Support selection algorithms

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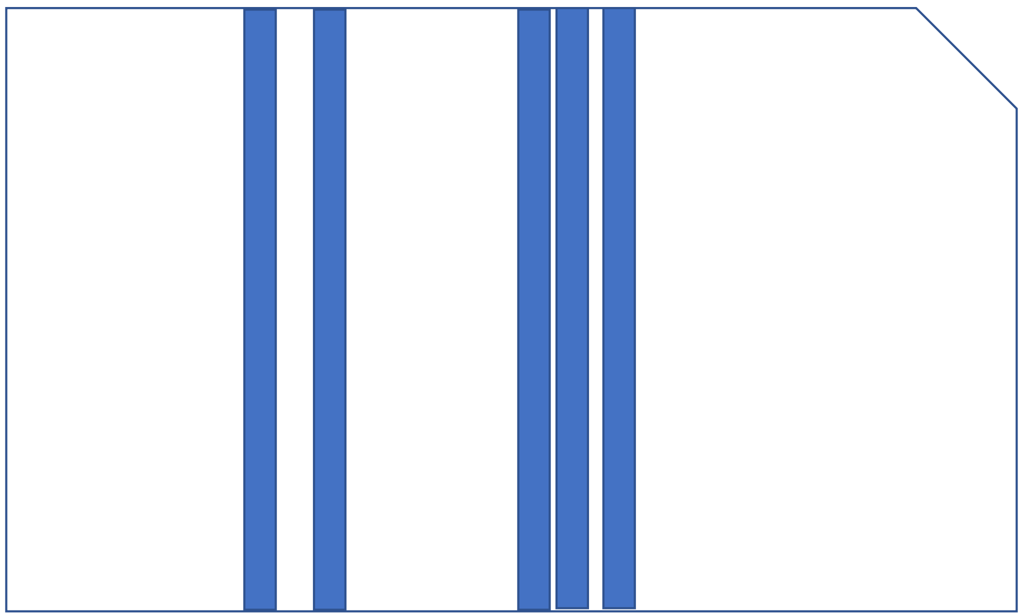
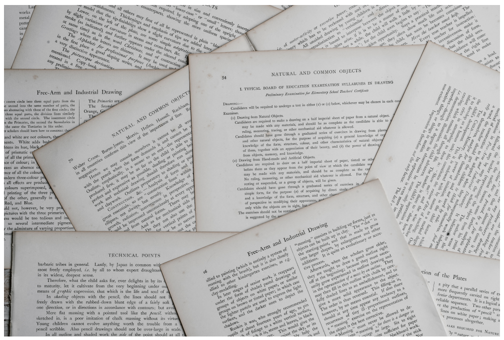
Sparsification by support selection

- Interpretability by modeling choice: Given a matrix, choose a few columns

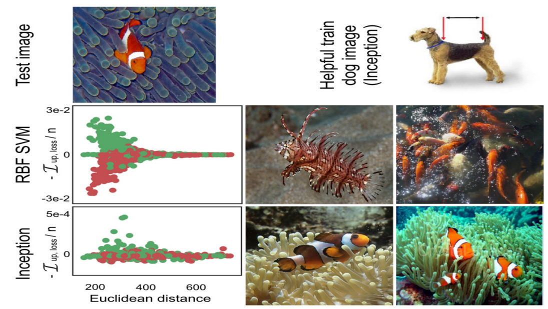


Greedy selection in practice



Document summarization.
[Vanderwende et. al. 2007]

Gene Analysis
[Paschou et. al. 2007]



Interpretability
[Koh et. al. 2017]

Greedy support selection

- Goal:

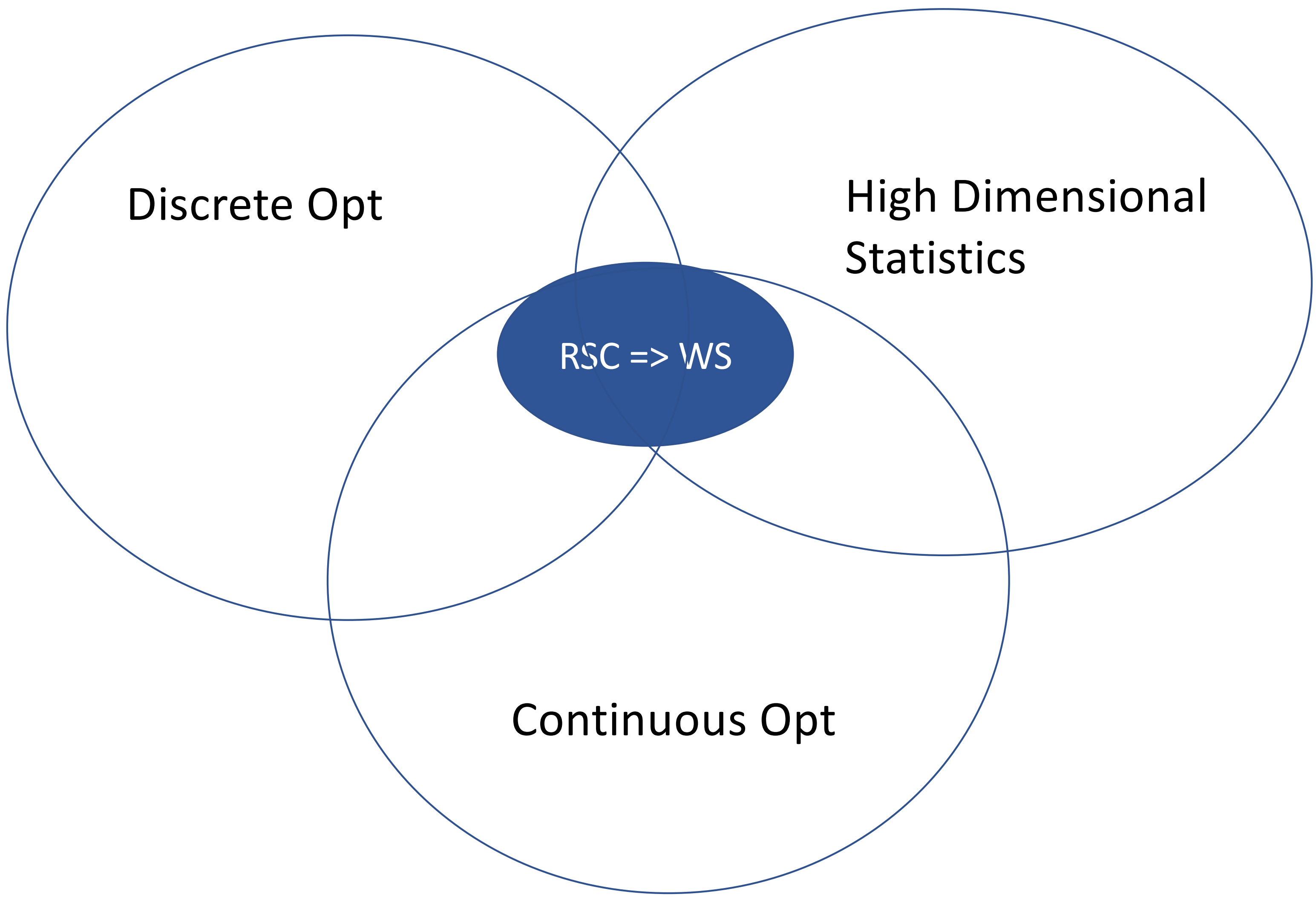
$$\max_{\mathsf{S}:|\mathsf{S}|\le k} f(\mathsf{S}) \Leftrightarrow \max_{\substack{\boldsymbol{\beta}:\boldsymbol{\beta}_{\mathsf{S}^c=0} \\ |\mathsf{S}|\le k}} l(\boldsymbol{\beta}) - l(\mathbf{0})$$

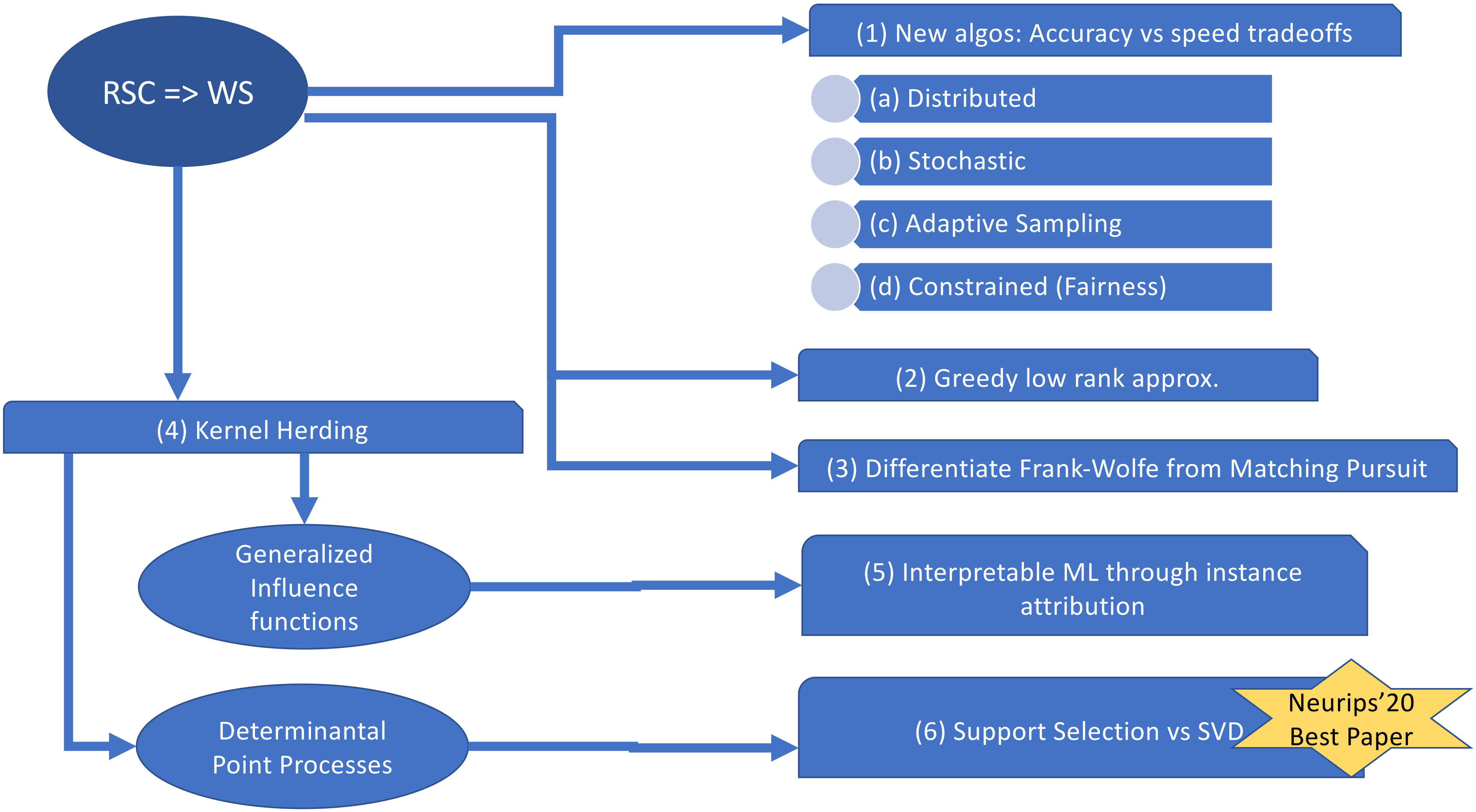
- If $l(\,)$ is:
  - m-Restricted strong concave on a certain subdomain, and
  - M-smooth on another subdomain,

  then,

RSC => WS

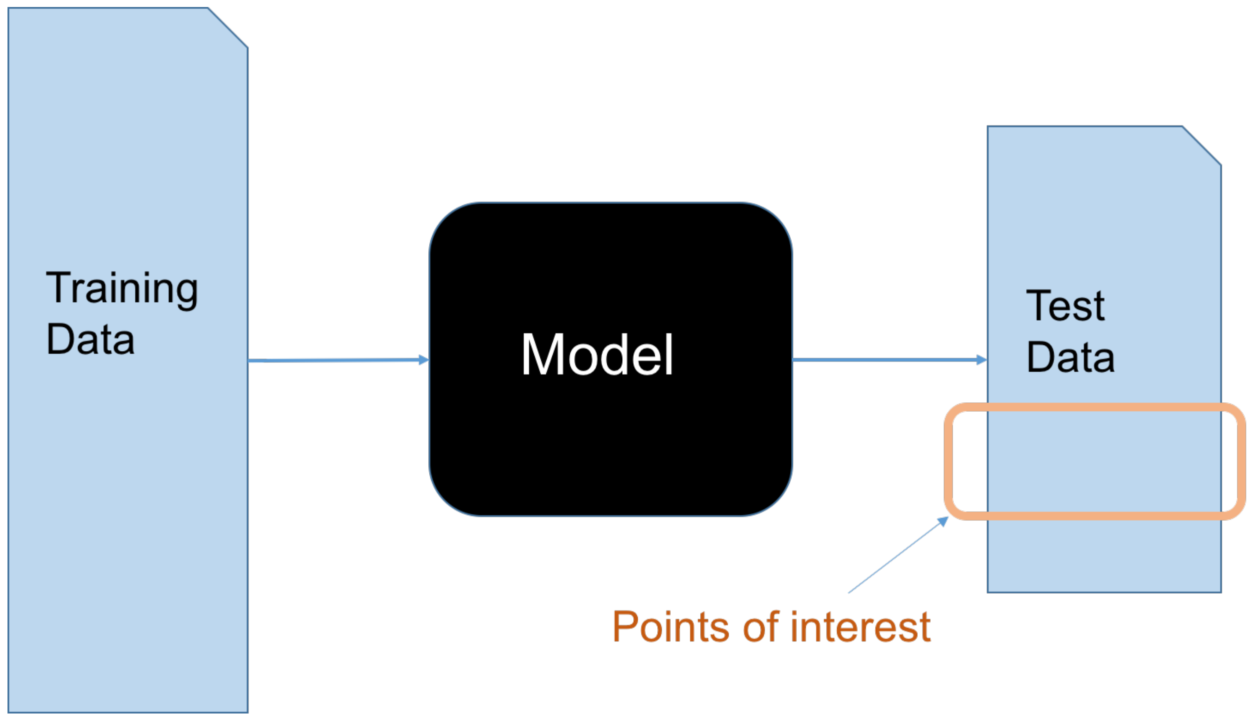
$$\underbrace{f(G_k)}_{\text{Greedy utility}} \ge \left(1 - \frac{1}{e\hat{}\{m/M\}}\right) \underbrace{f(S_k^*)}_{\text{Optimal utility}}$$


Discrete Opt
High Dimensional Statistics
RSC => WS
Continuous Opt



RSC => WS
(1) New algos: Accuracy vs speed tradeoffs
(a) Distributed
(b) Stochastic
(c) Adaptive Sampling
(d) Constrained (Fairness)
(2) Greedy low rank approx.
(3) Differentiate Frank-Wolfe from Matching Pursuit
(4) Kernel Herding
Generalized Influence functions
(5) Interpretable ML through instance attribution
Determinantal Point Processes
(6) Support Selection vs SVD
Neurips'20 Best Paper

Black-box interpretability



Which training data points are “most” responsible for predicting on points of interest ?

Research direction in near future: <u>Interpretability guided data-centric optimization</u>

- Sparse-training (coreset selection)
- Effect of increased generalization on privacy