

Invisible Design Part II: Machine Learning & Web/App Intelligence

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Software Design & Studio

Outline

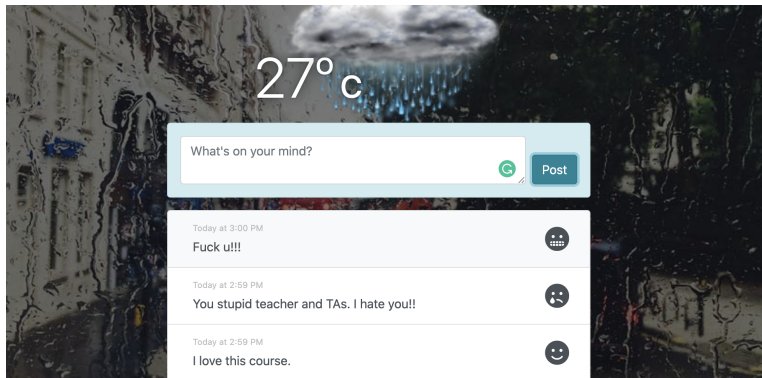
- 1 Web/App Intelligence
- 2 What's Machine Learning?
- 3 Deep Learning
- 4 Case Studies
 - Post Toxicity Detection
 - Object/Face Detection
- 5 Final Project

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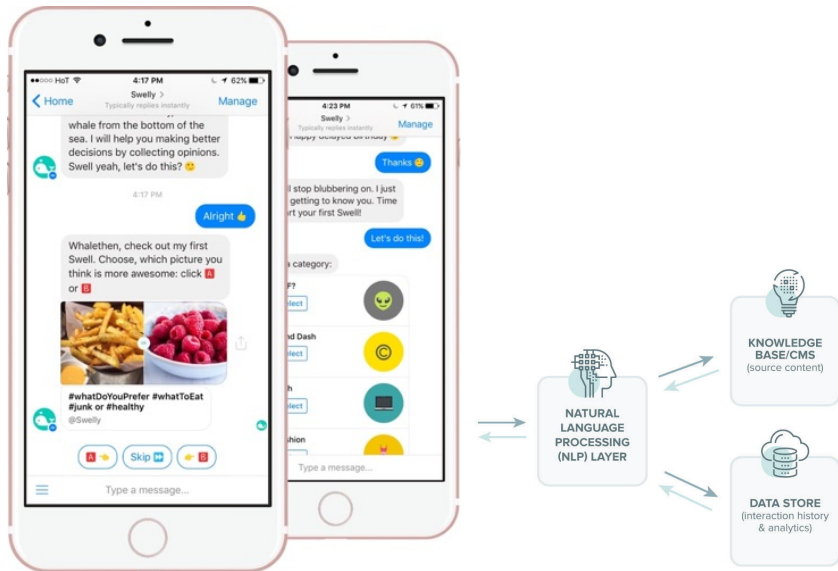
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How to Improve Your App by Collected Data?

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



Customer Service Automation



Spam or Toxicity 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



Price For All Three: \$258.02

Add all three to Cart

- 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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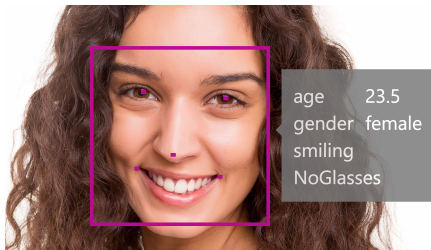
[Bayesian Data Analysis, Second Edition \(Texts in Applied Probability\)](#) by Andrew Gelman
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[Data Analysis Using Regression and Multilevel / ...](#) by Andrew Gelman
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Browse
Radio
YOUR MUSIC
Your Daily Mix
Songs
Albums
Artists
Stations
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PLAYLISTS
Discover Weekly...
SEARCH
Moorisse Tjokro
Discover Weekly
MADE FOR MOORISSE
Your weekly mixtape of fresh music. Enjoy new discoveries and deep cuts chosen just for you. Updated every Monday, so save your favourites!
Made for Moorisse Tjokro by Spotify · 30 songs, 2 hr 6 min
PAUSE FOLLOWING
Filter Download
TITLE ARTIST
Home (feat. Jeremy Camp) Adam Cappa, Jeremy C. 2 days ago

Customer Profiling

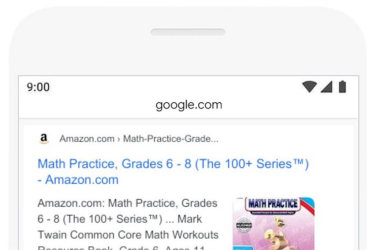


Intention Identification

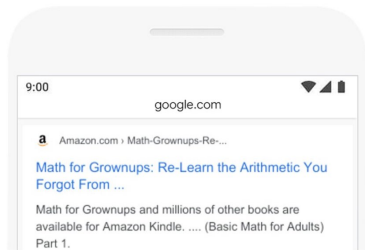


math practice books for adults

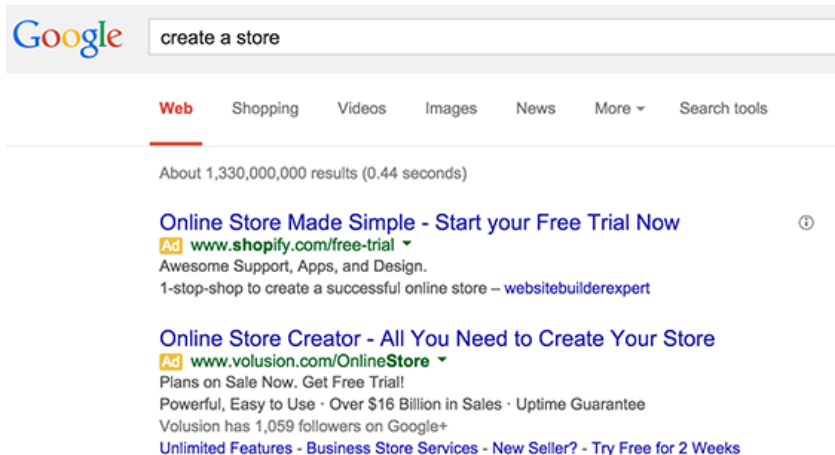
BEFORE



AFTER



Marketing & Advertisement



Google 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 ⓘ
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!
Powerful, Easy to Use · Over \$16 Billion in Sales · Uptime Guarantee
Volusion has 1,059 followers on Google+
[Unlimited Features](#) - [Business Store Services](#) - [New Seller?](#) - [Try Free for 2 Weeks](#)

- 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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- 1 Web/App Intelligence
- 2 What's Machine Learning?**
- 3 Deep Learning
- 4 Case Studies
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Prior vs. Posteriori Knowledge

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

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 - E.g., to tell if a post is toxic or not
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- For some problem, however, we do not have the a priori knowledge
 - E.g., to tell if a post is toxic or not
 - 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

Example Data \mathbb{X} as Extra Input

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

- 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

$$X \in \mathbb{R}^{N \times D} : \begin{array}{|c|c|c|c|c|} \hline 6 & 1 & 9 & 4 & 2 \\ \hline \end{array}$$

$$y \in \mathbb{R}^{N \times K} : [e^{(6)}, e^{(1)}, e^{(9)}, e^{(4)}, e^{(2)}]$$

$$x' \in \mathbb{R}^D : \begin{array}{|c|} \hline 5 \\ \hline \end{array}$$

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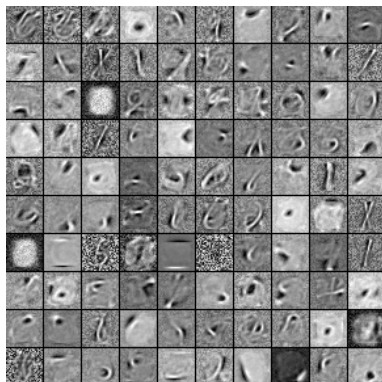
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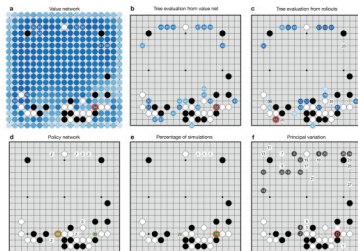
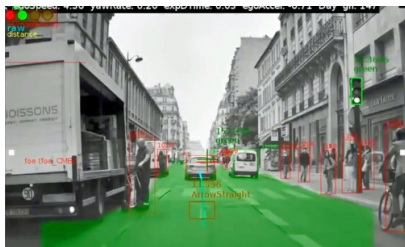
$$y' \in \mathbb{R}^K : ?$$

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



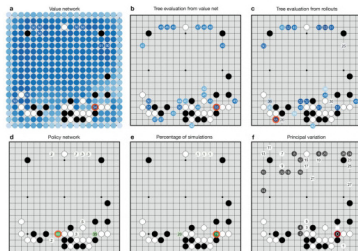
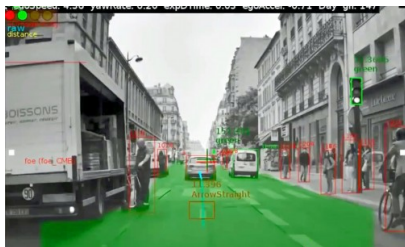
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- **Reinforcement learning**: learn from “good”/“bad” feedback of actions (instead of correct labels) to maximize the goal



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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

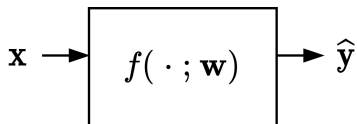
Supervised ML Step 1: Data Pre-processing

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



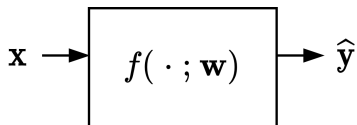
$$\mathbb{X} = \{(\mathbf{x}^{(i)}, \mathbf{y}^{(i)})\}_{i=1}^N$$

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 $\hat{\mathbf{y}}$ given an input \mathbf{x} , e.g., $\hat{\mathbf{y}} = \mathbf{w}^\top \mathbf{x}$
 - f is assumed to be parametrized by \mathbf{w}

Supervised ML Step 2: Model Development



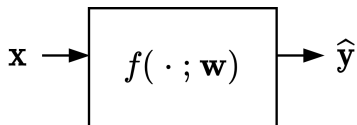
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$$C(\mathbf{w}; \mathbb{X})$$

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

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

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

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

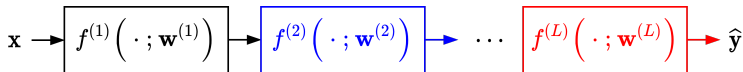
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What is Deep Learning?

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

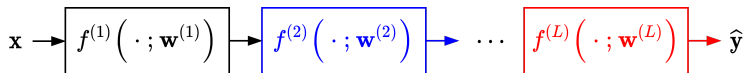
$$\hat{\mathbf{y}} = f^{(L)}(\dots f^{(2)}(f^{(1)}(\mathbf{x}; \mathbf{w}^{(1)}); \mathbf{w}^{(2)}) \dots; \mathbf{w}^{(L)})$$



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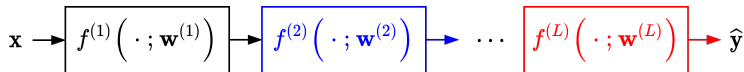


- Pros:
 - **Learns to pre-process data automatically**
 - Learns a complex function (e.g., visual objects to labels)

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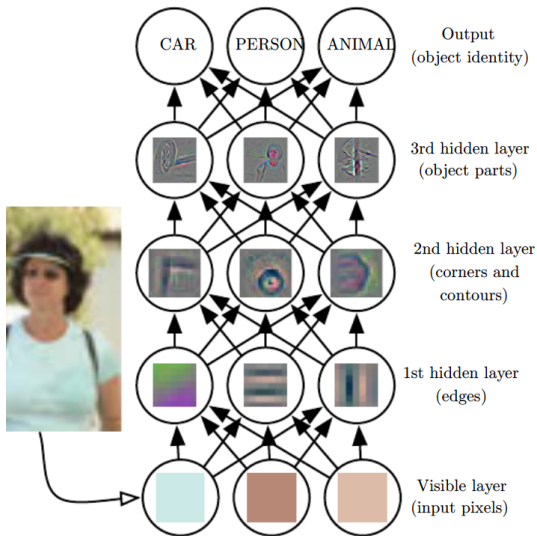
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- Pros:
 - Learns to pre-process data automatically**
 - Learns a complex function (e.g., visual objects to labels)
- Cons:
 - Usually needs **large data** to train a model well
 - High computation costs (at both training and test time)

Data Preprocessing via Representation Learning



- **Representation learning**

- Model learns hidden features in addition to labels
- Exponential gain of expressiveness
 - Counters the curse of dimensionality

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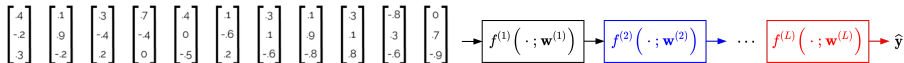
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- ① Then, integrate $f(\cdot; \mathbf{w}^*)$ into WeatherMood

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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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How to Detect Multiple Objects?

- Naive idea: let a model detect a single object in a sliding window
 - Assuming *fixed #labels*, e.g., face and background



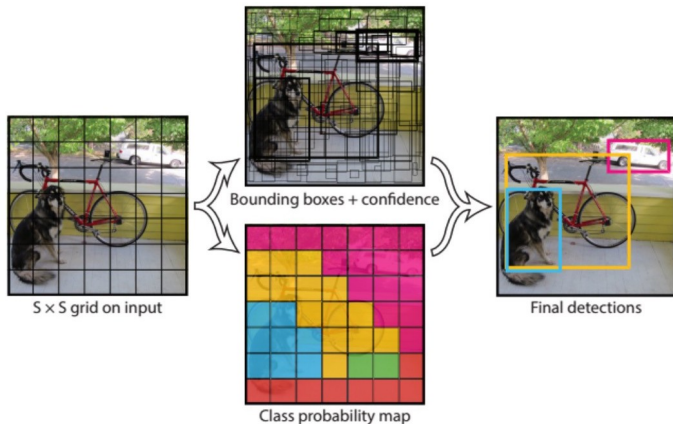
How to Detect Multiple Objects?

- Naive idea: let a model detect a single object in a sliding window
 - Assuming *fixed #labels*, e.g., face and background
- Problem: too many windows!
 - at different locations and scales



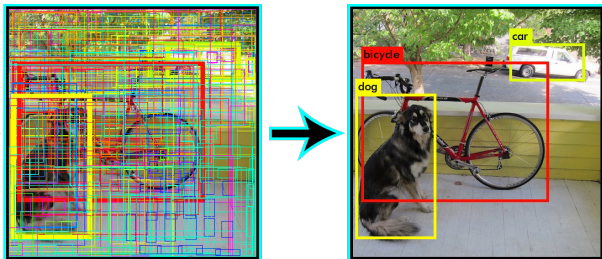
YOLO & SSD

- For each predefined grid, predicts the
 - candidate bounding boxes
 - label probability
 - object confidenceof an object (if any)



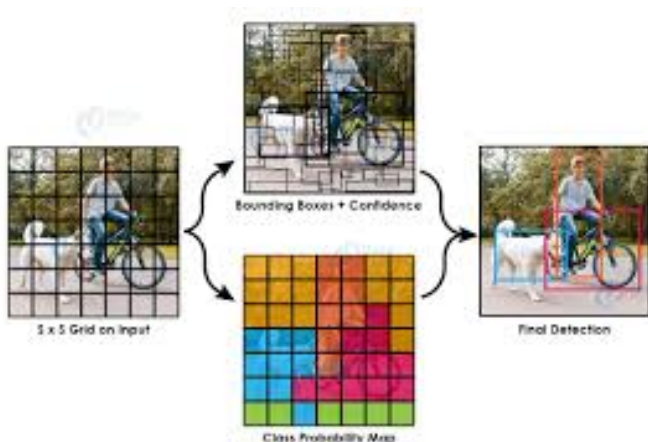
Reducing #Boxes at Test Time

- 1 Label each box by score = label probability \times object confidence
- 2 Discard boxes with low scores
- 3 **Non-max suppression**: repeat until there is no box left
 - Output the box b with highest score
 - Discard any remaining overlapping boxes with b



Age or Gender Detection

- For each predefined grid, predicts the
 - candidate bounding boxes
 - label (**face**) probability *+ age or gender*
 - object confidence
- of an object (if any)



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About Your Final Project...

- Implement the prototype shown in your midterm design pitch
- Final project demo:
 - On **6/14**
 - **5 min** for team (strict)
- Evaluation:
 - Completeness (40%)
 - System & software design (20%)
 - Complexity (20%)
 - Details (20%)

Completeness (40%)

- What's the main flow of your design?
- How is each step implemented?
 - *Demo each step of your main flow*
- Additional flows
 - Sign up/in
 - Account management
 - Settings
 - Edge cases
 - Error handling
 - ...

System & Software Design (20%)

- System architecture
 - Clients?
 - Servers?
 - Services used?
- Software architecture for *change-resilience*
 - UI/domain/data layers?
 - Dependency injection?
 - Reactive?

Complexity (20%)

- Explain *one or two* most
 - challenging features you implemented, or
 - difficult issues you resolved
- Why are they difficult?
- How did you solve it?

Details (20%)

- UI & interactions
- Animations & effects
- Content
- Features for execution
- Invisible features

Bonus

- Best Minimal Viable Products (MVPs)
 - **+20%**, **+10%**, and **+5%** for #1, #2, and #3, respectively
- Peer review
 - Each team has three non-self votes
 - Judged by completeness, system/software design, complexity, and details

