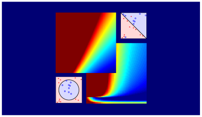
Machine Learning Foundations
(機器學習基石)



Lecture 11: Linear Models for Classification

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Roadmap

1. When Can Machines Learn?
2. Why Can Machines Learn?
3. **How** Can Machines Learn?

Lecture 10: Logistic Regression

gradient descent on **cross-entropy error** to get good **logistic hypothesis**

Lecture 11: Linear Models for Classification

- Linear Models for Binary Classification
- Stochastic Gradient Descent
- Multiclass via Logistic Regression
- Multiclass via Binary Classification

4. How Can Machines Learn Better?

Linear Models Revisited

linear scoring function: $s = \mathbf{w}^T\mathbf{x}$

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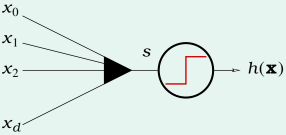
linear classification

$h(\mathbf{x}) = \text{sign}(s)$



plausible err = 0/1

discrete $E_{\text{in}}(\mathbf{w})$: NP-hard to solve

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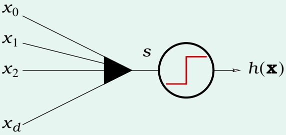

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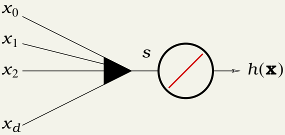

friendly err = squared

quadratic convex $E_{\text{in}}(\mathbf{w})$: closed-form solution

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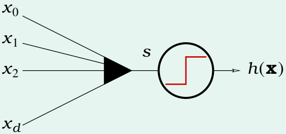

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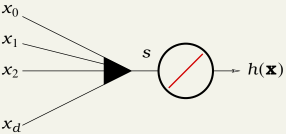

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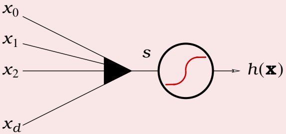

plausible err = cross-entropy

smooth convex $E_{\text{in}}(\mathbf{w})$:
gradient descent

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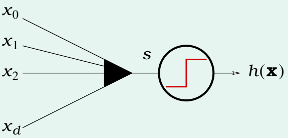

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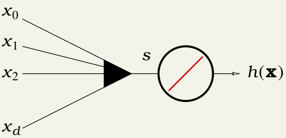

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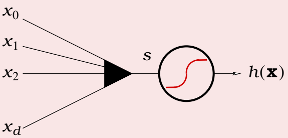

plausible err = cross-entropy

smooth convex $E_{\text{in}}(\mathbf{w})$: gradient descent

can linear regression or logistic regression **help linear classification**?

Error Functions Revisited

linear scoring function: $s = \mathbf{w}^T\mathbf{x}$

for binary classification $y \in \{-1, +1\}$

linear classification

$$h(\mathbf{x}) = \text{sign}(s)$$
$$\text{err}(h, \mathbf{x}, y) = [\![h(\mathbf{x}) \neq y]\!]$$

$$\text{err}_{0/1}(s, y)$$
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linear regression

$$\begin{aligned} h(\mathbf{x}) &= s \\ \text{err}(h, \mathbf{x}, y) &= (h(\mathbf{x}) - y)^2 \end{aligned}$$

$$\begin{aligned} &\text{err}_{\text{SQR}}(s, y) \\ =\ & \end{aligned}$$

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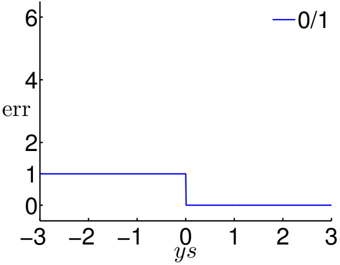
(ys): classification correctness score

Visualizing Error Functions

$$0/1 \quad \text{err}_{0/1}(s, y) = [\![\text{sign}(ys) \neq 1]\!]$$



- 0/1: 1 iff $ys \leq 0$

Visualizing Error Functions

$$\text{0/1} \quad \text{err}_{0/1}(s, y) = [\![\text{sign}(ys) \neq 1]\!]$$
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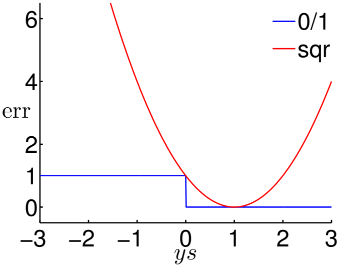

- 0/1: 1 iff $ys \leq 0$
- sqr: large if $ys \ll 1$
  but over-charge $ys \gg 1$
  small $\text{err}_{\text{SQR}} \rightarrow$ small $\text{err}_{0/1}$

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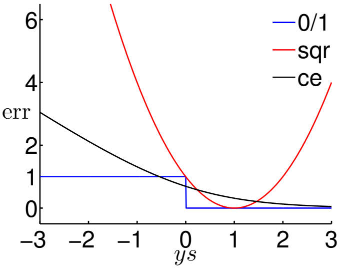

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- ce: monotonic of ys
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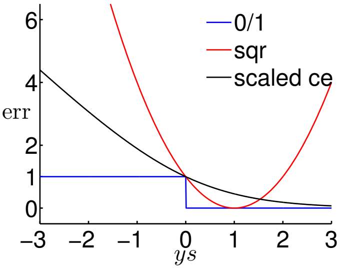
\text{scaled ce} \quad & \mathrm{err}_{\mathrm{SCE}}(s,y) &=& \log_2(1+\exp(-ys))
\end{aligned}
$$



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- ce: monotonic of ys
  small $\mathrm{err}_{\mathrm{CE}} \leftrightarrow$ small $\mathrm{err}_{0/1}$
- scaled ce: a proper upper bound of 0/1
  small $\mathrm{err}_{\mathrm{SCE}} \leftrightarrow$ small $\mathrm{err}_{0/1}$

upper bound:
useful for designing algorithmic error $\widehat{\mathrm{err}}$

Theoretical Implication of Upper Bound

For any ys where $s = \mathbf{w}^T\mathbf{x}$

$$\text{err}_{0/1}(s, y) \quad \leq \quad \text{err}_{\text{SCE}}(s, y) = \frac{1}{\ln 2}\text{err}_{\text{CE}}(s, y).$$

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VC on $0/1$:

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VC-Reg on CE :

$$E_{\text{out}}^{0/1}(\mathbf{w}) \quad \le \quad \frac{1}{\ln 2} E_{\text{out}}^{\text{CE}}(\mathbf{w})$$

$$\le$$

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VC-Reg on CE :

$$E_{\text{out}}^{0/1}(\mathbf{w}) \leq \frac{1}{\ln 2} E_{\text{out}}^{\text{CE}}(\mathbf{w})$$
$$\leq \frac{1}{\ln 2} E_{\text{in}}^{\text{CE}}(\mathbf{w}) + \frac{1}{\ln 2}\Omega^{\text{CE}}$$

small $E_{\text{in}}^{\text{CE}}(\mathbf{w}) \Longrightarrow$ small $E_{\text{out}}^{0/1}(\mathbf{w})$:
logistic/linear reg. for linear classification

Regression for Classification

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- **linear regression** sometimes used to set $\mathbf{w}_0$ for **PLA**/**pocket**/**logistic regression**
- **logistic regression** often preferred over **pocket**

Fun Time

Following the definition in the lecture, which of the following is not always $\geq \mathrm{err}_{0/1}(y, s)$ when $y \in \{-1, +1\}$?

1. $\mathrm{err}_{0/1}(y, s)$
2. $\mathrm{err}_{\mathrm{SQR}}(y, s)$
3. $\mathrm{err}_{\mathrm{CE}}(y, s)$
4. $\mathrm{err}_{\mathrm{SCE}}(y, s)$

Fun Time

Following the definition in the lecture, which of the following is not always $\geq \mathrm{err}_{0/1}(y, s)$ when $y \in \{-1, +1\}$?

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2. $\mathrm{err}_{\mathrm{SQR}}(y, s)$
3. $\mathrm{err}_{\mathrm{CE}}(y, s)$
4. $\mathrm{err}_{\mathrm{SCE}}(y, s)$

Reference Answer: ③

Too simple, uh? :-) Anyway, note that $\mathrm{err}_{0/1}$ is surely an upper bound of itself.

Two Iterative Optimization Schemes

For $t = 0, 1, \ldots$

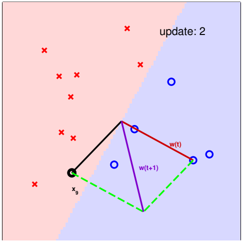
$$\mathbf{w}_{t+1} \leftarrow \mathbf{w}_t + \eta \mathbf{v}$$

when stop, return last $\mathbf{w}$ as g

PLA

pick $(\mathbf{x}_n, y_n)$ and decide $\mathbf{w}_{t+1}$ by **the one example**

$O(1)$ time per iteration **:-)**



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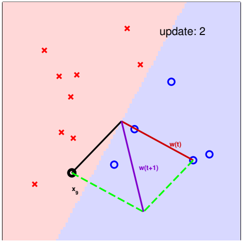
logistic regression (pocket)

check $\mathcal{D}$ and decide $\mathbf{w}_{t+1}$ (or new $\hat{\mathbf{w}}$) by **all examples**

$O(N)$ time per iteration :-(



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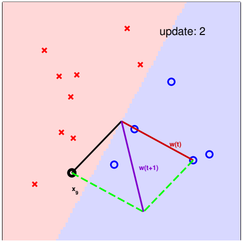

logistic regression with $O(1)$ **time per iteration?**

Logistic Regression Revisited

$$\mathbf{w}_{t+1} \leftarrow \mathbf{w}_t + \eta \underbrace{\frac{1}{N}\sum_{n=1}^{N}\theta\left(-y_n\mathbf{w}_t^T\mathbf{x}_n\right)\left(y_n\mathbf{x}_n\right)}_{-\nabla E_{\text{in}}(\mathbf{w}_t)}$$

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- want: update direction $\mathbf{v} \approx -\nabla E_{\text{in}}(\mathbf{w}_t)$
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stochastic gradient:
$\nabla_{\mathbf{w}} \ \mathrm{err}(\mathbf{w}, \mathbf{x}_n, y_n)$ with random n

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stochastic gradient:

$$\nabla_{\mathbf{w}} \; \text{err}(\mathbf{w}, \mathbf{x}_n, y_n) \text{ with random } n$$

true gradient:

$$\nabla_{\mathbf{w}} \; E_{\text{in}}(\mathbf{w}) = \underset{\text{random } n}{\mathcal{E}} \nabla_{\mathbf{w}} \; \text{err}(\mathbf{w}, \mathbf{x}_n, y_n)$$

Stochastic Gradient Descent (SGD)

stochastic gradient = true gradient + zero-mean 'noise' directions

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- pros: **simple & cheaper computation :-)**
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Stochastic Gradient Descent

- idea: replace true gradient by stochastic gradient
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  average true gradient ≈ average stochastic gradient
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SGD logistic regression, **looks familiar? :-)**:

$$\mathbf{w}_{t+1} \leftarrow \mathbf{w}_t + \eta \underbrace{\theta\left(-y_n \mathbf{w}_t^T \mathbf{x}_n\right)\left(y_n \mathbf{x}_n\right)}_{-\nabla \text{err}(\mathbf{w}_t, \mathbf{x}_n, y_n)}$$

PLA Revisited

SGD logistic regression:

$$\mathbf{w}_{t+1} \leftarrow \mathbf{w}_t + \eta \cdot \theta\left(-y_n \mathbf{w}_t^T \mathbf{x}_n\right)\left(y_n \mathbf{x}_n\right)$$

PLA:

$$\mathbf{w}_{t+1} \leftarrow \mathbf{w}_t + 1 \cdot \left[\!\left[y_n \neq \text{sign}(\mathbf{w}_t^T \mathbf{x}_n) \right]\!\right] \left(y_n \mathbf{x}_n\right)$$

PLA Revisited

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- SGD logistic regression $\approx$ ‘soft’ PLA

PLA Revisited

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two practical rule-of-thumb:

PLA Revisited

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- η?

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two practical rule-of-thumb:

- stopping condition? t **large enough**
- η? 0.1 when $\mathbf{x}$ in proper range

Fun Time

Consider applying SGD on linear regression for big data. What is the update direction when using the negative stochastic gradient?

1. $\mathbf{x}_n$
2. $y_n \mathbf{x}_n$
3. $2(\mathbf{w}_t^T \mathbf{x}_n - y_n)\mathbf{x}_n$
4. $2(y_n - \mathbf{w}_t^T \mathbf{x}_n)\mathbf{x}_n$

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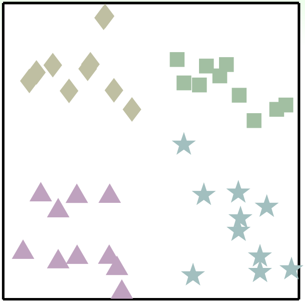
Reference Answer: 4

Go check lecture 9 if you have forgotten about the gradient of squared error. :-)

Anyway, the update rule has a nice physical interpretation: improve $\mathbf{w}_t$ by 'correcting' proportional to the residual $(y_n - \mathbf{w}_t^T\mathbf{x}_n)$.

Multiclass Classification



- $\mathcal{Y} = \{\square, \Diamond, \triangle, \star\}$ (4-class classification)
- **many applications** in practice, especially for 'recognition'

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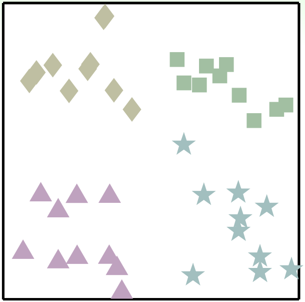

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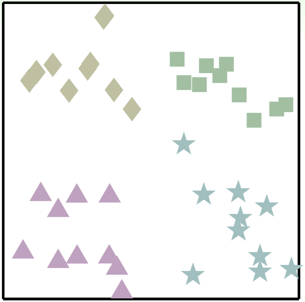
next: use **tools for $\{\times, \circ\}$ classification** to $\{\square, \Diamond, \triangle, \star\}$ classification

One Class at a Time



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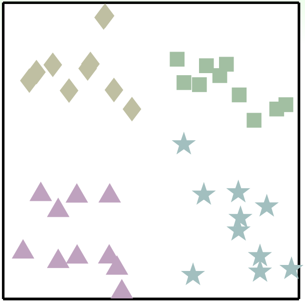

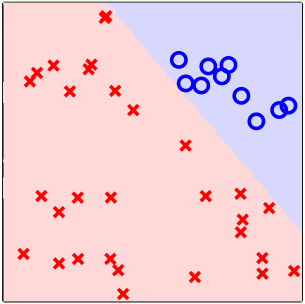

$\square$ or not? $\{\square = \circ, \Diamond = \times, \triangle = \times, \star = \times\}$

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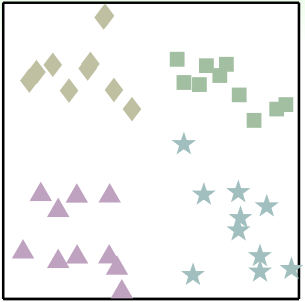
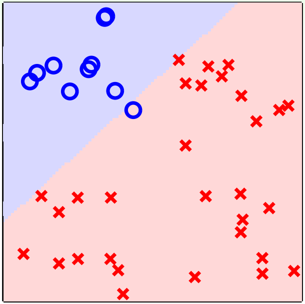
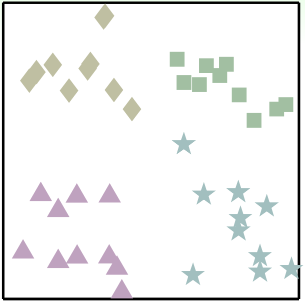
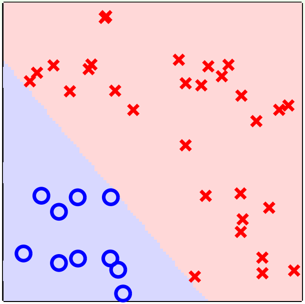




$\lozenge$ or not? $\{\square = \times, \lozenge = \circ, \triangle = \times, \star = \times\}$

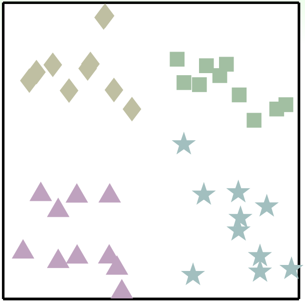
One Class at a Time

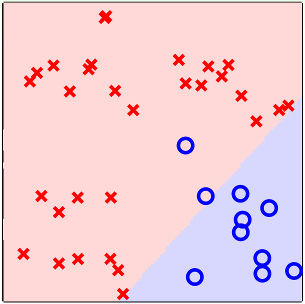




$\triangle$ or not? $\{\square = \times, \Diamond = \times, \triangle = \circ, \star = \times\}$

One Class at a Time





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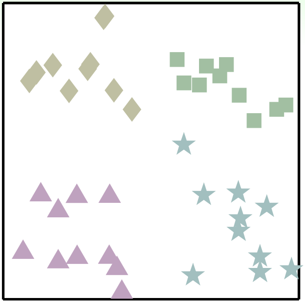
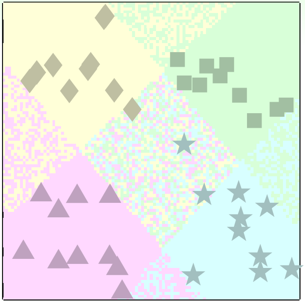
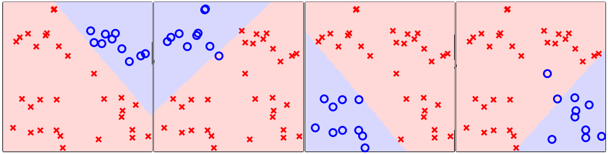
Multiclass Prediction: Combine Binary Classifiers

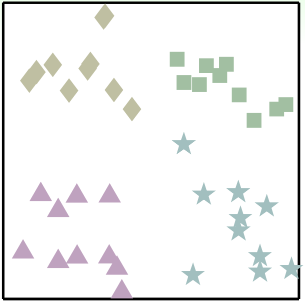


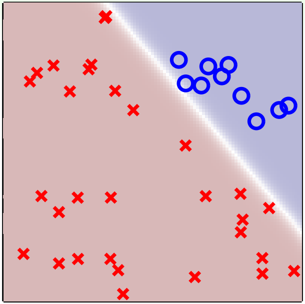


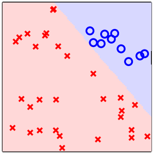


but **ties? :-)**

One Class at a Time **Softly**







$P(\square|\mathbf{x})?\ \{\square = \circ, \Diamond = \times, \triangle = \times, \star = \times\}$

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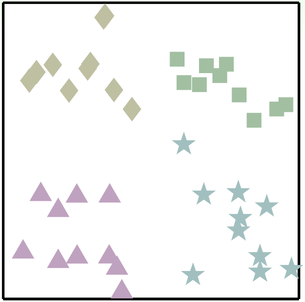

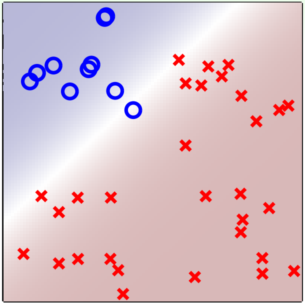

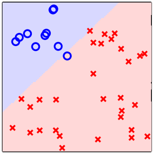

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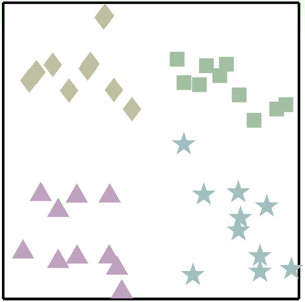

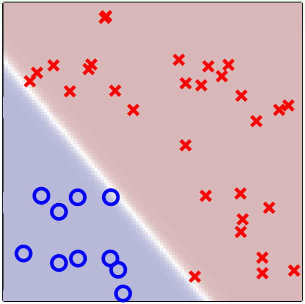

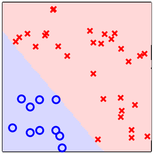

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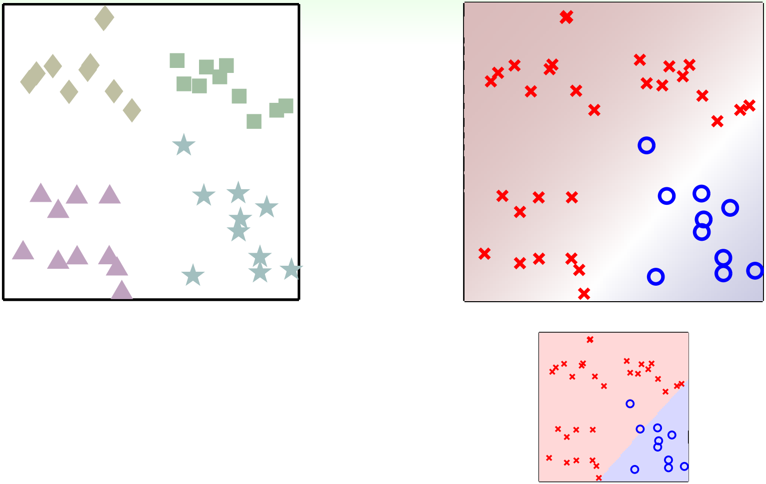

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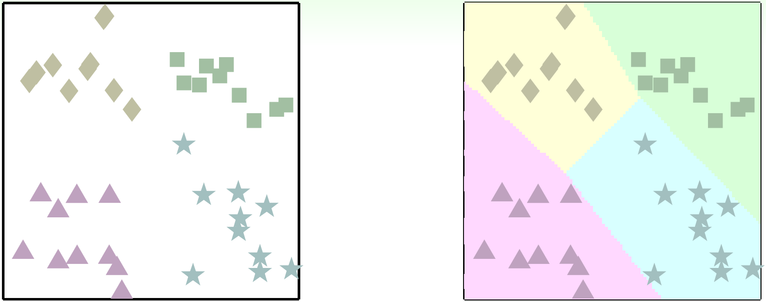
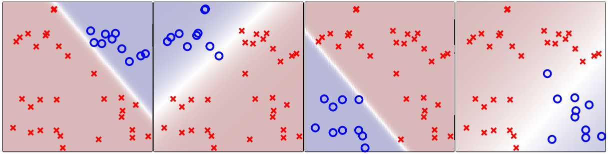
Multiclass Prediction: Combine **Soft** Classifiers





$$g(\mathbf{x}) = \text{argmax}_{k \in \mathcal{Y}}\, \theta\left(\mathbf{w}_{[k]}^T \mathbf{x}\right)$$

One-Versus-All (OVA) Decomposition

1. for $k \in \mathcal{Y}$

   obtain $\mathbf{w}_{[k]}$ by running logistic regression on

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OVA: a simple multiclass **meta-algorithm**
to keep in your toolbox

Fun Time

Which of the following best describes the training effort of OVA decomposition based on logistic regression on some K-class classification data of size N?

1. learn K logistic regression hypotheses, each from data of size N/K
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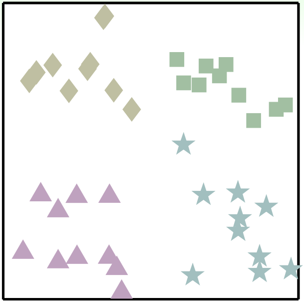
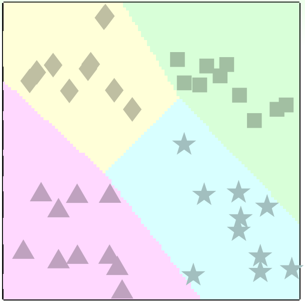
4. learn K logistic regression hypotheses, each from data of size NK

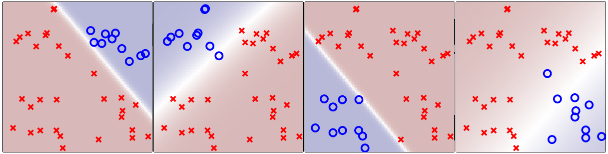
Reference Answer: ③

Note that the **learning part can be easily done in parallel**, while the data is essentially of the same size as the original data.

Source of **Unbalance**: One versus **All**







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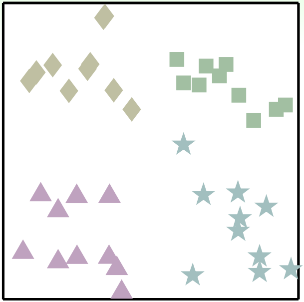
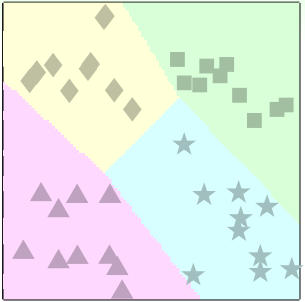
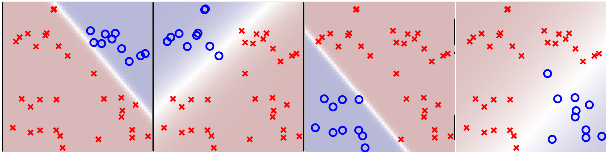
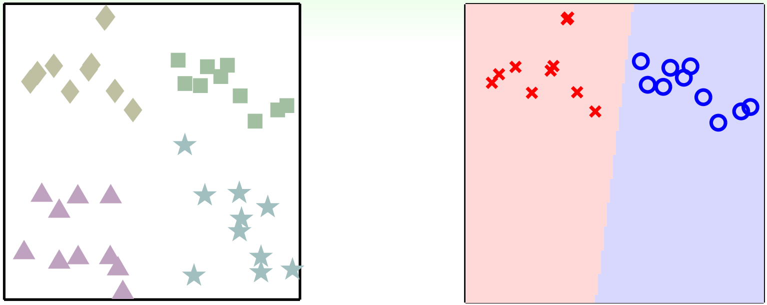






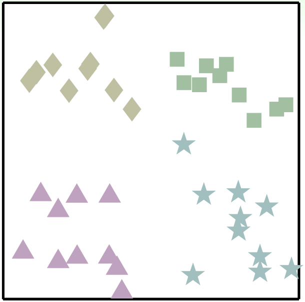
idea: make binary classification problems
more **balanced** by one versus **one**

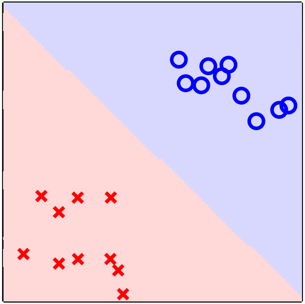
One versus One at a Time



$\square$ or $\diamond$? $\{\square = \circ, \diamond = \times, \triangle = \text{nil}, \star = \text{nil}\}$

One versus One at a Time





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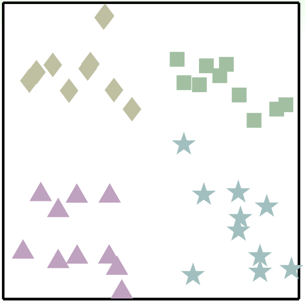

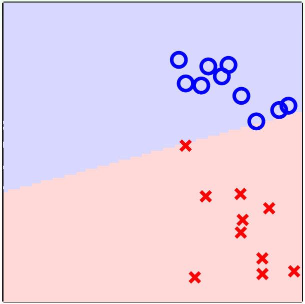

□ or ⋆? {□ = ∘, ◊ = nil, △ = nil, ⋆ = ×}

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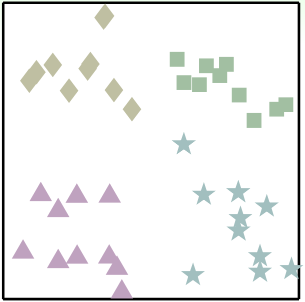

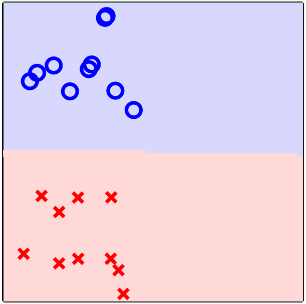

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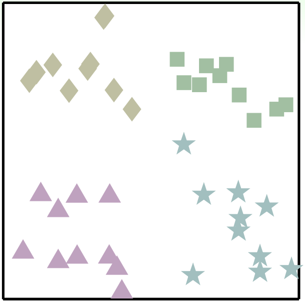

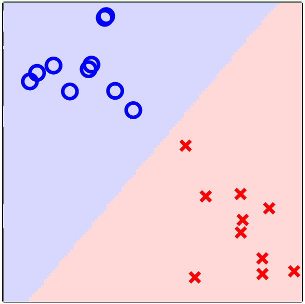

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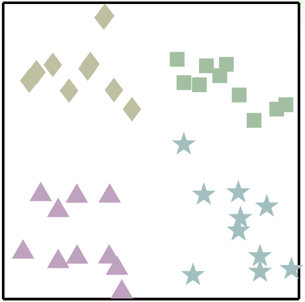

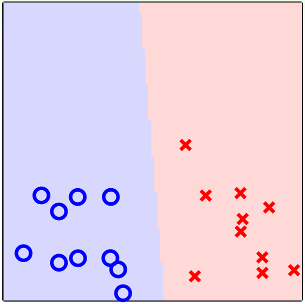

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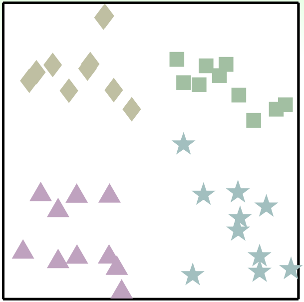
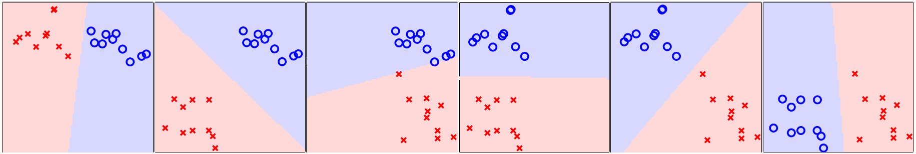
Multiclass Prediction: Combine **Pairwise** Classifiers





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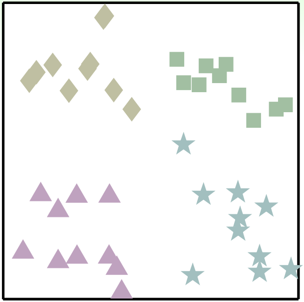

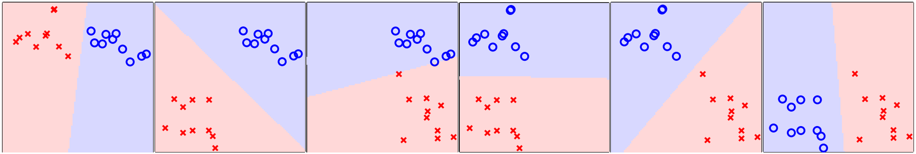

$$g(\mathbf{x}) = \text{tournament champion} \left\{ \mathbf{w}_{[k,\ell]}^T \mathbf{x} \right\}$$

(voting of classifiers)

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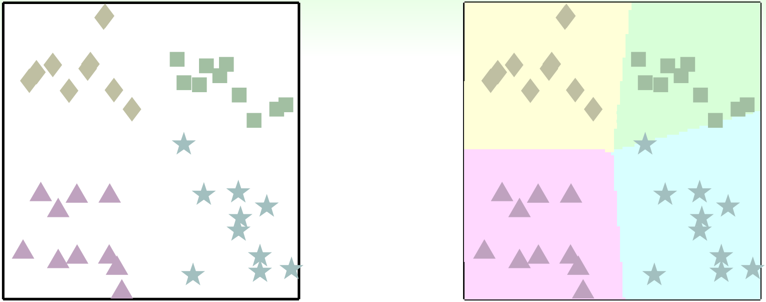

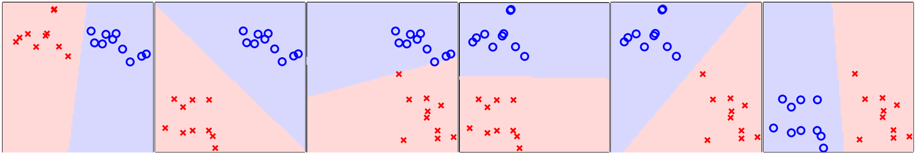

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Assume that some binary classification algorithm takes exactly N^3 CPU-seconds for data of size N. Also, for some 10-class multiclass classification problem, assume that there are $N/10$ examples for each class. Which of the following is total CPU-seconds needed for OVO decomposition based on the binary classification algorithm?

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Reference Answer: 2

There are 45 binary classifiers, each trained with data of size $(2N)/10$. Note that OVA decomposition with the same algorithm would take $10N^3$ time, much worse than OVO.

Summary

1. When Can Machines Learn?
2. Why Can Machines Learn?
3. **How** Can Machines Learn?

Lecture 10: Logistic Regression

Lecture 11: Linear Models for Classification

- Linear Models for Binary Classification
  three models useful in different ways
- Stochastic Gradient Descent
  follow negative stochastic gradient
- Multiclass via Logistic Regression
  predict with maximum estimated $P(k|\mathbf{x})$
- Multiclass via Binary Classification
  predict the tournament champion

- **next: from linear to nonlinear**

4. How Can Machines Learn Better?