Data Stream Query Optimization Using Deep Reinforcement Learning

Final presentation

Apoorva Tamaskar

Boston University
Metropolitan College

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Outline

Section 1

SQL

Introduction

Given a SQL query, how is it executed?

```
1        SELECT MovieTitle
2        FROM StarsIn
3        WHERE StarName IN(
4            SELECT name
5            FROM MovieStar
6            WHERE birthdate LIKE '%1960'
7        );
8
```

Listing 1: SQL query to execute.

SQL: Pipeline

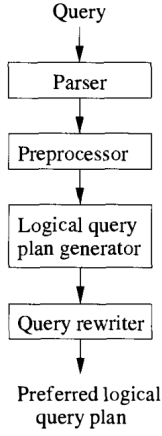

Figure: The pipeline for query processing

SQL: Parser

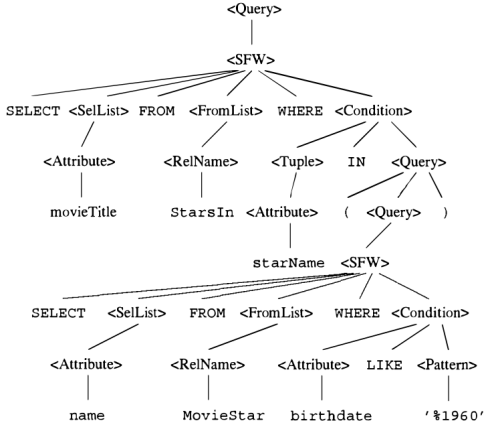

Figure: An example of parse tree

SQL: Preprocessing

Sanity checking

1. Check relation uses
2. Check and resolve attribute uses.
3. Check types.

SQL: Relational Algebra

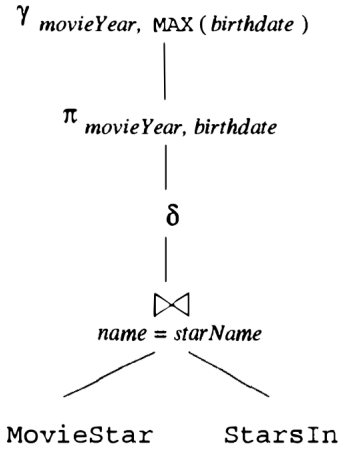

Figure: An example of join being optimized

SQL: Relational Algebra

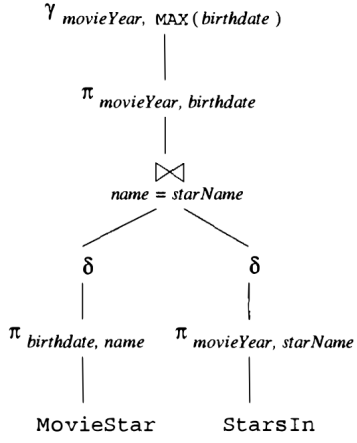

Figure: An example of Relational Algebra being used for optimization

SQL: Rewrite

Need to convert the query plan using Relational Algebra into a query plan which requires has lowest cost according to estimates.

SQL: Cost: Estimation

1. Give accurate estimates. No matter what method is used for executing query plans.
2. Are easy to compute.
3. Are logically consistent.

SQL: Cost: Methods

1. Histogram
2. Heuristics
3. Top-Down
4. Bottom-up
5. Dynamic Programming
6. Branch-and-Bound
7. Hill Climbing
8. Selinger-Style Optimization

SQL: Cost: Considerations

1. An order and grouping for associative-and-commutative operations
2. An algorithm for each operator
3. Additional operators - scanning, sorting
4. The way in which arguments are passed

SQL: Joins

1. Algorithm Nested-loop join
2. Algorithm Index join
3. Order Dynamic Programming
4. Order Greedy

SQL: Physical Plan

1. Selection, Index based
2. Selection, Table Scan
3. Join, One-pass join
4. Join, Hash join
5. Join, Index join

Section 2

Data Streams

Stream Query Optimization

Modifying queries by changing graph topology and/ or operators to get better performance, as measured by

1. Throughput
2. Latency
3. Resource Usage.

While preserving semantice of the original query.

Stream Graph

Queries on Data streams can be thought of as directed graphs,

1. Edges represent streams and nodes represent operators.
2. Root and leaf nodes are called sources and sinks, respectively.

Whereas for traditional Databases, we have parse trees.

Possible Optimizations

- Batching
- Placement
- State sharing
- Load Balancing
- Algorithm selection
- Load Shedding
- Fusion
- Operator Separation
- Operator Reordering
- Redundancy elimination
- Fission

Operator Reordering

A reordering operator moves more selective operators, which reduce the data volumen upstream. This has the benefit of reducing the amount of data flowing into downstream compuration. Thus eliminatin unnecessary work. We focus on finding the optimal method of executing associative opeators.

Research Question

Is it possible to apply deep reinforcement learning to find the optimal ordering of executing associative operators?

Section 3

Deep Reinforcement Learning

Deep Neural Networks

Deep neural networks is a layer wise combinations of neurons
Building up on the neuron seen in the last slide. We have

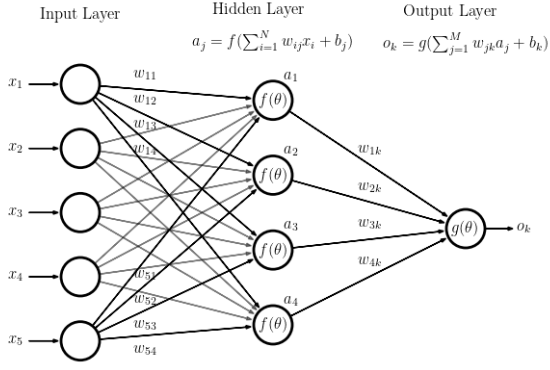

Figure: Example of a deep neural network

Backpropogation

By doing backpropogation on each node, we finish the process.

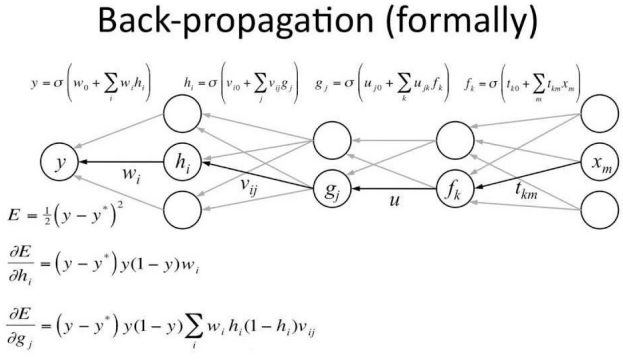

Figure: Example of backpropogation

Reinforcement Learning

What is reinforcement learning? How is it different from supervised and unsupervised learning?

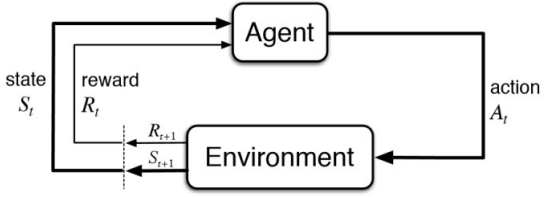

Figure: Example of a framework of a reinforcement learning agent

Value Iteration

```
    for s in S:
        V(s)=0
    while(not converged):
        for s in S:
            V(s)=R(s)+max over all action[gamma*(sum(P(s,a,s')V(s')))]

```

Listing 2: value iteration algorithm

Policy Iteration

```
initialize random pi
while(not converged):
    V=V(pi)
    for s in S:
        pi(s)=max over all actions[sum(P(s,a,s')V(S'))]
```

Listing 3: Policy iteration algorithm

Deep Reinforcement Learning

Deep reinforcement learning combines Deep learning and reinforcement learning

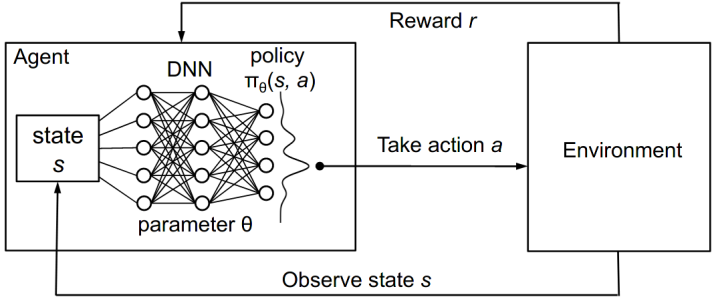

Figure: Deep Reinforcement learning(DQN) framework

Section 4

Linear Road

Linear Road

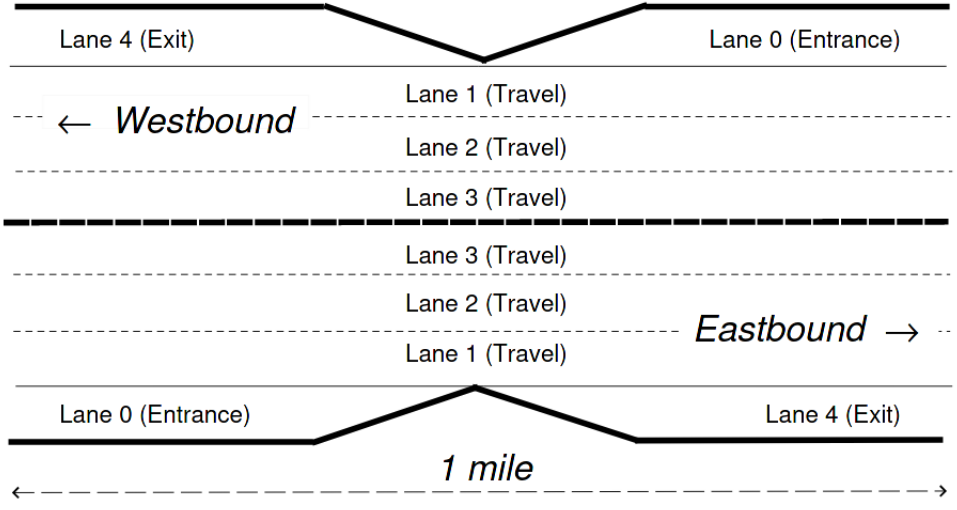

Figure: An Example Expressway Segment

Query to execute

```
1        SELECT S.exp_way, S.dir, S.seg, basetoll*(V.volume-150)*(V.volume-150)
2        FROM SegAvgSpeed as S, SegVol as V
3        WHERE S.exp_way = V.exp_way and S.dir = V.dir and S.seg = V.seg
4              and S.speed <= 40;
5
```

Listing 4: SEGTOLL linear road query

Section 5

Implementation and Justification

Implementation: Query Execution

1. Mimicked the execution of query in C++.
2. Given there are 24 possible orderings, executed all of them and recorded how much time and the number of operations they took.
3. For each window of data, extracted the entropy of columns, size of tables and stored these.

Implementation: DQN

Training

1. Input the column wise entropy, the size of tables and the 1-hot encoding of ordering of operations.
2. The reward for the training is taken to be the number of operations required.

Prediction

1. Predict the reward for each ordering, for given entropy vector+ table size.
2. The rewards represent number of operations required.
3. Check which ordering has least number of operations, this ordering is optimal.

Justification

The things considered while determining the neural network to use for training the DQN are :-

- Value of loss function
- Time for prediction/ Complexity of model
- Resources for training

Justification

What we found was:-

- Adding additional layers improves the prediction of the optimal moves but not by significant margin.
- Adding additional layers resulted in the time spent predicting the answer overshadowing the time saved by executing the optimal move.

These are only query and data specific findings.

Section 6

Results, Conclusion and Further Work

Data Distribution

The data obtained by executing all the orderings for the query plan on Linear road data, resulted in the following frequencies for optimal orderings.

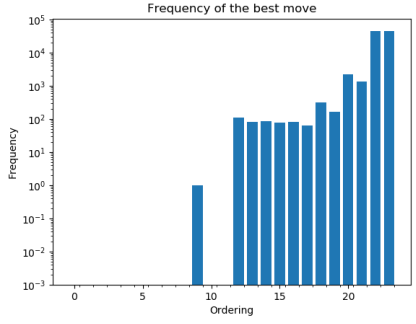

Figure: This figure shows the frequency distribution of the number of cases where each move is optimal

Data Distribution

While training and testing the DQN model, we divided the total data into a 70 : 30 for training and testing purposes respectively.

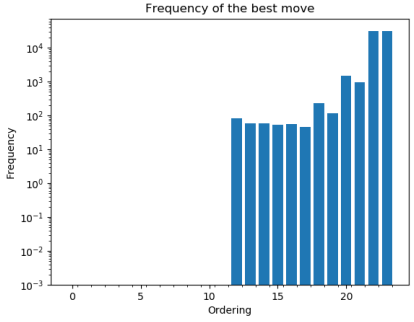

Figure: This figure shows the frequency distribution of cases where each move is optimal in the training dataset

Data Distribution

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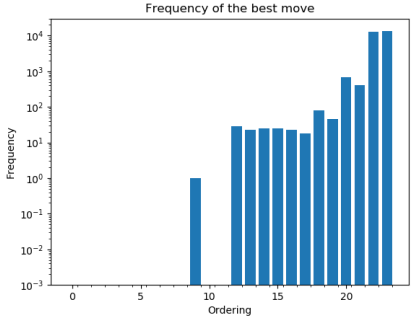

Figure: This figure shows the frequency distribution of cases where each move is optimal in the testing dataset

Confusion Matrix

The predictions on trained model lead to the following confusion matrix.

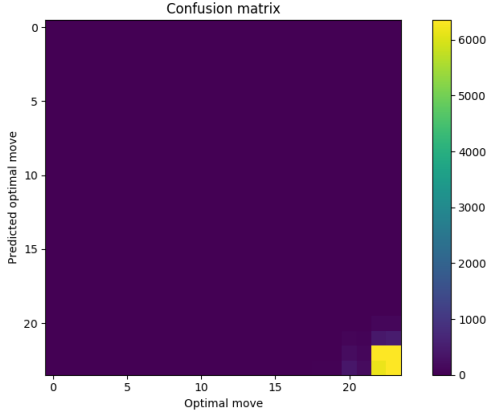

Figure: DQN predictions visualized as confusion matrix

Predictions

Some of the cases we were able to predict the correct answers.

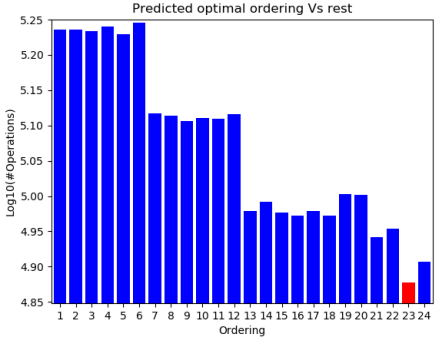

Figure: The figure shows the $\log_{10}$(number of operations) required to execute the query depending on the ordering of the selection operators chosen. The predicted optimal ordering is shown in red.

Predictions

Some of the cases we were able to predict the correct answers.

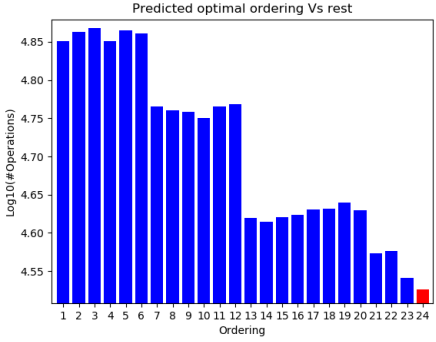

Figure: The figure shows the $\log_{10}$(number of operations) required to execute the query depending on the ordering of the selection operators chosen. The predicted optimal ordering is shown in red.

Section 7

Conclusion

Overall Performance

The model predicted optimal move correctly for 12978 data points, out of 27681, i.e. 47%.

Overall Performance

1. The sum of operations required by the optimal ordering 890640075.0
2. The sum of operations required by the predicted ordering 900269878.0
3. The sum of operations required by the optimal ordering 2310227856.0

Our model resulted in requiring 39% of operations as the query execution would have required if it executed the worst ordering every time.
Our model resulted in requiring 102% of operations as the query execution would have required if it executed the optimal ordering every time.

Section 8

Further Work

Further Work

- Better feature/ information extraction.
- Better training and testing data.
- Parallelizttion and scalability.
- The DQN used is simulating a single move game rather than a multi move game.
- Online training of DQN.
- Integration of DQN into stream processing systems.

Questions?