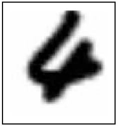
Linear Models for Classification

Greg Mori - CMPT 419/726

Bishop PRML Ch. 4

Classification: Hand-written Digit Recognition

$\boldsymbol{x}_i =$  $\quad \boldsymbol{t}_i = (0,0,0,1,0,0,0,0,0,0)$

- Each input vector classified into one of K discrete classes
  - Denote classes by $\mathcal{C}_k$
- Represent input image as a vector $\boldsymbol{x}_i \in \mathbb{R}^{784}$.
- We have target vector $\boldsymbol{t}_i \in \{0,1\}^{10}$
- Given a training set $\{(\boldsymbol{x}_1, \boldsymbol{t}_1), \ldots, (\boldsymbol{x}_N, \boldsymbol{t}_N)\}$, learning problem is to construct a "good" function $\boldsymbol{y}(\boldsymbol{x})$ from these.
  - $\boldsymbol{y} : \mathbb{R}^{784} \rightarrow \mathbb{R}^{10}$

Generalized Linear Models

- Similar to previous chapter on linear models for regression, we will use a “linear” model for classification:

$$y(\boldsymbol{x}) = f(\boldsymbol{w}^T\boldsymbol{x} + w_0)$$

- This is called a generalized linear model
- $f(\cdot)$ is a fixed non-linear function
  - e.g.

$$f(u) = \begin{cases} 1 \text{ if } u \geq 0 \\ 0 \text{ otherwise} \end{cases}$$

- Decision boundary between classes will be linear function of $\boldsymbol{x}$
- Can also apply non-linearity to $\boldsymbol{x}$, as in $\phi_i(\boldsymbol{x})$ for regression

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Outline

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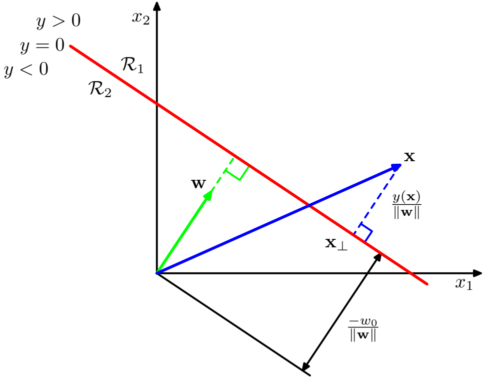
Discriminant Functions

Generative Models

Discriminative Models

Discriminant Functions with Two Classes



- Start with 2 class problem, $t_i \in \{0, 1\}$
- Simple linear discriminant

$$y(\boldsymbol{x}) = \boldsymbol{w}^T \boldsymbol{x} + w_0$$

  apply threshold function to get classification
- Projection of $\boldsymbol{x}$ in $\boldsymbol{w}$ dir. is $\frac{\boldsymbol{w}^T \boldsymbol{x}}{||\boldsymbol{w}||}$

Multiple Classes

- A linear discriminant between two classes separates with a hyperplane
- How to use this for multiple classes?
- One-versus-the-rest method: build $K-1$ classifiers, between $\mathcal{C}_k$ and all others
- One-versus-one method: build $K(K-1)/2$ classifiers, between all pairs

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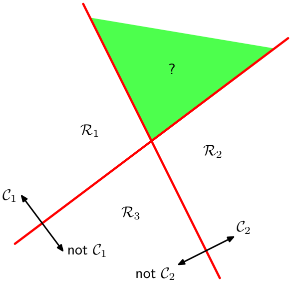

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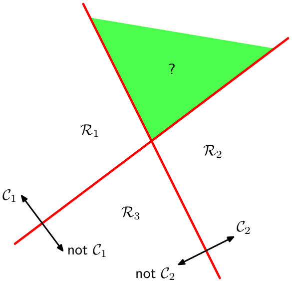

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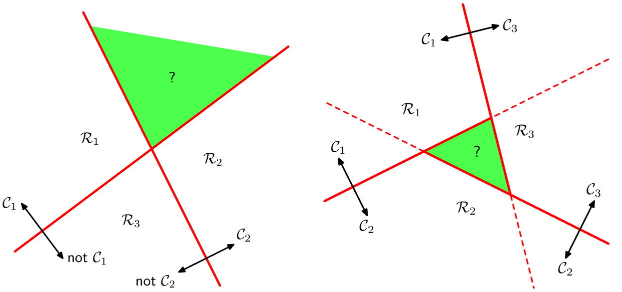

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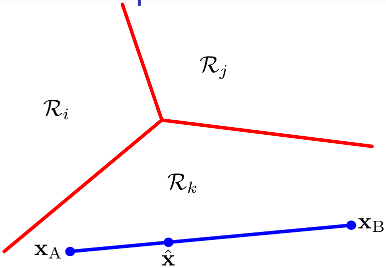

- A solution is to build K linear functions:

$$y_k(\boldsymbol{x}) = \boldsymbol{w}_k^T \boldsymbol{x} + w_{k0}$$

  assign $\boldsymbol{x}$ to class $\arg\max_k y_k(\boldsymbol{x})$
- Gives connected, convex decision regions

$$\begin{aligned}
\hat{\boldsymbol{x}} &= \lambda \boldsymbol{x}_A + (1-\lambda)\boldsymbol{x}_B \\
y_k(\hat{\boldsymbol{x}}) &= \lambda y_k(\boldsymbol{x}_A) + (1-\lambda) y_k(\boldsymbol{x}_B) \\
\Rightarrow y_k(\hat{\boldsymbol{x}}) &> y_j(\hat{\boldsymbol{x}}), \forall j \neq k
\end{aligned}$$

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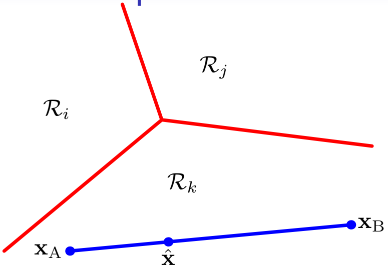

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Least Squares for Classification

- How do we learn the decision boundaries $(\boldsymbol{w}_k, w_{k0})$?
- One approach is to use least squares, similar to regression
- Find $\boldsymbol{W}$ to minimize squared error over all examples and all components of the label vector:

$$E(\boldsymbol{W}) = \frac{1}{2}\sum_{n=1}^{N}\sum_{k=1}^{K}(y_k(\boldsymbol{x}_n) - t_{nk})^2$$

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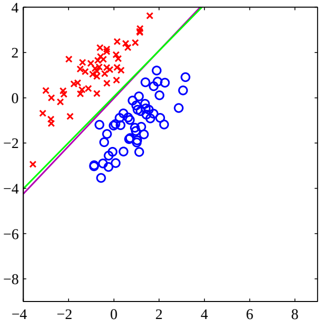

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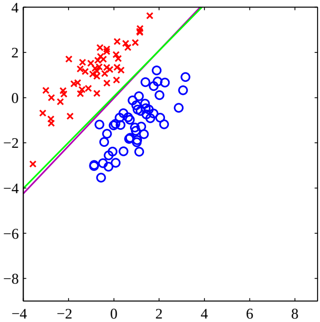

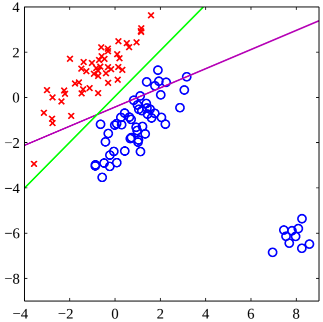

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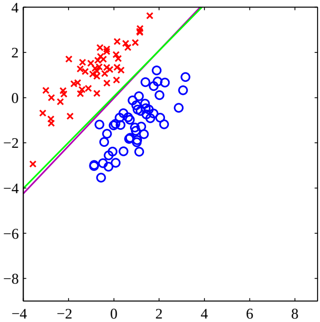

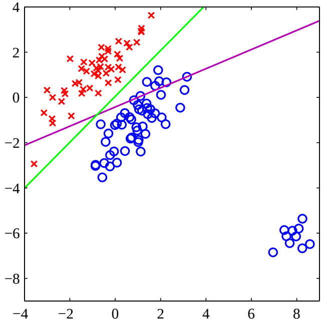

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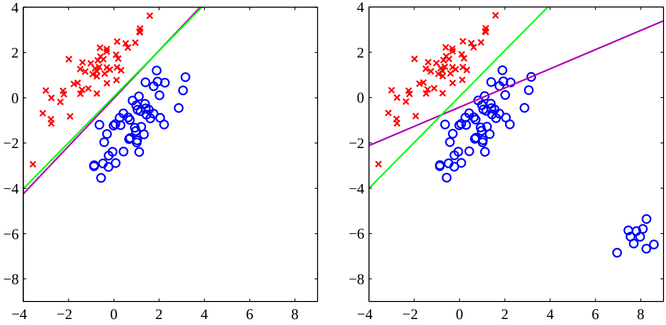

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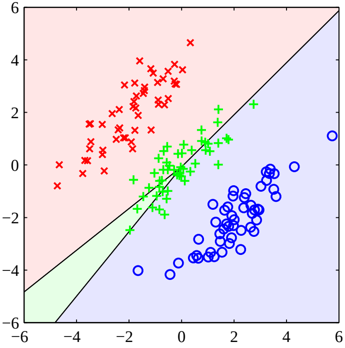
  - Similar to logistic regression decision boundary (more later)
- Gets worse by adding easy points?!
- Why?
  - If target value is 1, points far from boundary will have high value, say 10; this is a large error so the boundary is moved

More Least Squares Problems



- Easily separated by hyperplanes, but not found using least squares!
- We'll address these problems later with better models

Perceptrons

- Perceptrons is used to refer to many neural network structures (more next week)
- The classic type is a fixed non-linear transformation of input, one layer of adaptive weights, and a threshold:

$$y(\boldsymbol{x}) = f(\boldsymbol{w}^T \phi(\boldsymbol{x}))$$

  - Developed by Rosenblatt in the 50s
- The main difference compared to the methods we've seen so far is the learning algorithm

Perceptron Learning

- Two class problem
- For ease of notation, we will use $t = 1$ for class $\mathcal{C}_1$ and $t = -1$ for class $\mathcal{C}_2$
- We saw that squared error was problematic
- Instead, we'd like to minimize the number of misclassified examples
  - An example is mis-classified if $\boldsymbol{w}^T\phi(\boldsymbol{x}_n)t_n < 0$
  - Perceptron criterion:

$$E_P(\boldsymbol{w}) = -\sum_{n\in\mathcal{M}} \boldsymbol{w}^T\phi(\boldsymbol{x}_n)t_n$$

sum over mis-classified examples only

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Perceptron Learning Algorithm

- Minimize the error function using stochastic gradient descent (gradient descent per example):

$$\boldsymbol{w}^{(\tau+1)} = \boldsymbol{w}^{(\tau)} - \eta \nabla E_P(\boldsymbol{w})$$

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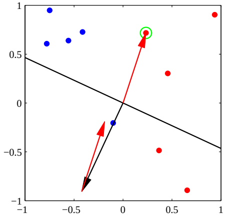
- Iterate over all training examples, only change $\boldsymbol{w}$ if the example is mis-classified
- Guaranteed to converge if data are linearly separable
- Will not converge if not
- May take many iterations
- Sensitive to initialization

Perceptron Learning Illustration



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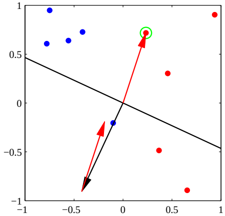

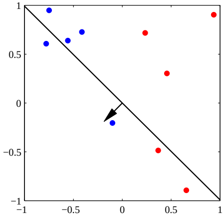

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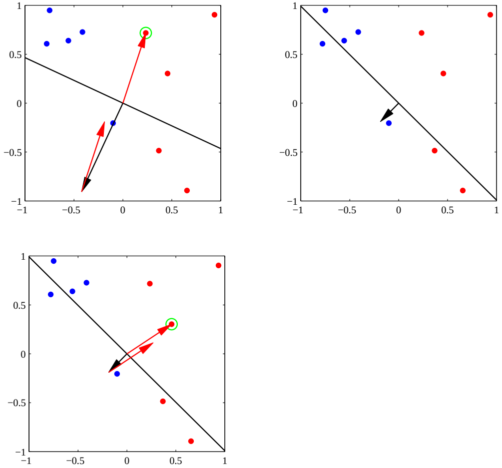

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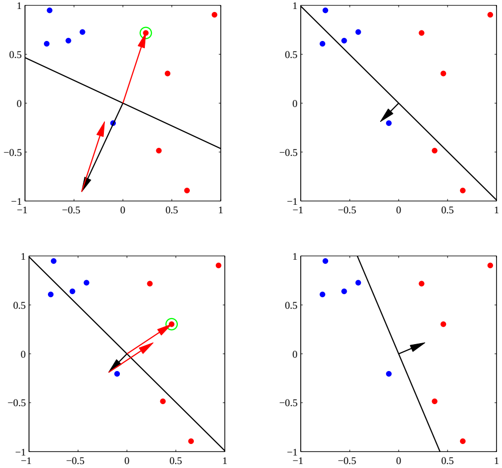

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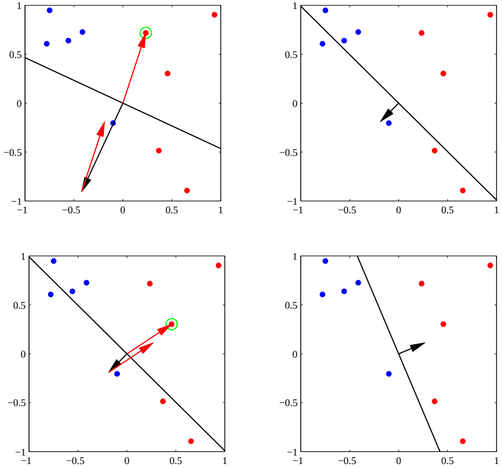
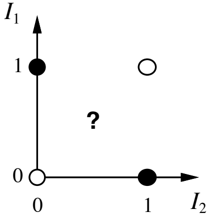


- Note there are many hyperplanes with 0 error
    - Support vector machines have a nice way of choosing one

Limitations of Perceptrons

- Perceptrons can only solve linearly separable problems in feature space
  - Same as the other models in this chapter
- Canonical example of non-separable problem is X-OR
  - Real datasets can look like this too



Outline

Probabilistic Generative Models

- Up to now we've looked at learning classification by choosing parameters to minimize an error function
- We'll now develop a probabilistic approach
- With 2 classes, $\mathcal{C}_1$ and $\mathcal{C}_2$:

$$p(\mathcal{C}_1|\boldsymbol{x}) = \frac{p(\boldsymbol{x}|\mathcal{C}_1)p(\mathcal{C}_1)}{p(\boldsymbol{x})} \text{ Bayes' Rule}$$

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Probabilistic Generative Models - Example

- Let's say we observe x which is the current temperature
- Determine if we are in Vancouver ($\mathcal{C}_1$) or Honolulu ($\mathcal{C}_2$)
- Generative model:

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  - $p(x|\mathcal{C}_1)$ is distribution over typical temperatures in Vancouver
    - e.g. $p(x|\mathcal{C}_1) = \mathcal{N}(x; 10, 5)$
  - $p(x|\mathcal{C}_2)$ is distribution over typical temperatures in Honolulu
    - e.g. $p(x|\mathcal{C}_2) = \mathcal{N}(x; 25, 5)$
  - Class priors $p(\mathcal{C}_1) = 0.1$, $p(\mathcal{C}_2) = 0.9$
- $p(\mathcal{C}_1|x = 15) = \frac{0.0484 \cdot 0.1}{0.0484 \cdot 0.1 + 0.0108 \cdot 0.9} \approx 0.33$

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  - $p(x|\mathcal{C}_2)$ is distribution over typical temperatures in Honolulu
    - e.g. $p(x|\mathcal{C}_2) = \mathcal{N}(x; 25, 5)$
  - Class priors $p(\mathcal{C}_1) = 0.1$, $p(\mathcal{C}_2) = 0.9$
- $p(\mathcal{C}_1|x = 15) = \frac{0.0484 \cdot 0.1}{0.0484 \cdot 0.1 + 0.0108 \cdot 0.9} \approx 0.33$

Generalized Linear Models

- We can write the classifier in another form

$$
\begin{aligned}
p(\mathcal{C}_1|\boldsymbol{x}) &= \frac{p(\boldsymbol{x}|\mathcal{C}_1)p(\mathcal{C}_1)}{p(\boldsymbol{x}|\mathcal{C}_1)p(\mathcal{C}_1) + p(\boldsymbol{x}|\mathcal{C}_2)p(\mathcal{C}_2)} \\
&= \frac{1}{1+\exp(-a)} \equiv \sigma(a) \\
\text{where} \quad a &= \ln \frac{p(\boldsymbol{x}|\mathcal{C}_1)p(\mathcal{C}_1)}{p(\boldsymbol{x}|\mathcal{C}_2)p(\mathcal{C}_2)}
\end{aligned}
$$

- This looks like gratuitous math, but if a takes a simple form this is another generalized linear model which we have been studying
  - Of course, we will see how such a simple form $a = \boldsymbol{w}^T\boldsymbol{x} + w_0$ arises naturally

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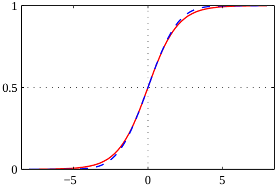
Logistic Sigmoid



- The function $\sigma(a) = \frac{1}{1+\exp(-a)}$ is known as the logistic sigmoid
- It squashes the real axis down to $[0, 1]$
- It is continuous and differentiable
- It avoids the problems encountered with the *too correct* least-squares error fitting (later)

Multi-class Extension

- There is a generalization of the logistic sigmoid to $K > 2$ classes:

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\begin{aligned}
p(\mathcal{C}_k|\boldsymbol{x}) &= \frac{p(\boldsymbol{x}|\mathcal{C}_k)p(\mathcal{C}_k)}{\sum_j p(\boldsymbol{x}|\mathcal{C}_j)p(\mathcal{C}_j)} \\
&= \frac{\exp(a_k)}{\sum_j \exp(a_j)}
\end{aligned}
$$

where $a_k = \ln p(\boldsymbol{x}|\mathcal{C}_k)p(\mathcal{C}_k)$

- a. k. a. softmax function
  - If some $a_k \gg a_j$, $p(\mathcal{C}_k|\boldsymbol{x})$ goes to 1

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Gaussian Class-Conditional Densities

- Back to that a in the logistic sigmoid for 2 classes
- Let's assume the class-conditional densities $p(\boldsymbol{x}|\mathcal{C}_k)$ are Gaussians, and have the same covariance matrix Σ:

$$p(\boldsymbol{x}|\mathcal{C}_k) = \frac{1}{(2\pi)^{D/2}|\Sigma|^{1/2}} \exp\left\{-\frac{1}{2}(\boldsymbol{x}-\boldsymbol{\mu}_k)^T\Sigma^{-1}(\boldsymbol{x}-\boldsymbol{\mu}_k)\right\}$$

- a takes a simple form:

$$a = \ln \frac{p(\boldsymbol{x}|\mathcal{C}_1)p(\mathcal{C}_1)}{p(\boldsymbol{x}|\mathcal{C}_2)p(\mathcal{C}_2)} = \boldsymbol{w}^T\boldsymbol{x} + w_0$$

  - Note that quadratic terms $\boldsymbol{x}^T\Sigma^{-1}\boldsymbol{x}$ cancel

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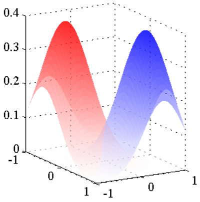

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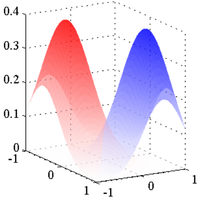

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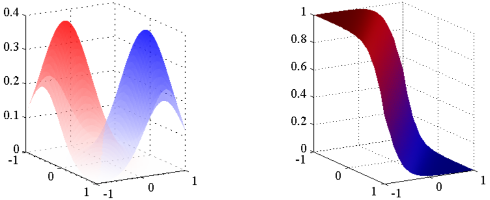

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Maximum Likelihood Learning

- We can fit the parameters to this model using maximum likelihood
  - Parameters are $\boldsymbol{\mu}_1$, $\boldsymbol{\mu}_2$, $\boldsymbol{\Sigma}^{-1}$, $p(\mathcal{C}_1) \equiv \pi$, $p(\mathcal{C}_2) \equiv 1 - \pi$
  - Refer to as θ
- For a datapoint $\boldsymbol{x}_n$ from class $\mathcal{C}_1$ $(t_n = 1)$:

$$p(\boldsymbol{x}_n, \mathcal{C}_1) = p(\mathcal{C}_1)p(\boldsymbol{x}_n|\mathcal{C}_1) = \pi\mathcal{N}(\boldsymbol{x}_n|\boldsymbol{\mu}_1, \Sigma)$$

- For a datapoint $\boldsymbol{x}_n$ from class $\mathcal{C}_2$ $(t_n = 0)$:

$$p(\boldsymbol{x}_n, \mathcal{C}_2) = p(\mathcal{C}_2)p(\boldsymbol{x}_n|\mathcal{C}_2) = (1 - \pi)\mathcal{N}(\boldsymbol{x}_n|\boldsymbol{\mu}_2, \Sigma)$$

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- The likelihood of the training data is:

$$p(\boldsymbol{t}|\pi, \boldsymbol{\mu}_1, \boldsymbol{\mu}_2, \boldsymbol{\Sigma}) = \prod_{n=1}^{N} [\pi \mathcal{N}(\boldsymbol{x}_n|\boldsymbol{\mu}_1, \boldsymbol{\Sigma})]^{t_n} [(1-\pi)\mathcal{N}(\boldsymbol{x}_n|\boldsymbol{\mu}_2, \boldsymbol{\Sigma})]^{1-t_n}$$

- As usual, ln is our friend:

$$\ell(\boldsymbol{t}; \theta) = \sum_{n=1}^{N} \underbrace{t_n \ln \pi + (1-t_n) \ln(1-\pi)}_{\pi} + \underbrace{t_n \ln \mathcal{N}_1 + (1-t_n) \ln \mathcal{N}_2}_{\boldsymbol{\mu}_1, \boldsymbol{\mu}_2, \boldsymbol{\Sigma}}$$

- Maximize for each separately

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Maximum Likelihood Learning - Class Priors

- Maximization with respect to the class priors parameter π is straightforward:

$$\frac{\partial}{\partial \pi} \ell(\boldsymbol{t}; \theta) = \sum_{n=1}^{N} \frac{t_n}{\pi} - \frac{1 - t_n}{1 - \pi}$$

$$\Rightarrow \pi = \frac{N_1}{N_1 + N_2}$$

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Maximum Likelihood Learning - Gaussian Parameters

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- Class means:

$$\boldsymbol{\mu}_1 = \frac{1}{N_1} \sum_{n=1}^{N} t_n \boldsymbol{x}_n$$

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  - Means of training examples from each class
- Shared covariance matrix:

$$\Sigma = \frac{N_1}{N} \frac{1}{N_1} \sum_{n \in \mathcal{C}_1} (\boldsymbol{x}_n - \boldsymbol{\mu}_1)(\boldsymbol{x}_n - \boldsymbol{\mu}_1)^T + \frac{N_2}{N} \frac{1}{N_2} \sum_{n \in \mathcal{C}_2} (\boldsymbol{x}_n - \boldsymbol{\mu}_2)(\boldsymbol{x}_n - \boldsymbol{\mu}_2)^T$$

  - Weighted average of class covariances

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Probabilistic Generative Models Summary

- Fitting Gaussian using ML criterion is sensitive to outliers
- Simple linear form for a in logistic sigmoid occurs for more than just Gaussian distributions
    - Arises for any distribution in the exponential family, a large class of distributions

Outline

Probabilistic Discriminative Models

- Generative model made assumptions about form of class-conditional distributions (e.g. Gaussian)
  - Resulted in logistic sigmoid of linear function of $\boldsymbol{x}$
- Discriminative model - explicitly use functional form

$$p(\mathcal{C}_1|\boldsymbol{x}) = \frac{1}{1 + \exp(-\boldsymbol{w}^T\boldsymbol{x} + w_0)}$$

  and find $\boldsymbol{w}$ directly
- For the generative model we had $2M + M(M+1)/2 + 1$ parameters
  - M is dimensionality of $\boldsymbol{x}$
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Generative vs. Discriminative

- Generative models
  - Can generate synthetic example data
  - Perhaps accurate classification is equivalent to accurate synthesis
    - e.g. vision and graphics
  - Tend to have more parameters
  - Require good model of class distributions
- Discriminative models
  - Only usable for classification
  - Don't solve a harder problem than you need to
  - Tend to have fewer parameters
  - Require good model of decision boundary

Maximum Likelihood Learning - Discriminative Model

- As usual we can use the maximum likelihood criterion for learning

$$p(\boldsymbol{t}|\boldsymbol{w}) = \prod_{n=1}^{N} y_n^{t_n} \{1 - y_n\}^{1-t_n} \text{ ; where } y_n = p(\mathcal{C}_1|\boldsymbol{x}_n)$$

- Taking ln and derivative gives:

$$\nabla \ell(\boldsymbol{w}) = \sum_{n=1}^{N} (t_n - y_n)\boldsymbol{x}_n$$

- This time no closed-form solution since $y_n = \sigma(\boldsymbol{w}^T \boldsymbol{x})$
- Could use (stochastic) gradient descent
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Iterative Reweighted Least Squares

- Iterative reweighted least squares (IRLS) is a descent method
  - As in gradient descent, start with an initial guess, improve it
  - Gradient descent - take a step (how large?) in the gradient direction
- IRLS is a special case of a Newton-Raphson method
  - Approximate function using second-order Taylor expansion:

$$\hat{f}(w+v) = f(w) + \nabla f(w)^T (v-w) + \frac{1}{2}(v-w)^T \nabla^2 f(w)(v-w)$$

  - Closed-form solution to minimize this is straight-forward: quadratic, derivatives linear
- In IRLS this second-order Taylor expansion ends up being a weighted least-squares problem, as in the regression case from last week
  - Hence the name IRLS

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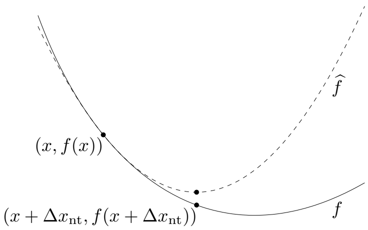

- Figure from Boyd and Vandenberghe, *Convex Optimization*
  - Excellent reference, free for download online
    `http://www.stanford.edu/~boyd/cvxbook/`

Conclusion

- Readings: Ch. 4.1.1-4.1.4, 4.1.7, 4.2.1-4.2.2, 4.3.1-4.3.3
- Generalized linear models $y(\boldsymbol{x}) = f(\boldsymbol{w}^T\boldsymbol{x} + w_0)$
- Threshold/max function for $f(\cdot)$
  - Minimize with least squares
  - Fisher criterion - class separation
  - Perceptron criterion - mis-classified examples
- Probabilistic models: logistic sigmoid / softmax for $f(\cdot)$
  - Generative model - assume class conditional densities in exponential family; obtain sigmoid
  - Discriminative model - directly model posterior using sigmoid (a. k. a. logistic regression, though classification)
  - Can learn either using maximum likelihood
- All of these models are limited to linear decision boundaries in feature space