

# Identifying Hateful Memes with Multimodal Classification

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# Background & Data

#### **Problem:**

Given a meme, can our model correctly classify it as either hateful or non-hateful based on the combined input of the text and image?

#### **Motivation:**

- This task involves *multimodal classification*, which requires the model to effectively combine representations from drastically different modalities.
- Three main methods that have been studied:
  - Unimodal models
  - Multimodal models with unimodal pre-trainings
- Multimodal models with multimodal pre-trainings

#### Goal:

Implement and improve on the vanilla VisualBERT model.

#### Data:

- From Meta's Hateful Meme challenge in 2020
- 11,040: 8500, 540, 2,000 in train, dev, and test
- Each set contains: 10% unimodal hate, and 40% multimodal hate; 20% benign text confounder, 20% benign image confounder, and 10% non-hateful - Challenging Set!





# Model Architecture and Training

#### Baseline

- Resnet152 Pretrain for Images
- Sentence-BERT Pretrain for text
- Concatentation Fusion
- Hidden Size: 1200

#### **VisualBERT**

- Detectron2 R-CNN for Images
  - Uses Resnet101 Backbone Model
- BERT Tokenizer for Text
- VisualBERT Pretrain
  - NLVR2-COCO Pretrain Weights
- Hidden Size: 1000

#### **General Feed-Forward Block**

- Linear Layer (Kaiming)
- LayerNorm
- Leaky ReLU
- Dropout (tuned)

#### **Feature Extraction**

- FairFace
  - Face in Image?
  - If Face, what race/gender/age?
  - Concatenated after embedding extraction

#### **Additional Details**

- All Models trained for 10 epochs
- Training set manually balanced

### Dense + Softmax Dropout Output Leaky ReLU Activation Fully-Connected Block Layer Normalization Dense Layer Concatenation Fusion Resnet152 **Baseline Model Architecture** Dense + Softmax Dropout Output Leaky ReLU Activation Fully-Connected Block Dense Layer R-CNN (Detectron)

**BERT Tokenizer** 

VisualBERT (Fairface)

Model Architecture

# Analyses

Predicted	Non-Hateful	Hateful
Actual		
None-Hateful	1202(60.1%)	48(2.4%)
Hateful	705(34.24%)	45(2.25%)

Confusion matrix of VisualBERT Fairface

Predicted	Non-Hateful	Hateful
Actual		
None-Hateful	870 (43.5%)	380 (19.0%)
Hateful	424 (21.2%)	326 (16.3%)

Confusion matrix of Baseline

- Each model wrongly classifies a meme as non-hateful more often than wrongly classifies a meme as hateful.
- From Model 1 to 3, more likely to classify a hateful meme as non-hateful  $\rightarrow$  which explains why AUC curve is lower for Model 3 (VisualBERT Fairface)



- Images that all models wrongly classified as hateful.
- Offensive languages largely contribute to the classification regardless of image meanings.
- Models are still somewhat incapable of considering textual and image representations in coherence.



Fairface Classifier

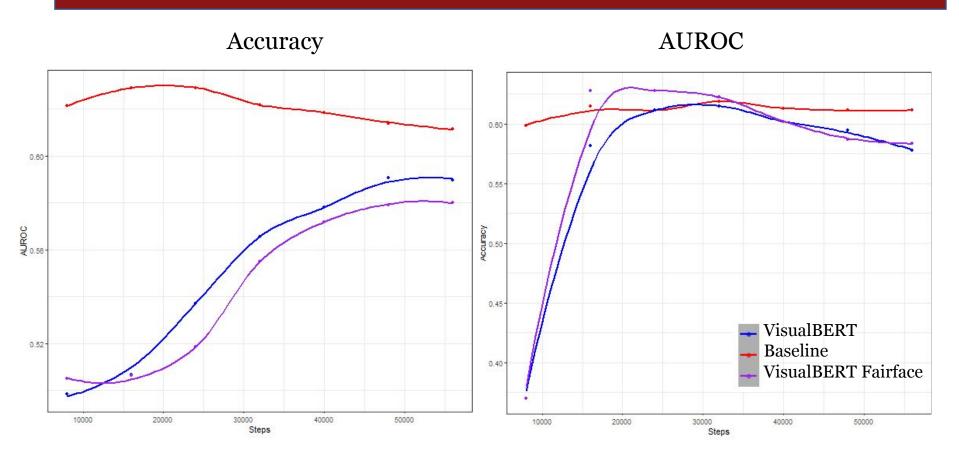
Race and Gender Tag

- Images that the vanilla VisualBERT classified correctly, but not the VisualBERT Fairface.
- VB Fairface relies too heavily on facial tags, and these tags could be wrong in the first place.
- Models are trained to be biased because of biases in our society.



- Images that VisualBERT Fairface classified correctly but not the vanilla VisualBERT. All are actually non-hateful.
- The bottom left may demonstrate that racial tags may be helpful.

### Results



Dev Accuracy and AUROC of three different models vs. Steps

Mixed results from the different models:

- Baseline Achieves 59.8% accuracy on test set (60.5% AUROC)
- VisualBERT accuracy reduces to 59.1%, with corresponding 57.1% AUROC
- VisualBERT with FairFace features has 62.4% accuracy, but 57.4% AUROC (examined in Analysis)

Tuned Hyperparameters via Validation:

- LR = 1e-3 for baseline
- LR = 1e-5 for VisualBERT
- pDrop = 0.2
- Adam Betas = (0.9, 0.999)

#### Key Takeaways:

- Results suggest large underfit of the data, stemming from small sample size and limited feature space most likely.
- Pre-training alone cannot overcome complex nature of meme understanding for machines

## Future Work

Due to time and compute limitations, there is still room for improvement. These include:

- Train on more data if available
- Explore more advanced fusion techniques, since we use early fusion with simple concatenation (e.g. CNN or RNN-based fusion)
- Explore other feature extractions (e.g. Web Entity Detection)
- Improve the current model architecture to decrease probability of wrongly classifying memes as non-hateful
- Use the current feature tags but fuse it prior to the VisualBERT pre-training

### References

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[2] Luinian Li, Mark Yatskar, Da Yin, Cho-Jui Hsieh, and KaiWei Chang. Visualbert: A simple and performant baseline for vision and language. arXiv:1908.03557 [cs.CV], 2019. [3] Jiquan Ngiam, Aditya Khosla, Mingyu Kim, Juhan Nam, Honglak Lee, and Andrew Y. Ng. Multimodal deep learning. In ICML, pages 689–696, 2011.