An Information Geometric Approach for Feature Selection

Lizhong Zheng

EECS, MIT

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in collaboration with Shao-Lun Huang, Anuran Makur, Greg Wornell

Who's NOT Doing BigData?

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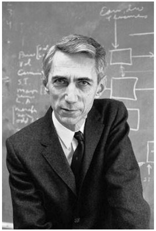

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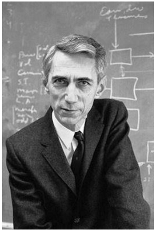

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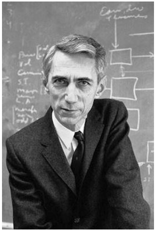

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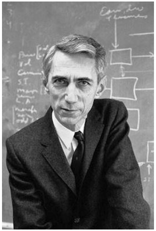

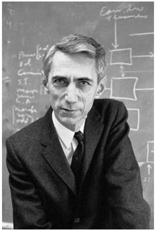

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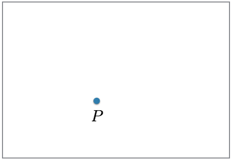

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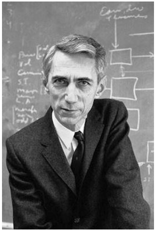

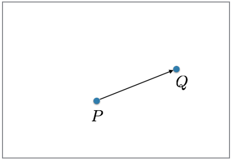

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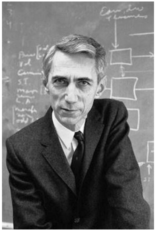

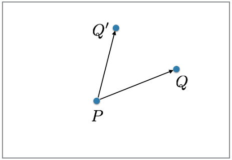

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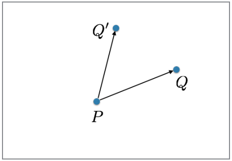

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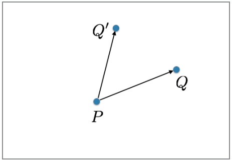

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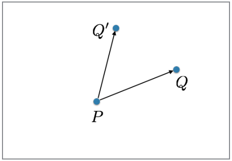

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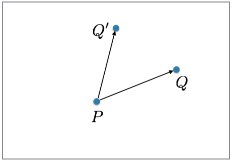

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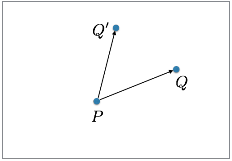

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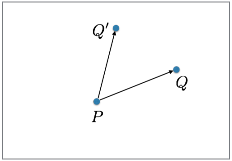

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  - Back to the picture: relevance and direction

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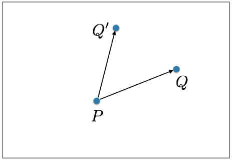

- The geometry of probability distributions is complex.
- Focus on a small neighborhood around P_0

$$P(y) = P_0(y)(1 + \epsilon \cdot L_P(y)), \quad y \in \mathcal{Y}$$
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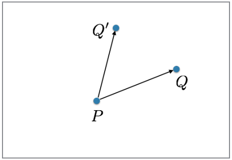

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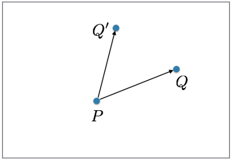
- Information Vector: 3 equivalent ways to write it.
  - Difference between two distributions $Q(y) - P_0(y)$
  - Log Likelihood functions

$$L_Q(y) = \log Q(y)/P_0(y)$$

  - Euclidean Vector form $\underline{\phi}$ with

$$\phi(y) = \frac{1}{\sqrt{P_0(y)}}(Q(y) - P_0(y))$$



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- Much more importantly, now information vector has directions

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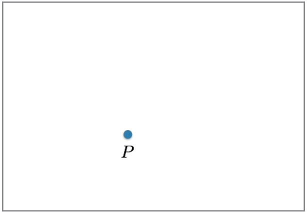

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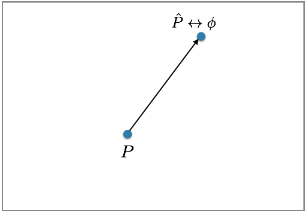

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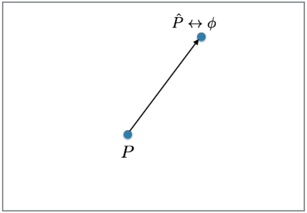

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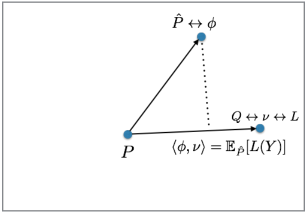

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- Suppose we evaluate a specific function with the data

$$\frac{1}{n} \sum_{i=1}^{n} L(y_i) \leftrightarrow \langle \underline{\phi}, \underline{\nu} \rangle \qquad \text{for some } Q \leftrightarrow L \leftarrow \underline{\nu}$$

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- Even if we don’t have the model, the picture still holds.

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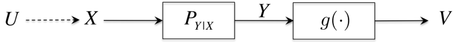

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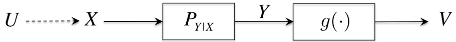

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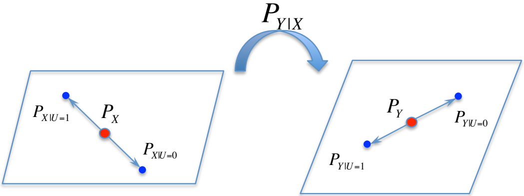

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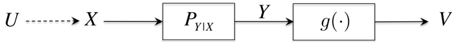

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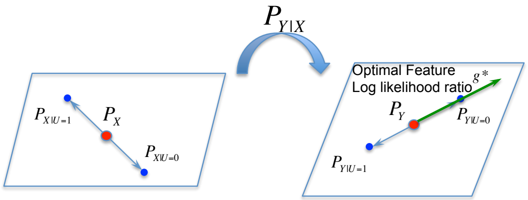

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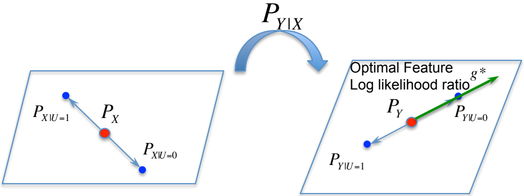

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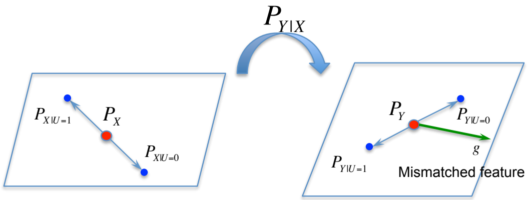

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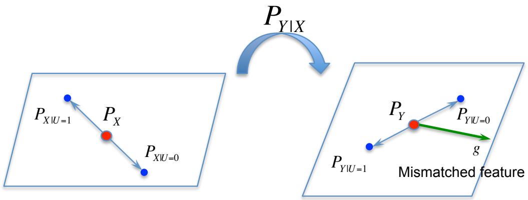

- When do we not know the model?
  - Data is too high-dimensional that we need to first reduce dimensionality before learning a model
  - We want to have a generic processing to serve multiple purposes
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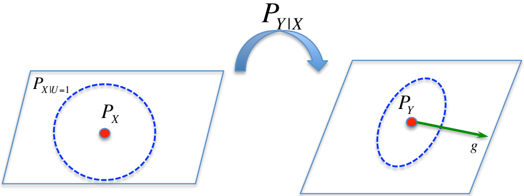

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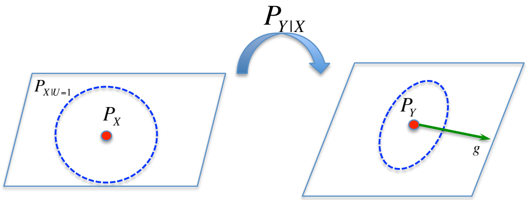

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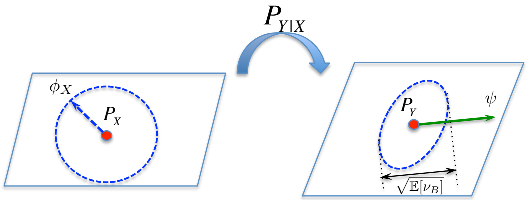

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- Average performance

$$\max_g \quad \mathbb{E}_{U-X}[D(P_{g(Y)|U=1}||P_{g(Y)|U=0})]$$

Equivalent Problems

Theorem

The following problems are equivalent (under local approximation)

- *Average inference performance over unknown models*

$$\max_{g} \quad \mathbb{E}_{U-X}[D(P_{g(Y)|U=1}||P_{g(Y)|U=0})]$$

- *Opportunistic formulation*

$$\max_{U-X}\max_{g} \quad \mathbb{E}_{U-X}[D(P_{g(Y)|U=1}||P_{g(Y)|U=0})]$$

- *PCA in the space of distributions*

$$\max_{\|\underline{\phi}_X\|^2=1} \quad \|\underline{\phi}_Y = B\underline{\phi}_X\|^2$$

- *Rényi maximal correlation (HGR)*

$$\rho = \max_{f,g:\mathbb{E}[f(X)]=\mathbb{E}[g(Y)]=1} \quad \mathbb{E}[f(X)\cdot g(Y)]$$

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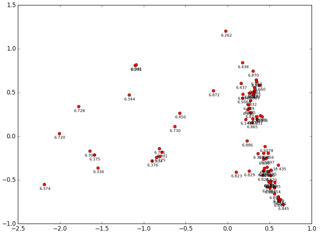

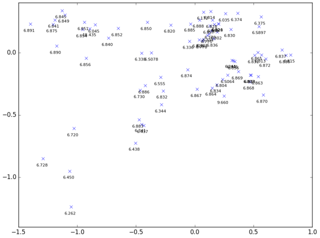

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A More Serious Problem: Cyber-Security/Network Management

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1438922809100	EVENT_LTE_RRC_PAGING_DRX_CYCLE	1614
1438922809100	RRC TIMER - DEADLOCK STOP	1605
1438922809100	EVENT_LTE_BSR_SR_REQUEST	1719
1438922809102	LTE_MAC_TIMER_ Start	1720
1438922809102	EVENT_LTE_TIMING_ADVANCE	1498
1438922809106	EVENT_LTE_BSR_SR_REQUEST	1719
1438922809110	EVENT_LTE_BSR_SR_REQUEST	1719
1438922809112	EVENT_LTE_REG_OUTGOING_MSG	1634
1438922809116	EVENT_LTE_BSR_SR_REQUEST	1719
1438922809126	EVENT_SD_EVENT_ACTION	621
1438922809129	EVENT_CM_SERVICE_CONFIRMED	558
1438922809135	EVENT_LTE_BSR_SR_REQUEST	1719
1438922809145	EVENT_LTE_BSR_SR_REQUEST	1719
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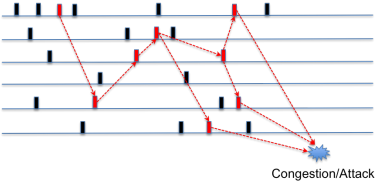
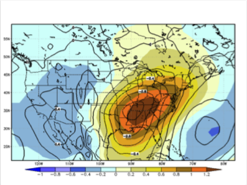
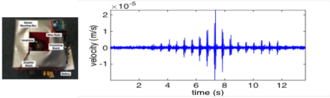




Detection of Extreme Weather Pattern

The NetFlix Problem



User Recognition by Footsteps

MNIST Handwriting Recognition

Community Detection on Social Networks, Cyber-Security of Large Networks, Joint Video-Audio Recognition...

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