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

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*Equal Contribution

Pre-trained Language Models for Downstream Tasks

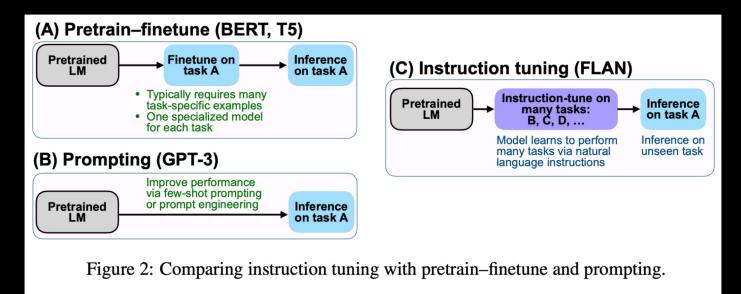


Image credit: Wei, Jason, et al. "Finetuned language models are zero-shot learners."

Language-only

Instruction Tuning on <u>Multimodal</u> Pre-trained Models

Imbalance in Instructional Datasets between NLP and Multimodal

1600+ Language-only instruction tasks

NO large-scale, publicly-available multimodal instruction tasks

Wang, Yizhong, et al. "Benchmarking generalization via in-context instructions on 1,600+ language tasks." arXiv preprint arXiv:2204.07705 (2022).

MULTIINSTRUCT

The *first* multimodal instruction tuning benchmark dataset

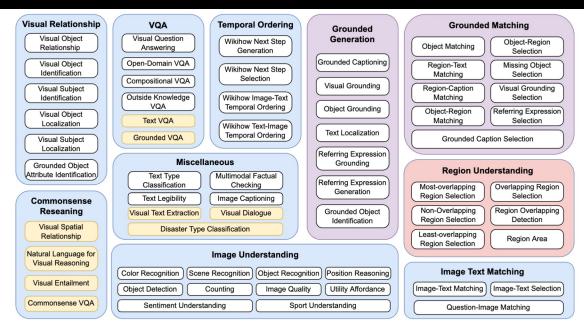
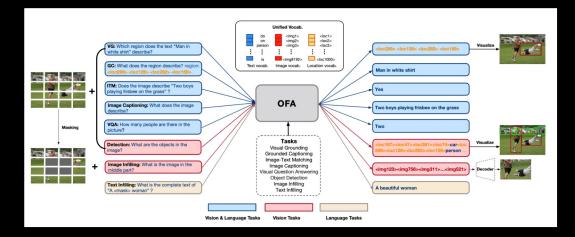


Figure 2: **Task Groups Included in MULTIINSTRUCT.** The yellow boxes represent tasks used for evaluation, while the white boxes indicate tasks used for training.

- 62 diverse multimodal tasks
- 10 broad groups
 5 expert-written instructions

OFA (One For All)

- A unified multi-modal pre-trained model that is capable of performing both understanding and generation tasks with single or multiple modalities.
- OFA has a *unified vocabulary* for language, image tokens and the coordinates of a bounding box.



Wang, Peng, et al. "Unifying architectures, tasks, and modalities through a simple sequence-to-sequence learning framework."

MULTIINSTRUCT

Grounded Caption	Text Localization	Referring Expression Selection	Question-Image Matching	
Input: Generate a caption for <bin_198> <bin_32> <bin_400> <bin_193>.</bin_193></bin_400></bin_32></bin_198>	Input: Select the region that contains the text "den". Options: <bin_206> <bin_119> <bin_448> <bin_181> <bin_357> <bin_518> <bin_456> <bin_518> <bin_456> <bin_574> <bin_229> <bin_604> <bin_304> <bin_654></bin_654></bin_304></bin_604></bin_229></bin_574></bin_456></bin_518></bin_456></bin_518></bin_357></bin_181></bin_448></bin_119></bin_206>	Input: Select the region of the object described by "A blue train in the front.". Options: <bin_242> <bin_180> <bin_736> <bin_475> <bin_88> <bin_291> <bin_203> <bin_473> <bin_193> <bin_339> <bin_247> <bin_442></bin_442></bin_247></bin_339></bin_193></bin_473></bin_203></bin_291></bin_88></bin_475></bin_736></bin_180></bin_242>	Input: Given the content of image, do you have enough information to answer "Is it a sunny day?"? Options: "the question is relevant to the image" or "the question is irrelevant to the image"	
Output: blue and white tennis racquet	Output: <bin_229> <bin_604> <bin_304> <bin_654></bin_654></bin_304></bin_604></bin_229>	Output: <bin_242> <bin_180> <bin_736> <bin_475></bin_475></bin_736></bin_180></bin_242>	Output: the question is irrelevant to the image	

Figure 1: Example Instances from MULTIINSTRUCT for Four Tasks.

Multi-modal Instruction Tuning

Multi-Modal Instruction Turning

• Training Dataset Construction:

- Use 53 tasks from 9 groups for training.
- Sample 10,000 instances per task.

• Testing Dataset Construction:

- Reserve the entire *Commonsense Reasoning* group for testing.
- Select additional 5 tasks from VQA and Miscellaneous groups.
- We use all the instances in the test split for each task.
- Randomly sample 20 tasks from the test split of *Natural Instructions* dataset as unseen tasks for NLP.

Implementation Details

• Training details:

- Pre-trained OFA-Large model (472M)
- Mix all the instances for all tasks.
- Each instance is randomly combined with one of its five instruction templates.

• Testing details:

- For each task, we conduct a total of five experiments by evaluating the model using one of the five instructions in each experiment.
- We report the mean and maximum performance and the standard deviation of the performance across all five experiments.

Evaluation Metrics

- For *multi-modal classification tasks* (Visual Entailment, Visual Spatial Reasoning, Natural Language Visual Reasoning, and Disaster Type Classification) we report the *Accuracy*.
- For *multi-modal generation tasks* (Commonsense VQA, Text VQA, Grounded VQA, Visual Text Extraction, and Visual Dialogue) we report the *Rouge-L*.
- For *NLP tasks*, we report *Rouge-L*.

 We also compute the aggregated performance for each model based on the mean of the model's performance on all multimodal and NLP unseen tasks. We use *Rouge-L* as the performance score for most tasks, and *Accuracy* for tasks that only have accuracy as a metric.

Sensitivity

How sensitive the model is towards to *variety* of instructions for the *same task*:

- Ability to consistently produce the same results for the same task, regardless of slight variations in the wording of instructions.

$$\mathbb{E}_{t \in T} \left[\frac{\sigma_{i \in I^t} \left[\mathbb{E}_{(x,y) \in \mathcal{D}^t} [\mathcal{L}(f_{\theta}(i,x),y)] \right]}{\mu_{i \in I^t} \left[\mathbb{E}_{(x,y) \in \mathcal{D}^t} [\mathcal{L}(f_{\theta}(i,x),y)] \right]} \right]$$

Effectiveness of Instruction Tuning on MULTIINSTRUCT

		Commons	ense V()A	Visu	al Entailment	Visual Spatial Reasoning		NLVR		
Model		RougeL		ACC		ACC		ACC		ACC	
	Max	$Avg \pm Std$	Max	$Avg \pm Std$	Max	Avg \pm Std	Max	Avg \pm Std	Max	Avg \pm 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	$\textbf{50.60} \pm 1.12$	33.01	31.17 ± 1.59	55.96	$\textbf{55.06} \pm 0.76$	55.81	53.90 ±1.38	56.97	56.18 ± 0.95	
Transfer Learni	ng from	NATURAL INS	TRUCTI	ONS							
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	$\textbf{31.23} \pm 1.09$	53.66	52.98 ± 0.56	54.86	53.11 ± 1.45	57.58	$\textbf{56.63} \pm 0.66$	

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

	Т	ext VQA	Gro	unded VQA	Visual	Text Extraction	Visu	Visual Dialogue RougeL		Disaster Type Classification		
Model		RougeL		RougeL		RougeL				ACC		
	Max	Avg± Std	Max	Avg± Std	Max	Avg \pm Std	Max	$Avg \pm Std$	Max	$Avg \pm Std$		
OFA	15.21	9.30 ± 5.42	0.02	0.00 ± 0.01	36.31	17.62 ± 16.82	45.46	$\textbf{28.71} \pm \textbf{9.81}$	14.30	9.64 ± 4.34		
OFA _{TaskName}	23.80	-	0.00	-	36.30	-	25.18	-	62.65	-		
OFA _{MultiInstruct}	27.22	26.46 ± 0.83	64.32	47.22 ± 23.08	74.35	62.43 ± 11.56	46.38	32.91 ± 7.59	64.88	56.00 ± 12.96		
Transfer Learni	ng from	NATURAL INST	RUCTION	IS								
OFA NaturalInstruct	5.59	5.40 ± 0.24	0.00	0.00 ± 0.00	5.65	1.24 ± 2.48	30.94	27.91 ± 2.16	56.64	38.21 ± 15.35		
OFA _{MixedInstruct}	24.15	23.67 ± 0.47	63.79	$\textbf{54.99} \pm 18.16$	62.43	46.56 ± 14.92	46.08	$\textbf{38.02} \pm 5.25$	68.31	$\textbf{64.31} \pm 2.39$		
OFA _{SeqInstruct}	27.03	$\textbf{26.67} \pm 0.47$	64.19	54.46 ± 15.96	71.63	60.62 ± 12.31	46.17	35.10 ± 6.92	64.46	57.89 ± 9.51		

Table 2: Zero-shot Performance on Question Answering and Miscellaneous. The best performance is in **bold**.

Impact of Increasing Multimodal Instruction Task Clusters

- Img Und
 - VQA + Image Understanding
- Grounding
 - Grounded Matching + Grounded Generation
- MISC, ITM
 - Temporal Ordering + Miscellaneous + Image Text Matching
- Relation
 - Visual Relationship
- Region
 - Region Understanding
- NLP
 - NLP tasks

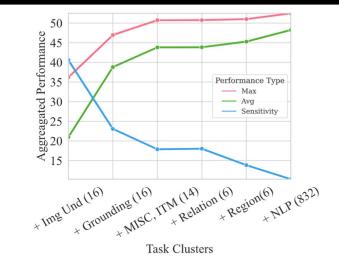


Figure 3: Model Performance as the Number of Multimodal Instruction Task Clusters Increases.

Effect of Diverse Instructions on Instruction Tuning

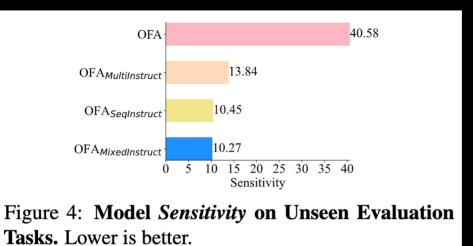
 OFA finetuned on 5 instructions achieves much <u>higher aggregated</u> <u>performance</u> on all evaluation tasks and shows <u>lower sensitivity</u>.

# of Instructions	Aggregated Performance ↑	$ $ Sensitivity \downarrow
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.



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*.

One More Thing!

We are collecting a much larger multimodal instruction tuning dataset with around 150 additional vision-language tasks and we will release them soon!

