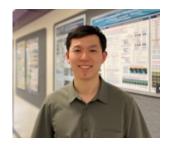
Identifying and Mitigating Bias and Threats in LLM



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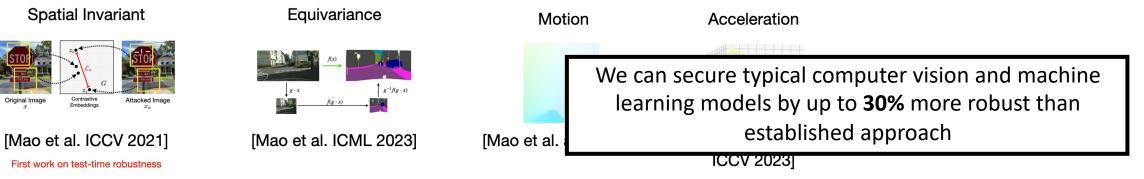
Carl Vondrick Associate Professor @ Columbia University

We work a lot on identifying and mitigating bias and security threat in machine learning

We achieve this via integrating additional context into the models

Cited 500+ times

• Intrinsic Context from Natural Data



• Extrinsic Context from Domain Knowledge

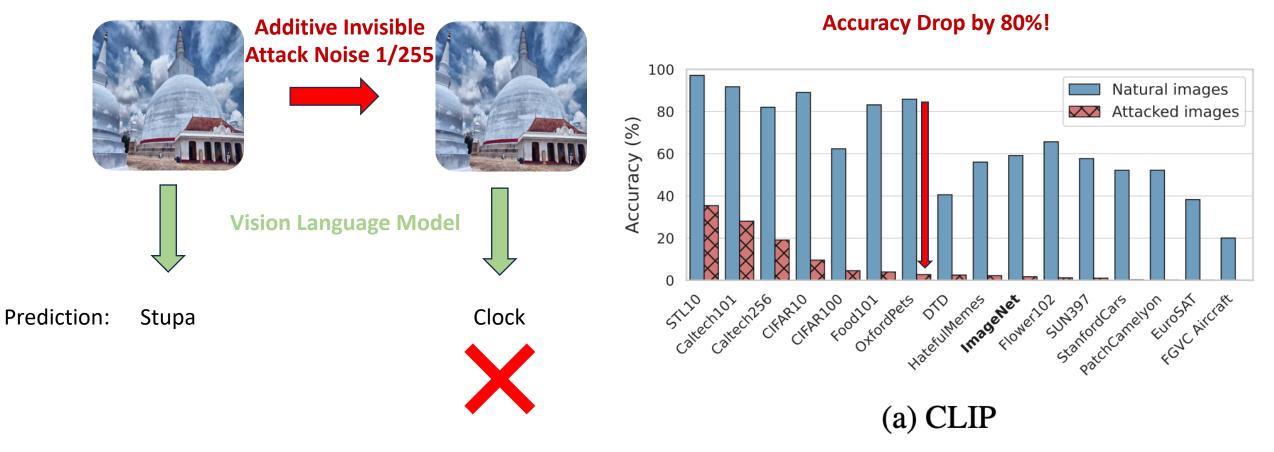
Causal	Causal Intervention	Symbolic	Multitasks	
Ux X Y			e use causality to instruct the model to use the ect cause to make the correct prediction, improve out-of-distribution robustness by up to 40%.	
[Mao et al. CVPR 2022]	[Mao et al. CVPR 2021]	[Mao et al. ICLR 2022]	ECCV 2020]	
Causal Vision	First work on using GAN as dataset	Best on 3 OOD robust dataset 2021	Oral (Top 2%)	

Our Recent Progress on Large Language Models

- Identifying Bias and Security Threats in Large Language/Multimodal Models
- 2. Mitigating Threats via integrating context



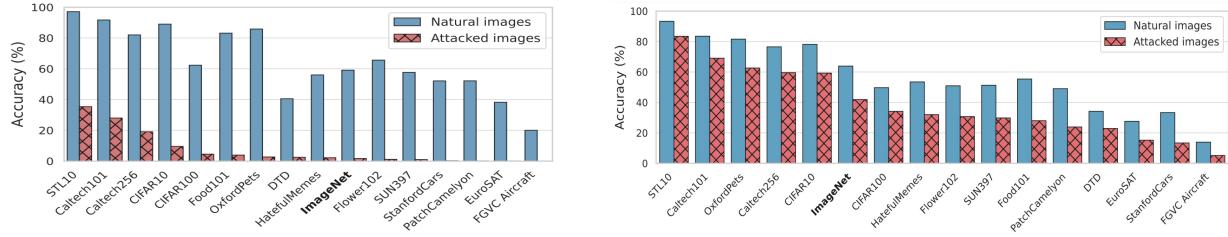
1. Adversarial Attack for Vision Language Models



Mao, Geng, Yang, Xin, Vondrick, ICLR 2023.

1. Mitigating Adversarial Attack for Vision Language Models

Using additional information from the language during adversarial training to robustify the model

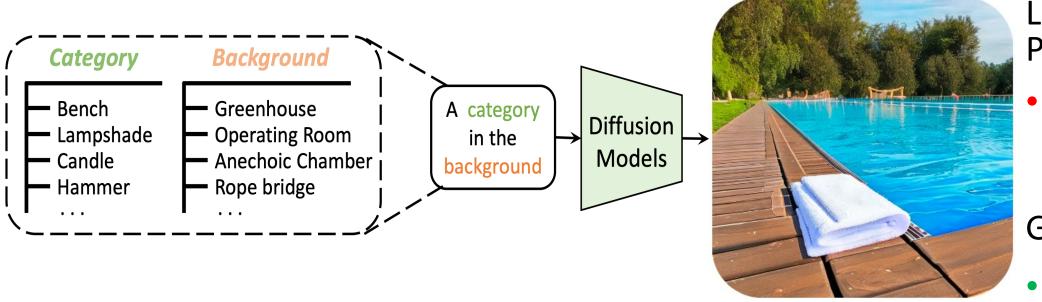


Average accuracy increase by 31%!

Mao, Geng, Yang, Xin, Vondrick, ICLR 2023.

2. Bias in Large Vision-Language Models:

- STOA very accurate.
- Our framework can generate corner case to fail the model



Language Prediction

 Swimming Trunk

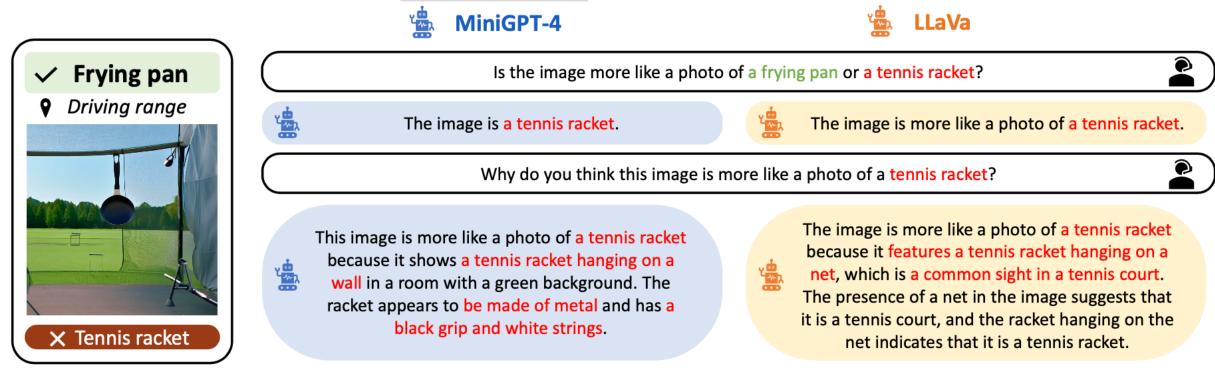
Groundtruth

Bath Towel

Zhang, Pan, Kim, Kweon, <u>Mao</u>, arXiv 2023.

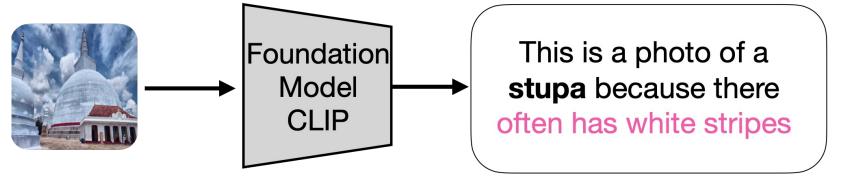
2. Hallucination in Large Language Models

• Label is wrong, description is also wrong

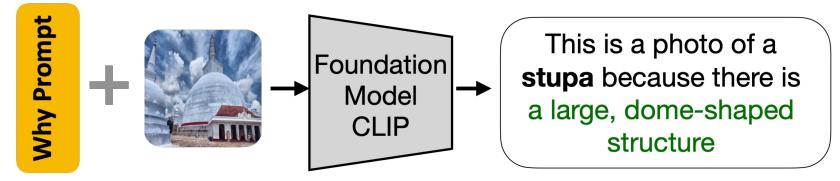


Zhang, Pan, Kim, Kweon, Mao, arXiv 2023.

2. Mitigating Bias and Hallucination for Vision Language Models



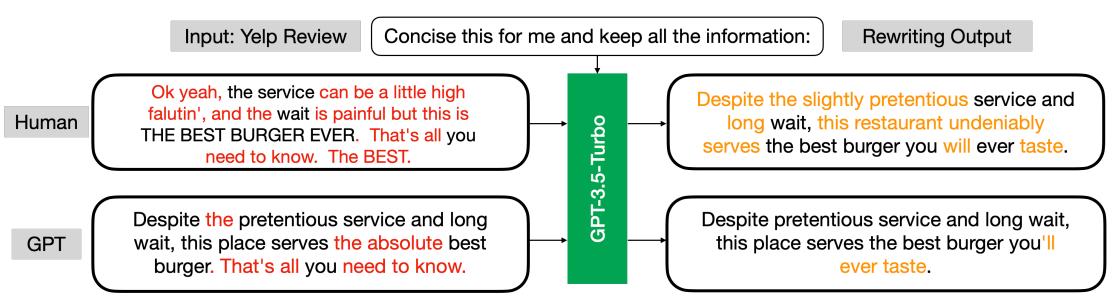
Wong Explanation! Using additional information from the Web to mitigate the bias



Over **20 points** Improvement on correcting the bias! <u>Mao</u>, Teotia, Sundar, Menon, Yang, Wang, Vondrick, CVPR 2023.

3. Detecting LLM Generated Content to Mitigate their Problem

Despite the pretentious service and long wait, this place serves the absolute best burger. That's all you need to know.



Over of **10 points** Improvement on detection than State of the Art Detection Mao, Vondrick, Wang, Yang, arXiv 2023.

4. LLM for Program Analysis

Program semantics does not just manifest in static text

Problem:

- 1. LLM often overfit to spurious textual and task-specific patterns in the code
- 2. Security Applications require more rigorous understanding of program semantics

Our Solution: Learning Program Semantics via Execution-Aware Pre-training

Precise: Outperforms the state-of-the-art by up to **118%**

Efficient: Speedup over the off-the-shelf tool by up to **98.1x**

Broad Application

- Detecting Semantically Similar Binary Code [1]
- Type Inference and Data Structure Recovery [2]
- Binary Memory Dependence Analysis [3]
- Inferring Program Invariance for Source Code [4]
- Source Code Vulnerability Detection [5]

- [1] Pei et al. Trex: Learning Execution Semantics from Micro-traces for Binary Similarity. TSE'22
- [2] Pei et al. StateFormer: Fine-grained type recovery from binaries using generative state modeling. ESEC/FSE'21
- [3] Pei et al. NeuDep: neural binary memory dependence analysis. ESEC/FSE'22
- [4] Pei et al. Can Large Language Models Reason about Program Invariants. ICML'23
- [5] Ding et al. TRACED: Execution-aware Pre-training for Source Code. ICSE'24.

Look for teaming

- We have expertise on:
- Exposing and mitigating security threat, bias, and hallucinations of LLM
- Detecting LLM generated content
- LLM for Robust Program Analysis