Online Advertising

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U.S. INTERNATIONAL 中文

The New York Times

Monday, January 12, 2015 | Today's Paper | Video | 38°F | Hang Seng +0.51%

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Times Reporter Will Not Be Called to Testify in Leak Case

By MATT APUZZO 9:00 PM ET

The decision ends a seven-year legal fight over whether James Risen could be forced to name the sources of his reports on a botched C.I.A. operation.

39 Comments

The Jiaozhou Bay Bridge, which cost $2.3 billion, is the world's longest sea-crossing bridge.

Yan Runbo/Xinhua, via Associated Press

1 of 7

The Opinion Pages

Choke First, Ask Questions Later

By THE EDITORIAL BOARD

A new report suggests that this disavowed tactic has never gone away and sometimes officers use it as a first, not last, resort.

- Editorial: United in Outrage
- Sheryl Sandberg and Adam Grant: Speaking While Female
- Taking Note: The Sony Hack and the Gender Pay Gap
- The Stone: Why Life Is Absurd

MENAGERIE

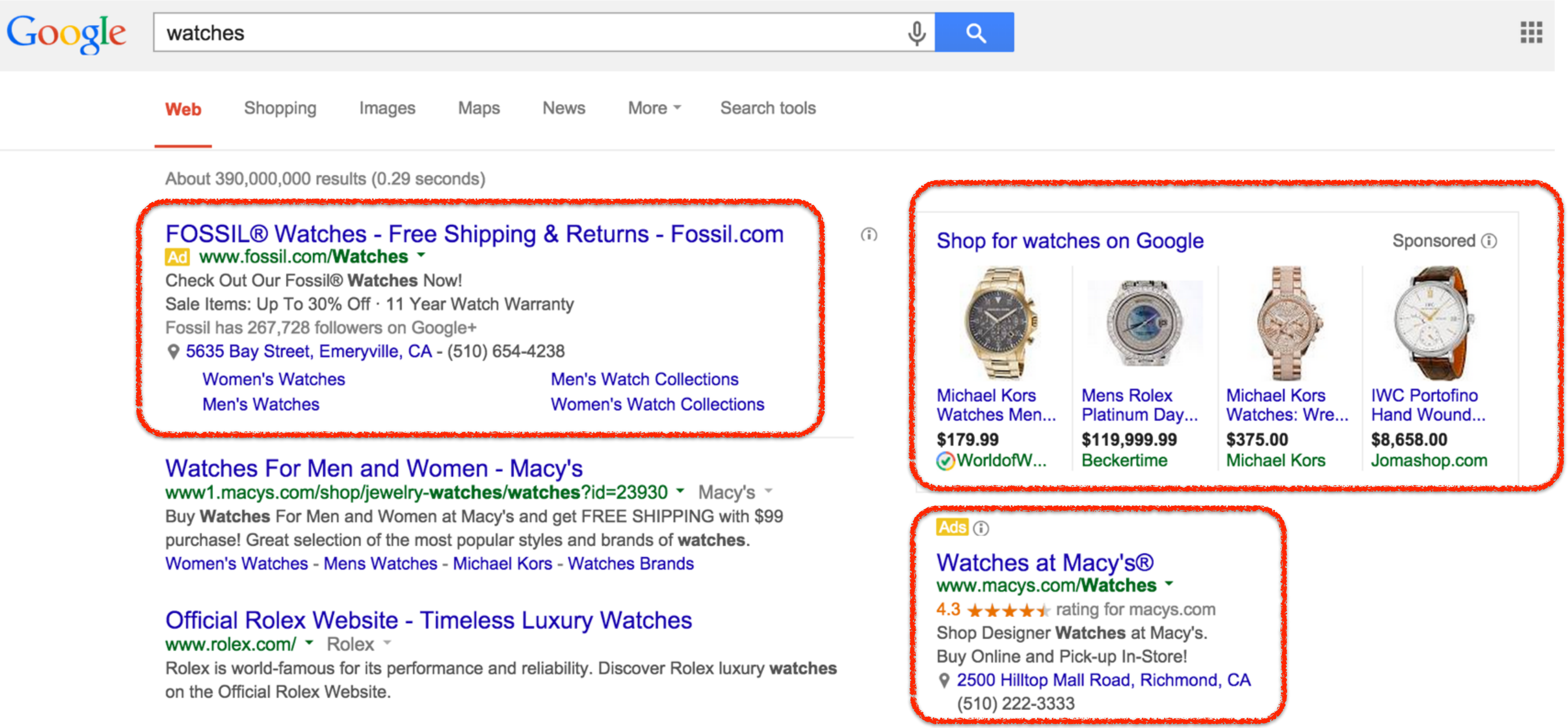
A Swarm in 'Dead City'

By GABRIELLE SELZ

At 14, I tried to run away. But millions of molting cicadas came between me and my freedom.

- Blow: Tamir Rice and the Value of Life
- Krugman: For the Love of Carbon
- Room for Debate: When Satire Cuts Both Ways
- Bruni, Douthat: Movies and Our Still-Wrenching History

France Orders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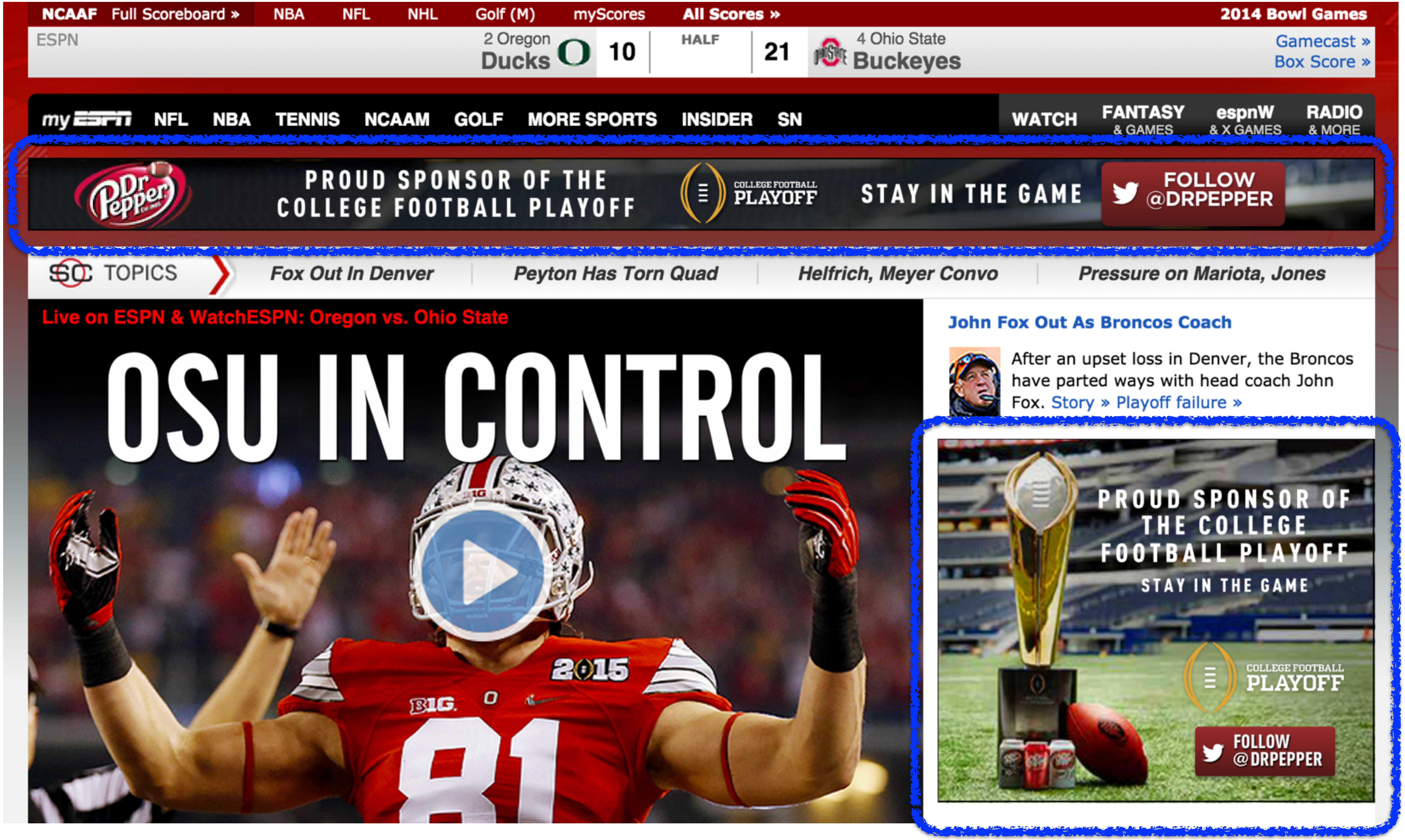
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Online Advertising is Big Business

Multiple billion dollar industry

$43B in 2013 in USA, 17% increase over 2012
[PWC, Internet Advertising Bureau, April 2013]

Higher revenue in USA than cable TV and nearly the same as broadcast TV
[PWC, Internet Advertising Bureau, Oct 2013]

Large source of revenue for Google and other search engines

Canonical Scalable ML Problem

Problem is hard; we need all the data we can get!

- Success varies by type of online ad (banner, sponsor search, email, etc.) and by ad campaign, but can be less than 1% [Andrew Stern, iMedia Connection, 2010]

Lots of Data

- Lots of people use the internet
- Easy to gathered labeled data

A great success story for scalable ML

The Players

Publishers: NYTimes, Google, ESPN

- Make money displaying ads on their sites

Advertisers: Marc Jacobs, Fossil, Macy's, Dr. Pepper

- Pay for their ads to be displayed on publisher sites
- They want to attract business

Matchmakers: Google, Microsoft, Yahoo

- Match publishers with advertisers
- In real-time (i.e., as a specific user visits a website)

Why Advertisers Pay?

Impressions

- Get message to target audience
- e.g., brand awareness campaign

Performance

- Get users to do something
- e.g., click on ad (pay-per-click) ← Most common
- e.g., buy something or join a mailing list

Efficient Matchmaking

Idea: Predict probability that user will click each ad and choose ads to maximize probability

- Estimate $\mathbb{P}(\text{click} \mid \text{predictive features})$
- Conditional probability: probability **given** predictive features

Predictive features

- Ad's historical performance
- Advertiser and ad content info
- Publisher info
- User info (e.g., search / click history)

Publishers Get Billions of Impressions Per Day

But, data is high-dimensional, sparse, and skewed

- Hundreds of millions of online users
- Millions of unique publisher pages to display ads
- Millions of unique ads to display
- Very few ads get clicked by users

Massive datasets are crucial to tease out signal

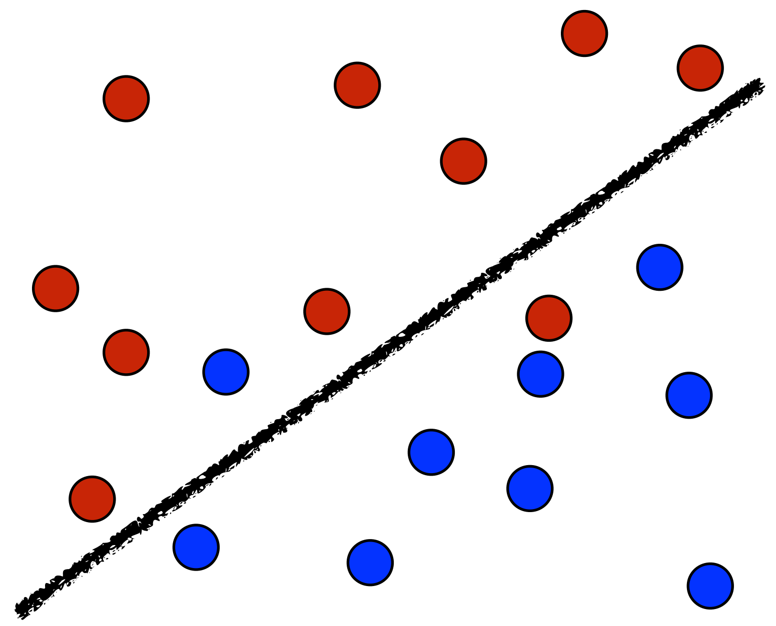
Goal: Estimate $\mathbb{P}(\text{click} \mid \text{user, ad, publisher info})$
Given: Massive amounts of labeled data

Linear Classification and Logistic Regresssion

UCLA Cal

databricks™

Classification

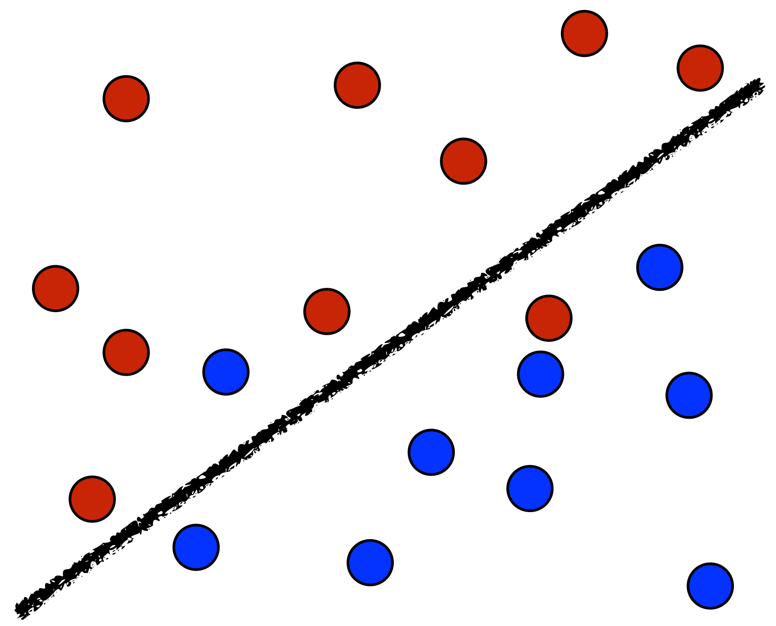


Goal: Learn a mapping from observations to discrete labels given a set of training examples (supervised learning)

Example: Spam Classification

- Observations are emails
- Labels are {spam, not-spam} (Binary Classification)
- Given a set of labeled emails, we want to predict whether a new email is spam or not-spam

Classification

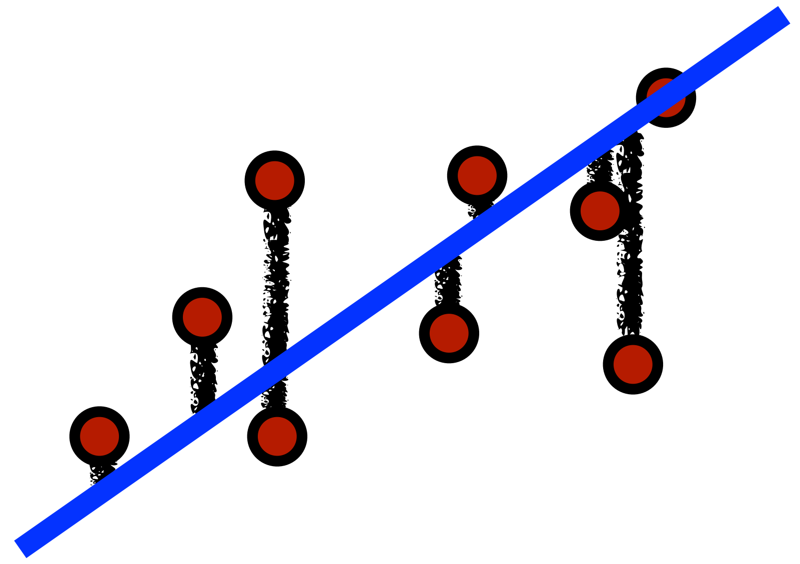


Goal: Learn a mapping from observations to discrete labels given a set of training examples (supervised learning)

Example: Click-through Rate Prediction

- Observations are user-ad-publisher triples
- Labels are {not-click, click} (Binary Classification)
- Given a set of labeled observations, we want to predict whether a new user-ad-publisher triple will result in a click

Reminder: Linear Regression



Example: Predicting shoe size from height, gender, and weight

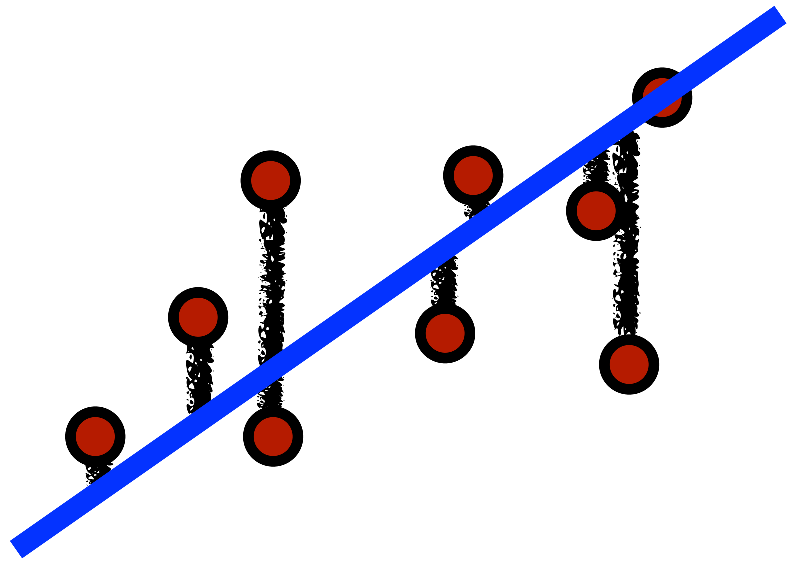
For each observation we have a feature vector, $\mathbf{x}$, and label, y

$$\mathbf{x}^\top = \begin{bmatrix} x_1 & x_2 & x_3 \end{bmatrix}$$

We assume a *linear* mapping between features and label:

$$y \approx w_0 + w_1 x_1 + w_2 x_2 + w_3 x_3$$

Reminder: Linear Regression



Example: Predicting shoe size from height, gender, and weight

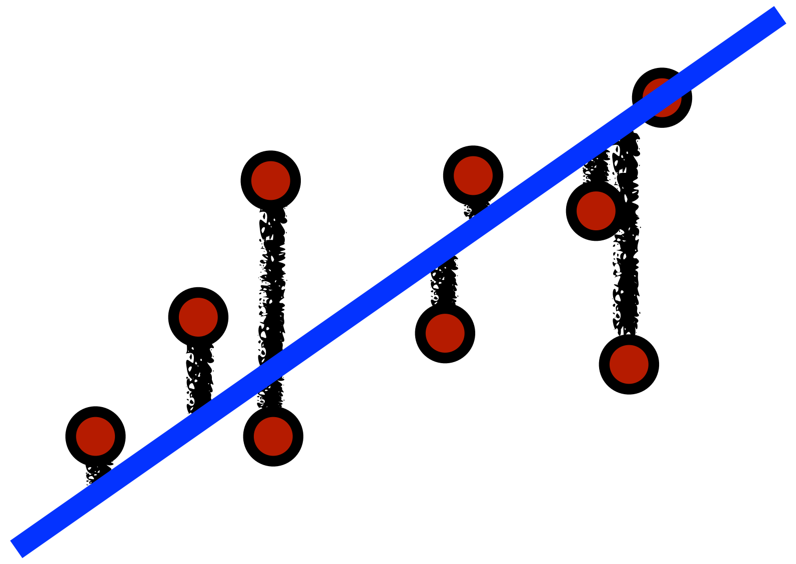
We can augment the feature vector to incorporate offset:

$$\mathbf{x}^\top = \begin{bmatrix} 1 & x_1 & x_2 & x_3 \end{bmatrix}$$

We can then rewrite this linear mapping as scalar product:

$$y \approx \hat{y} = \sum_{i=0}^{3} w_i x_i = \mathbf{w}^\top \mathbf{x}$$

Why a Linear Mapping?



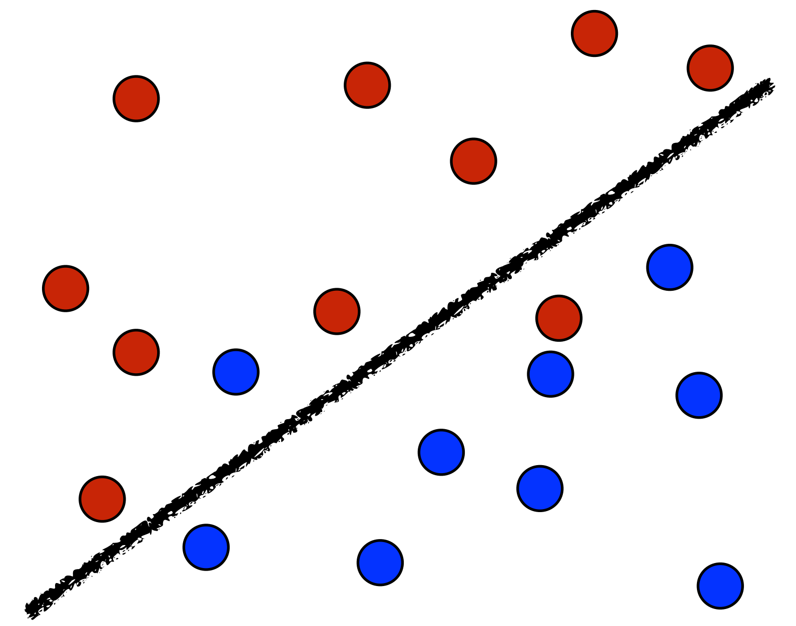
Simple

Often works well in practice

Can introduce complexity via feature extraction

Can we do something similar for classification?

Linear Regression ⇒ Linear Classifier



Example: Predicting rain from temperature, cloudiness, and humidity

Use the same feature representation: $\mathbf{x}^\top = \begin{bmatrix} 1 & x_1 & x_2 & x_3 \end{bmatrix}$

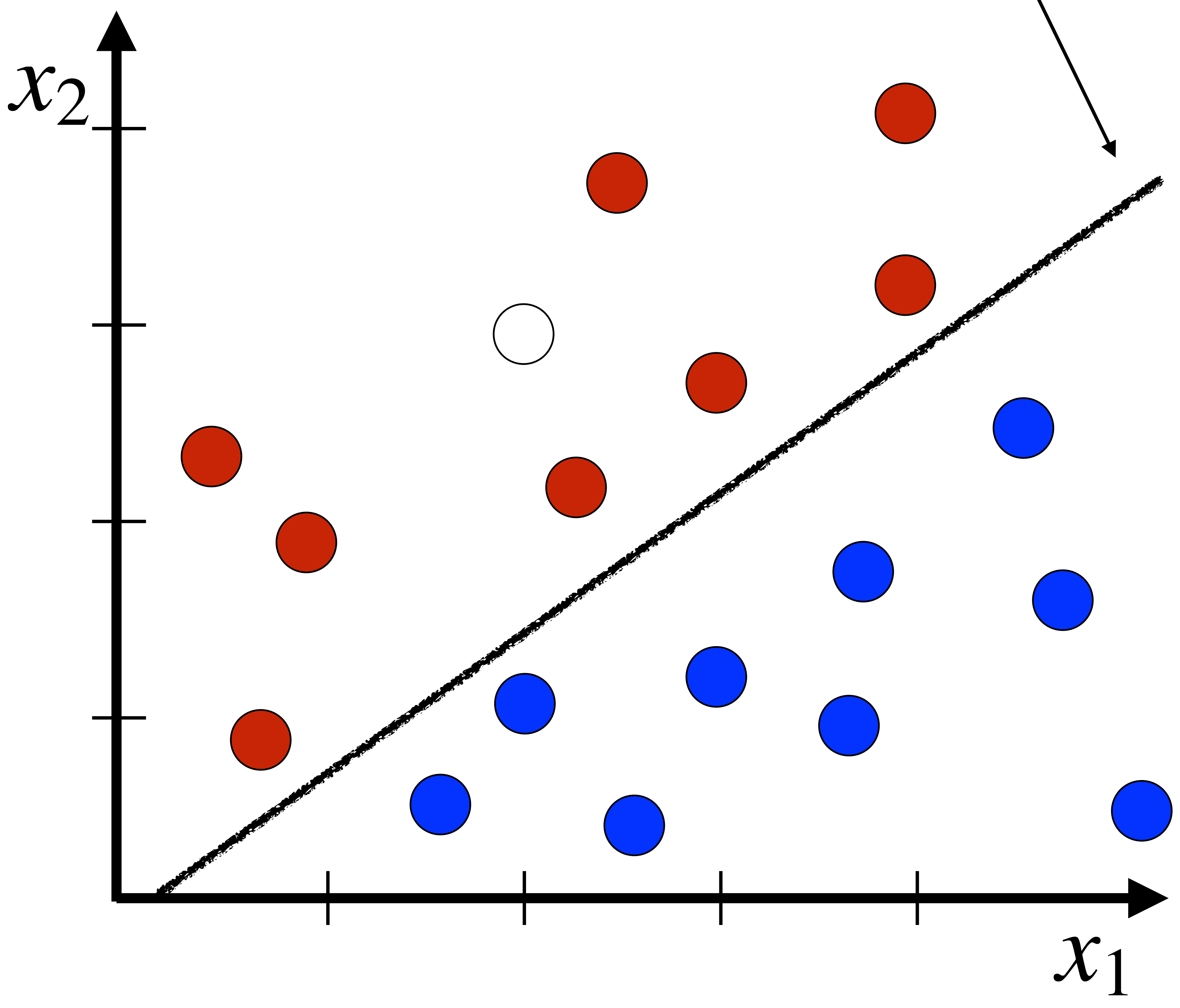
How can we make class predictions?

- {not-rain, rain}, {not-spam, spam}, {not-click, click}
- We can threshold by sign

$$\hat{y} = \sum_{i=0}^{3} w_i x_i = \mathbf{w}^\top \mathbf{x} \implies \hat{y} = \mathrm{sign}(\mathbf{w}^\top \mathbf{x})$$

Linear Classifier Decision Boundary

Decision Boundary $3x_1 - 4x_2 - 1 = 0$



Imagine $\mathbf{w}^\top = \begin{bmatrix} -1 & 3 & -4 \end{bmatrix}$

$\mathbf{x}^\top = \begin{bmatrix} 1 & 2 & 3 \end{bmatrix}$

$\mathbf{x}^\top = \begin{bmatrix} 1 & 2 & 1 \end{bmatrix} : \mathbf{w}^\top \mathbf{x} = 1$

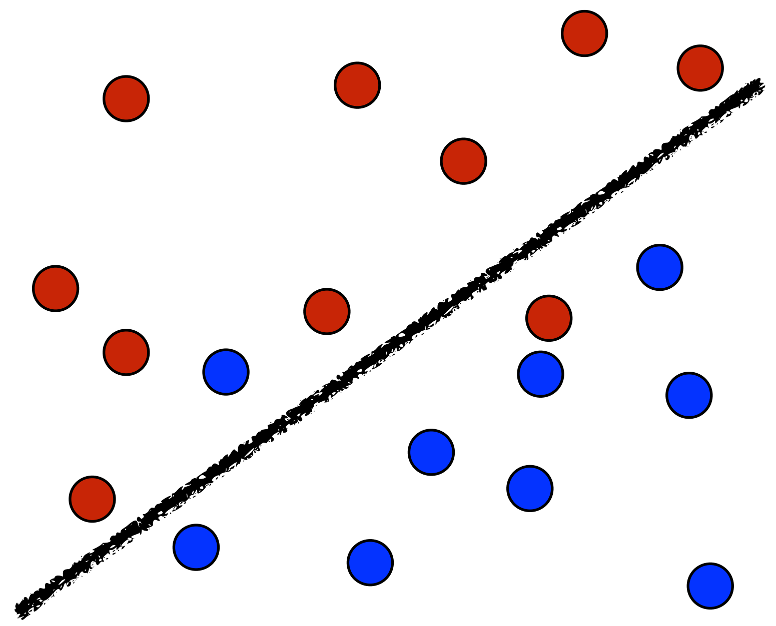
$\mathbf{x}^\top = \begin{bmatrix} 1 & 5 & .5 \end{bmatrix} : \mathbf{w}^\top \mathbf{x} = 12$

$\mathbf{x}^\top = \begin{bmatrix} 1 & 3 & 2.5 \end{bmatrix} : \mathbf{w}^\top \mathbf{x} = -2$

Let's interpret this rule: $\hat{y} = \textbf{sign}(\mathbf{w}^\top \mathbf{x})$

- $\hat{y} = 1 : \mathbf{w}^\top \mathbf{x} > 0$
- $\hat{y} = -1 : \mathbf{w}^\top \mathbf{x} < 0$
- Decision boundary: $\mathbf{w}^\top \mathbf{x} = 0$

Evaluating Predictions



Regression: can measure 'closeness' between label and prediction

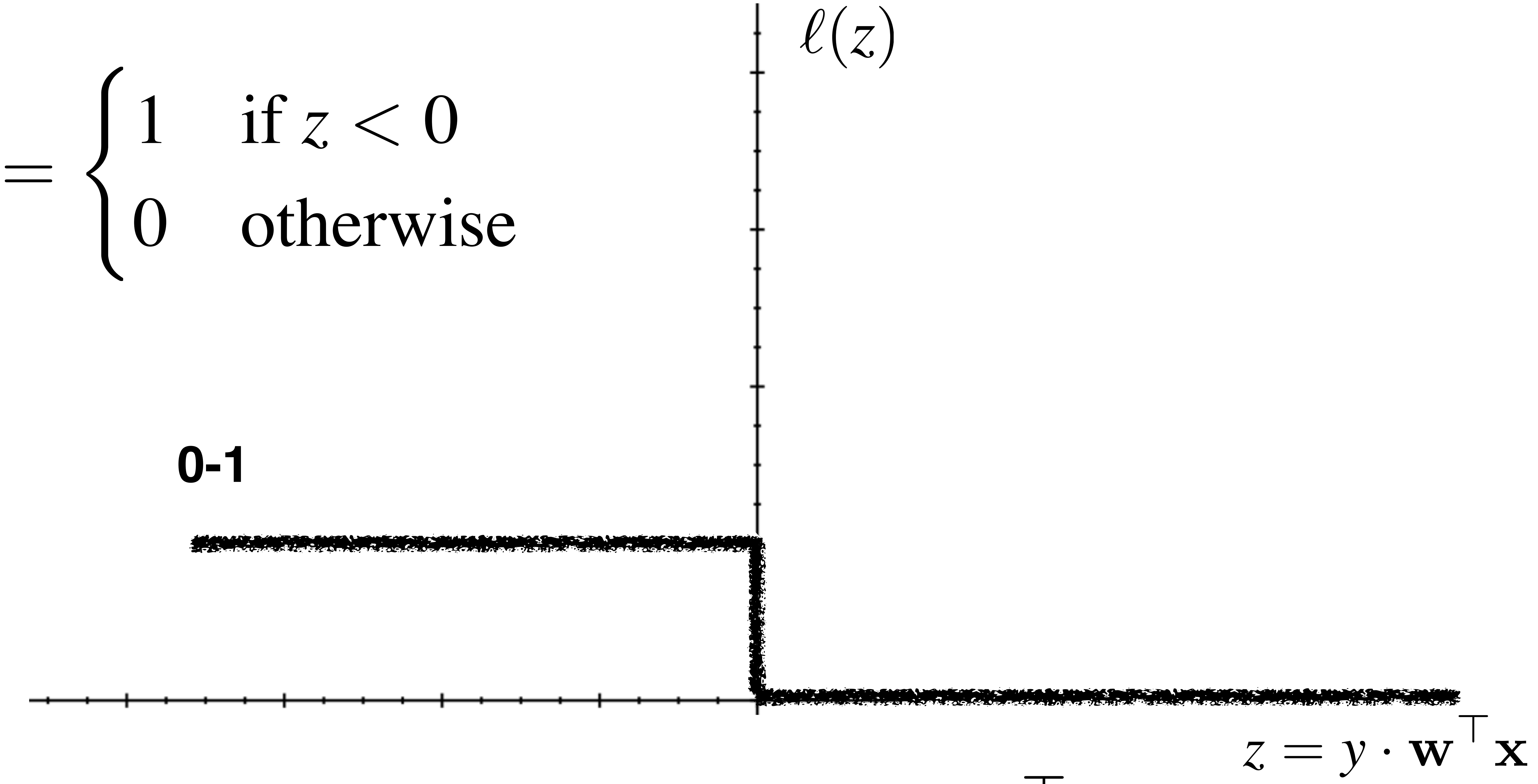
- Song year prediction: better to be off by a year than by 20 years
- Squared loss: $(y - \hat{y})^2$

Classification: Class predictions are discrete

- 0-1 loss: Penalty is 0 for correct prediction, and 1 otherwise

0/1 Loss Minimization

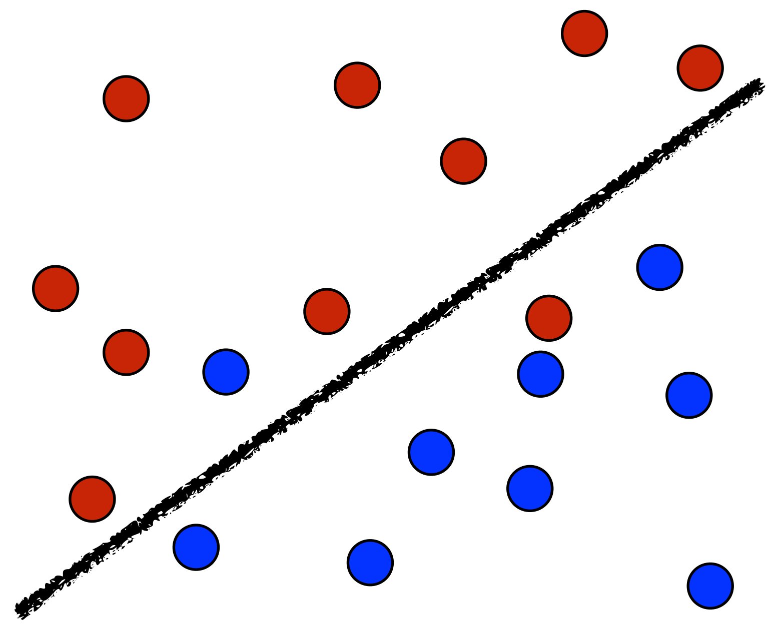
$$\ell_{0/1}(z) = \begin{cases} 1 & \text{if } z < 0 \\ 0 & \text{otherwise} \end{cases}$$



Let $y \in \{-1, 1\}$ and define $z = y \cdot \mathbf{w}^\top \mathbf{x}$

z is positive if y and $\mathbf{w}^\top \mathbf{x}$ have same sign, negative otherwise

How Can We Learn Model ($\mathbf{w}$)?



Assume we have n training points, where $\mathbf{x}^{(i)}$ denotes the ith point

Recall two earlier points:

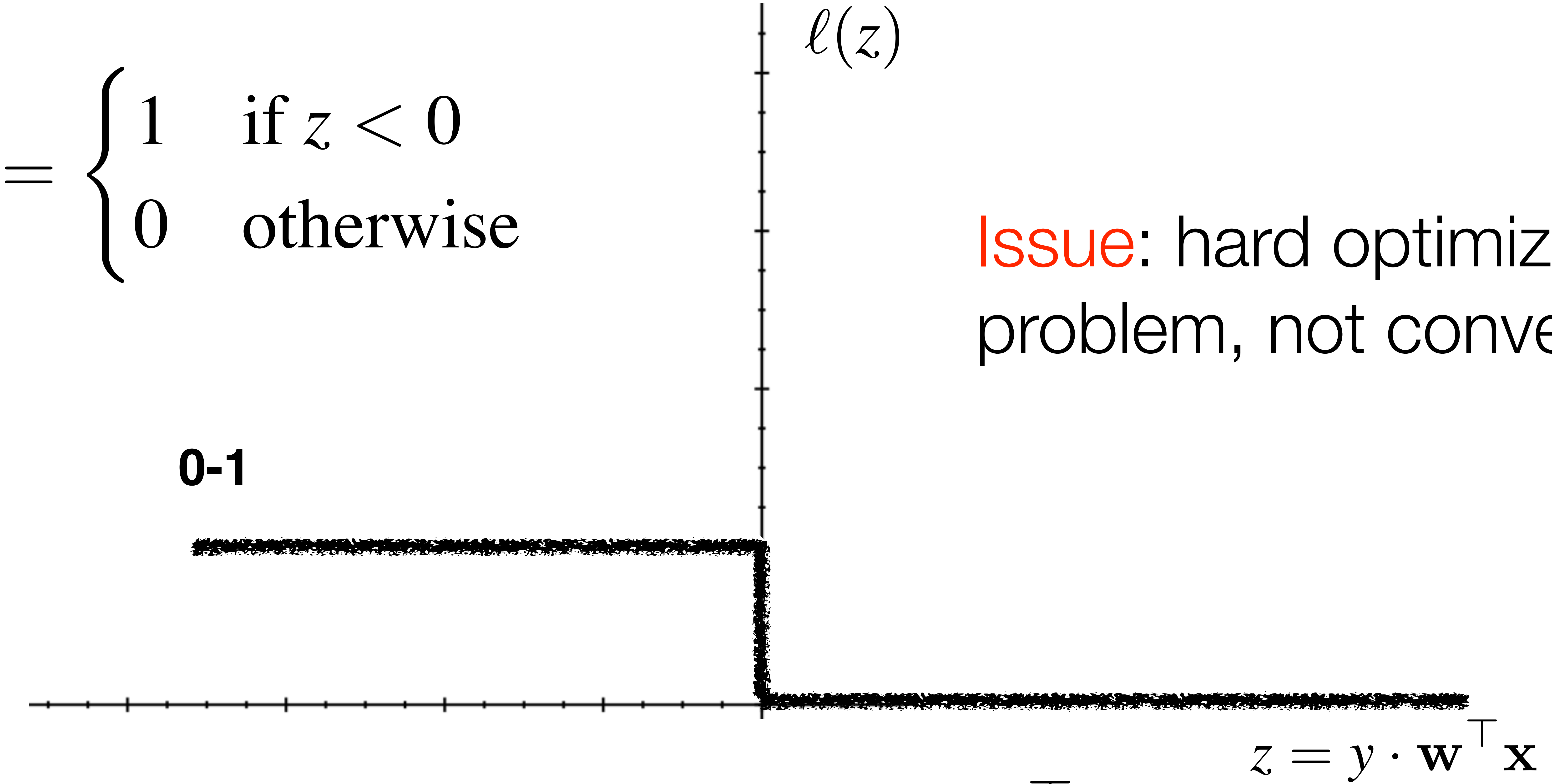
- *Linear* assumption: $\hat{y} = \mathbf{sign}(\mathbf{w}^\top \mathbf{x})$
- We use 0-1 *loss*: $\ell_{0/1}(z)$

Idea: Find $\mathbf{w}$ that minimizes average 0-1 loss over training points:

$$\min_{\mathbf{w}} \sum_{i=1}^{n} \ell_{0/1}\left(y^{(i)} \cdot \mathbf{w}^\top \mathbf{x}^{(i)}\right)$$

0/1 Loss Minimization

$$\ell_{0/1}(z) = \begin{cases} 1 & \text{if } z < 0 \\ 0 & \text{otherwise} \end{cases}$$

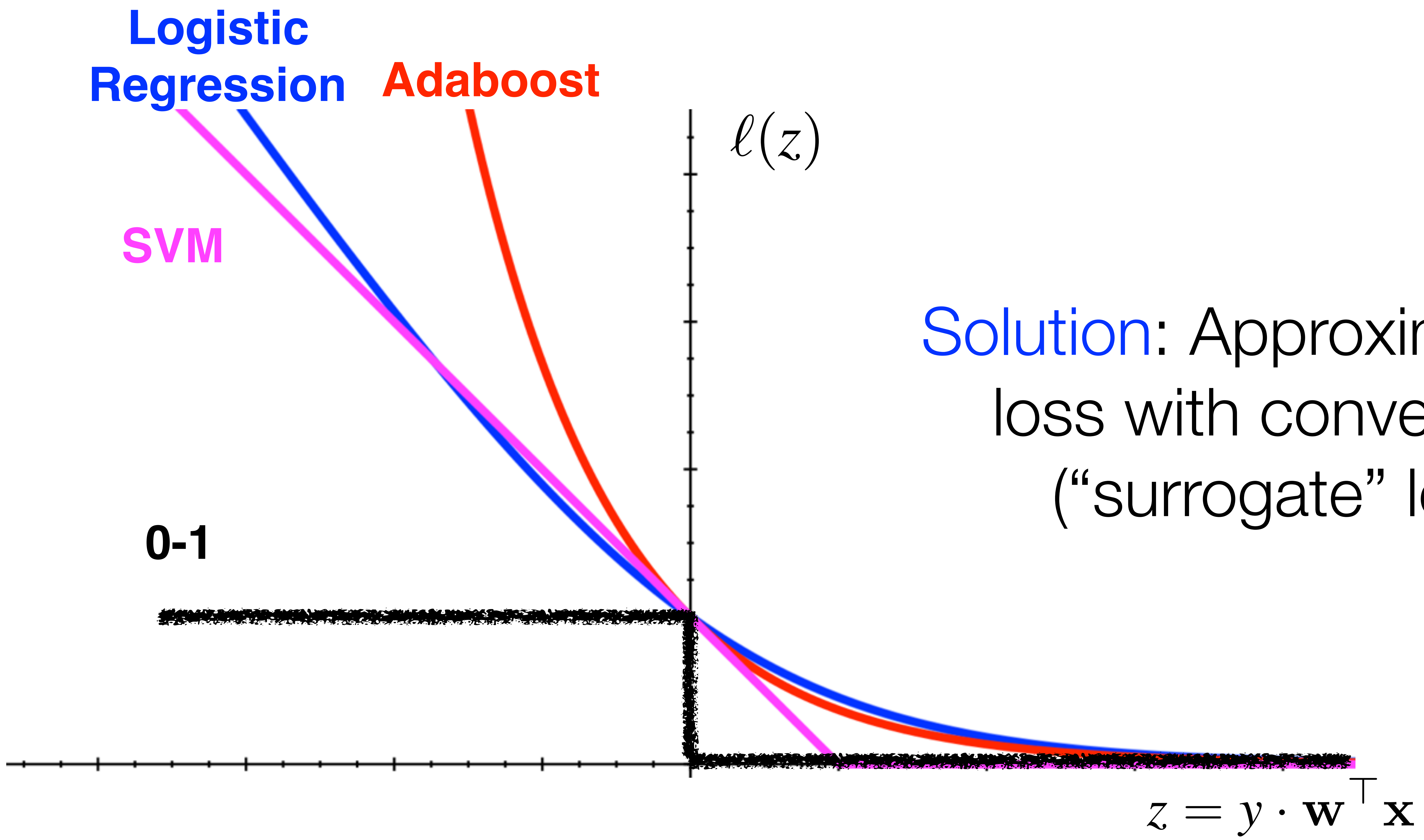


Issue: hard optimization problem, not convex!

Let $y \in \{-1, 1\}$ and define $z = y \cdot \mathbf{w}^\top \mathbf{x}$

z is positive if y and $\mathbf{w}^\top \mathbf{x}$ have same sign, negative otherwise

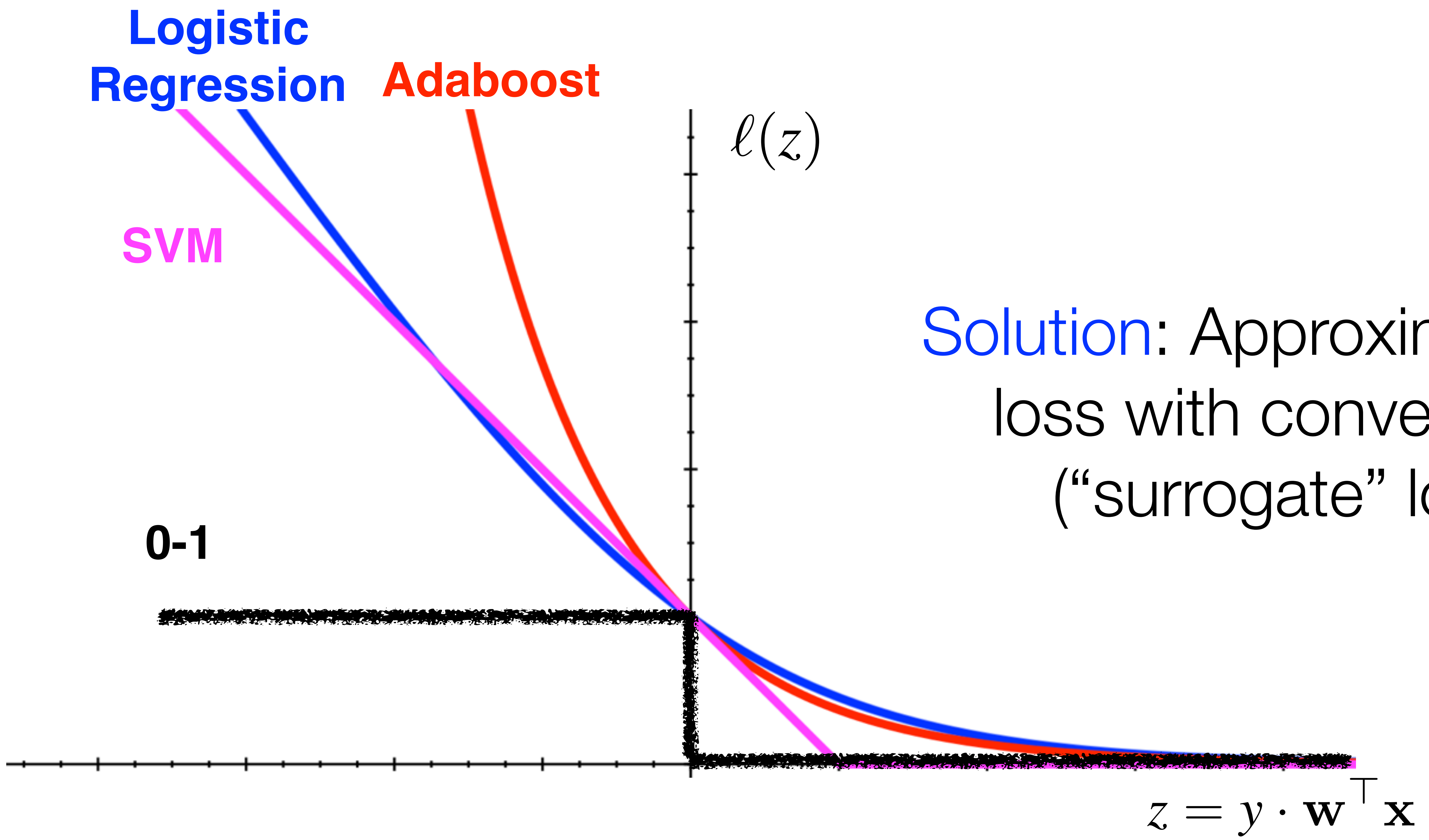
Approximate 0/1 Loss



Solution: Approximate 0/1 loss with convex loss ("surrogate" loss)

SVM (hinge), Logistic regression (logistic), Adaboost (exponential)

Approximate 0/1 Loss



Solution: Approximate 0/1 loss with convex loss ("surrogate" loss)

Logistic loss (logloss): $\ell_{log}(z) = \log(1 + e^{-z})$

Logistic Regression Optimization

Logistic Regression: Learn mapping ($\mathbf{w}$) that minimizes logistic loss on training data

$$\min_{\mathbf{w}} \sum_{i=1}^{n} \ell_{log}\left(y^{(i)} \cdot \mathbf{w}^\top \mathbf{x}^{(i)}\right)$$

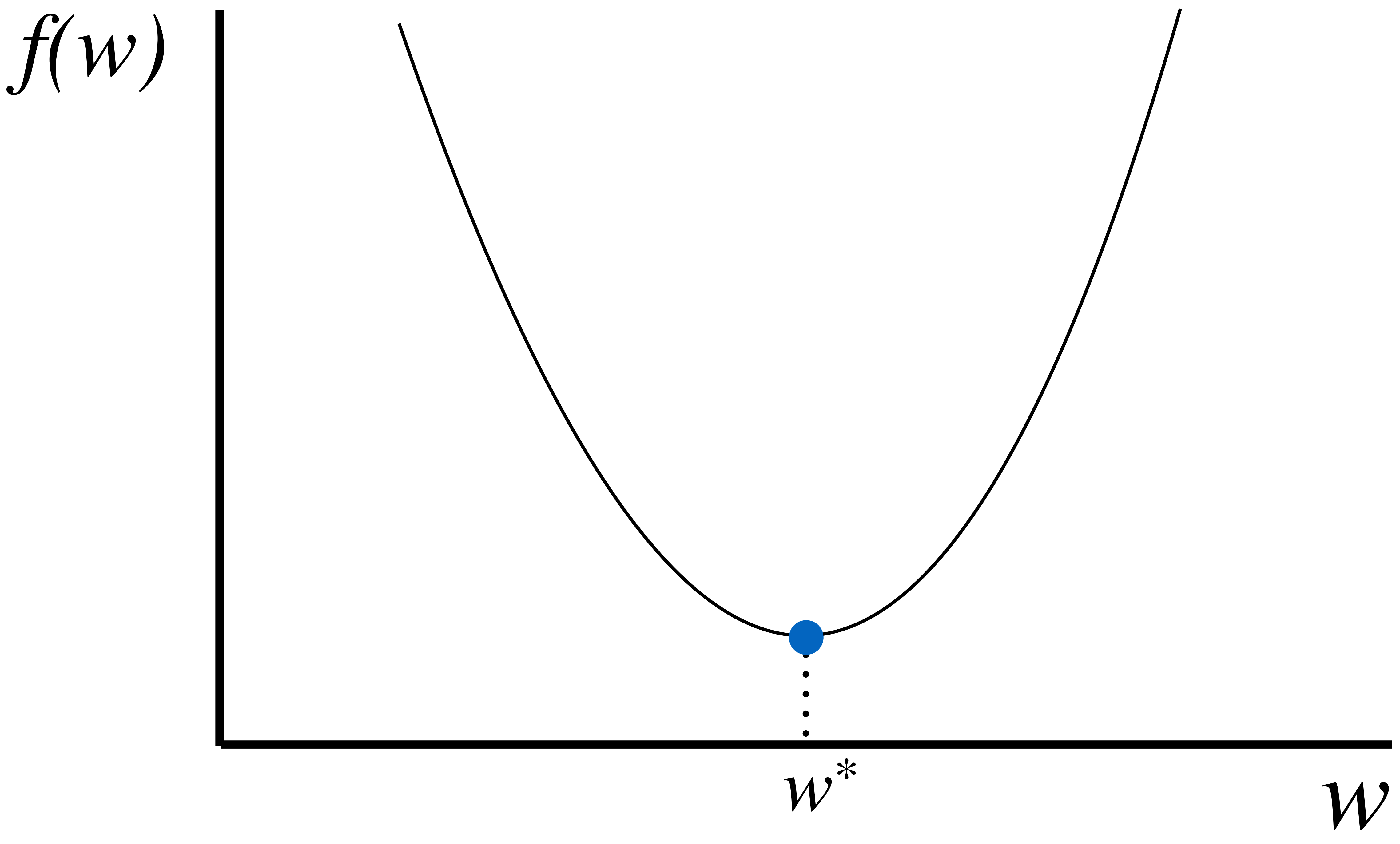
- Convex
- Closed form solution doesn't exist

Logistic Regression Optimization

Goal: Find $\mathbf{w}^*$ that minimizes

$$f(\mathbf{w}) = \sum_{i=1}^{n} \ell_{log}\left(y^{(i)} \cdot \mathbf{w}^\top \mathbf{x}^{(i)}\right)$$

- Can solve via Gradient Descent



Step Size

Update Rule: $\mathbf{w}_{i+1} = \mathbf{w}_i - \alpha \nabla f(\mathbf{w})$

$$\sum_{j=1}^{n}\left[1 - \frac{1}{1 + \exp(-y^{(j)}\mathbf{w}_i^\top \mathbf{x}^{(j)})}\right]\left(-y^{(j)}\mathbf{x}^{(j)}\right)$$

Gradient

Logistic Regression Optimization

Regularized

Logistic Regression: Learn mapping ($\mathbf{w}$) that minimizes logistic loss on training data

$$\min_{\mathbf{w}} \sum_{i=1}^{n} \ell_{log}\left(y^{(i)} \cdot \mathbf{w}^\top \mathbf{x}^{(i)}\right)$$

- Convex
- Closed form solution doesn't exist
- Can add regularization term (as in ridge regression)