



### Introduction

Recent result of information and estimation imply a correspondence between estimation and channel capacity. We apply these results to (causal) filtering of an AWGN-corrupted signal in continuous time. In this poster we focus on an example where the signal is known to be a linear combination of given orthonormal signal set with a power constraint, and we further know that some fraction of coefficients should be zero. In this setting, the corresponding channel capacity problem is that for Gaussian channels with a duty cycle and power constraints, as recently considered in [2].

### **Problem Setting**

• Orthonormal signals set : 
$$\{\phi_i(t), 0 \le t \le T\}_{i=1}^n$$
  
•  $X_t = \sum_{i=1}^n c_i \phi_i(t)$   
•  $C \sim P$  where  $P \in \mathcal{P} = \{P : \mathbb{E}_P ||C||_2^2 \le nA$  and  $\mathbb{E}_P ||C||_0 \le k\}$   
•  $dY_t = X_t dt + dW_t$   
Define  
•  $\operatorname{cmse}_{P,Q} = \mathbb{E}_P \left[ \int_0^T (X_t - \mathbb{E}_Q[X_t|Y^t])^2 dt \right]$   
•  $\operatorname{minimax}(\mathcal{P}) = \min_{\substack{\hat{X}_t(\cdot), \\ t \in [0,T]}} \max_{P \in \mathcal{P}} \left\{ \mathbb{E}_P \left[ \int_0^T (X_t - \hat{X}_t(Y^t))^2 dt \right] - \operatorname{cmse}_{P,P} \right\}$ 

#### Question

Characterize minimax  $(\mathcal{P})$  and the filter that achieves it.

**Equivalent Problem** 

 $\left\{\int_0^t \phi_i(s) dY_s\right\}_{i=1}^n$  is a sufficient statistic for estimating  $X_t$ . ▶ Define

$$\begin{split} \tilde{Y}_i(t) &= \int_0^t \phi_i(s) dY_s \\ \tilde{W}_i(t) &= \int_0^t \phi_i(s) dW_s \\ \tilde{X}_i(t) &= \int_0^t \phi_i(s) X_s ds \\ (\Gamma(t))_{i,j} &= \int_0^t \phi_i(s) \phi_j(s) ds \end{split}$$

Causal estimation is equivalent to following vector estimation problem,

 $\tilde{Y}(t) = \tilde{X}(t) + \tilde{W}(t) = \Gamma(t)A + \tilde{W}(t)$ 

where  $\tilde{W}(t) \sim \mathcal{N}(0, \Gamma(t))$ 

Note that  $\Gamma(t)$  does not have to be a full rank matrix. Using eigenvalue decomposition,

## $\Gamma(t) = V(t)\Lambda(t)V(t)^{T}$

Only using nonzero eigenvalues, we can get equivalent formula

 $\Lambda_{\text{eff}}(t)^{-1/2} V_{\text{eff}}(t)^T \tilde{Y}(t) = \Lambda_{\text{eff}}(t)^{1/2} V_{\text{eff}}(t)^T A + \Lambda_{\text{eff}}(t)^{-1/2} V_{\text{eff}}(t)^T \tilde{W}(t)$ Note  $\Lambda_{\text{eff}}(t)^{-1/2} V_{\text{eff}}(t)^T \tilde{W}(t) \sim \mathcal{N}(0, I_{n-m})$ 



**Theorem : Restrict to Bayesian Estimator** 

Suppose the signal  $X^{T}$  is governed by  $P \in \mathcal{P}$ . Let  $\mathcal{Q}$  denote convex hull of  $\mathcal{P}$ . Then, for a general loss function,

 $\min(\mathcal{P}) = \min_{\mathbf{Q} \in \mathcal{Q}} \max_{\mathbf{P} \in \mathcal{P}} \{ \operatorname{cmle}_{\mathbf{P}, \mathbf{Q}} - \operatorname{cmle}_{\mathbf{P}, \mathbf{P}} \}$ 

minimax( $\mathcal{P}$ )

Using the recent result of information and estimation[1],

mi

$$\min(\mathcal{P}) = \min_{Q \in \mathcal{Q}} \max_{P \in \mathcal{P}} \operatorname{cmse}_{P,Q} - \operatorname{cmse}_{P,P}$$
$$= \min_{Q \in \mathcal{Q}} \max_{P \in \mathcal{P}} D(P_{Y^T} || Q_{Y^T})$$
$$= \max_{W \in \mathcal{W}} I(\mathcal{P}; Y^T)$$
$$= \max_{P \in \mathcal{P}} I(X^T; Y^T)$$

• Minimum achieving distribution  $Q^*$  is equal to capacity achieving distribution  $P^*$ ▶ In our example,

minimax(
$$\mathcal{P}$$
) =  $\max_{\boldsymbol{P}\in\mathcal{P}} I(\boldsymbol{C}; \boldsymbol{B})$ 

where  $\boldsymbol{B} = (\boldsymbol{b}_1, \cdots, \boldsymbol{b}_n)^T$  and  $\boldsymbol{b}_i = \int_0^T \phi_i(t) dY_t$ . This problem coincides with the capacity of Gaussian Channels with duty cycle and power constraints.

• Capacity achieving distribution  $p_d$  is i.i.d. and discrete.

minimax
$$(\mathcal{P}) = nI(X; Y)$$

where  $X \sim p_d$  and Y = X + N is noise corrupted version of X by independent standard Gaussian noise **N**.

### **Optimal Causal Estimator**

Minimax estimator is a Bayesian estimator assuming prior distribution on *C* is i.i.d.  $p_d$ . Denote this distribution by  $Q^*$ , then the optimal causal minimax estiamtor is

$$\hat{X}_t = \mathbb{E}_{\boldsymbol{Q}^*}[X_t|Y^t]$$

We can compute  $\hat{X}_t = \mathbb{E}_{Q^*}[X_t | Y^t] = \mathbb{E}_{Q^*}[X_t | \tilde{Y}(t)].$ 

**Estimators for Comparison** 

Maximum likelihood estimator (with/without thresholding)

$$\hat{\boldsymbol{C}} = \left( \boldsymbol{\Lambda}_{\text{eff}}(t)^{1/2} \boldsymbol{V}_{\text{eff}}(t)^{T} \right)^{\dagger} \boldsymbol{\Lambda}_{\text{eff}}(t)^{-1/2} \boldsymbol{V}_{\text{eff}}(t)^{T} \tilde{\boldsymbol{Y}}(t)$$

Minimax estimator that only knows the power constraints

$$\mathbb{E}[\boldsymbol{C}|\boldsymbol{\Lambda}_{\text{eff}}(t)^{-1/2}\boldsymbol{V}_{\text{eff}}(t)^{T}\tilde{\boldsymbol{Y}}(t)]$$

$$= PV_{\text{eff}}(t) \left( P\Lambda_{\text{eff}}(t) + I_{n-m} \right)^{-1} V_{\text{eff}}(t)^T \tilde{Y}(t)$$

Genie aided estimator that also knows which coefficients are nonzero

$$\mathbb{E}[C_{\text{nonzero}}|\Lambda_{\text{eff}}(t)^{-1/2}V_{\text{eff}}(t)^{T}\tilde{Y}(t)]$$

$$= \frac{nP}{k} U_{\text{eff}}^{T} (U_{\text{eff}} U_{\text{eff}}^{T} + I_{n-m})^{-1} \Lambda_{\text{eff}}(t)^{-1/2} V_{\text{eff}}(t)^{T} \tilde{Y}(t)$$

# Minimax Filtering via Relations between Information and Estimation Albert No

STANFORD University







