Learning-based algorithms in DBMS

Hype or Future?

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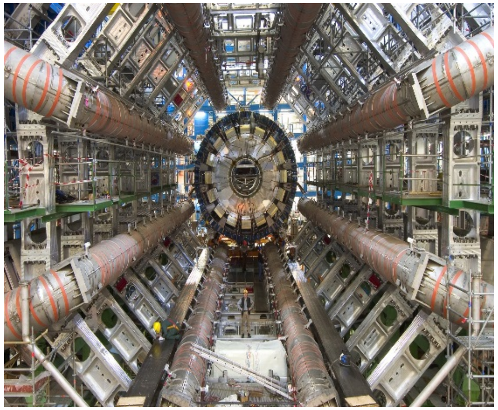
Why learning algorithms?

Ever growing data



(Ad hoc) data exploration

Multi-tenancy

Complex optimization problems, analytical modeling hard

Photos credit: Bloomberg, Stock market°, Atlas experiment, CERN*, Strato Data Centre, cloud^

Why now?

Computational power

Can adjust beyond history

Free telemetry (features)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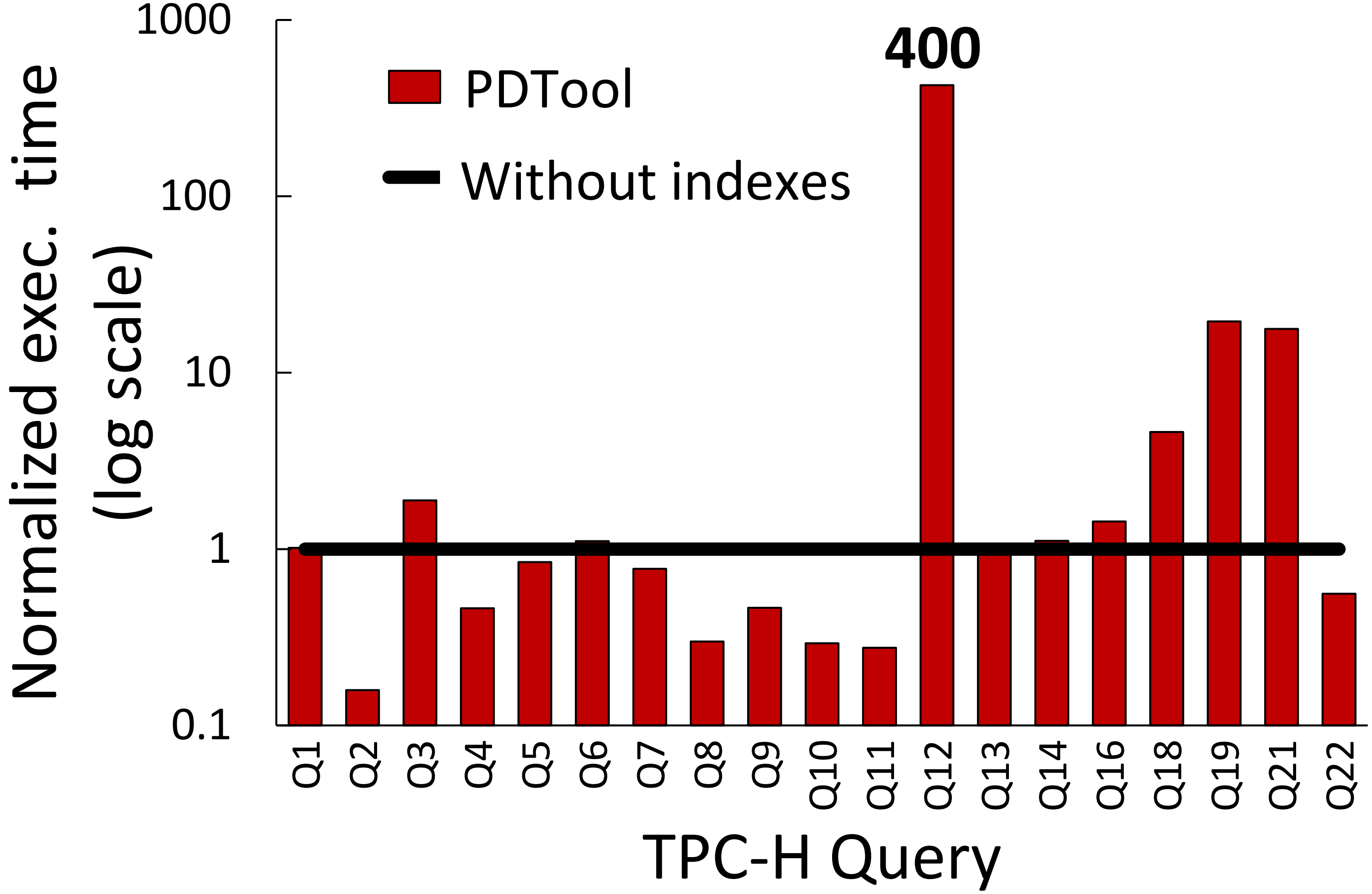
DBMS needs and ML capabilities = perfect match

Are there real use cases?

[VLDBJ'18, ICDE'15, DBTest'12]

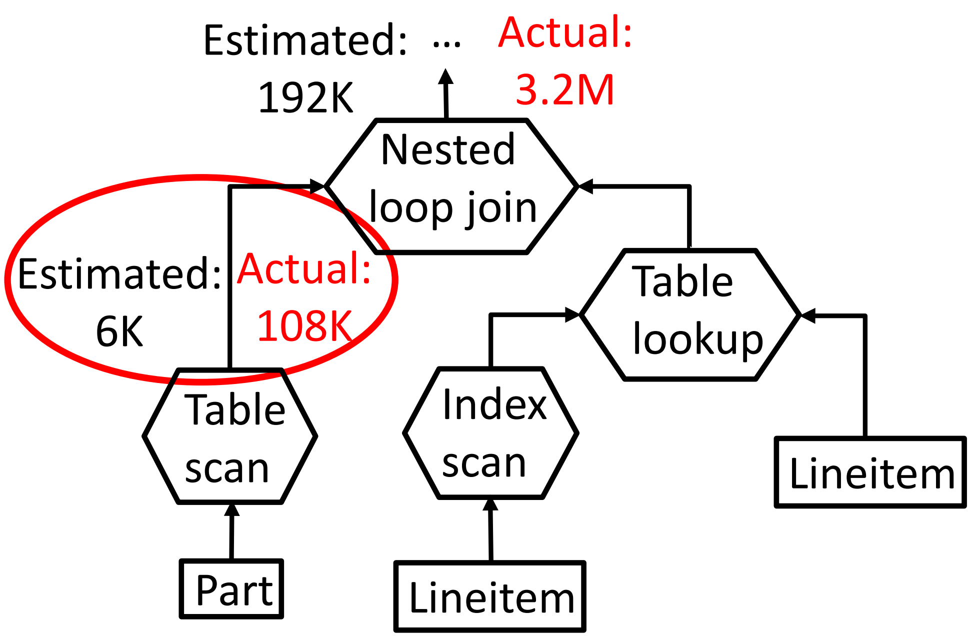
Setting: TPC-H, SF10, DBMS-X, Tuning tool (PDTool) 5GB for indexes



Plenty! Performance tuning an obvious choice

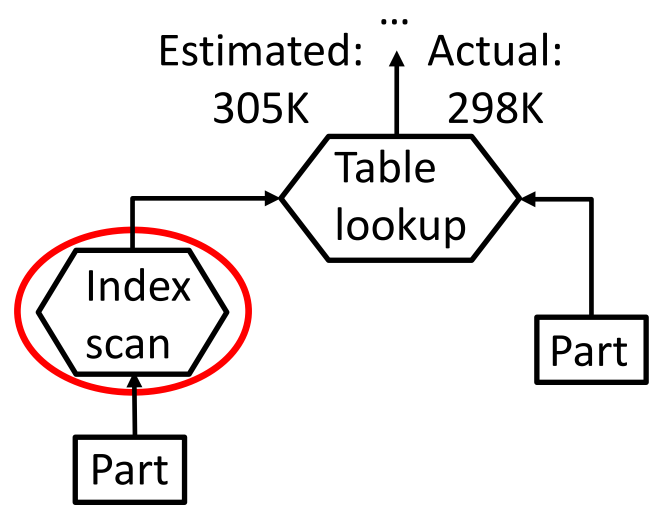
Cause for sub-optimal plans

Cardinality errors



Order of magnitude more tuples

Cost model

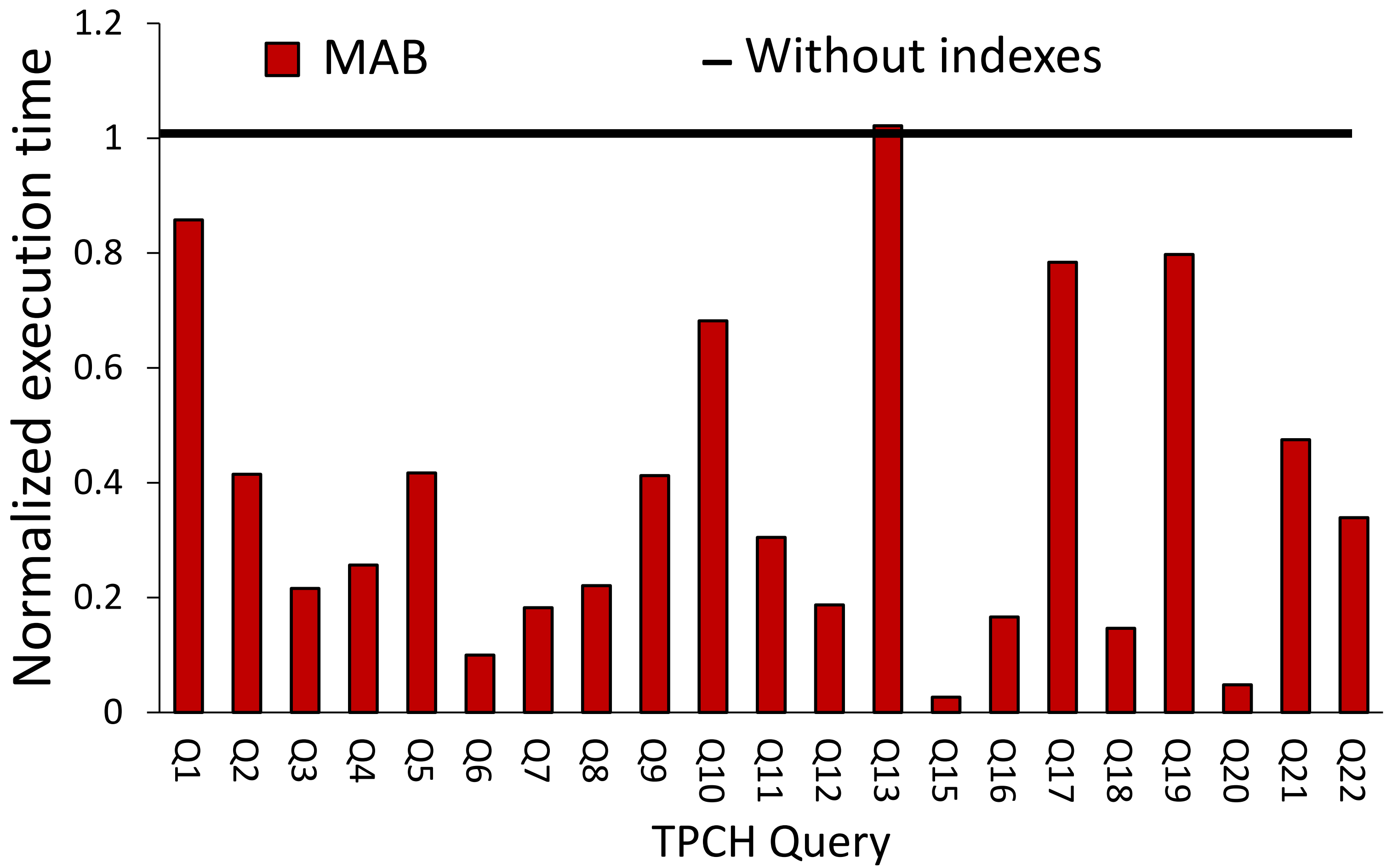


Wrong decision of cost model

Analytical modeling is hard!

Learning algorithms to the rescue

Setting: TPC-H, SF10, DBMS-X, Multi-armed bandits (MAB) for index tuning



3x Speed up vs. previous 22x slowdown

Outline

- **Performance tuning with MAB**

  [ICDE’21, ICDM’21]

- **Lightweight learned indices**

  [ADC’20]

- **Critical view at learning-based algorithms**

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  [ADC’20]

- **Critical view at learning-based algorithms**

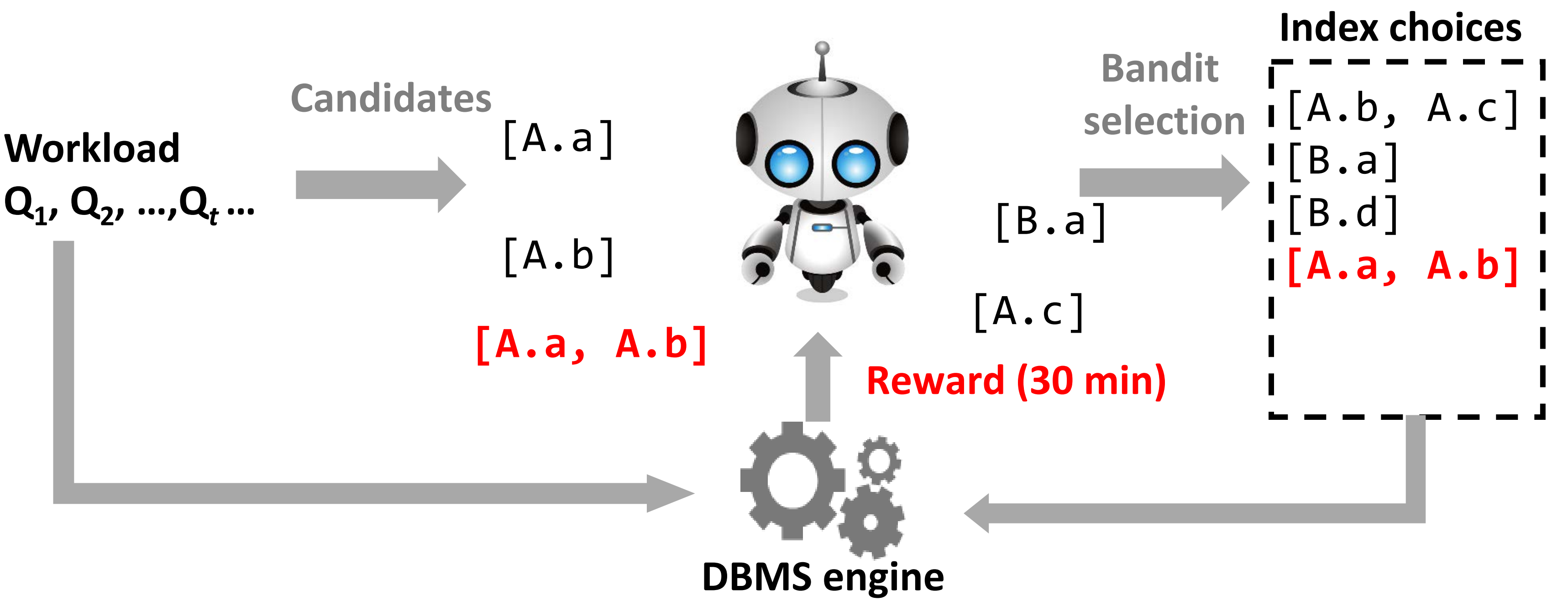
Learning with Multi-armed bandits (MAB)

- Pull an arm (slot machine) observe a reward (win/lose)
- Explore vs exploit
- Find a sequence of arms to maximize reward
- Many variants, but C^2UCB most interesting

Optimism in the face of uncertainty

Index tuning with MAB (C^2UCB)

[ICDE’21]



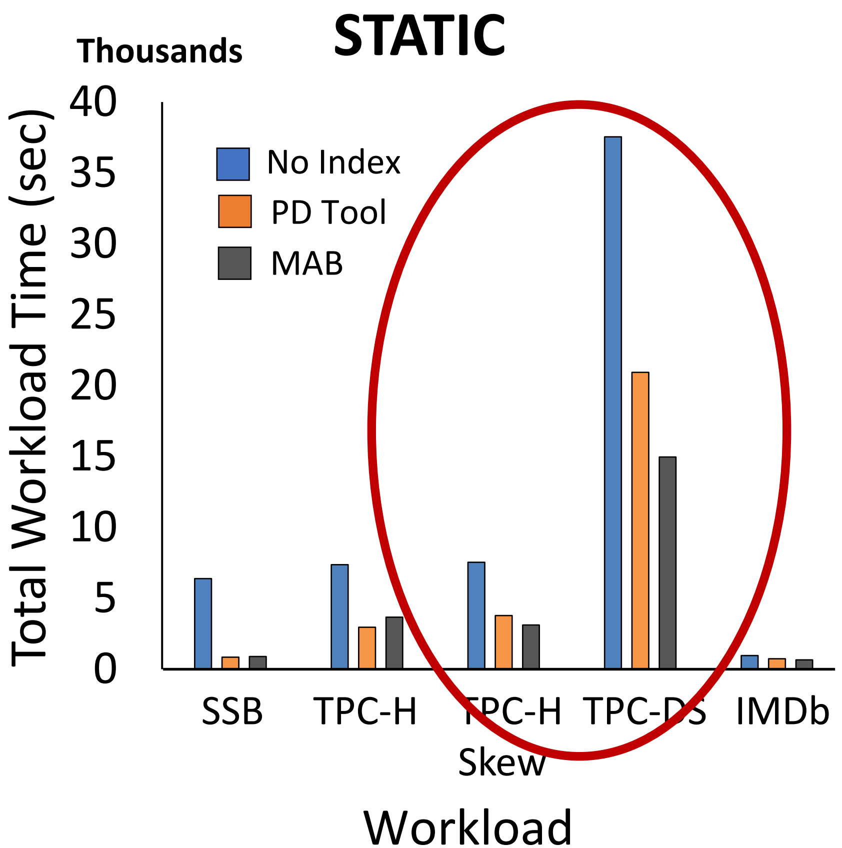
- **UCB** *guarantees* to converge to optimal policy
- **C** *(contextual)* learns benefit of arms *without* pulling them
- **C** *(combinatorial)* pulls a set of arms per round given constraints

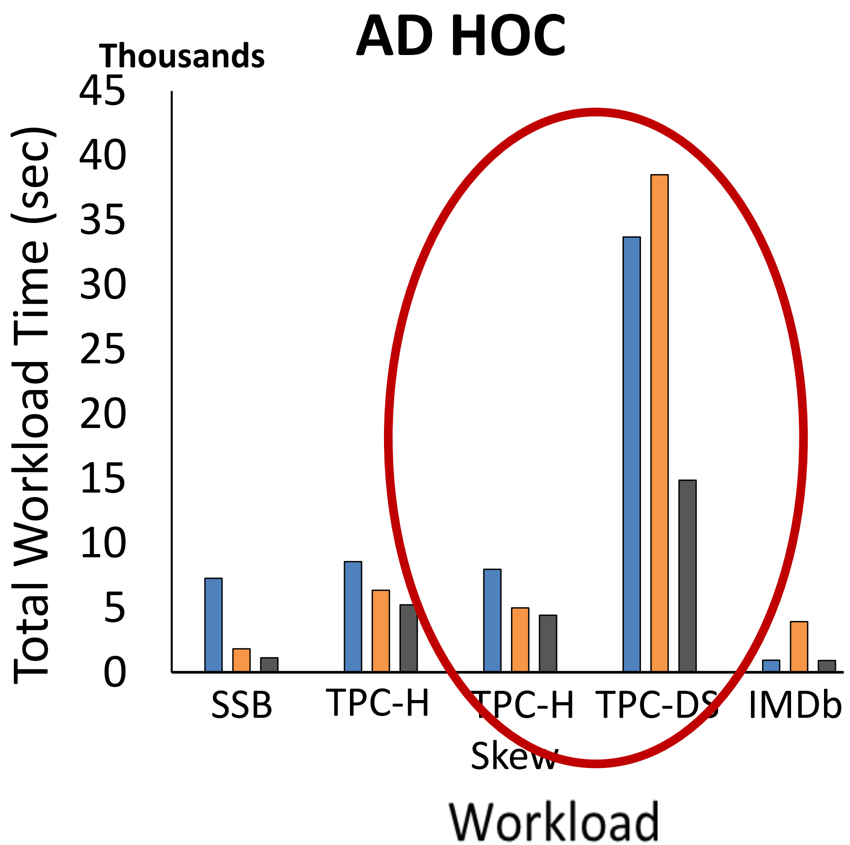
Safety guarantees with fast convergence

MAB in action

[ICDE'21]

Setting: TPCH, TPCH skew, TPC DS, SSB (10GB); IMDb(6GB) datasets
static (repetitive) vs random (ad hoc) queries, MAB vs PDTool, 25 rounds



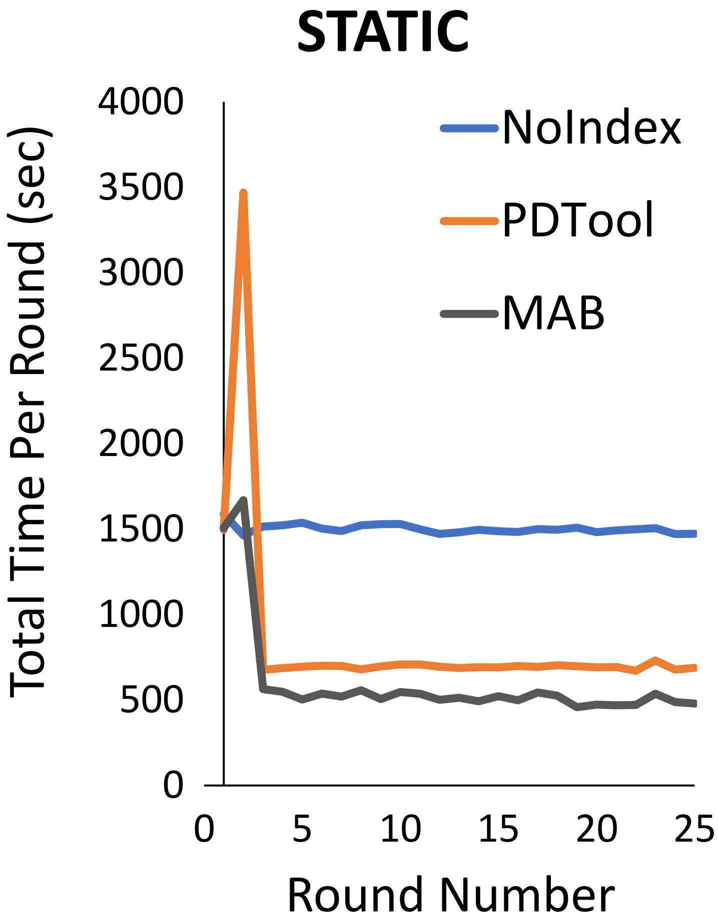


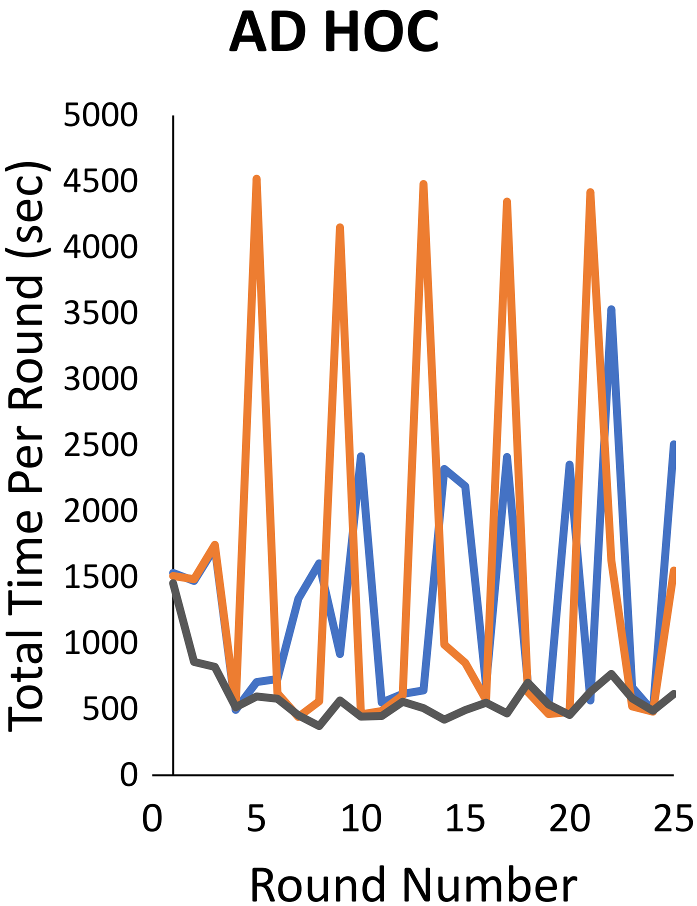
MAB robust against complex unpredictable workloads and skew

MAB in action: Zoom in TPC-DS

[ICDE’21]

Setting: TPC-DS, static vs ad hoc queries, MAB vs PDTool, 25 rounds

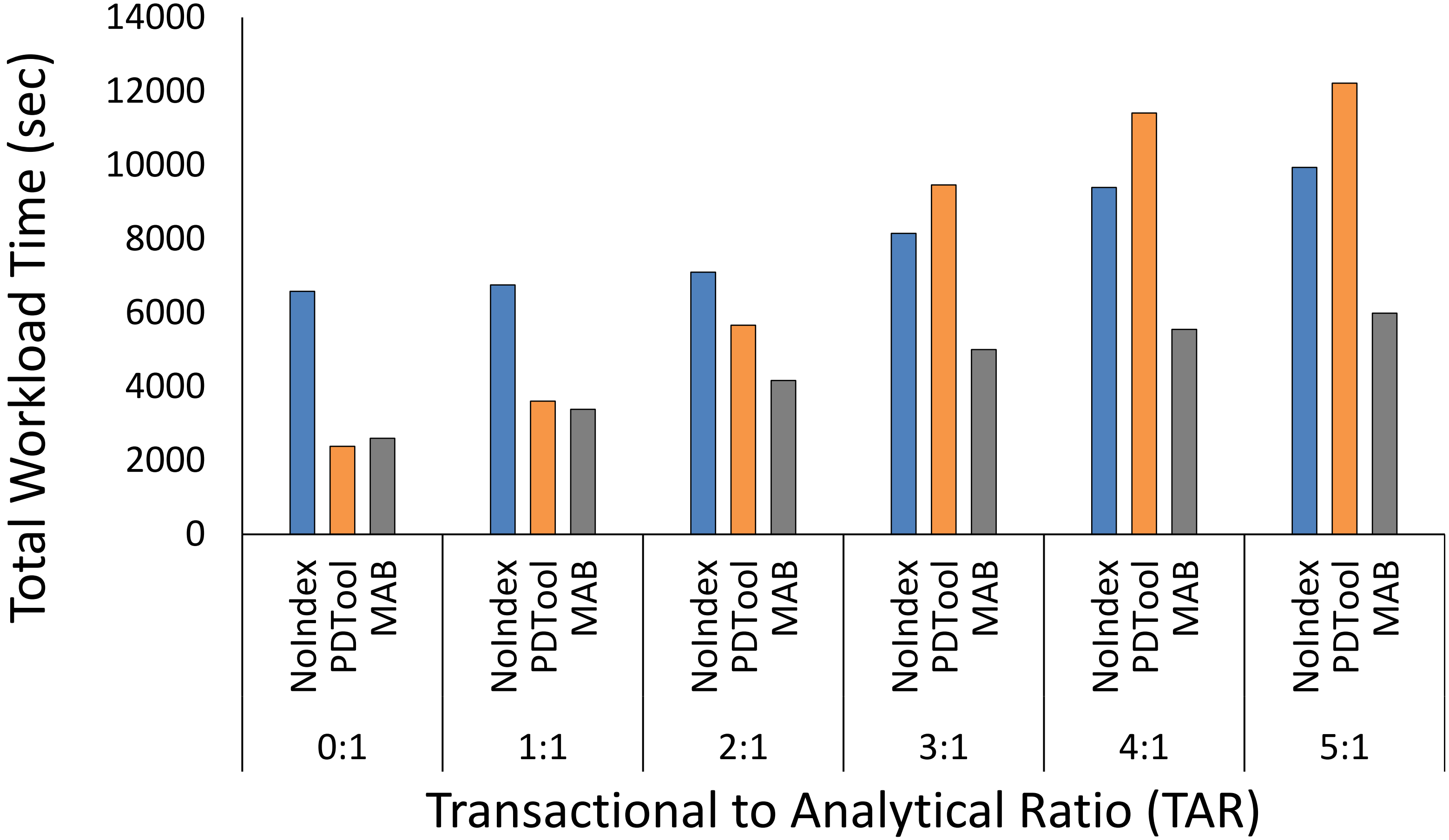




Lightweight, yet effective

Dealing with complexity (HTAP)

Setting: CH-BenCHmark under static workloads, MAB vs. PDTool, 25 rounds



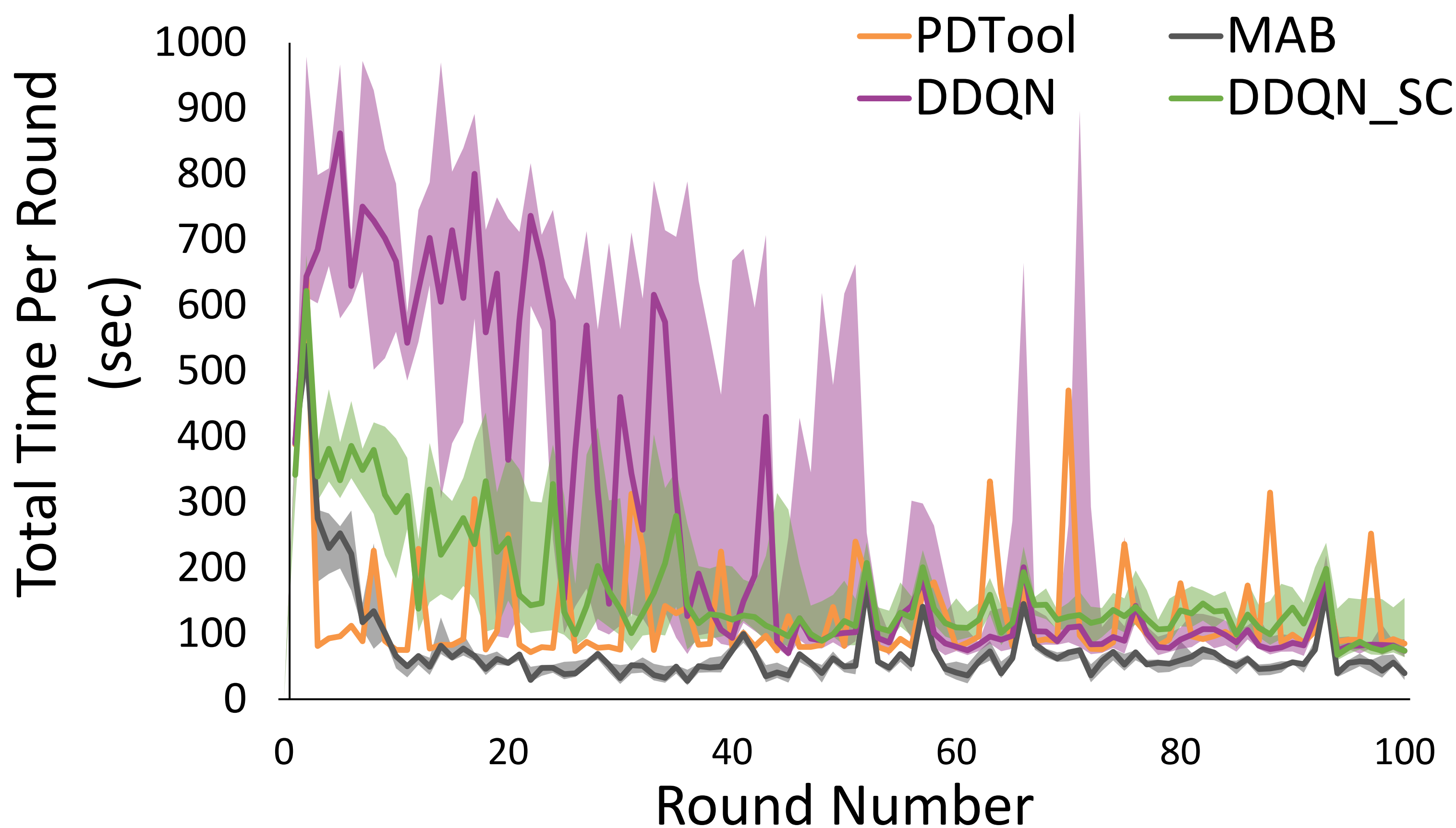
MAB adapts to complex environments

Choosing right tool for the job is key

Why not (general) RL

Setting: TPC-H Skew 10GB, 100 rounds *static*

[ICDE'21]



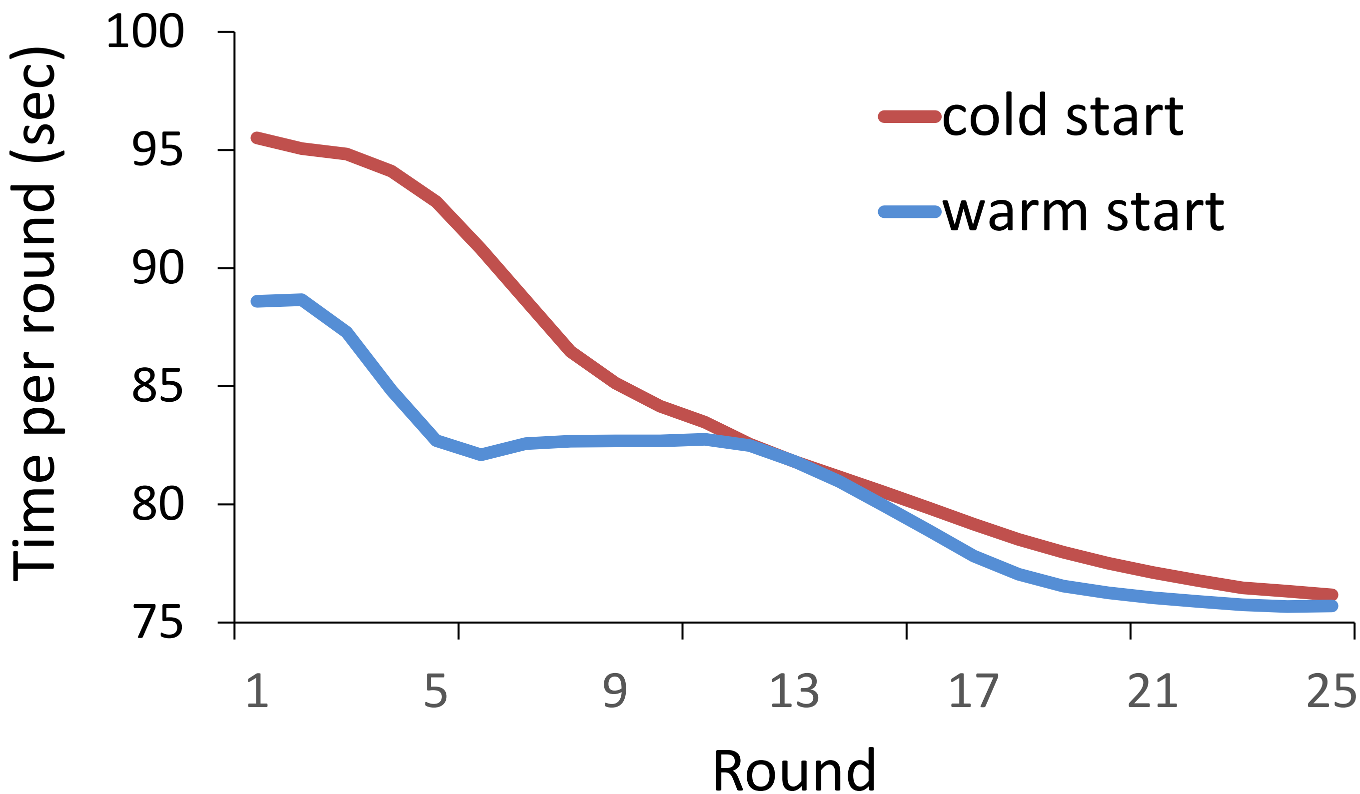
Faster convergence, less variance with MAB

But isn’t exploration too expensive?

Cutting to the chase with warm bandits

[ICDM’21]

Setting: TPC-H benchmark 10GB, 5 queries, 25 rounds *static*



(Inexpensive) warm up reduces exploration cost

Performance tuning with MAB

Summary

- MAB is a lightweight solution for index tuning
- C^2UCB enables exploration *without* pulling all arms
- Safety bounds guarantee convergence to optimal choice (in hindsight)
- MAB successfully deals with tuning tools' stumbling blocks (optimizer's misestimates, unpredictable workloads)
- Up to 75% improvement and 25% on average compared against a commercial tuning tool

Outline

- **Performance tuning with MAB**

  [ICDE’21, ICDM’21]

- **Lightweight learned indices**

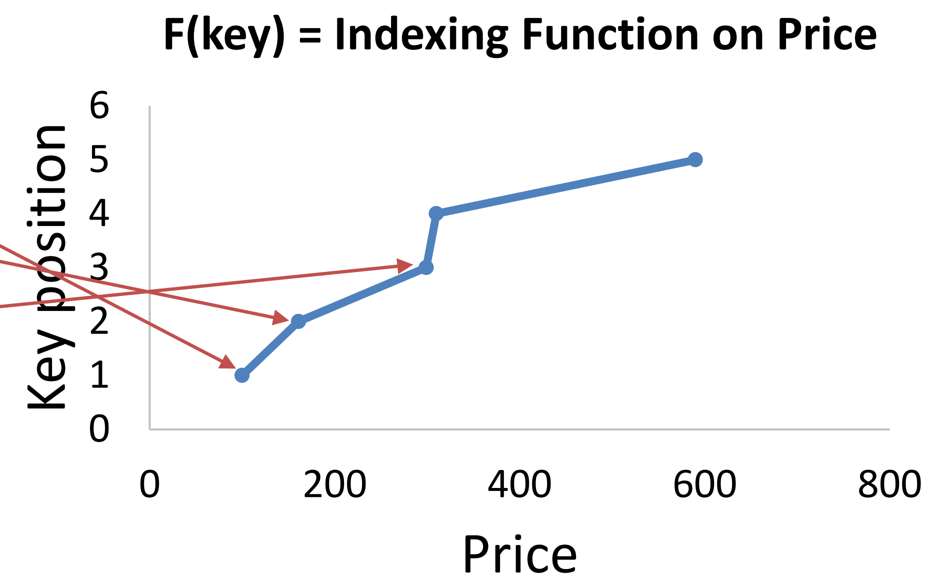
  [ADC’20]

- **Critical view at learning-based algorithms**

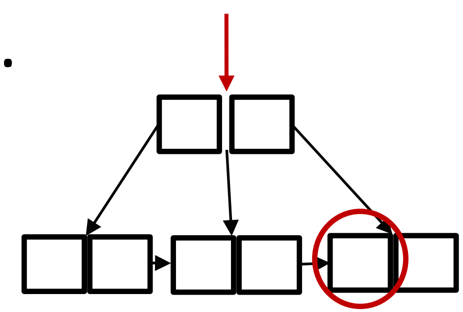
Mathematical view on indexing

I(price)

Product	Price (Key)
Product A	100
Product X	161
Product L	299
Product D	310
Product G	590

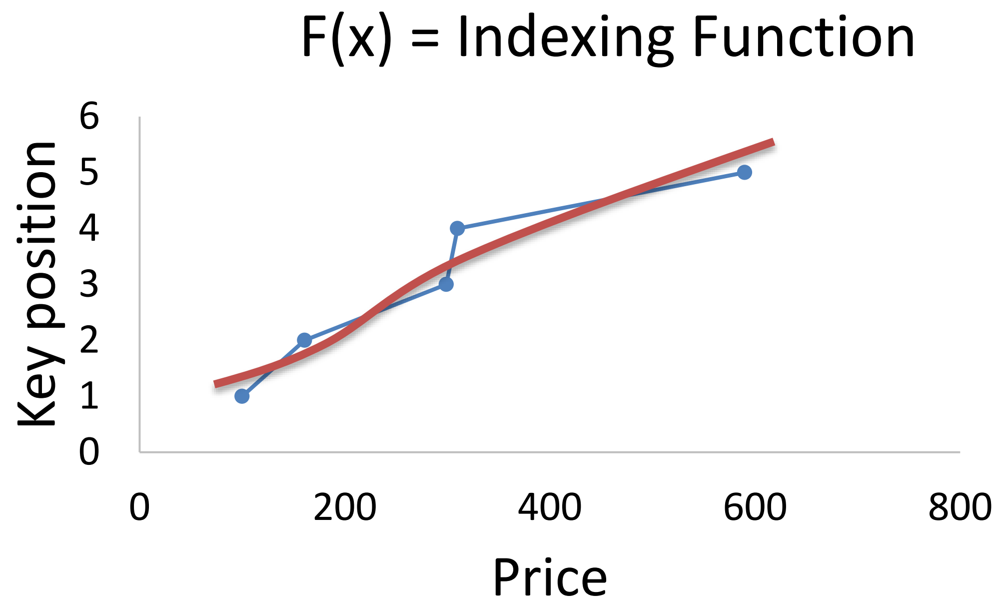


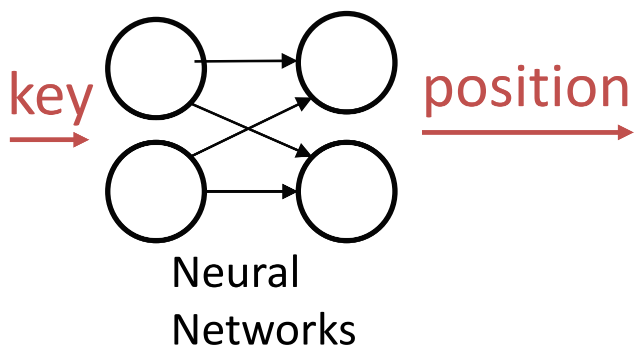
An index is a **function** $f: U \mapsto N$ that **takes** a **key** and **returns its position**.

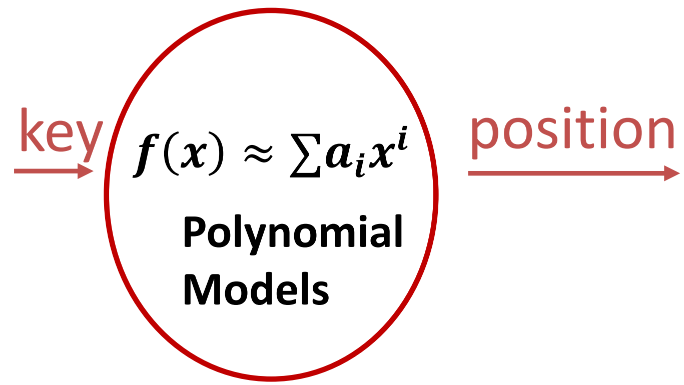


Keys form monotonically increasing CDF

So... we can build a model to predict them!







Kraska et al.[SIGMOD'18]

Learned index as a function approximation

[ADC'20]

For a chosen degree n

$$position \approx a_0 + a_1 x + a_2 x^2 + \cdots + a_n x^n$$

Coefficients given by Discrete Chebyshev Transform

$$\alpha_i = \frac{p_i}{N} \sum_{k=0}^{N-1} \left[f\left(-\cos\left(\frac{\pi}{N}\left(k + \frac{1}{2} \right) \right) \right) \cdot \cos\left(\frac{i\pi}{N}\left(N + k + \frac{1}{2} \right) \right) \right]$$

$$p_0 = 1, p_k = 2 \text{ (if } k > 0)$$

Need to store *only* coefficients…

Function interpolation for learned indices

[ADC'20]

Model Type	Average query time (nsec)			Creation time (sec)
	Normal	LogNormal	Uniform	
B-Tree	31.5	46.0	56.3	34.6
Function interpolation (Chebyshev Polynomials)	62.1	751	40.2	3.8
Neural Network Model	402	1100	516	1 hour

Model Type	Size of Database (in Entries)			
	500k Entries	1M Entries	1.5M Entries	2M Entries
B-Tree	33.034 MB	66.126 MB	99.123 MB	132.163 MB
Neural Network	210.73 kB	210.73 kB	210.73 kB	210.73 kB
Chebyshev Polynomials	1.8kB	1.8kB	1.8kB	1.8kB

30-90% faster at querying than NN, 99% space saving

Function interpolation to the rescue

Summary

- Use of simple function interpolation instead of NN for learned index approximation
- Benefits:
  - No hyperparameter tuning
  - Fast creation time (10x)
  - Higher compression rate (99% space saving)

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Properties for future DBMS adoption

- **Small computational overhead**
  - Pre-training important, yet often ignored
  - Resources plus time invested
- **Ability to adapt and generalize**
  - See the past, adjust to unpredictable future
  - Train on development port to product environment
  - Transfer learning critical
- **Safety guarantees required**
  - Prove it does the right thing
  - Explain the output (decisions made)

Lightweight, yet (provably) accurate is key

Numerous opportunities for innovation

- **ML within the DB Engine**
  - Physical database design
  - Learned vs traditional data structures
  - Configuration tuning
  - Resource management
  - Query optimization
- **Innovation in ML domain**
  - Hierarchical MABs (infinite arms)
  - Pretraining for faster convergence (warm start)
  - Lightweight transfer learning

Where to go from here

"It is not the strongest species that survive, nor the most intelligent, but the ones most responsive to change." Charles Darwin

Queries
[SIGMOD'12]
[VLDB'12]
[CACM'15]
[ICDE'21]
[ICDM'21]

Data
[DBTest'12]
[ICDE'15]
[VLDBJ'18]
[ADC'20]

Hardware
[VLDB'16]
[ADMS'17]
[CACM'19]

DBMS System

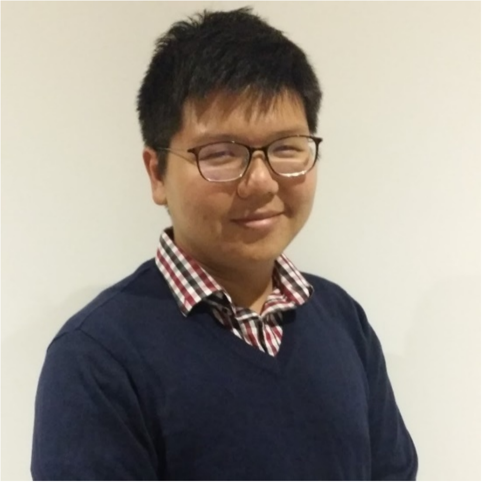
Fast response

Thank you!

Learning DBMSs for efficient data analysis

Special thanks to

Malinga Perera



Bastian Oetomo

Ben Rubinstein

Questions?

THANK YOU