THE DIDI dataset: Digital Ink Diagram data

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ABSTRACT

We are releasing a dataset of diagram drawings with dynamic drawing information. The dataset aims to foster research in interactive graphical symbolic understanding. The dataset was obtained using a prompted data collection effort.

1 INTRODUCTION

Handwritten text and hand-drawn sketches have been one of our primary means of processing, conveying and storing information. While optical character recognition (OCR) is one of the early approaches converting handwritten content into digital representation, digital ink allows for combining the flexibility and aesthetics of handwriting with the ability to process and edit interactively.

A vast range of mobile computing devices with touch screens provide interaction by means of digital ink in different forms. Smart watches or mobile phones enable users to write and draw on the screen. High-end laptops and tablets (Apple, Microsoft, Google), often with a stylus, allow to do fine-grained note-taking and document editing. Ink-based applications provide natural interaction and richer user experience. Handwriting recognition is a natural text input method (Yaeger et al., 1998; Pittman, 2007; Carbune et al., 2020). Recent works focus on assisting tools to preserve and enhance stylistic aspects of handwriting (Zitnick, 2013) as well as content editing (Aksan et al., 2018). Ha & Eck (2017) present a predictive model for completing hand-drawn objects.

While existing work has been successful on modeling and recognition of isolated hand-written and -drawn content, we argue that the real potential of digital ink lies in modeling of richer content where multiple categories such as handwritten text, hand-drawn shapes, and diagrams co-exist and are semantically related. To foster the research into this direction, we release the novel DIDI dataset of digital ink diagrams. DIDI consists of large number of user-drawn diagram samples with and without text, allowing for data-driven modelling.

We hope to create more interest in the academic community with the release of this dataset that enables research into the combination of machine learning and human computer interaction - which we believe both to be important for a practical diagram creation and editing tool.

2 RELATED WORK

To the best of our knowledge only few datasets of handwritten drawings are available to date:

1. Czech Technical University has released a dataset of diagram drawings with a total of 300 finite automata diagrams and 672 flowchart diagrams (Bresler et al., 2014, 2016).

2. The Nakagawa lab at Tokyo University of Agriculture and Technology has released the KONDATE dataset of 670 drawings (Matsushita & Nakagawa, 2014).

3. University of Nantes has released a dataset of 419 flowchart drawings collected from 36 writers (Awal et al., 2011).

Another related field of more specialized drawings is the creation of mathematical equations, another domain where using a freeform input maybe a big advantage in how natural and efficiently users are enabled to create digital content. In this field, the CROHME competition (Mouchre et al., 2016) has created a dataset of more than 10,000 mathematical expressions, including the dynamic time information since 2011.
Unfortunately, none of these datasets is large enough to be considered large from a deep learning perspective.

3 Dataset Description

We are releasing a dataset of flowchart drawings consisting of two parts: 22,287 diagrams with textual labels and 36,368 diagrams without textual labels. The data was collected from a total of 364 participants where the number of individual drawings any participant created was between 1 and 1291.

The data was collected in a prompted data collection effort where the participants were shown an image and asked to draw the shown diagram over the image (see figure 1).

We are releasing the data online under the Creative Commons Attribution 4.0 International License at https://github.com/google-research/google-research/tree/master/didi_dataset with example code demonstrating how to visualize the data and how to convert it into formats suitable to common machine learning frameworks.

In figure 1 we show a number of example drawings overlaid with the respective prompt images.

In the following we describe the data collection setup, the data format, and the dataset statistics.

3.1 Data Collection

The data collection was performed using an Android app on Chromebooks (with and without stylus) and Android devices. The app is used for a variety of data collection tasks related to online
handwriting recognition. Participants were mostly interns at Google’s Zurich (Switzerland) and Mountain View (California, US) offices.

The app was configured to show a prompt image of a flowchart to the user who was then asked to draw over it. See figure 2 for an example.

Flowcharts images were obtained through GraphViz, based on randomly-generated dot files. See section 3.3 for a description on how the prompt images were generated.

The data collection was organized in two sessions. The first session happened in summer 2018 and participants were asked to draw diagrams like the one shown in figure 2 including the textual content in the boxes. The second session happened in summer 2019 and participants were asked to draw the same type of diagrams but without any textual content in the boxes.

3.2 DATA FORMAT

The data is released in NDJSON format (newline delimited JSON) with additional supporting files. Each row of the files corresponds to one drawing and contains a number of fields:

key a 64-bit integer as an hexadecimal string - a unique identifier for that row.

label id a sha1 hash of the dot file that was used to generate the prompt image. Labels occur between 1 and 169 times in the dataset. For each label we also provide the original dot file that was used to render the prompt image, the resulting PNG image, and the extended xdot file generated by GraphViz.

drawing the drawing itself as an array of strokes, where each stroke is an array containing arrays for x, y, coordinates and timestamps (in milliseconds, starting at zero for each drawing).
writing guide  the width and height of the drawing area where the user has drawn. This information can be used to align the prompt image with the coordinates. See the accompanying colab notebook for more detail.

split  one of train, valid, or test, indicating whether

An example row from one of the NDJSON files is shown in figure 3.

3.3 Diagram Generation Process

Diagrams used as prompts were generated using GraphViz, from randomly generated dot files. The dotfiles were generated as follows:

1. Select a number of nodes between 2 and 6 uniformly
2. Select a text label topic from \{none, colors, process, clients\}
3. \texttt{graph\_has\_labeled\_edges := Bernoulli(p=.7)}
4. For each node
   (a) randomly assign a shape from \{box, oval, diamond, parallelogram, octagon\}
   (b) randomly assign a textual label from the topic selected above
5. while \#edges < \#nodes - 1 or there are unconnected nodes
   (a) while true:
      i. randomly select a start and stop node
      ii. if no edge already exists between the nodes, create it and break from the loop
   (b) if \texttt{graph\_has\_labeled\_edges}: randomly assign a label to the new edge

The possible labels for each of the topic are given in Appendix B.

3.4 Dataset Statistics

The complete dataset of 58655 drawings was collected from a total of 364 participants. The dataset uses a total of 6555 unique labels, with each label being used between 1 and 169 times, median 4.

The collected drawings use between 1 and 161 strokes (median 14) and contain between 2 and 17980 points (median 1559).

3.5 Experimental Protocol

For uses of the dataset where dedicated training, validation, and test sets are desirable, we define a split in the NDJSON files. The split was created based on writers (whose identifiers are not released) such that the sets of writers in the respective training, validation, and test parts of the datasets are disjoint.

Given the size of the dataset, we chose to use about 1/8th of the data for validation and test data, respectively, and to use the remaining 6/8th of the data as training set.
Table 1: Sizes of the training/validation/test parts of the dataset.

| Split | w/o text | w/ text | all   |
|-------|----------|---------|-------|
| Training | 27,278   | 16,717  | 43,995|
| Valid   | 4,545    | 2,785   | 7,330 |
| Test    | 4,545    | 2,785   | 7,330 |

4 CONCLUSION

We are releasing a dataset of online diagram drawings with their respective prompt in order to foster research in graphical symbolic understanding by combining machine learning and human computer interaction technologies.

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A Appendix: Statistics

- Total number of diagrams:
  - with text: 22287
  - without text: 36368
- Total number of nodes:
  - within graphs with text: 77682
  - within graphs without text: 139953
- Total number of edges
  - with a text label: 17865
  - within graphs with text: 64361
  - within graphs without text: 122535
- Node shapes:
  - within graphs with text:
    - box 15906
    - diamond 15360
    - octagon 15620
    - oval 15384
    - parallelogram 15412
  - within graphs without text:
    - box 28251
    - diamond 27886
    - octagon 29115
    - oval 27575
    - parallelogram 27126
## APPENDIX: WORD Lists

The word lists used for each of the topics are given in table 2.

Table 2: Words used as node and edge labels in the generation of the diagrams (cp. section 3.3). The numbers in parentheses indicate how often each label occurs in the dataset.

| Topic   | Node labels                                                                 | Edge labels                                                                 |
|---------|-----------------------------------------------------------------------------|-----------------------------------------------------------------------------|
| None    | –                                                                           | –                                                                           |
| Colors  | artichoke (680), auburn (684), azure (732), black (699), blue (746), bronze (654), brown (650), bubble gum (611), charcoal (742), chestnut (725), chocolate (707), cobalt blue (627), cyan (702), dark brown (1389), dark chestnut (575), dark chocolate (652), dark cyan (669), dark gray (617), dark green (729), dark red (640), eggshell (680), fuchsia (652), gold (738), gray (663), green (734), help (412), light blue (634), light brown (726), light green (661), lime (785), magenta (737), navy blue (736), orange (576), pink (727), purple (632), red (756), rose (648), ruby (770), saffron (720), silver (608), teal (640), violet (679), white (680), yellow (730) | –                                                                           |
| Process | Wait (1014), Plug (1113), Resume (928), Move (1066), Go (1035), Turn on (1047), Quit (936), Create (1066), Ready? (1099), Search (1040), Reload (997), Delete (992), Replace (959), Quit? (981), Switch (1186), Repair (1110), Close (1029), Open (1070), Turn off (969), Unplug (1128), Stop (1102), Copy (998), Advance (966) | bills (720), builds (692), calls (700), connects (677), drops (684), helps (675), manufactures (649), processes (774), produces (694), replies (693), sends (746), ships (665) |
| Clients | account no (435), address (484), bank (420), billing (449), business (395), city (485), communication (366), customer (456), customer care (337), customs (433), documentation (469), email (470), employee (346), evaluation (448), feedback (448), fees (406), first name (415), hotline (436), id (434), last name (398), letter (405), location (376), manager (428), market (425), name (355), number (450), order (462), payment (449), payroll (412), phone (527), place (417), price (433), process (417), product (444), promotion (485), purchase (446), recipient (356), sales (477), sender (452), shipment (508), street (457), street number (407), support (468), target (444), taxes (508), website (426), zip code (466) | bills (720), builds (692), calls (700), connects (677), drops (684), helps (675), manufactures (649), processes (774), produces (694), replies (693), sends (746), ships (665) |