

DeepStack: Deeply Stacking Visual Tokens is Surprisingly Simple and Effective for LMMs

Lingchen Meng^{1,2*} Jianwei Yang^{3*} Rui Tian^{1,2} Xiyang Dai³
Zuxuan Wu^{1,2†} Jianfeng Gao^{3†} Yu-Gang Jiang^{1,2}

¹Shanghai Key Lab of Intell. Info. Processing, School of CS, Fudan University

²Shanghai Collaborative Innovation Center of Intelligent Visual Computing

³Microsoft Corporation

<https://deepstack-vl.github.io/>

A Training Details

A.1 Custom Supervised Finetuning Dataset

We follow LLaVA-Next [12] to combine a custom data mixture containing 748K SFT data shown in Tab. 1. Following [13, 12], our 748K training data mixture contains (1) LLM instruction following data, *e.g.* ShareGPT [19]; (2) GPT4/GPT4V generated data, *e.g.* LLaVA-instruct [13], ShareGPT4V [1], LAION-GPT4V [9]; (3) academic-task-oriented data, *e.g.* VQAv2 [2], GQA [3], *etc.*

Dataset	Size	Task Prompt
ShareGPT [19]	40K	
LLaVA-instruct [13]	158K	
ShareGPT4V [1]	39K	
LAION-GPT4V [9]	11K	
VQAv2 [2]	83K	"Answer the question using a single word or phrase."
GQA [3]	72K	
OKVQA [14]	9K	
OCRvQA [17]	80K	
ChartQA [15]	7K	
DVQA [4]	16K	
DocVQA [16]	10K	
AI2D [6]	2K	
SynthDog-EN [7]	20K	
A-OKVQA [18]	66K	"Answer with the option's letter from the given choices directly."
RefCOCO [5]	48K	"Provide a short description for this region."
VG [8]	86K	"Provide the bounding box coordinate of the region this sentence describes"

Table 1: Data combination of our 748K SFT data.

A.2 Detailed Training Configuration

We list the detailed training hyper-parameters as follows. For evaluation, we utilize LLMs-Eval [10] for evaluation on several benchmarks.

Hyper-param	PT	DeepStack-L SFT	DeepStack-V SFT	DeepStack-HD SFT
global batch size	256	128	128	128
lr	1e-3	2e-5	2e-5	2e-5
backbone lr	freeze	freeze	2e-6	2e-6
lr schedule	cosine decay	cosine decay	cosine decay	cosine decay
lr warmup ratio	0.03	0.03	0.03	0.03
epoch	1	1	1	1
optimizer	AdamW	AdamW	AdamW	AdamW

Table 2: Training hyper-parameters.

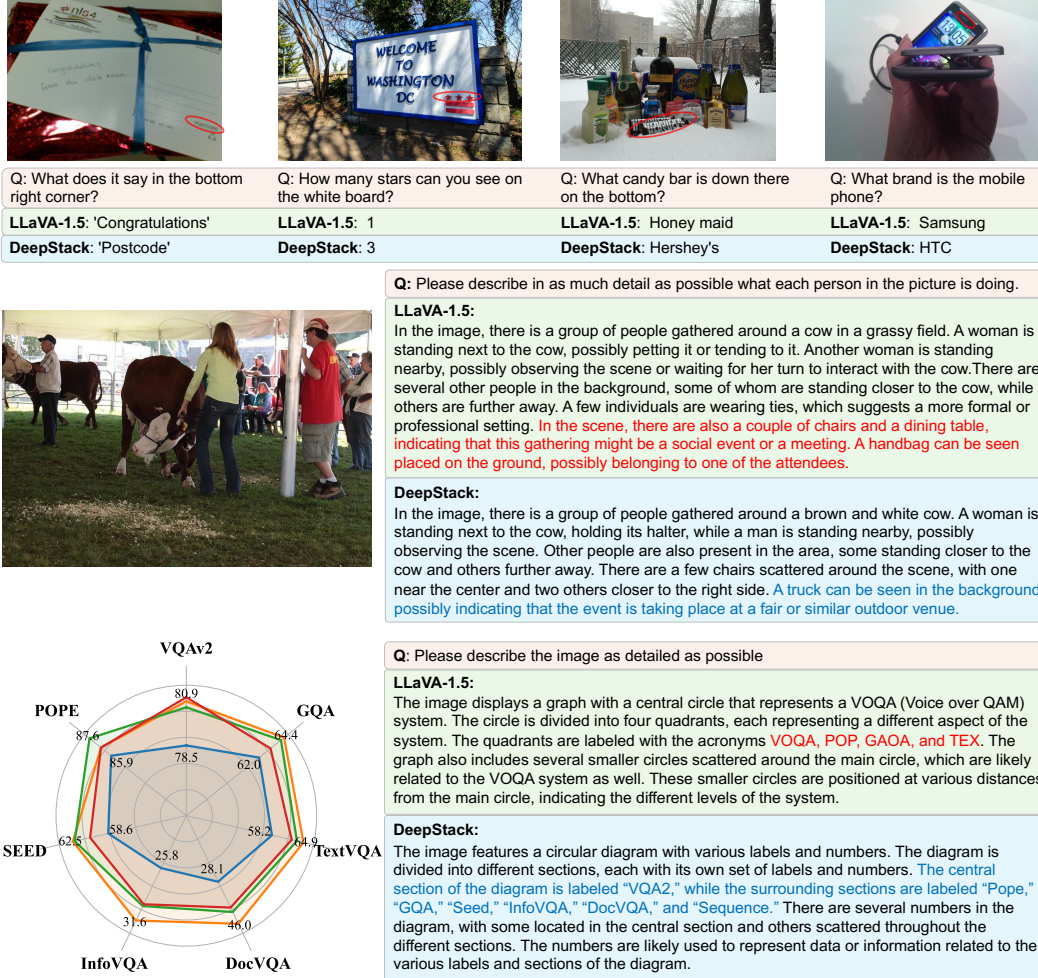


Figure 1: **Visualization.** Both LLaVA-1.5 and DeepStack use 576 visual context length for a fair comparison. Top: We mark the area corresponding to each question with a **red circle**. DeepStack can well answer the questions which need high-resolution and fine-grained understanding. Bottom: DeepStack demonstrates a more accurate visual understanding in detailed visual captioning.

B More Experiments

B.1 Improved DeepStack-L with Fintuning Vision Encoder

As shown in Tab. 3, after finetuning the vision encoder, our DeepStack-L achieves further improvement. This further demonstrates the effectiveness and the potential of our *DeepStack* strategy.

Method	LLM	Eff. Res.	Vis. Tok.	Cxt. Len.	PT	SFT	General VQA		Text-oriented VQA			LMM benchmarks			
							VQA ^{v2}	GQA	Text VQA [‡]	Doc VQA [‡]	Info VQA [‡]	SEED (all)	POPE (all)	MM MU [‡]	MM Vet
LLaVA-1.5 [11]	Vicuna-7B	336	576	576	558K	665K	78.5*	62.0*	58.2	28.1	25.8	58.6	85.9	35.3	30.5
DeepStack-L	Vicuna-7B	672	2880	576	558K	665K	79.5*	63.1*	62.4	39.1	29.8	60.6	86.7	35.7	29.9
DeepStack-L*	Vicuna-7B	672	2880	576	558K	665K	81.1*	63.9*	64.5	39.3	30.1	63.3	86.7	37.1	29.8
LLaVA-1.5 [11]	Vicuna-13B	336	576	576	558K	665K	80.0*	63.3*	61.3	30.3	28.4	61.6	85.9	34.8	35.4
DeepStack-L	Vicuna-13B	672	2880	576	558K	665K	80.9*	64.2*	64.6	41.5	33.0	63.5	87.7	35.2	35.9
DeepStack-L*	Vicuna-13B	672	2880	576	558K	665K	82.1*	65.1*	65.2	43.1	34.0	64.4	86.6	34.7	36.2

Table 3: Improved DeepStack-L with fintuning vision encoder. * indicates that the vision encoder is fine-tuned.

References

- [1] L. Chen, J. Li, X. Dong, P. Zhang, C. He, J. Wang, F. Zhao, and D. Lin. Sharegpt4v: Improving large multi-modal models with better captions. *arXiv preprint arXiv:2311.12793*, 2023.
- [2] Y. Goyal, T. Khot, D. Summers-Stay, D. Batra, and D. Parikh. Making the v in vqa matter: Elevating the role of image understanding in visual question answering. In *CVPR*, 2017.
- [3] D. A. Hudson and C. D. Manning. Gqa: A new dataset for real-world visual reasoning and compositional question answering. In *CVPR*, 2019.
- [4] K. Kafle, B. Price, S. Cohen, and C. Kanan. Dvqa: Understanding data visualizations via question answering. In *CVPR*, 2018.
- [5] S. Kazemzadeh, V. Ordonez, M. Matten, and T. Berg. Referitgame: Referring to objects in photographs of natural scenes. In *EMNLP*, 2014.
- [6] A. Kembhavi, M. Salvato, E. Kolve, M. Seo, H. Hajishirzi, and A. Farhadi. A diagram is worth a dozen images. In *ECCV*, 2016.
- [7] G. Kim, T. Hong, M. Yim, J. Nam, J. Park, J. Yim, W. Hwang, S. Yun, D. Han, and S. Park. Ocr-free document understanding transformer. In *ECCV*, 2022.
- [8] R. Krishna, Y. Zhu, O. Groth, J. Johnson, K. Hata, J. Kravitz, S. Chen, Y. Kalantidis, L.-J. Li, D. A. Shamma, et al. Visual genome: Connecting language and vision using crowdsourced dense image annotations. *IJCV*, 2017.
- [9] LAION-4V. <https://huggingface.co/datasets/laion/gpt4v-dataset>, 2023.
- [10] B. Li, P. Zhang, K. Zhang, F. Pu, X. Du, Y. Dong, H. Liu, Y. Zhang, G. Zhang, C. Li, and Z. Liu. Lmms-eval: Accelerating the development of large multimodal models, 2024.
- [11] H. Liu, C. Li, Y. Li, and Y. J. Lee. Improved baselines with visual instruction tuning. *ArXiv*, abs/2310.03744, 2023.
- [12] H. Liu, C. Li, Y. Li, B. Li, Y. Zhang, S. Shen, and Y. J. Lee. Llava-next: Improved reasoning, ocr, and world knowledge, 2024.
- [13] H. Liu, C. Li, Q. Wu, and Y. J. Lee. Visual instruction tuning. In *NeurIPS*, 2023.
- [14] K. Marino, M. Rastegari, A. Farhadi, and R. Mottaghi. Ok-vqa: A visual question answering benchmark requiring external knowledge. In *CVPR*, 2019.
- [15] A. Masry, D. X. Long, J. Q. Tan, S. Joty, and E. Hoque. Chartqa: A benchmark for question answering about charts with visual and logical reasoning. *arXiv preprint arXiv:2203.10244*, 2022.
- [16] M. Mathew, D. Karatzas, and C. Jawahar. Docvqa: A dataset for vqa on document images. In *WACV*, 2021.
- [17] A. Mishra, S. Shekhar, A. K. Singh, and A. Chakraborty. Ocr-vqa: Visual question answering by reading text in images. In *ICDAR*, 2019.
- [18] D. Schwenk, A. Khandelwal, C. Clark, K. Marino, and R. Mottaghi. A-okvqa: A benchmark for visual question answering using world knowledge. In *ECCV*, 2022.
- [19] ShareGPT. <https://sharegpt.com/>, 2023.

NeurIPS Paper Checklist

The checklist is designed to encourage best practices for responsible machine learning research, addressing issues of reproducibility, transparency, research ethics, and societal impact. Do not remove the checklist: **The papers not including the checklist will be desk rejected.** The checklist should follow the references and follow the (optional) supplemental material. The checklist does NOT count towards the page limit.

Please read the checklist guidelines carefully for information on how to answer these questions. For each question in the checklist:

- You should answer [Yes], [No], or [NA].
- [NA] means either that the question is Not Applicable for that particular paper or the relevant information is Not Available.
- Please provide a short (1–2 sentence) justification right after your answer (even for NA).

The checklist answers are an integral part of your paper submission. They are visible to the reviewers, area chairs, senior area chairs, and ethics reviewers. You will be asked to also include it (after eventual revisions) with the final version of your paper, and its final version will be published with the paper.

The reviewers of your paper will be asked to use the checklist as one of the factors in their evaluation. While "[Yes]" is generally preferable to "[No]", it is perfectly acceptable to answer "[No]" provided a proper justification is given (e.g., "error bars are not reported because it would be too computationally expensive" or "we were unable to find the license for the dataset we used"). In general, answering "[No]" or "[NA]" is not grounds for rejection. While the questions are phrased in a binary way, we acknowledge that the true answer is often more nuanced, so please just use your best judgment and write a justification to elaborate. All supporting evidence can appear either in the main paper or the supplemental material, provided in appendix. If you answer [Yes] to a question, in the justification please point to the section(s) where related material for the question can be found.

IMPORTANT, please:

- **Delete this instruction block, but keep the section heading “NeurIPS paper checklist”,**
- **Keep the checklist subsection headings, questions/answers and guidelines below.**
- **Do not modify the questions and only use the provided macros for your answers.**

1. Claims

Question: Do the main claims made in the abstract and introduction accurately reflect the paper’s contributions and scope?

Answer: [Yes]

Justification: We properly claim our contribution in abstract and introduction.

Guidelines:

- The answer NA means that the abstract and introduction do not include the claims made in the paper.
- The abstract and/or introduction should clearly state the claims made, including the contributions made in the paper and important assumptions and limitations. A No or NA answer to this question will not be perceived well by the reviewers.
- The claims made should match theoretical and experimental results, and reflect how much the results can be expected to generalize to other settings.
- It is fine to include aspirational goals as motivation as long as it is clear that these goals are not attained by the paper.

2. Limitations

Question: Does the paper discuss the limitations of the work performed by the authors?

Answer: [Yes]

Justification: The paper has discussed the limitations.

Guidelines:

- The answer NA means that the paper has no limitation while the answer No means that the paper has limitations, but those are not discussed in the paper.
- The authors are encouraged to create a separate "Limitations" section in their paper.
- The paper should point out any strong assumptions and how robust the results are to violations of these assumptions (e.g., independence assumptions, noiseless settings, model well-specification, asymptotic approximations only holding locally). The authors should reflect on how these assumptions might be violated in practice and what the implications would be.
- The authors should reflect on the scope of the claims made, e.g., if the approach was only tested on a few datasets or with a few runs. In general, empirical results often depend on implicit assumptions, which should be articulated.
- The authors should reflect on the factors that influence the performance of the approach. For example, a facial recognition algorithm may perform poorly when image resolution is low or images are taken in low lighting. Or a speech-to-text system might not be used reliably to provide closed captions for online lectures because it fails to handle technical jargon.
- The authors should discuss the computational efficiency of the proposed algorithms and how they scale with dataset size.
- If applicable, the authors should discuss possible limitations of their approach to address problems of privacy and fairness.
- While the authors might fear that complete honesty about limitations might be used by reviewers as grounds for rejection, a worse outcome might be that reviewers discover limitations that aren't acknowledged in the paper. The authors should use their best judgment and recognize that individual actions in favor of transparency play an important role in developing norms that preserve the integrity of the community. Reviewers will be specifically instructed to not penalize honesty concerning limitations.

3. Theory Assumptions and Proofs

Question: For each theoretical result, does the paper provide the full set of assumptions and a complete (and correct) proof?

Answer: [\[Yes\]](#)

Justification: The paper is not include theoretical result.

Guidelines:

- The answer NA means that the paper does not include theoretical results.
- All the theorems, formulas, and proofs in the paper should be numbered and cross-referenced.
- All assumptions should be clearly stated or referenced in the statement of any theorems.
- The proofs can either appear in the main paper or the supplemental material, but if they appear in the supplemental material, the authors are encouraged to provide a short proof sketch to provide intuition.
- Inversely, any informal proof provided in the core of the paper should be complemented by formal proofs provided in appendix or supplemental material.
- Theorems and Lemmas that the proof relies upon should be properly referenced.

4. Experimental Result Reproducibility

Question: Does the paper fully disclose all the information needed to reproduce the main experimental results of the paper to the extent that it affects the main claims and/or conclusions of the paper (regardless of whether the code and data are provided or not)?

Answer: [\[Yes\]](#)

Justification: We have provided all the details in the paper.

Guidelines:

- The answer NA means that the paper does not include experiments.

- If the paper includes experiments, a No answer to this question will not be perceived well by the reviewers: Making the paper reproducible is important, regardless of whether the code and data are provided or not.
- If the contribution is a dataset and/or model, the authors should describe the steps taken to make their results reproducible or verifiable.
- Depending on the contribution, reproducibility can be accomplished in various ways. For example, if the contribution is a novel architecture, describing the architecture fully might suffice, or if the contribution is a specific model and empirical evaluation, it may be necessary to either make it possible for others to replicate the model with the same dataset, or provide access to the model. In general, releasing code and data is often one good way to accomplish this, but reproducibility can also be provided via detailed instructions for how to replicate the results, access to a hosted model (e.g., in the case of a large language model), releasing of a model checkpoint, or other means that are appropriate to the research performed.
- While NeurIPS does not require releasing code, the conference does require all submissions to provide some reasonable avenue for reproducibility, which may depend on the nature of the contribution. For example
 - (a) If the contribution is primarily a new algorithm, the paper should make it clear how to reproduce that algorithm.
 - (b) If the contribution is primarily a new model architecture, the paper should describe the architecture clearly and fully.
 - (c) If the contribution is a new model (e.g., a large language model), then there should either be a way to access this model for reproducing the results or a way to reproduce the model (e.g., with an open-source dataset or instructions for how to construct the dataset).
 - (d) We recognize that reproducibility may be tricky in some cases, in which case authors are welcome to describe the particular way they provide for reproducibility. In the case of closed-source models, it may be that access to the model is limited in some way (e.g., to registered users), but it should be possible for other researchers to have some path to reproducing or verifying the results.

5. Open access to data and code

Question: Does the paper provide open access to the data and code, with sufficient instructions to faithfully reproduce the main experimental results, as described in supplemental material?

Answer: [No]

Justification: The code is under code reviewing, and we will release it to the public in the future.

Guidelines:

- The answer NA means that paper does not include experiments requiring code.
- Please see the NeurIPS code and data submission guidelines (<https://nips.cc/public/guides/CodeSubmissionPolicy>) for more details.
- While we encourage the release of code and data, we understand that this might not be possible, so “No” is an acceptable answer. Papers cannot be rejected simply for not including code, unless this is central to the contribution (e.g., for a new open-source benchmark).
- The instructions should contain the exact command and environment needed to run to reproduce the results. See the NeurIPS code and data submission guidelines (<https://nips.cc/public/guides/CodeSubmissionPolicy>) for more details.
- The authors should provide instructions on data access and preparation, including how to access the raw data, preprocessed data, intermediate data, and generated data, etc.
- The authors should provide scripts to reproduce all experimental results for the new proposed method and baselines. If only a subset of experiments are reproducible, they should state which ones are omitted from the script and why.
- At submission time, to preserve anonymity, the authors should release anonymized versions (if applicable).

- Providing as much information as possible in supplemental material (appended to the paper) is recommended, but including URLs to data and code is permitted.

6. Experimental Setting/Details

Question: Does the paper specify all the training and test details (e.g., data splits, hyper-parameters, how they were chosen, type of optimizer, etc.) necessary to understand the results?

Answer: [\[Yes\]](#)

Justification: The training and test details have been reported in this paper.

Guidelines:

- The answer NA means that the paper does not include experiments.
- The experimental setting should be presented in the core of the paper to a level of detail that is necessary to appreciate the results and make sense of them.
- The full details can be provided either with the code, in appendix, or as supplemental material.

7. Experiment Statistical Significance

Question: Does the paper report error bars suitably and correctly defined or other appropriate information about the statistical significance of the experiments?

Answer: [\[No\]](#)

Justification: The cost of training required to report error bars is excessively high.

Guidelines:

- The answer NA means that the paper does not include experiments.
- The authors should answer "Yes" if the results are accompanied by error bars, confidence intervals, or statistical significance tests, at least for the experiments that support the main claims of the paper.
- The factors of variability that the error bars are capturing should be clearly stated (for example, train/test split, initialization, random drawing of some parameter, or overall run with given experimental conditions).
- The method for calculating the error bars should be explained (closed form formula, call to a library function, bootstrap, etc.)
- The assumptions made should be given (e.g., Normally distributed errors).
- It should be clear whether the error bar is the standard deviation or the standard error of the mean.
- It is OK to report 1-sigma error bars, but one should state it. The authors should preferably report a 2-sigma error bar than state that they have a 96% CI, if the hypothesis of Normality of errors is not verified.
- For asymmetric distributions, the authors should be careful not to show in tables or figures symmetric error bars that would yield results that are out of range (e.g. negative error rates).
- If error bars are reported in tables or plots, The authors should explain in the text how they were calculated and reference the corresponding figures or tables in the text.

8. Experiments Compute Resources

Question: For each experiment, does the paper provide sufficient information on the computer resources (type of compute workers, memory, time of execution) needed to reproduce the experiments?

Answer: [\[Yes\]](#)

Justification: We provided the computation resources in this paper.

Guidelines:

- The answer NA means that the paper does not include experiments.
- The paper should indicate the type of compute workers CPU or GPU, internal cluster, or cloud provider, including relevant memory and storage.

- The paper should provide the amount of compute required for each of the individual experimental runs as well as estimate the total compute.
- The paper should disclose whether the full research project required more compute than the experiments reported in the paper (e.g., preliminary or failed experiments that didn't make it into the paper).

9. Code Of Ethics

Question: Does the research conducted in the paper conform, in every respect, with the NeurIPS Code of Ethics <https://neurips.cc/public/EthicsGuidelines?>

Answer: [Yes]

Justification: The paper conform the NeurIPS Code of Ethics.

Guidelines:

- The answer NA means that the authors have not reviewed the NeurIPS Code of Ethics.
- If the authors answer No, they should explain the special circumstances that require a deviation from the Code of Ethics.
- The authors should make sure to preserve anonymity (e.g., if there is a special consideration due to laws or regulations in their jurisdiction).

10. Broader Impacts

Question: Does the paper discuss both potential positive societal impacts and negative societal impacts of the work performed?

Answer: [Yes]

Justification: We have provided the broader impacts in our paper.

Guidelines:

- The answer NA means that there is no societal impact of the work performed.
- If the authors answer NA or No, they should explain why their work has no societal impact or why the paper does not address societal impact.
- Examples of negative societal impacts include potential malicious or unintended uses (e.g., disinformation, generating fake profiles, surveillance), fairness considerations (e.g., deployment of technologies that could make decisions that unfairly impact specific groups), privacy considerations, and security considerations.
- The conference expects that many papers will be foundational research and not tied to particular applications, let alone deployments. However, if there is a direct path to any negative applications, the authors should point it out. For example, it is legitimate to point out that an improvement in the quality of generative models could be used to generate deepfakes for disinformation. On the other hand, it is not needed to point out that a generic algorithm for optimizing neural networks could enable people to train models that generate Deepfakes faster.
- The authors should consider possible harms that could arise when the technology is being used as intended and functioning correctly, harms that could arise when the technology is being used as intended but gives incorrect results, and harms following from (intentional or unintentional) misuse of the technology.
- If there are negative societal impacts, the authors could also discuss possible mitigation strategies (e.g., gated release of models, providing defenses in addition to attacks, mechanisms for monitoring misuse, mechanisms to monitor how a system learns from feedback over time, improving the efficiency and accessibility of ML).

11. Safeguards

Question: Does the paper describe safeguards that have been put in place for responsible release of data or models that have a high risk for misuse (e.g., pretrained language models, image generators, or scraped datasets)?

Answer: [NA]

Justification: This paper did not release data or models for the main contribution.

Guidelines:

- The answer NA means that the paper poses no such risks.

- Released models that have a high risk for misuse or dual-use should be released with necessary safeguards to allow for controlled use of the model, for example by requiring that users adhere to usage guidelines or restrictions to access the model or implementing safety filters.
- Datasets that have been scraped from the Internet could pose safety risks. The authors should describe how they avoided releasing unsafe images.
- We recognize that providing effective safeguards is challenging, and many papers do not require this, but we encourage authors to take this into account and make a best faith effort.

12. Licenses for existing assets

Question: Are the creators or original owners of assets (e.g., code, data, models), used in the paper, properly credited and are the license and terms of use explicitly mentioned and properly respected?

Answer: [Yes]

Justification: This paper follows the CC-BY 4.0 license in experiments.

Guidelines:

- The answer NA means that the paper does not use existing assets.
- The authors should cite the original paper that produced the code package or dataset.
- The authors should state which version of the asset is used and, if possible, include a URL.
- The name of the license (e.g., CC-BY 4.0) should be included for each asset.
- For scraped data from a particular source (e.g., website), the copyright and terms of service of that source should be provided.
- If assets are released, the license, copyright information, and terms of use in the package should be provided. For popular datasets, paperswithcode.com/datasets has curated licenses for some datasets. Their licensing guide can help determine the license of a dataset.
- For existing datasets that are re-packaged, both the original license and the license of the derived asset (if it has changed) should be provided.
- If this information is not available online, the authors are encouraged to reach out to the asset's creators.

13. New Assets

Question: Are new assets introduced in the paper well documented and is the documentation provided alongside the assets?

Answer: [NA]

Justification: This paper did not introduce new assets.

Guidelines:

- The answer NA means that the paper does not release new assets.
- Researchers should communicate the details of the dataset/code/model as part of their submissions via structured templates. This includes details about training, license, limitations, etc.
- The paper should discuss whether and how consent was obtained from people whose asset is used.
- At submission time, remember to anonymize your assets (if applicable). You can either create an anonymized URL or include an anonymized zip file.

14. Crowdsourcing and Research with Human Subjects

Question: For crowdsourcing experiments and research with human subjects, does the paper include the full text of instructions given to participants and screenshots, if applicable, as well as details about compensation (if any)?

Answer: [NA]

Justification: No crowdsourcing and research with human subjects in our paper.

Guidelines:

- The answer NA means that the paper does not involve crowdsourcing nor research with human subjects.
- Including this information in the supplemental material is fine, but if the main contribution of the paper involves human subjects, then as much detail as possible should be included in the main paper.
- According to the NeurIPS Code of Ethics, workers involved in data collection, curation, or other labor should be paid at least the minimum wage in the country of the data collector.

15. Institutional Review Board (IRB) Approvals or Equivalent for Research with Human Subjects

Question: Does the paper describe potential risks incurred by study participants, whether such risks were disclosed to the subjects, and whether Institutional Review Board (IRB) approvals (or an equivalent approval/review based on the requirements of your country or institution) were obtained?

Answer: [NA]

Justification: No crowdsourcing experiments in this paper.

Guidelines:

- The answer NA means that the paper does not involve crowdsourcing nor research with human subjects.
- Depending on the country in which research is conducted, IRB approval (or equivalent) may be required for any human subjects research. If you obtained IRB approval, you should clearly state this in the paper.
- We recognize that the procedures for this may vary significantly between institutions and locations, and we expect authors to adhere to the NeurIPS Code of Ethics and the guidelines for their institution.
- For initial submissions, do not include any information that would break anonymity (if applicable), such as the institution conducting the review.