The Information Bottleneck: A Unified Information Theoretic View

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Outline

- **Information Bottleneck:**
- **Information Bottleneck in Deep/Machine Learning in Wireless Networks:**
- **Connections:**
  - Remote Source Coding.
  - Common Reconstruction.
  - Information Combining.
  - Wyner-Ahlswede-Korner Problem.
  - Efficiency of Investment Information.
  - Hypothesis Testing.
  - Compound Wiretap Channel.
- **Distributed Information Bottleneck:**
  - CEO Source Coding Problem under Log-Loss.
  - Oblivious Relay Processing, CRAN.
  - Distributed Information Bottleneck for Learning.
- **Some Perspectives**
- **References**

Information Bottleneck

$$X \longrightarrow Y \longrightarrow U$$

- 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]*.

Information Bottleneck in Deep/Machine Learning: Wireless Networks

* A theoretical tool to address unified strategies for communications:
  - Unification of: Universality, Reliability, Delay, Resource-Spread/Allocation, Connectivity, Networking . . .
  - Joint source channel coding; Channel state estimation; Universal Decoding; Modulation (de)/ Coding (de)/Equalization, Scheduling, Access, Resources (Frequency/Power/Bandwidth/Space), Muti-User Communications . . .
* Z. Goldfeld and Y. Polyanskiy, "The Information Bottleneck Problem and its Applications in Machine Learning", *IEEE Journal on Selected Areas in Information Theory*, vol. 1, no. 1, May 2020, pp. 19–38.
* A. Zaidi, I. E. Aguerri and S. Shamai (Shitz), "On the Information Bottleneck Problems: Models, Connections, Applications and Information Theoretic Views", *Entropy*, MDPI, Special Issue: Information Theory for Data Communications and Processing, January 2020.
* L. Dai, R. Jiao, F. Adachi, H. V. Poor and L. Hanzo, "Deep Learning for Wireless Communications: An Emerging Interdisciplinary Paradigm", IEEE Wireless Communications, vol. 27, no. 4, pp. 133–139, August 2020.
* H. Kim, S. Oh and P. Viswanath, "Physical Layer Communications via Deep Learning", *IEEE Journal on Selected Areas in Information Theory*, vol. 1, no. 1, May 2020, pp. 5–18.

Relevant Machine Learning Aspects in Wireless Network: Some Overviews

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- K. B. Letaief, W. Chen, Y. Shi, J. Zhang, and Y-J A. Zhang, "The Roadmap to 6G: AI Empowered Wireless Networks", *IEEE Communications Magazine*, pp. 84–49, August 2019.
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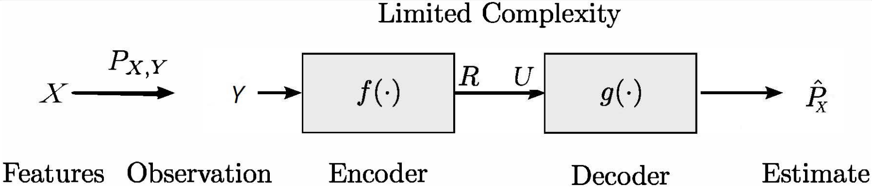
- G. L. Santos, P. T. Endo, D. Sadok and J. Kelner, “When 5G Meets Deep Learning: a Systematic Review”, <doi:10.20944/preprints202007.0693.v1>
- M. Chen, U. Challita, W. Saad, C. Yin, and M. Debbah, “Artificial Neural Networks-Based Machine Learning for Wireless Networks: A Tutorial”, arXiv:1710.02913, 30 June 2019.
- S. Ali, W. Saad, N. Rajatheva, K. Chang, D. Steinbach, B. Sliwa, C. Wietfeld, K. Mei, H. Shiri, H. Zepernick, T. M. C. Chu, I. Ahmad, J. Huusko, J. Suutala, S. Bhadauria, V. Bhatia, R. Mitra, S. Amuru, R. Abbas, B. Shao, M. Capobianco, G. Yu, M. Claes, T. Karvonen, M. Chen, M. Girnyk and H. Malik, “6G White Paper on Machine Learning in Wireless Communication Networks”, arXiv:2004.13875, 28 April 2020.
- U. Challita, H. A. Ryden and H. Tullberg, “When Machine Learning Meets Wireless Cellular Networks: Deployment, Challenges, and Applications”, arXiv:1911.03585, 1 May 2020.

Digression: Learning via the Information Bottleneck Method



- 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

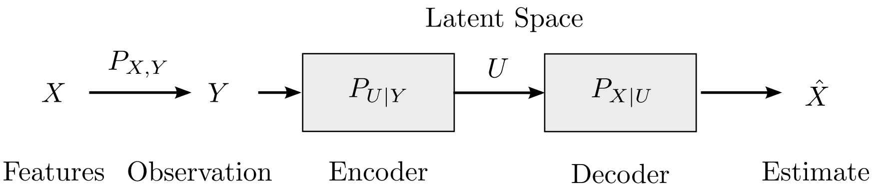
  Complexity: $I(U;Y)$ and Relevance: $I(U;X)$

- 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

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

- 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

- **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-Ahlswede-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 $X -\!\!\circ\!\!- Y -\!\!\circ\!\!- U$, 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 Inform. Theory, vol. 55, no. 11, pp. 4995–5010, Nov. 2009 (X – side information is not used for the 'source' Y common reconstruction).

$\ast$ 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**

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

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

- I. Sutskover, 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.)

- **Hypothesis Testing**

  Let $(X^n;Y^n)$ be an n length, iid sequence of pairs (X,Y). Assume that the sequences had been produced by two possible probability measures:

$$\begin{array}{llll} H0: & P_X P_Y: & (X,Y) & \text{Independent random variables.} \\ H1: & P_{X,Y}: & (X;Y) & \text{Dependent random variables.} \end{array}$$

  X^n is available at the destination, and Y^n, is encoded at rate R.

  $\Rightarrow$ For $n \to \infty$, the Stein error exponent (normalized by n), of the Neuman-Pearson type II error: (the sequences were governed by $\mathrm{H0}$, while the decision was $\mathrm{H1}$), is lower bounded by:

$$\max I(X;U), I(Y;U) \leq R : X - Y - U \,,$$

- (that is the information bottleneck result) for any type I decision error (the sequences were governed by $\mathrm{H1}$, while the decision was $\mathrm{H0}$) $\leq \varepsilon$.

R. Ahlswede and I. Csiszár, "Hypothesis Testing with Communication Constraints," IEEE Trans. Inform. Theory, vol. IT–32, no. 4, pp. 533–542, July 1986.

Other Connections (Cont.)

- **Compound Wiretap Channel**
- $X - Y - U$, (X-input, Y-legitimate receiver, U-eavesdropper).
  The wiretap capacity is:

$$I(X;Y) - I(X;U)\,.$$

- The compound degraded wiretap channel:
  The wiretapper can have anything, satisfying $I(Y;U) \leq C$.
- Evidently, as known *[Liang-Kramer-Poor-Shamai, EURASIP 2009]*, *[Bjelakovic-Boche-Sommerfeld, Problems of Information Transmission, 2013]*:

\- The wiretap capacity is $\min : I(X;Y) - I(X;U)$, over the allowable set: $I(Y;U) \leq C$, which is the bottleneck solution.

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

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

Other Connections (Cont.)

Proof:

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

Let

$$\tilde{X} = \sqrt{1+\mathrm{snr}}\,X = \sqrt{\beta}Y + M\ , \qquad \begin{array}{ccc} M & \sim & N(0,1) \\ M & \perp\!\!\!\perp & Y \end{array}$$

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

$$\begin{aligned} I(Y;X,U) &= I(Y;\tilde{X},U) = & I(Y;U) + I(Y;\tilde{X}|U) \\ I(Y;X|U) &= I(Y;\tilde{X}|U) = & \frac{1}{2}\int_0^\beta \mathrm{mmse}\,(Y:\gamma,U)\,d\gamma \end{aligned}$$

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

Other Connections (Cont.)

- **I-MMSE + Single Crossing Property** [Guo-Shamai-Verdú, FnT'13] $\Rightarrow$

$$\frac{1}{2}\int_0^{\beta} \mathrm{mmse}\,(Y:\gamma, U)\,d\gamma = \frac{1}{2}\int_0^{\beta} \frac{\rho\sigma^2_{Y|U}}{1+\gamma\rho\sigma^2_{Y|U}}\,d\gamma$$
$$= \frac{1}{2}\log\Big(1+\beta\rho\sigma^2_{Y|U}\Big)$$

$$\underline{0 \le \rho \le 1}\,, \quad \sigma^2_{Y|U} = E\Big(Y - E(Y|U)\Big)^2 = \mathrm{mmse}\,(Y:0, U)$$

Other Connections (Cont.)

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

$$h(Y) = \frac{1}{2} \log\Big(2\pi \exp\left(\mathrm{snr} + 1\right)\Big)$$

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

$$\underset{\text{single crossing point}}{\leq} \frac{1}{2} \int_0^\infty \left(\frac{\rho\sigma^2_{Y|U}}{1 + \gamma\rho\sigma^2_{Y|U}} - \frac{1}{2\pi e + \gamma}\right) d\gamma$$

Other Connections (Cont.)

$$\Rightarrow \qquad \rho\sigma^2_{Y|U} \geq \exp(-2R)\,(1+\mathrm{snr})$$

$$\underset{\text{information combining}}{\Rightarrow} \qquad I(Y;X,U) = I(Y;\tilde{X},U) \geq R + \frac{1}{2}\log\Big(1+\mathrm{snr}\ \exp(-2R)\Big)$$

$$\underset{\text{bottleneck}}{\Rightarrow} \qquad I(X;U) \leq \frac{1}{2}\log(1+\mathrm{snr}) - \frac{1}{2}\log\Big(1+\mathrm{snr}\ \exp(-2R)\Big)$$

- 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-Ahlswede-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

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

  So, we get

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

- R. F. Ahlswede 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 β
  [Chechik-Globerson-Tushby-Weiss, '05]

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

where

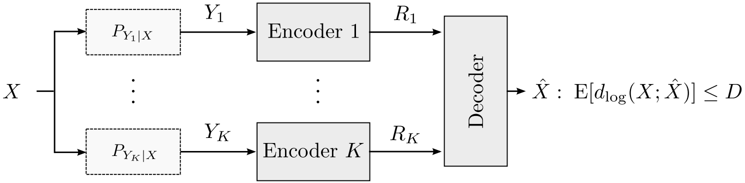
$$\mathbf{A} = \begin{cases} [\mathbf{0}^T; \ldots; \mathbf{0}^T], & \text{if } 0 \leq \beta \leq \beta_1^c \\ [\alpha_1 \mathbf{v}_1^T; \mathbf{0}^T; \ldots; \mathbf{0}^T], & \text{if } \beta_1^c \leq \beta \leq \beta_2^c \\ [\alpha_1 \mathbf{v}_1^T; \alpha_2 \mathbf{v}_2^T; \mathbf{0}^T; \ldots; \mathbf{0}^T],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

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

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

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, IT July 2020]: Accounts also for Gaussian side information about the source at the decoder.

- Full characterization
  (not the case for MMSE Distortion, [Ekrem-Ulukos, IT0214]).

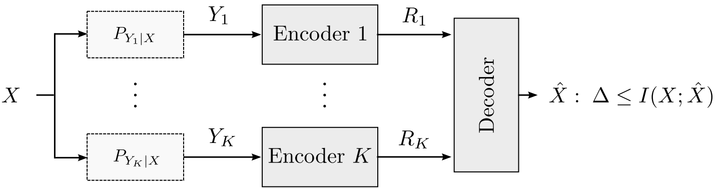
- Implications [Ugur-Aguerri-Zaidi, IT July 2020] Solutions of:

- 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*

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

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

Cost Function

Proposition

For every $(\Delta, R_{\text{sum}}) \in \mathbb{R}_+^2$ *that lies on the boundary of the optimal relevance complexity region there exist* $s \geq 0$ *such that* $(\Delta, R_{\text{sum}}) = (\Delta_s, R_s)$, *with*

$$\Delta_s = \frac{1}{(1+s)} \left[(1+sK)H(X) + sR_s + \max_{\mathbf{P}} \mathcal{L}_s(\mathbf{P}) \right]$$

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

and $\mathbf{P}^*$ *is the set of conditional pmfs* $\mathbf{P}$ *that maximize the cost function*

$$\mathcal{L}_s(\mathbf{P}) := -H(X|U_{\mathcal{K}}) - s \sum_{k=1}^{K} [H(X|U_k) + I(Y_k; U_k)].$$

A Variational Bound

- Let $\mathcal{L}_s^{\mathrm{VB}}(\mathbf{P}, \mathbf{Q})$ denote

$$\underbrace{\mathbb{E}[\log Q_{X|U_{\mathcal{K}}}(X|U_{\mathcal{K}})]}_{\text{av. logarithmic-loss}} + \underbrace{s \sum_{k=1}^{K} \Big(\mathbb{E}[\log Q_{X|U_k}(Y|U_k)] - D_{\mathrm{KL}}(P_{U_k|Y_k} \| Q_{U_k}) \Big)}_{\text{regularizer}}.$$

- It is not difficult to see that

$$\max_{\mathbf{P}} \mathcal{L}_s(\mathbf{P}) = \max_{\mathbf{P}} \max_{\mathbf{Q}} \mathcal{L}_s^{\mathrm{VB}}(\mathbf{P}, \mathbf{Q})$$

and

$$Q^*_{U_k} = P_{U_k}, \quad Q^*_{Y|U_k} = P_{Y|U_k}, \quad Q^*_{Y|U_1,\ldots,U_k} = P_{Y|U_1,\ldots,U_K}$$

Parametrization through Neural Networks

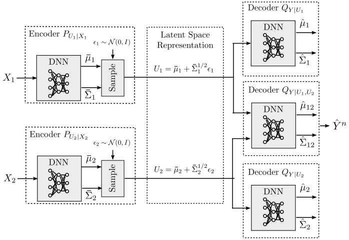
- Let

$$\mathcal{L}_s^{\mathrm{NN}}(\boldsymbol{\theta},\boldsymbol{\phi},\boldsymbol{\varphi}) := \mathbb{E}_{P_{Y,X}}\mathbb{E}_{\{P_{\theta_k}(U_k|X_k)\}}\Big[\log Q_{\phi_{\mathcal{K}}}(Y|U_{\mathcal{K}}) + s\sum_{k=1}^{K}\Big(\log Q_{\phi_k}(Y|U_k) - D_{\mathrm{KL}}(P_{\theta_k}(U_k|X_k)\|Q_{\varphi_k}(U_k))\Big)\Big].$$

- We have

$$\max_{\mathbf{P}}\max_{\mathbf{Q}}\mathcal{L}_s^{\mathrm{VB}}(\mathbf{P},\mathbf{Q}) \geq \max_{\boldsymbol{\theta},\boldsymbol{\phi},\boldsymbol{\varphi}}\mathcal{L}_s^{\mathrm{NN}}(\boldsymbol{\theta},\boldsymbol{\phi},\boldsymbol{\varphi})$$

- Optimization through Stochastic Gradient Descendent



Vector Gaussian Distributed Information Bottleneck

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

$$\mathbf{Y}_k = \mathbf{H}_k \mathbf{X} + \mathbf{N}_k, \qquad \mathbf{N}_k \sim \mathcal{N}(\mathbf{0}, \mathbf{\Sigma}_{\mathbf{n}_k})$$

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

Theorem ([Estella-Zaidi, IZS'18], [Ugur-Aguerri-Zaidi, IT July 2020])

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

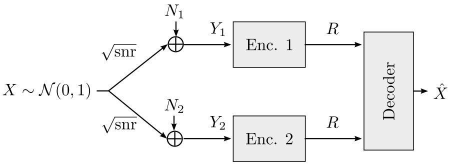
$$\Delta \leq \sum_{k \in \mathcal{S}} \left[R_k + \log |\mathbf{I} - \mathbf{B}_k|\right] + \log \left| \sum_{k \in \mathcal{S}^c} \bar{\mathbf{H}}_k^H \mathbf{B}_k \bar{\mathbf{H}}_k + \mathbf{I} \right|$$

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

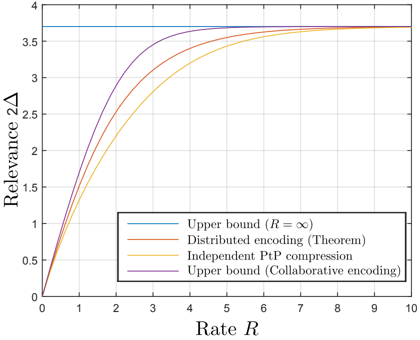
$$p^*(\mathbf{u}_k | \mathbf{y}_k, q) = \mathcal{CN}(\mathbf{y}_k, \Sigma_{\mathbf{n}_k}^{1/2}(\mathbf{B}_k - \mathbf{I})\mathbf{\Sigma}_{\mathbf{n}_k}^{1/2})$$

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

Example



$Y_k = \sqrt{\text{snr}}X + N_k$, with $N_k \sim \mathcal{N}(0,1)$, $k = 1, 2$



- 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 $2R$

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

- Lower bound: Y_1 and Y_2 independently encoded

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

The Cost of Oblivious Processing: an Example
Cut-Set Bound

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

- **Improved Upper Bound:** geometric analysis of typical sets (equivalent in this case to the "information constrained transportation inequality")
  [Wu-Ozgur-Peleg-Shamai, ITW'19]

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

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

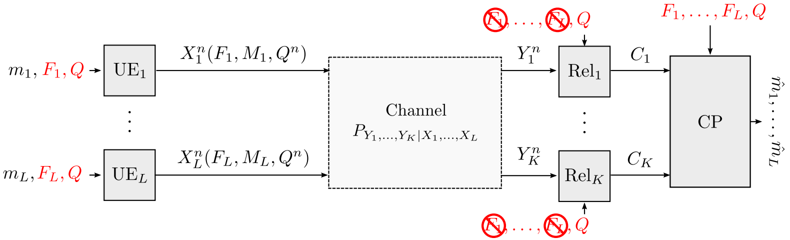
  where

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

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 obvlivious processing (disributed source coding under logarithmic loss).
  - → Capacity achieving for: $2R \leq \frac{1}{2}\log\left(1+\mathrm{snr}\right)$.

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: $P_{Y_1,\ldots,Y_K|X_1,\ldots,X_1}$
- User $l \in \{1, \ldots, L\}$: $\phi_l^n : [1, |\mathcal{X}_l|^{n2^{nR_l}}] \times [1, 2^{nR_l}] \times \mathcal{Q}^n \to \mathcal{X}_l^n$
- Relay $k \in \{1, \ldots, K\}$: $g_k^n : \mathcal{Y}_k{}^n \times \mathcal{Q}^n \to [1, 2^{nC_k}]$
- Decoder:

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

Capacity Region of a Class of CRAN Channels

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

For the class of discrete memoryless channels satisfying

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

with oblivious relay processing and enabled resource-sharing, a rate tuple $(R_1, \ldots, R_L)$ *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

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

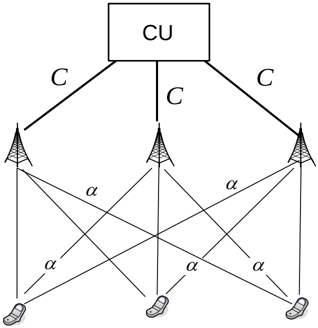
with the cardinality of Q *bounded as* $|\mathcal{Q}| \leq K + 2$.

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

$\Rightarrow$ *Directly related to quantize-map-forward (QMF) [Avestimehr-Diggavi-Tian-Tse, FnT'15, and references therein].*

Numerical Example

- Three-cell SISO circular Wyner model



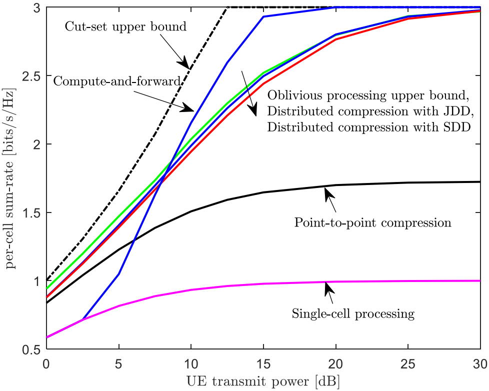
  - Each cell contains a single-antenna and a single-antenna RU.
  - Inter-cell interference takes place only between adjacent cells.
  - The intra-cell and inter-cell channel gains are given by 1 and α, respectively.
  - All RUs have a fronthaul capacity of C.

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 conding 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.)

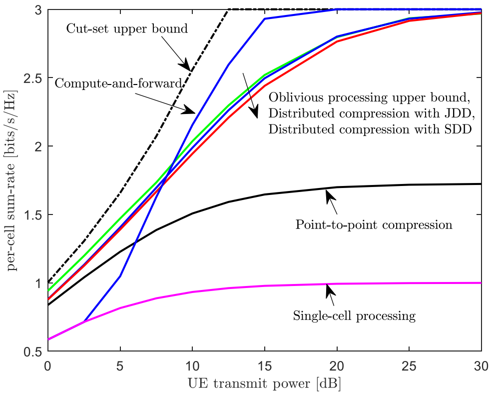
$\alpha = 1/\sqrt{2}$ and $C = 3$ bit/s/Hz



- 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.)

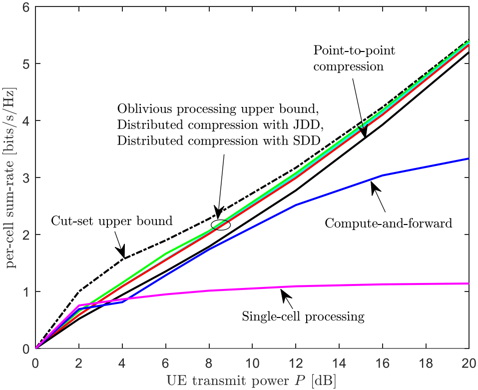
$\alpha = 1/\sqrt{2}$ and $C = 3$ bit/s/Hz



- 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.)

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



- When C increases as $\log(\mathrm{snr})$, 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]*

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

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

$$\begin{aligned} p(u_k|y_k) &= \frac{p(u_k)}{Z(\beta,u_k)} \exp\left(-\psi_s(u_k,y_k)\right), \\ p(x|u_k) &= \sum_{y_k \in \mathcal{Y}_k} p(y_k|u_k)p(x|y_k) \\ p(x|u_1,\ldots,u_K) &= \sum_{y_{\mathcal{K}} \in \mathcal{Y}_{\mathcal{K}}} p(y_{\mathcal{K}})p(u_{\mathcal{K}}|y_{\mathcal{K}})p(x|y_{\mathcal{K}})/p(u_{\mathcal{K}}) \end{aligned}$$

  where

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

- 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

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

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

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

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

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

$$\begin{aligned}
\mathbf{\Sigma}_{\mathbf{z}_k^{t+1}} &= \left(\left(1 + \frac{1}{\beta}\right) \mathbf{\Sigma}^{-1}_{\mathbf{u}_k^t|\mathbf{x}} - \frac{1}{s} \mathbf{\Sigma}^{-1}_{\mathbf{u}_k^t|\mathbf{u}^t_{\mathcal{K}\setminus k}} \right)^{-1}, \\
\mathbf{A}_k^{t+1} &= \mathbf{\Sigma}^{-1}_{\mathbf{z}_k^{t+1}} \left(\left(1 + \frac{1}{\beta}\right) \mathbf{\Sigma}^{-1}_{\mathbf{u}_k^t|\mathbf{x}} \mathbf{A}_k^t (\mathbf{I} - \mathbf{\Sigma}_{\mathbf{y}_k|\mathbf{x}} \mathbf{\Sigma}^{-1}_{\mathbf{y}_k}) \right. \\
&\quad \left. - \frac{1}{\beta} \mathbf{\Sigma}^{-1}_{\mathbf{u}_k^t|\mathbf{u}^t_{\mathcal{K}\setminus k}} \mathbf{A}_k^t (\mathbf{I} - \mathbf{\Sigma}_{\mathbf{y}_k|\mathbf{u}^t_{\mathcal{K}\setminus k}} \mathbf{\Sigma}^{-1}_{\mathbf{y}_k}) \right).
\end{aligned}$$

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 (á 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], [Liu-Liu-Patil-Yu, arXiv:2008.10901], [Ganguly-Kim, ISIT'17].

Some Perspectives cont.'

- 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) joint random variables $\Phi(U|Y)$-statistical Fisher information
  $= E_{Y,U} \left| \frac{\partial}{\partial Y} \log P(U|Y) \right|^2.$
- **Robust bottleneck** $X \to Y \to U$ (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 $\Rightarrow Y \to U$ 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 Bruijnis indentity, Cramer-Rao Inequality, Fano Inequality.
- Strong Data Processing Inequalities for Input Constrained Additive Noise [Calmon-Polyansky-Wu, IT'18].

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, COMCAS'19].
  - Broadcast Approach (oblivious and general) for the Information Bottleneck Channel [Steiner-Shamai, COMCAS'19], [Steiner-Shamai, ITA'20].
    - 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 Pespectives cont.'

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

- It is conjectured that the optimal input distribution is discrete.

- Universal Distortion: $X \in \mathcal{X}$ – features, V – observation,

  $\ell\Big(X, f(V)\Big)$ distortion, $f(V) \in \mathcal{X}$ – estimate:

  $f^*(\cdot)$ optimal estimate: $L^*(X|V) = \inf_{f(\cdot)} \mathbb{E}\, \ell\Big(X, f(V)\Big)$

  Example: MMSE – $\mathbb{E}\Big(X - f^*(V)\Big)^2$, $f^*(V) = \mathbb{E}(X|V)$

  $\| \, \ell \, \|_\infty = \sup \ell(\cdot,\cdot)$, $L^*(X|Y)$ – σ subGaussian or $\ell(\cdot,\cdot)$ uniformly bounded.

$$\Rightarrow L^*(X|U) - L^*(X|Y) \le \frac{\| \, \ell_\infty \, \|}{\sqrt{2}} \sqrt{I(Y;X|U)}$$

$$= \frac{\| \, \ell_\infty \, \|}{\sqrt{2}} \sqrt{I(X;Y) - I(X;U)}, \; X - Y - U, \text{ [Linder, 20]}$$

$IB \Rightarrow \max \, I(X;U), \; I(Y;U) \le R$ relevant to any distortion measure.

Some Perspectives cont.'

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

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

- Functions of features: $V = f(X)$, find:

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

- Entropy constaint bottleneck: $X - Y - U$ $\max\, I(X;U)$ under the constraint $H(U) \leq R$ practical applications: LZ distortionless compression.
  $\Rightarrow U = f(Y)$ is a deterministic function *[Homri-Peleg-Shamai, TCOM, Nov.'18]*.

- The 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: $Y = \sqrt{(\mathrm{snr})}\,X + N$, 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 $(b \to \infty)$ binary description of Y, such that $I(U;Y) = H(U) = R$ (m is R dependent). Evidently $I(U;X) \to 0$, as $I(Y;U,X) \to R + I(X;Y)$.
    - Helper problem [Bross-Lapidoth, ITW'19, TCOM-July 20]: $Y = X + N, X, N$ 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): $I(N;Y,U) = I(N;Y) + R \Rightarrow I(X;Y,U) = I(X;Y) + R$.

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The Viterbi EE Faculty, Technion

"The Information Bottleneck: 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-Ahlswede-Korner Problem; The Efficiency of Investment Information; CEO Source Coding under Log-Loss, Hypothesis Testing Error Exponent and others.
We overview the upink 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. 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 'relevance' for the Gaussian information bottleneck, under 'complexity' constraints.

The talk is based mainly on joint work with A. Zaidi, I.E. Auguerri, G. Caire, O. Simeone and S-H. Park.

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Thank you!