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ChatKG: Visualizing Temporal Patterns as Knowledge Graph

L. Christino[1,2] and F. V. Paulovich[2]

[1]Dalhousie University, Faculty of Computer Science, Canada
[2]Eindhoven University of Technology, The Netherlands

Abstract

Line-chart visualizations of temporal data enable users to identify interesting patterns for the user to inquire about. Using oracles, such as chat AIs, Visual Analytic tools can automatically uncover explicit knowledge related information to said patterns. Yet, visualizing the association of data, patterns, and knowledge is not straightforward. In this paper, we present ChatKG, a novel visualization strategy that allows exploratory data analysis of a Knowledge Graph which associates a dataset of temporal sequences, the patterns found in each sequence, the temporal overlap between patterns, and related explicit knowledge to each given pattern. We exemplify and informally evaluate ChatKG by analyzing the world's life expectancy. For this, we implement an oracle that automatically extracts relevant or interesting patterns, inquires chatGPT for related information, and populates the Knowledge Graph which is visualized. Our tests and an interview conducted showed that ChatKG is well suited for temporal analysis of temporal patterns and their related knowledge when applied to history studies.

CCS Concepts

• ***Human-centered computing*** → ***Visual analytics;*** • ***Computing methodologies*** → *Knowledge representation and reasoning;*

1 Introduction

An underlying presumption in most Visual Analytics (VA) tools is that users can collect new knowledge through interactivity with data and visualizations [SSS*14]. One instance is how line-chart visualizations of temporal data can tell whether a particular variable is trending upwards or downwards or if there are any interesting patterns for the user to inquire about. Despite their popularity as data democratization tools, in the absence of an oracle with the knowledge to explain the visible patterns, like Hans Rosling for GapMinder [Ros12], it is challenging to extract from line charts anything beyond the existence of said patterns. On the other hand, with the advent of general-purpose AI, such as chat AIs, users can now inquire with natural language for related information about patterns found in data. Indeed, the *explicit knowledge* retrieved from chat AIs can potentially aid users by providing new and relevant information during data analysis [LW23].

Generally speaking, some existing works focusing on this concept use information retrieval to collect information related to visual patterns [BMW16, THY*17, DHX*19], and the collected explicit knowledge can be overlaid as annotations on top of visualizations [CZW*19, SBWC18, LFAH18, BMW16]. Unlike usual databases, however, chat AIs like chatGPT [cha15] accept a more flexible input query: natural language and are trained in a much broader corpus of data. Examples of non-chat approaches would be Google or Wikipedia [wik01]. However, as of yet, their output is still an ordered list of relevant web pages, which does not have a straightforward way to be summarized and displayed to the user as part of a VA tool [CFP22].

In this paper, we present *ChatKG*, a novel visual analytics strategy that allows exploratory data analysis of the multi-modal task that associates temporal sequences, the patterns found in each sequence, the temporal overlap between patterns, and related explicit knowledge to each given pattern. ChatKG is proposed as a way to visualize a Knowledge Graph (KG) that models this multi-modal task. That is, the KG serves as a general knowledge repository and a connective layer between the temporal data, their patterns, and the explicit knowledge. We also exemplify ChatKG as a VA tool. For this, an oracle automatically extracts relevant or interesting patterns, such as *valleys* and *peaks*, from an example temporal dataset and inquires a chat AI for related information to each pattern. The data is structured as a KG, which populates ChatKG. With it, users can explore the temporal sequence, its patterns, and the explicit knowledge collected from the chat AI. ChatKG also enables users to analyze the temporal overlaps between the patterns among other temporal sequences. We demonstrate ChatKG by reproducing GapMinder's use case of world life expectancy analysis [Ros12]. We informally evaluate ChatKG with students and staff in our lab, which gave us confirmation that ChatKG achieved its goals. We also interviewed a historian and verified that ChatKG is well suited for the analysis when applied to world history data given that the temporal dataset matches the historian's research goal. In summary, our main contributions are: (1) modeling the association of explicit knowledge from chatGPT to temporal patterns of line charts as a KG; (2) Visualization of KGs with multi-modal data: temporal sequences, categories, and text;

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2 Related Works

Information retrieval has had significant research on how to generate and expand queries [CMS10] so the retrieved information is more relevant to users [ZDL09, CR12, AD19, DEQ21] and how to provide suggestions for future queries [OMQL15]. Other than the typical query discussed in information retrieval, it is also possible to retrieve information "by image" [RT17] to find images similar to a given image or "by natural language" [CE05, KB12] using descriptive texts. Yet, the inevitable comparison to chat AIs has shown that chat AIs are more naturally able to cope with complex or non-uniform queries [AGA*23] due to their capability to process and understand natural language input. Therefore, we use a chat AI to retrieve information, and results have shown that since the responses from the chat AI are also in the form of natural language, the user has a good experience when reading the results.

The use of chat AIs has been taking up interest. Text-based techniques where a VA tool provides a question-answer interface to interface users with visualizations have shown to be effective [KHA20, KSC*20, YZW*20]. More recently, Chat2Vis [MS23] proposed auto-generating visualizations based on chat input. In this work, the chat AI is a way to extract the explicit knowledge encoded in its Large Language Model (LLM) related to a specific temporal dataset's pattern.

VA has also attempted to process a given dataset and include external information related to the dataset in question as annotations. For instance, some generate new visual metaphors out of text [CZW*19, BMW16, HDA13, KSJ*14]. Others fetch existing visualizations from the web to be included as part of the system [LFAH18]. ChatKG is inspired by such works, yet overlaying the ChatKG with annotations was shown through tests to add complexity and, therefore, clutter the visualization, similar to how is discussed by Lafayette et al. [LQ]. Therefore, this work relegates the chat AI knowledge from what would be an annotation to a separate text contained within it.

Another aspect is the auto-discovery of patterns or insights. QuickInsights [DHX*19], proposes a way to quantify the "interestigness" of a visualization, wherein users might find it interesting to analyze. Tang et al. [THY*17] instead proposes a scoring system to systematically identify which insights or patterns will be most interesting for users. Although we do not propose a novel way of auto-identifying interesting patterns, our method does so by focusing on peaks and valleys of a temporal sequence, as opposed to the multi-varied approach of [THY*17] or the comparison between visualizations of QuickInsights [DHX*19].

3 Connective Knowledge Graph Generation

Our method consists of two main components: a Knowledge Graph (KG) that connects temporal visual patterns to explicit knowledge from a chat AI and ChatKG to visualize it. In this section, we describe the modeling process taken to generate the KG and describe how the graph's temporal-based nodes are its main connective component. In the following sections, we discuss the design and implementation of ChatKG and its example as a VA system for evaluation.

We aim to allow users to explore knowledge in the form of textual data through visualizations and visual findings through textual explanations. This is possible by an associative KG that links patterns found in visual representations of temporal data and explicit knowledge that holds relevant information about the said pattern. In order to populate this KG, three main steps are taken: pattern detection/extraction, automated retrieval of explicit knowledge from a chat AI, and modeling a KG ontology that relates the temporal datasets, patterns, and the chat AI's explicit knowledge.

In summary, by providing our method with a temporal dataset, such as one from UNData [und06], it interprets the data as line-chart visualizations of the datasets and runs a human-like oracle that auto-discovers potential *patterns* throughout the data. Each pattern is used to generate a unique question for the chat AI, which returns some sort of explicit knowledge in the form of a text, which is recorded. Then, a connective layer is modeled in the form of a KG to associate the dataset, the patterns, and the explicit knowledge from the chat AI. Finally, the resulting KG is visualized by ChatKG where users can explore the temporal dataset, its patterns, and the associated explicit knowledge.

The standard practice to design a KG is to define its classes and relationships through the Web Ontology Language (OWL) [MVH*04]. Therefore, the classes used are: *Dataset*, which defines the temporal dataset being analyzed; *Pattern*, which defines any pattern which was found; *TimeSpan*, which represents any range of time (e.g. years between 1800 and 1900); *Time*, which defines a singular time entry (e.g. the year of 1800); and *Knowledge*, which defines any explicit knowledge collected. The relationships of our model are: *dataset-pattern* associates a dataset to any pattern found within it; *pattern-timespan* associates the timespan of a given pattern; *timespan-time* associates timespans to its related time entries; and *pattern-knowledge* associates any explicit knowledge related to a given pattern. The ontology described is shown in Figure 1. Namely, the ontology centers around a *Pattern* class which identifies which dataset it came from, what was the time span of the pattern, and what knowledge was extracted from the chat AI regarding the pattern. This way, ChatKG is able to query the KG, for instance, to check other datasets which had similar patterns due to the same or overlapping time spans.

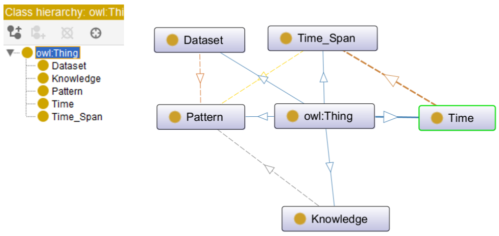


Figure 1: *Design of our Knowledge Graph following the Web Ontology Language [MVH*04]. It defines the classes and their relationships that will be visualized by ChatKG.*

The first step to populate our KG is selecting a temporal dataset. This dataset must contain a continuous value that changes over time. Datasets from UNData [und06] are great examples. A reference to the datasets is recorded into our KG as nodes of type *Dataset*. With the data in hand, our method runs an oracle to extract all findings from the data in order to populate our KG. The implemented oracle is based on the method described in the evaluation of Q4EDA [CFP22]. Q4EDA discusses two types of visual patterns. Of them, patterns related to trends, such as the overall increase or decrease of life expectancy (see UNData [und06]), were shown to retrieve inconsistent related information from Wikipedia. Therefore, we limited the extraction of patterns to "peaks" and "valleys", since they were shown to be much more valuable to end-users during Q4EDA's evaluation.

We then use a peak/valley strategy to detect all peaks and valleys throughout the data. This is done by comparing neighboring values of the temporal dataset [VGO*20, YHY09, CFP22]: $P = \sum_k W(k).Pr(k), k \in S$. In this equation, we see that for a given time-series S, every sub-section of the time-series $k \in S$ is analyzed by using its width W and its prominence or absolute height Pr. With this, we calculate the probability P of whether a given sub-section $k \in S$ is a peak. To estimate a valley probability, the same method is used with negated k as such: $k_v = -k, k \in S$. Finally, a threshold is used to define if the time-series S is either a pattern (peak or valley) or not. This pattern detector is run over all temporal datasets to extract a list of all potential pattern findings from the data. Each pattern is recorded in our KG as a *Pattern* and is associated with its related sub-section $k \in S$, which is recorded as a *TimeSpan*. The *Pattern* node is also associated with its related *Dataset*.

Finally, we go through all patterns extracted and query a chat AI through a templated prompt query which is exemplified in section 5. The knowledge repository we focus on in this work is chatGPT which, despite many limitations of potentially producing incorrect information, has demonstrated exceptional capability to uncover potential reasons why certain patterns are seen in temporal data. Of course, for this, we are required to assume that chatGPT and, consequently, the internet have information about the temporal patterns in question.

4 ChatKG Visualization

ChatKG is the proposed visualization that allows the exploration of the KG defined above by visually encoding the associations of temporal sequences, the patterns, the temporal overlap between patterns, and chatGPT's explicit knowledge of each pattern. In its essence, this visualization is designed to be exploratory in nature, therefore it is designed to thrive on user interactivity while not providing any specific visual guides to the user. By discussing with potential users, the design requirements found were:

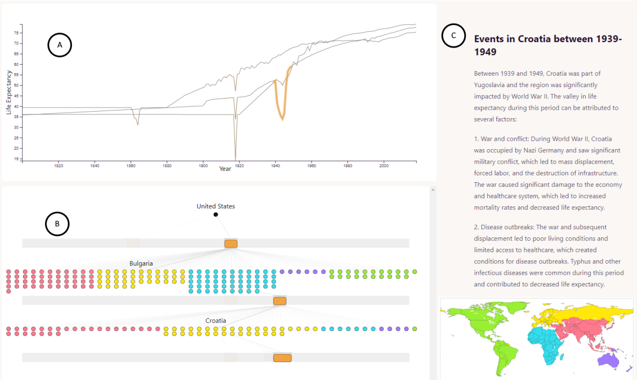
R1: Given a dataset, display the patterns for visualization;

R2: Given a pattern, display the explicit knowledge from chatGPT;

R3: Given a pattern, display other datasets which contain similar patterns;

By evaluating potential existing visualizations for each of the requirements, we define that for our goals, the visualization of line charts and text containers would be suitable to display the temporal data and chatGPT's explicit knowledge. Yet, developing a visual metaphor that displays the relationship of patterns, datasets, time, and knowledge proved to be less straightforward.

Here we propose a novel exploratory-focused visualization called *ChatKG*, which displays the relationships of the KG as links between elements and is exemplified in Figure 2. Considering the KG design of Figure 1, ChatKG displays an interactive unraveling of the graph in the y-axis. That is, by starting with a user-selected dataset, ChatKG displays the relationship dataset-pattern and pattern-timespan as a bar-visualization (Figure 2), from which users can interact by selecting a pattern-timestamp pair to display all related datasets, which are represented as square packing circles and, optionally, colored according to a categorical value. In the example of Figure 2, each circle represents a country that is colored by its continent following the example provided by GapMinder. The sequential exploration and clear exposition of the user's exploration path in the y-axis has enabled users to easily backtrack their own exploration behavior through mouse hovering to better understand and remember their findings [SBFK16].



Events in Croatia between 1939-1949

Between 1939 and 1949, Croatia was part of Yugoslavia and the region was significantly impacted by World War II. The valley in life expectancy during this period can be attributed to several factors:

1. War and conflict: During World War II, Croatia was occupied by Nazi Germany and saw significant military conflict, which led to mass displacement, forced labor, and the destruction of infrastructure. The war caused significant damage to the economy and healthcare system, which led to increased mortality rates and decreased life expectancy.

2. Disease outbreaks: The war and subsequent displacement led to poor living conditions and limited access to healthcare, which created conditions for disease outbreaks. Typhus and other infectious diseases were common during this period and contributed to decreased life expectancy.

Figure 2: *Example of ChatKG being used to investigate the life expectancy dataset. USA's valley between 1912-1924 shows a large number of other countries with patterns in the same time period. Of them, Bulgaria was selected. By selecting Bulgaria's right-most pattern, it was found that Croatia has two overlapping patterns with Bulgaria, and when hovering the patterns in ChatKG, chatGPT says both countries were impacted by WWII at that time.*

To design ChatKG, we informally tested different options of visualizations with users from our research lab. First, we attempted to use a network graph visualization through cystoscope.js [SOR*11], but the resulting network graph did not provide a good visual metaphor for the patterns and time spans. We considered using glyphs and other icons, but using nodes in a graph as the visual metaphor of time spans was shown to be lacking by showing to and collecting feedback from others. Therefore, we considered a Gantt chart to display the pattern's time spans in a visual manner, but its structure did not allow for the user to visualize and select the datasets which are related to each pattern (*R3*). Therefore, our devised visualization overlaps a node graph visualization to display categorical data and the relationships between this categorical data to a given pattern and a Gantt chart visualization to display the occurrences of patterns within a given dataset.

Although ChatKG can be used by itself, it was also designed as a way to link a line-chart visualization (Figure 2) of the temporal datasets and the text container which displays the collected chatGPT knowledge. Indeed, we exemplify ChatKG by using it as part of a VA tool composed of three main visualizations as is shown in Figure 2: (A) a line chart that displays the raw temporal data of all datasets and each of the patterns found in them; (B) the ChatKG visualization of the temporal datasets and extract patterns; and (C) a text display of the explicit knowledge extracted from the chat AI given a pattern being hovered by the mouse. To best analyze and explore the patterns (R2 and R3), ChatKG's bar-visualization is aligned to the line chart in its x-axis. Users choose which datasets they want to analyze by selecting in ChatKG, which causes the line chart to display the temporal data and the detected patterns of the selected datasets. Also, hovering a pattern-timespan in any bar-visualization will cause the related knowledge text from the chat AI to be displayed to the right. Finally, mouse hover is used to display all visual elements related to what is being hovered. For instance, by hovering a pattern in the line chart, the related pattern-timespan is highlighted, and by hovering any element of ChatKG, such as a dataset or a pattern-timespan, ChatKG highlights all elements and links between the hovered element until the original dataset, providing the map of how the user's exploration got to that element. Optionally, the dataset can be grouped and color-coded by some metadata, such as how the datasets from the example of Figure 2 are categorized by countries which are then grouped by and colored by continent following the dataset of [Kra].

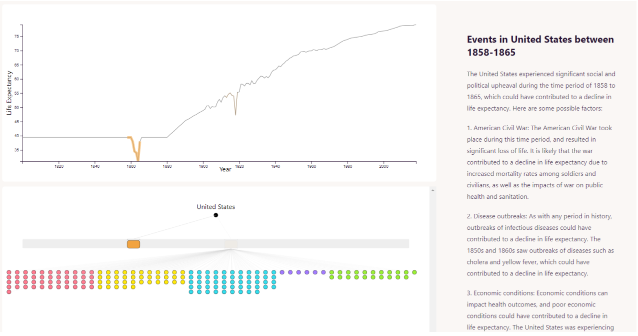
5 Use Case: Reasoning Life Expectancy Fluctuation

Inspired by GapMinder [Ros12], we implemented one main use-case to explore the world's life expectancy fluctuation. In this example, the datasets are temporal sequences of a specific country's life expectancy. Therefore, each *Dataset* node in our KG is a country, each *Time* is a year, and *TimeSpans* are measured in "span of years". We ran the pattern extraction algorithm setting the algorithm threshold to $P > 1.5$, following [CFP22]. Yet we noticed that the number of patterns was too great to query chatGPT on time for this work. Additionally, detecting all patterns sometimes returns the whole temporal dataset as a pattern. To reduce the number of patterns to a more reasonable size, we defined empirically that patterns should have at least 3 years and at most 8 of time span, and if two patterns with the same peak or valley were detected or if two patterns overlapped for more than two-thirds of their time-span, only the one with largest time-span was kept. With this, the number of patterns kept was 661. Although an adjustable parameter can regulate this, such values showed good results in our informal evaluation.

It is important to note that chatGPT is not yet a service that can be indefinitely queried, but the reduced number of patterns allowed us to collect all explicit knowledge from chatGPT within a couple of days. The patterns were queried in chatGPT, and the responses were recorded. In our example, two potential prompts were tested:"What impacted the *life expectancy* of *[country]* between *[starting year]* and *[end year]*?" and "What caused a *[peak or valley]* on the *[life expectancy]* of *[country* between *[starting year]* and *[end year]*?". Although both showed interesting potential, we used the first prompt to allow users to read an unbiased response from chatGPT and potentially discover inconsistencies between chatGPT and the temporal dataset from UNData. Indeed, some results have made us question the quality of the data we have.

Finally, the example of Figure 2 displays a ChatKG visualization for users to explore each country's life expectancy. The line chart displays fluctuations in life expectancy, all patterns found for each country being investigated, and the text displays the chatGPT result when inquiring about what happened in the specific country within the timespan of a given pattern. We extracted two usage scenarios within this setting and performed an expert interview.

Specific Usage - United States Investigation: Justin, a fictional high school student, was asked to investigate USA's history. Therefore, by using ChatKG, he identified two main patterns of interest. By hovering the right-most pattern, he discovered that at the time, the USA was impacted by WW1 and Influenza (Figure 4), which might have caused the life expectancy disturbance he saw. By clicking on the pattern, he was shown that more than a hundred countries had some event that impacted their life expectancy in the same period. He did the same to the left-most pattern but discovered that that event seems to have been caused by the American civil war (Figure 3) and that not many other countries had life expectancy drastic changes at that time. Here, Justin was able to learn potential reasons why USA's life expectancy was impacted and what other countries might have been similarly impacted.



Events in United States between 1858-1865

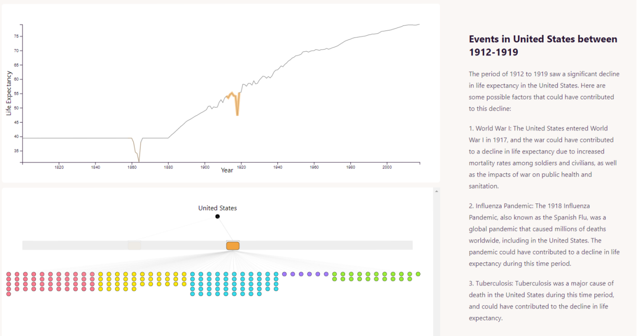
The United States experienced significant social and political upheaval during the time period of 1858 to 1865, which could have contributed to a decline in life expectancy. Here are some possible factors:

1. American Civil War: The American Civil War took place during this time period, and resulted in significant loss of life. It is likely that the war contributed to a decline in life expectancy due to increased mortality rates among soldiers and civilians, as well as the impacts of war on public health and sanitation.

2. Disease outbreaks: As with any period in history, outbreaks of infectious diseases could have contributed to a decline in life expectancy. The 1850s and 1860s saw outbreaks of diseases such as cholera and yellow fever, which could have contributed to a decline in life expectancy.

3. Economic conditions: Economic conditions can impact health outcomes, and poor economic conditions could have contributed to a decline in life expectancy. The United States was experiencing

Figure 3: *Example of ChatKG being used to investigate the life expectancy in the USA. The first valley from 1858-1868 was likely caused by the American Civil War as per ChatGPT.*



Events in United States between 1912-1919

The period of 1912 to 1919 saw a significant decline in life expectancy in the United States. Here are some possible factors that could have contributed to this decline:

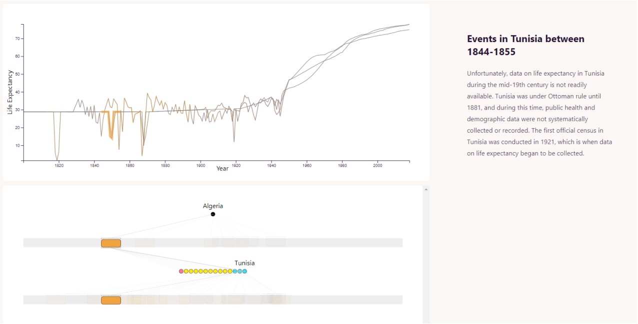
1. World War I: The United States entered World War I in 1917, and the war could have contributed to a decline in life expectancy due to increased mortality rates among soldiers and civilians, as well as the impacts of war on public health and sanitation.

2. Influenza Pandemic: The 1918 Influenza Pandemic, also known as the Spanish Flu, was a global pandemic that caused millions of deaths worldwide, including in the United States. The pandemic could have contributed to a decline in life expectancy during this time period.

3. Tuberculosis: Tuberculosis was a major cause of death in the United States during this time period, and could have contributed to the decline in life expectancy.

Figure 4: *Example of ChatKG being used to investigate the life expectancy in the USA. The second valley from 1912-1924 was likely caused by World War I, Influenza, and other factors, as per ChatGPT. Additionally, from the number of circles in ChatKG we conclude that many countries have also had some impact on their life expectancy during the same period.*

Open-ended Usage - Search for unexpected similarities: Angela, a fictional history major, wishes to explore the history of the world and see if there are any unexpected similarities between seemingly unrelated countries. She investigates Algeria and notices several unexpected patterns (Figure 5). Hovering the left-most pattern shows that, at the time, Algeria was not a proper country but a French colony, which makes her suspicious of how reliable the life expectancy value from UNData [und06] is. By clicking on that pattern, Angela investigates all countries listed as related and sees that some may also have questionable data, such as Mauritius and Tunisia. She finds it interesting that similar patterns were found between countries that, at the time, should have been colonies and wonders if the following Algerian pattern would have a different result. Here, Angela could explore the data and discover the unexpected, which prompts further data exploration.



Events in Tunisia between 1844-1855

Unfortunately, data on life expectancy in Tunisia during the mid-19th century is not readily available. Tunisia was under Ottoman rule until 1881, and during this time, public health and demographic data were not systematically collected or recorded. The first official census in Tunisia was conducted in 1921, which is when data on life expectancy began to be collected.

Figure 5: *Example of ChatKG being used to investigate the life expectancy in Algeria. The left-most pattern (1844-1855) has 3 African countries (in cyan) with patterns in the same period: Tunisia, Mauritius, and Algeria. The results from ChatGPT show that Algeria and Mauritius were colonies at the time of France and Great Britain, respectively, and Tunisia was under Ottoman Rule.*

Interview: We interviewed Catherine, a MA in history, to verify the usability of ChatKG to explore history data, verify its ease-of-use and gather insights from an expert. First, Catherine was given a brief explanation of how to use ChatKG and was asked to use it for a use-case she might be interested in. She said Russia's life expectancy is interesting to view, and by exploring it, she identified multiple factors that lead to death across Russia, confirming her expectations. She also checked the line-chart's "deepest valley" between 1927 and 1945 to find reasons. She exemplified how she would use ChatKG in practice: "Let's say I knew that WWII was a big deal to Russia, but not that Public Health was an issue. I would then go and find books on health and Russian history. It would be helpful because I hadn't thought of nutrition and public health." She concluded by saying that ChatKG "is good because it highlights major influencing factors reasons but maybe are not talked about as much as other factors." Catherine ended the interview by saying that the current example is interesting for educational purposes, but an example that would be very beneficial for history research would be either the exploration of all available data of a single country (e.g., other datasets from UNData such as democratic index and co2 emissions) or multivariate analysis of history datasets.

6 Limitations

Unfortunately, the space is limited, but other use cases were investigated. Within the same UNData [und06] repository, there are many other datasets, such as CO2 emissions, democracy index, and child mortality which would bring interesting information to the users as well. Such datasets could also be used to analyze a single country's indexes. Other potential use cases could involve sports, where users could investigate teams (dataset) statistics throughout a season (temporal data). Also, other potential heuristics for pattern detection could be added to the pattern detector, such as the inclusion of trends or other time-series algorithms [BLB*17]. Of course, such use cases would also be subject to the chatGPT's ability to provide relevant information.

ChatKG has shown potential, but its goals also show its limitations. For instance, ChatKG is not well-suited for inference or explanatory analysis. It is also not well suited for non-temporal or multi-variate data since it focuses on one dimension (e.g., country) of the temporal data. Finally, it also is not suited for simultaneously comparing a large amount of information. That is, with too many datasets or too many patterns, ChatKG becomes cluttered. If the use case was the life expectancy of each city in the world, the number of cities would cause the visualization to become cluttered. We estimate that anything above 200 different temporal datasets would start hindering the analysis, although this is expected to be tested in a future evaluation. Additionally, the line chart was only usable for up to three to four lines being displayed, but more than that would cause issues with the mouse-hover functionality and become hard to read due to overlapping. Although ChatKG may benefit users to identify time spans with many patterns, it is still necessary to investigate better ways to display overlapping patterns.

The visualization design of ChatKG focused on a specific ontology, which can be interpreted as a strict limitation of ChatKG and of ChatKG as a whole. A greater flexibility in the ontology definition could, perhaps, provide a more ample application of the ChatKG. However, we purposely decided against this to focus on our main goal, which is to allow users to explore a temporal dataset and the explicit knowledge collected from its patterns. The design of a flexible visualization that allows exploratory analysis of other temporal-based KGs is challenging and left as future work. Additionally, the text extracted from chatGPT could be enhanced through NLP methods, such as sentiment analysis, topic modeling, or prompt engineering, and such information could be included as part of ChatKG visual metaphor. Such extensions of our work are intended to be investigated as future work.

Finally, although ChatKG is novel as a visualization of a KG, the data we are visualizing is similar to visualizations of event data or process-mining data. In future work, we intend to investigate the applicability of KGs and, consequently, ChatKG as a way to visualize data from these domains and evaluate our approach versus research in those areas.

7 Conclusion

In this work, we laid out how to model a KG as a connective layer of a temporal dataset, patterns, and explicit knowledge from chatGPT. We presented ChatKG as a novel visualization to explore the KG and implemented an example VA tool which identifies patterns among the life expectancy fluctuations in history across many countries, extracts chatGPT's explicit knowledge of these patterns, and exposes the populated KG to the user. We discussed our findings from this example and interviewed an expert who verified the usability of ChatKG. Our results indicate that, within its goals, ChatKG has successfully aided users in their exploratory analysis of temporal datasets, existing patterns, and the explicit knowledge extracted from chatGPT.

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