Explainable Patterns: Going from Findings to Insights to Support Data Analytics Democratization

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Fig. 1. Explainable Patterns interface setup to explore world demographic indicators. Using the line chart visualization, users can select patterns of interest (A). A world map is then rendered to display if other places in the globe present similar behavior (B), and textual explanations are created using an external source of information to describe the selection (C). Also, recommendations of other countries and indicators are shown (D), offering an environment to promote data exploration without relying on domain experts.

Abstract—In the past decades, massive efforts involving companies, non-profit organizations, governments, and others have been put into supporting the concept of data democratization, promoting initiatives to educate people to confront information with data. Although this represents one of the most critical advances in our free world, access to data without concrete facts to check or the lack of an expert to help on understanding the existing patterns hampers its intrinsic value and lessens its democratization. So the benefits of giving full access to data will only be impactful if we go a step further and support the Data Analytics Democratization, assisting users in transforming findings into insights without the need of domain experts to promote unconstrained access to data interpretation and verification. In this paper, we present Explainable Patterns (ExPatt), a new framework to support lay users in exploring and creating data storytellings, automatically generating plausible explanations for observed or selected findings using an external (textual) source of information, avoiding or reducing the need for domain experts. ExPatt applicability is confirmed via different use-cases involving world demographics indicators and Wikipedia as an external source of explanations, showing how it can be used in practice towards the data analytics democratization.

Index Terms—Storytelling, Visualization to text, Data Analytics Democratization, Interpretability

1 INTRODUCTION

It is undeniable that the past decades represent a revolution without precedent in human history for information and knowledge dissemination. The amount of data available and accessible is increasing in a pace never seen before, with massive efforts involving companies, non-profit organizations, governments, and others to support its democratization. The concept of giving access to everyone, everywhere, anytime, unthinkable in the past, is becoming the norm. Initiatives like Gapminder [25] to help educate people to confront information with data has been showing how wrong are our premises about the world, biased by outdated information that does not reflect the current reality [27]. It is a paradigm shift in the way we handle information, even when official and (auto-declared) credible fonts release it.

Data democratization is one of the most critical advances in our free world. However, most of the initiatives are instrumental when hypotheses are known or when a domain expert is available to explain what we are seeing, being limited when such assumptions do not hold [28]. In exploratory scenarios, when users access data without concrete questions or facts to check, the lack of a domain expert to help...
on understanding the data patterns or findings hampers the intrinsic value of data, lessening the advantages of its democratization. Therefore, the benefits of giving full access to data will only be impactful for the general public if we go a step further and support the Data Analytics Democratization, assisting users in transforming findings into insights without the need of experts to promote unconstrained access to data interpretation and verification.

The idea of reducing the need for experts in data analytics pipelines is a recent trend in the machine learning community with AutoML methods, replacing them by automatic and exhaustive procedures to build computational models. A similar trend is also observed in the visualization community with the proliferation of approaches to facilitate and automate parts of the storytelling process, including automatic infographics creation and pattern identification. Although representing a step towards the data analysis democratization, both movements still rely on domain experts to provide explanations for the findings observed in the data, limiting the extent lay users can understand and take advantage of the produced results, even in domains of general public interest like government open data initiatives.

In this paper, we proposed Explainable Patterns (ExPatt), a new framework to explore and analyze world demographics indicators supporting lay users in understanding and creating storytelling, automatically generating plausible explanations for observed patterns without the need for domain experts. To provide the explanations, an external textual source of information is automatically linked to the data using different natural language processing and pattern analysis strategies so that every time a user selects a pattern or finding in a visual representation, potential explanations are derived to assist in understanding what is being observed. ExPatt also recommends similar indicators (or data sets) based on the selected pattern, enabling users to go from finding to finding to compose a story or narrative supported by automated explanations, representing another step towards the full implementation of Data Analytics Democratization.

In summary, the main contributions of this paper are:

- A novel query-based strategy to link data patterns with (textual) information contained in an external source of data;
- A recommendation strategy to go from textual information back to related data using different natural language methods;
- An approach to support users to go from findings to (textual) explanations and from explanations back to data, supporting an exploratory cycle to create narrative storytelling without demanding domain experts in the process.

The remainder of the paper is structured as follows. In Sect. 2, we discuss related work involving visualization techniques that seek to reduce the need for experts in the data analytics process. In Sect. 3, we formalize the problem and outline the ExPatt solution. In Sect. 4, we present ExPatt interface design and a usage scenario showing how it can be used in practice for user-driven data-based storytelling. Also, an evaluation is presented, indicating a good degree of stability and reproducibility in the results. Finally, in Sect. 5, we discuss ExPatt limitations and in Sect. 6, we draw our conclusions.

2 RELATED WORK

In general, two different experts are heavily involved in the data analytics process. One, the data science expert, is accountable for developing and deploying the analytics pipeline. The second, the domain expert, is responsible for using the developed tools to make sense of the data under analysis. In a data analytics democratization scenario, where the goal is to promote unconstrained access to lay users or the general public to data interpretation and verification, it is becoming more and more evident the need to reduce the dependency on having both types of experts in the process. Aiming at addressing this issue, an emerging field has been attracting considerable attention inside the machine learning area, the Automated Machine Learning (AutoML). AutoML strategies reduce or eliminate the need for data science experts focusing on automating the process to find the most suitable computational models and their parametrizations. A similar trend has also been observed in the visualization domain with some strategies that seek to automate parts of the visual analytics process to better support narrative and storytelling.

One example is the work presented by Cui et al. They introduce an approach to automatically generate infographics from natural language statements, providing visualizations to represent storytelling from textual information. Similarly, Lin et al. proposed a method to automatically render visual representations for news articles, including a contextual representation to improving the understanding of the extracted information. Although both approaches are related to narrative visualization and storytelling, they did not provide further interpretations or explanations for the data, limiting the extent a non-domain expert user can understand and take advantage of the visual representations. Gapminder, the well-know application for exploring world indicators data through visualizations, has a similar limitation, the lack of support to understand the observed data patterns. Aiming to enrich storytelling with explanations, Bryan et al. presents an approach, called Temporal Summary Images (TSIs), which includes an automatic annotation strategy to visually indicating relevant regions and features, connecting data exploration with storytelling. Although it provides textual explanations for the visualizations, their content needs to be provided by the user or domain expert. Tang et al. also present a strategy to improve storytelling, supporting automatic identification of findings or patterns. Likewise, Ding et al. propose a technique to automatically identify interesting patterns in multidimensional data, avoiding the detection of easily inferable common patterns. Although some level of automation is added to the data analytics process, all these techniques still rely upon domain experts to explain the discovered patterns, limiting the extent lay users can benefit.

In terms of approaches that unify visualization and natural language processing methods, Yu and Silva also propose the FlowSense system. FlowSense is a natural language interface to assist dataflow diagram construction where users can expand and adjust diagrams using plain English. Luo et al. also proposed a query-based system called DeepEye. DeepEye supports data exploration based on an information retrieval strategy where users provide a textual query, and the system returns the most meaningful visualizations. Although both provide support for storytelling considering textual and visual information, the textual query and the visual search do not offer explanations for the findings or features found in the data. Metoyer et al. also integrates text and visualization elements, using natural language process strategies to automatically linking narrative components (who, what, when, where) to data in an offline approach. Although representing a fascinating approach to connect textual information with data, it does not focus on using text to explain findings in the data but to link complementary information to better support storytelling.

In summary, the existing approaches to reduce the dependency on experts, although representing considerable advances in replacing data science experts, still require domain experts to provide explanations for the patterns or findings discovered in the data. For companies or in applied domains where the final user and domain expert are typically the same, reducing the need for data science experts is highly beneficial. However, in data democratization initiatives, like Gapminder and others, where users are lay people or the general public without deep knowledge on the domain under analysis, replacing data science experts is only one step to make them impactful. Such initiatives will only reach their ultimate goal if the need for domain experts is also reduced, henceforth democratizing the data analytics. This second step is the novelty of our framework, offering support to automatically derive plausible explanations for observed or selected patterns and unusual behaviors. We address this challenge linking the data sets under analysis with external sources of textual information, from where the explanations are derived. To promote the connection between data and the external sources, we devise a novel scheme based on pattern analysis and natural language process strategies to translate the findings selected by a user into textual queries that are used to fetch the explanations. Our framework also recommends similar data sets based on the selected pattern or recovered explanations, allowing users...
to navigate through the data and build up storytelling to understand its behavior, patterns, and features, replacing domain experts by (external) textual sources of information.

3 Methodology

3.1 Overview

In this paper, we present Explainable Patterns (ExPatt), a novel framework designed to support data exploration and interpretation of world demographics indicators time-series. Based on user-driven interactive selections of patterns (or findings) of interest, ExPatt supports the identification of related indicators and the creation of explanations automatically extracted from an external corpus of textual data containing general information about world history. Our reasoning is to allow users to identify and select findings in the time-series and automatically link them to the textual information, offering potential explanations for the selected findings. The story-telling cycle is then completed by using the retrieved textual information to recommend other related time-series indicators, effectively implementing a complete data analytics process without requiring experts to support it.

To set notation, consider a dataset $I = \{I_1, \ldots, I_N\}$ of $N$ indicators, where each indicator $I_r$ is composed by a set of time-series $I_r = \{S_{r_1}^{I_r}, \ldots, S_{r_k}^{I_r}\}$ representing real-valued measures over-time of $M_r$ distinct countries. In our framework, the user initially selects a time-series $S_{rc}^r = \{x_{r1}, \ldots, x_{rk}\} \in \mathbb{R}_r$ that represents the indicator $r$ of a particular country $c$. The selected time-series is then displayed using a line chart (Fig. 1(A)), where the user can select any finding of interest, that is any sequence of consecutive values $F_r^c = \{x_{rc1}, x_{rc2}, \ldots, x_{rcK}\} \subset S_{rc}^r$. Every time a pattern is selected by the user, a map is colored to indicate the similarity of the selected finding of the country under analysis with other countries considering the same indicator (Fig. 1(B)) and to suggest highly similar countries (Fig. 1(D)). Such selection is also translated into a query for the external source of information. The fetched information (documents) is then summarized using several natural language processing strategies to aid with the selected finding explanation and displayed to the user (Fig. 1(C)). Also, topic terms are extracted from the recovered documents and used to suggest other related indicators of the same country or other countries. These steps are detailed in the next sections.

3.2 From Findings to Documents

One of the core concepts in our framework is to automatically link the selected finding to textual information that (potentially) describes it. As discussed, this process is performed by translating the selected findings into textual queries that are submitted to a search engine. In this process, all information related to the user selection, that is indicator description, country, time period, and pattern type, is combined and decoded onto the text query. This text query is composed of a set of terms, each one representing a different attribute of the data, taking the form

$$q = \bigcup_{r \in D_r} t_r^c \cap \bigcup_{r \in C_r} t_r^v \cap \bigcup_{r \in P_r} t_r^p \cap \bigcup_{r \in E_r} t_r^q,$$

(1)

where $D_r = \{t_1^r, t_2^r, \ldots\}$ is the set of names or tags associated with the indicator $r$ under analysis (sect. 3.2.1), $C_r = \{t_1^c, t_2^c, \ldots\}$ is the country name, country citizen adjectives (sect. 3.2.2), or world regions, $P_r = \{t_1^p, t_2^p, \ldots\}$ is the pattern or finding description (sect. 3.2.3), and $E_r = \{t_1^e, t_2^e, \ldots\}$ is the time period. The strategy to compose $E$ is straightforward, all the years corresponding to the selected interval are added as terms. The process to compose the other sets are more complex and is described in the following sections.

3.2.1 Indicator tags

Each indicator is related to a different aspect of the countries. To be able to compose the set $D_r$ of terms to represent such aspect, we apply a text mining approach to assign to each indicator $I_r$ a set of related tags $G_r = \{g_1, g_2, \ldots\}$. For example, the “life expectancy” indicator besides representing real-valued measures over-time of $r$, $G_{life expectancy} = \{life, expectancy, longevity, lifetime\}$. In this way, each indicator has its semantic meaning defined by the tags associate with it.

In this paper, user-intervention is expected and encouraged with the purpose to best emulate how a specific user would encode the indicators relevant characteristics. In that sense, we allow users to select the $G_r$ tags from a list of words to compose the set $D_r$ used in the text query. $G_r$ tags are automatically generated every time a new indicator is uploaded into the system, in which the indicator’s name is tokenized and used (after removing stopwords) on a pre-trained GloVe model [24] to find the vector representation of each token. Then, we average the vectors to get one vector that represents the combined semantic of all tokens and search the external corpus for the $K$ most similar terms using the cosine distance, where $K$ is a system parameter. Also, we add synonyms and antonyms of the initial tokens to the candidate list using WordNet [10], resulting in a more comprehensive list of terms to represent the indicators’ semantics. Notice that this list of words is just a suggestion, and users are free to use other not suggested terms as tags for an indicator.

3.2.2 Geo-information

To create the set $C_r$ containing country’s information, the country’s name of the time-series $S_{rc}^r$ under analysis is added along with other related country names or world regions. Although some findings and their respective explanations/reasons may be specific for a single country, there are other findings that occur in multiple countries simultaneously. When this is the case, their explanations can either be specific for each individual country or for the aggregation of countries, that is, for the continent or sub-continent the country belongs to. This generalization is important to best match the external corpus, since some textual information may only contain more general references to the geographical location where a specific event occurred.

To complement $C_r$ with the continent or sub-continent information, we use similarity to analyse the set of time-series $S_{rc}^r \subset S_r$ that compose the indicator $I_r$ for different countries, considering only the time interval of the selected finding $F_r^c$. A continent or sub-continent name is added to $C_r$ if the average similarity of the finding $F_r^c$ and the same time interval for all other countries belonging to the same continent of the country under analysis is larger than a threshold as defined as follow

$$\frac{1}{|W_c|} \sum_{v \in W_c} \text{sim}(F_r^c, F_r^v) > \alpha,$$

(2)

where, $F_r^c \subset S_r$ is the selected finding in the indicator $r$ of country $c$, $W_c$ is the list of countries belonging to same continent of country $c$, $F_r^c \subset S_r$ represents the time-series interval of the same indicator $r$ of a different country $v \in W_c$, $\alpha$ is the threshold, and $\text{sim}(\cdot, \cdot)$ denotes the similarity between the interval time-series (see sect. 3.2). The threshold $\alpha$ was adjusted empirically to $\alpha = 0.7$ to enforce that most of the countries of a given continent has very high correlation for the continent to be added to the query. The result of this operation are the continent names (africa, asia, america, europe, australia) to be used in the query.

3.2.3 Findings description

The finding description, set $P_r$, is a list of terms describing the trend and the pattern of the selected finding $F_r = \{x_{rk1}, \ldots, x_{rKk}\} \subset S_{rk}^r$. The type of trend can be ascending, descending, or stable, while the pattern can be peak, valley, and neutral, resulting in 9 different combinations. Fig. 2 presents examples of these combinations.

To define the trending type, we apply the moving average (MA) strategy. MA is a well-known technique in time-series analysis to define if the series is stationary or not, providing the trend estimation [6]. MA first transform the time-series that defines the finding $F_r$ into a new series $F'_r$ setting its values $x_{rk} \in F_r$ to the average value in the time interval $x_{rk1}, x_{rk2}, \ldots, x_{rkK}$ (here we empirically define $q = 2$). After that, we compute the discrete derivative of $F'_r$ and sum the normalized values as follows
Fig. 2. Examples of combinations of types of trends and patterns in user selections. Each dotted line shows the patterns detected if the user selects the specific interval.

\[
t_{tr} = \sum_{x_i \in F_c} \frac{x_i - x_{i-1}}{|x_i - x_{i-1}|},
\]

(3)

Based on that, the trend type is defined as

\[
trend = \begin{cases} 
\text{ascending}, & t_{tr} > 0 \\
\text{descending}, & t_{tr} < 0 \\
\text{neutral}, & \text{otherwise}
\end{cases}
\]

(4)

To define the pattern type, we use a peak detection method that attempts to identify a local maximum by comparing neighboring values

\[
pf = |F_c| \times \frac{(w^+ - w^-)}{\sigma(F_c)},
\]

(5)

where \(w^+\) is the weight obtained from the peak detection method representing the peak width and prominence, \(w^-\) is the weight obtained from the peak detection method considering the inverse of \(F_c\) (multiplying its values by \(-1\)), and \(\sigma(F_c)\) is the standard deviation of \(F_c\). Based on the pattern factor \(pf\) the type of pattern is defined as

\[
\text{pattern} = \begin{cases} 
\text{peak}, & pf > \lambda_2 \text{ and } \sigma(F_c) > \lambda_1 \\
\text{valley}, & pf < -\lambda_2 \text{ and } \sigma(F_c) > \lambda_1 \\
\text{unstable}, & \lambda_2 \geq pf \geq -\lambda_2 \text{ and } \sigma(F_c) > \lambda_1
\end{cases}
\]

(6)

where \(\lambda_1\) is a threshold to consider if a finding contains a pattern or not, and, if a pattern is detected, \(\lambda_2\) is a threshold to define if the finding is a peak, a valley, or an unstable oscillation. Empirically we set \(\lambda_1 = 0.5\) and \(\lambda_2 = 1.5\) but these parameters can be changed by the user.

The result of this process is a pair of identifiers describing the finding tendency and pattern. Based on the resulting pair, we define the terms to be used to fill the description set \(P\). This process is the same presented in Sect. 3.2.1 in which a set of tags is associated with each identifier. In our framework, a list of suggested terms is taken from a Thesaurus with synonyms for the identifiers ascending, descending, peak, valley, and neutral, and the user selects, during a setup phase, what is more appropriate. Users can also add terms that are not suggested in this process to represent the identifiers. For example, we translate a stable and peak finding to \(P_{\text{stable,peak}} = \{\text{high}, \text{peak}, \text{boom}, \text{boost}\}\), and a ascending and neutral finding to \(P_{\text{ascending,neutral}} = \{\text{increase}, \text{higher}, \text{growth}\}\).

3.2.4 Search Engine

Once the terms of the query \(q\) are defined (Equation 1), it is submitted to a text-based search engine to fetch relevant documents inside the external corpus. In this process, we use an open-source search engine called Elasticsearch [16] since it is fast for text indexing, processing, and searching large databases. Besides fetching documents according to a given query, the Elasticsearch engine ranks each retrieved documents based on how well it matches the query, returning the top \(n\) documents (where \(n\) is a setup parameter). This ranking can be manipulated by boosting specific keywords or by giving more importance to terms of specific areas of a document, such as title or URL link. Since the document’s title represent a brief summary of what is expected to be contained within the document, we boost the search result ranking by two when the title matches the query \(q\) versus matching only in the text body. With this, there is a higher chance of documents with relevant titles, and, therefore, relevant information in the entire document, to be ranked higher than documents with less relevant titles and less likely to be specifically about the related subject portrayed by the query.

3.3 Visualizing the Explanations

Once the documents are retrieved, the last step on transforming findings into explanations is to present the fetched information. In this process, we present an overview visualization outlining the top \(k\) retrieved documents \((k\) is a user parameter) and visualizations summarizing each document on demand.

To create the overview visualization, we extract topic keywords for each retrieved document. In this process, we use Latent Dirichlet Allocation (LDA) [2] initially training a model using the entire external corpus but removing terms that occur in less than 15 documents and terms that occur in more than 50% of the documents. We empirically set these values following the common practice, but users can change that in the framework setup phase. Using this model, for each retrieved document, we compute the probability of its terms composing a meaningful topic and getting the top terms. In this process, we use LDA since it is nearly real-time considering a pre-trained model, an essential feature for an exploratory tool. Once the lists of topic terms per document are computed, we create an Explanation River Overview visualization based on the ThemeRiver metaphor [14]. In this overview, the documents are positioned on the x-axis, and the rivers’ width represent the probability of each topic term in each document. The topics terms are also listed below the rivers to facilitate navigation. Fig. 1C presents an example of such visual representation.

Using the explanation river overview to navigate the results, detailed information about each document is displayed on demand every time a mouse click in a document happens. In the detailed representation, instead of showing the content of the entire document, we opt to show summaries and a tag cloud. The tag cloud is composed of the extracted topic terms, and the summary is created using the Gensim’s summarization method [8][21]. The summary is displayed as a plain text with the terms used in the query in bold. Moreover, a map highlighting other countries mentioned in the document is displayed with a list of related datasets (see Sect. 3.3). This overview visualization is to present the fetched information. In this process, we present an overview visualization outlining the top \(k\) retrieved documents \((k\) is a user parameter) and visualizations summarizing each document on demand.

3.4 Similarity Map and Rankings

Every time a finding \(F_c = \{x_1, x_2, \ldots, x_k\} \subset S_r\) is selected in a time-series representing an indicator \(r\) of country \(c\), a world map is displayed comparing \(c\) to each other country in the world, and different ranking lists are computed. For the map, each other country \(c’\) is colored according to the similarity between \(F_c\) and \(F_c’ = \{x_{1’}, x_{2’}, \ldots, x_{k’}\} \subset S_{r’}\). For the lists, one ranks the countries using the same values used to color the map, from the highest to the lowest similarity. Another ranks all other indicators \(S_{r’}\) for the country \(c\) calculating the similarity between \(F_c’\) and \(F_c’ = \{x_{1’}, x_{2’}, \ldots, x_{k’}\} \subset S_{r’}\). This enables users to find other time-series with similar patterns and shapes, varying the country or the indicator, showing how similar or divergent is the data.

Our framework enables users to choose between different strategies to compute the similarity among patterns (or subsets of time-series): the Pearson correlation and the Dynamic Time-Warping (DTW) [15][22]. If the user wishes to compare time-series according to their shapes ignoring amplitude, Pearson Correlation is the choice. If the user wishes to compare time-series according to differences in
amplitude, DTW is the option. The Pearson correlation is calculated as follows

\[ \text{corr}(F, F') = \frac{1}{N^2} \sum_{i=1}^{N} \left( x_i - \mu(F) \right) \left( x'_i - \mu(F') \right) \frac{1}{\sigma(F) \sigma(F')} \],

(7)

where \( \mu(\cdot) \) is the average value, \( \sigma(\cdot) \) is the standard deviation, and \( N \) is the number of values in the patterns. Correlation \( \text{corr}(F, F') \) ranges in \([-1, 1]\). Positive values indicate linear related series, negative inversely related series, no relationship otherwise. The second option, the DTW, is a robust dissimilarity measure that finds the non-linear alignment that has the lowest accumulative Euclidean distances between points, resulting in an optimal shape match preserving magnitude \([15, 22]\). Since the correlation is a similarity and the DTW is an unbounded dissimilarity, we transform the DTW dissimilarity into a similarity to keep consistency using as follow

\[ \text{dtw}_{\text{sim}}(F, F') = \frac{1}{1 + \text{dtw}(F, F')} \],

(8)

where \( \text{dtw}(F, F') \) is the DTW distance between two patterns, and the resulting similarity \( \text{dtw}_{\text{sim}}(F, F') \) ranges in \([0, 1]\). In addition to the similarity ranking lists, we have a third list that, whenever a peak (or valley) in \( F' \) is detected (see Sect. 3.2.3), it ranks all other countries \( c' \) from the highest peak (or deepest valley) to the lowest peak (or shallowest valley). The idea is to rank the countries to show the ones that are more (negatively or positively) “impacted” by extracting and sorting all pattern factors, calculated through Equation 5, while considering a specific indicator in the same period of time.

3.5 From Documents to Indicators

In addition to the recommendations of countries or indicators given by the similarity ranking lists, our framework also recommends countries and indicators given the set of documents returned by the query \( q \), closing the loop (data to documents, documents to data). The recommendation of countries is straightforward: considering that \( q \) was derived from a finding \( F' \) of an indicator \( r \) and country \( c \), for each returned document, every other country \( c' \neq c \) that is mentioned in the document is listed as a recommendation (same indicator, different country \( S' \)). In this process, we look for country names or their corresponding adjectival and demonymic forms.

For the recommendation of other indicators (and the same country \( S' \)), the process is more involved. We use the topics extracted to represent the documents (see Sect. 3.3) and compare them to the indicators’ tags (see Sect. 3.2.1) to find indicators that are “semantically” related to the retrieved documents. To calculate the similarity among topics and indicators’ tags, we use the GloVe model \([24]\) to find the vector representation of indicators’ tags and topics and use the cosine dissimilarity to compare them. Considering \( T = \{t_1, t_2, \ldots\} \) the list of topic terms and \( T_r = \{t_1, t_2, \ldots\} \) the list of tags associated with an indicator \( r \), the similarity is calculated as

\[ \text{sim}(T, T_r) = \frac{|T|}{\| \sum_{t \in T} \text{glove}(t) \|} + \frac{|T_r|}{\| \sum_{t \in T_r} \text{glove}(t) \|} \]

(9)

where \( \text{glove}() \) returns the vector representation of a topic term or a tag.

The result of this process is a ranked list of the most similar indicators considering the retrieved documents. One alternative to it would be to evaluate the similarity between the keywords of the retrieved documents and the indicators’ tags. However, the advantage of training an LDA model using the entire external corpus is that we have a broader range of terms and topics to look at. Thus the suggestion might include something that is not mentioned in a document but is related to it in terms of its high-level theme or topic.

4 Results and Evaluation

In this section, we present Explainable Patterns (ExPatt) interface design, showing how to employ the features and how it can be used in practice for user-driven data-based storytelling through a usage scenario. For ExPatt implementation, we use javascript for the front-end and python for back-end\(^1\) ExPatt design is data agnostic, allowing its application in different scenarios as soon as textual information related to the time-series under analysis exists. However, for demonstration purposes, we loaded time-series datasets of world demographics indicators from the well-known Gapminder \([25]\) initiative and a cirrusearch dump of the English Wikipedia database \([11]\) as the external textual source of information.

4.1 Interface Design

We start presenting the design and implementation of the ExPatt interface. To develop this interface, we create a preliminary mock-up using well-established visual metaphors employed to display time-series data (line charts) and text (wordcloud and theme river). Staring from it, we performed multiple sessions using the thinking-aloud approach with different members of our lab to refine and define the final design. Fig. 1 presented the resulting interface composed of four distinct modules.

The Line Chart Module (A) is for loading one (or multiple) time-series indicator(s) of a particular country (we later explain how to change the country under analysis) and displaying it as a line chart. Using this graph, the user can interact with the time-series selecting findings by clicking and dragging the mouse. The selected pattern is them used to build the query for retrieving the explanations from the external source of information (see Sect. 3.2) and to update the other modules. Fig. 1(A) shows an example of selecting a finding (the gray area) – a massive decrease in the “Oil Production Per Person” for the “Iran” in the period between 1973 and 1981.

The Similarity Graph Module (B) contains a map showing the similarity between the country under analysis and other nations considering the same indicator and selection (time period). Users can use the map to investigate if the finding occurs in other countries (Fig. 1(B)), if the selected country is different from other regions of the world, or to get an overview of similarity distribution of the finding around the globe. By inspecting Fig. 1(B), it is possible to sense that similar behavior to the selected finding is also observed in multiple countries (e.g., United States, Canada, and Venezuela). In contrast, the behavior looks the opposite for some others (e.g., Mexico and the United Kingdom).

The Explanation Module (C) comprises a visual representation of the retrieved documents (or explanations) for the selected finding showing an overview of the documents’ topic keywords and details on demand. The explanation river overview shows the top 10 retrieved documents with their titles and topic terms. While titles and topic terms provide a summary of each document, details on demand are shown by clicking over the titles. The detailed view provides an overview of what can be found inside a document, as well as other mentioned countries and similar indicators, helping on navigating from the explanations back to the indicators (datasets). According to the example presented in Fig. 1(C), the finding observed in (A) is probably related to different oil crises in 1973 and 1979, in which the production was reduced due to an embargo and a strike, respectively.

Finally, the Recommendation Lists Module (D) includes a set of lists containing other recommended indicators or countries based on the selected finding. If a user wants to discover countries with similar findings, s/he can use the “Similar/Dissimilar Countries” lists, which shows the same (or inverse) information of the correlation map but in a ranked list. However, if a user wants to analyze similarities using other indicators while considering only the country under analysis, s/he can use the “Similar/Dissimilar Datasets” lists. Finally, to discover the most prominent peaks and valleys over the selected time-frame, the “Prominent Peaks/Valleys” lists can be used, allowing to see what are the most impacted country over the selected time-frame. According to the “Different Countries” list (Fig. 1(D), Mexico and the United Kingdom present considerable different behaviors in the same period of the decrease in the production of oil in Iran.

\(^1\)ExPatt can be accessed at http://vav.research.cs.dal.ca/explainable_patterns/
4.2 Usage Scenario – United States Life Expectancy

Using these modules, we present a hypothetical scenario to show how ExPatt can assist non-expert users in understanding discovered findings and building up storytelling based on data.

Justin, an American student in High School, wants to investigate how the average life-span has changed over the years in the United States. With that in mind, he selects the “Life Expectancy” indicator and the “United States” country. The resulting graph shows a positive trend towards increasing the overall American life-span over the years, but he notices two interesting patterns, one valley between 1860 and 1866 and another between 1917 and 1919 with some instability between 1901 and 1930 (see Fig. 3).

To further inspect these patterns aiming at understanding what is happening, Justin selects the first valley (between 1860 and 1866). Internally the ExPatt framework builds a query, retrieves documents, and generates a visual representation summarizing the results, describing the selected finding. By checking the similarity map (see Fig. 4(a)) and adding the two countries (Sweden and the United Kingdom) with the highest similarity, Justin realizes that this drop in life expectancy is probably an American effect (see Fig. 4(b)) since even the most related countries do not present similar valley in the same period. With that in mind, Justin goes to check the explanations starting with the explanation river overview (see Fig. 5(a)). He observes the prevalence of terms “war” and “wars” and the multiple resulting documents titles and concludes that the lower life expectancy rating may be the result of a civil war. Clicking in the documents “Union (American Civil War)” and “1862 and 1863 United States House of Representatives elections” and reading the summaries, he notices that the trigger of the civil war was the result of Abraham Lincoln’s election and the US southern states feeling unrepresented and/or challenged due to slavery (see Fig. 5(a)), being able to discover one important piece for the storytelling of the US life-span variations, including its trigger.

![United States, Sweden, United Kingdom](image)

(a) Similarity map using Pearson Correlation.

![Life expectancy line chart of the United States. Interesting patterns can be observed, one valley between 1860 and 1866, another between 1917 and 1919, and some instability between 1901 and 1930. The gray area represents the user selection.](image)

Fig. 3. Life expectancy line chart of the United States. Interesting patterns can be observed, one valley between 1860 and 1866, another between 1917 and 1919, and some instability between 1901 and 1930. The gray area represents the user selection.

Continuing from his previous experience with the system, Justin follows up to investigate the second dip in the life expectancy, between 1917 and 1919. The results are, however, less clear with different causes for the drop, as seen in Fig. 5(b). By investigating the correlation map and reading the summary snippet of each explanation, Justin builds a hypothesis in his mind of which area to drill down more. Differently from the correlation map of the 1860 – 1866 selection, this time, most of the map is red, which means that most of the world is suffering from a similar decrease in life expectancy (see Fig. 6(a)). Based on the explanations, he infers that the primary reasons for the changes in life expectancy are the World War I and the Influenza Pandemic (Spanish flu). To confirm the global impact, Justin adds other countries to the line chart and confirms that they all have valleys in the same period (see Fig. 6(b)). Among such countries, there are European, African, and South American. Justin selects the same time-frame in many of the other countries and finds more indications of both World War I and the Spanish flu (see Fig. 5(b)) impacting life expectancy. Justin decides to check for the most prominent valley among the ranking lists to see which was the country most impacted during this time (here omitted due to space constraints) and concludes that Samoa, a small island near Australia, was the heaviest impacted country during this period with their life-expectancy dropping to close to 1 year as seen in Fig. 5(b). Finally, Justin concludes that most of the world had its life expectancy affected by both Spanish flu and World War I in this period.

Justin, however, is not comfortable with the fact that one of the only countries that do not have a high similarity is Russia (see Fig. 6(a)), and he starts looking for reasons. Following the same investigation procedure, Justin finds out that the reason for the similarity to be low in this period is that Russia’s valley pattern is much wider (see Fig. 7(b)) than the United States. By focusing only on Russia’s line chart and selecting the valley, he obtains a different similarity map with neighborhood countries to Russia (Belarus, Ukraine, Turkmenistan, Uzbekistan, Tajikistan, and Kazakhstan) presenting a much higher similarity than the rest of the world, which is confirmed by the similarity ranking list. Justin switches to the Dynamic Time-Warping similarity map of Fig. 7(a) and verifies that Uzbekistan is the most similar country to Russia by adding it to the line-chart (see Fig. 7(b)). After checking the explanation overview (here omitted due to space constraints), he realizes that during the same period Russia was facing, besides the World War I and Spanish Flu, the abolition of Russia’s monarchy in 1917, a civil war, and the beginning of the Soviet Union.

While checking the “History of Soviet Russia and the Soviet Union (1917–1927)” explanation details, Justin notices that ExPatt recommends “Democracy Index” as one of the related indicators of this explanation (see Fig. 8(a)). At the same time, the “Different Datasets” ranking list (here omitted due to space constraints) also suggests the same indicator. Indeed, Justin confirms that by adding the second indicator to the line chart view. By removing the “life expectancy”
Explanation river overview of the finding selected in Fig. 3. Terms “war” and “wars” are frequent among the returned documents, and many of these are about the American civil war, indicating that the drop in the life expectancy in the United States in the period between 1860 and 1866 is probably a result of the American Civil War.

Explanation river overview for the United States life expectancy in the period between 1917 and 1919. Spanish flu or the Influenza Pandemic and the World War I are the most plausible explanations for the observed drop in the American’s life-span.

Fig. 5. Different examples of explanation river overviews for the two valleys observed in the United States life expectancy indicator (see Fig. 3).

Although an elementary analysis, through data, Justin was able to discover one piece for the storytelling of the life-span variations in the US, including its trigger. Two different global situations, World War I and the Spanish Flu, and why Russia was differently affected than the rest of the world. This simple storytelling generated from aggregating textual information with information obtained from the line chart and map shows how important it is for final users to be in the center of the analytical process without the need of a domain expert, that may not be available.

4.3 Evaluation

In this section, we present a formal evaluation of our framework. Although the standard practice would be to test it with users, since we rely on well-established and straightforward visual representations (line chart and theme river), the relevance of the test would be minimal to support what we are proposing. Also, user tests would not give us any better insight into our framework since the setup depends on users’ specific knowledge about the data being used, and the explanation accuracy shown to the users are heavily dependent on how well the textual source describes the events of the temporal datasets. User tests would only allow us to gather application-specific results, which would only apply to the datasets and not to the framework itself.

Therefore, instead of testing the interface design, we opt to check how stable our framework is given variations in the user interactions. In other words, how much the explanations differ if slightly different intervals in the time-series are selected representing a pattern. Again,
where \( p \) stability is computed as the list of documents returned using one of the derived findings, the given finding and the sets of documents fetched using the derived patterns.

The stability of our query process is then measured comparing the intersection of the set of documents retrieved using the original finding and the set documents retrieved using the original finding and \( P \). In many different time-series, considering the average variation among users could be involved in this test, but it would not be comprehensive enough. Instead, we follow Memon et al. [19] and create an oracle that emulates the user behavior, allowing us to test our approach exhaustively. Notice that we are not evaluating the quality of the provided explanations, since it reflects the accuracy of the search engine and the reliability of the external textual information, and it is not our objective to measure how reliable Wikipedia is nor if the Elasticsearch is good. Indeed, such an evaluation is not possible since we were not able to find a labeled dataset that allows us to evaluate the connection between time-series patterns and their textual explanations.

The oracle implementation we use is straightforward. For a time-series \( S_i \), it first automatically extracts the top findings, valleys and peaks classified by their magnitude, then varies a window around the patterns to generate similar selections that emulate the variations in users’ behaviors. Given a detected finding \( F'_i = \{x_k, x_{k+1}, \ldots, x_{k+q}\} \subset S'_i \), we first expand the selection interval to \( R_k^{\pm} = \{k - p_p, k - p_p + 1, \ldots, k + p_p + q\} \) where \( p_p \in [0, P] \), and then for each \( R_k^{\pm} \) a new query is generated centering the window with size \( q + p_p + p_p \) in the point, resulting in \( P^2 \) distinct queries for each original extracted top finding. In our tests, the expansion size \( P \) of the window was set to 3. This was defined running a test with our lab members asking them to manually select findings in many different time-series, considering the average variation among them to set \( P \).

The stability of our query process is then measured comparing the intersection of the set of documents retrieved using the original extracted finding and the sets of documents fetched using the derived patterns. Given \( D \) the set documents retrieved using the original finding and \( D_i \) the list of documents returned using one of the derived findings, the stability is computed as

\[
\frac{1}{|D_i| \cdot |\Delta|} \sum_{D_j \in \Delta} |(D \cap D_j)|,
\]

where \( \Delta \) is the set containing the lists of documents produced by all derived patterns. Notice that the number of documents in \( D \) and \( D_i \) is the same and defined by the number of documents we display in our interface. In our tests, we set it to 10.

To execute a comprehensive test, we select 960 time-series from our database and measure the query stability for each one. In total, we automatically detect 5,286 relevant patterns and generate 8 derived patterns per original pattern, resulting in 47,574 queries submitted to the search engine. Notice that, if we have tested with users, considering 50 users, each one should have executed approximately 951 selections to reach the same statistical representativity, an impractical number even if we triple the number of users. [Fig. 9] summarize the results for the 9 different combinations of trends and patterns. Overall, on average, the stability is 0.5121, meaning that slight variations in the selection return 51% of the documents returned by the original query. More specifically, peaks and valleys are more stable with an average of around 64% and std of 0.22, while ‘unstable patterns’ have less document stability with an average of 39% and std of 0.27. [Fig. 9] also shows how ‘neutral unstable’ patterns are the least stable, which is expected since this combination means no coherent pattern in the data. Although this cannot be used to quantify the quality of the explanations, it indicates that users with similar behavior are expected to receive similar explanations when selecting the same pattern, indicating a good degree of stability and reproducibility.

5 DISCUSSIONS AND LIMITATIONS

Since we finished the first implementations of our framework, most of the exploratory tests we executed resulted in useful explanations. However, in some cases, it failed to bring any meaningful information
In this paper, we present Explanaible Patterns (ExPatt), a framework to support exploratory analysis replacing the need for domain experts to aid in understanding discovered findings by explanations automatically derived from external textual sources of information. Although the employed strategies are generic, we have reported encouraging results using world demographics indicators databases and Wikipedia as an external source of information. The core of ExPatt is a novel strategy to translate user selections into queries used to fetch the information to compose the explanations. In our tests, such strategy shows to be very stable and reliable, returning practically the same list of explanations depending on the pattern type. Thereby, users with similar selections are expected to receive similar explanations from ExPatt when selecting the same pattern, indicating a good degree of stability and reproducibility especially for patterns like peaks and valleys.

Finally, our visualizations are not perfect. Line charts, for instance, have inherent limitations in terms of visual scalability when displaying too many time-series at once, the same restriction presented by the theme river metaphor and the wordcloud. However, we opt to use simple and popular visual representations that are (probably) familiar to our intended audience, the general public, and not only to computer science graduate students. So, although other more scalable visual representations can be used, the added complexity and the prolonged user learning curve would reduce the reach of our framework, confronting our primary goal of democratization.

6 CONCLUSION

In this paper, we have explored world indicators datasets as a way to exemplify the usage of our framework. However, other domains may also benefit from it. For instance, stock market time-series datasets could be explored, not for forecasting but for connecting observable patterns with facts in the same period. The challenge in this example is to find good sources of external information from where the explanations can be derived. Another example of a domain that can also benefit from our approach is more fine grainer demographics (e.g., cities or neighborhood levels) analysis supported by newspaper press datasets as external sources of information. In any case, a fundamental observation has to be made. The explanations are not intended to serve are causality information since spurious correlations can be derived. It is only a way to enrich users’ knowledge and a solution to break some barriers in the democratization of information.

7 ACKNOWLEDGMENTS

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