

$$\begin{bmatrix} \sigma_1 & & & \\ & \sigma_2 & & \\ & & \ddots & \\ 0 & & & \sigma_n \end{bmatrix}$$

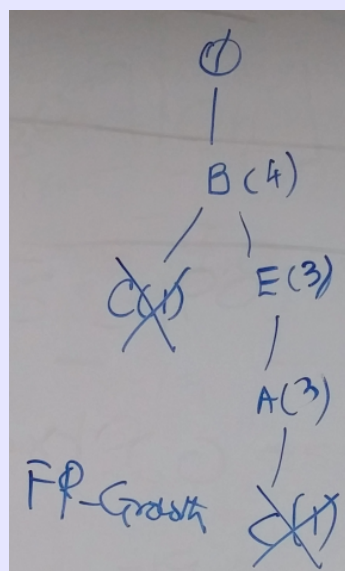
$$X = \sum_{i=1}^{\text{rank}(X)} \sigma_i u_i v_i^T = U \Sigma V^T$$

σ_i : i^{th} singular value of X
 u_i : i^{th} left singular value of X (i^{th} column of U)
 v_i : i^{th} right singular vector of X (i^{th} column of V^T)

Captures the patterns among attributes
 Captures the patterns among the objects

CS 422: Data Mining
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Lecture 2: Random variables, measures of central tendency and distributions



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Random variables

- A random variable, X , is a variable whose possible values are drawn from the outcome of a random phenomenon.
 - Tossing a coin
 - Tossing a die
- Two types:
 - Discrete
 - Continuous
- We will use mostly discrete r.v.

Random variables

- Population versus sample

- Consider a column vector, D :

$$D = \begin{pmatrix} X \\ x_1 \\ x_2 \\ \vdots \\ x_n \end{pmatrix} \quad X \in \mathbb{R}^n$$

- We assume that the observed data is a random sample drawn from X , each x_i is *iid*.
 - In general, the distribution from which X is drawn is unknown, as are the moments.
 - All we have is the sample, from which we will derive the distribution and moments, which (hopefully) are close to the population distribution and moments.

Random variables

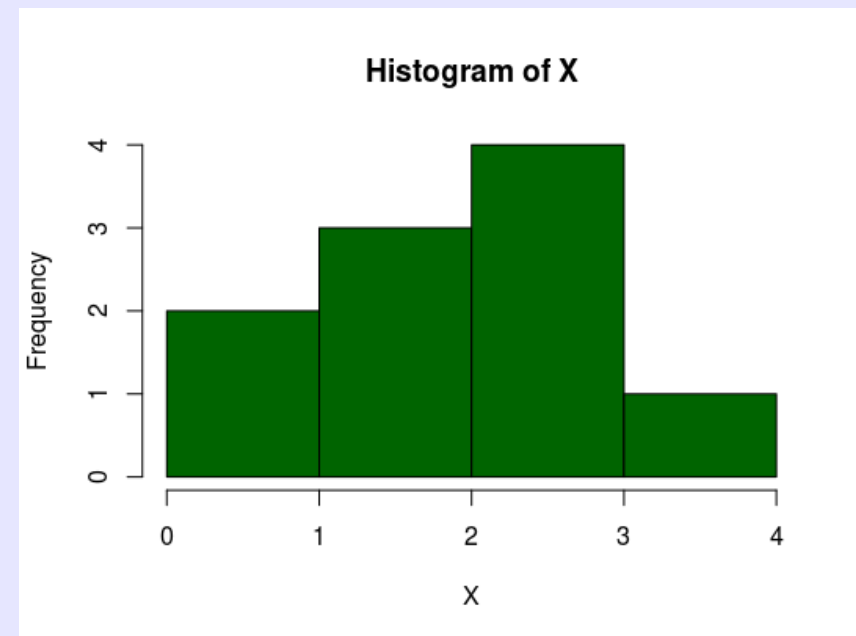
- Suppose a discrete variable X can take the values 1, 2, 3, 4 with the following probabilities:
 - 1 : 0.2; 2 : 0.3; 3 : 0.4; 4: 0.10

Then the probability mass function can be described by the following equation and histogram:

$$\hat{f}(x) = P(X=x) = \frac{1}{n} \sum_{i=1}^n I(x_i = x)$$

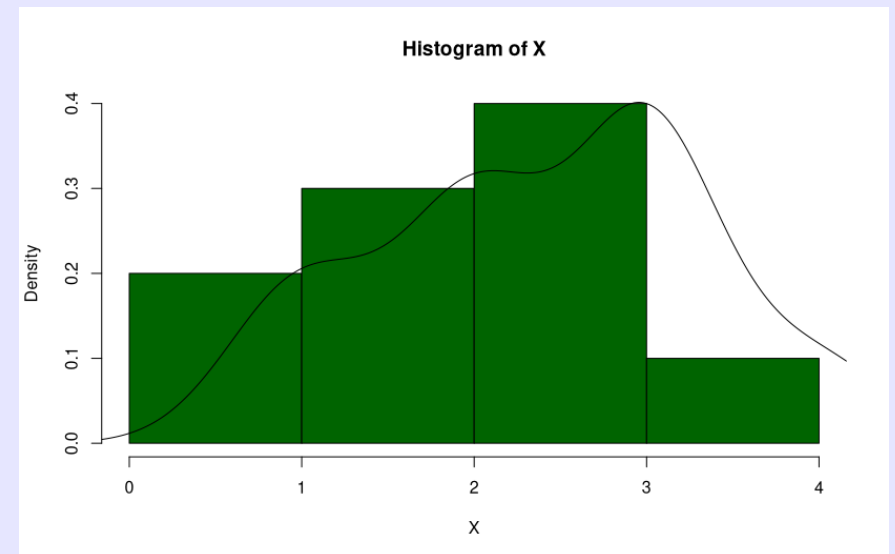
where

$$I(x_i = x) = \begin{cases} 1 & \text{if } x_i = x \\ 0 & \text{if } x_i \neq x \end{cases}$$



Random variables

- Associated with a PMF (discrete) is a PDF (continuous).
- A density plot visualizes the underlying probability distribution of the data by drawing an appropriate continuous curve.
 - Curve estimated from data using *kernel density* estimation.



```
> hist(X, c(0.0, 1.0, 2.0, 3.0, 4.0), prob=T, col="darkgreen")  
> lines(density(X))
```

Measures of central tendency

- Mean (sample):

- $\hat{\mu} = \frac{1}{n-1} \sum_{i=1}^n x_i$

- Is the mean robust (or stable)?

- We define *robustness* as the tendency not to be affected by extreme values.

Measures of central tendency

- Mean (sample):

- $\hat{\mu} = \frac{1}{n-1} \sum_{i=1}^n x_i$

- Is the mean robust (or stable)?

- We define *robustness* as the tendency not to be affected by extreme values.
 - Generally, the mean is not robust.
 - A robust measure is *trimmed mean*, which occurs after extreme values on either side are discarded.

Measures of central tendency

- Expectation of a r.v. (related to mean, but conceptually different).

- $E[X] = \sum_{i=1}^k x_i p_i = x_1 p_1 + x_2 p_2 + \dots + x_k p_k$

- Properties of expectation:

- $E[X+Y] = E[X]+E[Y]$ (Linearity of expectation)
 - $E[aX] = aE[X]$ *a is a constant*
 - $E[XY] = E[X] * E[Y]$ *iff X and Y are iid*
 - $E[E[X]] = E[X]$

Measures of central tendency

- Median (sample):
 - $P(X \leq m) \geq \frac{1}{2}$ and $P(X \geq m) \geq \frac{1}{2}$
- Is the median robust (or stable)?

Measures of central tendency

- Median (sample):
 - $P(X \leq m) \geq \frac{1}{2}$ and $P(X \geq m) \geq \frac{1}{2}$
- Is the median robust (or stable)?
 - Yes.
 - Not affected by extreme values.
 - Also, an actual value that a r.v. takes.

Measures of central tendency

- Mode (sample): mode of a r.v. X is the value at which the PMF attains its maximum value.

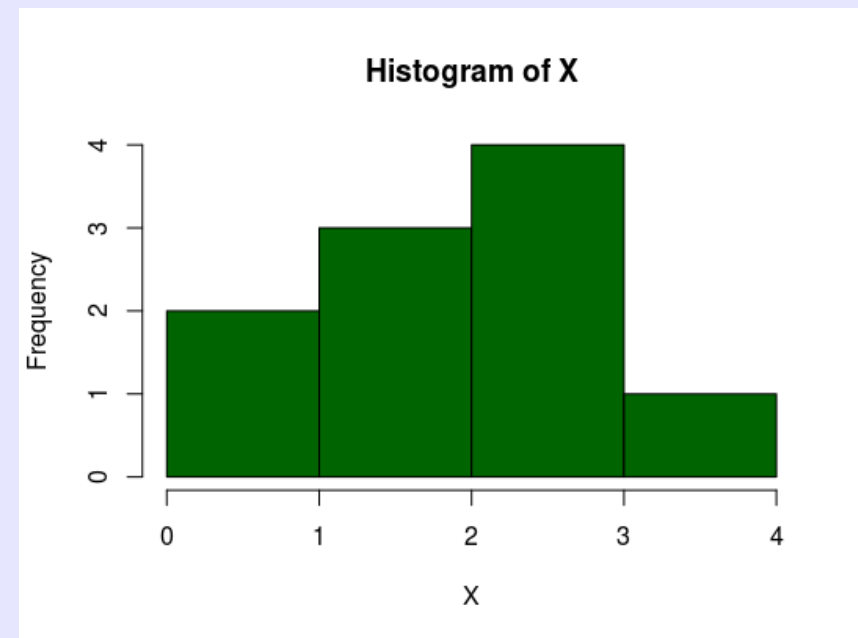
- $\text{mode}(X) = \arg \max_x \hat{f}(x)$

$$\hat{f}(x) = P(X=x) = \frac{1}{n} \sum_{i=1}^n I(x_i = x)$$

where

$$I(x_i = x) = \begin{cases} 1 & \text{if } x_i = x \\ 0 & \text{if } x_i \neq x \end{cases}$$

- May not be a useful measure of central tendency.



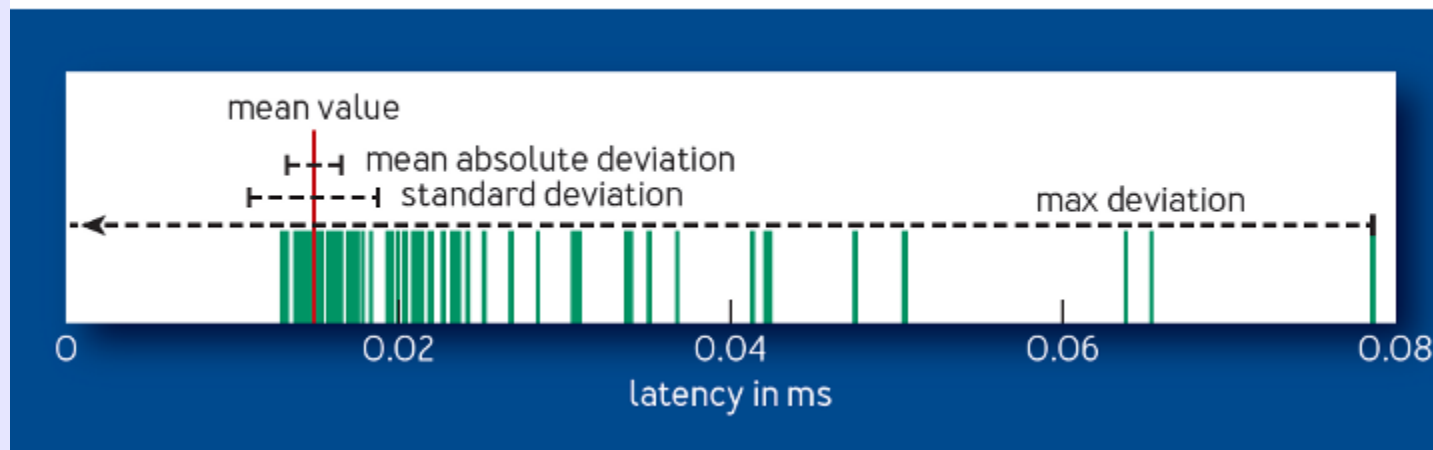
Measures of central tendency

- Measures of dispersion: Variance and standard deviation.
 - Variance: A measure of how much the values of X deviate from the expected (mean) value of X .
 - Sample variance: $\text{var}(X) = \sigma^2 = \frac{1}{n-1} \sum_{i=1}^n (x_i - \hat{\mu})^2$
 - Sample standard deviation is the squared root of the sample variance.
 - Sample standard deviation: $\sigma = \sqrt{\frac{1}{n-1} \sum_{i=1}^n (x_i - \hat{\mu})^2}$

Measures of central tendency

- Standard deviation is not the only game in town.
 - Maximal deviation: $\text{maxdev}(X) = \max(|x_i - \mu|) \forall x_i \in X$
 - Mean absolute deviation: $\text{mad}(X) = \frac{1}{n} \sum_{i=1}^n |x_i - \mu|, \forall x_i \in X$

FIGURE 11: A REQUEST LATENCY DATASET



Source: H. Hartmann, "Statistics for Engineers," CACM 50(7), July 2016.

Measures of central tendency of multivariates

- We will consider bivariate analysis for discussion. (Results generalize to n-D).
- We seek to understand the association or dependence of two attributes X_1 and X_2 .

$$\mathbf{D} = \begin{pmatrix} X_1 & X_2 \\ x_{11} & x_{12} \\ x_{21} & x_{22} \\ \vdots & \vdots \\ x_{n1} & x_{n2} \end{pmatrix}$$

- Geometrically, we can view them as vectors in 2-D space (row view), or vectors in an n-D space (column view).

Measures of central tendency of multivariates

- The first and second moments (mean and variance, respectively) are computed in the same manner, except a *vector* is returned.

$$\mathbf{D} = \begin{pmatrix} X_1 & X_2 \\ x_{11} & x_{12} \\ x_{21} & x_{22} \\ \vdots & \vdots \\ x_{n1} & x_{n2} \end{pmatrix}$$

- The variance can be computed for each attribute, σ_1^2 for X_1 and σ_2^2 for X_2 .
- The total variance is given by:
$$\text{var}(D) = \sigma_1^2 + \sigma_2^2$$

Measures of central tendency of multivariates

- Measure of association: Covariance.
- Covariance is the measure of association or linear dependence between two variables, X_1 and X_2 .

$$cov(X_1, X_2) = \hat{\sigma}_{12} = \frac{1}{n-1} \sum_{i=1}^n (x_{i1} - \hat{\mu}_1)(x_{i2} - \hat{\mu}_2)$$

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- The variance-covariance information for the two attributes can be summarized by a square (nxn) covariance matrix:

$$\hat{\Sigma} = \begin{pmatrix} \hat{\sigma}_1^2 & \hat{\sigma}_{12} \\ \hat{\sigma}_{12} & \hat{\sigma}_2^2 \end{pmatrix}$$

Measures of central tendency of multivariates

- The covariance matrix is: $\hat{\Sigma} = \begin{pmatrix} \hat{\sigma}_1^2 & \hat{\sigma}_{12} \\ \hat{\sigma}_{12} & \hat{\sigma}_2^2 \end{pmatrix}$
 - Square
 - Symmetrical
 - Attribute specific covariances on main diagonal; covariance between attributes on off-diagonal elements.
 - Total variance of the attributes is the sum of the diagonal elements (sometimes called the **trace** of the Σ).

Measures of central tendency of multivariates

- Example:

$$A = \begin{pmatrix} 3 & 6 & 0 \\ 6 & 12 & 16 \\ 5 & 10 & 59 \end{pmatrix}$$

- $\text{Cov}(A) = \begin{pmatrix} 2.3 & 4.6 & 20.5 \\ 4.6 & 9.3 & 41.0 \\ 20.5 & 41.0 & 931.0 \end{pmatrix}$

Measures of central tendency of multivariates

- Related to covariance is correlation.
- Correlation between two variables, X_1 and X_2 is the *standardized covariance* obtained by normalizing the covariance with the std. dev. of each variable:

$$\hat{\rho}_{12} = \frac{\hat{\sigma}_{12}}{\hat{\sigma}_1 \hat{\sigma}_2} = \frac{\sum_{i=1}^n (x_{i1} - \hat{\mu}_1)(x_{i2} - \hat{\mu}_2)}{\sqrt{\sum_{i=1}^n (x_{i1} - \hat{\mu}_1)^2 \sum_{i=1}^n (x_{i2} - \hat{\mu}_2)^2}}$$

Measures of central tendency of multivariates

- Example:

$$A = \begin{pmatrix} 3 & 6 & 0 \\ 6 & 12 & 16 \\ 5 & 10 & 59 \end{pmatrix}$$

- $\text{Cor}(A) = \begin{pmatrix} 1.00 & 1.00 & 0.44 \\ 1.00 & 1.00 & 0.44 \\ 0.44 & 0.44 & 1.00 \end{pmatrix}$

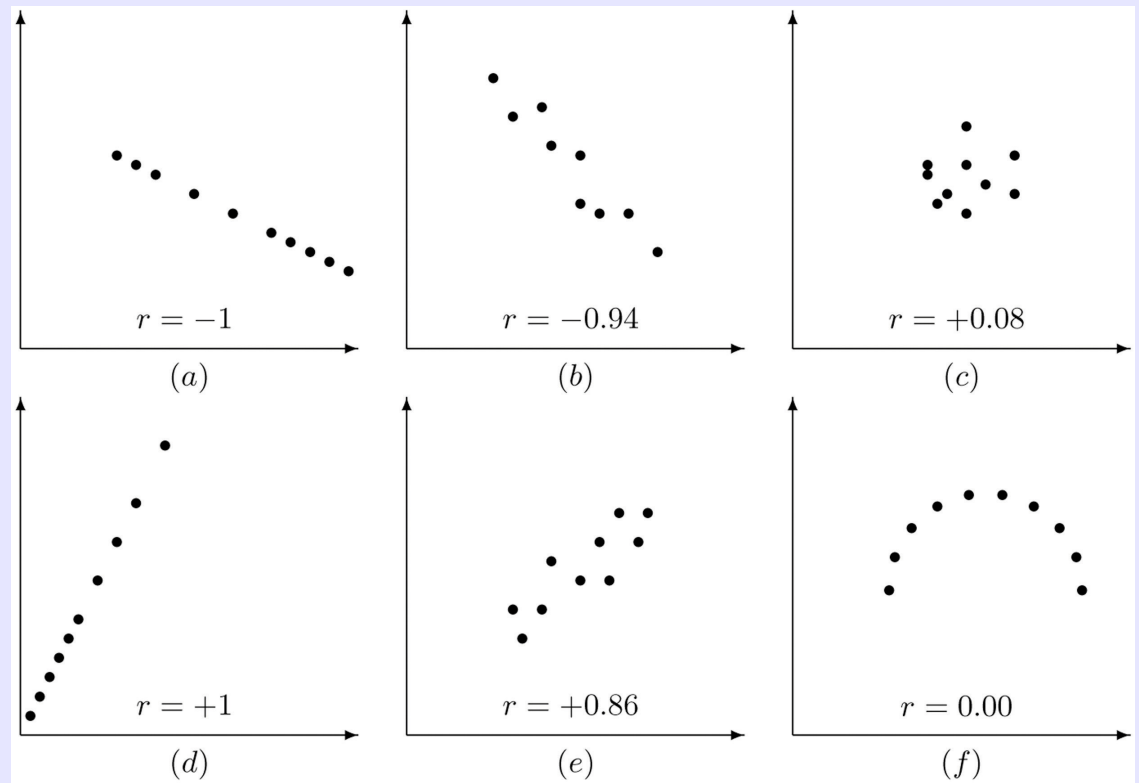
Measures of central tendency of multivariates

- Why have both covariance and correlation?
 - The range of covariance: $[-\infty, \infty]$
 - The range of correlation: $[-1, 1]$
 - Correlation is dimensionless.

- And remember:

**Correlation !=
Causation!!**

Code: cars.r



Measures of central tendency of multivariates

- Correlation and collinearity
 - Correlation measures the relationship between two variables.
 - Collinearity occurs when the two variables are so highly correlated that we can use one to predict another; i.e., one variable is a linear combination of the other variable.
 - Multicollinearity occurs when > 2 predictor variables are inter-correlated.