13.3 Friends and Links Suggestion Algorithms

DATASCI W261

Machine Learning at Scale

Social Networks and Link Prediction

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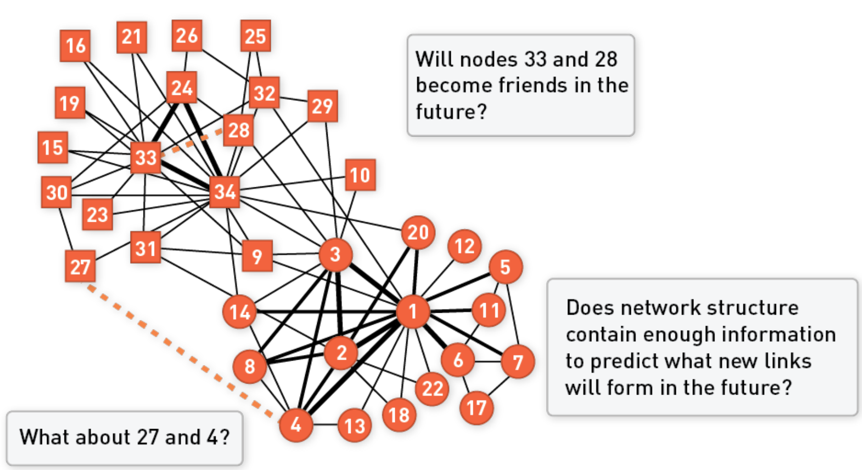
- A snapshot of a social network is used to suggest new friends and entities that should link.
- Social network sites such as LinkedIn, Google+, and Facebook use a friends suggestion algorithm to help users broaden their networks.

Link Prediction



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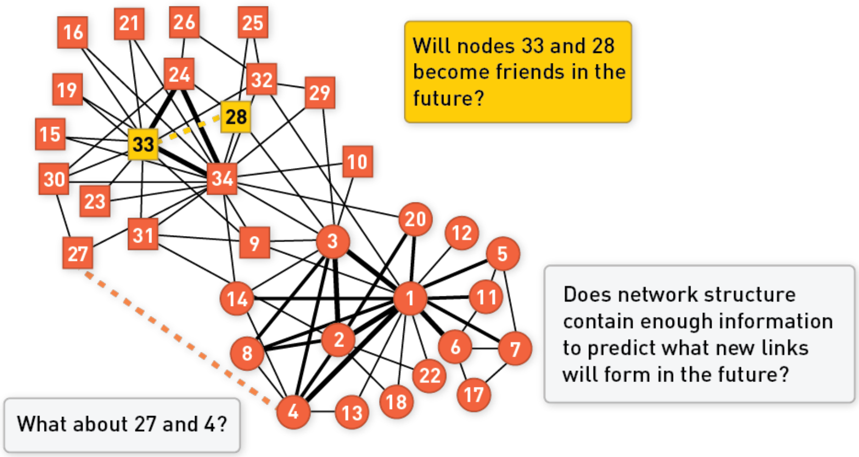

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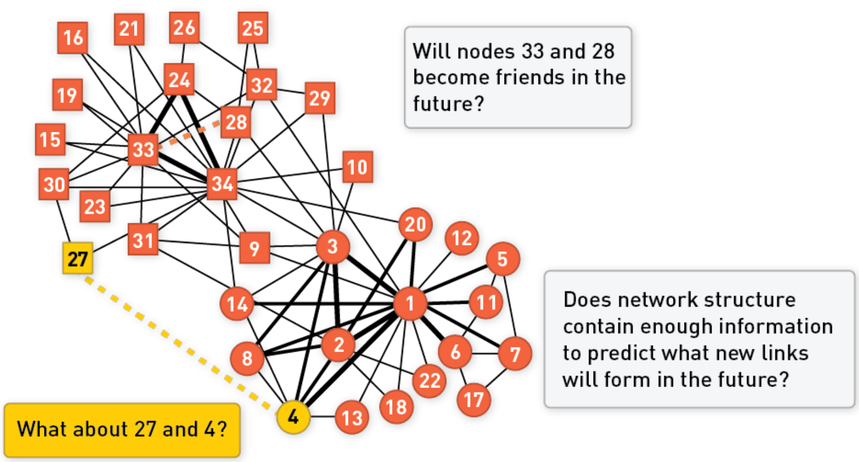

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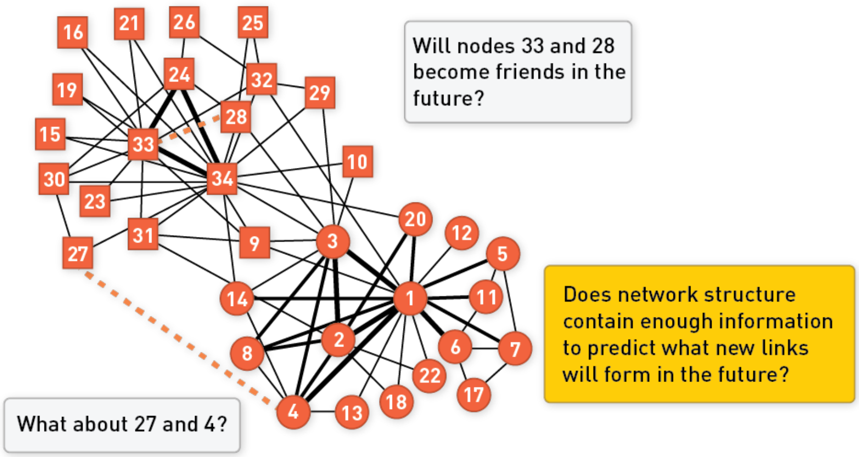
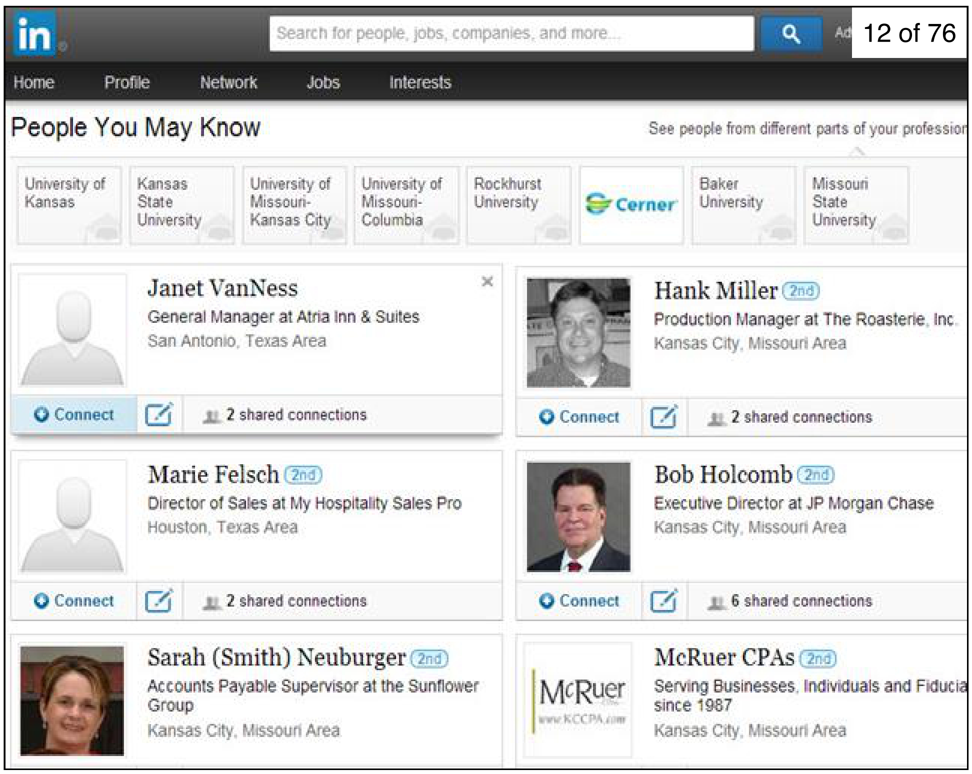
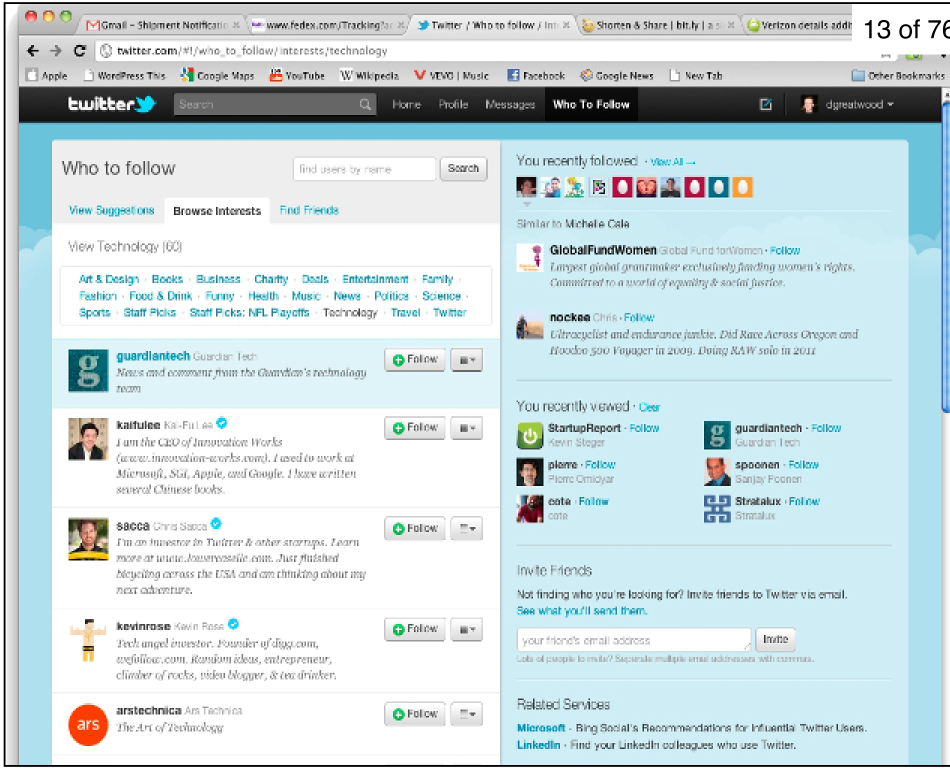




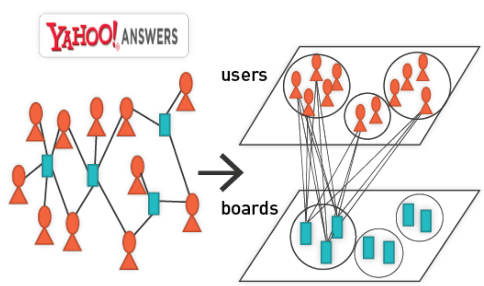


Link Prediction Methods

In order for the proximity measures to make sense while estimating similarity among vertices, we will need to modify these measures.

We will consider such proximity measures under three different categories:

- **Node-Neighborhood-Based Methods**
  - Common neighbors
  - Jaccard's coefficient
  - Adamic-Adar
- **All-Paths-Based Methodologies**
  - PageRank
  - SimRank
- **Higher-Level Approaches**
  - Unseen bigrams
  - Clustering



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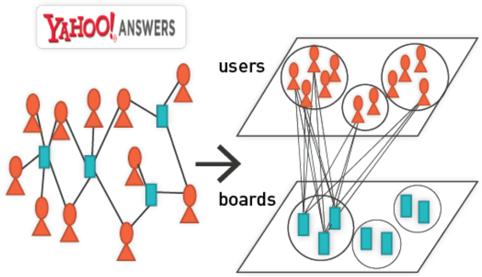

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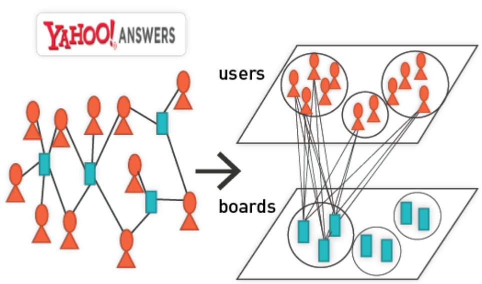

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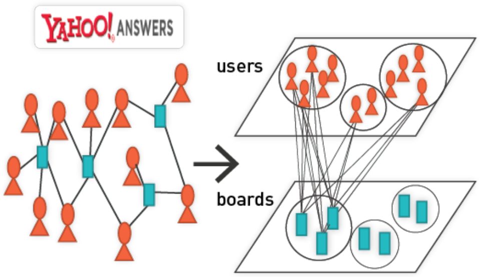

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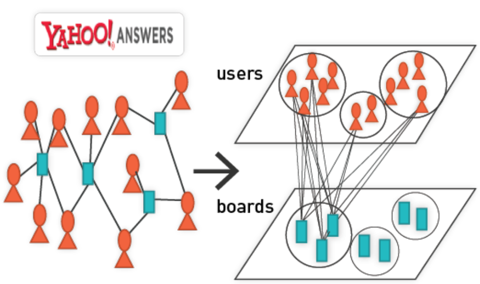

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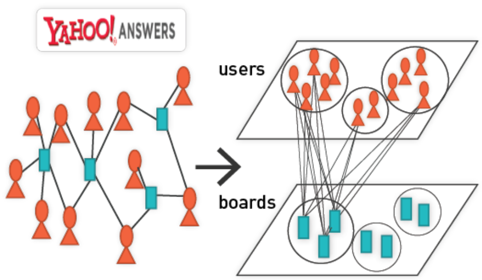

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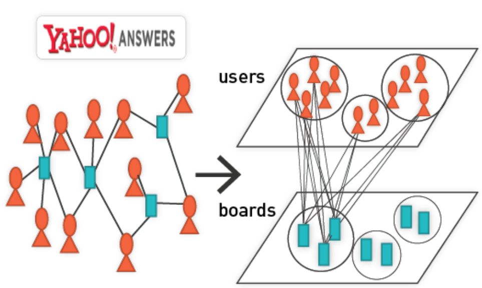

Friend Recommendation

- Learn to recommend potential friends
- **Facebook link creation** (L. Backstorm 2011)
  - 92% of new friendships on FB are **friend of a friend**
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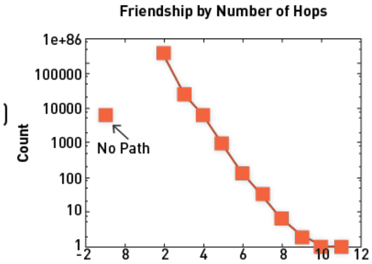

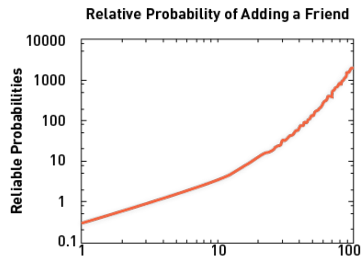

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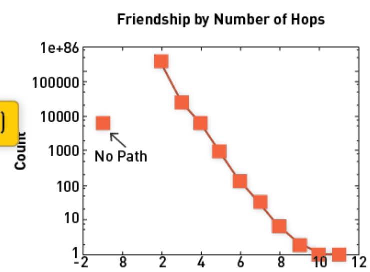

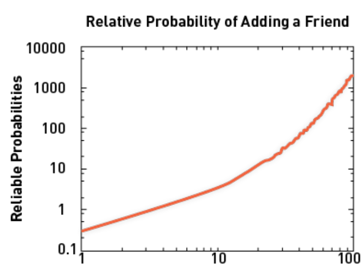

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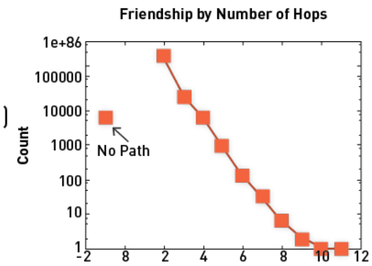

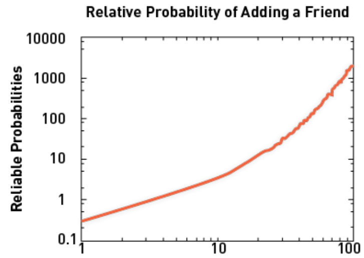

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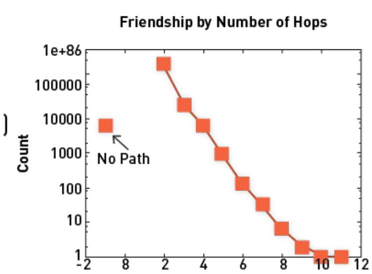

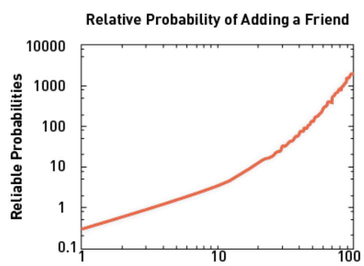

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- That works out to about 20,000 FoFs
- We want to suggest good links, rather than overload the user with suggestions

Heuristics Based on FoF

Limit ourselves to second degree network:
in other words, friends of friends

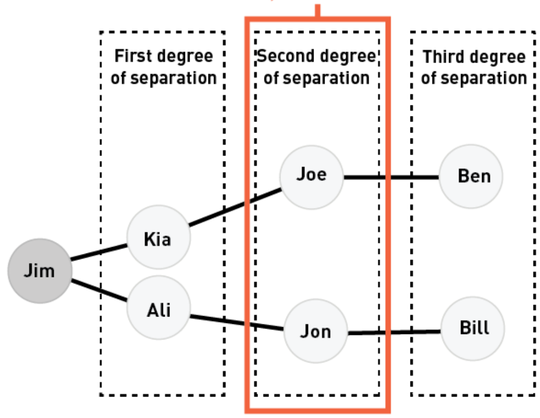

Figure 7.12
An example of FOF where Joe and Jon are considered FoFs to Jim

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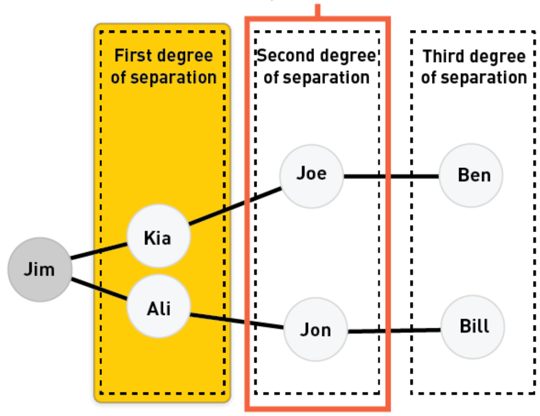

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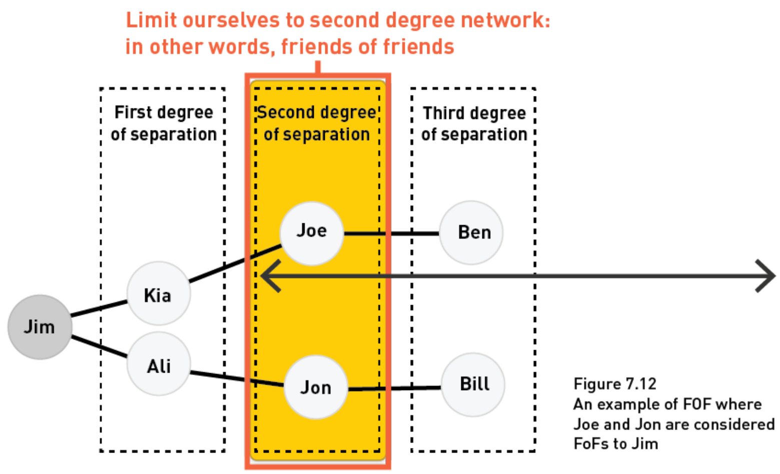

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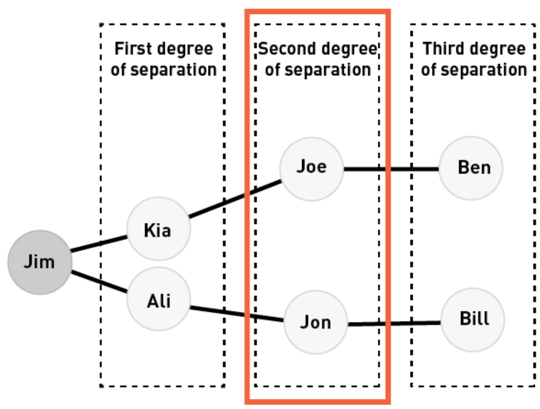
Algorithm Sketch: Most FoF Will Not Be Good Suggestions



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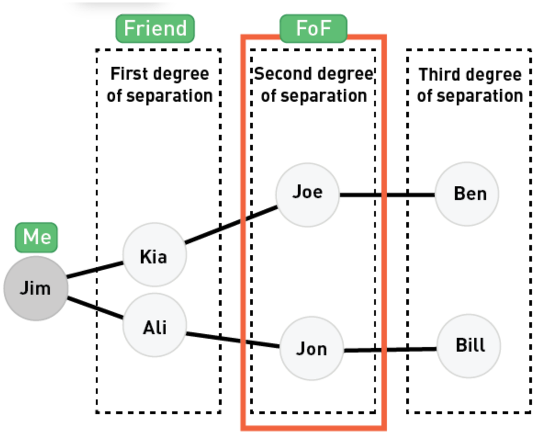
- FoF is a list of individuals who are indirectly connected to you through friends.
    - Not everybody in this list will be familiar to you.
    - E.g., I lived in Japan for five years, so just because you know me does not mean you know my friends in Japan.

FoF Ranking Algorithm



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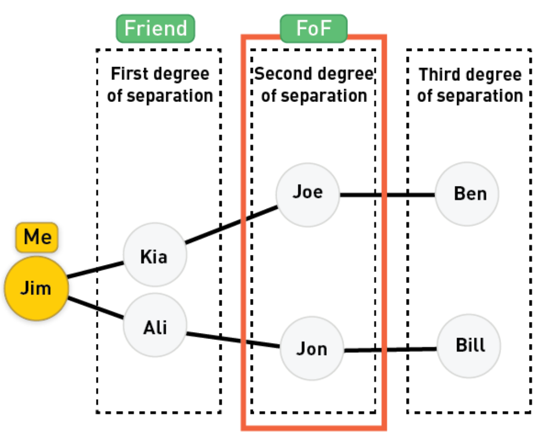

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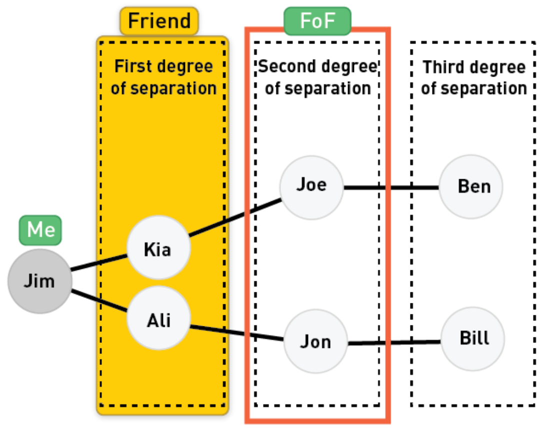

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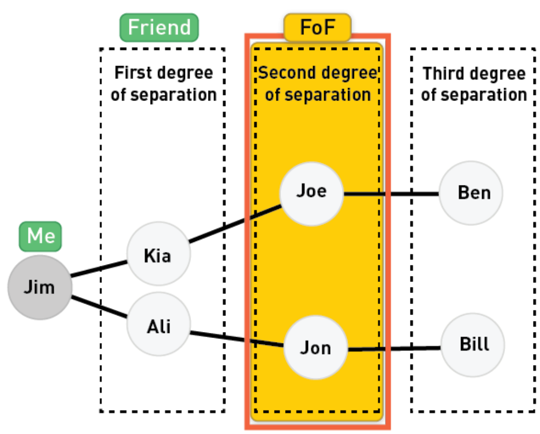

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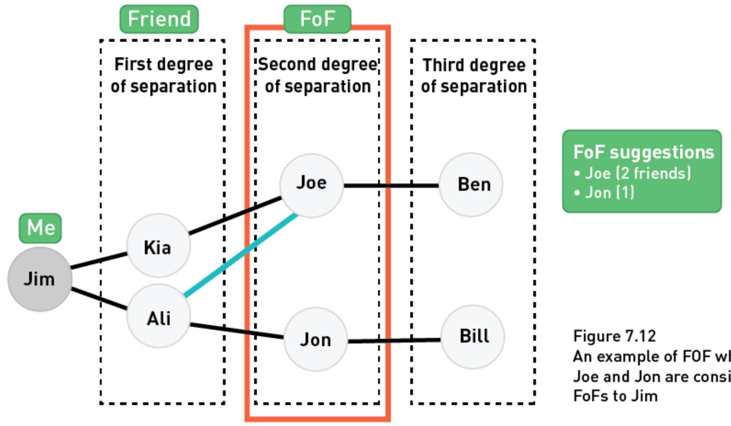

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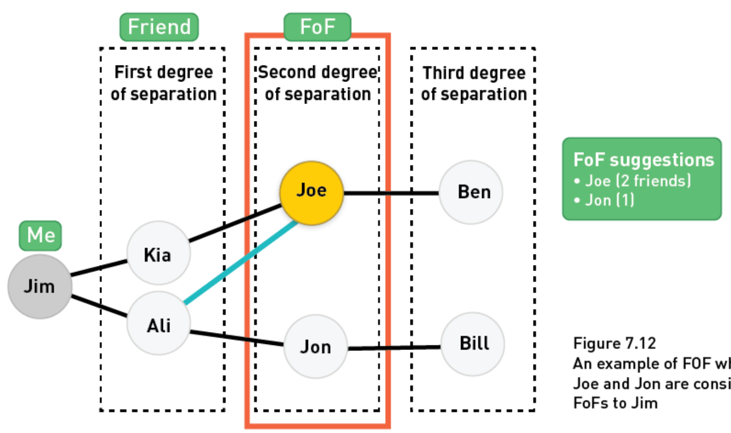

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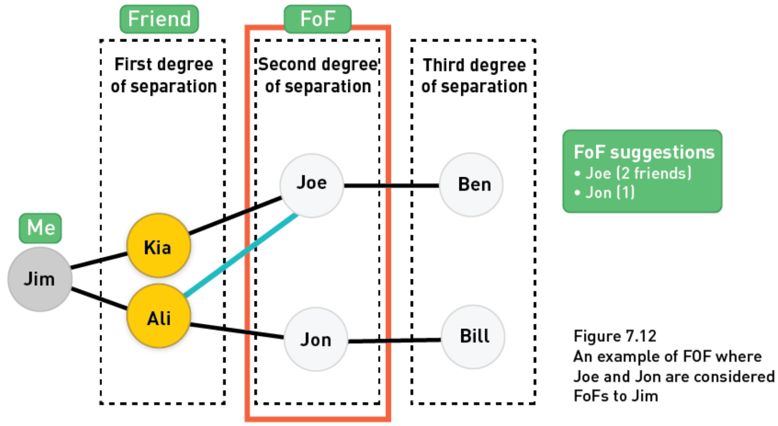

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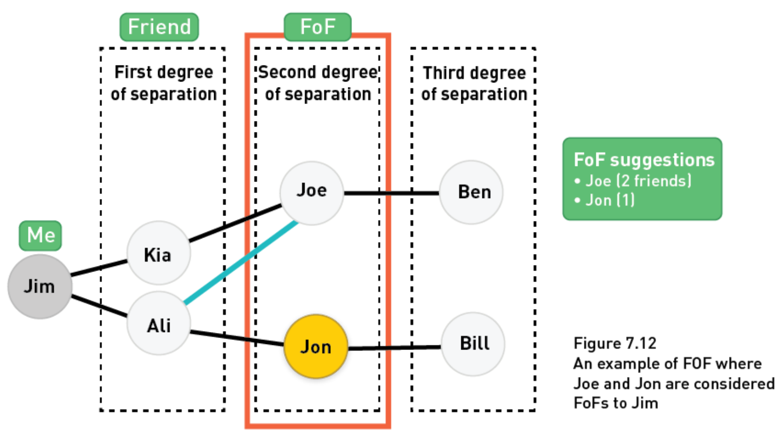

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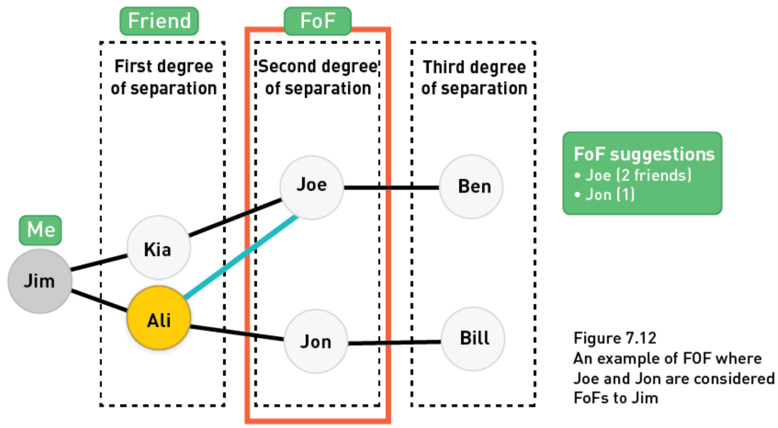

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Implement the FoF Algorithm in MapReduce

- Two MapReduce jobs are required to calculate the FoFs for each user in a social network.
- Job 1: Produce a list of FoFs and number of mutual friends.
  - Job calculates the common friends for each user.
- Job 2: Sort list of FoF suggestions.
  - The second job sorts the common friends by the number of connections to your friends.

Friend Graph as an Adjacency List

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$ cat test-data/ch7/friends.txt
joe  jon  kia  bob  ali
kia  joe  jim  dee
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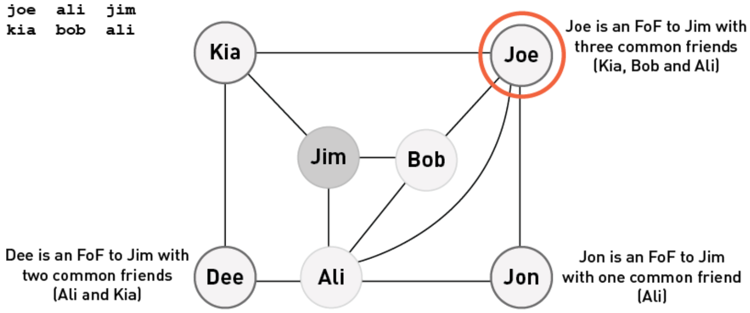

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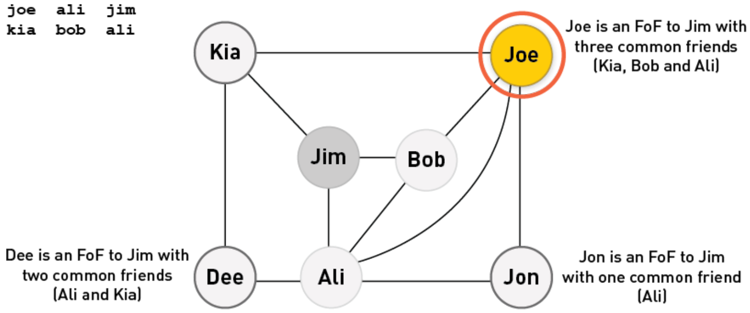

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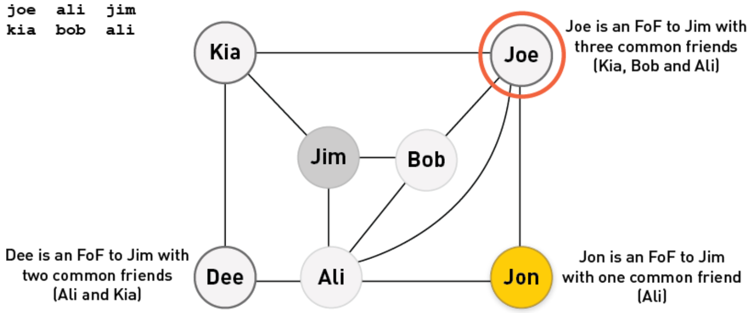

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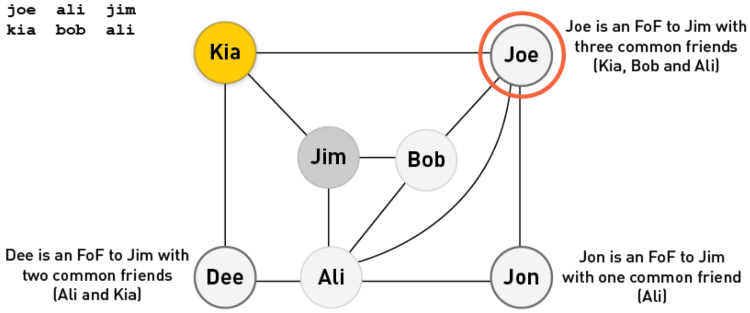

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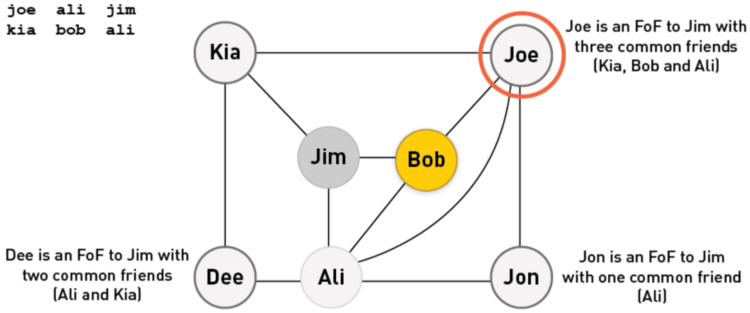

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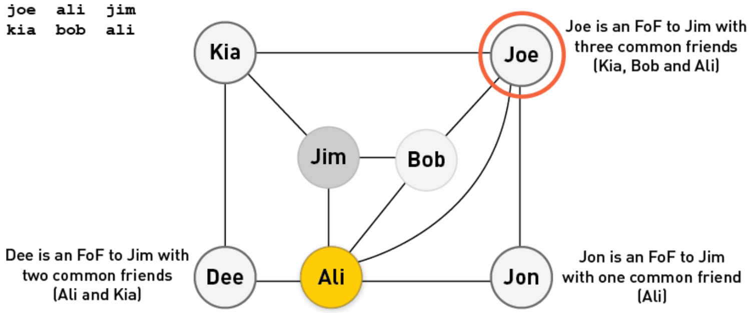

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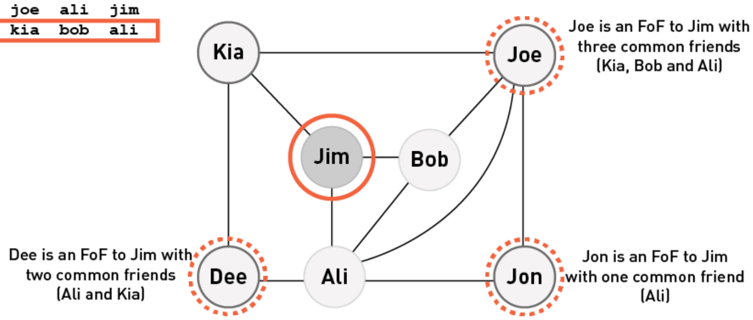

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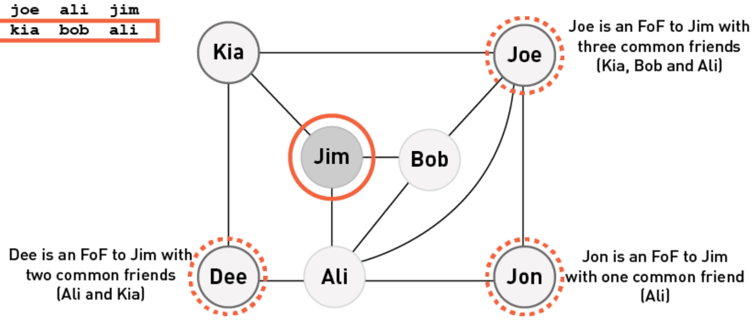

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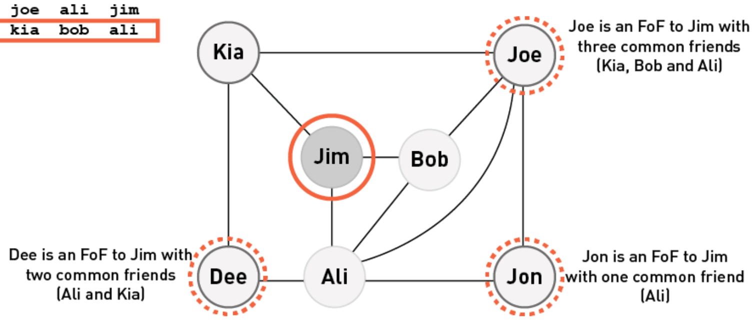

Summary on Friend Suggestion Algorithm: FoFs

- First cut at suggesting new connections on social networks
  - Can we do better?
- Limited our exploration new connections to friends of friends
  - Other sources of new connections
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Link and Friend Suggestion

- Version 2 machine learning (re)ranking of a friends-of-friends suggestion list

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Two-stage system

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- Step 1: Rank based on FoFs based on mutual friends (and possible other criteria such as hometown, high school, company, university).
- Step 2: Score each candidate suggestion and rerank using, say, a logistic regression model.
    - Select top N (say 1000) from step 1 and rescore using a machine learning logistic regression model.
    - Build a friend-connection model.
        - Build models at different levels:
            - Global model, local to a country, local to a type of person

Link Suggestion: ML Connection Model

- Goal: Expand a network for an individual (or a group)
- Collect training data:
  - Past suggestions that were accepted by a user
  - Past suggestions that were ignored by a user (possibly multiple times)
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    - Common likes
    - Common posts
    - Etc.

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