DSC 140B
Representation Learning

Lecture 08 | Part 1

Dimensionality Reduction

High Dimensional Data

- Data is often high dimensional (many features)
- Example: Netflix user
  - Number of movies watched
  - Number of movies saved
  - Total time watched
  - Number of logins
  - Days since signup
  - Average rating for comedy
  - Average rating for drama
  - $\vdots$

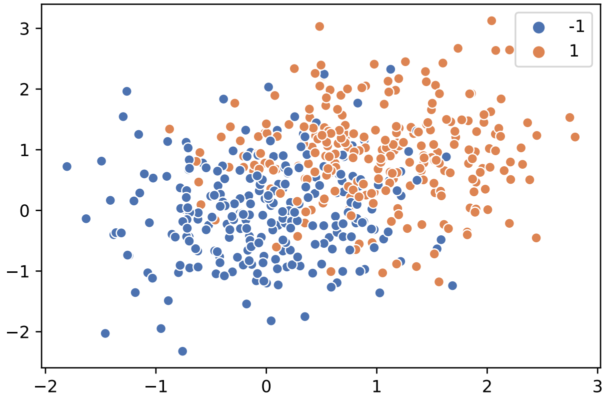
High Dimensional Data

- More features can give us more information
- But it can also cause problems
- **Today**: how do we reduce dimensionality without losing too much information?

More Features, More Problems

- Difficulties with high dimensional data:
    1. Requires more compute time / space
    2. Hard to visualize / explore
    3. The “curse of dimensionality”: it’s harder to learn

Experiment



- On this data, low 80% train/test accuracy
- Add 400 features of pure noise, re-train
- Now: 100% train accuracy, **58%** test accuracy
- **Overfitting!**

Task: Dimensionality Reduction

- We'd often like to **reduce** the dimensionality to improve performance, or to visualize.
- We will typically lose information
- Want to minimize the loss of useful information

Redundancy

- Two (or more) features may share the same information.
- Intuition: we may not need all of them.

Today

- Today we'll think about reducing dimensionality from $\mathbb{R}^d$ to $\mathbb{R}^1$
- Next time we'll go from $\mathbb{R}^d$ to $\mathbb{R}^{d'}$, with $d' \leq d$

Today's Example

- Let's say we represent a phone with two features:
  - x_1: screen width
  - x_2: phone weight

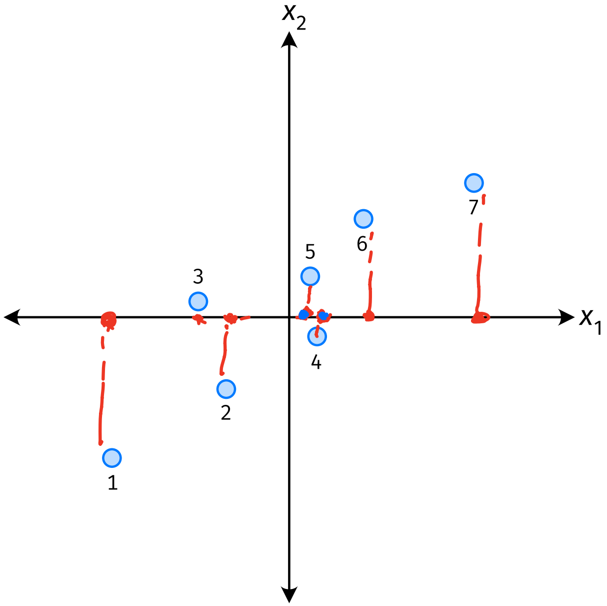
- Both measure a phone's "size".

- Instead of representing a phone with both x_1 and x_2, can we just use a single number, z?
  - Reduce dimensionality from 2 to 1.

First Approach: Remove Features

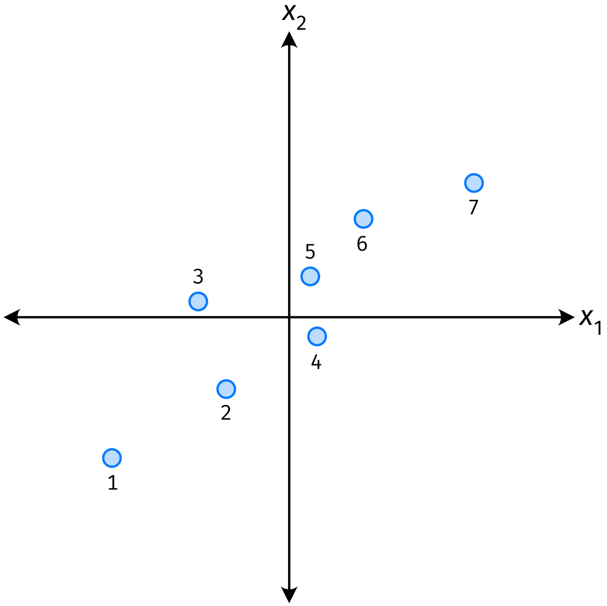
- Screen width and weight share information.
- **Idea:** keep one feature, remove the other.
- That is, set new feature $z = x_1$ (or $z = x_2$).

Removing Features



- Say we set $z^{(i)} = \vec{x}_1^{(i)}$ for each phone, i.
- Observe: $z^{(4)} > z^{(5)}$.
- Is phone 4 really "larger" than phone 5?

Removing Features



- Say we set $z^{(i)} = \vec{x}_2^{(i)}$ for each phone, i.
- Observe: $z^{(3)} > z^{(4)}$.
- Is phone 3 really “larger” than phone 4?

Better Approach: Mixtures of Features

- **Idea**: z should be a combination of x_1 and x_2.

- One approach: linear combination.

$$\begin{aligned} z &= u_1 x_1 + u_2 x_2 \\ &= \vec{u} \cdot \vec{x} \end{aligned}$$

$$\vec{u} = (u_1, u_2)$$
$$\vec{x} = (x_1, x_2)$$

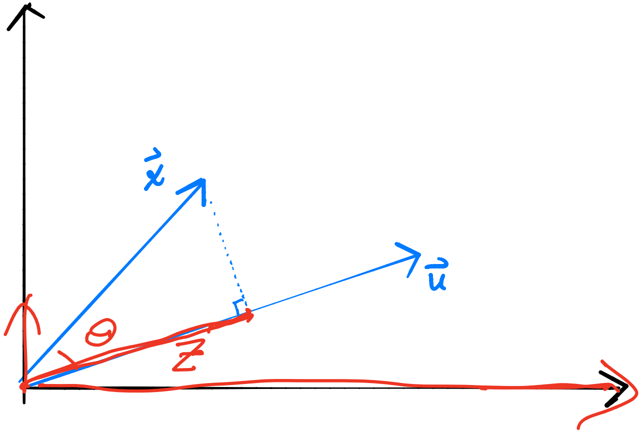
- $u_1, \ldots, u_2$ are the mixture coefficients; we can choose them.

Normalization

- Mixture coefficients generalize proportions.
- We could assume, e.g., $|u_1| + |u_2| = 1$.
- But it makes the math easier if we assume $u_1^2 + u_2^2 = 1$.
- Equivalently, if $\vec{u} = (u_1, u_2)^T$, assume $\|\vec{u}\| = 1$

$z = \vec{x} \cdot \vec{u} = \|\vec{x}\| \cdot \|\vec{u}\| \cos\theta$

Geometric Interpretation



- z measures how much of $\vec{x}$ is in the direction of $\vec{u}$
- If $\vec{u} = (1, 0)^T$, then $z = x_1$

$z = \vec{x} \cdot \begin{pmatrix} 1 \\ 0 \end{pmatrix} = x_1$

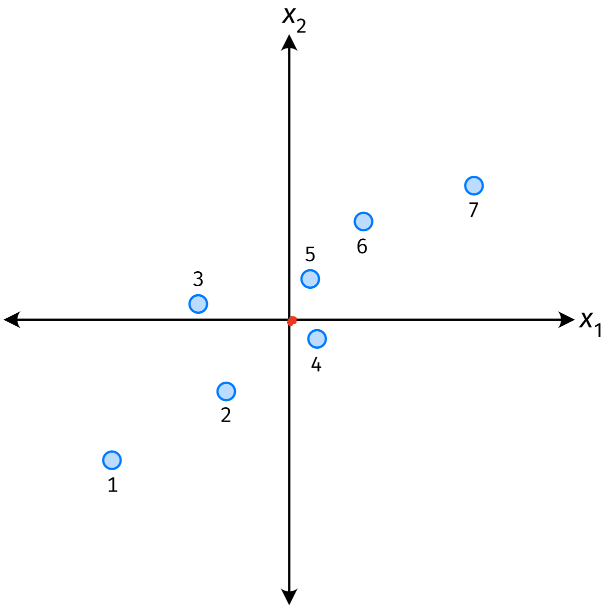
- If $\vec{u} = (0, 1)^T$, then $z = x_2$

$z = \vec{x} \cdot \begin{pmatrix} 0 \\ 1 \end{pmatrix} = x_2$

Choosing $\vec{u}$

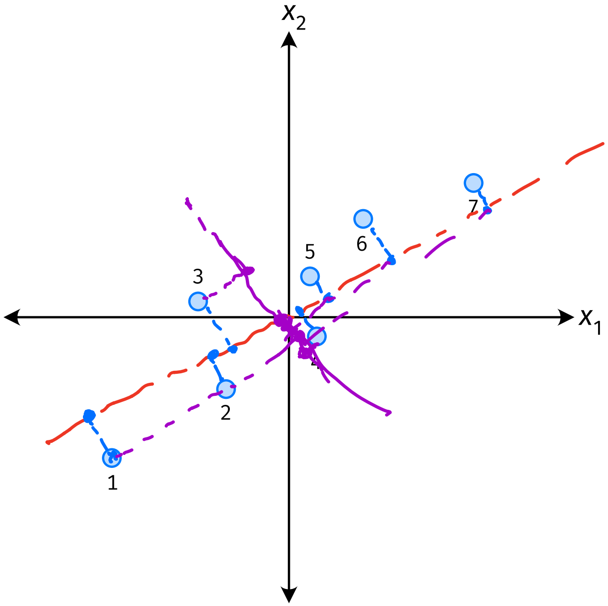
- Suppose we have only two features:
  - x_1: screen size
  - x_2: phone thickness
- We'll create single new feature, z, from x_1 and x_2.
  - Assume $z = u_1 x_1 + u_2 x_2 = \vec{x} \cdot \vec{u}$
  - Interpretation: z is a measure of a phone's size
- How should we choose $\vec{u} = (u_1, u_2)^T$?

Example



- $\vec{u}$ defines a direction
- $\vec{z}^{(i)} = \vec{x}^{(i)} \cdot \vec{u}$ measures position of $\vec{x}$ along this direction

Example



- Phone "size" varies most along a diagonal direction.
- Along direction of "max variance", phones are well-separated.
- **Idea:** $\vec{u}$ should point in direction of "max variance".

Our Algorithm (Informally)

- **Given**: data points $\vec{x}^{(1)}, \ldots, \vec{x}^{(n)} \in \mathbb{R}^d$
- Pick $\vec{u}$ to be the direction of "max variance"
- Create a new feature, z, for each point:

$$z^{(i)} = \vec{x}^{(i)} \cdot \vec{u}$$

PCA

- This algorithm is called **Principal Component Analysis**, or **PCA**.
- The direction of maximum variance is called the **principal component**.

Exercise

Suppose the direction of maximum variance in a data set is

$$\vec{u} = (1/\sqrt{2}, -1/\sqrt{2})^T$$

Let

- $\vec{x}^{(1)} = (3, -2)^T$
- $\vec{x}^{(2)} = (1, 4)^T$

What are $z^{(1)}$ and $z^{(2)}$?

$$z = \vec{u} \cdot \vec{x}$$

$$z^{(1)} = \vec{u} \cdot \vec{x}^{(1)} = \begin{pmatrix} 1/\sqrt{2} \\ -1/\sqrt{2} \end{pmatrix} \cdot \begin{pmatrix} 3 \\ -2 \end{pmatrix} = \frac{3}{\sqrt{2}} + \frac{2}{\sqrt{2}} = \frac{5}{\sqrt{2}}$$

Problem

- How do we compute the “direction of maximum variance”?

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Lecture 08 | Part 2

Covariance Matrices

Variance

- We know how to compute the variance of a set of numbers $X = \{x^{(1)}, \ldots, x^{(n)}\}$:

$$\mathrm{Var}(X) = \frac{1}{n} \sum_{i=1}^{n} (x^{(i)} - \mu)^2$$

- The variance measures the "spread" of the data

Generalizing Variance

- If we have two features, x_1 and x_2, we can compute the variance of each as usual:

$$\text{Var}(x_1) = \frac{1}{n}\sum_{i=1}^{n}(\vec{x}_1^{(i)} - \mu_1)^2$$

$$\text{Var}(x_2) = \frac{1}{n}\sum_{i=1}^{n}(\vec{x}_2^{(i)} - \mu_2)^2$$

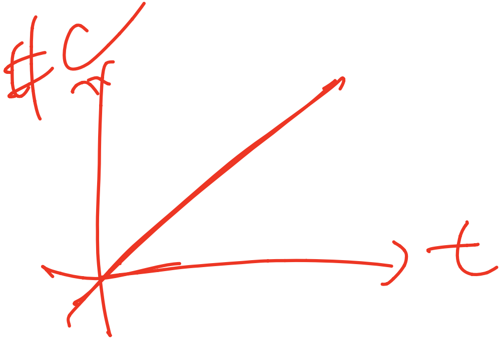
- Can also measure how x_1 and x_2 vary together.

Measuring Similar Information

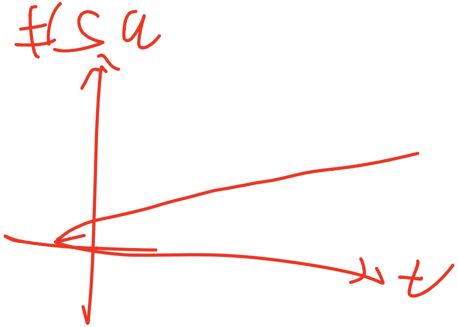
- Features which share information if they *vary together*.
  - A.k.a., they "co-vary"

- Positive association: when one is above average, so is the other

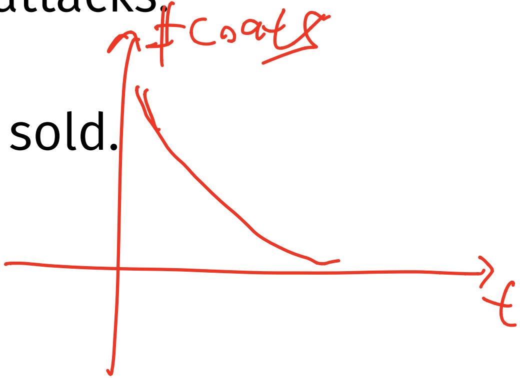
- Negative association: when one is above average, the other is below average



Examples

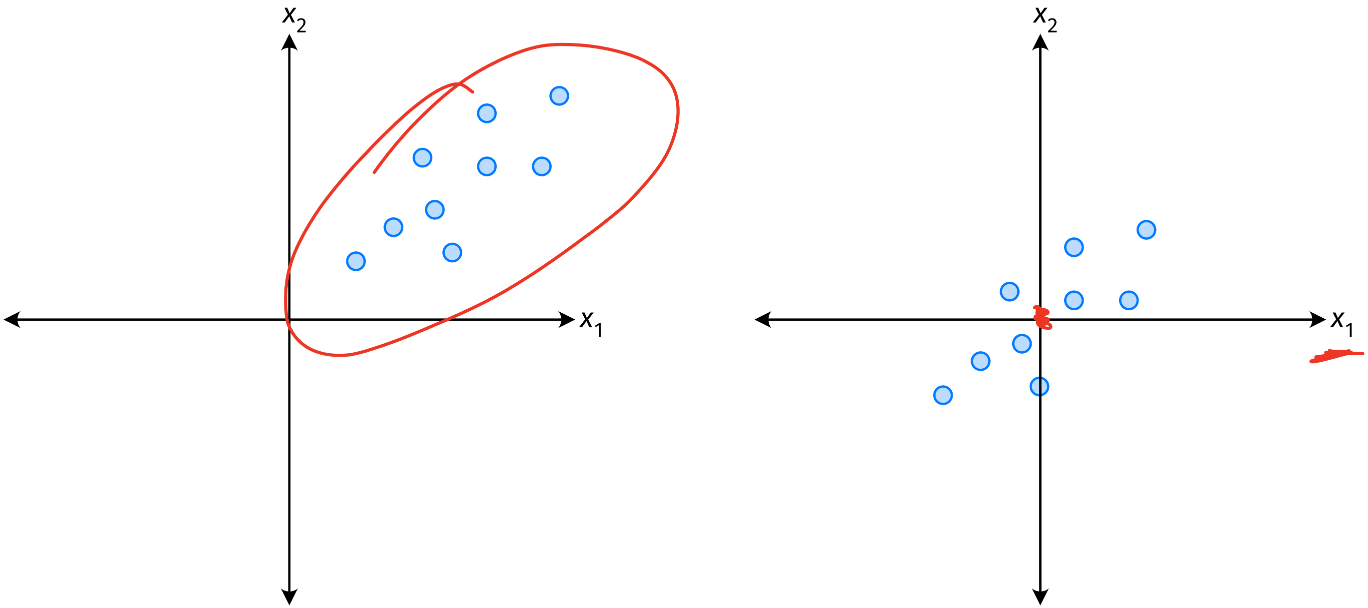


- Positive: temperature and ice cream cones sold.
- Positive: temperature and shark attacks.
- Negative: temperature and coats sold.



Centering

- First, it will be useful to **center** the data.



Centering

- Compute the mean of each feature:

$$\mu_j = \frac{1}{n} \sum_{1}^{n} \vec{x}_j^{(i)}$$

d

$\mu_1, \mu_2 \cdots \mu_j \cdots \mu_d$

- Define new centered data:

$$\vec{z}^{(i)} = \begin{pmatrix} \vec{x}_1^{(i)} - \mu_1 \\ \vec{x}_2^{(i)} - \mu_2 \\ \vdots \\ \vec{x}_d^{(i)} - \mu_d \end{pmatrix}$$

Centering (Equivalently)

- Compute the mean of all data points:

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

- Define new centered data:

$$\vec{z}^{(i)} = \vec{x}^{(i)} - \mu$$

Exercise

Center the data set:

$$\vec{x}^{(1)} = (1, 2, 3)^T$$
$$\vec{x}^{(2)} = (-1, -1, 0)^T$$
$$\vec{x}^{(3)} = (0, 2, 3)^T$$

$$\vec{x}^{(1)} - \vec{\mu} = (1, 1, 1)^T$$
$$\vec{x}^{(2)} - \vec{\mu} = (-1, -2, -2)^T$$

$$\vec{\mu} = \frac{\vec{x}^{(1)} + \vec{x}^{(2)} + \vec{x}^{(3)}}{3} = (0, 1, 2)^T$$

Quantifying Co-Variance

- One approach is as follows[1]:

$$\text{Cov}(x_i, x_j) = \frac{1}{n} \sum_{k=1}^{n} \vec{x}_i^{(k)} \vec{x}_j^{(k)}$$

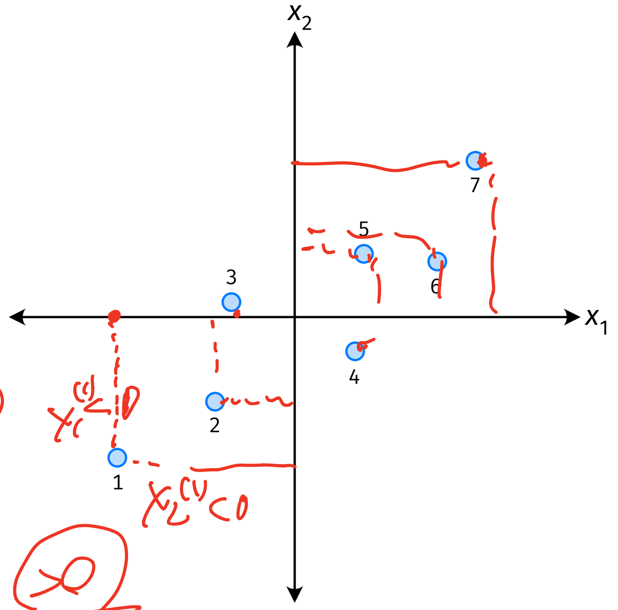
  - For each data point, multiply the value of feature i and feature j, then average these products.
  - This is the **covariance** of features i and j.

[1] Assuming centered data

Quantifying Covariance

- Assume the data are **centered**.

$$\text{Covariance} = \frac{1}{7}\sum_{i=1}^{7} \vec{x}_1^{(i)} \times \vec{x}_2^{(i)}$$



Quantifying Covariance

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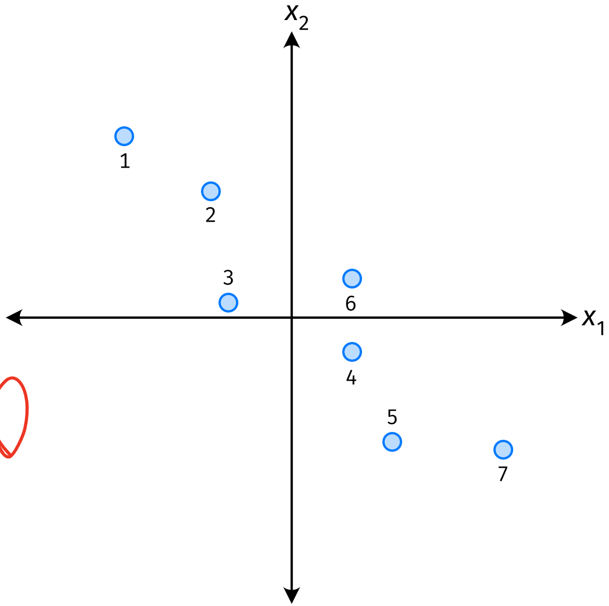

Quantifying Covariance

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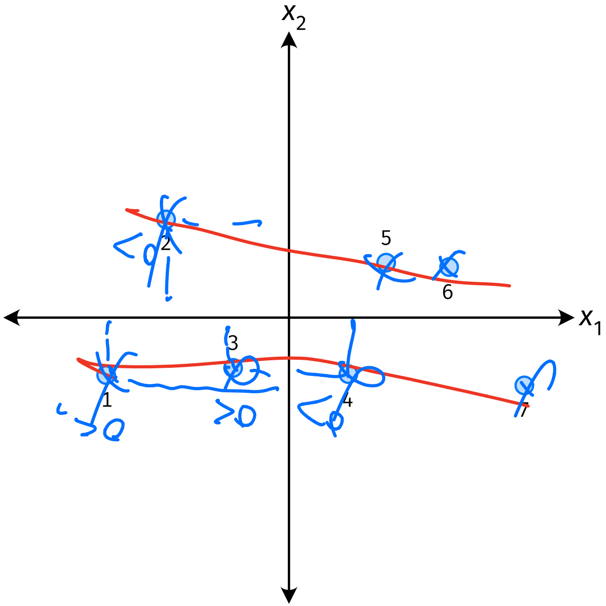

Quantifying Covariance

- The **covariance** quantifies extent to which two variables vary together.
- Assume we have centered the data.
- The **sample covariance** of feature i and j is:

$$\sigma_{ij} = \frac{1}{n} \sum_{k=1}^{n} \vec{x}_i^{(k)} \vec{x}_j^{(k)}$$

Exercise

True or False: $\sigma_{ij} = \sigma_{ji}$?

$$\sigma_{ij} = \frac{1}{n} \sum_{k=1}^{n} \vec{x}_i^{(k)} \vec{x}_j^{(k)}$$

Covariance Matrices

- Given data $\vec{x}^{(1)}, \ldots, \vec{x}^{(n)} \in \mathbb{R}^d$.
- The **sample covariance matrix** C is the $d \times d$ matrix whose ij entry is defined to be σ_{ij}.

$$\sigma_{ij} = \frac{1}{n} \sum_{k=1}^{n} \vec{x}_i^{(k)} \vec{x}_j^{(k)}$$

Observations

- Diagonal entries of C are the variances.
- The matrix is **symmetric**!

Note

- Sometimes you'll see the sample covariance defined as:

$$\sigma_{ij} = \frac{1}{n-1} \sum_{k=1}^{n} \vec{x}_i^{(k)} \vec{x}_j^{(k)}$$

  Note the $1/(n-1)$
- This is an **unbiased** estimator of the population covariance.
- Our definition is the **maximum likelihood** estimator.
- In practice, it doesn't matter: $1/(n-1) \approx 1/n$.
- For consistency, in this class use $1/n$.

Computing Covariance

- There is a “trick” for computing sample covariance matrices.
- Step 1: make $n \times d$ data matrix, X
- Step 2: make Z by centering columns of X
- Step 3: $C = \frac{1}{n} Z^T Z$

Computing Covariance (in code)[2]

```
»> mu = X.mean(axis=0)
»> Z = X - mu
»> C = 1 / len(X) * Z.T @ Z
```

[2] Or use `np.cov`

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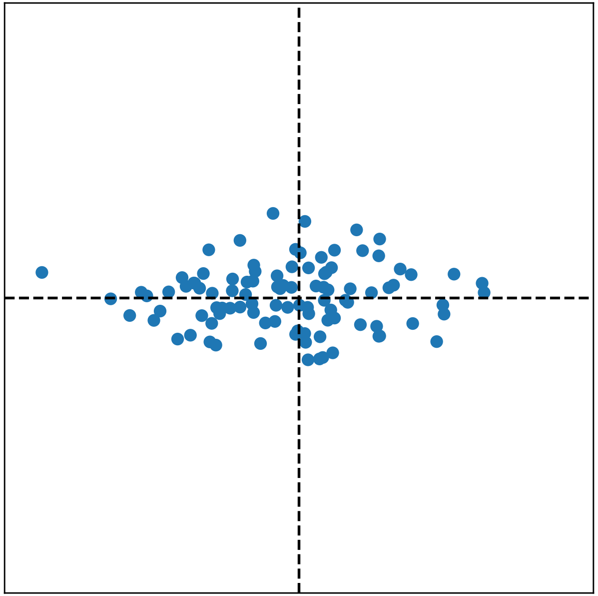
Lecture 08 | Part 3

Visualizing Covariance Matrices

Visualizing Covariance Matrices

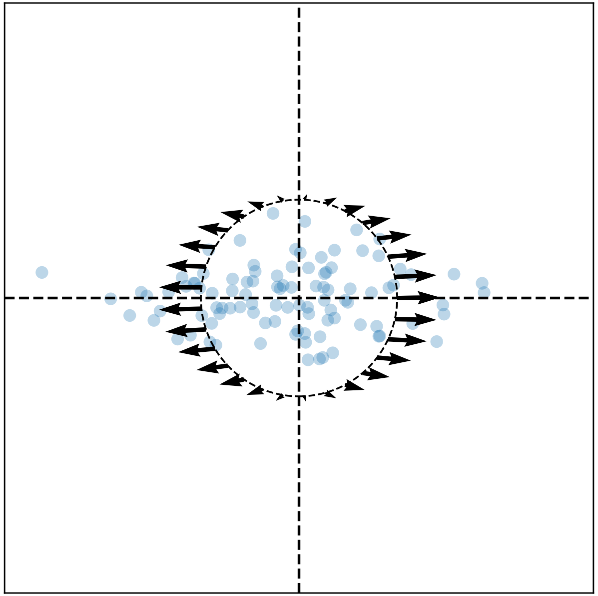
- Covariance matrices are symmetric.
- They have axes of symmetry (eigenvectors and eigenvalues).
- What are they?

Visualizing Covariance Matrices



$$C \approx \begin{pmatrix} & \\ & \end{pmatrix}$$

Visualizing Covariance Matrices

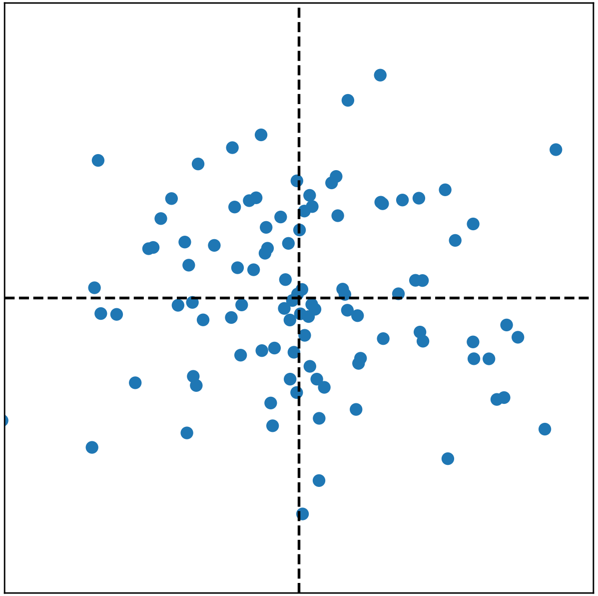


Eigenvectors:

$\vec{u}^{(1)} \approx$

$\vec{u}^{(2)} \approx$

Visualizing Covariance Matrices



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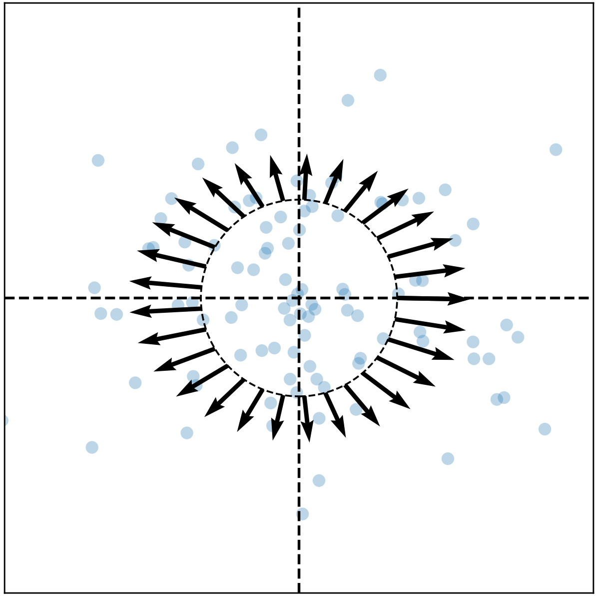
Visualizing Covariance Matrices



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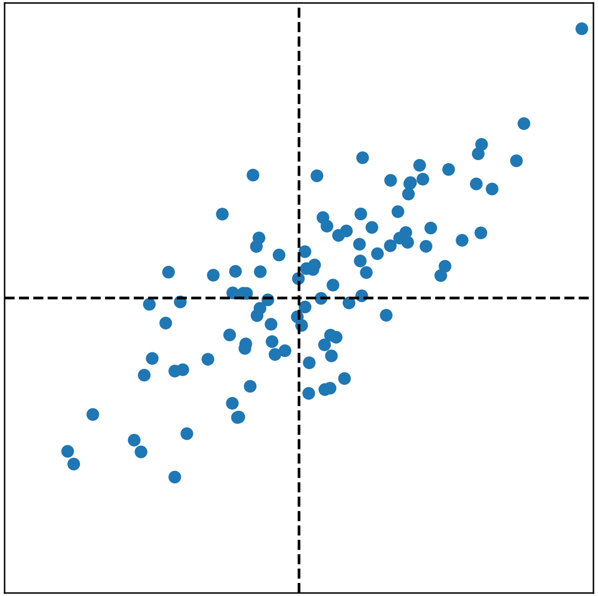
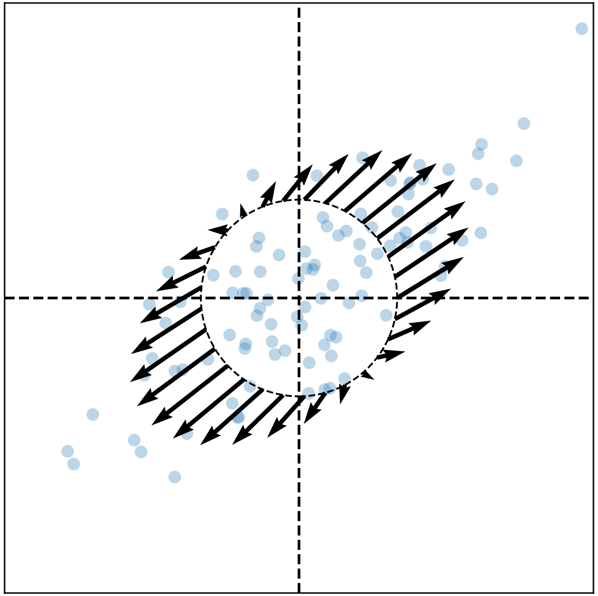


$$C \approx \left(\qquad \right)$$

Visualizing Covariance Matrices



Eigenvectors:

$\vec{u}^{(1)} \approx$

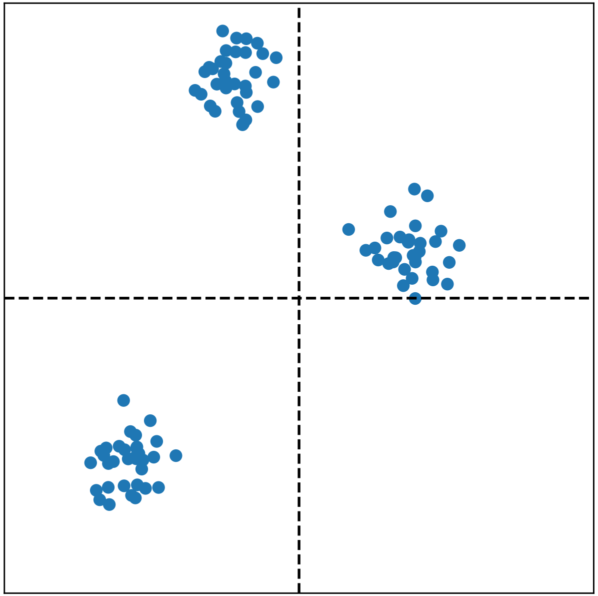
$\vec{u}^{(2)} \approx$

Intuitions

- The **eigenvectors** of the covariance matrix describe the data's "principal directions"
  - C tells us something about data's shape.
- The **top eigenvector** points in the direction of "maximum variance".
- The **top eigenvalue** is proportional to the variance in this direction.

Caution

- The data doesn’t always look like this.
- We can always compute covariance matrices.
- They just may not describe the data’s shape very well.



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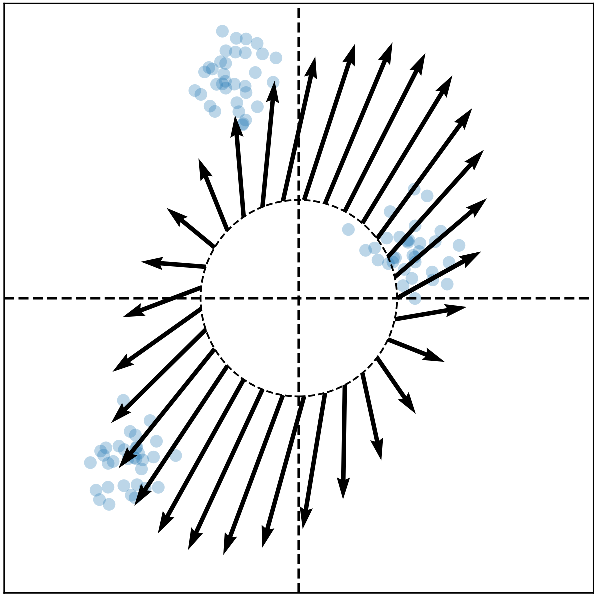

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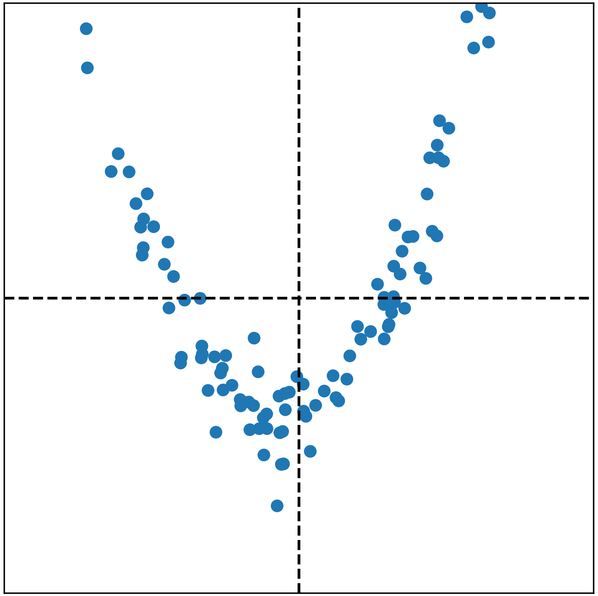

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