Journal Watch

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V . Vinuthna
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Collaborative Kalman Filtering for Dynamic Matrix Factorization

John Z. Sun, Dhruv Parthasarathy, and Kush R. Varshney

- **Contributions:**
  - Validated proposed CKF and shown its advantages over SVD and time SVD
  - Derived an EM algorithm to learn the parameters of the model considering temporal dynamics into account

- **System Model:**
  - User factor matrix, $U \in R^{N*K}$
  - Item factor matrix, $V \in R^{M*K}$
  - Preference Matrix, $O \in R^{N*M}$, computed as $O = U V^T$
- **Existing work :**
  - **SVD:**
    - Follows Stochastic gradient descent
    - Assumes both user and item factors are constant over time

- **Time SVD:**

  - $u_i\ (t) = u_i + \alpha_i\ dev_i\ (t)$

    Requires time factors to lie on same latent space

- **Proposed scheme - CKF :** uses Linear – Gaussian Dynamic State Space Model

- **State Evolution Equation:**

$$X_{i,t} = A_{i,t} X_{i,t} + W_{i,t}, i = 1,2,....N$$

$$X_{i,t} \sim \mathrm{N}(0, \mathrm{Q}_{\mathrm{i,t}}); X_{i,0} \sim \mathrm{N}(\mu_{\mathrm{i}}, \Sigma_{i})$$

- **State Observation Equation:**

$$Y_{i,t} = H_{i,t} X_{i,t} + Z_{i,t}, i = 1,2,....N$$

$$Z_{i,t} \sim \mathrm{N}(0, \mathrm{R}_{\mathrm{i,t}})$$

- The MAP estimates of the model, V, $A_{i,t}$, $Q_{i,t}$, $R_{i,t}$, μ_i, Σ_i are obtained using Kalman filtering

Group Sparse Signal Denoising: Non-Convex Regularizaton, Convex Optimization

Po- Yu Chen and Ivan W. Selesnick

- **Contribution:**
  - Formulation of group sparse signal denoising as convex optimization problem with a non convex regularization term.
  - Derivation of computationally efficient iterative algorithm that monotonically reduces the cost function value

- **System Model:** Group Sparse vector is estimated from an observation y, where

$$y(i) = x(i) + w(i), \quad w(i) \sim \mathrm{N}(0, \sigma_w^2 I)$$

- **Existing work:**

- Solution to such a problem is given by

$$x^* = \arg \min \{ F(x) = \frac{1}{2} \|y - x\|_2^2 + \lambda R(x) \}$$

where, cost function F(x), the penalty term R(x) are in general convex.

- **Proposed Scheme:** solves the same equation, except does convex optimization with non-convex penalty term
  - Penalty term assumed is a parameterized

    Eg : $\frac{1}{a}\log(1+ax)$

  - Derives an algorithm that minimizes F using Majorization - Minimization(MM) procedure.

- **MM:**

$$x^{(k+1)} = \arg\min_{x} Q(x, x^{(k)})$$

where, $Q : R^N \rightarrow R$, is Majorizer of F

- Q should satisfy

$$Q(x, v) \geq F(x), \forall x \in R^N$$

$$Q(v, v) = F(v)$$

Distributed Information Theoretic Clustering

Pengcheng Shen and Chunguang Li

- **Contributions:**
  - Incorporated an information theoretic measure (MMI) into the cost function of distributed clustering to present linear and kernel distributed clustering algorithms
  - Proposed a “global-like” local cost function for each node
  - Developed a two-step iterative scheme to protect the privacy and save communication resource

- **System Model:**

  - Network consists of J nodes
  - Each node collects a set of N_j , D- dimensional data items considered to be samples of a random variable X_j with probability measure p(X_j)
  - X_j , j = 1 to J are assumed to follow same probability measure.
  - B_j - Neighbour set
  - Node J clusters its local data into M different classes.

- **Existing work :**
  - K-means and GMM
  - Centralized clustering using information theoretic measures such as divergence and MI

- **Proposed Work :**
  - Incorporates MMI criterion into cost function in distributed clustering , to present distributed MMI- based (DMMI) clustering algorithms.

- **Linear DMMI :**
  - Solves only Linearly separable problems
  - Clustering model is modeled by Multi- Class Logistic Regression function
- **Complexity:**

$$O(N_j MD + |B_j|)$$

- **Kernel DMMI :**
  - Uses Kernel Multi-Logit Regression model
  - Requires that whole data items need to be available at each node that conflicts proposed framework

- **Modified Kernel DMMI:** choose a specific set of L base vectors instead of using all the data items

- **Complexity:**

$$O(N_j ML + |B_j|)$$

Joint Source-Channel Vector Quantization for Compressed Sensing

Amirpasha Shirazinia, Saikat Chatterjee and Mikael Skoglund

- **Contributions:**
  - Optimal encoding and decoding conditions for VQ
  - Theoretical bound on MSE performance
  - A practical VQ encoder- decoder design through an iterative algorithm (COVQ – CS)
  - A low complexity multi stage encoder- decoder design COMSVQ-CS

- **System Model:**

$$Y = \Phi X + W$$

$\bar{X}$ is reconstructed vector such that distortion is minimized

where,

$$D = E\left[\left\| X - \bar{X} \right\|_2^2\right]$$

- **Existing Work:**

  - Considers only pure source coding to quantize CS measurements

- **Proposed Scheme :**

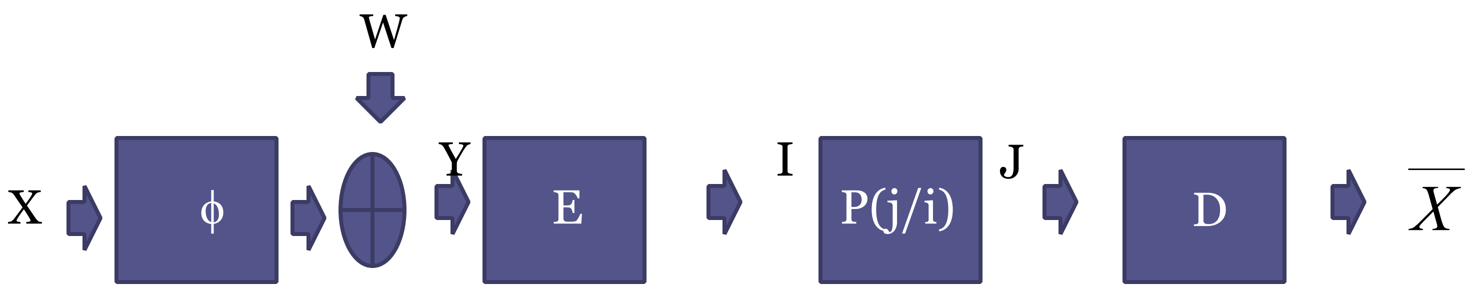

Fig 1. System Model for JS-C VQ of CS Measurements

- Channel – DMC
- Assume that channel transition probabilities are known in advance and transmitted index and received index share the same index set I

Practical encoder – decoder design is made called COVQ – CS

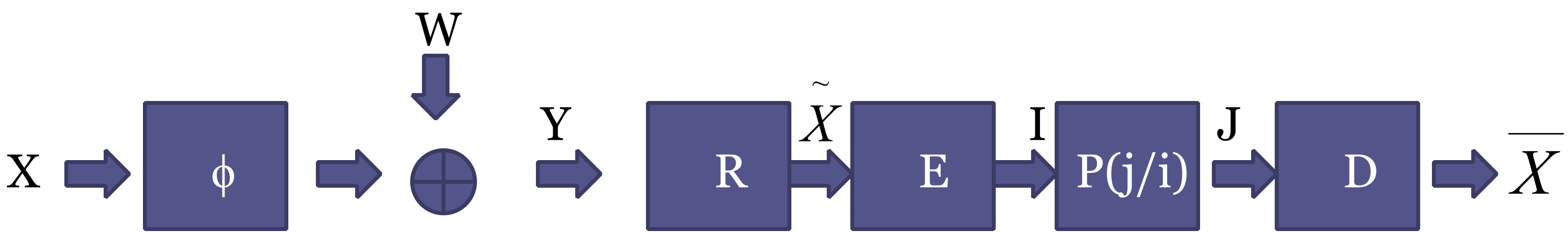

Fig 2. Equivalent block diagram with CS Reconstruction at encoder side

Complexity : $2N2^R$ FLOPs

To minimize propose MSVQ - CS

Other papers…

- **Adaptive Distributed Estimation Based on Recursive Least-Squares and Partial Diffusion**

  R. Arablouei, K. Dogancay, S. Werner and Y. F. Huang

- **Distributed Estimation and Detection with Bounded Transmissions Over Gaussian Multiple Access Channels**

  S. Dasarathan and C. Tepedelenlioglu

- **Prediction of Partially Observed Dynamical Processes over Networks via Dictionary Learning**

  P. A. Forero, K. Rajawat, and G. B. Giannakis

Thank you