Novel Applications of AI Techniques in Database Management

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Agenda

1. Overview
2. Short Summary of Natural Language Interfaces, ML in DB and Data Managment Applications
3. Self-Management of Databases
4. Software 2.0

Overview

Overview

1 Natural Language Interfaces

1 Data Management Applications

2 Self-Management of Databases X

1 Machine Learning in Databases

3 Optimization by "Software 2.0" X

Short Summary of Natural Language Interfaces, ML in DB and Data Managment Applications

Natural Language Interfaces & ML in DB

Natural Language Interfaces

- Idea of using AI to interpret NL questions or requests and react accordingly
- quite old concept improved by modern hardware and technology

Machine Learning in Databases

- machine learning methods on data
- e.g. *Apache MADlib*, which implements
  - decision trees
  - random forest
  - bayes classifier
  - clustering
  - association rules
  - ...

Data Management Applications

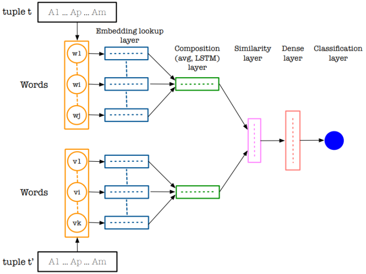


Figure 1: *by DeepER-Deep Entity Resolution, Muhammad Ebraheem et al*

Entity Resolution

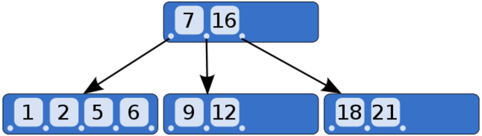
- Finding of Records that refer to the same entity
- Required if shape of data is not unitary

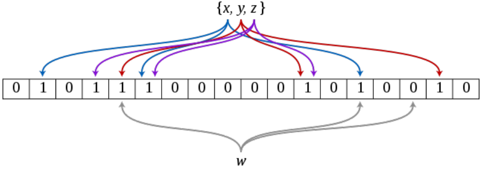
Self-Management of Databases

Self-Management of Databases

- *Tuning of parameters of Database Management Systems*
  - like cache amount and frequency of writing to storage
  - implementations like OtterTune *by Database Research Group at Carnegie Mellon University*
- *Elastic Scaling of Machine Allocation*
  - avoid latency spikes by action prediction through time-series prediction
  - implementations like P-Store *by Taft, MIT*
- *Learned Index Structures*
  - a “model can learn the sort order or structure of lookup keys and use this signal to effectively predict the position or existence of records”
  - alternative technology to exisiting Bloom-Filters or B-Trees

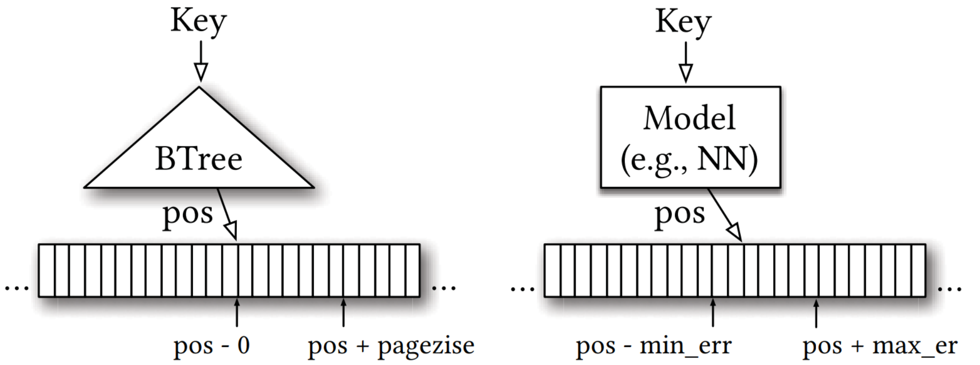
B-Tree Bloom-Filter





Learned Index Structures

What's the difference between Learned Index Structures and existing Models?



Learned Index Structures

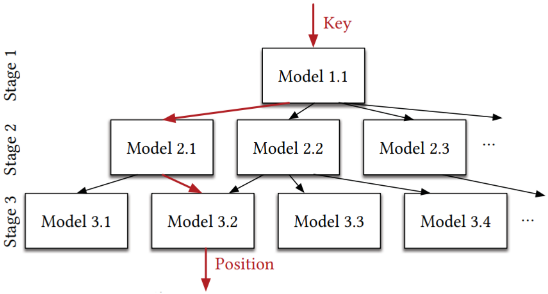
- Performance of Index Access can be unintuitively enhanced by predicting the index of a searched instance with a Neural Network or Linear Regression
- Shown to result in equally good or better performance than conventional Index Structures

Learned Index Structures by Example

Searching for a index

- Similar to every other model used
- Transform key to vector and use as input for trained NN

Enhancement of LIS: Recursive Model Index(RMI)



- refinement of models after every step to better display details
-

Learned Index Structucures Result

		Map Data			Web Data			Log-Normal Data		
Type	**Config**	Size (MB)	Lookup (ns)	Model (ns)	Size (MB)	Lookup (ns)	Model (ns)	Size (MB)	Lookup (ns)	Model (ns)
Btree	page size: 32	52.45 (4.00x)	274 (0.97x)	198 (72.3%)	51.93 (4.00x)	276 (0.94x)	201 (72.7%)	49.83 (4.00x)	274 (0.96x)	198 (72.1%)
	page size: 64	26.23 (2.00x)	277 (0.96x)	172 (62.0%)	25.97 (2.00x)	274 (0.95x)	171 (62.4%)	24.92 (2.00x)	274 (0.96x)	169 (61.7%)
	page size: 128	13.11 (1.00x)	265 (1.00x)	134 (50.8%)	12.98 (1.00x)	260 (1.00x)	132 (50.8%)	12.46 (1.00x)	263 (1.00x)	131 (50.0%)
	page size: 256	6.56 (0.50x)	267 (0.99x)	114 (42.7%)	6.49 (0.50x)	266 (0.98x)	114 (42.9%)	6.23 (0.50x)	271 (0.97x)	117 (43.2%)
	page size: 512	3.28 (0.25x)	286 (0.93x)	101 (35.3%)	3.25 (0.25x)	291 (0.89x)	100 (34.3%)	3.11 (0.25x)	293 (0.90x)	101 (34.5%)
Learned Index	2nd stage models: 10k	0.15 (0.01x)	98 (2.70x)	31 (31.6%)	0.15 (0.01x)	222 (1.17x)	29 (13.1%)	0.15 (0.01x)	178 (1.47x)	26 (14.6%)
	2nd stage models: 50k	0.76 (0.06x)	85 (3.11x)	39 (45.9%)	0.76 (0.06x)	162 (1.60x)	36 (22.2%)	0.76 (0.06x)	162 (1.62x)	35 (21.6%)
	2nd stage models: 100k	1.53 (0.12x)	82 (3.21x)	41 (50.2%)	1.53 (0.12x)	144 (1.81x)	39 (26.9%)	1.53 (0.12x)	152 (1.73x)	36 (23.7%)
	2nd stage models: 200k	3.05 (0.23x)	86 (3.08x)	50 (58.1%)	3.05 (0.24x)	126 (2.07x)	41 (32.5%)	3.05 (0.24x)	146 (1.79x)	40 (27.6%)

Figure 2: *The Case for Learned Index Structures by Kraska et al*

Learned Index Structures Conclusion

Advantages

- can take advantage of real world data patterns(ML) $\rightarrow$ allows for high optimization
- lower engineering costs

Disadvantages

- initial work on B-Trees and alike is lower since they do not require additional training

Software 2.0

Intro

- Classical Software Dev major downsides like difficult optimization of code and human error
- S2.0 doesn't base on declarative programming and tries to learn the desired functionality with a approximate base net
- enabled by development of Neural Networks in last 20 years allowing >100 layers deep networks
- program space is restricted for future training (backpropagation, gradien descent)
- many real world problems easier to detect desirable behaviour than to write a specific program

Advantages

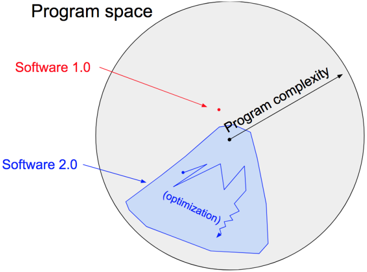
Higher Portability

- Smaller operation set
- Matrix Multiplication and thresholding at zero required
- small instruction set of chips with pretrained nets allows for

Better Performance

- allows for better performance and correctness predictions because closer implementation in hardware less core primitives are needed
- modules can be introduced to a single module reducing communication overhead by sacrificing clarity of separation, which is due to the human unlike nature of so2 sacrificed beforehand either way
- well trained neural nets outperform code implementation

Advantages



Better Runtime Predictability

- requires same amount of memory each iteration $\rightarrow$ low probability of infinite loops or locks
- speed well adjustable $\rightarrow$ speed can easily improved by reducing performance

Disadvantages

Unintuitivity

- can be treated as different new paradigm $\rightarrow$ requires rethinking of development style
- even though the network may work well, for humans difficult to understand
- developing in so2 is unintuitive and not well developed
- requires manually curating, maintaining, cleaning and labelling of datasets
- may not be applicable easily to all problems

Disadvantages

Nonrecognizable errors

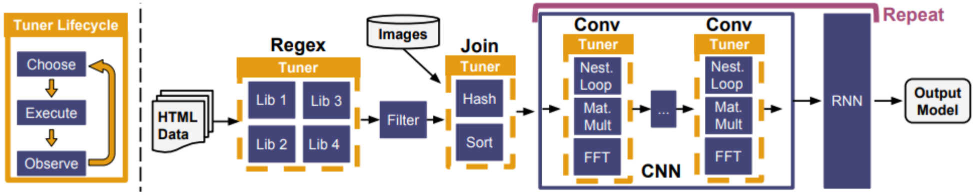
- errors may occur unpredictable
- can silently fail due to changed biases (hard to track since a large amount of them are being trained)

Lack of Tools

- no tools exist that support the development process like IDE, highlighting and alike for classical software

Example

Cuttlefish



Conclusion

Optimization

- Allows for greater optimization of complex problems
- e.g. Cuttlefish achieves 7.5x speedup to other query optimizers *Cuttlefish: A Lightweight Primitive for Adaptive Query Processing*

Development difficult

- No Tools and unexperienced developers

Thank you for your attention.

Do you have any questions? Ideas?
Be free to ask them.