Warm up: risk prediction with logistic regression

- Boss gives you a bunch of data on loans defaulting or not:

$$\{(x_i, y_i)\}_{i=1}^n \quad x_i \in \mathbb{R}^d, \quad y_i \in \{-1, 1\}$$

- You model the data as: $$P(Y = y|x, w) = \frac{1}{1 + \exp(-y\, w^T x)}$$
- And compute the maximum likelihood estimator:

$$\widehat{w}_{MLE} = \arg\max_w \prod_{i=1}^n P(y_i|x_i, w)$$

For a new loan application x, boss recommends to give loan if your model says they will repay it with probability at least .95 (i.e. low risk):

Give loan to x if $$\frac{1}{1 + \exp(-\widehat{w}_{MLE}^T x)} \geq .95$$

- One year later only half of loans are paid back and the bank folds. What might have happened? Model wrong, finite data, data shift, massive class imbalance (e.g. no 0 class), no regularization, not iid,

Projects

Proposal due Thursday 10/25

Guiding principles (for evaluation of project)

- Keep asking yourself "**why**" something works or not. Dig deeper than just evaluating the method and reporting a test error.
- Must use **real-world data** available NOW
- Must report **metrics**
- Must reference papers and/or books

- Study a real-world dataset
  - Evaluate multiple machine learning methods
  - Why does one work better than another? Form a hypothesis and test the hypothesis with a subset of the real data or, if necessary, synthetic data
- Study a method
  - Evaluate on multiple real-world datasets
  - Why does the method work better on one dataset versus another? Form a hypothesis…

Perceptron

Machine Learning – CSE546
Kevin Jamieson
University of Washington

October 23, 2018

Binary Classification

- **Learn**: f:**X** —>Y
  - **X** – features
  - Y – target classes

    $$Y \in \{-1, 1\}$$

- **Loss function:**

  $$\ell(f(x), y) = \mathbf{1}\{f(x) \neq y\}$$

- **Expected loss of f:**

$$\mathbb{E}_{XY}[\mathbf{1}\{f(X) \neq Y\}] = \mathbb{E}_X[\mathbb{E}_{Y|X}[\mathbf{1}\{f(x) \neq Y\}|X = x]]$$

$$\mathbb{E}_{Y|X}[\mathbf{1}\{f(x) \neq Y\}|X = x] = 1 - P(Y = f(x)|X = x)$$

- **Bayes optimal classifier:**

$$f(x) = \arg\max_y \mathbb{P}(Y = y|X = x)$$

Binary Classification

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- **Bayes optimal classifier:**

$$f(x) = \arg\max_y \mathbb{P}(Y = y|X = x)$$

- **Model of logistic regression:**

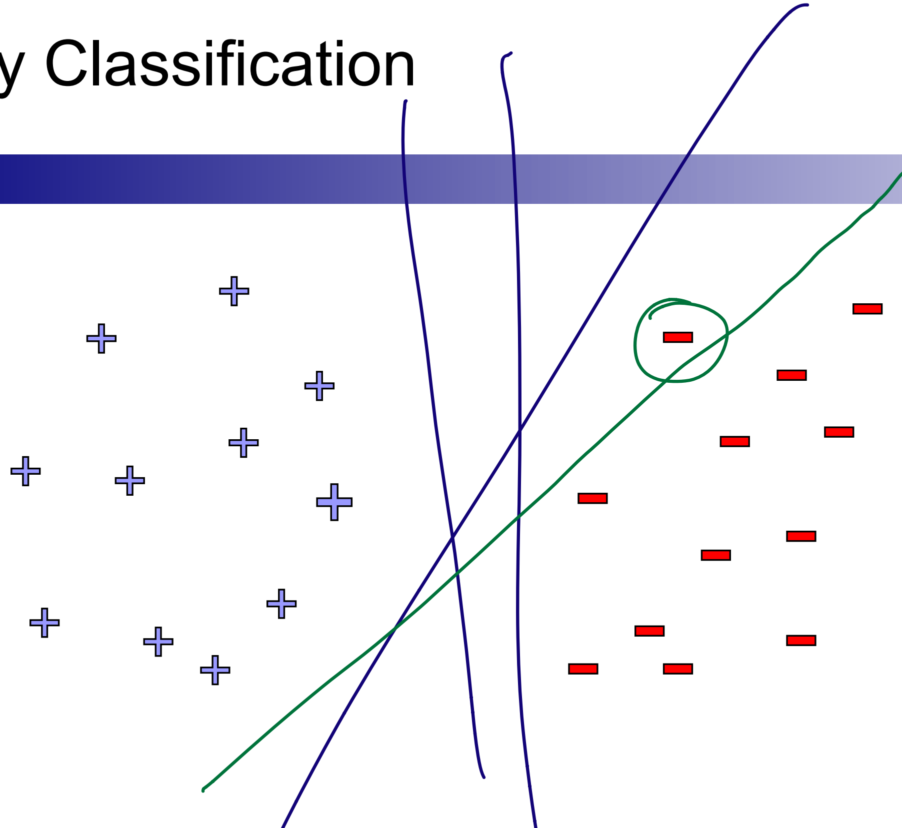
$$P(Y = y|x, w) = \frac{1}{1 + \exp(-y\, w^T x)}$$

- **Loss function:**

$$\ell(f(x), y) = \mathbf{1}\{f(x) \neq y\}$$

What if the model is wrong?

Binary Classification



Can we do classification without a model of $\mathbb{P}(Y = y | X = x)$?

The Perceptron Algorithm [Rosenblatt '58, '62]

- Classification setting: y in {-1,+1}
- Linear model
  - Prediction: $\text{SIGN}(w^T x + b)$ (parameters $w \in \mathbb{R}^d$, $b \in \mathbb{R}$)
- Training:
  - Initialize weight vector: $w = 0$, $b = 0$
  - At each time step:
    - Observe features: x_t
    - Make prediction: $\text{SIGN}(w^T x_t + b) = \hat{y}_t$
    - Observe true class: y_t
    - Update model:
      - If prediction is not equal to truth $\hat{y}_t \neq y_t$

$$\begin{bmatrix} w \\ b \end{bmatrix} = \begin{bmatrix} w \\ b \end{bmatrix} + \begin{bmatrix} x_t \\ 1 \end{bmatrix} y_t$$

The Perceptron Algorithm [Rosenblatt '58, '62]

- Classification setting: y in {-1,+1}
- Linear model
  - Prediction: $\text{sign}(w^T x_i + b)$
- Training:
  - Initialize weight vector: $w_0 = 0, b_0 = 0$
  - At each time step:
    - Observe features: x_k
    - Make prediction: $\text{sign}(x_k^T w_k + b_k)$
    - Observe true class: y_k
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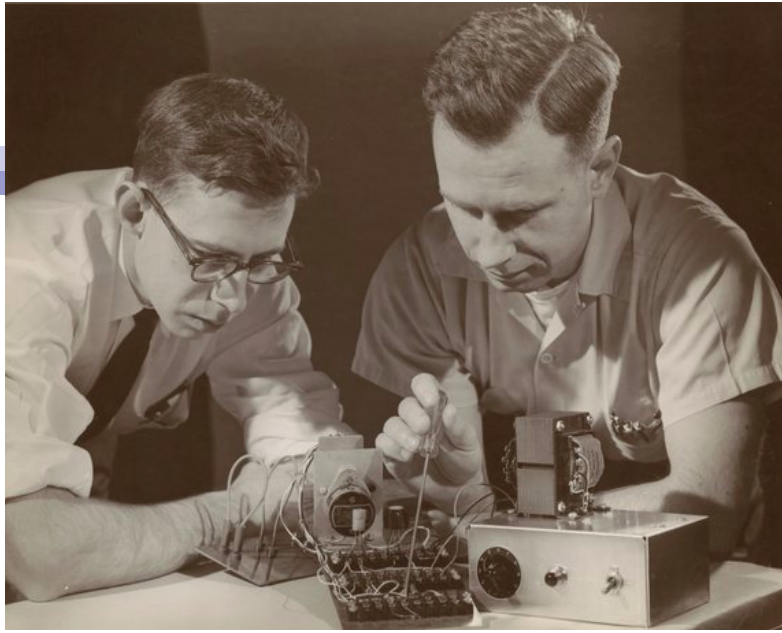
$$\begin{bmatrix} w_{k+1} \\ b_{k+1} \end{bmatrix} = \begin{bmatrix} w_k \\ b_k \end{bmatrix} + y_k \begin{bmatrix} x_k \\ 1 \end{bmatrix}$$

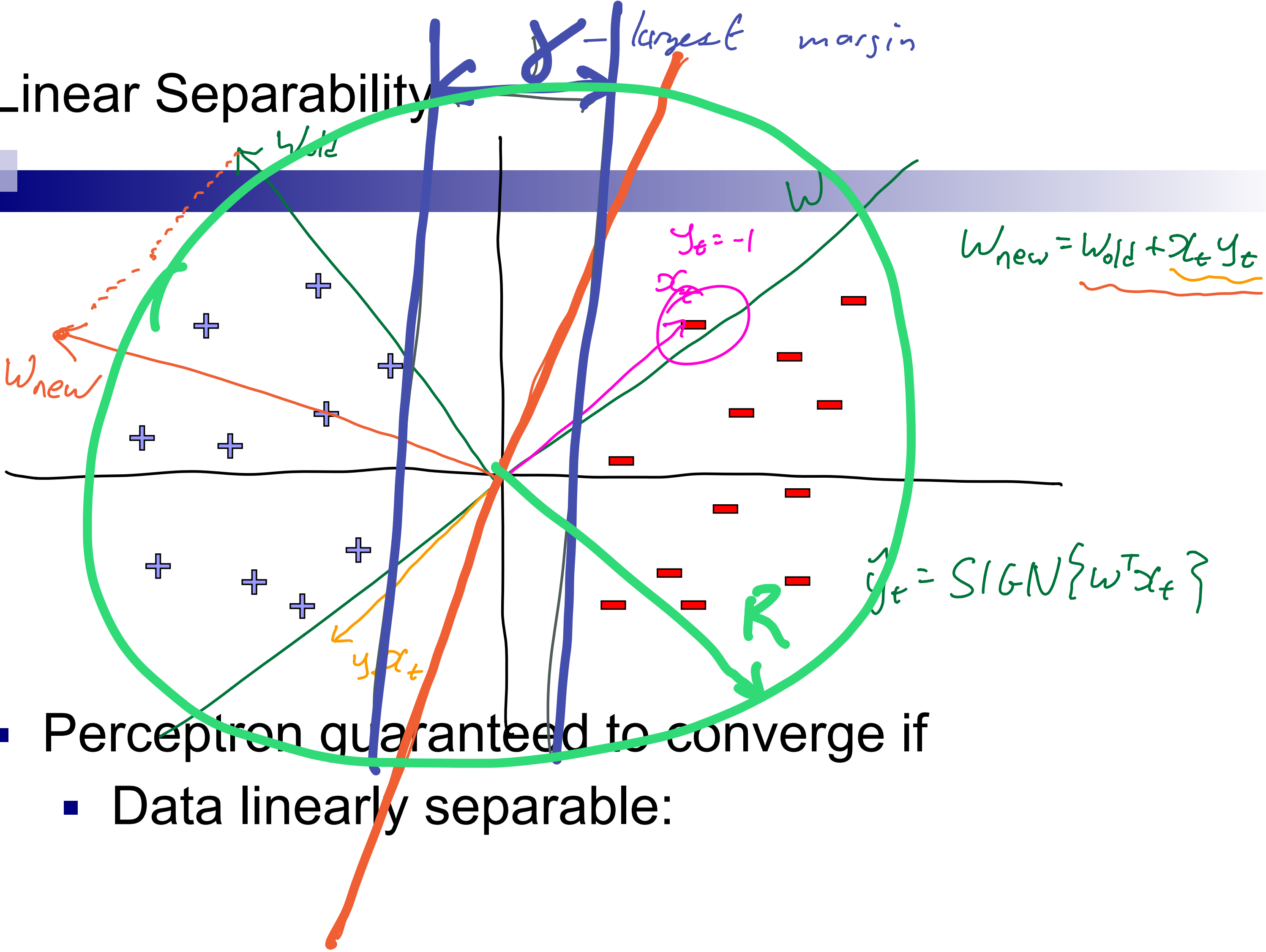


Rosenblatt 1957

"the embryo of an electronic computer that [the Navy] expects will be able to walk, talk, see, write, reproduce itself and be conscious of its existence."

The New York Times, 1958

Linear Separability



- Perceptron guaranteed to converge if
  - Data linearly separable:

Perceptron Analysis: Linearly Separable Case

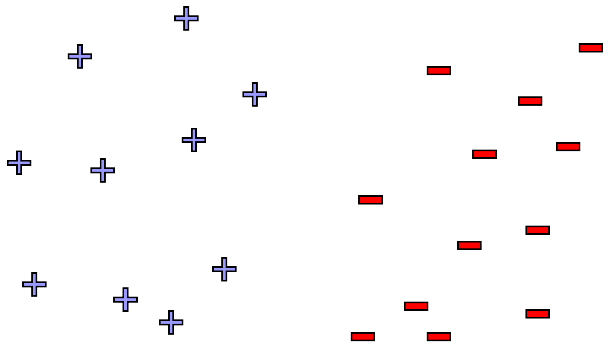
- Theorem [Block, Novikoff]:
  - Given a sequence of labeled examples: (x_t, y_t)
  - Each feature vector has bounded norm: $\|x_t\| \leq R$
  - If dataset is linearly separable: w/ margin γ

- Then the number of mistakes made by the online perceptron on any such sequence is bounded by

$$\frac{R^2}{\gamma^2}$$

Beyond Linearly Separable Case

- Perceptron algorithm is super cool!
  - No assumption about data distribution!
    - Could be generated by an oblivious adversary, no need to be iid
  - Makes a fixed number of mistakes, and it's done for ever!
    - Even if you see infinite data



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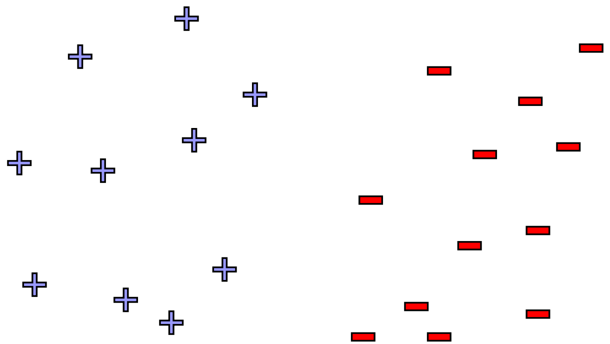

- Perceptron is useless in practice!
  - Real world not linearly separable
  - If data not separable, cycles forever and hard to detect
  - Even if separable may not give good generalization accuracy (small margin)

What is the Perceptron Doing???

- When we discussed logistic regression:
  - Started from maximizing conditional log-likelihood

modeling $P(Y=y|X=x)$

- When we discussed the Perceptron:
  - Started from description of an algorithm

Update w in some way.

- What is the Perceptron optimizing????

Support Vector Machines (SVM)

Machine Learning – CSE546

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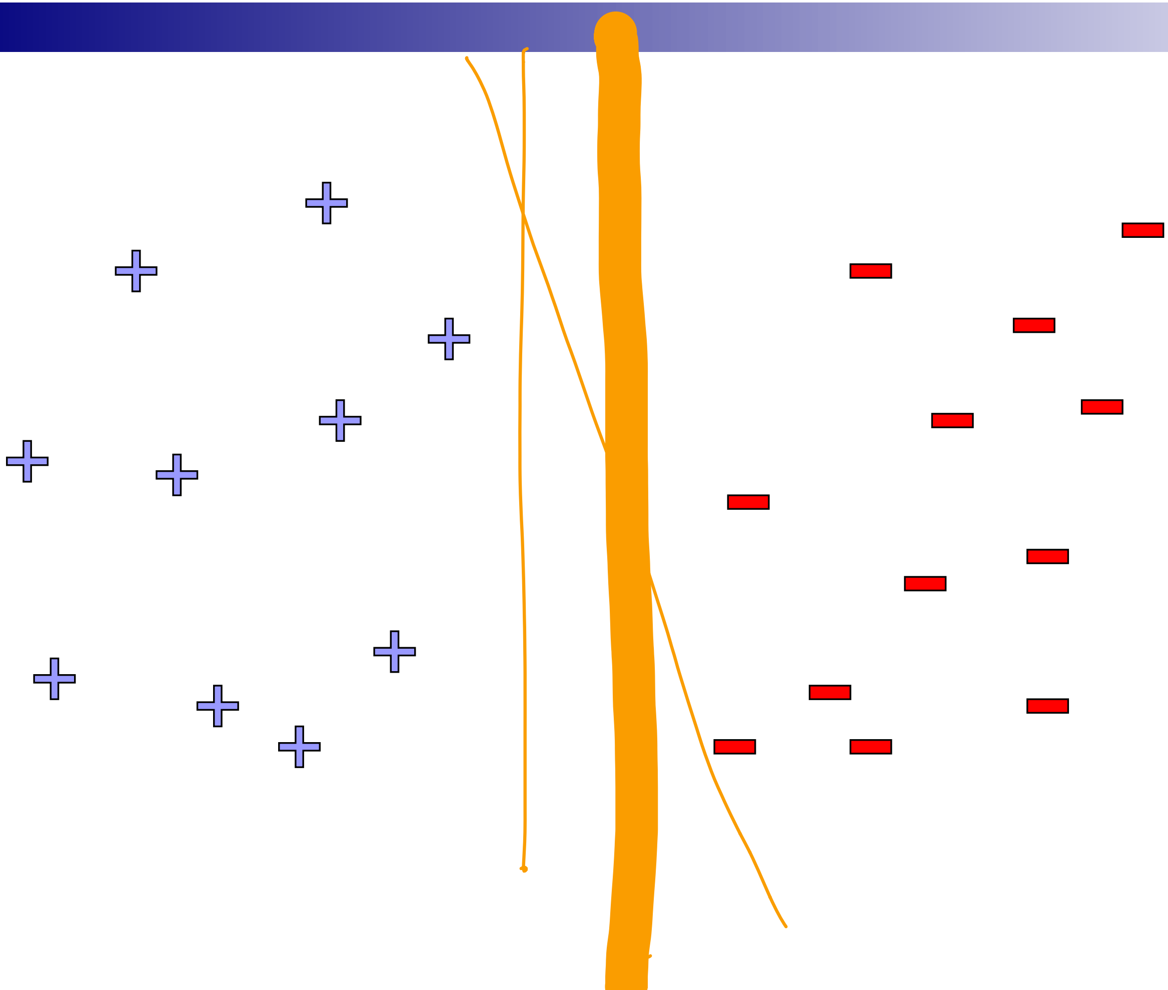
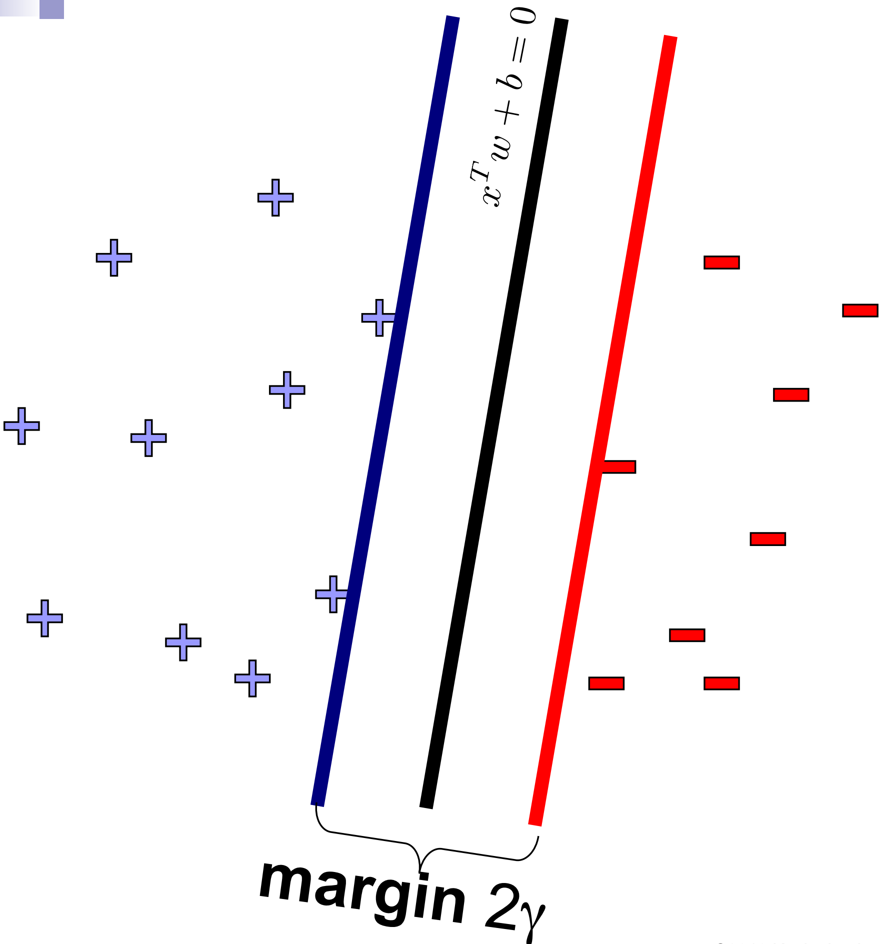
Linear classifiers – Which line is better?



Pick the one with the largest margin!



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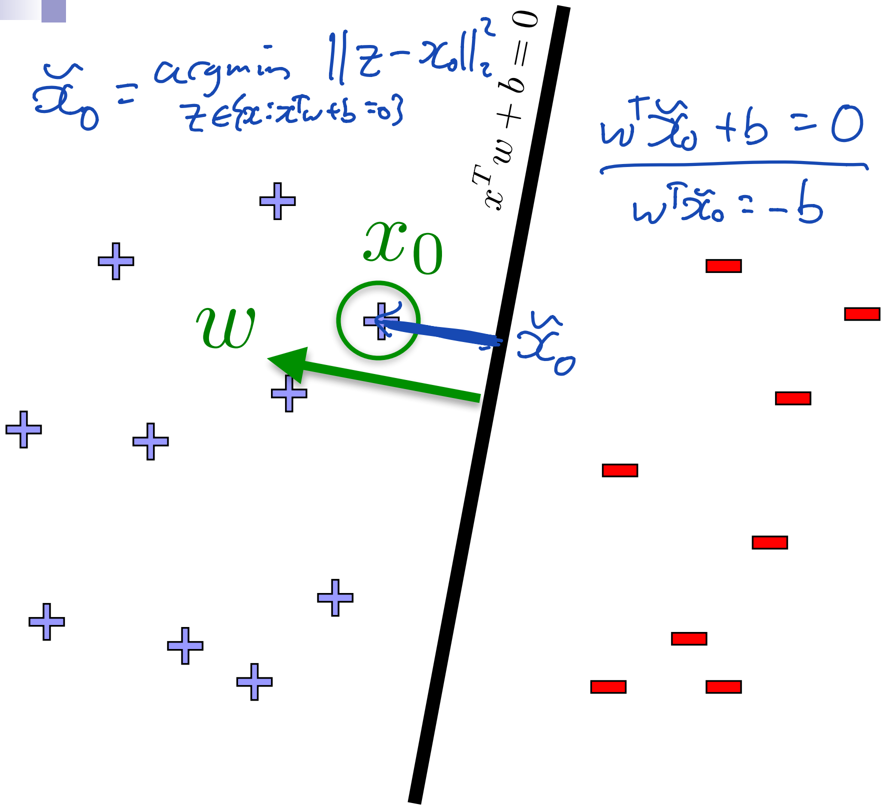


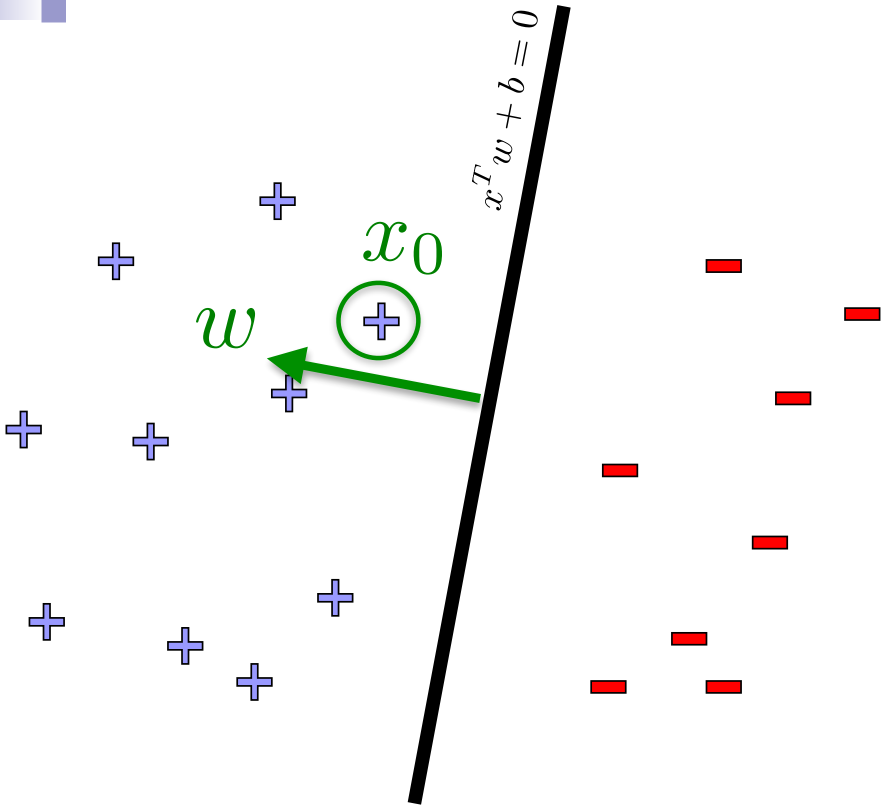
$$\tilde{x}_0 = \arg\min_{z \in \{x : x^T w + b = 0\}} \|z - x_0\|_2^2$$

$$w^T \tilde{x}_0 + b = 0$$
$$w^T \tilde{x}_0 = -b$$

Distance from x_0 to hyperplane defined by $x^T w + b = 0$?

$$\|x_0 - \tilde{x}_0\|_2 = \left| \frac{w^T}{\|w\|_2}(x_0 - \tilde{x}_0) \right|$$
$$= \frac{1}{\|w\|_2} \left| w^T x_0 + b \right|$$

Pick the one with the largest margin!



Distance from x_0 to hyperplane defined by $x^T w + b = 0$?

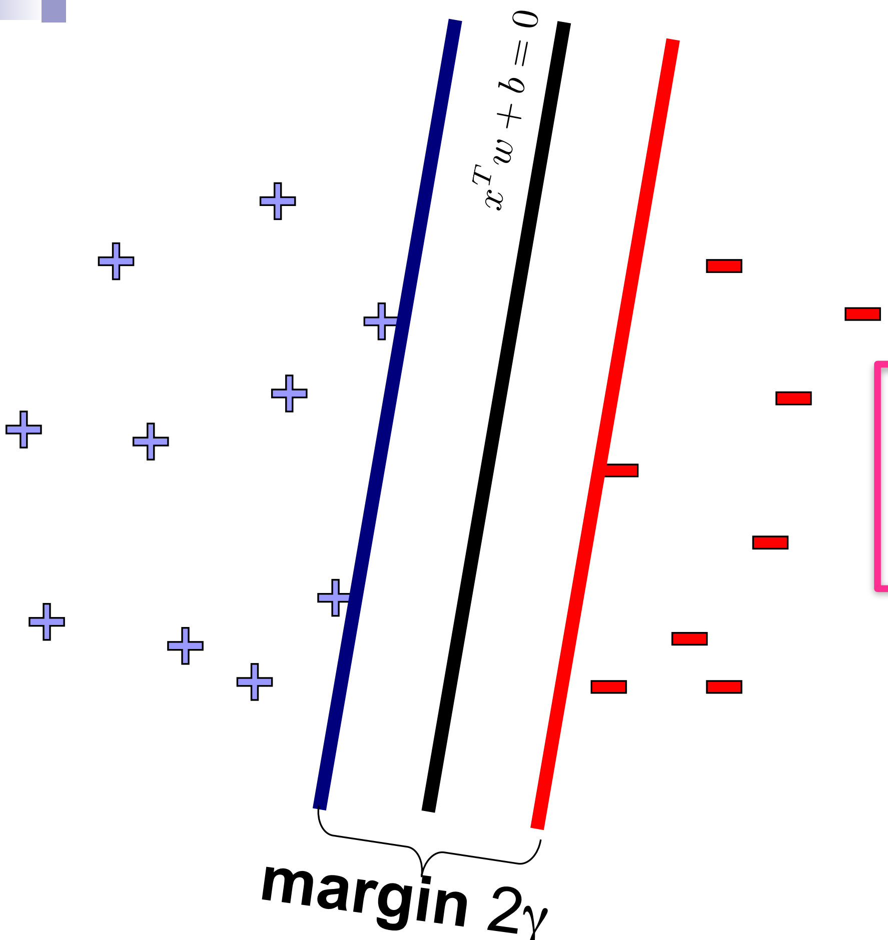
If $\widetilde{x}_0$ is the projection of x_0 onto the hyperplane then

$$||x_0 - \widetilde{x}_0||_2 = |(x_0^T - \widetilde{x}_0)^T \frac{w}{||w||_2}|$$

$$= \frac{1}{||w||_2} |x_0^T w - \widetilde{x}_0^T w|$$

$$= \frac{1}{||w||_2} |x_0^T w + b|$$

Pick the one with the largest margin!



Distance of x_0 from hyperplane $x^T w + b$:

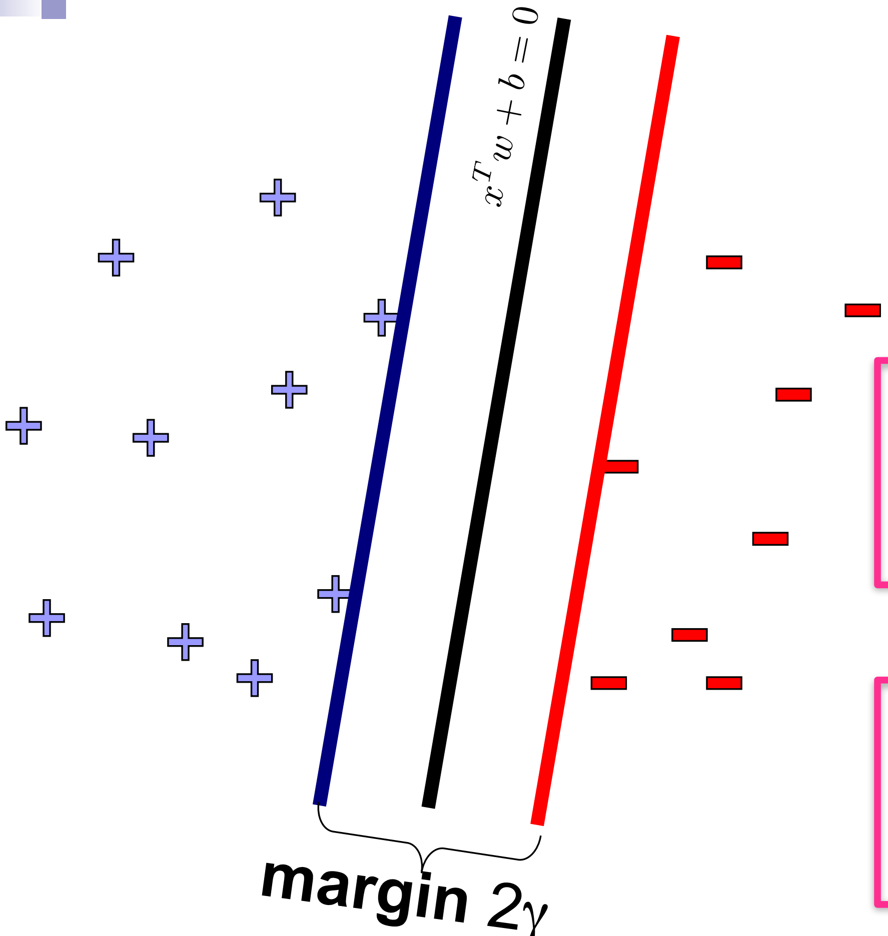
$$\frac{1}{||w||_2}(x_0^T w + b)$$

Optimal Hyperplane

$$\max_{w,b} \gamma$$

$$\text{subject to } \frac{1}{||w||_2} y_i (x_i^T w + b) \geq \gamma \quad \forall i$$

Pick the one with the largest margin!



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$$\max_{w,b} \gamma$$
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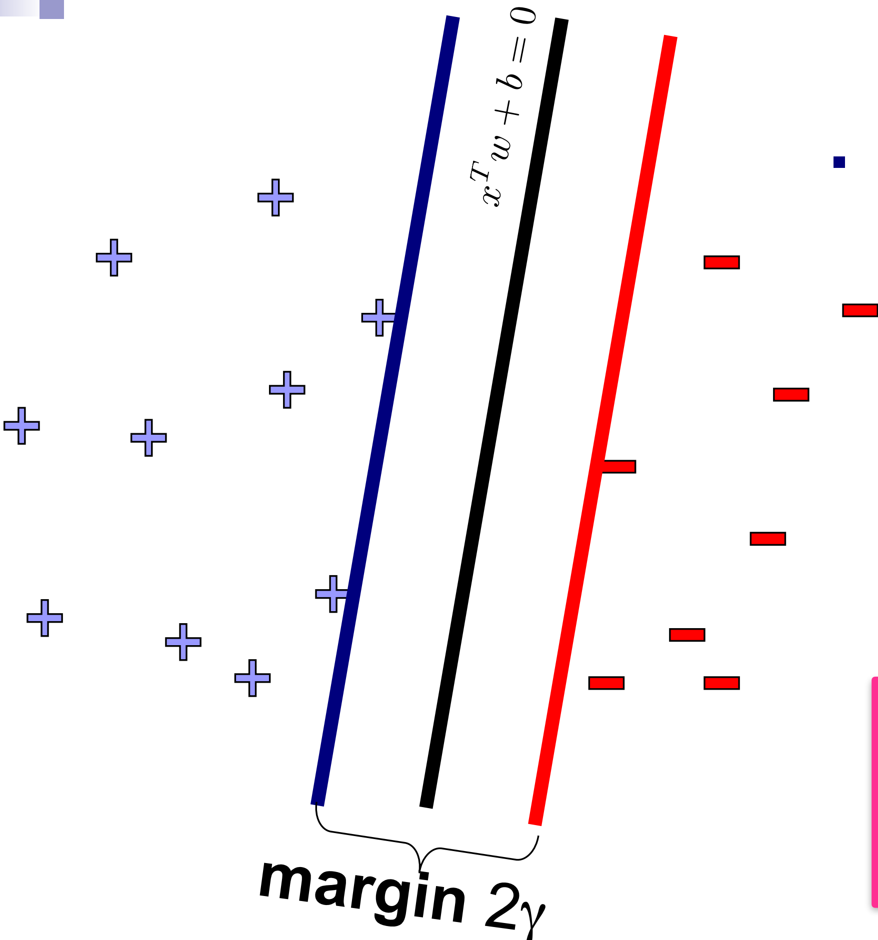
Optimal Hyperplane (reparameterized)

$$\min_{w,b} ||w||_2^2$$
$$\text{subject to } y_i (x_i^T w + b) \geq 1 \quad \forall i$$

Pick the one with the largest margin!



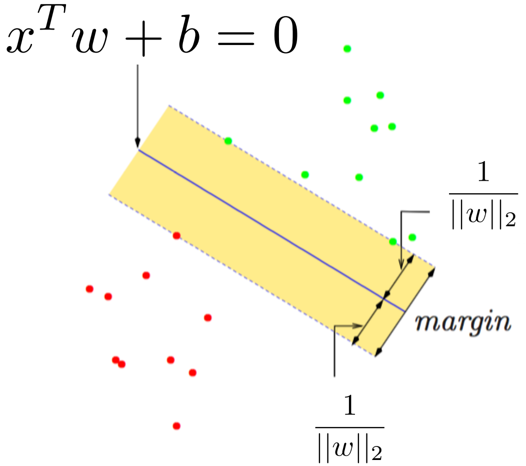
- Solve efficiently by many methods, e.g.,
  - quadratic programming (QP)
    - Well-studied solution algorithms
  - Stochastic gradient descent
  - Coordinate descent (in the dual)

Optimal Hyperplane (reparameterized)

$$\min_{w,b} ||w||_2^2$$

$$\text{subject to } y_i(x_i^T w + b) \geq 1 \quad \forall i$$

What if the data is still not linearly separable?

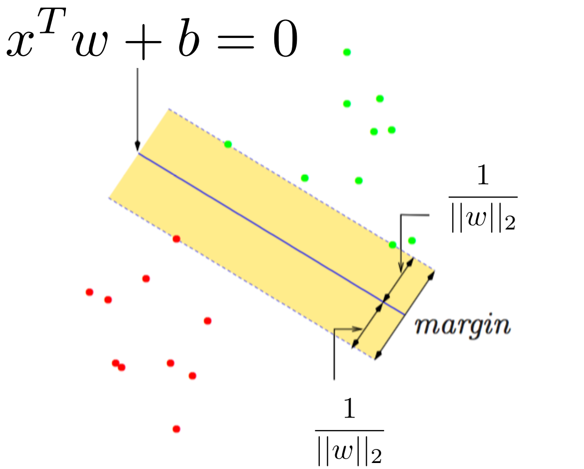


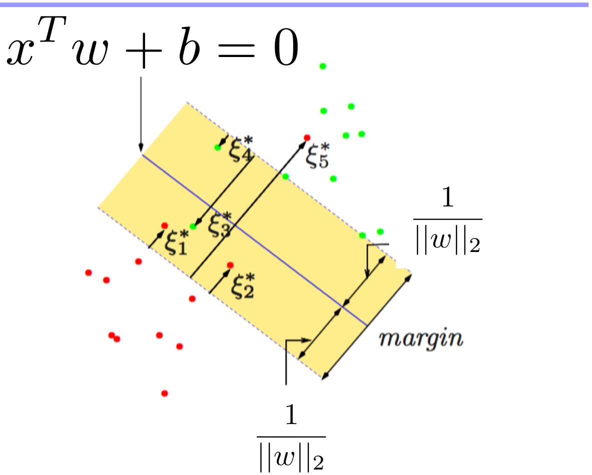
- If data is linearly separable

$$\min_{w,b} ||w||_2^2$$

$$y_i(x_i^T w + b) \geq 1 \quad \forall i$$

What if the data is still not linearly separable?





- If data is linearly separable

$$\min_{w,b} ||w||_2^2$$

$$y_i(x_i^T w + b) \geq 1 \quad \forall i$$

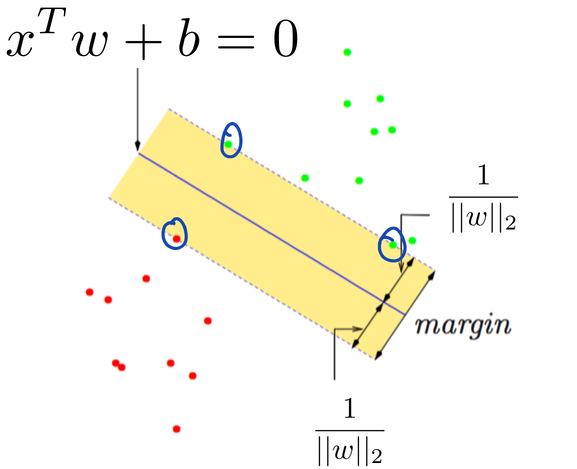
- If data is not linearly separable, some points don't satisfy margin constraint:

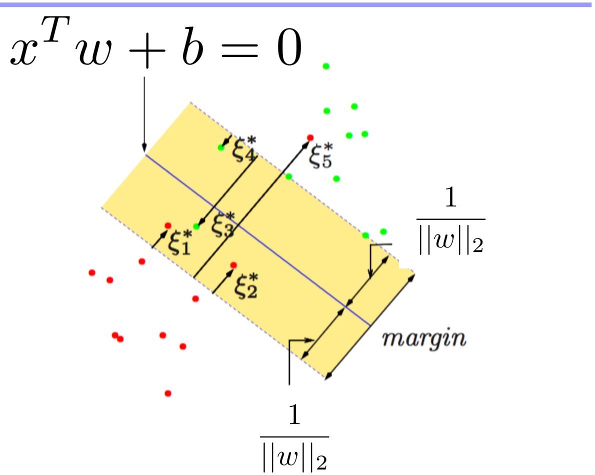
$$\min_{w,b} ||w||_2^2$$

$$y_i(x_i^T w + b) \geq 1 - \xi_i \quad \forall i$$

$$\xi_i \geq 0, \sum_{j=1}^{n} \xi_j \leq \nu$$

What if the data is still not linearly separable?





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$$\xi_i \geq 0, \sum_{j=1}^{n} \xi_j \leq \nu$$

- What are "support vectors?"

SVM as penalization method

- Original quadratic program with linear constraints:

$$\min_{w,b} ||w||_2^2$$

$$y_i(x_i^T w + b) \geq 1 - \xi_i \quad \forall i$$

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- Original quadratic program with linear constraints:

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$$\xi_i \geq 0, \sum_{j=1}^{n} \xi_j \leq \nu$$

$+ \frac{1}{\lambda} \sum \xi_i$

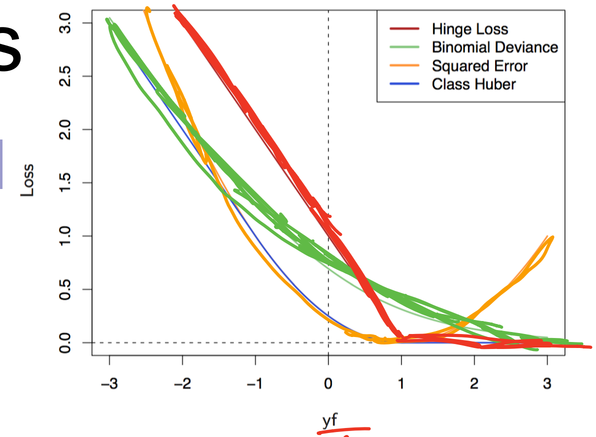
- Using same constrained convex optimization trick as for lasso:

For any $\nu \geq 0$ there exists a $\lambda \geq 0$ such that the solution the following solution is equivalent:

$$\sum_{i=1}^{n} \max\{0, 1 - y_i(b + x_i^T w)\} + \lambda ||w||_2^2$$

Largest margin classifier

Machine Learning Problems



- Have a bunch of iid data of the form:

$$\{(x_i, y_i)\}_{i=1}^n \qquad x_i \in \mathbb{R}^d \qquad y_i \in \mathbb{R}$$

- Learning a model's parameters:

$$\sum_{i=1}^n \ell_i(w)$$

Each $\ell_i(w)$ is convex.

Hinge Loss: $\ell_i(w) = \max\{0, 1 - y_i x_i^T w\}$

Logistic Loss: $\ell_i(w) = \log(1 + \exp(-y_i\, x_i^T w))$

Squared error Loss: $\ell_i(w) = (y_i - x_i^T w)^2$

How do we solve for *w*? The last two lectures!

Perceptron is optimizing what?

Perceptron update rule:

$$\begin{bmatrix} w_{k+1} \\ b_{k+1} \end{bmatrix} = \begin{bmatrix} w_k \\ b_k \end{bmatrix} + y_k \begin{bmatrix} x_k \\ 1 \end{bmatrix} \mathbf{1}\{y_i(b + x_i^T w) < 0\}$$

SVM objective:

$$\sum_{i=1}^n \underbrace{\max\{0, 1 - y_i(b + x_i^T w)\} + \lambda ||w||_2^2}_{\ell_i(w,b)} = \sum_{i=1}^n \ell_i(w,b)$$

$$\nabla_w \ell_i(w,b) = \begin{cases} -y_i x_i + \frac{2\lambda}{n} w & \text{if } 1 - y_i(b + x_i^T w) > 0 \\ \frac{2\lambda}{n} w & \text{otherwise.} \end{cases}$$

I_t unif at random (n).

$$w_{t+1} = w_t - \nabla_w \ell_{I_t}(w_t, b_t)\,\eta$$

Perceptron is optimizing what?

Perceptron update rule:

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SVM objective:

$$\sum_{i=1}^{n} \max\{0, 1 - y_i(b + x_i^T w)\} + \lambda ||w||_2^2 = \sum_{i=1}^{n} \ell_i(w, b)$$

$$\nabla_w \ell_i(w,b) = \begin{cases} -x_i y_i + \frac{2\lambda}{n} w & \text{if } y_i(b + x_i^T w) < 1 \\ 0 & \text{otherwise} \end{cases}$$

=0

$$\nabla_b \ell_i(w,b) = \begin{cases} -y_i & \text{if } y_i(b + x_i^T w) < 1 \\ 0 & \text{otherwise} \end{cases}$$

Perceptron is just ≈SGD on SVM with $\lambda = 0$, $\eta = 1$!

SVMs vs logistic regression

- We often want probabilities/confidences, logistic wins here?

SVMs vs logistic regression

- We often want probabilities/confidences, logistic wins here?
- No! Perform isotonic regression or non-parametric bootstrap for probability calibration. Predictor gives some score, how do we transform that score to a probability?

SVMs vs logistic regression

- We often want probabilities/confidences, logistic wins here?
- No! Perform isotonic regression or non-parametric bootstrap for probability calibration. Predictor gives some score, how do we transform that score to a probability?
- For classification loss, logistic and svm are comparable
- Multiclass setting:
  - Softmax naturally generalizes logistic regression
  - SVMs have
- What about good old least squares?

What about multiple classes?