Combining Image and Caption Analysis for Classifying Charts in Biodiversity Texts

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Abstract: Chart type classification through caption analysis is a new area of study. Distinct keywords in the captions that relate to the visualization vocabulary (e.g., for scatterplot: dot, y-axis, x-axis, bubble) and keywords from the specific domain (e.g., species richness, species abundance, phylogenetic associations in the case of biodiversity research), serve as parameters to train a text classifier. For better chart comprehensibility, along with the visual characteristics of the chart, a classifier should also understand these parameters well. Such conceptual/semantic chart classifiers then will not only be useful for chart classification purposes but also for other visualization studies. One of the applications of such a classifier is in the creation of the domain knowledge-assisted visualization recommendation system, where these text classifiers can provide the recommendation of visualization types based on the classification of the text provided along with the dataset. Motivated by this use case, in this paper, we have explored our idea of semantic chart classifiers. We have taken the assistance of state-of-the-art natural language processing (NLP) and computer vision algorithms to create a biodiversity domain-based visualization classifier. With an average test accuracy (F1-score) of 92.2% over all 15 classes, we can prove that our classifiers can differentiate between different chart types conceptually and visually.

1 INTRODUCTION

Automatic chart type classification is an increasingly common pursuit in visualization. In the majority of cases, the overall goal of the chart classification is automatic chart comprehension. Nonetheless, previous studies (Liu et al., 2013),(Abhijit Balaji, 2018),(Savva et al., 2011),(Jobin et al., 2019) have paid little attention to the role of the free text information provided along with the charts in the form of captions. Processing only the visual chart elements in the image can recognize the type of chart well, however, this recognition alone is not enough to understand the chart semantics. Captions on the other hand provide clear goals of the represented charts and resolve the ambiguity that arises due to visually similar chart types. For example, column charts look similar to histograms but their representative goals are different. Column charts are used to represent the comparison among various sizes of the data series while histograms show the frequency with which specific values occur in the dataset (Harris, 2000). Due to the different chart semantics, an image classifier alone, which might decode a histogram as a column chart would not be able to provide an accurate and efficient automatic interpretation.

After manually surveying a vast number of caption samples during the corpus creation process, we know that chart captions provide information about a) representative goals of the author which are not directly visible from the image itself, b) domain-specific tasks, depicted through the chart and c) chart layout and pictorial elements (e.g. text, colors, lines, shapes). Consider, for instance, Figure 1 and the original caption to the visualization depicted in Figure 1 (Moody and Jones, 2000).

"Fig. 5. Boxplots comparing the distribution of the measured soil variables at the different canopy positions at trunk, midcanopy, the canopy edge, and outside the canopy, respectively. The upper and lower boundaries of each box represent the interquartile distance (IQD). The horizontal midline is the median value. The whiskers extend to 1.5x IQD. Outliers are

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displayed as horizontal lines beyond the range of the whiskers. If the notches of any two boxes do not overlap vertically, this suggests a significant difference at a rough 5% confidence interval."

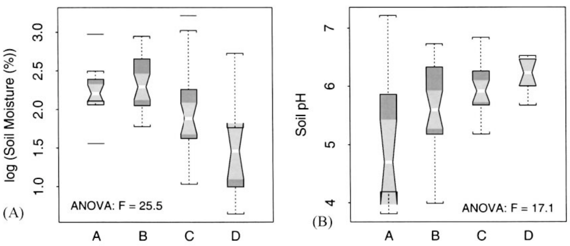


Figure 1: Example image adapted from a biodiversity publication (Moody and Jones, 2000).

The caption of this figure provides clues about the following information:

Chart type: Boxplots, box, horizontal midline, whiskers, horizontal lines, notches.

Representative goals: comparing, distribution.

Domain specific variables: soil variables, canopy positions, trunk, midcanopy, canopy edge.

Statistical or analytic information: interquartile distance (IQD), median value, confidence interval.

These identifiers can serve as important features for a text classifier.

In this work, we have taken the assistance of both computer vision and NLP technology in the production of a very first text classifier that identifies the best fitting chart from a set of fifteen different chart types given a biodiversity caption or data description. The classifier was incrementally trained, starting with a dataset of 4073 manually annotated biodiversity visualization captions and achieves an average test accuracy (F1-score) of 92.2% over all 15 classes. The classifier understands a specific chart vocabulary and related biodiversity vocabulary used for each particular chart type and will, therefore, only work on the biodiversity text. However, the described workflow can be used to train classifiers for other different domains as well.

Our primary contribution is the chart classification workflow that classifies a chart not only on the basis of chart elements in the image but also on the basis of captions. Following this workflow creates a semantic chart classifier that understands the visualization type along with the high level visualization goals. We also contribute by providing a novice approach in the field of data visualization recommendation system, to recommend visualization schema via visualization classifier based on the knowledge gathered at the training process. In our knowledge, we are the first who conceptualize and implement a visualization classifier that understands the semantics of the chart and can infer representative goals from the biodiversity text based on the different chart types.

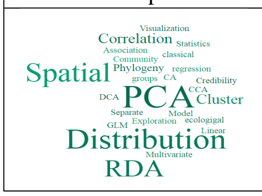
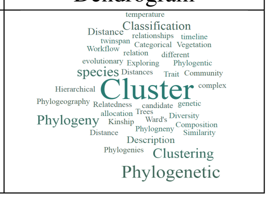
In Section 2 we present the motivation for this work, state-of-the-art in Section 3, classification process is presented in Section 4, result and discussion in Section 5, challenges and research directions in Section 6 and conclusion in Section 7.

2 MOTIVATION

The chart type classification we present in this paper will constitute one important step in a biodiversity knowledge-assisted visualization recommendation system that will suggest suitable visualization types based on biodiversity research data and goals.

To build such a system, a visualization designer needs to know the domain-based and the visual goals of the user (Munzer, 2009). In the earlier stages of our study, we tried to gather this information via a survey. Due to the limited responses, we could not get good representatives of the dataset. An excerpt of the result is shown in Table 1. It shows that scientists use scatterplot prominently to convey the result of different ordination analysis techniques (PCA, RDA, DA) and Dendrogram is more prominently used to represent Phylogeny, Classification and Clustering. To gather this knowledge in bulk and to use this knowledge to classify future biodiversity texts serve as the main motivation in the creation of biodiversity visualization classifier.

Table 1: Visualization types and the purposes they are used for in biodiversity domain (Kaur et al., 2018)

Scatterplot	Dendrogram
	

The proposed system, depicted in Figure 2, will work as follows: After the user provides a data table and a description of its contents, along with how it was created, its intended research goals, and so forth, a biodiversity visualization text classifier is applied to suggest the most suitable visualization types to represent the data based on its vast knowledge of similar data and research goals. In a second step, based on the visualization type, our context-aware algorithm will select the suitable data variables that can be mapped to the visualization.

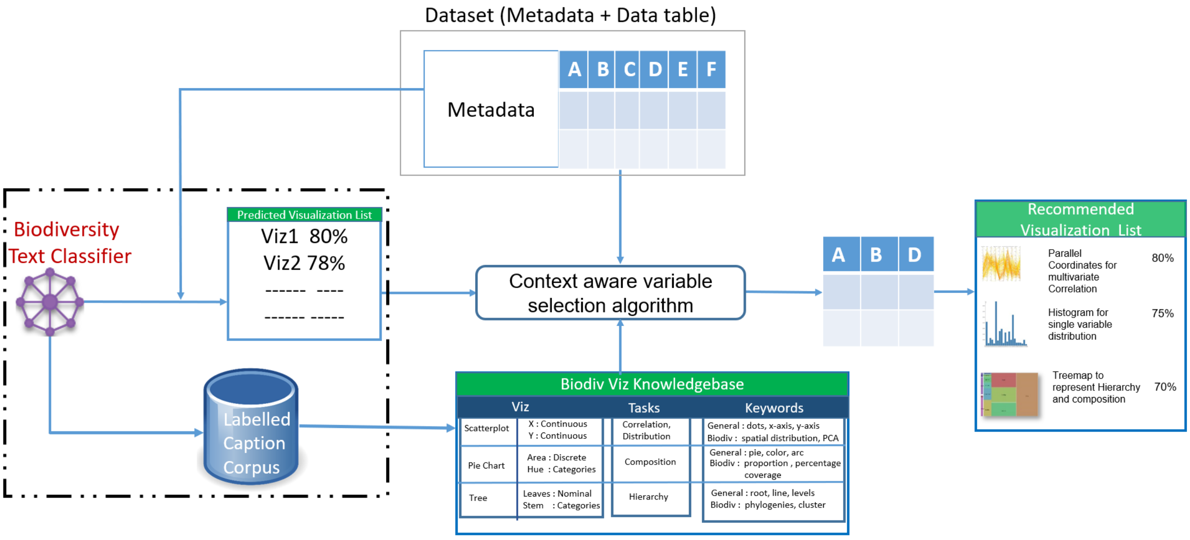


Figure 2: A conceptual diagram of biodiversity knowledge-assisted visualization recommendation system.

The goal of the chart type classification task described in this paper is the creation of a knowledge base for and the training of the biodiversity text classifier that will be responsible for inferring the best suited chart types from given metadata text which provides information about the what and why of the dataset. The biodiversity text classifier will output a 'predicted visualization list', which is a ranked list of suitable chart types for this dataset and related vocabulary. This information can then be used by scientists to create suitable visualizations and gain new insights into the selected dataset.

In this paper, we will focus on the creation of the biodiversity visualization text classifier.

3 STATE OF THE ART

In this section, we present the state of the art of chart image classification and image caption analysis.

3.1 Chart Image Classification

Many studies have used different computer vision algorithms for the classification of chart types from digital images. Typical representative of them are Table 2. We have found our study different from them in the following aspects:

- **Data source**: We have found that some studies have used automatically generated synthetic data (Abhijit Balaji, 2018) and others have used well curated data from previous studies (Jung et al., 2017). In their work, (Savva et al., 2011) have carefully downloaded their dataset from online search. The resulting dataset does not really reflect reality, where intra-class variation is a lot higher. In our work, we tried to reflect this by creating our corpus from scientific publications which have huge intra-class variations (see Table 3). Moreover, we have considered various forms of different charts by grouping them not only based on their visual similarities but also on their chart semantics.
- **Visualization classes**: The range of the classes that we have considered (15) is much larger than most of the previous studies, except (Jobin et al., 2019), who have also considered other document figure types as their classes. Moreover, their training dataset was far more balanced than what we had. In our case, we were not aware of the types of visualizations available in the downloaded corpus in advance. Therefore, it was important for us to include as many different visualization types as possible in our training set. This leads to the assignment of unequal proportion of examples for many classes.

Table 2: A summary of different chart image classification studies.

Name	Year	Data source	Classes	Accuracy
(Savva et al., 2011)	2011	Online	10	96%
(Jung et al., 2017)	2017	Online	10	76,7%
(Abhijit Balaji, 2018)	2018	Synthetic	5	99,72%
(Jobin et al., 2019)	2019	Conferences	28	92,86%

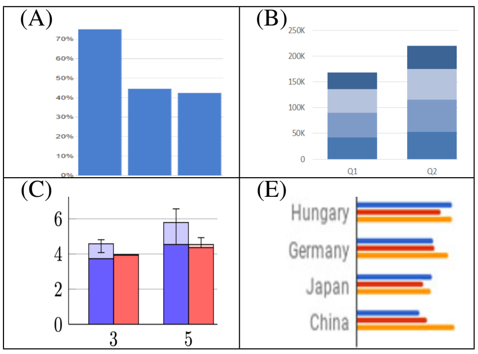
We consider our work to be closed to (Jobin et al., 2019), who has also done scientific document figure classification on publications from different conferences. They had also created their categories based on what was available to them in their downloaded corpus. Like us, they pre-selected the categories, grouped them into super classes and then had used iterative learning to gather more trained data. However, for their classification process, they had considered all different types of figures available in scientific documents, whereas our work is limited to visualization images only. They have only considered image classification, whereas we have taken the benefits of both text and image classifiers for semantically classifying the visualization types.

3.2 Use of Captions for Classification Purposes

Image captions are an important source of information and have been a long-studied subject in different domains. Earlier studies have used captions with computer vision algorithms to identify human faces in the newspapers (Srihari, 1991). Caption analysis has been predominantly used in biomedical domain for its various research goals. In their study, (Murphy et al., 2004) used joint caption image features in classifying protein sub-cellular location in images. The study by (Rafkind et al., 2006) was the first to use text identifiers from biomedical image captions ("diameter", "gene-expression", "histogram" etc) to identify graph chart images as a separate category from other biomedical image categories. More recent studies have utilized the information from the captions in biological documents for the purpose of image indexing and search (Charbonnier et al., 2018; Xu et al., 2008; Lee et al., 2017). So far, caption data has been used along with the computer vision algorithms to distinguish graph images from others, however, we could not find any study that has used caption data alone or caption data in conjunction with other media, to classify different chart types. Classifying chart types from caption data is still in a novice state. We have observed different use cases in which research in caption analysis could be beneficial for visualization as well as for linguistics research:

- **Visualization research**: The foremost is in the creation of domain specific visualization knowledgebases or corpus, 2) a machine learning model trained on the visualization captions can be evolved and reused by other users for different domain knowledge-assisted visualization products, 3) a text classifier trained on different chart types can be used for tagging, indexing and searching visualization documents, 4) it could be a valuable source for future theoretical visualization research problems (Chen et al., 2017) like the creation of visualization ontologies on the basis of classified visualization concepts.
- **Computer linguistics research**: Research on caption classification will help 1) to better understand the requirements of classifications on very short and convoluted texts, 2) to study the influence of domain specific language on classification and possibly exploit domain specific regularities to improve classification results and 3) to find effective ways to integrate domain expert knowledge into the classification process.

Table 3: Intra-class visual similarity for different variation of Column or Bar Chart.



4 CLASSIFICATION PROCESS

The process of creating the biodiversity text classifier consists of a sequence of complex steps, visualized in Figure 3. In order to reach the highest possible quality in recognizing the best suited chart types from biodiversity text – e.g. biodiversity image captions – the underlying training corpus needs to have a sufficient size (we estimated at least 15 000 samples to be enough, ideally 1 000 for each of the 15 classes) and quality. So, the first step was to manually create a starting dataset, that associates caption texts with their respective chart types. This set is then incrementally extended using a combination of image and caption classification in order to gain the highest possible quality on the automatic labeling of unlabeled data. The resulting dataset is then used as training set for the biodiversity text classifier, that can be integrated into the biodiversity knowledge assisted visualization recommendation system described in Section 2.

4.1 Data Preparation

In our data collection process, first we selected the reputed biodiversity journals which represents differ-

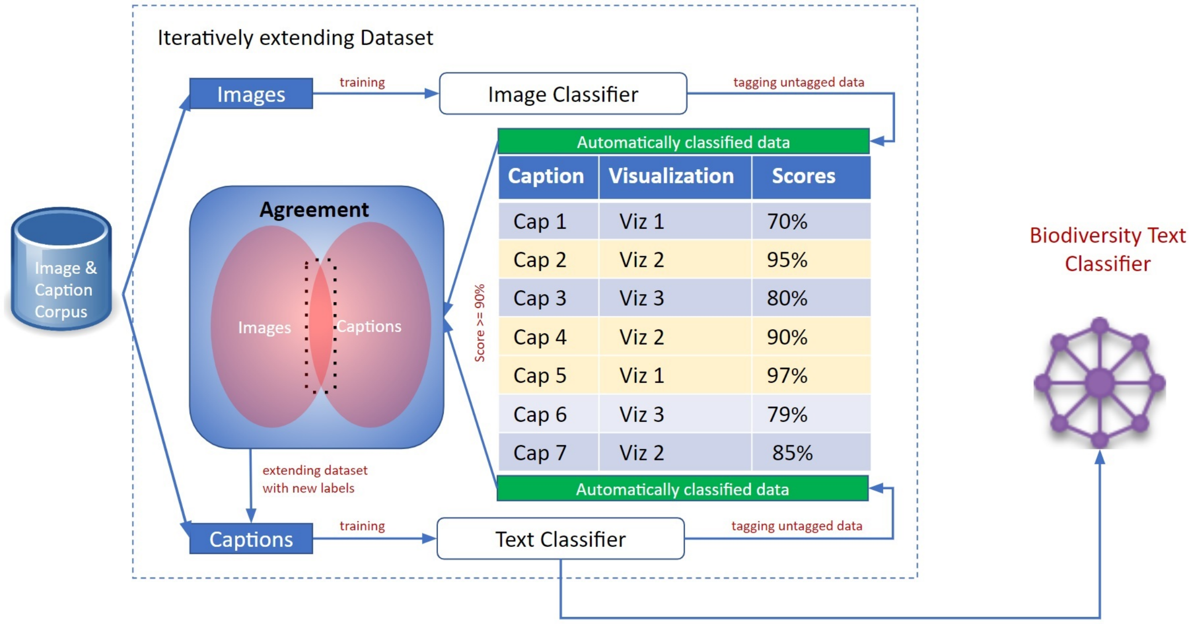


Figure 3: Workflow for the creation of the biodiversity visualization text classifier.

ent biodiversity sub-domains. For details please refer to Section 2 of appendix. We had downloaded all available volumes and issues of these journals till 2016 which is the year when this download was done. For creating the initial dataset, we downloaded 26 588 biodiversity publications through Elsevier ScienceDirect article retrieval API (api, 2018), which allows the download of a complete publication in an XML format. From these 26 588 downloaded publications, 96 837 images and their captions were extracted using a python script.

4.1.1 Class Formation and Annotation Process

Out of 96 837 image and caption samples, we created our training data by randomly selecting a subset of 4 073 visualization image captions and labeling them with their respective visualization types manually. The labelling task was done by one of the author of this paper who is a Ph.D. student in data visualization with four years of experience in this domain. In case of disambiguation regarding the selection of the visualization label for a particular caption, adequate guidance from visualization publications and reference books (Harris, 2000) was taken. Due to the sheer richness of different visualization types – a closer study revealed the sample to contain 59 different visualizations (see Section 1 of appendix) – we continued our annotation process in the following stages:

Class grouping: In order to gain adequate sample sizes for each of the visualization types or classes, we split / merged the original 59 classes into super / sub classes:

$>$ 50 **samples in class** Since we considered 50 examples to be sufficient for classification, all classes with same or more examples were kept as a super classes.

$<$ 10 **samples in class** These classes had very small set of examples and were not suitable match for our super classes. Therefore, they were rejected from the further annotation process.

all other classes All classes, that do not figure frequently enough to suffice for the classification task have been merged into super classes either based on their visual similarity or their representational goals. For example, chart types that use the same coordinate space (e.g. xy plot) and same visual marks (e.g. bars) were considered visually similar and then were merged. This way, all the chart types which are visually similar to Column Chart e.g. Bar Chart, Stacked Bar Chart, Multiset Bar Chart etc. were all merged into the super class 'Column Chart'.

On the other hand, Chord Diagrams, Alluvial Diagrams and Network diagrams are visually dissimilar but have the common representational goal of connecting entities. Same with the Pie Chart and Stacked Area Chart which are visually dissimilar but represent a common visual goal of representing proportion or composition among data entities.

Thus, they all were grouped in the class 'Network'. All non-visualization images (e.g., camera-clicked pictures, conceptual diagrams etc.) were grouped into the 'NoViz' class. Due to the variant structure of non-visualization images, 'NoViz' class was also excluded from the image classification process. An overview of retained classes are provided in Section 3 of appendix.

Doing so, we ended up with 15 different super classes.

Assignment of classes for caption classification: Once, we had formed the classes, we did another round of annotation. We have now labelled our selected corpus of 4 073 captions with these 15 classes. For detailed information about these classes, refer to Section 4 of appendix.

Assignment of classes for image classification: All classes were considered for image classification except for those which are visually similar to other classes. Histogram is visually similar to the column chart and timeseries is visually similar to the line chart (see appendix 3). Thus, histogram and timeseries were ignored from the image classification process. Alongside, due to the variant structure of non-visualization images, 'NoViz' class was also excluded from the image classification process.

We have provided the frequency distribution of classes for image and caption classification in Table 4. In appendix Section 4, we provide examples for each class, that consist of the replicated original image and caption from open-access publications. Due to the copyright issues, we are unable to provide original examples from our dataset.

Table 4: Frequency distribution of our manually annotated training dataset for Caption and Image classification

Classes	Caption Classes	Image Classes
Ordination Plot	503	278
Map	529	277
Scatterplot	399	272
Line Chart	320	283
Dendrogram	282	243
Column Chart	427	302
Heatmap	147	124
Boxplot	210	104
Area Chart	159	95
Network	58	32
Histogram	57	-
Timeseries	319	-
Noviz	511	-
Pie Chart	-	134
Proportion	157	-
Total	4073	2144

4.2 IMAGE CLASSIFICATION

4.2.1 Image Classification Model

For image classification, we have used Convolutional Neural Networks (CNNs). CNNs are a specialized kind of neural networks for processing data that has a known grid-like topology. Since images can also be thought as 2D-grid of pictures, thus CNNs have been tremendously successful in application to image data (Goodfellow et al., 2016).

For training, we have used reusable pre-trained neural network modules provided by Tensorflow Hub (TFH, 2019). TensorFlow Hub is a library for the publication, discovery, and consumption of reusable parts of machine learning models.

Out of the available CNN modules in TFHub, we chose MobileNet_V2 (Sandler et al., 2018) as our CNN architecture. MobileNet_V2 is a family of neural network architectures for efficient on-device image classification and related tasks.

Mobilenet_v2 module of Tensorflow Hub contains a trained instance of the network, packaged to do the image classification. This Tensorflow Hub module uses the Tendorflow Slim implementation of 'Mobilenet_v2' with a depth multiplier of 1.0 and an input size of 224x224 pixels. For training the classifier we used Keras (Chollet et al., 2015) with Tensorflow (Abadi et al., 2016) backend. To train the classification network on our data, we resized the images to a fixed size of 224 x 224 x 3 and normalized them before feeding into the network. We used Adam optimizing function (Kingma and Ba, 2014) with the learning rate of 0.001.

4.2.2 Results from Image Classification

For evaluation, we have used Keras' in-build evaluation function. When provided with the suitable parameters, Keras seperates and retains a portion from the training data and then uses that unseen retained data for evaluating the model. For evaluating our image model, 20% of the examples from the image dataset were retained from training. Our model has achieved a classification accuracy of 75% on automatically selected batch of 100 images. Then this classifier was used to classify the original corpus of 96837 IDs. Our image classifier was able to annotate 54%, i.e., 52921 IDs out of 96837 IDs, with the confidence interval of 95% and more.

4.3 CAPTION CLASSIFICATION

The 4 073 manually labeled image captions served as training set for the initial supervised classifier. In order to be able to optimize the classifier for each of the identified classes separately, we decided to build binary classifiers, that can distinguish one specific class from all others. From these specialized binary classifiers an assembly classifier is constructed (see Figure 4, Training Step). Given an input, the assembly asks each classifier to process the input separately (as detailed in Figure 4, Classification Step), and receives a probability score that states how likely it is, that the given sample is of the respective class. The classes of all classifiers, that give a positive response with a certain preset confidence (in our case usually 90%), will then be returned as result vector.

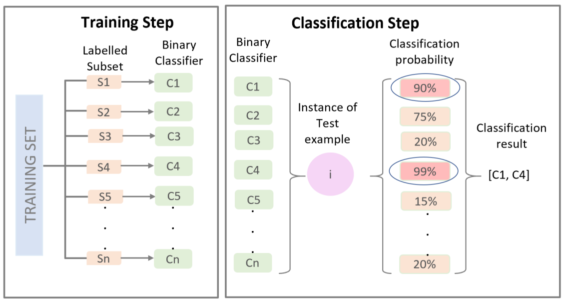


Figure 4: Workflow for the creation of the biodiversity visualization text classifier

To find out which binary classifiers to incorporate into the assembly, we implemented and optimized three standard classifiers in text classification (Joachims, 1998; Sebastiani, 2002): Support Vector Machines (SVM), CNN and Random Forests. SVMs (Cortes and Vapnik, 1995) are inherently binary supervised learners. In their linear form, they find the maximum-margin hyperplane in data space that best separates the data points of one class from the data points of the other class. Kernels (Boser et al., 1992) have been introduced to generalize the principle to polynomial, radial or sigmoid functions. Random Forests (Ho, 1995) are a assemblies of a – usually rather large – number of Decision Trees that contribute to the main decision in form of a majority vote. Additionally, in resemblance to the image classifier, a neural network solution – specifically a multilayer perceptron classifier with the same stochastic gradient-based optimizer as the image classifier and the same constant learning rate of 0.001 – was used.

4.3.1 Preprocessing

As is standard in natural language processing (Aggarwal and Zhai, 2012), the labels have been broken into tokens, stemmed and stop words have been removed before processing them. Additionally, some standard phrases that have been identified during manual n-gram evaluation of the data and are unrelated to the contents of the image, like phrases to make people aware of the modalities of the online version of the paper – e. g. *"For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article")*– , have been automatically removed. In order to keep the training data as pure as possible, captions referring to multiple visualizations were filtered out, leaving a dataset of 4 066.

The resulting word vectors contain the term frequency - inverse document frequency (tf-idf) scores (Ramos et al., 2003) per word.

4.3.2 Model Optimization or Parameterization

Each binary classifier has been trained separately on a data set consisting of all samples of the target class and an equal number of samples uniformly distributed over all other classes. Classifiers have been evaluated using a 5-fold-cross-validation, that splits the data set into 5 equal parts training on 4 parts and testing on the last. The final evaluation result constitutes as the average of all five runs.

In order to reach the best results, we optimized both the pre-processing of the data as well as the parameters of the classifier itself. On data level, we optimized the maximum size of the vocabulary, the minimum number of documents each word figures in and which n-grams should be included into the analysis. Applying an exhaustive grid search over the range of sensible parameters for each feature (vocabulary size: [250 to 1250 (steps of 250)], minimum document frequency: [0 to 4], n-grams: [1 to 6]), we achieved the best results using a base vocabulary that consists of the 750 most important words and 2-grams, that occur in at least 3 documents in the whole corpus.

We also optimized SVM for its kernel function (linear, polygonal, sigmoid, and radial basis function), finding a linear kernel to give the best results, and the Random Forest classifier for the number of Decision Trees in the assembly (100 to 2000 in steps of 100), finding that the impact on the classification accuracy is rather small. The neural network has been tested with different node sizes in its hidden layers (2, 10, 15, 50). The best result has been achieved with 15 nodes.

Figure 5 shows the best results on each class for each of the classifiers. The results show that Random Forests outperform the results of SVM and the neural network in all classes with up to 7% increase in the F1 score. One possible conclusion to draw from these results is that, the linguistic properties of caption data can be modelled more precisely through a series of parallel boolean operations than through a maximum-margin method. Following this finding, we will use

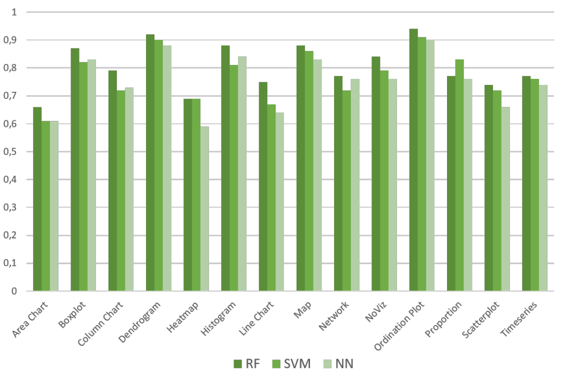


Figure 5: Classification results (F1 score) of the Random Forest (RF), Support Vecor Machine (SVM) and Neural Network (NN) classifiers for each class in our corpus.

Random Forests as binary classifiers for the assembly classifier.

4.3.3 Incremental Learning and Caption Dataset Extension

The purpose of the caption classification is twofold. First, we want to extend the existing dataset to reduce the risk of overfitting the single binary classifiers. Second, to train the binary classifiers to understand the words and phrases describing the underlying data of the chart in order to finally recommend chart types based on data set descriptions.

Incremental learning and an additional agreement step with the classification result of the image classifier (see Figure 3) was used to increase the size of the original 4 066 captions to a dataset of 22 881 captions.

The one iteration of the incremental learning algorithm includes the following steps:

Learning: Conduct 5-fold cross-validation on the current dataset to evaluate the quality of the set (results see Figure 6). Train all binary classifiers on the whole dataset.

Annotation: Use the assembly to label as many captions of the remainder of the untagged data as possible with at least 90 % confidence. Include new labels and captions into the extended dataset.

The two steps are repeated until a finishing criterion is met. Since we were focusing on extending the dataset in this phase, we stopped the algorithm when the number of newly included tags fell underneath a preset threshold (0.01% of the whole corpus in our case). This way, the caption classifier was able to annotate 44% of the total corpus which amounts to 43 256 IDs with a confidence interval of 90%.

4.3.4 Refining the Knowledgebase

In order to ensure highest quality in the creation of our knowledge base, we refined the resultant data from image and caption classification in a multi-step process:

- We start with 52 921 labeled images in Image Corpus (IC), and 43 256 labeled captions in Caption Corpus (CC).
- To get only the visualization image IDs, first we removed the 'NoViz' labelled IDs from the caption corpus. Leaving behind 43 256-451= 42 805 to be merged. After the merging process, these IDs were put back to the corpus for iterative learning.
- We merged the two corpora by only keeping those IDs that have been tagged by both classifiers. This set contains a total of 22 817 common IDs.
- This set is, then, reduced to only contain the most reliable ID/label pairs:

1. ID/label pairs with full or partial agreement in classified labels from image and caption classifier (11 108 samples). Partial agreement is reached if the label given by the image classifier is contained in the class list provided by the caption classifier; full agreement is reached if the caption classifier only provides one label and this label matches the class of the image classifier.
2. ID/label pairs with more than 98% confidence from image Classifier (10 728 samples)
3. ID/label pairs whose classes were absent in image classifiers (Area Chart, Time Series, Histogram, Proportion), if the source of disagreement between image and caption classifiers stems from these classes, like 'Timeseries' in CC and 'Line Chart' in IC or 'Histogram' in CC and 'Column Chart' in IC. All other conflicts have been resolved manually. In our manual verification, 'Proportion' has performed bad due to its similar vocabulary with 'Pie Chart' and all other classes that represent some 'Proportion' or 'Composition' representation goals for example different stacked chart: Stack Area or Stack Column. To avoid such confusions for incremental learning round, we had to merge some of these example to 'Pie Chart', 'Stack Area Chart' and 'Column Chart'. Rest of the examples were ignored.
4. ID/label pairs that have been manually checked upon due to the multi-assignment of the caption classifier and assigned the single true class

if possible. Captions representing multiple visualizations have been rejected.

This leaves us with 22 248 high-quality ID/label pairs.

- Finally, the automatically created dataset has been merged with the manually annotated dataset to further increase the quality and size of our knowledge-base (22 866 samples in total, 1 468 Ordination Plots, 4 989 Maps, 1 669 Scatterplots, 6 173 Line Charts, 452 Dendrograms, 5 459 Column Charts, 603 Heatmaps, 303 Boxplots, 99 Area Charts, 187 Network Diagrams, 69 Histograms, 330 Timeseries, 448 Noviz, 304 Pie Charts and 313 Stack Area Charts).

5 RESULTS AND DISCUSSION

5.1 Results

Figures 6 and 7 show the development of the quality of the classifiers as well as the number of samples for each label over the course of the 41 iterations necessary to reach the ending criterion (a tag rate of less then 0.01 % of the unlabeled samples of the corpus). In most cases, the quality of the classifiers rises the most within the first 3 iterations. After that phase, most classifiers do not change in quality any more. Exceptions are the line chart, with a drop after the steep rise in the beginning, the time series, with a drop at the eleventh iteration, and the histogram and area charts that fluctuate around 80% accuracy. The drops in the performances of both line chart and time series classifiers coincide with steep rises in the numbers of examples for the respective classes, suggesting that the classifier needed some iterations to adapt to the new dataset. The fluctuations in the quality of histogram and area chart classifiers stem from the small sample sizes for the respective classes. For the confusion matrix, please refer to Section 5 of appendix.

We have found the most consistent confusions between boxplots and column charts and maps and pie charts. The confusion between boxplots and column charts could stem from the presence of error bars in boxplots and a special type of column charts. The confusion between maps and pie charts could be explained with the presence of certain images where pie charts were overlaid on the maps. Another similar case is between pie charts and stacked area charts. The reason could be because both visualizations share a similar representation goal as 'Proportion' and the division of some examples from 'Proportion' into

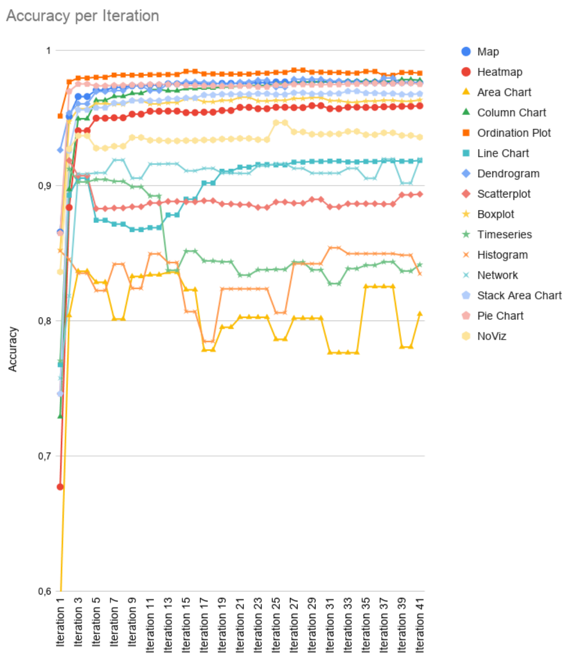


Figure 6: Line graph of the development of the accuracy of each binary classifier during the iterative learning phase. Notably, even though most classifiers began with classification accuracy of less than 80%, almost all of them increase their accuracy drastically after the first five iterations.

these two charts at the previous stage (see subsubsection 4.3.4).

Table 5: Scores from Incremental Learning

Classes	Accuracy
Ordination Plot	0.98
Map	0.97
Scatterplot	0.89
Line Chart	0.91
Dendrogram	0.97
Column Chart	0.97
Heatmap	0.95
Boxplot	0.96
Area Chart	0.80
Network	0.91
Histogram	0.83
Timeseries	0.84
Noviz	0.93
Pie Chart	0.97
Stack Area Chart	0.96

5.2 Reasons for Misclassifications

In our extensive study of the misclassification cases, we were able to extract several categories of reasons, why these misclassifications happened.

- **Mixed vocabulary from different chart types:**

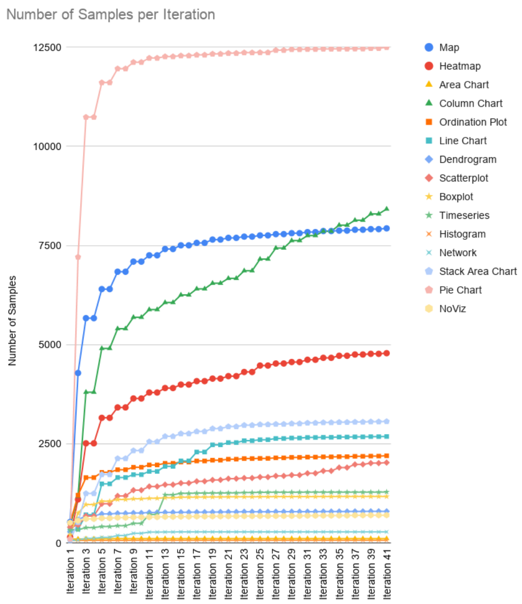


Figure 7: The development of the sample sizes for each class during the iterative annotation. Similar to the increase in accuracy of the binary classifiers in Figure 6, the numbers of sample sizes increase very quickly within the first few iterations.

The main reasons for this problem was a) often, multiple different visualizations are used in conjunction in one image, showing, for example, pie charts on different locations on a map. We have observed that the classifier could not perform well on those image captions, as the information about multiple chart types in the same text seemed to offer conflicting clues. b) In one image, multiple different visualizations are used to represent multidimensionality of the results. For example, the use of scatterplot for showing the distribution of some species and in the same image use of column chart for illustrating the comparison with other species. Although all efforts were made to remove such instances from our training set, however, we can't deny the existence of them in the rest of the corpus.

- **Similar representational goal:** Histograms, boxplot and scatterplot share same goal of showing distribution among continuous variables. Where histogram shows the frequency distribution of a variable, boxplot provides detail information about this distribution among different quartiles. Then, scatterplot shows relationship and causation of this distribution with other variable/s. Unfortunately, although the visual representation is different, the language describing both visualizations tends to use similar wording, likely causing misclassifications.

- **Mixture of definition/description and interpretation vocabulary:** A caption can be used to fulfill different tasks: define/describe the contents and/or interpret them. As the language differs very heavily from one task to the other and the ratio between definitions and interpretations varies from sample to sample even within a given class, a classifier might be drawn to either specialize in the definition/interpretation parts of the samples (high precision, low recall) or generalize to a point that it cannot exclude other classes (low precision, high recall).

- **Level of abstraction of some classes:** Due to limited examples for some of the classes, we had to form superclasses of visualization types. For example, 'Column Chart' class is created by merging examples from 14 related visualizations. This also leads confusion with other classes. For example boxplots are confused with column charts due to the presence of error bars in certain types of column chart.

- **Wrongly mentioned visualization types:** In addition to the regular vocabulary, the binary classifiers also look for specific visualization name in the caption texts. Unfortunately, in some captions, wrong visualization names are referred, mistaking for example a column chart for a histogram.

5.3 Comparison

Table 5 provides individual scores for different classes. Due to the special goal and characteristics of our study, currently we do not have any base study to compare our results with. None of the previous studies have considered both aspects of charts (visuals from images and chart semantics from captions) for chart classification. In Figure 8, we have provided the comparison among scores from common classes in 3 different studies.

Figure 8 shows that in comparison to other studies, we are only lacking in two classes i.e Scatterplot and Area Chart. In our work, 'Ordination Plot' and 'Stack Area Chart' which is similar to 'Scatterplot' and 'Area Chart' were considered as a separate class based on their representative goal and visual dissimilarities. No such fine differences were made in the other studies. Scores of Ordination plot is 98% and Stack area chart score 96% and if we compare them with the other studies, then our performance is better. With an average accuracy (F1-score) of 92.2%

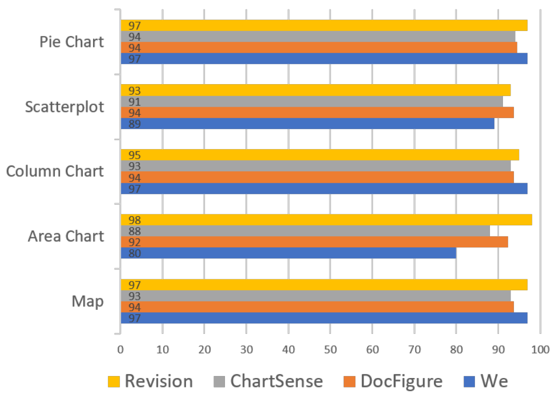


Figure 8: Comparison with other studies: Revision (Savva et al., 2011), ChartSense (Jung et al., 2017) and DocFigure (Jobin et al., 2019).

we have proved that our approach of chart classification is better than other chart image classification technique.

6 Challenges and Research Direction

The result from our study lays a strong foundation that for better chart classification apart from visual chart elements, caption and other chart related text could be a major source of information.It is just a preliminary step. For an enhanced semantic chart recognition systems, there are many problems that needs to be answered-

- As our classifiers were only trained on the biodiversity text, we are not sure how well they will perform on general text or text from other domains. More studies are needed in this direction wherein a classifier trained in one domain can be generalized to other domain. This work is out of scope for our research therefore, we leave it on future studies.
- Apart from only using the captions in the training process, text in the publication refers to the chart images could yield better results. Moreover, if the data is enriched with more semantic knowledge like synonyms, concurrent words, ontologies etc, then better classification accuracy can be achieved.
- The real population is not always as clean as the training data that is fed to the classifiers. Therefore, more studies are required that can understand the common variations found in the visualization images and captions. For example, hybrid visualizations, multi-embed visualizations etc.
- Semantic chart classification classify the charts not only based on the chart elements but also their representation goals. We have found that those visualizations that tend to share the same goals are the one with most false positives. The way out for this is to create the classes solely based on the visualization goals. Then such work will be more helpful for task-based visualization recommendation systems.

7 CONCLUSION AND FUTURE WORK

In this work on chart classification, along with the visual similarity of different chart types, we have also considered the conceptual similarities of the charts. We have manually labelled the chart images and captions from biodiversity publications. We have trained both the image and chart classifiers on this data. From the best results of these two classifiers, we have incrementally trained our text classifier. Doing so, we have achieved an average (F1-score) of 92.2% from ensembles of binary caption classifiers. Our result proves that conceptual/semantic chart classifiers can efficiently differentiate between those chart types which are visually similar and are as efficient as image classifiers. Along with that due to the conceptual understanding of such classifiers, they can be used for different purposes. One of these is the creation of knowledge-assisted visualization recommendation systems. We will be using these classifiers to infer different visualizations/chart types from biodiversity text.

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APPENDIX

Appendix and scripts are available online at: https://github.com/fusion-jena/Biodiv-Visualization-Classifier