# Multimodal Political Bias Identification and Neutralization

By Cedric Bernard, Xavier Pleimling, Amun Kharel and Chase Vickery
CS 6804: Multimodal Vision
Spring 2023
Instructor- Dr. Chris Thomas

# Presentation Overview

# Introduction

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- Introduction and Motivation
- Background and Related Works
- Other Debiasing Approaches
- Proposed Approach
- Results and Evaluation
- Future Work, Strengths and Weaknesses

# Introduction and Motivation

- Data from the 2020 election on Growing Political Divide

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- 8 out of 10 people believe the opposite candidate have diametrically different values

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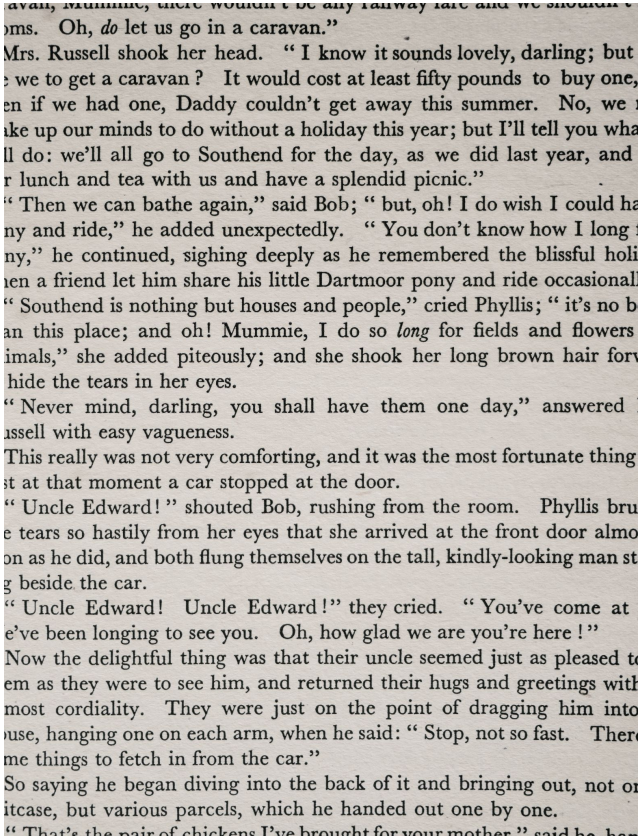
- Presence of Political Echo Chamber

# Textual Bias

- Subjective Bias



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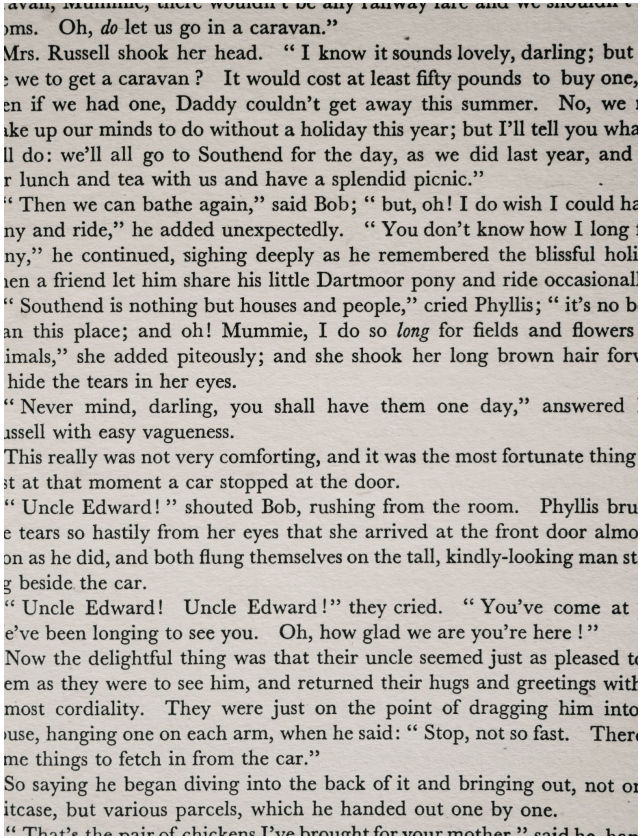
# Textual Bias

- Subjective Bias
- Emotionally Charged Language (Our focus)



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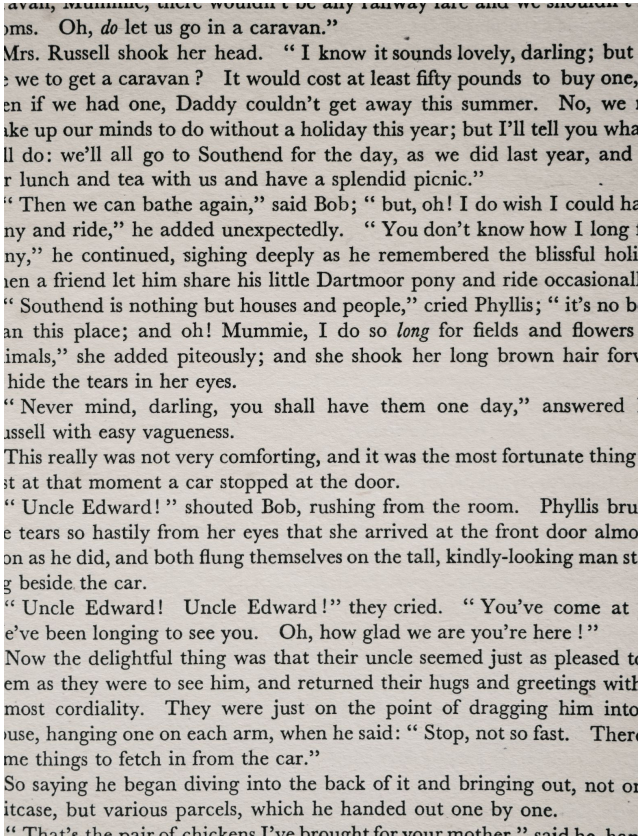
- Omission of all the facts (Non-trivial problem)



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"That's the pair of chickens I've brought for your mother," said he, hea

# Image Bias

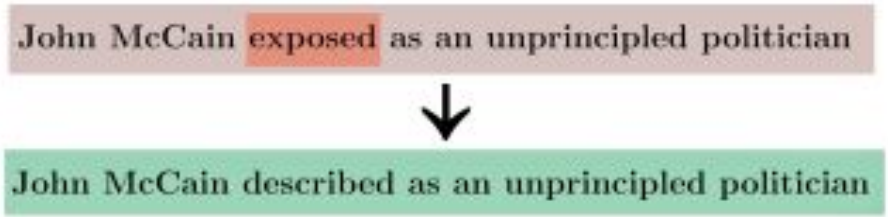
- Facial Expression and correlation with Bias

# Image Bias

- Facial Expression and correlation with Bias
- Replacing biased images with neutralized images on the same topic

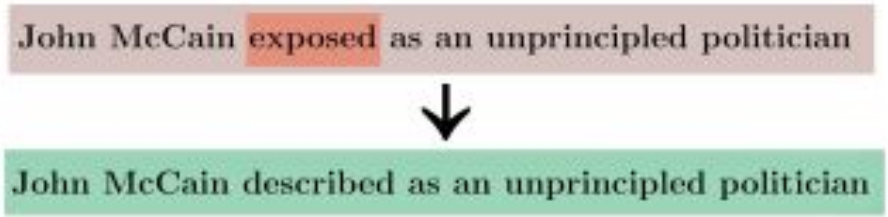
# Related Works

# Automatically Neutralizing Subjective Bias in Text




Reid Pryzant, Richard Diehl Martinez, Nathan Dass, Sadao Kurohashi, Dan Jurafsky, and Diyi Yang. Automatically Neutralizing Subjective Bias in Text, Dec. 2019. arXiv:1911.09709 [cs].

# Automatically Neutralizing Subjective Bias in Text




**Goal: detect and edit biased text in a controllable manner**

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**Proposed Solutions:**

1. **MODULAR**
2. **CONCURRENT**

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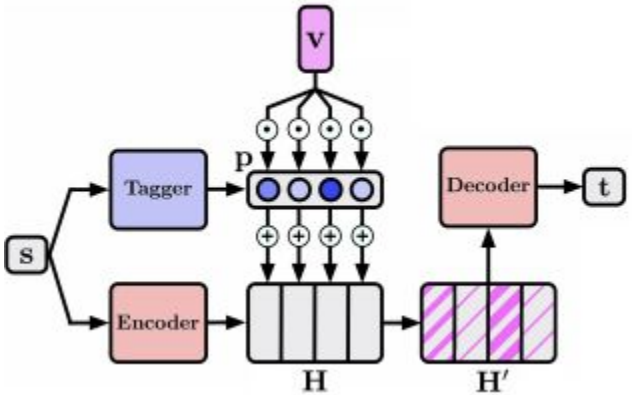


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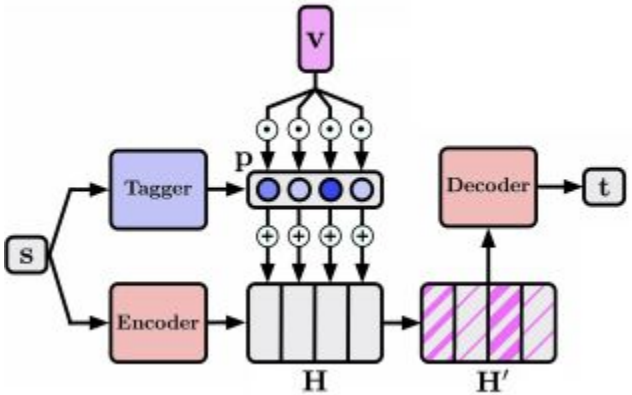
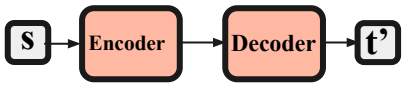



**CONCURRENT**

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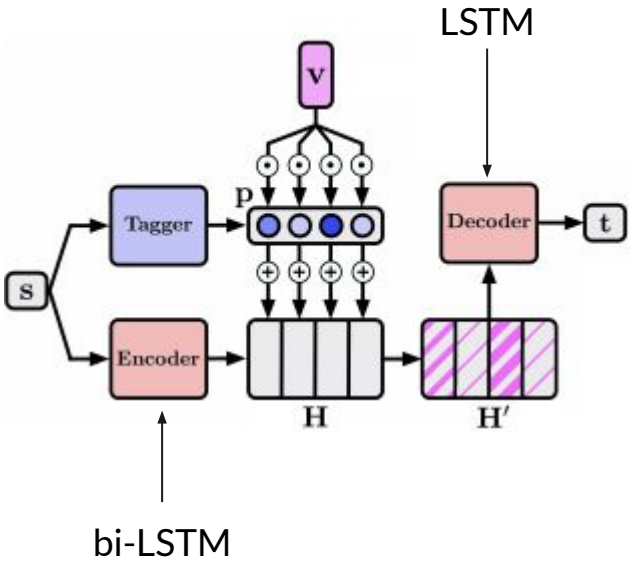


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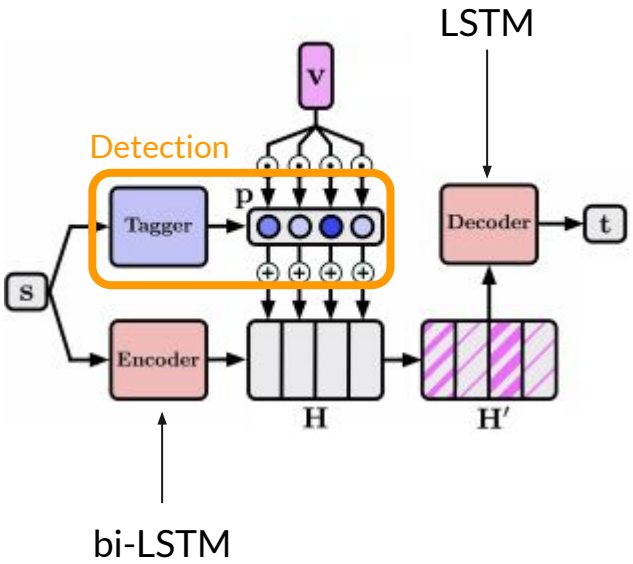


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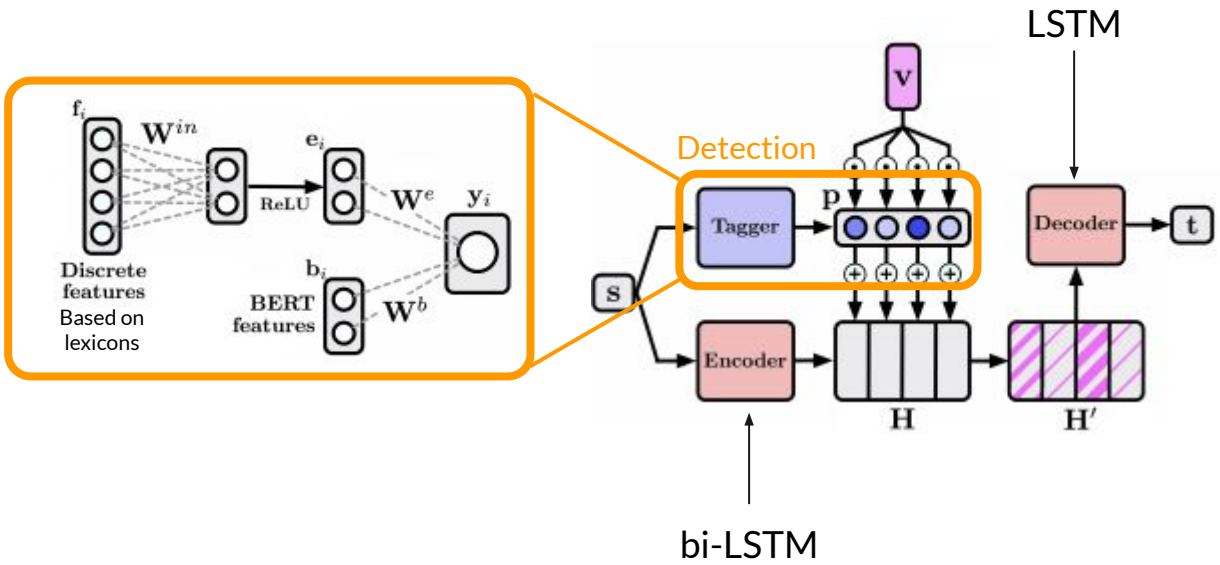


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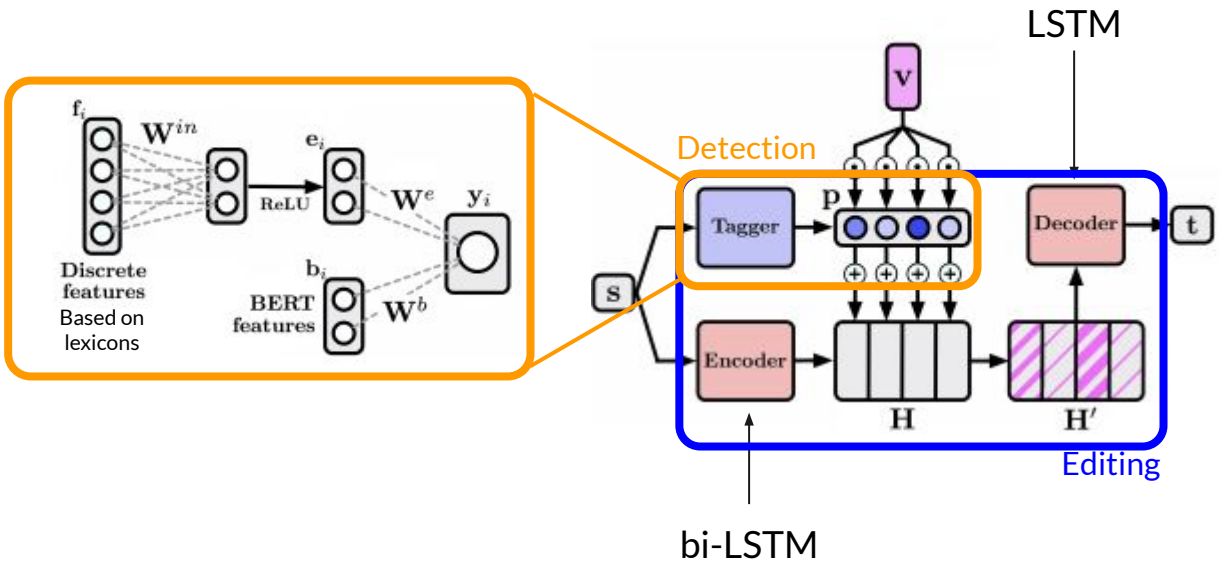


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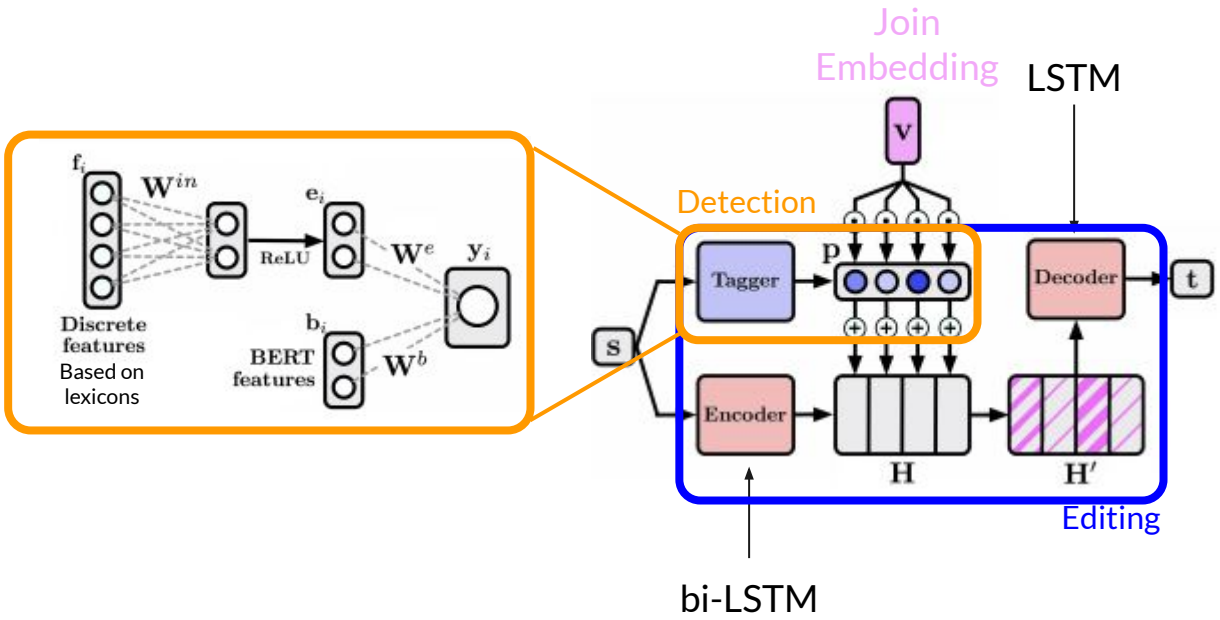


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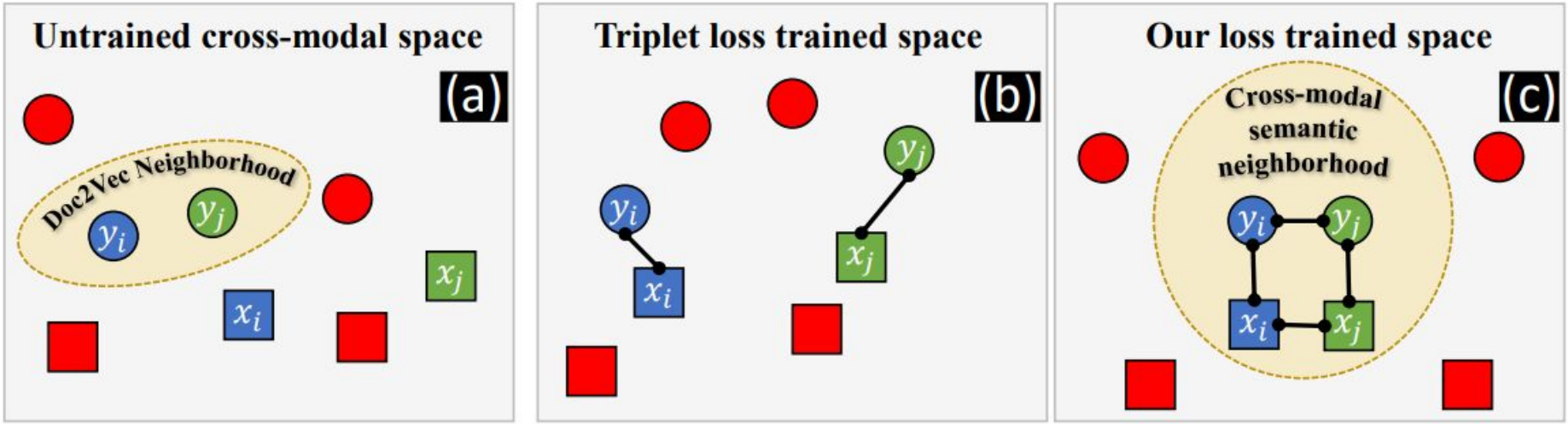
# Semantic Neighborhoods

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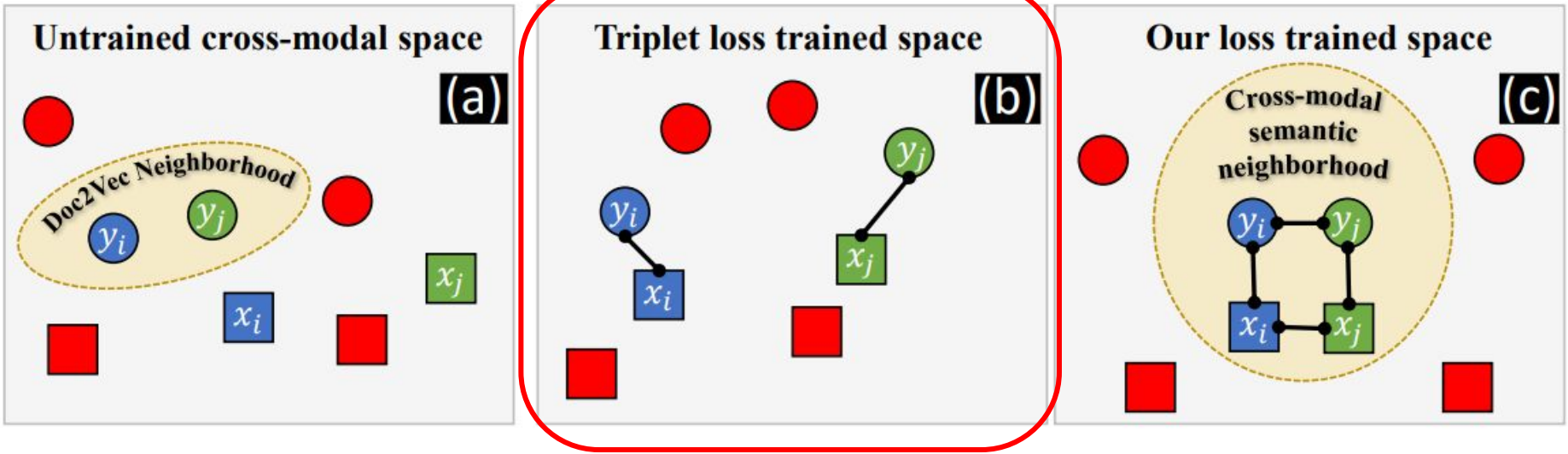


$$\mathcal{L}_{ang}^{NP+SYM}\left(\mathcal{T}, \mathcal{T}_{sym}\right) = \mathcal{L}_{ang}^{NP}\left(\mathcal{T}\right) + \mathcal{L}_{ang}^{NP}\left(\mathcal{T}_{sym}\right)$$

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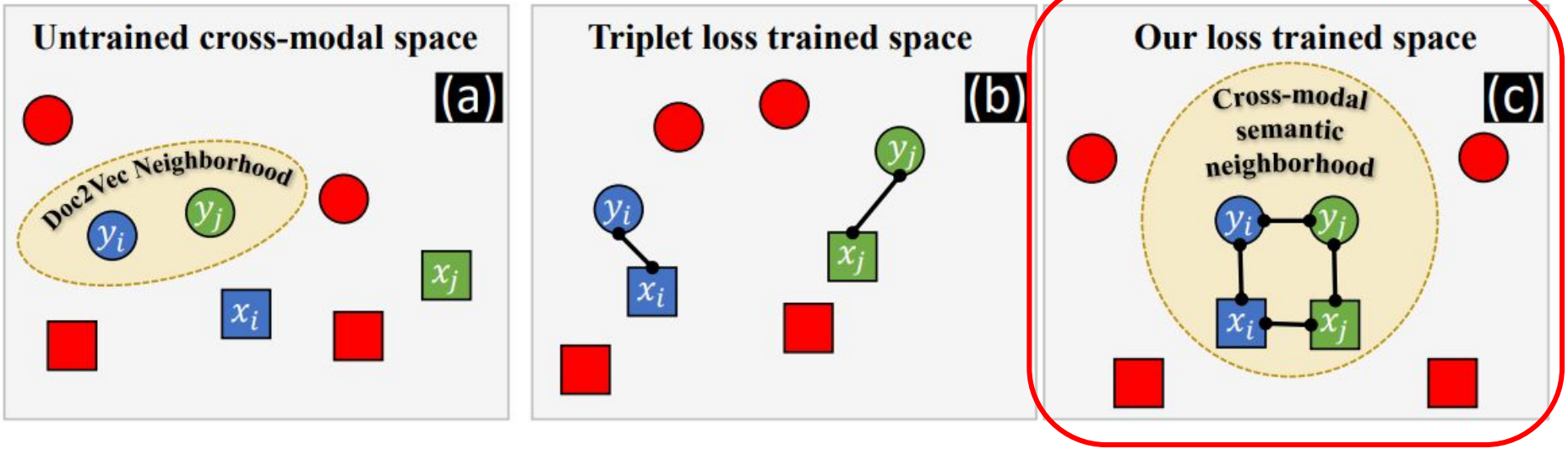


$$\mathcal{L}_{text}\left(\mathcal{T}'_{text}\right) = \mathcal{L}_{ang}\left(\mathcal{T}'_{text}\right) \qquad \mathcal{L}_{img}\left(\mathcal{T}'_{img}\right) = \mathcal{L}_{ang}\left(\mathcal{T}'_{img}\right)$$

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# Bias Identification in Text

Several techniques used:

- Pre-trained BERT/models  for detection and editing of bias
- Adversarial training
- Attention-based mechanisms for detection
- Gaussian mixture models

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Several techniques used:

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- Adversarial training
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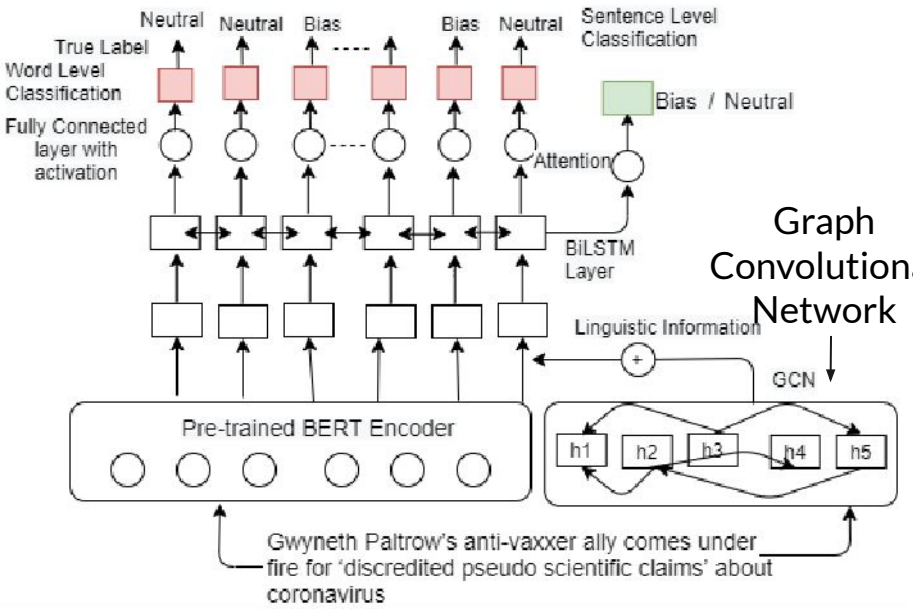
**These approaches only focus on text data and thus do not take advantage of leveraging visual data**

# Other Debiasing Approaches




Graph Convolutional Network

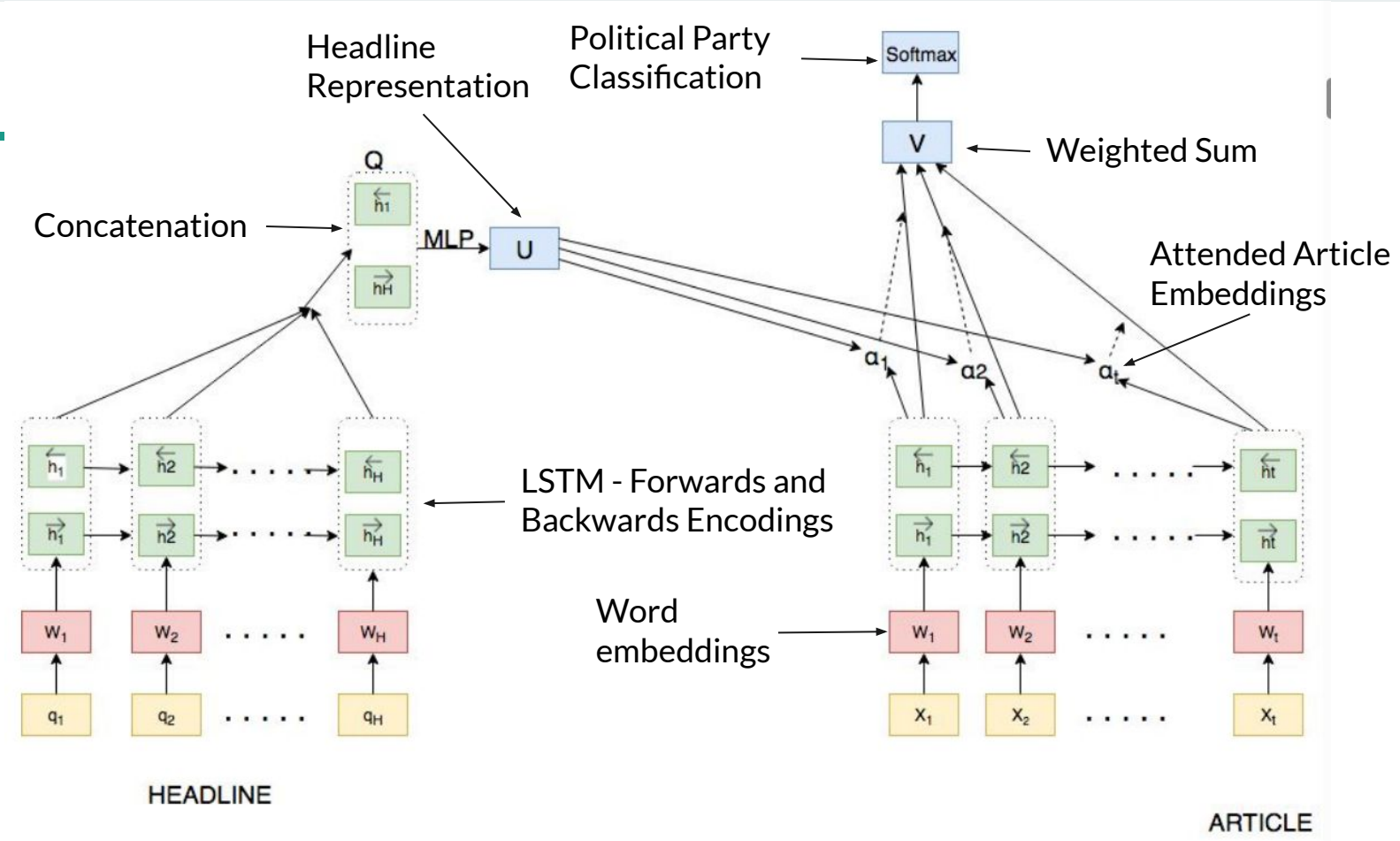
H = Encoder

$$\min_{D} \frac{1}{N} \sum_{i=1}^{N} \mathcal{L}(D(H(x_i)), z_i) \quad (2)$$

C = Classifier

$$\min_{H,C} \frac{1}{N} \sum_{i=1}^{N} \alpha \cdot \mathcal{L}(C(H(x_i)), y_i) + (1-\alpha) \cdot \mathcal{L}(D(H(x_i)), 0.5) \quad (3)$$

D = Decoder


Headline Representation
Political Party Classification
Softmax
V
Weighted Sum
Q
Concatenation
MLP
U
Attended Article Embeddings
LSTM - Forwards and Backwards Encodings
Word embeddings
HEADLINE
ARTICLE

# Bias Score Annotation

# Politics Dataset

- Article Text - Image Pairs
- Left vs. Right
- 20 Topics

Thomas, C., & Kovashka, A. (2019, December). Predicting the politics of an image using webly supervised data. In Proceedings of the 33rd International Conference on Neural Information Processing Systems (pp. 3630-3642).

# Labelling Bias Score

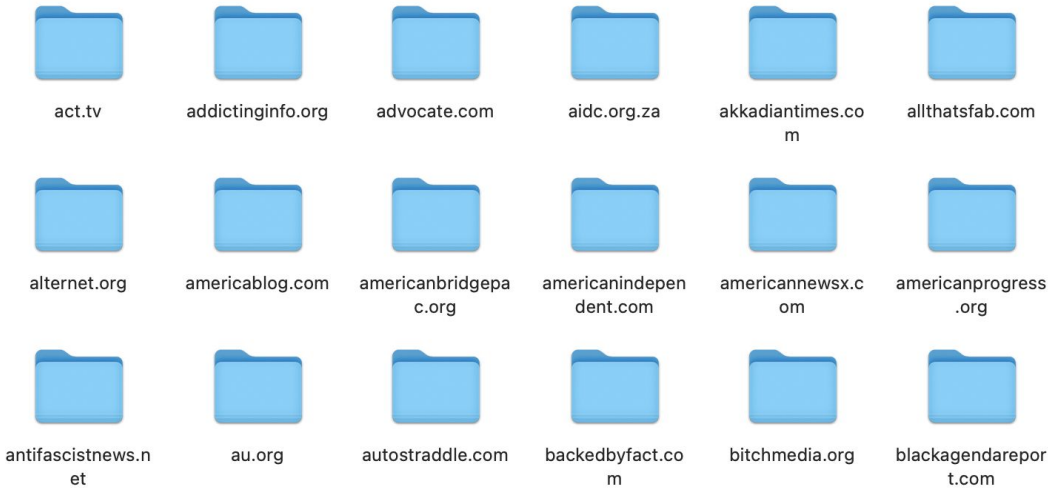
- Each website given score of -1 to 1
- -1 being Far Left, 0 being neutral and 1 being Far right
- For example: Score of -0.5 will be considered moderately left leaning

# Labelling Bias Score

- We have 20 different topics in the Politics Dataset images

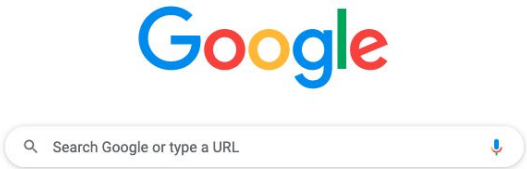
# Labelling Bias Score

- We have the same websites under each topic for left leaning websites and right leaning website



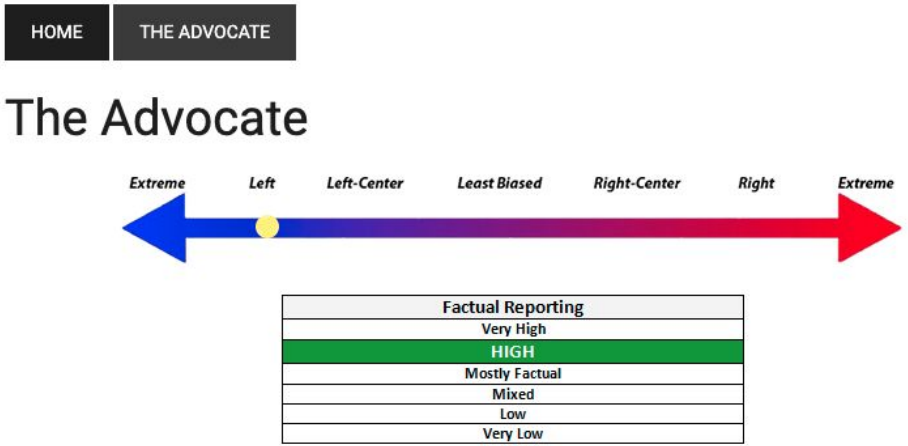
# Labelling Bias Score (Media Bias Fact Check)

- Google the website with Media Bias Fact Check added to it

# Labelling Bias Score

- From mediabiasfactcheck.com we retrieve the score.



# Labelling Bias Score

- Get the score and put it on spreadsheet

| | A | B | C |
|---|---|---|---|
| 1 | Name | Leaning | Bias |
| 2 | act.tv | left | -0.8 |
| 3 | addictinginfo.org | left | -0.9 |
| 4 | advocate.com | left | -0.95 |
| 5 | aidc.org.za | left | -0.3 |
| 6 | akkadiantimes.com | left | -0.5 |
| 7 | allthatsfab.com | left | -0.85 |
| 8 | alternet.org | left | -0.9 |
| 9 | americablog.com | left | -0.5 |
| 10 | americanbridgepac.org | left | -0.6 |
| 11 | americanindependent.com | left | -0.5 |
| 12 | americannewsx.com | left | -0.7 |
| 13 | americanprogress.org | left | -0.5 |
| 14 | antifascistnews.net | left | -0.3 |
| 15 | au.org | left | -0.3 |
| 16 | autostraddle.com | left | -0.5 |
| 17 | backedbyfact.com | left | -0.25 |
| 18 | bitchmedia.org | left | -0.45 |
| 19 | blackagendareport.com | left | -0.95 |
| 20 | blacklivesmatter.com | left | -0.45 |
| 21 | blue-route.org | left | -0.6 |
| 22 | bluedotdaily.com | left | -1 |
| 23 | bluenationreview.com | left | -0.9 |
| 24 | boingboing.net | left | -0.5 |

# Labelling Bias Score  (Exceptions)

- 0-2 = Least Biased
- 2-5 = Left/Right Center Bias
- 5-8 = Left/Right Bias
- 8-10 = Extreme Bias

# Labelling Bias Score  (Exceptions)

The categories are as follows:

1) Biased Wording/Headlines- Does the source use loaded words to convey emotion to sway the reader. Do headlines match the story?
2) Factual/Sourcing- Does the source report factually and back up claims with well-sourced evidence?
3) Story choices: Does the source report news from both sides, or do they only publish one side?
4) Political Affiliation: How strongly does the source endorse a particular political ideology? Who do the owners support or donate to?

# Labelling Bias Score  (Exceptions)

Here is an example of how CNN scored and why they were placed in the middle of Left Bias:

Biased Wording= 4  (CNN uses moderate biased words that favor liberals, and headlines typically match the story)

Factual/Sourcing=5 (CNN has failed fact checks and sometimes omits critical information from stories to favor their perspective)

Political Affiliation = 5 (CNN's ownership owns other leaf-leaning outlets and favors Democratic Candidates)

# Labelling Bias Score  (Exceptions)

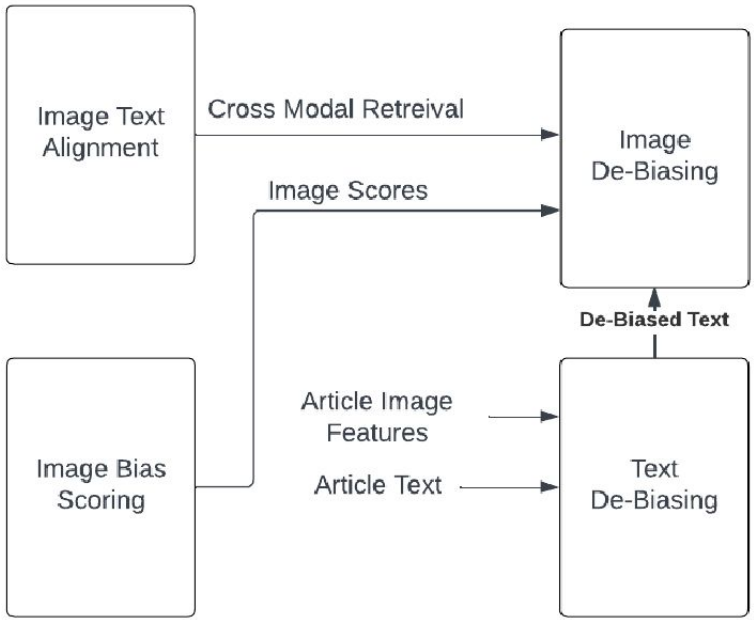
Total = 23

Average = 23/4 = 5.75

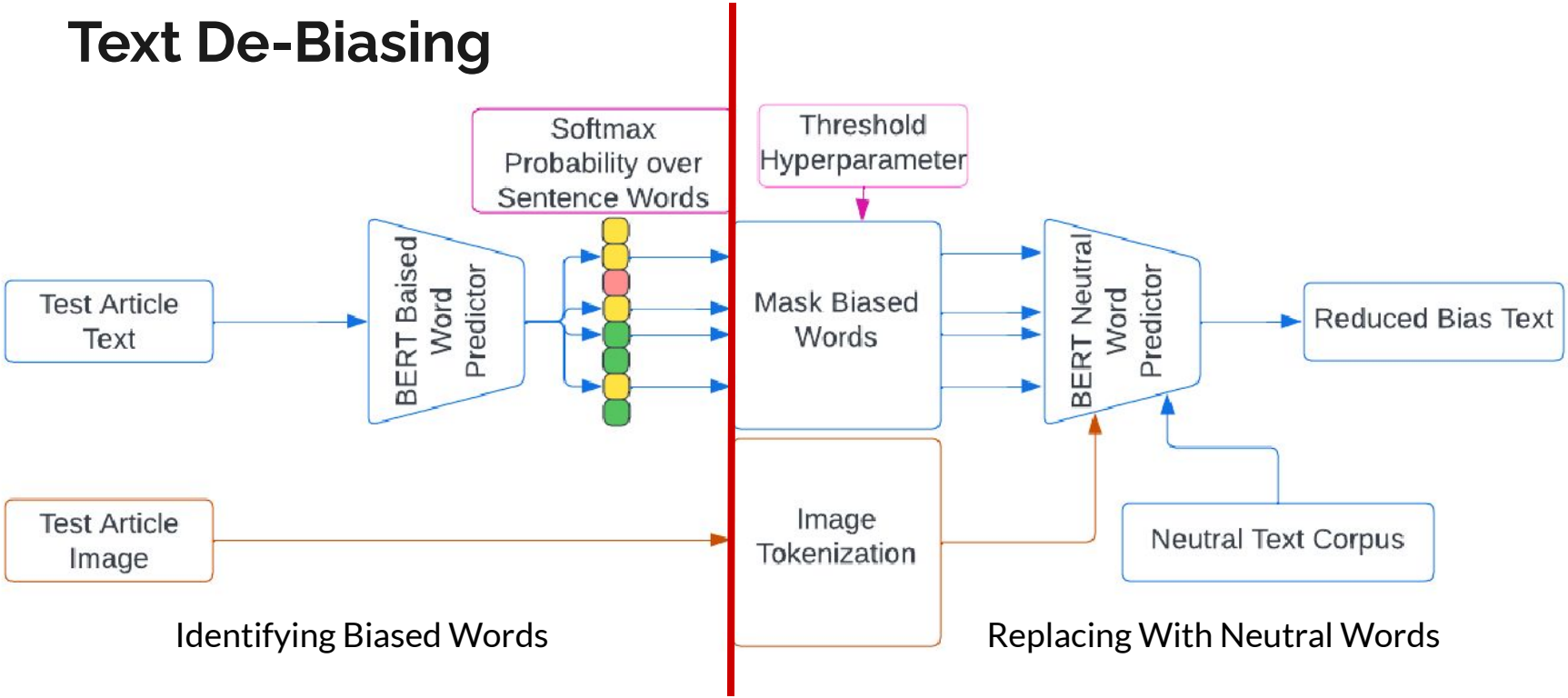
5.75 = Moderate Left Bias

# Proposed Approach

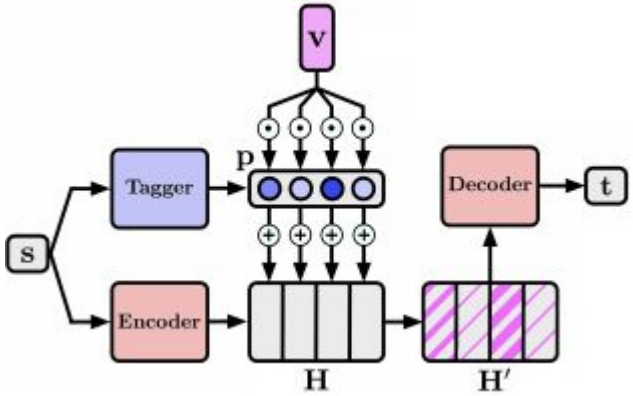
# Proposed Approach Overview



# Text De-Biasing



# Biased Word Identification




- Adopting the MODULAR detection module
- Trained with the Wikipedia Neutrality Corpus (WNC)
- Returns a set of probabilities that are transferred to the Editing portion of the model

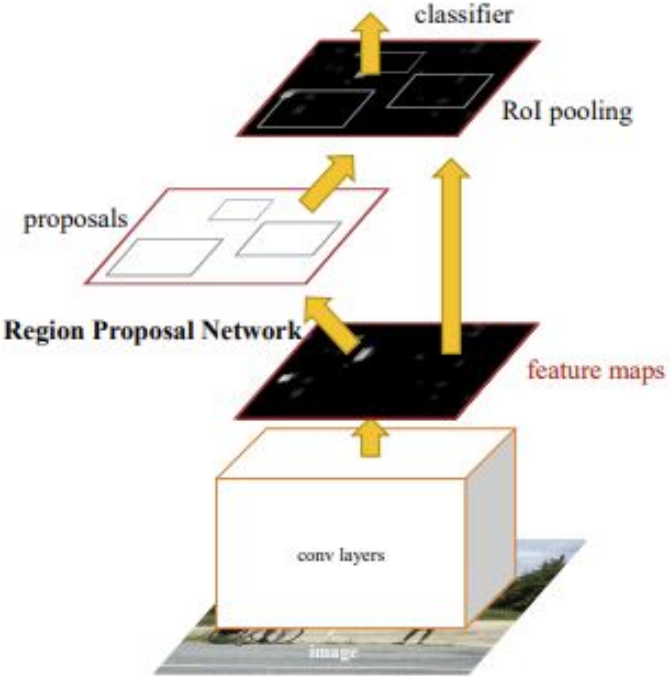
# Wikipedia Image Text Dataset

- 3.5 Million paired Image and text samples
  - Using 1% (35,000)
- Scraped from text and images from Wikipedia
- Images compressed to 124,124,3
- Used as neutral data inputs

wit/DATA.md at main · google-research-datasets/wit (github.com)

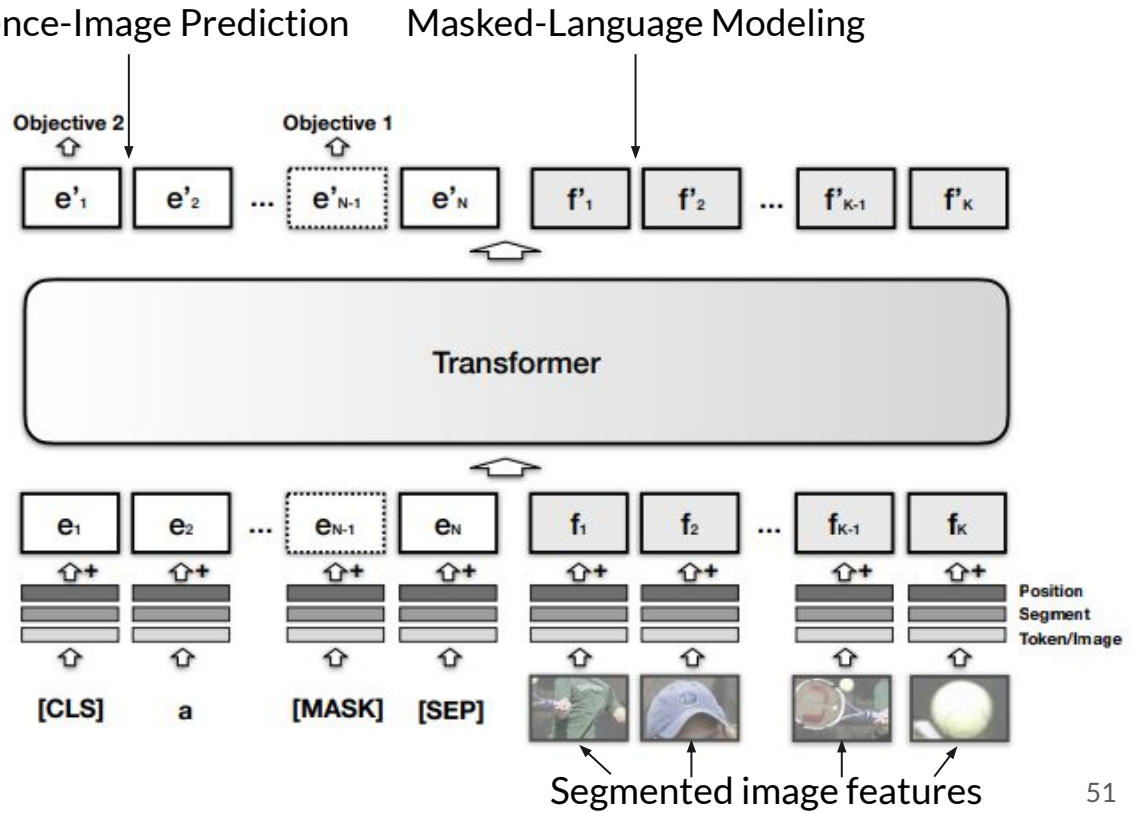
Wikipedia

# Faster RCNN

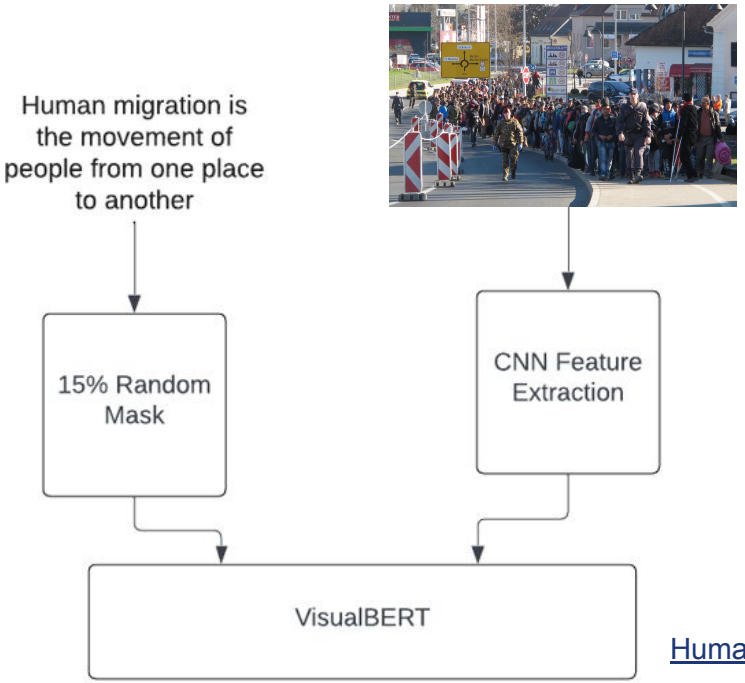

classifier
RoI pooling
proposals
Region Proposal Network
feature maps
conv layers
image

# Visual BERT

A person hits a ball with a tennis racket



# Train Time Word Prediction

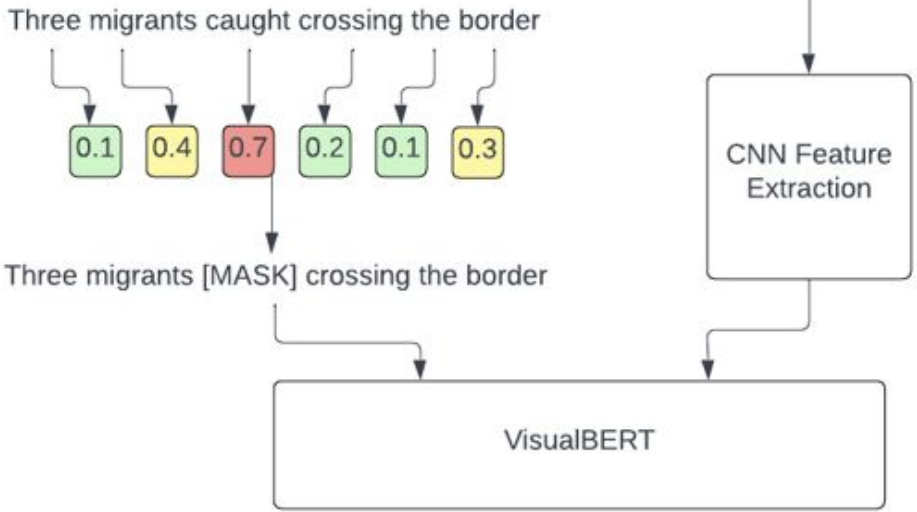



Human migration - Wikipedia

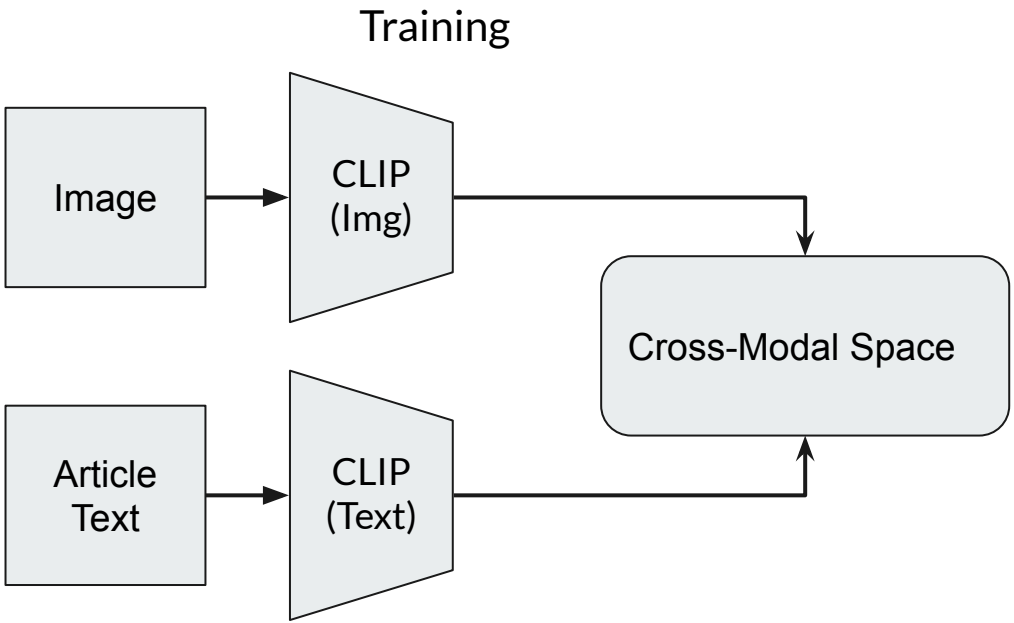
# Text Predictor Model Parameters

- Faster RCNN ~ 65M parameters (frozen)
- VisualBERT ~ 112M parameters, 3704 trainable parameters
    - Freeze all but last four layers which contains the weights and bias for the predictor and sequential relationship

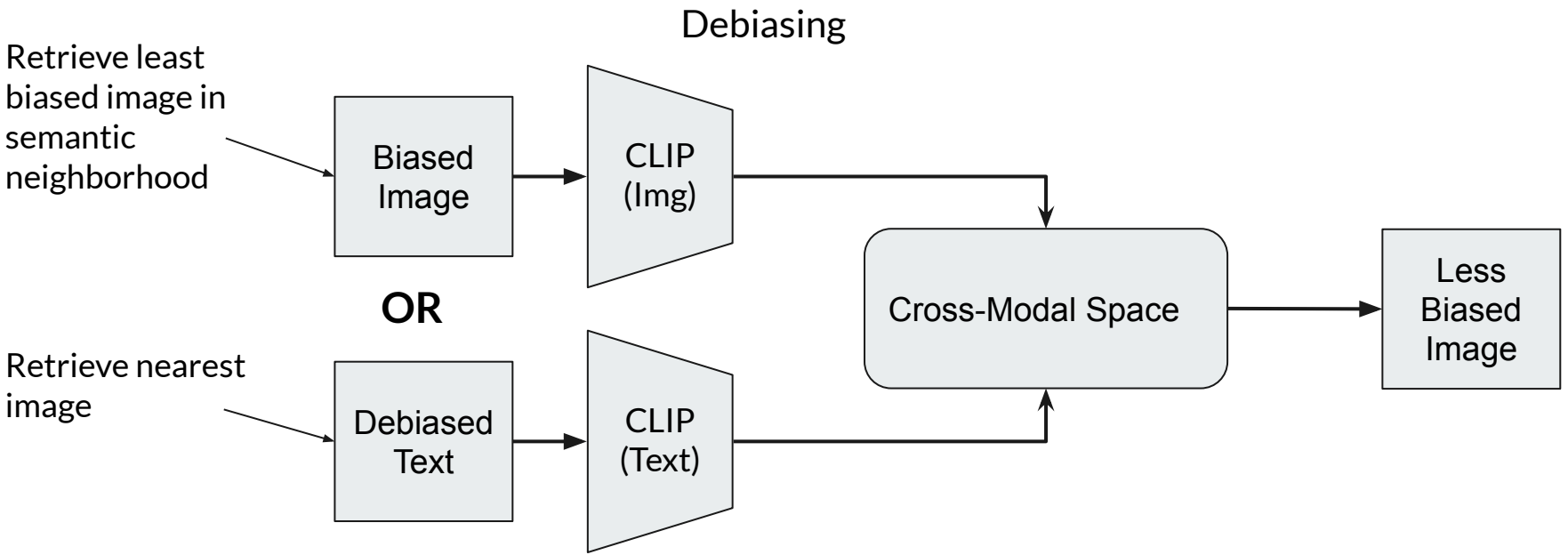
# Test Time Word Prediction



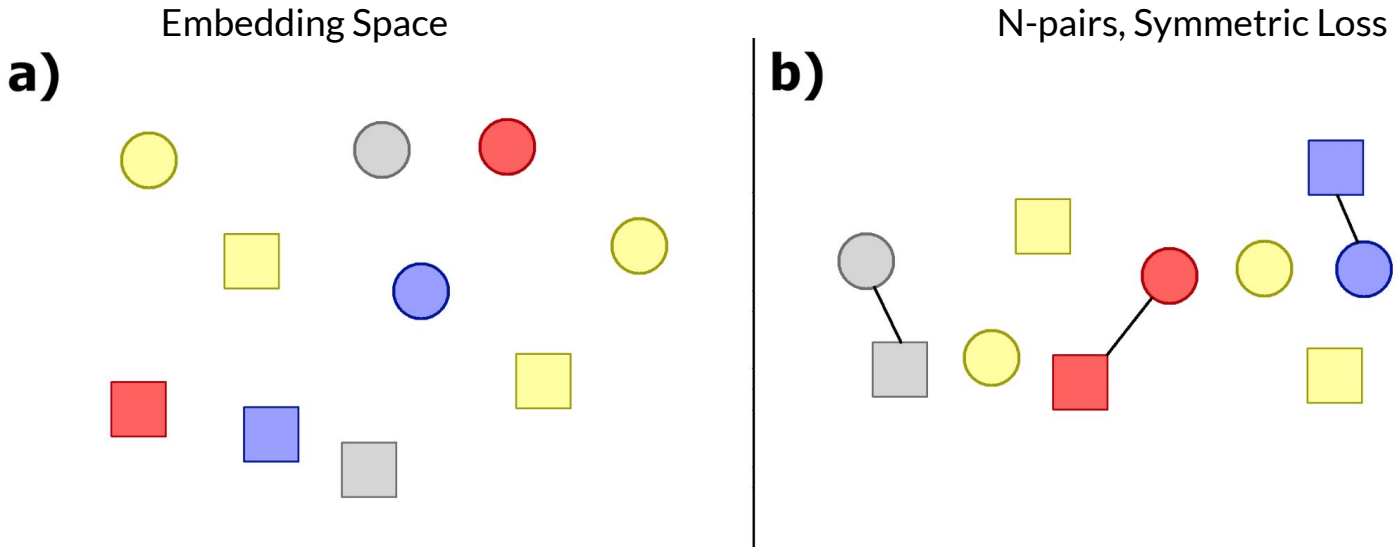
# Image De-Biasing



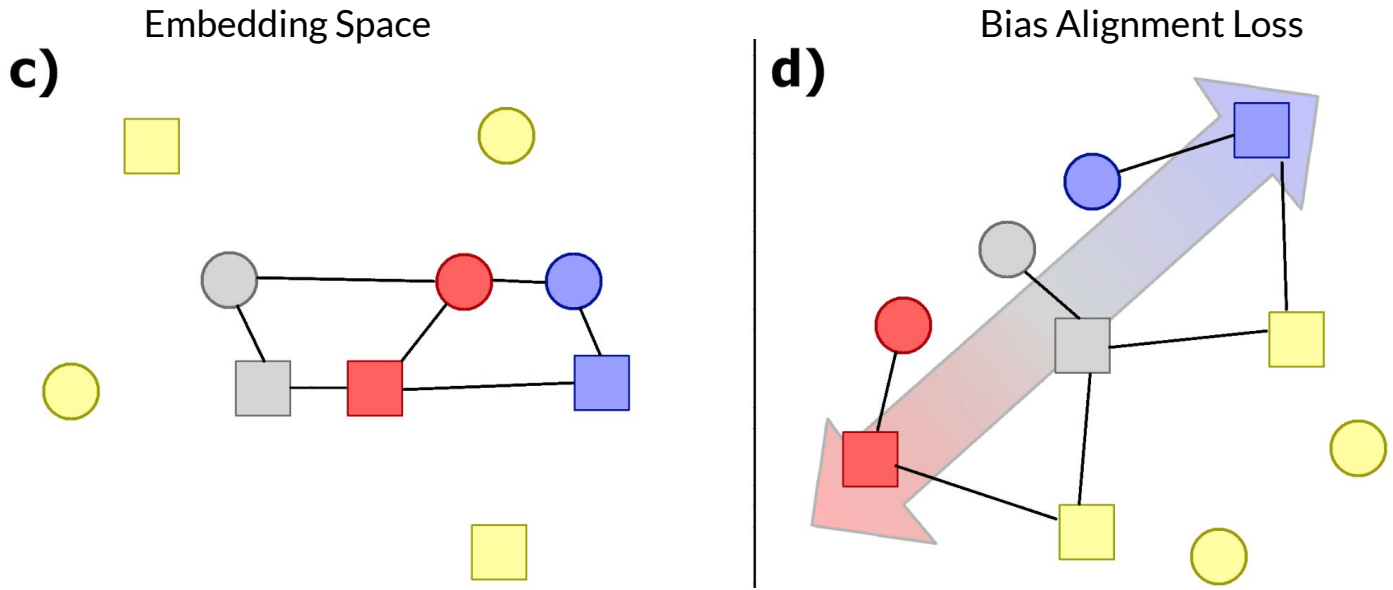
# Image De-Biasing



# Image De-Biasing

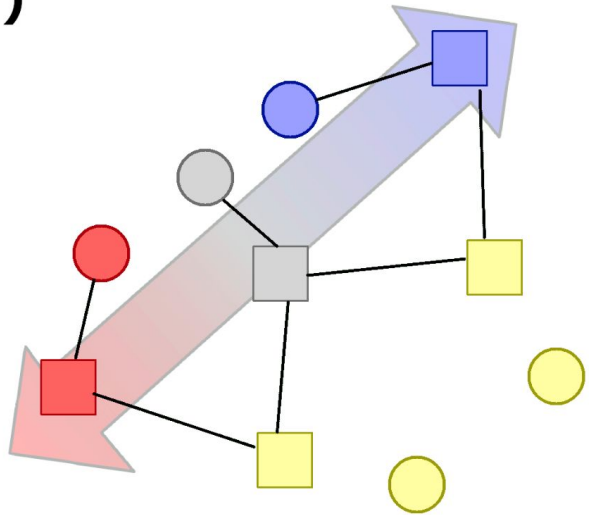


# Image De-Biasing



# Image De-Biasing

d)



Anchor

Bias Neighborhood

Negative Sample

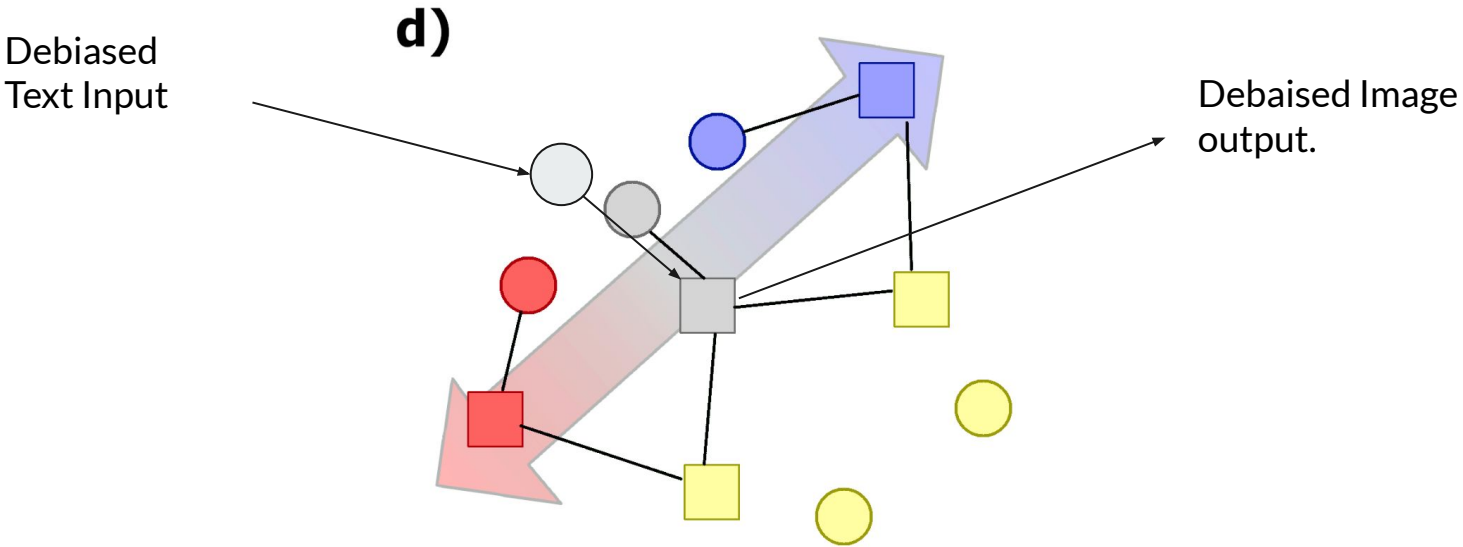
$$\mathcal{T}'_{img} = \left(x_i^a, x_{i'}^p, x_j^n\right)$$

$$\mathcal{L}_{img}\left(\mathcal{T}'_{img}\right) = \mathcal{L}_{ang}\left(\mathcal{T}'_{img}\right)$$

$$\mathcal{L}_{ang}\left(\mathcal{T}'_{img}\right) = \left[\|x_i^a - x_{i'}^p\|_2^2 - 4\tan^2\alpha\|x_j^n - \mathcal{C}_i\|_2^2\right]_+$$

Thomas, C., & Kovashka, A. (2020, August). Preserving semantic neighborhoods for robust cross-modal retrieval. In European Conference on Computer Vision (pp. 317-335). Springer, Cham.

# Image De-Biasing (Retrieval)

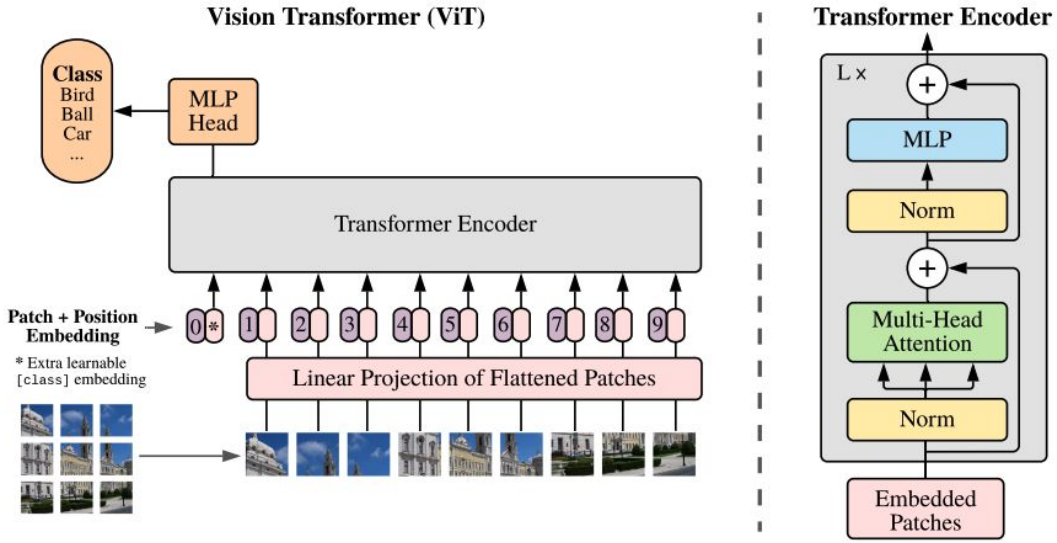



Thomas, C., & Kovashka, A. (2020, August). Preserving semantic neighborhoods for robust cross-modal retrieval. In European Conference on Computer Vision (pp. 317-335). Springer, Cham.

# ViT Alignment (Overview)

- Divide an input image into 196 (14 X 14) small images of size (16 X 16)
- Treat it as embedding in NLP
- Use it as input for traditional transformer encoder (like in BERT)
- We modified it to 2  instead of 12 Transformer layers because of the size of our data and resources we had available
- Take the last output, use it as input for Dense layer with one linear output (original paper 1000 classes)

# ViT Alignment (Overview)



# Why Don’t We Use A Full Image for Transformer?

- Because of n squared parameters
- Equates to 22 billion parameters only for 224 X 224 X 3 image

# Our modifications to the model

- Our Dataset has 224 X 224 images with respective bias score
- Changed MLP head to output a linear classifier instead of multi-class classifier
- We use Mean Squared Loss instead of Cross Entropy Loss
- We transformed from 12 layers to 2  Transformer Layers
- We changed MLP size to 512

# Results and Evaluation

# Biased Word Identification - Results

Qualitative Analysis

# Biased Word Identification - Results

Qualitative Analysis

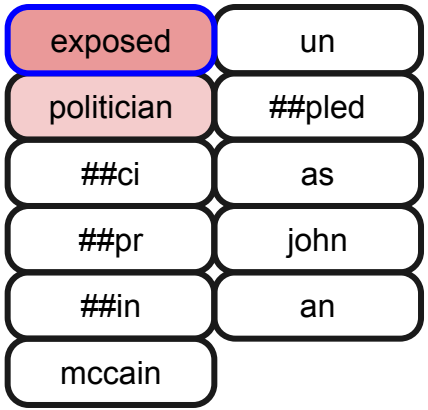
Main example from paper

**Input**

John McCain exposed as an unprincipled politician

**Tokens**

(descending order of bias)



# Biased Word Identification - Results

Qualitative Analysis

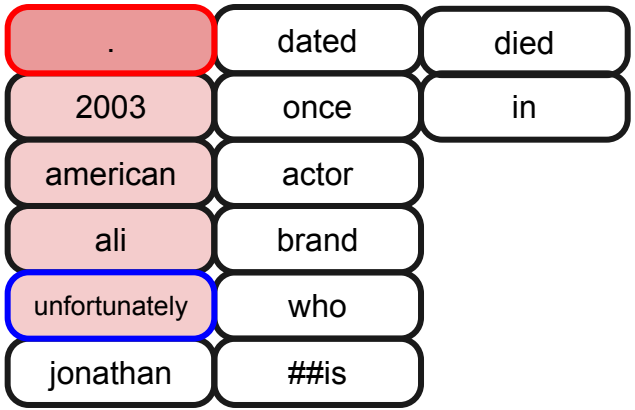
Randomly selected from WNC test set

**Input**

ali once dated american actor jonathan brandis who unfortunately died in 2003.

**Tokens**

(descending order of bias)



# Biased Word Identification - Results

## Input

The leader of the centre left SPD party, currently playing a supporting role as the junior coalition partner in the German government, hopes the capitalise on voter weariness to prevent Mrs Merkel gaining a fourth term in office. He is due to announce whether he will officially run at the end of this month, but Bild announced on Tuesday that he is the candidate.

## Tokens

(descending order of bias)

| | | | |
|---|---|---|---|
| fourth | office | whether | the |
| the | partner | german | of |
| ##ise | announced | the | a |
| capital | tuesday | due | mrs |
| term | bi | will | as |
| that | coalition | voter | role |
| is | ##ld | officially | government |
| . | he | this | ••• |

# Biased Word Identification - Results

## Input

The Wall around Jerusalem (Photo: Musa Al-Shaer) GENEVA -- The Commission on Human Rights today started its general debate on the violation of human rights in the occupied Arab territories, including Palestine, after it concluded its discussion on the right to development. Many speakers denounced Israel's actions in the occupied Palestinian territory, in particular the construction of a separation Wall.

## Tokens

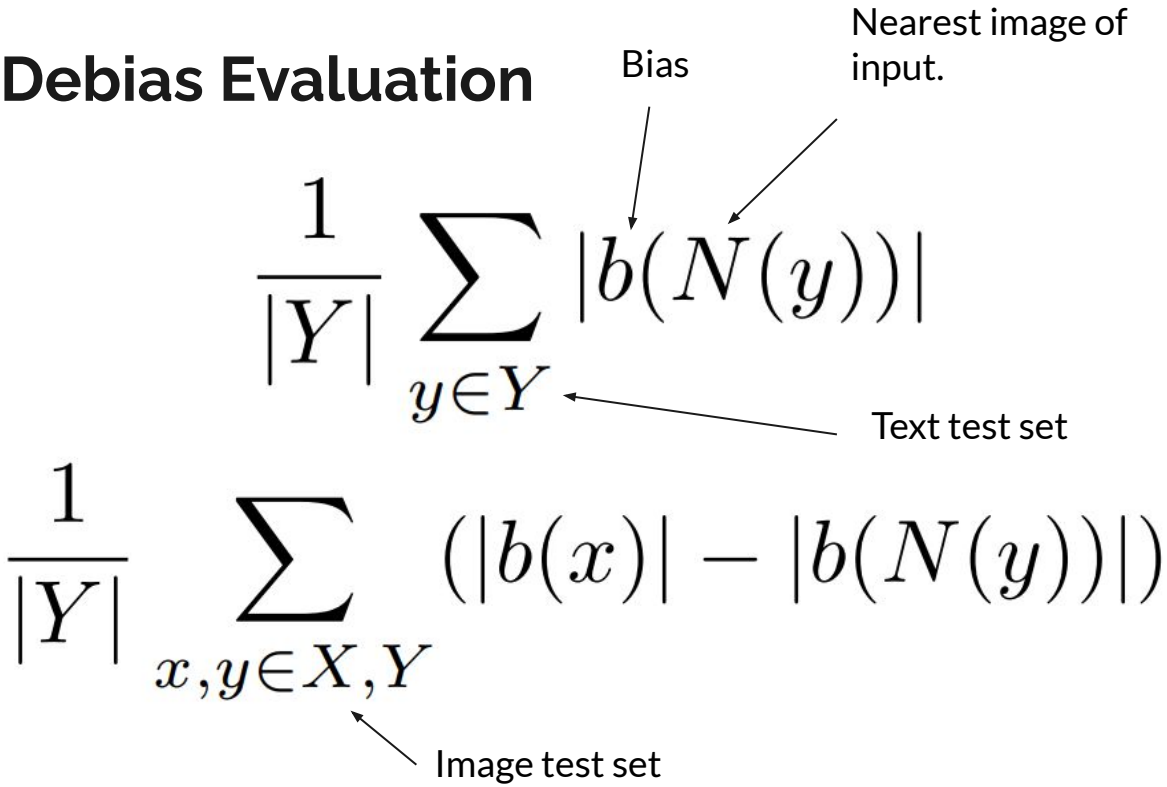
(descending order of bias)

| | | | |
|---|---|---|---|
| right | s | - | the |
| particular | territory | the | arab |
| rights | the | , | palestine |
| rights | the | the | . |
| development | occupied | human | violation |
| discussion | . | its | - |
| its | occupied | human | : |
| the | general | actions | ••• |

# Biased Word Replacement - Results

- Cosine similarity between predicted masked words and original word embeddings. Word embeddings obtained through pre-trained Gensim
- Human evaluation for bias measurement

# Image Debias Evaluation



# ViT Model evaluation (RMSE)

- Stands for Root Mean Square Error (RMSE)
- Standard Deviation of the residuals (prediction errors).

$$\mathrm{RMSE}_{fo} = \left[\sum_{i=1}^{N} (z_{f_i} - z_{o_i})^2 / N\right]^{1/2}$$

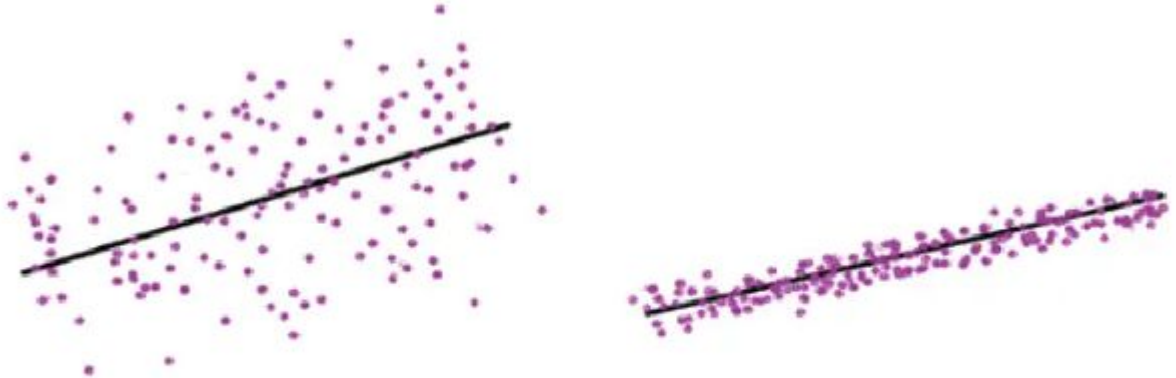
**Where**:

- $\Sigma$ = summation ("add up")
- $(z_{f_i} - Z_{oi})^2$ = differences, squared
- N = sample size.

# ViT Model evaluation (R-squared Score)

- Regression Score function
- Negative score- Model can be arbitrarily worse
- Zero score- Model that does not explain the variability of the response data around its mean
- Best possible is 1.0, which corresponds to a model that explains the variability of the the response variable around its mean

# ViT Model evaluation (R-squared Score)



R-squared : 17%

R-squared : 83%

# Human Evaluation

- Form to evaluate 4 key questions comparing novel image and text with original
  - If novel image and text are semantically similar to original
  - If novel text has reduced bias
  - If novel image has reduced bias
  - If novel image and novel text are still aligned

https://docs.google.com/forms/d/e/1FAIpQLSfG3aR9B0VTDJvGKLPN4vy8mqRkBoFz59l5VmXgbSaXAyWoWQ/viewform?usp=sf_link

# Strengths and Weaknesses

- Weaknesses
  - Reduced bias text may be less truthful
  - Stacked models may compound error
  - Overall model may be sensitive to rare words, punctuation, etc.
  - People watch audio and video sources and our method does not have neutralizing video and audio.

- Strengths
  - Considers both text and visual information for bias reduction
  - Image debias is a retrieval task. Should make debiasing fast.
  - Our paper, if successful in its implementation, will give people an opportunity to consider viewing news that are neutralized. Also,  since we are bombarded by news through the internet, we can analyze the effects of neutralized news and its effect on a person's well being.

# Ethical Considerations

- When would debiasing an article's images or text be considered censorship?
- If the negative or positive aspects being covered are truthful, is it appropriate to replace an image that reflects that emotional element with one that does not?
- Public perception of model itself.

# Future Work

- Examine “directionality” of bias in embedding space. New loss likely makes regions of neutral representations. Generation?
- Weight bias loss on difference b/w biases (Higher bias difference leads to greater separation).
- Image debiasing metric: Do they still match the context & semantics?
- Image debiasing metric: Measure variety of retrieved images.

# Future Work (Timestamp Videos)