Journal Watch: IEEE Transactions on Information Theory, July 2014

Venugopalakrishna Y. R.

SPC Lab, IISc

2^{nd} August, 2014

A New Entropy Power Inequality for Integer-valued Random Variables

Saeid Haghighatshoar, EPFL,
Emmanuel Abbe, Princeton Univ.
and Emre Telatar, EPFL

- Entropy power inequality (EPI): Tight lower bound on differential entropy of sum of two independent real RVs in terms of individual entropies (EPI: $h(X + X') - h(X) \geq \frac{1}{2}$)

- Used as a key ingredient to prove converse results in coding theorems

- Literature: Universal EPI inequality for discrete RVs is not known

- Recent result from Tao: $H(X + X') - H(X) \geq \frac{1}{2} - o(1)$ when X, X' are i.i.d. with high entropy

- This paper: $H(X + X') - H(X) \geq g(H(X))$ where X, X' are integer valued RVs and g is a strictly increasing function on $\mathcal{R}_+$ with $g(0) = 0$

Upper and Lower Bounds to the Information Rate Transferred Through First-Order Markov Channels With Free-Running Continuous State

L. Barletta, Technische Universitat Munchen, Germany
M. Magarini, S. Pecorino, and A. Spalvieri, Politecnico di Milano, Italy

- This paper considers a dynamic system
  - State equation: $S_k = f_k(S_{k-1}, V_{k-1})$, $k = 1, 2, \ldots,$ V is process noise
  - Measurement equation: $Y_k = h_k(S_k, N_k)$, N is measurement noise
  - f_k and h_k are sequence of known functions
- Mutual information rate between state and measurement $I(S; Y) = \lim_{n\to\infty} \frac{1}{n} \sum_{k=1}^{n} \mathbb{E}\left[\log_2 \frac{p(Y_k/S_k)}{p(Y_k/Y_{k-1})}\right]$
- Sample estimate of $I(S; Y)$ can be obtained by generating the joint sequence (s_0^n, y_1^n) according to state transition prob. and measurement prob.

- Gaussian and Linear case, the probabilities can be obtained by Bayesian tracking
- If probabilities are non tractable, upper and lower bounds on $I(S; Y$ by approximate Bayesian tracking
- If f and h are non-linear functions, particle filters are used for deriving bounds
- Applied to multiplicative phase noise channel and Gauss-Markov fading channel

Sparse Recovery With Unknown Variance: A LASSO-Type Approach

S. Chretien, Universite de Franche-Comte, Besancon, France
S. Darses, UniversitÃ© Aix-Marseille, Marseille Cedex, France

- $y = X\beta + z$, X is $n \times p$ design matrix, $n < p$, β regression vector, $z \sim \mathcal{N}(0, \sigma^2 I)$ is noise
- β and σ^2 are both unknown
- For LASSO, λ should be of the order of $\sigma\sqrt{\log p}$
- This paper gives two LASSO-type strategies to obtain β, when σ is unknown
- Strategy A: Variance estimator, Strategy B: Trade-off between fidelity and penalty

Known variance	Unknown variance: Strategy (A)	Unknown variance: Strategy (B)
$\widehat{\beta} \in \underset{b\in\mathbb{R}^p}{\operatorname{argmin}} \frac{\|y-Xb\|_2^2}{2} + \lambda\|b\|_1$	$\widehat{\beta}_\lambda \in \underset{b\in\mathbb{R}^p}{\operatorname{argmin}} \frac{\|y-Xb\|_2^2}{2} + \lambda\|b\|_1$	$\widehat{\beta}_\lambda \in \underset{b\in\mathbb{R}^p}{\operatorname{argmin}} \frac{\|y-Xb\|_2^2}{2} + \lambda \|b\|_1$
$\lambda = O(\sigma\sqrt{\log p})$	Tune λ to $\widehat{\lambda}$ s.t. : $\widehat{\lambda} = C_{\text{var}}\widehat{\sigma}\sqrt{\log p}$ with : $\widehat{\sigma}^2 = \frac{\|y-X\widehat{\beta}_{\widehat{\lambda}}\|_2^2}{n}$, $C_{\text{var}} > 0$	Tune λ to $\widehat{\lambda}$ s.t. : $\widehat{\lambda}\|\widehat{\beta}_{\widehat{\lambda}}\|_1 = C\ \|y - X\widehat{\beta}_{\widehat{\lambda}}\|_2^2$, $C > 0$

Reconstruction of Signals From Frame Coefficients With Erasures at Unknown Locations

D. Han, Univ. of Central Florida, Orlando
W. Sun, Nankai Univ., China

- Frames $\{\phi_i\}_{i=1,\dots,n}$ of a vector space are an over-complete dictionary that can span the vector space (generalization of bases) but satisfy $\alpha||f||^2 \leq \sum_{i=1}^{n} | < f, \phi_i > |^2 \leq \beta||f||^2$
- The advantage with frames is it has redundant frame vectors, thus robust to erasures
- This paper considers recovery of erased frame coefficients at known and unknown locations and ordering of frame coefficients
- Known erasure locations case: assumes that $\{\phi_i\}$ with erasures still remains frame, proposes solving a simple linear system of equations to recover erasures (need not use inversion)
- Main result: There exists a large class of encoding frames that ensure the full recovery of the indices for almost all signals