Multimodal CL and NLP: Combining Language and Vision for (Computational) Semantics

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Outline

Behind the Scene: Revealing the Secrets of Pre-trained Vision-and-Language Models [Cao et al., 2020]

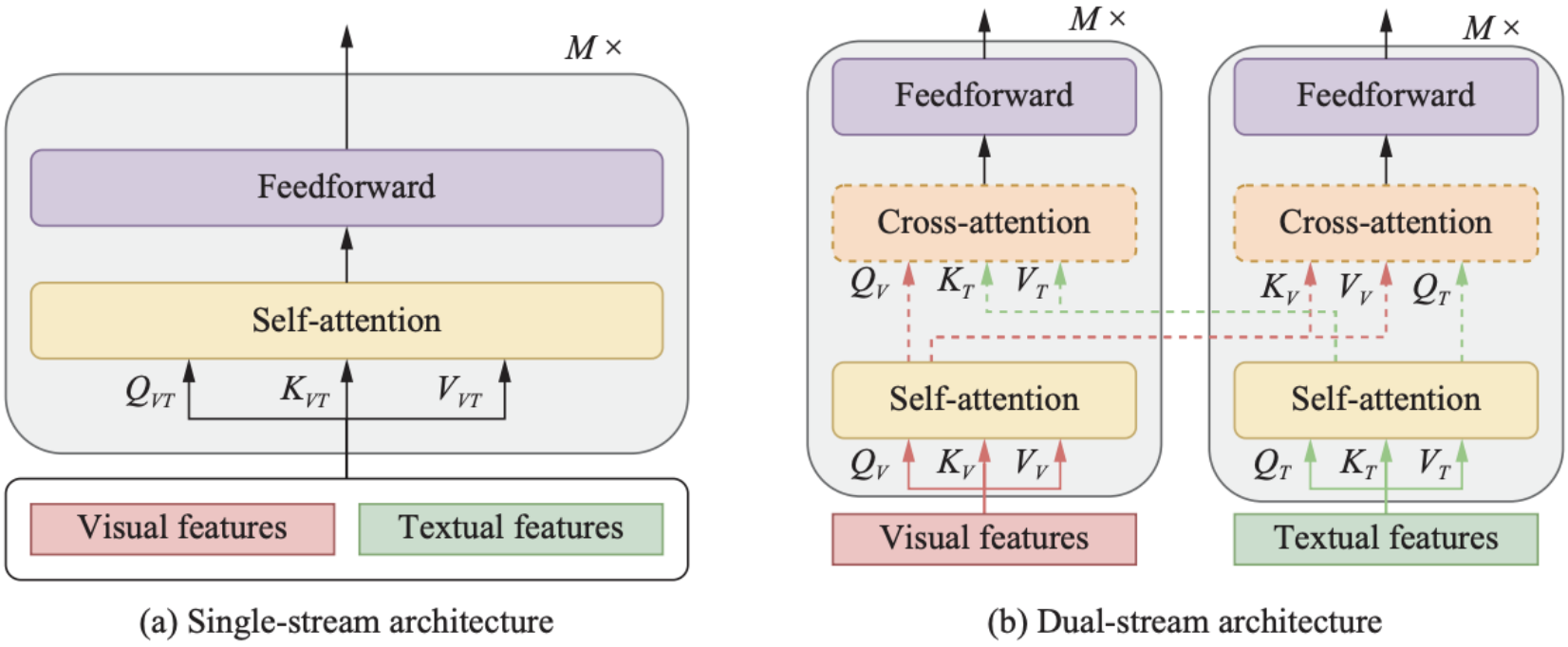
Focus

Multimodal fusion degree (integration);

- Single-stream vs. dual-stream models
- Modality importance

Recap: Vision–Language Models

BERT-like

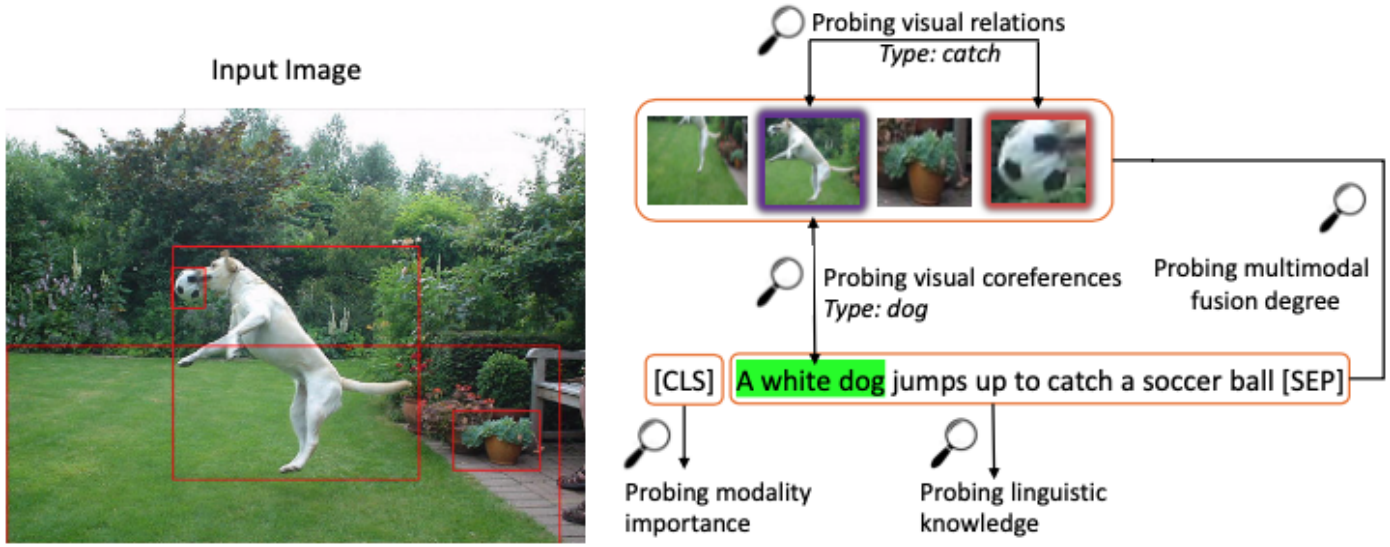


(a) Single-stream architecture

(b) Dual-stream architecture

source: [Chen et al., 2022]

Behind the Scene: Revealing the Secrets of Pre-trained Vision-and-Language Models [Cao et al., 2020]



Behind the Scene: Revealing the Secrets of Pre-trained Vision-and-Language Models [Cao et al., 2020]

- Multimodal Fusion Degree: Single-stream models learn more intertwined fusion of modalities, increasing with network layer depth (and decreasing in two-stream models)
- Modality Importance: Text more dominant than Vision
- Single-stream models better at capturing cross-modal interaction (visual coreference resolution), image-to-image interaction (visual relationship detection), and text-to-text interaction (linguistic knowledge - SentEval task)

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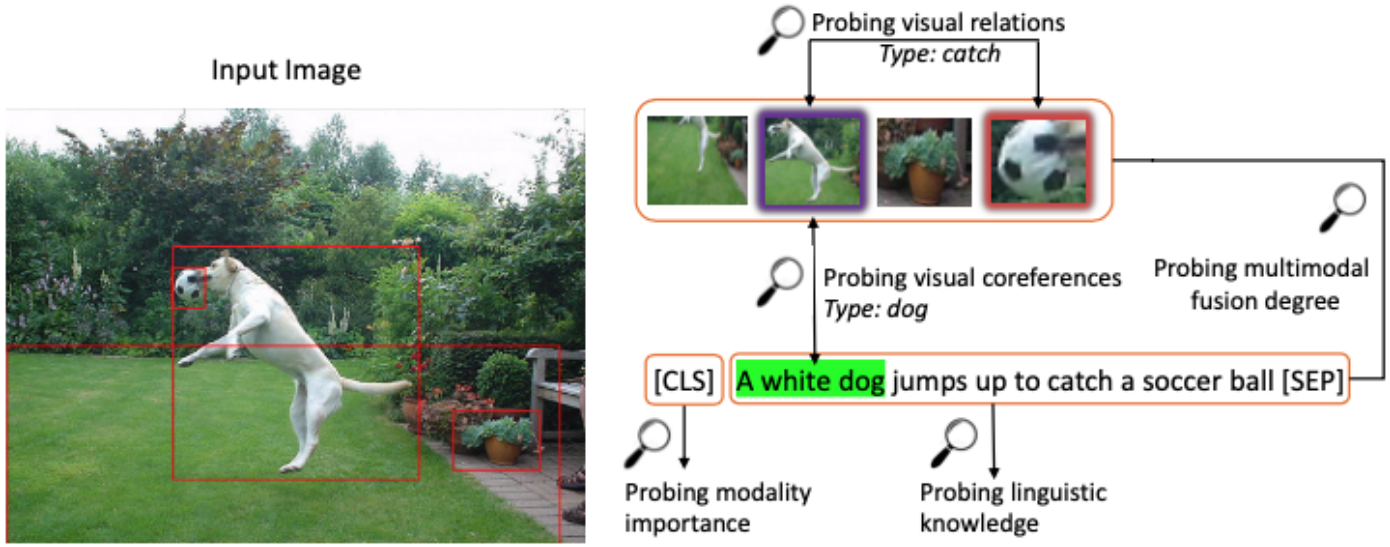

Behind the Scene: Revealing the Secrets of Pre-trained Vision-and-Language Models [Cao et al., 2020]

- Multimodal Fusion Degree
  - Extract multimodal embeddings of all tokens and image regions

visual and textual embeddings

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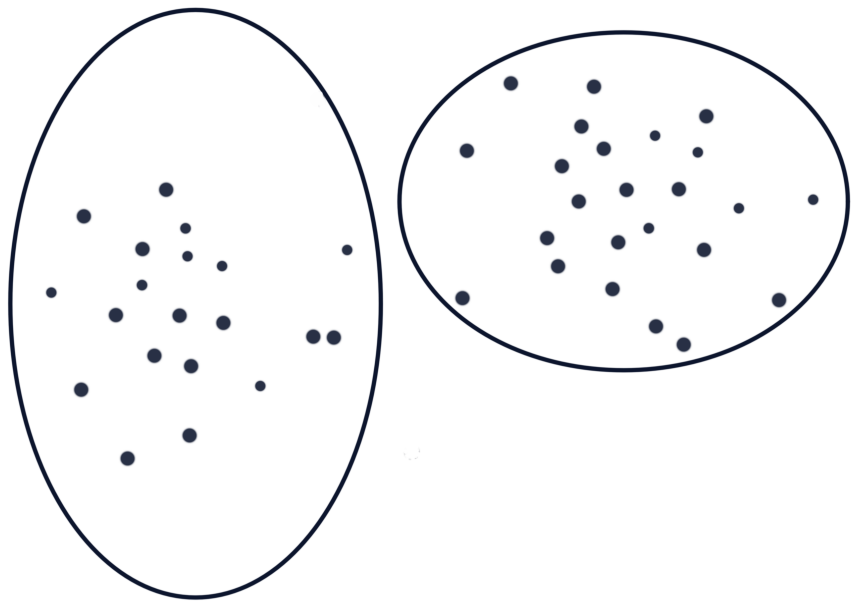

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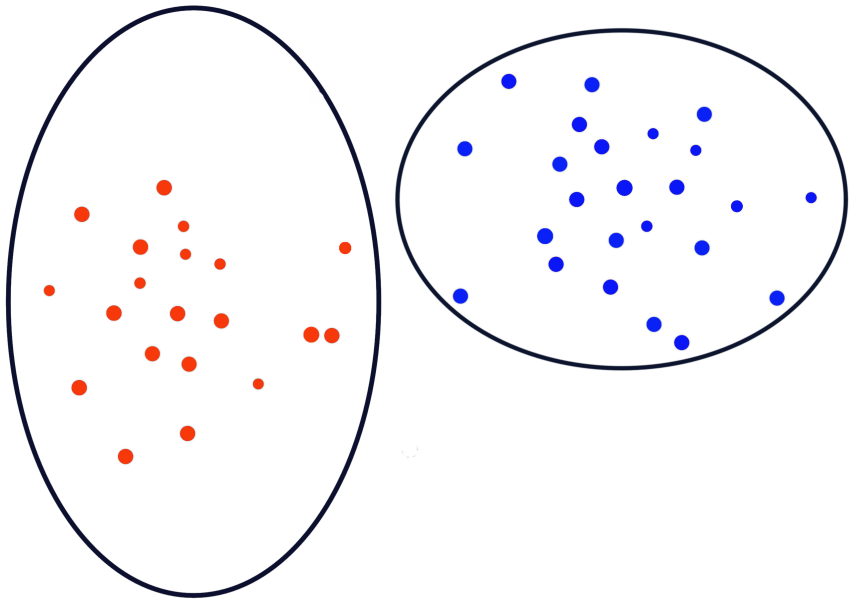
- Multimodal Fusion Degree
  - Extract multimodal embeddings of all tokens and image regions
  - Cluster into two sets
  - Measure difference of clusters and ground-truth visual / textual clusters (Normalised Mutual Information)

$$MI(x, y) = P(x, y) \log \frac{P(x,y)}{P(x)P(x)}$$

  - High difference $\Rightarrow$ each cluster $\approx$ single modality $\Rightarrow$ low degree of multimodal fusion

visual and textual embeddings



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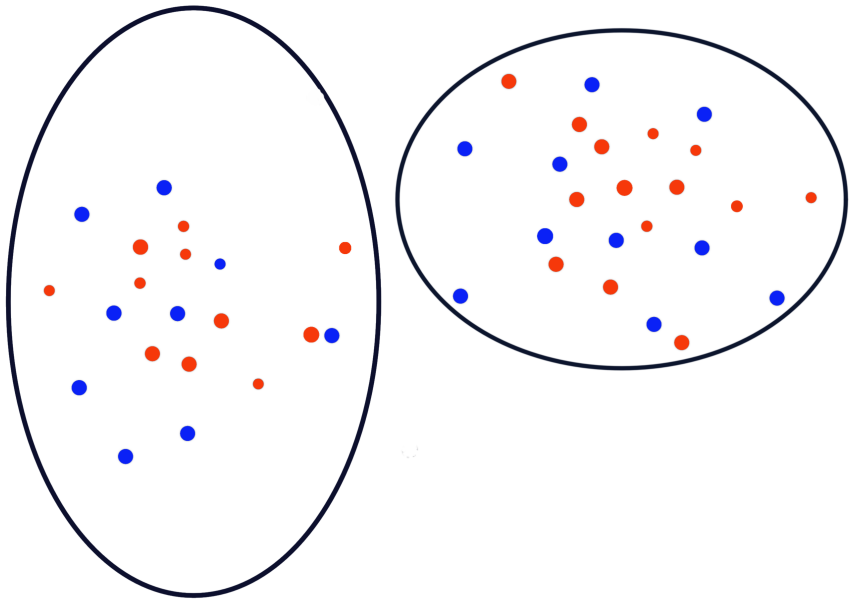
  - Low difference $\Rightarrow$ each cluster captures both modalities $\Rightarrow$ high degree of multimodal fusion

visual and textual embeddings



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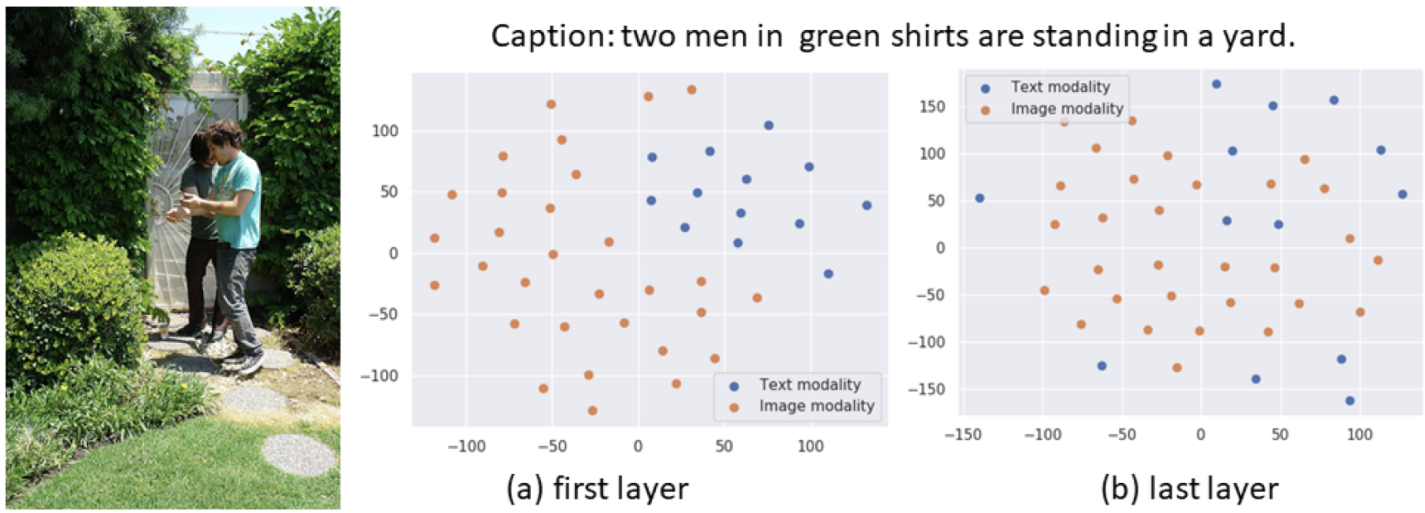

Fig. 6: An t-SNE visualization of multimodal fusion degree of the first and last layer of UNITER over one image-text pair. Each yellow and blue dot corresponds to a visual and textual token, respectively.

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Layer	**0**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**
single-stream												
Flickr30k	0.36	0.38	0.39	0.41	0.38	0.38	0.38	0.38	0.32	**0.20**	0.26	**0.20**
Visual Genome	0.25	0.25	0.24	0.24	0.22	0.22	0.21	0.21	0.20	0.17	**0.16**	**0.16**
two-stream (cross)												
Flickr30k	**0.42**	0.48	0.67	0.75	0.43	–	–	–	–	–	–	–
Visual Genome	**0.43**	0.56	0.68	0.78	0.57	–	–	–	–	–	–	–

Table 1: NMI scores on multimodal fusion probing. A smaller NMI value indicates a higher fusion degree. Note that the two-stream model (LXMERT) only has 5 layers in its cross-modality encoder. A larger layer number corresponds to an upper layer.

Analysis: VL decoders and their multimodal degree

[Parcalabescu and Frank, 2024a]

Overview

- VL decoders
  - Can generate text given an image and text
  - $\Rightarrow$ Can produce predictions *and* explanations
- *How much is each modality used when generating predictions vs. explanations?*
- *How self-consistent are the models in their explanations?*

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[Parcalabescu and Frank, 2024a]

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MM-SHAP for multimodal degree [Parcalabescu and Frank, 2023]

- Determines the contribution of each modality in VL encoders:
- Computes Shapley values for each input token, i.e., the contribution of each input token to each generated token
- Normalises and aggregates them modality-wise
- Textual degree - T-SHAP, visual degree - V-SHAP (proportion of modality contributions)

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CC-SHAP for self-consistency [Parcalabescu and Frank, 2024b]

- Determines the contribution of each input token to the *prediction*:
  Compares input contributions when generating answers to input contributions when generating explanation

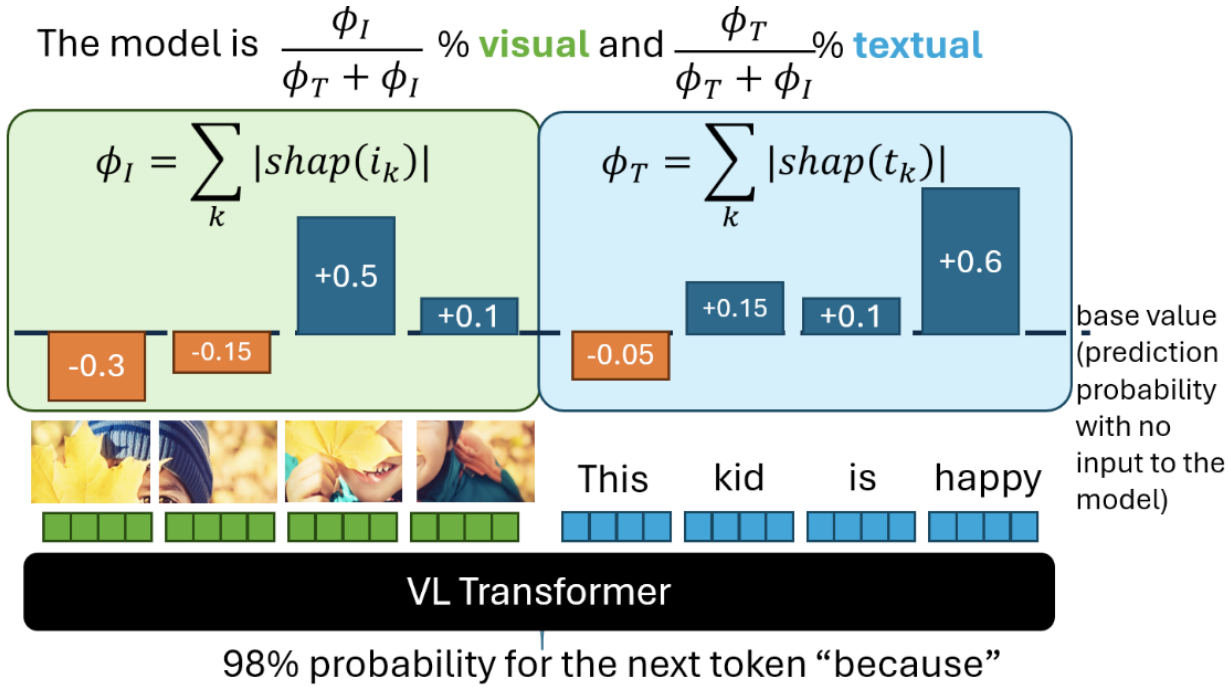
Explanation Self-Consistency Tests

- Compares model outputs before and after input edits

Analysis: VL decoders and their multimodal degree

[Parcalabescu and Frank, 2024a]

MM-SHAP



Analysis: VL decoders and their multimodal degree

[Parcalabescu and Frank, 2024a]

Experimental Setup

- Three LLaVA models with strong LLMs
- VALSE benchmark and VQA benchmarks

Results:

- **Prediction**: Text modalities predominating during *prediction*: T-SHAP $> 89\%$
- **Explanation generation:** Visual modalities more influential compared to prediction

$\Rightarrow$ Misalignment between contributions during prediction and explanation — model inconsistency

- Linguistic abilities: decoders still struggle, especially on counting, but less on nouns and existence

Analysis: VL decoders and their multimodal degree

[Parcalabescu and Frank, 2024a]

Results on VALSE

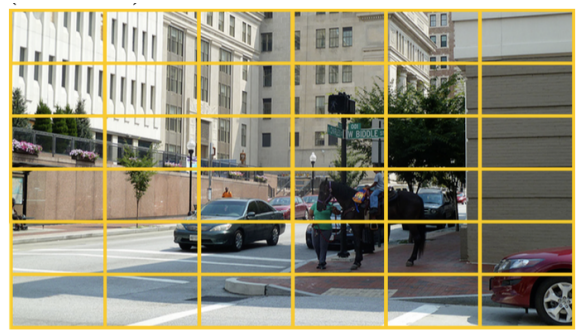
Metric	Model	Existence quantifiers	Plurality number	Counting bal.†	Counting sns.†	Counting adv.†	Sp.rel.‡ relations	Action repl.†	Action swap†	Coreference std.†	Coreference clean	Foil-it nouns
acc_r	BakLLaVA	92	78	77	80	**73**	**84**	**89**	82	78	78	**98**
	LV-Mistral	**96**	**81**	**78**	**82**	67	79	**89**	**90**	**84**	**84**	**98**
	LV-Vicuna	88	71	73	76	59	73	86	88	83	78	96
acc	BakLLaVA	50	50	50	50	**50**	50	50	50	50	50	50
	LV-Mistral	62	**55**	51	50	**50**	**58**	54	54	**57**	**59**	66
	LV-Vicuna	**78**	52	**59**	**60**	48	52	**64**	**62**	55	52	**68**
p_c	BakLLaVA	0	0	0	0	0	0	0	0	0	0	0
	LV-Mistral	24	17	1	1	0	30	9	9	29	39	34
	LV-Vicuna	**64**	**98**	**26**	**35**	10	**99**	**82**	**83**	**97**	**95**	**96**
p_f	BakLLaVA	**100**	**100**	**100**	**100**	**100**	**100**	**100**	**100**	**100**	**100**	**100**
	LV-Mistral	**100**	94	**100**	**100**	**100**	86	98	99	86	78	98
	LV-Vicuna	92	6	91	86	85	4	46	42	13	9	40

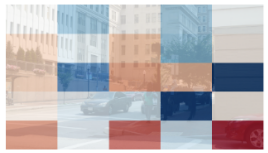
Table 1: Performance (cf. §4.2) of three **VL decoders** on *all samples* of VALSE. We bold-face the b result per metric, and highlight with red results at or below random baseline (50%). The scores in the la are compared in Fig. 1 to VLM encoders and unimodal models. **LV-***: LLaVA-NeXT-*. †**bal.** Counting †**sns.** Counting small numbers. **adv.** Counting adversarial. **repl.** Action replacement. **swap.** Actant swap Spatial relations. †**std.** Coreference standard. **Avg.** ± **SD**: Average over rows and standard deviation.

Analysis: VL decoders and their multimodal degree

[Parcalabescu and Frank, 2024a]

Prediction vs. Explanation (post-hoc)



	Model Prediction		Model Explanation	
	V-SHAP: 3%	T-SHAP: 97%	V-SHAP 40%	T-SHAP: 60% CC-SHAP: 0.22
LLaVA-NeXT-Mistral		[INST]: <image> Where is the horse? [/INST] The best short answer is: The horse is on a street		[INST]: <image> Where is the horse? [/INST] The best short answer is: The horse is on a street [INST] Why? Please explain how you arrived at your answer. [/INST] Explanation: In the image provided, there is a person leading a horse on a city street, most likely navigating through the busy urban environment for a specific purpose, perhaps a special event or a cultural activity that incorporates horse riding. The horse is being guided by its handler across the crosswalk with a person on its back, which could indicate it's being ridden, possibly for ceremonial reasons, tourist attractions, or local customs.
		[INST]: <image> Where is the horse? [/INST] The best short answer is: The horse is on a street		[INST]: <image> Where is the horse? [/INST] The best short answer is: The horse is on a street [INST] Why? Please explain how you arrived at your answer. [/INST] Explanation: In the image provided, there is a person leading a horse on a city street, most likely navigating through the busy urban environment for a specific purpose, perhaps a special event or a cultural activity that incorporates horse riding. The horse is being guided by its handler across the crosswalk with a person on its back, which could indicate it's being ridden, possibly for ceremonial reasons, tourist attractions, or local customs.

Outline

ViLMA: Video–Language Model Assessment

A zero-shot benchmark for linguistic and temporal grounding in video–language models [Kesen et al., 2023]

Overview

- Videos can account for the temporal dimension, for dynamically evolving phenomena (events, actions, physical processes)
- Task-agnostic probing benchmark focusing on temporal understanding and reasoning
- 5177 **Counterfactuals** (foils), each paired with a **proficiency test** (considered as prerequisite to solve the main tests)
- Finding: Grounding abilities of video–language models (VidLMs) not better than vision–language models with still images (VLMs)

ViLMA: Video–Language Model Assessment

[Kesen et al., 2023]

Foils (Counterfactuals)

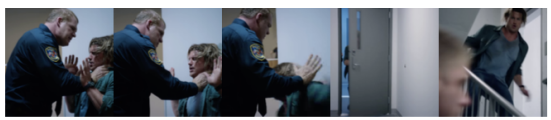
- Created from existing datasets and (V)LLMs using, e.g., Masked Language Modelling
- Validated using NLP tools and manual validation via Amazon Mechanical Turk

Proficiency tests

- Less challenging than the main tests, they do not require temporal modelling
- Bias indicator: Does the model succeed in main test but fail in proficiency test?
- Manually validated

ViLMA: Video–Language Model Assessment

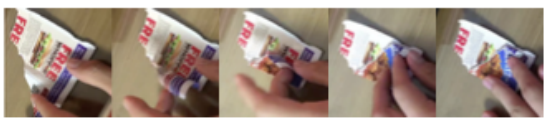
[Kesen et al., 2023]

Test (#exs.)	Video Caption (blue) / Foil (orange)	Foil Generation	Sample Frames
Situation Awareness (911)	A policeman / blond man holds a blond man / policeman against a wall.	Actor swapping	
	A man in blue holds / chops up a man in green.	Action replacement	
Spatial Relations (393)	Moving steel glass towards / from the camera.	Relation replacement	

Proficiency test: Object identification

ViLMA: Video–Language Model Assessment

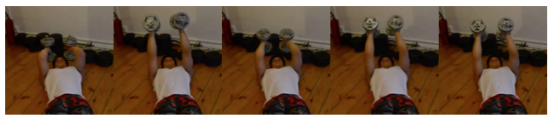
[Kesen et al., 2023]

Test (#exs.)	Video Caption (blue) / Foil (orange)	Foil Generation	Sample Frames
Change of State (998)	Someone folds / unfolds the paper.	Action replacement	
	Initially, the paper is unfolded / folded.	Pre-state replacement	
	At the end, the paper is folded / unfolded.	Post-state replacement	
	Initially, the paper is unfolded / folded. Then, someone folds / unfolds the paper. At the end, the paper is folded / unfolded.	Swap-and-replacement	

Proficiency test: Object identification

ViLMA: Video–Language Model Assessment

[Kesen et al., 2023]

Test (#exs.)	Video Caption (blue) / Foil (orange)	Foil Generation	Sample Frames
Action Counting (1432)	Someone lifts weights exactly two / five times.	Number replacement	
Rare Actions (1443)	Drilling into / Calling on a phone.	Action replacement	
	Drilling into a phone / wall.	Object replacement	

Do VidLMs identify novel compositions or recognise unusual human–object interactions?

Proficiency test: Action recognition & Object existence

ViLMA: Video–Language Model Assessment

[Kesen et al., 2023]

Action Counting

Proficiency Test: a man skips / climbs a rope.
Main Test: a man skips rope exactly three / nine times.

Proficiency Test: someone peels a melon / lemon.
Main Test: someone peels a melon in exactly two / five moves.

ViLMA: Video–Language Model Assessment

[Kesen et al., 2023]

Situation Awareness: Action replacement / Actor swapping

Proficiency Test: A shirtless man opens the window / door hurriedly.
Main Test: A shirtless man opens / smashes the window hurriedly.

Proficiency Test: The woman in red looks upward at the man in a hat / wheelchair.
Main Test: The woman in red / man in a hat looks upward at the man in a hat / woman in red.

ViLMA: Video–Language Model Assessment

[Kesen et al., 2023]

Change of State: Post state / Reverse

Proficiency Test: Someone connects the chair and the base / dots.
Main Test: At the end, the chair and the base is attached / detached.

Proficiency Test: Someone chops an onion / apple.
Main Test: Initially, an onion is whole / in pieces. Then, someone chops / connects an onion. At the end, an onion is in pieces / whole.

ViLMA: Video–Language Model Assessment

[Kesen et al., 2023]

Rare Actions (Action replacement)

Proficiency Test: there is at least one banana / blender
Main Test: weighing / eating a banana

ViLMA: Video–Language Model Assessment

[Kesen et al., 2023]

Comparison: Unimodal, VL and VidL models

Model	Action Counting			Situ. Awareness			Change of State			Rare Actions			Spatial Relations			Avg.
	P	T	P+T	P	T	P+T	P	T	P+T	P	T	P+T	P	T	P+T	P+T
Random	50.0	50.0	25.0	50.0	37.9	18.9	50.0	50.0	25.0	50.0	50.0	25.0	50.0	50.0	25.0	23.8
GPT-2†	50.3	53.3	27.6	44.5	66.6	31.7	18.0	52.4	10.8	58.4	25.9	17.7	49.1	72.8	43.0	26.2
OPT†	56.2	54.6	31.0	51.7	71.3	38.7	23.1	48.0	12.9	59.0	23.9	14.9	59.0	84.7	55.7	30.6
CLIP‡	90.5	50.9	46.2	71.0	45.5	33.6	93.0	**55.2**	**52.2**	92.7	93.9	87.8	78.6	58.3	44.8	52.9
BLIP2‡	80.9	54.5	43.7	73.4	**75.4**	**55.7**	74.5	52.1	38.1	93.8	74.5	70.5	**91.1**	**86.0**	**79.4**	**57.5**
ClipBERT	56.4	49.6	28.0	54.1	56.9	31.9	63.7	50.0	33.5	43.5	40.7	17.7	39.7	39.8	14.1	25.0
UniVL	73.4	43.6	32.2	51.6	46.6	24.1	81.3	54.3	43.0	77.5	78.0	59.9	62.5	51.7	33.2	38.5
VideoCLIP	79.1	46.4	36.5	61.6	40.3	24.9	49.8	50.8	25.9	84.0	77.8	67.5	67.9	54.7	39.7	38.9
FiT	83.9	52.4	44.6	69.8	40.0	29.1	93.0	52.1	47.8	89.7	89.4	80.7	70.5	51.9	38.7	48.2
CLIP4Clip	**91.2**	52.3	**48.0**	**73.8**	49.0	37.6	**94.8**	54.1	52.1	83.0	**94.1**	78.7	79.8	56.7	44.2	52.1
VIOLET	79.6	50.6	36.5	70.2	41.6	32.4	88.2	54.6	49.1	87.1	86.6	74.6	73.3	50.4	38.7	46.3
X-CLIP	84.1	55.1	46.4	63.5	44.8	31.0	85.7	52.7	46.0	83.9	85.7	72.3	74.8	56.2	43.5	47.8
MCQ	81.4	50.4	41.5	67.0	37.1	26.3	90.3	50.3	45.3	91.3	88.7	82.3	79.4	48.9	39.4	47.0
Singularity	79.6	51.1	41.5	68.8	40.9	30.1	92.8	54.6	50.3	92.7	88.4	83.1	80.7	46.8	38.9	48.8
UniPerceiver	50.6	46.4	23.0	51.4	42.1	21.1	67.5	46.1	29.1	58.2	58.8	34.7	45.5	48.0	20.1	25.6
Merlot Reserve	84.2	**56.0**	46.9	70.5	35.6	25.3	93.4	53.6	50.4	83.8	90.6	77.6	63.1	41.9	29.2	45.9
VindLU	84.5	51.2	43.5	70.5	41.6	31.2	85.4	52.6	45.6	**94.2**	93.1	**88.0**	83.2	45.6	39.4	49.5

- Temporal reasoning capabilities of VidLMs limited – VLMs and VidLMs mostly comparable

Outline

Take-away Messages

- Innovations in models and training losses more beneficial than scaling up training data
- Rich data sources are relevant
- Two key ingredients for models: contrastive learning and cross-modal attention

References I

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- Worst of Both Worlds: Biases Compound in Pre-trained Vision-and-Language Models [Srinivasan and Bisk, 2022]
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- MAEA: Multimodal Attribution for Embodied AI [Jain et al.,]
- Winoground: Probing Vision and Language Models for Visio-Linguistic Compositionality [Thrush et al., 2022]
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- [Dönmez et al., 2023]

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