Summary of a Bulletin Video entitled:

Propagating Visual Designs to Numerous Plots and Dashboards

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1 Introduction

The bulletin summarizes the work presented in our paper [7]. In this paper, we proposed a technical solution to address the challenges encountered in developing a visualization and visual analytics system to support epidemiologists and modeling scientists during the COVID-19 pandemic. Our goal was to enable rapid and reliable propagation of various visual designs to numerous datasets while streamlining the development workflow.

The technical solution proposed involves the separation of data management, visual design, and plot and dashboard [3] deployment tasks. To achieve this, we employed an ontology for knowledge management [5, 6] that unifies datasets, visual designs, and deployable plots and dashboards under a common management system. Furthermore, we leverage multi-criteria search and ranking algorithms to discover datasets that match specific visual designs, and we develop a purposefully-designed user interface to facilitate the propagation of visual designs to appropriate datasets and ensure quality assurance before deployment.

This is part of the infrastructure, named RAMPVIS [4] was developed by a group of volunteers [1] specialized in visualization and visual analytics, in collaboration with the Scottish COVID-19 Response Consortium (SCRC) [2]. The consortium faced challenges in accessing and visualizing vast amounts of data from various sources, requiring time-consuming processing and limited visualization expertise.

2 Challenges

During the COVID-19 emergency response, we encountered a major challenge due to the limited volunteer resources available to us. Our objective was to provide a visualization system to epidemiologists and modeling scientists for a large number of COVID-19 timeseries data from various regions and modalities. This included analytical data, model data, and more. Different visual designs were needed to effectively represent the various modalities of COVID-19 data depending on the type of data being presented. Managing a wide range of data and developing various visual designs that cater to different data posed a significant challenge.

3 Solution

To efficiently use our volunteer resources and reuse visualization designs, we developed a streamlined workflow. The workflow manages data, visualizations, and web pages. Additionally, we created a propagation algorithm that efficiently repurposes existing visual designs for new data streams or regions. A key component of our architecture is ontology, which serves as a central knowledge base [5, 6].

3.1 Ontology

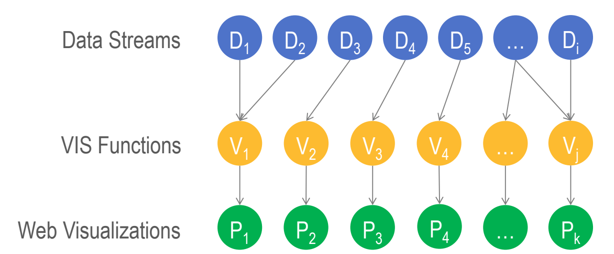

Figure 1: The ontology stores the relationships or links between data streams, visualization (VIS) functions, and web pages. When data streams (e.g., D_1, D_2) are linked to a relevant VIS function (e.g., V_1), a web visualization (e.g., P_1) is created. Furthermore, the propagation algorithm creates new visualizations for new data streams by reusing existing VIS functions.

The ontology is the central component of our RAMPVIS architecture which organizes data streams, visualization or VIS functions, and generated web visualization or pages as shown in Fig. 1. With a large number of diverse data streams and visualizations, the ontology efficiently manages their relationships.

The ontology is implemented as a graph data structure, with objects mapped to nodes and relationships mapped to edges. Data streams in the ontology have attributes such as endpoint, description, and keywords. A text search engine creates an inverted index for quick searches of data streams. VIS functions are implemented using libraries like D3.js. The web pages in the ontology are essentially links or bindings between VIS functions with data streams and are rendered in the web browser using web templates. A detailed description of the ontology, various components of the system, and services can be found in our paper [7, 8].

3.2 Propagation

Propagation refers to the process of reusing existing visualization designs for new data streams, as shown in Figs. 2 and 3. This avoids the need for additional development effort from visualization developers. In this work, an ontology-based approach was implemented to achieve propagation. The process involved two tasks performed by a user. Firstly, they formulated a query to identify data streams that could be paired with a specific visualization. Secondly, they reviewed the search results to ensure the visualization was suitable for propagation and publication.

The implementation of propagation significantly improved the efficiency and reliability of reusing visualization designs for new data streams. This enabled the infrastructure manager to quickly identify suitable data streams for visualization, reducing the time and effort required to disseminate new visualizations. This streamlined the process of scaling the system with new data streams and complex visualizations, resulting in the effective utilization of limited volunteer resources. A detailed description of the propagation technique and

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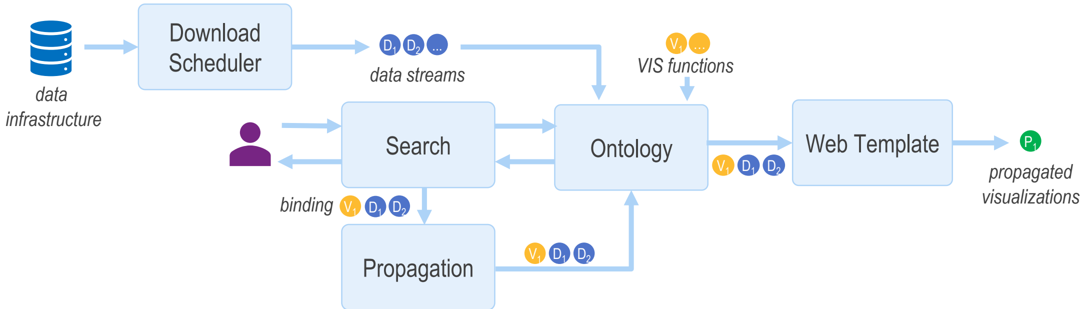

Figure 2: This flowchart illustrates a propagation workflow. The first step involves fetching data from an external infrastructure and registering data streams to the ontology. VIS functions are also registered to the ontology. Simultaneously, a reference web visualization is created by linking or binding a VIS function and relevant data streams, and the knowledge of this binding is saved to the ontology as a reference. A user formulates a search query to search for new data streams to propagate a VIS function (e.g., V_1). The propagation algorithm uses reference binding (of V_1) as a guide to return a list of data stream groups (e.g., [D_1, D_2], ...) to the user. The user then goes through all groups and propagates the visual design (V_1) to generate many plots (e.g., [V_1, D_1, D_2], [V_1, ...], ...).

Figure 3: This figure illustrates an example of propagation. First, the user chooses a reference visualization, e.g., showing the weekly number of deaths in the Oxford region. Then, formulates a search query. The propagation process uses the search query and reference visualization to generate a list of data stream groups that include thousands of other regions in England. The user reviews and propagates the correct data stream groups of regions, e.g., Lincoln, Liverpool, Maidstone, etc.

the algorithms can be found in our paper [7] and the supplementary material attached to it.

4 Summary

The propagation technique discussed here is important because it uses an ontology-based approach that enables the efficient reuse of visualization designs for different data streams. This approach was particularly helpful in quickly disseminating new visualizations during the COVID-19 emergency response, especially when volunteer resources were limited. This work can be used as a blueprint for developing a visualization and visual analytics system in any data-intensive setting.

Acknowledgments

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