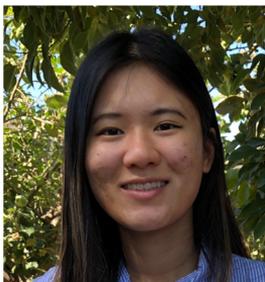


NewsCLIPpings

Automatic Generation of Out-of-Context Multimodal Media

Grace Luo, Trevor Darrell, Anna Rohrbach



University of California, Berkeley



Motivation: Out-of-Context Images

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UNELECTED **House of Lords** told to stop FALLING ASLEEP.



EXPRESS 

Legitimate old photograph

Motivation: Out-of-Context Images

UNELECTED **House of Lords** told to stop FALLING ASLEEP.



EXPRESS 

Legitimate old photograph

\$85/hr is too much to pay our **senators** to literally do nothing.



Evidence of recent events

Motivation: Out-of-Context Images

UNELECTED House of
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Legitimate old photograph

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Evidence of recent events

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EXPRESS

Legitimate old photograph

\$85/hr is too much to
pay our senators to
literally do nothing.



Evidence of recent events

Alert! Automation of cheapfakes.

Prior Out-of-Context Datasets

Dataset	Method	Notes
MAIM (Jaiswal et al, 2017)	Random	Little text-image alignment
TamperedNews (Muller-Budack et al, 2020)	Text entity manipulation	Linguistic biases
COSMOS (Aneja et al, 2021)	Human generated	Small number of labelled samples
NewsCLIPpings (Ours)	Automatic retrieval	Convincing to humans No linguistic biases Almost 1M labelled samples

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NewsCLIPpings Dataset Overview

- Dataset of ~1M samples of **news image repurposing**.
- Diagnostic benchmark for **machine generated misinformation**.
- General automatic framework for generating **challenging mismatches**.

Approach

“Angela Merkel speaks”

Pool of candidate images



*Angela Merkel
speaks*



Approach

✓ Semantics

✓ Person

✓ Scene

Approach: In-the-Wild

Photo shows U.S. Sen.
Tom Cotton of Arkansas
sitting on a bed of gold bars...



✓ Semantics
✗ NE

✓ Person
✗ Semantics

✓ Scene
✗ NE

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Approach: NewsCLIPpings

Angela Merkel speaks to the
German parliament...



✓ Semantics
✗ NE

✓ Person
✗ Semantics

✓ Scene
✗ NE

Approach: NewsCLIPpings

Angela Merkel **speaks** to the
German parliament...



✓ Semantics
✗ NE

✓ Person
✗ Semantics

✓ Scene
✗ NE

Approach: NewsCLIPpings

Angela Merkel speaks to the
German parliament...



✓ Semantics
X NE

✓ Person
X Semantics

✓ Scene
X NE

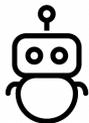
Approach: NewsCLIPpings

Semantics CLIP Text-Image

Approach: NewsCLIPpings

Semantics CLIP Text-Image

*Angela Merkel speaks
to the German parliament...*



Approach: NewsCLIPpings

Semantics CLIP Text-Image



CTI Sim: 0.2940

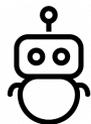


CTI Sim: 0.2799



CTI Sim: 0.2114

*Angela Merkel speaks
to the German parliament...*



Approach: NewsCLIPpings

Semantics CLIP Text-Image



CTI Sim: 0.2940

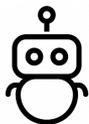


CTI Sim. 0.2799



CTI Sim. 0.2114

*Angela Merkel speaks
to the German parliament...*



Falsified

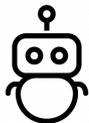
*Angela Merkel speaks
to the German parliament...*



Approach: NewsCLIPpings

Semantics CLIP Text-Text

*Angela Merkel speaks
to the German parliament...*



Approach: NewsCLIPpings

Semantics CLIP Text-Text

*Angela Merkel speaks
to the German parliament...*



Ingeborg Berggreen
Merkel delivers the task
force s report in Berlin.

CTT Sim. 0.8006

Half of Tessa Jowell s
settlement will go direct to
a charity in her south
London constituency.

CTT Sim. 0.5467

Tennessee Gov Bill
Haslam delivers his State
of the State address to a
joint session of the
General Assembly on
Monday in Nashville.

CTT Sim.: 0.4942

Approach: NewsCLIPpings

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*Angela Merkel speaks
to the German parliament...*



Falsified

*Angela Merkel speaks
to the German parliament...*



Approach: In-the-Wild

Photo shows Tampa Mayor Jane Castor maskless at Super Bowl.



✓ Semantics
X NE

✓ Person
X Semantics

✓ Scene
X NE

Approach: In-the-Wild

Photo shows Tampa Mayor
Jane Castor maskless at
Super Bowl.



✓ Semantics
X NE

✓ Person
X Semantics

✓ Scene
X NE

Approach: In-the-Wild

Photo shows Tampa Mayor
Jane Castor maskless at
Super Bowl.



✓ Semantics
X NE

✓ Person
X Semantics

✓ Scene
X NE

Approach: NewsCLIPpings

Prince William and Duchess Kate introduce their son to the world.



✓ Semantics
X NE

✓ Person
X Semantics

✓ Scene
X NE

Approach: NewsCLIPpings

Prince William and Duchess Kate introduce their son to the world.



✓ Semantics
X NE

✓ Person
X Semantics

✓ Scene
X NE

Approach: NewsCLIPpings

Prince William and Duchess Kate introduce their son to the world.



✓ Semantics
X NE

✓ Person
X Semantics

✓ Scene
X NE

Approach: NewsCLIPpings

Person SBERT-WK Text-Text

Approach: NewsCLIPpings

Person SBERT-WK Text-Text



*Prince William and Duchess
Kate introduce their son to
the world.*

Approach: NewsCLIPpings

Person SBERT-WK Text-Text

Prince William the Duke of Cambridge carries his newborn baby boy to the car after leaving the hospital.

STT Sim. 0.8753

William Catherine and Harry attend the forum.

STT Sim. 0.8480

Prince William missed the net this summer at the Somba K e Civic Plaza Yellowknife.

STT Sim. 0.7854

Prince William and Duchess Kate introduce their son to the world.



Approach: NewsCLIPpings

Person SBERT-WK Text-Text

Prince William the Duke of Cambridge carries his newborn baby boy to the car after leaving the hospital.

STT Sim. 0.8753

William Catherine and Harry attend the forum.

STT Sim. 0.8480

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STT Sim. 0.7854

Prince William and Duchess Kate introduce their son to the world.



Falsified

Prince William and Duchess Kate introduce their son to the world.



Approach: In-the-Wild

... trash that was left behind
by ... refugees traveling ... to
the United States



✓ Semantics
X NE

✓ Person
X Semantics

✓ Scene
X NE

Approach: In-the-Wild

... **trash that was left behind**
by ... refugees traveling ... to
the United States



✓ Semantics
X NE

✓ Person
X Semantics

✓ Scene
X NE

Approach: In-the-Wild

... trash that was left behind
by ... refugees traveling ... to
the **United States**



✓ Semantics
X NE

✓ Person
X Semantics

✓ Scene
X NE

Approach: NewsCLIPpings

Fukushima Daiichi nuclear power plant after Japan s earthquake and tsunami...



✓ Semantics
X NE

✓ Person
X Semantics

✓ Scene
X NE

Approach: NewsCLIPpings

Fukushima Daiichi nuclear power plant after Japan s earthquake and tsunami...



✓ Semantics
X NE

✓ Person
X Semantics

✓ Scene
X NE

Approach: NewsCLIPpings

Fukushima Daiichi nuclear power plant after **Japan s** earthquake and tsunami...



✓ Semantics
X NE

✓ Person
X Semantics

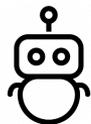
✓ Scene
X NE

Approach: NewsCLIPpings

Scene ResNet Place

Approach: NewsCLIPpings

Scene ResNet Place



Approach: NewsCLIPpings

Scene ResNet Place



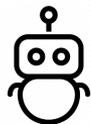
RP Sim. 0.8272



RP Sim. 0.7829



RP Sim. 0.7823



Approach: NewsCLIPpings

Scene ResNet Place



RP Sim. 0.8272



RP Sim. 0.7829



RP Sim. 0.7823

Falsified

*Fukushima Daiichi
nuclear power plant after
Japan's earthquake and
tsunami in March.*



Approach

✓ **Semantics**

CLIP Text-Image, CLIP Text-Text

✓ **Person**

SBERT-WK Text-Text

✓ **Scene**

ResNet Place

Approach

✓ Semantics

CLIP Text-Image, CLIP Text-Text

✓ Person

SBERT-WK Text-Text

✓ Scene

ResNet Place

Approach

✓ **Semantics**

CLIP Text-Image, CLIP Text-Text

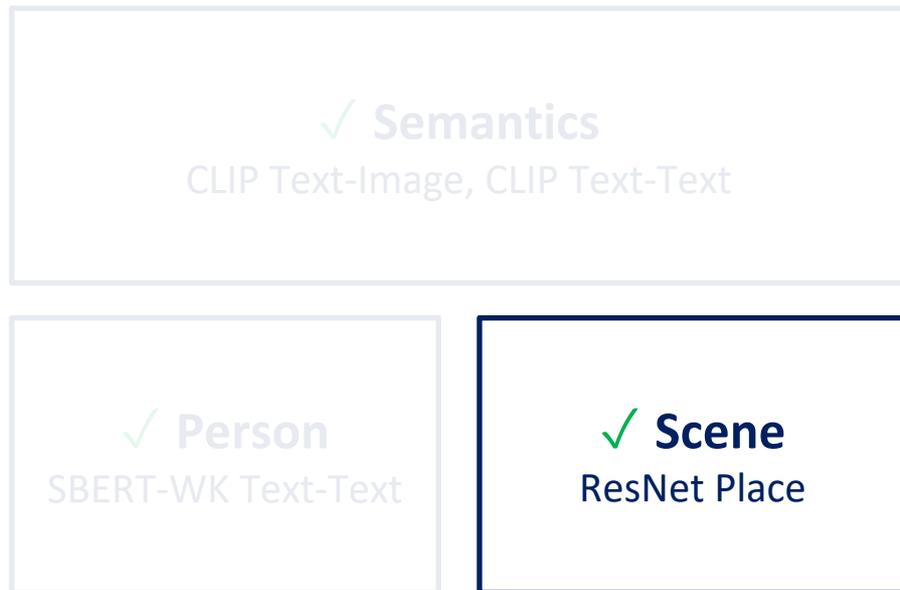
✓ **Person**

SBERT-WK Text-Text

✓ **Scene**

ResNet Place

Approach



Experimental Setup

- Binary classification: pristine or falsified

Pristine or Falsified?



The fire at the Darul
Uloom school...

Experimental Setup

- Binary classification: pristine or falsified
- Balanced wrt captions, labels

Pristine or Falsified?



The fire at the Darul
Uloom school...

Experimental Setup

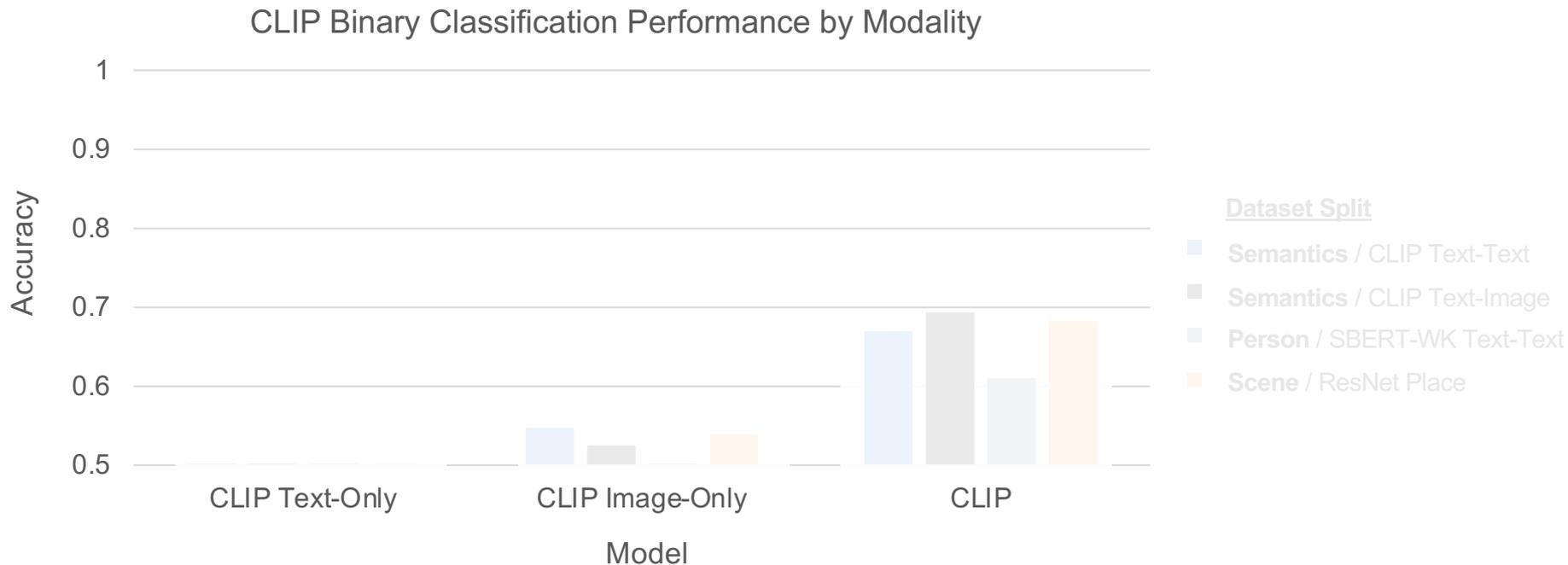
- Binary classification: pristine or falsified
- Balanced wrt captions, labels
- **CLIP** (Radford et al., 2021): pretrained on 400M web corpus
- **VisualBERT** (Li et al., 2019): pretrained on 3M Conceptual Captions (Sharma et al., 2018) or 1M VisualNews (Liu et al., 2020)

Pristine or Falsified?

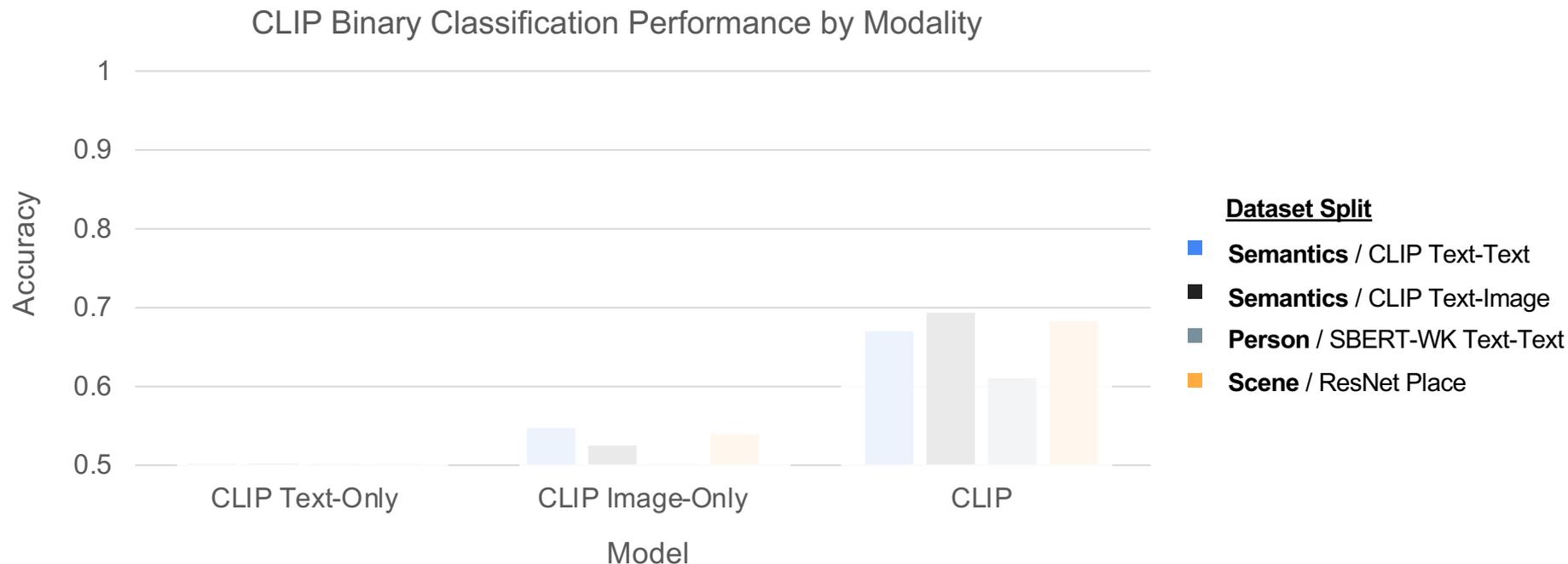


The fire at the Darul Uloom school...

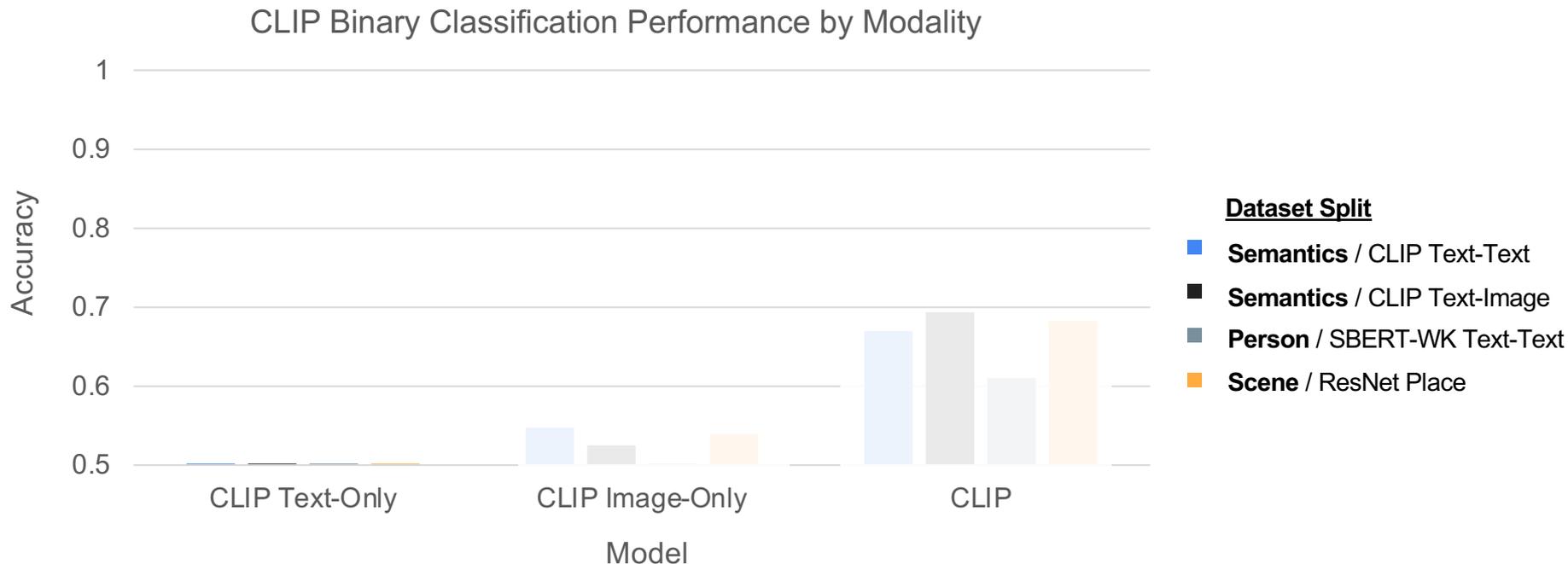
Experiments: Unimodal vs Multimodal



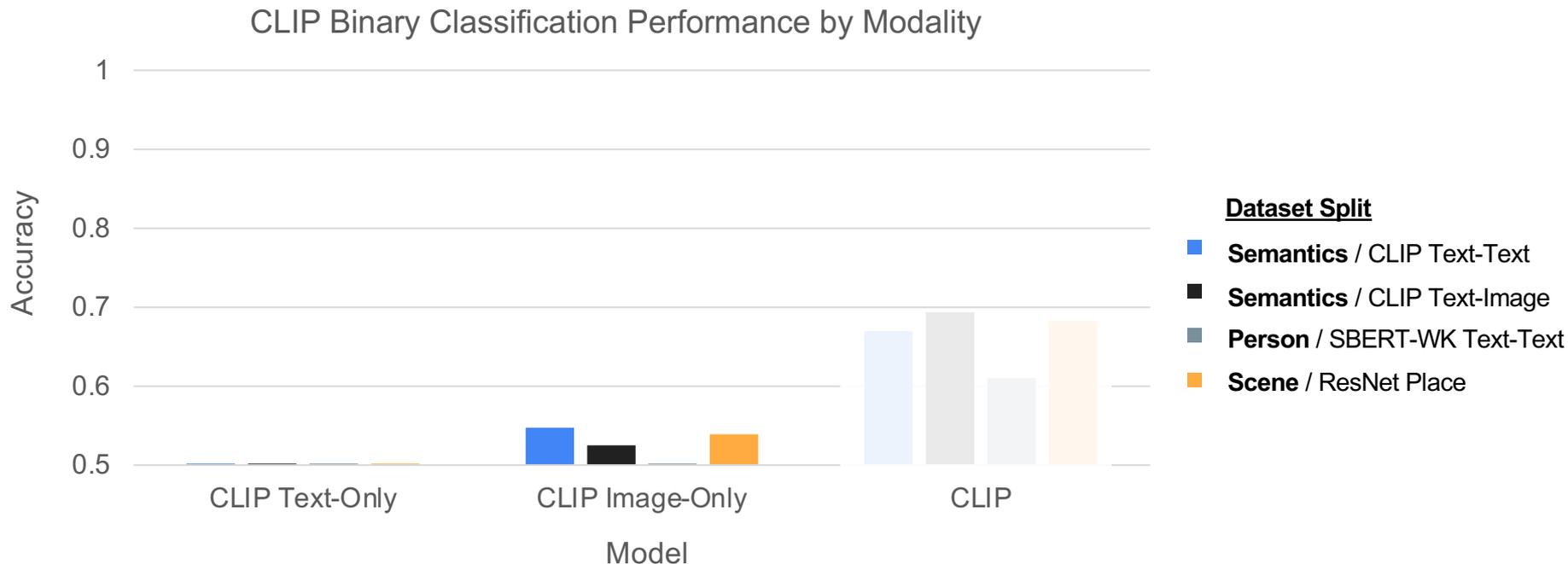
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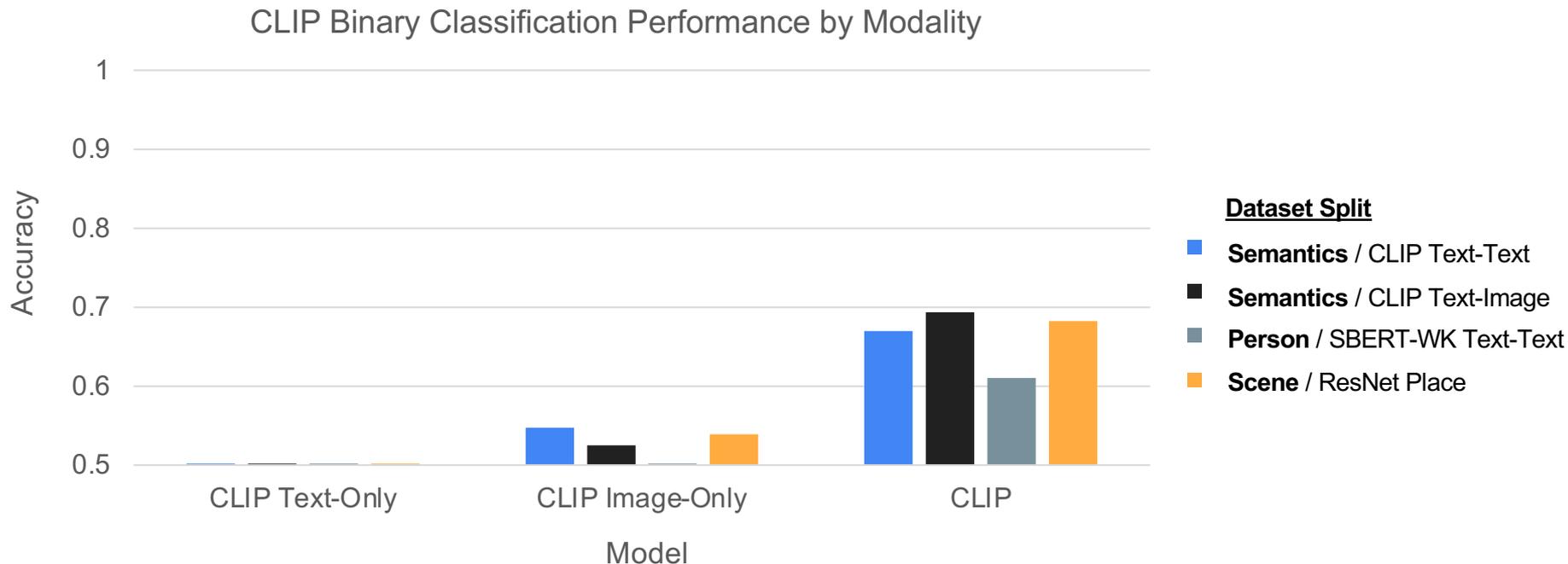
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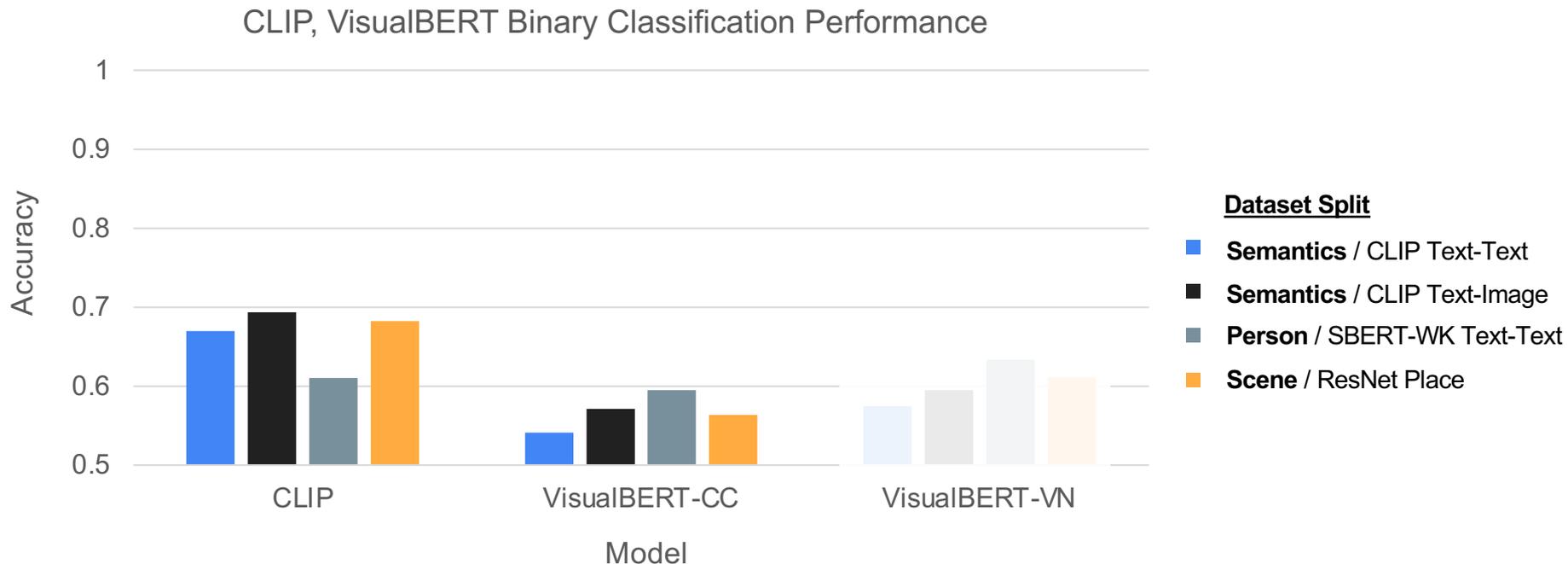
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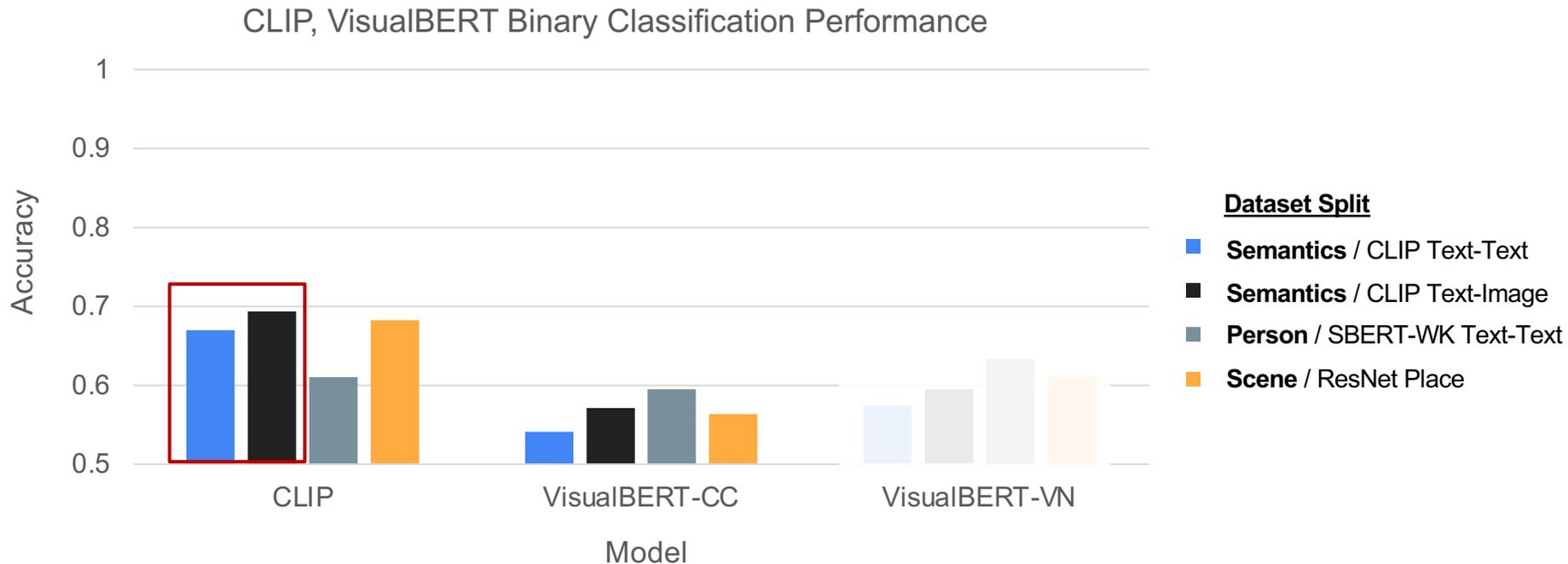
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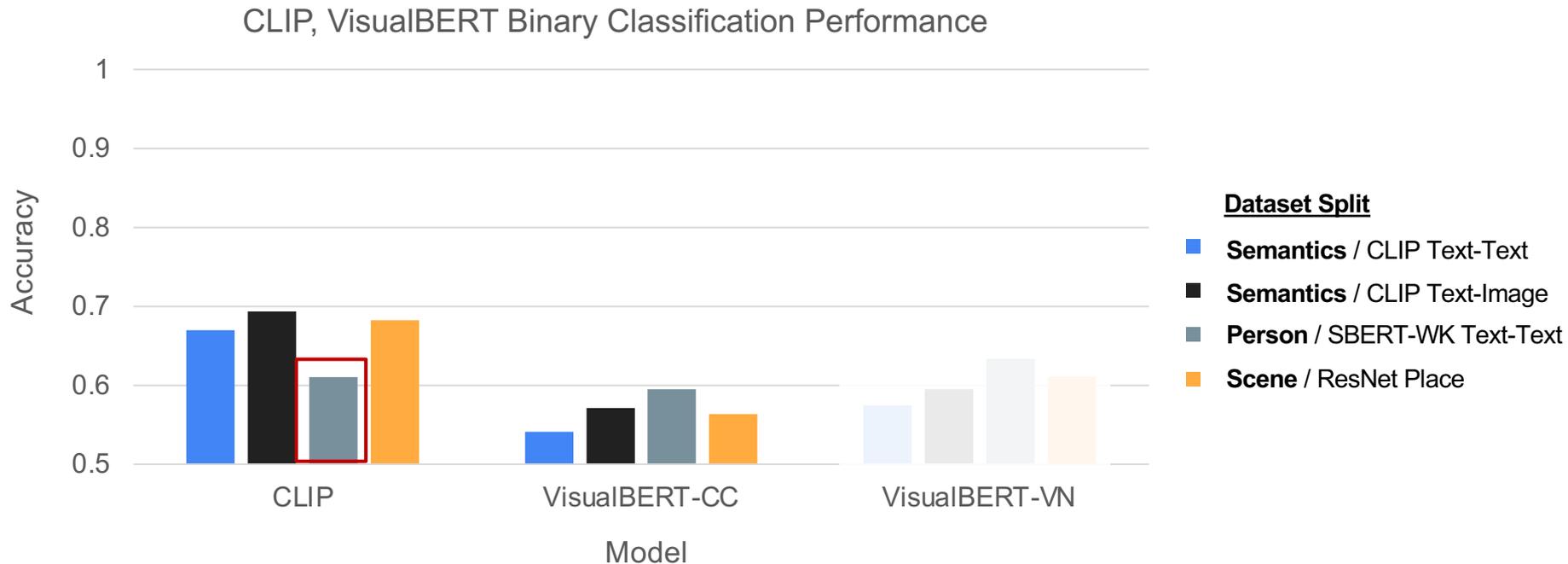
Experiments: Multimodal



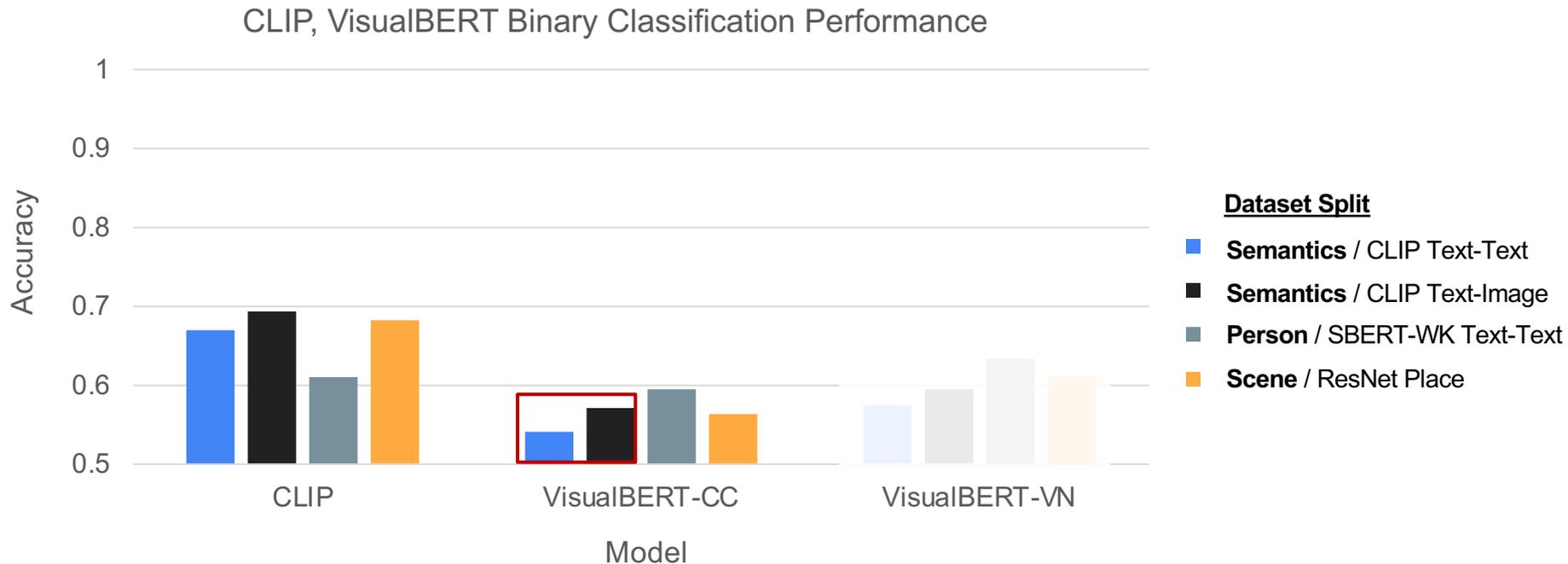
Experiments: Multimodal



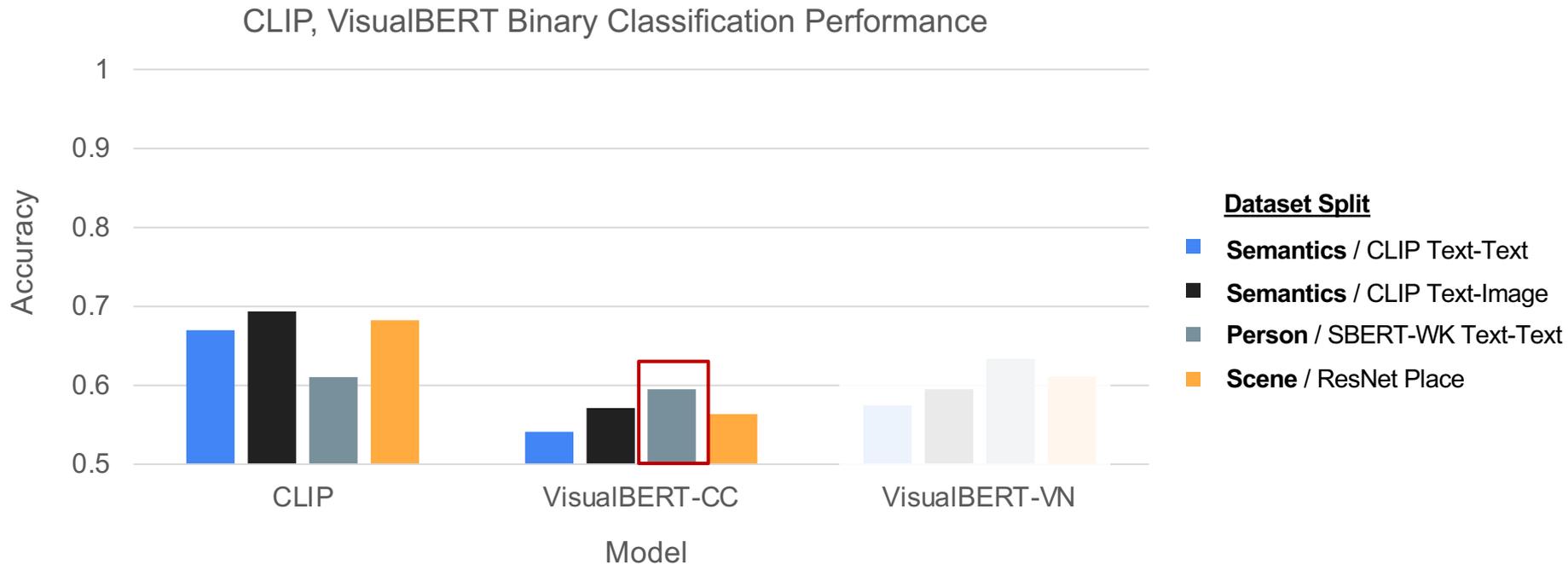
Experiments: Multimodal



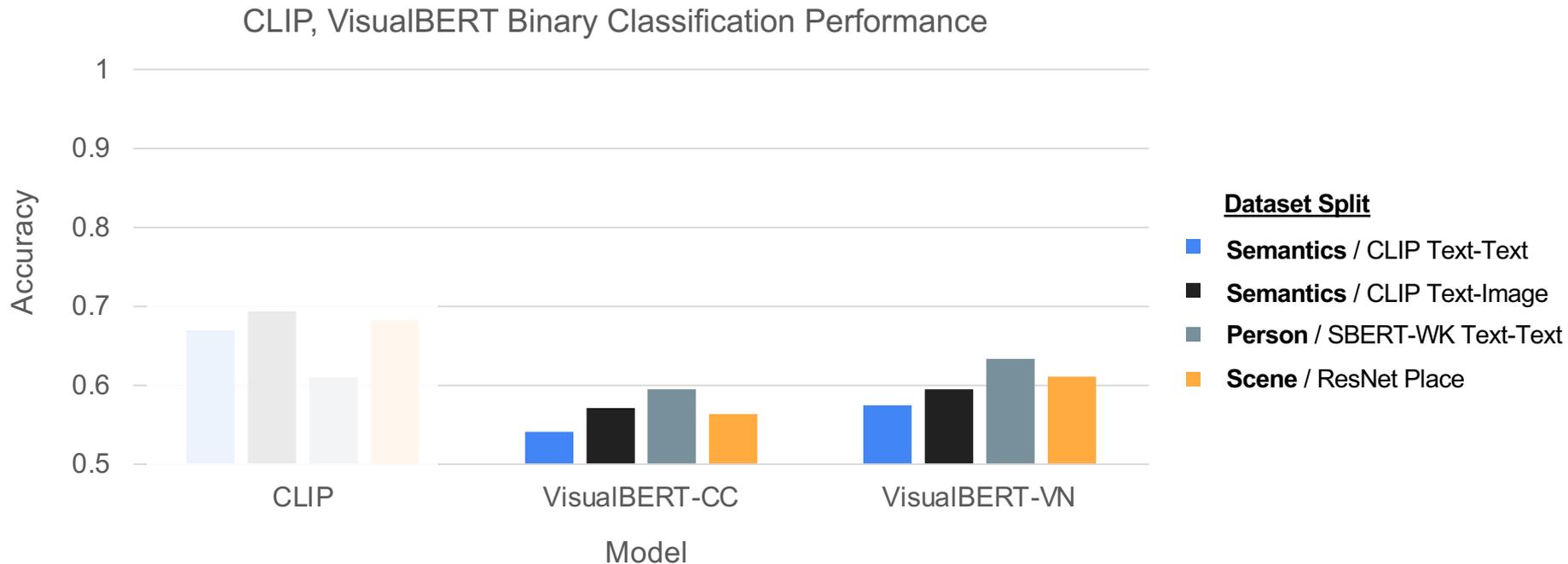
Experiments: Multimodal



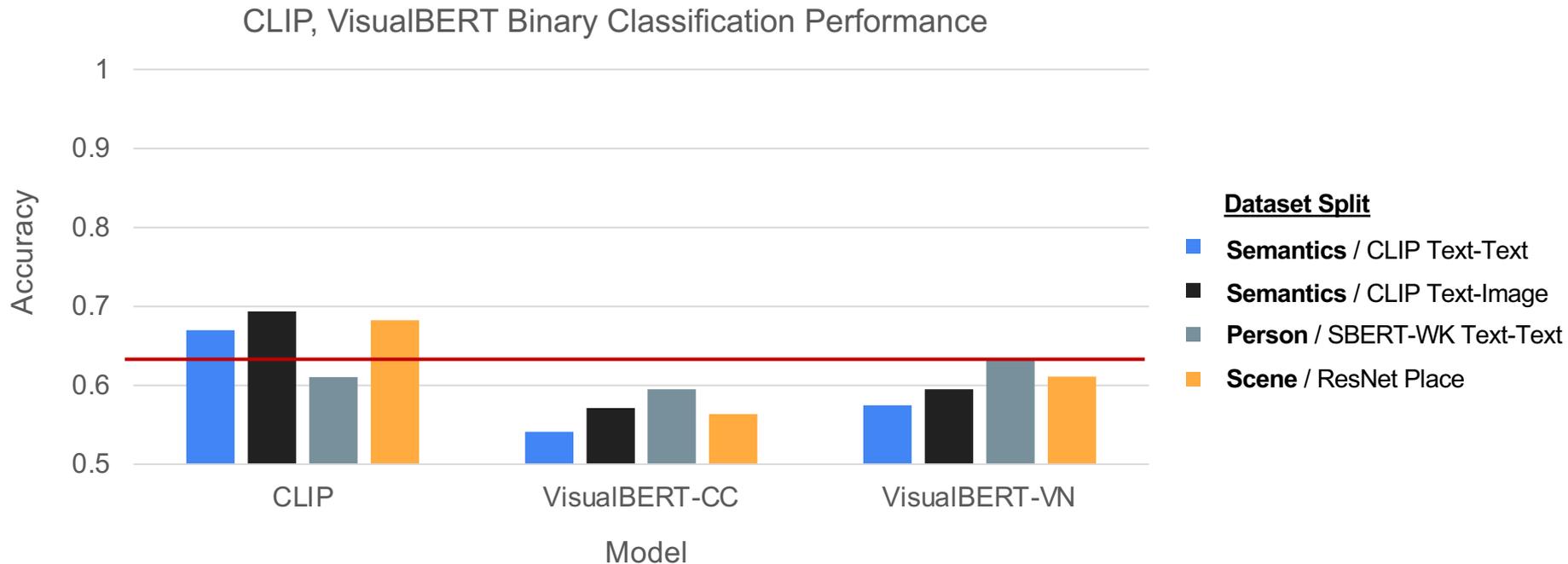
Experiments: Multimodal



Experiments: Multimodal



Experiments: Multimodal



Human Evaluation

- Same binary classification task

Does the image belong to the given caption?



The fire at the Darul Uloom school...

Human Evaluation

- Same binary classification task
- 100 sample subset
 - ~25% from each split
 - ~50% pristine, falsified

Does the image belong to the given caption?



The fire at the Darul Uloom school...

Human Evaluation

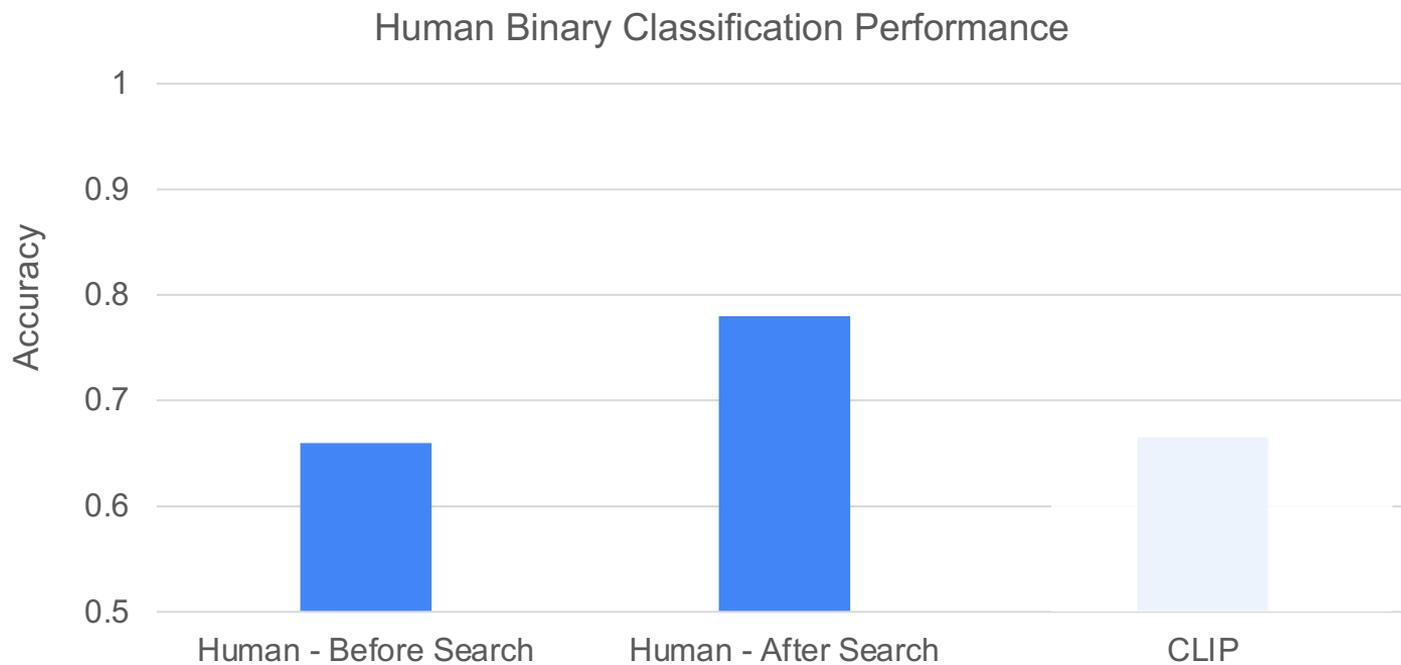
- Same binary classification task
- 100 sample subset
 - ~25% from each split
 - ~50% pristine, falsified
- Before and after internet search

Does the image belong to the given caption?

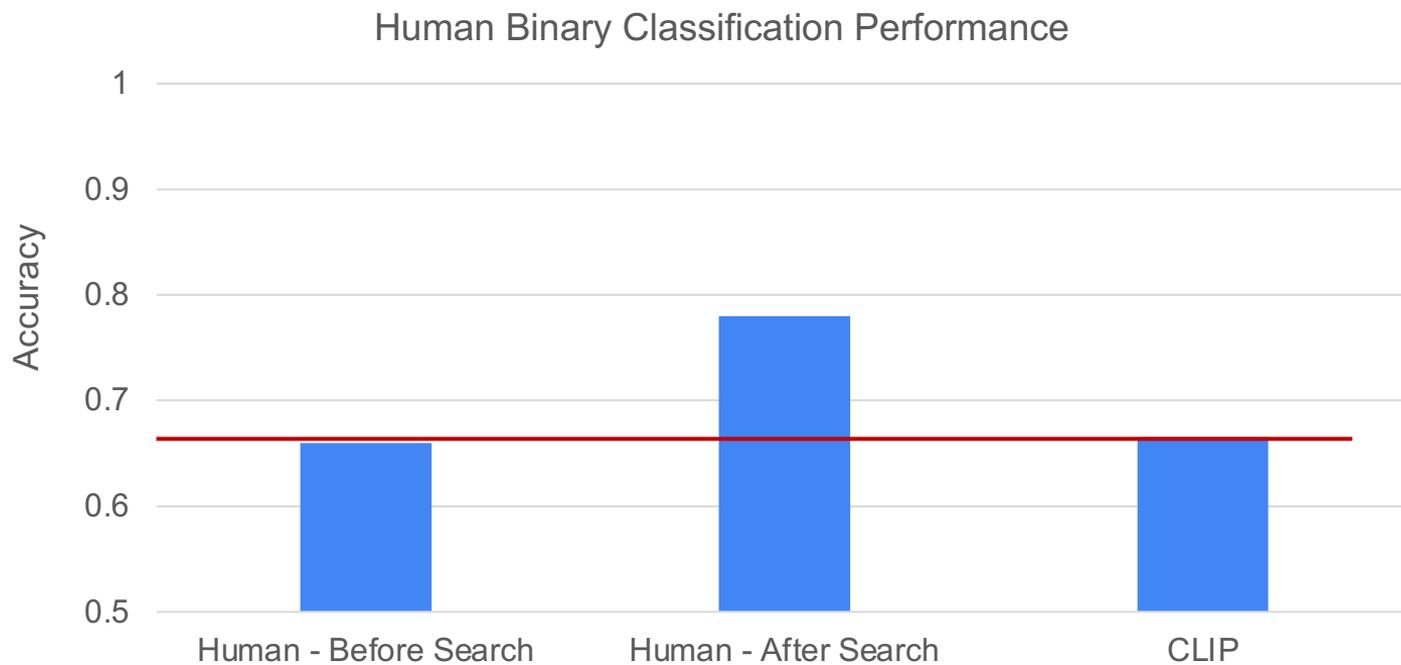


The fire at the Darul Uloom school...

Human Evaluation



Human Evaluation



Future Directions

North Carolina State

Wolfpack forward

Beejay Anya...



Symbols

Guinea s David Alvarez
celebrates after scoring
the winner against
Senegal.



Actions

... rally against labour
reforms in Athens ...



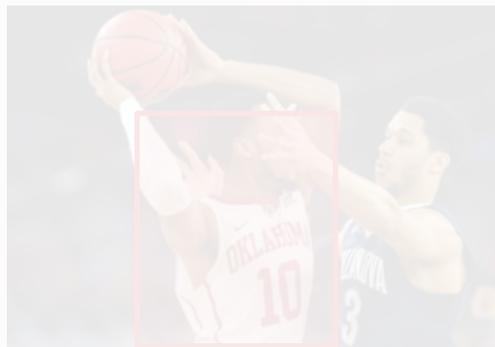
Locations

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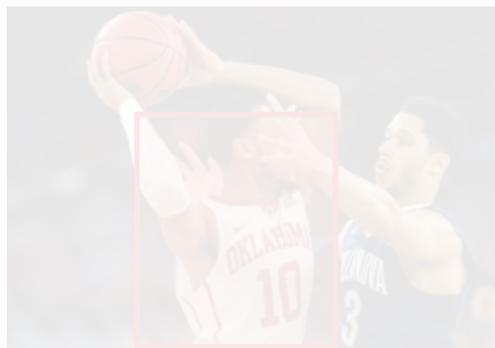
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Locations

Takeaways

- The automation of cheapfakes is now a realistic threat.
- Humans are susceptible to fakes from NewsCLIPpings.
- Models require improvements in understanding of symbols, facial expressions, and locations.

Thank you!

https://github.com/g-luo/news_clippings

<http://arxiv.org/abs/2104.05893>

