YOLO-SG: An Efficient Framework for Scene Graph Generation

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Abstract

Scene graph generation (SGG) is the task of detecting object pairs and their relations in a visual medium, widely used for captioning, generation, and visual question answering. 2D scene graph generation is a subtask that focuses on the generation of a 2D graph given an image. While development on models capable of performing 2D SGG have improved in both accuracy and speed, the computational complexity of the problem and the inherently long-tailed distribution of large, available datasets has led to generation speed and accuracy less than ideal for real-time use. Mainstream approaches focus on two-stage generation, where object detection is performed first, followed by a series of comparisons for relation inference. However, these have an inherent drawback where the computational complexity of detecting n objects and their relationships is n^2. More recent models have utilized encoder-decoder structures to reduce generation into a 1-stage problem. Unfortunately, the speed of generation for this models is still insufficient for real-time generation. Additionally, the long-tailed distribution of the training data leads to heavy bias in both approaches. To solve these two problems, we propose YOLO-SG, a novel SGG framework which achieves state of the art results on the COCO dataset. YOLO-SG performs its task by decoupling object detection and relation detection entirely and by performing relationship inference with multiple detection models in parallel. <RESULTS>, <RESULTS>

1 Introduction

In recent decades, object detection problems have become an increasingly popular subject in research literature[10] as the rise of deep learning[6] has led to many breakthroughs in the field. increase in research popularity has led to rapid advancements in downstream tasks such as scene graph generation (SGG)[4]. SGG encompasses the set of tasks that focus on detecting object pairs and their relationships in visual media, creating scene graphs which can then be used for applications involving captioning[3], generation, and visual question answering <!!!>.

This paper focuses on the task of 2D scene graph generation, which uses an image as the input to generate a graph which represents a set of object bounding boxes as nodes and a set of triplets comprised of a subject, an object, and their relationship (referred to as the *predicate*) as edges. Performance on 2D SGG is measured in two ways: the speed of the generation, and how close it is to the ground truth.

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Two barriers stand in the way of modern frameworks achieving higher performances on these two metrics. The first is the long-tailed distribution of available training data. When annotators create data for scene graph generation, a large majority of triplets in the dataset contain only a small fraction of predicates due to the inherent differences in the appearance of various subject-object relationships in real life. For example, 'on' can be used to describe the relation between almost any subject-object pair where one is 'above' the other, and hence will appear significantly more than predicates such as 'mounted' or 'reaching'. The second barrier is the computation required in proposed approaches to the problem. Mainstream approaches tend to have two-stages, where an object detection model finds the objects in the image, and then each possible subject-object pair is checked for a potential predicate. Unfortunately, the computation required in the second stage scales exponentially with the number of objects found, as n objects would have n^2 potential predicates that need to be checked. Recent works have proposed a one-stage approach which leverages transformers to generate a set of triplets using object information. However, the large number of computations required in a transformer architectures introduces a new speed bottleneck, preventing the use of these approaches in real-time applications.

This paper addresses the computation bottleneck of predicate prediction with YOLO-SG, a novel object detection framework which returns a set of objects and a set of subject-predicate-objects given an image. YOLO-SG leverages the rapid advancements in the upstream task of object detection by treating the predicates between objects as objects in themselves. By doing so, we are able to perform detection of objects in an image in parallel with predicates in an image. Additionally, we address the long-tailed distribution problem by dividing the data into subsets by predicate frequency and training one object detection model for each subset. By doing so, instead of obtaining one model with high bias, we obtain multiple unbiased models that classify different predicates.

2 Background and Related Work

Scene graph generation was first proposed in 2015 as an improvement to semantic image retrieval, where a generated scene graph is used as comparison instead of image object features[4]. This was improved upon with the development of two-stage scene graph generation approaches and the use of convolutional neural networks as object detection models in SGG[9, 2, 8]. In order to address the exponential complexity problem of two-stage models, recent works have proposed several one-stage approaches to the problem[1, 7].

3 Method

Our proposed framework, YOLO-SG, decouples the process of object and predicate detection by framing both subproblems as standard object detection tasks. Rather than inferring predicates between every pair of detected objects in a computationally expensive second stage, we directly detect "predicate entities" in parallel alongside object detection. By modeling predicates as distinct objects, we leverage <YOLO VERSION> for both object and predicate recognition. This approach reduces the complexity of pairwise comparisons from n^2 operations to a more manageable parallel detection task.

3.1 Dataset

We use Visual Genome 1.2 [5] as our dataset and split it into training, validation, and test sets. To treat predicates as objects, we assign each annotated predicate to a bounding box that encapsulates both the subject and object bounding boxes. For example, given a pair of objects $A, B \in \mathbb{R}^2$ with predicate r in Visual Genome 1.2, we create a new bounding box R that minimally encloses both A and B. such that

$$R = (\min(A[1], B[1]), \max(A[2], B[2]))$$

This ensures that each predicate is represented as a single entity in the image. We use the original scene graph annotations to produce a secondary dataset of predicate bounding boxes, each labeled with its corresponding predicate. We now have two datasets which are composed of the same images but different bounding boxes and labels: one has the bounds and labels for objects, while the other has the bounds and labels of predicates.

Cleaning Older versions of Visual Genome contain a multitude of object and predicate labels which are equivalent to one another (for example, 'under' and 'below'). We use the latest version of Visual Genome at time of writing, which provides us with a set of synonyms that group similar objects and predicates into the same class, with one term assigned by group. After converting all synonymous terms to their respective group representative term, we remove objects which rarely appear along with any associated triplets.

3.2 Model training

Object detection models Here we arrive at the long-tailed distribution problem. For objects, we train a YOLO model on objects Object YOLO: Trained on the object dataset, this model detects all objects in a given image. predicate YOLO: Trained on the predicate dataset, this model detects all predicate entities R in the same image. Each model is trained using conventional object detection procedures and loss functions, taking advantage of YOLO's efficient architecture. By isolating objects and predicates into their own detection tasks, we allow each model to specialize and minimize biases that often arise when both tasks are intertwined.

3.3 Inference

We start with weights pro the YOLO v11 model on the COCO dataset and evaluate it on the CoCo Dataset on 5 NVIDIA 4090Ti graphics cards. Training took 25 hours, with a maximum epoch of 300 and a batch size of 8. We evaluate our model using mean Recall@50.

Parallel detection For a given test image, we pass it through both the Object YOLO and the predicate YOLO models independently and in parallel. The Object YOLO output gives us a set of detected objects with corresponding bounding boxes and class labels. The predicate YOLO output provides a set of detected "predicate boxes," each with a predicted predicate label.

Clustering and association we need to determine which objects are involved in each detected predicate. We apply a clustering algorithm to group each predicate bounding box R with candidate object bounding boxes that it encloses or overlaps. This gives us one or more candidate subject-object pairs for each predicate detection.

Triplet selection using MLP scoring After obtaining two sets of detections—one for objects and one for predicates—we need the determine the subject and object associated with each triplet. For every predicate bounding box and label, we collect a list of detected objects have have a large overlap within the predicate box. To select the most like subject-object pair associated with the label, we use a lightweight MLP classifier trained to score the plausibility of a triplet (subject, predicate, object). For each predicate detection, we run the MLP once with every potential object pair that can be formed by objects in the list, selecting the triplet which returns the highest confidence score.

4 Evaluation

4.1 Evaluation Metrics

4.2 dataset

4.3 setting

4.4 implementation

4.5 results

5 Conclusion

6 Submission of papers to NeurIPS 2024

Please read the instructions below carefully and follow them faithfully.

6.1 Style

Papers to be submitted to NeurIPS 2024 must be prepared according to the instructions presented here. Papers may only be up to **nine** pages long, including figures. Additional pages *containing only acknowledgments and references* are allowed. Papers that exceed the page limit will not be reviewed, or in any other way considered for presentation at the conference.

The margins in 2024 are the same as those in previous years.

Authors are required to use the NeurIPS LaTeX style files obtainable at the NeurIPS website as indicated below. Please make sure you use the current files and not previous versions. Tweaking the style files may be grounds for rejection.

6.2 Retrieval of style files

The style files for NeurIPS and other conference information are available on the website at

`http://www.neurips.cc/`

The file `neurips_2024.pdf` contains these instructions and illustrates the various formatting requirements your NeurIPS paper must satisfy.

The only supported style file for NeurIPS 2024 is `neurips_2024.sty`, rewritten for LaTeX 2_{ε}. **Previous style files for LaTeX 2.09, Microsoft Word, and RTF are no longer supported!**

The LaTeX style file contains three optional arguments: `final`, which creates a camera-ready copy, `preprint`, which creates a preprint for submission to, e.g., arXiv, and `nonatbib`, which will not load the `natbib` package for you in case of package clash.

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The formatting instructions contained in these style files are summarized in Sections 7, 8, and 9 below.

7 General formatting instructions

The text must be confined within a rectangle 5.5 inches (33 picas) wide and 9 inches (54 picas) long. The left margin is 1.5 inch (9 picas). Use 10 point type with a vertical spacing (leading) of 11 points. Times New Roman is the preferred typeface throughout, and will be selected for you by default. Paragraphs are separated by ½ line space (5.5 points), with no indentation.

The paper title should be 17 point, initial caps/lower case, bold, centered between two horizontal rules. The top rule should be 4 points thick and the bottom rule should be 1 point thick. Allow ¼ inch space above and below the title to rules. All pages should start at 1 inch (6 picas) from the top of the page.

For the final version, authors' names are set in boldface, and each name is centered above the corresponding address. The lead author's name is to be listed first (left-most), and the co-authors' names (if different address) are set to follow. If there is only one co-author, list both author and co-author side by side.

Please pay special attention to the instructions in Section 9 regarding figures, tables, acknowledgments, and references.

8 Headings: first level

All headings should be lower case (except for first word and proper nouns), flush left, and bold.

First-level headings should be in 12-point type.

8.1 Headings: second level

Second-level headings should be in 10-point type.

8.1.1 Headings: third level

Third-level headings should be in 10-point type.

Paragraphs There is also a `\paragraph` command available, which sets the heading in bold, flush left, and inline with the text, with the heading followed by 1 em of space.

9 Citations, figures, tables, references

These instructions apply to everyone.

9.1 Citations within the text

The `natbib` package will be loaded for you by default. Citations may be author/year or numeric, as long as you maintain internal consistency. As to the format of the references themselves, any style is acceptable as long as it is used consistently.

The documentation for `natbib` may be found at

`http://mirrors.ctan.org/macros/latex/contrib/natbib/natnotes.pdf`

Of note is the command `\citet`, which produces citations appropriate for use in inline text. For example,

```
\citet{hasselmo} investigated\dots
```

produces

> Hasselmo, et al. (1995) investigated...

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```
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```

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```
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```

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9.2 Footnotes

Footnotes should be used sparingly. If you do require a footnote, indicate footnotes with a number[1] in the text. Place the footnotes at the bottom of the page on which they appear. Precede the footnote with a horizontal rule of 2 inches (12 picas).

[1] Sample of the first footnote.

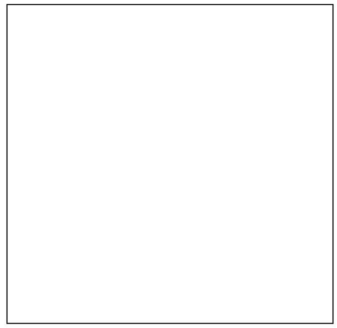

Figure 1: Sample figure caption.

Table 1: Sample table title

Part		
Name	Description	Size (μm)
Dendrite	Input terminal	$\sim$100
Axon	Output terminal	$\sim$10
Soma	Cell body	up to 10^6

Note that footnotes are properly typeset *after* punctuation marks.[2]

9.3 Figures

All artwork must be neat, clean, and legible. Lines should be dark enough for purposes of reproduction. The figure number and caption always appear after the figure. Place one line space before the figure caption and one line space after the figure. The figure caption should be lower case (except for first word and proper nouns); figures are numbered consecutively.

You may use color figures. However, it is best for the figure captions and the paper body to be legible if the paper is printed in either black/white or in color.

9.4 Tables

All tables must be centered, neat, clean and legible. The table number and title always appear before the table. See Table 1.

Place one line space before the table title, one line space after the table title, and one line space after the table. The table title must be lower case (except for first word and proper nouns); tables are numbered consecutively.

Note that publication-quality tables *do not contain vertical rules.* We strongly suggest the use of the `booktabs` package, which allows for typesetting high-quality, professional tables:

`https://www.ctan.org/pkg/booktabs`

This package was used to typeset Table 1.

9.5 Math

Note that display math in bare TeX commands will not create correct line numbers for submission. Please use LaTeX (or AMSTeX) commands for unnumbered display math. (You really shouldn't be using $$ anyway; see `https://tex.stackexchange.com/questions/503/why-is-preferable-to` and `https://tex.stackexchange.com/questions/40492/what-are-the-differences-between-align-equation-and-displaymath` for more information.)

[2] As in this example.

9.6 Final instructions

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Fonts were the main cause of problems in the past years. Your PDF file must only contain Type 1 or Embedded TrueType fonts. Here are a few instructions to achieve this.

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- You can check which fonts a PDF files uses. In Acrobat Reader, select the menu Files>Document Properties>Fonts and select Show All Fonts. You can also use the program `pdffonts` which comes with `xpdf` and is available out-of-the-box on most Linux machines.
- `xfig` "patterned" shapes are implemented with bitmap fonts. Use "solid" shapes instead.
- The `\bbold` package almost always uses bitmap fonts. You should use the equivalent AMS Fonts:

  ```
  \usepackage{amsfonts}
  ```

  followed by, e.g., `\mathbb{R}`, `\mathbb{N}`, or `\mathbb{C}` for $\mathbb{R}$, $\mathbb{N}$ or $\mathbb{C}$. You can also use the following workaround for reals, natural and complex:

  ```
  \newcommand{\RR}{I\!\!R} %real numbers
  \newcommand{\Nat}{I\!\!N} %natural numbers
  \newcommand{\CC}{I\!\!\!\!C} %complex numbers
  ```

  Note that `amsfonts` is automatically loaded by the `amssymb` package.

If your file contains type 3 fonts or non embedded TrueType fonts, we will ask you to fix it.

10.1 Margins in LaTeX

Most of the margin problems come from figures positioned by hand using `\special` or other commands. We suggest using the command `\includegraphics` from the `graphicx` package. Always specify the figure width as a multiple of the line width as in the example below:

```
\usepackage[pdftex]{graphicx} ...
\includegraphics[width=0.8\linewidth]{myfile.pdf}
```

See Section 4.4 in the graphics bundle documentation (`http://mirrors.ctan.org/macros/latex/required/graphics/grfguide.pdf`)

A number of width problems arise when LaTeX cannot properly hyphenate a line. Please give LaTeX hyphenation hints using the `\-` command when necessary.

Acknowledgments and Disclosure of Funding

Use unnumbered first level headings for the acknowledgments. All acknowledgments go at the end of the paper before the list of references. Moreover, you are required to declare funding (financial activities supporting the submitted work) and competing interests (related financial activities outside the submitted work). More information about this disclosure can be found at: `https://neurips.cc/Conferences/2024/PaperInformation/FundingDisclosure`.

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References

References follow the acknowledgments in the camera-ready paper. Use unnumbered first-level heading for the references. Any choice of citation style is acceptable as long as you are consistent. It is permissible to reduce the font size to `small` (9 point) when listing the references. Note that the Reference section does not count towards the page limit.

References

[1] CONG, Y., YANG, M. Y., AND ROSENHAHN, B. Reltr: Relation transformer for scene graph generation. *IEEE Transactions on Pattern Analysis and Machine Intelligence 45*, 9 (2023), 11169–11183.

[2] DESAI, A., WU, T.-Y., TRIPATHI, S., AND VASCONCELOS, N. Learning of visual relations: The devil is in the tails. In *Proceedings of the IEEE/CVF International Conference on Computer Vision* (2021), pp. 15404–15413.

[3] GU, J., JOTY, S., CAI, J., ZHAO, H., YANG, X., AND WANG, G. Unpaired image captioning via scene graph alignments. In *Proceedings of the IEEE/CVF International Conference on Computer Vision* (2019), pp. 10323–10332.

[4] JOHNSON, J., KRISHNA, R., STARK, M., LI, L.-J., SHAMMA, D., BERNSTEIN, M., AND FEI-FEI, L. Image retrieval using scene graphs. In *Proceedings of the IEEE conference on computer vision and pattern recognition* (2015), pp. 3668–3678.

[5] KRISHNA, R., ZHU, Y., GROTH, O., JOHNSON, J., HATA, K., KRAVITZ, J., CHEN, S., KALANTIDIS, Y., LI, L.-J., SHAMMA, D. A., ET AL. Visual genome: Connecting language and vision using crowdsourced dense image annotations. *International journal of computer vision 123* (2017), 32–73.

[6] LECUN, Y., BENGIO, Y., AND HINTON, G. Deep learning. *nature 521*, 7553 (2015), 436–444.

[7] LI, R., ZHANG, S., AND HE, X. Sgtr: End-to-end scene graph generation with transformer. In *proceedings of the IEEE/CVF conference on computer vision and pattern recognition* (2022), pp. 19486–19496.

[8] LI, R., ZHANG, S., WAN, B., AND HE, X. Bipartite graph network with adaptive message passing for unbiased scene graph generation. In *Proceedings of the IEEE/CVF conference on computer vision and pattern recognition* (2021), pp. 11109–11119.

[9] YANG, J., LU, J., LEE, S., BATRA, D., AND PARIKH, D. Graph r-cnn for scene graph generation. In *Proceedings of the European conference on computer vision (ECCV)* (2018), pp. 670–685.

[10] ZOU, Z., CHEN, K., SHI, Z., GUO, Y., AND YE, J. Object detection in 20 years: A survey. *Proceedings of the IEEE 111*, 3 (2023), 257–276.

A Appendix / supplemental material

Optionally include supplemental material (complete proofs, additional experiments and plots) in appendix. All such materials **SHOULD be included in the main submission.**

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   Question: Does the paper provide open access to the data and code, with sufficient instructions to faithfully reproduce the main experimental results, as described in supplemental material?

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   - The authors should provide scripts to reproduce all experimental results for the new proposed method and baselines. If only a subset of experiments are reproducible, they should state which ones are omitted from the script and why.
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