

Entropy profiles and algebraic matroids

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- ▶ Entropy profiles are “rank functions”: monotone and submodular.

Entropy as information

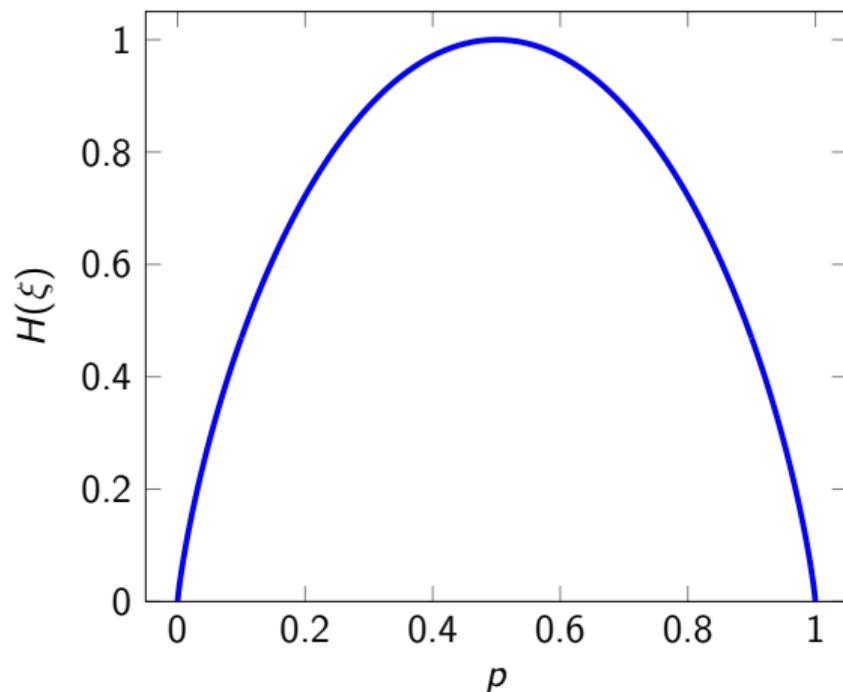


Figure: Entropy of a binary random variable ξ as a function of $p = p(\xi = \text{heads})$.

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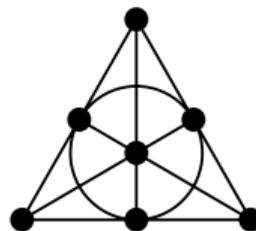
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- ▶ **Cryptographic protocols** use FD and CI constraints to specify operation and information-theoretic security (e.g., secret sharing).
- ▶ Quantities in **information theory** are defined by linear optimization over entropy profiles with FD and CI constraints (e.g., common information).

Example: Perfect secret sharing

- ▶ Given: participants $N = \{1, \dots, n\}$ and a set of qualified subsets $\mathcal{Q} \subseteq 2^N$.

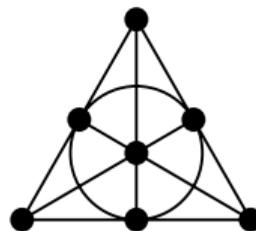
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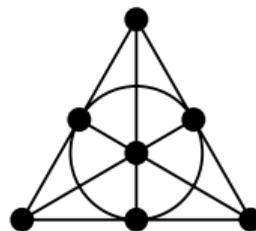
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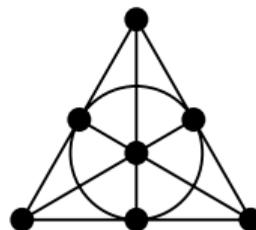
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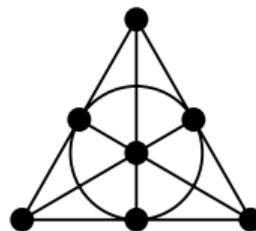
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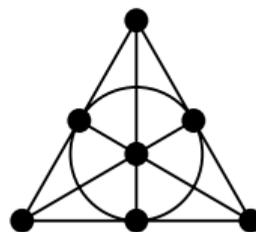
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- ▶ The **information ratio** is $\sigma(h) = 1/h(s) \max \{h(p) : p \in N\}$.
- ▶ The optimal information ratio $\sigma(\mathcal{Q}) = \inf \{\sigma(h) : h \models \mathcal{Q}\}$ can be determined by **linear optimization** over the set of all entropy profiles satisfying linear conditions.



The entropy region and information inequalities

Let $H_N^* \subseteq \mathbb{R}^{2^N}$ consist of all h_ξ where ξ is an N -variate discrete random vector. H_N^* is the image of $\bigcup_{d_1=1}^{\infty} \cdots \bigcup_{d_n=1}^{\infty} \Delta(d_1, \dots, d_n)$ under the transcendental map $\xi \mapsto h_\xi$.

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Theorem ([Mat07a])

$\overline{H_N^*}$ is not polyhedral for $|N| \geq 4$.

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- ▶ Kaced and Romashchenko [KR13] proved that (1) is **essentially conditional**, i.e., there are no $\lambda, \mu \in \mathbb{R}$ such that (2) holds.

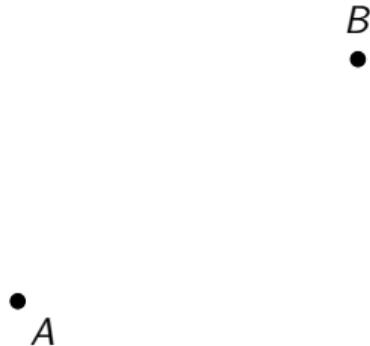
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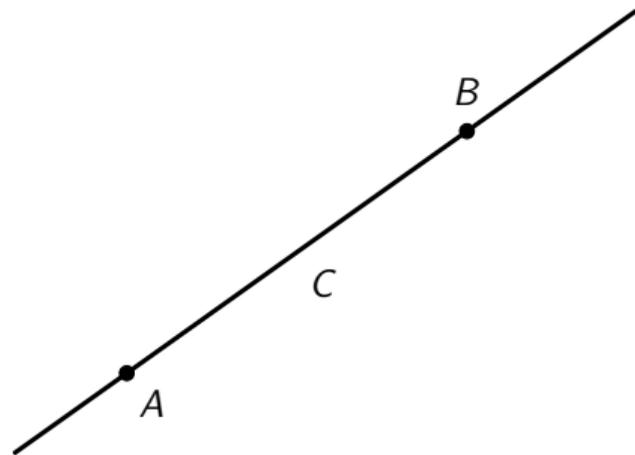
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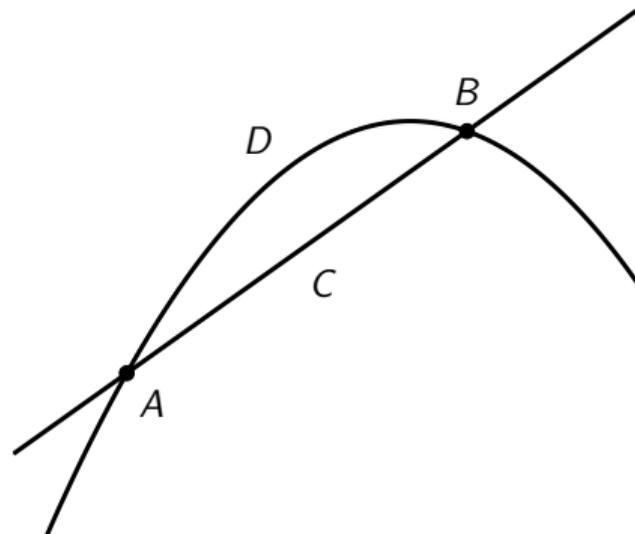
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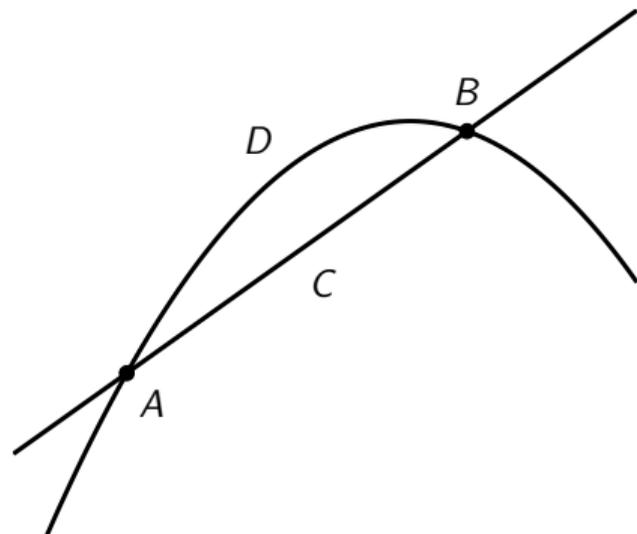
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The coordinates of (A, B, C, D) define the support of a distribution on $\mathbb{F}_q^2 \times \mathbb{F}_q^2 \times \mathbb{F}_q^2 \times \mathbb{F}_q^3$ and the distribution is uniform on this set.

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- ▶ Elementary parameter counting yields

$$H(A : B) = H(A : B \mid C) = \log(q) - \log(q - 1) \text{ and} \\ H(C : D \mid A) = H(C : D \mid B) = \log(q - 1) - \log(q - 2).$$

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which becomes negative for **any** λ, μ as $q \rightarrow \infty$.

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Can this be done by computer algebra?

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Theorem ([CDM92])

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- ▶ *There exists a unique $k \in K$ such that $\mathbb{F}_q \models \psi_k(b)$.*

Model theory of finite fields

\mathbb{F}_q -definable sets are sets of the form $\varphi(\mathbb{F}_q^n; b) = \{ a \in \mathbb{F}_q^n : \mathbb{F}_q \models \varphi(a, b) \}$ where $\varphi(x_1, \dots, x_n, y_1, \dots, y_m)$ is a first-order formula in the language of rings and $b \in \mathbb{F}_q^m$.

- ▶ More briefly: the smallest set of sets containing all varieties defined over \mathbb{F}_q and closed under complement and projection.

Theorem ([CDM92])

Consider a formula $\varphi(x_1, \dots, x_n, y_1, \dots, y_m)$. There exist finitely many formulas $\psi_k(y_1, \dots, y_m)$, indexed by $k \in K$, with accompanying $\mu_k \in \mathbb{Q}$ and $d_k \in \mathbb{N}$ such that for every sufficiently large finite field \mathbb{F}_q and every $b \in \mathbb{F}_q^m$:

- ▶ *There exists a unique $k \in K$ such that $\mathbb{F}_q \models \psi_k(b)$.*
- ▶ *$\mathbb{F}_q \models \psi_k(b)$ if and only if $|\varphi(\mathbb{F}_q^n; b)| = \mu_k q^{d_k} + \mathcal{O}(\mu_k q^{d_k-1/2})$.*

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- ▶ $\mathbb{G}^I = \bigsqcup_{k \in K} Y_k(\mathbb{G})$, and
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Theorem ([FHJ94])

Fiber decompositions are computable. Moreover, one can compute a bound $m \in \mathbb{N}$, numbers $d_k \in \mathbb{N}$ and non-negative $\mu_k \in \mathbb{Q}$ such that for every finite extension \mathbb{G}/\mathbb{F} :

$$|X(\mathbb{G})| = \mu_k |\mathbb{G}|^{d_k} + \mathcal{O}(\mu_k |\mathbb{G}|^{d_k - 1/2}), \text{ where } k \equiv [\mathbb{G} : \mathbb{F}] \pmod{m}.$$

Computability of the entropy profiles

Theorem

Let X be an \mathbb{F} -definable set in n free variables and $\xi(\mathbb{G})$ the uniform distribution on $X(\mathbb{G})$. For a projection $\pi_I(X)$ let $(Y_k : k \in K)$, be a fiber decomposition and set $X_k = X \cap \pi_I^{-1}(Y_k)$. For large enough \mathbb{G}/\mathbb{F} , the entropy profile satisfies

$$h_{\xi(\mathbb{G})}(I) = \sum_{\dim_{\mathbb{G}}(X_k) = \dim_{\mathbb{G}}(X)} \frac{\mu_{\mathbb{G}}(X_k)}{\mu_{\mathbb{G}}(X)} \log \left(\frac{\mu_{\mathbb{G}}(X) \mu_{\mathbb{G}}(Y_k)}{\mu_{\mathbb{G}}(X_k)} |\mathbb{G}|^{\dim_{\mathbb{G}}(Y_k)} \right) + \mathcal{O} \left(\frac{\log |\mathbb{G}|}{\sqrt{|\mathbb{G}|}} \right).$$

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- ▶ The sequence $\left(\frac{1}{\log |\mathbb{G}|} h_{\xi(\mathbb{G})} : \mathbb{G} \supseteq \mathbb{F} \right)$ has finitely many convergent subsequences and their (rational!) limits can all be computed.

Algebraic matroids

Theorem

Moreover, if X is an \mathbb{F} -irreducible algebraic variety, then there exists a tower of finite fields $\mathbb{F} = \mathbb{G}_0 \subseteq \mathbb{G}_1 \subseteq \dots$ with

$$\lim_{n \rightarrow \infty} \frac{1}{\log |\mathbb{G}_n|} h_{\xi(\mathbb{G}_n)}(I) = \dim \pi_I(X(\overline{\mathbb{F}})), \text{ for every } I \subseteq N.$$

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Corollary ([Mat24])

Algebraic matroids are almost-entropic.

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- ▶ Entropy profile can be seen as a “valuated” refinement of the algebraic matroid.

Example using Galois stratification

- ▶ To eliminate x from the variety defined by $x^3 + ax^2 + bx + c = 0$, stratify the triples (a, b, c) according to the number of rational roots of $f(a, b, c) \in \mathbb{F}[x]$.

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- ▶ The **Chebotarev density theorem** computes the density of triples with given conjugacy class \mathcal{C} :

$$\frac{|\mathcal{C}|}{[\Omega : \mathbb{F}(a, b, c)]} = \frac{|\mathcal{C}|}{6},$$

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Splitting type	$[1, 1, 1]$	$[1, 2]$	$[3]$	$[1, 1^2]$	$[1^3]$
Conjugacy class	id	$(1\ 2)$	$(1\ 2\ 3)$	—	—
Density	$1/6$	$3/6$	$2/6$	0	0
Rational roots	3	1	0	2	1

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