Monotonicity, thinning and discrete versions of the Entropy Power Inequality

Joint work with Yaming Yu - see arXiv:0909.0641

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Differential entropy h = − ∫ f(x) log f(x)dx has many nice properties.

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- Often Gaussian provides case of equality.

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- Focus on 3 such properties:

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 - 1. Maximum entropy

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- ▶ Will discuss discrete analogues for discrete entropy $H = \sum_{x} p(x) \log p(x)$.

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- ▶ Will discuss discrete analogues for discrete entropy $H = \sum_{x} p(x) \log p(x)$.
- Infinite divisibility suggests Poisson should be case of equality.

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Property 1: Maximum entropy

Theorem (Shannon 1948) If X has mean μ and variance σ and $Y \sim N(\mu, \sigma^2)$ then

 $h(X) \leq h(Y),$

with equality if and only if $X \sim N(\mu, \sigma^2)$.

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EPI

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Property 2: Entropy Power Inequality

• Define $\mathcal{E}(t) = h(N(0, t)) = \frac{1}{2} \log_2(2\pi e t)$.

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- Define $\mathcal{E}(t) = h(N(0, t)) = \frac{1}{2} \log_2(2\pi e t)$.
- Define entropy power $v(X) = \mathcal{E}^{-1}(h(X)) = 2^{2h(X)}/(2\pi e)$.

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Theorem (EPI)

Consider independent continuous X and Y. Then

$$v(X+Y) \geq v(X) + v(Y),$$

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

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- Lots of proofs (Stam/Blachman, Lieb, Dembo/Cover/Thomas, Tulino/Verdú/Guo).

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- First stated by Shannon.
- Lots of proofs (Stam/Blachman, Lieb, Dembo/Cover/Thomas, Tulino/Verdú/Guo).
- Restricted versions easier to prove? (cf Costa).

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Equivalent formulation

Theorem (ECI – not proved here!)

For independent X^* , Y^* with finite variance, for all $\alpha \in [0, 1]$,

$$h(\sqrt{\alpha}X^* + \sqrt{1-\alpha}Y^*) \ge \alpha h(X^*) + (1-\alpha)h(Y^*).$$

Lemma EPI is equivalent to ECI.

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Lemma EPI is equivalent to ECI.

Key role played in Lemma by fact about scaling:

$$v(\sqrt{\alpha}X) = \alpha v(X). \tag{1}$$

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Lemma

EPI is equivalent to ECI.

Key role played in Lemma by fact about scaling:

$$v(\sqrt{\alpha}X) = \alpha v(X). \tag{1}$$

This holds since
$$h(\sqrt{\alpha}X) = h(X) + \frac{1}{2}\log \alpha$$
, and $v(\sqrt{\alpha}X) = \frac{2^{2h(\sqrt{\alpha}X)}}{(2\pi e)}$.

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EPI

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▶ By the EPI (where $X = \sqrt{\alpha}X^*$ and $Y = \sqrt{1-\alpha}Y^*$) and scaling relation (1),

$$\begin{aligned} \mathsf{v}(\sqrt{\alpha}\mathsf{X}^* + \sqrt{1-\alpha}\mathsf{Y}^*) &\geq \mathsf{v}(\sqrt{\alpha}\mathsf{X}^*) + \mathsf{v}(\sqrt{1-\alpha}\mathsf{Y}^*) \\ &= \alpha\mathsf{v}(\mathsf{X}^*) + (1-\alpha)\mathsf{v}(\mathsf{Y}^*). \end{aligned}$$

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▶ Applying *E* to both sides and using Jensen (since *E* ~ log, so is concave):

$$\begin{split} h(\sqrt{\alpha}X^* + \sqrt{1-\alpha}Y^*) &\geq \mathcal{E}\bigg(\alpha v(X^*) + (1-\alpha)v(Y^*)\bigg) \\ &\geq \alpha \mathcal{E}(v(X^*)) + (1-\alpha)\mathcal{E}(v(Y^*)) \\ &= \alpha h(X^*) + (1-\alpha)h(Y^*) \end{split}$$

which is the ECI.

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EPI

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▶ For some α , define $X^* = X/\sqrt{\alpha}$ and $Y^* = Y/\sqrt{1-\alpha}$.

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- ► For some α , define $X^* = X/\sqrt{\alpha}$ and $Y^* = Y/\sqrt{1-\alpha}$.
- ▶ Then the ECI and scaling (1) imply that

$$\begin{split} h(X+Y) &= h(\sqrt{\alpha}X^* + \sqrt{1-\alpha}Y^*) \\ &\geq \alpha h(X^*) + (1-\alpha)h(Y^*) \\ &= \alpha \mathcal{E}(v(X^*)) + (1-\alpha)\mathcal{E}(v(Y^*)) \\ &= \alpha \mathcal{E}\left(\frac{v(X)}{\alpha}\right) + (1-\alpha)\mathcal{E}\left(\frac{v(Y)}{1-\alpha}\right) \end{split}$$

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- ► For some α , define $X^* = X/\sqrt{\alpha}$ and $Y^* = Y/\sqrt{1-\alpha}$.
- ▶ Then the ECI and scaling (1) imply that

$$h(X + Y) = h(\sqrt{\alpha}X^* + \sqrt{1 - \alpha}Y^*)$$

$$\geq \alpha h(X^*) + (1 - \alpha)h(Y^*)$$

$$= \alpha \mathcal{E}(v(X^*)) + (1 - \alpha)\mathcal{E}(v(Y^*))$$

$$= \alpha \mathcal{E}\left(\frac{v(X)}{\alpha}\right) + (1 - \alpha)\mathcal{E}\left(\frac{v(Y)}{1 - \alpha}\right)$$

► Pick $\alpha = \frac{v(X)}{v(X)+v(Y)}$ and the above inequality becomes $h(X + Y) \ge \mathcal{E}(v(X) + v(Y)),$

and applying \mathcal{E}^{-1} to both sides gives the EPI.

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Rephrased EPI

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Rephrased EPI

Note that this choice of α makes
v(X*) = v(Y*) = v(X) + v(Y).

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Rephrased EPI

• Note that this choice of α makes

$$v(X^*) = v(Y^*) = v(X) + v(Y).$$

This choice of scaling suggests the following rephrased EPI:

Corollary (Rephrased EPI)

Given independent X and Y with finite variance, there exist X^{*} and Y^{*} such that $X = \sqrt{\alpha}X^*$ and $Y = \sqrt{1-\alpha}Y^*$ for some α , and such that $h(X^*) = h(Y^*)$. The EPI is equivalent to the fact that

$$h(X+Y) \ge h(X^*), \tag{2}$$

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

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Property 3: Monotonicity

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Property 3: Monotonicity

 Exciting set of strong recent results, collectively referred to as 'monotonicity'.

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Property 3: Monotonicity

- Exciting set of strong recent results, collectively referred to as 'monotonicity'.
- First proved by Artstein/Ball/Barthe/Naor, alternative proofs by Tulino/Verdú and Madiman/Barron.

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Monotonicity theorem

Theorem

Given independent continuous X_i with finite variance, for any positive α_i such that $\sum_{i=1}^{n+1} \alpha_i = 1$, writing $\alpha^{(j)} = 1 - \alpha_j$, then

$$nh\left(\sum_{i=1}^{n+1}\sqrt{\alpha_i}X_i\right)\geq \sum_{j=1}^{n+1}\alpha^{(j)}h\left(\sum_{i\neq j}\sqrt{\alpha_i/\alpha^{(j)}}X_i\right).$$

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• Choosing $\alpha_i = 1/(n+1)$ for IID X_i shows $h\left(\sum_{i=1}^n X_i/\sqrt{n}\right)$ is monotone increasing in n.

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- Choosing $\alpha_i = 1/(n+1)$ for IID X_i shows $h\left(\sum_{i=1}^n X_i/\sqrt{n}\right)$ is monotone increasing in n.
- ► Equivalently relative entropy D (∑_{i=1}ⁿ X_i/√n || Z) is monotone decreasing in n.

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- Choosing $\alpha_i = 1/(n+1)$ for IID X_i shows $h\left(\sum_{i=1}^n X_i/\sqrt{n}\right)$ is monotone increasing in n.
- Equivalently relative entropy $D\left(\sum_{i=1}^{n} X_i / \sqrt{n} \| Z\right)$ is monotone decreasing in *n*.
- Means CLT is equivalent of 2nd Law of Thermodynamics?

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Monotonicity strengthens EPI

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Monotonicity strengthens EPI

By the right choice of α, monotonicity implies the following strengthened EPI.

Theorem (Strengthened EPI)

Given independent continuous Y_i with finite variance, the entropy powers satisfy

$$nv\left(\sum_{i=1}^{n+1}Y_i\right)\geq \sum_{j=1}^{n+1}v\left(\sum_{i\neq j}Y_i\right),$$

with equality if and only if all the Y_i are Gaussian.

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Discrete Property 1: Poisson maximum entropy

Definition

For any λ , define class of ultra-log-concave V with mass function p_V satisfying

 $\mathsf{ULC}(\lambda) = \{ V : \mathbb{E}V = \lambda \text{ and } p_V(i) / \Pi_{\lambda}(i) \text{ is log-concave} \}.$

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That is

$$ip_V(i)^2 \ge (i+1)p_V(i+1)p_V(i-1)$$
, for all *i*.

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, for all *i*.

Class includes Bernoulli sums and Poisson.

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Maximum entropy and $ULC(\lambda)$

Theorem (Johnson, Stoch. Proc. Appl. 2007) If $X \in ULC(\lambda)$ and $Y \sim \Pi_{\lambda}$ then

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

with equality if and only if $X \sim \Pi_{\lambda}$. (see also Harremoës, 2001)

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Definition

Given *Y*, define the α -thinned version of *Y* by

$$T_{\alpha}Y=\sum_{i=1}^{Y}B_{i},$$

where $B_1, B_2 \dots$ i.i.d. Bernoulli(α), independent of Y.

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Thinning has many interesting properties.

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- Thinning has many interesting properties.
- We believe T_{α} is the discrete equivalent of scaling by $\sqrt{\alpha}$.

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- Thinning has many interesting properties.
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- Preserves several parametric families.

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- Thinning has many interesting properties.
- We believe T_{α} is the discrete equivalent of scaling by $\sqrt{\alpha}$.
- Preserves several parametric families.
- 'Mean-preserving transform' $T_{\alpha}X + T_{1-\alpha}Y$ equivalent to 'variance-preserving transform' $\sqrt{\alpha}X + \sqrt{1-\alpha}Y$ in continuous case? (Matches max. ent. condition).

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- Define $V(X) = \mathcal{E}^{-1}(H(X))$.

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- Define $\mathcal{E}(t) = H(\Pi_t)$, an increasing, concave function.
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Conjecture

Consider independent discrete X and Y. Then

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

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Turns out not to be true!

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- Turns out not to be true!
- Even natural restrictions e.g. ULC, Bernoulli sums don't help
- Counterexample (not mine!): $X \sim Y$, $P_X(0) = 1/6$, $P_X(1) = 2/3$, $P_X(2) = 1/6$.

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Conjecture (TEPI)

Consider independent discrete ULC X and Y. For any α , conjecture that

$$V(T_{\alpha}X + T_{1-\alpha}Y) \geq \alpha V(X) + (1-\alpha)V(Y),$$

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• Again, not true in general!

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- Have partial results, but not full description of which α .

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- Again, not true in general!
- Perhaps not all α ?
- Have partial results, but not full description of which α .
- For example, true for Poisson Y with $H(Y) \leq H(X)$.

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Two weaker results

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Two weaker results

 Analogues of the continuous concavity and scaling results do hold. (Again, proofs not given here!)

Theorem (TECI, Johnson/Yu, ISIT '09) Consider independent ULC X and Y. For any α ,

$$H(T_{\alpha}X + T_{1-\alpha}Y) \geq \alpha H(X) + (1-\alpha)H(Y).$$

Theorem (RTEPI, Johnson/Yu, arXiv:0909.0641) Consider ULC X. For any α ,

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V(T_{\alpha}X) \geq \alpha V(X).
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Discrete EPI?

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Discrete EPI?

 Duplicating steps from the continuous case above, we deduce an analogue of rephrased EPI

Theorem (Johnson/Yu, arXiv:0909.0641)

Given independent ULC X and Y, suppose there exist X^{*} and Y^{*} such that $X = T_{\alpha}X^*$ and $Y = T_{1-\alpha}Y^*$ for some α , and such that $H(X^*) = H(Y^*)$. Then

$$H(X+Y) \ge H(X^*), \tag{3}$$

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

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• Write D(X) for $D(X || \Pi_{\mathbb{E}X})$.

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- Write D(X) for $D(X || \Pi_{\mathbb{E}X})$.
- By convex ordering arguments, Yu showed that for IID X_i :
 - 1. relative entropy $D\left(\sum_{i=1}^{n} T_{1/n} X_i\right)$ is monotone decreasing in *n*,
 - 2. for ULC X_i the entropy $H\left(\sum_{i=1}^{n} T_{1/n}X_i\right)$ is monotone increasing in n.

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- ▶ In fact, implicit in work of Yu is following stronger theorem:

Theorem

Given positive α_i such that $\sum_{i=1}^{n+1} \alpha_i = 1$, and writing $\alpha^{(j)} = 1 - \alpha_j$, then for any independent ULC X_i ,

$$nD\left(\sum_{i=1}^{n+1}T_{\alpha_i}X_i\right) \leq \sum_{j=1}^{n+1}\alpha^{(j)}D\left(\sum_{i\neq j}T_{\alpha_i/\alpha^{(j)}}X_i\right)$$

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Generalization of monotonicity

Theorem (Johnson/Yu, arXiv:0909.0641)

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Generalization of monotonicity

Theorem (Johnson/Yu, arXiv:0909.0641)

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$$nH\left(\sum_{i=1}^{n+1}T_{\alpha_i}X_i\right)\geq \sum_{j=1}^{n+1}\alpha^{(j)}H\left(\sum_{i\neq j}T_{\alpha_i/\alpha^{(j)}}X_i\right).$$

Exact analogue of Artstein/Ball/Barthe/Naor result,

$$nh\left(\sum_{i=1}^{n+1}\sqrt{\alpha_i}X_i\right)\geq\sum_{j=1}^{n+1}\alpha^{(j)}h\left(\sum_{i\neq j}\sqrt{\alpha_i/\alpha^{(j)}}X_i\right),$$

replacing scalings by thinnings.

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Future work

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Future work

• Resolve for which α , the

$$V(T_{\alpha}X + T_{1-\alpha}Y) \geq \alpha V(X) + (1-\alpha)V(Y).$$

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Monotonicity, thinning and discrete versions of the Entropy Power Inequality: Warwick Statistical Mechanics Seminar

Future work

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Relation to Shepp-Olkin conjecture

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Future work

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- Relation to Shepp-Olkin conjecture
- ► **Conjecture**: if there exist X^* and Y^* such that $X = T_{\alpha}X^*$ and $Y = T_{1-\alpha}Y^*$, where $\alpha = V(X)/(V(X) + V(Y))$, then

$$V(X+Y) \ge V(X) + V(Y).$$

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