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Design and Analysis of Algorithms class
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PageRank

PageRank |

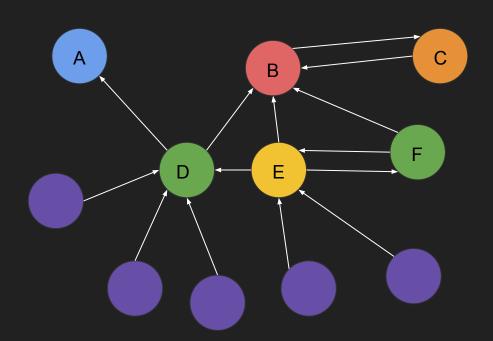
PageRank is a method for rating Web pages objectively and mechanically, effectively measuring the human interest and attention devoted to them.

Sergey Brin and Larry Page, 1998

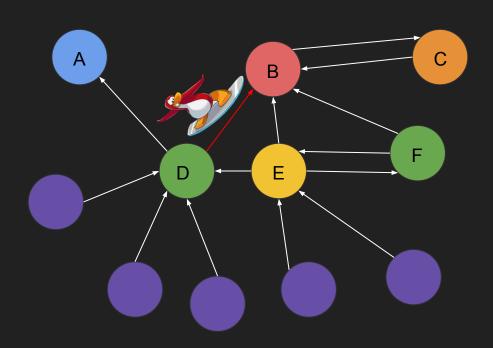
PageRank: The Origin

- 1976: Eigenvalue problem proposed by Gabriel Pinski and Francis Narin
- Sergey Brin has the idea to order web data in a hierarchy by "link popularity"
- **1998**: PageRank Citation Ranking: Bringing order to the internet
- 1998: Google paper
- 1998: Google is founded by Sergey Brin and Larry Page
- Named after Larry Page and web page
- Patented assigned to **Stanford** University, not Google

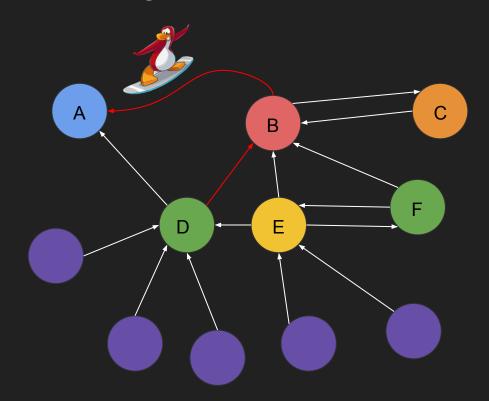
PageRank: How?



PageRank: Random surfer model



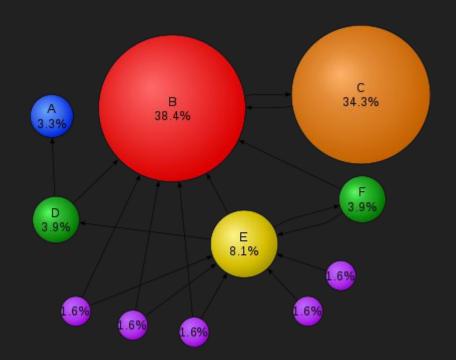
PageRank: Damping factor



PageRank: Real formula

$$PR(B) = rac{1-d}{N} + d(rac{PR(D)}{L(D)} + rac{PR(E)}{L(E)} + rac{PR(F)}{L(F)} + rac{PR(C)}{L(C)})$$

PageRank: Result



Dataset

Twitter Data

- Twitter data openly available for research
- Public REST API
- Returns: list of tweets and retweets
- Relational data:
 - Retweets: Publish other users tweets in your own timeline
 - **Likes**: User likes content
 - Follow/Followed: Aggregate users data to see in home timeline

Dataset

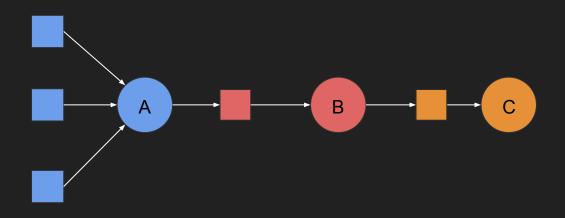
- **18215** tweets and retweets.
- **4197** tweets
- Collected at Project EPIC
 - Analysis of tweets generated during crisis to improve public response
- Tweets about hurricanes Harvey and Irma

TweetRank

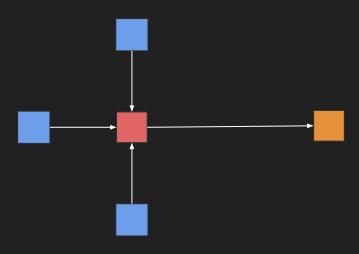
TweetRank: Motivation

- Users in disasters usually retweet tweets in the **same disaster area** [Marina Kogan et al. 2015]
- Tweets locally retweeted usually have local utility [Marina Kogan et al. 2015]
- **Faster** than news outlets (or similar)
- Interesting for disaster emergency response on site

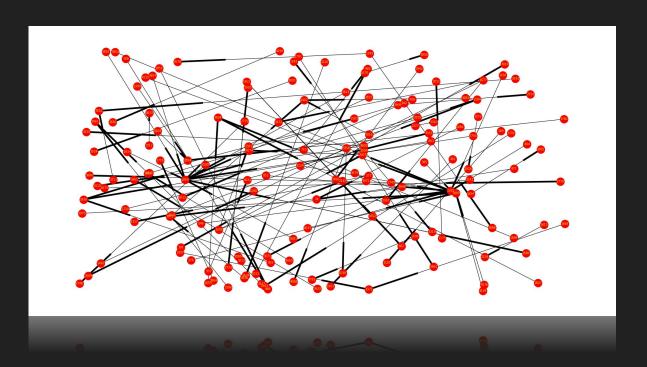
TweetRank: Random twitter user model



TweetRank: Random twitter user model



TweetRank: Graph Visualization



This Di-Graph shows the relationships between the tweets and their retweets.

TweetRank: Implementation

- Coded in Python
- 2 main parts
 - Graph generation (json, dictionaries)
 - Algorithm execution (Panda dataframes)
- Not really scalable, but can be easily updated to Spark Dataframes



TweetRank: Results

- Damping factor: **0.85**
- Error below **0.0001**
- Convergence in **3 iterations** for dataset

Running TweetRank	done
904814761141030912	0.000238
904813816965459969	0.000238
904815764733120512	0.000157
903201962744836096	0.000153
904813409136463879	0.000127
904811943755644928	0.000096
904815149617426433	0.000096
904814132888834048	0.000096
904557396340637696	0.000096
904704308838625282	0.000072
904704308838625282	0.000072

TweetRank: Top10 sample



TweetRank: "Interpretation"

- Tweets ranked by importance **inside** dataset
- If user has more tweets in dataset, user's retweets more "meaningful"
- More to come?

TweetRank: Future

- More research
 - Check results interpretation
 - Study scalability
 - Compare with other methods
- Run algorithm in **bigger** datasets
- Locally geo bounded datasets [Marina Kogan et al. 2015]

References

- PageRank Citation Ranking: Bringing order to the internet [Larry Page et al.
 1998]
- The Anatomy of a Large-Scale Hypertextual Web Search Engine [Sergey Brin and Larry Page. 1998]
- Think Local, Retweet Global: Retweeting by the Geographically-Vulnerable during Hurricane Sandy [Marina Kogan et al. 2015]

Questions?

Thanks!

TweetRank: Graph

106 edges

N tweets with an edge

PageRank: Time analysis

- 322 million links -> 52 iterations
- 161 million links -> 45 iterations until similar convergence
- Logarithmic time on the size of the graph if the graph is expander

PageRank: Formula in the original paper

$$PR(B) = {}_{1-d} + d(rac{PR(D)}{L(D)} + rac{PR(E)}{L(E)} + rac{PR(F)}{L(F)} + rac{PR(C)}{L(C)})$$