ChartText: Linking Text with Charts in Documents

Joao Pinheiro, and Jorge Poco

Abstract—Recent works show that interactive documents connecting text with visualizations facilitate reading comprehension. However, creating this type of content requires specialized knowledge. We present ChartText, a method that links text with visualizations in this work. Our approach supports documents that include bar charts, line charts, and scatter plots. ChartText receives the visual encoding of the visualization and its associated text as input. It then performs the linking in two stages: The matching stage creates individual links relating simple phrases between the text and the chart. Then, it combines the individual links according to the visual channels in the grouping stage, building more meaningful connections. We use two datasets to design and evaluate our method: the first comes from web documents (24 bar charts and texts) and the second from academic documents (25 bar charts, 25 line charts, and 25 scatter plots with their texts). Our experiments show that our method obtains F1 scores of 0.50 and 0.66 on both datasets. We can also use a semi-automatic approach correcting individual links; in this case, the scores rise to 0.68 and 0.84, respectively. To show the usefulness of our technique, we implement two proofs of concept. We create interactive documents using graphic overlays in the first one, facilitating the reading experience. We use voice instead of text to annotate charts in real-time in the second. For example, in a videoconference, our technique can automatically annotate a chart following the presenter’s description.

1 INTRODUCTION

Visualizations are relevant in the reading comprehension process because they help understand data more naturally. Many content sources, such as scientific papers and news websites, present the information using charts, diagrams, or tables that complement the text to improve understanding of concepts and ideas [10]. However, to read this kind of document, we must split our attention between elements and mentally integrate the story, requiring more cognitive work [34]. In response to this problem, some content creators incorporate interactive charts in their documents that serve as a visual guide for the reader [32]. In Figure 1, we can see an example where the user hovers a text, and the chart highlights the associated region. This type of interactivity facilitates the exploration of the document content.

For instance, imagine a news website writer who wants to embed an existing graphic that complements a text presented in an article to generate an interactive experience that guides the reader to a quick understanding of the text-graphic document. Generating interactive content is a tedious task, even with programming knowledge. Also, the content creator must manually annotate the links between the text and the graphic. Moreover, the writer does not always have access to edit an existing chart or the underlying data to redesign the chart for this type of content. Having a tool that reduces the effort in creating interactive content from text-graphic documents is the primary motivation for this research. To build a tool that automatically generates interactive text-chart documents, it is necessary to combine the three main tasks studied in recent years: (i) it identifies the chart in a document and maps it with the text that references it [13, 33] (ii) obtain the underlying data that makes up the chart (i.e., identify the type of chart, get the texts that appear on the chart, identify the visual channels) [8, 12, 27, 28, 31], and (iii) find the links between the text and parts of the chart [17, 20].

The latter is the least addressed, and the existing techniques are limited and do not automatically solve this task.

In this work, we propose ChartText, a new method that automatically connects text with its respective area associated with the chart. Our method is the starting point for building a tool to help content creators generate interactive visualizations from static documents. Moreover, it is essential to clarify that we take for granted tasks (i) and (ii) to achieve this research result. This approach can also work in semi-automatic mode, allowing the user to fix intermediate errors. Our method comprises two stages: In the matching stage, we generate individual links using different comparison operators between phrases in the text and textual elements in the chart. We combine the individual links in the grouping stage using each link’s visual channel information.

Most refugee illnesses are related to poor hygiene and harsh living conditions. Respiratory infections and Acute Watery Diarrhoea account for more than half of all illnesses. Skin infections and injuries due to unsafe camp conditions are also common.

Fig. 1. Screenshot of an interactive document taken from the news website Reuters Graphics [29]. It shows how the links between the text and the chart are highlighted to provide a visual guide to the reader.

Grouped links, in general, are more meaningful and allow the creation of multiple applications. Here, we present two prototypes: In the first one, we make interactive documents using graphic overlays, facilitating the reading experience. We use voice instead of text to annotate charts in real-time in the second. For example, in a videoconference, our technique can automatically annotate a chart following the presenter’s description. We evaluate our results by measuring how similar the inferred links are to links manually annotated by experts in two datasets from academic and web documents. Also, we compare our results with KongExtraction [20], a non-automated method based on crowdsourcing, which works only with bar charts. In summary, the contributions of this work are:

• A method for linking text with visualization for multiple chart types. This method can work in two modes, fully automated and semi-automatic.

• An application to make interactive documents by visualizing the links generated by our technique.

• A proof of concept where we use audio instead of text to create video annotated charts in real-time.

• A new dataset (text and charts) fully annotated for future comparisons. This dataset includes three chart types (bar chart, line chart, and scatter plots).
2 Related Work

Our work relates to two main areas: (i) chart interpretation and (ii) techniques and applications to facilitate the reading of documents.

2.1 Chart Interpretation

In recent years, methods and techniques have been developed to automatically extract the underlying data and visual encoding that build charts. These techniques have applications such as the reuse and redesign of charts. One of the pioneers in this area is ReVision [31]. ReVision extracts the data that generates a visualization from an image in a bitmap format. ReVision proposed a pipeline where initially the images are classified using the Support Vector Machine model [13] to determine the type of chart (e.g., bar chart, line chart, and scatter plot). Then, they used different image processing techniques and heuristics. These methods are adapted to the chart type and then used to filter elements in the image and identify the data. Other works maintain the initial idea of ReVision but vary some components with more sophisticated models. For instance, FigureSeer [33] and Scattarector [8] use a Convolutional Neural Network [24]. The input of these systems consists of images and features based on the spatial information of the chart elements to enhance the classification task. They also take advantage of the axis information and text labels to infer the data on line charts and scatter plots. Later, ChartSense [16] extended the data extraction support for five chart types (line chart, bar chart, area chart, foot chart, and radar chart), diversifying the heuristics to extract the data for each chart type but keeping the main idea proposed in the previous works.

Other works focused on recovering the visual encoding of the chart. For instance, Harper et al. [12] developed a system to deconstruct visualizations created with the D3 library [3]. This technique uses the data and graphic elements, which are easier to access in SVG images, to compose the visual encoding. In the same vein, Poco and Heer [27] proposed a pipeline to recover the visual encoding but for bitmap images. The technique exploits only the textual elements and retrieves a visual encoding in a declarative language similar to VegaLite [30]. Later, Chen et al. [6] presented a method to deconstruct bitmap infographics and generate templates that can be reused to create new infographics. This method uses deep learning models to identify graphics elements. Although we do not deconstruct charts in our work, we assume visual encoding as input. This assumption is valid since we can create visual encoding using the methods described above.

2.2 Facilitating Reading of Documents

Recently many works have appeared in this line. Kong and Agrawala [19] introduced Graphical Overlays to create interactive charts by accessing the data and visual encoding (using ReVision [31]). We also have a similar application: however, we generate overlays based on the text accompanying a chart; in this sense, our goal is to facilitate document reading.

Other works take advantage of additional information that is accessible to enrich documents and visualizations. For instance, Metoyer et al. [26] presented a technique that works on data-rich stories (i.e., texts with access to additional data such as tables). They proposed using text analysis to connect narrative sentences with visual elements that describe the rich data. Bryan et al. [4] proposed a method to explore temporal data and find, through heuristics, points of interest in the data that allow the creation of explanatory visualizations. Hullman et al. [15] proposed a system that takes time series data on a company’s stock to automatically create a line chart enriched with annotations from text analysis and metadata from news articles related to the company. These approaches are helpful when we have access to the data that accompanies the document or visualization. However, we only need the chart texts available in the visual encoding, and it is easy to extract with fewer errors in our approach.

Later, Kong et al. [20] presented a crowdsourcing-based method for extracting links between charts and text in documents. Nevertheless, they use people to annotate the document using crowdsourcing, unlike our work, which is fully automatic. On the other hand, some works use tables instead of using visualizations. Kim et al. [17] presented an automatic technique to find links between tables and paragraphs. This work uses NLP and heuristic techniques to connect table cells with text sentences. Similarly, Badam et al. [2] proposed a web tool that renders the text to the tables and creates visualizations using these links. To reduce the effort to create interactive documents, Latif et al. [22] proposed a framework for systematically generating documents that support text-visualization interaction. This system allows users to annotate the links in declarative language. Then, Cui et al. [9] proposed a method that converts text into infographics to facilitate reading. First, they identify parts of the text that refer to some data (e.g., numbers) and then use this information in templates that generate the images.

In recent years, methods and techniques have been developed to automatically convert data into a visual representation. In a visual encoding, we specify the graphical marks (e.g., points, bar, line) and map data variables to the visual channels (e.g., position, length, size). For instance, Figure 2(a) is an example of visual encoding that describes the channel associated with the x-axis of the line chart shown in Figure 2(b). Note that we have the scale information in this specification — which maps values from the data domain to the image range. Our visual encoding also has information about the labels used in the chart (text and bounding boxes) for this particular case.

Our technique assumes that we receive the visual encoding specification containing visual channel information (i.e., x-axis, y-axis, and color-legend), which can be automatically generated by methods proposed in previous works [12, 27].

Textual Element: It is a region on the chart that contains the text. For example, in Figure 2(b), the x-axis has textual elements such as “$100 million”, and the color legend has the textual element “deptype”.

Phrase: A phrase is any text fragment in a paragraph. For example, in Figure 2(b), the colored texts represent three phrases.
Individual Link: We define as an individual link a connection between a phrase and a textual element. Figure 2(b) shows some examples of individual links, each formed by a textual element and a phrase with the same number and color.

Grouped Link: A grouped link is a set of individual links. ChartText combines the links shown in Figure 2(b) to create a grouped link. Using this meaningful link, we can create a graphical overlay on the chart (more details in Sec. 4.2).

Case: A case is a pair consisting of a chart and its associated paragraph. A case could contain many grouped links.

3.2 Supported Visualizations

Our method supports bar, line, and scatter plots as a result of the restrictions we defined to delimit the scope of this investigation: i) the charts must represent the data using the cartesian space and a single color channel. We do not support visual channels such as orientation or size (e.g., it does not work for bubble charts); ii) we do not support charts composed of multiple views. Trellis plot is an example of a chart type violating this constraint; and iii) we only consider charts that use a single visual mark. For instance, Pareto plots violate this rule because it uses two graphical marks: bars and lines.

3.3 Gold Standard (GS) Set

to annotate the grouped links and visual encoding manually. For that, we decompose the paragraph into sentences using the sentence segmentation module of the spaCy library [14]. Then, we compute the syntactic constituency tree for each sentence using the constituency parser method proposed by Kitaev et al. [18] — the constituency tree subdivides the sentence into syntactic phrases.

Each node in the tree represents a syntactic phrase; for instance, Figure 3 shows the tree for the sentence "With 100 million tokens, the accuracy of the DepType system rises to 27.0%". In this example, the first node with the label $S$ represents the first syntactic phrase corresponding to the complete sentence. This phrase is then subdivided into three children nodes: $PP$, $NP$, and $VP$ that correspond to three syntactic phrases, prepositional phrase, noun phrase and verbal phrase, respectively. After that, we traverse the tree and check whether the phrase associated with a node is related to any textual element in the chart. For instance, in Figure 3, the node QP (green box) corresponds to the phrase "100 million", and it is related to the textual element "100 million" in the x-axis label. The same happens with the other two phrases in Figure 3 (orange, purple and red boxes). Finally, we use different operators to compare the phrases with the textual elements: direct, unique word, semantic, and numerical value comparison.

Direct Comparison. For each previously generated sentence, we check if any textual element is written precisely the same. If there is, then we create an individual link. This comparison helps identify proper nouns that are not defined in a vocabulary e.g., in Figure 3 the phrase "DepType" is the same as the textual element in the color legend.

Unique Word Comparison. It is common to have repeated terms in the textual elements with the same text role in the chart (see, for instance, legend labels in Figure 4(a)). This problem causes our direct comparison to generate false negatives because the phrases tend to reference the legend’s terms that differentiate them (we call these terms unique words). To solve this issue, we eliminate repeated words and keep the unique words on each textual element with the same text role. In our example, we keep the terms “correct” and “incorrect” in the textual elements. These words are better candidates to match the phrases in the paragraph.

Semantic Comparison. Sometimes phrases and textual elements are written using different words with the same meaning. For instance, in Figure 4(b), the phrase “religious wear” is related to the text...
We use the threshold that returns the best score. We perform an analogous process for textual elements. Finally, we with numerical variables in the visual encoding. If the numerical value

... Request for permission to have sacred items or religious wear such as crucifixes, eagle feathers and turbans (51%) also are usually granted.

Fig. 4. (a) Example of matching with the unique words strategy. (b) Example of matching with the semantic comparison strategy.

Fig. 5. Initial errors in numerical comparison: (a) Assignment of the number (‘72’%) to an incorrect axis. (b) Number ‘38%’ could be associated to both numerical axes.

Fig. 6. (a) Patterns are used to identify the attribute of a numerical phrase. (b) Ambiguity problem, using the syntactic dependency tree, we find the distances between the numerical phrase (‘38%’) and the phrases associated with the axes titles (‘coverage’ and ‘C4.5 error’), we keep the phrase with the shortest distance.

Error type I. In Figure 5(a), the phrase “72%” is within the y-axis domain. However, the “72%” does not refer to the “accuracy” (y-axis) or any other axis. To fix the first type error, we proceed as follows. First, we make sure that the numerical phrase has a NUM tag. Then, using the dependency tree, we find the NOUN associated with this number. After that, we verify if it coincides with some of the four cases shown in Figure 6(a). Finally, once we have the NOUN phrase, we compare it with the titles of the chart’s axes (we use the same comparisons of the previous stage: direct, unique, and semantic) and create the individual link; otherwise, we discard it. The four cases we show in Figure 6(a) results from an extensive analysis with different documents to cover as many scenarios as possible.

Error type II. In Figure 5(b), we have an “ambiguity” error, where the phrase “38%” could belong to both the x-axis and the y-axis. However, reading the paragraph deduces that it refers to the x-axis (“coverage PC”). To solve these problems, we generate a data structure that contains two types of information for each word: i) the syntactic dependency tree and ii) the Part of Speech (POS) tags. To fix the second type of error, we proceed as follows. Remember that the numerical phrase is associated with both axes (ambiguity). Then, we look for the axes’ textual elements) and the numerical phrase in the tree. This search uses the same comparison as the previous steps. In Figure 6(b), we can see an example for Figure 5(b); text in red is the numerical phrase, and the titles of the x-axis and y-axis are in green and blue, respectively. After that, we calculate the paths between the numerical phrase and the axes titles in the dependency tree (in Figure 6(b), we can see these paths with blue and green lines). Finally, we select the phrase that has the shortest route. In our example, we will choose the phrase “Coverage PC”, discarding the link with the y-axis.

4.2 Grouping

While individual links can already help generate interactive documents, as presented in Lai et al. [21]. Combining individual links can get more meaningful relationships related to a narrative aspect. For instance, Figure 2(b) shows the individual links; with that, we can only highlight the areas where the textual elements and phrases are located in the chart or paragraph, respectively. In this example, phrases “100 million”, “27.0%”, and “DepType” correspond to the x-position, y-position, and color channels, respectively. However, if we combine them, as the phrase “In the end, with 100 million tokens, the accuracy of the DepType system rises to 27.0%” suggests, we can find a specific location in the plotting area. To do so, we noticed that in our Gold Standard set, the grouped links annotated by the experts usually combine textual elements from different visual channels (x-position, y-position, and color). Thus, our method for grouping attempts to imitate how a human would do it.

Transferring of the Visual Channel to the Phrases. The first step is to transfer the visual channel information (i.e., x-position, y-position, or color) from the textual elements to the associated phrases in the links. For example, in Figure 3 the phrase “100 million” is linked to the textual element corresponding to an x-axis label. Therefore, we transfer the channel x-position to that phrase “100 million” is linked to the textual element corresponding to an x-axis label.
In this section, we first describe the metric used for our evaluations. Then, we discuss some quantitative and qualitative results to reason about good and bad scenarios.

5.1 Metric

Our work’s metric adapts the metrics proposed in object detection in images and information retrieval in texts. The objective is to evaluate how similar our grouped links are to the Gold Standard (GS) set. Figure 8 will serve as a reference to explain each stage. The F1 score gives us a value of 1 when two sets are identical and 0 when they are different. To interpret this score, let us see Figure 11 as an example. On the right side of the figure, we can see the links on the GS, and on the left side, the links obtained by our method. If we had found all the correct links, we would have an F1 score of 1, but we failed to find the textual element for the phrase “84%” (ChartText wrongly assigned the phrase with a numeric value in the x-axis, when in fact it belongs to the y-axis — causing the F1 score to decrease to 88%). As the errors increase, the score decrease, e.g., if we remove the links related to the phrases “10%” and “active agents” we will obtain a score of 66%.

As we can see, each error in an individual link is, on average, a 12% error, which gives us a clearer idea of how our method is behaving in all the cases.

To facilitate the description, we concentrate on a single case, i.e., a set of grouped links. In Figure 8 (a), the blue and red circles represent the grouped links of ChartText and the GS set, respectively. Ideally, there should be a one-to-one pairing; however, this seldom happens. The similarity value we use is the $F_1 = \frac{2 \cdot \text{precision} \cdot \text{recall}}{\text{precision} + \text{recall}}$ score; therefore, we need to calculate the precision and recall. To calculate the precision, we take each grouped link from ChartText and look for the most similar grouped link in the GS set — later, we will explain what we mean by the most similar. Once we have the matching, we add their similarities and divide them by the total number of pairs (for our example in (a), the precision is 0.65). Intuitively, the precision tells us how good are the grouped links generated by ChartText. Similar reasoning applies for recall but goes from the GS set to the grouped links generated by ChartText. (in our example in (b), the recall is 0.47). Intuitively, this value tells us to recover all the grouped links from the GS set. Finally, the F1 score for our case is 0.55.

In the previous paragraph, we mentioned that we look for the most similar grouped link in the other set given a grouped link. To assign a similarity value between grouped links, we first calculate the similarity between textual elements and phrases. The average of these values will be the similarity of the grouped link. Next, we explain how to compute both values.

Textual Elements Similarity. Here, we also use the F1 score, and the procedure is similar to before but using the textual elements from the ChartText and GS set. For precision, we take each textual element from ChartText and look for its corresponding one in the GS set (this value will be 1 or 0, if it is correct or not), then we add these values and divide them by the number of connections. Similar reasoning is used to calculate the recall, but we go from the GS to the ChartText results.

Phrases Similarity. Similarly, we use the F1, precision, and recall scores as in the previous paragraph. The difference is that we use two sets of phrases, and the similarity between phrases is calculated with the Intersection over Union (IoU) metric since the sentences generated...
Fig. 9. (a) Similarity for each case in the WEB datasets, obtained by our method and by the method proposed by Kong et al. [20]. (b) Similarity for each case of the ACA dataset. Each bar represents the similarity with respect to the GS set.

Fig. 10. Scores for each phase in our pipeline; we can see the similarity (score F1), precision and recall for each phase in both data sets.

by ChartText do not precisely match the GS set. In our example in (d), we have a precision of 0.4, a recall of 0.5, and an F1 score of 0.5.

5.2 Quantitative Results

Using the metrics described above, we performed a series of experiments to validate the results generated by ChartText.

**Comparison with KongExtraction** [20]. We performed this comparison with the WEB dataset, which is the same used by KongExtraction. Our method obtains an average similarity of 50%, while KongExtraction obtains 58%. Figure 9 (a) shows the similarity for each case in this dataset. It is important to note that although KongExtraction has a higher similarity, ChartText has certain benefits: i) our approach is fully automatic, while KongExtraction requires human participation through crowdsourcing; ii) KongExtraction needs to access the underlying data of the chart, while ChartText only requires access to the text present in the chart (available in the visual encoding), which is a simpler and less error-prone task in automation. Additionally, we evaluate ChartText with the ACA dataset, and we get an average similarity of 66%. Figure 9 (b) shows the similarity for each case in this dataset. In this experiment, we could not compare with KongExtraction since its code is unavailable, and it would be necessary to recreate the crowdsourcing environment.

**Evaluating phases for individual links.** This experiment’s objective is to validate the usefulness of each of the comparisons in the matching stage. For that, we compute our metrics after each comparison (i.e., before grouping): Direct, Unique Word, Semantic, and Numerical-value. Given that we do not have groups at this stage yet, we need to distribute the grouped links of the GS set into individual links. In Figure 10, we can see the results of this experiment. As we advance in the pipeline, the F1, precision, and recall scores increase, validating each comparison’s need. However, the precision score decreases slightly in the last comparison (Numerical-value). To explain this, let’s remember that our method finds new individual links in each step, and some of them can be false positives. Nevertheless, this effect is compensated by an increase in the recall since we bring individual links with numerical values necessary for the grouping stage and the applications.

**Semi-automatic evaluation.** On the other hand, it is possible to use ChartText in a semi-automatic mode where the user can intervene to solve specific problems (more details about human intervention in the Applications section). In the semi-automatic mode, the user can manipulate and fix individual links so that the grouping stage will get better results. We calculate each case’s similarities to validate this statement, assuming that we have the perfect individual links. Our results show similarities increased from 50% to 68% for the WEB dataset and from 66% to 84% for the ACA dataset.

5.3 Qualitative Results

In this section, we present qualitative observations to explain the behavior in some relevant cases, taking into account the design of our method.

**Well-Performed Results.** ChartText has good results when it is easy to associate the phrases with the visual channels (x-position, y-position, and color). For instance, in Figure 12 the phrase “Oracle” is easily associated with a color legend label (color channel) in the chart.
Similarly, the phrase “96.23%” is directly associated with a value on the y-axis (y-position channel), without any chance of being wrong because the x-axis only admits values less than or equal to 10. Finally, the phrase “k = 10” explicitly indicates that the value 10 belongs to the axis with the title “k” which is the x-axis (x-position channel). In this example, we notice that the three phrases that form the grouped link belong to the short phrase “the Oracle achieve 96.23% when k = 10”. We designed our method to create grouped links with multiple channels, and the phrases are close to each other. This behavior emulates how experts annotated the grouped links following this same criterion.

**Poorly Performed Results.** ChartText does not get correct results when there is ambiguity in assigning the visualization role to a phrase. Consider the case illustrated in Figure 11 (a). On the left side, we can see the wrong output generated by ChartText, and on the right side, we can see the correct overlays generated with the grouped links in the Gold Standard Set. Analyzing this case, notice that ChartText identified all the phrases correctly; however, the phrase “84%” was incorrectly associated with the x-axis. This error happens in the matching stages. The phrase “84%” is assigned to the x/y-axis because the value 84 fit in both scale’s domains. Then, using our rule-based approach and the syntactic distances to the phrases, ChartText determines that the phrase “84%” belongs to the axis associated with the nearby phrase “active agents” (x-axis). In other words, our approach could not identify the attribute (NOUN) related to the numerical phrase. For this particular example, we can see in the text that no phrase indicates that the “84%” refers to the y-axis (“Cumulative probability”).

Another problematic case is shown in Figure 11 (b). The main problem is that ChartText requires additional context information to reference a phrase with a textual element. In the GS set, the experts found two phrases associated with the chart. For instance, experts decided that the phrase “40-something” means people between 40 and 49. It makes sense to link this phrase with the textual element “40-somethings to retirees.” We designed our method to create grouped links with multiple channels, and the phrases are close to each other. This behavior emulates how experts annotated the grouped links following this same criterion.

**Overlays Generation.** We built a web tool that supports text visualization interaction to show the overlays. Figure 12 shows an example of how the tool produces an overlay when the user selects a phrase in the text. In the example, the tool highlights a point at the end of the curve that corresponds to the color legend “Oracle” (intersection of red lines). This overlay corresponds to three phrases (highlighted in yellow): “Oracle”, “K=10”, and “96.23%”. These phrases belong to individual links in the same group, and we use the color channel associated with each link to build the overlay. For instance, we use the color information associated with the phrase “Oracle” to filter out only the pixels that correspond to that color in the chart. Using this strategy, we highlight the correct curve in the chart. To identify the point at the end of the curve, we use the spatial information associated with the phrases “K=10” and “96.23%”. Different overlays can be generated, depending on the type of chart and the visual channel associated with the group’s links. Now we explain the six overlay types supported by our application:

**a) Line Segment.** This overlay is used to represent a single value of an axis. We use the numerical value in the grouped link to draw a line segment along the chart’s width or height. The orientation depends on the visual channel associated with the textual element (x-position or y-position). Figure 13 (a), shows an example when the numerical value belongs to the x-axis.

**b) Target Point.** This type of overlay is generated when, in the grouped link, there are two textual elements related to two different chart numerical axes. In this case, as shown in Figure 13 (b), we draw two line segments from the axes (orthogonal directions). The intersection represents the target point to which the phrase refers.

**c) Color Filter.** When a phrase in the grouped link refers to a color legend on the chart, we filter out the chart’s pixels with other colors, highlighting only the relevant color. To achieve this, we increase the transparency of the pixels that do not correspond to the target color (Figure 13 (c)).

**d) Bounding Box.** We use this type of overlay to highlight a bar or a group of bars, as shown in Figure 13 (d). The Bounding Box is used it. This application exemplifies how our method would allow us to build tools that generate interactive documents. This idea can be easily extrapolated in other more valuable applications in the real world. For instance, a document editor allows a content creator (such as a web news writer) to embed a chart on a text and generate interactive documents with minimal effort and without programming knowledge. Even at a more practical level, a plugin for a browser or a document reader (e.g., Adobe reader [1]) that allows the end-users to select the graphic and the text on which they wish to inquire and automatically generate the highlights between the chart and the phrases of the corresponding text.
We can use ChartText as the primary system component to convert voice to overlays. This functionality provides interactivity to static charts in environments such as conferences and video calls. We use ChartText to detect pauses in speech and generate chart. Then, we use a speech-to-text tool to convert audio into text. We then use the Google speech-to-text API to convert the audio to text. Finally, we use our method to extract the links and generate the overlays for each sentence in the audio.

The first video is entitled "Why you should love statistics". In the video, the presenter uses a bar chart to explain the percentage of young people with low numeracy in 12 countries. Figure 15 shows the results obtained for the first video. The top shows the frames of the original video and the sentences referring to the chart. The bottom shows the overlays on the chart generated by ChartText. For instance, for the first phrase "Leading the way the USA nearly 40 percent", there is an overlay that highlights the first bar of the chart. We can see the results of this example in the accompanying video.

The second video is entitled "Germany: Low Crime, Clean Prisons, Lessons for America". The presenter explains the U.S. incarceration rate between 1925 and 2012 using a scatter plot in this video. Figure 16 shows the results obtained. The top part shows the sentences extracted from the original video with a reference frame as in the first video. The bottom part shows the overlays generated by our method. In this example, we obtained three overlays: The first overlay highlights a date range ("1925 to 1975") on the x-axis and a value ("100") on the y-axis. The second and third overlays highlight specific dates on the x-axis ("1940" and "1970", respectively).

7 Limitations and Future Work

Our work has some limitations and possible improvements presented in this section.

Dataset. One of the significant limitations of this work is the small amount of annotated data available to relate the text to visualizations. In this work, we are making another fully annotated dataset, including three chart types; however, this is still insufficient to archive this task successfully. It is impossible to explore other techniques and approaches without an extensive dataset, such as using machine learning models instead of the rule-based system currently used. As future work, we propose to design the processes of annotating an extensive dataset to relate text and visualizations.

Improvement in the Numerical-value phase. As we saw in our evaluation, the Numerical-value comparison is necessary for the grouping stage, affecting the generation of overlays. However, our method is not robust enough, generating false positives in the individual links. The main problem lies in using heuristics and templates to identify the numerical phrases that do not correspond to the chart axes. In future work, we intend to experiment with more robust methods from natural language processing. We will have to generate a larger dataset with annotated text examples. Using it, we could train a machine learning model to identify the NOUNs associated with the numerical phrases more precisely without rules.

Support for complex charts. In this research, we limited the scope of ChartText to simple charts but were commonly used to display results with descriptive statistics (bar charts, line charts, and scatterplots). However, this is a starting point for future works that perform the same task on more sophisticated graphics (i.e., that overload graphic markup and visual channels). For instance, there are two graphic marks in a Pareto chart: bars and lines. Our technique does not support this chart type but supports each type separately. A possible extension of our approach, having the data properly annotated, would help solve this problem.

End-to-end Generation of Interactive Documents. ChartText assumes that we have: i) visual encoding and ii) chart and text loca-
We also make a second dataset containing 75 cases, including three web and academic documents, respectively. Finally, we presented two plugins for web browsers or document readers tools such as Adobe Acrobat Reader [1].

8 CONCLUSIONS

This paper presents ChartText, a method automatically extracting links between text and visualizations. We evaluated our results by comparing them with manual annotations made by experts on two datasets (web and academic documents). We compare our ChartText with KongExtraction [20] (a non-automatic method based on crowdsourcing strategy) for the web documents. Our approach obtained a similarity of 50% compared to 58% of KongExtraction. Despite our lower score, it is essential to highlight that: i) our method provides a fully automatic approach, ii) we support more chart types, and iii) we do not need access to the underlying data; we only need the charts’ textual elements. We also make a second dataset containing 75 cases, including three chart types from academic documents. In this dataset, ChartText got an average similarity of 66%. Although our method is automatic, we have a semi-automatic mode that allows the user to fix intermediate errors (individual links). We experimented with perfect individual links to evaluate this functionality, and our scores rose to 68% and 84% for the web and academic documents, respectively. Finally, we presented two applications. The first is a tool to generate interactive documents. The second is Voice2Overlays, which converts a speaker’s voice into visual aids on a chart.

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Fig. 15. The application uses our proposed method to convert voice into visual guides or overlays on the chart. First, the application receives a video where a presenter describes a chart to the audience. The video's voice is extracted and converted into text using a speech-to-text tool. The application also receives the visual encoding of the chart in the video as input. Then, the texts extracted from the audio are processed by ChartText, generating as output the overlays shown in the lower part of the figure.

Fig. 16. Result of the Voice2Overlays application to convert a presenter’s voice into overlays in real-time. At the top are shown the frames and the extracted phrases from the original video used as input. At the bottom are shown the overlays that our method obtained as output.

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