

DSC 140A

Probabilistic Modeling & Machine Learning

Lecture 14 | Part 1

Bayes with Multiple Features

Recap

- ▶ **Bayes Classifier:** predict y that maximizes $\mathbb{P}(Y = y | X = x)$

- ▶ **Alternatively:** predict y that maximizes

$$p_X(x | Y = y)\mathbb{P}(Y = y)$$

- ▶ We must estimate these probabilities/densities.

Example: NBA Players

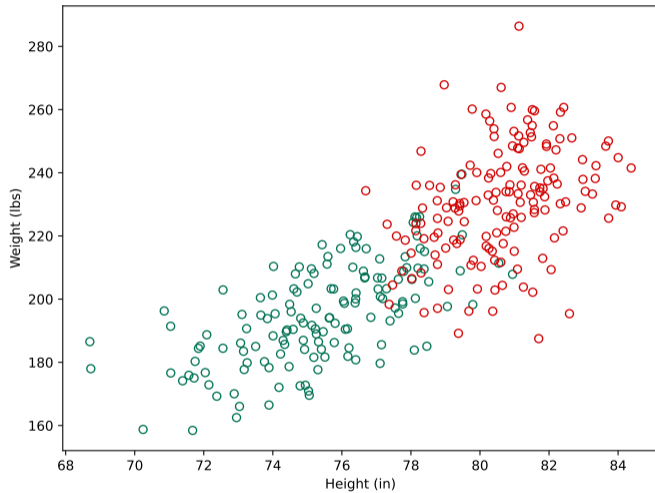
- ▶ **Guard** and **Forward** are two positions in basketball.
- ▶ Forwards tend to be larger than guards.



Example: NBA Players

- ▶ Suppose we have a data set of n NBA players:
 - ▶ X_1 : the player's height
 - ▶ X_2 : the player's weight
 - ▶ Y : the player's position (1 = guard, 0 = forward)

- ▶ **Given:** a new player's height and weight, predict their position.



Bayes in ≥ 2 Dimensions

- ▶ With one feature, Bayes said to pick y maximizing:

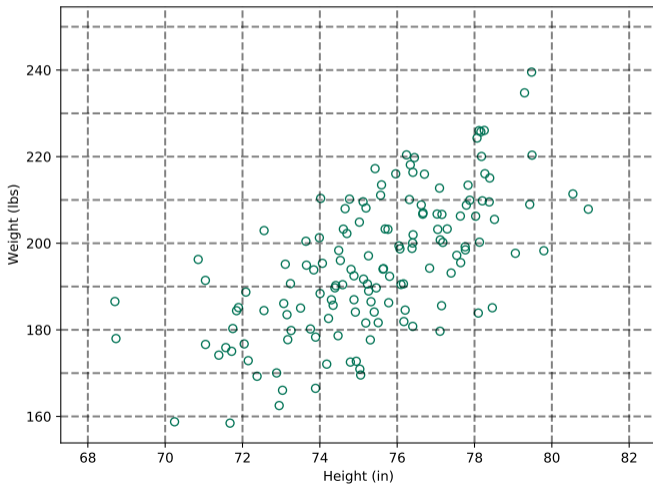
$$p_x(x | Y = y)\mathbb{P}(Y = y)$$

- ▶ With k features, pick y maximizing:

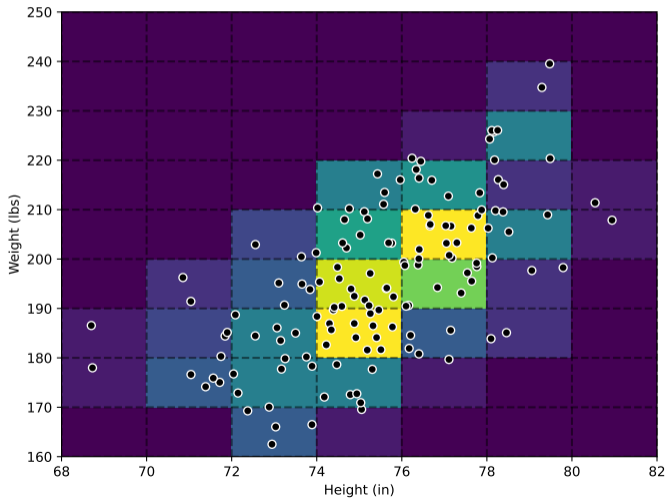
$$p_{\vec{x}}(\vec{x} | Y = y)\mathbb{P}(Y = y)$$

- ▶ \vec{x} is the **feature vector**. Here: (height, weight)^T
- ▶ We need to estimate density $p(\vec{x} | Y = y)$ for each class.

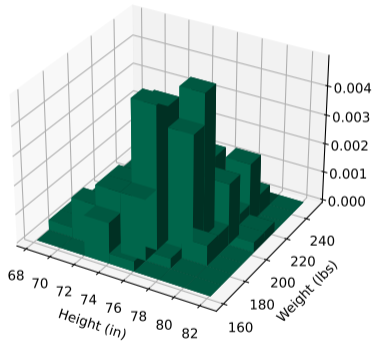
Estimating with Histograms



Estimating with Histograms



Estimating with Histograms



Predicting with Histograms

To predict the class of an input \vec{x} :

1. Use histograms to estimate $p_{\vec{x}}(\vec{x} | Y = y)$ for each class separately.
2. Predict the class y maximizing

$$p_{\vec{x}}(\vec{x} | Y = y) \mathbb{P}(Y = y)$$

Histogram Estimators

- ▶ Histogram density estimators are very flexible.
- ▶ But suffer heavily from **curse of dimensionality**.
- ▶ Not feasible for estimating density in more than a few dimensions.

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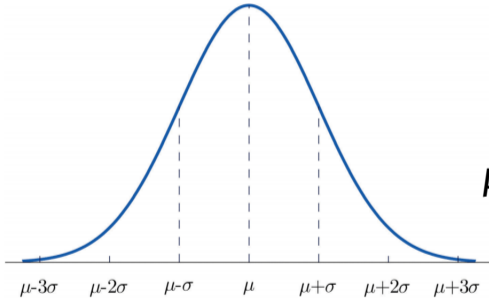
Lecture 14 | Part 2

Multivariate Gaussians

Multivariate Gaussians

- ▶ In 1 dimension, a Gaussian seemed to describe distribution of heights.
- ▶ Does a **multivariate** Gaussian describe distribution of heights and weights?

“Building” Multivariate Gaussians



$$X \sim \mathcal{N}(\mu, \sigma^2)$$

$$p(x) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{1}{2}(x-\mu)^2/\sigma^2}$$

Setting #1

- ▶ Suppose we have d independent random variables X_1, \dots, X_d .
- ▶ Assume that each is Gaussian; different mean, but **same** variance:

$$X_1 \sim \mathcal{N}(\mu_1, \sigma^2), \quad X_2 \sim \mathcal{N}(\mu_2, \sigma^2), \dots, \quad X_d \sim \mathcal{N}(\mu_d, \sigma^2).$$

Setting #1

- ▶ What is the **joint density** $p(x_1, x_2, \dots, x_d)$?
- ▶ Since we assumed X_1, \dots, X_d are independent:

$$\begin{aligned} p(x_1, x_2, \dots, x_d) &= p(x_1)p(x_2) \cdots p(x_d) \\ &= \left(\frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{1}{2}(x_1-\mu_1)^2/\sigma^2} \right) \cdot \left(\frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{1}{2}(x_2-\mu_2)^2/\sigma^2} \right) \cdots \left(\frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{1}{2}(x_d-\mu_d)^2/\sigma^2} \right) \end{aligned}$$

Setting #1

- ▶ What is the **joint density** $p(x_1, x_2, \dots, x_d)$?
- ▶ Since we assumed X_1, \dots, X_d are independent:

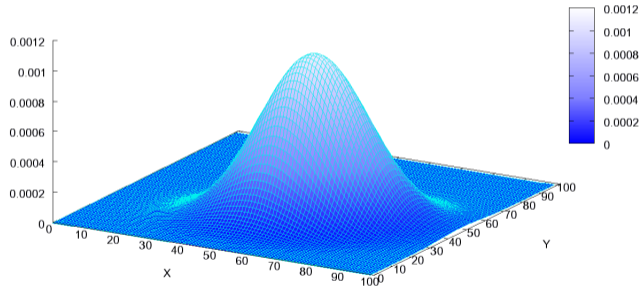
$$\begin{aligned} p(x_1, x_2, \dots, x_d) &= p(x_1)p(x_2) \cdots p(x_d) \\ &= \left(\frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{1}{2}(x_1-\mu_1)^2/\sigma^2} \right) \cdot \left(\frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{1}{2}(x_2-\mu_2)^2/\sigma^2} \right) \cdots \left(\frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{1}{2}(x_d-\mu_d)^2/\sigma^2} \right) \\ &= \frac{1}{(2\pi\sigma^2)^{d/2}} \exp\left(-\frac{(x_1-\mu_1)^2 + (x_2-\mu_2)^2 + \dots + (x_d-\mu_d)^2}{2\sigma^2}\right) \end{aligned}$$

Setting #1

- ▶ What is the **joint density** $p(x_1, x_2, \dots, x_d)$?
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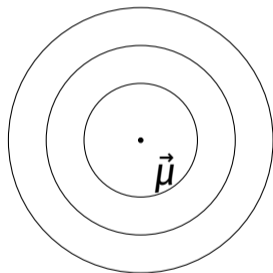
Setting #1



Setting #1: Spherical Gaussians

$$p(\vec{x}) = \frac{1}{(2\pi\sigma^2)^{d/2}} \exp\left(-\frac{1}{2} \frac{\|\vec{x} - \vec{\mu}\|^2}{\sigma^2}\right)$$

- ▶ Contours are (hyper)spheres.
- ▶ Every slice through middle gives same Gaussian.



Setting #2

- ▶ Still assume X_1, \dots, X_d are independent, Gaussian.
- ▶ But they now have different variances:

$$X_1 \sim \mathcal{N}(\mu_1, \sigma_1^2), \quad X_2 \sim \mathcal{N}(\mu_2, \sigma_2^2), \dots, \quad X_d \sim \mathcal{N}(\mu_d, \sigma_d^2).$$

Setting #2

$$\begin{aligned} p(x_1, x_2, \dots, x_d) &= p(x_1)p(x_2) \cdots p(x_d) \\ &= \left(\frac{1}{\sqrt{2\pi\sigma_1^2}} e^{-\frac{1}{2}(x_1-\mu_1)^2/\sigma_1^2} \right) \cdot \left(\frac{1}{\sqrt{2\pi\sigma_2^2}} e^{-\frac{1}{2}(x_2-\mu_2)^2/\sigma_2^2} \right) \cdots \left(\frac{1}{\sqrt{2\pi\sigma_d^2}} e^{-\frac{1}{2}(x_d-\mu_d)^2/\sigma_d^2} \right) \end{aligned}$$

Setting #2

$$\begin{aligned} p(x_1, x_2, \dots, x_d) &= p(x_1)p(x_2) \cdots p(x_d) \\ &= \left(\frac{1}{\sqrt{2\pi\sigma_1^2}} e^{-\frac{1}{2}(x_1-\mu_1)^2/\sigma_1^2} \right) \cdot \left(\frac{1}{\sqrt{2\pi\sigma_2^2}} e^{-\frac{1}{2}(x_2-\mu_2)^2/\sigma_2^2} \right) \cdots \left(\frac{1}{\sqrt{2\pi\sigma_d^2}} e^{-\frac{1}{2}(x_d-\mu_d)^2/\sigma_d^2} \right) \\ &= \frac{1}{(2\pi)^{d/2} \sigma_1 \cdot \sigma_2 \cdots \sigma_d} \exp\left(-\frac{1}{2} \left[\frac{(x_1 - \mu_1)^2}{\sigma_1^2} + \frac{(x_2 - \mu_2)^2}{\sigma_2^2} + \dots + \frac{(x_d - \mu_d)^2}{\sigma_d^2} \right]\right) \end{aligned}$$

Setting #2

- ▶ Define

$$C = \begin{pmatrix} \sigma_1^2 & 0 & \dots & 0 \\ 0 & \sigma_2^2 & \dots & 0 \\ \dots & \dots & \dots & \dots \\ 0 & 0 & 0 & \sigma_d^2 \end{pmatrix}$$

- ▶ Then:

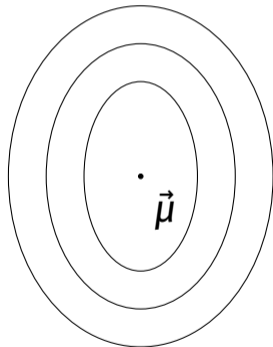
$$p(\vec{x}) = \frac{1}{(2\pi)^{d/2} |C|^{\frac{1}{2}}} \exp\left(-\frac{1}{2}(\vec{x} - \vec{\mu})^T C^{-1}(\vec{x} - \vec{\mu})\right)$$

where $|C|$ is the **determinant** of C .

Setting #2: **Axis-Aligned** Gaussians

$$p(\vec{x}) = \frac{1}{(2\pi)^{d/2} |\mathbf{C}|^{\frac{1}{2}}} \exp\left(-\frac{1}{2}(\vec{x} - \vec{\mu})^T \mathbf{C}^{-1}(\vec{x} - \vec{\mu})\right)$$

- ▶ Contours are axis-aligned (hyper)ellipses.
- ▶ \mathbf{C} is the **covariance matrix**.
 - ▶ Diagonal.
 - ▶ Entries are variances.



Setting #3: **General** Gaussians

- ▶ We have assumed that X_1, \dots, X_d are independent.
- ▶ Now assume that they're not. Define **covariance**:

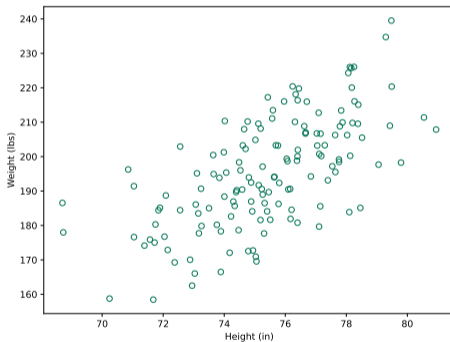
$$\text{Cov}(X_i, X_j) = \mathbb{E}[(X_i - \mu_i)(X_j - \mu_j)]$$

- ▶ **Note:**

$$\text{Var}(X_i) = \text{Cov}(X_i, X_i)$$

Covariance

- ▶ Covariance measures how much two quantities **vary together**.



$$\text{Cov}(X_i, X_j) = \mathbb{E}[(X_i - \mu_i)(X_j - \mu_j)]$$

Setting #3: General Gaussians

- ▶ Now the **covariance matrix** has off-diagonal elements:

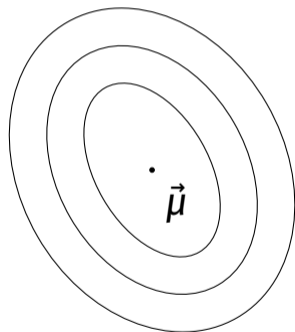
$$C = \begin{pmatrix} \text{Var}(X_1) & \text{Cov}(X_1, X_2) & \cdots & \text{Cov}(X_1, X_d) \\ \text{Cov}(X_2, X_1) & \text{Var}(X_2) & \cdots & \text{Cov}(X_2, X_d) \\ \cdots & \cdots & \cdots & \cdots \\ \text{Cov}(X_d, X_1) & \text{Cov}(X_d, X_2) & \cdots & \text{Var}(X_d) \end{pmatrix}$$

- ▶ Since $\text{Cov}(X_i, X_j) = \text{Cov}(X_j, X_i)$, C is symmetric.

Setting #3: **General** Gaussians

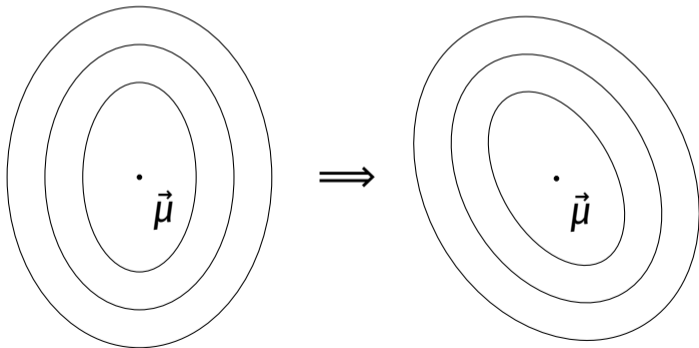
$$p(\vec{x}) = \frac{1}{(2\pi)^{d/2} |\mathbf{C}|^{1/2}} \exp\left(-\frac{1}{2}(\vec{x} - \vec{\mu})^T \mathbf{C}^{-1}(\vec{x} - \vec{\mu})\right)$$

Contours are general (hyper)ellipses.
 \mathbf{C} need not be diagonal.



General Gaussians: Another View

- ▶ A **general** Gaussian is an **axis-aligned** Gaussian that has been rotated:



General Gaussians: Another View

- ▶ Which matrices are **valid** covariance matrices?
- ▶ 1. If C is the rotation of some diagonal covariance matrix C_0 . That is, $C = RC_0$
- ▶ 2. Equivalently, C is symmetric, positive semi-definite.

Overview

- ▶ The probability density function for a multivariate Gaussian distribution is:

$$p(\vec{x}) = \frac{1}{(2\pi)^{d/2} |C|^{\frac{1}{2}}} \exp\left(-\frac{1}{2}(\vec{x} - \vec{\mu})^T C^{-1}(\vec{x} - \vec{\mu})\right)$$

- ▶ Here, C is the **covariance matrix**.

Overview

- ▶ There are three cases, from least to most general:
 1. C is diagonal, with all the same entries.
 - ▶ **Spherical** Gaussians.
 2. C is diagonal, with different entries.
 - ▶ **Axis-Aligned** Gaussians.
 3. C is not diagonal.
 - ▶ **General** Gaussians.

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Probabilistic Modeling & Machine Learning

Lecture 14 | Part 3

Fitting Multivariate Gaussians

Fitting Multivariate Gaussians

- ▶ Suppose $\vec{x}^{(1)}, \dots, \vec{x}^{(n)}$ came from a multivariate Gaussian.
- ▶ What were the parameters of that Gaussian?
- ▶ We can use the principle of **maximum likelihood**.

What are the parameters?

$$p(\vec{x}) = \frac{1}{(2\pi)^{d/2} |\mathbf{C}|^{\frac{1}{2}}} \exp\left(-\frac{1}{2}(\vec{x} - \vec{\mu})^T \mathbf{C}^{-1}(\vec{x} - \vec{\mu})\right)$$

- ▶ $\vec{\mu}$: controls Gaussian's location
- ▶ \mathbf{C} : controls Gaussian's shape

Estimating $\vec{\mu}$

- ▶ The maximum likelihood estimator for μ is:

$$\vec{\mu}_{\text{MLE}} = \frac{1}{n} \sum_{i=1}^n \vec{x}^{(i)}$$

Estimating C

- ▶ First: make assumptions on covariance matrix.
- ▶ In order from strict to weak:
 - ▶ Spherical: C is diagonal, with all the same entries.
 - ▶ Axis-Aligned: C is diagonal, with different entries.
 - ▶ General: C is not diagonal.
- ▶ The weaker the assumptions, the more parameters to estimate.

Fitting Spherical Gaussians

- ▶ Only one variance parameter: σ^2 .
- ▶ The density function becomes:

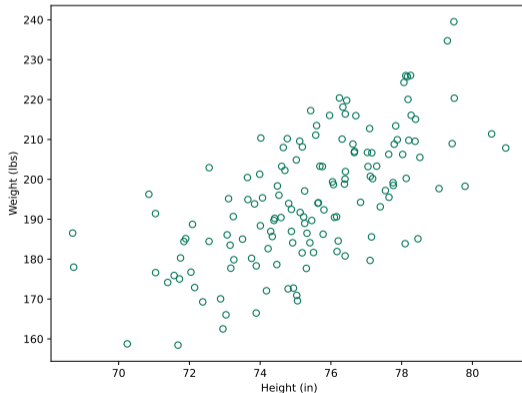
$$p(\vec{x}) = \frac{1}{(2\pi\sigma^2)^{d/2}} \exp\left(-\frac{(\vec{x} - \vec{\mu})^T(\vec{x} - \vec{\mu})}{2\sigma^2}\right)$$

- ▶ The maximum likelihood estimator:

$$\sigma_{\text{MLE}}^2 = \frac{1}{n} \sum_{i=1}^n \|\vec{x}^{(i)} - \vec{\mu}_{\text{MLE}}\|^2$$

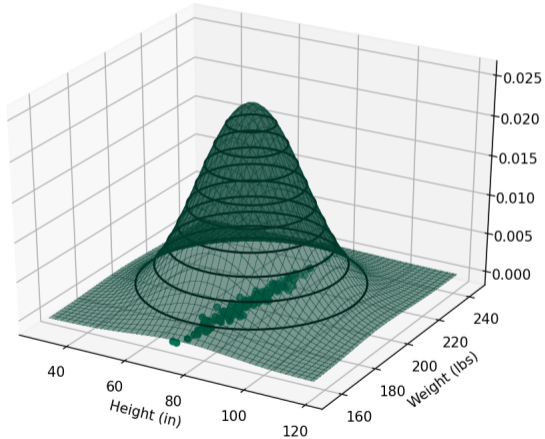
Example: NBA Data

- ▶ What if we fit a spherical Gaussian to the NBA data?



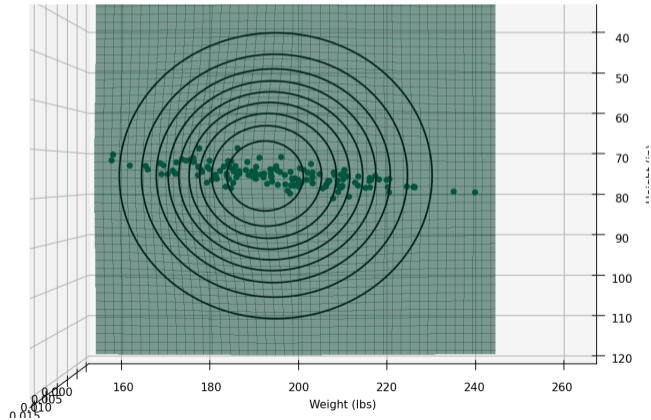
Fitting Spherical Gaussians

Doesn't fit!



Fitting Spherical Gaussians

Doesn't fit!



Example: NBA Data

- ▶ Spherical Gaussians are not well-suited to this data.
- ▶ Perhaps if the data were **standardized...**
- ▶ Instead, try axis-aligned Gaussians.

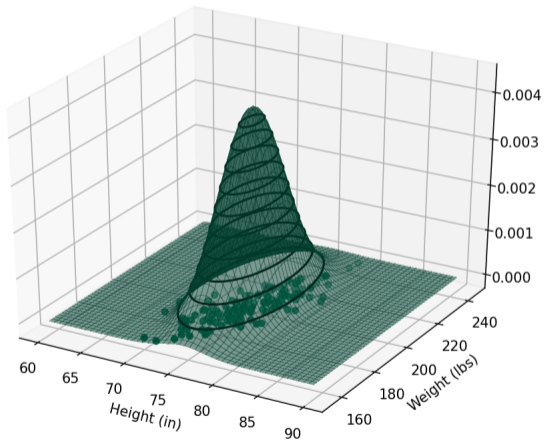
Fitting Axis-Aligned Gaussians

- ▶ Variance for each axis: σ_1^2 and σ_2^2 .
- ▶ Maximum likelihood estimates:

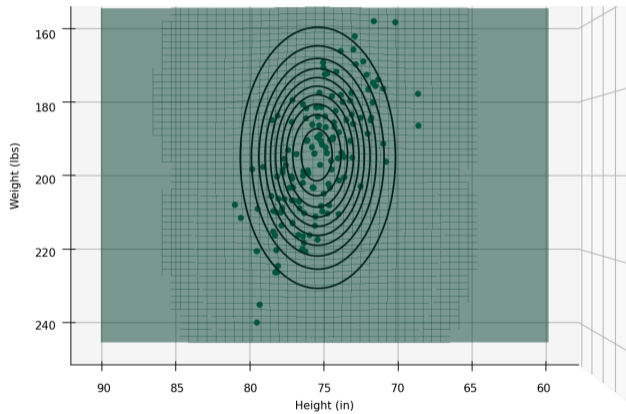
σ_1^2 = sample variance of heights

σ_2^2 = sample variance of weights

Fitting Axis-Aligned Gaussians



Fitting Axis-Aligned Gaussians



Example: NBA Data

- ▶ Better, but still not great.
- ▶ Axis-aligned Gaussian does not capture correlation between height and weight.
- ▶ Try general Gaussian with full covariance.

Fitting General Gaussians

- ▶ Must compute covariance for each pair of dimensions.
- ▶ Maximum likelihood estimate for covariance of feature i and j :

$$C_{ij} = \left(\frac{1}{n} \sum_{k=1}^n \vec{x}_i^{(k)} \vec{x}_j^{(k)} \right) - \mu_i \mu_j$$

Computing the Covariance Matrix

Step 1. Make matrix with heights in first column, weights in second:

$$\begin{pmatrix} \text{height 1} & \text{weight 1} \\ \text{height 2} & \text{weight 2} \\ \dots & \dots \\ \text{height } n & \text{weight } n \end{pmatrix}$$

Computing the Covariance Matrix

Step 2. Subtract sample mean height, mean weight from each column. Call this matrix X :

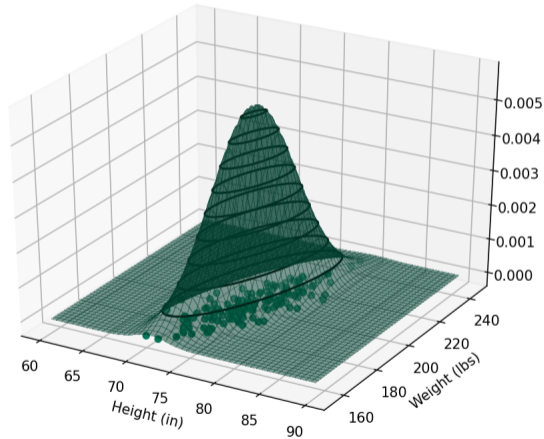
$$X = \begin{pmatrix} \text{height 1} - \text{mean height} & \text{weight 1} - \text{mean weight} \\ \text{height 2} - \text{mean height} & \text{weight 2} - \text{mean weight} \\ \dots & \dots \\ \text{height } n - \text{mean height} & \text{weight } n - \text{mean weight} \end{pmatrix}$$

Computing the Covariance Matrix

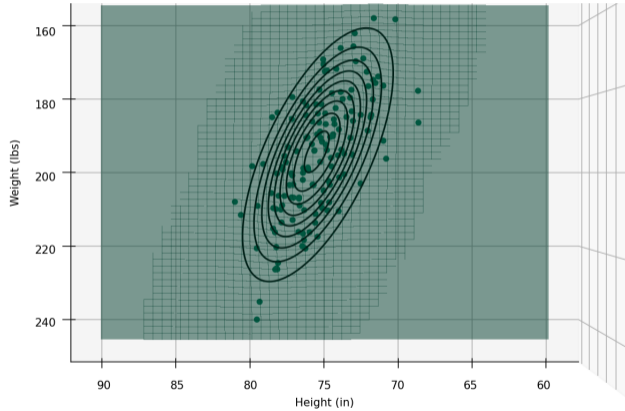
The empirical covariance matrix is then:

$$C = \frac{1}{n}X^T X$$

Fitting General Gaussians



Fitting General Gaussians



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Lecture 14 | Part 4

Discriminant Analysis

Bayes Classifier with MV Gaussians

1. Fit Gaussian for $p(\vec{X} | Y = y)$ for each class, y .
2. For new point, predict y maximizing:

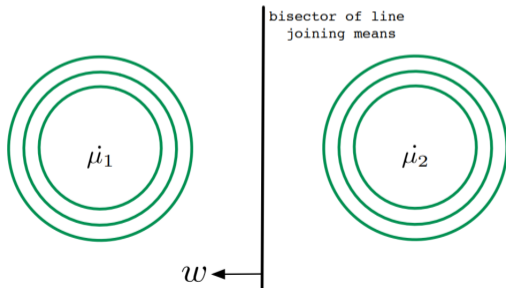
$$p(\vec{X} = \vec{x} | Y = y)\mathbb{P}(Y = y)$$

Decision Boundary

- ▶ For every point in space, we have a classification.
- ▶ The **decision boundary**: surface between different classifications.
 - ▶ On one side, prediction is y_1 ;
 - ▶ on the other, prediction is y_2 .

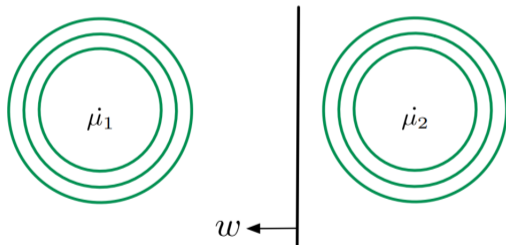
Example #1

- ▶ Assume:
 - ▶ classes equally likely: $\mathbb{P}(Y = 1) = \mathbb{P}(Y = 0)$
 - ▶ identical covariance matrices



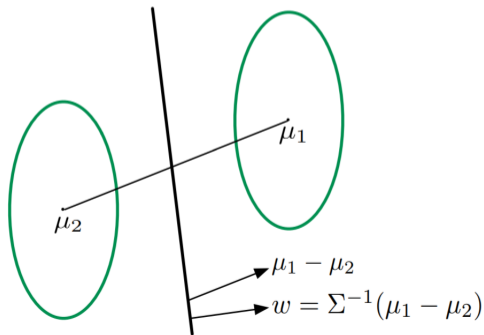
Example #1

- ▶ If $\mathbb{P}(Y = y_1) > \mathbb{P}(Y = y_2)$:



Example #2

- ▶ Assume:
 - ▶ covariance matrices identical, diagonal
 - ▶ that is: axis-aligned Gaussians

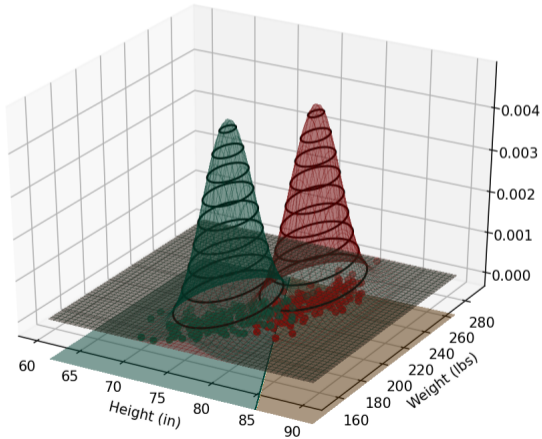


Example

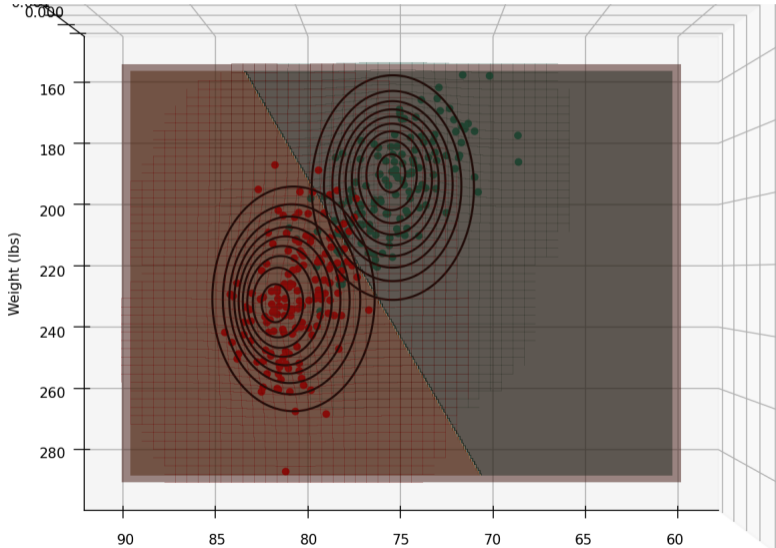
- ▶ Using identical Gaussians for each class, predict position given height and weight.
- ▶ How do we get one covariance matrix?
- ▶ **Don't** lump data together...
- ▶ Instead, compute covariance matrix for each class, perform weighted average:

$$C = \frac{n_1 C_1 + n_2 C_2}{n_1 + n_2}$$

Example



Example

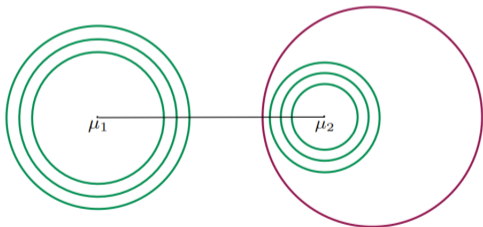


Linear Discriminant Analysis

- ▶ When covariance matrices are **equal**, decision boundary is linear.
- ▶ This procedure is called **linear discriminant analysis** (LDA).
- ▶ True even if the Gaussians have full covariance.

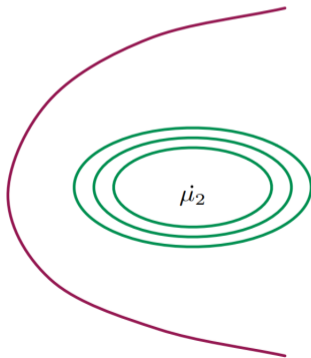
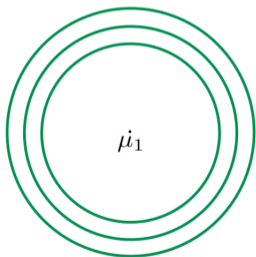
Example #3

- ▶ Assume:
 - ▶ covariance matrices C_1, C_2 different, non-diagonal

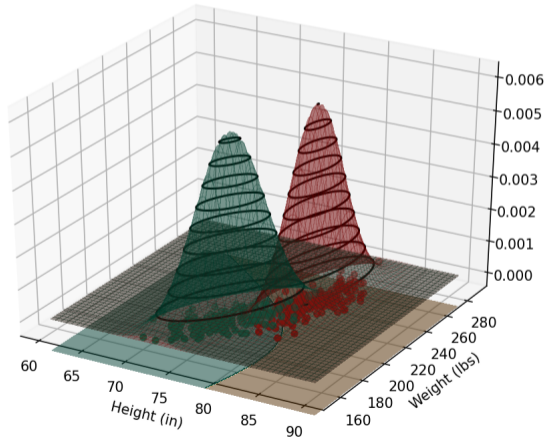


Example #3

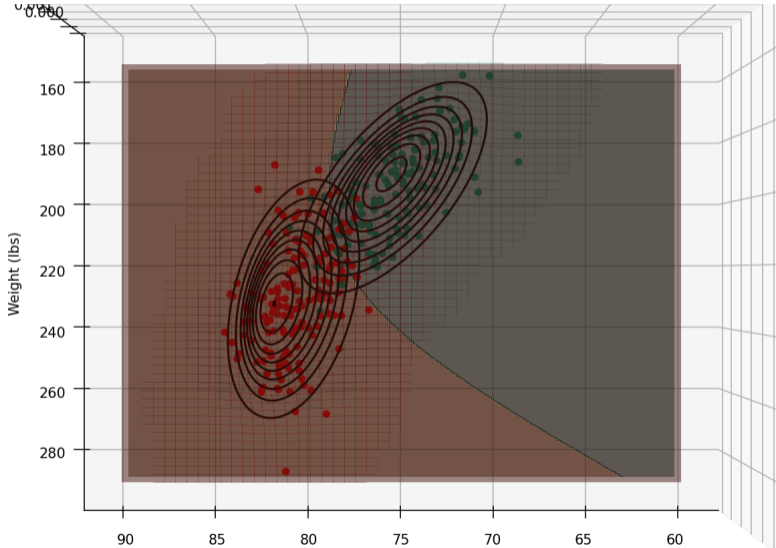
- ▶ Assume:
 - ▶ covariance matrices C_1, C_2 different, non-diagonal



Example



Example

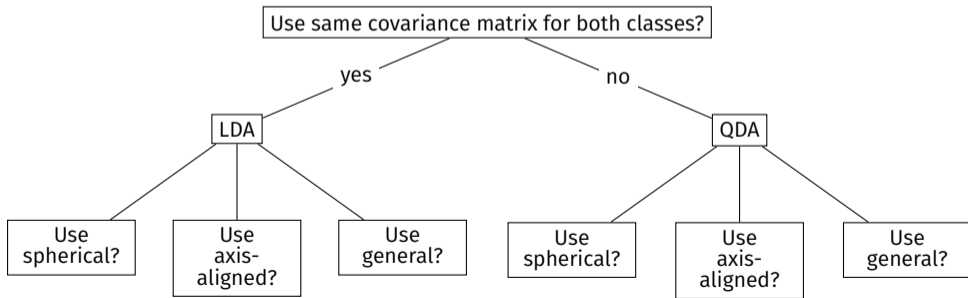


Quadratic Discriminant Analysis

- ▶ When covariance matrices are **not** equal, decision boundary is quadratic (ellipsoidal, paraboloidal, hyperboloidal).
- ▶ This procedure is called **quadratic discriminant analysis** (QDA).

LDA/QDA and Gaussian Type

- ▶ You can use any type of Gaussian within both LDA and QDA.



In practice...

- ▶ A full covariance requires estimating $\Theta(d^2)$ parameters; needs more data.
- ▶ Gaussian assumption may be a poor match for data.