As time passes, older posts are pushed down on the timeline. Typically, a user only looks at a certain number of new posts when they check their timeline, which we call the cutoff window.

In order for a piece of content to create an impression from a target user, the following must occur. First, the content is posted at a time that is chosen by the content producer. The target user will check his timeline at a time after the content is posted. The timeline checking time is determined by the arrival process. In the time interval between the posting of the content and the user arrival there will be a number of new posts on the user's timeline, which is determined by the timeline process. If this number of posts is less than the cutoff window, the user will see the post and an impression is created.

To calculate the impression probability, we require values for the arrival and timeline rates. We studied the behavior of 100 Twitter users and found that there are daily and weekly variations in their posting frequency. This motivates us to model the arrival process of a user as an inhomogeneous Poisson process with a rate that has oscillation periods of one day and one week. The timeline process can be viewed as the merging of posts from several users, so we also model it as an inhomogeneous Poisson process whose rate has a similar parametric form as the arrival process, but with different parameter values.

We construct a hierarchical Bayesian model for both processes which allows for user heterogeneity, but also sharing of common behaviors. We fit our model to data for 100 Twitter users. For each user we obtain the times of the posts on their timelines and the times of their own posts. We cannot measure the arrival times, but we expect the posting times to reflect the main temporal features of the arrival times. Model fitting is done with a Markov Chain Monte Carlo procedure.

**Main Results**

In our model an impression is created if the number of timeline posts between the time of the source post and the time the target user arrives is less than the cutoff window. Because we have modeled the arrival and timeline processes as inhomogeneous Poisson processes, once their rates are specified, a closed form expression can be obtained for the probability of this event, which is the impression probability. This expression is rather complicated, but it can be approximated by a much simpler expression which provides important insights. The approximation states that the impression probability is approximately equal to the cutoff window multiplied by the arrival rate divided by the timeline rate. This expression captures the main insights of strategic timing of content. To maximize the impression probability, choose a time where the user is likely to be checking his timeline (large arrival rate) and there are not many posts from other users on his timeline (low timeline rate).

We calculate the impression probability for each Twitter user in our dataset using the posterior median values of their rate parameters. To evaluate the impact of strategic timing, we define the gain as the ratio of the maximum impression probability to the time average (over one week) impression probability. The gain measures the benefit of strategic versus random timing. We find that across 100 different users, using a typical value for the cutoff window, the median gain is 1.8 (5 % and 95% quantiles are 1.0 and 2.0, respectively). This result is robust to the value of the cutoff window. Therefore, we see that strategic timing can give an 80% increase in the impression probability.

**Conclusion**

Strategic timing can increase the number of impressions received by content in social media. Our proposed model allows one to easily optimize the timing of content. Using models fit to real Twitter user data, we find that an 80% increase in impressions can be achieved with strategic timing. Also, our modeling framework allows us to optimize the timing of content over multiple target users simultaneously and also to optimize the timing and duration of social media advertising campaigns.

# References

[1] Liangjie Hong, Ovidiu Dan, and Brian D Davison. Predicting popular messages in twitter. In *Proceedings of the 20th international conference companion on the world wide web*, pages 57–58. ACM, 2011.

[2] Bongwon Suh, Lichan Hong, Peter Pirolli, and Ed H Chi. Want to be retweeted? large scale analytics on factors impacting retweet in twitter network. In *Second international conference on social computing*, pages 177–184. IEEE, 2010.