



## How to kill two birds with one stone Leveraging Al investments to accelerate database systems



Microsoft Azure Data Gray Systems Lab



## The minds behind this talk:

#### **Query Processing on Tensor Computation Runtimes**

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#### Tensors: An abstraction for general data processing

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#### Share the Tensor Tea: How Databases can Leverage the Machine Learning Ecosystem

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A Tensor Compiler for Unified Machine Learning Prediction Serving

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#### WINDTUNNEL: Towards Differentiable ML Pipelines Beyond a **Single Model**

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ARTIFACT EVALUATED

## Al is growing (especially NN)





Predicting the Future of AI with AI: High-Quality link prediction in an exponentially growing knowledge network



## Big \$\$\$ spent on Special HW for NN

VCs are pouring \$2B/quarter

Market expected to exceed \$200B/year by 2025.





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https://www.statista.com/statistics/1003890/worldwide-artificial-intelligence-hardware-market-revenues/

#### **Tensor** Runtime



#### Very large/active communities

#### Tensor as de-facto API

PyTorch for AMD ROCm<sup>™</sup> Platform now available

Introducing Accelerated PyTorch Training on Mac







# How can Databases take advantage of this?

#### **Core Idea: Tensor Query Processing**

CPU



#### **Core Idea: Tensor Query Processing**









#### Pros

Leverage the massive investments in special HW

Scalable Approach (tensor runtimes are getting ported to each new HW)

#### Cons

- **?** Is this even possible?
- **?** What about performance?

? How expensive is it going to be? (engineering wise)

SELECT

GROUP BY

ORDER BY price DESC;

AS price,











#### **Example:** Tensor Program for Filter







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Scalable Approach (tensor runtimes are getting ported to each new HW)

#### Cons

- **?** Is this even possible?
- What about performance? (as compared with state-of-the-art)
- ? How expensive is it going to be? (engineering wise)



#### Pros

Leverage the massive investments in special HW

Scalable Approach (tensor runtimes are getting ported to each new HW)

✓ Is this even possible?  $\rightarrow$  YES we can easily cover TPC-H

#### Cons

What about performance?

? How expensive is it going to be? (engineering wise)

TQP Performance vs State of the Art





TPC-H Scale Factor 10GB, running on: 6 vCores, 112 GBRAM, P100 GPU

## **TQP** Portability (different HW)



TPC-H Scale Factor 1GB, running on: 6 vCores, 112 GBRAM (P100 relative speedup)

#### **TQP Price/Perf Comparison (vs DuckDB)**



TPC-H Scale Factor 10GB, running on: 8 vCores, 32 GBRAM (speed up vs DuckDB)

#### Performance on queries mixing ML and SQL



TQP supports mixing SQL and predictions of models built using PyTorch, scikit-learn and HuggingFace libraries.



Query time (in seconds) on a query mixing tree ensemble, one-hot encoding, feature scaling & concatenation with relational join, aggregation and filtering. In parentheses are the numbers of cores for CPU-based systems.



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#### Less than 10k LoC for TQP+ HB



Broader implications of having a DBMS co-existing with an ML runtime

1. Multi-modal data support



#### SELECT

input AS images, image\_text\_similarity\_model("KFC Receipt", input) AS score FROM attachments ORDER BY score DESC LIMIT 1



#### Future Directions: Al-Centric Database System

#### Broader implications of having a DBMS co-existing with an ML runtime

Multi-modal data support
Automatic Differentiation



Example Query Inputs



Example Query Outputs

	Digit	Size		Count
	0	S	mall	1
Digi		L	arge	0
0	1	S	mall	1
		L	arge	0
1	2	S	mall	0
		L	arge	1
2	3	S	mall	0
		Large		1
3	4	S	mall	0
		L	arge	0
4	5	Small		0
		Large		1
5	6	Small		0
		Large		0
6	7	Small		2
		Large		0
7	8	Small		0
		Large		2
8	9	Small		0
		L	arge	0
9	Sma	0		-1.5
	Large	2	2	



#### Conclusion



# Compile SQL to Tensor Programs Free-ride on \$B of dollars of HW/SW investments Performance looks great Low engineering costs Fun future directions



## Thanks!

#### https://aka.ms/gsl

Video credits: http://storyblocks.com