

Web/App Intelligence Part I: Supervised Machine Learning

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Software Design & Studio

Outline

① Web/App Intelligence

② What's Machine Learning?

③ Post Toxicity Detection

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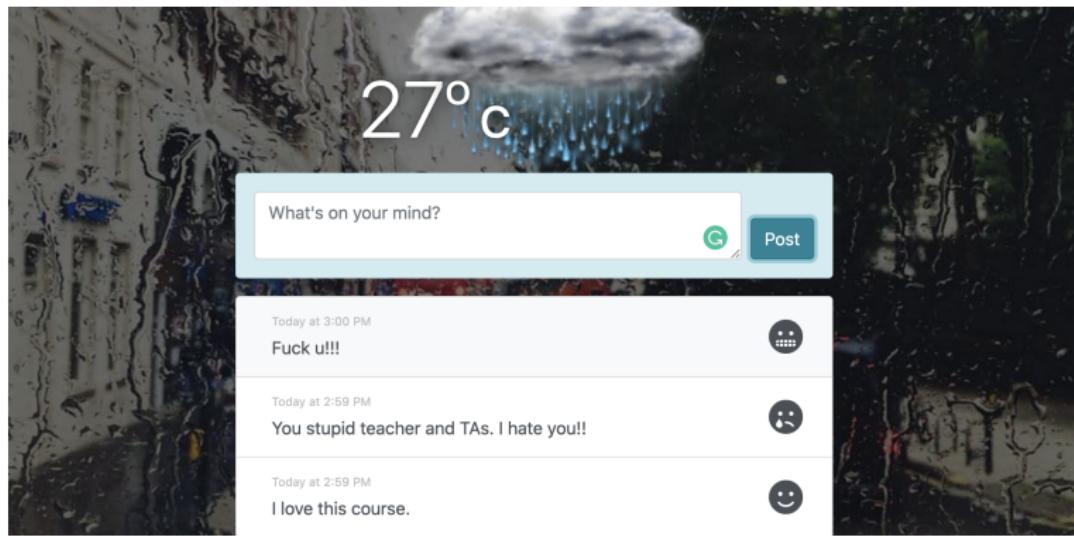
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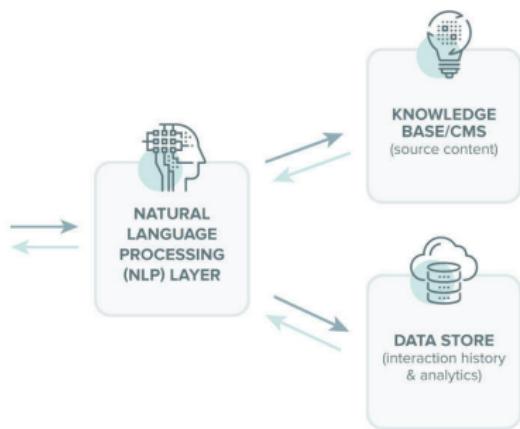
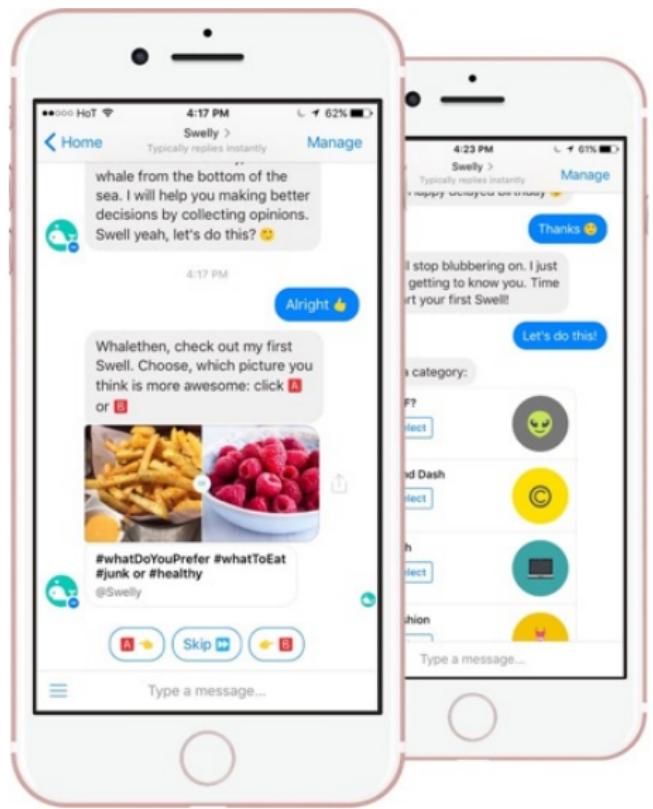
③ Post Toxicity Detection

Let's Make WeatherMood More Intelligent...

```
$ git clone weathermood-toxicity-detection  
$ npm install  
$ npm run start
```



Customer Service Automation



Spam Detection

 **Donald J. Trump**  @realDonaldTrump · 12h

There is NO WAY (ZERO!) that Mail-In Ballots will be anything less than substantially fraudulent. Mail boxes will be robbed, ballots will be forged & even illegally printed out & fraudulently signed. The Governor of California is sending Ballots to millions of people, anyone.....

 [Get the facts about mail-in ballots](#)

 31.2K  29.2K  100.8K 

 **Donald J. Trump**  @realDonaldTrump

....living in the state, no matter who they are or how they got there, will get one. That will be followed up with professionals telling all of these people, many of whom have never even thought of voting before, how, and for whom, to vote. This will be a Rigged Election. No way!

 [Get the facts about mail-in ballots](#)

Product Recommendations

Frequently Bought Together



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- [This item: The Elements of Statistical Learning: Data Mining, Inference, and Prediction, Second Edition \(Springer Series in Statistics\) by Trevor Hastie](#)
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- [Pattern Classification \(2nd Edition\) by Richard O. Duda](#)

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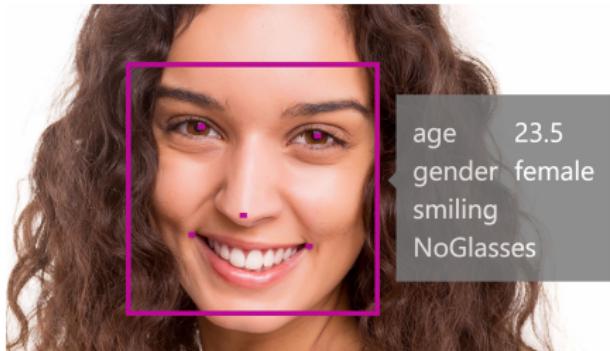
Bayesian Data Analysis, Second Edition (Texts in... by Andrew Gelman
★★★★★ (10) \$56.20



Data Analysis Using Regression and Multilevel /... by Andrew Gelman
★★★★★ (13) \$39.59

The screenshot shows a Spotify interface for a user named Moorissa Tjokro. On the left, there's a sidebar with navigation links like 'Browse', 'Radio', 'YOUR MUSIC', 'Your Daily Mix', 'Songs', 'Albums', 'Artists', 'Stations', 'Local Files', 'PLAYLISTS', and a 'Discover Weekly...' button. The main area features a 'Discover Weekly' section with a photo of Moorissa and the text: 'MADE FOR MOORISSA Discover Weekly Your weekly mixtape of fresh music. Enjoy new discoveries and deep cuts chosen just for you. Updated every Monday, so save your favourites!' Below this, it says 'Made for Moorissa Tjokro by Spotify • 30 songs, 2 hr 6 min'. There are buttons for 'PAUSE', 'FOLLOWING', and a three-dot menu. At the bottom, there's a track list with columns for 'TITLE', 'ARTIST', and a download switch. The first track listed is 'Home (feat. Jeremy Camp)' by Adam Cappa, Jeremy C., uploaded 2 days ago. To the right, there's a 'FIND FRIENDS' button and a 'See what your friends are playing' section showing friends like Julia Eger and Ben Khan.

Customer Profiling

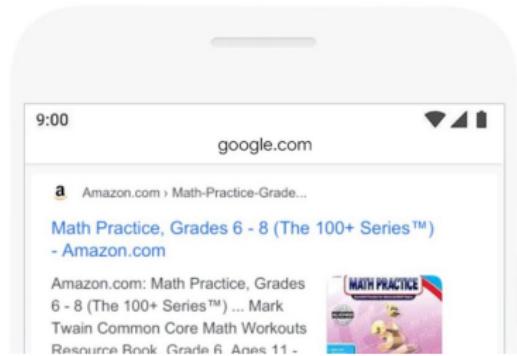


Intention Identification

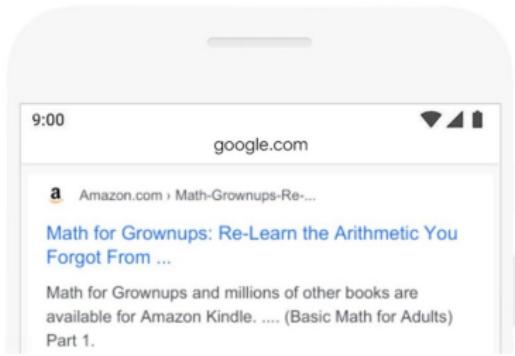


math practice books for adults

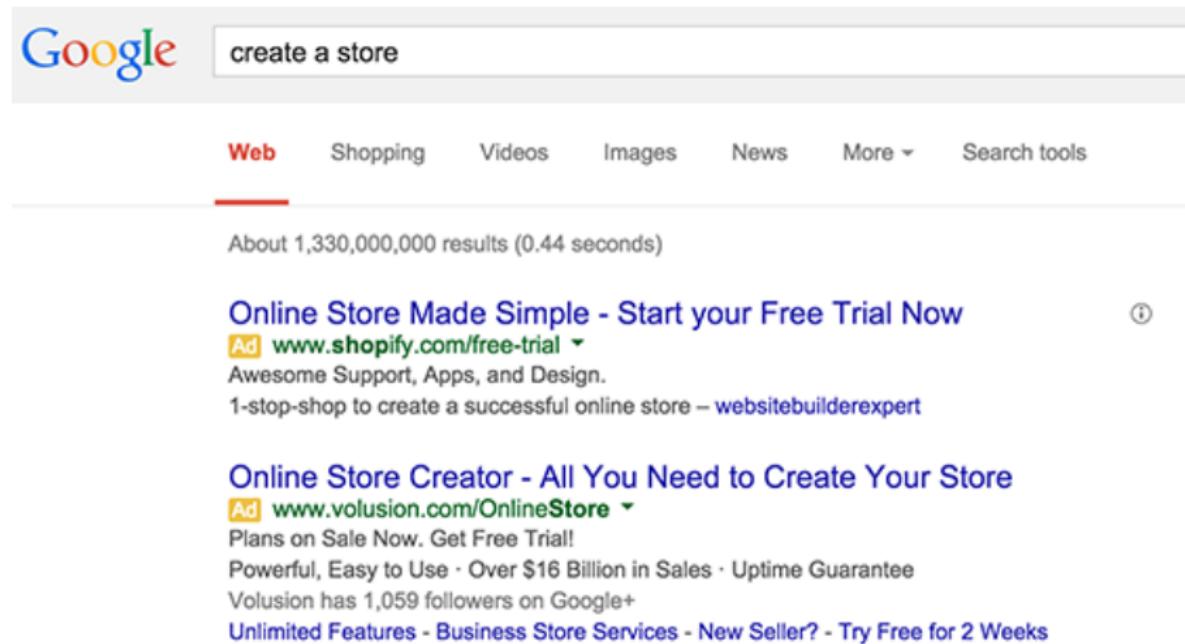
BEFORE



AFTER



Marketing & Advertisement



A screenshot of a Google search results page. The search query "create a store" is entered in the search bar. The results are filtered by "Web". The first result is an advertisement for Shopify, titled "Online Store Made Simple - Start your Free Trial Now". It includes a link to www.shopify.com/free-trial, a description mentioning "Awesome Support, Apps, and Design.", and a tagline "1-stop-shop to create a successful online store – websitebuilderexpert". The second result is another advertisement for Volusion, titled "Online Store Creator - All You Need to Create Your Store". It includes a link to www.volusion.com/OnlineStore, a description mentioning "Plans on Sale Now. Get Free Trial!", "Powerful, Easy to Use · Over \$16 Billion in Sales · Uptime Guarantee", "Volusion has 1,059 followers on Google+", and a tagline "Unlimited Features - Business Store Services - New Seller? - Try Free for 2 Weeks".

create a store

Web Shopping Videos Images News More Search tools

About 1,330,000,000 results (0.44 seconds)

Online Store Made Simple - Start your Free Trial Now ①

Ad www.shopify.com/free-trial ▾

Awesome Support, Apps, and Design.
1-stop-shop to create a successful online store – websitebuilderexpert

Online Store Creator - All You Need to Create Your Store

Ad www.volusion.com/OnlineStore ▾

Plans on Sale Now. Get Free Trial!
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- And much more...

How to do it?

How to do it?

Machine Learning

or Data Mining, Deep Learning, NLP, CV, etc.

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- To solve a problem, we need an algorithm
 - E.g., sorting

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 - The correct answer varies in time and from site to site
- Machine learning algorithms use the ***a posteriori knowledge*** to solve problems
 - Takes ***examples*** as extra input

Example Data \mathbb{X} as Extra Input

- Unsupervised:

$$\mathbb{X} = \{\mathbf{x}^{(i)}\}_{i=1}^N, \text{ where } \mathbf{x}^{(i)} \in \mathbb{R}^D$$

- E.g., $\mathbf{x}^{(i)}$ a post

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- Supervised:

$$\mathbb{X} = \{(\mathbf{x}^{(i)}, \mathbf{y}^{(i)})\}_{i=1}^N, \text{ where } \mathbf{x}^{(i)} \in \mathbb{R}^D \text{ and } \mathbf{y}^{(i)} \in \mathbb{R}^K,$$

- E.g., label $y^{(i)} \in \{0, 1\}$ indicates if the post $\mathbf{x}^{(i)}$ is toxic

3 General Types of Learning (1/2)

- **Supervised learning**: learn to predict the labels of future data points

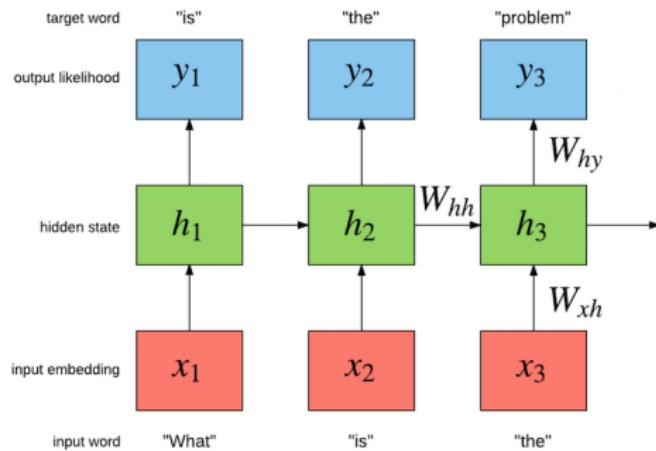
$$X \in \mathbb{R}^{N \times D} : \quad \begin{matrix} 6 \\ | \\ 1 \\ | \\ 9 \\ | \\ 4 \\ | \\ 2 \end{matrix} \quad x' \in \mathbb{R}^D : \quad \begin{matrix} 5 \end{matrix}$$
$$y \in \mathbb{R}^{N \times K} : \quad [e^{(6)}, e^{(1)}, e^{(9)}, e^{(4)}, e^{(2)}] \quad y' \in \mathbb{R}^K : \quad ?$$

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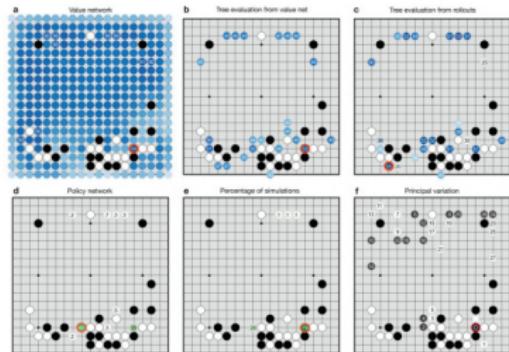
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- **Unsupervised learning**: learn patterns or latent factors in X



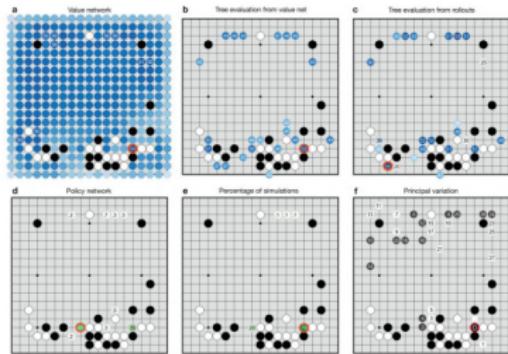
3 General Types of Learning (2/2)

- **Reinforcement learning:** learn from “good”/“bad” feedback of actions (instead of correct labels) to maximize the goal



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- AlphaGo is a hybrid of reinforcement learning and supervised learning
 - Supervised learning from the game records
 - Then, reinforcement learning from self-play

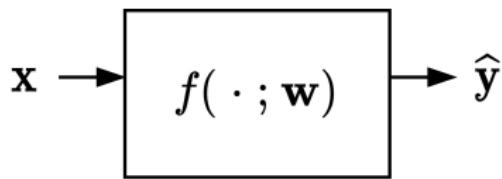
Supervised ML Step 1: Data Pre-processing

- ① Data collection and exploration
- ② Data preprocessing (e.g., integration, cleaning, etc.)



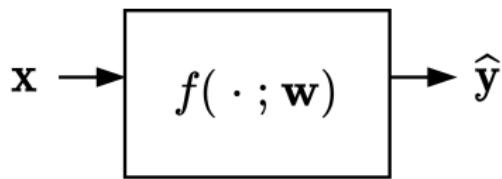
$$\mathbb{X} = \{(\mathbf{x}^{(i)}, \mathbf{y}^{(i)})\}_{i=1}^N$$

Supervised ML Step 2: Model Development



- ① Assume a **model** $\{f(\cdot; \mathbf{w})\}_{\mathbf{w}}$ that is a collection of candidate functions f 's
 - Each f predicts label \hat{y} given an input x
 - f is assumed to be parametrized by \mathbf{w}

Supervised ML Step 2: Model Development

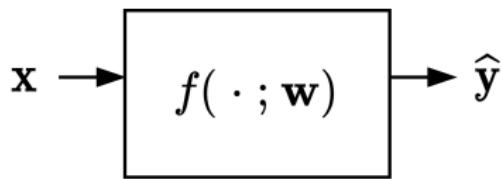


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$$C(\mathbf{w}; \mathbb{X})$$

that measures “how good a particular $f(\cdot; \mathbf{w})$ can explain the training data \mathbb{X} ” (posteriori knowledge)

Supervised ML Step 2: Model Development



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③ **Training**: employ an algorithm that solves

$$w^* = \arg \min_w C(w; \mathbb{X})$$

Supervised ML Step 3: Testing & Deployment

- ① **Testing**: evaluate the performance of the learned $f(\cdot; \mathbf{w}^*)$ using another, *unseen* test dataset \mathbb{X}'
 - Examples in \mathbb{X}' should have the same distribution with those in \mathbb{X}

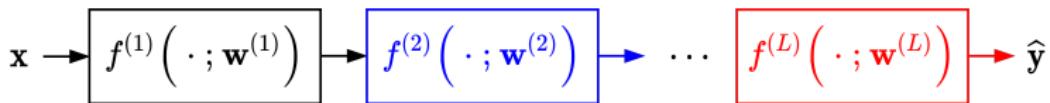
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- ② If $f(\cdot; \mathbf{w}^*)$ has a good test performance, deploy it in a real world system

What is Deep Learning?

- ML where an $f(\cdot; \mathbf{w})$ has many (deep) layers

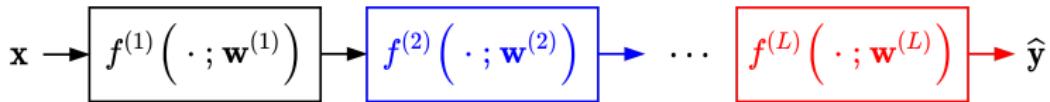
$$\hat{\mathbf{y}} = f^{(L)}(\dots f^{(2)}(f^{(1)}(\mathbf{x}; \mathbf{w}^{(1)}); \mathbf{w}^{(2)}) \dots; \mathbf{w}^{(L)})$$



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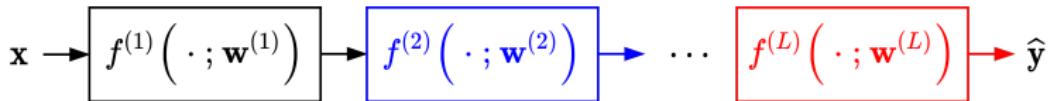
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- Pros:

- Learns to pre-process data automatically
- Learns a complex function (e.g., visual objects to labels)

- Cons:

- Usually needs large data to train a model well
- High computation costs (at both training and test time)

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Supervised Learning

text	identity attack	insult	obscene	severe toxicity	sexual explicit	threat	toxicity
We're dudes on computers, moron. You are quite astonishingly stupid.	false	true	false	false	false	false	true

- ① Get and preprocess a dataset, e.g., [civil comments](#)

- ① Training dataset: $\mathbb{X} = \{(\mathbf{x}^{(i)}, \mathbf{y}^{(i)})\}_i$
- ② Testing dataset: $\mathbb{X}' = \{(\mathbf{x}'^{(i)}, \mathbf{y}'^{(i)})\}_i$

¹ $1(\text{condition}) = 1$ if condition is true; otherwise 0.

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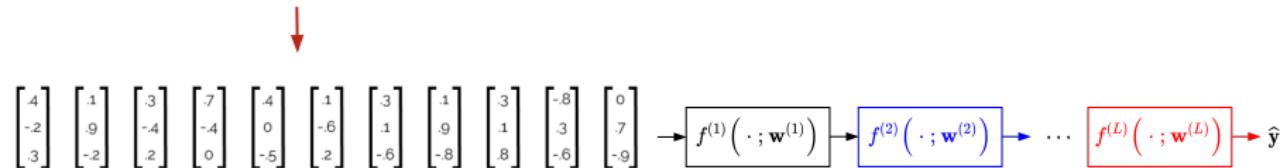
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- ① Then, integrate $f(\cdot; \mathbf{w}^*)$ into WeatherMood

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Pre-trained Toxicity Classifier

The chef who ran to the store was out of food



- [Google's Pre-trained Toxicity Classifier on GitHub](#)
 - It's free
- Deep model:
 - ① Transforms each word into a fixed-length vector
 - ② Sums then normalizes the word vectors
 - ③ Feeds the sum into a deep classification model

Using the Pre-trained Toxicity Classifier

```
// installation
$ npm install @tensorflow/tfjs @tensorflow-models/toxicity

// usage in code
const toxicity = require('@tensorflow-models/toxicity');
const model = await toxicity.load(0.9); // threshold
const inputs = [ 'We're dudes on computers, moron...'];
const classes = await model.classify(inputs);
inputs.forEach((text, i) => {
  console.log(text);
  classes.forEach(cls => {
    console.log(cls.label, cls.results[i].match);
  });
});
```

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Demo 3

- Implement the prototype you shown in Demo 2
- Final project demo:
 - 6/20 1pm-6pm
 - 4 min for team (strict)
 - 10 min for QA

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- Evaluation:
 - Completeness (60%)
 - Complexity (40%)

Completeness (60%)

- How many main features have you completed?
- List each of them
- How well does your final implementation match your Demo 2 design?
(40%)
 - Key features
 - Key flows
 - UI & transitions

Complexity (40%)

- Explain *one or two* most
 - challenging aspects you implemented, or
- Discuss issues encountered and your solutions

Bonus

- Best Minimal Viable Products (MVPs)
 - **+15%, +10%, and +5%** for #1, #2, and #3, respectively
- Cross-team peer review
 - Each team has three non-self votes
 - Judged by completeness, complexity, and design
- Intra-team peer review
 - Scaled based on team score

