NEURAL INFORMATION PROCESSING SYSTEMS

Jury-and-Judge Chain-of-Thought for Uncovering Toxic Data in 3D Visual Grounding

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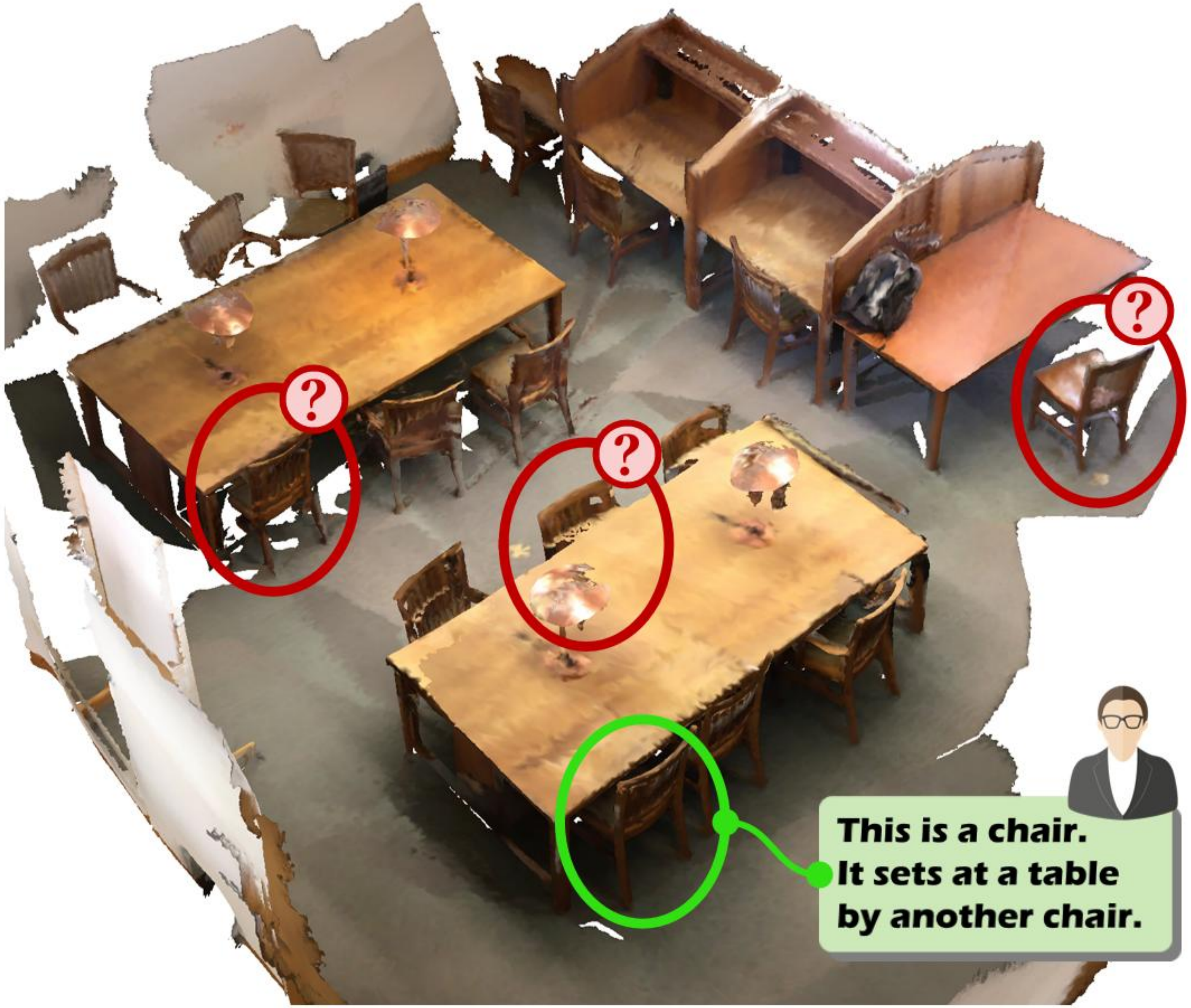
ZHEJIANG UNIVERSITY 1897

CARNEGIE MELLON UNIVERSITY PITTSBURGH PENNSYLVANIA 1900

SINGAPORE MANAGEMENT UNIVERSITY

Motivation



Background

3D Visual Grounding Data Requires:

- Each annotation **uniquely** corresponds to **one object** in the scene.

Bad Annotations

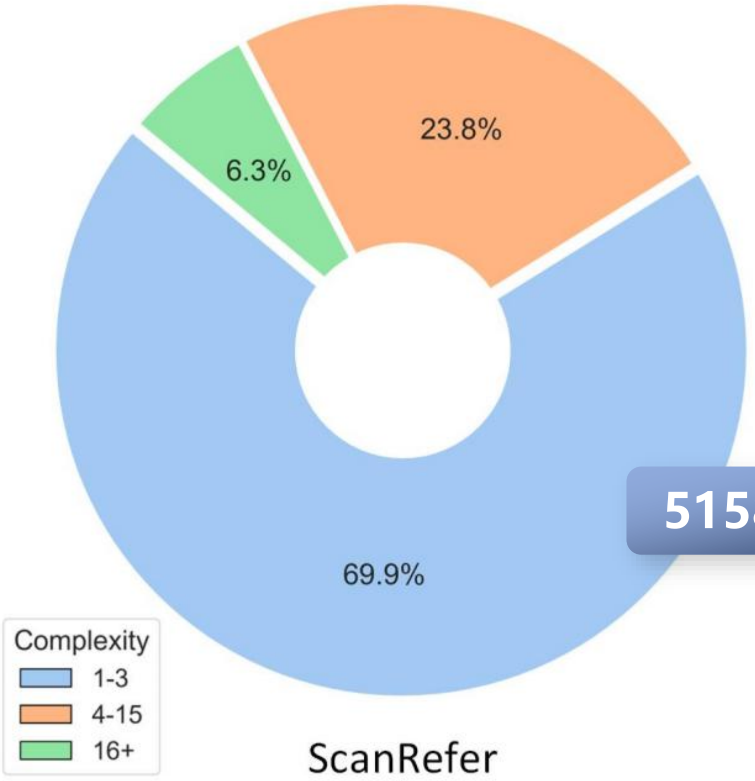
However, the annotation process of 3DVG is difficult and requires sustained focus. Annotators need to extract clues from **sparse 3D point clouds** and **disjointed 2D frames**.

↓

This leads to a sharp increase in the risk of **annotation errors**.

Motivation

So **how serious** is the data problem in 3DVG now?



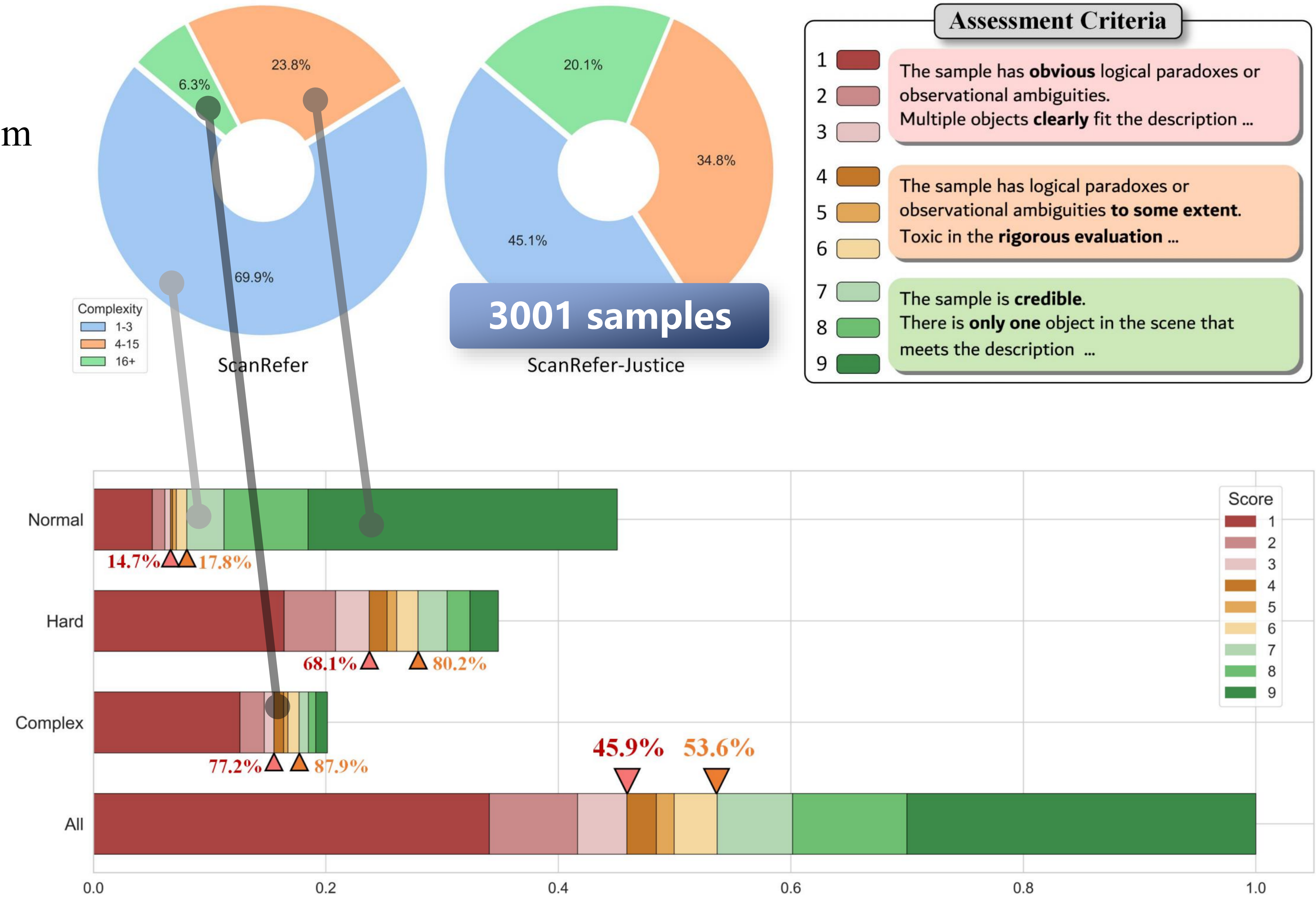
51583 samples

Motivation

So **how serious** is the data problem in 3DVG now?

- As the complexity of the scene increases, the incidence of annotation errors made by annotators **gradually rises**.

- High-confidence annotations for some complex scenes are **even below 50%.**



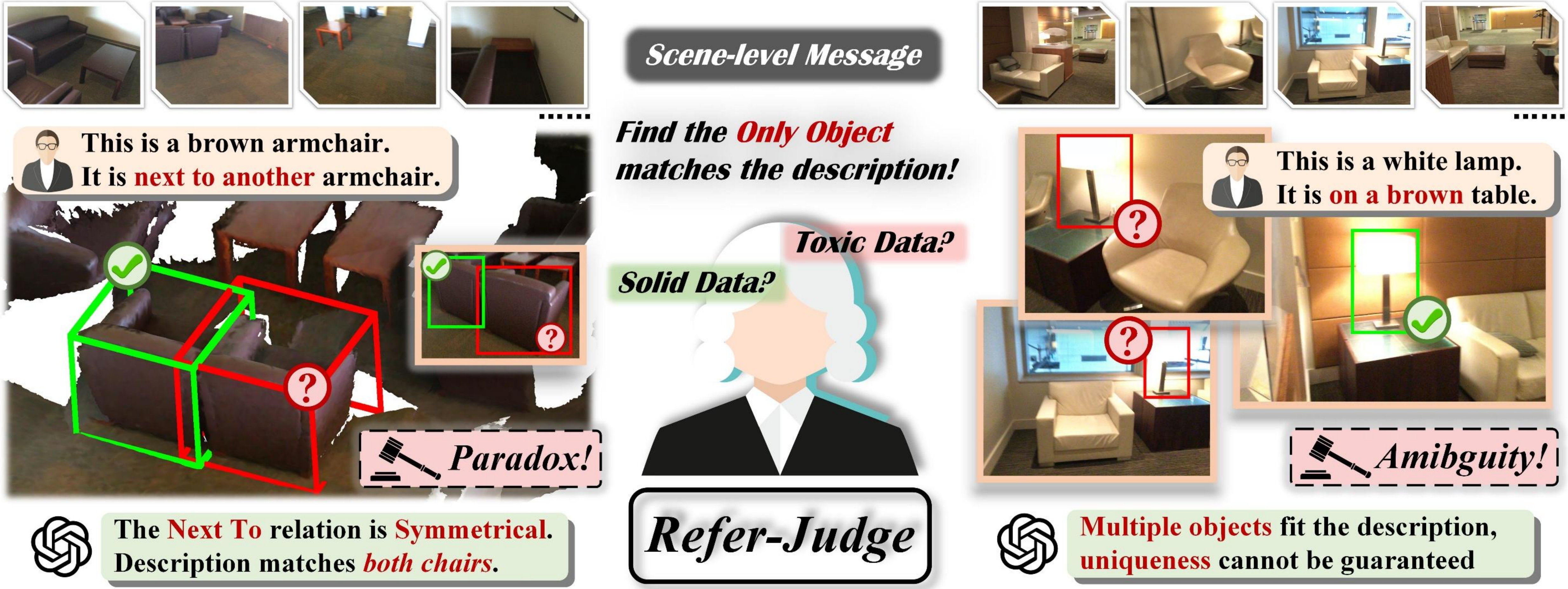
Assessment Criteria

1, 2, 3: The sample has **obvious** logical paradoxes or observational ambiguities. Multiple objects **clearly** fit the description ...

4, 5, 6: The sample has logical paradoxes or observational ambiguities **to some extent**. Toxic in the **rigorous evaluation** ...

7, 8, 9: The sample is **credible**. There is **only one** object in the scene that meets the description ...

Refer-Judge



Scene-level Message

Find the Only Object matches the description!

This is a brown armchair. It is next to another armchair.

Paradox!

The Next To relation is Symmetrical. Description matches *both chairs*.

Solid Data?

Toxic Data?

Refer-Judge

This is a white lamp. It is on a brown table.

Amibguity!

Multiple objects fit the description, uniqueness cannot be guaranteed

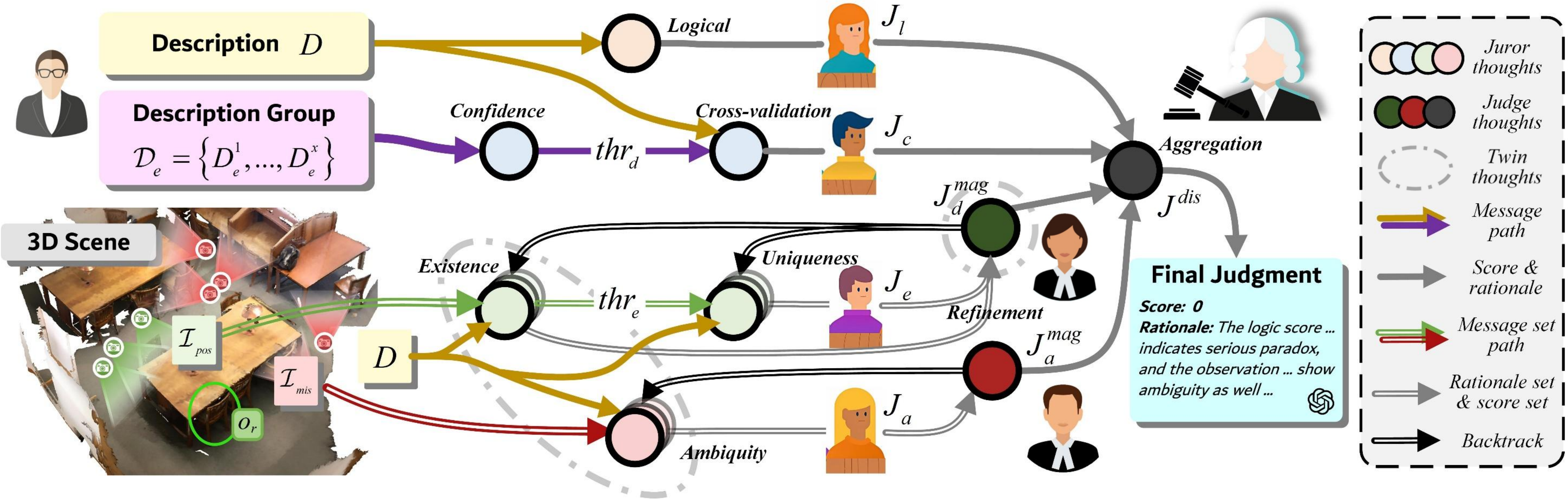
Toxic samples arise from **two sources**:

- ➢ ***Logical paradoxes***
- ➢ ***Referential ambiguities***

Impacts model **training**

Affects algorithm **evaluation**

Refer-Judge



Final Judgment

***Score:* 0**

Rationale: *The logic score ... indicates serious paradox, and the observation ... show ambiguity as well ...*

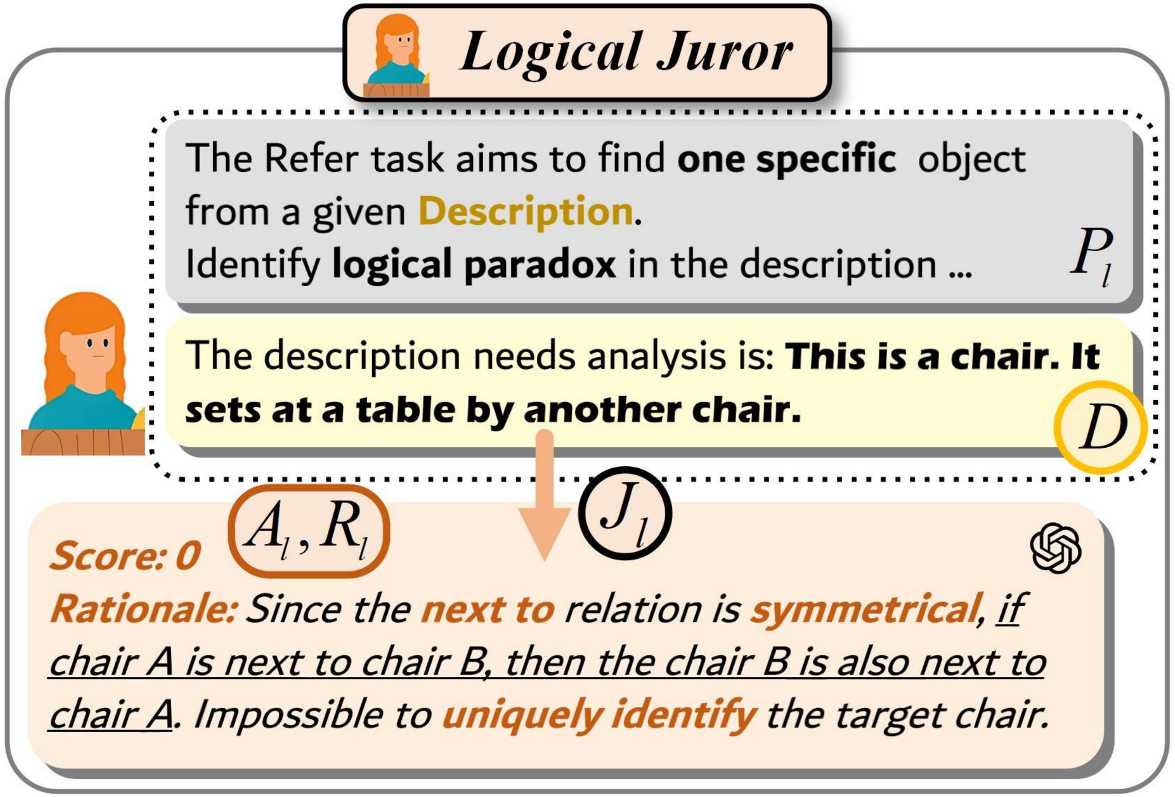
Refer-Judge

- **Hypergraph-of-Thoughts**
- **Agentic framework**
- **Deliberation-based structured analysis**

Jury-and-Judge

- **Jury：** multi-faceted evaluations for scene-level data
- **Judge：** self-consistency evaluation and corroborative refinement
- No task-specific fine-tuning or external perception

Refer-Judge



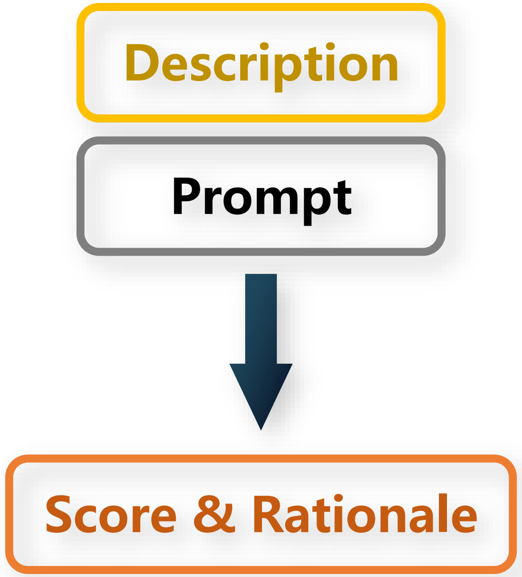
Logical Juror

The Refer task aims to find **one specific** object from a given **Description**.
Identify **logical paradox** in the description ...

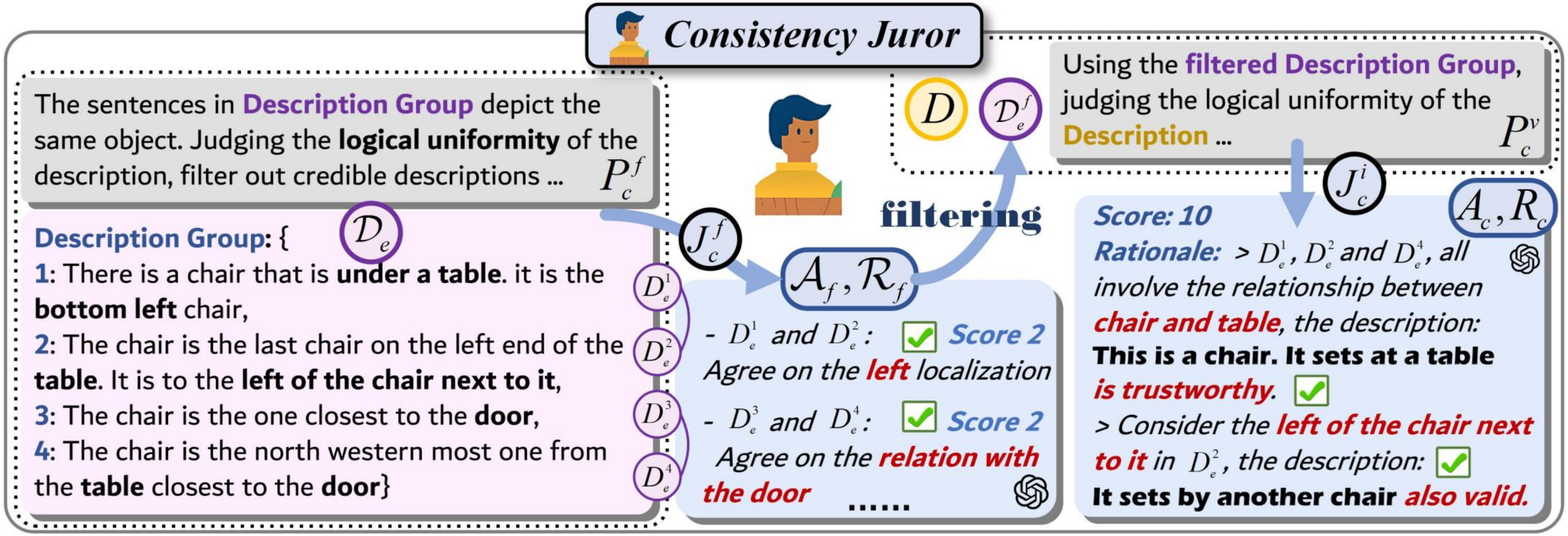
The description needs analysis is: **This is a chair. It sets at a table by another chair.**

Score: 0

Rationale: *Since the* ***next to*** *relation is* ***symmetrical****, if chair A is next to chair B, then the chair B is also next to chair A. Impossible to* ***uniquely identify*** *the target chair.*



Refer-Judge



The sentences in Description Group depict the same object. Judging the **logical uniformity** of the description, filter out credible descriptions ... P_c^f

Description Group: { D_e

1: There is a chair that is **under a table**. it is the **bottom left** chair, D_e^1

2: The chair is the last chair on the left end of the **table**. It is to the **left of the chair next to it**, D_e^2

3: The chair is the one closest to the **door**, D_e^3

4: The chair is the north western most one from the **table** closest to the **door**} D_e^4

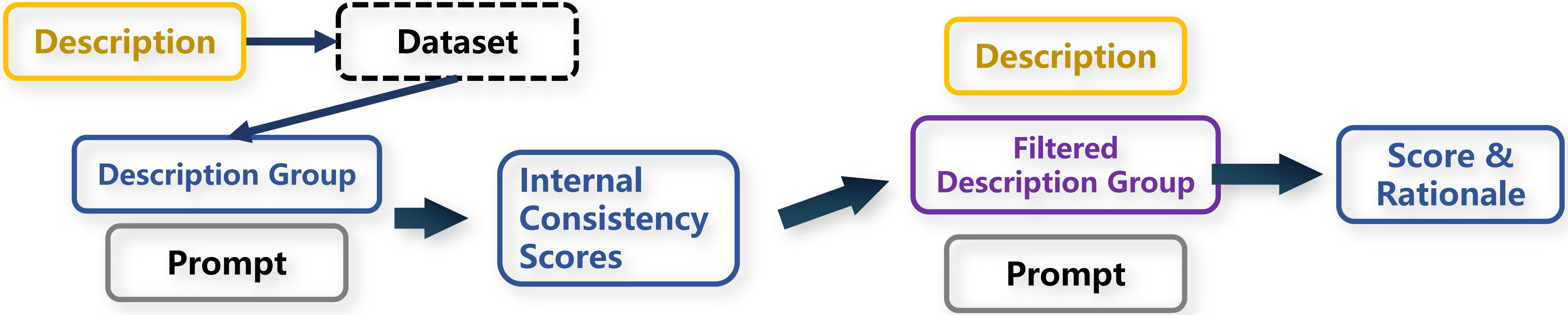
- D_e^1 and D_e^2: ✓ *Score 2*
  Agree on the ***left*** *localization*
- D_e^3 and D_e^4: ✓ *Score 2*
  Agree on the ***relation with the door*** ……

Using the **filtered Description Group**, judging the logical uniformity of the **Description** ... P_c^v

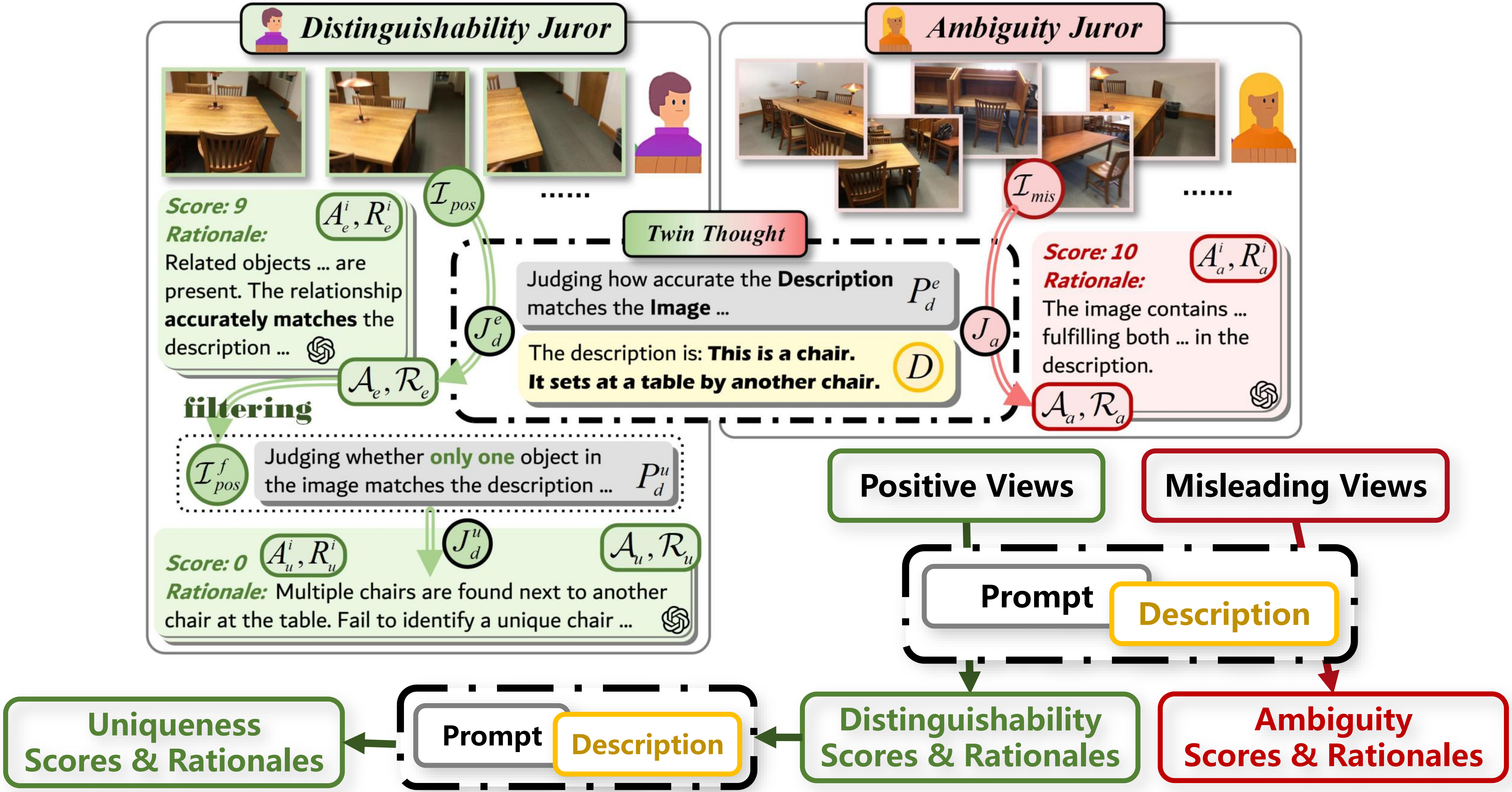
Score: 10

Rationale: *> D_e^1, D_e^2 and D_e^4, all involve the relationship between* ***chair and table****, the description:* **This is a chair. It sets at a table** ***is trustworthy.*** ✓

> Consider the ***left of the chair next to it*** *in D_e^2, the description:* ✓ **It sets by another chair** ***also valid.***



Refer-Judge



Score: 9
Rationale: Related objects ... are present. The relationship **accurately matches** the description ...

Judging how accurate the **Description** matches the **Image** ...

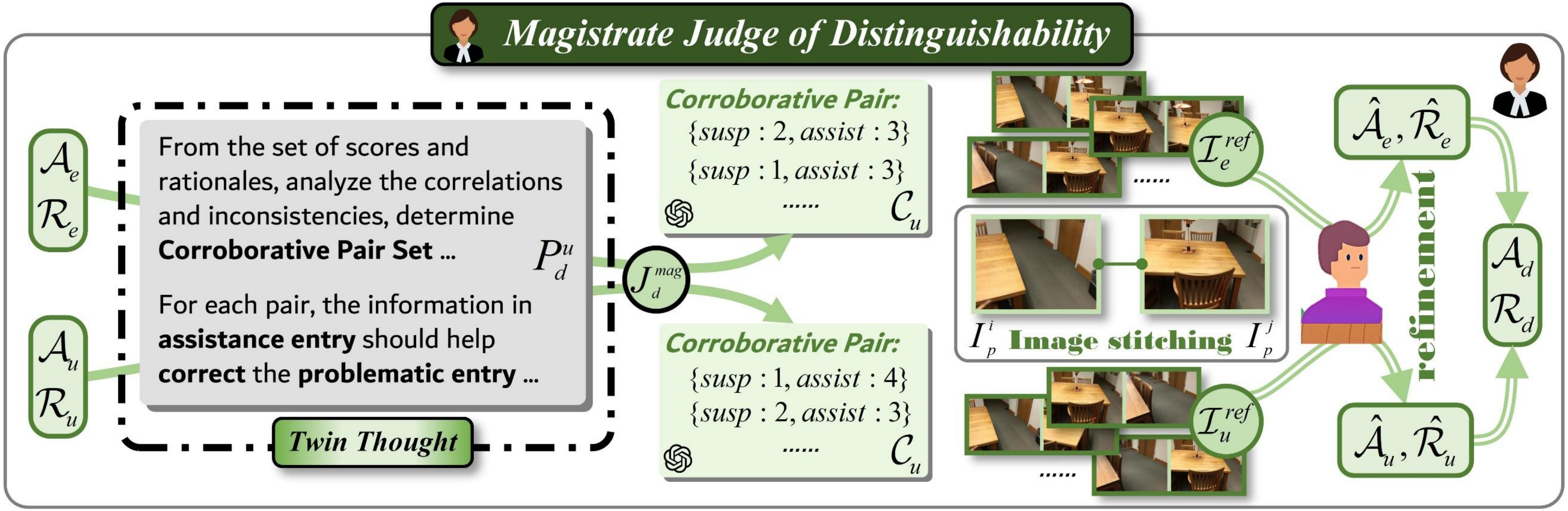
The description is: ***This is a chair. It sets at a table by another chair.***

Score: 10
Rationale: The image contains ... fulfilling both ... in the description.

Judging whether **only one** object in the image matches the description ...

Score: 0
Rationale: Multiple chairs are found next to another chair at the table. Fail to identify a unique chair ...

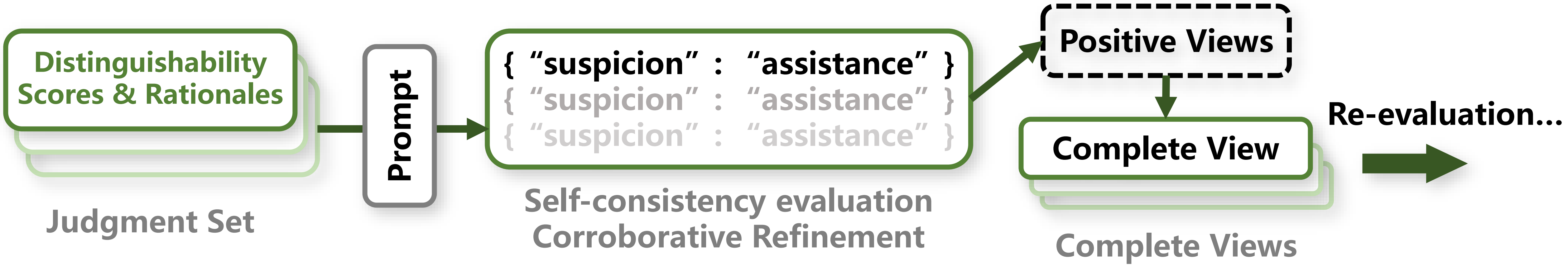
Refer-Judge



Magistrate Judge of Distinguishability

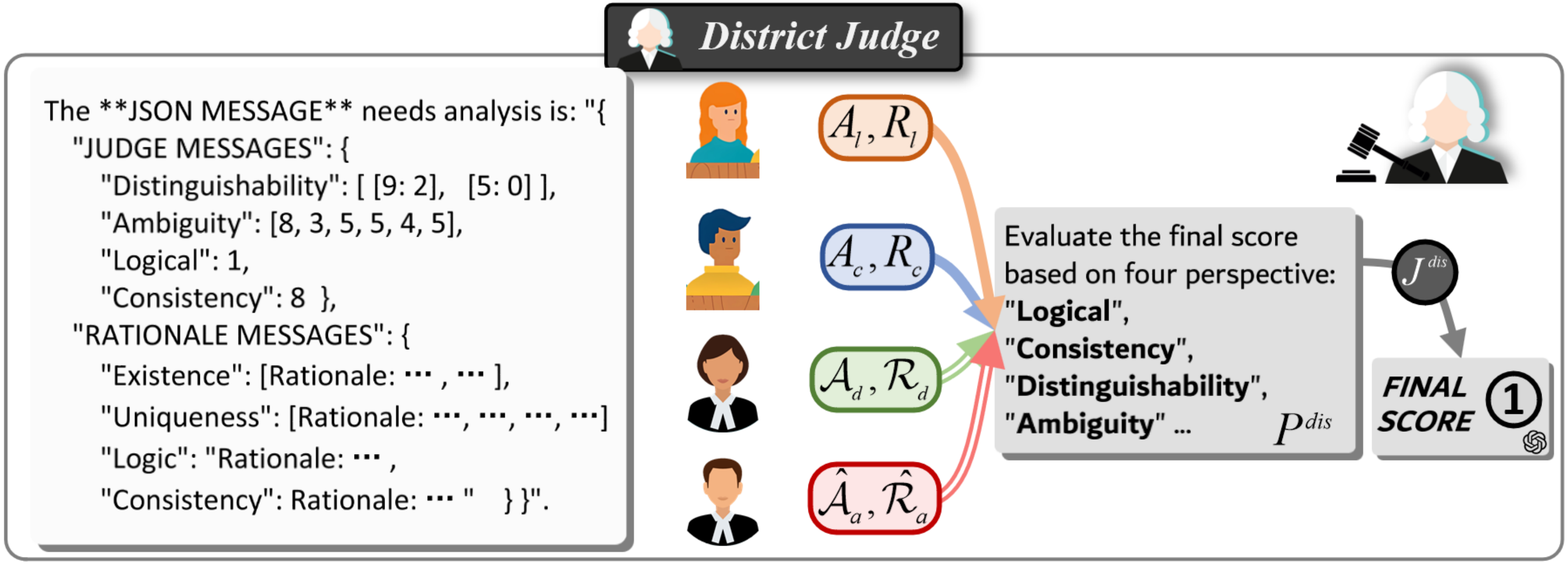
From the set of scores and rationales, analyze the correlations and inconsistencies, determine **Corroborative Pair Set ...**

For each pair, the information in **assistance entry** should help **correct** the **problematic entry ...**



Distinguishability Scores & Rationales
Judgment Set
Prompt
{ "suspicion" : "assistance" }
{ "suspicion" : "assistance" }
{ "suspicion" : "assistance" }
Self-consistency evaluation
Corroborative Refinement
Positive Views
Complete View
Complete Views
Re-evaluation...

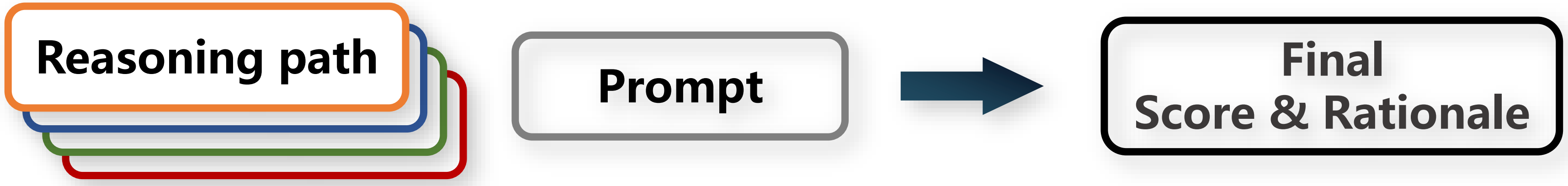
Refer-Judge



District Judge

```
The **JSON MESSAGE** needs analysis is: "{
   "JUDGE MESSAGES": {
      "Distinguishability": [ [9: 2],   [5: 0] ],
      "Ambiguity": [8, 3, 5, 5, 4, 5],
      "Logical": 1,
      "Consistency": 8  },
   "RATIONALE MESSAGES": {
      "Existence": [Rationale: ··· , ··· ],
      "Uniqueness": [Rationale: ···, ···, ···, ···]
      "Logic": "Rationale: ··· ,
      "Consistency": Rationale: ··· "    } }".
```

Evaluate the final score based on four perspective: **"Logical", "Consistency", "Distinguishability", "Ambiguity"** ... P^{dis}

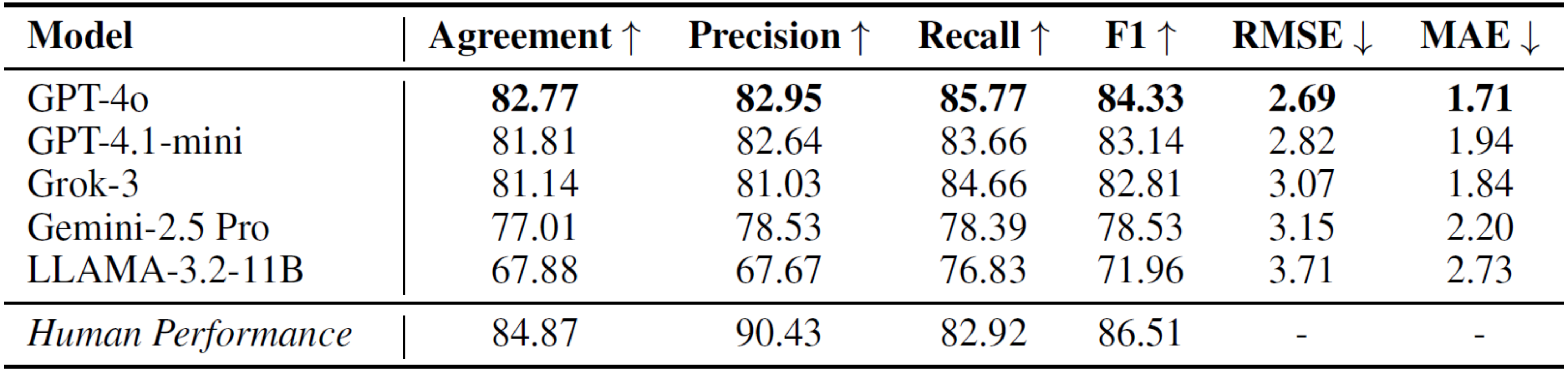


Reasoning path

Prompt

Final Score & Rationale

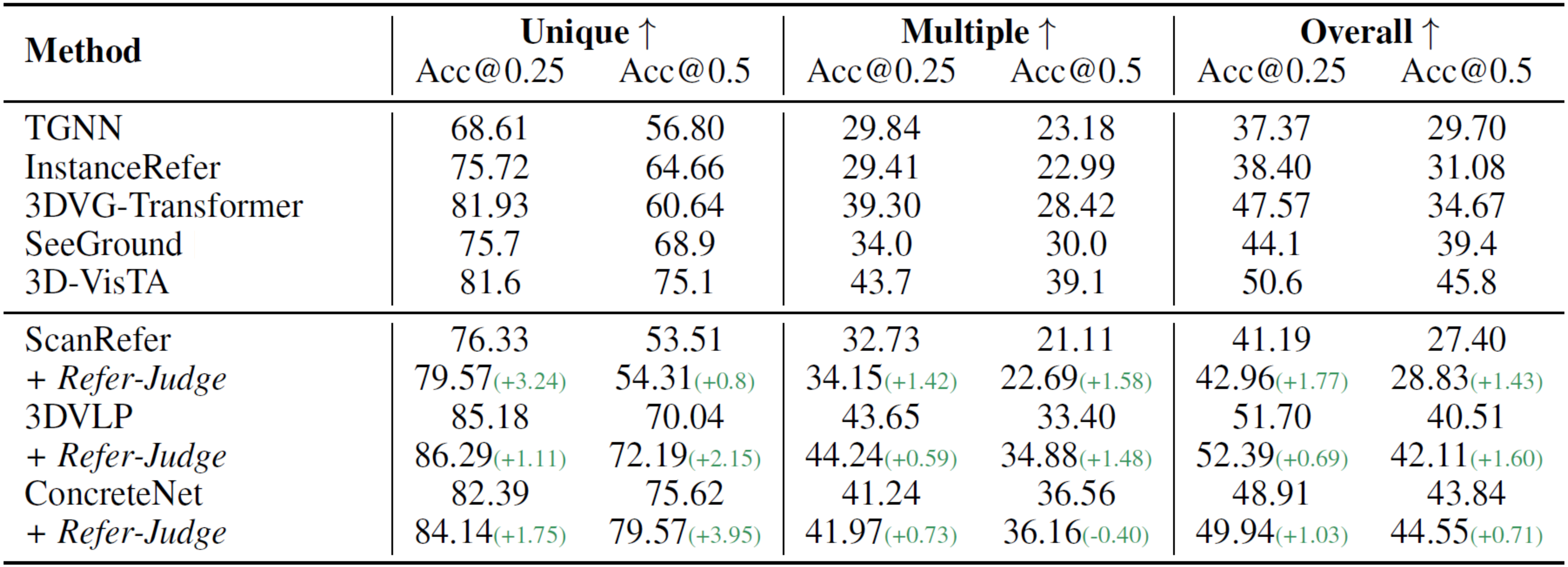
Experiment



Model	Agreement ↑	Precision ↑	Recall ↑	F1 ↑	RMSE ↓	MAE ↓
GPT-4o	**82.77**	**82.95**	**85.77**	**84.33**	**2.69**	**1.71**
GPT-4.1-mini	81.81	82.64	83.66	83.14	2.82	1.94
Grok-3	81.14	81.03	84.66	82.81	3.07	1.84
Gemini-2.5 Pro	77.01	78.53	78.39	78.53	3.15	2.20
LLAMA-3.2-11B	67.88	67.67	76.83	71.96	3.71	2.73
Human Performance	84.87	90.43	82.92	86.51	-	-

- ➢ Refer-Judge achieves **human-level judgment capability**, slightly lagging with human experts.
- ➢ The Refer-Judge algorithm can **generalize** to multiple models.
- ➢ Better base models result in better performance.

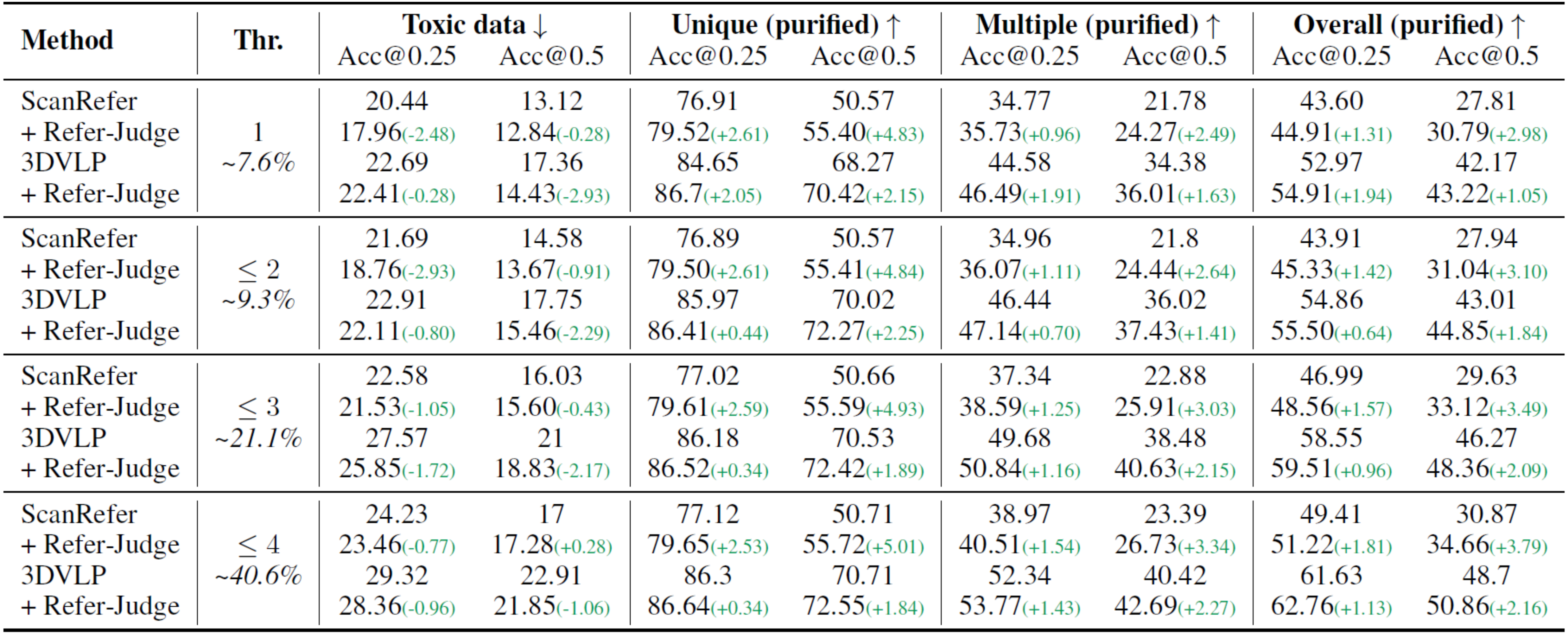
Experiment



Method	Unique ↑		Multiple ↑		Overall ↑	
	Acc@0.25	Acc@0.5	Acc@0.25	Acc@0.5	Acc@0.25	Acc@0.5
TGNN	68.61	56.80	29.84	23.18	37.37	29.70
InstanceRefer	75.72	64.66	29.41	22.99	38.40	31.08
3DVG-Transformer	81.93	60.64	39.30	28.42	47.57	34.67
SeeGround	75.7	68.9	34.0	30.0	44.1	39.4
3D-VisTA	81.6	75.1	43.7	39.1	50.6	45.8
ScanRefer	76.33	53.51	32.73	21.11	41.19	27.40
+ *Refer-Judge*	79.57(+3.24)	54.31(+0.8)	34.15(+1.42)	22.69(+1.58)	42.96(+1.77)	28.83(+1.43)
3DVLP	85.18	70.04	43.65	33.40	51.70	40.51
+ *Refer-Judge*	86.29(+1.11)	72.19(+2.15)	44.24(+0.59)	34.88(+1.48)	52.39(+0.69)	42.11(+1.60)
ConcreteNet	82.39	75.62	41.24	36.56	48.91	43.84
+ *Refer-Judge*	84.14(+1.75)	79.57(+3.95)	41.97(+0.73)	36.16(-0.40)	49.94(+1.03)	44.55(+0.71)

- After **removing the toxic data** from the ScanRefer training set, all baseline achieving **consistent improvements**.

Experiment



Method	Thr.	Toxic data ↓		Unique (purified) ↑		Multiple (purified) ↑		Overall (purified) ↑	
		Acc@0.25	Acc@0.5	Acc@0.25	Acc@0.5	Acc@0.25	Acc@0.5	Acc@0.25	Acc@0.5
ScanRefer		20.44	13.12	76.91	50.57	34.77	21.78	43.60	27.81
+ Refer-Judge	1	17.96(-2.48)	12.84(-0.28)	79.52(+2.61)	55.40(+4.83)	35.73(+0.96)	24.27(+2.49)	44.91(+1.31)	30.79(+2.98)
3DVLP	~*7.6%*	22.69	17.36	84.65	68.27	44.58	34.38	52.97	42.17
+ Refer-Judge		22.41(-0.28)	14.43(-2.93)	86.7(+2.05)	70.42(+2.15)	46.49(+1.91)	36.01(+1.63)	54.91(+1.94)	43.22(+1.05)
ScanRefer		21.69	14.58	76.89	50.57	34.96	21.8	43.91	27.94
+ Refer-Judge	≤ 2	18.76(-2.93)	13.67(-0.91)	79.50(+2.61)	55.41(+4.84)	36.07(+1.11)	24.44(+2.64)	45.33(+1.42)	31.04(+3.10)
3DVLP	~*9.3%*	22.91	17.75	85.97	70.02	46.44	36.02	54.86	43.01
+ Refer-Judge		22.11(-0.80)	15.46(-2.29)	86.41(+0.44)	72.27(+2.25)	47.14(+0.70)	37.43(+1.41)	55.50(+0.64)	44.85(+1.84)
ScanRefer		22.58	16.03	77.02	50.66	37.34	22.88	46.99	29.63
+ Refer-Judge	≤ 3	21.53(-1.05)	15.60(-0.43)	79.61(+2.59)	55.59(+4.93)	38.59(+1.25)	25.91(+3.03)	48.56(+1.57)	33.12(+3.49)
3DVLP	~*21.1%*	27.57	21	86.18	70.53	49.68	38.48	58.55	46.27
+ Refer-Judge		25.85(-1.72)	18.83(-2.17)	86.52(+0.34)	72.42(+1.89)	50.84(+1.16)	40.63(+2.15)	59.51(+0.96)	48.36(+2.09)
ScanRefer		24.23	17	77.12	50.71	38.97	23.39	49.41	30.87
+ Refer-Judge	≤ 4	23.46(-0.77)	17.28(+0.28)	79.65(+2.53)	55.72(+5.01)	40.51(+1.54)	26.73(+3.34)	51.22(+1.81)	34.66(+3.79)
3DVLP	~*40.6%*	29.32	22.91	86.3	70.71	52.34	40.42	61.63	48.7
+ Refer-Judge		28.36(-0.96)	21.85(-1.06)	86.64(+0.34)	72.55(+1.84)	53.77(+1.43)	42.69(+2.27)	62.76(+1.13)	50.86(+2.16)

- A more significant improvement in model performance can be observed on the **purified validation set**.
- The **original model** outperforms the purified model on toxic validation set (*due to toxic prior knowledge*).

Thanks for watching