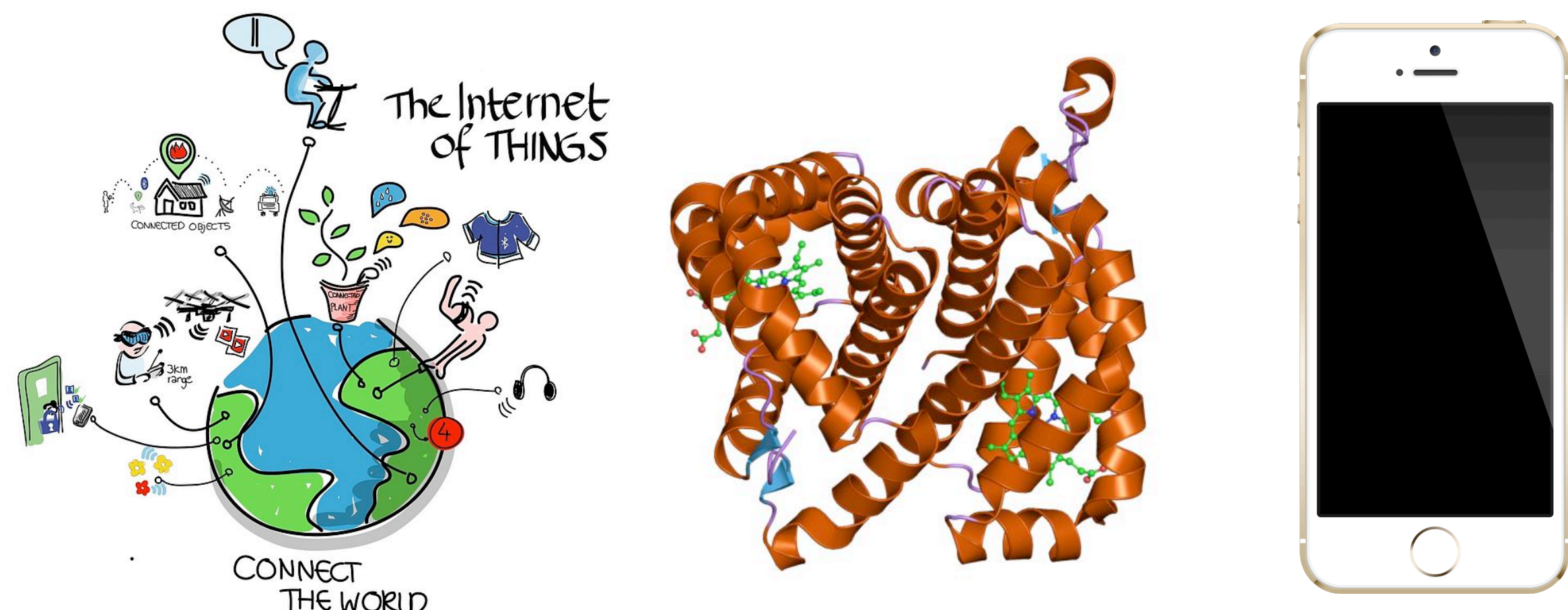


Scaling Feature Selection with Aggressive Subsets

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INTRODUCTION

- Big data: not just many data points, also many features



- A popular approach is feature selection:

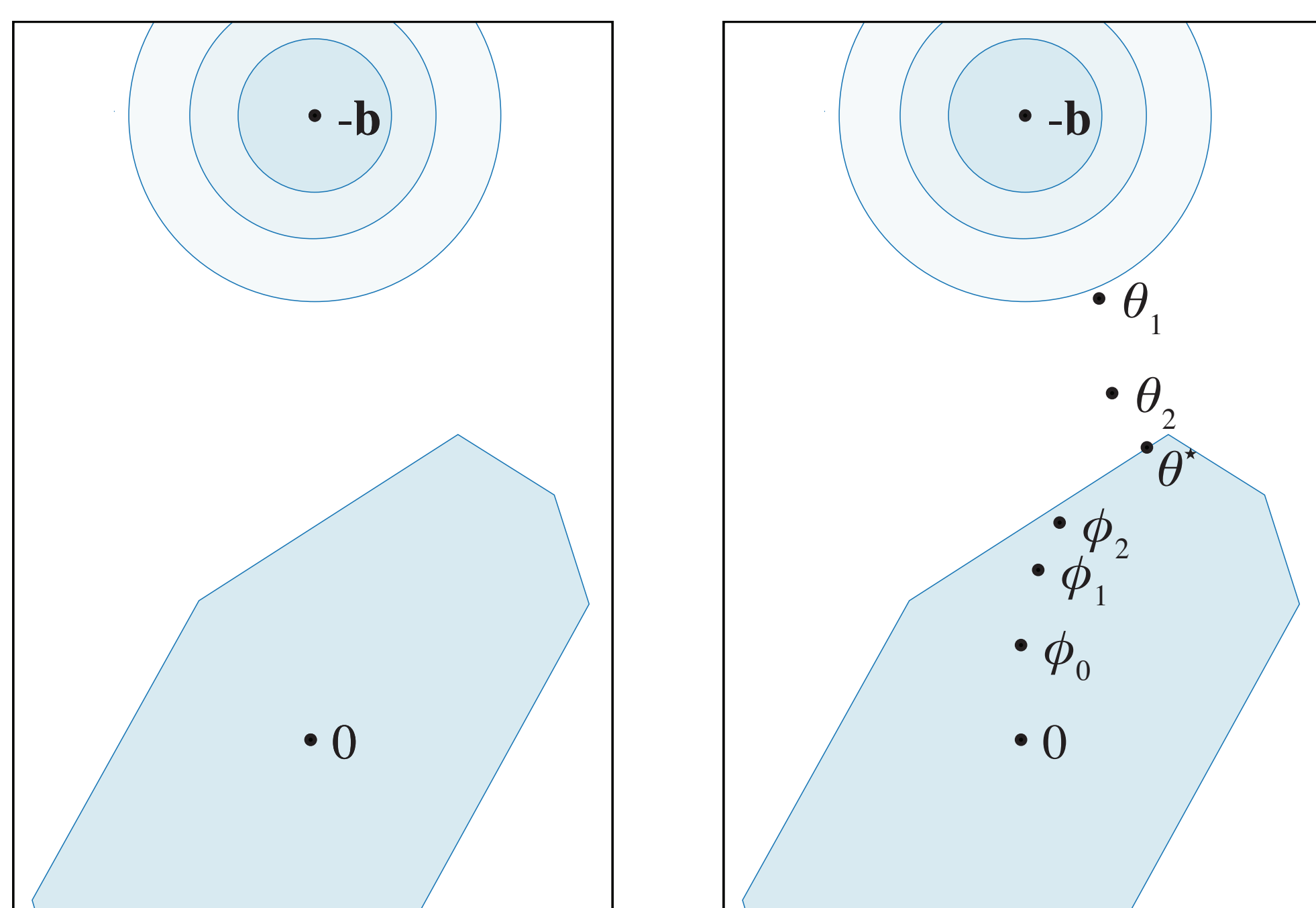
$$\underset{\mathbf{x} \in \mathbb{R}^d}{\text{minimize}} \sum_{i=1}^n f(\mathbf{x}^T \mathbf{a}_i, b_i) + \lambda \|\mathbf{x}\|_1$$

- Selects most important features, others set to zero
- Existing approaches limited:
 - Distributed algorithms require intensive communication
 - Computation per feature disproportionate to importance

OUR CONTRIBUTIONS

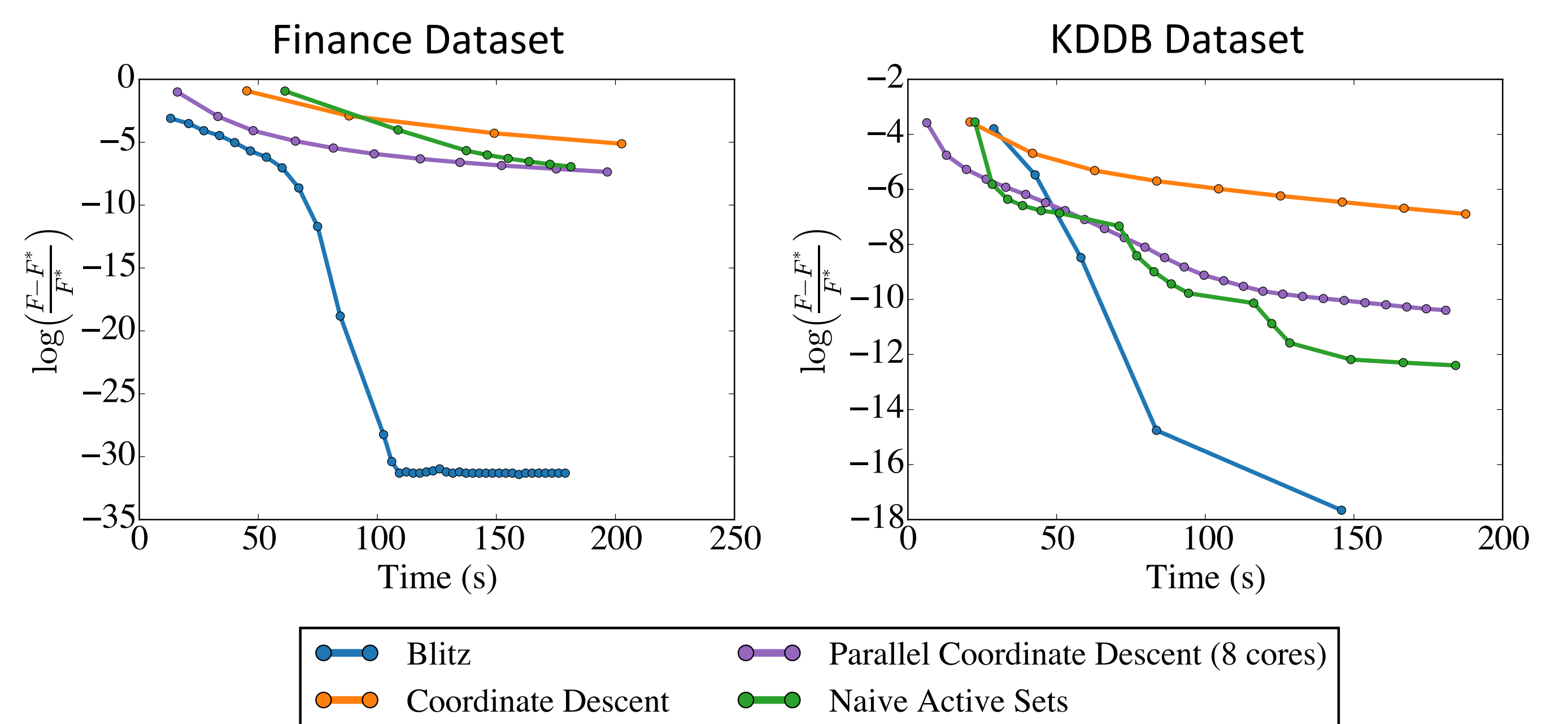
- Algorithms that **aggressively prioritize features**
 - Significantly reduces communication
 - Prioritizes resources in theoretically sound manner
 - Runs fast in distributed, multicore, and memory-limited settings
- Effective use of subproblems on **feature subsets**
 - Eliminates features guaranteed to be irrelevant
 - Discovers important features with high probability

BLITZ ALGORITHM IN PICTURES

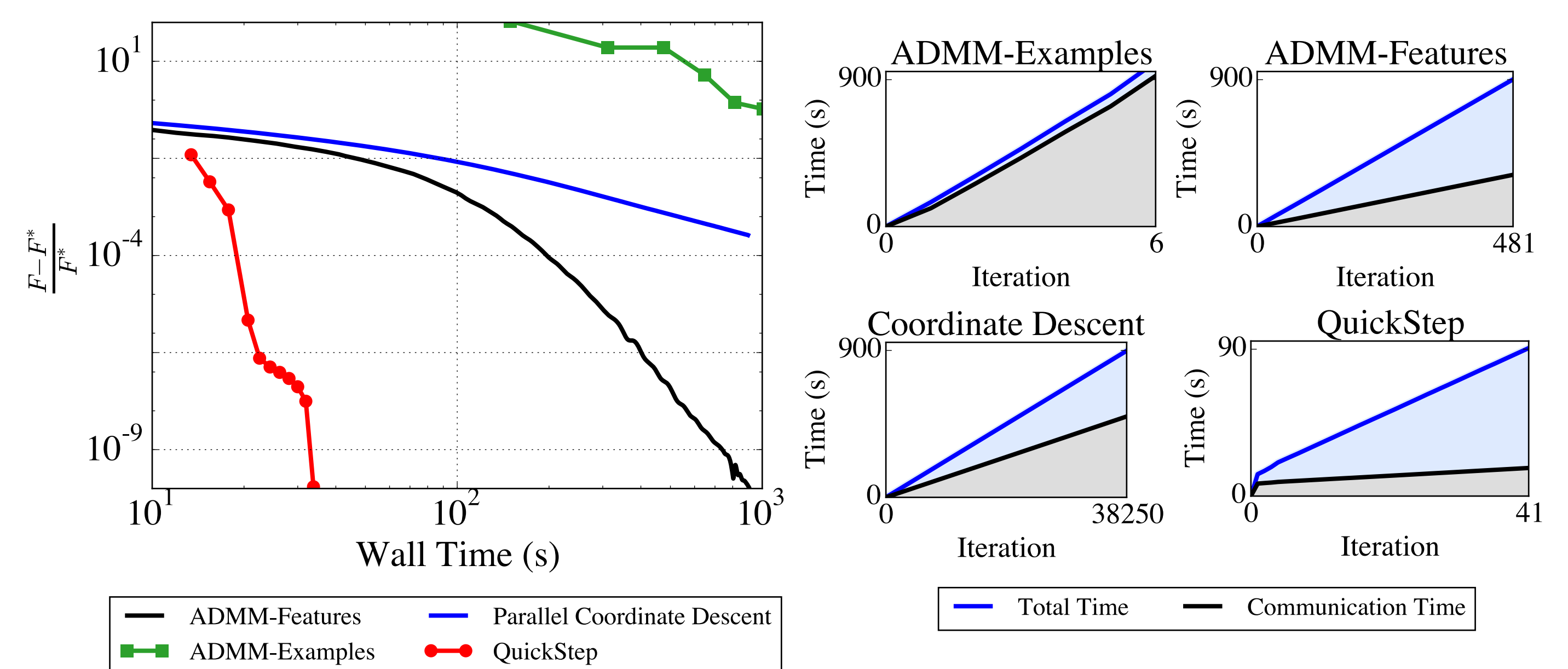


EMPIRICAL RESULTS

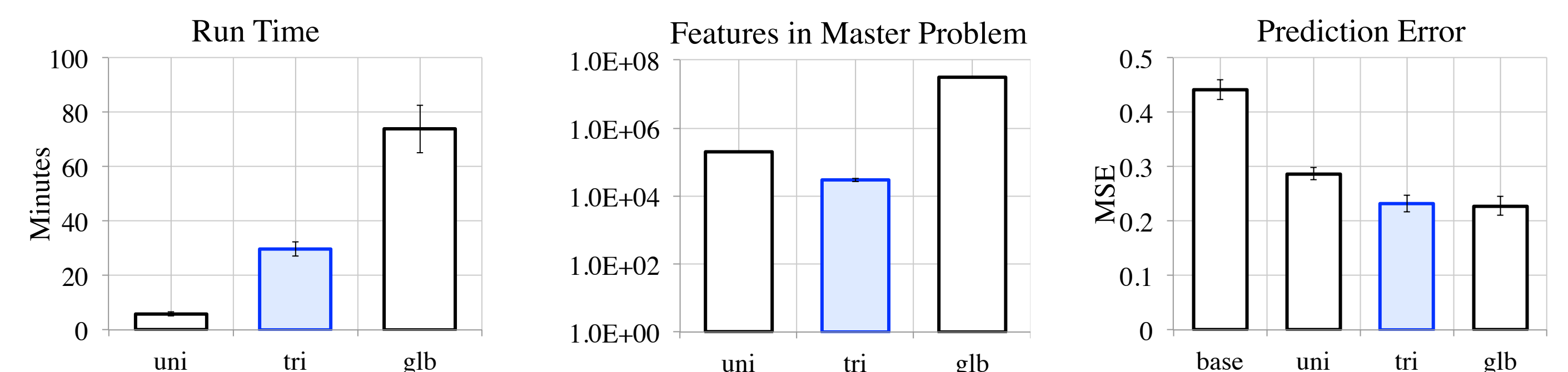
- Blitz algorithm, sequential setting (1 CPU)



- QuickStep, Distributed Setting (16 nodes)



- Communicates data, solving subproblems on master node
- Can be run in with other set-ups – aggressive subsets is the key!
- Distributed feature engineering
 - Problem: predict stock volatility from financial report data
 - Consider candidate features in parallel on worker nodes
 - Solve subproblems on master, reducing runtimes considerably



(tri = our method, uni = simplified problem, glb = equivalent problem not using our method)

CONCLUSIONS & FUTURE WORK

- Feature subsets effective for large-scale feature selection
- Can be used in distributed, sequential, or approximate settings
- In future, continue push to understand feature engineering
- Extend ideas to other important optimization problems