Microsoft

Research
Faculty Summit 2018

Systems | Fueling future disruptions

Work partially done at Google

Learned Index Structures

(joint work with Alex Beutel, Ed H. Chi, Jeffrey Dean, Neoklis Polyzotis)

Tim Kraska <kraska@mit.edu>

[Disclaimer: I am NOT talking on behalf of Google]

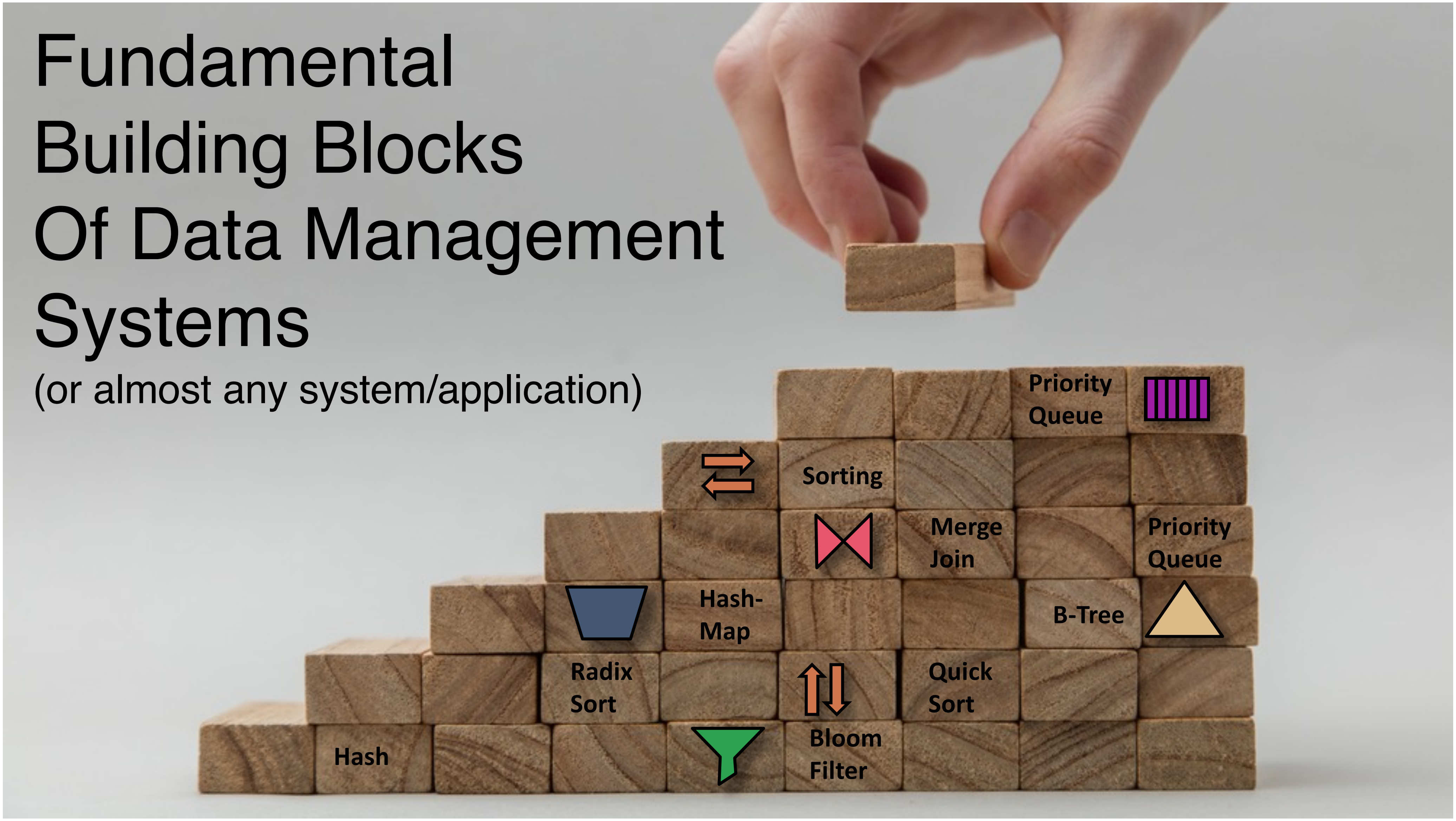
Comments on Social Media

"Machine Learning Just Ate Algorithms In One Large Bite…." [Christopher Manning, Professor at Stanford]

Disclaimer

Fundamental Building Blocks Of Data Management Systems

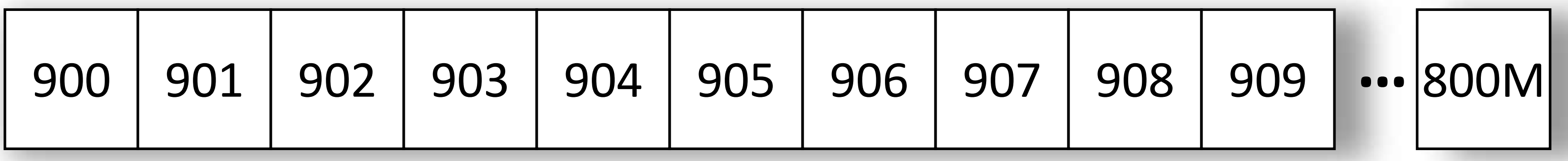
(or almost any system/application)



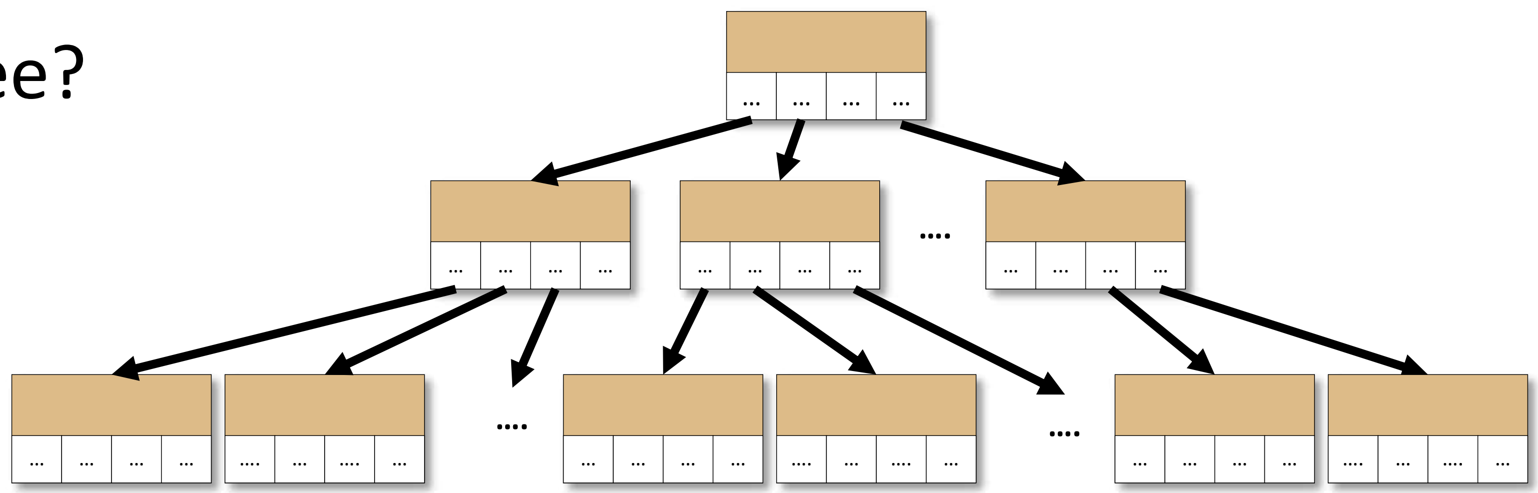

NO
ASSUMPTIONS

Goal:

Index All Integers from 900 to 800M



B-Tree?



Goal:

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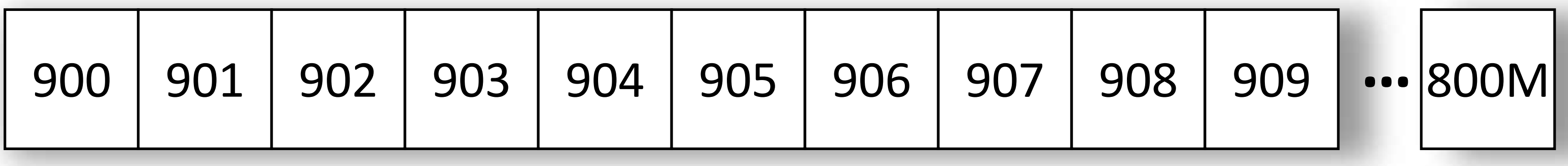



```
data_array[lookup_key - 900]
```

Goal:

Index All Integers from 900 to 800M

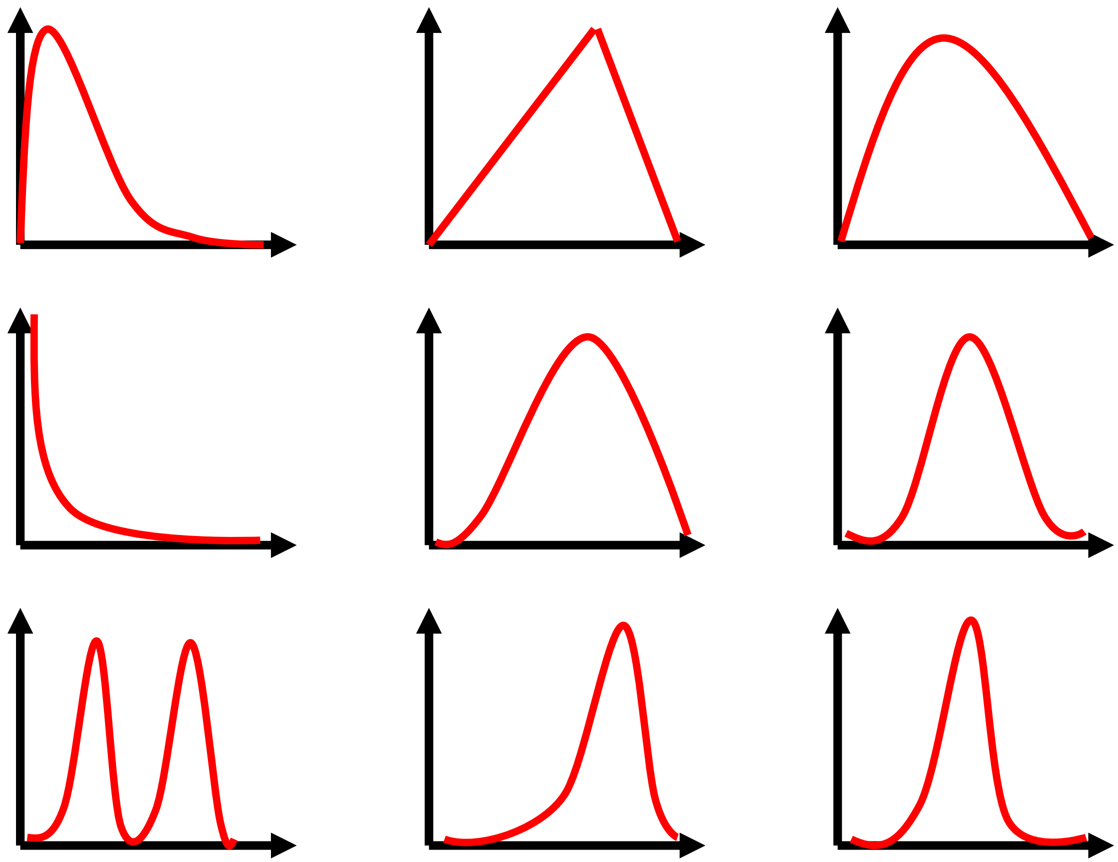
900	901	902	903	904	905	906	907	908	909	•••	800M

Index All Even Integers from 900 to 800M

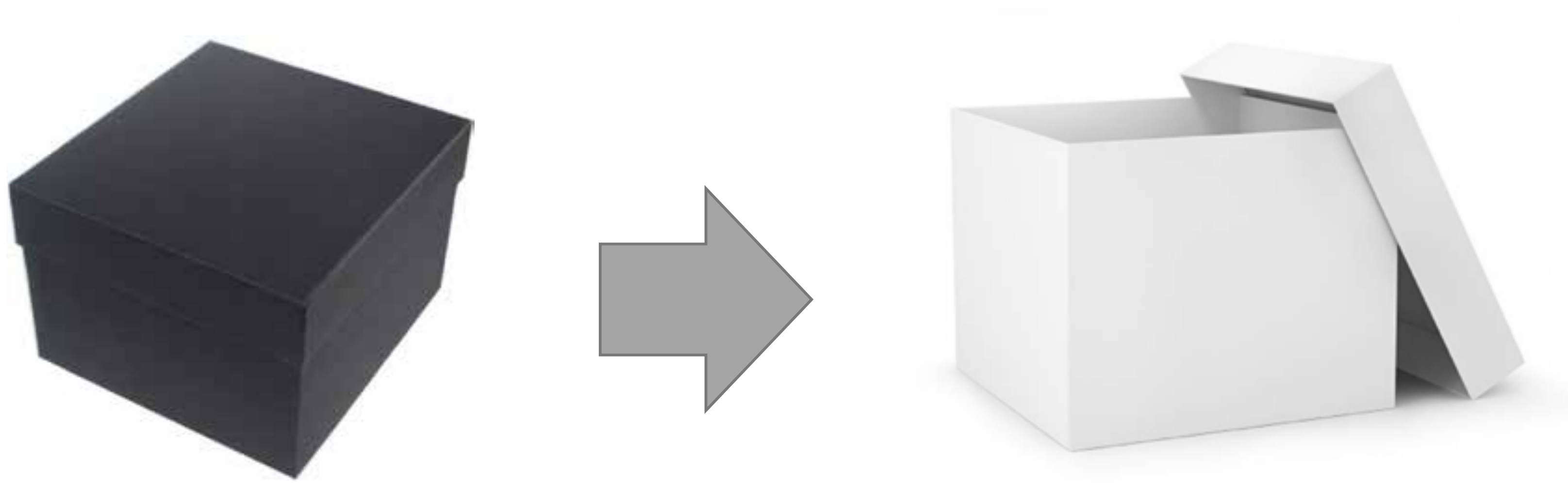
900	902	904	906	908	910	912	914	916	918	•••	800M

```
data_array[(lookup_key – 900) / 2]
```

Still holds for other data distributions



Key Insight

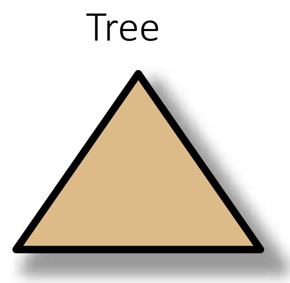


Knowing the (empirical) Data Distribution allows for Instance-based Optimizations

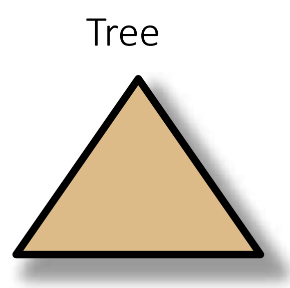
(e.g., lookups: O(log n) → O(1)
storage: O(n) → O(1))

Building A System From Scratch For Every Use Case Is Not Economical

B-Tree As An Example



B-Tree As An Example



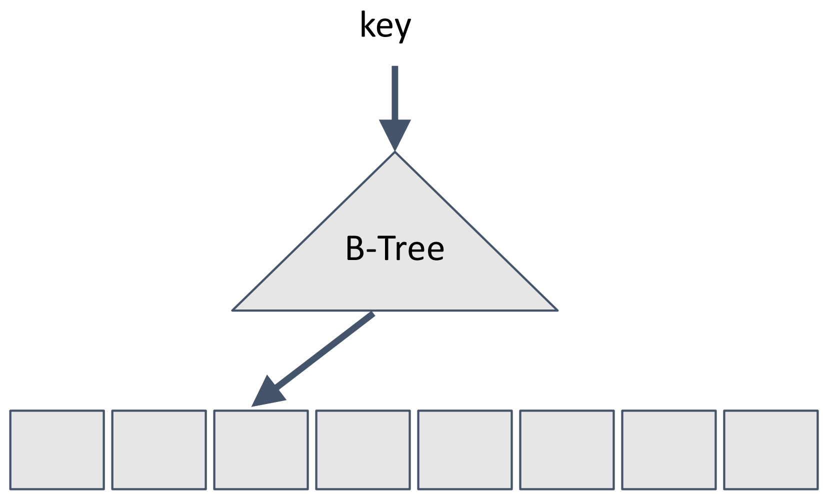
For the moment focus on
in-memory immutable B-Trees

Assumptions **No Inserts**

No Paging

will talk about those issues later.

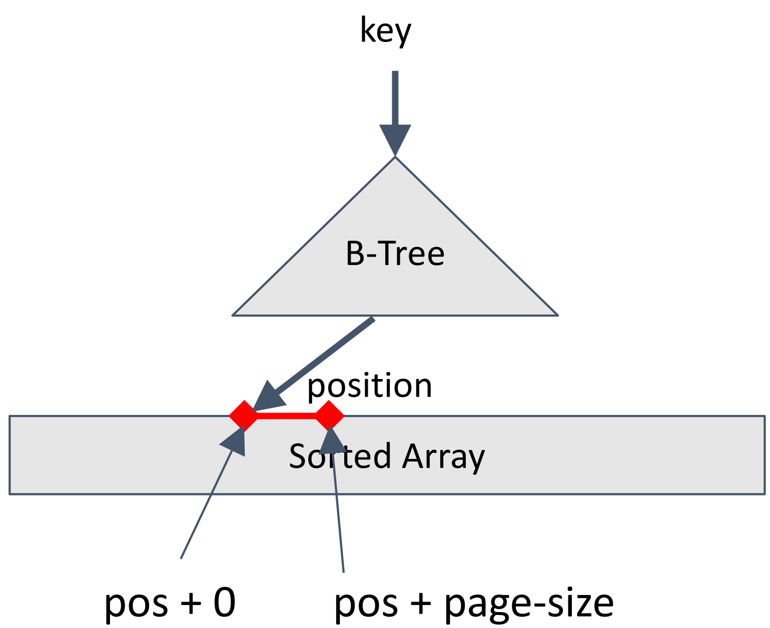
Conceptually *a*
B-Tree maps a key to a page



Assume: Data is stored in a continuous main memory region

Alternative View

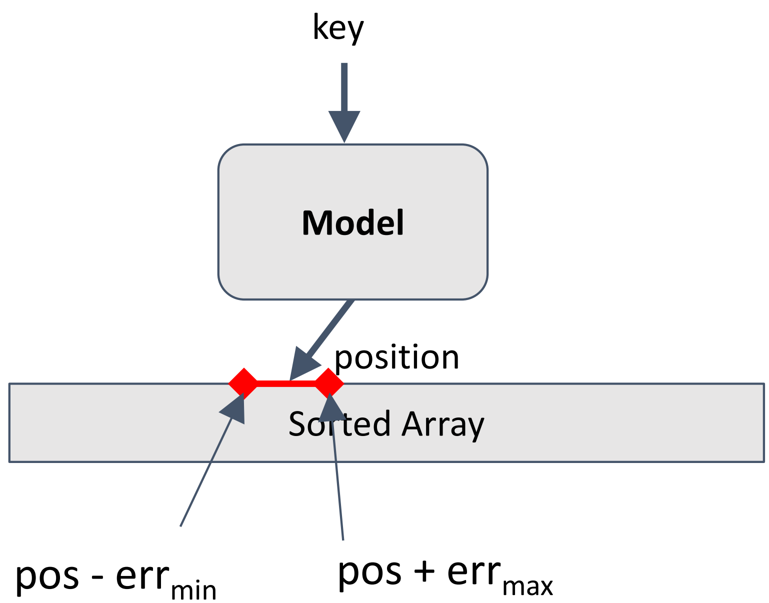
B-Tree maps a key to a position with a fixed min/max error



1. B-tree: key→pos
2. Binary search within err_{min} (0) and err_{max} (page-size)

For simplicity assume all pages are continuously stored in main memory

A B-Tree Is A Model



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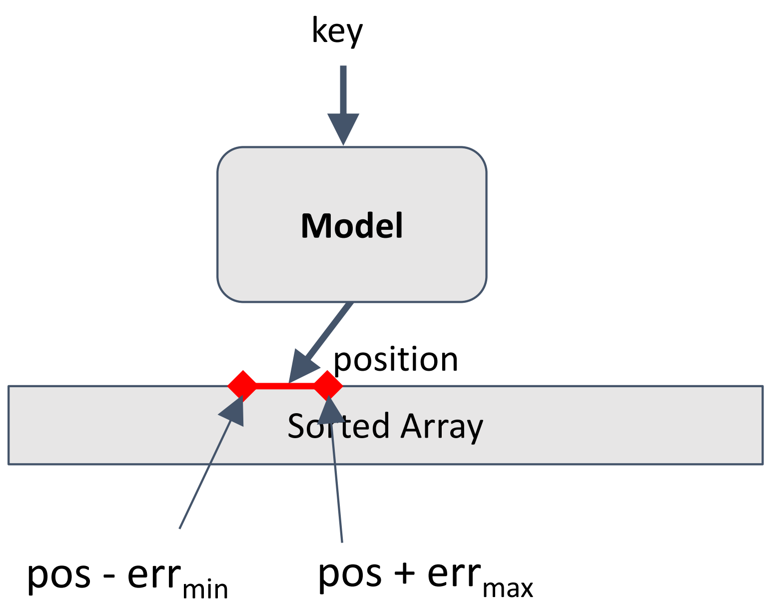
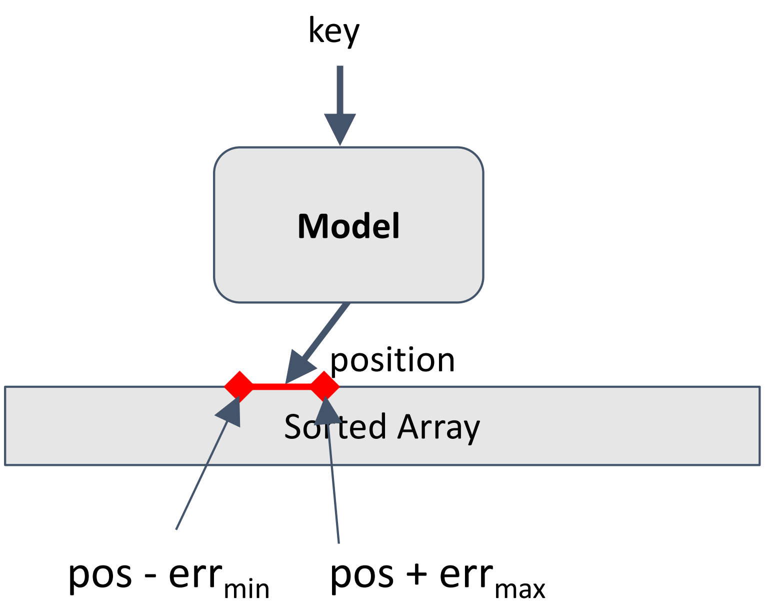


Finding an item

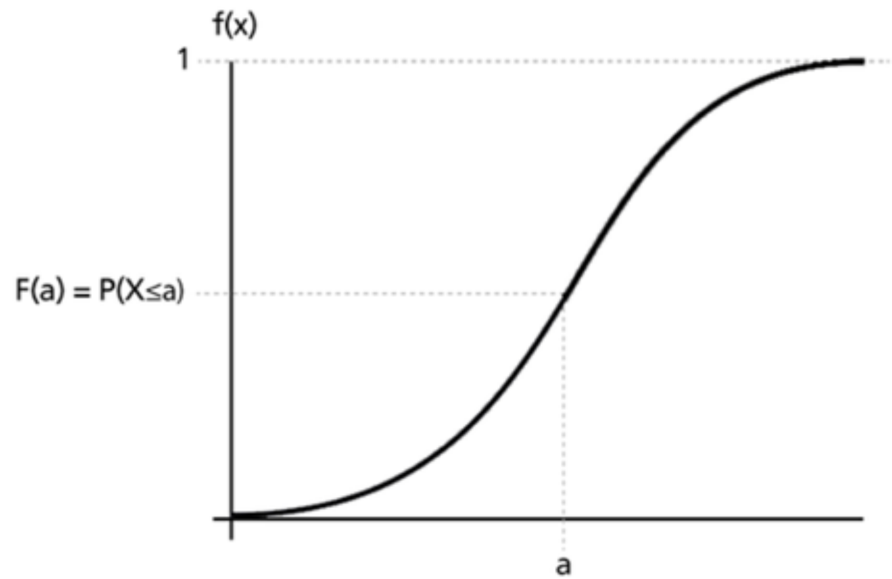
1. Any model: key → pos
2. Binary search in
   [pos - err$_{min}$, pos + err$_{max}$]

err$_{min}$ and err$_{max}$ are known from the training process

A B-Tree Is A Model

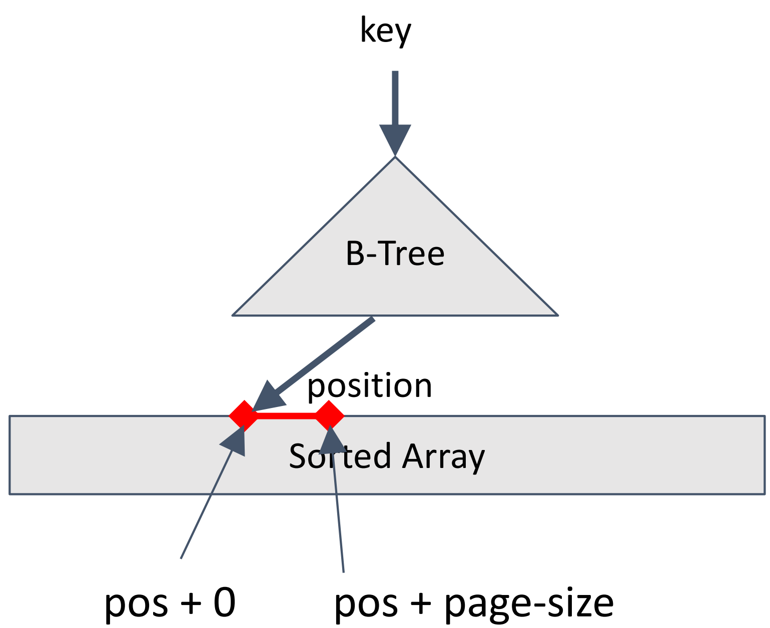


A CDF model



Pos-estimate = F(key) * #keys

The B-Tree is Also A Model



Regression Tree

What Does This Mean

What Does This Mean

Database people
were the first to do
large scale machine learning :)

Potential Advantages of Learned B-Tree Models

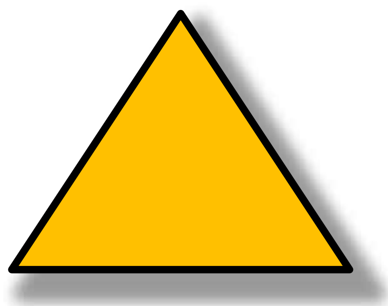
- **Smaller indexes** → less (main-memory) storage
- **Faster Lookups?**
- **More parallelism** → Sequential if-statements are exchanged for multiplications
- **Hardware accelerators** → Lower power, better $/compute….
- **Cheaper inserts?** → more on that later. For the moment, assume read-only

A First Attempt

TensorFlow™

- 200M web-server log records by timestamp-sorted
- 2 layer NN, 32 width, ReLU activated
- Prediction task: timestamp → position within sorted array

A First Attempt

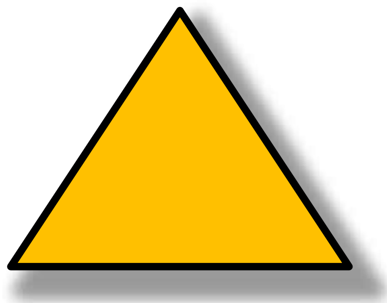


Cache-Optimized B-Tree

≈250ns

???

A First Attempt



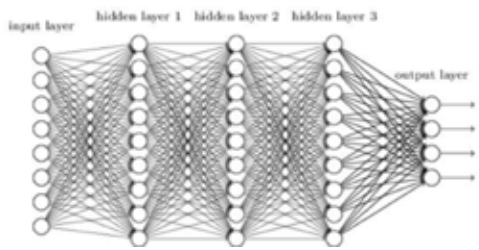
Cache-Optimized B-Tree

≈250ns

≈80,000ns

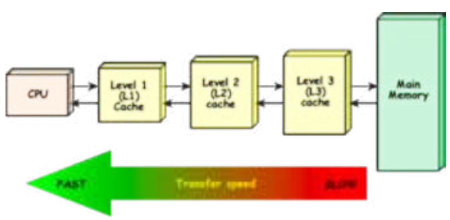
Reasons

Problem I: Tensorflow is designed for large models

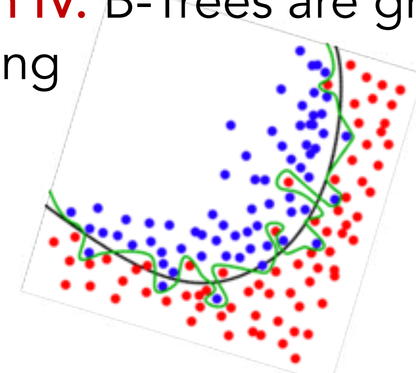


Problem II: Search does not take advantage of the prediction

Problem III: B-Trees are cache-efficient



Problem IV: B-Trees are great for overfitting



Reasons

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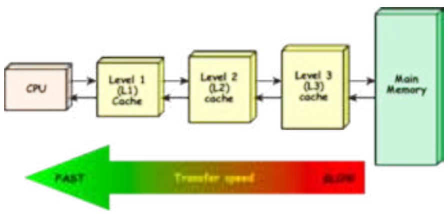

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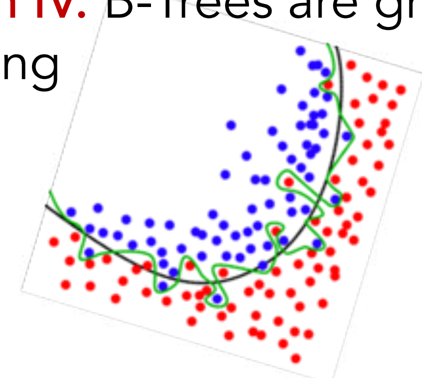
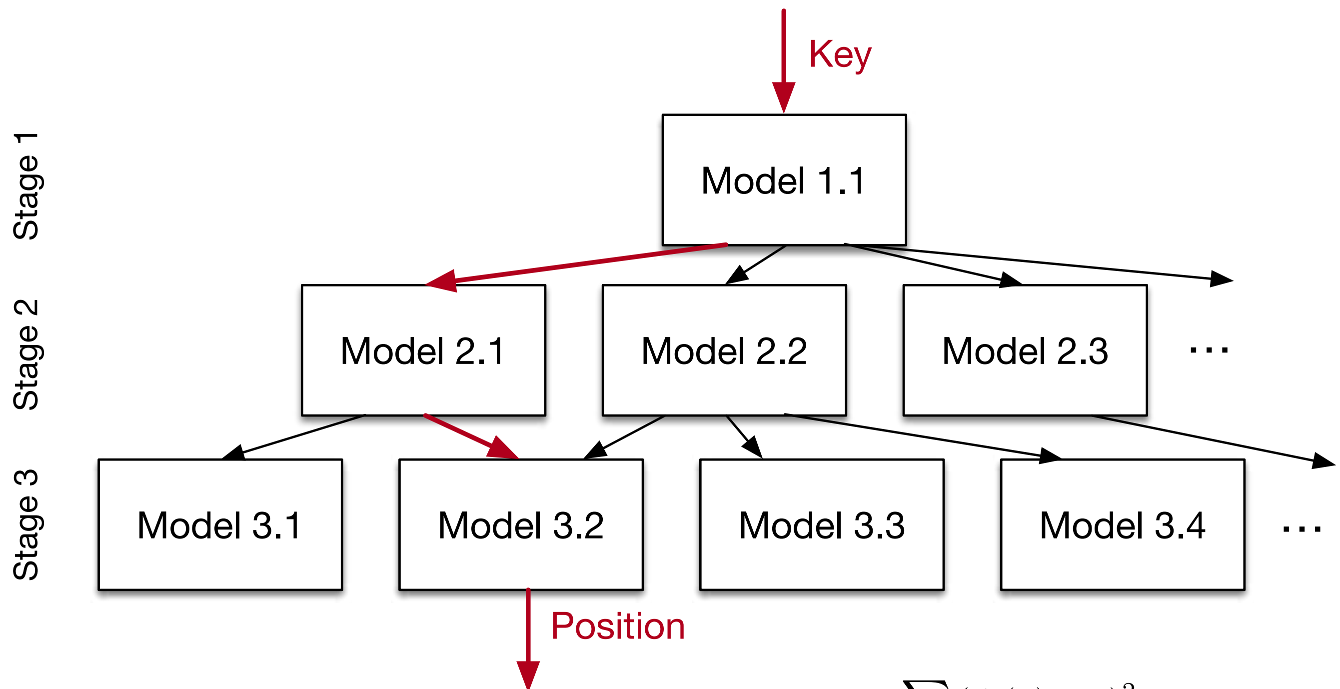


Solution:
Recursive Model Index (RMI)



$$L_0 = \sum_{(x,y)} (f_0(x) - y)^2$$

$$L_\ell = \sum_{(x,y)} (f_\ell^{(\lfloor M_\ell f_{\ell-1}(x)/N \rfloor)}(x) - y)^2$$

How Does The Lookup-Code Look Like

Model on stage 1: **`f0(key_type key)`**

Models on stage two: **`f1[]`**
(e.g., the first model in the second stage is is **`f1[0](key_type key)`**)

Lookup Code for a 2-stage RMI:

```
pos_estimate ← f1[f0(key)](key)
pos ← exp_search(key, pos_estimate, data);
```

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```

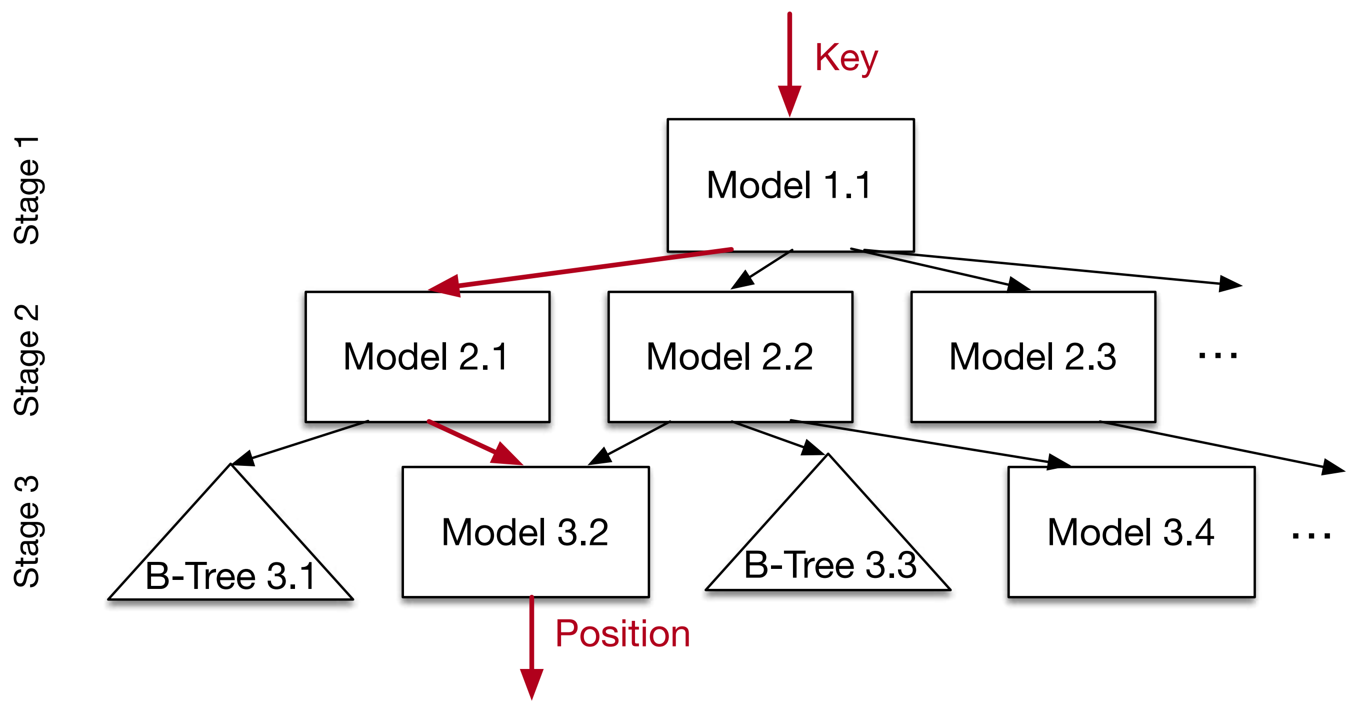
Operations with a 2-stage RMI with linear regression models

```
offset ← a + b * key
weights2 ← weights_stage2[offset]
pos_estimate ← weights2.a +
               weights2.b * key
```

2x multiplies
2x additions
1x array-lookup

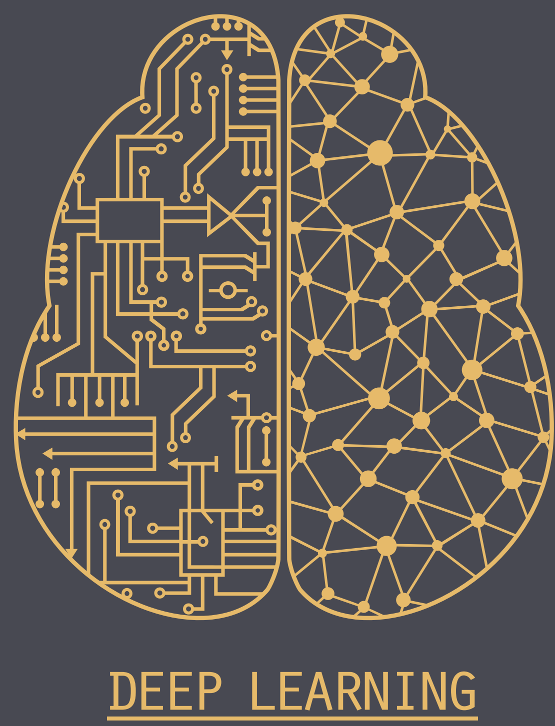
```
pos ← exp_search(key, pos_estimate, data)
```

Hybrid RMI



Worst-Case Performance is the one of a B-Tree

Does it have to be



Does It Work?

200M records of map data (e.g., restaurant locations). index on longitude
Intel-E5 CPU with 32GB RAM **without** GPU/TPUs **No Special SIMD optimization** (there is a lot of potential)

Type	Config	Lookup time	Speedup vs. BTree	Size (MB)	Size vs. Btree
BTree	page size: 128	260 ns	1.0X	12.98 MB	1.0X

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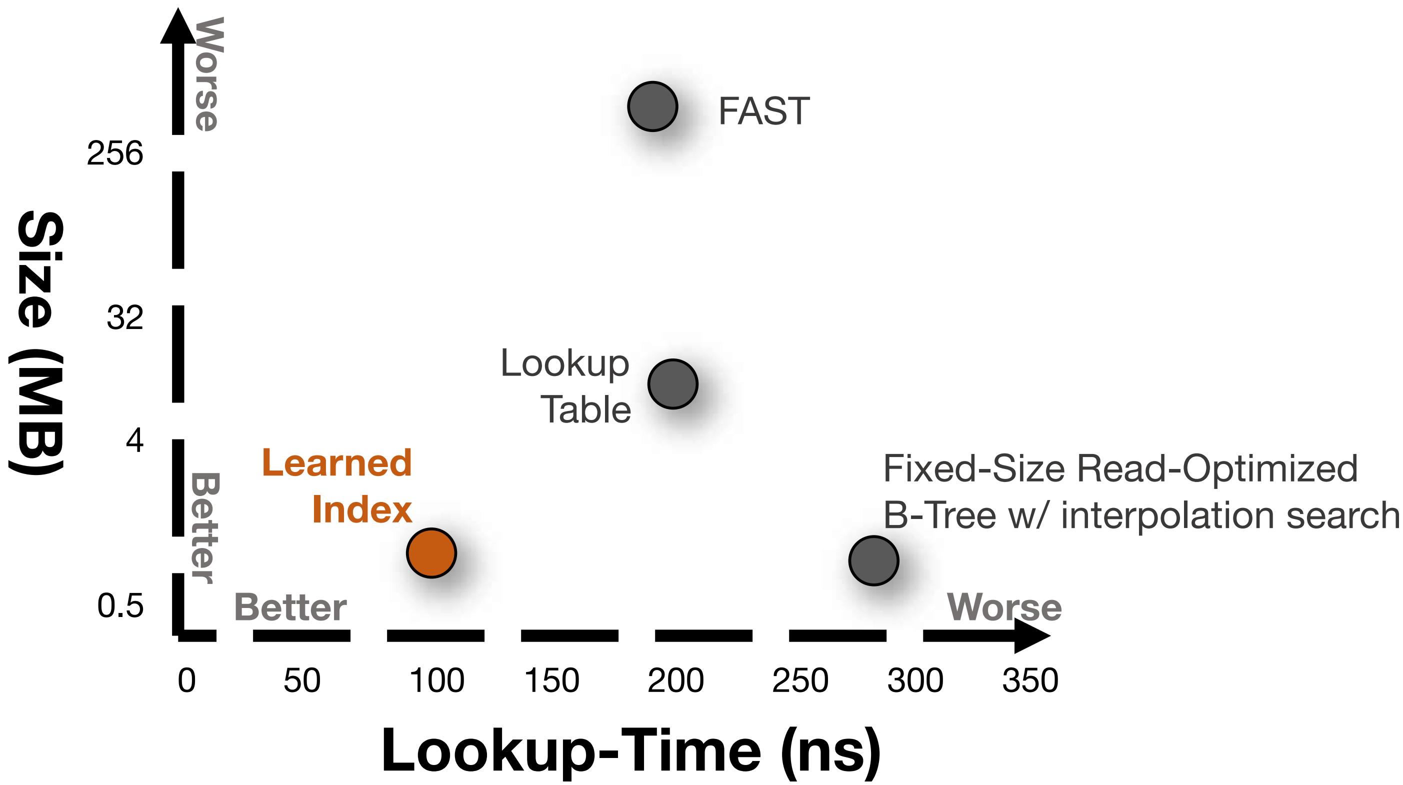
Type	Config	Lookup time	Speedup vs. BTree	Size (MB)	Size vs. Btree
BTree	page size: 128	260 ns	1.0X	12.98 MB	1.0X
Learned index	2nd stage size: 10000	222 ns	1.17X	0.15 MB	0.01X
Learned index	**2nd stage size: 50000**	**162 ns**	**1.60X**	**0.76 MB**	**0.05X**
Learned index	2nd stage size: 100000	144 ns	1.67X	1.53 MB	0.12X
Learned index	2nd stage size: 200000	126 ns	2.06X	3.05 MB	0.23X

60% faster at 1/20th the space, or 17% faster at 1/100th the space


You Might
Have Seen
Certain
Blog Posts



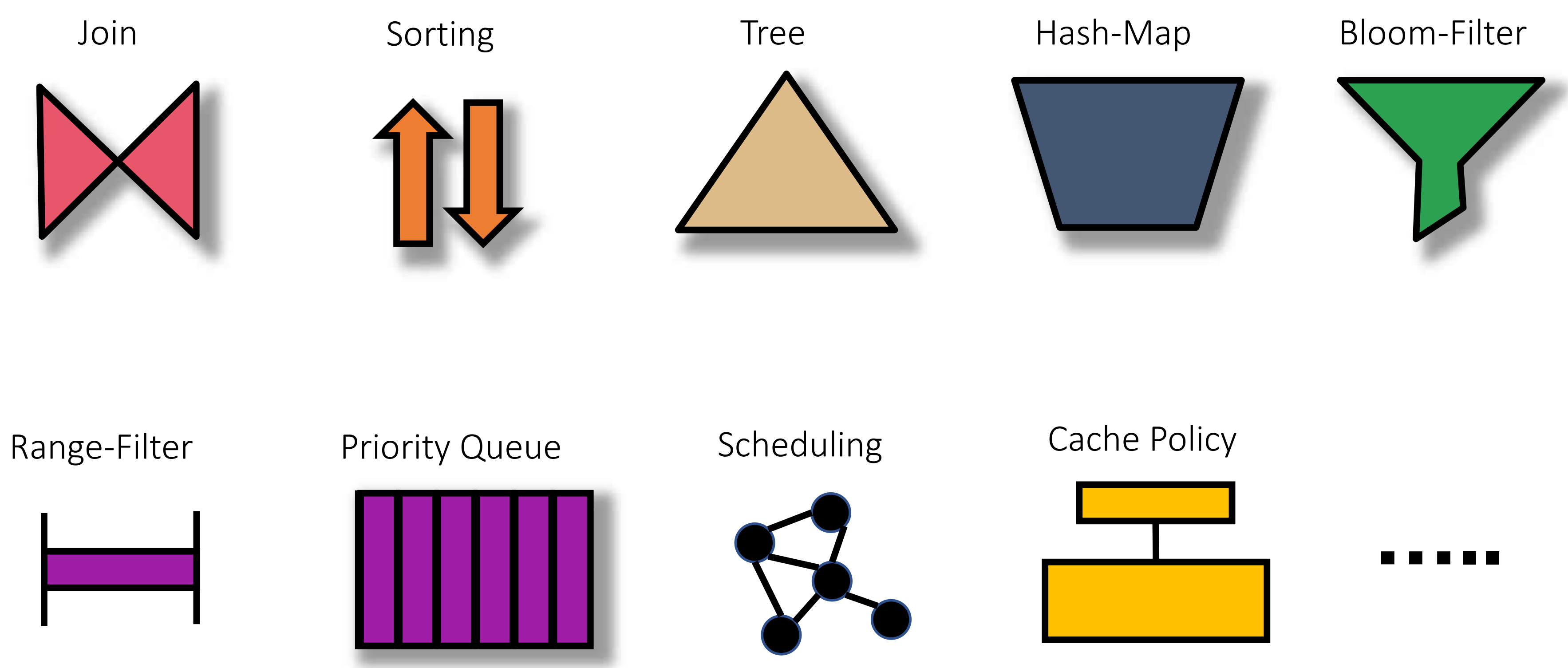
Big thanks to **Thomas Neumann** as his blog post actually helped us a lot to improve our experiment section.

What About Our Assumptions

- Updates and Inserts[1]
- Paging

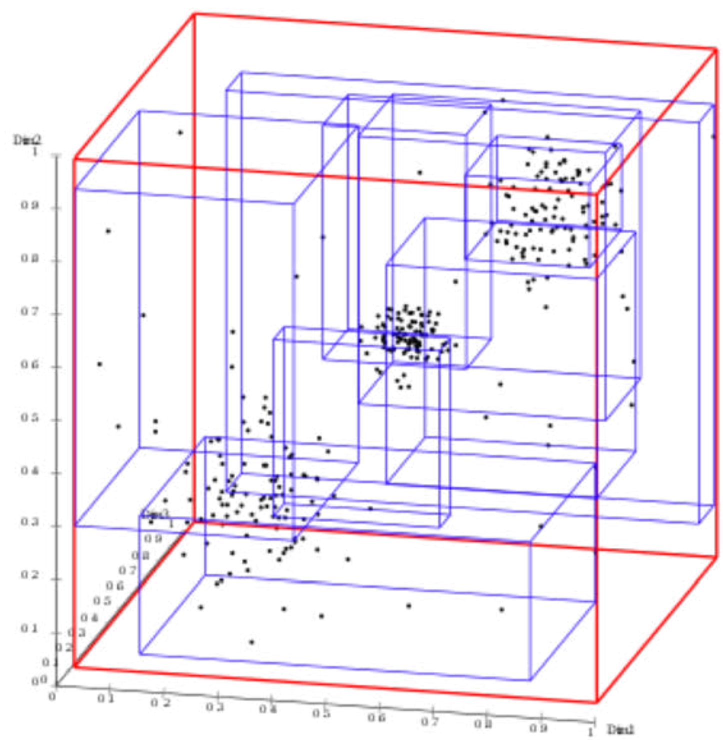
[1] **A-Tree: A Bounded Approximate Index Structure,**
https://arxiv.org/abs/1801.10207

Fundamental Algorithms & Data Structures



Multi-Dimensional Index

Problems with (R-Tree / KD-Tree)

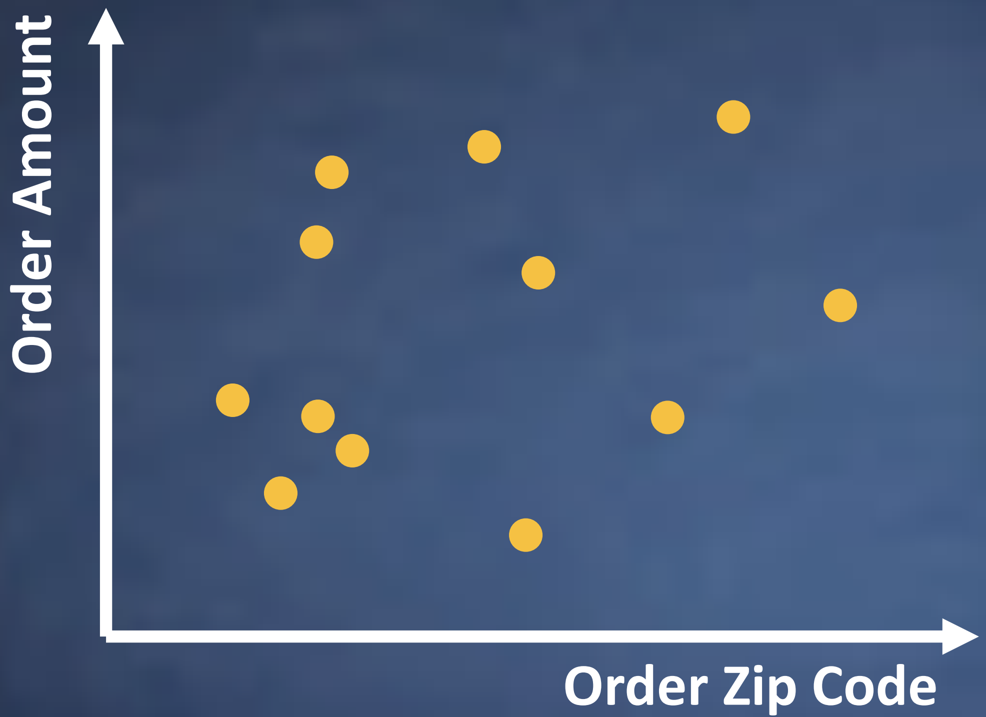


Machine Learning Is Good For Multi-Dimensional Data

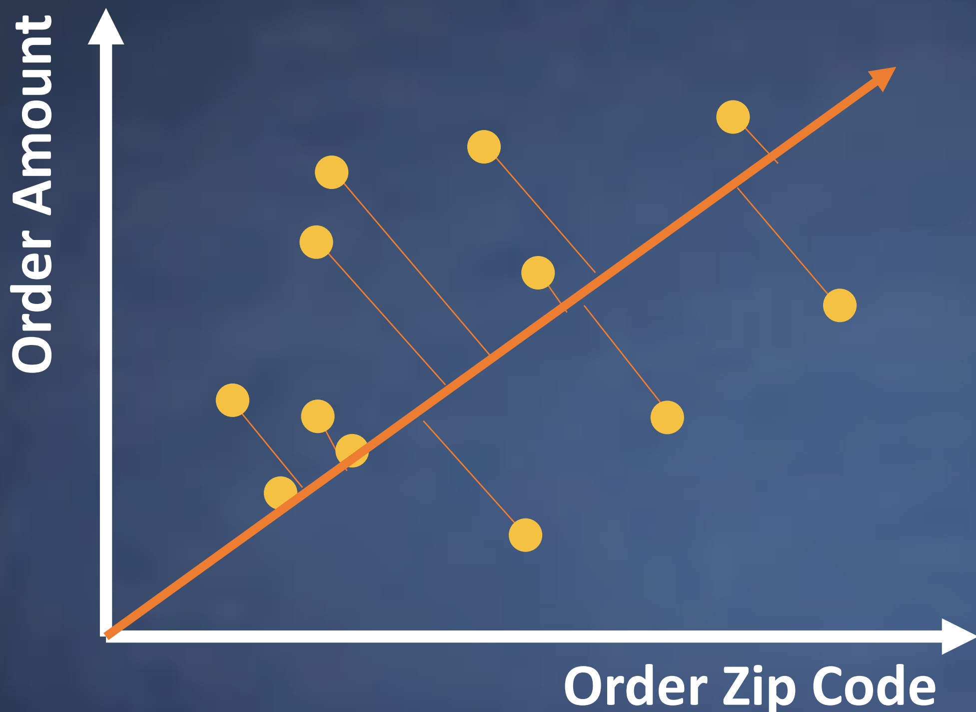
There is Only 1-Dim Order On Disk*

*Sure the disk is more complicated, but the API and the scanning of records is usually 1-dim

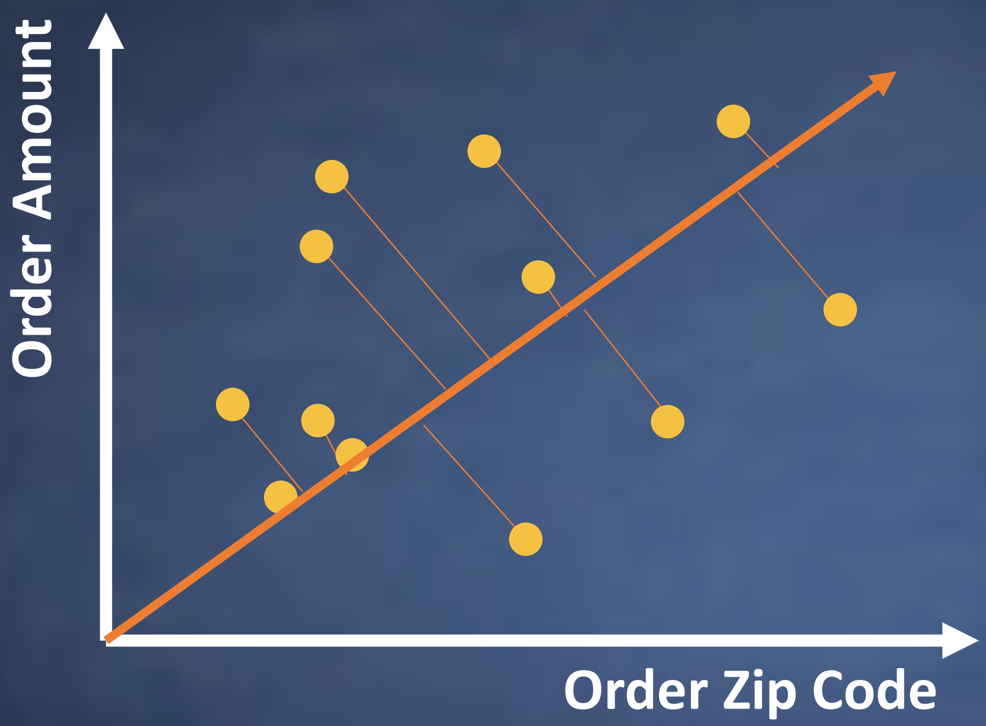
Example



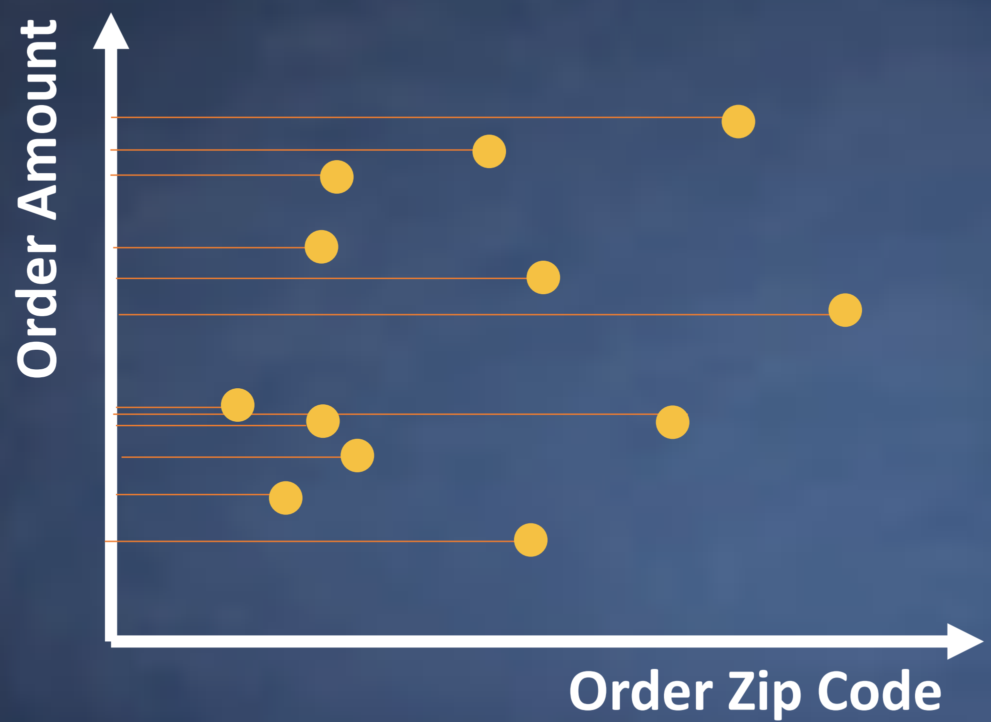
Equal Importance



Is It PCA?



Most Queries Are about **Order Amount**

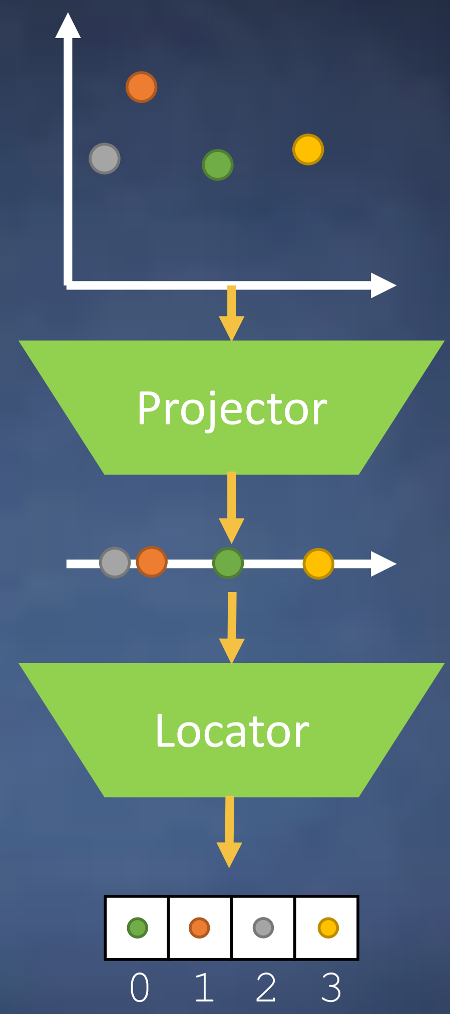


Most Queries Are about **Order Zip Code**

Can I mix the projections?

Can I mix the projections?

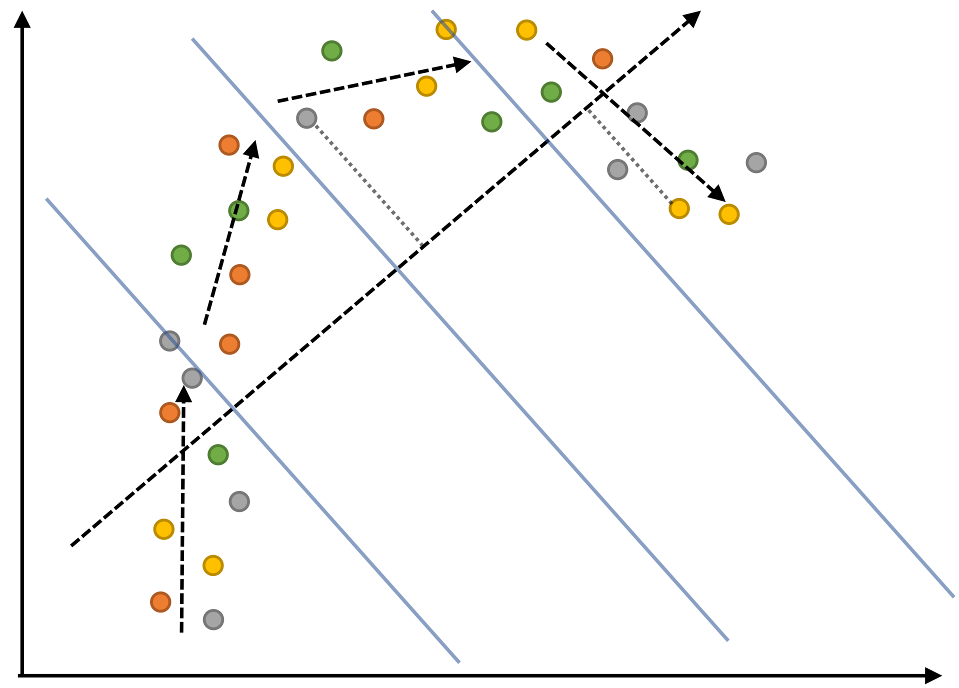
2 Models

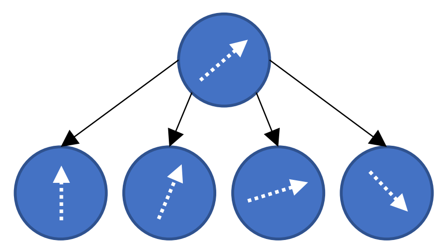


The projector

1. Root node define a primary direction
2. Project points on the root
3. Partition the space
4. Define directions for each sub-space

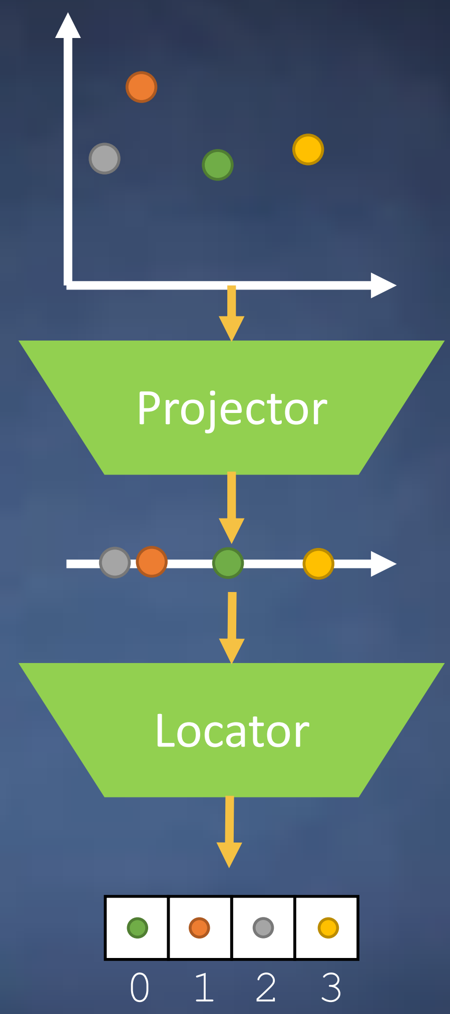
k. Recurse for any depth





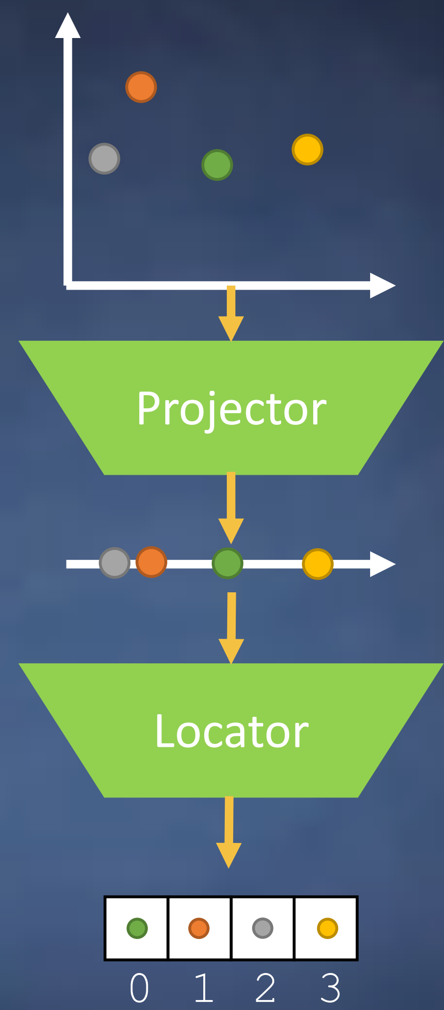
This is an RMI Model not a BTree

After Projection Locator is a Normal BTree RMI

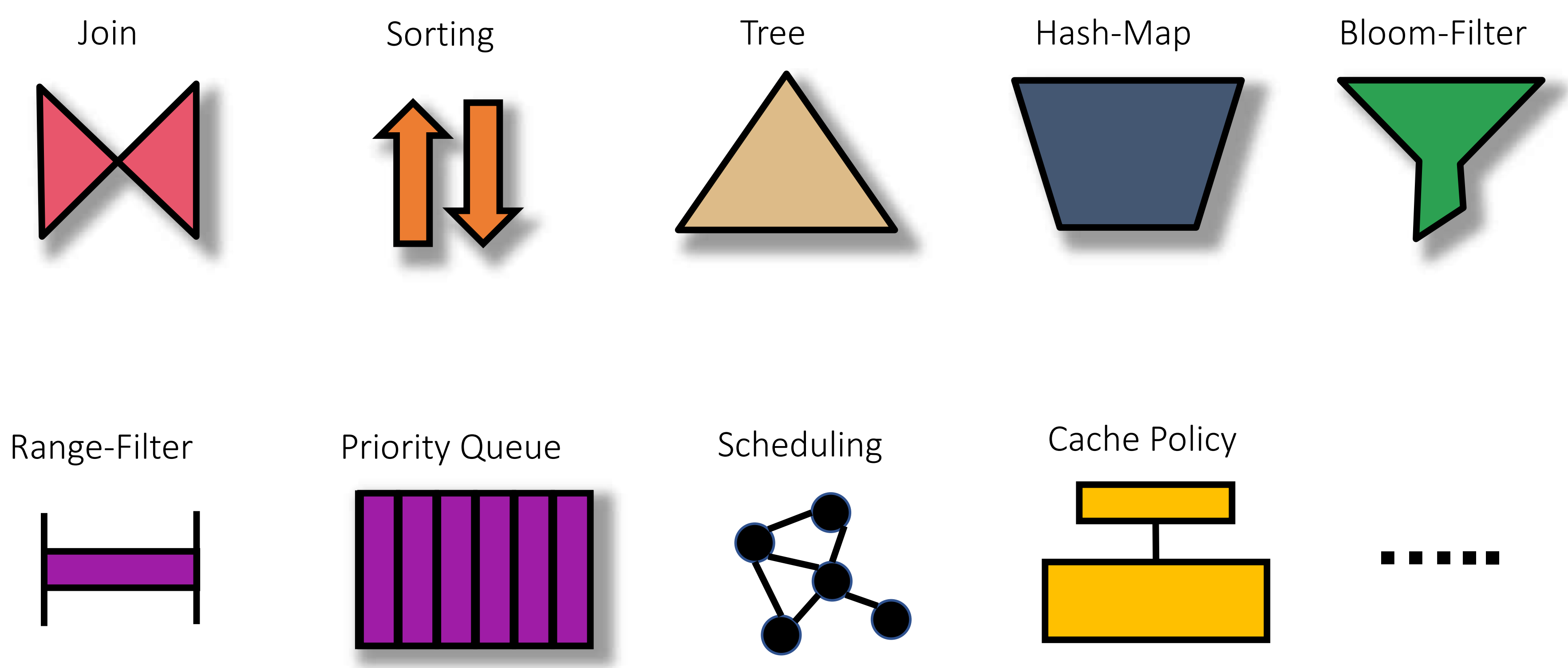


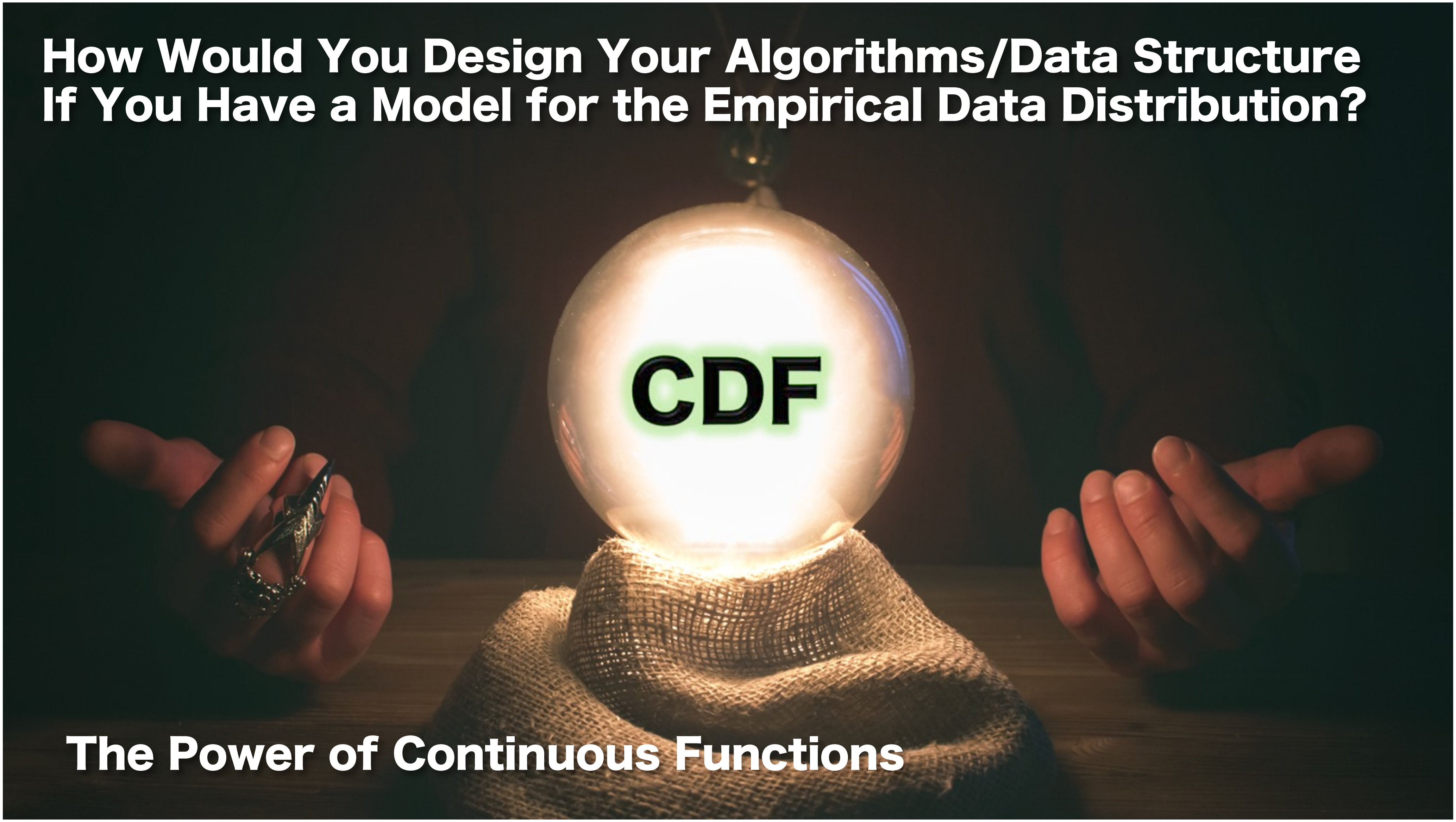
Early results (1M points, synthetic)

- ~200ns for point queries
- ~2x speed, ~10x space vs R-Trees



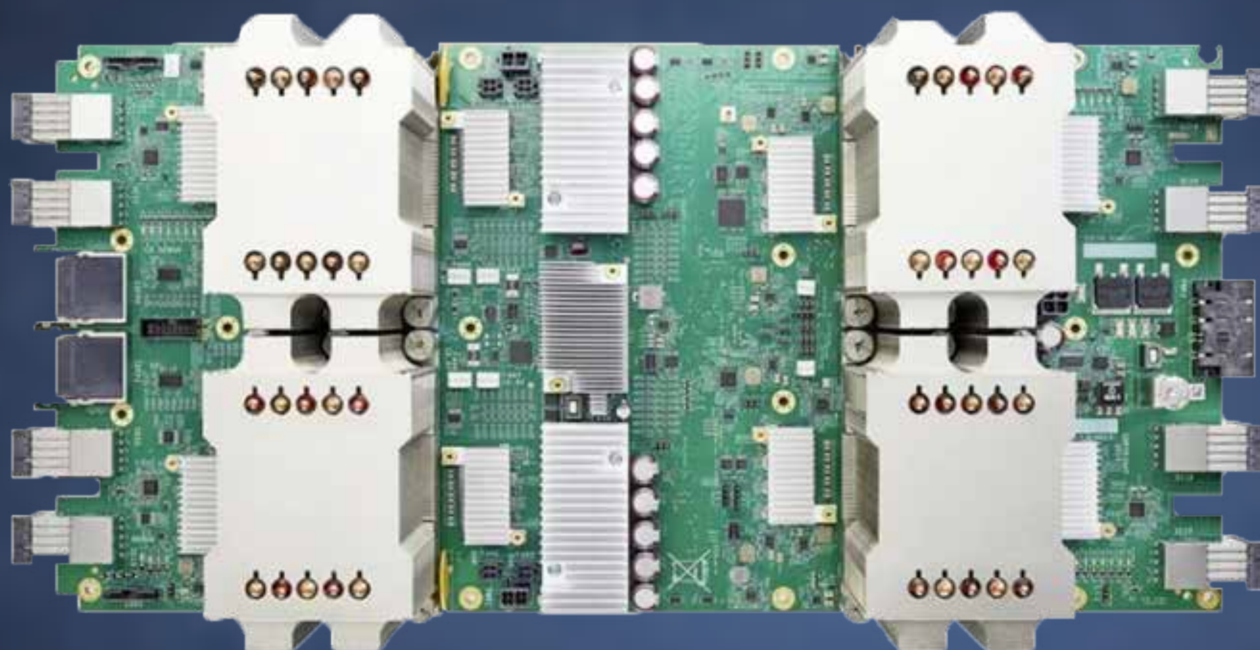
Future Work


Join
Sorting
Tree
Hash-Map
Bloom-Filter
Range-Filter
Priority Queue
Scheduling
Cache Policy
......

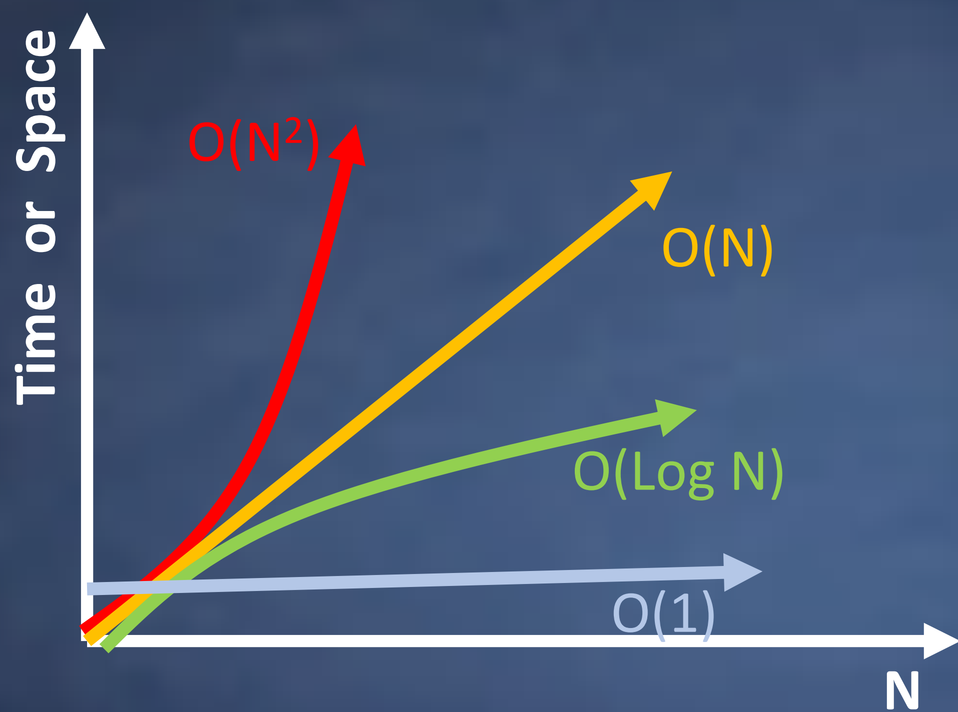

How Would You Design Your Algorithms/Data Structure
If You Have a Model for the Empirical Data Distribution?
CDF
The Power of Continuous Functions


Learned Adaptation

Big Potential For TPUs/GPUs



Can Lower the Complexity Class




```
data_array[(lookup_key – 900)]
```


Warning
Not An Almighty Solution

Data System for AI Lab DSAIL@CSAIL

Research Area

Data Systems for AI

AI for Data Systems

System Faculty

ML Faculty

Founding Sponsors

Google Microsoft intel

Work partially done at

Tim Kraska
<kraska@mit.edu>

- A new approach to indexing
- Framework to rethink many existing data structures/algorithms
- Under certain conditions, it might allow to change the complexity class of data structures
- The idea might have implications within and outside of DBMS

Related Work

- Succinct Data Structures → Most related, but succinct data structures usually are carefully, manually tuned for each use case
- B-Trees with Interpolation search → Arbitrary worst-case performance
- Perfect Hashing → Connection to our Hash-Map approach, but they usually increase in size with N
- Mixture of Expert Models → Used as part of our solution
- Adaptive Data Structures / Cracking → orthogonal problem
- Local Sensitive Hashing (LSH) (e.g., learened by NN)
  → Has nothing to do with Learned Structures

Thank you!

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