

MULTIINSTRUCT: Improving Multi-Modal Zero-Shot Learning via Instruction Tuning

Zhiyang Xu*, Ying Shen*, Lifu Huang

Computer Science Department
Virginia Tech



Motivation

Instruction tuning has shown promising zero-shot performance on various natural language processing tasks. However, it has yet to be explored for vision and multimodal tasks. In this work, we introduce MultiInstruct, the first multimodal instruction tuning benchmark dataset.

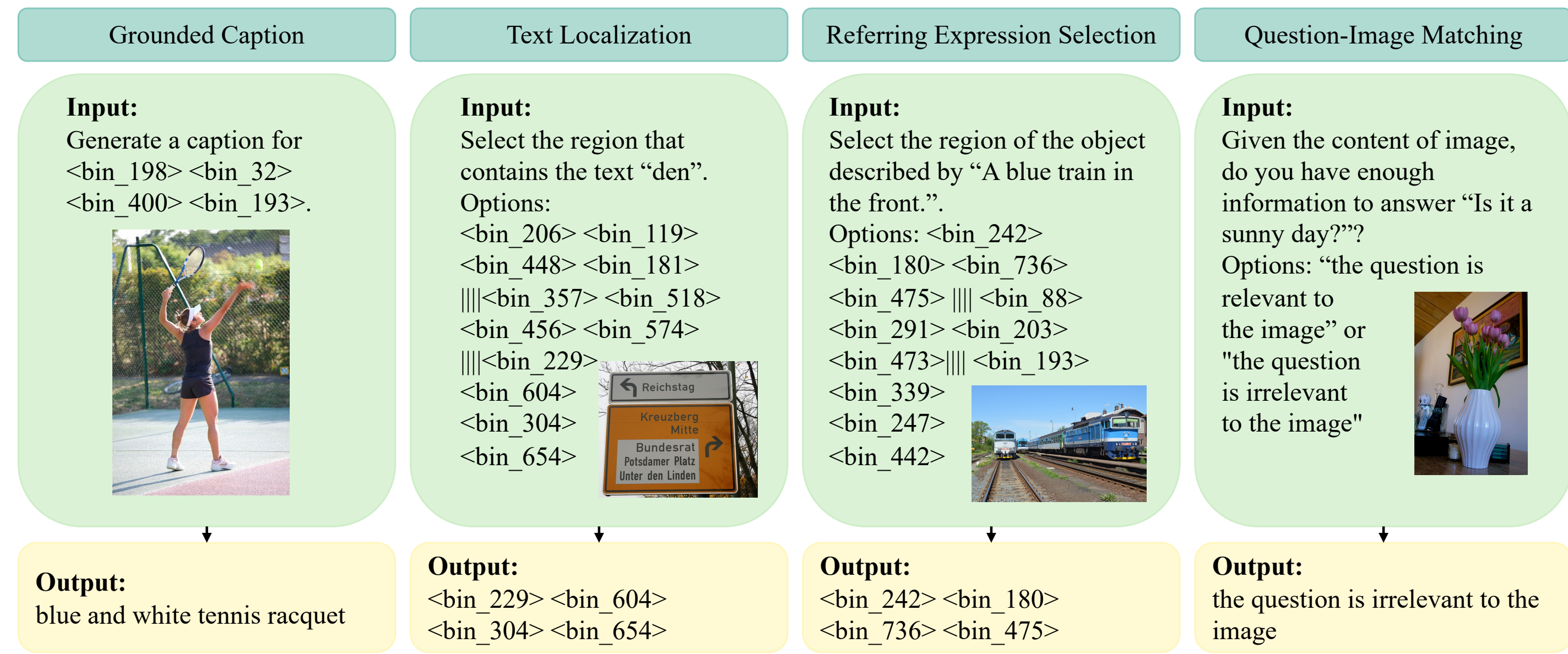


Figure 1. Example Instances from MultiInstruct for Four Tasks.

MULTIINSTRUCT

MultiInstruct, the first multimodal instruction tuning benchmark dataset, consists of 62 diverse multimodal tasks in a unified seq-to-seq format covering 10 broad categories. The tasks are derived from 21 existing open-source datasets and each task is equipped with 5 expert-written instructions.

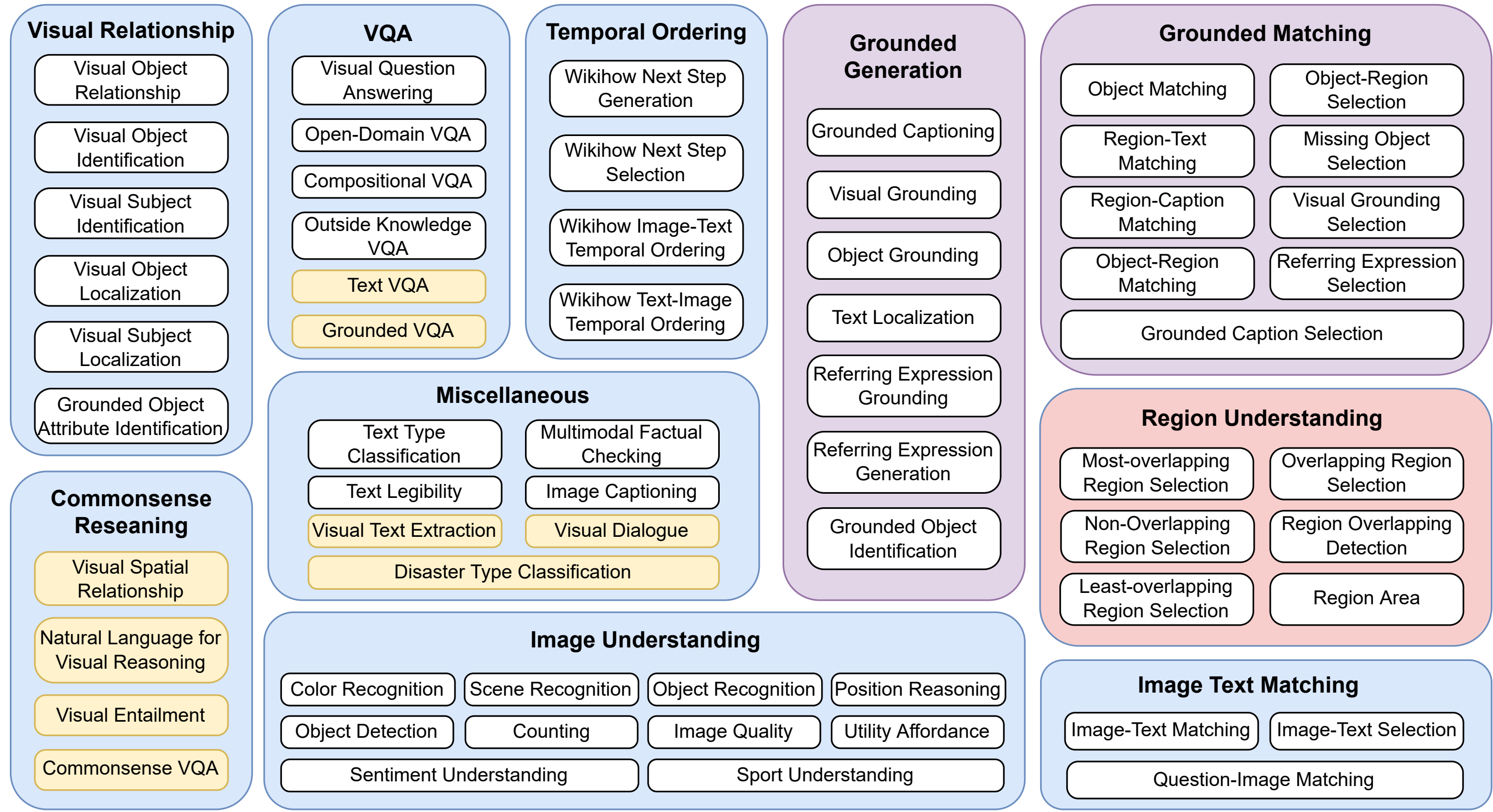


Figure 2. Task Groups Included in MultiInstruct. The yellow boxes represent tasks used for evaluation, while the white boxes indicate tasks used for training.

Multimodal Instruction Tuning

- We finetune OFA on 53 tasks from the MultiInstruct dataset and evaluate it on 9 unseen tasks.
- We explore multiple transfer learning strategies to leverage the large-scale Natural Instructions dataset and propose the following strategies.

Multimodal Instruction Tuning (OFA_{MultiInstruct}) finetunes OFA on MultiInstruct.

Mixed Instruction Tuning (OFA_{MixedInstruct}) finetunes OFA on the mixture of MultiInstruct and Natural Instructions.

Sequential Instruction Tuning (OFA_{SeqInstruct}) first finetunes OFA on Natural Instructions and then on MultiInstruct.

- We also design a new evaluation metric – *Sensitivity*, to evaluate how sensitive the model is to the variety of instructions.

Effectiveness of Instruction Tuning on MULTIINSTRUCT

- Experimental results demonstrate strong zero-shot performance on various unseen multimodal tasks and the benefit of transfer learning from a text-only instruction dataset.
- Our results indicate that fine-tuning the model on a diverse set of tasks and instructions leads to a reduced sensitivity to variations in instructions for each task.

Model	Commonsense VQA				Visual Entailment		Visual Spatial Reasoning		NLVR	
	RougeL		ACC		ACC		ACC		ACC	
	Max	Avg ± Std	Max	Avg ± Std	Max	Avg ± Std	Max	Avg ± Std	Max	Avg ± Std
OFA	17.93	14.97 ± 4.30	0.73	0.40 ± 0.29	49.99	41.86 ± 10.99	54.99	35.29 ± 22.21	56.06	52.10 ± 3.35
OFA _{TaskName}	48.99	-	29.01	-	55.70	-	53.76	-	55.35	-
OFA _{MultiInstruct}	52.01	50.60 ± 1.12	33.01	31.17 ± 1.59	55.96	55.06 ± 0.76	55.81	53.90 ± 1.38	56.97	56.18 ± 0.95
Transfer Learning from Natural Instructions										
OFA _{NaturalInstruct}	27.15	14.99 ± 9.12	7.35	2.04 ± 3.01	33.28	14.86 ± 16.68	51.44	36.44 ± 20.72	56.06	35.98 ± 21.64
OFA _{MixedInstruct}	50.40	49.34 ± 1.04	31.31	30.27 ± 0.94	54.63	53.74 ± 0.97	55.13	52.61 ± 1.64	56.67	55.96 ± 0.48
OFA _{SeqInstruct}	50.93	50.07 ± 1.07	32.28	31.23 ± 1.09	53.66	52.98 ± 0.56	54.86	53.11 ± 1.45	57.58	56.63 ± 0.66

Table 1. Zero-shot Performance on Multimodal Commonsense Reasoning. The best performance is in bold.

Model	Text VQA				Grounded VQA	
	RougeL		ACC		ACC	
	Max	Avg ± Std	Max	Avg ± Std	Max	Avg ± Std
OFA	15.21	9.30 ± 5.42	12.32	7.96 ± 4.20	0.02	0.00 ± 0.01
OFA _{TaskName}	23.80	-	20.02	-	0.00	-
OFA _{MultiInstruct}	27.22	26.46 ± 0.83	22.70	22.00 ± 0.70	64.32	47.22 ± 23.08
Transfer Learning from Natural Instructions						
OFA _{NaturalInstruct}	5.59	5.40 ± 0.24	4.18	3.78 ± 0.27	0.00	0.00 ± 0.00
OFA _{MixedInstruct}	24.15	23.67 ± 0.47	20.10	19.62 ± 0.46	63.79	54.99 ± 18.16
OFA _{SeqInstruct}	27.03	26.67 ± 0.47	22.64	22.28 ± 0.46	64.19	54.46 ± 15.96

Table 2. Zero-shot Performance on Question Answering datasets. The best performance is in bold.

Impact of Increasing Multimodal Instruction Task Clusters

As we increase the number of task clusters, we observe an improvement in both the mean and maximum aggregated performance and a decrease in *sensitivity*.

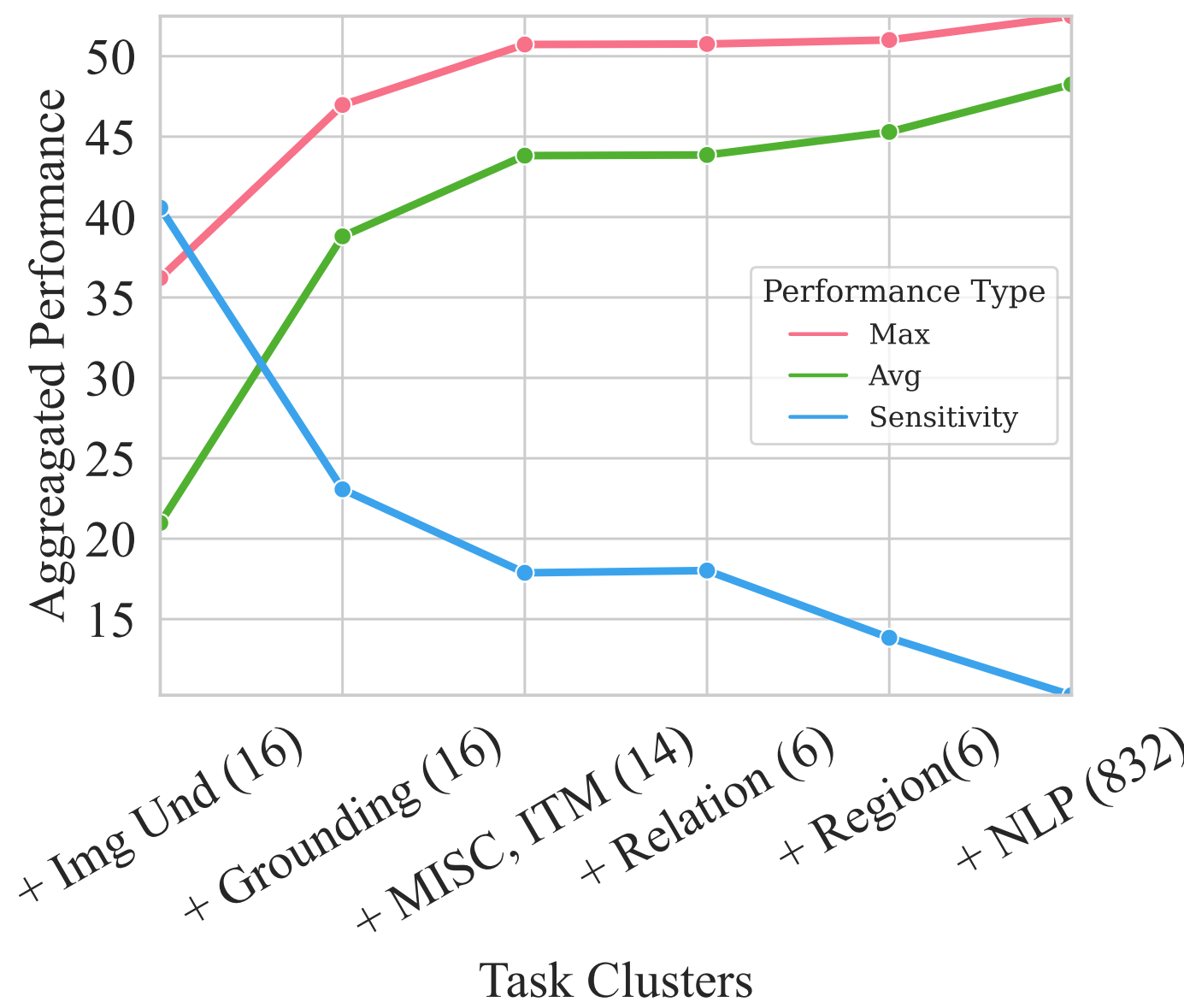


Figure 3. Model Performance as the Number of Multimodal Instruction Task Clusters Increases. The number in the parenthesis of each cluster denotes the number of tasks.

Effect of Diverse Instructions on Instruction Tuning

OFA finetuned on 5 instructions achieves much higher aggregated performance on all evaluation tasks and shows lower sensitivity.

# of Instructions	Aggregated Performance ↑	Sensitivity ↓
1 Instruction	42.81	24.62
5 Instructions	47.82	10.45

Table 3. Effect of Different Number of Instructions. Performance of OFA_{MultiInstruct} finetuned on different numbers of instructions.

Effect of Fine-tuning Strategies on Model Sensitivity

- Instruction tuning on MultiInstruct can significantly reduce the sensitivity of OFA.
- Transfer learning from Natural Instructions dataset can further reduce the sensitivity of the model.

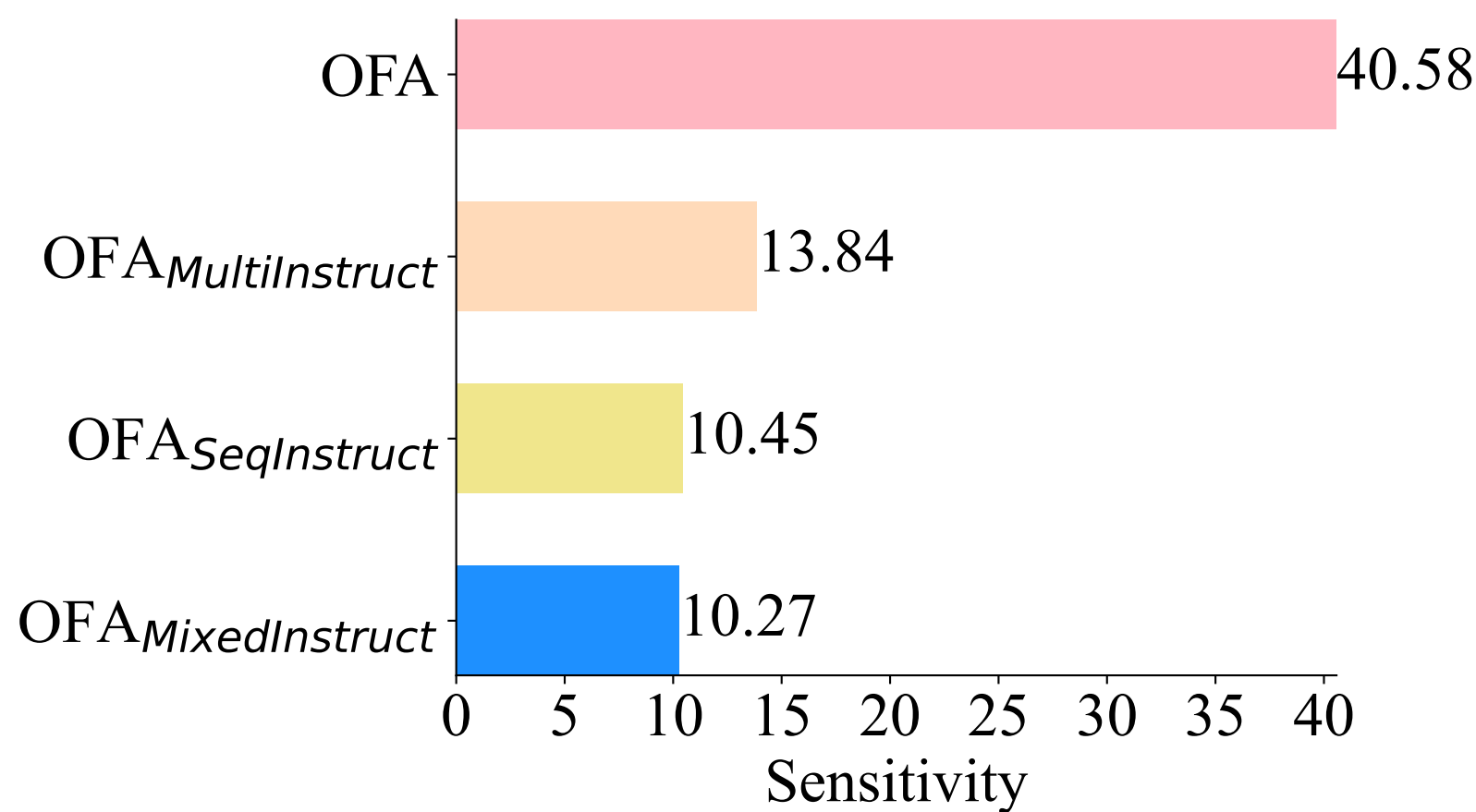


Figure 4. Model Sensitivity on Unseen Evaluation Tasks. Lower is better.

Zero-Shot Performance on NLP Tasks

- Instruction Tuning on MultiInstruct can improve zero-shot performance on unseen NLP tasks.
- The transfer learning strategy MixedInstruct can best preserve the zero-shot capability gained on Natural Instructions dataset.

Model	RougeL
OFA	2.25
OFA _{MultiInstruct}	12.18
Transfer Learning from Natural Instructions	
OFA _{NaturalInstruct}	43.61
OFA _{MixedInstruct}	43.32
OFA _{SeqInstruct}	30.79

Table 4. Zero-shot Performance on NLP tasks. The performance is reported in Rouge-L and the best performance is in bold.

Conclusion

- First large-scale multi-modal instruction tuning dataset. (Contains 62 multi-modal tasks from 10 broad categories.)
- Significantly improve the zero-shot capability of OFA via instruction tuning.
- Explore several transferring learning techniques and show their benefits. Design a new metric sensitivity.

Dataset, Code, and Model

The dataset, source code, and model checkpoints are publicly available at <https://github.com/VT-NLP/MultiInstruct>.

