GeneticFlow: Exploring Scholar Impact with Interactive Visualization

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ABSTRACT

Visualizing a scholar's scientific impact is important for many challenging tasks in academia such as tenure evaluation and award selection. Existing visualization and profiling approaches do not focus on the analysis of individual scholar's impact, or they are too abstract to provide detailed interpretation of high-impact scholars. This work builds over a new scholar-centric impact-oriented profiling method called GeneticFlow. We propose a visualization design of scholar's self-citation graphs using a time-dependent, hierarchical representation method. The graph visualization is augmented with color-coded topic information trained with cutting-edge deep learning techniques, and also temporal trend chart to illustrate the dynamics of topic/impact evolution. The visualization method is validated on a benchmark dataset established for the visualization field. Visualization results reveal key patterns of high-impact scholars and also demonstrate its capability to serve ordinary researchers for their impact visualization task.

Index Terms: Human-centered computing—Visualization

1 INTRODUCTION

Scholars are the gravity center of academic world and analyzing their impact has been a fundamental subject in scholarly data analysis. Understanding and quantifying scholar's impact are essential for many real-world tasks such as academic award selection, tenure evaluation [26], and academic output inference [8]. Here the scholar impact is defined as one's scientific contribution (e.g., publications), as well as their recognition in the community (e.g., citations). The topic has attracted great attention in both academia and industry, as exemplified by the field of Scientometrics [10] and the numerous academic platforms such as Google Scholar [4] and Microsoft Academic Graph (MAG) [1].

Visualizations have been indispensable constituent for scholar impact analysis. The support of intuitive and interactive analysis capability fits well with the subjective nature of scholarly impact. For example, Google Scholar presents dashboard for scholar profiling by a combination of author-level indicators, such as total citation, h-index, and i-10 index. They also introduce interactive charts to depict a scholar's impact, including citation count time series. Their approach brings together different aspects of a scholar's impact, but does not integrate and interlink them into a single impact analysis apparatus, nor do they offer detailed interpretation of high-impact scholars. On the other hand, graph visualizations have long been deployed to display academic information, such as co-authorship network for collaboration history comprehension [19] and co-citation network for emerging topic detection [5]. Yet, very few of these network visualization design focuses on scholar-centric analysis of academic impact.

This work builds over our latest scholar-centric impact analysis proposal called GeneticFlow (GF) [23]. The core idea is to explore the self-citation graph of a scholar which connects all his/her publications into a structured context for interpreting scholar's impact. Moreover, profiling methods are developed to only expose core papers in the graph that represent one's own research idea, and extend-type self-citations delineating one's idea evolution. This ensures the resulting GF graph scholar-centric. Nevertheless, the complexity of GF graphs makes it hard for ordinary users to comprehend. In comparison, impact indicators such as h-index are easy to interpret, and classical bibliometric networks are already familiar to the community. In this paper, we propose a visualization system for GeneticFlow which makes following contributions to tackle several nontrivial challenges:

- We design and implement a visualization method for GF using time-dependent, hierarchical graph representation. An elaborate topic generation and color mapping mechanism is proposed, by applying the cutting-edge deep text embedding algorithm. The GF visualization is also complemented with dynamic trend chart and topic map view to support scholar impact analysis in temporal and topical dimensions.
- We establish a benchmark dataset encompassing top scholars in the visualization research field, over general-purpose MAG corpus. Case studies on both award-winning visualization researchers and ordinary scholar demonstrate the effectiveness of GF visualization in analyzing scholar's impact. The core profile and characteristics of these scholars are easily identified with the proposed visualization system.

2 RELATED WORK

2.1 Scholar Indicator Profiling

There are many kinds of indicators for evaluating the scientific impact of a scholar. The representative one is h-index [15], which only considers papers with high citation counts. Specifically, it tells that among all papers of a scholar, there are h papers cited at least h times. In addition, h-index has many variants such as g-index [6]. g-index refers to the top g papers of the scholar with the highest number of citations, which are cited at least a total of g^2 times. Although indicators like h-index take into account both the quantity and quality of papers, it may often lose a lot of other information important for scientific impact. That said, we may need to analyze the scholar's academic data from multiple perspectives including publication, citation, and collaboration networks. For example, Egoslider [32] and Egolines [33] distill the evolutionary collaboration networks to learn the academic interactions. Fung et al. designed a tree metaphor to visualize one's publications [9]. Though intuitive, the above works lack the potential to analyze individual and social factors that can contribute to career success. Wang et al. apply a multi-factor impact analysis framework to estimate the effect of different factors on academic career success over time [31]. In their visualization design, a Impact Timeline is introduced for comparing the effects of different categories within a factor, and a CareerLine shows one's academic career development affected by multiple factors.

2.2 Career Trajectory Visualization

Google Scholar [4] has the world's largest source of academic information, with more than 389 million documents [13]. It provides

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Table 1: statistics of the subset of MAG data related to visualization

	# of paper	# of author	# of reference	# of paper_author
VIS subset	225K	429K	4.7M	664K

a list of publications for each scholar including the year and citations, which can delineate the scholar's academic career trajectory. Systems like AMiner [2] and DBLP [3] also arrange relevant academic information in an organized manner. More recently, with the surge of digital libraries on academic publications, various proposals have emerged in the field of visualization for academic data. Latif et al. used generated natural language text as part of the visualization of a scholar's profile to facilitate the exploration of one's academic career in VIS [21]. Several other visualization techniques are also presented, e.g. ego-centric scholar visualizations [14] [16] [22] [25] [27], but they do not work for impact-oriented scholar profile visualization. For example, Reitz uses links in an ego-centric node-link diagram to encode temporal distributions of the joint work [25]. MENA represents the ego-centric network as a dynamic graph in small multiples [14]. Fung et al. suggest a botanically inspired tree visualization to summarize the collaborations in each branch of a time span, with co-authors encoded as leaves [9].

The aforementioned works describe a scholar's academic career from a global perspective via generative text or timeline of changes. In comparison, our research mainly focuses on constructing a scholar's self-citation graph and its core components for building scientific impact, which help users better understand the evolution of a scholar's academic ideas.

3 GeneticFlow Analytics

3.1 Background

To resolve the impact-oriented scholar profiling problem, GF analytics is proposed to construct the self-citation graph of each individual scholar, which encompasses all publications of the scholar and the self-citations among the papers. We find that besides its impact-expanding role, self-citation also serves a crucial function in delineating the trajectory of a scholar's innovative flows. This design allows to integrate multifaceted academic data into a structured context for scholar-centric impact profiling and also support the tracking of evolution of scholar's scientific impact. In more detail, GF employs an advisor-advisee detection algorithm based on co-authorship ties to identify a scholar's core papers, and introduces an optimized classifier to detect the scholar's extend-type citations. By constructing this core GF graph, the approach achieves significantly better performance on award inference for 6 key fields in Computer Science, compared to classical indicator-based and network-based scholar profiling methods [23].

The GF analytics method is composed of two algorithms: node profiling to detect core papers with this scholar as first or corresponding author, and edge profiling to detect the set of core, extend-type citation edges that represent the evolution of the scholar's scientific contribution. In more detail, the GF node profiling method identifies advisor-advisee relationships on papers published by the target scholar, using an unsupervised, human-interpretable algorithm. Then the author order information is used to detect the core papers, including those with the scholar as first author or the scholar's student as first author. To avoid issues with alphabetically ordered papers, a statistical method is used to detect and eliminate sub-fields in CS where alphabetical authorship is heavily used.

The GF edge profiling method detects extend-type citations by synthesizing existing studies on citation type classification [29] [30] [18]. In short, supervised learning techniques are applied on a labeled dataset combining those in the literature, with manually labeled extend-type and other citations. Four categories of raw features, including metadata of cited and citing papers, features extracted from their citation networks, temporal correlation measures, and content and lexical patterns from the citation context and full text, are hand-crafted and evaluated for their significance in differentiating extend-type and non-extend citations. Twenty features are finally selected based on correlation analysis and significance tests. The Extra-Tree model [11] is selected as the best classifier, achieving an F1 score of 0.646 with 10-fold cross-validation.

More details can be found in Ref. [23] (the algorithm paper).

Table 2: Statistics of GF Graphs for top-1000 visualization scholars

	Full graph	Core graph	Ratio of core
average papers	35	20	57%
average citations	31	17	55%

3.2 Academic Data Source

We mainly use MAG, the largest open academic data source nowadays. MAG contains papers and their metadata (authors, citations, fields of study, etc.) from all disciplines, including computer science, physics, biology, etc. In total, over 237 million papers, 240 million authors, and 1.63 billion citations are recorded. Therefore, MAG offers most of the required data to build GF profiles.

To derive GF profile for the scholars in the visualization field, we also conducted preprocessing on the raw dataset. We selected four primary fields of study in the MAG topic hierarchy related to visualization, which collectively cover almost all papers in the visualization field. With these papers as starting point, we further obtain all authors in the field. All citation links associated with visualization papers are extracted from MAG to build the self-citation graph of visualization scholars. Statistics of this specific dataset are listed in Table 1.

3.3 GF Graph Processing

Given the large number of scholars in the field of visualization, we rank them by their paper counts in the field and select top-1000 scholars for further analysis. The GF node/edge profiling algorithms are applied to obtain the GF profile of these top scholars. As listed in Table 2, the number of core papers for each scholar decrease to 43% of the full GF graph in average, and the number of extend-type citations are estimated to be 45% of all citations.

MAG has a built-in topic hierarchy pre-trained on its large data corpus [1]. Each paper is provided with one or more topic tags in the hierarchy. However, we found that the research topics provided by MAG do not match well with the reality. Therefore, we do not apply the MAG topic tags but used a BERT-based topic modeling approach instead. We collected the titles and abstracts of all visualization papers in MAG as text data, and used a pre-trained BERT model to generate the text embeddings. The BERTopic implementation [12] is used as it performs well on academic data sets. A list of 90 topics were obtained on the visualization field. We then cluster similar topics into higher-level topics to create a topic tree. Each paper is mapped to a single topic at the leaf of the tree. The UMAP algorithm [24] is applied to reduce the dimensionality of text embedding for clustering. After the clustering, 11 top-level topics are formed, resulting a two-level topic hierarchy.

4 Scholar-Centric Impact Visualization

Over GF analytics, we propose an interactive system to visualize GF profiles of top scholars in a given field. Here we introduce the system design, showcased in the visualization field.

4.1 Design and Implementation

GeneticFlow graph visualization. The main interface of GeneticFlow is composed of multiple coordinated views, as shown in Fig. 1. For a specific scholar, the left panel provides his/her demographics such as paper/citation count and h-index (Fig. 1(b)), and the node/edge statistics of corresponding GF graph (Fig. 1(c)).

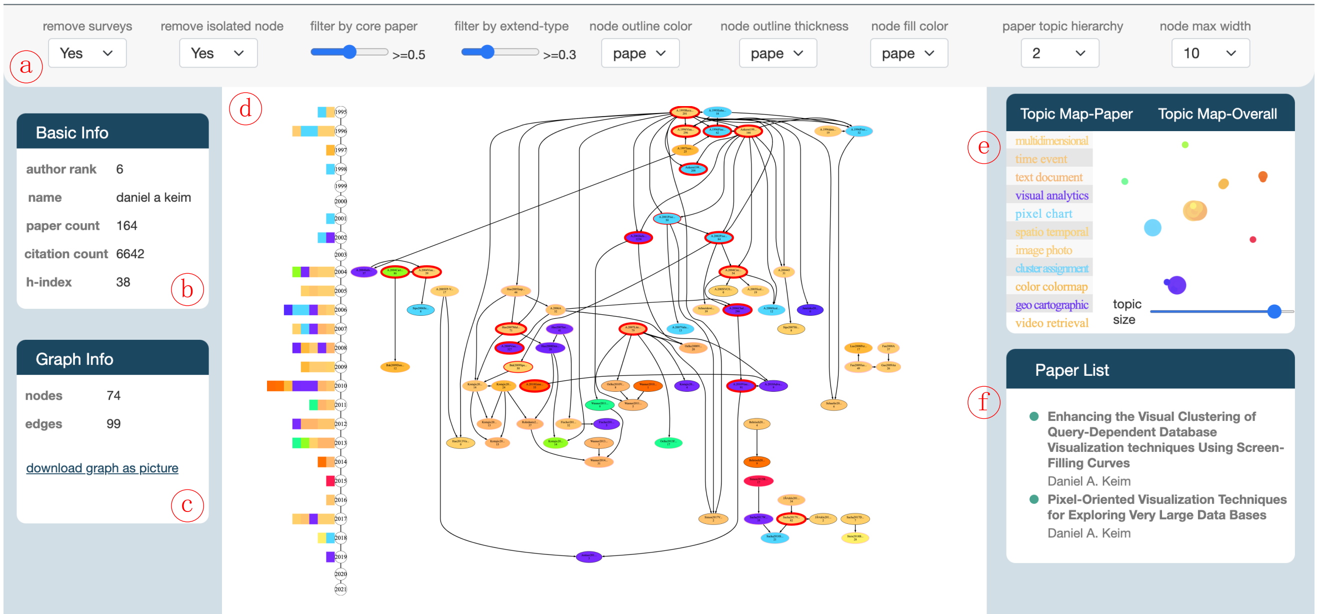

Figure 1: GeneticFlow visualization interface (Prof. Keim's graph): (a) system control panel; (b) scholar demographics; (c) graph statistics; (d) GF graph visualization; (e) topic distribution map; (f) author/paper/citation detail panel.

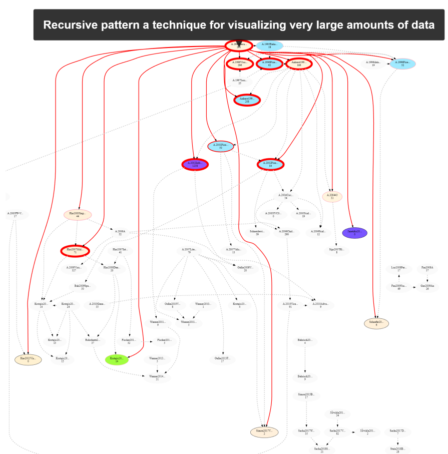

Figure 2: The impact of Prof. Keim's "recursive pattern" paper.

This design inherits the merit of classical scholar profiling platforms such as Google Scholar, which help to gain an overview of the scholar's scientific impact. In the right panel of our interface, a topic map presents the distribution and strength of all topics learned on the scholar's paper (Fig. 1(e)). A detail panel in the bottom right (Fig. 1(f)) provides expanded bibliographic information about the selected scholar, paper (node in GF), or citation (edge in GF).

The key visualization design lies in the display of GF graph as a hierarchical graph with one layout dimension attached to the paper publication year (Fig. 1(d)). Each node in the GF graph represents one paper published by the displayed scholar. The color and thickness of the node border represent the amount of citations of the paper, with darker red and thicker border representing more citations. The paper with more than 50 citations will be illustrated in the most thick/red outline. Due to possibly long paper titles, we depict node labels as "publication year + first word in paper title". Users can hover the nodes to display the full paper title. The node fill color represents the topic of corresponding paper, with analogous color mapped to similar research topics. Among paper nodes, curved edges are drawn to indicate self-citation relationship. On the left side of GF graph visualization, a timed list of bar charts are designed to display the topic distribution of the scholar's research over time. Each bar chart is stacked with mini-bars representing the strength of each topic in a year, sorted by the topic's overall significance in the target scholar's career.

To determine color mapping for all the topics, we first apply high-dimensional embeddings to project topic keywords into a new 2D space. Moreover, we choose the HSV color space to represent the color of each topic. The selection of HSV space is to ensure that topics with similar semantics will have similar colors. In the HSV color space, we fix the brightness of the HSV color to 1, and obtain a 2D color subspace. This subspace is mapped with the 2D projection of topics. The color hue is computed by the rotated angle of topic vector. The color saturation is computed by the length of topic vector. To help users gain a clear view of the topic distribution of top scholars and research fields, we also design a topic map visualization for coordinated analysis with GF graph visualization. As shown in Fig. 1(e), the projection view on the right displays the distribution of topics of the selected scholar by default, with the size of each topic circle indicating topic intensity.

We apply a hierarchical layout algorithm to arrange the paper nodes where each node is placed in the layer corresponding to its publication year. To layout the self-citation edges between papers in the graph, we add dummy nodes at each layer so that each edge only connects to nodes in adjacent layers. Each edge is drawn as a third-order Bezier curve for a smooth and aesthetic display. The user is provided with citation context when clicking on the directed edges in the graph. In order to reduce edge crossings in the graph, the nodes in the same layer is re-arranged by a Sugiyama-style algorithm [28]. The popular package of GraphViz (with dot command) [7] is introduced to implement our layout algorithm.

Interactive visual analysis. Considering that most scholars have published a large number of papers, the GF graph can be too cluttered to perceive. In our design, we apply GF profiling methods to filter out insignificant papers and citations, which is interactively adjusted through two sliders. The node filtering is by the probability of being a core paper and the edge filtering is by the probability of being extend-type citations. A drop-down box is available to remove isolated node from GF graph. Users can better focus on the idea flow and topic evolution of the selected scholar, by working with the extracted core GF graphs. Upon a click on the graph node, more

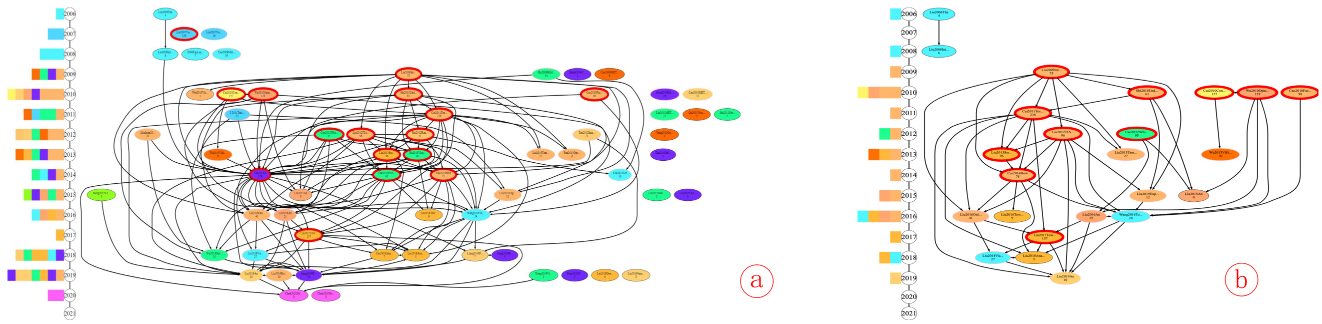

Figure 3: Prof. Liu's GF visualization: (a) full GF graph, including isolated nodes; (b) core GF graph.

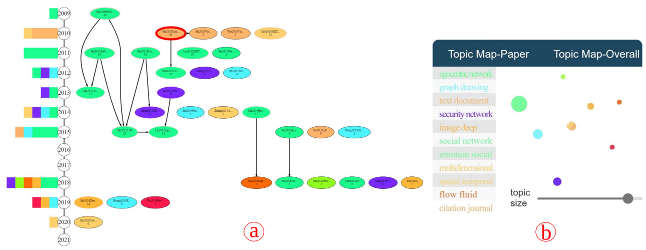

Figure 4: Prof. Shi's GF visualization: (a) full graph; (b) topic map.

detailed info about the paper, including abstract and research topics can be expanded for analysis. As the default view showing all 90 low-level topics can be cluttered, we introduce another drop-down option to switch to the top-level topics with 11 classes.

System implementation. In the system interface, we list most important author-level impact indicators, including citation count, h-Index, and paper count. Additionally, we build a search page and retrieval system for users to perform query for interested scholar names and proceed to the scholar's GF graph visualization after that.

4.2 Case Study

We apply the GF visualization system to study the scientific impact of top visualization researchers. As junior researchers rely more heavily on citing/extending other's research idea, GF method could be less effective in profiling their impact. We also note that our method focuses on delineating an objective-at-best scholar profile with openly published academic data. Hence, the case study is done in the third-person view, without interviews on the studied scholars.

First, we consider Prof. Daniel Keim who is one of pioneers in visualization and visual analytics research. Fig. 1 illustrates his GF graph with the default setting to exclude non-core papers/citations and isolated nodes. It can be observed that Prof. Keim's research on visualization began from 1995 when most of his early year's work were highly influential (in red and thick node outlines, indicating # of citations > 50). His research topics in these years include pixel-oriented database visualization (cyan) and multidimensional data visualization (light yellow), which can be expected because he was an academic descendant of Hans-Peter Kriegel, the famous database scientist. Later, his research came at peak by the number of papers during 2004$\sim$2013. The research focus shifted to both visual analytics (purple) and information visualization on multiple data types (light yellow) such as text and time series. Prof. Keim's career echoed a historical trend in the field, from the direct visualization of classical multidimensional data to visual analytics on new types of data, combining automatic data analysis algorithms.

Drilling down to the detail of Prof. Keim's research, we find that his "Recursive Pattern" paper [20] in 1995 had the most comprehensive impact. As shown in Fig. 2, the longest self-citation edge crosses 22 years, and the influenced topics have covered most of Prof. Keim's research areas: database visualization, visual analytics, time series visualization, etc.

In another case, we study Prof. Shixia Liu's GF graph, another senior researcher in the visualization field. Fig. 3(a) depict her full GF graph with all isolated papers included. The full graph is quite difficult to comprehend as too many papers are linked together. Using the functionality of GF analytics, we extract the core papers/citations of her GF graph. Fig. 3(b) presents a much clearer view of her research topic evolution. Importantly, the survey paper in Fig. 3(a) (purple node at 2014) has been removed because of lacking extend-type citation links. Fig. 3(b) indicates that Prof. Liu focused on the text and document visualization topic (light yellow) during 2009$\sim$2016, according to the side bar on the left side of GF graph. Many of these works are highly influential (# of citations > 50). This finding corresponds well with the fact that she was elevated to IEEE fellow for the primary contribution on visual text analysis. It also implies a key pattern for high-impact scholars: the existence of *well-connected, highly-cited core graph* in his/her GF profile.

Our method is also useful for ordinary researchers. As illustrated by the GF graph of Fig. 4, the last author of this work ever focused on network visualization research before 2015. This experience is captured by a few paper clusters in green (egocentric network) and other isolated papers in cyan (graph drawing) and purple (security networks). Most recently, he turned to work on visual analytics applications, so that the topic color distribution becomes diversified and the works are quite isolated without self-citations. The GF approach precisely demonstrates the trait of one's research evolution as well as their magnitude of scientific impact.

5 Conclusion and Discussion

This paper presents GeneticFlow visualization, the method that illustrates structural, topical, and evolutionary context of a scholar's scientific impact. It is developed based on a suite of new analytics methods that extract core papers and extend-type citations out of the scholar's self-citation graph. The visualization design also incorporates multiple coordinated views to display the distribution and temporal dynamics of research topics, as well as detailed demographics of the scholar and associated publication/citation lists. We build an online system over a well-curated academic dataset of the visualization community. Case studies on top visualization researchers both reveal essential patterns on high-impact scholars and demonstrate its capability to benefit ordinary researchers with a clear view of their academic impact.

Our work does have limitations. First, we choose MAG instead of VIS-specific data sources such as VisPubData [17] due to the broader coverage of MAG. The result could be disturbed by potential data error and incompletion, though MAG has been the best open academic data source for all disciplines. Second, we only showcase the application in the visualization community. Deployments in more research fields would be demanding. Third, self-citation links can be absent due to various reasons, e.g., published in the same year. Admitting more links in the graph by topic affinity criterion beyond self-citations could be a direction for better impact visualization. We plan to address these limitations in future.

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