Auto-Differentiation of Relational Computations for Very Large-Scale Machine Learning

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Auto-Differentiation (auto-diff) has been a key component in modern machine learning systems (JAX, PyTorch, Tensorflow)

- Forward Pass is specified by user. Backward Pass is generated by system
- The process of evaluating gradient can be error-prone and tedious

However, current auto-differentiation library is only based on Linear Algebra What if differentiating ML computations in Relational Algebra?

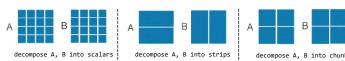
Central Questions

(1) How to auto-differentiate arbitrary computation in Relational Algebra? (2) Database systems (DBMS) are built on top of Relational Algebra. If DBMS are equipped with differentiation ability, what are the benefits?

Background: Database for Machine Learning

Relational Algebra is the theoretical foundation for SQL, which is the query language on top of modern relational databases. For example, a distributed matrix multiplication can be specified in Relational Algebra/SQL:





Benefits:

- Declarative Interface
- Automatic Parallelization, Distribution and Optimization
- No data export/import overhead

BigQuery

Easy to scale to large-scale datasets and models

Vector Database support ML:









Functional Relational Algebra

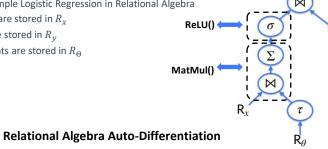
∇ denotes the vector differential operator which is a high-order function, requiring functions as input and output. We define relational algebra operations are high-order functions:

- Select (σ):(predicate, projection, kernel function, input)->R
- Join (\bowtie): (predicate, projection, kernel function, left input, right input)->R



Example: a simple Logistic Regression in Relational Algebra

- Features are stored in R_r
- Labels are stored in R_{ν}
- Coefficients are stored in R_{Θ}



We derive Relation-Jacobian Products (RJP) for Select (σ) , Join (\bowtie) , Aggregation (Σ) , TableScan (τ) in relational domain. They are analogous to Vector-Jacobian Product (VJP) in Linear Algebra

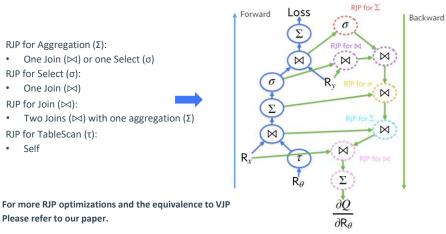
- The kernel functions can be differentiated by utilizing JAX/autograd
- RJP rules are implemented efficiently without materialization of Jacobian

RJP for Aggregation (Σ): One Join (⋈) or one Select (σ) RJP for Select (σ) : One Join (⋈) RJP for Join (\bowtie) :

 Two Joins (⋈) with one aggregation (Σ) RJP for TableScan (τ):

Self

Please refer to our paper.



Loss

Main Experiment Results

Experiment settings: AWS m5.4xlarge instances (1 to 16 nodes).

All the Implementation is on top of a relational database engine - plinycompute

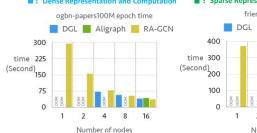
- Non-Negative Matrix Factorization (RA-NNMF)
- Graph Convolutional Networks (RA-GCN)
- Large-scale Knowledge Graph Embeddings (RA-KGE)

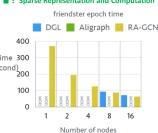
Baseline systems for GCN: DGL, Aligraph (graph-learn)

Datasets: ogbn-papers100M (N=0.1B, E=1.6B), friendster (N=65.6M, E=3.6B)

Graph Convolution in Relational Algebra/SQL

Node (ID INT, vec VECTOR [2048]) Edge (sourceID INT , destID INT) SELECT n1.ID as n.ID , ReLU(MAT_MUL(AVG(Normalize(n2.vec)))) as n.vec FROM Node as n1 , Edge as e , Node as n2 WHERE n1.ID = e.sourceID and n2.ID = e.destID GROUP BY n1.ID ■: Dense Representation and Computation : Sparse Representation and Computation

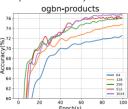




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Boost performance through Large Embedding (64 to 1024 embedding vector)

1024 embedding can only be handled by RA-GCN



Key findings:

- (1) A relational system, equipped with this auto-diff technology, could show better scalability than other systems, even special purposed ML engines.
- (2) RA-GCN is the only one that can handle graph preprocessing, graph loading and training without any OOM error.

Further details and the relevant code:

https://github.com/yuxineverforever/Relational-Algebra-Auto-Differentiation