

# Conjugate prior summary

Distribution	Likelihood $p(\mathbf{x} \theta)$	Prior $p(\theta)$	Distribution
Bernoulli	$(1 - \theta)^{(1-x)}\theta^x$	$\propto (1 - \theta)^{(a-1)}\theta^{(b-1)}$	Beta
Binomial	$\propto (1 - \theta)^{(N-x)}\theta^x$	$\propto (1 - \theta)^{(a-1)}\theta^{(b-1)}$	Beta
Multinomial	$\propto \theta_1^{x_1}\theta_2^{x_2}\theta_3^{x_3}$	$\propto \theta_1^{\alpha_1-1}\theta_2^{\alpha_2-1}\theta_3^{\alpha_3-1}$	Dirichlet
Normal (fixed $\sigma^2$ )	$\propto \exp\left(-\frac{(x-\theta)^2}{2\sigma^2}\right)$	$\propto \exp\left(-\frac{(\theta-\mu_0)^2}{2\sigma_0^2}\right)$	Normal
Normal (fixed $\mu$ )	$\propto \sqrt{\theta} \exp\left(-\frac{\theta(x-\mu)^2}{2}\right)$	$\propto \theta^{a-1} \exp(-b\theta)$	Gamma
Poisson	$\propto \theta^x \exp(-\theta)$	$\propto \theta^{a-1} \exp(-b\theta)$	Gamma

# An example

- Simple economy:  $m$  prosumers,  $n$  different goods<sup>1</sup>
- Each individual: production  $\mathbf{p}_i \in \mathbb{R}_n$ , consumption  $\mathbf{c}_i \in \mathbb{R}_n$
- Expense of producing “ $\mathbf{p}$ ” for agent  $i = e_i(\mathbf{p})$
- Utility (happiness) of consuming “ $\mathbf{c}$ ” units for agent  $i = u_i(\mathbf{c})$
- Maximize happiness

$$\max_{\mathbf{p}_i, \mathbf{c}_i} \sum_i (u_i(\mathbf{c}_i) - e_i(\mathbf{p}_i)) \quad \text{s.t.} \quad \sum_i \mathbf{c}_i = \sum_i \mathbf{p}_i$$

<sup>1</sup>Example borrowed from the first lecture of Prof Gordon's CMU CS-10-725

# Walrasian equilibrium

$$\max_{\mathbf{p}_i, \mathbf{c}_i} \sum_i (u_i(\mathbf{c}_i) - e_i(\mathbf{p}_i)) \quad s.t. \quad \sum_i \mathbf{c}_i = \sum_i \mathbf{p}_i$$

- Idea: introduce price  $\lambda_j$  to each good  $j$ . Let the market decide
  - Price  $\lambda_j \uparrow$ : consumption of good  $j \downarrow$ , production of good  $j \uparrow$
  - Price  $\lambda_j \downarrow$ : consumption of good  $j \uparrow$ , production of good  $j \downarrow$
  - Can adjust price until consumption = production for each good

# Algorithm: tâtonnement

Assume that the appropriate prices are found, we can ignore the equality constraint, then the problem becomes

$$\max_{\mathbf{p}_i, \mathbf{c}_i} \sum_i (u_i(\mathbf{c}_i) - e_i(\mathbf{p}_i)) \Rightarrow \sum_i \max_{\mathbf{p}_i, \mathbf{c}_i} (u_i(\mathbf{c}_i) - e_i(\mathbf{p}_i))$$

So we can simply optimize production and consumption of each individual independently

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## Algorithm 1 tâtonnement

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- 1: **procedure** FINDBESTPRICES
  - 2:      $\lambda \leftarrow [0, 0, \dots, 0]$
  - 3:     **for**  $k = 1, 2, \dots$  **do**
  - 4:         Each individual solves for its  $c_i$  and  $p_i$  for the given  $\lambda$
  - 5:          $\lambda \leftarrow \lambda + \delta_k \sum_i (c_i - p_i)$
-

# Lagrange multiplier

## Problem

$$\begin{aligned} \max_{\mathbf{x}} f(\mathbf{x}) \\ g(\mathbf{x}) = 0 \end{aligned}$$

Consider  $L(\mathbf{x}, \lambda) = f(\mathbf{x}) - \lambda g(\mathbf{x})$  and let  $\tilde{f}(\mathbf{x}) = \min_{\lambda} L(\mathbf{x}, \lambda)$ .

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$$\tilde{f}(\mathbf{x}) = \begin{cases} f(\mathbf{x}) & \text{if } g(\mathbf{x}) = 0 \\ -\infty & \text{otherwise} \end{cases}$$

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Therefore, the problem is identical to  $\max_{\mathbf{x}} \tilde{f}(\mathbf{x})$  or

$$\max_{\mathbf{x}} \min_{\lambda} (f(\mathbf{x}) - \lambda g(\mathbf{x})),$$

where  $\lambda$  is known to be the Lagrange multiplier.

# Lagrange multiplier (con't)

Assume the optimum is a saddle point,

$$\max_{\mathbf{x}} \min_{\lambda} (f(\mathbf{x}) - \lambda g(\mathbf{x})) = \min_{\lambda} \max_{\mathbf{x}} (f(\mathbf{x}) - \lambda g(\mathbf{x})),$$

the R.H.S. implies

$$\nabla f(\mathbf{x}) = \lambda \nabla g(\mathbf{x})$$



# Inequality constraint

## Problem

$$\begin{aligned} \max_{\mathbf{x}} f(\mathbf{x}) \\ g(\mathbf{x}) \leq 0 \end{aligned}$$

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Therefore, we can rewrite the problem as

$$\max_{\mathbf{x}} \min_{\lambda \geq 0} (f(\mathbf{x}) - \lambda g(\mathbf{x}))$$

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Assume

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Moreover, at the optimum point  $(\mathbf{x}^*, \lambda^*)$ , we should have the so-called “complementary slackness” condition

$$\lambda^* g(\mathbf{x}^*) = 0$$

since

$$\max_{\substack{\mathbf{x} \\ g(\mathbf{x}) \leq 0}} f(\mathbf{x}) \equiv \max_{\mathbf{x}} \min_{\lambda \geq 0} (f(\mathbf{x}) - \lambda g(\mathbf{x}))$$

# Karush-Kuhn-Tucker conditions

## Problem

$$\begin{aligned} \max_{\mathbf{x}} f(\mathbf{x}) \\ g(\mathbf{x}) \leq 0, \quad h(\mathbf{x}) = 0 \end{aligned}$$

## Conditions

$$\begin{aligned} \nabla f(\mathbf{x}^*) - \mu^* \nabla g(\mathbf{x}^*) - \lambda^* \nabla h(\mathbf{x}^*) &= 0 \\ g(\mathbf{x}^*) &\leq 0 \\ h(\mathbf{x}^*) &= 0 \\ \mu^* &\geq 0 \\ \mu^* g(\mathbf{x}^*) &= 0 \end{aligned}$$

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- However, we want to make sure that we can losslessly decode the message also!

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- Even when a code is not “singular”, we still cannot guarantee that we can always recover the original message losslessly, consider 4 different possible input symbols  $a, b, c, d$  and an encoding map  $c(\cdot)$  :
  - $a \mapsto 0, b \mapsto 1, c \mapsto 10, d \mapsto 11$
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- So it is not sufficient to just have  $c(\cdot)$  to map to different output for each input. Let's overload the notation  $c(\cdot)$  a little bit and for any message sequence  $\mathbf{x} = x_1, x_2, \dots, x_n$ , encode sequence  $x_1, x_2, \dots, x_n$  to  $c(\mathbf{x}) = c(x_1, x_2, \dots, x_n) = c(x_1)c(x_2) \cdots c(x_n)$

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  - We say  $c(\mathbf{x})$  is **uniquely decodable** if all input sequences map to different outputs

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  - Note that the catch is that there is no codeword being the “prefix” of another codeword
  - We call such code a prefix-free code or an instantaneous code



# Kraft's Inequality

Let  $l_1, l_2, \dots, l_K$  satisfy  $\sum_{k=1}^K 2^{-l_k} \leq 1$ . Then, there exists a uniquely decodable code for symbols  $x_1, x_2, \dots, x_K$  such that  $l(x_1) = l_1$ ,  $l(x_2) = l_2, \dots, l(x_K) = l_K$ .

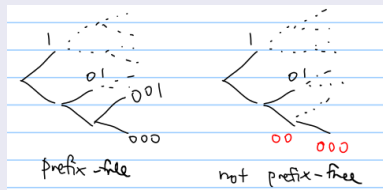
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## Intuition

Consider # “descendants” of each codeword at the “ $l_{max}$ ”-level, then for prefix-free code, we have

$$\sum_{k=1}^K 2^{l_{max}-l} \leq 2^{l_{max}}$$



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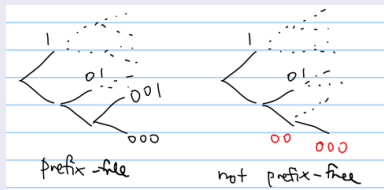
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$$\sum_{k=1}^K 2^{l_{max}-l_k} \leq 2^{l_{max}}$$

$$\Rightarrow \sum_{k=1}^K 2^{-l_k} \leq 1$$



# Forward Proof

Given  $l_1, l_2, \dots, l_K$  satisfy  $\sum_{k=1}^K 2^{-l_k} \leq 1$ , we can assign nodes on a tree as previous slides. More precisely,

- Assign  $i$ -th node as a node at level  $l_i$ , then cross out all its descendants
- Repeat the procedure for  $i$  from 1 to  $K$
- We know that there are sufficient tree nodes to be assigned since the Kraft's inequality is satisfied

The corresponding code is apparently prefix-free and thus is uniquely decodable

# Converse Proof

Consider message from coding  $k$  symbols  $\mathbf{x} = x_1, x_2, \dots, x_k$

$$\begin{aligned} \left( \sum_{\mathbf{x} \in \mathcal{X}} 2^{-l(\mathbf{x})} \right)^k &= \left( \sum_{x_1 \in \mathcal{X}} 2^{-l(x_1)} \right) \left( \sum_{x_2 \in \mathcal{X}} 2^{-l(x_2)} \right) \dots \left( \sum_{x_k \in \mathcal{X}} 2^{-l(x_k)} \right) \\ &= \sum_{x_1, x_2, \dots, x_k \in \mathcal{X}^k} 2^{-l(x_1) + l(x_2) + \dots + l(x_k)} \\ &= \sum_{\mathbf{x} \in \mathcal{X}^k} 2^{-l(\mathbf{x})} \end{aligned}$$

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Consider message from coding  $k$  symbols  $\mathbf{x} = x_1, x_2, \dots, x_k$

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 &= \sum_{x_1, x_2, \dots, x_k \in \mathcal{X}^k} 2^{-l(x_1) + l(x_2) + \dots + l(x_k)} \\
 &= \sum_{\mathbf{x} \in \mathcal{X}^k} 2^{-l(\mathbf{x})} = \sum_{m=1}^{kl_{\max}} a(m) 2^{-m},
 \end{aligned}$$

where  $a(m)$  is the number of codeword with length  $m$ . However, for the code to be uniquely decodable,  $a(m) \leq 2^m$ , where  $2^m$  is the number of available codewords with length  $m$ .

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$$\sum_{x \in \mathcal{X}} 2^{-l(x)} \leq (kl_{\max})^{1/k} \approx 1 \text{ as } k \rightarrow \infty$$



# Minimum rate required to compress a source

$$\begin{aligned} & \min_{l_1, l_2, \dots, l_K} \sum_{k=1}^K p_k l_k \text{ subject to } \sum_{k=1}^K 2^{-l_k} \leq 1 \text{ and } l_1, \dots, l_K \geq 0 \\ & \equiv \max_{l_1, l_2, \dots, l_K} - \sum_{k=1}^K p_k l_k \text{ subject to } \sum_{k=1}^K 2^{-l_k} - 1 \leq 0 \text{ and } -l_1, \dots, -l_K \leq 0 \end{aligned}$$

## KKT conditions

$$-\nabla \left( \sum_{k=1}^K p_k l_k \right) - \mu_0 \nabla \left( \sum_{k=1}^K 2^{-l_k} - 1 \right) + \sum_{k=1}^K \mu_k \nabla l_k = 0$$

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$$\equiv \max_{l_1, l_2, \dots, l_K} - \sum_{k=1}^K p_k l_k \text{ subject to } \sum_{k=1}^K 2^{-l_k} - 1 \leq 0 \text{ and } -l_1, \dots, -l_K \leq 0$$

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$$\sum_{k=1}^K 2^{-l_k} - 1 \leq 0, \quad l_1, \dots, l_K \geq 0, \quad \mu_0, \mu_1, \dots, \mu_K \geq 0$$

# Minimum rate required to compress a source

$$\min_{l_1, l_2, \dots, l_K} \sum_{k=1}^K p_k l_k \text{ subject to } \sum_{k=1}^K 2^{-l_k} \leq 1 \text{ and } l_1, \dots, l_K \geq 0$$

$$\equiv \max_{l_1, l_2, \dots, l_K} - \sum_{k=1}^K p_k l_k \text{ subject to } \sum_{k=1}^K 2^{-l_k} - 1 \leq 0 \text{ and } -l_1, \dots, -l_K \leq 0$$

## KKT conditions

$$-\nabla \left( \sum_{k=1}^K p_k l_k \right) - \mu_0 \nabla \left( \sum_{k=1}^K 2^{-l_k} - 1 \right) + \sum_{k=1}^K \mu_k \nabla l_k = 0$$

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Note that as  $\mu_0 \downarrow$ ,  $\frac{p_j}{\mu_0 \log 2} \uparrow$  and  $l_j \downarrow$ . Therefore, if we want to decrease code rate, we should reduce  $\mu_0$  as much as possible. Thus, take  $\mu_0 = \frac{1}{\log 2}$ . Then  $2^{-l_j} = p_j \Rightarrow l_j = -\log_2 p_j$ . Thus, the minimum rate becomes

$$\sum_{k=1}^K p_k l_k = -\sum_{k=1}^K p_k \log_2 p_k \triangleq H(p_1, \dots, p_K)$$



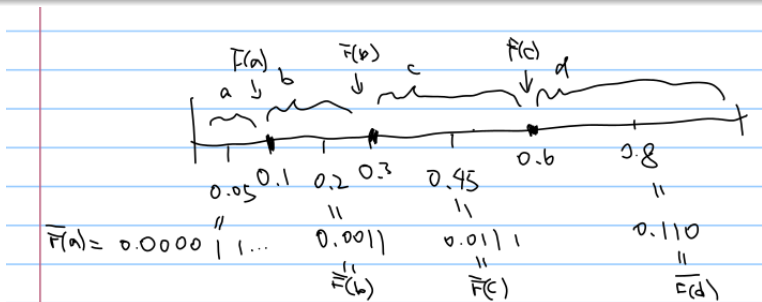
# Shannon-Fano-Elias code

## Key idea

Each codeword corresponds to an interval of  $[0, 1]$

## Example

110 corresponds to  $[0.110, 0.1101] = [0.11, 0.111) = [0.75, 0.875)$



# Shannon-Fano-Elias code

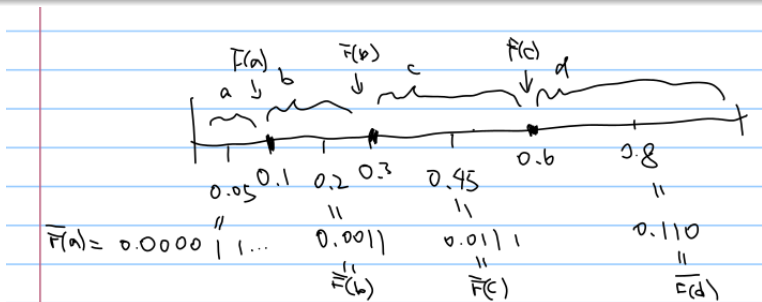
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011 corresponds to  $[0.011, 0.0111] = [0.011, 0.1) = [0.375, 0.5)$



# Example

Consider a source that

$$p(x_1) = 0.25, p(x_2) = 0.25, p(x_3) = 0.2, p(x_4) = 0.15, p(x_5) = 0.15$$

$x$	$p(x)$	$F(x)$	$\overline{F}(x)$	$\overline{F}(x)$ in Binary	$l(x) = \left\lceil \log \frac{1}{p(x)} \right\rceil + 1$	Codeword
1	0.25	0.25	0.125	0.001	3	001
2	0.25	0.5	0.375	0.011	3	011
3	0.2	0.7	0.6	0.10011	4	1001
4	0.15	0.85	0.775	0.1100011	4	1100
5	0.15	1.0	0.925	0.1110110	4	1110

# Property

- The length of the codeword of  $x$  is  $\lceil \log_2 \frac{1}{p(x)} \rceil + 1$ . This ensures that the “code interval” of each codeword does not overlap

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  - Since no codeword can overlap in SFE, no code word can be prefix of another
- Average code rate is upper bounded by  $H(X) + 2$

$$\begin{aligned} \sum_{x \in \mathcal{X}} p(x) l(x) &= \sum_{x \in \mathcal{X}} p(x) \left( \left\lceil \log_2 \frac{1}{p(x)} \right\rceil + 1 \right) \\ &\leq \sum_{x \in \mathcal{X}} p(x) \left( \log_2 \frac{1}{p(x)} + 2 \right) = H(X) + 2 \end{aligned}$$



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- Let's consider two symbols as a super-symbol and compress the pair at each time with SFE code
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 &= - \sum_{x_1, x_2 \in \mathcal{X}^2} p(x_1, x_2) \log_2 p(x_1) - \sum_{x_1, x_2 \in \mathcal{X}^2} p(x_1, x_2) \log_2 p(x_2) \\
 &= - \sum_{x_1 \in \mathcal{X}} p(x_1) \log_2 p(x_1) - \sum_{x_2 \in \mathcal{X}} p(x_2) \log_2 p(x_2) \\
 &= 2H(X)
 \end{aligned}$$

Therefore, the code rate per original symbol is upper bounded by

$$\frac{1}{2} (H(X_S) + 2) = H(X) + 1$$

# Forward proof of Source Coding Theorem

In theory, we can group as many symbol as we want (we want do it in practice, why?), say we group  $N$  symbols at a time and compress it using SFE code.

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Therefore as long as a given rate  $R > H(X)$ , we can always find a large enough  $N$  such that the code rate using the “grouping trick” and SFE code is below  $R$ . This concludes the forward proof