## **CompoVis:** Probing the Compositional Understanding in VLMs with Visualization Representation and Insights

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In vision-language research, "compositional understanding" refers to the ability of a model to jointly handle images and texts.

The model should be able to recognize, comprehend and align each component in vision and textual modality (such as *"red"*, *"hydrant"*, *"man"*) and their combination (the scene semantics of *"a man in white T-shirt leans on a red hydrant"*).

Recent studies reveal even advanced vision-language models (VLMs) struggle with "compositional understanding", particularly when dealing with fine-grained linguistic phenomena.

As shown in the figure, CLIP assigns higher scores to the permutation caption. Computer vision methods focus on quantitative metrics and model architectures, constrained by closed datasets and predefined parameters.

To our knowledge, we are the first to elucidate the "bag-of-objects" behavior of VLMs from a visualization perspective. In summary, the contributions of our paper are as follows:

We introduce a visual analysis tool that supports non-expert users in exploring comprehension defects in VLMs, promoting user-guided fine-tuning evaluation.



## vision-linguistic compositionality

➤ We optimize the topological layout to enhance the visual proximity between semantically consistent samples in largescale data, providing a reference for grid layout in the visualization community.

We introduce a permutation dataset, supporting the visual probing of cross-modal alignment ability, and facilitating human-inthe-loop alignment evaluation.



02 Pipeline







## 04 Evaluation

The table compares self-organizing map (SOM), resource-controlled selforganizing map (RC-SOM), and HERC-SOM (ours) in terms of quantization error (QE), topological error (TE), boundary entropy (BE), and neuron activation ratio (NA).

Methods	Indicators			
	QE.	TE.	BE.	NA.
SOM	3.899	0.032	1.113	0.310





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