SEMANTIC SEGMENTATION FOR COMPOUND FIGURES

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ABSTRACT

Scientific literature contains large volumes of unstructured data, with over 30% of figures constructed as a combination of multiple images, these compound figures cannot be analyzed directly with existing information retrieval tools. In this paper, we propose a semantic segmentation approach for compound figure separation, decomposing the compound figures into "master images". Each master image is one part of a compound figure governed by a subfigure label (typically "(a), (b), (c), etc"). In this way, the separated subfigures can be easily associated with the description information in the caption. In particular, we propose an anchor-based master image detection algorithm, which leverages the correlation between master images and subfigure labels and locates the master images in a two-step manner. First, a subfigure label detector is built to extract the global layout information of the compound figure. Second, the layout information is combined with local features to locate the master images. We validate the effectiveness of proposed method on our labeled testing dataset both quantitatively and qualitatively.

Index Terms— Object Detection, Deep Learning, Information Retrieval, Semantic Segmentation

1. INTRODUCTION

Scientific results are typically communicated in the form of papers, and scientific literature is becoming a very important data source as the number of papers are ever-increasing. Quite a few information retrieval tools have been built for scientific literature, such as PubMed/PMC, Semantic Scholar, ScienceDirect. However, most of the existing tools only focus on textual information retrieval. According to previous studies[1, 2], humans are known to better retain information presented visually, leading to the fact that high-impact ideas tend to be conveyed visually[3]. An obstacle towards image data retrieval from scientific literature is that over 30% of figures are compound figures[4], which consists of more than one subfigures. The issue of analyzing a compound figure containing multiple subfigures directly is that those subfigures do not necessarily have the same semantic meaning. As is known to all, figures usually come with captions in scientific literature. Captions provide important information to help readers understand the semantic meaning of each part of figures. Thus, caption information plays an important role in decomposing compound figures.

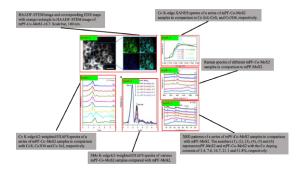


Fig. 1. Example of semantic segmentation for a compound figure. The compound figure is segmented into several master images. Each master image is assigned a classification label, demonstrating the category of the image, as well as a subfigure label, with which we can refer to the description in the caption.

Compound figure separation aims at decomposing figures into small parts so that each part can be easily analyzed. Previous work on compound figure separation relies heavily on hand-crafted features and rule-based approaches[5, 6, 7]. These approaches are typically successful for particular types of figures, where the assumptions used to construct the features are hold, but the performance drops significantly if the assumptions fail. Later, Tsutsui et al.[8] proposed a datadriven approach to decompose compound figures into individual images on top of an object detection algorithm. Decomposing the compound figure into individual images, which we call decomposition at fine granularity, guaranteeing the semantic consistency in each separated part. However, it breaks the connection between the caption information and the compound figure, making it difficult to analyze the semantic meaning of each separated part. More recently, Shi et al.[9] assumed subfigures should be distributed in a grid-like structure and proposed a layout-aware subfigure decomposition approach for compound figure separation. This layoutaware approach tries to decompose figures at intermediate granularity by grouping individual images which are spatially correlated together. However, this does not guarantee the semantic consistency in each separated part.

In this paper, we propose a semantic segmentation approach to decompose compound figures at intermediate gran-

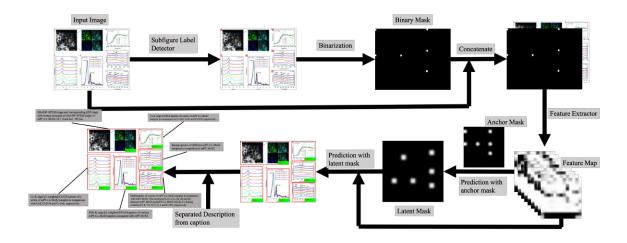


Fig. 2. Overview of the proposed method.

ularity, keeping semantic consistency in each separated part while maintaining the association between each separated part and the caption information. As shown in Fig. 1, the compound figure is decomposed into several mid-level subfigures, named master images, each of which can be easily associated with information in the caption through its respective subfigure label. Master image is an intermediate concept between compound figure and individual image, it can be an individual image or a set of individual images. In particular, we design a two-step framework to detect master images. In the first step, a subfigure label detector is trained to locate and recognize the subfigure labels. In the second step, the global layout information, extracted from the distribution of subfigure labels, is combined with the local features of images to locate the master images. Separated master image are then associated with information in the caption. The overall framework of the proposed method can be viewed in Fig.2. It is worth mention that data imbalance problem occurs during training the subfigure label detector, affecting the performance of the detector. In this paper, we circumvent this problem by splitting the detector into two individual parts and training them respectively.

To summarize, the contribution of this paper is as follows:

- We propose a semantic segmentation approach to decompose compound figures, with each separated part easily associated with the caption information via its subfigure label.
- We propose an anchor-based object detection algorithm, which combines external information and internal features to locate ambiguously defined objects.
- We propose a simple yet effective approach to address data imbalance problem in object detection.

2. RELATED WORKS

2.1. Compound figure separation

Scientific results are communicated visually in the literature through plots, visualization, images, and diagrams. According to a recent study[3], figures play a critical role in scientific communication, affecting the impact factor of scientific papers. It has been estimated that more than 30% of figures consists of more than one subfigures[4], suppressing the functionality of existing information extraction tools. Previous work has mostly focused on hand-craft features and rule-based methods, such as identifying large regions of background color and layout patterns[5], or detecting lines as boundaries of subfigures[6]. Learning-based methods were proposed in recent years. Tsutsui et al.[8] built a compound figure separator on top of YOLOv2[10] and trained the model with synthesized data. Shi et al.[9] proposed LADN to decompose compound figure in a grid-like structured manner. In this paper, we retain the semantic information during compound figure separation, decomposing them at an intermediate granularity.

2.2. Object detection

Object detection algorithms aims at locating the position of objects in the target image and recognize them. In the past decade, hand-craft feature (SIFT[11], HOG[12]) are used to address object detection problem. More recently, convolutional neural network (CNN)-based approaches are leading to dramatically higher object detection performance on public benchmarks. The Overfeat[13] detection system uses a sliding-window strategy to move the CNN feature extractor around the image to locate the objects. The R-CNN detection family[14, 15, 16] addresses the object detection task

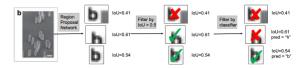


Fig. 3. Illustration of how to use a pre-trained classifier in the training process to regularize the region proposal network.

in a two-step manner, proposing candidate regions and recognizing the objects in each region. The YOLO detection family[17, 10, 18] designs an end-to-end framework for object detection, in which region proposal and classification are performed simultaneously. Our work is built on top of the YOLOv3 detection framework.

2.3. Visual relationships

Visual relationships aim at a higher level of image understanding, which not only locates and recognizes the objects, but also determines the interaction between object pairs. Recent research on visual relationships[19, 20, 21] is mainly focus on completing a phrase from the image content given the agent and the target. Gkioxari et al.[21] proposed a human-centric interaction prediction, introducing a bi-directional validation to confirm the interaction in-between. Inspired by their work, in this paper, we proposed an anchor-based master image detection method, which uses location of the subfigure labels and the implicit correlation between subfigure labels and master images to get rough estimation of the location and refine the estimation with local features.

3. METHODS

In this section, we discuss the details of our proposed approach. The challenge here is that "master image" does not have rigorous definition, meaning that locating master images by their internal feature is an ill-posed problem. A common way to address this kind of problem is introducing some additional priors or constraints. In this case, we take the knowledge of subfigure labels as an additional prior because of the inherent correlation.

3.1. Subfigure Label detector

Subfigure label detection is a key component in our model, because it helps extract the global layout information from the compound figure. Since master images cannot be fully describe by their internal features, the global layout information plays a very important role. The obstacle towards acquiring the well-performed subfigure label detector is the data imbalance problem, which commonly exists in learning based methods. For example, in a collection of compound figures, the number of letters toward beginning of alphabet, such as

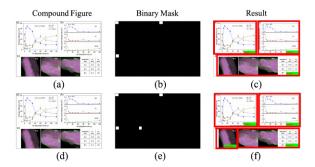


Fig. 4. Master image detection with different binary masks.

"a", is usually far more than the letters toward end of alphabet, such as "h". In our training dataset, the number of occurrences of "a" is 794 while the number of occurrences of "h" is 69. Feeding such a imbalanced dataset into an object detector more likely results in a biased detector, performing well on "a" while poorly on "h", as shown in Table.1.

To address this problem, we split the task of object detection into two parts and train them sequentially. The first part is to train a balanced subfigure label classifier with synthesized data. In particular, our subfigure label classifier is built on top of ResNet-152[22], trained with a mixture of real data and synthetic data, resulting in over 99% recognition accuracy on the testing dataset.

In the second part, we take advantage of the well-trained, balanced subfigure label classifier to improve the performance of the region proposal module. Intersection-over-Union (IoU) is an important criteria used in object detection to measure the distance between predicted bounding box and the desired one. Usually, a proposed bounding box with a high IoU score is assumed to be a successful prediction. For example, in R-CNN, regions with IoU over 70% are considered a positive detection while those with IoU under 30% are assigned negative labels. This assumption does not always hold in this subfigure label detection task. For example, if we consider letter "b", a slightly misdrawn box at the top still leads to a "b", but a slightly misdrawn box from the bottom might lead to misclassification as "h". Here, to correct this problem, the well-trained subfigure label classifier is used as an additional constraint added to the training process, as shown in Fig.3.

3.2. Master Image detector

In this section, we discuss how to combine the external knowledge with internal features to semantically segment the compound figures. One key assumption we make is that master images come with subfigure labels. For compound figures which do not satisfy this assumption, our system will fail.

Consider how a human reads a compound figure. At the first glance, we search for subfigure labels, then we come up with a rough layout of the compound figure, i.e. how many

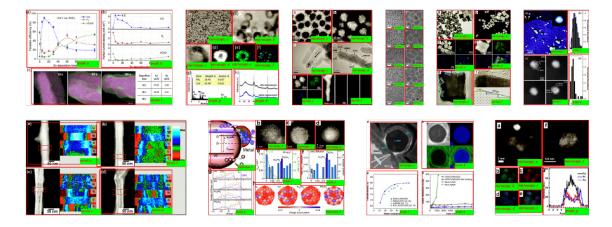


Fig. 5. Examples of experimental results.

parts the figure contains. Then, we look carefully into the figure, determining what exactly each part is by identifying the boundary and analyzing the semantic similarity. Following these considerations, we design our master image detector in a similar way. First, we make a rough estimation of how master images are distributed in the compound figure from knowledge of the subfigure label. Second, we use the local features to regularize and refine the coarse estimation. In the rest of the section, we discuss the master image detection system in detail.

The first step is layout information separation, removing the semantic information and keeping the information related the layout of the figure. A binary mask is generated based on the distribution of subfigure labels. A simple way to correlate the layout information with local features is concatenation, resulting in a 4-D image tensor. The 4-D image tensor is then fed into a YOLO-style object detection network, which makes prediction in a grid-based manner.

For conventional object detection system, we rely on the confidence scores to distinguish good predictions from bad ones. The issue of using this criteria in our master image detection task is: 1) Given the knowledge of the subfigure labels, we can expect the number of master images to be detected, but this confidence level based criteria does not allow the setting of the number of predictions. 2). This criterion does not correlate each master image with a subfigure label. To meet our expectation, we proposed an anchor-based object detection method to locate the master images.

According to YOLO[17], feature map extracted by convolutional layers retains the same spatial relativity as the input image. By projecting the binary mask onto the feature space, which we call anchor mask, we are able to locate the feature vector corresponding to each subfigure label. Since there is high correlation between subfigure labels and master images, the selected feature vectors are used to make a rough estimation (latent mask) for master images. Latent mask is then used

to locate the feature vectors for each master image, eventually resulting in a more fine-grained way for compound figure separation.

The binary mask plays a very important role in semantic segmentation. As shown in Fig.4, given the same compound figure, different binary masks lead to different segmentation results. In the first row, given the compound figure in (a), a binary mask could be generated via our proposed framework (shown in (b)). With our anchor-based master image detection method, the compound figure is separated into three parts, each associated with a subfigure label. Now assume that we decide to change the layout of the compound figure by adding another subfigure label (e.g. d) next to the subfigure label (c), resulting in a different binary mask, as shown in (e). Then we feed the original compound figure and the new binary mask into our detection model, and as a result, the figure is segmented in a different way (shown in (f)). This example demonstrates that the proposed detection system does use the external information while making predictions as we mentioned above.

4. RESULTS

In this section, we discuss the details of the experiments and validate the effectiveness of the proposed method quantitatively and qualitatively.

4.1. Dataset and training process

We prepared about 1000 labeled compound figures, which are taken from The Royal Chemistry Society (RCS), Springer Nature, and American Chemical Society (ACS) journal families. Then we selected 794 figures for training and 198 for testing. All compound figures are labeled through Amazon Mechanical Turk (MTurk), a platform for crowdsourcing labeling. Each compound figure is segmented into multiple

Table 1 . Comparison of	he performance of dif	erent methods on subfigur	re label detection with the metric of mAP.
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Method	a	b	С	d	e	f	g	h	average
YOLOv3	85.3%	92.2%	78.6%	86.0%	67.5%	69.3%	67.7%	71.0%	77.2%
SLDv1	87.5%	92.4%	86.2%	88.4%	86.2%	83.0%	79.6%	78.1%	85.1%
SLDv2	88.3%	93.4%	85.4%	88.5%	85.7%	87.8%	84.7%	96.7%	88.8%

master images, with a label describing the type of the master image, i.e. microscopy, parent, diffraction, graph, illustration. Then we manually check the quality of the labels and keep the ones with correct labels and accurate bounding boxes. The entire model training process can be divided into three parts: training the subfigure label classifier, training the subfigure label detector, and training the master image detector.

For subfigure label classifier, the model is trained with a mixture of real data labeled by MTurk and synthesized data. The synthetic data is generated by two steps: cropping background patches from the compound figures, which do not have a letter inside, and pasting a random letter onto each patch, in which the font of the letter varies through different patches and the letter is randomly set to be in lower case or upper case. Also the synthetic data is generated on the fly during the training, preventing the classifier from overfitting.

For subfigure label detector, the model is trained without the classifier for about 10,000 iterations, and then fine tuned for another 3,000 iterations with the classifier. For the master image detector, the model is trained with ground truth subfigure labels for 12,000 iterations.

4.2. Experimental results

For the subfigure label classifier, among the 1016 subfigure labels in the 198 testing compound figures, 1015 of them are correctly recognized while only 1 is misclassified.

For the subfigure label detector, we compare the performance between different methods with the metric of mean Average Precision (mAP), which is heavily used in object detection to evaluate the performance of the methods while considering the precision and recall simultaneously. We denote SLDv1 as the proposed subfigure label detector without using the classifier for fine tuning, and SLDv2 as the proposed subfigure label detector using the classifier for fine tuning. We also take YOLOv3[18], a state-of-the-art object detection algorithm, as a baseline for comparison. As shown in Table.1, proposed subfigure label detectors, both SLDv1 and SLDv2, outperform the general object detector. The YOLOv3 detector suffers from the imbalanced dataset. It performs fairly well when the training data is sufficient (e.g. "a", "b", "d"), but the performance drops significant when the training data is more scarce (e.g. "f", "g", "h"). The proposed methods handle the data imbalance problem quite well, resulting a robust performance on different targets. Also, fine tuning with the well trained classifier successfully suppresses the number

Table 2. Comparison of the performance of different methods on compound figure separation. IoU threshold is 0.5.

Method	True Positive	False Positive	AP	
Tsutusi[8]	900	309	80.23%	
Proposed	961	24	94.38%	

of false positive cases, causing a significant improvement on mAP by another 3%.

For the master image detection, we first made a comparison between model from Tsutusi[8] and the proposed model. Tsutusi only considers decomposing the compound figure into several subfigures, while the proposed method further classify each subfigure, we remove the label tag for a fair comparison. As shown in Table. 2, the proposed method tends to detect more precisely, with more true positive detection and less false positive detection, and the average precision increased by 14%. We also demonstrate the effectiveness of the proposed method visually. As shown in Fig.5, the proposed method successfully segment compound figures even though the layout of the figures vary significantly.¹

5. CONCLUSION AND DISCUSSION

In this paper, we propose a semantic segmentation approach for compound figure separation. Compound figures are decomposed at an intermediate granularity, which can be easily associated with information in the captions. In particular, we propose an anchor-based object detection, which incorporates the external information and internal features to detect ambiguously defined objects.

There are still some remaining work left for further improvements. The first problem is error accumulation in sequential framework. For example, any missing subfigure labels in the first step will fail the master image detection task, as shown in Fig.6(a). Another problem is bounding box precision drops when the shape of the master image is far away from the reference anchor box. Reference anchor boxes are used as an initial guess in the state-of-the-art object detection

¹Figures obtained from the following journal articles: 10.1039/C3CE42362J, 10.1039/C3NR06888A, 10.1039/C6RA04990G, 10.1039/C6TA04155H, 10.1039/C3NR33989K, 10.1039/C3CP52485J, 10.1039/C3CE41187G, 10.1039/C3NR05722D, 10.1039/C6RA10539D, 10.1038/am.2014.36

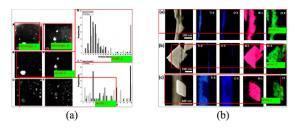


Fig. 6. Examples of failure cases.

systems, improving the recall rate of the system. But performance drops when the initial guess is really bad, as shown in Fig.6(b).

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