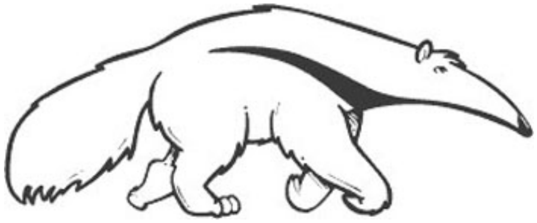
CS178: Machine Learning and Data Mining

VC Dimension

Prof. Erik Sudderth



Some materials courtesy Alex Ihler & Sameer Singh

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CS178 Zoom Lectures

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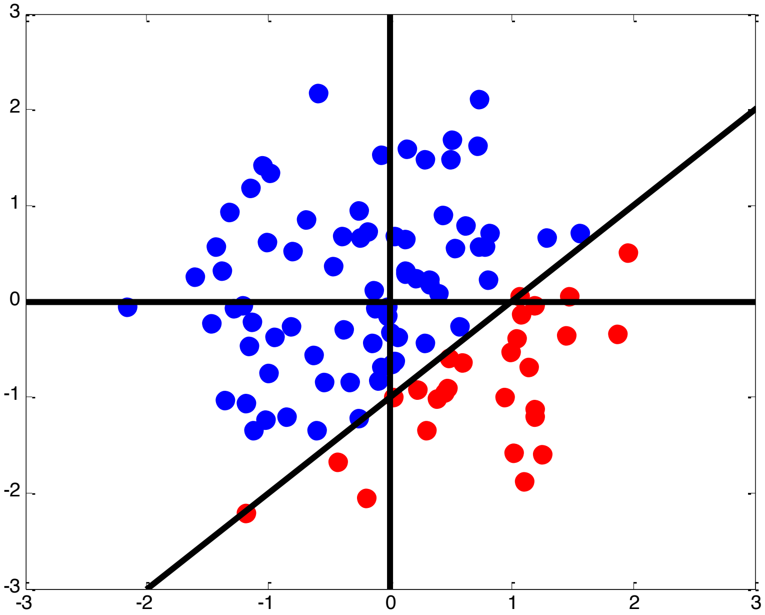
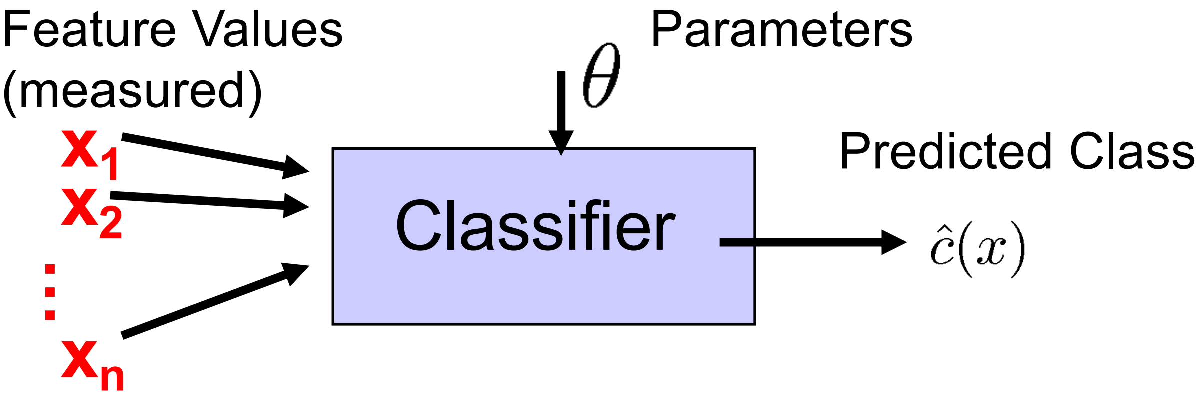
- Use the **Raise Hand** feature. Prof. Sudderth will then call on you by name, unmute your microphone, and let you ask a question. *Your question will be recorded. Please be respectful of your instructor and classmates.*
- Use the **Q&A Window** to type a question. Prof. Sudderth will read your question to the class before answering it, but *will not personally identify you.*

Learners and Complexity

- We’ve seen many versions of underfit/overfit trade-off
  - Complexity of the learner
  - “Representational Power”
- Different learners have different power




Feature Values (measured)

x_1

x_2

$\vdots$

x_n

Parameters

θ

Classifier

Predicted Class

$\hat{c}(x)$

Example:

$$\hat{c}(x) = \text{sign}(\theta_1 x_1 + \theta_2 x_2 + \theta_0)$$

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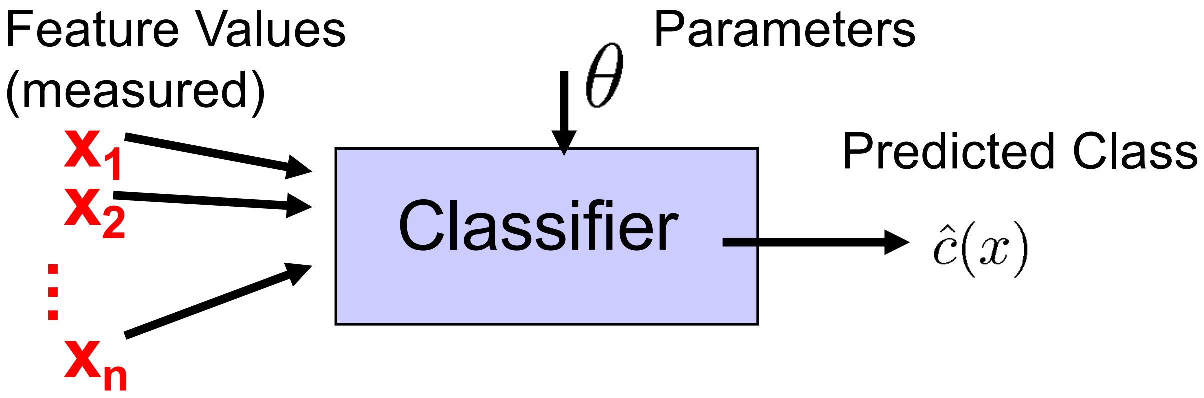

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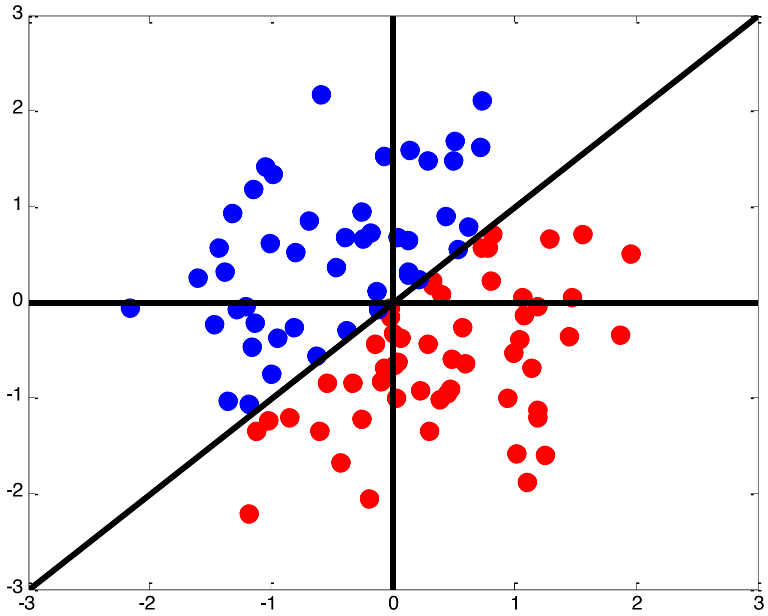

Example:

$$\hat{c}(x) = \text{sign}(\theta_1 x_1 + \theta_2 x_2)$$

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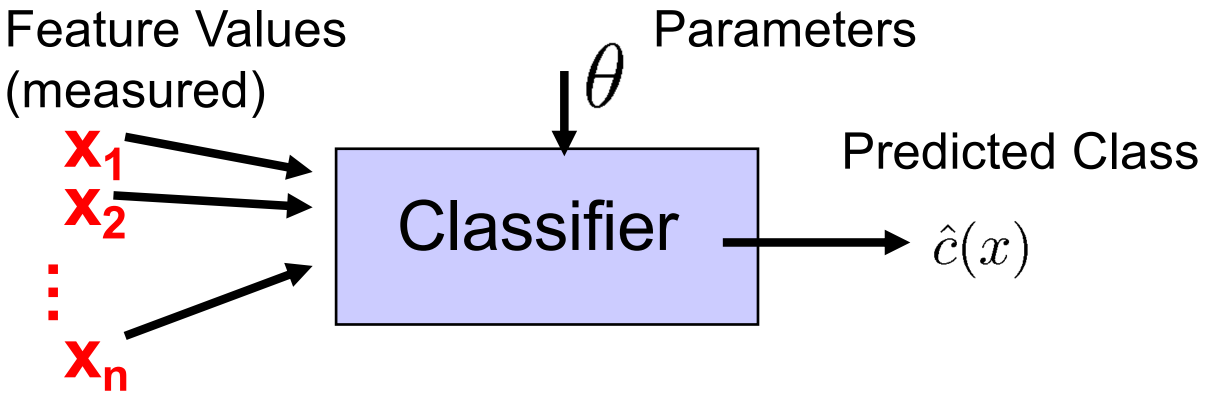

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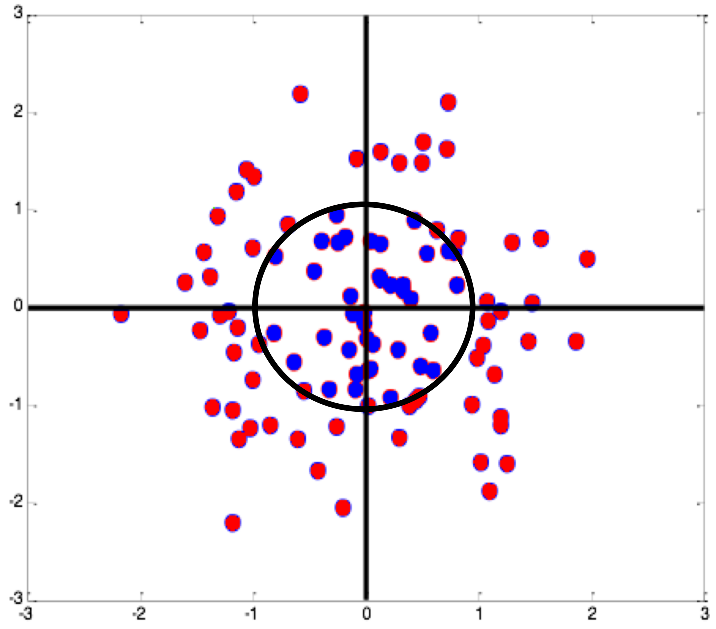


Example:

$$\hat{c}(x) = \text{sign}(\,(x_1^2 + x_2^2) - \theta_0)$$

Learners and Complexity

- We’ve seen many versions of underfit/overfit trade-off
  - Complexity of the learner
  - “Representational Power”
- Different learners have different power
- Usual trade-off:
  - More power = represent more complex systems, might overfit
  - Less power = won’t overfit, but may not find “best” learner
- How can we quantify representational power?
  - Not easily…
  - One solution is VC (Vapnik-Chervonenkis) dimension

Some notation

- Assume training data are iid (independent & identically distributed samples) from some distribution p(x,y)

- Define "risk" and "empirical risk"
  - These are just "long term" test and observed training error

$$R(\theta) = \mathrm{TestError} = \mathbb{E}[\mathbb{1}[c \neq \hat{c}(x\,;\,\theta)]]$$

$$R^{\mathrm{emp}}(\theta) = \mathrm{TrainError} = \frac{1}{m}\sum_i \mathbb{1}[c^{(i)} \neq \hat{c}(x^{(i)}\,;\,\theta)]$$

- How are these related? Depends on overfitting…
  - Underfitting domain: pretty similar…
  - Overfitting domain: test error might be lots worse!

VC Dimension and Risk

- Given some classifier, let H be its VC dimension
  - Represents "representational power" of classifier

$$R(\theta) = \text{TestError} = \mathbb{E}[\mathbb{1}[c \neq \hat{c}(x\,;\,\theta)]]$$

$$R^{\text{emp}}(\theta) = \text{TrainError} = \frac{1}{m}\sum_i \mathbb{1}[c^{(i)} \neq \hat{c}(x^{(i)}\,;\,\theta)]$$

- With "high probability" (1-η), Vapnik showed

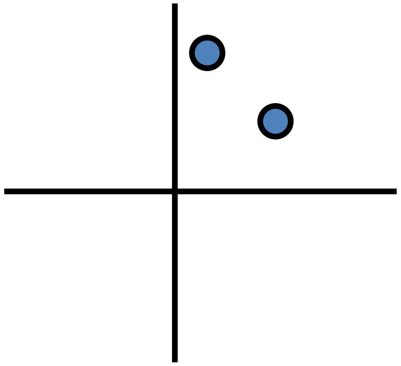
$$\boxed{\text{TestError} \leq \text{TrainError} + \sqrt{\frac{H\log(2m/H) + H - \log(\eta/4)}{m}}}$$

Shattering

- We say a classifier f(x) can *shatter* points $x^{(1)} \ldots x^{(h)}$ iff For *all* $y^{(1)} \ldots y^{(h)}$, f(x) can achieve zero error on training data $(x^{(1)},y^{(1)}), (x^{(2)},y^{(2)}), \ldots (x^{(h)},y^{(h)})$

  (i.e., there exists some θ that gets zero error)

- Can $f(x;\theta) = \text{sign}(\theta_0 + \theta_1 x_1 + \theta_2 x_2)$ shatter these points?



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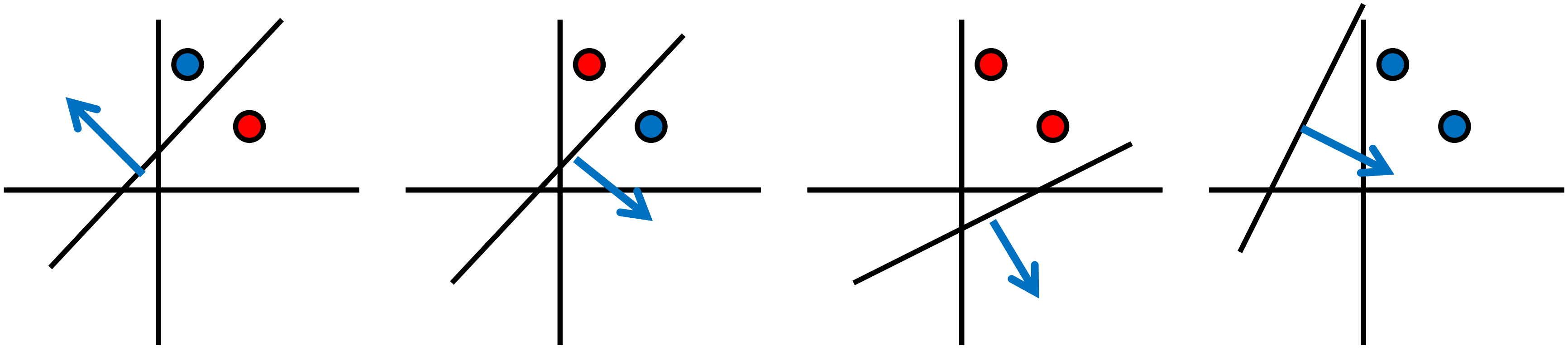
- Can f(x;θ) = sign($\theta_0 + \theta_1 x_1 + \theta_2$x2) shatter these points?
- Yes: there are 4 possible training sets…



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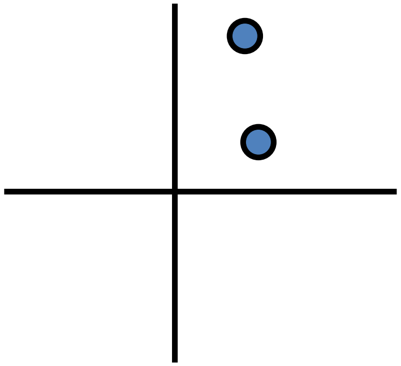

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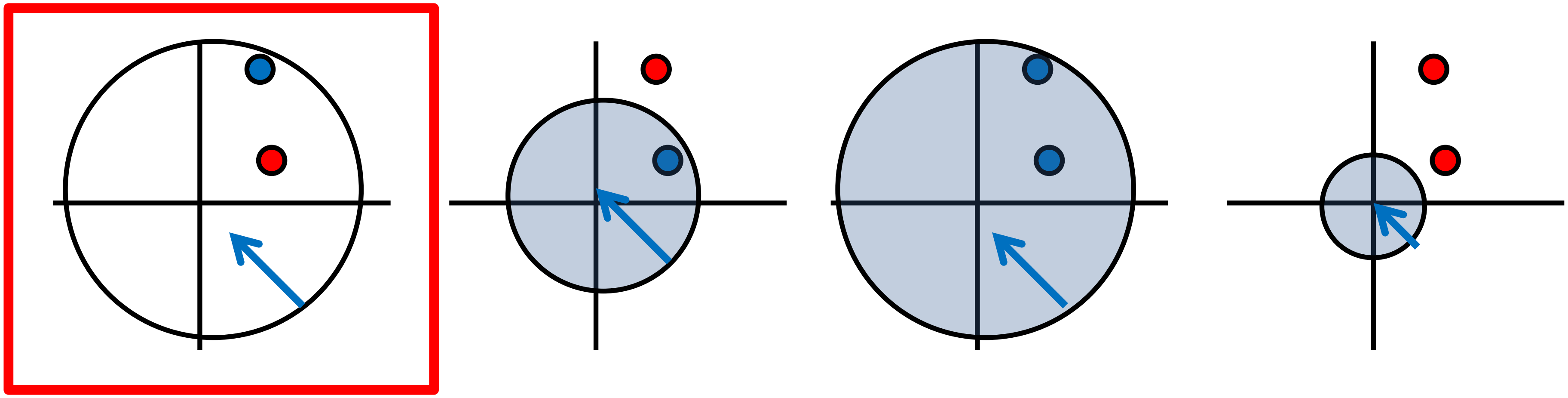
- Can $f(x;\theta) = \text{sign}(x_1^2 + x_2^2 - \theta)$ shatter these points?
- Nope!



VC Dimension

- The VC dimension H is defined as:

  The maximum number of points h that *can be arranged* so that f(x) can shatter them

- A game:
  - Fix the definition of f(x;θ)
  - Player 1: choose locations $x^{(1)}\ldots x^{(h)}$
  - Player 2: choose target labels $y^{(1)}\ldots y^{(h)}$
  - Player 1: choose value of θ
  - If f(x;θ) can reproduce the target labels, P1 wins

$$\exists\{x^{(1)}\ldots x^{(h)}\}\ s.t.\ \ \forall\{y^{(1)}\ldots y^{(h)}\}\ \ \exists\theta\ s.t.\ \ \forall i\ f(x^{(i)};\theta)=y^{(i)}$$

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- Example: what's the VC dimension of the (zero-centered) circle, $f(x;\theta) = \text{sign}(x_1^2 + x_2^2 - \theta)$?

VC Dimension

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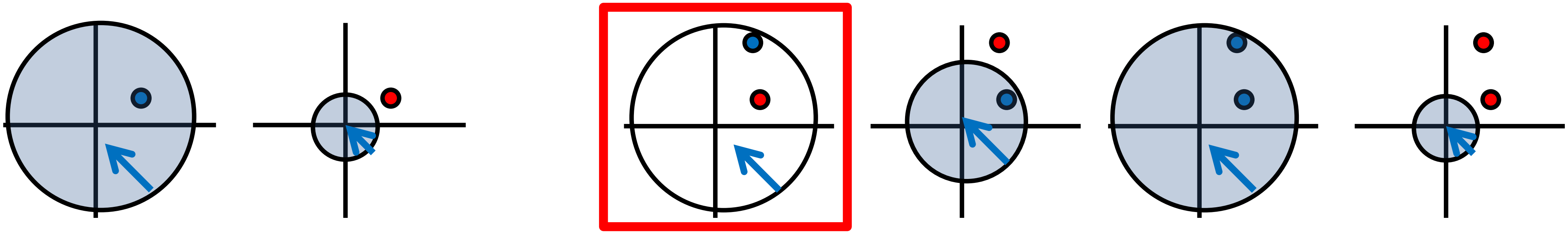
- Example: what’ s the VC dimension of the (zero-centered) circle, $f(x;\theta) = \mathrm{sign}(x_1^2 + x_2^2 - \theta)$?
- VCdim = 1 : can arrange one point, cannot arrange two (previous example was general)



VC Dimension

- Example: what's the VC dimension of the two-dimensional line, $f(x;\theta) = \mathrm{sign}(\theta_1 x_1 + \theta_2 x_2 + \theta_0)$?

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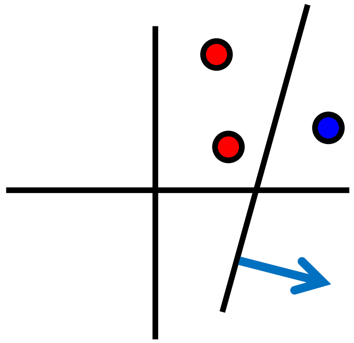
- VC dim >= 3? Yes



VC Dimension

- Example: what's the VC dimension of the two-dimensional line, f(x;θ) = sign(θ_1 x$_1$ + θ_2 x$_2$ + θ_0)?

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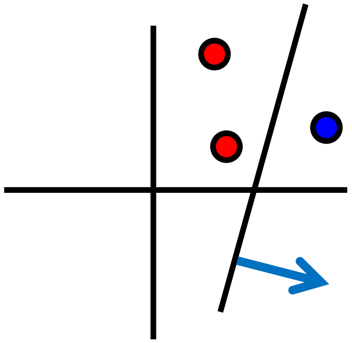
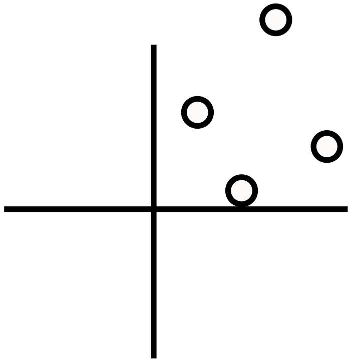


- VC dim >= 4?



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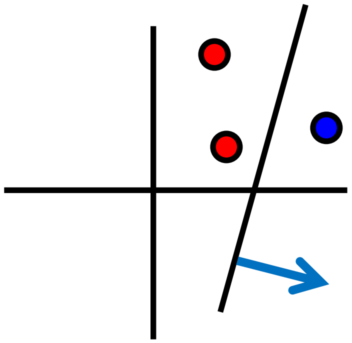
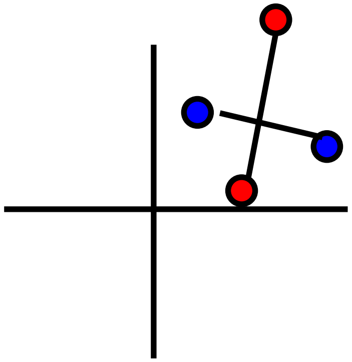


- VC dim >= 4? No…

  Any line through these points must split one pair (by crossing one of the lines)



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- Example: what’s the VC dimension of the two-dimensional line, $f(x;\theta) = \text{sign}(\theta_1 x_1 + \theta_2 x_2 + \theta_0)$?

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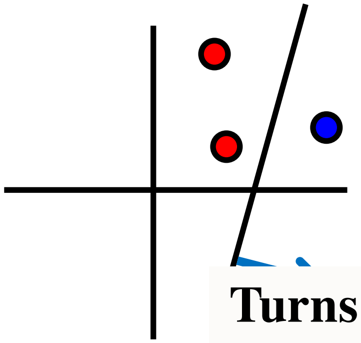

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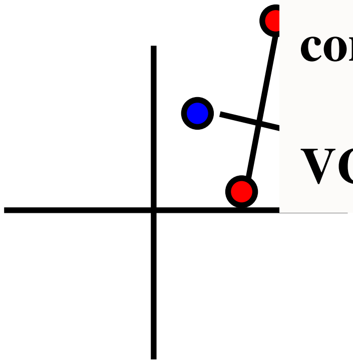


Turns out:
For a general , linear classifier (perceptron) in d dimensions with a constant term:

VC dim = d+1

VC Dimension

- VC dimension measures the “power” of the learner
- Does *not* necessarily equal the # of parameters!

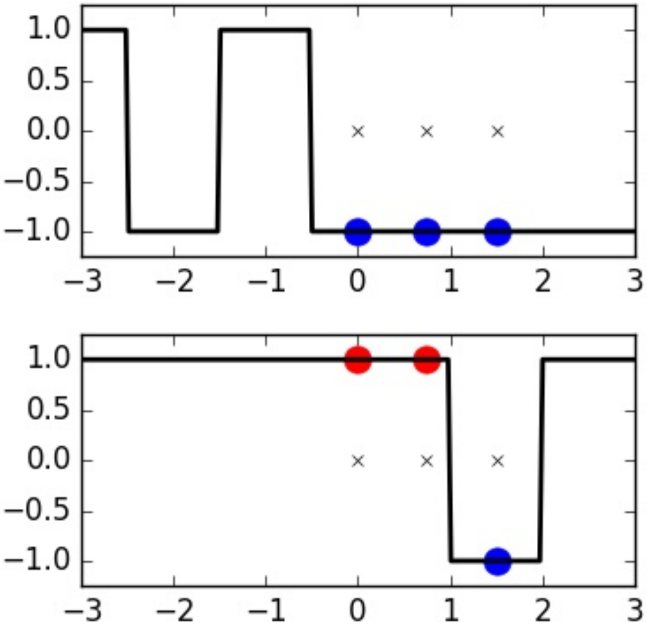
- Number of parameters does not necessarily equal complexity
  - Can define a classifier with a lot of parameters but not much power (how?)
  - Can define a classifier with one parameter but lots of power (how?)

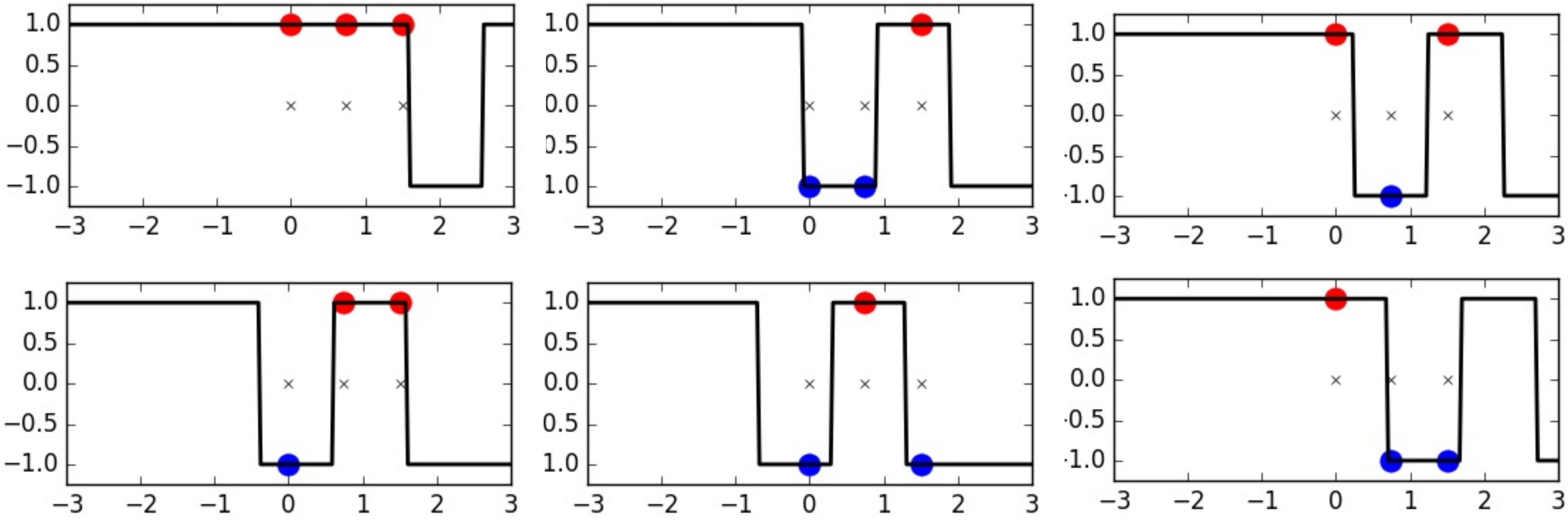
- Lots of work to determine what the VC dimension of various learners is…

Example

$$f(x;t) = \begin{cases} +1 & x \in [-\inf, t] \cup [t+1, t+2] \\ -1 & \text{otherwise} \end{cases}$$

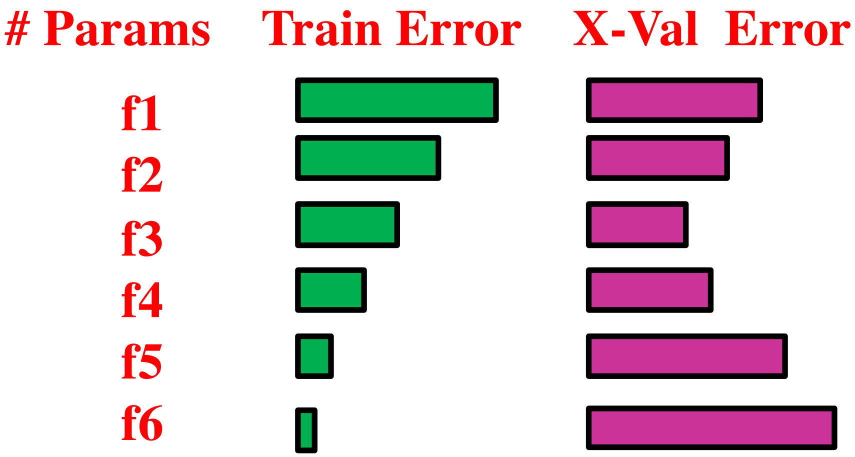
- VC Dim >= 3?
- VC Dim >= 4 ?





Using VC dimension

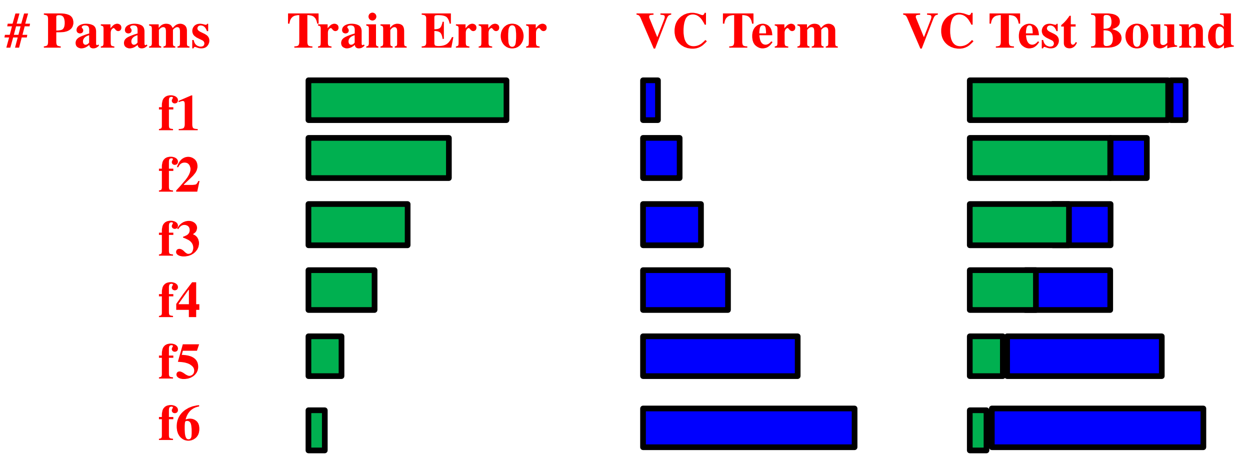
- Used validation / cross-validation to select complexity



Using VC dimension

- Used validation / cross-validation to select complexity
- Use VC dimension based bound on test error similarly

- “Structural Risk Minimization” (SRM)



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- Other Alternatives
  - Probabilistic models: likelihood under model (rather than classification error)
  - AIC (Aikike Information Criterion)
    - Log-likelihood of training data - # of parameters
  - BIC (Bayesian Information Criterion)
    - Log-likelihood of training data - (# of parameters)*log(m)
- Similar to VC dimension: performance + penalty

- BIC conservative; SRM very conservative
- Also, “true Bayesian” methods (take prob. learning…)