USC Viterbi School of Engineering

Active Methods:

Learning as you go and as fast as you can

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National Science Foundation

Swedish Research Council

AIR FORCE OFFICE OF SCIENTIFIC RESEARCH
UNITED STATES AIR FORCE

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Office of Naval Research
ONR
Science & Technology

DEPARTMENT OF ENERGY
UNITED STATES OF AMERICA

Thanks!

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Jeongmin Chae

Special thanks

Dhruva Kartik PhD'21
Amazon

BIG PICTURE

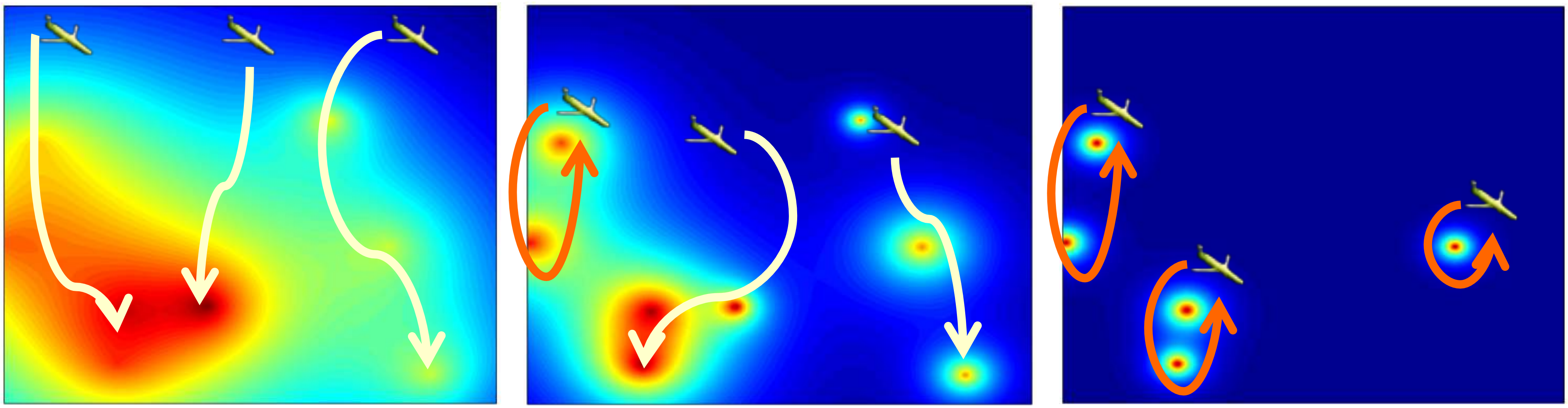
- Active hypothesis testing
  - So many applications!
  - Information theory in the wild

- Important questions
  - How do you build your tree of actions/observations?
  - What is the right measure of informativeness that allows you to prune the tree?

- Martingales, concentration inequalities
  - Very useful tools for a wide-range of applications (need more than the CLT)

- The classics still matter
  - Chernoff, Stein, Wald, Blackwell, Fisher, Bayes, Neyman, Pearson

Exploration-Exploitation

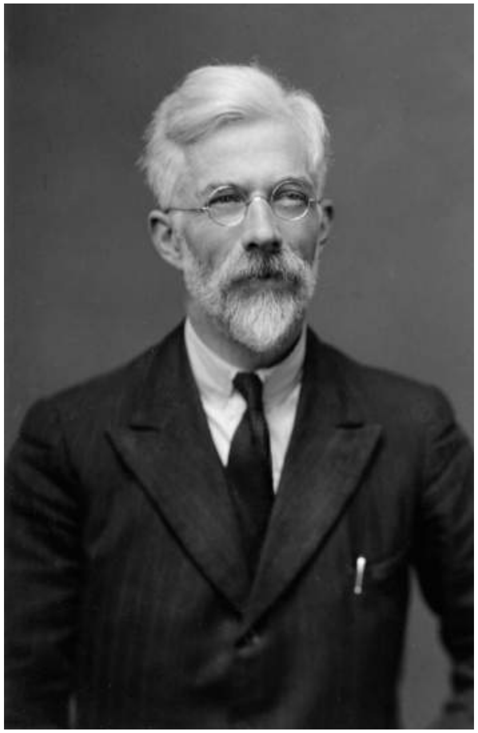


exploration
environment unknown

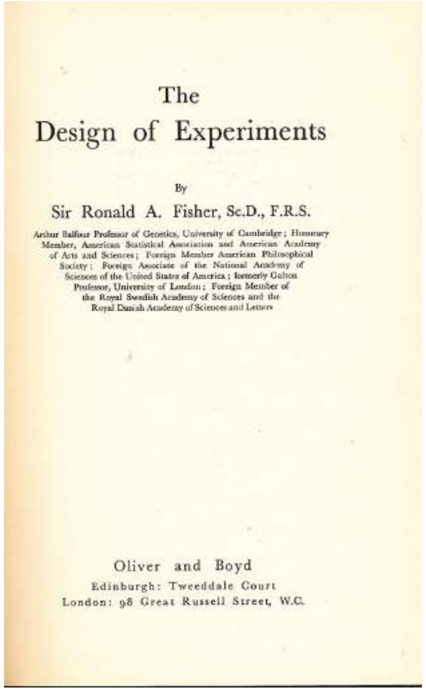
collect observations
learn

exploitation
focus on areas of interest

Design of Experiments



Sir Ronald Fisher
1890-1962



The
Design of Experiments

By

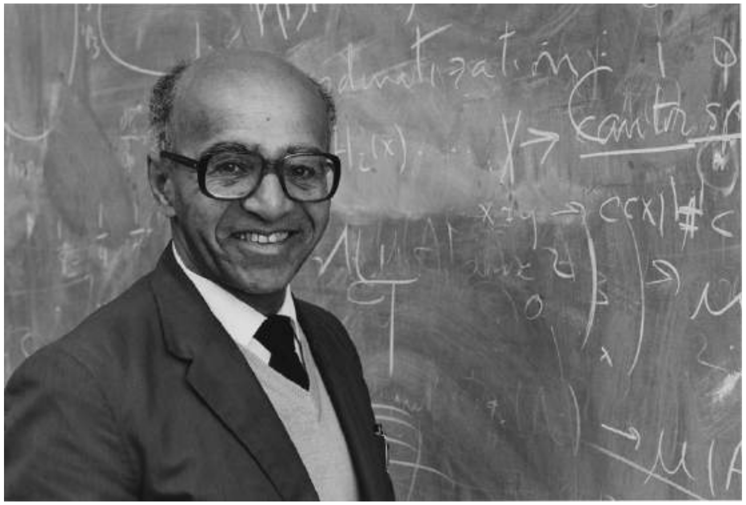
Sir Ronald A. Fisher, Sc.D., F.R.S.

Arthur Balfour Professor of Genetics, University of Cambridge; Honorary Member, American Statistical Association and American Academy of Arts and Sciences; Foreign Member American Philosophical Society; Foreign Associate of the National Academy of Sciences of the United States of America; formerly Galton Professor, University of London; Foreign Member of the Royal Swedish Academy of Sciences and the Royal Danish Academy of Sciences and Letters

Oliver and Boyd
Edinburgh: Tweeddale Court
London: 98 Great Russell Street, W.C.

1935

More broadly



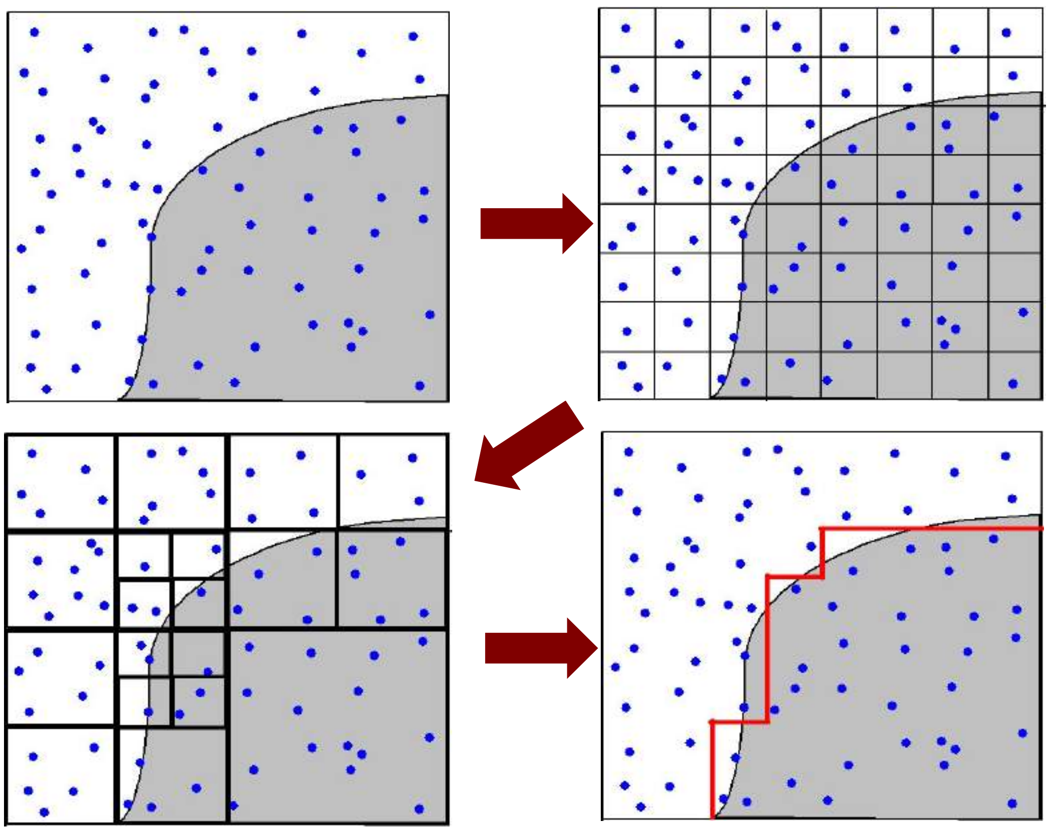
David Blackwell
1919-2010

Herman Chernoff
1923-

Abraham Wald
1902-1950

MOTIVATING EXAMPLE

Boundary Detection



- **SENSOR NETWORKS**:

  Actively build boundary

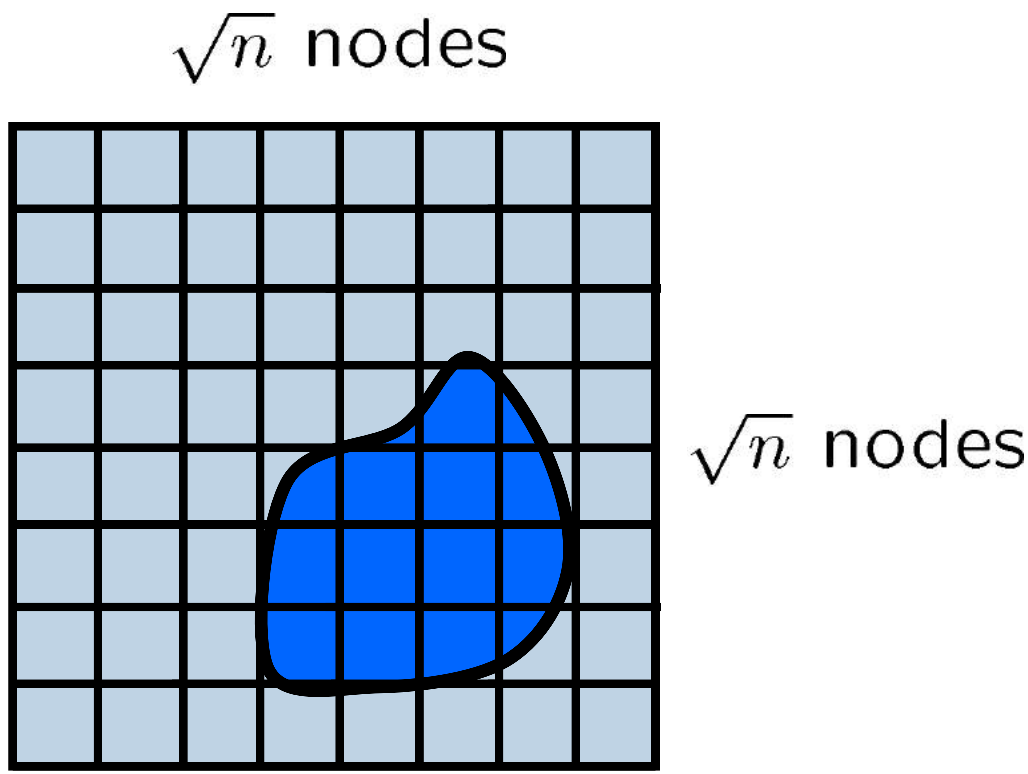
  Data aggregation at each layer

- Intrinsic complexity of boundary is

$$O(\sqrt{n})$$

Nowak, **M** & Willett, JSAC 2004, IPSN 2003

Recursive Dyadic Partitions

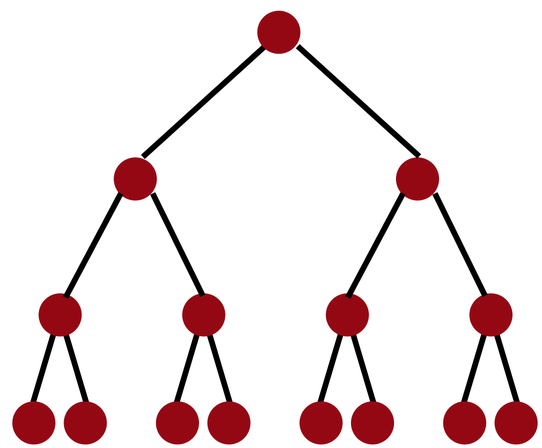


complete representation

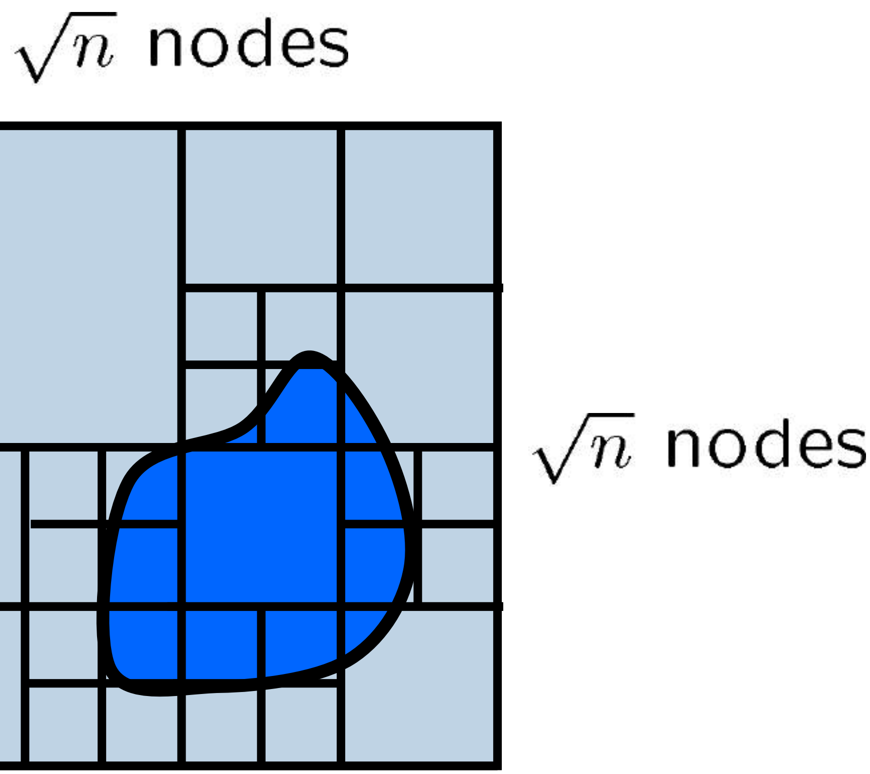
transmit all measurements

Complete Representation

- This is the full tree



Recursive Dyadic Partitions

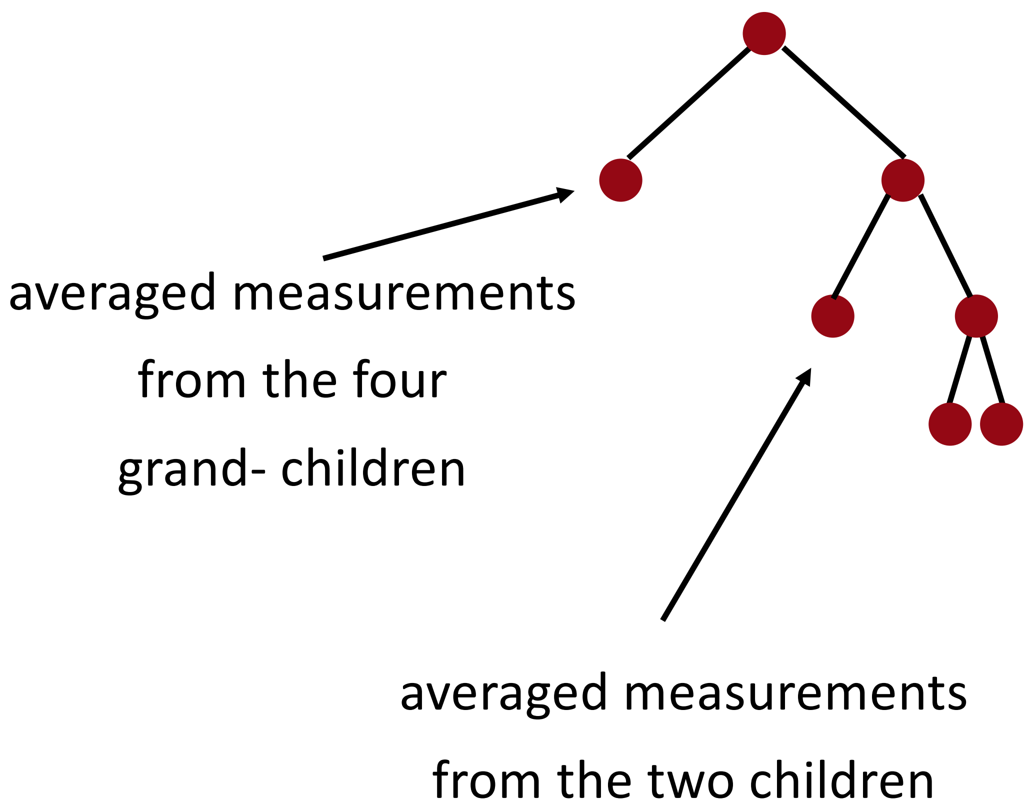


pruned representation

transmit averages/some measurements

Recursive Dyadic Partition

- The pruned tree



The question

- What is the optimal grouping?
  - The cost of keeping fine-grained measurements/size of the tree

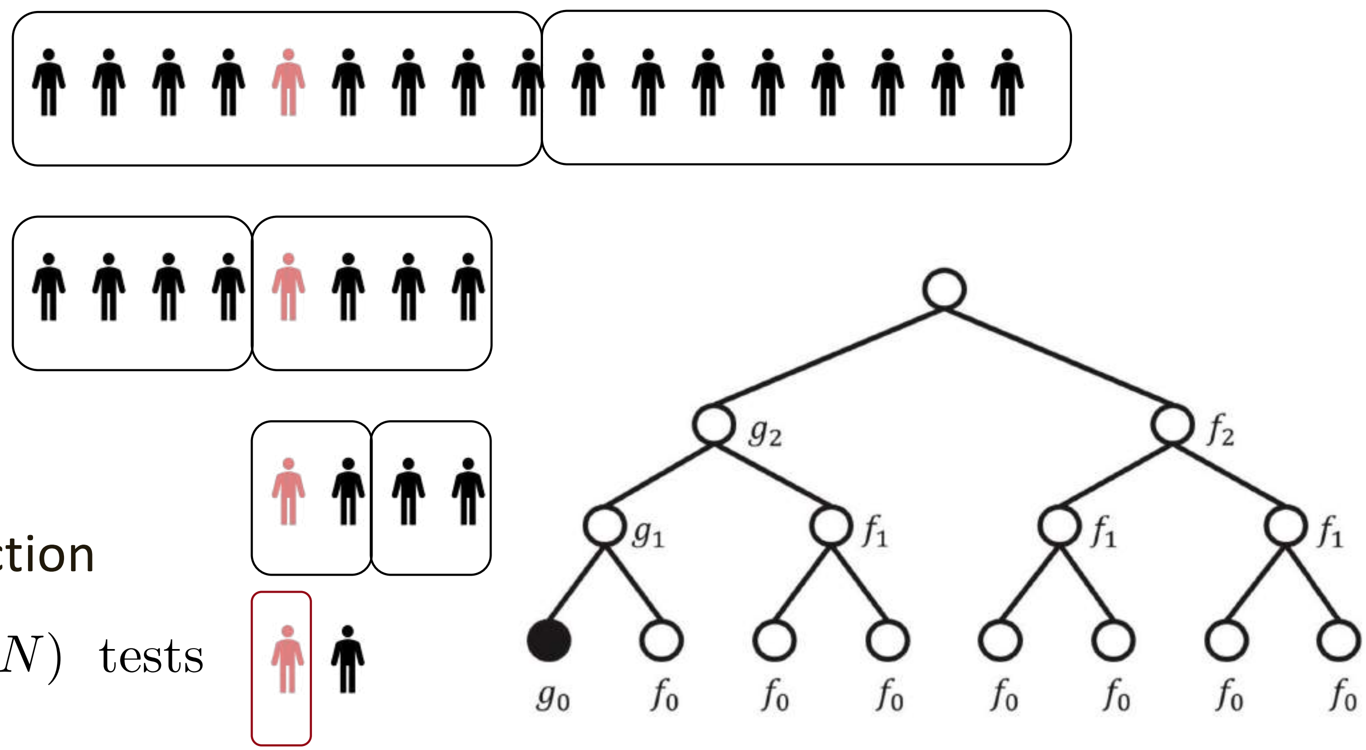
$$\begin{aligned} P &= \text{partition} \\ |\theta(P)| &= \text{size of partition/complexity} \end{aligned}$$

  - The cost of reducing fidelity – squared error

$$R(\theta, x) = \sum_{i,j=1}^{\sqrt{n}} \left(\theta(i,j) - x_{i,j}\right)^2$$

Connections to Group Testing

- Used in WW2 to test soldiers for syphilis
  - R. Dorfman, "The Detection of Defective Members of Large Populations," The Annals of Mathematical Statistics, 1943
  - Binary search



- Complexity reduction

$$N \text{ tests} \rightarrow \log(N) \text{ tests}$$

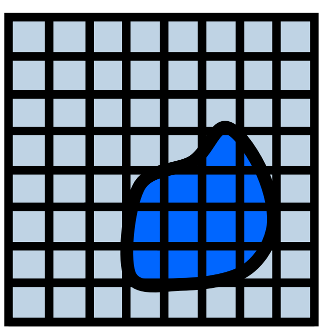
Estimation Criterion

- Penalized empirical risk
  - Squared error

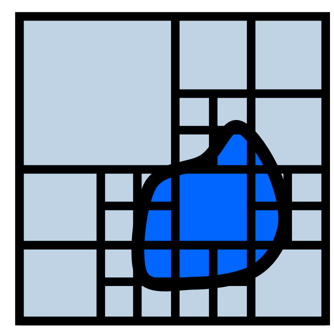
$$R(\theta, x) = \sum_{i,j=1}^{\sqrt{n}} \left(\theta(i,j) - x_{i,j}\right)^2$$

  - Complexity of RDP

$$\widehat{\theta}_n = \arg \min_{\theta(P):P\in\mathcal{P}_n} \left\{R(\theta, x) + 2\sigma^2 f(n)|\theta(P)|\right\}$$



$$|\theta(P)| \sim 64 \text{ versus } |\theta(P')| \sim 28$$



Metric for Pruning

- Over a dyadic partition compare penalized cost of average measurement versus measurements from a finer scale

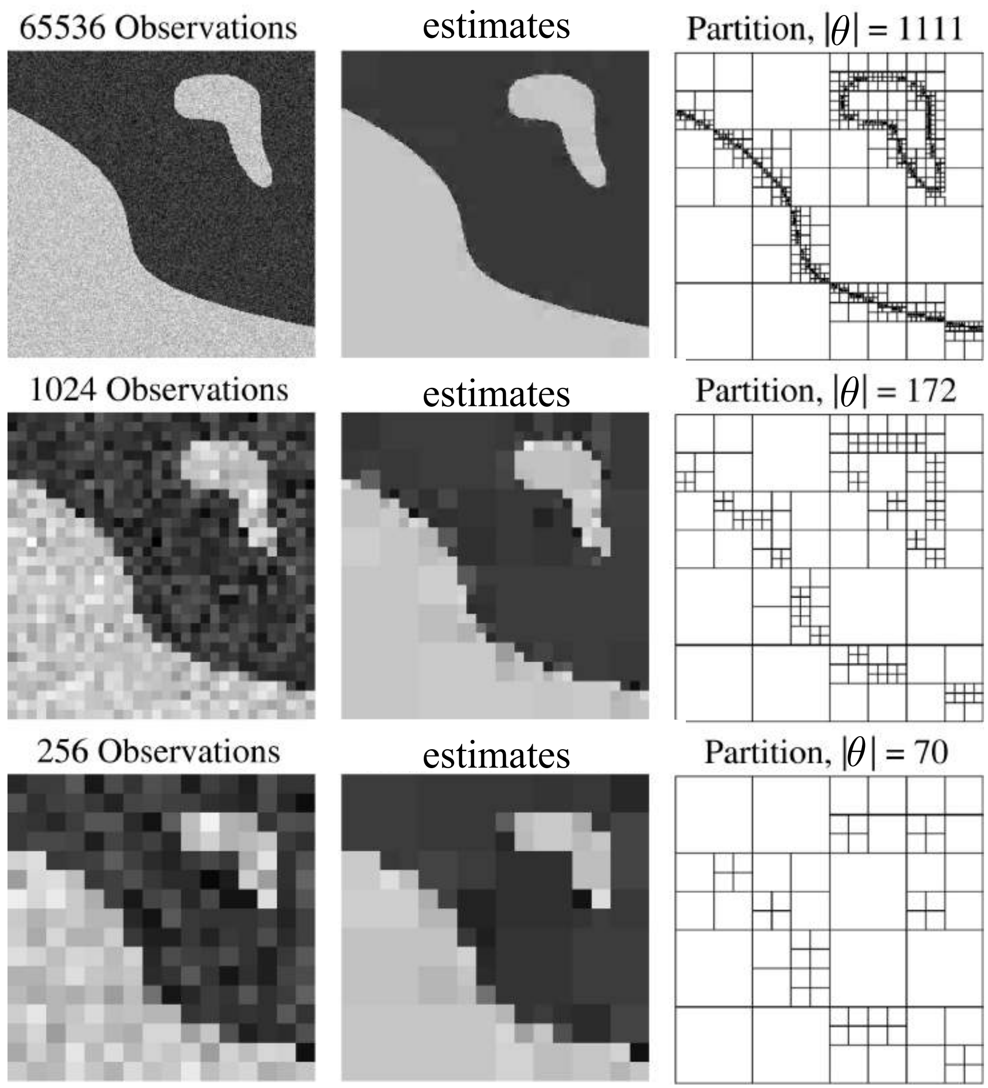
- Can show

$$\frac{1}{n}\sum_{i,j=1}^{\sqrt{n}} E\left[\left(\widehat{\theta}_n(i,j)-\theta^*(i,j)\right)^2\right] \leq O\left(\sqrt{\frac{\log n}{n}}\right)$$

  - Versus minimax lower bound $\mathrm{MSE} \geq O\left(\frac{1}{\sqrt{n}}\right)$

- Optimally pruned partition of order $O\left(\sqrt{n}\right)$

Numerical Results



Adaptive Boundary Estimation

- Actively building up representation, BUT
- All measurements taken once
  - Reverse engineering representation
  - Notion of higher utility/reward
- Notion of one representation being better than another
- Not active in measurement collection

BASICS OF HYPOTHESIS TESTING

Hypotheses and Likelihoods

- Binary Hypotheses:

$$\begin{aligned} H_0 &: \text{null hypothesis} \\ H_1 &: \text{alternate hypothesis} \end{aligned}$$

$X = 0$: If H_0 is true

$X = 1$: If H_1 is true

- Model:

$$\mathbb{P}[Y = y \mid X = 0] = p_0(y)$$
$$\mathbb{P}[Y = y \mid X = 1] = p_1(y)$$

$Y \in \mathcal{Y}$

finite alphabet

observation

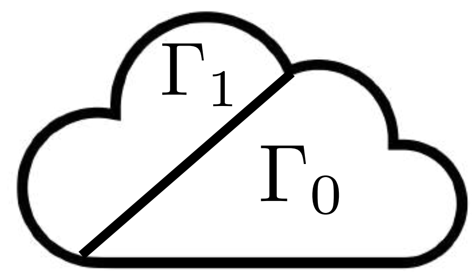
likelihood functions

Binary Hypothesis Testing

H_1 : alternative hypothesis

H_0 : null hypothesis

partition observation space



$Y_k \sim p_X$

i.i.d. observations

$$f(y) = \text{decision rule}$$
$$= \{0, 1\}$$

$$y = \text{observation}$$
$$p_i(y) = \text{pdf of } y \text{ given } H_i$$

$$\hat{X} = f(Y^n, \text{random})$$

inference

decision rule

Good Decision Rules

- Log-likelihood Ratio (LLR):

$$L_n = \log \frac{p_0(Y^n)}{p_1(Y^n)} = \sum_{k=1}^{n} \log \frac{p_0(Y_k)}{p_1(Y_k)}$$

- Good decision rules

change the metric
change the threshold

$$\hat{X} = \begin{cases} H_0 & \text{if } L_n \geq \tau \\ H_1 & \text{if } L_n < \tau \end{cases}$$

likelihood ratio test

τ_B

τ_{NP}

Kullback-Leibler Divergence

- DEFINITION:

$$D(p||q) = \sum_y p(y) \log \frac{p(y)}{q(y)}$$

Expectation of LLR is related to KL-Divergence

- Like a ``distance'' between two distributions
- BUT, **not** symmetric: $D(p||q) \neq D(q||p)$
- Will determine the asymptotic performance of NP rule

Likelihood Ratio Tests

- Equivalent representation with respect to the KL divergence

$$L(y^n) \quad > \quad \tau$$

$$D\left(p(y^n) \| p_0(y^n)\right) - D\left(p(y^n) \| p_1(y^n)\right) \quad > \quad \frac{1}{n} \log \tau$$

- The empirical distribution is closest to which hypothesis?
- NOTE:

$$\mathbb{E}_0[L_n] = nD(p_0 || p_1)$$
$$\mathbb{E}_1[L_n] = -nD(p_1 || p_0)$$

- Bayes optimal rule versus Neyman-Pearson rule
  - How to select τ ?

Bayes Rule

- Bayesian Risk:

$$C_{ij} = \text{cost of selecting } i \text{ when } j \text{ is true}$$

$$r(f) = \sum_j \pi_j \sum_i C_{ij} \mathbb{P}[\hat{X} = i \mid X = j]$$

priors costs infer i given truth is j

- Bayes rule:

$$\hat{X} = \begin{cases} H_0 & \text{if } L_n \geq \tau \\ H_1 & \text{if } L_n < \tau \end{cases}$$

likelihood ratio test

$$\tau = \log \frac{\pi_1 (C_{01} - C_{11})}{\pi_0 (C_{10} - C_{00})}$$

Special Cases

- Uniform costs

$$\begin{aligned} C_{ij} &= \delta(i-j) \\ \rightarrow \tau &= \log \frac{\pi_0}{\pi_1} \end{aligned}$$

  - *Maximum a posteriori rule*

- Uniform costs and equal priors

all likelihood ratio tests

$$\tau = \log(1) = 0$$

  - Maximum likelihood rule

Gaussian Example

$$\mathcal{H}_i \quad : \quad Y \sim \mathcal{N}(\mu_i, \sigma^2)$$

$$L(y) \quad = \quad \left[\left(\frac{\mu_1 - \mu_0}{\sigma^2} \right) \left(y - \frac{\mu_0 + \mu_1}{2} \right) \right]$$

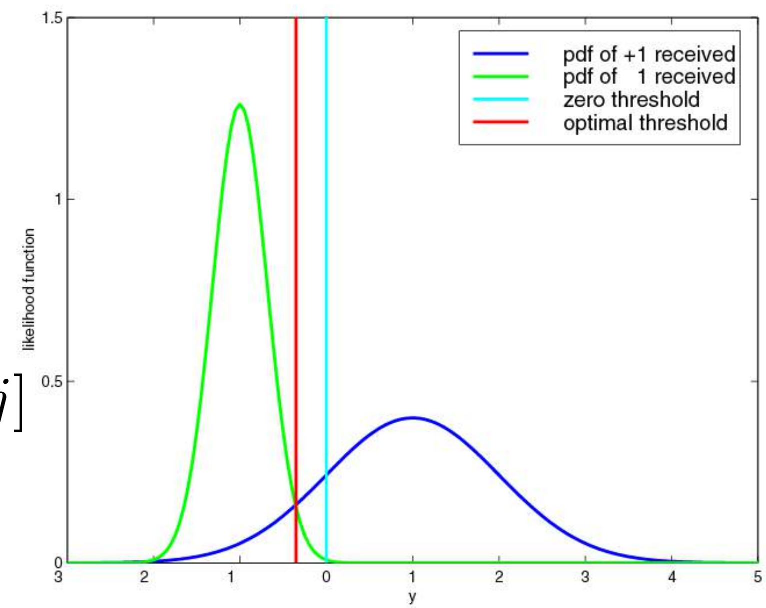
$$L(y) \quad \gtrless \quad \tau$$

$$y \quad \gtrless \quad \tau' = \frac{\sigma^2}{\mu_1 - \mu_2} \ln \tau + \frac{\mu_0 + \mu_1}{2}$$

$$r(f) = \sum_j \pi_j \sum_i C_{ij} \mathbb{P}[\hat{X} = i \mid X = j]$$

$$\mathbb{P}\left[\hat{X} = 1 | X = j\right] \quad = \quad \mathbb{P}\left[\mathbf{Y} \geq \tau' | X = j\right]$$

$$= \quad Q\left(\frac{\tau' - \mu_j}{\sigma} \right)$$



How to bound Performance?

- Y is a random variable
  - Moment generating function

$$\mu(s) = \mathbb{E}[\text{exp}(-sY)]$$

- Chernoff Bound

$$\forall \;\; s \geq 0 \quad \mathbb{P}\left[Y \geq a\right] \leq e^{-sa}\mu(s) \;\; \forall \; s$$
$$\rightarrow \; \mathbb{P}\left[Y \geq a\right] \leq \min_s e^{-sa}\mu(s)$$

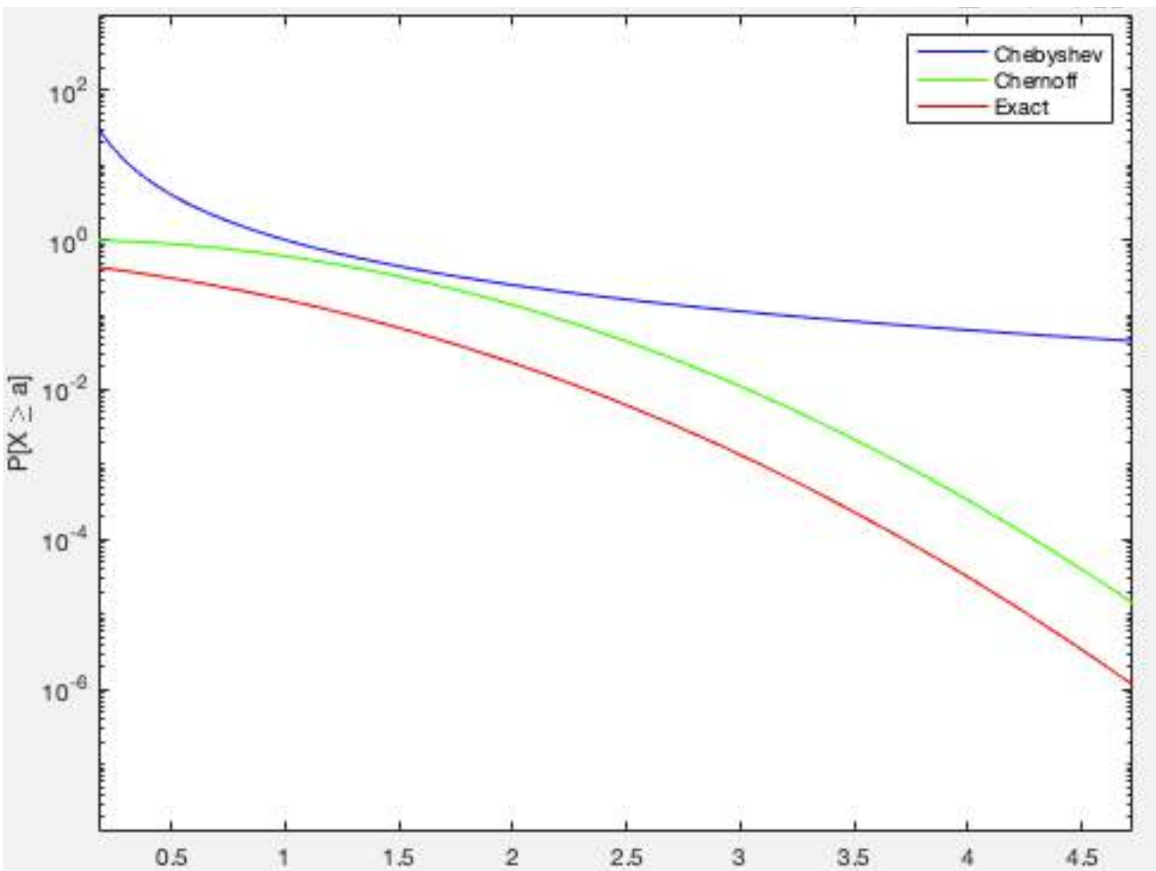
- Proof - via Markov inequality

$$\mathbb{P}\left[X \leq a\right] \quad \leq \quad \frac{\mathbb{E}\left[X\right]}{a}$$
$$X \quad = \quad e^{sY}$$

Chernoff Bound

$$\mathbb{P}\left[Y \geq a\right] \quad \leq \quad \min_{s} e^{-sa}\mathbb{E}\left[e^{sY}\right]$$

Gaussian example



Error Decay Rates

- Often more easily computable than exact probabilities
- Enable straightforward comparison across detectors
- Provide a measure for how far from asymptotic performance
  - *When do asymptotics kick in?*

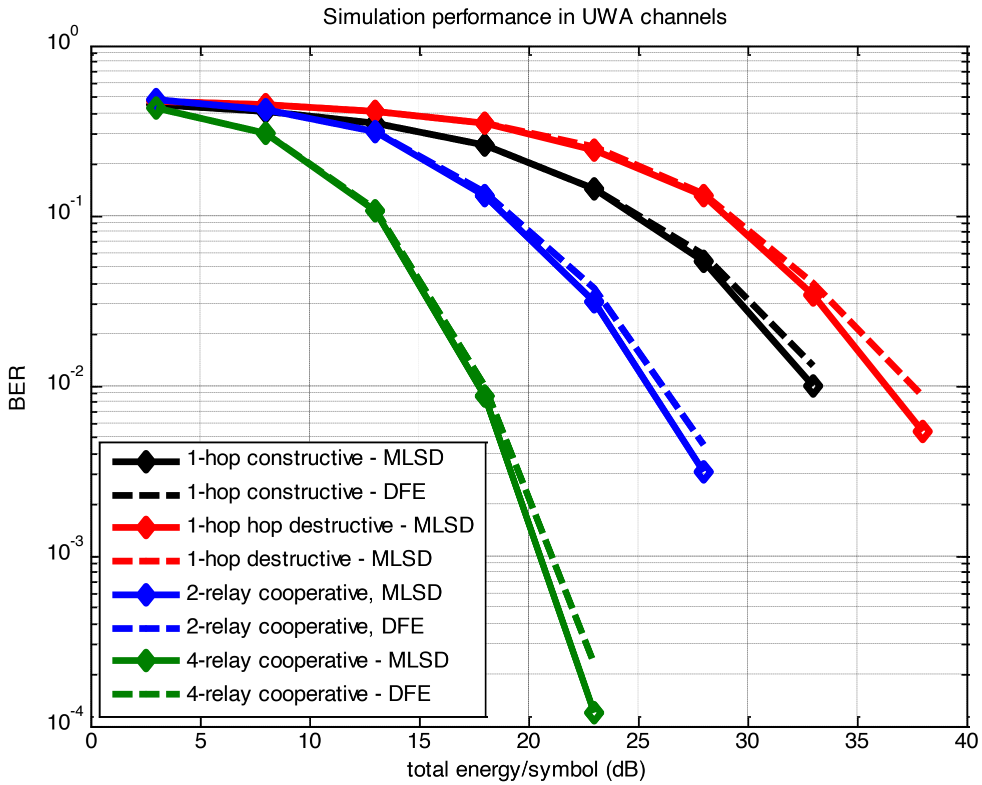
$$\text{Error rate}(\delta) = \lim_{n \to \infty} -\frac{1}{n} \log P_e(f)$$

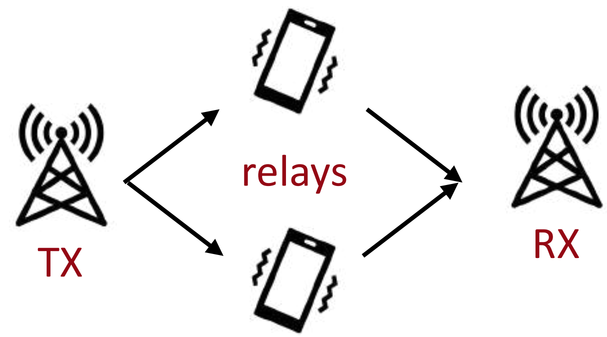
what about fixed n?

$$\begin{aligned} f(y) &= \text{decision rule} \\ &= \{0, 1\} \end{aligned}$$

Error Decay Rates

underwater acoustic communication





diversity

$$\text{decay rate} \quad 2 - 2\frac{\log \log P}{\log P}$$

cost: error propagation at relay

IEEE JOURNAL OF OCEANIC ENGINEERING, VOL. 33, NO. 4, OCTOBER 2008 489

Distributed Space–Time Cooperative Schemes for Underwater Acoustic Communications

Madhavan Vajapeyam, *Member, IEEE*, Satish Vedantam, Urbashi Mitra, *Fellow, IEEE*, James C. Preisig, *Member, IEEE*, and Milica Stojanovic, *Senior Member, IEEE*

Error Rate for Bayes Rule

- Error rate:

$$\text{Error rate}(f) = \lim_{n \to \infty} -\frac{1}{n} \log r(f)$$

$$r(f) = \sum_j \pi_j \sum_i C_{ij} \mathbb{P}[\hat{X} = i \mid X = j] \quad \text{Bayes risk}$$

- Theorem: error rate for the Bayes optimal rule

$$\text{Error rate(LRT)} = \underbrace{-\min_{0 \le \lambda \le 1} \log \sum_y (p_0(y))^\lambda (p_1(y))^{(1-\lambda)}}_{\text{Chernoff Information}}$$

- Not a function of the priors! π_i

Neyman-Pearson Formulation

- Performance Measures:

$$\mathbb{P}[\hat{X} = 0 \mid X = 1] = \mathbb{P}_1[\hat{X} = 0] \text{ (Miss probability)}$$

$$\mathbb{P}[\hat{X} = 1 \mid X = 0] = \mathbb{P}_0[\hat{X} = 1] \text{ (False alarm probability)}$$

- Formulation: minimize miss probability while ensuring that false alarm probability is low

$$\begin{aligned} \min_{f} \quad & \mathbb{P}_1[\hat{X} = 0] \\ \text{subject to} \quad & \mathbb{P}_0[\hat{X} = 1] \le \epsilon \end{aligned}$$

Neyman Pearson Rule

- Optimal Decision Rule is a LRT:

$$\hat{X} = \begin{cases} H_0 & \text{if } L_n > \tau \\ H_0 \text{ w.p. } \gamma & \text{if } L_n = \tau \\ H_1 & \text{if } L_n < \tau \end{cases}$$

- How to select parameters:
  - Challenge when mismatched support and/or discrete RVs

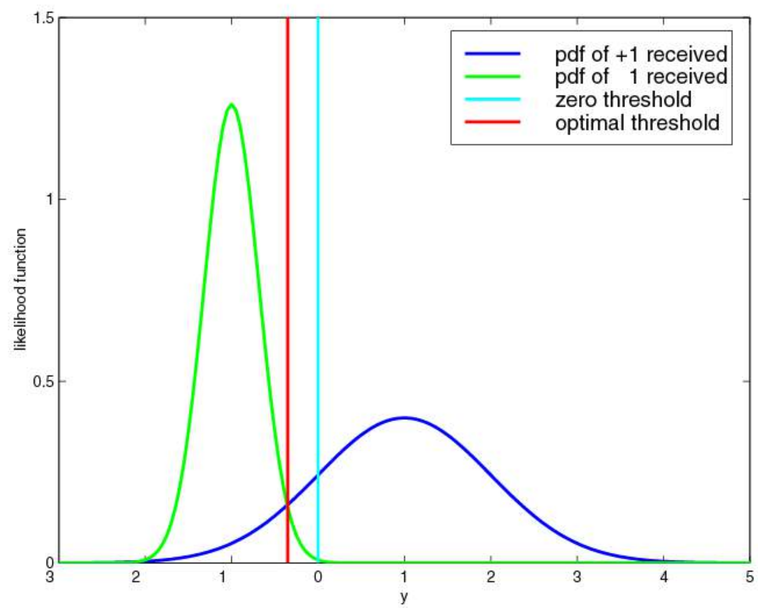
$$\text{threshold } \tau \text{ and randomization } \gamma \text{ unique solutions to}$$
$$\epsilon = \mathbb{P}_0[L_n > \tau] + \gamma \mathbb{P}_0[L_n = \tau]$$

randomization to achieve P_F exactly

Gaussian Example

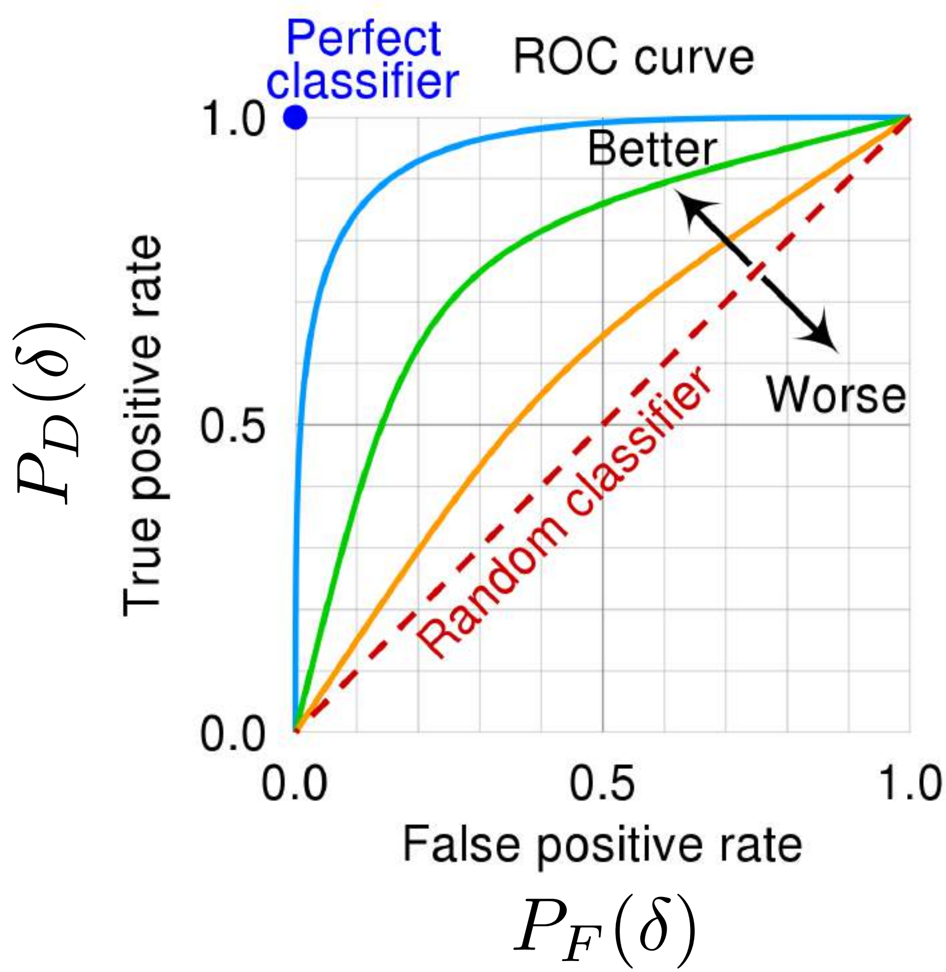
- Continuous valued RVs, matching support
- No randomization necessary
- False alarm rate determines threshold

$$
\begin{aligned}
\alpha &= \mathbb{P}\left[\hat{X} = 1 | X = 0\right] \\
&= Q\left(\frac{\tau' - \mu_0}{\sigma}\right) \\
\rightarrow \quad \tau' &= \mu_0 + \sigma Q^{-1}(\alpha)
\end{aligned}
$$



Receiver Operating Characteristics

- NP best tradeoff between $P_F(\delta)$ and $P_D(\delta)$



Chernoff-Stein Lemma

- Kullback-Leibler Divergence:

$$D(p||q) = \sum_y p(y) \log \frac{p(y)}{q(y)}$$

$$\mathbb{E}_0[L_n] = nD(p_0||p_1)$$
$$\mathbb{E}_1[L_n] = -nD(p_1||p_0)$$

Expectation of LLR is related to KL-Divergence

- Chernoff-Stein Lemma: Miss rate of NP rule is

$$\lim_{n\to\infty} -\frac{1}{n} \log \mathbb{P}_1[\hat{X} = 0] = D(p_0||p_1)$$

Bayes Rule versus NP Rule

- Bayes rule

$$\text{Error rate(Bayes)} = \underbrace{-\min_{0\leq\lambda\leq 1}\log\sum_{y}(p_0(y))^{\lambda}(p_1(y))^{(1-\lambda)}}_{\text{Chernoff Information}}$$

- Neyman Pearson rule

$$\text{Error rate(NP)} = \underbrace{D(p_0\|p_1)}_{\text{Chernoff-Stein exponent}}$$

SEQUENTIAL OBSERVATIONS

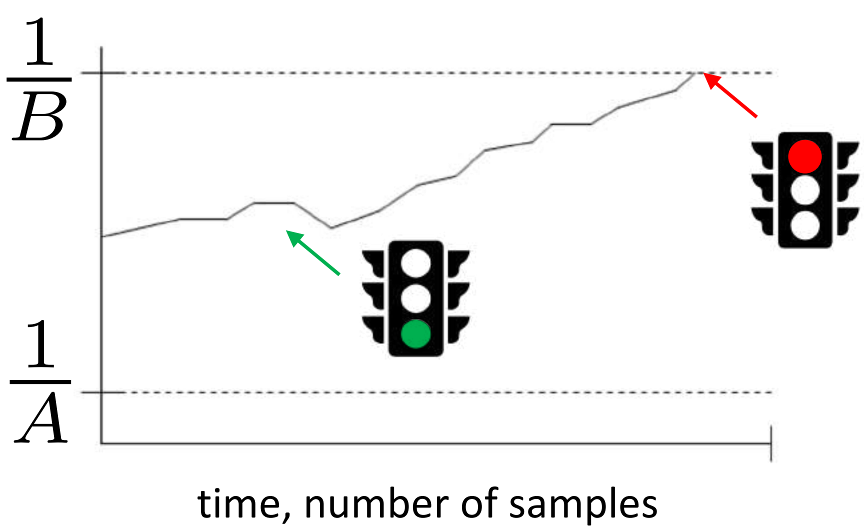
Sequential Probability Ratio Tests

- Should you always use all of the data?
  - Stop when confident!
- A Wald, *The Annals of Mathematical Statistics*, 1945
- Problem set up
  - Samples $\mathbf{y}_m = [y_1, y_2, \cdots, y_m]$

$$
\begin{aligned}
L_m &= \log \frac{p_0(\mathbf{y}_m)}{p_1(\mathbf{y}_m)} \\
\alpha &= \text{false alarm rate} \\
\beta &= \text{miss probability}
\end{aligned}
$$

SPRT solution

$$f(\mathbf{y}_m) = \begin{cases} H_0 & L_m \geq \frac{1}{B} \\ H_1 & L_m < \frac{1}{A} \\ \text{keep sampling} & \text{else} \end{cases}$$

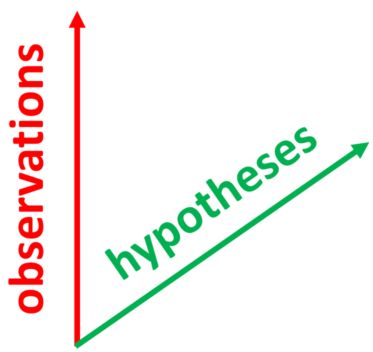


$$A \approx \log \frac{1-\beta}{\alpha}$$

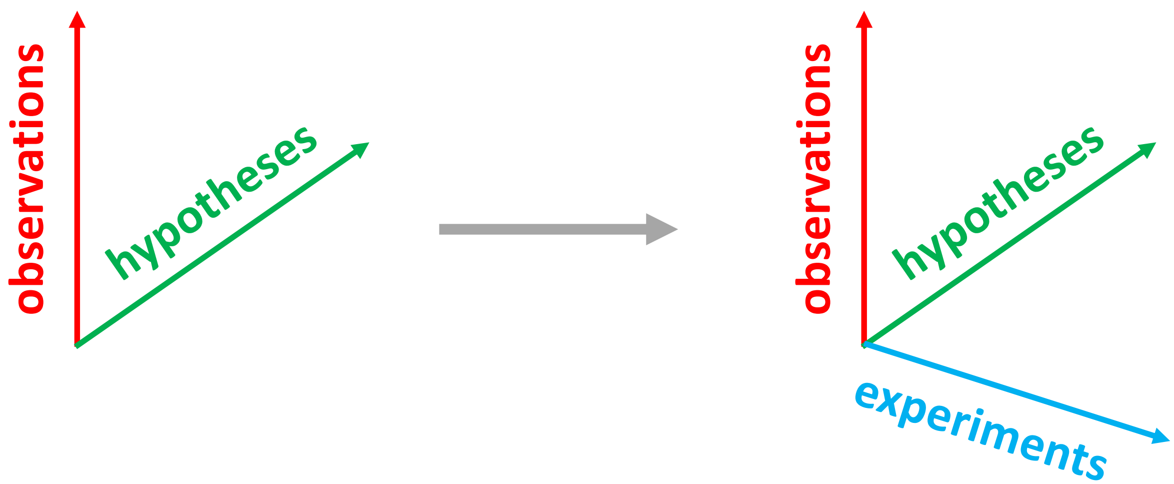
$$B \approx \log \frac{\beta}{1-\alpha}$$

same experiment

Now….

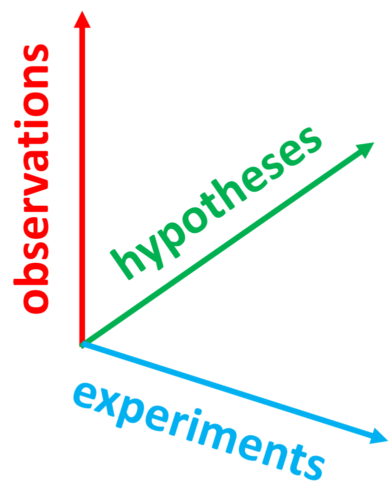


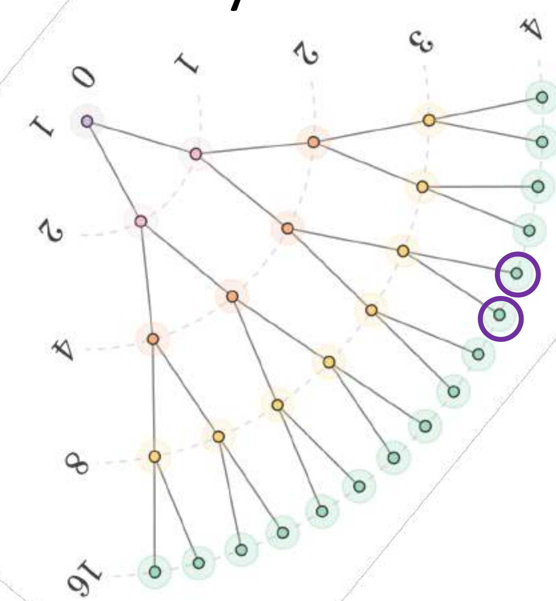
Now….


observations
hypotheses
observations
hypotheses
experiments

Now….

- Allow myself to take more observations and change experiment
  - Different experiments: different sensors, different groupings
- Now, how to develop algorithms and analyze?



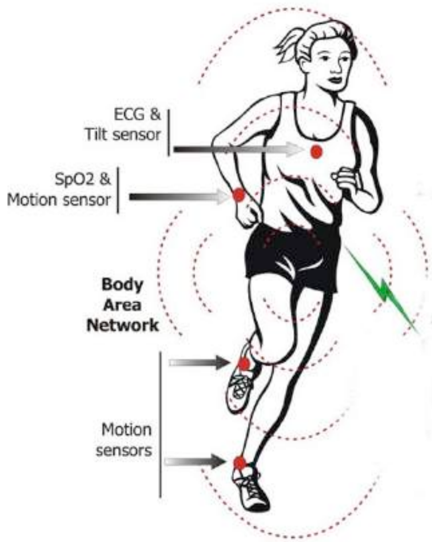


which action is more informative?

wumbo.net

ACTIVE SENSOR SELECTION

Wireless Body Area Sensing Network



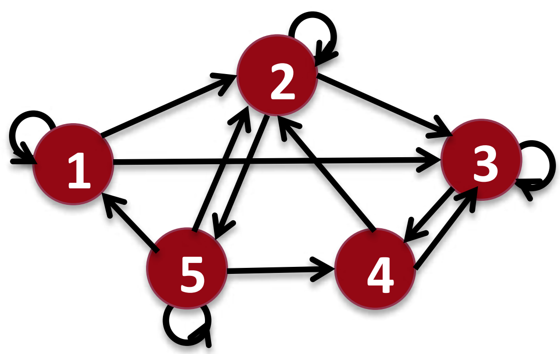
COMMUNICATIONS IN UBIQUITOUS HEALTHCARE

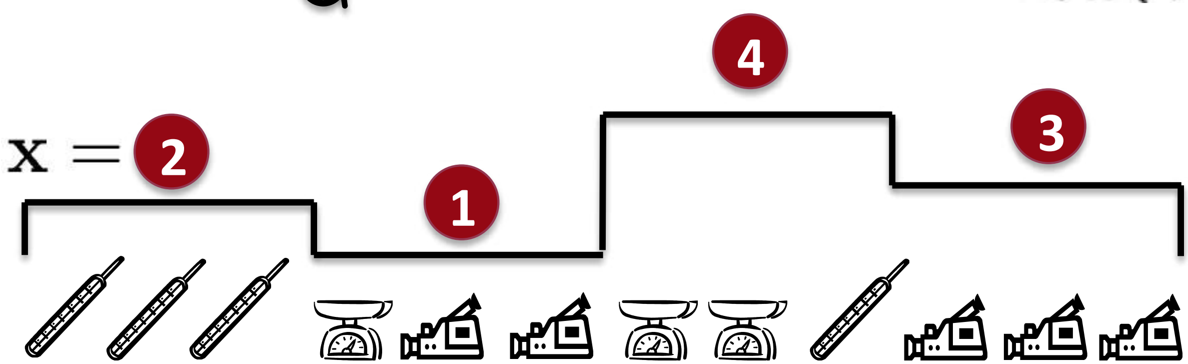
KNOWME: A Case Study in Wireless Body Area Sensor Network Design

Urbashi Mitra, B. Adar Emken, Sangwon Lee, and Ming Li, University of Southern California
Viktor Rozgic, Raytheon BBN Technologies
Thatte, TrellisWare Technologies, Inc.
rdhan Vathsangam, Daphney-Stavroula Zois, Murali Annavaram, and Shrikanth Narayanan, Uni-
f Southern California
vorato, Stanford University and University of Southern California
oruijt-Metz and Gaurav Sukhatme, University of Southern California

Jovanov *et al. Journal of NeuroEngineering and Rehabilitation* 2005

What is my problem?





$$\mathbf{y} = f(\mathbf{x}, \mathbf{u}) \rightarrow \hat{\mathbf{x}}$$

observation state, control

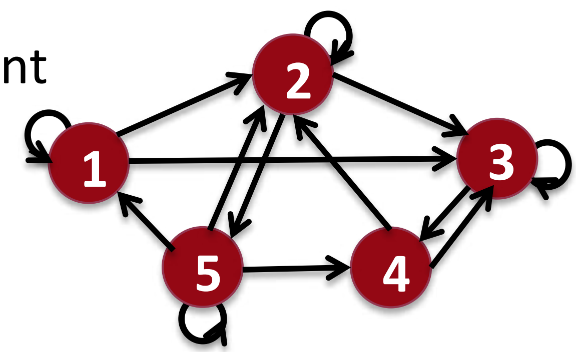
this is **active hypothesis testing**
for a **time-varying process**

Problem Framework

- Sensor time-series (ECG, accelerometer, etc.) converted to features
- Each state indicated by a standard basis vector

$$\mathbf{e}_i \quad = \quad [0, \cdots, 0, 1, 0 \cdots 0]$$

i'th component

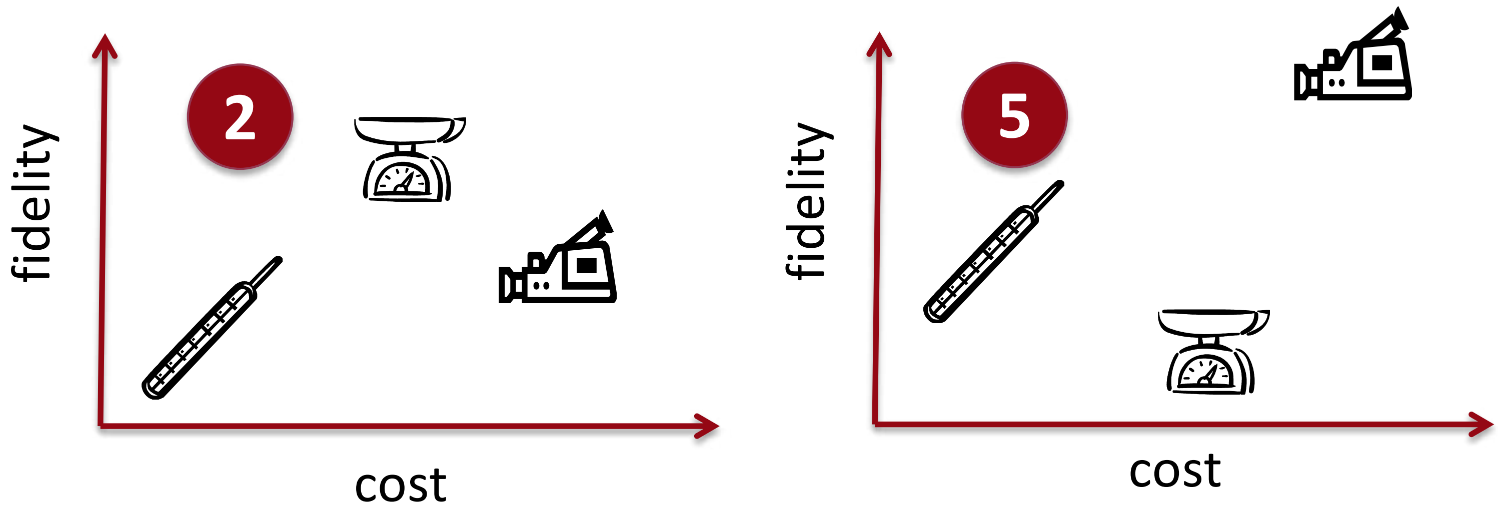


- add one more part: a control or action
  - Yields a Markov Decision Process
  - Also randomness from actions/environment

Zois & **M**, TSP'17, ICASSP'14, ISIT'14, Globecom'14, Asilomar'13, GlobalSIP'13

Zois, Levorato &**M**, TSP'14, TSP'13

Heterogeneity



- Different sensors are good at discriminating different states
- Chicken and egg problem…

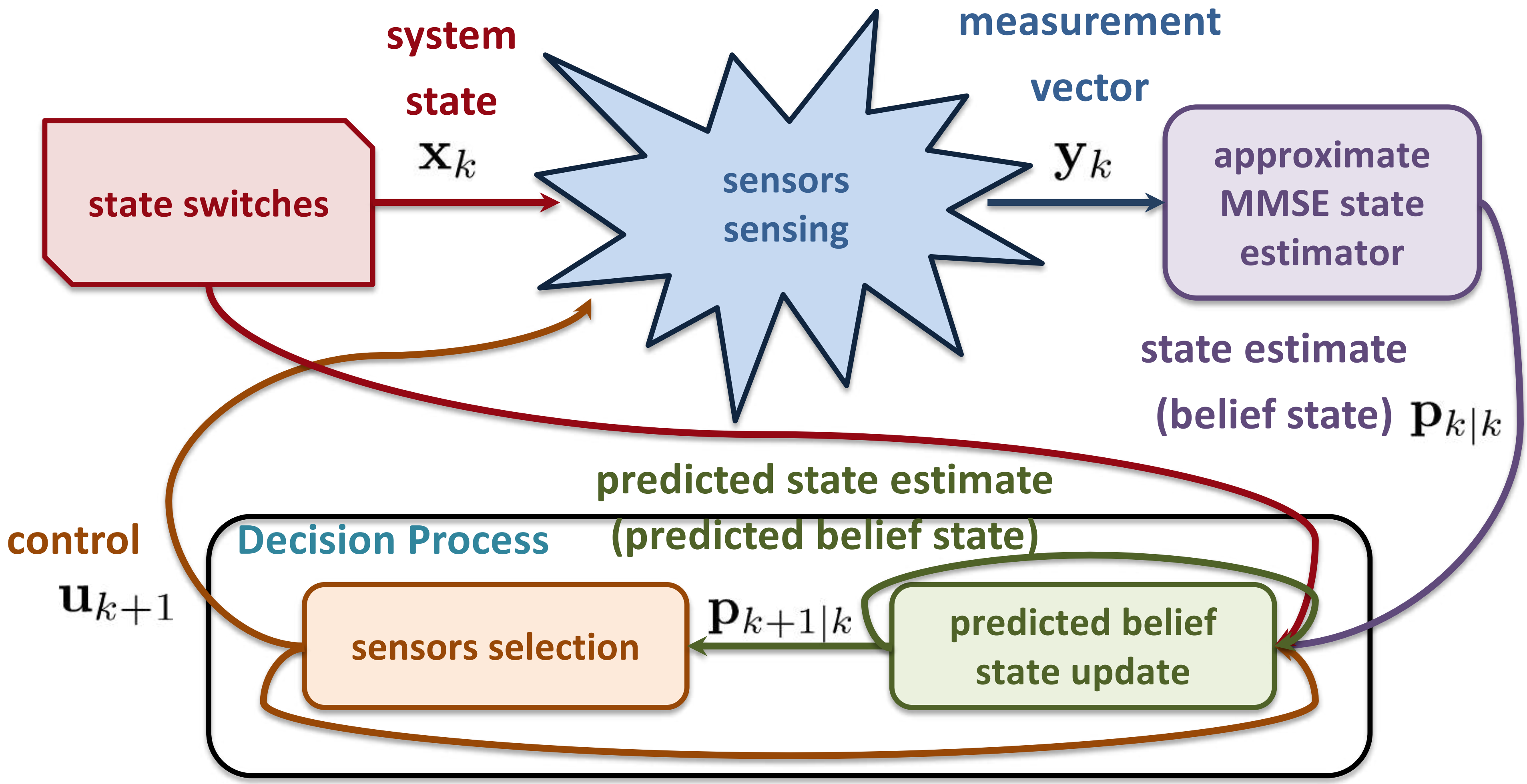
What is my problem?

- Goal: track temporal evolution of a discrete–time, finite–state Markov chain

- Design control (sensor allocation problem)
  - Heterogeneous fidelity across sensors
  - Heterogeneous costs across sensors
  - **Optimize performance, minimize cost**

- Contrast to standard control problems:
  - **control influences observations (not state)**

POMDP System



partially observable Markov decision process (POMDP)

Signal Model

- System state
  - First order Markov process

$$\mathcal{X} = \{\mathbf{e}_1, \mathbf{e}_2, \ldots, \mathbf{e}_n\}$$
$$\mathbf{e}_i = [0, \ldots, 0, 1, 0, \ldots, 0]^T$$

state vectors binary valued

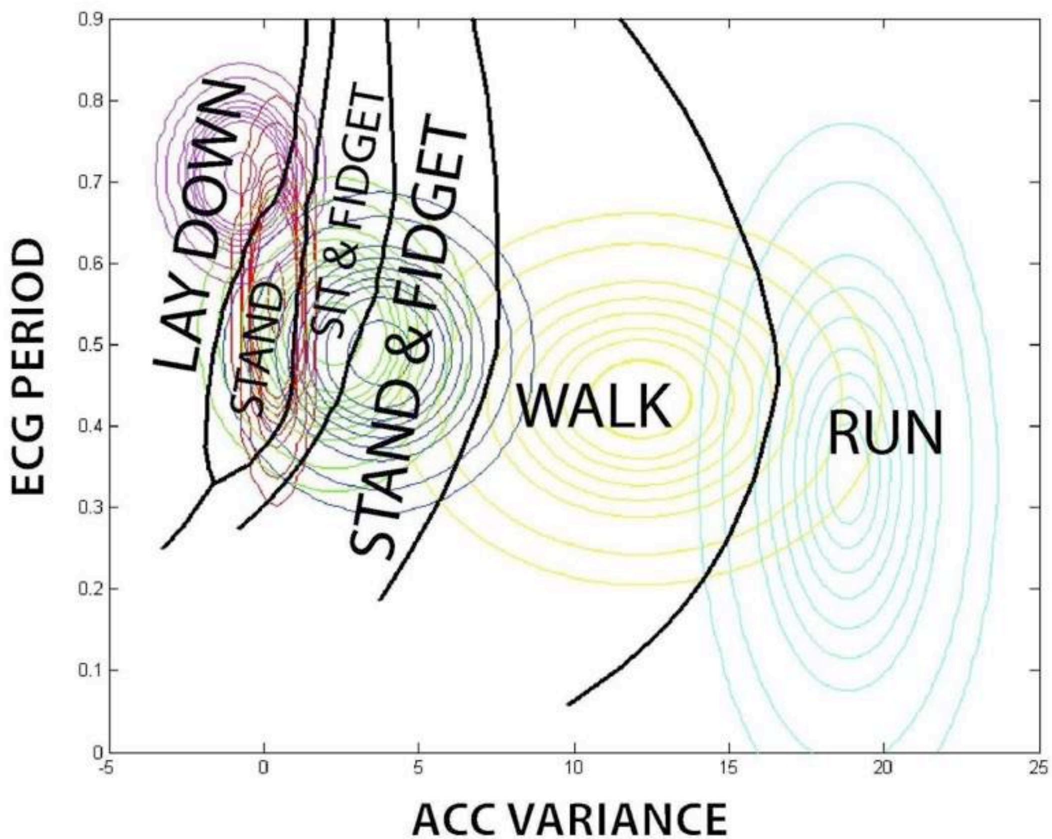
- Sensor features

$$\mathbf{y}_k \Big| \mathbf{e}_i, \mathbf{u}_{k-1} \sim \mathcal{N}(\mathbf{m}_i^{\mathbf{u}_{k-1}}, \mathbf{Q}_i^{\mathbf{u}_{k-1}})$$

control input *(can affect size, form, etc)*

  - control is which sensor to listen to and for how long
  - Validated by real world experiments

Non-linear Decision Regions



Decision regions for bivariate Gaussians for six activities

- Distinct means and covariance matrices for each subject | personalized training

Entropy

- Entropy – discrete RVs

$$
\begin{aligned}
H(X) &= -\sum_{x\in\mathcal{X}} p(x)\log p(x) \\
&= \log|\mathcal{X}| \;\text{ if }\; p(x) = \frac{1}{|\mathcal{X}|}\;\forall\, x \\
&\geq 0
\end{aligned}
$$

  - Entropy does not depend on the values of the alphabet
  - Measures uncertainty/randomness in an RV, or amount of information needed to describe an RV

- Joint Entropy

$$
H(X,Y) = -\sum_{x\in\mathcal{X}}\sum_{y\in\mathcal{Y}} p(x,y)\log p(x,y)
$$

More definitions

- Conditional entropy

$$
\begin{aligned}
H(Y|X) &= \sum_{x \in \mathcal{X}} p(x) H(Y|X = x) \\
&= -\sum_{x \in \mathcal{X}} \sum_{y \in \mathcal{Y}} p(y, x) \log p(y|x)
\end{aligned}
$$

- Conditioning reduces entropy

$$
\begin{aligned}
H(Y|X) &\leq H(Y) \\
\text{BUT } H(Y|X = x) &\gtreqless H(Y)
\end{aligned}
$$

- Chain rule

$$
H(Y, X) = H(X) + H(Y|X)
$$

Differential Entropy

- Definition – continuous RVs

$$h(X) \quad = \quad -\int_{\mathcal{X}} f(x) \log f(x) dx \quad X \sim f(x)$$

- Properties

1. $h(X+c) = h(X)$ c is a constant
2. $h(cX) = h(X) + \log |c|$ $c \neq 0, c$ is a constant
3. $X \sim \mathcal{N}(0, \sigma^2)$
   $\rightarrow \quad h(X) = \frac{1}{2} \log \left(2\pi e \sigma^2\right)$ maximal differential entropy
4. X is a mixed random variable $\rightarrow h(X) = -\infty$

Bounds on estimation error

$$\mathbb{E}\left[\left(X - \hat{X}\right)^2\right] \geq \frac{1}{2\pi e} e^{2h(X)}$$

$$\hat{X} = \mathbb{E}[X]$$ *MSE optimizing estimator*

$$\mathbb{E}\left[\left(X - \hat{X}|Y\right)^2\right] \geq \frac{1}{2\pi e} e^{2h(X|Y)}$$

$$\boxed{\hat{X} = \mathbb{E}[X|Y]}$$ *MSE optimizing estimator*

these are the variances
differential entropy bounded by that of a Gaussian

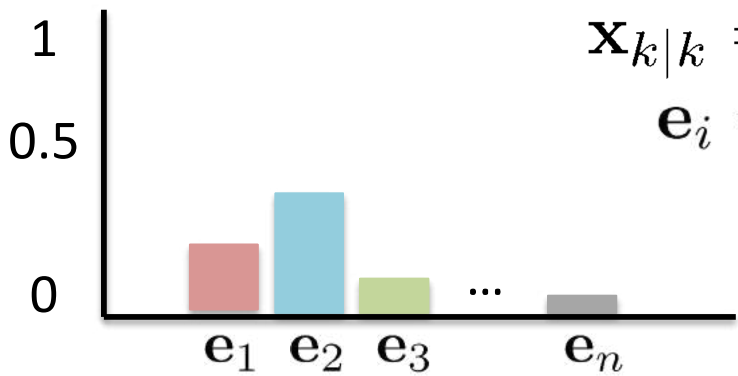
State Estimator

- Minimize: Mean-Square Error (MSE)

MMSE estimator $\mathbf{x}_{k|k} \doteq \mathbb{E}\{\mathbf{x}_k | \mathcal{F}_k\}$

history of observations and control inputs

- MMSE estimator equals conditional belief (probability)



$$\mathbf{x}_{k|k} = \mathbf{p}_{k|k}$$

$$\mathbf{e}_i = [0, \ldots, 0, 1, 0, \ldots, 0]^T$$

$$\mathbf{p}_{k|k} = [p^1_{k|k}, p^2_{k|k}, \ldots, p^n_{k|k}]^T$$

with

$$p^i_{k|k} = P(\mathbf{x}_k = \mathbf{e}_i | \mathcal{F}_k)$$

- Designed a Kalman-like estimator (recursive/discrete states)

Optimal Control Policy

- Control inputs sequence to optimize filter performance (MSE performance)

Cost function $$J_\gamma = \mathbb{E}\left\{ \sum_{k=1}^{L} \boxed{\text{tr}\left(\boldsymbol{\Sigma}_{k|k}(\mathbf{y}_k, \mathbf{u}_{k-1})\right)} \right\}$$

filtering error covariance matrix

- Optimal solution via dynamic programming (DP)

$$\text{optimal cost to go} = \min_{\mathbf{u}_{k-1} \in \mathcal{U}} \Big[\text{current cost} + \text{expected future cost} \Big]$$

Zois, Levorato, **M**, ICASSP 2013

Include energy cost

Cost function

$$J = \mathbb{E}\left\{ \sum_{k=1}^{L} (1-\lambda)\mathrm{MSE}(\mathbf{y}_k, \mathbf{u}_{k-1}) + \lambda \mathcal{E}(\mathbf{u}_{k-1}) \right\}$$

trade–off parameter

- Partially observable stochastic control problem: *determine <u>control sequence</u> to optimize trade–off between MSE performance and energy cost*

$$\min_{\mathbf{u}_0, \mathbf{u}_1, \ldots, \mathbf{u}_{L-1}} J$$

Challenges of DP

- Curse of dimensionality
  - Predicted belief state drawn from uncountably infinite set
  - Control space can be exponentially large in N, K
- Non-linear POMDP
- expected future cost requires N–dimensional integration, N = number of measurements

DP impractical for large-scale applications

Goal & Approach

- **Goal**: determine
  - Structural properties of the cost – to – go function
  - Sufficient conditions to characterize optimal control

- **Assumptions**:
  - discriminate between *two states*, $\mathbf{e}_1$ and $\mathbf{e}_2$
  - Select 1 out of *N* available sensors (scalar measurements)

- Two hypotheses

$$\mathbf{p}_{k|k} = [p, 1-p]$$

Cost – to – go function properties

- Current cost

  ``linear'' formulation

$$\ell(\mathbf{p}_{k|k-1}, \mathbf{u}_{k-1}) \doteq \mathbf{p}_{k|k-1}^T \mathbf{h}(\mathbf{p}_{k|k-1}, \mathbf{u}_{k-1})$$

- **Lemma**: current cost is concave function of

$$\mathbf{p}_{k|k-1}$$

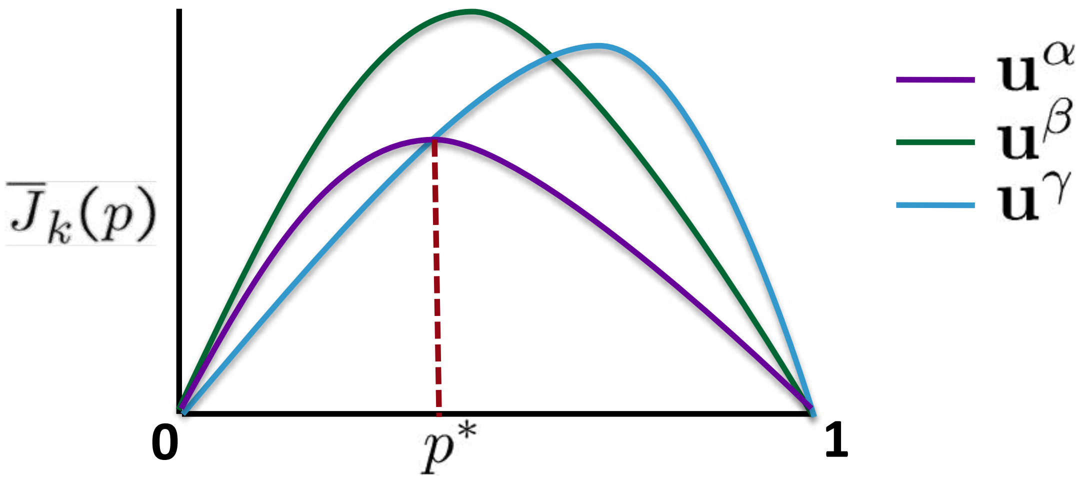
- **Theorem**: The cost – to – go function $\overline{J}_k(\mathbf{p}_{k|k-1})$ is a concave function of $\mathbf{p}_{k|k-1}$

$$k = L, L-1, \ldots, 1$$

Zois, Levorato, **M**, GlobalSIP 2013

Graphical interpretation

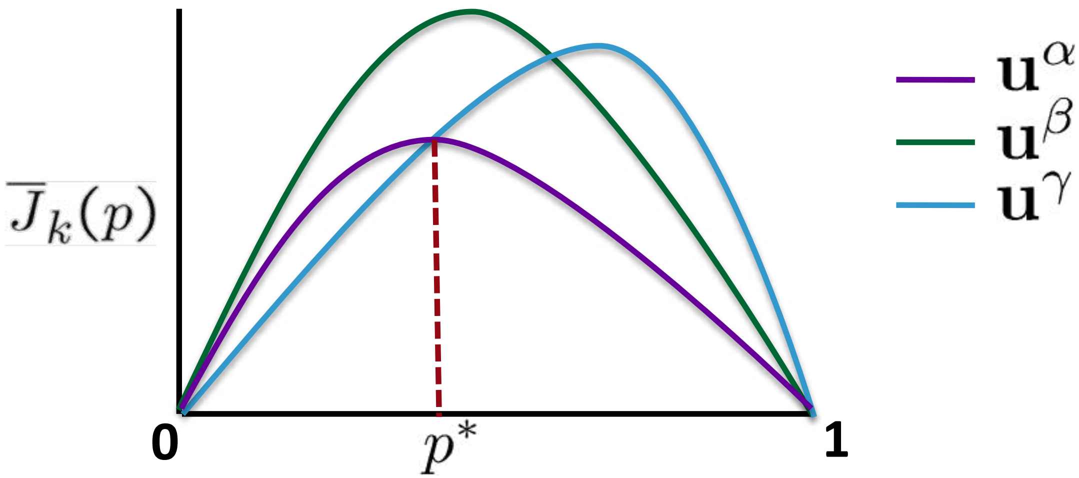
- What does the **Theorem** really mean?



cost versus belief for different controls/observation modes

Graphical interpretation

- What does the **Theorem** really mean?



- Optimal policy has **threshold structure**

$$\mathbf{u}^{opt} = \begin{cases} \mathbf{u}^\gamma, & p \leqslant p^* \\ \mathbf{u}^\alpha, & p > p^* \end{cases}$$

well – known for **linear POMDPs**

our system is **non-linear**

Informativeness

- **Definition**: Given two conditional pdfs f_α and f_β from $\mathcal{X}$ to $\mathcal{Y}$, f_β is *less informative than* f_α ($f_\beta \leqslant_B f_\alpha$) if $\exists$ *stochastic transformation* $W : \mathcal{Y} \to \mathcal{Y}$

Blackwell Ordering

$$f_\beta(\mathbf{y}|\mathbf{x}) = \int f_\alpha(\mathbf{z}|\mathbf{x}) W(\mathbf{z};\mathbf{y}) d\mathbf{z}, \ \forall \mathbf{x} \in \mathcal{X}$$

Informativeness

- **Fact**: Consider observation kernels $f(y|\mathbf{x}, \mathbf{u}^\alpha)$ and $f(y|\mathbf{x}, \mathbf{u}^\beta)$. If $f(y|\mathbf{x}, \mathbf{u}^\beta) \leqslant_B f(y|\mathbf{x}, \mathbf{u}^\alpha)$, then $\mathbf{u}^\alpha$ better than $\mathbf{u}^\beta$
  - Why? *Lower future cost* $V(p, \mathbf{u}^\alpha) \leqslant V(p, \mathbf{u}^\beta)$
  - Directly exploits the concavity of the cost-to-go function

- *Like a data processing inequality*
  - The stochastic transformation $W : \mathcal{Y} \to \mathcal{Y}$ is processing the kernel $f(y|\mathbf{x}, \mathbf{u}^\alpha)$

Recall

- Entropy

$$
\begin{aligned}
H(X) &= -\sum_{x \in \mathcal{X}} p(x) \log p(x) \\
&= \log |\mathcal{X}| \;\text{ if }\; p(x) = \frac{1}{|\mathcal{X}|} \;\forall\, x \\
&\geq 0
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$$

  - Entropy does not depend on the values of the alphabet
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- Joint Entropy

$$
H(X,Y) = -\sum_{x \in \mathcal{X}} \sum_{y \in \mathcal{Y}} p(x,y) \log p(x,y)
$$

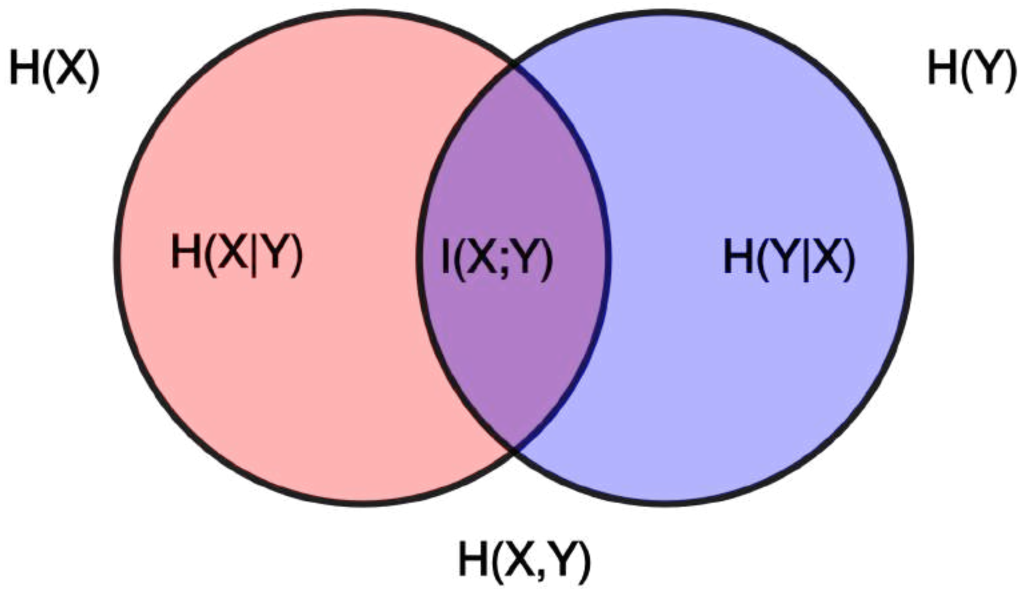
Mutual Information

- DEF:

$$\begin{aligned} I(X;Y) &= D(p(x,y)||p(x)p(y)) \\ &= H(Y) - H(Y|X) \\ &= H(X) - H(X|Y) \\ &= I(Y;X) \quad \text{symmetric} \\ &\geq 0 \\ I(X;X) &= H(X) \end{aligned}$$

  - *How much does X tell me about Y and vice versa?*

Information Diagrams



Konrad Voelkel, https://commons.wikimedia.org/w/index.php?curid=11245361

Data Processing Inequality

- If we have a Markov chain

$$\begin{aligned} p(x,y,z) &= p(x)p(y|x)p(z|y) \\ p(x,z|y) &= p(x|y)p(z|y) \end{aligned}$$

- Then, the inequalities hold

$$\begin{aligned} X - Y - Z \quad &\rightarrow \quad I(X;Y) \geq I(X;Z) \\ &\rightarrow \quad I(Y;Z) \geq I(X;Z) \end{aligned}$$

  - *processing Y cannot increase the information about X*

Informativeness

- **Fact**: Consider observation kernels $f(y|\mathbf{x}, \mathbf{u}^{\alpha})$ and $f(y|\mathbf{x}, \mathbf{u}^{\beta})$. If $f(y|\mathbf{x}, \mathbf{u}^{\beta}) \leqslant_B f(y|\mathbf{x}, \mathbf{u}^{\alpha})$, then $\mathbf{u}^{\alpha}$ better than $\mathbf{u}^{\beta}$
  - Why? *Lower future cost* $V(p, \mathbf{u}^{\alpha}) \leqslant V(p, \mathbf{u}^{\beta})$
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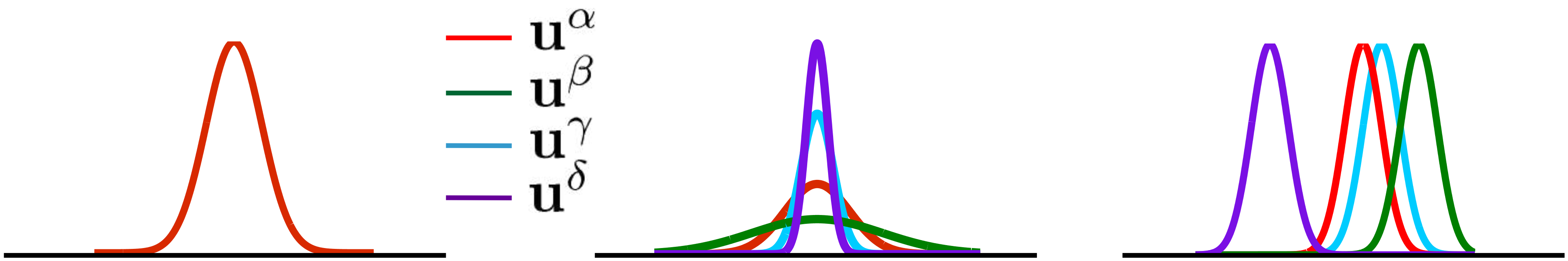
- *Like a data processing inequality*
  - The stochastic transformation $W : \mathcal{Y} \to \mathcal{Y}$ is processing the kernel $f(y|\mathbf{x}, \mathbf{u}^{\alpha})$

Determining optimal control



Case I: *same mean, same variance*

Case II: *same mean, different variance*

Case III: *different mean, same variance*

- **Case II**: Blackwell ordering of observation kernels determines optimal control
- **Case III**: ordering of current cost is achieved by ordering a function of the means $(m_1^{\mathbf{u}} - m_2^{\mathbf{u}})^2$

Myopic Solution

Zois, Levorato, **M**, Asilomar 2013

- Optimal solution: expensive to determine over finite horizon
  - Classical engineering fix: don't look too far into the future

- **Basic idea:** minimize one – step ahead cost

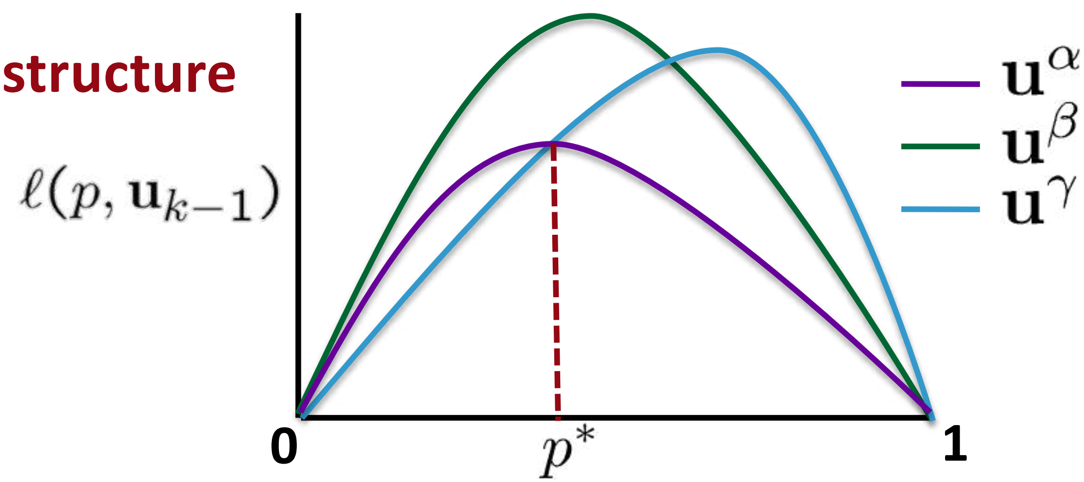
$$\mathbf{u}_{k-1}^{myopic} = \arg\min \ell(\mathbf{p}_{k|k-1}, \mathbf{u}_{k-1})$$

Myopic Solution

Zois, Levorato, **M**, Asilomar 2013

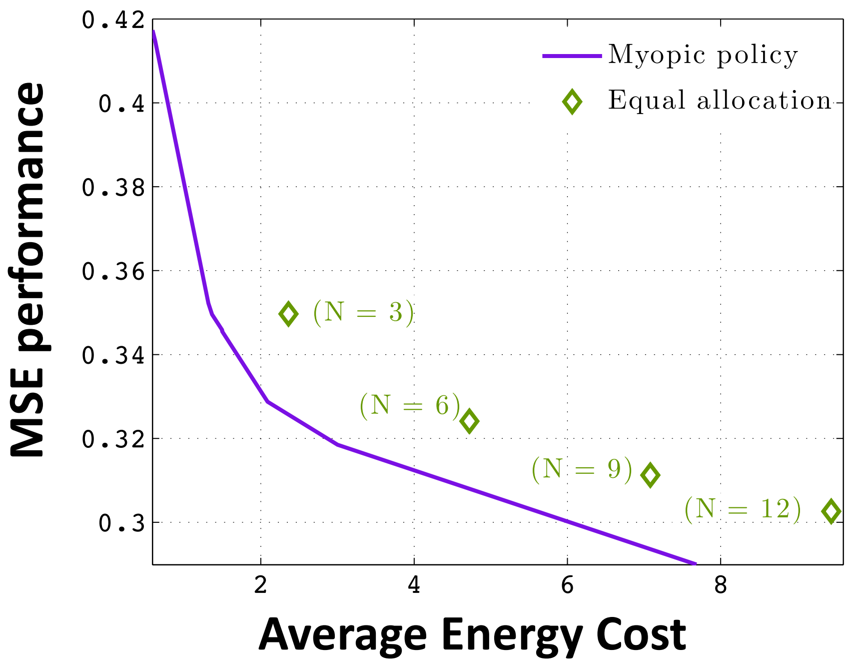
- Current cost is concave with respect to $\mathbf{p}_{k|k-1}$ for 2 activity states and 1 measurement
  - Policy has a **threshold structure also!**

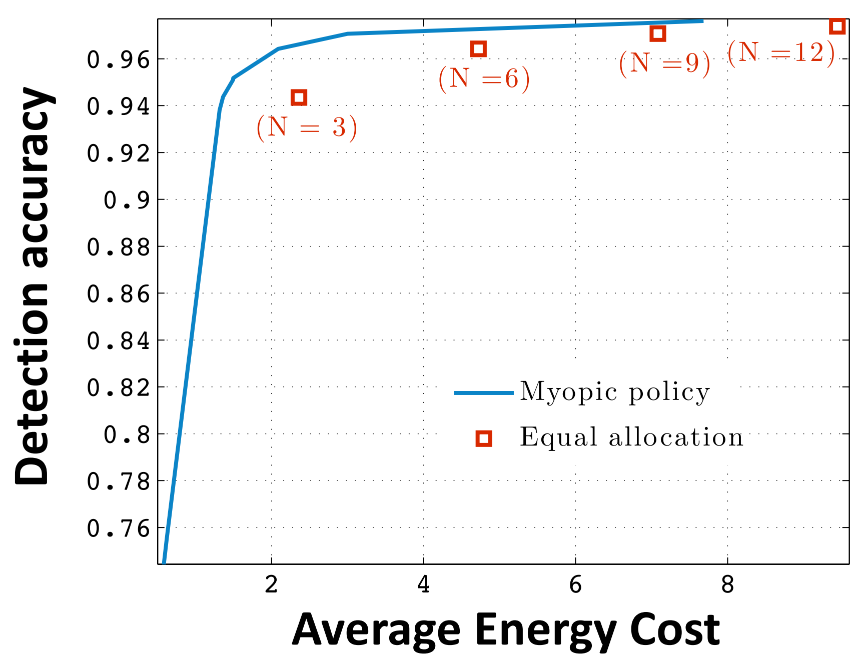
$$\mathbf{u}^{myopic} = \begin{cases} \mathbf{u}^{\gamma}, & p \leqslant p^* \\ \mathbf{u}^{\alpha}, & p > p^* \end{cases}$$



- This seems to be true for > 2 activity states and multi-dimensional measurement vectors (via *numerical validation*)

Trade–off Curves





- Equal allocation: request same number of samples from each sensor
- Compared to equal allocation, energy gains as high as 60% for the same estimation/detection performance

Summary

- Active hypothesis testing problem
  - Individual's state is time-varying across time
  - Allocate # measurements/which sensor (observation mode)

- Notion of informative observation modes
  - Blackwell ordering/data processing inequality

- Given belief for each state, we know which sensor to select

$$\mathbf{p}_{k|k-1} \rightarrow \mathbf{u}^{\alpha}$$

- How do we analyze performance?

OPTIMAL DECAY RATE?

Analysis of Interest

- Determining closed form probability of error intractable for WBAN case
  - How to analyze so that we can determine design strategies/resource choices?
- How well does the approach work as the number of observations get large?
  - Still interested in non-asymptotic/finite horizon performance

$$\lim_{N\to\infty} -\frac{1}{N}\mathbb{P}[\hat{X} = j | X \neq j]$$

probability of error

$$\text{subject to } \mathbb{P}[\hat{X} = j | X = j] \geq 1 - \epsilon$$

correct detection

Let's go back to basics

- To find desired results, need to go simpler/abstract
- Fixed true hypothesis (not time-varying)

candidate hypotheses

h_1	h_1	h_1	h_1	h_1									
h_2	h_2	h_2	h_2	h_2	h_2	h_2		h_2	h_2	h_2	h_2	h_2	h_2
h_3	h_3	h_3	h_3	h_3	h_3	h_3		h_3	h_3	h_3			
h_4	h_4	h_4	h_4	h_4	h_4	h_4							
h_5	h_5	h_3	h_5										

policies/experiments

u_1	u_2	u_2	u_3	u_2	u_1	u_3		u_2	u_3	u_3	u_2	u_2	u_2
$\downarrow$	$\downarrow$	$\downarrow$											
y_1	y_2	y_3											

observations


Kartik, Nayyar & **M**, TAC'22, ISIT'20, ISIT'19, Asilomar'18

Kartik & **M**, TSP'22

OPTIMAL DECAY RATE?
non-sequential case

Recall: Neyman Pearson Rule

- Optimal Decision Rule is a LRT:

$$\hat{X} = \begin{cases} H_0 & \text{if } L_n > \tau \\ H_0 \text{ w.p. } \gamma & \text{if } L_n = \tau \\ H_1 & \text{if } L_n < \tau \end{cases}$$

- How to select parameters:
  - Challenge when mismatched support and/or discrete RVs

$$\text{threshold } \tau \text{ and randomization } \gamma \text{ unique solutions to}$$
$$\epsilon = \mathbb{P}_0[L_n > \tau] + \gamma \mathbb{P}_0[L_n = \tau]$$

threshold choice determines NP rule

Near-Optimal Decision Rule

- Simpler Near-optimal Decision Rule:

$$\hat{X} = \begin{cases} H_0 & \text{if } L_n \geq \tau \\ H_1 & \text{if } L_n < \tau \end{cases}$$

$$\tau \approx nD(p_0||p_1)$$

a threshold test like optimal likelihood ratio test

- Lemma: miss probability probability for this decision rule

$$\begin{aligned} \mathbb{P}_1[\hat{X} = 0] &\leq \text{exp}(-\tau) \\ &\approx \text{exp}(-nD(p_0||p_1)) \end{aligned}$$

Large τ leads to high false-alarm probability
need to balance miss and false-alarm probabilities

Moment Generating Function of LLR

- MGF of LLR:

$$\mu(s) = \mathbb{E}[\text{exp}(-sL) \mid H_0] = \sum_{y \in \mathcal{Y}} (p_0(y))^{1-s} (p_1(y))^s \qquad L = \text{log} \frac{p_0(Y)}{p_1(Y)}$$

- Recall Chernoff Information

$$-\min_{0 \le \lambda \le 1} \text{log} \sum_y (p_0(y))^{\lambda} (p_1(y))^{(1-\lambda)}$$

  - (and recall Chernoff bound)

- The idea: use new measures to drive hypothesis testing

MGF of LLR – connections

- MGF of LLR:

$$\mu(s) = \mathbb{E}[\exp(-sL) \mid H_0] = \sum_{y \in \mathcal{Y}} (p_0(y))^{1-s} (p_1(y))^s \qquad L = \log \frac{p_0(Y)}{p_1(Y)}$$

- Chernoff Information:

$$C(p_0 || p_1) = -\min_{0 \le s \le 1} \log \mu(s)$$

- Kullback-Leibler Divergence:

$$D(p_0 || p_1) = \lim_{s \to 0} -\frac{1}{s} \log(\mu(s))$$

MGF of LLR – connections

- MGF of LLR:

$$\mu(s) = \mathbb{E}[\exp(-sL) \mid H_0] = \sum_{y \in \mathcal{Y}} (p_0(y))^{1-s} (p_1(y))^s \qquad L = \log \frac{p_0(Y)}{p_1(Y)}$$

- Chernoff Information:

$$C(p_0||p_1) = -\min_{0 \le s \le 1} \log \mu(s)$$ Bayes rate

- Kullback-Leibler Divergence:

$$D(p_0||p_1) = \lim_{s \to 0} -\frac{1}{s} \log(\mu(s))$$ NP rate

Example: Gaussian Likelihoods

- Null and Alternate Hypotheses:

$$H_0 : Y_n \sim \mathcal{N}(0, \sigma^2)$$
$$H_1 : Y_n \sim \mathcal{N}(\mu, \sigma^2)$$

$$p_0(y) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{y^2}{2\sigma^2}}$$
$$p_1(y) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{(y-\mu)^2}{2\sigma^2}}$$

- Log-likelihood ratio is also Gaussian:

$$L_n = \sum_{k=1}^{n} \frac{\mu^2 - 2\mu Y_n}{2\sigma^2}$$

Mean: $\frac{\mu^2}{2\sigma^2}$ under H_0

Variance: $\frac{\mu^2}{\sigma^2}$ under H_0

Example: Gaussian Likelihoods

- Decision-rule:

$$\hat{X} = \begin{cases} H_0 & \text{if } L_n \geq \tau \\ H_1 & \text{if } L_n < \tau \end{cases}$$

likelihood ratio test

- Probability of error: (exploit previous lemma)

$$-\frac{\log(\epsilon)}{n} \geq -\frac{\log(\mathbb{P}_0[L_n < \tau])}{n}$$
$$\geq -\inf_{s \geq 0} \left(\log(\mu(s)) + s\tau/n\right)$$

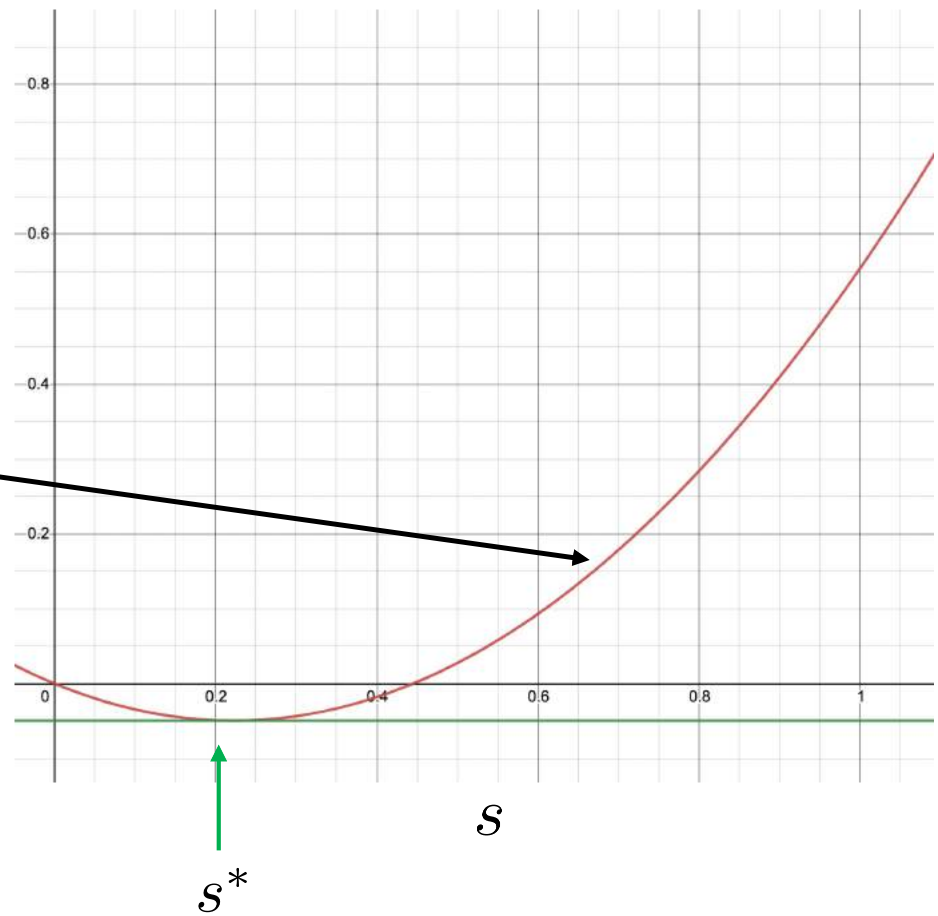
  - Optimize via choice of **s**

Example: Gaussian Likelihoods

- MGF of negative LLR:

$$\mu(s) = \exp\left(\frac{-\mu^2 s}{2\sigma^2} + \frac{\mu^2 s^2}{2\sigma^2}\right)$$

$\inf_{s \geq 0} \left(\log(\mu(s)) + s\tau/n\right)$
can be obtained in closed form



Example: Gaussian Likelihoods

- False-alarm decay rate:

$$
\begin{aligned}
-\frac{\log(\epsilon)}{n} &\geq -\frac{\log(\mathbb{P}_0[L_n < \tau])}{n} \\
&\geq -\inf_{s\geq 0}\left(\log(\mu(s)) + s\tau/n\right) \\
&= -\inf_{s\geq 0}\left(\left(\frac{-\mu^2}{2\sigma^2} + \frac{\tau}{n}\right)s + \frac{\mu^2 s^2}{2\sigma^2}\right) \\
&= \frac{\left(\frac{-\mu^2}{2\sigma^2} + \frac{\tau}{n}\right)^2}{\frac{4\mu^2}{2\sigma^2}} \qquad \text{if } \frac{\tau}{n} \leq \frac{\mu^2}{2\sigma^2}
\end{aligned}
$$

$$
\therefore \tau \leq \frac{\mu^2 n}{2\sigma^2} - \sqrt{\frac{2\mu^2 n \log(\frac{1}{\epsilon})}{\sigma^2}}
$$

Summary: Gaussian Likelihoods

- Decision-rule:

$$\hat{X} = \begin{cases} H_0 & \text{if } L_n \geq \tau \\ H_1 & \text{if } L_n < \tau \end{cases}$$

likelihood ratio test

- Miss probability lemma: large threshold desirable

$$\mathbb{P}_1[\hat{X} = 0] \leq \exp(-\tau)$$

- False-alarm probability: cannot have very large threshold

Sufficient to satisfy constraint

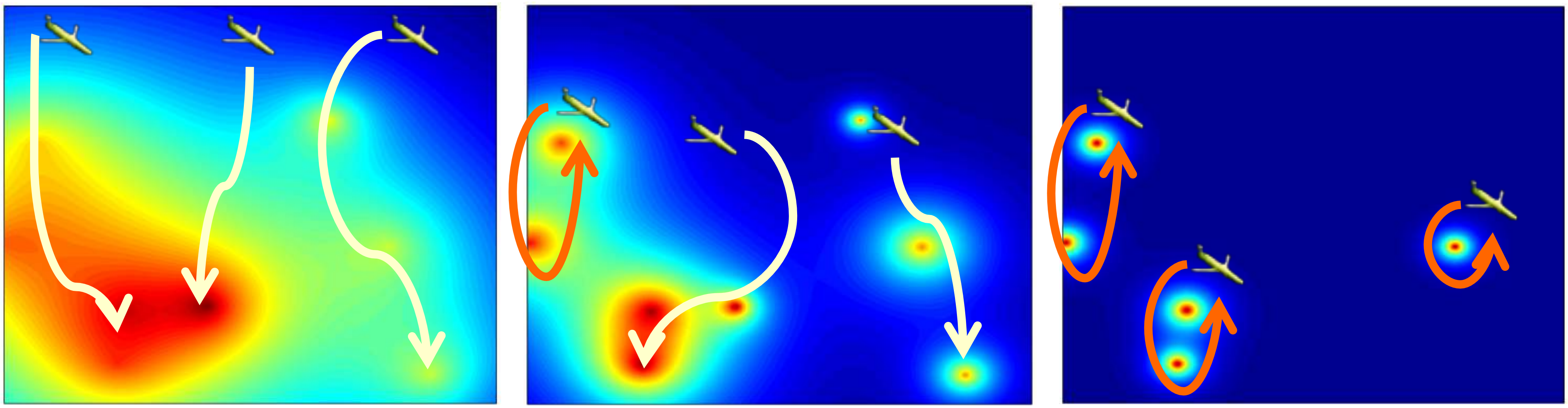
$$\tau \leq \frac{\mu^2 n}{2\sigma^2} - \sqrt{\frac{2\mu^2 n \log(\frac{1}{\epsilon})}{\sigma^2}}$$

asymptotically optimal error rate

non-asymptotic term

BREAK

Exploration-Exploitation



exploration	*collect observations*	*exploitation*
environment unknown	learn	focus on areas of interest

now, sequential

Active Hypothesis Testing

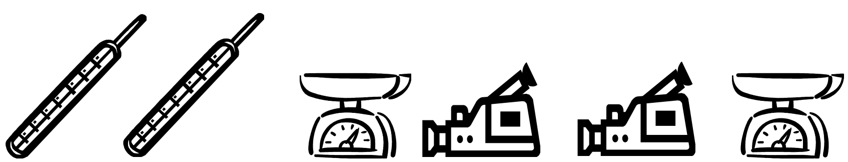
EXPLORATION

candidate hypotheses

h_1	h_1	h_1	h_1	h_1								
h_2	h_2	h_2	h_2	h_2	h_2	h_2	h_2	h_2	h_2	h_2	h_2	h_2
h_3	h_3	h_3	h_3	h_3	h_3	h_3	h_3	h_3	h_3			
h_4	h_4	h_4	h_4	h_4	h_4	h_4						
h_5	h_5	h_3	h_5									
u_1	u_2	u_2	u_3	u_2	u_1	u_3	u_2	u_3	u_3	u_2	u_2	u_2

EXPLOITATION

policies/experiments



focus on exploitation

Active Hypothesis Testing – Prior Work

- Chernoff, H., 1959. Sequential design of experiments. *The Annals of Mathematical Statistics*
- Nitinawarat, S., Atia, G.K. and Veeravalli, V.V., 2013. Controlled Sensing for Multihypothesis Testing. *IEEE Transactions on Automatic Control*
  - Considers decay rate of maximal error probability with fixed sample size
  - Asymptotic optimality of stopping time formulation
- Naghshvar, M. and Javidi, T., 2013. Active sequential hypothesis testing. *The Annals of Statistics*
  - POMDP formulation - Bounds on value function and asymptotic optimality
- Huang, B., Cohen, K. and Zhao, Q., 2019. Active Anomaly Detection in Heterogeneous Processes. *IEEE Transactions on Information Theory*
  - Group testing-type approach and asymptotic optimality

We focus on **non-asymptotics**:
performance analysis and policy design

Stopping Time Formulation

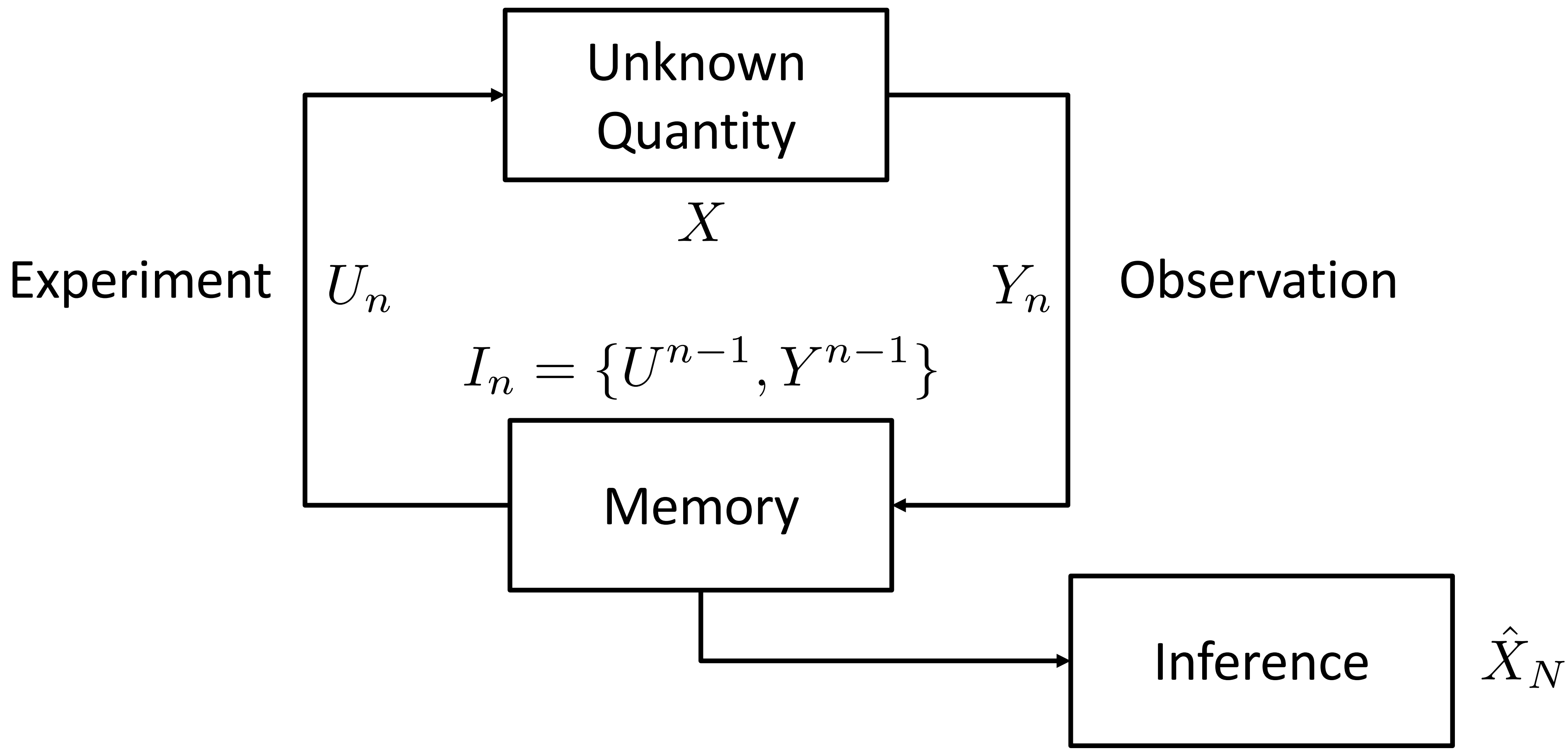
- **Classical approach**
- Perform experiments until confident – inconclusive declaration not allowed
- Stochastic time-horizon

- Minimize: $$\underbrace{\mathbb{E}[N]}_{\text{expected stopping time}} + \underbrace{L}_{\text{fixed, usually very large}} \times \underbrace{\mathbb{P}[\hat{X} \neq X]}_{\text{Bayesian error probability}}$$

room for improvement in the *non-asymptotic* regime

Active Hypothesis Testing

- Access to multiple **experiments** and can select them in a data-driven fashion



System Model

- Experiment Selection Strategy:

inference

$$(U_1, Y_1) \quad (U_2, Y_2) \quad \ldots \quad (U_n, Y_n) \quad \ldots \quad (U_N, Y_N) \quad \hat{X}_N$$

$$\underbrace{(U_1, Y_1) \quad (U_2, Y_2) \quad \ldots \quad (U_n, Y_n)}_{\text{Past information } I_n}$$

$$U_n = g_n(I_n, \text{random}) \in \mathcal{U}$$

Observation Y_n independent of past given U_n and X

- Inference Strategy: infer after gathering all data – may declare inconclusive if necessary

$$\hat{X}_N = f(I_{N+1}, \text{random}) \in \mathcal{X} \cup \{\varnothing\}$$

System Model

- Observations:

$$\mathbb{P}[Y = y \mid X = i, U_n = u] = p_i^u(y)$$

$Y \in \mathcal{Y}$
Finite alphabet

Observation — Experiment — Likelihood functions

Observation Y_n independent of past given U_n and X

Neyman-Pearson Formulation (P1)

- Incorrect conclusion: very expensive – must be avoided

$$\gamma_N = \mathbb{P}^{f,g}[\cup_{i\in\mathcal{X}}\{\hat{X}_N = i, X \neq i\}]$$

Misclassification probability: Probability of making an incorrect conclusion

Misclassification probability 0 if always declare inconclusive

- Correct inference: need to make correct inference with sufficiently large probability

$$\psi_N(i) \doteq \mathbb{P}^{f,g}[\hat{X}_N = i \mid X = i]$$

Correct inference probability of type-i

Neyman-Pearson Formulation (P1)

- Optimization Problem:

$$\begin{aligned} \min_{f \in \mathcal{F}, g \in \mathcal{G}} \quad & \gamma_N \\ \text{subject to} \quad & \psi_N(i) \geq 1 - \epsilon_N, \ \forall i \in \mathcal{X} \end{aligned}$$

Infimum value: γ_N^*

among all strategies that make correct inference with high probability, pick those that misclassify the least

symmetric formulation

Symmetric Cases

misclassification probability

$$\gamma_N = \mathbb{P}^{f,g}[\cup_{i \in \mathcal{X}} \{\hat{X}_N = i, X \neq i\}]$$

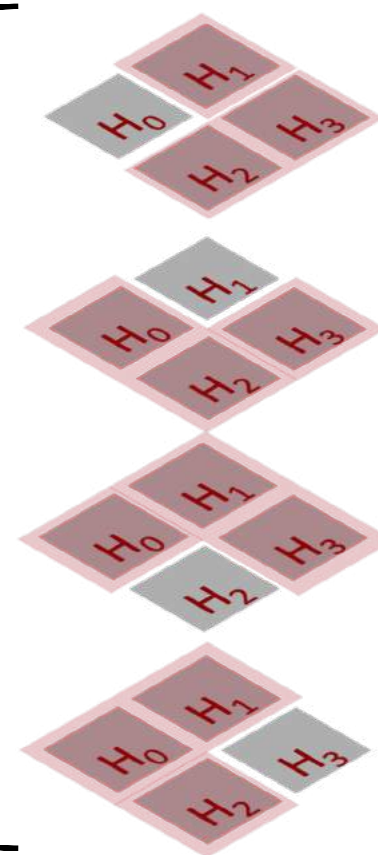
$$\min_{f \in \mathcal{F}, g \in \mathcal{G}} \quad \gamma_N$$

subject to $\quad \psi_N(i) \geq 1 - \epsilon_N, \; \forall i \in \mathcal{X}$

correct inference probability

P1

symmetric
formulation



Neyman-Pearson Formulation (P2)

- Incorrect conclusion: focus on a particular hypothesis

$$\phi_N(i) \doteq \mathbb{P}^{f,g}[\hat{X}_N = i \mid X \neq i]$$

Incorrect inference probability of type-i

Probability of incorrectly inferring hypothesis i

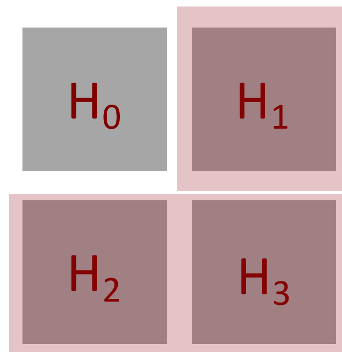
- Correct inference: need to make correct inference with sufficiently large probability

$$\psi_N(i) \doteq \mathbb{P}^{f,g}[\hat{X}_N = i \mid X = i]$$

Correct inference probability of type-i

Asymmetric Case

P2



asymmetric

$$H_0 \text{ versus } \{H_1, H_2, H_3\}$$

Composite Test

- H_i is a single hypothesis
- H_i^c is all other hypotheses

$$H_i \ \text{ versus } \ H_i^c$$

$$H_i^c = \{H_0, H_1 \cdots H_{i-1}, H_{i+1}, \cdots H_M\}$$

$$\phi_N(i) \doteq \mathbb{P}^{f,g}[\hat{X}_N = i \mid X \neq i]$$
$$= \mathbb{P}[\hat{X}_N = i | H_i^c] \quad \text{incorrect inference}$$

$$\psi_N(i) \doteq \mathbb{P}^{f,g}[\hat{X}_N = i \mid X = i]$$
$$= \mathbb{P}[\hat{X}_N = i | H_i] \quad \text{correct inference}$$

Neyman-Pearson Formulation (P2)

- Optimization Problem:

$$\min_{f \in \mathcal{F}, g \in \mathcal{G}} \quad \phi_N(i)$$
$$\text{subject to} \quad \psi_N(i) \geq 1 - \epsilon_N$$

Infimum value:
$\phi_N^*(i)$

Simple Null $\{X = i\}$ vs Composite Alternate $\{X \neq i\}$

Problem (P2) is easier to analyze
P2 will get us to solving P1

Neyman-Pearson Formulation (P2)

- Asymmetric Hypothesis Test:

Fix experiment selection strategy g
and view as single-shot hypothesis testing problem

$$\underbrace{(U_1, Y_1) \quad (U_2, Y_2) \quad \ldots \quad (U_n, Y_n) \quad \ldots \quad (U_N, Y_N)}_{I_{N+1}}$$

$$P^g_{N,i}(\mathcal{I}_{N+1}) \qquad\qquad Q^g_{N,i}(\mathcal{I}_{N+1})$$

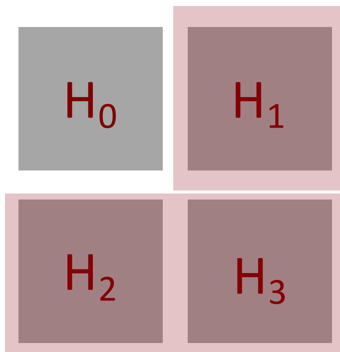
$$\mathbb{P}^g[I_{N+1} = \mathcal{I}_{N+1} \mid X = i] \qquad \mathbb{P}^g[I_{N+1} = \mathcal{I}_{N+1} \mid X \neq i]$$

test if I_{N+1} comes from P or Q

asymmetric formulation

Asymmetric vs Symmetric Cases

P2



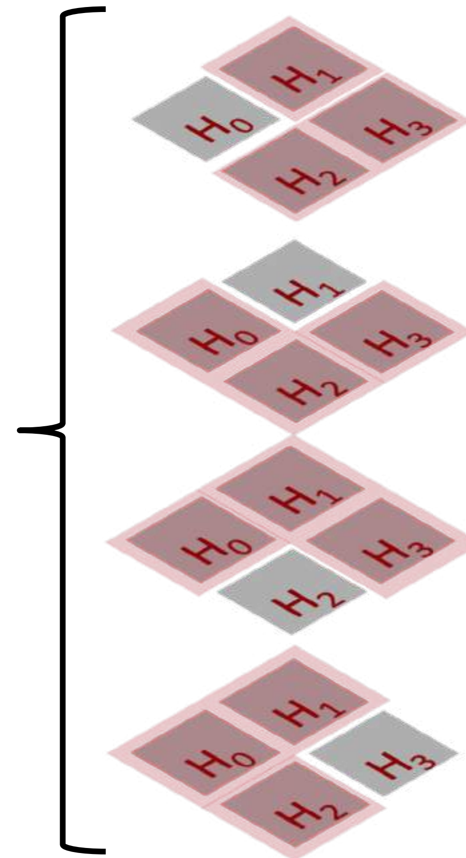
asymmetric

H_0 versus $\{H_1,H_2,H_3\}$

P1

symmetric

formulation



$$\gamma_N = \mathbb{P}^{f,g}[\cup_{i\in\mathcal{X}}\{\hat{X}_N = i, X \neq i\}]$$

$$\min_{f\in\mathcal{F},g\in\mathcal{G}} \quad \gamma_N$$

subject to $\quad \psi_N(i) \geq 1 - \epsilon_N, \ \forall i \in \mathcal{X}$

Useful Information-theoretic Quantities

- Confidence Level:

$$\mathcal{C}_i(\rho) \doteq \log \frac{\rho(i)}{1-\rho(i)}$$

i versus **not** i

$$\rho_n(i) = \mathbb{P}[X = i \mid U_{1:n-1}, Y_{1:n-1}]$$

posterior belief

- Expected Confidence Rate: Average Kullback-Leibler Divergence of the Asymmetric Hypothesis Test

$$J_N^g(i) \doteq \frac{1}{N}\mathbb{E}_i^g\left[\mathcal{C}_i(\rho_{N+1}) - \mathcal{C}_i(\rho_1)\right] = \frac{1}{N}\mathbb{E}_i^g\left[\log \frac{P^g(I_{N+1})}{Q^g(I_{N+1})}\right]$$

Useful Information-theoretic Quantities

Max-min KL-Divergence

$$D^*(i) \doteq \max_{\alpha \in \Delta\mathcal{U}} \min_{j \neq i} \sum_{u} \alpha(u) D(p_i^u || p_j^u)$$
$$= \min_{\beta \in \Delta\tilde{\mathcal{X}}_i} \max_{u \in \mathcal{U}} \sum_{j \neq i} \beta(j) D(p_i^u || p_j^u)$$

- Distributions over set of experiments: $\Delta\mathcal{U}$
- Max-minimizer: α^{i^*}
- Distributions over set of alternate hypotheses: $\Delta\tilde{\mathcal{X}}_i$
- Min-maximizer: β^{i^*}

Max-min Divergence

- Max-min KL-Divergence

$$D^*(i) \doteq \max_{\alpha \in \Delta\mathcal{U}} \boxed{\min_{j \neq i} \sum_u \alpha(u) D(p_i^u || p_j^u)}$$

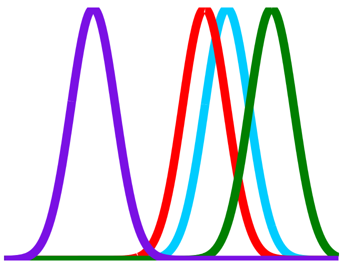
$$\alpha(u) = \mathbb{P}\left[\text{select experiment } u\right]$$

- Distributions over set of experiments: $\Delta\mathcal{U}$
- Max-minimizer: α^{i^*}

given α, averaging over all experiments which two hypotheses yield the smallest divergence?
→ hardest to distinguish

best probability distribution for hypothesis *i*

Max-min optimization



- Distributions over set of experiments: $\Delta\mathcal{U}$
- Max-minimizer: α^{i^*}

we want to select the experiment that maximally separates the distributions for each hypothesis

Min-Max optimization

- Equivalent optimization

$$D^*(i) \doteq \max_{\alpha \in \Delta \mathcal{U}} \min_{j \neq i} \sum_u \alpha(u) D(p_i^u || p_j^u)$$

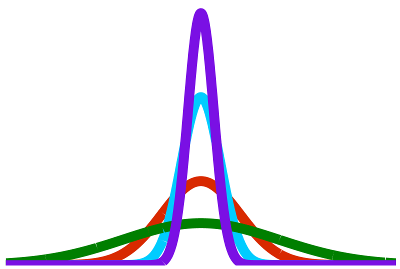
$$= \min_{\beta \in \Delta \tilde{\mathcal{X}}_i} \boxed{\max_{u \in \mathcal{U}} \sum_{j \neq i} \beta(j) D(p_i^u || p_j^u)}$$

- Distributions over set of alternate hypotheses: $\Delta \tilde{\mathcal{X}}_i$
- Min-maximizer: β^{i^*}

given the best u , which priors make the two easiest hypothesis hard to distinguish

worst prior probability distribution for the other null hypotheses
prior on hypotheses

Min-max optimization



- Distributions over set of alternate hypotheses: $\Delta\tilde{\mathcal{X}}_i$
- Min-maximizer: β^{i^*}

the adversary wants to maximize the ``prior'' of the wrong hypothesis closest to the true hypothesis

P[purple] <<< P[blue]

Data Processing Inequality

- Markov chains

$$
\begin{aligned}
p(x, y, z) &= p(x)p(y|x)p(z|y) \\
p(x, z|y) &= p(x|y)p(z|y)
\end{aligned}
$$

- The inequality

$$
\begin{aligned}
X - Y - Z \quad &\rightarrow \quad I(X;Y) \geq I(X;Z) \\
&\rightarrow \quad I(Y;Z) \geq I(X;Z)
\end{aligned}
$$

  - *processing Y cannot increase the information about X*

DPI for Divergence

- Channel $X \to \boxed{p_{y|x}} \to Y$
- Two input distributions: if $X \sim p_X$ then $Y \sim p_Y$
  if $X \sim q_X$ then $Y \sim q_Y$
- DPI: $D(p_x \| q_x) \geq D(p_y \| q_y)$
  - Processing the observation makes it more challenging to determine whether it came from p or q
- $p_{y|x}$ can be deterministic $Y = \mathbf{1}_{\mathcal{A}}(X)$ for event $\mathcal{A}$

  $Y \sim$ Ber with probability $\mathbb{P}(\mathcal{A})$ or $\mathbb{Q}(\mathcal{A})$

  $$D(p_x \| q_x) \geq D\left(\text{Ber}(\mathbb{P}(\mathcal{A}) \| \text{Ber}(\mathbb{Q}(\mathcal{A}))\right)$$

Asymmetric Converse (P2)

- Weak converse: using DPI for binary hypothesis testing

$$-\frac{1}{N}\log \phi_N(i) \leq J_N^g(i) + \Theta(1/N) \leq D^*(i) + \Theta(1/N)$$

- Asymptotically optimal strategies: Using Chernoff bound
  - achievability

$$-\frac{1}{N}\log \phi_N^*(i) > D^*(i) - \Theta(1/\sqrt{N})$$

Chernoff's Strategy

- For asymmetric formulation, *i* specified
- Randomly select experiment, open-loop from distribution

Set of all distributions on experiments

$$\boldsymbol{\alpha}_i^* := \arg\max_{\boldsymbol{\alpha}\in\Delta\mathcal{U}} \min_{j\neq i} \sum_u \alpha_u D(p_i^u || p_j^u)$$

Kullback-Leibler divergence

- For symmetric formulation,
  - select most likely *i* based on data
  - For most likely I, use α_i^* above
- Other works use a similar approach
- NOT DATA DRIVEN

Asymmetric Achievable Strategy (P2)

$$f(\rho_{N+1}) = \begin{cases} i & \text{if } \mathcal{C}_i(\rho_{N+1}) - \mathcal{C}_i(\rho_1) \geq \theta \\ \varnothing & \text{otherwise.} \end{cases}$$

Threshold based inference strategy

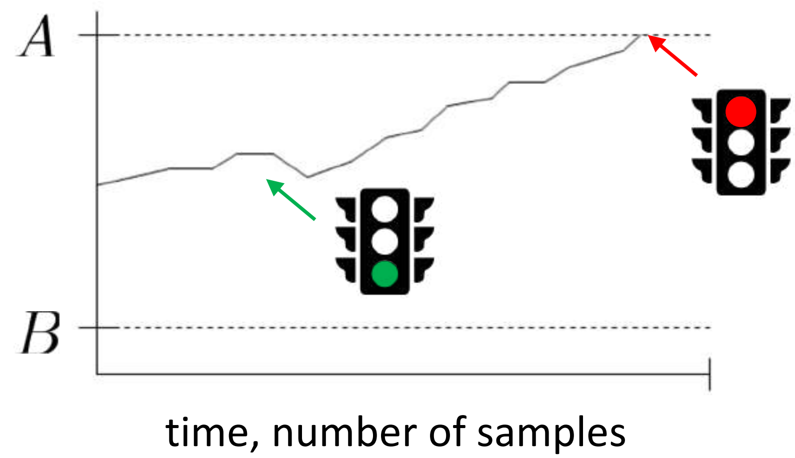
Randomly select experiment with distribution α^{i*}

Experiment selection strategy

Asymmetric Achievable Strategy (P2)

$$f(\rho_{N+1}) = \begin{cases} i & \text{if } \mathcal{C}_i(\rho_{N+1}) - \mathcal{C}_i(\rho_1) \geq \theta \\ \varnothing & \text{otherwise.} \end{cases}$$

Threshold based inference strategy



recall SPRT:
stop if confident enough

Randomly select experiment with distribution α^{i*}

Experiment selection strategy

Achievable Strategy

- Note that achievable strategy is
  - Data driven in inference (hypothesis selection)
    - Confidence function is a function of the data
  - Randomized in experiment selection
  - Devised to prove asymptotic results of best possible strategy

Optimal Error Rates

- **Theorem:** Chernoff-Stein Exponent for Asymmetric case (P2):

$$\lim_{N\to\infty} -\frac{1}{N} \log \phi_N^*(i) = D^*(i)$$

- **Theorem:** Chernoff-Stein Exponent for Symmetric case (P1):

$$\lim_{N\to\infty} -\frac{1}{N} \log \gamma_N^* = \min_{i\in\mathcal{X}} D^*(i)$$

Active Experiment Selection Strategy

- MGF of LLR: now depends on the experiment

$$\mu_j^i(u, s) \doteq \mathbb{E}_i \exp\left(-s \log \frac{p_i^u(Y)}{p_j^u(Y)}\right)$$

- MGF based metric for experiment selection:

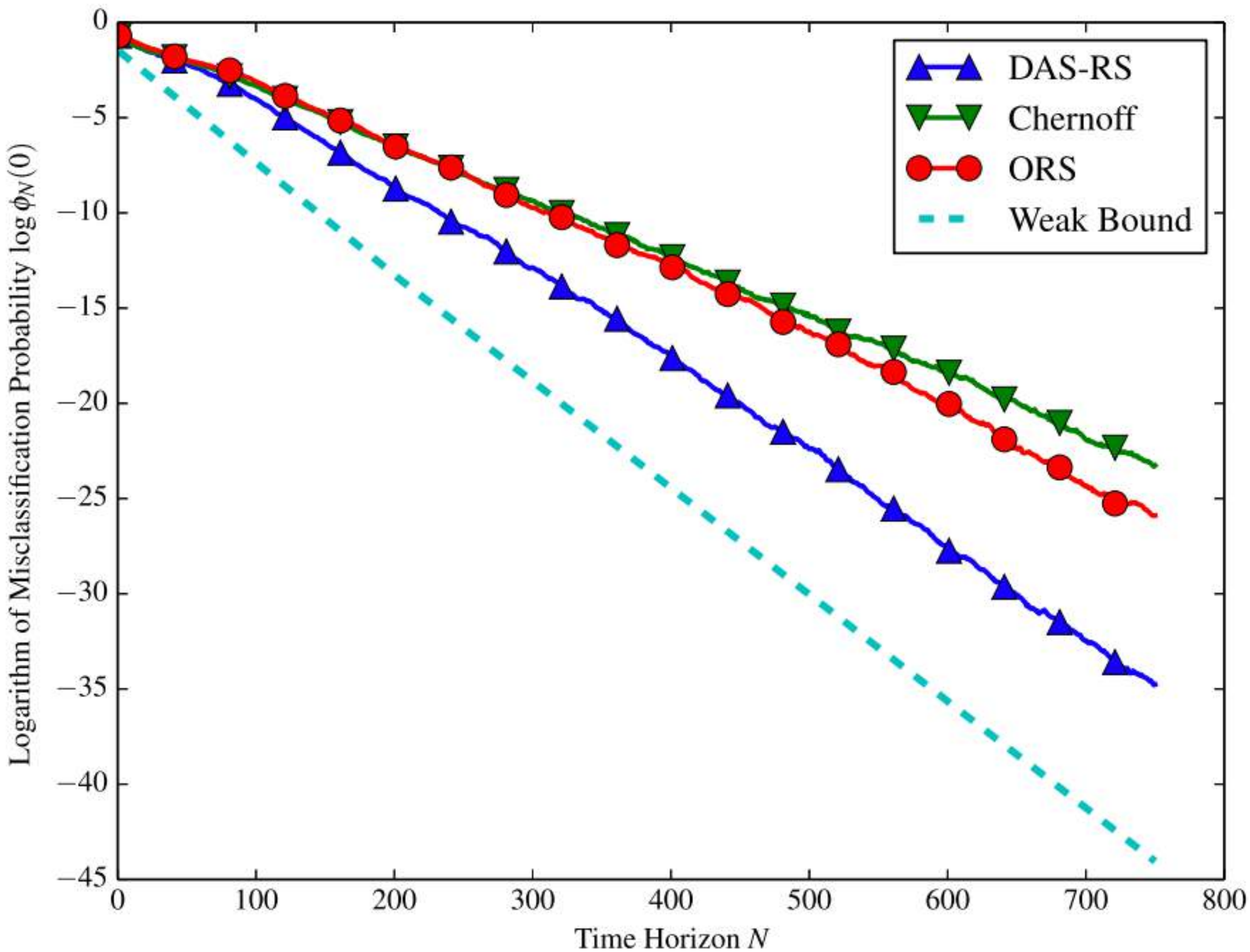
$$\mathcal{M}_i(u, \rho, s) \doteq \frac{\sum_{j \neq i} (\rho(j))^s \mu_j^i(u, s)}{\sum_{j \neq i} (\rho(j))^s} \qquad s_N \doteq \sqrt{\frac{2 \log \frac{M}{\epsilon_N}}{N B^2}}$$

Select the experiment $u \in \mathcal{U}$ that minimizes $\mathcal{M}_i(u, \rho_n, s_N)$

Performance Guarantees

- **Theorem**: the experiment selection strategy is asymptotically optimal and achieves significantly better performance in the non-asymptotic regime
  - $s = s_N$ chosen ``just right'' so the right sums converge
- Can specialize results to finite horizon

Numerical Results



Some Takeaways

- For binary hypothesis testing, select the experiment with largest KL-Divergence
  - Exploitation does not need to be active
  - NOT always true for M-ary testing (multiple alternatives)

- For M-ary case, we care about the event

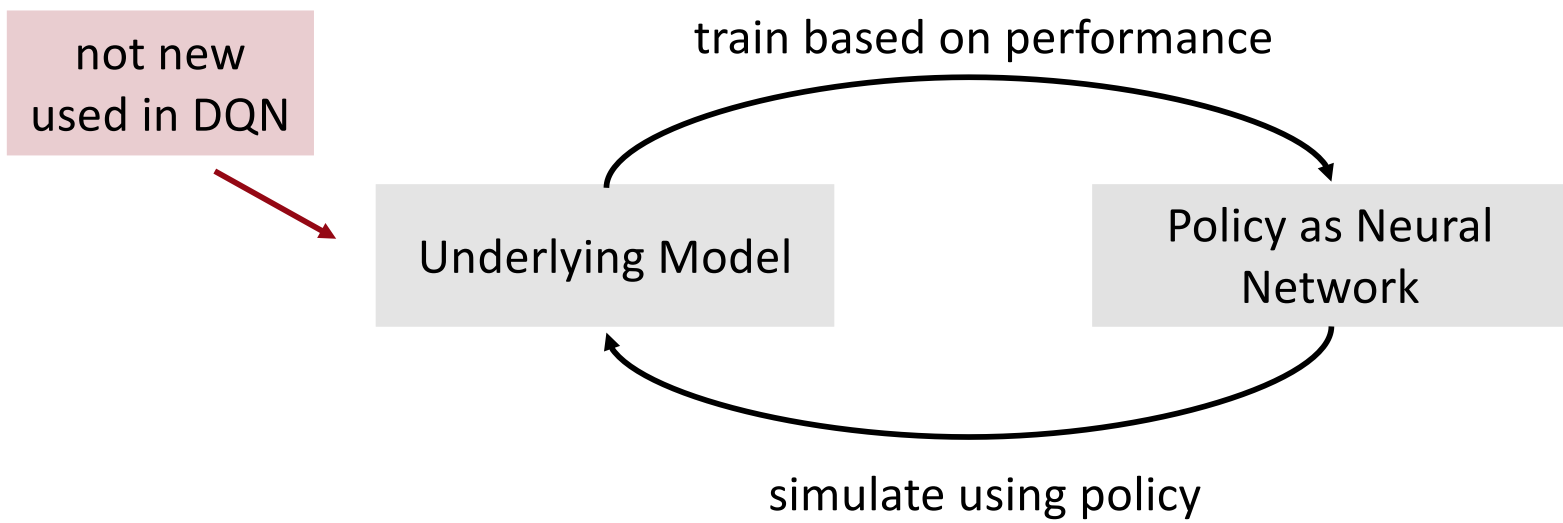
$$\min_{j \in \text{alt. hyp}} L_n^j \geq \tau$$

  Pairwise LLR for each alternate must exceed the threshold

- Similar achievability bounds can be derived in this case – these achievability bounds lead to our MGF based scheme

Neural Networks as Policy Optimizers

- Consider the following framework
  - DNNs as policy optimizers
  - Simulate underlying model, generate data, evaluate performance
  - With simulated data, train DNN via gradient descent



Q: How to properly design NNs for experiment selection and classification?

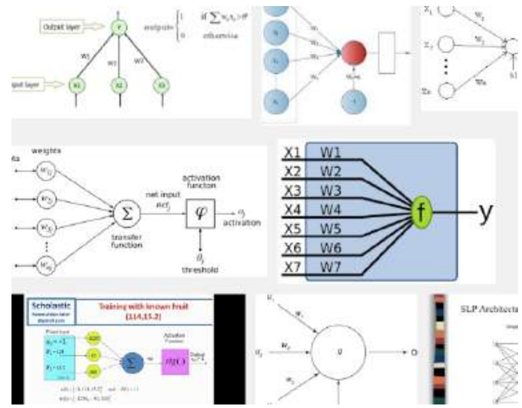
Third Wave of NN

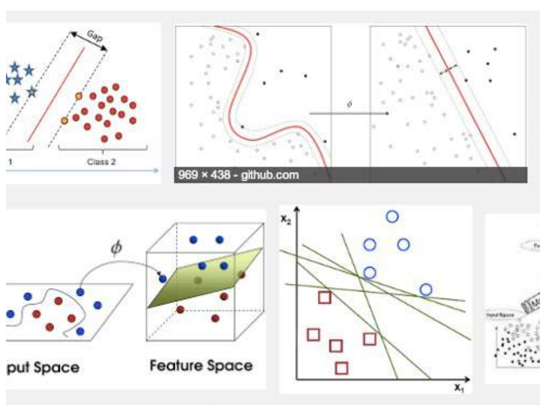
ANSACTIONS ON COMMUNICATIONS, VOL. 43, NO. 2/3/4, FEBRUARY/MARCH/APRIL 1995

Adaptive Receiver Algorithms for Near-Far Resistant CDMA

Urbashi Mitra, *Member, IEEE* and H. Vincent Poor, *Fellow, IEEE*

single layer perceptron





IEEE JOURNAL ON SELECTED AREAS IN COMMUNICATIONS, VOL. 12, NO. 9, DECEMBER

Neural Network Techniques for Adaptive Multiuser Demodulation

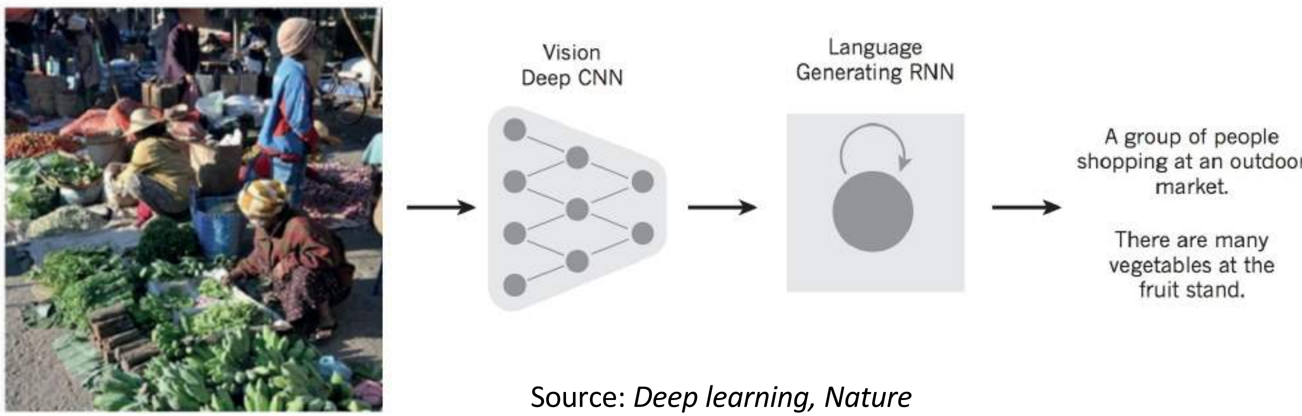
U. Mitra and H. Vincent Poor, *Fellow, IEEE*

support vector machine

NOW: COMPUTATIONAL HORSEPOWER & NEW ANALYSIS TOOLS

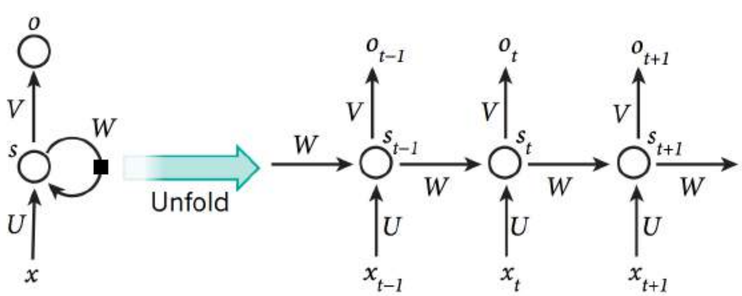
Architecture Challenge

- Theoretically, neural networks are universal approximators
- Challenge is finding the right architecture



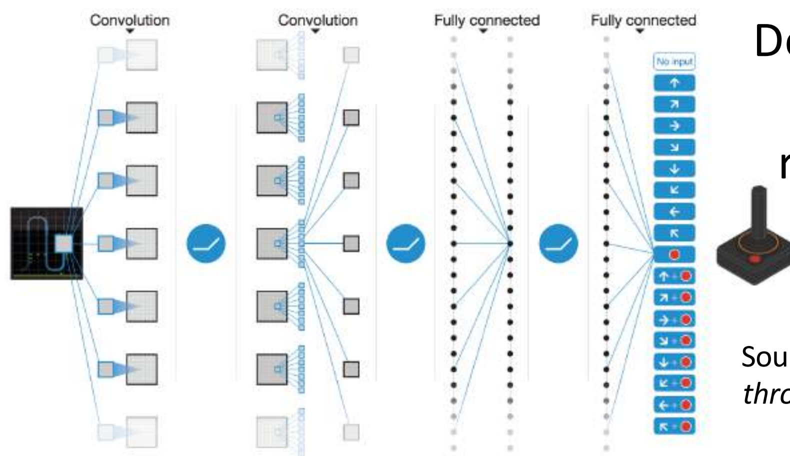
Convolutional Neural Network and Recurrent Neural Network for caption generation

Source: *Deep learning, Nature*



Recurrent Neural Network

Source: *Deep learning, Nature*



Deep Q Network for reinforcement learning

Source: *Human-level control through deep reinforcement learning, Nature*

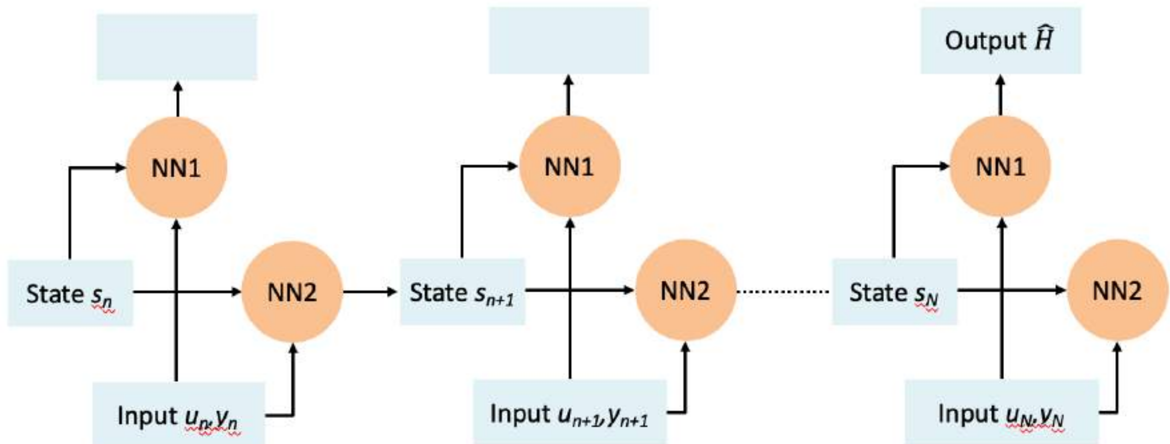
Design Goals

use insights from information and control theory
to design architecture and features

- Deep reinforcement learning is an adaptation of Q-learning
  - examined Recurrent Neural Networks and Q-Networks
  - Q-Networks learn efficient query selection policies

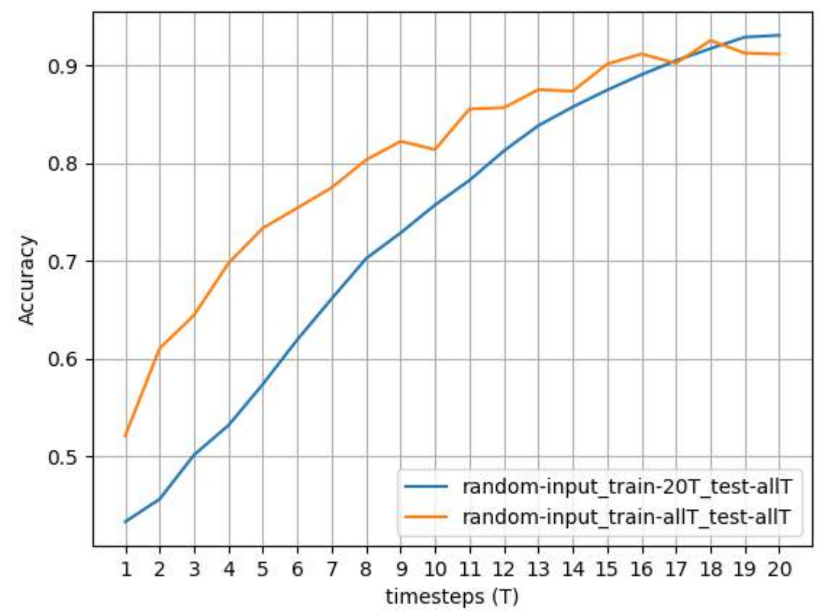
Kartik, Sabir, **M** & Natarajan, *Allerton'18*

Recurrent Neural Network



Learns to classify

- Sequentially provide query-observation pairs
- After N time steps, guess hypothesis
- If correct, 0 loss and 1 otherwise
- BUT
    - Fails to learn policy
    - Backpropagation has numerical stability issues



Solution: Deep Q-Network

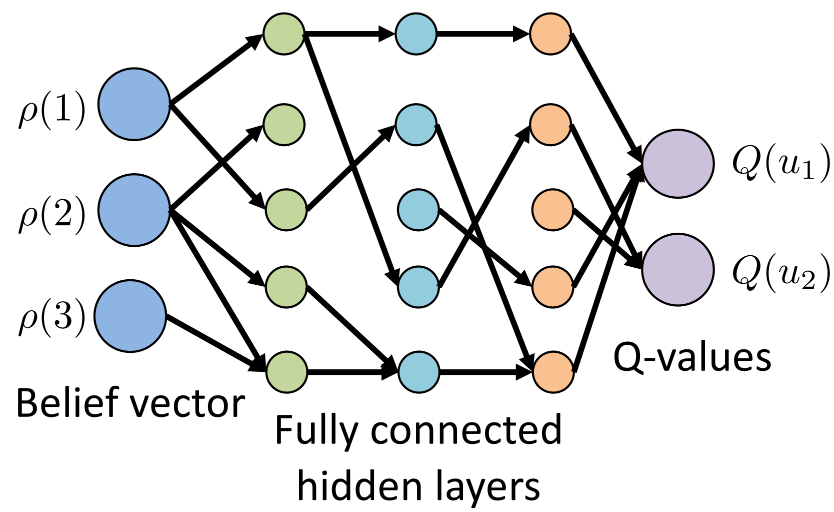
Represent Q values as a neural network vs a matrix

- Cannot simply assign Q-value updates

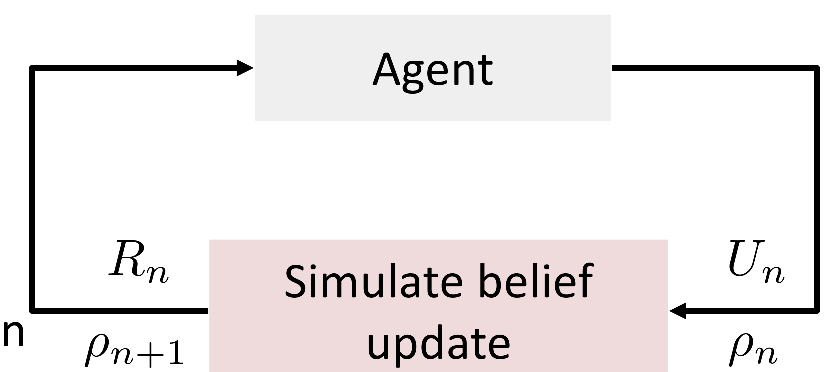
Fit Q-value update to network with MSE loss using gradient descent

- Optimize loss using gradient descent

$$\mathrm{MSE} = ||\mathrm{DQN}(\rho) - Q'(\rho)||^2$$



- Issues
  - Belief space infinite – ε exploration
  - Numerical stability issues/normalization



Numerical Comparison

- Extrinsic Jensen-Shannon Divergence (EJS):

$$EJS(\boldsymbol{\rho}, u) = \mathbb{E}[\mathcal{C}(F(\boldsymbol{\rho}, u, \mathbf{Y})) - \mathcal{C}(\boldsymbol{\rho})]$$

  - Greedy: select experiment that maximizes EJS
  - Naghshvar & Javidi, *Extrinsic Jensen-Shannon divergence with application in active hypothesis testing,* ISIT, 2012

- Open loop verification (OPE):
  - Explore using EJS
  - If $\rho_i > 0.7$ (confidence) select experiment with distribution $\boldsymbol{\alpha}_i > 0.7$
    - Recall Chernoff approach
  - Naghshvar and Javidi, *Active Sequential Hypothesis Testing,* The Annals of Statistics, 2013

Numerical Comparison

- Our adaptive best-response heuristic (KLZ):
  - Explore using EJS
  - If $\rho_i > 0.7$, select action from support (i) that maximizes $J_i(\boldsymbol{\rho}, u)$

$$J_i(\boldsymbol{\rho}, u) = \sum_{j \neq i} \frac{\rho_j}{1-\rho_i} D\left(p_i^u \| p_j^u\right)$$

- Compare to our final general strategy

- Compare these three strategies to DQN
  - EJS work states conditions under which EJS is asymptotically optimal
  - Example selected to violate those conditions

Additional Queries

$\epsilon = 10^{-7}$

	$y=0$	$y=1$
h_0	0.8	0.2
h_1	0.2	0.8
h_2	0.8	0.2

u_1

	$y=0$	$y=1$
h_0	0.8	0.2
h_1	0.8	0.2
h_2	0.2	0.8

u_2

	$y=0$	$y=1$
h_0	0.8	0.2
h_1	$1-\epsilon$	ϵ
h_2	0.8	0.2

u_3

	$y=0$	$y=1$
h_0	0.8	0.2
h_1	0.8	0.2
h_2	$1-\epsilon$	ϵ

u_4

KL-divergence is asymmetric

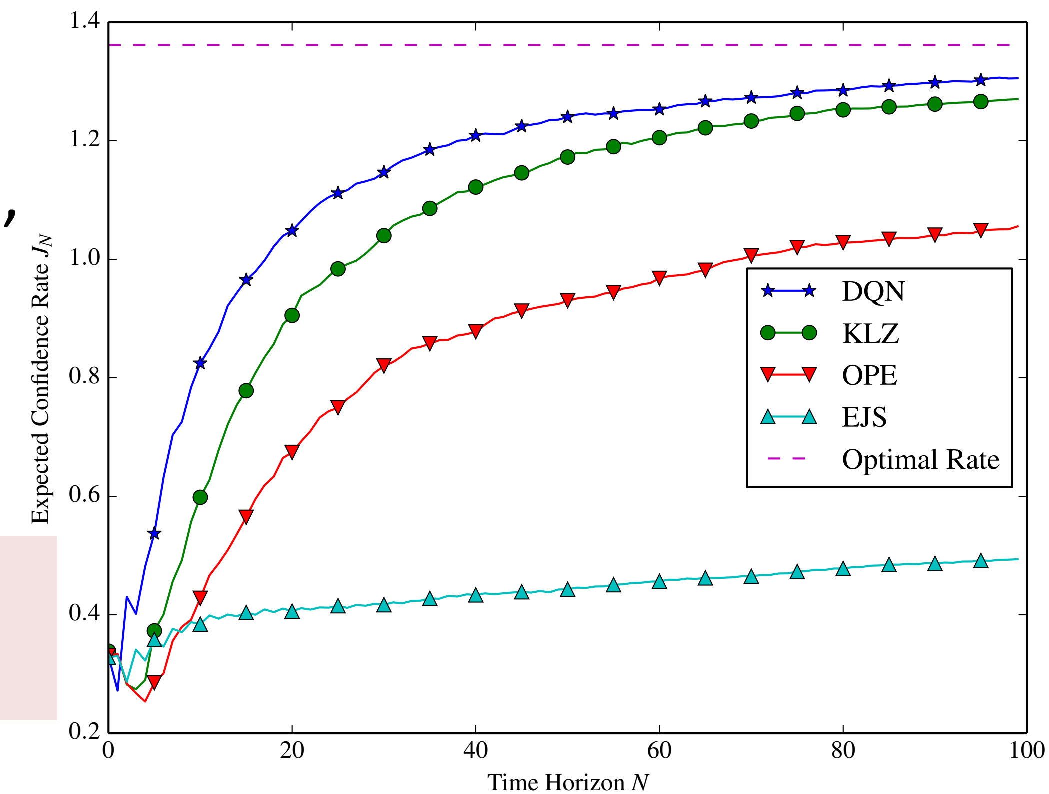
Deep Q Network for Active Classification

USC Viterbi

- Optimal strategy computationally expensive
  - Infinite state space
- New measure from theoretical analysis: structural properties

- **KLZ** close to optimal rate
- **OPE** asymptotically optimal, but very slow convergence
- **EJS** not optimal

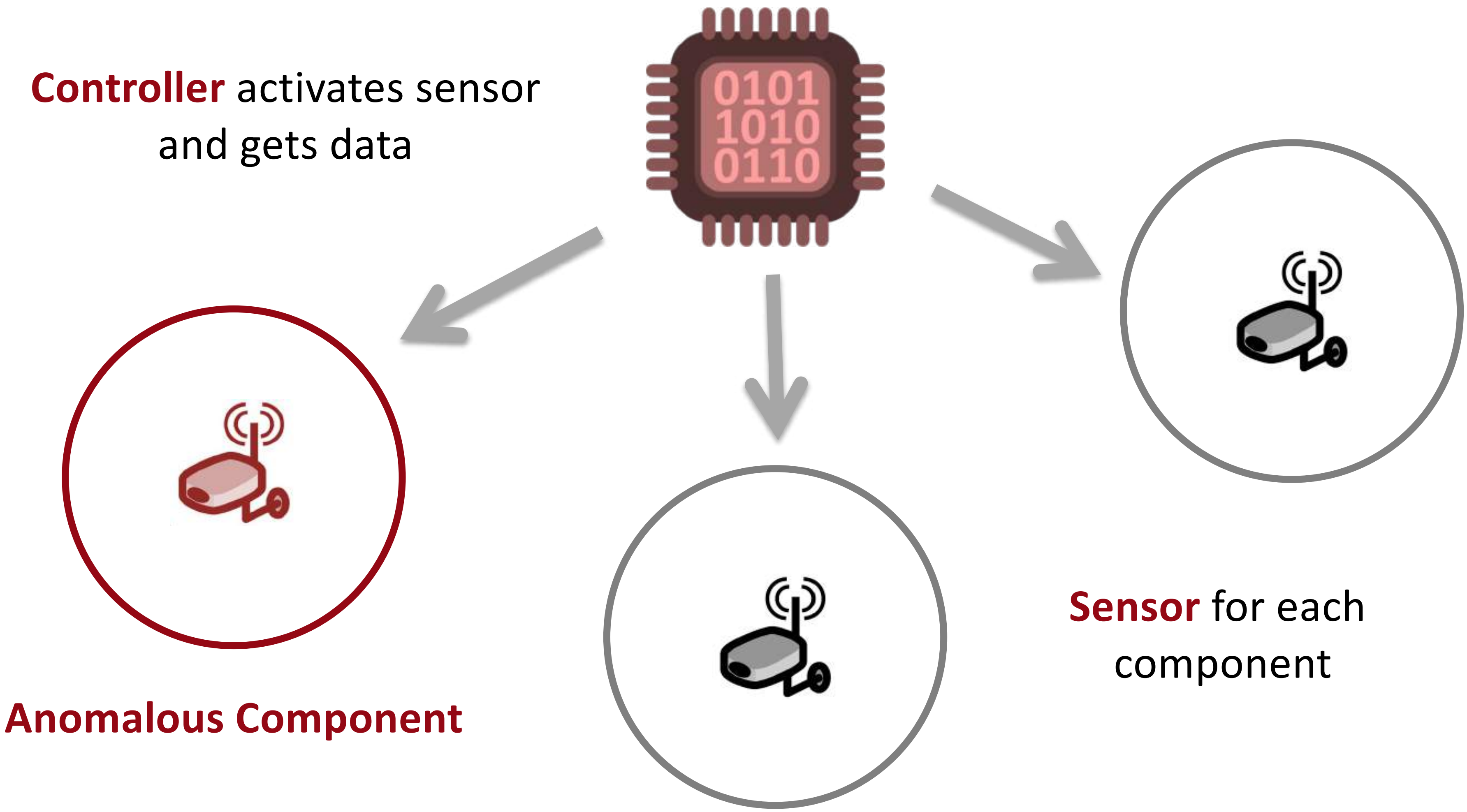
DQN learns the best policy



(TIGHT) FINITE HORIZON?

Testing for Anomalies

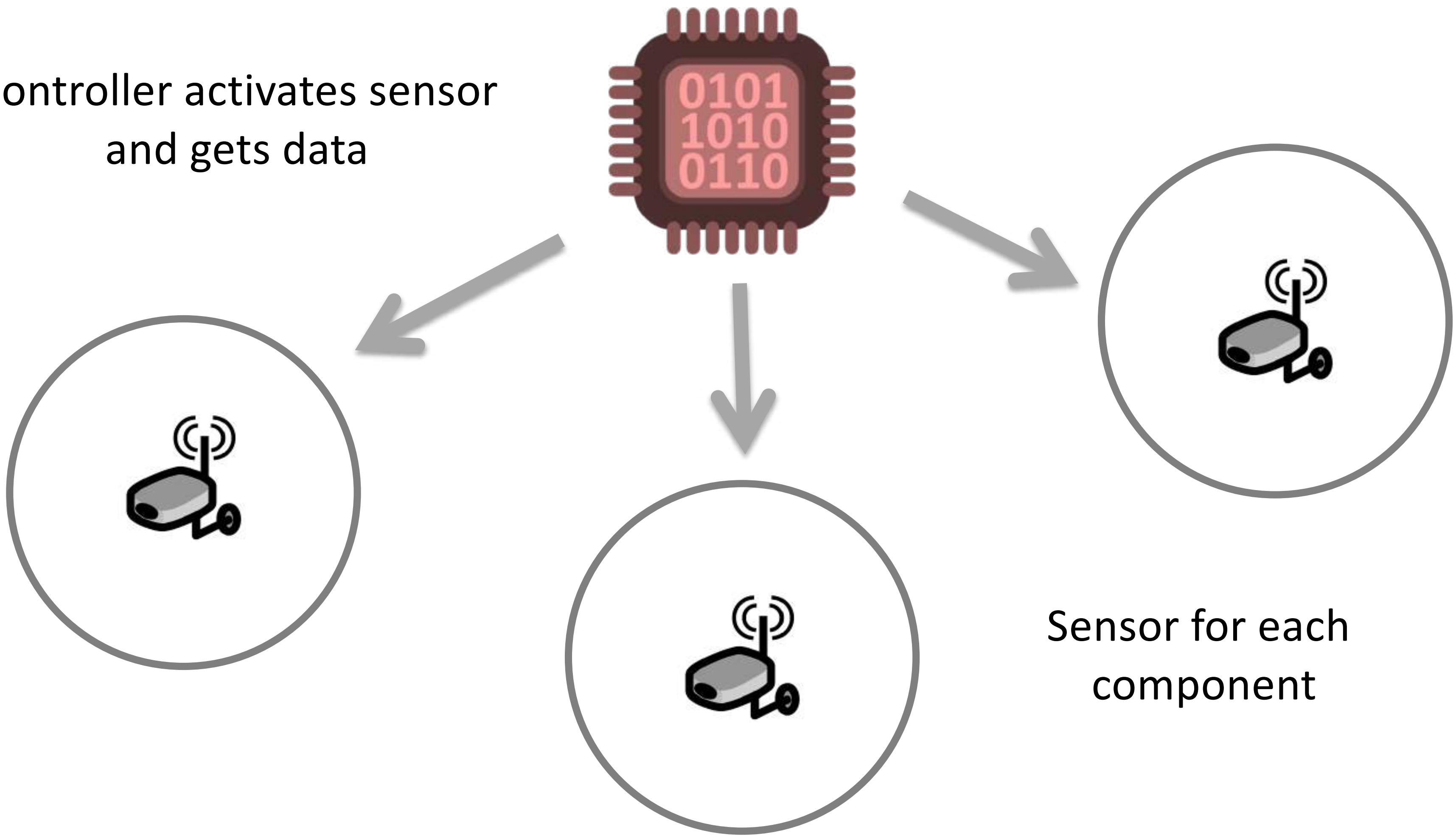
Multicomponent system with potential anomalies



Testing for Anomalies

Goal: Test whether there is anomaly or not

Controller activates sensor and gets data

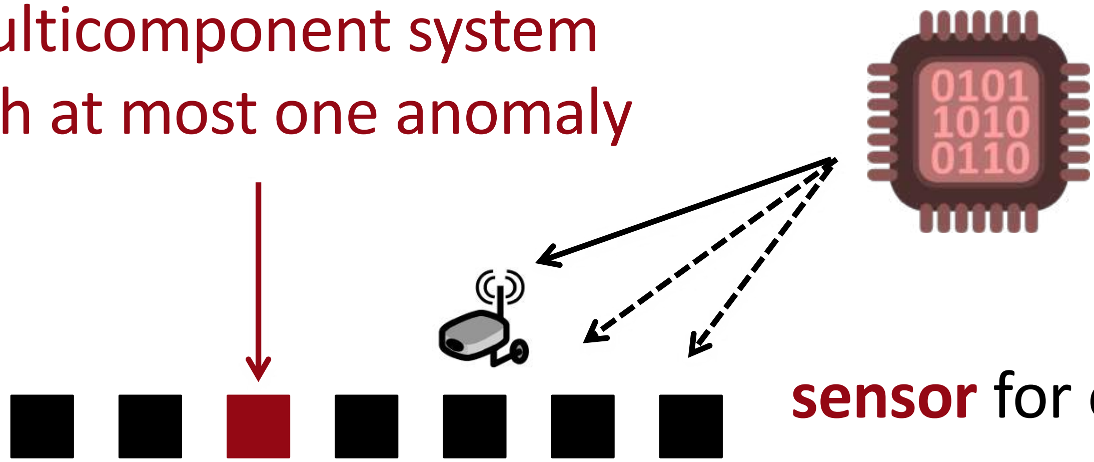


Sensor for each component

Anomaly Detection – a problem with symmetries

multicomponent system with at most one anomaly

controller activates sensors at different components at each time slot



sensor for each component

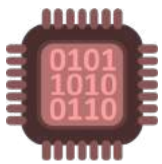
Number of components: $M (= 7)$

True system state: $X (= 3)$

$$X = \begin{cases} 0 & \text{if no anomaly} \\ j & \text{if component } j \text{ anomalous} \end{cases}$$

$$X \in \{0, 1, \dots, M\}$$

System Model



Component u

Observation y

Conditional Density

$p_1^u(y)$ if $X = u$

Anomalous

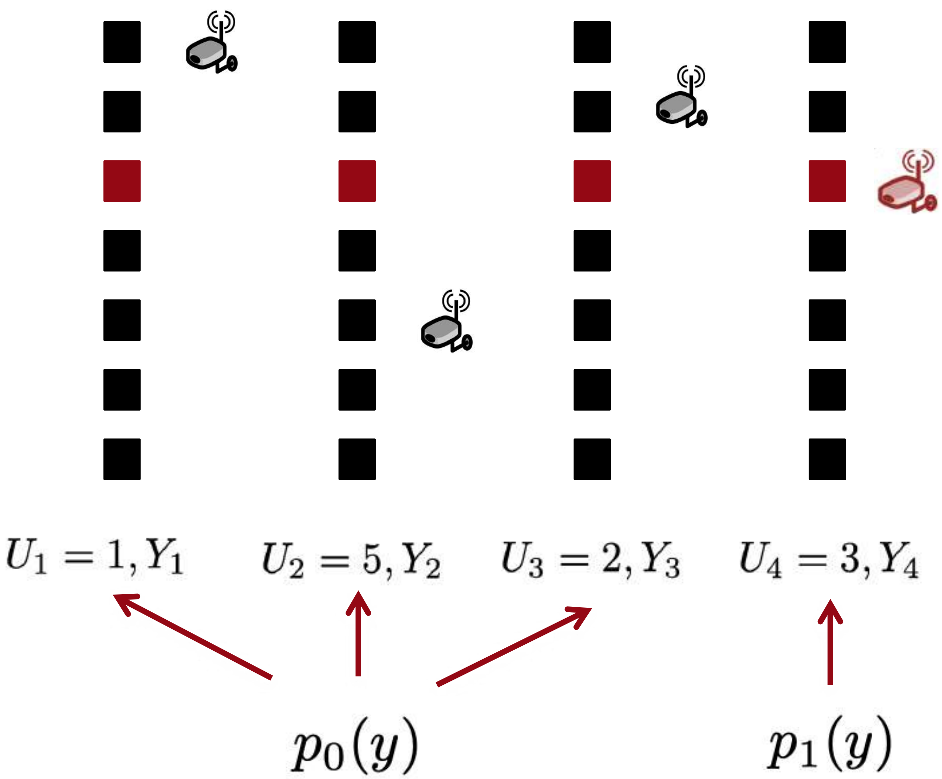
$p_0^u(y)$ if $X \neq u$

Not Anomalous

Symmetric if density does not depend on u

$$p_i^u(y) \quad = \quad p_i(y) \;\; \forall \; u$$

System Model



Component u

Observation y

conditional density

Symmetric if density does not depend on u

Recall: Symmetric Case

USC Viterbi

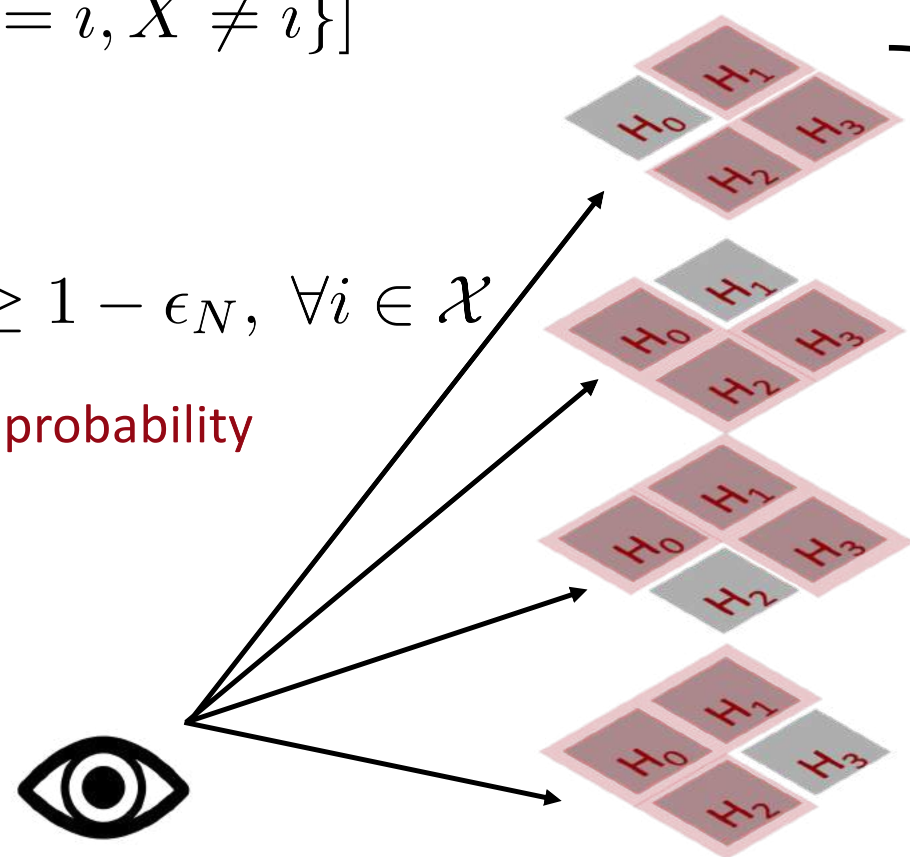
misclassification probability

$$\gamma_N = \mathbb{P}^{f,g}[\cup_{i \in \mathcal{X}} \{\hat{X}_N = i, X \neq i\}]$$

$$\min_{f \in \mathcal{F}, g \in \mathcal{G}} \quad \gamma_N$$

subject to $\quad \psi_N(i) \geq 1 - \epsilon_N, \; \forall i \in \mathcal{X}$

correct inference probability

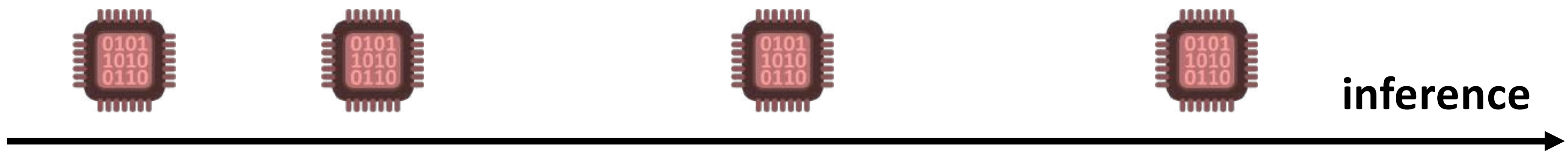


symmetric formulation

these all look the same!

Same framework as before

- Experiment Selection Strategy:



$$\underbrace{(U_1, Y_1) \quad (U_2, Y_2) \quad \ldots \quad (U_n, Y_n)}_{\text{Past information } I_n} \quad \ldots \quad (U_N, Y_N) \quad \hat{X}_N$$

$$U_n \sim g_n(I_n)$$

Observation Y_n independent of past given U_n and X

- Inference Strategy: decide safe or not safe

binary valued inference

$$\hat{X}_N \sim f(I_{N+1})$$

also randomized

safe: $X = 0$

not safe: $X \neq 0$

Contributions

- Pose fixed-horizon active Neyman-Pearson anomaly detector
  - asymptotically optimal error rates
  - For a symmetric system, even stronger non-asymptotic converse bounds
- Design deterministic experiment selection strategies
  - Achieve asymptotic bounds
  - Up to an additive logarithmic term (strong sense) in non-asymptotic regime → 2nd order optimal
- *Open loop strategies (asymptotically optimal) not strong in finite case*

Neyman-Pearson Formulation

$$\psi_N \doteq \mathbb{P}^{f,g}[\hat{X}_N = 0 \mid X = 0]$$

correct detection probability

$$\phi_N \doteq \mathbb{P}^{f,g}[\hat{X}_N = 0 \mid X \neq 0]$$

incorrect detection probability

Problem (P)

$$\inf_{f \in \mathcal{F}, g \in \mathcal{G}} \quad \phi_N$$

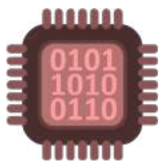
$$\text{subject to} \quad \psi_N \geq 1 - \epsilon_N$$

Infimum value: ϕ_N^*

minimize error subject to correct detection constraint

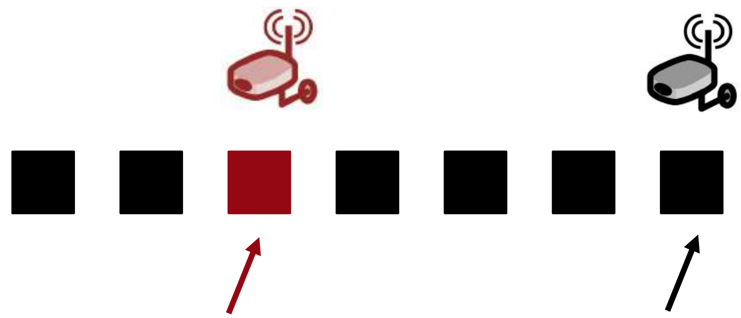
- Incorrect safe declaration very expensive – can tolerate a few false alarms
- **GOAL**: Find detection/inference & experiment selection strategies to solve (P)

Log-likelihood Ratios



Component u

Observation y



Conditional Density

$p_1^u(y)$ if $X = u$

Anomalous

$p_0^u(y)$ if $X \neq u$

Not Anomalous

$$L_j(u,y) \doteq \begin{cases} \log \frac{p_0^u(y)}{p_1^u(y)} & \text{if } u = j \\ 0 & \text{otherwise.} \end{cases} \longrightarrow \boxed{D_j^u = \mathbb{E}[L_j(u,Y)]}$$

$Y \sim p_0^u$

log-likelihood ratios $X = 0$ vs $X = j$

Kullback-Leibler Divergences

Accumulated LLR and Confidence Level

- Accumulate log-likelihood ratios for each component

$$Z_n(j) \doteq \sum_{k=1}^{n} L_j(U_k, Y_k)$$

- Confidence level: recall is a log-likelihood ratio
  - can rewrite in this form:

$$\mathcal{C}(I_{n+1}, \rho_1) = -\log \left[\sum_{j \in \mathcal{U}} \exp \left(\log \tilde{\rho}_1(j) - Z_n(j) \right) \right]$$

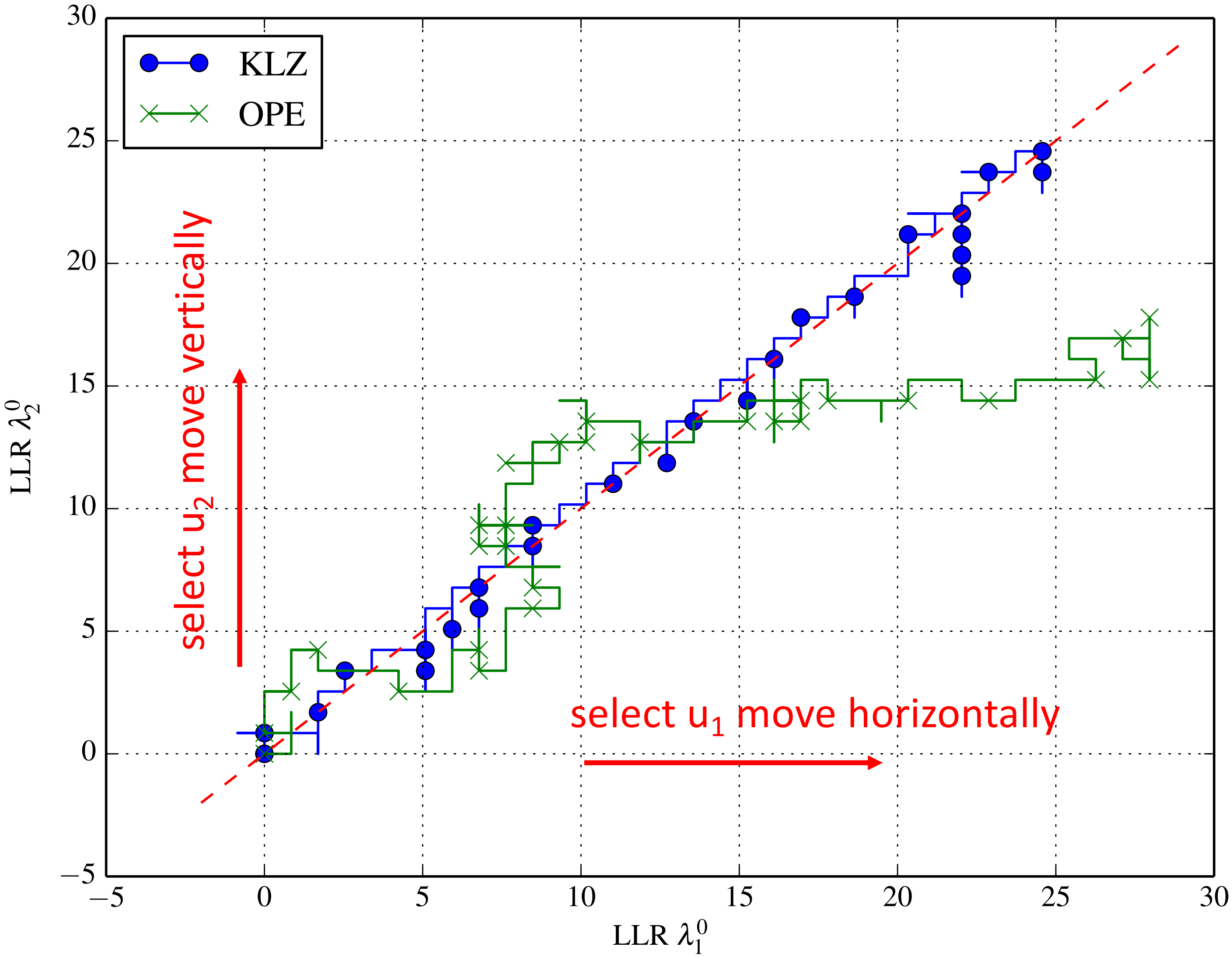
prior belief

$$\approx \min_{j \in \mathcal{U}} \{ Z_n(j) \}$$

$$\tilde{\rho}_1(j) = \rho_1(j)/(1-\rho_1(0))$$

Accumulated LLR Evolution

evolution of LLRs under different experiment selection strategies

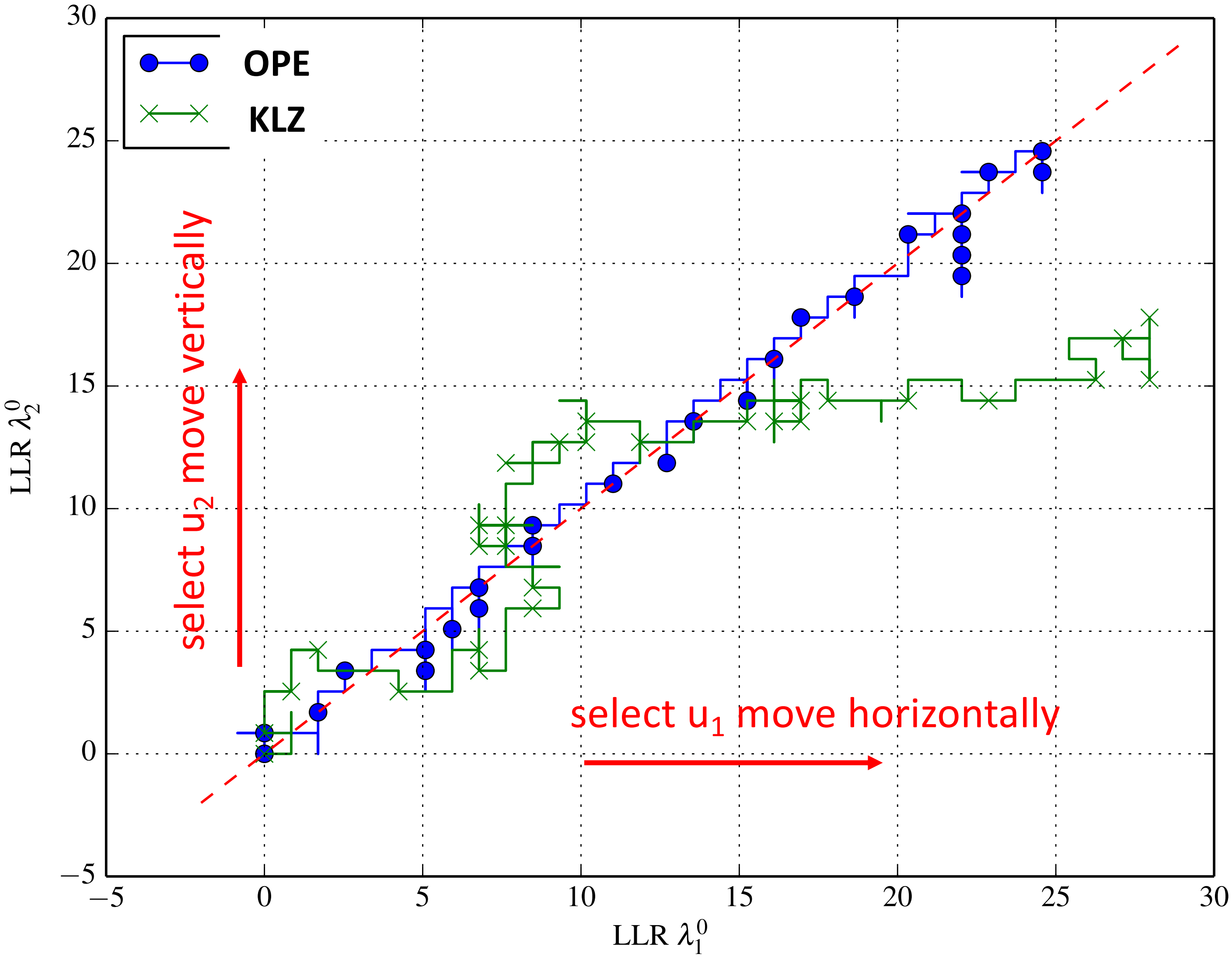


study the evolution of accumulated LLR vector

analysis easier for random walks difficult otherwise

Accumulated LLR Evolution

evolution of LLRs under different experiment selection strategies



study the evolution of accumulated LLR vector

analysis easier for random walks difficult otherwise

Interpreting the plot

- Kullback-Leibler Divergence:

$$D(p||q) = \sum_y p(y) \log \frac{p(y)}{q(y)}$$

$$\mathbb{E}_0[L_n] = nD(p_0||p_1)$$
$$\mathbb{E}_1[L_n] = -nD(p_1||p_0)$$

Expectation of LLR is related to KL-Divergence

- Random walk

$$L_n \rightarrow nD(p_0||p_1) \text{ under } H_0$$
$$L_n \rightarrow -nD(p_1||p_0) \text{ under } H_1$$

Recall Max-min KL-Divergence

- Define α, β distributions

$$D^* \doteq \max_{\alpha \in \Delta\mathcal{U}} \min_{j \in \mathcal{U}} \sum_{u \in \mathcal{U}} \alpha(u) D_j^u \qquad \text{argmax: } \alpha^*$$

$$= \min_{\beta \in \Delta\mathcal{U}} \max_{u \in \mathcal{U}} \sum_{j \in \mathcal{U}} \beta(j) D_j^u \qquad \text{argmin: } \beta^*$$

- Lemma: for anomaly detection/symmetric case

$$\boxed{D^* = \left(\sum_{u \in \mathcal{U}} \frac{1}{D_u^u} \right)^{-1}}$$

$$\alpha^*(u) = \beta^*(u) = D_u^u / D^*$$

recall $D_u^u \neq 0$ when anomaly

uniform when symmetric

Asymptotic Results

- Asymptotic achievability:
  - Experiment selection strategy: randomly select component from distribution α^* (Open loop sufficient!)
  - Inference strategy: decide safe only if confidence sufficiently large

$$\mathcal{C}(I_{n+1}, \rho_1) = -\log \left[\sum_{j \in \mathcal{U}} \exp \left(\log \tilde{\rho}_1(j) - Z_n(j) \right) \right]$$

- Strategy essentially the same, but can decompose confidence function better due to symmetry of distributions

Asymptotic Results

- Optimal error rate: under some minor assumptions

$$\lim_{N\to\infty} -\frac{1}{N}\log \phi_N^* = D^*$$

Generalization of Chernoff-Stein Lemma

$$D^* = \left(\sum_{u\in\mathcal{U}} \frac{1}{D_u^u}\right)^{-1}$$

$$L_j(u,y) \doteq \begin{cases} \log \frac{p_0^u(y)}{p_1^u(y)} & \text{if } u = j \\ 0 & \text{otherwise.} \end{cases} \xrightarrow{\qquad} \boxed{D_j^u = \mathbb{E}[L_j(u,Y)]}$$

$$Y \sim p_0^u$$

NON-ASYMPTOTIC RESULTS

Martingales

- Definition

$$\{M_n\}_{n=0}^{\infty} \text{ is a Martingale wrt } \{X_n\}_{n=0}^{\infty} \text{ if } \forall \;\; n \geq 0$$

1. $M_n = f(X_0, \cdots X_n)$
2. $\mathbb{E}\left[|M_n|\right] < \infty$
3. $\mathbb{E}\left[M_{n+1} | M_n, \cdots M_0\right] = M_n$ almost surely
   - $\{X_n\}_{n=0}^{\infty}$ need not be specified, only items 2. and 3.

- Why:
  - *Martingale theory allows for a lack of Markovity and linearity*
  - Can generalize CLTs and LLNs

Concentration Inequalities

- Azuma-Hoeffding inequality (1963/1967)

$\{M_n\}$ is Martingale, if $\exists \ \{\delta_i\} \in \mathbb{R}$ such that

$$\mathbb{P}\left[|M_n - M_{n-1}| \leq \delta_i\right] \quad = \quad 1 \quad \forall \quad n$$

then

$$\mathbb{P}\left[|M_n - M_0| \geq C\right] \quad \leq \quad 2\exp\left(-\frac{C^2}{2\sum \delta_i^2}\right) \quad C > 0$$

- If increments bounded, probability of a large deviation is small
- Samples *concentrate* about a point as *n* gets large

Proof Ingredients

- Proof of AH
  - Chernoff bound/Markov inequality
  - Convexity/Jensen's inequality
  - Martingale property
  - Minimize over Chernoff variable

$$Z_n(j) \doteq \sum_{k=1}^{n} L_j(U_k, Y_k)$$

- AH versus us…
  - General Martingales, bounded increments
  - We will exploit conditional independence, but possibly unbounded increments
  - BIG PICTURE, very similar

Non-asymptotic Bounds - Symmetric

- **Theorem**

Strong converse: follows from decomposition and strong converse in Polyanskiy, Poor and Verdu, IT Transactions 2010

$$-\log \phi_N^* \leq \mathsf{INV}_N\left(\epsilon_N + \frac{\epsilon_N}{\eta}\right) + \log \frac{\eta}{\epsilon_N}$$

$$-\log \phi_N^* \geq \mathsf{INV}_N\left(\epsilon_N - \frac{\epsilon_N}{\eta}\right) - O\left(\log \frac{\eta}{\epsilon_N}\right)$$

Strong achievability: based on decomposition, an adaptive experiment selection strategy and a Chernoff bound

$\eta > 0$: may depend on N

INV_N: quantile function of $\bar{Z}_N + D(\beta^*||\tilde{\rho}_1)$

Two Experiment Selection Strategies

- Open-loop randomized: asymptotically optimal

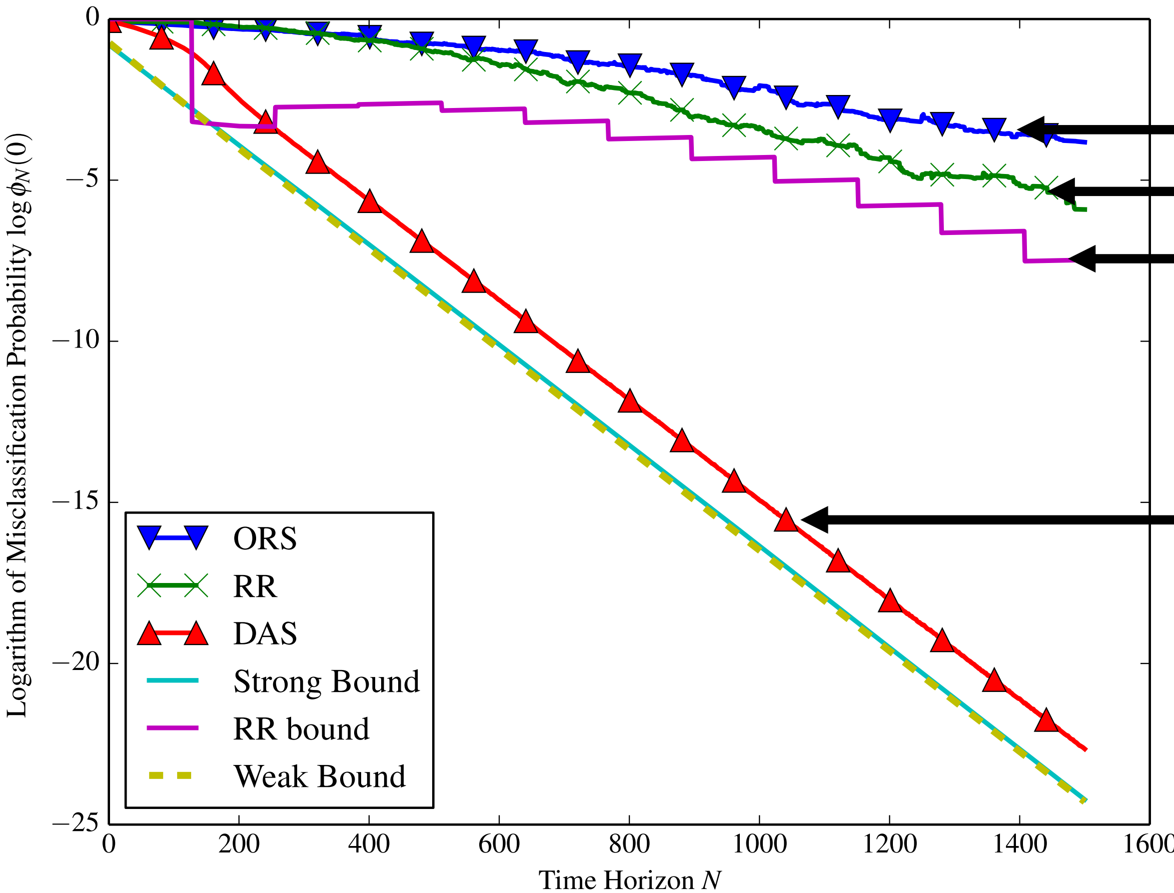
  randomly select component from distribution α^*

- Adaptive deterministic: also asymptotically optimal
  at each time n, select the component j
  that minimizes $Z_{n-1}(j) - \log \tilde{\rho}_1(j)$

confidence $$\mathcal{C}(I_{n+1}, \rho_1) = -\log \left[\sum_{j \in \mathcal{U}} \exp \Big(\log \tilde{\rho}_1(j) - Z_n(j) \Big) \right]$$

- Example setting: two-component and binary observations

Individual Sampling Results



Open-loop strategies:

1. Uniform random selection
2. Round robin
3. Open-loop sampling cannot get better than this

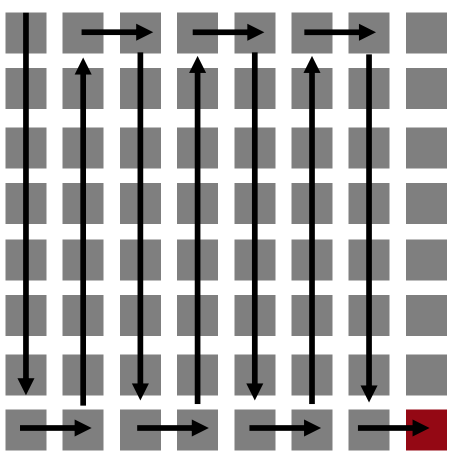
Adaptive Selection

Note that computed strong lower bounds are fairly tight

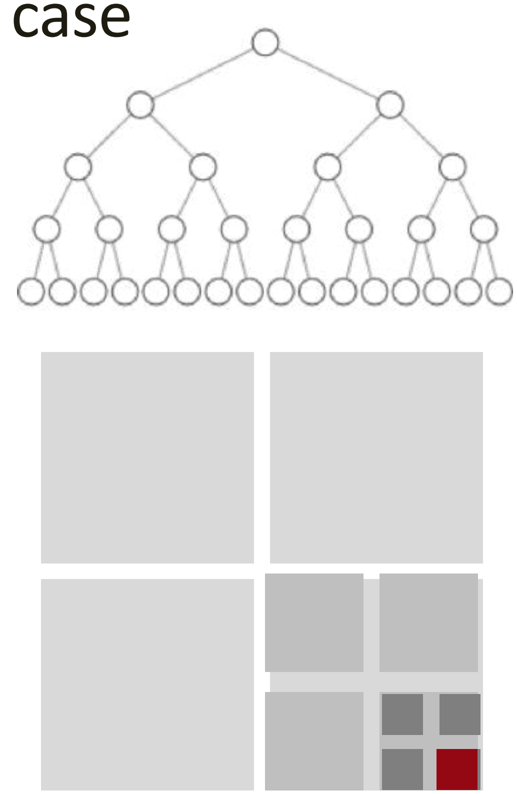
128 component system with Gaussian likelihoods and individual sampling

Exploration Phase

- Exploration important for symmetric case
  - Search for anomaly based using grouped observations



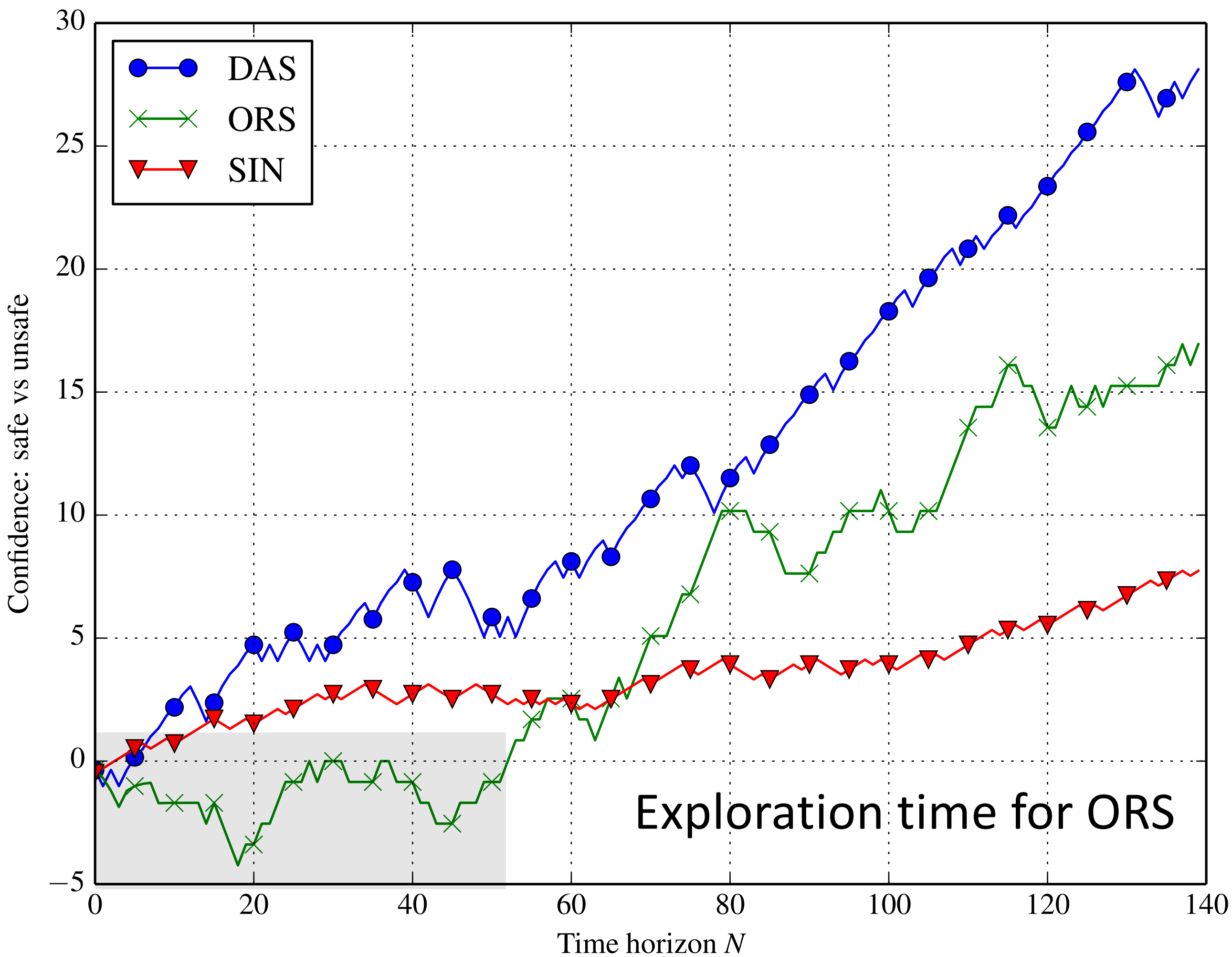
Classical approaches suggest lawnmower-type exhaustive search
Chernoff, 1959; Nitinawarat, Atia, Veeravalli 2013



Binary-search type approaches more efficient
Naghshvar, Javidi 2012, 2013; Chiu, Javidi 2020

Exploration Time

Exploration time: $T \doteq \min\{n' : \mathcal{C}_X(\rho_n) \geq 0 \; \forall n \geq n'\}$



After exploration time our most likely hypothesis is **always** the true hypothesis

compute exploration time only in hindsight

Exploration strategy should ensure exploration time is small – we derive high probability upper bounds on this

SARS-CoV-2 Testing

- A few realities have emerged
  - Insufficient number of tests
  - Tests have different efficacies
  - Timing of test administration matters
    - Both for serological (antibody) and PCR (RNA) tests
- The future should enable
  - Heterogeneous tests
  - Regular testing
- How can active methods help?

UCSF | About | Patient Care | Research | Educat

Research · April 27, 2020

Testing the Tests: COVID-19 Antibody Assays Scrutinized for Accuracy by UCSF, UC Berkeley Researchers

By Pete Farley and Robert Sanders

MEDTECHDIVE | Deep Dive | Library | Events | Topics

BRIEF

FDA OKs updated instructions for Abbott POC coronavirus test amid accuracy concerns

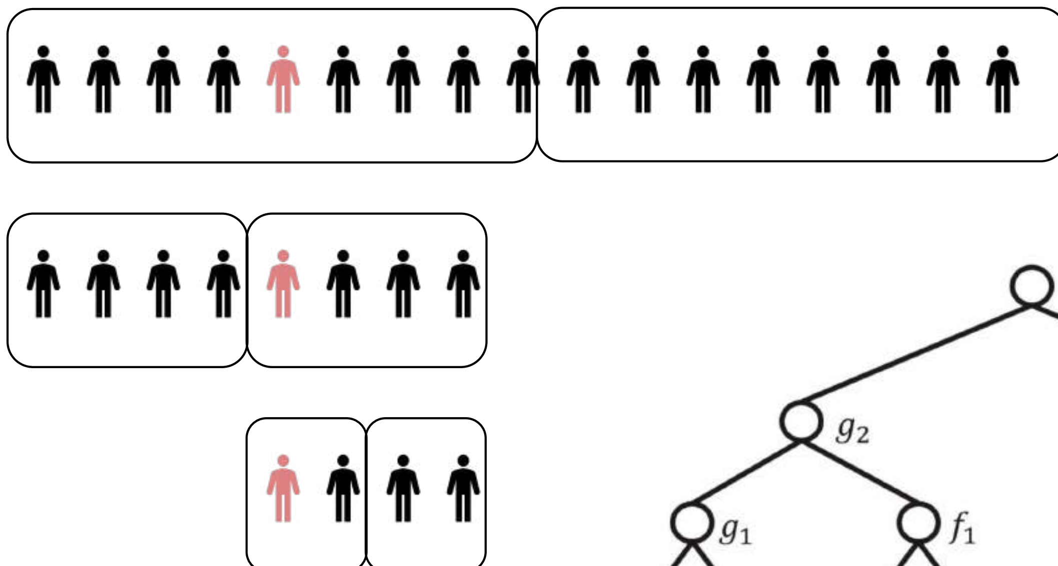
NEWS | CORONAVIRUS (COVID-19) | JUNE 10, 2020

COVID-19 Genetic PCR Tests Give False Negative Results if Used Too Early

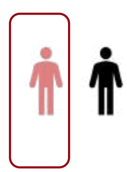
A new study confirms what many suspected, that PCR testing even 8 days after infection shows 20 percent false positives

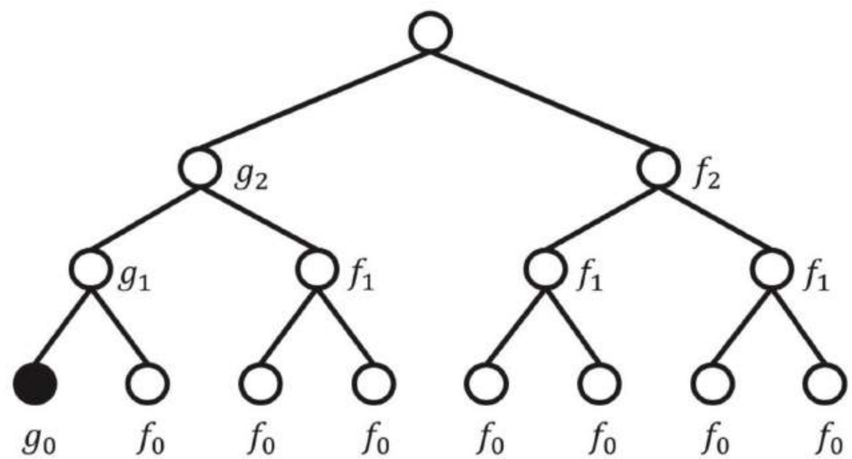
Recall Group Testing

- Used in WW2 to test soldiers for syphilis
  - R. Dorfman, "The Detection of Defective Members of Large Populations," The Annals of Mathematical Statistics, 1943
  - Binary search



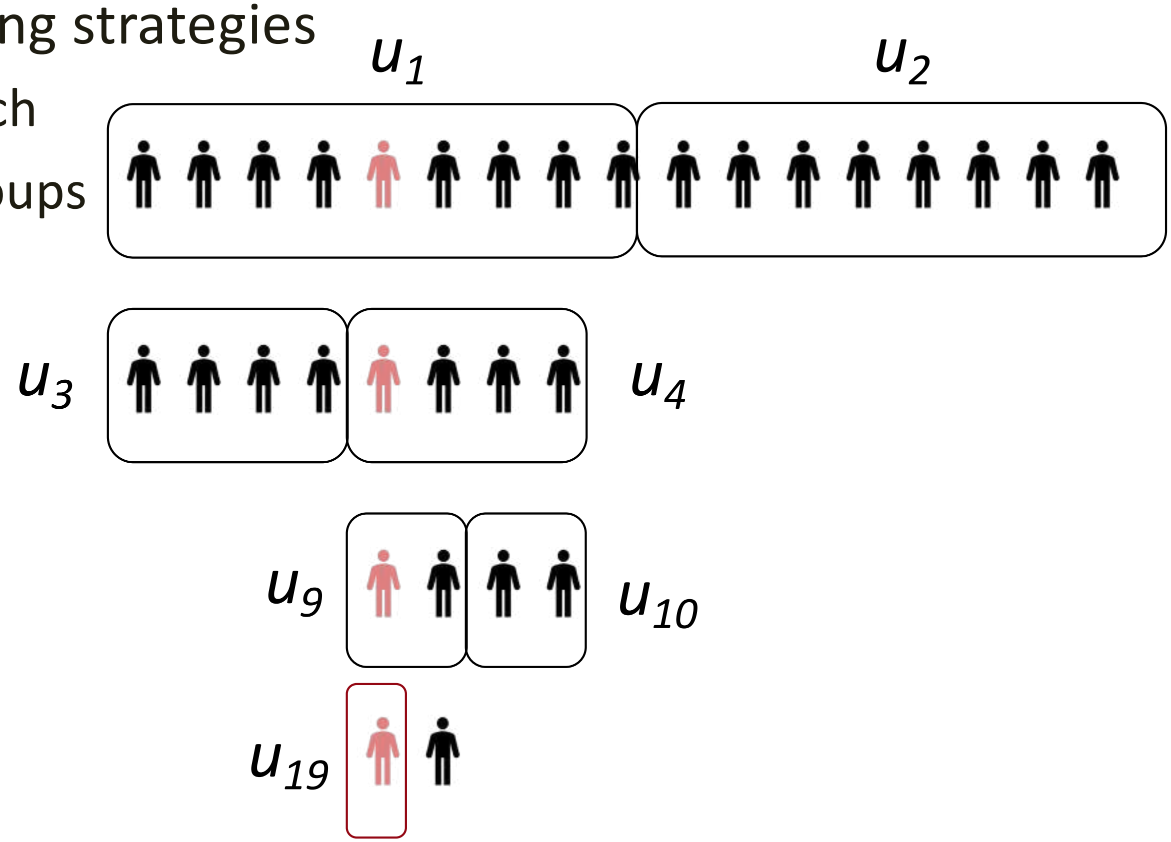
- N tests → log(N) tests



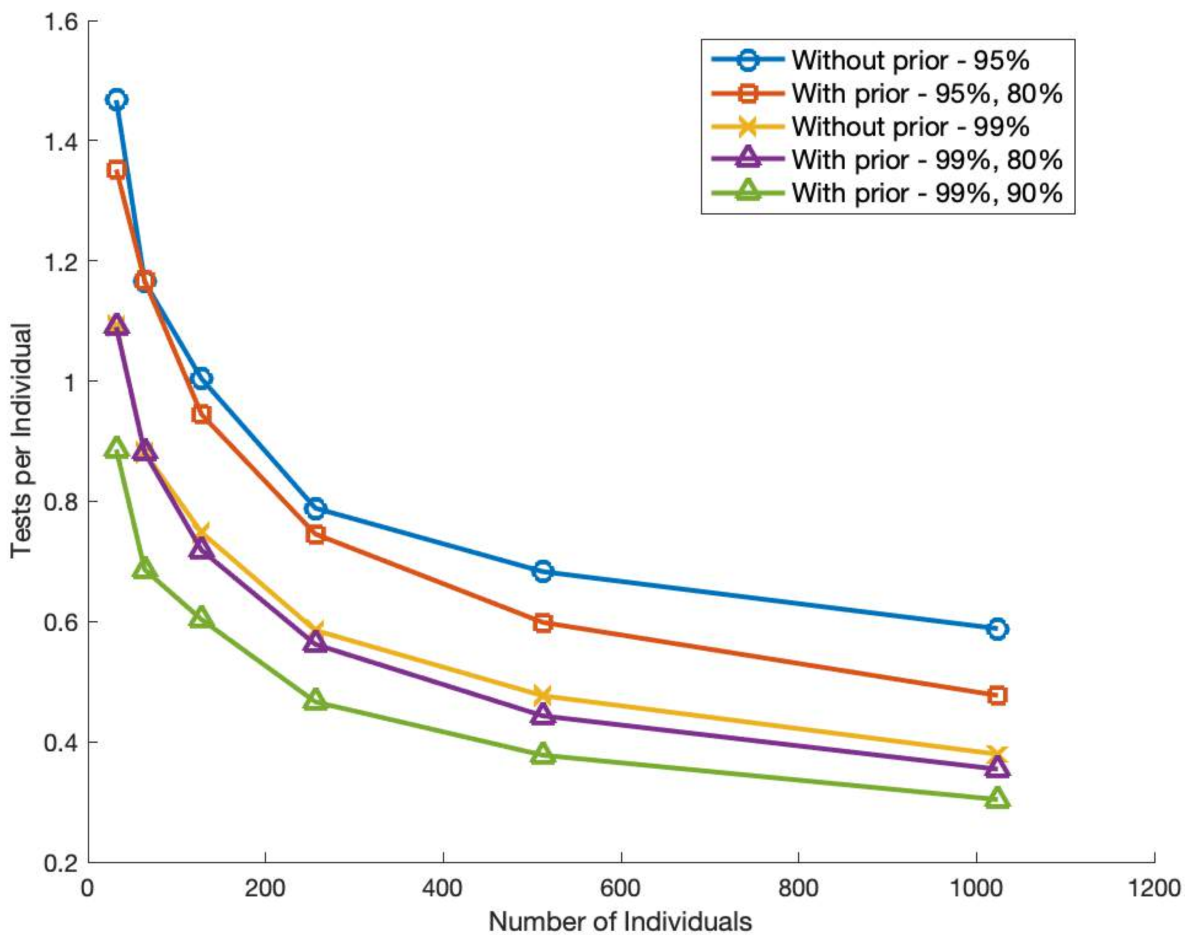


Mapping to Active Testing

- A variety of formulations
  - Form all possible groups, each distinct group is an experiment
    - Computationally expensive
  - Pre-select grouping strategies
    - E.g. Binary search
    - Time-varying groups



Fully-adaptive Tests



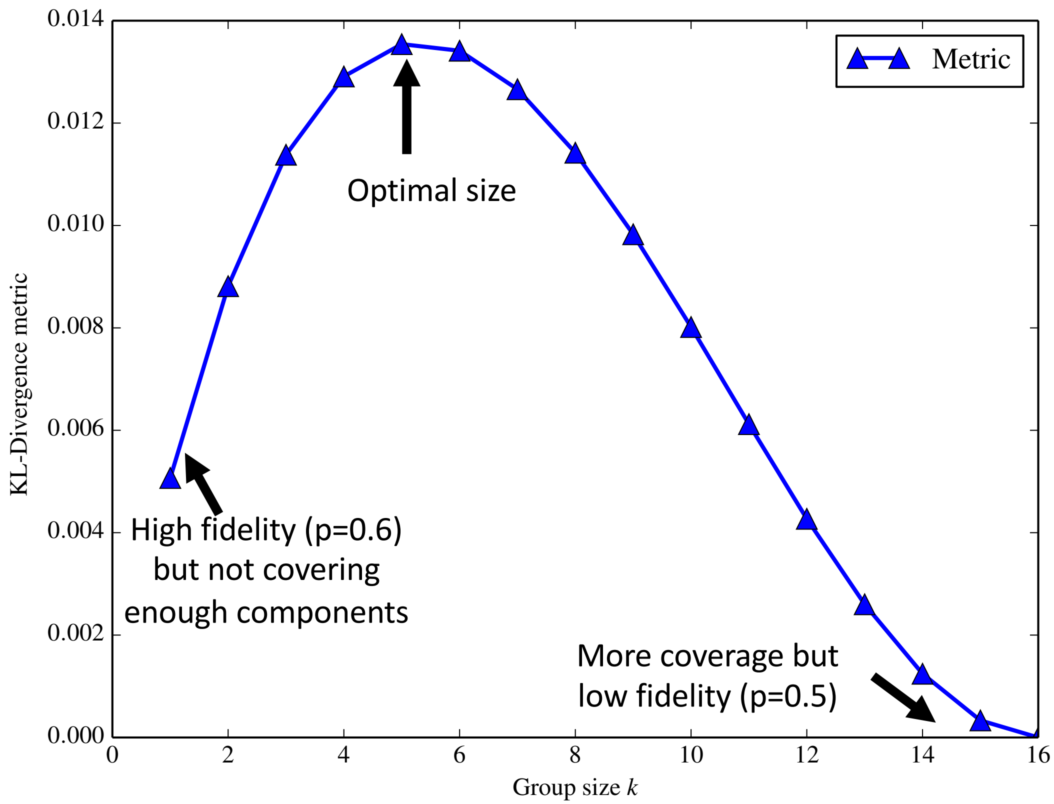
- Perform a cheap test first on each individual – we consider tests with 80% and 90% accuracy
- Use the prior for group testing subsequently
- Can reduce number of group tests by 20%

- Performing cheap tests first better when the cost of cheap test is about 10-15 times smaller

fully adaptive tests can take a lot of time – need to parallelize

Group Sampling Results

Selecting optimal group size



Optimal rate

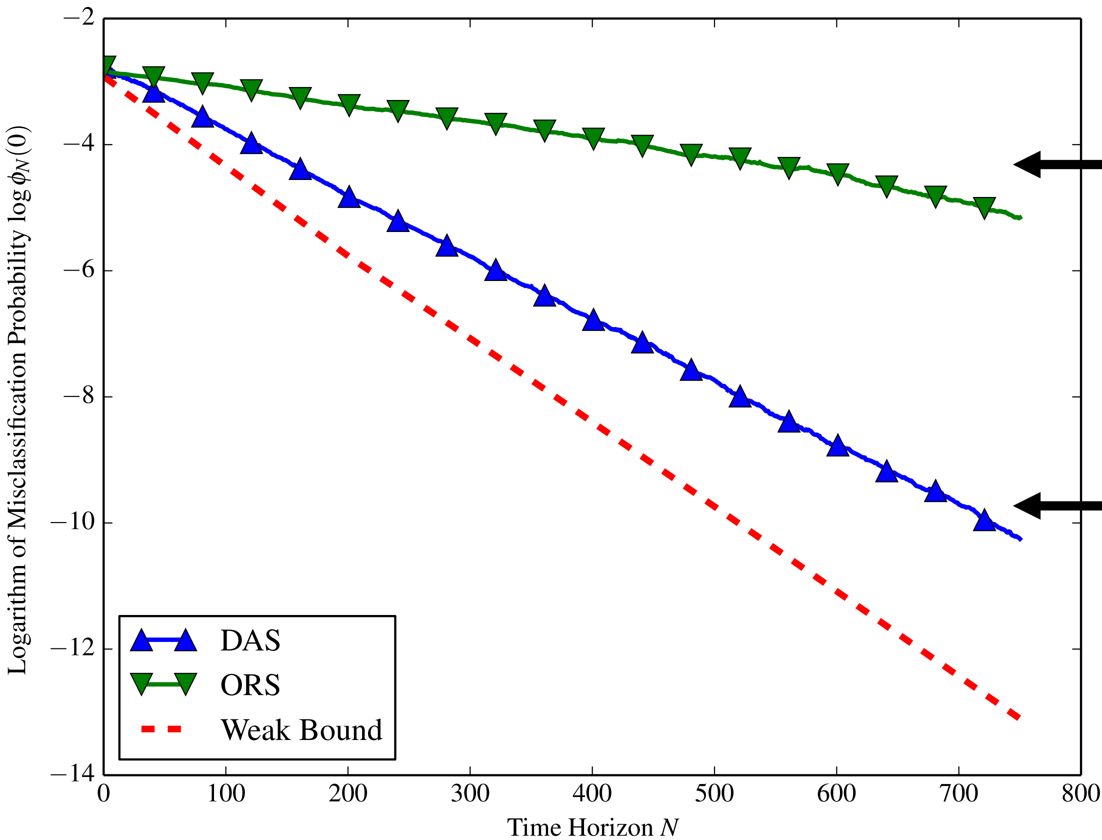
$$D^* \doteq \max_{1 \leq k \leq M} \frac{k D_{\{1\}}^{\{1,\ldots,k\}}}{M}$$

$$k^* \doteq \arg \max_{1 \leq k \leq M} \frac{k D_{\{1\}}^{\{1,\ldots,k\}}}{M}$$

Optimal size

A 16-component system with linear dilution: binary symmetric noise goes from 0.6 to 0.5 (indistinguishable)

Group Sampling Results



Open-loop strategy: randomly select a subset with size k^*

Adaptive Selection: select k^* most likely elements

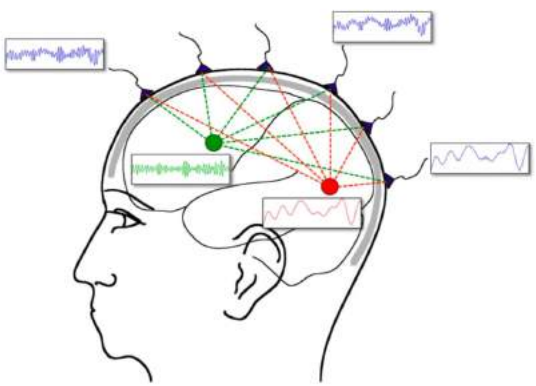
Dramatic performance gap between open-loop and adaptive selection

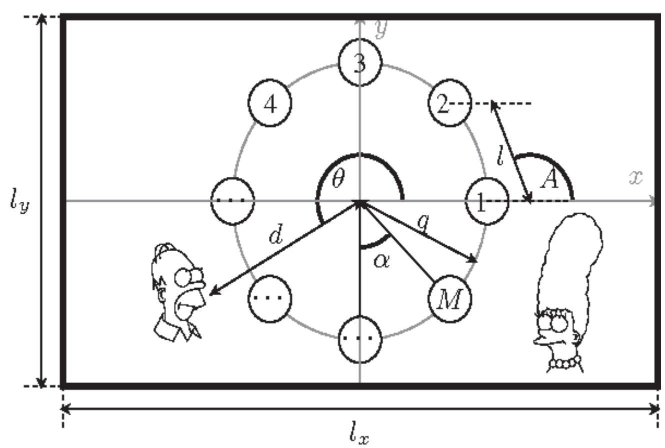
A 16-component system with linear dilution

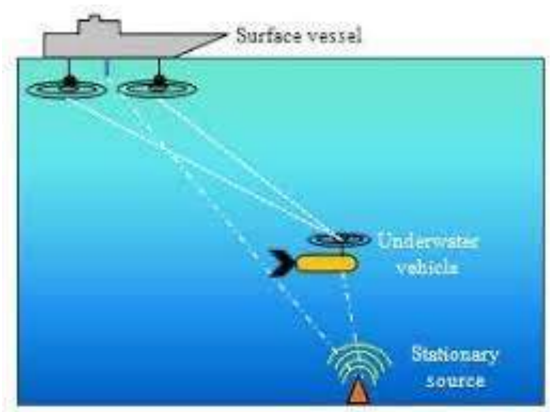
ONE LAST APPLICATION

Source Localization

- classical signal processing problem
- *Applications:*







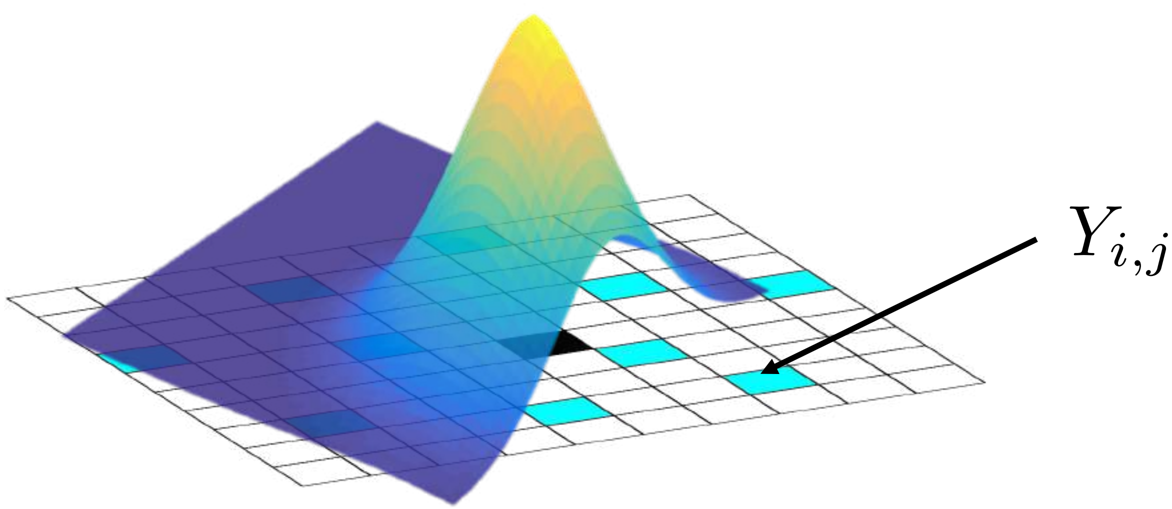
- Drawbacks of existing works:
  - Parametric methods – model mismatch issues
  - Model parameters hard to estimate
  - Model-free approaches coarse localization
  - ML-based approaches require lots of training data

Localization Challenge

- Source location $\boldsymbol{s}^* \in \mathbb{R}^2$ (unknown) ■

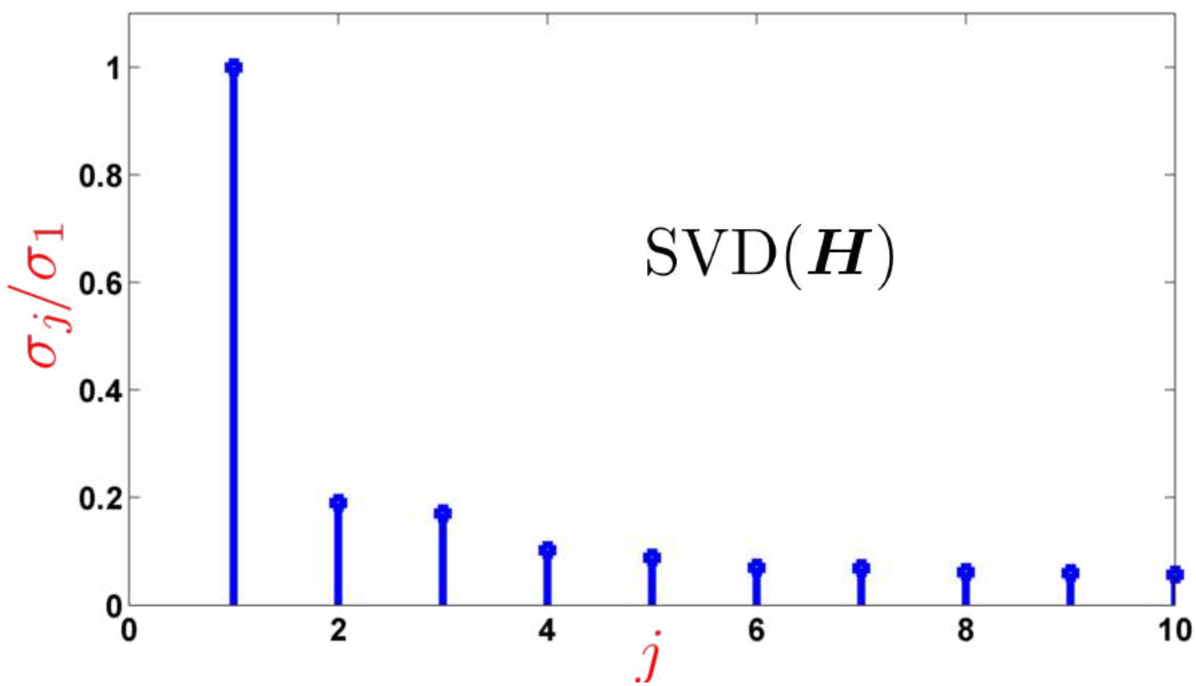
$$\boldsymbol{Y} \doteq \boldsymbol{H}(\boldsymbol{s}^*) + \boldsymbol{Z}$$

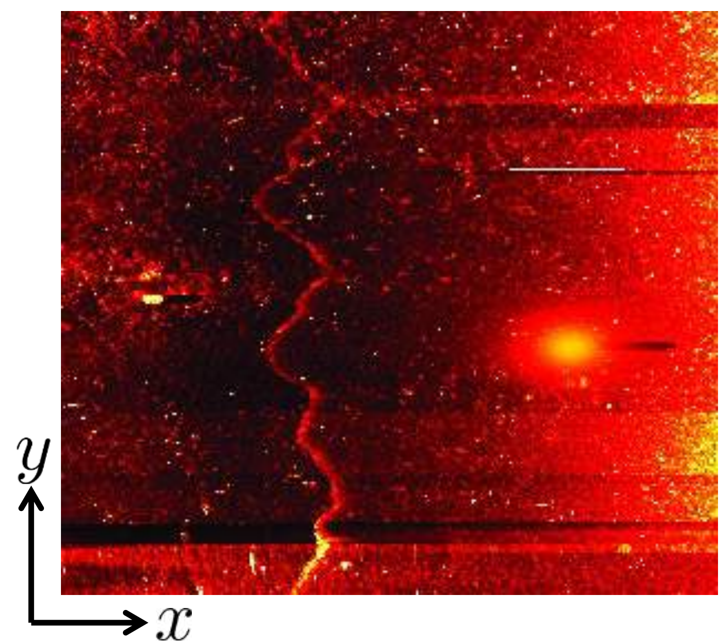
- If $\mathbf{Y} \in \mathbb{R}^{N \times N}$, N^2 hypothesis testing problem
  - Trade-off known distributions for signal structure
- Random samples at locations
- Only knowledge about target signal is that it is unimodal



Low Rank!

- Real sidescan sonar data
- Approximate target as **rank one matrix** in image space





Intensity $= \boldsymbol{H}(x, y)$

The Model

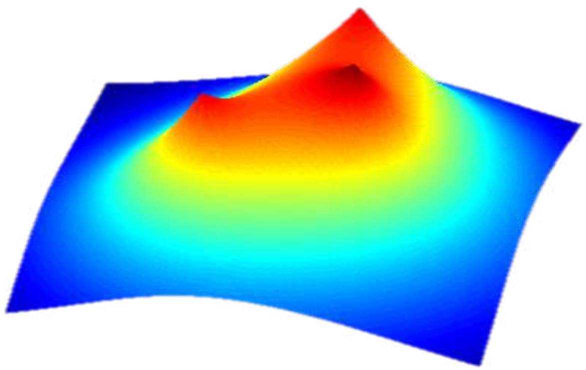
- Largest singular value $(\sigma_1, \mathbf{u}_1, \mathbf{v}_1)$
- Best rank one approximation $\hat{\mathbf{X}} = \sigma_1 \mathbf{u}_1 \mathbf{v}_1^H$
- $\mathbf{u}_1, \mathbf{v}_1$ are also unimodal, if $\mathbf{X}$ unimodal [Chen & M TSP'19]

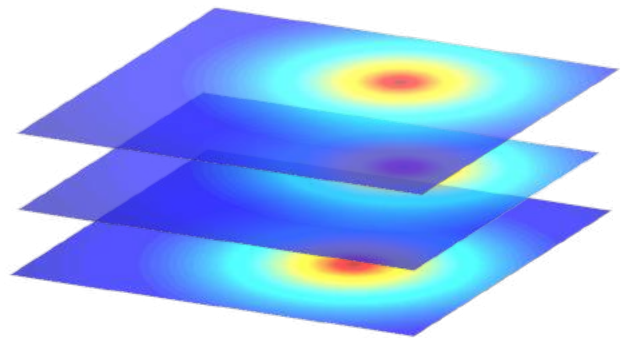

Choudhary, Kartik, Kumar,
Narayanan & **M**, Allerton 2014
Choudhary & **M** , ICASSP 2015

Our Prior Work

- Multisource localization from random samples
  - Exploit unimodality of each source signal

$\hat{\mathbf{H}}$



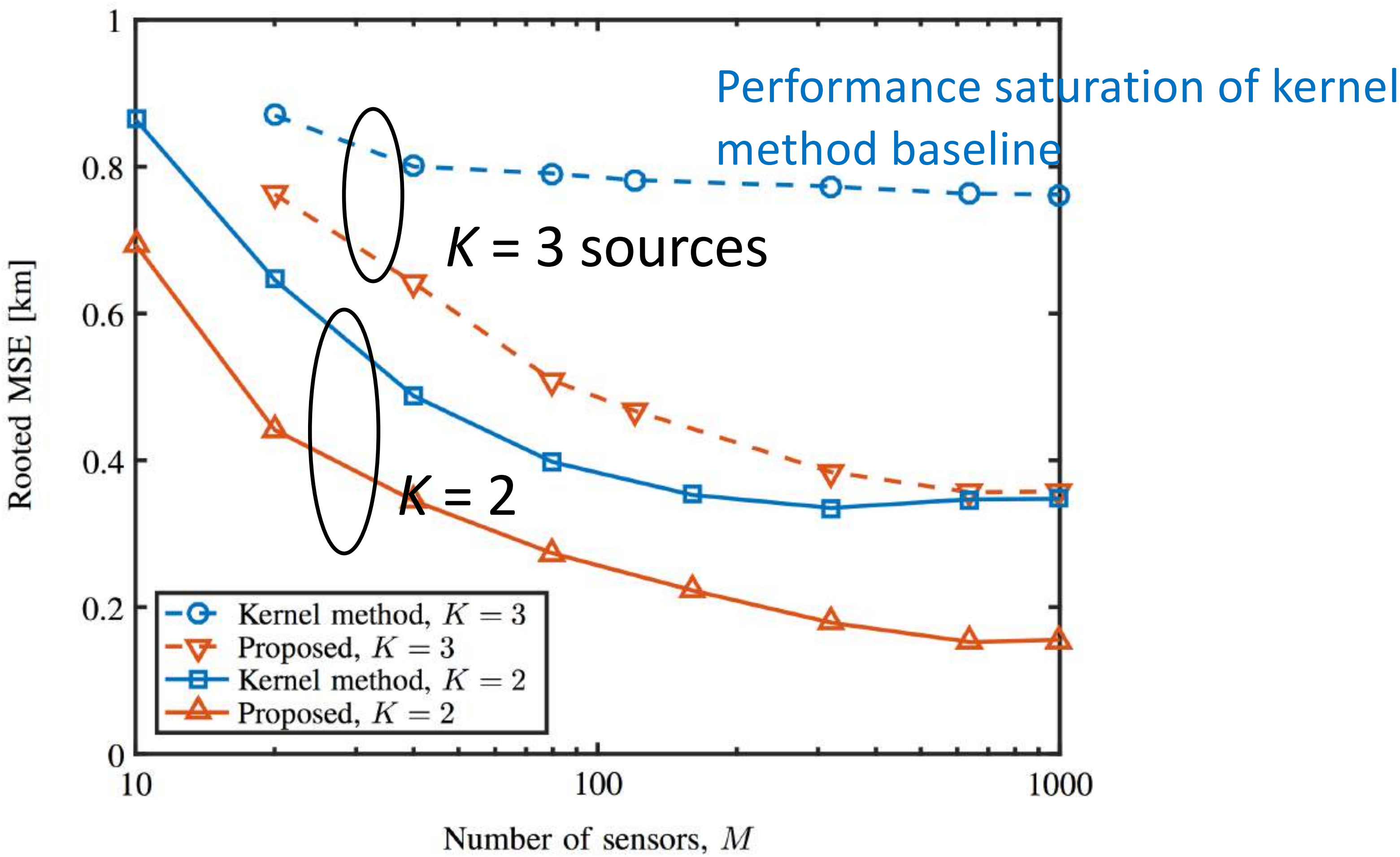


$$\begin{aligned} \underset{\{\alpha_k, \mathbf{u}_k, \mathbf{v}_k\}}{\text{minimize}} \quad & \left\| \mathcal{P}_{\Omega}\Big(\hat{\mathbf{H}} - \sum_{k=1}^{K} \alpha_k \mathbf{u}_k \mathbf{v}_k^{\mathrm{T}}\Big) \right\|_F^2 \\ \text{subject to} \quad & \mathbf{u}_k, \mathbf{v}_k \text{ are unimodal} \end{aligned}$$

- Can be solved via projected gradient methods

Chen & **M**, DSP'17,Asilomar'17, ICASSP'18,ICASSP'19, TSP'19
Zhang, Chen, Xie, Shapiro & **M**, SPL'21

Multiple Sources



do not need to complete matrix first

CAN WE MAKE THIS ACTIVE?

Signal Model

- Source at location $\boldsymbol{s}^* \in \mathbb{R}^2$ (unknown)

$$\boldsymbol{Y} \doteq \boldsymbol{H}(\boldsymbol{s}^*) + \boldsymbol{Z}$$

- $\boldsymbol{H}(\boldsymbol{s}^*)$ unimodal
  - For a single source $\boldsymbol{H}(\boldsymbol{s}^*)$ is rank 1 [Chen & M TSP'19]
- Definition: Matrix is unimodal with mode at (i^*, j^*) if
  - $\boldsymbol{M}_{1,j} \leq \boldsymbol{M}_{2,j} \cdots \leq \boldsymbol{M}_{i^*,j} \geq \boldsymbol{M}_{i^*+1,j} \geq \cdots \geq \boldsymbol{M}_{n,j} \quad \forall j$

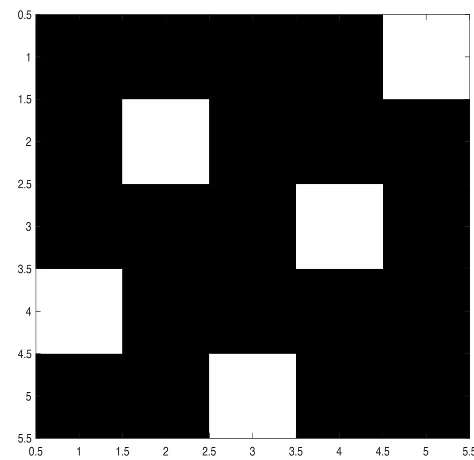
    $\boldsymbol{M}_{i,1} \leq \boldsymbol{M}_{i,2} \cdots \leq \boldsymbol{M}_{i,j^*} \geq \boldsymbol{M}_{i,j^*+1} \geq \cdots \geq \boldsymbol{M}_{i,n} \quad \forall i$
- No assumptions except unimodality (non-parametric) $\Longrightarrow$

  convergence + optimal error bounds HARD!

Narayanamurthy & **M**, ISIT'22, Asilomar'22

Algorithm - Exploration

- Initial Exploration: Latin Squares



- choose each row, column exactly once, with equal probability
  - widely used in experiment design, cryptography, board games
- Randomized initialization insufficient
- complete rank-1 matrix to get initial row, col estimate
  - Recall from matrix completion, SVD, $\mathbf{u}_1, \mathbf{v}_1$ are also unimodal if $\mathbf{X}$ unimodal

Adaptive Sampling - Exploitation

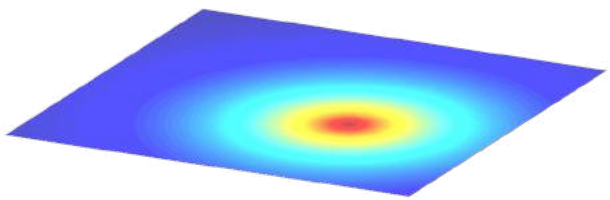
- Given initialization/exploration, how we do we exploit?
  - Uncertainty-Based approach: query max entropy location

- Theorem: (Uncertainty Quantification for MC, Chen et al. '21)
  - Consider a rank r matrix $\boldsymbol{Y} \overset{\text{SVD}}{=} \boldsymbol{U}\boldsymbol{\Sigma}_y\boldsymbol{V}^\top$
  - given $\mathcal{O}(nr^5\text{polylog}(n))$ entries sampled uniformly at random
  - let $\hat{\boldsymbol{Y}}$ denote output of ANY matrix completion algorithm
  - With probability at least $1 - n^{-3}$

$$\hat{\boldsymbol{Y}}_{i,j} \sim \mathcal{N}(\boldsymbol{Y}_{i,j}, C\sqrt{r/n}(\|\boldsymbol{U}^{(i)}\|^2 + \|\boldsymbol{V}^{(j)}\|^2)$$

Decomposing the problem

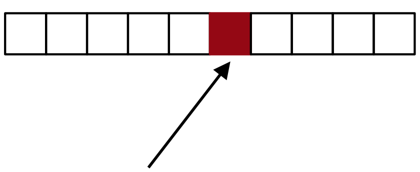
- Consider our single source
  - The two singular vectors are individually unimodal



$\mathbf{u}_1 \mathbf{v}_1^{\mathrm{T}}$

  - We can look in “each” direction independently
  - Recall unimodality definition:

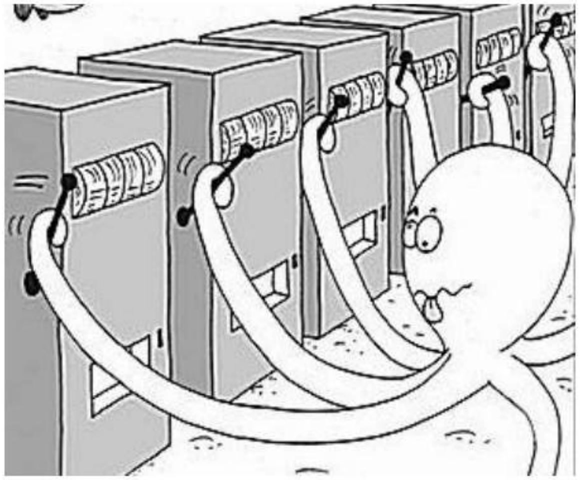
$$\boldsymbol{M}_{1,j} \leq \boldsymbol{M}_{2,j} \cdots \leq \boldsymbol{M}_{i^*,j} \geq \boldsymbol{M}_{i^*+1,j} \geq \cdots \geq \boldsymbol{M}_{n,j}$$



which component is maximum?

Stochastic Multi Armed Bandits I

- For each t, agent chooses one of K arms and plays it
- The $i\text{-th}$ arm produces reward $r_{i,t} \sim \mathcal{P}_i$ with mean μ_i (unknown)



source: Microsoft Research

- Agent's objective: maximize cumulative rewards
  - or, find $i^* \doteq \arg\max_i \mu_i$
- Several variants studied based on differing $\mathcal{P}_i$

Stochastic Multi Armed Bandits II

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- Example: Stochastic Bernoulli Bandit -- $\mathcal{P}_i$ are Bernoulli
  - Let $r_{i,t} \in \{0,1\}$and $\mathbb{E}[r_{i,t}] = \mu_i$
  - If μ_i were known, optimal policy is to play fixed action $i^* \doteq \arg\max_i \mu_i$
  - If unknown, need to do something better
- Regret: $R_n \doteq n \max_i \mu_i - \mathbb{E}[\sum_{t=1}^{n} r_{i,t}]$
  - Q: how does R_n scale with n ?
  - A: a "good learner" attains sub-linear regret, i.e., $\lim_{n\to\infty} \frac{R_n}{n} = 0$
- For Bernoulli bandits (our example), $R_n = \Theta(\sqrt{n})$
  - [Lattimore and Szepesvari] Bandit Algorithms, '20

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Algorithms: ETC

- Explore-then-Commit (ETC):
  - Play each arm a fixed number of times, m (Exploration)
  - After Km rounds, always play "best" arm (Exploitation)
    - Recall that we have K arms

Algorithms: UCB

- Upper Confidence Bound (UCB): optimism in the face of uncertainty
  - UCB of arm i, in round t is

$$\mathrm{UCB}_i(t-1,\delta) = \hat{\mu}_i(t-1) + \sqrt{\frac{2\log(1/\delta)}{T_i(t-1)}}$$

  - δ confidence parameter – controls exploration vs exploitation tradeoff
  - $T_i(t-1)$ number of times arm i has been played till round t
    - If arm has been tried many times, second term will be small (less uncertainty)
  - $\hat{\mu}_i(t-1)$ empirical reward of arm i at round t (averaging)
  - In each round, pick the arm with largest UCB

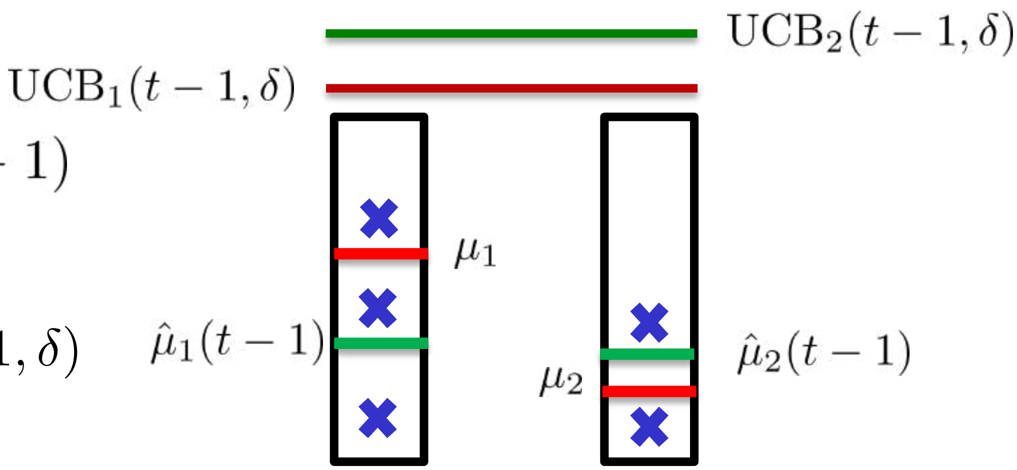
  - δ large ➡ a lot of initial exploration (limited optimism)

UCB intuition I

- Consider 2-arm bandit problem with $\mu_1 = 0, \mu_2 = -0.5$

- Initially, variance⬆
  "confidence"⬇
- although $\hat{\mu}_1(t-1) \approx \hat{\mu}_2(t-1)$
  arm 2 picked next since

$$\mathrm{UCB}_2(t-1,\delta) \quad > \quad \mathrm{UCB}_1(t-1,\delta)$$



- hope is that as time progresses,

$$\mathrm{UCB}_1(t-1,\delta) \gg \mathrm{UCB}_2(t-1,\delta)$$

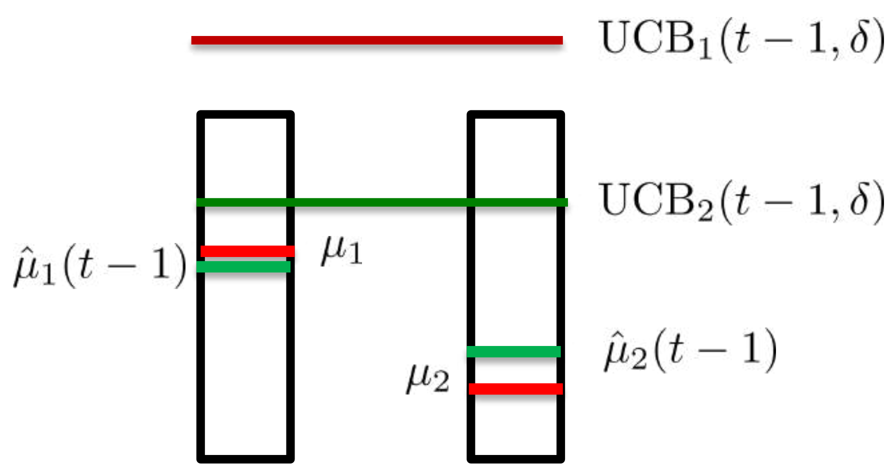
UCB intuition II

- as time progresses, LLN/CLT says

$$\hat{\mu}_i(t) \to \mu_i$$

- CLT also provides "Gaussian like" tails and thus (informally)

$$\mathbb{P}\left(|\hat{\mu}_i - \mu_i| \geq \sqrt{\frac{2\log(1/\delta)}{T_i(t-1)}}\right) \leq \delta$$

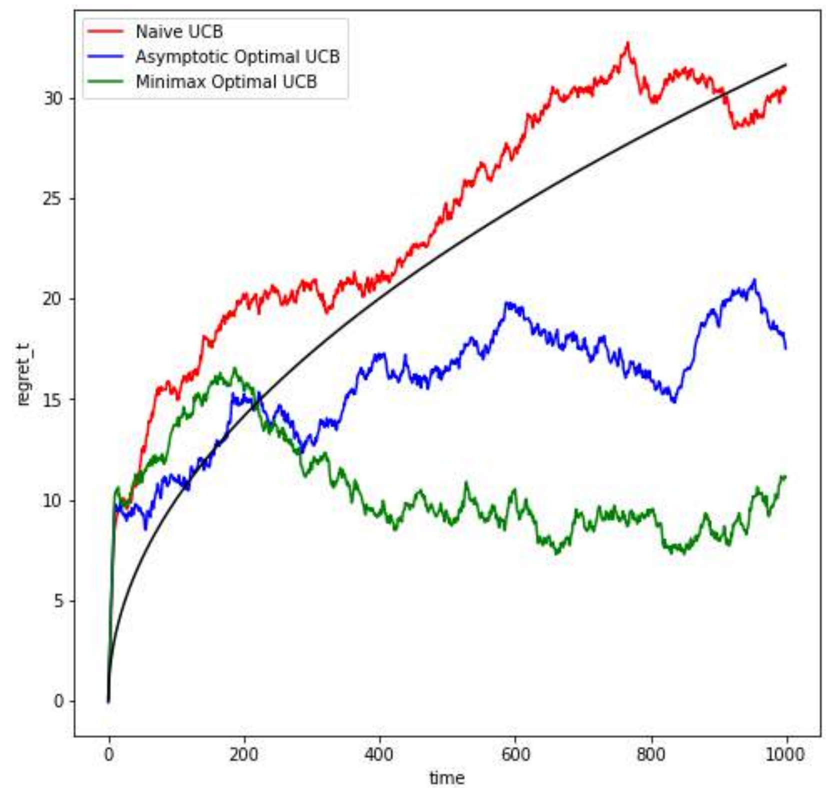


- UCB picks the "correct" arm and guarantees sub-linear regret
- Actual regret bounds depend on
  - choice of δ
  - sub-optimality gaps, i.e., $\Delta_i \doteq (\max_i \mu_i) - \mu_i$
  - …

MAB: Algorithms II

- Gaussian rewards, 10 arm problem

  - Naïve UCB, Asymptotic UCB, Minimax UCB vary only in choice of δ
  - Black line is $y = c\sqrt{t}$



What is our main result?

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- With our Latin Squares exploration, followed by UCB-based active sampling, we have
- **Theorem:** With probability at least $1 - o(1)$

$$\mathbb{E}\left[\text{regret}\right] \leq C \sum_{k,l} \frac{\text{correct}^{u}_{k,l}}{\text{sub opt gap}^{u}_{k,l}{}^{2}} \frac{\text{correct}^{v}_{k,l}}{\text{sub opt gap}^{v}_{k,l}{}^{2}} \|\text{coord err}\|^{2} \frac{\log^{2} m}{m}$$

  - Terms for each direction independently – 2 MABs
  - Can exploit prior results on MAB with sub-Gaussian random variables (bounds on regret)
    - *sub-Gaussianity and concentration inequalities again*

Main Result

- Define
  - $\boldsymbol{Y} \doteq \lambda_y^2 \boldsymbol{u}\boldsymbol{v}^\top$ with $\|\boldsymbol{u}\| = \|\boldsymbol{v}\| = 1$ (SVD)
  - $b \doteq \max_{i,j} \boldsymbol{Y}_{i,j}$ (max value)
  - $\Delta_{k|l}^u \doteq \boldsymbol{Y}_{i^*,l} - \boldsymbol{Y}_{k,l}$ and $\Delta_{l|k}^v \doteq \boldsymbol{Y}_{k,j^*} - \boldsymbol{Y}_{k,l}$ (sub-optimality gaps)
  - $\gamma_{k,l}^u \doteq \boldsymbol{u}_k + 2b\Delta_{k|l}^u$ and $\gamma_{k,l}^v \doteq \boldsymbol{v}_l + 2b\Delta_{l|k}^v$ ($\approx$ correction terms)
  - $\boldsymbol{c}_{k,l} \doteq (k,l)^\top$ and $\boldsymbol{c}^* \doteq (i^*, j^*)^\top$ (coordinates)
  - $\boldsymbol{R}_m \doteq \frac{1}{m} \sum_{\tau=1}^m \|\hat{\boldsymbol{s}}_\tau - \boldsymbol{s}^*\|^2$ (regret)

- **Theorem:** With probability at least $1 - o(1)$

$$\mathbb{E}[\boldsymbol{R}_m] \leq C \sum_{k,l=1}^{n} \frac{\gamma_{k,l}^u}{(\Delta_{k|l}^u)^2} \cdot \frac{\gamma_{k,l}^v}{(\Delta_{l|k}^v)^2} \cdot \|\boldsymbol{c}_{k,l} - \boldsymbol{c}^*\|^2 \frac{\log^2 m}{m}$$

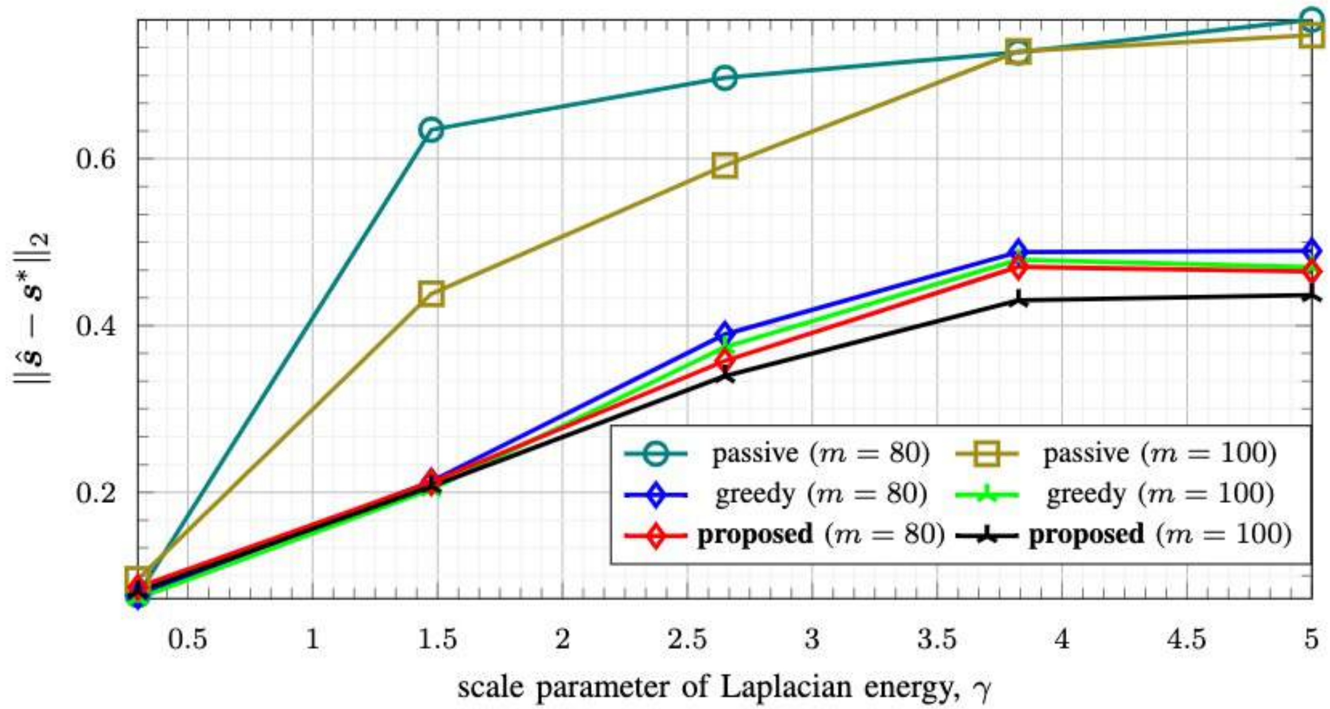
Discussion of Result

- $\Delta^u_{k|l}, \Delta^v_{l|k}$ are "sub-optimality" gaps
  - as in multi-armed bandit literature, regret $\propto \frac{1}{(\Delta^u_{k|l})^2}$
  - can potentially be improved to $\frac{1}{(\Delta^u_{k|l})}$ (better stopping time analysis)
- $\gamma^u_{k,l}, \gamma^v_{k,l}$ are "correction" factors
  - typical results in MAB consider equal, known variance
  - our problem – potentially distinct variance estimates
- $\frac{\log^2 m}{m}$ factor standard in MAB regret bounds
  - best known results (for equal variance case) scale as $\frac{\log m}{m}$
  - Q: can we adapt to our problem? (likely need "better" variance estimates)

$$\mathbb{E}[\boldsymbol{R}_m] \leq C \sum_{k,l=1}^{n} \frac{\gamma^u_{k,l}}{(\Delta^u_{k|l})^2} \cdot \frac{\gamma^v_{k,l}}{(\Delta^v_{l|k})^2} \cdot \|\boldsymbol{c}_{k,l} - \boldsymbol{c}^*\|^2 \frac{\log^2 m}{m}$$

Variance Parameter

- Laplacian energy function, vary γ
- As γ increases, proposed method better
- Greedy, proposed methods uniformly better than passive



Summary + Future Work

- Proposed method for active non-parametric peak location
- Showed experimental improvement for several energy functions
- Provide preliminary theoretical guarantees

- Improve error bounds
- Consider multiple sources
- Apply to zeroth-order optimization problems

BIG PICTURE

- Active hypothesis testing
  - So many applications!
  - Information theory in the wild

- Important questions
  - How do you build your tree of actions/observations?
  - What is the right measure of informativeness that allows you to prune the tree?

- Martingales, concentration inequalities
  - Very useful tools for a wide-range of applications (need more than the CLT)

- The classics still matter
  - Chernoff, Stein, Wald, Blackwell, Fisher, Bayes, Neyman, Pearson