The Tensor Data Platform
Towards an AI-centric Database System

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AI is growing...and having an impact on applications...and DBMS.

Enter your favorite chart showing how AI is taking over the world.

Unlocking the value of unstructured data at scale using BigQuery ML and object tables.
Anatomy of next gen data-driven applications

1. Support for multimodal data (image, video, relational, audio, etc.)
   • Not many relational systems with proper image/video/etc. support
   • Many specialized systems are moving towards supporting “scalar” queries

2. Tight integration and interoperability with ML
   • Most systems either (partially) re-implement ML features in SQL ...
   • ... Or call external ML runtimes

3. Native support for hardware acceleration
   • Most systems are built on single vendor tech (CUDA)
   • Supporting other stacks (AMD, Apple, etc.) requires nontrivial engineering effort

Claim: Building a data engine with all three is hard!
Tensor Runtimes

1. Support for multimodal data
   • Thanks to the Tensor abstraction

2. Native support for hardware acceleration
   • Large open-source communities with HW vendors involvement

3. Tight integration and interoperability with ML
   • ML capabilities embedded into the system and language (e.g., autodiff)

Question: Can we build a database on top of tensor runtimes?
AI-centric Database: Outline

1. Support for multimodal data
2. Native support for hardware acceleration
3. Tight integration and interoperability with ML
Tensor data representation

Def Tensor:

A multidimensional matrix that is a cornerstone data structure in AI

| Sales | saleid | prodid | date | region |
|-------|--------|--------|------|--------|
| 1     |        |        |      |        |
| 2     |        |        |      |        |
| 3     |        |        |      |        |
| 4     |        |        |      |        |
| 5     |        |        |      |        |
| 6     |        |        |      |        |
| 7     |        |        |      |        |
| 8     |        |        |      |        |
| 9     |        |        |      |        |
| 10    |        |        |      |        |
Tensor data representation

**Def Tensor:**

A multidimensional matrix that is a cornerstone data structure in AI.
Tensor data representation

**Def Tensor:**

A multidimensional matrix that is a cornerstone data structure in AI

We leverage torch, torchaudio, torchvideo, etc, for loading data into tensor format

We have our own custom tensor class: **EncodedTensor** = tensor + metadata

PlainEncoding,

DictionaryEncoding (data tensor + 2-d dictionary metadata tensor)

ProbabilisticEncoding (data tensor + a domain dictionary)

...
SQL on Images Demo
Quering images

The goal of this notebook is to show how image data can be loaded on TQP and how we can use TQP capabilities to query images.

1. Setup

2. Filter images based on Natural Language Query
AI-centric Database: Outline

1. Support for multimodal data

2. Native support for hardware acceleration

3. Tight integration and interoperability with ML
The Tensor Data Platform (TDP)

In process and 100% Python!

Classical ML Inference: Hummingbird
SQL: TQP

Performance highlights

| Dataset      | Speedup |
|--------------|---------|
| TPCH SF 100  | 103     |

Spark 5, SQL Server 10, DuckDB 3, RateUpDB
Al-centric Database: Outline

1. Support for multimodal data
2. Native support for hardware acceleration
3. Tight integration and interoperability with ML
SQL as a declarative language for Differentiable Programming

Gradients are the staple mechanism by which we learn in machine learning.

Tensor runtimes have a remarkable tool to compute gradients Automatic Differentiation

TDP extends SQL by taking advantage of automatic differentiation in PyTorch

Particularly, we add the following to SQL:
1. Trainable User Defined Functions (UDFs) and Table Valued Functions (TVFs)
2. Differentiable Relational Operators (e.g., Differentiable Group By, Aggregation, Filters, etc.)
Trainable SQL Queries

We can execute SQL queries that combines trainable operations with relational operators.

MNISTGrid Dataset

| Digit | Size | Count |
|-------|------|-------|
| 0     | Small| 1     |
|       | Large| 0     |
| 1     | Small| 1     |
|       | Large| 0     |
| 2     | Small| 0     |
|       | Large| 1     |
| 3     | Small| 0     |
|       | Large| 1     |
| 4     | Small| 0     |
|       | Large| 0     |
| 5     | Small| 0     |
|       | Large| 1     |
| 6     | Small| 0     |
|       | Large| 0     |
| 7     | Small| 2     |
|       | Large| 0     |
| 8     | Small| 0     |
|       | Large| 2     |
| 9     | Small| 0     |
|       | Large| 0     |

MNISTGrid Task

Compute the grouped (Digit, Size) counts from the image.

Trainable Query

```
SELECT Digit, Size, COUNT(*)
FROM parseMNISTGrid(MNISTGrid)
GROUP BY Digit, Size
```
Anatomy of a Trainable Query

```sql
SELECT Digit, Size, COUNT(*)
FROM parseMNISTGrid(MNISTGrid)
GROUP BY Digit, Size
```
SELECT Digit, Size, COUNT(*)
FROM parseMNISTGrid(MNISTGrid)
GROUP BY Digit, Size
Anatomy of a Trainable Query

```
SELECT Digit, Size, COUNT(*)
FROM parseMNISTGrid(MNISTGrid)
GROUP BY Digit, Size
```

digit_parser = CNN(out_classes=10).to(device)
size_parser = CNN(out_classes=2).to(device)

@tdp_udf("Digit float, Size float")
def parseMNISTGrid(x: torch.Tensor) -> torch.Tensor:
    # Break up grid into a batch of 9 images
    grid = rearrange(x[0], "(h1 h2) (w1 w2) -> (h1 w1) 1 h2 w2", h1=3, w1=3)

    # Parse digits from images
    parsed_digits = digit_parser(grid)
digit_domain = np.arange(10)
encoded_digits = ProbabilisticEncoding.encode(parsed_digits, digit_domain)

    # Parse size from images
    parsed_sizes = size_parser(grid)
size_domain = np.arange(2)
encoded_sizes = ProbabilisticEncoding.from_encoded_data(parsed_sizes, size_domain)

    return encoded_digits, encoded_sizes
```
SELECT Digit, Size, COUNT(*)
FROM parseMNISTGrid(MNISTGrid)
GROUP BY Digit, Size

Anatomy of a Trainable Query
Anatomy of a Trainable Query

**SELECT** Digit, Size, \(\text{COUNT}(*)\)

**FROM** `parseMNISTGrid(MNISTGrid)`

**GROUP BY** Digit, Size

The query combines neural and relational operators and is end-to-end differentiable.

**Digit**

| Digit | Size | Count |
|-------|------|-------|
| 0     | Small| 1     |
| 1     | Large| 0     |
| 2     | Small| 0     |
| 3     | Large| 1     |
| 4     | Small| 0     |
| 5     | Large| 1     |
| 6     | Small| 0     |
| 7     | Large| 0     |
| 8     | Small| 0     |
| 9     | Large| 0     |
The alternative: pure Deep Learning

The standard way to tackle this problem would be to pose it as a multiple regression problem with a single monolithic neural network.

```
| Digit | Size | Count |
|-------|------|-------|
| 0     | Small| 1     |
|       | Large| 0     |
| 1     | Small| 1     |
|       | Large| 0     |
| 2     | Small| 0     |
|       | Large| 1     |
| 3     | Small| 0     |
|       | Large| 1     |
| 4     | Small| 0     |
|       | Large| 0     |
| 5     | Small| 0     |
|       | Large| 1     |
| 6     | Small| 0     |
|       | Large| 0     |
| 7     | Small| 2     |
|       | Large| 0     |
| 8     | Small| 0     |
|       | Large| 2     |
| 9     | Small| 0     |
|       | Large| 0     |
```

Disadvantages:
1. Entanglement of tasks (cannot separate digit classification from size classification or aggregation)
2. Cannot generalize to other tasks
3. Needs to learn from scratch what it means to group and count
Trainable Query vs pure Deep Learning

- **Datasets:**
  - MNISTGrid Train/Test: 5000/1000 Grids

- **Training Hyperparameters (Fixed):**
  - Learning Rate = 0.0001
  - Training Iterations = 40,000 iterations

- **Architecture (Varied):**
  - TDP Trainable Query (860K Parameters)
  - Pure Deep Learning CNN-Small (850K Parameters)
  - Resnet-18 (11.1M Parameters)

- 5 runs per architecture

Our approach trains significantly faster than a purely deep learning model

Our SQL can declaratively express **Neurosymbolic** [1] systems that are end-to-end trainable

[1] Neurosymbolic AI CACM oct 2022
Summary

🔥 The space of AI-powered databases is heating up

🚀 Al-centric Database could be a leap forward. Free-ride on:

1. $B of HW/SW investments for AI
2. Multimodal support
3. Seamless integration with latest and biggest ML models
4. Novel querying paradigms such as trainable queries

Exciting future directions

1. TensorFrame API
2. Expressing some ML tasks in a more natural way
   - Learning from Label Proportions
Thank you!

https://aka.ms/gsl
ML-first user experience

ML within SQL: UDF-based programming model
- We use UDF to access the tensor API
- Still end-to-end on HW accelerators

```python
SELECT images
FROM Attachments
WHERE image_text_similarity("dog", images) > 0.80

model = CLIPModel.from_pretrained("openai/clip-vit-base-patch32")
processor = CLIPProcessor.from_pretrained("openai/clip-vit-base-patch32")

@tdp_udf("float")
def image_text_similarity(query: str, images: torch.Tensor) -> torch.Tensor:
    inputs = processor(text=[query], images=images, return_tensors="pt", padding=True)
    inputs.to(device)
    outputs = model(**inputs)
    scores = outputs.logits_per_image.flatten() / 30
    return scores
```
ML-first user experience

ML within SQL: UDF-based programming model
- We use UDF to access the tensor API
- Still end-to-end on HW accelerators

SQL within ML: Embedding queries into PyTorch programs
- Use the right tool for the right task
- Thanks to trainable SQL queries

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    inputs.to(device)
    outputs = model(**inputs)
    scores = outputs.logits_per_image.flatten() / 30
    return scores

def train(compiled_query, num_iterations, optimizer, mnist_grids, target_counts):
    for i in range(num_iterations):
        optimizer.zero_grad()

        # Register MNISTGrid and perform inference with the query
        tqp.sql.register_tensor(mnist_grids[i], "MNIST_Grid")
        predicted_counts = compiled_query.run()

        # Compute loss. Here we use MSE between the counts.
        loss = ((predicted_counts - target_counts[i]) ** 2).mean()

        # Backpropagate and perform optimization step
        loss.backward()
        optimizer.step()
```
TQP

100% Python
TQP supports the full TPCH benchmark
Performance highlights

```
SELECT MAX(p_supplycost) AS price, s_name AS supp
FROM supplier
JOIN partsupp
ON ps_suppkey=s_suppkey
GROUP BY supplier.s_name
ORDER BY price DESC;
```
TQP: A100 with 80GB. Spark/SQLServer/DuckDB: 32 cores machine with 256GB. RateUp: Nvidia Quadro RTX 8000
Differentiable Grouped Aggregation

Let’s see how we might make the “Group By + Aggregation” operation differentiable.

| Inventory |
|-----------|
| Fruit    | Vegetable | Price |
| apple    | carrot    | 4.0   |
| banana   | carrot    | 2.0   |
| apple    | carrot    | 4.0   |
| banana   | potato    | 3.5   |

| Query |
|-------|
| SELECT Fruit, Vegetable, COUNT(*) |
| FROM Inventory |
| GROUP BY Fruit, Vegetable |

| Query Answer |
|--------------|
| Fruit | Vegetable | Count |
| apple | carrot    | 2     |
| apple | potato    | 0     |
| banana| carrot    | 1     |
| banana| potato    | 1     |
Differentiable Grouped Aggregation

Let’s see how we might make the “Group By + Aggregation” operation differentiable.

We can do this in three steps:
1. Relax discrete data to continuous representation.
2. Create masks corresponding to each group.
3. Perform aggregation using the mask and data.
Differentiable Grouped Aggregation

Let’s see how we might make the “Group By + Aggregation” operation differentiable.

| Fruit | Vegetable | Price |
|-------|-----------|-------|
| apple | carrot    | 4.0   |
| banana| carrot    | 2.0   |
| apple | carrot    | 4.0   |
| banana| potato    | 3.5   |

We can do this in three steps:
1. Relax discrete data to continuous representation. *(Assume data is pre-encoded)*
2. Create masks corresponding to each group. *(Needs to be differentiable)*
3. Perform aggregation using the mask and data. *(Needs to be differentiable)*
Differentiable Grouped Aggregation

Step 1: Relax discrete data to continuous representation.

| Fruit | Vegetable | Price |
|-------|-----------|-------|
| apple | carrot    | 4.0   |
| banana| carrot    | 2.0   |
| apple | carrot    | 4.0   |
| banana| potato    | 3.5   |

We can use One Hot Encoding (OHE) for categorical columns.

| Inventory |
|-----------|
| Fruit     | Vegetable | Price |
|-----------|-----------|-------|
| apple     | banana    | 0     |
| carrot    | carrot    | 1     |
| apple     | carrot    | 0     |
| banana    | potato    | 1     |

We assume data is pre-encoded to this format before being fed into our differentiable operator.
Differentiable Grouped Aggregation

Step 2: Create masks corresponding to each group.

With the OHE strategy of categorical data representation, creating a group mask requires only element-wise product (which is differentiable).

| Fruit | Vegetable | Price |
|-------|-----------|-------|
| 1.0   | 0.0       | 4.0   |
| 0.1   | 1.0       | 2.0   |
| 1.0   | 0.0       | 4.0   |
| 0.1   | 1.0       | 3.5   |

With the OHE strategy of categorical data representation, creating a group mask requires only element-wise product (which is differentiable).
Differentiable Grouped Aggregation

Step 3: Perform aggregation using the mask and data.

| Fruit | Vegetable | Price |
|-------|-----------|-------|
| 1.    | 0.        | 4.0   |
| 0.    | 1.        | 2.0   |
| 1.    | 0.        | 4.0   |
| 0.    | 1.        | 3.5   |

Inventory

Mask for Group: (apple, carrot)

| (apple, carrot) |
|-----------------|
| 1.0             |
| 0.0             |
| 1.0             |
| 0.0             |

Aggregation

\[ \sum \] 2.0
Differentiable Grouped Aggregation (GROUP BY + COUNT)

Step 3: Perform aggregation using the mask and data.

| Inventory | Mask for Group: (apple, carrot) | Aggregation |
|-----------|--------------------------------|-------------|
| Fruit | Vegetable | Price | (apple, carrot) | Count |
| apple | banana | carrot | potato |
| 1. | 0. | 1. | 0. | 4.0 | 1.0 |
| 0. | 1. | 1. | 0. | 2.0 | 0.0 |
| 1. | 0. | 1. | 0. | 4.0 | 1.0 |
| 0. | 1. | 0. | 1. | 3.5 | 0.0 |

Query Answer

| Fruit | Vegetable | Count |
|-------|-----------|-------|
| apple | carrot | 2 |
| apple | potato | 0 |
| banana | carrot | 1 |
| banana | potato | 1 |

We have only used product and sum, both of which are differentiable.
Differentiable Grouped Aggregation (GROUP BY + SUM)

Step 3: Perform aggregation using the mask and data.

| Fruit | Vegetable | Price |
|-------|-----------|-------|
| 1.    | 0.        | 4.0   |
| 0.    | 1.        | 2.0   |
| 1.    | 0.        | 4.0   |
| 0.    | 1.        | 3.5   |

Inventory

Fruit
- apple
- banana
- carrot
- potato

Vegetable
- apple
- carrot
- potato

Price
- 4.0
- 2.0
- 4.0
- 3.5

Summands for Group:
- (apple, carrot)

Aggregation

\[ \sum \]

8.0

Query Answer

| Fruit   | Vegetable | SUM(Price) |
|---------|-----------|------------|
| apple   | carrot    | 8.0        |
| apple   | potato    | 0.0        |
| banana  | carrot    | 2.0        |
| banana  | potato    | 3.5        |

Query

SELECT Fruit, Vegetable, SUM(Price)
FROM Inventory
GROUP BY Fruit, Vegetable
Differentiable Grouped Aggregation (GROUP BY + MAX)

Step 3: Perform aggregation using the mask and data.

**Inventory**

| Fruit | Vegetable | Price |
|-------|-----------|-------|
| 1.    | 0.        | 4.0   |
| 0.    | 1.        | 2.0   |
| 1.    | 0.        | 4.0   |
| 0.    | 1.        | 3.5   |

**Query**

```
SELECT Fruit, Vegetable, MAX(Price)
FROM Inventory
GROUP BY Fruit, Vegetable
```

**Aggregation**

![Diagram showing the aggregation process and resulting query answer]

**Query Answer**

| Fruit   | Vegetable | SUM(Price) |
|---------|-----------|------------|
| apple   | carrot    | 3.93       |
| banana  | carrot    | 2.0        |
| banana  | potato    | 3.5        |
Differentiable Filtered Aggregation (WHERE + SUM)

| Fruit | Vegetable | Price |
|-------|-----------|-------|
| 1.    | 0.        | 1.0.  |
| 0.    | 1.        | 1.0.  |
| 1.    | 0.        | 1.0.  |
| 0.    | 1.        | 1.0.  |

Fruit: apple, banana, carrot, potato

Query:

```
SELECT SUM(Price)
FROM Inventory
WHERE Price > 2.5
```

Aggregation: \( \sum \) 11.51
Case Study: Multimodal Email Search

MAIDAP has been working with MSAI to explore multimodal search capabilities for outlook.

An example of relevant data analysis:

What is the count of the different types of image attachments in outlook emails?

Regular Images  Receipts  Company Logos

Surakav’s multimodal support makes it easy to answer such queries.
Tensors are the de facto data structure for multimodal computation

The tensor data structure has been used to represent numerous rich entities.

Surakav can exploit tensors for multimodal query support.