ARL Visit July 8, 2015

Value-centered Information Theory for Adaptive Learning, Inference, Tracking, and Exploitation

[http://wiki.eecs.umich.edu/voimuri]

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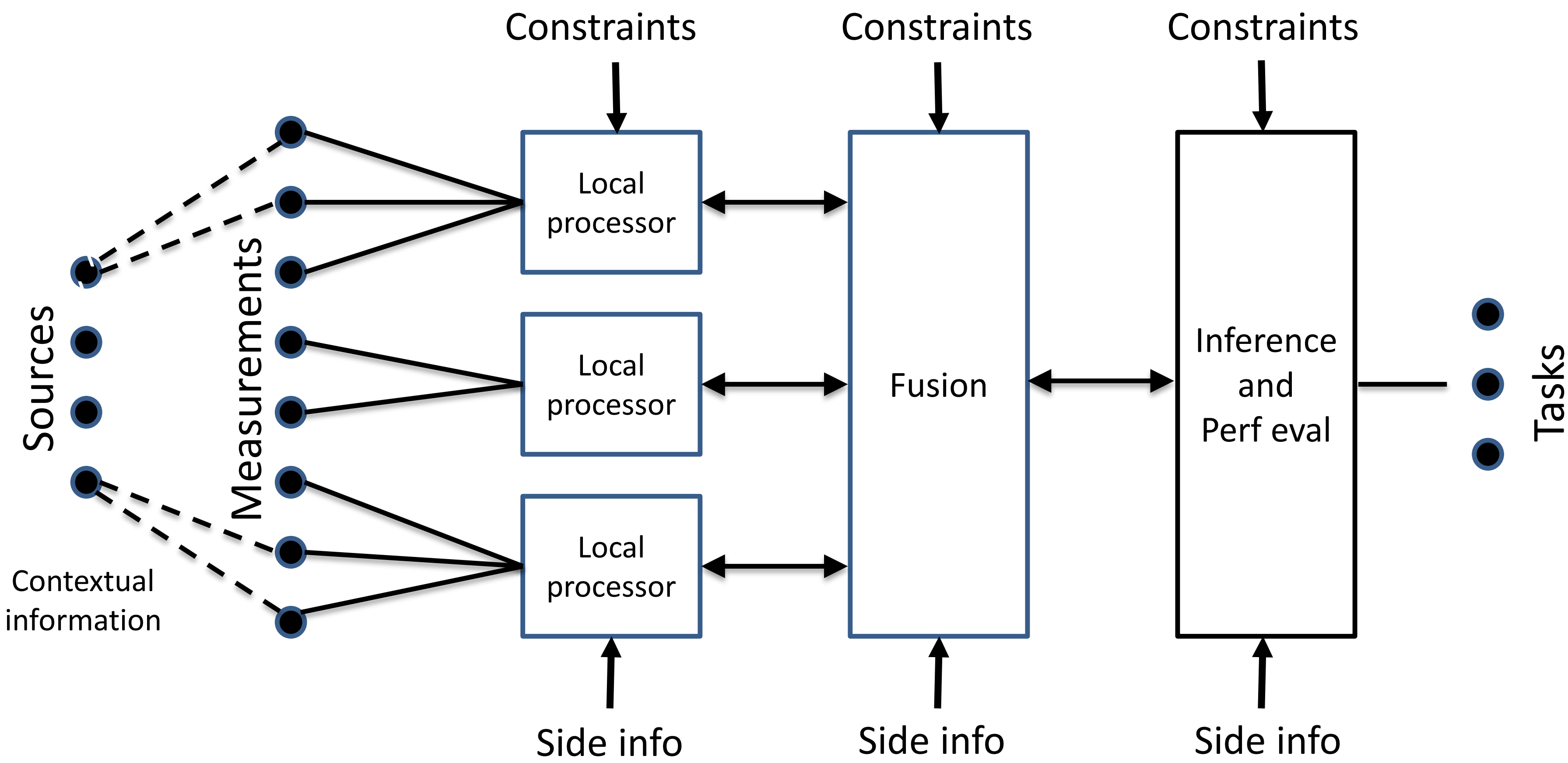
Learning, inference, tracking, and exploitation system

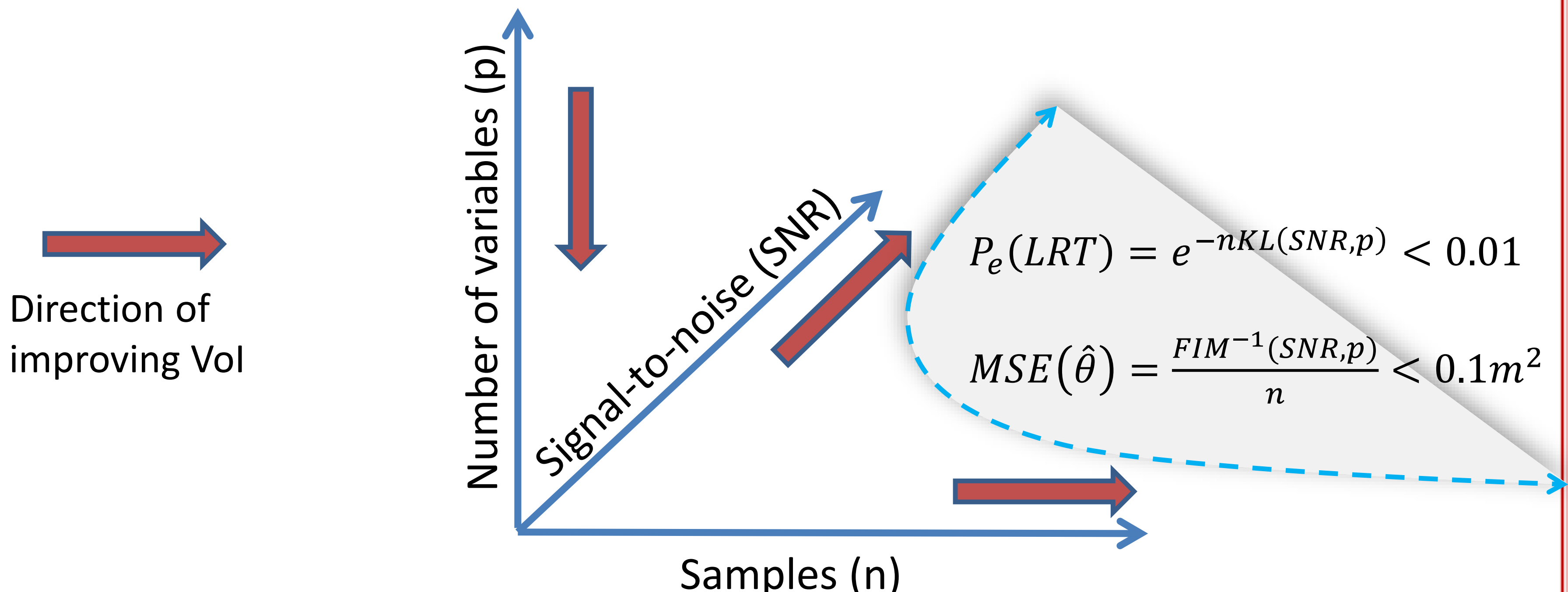


Learning, inference, tracking, and exploitation system

- Different types of data collection actions
  - Take a measurement from selected sensor S
  - Share information between two local processors
  - Acquire contextual knowledge and side info
  - Incorporate human experts in the loop
- Different types of constraints
  - Communications, computation, delay, privacy
- Central questions
  - What data collection actions maximize VoI?
  - How is VoI affected by constraints?
  - How can VoI be translated into design principles?

Value-centric information theory for learning, inference, tracking, and exploitation

- Develop theory of VoI in terms of fundamental limits depending on the task, the selected performance criterion, and the resource constraints.
- Apply VoI theory to develop better feature learning algorithms, information fusion methods, and sensor planning strategies.



Why is this problem difficult?

- There is lots of relevant theory…
  1. **Communication theory**: Shannon theory, rate exponents, entropy inequalities
  2. **Signal representation theory**: statistical modeling/representation, detection/estimation, convex relaxation
  3. **Control theory**: Markov Decision Processes (MDPs), value-function bounds, bandit approximations

- …and these are foundational building blocks that we are using…
- …but, there are gaps that have to be filled
  – Existing theories are inadequate when there are algorithmic complexity constraints
  – Existing theories are inadequate when there are human factors
  – Shannon theory was developed for communications and almost all propositions hold only for infinite block length (not real-time)
  – MDPs do not scale well to practical problem sizes

- We have made progress on filling these gaps

VoI in communications

- Value of information in communications theory
  - Primary task: reliable communication over noisy channel
  - Cost function: bit error rate (ber), information rate (bps)
  - Information measures: Shannon entropy, Shannon mutual information
  - Foundational principle: Shannon's coding and data processing theorems, Nyquist thm
  - Asymptotic regimes: infinite block length, high SNR
  - Deficiencies: asymptotic, no feedback, no real time or timeliness constraints

34 *The Mathematical Theory of Communication*

CE Shannon, BSTJ 1948

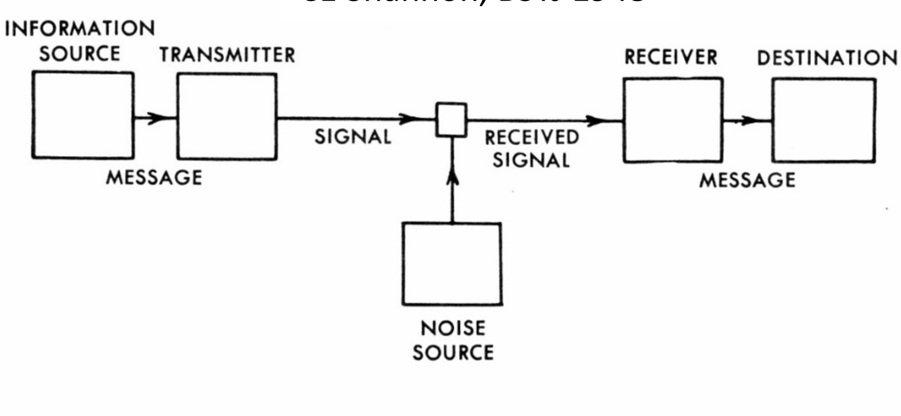
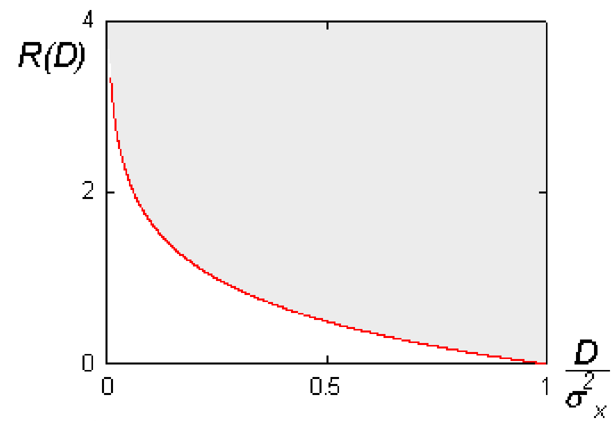
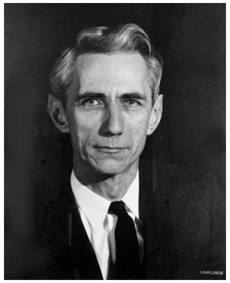
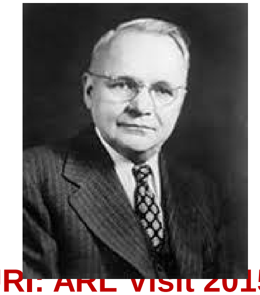


Fig. 1. — Schematic diagram of a general communication system.



http://en.wikipedia.org/wiki/Ratedistortion_theory

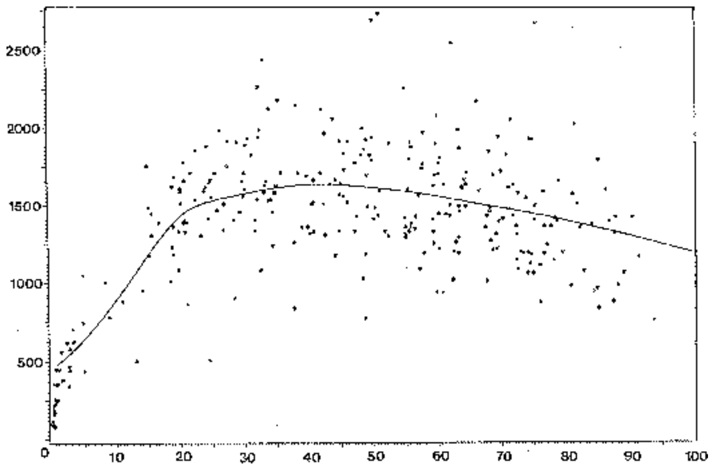


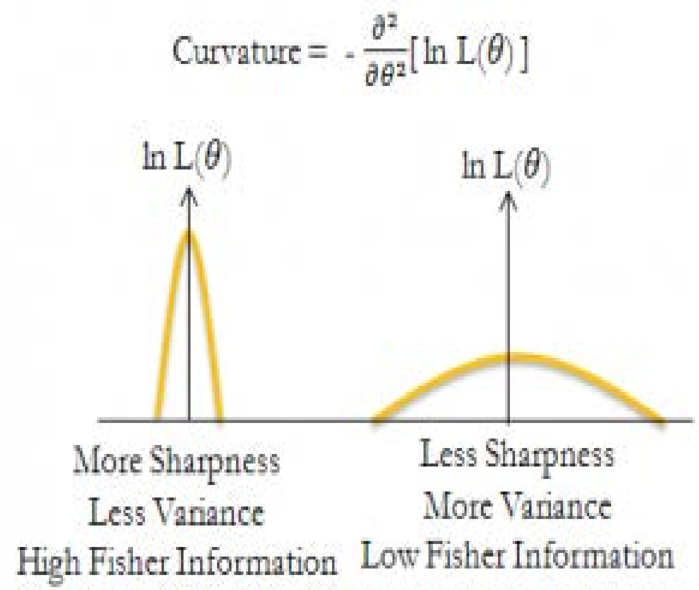


VoI in mathematical statistics

- Value of information in mathematical statistics
  - Primary task: fitting data to a model, parameter estimation or prediction
  - Cost function: risk, empirical risk, bias, variance, misclassification error
  - Information measures: Fisher information, Hellinger affinity
  - Foundational principle: Fisher sufficiency, asymptotic efficiency, Wiener filtering
  - Asymptotic regimes: stationarity, CLT, LLNs, concentration inequalities
  - Deficiencies: no real time constraint, no timeliness or human-in-the-loop

Hardle and Marron, 1985

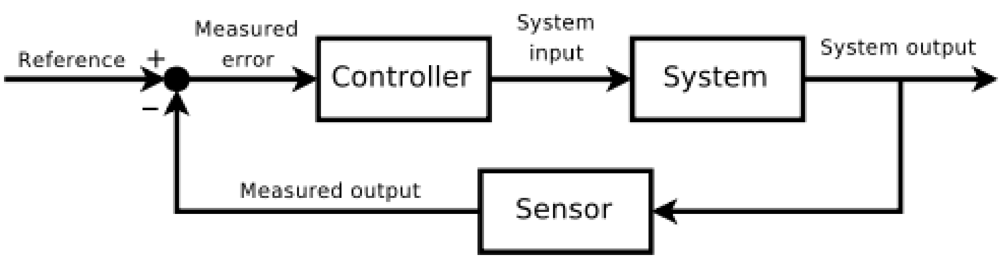




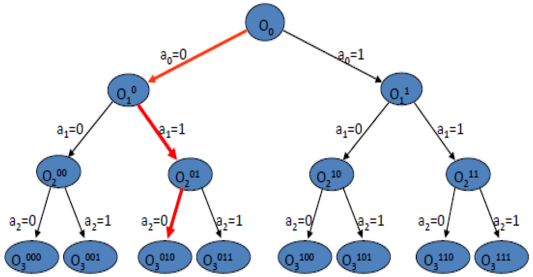
http://www.gaussianwaves.com/tag/fisher-information/

VoI in stochastic control theory

- Value of information in stochastic control theory
  - Primary task: maximize a reward by controlling actions on a measurement space
  - Cost function: general risk function, cost-to-go, future payoff, value functions
  - Information measures: information invariants on belief states (KL divergence)
  - Foundational principle: value-optimal policies via Bellman’s DP, Gittins index thm
  - Asymptotic regimes: myopic limit, limit of infinite horizon
  - Deficiencies: high computational complexity, approximation complexity, no HMI



http://en.wikipedia.org/wiki/Control_theory



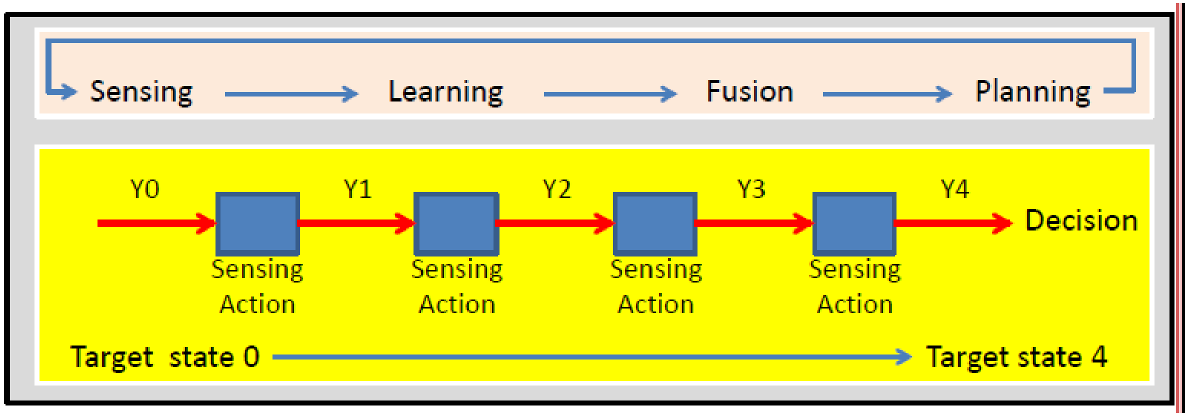
Source: Blatt H 2006

贝尔曼, R.

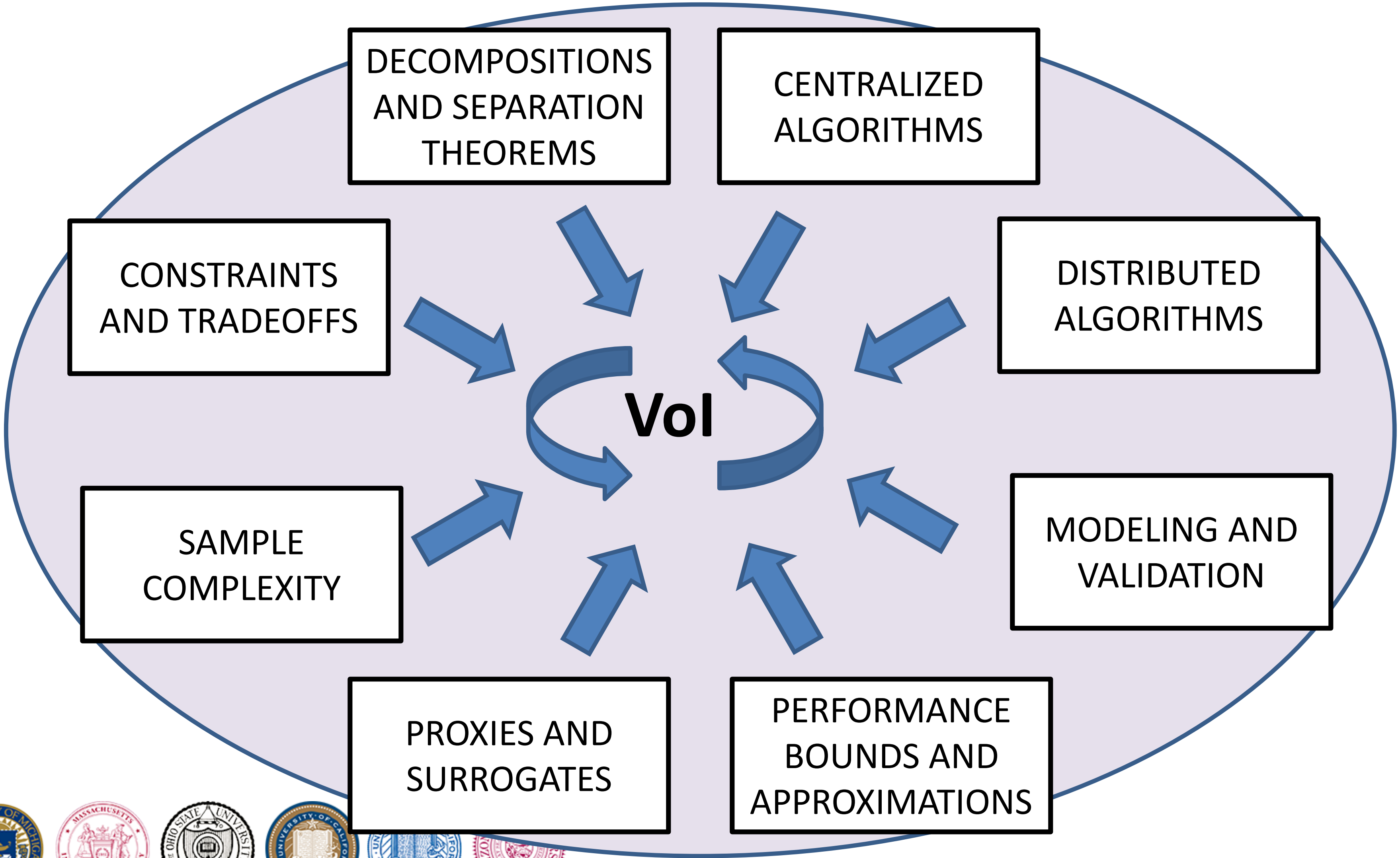
$$V_t(\pi_t) = \max_{a_t} \{R(a_t, \pi_t) + E[V_{t+1}(\pi_{t+1})|a_t, \pi_t]\}$$

VoI theory for sensing and data collection

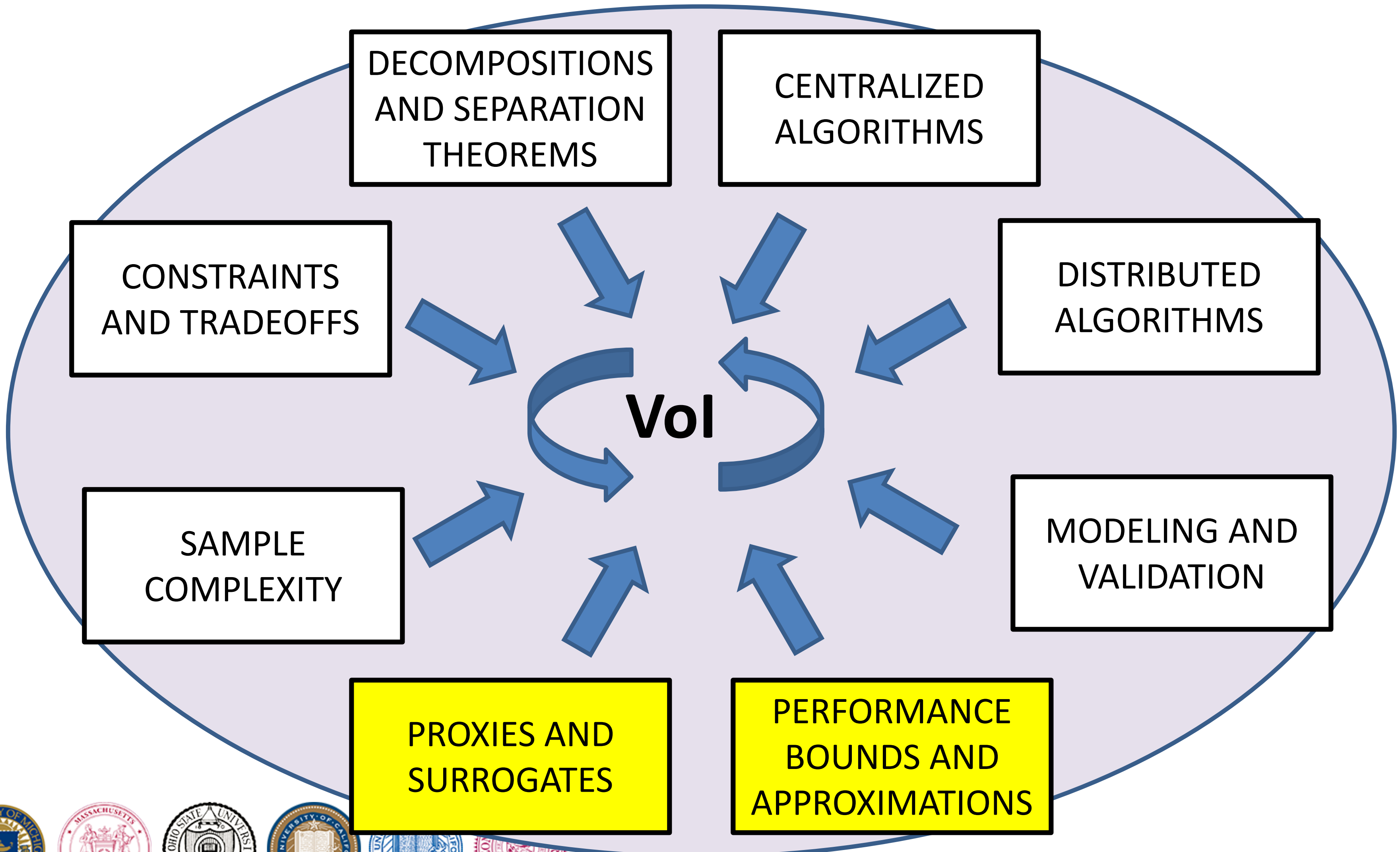
- Value of information in sensing and data collection
  - Primary task: data collection, distributed fusion, and decision-making
  - Cost function: decision-error with constraints on comms, computation, energy, etc
  - Information measures: invariant surrogates and proxies for performance
  - Foundational principle: a data processing theorem for multi-modal sensing
  - Asymptotic regimes: must apply to small sample sizes, distributed collection
  - Opportunities: real-time, time sensitive, mission sensitive, human-in-the-loop



Components of VoI theory



Components of VoI theory



Performance and proxies: some refs

- Non-parametric estimation of information directly from data
  - V. Berisha and A. O. Hero, "Empirical non-parametric estimation of the Fisher Information," IEEE Signal Processing Letters, vol. 22, no. 7, pp 988-992, July 2015.
- Information theoretic bounds on distributed estimation
  - J. C. Duchi, M. I. Jordan, M. J. Wainwright, and Y. Zhang, "Information-theoretic lower bounds for distributed statistical estimation with communication constraints,“ Proceedings of NIPS, 2014.
- Information geometric proxies for planning
  - S. D. Howard, W. Moran, and D. Cochran, "Intrinsic Fisher information on manifolds," *Proceedings of the Asilomar Conference on Signals, Systems, and Computers,* November 2014
- Convex proxies for resource allocation and mission planning
  - D. Wei and A.O. Hero, " Performance Guarantees for Adaptive Estimation of Sparse Signals," IEEE Transactions on Information Theory, to appear 2015.
  - G. Newstadt, B. Mu, D. Wei, J. P. How and A.O Hero, ""Importance-weighted adaptive search for multi-class targets," IEEE Trans on Signal Processing, to appear 2015
- Minimal sufficient and invariant proxies for deep learning networks
  - S. Soatto and A. Chiuso, "Visual Scene Representations: sufficiency, minimality, invariance and deep approximation", *International Conference on Learning Representations*, 2015.

What constitutes a good proxy for VoI?

- P0: Computability. Computational complexity of optimizing over policy space A
  - Example: greedy myopic approximation to multi-stage planning (Fisher, Hero, How, Cochran)
- P1: Intrinsic monotonicity: If proxy increases then expected reward should too
  - Example: correct classification probability asymptotically non-decreasing in KL divergence (Hero, Soatto)
- P2: Order preservation. Highest ranked actions same/similar to reward-intrinsic ranking.
  - Example: rank-preserving index proxies in multi-armed bandit approximations (Yu)
- P3: Intrinsic-to-task. Proxy is a fundamental limit or bound
  - Example: Fisher information, Chernoff information (Ertin, Soatto, Hero)
- P4: Side-information. Proxy approximation adapts to availability of new side information.
  - Example: Bayes update to fuse side-information into belief function (Hero)
- P5: Sample monotonicity of information: taking additional measurements can do no harm
  - Example: All proxies without measurement penalty terms or stopping rules
- P6: Action monotonicity: expanding available actions cannot decrease reward
  - Example: Any proxy that is maximized over nested action spaces
- P7: Data processing theorem: proxy is non-decreasing over processing resources
  - Example: Mutual information (Fisher)
- P8: Information invariance: information preserving transformations preserve proxy
  - Example: Mutual information (Fisher)
- P9: Proxy captures exploitation vs exploration tradeoff
  - Example: knowledge-gradient, single stage proxies with intervisibility penalties (Yu, Hero)

Proxies and surrogates: Multistage proxies

Proxy design strategies for multistage planning

- Multistage planning **index proxies** to reduce search complexity
  - Assign score functions to actions and choose action w/ max score at each stage
  - Reduces search complexity from $O(|A|^T)$ to $O(|A|T)$
  - Optimal when action space is finite and feasible performance space is polymatroid
  - Example: multi-armed bandit approximation (Yu)

- Multistage planning **myopic proxies** to reduce search complexity
  - Implement a sequence of T one-step lookahead policies
  - Reduction of search complexity from $O(|A|^T)$ to $O(|A|T)$
  - Optimizing φ_a over myopic policies comes within a constant factor of gold-standard VoI when avg reward R is a sub-modular (Krause and Guestrin 2007).
  - Examples: E[R]=mutual information (Fisher), E[R]=community detection (Hero)

- Multistage planning **myopic+ proxies**
  - Add randomization to myopic policy to promote exploration of action space
  - Example: Mission adaptive search policies [Hero and How], Knowledge gradient [Yu]

Proxies and surrogates: single-stage proxies

Proxy design strategies for single stage planning

- **Asymptotic proxies** for VoI
  - Use limiting form VoI measures: large sample size, large action space, high SNR,…
  - Asymptotic expressions for performance are often tractable and lead to insight
  - Asymptotic optimizers of asymptotic proxies often close to finite sample optimal
  - Example: CLT, LLNS, high dimensional limiting forms [Nadakuditi], [Hero].

- **Information theoretic proxies** for VoI
  - Optimize an information measure instead of the average reward
  - Information theoretic planning asymptotically concentrates posterior distribution
    - Data-processing theorem, Cramer-Rao theorem, Hoeffding-Chernoff theorem, Duncan's theorem, Shannon's rate distortion theorem.
  - Using an information proxy for planning is a "hedge" against overfitting to task
  - Example: information geometric planning [Cochran], Fisher info [Ertin and Moses], divergence estimation [Hero], mobile sensing and navigation [Soatto]

Proxies and surrogates: single-stage proxies

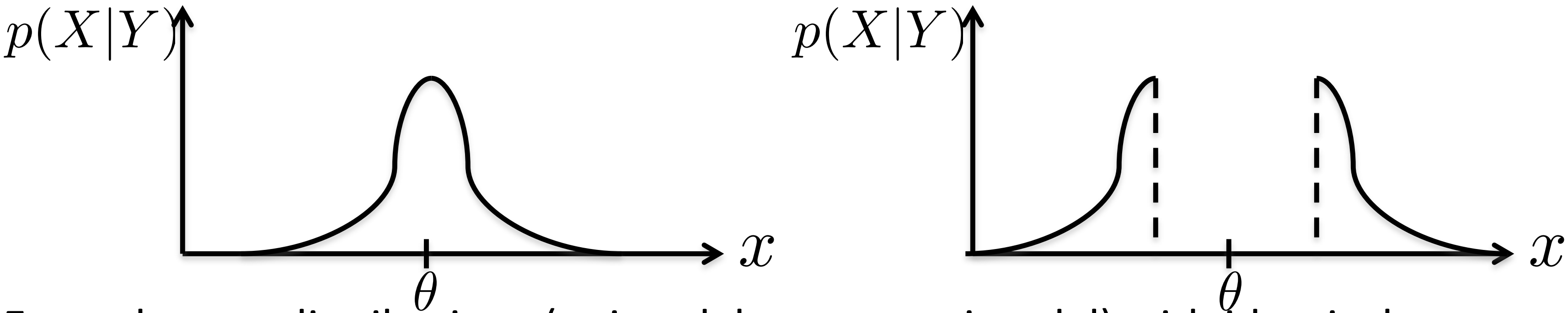
Proxy design strategies for single stage planning (ctd)

- **Convex proxies** for VoI
  - Drive the choice of proxy by computational considerations: convex optimization
  - Especially useful when multiple actions are to be selected in combination
  - Reduce combinatorial problem to a continuous optimization, e.g., via L1 relaxation
  - Example: L1/L0/trace norm feature selection [Hero], [Nadakuditi], [Jordan]

- **Bound proxies** for VoI
  - Maximize a lower bound on average reward over action space
  - Performance upper bounded by that of an oracle with access to hidden info
  - Sometimes bound proxies are also asymptotic proxies **and** information proxies
    - Cramer-Rao lower bound on MSE, Chernoff lower bound on Pe, Fano lower bound on Pe
  - Example: heterogenous mission planning [Hero and How], adversarial planning [Ertin], sensor networks [Moses]

A theorem on entropy proxies

Q: When does an entropy proxy progressively concentrate posterior?



Example: two distributions (unimodal vs. non-unimodal) with identical entropy

Theorem: unimodal distribution $p(X|Y)$, exponentially decreasing tails,

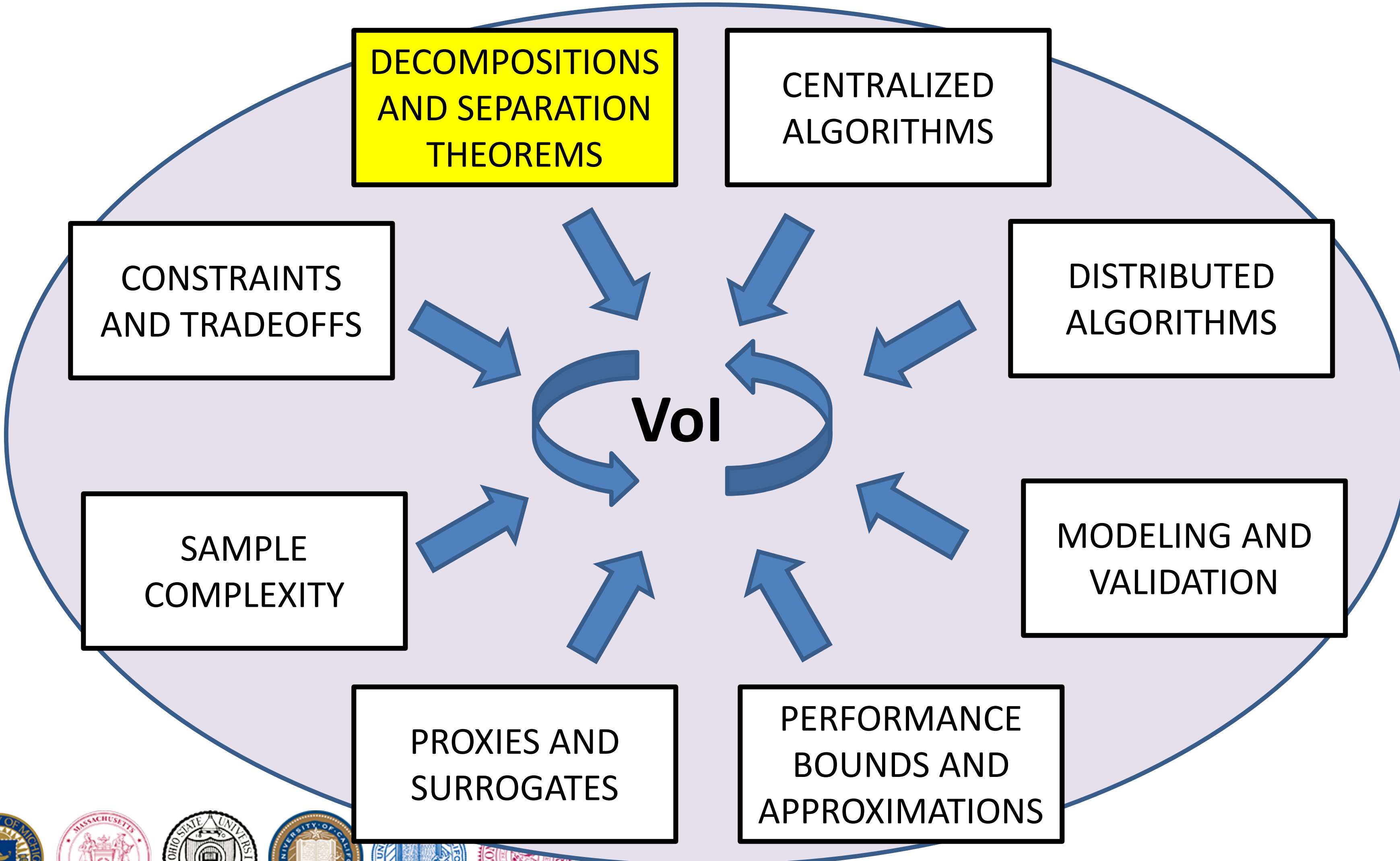
$$\frac{e^{2\cdot h(p(X|Y))}}{2\pi e} \overset{(a)}{\leq} \mathrm{var}(X|Y) \overset{(b)}{\leq} \frac{\alpha}{(\mathcal{I}(p(X|Y)))^{\beta}} \overset{(c)}{\leq} \frac{\alpha \cdot e^{2\beta\cdot h(p(X|Y))}}{2\pi e}$$

Differential entropy $h(p(X|Y))$ and Fisher information $\mathcal{I}(p(X|Y))$

Proof: (a): Estimation counterpart to Fano's inequality, (b):[Chung et al 2015], (c): Stam's inequality

Ref: Chung, Sadler, Hero. submitted 2015.

Components of VoI theory



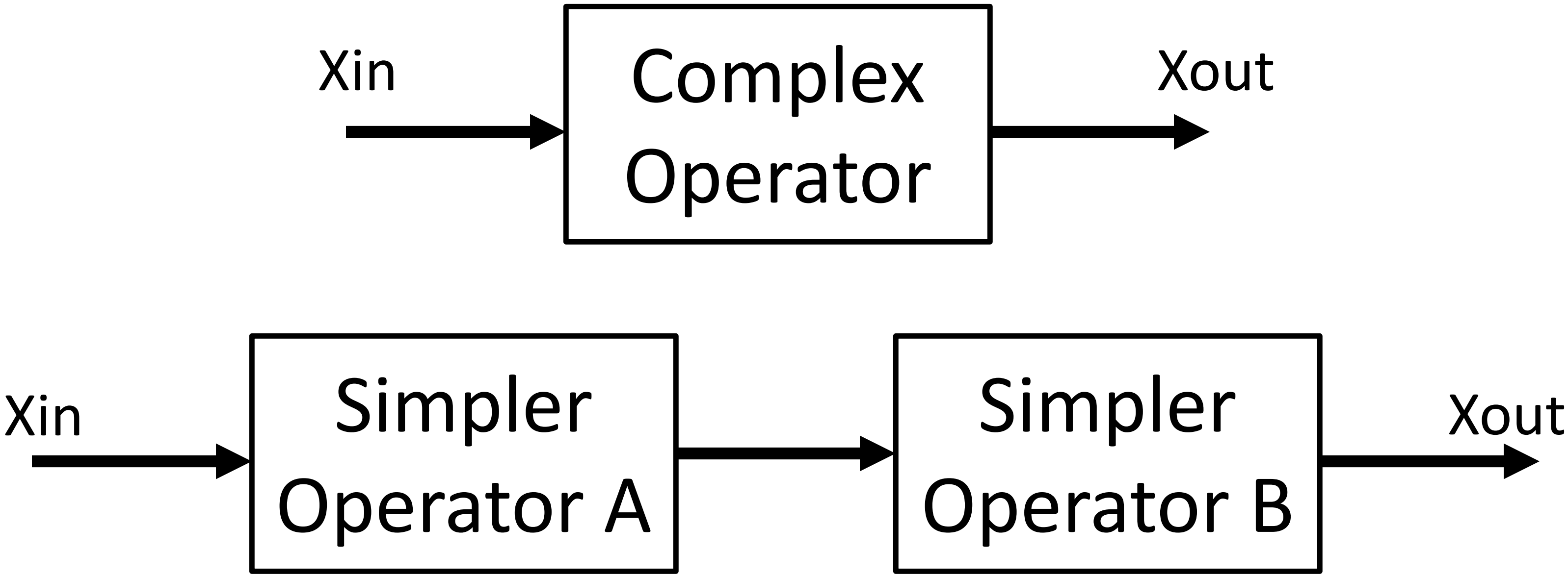
VOI

Decompositions and separations: some refs

- Myopic multistage-planning decompositions
  - G. Papachristoudis and J. W. Fisher III, "Efficient information planning in Markov chains" (in review 2015).
  - P-Y Chen and A.O. Hero, "Phase transitions in spectral community detection of large noisy networks," IEEE Intl Conf on Acoustics, Speech, and Signal Processing (ICASSP), Brisbane, April 2015.
- Separation theorem for collaborative 20 questions
  - T. Tsiligkaridis, B. M. Sadler, and A. O. Hero, "Collaborative 20 questions for localization," *IEEE Transactions on Information Theory.* vol. 60, no. 4, pp 2233-2252, April 2014.
- Separation of fusion and denoising
  - R. R. Nadakuditi, "OptShrink: An Algorithm for Improved Low-Rank Signal Matrix Denoising by Optimal, Data-Driven Singular Value Shrinkage," *IEEE Transactions on Information Theory*, vol. 60, no. 5, pp. 3002 - 3018, May 2014
- Kronecker decomposition for spatio-temporal analysis
  - T. Tsiligkaridis and A. O. Hero, "Covariance estimation in high dimensions via Kronecker product expansions," *IEEE Transactions on Signal Processing,* vol. 61, no. 21, pp. 5347 - 5360, Nov 2013.
  - K. Greenewald, E. Zelnio, A.O. Hero, "Kronecker PCA Based Robust SAR STAP,“ (in review 2015).

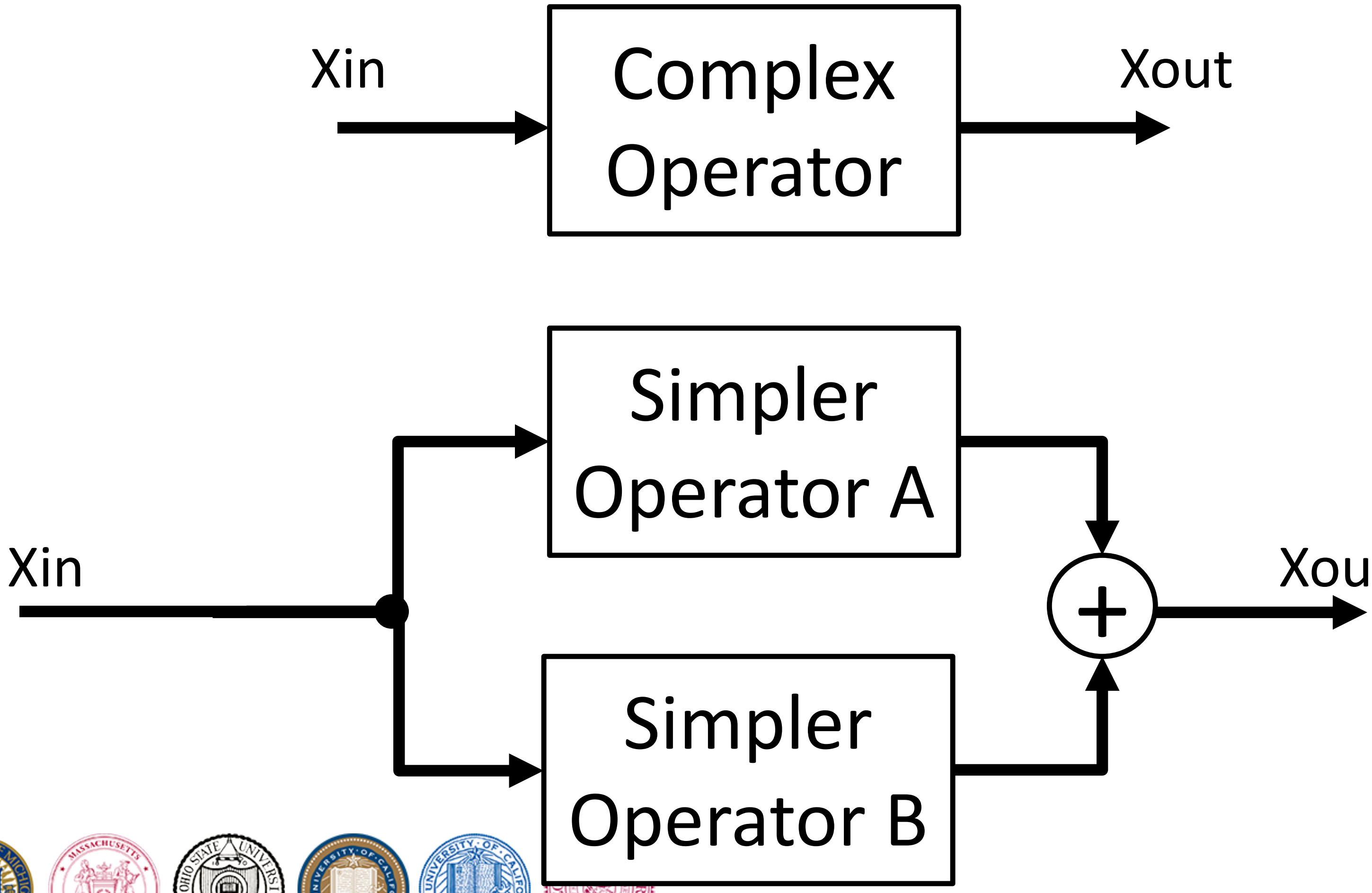
Decompositions and separation theorems

A serial **separation principle** is a decomposition of an operator into a cascade of simpler operators A and B



Decompositions and separation theorems

A parallel **separation principle** is a decomposition of an operator into a sum of simpler operators



Examples of serial separation principles

- Communication
  – Source/channel coding separation theorem for discrete memoryless channels (DMC) (Shannon 1948)
- Stochastic control
  – Separation of estimation and control in LQG (Wonham 1968)
- Mathematical statistics
  – Separation property for estimator of a function of a parameter – transformation invariance property of MLE.
- Convex optimization
  – Variables splitting via augmented Lagrangian - alternating direction method of multipliers (ADMM)

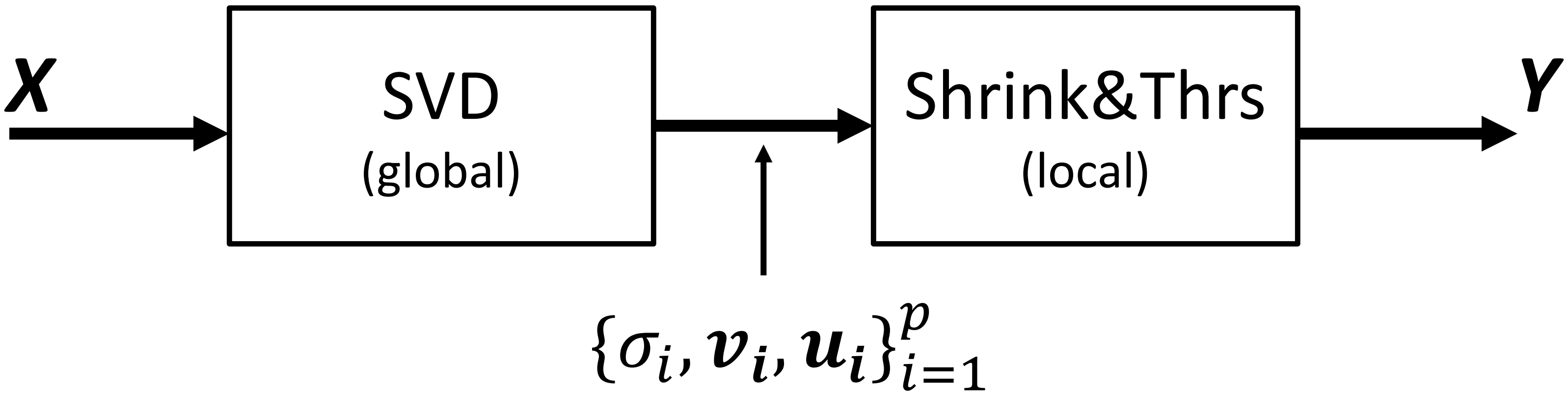
Serial separation principles for data collection

VOI

Application to subspace processing and information fusion

- Low rank plus noise model: $\boldsymbol{Y} = \boldsymbol{X} + \boldsymbol{W}$. $\boldsymbol{X} = \boldsymbol{A}\boldsymbol{\Lambda}\boldsymbol{B}$.
- Estimation proxy: $||\boldsymbol{X} - \boldsymbol{Y}||^2 + \beta||\boldsymbol{Y}||_*$. Frobenius + nuclear.
- Solution ***Y*** that minimizes proxy is (Lounici 2013, Tsiligkaridis 2014)

$$\boldsymbol{Y} = \sum_{i=1}^{p} \left[\sigma_i - \frac{\beta}{2}\right]_+ \boldsymbol{v}_i \boldsymbol{u}_i^T$$

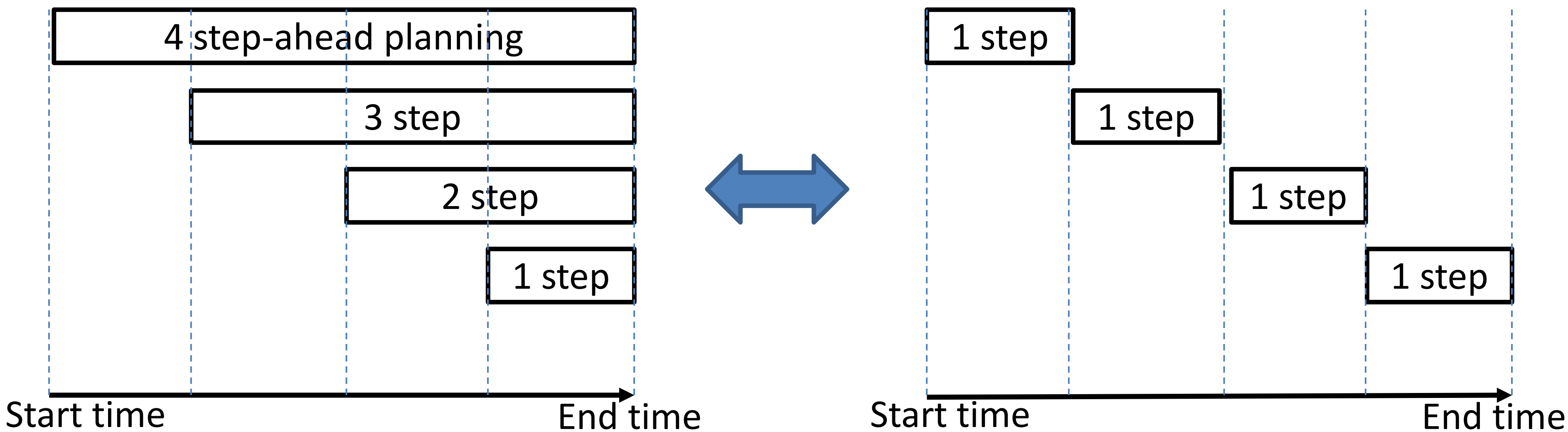


- Denoising proxy (Nadakuditi 2014) gives better local Shrink&Thrs

Serial separation principles for data collection

- Multistage planning for state tracking (Fisher 2013) and for network community detection (Chen, Hero 2014).
- Weighted MI proxy is sub-modular (Fisher 2013)
- Fiedler spectral centrality proxy is sub-modular (Chen, Hero 2014)
- Myopic proxy approximates optimal Value up to constant factor

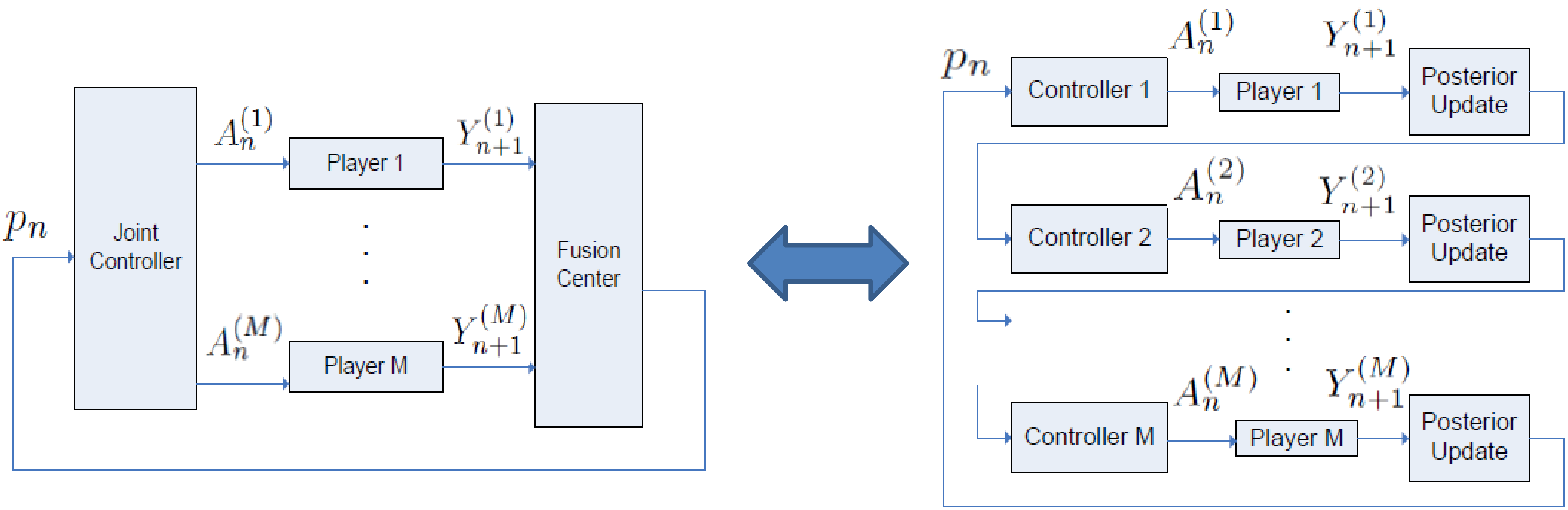
Optimal multistage planning **Myopic multistage planning**



$$E[\varphi_\pi] \geq (1 - \mathrm{e}^{-1})\, V_\pi$$

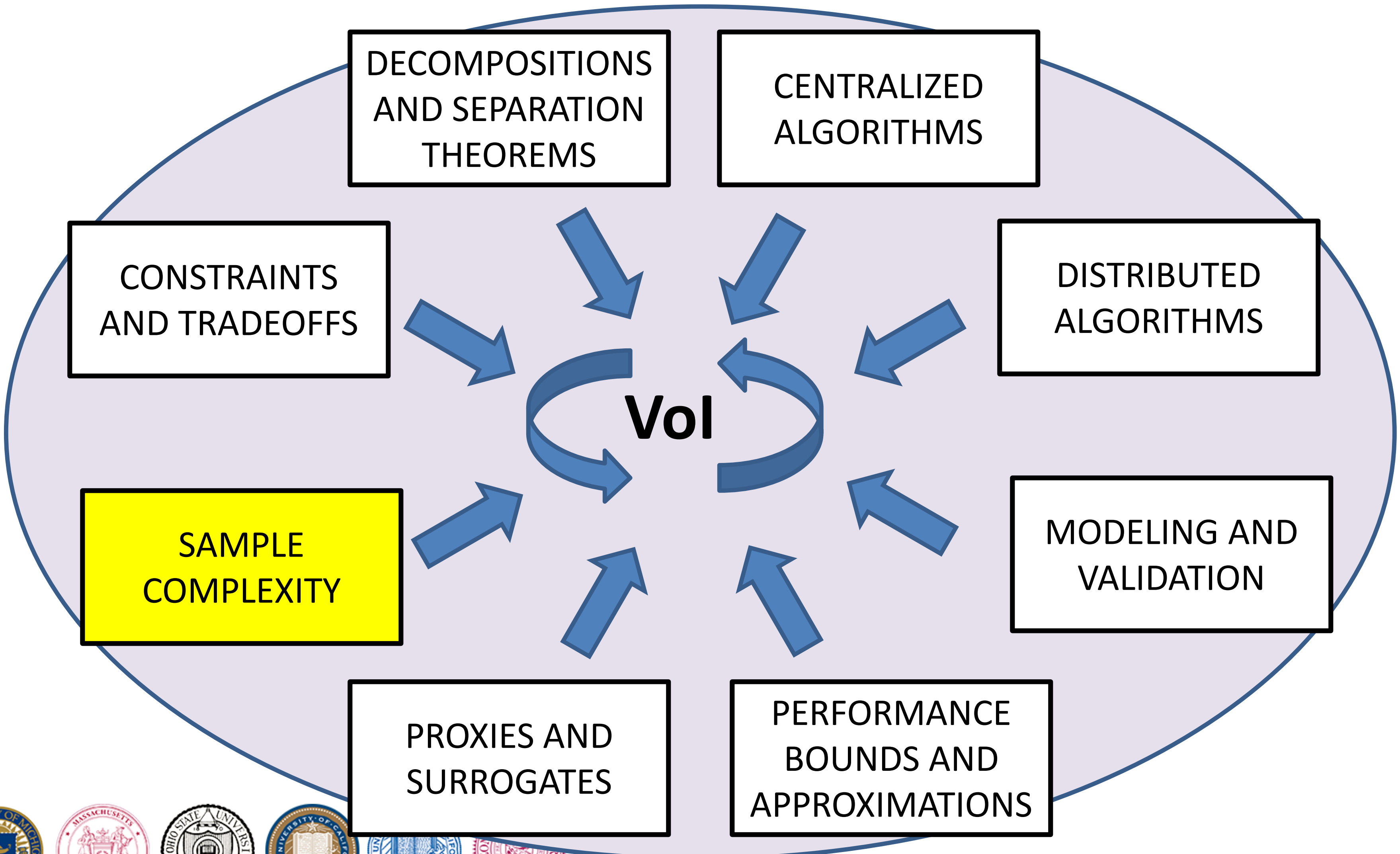
Example: parallel vs serial querying

- Collaborative 20 questions target search with multiple agents
- Entropy-optimal joint query control policy is same as entropy-optimal serial query control policy (Tsiligkaridis, Sadler, H 2013)
- This is a serial commutative separation principle
- May not hold for non-entropic proxies



Ref: Tsiligkaridis,Sadler, H IEEE TSP 2013

Components of VoI theory



Sample complexity: some refs

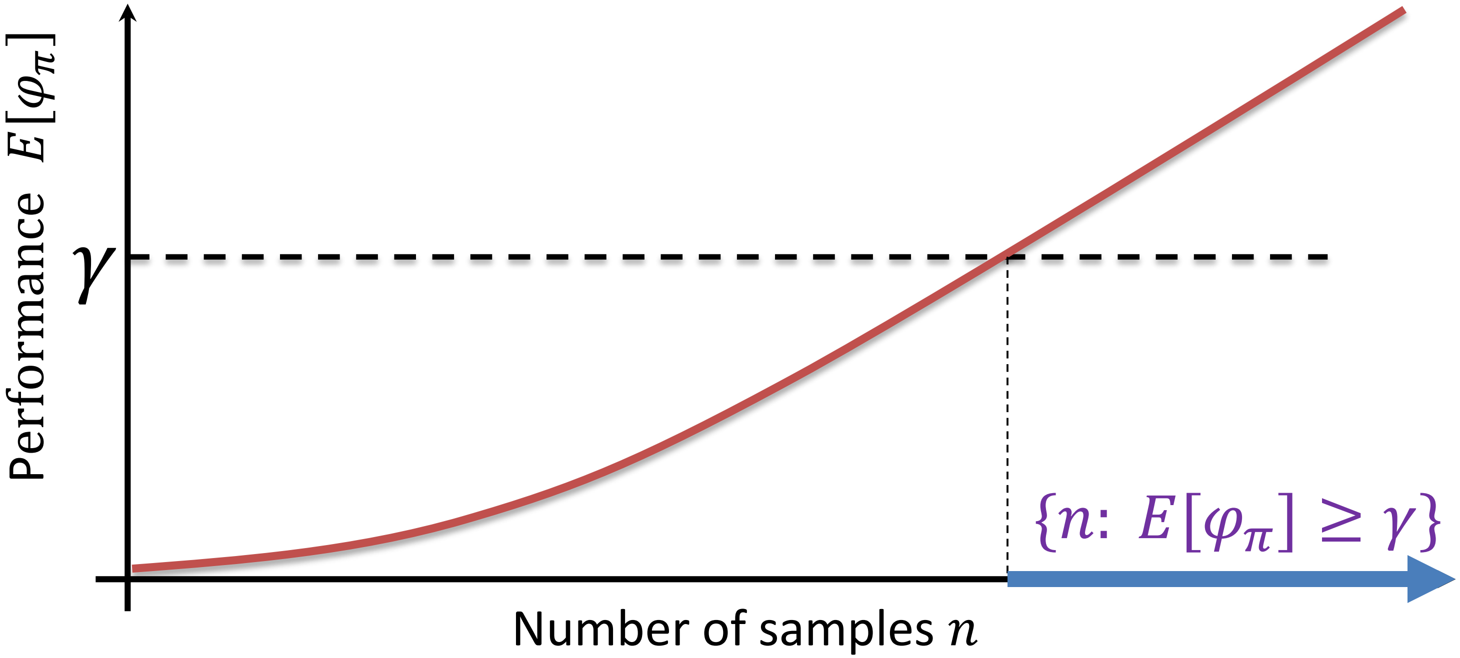
- High dimensional learning rates for low rank + sparse GGM
  - Z. Meng, B. Erikson, A.O. Hero, "Learning Latent Variable Gaussian Graphical Models," *Proceedings of the International Conference on Machine Learning (ICML),* Beijing, July 2014.
- High dimensional learning rates for spatio-temporal covariance estimation
  - T. Tsiligkaridis and A. O. Hero, "Covariance estimation in high dimensions via Kronecker product expansions," IEEE Transactions on Signal Processing, vol. 61, no. 21, pp. 5347 - 5360, Nov 2013.
  - T. Tsiligkaridis and A.0. Hero, and S. Zhou, "On convergence of Kronecker graphical lasso algorithms," IEEE Transactions on Signal Processing, vol. 61, no. 9, pp. 1743--1755, 2013
  - A. O. Hero and B. Rajaratnam, "Foundational principles for large scale inference: Illustrations through correlation mining," IEEE Proceedings. In press 2015.
- Tradeoffs between performance and computation as function of samples
  - M. I. Jordan, "On statistics, computation, and scalability," Bernoulli, 19, 1378-1390, (2013).
- High dimensional learning rates for uncertainty (divergence) estimation
  - K. Moon and A.O. Hero, "Ensemble estimation of multivariate f-divergence," Proc. of IEEE Intl. Symposium on Information Theory (ISIT), Hawaii, June 2014.

Sample sufficiency

- Let γ specify a desired performance benchmark for a task

$$E[\varphi_\pi] \geq \gamma$$

  - Sample sufficiency: $\min\{\text{samples n} \mid \varphi_n \geq \gamma\}$
  - Computation sufficiency: $\min\{\text{flops f} \mid \varphi_f \geq \gamma\}$
  - Communications sufficiency: $\min\{\text{transmissions t} \mid \varphi_t \geq \gamma\}$

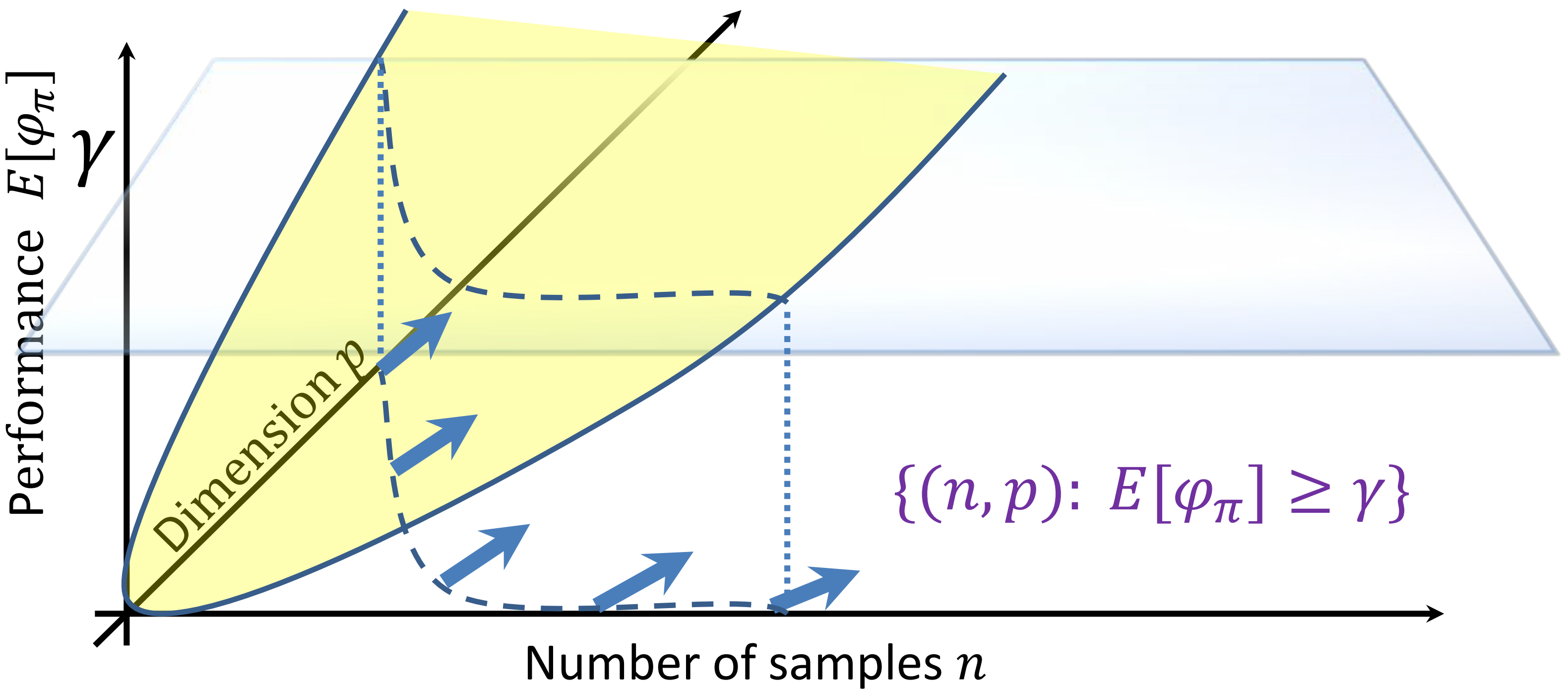


Sample complexity

- Let γ specify a desired performance benchmark for a task

$$E[\varphi_\pi] \geq \gamma$$

- Assume n samples and p unknown variables (dimension)
- Sample complexity is: minvalue of $n = n(p)$ ensuring benchmark



Sample complexity

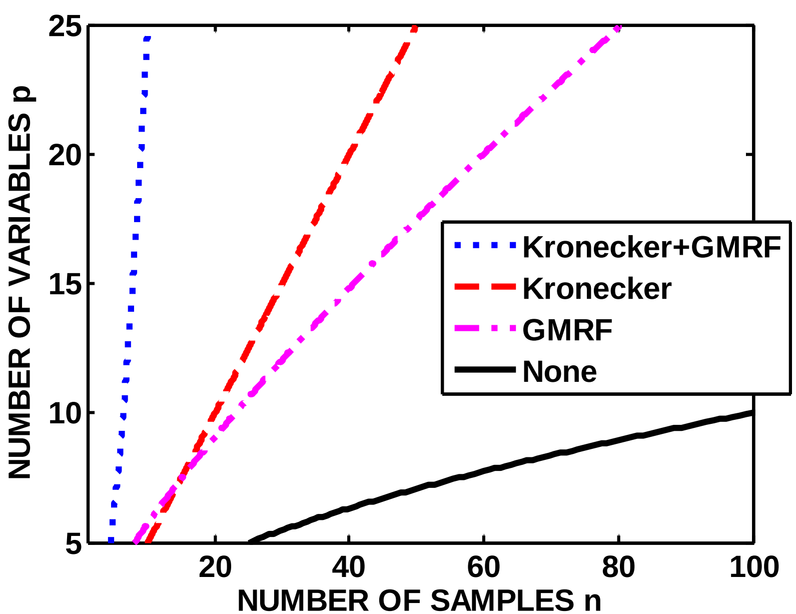
- Questions of interest
  - Question 1: what is intrinsic value of contextual info for a task?
    - How would environmental domain knowledge improve performance?
  - Question 2: how does the VoI intrinsically depend on the task?
    - How many samples required to attain performance benchmarks?
  - Question 3: what is the effect of data collection or processing constraints on attainable VoI?
    - What additional resources are required to achieve benchmark?

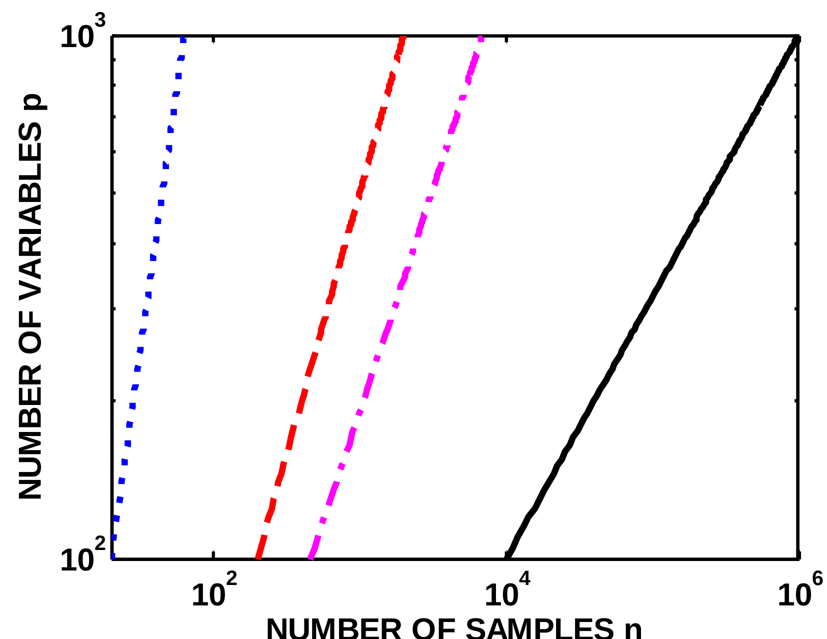
Sample complexity: inference on covariance

Effect of **contextual information** on VoI and sample complexity

- **Regimes:** The sample complexity decreases as more info is available

Information	None	GMRF	Kronecker	Kronecker+GMRF
Model	saturated $\mathbf{\Omega}$	sparse $\mathbf{\Omega}$	$\mathbf{\Omega} = \mathbf{A} \otimes \mathbf{B}$	sparse $\mathbf{\Omega} = \mathbf{A} \otimes \mathbf{B}$
$\log f(\mathbf{\Omega})$	constant	$\lambda \Vert\mathbf{\Omega}\Vert_1$	$\delta\left(\text{rank}\mathcal{R}(\mathbf{\Omega}) - 1\right)$	$\delta\left(\text{rank}\mathcal{R}(\mathbf{\Omega}) - 1\right) + \lambda_1 \Vert\mathbf{A}\Vert_1 + \lambda_2 \Vert\mathbf{B}\Vert_2$
Proxy	$\frac{1}{2}\log\left(\frac{q^2r^2}{n}\right)$	$\frac{1}{2}\log\left(\frac{qr\log qr}{n}\right)$	$\frac{1}{2}\log\left(\frac{(q^2+r^2)\log M}{n}\right)$	$\frac{1}{2}\log\left(\frac{(q+r)\log M}{n}\right)$
Regime	$\frac{q^2r^2}{n} \to \alpha$	$\frac{qr\log qr}{n} \to \alpha$	$\frac{(q^2+r^2)\log M}{n} \to \alpha$	$\frac{(q+r)\log M}{n} \to \alpha$





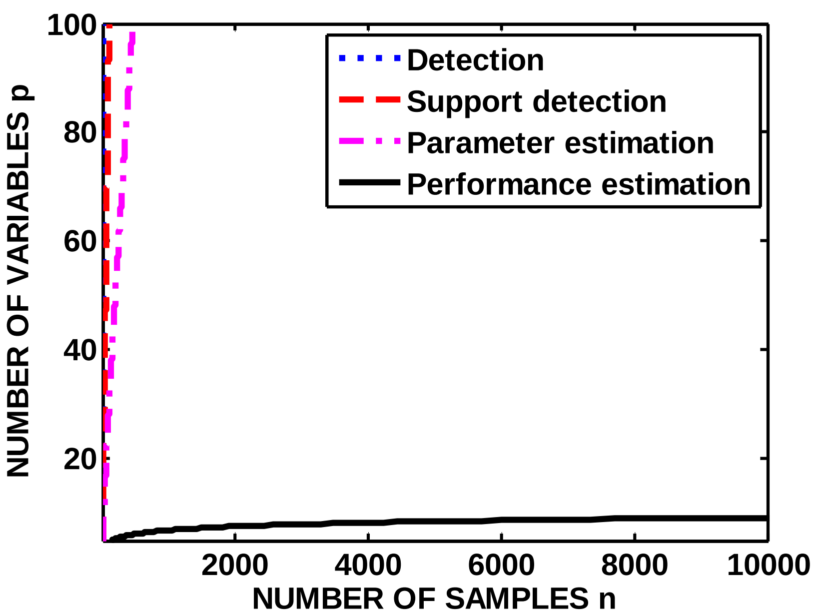
Hero and Rajaratnam, IEEE Proc. (2015)

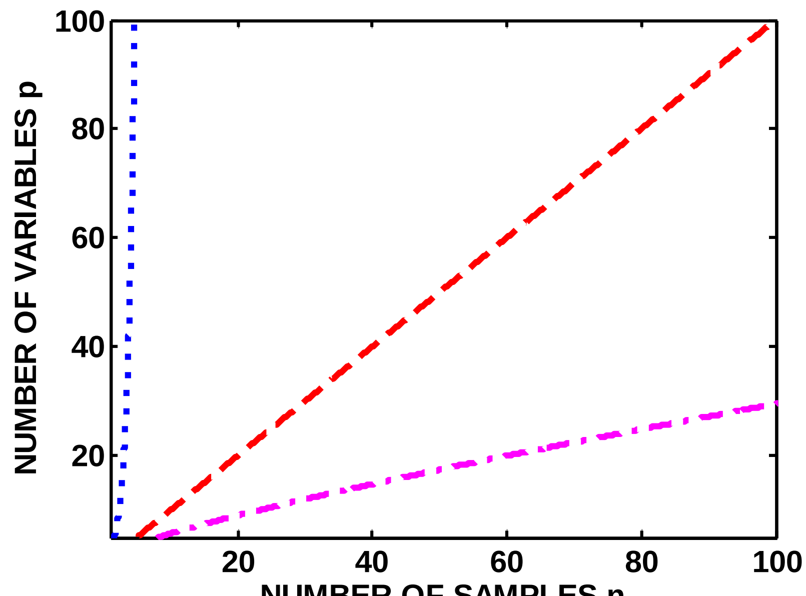
Sample complexity: inference on covariance

Effect of **task** on VoI and sample complexity

- **Regimes:** The sample complexity decreases as task becomes easier

Task	Screening	Detection	Support detection	Param. estimation	Perform. estimation
Risk	$P(N_e > 0)$	$P(N_e > 0)$	$P(\mathrm{card}\{\mathcal{S}\Delta\hat{\mathcal{S}}\} = \phi)$	$E[\lVert\mathbf{\Sigma} - \hat{\mathbf{\Sigma}}\rVert_F^2]$	$\int E[(f_{\Sigma}(\mathbf{x}) - \hat{f}(\mathbf{x}))^2]d\mathbf{x}$
Proxy	$1 - e^{-\kappa_n}$	$pe^{-n\alpha}$	$2^p e^{-n\alpha}$	$\frac{p}{n}\alpha$	$n^{-2/(1+p)}\alpha$
Regimes	$\frac{\log p}{n} \to \infty$	$\frac{\log p}{n} \to \alpha$	$\frac{p}{n} \to \alpha$	$\frac{p \log p}{n} \to \alpha$	$\frac{p}{\log n} \to \alpha$
Threshold	$\rho_c \to 1$	$\rho_c \to \rho^*$	$\rho_c \to 0$	$\rho_c \to 0$	$\rho_c \to 0$

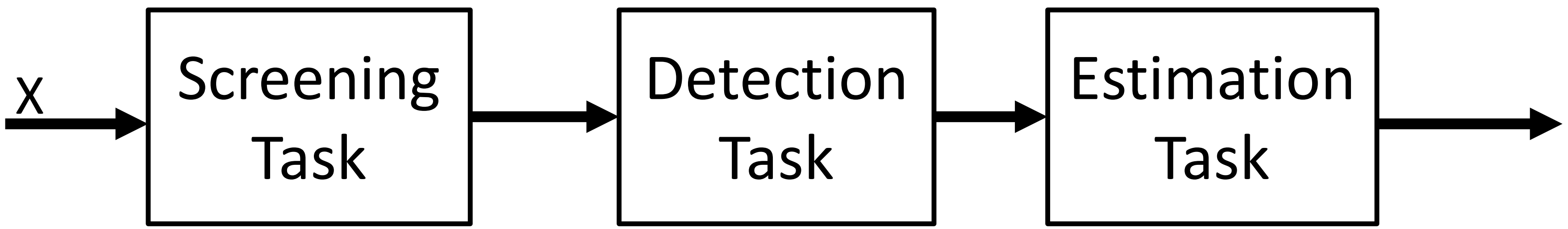


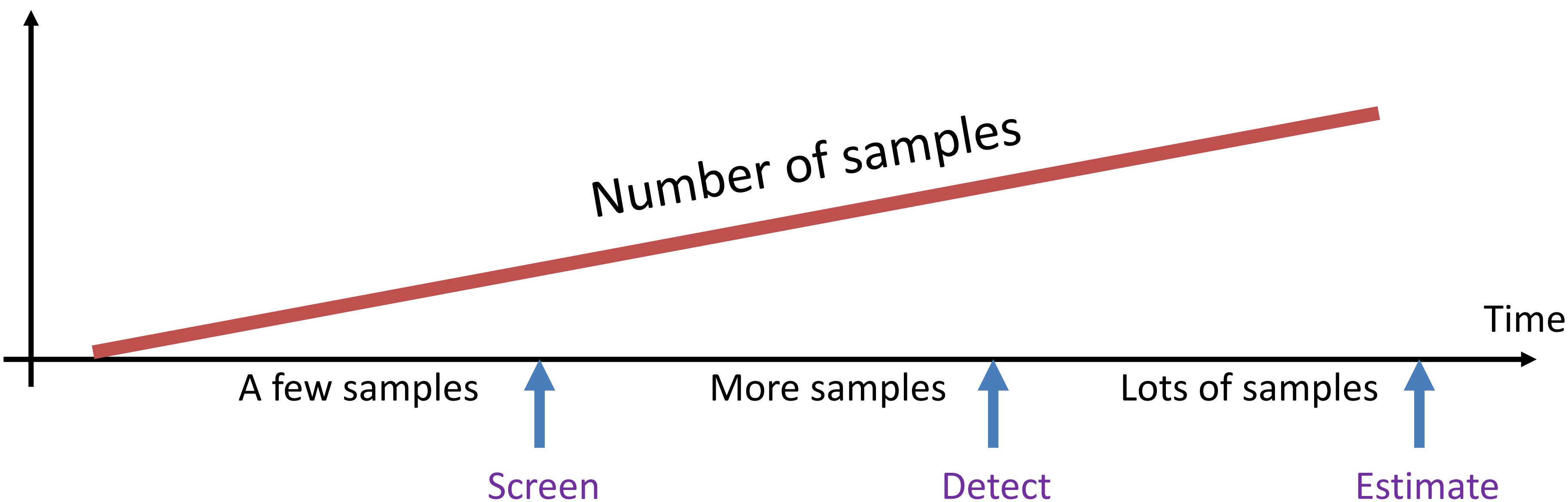


Hero and Rajaratnam, IEEE Proc. (2015)

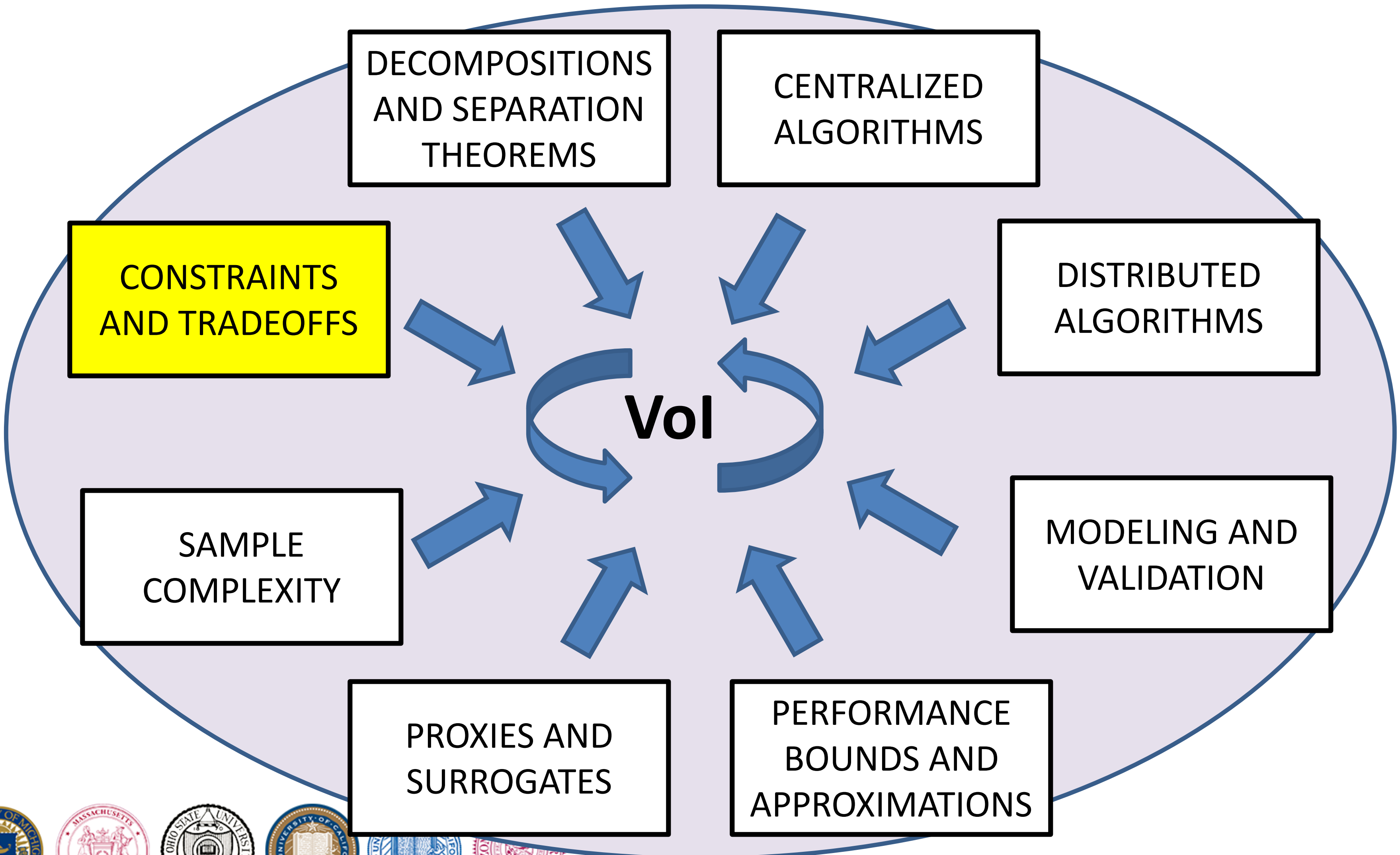
Implication: matching tasks to sample size

Sequence tasks in order of increasing sample complexity requirements (Firouzi, Hero, Rajaratnam, 2014)





Components of VoI theory



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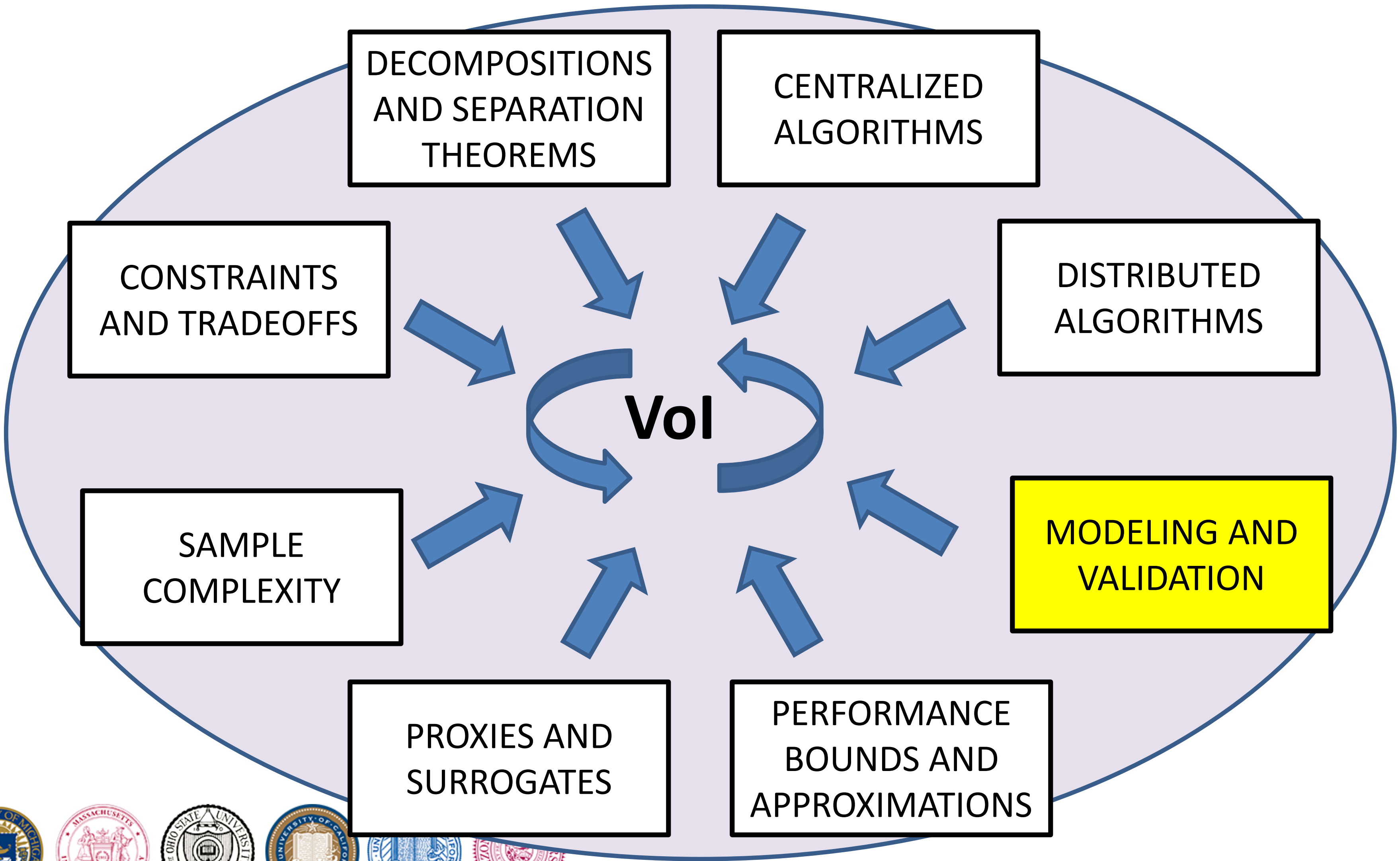
Components of VoI theory



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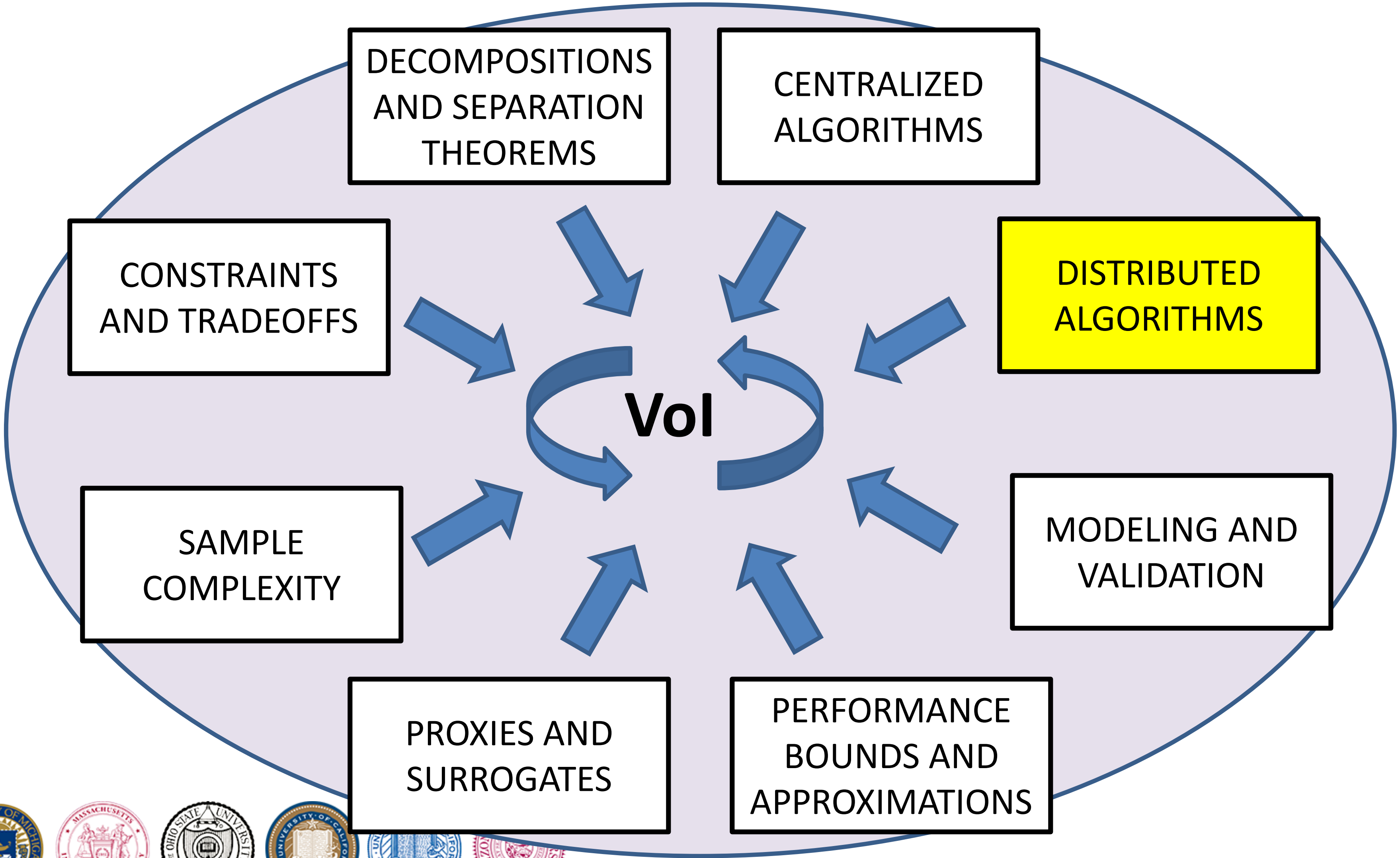
Components of VoI theory



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Conclusions

- Team is making fundamental advances in building a VoI framework in sensing and data collection
- Elements of framework
  – Performance bounds and approximations
  – Proxies and surrogates for performance
  – Sample complexity (sampling requirements)
  – Constraints and tradeoffs (computation, communication, privacy)
  – Decompositions and separation theorems
- Fresh VoI perspective to design of (de)centralized algorithms
- Importance of experimental validation
  – Experiments on real data from domains including: radar, vision, acoustic, knowledge bases, social media feeds, web crowds, IRB approved human experiments (Hero, Ertin, Soatto, Fisher, Nadakuditi, Jordan, Yu)
  – Software radar testbed is being deployed (Ertin, Cochran, Fisher, How)