A good data visualization is not only a distortion-free graphical representation of data but also a way to reveal underlying statistical properties of the data. Despite its common use across various stages of data analysis, selecting a good visualization often is a manual process involving many iterations. Recently there has been interest in reducing this effort by developing models that can recommend visualizations, but they are of limited use since they require large training samples (data and visualization pairs) and focus primarily on the design aspects rather than on assessing the effectiveness of the selected visualization.

In this paper, we present VizAI, a generative-discriminative framework that first generates various statistical properties of the data from a number of alternative visualizations of the data. It is linked to a discriminative model that selects the visualization that best matches the true statistics of the data being visualized. VizAI can easily be trained with minimal supervision and adapts to settings with varying degrees of supervision easily. Using crowdsourced judgements and a large repository of publicly available visualizations, we demonstrate that VizAI outperforms the state of the art methods that learn to recommend visualizations.

**ABSTRACT**

A good data visualization is not only a distortion-free graphical representation of data but also a way to reveal underlying statistical properties of the data. Despite its common use across various stages of data analysis, selecting a good visualization often is a manual process involving many iterations. Recently there has been interest in reducing this effort by developing models that can recommend visualizations, but they are of limited use since they require large training samples (data and visualization pairs) and focus primarily on the design aspects rather than on assessing the effectiveness of the selected visualization.

In this paper, we present VizAI, a generative-discriminative framework that first generates various statistical properties of the data from a number of alternative visualizations of the data. It is linked to a discriminative model that selects the visualization that best matches the true statistics of the data being visualized. VizAI can easily be trained with minimal supervision and adapts to settings with varying degrees of supervision easily. Using crowdsourced judgements and a large repository of publicly available visualizations, we demonstrate that VizAI outperforms the state of the art methods that learn to recommend visualizations.

**CCS CONCEPTS**

- Computing methodologies → Machine learning; · Human-centered computing → Visualization toolkits; Visualization theory, concepts and paradigms.

**ACM Reference Format:**

Ritvik Vij, Rohit Raj, Madhur Singhal, Manish Tanwar, and Srikanta Bedathur. 2022. VizAI: Selecting Accurate Visualizations of Numerical Data. In *5th Joint International Conference on Data Science & Management of Information*.

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CODS-COMAD 2022, January 8–10, 2022, Bangalore, India
© 2022 Copyright held by the owner/authors. Publication rights licensed to ACM. ACM ISBN 978-1-4503-8582-4/22/01.. $15.00
https://doi.org/10.1145/3493700.3493717

1 pronounced similar to Hindi word vijay (n): meaning success.
work, our work also goes towards developing a systematic perfor-

VizAI selected the Density visualization (highlighted in red

17]. All three visualizations represent the same data. VizAI selected the Density visualization (highlighted in red box), and in our crowdsourcing evaluation it had a perfect agreement among all judges as the best visualization choice.

a number of alternative visualizations for the given dataset, evaluates them on how well they (statistically) represent the underlying data and then selects the best performing one. The evaluation of the visualization itself is done using a deep convolutional neural network, based on an ensemble of standard ConvNets, that extracts features from the visualization which can be used to predict the aggregate statistics of the data. For example, in Figure 1 the underlying data was plotted using scatter, line and density plots (we used Chart Studio by Plotly for plotting these, although our work can be easily used with any other plotting software). Of these, VizAI ranked the density plot as the best and this was further confirmed by our crowdsourcing evaluation (details are in Section 6).

Note that our focus in this paper is on generating visualizations of numerical datasets rather than datasets with varied data types, such as textual, categorical, temporal, etc., across data fields. Often these data types are transformed as part of data preprocessing into an appropriate numerical representation before their visualization [5, 17]. VizAI can be adapted to incorporate these preprocessing steps as well. With numerical data, commonly used visualizations are line, scatter, area, bar and pie charts, and more sophisticated settings require density plots.

Apart from developing a visualization recommendation framework, our work also goes towards developing a systematic performance evaluation measure of various visualizations. In fact, it is an important topic among visualization researchers [2]. We believe that our approach of extracting statistical features of the underlying data mimics the human perception of these visualizations, and offers a framework that can be extended to take into account aspects like choice of colorschemes for the plots and so on.

2.1 Human Perception of Visualizations

Early works experimentally demonstrated that aggregate statistics of data, means and correlations respectively could be perceived with high accuracy and compared across classes by humans from data visualizations [7, 9]. Subsequent analysis of chart perception through extensive human studies found that both individual features as well as aggregate of data could be inferred from good visualizations [14]. They varied the number of columns and the entropy of data, showing that for a small number of columns humans can perceive differences and even individual values of aggregates like averages with low error rates.

Using a large-scale crowdsourced study, [21] demonstrated that human performance (accuracy as well as time taken) in tasks like finding aggregates (sum for example) of data as well as extremums is highly affected by the type of visualization (scatter, bar, table etc).
Our work builds on these insights to model the perception of aggregates and extremums to help in identifying the most appropriate visualization form for the given data.

2.2 CNNs for Data Visualization Understanding
Deep CNNs are extremely popular for various learning tasks over images [10, 20]. Considering data visualizations as images, they have been applied for tasks such as visual QA, focus tracking etc. For example, [13] use a combination of CNN and OCR output for question answering on visualizations. As a solution to the problem of automatically learning visual importance i.e., the places in an infographic a user is likely to focus on, [4] used a fully convolutional network for creating importance maps.

Recently [8] did an evaluation of CNNs as applied to visualizations. They tried to regress elementary quantitative features like position, length and area from the images of visualizations presented to the network. They suggest that though CNNs can regress quantities for well constrained problems, they would require extensive training to generalize across tasks.

2.3 Visualization recommendation
There have been many recent efforts towards automating the visualization recommendation process for a given dataset. We briefly survey four of the most recent works that have shown significant promise in this direction.

Data2Vis [5] tackles the visualization generation problem as a language translation problem where data specifications are mapped to visualization specifications. It uses an LSTM based neural translation model to learn a mapping between JSON encoded data and a Vega-lite visualization specification. The model is trained using 4,300 Vega-lite examples. Their model was in an elementary way able to learn the vocabulary and syntax for a valid visualization specification, appropriate transformations (count, bins, mean) and how to use common data selection patterns that occur within data visualizations.

VizML [11] formulates visualization recommendation as making design choices. It learns these choices from a large corpus of one million dataset-visualization pairs collected from Plot.ly public studio of visualizations. They use 841 hand-coded features to train their recommendation networks to make encoding-level and visualization-level design choices. VizML verified that certain steps in a visualization generation pipeline can be learned well using neural networks.

DeepEye [17] combines rule based visualization generation with models trained to 1) classify a visualization ‘good’ or ‘bad’ using a decision tree classifier and 2) rank lists of visualizations using a ranking neural network. The DeepEye corpus consists visualizations drawn from 42 public datasets. 100 students annotated these visualizations as good/bad. These annotations, combined with 14 features for each column pair and rule based heuristics are used to train their models.

Draco [18] tackles the visualization recommendation in a more formal framework. It uses Answer Set Programming (ASP), a constraint logic programming to specify and generate visualizations with soft weights for constraints learnt from training data.

3 PROBLEM FORMULATION
The visualization of a dataset is a collection of visual elements used to communicate the data in a distortion-free manner. While there are many aspects of visually communicating the contents of a dataset, including the choice of colors, domain-specific imagery such as maps, overlays, etc., our work is based on a fairly simple and fundamental premise that one should be able to derive the core statistical features of the underlying dataset accurately from the visualization [22, 23]. Since finding the best visualization is a normative question, we make the following assumptions and later validate them through user studies:

- Humans prefer visualizations from which they can perceive features about the underlying data accurately.
- The modern neural network based models, trained to predict data features from plots, naturally emulate human perception to some extent. That is, if the model makes larger errors in estimating statistical features from one visualization over from another visualization of the same data, we expect that humans when asked to perceive the same statistics end up making corresponding scale of errors.

With these assumptions our problem of finding the best visualization is reduced to the task of designing and training a model which satisfies the above criteria and finding a set of features.

4 VIZAI FRAMEWORK
VizAI consists of the following three phases:

1. True Statistics Computation and Candidate Generation: We compute a set of statistics from the underlying data tables and use them as features that need to be estimated by our model from the given visualizations. We keep these statistics to be easily computable and, more importantly, easily interpretable by our users. Next, we programmatically generate a number of visualizations of each data table using a visualization generator such as Plotly, gnuplot, Vegalite etc.

2. Statistical-Feature Regression: This is the core model building stage where visualizations are input as images to a supervised Convolution Neural Network (CNN) regression model that extracts (regresses) the statistical features from these images, and trains to minimize the loss between the true statistics and the extracted statistical features. Note that during training, we optimize the statistics regression for each visualization type separately. Thus, adding another visualization type has no impact on the models built on earlier visualization types.

3. Visualization Selection: Finally, we compute the loss between the true statistics computed in the first stage and the extracted statistics by the model trained the second stage. The visualization that is considered to be performing best in terms of this loss is recommended for the given data table.

The overall model architecture is depicted in Figure 2. In the rest of the section, we discuss each of these parts of VizAI in detail.

\(^{2}\)It should be noted that we do not expect the same exact amount of statistical errors between human and our model, but rather their relative scale.
Figure 2: Architecture of the Proposed VizAI Model. The components within the dotted box are trained end-to-end – note that VizAI does not rely on human labeled data during model training.

| Column level aggregation | Table level aggregation |
|--------------------------|-------------------------|
| Min                      | Min                     |
| Max                      | Max                     |
| Mean                     | Mean                    |
| Std                      | Std                     |
| Skew                     | MAD                     |

Table 1: Aggregation metrics used to get data features. We also use the correlation feature along with this.

4.1 True Statistics Computation and Candidate Visualization Generation

We tried several approaches of selecting a set of statistics as features to extract from data tables. We initially experimented with table embeddings[6] and other neural feature extraction approaches but their major disadvantage was that these features are not understood or interpretable by end users. Since understanding the various aspects of why a particular visualization is good is relevant for data analysts, for us the interpretability is an essential requirement[16]. Thus finally we settled on a set of simple and commonly used features that most people working with data have some understanding of. These are listed in 1. Note that these are consistent with the recommendation of focusing on extremes, medians and relationships [23]. Note that these core statistics can be further enriched as required by specific application settings.

Although the data tables we currently experiment with consist of only two columns to be visualized, in a general setting we will have to deal with tables with variable number columns. If only individual column-level statistics are used as features, then each data table can result in different feature dimensionality. To overcome this, we introduce the use of 2-stage feature aggregation. First, column wise statistics (mentioned in the first column of 1) are calculated for each column. Then a data-table level aggregation is carried out using the metrics mentioned in the second column of 1. Thus we use two levels of features, e.g., ‘max of mean’ is the maximum of the mean values of each column. Along with this, we also use Pearson’s correlation coefficient, $r$, between any two columns $X$ and $Y$ of our table, written as:

$$
r = \frac{\sum_{i=1}^{n} (x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^{n} (x_i - \bar{x})^2 \sum_{i=1}^{n} (y_i - \bar{y})^2}},$$

where $x_i$ and $y_i$ are the $i^{th}$ row for each column and $\bar{x}$ and $\bar{y}$ represents the mean of each column. The generated correlation coefficient is unique for each table as we have only 2 columns in current setup of tables in the dataset. This can be easily modified to performing a table level aggregation of the correlation coefficient to accommodate tables with variable number of columns. As a result, in the current setup each data-table is represented using the same 26 statistical features which are used by the next stage of model building.

**Visualization Candidate Generation.** Next, we generate a number of different visualizations for each data table and feed them to a convolutional neural network (CNN) layer coupled with a regressor that extracts statistics from each of these visualizations. As we already mentioned we make use of Plot.ly Chart Studio ³ for generating visualizations of the table to keep our visualizations consistent with the publicly available datasets from VizNet repository (details in Section 5). These visualizations are input to the CNN + regressor model during training, and also as candidate visualizations to select from during the test/inference.

4.2 Statistical-Feature Regression

The visualizations are given as image input to the CNN model that generates their embeddings. We train a multivariate regressor to extract various statistical features of the underlying data.

³https://plot.ly/chart-studio/
The output embedding from the convolutional layers passes through a fully connected regression layer trained to output the values of statistical features for the given visualization. For the regressor, we used weighted smooth L1 loss between the predicted vector and the features extracted from the data table. The model is trained in a supervised fashion (using the true statistics computed from the previous phase) to predict the statistical features of each visualization.

4.3 Visualization Selection

At the time of evaluation, we take a data table as our input, extract its data features for use as true values and produce different types of plot images for it. The regression model is run on each of these to obtain predicted feature values. Based on how close these values are to the actual features of the data, each plot is assigned a score. The best plots are chosen by our model using this score. This not only helps in selecting the best plot for some given data, but also helps in realizing how good a visualization is by analyzing the score. In our experiments, we consider two such types of scoring functions:

- **Normalised L1 Loss** - For our setup, we define the well known normalised L1 loss as

  \[
  \ell_{L1}(\hat{y}, y) = \sum_{i=1}^{26} \frac{|\hat{y}_i - y_i|}{\tilde{t}_i}
  \]

  (1)

  where \( \hat{y} \) is the features predicted by our CNN Encoder, \( y \) is the true value of all the feature and \( \tilde{t}_i \) is the average value of the \( i^{th} \) feature from the training dataset.

- **Top-K Closest Loss** - We define the Top-K Closest loss as the cumulative L1 loss for only the Top-K Statistical features for each plot type prediction closest to true values.

  \[
  \ell_{topK}(\hat{y}, y) = \min_{\forall \text{tup}} \left( \sum_{i=1}^{26} \frac{|\hat{y}_i - y_i|}{\tilde{t}_i} \right) \forall \text{tup} \in \{1,2,...,26\}^k
  \]

  (2)

  Evidently, this will be nothing but the sum of normalised L1 Loss for the k features whose prediction is closest to true feature values relative to the true value.

  We will use Normalised L1 Loss, Top-5 and Top-10 Closest Loss in our experiments.

4.4 Advantages of VizAI

Based on the literature survey done in section 2.3, we identify two major limitations of the existing recommendation systems and discuss how VizAI can solve these limitations:

- **Rule-based recommendation systems** like [1, 17] have obvious limitations when it comes to adapting to new data tables and new types of visualizations. Also machine learning based models such as [5, 11] require complete re-training of the complete dataset in such a setup. VizAI is highly flexible and only requires additional training on new data to adapt to the new setup.

- None of these works provide quantification on how well the recommended plots are able to depict the data they were created on. Based on our previous studies, we know the importance of such a quantification, especially for visualisations of data in the numeric domain. Overcoming this limitation, VizAI tries to generate a score for each visualization type based on it’s ability to depict data statistics easily.
We used min-max normalization within a column to keep the range of values within a dataset. We extracted data-visualization pairs of the following plot types: scatter, line, and density. We conducted experiments using publicly available Plotly data-visualization pairs and a subset from VizNet collection to carefully examine the performance of various choices of statistical-feature regression models, and the loss models used in the visualization selection. We generate plots using the Chart Studio Python API for all of these datasets to maintain uniformity.

5 DATASETS

As we mentioned earlier, finding the best visualization for a data table is a normative question, user studies are necessary to evaluate the overall performance of recommendations. For this purpose, we conduct experiments using publicly available Plotly data-visualization pairs and a subset from VizNet collection to carefully examine the performance of various choices of statistical-feature regression models, and the loss models used in the visualization selection. We generate plots using the Chart Studio Python API for all of these datasets to maintain uniformity.

5.1 Plotly Dataset

Plot.ly [19] is an online service used by a large number of people to generate various types of plots of data. We wrote our own crawler which extracted data-visualization pair from the Plot.ly raw feed. We extracted data-visualization pairs of the following plot types: (i) scatter, (ii) line, (iii) density. We filtered out data tables with categorical and text columns. For line and scatter plots with more than one dataset in the same plot, we separated up to 5 of them and treated them as different data-visualization pairs.

After the preprocessing, the dataset had a total of 24547 data-visualization pairs, the distribution of the data is shown in Table 2. We used min-max normalization within a column to keep the range of x and y in [0,1]. Each visualization type was split in 80:10:10 ratio into training, validation and test respectively.

| Plot Type | Train | Val | Test |
|-----------|-------|-----|------|
| scatter   | 4493  | 562 | 562  |
| line      | 11442 | 1430| 1430 |
| density   | 3702  | 463 | 463  |

Table 2: Plotly Data Distribution after preprocessing

5.2 VizNet

VizNet [12] is a large-scale repository of data as used in practice, compiled from the web, open data repositories, and online visualization platforms. VizNet repository contains more than 23 visualization types, and a set of unique data tables and corresponding visualization to represent the data table – thus, the visualization type used is considered the gold label for the data table. We extract 2,042 data table and visualization pairs from the plot.ly fraction of VizNet to build our test dataset. We extract only those instances where (i) the size of data table (i.e., the number of rows) ≥ 5, and, (ii) the gold labels are either of scatter or line plots as VizNet does not contain density plots as gold label. For each data table extracted, we generate 3 plots of type line, scatter and density. We conducted several experiments and crowd-sourced judgments on this data to validate the performance of our model.

6 CROWD SOURCING FRAMEWORK

For evaluation, we employed a Turkle[24] instance running on a university server, offering features similar to Amazon Mechanical Turk (AMT) platform. Since the evaluation required expert users who could understand various statistical properties of the data we are interested in inferring, we did not run these experiments directly on AMT. Participants in our evaluation were CS graduate students and faculty members in our university. We defined the following three tasks designed to study our hypothesis about whether statistical features of the underlying data tables are reproduced by the recommended visualizations:

1. Complex Statistics Inference (CSI): Given the mean and standard deviation values of X and Y columns of some data table, the users must select the plot which represents them the best. Similar to the above task, all plots given as choices in every task depict the same data whose statistics are shown to the users (but not the data table itself). The user has to choose on which plots it is easiest, doable and impossible for them from the true value of the statistic – upto 20% error we award 3 points, up to 40% error we award 2 points, up to 60% error we award 1 point, and 0 points are awarded for errors beyond 40%. The cumulative points are calculated for each plot type for each data table and the plot type with most number of points is chosen as the overall preferred choice of plot type.

2. Fraction Above Threshold (FT): We provide the users with a single plot per question and ask them to estimate the fraction of points in the given plot which have y (or x) value > 0.5. While Answering these questions, It might be trivial to count points for some plots and answer the question so we instructed evaluators to estimate the fraction by looking at the plot without counting the number of points one by one.

We assign points to each plot type for each data table on the basis of answers given by users in the crowdsourcing experiment for VizNet data as shown in Table 3. For CSI task, the points are awarded based on the choice indicating the ease of statistics inference from the plot. In the FT task, where the evaluators have to estimate the fraction, the points are awarded based on the relative error made by them from the true value of the statistic – upto 20% error we award 3 points, up to 40% error we award 2 points, up to 60% error we award 1 point, and 0 points are awarded for errors beyond 40%. The cumulative points are calculated for each plot type for each data table and the plot type with most number of points is chosen as the overall preferred choice of plot type.
7 EXPERIMENTAL RESULTS

7.1 Statistics Extraction Accuracy
As already mentioned, the statistics extraction model consisting of CNN followed by a fully connected regressor was trained and tested using Plotly dataset. Figure 3 presents the heatmaps of statistics extraction error with different choices of CNNs including our AlexNet+VGG19 ensemble. In Figure 6 we show the loss in the Skew column aggregation over each of the table level aggregations given in Table 1. Similarly, Figure 7 plots the loss in estimating Pearson’s correlation coefficient between X and Y columns of the data table from the visualization alone. As one can observe, the larger CNN models (ResNet18 and ResNet50) perform much poorer than smaller models, and our (VGG19+AlexNet) ensemble further improves on statistics extraction accuracy.

7.2 VizAI Performance on VizNet
We now turn our attention to evaluating the performance of VizAI on real-world data from VizNet [12] based on a crowd-sourced experiment. We selected samples from VizNet which are 2-Dimensional and have gold labels as either line or scatter plots (note that VizNet does not have density plots). We generated the same three plots for each sample for the crowd sourcing experiment. We removed the labels of the data and just treated the two columns as X and Y.

We asked each participants in the crowdsourcing to complete a total of 245 SI and FT (both for Y and X axis) tasks, on a randomly selected 35 tables from the test set. We aggregate points based on the scheme described earlier (Table 3) for CSI and FT tasks. The plot type with maximum points is chosen as the preferred plot type. The resulting count of preferred plot type for each visualization type is summarized in Table 5. Note that the sum of these counts is greater than 35 due to ties in the points between two or more plot types. It is interesting to observe that although VizNet did not have density plots, there were a significant instances where crowd evaluators shown preference to density plots over line chart. In our subsequent evaluation, we used our crowd sourced plot types as gold labels.

We experiment using all combinations of statistics extraction models (AlexNet, VGG19 or (VGG19+AlexNet) ensemble) and the visualization selection (L1-loss, Top-5 Closest and Top-10 Closest loss) models. The results are summarized in Table 4. From these results, we can evidently see that the use of the (VGG19+AlexNet) ensemble, followed by the use of Top-5 Closest loss in the visualization selection performs the best in terms of accuracy and F1-scores of individual plot types as well as aggregated weighted F1-score using the counts from Table 5.

7.3 Issues with VizNet Gold Labels
As we observed deviations in crowdsourced gold labels we collected from the gold labels given in VizNet dataset, we felt it prudent to investigate this issue further. We first evaluate our best performing combination – (VGG19+AlexNet) with Top-5 Closest loss – when using the gold labels as given in VizNet. Table 6 shows that the use of VizNet gold label results in much worse performance. However,
## Table 4: Performance of different Statistics Extraction and Visualization Selection models on VizNet. The bold-faced values represent the best performing combination.

| Statistics Extraction Model | Visualization Selection Model | Accuracy | F1-Score(Scatter) | F1-Score(Density) | F1-Score(Line) | Weighted F1-Score |
|-----------------------------|-------------------------------|----------|-------------------|------------------|---------------|------------------|
| AlexNet                     | L1-Loss                       | 0.60     | 0.65              | 0.56             | 0.46          | 0.59             |
|                             | Top-5 Closest Loss            | 0.71     | 0.80              | 0.62             | 0.40          | 0.68             |
|                             | Top-10 Closest Loss           | 0.69     | 0.76              | 0.59             | 0.46          | 0.66             |
| VGG19                       | L1-Loss                       | 0.54     | 0.50              | 0.54             | 0.50          | 0.51             |
|                             | Top-5 Closest Loss            | 0.63     | 0.61              | 0.46             | 0.67          | 0.57             |
|                             | Top-10 Closest Loss           | 0.63     | 0.61              | 0.46             | 0.67          | 0.57             |
| (AlexNet+VGG19)             | L1-Loss                       | 0.66     | 0.70              | 0.61             | 0.43          | 0.63             |
|                             | Top-5 Closest Loss            | 0.80     | 0.86              | 0.67             | 0.55          | 0.75             |
|                             | Top-10 Closest Loss           | 0.77     | 0.83              | 0.62             | 0.67          | 0.74             |

Table 5: This table shows the number of times each plot type is chosen as the preferred user plot type after assigning points in the VizNet data.

| Plot Type | Preferred Plot Type Count |
|-----------|---------------------------|
| Scatter   | 21                        |
| Density   | 12                        |
| Line      | 6                         |

Table 6: Performance comparison of VizAI vs plot type labels given in the original VizNet dataset.

| Metrics       | VizAI  | VizNet Gold Label |
|---------------|--------|-------------------|
| Accuracy      | 0.80   | 0.43              |
| F1-Score(Scatter) | 0.86 | 0.59              |
| F1-Score(Line)  | 0.55   | 0.29              |

Figure 8: VizNet Gold Label choice is highlighted in red box, VizAI’s choice is highlighted in the black box and the crowdsourcing users 1,2 and 3’s choice are highlighted in the blue, yellow and green boxes respectively. VizNet Gold Label choice is unreliable as the line plot gives us no idea about the distribution of the points and hence the underlying statistics of the data.

### 8.1 Limitations

A limitation of our work is that we make use of an algorithmic system, viz., deep convolutional neural network (refer Section 4), as a proxy for human visual perception to determine the extent to which a visualization is representing various data statistics. However, it is well-known in visualization literature that human visual perception is highly context dependent (e.g., it is subject to optical illusions), and varies greatly from person to person. Naturally, CNNs are not expected to fully mimic the human perception of visualizations. We believe that further research is required, especially in complex visualizations of semantically rich data. Despite this, VizAI offers a unique and flexible approach to recommending visualizations for a dataset.
8.2 Future Work

We plan to pursue research in extending VizAI along following three directions:

(1) Incorporation of more plot variables such as - which columns to plot, what goes on which axis and more plot types into our prediction framework. For simplicity and easy testing, we chose only to predict plot types but for usability purposes it would be desirable to have multiple decision variables inferred automatically.

(2) Applications of our model, which predicts human perceived data features from plot images and compares them with actual data features, in different tasks like identifying mis-leading visualizations (for detecting fake news for example) and helping analysts to interpret plot visualizations.

(3) More robust scale and data statistic invariance in our feature prediction model. Right now we use a simple normalization procedure to deal with different scales in our input data features. An approach based on learning scale invariant models should improve performance and make the model more adaptable.

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