Estimating Contagion Rates in Kickstarter Twitter Cliques

VIRGINIA TECH™

DAVON WOODARD/MD SALMAN AHMED CS 6604 FALL 2017

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Introduction

- Crowdfunding has emerged as a popular community-based, micro-financing model for entrepreneurs, artists, and activists alike to bring their respective dreams into fruition.
- Successful campaigns, those which meet their financial goals, bring with them not only the financial utility for the creator, but also social utility for the backers.

Motivation

Initial: Can the prediction power of Twitter data be extended by complementing static data with the model of social media exposure curves (stickiness and persistence) presented by Romero[1], et. al coupled with the use of censored data presented by Li, et. al[2]?

Secondary: Given a set of assumptions, can the rate of spread of Kickstarter campaigns in a Twitter network be estimated using simple contagion and complex contagion models?

Data Collection

- **Crowdfunding dataset**
  - From Chandan K. Reddy's Team

- **Twitter dataset**
  - Using Twitter public API & GetOldTweets-python[1])
  - Modifying the APIs of GetOldTweets-python to meet our needs

1. https://github.com/Jefferson-Henrique/GetOldTweets-python

Dataset Characteristics

- Crowdfunding dataset[1] – 18k total records
  - Each record corresponds a project
  - Contains project id, name, URL, duration, goal amount, pledged amount, …
- Twitter dataset[2] – 162k total records
  - Each record corresponds to a tweet
  - Contains the text, user, date of tweet, tweet link, retweet, etc.

1 & 2. You can get the two datasets on http://people.cs.vt.edu/ahmedms/cs6604.html

Relevancy [Crowdfunding dataset x Twitter dataset]

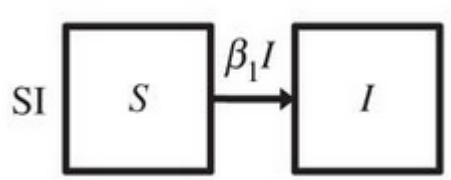
- Out of 18k projects, 10k projects have tweets
- Out of the 10k, 4k projects have enough tweets to take part in the model develop

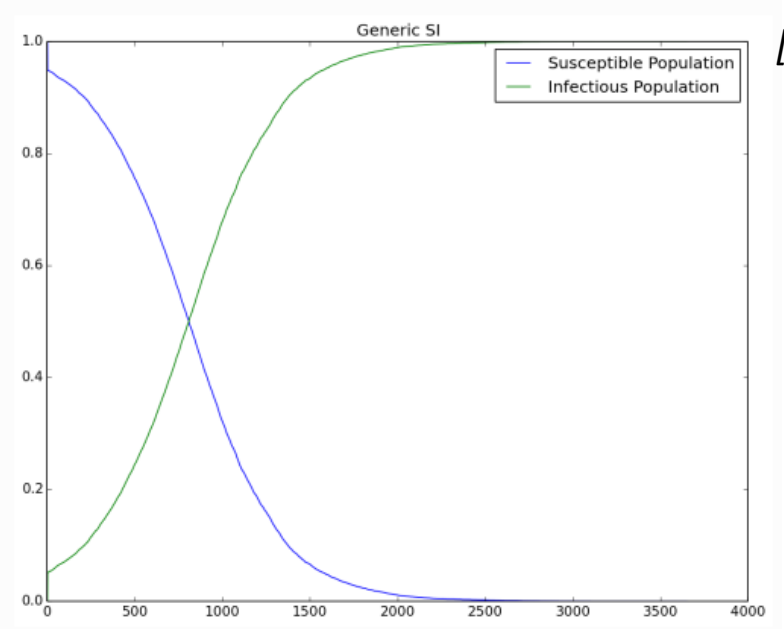
Assumptions

Our crawling program retrieves only the information about tweets.

- Twitter user network as a clique
- Total nodes of the Twitter user network is twice the unique Twitter users

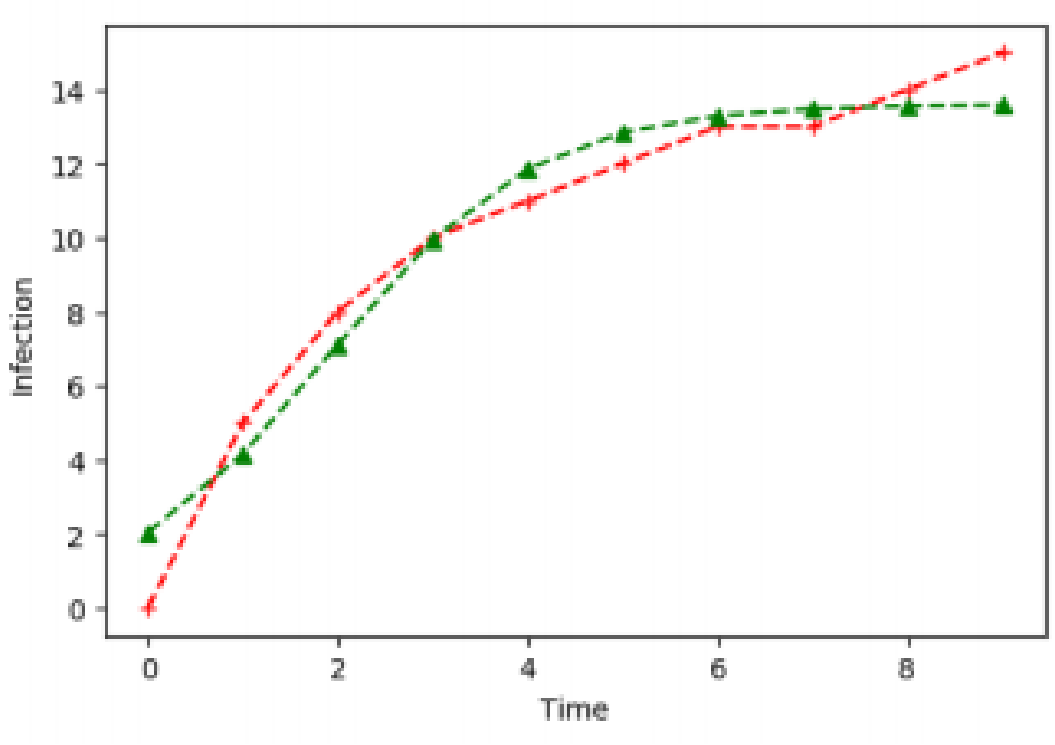
Model – Simple Contagion





[4]

Model – Simple Contagion

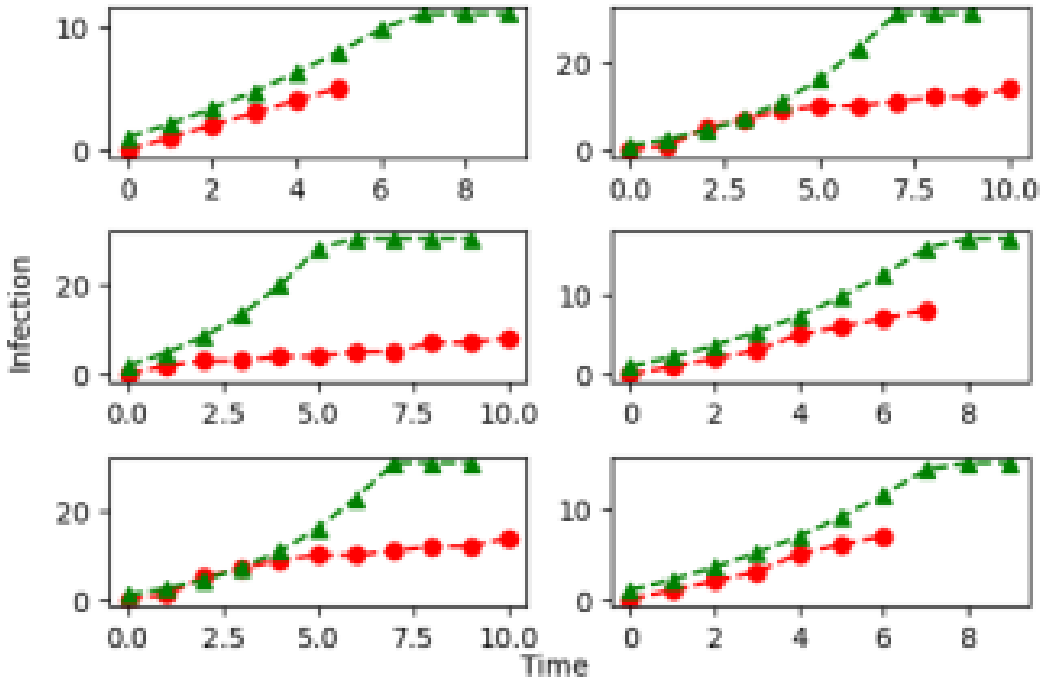


$$\frac{dS}{dt} = -\beta SI$$
$$\frac{dI}{dt} = \beta SI - \gamma I$$
$$\frac{dR}{dt} = \gamma I$$

$B_{(successful)} = .0092$

$B_{(failed)} = .0120$

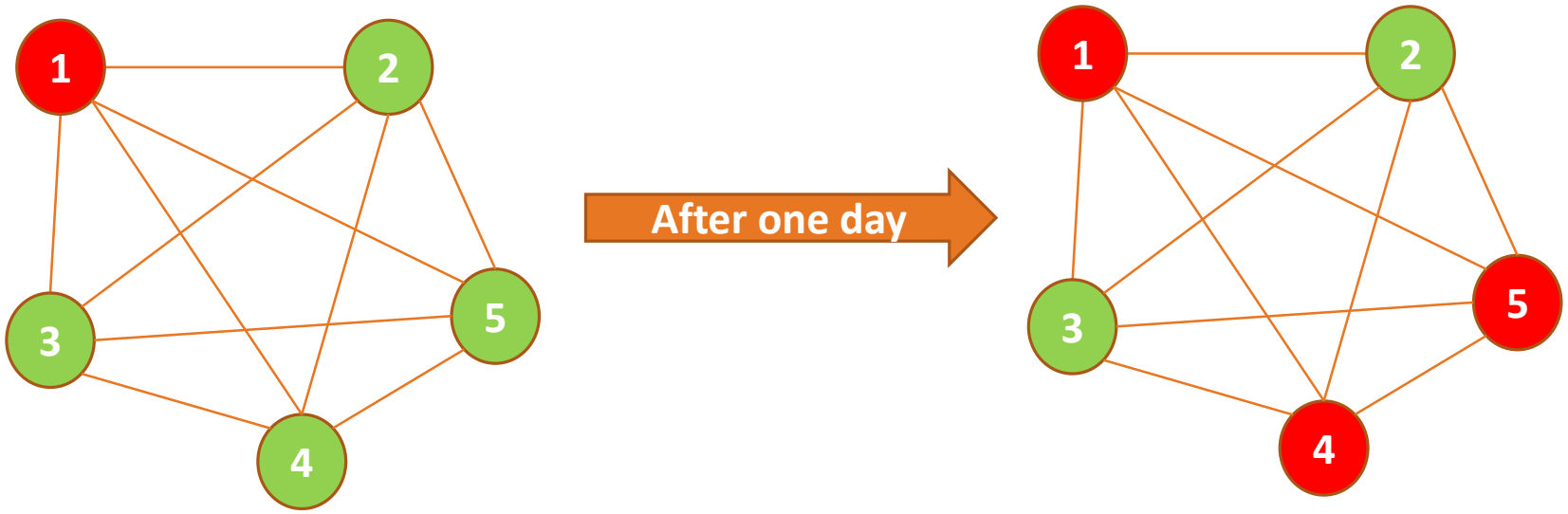
Results– Simple Contagion



$$I(t) = \frac{NI_0 e^{\beta N t}}{N + I_0[e^{\beta N t} - 1]}$$

- Variance:
  - Assumptions
  - Network Structure

Model - Complex Contagion [Concept of Exposure Curve]



Day 1

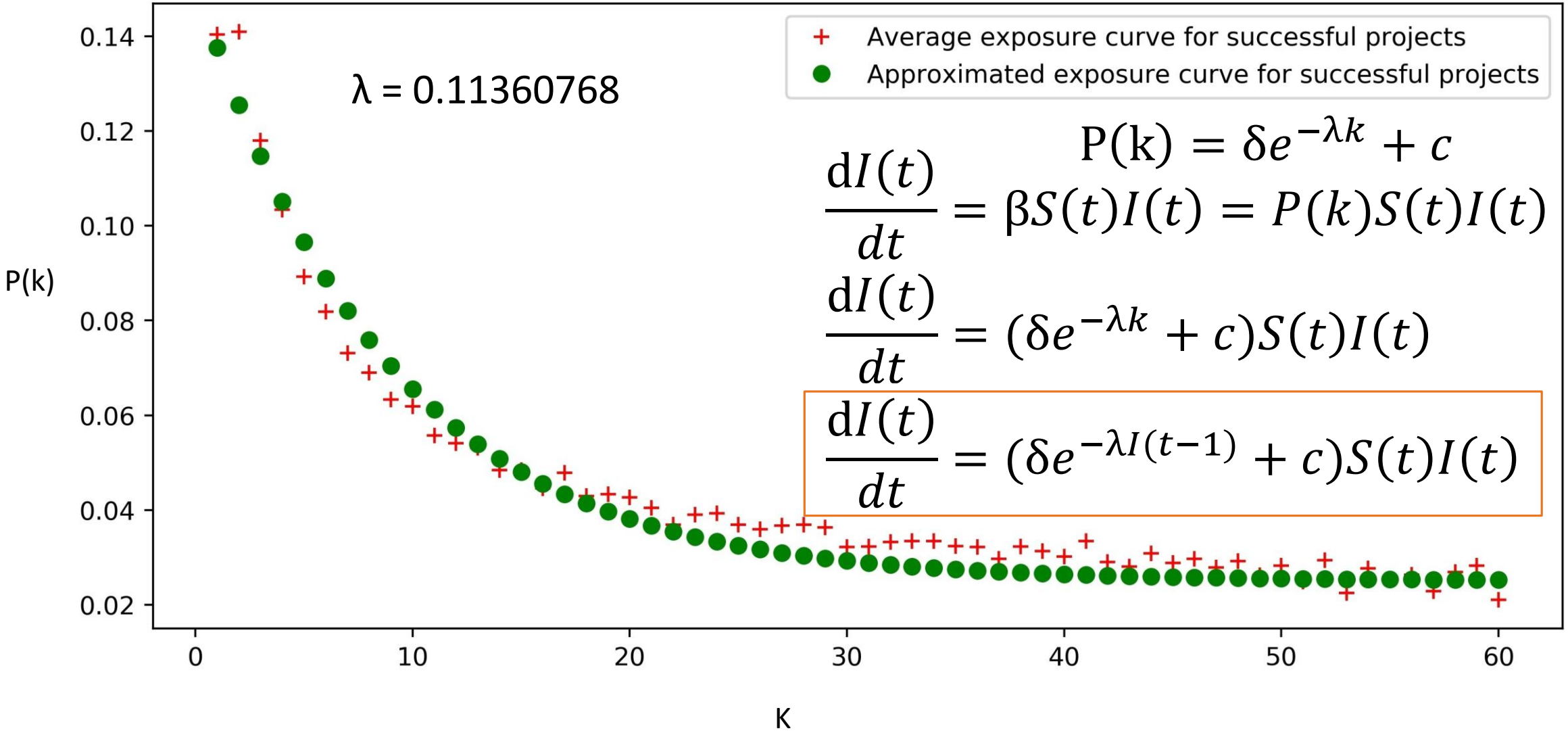
Day 2

$E_k = \{2, 3, 4, 5\}$

$P(k) = 2/4$
Where $k = 1$

$I_k = \{4, 5\}$

Exposure Curve



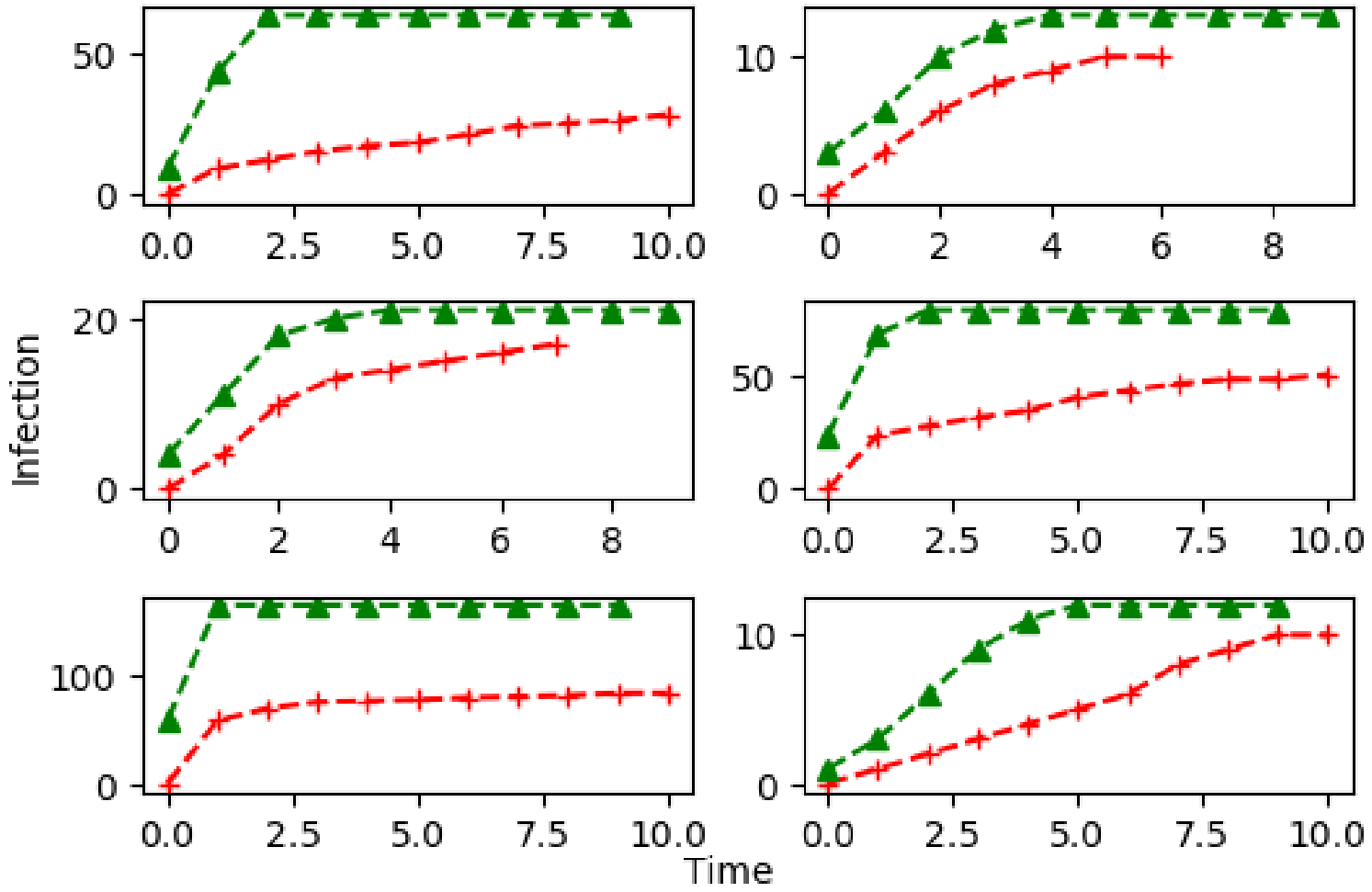
$$P(k) = \delta e^{-\lambda k} + c$$

$$\frac{dI(t)}{dt} = \beta S(t) I(t) = P(k) S(t) I(t)$$

$$\frac{dI(t)}{dt} = (\delta e^{-\lambda k} + c) S(t) I(t)$$

$$\frac{dI(t)}{dt} = (\delta e^{-\lambda I(t-1)} + c) S(t) I(t)$$

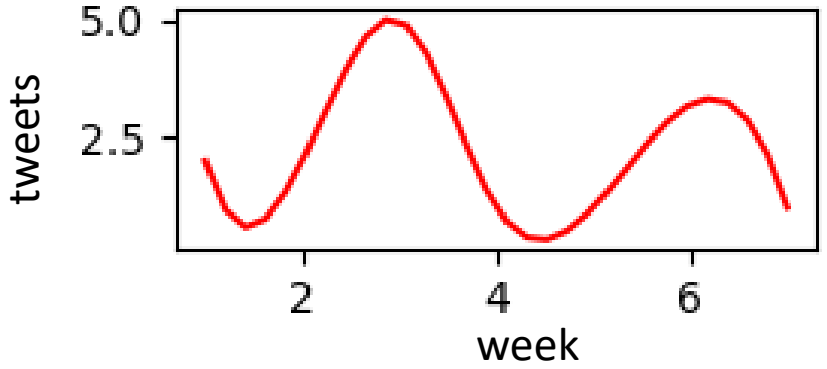
Results - Complex Contagion [Actual vs. Prediction]



- A big approximation error
- Inadequate twitter data
- Poor assumptions

Challenges

- Heading wrong direction until the last moment
- Thinking the output as the input to our models
- Inadequate associated Twitter data
- Poor assumptions



Conclusion

- Assumptions are critical
- Model should fit the dataset available
- With additional Network Information additional research on information diffusion of Kickstarter campaigns help guide marketing efforts

References

1. Romero, et. al . “Differences in the Mechanics of Information Diffusion Across Topics: Idioms, Political Hashtags, and Complex Contagion on Twitter”

2. Yan Li, Vineeth Rakesh, and Chandan K. Reddy. 2016. Project Success Prediction in Crowdfunding Environments.

3. Prakash, Aditya. “Epidemics: Probabilistic Models”, Lecture, 9/25/17, VT

4. https://institutefordiseasemodeling.github.io/Documentation/general/generic-tutorial7SI.html