CSE 6242: Team #131 (GeoSpecial): Project Proposal

What are you trying to do? Articulate your objectives using absolutely no jargon.

Using Newman's Ground Truth Algorithm (NGTA) on a patent network extracted from the PatentsView database, we will filter prolific inventors from network noise. Because the patent network is noisy, we are skeptical that it accurately reflects reality. NGTA will allow us to quantify our confidence that each edge is "real" and not noise. NGTA will produce statistics that quantify the reliability of the network.

How is it done today; what are the limits of current practice?

Noisy graphs are often filtered on weights. This assumes a linear relationship between weights and confidence. Robust ML solutions, such as Namata's Coupled Collective Classifiers (C3)[2], can perform network inference (extract the "real" graph from the observed). These approaches use semi-supervised learning and inference models[2], which are computationally expensive. While some semi-supervised models process noisy graphs, they are usually limited to clustering, (do not assess components individually[12]). Others use ensembles (generative stochastic graph models)[3]. These rarely have closed-form solutions, requiring simulations. A common goal with noisy networks is community detection,[15, 16] which also does not assess individual components). A method developed by Dr. Du (Beijing U of T) processes patent networks to find influential inventors[18]. His is more efficient than prior approaches, but does not distinguish ground truth. If non-noisy patent data is acquired at scale, comparisons between Du's and Newman's methods would be insightful. In 1999, US patents contained 3.8 million nodes. This data is rich, with attributes for inventors, assignee, etc.[5] This richness results in noise, with innovators hidden by peripheral individuals. Older patent records can suffer from duplicate inventors, which present as false discoveries[6]. This data has historically been used to describe and forecast economic conditions, with common algorithms including shortest paths, and maximum flow.[5] Modern patent analysis has matured in several areas, including patent infringement, hotspots, and competitors[17]. Traditionally the talent industry relied on passive acquisition[8]. Today, "head-hunting" is limited to small groups. Patent data is rarely used, and only as a reference. NGTA brings patents to the forefront, enabling a data-driven recruiting strategy.

What's new in your approach? Why will it be successful?

In 2000, research on patent networks was primarily trend analysis of global structures, which fueled macroeconomic decisions[13]. Recently, patent analysis has been utilized to find impactful inventions and highly innovative companies[14] - largely fueling stock speculations. Never before has NGTA been executed on a patent network. NGTA will enable us to quantify confidence in each edge's existence in the network (where nodes represent inventors/ businesses, edges represent patents), then filter the network dynamically by confidence levels. After filtering, remaining connected nodes constitute significant inventors. Thus, NGTA extracts inventors who are "real" contributors, and filters out those who are less important to a company's patent portfolio. NGTA produces three network-level descriptive statistics. The true positive rate (low TP implies missing edges[1]), the false positive rate (low FP implies an edge is rarely observed where none exists[1]), and false discovery rate (low FDR implies observed edges are part of the network[1]). This implementation has a strong chance of success due to the algorithm being lightweight, with rapid convergence. NGTA can be run on tabular data, and does not require a graph database. The network will be instantiated using NetworkX, and visualized with Graphviz[4]. These open source packages offer robust, effective, and lightweight processing and interactive visualization capabilities.

Who cares?

Most empirical studies of networks take a naive view of structural data, where one assumes that the data are the network[1]. Accurate analysis and understanding of networked systems requires a way of estimating the true structure of networks from such rich but noisy data[1]. NGTA quantifies this discrepancy, and level-sets confidence in downstream outputs. Human capital has a profound impact on a firm's strategy, outcomes, and performance. Furthermore, it is the most challenging resource for competitors to replicate.[9] In an ever-competitive war for talent, companies will increasingly turn to data-driven recruiting strategies. Patent networks are directly related statistically to a firm's acquisition and dispersion of new technology[7]. Identifying true innovators allows firms to poach those people for competitive advantage. NGTA allows recruiters to confidently identify the best individuals to pursue.

If you're successful, what difference and impact will it make, and how do you measure them (e.g., via user studies, experiments, ground truth data, etc.)?

Successful implementation of NGTA will enable organizations to greatly increase their confidence in any business intelligence based upon the network. Recruiters can focus their efforts where the effort is worthwhile - the pursuit of valuable candidates. NGTA can be tested using a test set. If the resulting statistics are similar between the two, we can be confident that the algorithm reached true convergence.

What are the risks and payoffs?

This is a low-risk, high-reward implementation. One risk is that the network exhibits heteroskedasticity across industries, prohibiting NGTA from converging. If so, the network will be segregated by industry, with NGTA run upon sub-networks. Successful NGTA implementation upon patents results in business intelligence for the talent industry - extracting performant individuals, upon whom recruiters can focus.

How much will it cost?

Nothing. We can operate on the patent data in GCP within the limits of the free tier. While weekly updates to the US patent database can be hundreds of megabytes in size, the *patentpy* and *patentr* libraries allow for tidy and small records[10]. This greatly reduces the required data volume. Established conversion models between relational data and target graph data will further reduce the data volume[11].

How long will it take?

TASK TITLE	TASK OWNER	START DATE	DUE DATE	DURATION	% COMPLETE
Data Acquisitiona and Cloud Storage	Sang Yoon, Erik S	10/15	10/22	7	0%
Data Engineering	Xingpeng , Erik W	10/22	10/29	7	0%
Algorithm Development & Cloud Execution	Tylor	10/29	11/5	6	0%
Front End Development	Sandro, Xingpeng	11/5	11/12	7	0%
Front End Testing	Everyone	11/12	11/19	7	0%

* All team members will contribute a similar volume of effort.

What are the midterm and final "exams" to check for success? How will progress be measured?

The midterm consists of a small scale experimental run of NGTA on a subset of the network, with limited visualization. The final consists of a full run of NGTA on the full network, with interactive visualization.

References:

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