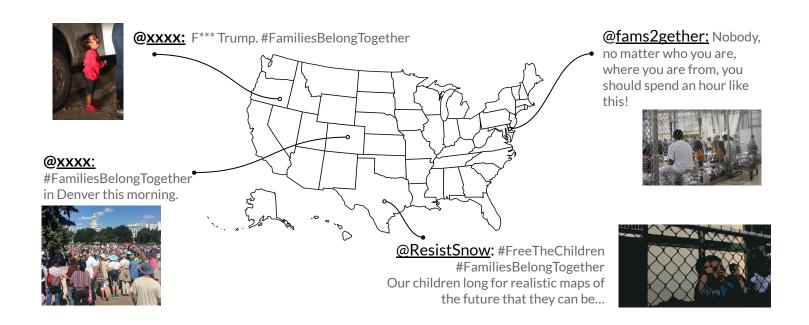
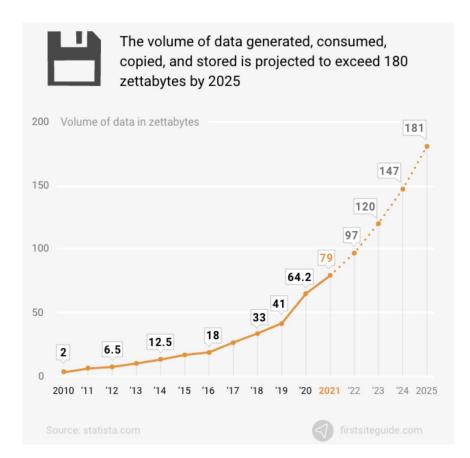
Multimodal Modeling for Political Science Research

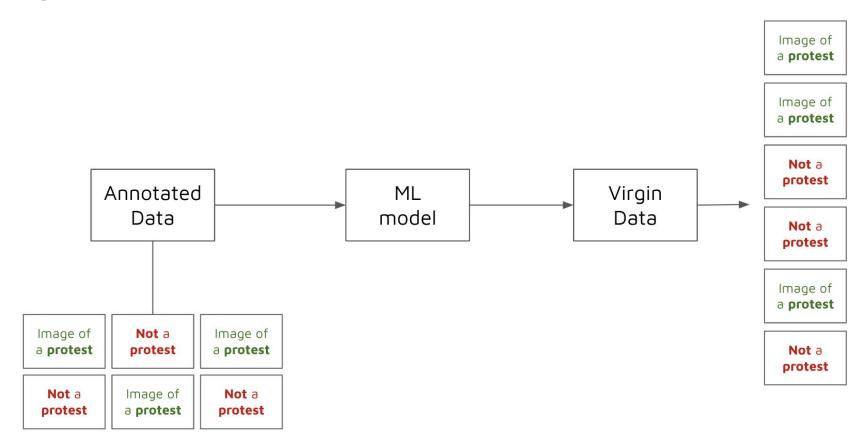


Andreu CasasRoyal Holloway Univ. of London

Freek Cool Vrije Universiteit Amsterdam (Political) scientists have an **increasing amount of (digital) data available** for addressing their questions of interest



Supervised machine learning is often used to identify a defined concept in large amounts of data



Often this data is multimodal: with text, visuals, audio



Donald J. Trump ② @realDonaldTrump · Sep 21

Hello everyone! I have something incredible to share today, as we are introducing the launch of our Official Trump Coins! The ONLY OFFICIAL coin designed by me—and proudly minted here in the U.S.A. The President Donald J. Trump First Edition Silver Medallion will be available Show more



THE NEW YORK TIMES/SIENA COLLEGE POLL Sept. 17 to 21 If the 2024 presidential election were held today, who would you vote for if the candidates were Kamala Harris and Donald Trump? 45% 50% Arizona 49 45 Georgia **North Carolina** 52 40 Among likely voters. Shaded areas represent margins of error.

Yet we mostly only use one data modality to train supervised ML (e.g. text)



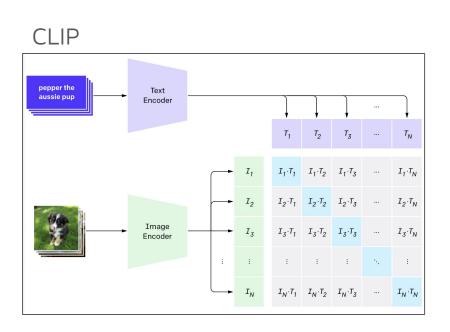
Hello everyone! I have something incredible to share today, as we are introducing the launch of our Official Trump Coins! The ONLY OFFICIAL coin designed by me—and proudly minted here in the U.S.A. The President Donald J. Trump First Edition Silver Medallion will be available

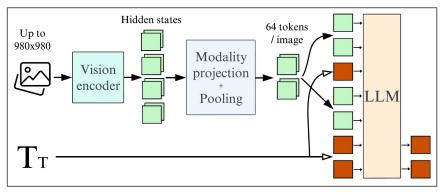
Show more



THE NEW YORK TIMES/SIENA COLLEGE POLL Sept. 17 to 21 If the 2024 presidential election were held today, who would you vote for if the candidates were Kamala Harris and Donald Trump? 45% 50% Arizona 49 45 Georgia **North Carolina** 40 52 Among likely voters. Shaded areas represent margins of error.

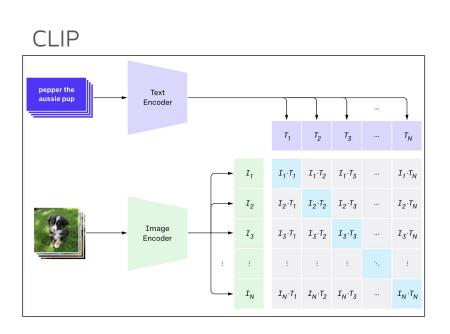
Recent computational advances make multimodal modeling easier

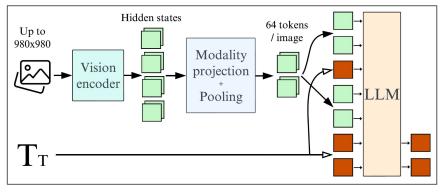




Idefics2

But we don't know much about whether nor the conditions under which multimodality can help improve the performance of supervised ML





Idefics2

Two **original annotated dataset** (10 tasks)

(1) **YouTube Videos** from channels posting on US politics (N = \sim 4,000) \rightarrow 6 tasks

(2) **Twitter Posts** from interest groups from US, ES, DK, GE (N = \sim 4,000) \rightarrow 4 tasks

Seven models:

- (1) **Text only**: SVM, BERT, Llama2, and Llama3
- (2) **Image only:** CNN
- (3) **Text + Image**: CLIP, Idefics2

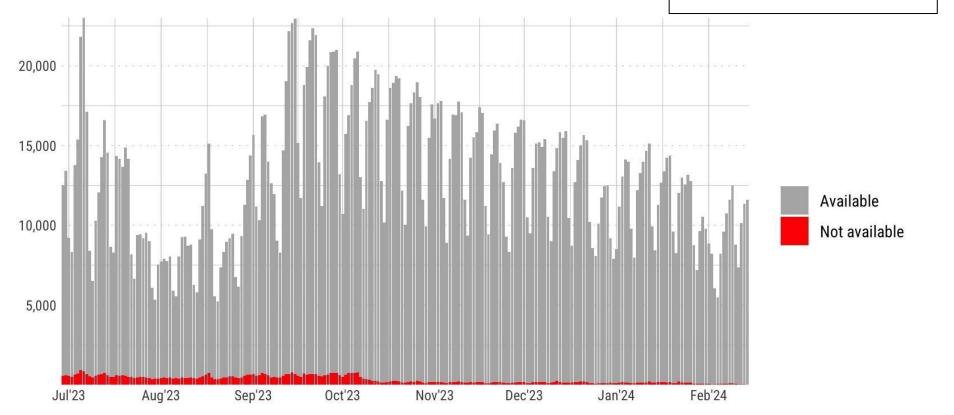
- (1) YouTube Videos from channels that post about US politics (N = ~4,000)
 - (a) US politics: is the video about US politics?
 - (b) Hateful: does the video have hateful content?
 - (c) Typology: what type of video? (e.g. opinion, high-quality news, etc.)
 - (d) Ideology: ideology of the video (liberal, moderate, conservative, neutral)

Seven models:

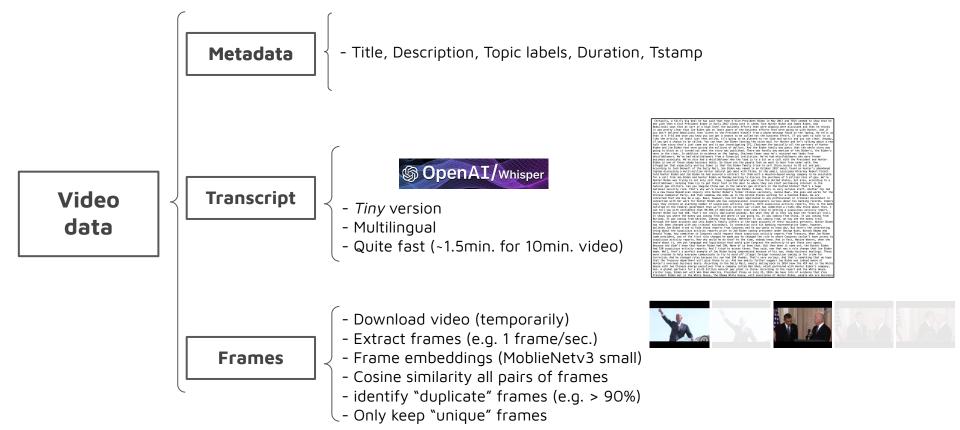
- (1) **Text only**: SVM, BERT, Llama2, and Llama3
- (2) **Image only:** CNN
- (3) **Text + Image**: CLIP, Idefics2

Data

- about 6 million videos
- from about 12k channels
- 3% channels not available
- 2% videos not available



Data



Data

Task	Description	Values	\mathbf{N}	%
US Politics	Whether the video is about, or relevant to, US politics	0	1,935	49.8%
		1	1,945	50.2%
		N	3,880	100.0%
Hateful	Whether the video contains hateful language/behavior	0	3,431	88.4%
		1	449	11.6%
		N	3,880	100%
Idology	The ideological leaning of the video	Neutral	238	21.7%
		Conservative	476	41.9%
		Moderate	176	15.5%
		Liberal	247	20.9%
		N	1,137	100%
Typology	Type of video	Campaign	16	1.4%
		Educational	61	5.2%
		Satire	73	6.2%
		Low-Qual News	108	9.2%
		High-Qual News	332	28.4%
		Opinion	581	49.6%
		N	1,171	100%

Text only:

- (1) SVM
- (2) BERT
- (3) Llama2
- (4) Llama3

Image only

(5) CNN

- (6) CLIP
- (7) Idefics2

Text only:

- (1) **SVM**
- (2) BERT
- (3) Llama2
- (4) Llama3

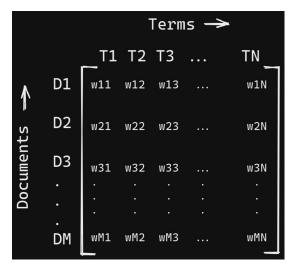
Image only

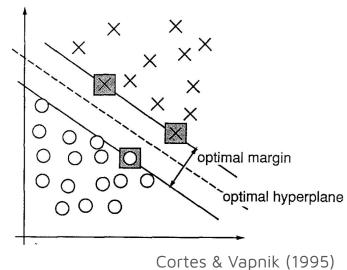
(5) CNN

Text + Image

- (6) CLIP
- (7) Idefics2

Ngram-based, no prior language knowledge, fully task dependent.





Text only:

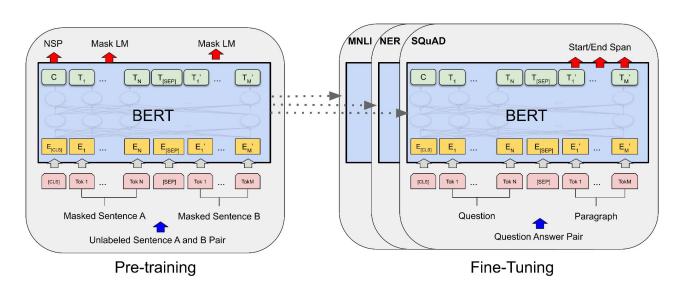
- (1) SVM
- (2) BERT
- (3) Llama2
- (4) Llama3

Image only

(5) CNN

- (6) CLIP
- (7) Idefics2

- Transformed-based, self-supervised, language model (prior knowledge),
 fine-tuned on next sentence, can be fine-tuned to do new tasks.
- Trained on:11k books (800mil tokens) + English wikipedia (2.5 bil tokens)
- **bert-base-uncased**: **110 mil** parameters
- Context length: **512** tokens



Text only:

- (1) SVM
- (2) BERT
- (3) Llama2
- (4) Llama3

- Transformed-based, self-supervised, language model (prior knowledge),
 fine-tuned on instruction task, can be fine-tuned on new instructions
- Trained on: 2 tril tokens, publicly available sources (although unknown)
- 7Bil/13bil/70bil parameters → Llama-2-7b-chat
- Context length: 4,096 tokens

Image only

(5) CNN

- (6) CLIP
- (7) Idefics2

Text only:

- (1) SVM
- (2) BERT
- (3) Llama2
- (4) Llama3

- Transformed-based, self-supervised, language model (prior knowledge),
 fine-tuned on instruction task, can be fine-tuned on new instructions
- Trained on: **15 tril** tokens, publicly available sources (although *unknown*)
- 8Bil/70/405 bil parameters → Llama-3-8b-instruct
- Context length: **8,000**

Image only

(5) CNN

- (6) CLIP
- (7) Idefics2

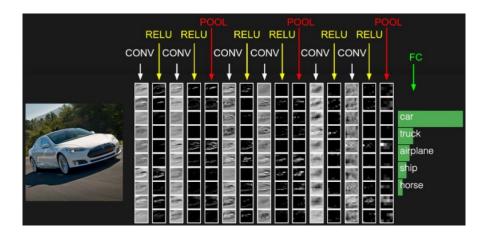
Text only:

- (1) SVM
- (2) BERT
- (3) Llama2
- (4) Llama3

- Pre-trained for object recognition: 1,000 ImageNet object classes
- Trained on: **1.28 mil** images
- 25.6 mil parameters → ResNet50
- Input size: 224 x 224 x 3

Image only (5) CNN

- (6) CLIP
- (7) Idefics2



Text only:

- (1) SVM
- (2) BERT
- (3) Llama2
- (4) Llama3

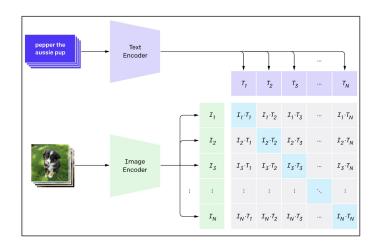
Image only

(5) CNN

Text + Image (6) CLIP

(7) Idefics2

- Text and image encoder
- Trained on 400 mil text-image pairs: e.g. image and its caption
- **Self-trained**: predicting correct text-image pair
- Image input size: 224 x 224 x 3
- **150/**400 **mil** parameters → **ViT-B/32**
- Context length: **77 tokens**



- Text and image transformer encoder
- Trained on:

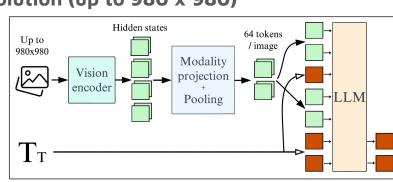
Text only:

- (1) SVM
- (2) BERT
- (3) Llama2
- (4) Llama3

Image only

- (5) CNN
- Text + Image
 - (6) CLIP
 - (6) CLII
 - (7) Idefics2

- interleaved image-text document: 350 mil images and 115 bil text tokens.
- Image-text pairs
- PDF OCR extraction: 40 mil
- instruction/chat: 50 open-source datasets
- o Total: **1.5 bil** images and **225 bil** text tokens
- 8 bil parameters → idefics2-8b
- Image input size: native resolution (up to 980 x 980)
- Context length: ?



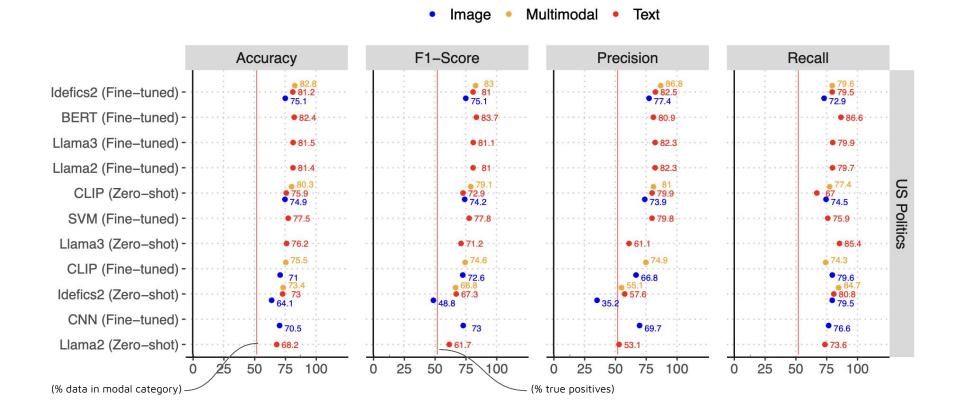
Set Up

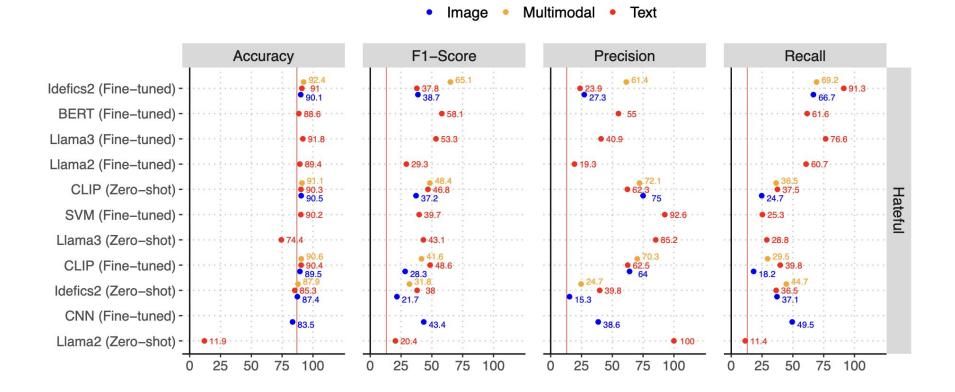
- Text only:
 - (1) **SVM**
 - (2) BERT
 - (3) Llama2
 - (4) Llama3
- Image only
 - (5) CNN
- Text + Image
 - (6) CLIP
 - (7) Idefics2

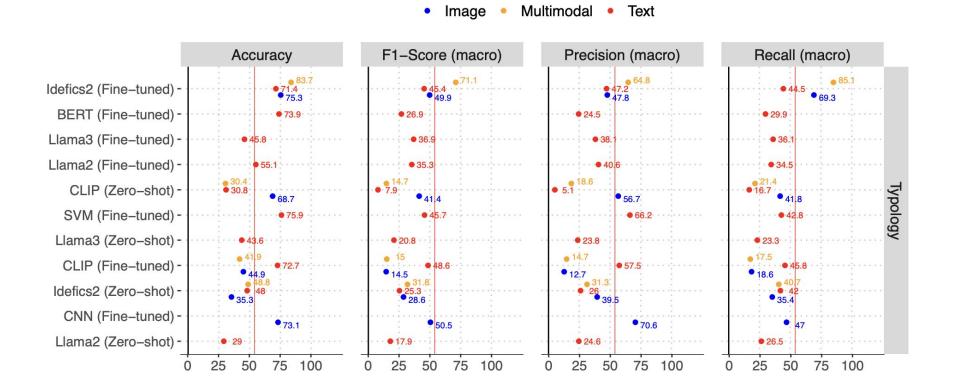
- Same **train** (80%) **test** (20%) sets across models
- Further split train set 80/20 into train/validation per fold
- 3 folds (today results only for 1 fold) and 10 epochs/fold
- Image processing/input:
 - Resize + center_crop all images: 224 x 224 x 3
- Text processing/input:
 - o 20,000 token vocabulary; no stopwords; linear kernel
 - 512 tokens/video
 - o 800 tokens/video
 - 77 tokens/video
- Fine-tuning:
 - Transcript $_{v}$ + Frame $_{v,f}$ → Label $_{v}$
 - BERT, CNN: new prediction head for each of our tasks
 - Llama2, Llama3, Idefics: same prompts across models
- Evaluation of image and text + image models:
 - O Binary: Pred = 1 if $sum(Frame_{v,f}) > threshold (=0 otherwise)$
 - Multiclass: Pred = mode(Framev.f)

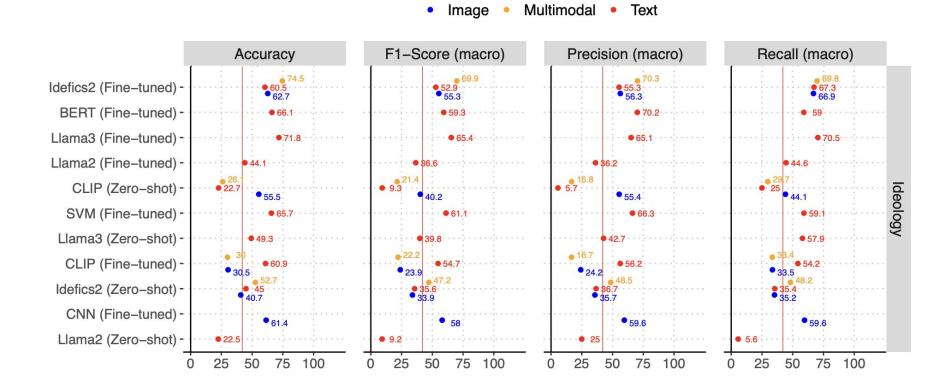
A quick look at how to fine tune a VLM (Idefics2)

```
messages = [
     "role": "user",
     "content": [
         {"type": "image"}, # frame_v1_f1
         {"type": "image"}, # frame_v1_f2
         {"type": "image"}, # frame_v1_f3
         {"type": "text", "text": transcript_v1,
         {"type": "text", "text": "Is the previous text and images about or relevant to US politics? Answer YES or NO."}
     "role": "assistant",
     "content": [
         {"type": "text", "text":"YES"}
```

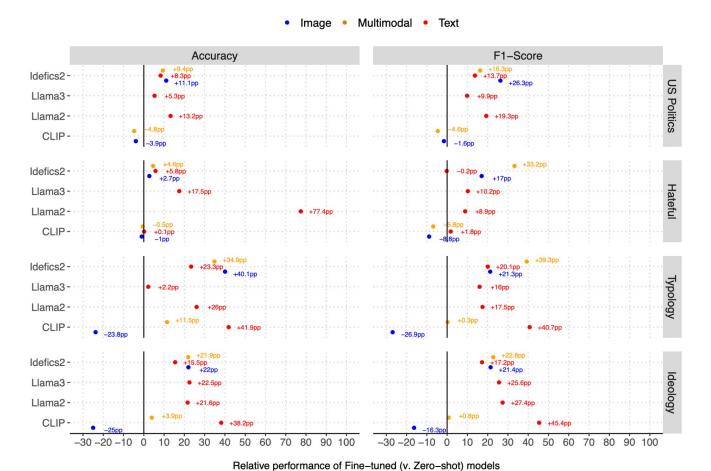




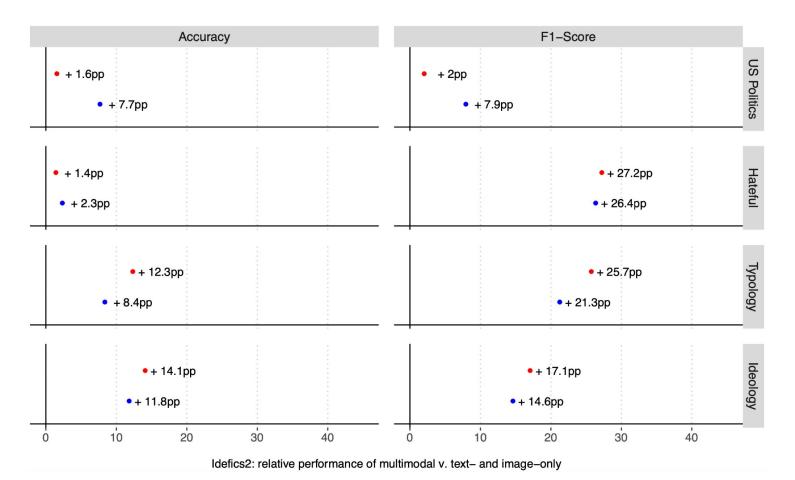




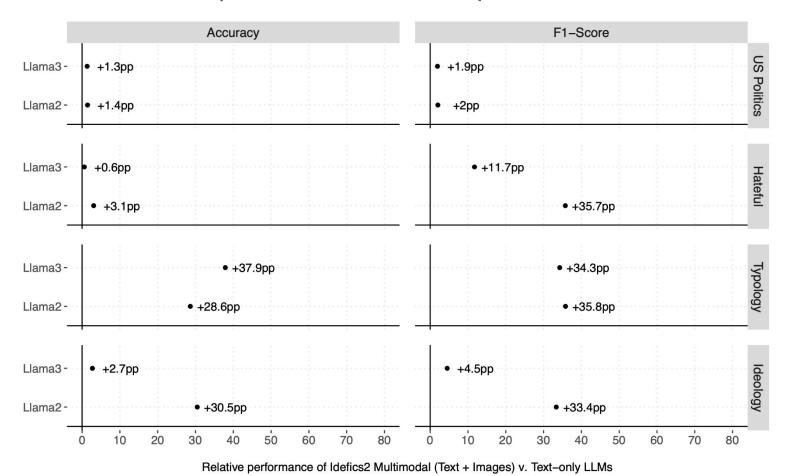
Results: fine-tuning makes a big difference



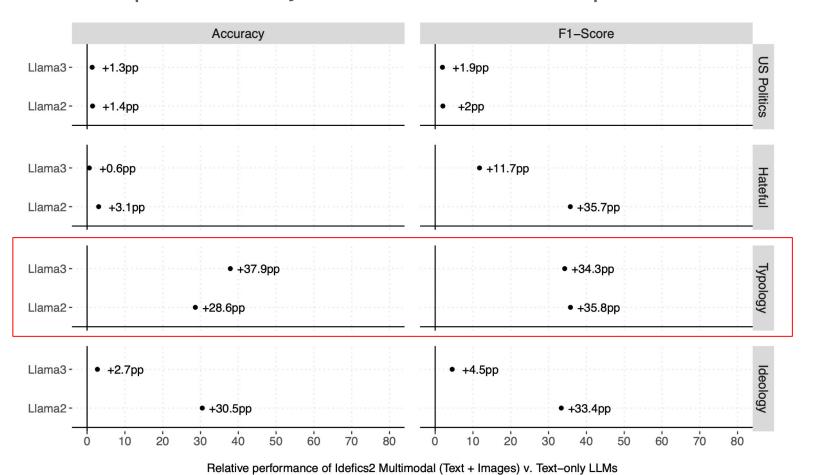
Results: VLM performs better in multimodal settings



Results: VLM outperforms SOTA open-source LLMs



Results: ... particularly on more visual-dependent task



Limitations

- Current results based on only 1 fold
- Smaller Llama2 and Llama3 models (7B v. 40-400B parameters)
- Only max. of 800 text tokens per video
- Probably some more prompt engineering is needed
- NEW promising open-source VLM: Idefics3-8B-llama3

Conclusions and next steps

- Multimodality helps to improve performance (v. text-only LLMs)
- Particularly on more visual-dependent tasks
- Next steps:
 - address limitations discussed in previous slide (folds, prompts, add larger/new models)
 - run the same computational experiments on the missing target variables for the YouTube dataset; and also on the Interest Group Twitter data
 - o potentially adding one more dataset (TikTok) with higher visual dependence