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# CPViz: Visualizing Clinical Pathways Represented in Higher-Order Networks

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## Abstract

*To improve clinical care practice, it is important to understand the variability of clinical pathways executed in different contexts (e.g., pathways in different geographical locations, demographics, and phenotypic groups). A common way of representing clinical pathways is through network-based representations that capture the trajectories of treatment steps. However, first-order networks, which are based on the Markovian property and the de facto standard model to represent transitions between steps, often fail to capture real trajectories. This paper introduces a visual analytic tool to explore and compare pathways represented in higher-order networks. Because each higher node in the network is a sub-trajectory (i.e., partial or full history of treatment steps), the tool can display true sequences of treatment steps and compute the similarity of the two networks in the space of higher-order nodes. The tool also highlights areas where the two networks are similar and dissimilar and how a certain sub-trajectory is realized differently in different pathways. The paper demonstrates the tool's usefulness by applying it to multiple antidepressant pharmacotherapy pathways for veterans diagnosed with major depressive disorder and by illustrating heterogeneity in prescription patterns across pathways.*

## Introduction

Clinical pathways (CPs) are typically structured healthcare plans designed to implement evidence-based clinical guidelines, medical algorithms, and protocols [13]. Intended to improve the quality of personalized care, establish cost-effective and evidence-based care management, and standardize care procedures, CPs have become increasingly important for clinical process optimization and communication between different stakeholders in clinical process management. To improve CPs or enforce a new policy, it is essential to capture CP variability in different contexts, such as hospitals in different geographical locations or demographic subgroups, and perform comparative analysis for various outcome measures (e.g., cost, survival rate).



A comparison of pathway pairs (i.e., pathway variants) is often conducted by measuring topological similarities in their graph representations (Figure 1 (Top)). The Markov property-based (first-order dependency) network is mainly used to model a pathway and portrays a compact and intuitive representation. However, it does not show complete trajectories (i.e., treatment histories) and thus often presents the wrong impression about the treatment process. Therefore, this paper adopts the higher-order network [15] to represent a CP, in which a trajectory of a treatment sequence appears as a node (Figure 1 (Bottom)).

A higher-order network invariably has a more complex structure than a first-order network. Therefore, we created the Clinical Pathway Visualization system (CPViz) to handle the increased complexity. Given many CPs to compare, CPViz compares distances between all pairs and offers interactive functionalities to explore similar and dissimilar treatment patterns between a given pair of pathways. As an example, we describe how CPViz is used to conduct a comparative analysis of ten US Department of Veterans Affairs (VA) antidepressant pharmacotherapy treatment pathways for an Operation Enduring Freedom (OEF) and Operation Iraqi Freedom (OIF) cohort diagnosed with major depressive disorder (MDD) [12].

## Background and Related Work

This section briefly describes how clinical pathways can be represented as higher-order networks. Also, we discuss previous studies focusing on visualizing clinical pathways and events. Finally, we conclude the section with a review of existing work regarding higher-order network visualization.

### *Background: Higher-Order Network for Clinical Pathways*

A network, $G = (V,E)$, is a graph with vertices, $V$, as objects and edges, $E$, as links between objects. In a first-order network representation of a CP, $V$ is a set of single treatment steps (e.g., taking 50 mg of an antidepressant daily for 2 months). In a higher-order network representation, $v \in V$ may represent a sequence of treatment steps (e.g., starting with 25 mg of an antidepressant daily for 2 months, followed by increasing the dose to 50 mg and continuing for 3 months). Formally, an $n^{th}$-order node, $v$, denotes a path through $(s_1,...,s_{n-1},s_n)$, where $s_i$ is the $i$-th step in the path. Although a node can represent a sequence of steps, all other properties can be considered the same as the first-order network. For example, a path from one node $(h,i)$ to the next node $j$ (i.e., steps $h$–$i$) is denoted as $(h,i) \rightarrow j$, and its transition

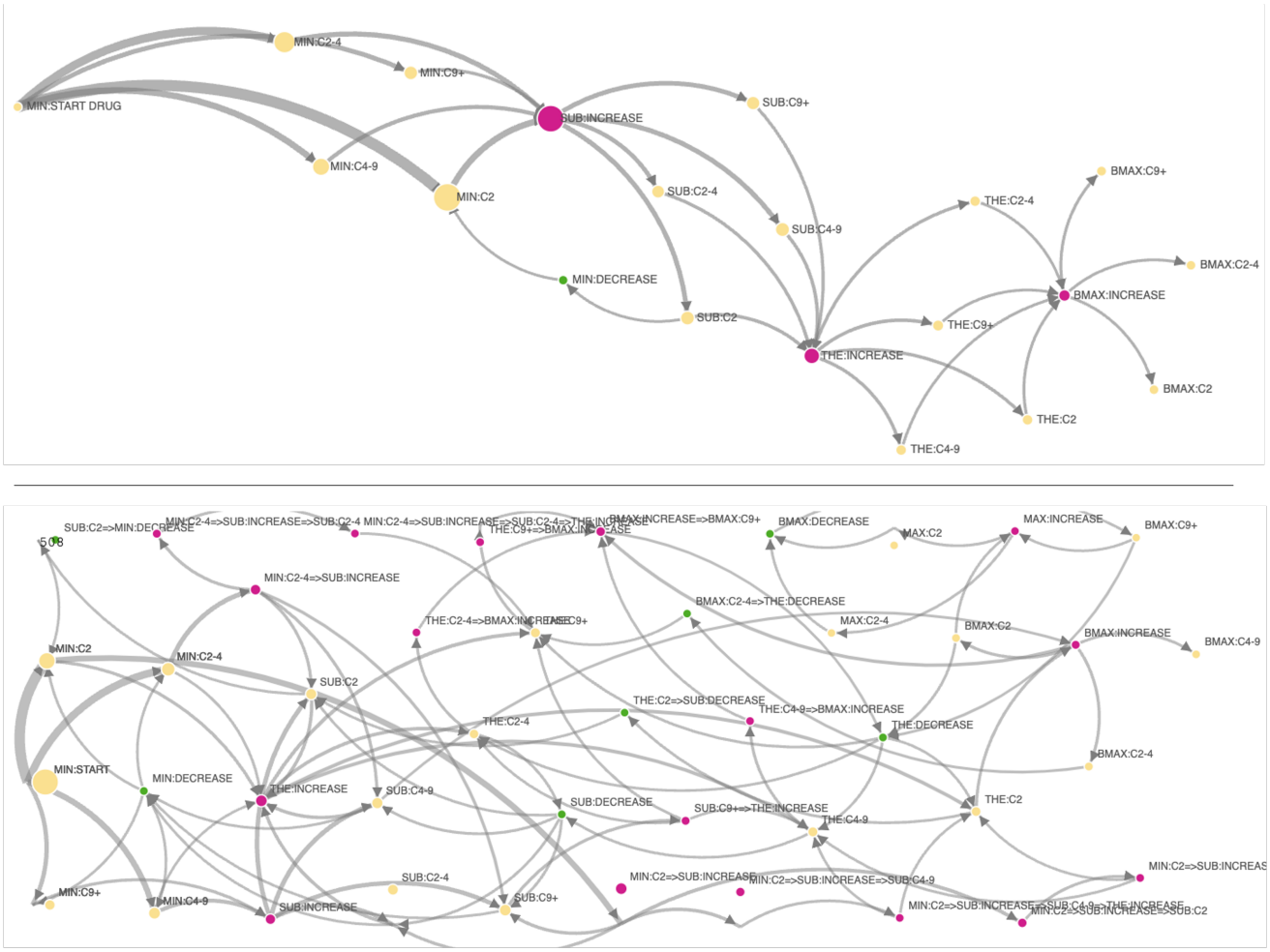


***Figure 1.*** *A CP is represented in two different network types: first-order network (top) and higher-order network (bottom). The first-order version denotes a single treatment step as a node, and the treatment transitions as edges. The higher-order version represents a sequence of treatment steps as a node and the dependencies of the treatment steps as edges.*

probability is

$$P((h,i) \to j) = \frac{W((h,i) \to j)}{\sum_n W((h,i) \to n)}, \tag{1}$$

where $W(i \to j)$ is the sum of connections $i \to j$ found in the data.

## Visual Analytics for Clinical Data

Most previous studies on visualizing clinical pathways and clinical events focused on summarizing large-scale electronic health records (EHRs) as flow-based visualizations to highlight frequent patterns of clinical events [7, 9] to aid decisions for future health care plan [5, 8]. Perer *et al.* [9] preprocessed EHR data to extract and map information to hierarchical standard clinical diagnosis codes and detect frequent patterns from the pre-processed data using Sequential PAttern Mining using a bitmap representation (SPAM) [1]. The visualization interfaces based on Sankey Diagrams represent the frequent pathway events with which users explore paths of interest in detail. Guo *et al.* [7] introduced a visual analytics system that aligns clinical pathways based on dynamic time wrapping and segments into more detailed stages to help illustrate the disease progression in the context of a care plan. DecisionFlow [5] analyzes disease progress and outcomes in EHR by aggregating patients at each stage of the disease. It was also designed to handle varying sequences of events. DecisionFlow visualizes the aggregated symptoms and their average development time for the patients in color-coded paths using Sankey Diagram visualization.

## Higher-Order Network Visualization

To the best of our knowledge, only a few works exist on the visualization of higher-order networks. Processing a rich set of information and complex dependencies in higher-order networks are major obstacles to pattern discovery and interpretation. HoNVis [14] delivered a significant contribution in this area. With a global shipping network as an example, it demonstrated how an interactive exploration of higher-order networks could help a decision process. Multiple coordinated visualizations allowed users to quickly identify patterns of interest and the formation and evolution of higher-order dependencies. HOTVis [10] proposed a dynamic graph visualization algorithm that utilizes higher-order

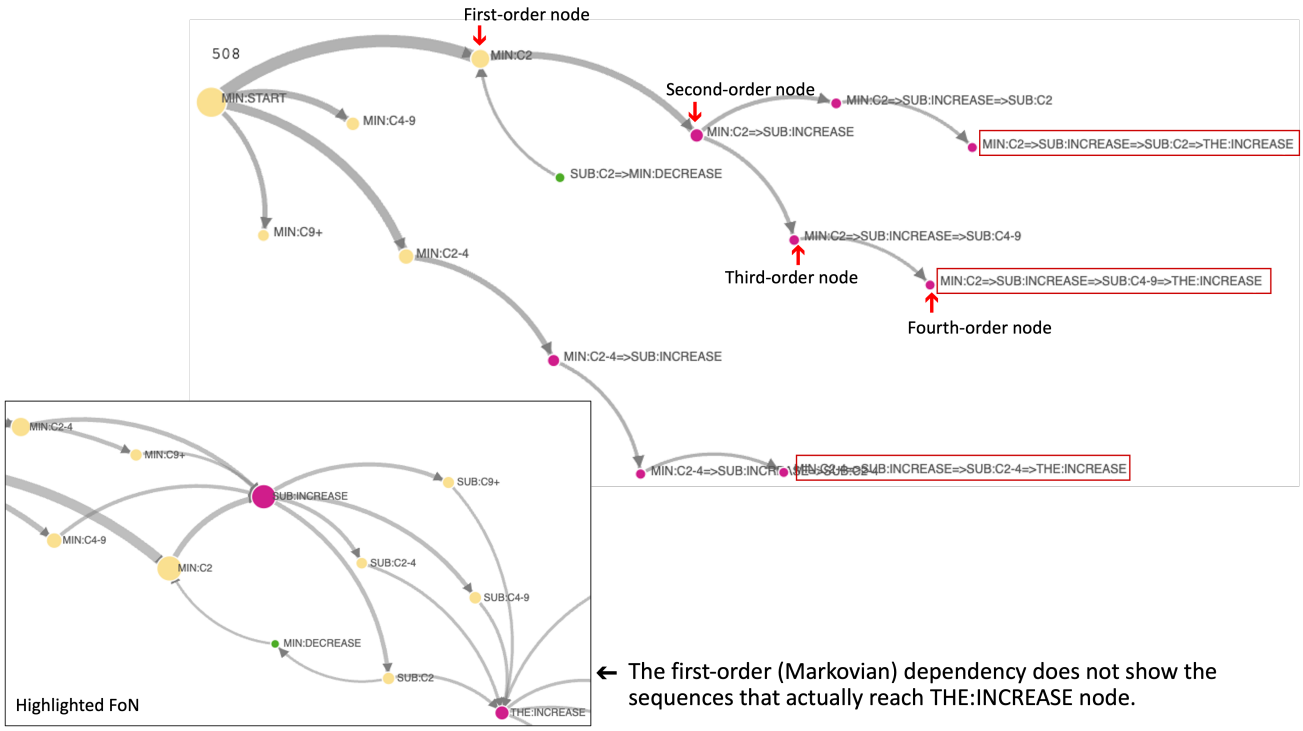


***Figure 2.*** *Exploration of higher-order dependencies (treatment sequences) in a CP using CPViz. The dominant sequences from MIN:C2 and MIN:C2-4 to THE:INCREASE are shown. The graph on the bottom-left, part of a first-order network, shows difficulty tracing the sequences.*

graphical models of causal paths in temporal data based on time slices. The generated time-aware static visualizations of temporal graphs can highlight patterns in the underlying temporal data. CCVis [6] also utilized a higher-order network construction algorithm to extract the critical sequences that lead to different transition probabilities. Their algorithm extracted the critical activity sequences to describe students' online learning behavior patterns. In addition, multiple coordinated views provide an effective overview of vast amounts of behavioral data and detailed comparisons of individual student behaviors.

## Design Requirements

The overall goal of exploring and comparing CPs represented as higher-order networks is to visualize complex dependencies and identify similarities between multiple CPs. To achieve the goal, multiple requirements should be achieved. We had many discussions with domain experts, such as clinicians and health services researchers. As a result, we identified four design requirements below.

- **R1. Exploring Higher-order Networks:** The visualization system should support the effective exploration of higher-order networks. It should reduce the visual clutter issue as complex in the structure of a higher-order network. Also, it should support discovering important higher-order dependencies.
- **R2. Identifying Salient Patterns:** The visualization system should support finding salient nodes (treatment or a sequence of treatments) and specific treatment patterns (e.g., aggressive or conservative).
- **R3. Finding (Dis)Similar CPs:** The visualization system should enable users to find (dis)similar CPs. Given a set of CPs, the system should provide the similarities of all CP pairs.
- **R4. Comparing CPs in-depth :** Given the similarity of all pairs, the visualization system should be able to perform a deep comparative analysis of the selected pair. Users need to know how they are (dis)similar to each other, such as different dependency patterns.

## Antidepressant Pharmacotherapy CP Model

Antidepressants are medications prescribed to treat MDD [4]. Pharmacotherapy (pharmacology) is the treatment of a disorder or disease with medication. Antidepressant pharmacotherapy consists of acute therapy until the best clinical response or remission (usually 6 to 12 weeks) and continued therapy for an additional 4 to 6 months to prevent relapse. In some cases, for recurrent or persistent disability, maintenance therapy is continued for months or years. There are many different types of medications used to treat depression. To select a drug, doctors consider several factors [2]. Our pathway model was designed to represent three aspects of pharmacotherapy sequences: dosage, ramping up/down of dosage, and duration of dosage. Based on this model, we developed a nomenclature for each step in a pathway using intuitive labels. For example, *SUB:INCREASE* means to ramp up to subtherapeutic dosage, and *THE:C4-9* means to continue the current therapeutic dosage for 4–9 months. To include different antidepressant medications in the same pathway, we converted all medications into Fluoxetine-equivalent

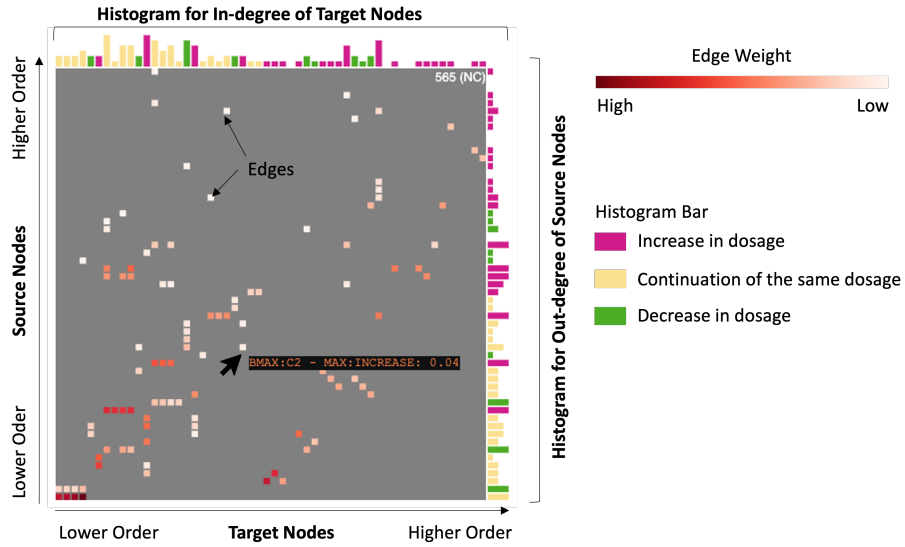


***Figure 3.*** *The matrix view visualizes edges—intersections between rows and columns are displayed as squares in a 2D layout. Also, it shows edge weights and the in/out-degrees of target and source nodes.*

doses. Table 1 shows all the labels we use for the study.

## Similarity Measure

We define the distance metric between two CPs using their topological similarity and the fraction of patient cases that fall on nodes and edges. Let $M$ be a square matrix, and let $m_{ij}$ be the value of the $i^{th}$ row and the $j^{th}$ column that represents the transition probability of edge $(v_i, v_j)$.

We compute the distance between two pathways using random walks. More specifically, we randomly select first-order nodes from each pathway using the proportions of their occurrences in data as initial probabilities. Then we produce random walks up to ten in length by traversing the network using the transition probability matrix, $M$. Formally, the distance between pathways $A$ and $B$ is defined as $D(A,B)$.

$$D(A,B) = 1 - S(A,B) \tag{2a}$$

$$S(A,B) = \frac{\sum_i^{N_{AB}} A_i B_i}{\sqrt{\sum_i^{N_{AB}} {A_i}^2}\sqrt{\sum_i^{N_{AB}} {B_i}^2}} \tag{2b}$$

Here, $D(A,B)$ is the distance between the two pathways, $A$ and $B$, defined as one minus the similarity of two pathways, $S(A,B)$, where $S(A,B)$ is the cosine similarity between the two vectors derived from random walks on pathways $A$ and $B$. Two vectors with the same number of dimensions, denoted by $N_{AB}$, are the union of the random walks on the two pathways $A$ and $B$. This is the number of unique paths generated by a random walk at least once in path $A$ or $B$. $A_i$ and $B_i$ represent occurrences where $i$-th path is sampled at $A$ and $B$, respectively. $S(A,b)$ measures how similar two pathways are by comparing the overall topology by comparing the sampled random walk representing the local topology.

To place all distances among stations in a global context, an embedding space has been created by applying kernel PCA onto a matrix where each row corresponds to pairwise distances to all other stations from the given station. We tested various kernels, including linear, poly, RBF, sigmoid, and cosine. We then computed Spearman's correlation between $D(A,B)$ and the euclidean distance within each embedding space, where a larger correlation value means better similarity. As a result, the sigmoid kernel was selected to create the embedding space.

***Table 1. Labels used to denote treatment steps in a CP***

| Label | Description |
|---|---|
| MIN | Minimum dosage |
| SUB | Subtherapeutic dosage (below 20 mg) |
| THE | Therapeutic dosage (20–40 mg) |
| BMAX | Below max dosage (40–60 mg) |
| MAX | Max dosage (60–80 mg) |
| INCREASE | Increase dosage |
| DECREASE | Decrease dosage |
| C2 | Continue for 2 months |
| C2-4 | Continue for 2–4 months |
| C4-9 | Continue for 4–9 months |
| C9+ | Continue for 9+ months |

## Functional Aspects of CPViz

At a high level, CPViz provides two types of visual analytic functionalities: exploration of a single CP and comparison of multiple CPs. The first is to shift treatment sequences that involve steps of interest (e.g., all treatment sequences starting from step *MIN:C2* to step *MAX:INCREASE*). The second is to understand how multiple CPs can be identified and grouped as similar CPs and study how a given pair of CPs are similar or dissimilar.

### *Exploration of a Single Pathway*

For browsing a given pathway, CPViz places a first-order network version of the pathway over the higher-order version (Fig-

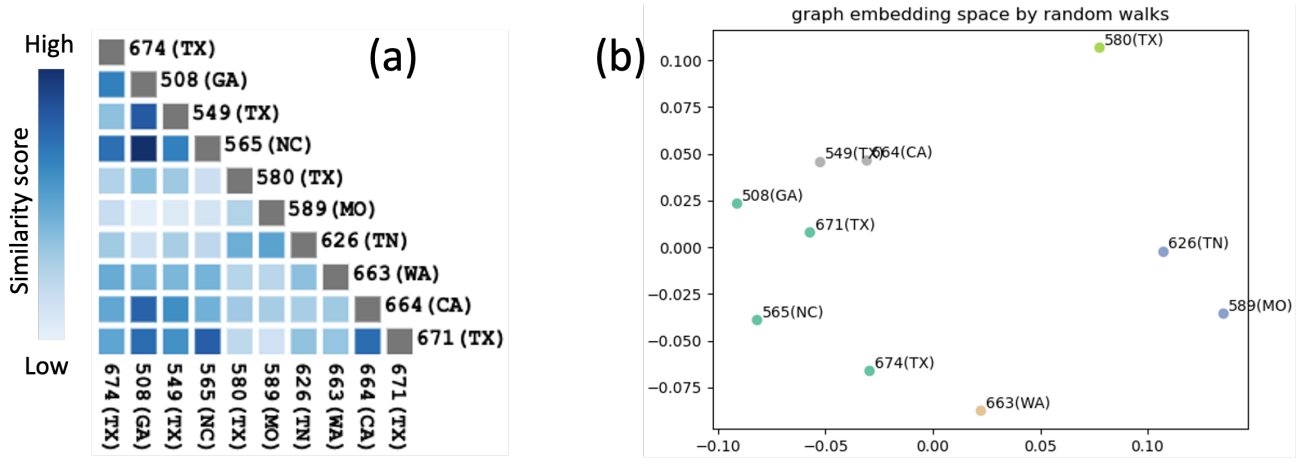


***Figure 4.*** *A heat map that represents similarities between all pairs of stations calculated by random walks (Left). 2D embedding space where all stations are placed, preserving their pairwise distances from the others (Right). The map is created using the random walk distances and kernel PCA (Right).*

ure 1). Users can select steps of interest on the first-order network, where steps are nodes, and the complete pharmacotherapy sequences (i.e., paths or sequences of steps) that include the selected steps are shown in the higher-order network. Figure 2 shows an example in which steps *MIN:C2, MIN:C2-4, MIN:C4-9, and MIN:C9+* are selected. We can see the two nodes, *MIN:C2* and *MIN:C2-4*, have fourth-order dependencies ending *THE:INCREASE* and the connected paths and intermediate higher-order nodes are visualized. This significantly decreases the visual clutter issue and efficiently extracts traces from the selected nodes to the highest-order nodes (R1). To aid clinicians in interpreting these paths, CPViz uses three different colors to denote the type of the last step in the node. The dark pink represents nodes with an *increase in dosage*, the green represents a *decrease in dosage*, and the yellow represents a *continuation of the same dosage*. The radius of a node is proportional to the number of cases found in the data. The thickness of the edge indicates the weight of the edge. We also adopted a force-directed layout [3], which brings together nodes with mutual connections to better track paths of interest (R1 and R2).

### Comparison of Multiple Pathways

Given many pathways, CPViz offers another visual analytic capability to compare pathways at two levels. First, it shows similarities of all pairs of pathways by a grid-based heat map and places all pathways in a 2D embedding space so that clusters of similar pathways can be detected (see Figure 4). Second, when users select a square on the heat map, CPViz provides an in-depth comparison of two selected pathways by visualizing the common and unique edges (see Figure 5).

When comparing two pathways, CPViz displays a pathway's edges in a matrix, which we call the *matrix view*. As shown in Figure 3, a square located in the $i^{th}$ row and the $j^{th}$ column is an edge coming out of the $i^{th}$ node from the vertically arranged nodes and going into the $j^{th}$ node from the horizontally arranged nodes. The color of a square represents the edge weight, with the minimum value colored in white and the maximum value in dark red. Additionally, CPViz adds an in-degree histogram (number of incoming edges) on the top and an out-degree histogram (number of outgoing edges) on the right side. This helps identify hub nodes (nodes with a large neighbor) and outliers (R1 and R2). The coloring scheme for histogram bars is the same as in Figure 2. To aid visual analytics, CPViz shows labels as a tooltip when the mouse hovers over a node, even though the tooltip is not shown in this paper. For edges, it shows tooltips that contain the source nodes, target nodes, and edge weights.

The matrix view is also used to compare two pathways. Given a set of pathways, CPViz illustrates all pairwise similarities in a heat map, which is shown as a lower-triangular form in Figure 4 (a) showing a displacement of each pathway that preserves their similarities with all other pathways (R3). The colors of the squares indicate similar scores. The dark blue means that the pair is relatively similar, while the white color does a dissimilar pair. The grey squares are pairs of the same HoNs. Also, it shows the similarity metric and projection to a 2D space in Figure 4 (b). The similarity measurement is explained in Section of Similarity Measure below.

Once a user selects a pair of pathways, three matrix views are displayed: two for each chosen pathway and the third for their combined view. The third view displays the union edges from both pathways for comparative analysis in depth (R4), as shown in the rightmost view in Figure 5, in which the red squares represent the edges of the first pathway, and the blue squares represent the edges of the second pathway. The outlined squares indicate the edges that appear in both pathways. The histograms show the in-degree and out-degree values of the combined node-set. A histogram bar for a node that appears in both pathways is split by a black line to indicate the separate portions from each pathway.

## Results

For the case study using CPViz, we collected data from OEF/OIF veterans with MDD from ten different VA facilities. We used data between January 1, 2006, and January 1, 2020, from the VA's Corporate Data Warehouse [11]. After processing data based on the labels in Table 1, we constructed pathways as higher-order networks. We conducted two types of tasks using CPViz: (1) identification of correct pharmacotherapy sequences and (2) visual comparative analysis of multiple pathways to highlight clini-

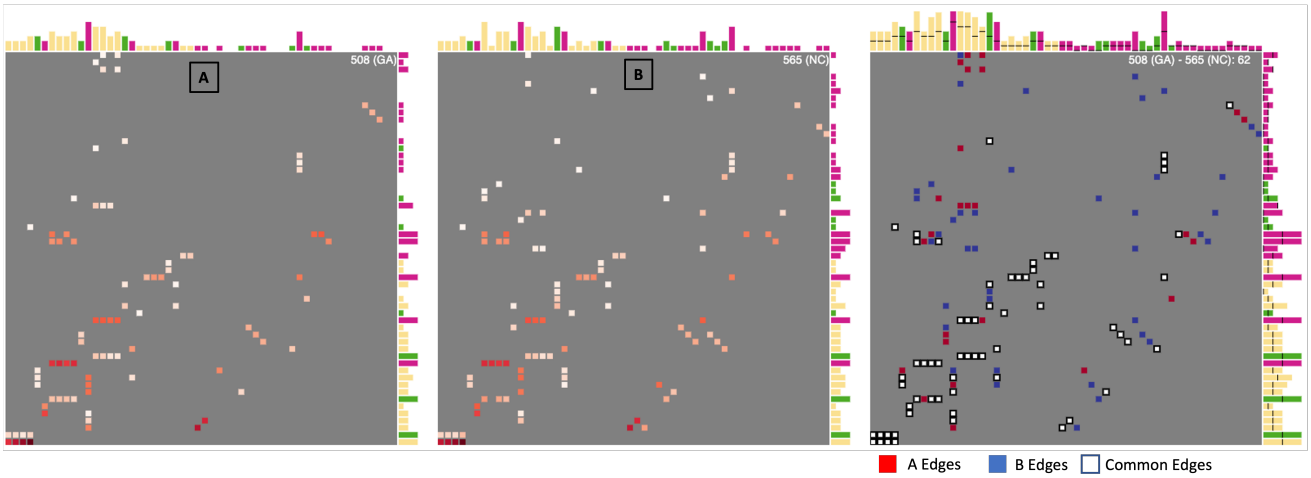


***Figure 5.*** *CPViz for comparative analysis of two CPs. Three matrix views for the selected pair A (left) and B (center), and the combined view of A and B (right).*

cal differences.

### *Identification of Pharmacotherapy Sequences*

Figure 2 illustrates CPViz identifying all pharmacotherapy sequences that start with the minimum dosage. It only shows paths of higher-order nodes that span through four first-order nodes following *MIN:START*: *MIN:C2*, *MIN:C2-4*, *MIN:C4-9*, and *MIN:C9+* from the CP of a facility in Georgia (station ID 508). As illustrated, the three paths that lead to an increase of the antidepressant to a therapeutic dosage (*THE:INCREASE*) are highlighted. A closer investigation shows that no such path exists through *MIN:C9+* nor *MIN:C4-9* (R1 and R2). In other words, if a patient stays at the minimum dosage for more than 4 months, it is less likely that the patient will ramp up to the therapeutic dosage. In contrast, a network of Markovian dependency (i.e., first-order) fails to expose this pattern. To highlight this issue, the bottom-left corner of Figure 2 shows a part of the first-order version of the CP in which we can find paths to *THE:INCREASE* from both *MIN:C4-9* and *MIN:C9+*.

### *Visual Comparative Analysis (Most Similar Pair)*

The heat map shown in Figure 4 (a) shows the all-pairwise similarity scores of the ten pathways (R3). We selected the pair with the highest similarity: station ID 508 of Georgia and station ID 565 of North Carolina. The rightmost matrix view shows few common edges at the upper-right area where the higher-order nodes are placed, but it shows many common edges around the lower-left area where the lower-order nodes are placed. Furthermore, we observed the same pattern in most pairs, which suggests that the difference in patterns is slight at the beginning of treatment, but the difference increases as treatment sequences move toward the end of the treatment step.

### *Visual Comparative Analysis (Least Similar Pair)*

Next, we select another pair of pathways with the smallest similarity score: station ID 508 of Georgia and station ID 589 of Missouri. Figure 6 illustrates the matrix view that compares the two pathways. As can be seen from the low similarity score, CPViz exposes very few common edges between the two pathways. Most of all, CP 589 has noticeably more higher-order nodes and edges than CP 508. A closer examination reveals that the two pathways differ (R4). We call out three regions in the matrix view to highlight the differences.

In region (1), the edges of CP 589 (blue) run diagonally upwards, whereas no such edges are found in CP 508 (red). This means that many lower-order nodes progress into higher-order nodes in CP 589. In other words, there are more unique paths that include higher-order ones in CP 589 than in CP 508. Region (2) shows that CP 589 has two target nodes with high in-degree values: *BMAX:INCREASE* and *MAX:INCREASE*, whereas the same nodes in CP 508 have small in-degree values. In region (3), some edges (paths) range from minimum and subtherapeutic dosage treatments to below max and max dosage treatments. This means that CP 589 has more aggressive treatment sequences (i.e., ramping up to maximum dosage and bypassing therapeutic or subtherapeutic dosages) than ones in CP 508.

## Conclusion

Unlike pathways represented in the Markovian property (first-order network), pathways of higher-order networks portray both partial and complete histories because the nodes provide the actual trajectories of treatment sequences. However, they are often too complex to comprehend. CPViz offers interactive visual analytic functionalities for higher-order networks to facilitate the exploration of a single pathway and the comparison of multiple pathways. We demonstrated that CPViz captured some treatment sequences from a higher-order CP, which was infeasible with first-order networks. We also showed that CPViz exposes heterogeneity in the prescription of antidepressants across different pathways by mapping and visualizing dependencies of connections between treatment sequences.

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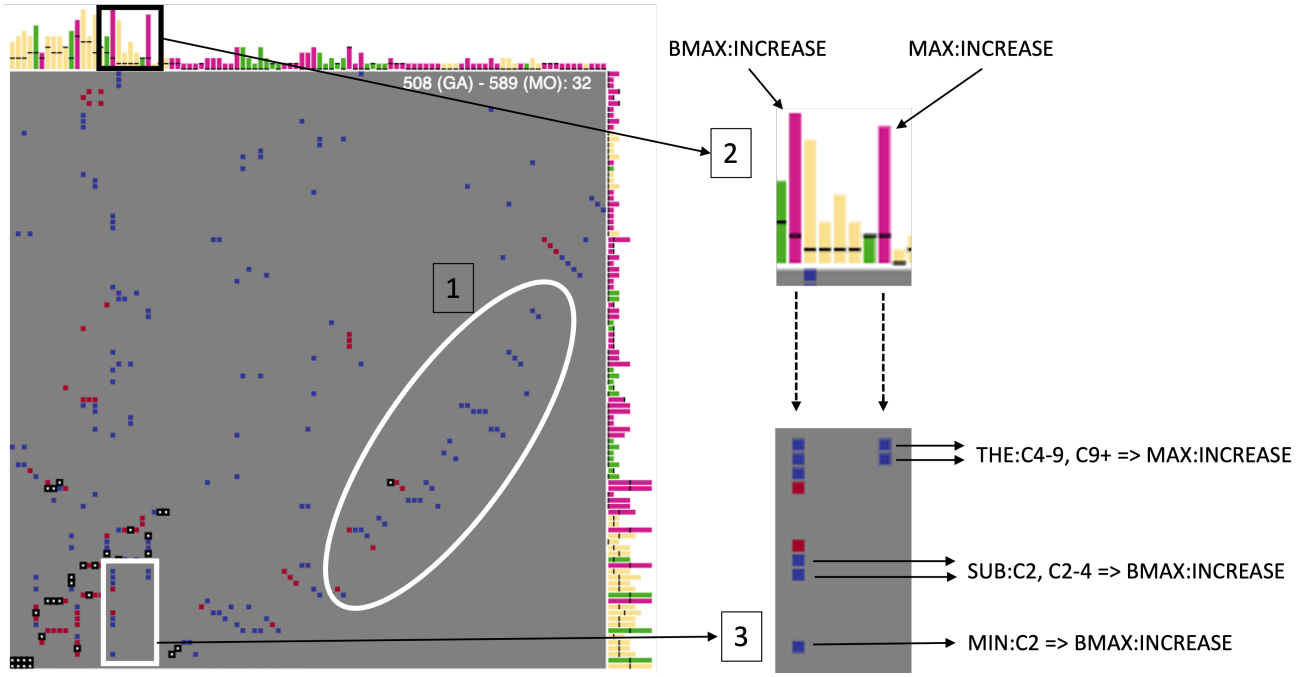


***Figure 6.*** *Matrix view comparing pathways of two VA facilities: station ID 508 from Georgia (red squares) and station ID 589 from Missouri (blue squares). The view shows that CP 589 has longer treatment sequences and more aggressive paths that increase dosage to the maximum dosage and bypass the therapeutic dosage.*

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