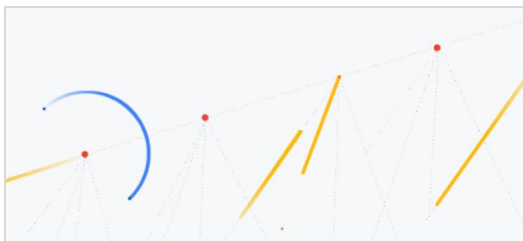


# Model Cards for Model Reporting

Andrew Zaldivar, Ph.D.

In Collaboration with Margaret Mitchell, Simone Wu, Parker Barnes, Lucy Vasserman, Ben Hutchinson, Elena Spitzer, Inioluwa Deborah Raji & Timnit Gebru

# Background



## GUIDE

### Responsible AI practices

We're committed to progress in the responsible development of AI and to sharing knowledge, research, tools, datasets, and other resources. Learn more about recommended practices and our current work.

[ai.google/education/responsible-ai-practices](https://ai.google/education/responsible-ai-practices)

**T520B107M006ATE040**

**Mouser #:** 80-T520B107M06ATE40  
**Mfr. #:** T520B107M006ATE040  
**Mfr.:** KEMET  
**Customer #:**   
**Description:** Tantalum Capacitors - Polymer SMD 6.3volts 100uF 20% ESR=40  
 Available in MultiSIM BLUE  
 View Simulation and SPICE Model in K-SIM

**Datasheet:** [T520B107M006ATE040 Datasheet](#)  
**More Information:** [Learn more about KEMET T520B107M006ATE040](#)

**In Stock: 7,998**

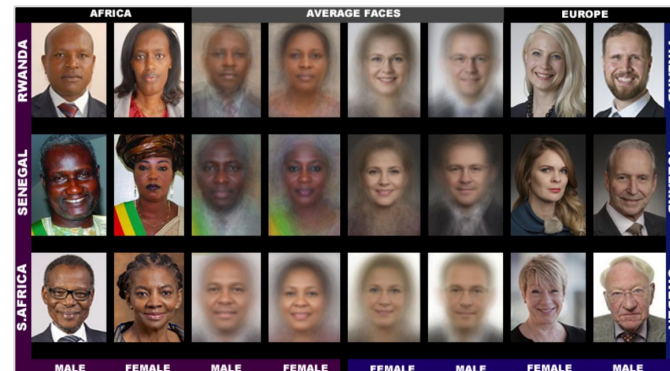
**Stock:** 7,998 Can Ship Immediately  
**On Order:** 2000 [View Delivery Dates](#)  
**Factory Lead-Time:** 21 Weeks  
**Enter Quantity:** Minimum: 1 Multiples: 1 [Buy](#)

**Pricing (USD)**

Qty.	Unit Price	Ext. Price
1	\$1.22	\$1.22
10	\$0.838	\$8.38
100	\$0.644	\$64.40

Timnit Gebru, et al.  
 "Datasheets for  
 Datasets."  
 arXiv preprint  
[arXiv:1803.09010](https://arxiv.org/abs/1803.09010)  
 (2018)

Buolamwini, Joy, and Timnit Gebru. "[Gender Shades: Intersectional Accuracy Disparities in Commercial Gender Classification.](#)" Conference on Fairness, Accountability and Transparency. 2018.



# Motivation

Disaggregated Evaluation

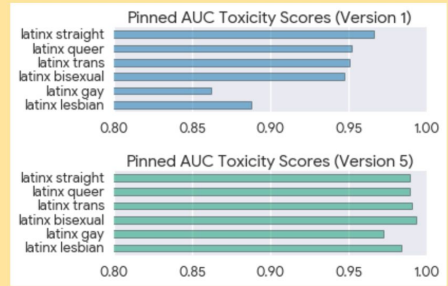
Transparency

Unitary / Intersectional Analyses

Context Around Model

# Model Cards: A Proposal

*Model Cards* is a framework that serve to disclose information about a trained machine learning model.

Example Model Card - Toxicity in Text																													
Model Details	Developed by Jigsaw in 2017 as a convolutional neural network trained to predict the likelihood that a comment will be perceived as toxic.																												
Intended Use	Supporting human moderation, providing feedback to comment authors, and allowing comment viewers to control their experience.																												
Factors	Identity terms referencing frequently attacked groups focusing on the categories of sexual orientation, gender identity and race.																												
Metrics	<i>Pinned AUC</i> , which measures threshold-agnostic separability of toxic and non-toxic comments for each group, within the context of a background distribution of other groups.																												
Evaluation Data	A synthetic test set generated using a template-based approach, where identity terms are swapped into a variety of template sentences.																												
Training Data	Includes comments from a variety of online forums with crowdsourced labels of whether the comment is "toxic". "Toxic" is defined as, "a rude, disrespectful, or unreasonable comment that is likely to make you leave a discussion".																												
Ethical Considerations	A set of values around community, transparency, inclusivity, privacy and topic-neutrality to guide their work.																												
Caveats	Synthetic test data covers only a small set of very specific comments. While these are designed to be representative of common use cases and concerns, it is not comprehensive.																												
Quantitative Analysis	 <p><b>Pinned AUC Toxicity Scores (Version 1)</b></p> <table border="1"><thead><tr><th>Identity Group</th><th>Pinned AUC Score (Version 1)</th></tr></thead><tbody><tr><td>latinx straight</td><td>0.97</td></tr><tr><td>latinx queer</td><td>0.95</td></tr><tr><td>latinx trans</td><td>0.95</td></tr><tr><td>latinx bisexual</td><td>0.95</td></tr><tr><td>latinx gay</td><td>0.87</td></tr><tr><td>latinx lesbian</td><td>0.90</td></tr></tbody></table> <p><b>Pinned AUC Toxicity Scores (Version 5)</b></p> <table border="1"><thead><tr><th>Identity Group</th><th>Pinned AUC Score (Version 5)</th></tr></thead><tbody><tr><td>latinx straight</td><td>0.99</td></tr><tr><td>latinx queer</td><td>0.99</td></tr><tr><td>latinx trans</td><td>0.99</td></tr><tr><td>latinx bisexual</td><td>0.99</td></tr><tr><td>latinx gay</td><td>0.97</td></tr><tr><td>latinx lesbian</td><td>0.97</td></tr></tbody></table>	Identity Group	Pinned AUC Score (Version 1)	latinx straight	0.97	latinx queer	0.95	latinx trans	0.95	latinx bisexual	0.95	latinx gay	0.87	latinx lesbian	0.90	Identity Group	Pinned AUC Score (Version 5)	latinx straight	0.99	latinx queer	0.99	latinx trans	0.99	latinx bisexual	0.99	latinx gay	0.97	latinx lesbian	0.97
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# Model Details, Intended Use & Factors

Example Model Card - Toxicity in Text	
<b>Model Details</b>	Developed by Jigsaw in 2017 as a convolutional neural network trained to predict the likelihood that a comment will be perceived as toxic.
<b>Intended Use</b>	Supporting human moderation, providing feedback to comment authors, and allowing comment viewers to control their experience.
<b>Factors</b>	Identity terms referencing frequently attacked groups focusing on the categories of sexual orientation, gender identity and race.

# Metrics, Evaluation Data & Training Data

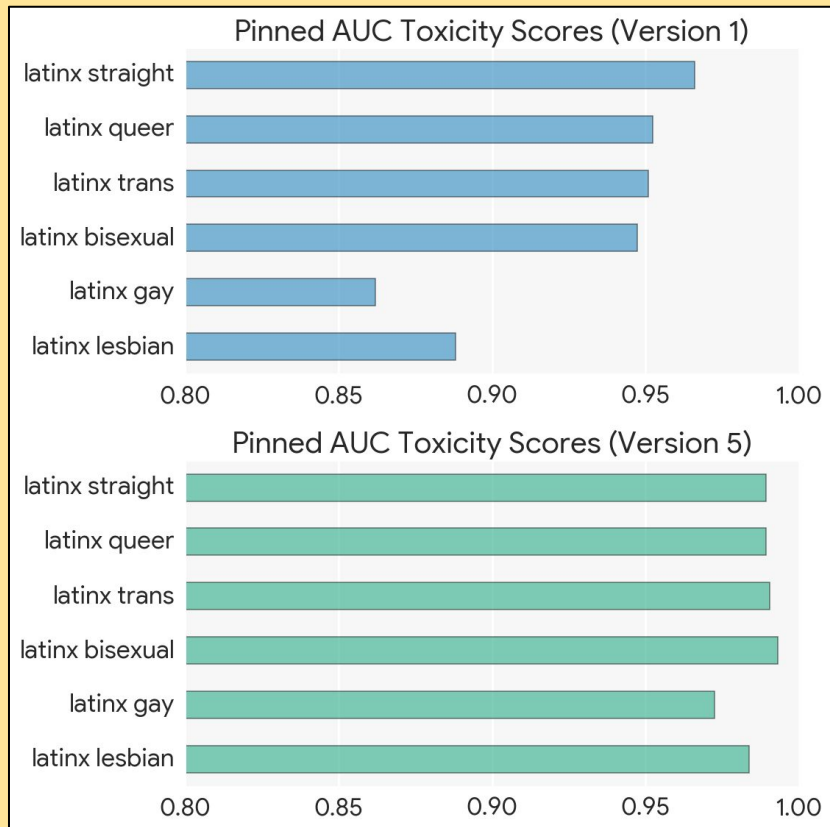
<b>Metrics</b>	<i>Pinned AUC</i> , which measures threshold-agnostic separability of toxic and non-toxic comments for each group, within the context of a background distribution of other groups.
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# Ethical Consideration & Caveats

<b>Ethical Considerations</b>	A set of values around community, transparency, inclusivity, privacy and topic-neutrality to guide their work.
<b>Caveats &amp; Recommendations</b>	Synthetic test data covers only a small set of very specific comments. While these are designed to be representative of common use cases and concerns, it is not comprehensive.

# Quantitative Analysis

## Quantitative Analysis





# Discussion

## Responsible AI

We propose *Model Cards* as a step towards the responsible democratization of machine learning and related AI technology, intended to be applicable across different institutions, contexts, and stakeholders.

## Refine Framework

Usefulness and accuracy of a model card relies on the integrity of the card creator(s). Future work will aim to refine this framework by studying how model information is interpreted and used by different stakeholders.

## Other Transparency Methods

Similar work has begun for datasets and AI services (e.g., [Datasheets for Datasets](#), [Nutrition Labels for ML Datasets](#), [IBM's Factsheets for AI Services](#)). Worth exploring how *Model Cards* can strengthen and complement other transparency methods.

# What's Next?

## **Model Cards for Model Reporting**

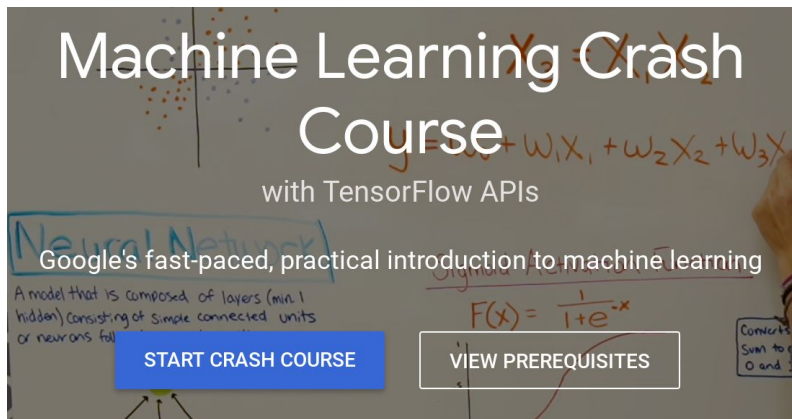
Margaret Mitchell, Simone Wu, Andrew Zaldivar, Parker Barnes, Lucy Vasserman, Ben  
Hutchinson, Elena Spitzer, Inioluwa Deborah Raji, Timnit Gebru  
{mmitchellai,simonewu,andrewzaldivar,parkerbarnes,lucyvasserman,benhutch,espitzer,tgebru}@google.com

Accepted at ACM Conference on Fairness, Accountability,  
and Transparency

Poster Presentations at Women in Machine Learning,  
Black in AI & LatinX in AI Workshops, NeurIPS 2018

<https://arxiv.org/abs/1810.03993>

# Learn More!



**Machine Learning Crash Course**  
with TensorFlow APIs

Google's fast-paced, practical introduction to machine learning

A model that is composed of layers (min. 1 hidden) consisting of simple connected units or neurons follows the equation:  $y = w_0 + w_1x_1 + w_2x_2 + w_3x_3$

Signum:  $F(x) = \frac{1}{1+e^{-x}}$

Convert Sum to 0 and 1

[START CRASH COURSE](#) [VIEW PREREQUISITES](#)

The following cell define a function that uses the `sklearn.metrics.confusion_matrix` module to calculate all the instances (true positive, true negative, false positive, and false negative) needed to compute our binary confusion matrix and evaluation metrics.

#### [ ] Define Function to Compute Binary Confusion Matrix Evaluation Metrics

Binary confusion matrix and evaluation metrics defined.

We will also need help plotting the binary confusion matrix. The function below combines various third-party modules (pandas DataFrame, Matplotlib, Seaborn) to draw the confusion matrix.

#### [51] Define Function to Visualize Binary Confusion Matrix

Binary confusion matrix visualization defined.

Now that we have all the necessary functions defined, we can now compute the binary confusion matrix and evaluation metrics using the outcomes from [our deep neural net model](#). The output of this cell is a tabbed view, which allows us to toggle between the confusion matrix and evaluation metrics table.

#### FairAware Task #4

Use the form below to generate confusion matrices for the two gender subgroups: Female and Male. Compare the number of False Positives and False Negatives for each subgroup. Are there any significant disparities in error rates that suggest the model performs better for one subgroup than another?

#### [65] Visualize Binary Confusion Matrix and Compute Evaluation Metrics Per Subgroup

CATEGORY: gender

SUBGROUP: Male

INFO:tensorflow:Calling model fn.  
INFO:tensorflow:Done calling model fn.  
INFO:tensorflow:Graph was finalized.  
INFO:tensorflow:Restoring parameters from /tmp/tmp5a34Fy/model.ckpt-1000  
INFO:tensorflow:Running local\_init op.  
INFO:tensorflow:Done running local\_init op.

Confusion Matrix Evaluation Metrics

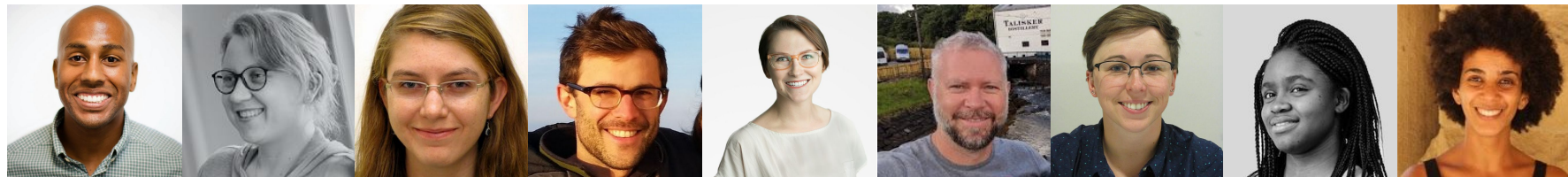
Precision	Recall	False Positive Rate	False Omission Rate
0.7315	0.5062	0.0834	0.1947

#### Solution

Click below for some insights we uncovered

[developers.google.com/machine-learning/crash-course/fairness/](https://developers.google.com/machine-learning/crash-course/fairness/)

# Thank You & Acknowledgements



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