



# RS2G: Data-Driven Scene-Graph Extraction and Embedding for Robust Autonomous Perception and Scenario Understanding

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## **An Overview of Autonomous Driving**



#### RS2G focuses on subject risk assessment.





### **Keyword: Relations**



Effectively modeling the **relations** among road users is very important for autonomous vehicle to understand the surrounding environment.



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#### Data-Driven Scene-Graph vs. Rule-Based Scene-Graph





### **RS2G Workflow**





## **Data-Driven Scene-Graph Extraction**

Algorithm 1: Data-Driven Scene-Graph Extraction1 Input: Objects  $\mathcal{O}_t$  and their attributes  $\mathcal{D}_t$  at time t.2 Output: Scene-graph  $\mathcal{G}_t$  at time t.3 def  $\Psi$  ( $\mathcal{O}_t, \mathcal{D}_t$ ):4 $\mathcal{H}_t \leftarrow \emptyset, \mathcal{A}_t \leftarrow \mathbf{0}_{n \times n}$ 5for  $o_j, \mathbf{d}_j \in \mathcal{O}_t, \mathcal{D}_t$  do

 12
  $\mathcal{G}_t \leftarrow \{\mathcal{H}_t, \mathcal{A}_t\}$  

 13
 return  $\mathcal{G}_t$ 



## **Experimental Result**

#### Subjective Risk Assessment

• Transfer Learning

Dataset	Graph Extraction	Accuracy	MCC	AUC							
271-carla	None	73.17%	0.1887	0.8043	Dataset	Graph	Accuracy	MCC	AUC		
	Rule-Based	82.93%	0.5173	0.8098		Extraction					
	RS2G (1D MLP)	84.51%	0.2093	0.9338		None	52 58%	0.0333	0 5126		
	RS2G (2D MLP)	86.59%	0.468	0.9578	071 1		J2.J0 10	0.0333	0.5120		
	RS2G (Transformer)	84.15%	0.402	0.9362	271-carla	Rule-Based	48.22%	0.0238	0.4975		
1043-carla	None	71.66%	0.1111	0.7173	to 620-dash	RS2G(2D MLP)	57.25%	0.1398	0.5669		
	Rule-Based	91.43%	0.7217	0.971		RS2G(Transformer)	<b>64.68</b> %	0.2957	0.6831		
	RS2G (1D MLP)	91.72%	0.6840	0.9643	1042 carla	None	49.03%	-0.0432	0.4999		
	RS2G (2D MLP)	93.31%	0.7426	0.7949		Pule Based	50.06%	0.0021	0 5003		
	RS2G (Transformer)	97.13%	0.8823	0.9686	10 <del>4</del> 5-curiu		J0.90%	0.0021	0.5095		
1361-honda	None	60.39%	0.0391	0.7110	to 620-dash	RS2G(2D MLP)	60.65%	0.2089	0.6265		
	Rule-Based	86.31%	0.2445	0.9341		RS2G (Transformer)	66.29%	0.3293	0.6964		
	RS2G (1D MLP)	87.04%	0.1626	0.9315							
	RS2G (2D MLP)	89.00%	0.3029	0.9383	Transfer Learning comparison between (i) the SOTA deep learning						
	RS2G (Transformer)	89.98%	0.404	0.9495	model, (ii) the SOTA graph learning model with rule-based graph						
620-dash	None	48.92%	-0.1749	0.5256	extraction, and (iii) RS2G(2D MLP) and RS2G(Transformer)						
	Rule-Based	67.20%	0.3428	0.6966							
	RS2G (1D MLP)	68.82%	0.3967	0.7403							
	RS2G (2D MLP)	72.04%	0.4398	0.8047							
	RS2G (Transformer)	68.28%	0.3635	0.7354							

Comparing experimental result for subjective risk assessment.



### **Ablation Study I: Downstream Component Analysis**

Graph	Spatial	Temporal	Accuracy	MCC	AUC
Extraction	Model	Model			
Rule-Based	MLP	mean	52.15%	0.0000	0.4973
Rule-Based	MLP	LSTM	62.90%	0.2741	0.6811
Rule-Based	MRGCN	mean	63.44%	0.2696	0.6867
Rule-Based	MRGCN	LSTM	75.27%	0.5197	0.8248
RS2G	MLP	mean	81.74%	0.1857	0.9228
RS2G	MLP	LSTM	81.45%	0.402	0.9472
RS2G	MRGCN	mean	87.80%	0.5403	0.9468
RS2G	MRGCN	LSTM	84.15%	0.402	0.9362

Impact of each component of the downstream model. Models are trained and evaluated on the 271-dash dataset. We demonstrate the impact of different spatial and temporal modules using rule-based graph extraction and RS2G (Transformer).





## **Ablation Study II: Cosine Relation Similarity**











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#### Open-sourced code at <a href="https://github.com/AICPS/RS2G.git">https://github.com/AICPS/RS2G.git</a>

