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Infographics Wizard: Flexible Infographics Authoring and Design Exploration

1. Appendix A Infographics Dataset Annotation with Visual Groups

1.1. Source Images

We used the study results by Lu *et al.* [LWL*20] to sample 1000 infographics belonging to each of the 12 VIF categories (as proposed in their work [LWL*20]) and in the ratio as they appear in the original dataset (Figure 8 in [LWL*20]). Because of our framework's design aspect, since we aimed to relate the VG designs with VIF layouts, sampling infographic images based on the VIF layout was crucial for consistency with real-world designs.

1.2. Experiment Setup

We annotated the infographics using Amazon Mechanical Turk [Ama21]. The workers were first introduced to the concept of VGs and their individual components with some example images. The task was to segment individual VGs, the components inside the VGs (refer to Figure 3B of the paper), and annotate VGs with a bounding box in each of the infographic images. For consistency, each image was annotated by three different workers, and we chose the best annotated VGs for each image manually. An example user annotated image is shown in Figure 3C in the paper. Some example user annotations are provided in the supplementary material.

1.3. Processing the Segmentation Maps

Human-generated segmentation maps are coarse with ill-defined shapes. To generate a well-defined VG segmentation map, we employed the automated GrabCut [RKB04] algorithm, similar to [CWW*19]. The human annotations were used as input to the algorithm to generate high-quality segmentation masks for VGs. This mask was then passed as input to Solaris [Sol21] which generated SVG paths for segmented VG designs. Finally, we added additional components to the SVG based on bounding box annotations of individual VGs, provided with the dataset by Lu *et al.* [LWL*20].

2. Appendix B Design Component Extraction

In this section, we discuss the process of extracting VIF, VGs and Connection designs from the infographics dataset.

2.1. Visual Information Flow (VIF) Extraction

VIF is the first component of our framework (**D1**), representing the backbone layout inside an infographic. As shown in Figure 3A of the paper, VIF represents the direction of information flow following the positions of repeated VGs inside an infographic. It is represented as a series of 2D points where each point represents a VG position in two dimensions corresponding to a design area, and the number of points represents the number of VGs in that particular flow. The sequence of points represents the sequence of visual groups based on the information flow. To calculate the VIF for a given infographic, we used the algorithm discussed in [LWL*20].

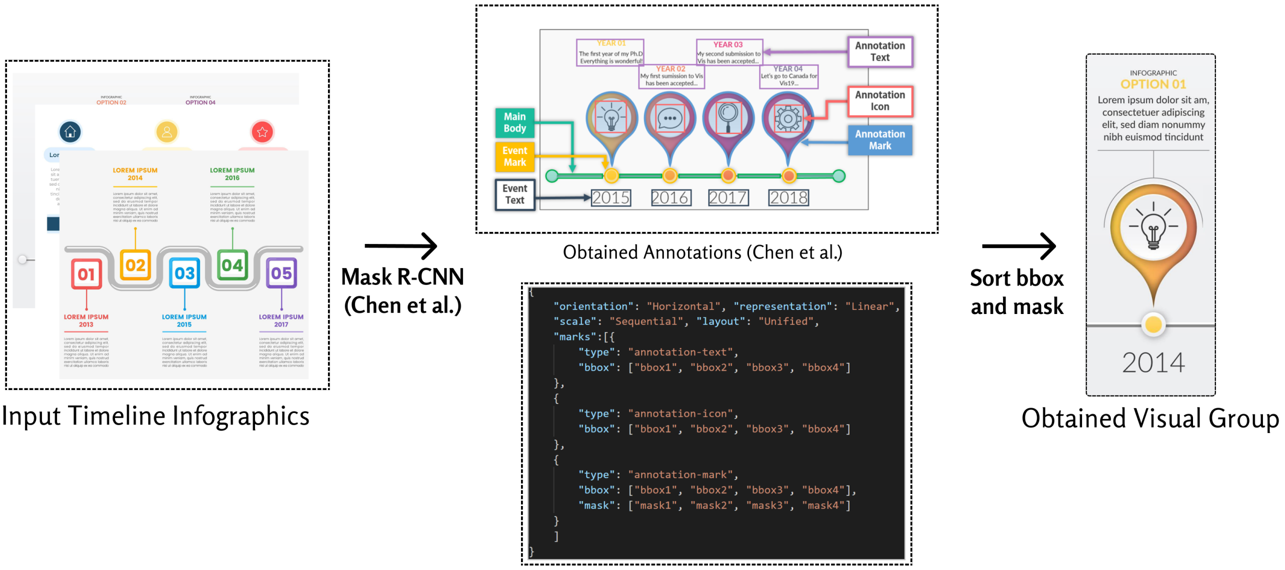
2.2. Visual Group Design Extraction

Since VG designs are the basic building block for infographic generation in our framework (**D2**), we chose multiple sources to collect VG designs to attain maximum coverage. Out of the total three sources we used, the first one is Adobe Stock [Ado21], which contains SVG designs of several human-generated infographics, from which we manually separated the VG designs; the second source is our human segmented VG dataset which we curated for this work, explained in Appendix A; the third source is taken from the work by Chen *et al.* [CWW*19] where we extracted VGs from timeline infographics using a Mask R-CNN [HGDG17], explained in the following text.

These sources were carefully chosen so that we get the VG designs created directly by humans and also using automated deep learning networks. We chose the SVG format to store the VG designs because of various benefits like scaling, color, and widespread usability. Each VG is further divided into four components as shown in Figure 3B in the paper, namely: *Label*, *Text*, *Title*, and *Image*. Each VG can contain any number of these elements, and each SVG design contains separate markings for each component, which the user's content can then replace as per our design pipeline.

2.2.1. Mask R-CNN for Initial Element Segmentation

In addition to the VG designs generated from the datasets available at Adobe Stock [Ado21], we modified the timeline infographics work by Chen *et al.* [CWW*19] to extract more VG designs. The timeline infographics dataset released with this work contains 9592 manually created timeline infographics from Timeline Storyteller [BLR*19] and 1138 infographics from online sources. It includes 4689 images with manually labeled infographics components.



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    "orientation": "Horizontal", "representation": "Linear",
    "scale": "Sequential", "layout": "Unified",
    "marks":[{
        "type": "annotation-text",
        "bbox": ["bbox1", "bbox2", "bbox3", "bbox4"]
    },
    {
        "type": "annotation-icon",
        "bbox": ["bbox1", "bbox2", "bbox3", "bbox4"]
    },
    {
        "type": "annotation-mark",
        "bbox": ["bbox1", "bbox2", "bbox3", "bbox4"],
        "mask": ["mask1", "mask2", "mask3", "mask4"]
    }
    ]
}
```

Figure 1: *Process of generating VG designs from the Mask R-CNN network. After generating the network's annotations, the bounding box and mask values are sorted in the direction perpendicular to the predicted orientation. Then the first values of every bounding box and mask are grouped to get a VG.*

Table 1: *Relations of VG Elements with the Timeline Infographics prediction from Mask-RCNN*

Timeline Component	Visual Group Component
Annotation Text	Text and Title
Annotation Icon	Icon
Annotation Mark	Visual Group Design
Event Mark	Connecting Point
Event Text	Label

We used Mask R-CNN [HGDG17] with this dataset to generate the segmentation maps for the infographic components. Besides predicting the segmentation masks, a modified network predicts the local and global information about a timeline infographic image. The global information predicted by the network is the infographic *Representation*, *Scale*, *Layout*, and *Orientation*. For example, an infographic can have the global properties *Linear*, *Sequential*, *Unified*, and *Horizontal*, as shown in Figure 1. Besides the global information, the network also predicts the bounding boxes for local information like *Text*, *Label*, *Title* and *Icon* along with the segmentation masks for the designs containing these elements. Figure 1 shows the network and sample annotations, respectively. The complete details of these global and local properties can be found in [CWW*19].

As we can see, the output of the above model provides us with the annotation labels of *Text*, *Icon* and *Mark* and event labels of *Mark* and *Text* along with *Main Body* labels. We can convert each of these labels to the corresponding VG elements based on the relations shown in Table 1. The entire pipeline is shown in Figure 1.

2.2.2. Visual Group SVG Generation

Creating reusable VG designs from the Mask R-CNN predictions requires binding several predicted bounding boxes based on their respective VGs. Since the Mask R-CNN output does not predict which VG a particular bounding box belongs to, we developed a simple scheme to bind the bounding boxes based on their respective VG positions. Also, since the purpose here is to get the VG design, we only created one VG component from each infographic. We assume that the design of the VGs remains consistent within the infographic, which was found to be true in all the timeline infographics from the dataset by Lu *et al.*

Hence, after predicting various elements for a given infographic image, we used the *Orientation* as predicted by the Mask R-CNN to generate the VG design. We assumed that VGs are spread in the direction perpendicular to the infographic orientation. For example, in Figure 1, the VGs extend in a vertical direction when the infographic is horizontal. Using this assumption, after generating the marks from Mask R-CNN for each of the infographic design elements, we sorted every element based on the bounding box centers in the direction perpendicular to the predicted orientation. After, we assigned the first element of each predict mark to the same VG.

For simplicity, to solve the purpose of extracting meaningful VG designs, we only used the infographics with *Horizontal* and *Vertical* orientations. Also, we confirmed the extracted VG designs by a human analyst for their correctness and discarded the incorrectly generated VGs. The final bounding boxes and masks obtained from this process were converted to the SVG-based VG designs using Solaris [Sol21].

Table 2: *A VG-VIF index stores the information of VGs, and the corresponding VIF cluster centers CL-X in which they appear. Each VIF layout is clustered into one of the total twelve classes, shown as CL-X.*

Visual Group ID	VIF Layout Cluster IDs
VG-1	CL-1, CL-3, CL-4, CL-7
VG-2	CL-1, CL-2
VG-3	CL-4, CL-5, CL-6
VG-4	CL-1, CL-2, CL-3, CL-4, CL-5, CL-6

2.3. Connection SVG Generation

We collected connection SVG designs from adobe stock similar to the collected 200 infographics from the formative study. All connections from these images were found on the portal, which mainly were simple shapes (like arrow, line, circle, etc.) which could be modified based on certain conditions.

3. Appendix C
VIF layout Recommendation

Following up from Equation 1 from the paper, E_O is an indicator function that is 1 if and only if none of the VIF flow elements lie in the boundaries of the bounding box of the pivot element, and 0 otherwise. Another component of the layout scoring energy function is E_C, which calculates the score based on the coverage a VIF layout provides. More the coverage, the higher the value of E_C, as shown in Equation (1). Here $Hull(VIF)$ means the convex hull of the points in a particular VIF layout.

$$E_C = \frac{Area\ of\ Hull(VIF)}{Area\ of\ Canvas} \tag{1}$$

The last component of the layout scoring function is the uniformity in the distance of the VIF elements wrt to the center of the pivot elements. To calculate this, we first calculate the center of the bounding box of the pivot element, denoted as P_{XC} and P_{YC}, shown in Equation (2) and (3).

$$P_{XC} = P_X + \frac{P_L}{2} \tag{2}$$

$$P_{YC} = P_Y + \frac{P_W}{2} \tag{3}$$

Then, we calculate the variance of the distance between each VIF element and the pivot center, which gives a score of uniformity in the spread of the layout, shown in Equation (4). Lesser the value of E_U, the better the uniformity and vice versa. $\bar{D}$ is the mean Euclidean distance between the VIF elements and the pivot center.

$$E_U = \frac{\sum_{X_i,Y_i \in VIF} \sqrt{(X_i - P_{XC})^2 + (Y_i - P_{YC})^2} - \bar{D}}{N} \tag{4}$$

3.0.1. VG-VIF Index

The VG-VIF index aims to capture a global relationship between the VG designs and the VIF layouts to support a ranking system that allows accurate recall of the suitable VG designs given a VIF layout. To develop the VG-VIF index, we first clustered all the VIF flows in our dataset into 12 categories as mentioned in [LWL*20]. We first generated the VIF images for each infographic in our dataset to generate these clusters. These images were then reduced to 50 dimensions using PCA [JM92] to get the principal components, which were then further reduced to 2D using t-SNE [VdMH08]. This 2D space was divided into clusters with centers around the high-density regions with DBSCAN [Liu06] and then iteratively clustering all the points into one of the centers. We repeated this procedure until there was no further improvement in the forming clusters. We used the same 12 classes discussed in [LWL*20] to form the basis of the VIF layouts (denoted as CL-X in Table 2).

Following this, we extracted the VG designs from each of the infographics. Table 2 shows an example of 4 Visual Groups (denoted as VG-x) that can occur in multiple VIF flow categories (denoted as VIF-x). This example shows the one-to-many relationship between the VG designs and the VIF layouts. We can treat these relations as “words” occurring in some “documents”, where the VGs are the documents and the corresponding cluster centers are the words in each document. Using this analogy, we obtain the ranking of VGs given a VIF cluster ID by calculating the *TF-IDF* score [R*03] for each VG. The TF-IDF score has been extensively used in information retrieval and has properties that we can use to rank the VGs. Firstly, the TF-IDF score down-weights the most commonly appearing words; in this case, it results in higher rankings of less frequent VGs. Thus, our recommendation engine generates infographics using the VGs, which are less common. Also, the TF-IDF scores are generated covering the entire domain, in this case, the domain of VIFs, which is a desirable property while generating infographic designs.

To summarize the VG ranking process, we choose the best VIF layout vectors to place the VGs based on the canvas elements. The VG scores are obtained from the VG-VIF index, which shows how well-fitting a VG is for a given layout. The VG-VIF index scores are sorted, and a subset of high-scoring VGs are selected, which match the user’s markdown input (i.e., the number and type of components inside a VG). In some cases, users might want to design their own VG designs, an example of it can be a VG with some chart information. Since generating VGs with multidimensional data information is not yet supported in Infographics Wizard, users can use tools like Text-2-Viz [CZW*19] to design custom VGs and upload into Infographics Wizard to generate infographics.

3.0.2. Visual Group Placement and Information Embedding

The ranking algorithm discussed above provides a list of VGs, which can be used with a selected VIF layout. However, placing the VG on the VIF layout requires proper rotation and scaling. The rotation of a VG is defined based on whether or not the infographic has a pivot graphic. In case the pivot graphic is present, each VG should face towards the pivot graphic, and hence the rotation angle is calculated by measuring the angle of the arc connecting the VG from the center of the pivot graphic on the circle centered at the pivot graphic. After the rotation angle for each VG is fixed, the input information can be embedded inside each VG.

To embed the user input, each VG has placeholders defined in their respective SVG files for placing individual components (i.e., image, text, title, and label). Text's font size and dimensions of the image to be embedded are calculated based on the size of these placeholders and the content's size. Also, embedded text and images are invariant to the VG rotation and are always placed at the same angle in each of the VGs.

4. Appendix D Exceptional Cases

Referring to the exceptional Infographic designs not covered under our framework from Section 3.1 from the paper, some examples are shown in Figure 2. These cases include designs where the VGs are scaled following the VIF layout in images *A*, *B*, and *C*. Also, in images *A* and *C*, the pivot graphics are composed of multiple objects and contain additional icons. Sometimes, the VG design is not fixed, as in the case of image *B*. Such designs are hard to generalize with our tool, which was developed to support general-purpose infographic design and exploration.

5. Appendix E Evaluating Design Experience with User Study

5.1. Tasks and Procedures

We initially familiarized the participants with the concepts of Infographics and related terminologies, such as the definition of VG, VIF, Pivot Graphic, and Connections for our framework. Next, we showed a few examples of infographics chosen from our dataset to familiarize them with infographic designs. The participants were then allowed to experiment with Infographics Wizard and ask clarifying questions regarding the tool. The task was to generate an infographic design from the content and design input of choice and evaluate the design support features of Infographics Wizard. We also provided sample markdown inputs to users, and they had an option to either generate infographics from the content of their choice or use the provided examples.

After the participants were satisfied with their generated or filtered infographic designs, we conducted a short semi-structured interview to collect qualitative feedback. We asked the participants to rank their experience with Infographics Wizard on a five-point Likert scale. The questionnaire was based on a total of six factors: *Enjoyment*, *Exploration*, *Expressiveness*, *Results worth the effort*, *Ease of use*, and *Workflow*. Four of these factors were taken from the work by Cherry *et al.* [CL14] for quantifying the creativity support for design tools. Two specific factors, *Effort* and *Workflow*, were added in the questionnaire to specifically evaluate Infographics Wizard for its support in infographics design and exploration tasks. The whole study took about 45 minutes for each participant.

References

[Ado21] ADOBE: Adobe stock, 2021. URL: https://stock.adobe.com/. 1

[Ama21] AMAZON: Amazon mechanical turk, 2021. URL: https://www.mturk.com/. 1

[BLR*19] BREHMER M., LEE B., RICHE N. H., TITTSWORTH D., LYTVYNETS K., EDGE D., WHITE C.: Timeline storyteller. 1

[CL14] CHERRY E., LATULIPE C.: Quantifying the creativity support of digital tools through the creativity support index. *ACM Transactions on Computer-Human Interaction (TOCHI) 21*, 4 (2014), 1–25. 4

[CWW*19] CHEN Z., WANG Y., WANG Q., WANG Y., QU H.: Towards automated infographic design: Deep learning-based auto-extraction of extensible timeline. *IEEE transactions on visualization and computer graphics 26*, 1 (2019), 917–926. 1, 2

[CZW*19] CUI W., ZHANG X., WANG Y., HUANG H., CHEN B., FANG L., ZHANG H., LOU J.-G., ZHANG D.: Text-to-viz: Automatic generation of infographics from proportion-related natural language statements. *IEEE transactions on visualization and computer graphics 26*, 1 (2019), 906–916. 3

[HGDG17] HE K., GKIOXARI G., DOLLÁR P., GIRSHICK R.: Mask r-cnn. In *Proceedings of the IEEE international conference on computer vision* (2017), pp. 2961–2969. 1, 2

[JM92] JOLIFFE I. T., MORGAN B.: Principal component analysis and exploratory factor analysis. *Statistical methods in medical research 1*, 1 (1992), 69–95. 3

[Liu06] LIU B.: A fast density-based clustering algorithm for large databases. In *2006 International Conference on Machine Learning and Cybernetics* (2006), IEEE, pp. 996–1000. 3

[LWL*20] LU M., WANG C., LANIR J., ZHAO N., PFISTER H., COHEN-OR D., HUANG H.: Exploring visual information flows in infographics. In *Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems* (2020), pp. 1–12. 1, 3

[R*03] RAMOS J., ET AL.: Using tf-idf to determine word relevance in document queries. In *Proceedings of the first instructional conference on machine learning* (2003), vol. 242, Citeseer, pp. 29–48. 3

[RKB04] ROTHER C., KOLMOGOROV V., BLAKE A.: " grabcut" interactive foreground extraction using iterated graph cuts. *ACM transactions on graphics (TOG) 23*, 3 (2004), 309–314. 1

[Sol21] SOLARIS: Solaris by cosmiq works, 2021. URL: https://solaris.readthedocs.io/en/latest/index.html. 1, 2

[VdMH08] VAN DER MAATEN L., HINTON G.: Visualizing data using t-sne. *Journal of machine learning research 9*, 11 (2008). 3

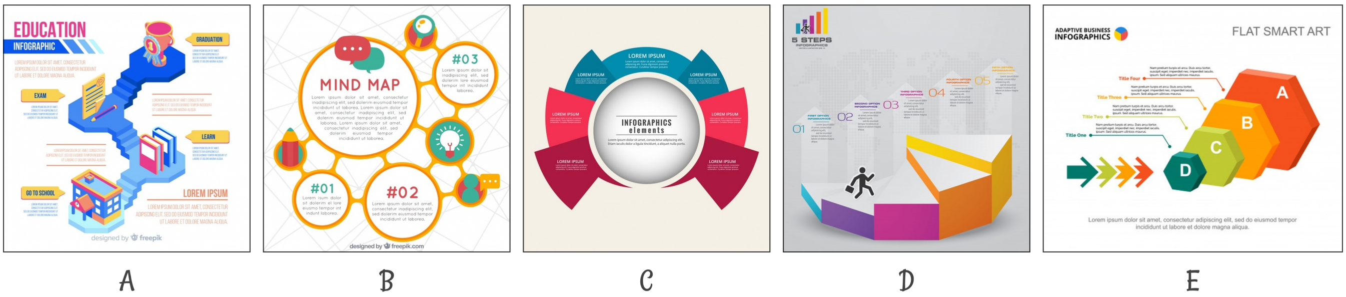


Figure 2: *Infographic designs out of the scope of our framework. Some of these features include VG scaling (A, B, and C), inconsistent VG designs (A and B), complex pivot graphics composed of multiple SVG paths (A and D), and complex connection designs (E).*

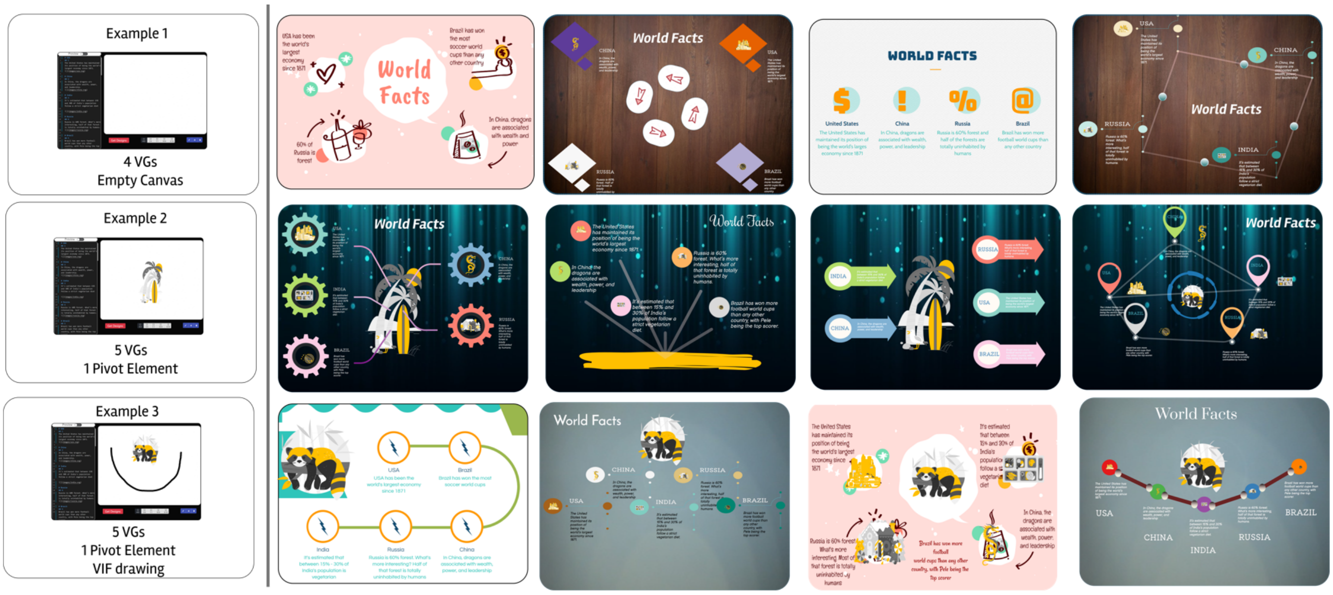
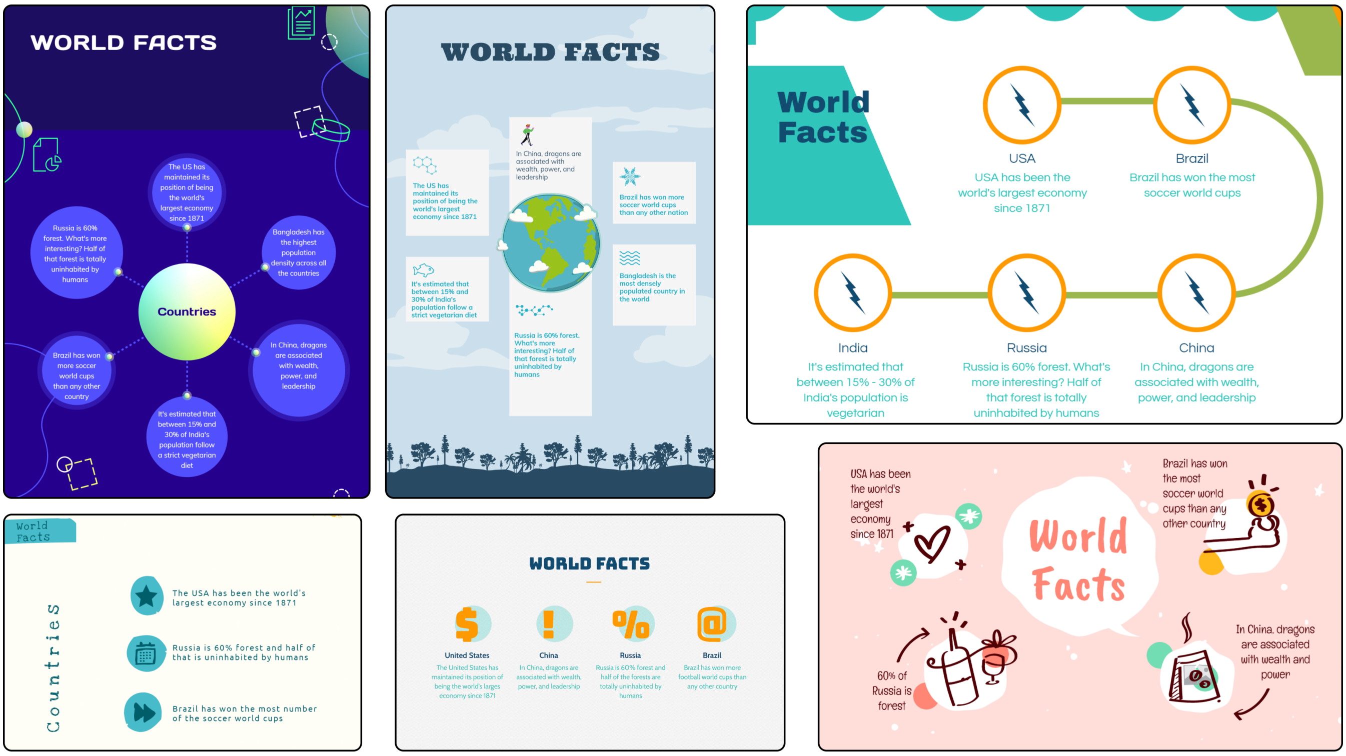


Figure 3: *Example infographics generated using our framework using the example cases. We evaluated our framework with three example inputs, each of which had different content and design, shown on the left of each row. For each input, our framework recommended infographics, where we show some recommended infographics in each row for similar inputs.*



WORLD FACTS

Countries

The US has maintained its position of being the world's largest economy since 1871

Russia is 60% forest. What's more interesting? Half of that forest is totally uninhabited by humans

Bangladesh has the highest population density across all the countries

Brazil has won more soccer world cups than any other country

In China, dragons are associated with wealth, power, and leadership

It's estimated that between 15% and 30% of India's population follow a strict vegetarian diet

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Figure 4: *Sample infographic designs generated with our framework collected during a user study.*