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Popularity Dynamics of Foursquare Micro Reviews

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Micro-reviews

- extremely concise review
- e.g. 200 character "tip" on Foursquare
- Often posted on a mobile device
- Typically very subjective

Micro Review (continued)

- May use emoticons or all caps
- May be posted in the moment the thing being reviewed is being experienced
- Often binary rating (like or not)
- The reviews *themselves* are often rated (helpful or not, like, etc.)

Goals

Reviews are important-- increasing number of customers are influenced by reviews

Goal:

Understand popularity evolution of microreviews over time

Investigate if we can predict popularity

Data

Foursquare: Location-based social network

10M tips and 9M likes posted by over 13 million users in 16M venues

Peaks

- Peaks: Largest number of likes a tip receives in a single day
- 72% of reviews get a peak within their first month of posting
- For 50% of tips, peak corresponds to 25% of total likes
- Some tips received heavy bursts of popularity on the peak day
- For those tips, peak corresponds to at least 67% of their likes

Visibility Mechanisms

- Foursquare tips may be sorted by date or popularity
- Ranking by popularity privileges tips that are already popular
- Gives a classic rich-get-richer dynamic

Rich-get-richer?

Much weaker rich-get-richer effect compared to other content.

Less than 25% of likes are in a peak, very different compared to other user-generated content.

Social Likes

- Half of likes come from author's social network
- Percentage of social likes tends to decrease as tips become older in the system
- Social likes correspond to 62% of all likes in the 1st hour and decreases to 54% after 6 hours
- Social network is responsible for boosting the tip popularity

Prediction

Can we predict what tips will be popular in the future?

Used smaller data set-- narrowed down to "Food" venues in New York City

Prediction

Created many features of a tip and used classical machine learning.

Types of features:

- Social network features (e.g. number of followers)
- Tip content (e.g. number of adjectives used)
- Venue (e.g. fancy French place vs. McDonald's)

Prediction Results

Prediction was not very strong.

Most useful features:

- Most important: current tip popularity
- 2nd - 5th: # of likes received in previous tips posted by author
- 8th and 10th: social network features
- 21st: # of characters
- 24th and 25th: # check-ins, ranking at the venue

Summary

- User generated content interesting area of study!
- Tips have a slow popularity evolution, acquire most likes after a few months
- Social network plays important role on tip popularity
- low correlation between early and long-term popularities of the tip
- The use of features related to the user, venue, and text can improve prediction accuracy to some extent

Computing closeness centrality, at Scale

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Importance of Nodes

Question:

Given a graph, what nodes are important?

Classic Cloeness Centrality

The closer a node is to all other nodes, the more important it is.

Centrality:

B^(-1) (v) = (n-1) / SUM(dist(v, u))

How to compute?

Scaling Approaches

- Sampling
- Pivoting

Sampling

Pivoting