

COMP2610 / COMP6261 Information Theory

Lecture 8: Some Fundamental Inequalities

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Australian
National
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Assignment 1

- Available via Wattle
- Worth 10% of Course total
- Due Monday 29 August 2022, 5:00 pm
- Answers could be typed or handwritten

You can use latex LaTeX primer:

<http://tug.ctan.org/info/lshort/english/lshort.pdf>

Last time

- Decomposability of entropy
- Relative entropy (KL divergence)
- Mutual information

Review

Relative entropy (KL divergence):

$$D_{\text{KL}}(p\|q) = \sum_{x \in \mathcal{X}} p(x) \log \frac{p(x)}{q(x)}$$

Mutual information:

$$\begin{aligned} I(X; Y) &= D_{\text{KL}}(p(X, Y) \| p(X)p(Y)) \\ &= H(X) + H(Y) - H(X, Y) \\ &= H(X) - H(X|Y). \end{aligned}$$

- Average reduction in uncertainty in X when Y is known
- $I(X; Y) = 0$ when X, Y statistically independent

Conditional mutual information of X, Y given Z :

$$I(X; Y|Z) = H(X|Z) - H(X|Y, Z)$$

This time

Mutual information chain rule

Jensen's inequality

“Information cannot hurt”

Data processing inequality

Outline

- 1 Chain Rule for Mutual Information
- 2 Convex Functions
- 3 Jensen's Inequality
- 4 Gibbs' Inequality
- 5 Information Cannot Hurt
- 6 Data Processing Inequality
- 7 Wrapping Up

1 Chain Rule for Mutual Information

2 Convex Functions

3 Jensen's Inequality

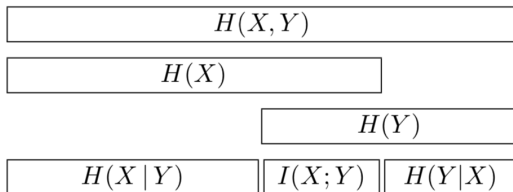
4 Gibbs' Inequality

5 Information Cannot Hurt

6 Data Processing Inequality

7 Wrapping Up

Breakdown of Joint Entropy



(From Mackay, p140; see his exercise 8.8)

Recall: Joint Mutual Information

Recall the mutual information between X and Y :

$$I(X; Y) = H(X) + H(Y) - H(X, Y) = I(Y; X).$$

We can also compute the mutual information between X_1, \dots, X_N and Y_1, \dots, Y_M :

$$\begin{aligned} I(X_1, \dots, X_N; Y_1, \dots, Y_M) &= H(X_1, \dots, X_N) + H(Y_1, \dots, Y_M) \\ &\quad - H(X_1, \dots, X_N, Y_1, \dots, Y_M) \\ &= I(Y_1, \dots, Y_M; X_1, \dots, X_N). \end{aligned}$$

Note that $I(X, Y; Z) \neq I(X; Y, Z)$ in general

- Reduction in uncertainty of X and Y given Z versus reduction in uncertainty of X given Y and Z

Chain Rule for Mutual Information

Let X, Y, Z be r.v. and recall that:

$$p(Z, Y) = p(Z|Y)p(Y)$$

$$H(Z, Y) = H(Z|Y) + H(Y)$$

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$$\begin{aligned} I(X; Y, Z) &= I(Y, Z; X) \quad \text{symmetry} \\ &= H(Z, Y) - H(Z, Y|X) \quad \text{definition of mutual info.} \end{aligned}$$

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Chain Rule for Mutual Information

Let X, Y, Z be r.v. and recall that:

$$p(Z, Y) = p(Z|Y)p(Y)$$

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$$\underline{I(X; Y, Z)} = \underline{I(Y, Z; X)} \quad \text{symmetry}$$

$$= H(Z, Y) - H(Z, Y|X) \quad \text{definition of mutual info.}$$

$$= H(Z|Y) + H(Y) - H(Z|X, Y) - H(Y|X) \quad \text{entropy's chain rule}$$

$$= \underbrace{H(Y) - H(Y|X)}_{I(Y; X)} + \underbrace{H(Z|Y) - H(Z|X, Y)}_{I(Z; X|Y)}$$

$$\underline{I(X; Y, Z)} = \underline{I(X; Y) + I(X; Z|Y)} \quad \text{definition of mutual info and conditional mutual info}$$

Similarly, by symmetry:

$$\underline{I(X; Y, Z)} = \underline{I(X; Z) + I(X; Y|Z)}$$

Chain Rule for Mutual Information

General form

For any collection of random variables X_1, \dots, X_N and Y :

$$\begin{aligned} I(X_1, \dots, X_N; Y) &= I(X_1; Y) + I(X_2, \dots, X_N; Y|X_1) \\ &= I(X_1; Y) + I(X_2; Y|X_1) + I(X_3, \dots, X_N; Y|X_1, X_2) \\ &= \dots \\ &= \sum_{i=1}^N I(X_i; Y|X_1, \dots, X_{i-1}) \\ &= \sum_{i=1}^N I(Y; X_i|X_1, \dots, X_{i-1}). \end{aligned}$$

1 Chain Rule for Mutual Information

2 **Convex Functions**

3 Jensen's Inequality

4 Gibbs' Inequality

5 Information Cannot Hurt

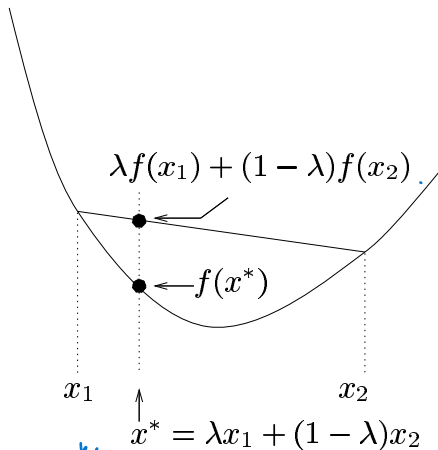
6 Data Processing Inequality

7 Wrapping Up

Convex Functions:

Introduction


凸函数



所有弦都在函数
上方

$$0 \leq \lambda \leq 1$$


(Figure from Mackay, 2003)

A function is convex  if every chord of the function lies above the function


Convex and Concave Functions



Definitions

Definition

A function $f(x)$ is **convex**  over (a, b) if for all $x_1, x_2 \in (a, b)$ and $0 \leq \lambda \leq 1$:

$$f(\lambda x_1 + (1 - \lambda)x_2) \leq \lambda f(x_1) + (1 - \lambda)f(x_2)$$

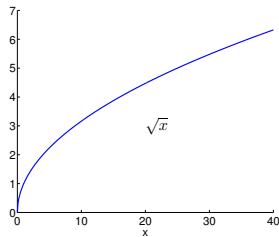
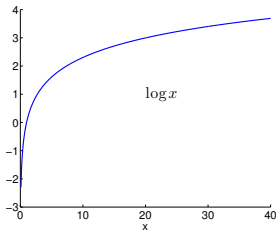
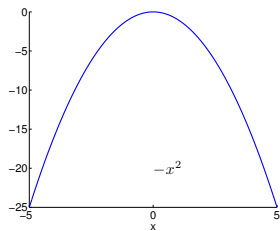
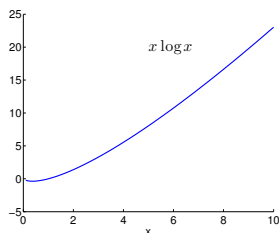
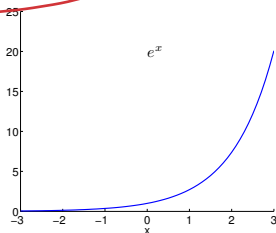
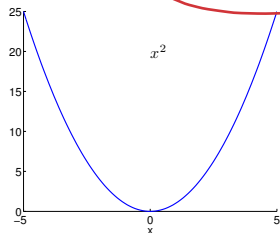
We say f is **strictly convex**  if for all $x_1, x_2 \in (a, b)$ equality holds only for $\lambda = 0$ and $\lambda = 1$.

Similarly, a function f is **concave**  if $-f$ is convex , i.e. if every chord of the function lies below the function.

注意是向下的凸和凹。

Examples of Convex and Concave Functions

所有都是！



Verifying Convexity

= 阶导.

Theorem (Cover & Thomas, Th 2.6.1)

If a function f has a second derivative that is non-negative (positive) over an interval, the function is convex \smile (strictly convex \smile) over that interval.

This allows us to verify convexity or concavity.

Examples:

- x^2 : $\frac{d}{dx} \left(\frac{d}{dx} (x^2) \right) = \frac{d}{dx} (2x) = 2$

- e^x : $\frac{d}{dx} \left(\frac{d}{dx} (e^x) \right) = \frac{d}{dx} (e^x) = e^x$

- $\sqrt{x}, x > 0$: $\frac{d}{dx} \left(\frac{d}{dx} (\sqrt{x}) \right) = \frac{1}{2} \frac{d}{dx} \left(\frac{1}{\sqrt{x}} \right) = -\frac{1}{4} \frac{1}{\sqrt{x^3}}$

Convexity, Concavity and Optimization

If $f(x)$ is concave \cap and there exists a point at which

$$\frac{df}{dx} = 0,$$

then $f(x)$ has a maximum at that point.

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Note: the converse does not hold: if a concave \cap $f(x)$ is maximized at some x , it is not necessarily true that the derivative is zero there.

- $f(x) = -|x|$: is maximized at $x = 0$ where its derivative is undefined
- $f(p) = \log p$ with $0 \leq p \leq 1$, is maximized at $p = 1$ where $\frac{df}{dp} = 1$

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- Similarly for minimisation of convex functions

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Jensen's Inequality for Convex Functions

Theorem: Jensen's Inequality

If f is a convex function and X is a random variable then:

$$f(\mathbb{E}[X]) \leq \mathbb{E}[f(X)].$$

Moreover, if f is strictly convex, equality implies that $X = \mathbb{E}[X]$ with probability 1, i.e. X is a constant.

In other words, for a probability vector \mathbf{p} ,

$$f\left(\sum_{i=1}^N p_i x_i\right) \leq \sum_{i=1}^N p_i f(x_i).$$

Similarly for a concave function: $\mathbb{E}[f(X)] \leq f(\mathbb{E}[X])$. \hookrightarrow convex 相反
 $f(\mathbb{E}[X]) \geq \mathbb{E}[f(X)]$

Jensen's Inequality for Convex Functions

Proof by Induction

(1) $K = 2$:

- ▶ Two-state random variable $X \in \{x_1, x_2\}$
- ▶ With $\mathbf{p} = (p_1, p_2) = (p_1, 1 - p_1)$
- ▶ $0 \leq p_1 \leq 1$

we simply follow the definition of convexity:

$$\underbrace{p_1 f(x_1) + p_2 f(x_2)}_{\mathbb{E}[f(X)]} \geq f(\underbrace{p_1 x_1 + p_2 x_2}_{\mathbb{E}[X]})$$

Jensen's Inequality for Convex Functions

Proof by Induction — Cont'd

(2) $(K - 1) \rightarrow K$: Assuming the theorem is true for distributions with $K - 1$ states, and writing: $p'_i = p_i / (1 - p_K)$ for $i = 1, \dots, K - 1$:

$$\sum_{i=1}^K p_i f(x_i) = p_K f(x_K) + (1 - p_K) \sum_{i=1}^{K-1} p'_i f(x_i)$$

Jensen's Inequality for Convex Functions

Proof by Induction — Cont'd

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$$\begin{aligned}\sum_{i=1}^K p_i f(x_i) &= p_K f(x_K) + (1 - p_K) \sum_{i=1}^{K-1} p'_i f(x_i) \\ &\geq p_K f(x_K) + (1 - p_K) f\left(\sum_{i=1}^{K-1} p'_i x_i\right) \quad \text{Induction hypothesis}\end{aligned}$$

Jensen's Inequality for Convex Functions

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$$\sum_{i=1}^K p_i f(x_i) \geq f\left(\sum_{i=1}^K p_i x_i\right) \Rightarrow \mathbb{E}[f(X)] \geq f(\mathbb{E}[X]) \quad \text{equality case?}$$

Jensen's Inequality Example: The AM-GM Inequality

Recall that for a **concave** \cap function: $\mathbb{E}[f(X)] \leq f(\mathbb{E}[X])$.

Consider $X \in \{x_1, \dots, x_N\}$, $X \geq 0$ with uniform probability distribution $\mathbf{p} = (\frac{1}{N}, \dots, \frac{1}{N})$ and the strictly concave \cap function $f(x) = \log x$:

$$\frac{1}{N} \sum_{i=1}^N \log x_i \leq \log \left(\frac{1}{N} \sum_{i=1}^N x_i \right)$$

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$$\frac{1}{N} \sum_{i=1}^N \log x_i \leq \log \left(\frac{1}{N} \sum_{i=1}^N x_i \right)$$
$$\log \left(\prod_{i=1}^N x_i \right)^{\frac{1}{N}} \leq \log \left(\frac{1}{N} \sum_{i=1}^N x_i \right)$$

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Gibbs' Inequality

Theorem

The relative entropy (or KL divergence) between two distributions $p(X)$ and $q(X)$ with $X \in \mathcal{X}$ is non-negative:

$$D_{\text{KL}}(p||q) \geq 0$$

with equality if and only if $p(x) = q(x)$ for all x .

Gibbs' Inequality

Proof (1 of 2)

Recall that: $D_{\text{KL}}(p||q) = \sum_{x \in \mathcal{X}} p(x) \log \frac{p(x)}{q(x)} = \mathbb{E}_{p(X)} \left[\log \frac{p(X)}{q(X)} \right]$

Let $\mathcal{A} = \{x : p(x) > 0\}$. Then:

Gibbs' Inequality

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$$- D_{\text{KL}}(p\|q) = \sum_{x \in \mathcal{A}} p(x) \log \frac{q(x)}{p(x)}$$

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Let $\mathcal{A} = \{x : p(x) > 0\}$. Then:

$$\begin{aligned} -D_{\text{KL}}(p\|q) &= \sum_{x \in \mathcal{A}} p(x) \log \frac{q(x)}{p(x)} \\ &\leq \log \sum_{x \in \mathcal{A}} p(x) \frac{q(x)}{p(x)} \end{aligned}$$

Jensen's inequality

Gibbs' Inequality

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Proof (1 of 2)

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Gibbs' Inequality

Proof (2 of 2)

Since $\log u$ is strictly convex we have equality if $\frac{q(x)}{p(x)} = c$ for all x . Then:

$$\sum_{x \in \mathcal{A}} q(x) = c \sum_{x \in \mathcal{A}} p(x) = c$$

Also, the last inequality in the previous slide becomes equality only if:

$$\sum_{x \in \mathcal{A}} q(x) = \sum_{x \in \mathcal{X}} q(x).$$

Therefore $c = 1$ and $D_{\text{KL}}(p \| q) = 0 \Leftrightarrow p(x) = q(x)$ for all x .

Alternative proof: Use the fact that $\log x \leq x - 1$.

Non-Negativity of Mutual Information

Corollary

For any two random variables X, Y :

$$I(X; Y) \geq 0,$$

with equality if and only if X and Y are statistically independent.

Proof: We simply use the definition of mutual information and Gibbs' inequality:

$$I(X; Y) = D_{\text{KL}}(p(X, Y) \| p(X)p(Y)) \geq 0,$$

with equality if and only if $p(X, Y) = p(X)p(Y)$, i.e. X and Y are independent.

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2 Convex Functions

3 Jensen's Inequality

4 Gibbs' Inequality

5 Information Cannot Hurt

6 Data Processing Inequality

7 Wrapping Up

Conditioning Reduces Entropy

Information Cannot Hurt — Proof

Theorem

For any two random variables X, Y ,

$$H(X|Y) \leq H(X),$$

with equality if and only if X and Y are independent.

Conditioning Reduces Entropy

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with equality if and only if X and Y are independent.

Proof: We simply use the non-negativity of mutual information:

$$I(X; Y) \geq 0$$

$$H(X) - H(X|Y) \geq 0$$

$$H(X|Y) \leq H(X)$$

with equality if and only if $p(X, Y) = p(X)p(Y)$, i.e X and Y are independent.

Data are helpful, they don't increase uncertainty on average.

Conditioning Reduces Entropy

Information Cannot Hurt — Example (from Cover & Thomas, 2006)

Let X, Y have the following joint distribution:

$p(X, Y)$		X	
		1	2
Y	1	0	$3/4$
	2	$1/8$	$1/8$

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$$\mathbf{p}(X) = (1/8, 7/8)$$

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$$\mathbf{p}(X|Y=1) = (0, 1)$$

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$$H(X) \approx 0.544 \text{ bits} \quad H(X|Y=1) = 0 \text{ bits} \quad H(X|Y=2) = 1 \text{ bit}$$

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$H(X|Y=y_k)$ may be greater than $H(X)$ but the average: $H(X|Y)$ is always less or equal to $H(X)$.

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Information cannot hurt on average

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2 Convex Functions

3 Jensen's Inequality

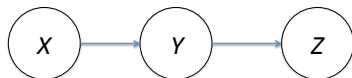
4 Gibbs' Inequality

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Markov Chain

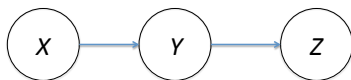


Definition

Random variables X, Y, Z are said to form a **Markov chain** in that order (denoted by $X \rightarrow Y \rightarrow Z$) if their joint probability distribution can be written as:

$$p(X, Y, Z) = p(X)p(Y|X)p(Z|Y) = p(Z|Y)p(Y|X)p(X)$$

Markov Chain



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Consequences (prove these facts!):

- $X \rightarrow Y \rightarrow Z$ if and only if X and Z are conditionally independent given Y .
- $X \rightarrow Y \rightarrow Z$ implies that $Z \rightarrow Y \rightarrow X$.
- If $Z = f(Y)$, then $X \rightarrow Y \rightarrow Z$

1. $X \rightarrow Y \rightarrow Z$ (X, Y and Z form a Markov chain)
• • • $P(X, Y, Z) = P(Z|Y) P(Y|X) P(X)$ — (1)

2. X and Z are conditionally independent given Y ,
 $\Rightarrow P(X, Z|Y) = P(X|Y) P(Z|Y)$ — (2)

Start with (2)

$$P(X, Z|Y) = \frac{P(X, Z, Y)}{P(Y)} \quad \text{--- (3)}$$

(2), (3) \Rightarrow

$$P(X, Z, Y) = P(Z|Y) \underbrace{P(Y) P(X|Y)}_{P(Y|X) P(X)}$$

$$= P(Z|Y) P(Y|X) P(X)$$

Same as (1).

Data-Processing Inequality

Definition

Theorem

if $X \rightarrow Y \rightarrow Z$ then: $I(X; Y) \geq I(X; Z)$

- X is the state of the world, Y is the data gathered and Z is the processed data
- No “clever” manipulation of the data can improve the (best-possible) inferences that can be made from the data
- No processing of Y , deterministic or random, can increase the information that Y contains about X

Data-Processing Inequality

Proof

Recall that the chain rule for mutual information states that:

$$\begin{aligned} I(X; Y, Z) &= I(X; Y) + I(X; Z|Y) \\ &= I(X; Z) + I(X; Y|Z) \end{aligned}$$

Therefore:

Data-Processing Inequality

Proof

Recall that the chain rule for mutual information states that:

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Therefore:

$$I(X; Y) + \underbrace{I(X; Z|Y)}_0 = I(X; Z) + I(X; Y|Z) \quad \text{Markov chain assumption}$$

$$I(X; Z|Y) = H(Z|Y) - H(Z|X, Y)$$

$$= E \left\{ \log_2 \frac{P(X, Z|Y)}{P(X|Y) P(Z|Y)} \right\}$$

$$= E \left[\log_2 \frac{P(X, Z, Y)}{\underbrace{P(Y) P(X|Y) P(Z|Y)}_{P(Y|X) P(X)}} \right]$$

$$= E \left[\log_2 \frac{P(X, Y, Z)}{\underbrace{P(Z|Y) P(Y|X) P(X)}_{P(X, Y, Z)}} \right]$$

$$= E \left\{ \log_2 1 \right\}$$

$$= 0$$

∴ For $X \rightarrow Y \rightarrow Z$

$$I(X; Z|Y) = 0$$

Data-Processing Inequality

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$$\begin{aligned} I(X; Y) + \underbrace{I(X; Z|Y)}_0 &= I(X; Z) + I(X; Y|Z) && \text{Markov chain assumption} \\ I(X; Y) &= I(X; Z) + I(X; Y|Z) && \text{but } I(X; Y|Z) \geq 0 \end{aligned}$$

Data-Processing Inequality

Proof

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Data-Processing Inequality

Functions of the Data

Corollary

In particular, if $Z = g(Y)$ we have that:

$$I(X; Y) \geq I(X; g(Y))$$

Proof: $X \rightarrow Y \rightarrow g(Y)$ forms a Markov chain.

Functions of the data Y cannot increase the information about X

数据处理无法使原数据包含更多信息。

Data-Processing Inequality

Observation of a “Downstream” Variable

Corollary

If $X \rightarrow Y \rightarrow Z$ then $I(X; Y|Z) \leq I(X; Y)$

Proof: We again use the chain rule for mutual information:

$$\begin{aligned} I(X; Y, Z) &= I(X; Y) + I(X; Z|Y) \\ &= I(X; Z) + I(X; Y|Z) \end{aligned}$$

Therefore:

$$I(X; Y) + \underbrace{I(X; Z|Y)}_0 = I(X; Z) + I(X; Y|Z) \quad \text{Markov chain assumption}$$

$$I(X; Y|Z) = I(X; Y) - I(X; Z) \quad \text{but } I(X; Z) \geq 0$$

$$I(X; Y|Z) \leq I(X; Y)$$

The dependence between X and Y cannot be increased by the observation of a “downstream” variable.

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Summary & Conclusions

- Chain rule for mutual information
- Convex Functions
- Jensen's inequality, Gibbs' inequality
- Important inequalities regarding information, inference and data processing
- **Reading:** Mackay §2.6 to §2.10, Cover & Thomas §2.5 to §2.8

Next time

- Law of large numbers
- Markov's inequality
- Chebychev's inequality

Acknowledgement

These slides were originally developed by Professor Robert C. Williamson.