

An Interpretable Approach to Hateful Meme Detection

Tanvi Deshpande
Irvington High School
Fremont, CA, USA
tanvi.md@gmail.com

Nitya Mani
Massachusetts Institute of Technology
Cambridge, MA, USA
nmani@mit.edu

ABSTRACT

Hateful memes are an emerging method of spreading hate on the internet, relying on both images and text to convey a hateful message. We take an interpretable approach to hateful meme detection, using machine learning and simple heuristics to identify the features most important to classifying a meme as hateful. In the process, we build a gradient-boosted decision tree and an LSTM-based model that achieve comparable performance (73.8 validation and 72.7 test auROC) to the gold standard of humans and state-of-the-art transformer models on this challenging task.

CCS CONCEPTS

• **Computing methodologies** → **Artificial intelligence; Machine learning.**

KEYWORDS

machine learning; multimodal fusion; multimodal representations

ACM Reference Format:

Tanvi Deshpande and Nitya Mani. 2021. An Interpretable Approach to Hateful Meme Detection. In *Proceedings of the 2021 International Conference on Multimodal Interaction (ICMI '21)*, October 18–22, 2021, Montréal, Canada. ACM, New York, NY, USA, 5 pages. <https://doi.org/10.1145/3462244.3479949>

1 INTRODUCTION

Memes have evolved into one of the most powerful mediums of spreading hate online. The ubiquity of social media has fanned the flames of *hate speech*, communication conveying prejudiced messages towards members of minority groups. Memes are frequently used to spread hate, alt-right, and even neo-Nazi rhetoric on Reddit, 4chan, and other mainstream social media websites. Recently, r/The_Donald and 4chan have been responsible for a large fraction of hateful memes that spread virally from fringe to mainstream media platforms, and about 5% of all memes posted on /pol/ were racist, meaning that over 600,000 racist memes were shared in a span of 13 months from *just this community* [28].

Flagging hateful memes before they spread is a challenging problem for humans and AI-based models due to the nuance and sociopolitical contexts that drive their interpretation. The ineffectiveness

Permission to make digital or hard copies of all or part of this work for personal or classroom use is granted without fee provided that copies are not made or distributed for profit or commercial advantage and that copies bear this notice and the full citation on the first page. Copyrights for components of this work owned by others than the author(s) must be honored. Abstracting with credit is permitted. To copy otherwise, or republish, to post on servers or to redistribute to lists, requires prior specific permission and/or a fee. Request permissions from permissions@acm.org.

ICMI '21, October 18–22, 2021, Montréal, Canada

© 2021 Copyright held by the owner/author(s). Publication rights licensed to ACM.
ACM ISBN 978-1-4503-8481-0/21/10...\$15.00
<https://doi.org/10.1145/3462244.3479949>

of current hate speech moderation methods highlights the acute need to make automatic hate speech detection more efficient.

In May 2020, Facebook AI released a dataset of over 10,000 multimodal memes as part of the Hateful Memes Challenge [12], a challenge hosted by DrivenData to drive progress on this task.

1.1 Motivation

On the Hateful Memes dataset, trained humans achieved an auROC of 82.65 [12]; the relatively poor performance of even this gold standard suggests that a hybrid approach of augmenting human classification with machine learning-derived scores and tags may be promising for effective hateful meme identification. To that end, in this work we consider human-interpretable machine learning algorithms, such as a gradient-boosted decision tree model that utilizes machine learning and engineered features to achieve performance that outperforms non-transformer baselines and achieves comparable performance to complex transformer baselines. We create a reasonably-performant model that can be used to flag memes and augment them with the most important features to aid human classification.

A decision tree model allows us to easily extract a ranking of derived features that can be used to augment meme images and aid humans in final classification. Such scoring provides valuable insights into common characteristics of hateful memes that may warrant further investigation. We look at textual sentiment, named entities in images and text, and semantic similarity between image and text as some of the most important features.

2 DATASET/CHALLENGE DESCRIPTION

The Hateful Memes dataset is a challenge dataset with 12,140 total samples, of which about 63% are non-hateful and 37% are hateful memes. Many hateful memes come with text and image confounders, which alter the text or image of the hateful meme to change its connotation to non-hateful, meaning models must utilize both modalities to succeed at the task.



Figure 1: Hateful meme and text/image confounders. Image above is a compilation of assets, including ©Getty Images.

Exploratory data analysis found that the majority of hate attacks minority groups by playing off of common stereotypes and going beyond them to imply threats or violence.

The Hateful Memes challenge was a competition from May to October 2020 intended for researchers to fine-tune large-scale state-of-the-art transformer models. The competition metric was auROC.

3 RELATED WORK

3.1 Related datasets

Although the Hateful Memes dataset is one of the first of its kind, there are a few similar datasets. SemEval-2020 Task 8 (Memotion analysis) [21] involves classifying sentiment, humor, offensiveness, and motivation on a dataset of 10,000 human-annotated memes. The macro F1-score for the baseline model was 0.21 for sentiment and 0.50 for humor type classification using image-text models, emphasizing how challenging interpreting memes can be. Additionally [15] is a similar dataset, but with 2,631 Italian memes.

3.2 Text-only hate speech detection

There has been a myriad of work on text-based hate speech detection, focused on Twitter-style text data. Current state-of-the-art approaches [3, 8, 10] have involved the standard natural language processing toolkit, including BERT and other embedding schemes.

3.3 Multimodal/meme hate detection

State-of-the-art multimodal hate speech detection often includes unimodally pretraining models for each modality, for early and late fusion, as well as multimodal pretraining [4]. For example, [12]’s baseline using BERT on meme text is an example of unimodal pretraining, whereas their use of a VisualBERT COCO model to pre-train constitutes multimodal pretraining. Hateful Memes challenge winners achieved auROC’s between 0.78 and 0.84, relying heavily on large multimodal transformer models such as OSCAR, UNITER, VisualBERT, and LXMERT [13, 16, 19, 22, 29], largely taking the same approach of fine-tuning and ensembling very high-capacity single- and dual-stream transformer models or other recurrent architectures with minimal data preprocessing. Despite outperforming baselines, such models are still very far from an ideal resolution to the problem of identifying hateful memes.

4 METHODS/APPROACH

Here, we take a divergent approach from much of the literature on hateful meme detection. Rather than focusing on high capacity ensembles of transformer models, we use thoughtfully engineered features and pass these to two models for final classification: a gradient boosted decision tree and simple LSTM. This methodology allows us to easily isolate crucial features for identifying memes as hateful and extract underpinning logic from our models that may be useful to augment a human in performing this challenging classification task.

In addition to straightforwardly embedding the text and images associated to a meme, we augment our feature set with a variety of common-sense and machine-learning derived features that represent criteria that a human uses when attempting to contextualize a meme and uncover its underlying meaning.

4.1 Text and image embedding

For our gradient-boosted decision tree, we use a captioning model [23] to capture the relevant content of an image in text format. We then embed both text and images using tf-idf to upweight individual words of high interest.

In our LSTM model, we concatenate meme image captions and the meme text and embed them via DistilBERT [20].

4.2 Additional textual features

In addition to our embeddings, we develop features using named-entity recognition, profanity and slur detection, counts of hateful words, text sentiment, and emotion detection.

4.2.1 Named-entity detection. We use SpaCy named-entity detection [9] to extract culturally relevant components of the meme text, identifying and individually encoding 2085 named entities.

4.2.2 Profanity/Slurs. We further augment our feature set with counts of profanity and slurs banned by Google [11].

4.2.3 Hateful words. Based on a frequency search and corpuses such as top hits on Urban Dictionary, we supplement our feature set with flags for words commonly used to dogwhistle hate in memes despite having an innocuous meaning in ordinary speech. For example, we flag “dishwasher,” which is often used in a derogatory manner in memes to refer to women.

4.2.4 Text Sentiment. We use TextBlob [14] to identify the polarity (positivity or negativity of sentiment) and subjectivity (how opinionated or objective views expressed in the text are) of a meme’s text.

4.2.5 Emotion detection. We use the text2emotion [5] library to score our meme text based on its happiness, sadness, fear, surprise, and anger. We find that high fear and anger scores are often indicative of hateful memes.

4.2.6 Semantic Similarity. We use a fine-tuned RoBERTa model [18, 25] using a combination of various natural language inference datasets such as SNLI [6], multiNLI [24], FeverNLI [17], and ANLI [18] to detect *semantic similarity* between meme text and the generated meme captions and detected image web entities. The result is a probability vector for the 3 possible classes of “contradiction” (texts that contradict each other), “entailment” (one piece of text can be inferred from the other), or “neutral” (neither entailment nor contradiction, but texts can be semantically similar). These features are particularly useful, as a number of image confounders in the dataset have meme text which simply captions the image; then, a high score on the “entailment” or “neutral” classes can help conclude that a meme is benign; similarly, high scores on contradiction can help detect irony in a meme between the meme text and what is expressed in the meme image.

4.3 Image-based features

Many multimodal hate speech detection models overweight text. Here, we focus on extracting additional image-based features. We first preprocess images by removing meme text using OCR, then caption them, then detect objects and web entities in the image. These steps serve to summarize some relevant content of an image.

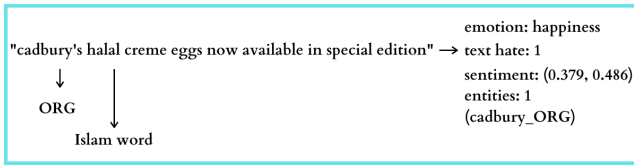


Figure 2: Text preprocessing steps

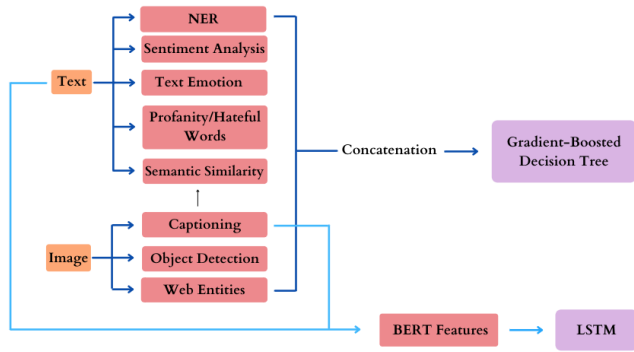


Figure 3: Total preprocessing pipeline.

4.3.1 *Image Preprocessing.* We preprocess meme images using OCR to detect textual regions and inpainting using OpenCV [7], increasing accuracy downstream.

4.3.2 *Image Captioning.* We use a visual attention-based captioning model trained on COCO [23, 27] to learn the relations between objects present in meme images.

4.3.3 *Object Detection.* We tag objects within meme images using Facebook’s Detectron2 [26] tagger, which is able to provide specific descriptions of items that may be omitted from our image captions.

4.3.4 *Web Entity Detection.* As in [29], we use Google Vision API’s Web Entity Detection [1], which contextualizes images using knowledge from the web, enabling our model to account for the rapid shifts that occur in meme culture in a matter of weeks, days, or minutes.

4.4 Total Preprocessing

After preprocessing in both channels, we concatenate the emotion, sentiment, semantic similarity, profanity, and hateful words features (13×1). Meme text, captions, detected objects, and named and web entities are concatenated and embedded jointly (19651×1), forming the final input of 19664×1 .

4.5 Models

We use an 90-10 train/validation-test split and build two classes of models, tuning each set of hyperparameters with a grid search and performing 5-fold cross-validation on each model.

4.5.1 *GBDT.* In our gradient boosted-decision trees, we input (1) the joint tf-idf embeddings for image captions and meme text as well as (2) the engineered features for image and text, as described in 4.4. We train the model with 100 estimators, a learning rate of 1.0,

and a maximum depth of 40, and a scale_pos_weight of 1.5, with an average of 900 nodes per tree after pruning.

4.5.2 *LSTM.* We use a pretrained DistilBERT model to preprocess our meme text and image captions jointly, forming a 768-dimensional input to the model, which has a 9-unit LSTM layer followed by two Dense layers with 8 and 2 neurons respectively. We train for 45 epochs using Adam and binary-cross entropy loss.

5 RESULTS AND DISCUSSION

5.1 Summary of Results

We achieve a significant improvement from non-transformer baseline models and comparable results to transformer baselines using more lightweight and interpretable models. We are able to augment memes with the most important features, determined by the model, for easier human classification.

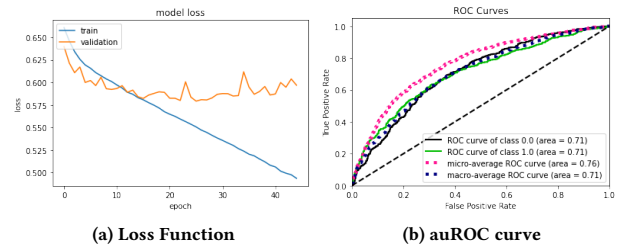


Figure 4: Plots from the LSTM Model.

5.2 Discussion

5.2.1 *GBDT feature importances.* The gradient-boosted decision tree yields 494 predictive features, ranked by the feature_importances_ property, and a precision of 0.53 and a recall of 0.58. Top features are certain tf-idf embedded words and text emotion; named entities such as Hitler and ethnic groups such as “asians” or “mexicans” also rank highly; top named-entity and overall features are included in Table 2.

5.2.2 *GBDT vs. recurrent network.* Gradient-boosted decision tree-based models provide the advantages of faster computation time and a ranking of the most important features to meme detection, providing computer insight into meme rhetoric. They are also effective at including engineered features, such as text sentiment, which would be meaningless to LSTMs, which are meant for sequence-based

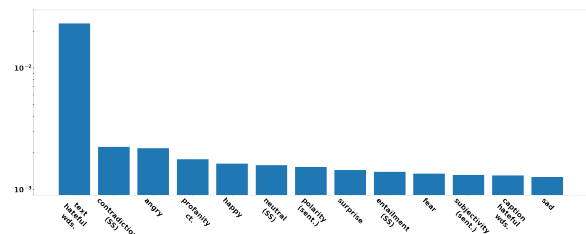


Figure 5: Feature importances of top engineered features.

Table 1: Results

Source	Model	AUROC		Accuracy	
		Validation	Test	Validation	Test
	Human	-	82.65	-	84.70
Hateful Memes Non-transformer Baselines	Image-grid	58.79	52.63	52.73	52.00
	Image-region	57.98	55.92	52.66	52.13
	Text-only BERT	64.65	65.08	58.26	59.20
	Late Fusion	65.97	64.75	61.53	59.66
Hateful Memes Transformer Baselines	ViLBERT	71.13	70.45	62.20	62.30
	VisualBERT	70.60	71.33	62.10	63.20
	ViLBERT CC	70.07	70.03	61.40	61.10
	VisualBERT COCO	73.97	71.41	65.06	64.73
Our Models	GBDT w/ image tagging	70.86	71.11	70.27	71.19
	GBDT w/ tagging/captions	71.67	70.90	69.58	68.45
	GBDT w/ BERT only	70.38	71.52	68.97	69.36
	LSTM w/ BERT features	73.78	72.72	67.83	66.39



Table 2: Top features ranked from gradient-boosted tree.

Named Ents.		Total Features	
Name	Score	Name	Score
ent_jews_norp	3.4×10^{-2}	text hate wds.	2.3×10^{-1}
ent_muslim_norp	3.0×10^{-2}	club	1.1×10^{-1}
ent_hitler_person	2.6×10^{-2}	isis	6.4×10^{-2}
ent_mexicans_norp	2.5×10^{-2}	jews	5.3×10^{-2}
ent_islamic_norp	2.4×10^{-2}	muslims	5.1×10^{-2}
ent_asians_norp	2.3×10^{-2}	teacher	4.3×10^{-2}

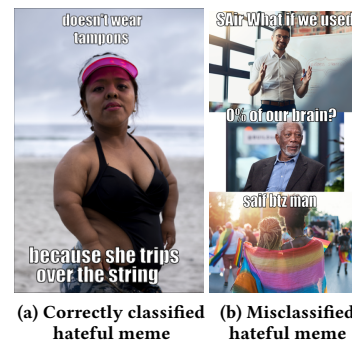
data. Recurrent networks are able to learn from DistilBERT features more effectively, as they have more computational scope and overall better performance than gradient-boosted decision trees.

5.2.3 Confounders. The model is able to correctly identify not only simple hateful memes but also distinguish between hateful memes and nontrivial confounders, leveraging both modalities for classification. We present one such correctly classified image confounder and hateful meme pair.

Table 3: Confounder/hateful meme comparison. Images below are a compilation of assets, including ©Getty Images.

Label	Hateful meme	Image confounder
Meme		
Caption	“a group of people playing on a beach”	“a black and white photo of a monkey”
Pred. Label	1 (hateful)	0 (not hateful)
Label	1 (hateful)	0 (not hateful)

5.2.4 Analysis of difficult-to-classify memes. We give examples of correctly and incorrectly classified hateful memes from the dataset.

**Figure 6: Classified hateful memes from test set. Images above are a compilation of assets, including ©Getty Images.**

The first meme, despite nonhateful individual modalities, is flagged by the model by leveraging the image to gain the context needed to understand the text. The misclassified meme contains several words unfamiliar to models and most humans, such as “SAif” and “btz.” To classify similarly niche samples, knowledge pulled from repositories such as Know Your Meme [2] could give humans better context.

5.3 Conclusion and Extensions

We develop a lightweight multimodal model that classifies memes with performance comparable to transformer baselines. Since even humans achieve low auROCs, our approach, rather than aiming to replace humans with end-to-end models, flags hateful memes and pinpoints relevant engineered features to improve human classification. Further extensions include measuring human performance on classifying augmented memes and developing features based on metadata such as shares and user post history.

REFERENCES

- [1] [n.d.]. Google Vision API. <https://github.com/googleapis/python-vision>.
- [2] [n.d.]. Know Your Meme. <http://knowyourmeme.com/>.
- [3] S. Abro, Sarang Shaikh, Z. Ali, Sajid Khan, G. Mujtaba, and Z. H. Khand. 2020. Automatic Hate Speech Detection using Machine Learning: A Comparative Study. *International Journal of Advanced Computer Science and Applications* 11 (2020).
- [4] Tariq Habib Afridi, Aftab Alam, M. N. Khan, Jawad Khan, and Young-Koo Lee. 2020. A Multimodal Memes Classification: A Survey and Open Research Issues. *ArXiv abs/2009.08395* (2020).
- [5] Amey Band, Karan Bilakhiya, Aman Gupta, and Shivam Sharma. 2020. Text2Emotion Python Library. <https://github.com/aman2656/text2emotion-library>.
- [6] Samuel R. Bowman, Gabor Angeli, Christopher Potts, and Christopher D. Manning. 2015. A large annotated corpus for learning natural language inference. In *Proceedings of the 2015 Conference on Empirical Methods in Natural Language Processing (EMNLP)*. Association for Computational Linguistics.
- [7] G. Bradski. 2000. The OpenCV Library. *Dr. Dobb's Journal of Software Tools* (2000).
- [8] Rui Cao, Roy Ka-Wei Lee, and Tuan-Anh Hoang. 2020. DeepHate: Hate Speech Detection via Multi-Faceted Text Representations. In *12th ACM Conference on Web Science (Southampton, United Kingdom) (WebSci '20)*. Association for Computing Machinery, New York, NY, USA, 11–20. <https://doi.org/10.1145/3394231.3397890>
- [9] Diego Esteves. 2018. Named Entity Recognition on Noisy Data using Images and Text (1-page abstract). *arXiv:1809.01964 [cs.IR]*
- [10] Paula Fortuna and Sérgio Nunes. 2018. A survey on automatic detection of hate speech in text. *ACM Computing Surveys (CSUR)* 51, 4 (2018), 1–30.
- [11] Robert James Gabriel. 2017. Google Profanity Words. <https://github.com/RobertJGabriel/Google-profanity-words>.
- [12] Douwe Kiela, Hamed Firooz, Aravind Mohan, Vedanuj Goswami, Amanpreet Singh, Pratik Ringshia, and Davide Testuggine. 2021. The Hateful Memes Challenge: Detecting Hate Speech in Multimodal Memes. *arXiv:2005.04790 [cs.AI]*
- [13] Phillip Lippe, Nithin Holla, Shantanu Chandra, Santhosh Rajamanickam, Georgios Antoniou, Ekaterina Shutova, and Helen Yannakoudakis. 2020. A Multimodal Framework for the Detection of Hateful Memes. *arXiv:2012.12871 [cs.CL]*
- [14] Steven Loria. 2018. textblob Documentation. *Release 0.15.2* (2018).
- [15] Martina Miliani, Giulia Giorgi, Ilir Rama, G. Anselmi, and Gianluca E. Leboni. 2020. DANKMEMES @ EVALITA 2020: The Memeing of Life: Memes, Multimodality and Politics. In *EVALITA*.
- [16] Niklas Muennighoff. 2020. Vilio: State-of-the-art Visio-Linguistic Models applied to Hateful Memes. *arXiv:2012.07788 [cs.AI]*
- [17] Yixin Nie, Haonan Chen, and Mohit Bansal. 2019. Combining Fact Extraction and Verification with Neural Semantic Matching Networks. In *Association for the Advancement of Artificial Intelligence (AAAI)*.
- [18] Yixin Nie, Adina Williams, Emily Dinan, Mohit Bansal, Jason Weston, and Douwe Kiela. 2020. Adversarial NLI: A New Benchmark for Natural Language Understanding. In *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics*. Association for Computational Linguistics.
- [19] Vlad Sandulescu. 2020. Detecting Hateful Memes Using a Multimodal Deep Ensemble. *arXiv:2012.13235 [cs.LG]*
- [20] Victor Sanh, Lysandre Debut, Julien Chaumond, and Thomas Wolf. 2019. DistilBERT, a distilled version of BERT: smaller, faster, cheaper and lighter. *ArXiv abs/1910.01108* (2019).
- [21] Chhavi Sharma, Deepesh Bhageria, William Scott, Srinivas PYKL, Amitava Das, Tanmoy Chakraborty, Viswanath Pulabaigari, and Björn Gambäck. 2020. SemEval-2020 Task 8: Memotion Analysis- the Visuo-Lingual Metaphor!. In *Proceedings of the Fourteenth Workshop on Semantic Evaluation*. International Committee for Computational Linguistics, Barcelona (online), 759–773. <https://www.aclweb.org/anthology/2020.semeval-1.99>
- [22] Riza Velioglu and Jewgeni Rose. 2020. Detecting Hate Speech in Memes Using Multimodal Deep Learning Approaches: Prize-winning solution to Hateful Memes Challenge. *arXiv:2012.12975 [cs.AI]*
- [23] Guoming Wang. 2018. image_captioning. https://github.com/DeepRNN/image_captioning.
- [24] Adina Williams, Nikita Nangia, and Samuel Bowman. 2018. A Broad-Coverage Challenge Corpus for Sentence Understanding through Inference. In *Proceedings of the 2018 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long Papers)* (New Orleans, Louisiana). Association for Computational Linguistics, 1112–1122. <http://aclweb.org/anthology/N18-1101>
- [25] Thomas Wolf, Lysandre Debut, Victor Sanh, Julien Chaumond, Clement Delangue, Anthony Moi, Pierric Cistac, Tim Rault, Rémi Louf, Morgan Funtowicz, Joe Davison, Sam Shleifer, Patrick von Platen, Clara Ma, Yacine Jernite, Julien Plu, Canwen Xu, Teven Le Scao, Sylvain Gugger, Mariama Drame, Quentin Lhoest, and Alexander M. Rush. 2020. Transformers: State-of-the-Art Natural Language Processing. In *Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing: System Demonstrations*. Association for Computational Linguistics, Online, 38–45. <https://www.aclweb.org/anthology/2020.emnlp-demos.6>
- [26] Yuxin Wu, Alexander Kirillov, Francisco Massa, Wan-Yen Lo, and Ross Girshick. 2019. Detectron2. <https://github.com/facebookresearch/detectron2>.
- [27] Kelvin Xu, Jimmy Lei Ba, Ryan Kiros, Kyunghyun Cho, Aaron Courville, Ruslan Salakhutdinov, Richard S. Zemel, and Yoshua Bengio. 2015. Show, Attend and Tell: Neural Image Caption Generation with Visual Attention. In *Proceedings of the 32nd International Conference on Machine Learning (ICML '15)*. JMLR.org, 2048–2057.
- [28] Savvas Zannettou, Tristan Caulfield, Jeremy Blackburn, Emiliano De Cristofaro, Michael Sirivianos, Gianluca Stringhini, and Guillermo Suarez-Tangil. 2018. On the Origins of Memes by Means of Fringe Web Communities. *arXiv:1805.12512 [cs.SI]*
- [29] Ron Zhu. 2020. Enhance Multimodal Transformer With External Label And In-Domain Pretrain: Hateful Meme Challenge Winning Solution. *arXiv:2012.08290 [cs.CL]*