





Beyond Words: Analyzing Social Media with Text and Images

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About me

ITAM, Mexico City № (BSc & 🔯) → Sheffield University 💥 (MSc & PhD) → Copenhagen University 💳 (Postdoc).

I'm passionate about working on multimodal learning projects that create a meaningful social impact.

My background is in computer science and NLP, with experience in computational social science during my PhD. Currently, my research focuses on advancing large multimodal models for multi-image reasoning and its real-world applications.

I'm also interested in developing multilingual models with a focus on supporting low-resource languages across the Americas.*

^{*}Sheffield's Submission to the AmericasNLP Shared Task on Machine Translation into Indigenous Languages. 5 Best Submission. In Workshop on Natural Language Processing for Indigenous Languages of the Americas 2023. Edward Gow-Smith, Danae Sánchez Villegas.

Multimodal posts offer a creative and engaging means of communication for users.

Applications in natural language processing

- Sentiment analysis
- Rumor detection and fact checking
- Sarcasm Detection



Modeling text-image pairs from social media posts presents particular challenges.

 While image captions have a clear visual-language connection, image-text relationships in social media posts may no be apparent

Image	Text (Post)	Image-Text Relation in Post	Image Caption
	When @USER gets more followers than you in 12 hours	The image complements the text to provide meaning of the post	A close up of a hockey player wearing a helmet
	My baby approves	The image does not add to the meaning of the post and the text does not provide a description of the image	A gray and white chicken standing in the dirt

Crucial to advancing natural language understanding:

- Enhances the understanding of the user's intentions, emotions, and opinions.
- Disambiguating the intended meaning
- Visual context can help handling noisy text (e.g., abbreviations and typos)

Introducing challenging tasks as well as methods to gain a better understanding of multimodal content in the context of social media.

Online Political Advertising



Influencer Content Analysis



Online Political Advertising Analysis

Danae Sánchez Villegas, Saeid Mokaram, Nikolaos Aletras. "<u>Analyzing Online Political Advertisements</u>", **ACL Findings 2021**

Motivation

- Online advertising is an integral part of modern digital election campaigning
- The 2020 U.S. election campaign spending hit a record \$10.8 billion¹



Source: https://twitter.com/OpenSecretsDC/status/1321589058993332224

Motivation

Third-party advertising had an increased presence in 2018 and 2020 US elections

Almost half of the third-party sponsored ads were funded by dark-money sources



Freedom Club is the premier non-profit organization making a difference in Minnesota. Not only do our members talk about the problems facing our state and nation, but we also put our money where our mouth is and lead the way.

Motivation

- Serious implications about transparency and accountability
 - How voters were targeted?
 - o By whom?

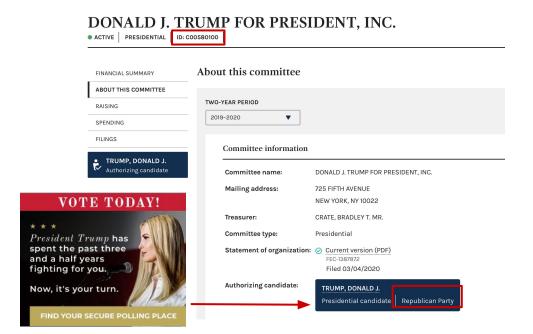




Task 1

Political Ideology Prediction

 Label an ad according to the dominant political ideology of the party that sponsored the ad either as: Conservative or Liberal



Task 2

Ad sponsor type Prediction

- Classify an ad according to the type of the organization that sponsored the ad as: Political Party or Third-Party
 - Political Party: official political committees
 - Third-Party sponsors: not-for-profit organizations and businesses



Collecting Ads

Political Advertising on Google US (2018-2020)

Ads

Text:

FIGHTING FOR WORKING FAMILIES, FOR GOOD JOBS, AND FAIR PAY.

FIGHTING FOR WORKING FAMILIES, DEFAZIO FOR GOOD JOBS, AND FAIR PAY.

Densecaps:

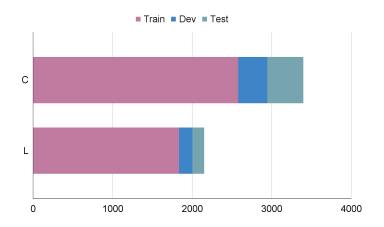
the man is wearing glasses, the background is blue

Eliminate duplicates
Filter English only

Data Splits

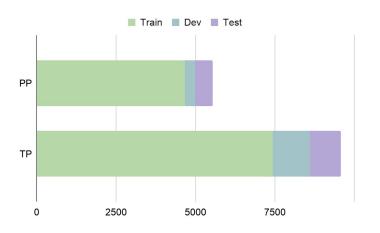
Conservative/Liberal

- Train 79.51%
- Dev 9.63%
- Test 10.86%



Political Party (PP)/Third-Party (TP)

- Train 79.98%
- Dev 10.00%
- Test 10.02%



Models

Text-only

- BERT_D
- BERT_{IT}
- BERT_{IT+D}

Image-only

EfficientNet

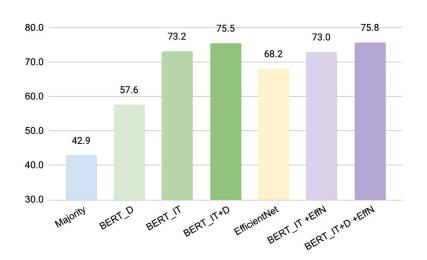
Text & Image

- BERT_{IT}+EffN
- BERT_{IT+D}+EffN

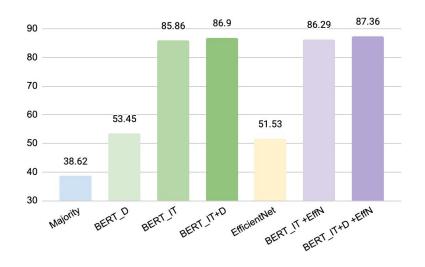
- ★ IT: Image Text
- ★ D: Densecaps

Data Splits

Conservative/Liberal



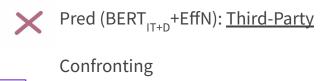
Political Party (PP)/Third-Party (TP)



F1

Error AnalysisPolitical Party/Third Party



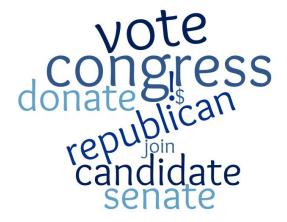


Political Party

Negative style

Negative campaigning

Content AnalysisPolitical Party/Third Party



Political Party



Third-Party

Content AnalysisPolitical Party/Third Party





Third-Party

Linguistic Analysis

Conservative/Liberal



Conservative



Liberal

Summary

- We presented the first study on Political Ideology and Ad Sponsor Type Prediction
- Built a dataset with ads mapped to their category → https://archive.org/details/pol_ads
 - Political Ideology
 - Ad sponsor Type
- Trained predictive models using
 - Text
 - Image descriptions
 - o Image
- Analysis of the Ad content







What do parties want from their digital campaigns? Evidence from the United Kingdom

Political advertising on Facebook: campaign strategies deployed by major political parties in the UK. **ECPR 2024** Panel Digital campaigning: empirical research and normative implications.

Junyan Zhu, Andrew Barclay and Danae Sanchez Villegas

Campaign Strategies Through Political Advertising

Further research is required to explore how campaigns use digital platforms to achieve electoral goals as part of a broader, integrated communications strategy.



Research Questions

- What are the **primary goals** of political parties' online advertising activity?
- Which policy issues do parties address most frequently in their posts?
- What is the level and extent of negative campaigning undertaken by political parties?
- Was negative messaging more commonly associated with certain policies?

Data

Meta Ad Library: All ads categorized under 'issues, elections, or politics' placed by the Labour Party, the Conservatives, and the Liberal Democrats between December 1, 2018 and December 1, 2023.

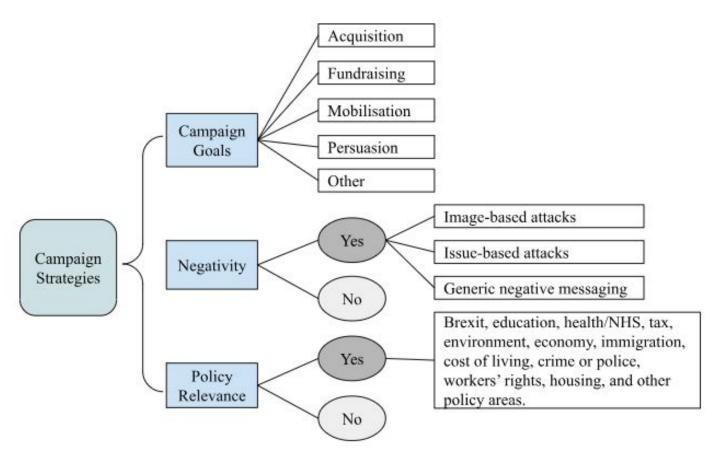
Double coding of the content of each ad, alongside:

- Ad impressions
- Date of placement

Party	Ads (n)
Labour	3,350
Conservatives	1,127
Liberal Democrats	567
Total	5,044



Coding Framework





The Labour Party

Labour would reform the NHS and train 10,000 extra nurses and midwives every year.

Your Tory MP, Ben Bradley, is threatening to sack nurses in Mansfield.



Goal: Acquisition

Negative: Issue-based attack

Policy: Health Workers' Rights



Your vote can save Notting Hill Police Station. Only a Conservative run K&C Council will fight Sadig Khan's plan to sell the station. Vote Conservative.

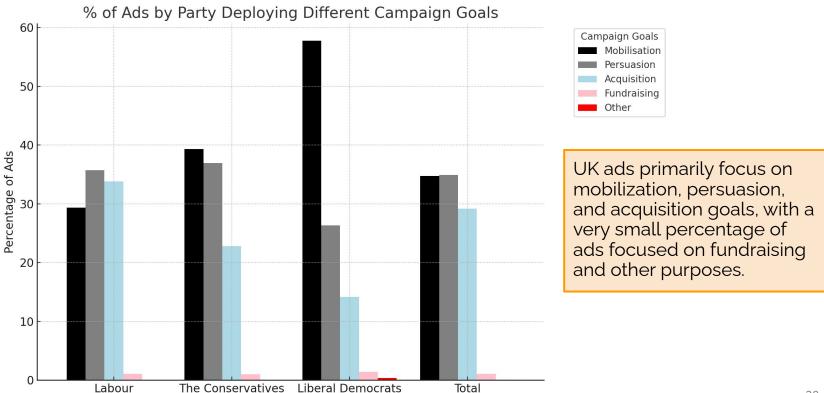


Goal: Mobilisation

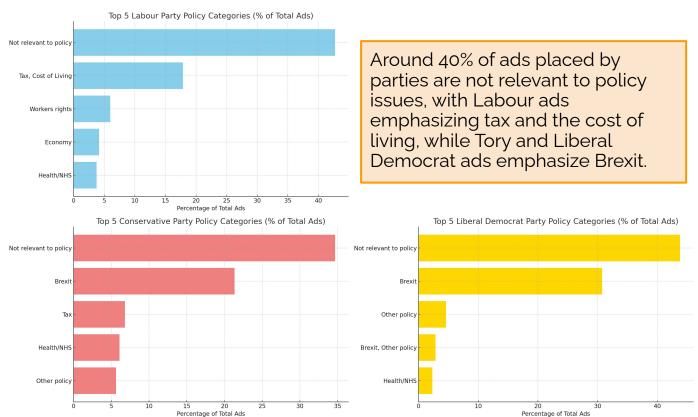
Negative:

Policy: Crime/Law & Order

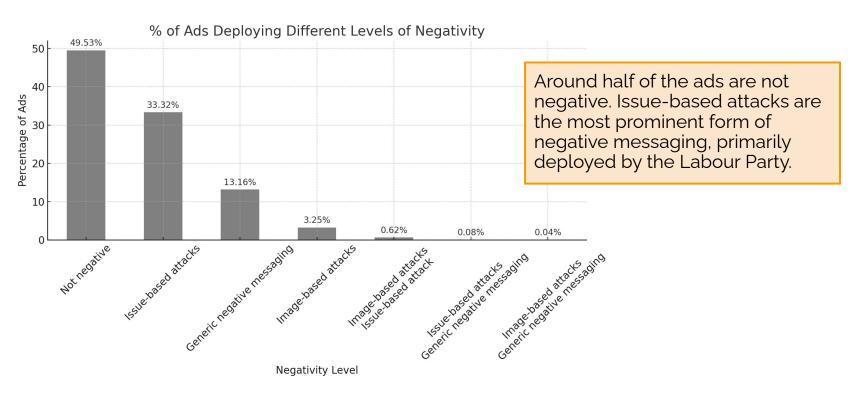
What are the primary goals of political parties' online advertising activity?



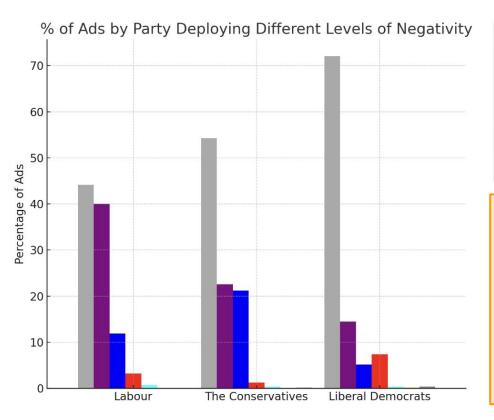
What policy issues do parties address most frequently in their posts?

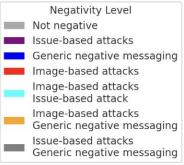


What is the level and extent of negative campaigning undertaken by political parties?



Was negative messaging more commonly associated with certain policies?





Top Policies Associated with Negative Messaging

- The Conservative Party Brexit; Tax; Immigration
- Liberal Democrats Brexit; Health/NHS; Tax;
 Other; Environment
- The Labour Party Tax, Cost of Living; Workers rights; Health/NHS

Summary

We conduct an analysis of UK political advertisements from the Meta Ads Library.

Propose a comprehensive annotation framework for examining campaign strategies.

Framework focuses on identifying:

- Primary goals
- Policy issues
- Negative messaging in political ads

Future research includes:

- Comparing how political messaging shifts between paid ads and organic content.
- Exploring the potential of large multimodal models (LMMs) for large-scale analysis of campaign strategies in political advertising, enabling insights into the interplay between textual and visual elements across diverse platforms.

Influencer Content Analysis

Danae Sánchez Villegas, Catalina Goanta, Nikolaos Aletras. "<u>A multimodal analysis of influencer content</u> on twitter", in AACL 2023 -- Area Chair Award: Society & NLP

Social Media Influencers

Social media influencers are content creators who have established credibility in a specific domain (e.g., fitness, technology), are followed by a large number of accounts and can impact the buying decisions of their followers.

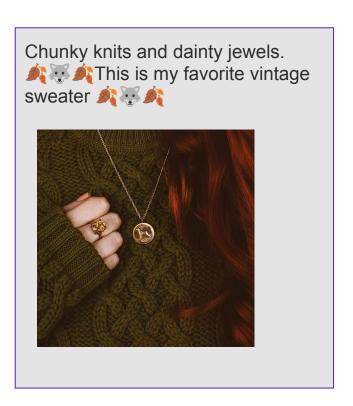
Influencer Marketing

- Influencer marketing is more effective than traditional paid advertising.
- Online creators can help brands reach new, engaged audiences through endorsements and product placements, leveraging the trust these influencers have built with their followers.

Influencer Marketing

Influencer marketing is dominated by native advertising

 there is no obvious distinction between commercial and non-commercial content



Detecting commercial content

Automatically identifying commercial content by influencers is important

- Transparency: it helps ensure transparency in advertising and marketing.
- Consumer Protection: it protects consumers from deceptive advertising.
- Regulatory Compliance: some countries have laws and regulations governing advertising and disclosure requirements for influencers and brands.
- Analysis of commercial language characteristics on a large scale.

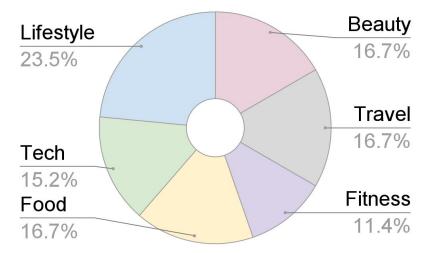
Detecting commercial content

Automatic detection of influencers commercial content is difficult.

- Disclosure guidelines (including keywords such as #ad, #sponsored) are not always followed
- Brand cues may appear in different modalities such as text and images

A large publicly available dataset of 14, 384 text-image pairs and 1, 614 text-only influencer tweets written in English.

- 132 Influencer Accounts
- 6 domains
- Jan 2015- Aug 2021



Tweets are mapped into commercial and non-commercial categories

- Keyword-based Weak Labeling (train & dev sets)
- Human Data Annotation (test sets)

Keyword-based Weak Labeling

Extend the keyword lists (verified by members of a national consumer authority)

- Disclosure terms: #ad, #sponsored
- Terms relevant to different business models:
 - Gifting: #gift
 - Endorsements: #ambassador
 - Affiliate marketing: #aff
- All of the keywords used for data labeling are removed for the experiments

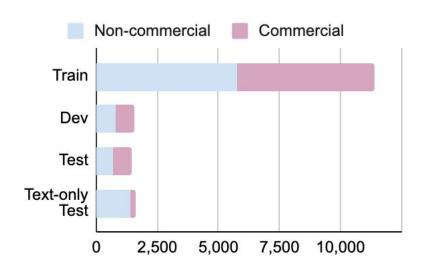
Human Data Annotation (test sets)

Four annotators with a substantial legal background and knowledge of advertising regulation

Data Splits

Account-level splits

Split	Total	
Train	11,377 (79.1%)	
Dev	1,572 (10.9%)	
Test	1,435 (10%)	
Text-only Test	1,614	
All	15,998	



Dataset	Publicly Available	Posts w/o brand mentions	Human Annotation	Keyword Matching	No. of Commercial Keywords	Platform	Modality	Time Range	Domains
Han et al. (2021)	X	X	×	×	0	Twitter	Text	not specified	fashion
Zarei et al. (2020)	×	1	×	1	7	Instagram	Text	Jul 2019 - Aug 2019	not specified
Yang et al. (2019)	Х	×	×	✓	3	Instagram	Text & Image	not specified	not specified
Kim et al. (2021b)	✓	✓	×	1	3	Instagram	Text & Image	not specified	not specified
Kim et al. (2020)	1	×	×	1	1	Instagram	Text & Image	Oct 2018 - Jan 2019	beauty, family, food, fashion, pet, fitness, interior, travel,
MICD (Ours)	1	1	1	1	26	Twitter	Text & Image	Jan 2015 - Aug 2021	beauty, travel, food fitness, technology, lifestyle

Comparison of existing datasets for influencer content analysis

Influencer Content Classification Models

Prompting

- Flan-T5 (zero-shot, few-shot)
- GPT-3 (zero-shot, few-shot)

Text-only

- BiLSTM-Att
- BERT
- BERTweet

Image-only

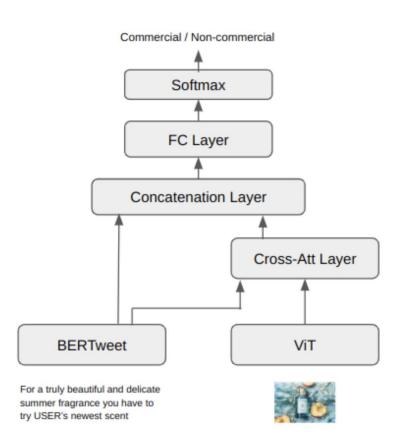
- ResNet
- ViT

Text & Image

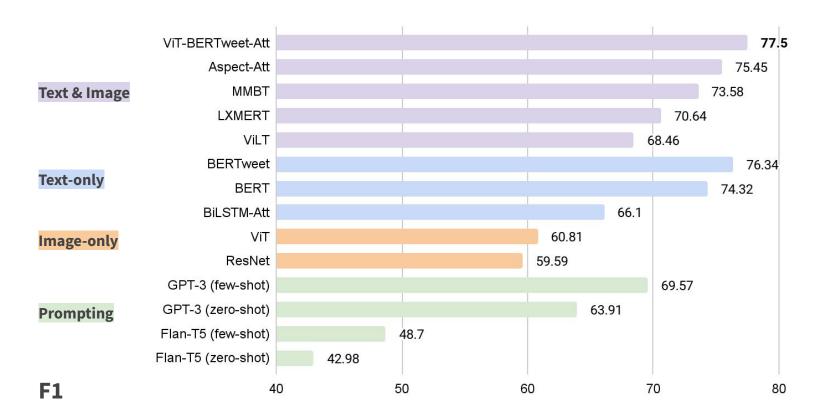
- ViLT
- LXMERT
- MMBT
- Aspect-Att
- ViT-BERTeet-Att (Ours)

ViT-BERTweet-Att

Combine unimodal pretrained representations via cross-attention fusion strategy so that text features can guide the model to pay attention to the relevant image regions.

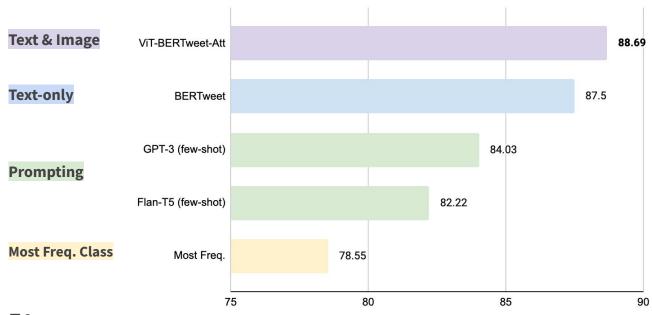


Identifying Commercial Influencer Content



Identifying Commercial Influencer Content

Text-only Test Set



F1

Analysis

 Multimodal modeling captures context beyond keyword-matching.

Just seen that Pepsi ad...awkward.

ViT-BERTweet-Att: NC

 Multimodal modeling aids in the discovery of undisclosed commercial posts



chunky knits and dainty jewels. This is my favorite vintage sweater

Actual: C

BERTweet: NC

ViT-BERTweet-Att: C

Analysis

Challenging cases for text and multimodal models:

- Posts that describe their "personal" experiences, particularly while traveling
- Posts include "natural photos" rather than product promotions



Cherry tree hill is hands down the best view in #Barbados.

#VisitBarbados

Actual: C

BERTweet: NC

ViT-BERTweet-Att: NC

Summary

- Introduced a novel dataset of multimodal influencer content consisting of tweets labeled as commercial or non-commercial.
- First dataset to include high quality annotated posts by experts in advertising regulation.
- Experiments including vision, language and multimodal approaches for identifying commercial content
- Multimodal modeling is useful for identifying commercial posts
 - Reducing the amount of false positives
 - Capturing relevant context that aids in the discovery of undisclosed commercial posts.
- Dataset: https://github.com/danaesavi/micd-influencer-content-twitter

Improving Multimodal Classification of Social Media Posts by Leveraging Image-Text Auxiliary Tasks

Sánchez Villegas, Danae, D. Preotiuc-Pietro and N. Aletras, "Improving Multimodal Classification of Social Media Posts by Leveraging Image-Text Auxiliary Tasks", EACL Findings 2024

Multimodal Social Media Posts

Combining text and image information is challenging because cross-modal semantics might be hidden or the relation between image and text is weak

Image	Text (Post)	Image-Text Relation in Post	Image Caption
	When @USER gets more followers than you in 12 hours	The image complements the text to provide meaning of the post	A close up of a hockey player wearing a helmet
	My baby approves	The image does not add to the meaning of the post and the text does not provide a description of the image	A gray and white chicken standing in the dirt

Leveraging Image-Text Auxiliary Tasks

Extensive study on the effectiveness of using two auxiliary losses jointly with the main task during fine-tuning multimodal models to address these cases

- Image-Text Contrastive (ITC)
- Image-Text Matching (ITM)

Image-Text Contrastive (ITC)

• Image-Text Contrastive (ITC) is designed to minimize the distance between image-text representations within a post

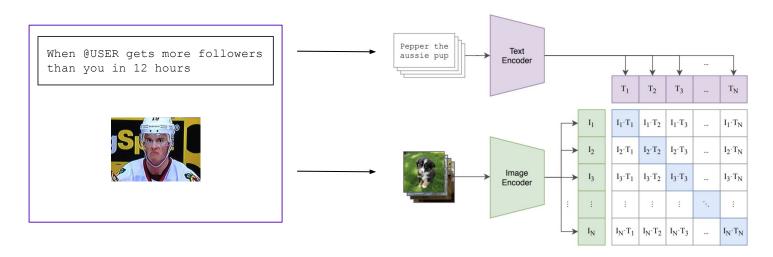
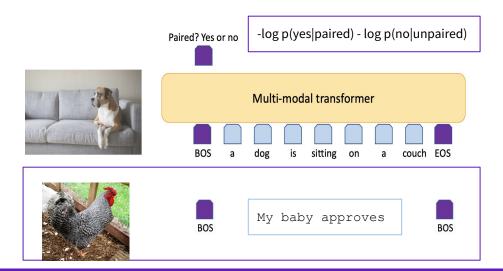


Image-Text Matching (ITM)

 Image-Text Matching (ITM) enhances the model's ability to understand the semantic relationship between images and text



Models

Text-only

- Bert
- Bernice
- Flan-T5 (FS prompt)
- GPT-3 (FS prompt)

Image-Only

- ResNet
- ViT

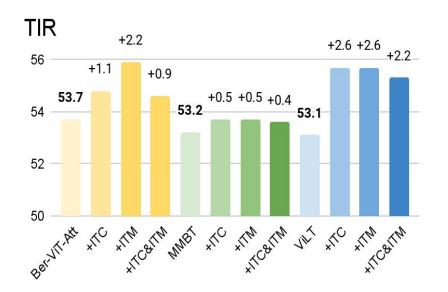
Text & Image

- Ber-ViT-Conc
- Ber-ViT-Att
- MMBT
- LXMERT
- ViLT

Text & Image + AUX

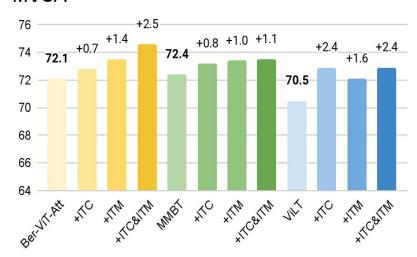
- + ITC
- + ITM
- + ITC & ITM

Datasets & Results



- Text-Image Relation
- 4 classes

MVSA



- Multi-View Sentiment Analysis
- 3 classes

Analysis

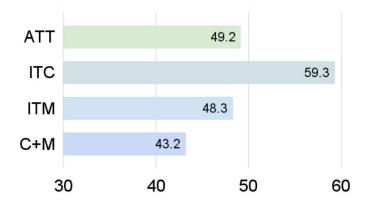
ITC performs best when the visual content is important for conveying the post's meaning.

Label (TIR): Image adds to the meaning & text is not represented in the image



When @USER gets more followers than you in 12 hours





Accuracy using Ber-ViT-Att (ATT)

Analysis

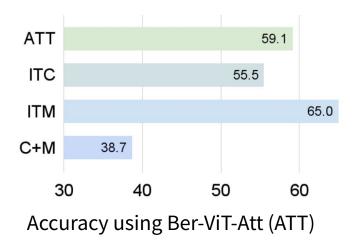
ITM performs best in posts with weaker image-text relationships

Label (TIR): Image does not add to the meaning & text is not represented in the image



My baby approves

ATT:**X** | ITC:**X** | ITM: ✓ | C+M:**X**



Contributions

- An empirical study on comparing multimodal models jointly fine-tuned with ITC and ITM.
- We show that models using ITC and ITM as auxiliary losses consistently improve their performance on four popular multimodal social media classification datasets.
- We provide a comprehensive analysis that sheds light on the effectiveness of each auxiliary task and their combination.

What's next?

Advancing Multimodal Social Media Research: Key Challenges

Data Collection: Adhering to platform-specific API guidelines.

Access Limitations: Platforms often restrict the amount and type of data accessible through their APIs. For example, there may be rate limits or restrictions on retrieving historical data as well as access fees.

Data Availability: Not all user interactions (likes, shares, comments) or specific types of content (e.g., private posts, stories) are available through APIs.

Frequent Changes: Social media platforms frequently change their API terms, data structures, or access protocols, which can disrupt data collection efforts.

 Video Understanding: Developing models for video analysis or multi-frame reasoning.



IGPT-40]: In this image sequence, a young girl is sitting on a bench holding an ice cream cone, while a toddler next to her becomes increasingly interested in the treat. Initially, the toddler is looking at the ice cream, then leans in closer, and finally reaches out to grab it, causing the girl to look on with a mix of surprise and concern. The toddler, after successfully taking the ice cream, seems satisfied and begins to turn away, leaving the girl holding only the cone's bottom part.

Advancing Multimodal Social Media Research: Key Challenges

- Multilingual Models: Addressing challenges in diverse content across languages.
 - a. **Cultural Context**: Even when models can handle multiple languages, they may struggle to interpret cultural contexts, idiomatic expressions, or regional variations, which are important for understanding user intent on social media.
- Ethics and Privacy: Maintaining ethical standards and protecting user privacy.
 - a. **Difficulty in Anonymizing Multimodal Data**: It's more challenging to anonymize images, videos, and associated metadata compared to text.

