

# Bounding Techniques for the Intrinsic Uncertainty of Channels

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- Calculating  $I(X; Y)$  is easy

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Want lower bounds on  $I(\mathbf{X}; \mathbf{Y})$  that are useful for such channels

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- Lower bound by replacing  $\mathcal{T}$  with some  $\mathcal{S} \supseteq \mathcal{T}$
- A simple choice is the **support**  $\mathcal{S} \triangleq \{(\mathbf{x}, \mathbf{y}) : P_{\mathbf{X}\mathbf{Y}}(\mathbf{x}, \mathbf{y}) > 0\}$

# Motivation

$$I(\mathbf{X}; \mathbf{Y}) \geq -\log \left( \mathbb{E}_{\mathbf{X}} \mathbb{E}_{\mathbf{Y}} \mathbb{1}_{\{(\mathbf{X}, \mathbf{Y}) \in \mathcal{S}\}} \right)$$

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- Gives reasonable results for certain “sparse” distributions

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Can we find better bounds that only involve marginals and support?

- Yes - replace  $\mathcal{S}$  with  $\bar{\mathcal{S}} \triangleq \{\mathbf{x} \in \mathcal{T}_{\mathbf{X}}, \mathbf{y} \in \mathcal{T}_{\mathbf{Y}} : P_{\mathbf{X}\mathbf{Y}}(\mathbf{x}, \mathbf{y}) > 0\}$

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[Diggavi & Grossglauser '01] [Drinea & Mitzenmacher '07]...

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## Main Result

$$I(\mathbf{X}; \mathbf{Y}) \geq -\mathbb{E}_{\mathbf{Y}} \log \mathbb{E}_{\mathbf{X}} \mathbb{1}_{\{(\mathbf{X}, \mathbf{Y}) \in \mathcal{S}\}} - \mathbb{E}_{\mathbf{X}} \log \mathbb{E}_{\mathbf{Y}} \frac{\mathbb{1}_{\{(\mathbf{X}, \mathbf{Y}) \in \mathcal{S}\}}}{\mathbb{E}_{\mathbf{X}} \mathbb{1}_{\{(\mathbf{X}, \mathbf{Y}) \in \mathcal{S}\}}}$$

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When is this bound useful?

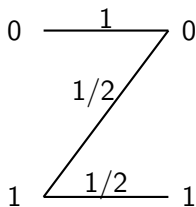


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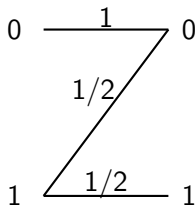
When is this bound useful?

- **Not for “fully-connected” channels:**  
All pairs  $(\mathbf{x}, \mathbf{y}) \in \mathcal{S}$  - the bound gives  $I(\mathbf{X}; \mathbf{Y}) \geq 0$
- Can be pretty good for channels with “low-connectivity”

# Example: Z-Channel



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### Bounds for IID $\text{Ber}(p)$ Input

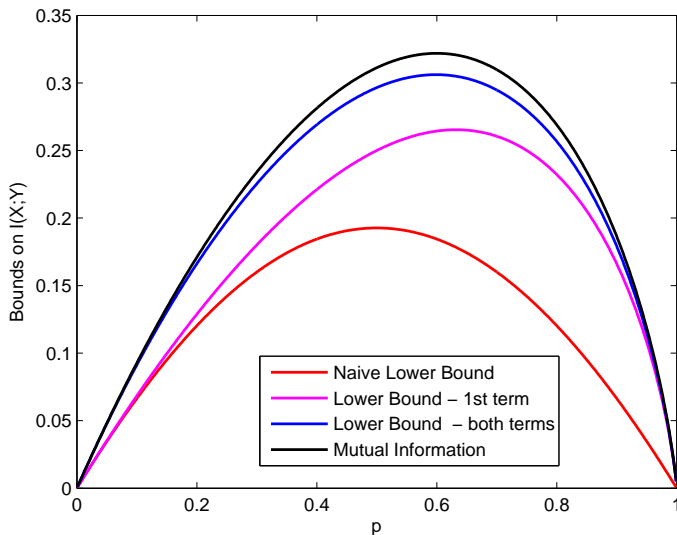
- Mutual information:  $I(X; Y) = H\left(\frac{1}{2}(1+p)\right) - (1-p)$
- Naive bound:

$$I(X, Y) \geq \log(\mathbb{E}_X \mathbb{E}_Y \mathbb{1}_{\{(X, Y) \in \mathcal{S}\}}) = -\frac{1}{2} \log\left(1 - \frac{p}{2}(1-p)\right)$$

- Our bound:

$$I(X, Y) \geq -\frac{1}{2}(1-p) \log(1-p) - p \log\left(\frac{1}{2}(1+p)\right) - (1-p) \log\left(\frac{1}{2}(2+p)\right)$$

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## Channels via Conditional Probability

- Channel  $\Leftrightarrow$  Conditional distribution  $P_{Y|X}$
- Input alphabet  $\mathcal{X}^n$
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## Channels via Actions (Functional Representation Lemma)

- $P_{\mathbf{A}}$  - a distribution over mappings  $\mathcal{X}^n \mapsto \mathcal{Y}^*$
- Channel  $\Leftrightarrow$  Action  $\mathbf{A} \sim P_{\mathbf{A}}, \mathbf{A} \perp\!\!\!\perp \mathbf{X}$

$$\mathbf{Y} = \mathbf{A}(\mathbf{X})$$

- The choice of  $P_{\mathbf{A}}$  is not unique

## The Intrinsic Uncertainty

- Input distribution  $P_{\mathbf{X}}$
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## Capacity

$$\begin{aligned} I(\mathbf{X}; \mathbf{Y}) &= H(\mathbf{Y}) - H(\mathbf{Y}|\mathbf{X}) \\ &= H(\mathbf{Y}) - (H(\mathbf{Y}, \mathbf{A}|\mathbf{X}) - H(\mathbf{A}|\mathbf{X}, \mathbf{Y})) \\ &= H(\mathbf{Y}) - H(\mathbf{A}|\mathbf{X}) - H(\mathbf{Y}|\mathbf{A}, \mathbf{X}) + H(\mathbf{A}|\mathbf{X}, \mathbf{Y}) \\ &= H(\mathbf{Y}) - H(\mathbf{A}) + H(\mathbf{A}|\mathbf{X}, \mathbf{Y}) \end{aligned}$$

- Lower bounding the intrinsic uncertainty = lower bounding MI



# Examples for Action Sets and Intrinsic Uncertainty

## The Binary Symmetric Channel

- Action  $\Leftrightarrow$  IID Noise sequence  $\mathbf{W} \sim \text{Ber}(p)$
- $\mathbf{Y} = \mathbf{A}(\mathbf{X}) = \mathbf{X} \oplus \mathbf{W}$
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## The Z-Channel

- Action  $\Leftrightarrow$  IID Noise sequence  $\mathbf{W} \sim \text{Ber}(\frac{1}{2})$
- $Y_i = \{\mathbf{A}(\mathbf{X})\}_i = \begin{cases} X_i & X_i = 0 \\ X_i \oplus W_i & X_i = 1 \end{cases}$
- Action masked when  $X_i = 0 \Rightarrow H(\mathbf{A}|\mathbf{X}, \mathbf{Y}) > 0$

# Examples for Action Sets and Intrinsic Uncertainty

## The Binary Deletion Channel

- Deletes bits independently with probability  $d$
- Action  $\Leftrightarrow$  IID deletion pattern  $\mathbf{W} \sim \text{Ber}(d)$
- $\mathbf{X} \mapsto \mathbf{Y}$  via many different actions  $\Rightarrow H(\mathbf{A}|\mathbf{X}, \mathbf{Y}) > 0$
- For example:  $\mathbf{x} = 01100$  and  $\mathbf{y} = 110$

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## Other Channels with memory and positive intrinsic uncertainty

- Insertion channel
- Trapdoor channel
- Permutation channels
- ....

# Main Tool

We would like to lower bound the intrinsic uncertainty

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## Variational Principle [Dupuis & Ellis]

For any distribution  $P$  and function  $f(x)$  s.t.  $|\mathbb{E}_P \log f(X)| < \infty$ ,

$$\mathbb{E}_P \log f(X) = \min_Q (\log \mathbb{E}_Q f(X) + D(P||Q))$$

The minimum is uniquely attained by

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In our case  $f = 1/P(\mathbf{A}|\mathbf{X}, \mathbf{Y})$

# A General Bound

Using the variational principle + chain rule of relative entropy + convexity of relative entropy

## Theorem

The intrinsic uncertainty is lower bounded by

$$H(\mathbf{A}|\mathbf{X}, \mathbf{Y}) \geq -H(\mathbf{Y}) - \mathbb{E}_{\mathbf{Y}} \log \mathbb{E}_{\mathbf{X}, \mathbf{A}} P(\mathbf{A}|\mathbf{X}, \mathbf{Y}) \\ - \mathbb{E}_{\mathbf{X}, \mathbf{A}} \log \mathbb{E}_{\mathbf{Y}} \frac{P(\mathbf{A}|\mathbf{X}, \mathbf{Y})}{E_{\mathbf{X}, \mathbf{A}} P(\mathbf{A}|\mathbf{X}, \mathbf{Y})}$$

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- For BSC certain choices of  $P_{\mathbf{A}}$  yield tight bounds and other choices yield  $I(\mathbf{X}; \mathbf{Y}) \geq 0$

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For a certain choice of  $P_{\mathbf{A}}$  the bound becomes much simpler...

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## Definition

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For channels with uniform action set:

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where

$$\mathcal{S} \triangleq \{(\mathbf{x}, \mathbf{y}) : \exists \mathbf{a} \in \mathcal{A} \text{ s.t. } \mathbf{a}(\mathbf{x}) = \mathbf{y}\} = \{(\mathbf{x}, \mathbf{y}) : P_{\mathbf{X}\mathbf{Y}}(\mathbf{x}, \mathbf{y}) > 0\}$$

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## Proof

- Let  $\mathcal{A} = \{\mathbf{a}_1, \dots, \mathbf{a}_{|\mathcal{A}|}\}$  be some action set
- $P_{\mathbf{A}}$  is a probability assignment on  $\mathcal{A}$  consistent with  $P_{\mathbf{Y}|\mathbf{X}}$
- Duplicate each action  $\mathbf{a}_i$  to  $M_i$  identical actions with equal probabilities  $\frac{P_{\mathbf{A}}(\mathbf{a}_i)}{M_i}$
- Choose the  $M_i$ s such that all actions in the extended set are equiprobable

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## Proposition

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## Corollary (Our Main Result)

For any joint distribution  $P_{\mathbf{X}\mathbf{Y}}$

$$I(\mathbf{X}; \mathbf{Y}) \geq -\mathbb{E}_{\mathbf{Y}} \log \mathbb{E}_{\mathbf{X}} \mathbb{1}_{\{(\mathbf{X}, \mathbf{Y}) \in \mathcal{S}\}} - \mathbb{E}_{\mathbf{X}} \log \mathbb{E}_{\mathbf{Y}} \frac{\mathbb{1}_{\{(\mathbf{X}, \mathbf{Y}) \in \mathcal{S}\}}}{\mathbb{E}_{\mathbf{X}} \mathbb{1}_{\{(\mathbf{X}, \mathbf{Y}) \in \mathcal{S}\}}}$$

where  $\mathcal{S} \triangleq \{(\mathbf{x}, \mathbf{y}) : P_{\mathbf{X}\mathbf{Y}}(\mathbf{x}, \mathbf{y}) > 0\}$ .

# Example: Binary Deletion Channel

## Capacity

- Only bounds are known
- Best lower bounds use input with memory [*Diggavi & Grossglauser '01*] [*Drinea & Mitzenmacher '07*] [*Kirsch & Drinea '10*] ...
- Some implicitly analyze the first summand in our bound

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## Rates for a memoryless input

- Only bounds are known
- $1 - H_2(d)$  achievable for  $d \in [0, \frac{1}{2})$  [*Gallager '61*]
- Recently improved for
  - ▶ Small  $d$  [*Rahmati & Duman '13*]
  - ▶  $d \rightarrow 0$  [*Kanoria & Montanari '13*] [*Drmotič et al '12*]
- And our bound?

# Example: Binary Deletion Channel

## New Bound (Memoryless Input)

$$\lim_{n \rightarrow \infty} \frac{1}{n} I(\mathbf{X}; \mathbf{Y}) \geq 1 - H_2(d) + g(d)$$

where  $g(d) > 0$  for all  $d \in (0, \frac{1}{2})$ , and is given by

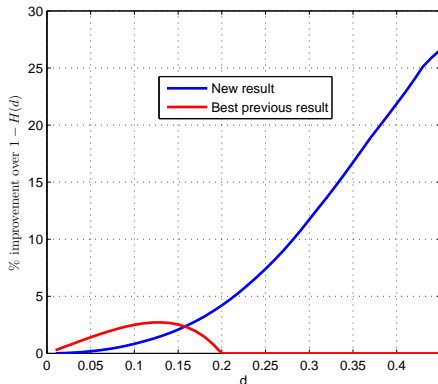
$$g(d) = \min_{\alpha \in [0,1]} (D_2(\alpha \| 1-d) - (1 - H_2(\langle \alpha \rangle)) + \Lambda^*(\alpha))$$

$$\Lambda^*(\alpha) = \max_{t > 0} \left( \alpha t - \frac{1}{5} \sum_{k_1} \sum_{k_2} 2^{-(k_1+k_2-1)} \log \lambda_{Z_{k_1, k_2}}(t) \right)$$

$$\lambda_{Z_i}^{k_1, k_2}(t) = 2^{k_1(t-1)} + 2^{t-1} \frac{1 - 2^{k_1(t-1)}}{1 - 2^{t-1}} \left( 2^{t-1} \frac{1 - 2^{k_2(t-1)}}{1 - 2^{t-1}} + 2^{k_2(t-1)-t} \right)$$

# Example: Binary Deletion Channel

% improvement over Gallager's bound  $1 - H_2(d)$  (IID input):



# Concluding Remarks

## Summary

- Novel lower bound on  $I(\mathbf{X}; \mathbf{Y})$  that depends only on  $P_{\mathbf{X}}, P_{\mathbf{Y}}$  and the support of  $P_{\mathbf{X}\mathbf{Y}}$
- Bound is useful for channels with memory and low-connectivity
- Main tool: The Variational Principle
- For the deletion channel with IID input our bound improves best existing bounds (for some regime of  $d$ )

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## Future Research

- Evaluate bound for different inputs and different channels, e.g., deletion with Markov input, trapdoor channels, etc...
- Can improve the bound to better trade-off complexity and accuracy: Replace  $\mathcal{S}$  with a subset of the support whose probability approaches 1



**Thanks for your attention!**