Benchmarking Video-Language Models to understand their grounding capabilities

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Work under review for ICLR 2024

Counterfactual probing using foils

Introduced in V&L research by Shekhar et al (2017) with the FOIL-It task.

Given an image and **caption** pair, change a word in the caption to create a **foil**.

Is the model able to distinguish the two?

People riding bicycles down a road approaching a ***bird.***

People riding bicycles down a road approaching a ***dog.***

Shekhar, R., Pezzelle, S., Klimovich, Y., Herbelot, A., Nabi, M., Sangineto, E., & Bernardi, R. (2017). FOIL it! Find One mismatch between Image and Language caption. *Proceedings of the 55th Annual Meeting of the Association for Computational Linguistics (ACL'17)* (pp. 255–265).

Madhyastha, P., Wang, J., & Specia, L. (2018). Defoiling Foiled Image Captions. *Proceedings Of the Conference of the North American Chapter Of the Association for Computational Linguistics: Human Language Technologies (NAACL-HLT'18)*, 433–438. http://arxiv.org/abs/1805.06549

VALSE: Vision And Language Structured Evaluation

A foil-based benchmark focusing on linguistic phenomena

VALSE:

- Targets pretrained V&L models.
- Intended as a zero-shot evaluation benchmark.
- (V&L models have pretrained image-caption alignment heads.)
- Targets specific linguistic features.
- Designed to ensure validity & reliability, especially by mitigating **distributional** and **plausibility** bias.

L Parcalabescu, M Cafagna, L Muradjan, A Frank, I Calixto, and A Gatt (2022). VALSE: A Task-independent benchmark for Vision and Language models centered on linguistic phenomena. (2021). *Proceedings of the 60th Annual Meeting of the Association for Computational Linguistics (ACL'22),*

Meet ViLMA...
(Video-Language Model Assessment)

A successor to VALSE. This time we're waltzing with video.

If we model the interaction between language and vision using videos, then we also have a better grasp of the **temporal dimension**.

Temporal information features strongly in our interpretation of certain linguistic constructions and the inferences we draw from them.

E.g. *changes of state:* X <u>opened</u> the door

E.g. *iterativity*: I knocked <u>several/two</u> times

E.g. *spatio-temporal relations:* He kicked the ball <u>towards</u> the net

We use a counterfactual setup

- Start from a video clip + caption (from an existing dataset)
  - Sometimes captions are generated from templates
- Replace something in the caption which:
  - Makes the caption no longer true wrt the video
  - Is related to a phenomenon of interest (e.g. change of state)
- Every single item in this benchmark is validated with human judges
- We target pretrained Video-Language models and use them in a zero-shot setting (usually, by exploiting their pretrained video/image-text alignment head)

Tests (and subtests) in ViLMA

Test (#exs.)	**Video Caption (blue) / Foil (orange)**	**Foil Generation**	**Sample Frames**
Action Counting (1432)	Someone lifts weights exactly two / five times.	Number replacement	
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	
Change of State (998)	Someone folds the paper / laundry.	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	
Rare Actions (1443)	Drilling into / Calling on a phone.	Action replacement	
	Drilling into a phone / wall.	Object replacement	
Spatial Relations (393)	Moving steel glass towards / from the camera.	Relation replacement	

Proficiency tests

Key idea:

For a model to "solve" a ViLMA test and demonstrate real grounding abilities, it must first have certain "basic" abilities, which are simpler.

Each ViLMA test item has a corresponding "proficiency test" item, which tests for the basic ability. (NB: they are one-to-one)

If the model fails the basic PT and succeeds on the main T, this is likely due to spurious features.

Example:

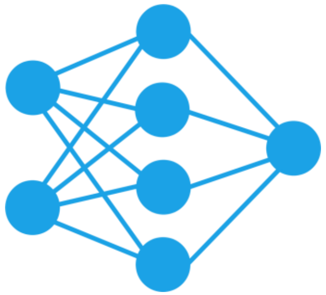
To successfully count the occurrences of an action, the model needs to recognise the event itself. (= Event recognition)

To successfully determine that a door was opened and is therefore no longer closed, the model needs to be able to recognise the door. (= Object recognition)

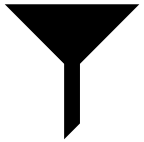
Our testing rationale
(example from situation awareness test)

Proficiency test
C_P: A shirtless man opens the **window** hurriedly
F_P: A shirtless man opens the **door** hurriedly

Main test
C: A shirtless man **opens** the window hurriedly
F: A shirtless man **smashes** the window hurriedly



P-score:
Proportion of cases where:
P(match|v, C_P) > P(match|v, F_P)



Filter for the final, combined score: P+T

T(est)-score:
Proportion of cases where:
P(match|v, C) > P(match|v, F)

We tested a gazillion models

- Random baseline (50%)
- Unimodal models (GPT-2, OPT)
    - *To what extent is the caption/foil distinction solvable based on textual features only?*
- Image-text models (CLIP, BLIP-2)
    - *Offer a baseline against which to compare grounding with and without an explicit temporal dimension*.
- Video-language models
    - ClipBERT, UniVL, VideoCLIP, FiT, CLIP4CLIP, VIOLET, X-CLIP, MCQ, Singularity, UniPerceiver, Merlot Reserve, VindLU
    - *Several architectures and a variety of pretraining objectives (out of scope for today)*

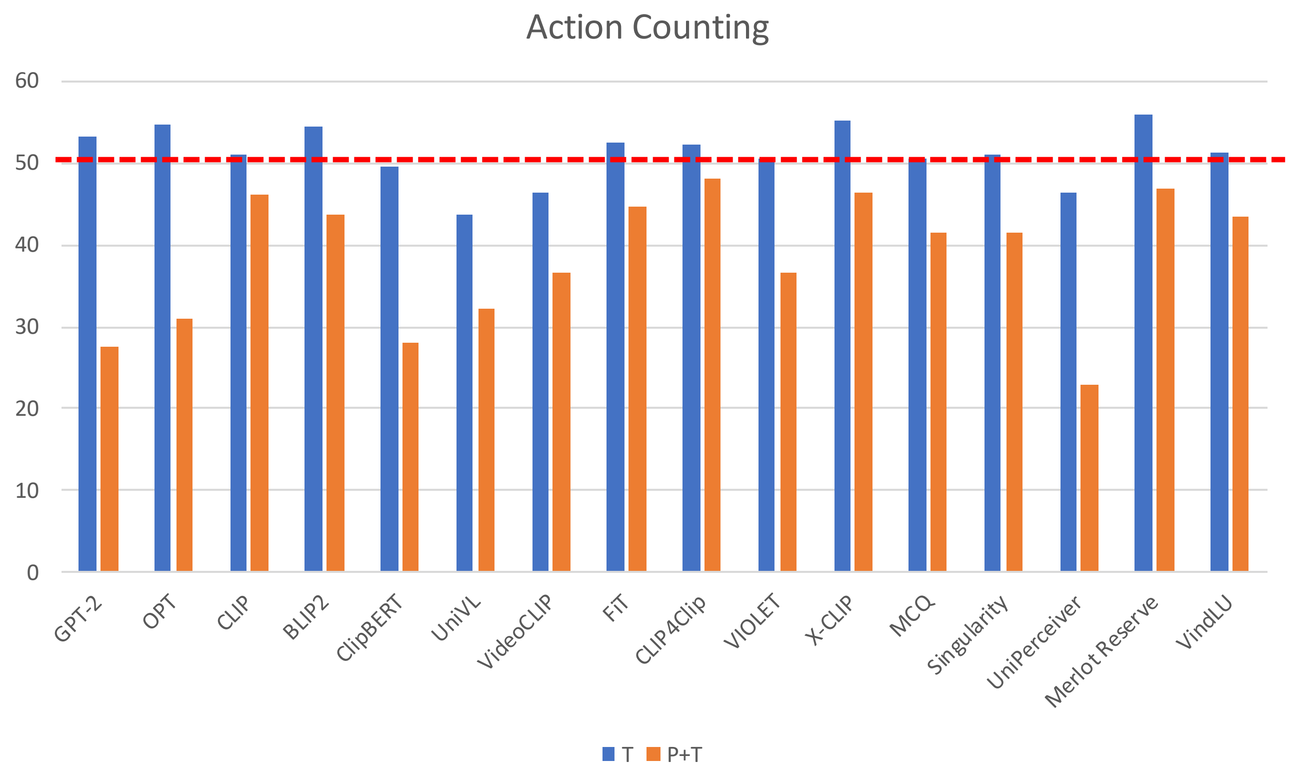
Results (selection)

Performance poor even without taking proficiency into account.

Video-Language models are not notably better than models using static images!

Confirms previous results with image-text models.

Counting is hard!

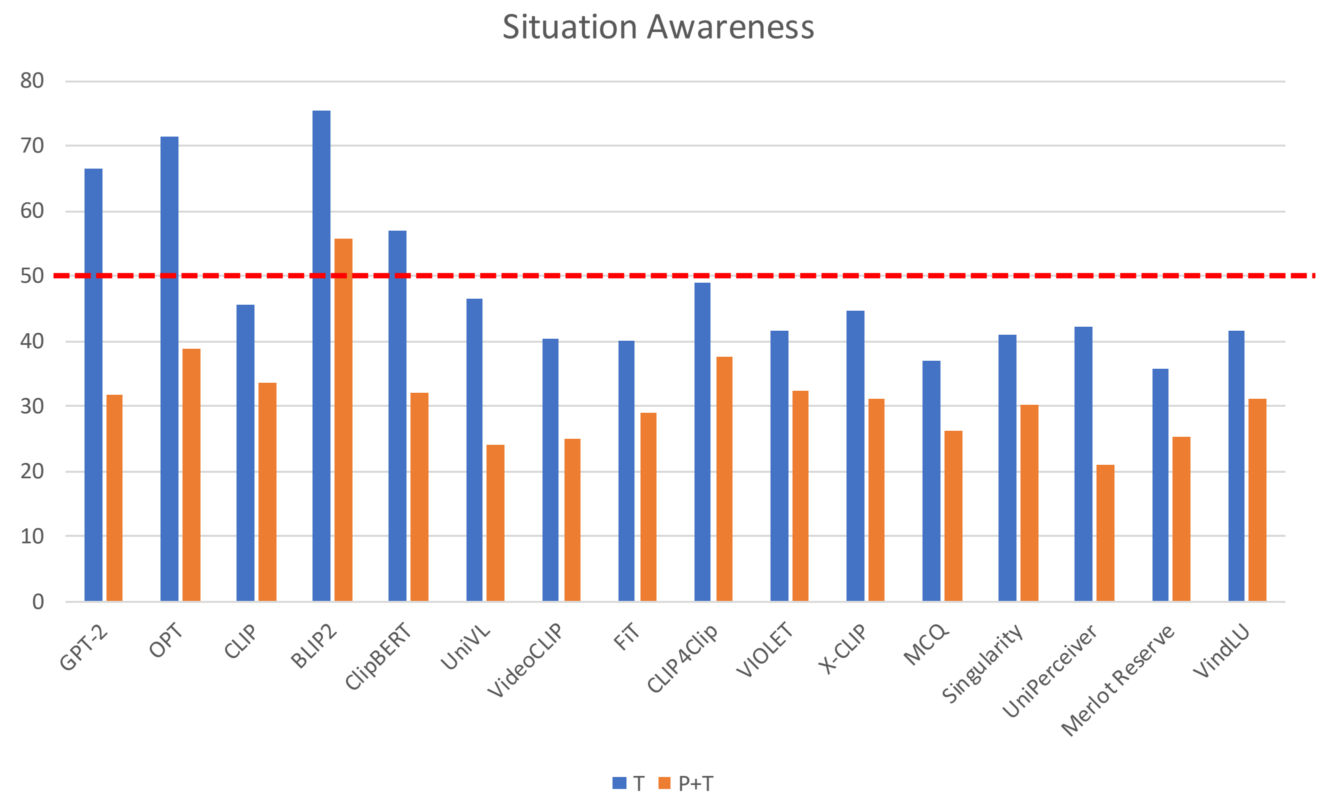


Results (selection)

Unimodal models do better overall. Could be because swapping actors or verbs results in “surprising” foils.

Again, BLIP-2 (static) outperforms a lot of the Video-Language models.

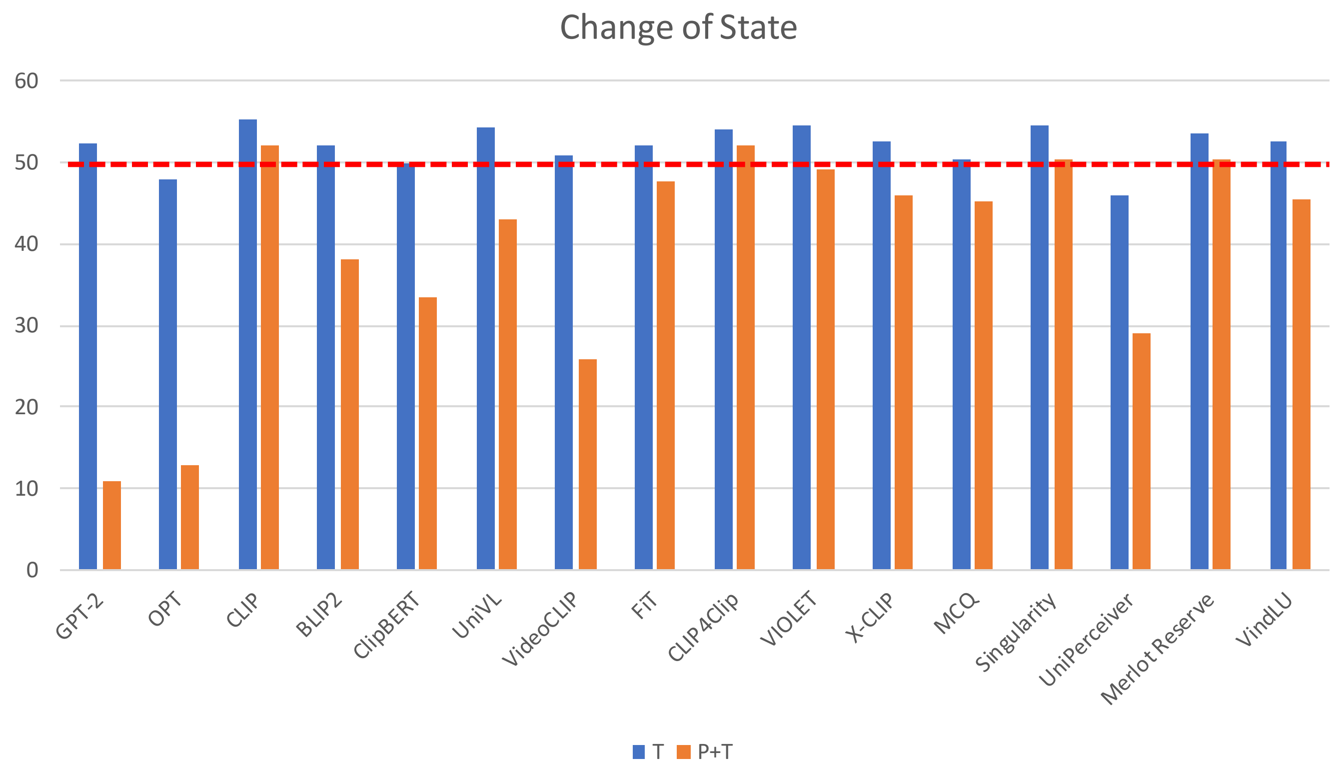
The temporal info in videos isn’t helping.



Results (selection)

Models are barely above chance.

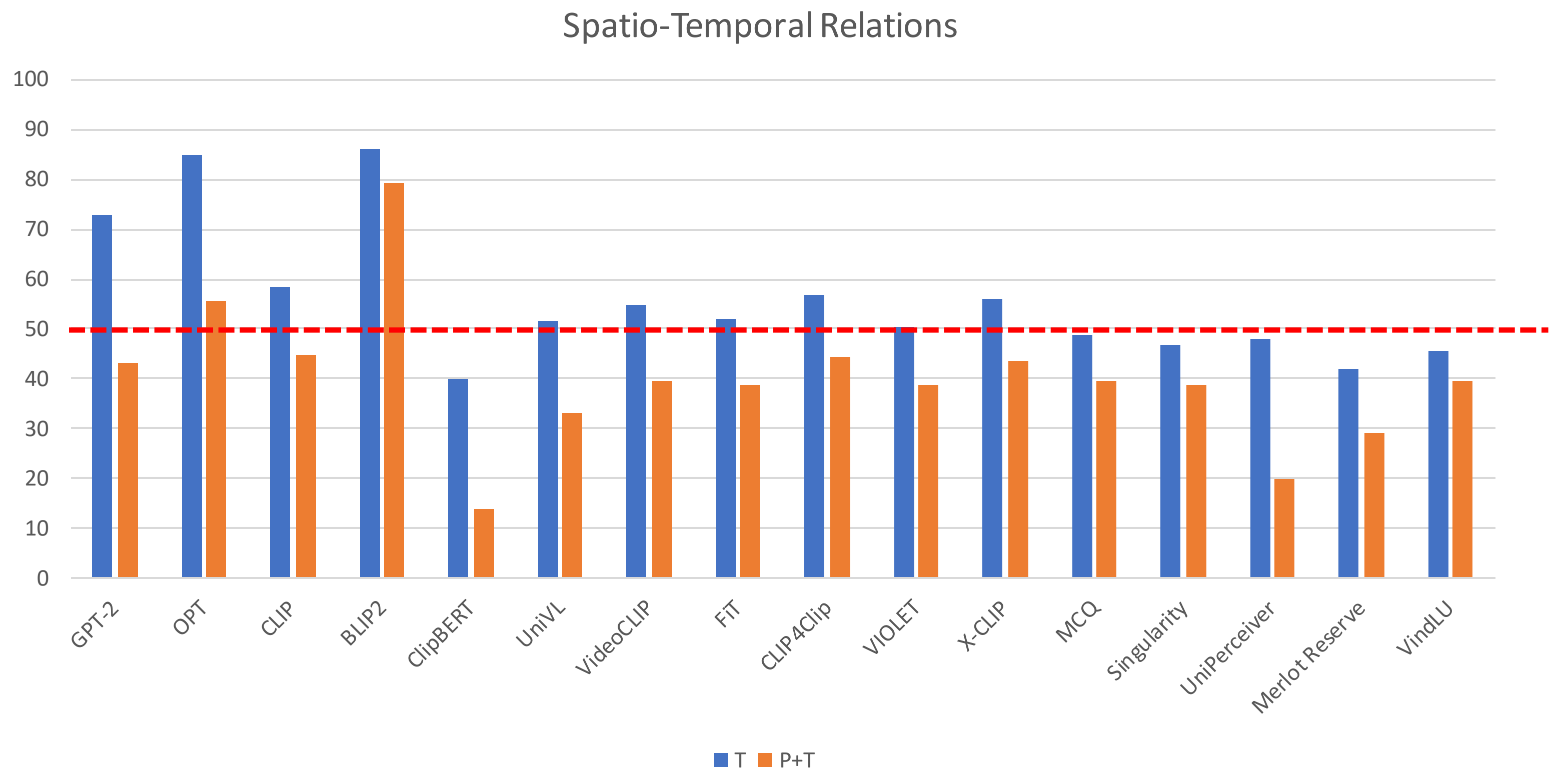
This is one test where temporal info should matter a lot.



Results (selection)

Only static models stay above chance once P is taken into account.

Video-language models do not seem to gain an advantage from the temporal info.



Main observation

Proficiency / main task

- Big drops suggest a reliance on spurious features in the training data.

Video vs. Image

- No clear differences in many tasks – the temporal information in videos doesn't necessarily help.
- (But could also be an impact of pretraining data size etc).

Main takeaway

- The training objectives used do not guarantee that models ground language in video data, making full use of the temporal dimension in that data.