Is multimodal vision supervision beneficial to language?

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Abstract

Vision (image and video) - Language (VL) pre-training is the recent popular paradigm that achieved state-of-the-art results on multi-modal tasks like image-retrieval, video-retrieval, visual question answering etc. These models are trained in an unsupervised way and greatly benefit from the complementary modality supervision. In this paper, we explore if the language representations trained using vision supervision perform better than vanilla language representations on Natural Language Understanding and commonsense reasoning benchmarks. We experiment with a diverse set of image-text models such as ALBEF, BLIP, METER and video-text models like ALPRO, Frozen-in-Time (FiT), VIOLET. We compare the performance of language representations of stand-alone text encoders of these models to the language representations of text encoders learnt through vision supervision. Our experiments suggest that vanilla language representations show superior performance on most of the tasks. These results shed light on the current drawbacks of the vision-language models. The code is available at https://github.com/avinashsai/MML

1 Introduction

Vision-language (VL) pre-training Radford et al. (2021); Li et al. (2021; 2022b); Bain et al. (2021); Fu et al. (2021) has shown tremendous success in the areas of image-text retrieval Li et al. (2021; 2022b), visual question answering Wang et al. (2021); Dou et al. (2022), video retrieval Bain et al. (2021); Fu et al. (2021); Madasu et al. (2022; 2023). These models benefit from the mutual supervision of vision and language leading to the superior results on multi-modal tasks. So, the natural question arises: *"Are vision supervised language representations beneficial compared to vanilla language representations on Natural Language Understanding (NLU) tasks?"* To understand this, we conduct a study comparing the language representations trained using only the text to the language representations trained using vision supervision. More specifically, we compare the performance of the text encoders used in vision-language models to the vanilla pre-trained text encoders.

Few works Iki & Aizawa (2021); Singh et al. (2022) evaluated the performance of vision-language and vanilla language models on GLUE. However, there exists a data discrepancy as these models are pre-trained on different domains of data making the comparisons unfair. To overcome this, we pre-train all the vanilla language models with the text captions used in multi-modal pre-training while keeping the identical training setting. Therefore, the only difference in training between vision-language and vanilla language models is the use of vision data.

For our experiments we use a diverse set of image-text models: ALBEF Li et al. (2021), BLIP Li et al. (2022b) and METER Dou et al. (2022) and video-text models: ALPRO Li et al. (2022a), Frozen-in-time (FiT) Bain et al. (2021) and VIOLET Fu et al. (2021). We evaluate these models on NLU benchmarks GLUE Wang et al. (2018), Superglue Wang et al. (2019) and Common sense reasoning datasets such as SocialIQA Sap et al. (2019), CosmosQA Huang et al. (2019), WinoGrande Sakaguchi et al. (2021), CODAH Chen et al. (2019) and HellaSwag Zellers et al. (2019).

Our experiments show that (i) vision supervised language representations under perform compared to vanilla language representations on most of the Natural Language Understanding tasks like Nat-

Table 1: Comparison among different image-text and video-text models in-terms of pre-training data, architecture of the text encoders and size of the text encoder. CC denotes Conceptual captions Bain et al. (2021), SBU denotes SBU captions Ordonez et al. (2011) and VG represents visual genome Krishna et al. (2017).

Type	**Model**	**Pre-training Data**	**Text Encoder**	**Num. layers**
Image-text	ALBEF	CC12M + COCO + SBU + VG (14M)	BERT	6
	BLIP	CC12M + COCO + SBU + VG (14M)	BERT	12
	METER	CC3M + SBU + VG (4M)	RoBERTa	6
Video-text	ALPRO	CC3M + WebVid-2M (5M)	BERT	6
	FiT	CC3M + WebVid-2M (5M)	DistilBERT	6
	VIOLET	YT180M + CC3M + WebVid-2M (11M)	BERT	12

ural Language Inference (NLI), sentence similarity, reading comprehension, linguistic probe and textual entailment. (ii) A similar trend is observed for commonsense reasoning benchmarks.

2 Related Work

Over the recent years there has been a tremendous progress in training vision and language together using large-scale multi-modal data. Li et al. (2019); Chen et al.; Li et al. (2020). These models combine both the modalities into a single input and are trained using objectives similar to masked language modelling. Another line of work Radford et al. (2021); Li et al. (2021; 2022b); Bain et al. (2021) explore dual stream architectures in which there is a separate encoder for each of the modalities and the final representations are minimized using contrastive loss.

Natural Language Understanding involves several tasks such as text classification Wang & Manning (2012); Madasu & Rao (2019), sentence similarity Mueller & Thyagarajan (2016), Natural Language Inference Williams et al. (2018) etc. However to evaluate the capability of models towards a broad range of NLU tasks, benchmarks such as GLUE Wang et al. (2018), Superglue Wang et al. (2019) are introduced. Since then, these benchmarks are being used to comprehensively evaluate the performance of language models.

3 Experiments

3.1 Models

We experiment with a diverse set of image-text and video-text models. These models differ in the type of pre-training data used, in the architecture of the text encoder and in the sizes the text encoder. The comparison among the models is shown in the table 1.

3.1.1 ALBEF

ALBEF Li et al. (2021) is an image-text model pretrained on conceptual captions 12M (CC12M) Sharma et al. (2018), COCO Lin et al. (2014), SBU captions Ordonez et al. (2011) and visual genome Krishna et al. (2017). It's text encoder has a pre-trained BERT Kenton & Toutanova (2019) architecture with six transformer encoder layers.

3.1.2 BLIP

BLIP Li et al. (2022a) is proposed as an extension to ALBEF model pretrained using the same data albeit with a large text encoder. It's text encoder has the same configuration as pre-trained BERT.

3.1.3 METER

METER Dou et al. (2022) is an image-text model pretrained on conceptual captions 3M (CC3M), SBU captions and visual genome. Pre-trained RoBERTa Liu et al. (2019) with six transformer encoder layers is used as the text encoder.

3.1.4 ALPRO

ALPRO Li et al. (2021) is a video-text model whose text encoder has a pre-trained BERT architecture with six transformer encoders. It is pre-trained on a combined data of conceptual captions 3M (CC3M) and WebVid-2M Bain et al. (2021).

3.1.5 Frozen-in-time (FiT)

Frozen-in-time Bain et al. (2021) is a dual stream transformer model pre-trained on both image data conceptual captions 3M (CC3M) and video data WebVid-2M. DistillBERT Sanh et al. (2019) is used as the text encoder.

3.1.6 VIOLET

VIOLET Fu et al. (2021) is a multi-modal transformer model pre-trained end-to-end on YouTube 180M (YT180M) Zellers et al. (2021), conceptual captions 3M (CC3M) and WebVid-2M. The text encoder follows the BERT architecture.

3.2 Datasets

For our analysis, we use GLUE, Superglue and commonsense reasoning datasets such as SocialQA, CosmosQA, WinoGrande, CODAH and HellaSwag. For all these datasets, we evaluate the models on the dev data.

3.3 Implementation

For fair comparison between the vision supervised text models and vanilla text models, we pre-train the vanilla text models with the text captions from the datasets used for large scale training of image-text and video-text models. Now, the only difference between these models is the use of vision data. We pre-train vanilla text models in the exact setup as vision-language models. We then fine-tune both the vision supervised text models and vanilla text models on downstream tasks. For GLUE, the maximum sentence length used is 200 and the models are trained for 5 epochs. In case of superglue, 250 is the maximum sentence length and the model are trained for 25 epochs. For commonsense reasoning, the models are trained for 10 epochs and 300 is the maximum sentence length. Unless otherwise stated, the results reported are the average of 5 runs.

4 Results

Table 2 shows the results on GLUE benchmark. From the tables, it is evident that vanilla language representations show superior performance compared to vision supervised language representations on most of the tasks across all the models. The drop in performance is significant for NLI tasks like MNLI and MNLI-mismatched (MNLI-mis). A similar trend is observed for sentence similarity (QQP), sentiment classification (SST2), reading comprehension (MRPC), linguistic probe (CoLA) and textual entailment (RTE). However, we see a huge improvement in performance for the Winograd NLI (WNLI) task.

Table 3 illustrates the results on superglue benchmark. From the table, we observe that vision supervised language representations under perform compared to vanilla language representations. For the tasks question answering (BoolQ), word in context (WiC), discourse (CB) we see a huge drop in performance. However, we see a significant improvement in performance for the casual reasoning (COPA) task. It is worth-noting that the performance is same for both the vanilla and vision supervised language representations on winograd schema challenge (WSC).

Table 2: Results on GLUE benchmark. MNLI-mis refers to the task MNLI mismatched and WNLI denotes the Winograd Schema Challenge. We see that language representations learnt through vision supervision under performs compared to vanilla language representations on all the tasks except WNLI.

Model	Type	MNLI	MNLI-mis	QQP	SST2	MRPC	CoLA	RTE	WNLI
ALBEF	Text	82.77	82.68	90.54	91.44	72.81	81.50	58.12	46.01
	Image-text	61.38	61.68	79.02	80.39	66.49	69.13	50.30	56.34
BLIP	Text	83.04	82.70	90.54	91.44	72.81	81.50	58.12	46.01
	Image-text	61.38	61.68	79.02	80.39	66.49	69.13	50.30	56.34
METER	Text	86.59	86.15	90.99	93.27	76.06	82.58	64.02	56.34
	Image-text	31.82	31.82	77.91	81.12	66.49	69.13	47.29	56.34
ALPRO	Text	82.96	82.81	90.64	92.05	70.96	79.93	60.41	45.07
	Video-text	62.53	63.26	79.35	80.96	66.49	69.13	54.39	56.34
FiT	Text	79.10	80.23	89.51	52.03	72.58	69.13	57.28	48.83
	Video-text	59.54	59.45	79.01	52.18	66.78	69.13	48.01	56.34
VIOLET	Text	83.19	83.59	90.68	92.74	71.92	81.66	59.93	52.58
	Video-text	61.38	61.68	79.02	80.39	66.49	69.13	50.30	56.34

Table 3: Results on Superglue benchmark. WiC represents Word-in-Context, CB represents CommitmentBank, COPA denotes Choice of Plausible Alternatives and WSC means The Winograd Schema Challenge.

Model	Type	BoolQ	WiC	CB	COPA	WSC
ALBEF	Text	70.41	63.13	76.79	48.00	63.46
	Image-text	63.30	55.02	63.93	51.60	63.46
BLIP	Text	70.41	63.13	76.43	48.00	63.46
	Image-text	63.30	55.02	63.93	51.60	63.46
METER	Text	72.40	66.11	75.00	46.80	63.46
	Image-text	66.87	53.98	69.64	50.80	63.46
ALPRO	Text	71.16	67.18	76.79	42.20	63.46
	Video-text	65.17	53.17	62.50	50.60	62.50
FiT	Text	68.91	62.38	69.29	44.80	63.46
	Video-text	64.69	53.20	70.71	53.80	63.46
VIOLET	Text	63.85	57.37	66.07	56.00	63.46
	Video-text	63.44	54.11	63.93	52.60	63.46

Table 4: Results on Commonsense reasoning tasks.

Model	Type	SocialQA	CosmosQA	WinoGrande	CODAH	HellaSwag
ALBEF	Text	40.50	26.45	53.12	25.72	25.04
	Image-text	33.47	25.24	49.57	25.72	24.48
BLIP	Text	52.27	25.72	56.88	26.02	25.24
	Image-text	33.47	25.24	49.57	25.72	24.48
METER	Text	58.39	31.32	59.59	24.40	25.04
	Image-text	33.47	25.00	49.57	25.72	24.48
ALPRO	Text	49.90	27.45	56.56	24.10	24.89
	Video-text	33.96	25.70	50.28	25.72	24.48
FiT	Text	45.46	30.87	56.75	25.12	26.54
	Video-text	33.35	25.77	50.33	24.52	24.59
VIOLET	Text	43.36	33.17	57.09	24.28	25.27
	Video-text	33.47	25.24	49.57	25.72	24.48

Table 4 demonstrates the results on commonsense reasoning datasets. As shown in the table, the performance of vanilla language representations surpass vision supervised language representations. There is a notable difference in performance on SocialQA, CosmosQA, WinoGrande and HellaSwag commonsense tasks. However for the CODA dataset, we observe vision supervised language representations outperform vanilla language representations for METER, ALPRO and VIOLET models.

5 CONCLUSION AND FUTURE DIRECTIONS

In this paper we comprehensively evaluated if the vision supervised language representations are beneficial to the language. We experimented with three image-text models ALBEF, BLIP, METER and three video-text models ALPRO, FiT, VIOLET on NLU benchmarks GLUE, superglue and commonsense reasoning tasks. Our experiments showed that vanilla language representations significantly outperform vision supervised language representations on most of the tasks. We believe these findings can shed light on the future directions to improve the vision-language pre-training that is beneficial to understanding the language.

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