

Conformal Prediction and MLLM aided Uncertainty Quantification in Scene Graph Generation

POSTER #99



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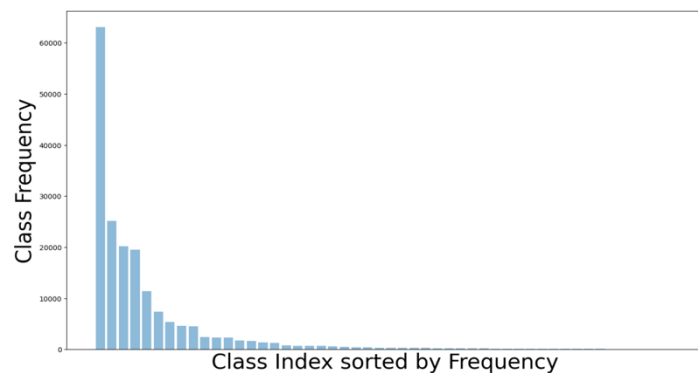


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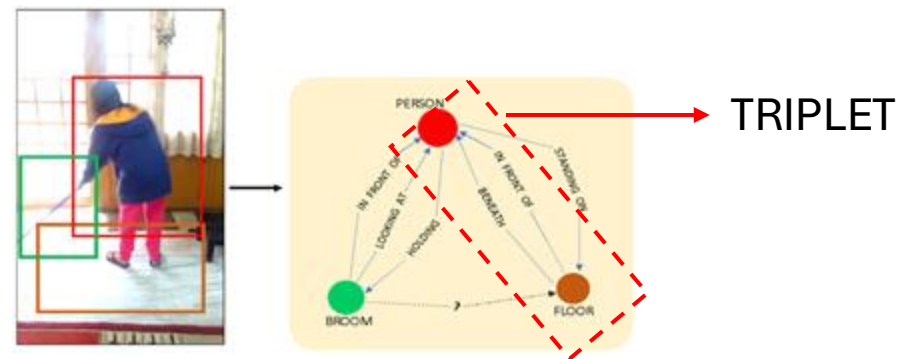


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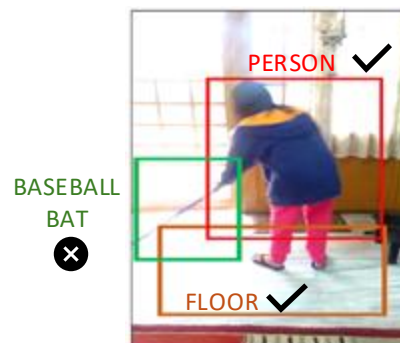
MOTIVATION



Long-tail distribution of Relationships/Predicates



Imprecise or missing scene descriptions



Object detection failure

- Results in generation of noisy scene graphs
- Necessary to quantify the uncertainty of SGG methods in a *post-hoc* manner with statistical guarantees.

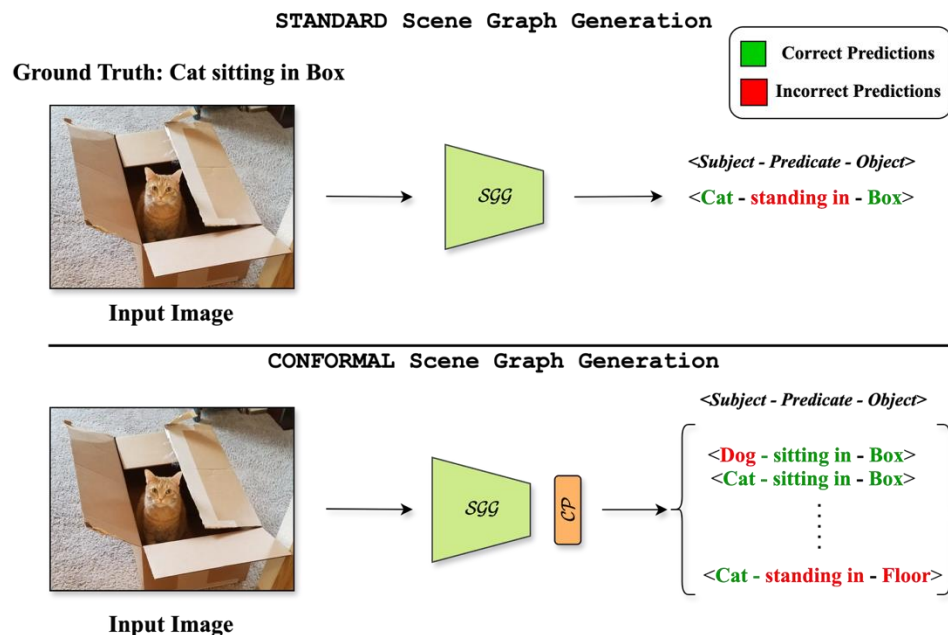
CONFORMAL PREDICTION

OVERVIEW

- Given dataset $\mathcal{D} = \{\mathcal{D}_{tr}, \mathcal{D}_{cal}, \mathcal{D}_{test}\}$
- Under the assumption of exchangeability $\mathcal{D}_{cal} \cup (X_{n+1}, Y_{n+1})$,
 $\square P(Y_{n+1} \in \hat{\mathcal{C}}(X_{n+1})) \geq 1 - \alpha$
- Class-conditional conformal prediction,
 $\square P(Y_{n+1} \in \hat{\mathcal{C}}(X_{n+1}) \mid Y_{n+1} = y) \geq 1 - \alpha_y \quad \forall y \in \mathcal{Y}$

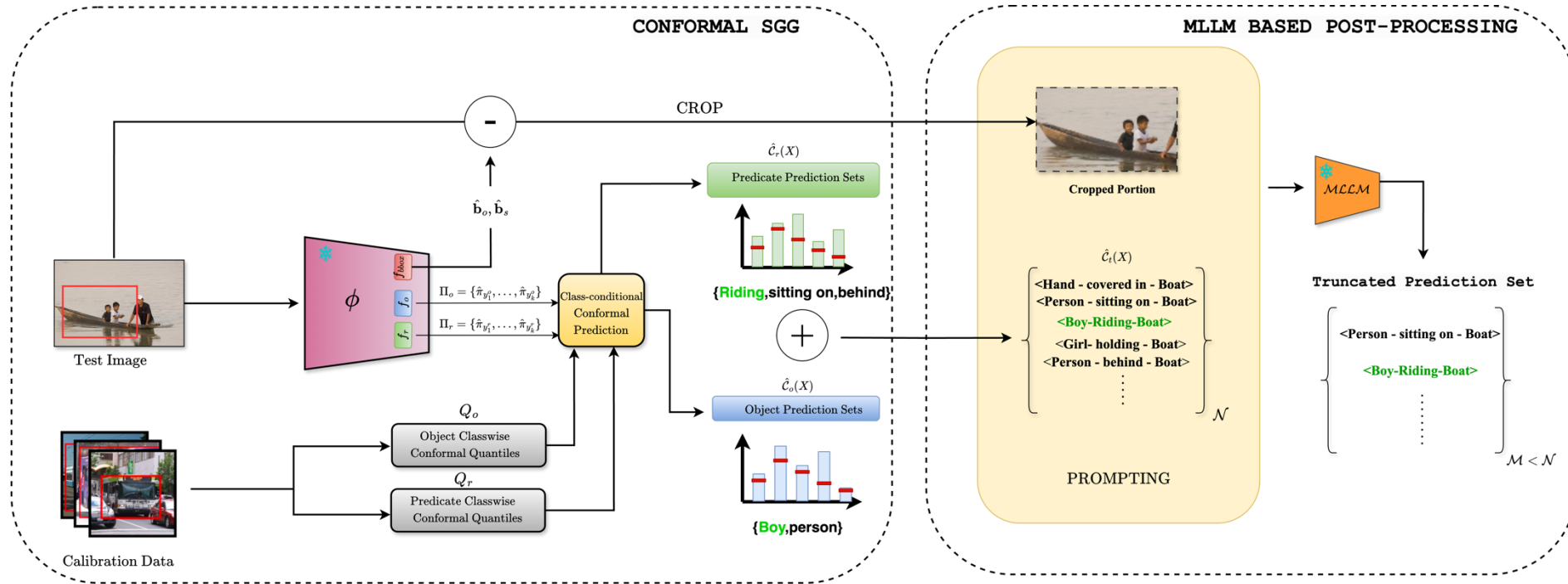
CONFORMAL CALIBRATION

- Design a nonconformity measure $A()$
- Compute class-wise non-conformity scores for samples in \mathcal{D}_{cal}
- Sort class-wise non-conformity scores to obtain $1 - \alpha_y$ th quantile.



FRAMEWORK

Plausibility ensured Conformal SGG or PC-SGG



$$\mathcal{A} : \mathcal{X} \times \mathcal{Y} \rightarrow [0, 1], (\hat{f}(X), y) \mapsto 1 - \hat{\pi}_y(X)$$

Non-conformity measure

$$\hat{\mathcal{C}}_o(X_{n+1}^o) = \{y_k^o \in \mathcal{Y}_o : \hat{\pi}_{y_k^o} \geq 1 - \hat{q}_{y_k^o}\}$$

$$\hat{\mathcal{C}}_r(X_{n+1}^r) = \{y_k^r \in \mathcal{Y}_r : \hat{\pi}_{y_k^r} \geq 1 - \hat{q}_{y_k^r}\}$$

Object and Predicate Conformal Sets

$$\hat{q}_{y_i^o} = \lceil (n_{y_i^o} + 1)(1 - \alpha_o) / n_{y_i^o} \rceil$$

$$\hat{q}_{y_i^r} = \lceil (n_{y_i^r} + 1)(1 - \alpha_r) / n_{y_i^r} \rceil$$

Class-wise calibrated quantile scores

MLLM BASED POST-PROCESSING

System Prompt


You are an AI assistant designed to evaluate the plausibility of visual scene graphs in a given image. For each image, assess multiple-choice statements that describe possible relationships in the scene. Respond only with 'OK' if you understand these instructions.

TEXT PART

Example Prompt

For Example:
Question: Given the image, which of the following scene graphs is most plausible? Answer with a single letter.
A) dog jumping over car
B) **dog standing on car**
C) dog inside house
D) cat standing on car
E) dog flying in sky
F) none of the above
You: B
Response with 'I Understand' if you understand the example and instructions.

VISION PART



- Leverages one shot in context learning in a MCQA setup.
- Compresses prediction sets into most plausible ones.
- MLLM: BLIP2-Flan-T5-XL


INFERENCE SCENARIO

Triplet Prediction Set

Test Sample's Prompt

For Example:
Question: Given the image, which of the following scene graphs is most plausible? Answer with a single letter.
A) hand covered in boat
B) person sitting on boat
C) **boy riding boat**
D) girl holding boat
E) person behind boat
F) none of the above
You:

VISION PART



Token Likelihood Values

$\tau = 0.1$

A: 0.02, B: 0.3, C: 0.6, D: 0.02, E: 0.02, F: 0.01

CONFORMAL SGG COVERAGE GUARANTEE

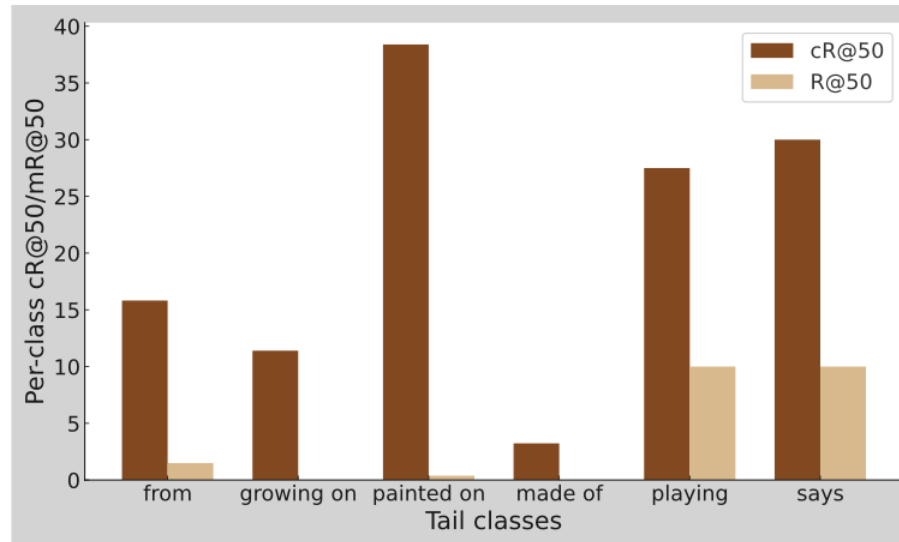
Theorem 1. *Given the ground truth class of the k^{th} triplet is denoted as $y_k^t = [y_k^s, y_k^r, y_k^o] \in \mathbb{R}^3$ where $y_k^s, y_k^o \in \mathcal{Y}_o$ and $y_k^r \in \mathcal{Y}_r$, the triplet coverage guarantee is given as*

$$P(y_k^t \in \hat{\mathcal{C}}_t(X_{n+1}^r)) = P(Y_{n+1}^o \in \hat{\mathcal{C}}_o(X_{n+1}^o) \mid Y_{n+1}^o = y_k^o) \cdot P(Y_{n+1}^r \in \hat{\mathcal{C}}_o(X_{n+1}^r) \mid Y_{n+1}^r = y_k^r) \forall y_k^s \in \mathcal{Y}_o, y_k^o \in \mathcal{Y}_o, y_k^r \in \mathcal{Y}_r.$$

Corollary 1. *Following Theorem 1, $P(y_k^t \in \hat{\mathcal{C}}_t(X_{n+1}^r)) \geq (1 - \alpha_o)(1 - \alpha_r)$, $\forall y_k^s \in \mathcal{Y}_o, y_k^o \in \mathcal{Y}_o, y_k^r \in \mathcal{Y}_r$.*

RESULTS

Method	Objects			Predicates			Triplets
	<i>Cov</i> ↑	<i>CovGap</i> ↓	<i>AvgSize</i> ↓	<i>Cov</i> ↑	<i>CovGap</i> ↓	<i>AvgSize</i> ↓	<i>Cov_T</i> ↑
MOTIFS [57]	88.94	5.8	4.87	84.11	6.2	16.09	74.97
MOTIFS-D [11]	88.94	5.8	4.87	86.67	5.9	16.81	76.67
VCTREE [44]	89.38	5.7	4.23	88.61	5.9	16.41	80.06
SQUAT [20]	90.26	4.9	4.48	90.25	4.6	14.48	80.25
BGNN [26]	90.35	4.8	4.48	89.68	5.2	16.23	80.45



Method	w/o MLLM Plausibility Assessment		w/ MLLM Plausibility Assessment	
	<i>Cov_T</i> ↑	<i>AvgSize</i> ↓	<i>Cov_T</i> ↑	<i>AvgSize</i> ↓
MOTIFS [57]	74.97	866.09	74.97	403.21
MOTIFS-D [11]	76.93	893.21	76.67	411.58
VCTREE [44]	80.06	818.76	80.06	389.24
SQUAT [20]	80.43	816.68	80.25	398.67
BGNN [26]	80.45	971.69	80.45	464.11

Method	R@50	R@100	mR@50	mR@100
MOTIFS [57]	23.61	29.08	4.52	6.22
MOTIFS-D [11]	24.33	30.12	5.26	7.06
VCTREE [44]	26.77	31.46	5.73	7.14
SQUAT [20]	26.81	32.06	9.95	12.05
BGNN [26]	30.07	34.90	9.63	11.92

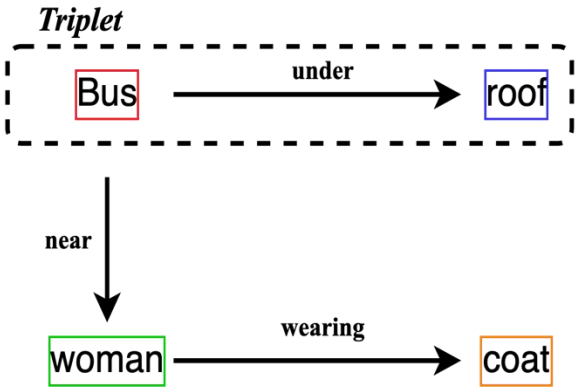
Method+PC-SGG	cR@50	cR@100	cmR@50	cmR@100
MOTIFS [57]	38.45	46.79	25.49	34.03
MOTIFS-D [11]	40.21	47.46	26.17	35.63
VCTREE [44]	41.89	49.90	27.84	36.75
SQUAT [20]	43.23	51.87	30.94	39.23
BGNN [26]	46.32	53.81	32.52	40.36

$$\alpha_o = 0.05, \alpha_r = 0.1$$

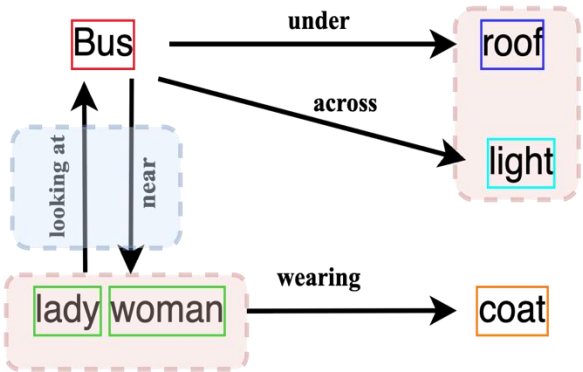
RESULTS



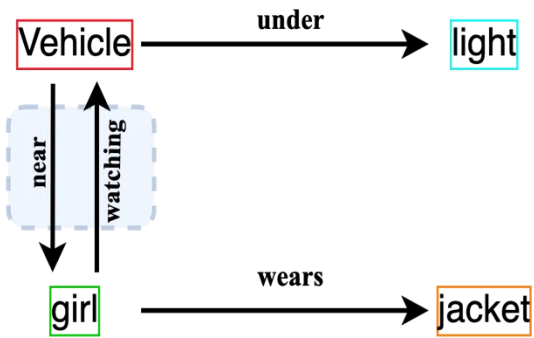
(a) Input Image



(b) Ground Truth



(b) Plausible Scene Graph 1



(c) Plausible Scene Graph 2

: *Object Prediction Set* : *Predicate Prediction Set*

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Poster ID: 99



PAPER