

Empirical Analysis of Multi-Task Learning for Reducing Model Bias in Toxic Comment Detection

Ameya Vaidya,¹ Feng Mai,² Yue Ning³

¹Bridgewater-Raritan Regional High School

²School of Business, Stevens Institute of Technology

³Department of Computer Science, Stevens Institute of Technology
ameyav993@gmail.com, fmai@stevens.edu, yue.ning@stevens.edu

Abstract

With the recent rise of toxicity in online conversations on social media platforms, using modern machine learning algorithms for toxic comment detection has become a central focus of many online applications. Researchers and companies have developed a variety of shallow and deep learning models to identify toxicity in online conversations, reviews, or comments with mixed successes. However, these existing approaches have learned to incorrectly associate non-toxic comments that have certain trigger-words (e.g. gay, lesbian, black, muslim) as a potential source of toxicity. In this paper, we evaluate dozens of state-of-the-art models with the specific focus of reducing model bias towards these commonly-attacked identity groups. We propose a multi-task learning model with an attention layer that jointly learns to predict the toxicity of a comment as well as the identities present in the comments in order to reduce this bias. We then compare our model to an array of shallow and deep-learning models using metrics designed especially to test for unintended model bias within these identity groups.

Introduction

The identification of potential toxicity within online conversations has always been a significant task for current platform providers. Toxic comments have the unfortunate effect of causing users to leave a discussion or give up sharing their perspective and can give a bad reputation to platforms where these discussions take place. Twitter’s CEO reaffirmed that Twitter is still being overrun by spam, abuse, and misinformation.¹ To deal with this problem, researchers and companies have done extensive research into the field of toxic comment detection. Current research involves investigating common challenges in toxic comment classification (van Aken et al. 2018), identifying subtle forms of toxicity (Noever 2018), detecting early signs of toxicity (Zhang et al. 2018), and analysing sarcasm within conversations (Ghosh, Fabbri, and Muresan 2018).

Over the past few years, a variety of models and methods have been proposed to deal with this challenge. Current baseline methods deal with the representation of documents as character n-grams or TF-IDF (Badjatiya et al.

¹<https://money.cnn.com/2018/08/19/media/twitter-jack-dorsey-reliable-sources/index.html>

Table 1: Example of toxic comments with identity attack where Identity can be replaced by “gay”, “black” etc.

Identity	Toxic(+)	Non-toxic(-)
Positive	<i>⟨ Identity ⟩ people are gross and universally hated!</i>	<i>I am a ⟨ Identity ⟩ person, ask me anything.</i>
Negative	<i>What the heck is wrong with you?</i>	<i>Thanks for the help. I really appreciate it!</i>

2017) which are then learned by Logistic Regression or Support Vector Machines (Noever 2018). Recently, deep learning research such as convolutional neural networks (Georgakopoulos et al. 2018) and recurrent neural networks has been popularized in natural language processing. Furthermore, bidirectionality (Zhou et al. 2016), attention mechanisms (Bahdanau, Cho, and Bengio 2015), and ensemble learning (Dietterich 2000) have shown improved performance in text sentiment analysis.

However, many existing works have documented that current toxic comment classification models introduce bias into their predictions. They tend to classify comments that contain certain commonly-attacked identities (e.g. gay, black, Muslim) as toxic even though there was no toxicity present in the comment (Dixon et al. 2018; Borkan et al. 2019) as shown in Table 1. For example, the comment “I am a black woman, how can I help?” might be interpreted by a classifier as toxic because it references the ‘black’ identity. The Conversation AI team at Google Jigsaw has come forth and acknowledged that their Perspective API framework, which attempts to detect toxicity in online conversations, seems to generate higher toxicity scores for sentences containing commonly targeted identity groups.² Current research in this field includes identifying specific racial biases in popular models (Sap et al. 2019; Davidson, Bhattacharya, and Weber 2019), and developing evaluation metrics to test for specific biases against different identities (Dixon et al. 2018).

In this paper, we focus on detecting toxic comments while reducing the false positive rate on non-toxic comments that

²<https://medium.com/the-false-positive/unintended-bias-and-names-of-frequently-targeted-groups-8e0b81f80a23>

make reference to certain identities. To deal with this challenge, we propose a multi-task learning framework to simultaneously identify toxicity and identity information in a comment. We believe that learning these tasks jointly will allow our model to better distinguish between toxic and non-toxic comments that contain identity information. This paper also aims to implement and evaluate various baseline and deep learning models, including logistic regression and recurrent neural networks, on the task of mitigating bias. We evaluate our models on a dataset of 1,804,874 unique comments published by Google Jigsaw during Kaggle’s Unintended Bias in Toxicity Classification Challenge.³ We utilize a set of evaluation metrics and experiments specifically designed for measuring bias in the model outputs. This challenge is treated as a binary classification problem with multiple auxiliary tasks such as determining identity groups of a comment.

The ultimate goal of our research is to help maintain the civility of conversations on common social media platforms while minimizing the amount of non-toxic comments that are classified as toxic. Our main contributions are summarized as below:

1. We are the first to perform an empirical study of a range of classifiers to a new public dataset of over 1.8 million comments. We are also the first to compare classifiers with the specific focus of reducing unintended model bias within online conversations.
2. We propose three multi-task learning models that outperform other models at mitigating unintended bias and distinguishing between non-toxic and toxic comments. In addition, we also implement an attention mechanism in one of our multi-task learning models with the intention of capturing hidden state dependencies.
3. We compare the classifiers’ predictions using a variety of measures. These measures include F1-measures and the AUC-ROC score. In addition, we evaluate our models on metrics designed specifically to test for unintended model bias: Generalized Mean Bias AUC, Subgroup AUC, and BPSN AUC. We also compare actual non-toxic and toxic comments with identity information across models and with Google’s Perspective API framework.

In the following sections, we will introduce the related work and the investigated dataset followed by the proposed multi-task learning frameworks. Then we discuss the experimental evaluation and results. Finally we conclude our work with future directions.

Related Work

In this section, we will briefly review recent developments in multi-task learning. We will then focus on new attempts on toxic comment classification and identity bias in language models.

³<https://www.kaggle.com/c/jigsaw-unintended-bias-in-toxicity-classification/overview>

Multi-Task Learning

Multi-task learning (Caruana 1998; Argyriou, Evgeniou, and Pontil 2007a) has been widely studied and applied in natural language processing (NLP) (Collobert and Weston 2008; Deng, Hinton, and Kingsbury 2013), computer vision, and other machine learning applications (Ramsundar et al. 2015). In deep learning models, multi-task learning is usually implemented by either sharing hidden layer model parameters (Long et al. 2017) or regularizing parameters among related tasks to be similar (Duong et al. 2015). Recent works show that multi-task learning can improve performance on various NLP tasks while revealing novel insights about language modeling (Søgaard and Goldberg 2016). In terms of network architecture, our work is closest to the LSTM-based multi-task learning frameworks (Liang and Shu 2017; Suresh, Gong, and Guttat 2018). However it is known that the performance of multi-task learning is task specific (Misra et al. 2016). Which framework is more effective at teasing out identity information while detecting toxic comments is an open empirical question.

Toxic Comment Detection

Machine learning for detecting toxic comments has been a significant focus in Natural Language Processing research over the past few years. This is in part due to the availability of large corpora of online social interactions. Wikimedia Foundation (Wulczyn, Thain, and Dixon 2017) released an annotated dataset of personal attacks, toxic messages, and aggression from the English Wikipedia Talk pages. Google Jigsaw also published two Kaggle competitions which have allowed researchers to gain access to datasets with 2.5 million training examples of toxic comments. In terms of methods, most research takes a text classification approach similar to sentiment analysis and spam detection (Mishra et al. 2018; Davidson et al. 2017; Wulczyn, Thain, and Dixon 2017). These methods rely on document features (readability, emotion, sentiment, n-grams), author features (demographics, social network positions), or contextual features (the relationship of a document to others) to train classifiers.

More recent research advances toxic comment detection models on two fronts. Some studies move beyond using documents as the units of analyses and model the behavior of the users (Cheng, Danescu-Niculescu-Mizil, and Leskovec 2015), or take a more proactive approach to detect online conversations that are susceptible to escalation (Zhang et al. 2018). Another stream of work uses neural network models to classify toxic comments and has shown impressive results (Georgakopoulos et al. 2018; Chen, McKeever, and Delany 2019). Although these new models can achieve good performance without hand-crafted features, a potential downside is that the decisions made by the classifiers are more opaque. When the model is deployed, it may conflate identity attacks with identity disclosures, and make a biased decisions against the latter. Our work extends this stream of research and uses multi-task learning to explicitly account for the identity bias.

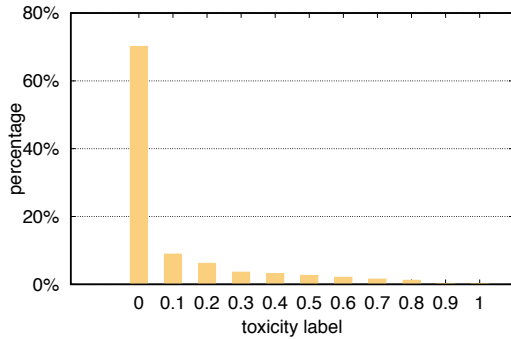


Figure 1: Percentage distribution of toxicity labels in the dataset. X-axis is the interval of toxicity scores (e.g. ‘0’=[0,0.1)) and Y-axis is the combined percentages of comments in each interval. It shows a clear imbalanced distribution of toxic and non-toxic comments in the dataset.

Unintended Identity Bias in NLP Models

A growing number of studies have called attention to the identity related biases in natural language models. Several studies have highlighted how word embedding models exhibit human stereotypes towards genders and ethnic groups (Bolukbasi et al. 2016; Caliskan, Bryson, and Narayanan 2017; Garg et al. 2018). One way to counter such biases is to enhance the interpretability of black box models (Guidotti et al. 2019) so that humans can intervene when a model makes an unfair decision. Another way to address the issue, which is the focus of this study, is to design models so that they learn to circumvent protected identity attributes. Several methods have been proposed in the context of structured or numerical data (Corbett-Davies and Goel 2018), but methods applicable to text data generated by online users are rare. Our study fills this important gap.

Dataset

We analyse a dataset published by the Jigsaw Unintended Bias in Toxicity Classification Challenge on Kaggle. It contains 1,804,874 comments annotated by the Civil Comments platform. Each comment is shown up to 10 annotators who classify each comment as either *Very Toxic*, *Toxic*, *Hard To Say*, or *Not Toxic*. Each comment is then given a toxicity label based on the fraction of annotators that classified it as either *Toxic* or *Very Toxic*. For evaluation, every comment with a toxicity label greater than or equal to 0.5 was considered to be toxic (the positive class). As discussed by Jigsaw, a toxic comment usually contains rude, disrespectful, or unreasonable content that is somewhat likely to make you leave a discussion or give up on sharing your perspective.

In addition, each comment was also labeled with a multitude of identity attributes (non-exclusive), which demonstrates the presence of a specific identity in a comment. These identities include *male*, *female*, *homosexual (gay or lesbian)*, *christian*, *jewish*, *muslim*, *black*, *white*, and *psychiatric or mental illness*. Label values were given based on the fraction of annotators who believed a comment fit the identity mentioned. Each comment was also labeled with

Table 2: Number of comments labeled with each identity and percent of comments in each identity that are non-toxic.

Identities	Count	Non-Toxic
male	64,544	90.40%
female	55,048	90.86%
homosexual (gay or lesbian)	11,060	80.99%
christian	40,697	94.41%
muslim	21,323	85.06%
jewish	7,669	89.75%
black	17,161	80.31%
white	28,831	82.24%
psychiatric or mental illness	6,218	85.91%
All Identities	191,671	85.56%

five subtype attributes: *severe toxicity*, *obscene*, *threat*, *identity attack*, and *insult* based on the percent of annotators who identified a comment with the aforementioned subtype. This is further discussed in the MTL-Aux section below.

Figure 1 suggests that the distribution of the toxicity label within the dataset follows a long tail distribution. Approximately 92% of the comments are classified as non-toxic (negative class). Table 2 shows the distribution of identity labels in the dataset. While the distribution still shows a strong imbalanced dataset, some identity groups have a more balanced distribution than the overall distribution for an average of 85.56% of comments being non-toxic. In addition, within this dataset, the average document length is approximately 51.28 words long, meaning that identifying long-range dependencies is an important consideration in this paper. We discuss the use of Long Short-Term Memory Networks (LSTM) later in this paper to deal with this challenge.

Models and Tasks

In this section, we explore and propose a few multi-task learning frameworks as shown in Figures 2 and 3 for separate toxicity and identity tasks. The toxicity task aims to correctly predict the toxicity score for a comment. The identity task is designed to predict the presence of an identity in a comment. These tasks work jointly to reduce the model bias towards commonly attacked identities in Table 2.

Embedding & LSTM layers Each word in a sentence is converted to a word embedding vector of dimension D which concatenates two parts: 1) embeddings from the global vectors for word representation (GloVe) and 2) embeddings from the vectors provided by FastText.

Assuming there are N total comments in the training dataset, each comment example has M words ($M = \text{max length}$) and is represented as $s = [x_1, \dots, x_M]$. Each comment is associated with a toxicity label y and a set of identity labels y^1, \dots, y^K . Each word $x_m \in \mathbb{R}^D$ is represented by an embedding vector. Then we apply a bi-directional recurrent neural network (e.g. LSTM), a forward LSTM and a backward LSTM, to the sentence s . We obtain the hidden state h_m for each word x_m by concatenating the forward hidden state \vec{h}_m and the backward hidden state \overleftarrow{h}_m .

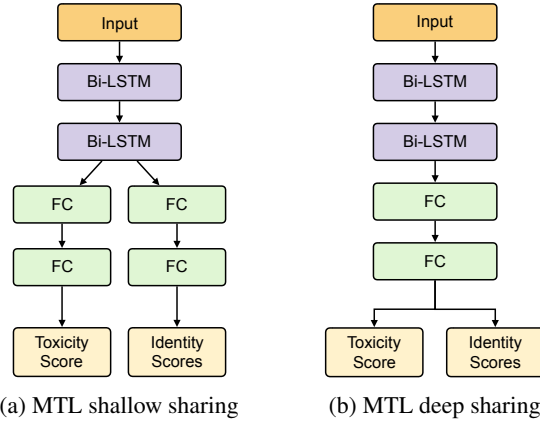


Figure 2: An overview of the proposed MTL frameworks. ‘FC’ indicates a fully connected layer. ‘Bi-LSTM’ indicates a bidirectional LSTM layer. The output scores are generated from a sigmoid function.

Multi-Task Learning Rather than learning each task individually, learning multiple tasks simultaneously has been theoretically and empirically proven to improve prediction performance. Multi-task learning works the best when multiple tasks are related in some shape or form (Argyriou, Evgeniou, and Pontil 2007b). In order to reduce unintended model bias, we take advantage of multi-task learning to model related tasks and capture their internal patterns. For instance, when predicting the toxic comment “gay people are gross and universally hated”, the toxicity task will focus on the toxic elements “gross and universally hated” while the identity task will identify the trigger word “gay” in the comment. We expect involving identity tasks will reduce model bias by mitigating the confusion between identity and toxicity in predictions. Our model will utilize hard-parameter sharing as mentioned in (Ruder 2017).

Multi-task learning: shallow sharing In the proposed model (as shown in Figure 2a), for different tasks, we design two separate dense layers after the bi-directional LSTM layers. The prediction for toxic label \hat{y} is then modeled as a sigmoid function on the output of the dense layers. Here ‘ t ’ represents the toxicity task:

$$\mathbf{h}_t^{(1)} = g(\mathbf{W}_t^{(1)} \mathbf{h} + \mathbf{b}_t^{(1)}), \quad (1)$$

$$\mathbf{h}_t^{(2)} = g(\mathbf{W}_t^{(2)} \mathbf{h}_t^{(1)} + \mathbf{b}_t^{(2)}), \quad (2)$$

$$\hat{y} = \sigma(\mathbf{w}_t^\top \mathbf{h}_t^{(2)} + b_t), \quad (3)$$

where g is the activation function (e.g. relu) applied in the dense layer. $\mathbf{W}_t^{(1)}, \mathbf{b}_t^{(1)}, \mathbf{W}_t^{(2)}, \mathbf{b}_t^{(2)}, \mathbf{w}_t, b_t$ are the model parameters. Similarly, we apply two dense layers on the learned hidden states for each identity prediction task (K is the number of identity groups and ‘ i ’ indicates the identity task):

$$\mathbf{h}_i^{(1)} = g(\mathbf{W}_i^{(1)} \mathbf{h} + \mathbf{b}_i^{(1)}), \quad (4)$$

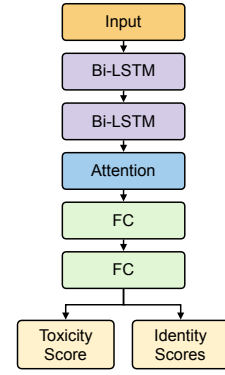


Figure 3: MTL with an attention layer.

$$\mathbf{h}_i^{(2)} = g(\mathbf{W}_i^{(2)} \mathbf{h}_i^{(1)} + \mathbf{b}_i^{(2)}), \quad (5)$$

$$\hat{y}^k = \sigma(\mathbf{w}_k^\top \mathbf{h}_i^{(2)} + b_k), \quad k = 1 \dots K. \quad (6)$$

Multi-task learning: deep sharing For the deep sharing model as shown in Figure 2b, for different tasks, we share the same structure of the network till the last output layer. The predictions for toxic label \hat{y} and identity labels $\hat{y}^k (k = 1 \dots K)$ are then modeled as below:

$$\hat{y} = \sigma(\mathbf{w}_t^\top \mathbf{h}^{(2)} + b_t), \quad (7)$$

$$\hat{y}^k = \sigma(\mathbf{w}_k^\top \mathbf{h}^{(2)} + b_k), \quad k = 1 \dots K, \quad (8)$$

where $\mathbf{h}^{(2)}$ is the output from the dense layers.

Multi-task learning with attention Attention mechanisms have shown to produce state-of-the-art results in many natural language processing tasks such as machine translation (Bahdanau, Cho, and Bengio 2015) when combined with neural word embeddings. In this paper, we explore an attention mechanism on the bidirectional LSTM to “memorize” the influence of each hidden state:

$$a_m = \frac{\exp(\tanh(\mathbf{w}_m \mathbf{h}_m))}{\sum_j \exp(\tanh(\mathbf{w}_j \mathbf{h}_j))}, \quad (9)$$

$$\mathbf{h} = \sum_m a_m \mathbf{h}_m. \quad (10)$$

Then two fully connected dense layers are applied on the updated hidden state \mathbf{h} as shown in Figure 3.

Model loss Finally, a weighted binary cross-entropy (CE) loss is applied to all the label estimates. Given that a comment can have multiple identity labels, a general cross-entropy is not used in this case:

$$L = \sum_{n=1}^N [\alpha J_{CE}(\hat{y}_n, y_n) + (1-\alpha) \sum_{k=1}^K J_{CE}(\hat{y}_n^k, y_n^k)]. \quad (11)$$

All model parameters can be trained via back-propagation and optimized by the Adam algorithm (Kingma and Ba 2015) given its efficiency and ability to avoid overfitting. The task weight $\alpha \in [0, 1]$ is selected by a grid search in validation set.

Expiremental Study

The purpose of our experiment is to compare the performance of our multi-task learning model to other baseline models. The four types of baseline models that will be used for comparison will be: Logistic Regression, LSTMs, CNNs, and GRUs. Our hypothesis is that the multi-task learning models will be able to outperform the other baseline models in multiple categories, especially in those that measure unintended bias. In this expirement we focus on the toxicity task and the toxicity scores predicted by the model, not the identity scores.

Experiment Setup

Text preprocessing. Before the model training, we perform some basic preprocessing on the data. To convert the raw text to a usable format, we first tokenize the comments. Because comments vary in length, the max-length is defined as 220 words. Sequences that had less than 220 words are padded with zeroes. During the process of tokenization, each comment is stripped of certain punctuation marks but was not converted to lowercase.

Model-specific preprocessing. We also perform preprocessing specific to the multi-task learning model. Because only 405,130 out of 1,804,874 comments are annotated for each of the identities, we need to fill in the scores for the rest of the identities in order to employ an effective multi-task model. To fill in the rest of the identities, we train a multi-class classifier on the 400,000 training examples with the annotated identity scores to predict the identity scores for the remaining 1.4 million training examples. This is then fed into our multi-task learning model for prediction as shown in Figure 4.

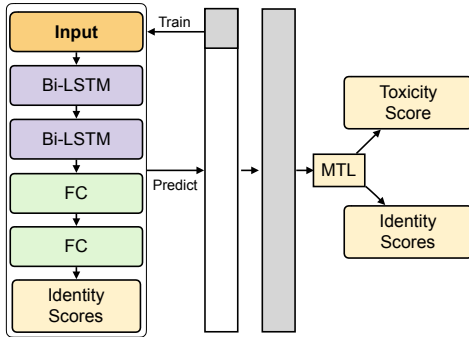


Figure 4: Multi-task learning model with model-specific preprocessing for propagating identity labels.

Cross-Validation In our experiments, we perform K-fold (K=5) cross-validation on the dataset. In each fold, 80% of the data is set aside for training and 20% is used for validation, which translates into roughly 1.4 million and 400,000 comments respectively.

Hyper-parameter settings. We select α (model loss eq.) by a grid search in our validation set and α is chosen to be 0.6 with the best performance. The dimension of hidden states in the bi-directional LSTM layers is set to be 256.

Comparison Methods (Baseline Models)

- **Logistic Regression** Logistic Regression (Neter et al. 1996) has widely been used for binary classification tasks. For text classification tasks, documents are usually vectorized into bag-of-words (BoW) features (e.g. TF-IDF). As a comparison to dense vectors in deep learning models, our model applies a TF-IDF vectorizer to the raw comments and then passes it through a standard logistic regression model to obtain the final predictions.
- **Convolutional Neural Networks** Convolutional Neural Networks (Lecun et al. 1998) have proved to be very successful when it comes to sentence or character-level sentence classification (Kim 2014). CNNs have been known to work better for datasets with a large amount of training examples and can work well for user-generated data. CNNs can deal with the “obfuscation of words” in comments and “detect specific combinations of features” within the area of text classification.
- **Long Short-Term Memory Network** LSTMs (Hochreiter and Schmidhuber 1997) were introduced primarily to overcome the problem of the vanishing gradient. As a variant of Recurrent Neural Networks (RNN), it has proven to have a better ability to learn long-range dependencies. In the Simple LSTM baseline model, we introduced a 20% spatial dropout. The input is passed through two LSTM layers of 256 units each. Afterwards, the input passes through two dense layers of 512 units each with a rectified linear activation function. Finally, we obtain a single output (toxicity score) by applying a sigmoid activation function to the final dense layer.
- **Gated Recurrent Unit** GRU (Chung et al. 2014) operates similarly to an LSTM but instead uses a reset and update gate, where the reset gate acts to forget the previous state and the update gate decides how much of the candidate activation to use in updating the cell state. Our GRU model is similar to the structure of our LSTM model, with the exception that only 128 units were used per GRU layer.
- **Bidirectionality** Introducing bidirectionality into a RNN can help a network learn from both past and future context (Schuster and Paliwal 1997). In this architecture, two layers of hidden nodes are introduced. In the second layer, the input is reversed and the sequence is passed backwards into the network. Within the scope of this task, understanding and learning from a sequence in both directions can lead to a more complex and more accurate understanding of the document. In this paper, we implement a Bidirectional LSTM and a Bidirectional GRU. They follow the same structures as the Simple LSTM and GRU specified in the previous paragraphs.
- **MTL-Aux** In addition to the baseline models specified above, we developed another multi-task learning model for comparison. Instead of using the nine identity labels,

Table 3: Binary classification performance of different methods on toxic comments. Bold face indicates the best result of each column and underlined the second-best.

Model	Generalized Mean AUC	AUC	Precision	Recall	F1-Score	Code
Logistic Regression	0.8999	0.9488	0.79	0.50	0.61	LR
CNN	0.9212	0.9635	0.86	0.47	0.60	CNN
Simple LSTM	0.9267	0.9662	<u>0.85</u>	0.50	0.63	LSTM
Bidirectional LSTM	0.9316	0.9694	0.83	0.55	0.66	B-LSTM
Simple GRU	0.9284	0.9676	0.83	0.54	0.65	GRU
Bidirectional GRU	0.9319	0.9637	0.84	0.52	0.64	B-GRU
MTL-Aux	0.9317	0.9693	0.84	0.53	0.65	MTA
MTL-shallow	0.9358	0.9696	0.83	<u>0.55</u>	<u>0.66</u>	MTL-s
MTL-deep	<u>0.9359</u>	<u>0.9698</u>	<u>0.85</u>	0.53	0.65	MTL-d
MTL-attention	0.938*	0.9703	0.82	0.58*	0.69*	MTL-attn

* Identifies significance ($p < 0.05$) compared to best baseline model in the category.

this model focuses on five alternate subtype toxicity attributes: *severe toxicity*, *obscene*, *threat*, *insult*, and *identity attack*. The model follows the same structure as MTL with deep sharing but predicts the aforementioned five subtype outputs rather than the nine identity outputs.

Evaluation Metrics

For basic toxicity detection evaluation, we calculate the ROC-AUC, precision, recall, and F1-scores for the full test set. Predictions with toxicity scores that are greater than or equal to 0.5 are considered to be part of the positive (toxic) class and vice-versa.

Unintended bias evaluation metrics are introduced and specified by the Google Conversation AI Team in their paper (Borkan et al. 2019). The Generalized Mean of Bias AUCs metric was introduced by their Kaggle competition³.

- **Subgroup AUC** We restrict the test set to comments for which each identity label is positive. An ROC-AUC score is then calculated for each of the identity groups which is hereby called the Subgroup AUC.
- **BPSN (Background Positive, Subgroup Negative) AUC** To calculate this metric, we restrict the test set to non-toxic comments that mention the identity and toxic examples that don't mention the identity. We obtain the BPSN AUC by getting the ROC-AUC score from this restricted test set. Low BPSN AUC scores specifically indicate that a model predicts higher toxicity scores for non-toxic comments that mention the identity (introduces model bias).
- **Generalized Mean of Bias AUCs** One overall measure is calculated from the Subgroup AUCs using the following formula:

$$M_p(m_s) = \left(\frac{1}{N} \sum_{s=1}^N m_s^p \right)^{1/p}$$

where M_p is the p -th power-mean function, m_s is the bias metric calculated for subgroup s , and $N = 9$ which is the number of identity subgroups. We set $p = -5$ as suggested in the competition. A low value indicates model bias toward one or more of the identities.

Results

Toxic Comment Detection

The overall binary classification performance is summarized in Table 3. Considering each identity as a task, MTL and MTL-attention models outperform the baseline models when it comes to the Generalized Mean AUCs, suggesting that multi-task learning is able to effectively reduce model bias in comparison to the other baseline models. MTL-attention outperformed all other models in recall and F1-Score. MTL-shallow outperformed the baseline models with an F1-Score of 0.66. In addition, MTL-deep significantly outperformed the other MTL models and Bi-LSTM in precision.

The best baseline model is Bidirectional LSTM with the highest recall and F1-Score. MTL-Aux had comparable performance to Bidirectional LSTM, suggesting that multi-task learning with the five subtype attributes (*severe toxicity*, *obscene*, *threat*, *insult*, *identity attack*) does not serve to improve performance in the test set. This is understandable given that four subtypes are not significantly related to identity information and the *identity attack* does not recognize different identity groups.

CNN outperforms other models in precision despite having the lowest overall F1-Score. We believe the convolutional layer helps in capturing key local patterns with respect to the toxicity score. In addition, LSTMs and GRUs perform better than many of the other baseline models given its ability to retain memory which can help solve problems with long-range dependencies. Introducing bidirectionality to LSTMs and GRUs also offers a significant advantage in performance because the model is better able to understand the entire context of a comment by having it passed in forwards and backwards. This effect can be demonstrated by looking at the improvement in the Generalized Mean AUC when bidirectionality is introduced, suggesting that it also leads to a reduction in unintended model bias. Logistic Regression has the lowest performance thus far, which can be explained by the sparse nature of a Bag-of-Words model and the disregard of the order of words in a sentence.

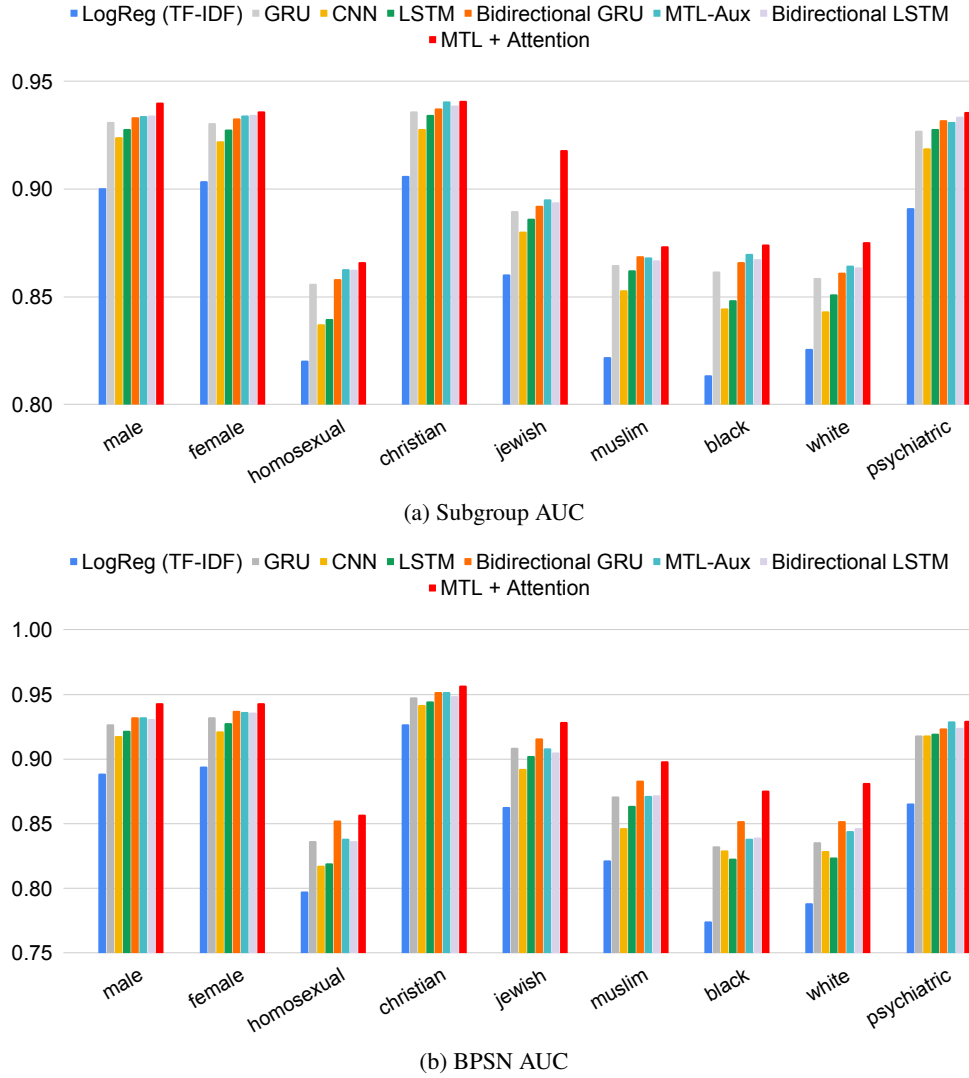


Figure 5: Comparison of seven methods for nine identity categories. Subgroup AUCs are provided in figure 5a and BPSN AUCs are provided in figure 5b. MTL-shallow and MTL-deep are skipped for clarity given that they have similar performance as MTL-Attention.

Subgroup & BPSN AUCs

As shown in Figure 5a, the attention-based MTL model outperforms other models when looking at Subgroup AUC. Significant improvements are noted with the following identities: *jewish*, *black*, *white*, and *muslim*. We note an increase of an average of approximately 1% in the Subgroup AUCs when compared to the best baseline model.

In the context of the BPSN AUC metric (Figure 5b), significant improvements were noted with the *male*, *homosexual*, *christian*, *jewish*, *muslim*, *black*, and *white* identities. On average, the MTL-Attn model achieves an increased BPSN AUC performance by approximately 2%, suggesting it is able to considerably reduce model bias for the aforementioned identities. Overall, multi-task learning models have achieved better performance in distinguishing toxic comments and non-toxic comments with identity information.

Case Studies

Comment Comparison

We conducted an additional experiment where we studied the toxicity score given to individual toxic and non-toxic comments that referenced certain identities. Two examples (A and B) were selected to model potential comments that could be found on social media platforms. Each comment was then tokenized and passed through each of the ten models specified in our experiment to obtain a toxicity score. In addition, we obtained toxicity scores for comments A and B from Google’s Perspective API framework with the intention of comparing it with our multi-task learning and baseline models. Comment A is non-toxic and defined as “I am a *<Identity>* person, ask me anything”. Comment B is toxic and defined as “*<Identity>* people are gross and universally hated”. For each model *<Identity>* will be replaced by one of

Table 4: Toxicity prediction scores on two template examples (A.⁽⁻⁾: non toxic; B.⁽⁺⁾: toxic). API represents the Perspective API. We expect the prediction scores for the A. groups to be low. Bold faces represents the lowest scores of deep learning models compared to API and underline means the second lowest.

Model	Template	Gay	Lesbian	Bisexual	Transgender	Muslim	Jew	Black	White	Disabled
LR	A. ⁽⁻⁾	0.70	0.20	0.05	0.16	0.12	0.11	0.40	0.18	0.02
	B. ⁽⁺⁾	0.87	0.41	0.16	0.34	0.40	0.30	0.78	0.68	0.17
CNN	A. ⁽⁻⁾	0.39	0.38	0.37	0.21	0.14	0.23	0.44	0.30	0.04
	B. ⁽⁺⁾	0.76	0.76	0.71	0.65	0.71	0.63	0.73	0.67	0.42
GRU	A. ⁽⁻⁾	0.31	0.23	0.15	0.21	0.13	0.11	0.43	0.28	0.10
	B. ⁽⁺⁾	0.78	0.75	0.71	0.71	0.74	0.60	0.83	0.78	0.50
B-GRU	A. ⁽⁻⁾	0.35	0.29	0.19	0.22	0.23	0.11	0.41	0.23	0.09
	B. ⁽⁺⁾	0.75	0.71	0.70	0.67	0.69	0.68	0.76	0.72	0.52
LSTM	A. ⁽⁻⁾	0.40	0.30	0.25	0.16	0.14	0.24	0.32	0.18	0.13
	B. ⁽⁺⁾	0.78	0.72	0.72	0.68	0.76	0.74	0.76	0.72	0.58
B-LSTM	A. ⁽⁻⁾	0.400	0.36	0.31	0.29	0.20	0.11	0.47	0.25	0.20
	B. ⁽⁺⁾	0.79	0.77	0.73	0.74	0.76	0.70	0.79	0.75	0.56
MTL Aux	A. ⁽⁻⁾	0.29	0.27	0.16	0.20	0.19	0.18	0.31	0.20	0.10
	B. ⁽⁺⁾	0.81	0.79	0.78	0.76	0.80	0.78	0.80	0.76	0.61
Perspective API	A. ⁽⁻⁾	0.42	0.37	0.44	0.28	0.12	0.11	0.28	0.23	0.15
	B. ⁽⁺⁾	0.95	0.95	0.9	0.93	0.95	0.94	0.93	0.93	0.84
MTL-shallow	A. ⁽⁻⁾	0.29	0.24	0.13	0.19	0.18	0.11	0.33	0.20	0.09
	B. ⁽⁺⁾	0.80	0.75	0.67	0.72	0.79	0.70	0.82	0.74	0.51
MTL-deep	A. ⁽⁻⁾	0.37	0.30	0.26	0.30	0.19	0.20	0.36	0.15	0.09
	B. ⁽⁺⁾	0.83	0.82	0.76	0.76	0.84	0.80	0.84	0.79	0.66
MTL-attn	A. ⁽⁻⁾	0.32	0.25	0.22	0.14	0.15	0.11	0.35	0.15	0.05
	B. ⁽⁺⁾	0.81	0.76	0.72	0.71	0.79	0.81	0.82	0.73	0.64

A.⁽⁻⁾ “I am a <Identity> person, ask me anything” is a negative example.

B.⁽⁺⁾ “<Identity> people are gross an universally hated” is a positive example.

the following nine keywords, meant to represent the identities defined in Table 2: *gay*, *lesbian*, *bisexual*, *transgender*, *muslim*, *jew*, *black*, *white*, *disabled*. After obtaining scores for each of these comments we can see which identities face the most model bias and how well our model is able to distinguish between toxic and non-toxic comments. An example of a comment that we use to test model bias is “I am a gay person, ask me anything”. If a model gives a high toxicity score for this comment, the model is potentially biased towards gay people. This case study is intended to give us a good example of how our and other baseline models will perform when applied to online conversations on traditional social media platforms.

The results of our case study are included in Table 4. We observe that MTL models are able to distinguish very well between toxic and non-toxic comments for each of the identities. For template example A (non-toxic), the proposed MTL models never predict a toxicity score above 0.40. For template example B (toxic), MTL models are able to successfully classify each comment as toxic regardless of the identity. MTL-deep seems to have higher toxicity scores overall (for both toxic and non-toxic comments) when compared to the other MTL models. While Google’s Perspective API does not misclassify any comments, it is important to note that their toxicity scores for gay, lesbian, and bisexual keywords are higher than expected. This suggests that there may be some bias towards these three identities which could potentially lead to problems in the future. As an exception, Logistic Regression does not successfully detect the toxic-

ity in the positive templates, despite the scores for negative examples being low. The baseline models also perform well, with only one misclassification by CNN in the disabled category. With this case study, we are able to confirm that multi-task learning models help to reduce the amount of model bias towards attacked identity groups. We prevent classifying non-toxic comments as toxic while ensuring that we are still able to detect toxic comments in order to keep social media platforms positively engaged.

Identity Detection

The nature of a multi-task learning model is to perform multiple tasks at once. In this paper, we focus mainly on getting the most accurate toxicity score for each comment which is the first task of our MTL models. The second task is to identify the presence of any one of the identities specified in Table 5. Identities are not mutually-exclusive because a comment can contain multiple identities (e.g. “I am a gay black woman”). Therefore, we treat this challenge as a multi-label classification problem.

Our results are summarized in Table 5 below. We calculate the F1-score for each identity using the three multi-task learning models. Overall, our models were able to correctly identify the presence of an identity in a comment, with average F1-scores of 0.921, 0.924, and 0.922 for MTL-shallow, MTL-deep, and MTL-attn respectively. We did not observe any significant differences with the F1-scores for these three models, suggesting that they were equally successfully at identifying the presence of an identity in a comment.

Table 5: F1-scores of the MTL models on identity prediction. “Homosexual” includes “homosexual, gay, or, lesbian” and “psychiatric” includes “psychiatric or mental illness”.

Identity	MTL-shallow	MTL-deep	MTL-attn
male	0.94	0.94	0.94
female	0.95	0.95	0.96
homosexual	0.93	0.94	0.94
christian	0.89	0.89	0.89
jewish	0.96	0.97	0.96
muslim	0.92	0.92	0.93
black	0.92	0.93	0.93
white	0.97	0.96	0.96
psychiatric	0.81	0.82	0.79

Conclusion & Future Work

In this work, we presented multiple approaches to deal with the task of reducing unintended model biases towards commonly-attacked identities in the scope of toxic comment detection. An empirical study was conducted to compare multiple state-of-the-art models in order to determine the individual strengths of each model in reducing unintended model bias. In addition, we proposed three separate multi-task learning models, one of which implements shallow sharing, another which implements deep sharing, and another that introduces an attention mechanism. Our multi-task learning models outperformed other models when it came to metrics that specifically measure unintended bias, while still being able to correctly identify and classify toxic comments. Through our research, we noted that our multi-task learning models significantly increased performance for the following identities: *homosexual*, *jewish*, *muslim*, *black*, *white*. We also conducted two additional case studies: 1) evaluate our models’ performance on social media modeled individual comments and 2) investigate the ability of our multi-task learning model to identify the presence of an identity in a comment. Overall, we were able to confirm our initial hypothesis and show that learning multiple related tasks simultaneously can bring advantages to reducing biases towards certain identities while improving the health of online conversations. We hope that the multi-task learning models proposed in this paper will allow social media platforms to better understand and identify toxicity in online conversations without needing to worry about introducing potential model biases towards certain identities.

In the future, we plan to focus on a few directions: 1) Given the limited identity labels for comments, we will explore pre-trained models such as semi-supervised knowledge transfer models or knowledge distillation methods. 2) We will also investigate other hidden cultural bias in on-line toxic comments other than identities. 3) Most existing models focus on the prediction of toxic comments and identity group recognition. We will study interpretable machine learning methods to identify the trigger words or phrases for determining toxicity in a comment. 4) We will explore other text encoding methods to improve our model’s understanding of each individual comment (e.g. BERT).

References

- [Argyriou, Evgeniou, and Pontil 2007a] Argyriou, A.; Evgeniou, T.; and Pontil, M. 2007a. Multi-task feature learning. In Schölkopf, B.; Platt, J. C.; and Hoffman, T., eds., *Advances in Neural Information Processing Systems 19*. MIT Press. 41–48.
- [Argyriou, Evgeniou, and Pontil 2007b] Argyriou, A.; Evgeniou, T.; and Pontil, M. 2007b. Multi-task feature learning. In Schölkopf, B.; Platt, J. C.; and Hoffman, T., eds., *Advances in Neural Information Processing Systems 19*. MIT Press. 41–48.
- [Badjatiya et al. 2017] Badjatiya, P.; Gupta, S.; Gupta, M.; and Varma, V. 2017. Deep learning for hate speech detection in tweets. In *Proceedings of the 26th International Conference on World Wide Web Companion*, WWW ’17 Companion, 759–760. Republic and Canton of Geneva, Switzerland: International World Wide Web Conferences Steering Committee.
- [Bahdanau, Cho, and Bengio 2015] Bahdanau, D.; Cho, K.; and Bengio, Y. 2015. Neural machine translation by jointly learning to align and translate. In *The 3rd International Conference on Learning Representations*.
- [Bolukbasi et al. 2016] Bolukbasi, T.; Chang, K.-W.; Zou, J. Y.; Saligrama, V.; and Kalai, A. T. 2016. Man is to computer programmer as woman is to homemaker? debiasing word embeddings. In *Advances in neural information processing systems*, 4349–4357.
- [Borkan et al. 2019] Borkan, D.; Dixon, L.; Sorensen, J.; Thain, N.; and Vasserman, L. 2019. Nuanced metrics for measuring unintended bias with real data for text classification. In *Companion Proceedings of The 2019 World Wide Web Conference, WWW ’19*, 491–500. New York, NY, USA: ACM.
- [Caliskan, Bryson, and Narayanan 2017] Caliskan, A.; Bryson, J. J.; and Narayanan, A. 2017. Semantics derived automatically from language corpora contain human-like biases. *Science* 356(6334):183–186.
- [Caruana 1998] Caruana, R. 1998. *Multitask Learning*. Boston, MA: Springer US. 95–133.
- [Chen, McKeever, and Delany 2019] Chen, H.; McKeever, S.; and Delany, S. J. 2019. The use of deep learning distributed representations in the identification of abusive text. In *Proceedings of the International AAAI Conference on Web and Social Media*, volume 13, 125–133.
- [Cheng, Danescu-Niculescu-Mizil, and Leskovec 2015] Cheng, J.; Danescu-Niculescu-Mizil, C.; and Leskovec, J. 2015. Antisocial behavior in online discussion communities. In *Ninth International AAAI Conference on Web and Social Media*.
- [Chung et al. 2014] Chung, J.; Gulcehre, C.; Cho, K.; and Bengio, Y. 2014. Empirical evaluation of gated recurrent neural networks on sequence modeling. In *NIPS 2014 Workshop on Deep Learning, December 2014*.
- [Collobert and Weston 2008] Collobert, R., and Weston, J. 2008. A unified architecture for natural language processing: Deep neural networks with multitask learning. In *Proceedings of the 25th International Conference on Machine Learning, ICML ’08*, 160–167. New York, NY, USA: ACM.
- [Corbett-Davies and Goel 2018] Corbett-Davies, S., and Goel, S. 2018. The measure and mismeasure of fairness: A critical review of fair machine learning. *arXiv preprint arXiv:1808.00023*.
- [Davidson et al. 2017] Davidson, T.; Warmusley, D.; Macy, M.; and Weber, I. 2017. Automated hate speech detection and the problem of offensive language. In *Eleventh international aaai conference on web and social media*.
- [Davidson, Bhattacharya, and Weber 2019] Davidson, T.; Bhattacharya, D.; and Weber, I. 2019. Racial bias in hate speech and

- abusive language detection datasets. In *Proceedings of the Third Workshop on Abusive Language Online*, 25–35. Florence, Italy: Association for Computational Linguistics.
- [Deng, Hinton, and Kingsbury 2013] Deng, L.; Hinton, G.; and Kingsbury, B. 2013. New types of deep neural network learning for speech recognition and related applications: an overview. In *2013 IEEE International Conference on Acoustics, Speech and Signal Processing*, 8599–8603.
- [Dietterich 2000] Dietterich, T. G. 2000. Ensemble methods in machine learning. In *Proceedings of the First International Workshop on Multiple Classifier Systems*, MCS '00, 1–15. London, UK, UK: Springer-Verlag.
- [Dixon et al. 2018] Dixon, L.; Li, J.; Sorensen, J.; Thain, N.; and Vasserman, L. 2018. Measuring and mitigating unintended bias in text classification. In *Proceedings of the 2018 AAAI/ACM Conference on AI, Ethics, and Society*, AIES '18, 67–73. New York, NY, USA: ACM.
- [Duong et al. 2015] Duong, L.; Cohn, T.; Bird, S.; and Cook, P. 2015. Low resource dependency parsing: Cross-lingual parameter sharing in a neural network parser. In *Proceedings of the 53rd Annual Meeting of the Association for Computational Linguistics and the 7th International Joint Conference on Natural Language Processing (Volume 2: Short Papers)*, 845–850. Beijing, China: Association for Computational Linguistics.
- [Garg et al. 2018] Garg, N.; Schiebinger, L.; Jurafsky, D.; and Zou, J. 2018. Word embeddings quantify 100 years of gender and ethnic stereotypes. *Proceedings of the National Academy of Sciences* 115(16):E3635–E3644.
- [Georgakopoulos et al. 2018] Georgakopoulos, S. V.; Tasoulis, S. K.; Vrahatis, A. G.; and Plagianakos, V. P. 2018. Convolutional neural networks for toxic comment classification. In *Proceedings of the 10th Hellenic Conference on Artificial Intelligence*, SETN '18, 35:1–35:6. New York, NY, USA: ACM.
- [Ghosh, Fabbri, and Muresan 2018] Ghosh, D.; Fabbri, A. R.; and Muresan, S. 2018. Sarcasm analysis using conversation context. *Computational Linguistics* 44(4):755–792.
- [Guidotti et al. 2019] Guidotti, R.; Monreale, A.; Ruggieri, S.; Turini, F.; Giannotti, F.; and Pedreschi, D. 2019. A survey of methods for explaining black box models. *ACM computing surveys (CSUR)* 51(5):93.
- [Hochreiter and Schmidhuber 1997] Hochreiter, S., and Schmidhuber, J. 1997. Long short-term memory. *Neural Comput.* 9(8):1735–1780.
- [Kim 2014] Kim, Y. 2014. Convolutional neural networks for sentence classification. In *Proceedings of the 2014 Conference on Empirical Methods in Natural Language Processing (EMNLP)*, 1746–1751. Doha, Qatar: Association for Computational Linguistics.
- [Kingma and Ba 2015] Kingma, D. P., and Ba, J. 2015. Adam: A method for stochastic optimization. In *Proceedings of the 2015 International Conference on Learning Representations*, volume abs/1412.6980.
- [Lecun et al. 1998] Lecun, Y.; Bottou, L.; Bengio, Y.; and Haffner, P. 1998. Gradient-based learning applied to document recognition. *Proceedings of the IEEE* 86(11):2278–2324.
- [Liang and Shu 2017] Liang, D., and Shu, Y. 2017. Deep automated multi-task learning. In *Proceedings of the Eighth International Joint Conference on Natural Language Processing (Volume 2: Short Papers)*, 55–60. Taipei, Taiwan: Asian Federation of Natural Language Processing.
- [Long et al. 2017] Long, M.; Cao, Z.; Wang, J.; and Yu, P. S. 2017. Learning multiple tasks with multilinear relationship networks. In *Proceedings of the 31st International Conference on Neural Information Processing Systems*, NIPS'17, 1593–1602. USA: Curran Associates Inc.
- [Mishra et al. 2018] Mishra, P.; Del Tredici, M.; Yannakoudakis, H.; and Shutova, E. 2018. Author profiling for abuse detection. In *Proceedings of the 27th International Conference on Computational Linguistics*, 1088–1098.
- [Misra et al. 2016] Misra, I.; Shrivastava, A.; Gupta, A.; and Hebert, M. 2016. Cross-stitch networks for multi-task learning. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, 3994–4003.
- [Neter et al. 1996] Neter, J.; Kutner, M. H.; Nachtsheim, C. J.; and Wasserman, W. 1996. *Applied linear statistical models*, volume 4. Irwin Chicago.
- [Noever 2018] Noever, D. 2018. Machine learning suites for online toxicity detection. *ArXiv abs/1810.01869*.
- [Ramsundar et al. 2015] Ramsundar, B.; Kearnes, S. M.; Riley, P.; Webster, D.; Konerding, D. E.; and Pande, V. S. 2015. Massively multitask networks for drug discovery. *ArXiv abs/1502.02072*.
- [Ruder 2017] Ruder, S. 2017. An overview of multi-task learning in deep neural networks. *ArXiv abs/1706.05098*.
- [Sap et al. 2019] Sap, M.; Card, D.; Gabriel, S.; Choi, Y.; and Smith, N. A. 2019. The risk of racial bias in hate speech detection. In *Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics*, 1668–1678. Florence, Italy: Association for Computational Linguistics.
- [Schuster and Paliwal 1997] Schuster, M., and Paliwal, K. 1997. Bidirectional recurrent neural networks. *Trans. Sig. Proc.* 45(11):2673–2681.
- [Søgaard and Goldberg 2016] Søgaard, A., and Goldberg, Y. 2016. Deep multi-task learning with low level tasks supervised at lower layers. In *Proceedings of the 54th Annual Meeting of the Association for Computational Linguistics (Volume 2: Short Papers)*, 231–235.
- [Suresh, Gong, and Gutttag 2018] Suresh, H.; Gong, J. J.; and Gutttag, J. V. 2018. Learning tasks for multitask learning: Heterogeneous patient populations in the icu. In *Proceedings of the 24th ACM SIGKDD International Conference on Knowledge Discovery & #38; Data Mining*, KDD '18, 802–810. New York, NY, USA: ACM.
- [van Aken et al. 2018] van Aken, B.; Risch, J.; Krestel, R.; and Löser, A. 2018. Challenges for toxic comment classification: An in-depth error analysis. In *Proceedings of the 2nd Workshop on Abusive Language Online (ALW2)*, 33–42. Brussels, Belgium: Association for Computational Linguistics.
- [Wulczyn, Thain, and Dixon 2017] Wulczyn, E.; Thain, N.; and Dixon, L. 2017. Ex machina: Personal attacks seen at scale. In *Proceedings of the 26th International Conference on World Wide Web*, 1391–1399. International World Wide Web Conferences Steering Committee.
- [Zhang et al. 2018] Zhang, J.; Chang, J. P.; Danescu-Niculescu-Mizil, C.; Dixon, L.; Taraborelli, D.; Thain, N.; and Taraborelli, D. 2018. Conversations gone awry: Detecting warning signs of conversational failure. In *Proceedings of ACL*.
- [Zhou et al. 2016] Zhou, P.; Qi, Z.; Zheng, S.; Xu, J.; Bao, H.; and Xu, B. 2016. Text classification improved by integrating bidirectional LSTM with two-dimensional max pooling. In *Proceedings of COLING 2016, the 26th International Conference on Computational Linguistics: Technical Papers*, 3485–3495. Osaka, Japan: The COLING 2016 Organizing Committee.