

# Distributed Compression, the Information Bottleneck and Cloud Radio Access Networks: A Unified Information Theoretic View

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# Outline

- \* **Information Bottleneck:**

- \* **Connections:**

- Remote Source Coding.
- Common Reconstruction.
- Information Combining.
- Wyner-Ahlsvede-Korner Problem.
- Efficiency of Investment Information.

- \* **Distributed Information Bottleneck:**

- CEO Source Coding Problem under Log-Loss.
- Oblivious Relay Processing, CRAN.
- Distributed Information Bottleneck for Learning.

- \* **Some Perspectives**

- \* **References**

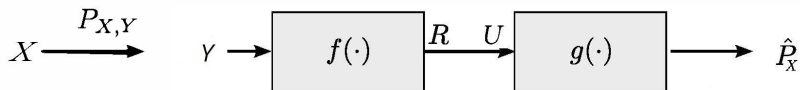
# Information Bottleneck



- Efficiency of a given representation  $U = f(Y)$  measured by the pair  
**Rate** (or *Complexity*):  $I(U; Y)$  and **Information** (or *Relevance*):  $I(U; X)$
- Information  $I(X; U)$  can be achieved by OBLIVIOUS coding  $Y$  while with the logarithmic distortion with respect to  $X$
- Single letter-wise,  $U$  is not necessarily a deterministic function of  $Y$
- The non-oblivious bottleneck problem is immediate as the  $\min(I(X; Y), R)$  is achievable by having the relay decoding the message transmitted by  $X$
- The bottleneck problem connects to many timely aspects, such as 'deep learning' [Tishby-Zaslavsky, ITW'15].

# Digression: Learning via the Information Bottleneck Method

Limited Complexity



Features    Observation    Encoder    Decoder    Estimate

- Preserving all the information about  $X$  that is contained in  $Y$ , i.e.,  $I(X; Y)$ , requires high *complexity* (in terms of *minimum description coding length*).
  - Other measures of complexity may be (Vapnik-Chervonenkis) VC-dimension, covering numbers, ..

- Efficiency of a given representation  $\mathbf{U} = f(\mathbf{Y})$  measured by the pair

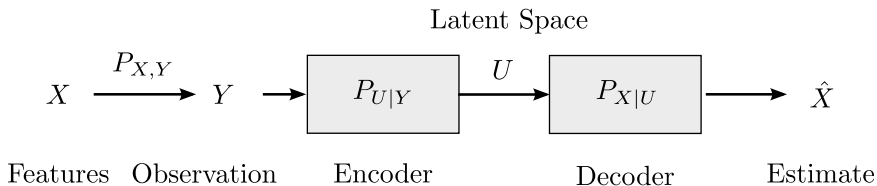
**Complexity:**  $I(U; Y)$                       and                      **Relevance:**  $I(U; X)$

- Example:

$$\max_{p(u|x)} I(U; X) \quad \text{s.t.} \quad I(U; Y) \leq R, \quad \text{for} \quad 0 \leq R \leq H(Y)$$

$$\min_{p(u|x)} I(U; Y) \quad \text{s.t.} \quad I(U; X) \geq \Delta, \quad \text{for} \quad 0 \leq \Delta \leq I(X; Y)$$

# Basically, a Remote Source Coding Problem !



- Reconstruction at decoder is under log-loss measure,

$$R(\Delta) = \min_{p(u|y)} I(U; Y)$$

where the minimization is over all conditional pmfs  $p(u|y)$  such that

$$\mathbb{E}[\ell_{\log}(X, U)] \leq H(X) - H(X|U) = H(X) - \Delta$$

- R. L. Dobrushin and B. S. Tsybakov, "Information transmission with additional noise", IRE Tran. Info. Theory, Vol. IT-8, pp. 293-304, 1962.

- H. Witsenhausen, A. Wyner, "A conditional entropy bound for a pair of discrete random variables", IEEE Trans. on Info. Theory, Vol. 21, pp. 493-501, 1975.

- Solution also coined as the Information Bottleneck Method [Tishby'99]

$$L_{\text{IB}}(\beta, P_{X,Y}) = \min_{p(u|y)} I(Y; U) - \beta I(X; U)$$

# Other Connections

- **The Efficiency of Investment Information**

- $X$  - Stock Market Data.

- $Y$  - Correlated Information about  $X$ .

- $\Delta(R)$  the maximum increase in growth rate when  $Y$  is described to the investor at rate  $R$  (a logarithmic distortion that relates to the Wyner-Ahlsvede-Korner Problem).

- Solution of the bottleneck for:  $(X, Y)$  are binary and  $(X, Y)$  Gaussian (horse race examples).

- E. Erkip and T. M. Cover, "The Efficiency of Investment Information", IEEE Trans. on Info. Theory, Vol. 44, May 1998.

## Other Connections (Cont.)

- **Common Reconstruction.** Because  $X \oplus Y \oplus U$ , we have

$$\begin{aligned} I(U; X) &= I(U; Y) - I(U; Y|X) \\ &\leq R - I(U; Y|X) \end{aligned}$$

- Y. Steinberg, “Coding and common reconstruction”, IEEE Trans. on Info. Theory, vol. 55, no. 11, pp. 4995–5010, Nov. 2009 ( $X$  – side information is not used for the ‘source’  $Y$  common reconstruction).
- \* Heegard-Berger Problem with Common Reconstruction:  $Y$ -source, to be commonly reconstructed (with logarithmic distortion), with and without side information ( $X$ ), as to maximize  $I(U; X)$ .
- M. Benammar, A. Zaidi, “Rate-Distortion of a Heegard-Berger Problem with Common Reconstruction Constraint,” IZS, March 2–4, 2016.

## Other Connections (Cont.)

- **Information Combining**

$$I(Y; U, X) = I(U; Y) + I(X; Y) - I(U; X) \quad (\text{since } X \oplus Y \oplus U)$$

Since  $I(X; Y)$  is given and  $I(Y; U) = R$ , maximizing  $I(U; X)$  is equivalent to minimizing  $I(Y; U, X)$ .

- I. Sutskever, S. Shamai and J. Ziv, "Extremes of Information Combining", IEEE Trans. Inform. Theory, vol. 51, no. 4, pp. 1313–1325, April 2005.
- I. Land and J. Huber, "*Information combining*," Foundations and trends in Commun. and Inform. Theory, vol. 3, pp. 227–330, Nov. 2006.



## Other Connections (Cont.)

- **Elegant Proofs of Classical Bottleneck Results**

- $X, Y$  binary symmetric connected through a Binary Symmetric Channel (error probability  $e$ ):  $U$ - $Y$ , **also a BSC**,  $I(U; X) = \{1 - h(e^*v)\}$  where  $e^*v = e(1 - v) + v(1 - e)$ ,  $R = 1 - h(v)$ .

Directly extends to  $X - Y$  symmetric, where  $Y$  is symmetric binary (one bit output quantization).

- $X$  standard Gaussian, and  $Y = \sqrt{\text{snr}}X + N$  ( $N$  standard Gaussian).  
Elegant proof via I-MMSE [Guo-Shamai-Verdu, FnT'13].

$$I(U; X) = \frac{1}{2} \log(1 + \text{snr}) - \frac{1}{2} \log\left(1 + \text{snr} \exp(-2R)\right)$$

## Other Connections (Cont.)

**Proof:**

$$\min I(Y; X, U) \text{ subject to: } I(Y; U) = R .$$

Let

$$\tilde{X} = \sqrt{1 + \text{snr}} X = \sqrt{\beta} Y + M , \quad \begin{array}{l} M \sim N(0, 1) \\ M \perp Y \end{array}$$

$$\beta = \text{snr} / (1 + \text{snr})$$

$$I(Y; X, U) = I(Y; \tilde{X}, U) = I(Y; U) + I(Y; \tilde{X} | U)$$

$$I(Y; X | U) = I(Y; \tilde{X} | U) = \frac{1}{2} \int_0^\beta \text{mmse}(Y : \gamma, U) d\gamma$$

$$\text{mmse}(Y : \gamma, U) = E \left( Y - E(Y | \sqrt{\gamma} Y + M, U) \right)^2$$

## Other Connections (Cont.)

- **I-MMSE + Single Crossing Property**

[Guo-Shamai-Verdú, FnT'13]  $\Rightarrow$

$$\begin{aligned}\frac{1}{2} \int_0^\beta \text{mmse}(Y : \gamma, U) d\gamma &= \frac{1}{2} \int_0^\beta \frac{\rho\sigma_{Y|U}^2}{1 + \gamma\rho\sigma_{Y|U}^2} d\gamma \\ &= \frac{1}{2} \log(1 + \beta\rho\sigma_{Y|U}^2)\end{aligned}$$

$$\underline{0 \leq \rho \leq 1}, \quad \sigma_{Y|U}^2 = E\left(Y - E(Y|U)\right)^2 = \text{mmse}(Y : 0, U)$$

## Other Connections (Cont.)

$$R = I(Y; U) = h(Y) - h(Y|U)$$

$$h(Y) = \frac{1}{2} \log(2\pi \exp(\text{snr} + 1))$$

$$h(Y|U) = \frac{1}{2} \int_0^\infty \left( \text{mmse}(Y : \gamma, U) - \frac{1}{2\pi\rho + \gamma} \right) d\gamma$$

single crossing point  $\leq$

$$\frac{1}{2} \int_0^\infty \left( \frac{\rho\sigma_{Y|U}^2}{1 + \gamma\rho\sigma_{Y|U}^2} - \frac{1}{2\pi e + \gamma} \right) d\gamma$$

## Other Connections (Cont.)

$$\Rightarrow \rho \sigma_{Y|U}^2 \geq \exp(-2R) (1 + \text{snr})$$

$$\begin{array}{l} \Rightarrow \\ \text{information} \\ \text{combining} \end{array} \quad I(Y; X, U) = I(Y; \tilde{X}, U) \geq R + \frac{1}{2} \log\left(1 + \text{snr} \exp(-2R)\right)$$

$$\begin{array}{l} \Rightarrow \\ \text{bottleneck} \end{array} \quad I(X; U) \leq \frac{1}{2} \log(1 + \text{snr}) - \frac{1}{2} \log\left(1 + \text{snr} \exp(-2R)\right)$$

- Directly extends to the Gaussian vector case, where the vector version of the single crossing point [Bustin-Payaro-Palomar-Shamai, IT13] is used.

## Other Connections (Cont.)

- **Wyner-Ahlsvede-Körner Problem**

If  $X$  and  $Y$  are encoded at rates  $R_X$  and  $R_Y$ , respectively. For given  $R_Y = R$ , the minimum rate  $R_X$  that is needed to recover  $X$  losslessly is

$$R_X^*(R) = \min_{p(u|y) : I(U;Y) \leq R} H(X|U)$$

So, we get

$$\max_{p(u|y) : I(U;Y) \leq R} I(U;X) = H(X) - R_X^*(R)$$

- R. F. Ahlsvede and J. Korner, "Source coding with side information and a converse for degraded broadcast channels", IEEE Trans. on Info. Theory, Vol. 21, pp. 629-637, 1975.
- A. D. Wyner, "On source coding with side information at the decoder", IEEE Trans. on Info. Theory, Vol. 21, pp. 294-300, 1975.

# Vector Gaussian Information Bottleneck

- $(\mathbf{X}, \mathbf{Y})$  jointly Gaussian,  $\mathbf{X} \in \mathbb{R}^N$  and  $\mathbf{Y} \in \mathbb{R}^M$
- Optimal encoding  $P_{U|Y}$  is a noisy linear projection to a subspace whose dimensionality is determined by the bottleneck Lagrangian multiplier  $\beta$   
[Chechik-Globerson-Tushby-Weiss, '05]

$$\mathbf{U} = \mathbf{A}\mathbf{Y} + \mathbf{Z}, \quad \mathbf{Z} \sim \mathcal{N}(\mathbf{0}, \mathbf{I})$$

where

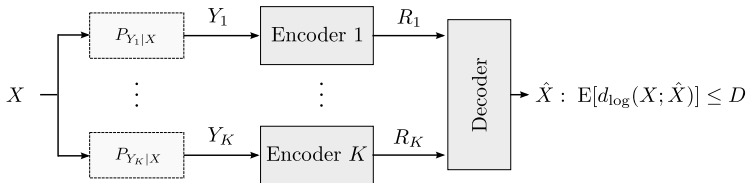
$$\mathbf{A} = \begin{cases} [\mathbf{0}^T; \dots; \mathbf{0}^T], & \text{if } 0 \leq \beta \leq \beta_1^c \\ [\alpha_1 \mathbf{v}_1^T; \mathbf{0}^T; \dots; \mathbf{0}^T], & \text{if } \beta_1^c \leq \beta \leq \beta_2^c \\ [\alpha_1 \mathbf{v}_1^T; \alpha_2 \mathbf{v}_2^T; \mathbf{0}^T; \dots; \mathbf{0}^T], & \text{if } \beta_2^c \leq \beta \leq \beta_3^c \\ \vdots & \end{cases}$$

and  $\{\mathbf{v}_1^T, \dots, \mathbf{v}_N^T\}$  are the left eigenvectors of  $\Sigma_{y|x} \Sigma_y^{-1}$ , sorted by their ascending eigenvalues  $\{\lambda_1, \dots, \lambda_N\}$ ;  $\beta_i^c = 1/(1 - \lambda_i)$  are critical  $\beta$  values;  $r_i = \mathbf{v}_i^T \Sigma_y \mathbf{v}_i$  and

$$\alpha_i = \sqrt{\frac{\beta(1 - \lambda_i) - 1}{\lambda_i r_i}}$$

Rate-Information Trade-off Gaussian Vector Channel [Winkelbauer-Matz, ISIT'14].

# CEO Source Coding Problem under Log-Loss



- CEO source coding problem under log-loss distortion:

$$d_{\log}(x, \hat{x}) := \log\left(\frac{1}{\hat{x}(x)}\right)$$

where  $\hat{x} \in \mathcal{P}(\mathcal{X})$  is a probability distribution on  $\mathcal{X}$ .

- Characterization of rate-distortion region in [Courtade-Weissman'14]
  - Key step: log-loss admits a lower bound in the form of conditional entropy of the source conditioned on the compression indices:

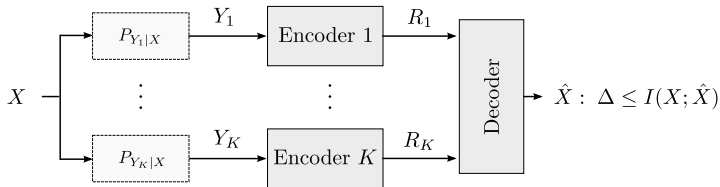
$$nD \geq E[d_{\log}(X^n; \hat{X}^n)] \geq H(X^n | J_{\mathcal{X}}) = H(X^n) - I(X^n; J_{\mathcal{X}})$$



## CEO Source Coding Problem under Log-Loss (Cont.)

- Converse of Theorem 1 for Oblivious CRAN leverages on this relation applied to multiple channel inputs, which can be designed.  
Multiple description CEO problem-logloss distortion [Pichler-Piantanida-Matz, ISIT'17].
- Vector Gaussian CEO Problem Under Logarithmic Loss and Applications [Ugur-Aguerri-Zaidi, arxiv:1811.03933]: Accounts also for Gaussian side information about the source at the decoder.
  - Full characterization (not the case for MMSE Distortion, [Ekrem-Ulukos, IT0214]).
- Implications [Ugur-Aguerri-Zaidi, arxiv:1811.03933] Solutions of:
  - Vector Gaussian distributed hypothesis testing against conditional independence [Rahman-Wagner, IT2012].
  - A quadratic vector Gaussian CEO problem with determinant constraint.
  - Vector Gaussian distributed Information Bottleneck Problem.

# Distributed Information Bottleneck



- Information Bottleneck introduced by [Tishby'99] and [Witsenhausen'80] "Indirect Rate Distortion Problems", IT-26, no. 5, pp. 518–521, Sept. 1980.
- It is a CEO source-coding problem under log-loss!

Theorem (Distributed Information Bottleneck [ Estella-Zaidi, IZS'18 ])

The  $D$ -IB region is the set of all tuples  $(\Delta, R_1, \dots, R_K)$  which satisfy

$$\Delta \leq \sum_{k \in \mathcal{S}} [R_k - I(Y_k; U_k | X, Q)] + I(X; U_{\mathcal{S}^c} | Q), \quad \text{for all } \mathcal{S} \subseteq \mathcal{K}$$

for some joint pmf  $p(q)p(x) \prod_{k=1}^K p(y_k|x) \prod_{k=1}^K p(u_k|y_k, q)$ .

# Vector Gaussian Distributed Information Bottleneck

- $(\mathbf{Y}_1, \dots, \mathbf{Y}_K, \mathbf{X})$  jointly Gaussian,  $\mathbf{Y}_k \in \mathbb{R}^N$  and  $\mathbf{X} \in \mathbb{R}^M$ ,

$$\mathbf{Y}_k = \mathbf{H}_k \mathbf{X} + \mathbf{N}_k, \quad \mathbf{N}_k \sim \mathcal{N}(\mathbf{0}, \Sigma_{\mathbf{n}_k})$$

- Optimal encoding  $P_{U_k|Y_k}^*$  is Gaussian and  $Q = \emptyset$  [Estella-Zaidi'17]

Theorem ([Estella-Zaidi, IZS'18], [Ugur-Aguerri-Zaidi, arxiv:1811.03933] )

If  $(\mathbf{X}, \mathbf{Y}_1, \dots, \mathbf{Y}_K)$  are jointly Gaussian, the D-IB region is given by the set of all tuples  $(\Delta, R_1, \dots, R_L)$  satisfying that for all  $\mathcal{S} \subseteq \mathcal{K}$

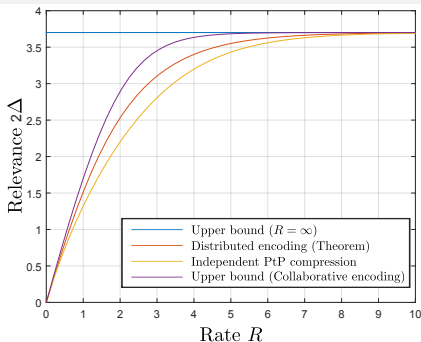
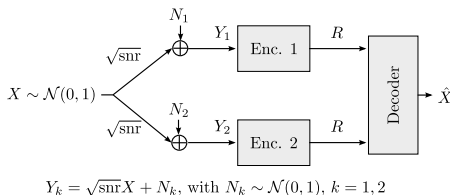
$$\Delta \leq \sum_{k \in \mathcal{S}} [R_k + \log |\mathbf{I} - \mathbf{B}_k|] + \log \left| \sum_{k \in \mathcal{S}^c} \bar{\mathbf{H}}_k^H \mathbf{B}_k \bar{\mathbf{H}}_k + \mathbf{I} \right|$$

for some  $\mathbf{0} \preceq \mathbf{B}_k \preceq \mathbf{I}$ , where  $\bar{\mathbf{H}}_k = \Sigma_{\mathbf{n}_k}^{-1/2} \mathbf{H}_k \Sigma_{\mathbf{x}}^{1/2}$ , and achievable with

$$p^*(\mathbf{u}_k | \mathbf{y}_k, q) = \mathcal{CN}(\mathbf{y}_k, \Sigma_{\mathbf{n}_k}^{1/2} (\mathbf{B}_k - \mathbf{I}) \Sigma_{\mathbf{n}_k}^{1/2})$$

- Reminiscent of the sum-capacity in Gaussian Oblivious CRAN with Constant Gaussian Input constraint.

# Example



- Optimal information (relevance):

$$\Delta^*(R, \text{snr}) = \frac{1}{2} \log \left( 1 + 2 \text{snr} \exp(-4R) \left( \exp(4R) + \text{snr} - \sqrt{\text{snr}^2 + (1 + 2 \text{snr}) \exp(4R)} \right) \right)$$

- Collaborative encoding upper bound:  $(Y_1, Y_2)$  encoded at rate  $2R$

$$\Delta_{\text{ub}}(R, \text{sr}) = \frac{1}{2} \log(1 + 2 \text{snr}) - \frac{1}{2} \log(1 + 2 \text{snr} \exp(-4R))$$

- Lower bound:  $Y_1$  and  $Y_2$  independently encoded

$$\Delta_{\text{lb}}(R, \text{snr}) = \frac{1}{2} \log(1 + 2 \text{snr} - \text{snr} \exp(-2R)) - \frac{1}{2} \log(1 + \text{snr} \exp(-2R))$$

# The Cost of Oblivious Processing: an Example

## Cut-Set Bound

$$\sum (R, \text{snr}) = \min \left\{ 2R, \frac{1}{2} \log(1 + 2\text{snr}), R + \frac{1}{2} \log(1 + \text{snr}) \right\}$$

- **Improved Upper Bound:** geometric analysis of typical sets

[Wu-Ozgun-Peleg-Shamai, ITW'19]

There exists:  $\theta \in E[\arcsin(2^{-R}), \pi/2]$  such that:

$$\sum (R, \text{snr}) \leq \frac{1}{2} \log(1 + \text{snr}) + R + \log \sin \theta,$$

$$\sum (R, \text{snr}) \leq \frac{1}{2} \log(1 + \text{snr}) + \min_{\omega \in \left[\frac{\pi}{2} - \theta, \frac{\pi}{2}\right]} h(\omega; \theta)$$

$$\sum (R, \text{snr}) \leq 2R + 2 \log \sin \theta$$

where

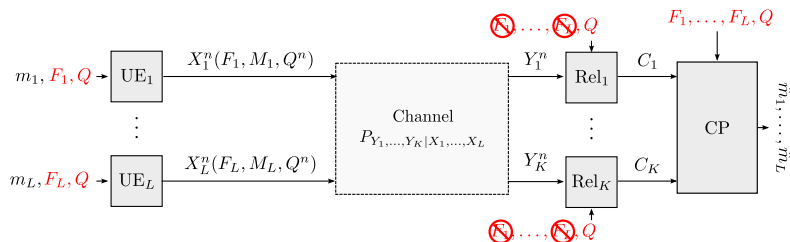
$$h(\omega; \theta) = \frac{1}{2} \log \left( \frac{[2\text{snr} + \sin^2 \omega - 2\text{snr} \cos \omega] \sin^2 \theta}{(\text{snr} + 1)(\sin^2 \theta - \cos^2 \theta)} \right).$$

# The Cost of Oblivious Processing: an Example Cut-Set Bound (Cont).

- **Achievable Scheme**

- \* Optimization (optimized time sharing)
- Fully decode & forward (both relays decode) & rate splitting over the fronthaul links.
- Optimal oblivious processing (distributed source coding under logarithmic loss).
- Capacity achieving for:  $2R \leq \frac{1}{2} \log(1 + \text{snr})$ .

# Oblivious Relay Processing-CRAN System



- Resource-sharing random variable  $Q^n$  available at all terminals [Simeone et al'11].
- $Q^n$  way easier to share, (e.g., on/off activity ).

• Memoryless Channel:  $P_{Y_1, \dots, Y_K | X_1, \dots, X_L}$

• User  $l \in \{1, \dots, L\}$ :  $\phi_l^n : [1, |\mathcal{X}_l|^{n2^{nR_l}}] \times [1, 2^{nR_l}] \times \mathcal{Q}^n \rightarrow \mathcal{X}_l^n$

• Relay  $k \in \{1, \dots, K\}$ :  $g_k^n : \mathcal{Y}_k^n \times \mathcal{Q}^n \rightarrow [1, 2^{nC_k}]$

• Decoder:

$\psi^n : [1, |\mathcal{X}_1|^{n2^{nR_1}}] \times \dots \times [1, 2^{nC_K}] \times \mathcal{Q}^n \rightarrow [1, 2^{nR_1}] \times \dots \times [1, 2^{nR_L}]$

# Capacity Region of a Class of CRAN Channels

Theorem (Aguerri-Zaidi-Caire-Shamai 'IT19)

For the class of discrete memoryless channels satisfying

$$Y_k \text{ --- } X_{\mathcal{L}} \text{ --- } Y_{\mathcal{K} \setminus k}$$

with oblivious relay processing and enabled resource-sharing, a rate tuple  $(R_1, \dots, R_L)$  is achievable if and only if for all  $\mathcal{T} \subseteq \mathcal{L}$  and for all  $\mathcal{S} \subseteq \mathcal{K}$ ,

$$\sum_{t \in \mathcal{T}} R_t \leq \sum_{s \in \mathcal{S}} [C_s - I(Y_s; U_s | X_{\mathcal{L}}, Q)] + I(X_{\mathcal{T}}; U_{\mathcal{S}^c} | X_{\mathcal{T}^c}, Q),$$

for some joint measure of the form

$$P_Q \prod_{l=1}^L P_{X_l | Q} \prod_{k=1}^K P_{Y_k | X_{\mathcal{L}}} \prod_{k=1}^K P_{U_k | Y_k, Q},$$

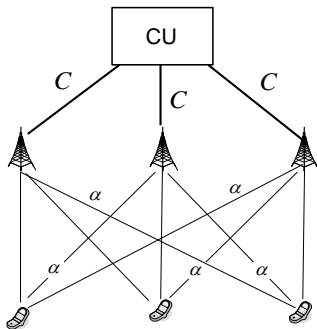
with the cardinality of  $Q$  bounded as  $|Q| \leq K + 2$ .

$\Rightarrow$  Equivalent to Noisy Network Coding [Lim-Kim-El Gamal-Chung, IT '11].



## Numerical Example

- Three-cell SISO circular Wyner model



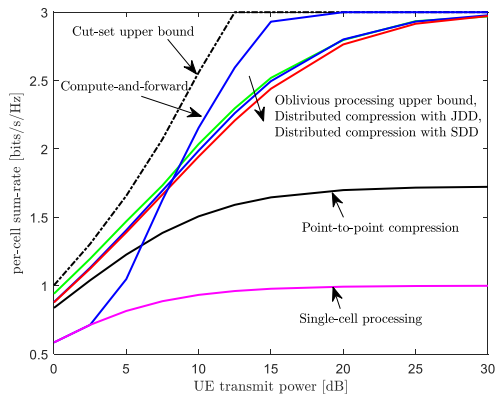
- Each cell contains a single-antenna and a single-antenna RU.
- Inter-cell interference takes place only between adjacent cells.
- The intra-cell and inter-cell channel gains are given by 1 and  $\alpha$ , respectively.
- All RUs have a fronthaul capacity of  $C$ .

## Numerical Example (Cont.)

- Compare the following schemes [Park-Simeone-Sahin-Shamai '14]
  - Single-cell processing
    - Each RU decodes the signal of the in-cell MS by treating all other MSs' signals as noise.
  - Point-to-point fronthaul compression
    - Each RU compresses the received baseband signal and the quantized signals are decompressed in parallel at the control unit.
  - Distributed fronthaul compression [dCoso-Simoens '09]
    - Each RU performs Wyner-Ziv coding on the received baseband signal and the quantized signals are successively recovered at the control unit.
    - Joint Decompression and Decoding (noisy network coding [Sanderovich-Shamai-Steinberg-Kramer'08])
  - Compute-and-forward [Hong-Caire '11]
    - Each RU performs structured coding.
  - Oblivious processing upper bound
    - RUs cooperate and optimal compression is done over  $3C$  fronthaul link.
  - Cutset upper bound [Simeone-Levy-Sanderovich-Somekh-Zaidel-Poor-Shamai '12]

## Numerical Example (Cont.)

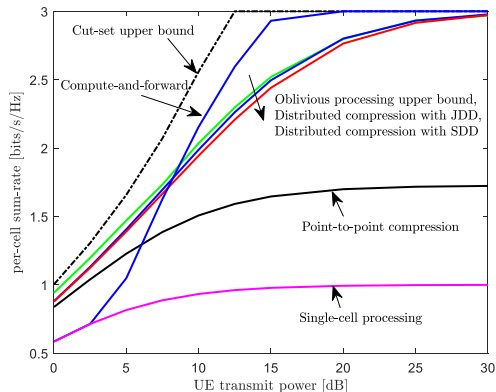
$$\alpha = 1/\sqrt{2} \text{ and } C = 3 \text{ bit/s/Hz}$$



- The performance advantage of distributed compression over point-to-point compression increases as SNR grows larger.
  - At high SNR, the correlation of the received signals at RUs becomes more pronounced.
- Compute-and-Forward
  - At low SNR, its performance coincides with single-cell processing.
    - RUs tend to decode trivial combinations.
  - At high SNR, the fronthaul capacity is the main performance bottleneck, so CoF shows the best performance.

# Numerical Example (Cont.)

$$\alpha = 1/\sqrt{2} \text{ and } C = 3 \text{ bit/s/Hz}$$

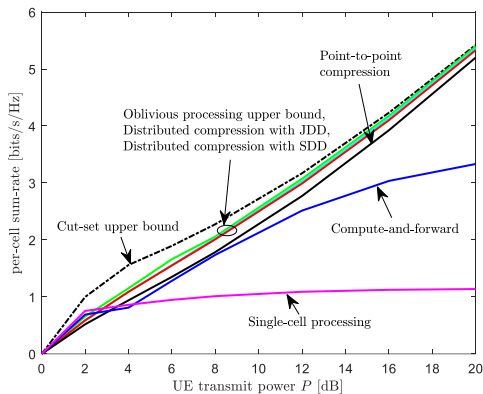


## - Distributed compression

- Joint decompression and decoding does not provide much gain compared to separate decompression and decoding.
- Optimality of joint decompression and decoding in symmetric case [Zaidi-Aguerri-Caire-Shamai'19].

## Numerical Example (Cont.)

$$\alpha = 1/\sqrt{2} \text{ and } C = 5 \log_{10} P \text{ bit/s/Hz}$$



- When  $C$  increases as  $\log(\text{snr})$ , CoF is not the best for high SNR.
  - i.e., if  $C$  does not limit the performance, the oblivious compression technique will be advantageous than CoF.

# The Distributed Information Bottleneck for Learning

- For simplicity, we look at the D-IB under sum-rate [Aguerri-Zaidi'18]

$$P_{U_k|Y_k}^* = \arg \min_{P_{U_k|Y_k}} I(X; U_{\mathcal{X}}) + \beta \sum_{k=1}^K [I(Y_k; U_k) - I(X; U_k)]$$

- The optimal encoders-decoder of the D-IB under sum-rate constraint satisfy the following self consistent equations,

$$p(u_k|y_k) = \frac{p(u_k)}{Z(\beta, u_k)} \exp(-\psi_s(u_k, y_k)),$$

$$p(x|u_k) = \sum_{y_k \in \mathcal{Y}_k} p(y_k|u_k)p(x|y_k)$$

$$p(x|u_1, \dots, u_K) = \sum_{y_{\mathcal{X}} \in \mathcal{Y}_{\mathcal{X}}} p(y_{\mathcal{X}})p(u_{\mathcal{X}}|y_{\mathcal{X}})p(x|y_{\mathcal{X}})/p(u_{\mathcal{X}})$$

where

$$\psi_s(u_k, y_k) := D_{\text{KL}}(P_{X|y_k} \| Q_{X|u_k}) + \frac{1}{s} \mathbb{E}_{U_{\mathcal{X} \setminus k} | y_k} [D_{\text{KL}}(P_{X|U_{\mathcal{X} \setminus k}, y_k} \| Q_{X|U_{\mathcal{X} \setminus k}, u_k})].$$

- Alternating iterations of these equations converge to a a solution for any initial  $p(u_k|x_k)$ , similarly to a Blahut-Arimoto algorithm.

# D-IB for Vector Gaussian Sources: Iterative Optimization

- $(\mathbf{Y}_1, \dots, \mathbf{Y}_K, \mathbf{X})$  jointly Gaussian,  $\mathbf{Y}_k \in \mathbb{R}^N$  and  $\mathbf{X} \in \mathbb{R}^M$ ,

$$\mathbf{Y}_k = \mathbf{H}_k \mathbf{X} + \mathbf{N}_k, \quad \mathbf{N}_k \sim \mathcal{N}(\mathbf{0}, \mathbf{I})$$

- Optimal encoding  $P_{U_k|Y_k}^*$  is Gaussian [Aguerri-Zaidi'17] and given by

$$\mathbf{U}_k = \mathbf{A}_k \mathbf{Y}_k + \mathbf{Z}_k, \quad \mathbf{Z}_k \sim \mathcal{N}(\mathbf{0}, \Sigma_{z,k})$$

- For this class of distributions, the updates in the Blahut-Arimoto type algorithm simplify to:

$$\begin{aligned} \Sigma_{z_k}^{t+1} &= \left( \left( 1 + \frac{1}{\beta} \right) \Sigma_{\mathbf{u}_k^t | \mathbf{x}}^{-1} - \frac{1}{S} \Sigma_{\mathbf{u}_k^t | \mathbf{u}_{\mathcal{X} \setminus k}^t}^{-1} \right)^{-1}, \\ \mathbf{A}_k^{t+1} &= \Sigma_{z_k}^{-1} \left( \left( 1 + \frac{1}{\beta} \right) \Sigma_{\mathbf{u}_k^t | \mathbf{x}}^{-1} \mathbf{A}_k^t (\mathbf{I} - \Sigma_{\mathbf{y}_k | \mathbf{x}} \Sigma_{\mathbf{y}_k}^{-1}) \right. \\ &\quad \left. - \frac{1}{\beta} \Sigma_{\mathbf{u}_k^t | \mathbf{u}_{\mathcal{X} \setminus k}^t}^{-1} \mathbf{A}_k^t (\mathbf{I} - \Sigma_{\mathbf{y}_k | \mathbf{u}_{\mathcal{X} \setminus k}^t} \Sigma_{\mathbf{y}_k}^{-1}) \right). \end{aligned}$$

## Some Perspectives

- Optimal input distributions for the input power constrained Gaussian bottleneck.
  - Discrete signaling is already known to sometimes outperform Gaussian signaling for single-user Gaussian CRAN [*Sanderovich-Shamai-Steinberg-Kramer '08*].
  - It is conjectured that the optimal input distribution is discrete.
  - Improved upper bounds (over cut-set) for non-oblivious relay based schemes, to better evaluate the cost of oblivious processing (à la: Vu-Barnes-Ozgur, arXiv:1701.02043 (IT'19) Gaussian primitive relay, [Wu-Ozgur-Peleg-Shamai, ITW'19]).
  - Up/Down link CRAN duality aspects [Patil-Yu, IT'19], [Ganguly-Kim, ISIT'17].
- Connections between classical bottleneck problems and Common Information [*Wyner'75*]: For given  $(X, U)$  find  $Y : X - Y - U$  minimizing  $I(Y; X, U)$ , and *Gacs-Korner-Witsenhausen Common Information* [*Gacs-Korner '73*].
  - Lossy common information [*Viswanatha-Akyol-Rose, IT2014*].
  - Network source-coding [*Gray-Wyner'74*], viewed as a general common information characterization [El Gamal-Kim, Cambridge'15].
  - Gray-Wyner models with side information [Bennamar-Zaidi, Entropy'17].
  - Information Decomposition, Common Information and Bottleneck [*Banerjee, arXiv: 1503.00709*].



## Some Perspectives cont.'

- **Robust Information Bottleneck**

- Robustness is an important feature in bottleneck applications to deep learning.
- Measuring robustness in terms of Fisher Information [Pensia-Jog-Loh, arXiv: 1910.068993].

$$(Y, U) \text{ joint random variables } \Phi(U|Y)\text{-statistical Fisher information} \\ = E_{Y,U} \left| \frac{\partial}{\partial Y} \log P(U|Y) \right|^2 .$$

- **Robust bottleneck**  $X \rightarrow Y \rightarrow U$  (given  $P(X, Y)$ )

$$\max_{P(U|Y)} \left\{ I(X; U) - \beta I(Y; U) - \gamma \Phi(U|Y) \right\}$$

- direct extensions to vector  $(X, Y, U)$  spaces.
- $(X, Y)$  jointly Gaussians  $\Rightarrow Y \rightarrow U$  Gaussian.
- General  $(X, Y)$  – stochastic gradient based algorithms.
- MMSE based features: minimizing MMSE  $(X|U)$  replaces maximizing  $I(X; U)$ .  
 $\Rightarrow$  Connections: I-MMSE, De Bruijn's identity, Cramer-Rao Inequality, Fano Inequality.

## Some Perspectives cont.'

- Bounds on general information bottleneck problems [Painsky-Tishby, arXiv:1711.02421], [Eswaran-Gastpar, arXiv:1805.06515].
- A variety of related C-RAN & Distributed bottleneck problems:
  - Impact of block length  $n$  [ $R$  may not scale linearly with  $n \Rightarrow$  Courtade conjecture ( $R = 1$ )] relates to [Courtade-Kumar, IT'14], [Yang-Wesel, arXiv:1807.11289, July'19], [Ordentlich-Shayevitz-Weinstein, ISIT'16].  
The  $R = n - 1$  relates to [Huleihel-Ordentlich, arXiv:1701.03119v2, ISIT '17].
  - Bandlimited time-continuous models [Homri-Peleg-Shamai, TCOM, Nov.'18], [Katz-Peleg-Shamai, Nov. '19].
  - Broadcast Approach (oblivious and general) for the Information Bottleneck Channel [Steiner-Shamai '19].
    - Channel State Information (CSI) availability and cost (fronthaul usage).
  - Multi-layer Information Bottleneck Problem [Yang-Piantanida-Gündüz, arXiv:1711.05102].
  - Gaussian version  $\Rightarrow$  half space indicator [Kindler-O'Donnell-Witmer, arXiv July 2016].

## Some Perspectives cont.'

- Distributed Information-Theoretic Clustering (Pichler-Piantanida-Matz, arXiv:1602.04605, Dictator Functions, arXiv:1604.02109).

- Two sided Information Bottleneck: For:  $V - X - Y - U$ , find:

$$\max I(U; V) \text{ subjected to: } I(V; X) \leq R_1, I(U; Y) \leq R_2 .$$

- Entropy constraint bottleneck:

$$X - Y - U$$

$\max I(X; U)$  under the constraint  $H(U) \leq R$  practical applications:  
LZ distortionless compression.

$\Rightarrow U = f(Y)$  a deterministic function [Homri-Peleg-Shamai, TCOM, Nov.'18]

- With resource sharing  $Q \Rightarrow \max I(X; U|Q)$  subjected to:  $H(U|Q) \leq R$ .

- The deterministic bottleneck: advantages in complexity as compared to a classical bottleneck: [Strouse-Schwab, Neural Comp.'17].

## Some Perspectives cont.'

- Privacy Funnel, dual of bottleneck:  $X - Y - U$ , minimize:  $I(X;U)$ , under the constraint:  $I(Y;U) = R$ . [*Calmon-Makhdoumi-Medard-Varia-Christiansen-Duffy IT2017*].
  - Direct connection to Information combining, maximize:  
 $I(Y;U, X) = I(X;Y) + I(U;Y) - I(U;X)$ , under the constraint:  
 $I(U;Y) = R$ .
  - Example:  $(X, Y)$  binary symmetric connected via a BSC,  $X - Y$ .  
The channel  $Y - U$  is an Erasure Channel.
  - Example (Ordentlich-Shamai): For the Gaussian model:  $Y = \sqrt{(\text{snr})} X + N$ , where  $(X, N)$  are unit norm independent Gaussians: Take  $U$  to be a deterministic function of  $Y$ , say describes the  $m$  last digits of a  $b$  long ( $b \rightarrow \infty$ ) binary description of  $Y$ , such that  $I(U;Y) = H(U) = R$  ( $m$  is  $R$  dependent). Evidently  $I(U;X) \rightarrow 0$ , as  $I(Y;U, X) \rightarrow R + I(X;Y)$ .
  - Helper problem [Bross-Lapidoth, ITW2019]:  $Y = X + N$ ,  $X, N$  independent finite differential entropy. Noise helper:  $I(N;U) = R$ . Direct solution via information combining (Ordentlich-Shamai): We have:  $Y - N - U$ , and (example above):  $I(N;Y, U) = I(N;Y) + R \Rightarrow I(X;Y, U) = I(X;Y) + R$ .

# References

- I. E. Aguerri, A. Zaidi, G. Caire and S. Shamai (Shitz), "On the Capacity of Cloud Radio Access Networks with Oblivious Relaying", IEEE Trans. Inform. Theory, vol. 65, no. 7, pp. 4575–4596, July 2019.
- I. E. Aguerri and A. Zaidi, "Distributed Information Bottleneck Method for Discrete and Gaussian Sources," 2018 International Zurich Seminar on Information and Communication, Zurich, 21–23, February 2018.
- R. F. Ahlswede and J. Körner, "Source coding with side information and a converse for degraded broadcast channels", IEEE Trans. on Info. Theory, Vol. 21, pp. 629–637, 1975.
- A. Alemi, I. Fischer, J. Dillon and K. Murphy, "Deep Variational Information Bottleneck", ICLR, 2017.
- P.K. Banerjee, "Some New Insights into Information Decomposition in Complex Systems Based on Common Information", arXiv:1503.00709, 2015.
- M. Benammar and A. Zaidi, "Rate-Distortion of a Heegard-Berger Problem with Common Reconstruction Constraint," Zürich Seminar on Communications and Information, Zürich, Switzerland, March 2–4, 2016.
- M. Benammar and A. Zaidi, "Rate-Distortion Region of a Gray-Wyner Model with Side Information," Entropy, Special Issue Rate-Distortion Theory and Information Theory, December 2017.
- S.I. Bross and A. Lapidoth, "The Additive Noise Channel with a Helper," The IEEE Information Theory Workshop (ITW2019), Aug. 25–28, Visby, Gotland, Sweden.
- R. Bustin, M. Payaro, D. P. Palomar and S. Shamai (Shitz), "On MMSE Properties and I-MMSE Implications in Parallel MIMO Gaussian Channels," IEEE Trans. Inform. Theory, vol. 59, no. 2, pp. 818–844, Feb. 2013.
- F. P. Calmon, A. Makhdoumi, M. Médard, M. Varia, M. Christiansen, and K. R. Duffy, "Principal inertia components and applications", vol. 63, no. 9, pp. 5011–5038, 2017.
- G. Chechik, A. Globerson, N. Tishby and Y. Weiss, "Information Bottleneck for Gaussian Variables", Journal of Machine Learning Research 6 (2005), pp. 165–188.
- G. Chechik, A. Globerson, N. Tishby, and Y. Weiss, "Information bottleneck for Gaussian variables," Journal of Machine Learning Research, vol. 6, pp. 165–188, Feb. 2005.

## References (cont.)

- A. D. Coso and S. Simoens, "Distributed compression for MIMO coordinated networks with a backhaul constraint," *IEEE Trans. Wireless Comm.*, vol. 8, no. 9, pp. 4698–4709, Sep. 2009.
- T.A. Courtade and G.R. Kumar, "Which Boolean Functions Maximize Mutual Information on Noisy Inputs?", *IEEE Trans. on Information Theory*, vol. 60, pp. 4515–4525, Aug. 2014.
- T. A. Courtade and T. Weissman, "Multiterminal source coding under logarithmic loss", *IEEE Trans. Inf. Theory*, vol. 60, pp. 740–761, Jan. 2014.
- R. Dobrushin and B. Tsybakov, "Information transmission with additional noise," *IRE Transactions on Information Theory*, vol. 8, no. 5, pp. 293–304, September 1962.
- A. El Gamal and Y-H. Kim, *Network Information Theory*, Cambridge University Press, 2015.
- E. Ekrem and S. Ulukus, "An Outer Bound for the Vector Gaussian CEO Problem", *IEEE Trans. Inform. Theory*, vol. 60, no. 11, pp. 6870–6887, November 2014.
- E. Erkip and T. M. Cover, "The Efficiency of Investment Information," *IEEE Transactions Information Theory*, vol. 44, pp. 1026–1040, May 1998.
- K. Eswaran and M. Gastpar, "Remote Source Coding under Gaussian Noise: Dueling Roles of Power and Entropy Power", *arXiv:1805.06515*.
- P. Gacs and J. Körner, "Common information is much less than mutual information," *Problems of Control and Information Theory*, vol. 2, pp. 149–162, 1973.
- S. Ganguly and Y.-H. Kim, "On the Capacity of Cloud Radio Access Networks," *IEEE International Symposium on Inform. Theory (ISIT2017)*, Aachen, Germany, June 25–30, 2017.
- R. Gray and A. Wyner, "Source coding for a simple network", *Bell systems Technical Journal*, vol. 53, no. 9, pp. 1681–1721, 1974.
- R.M. Gray and A.D. Wyner, "Source Coding for a Simple Network," *The Bell System Technical Journal*, vol. 53, no. 9, November 1974, pp. 1681–1720.

## References (cont.)

- P. Gilad-Bachraf, A. Navot, and N. Tishby, "An information theoretic tradeoff between complexity and accuracy," in Proc. COLT, 2003, pp. 595–609.
- B. R. Gálvez, R. Thobaben and M. Skoglund, "The Convex Information Bottleneck Lagrangian", Entropy 2020, 22(1).
- D. Guo, S. Shamai, and S. Verdú, "The interplay between information and estimation measures," Foundations and Trends in Signal Processing, vol. 6, pp. 243–429, 2013.
- R. M. Hecht and N. Tishby, "Extraction of relevant speech features using the information bottleneck method," in Proc. of InterSpeech, 2005, pp. 353–356.
- A. Homri, M. Peleg and S. Shamai (Shitz), "Oblivious Fronthaul-Constrained Relay for a Gaussian Channel", IEEE Trans. on Communications, vol. 66, no. 11, November 2018, pp. 5112–5123.
- S.-N. Hong and G. Caire, "Compute-and-forward strategy for cooperative distributed antenna systems," IEEE Trans. Inf. Theory, vol. 59, no. 9, pp. 5227–5243, Sep. 2013.
- W. Huleihel and O. Ordentlich, "How to Quantize  $n$  Outputs of a Binary Symmetric Channel to  $n-1$  Bits?", IEEE International Symposium on Information Theory (ISIT2017), Aachen, Germany, June 25–30, 2017.
- A. Katz, M. Peleg and S. Shamai (Shitz), "Gaussian Diamond Primitive Relay with Oblivious Processing", International IEEE Conf. on Microwaves, Communications, Antennas and Electronic Systems, COMCAS 2013 Tel Aviv, November 4–6, 2019.
- G. Kindler, R. O'Donnell and D. Witmer, "Remarks on the Most Informative Function Conjecture at Fixed Mean", arXiv 1506.03167 v3, 25 Jan. 2016.
- I. Land and J. Huber, "Information combining", Foundations and trends in Commun. and Inform. Theory, vol. 3, pp. 227–330, Nov. 2006.
- S. H. Lim, Y.-H. Kim, A. El-Gamal and S.-Y. Chung, "Noisy Network Coding", IEEE Trans. Information Theory, vol. 57, no. 5, pp. 3132–3152, May 2011.

## References (cont.)

- S. Mukherjee, "Machine Learning using the Variational Predictive Information Bottleneck with a Validation Set", 2019, [arXiv:cs.LG/1911.02210].
- O. Ordentlich, O. Shayevitz and O. Weinstein, "An improved Upper bound for the Most Informative Boolean Function Conjecture", 2016 IEEE International Symp. on Information Theory (ISIT2016), Barcelona, Spain, July 2016.
- A. Painsky and N. Tishby, "Gaussian Lower Bound for the Information Bottleneck Limit", arXiv:1711.02421.
- A. Painsky and G. W. Wornell, "On the Universality of the Logistic Loss Function", 2018: arXiv:1805.03804
- S.-H. Park, O. Simeone, O. Sahin and S. Shamai (Shitz), "Fronthaul compression for cloud radio access networks", IEEE Sig. Proc. Mag., Special Issue on Signal Processing for the 5G Revolution, vol. 31, pp. 69–79, Nov. 2014.
- P. Patil and W. Yu, "Generalized Compression Strategy for the Downlink Cloud Radio Access Network", IEEE Trans. on Inform. Theory, vol. 65, no. 10, pp. 6766–6780, Oct. 2019.
- A. Pensia, V. Log and P.-L. Loh, "Extracting robust and accurate features via a robust information bottleneck", 2019, [arXiv:1910.06893].
- G. Pichler and G. Koliander, "Information Bottleneck on General Alphabets", arXiv:1801.01050.
- G. Pichler, P. Piantanida and G. Matz, "A multiple description CEO problem with log-loss distortion", Proc. IEEE Int. Symp. Inform. Theory, Aachen, Germany, June 25–30, 2017.
- G. Pichler, P. Piantanida and G. Matz, "Two Dictator Functions Maximize Mutual Information", arXiv:1604.02109.
- G. Pichler, P. Piantanida and G. Matz, "Distributed Information-Theoretic Biclustering", arXiv:1602.04605.
- M.S. Rahman and A. B. Wagner, "On the Optimality of Binning for Distributed Hypothesis Testing", IEEE Trans. Inform. Theory, vol. 58, no. 10, pp. 6282–6303, October 2012.



## References (cont.)

- A. Sanderovich, S. Shamai, Y. Steinberg and G. Kramer, "Communication Via Decentralized Processing," *IEEE Trans. Inf. Theory*, vol. 54, no. 7, July 2008, pp. 3008–3023.
- O. Simeone, N. Levy, A. Sanderovich, O. Somekh, B. M. Zaidel, H. V. Poor and S. Shamai (Shitz), "Cooperative wireless cellular systems: An information-theoretic view," *Foundations and Trends in Communications and Information Theory*, vol. 8, nos. 1–2, pp. 1–177, 2012.
- N. Slonim and N. Tishby, "Document clustering using word clusters via the information bottleneck method", in *Proc. of 23rd Ann. Int'l ACM SIGIR Conf. on Res. and Dev. in Info. Retrieval*, 2000, pp. 208–215.
- Y. Steinberg, "Coding and common reconstruction", *IEEE Trans. on Info. Theory*, vol. 55, no. 11, pp. 4995–5010, Nov. 2009.
- A. Steiner and S. Shamai (Shitz), "Broadcast Approach for the Information Bottleneck Channel", *Int. IEEE Conf. on Microwave, Communications, Antennas and Electronic Systems (COMCAS 2019)*, Tel Aviv, Nov. 4–6, 2019.
- D. Strouse and D. J. Schwab, "The deterministic information bottleneck", 2017 MIT, *Neural Computation*, vol. 29, no. 6, pp. 1611–1630.
- I. Sutskever, S. Shamai and J. Ziv, "Extremes of Information Combining", *IEEE Trans. Inform. Theory*, vol. 51, pp. 1313–1325, April 2005.
- N. Tishby, F. C. Pereira, and W. Bialek, "The information bottleneck method," in *Proc. 37th Annual Allerton Conf. on Comm., Control, and Computing*, 1999, pp. 368–377.
- N. Tishby and N. Zaslavsky, "Deep learning and the information bottleneck principle," *Information Theory Workshop (ITW)*, 2015, 26 April–1 May 2015, Jerusalem, Israel.
- Y. Ugur, I. E. Aguerri and A. Zaidi, "Vector Gaussian CEO Problem Under Logarithmic Loss and Applications," *arXiv:1811.03933*, 9 Nov. 2018.
- K. Viswanatha, E. Akyol and K. Rose, "The Lossy common information of Correlated Sources", *IEEE Trans. Inform. Theory*, vol. 60, no. 6, pp. 3238–3253, June 2014.

## References (cont.)

- A. Wiczorek and V. Roth, "On the Difference Between the Information Bottleneck and the Deep Information Bottleneck", 2019, [arXiv:cs.LG/1912.13480].
- A. Winkelbauer, S. Farthofer, and G. Matz, "The Rate-Information Trade-off for Gaussian Vector Channels", 2014 IEEE International Symposium on Information Theory, Honolulu, Hawaii, USA, June 29–July 4, 2014.
- H. Witsenhausen and A. Wyner, "A conditional entropy bound for a pair of discrete random variables", IEEE Trans. Inform. Theory, vol. 21, pp. 493–501, Sep. 1975.
- H. Witsenhausen, "Indirect rate distortion problems", IEEE Trans. IT, vol. 26, pp. 518–521, Sep. 1980.
- X. Wu, L. P. Barnes and Ozgur, "The Capacity of the Relay Channel: Solution to Covers Problem in the Gaussian Case," IEEE Trans. Inform. Theory, vol. 65, no. 1, January 2019, pp. 255–275.
- X. Wu, A. Ozgur, M. Peleg and S. Shamai (Shitz), "New Upper Bounds on the Capacity of Primitive Diamond Relay Channels," The IEEE Information Theory Workshop (ITW2019) Visby, Gotland, Sweden, 25–28 August 2019.
- A. D. Wyner, "On source coding with side information at the decoder", IEEE Trans. on Info. Theory, vol. 21, pp. 294–300, 1975.
- A. D. Wyner, "The Common Information of Two Dependent Random Variables," Inf. Theory, vol. 21, no. 2, pp. 163–179, March 1975.
- Q. Yang, P. Piantanida and D. Gunduz, "The Multi-layer Information Bottleneck Problem", arXiv:1711.05102.
- H. Yang and R. D. Wesel, "On the Most Informative Boolean Functions of the Very Noisy Channel", arXiv:1807.11289.
- A. Zaidi, I. E. Aguerri, G. Caire and S. Shamai (Shitz), "Uplink Oblivious Cloud Radio Access Networks: An Information Theoretic Overview", Inform. Theory & Applic. (ITA2018), Feb. 11–16, 2018, San-Diego, USA.

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## “Distributed Compression, the Information Bottleneck and Cloud Radio Access Networks: A Unified Information Theoretic View”

### Abstract:

This talk focuses on connections between relatively recent notions and variants of the Information Bottleneck and classical information theoretic frameworks such as: Remote Source-Coding; Information Combining; Common Reconstruction; The Wyner-Ahlsvede-Korner Problem; The Efficiency of Investment Information; CEO Source Coding under Log-Loss and others. We overview the uplink Cloud Radio Access Networks (CRAN) with oblivious processing, which is an attractive model for future wireless systems and highlight the basic connections to distributed Gaussian information bottleneck framework. For this setting, the optimal trade-offs between rates (i.e. complexity) and information (i.e. accuracy) in the discrete and vector Gaussian schemes is determined, taking an information-estimation viewpoint. Further, the performance cost of the simple 'oblivious' universal processing in CRAN systems is exemplified via novel bounding techniques.

The concluding overview and outlook addresses in a unified way the dual problem of the privacy funnel and recent observations on the additive noise channels with a helper. Further, connections to the finite block length bottleneck features (related to the Courtade-Kumar conjecture) and entropy complexity measures (rather than mutual-information) are shortly discussed. Some challenging problems are mentioned such as the characterization of the optimal power limited inputs ('features') maximizing the 'accuracy' for the Gaussian information bottleneck, under 'complexity' constraints.

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