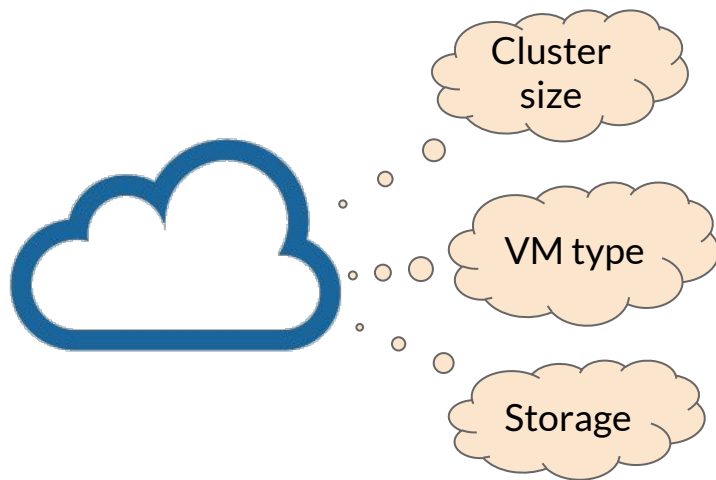


# Selecta: Heterogeneous Cloud Storage Configuration for Data Analytics

Ana Klimovic\*, Heiner Litz+, Christos Kozyrakis\*



# Configuring analytics in the cloud



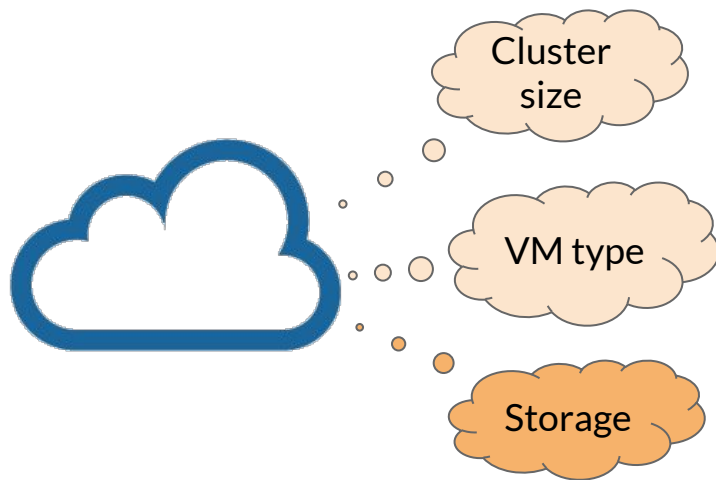
# of VMs in cluster?

# CPU cores, GB of DRAM,  
network bandwidth, accelerators?

Block, file, object, key-value storage?  
Directly attached to VM or remote?  
Storage media: HDD, Flash, DRAM?

**Cloud cluster configuration is difficult yet critical for performance & cost.**

# Configuring analytics in the cloud



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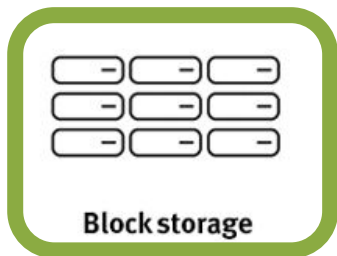
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**Cloud cluster configuration is difficult yet critical for performance & cost.**

# Configuring storage for analytics

- Storage configuration is particularly critical for data analytics



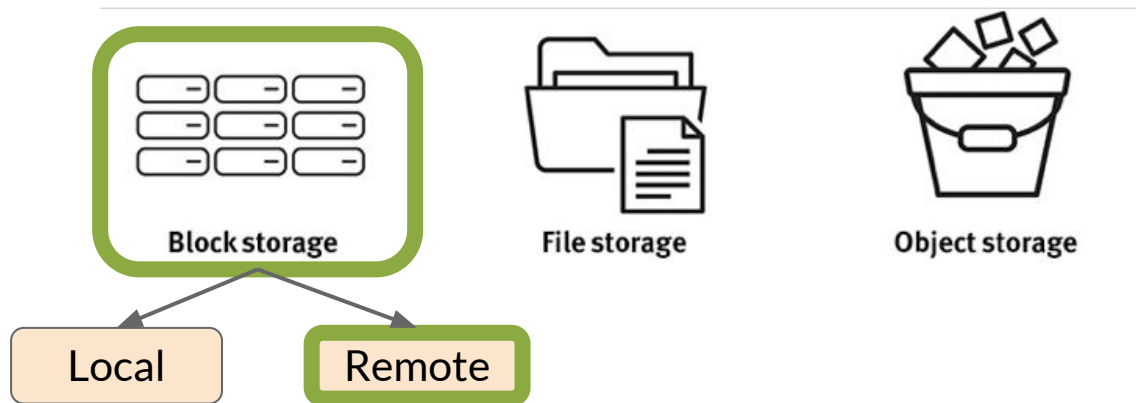
**File storage**



**Object storage**

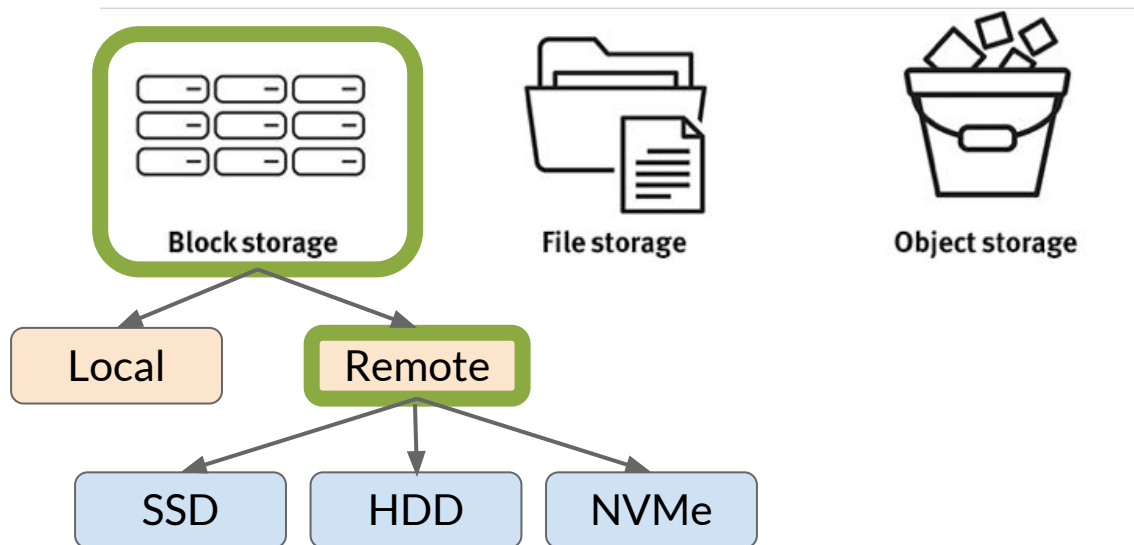
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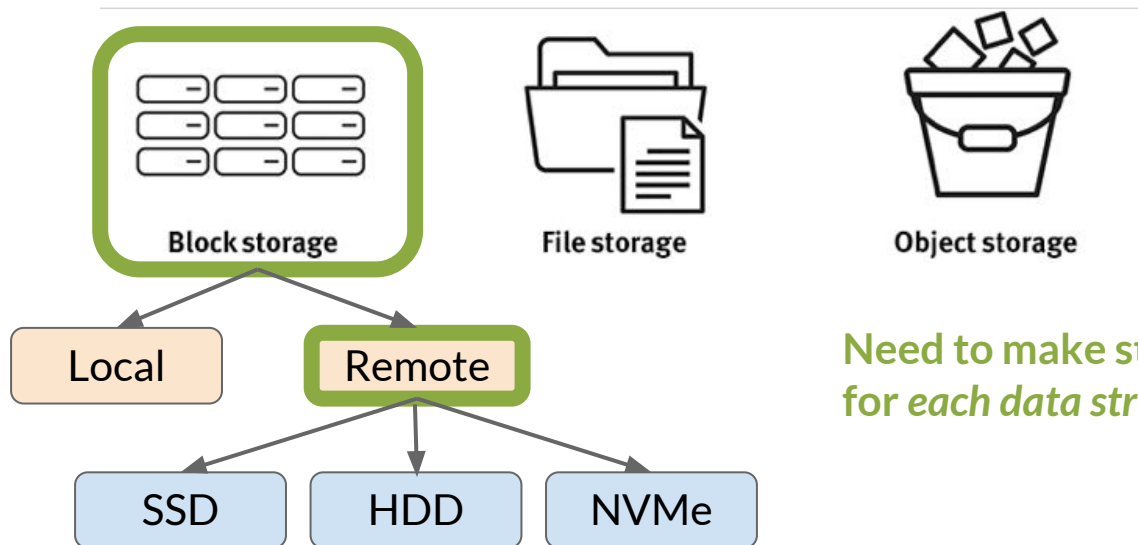
# Configuring storage for analytics

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# Configuring storage for analytics

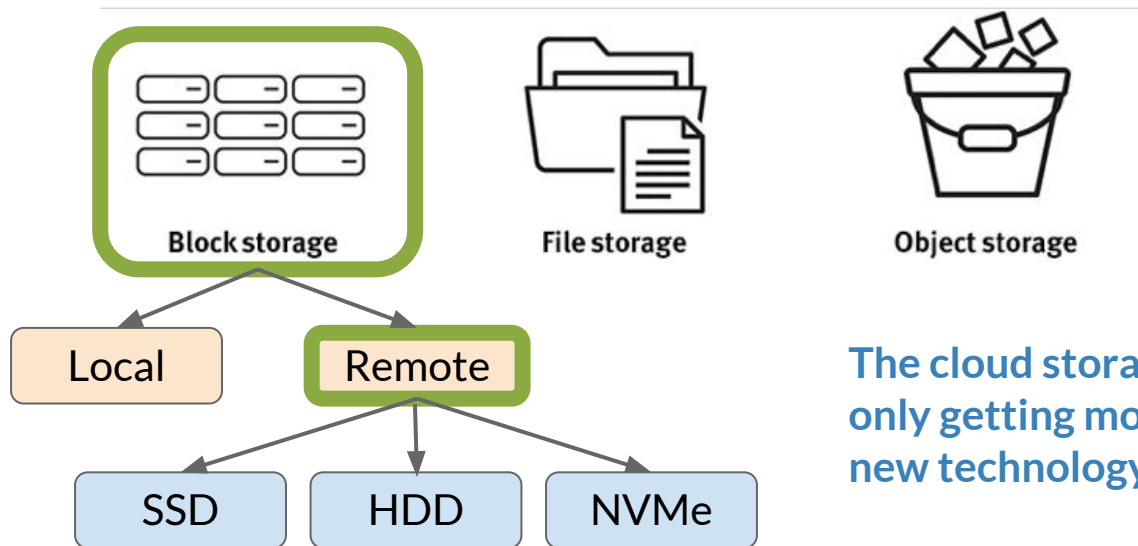
- Storage configuration is particularly critical for data analytics
- Jobs often have multiple data streams (e.g., shuffle, input/output data) with diverse I/O characteristics, making them suitable for different storage options



**Need to make storage decisions  
for each data stream in a job**

# Configuring storage for analytics

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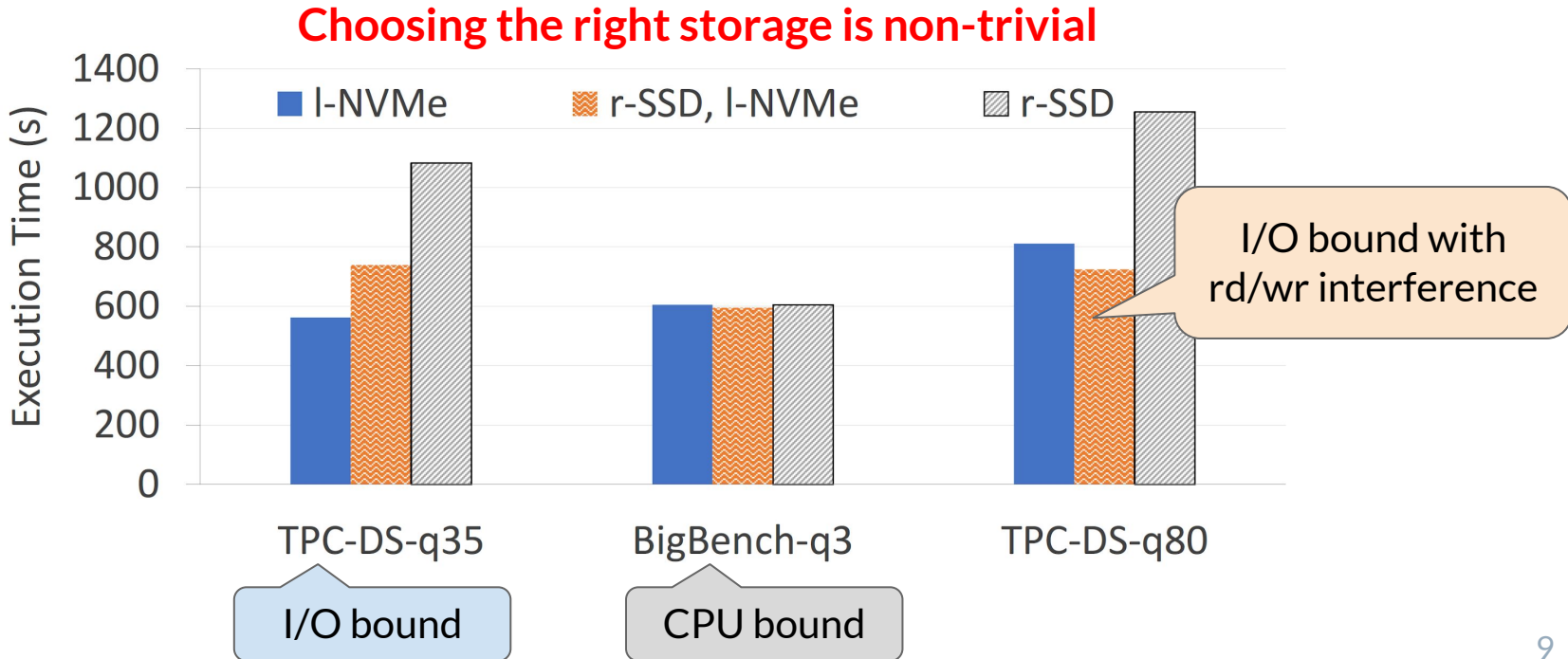


The cloud storage landscape is only getting more diverse with new technology (e.g., 3D X-point).



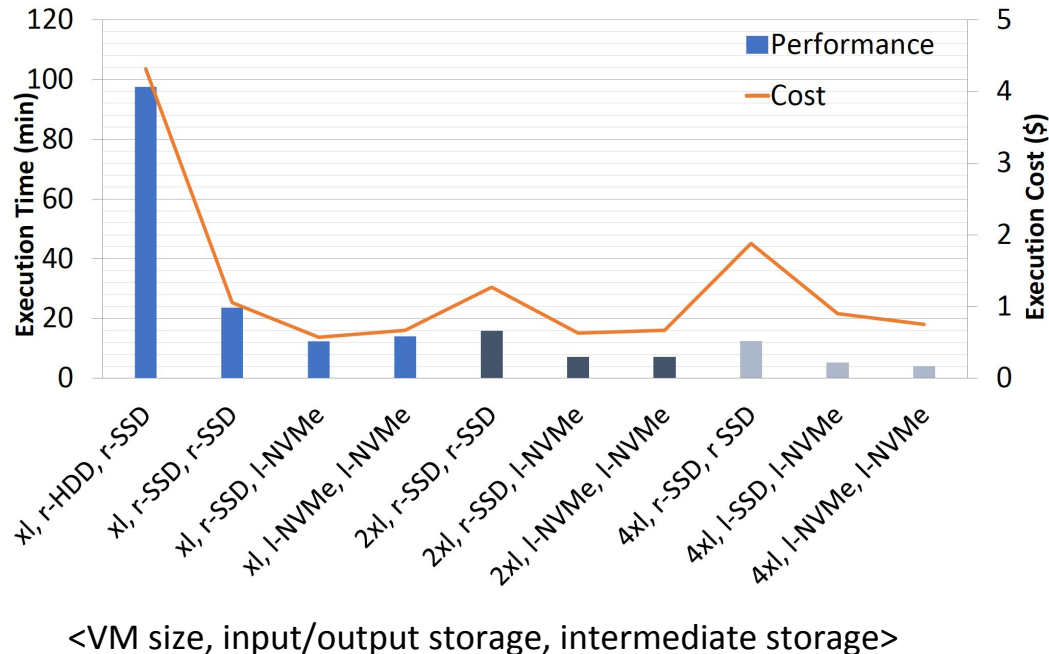
# Storage configuration is challenging

- Example: selecting between 3 storage options — all other parameters constant



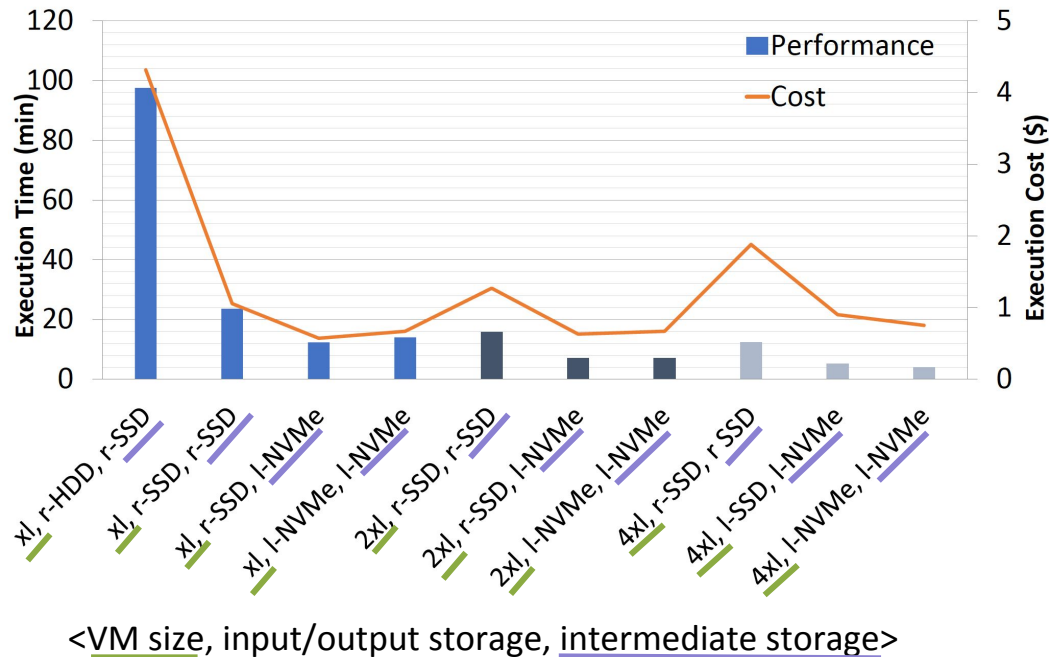
# Performance and cost impact

- Compare the performance and cost of TPC-DS query 64 on 10 configurations



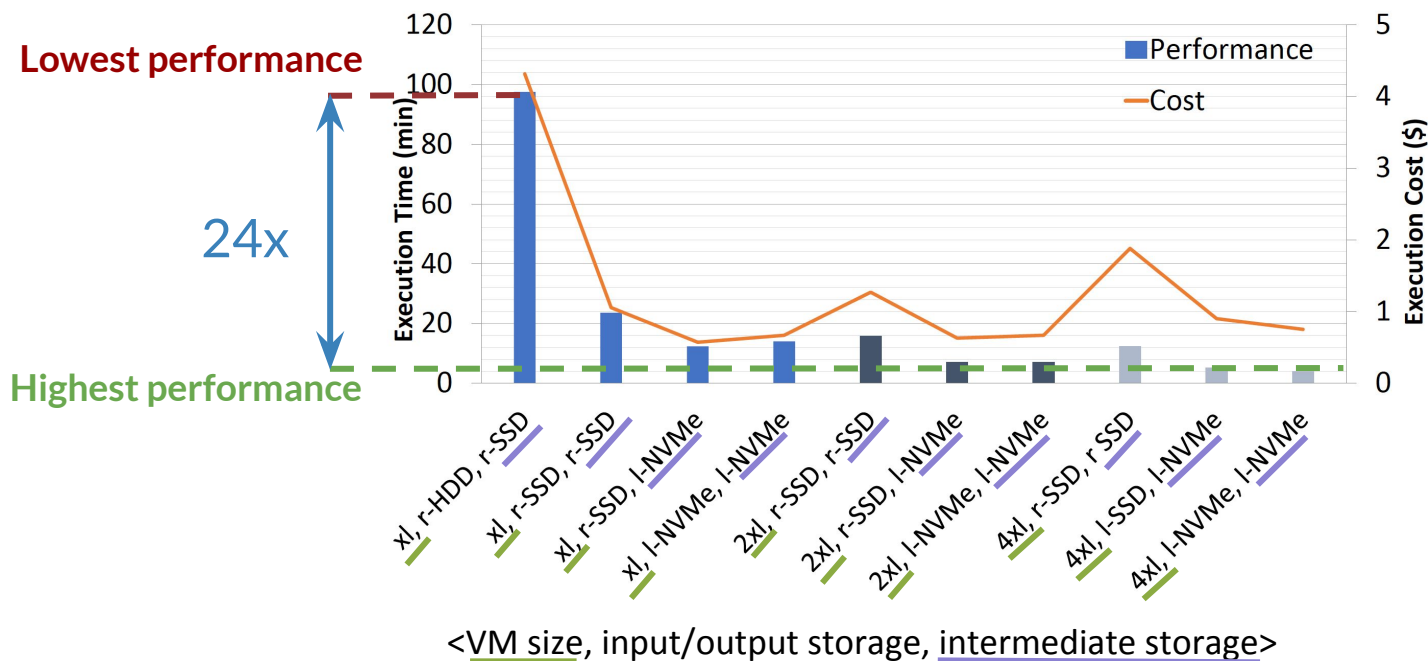
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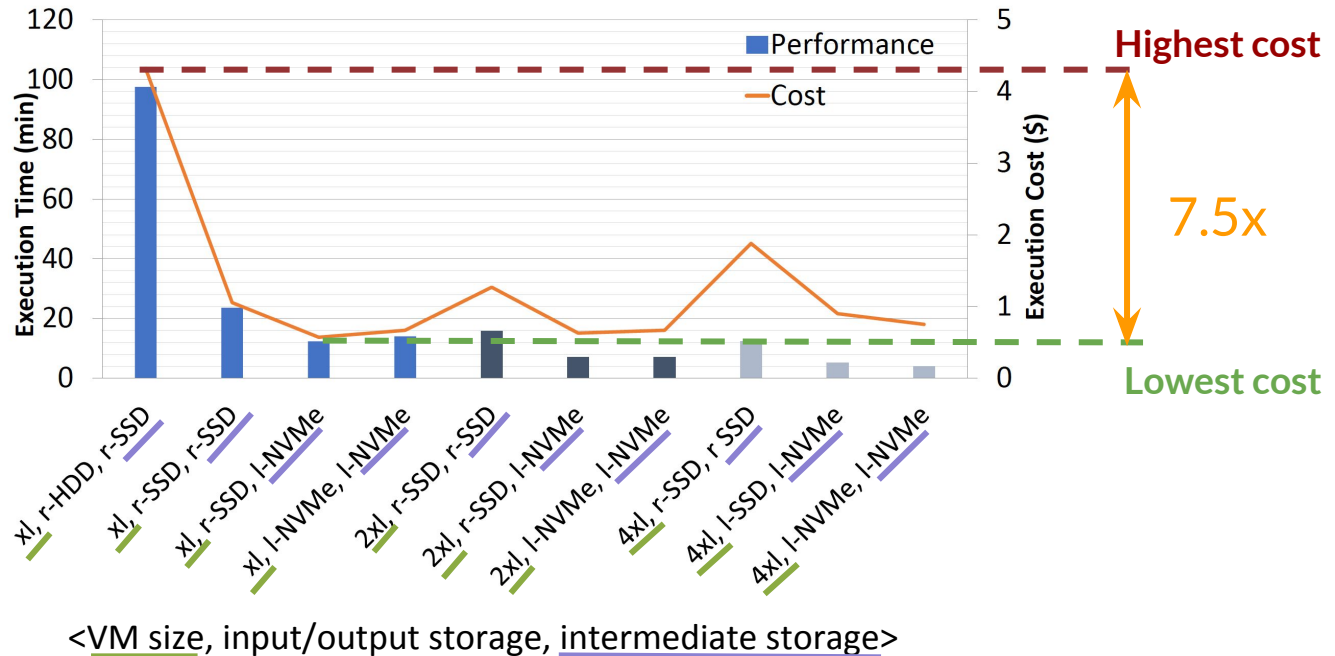


Contrary to a previous study [1] that showed optimizing storage improves Spark performance by only 19%.

[1] Ousterhout, K., et al. *Making Sense of Performance in Data Analytics Frameworks*. NSDI'15.

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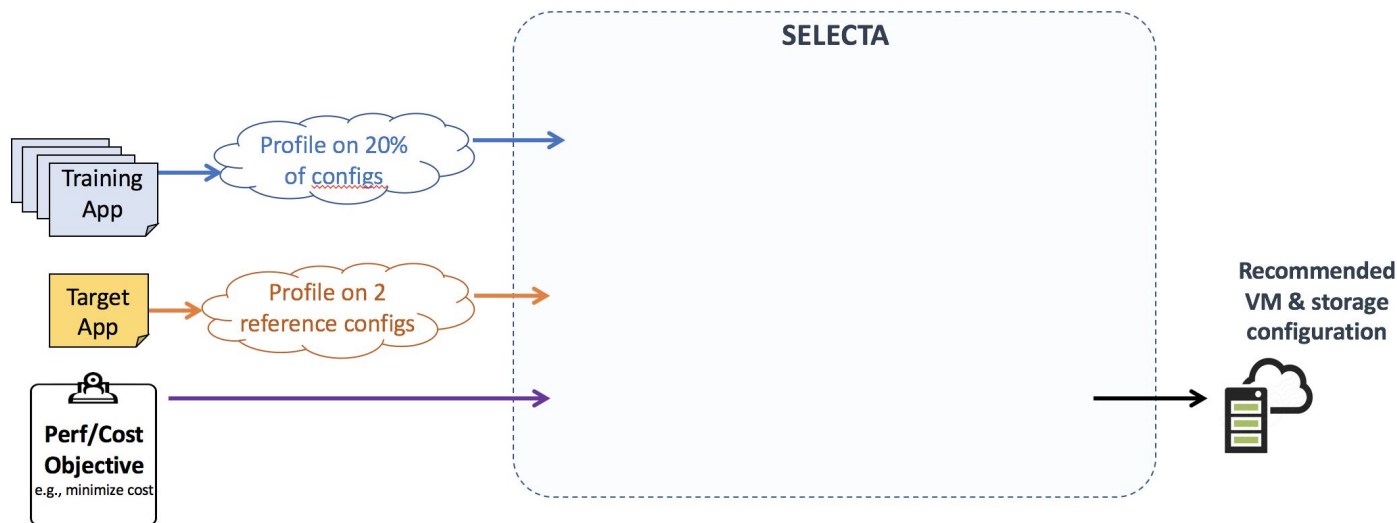


# Contributions

1. **Selecta**, a tool that recommends near-optimal cloud VM and storage configurations for target applications based on sparse training data
2. Analysis of data analytics performance with different storage options:
  - Which storage options are good fit and for different data streams?
  - What lessons do we learn for the design of future cloud storage systems?

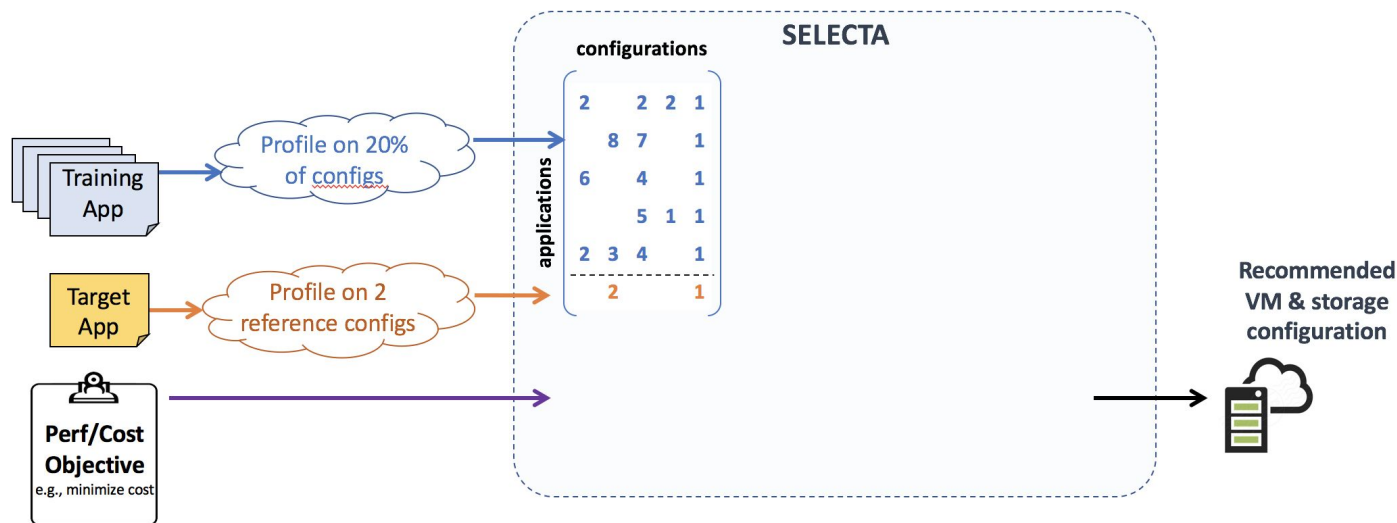
# Selecta

- A system that predicts the performance of a target application on candidate configurations using *sparse* training data across jobs → recommend the right config



# Selecta

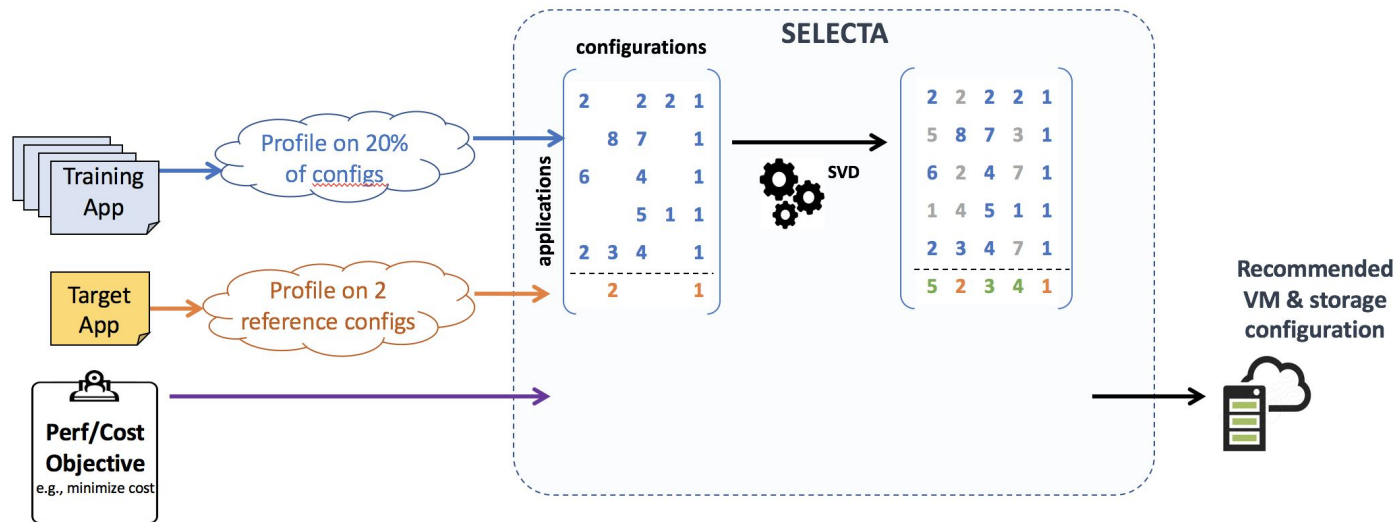
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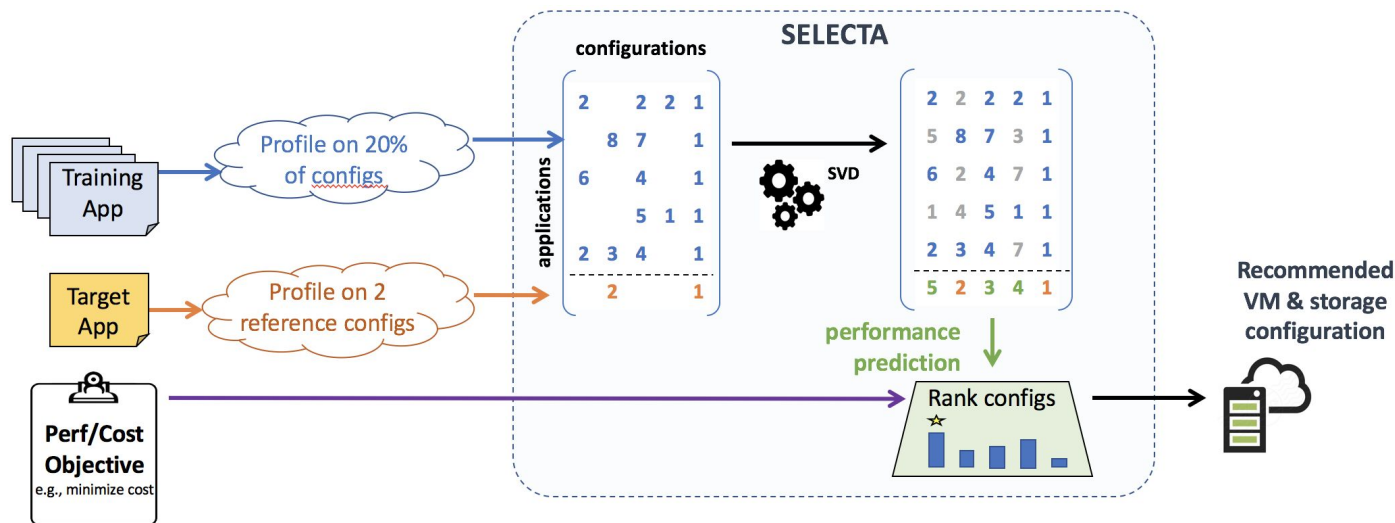
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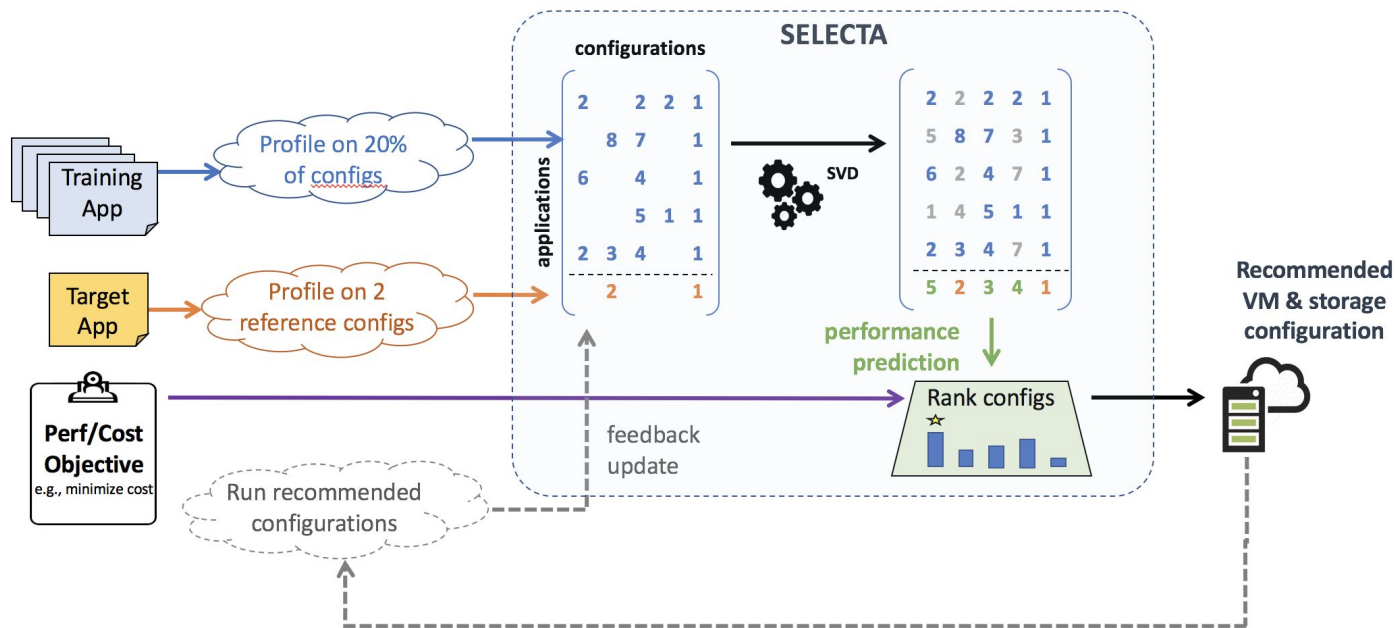
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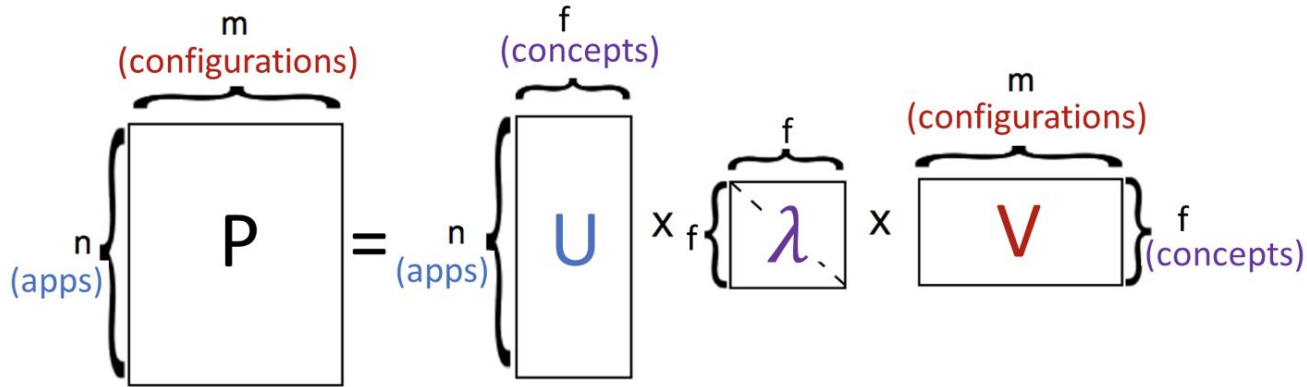
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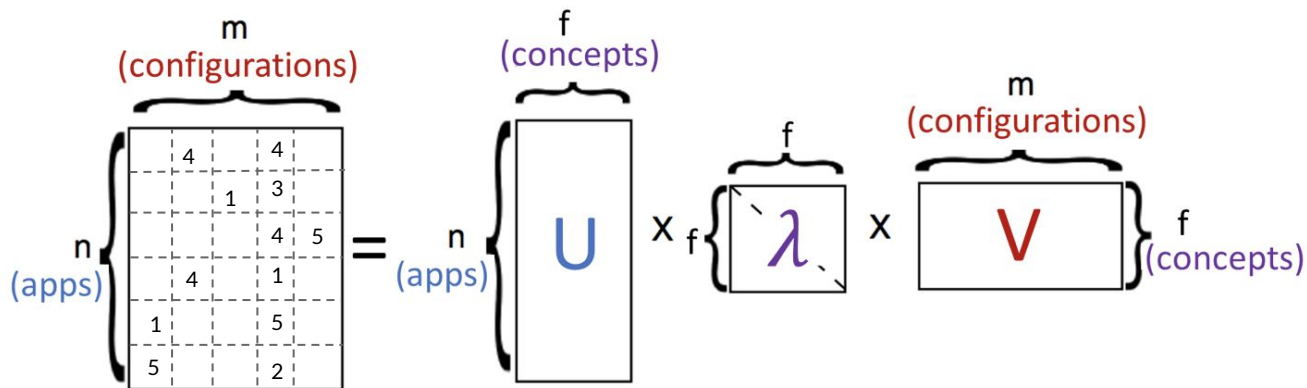
# Collaborative Filtering

- Collaborative filtering approach: use singular value decomposition (SVD) to decompose **app-config** matrix **P** to uncover latent (“hidden”) similarity concepts



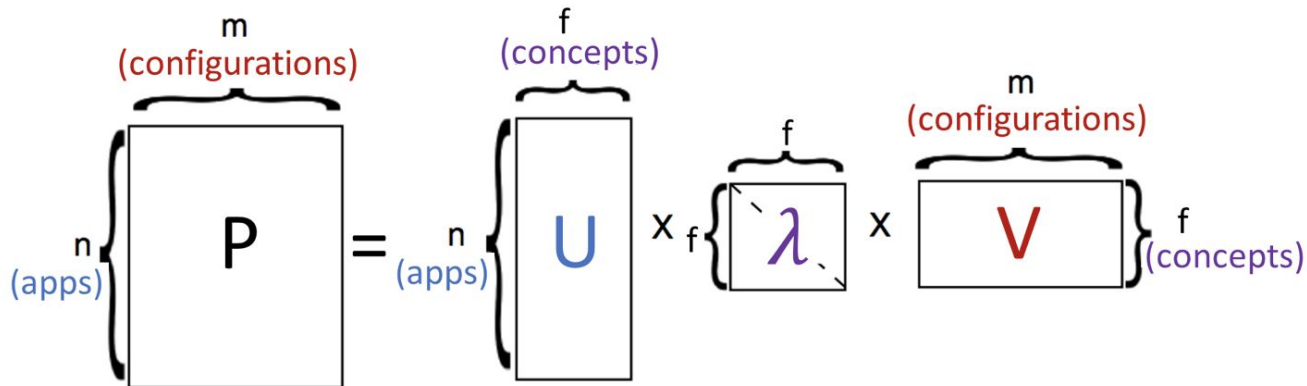
# Collaborative Filtering

- Collaborative filtering approach: use singular value decomposition (SVD) to decompose **app-config** matrix **P** to uncover latent (“hidden”) similarity concepts
- **P** is sparse and SVD requires dense matrix → use stochastic gradient descent to update unknown entries; objective function minimizes error on known entries



# Collaborative Filtering

- Collaborative filtering approach: use singular value decomposition (SVD) to decompose **app-config** matrix **P** to uncover latent (“hidden”) similarity concepts
  - ✓ Automatically infers (latent) features
  - ✓ Works well with sparse training set
  - ✓ Agnostic to the applications and configurations used

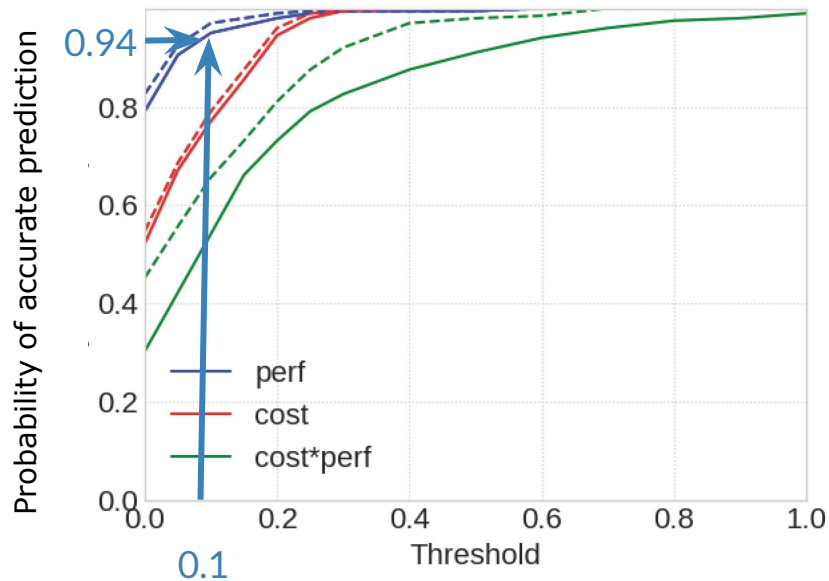


# Evaluation Methodology

- Run >100 different Spark SQL/ML applications on 17 different configurations
- Two dataset sizes for each application
- Our candidate configuration space (in Amazon EC2):
  - 8-node clusters of 3 different VM sizes (vary CPU cores & DRAM per node)
  - Storage options:
    - Remote block storage (EBS) HDD
    - Remote block storage (EBS) SSD
    - Local block storage NVMe
    - S3 object storage

# Selecta's Accuracy

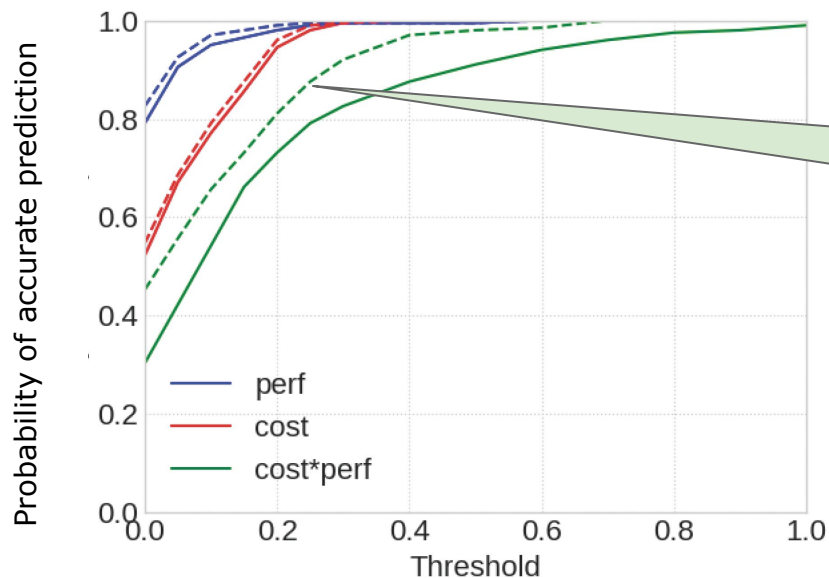
- What is the probability of predicting a configuration that is near-optimal?





# Selecta's Accuracy

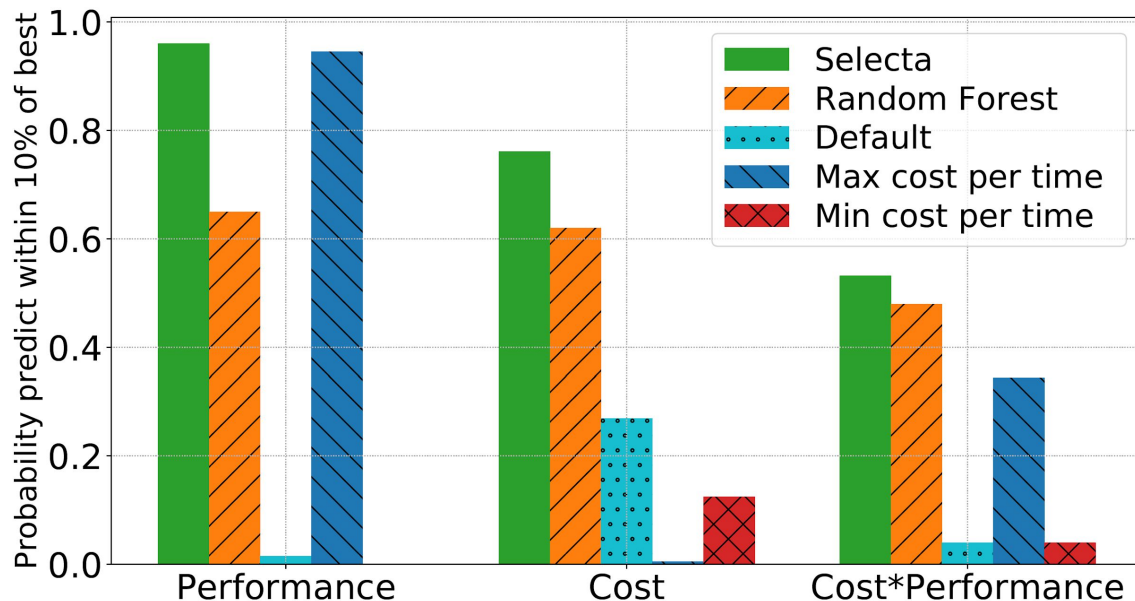
- Recommend near-optimal ( $T = 0.1$ ) config for best **perf** with 94% probability
- Recommend near-optimal ( $T = 0.1$ ) config for best **cost** with 80% probability



Dotted line shows improvement with one feedback round

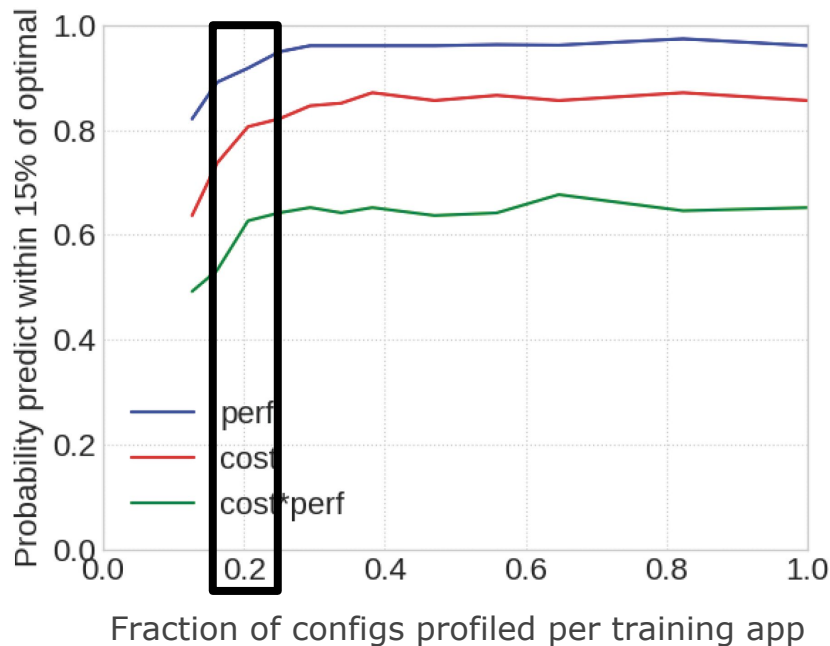
# Comparison to alternative approaches

- Selecta's collaborative filtering learns best from the sparse training data even though it does not leverage as many features as the random forest predictor



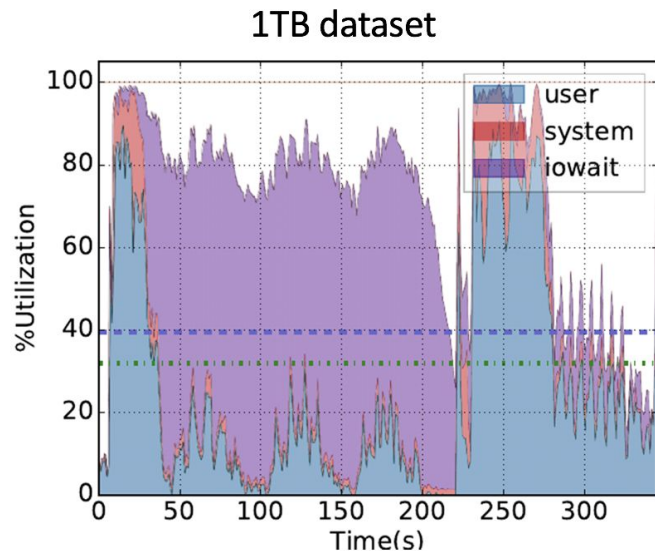
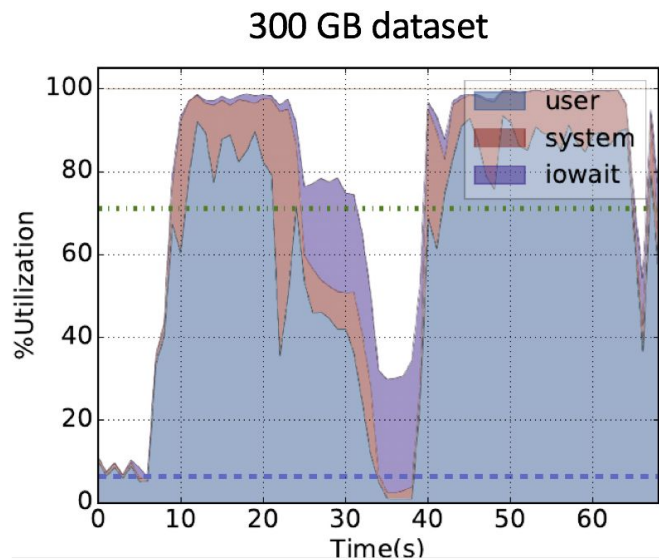
# Sensitivity analysis

- Training matrix should be ~20% dense in steady state for good accuracy



# Dealing with application changes

- Changes in the input dataset can alter the CPU vs. I/O intensity of the job and influence the choice of optimal configuration
- When CPU utilization varies beyond a threshold, treat the job as a new application



# Lessons for storage system design

- NVMe storage is performance *and* cost efficient for data analytics
  - Great fit for intermediate data (shuffle, broadcast, etc.)
  - Good performance for input/output data but can get expensive to store the data long-term (use S3 instead)
- Fine-grain allocation of storage capacity and bandwidth -- disaggregated from compute resources -- is desired for better utilization
- There is a need to optimize across layers (apps, frameworks, OS) as many configurations fail to achieve their potential due to software inefficiencies

# Conclusion

- Cloud cluster configuration is difficult yet critical for performance and cost
- Selecta is a tool that uses collaborative filtering to make near-optimal configuration recommendations for a user's performance-cost objective
  - 94% probability of predicting configuration with near-optimal performance
  - 80% probability of predicting configuration with near-optimal cost
- We use Selecta to explore the cloud storage landscape in the context of data analytics to guide the design of future storage systems