

# **Classification**

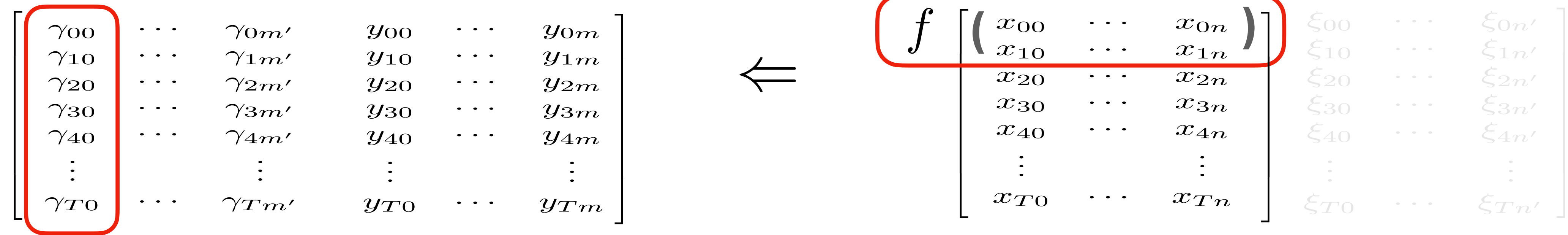
**ML - Supervised Learning**

# Classification

**OUTPUTS**  
(Dependent Variables)

$$\gamma_t = \text{sgn}(\theta^T x_t - \theta_0)$$

**INPUTS**  
(Independent Variables)



“Binary classifier”

Support Vector Machine (SVM)

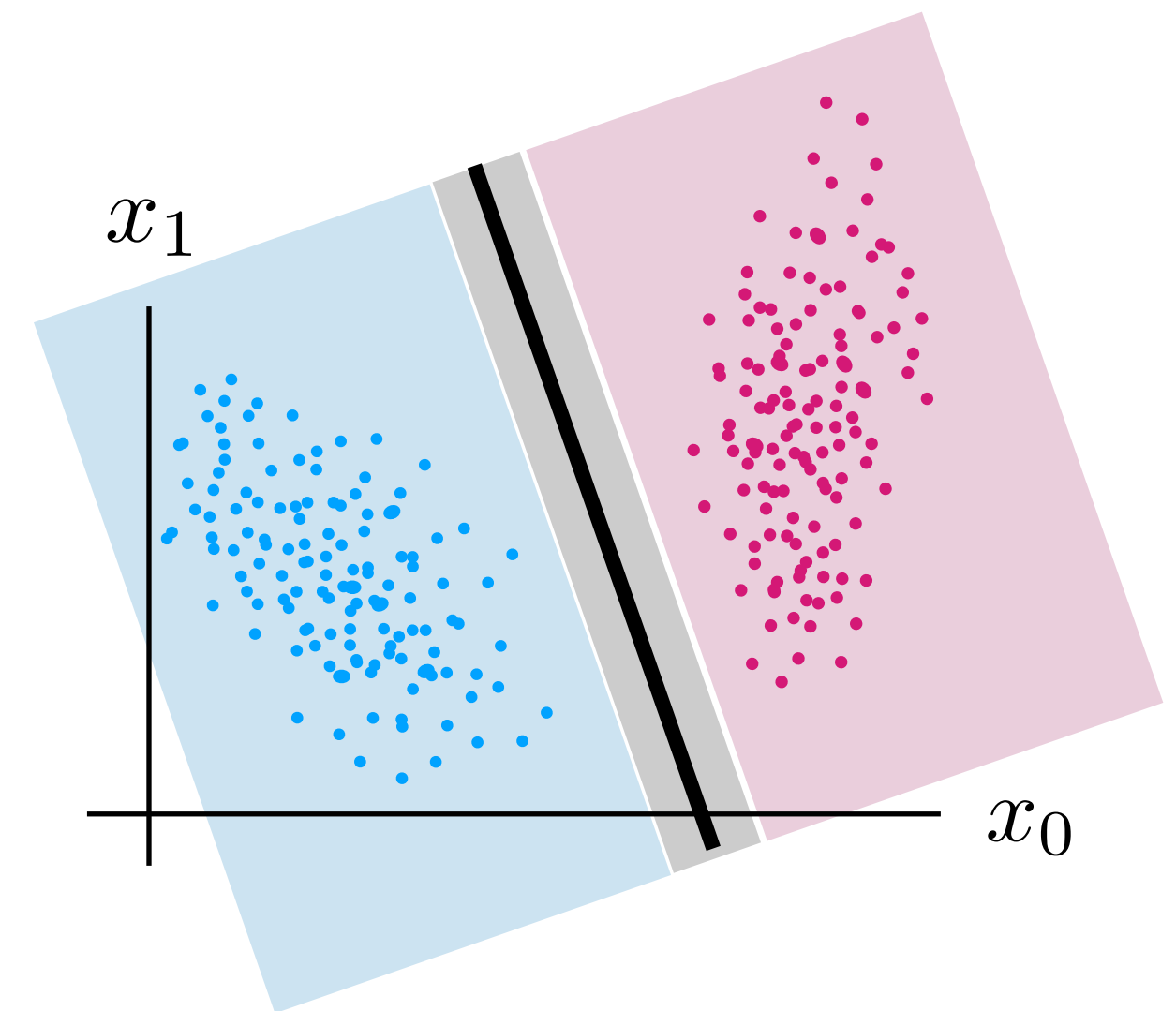
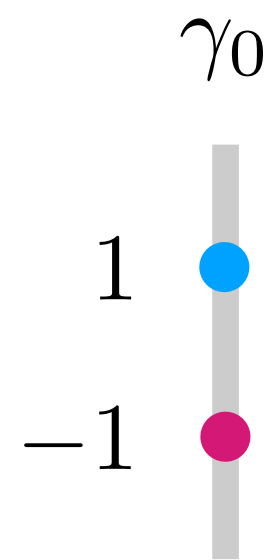
**COST:**

$$\min_{\theta} \|\theta_{1:n}\|_2^2$$

s.t.  $\gamma_t(\theta_{1:n}^T x_t - \theta_0) \geq 1$

Hard boundary

“Binary classifier”

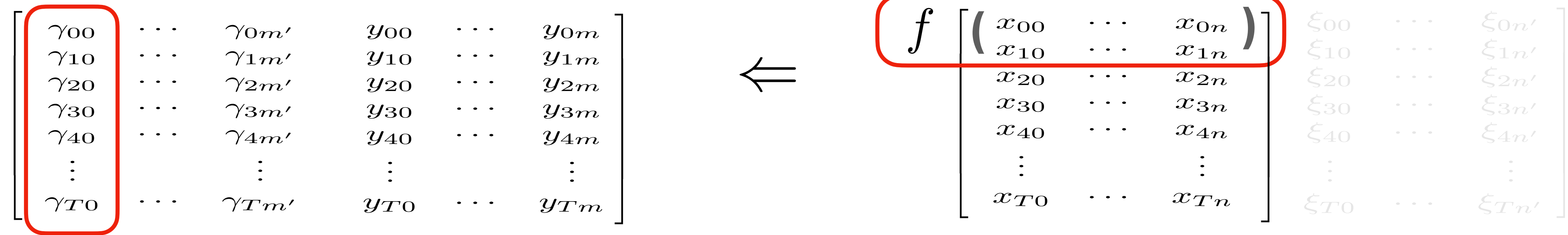


# Classification

**OUTPUTS**  
(Dependent Variables)

$$\gamma_t = \text{sgn}(\theta^T x_t - \theta_0)$$

**INPUTS**  
(Independent Variables)

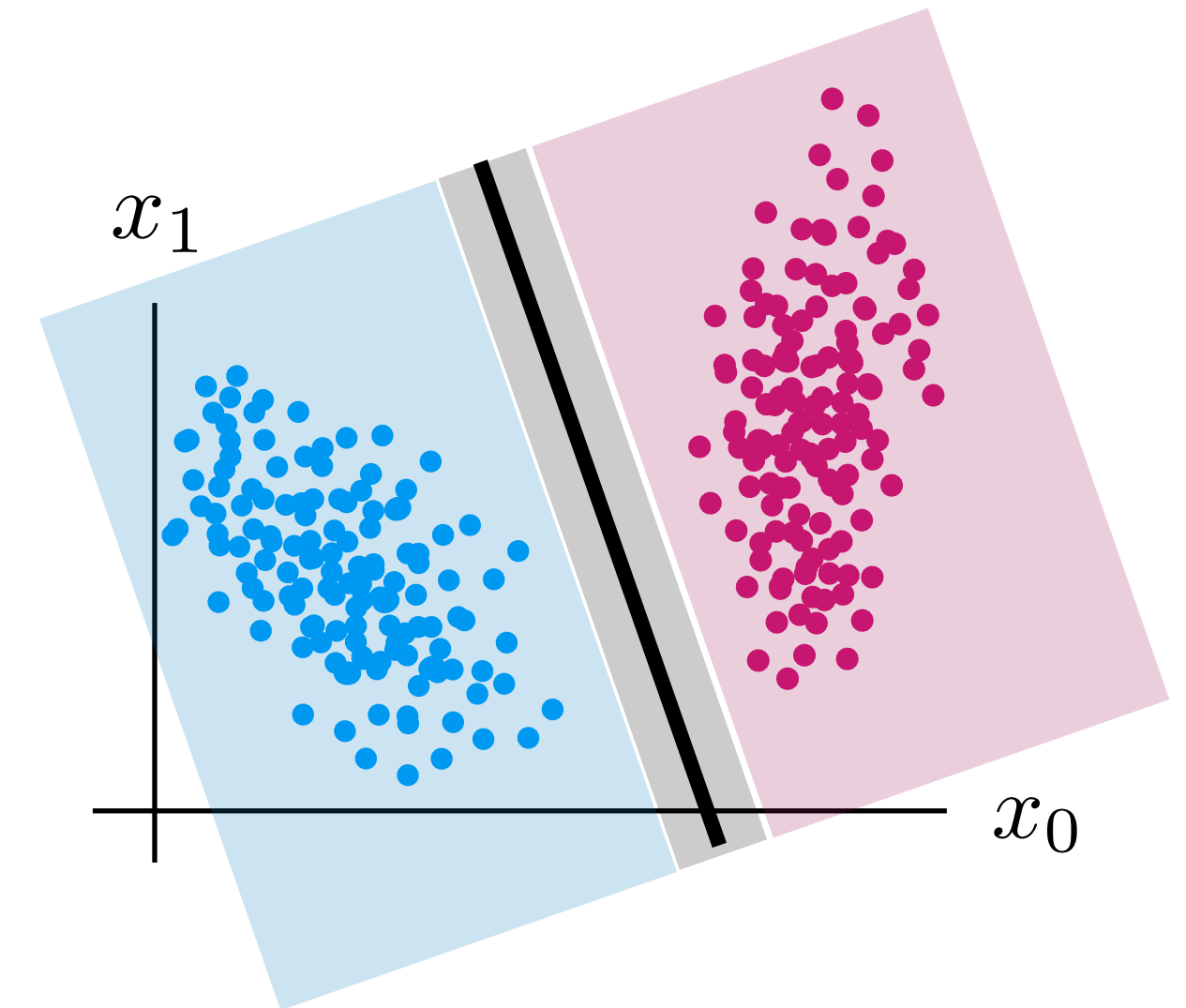
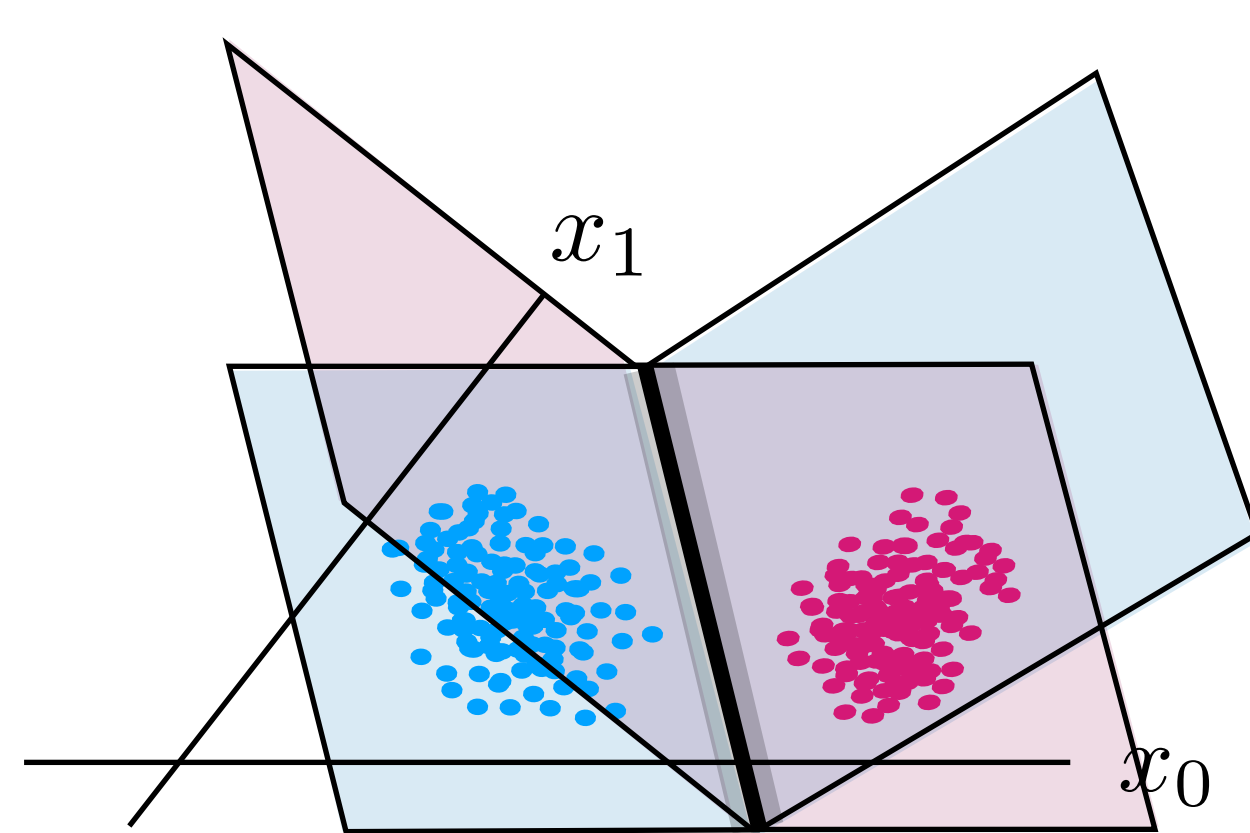
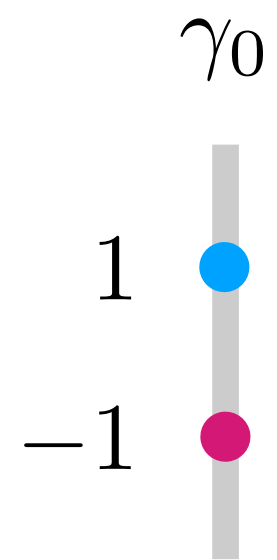


“Binary classifier”

Support Vector Machine (SVM)

**COST:** 
$$\min_{\theta} \lambda \|\theta_{1:n}\|_2^2 + \frac{1}{T} \sum_t \max\{0, 1 - \gamma_t(\theta_{1:n}^T x_t - \theta_0)\}$$

Soft boundary

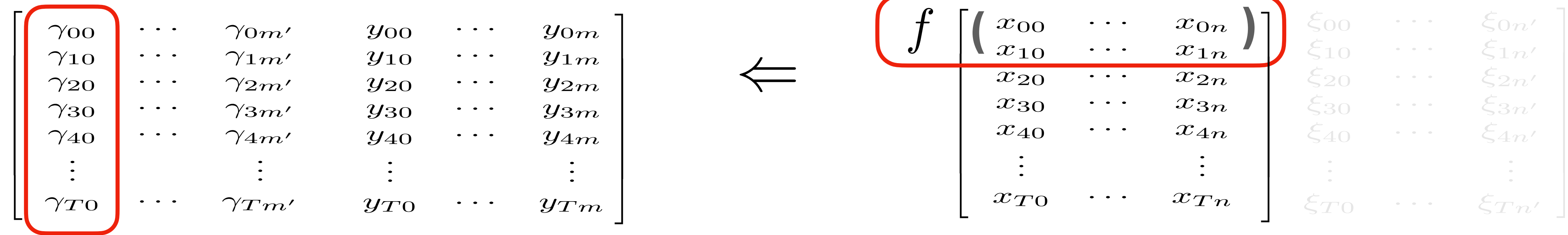


# Classification

**OUTPUTS**  
(Dependent Variables)

$$\gamma_t = \text{sgn}(\theta^T x_t - \theta_0)$$

**INPUTS**  
(Independent Variables)

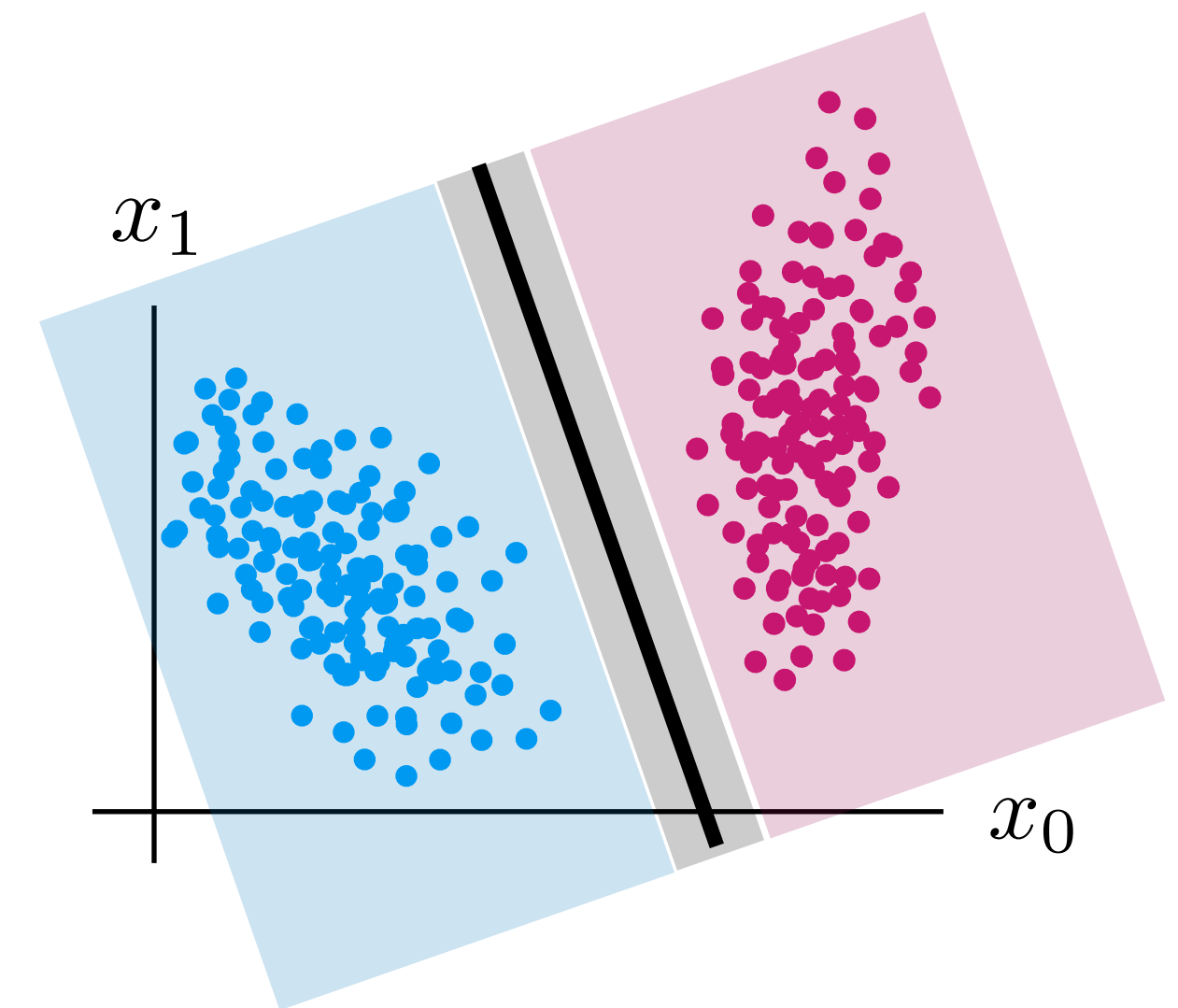
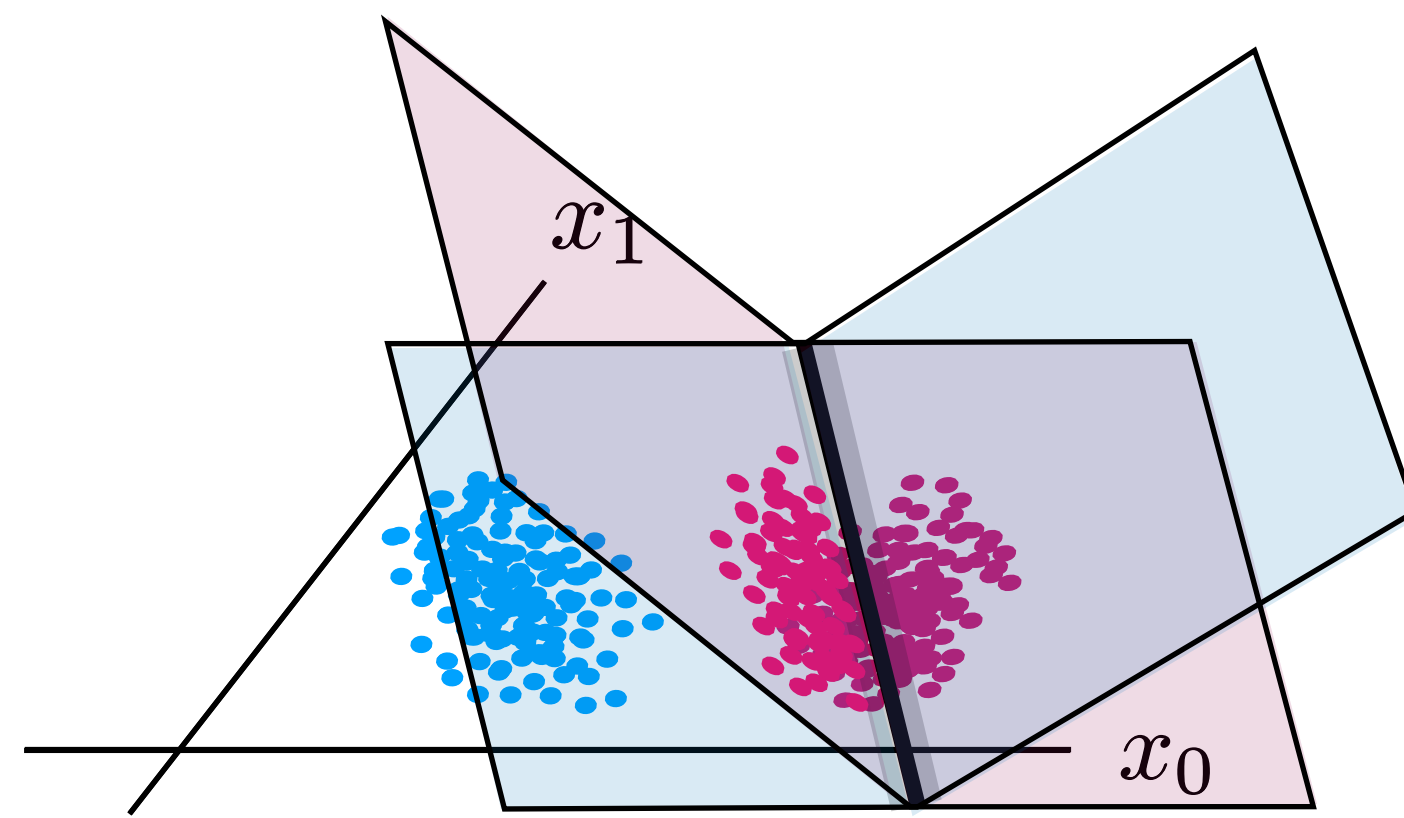
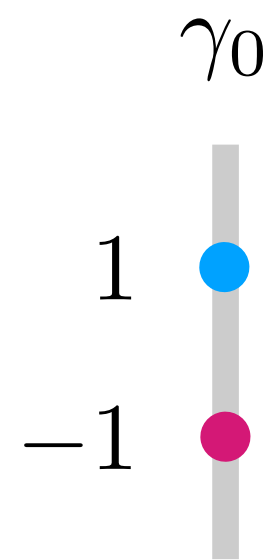


“Binary classifier”

Support Vector Machine (SVM)

**COST:** 
$$\min_{\theta} \lambda \|\theta_{1:n}\|_2^2 + \frac{1}{T} \sum_t \max\{0, 1 - \gamma_t(\theta_{1:n}^T x_t - \theta_0)\}$$

Soft boundary

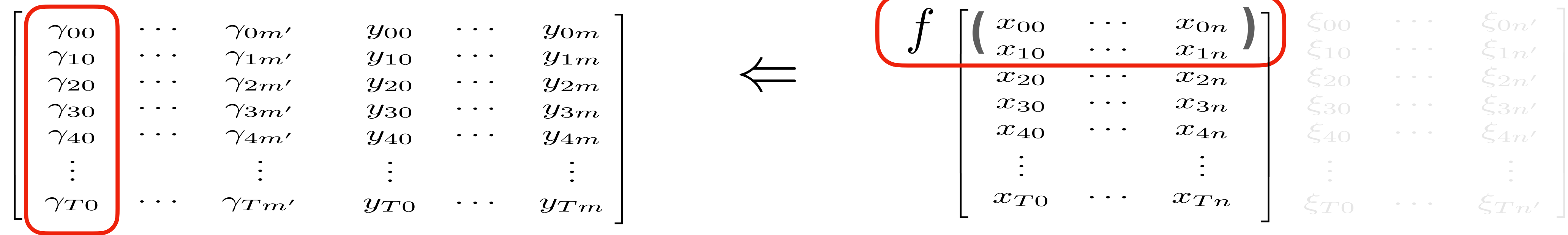


# Classification

**OUTPUTS**  
(Dependent Variables)

$$\gamma_t = \text{sgn}(\theta^T x_t - \theta_0)$$

**INPUTS**  
(Independent Variables)

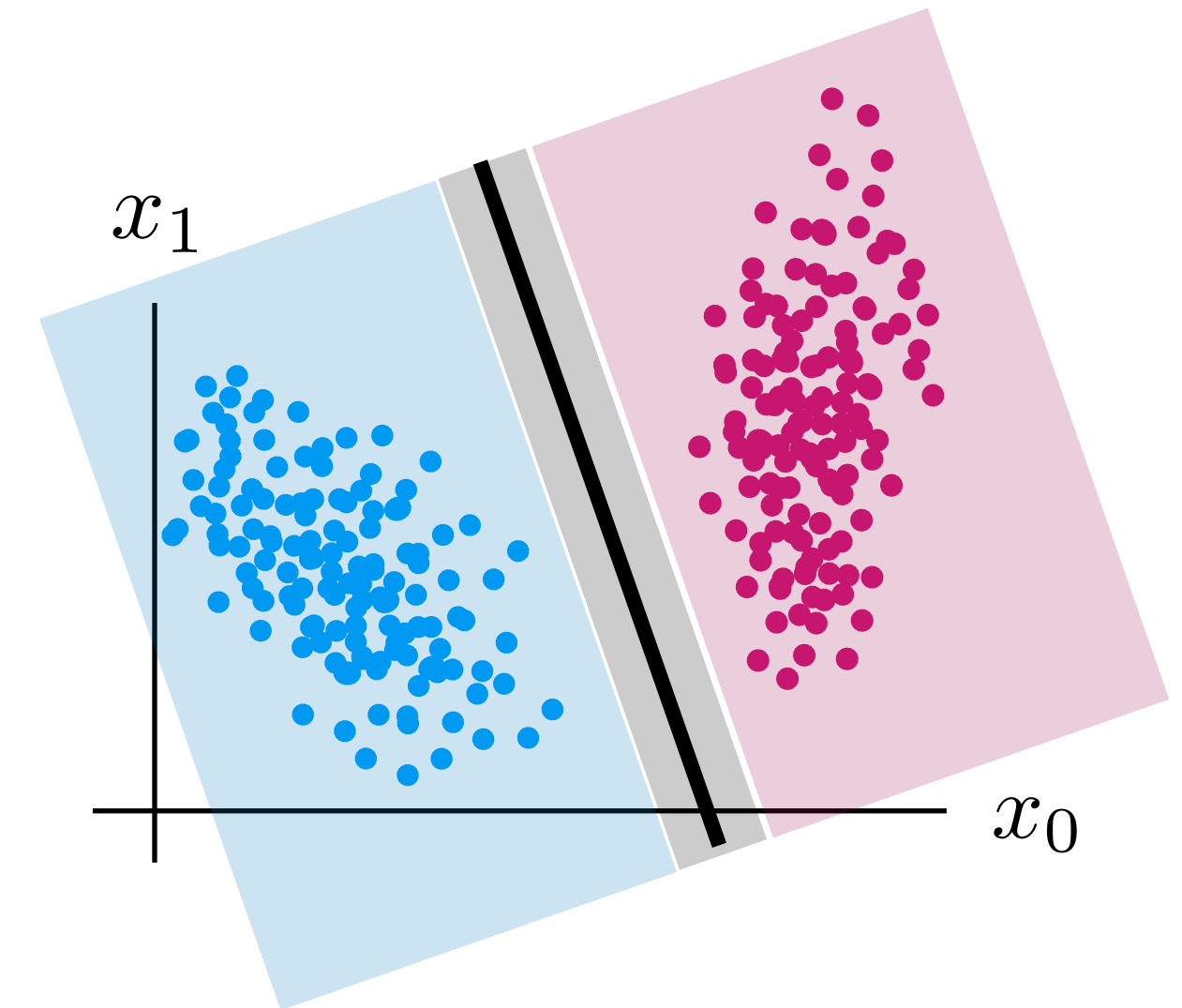
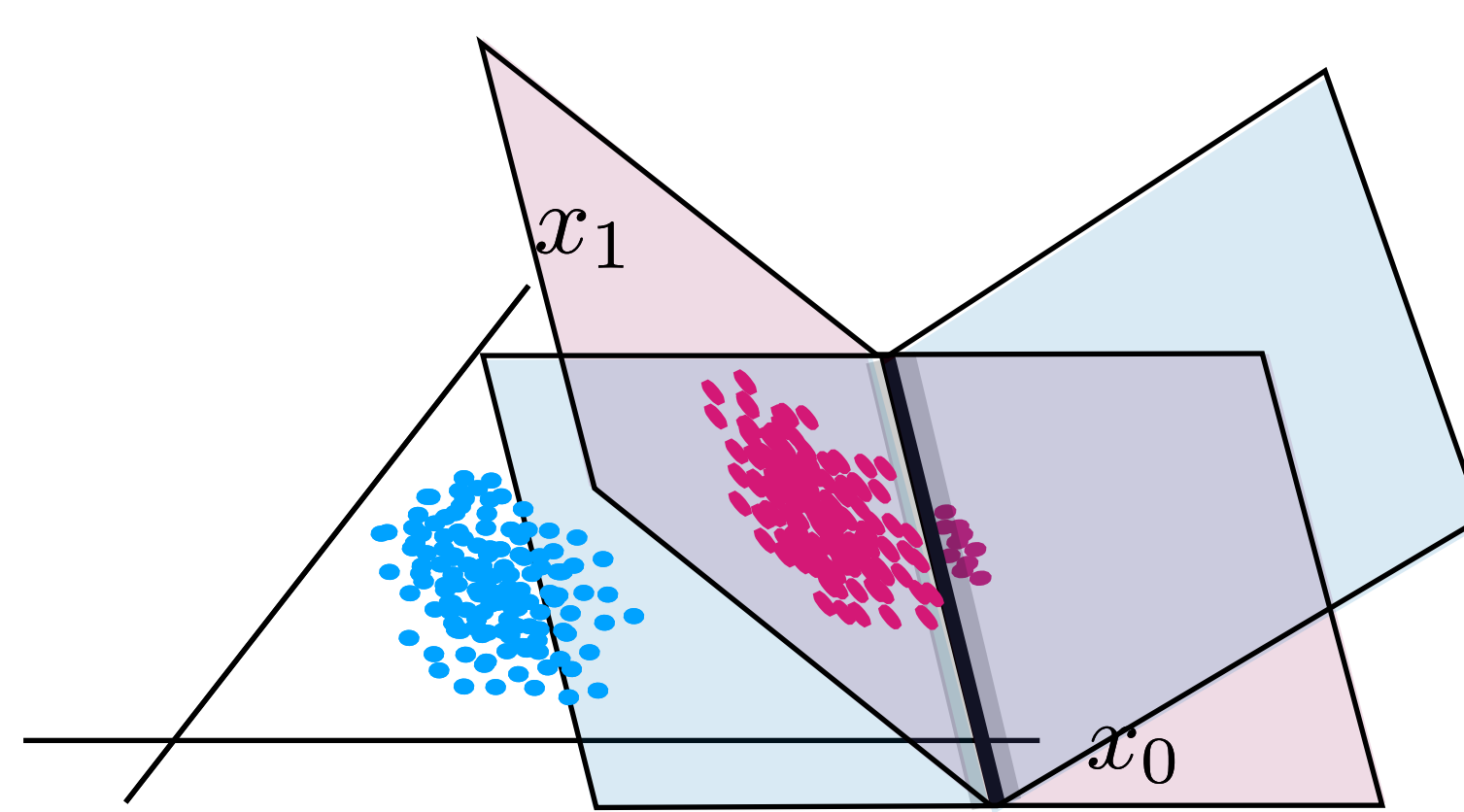
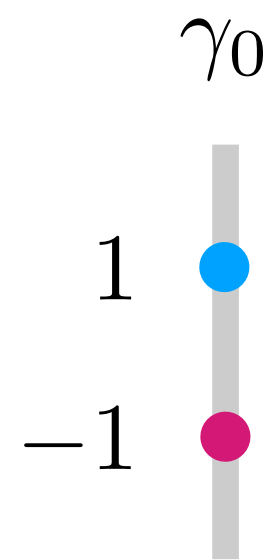


“Binary classifier”

Support Vector Machine (SVM)

**COST:** 
$$\min_{\theta} \lambda \|\theta_{1:n}\|_2^2 + \frac{1}{T} \sum_t \max\{0, 1 - \gamma_t(\theta_{1:n}^T x_t - \theta_0)\}$$

Soft boundary

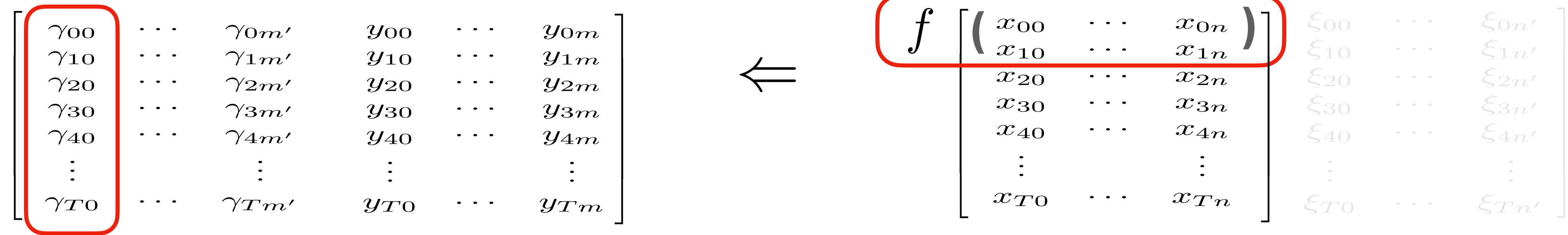


# Classification

**OUTPUTS**  
(Dependent Variables)

$$\gamma_t = \text{sgn}(\theta^T x_t - \theta_0)$$

**INPUTS**  
(Independent Variables)

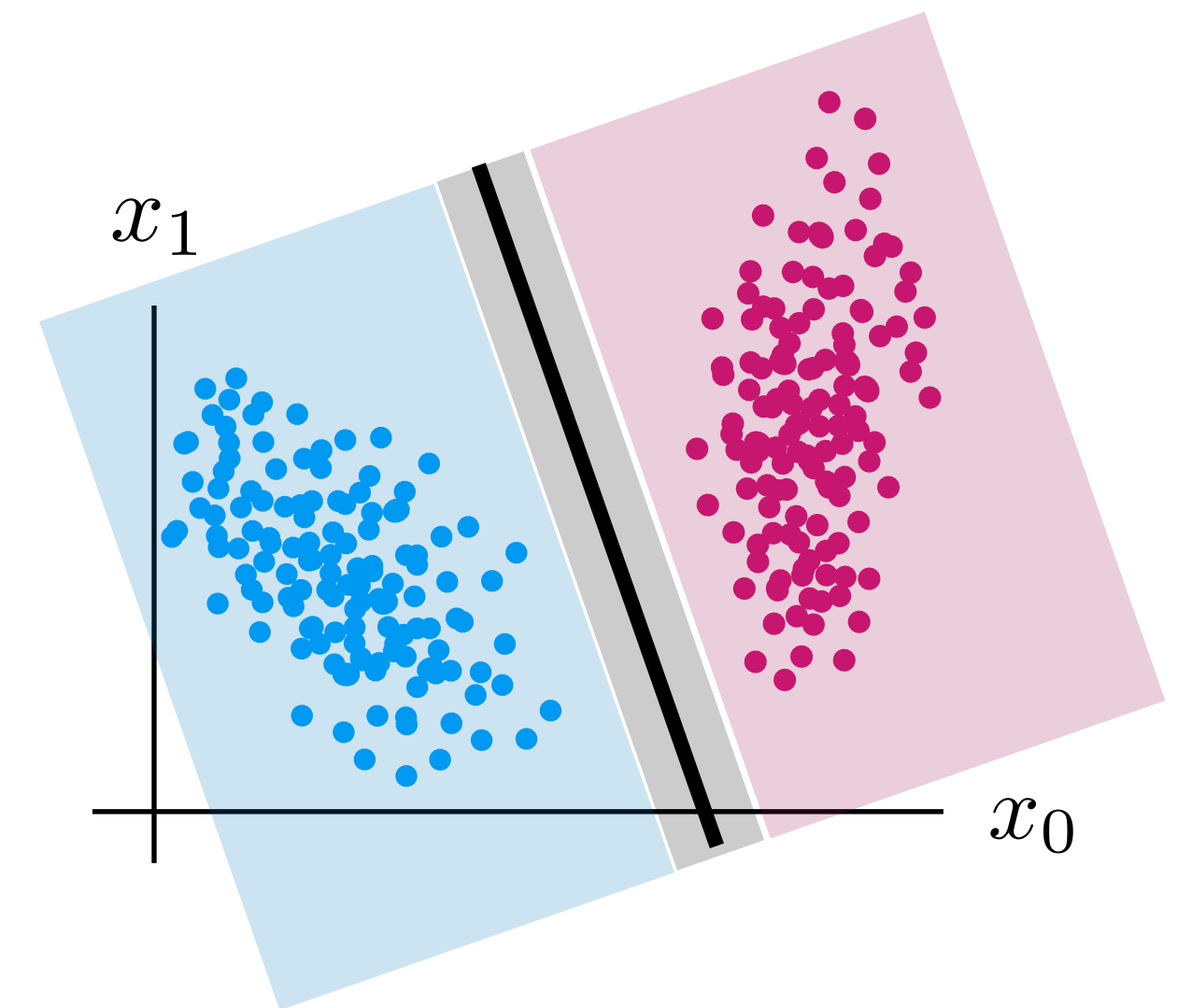
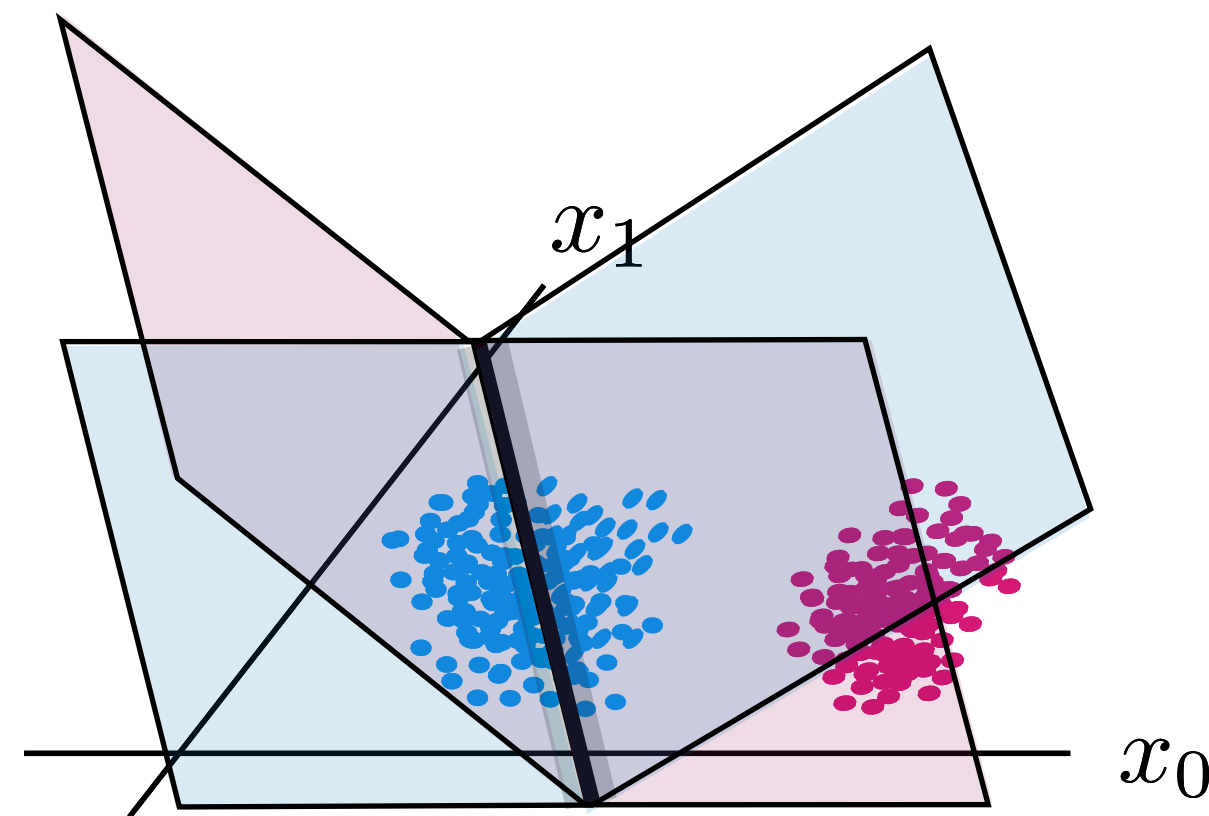
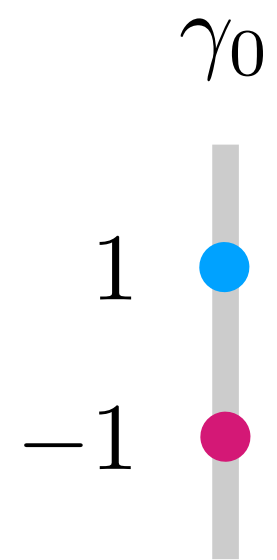


“Binary classifier”

Support Vector Machine (SVM)

**COST:** 
$$\min_{\theta} \lambda \|\theta_{1:n}\|_2^2 + \frac{1}{T} \sum_t \max\{0, 1 - \gamma_t(\theta_{1:n}^T x_t - \theta_0)\}$$

Soft boundary





# Classification

## OUTPUTS

(Dependent Variables)

$$\gamma_t = \text{sgn}(\theta^T x_t - \theta_0)$$

## INPUTS

(Independent Variables)

$$\begin{bmatrix} \gamma_{00} & \cdots & \gamma_{0m'} & y_{00} & \cdots & y_{0m} \\ \gamma_{10} & \cdots & \gamma_{1m'} & y_{10} & \cdots & y_{1m} \\ \gamma_{20} & \cdots & \gamma_{2m'} & y_{20} & \cdots & y_{2m} \\ \gamma_{30} & \cdots & \gamma_{3m'} & y_{30} & \cdots & y_{3m} \\ \gamma_{40} & \cdots & \gamma_{4m'} & y_{40} & \cdots & y_{4m} \\ \vdots & & \vdots & \vdots & & \vdots \\ \gamma_{T0} & \cdots & \gamma_{Tm'} & y_{T0} & \cdots & y_{Tm} \end{bmatrix} \leftarrow f \begin{bmatrix} \left( \begin{array}{ccc} x_{00} & \cdots & x_{0n} \\ x_{10} & \cdots & x_{1n} \\ x_{20} & \cdots & x_{2n} \\ x_{30} & \cdots & x_{3n} \\ x_{40} & \cdots & x_{4n} \\ \vdots & & \vdots \\ x_{T0} & \cdots & x_{Tn} \end{array} \right) \\ \xi_{00} & \cdots & \xi_{0n'} \\ \xi_{10} & \cdots & \xi_{1n'} \\ \xi_{20} & \cdots & \xi_{2n'} \\ \xi_{30} & \cdots & \xi_{3n'} \\ \xi_{40} & \cdots & \xi_{4n'} \\ \vdots & & \vdots \\ \xi_{T0} & \cdots & \xi_{Tn'} \end{bmatrix}$$

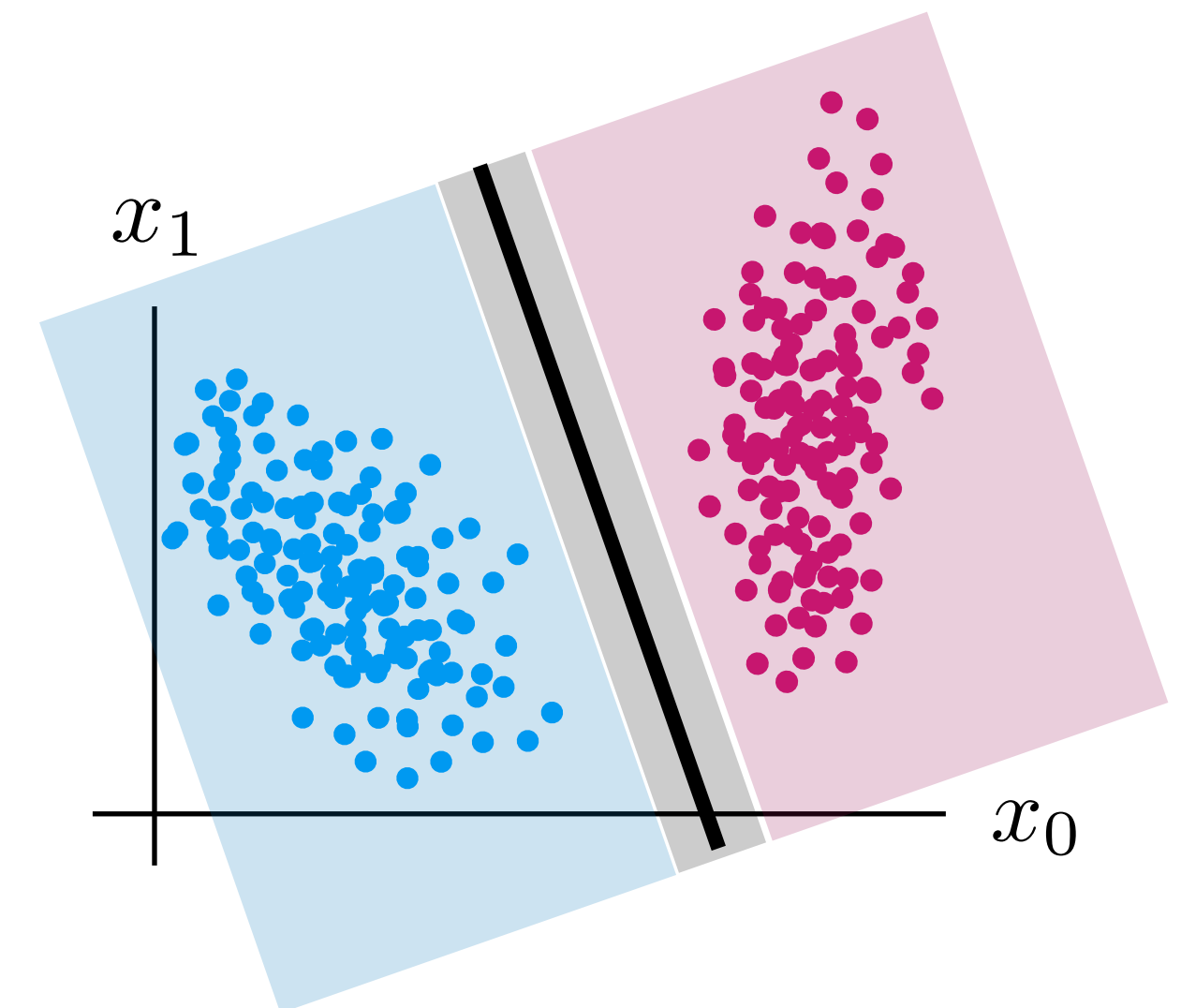
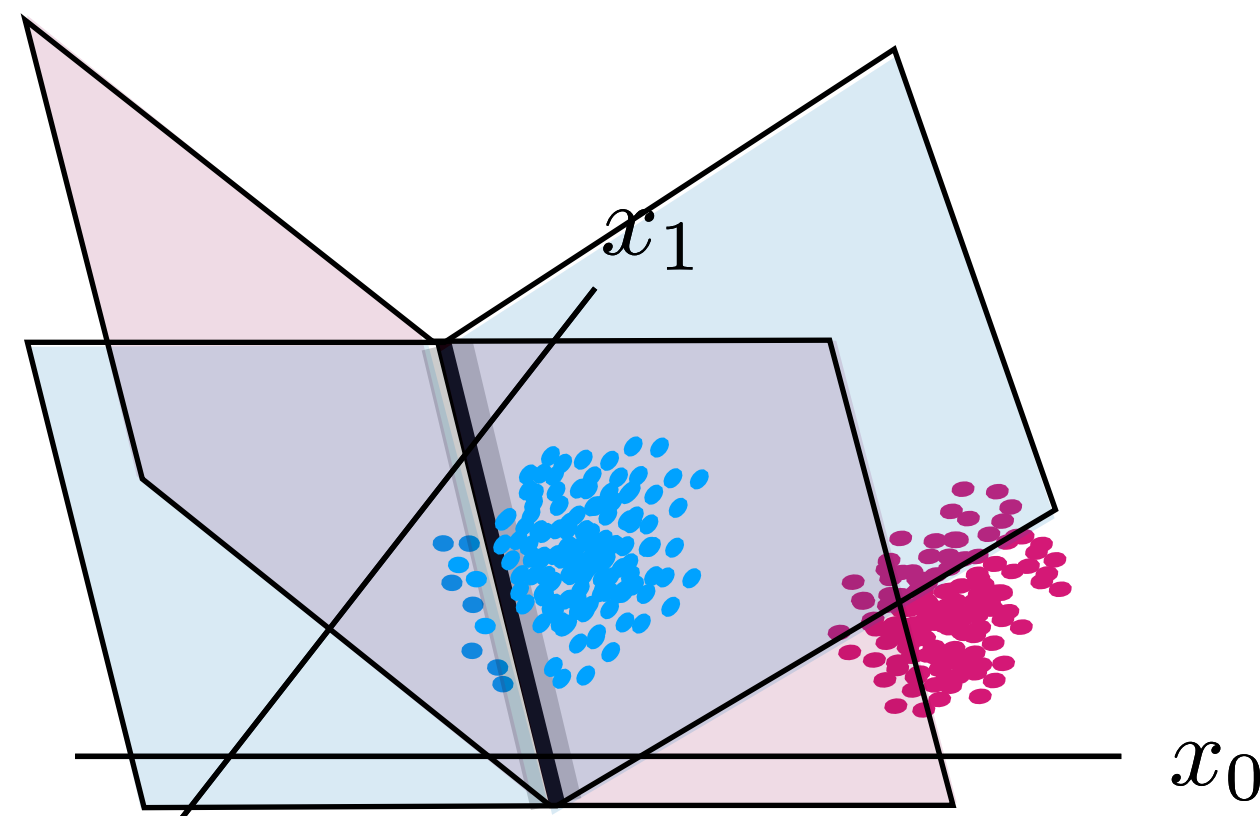
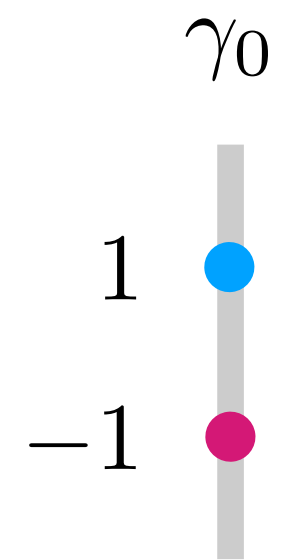
“Binary classifier”

Support Vector Machine (SVM)

**COST:**

$$\min_{\theta} \lambda \|\theta_{1:n}\|_2^2 + \frac{1}{T} \sum_t \max\{0, 1 - \gamma_t(\theta_{1:n}^T x_t - \theta_0)\}$$

Soft boundary

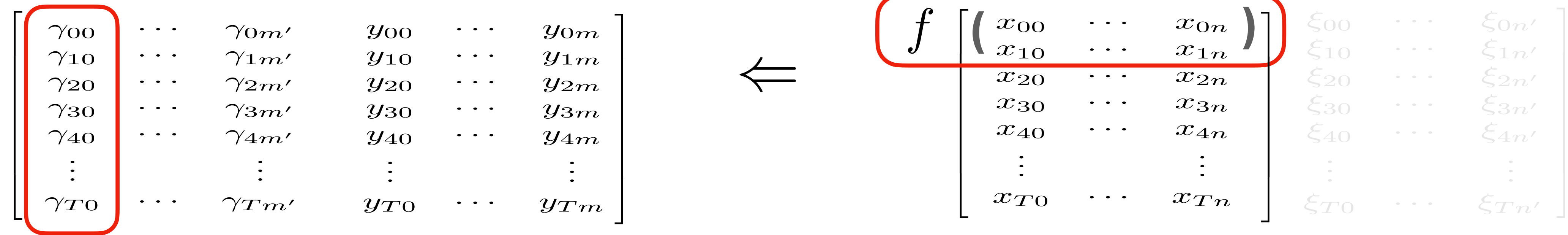


# Classification

**OUTPUTS**  
(Dependent Variables)

$$\gamma_t = \text{sgn}(\theta^T x_t - \theta_0)$$

**INPUTS**  
(Independent Variables)

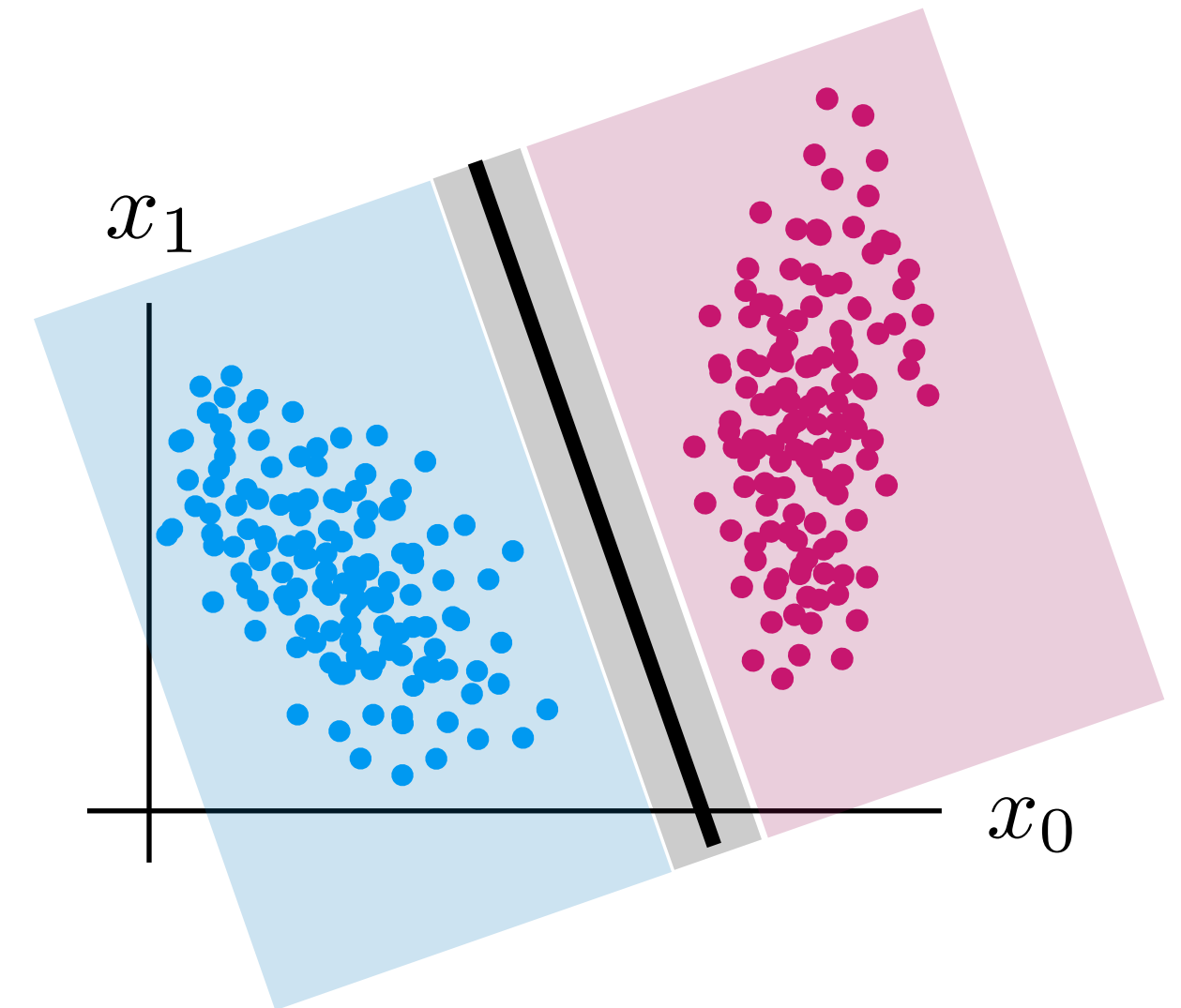
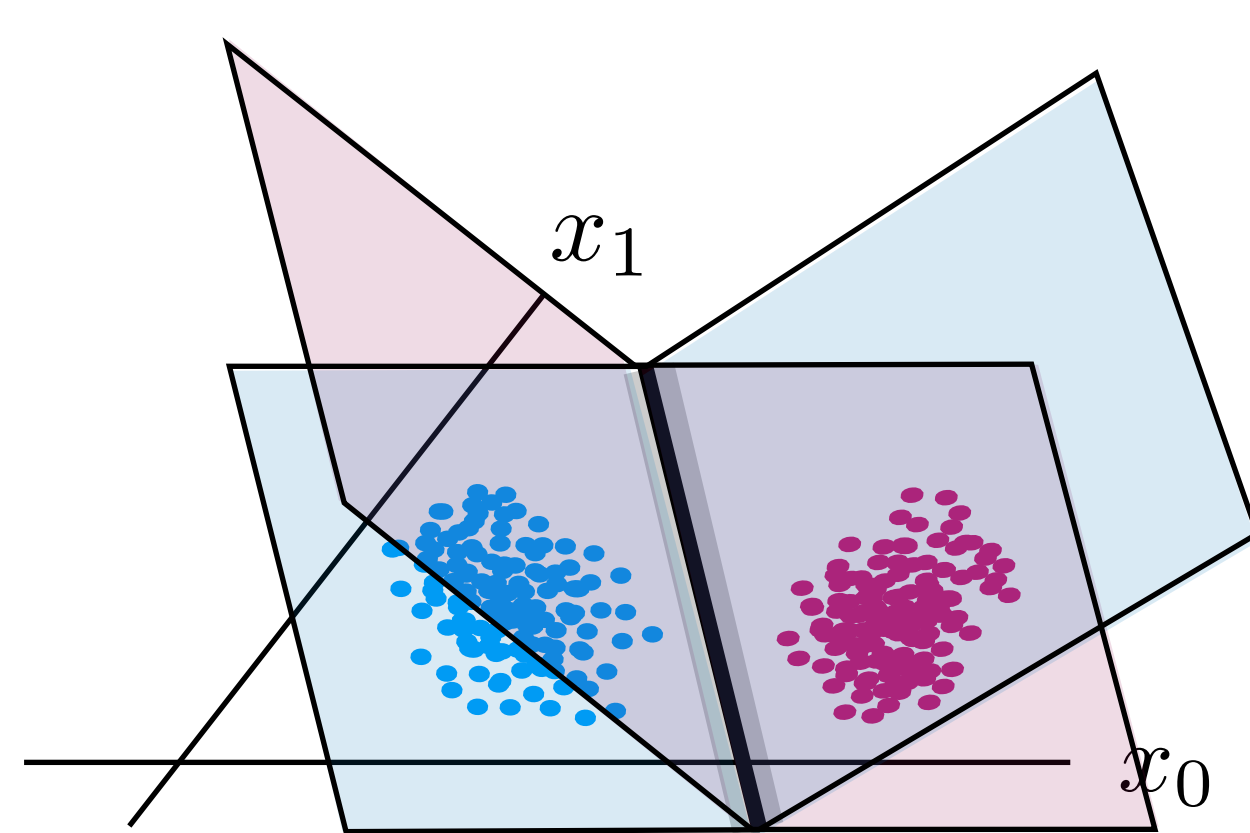
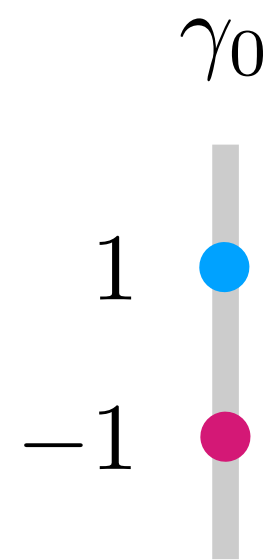


“Binary classifier”

Support Vector Machine (SVM)

**COST:** 
$$\min_{\theta} \lambda \|\theta_{1:n}\|_2^2 + \frac{1}{T} \sum_t \max\{0, 1 - \gamma_t(\theta_{1:n}^T x_t - \theta_0)\}$$

Soft boundary



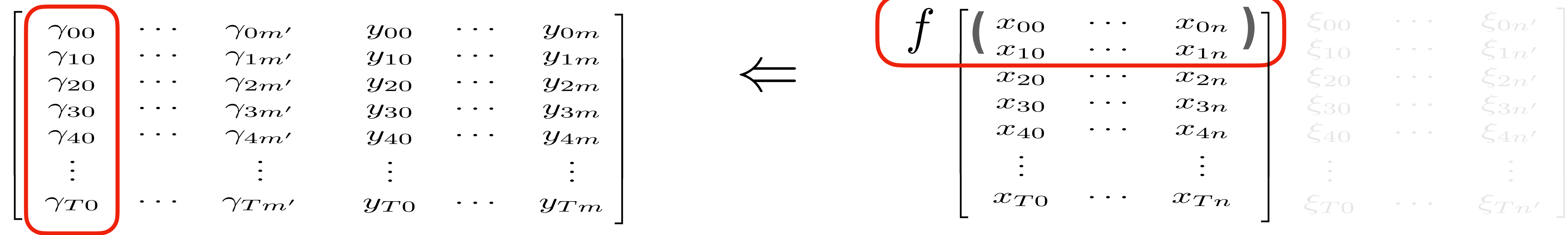


# Classification

**OUTPUTS**  
(Dependent Variables)

$$\gamma_t = \text{sgn}(\theta^T x_t - \theta_0)$$

**INPUTS**  
(Independent Variables)

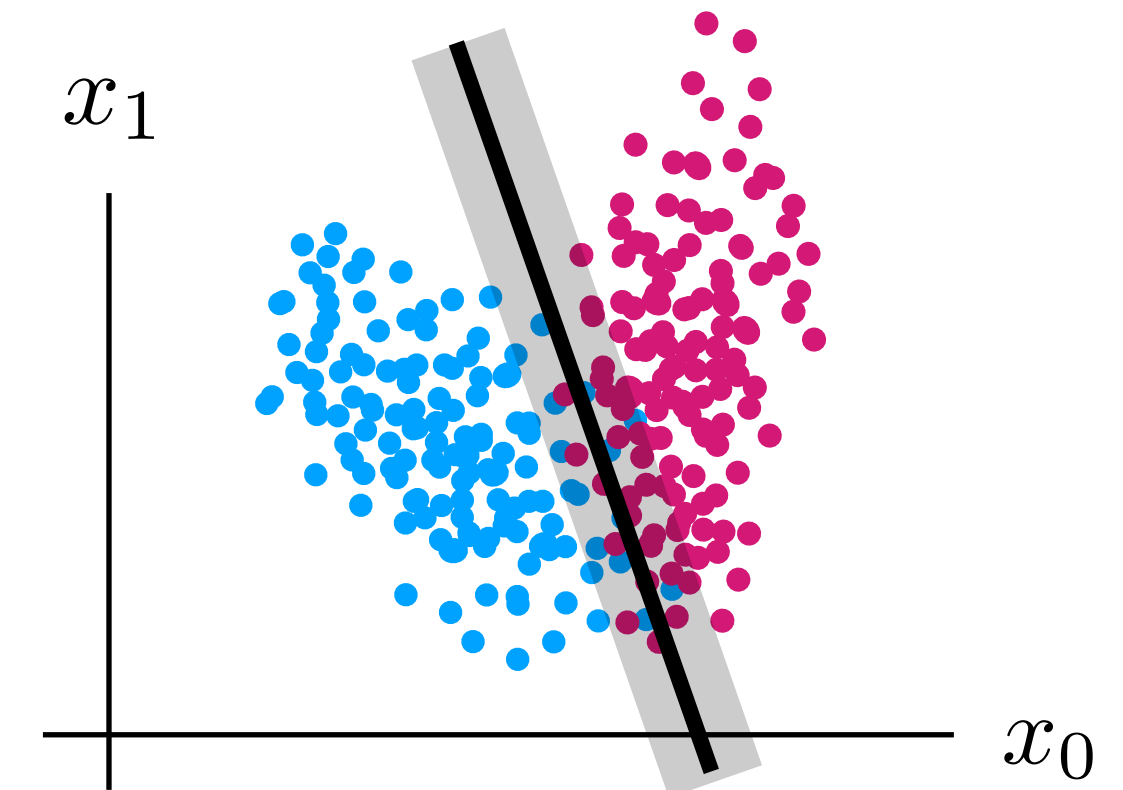
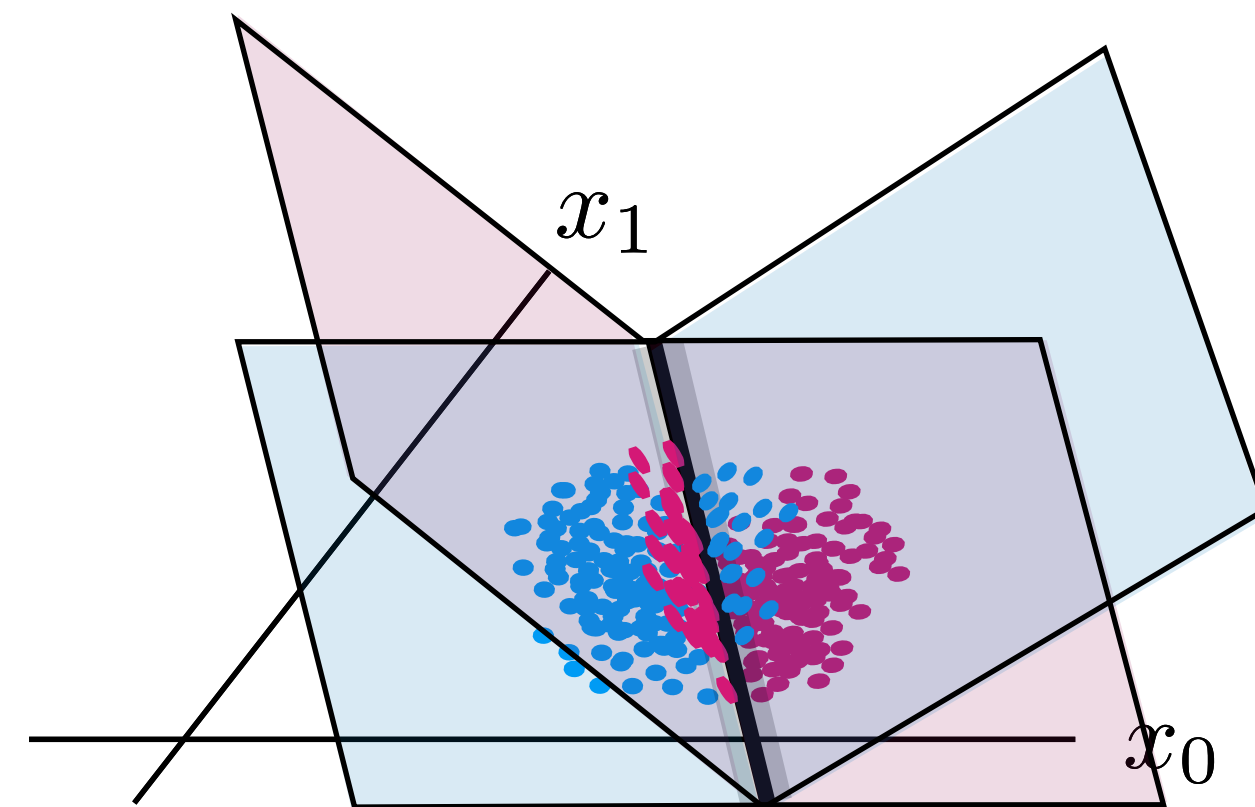
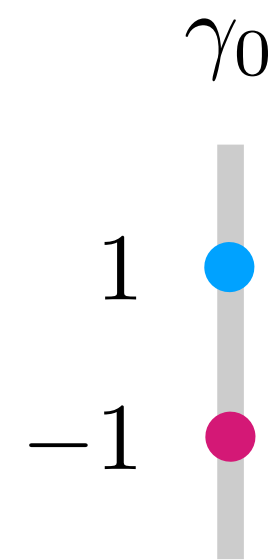


**COST:** 
$$\min_{\theta} \lambda \|\theta_{1:n}\|_2^2 + \frac{1}{T} \sum_t \max\{0, 1 - \gamma_t(\theta_{1:n}^T x_t - \theta_0)\}$$

“Binary classifier”

Support Vector Machine (SVM)

Soft boundary



# Classification

## OUTPUTS

(Dependent Variables)

$$\begin{bmatrix} \gamma_{00} & \cdots & \gamma_{0m'} & y_{00} & \cdots & y_{0m} \\ \gamma_{10} & \cdots & \gamma_{1m'} & y_{10} & \cdots & y_{1m} \\ \gamma_{20} & \cdots & \gamma_{2m'} & y_{20} & \cdots & y_{2m} \\ \gamma_{30} & \cdots & \gamma_{3m'} & y_{30} & \cdots & y_{3m} \\ \gamma_{40} & \cdots & \gamma_{4m'} & y_{40} & \cdots & y_{4m} \\ \vdots & & \vdots & \vdots & & \vdots \\ \gamma_{T0} & \cdots & \gamma_{Tm'} & y_{T0} & \cdots & y_{Tm} \end{bmatrix}$$

$$\gamma_t = \text{sgn}(\theta^T x_t - \theta_0)$$

## INPUTS

(Independent Variables)

$$f \begin{bmatrix} (x_{00} \cdots x_{0n}) \\ x_{10} \cdots x_{1n} \\ x_{20} \cdots x_{2n} \\ x_{30} \cdots x_{3n} \\ x_{40} \cdots x_{4n} \\ \vdots \\ x_{T0} \cdots x_{Tn} \end{bmatrix} \begin{matrix} \xi_{00} \cdots \xi_{0n'} \\ \xi_{10} \cdots \xi_{1n'} \\ \xi_{20} \cdots \xi_{2n'} \\ \xi_{30} \cdots \xi_{3n'} \\ \xi_{40} \cdots \xi_{4n'} \\ \vdots \\ \xi_{T0} \cdots \xi_{Tn'} \end{matrix}$$

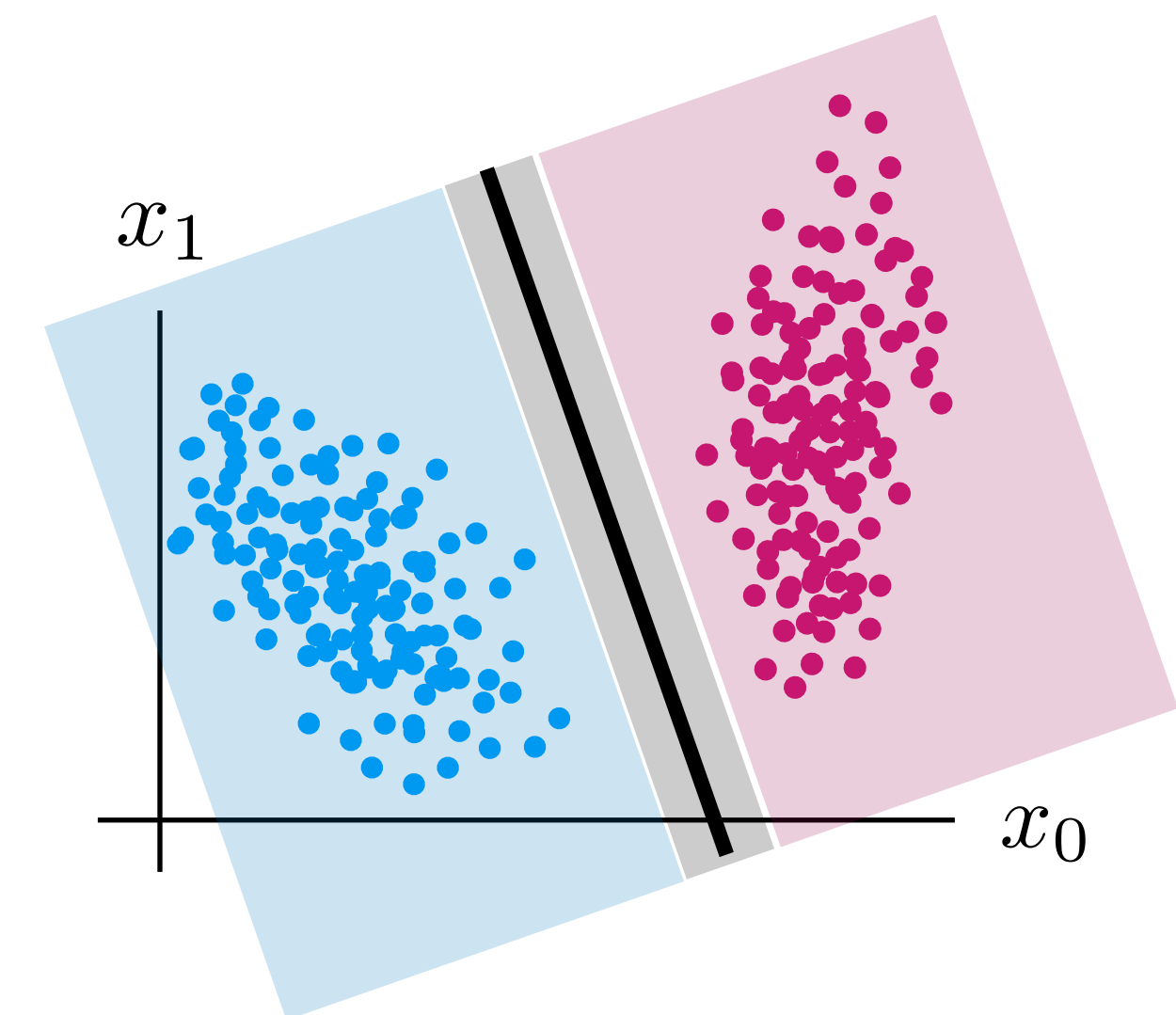
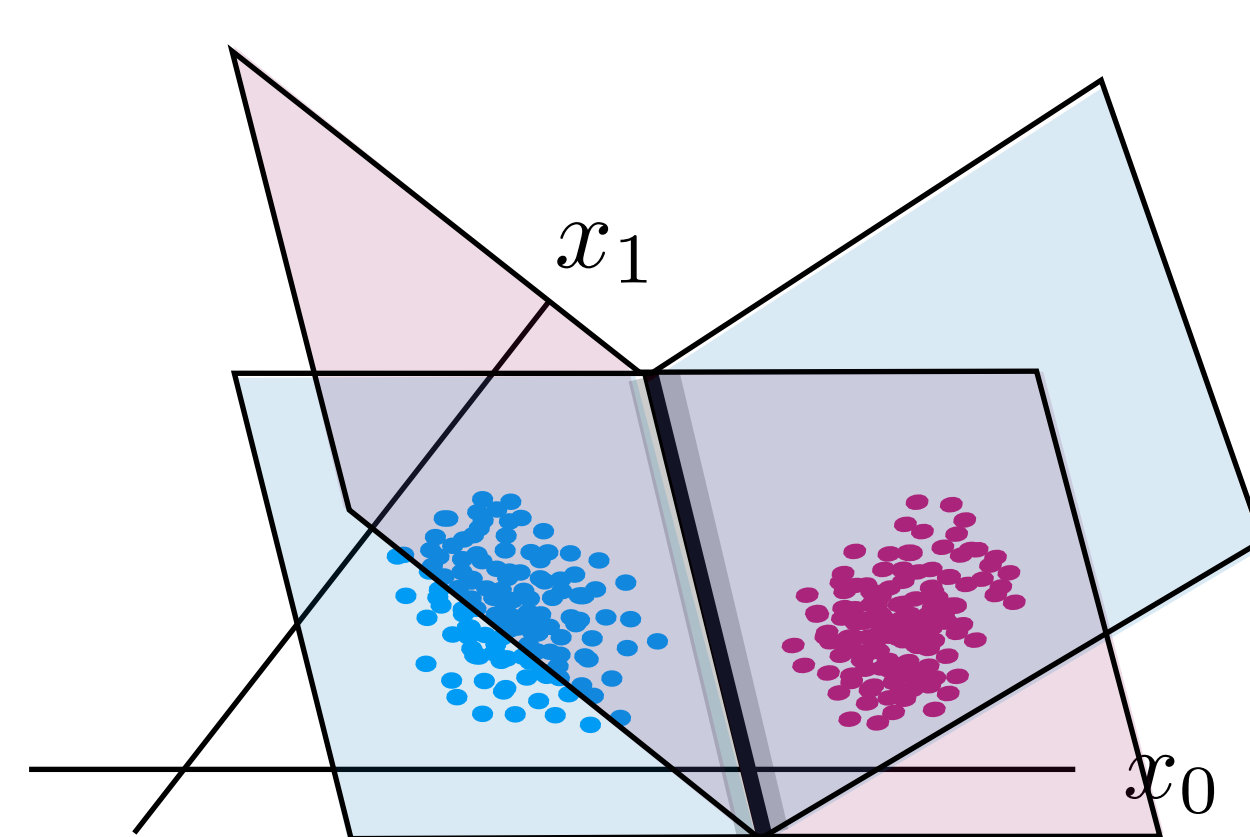
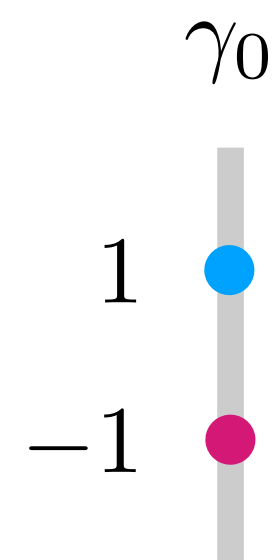
“Binary classifier”

Support Vector Machine (SVM)

**COST:**

$$\min_{\theta} \lambda \|\theta_{1:n}\|_2^2 + \frac{1}{T} \sum_t \max\{0, 1 - \gamma_t(\theta_{1:n}^T x_t - \theta_0)\}$$

Soft boundary

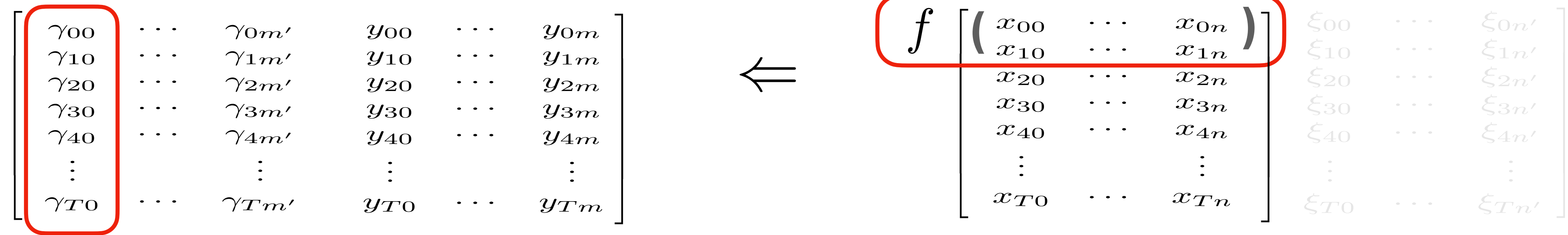


# Classification

**OUTPUTS**  
(Dependent Variables)

$$\gamma_t = \text{sgn}(\theta^T x_t - \theta_0)$$

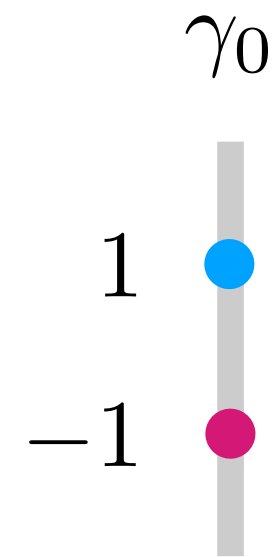
**INPUTS**  
(Independent Variables)



“Binary classifier”

Support Vector Machine (SVM)

Logistic Regression (smoothed)

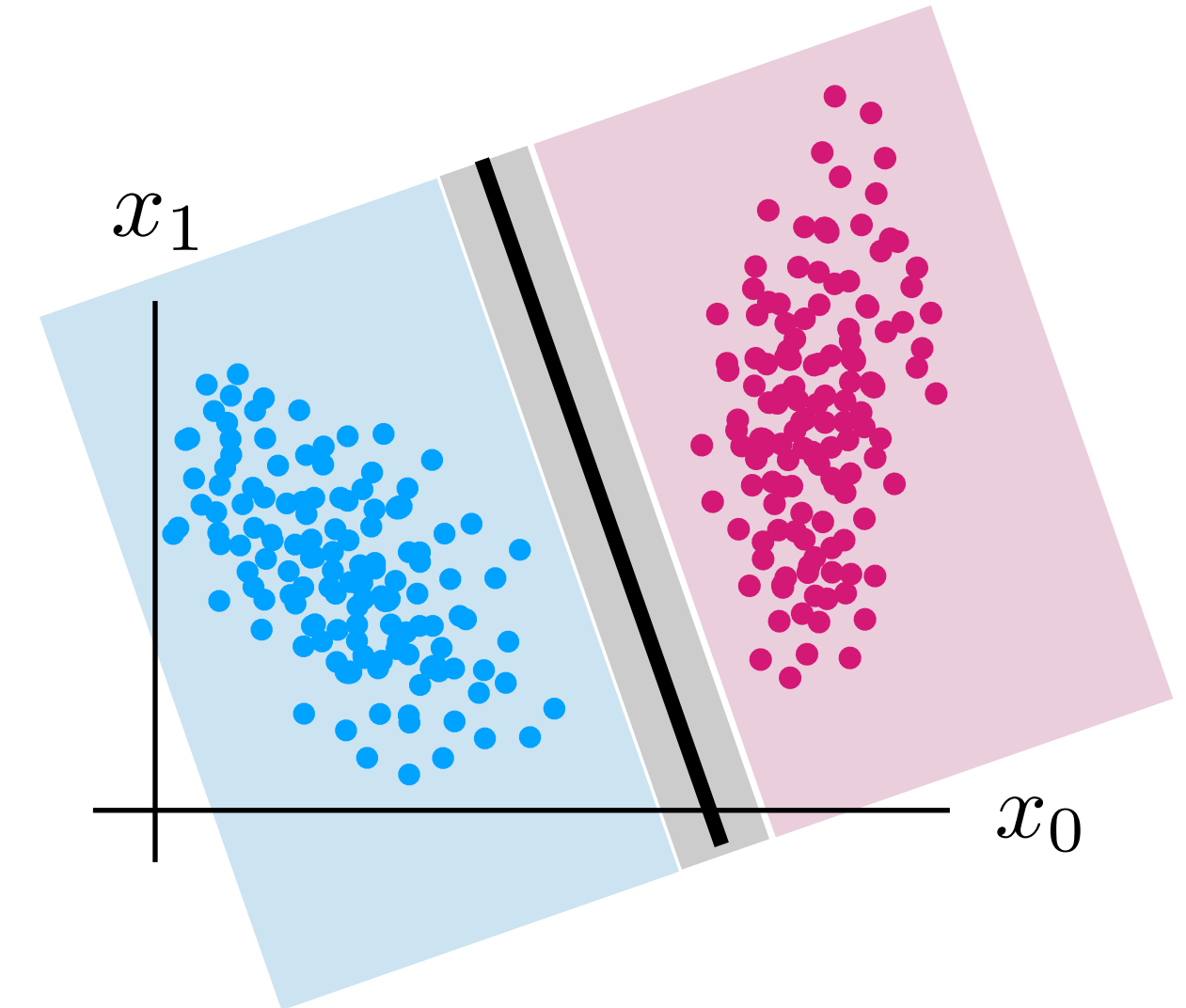
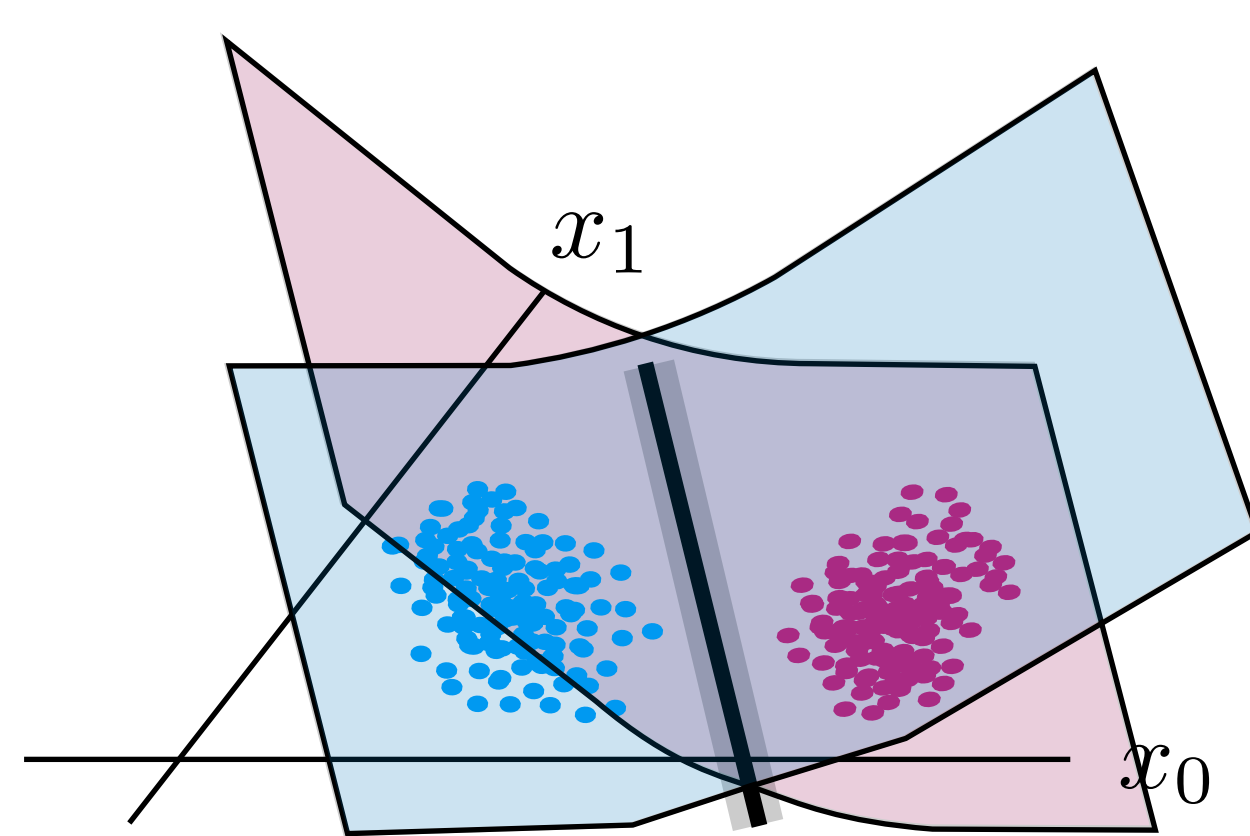


**COST:**

$$\min_{\theta} \lambda \|\theta_{1:n}\|_2^2 + \frac{1}{T} \sum_t \max\{0, 1 - \gamma_t(\theta_{1:n}^T x_t - \theta_0)\}$$

$$\lambda \|\theta_{1:n}\|_2^2 + \frac{1}{T} \sum_t \log(e^{-\gamma_t(\theta_{1:n}^T x_t - \theta_0)} + 1)$$

Soft boundary

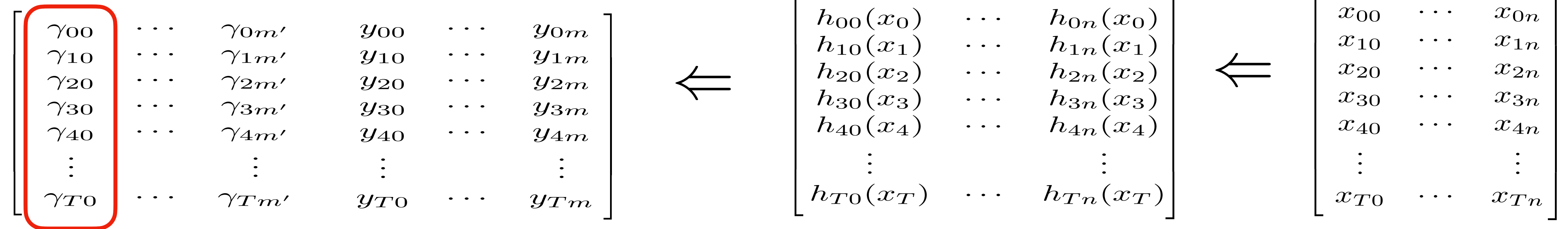


**Z**

**OUTPUTS**  
(Dependent Variables)

$$\gamma_t = \text{sgn}(\theta^T x_t - \theta_0)$$

**INPUTS**  
(Independent Variables)

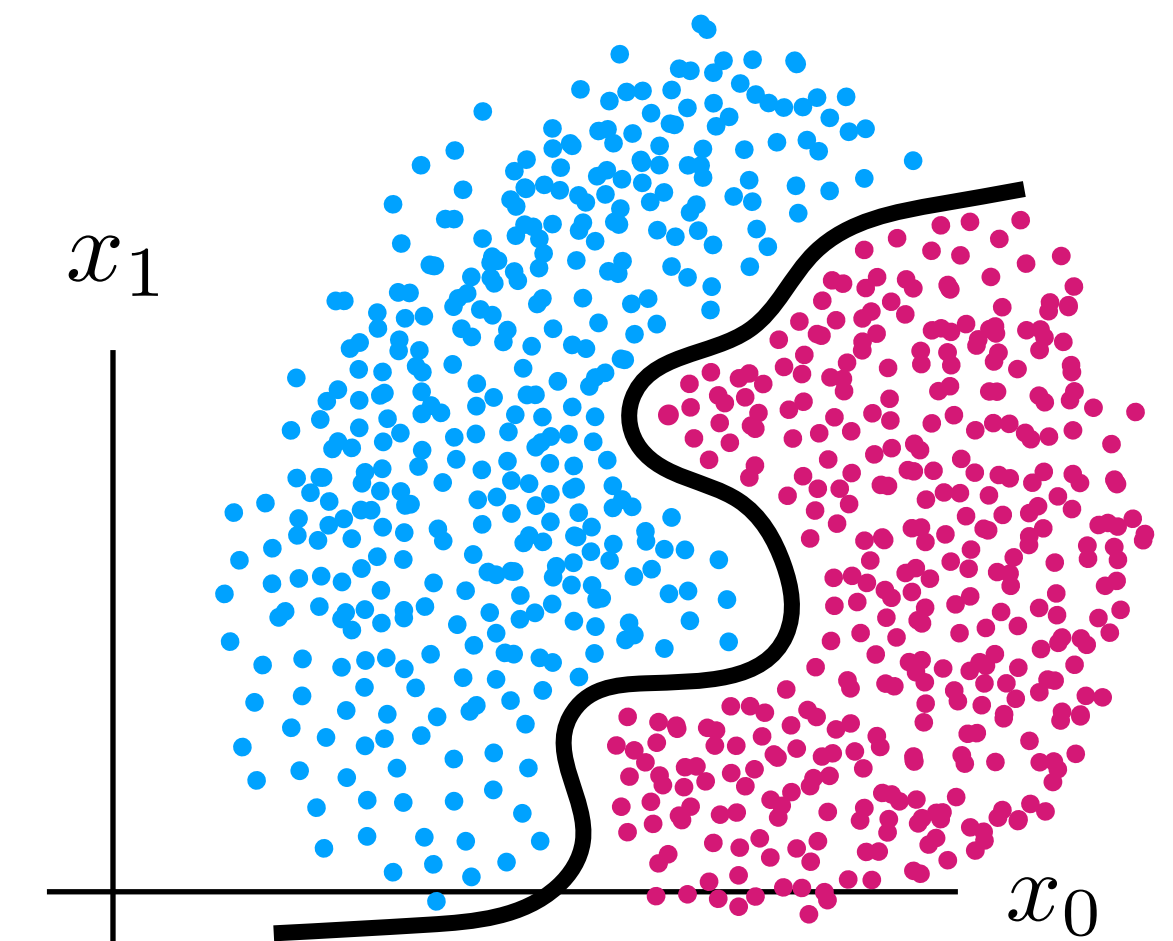
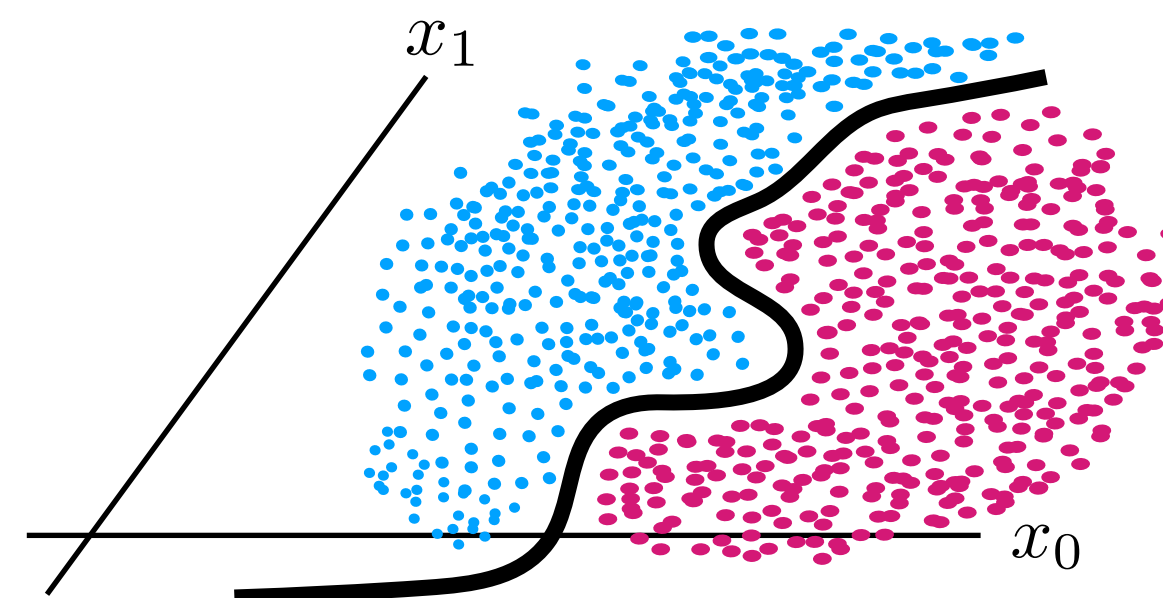
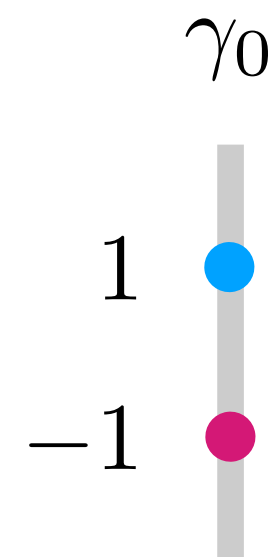


“Binary classifier”

Support Vector Machine (SVM)

**COST:** 
$$\min_{\theta} \lambda \|\theta_{1:n}\|_2^2 + \frac{1}{T} \sum_t \max\{0, 1 - \gamma_t(\theta_{1:n}^T h_t(x_t) - \theta_0)\}$$

Soft boundary



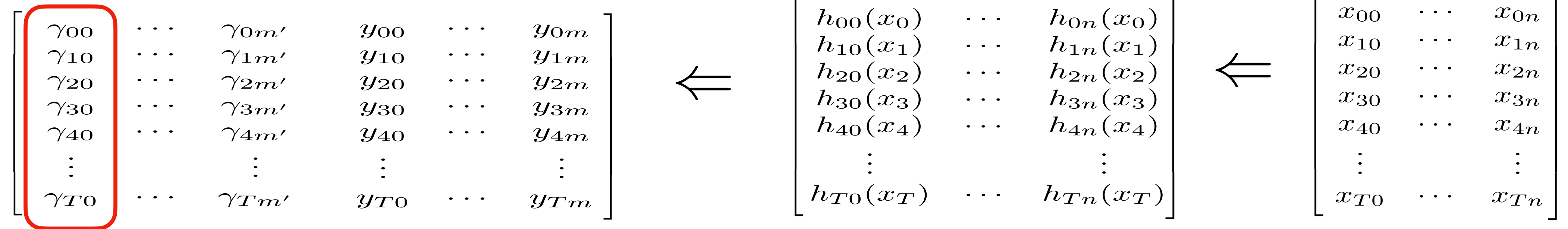


**Z**

**OUTPUTS**  
(Dependent Variables)

$$\gamma_t = \text{sgn}(\theta^T x_t - \theta_0)$$

**INPUTS**  
(Independent Variables)



“Binary classifier”

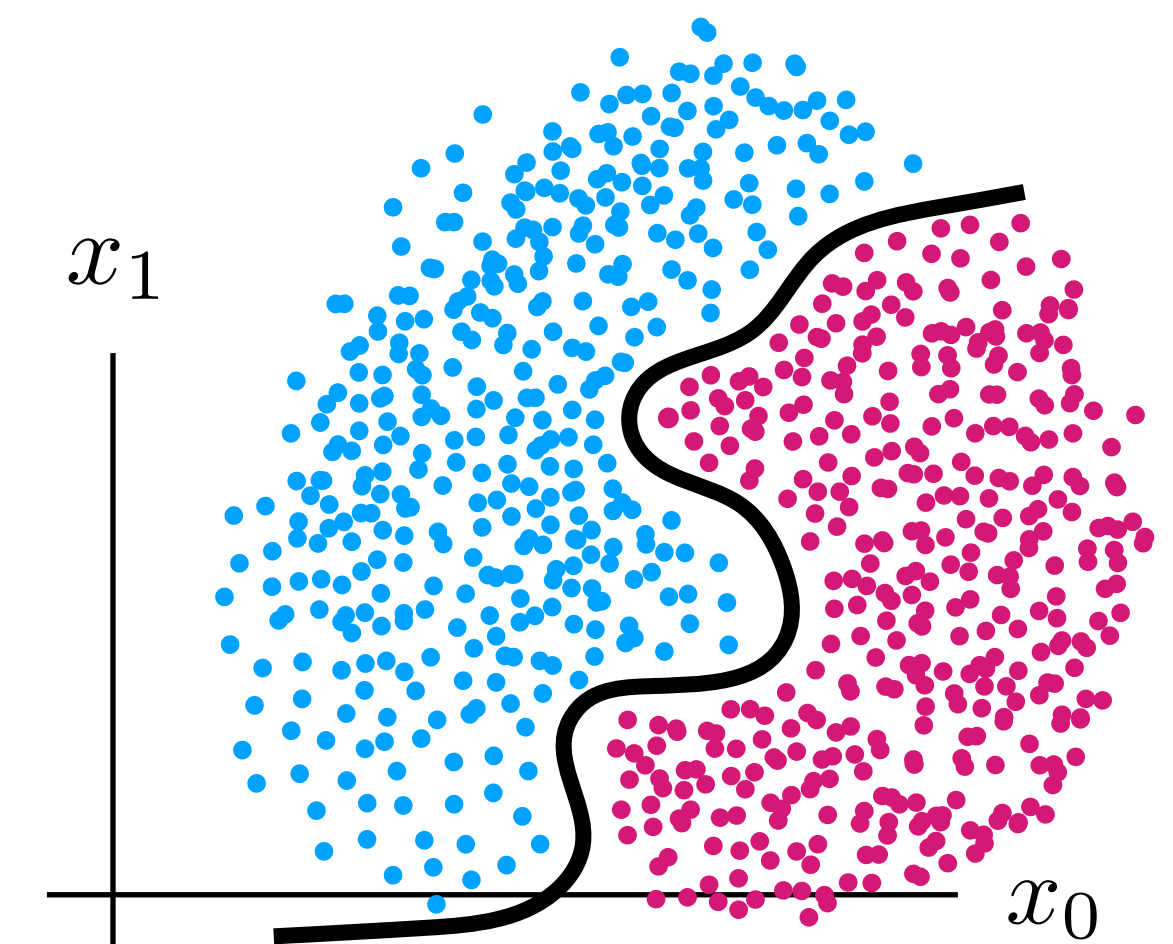
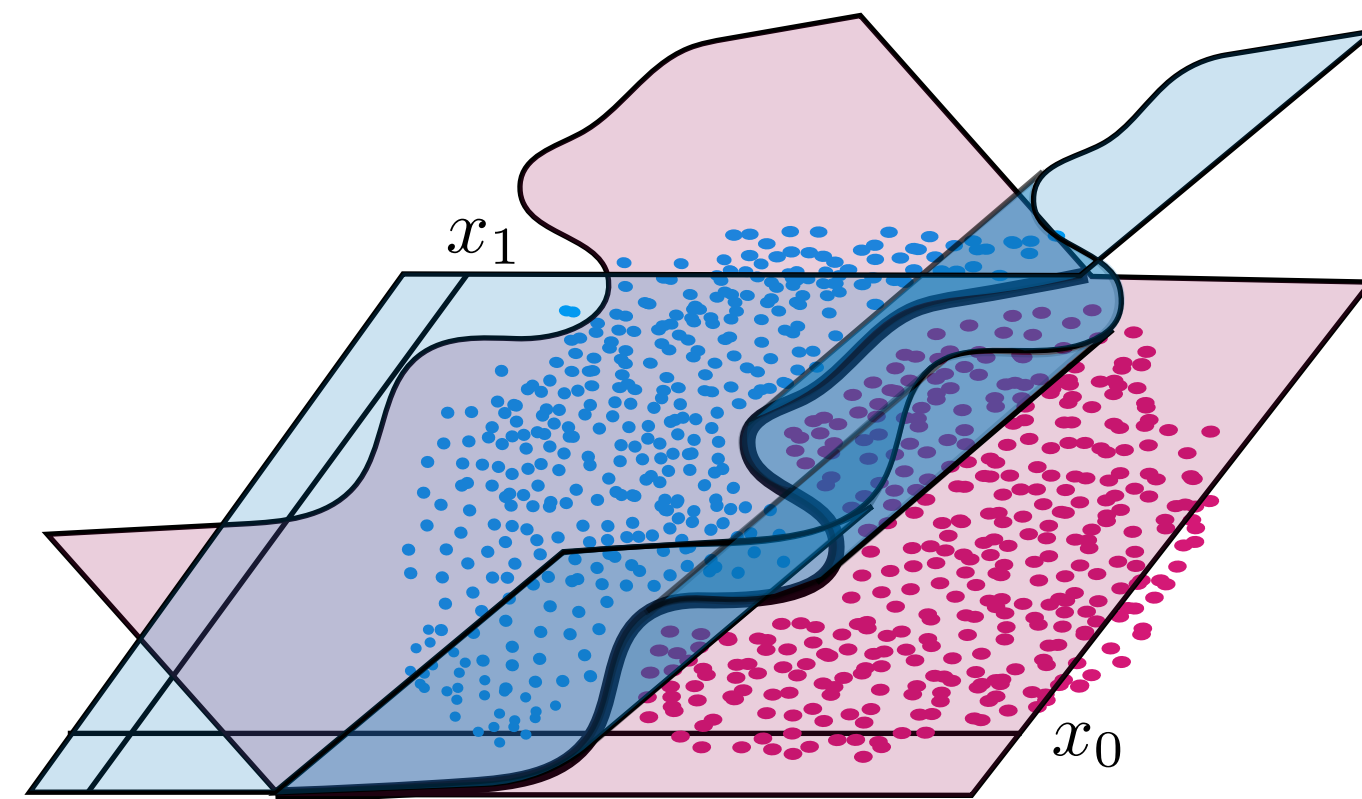
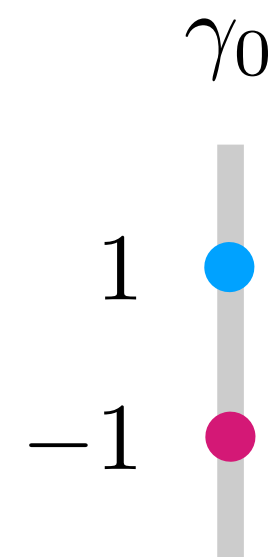
Support Vector Machine (SVM)

**COST:**

$$\min_{\theta} \lambda \|\theta_{1:n}\|_2^2 + \frac{1}{T} \sum_t \max\{0, 1 - \gamma_t(\theta_{1:n}^T h_t(x_t) - \theta_0)\}$$

Soft boundary

Logistic Regression (smoothed)

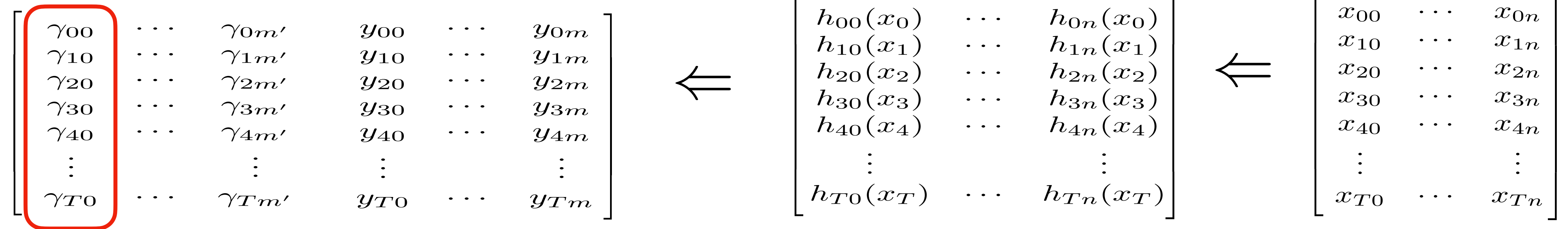


# Classification

**OUTPUTS**  
(Dependent Variables)

$$\gamma_t = \text{sgn}(\theta^T x_t - \theta_0)$$

**INPUTS**  
(Independent Variables)

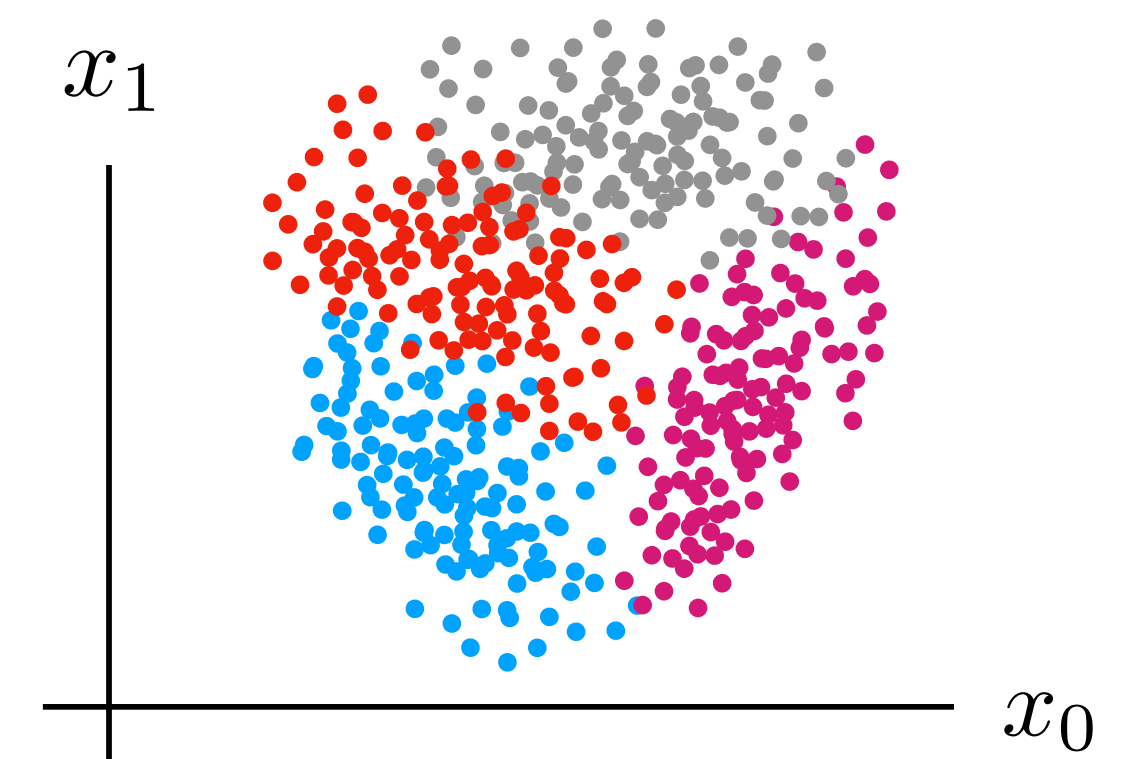
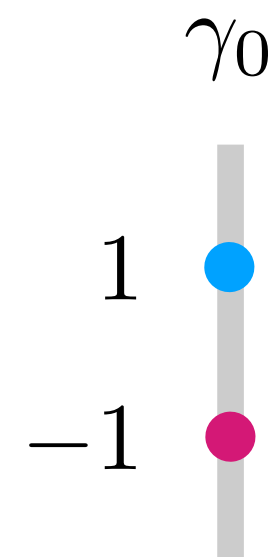


Collection of  
Binary Classifiers  
“One to the others”  
# of classifiers: m

**Support Vector  
Machine (SVM)**  
  
**Logistic  
Regression  
(smoothed)**

**COST:** 
$$\min_{\theta} \lambda \|\theta_{1:n}\|_2^2 + \frac{1}{T} \sum_t \max\{0, 1 - \gamma_t(\theta_{1:n}^T h_t(x_t) - \theta_0)\}$$

**Soft boundary**



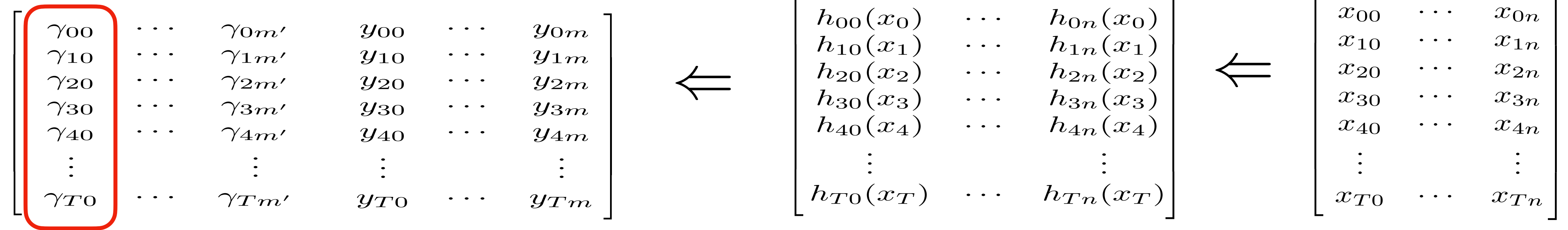


# Classification

**OUTPUTS**  
(Dependent Variables)

$$\gamma_t = \text{sgn}(\theta^T x_t - \theta_0)$$

**INPUTS**  
(Independent Variables)



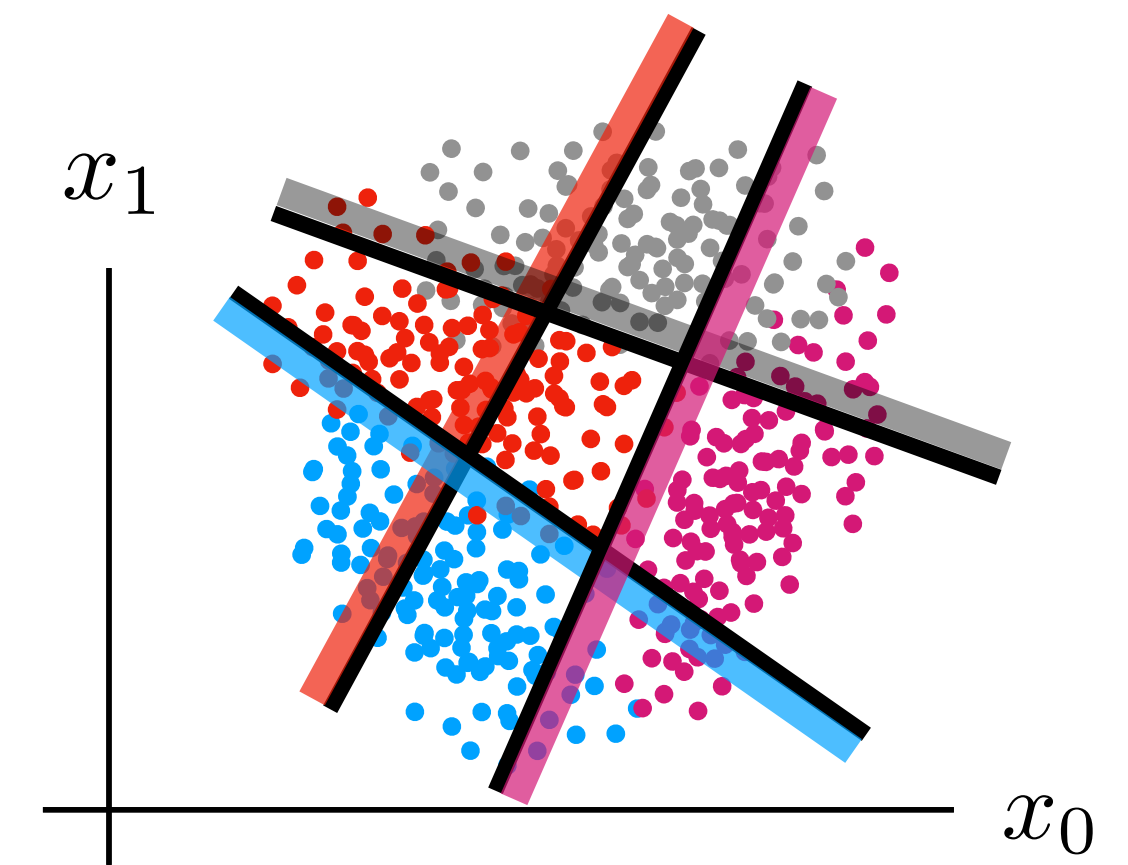
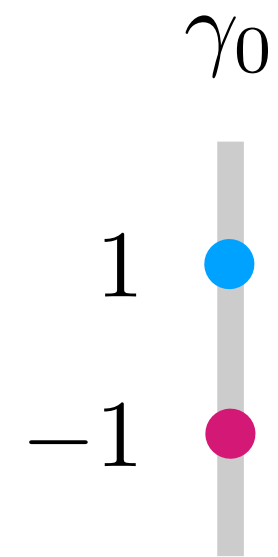
Collection of Binary Classifiers  
"One to the others"  
# of classifiers: m

Support Vector Machine (SVM)  
  
Logistic Regression (smoothed)

**COST:**

$$\min_{\theta} \lambda \|\theta_{1:n}\|_2^2 + \frac{1}{T} \sum_t \max\{0, 1 - \gamma_t(\theta_{1:n}^T h_t(x_t) - \theta_0)\}$$

Soft boundary

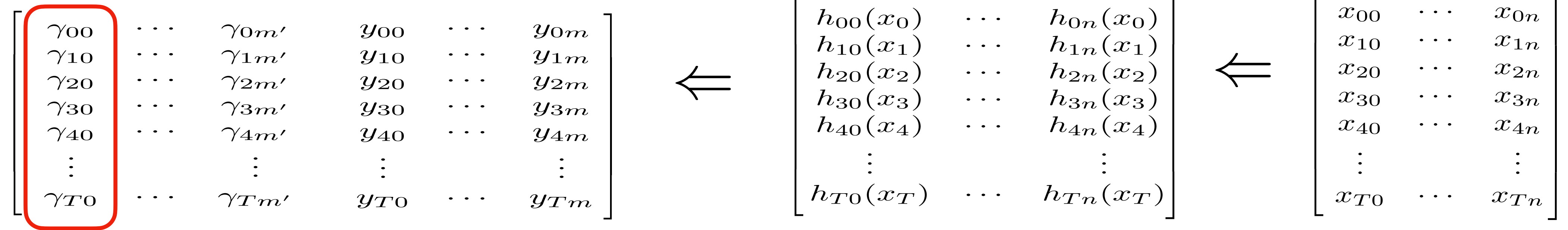


# Classification

**OUTPUTS**  
(Dependent Variables)

$$\gamma_t = \text{sgn}(\theta^T x_t - \theta_0)$$

**INPUTS**  
(Independent Variables)



Collection of  
Binary Classifiers  
"One to the others"  
# of classifiers: m

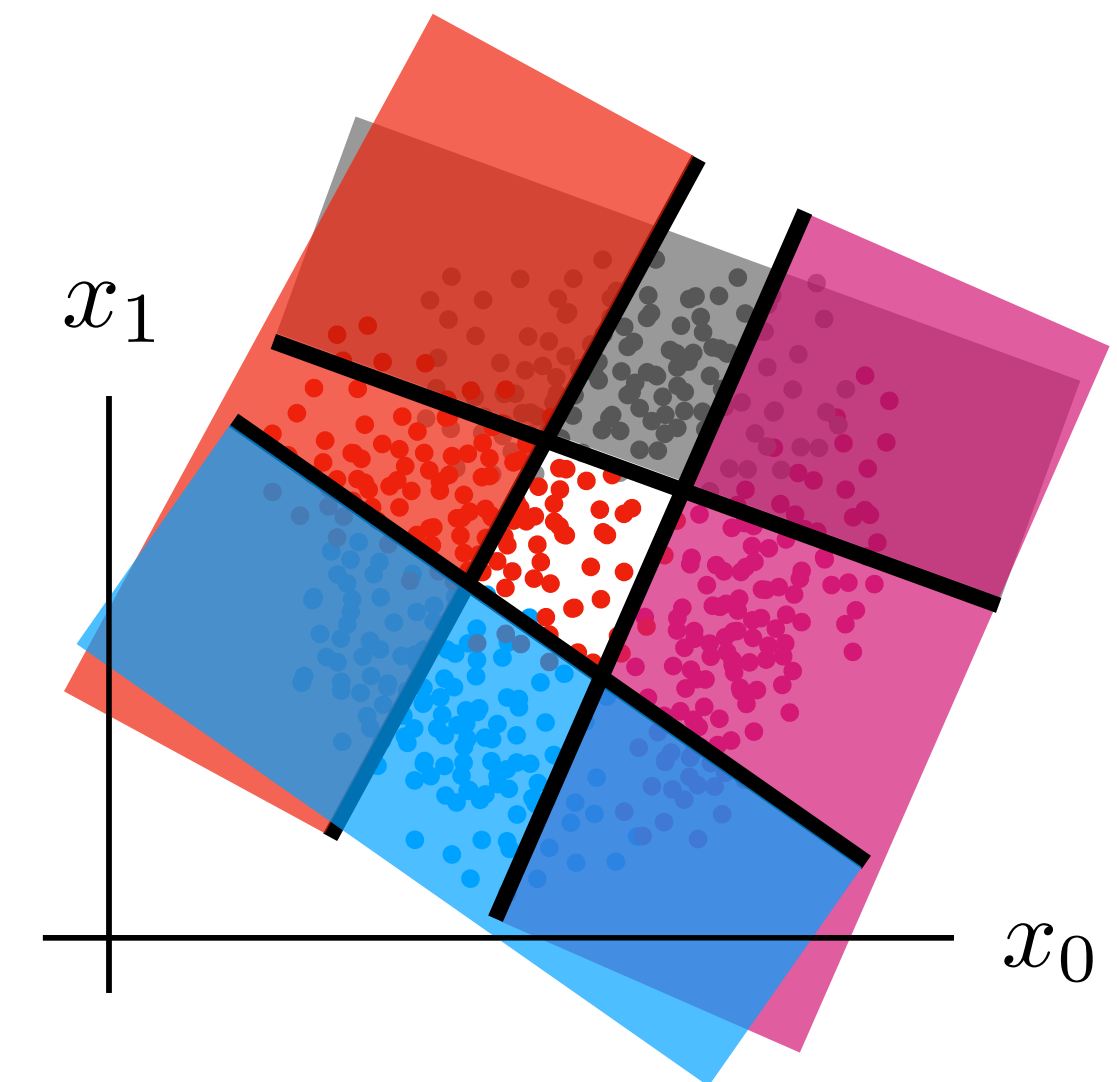
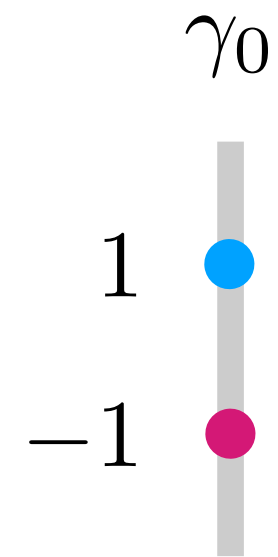
Support Vector  
Machine (SVM)

Logistic  
Regression  
(smoothed)

**COST:**

$$\min_{\theta} \lambda \|\theta_{1:n}\|_2^2 + \frac{1}{T} \sum_t \max\{0, 1 - \gamma_t(\theta_{1:n}^T h_t(x_t) - \theta_0)\}$$

Soft boundary

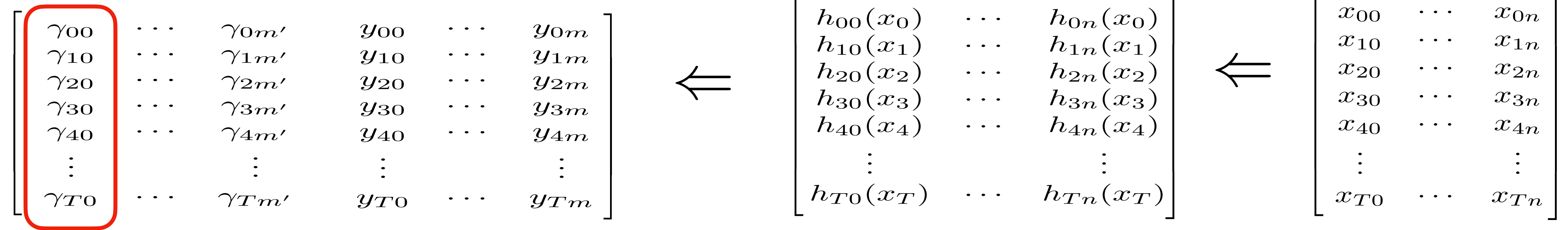


# Classification

**OUTPUTS**  
(Dependent Variables)

$$\gamma_t = \text{sgn}(\theta^T x_t - \theta_0)$$

**INPUTS**  
(Independent Variables)



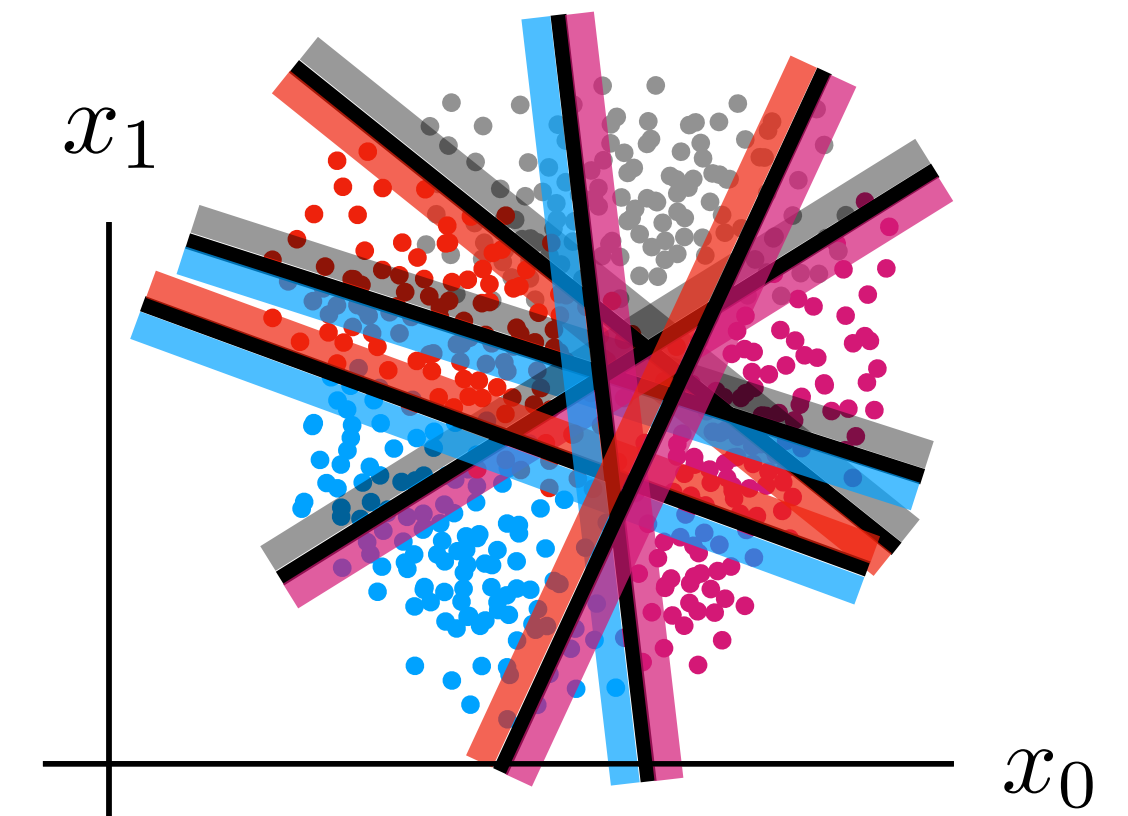
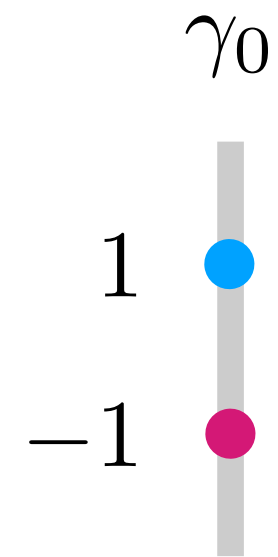
Collection of  
Binary Classifiers  
Pairwise -  
"One to another"  
# of classifiers:  $m(m+1)/2$

Support Vector  
Machine (SVM)  
  
Logistic  
Regression  
(smoothed)

**COST:**

$$\min_{\theta} \lambda \|\theta_{1:n}\|_2^2 + \frac{1}{T} \sum_t \max\{0, 1 - \gamma_t(\theta_{1:n}^T h_t(x_t) - \theta_0)\}$$

Soft boundary

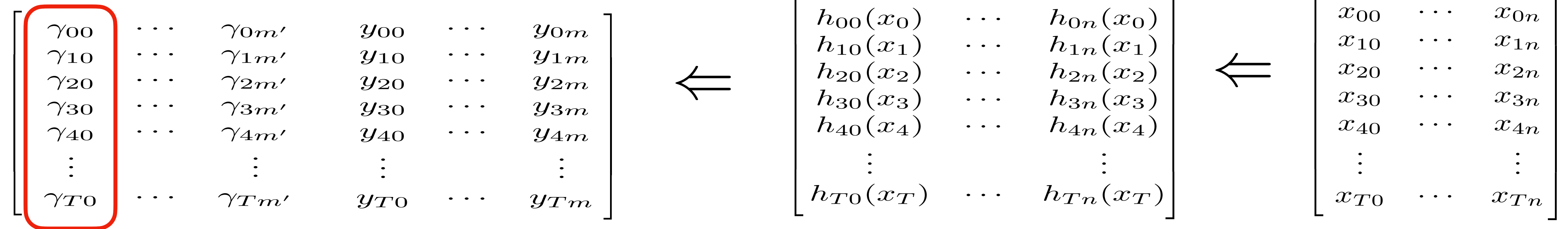


# Classification

**OUTPUTS**  
(Dependent Variables)

$$\gamma_t = \text{sgn}(\theta^T x_t - \theta_0)$$

**INPUTS**  
(Independent Variables)

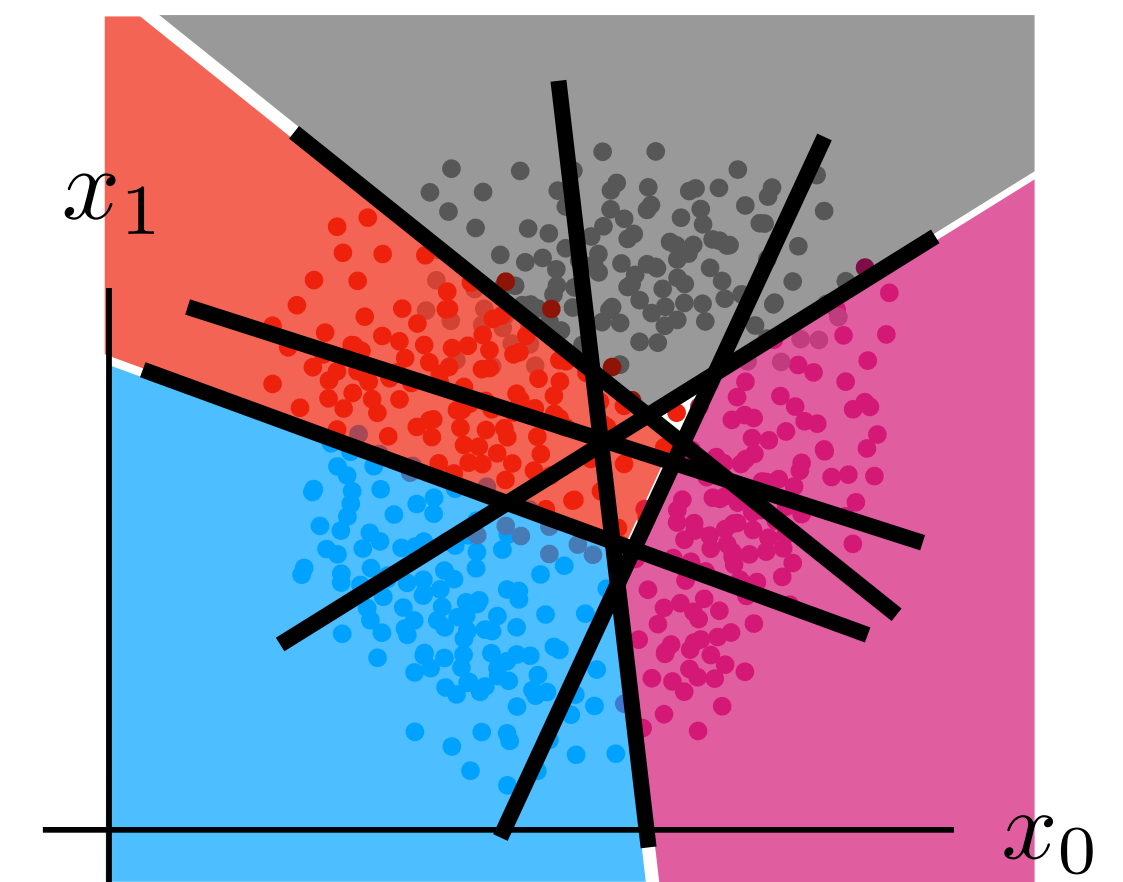
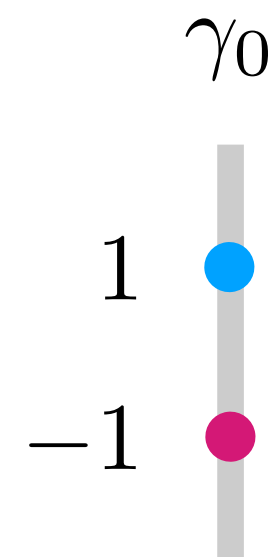


Collection of  
Binary Classifiers  
Pairwise -  
"One to another"  
# of classifiers:  $m(m+1)/2$

Support Vector  
Machine (SVM)  
  
Logistic  
Regression  
(smoothed)

**COST:**  $\min_{\theta} \lambda \|\theta_{1:n}\|_2^2 + \frac{1}{T} \sum_t \max\{0, 1 - \gamma_t(\theta_{1:n}^T h_t(x_t) - \theta_0)\}$

Soft boundary

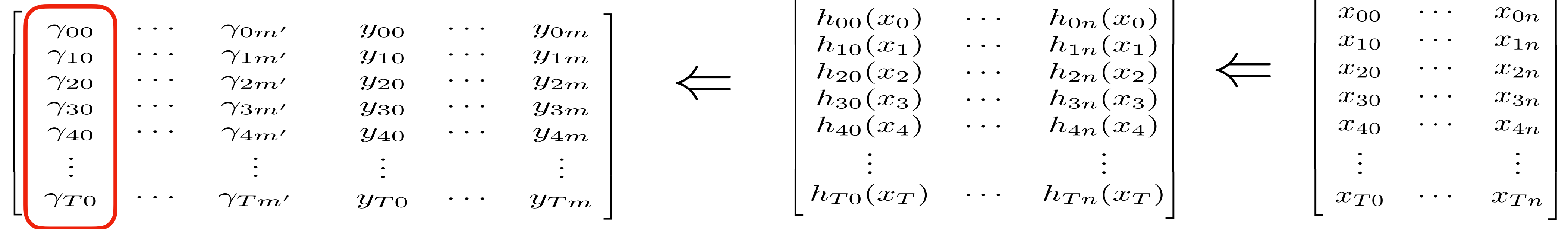


# Classification

**OUTPUTS**  
(Dependent Variables)

$$\gamma_t = \text{sgn}(\theta^T x_t - \theta_0)$$

**INPUTS**  
(Independent Variables)



Collection of Binary Classifiers

Pairwise - "One to another"

# of classifiers:  $m(m+1)/2$

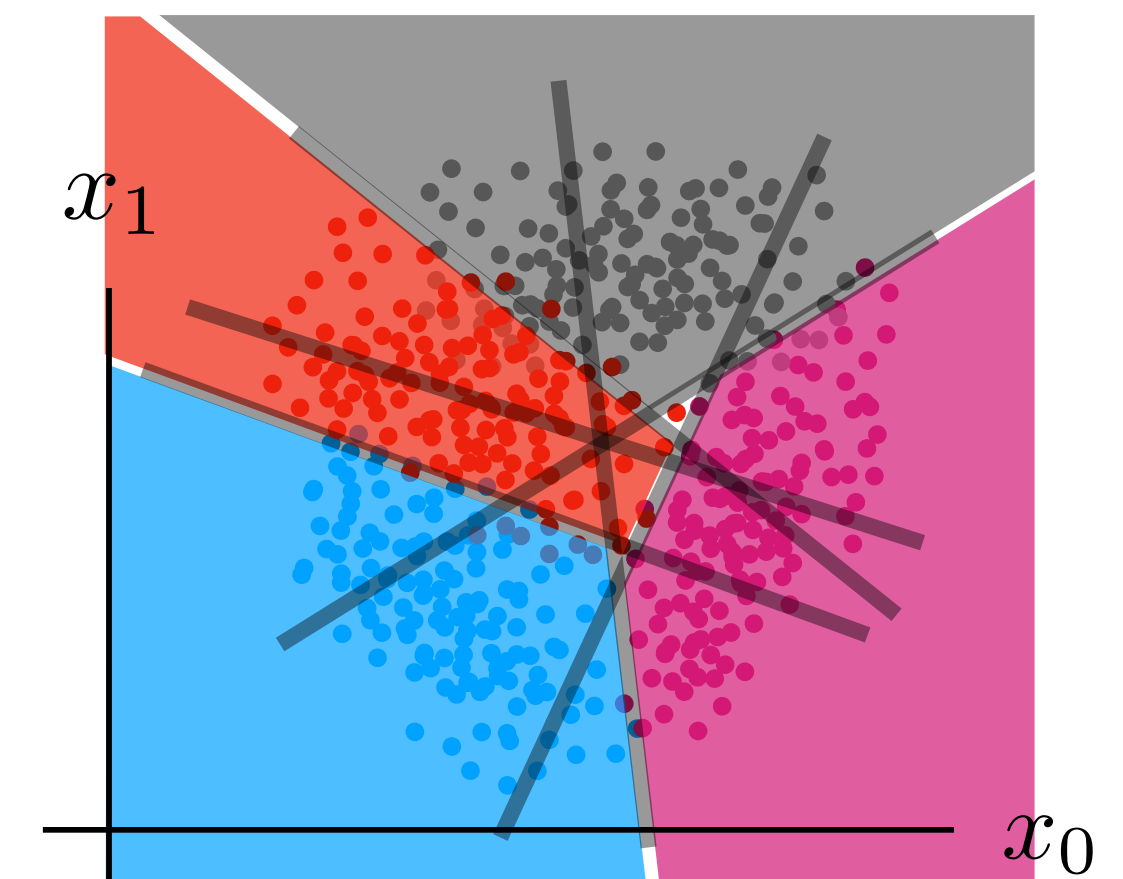
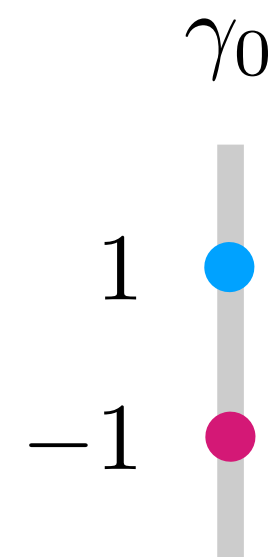
Support Vector Machine (SVM)

Logistic Regression (smoothed)

**COST:**

$$\min_{\theta} \lambda \|\theta_{1:n}\|_2^2 + \frac{1}{T} \sum_t \max\{0, 1 - \gamma_t(\theta_{1:n}^T h_t(x_t) - \theta_0)\}$$

Soft boundary



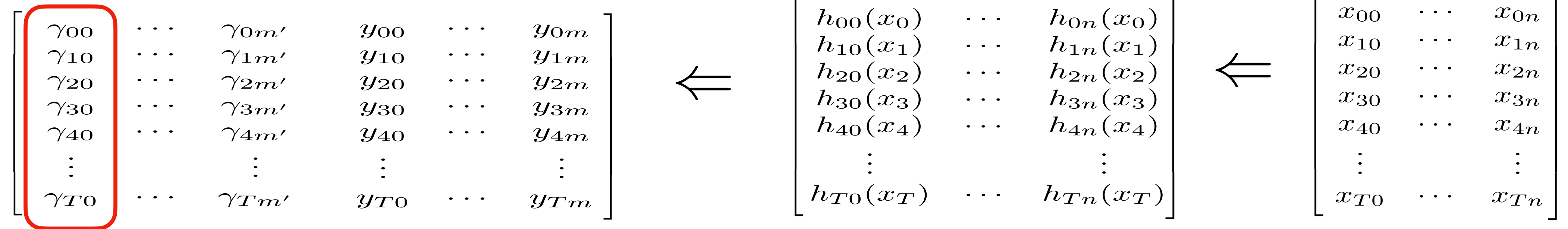


# Classification

**OUTPUTS**  
(Dependent Variables)

$$\gamma_t = \text{sgn}(\theta^T x_t - \theta_0)$$

**INPUTS**  
(Independent Variables)



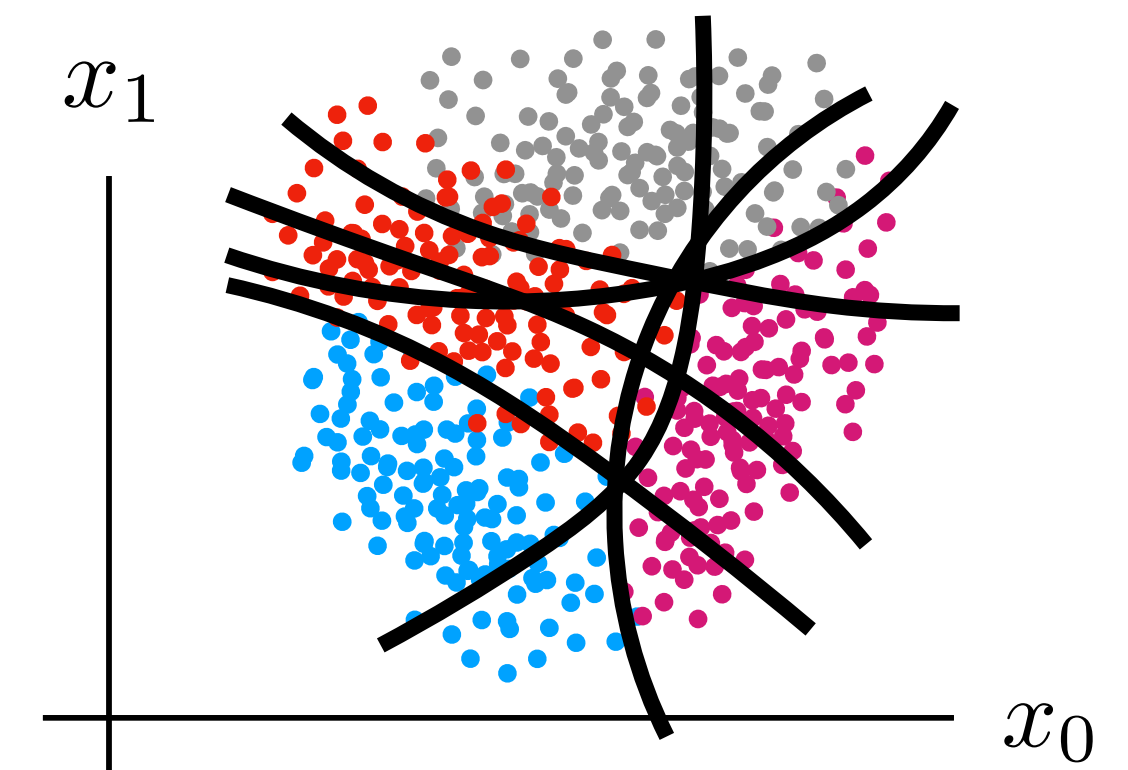
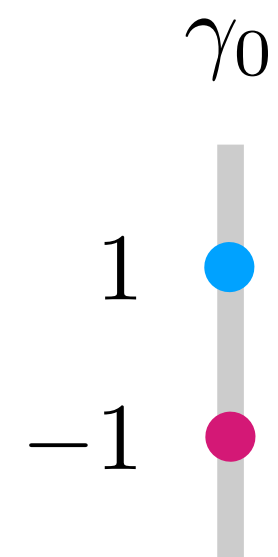
Collection of  
Binary Classifiers  
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# of classifiers:  $m(m+1)/2$

Support Vector  
Machine (SVM)  
  
Logistic  
Regression  
(smoothed)

**COST:**

$$\min_{\theta} \lambda \|\theta_{1:n}\|_2^2 + \frac{1}{T} \sum_t \max\{0, 1 - \gamma_t(\theta_{1:n}^T h_t(x_t) - \theta_0)\}$$

Soft boundary



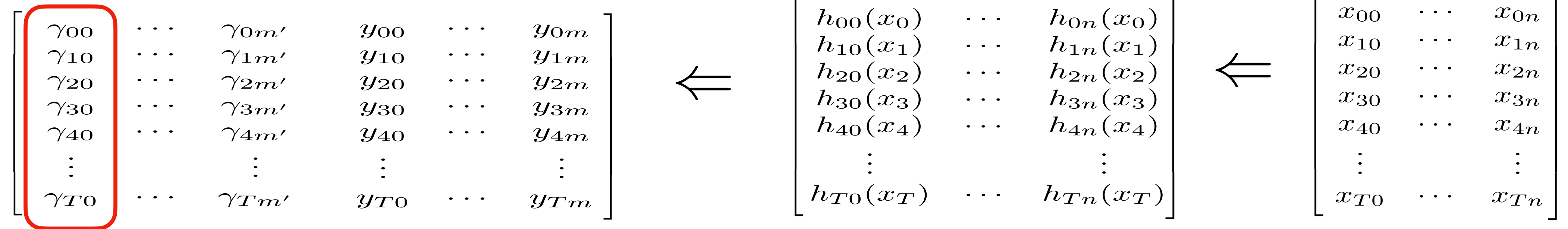


# Classification

**OUTPUTS**  
(Dependent Variables)

$$\gamma_t = \text{sgn}(\theta^T x_t - \theta_0)$$

**INPUTS**  
(Independent Variables)



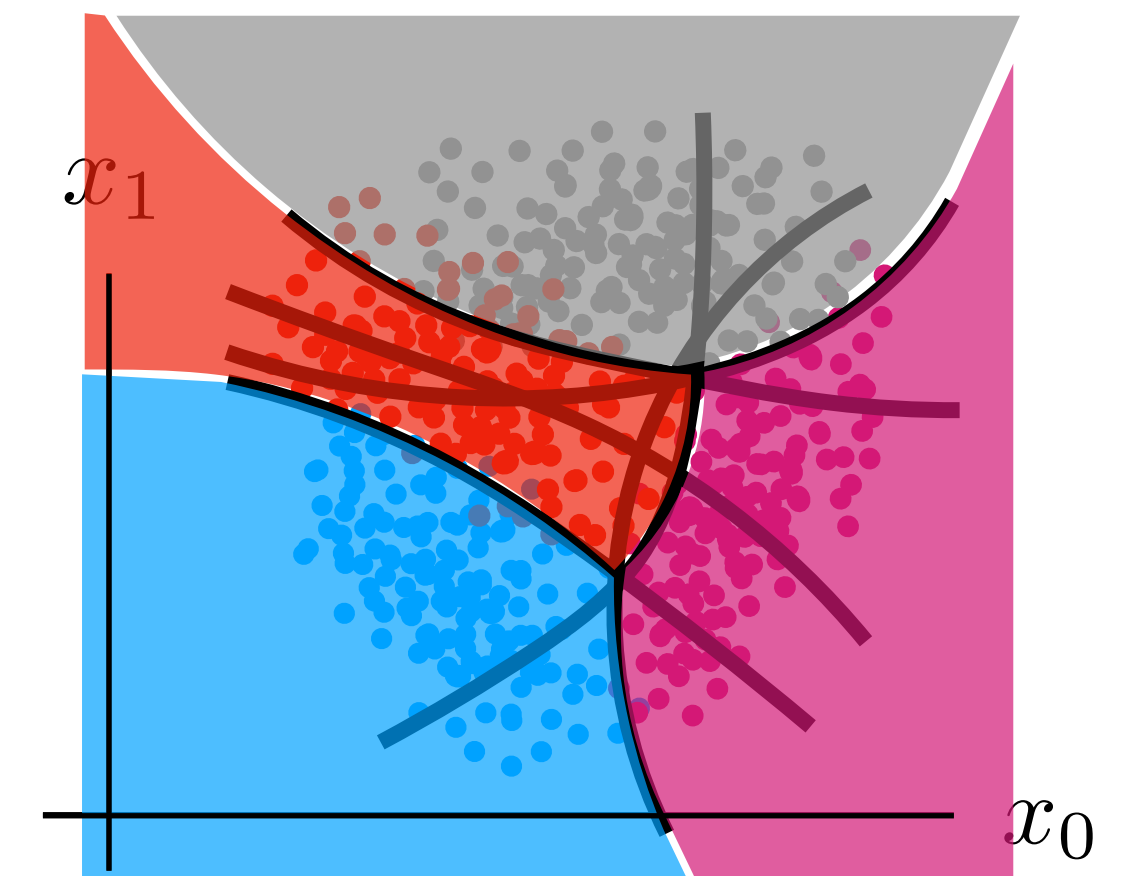
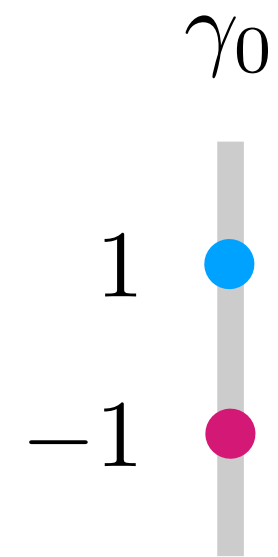
Collection of Binary Classifiers  
Pairwise -  
"One to another"  
# of classifiers:  $m(m+1)/2$

Support Vector Machine (SVM)  
  
Logistic Regression (smoothed)

**COST:**

$$\min_{\theta} \lambda \|\theta_{1:n}\|_2^2 + \frac{1}{T} \sum_t \max\{0, 1 - \gamma_t(\theta_{1:n}^T h_t(x_t) - \theta_0)\}$$

Soft boundary



# Discriminant Analysis

**OUTPUTS**  
(Dependent Variables)

**INPUTS**  
(Independent Variables)

$$\begin{bmatrix} \gamma_{00} & \cdots & \gamma_{0m'} & y_{00} & \cdots & y_{0m} \\ \gamma_{10} & \cdots & \gamma_{1m'} & y_{10} & \cdots & y_{1m} \\ \gamma_{20} & \cdots & \gamma_{2m'} & y_{20} & \cdots & y_{2m} \\ \gamma_{30} & \cdots & \gamma_{3m'} & y_{30} & \cdots & y_{3m} \\ \gamma_{40} & \cdots & \gamma_{4m'} & y_{40} & \cdots & y_{4m} \\ \vdots & & \vdots & \vdots & & \vdots \\ \gamma_{T0} & \cdots & \gamma_{Tm'} & y_{T0} & \cdots & y_{Tm} \end{bmatrix}$$



$$f \begin{bmatrix} (x_{00} \cdots x_{0n}) \\ x_{10} \cdots x_{1n} \\ x_{20} \cdots x_{2n} \\ x_{30} \cdots x_{3n} \\ x_{40} \cdots x_{4n} \\ \vdots \\ x_{T0} \cdots x_{Tn} \end{bmatrix} \begin{bmatrix} \xi_{00} \cdots \xi_{0n'} \\ \xi_{10} \cdots \xi_{1n'} \\ \xi_{20} \cdots \xi_{2n'} \\ \xi_{30} \cdots \xi_{3n'} \\ \xi_{40} \cdots \xi_{4n'} \\ \vdots \\ \xi_{T0} \cdots \xi_{Tn'} \end{bmatrix}$$

**CONDITIONAL PROBABILITY**

$$P(y|x)P(x) = P(x|y)P(y)$$

$$P(x|y = k)$$

...height of density k

**BAYES RULE**

$$P(y|x) = \frac{P(x|y)P(y)}{P(x)}$$

$$P(y = k)$$

...prior probability of k

$$P(x)$$

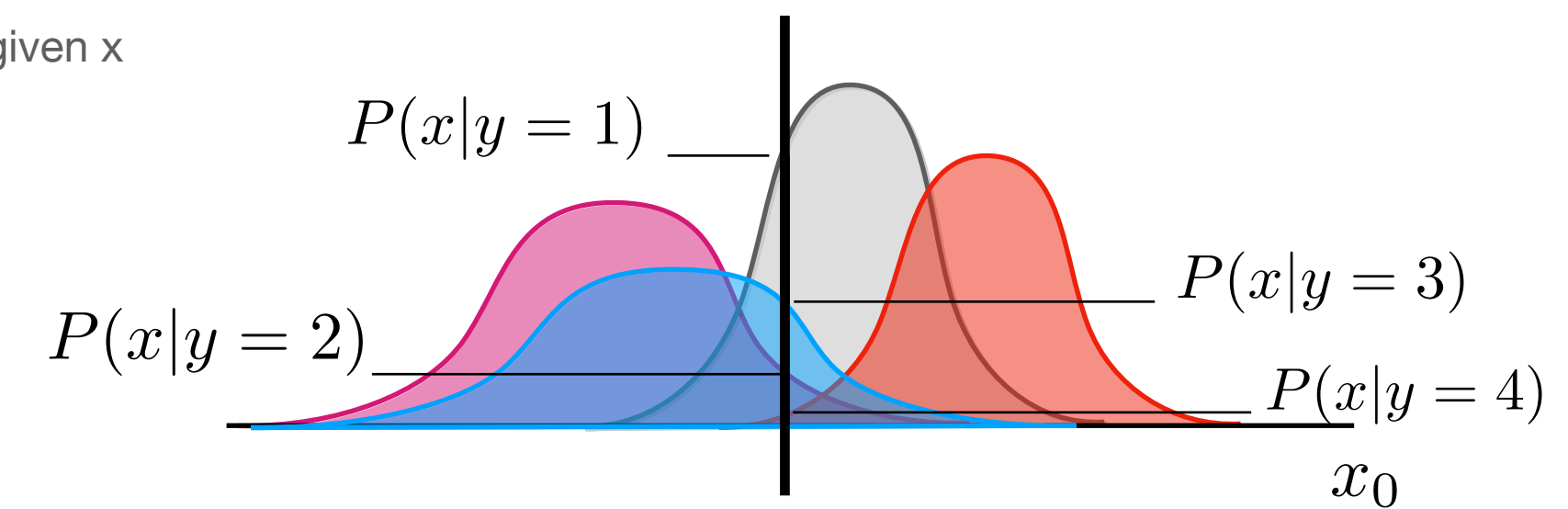
...normalize factor

$$P(y = k|x)$$

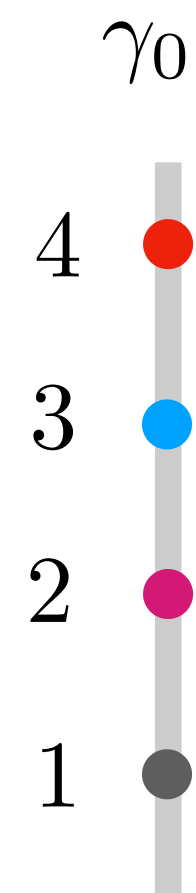
...probability of class k given x

$$\log P(y = k|x) = -\frac{1}{2} \log |\Sigma_k| - \frac{1}{2} (x - \mu_k)^T \Sigma_k^{-1} (x - \mu_k) + \log P(y = k) + \text{const}$$

$$\arg \max_k \log P(y = k|x)$$



$$P(x|y = k) = \frac{1}{(2\pi)^{n/2} |\Sigma_k|^{1/2}} e^{-\frac{1}{2} (x - \mu_k)^T \Sigma_k^{-1} (x - \mu_k)}$$



Class score

Predicted class

# Discriminant Analysis

**OUTPUTS**  
(Dependent Variables)

**INPUTS**  
(Independent Variables)

$$\begin{bmatrix} \gamma_{00} & \dots & \gamma_{0m'} & y_{00} & \dots & y_{0m} \\ \gamma_{10} & \dots & \gamma_{1m'} & y_{10} & \dots & y_{1m} \\ \gamma_{20} & \dots & \gamma_{2m'} & y_{20} & \dots & y_{2m} \\ \gamma_{30} & \dots & \gamma_{3m'} & y_{30} & \dots & y_{3m} \\ \gamma_{40} & \dots & \gamma_{4m'} & y_{40} & \dots & y_{4m} \\ \vdots & & \vdots & \vdots & & \vdots \\ \gamma_{T0} & \dots & \gamma_{Tm'} & y_{T0} & \dots & y_{Tm} \end{bmatrix} \leftarrow f \begin{bmatrix} (x_{00} \dots x_{0n}) \\ x_{10} \dots x_{1n} \\ x_{20} \dots x_{2n} \\ x_{30} \dots x_{3n} \\ x_{40} \dots x_{4n} \\ \vdots \\ x_{T0} \dots x_{Tn} \end{bmatrix} \begin{bmatrix} \xi_{00} \dots \xi_{0n'} \\ \xi_{10} \dots \xi_{1n'} \\ \xi_{20} \dots \xi_{2n'} \\ \xi_{30} \dots \xi_{3n'} \\ \xi_{40} \dots \xi_{4n'} \\ \vdots \\ \xi_{T0} \dots \xi_{Tn'} \end{bmatrix}$$

**CONDITIONAL PROBABILITY**

$$P(y|x)P(x) = P(x|y)P(y)$$

$$P(x|y = k)$$

...height of density k

**BAYES RULE**

$$P(y|x) = \frac{P(x|y)P(y)}{P(x)}$$

$$P(y = k)$$

...prior probability of k

$$P(x)$$

...normalize factor

$$P(y = k|x)$$

...probability of class k given x

Class score

$$\log P(y = k|x) = -\frac{1}{2} \log |\Sigma_k| - \frac{1}{2} (x - \mu_k)^T \Sigma_k^{-1} (x - \mu_k) + \log P(y = k) + \text{const}$$

Predicted class

$$\arg \max_k \log P(y = k|x)$$

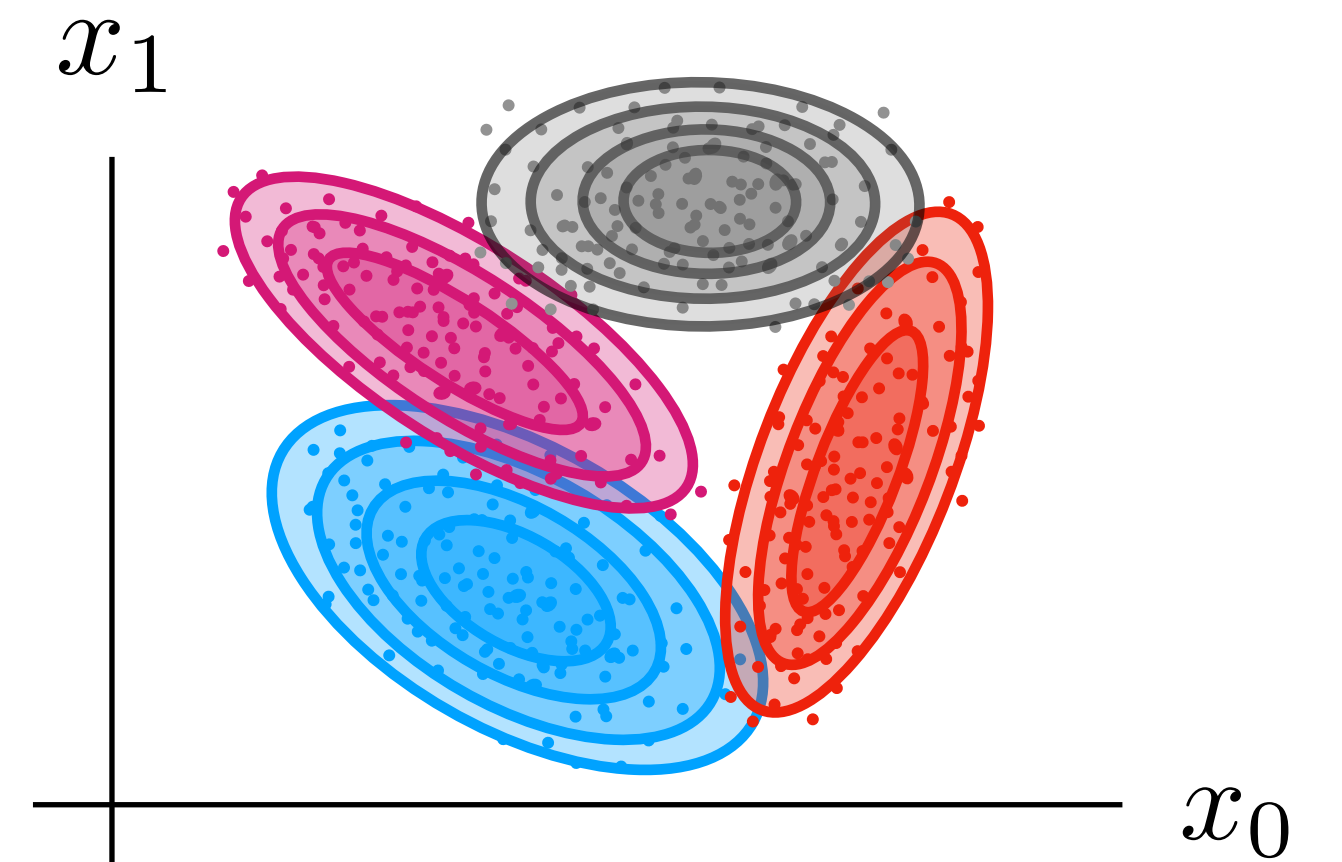
Discrimination Surfaces

$$\log P(y = k|x) = \log P(y = k'|x) \quad \text{k vs. k'}$$

**Quadratic Discriminant Analysis**

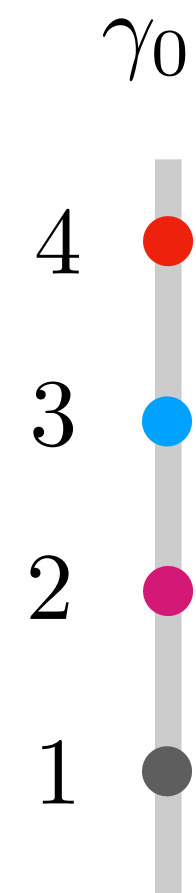
$$\Rightarrow \frac{1}{2} x^T (\underbrace{\Sigma_k^{-1} - \Sigma_{k'}^{-1}}) x - (\mu_k^T \Sigma_k^{-1} - \mu_{k'}^T \Sigma_{k'}^{-1}) x + C_{kk'}$$

ellipses or hyperbolas (or parabolas)



$$P(x|y = k) = \frac{1}{(2\pi)^{n/2} |\Sigma_k|^{1/2}} e^{-\frac{1}{2} (x - \mu_k)^T \Sigma_k^{-1} (x - \mu_k)}$$

with:  $C_{kk'} = \mu_k^T \Sigma_k^{-1} \mu_k - \mu_{k'}^T \Sigma_{k'}^{-1} \mu_{k'} + \frac{1}{2} \log |\Sigma_k| - \frac{1}{2} \log |\Sigma_{k'}| + \log P(y = k') - \log P(y = k)$



# Discriminant Analysis

**OUTPUTS**  
(Dependent Variables)

$$y_t = \theta^T x_t$$

**INPUTS**  
(Independent Variables)

$$\begin{bmatrix} \gamma_{00} & \dots & \gamma_{0m'} & y_{00} & \dots & y_{0m} \\ \gamma_{10} & \dots & \gamma_{1m'} & y_{10} & \dots & y_{1m} \\ \gamma_{20} & \dots & \gamma_{2m'} & y_{20} & \dots & y_{2m} \\ \gamma_{30} & \dots & \gamma_{3m'} & y_{30} & \dots & y_{3m} \\ \gamma_{40} & \dots & \gamma_{4m'} & y_{40} & \dots & y_{4m} \\ \vdots & & \vdots & \vdots & & \vdots \\ \gamma_{T0} & \dots & \gamma_{Tm'} & y_{T0} & \dots & y_{Tm} \end{bmatrix} \leftarrow f \begin{bmatrix} (x_{00} \dots x_{0n}) \\ x_{10} \dots x_{1n} \\ x_{20} \dots x_{2n} \\ x_{30} \dots x_{3n} \\ x_{40} \dots x_{4n} \\ \vdots \\ x_{T0} \dots x_{Tn} \end{bmatrix} \begin{bmatrix} \xi_{00} & \dots & \xi_{0n'} \\ \xi_{10} & \dots & \xi_{1n'} \\ \xi_{20} & \dots & \xi_{2n'} \\ \xi_{30} & \dots & \xi_{3n'} \\ \xi_{40} & \dots & \xi_{4n'} \\ \vdots & & \vdots \\ \xi_{T0} & \dots & \xi_{Tn'} \end{bmatrix}$$

**CONDITIONAL PROBABILITY**

$$P(y|x)P(x) = P(x|y)P(y)$$

$$P(x|y = k)$$

...height of density k

**BAYES RULE**

$$P(y|x) = \frac{P(x|y)P(y)}{P(x)}$$

$$P(y = k)$$

...prior probability of k

$$P(x)$$

...normalize factor

$$P(y = k|x)$$

...probability of class k given x

Class score

$$\log P(y = k|x) = -\frac{1}{2} \log |\Sigma_k| - \frac{1}{2} (x - \mu_k)^T \Sigma_k^{-1} (x - \mu_k) + \log P(y = k) + \text{const}$$

Predicted class

$$\arg \max_k \log P(y = k|x)$$

Discrimination Surfaces

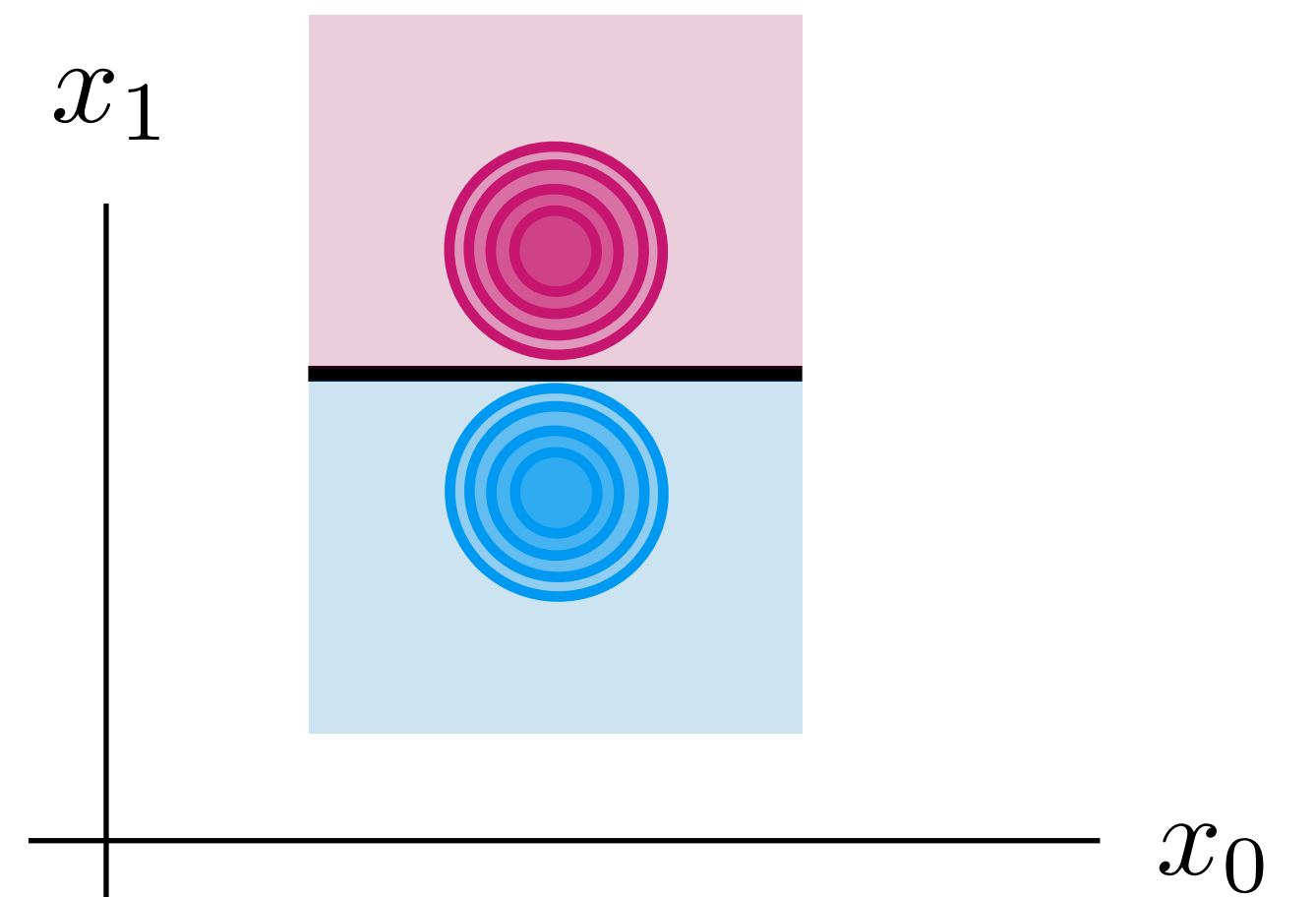
$$\log P(y = k|x) = \log P(y = k'|x) \quad \text{k vs. k'}$$

**Quadratic Discriminant Analysis**

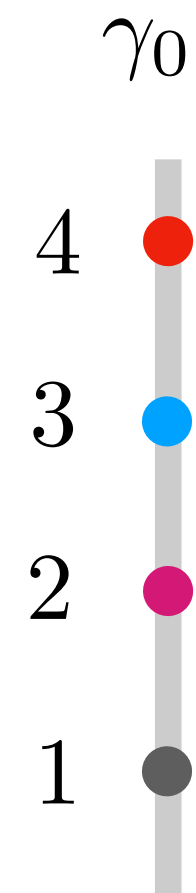
$$\Rightarrow \frac{1}{2} x^T (\underbrace{\Sigma_k^{-1} - \Sigma_{k'}^{-1}}) x - (\mu_k^T \Sigma_k^{-1} - \mu_{k'}^T \Sigma_{k'}^{-1}) x + C_{kk'}$$

ellipses or hyperbolas (or parabolas)

with:  $C_{kk'} = \mu_k^T \Sigma_k^{-1} \mu_k - \mu_{k'}^T \Sigma_{k'}^{-1} \mu_{k'} + \frac{1}{2} \log |\Sigma_k| - \frac{1}{2} \log |\Sigma_{k'}| + \log P(y = k') - \log P(y = k)$



$$P(x|y = k) = \frac{1}{(2\pi)^{n/2} |\Sigma_k|^{1/2}} e^{-\frac{1}{2} (x - \mu_k)^T \Sigma_k^{-1} (x - \mu_k)}$$

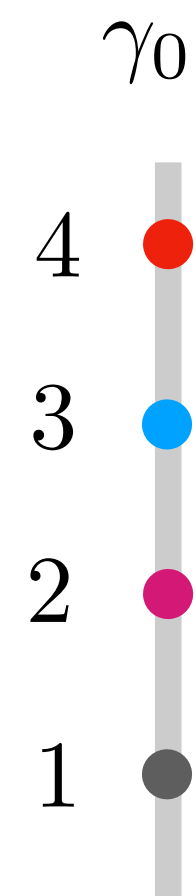


# Discriminant Analysis

**OUTPUTS**  
(Dependent Variables)

$$y_t = \theta^T x_t$$

**INPUTS**  
(Independent Variables)



**CONDITIONAL PROBABILITY**  
**BAYES RULE**  
  
Class score  
Predicted class  
  
Discrimination Surfaces  
  
Quadratic Discriminant Analysis

$$P(y|x)P(x) = P(x|y)P(y)$$

$$P(y|x) = \frac{P(x|y)P(y)}{P(x)}$$

$$P(x|y = k)$$

$$P(y = k)$$

$$P(x)$$

$$P(y = k|x)$$

...height of density k

...prior probability of k

...normalize factor

...probability of class k given x

$$\log P(y = k|x) = -\frac{1}{2} \log |\Sigma_k| - \frac{1}{2} (x - \mu_k)^T \Sigma_k^{-1} (x - \mu_k) + \log P(y = k) + \text{const}$$

$$\arg \max_k \log P(y = k|x)$$

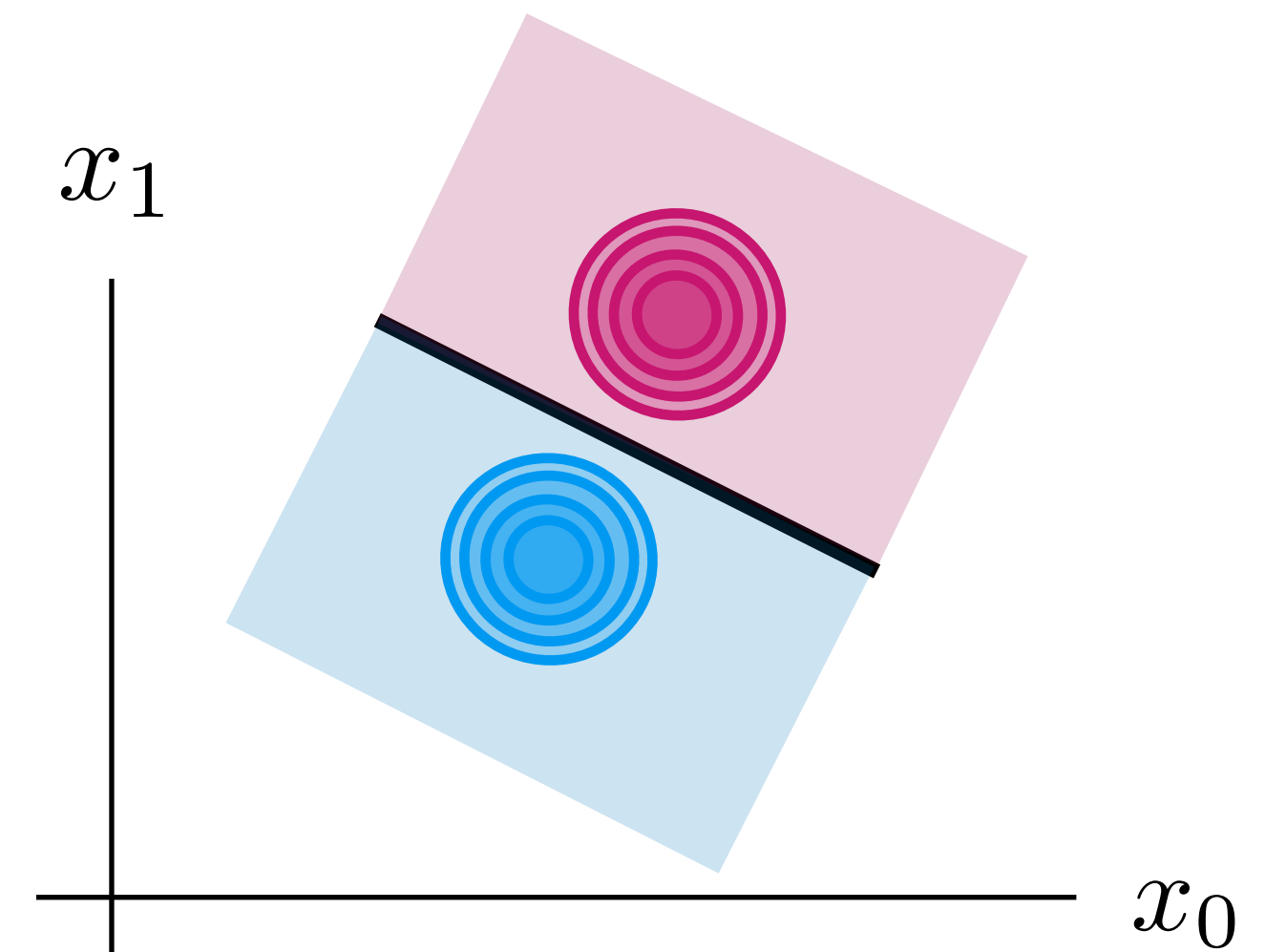
$$\log P(y = k|x) = \log P(y = k'|x) \quad \text{k vs. k'}$$

⇒

$$\frac{1}{2} x^T (\underbrace{\Sigma_k^{-1} - \Sigma_{k'}^{-1}}) x - (\mu_k^T \Sigma_k^{-1} - \mu_{k'}^T \Sigma_{k'}^{-1}) x + C_{kk'}$$

ellipses or hyperbolas (or parabolas)

with:  $C_{kk'} = \mu_k^T \Sigma_k^{-1} \mu_k - \mu_{k'}^T \Sigma_{k'}^{-1} \mu_{k'} + \frac{1}{2} \log |\Sigma_k| - \frac{1}{2} \log |\Sigma_{k'}| + \log P(y = k') - \log P(y = k)$



$$P(x|y = k) = \frac{1}{(2\pi)^{n/2} |\Sigma_k|^{1/2}} e^{-\frac{1}{2} (x - \mu_k)^T \Sigma_k^{-1} (x - \mu_k)}$$



# Discriminant Analysis

**OUTPUTS**  
(Dependent Variables)

$$y_t = \theta^T x_t$$

**INPUTS**  
(Independent Variables)

$$\begin{bmatrix} \gamma_{00} & \dots & \gamma_{0m'} & y_{00} & \dots & y_{0m} \\ \gamma_{10} & \dots & \gamma_{1m'} & y_{10} & \dots & y_{1m} \\ \gamma_{20} & \dots & \gamma_{2m'} & y_{20} & \dots & y_{2m} \\ \gamma_{30} & \dots & \gamma_{3m'} & y_{30} & \dots & y_{3m} \\ \gamma_{40} & \dots & \gamma_{4m'} & y_{40} & \dots & y_{4m} \\ \vdots & & \vdots & \vdots & & \vdots \\ \gamma_{T0} & \dots & \gamma_{Tm'} & y_{T0} & \dots & y_{Tm} \end{bmatrix} \leftarrow f \begin{bmatrix} \left( \begin{matrix} x_{00} & \dots & x_{0n} \\ x_{10} & \dots & x_{1n} \\ x_{20} & \dots & x_{2n} \\ x_{30} & \dots & x_{3n} \\ x_{40} & \dots & x_{4n} \\ \vdots & & \vdots \\ x_{T0} & \dots & x_{Tn} \end{matrix} \right) \\ \xi_{00} & \dots & \xi_{0n'} \\ \xi_{10} & \dots & \xi_{1n'} \\ \xi_{20} & \dots & \xi_{2n'} \\ \xi_{30} & \dots & \xi_{3n'} \\ \xi_{40} & \dots & \xi_{4n'} \\ \vdots & & \vdots \\ \xi_{T0} & \dots & \xi_{Tn'} \end{bmatrix}$$

**CONDITIONAL PROBABILITY**

$$P(y|x)P(x) = P(x|y)P(y)$$

$$P(x|y = k)$$

...height of density k

**BAYES RULE**

$$P(y|x) = \frac{P(x|y)P(y)}{P(x)}$$

$$P(y = k)$$

...prior probability of k

$$P(x)$$

...normalize factor

$$P(y = k|x)$$

...probability of class k given x

Class score

$$\log P(y = k|x) = -\frac{1}{2} \log |\Sigma_k| - \frac{1}{2} (x - \mu_k)^T \Sigma_k^{-1} (x - \mu_k) + \log P(y = k) + \text{const}$$

Predicted class

$$\arg \max_k \log P(y = k|x)$$

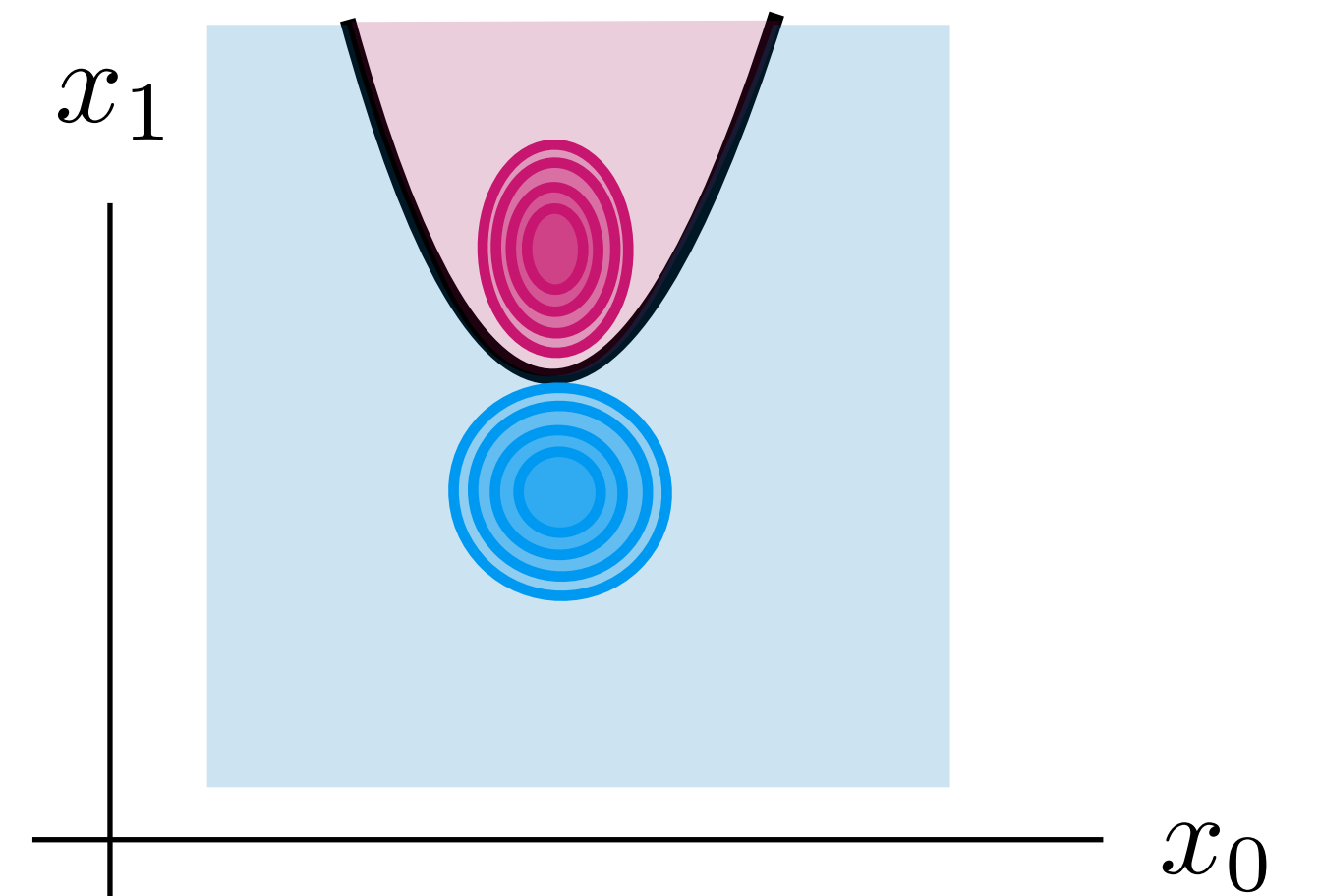
Discrimination Surfaces

$$\log P(y = k|x) = \log P(y = k'|x) \quad \text{k vs. k'}$$

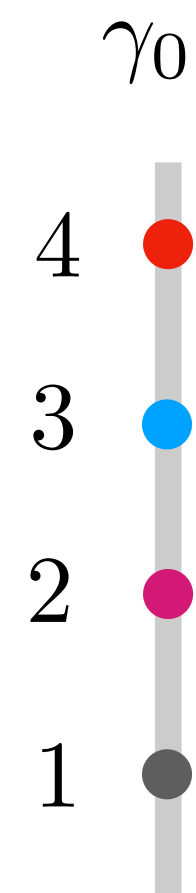
**Quadratic Discriminant Analysis**

$$\Rightarrow \frac{1}{2} x^T (\underbrace{\Sigma_k^{-1} - \Sigma_{k'}^{-1}}_{\text{ellipses or hyperbolas (or parabolas)}}) x - (\mu_k^T \Sigma_k^{-1} - \mu_{k'}^T \Sigma_{k'}^{-1}) x + C_{kk'}$$

with:  $C_{kk'} = \mu_k^T \Sigma_k^{-1} \mu_k - \mu_{k'}^T \Sigma_{k'}^{-1} \mu_{k'} + \frac{1}{2} \log |\Sigma_k| - \frac{1}{2} \log |\Sigma_{k'}| + \log P(y = k') - \log P(y = k)$



$$P(x|y = k) = \frac{1}{(2\pi)^{n/2} |\Sigma_k|^{1/2}} e^{-\frac{1}{2} (x - \mu_k)^T \Sigma_k^{-1} (x - \mu_k)}$$





# Discriminant Analysis

**OUTPUTS**  
(Dependent Variables)

$$y_t = \theta^T x_t$$

**INPUTS**  
(Independent Variables)

$$\begin{bmatrix} \gamma_{00} & \dots & \gamma_{0m'} & y_{00} & \dots & y_{0m} \\ \gamma_{10} & \dots & \gamma_{1m'} & y_{10} & \dots & y_{1m} \\ \gamma_{20} & \dots & \gamma_{2m'} & y_{20} & \dots & y_{2m} \\ \gamma_{30} & \dots & \gamma_{3m'} & y_{30} & \dots & y_{3m} \\ \gamma_{40} & \dots & \gamma_{4m'} & y_{40} & \dots & y_{4m} \\ \vdots & & \vdots & \vdots & & \vdots \\ \gamma_{T0} & \dots & \gamma_{Tm'} & y_{T0} & \dots & y_{Tm} \end{bmatrix} \leftarrow f \begin{bmatrix} (x_{00} \dots x_{0n}) \\ x_{10} \dots x_{1n} \\ x_{20} \dots x_{2n} \\ x_{30} \dots x_{3n} \\ x_{40} \dots x_{4n} \\ \vdots \\ x_{T0} \dots x_{Tn} \end{bmatrix} \begin{bmatrix} \xi_{00} & \dots & \xi_{0n'} \\ \xi_{10} & \dots & \xi_{1n'} \\ \xi_{20} & \dots & \xi_{2n'} \\ \xi_{30} & \dots & \xi_{3n'} \\ \xi_{40} & \dots & \xi_{4n'} \\ \vdots & & \vdots \\ \xi_{T0} & \dots & \xi_{Tn'} \end{bmatrix}$$

**CONDITIONAL PROBABILITY**

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$$P(x|y = k)$$

...height of density k

**BAYES RULE**

$$P(y|x) = \frac{P(x|y)P(y)}{P(x)}$$

$$P(y = k)$$

...prior probability of k

$$P(x)$$

...normalize factor

$$P(y = k|x)$$

...probability of class k given x

Class score

$$\log P(y = k|x) = -\frac{1}{2} \log |\Sigma_k| - \frac{1}{2} (x - \mu_k)^T \Sigma_k^{-1} (x - \mu_k) + \log P(y = k) + \text{const}$$

Predicted class

$$\arg \max_k \log P(y = k|x)$$

Discrimination Surfaces

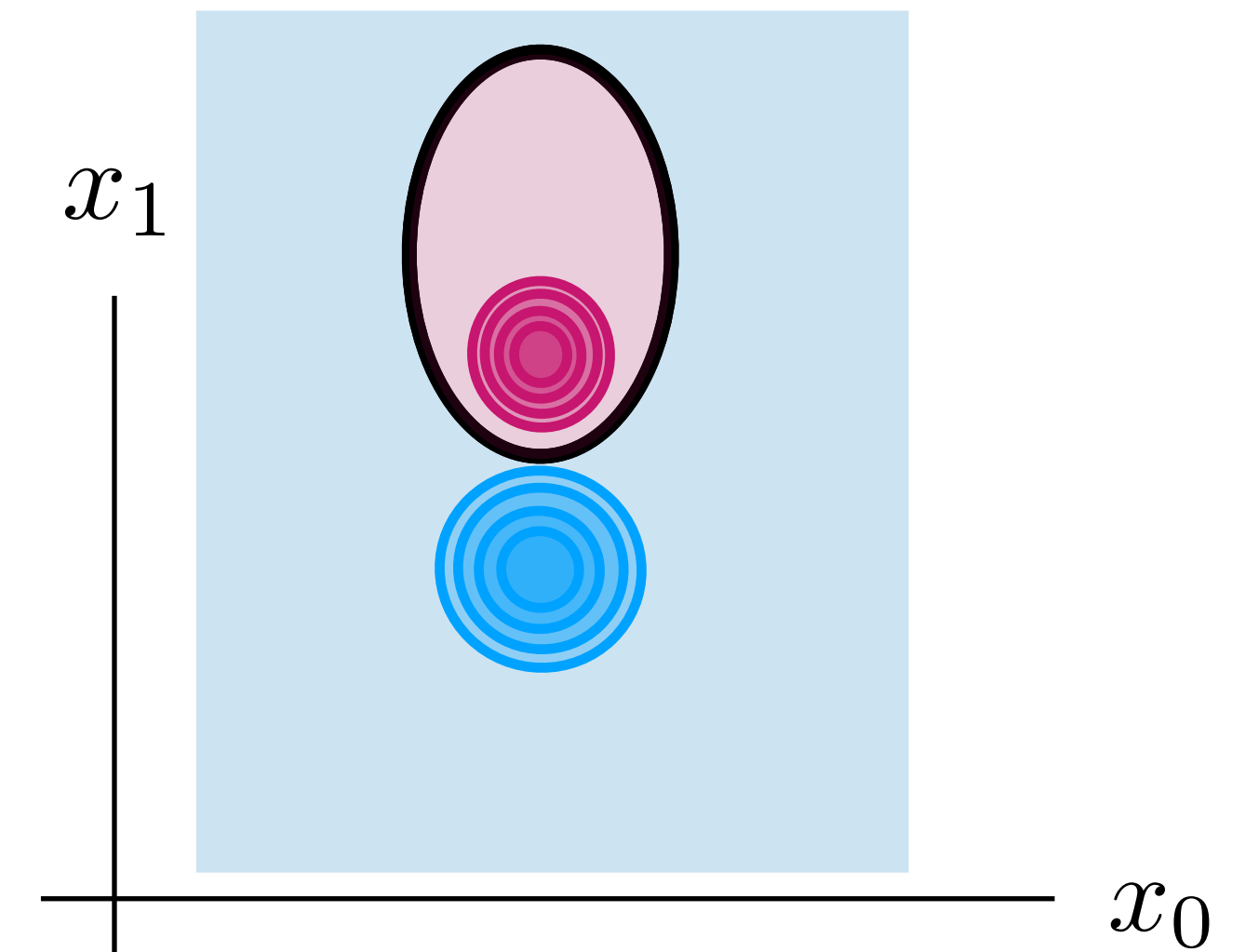
$$\log P(y = k|x) = \log P(y = k'|x) \quad \text{k vs. k'}$$

**Quadratic Discriminant Analysis**

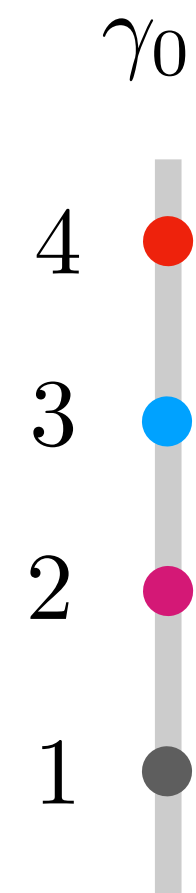
$$\Rightarrow \frac{1}{2} x^T (\underbrace{\Sigma_k^{-1} - \Sigma_{k'}^{-1}}) x - (\mu_k^T \Sigma_k^{-1} - \mu_{k'}^T \Sigma_{k'}^{-1}) x + C_{kk'}$$

ellipses or hyperbolas (or parabolas)

with:  $C_{kk'} = \mu_k^T \Sigma_k^{-1} \mu_k - \mu_{k'}^T \Sigma_{k'}^{-1} \mu_{k'} + \frac{1}{2} \log |\Sigma_k| - \frac{1}{2} \log |\Sigma_{k'}| + \log P(y = k') - \log P(y = k)$



$$P(x|y = k) = \frac{1}{(2\pi)^{n/2} |\Sigma_k|^{1/2}} e^{-\frac{1}{2} (x - \mu_k)^T \Sigma_k^{-1} (x - \mu_k)}$$



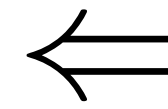
# Discriminant Analysis

**OUTPUTS**  
(Dependent Variables)

$$y_t = \theta^T x_t$$

**INPUTS**  
(Independent Variables)

$$\begin{bmatrix} \gamma_{00} & \cdots & \gamma_{0m'} & y_{00} & \cdots & y_{0m} \\ \gamma_{10} & \cdots & \gamma_{1m'} & y_{10} & \cdots & y_{1m} \\ \gamma_{20} & \cdots & \gamma_{2m'} & y_{20} & \cdots & y_{2m} \\ \gamma_{30} & \cdots & \gamma_{3m'} & y_{30} & \cdots & y_{3m} \\ \gamma_{40} & \cdots & \gamma_{4m'} & y_{40} & \cdots & y_{4m} \\ \vdots & & \vdots & \vdots & & \vdots \\ \gamma_{T0} & \cdots & \gamma_{Tm'} & y_{T0} & \cdots & y_{Tm} \end{bmatrix}$$



$$f \begin{bmatrix} (x_{00} \cdots x_{0n'}) \\ x_{10} \cdots x_{1n'} \\ x_{20} \cdots x_{2n'} \\ x_{30} \cdots x_{3n'} \\ x_{40} \cdots x_{4n'} \\ \vdots \\ x_{T0} \cdots x_{Tn'} \end{bmatrix} \begin{matrix} \xi_{00} \cdots \xi_{0n'} \\ \xi_{10} \cdots \xi_{1n'} \\ \xi_{20} \cdots \xi_{2n'} \\ \xi_{30} \cdots \xi_{3n'} \\ \xi_{40} \cdots \xi_{4n'} \\ \vdots \\ \xi_{T0} \cdots \xi_{Tn'} \end{matrix}$$

**CONDITIONAL PROBABILITY**

$$P(y|x)P(x) = P(x|y)P(y)$$

$$P(x|y = k)$$

...height of density k

**BAYES RULE**

$$P(y|x) = \frac{P(x|y)P(y)}{P(x)}$$

$$P(y = k)$$

...prior probability of k

$$P(x)$$

...normalize factor

$$P(y = k|x)$$

...probability of class k given x

Class score

$$\log P(y = k|x) = -\frac{1}{2} \log |\Sigma_k| - \frac{1}{2} (x - \mu_k)^T \Sigma_k^{-1} (x - \mu_k) + \log P(y = k) + \text{const}$$

Predicted class

$$\arg \max_k \log P(y = k|x)$$

Discrimination Surfaces

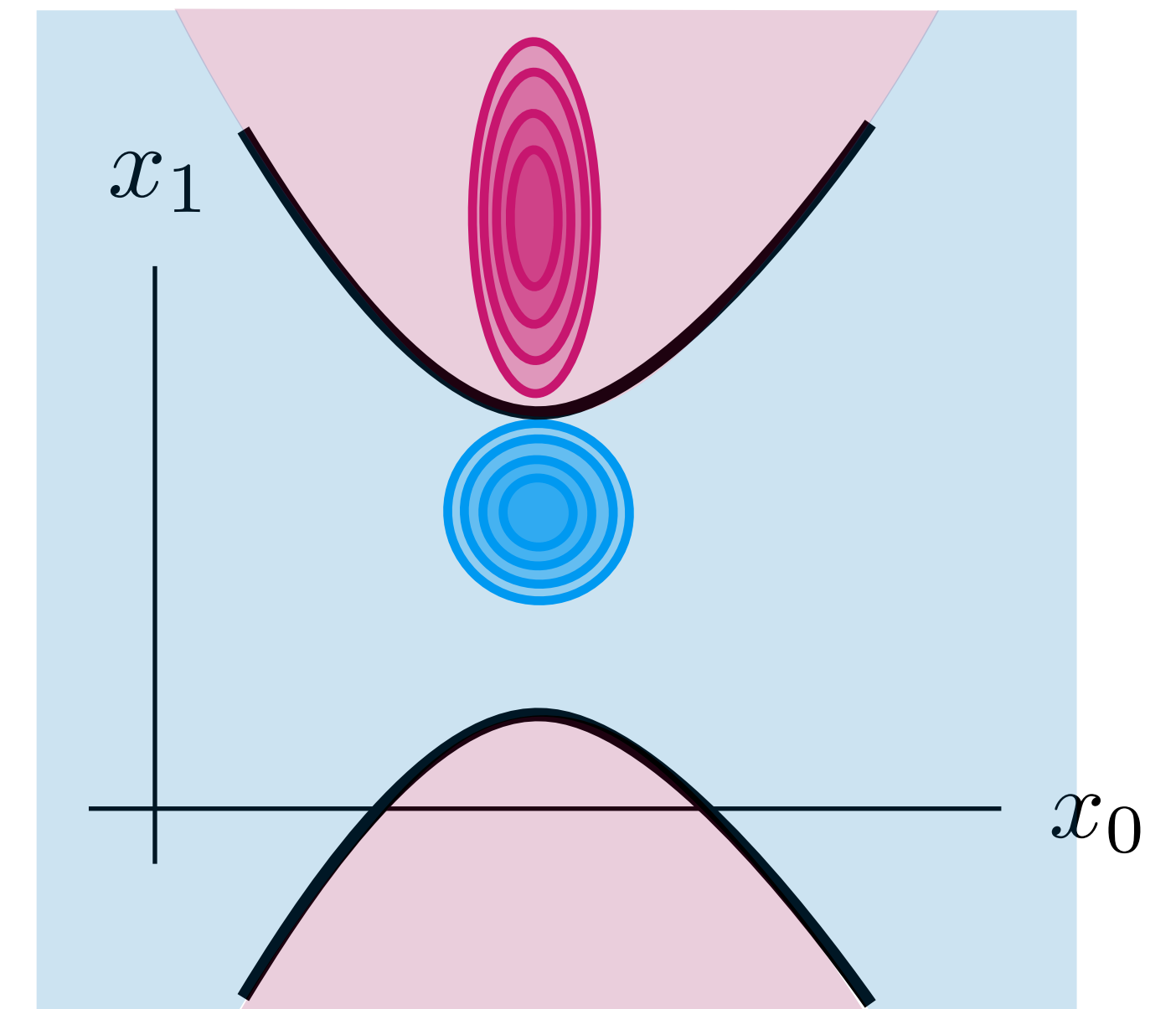
$$\log P(y = k|x) = \log P(y = k'|x) \quad \text{k vs. k'}$$

**Quadratic Discriminant Analysis**

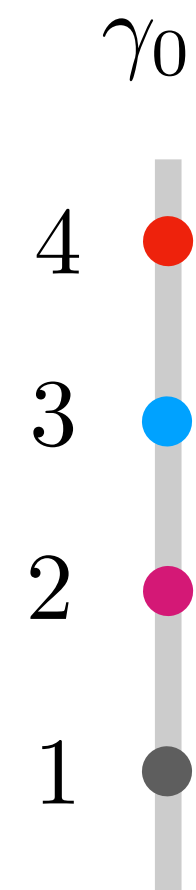
$$\Rightarrow \frac{1}{2} x^T (\underbrace{\Sigma_k^{-1} - \Sigma_{k'}^{-1}}) x - (\mu_k^T \Sigma_k^{-1} - \mu_{k'}^T \Sigma_{k'}^{-1}) x + C_{kk'}$$

ellipses or hyperbolas (or parabolas)

with:  $C_{kk'} = \mu_k^T \Sigma_k^{-1} \mu_k - \mu_{k'}^T \Sigma_{k'}^{-1} \mu_{k'} + \frac{1}{2} \log |\Sigma_k| - \frac{1}{2} \log |\Sigma_{k'}| + \log P(y = k') - \log P(y = k)$



$$P(x|y = k) = \frac{1}{(2\pi)^{n/2} |\Sigma_k|^{1/2}} e^{-\frac{1}{2} (x - \mu_k)^T \Sigma_k^{-1} (x - \mu_k)}$$



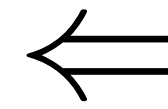
# Discriminant Analysis

**OUTPUTS**  
(Dependent Variables)

$$y_t = \theta^T x_t$$

**INPUTS**  
(Independent Variables)

$$\begin{bmatrix} \gamma_{00} & \cdots & \gamma_{0m'} & y_{00} & \cdots & y_{0m} \\ \gamma_{10} & \cdots & \gamma_{1m'} & y_{10} & \cdots & y_{1m} \\ \gamma_{20} & \cdots & \gamma_{2m'} & y_{20} & \cdots & y_{2m} \\ \gamma_{30} & \cdots & \gamma_{3m'} & y_{30} & \cdots & y_{3m} \\ \gamma_{40} & \cdots & \gamma_{4m'} & y_{40} & \cdots & y_{4m} \\ \vdots & & \vdots & \vdots & & \vdots \\ \gamma_{T0} & \cdots & \gamma_{Tm'} & y_{T0} & \cdots & y_{Tm} \end{bmatrix}$$



$$f \begin{bmatrix} (x_{00} \cdots x_{0n'}) \\ x_{10} \cdots x_{1n'} \\ x_{20} \cdots x_{2n'} \\ x_{30} \cdots x_{3n'} \\ x_{40} \cdots x_{4n'} \\ \vdots \\ x_{T0} \cdots x_{Tn'} \end{bmatrix} \begin{bmatrix} \xi_{00} \cdots \xi_{0n'} \\ \xi_{10} \cdots \xi_{1n'} \\ \xi_{20} \cdots \xi_{2n'} \\ \xi_{30} \cdots \xi_{3n'} \\ \xi_{40} \cdots \xi_{4n'} \\ \vdots \\ \xi_{T0} \cdots \xi_{Tn'} \end{bmatrix}$$

**CONDITIONAL PROBABILITY**

$$P(y|x)P(x) = P(x|y)P(y)$$

$$P(x|y = k)$$

...height of density k

**BAYES RULE**

$$P(y|x) = \frac{P(x|y)P(y)}{P(x)}$$

$$P(y = k)$$

...prior probability of k

$$P(x)$$

...normalize factor

$$P(y = k|x)$$

...probability of class k given x

Class score

$$\log P(y = k|x) = -\frac{1}{2} \log |\Sigma_k| - \frac{1}{2} (x - \mu_k)^T \Sigma_k^{-1} (x - \mu_k) + \log P(y = k) + \text{const}$$

Predicted class

$$\arg \max_k \log P(y = k|x)$$

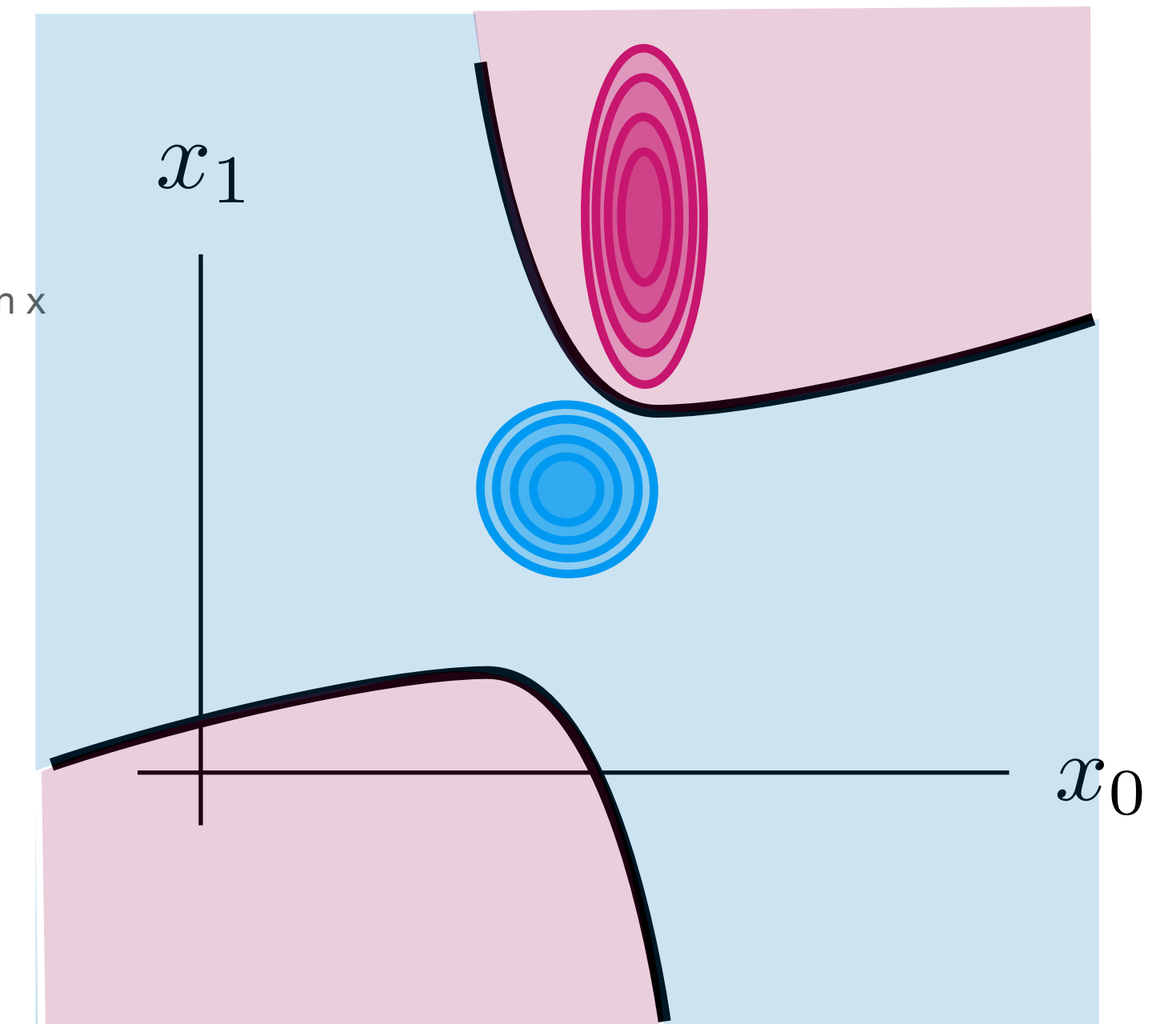
Discrimination Surfaces

$$\log P(y = k|x) = \log P(y = k'|x) \quad k \text{ vs. } k'$$

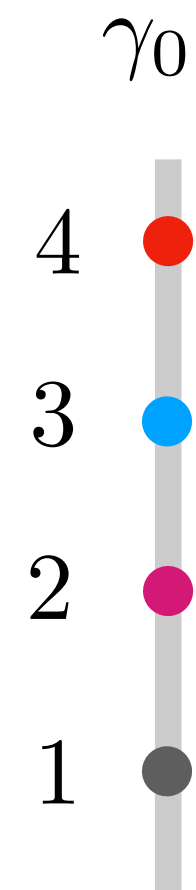
**Quadratic Discriminant Analysis**

$$\Rightarrow \frac{1}{2} x^T (\underbrace{\Sigma_k^{-1} - \Sigma_{k'}^{-1}}_{\text{ellipses or hyperbolas (or parabolas)}}) x - (\mu_k^T \Sigma_k^{-1} - \mu_{k'}^T \Sigma_{k'}^{-1}) x + C_{kk'}$$

with:  $C_{kk'} = \mu_k^T \Sigma_k^{-1} \mu_k - \mu_{k'}^T \Sigma_{k'}^{-1} \mu_{k'} + \frac{1}{2} \log |\Sigma_k| - \frac{1}{2} \log |\Sigma_{k'}| + \log P(y = k') - \log P(y = k)$



$$P(x|y = k) = \frac{1}{(2\pi)^{n/2} |\Sigma_k|^{1/2}} e^{-\frac{1}{2} (x - \mu_k)^T \Sigma_k^{-1} (x - \mu_k)}$$



# Discriminant Analysis

**OUTPUTS**  
(Dependent Variables)

$$y_t = \theta^T x_t$$

**INPUTS**  
(Independent Variables)

$$\begin{bmatrix} \gamma_{00} & \dots & \gamma_{0m'} & y_{00} & \dots & y_{0m} \\ \gamma_{10} & \dots & \gamma_{1m'} & y_{10} & \dots & y_{1m} \\ \gamma_{20} & \dots & \gamma_{2m'} & y_{20} & \dots & y_{2m} \\ \gamma_{30} & \dots & \gamma_{3m'} & y_{30} & \dots & y_{3m} \\ \gamma_{40} & \dots & \gamma_{4m'} & y_{40} & \dots & y_{4m} \\ \vdots & & \vdots & \vdots & & \vdots \\ \gamma_{T0} & \dots & \gamma_{Tm'} & y_{T0} & \dots & y_{Tm} \end{bmatrix} \leftarrow f \begin{bmatrix} (x_{00} \dots x_{0n}) \\ x_{10} \dots x_{1n} \\ x_{20} \dots x_{2n} \\ x_{30} \dots x_{3n} \\ x_{40} \dots x_{4n} \\ \vdots \\ x_{T0} \dots x_{Tn} \end{bmatrix} \begin{bmatrix} \xi_{00} & \dots & \xi_{0n'} \\ \xi_{10} & \dots & \xi_{1n'} \\ \xi_{20} & \dots & \xi_{2n'} \\ \xi_{30} & \dots & \xi_{3n'} \\ \xi_{40} & \dots & \xi_{4n'} \\ \vdots & & \vdots \\ \xi_{T0} & \dots & \xi_{Tn'} \end{bmatrix}$$

**CONDITIONAL PROBABILITY**

$$P(y|x)P(x) = P(x|y)P(y)$$

$$P(x|y = k)$$

...height of density k

**BAYES RULE**

$$P(y|x) = \frac{P(x|y)P(y)}{P(x)}$$

$$P(y = k)$$

...prior probability of k

$$P(x)$$

...normalize factor

$$P(y = k|x)$$

...probability of class k given x

Class score

$$\log P(y = k|x) = -\frac{1}{2} \log |\Sigma_k| - \frac{1}{2} (x - \mu_k)^T \Sigma_k^{-1} (x - \mu_k) + \log P(y = k) + \text{const}$$

Predicted class

$$\arg \max_k \log P(y = k|x)$$

Discrimination Surfaces

$$\log P(y = k|x) = \log P(y = k'|x) \quad \text{k vs. k'}$$

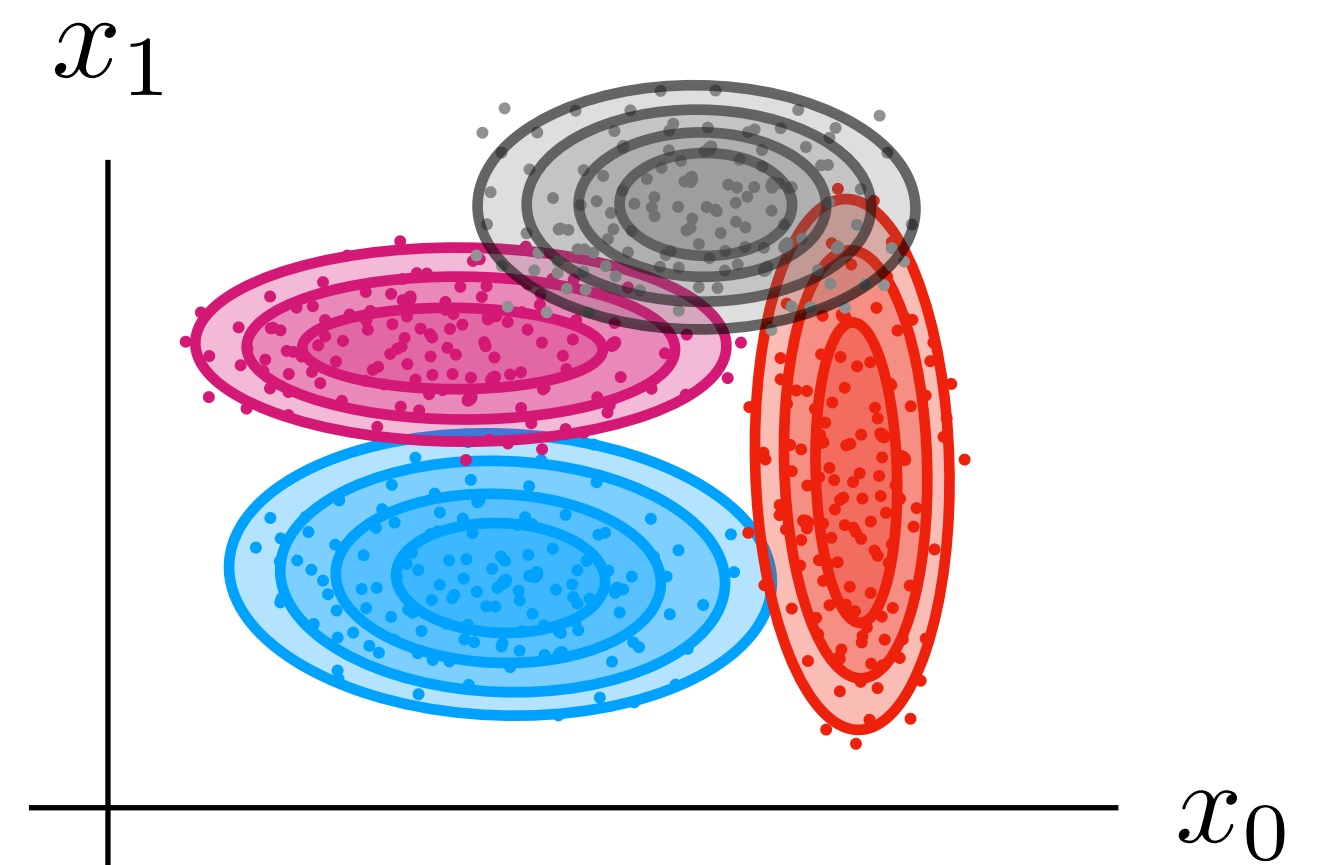
**Gaussian Naive Bayes Classifier**

$$\Rightarrow \frac{1}{2} x^T (\underbrace{\Sigma_k^{-1} - \Sigma_{k'}^{-1}}) x - (\mu_k^T \Sigma_k^{-1} - \mu_{k'}^T \Sigma_{k'}^{-1}) x + C_{kk'}$$

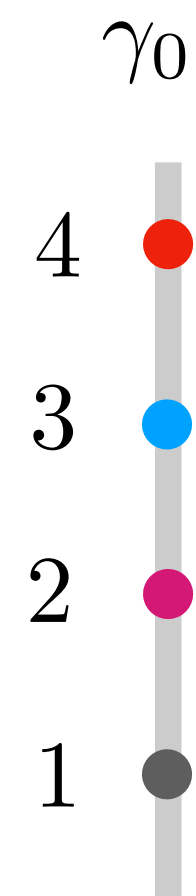
ellipses or hyperbolas (or parabolas)

$\Sigma_k, \Sigma_{k'}$  diagonal

with:  $C_{kk'} = \mu_k^T \Sigma_k^{-1} \mu_k - \mu_{k'}^T \Sigma_{k'}^{-1} \mu_{k'} + \frac{1}{2} \log |\Sigma_k| - \frac{1}{2} \log |\Sigma_{k'}| + \log P(y = k') - \log P(y = k)$



$$P(x|y = k) = \frac{1}{(2\pi)^{n/2} |\Sigma_k|^{1/2}} e^{-\frac{1}{2} (x - \mu_k)^T \Sigma_k^{-1} (x - \mu_k)}$$





# Discriminant Analysis

**OUTPUTS**  
(Dependent Variables)

$$y_t = \theta^T x_t$$

**INPUTS**  
(Independent Variables)

$$\begin{bmatrix} \gamma_{00} & \dots & \gamma_{0m'} & y_{00} & \dots & y_{0m} \\ \gamma_{10} & \dots & \gamma_{1m'} & y_{10} & \dots & y_{1m} \\ \gamma_{20} & \dots & \gamma_{2m'} & y_{20} & \dots & y_{2m} \\ \gamma_{30} & \dots & \gamma_{3m'} & y_{30} & \dots & y_{3m} \\ \gamma_{40} & \dots & \gamma_{4m'} & y_{40} & \dots & y_{4m} \\ \vdots & & \vdots & \vdots & & \vdots \\ \gamma_{T0} & \dots & \gamma_{Tm'} & y_{T0} & \dots & y_{Tm} \end{bmatrix}$$



$$f \begin{bmatrix} (x_{00} \dots x_{0n}) \\ x_{10} \dots x_{1n} \\ x_{20} \dots x_{2n} \\ x_{30} \dots x_{3n} \\ x_{40} \dots x_{4n} \\ \vdots \\ x_{T0} \dots x_{Tn} \end{bmatrix} \begin{matrix} \xi_{00} & \dots & \xi_{0n'} \\ \xi_{10} & \dots & \xi_{1n'} \\ \xi_{20} & \dots & \xi_{2n'} \\ \xi_{30} & \dots & \xi_{3n'} \\ \xi_{40} & \dots & \xi_{4n'} \\ \vdots & & \vdots \\ \xi_{T0} & \dots & \xi_{Tn'} \end{matrix}$$

**CONDITIONAL PROBABILITY**

$$P(y|x)P(x) = P(x|y)P(y)$$

$$P(x|y = k)$$

...height of density k

**BAYES RULE**

$$P(y|x) = \frac{P(x|y)P(y)}{P(x)}$$

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$$P(y = k|x)$$

...probability of class k given x

Class score

$$\log P(y = k|x) = -\frac{1}{2} \log |\Sigma_k| - \frac{1}{2} (x - \mu_k)^T \Sigma_k^{-1} (x - \mu_k) + \log P(y = k) + \text{const}$$

Mahalanobis Distance

Predicted class

$$\arg \max_k \log P(y = k|x)$$

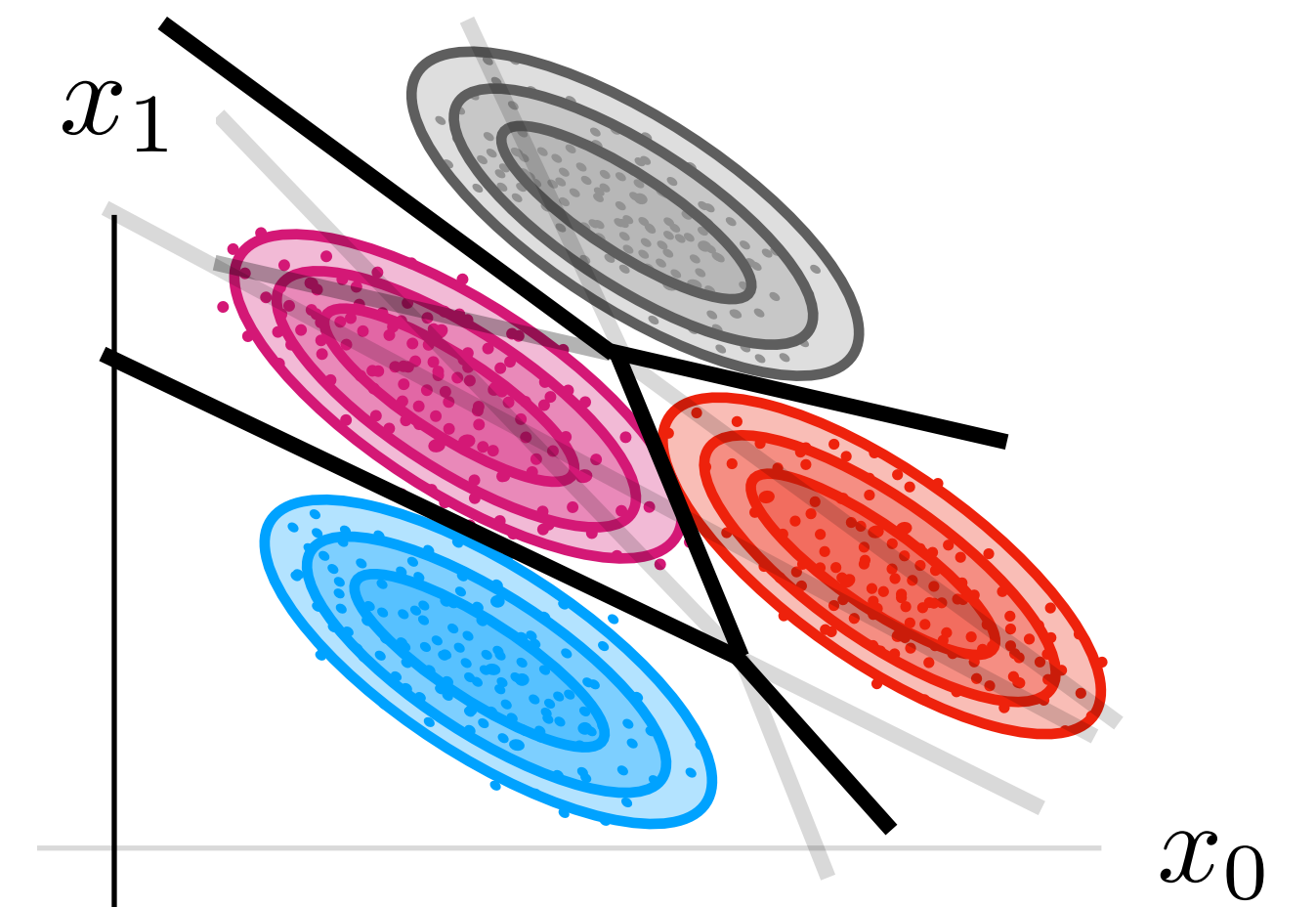
Discrimination Surfaces

$$\log P(y = k|x) = \log P(y = k'|x) \quad k \text{ vs. } k'$$

**Linear Discriminant Analysis**

$$\Rightarrow \frac{1}{2} x^T (\Sigma_k^{-1} - \Sigma_{k'}^{-1}) x - (\mu_k^T \Sigma_k^{-1} - \mu_{k'}^T \Sigma_{k'}^{-1}) x + C_{kk'}$$

$\Rightarrow$  hyperplanes



$$P(x|y = k) = \frac{1}{(2\pi)^{n/2} |\Sigma_k|^{1/2}} e^{-\frac{1}{2} (x - \mu_k)^T \Sigma_k^{-1} (x - \mu_k)}$$

$$\Sigma_k = \Sigma_{k'}$$

with:  $C_{kk'} = \mu_k^T \Sigma_k^{-1} \mu_k - \mu_{k'}^T \Sigma_{k'}^{-1} \mu_{k'} + \frac{1}{2} \log |\Sigma_k| - \frac{1}{2} \log |\Sigma_{k'}| + \log P(y = k') - \log P(y = k)$

