Effects of Decision-Making when Generating a Network from Soundcloud

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Why are we scraping data?

Our network analysis is computationally intensive and would take too long to finish on the full network. (Clauset, Lecture9 2017)

Soundcloud does not have a freely available API for attaining user data.

Why Soundcloud?

- We're both musicians and were naturally curious
- Increasing commercial potential of Soundcloud artists
- Profile pages provided an easy interface for html based scraping

Big Goals

- Top Artist Prediction
- Link Prediction

The Woes of Scraping Data

Loading webpages
- Some artists have over 1 million followers with unique urls.
- Unreasonable to gather all data
- DDoS protection prevents from scraping too fast

Scrolling through web pages
- Soundcloud only loads a small amount of artists to display
- Used a package to trigger a scroll event to load more of our desired data

Design Decisions
- How many artists to grab?
- How to branch to new artists?
- What attributes to grab?

Network Topologies: Planning

Types of sampling to be used:

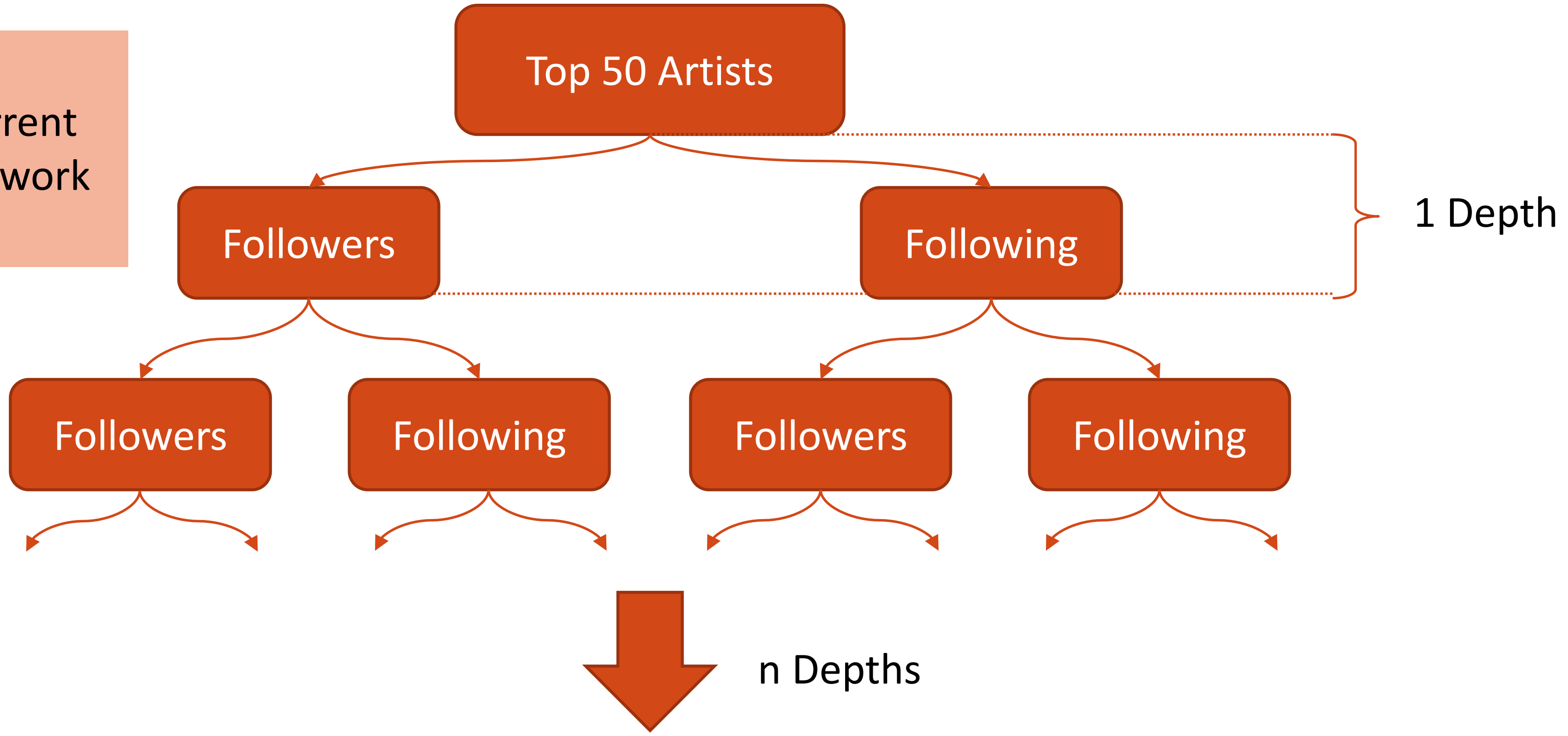
- Snowball Sampling
  - for each seed vertex i, and distance *l,* include all vertices (and their neighbors) for an *l*-step breadth-first search tree rooted at i
  - In our models, *l* = depth, and i = a particular artist
  - The snowballing can occur via links to an artists FOLLOWERS or FOLLOWING accounts
- Adaptive Sampling
  - for each seed vertex i, and integer s, include all vertices (and their neighbors), or include all edges, in an adaptively-grown tree containing s vertices rooted at i

- Different approaches to adaptively sampling the Soundcloud network:
  - Removing followers
  - Only adding artists (number of tracks > 0)
  - Only adding artists/users over a certain number of followers

Network Topologies: Take 1

Depth = 0:
Each artist from the current top 50 songs is added as network nodes.

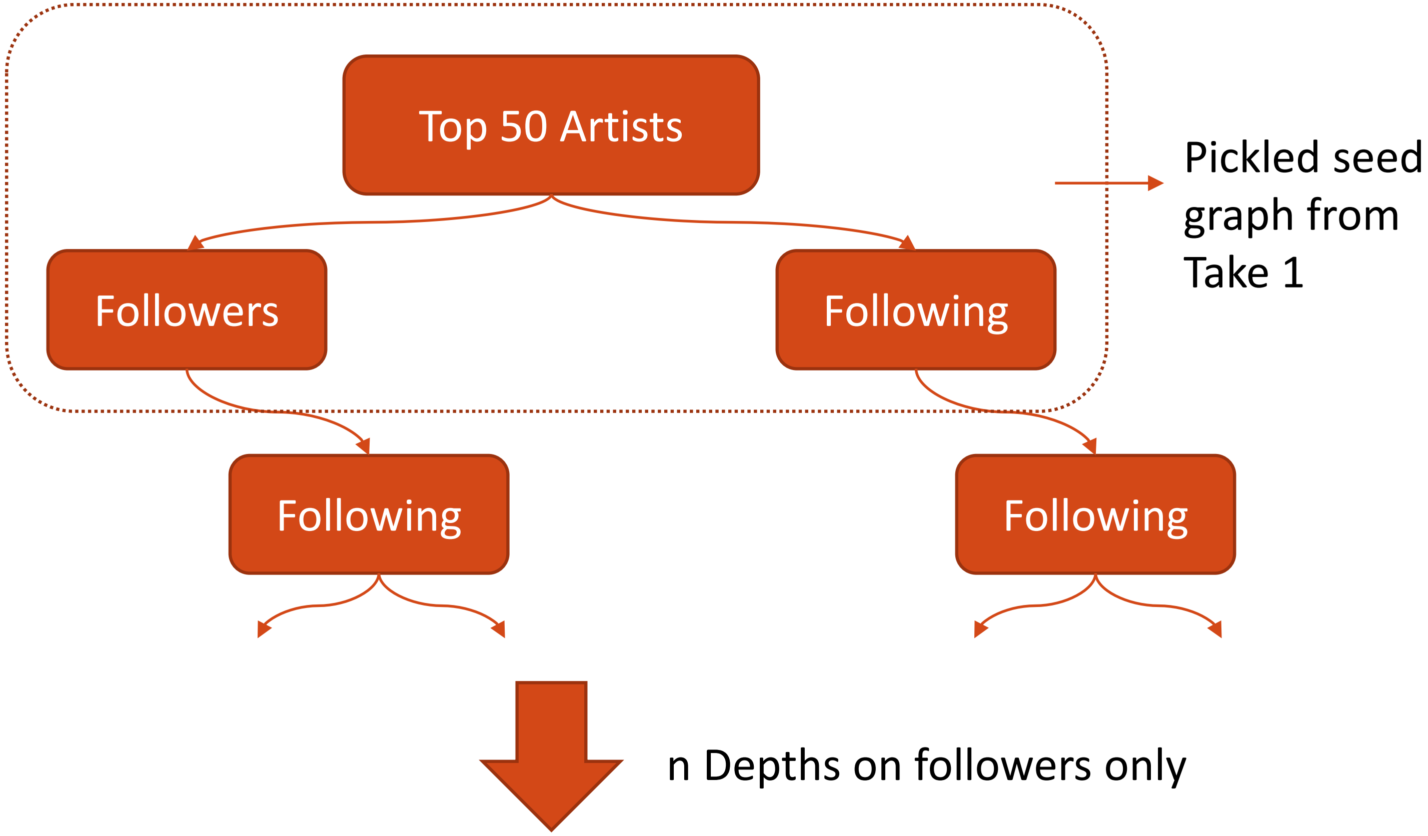
Depth > 0:
Each artist's "following" list is added as new artists, as well as a random sample of followers.



Network Topologies: Take 2

Depth = 0:
Each artist from the current top 50 songs is added as network nodes.

Depth > 0:
Each artist's "following" list is added as new artists. The random sample of followers is added to the network but not branched.



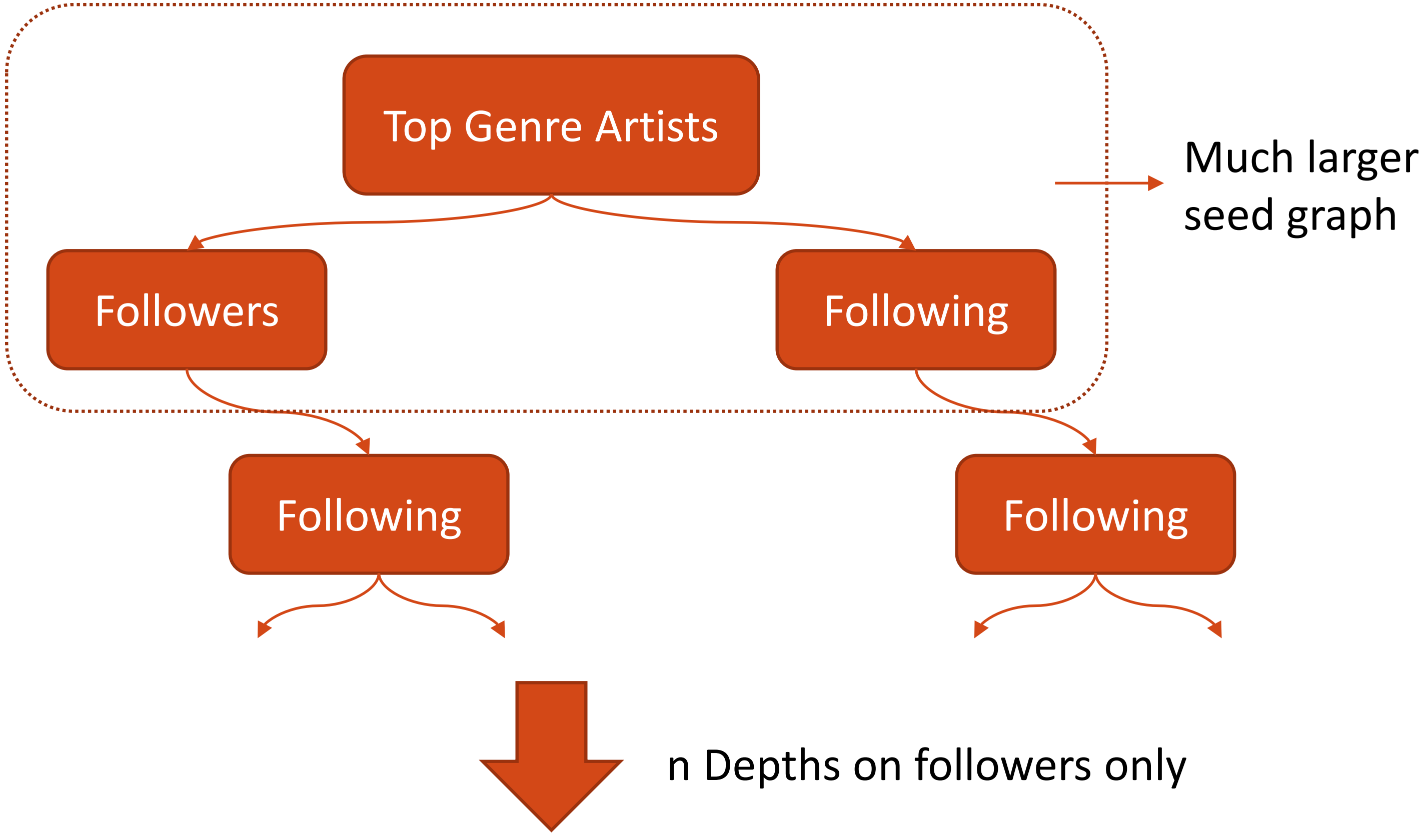
Network Topologies: Take 3

Depth = 0:

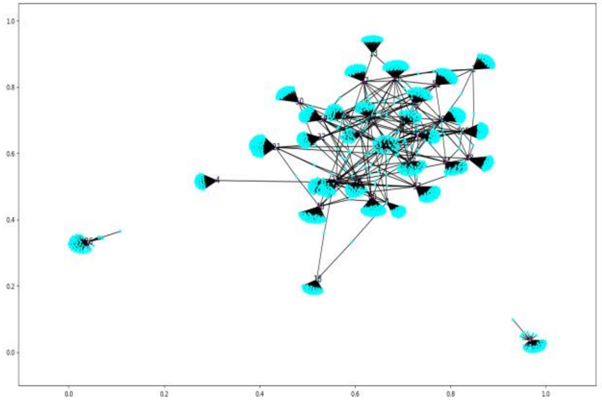
Each artist from the current top 50 songs of the top 30 genres is added as network nodes.

Depth > 0:

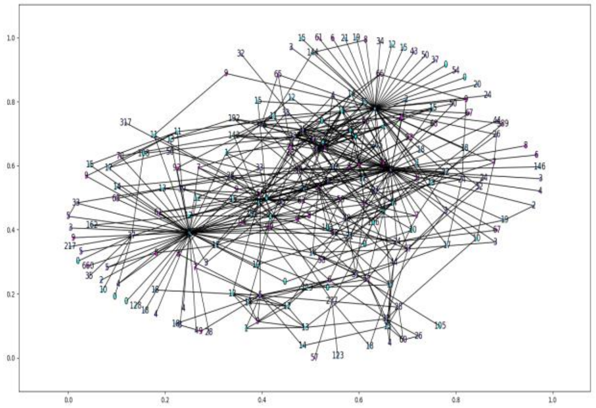
Each artist's "following" list is added as new artists. The random sample of followers is added to the network but not branched.



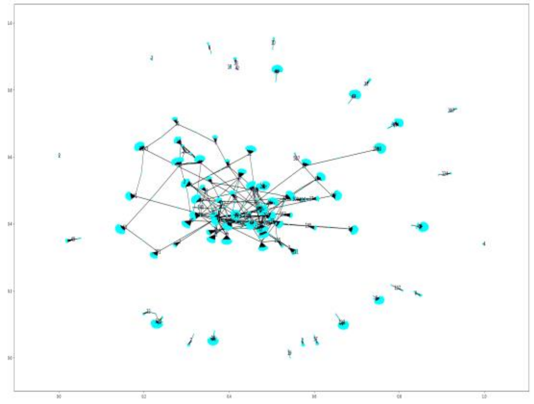
Network Topologies: Visualized



Take 1
N = 21258
Edges = 29210



Take 2
N = 39734
Edges = 59836



Take 3
N = 5598
Edges = 6016

Metrics

Clustering Coefficient (Nodes)

- Fraction of possible triangles through the node that exist

Number of Triangles

Degree

GbA Heuristic

- Guessing attributes such as whether a node is a user or an artist

Link Prediction

- Degree Product AUC
- Common Neighbors AUC
- Shortest Path AUC

Graph Metrics Detailed

	Take 1	Take 2	Take 3
N	21258	39734	5598
Edges	29210	59836	6016
Number of Triangles	11715	11229	411
Max Clustering Coeff	1 (The Actual Tanis)	1 (SEBASTIAN)	1 (MAX)
Clustering Coeff	0.023	0.012	0.0095
Max Degree	183 (Wicca Phase GBC ETERNAL, 25k followers)	184 (G-EAZY, 1.4million followers)	157 (IOF,
Mean Degree	2.75	3.02	2.15

Future Work:

Sampling Decisions:

- Add larger sampling of followers at every step and connect any existing artists they follow
  - Generate a larger network in general
- Probabilistic Sampling
  - Add edges with a probability, to lessen possible bias applied when sampling from only the popular artists

Random Graphs:

- Comparing our model to random graph models such as Erdos-Renyi, configuration model, etc.

Metrics:

- Link Prediction
  - Need larger sampling of followers (user)