

Large-Scale Machine Learning (2)

CSEP590A Machine Learning for Big Data

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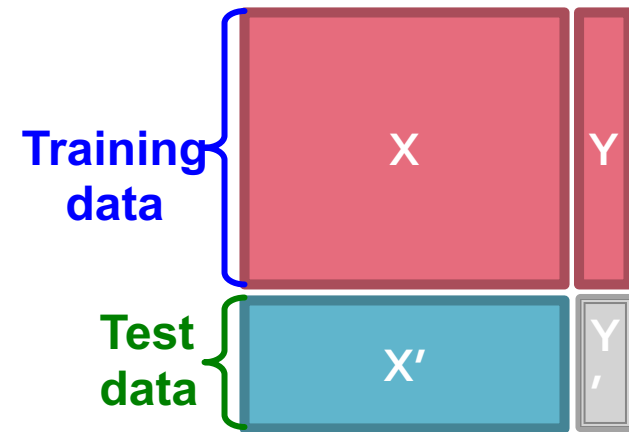
Supervised Learning

- Would like to do **prediction**:
estimate a function $f(x)$ so that $y = f(x)$
- Where y can be:
 - **Real number**: Regression
 - **Categorical**: **Classification**
 - **Complex object**:
 - Ranking of items, Parse tree, etc.
- **Data is labeled**:
 - Have many pairs $\{(x, y)\}$
 - x ... vector of binary, categorical, real valued features
 - y ... class: $\{+1, -1\}$, or a real number

Supervised Learning

- **Task:** Given data (X, Y) build a model $f()$ to predict Y' based on X'
- **Strategy:** Estimate $y = f(x)$ on (X, Y) .

Hope that the same $f(x)$ also works to predict unknown Y'

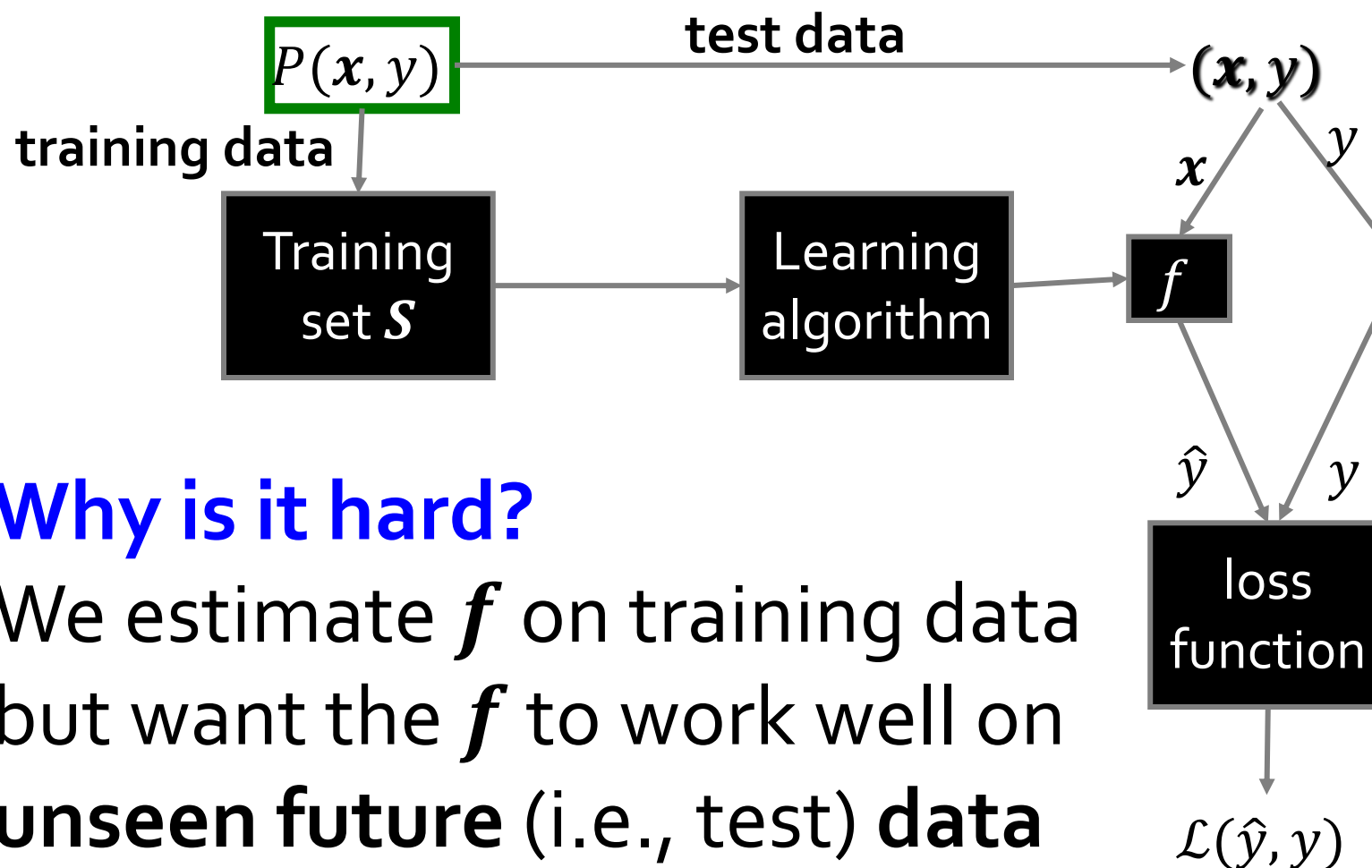


- The “hope” is called **generalization**
 - **Overfitting:** If $f(x)$ predicts well Y but is unable to predict Y'
- **We want to build a model that generalizes well to unseen data**

Formal Setting

- **1)** Training data is drawn independently at random according to unknown probability distribution $P(\mathbf{x}, y)$
- **2)** The learning algorithm analyzes the examples and produces a classifier f
- Given **new** data (\mathbf{x}, y) drawn from P , the classifier is given \mathbf{x} and predicts $\hat{y} = f(\mathbf{x})$
- The **loss** $\mathcal{L}(\hat{y}, y)$ is then measured
- **Goal of the learning algorithm:**
Find f that minimizes **expected loss** $E_P[\mathcal{L}]$

Formal Setting



Minimizing the Loss

- **Goal: Minimize the expected loss**

$$\min_f \mathbb{E}_P[\mathcal{L}]$$

- **But, we don't have access to P but only to training sample D :**

$$\min_f \mathbb{E}_D[\mathcal{L}]$$

- **So, we minimize the average loss on the training data:**

$$\min_f J(f) = \frac{1}{N} \sum_{i=1}^N \mathcal{L}(f(x_i), y_i)$$

Problem: Just memorizing the training data gives us a perfect model (with zero loss)

ML == Optimization

■ Given:

- A set of **N** training examples
 - $\{(x_1, y_1), (x_2, y_2), \dots, (x_n, y_n)\}$
- A loss function \mathcal{L}

■ Choose the model: $f_w(x) = w \cdot x + b$

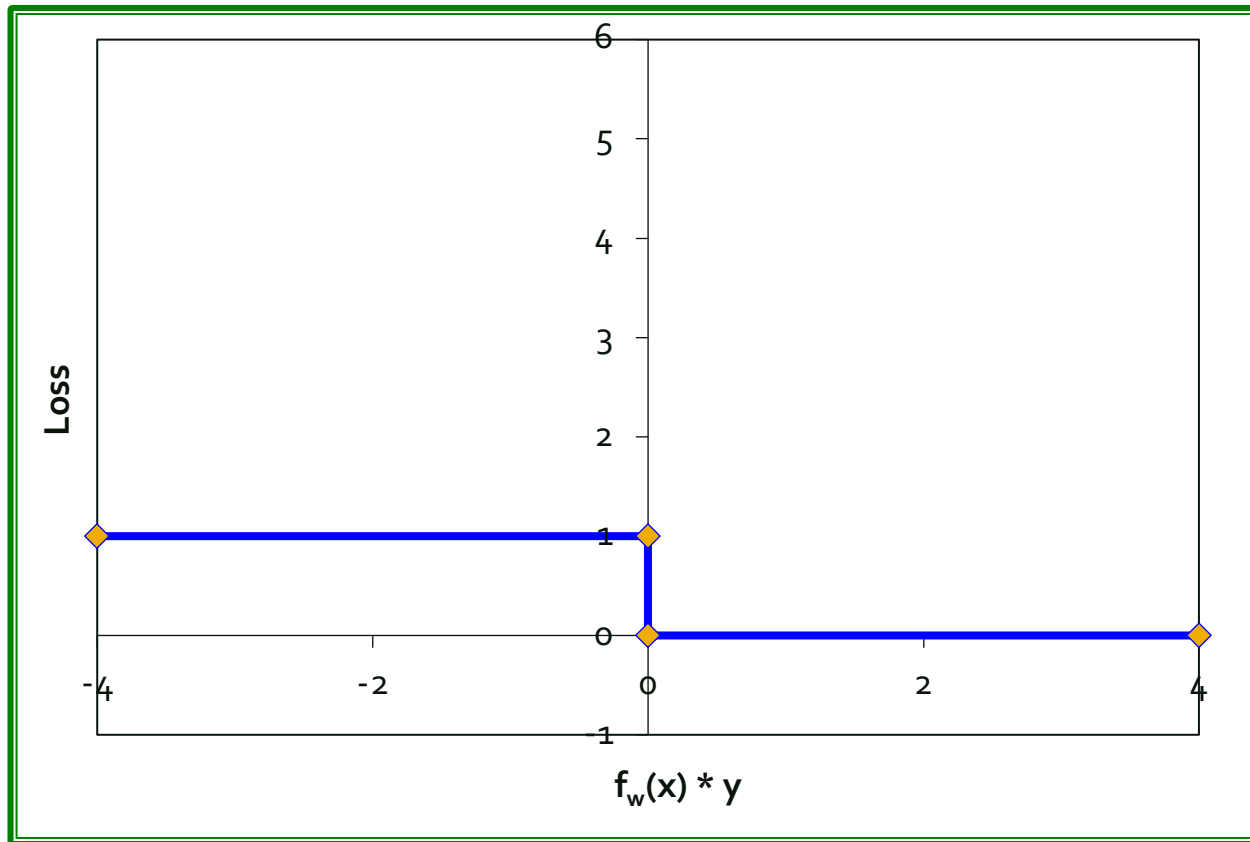
■ Find:

- The weight vector w that minimizes the **expected loss on the training data**

$$J(f) = \frac{1}{N} \sum_{i=1}^N \mathcal{L}(w \cdot x_i + b, y_i)$$

Problem: Loss

- **Problem:** Step-wise Constant 0-1-Loss function



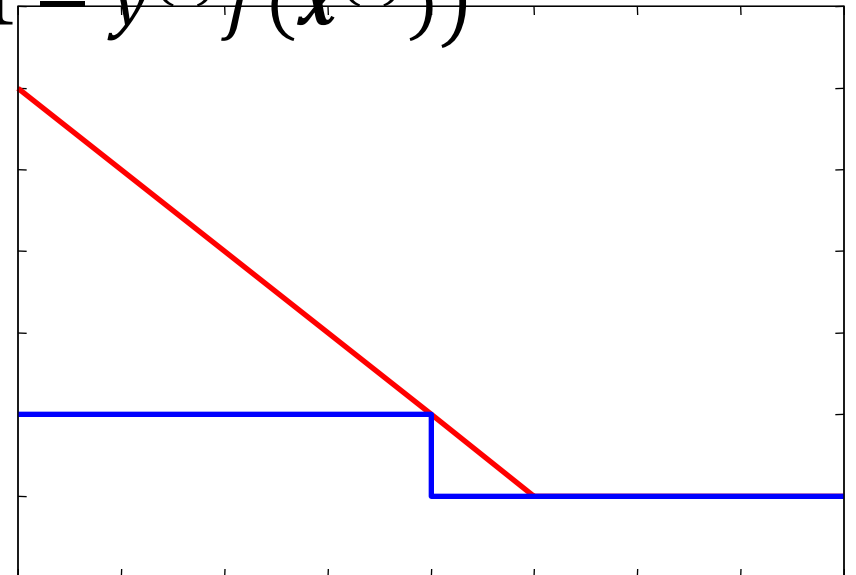
Derivative is either 0 or not differentiable

Approximating the Loss

- **Approximating the expected loss by a smooth function**
 - Replace the original objective function by a surrogate loss function. E.g., **hinge loss**:

$$\tilde{J}(\mathbf{w}) = \frac{1}{N} \sum_{i=1}^N \max(0, 1 - y^{(i)} f(\mathbf{x}^{(i)}))$$

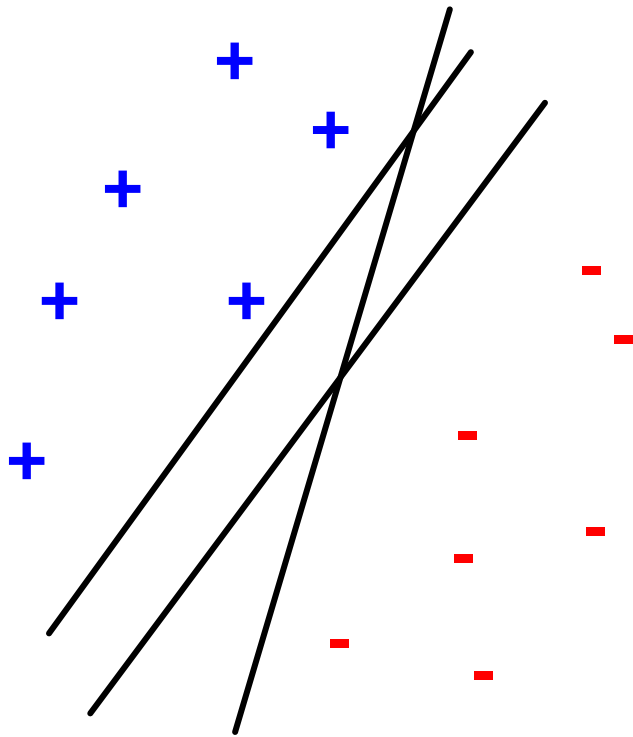
When $y = 1$:



Support Vector Machines

Support Vector Machines

- Want to separate “+” from “-” using a line



Data:

- Training examples:

- $(x_1, y_1) \dots (x_n, y_n)$

- Each example i :

- $x_i = (x_i^{(1)}, \dots, x_i^{(d)})$

- $x_i^{(j)}$ is real valued

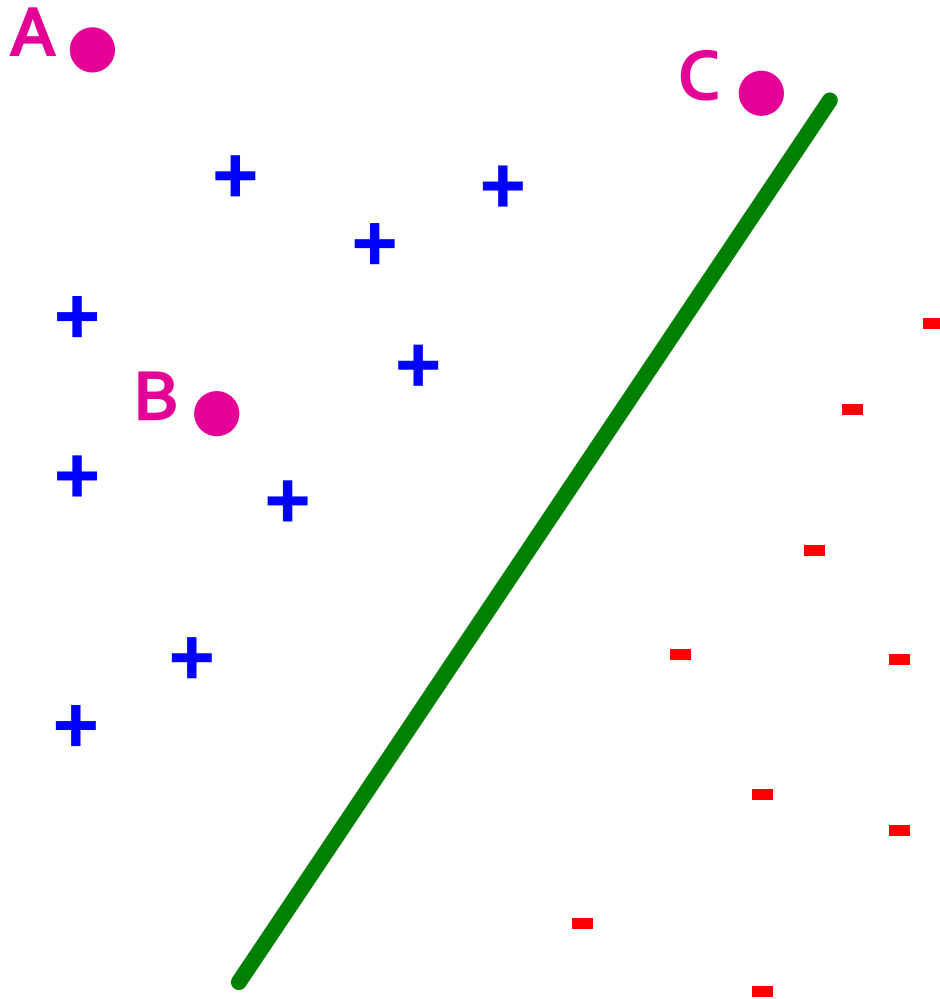
- $y_i \in \{-1, +1\}$

- Inner product:

$$w \cdot x = \sum_{j=1}^d w^{(j)} \cdot x^{(j)}$$

Which is best linear separator (defined by w, b)?

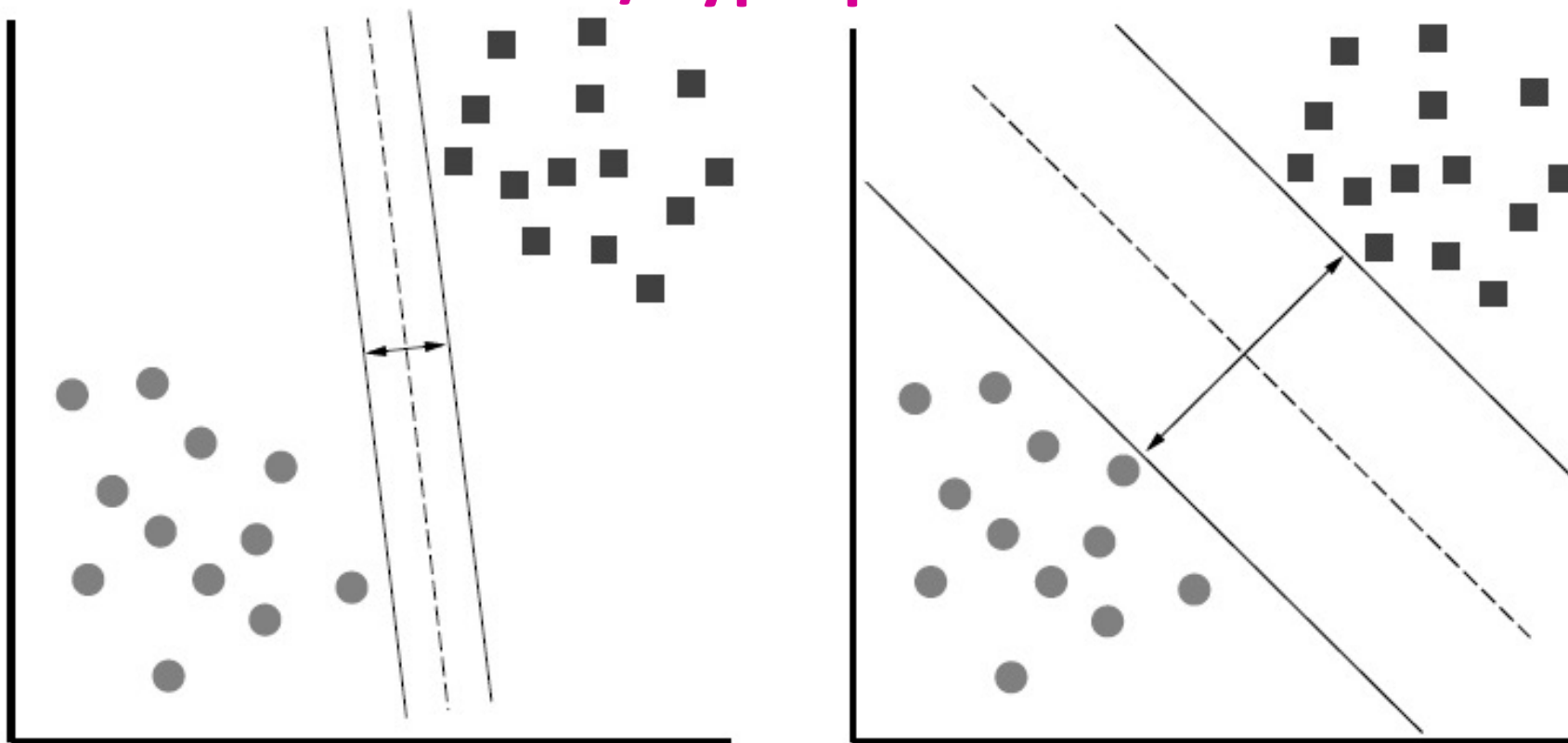
Maximum Margin



- Distance from the separating hyperplane corresponds to the “confidence” of prediction
- Example:
 - We are more sure about the class of **A** and **B** than of **C**

Maximum Margin

- **Margin γ : Distance of closest example from the decision line/hyperplane**

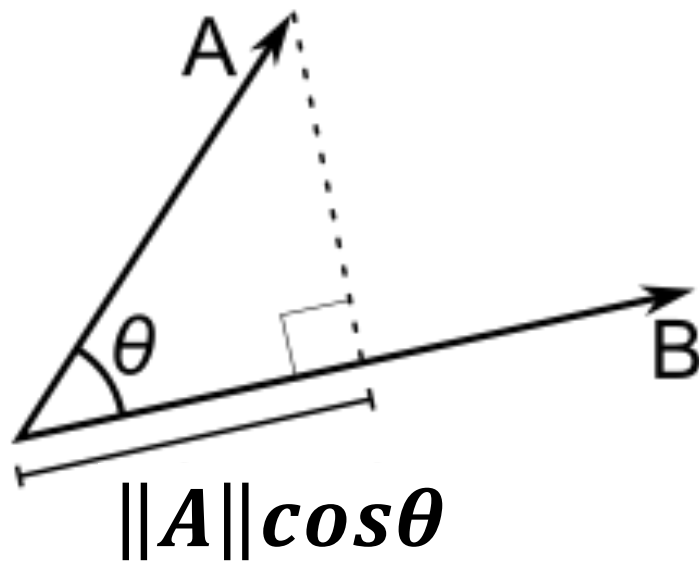


The reason we define margin this way is due to theoretical convenience and existence of generalization error bounds that depend on the value of margin.

Why maximizing γ a good idea?

- Remember: The Dot product

$$\mathbf{A} \cdot \mathbf{B} = \|\mathbf{A}\| \cdot \|\mathbf{B}\| \cdot \cos \theta$$



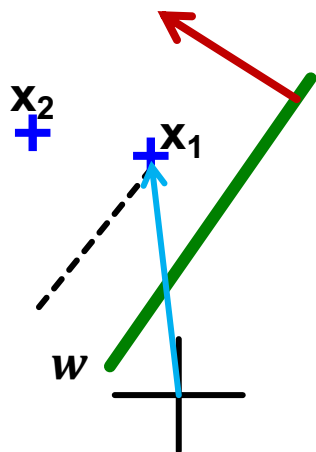
$$\|\mathbf{A}\| = \sqrt{\sum_{j=1}^d (\mathbf{A}^{(j)})^2}$$

Why maximizing γ a good idea?

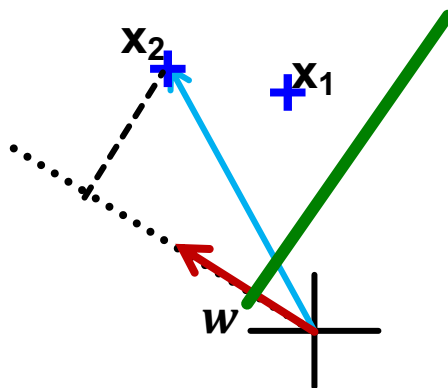
- **Dot product**

$$A \cdot B = \|A\| \|B\| \cos \theta$$

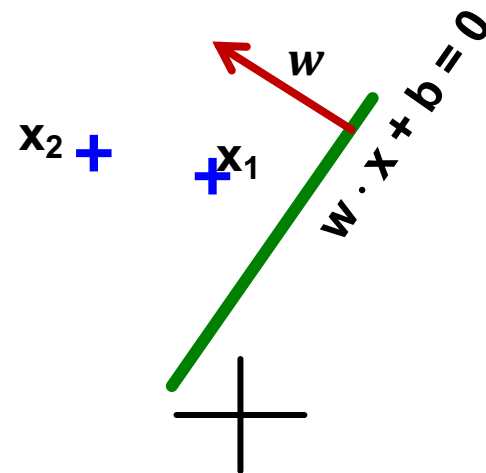
- **What is $w \cdot x_1$, $w \cdot x_2$?**



In this case
 $\gamma_1 \approx \|w\|^2$



In this case
 $\gamma_2 \approx 2\|w\|^2$

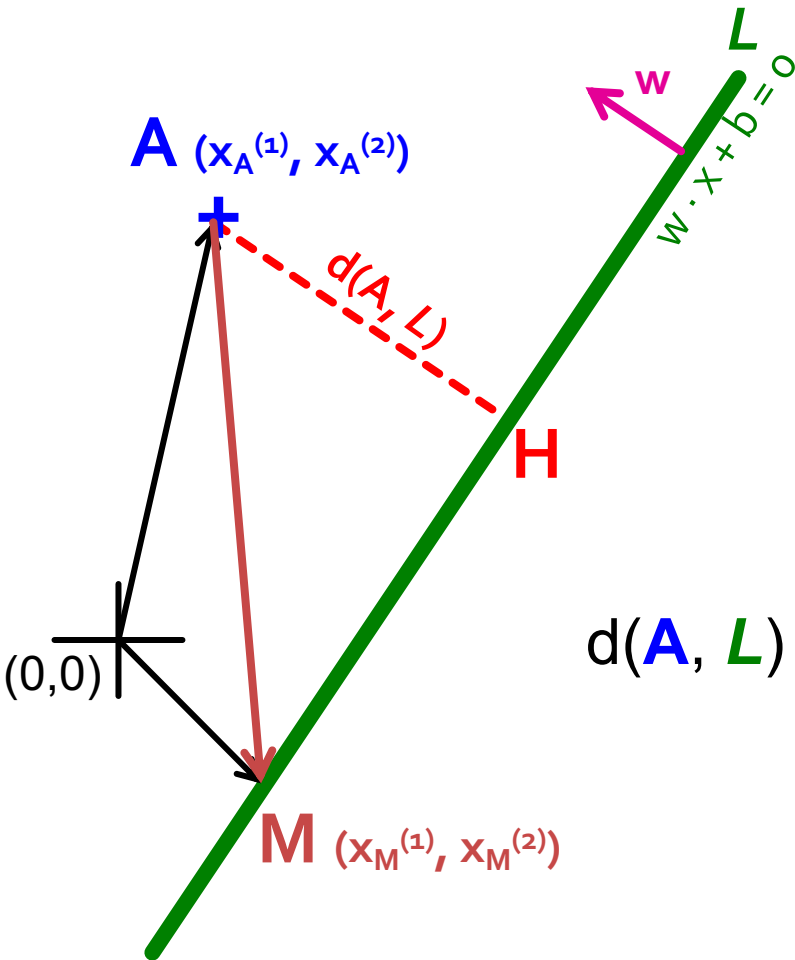


- **So, γ roughly corresponds to the margin**

- **Bottom line: Bigger γ , bigger the separation**

What is the margin?

Note we assume
 $\|w\|_2 = 1$



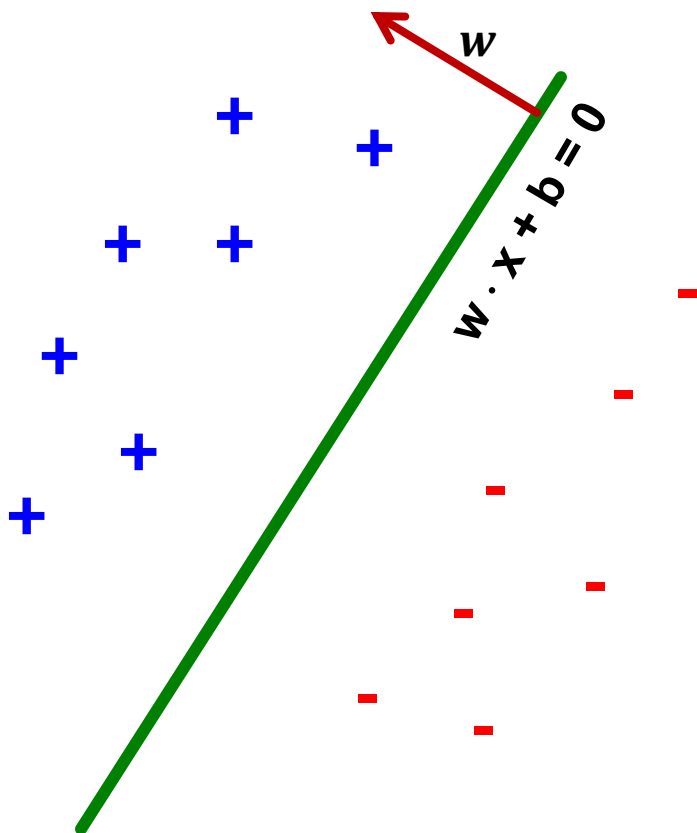
Let:

- **Line L:** $w \cdot x + b = 0$
 $w^{(1)}x^{(1)} + w^{(2)}x^{(2)} + b = 0$
- $w = (w^{(1)}, w^{(2)})$
- **Point A** = $(x_A^{(1)}, x_A^{(2)})$
- **Point M** on a line = $(x_M^{(1)}, x_M^{(2)})$

$$\begin{aligned}
 d(\mathbf{A}, \mathbf{L}) &= |\mathbf{AH}| \\
 &= |(\mathbf{A} - \mathbf{M}) \cdot \mathbf{w}| \\
 &= |(x_A^{(1)} - x_M^{(1)})w^{(1)} + (x_A^{(2)} - x_M^{(2)})w^{(2)}| \\
 &= |x_A^{(1)}w^{(1)} + x_A^{(2)}w^{(2)} + b| \\
 &= |\mathbf{w} \cdot \mathbf{A} + b|
 \end{aligned}$$

Remember $x_M^{(1)}w^{(1)} + x_M^{(2)}w^{(2)} = -b$
 since **M** belongs to line **L**

Largest Margin



- Prediction = $\text{sign}(w \cdot x + b)$
- “Confidence” = $(w \cdot x + b) y$
- For i -th datapoint:
$$\gamma_i = (w \cdot x_i + b) y_i$$

- Want to solve:

$$\max_{w,b} \min_i \gamma_i$$

- Can rewrite as

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

$$s.t. \forall i, y_i (w \cdot x_i + b) \geq \gamma$$

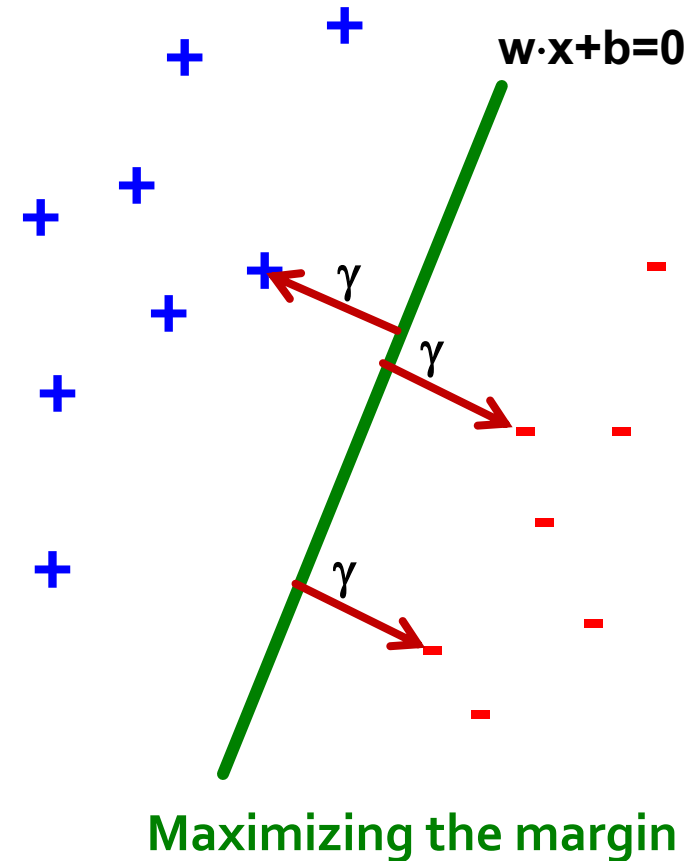
Support Vector Machine

- **Maximize the margin:**
 - Good according to intuition, theory (c.f. “VC dimension”) and practice

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

$$s.t. \forall i, y_i (w \cdot x_i + b) \geq \gamma$$

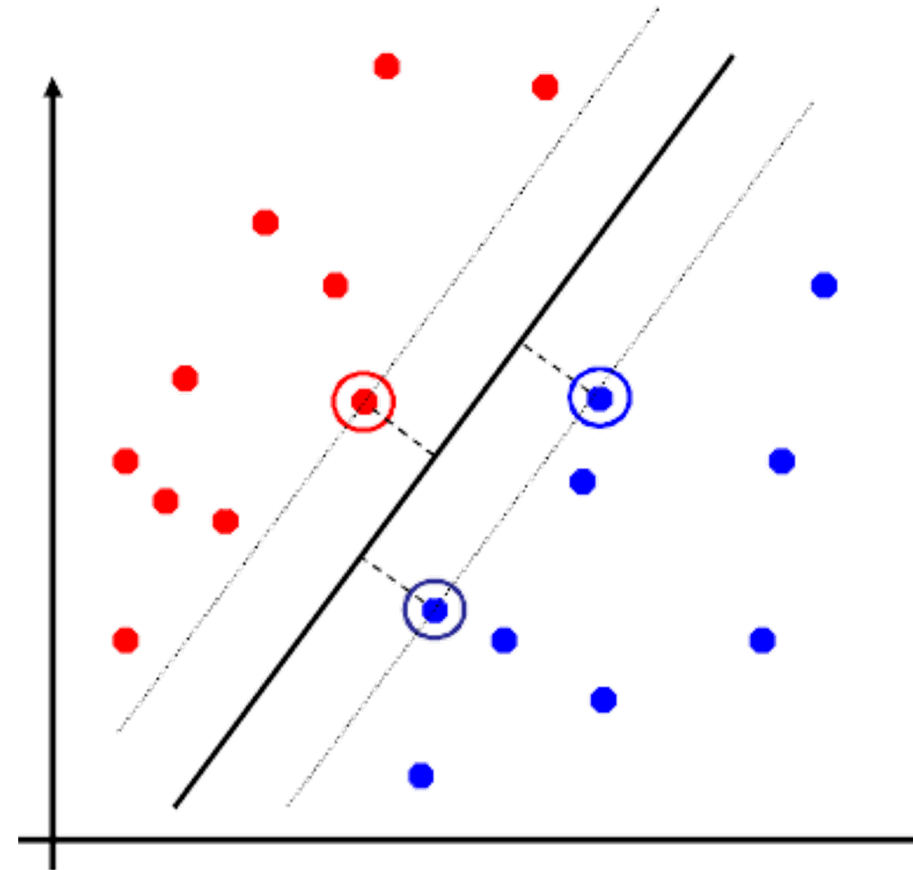
- γ is margin ... distance from the separating hyperplane



Support Vector Machines: Deriving the margin

Support Vector Machines

- Separating hyperplane is defined by the support vectors
 - Points on +/- planes from the solution
 - If you knew these points, you could ignore the rest
 - Generally, $d+1$ support vectors (for d dim. data)



Canonical Hyperplane: Problem

■ Problem:

- Let $(\mathbf{w} \cdot \mathbf{x} + b)y = \gamma$
then $(2\mathbf{w} \cdot \mathbf{x} + 2b)y = 2\gamma$

- Scaling \mathbf{w} increases margin!

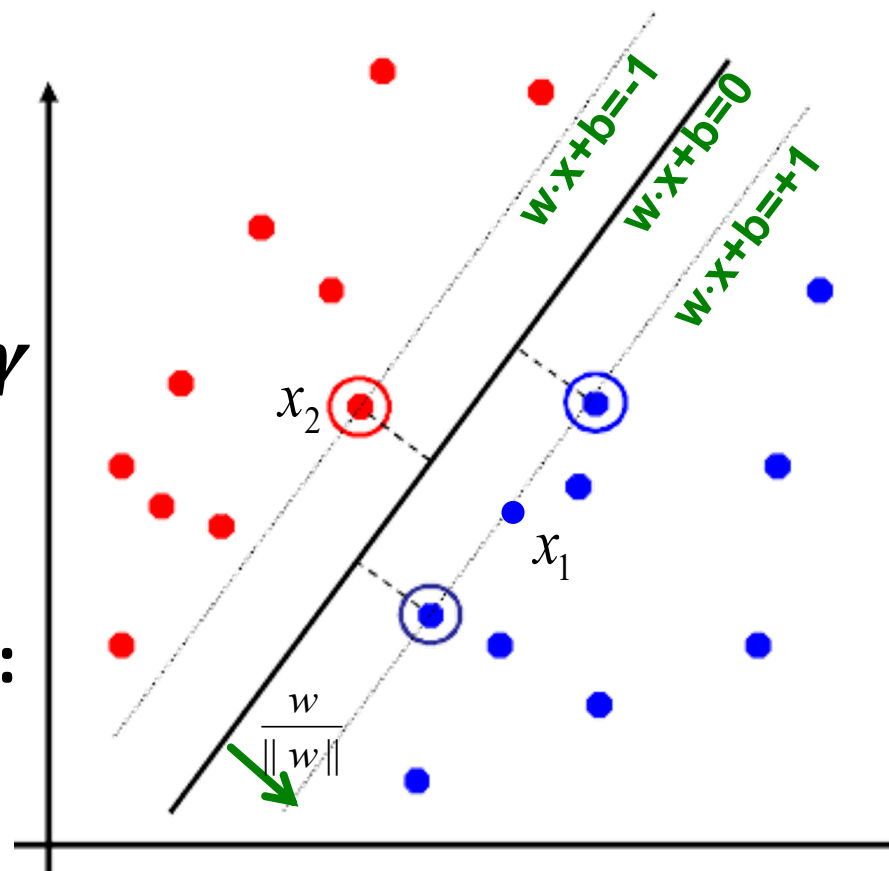
■ Solution:

- Work with normalized \mathbf{w} :

$$\gamma = \left(\frac{\mathbf{w}}{\|\mathbf{w}\|} \cdot \mathbf{x} + b \right) y$$

- Let's also require **support vectors** \mathbf{x}_j
to be on the plane defined by:

$$\mathbf{w} \cdot \mathbf{x}_j + b = \pm 1$$



$$\|\mathbf{w}\| = \sqrt{\sum_{j=1}^d (w^{(j)})^2}$$

Canonical Hyperplane: Solution

- Want to maximize margin!
- What is the relation between x_1 and x_2 ?

- $x_1 = x_2 + 2\gamma \frac{w}{\|w\|}$

- We also know:

- $w \cdot x_1 + b = +1$

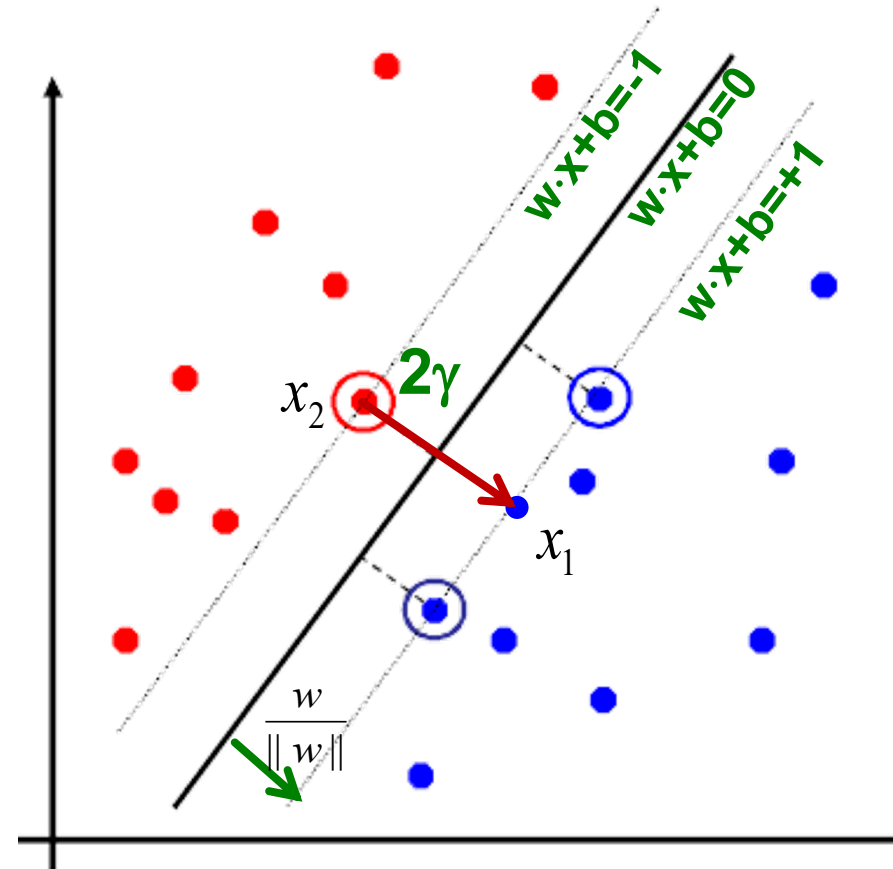
- $w \cdot x_2 + b = -1$

- So:

- $w \cdot x_1 + b = +1$

- $w \left(x_2 + 2\gamma \frac{w}{\|w\|} \right) + b = +1$

- $\underbrace{w \cdot x_2 + b}_{-1} + 2\gamma \frac{w \cdot w}{\|w\|} = +1$



$$\Rightarrow \gamma = \frac{\|w\|}{w \cdot w} = \frac{1}{\|w\|}$$

Note:

$$w \cdot w = \|w\|^2$$

Maximizing the Margin

- We started with

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

$$s.t. \forall i, y_i (w \cdot x_i + b) \geq \gamma$$

But w can be arbitrarily large!

- We normalized and...

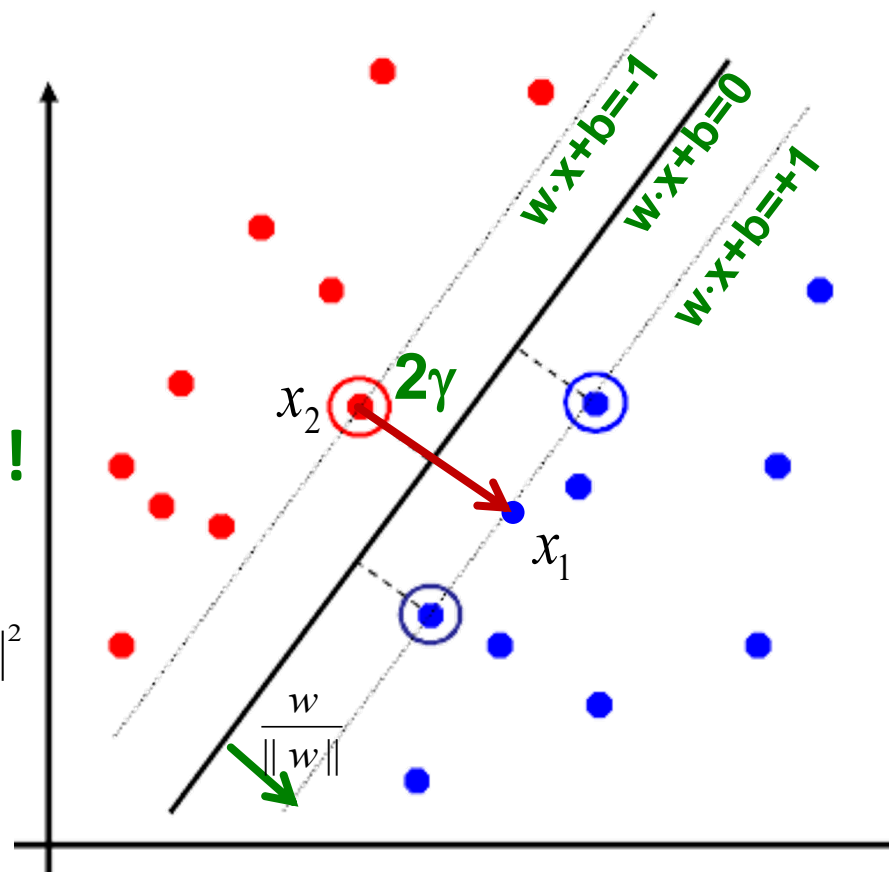
$$\arg \max \gamma = \arg \max \frac{1}{\|w\|} = \arg \min \|w\| = \arg \min \frac{1}{2} \|w\|^2$$

- Then:

$$\min_{w, b} \frac{1}{2} \|w\|^2$$

$$s.t. \forall i, y_i (w \cdot x_i + b) \geq 1$$

This is called SVM with “hard” constraints



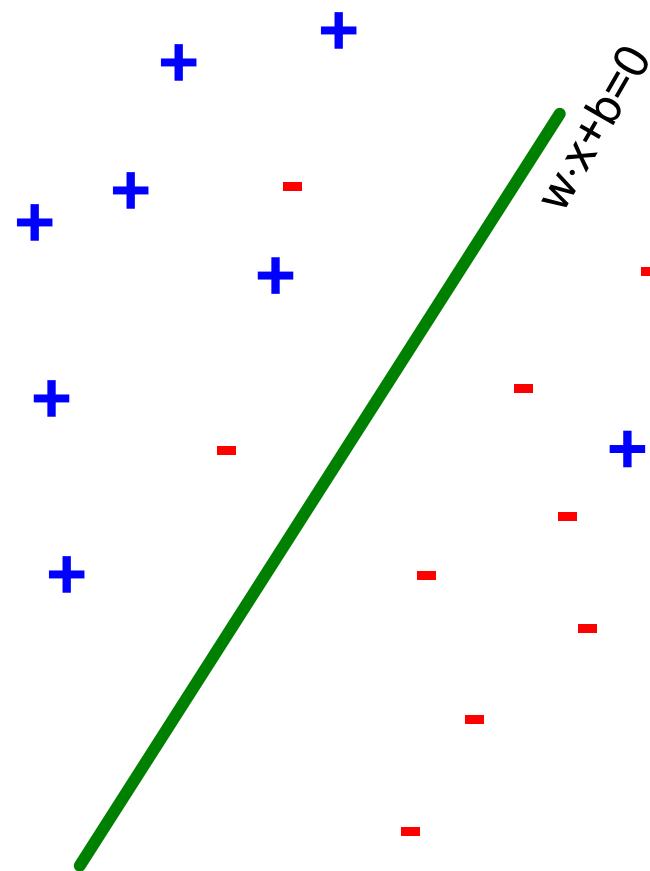
Non-linearly Separable Data

- If data is **not separable** introduce **penalty**:

$$\min_{w,b} \frac{1}{2} \|w\|^2 + C \cdot (\# \text{ number of mistakes})$$

$$s.t. \forall i, y_i (w \cdot x_i + b) \geq 1$$

- Minimize $\|w\|^2$ plus the number of training mistakes
- Set C using cross validation
- **How to penalize mistakes?**
 - All mistakes are not equally bad!



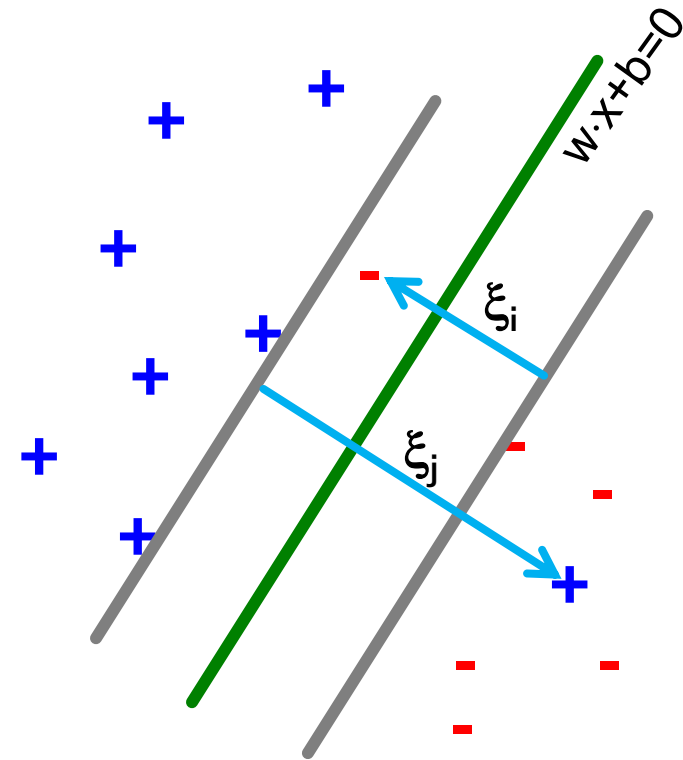
Support Vector Machines

- Introduce **slack variables** ξ_i

$$\min_{w, b, \xi_i \geq 0} \frac{1}{2} \|w\|^2 + C \cdot \sum_{i=1}^n \xi_i$$

$$s.t. \forall i, y_i (w \cdot x_i + b) \geq 1 - \xi_i$$

- If point x_i is on the wrong side of the margin then get penalty ξ_i



For each data point:
If margin ≥ 1 , don't care
If margin < 1 , pay linear penalty

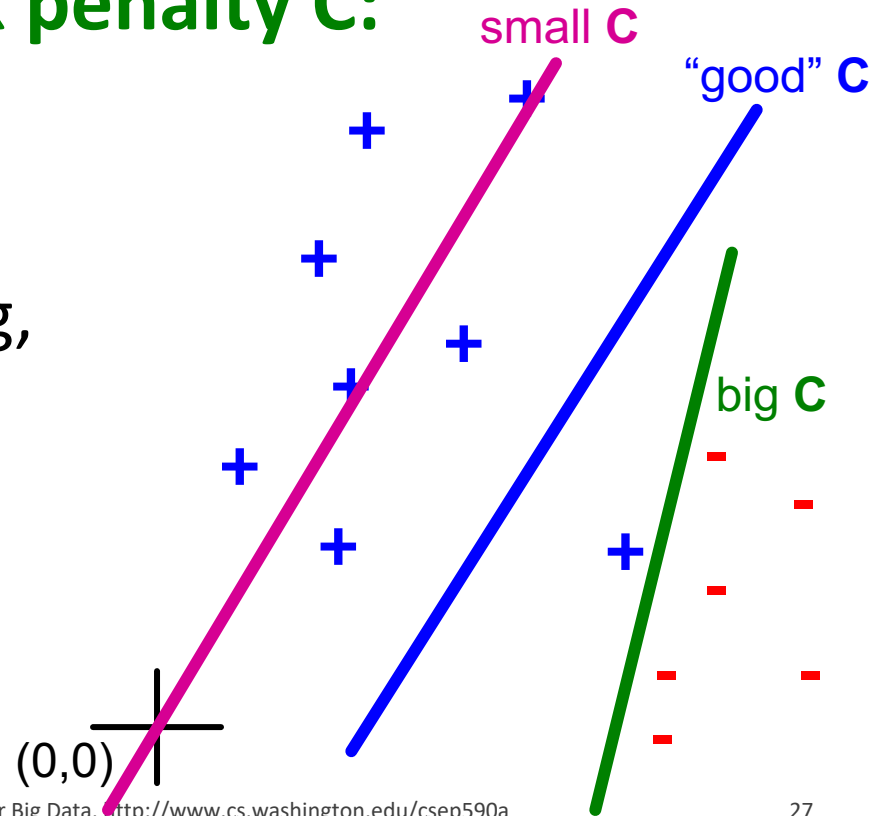
Slack Penalty C

$$\min_{w, b, \xi_i \geq 0} \frac{1}{2} \|w\|^2 + C \cdot \sum_{i=1}^n \xi_i$$

$$s.t. \forall i, y_i (w \cdot x_i + b) \geq 1 - \xi_i$$

■ What is the role of slack penalty C :

- $C = \infty$: Only want to w , b that separate the data
- $C = 0$: Can set ξ_i to anything, then $w = \mathbf{0}$ (basically ignores the data)



How do we obtain the Natural Form?

■ **Previously**

$$\min_{\substack{w, b \\ \xi_i \geq 0}} \frac{1}{2} \|w\|^2 + C \sum_{i=1}^n \xi_i$$
$$s.t. \forall i, y_i \cdot (w \cdot x_i + b) \geq 1 - \xi_i$$

■ Solve for ξ :

$$\xi_i \geq 1 - y_i \cdot (w \cdot x_i + b)$$
$$\xi_i \geq 0$$
$$\Rightarrow \xi_i \geq \max(0, 1 - y_i \cdot (w \cdot x_i + b))$$

■ **Natural form:**

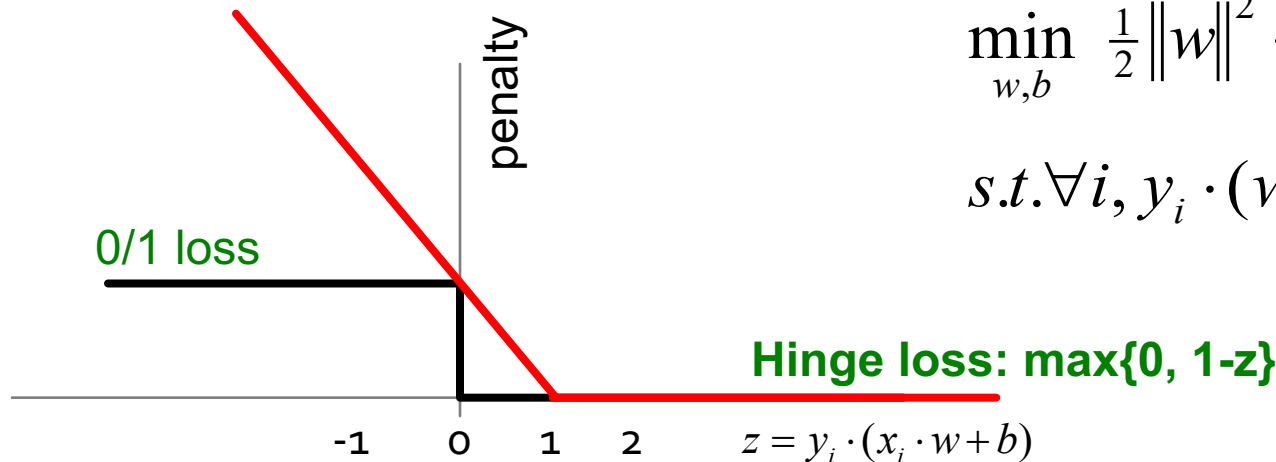
$$\arg \min_{w, b} \frac{1}{2} w \cdot w + C \cdot \sum_{i=1}^n \max\{0, 1 - y_i (w \cdot x_i + b)\}$$

Support Vector Machines

- SVM in the “natural” form

$$\arg \min_{w,b} \underbrace{\frac{1}{2} w \cdot w}_{\text{Margin}} + \underbrace{C}_{\text{Regularization parameter}} \cdot \underbrace{\sum_{i=1}^n \max\{0, 1 - y_i (w \cdot x_i + b)\}}_{\text{Empirical loss L (how well we fit training data)}}$$

- SVM uses “Hinge Loss”:



$$\min_{w,b} \frac{1}{2} \|w\|^2 + C \sum_{i=1}^n \xi_i$$

$$s.t. \forall i, y_i \cdot (w \cdot x_i + b) \geq 1 - \xi_i$$

Support Vector Machines: How to estimate the parameters?

SVM: How to estimate w ?

$$\min_{w,b} \frac{1}{2} w \cdot w + C \cdot \sum_{i=1}^n \xi_i$$

$$s.t. \forall i, y_i \cdot (x_i \cdot w + b) \geq 1 - \xi_i$$

- **Want to estimate w and b !**
 - **Standard way:** Use a solver!
 - **Solver:** software for finding solutions to “common” optimization problems
- **Use a quadratic solver:**
 - Minimize quadratic function
 - Subject to linear constraints
- **Problem:** Solvers are inefficient for big data!

SVM: How to estimate w ?

- **Want to minimize $J(w, b)$:**

$$J(w, b) = \frac{1}{2} \sum_{j=1}^d \left(w^{(j)} \right)^2 + C \sum_{i=1}^n \max \left\{ 0, 1 - y_i \left(\sum_{j=1}^d w^{(j)} x_i^{(j)} + b \right) \right\}$$

Empirical loss $L(x_i, y_i)$

- **Compute the gradient $\nabla(j)$ w.r.t. $w^{(j)}$**

$$\nabla J^{(j)} = \frac{\partial J(w, b)}{\partial w^{(j)}} = w^{(j)} + C \sum_{i=1}^n \frac{\partial L(x_i, y_i)}{\partial w^{(j)}}$$

$$\frac{\partial L(x_i, y_i)}{\partial w^{(j)}} = 0 \quad \text{if } y_i (w \cdot x_i + b) \geq 1$$

$$= -y_i x_i^{(j)} \quad \text{else}$$

SVM: How to estimate w ?

■ Gradient descent:

Iterate until convergence:

• For $j = 1 \dots d$

• **Evaluate:** $\nabla J^{(j)} = \frac{\partial f(w, b)}{\partial w^{(j)}} = w^{(j)} + C \sum_{i=1}^n \frac{\partial L(x_i, y_i)}{\partial w^{(j)}}$

• **Update:**

$$w^{(j)'} \leftarrow w^{(j)} - \eta \nabla J^{(j)}$$

• $w \leftarrow w'$

■ Problem:

η ... learning rate parameter
 C ... regularization parameter

■ Computing $\nabla J^{(j)}$ takes $O(n)$ time!

■ n ... size of the training dataset

SVM: How to estimate w ?

■ Stochastic Gradient Descent

- Instead of evaluating gradient over all examples evaluate it for each **individual** training example

$$\nabla J^{(j)}(x_i) = w^{(j)} + C \cdot \frac{\partial L(x_i, y_i)}{\partial w^{(j)}}$$

We just had:

$$\nabla J^{(j)} = w^{(j)} + C \sum_{i=1}^n \frac{\partial L(x_i, y_i)}{\partial w^{(j)}}$$

← Notice: no summation over i anymore

■ Stochastic gradient descent:

Iterate until convergence:

- For $i = 1 \dots n$
 - For $j = 1 \dots d$
 - **Compute:** $\nabla J^{(j)}(x_i)$
 - **Update:** $w^{(j)} \leftarrow w^{(j)} - \eta \nabla J^{(j)}(x_i)$

Other variations of GD

■ Batch Gradient Descent

- Calculates error for each example in the training dataset, but updated model **only after** all examples have been evaluated (i.e., end of training epoch)
- **PROS**: fewer updates, more stable error gradient
- **CONS**: usually requires whole dataset in memory, slower than SGD

■ Mini-Batch Gradient Descent

- Like BGD, but using smaller batches of training data. Balance between robustness of SGD, and efficiency of BGD.

Support Vector Machines: Example

Example: Text categorization

- **Dataset:**
 - **Reuters RCV1** news document corpus
 - Predict a category of a document
 - One **vs.** the rest classification
 - **$n = 781,000$** training examples (documents)
 - 23,000 test examples
 - **$d = 50,000$** features
 - One feature per word
 - Remove stop-words
 - Remove low frequency words

Example: Text categorization

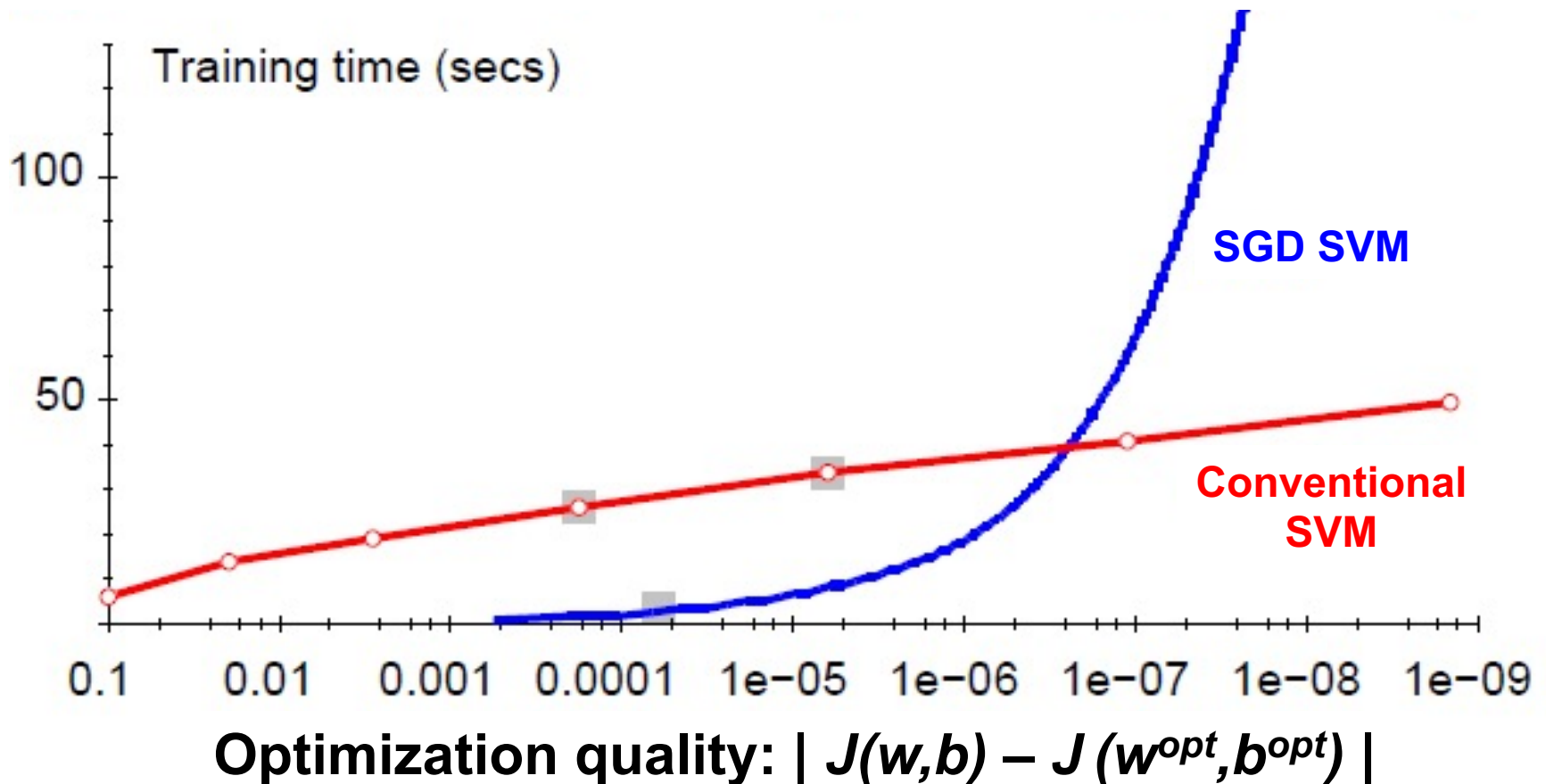
■ Questions:

- (1) Is **SGD** successful at minimizing $J(\mathbf{w}, \mathbf{b})$?
- (2) How quickly does **SGD** find the min of $J(\mathbf{w}, \mathbf{b})$?
- (3) What is the error on a test set?

	<i>Training time</i>	<i>Value of $J(\mathbf{w}, \mathbf{b})$</i>	<i>Test error</i>
Standard SVM	23,642 secs	0.2275	6.02%
“Fast Linear SVM”	66 secs	0.2278	6.03%
SGD-SVM	1.4 secs	0.2275	6.02%

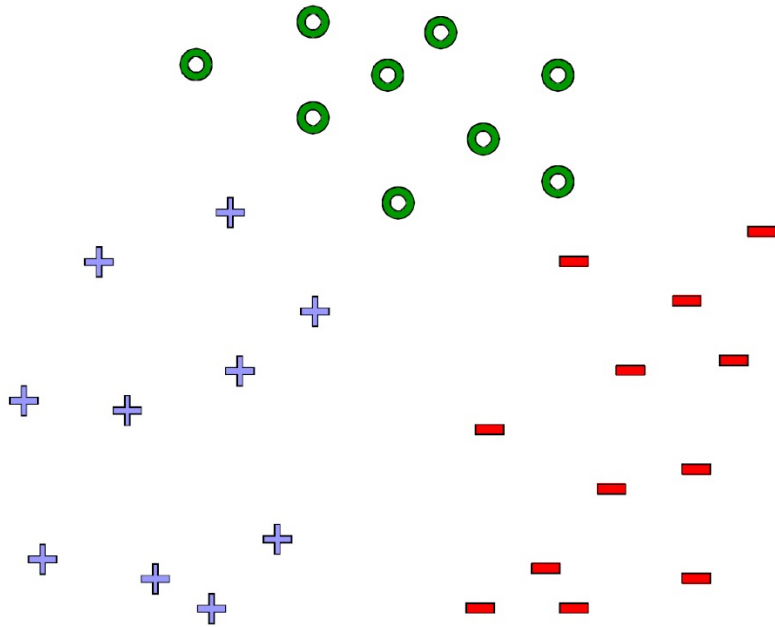
- (1) SGD-SVM is successful at minimizing the value of $J(\mathbf{w}, \mathbf{b})$
- (2) SGD-SVM is super fast
- (3) SGD-SVM test set error is comparable

Optimization "Accuracy"



For optimizing $J(w,b)$ within reasonable quality
SGD-SVM is super fast

What about multiple classes?



- **Idea 1:**

- One against all**

- Learn 3 classifiers

- + vs. {o, -}

- - vs. {o, +}

- o vs. {+, -}

- Obtain:

- $w_+ b_+, w_- b_-, w_o b_o$

- **How to classify?**

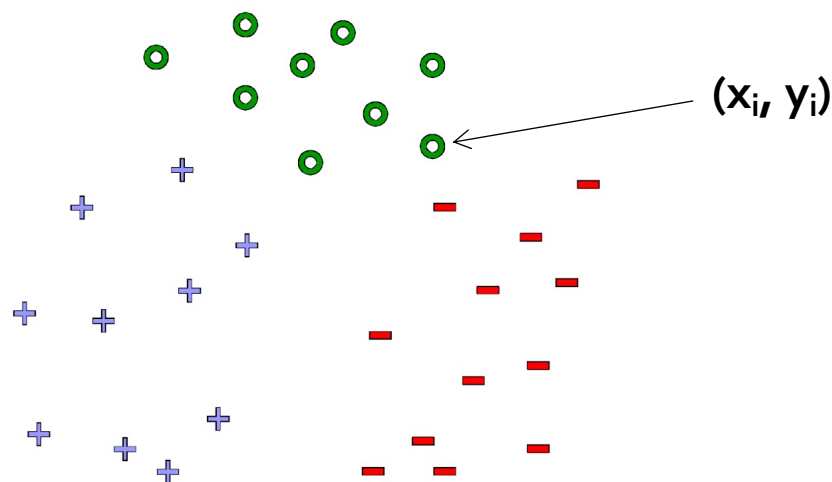
- Return class c

- $$\arg \max_c w_c \mathbf{x} + \mathbf{b}_c$$

Learn 1 classifier: Multiclass SVM

- **Idea 2: Learn 3 sets of weights simultaneously!**
 - For each class c estimate w_c, b_c
 - **Want the correct class y_i to have highest margin:**

$$w_{y_i} x_i + b_{y_i} \geq 1 + w_c x_i + b_c \quad \forall c \neq y_i, \forall i$$



Multiclass SVM

- **Optimization problem:**

$$\min_{w,b} \frac{1}{2} \sum_c \|w_c\|^2 + C \sum_{i=1}^n \xi_i \quad \forall c \neq y_i, \forall i$$

$$w_{y_i} \cdot x_i + b_{y_i} \geq w_c \cdot x_i + b_c + 1 - \xi_i \quad \xi_i \geq 0, \forall i$$

- To obtain parameters w_c, b_c (for each class c) we can use similar techniques as for 2 class **SVM**

- **SVM is widely perceived a very powerful learning algorithm**

ML Parallelization

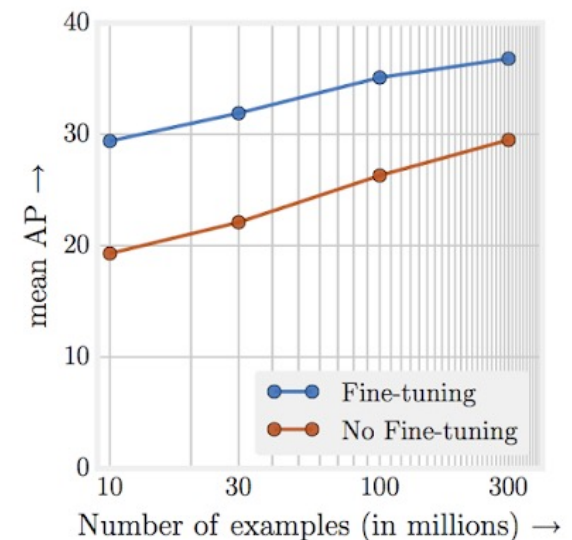
Why Large-Scale ML?

■ The Unreasonable Effectiveness of Data

- In 2017, Google revisited a 15-year-old experiment on the effect of data and model size in ML, focusing on the latest Deep Learning models in computer vision

■ Findings:

- Performance increases logarithmically based on volume of training data
- Complexity of modern ML models (i.e., deep neural nets) allows for even further performance gains



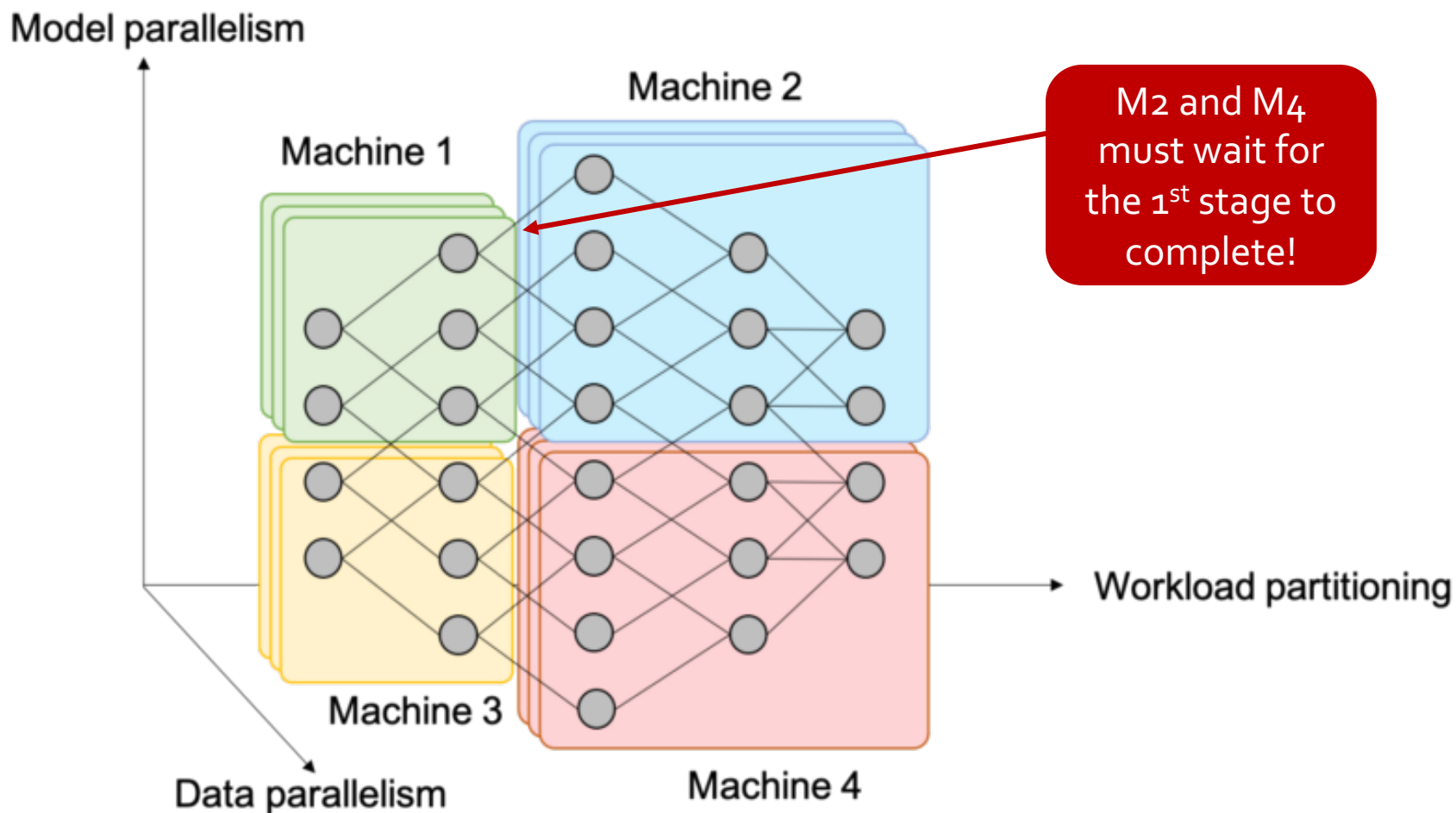
■ Large datasets + large ML models => amazing results!!

“Revisiting Unreasonable Effectiveness of Data in Deep Learning Era”: <https://arxiv.org/abs/1707.02968>

Recap

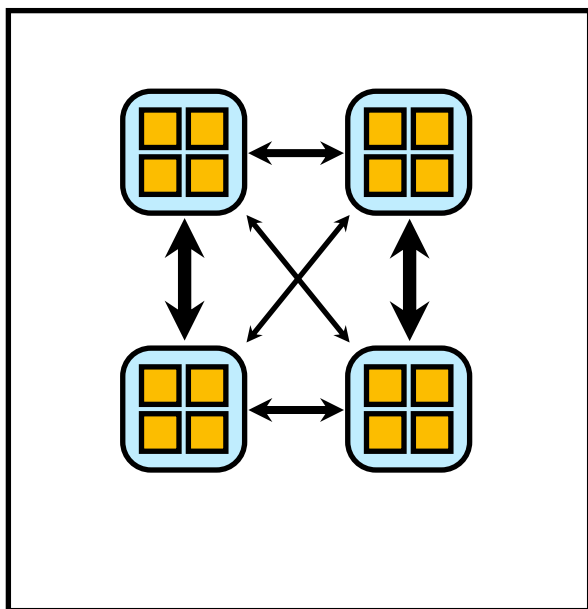
- Last lecture: Decision Trees (and PLANET) as a prime example of **Data Parallelism** in ML
- Today's lecture: Multiclass SVMs, Neural Networks (especially Deep ones), etc. can leverage both **Data Parallelism and Model Parallelism**
 - State-of-the-art Deep Neural Networks for visual recognition tasks (e.g., ImageNet challenge) or NLP can have **more than 1 billion parameters!**

Parallelization overview

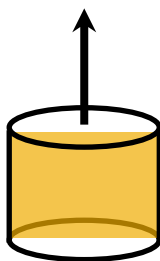


Parallelization overview

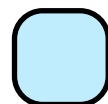
Model



- Unsupervised or Supervised Objective
- Minibatch Stochastic Gradient Descent (SGD)
- Model parameters sharded by partition
- 10s, 100s, or 1000s of cores per model



Training Data



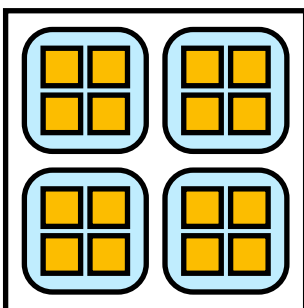
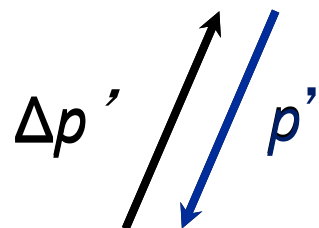
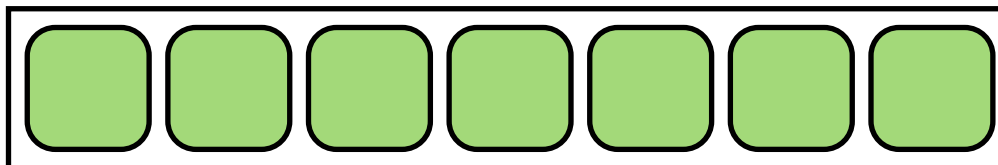
Machine (Model Partition)



Core

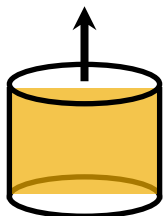
Parameter Server

Parameter Server $p' = p + \Delta p$



Model

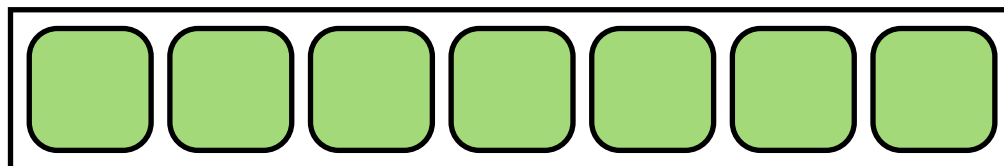
Data



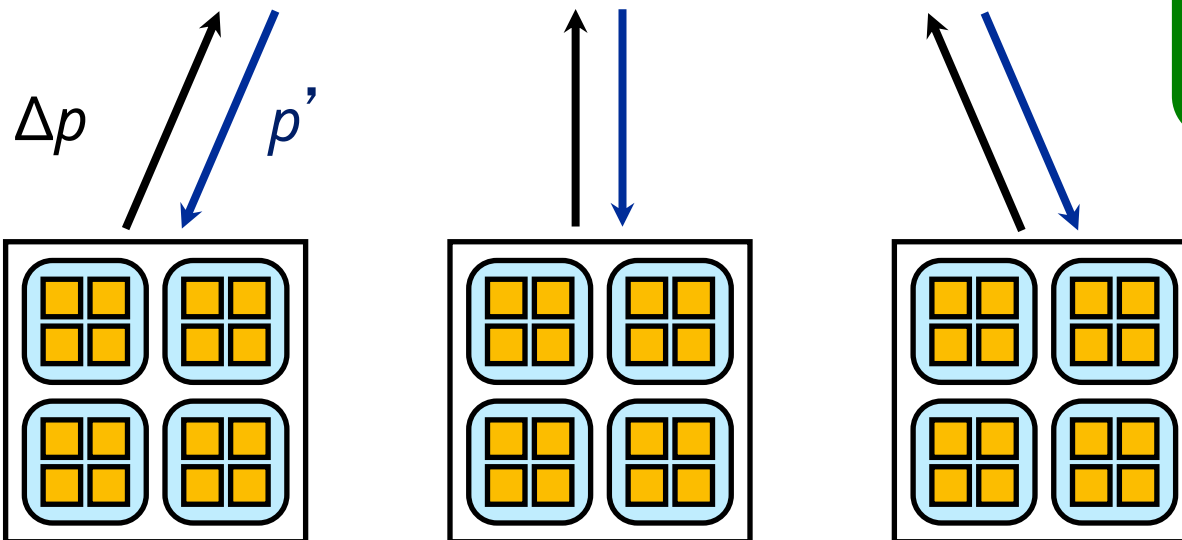
- Parameter Server: **Key/Value store**
- **Keys** index the model parameters (e.g., weights)
- **Values** are the parameters of the ML model (e.g., a neural network)
- **Systems challenges:**
 - **High bandwidth**
 - **Synchronization**
 - **Fault tolerance**

Parameter Server

Parameter Server $p' = p + \Delta p$

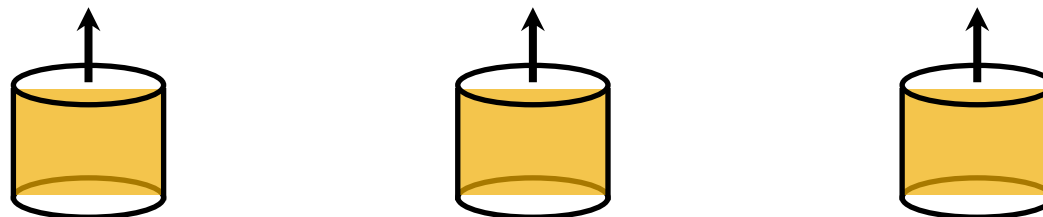


Why do parallel updates work?



Model Workers

Data Shards

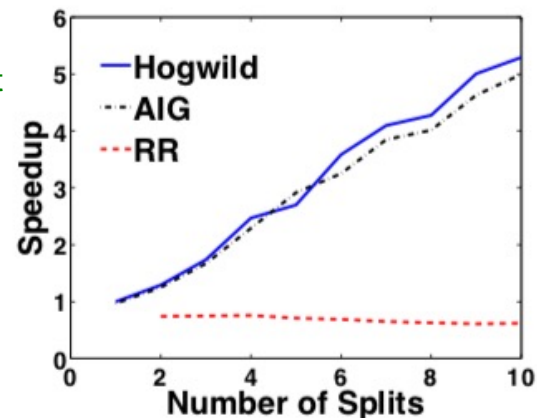


Async SGD

- **Key idea:** don't synchronize, just **overwrite** parameters opportunistically from multiple workers (i.e., servers)
 - Same implementation as SGD, **just without locking!**
- **In theory**, Async SGD converges, but a slower rate than the serial version.
- In practice, **when gradient updates are sparse** (i.e., high dimensional data), **same convergence!**

RR is a super optimized version of online Gradient Descent, but with synchronization

- Recht et al. "[HOGWILD!: A Lock-Free Approach to Parallelizing Stochastic Gradient Descent](#)", 2011



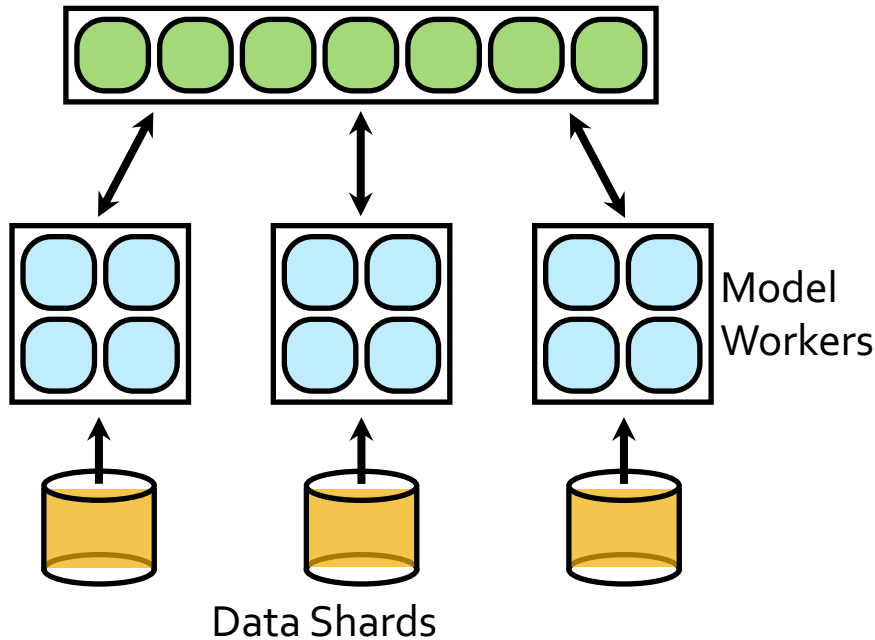
HOGWILD!

```
1 Initialize  $w$  in shared memory // in parallel, do
2 for  $i = \{1, \dots, p\}$  do     $\leq P$  is the number of partitions / processors
3   while TRUE do
4     if stopping criterion met then
5       | break
6     end                                SGD
7     Sample  $j$  from  $1, \dots, n$  uniformly at random.
8     Compute  $f_j(w)$  and  $\nabla f_j(w)$  using whatever  $w$  is currently available.
9     Let  $e_j$  denote non-zero indices of  $x_j$ 
10    for  $k \in e_j$  do
11      |  $w_{(k)} \leftarrow w_{(k)} - \alpha [\nabla f_j(w)]_{(k)}$ 
12    end
13  end
14 end
```

Component-wise gradient updates
(relies on sparsity)

Asynchronous Distributed SGD

Parameter Server



- Google, “[Large Scale Distributed Deep Networks](#)” [2012]
- All ingredients together:
 - Model and Data parallelism
 - Async SGD
- Dawn of modern Deep Learning

From an engineering standpoint, this is much better than a single model with the same number of total machines:

- Synchronization boundaries involve fewer machines
- Better robustness to individual slow machines
- Makes forward progress even during evictions/restarts

Example Implementations

- [Google: Tensorflow Distributed Training](#)
- [Uber: Horovod](#)
- [Ray \(UC Berkeley\)](#)
 - [Ray](#) is a general-purpose framework for parallel and distributed Python.
 - Spark isn't optimized for these low latency communication workflow.
 - 15 lines of python for parameter server
- Mu Li et al. [Scaling Distributed Machine Learning with the Parameter Server.](#) OSDI 2014