### **Dynamic and Decentralized Global Analytics via Machine Learning**

Hao Wang<sup>1</sup>, Di Niu<sup>2</sup>, Baochun Li<sup>1</sup> <sup>1</sup>University of Toronto, <sup>2</sup>University of Alberta

### SoCC'18, Carlsbad, CA, USA



UNIVERSITY OF



### 1.CREATE VIEW MoviesOf1996 AS

- 2. SELECT \*
- FROM Movies 3.
- **WHERE** year = 1996;4.
- 5.
- 6.SELECT starName, studioName
- 7.FROM MoviesOf1996 JOIN StarsIN;



# **Decentralized Global Analytics**



# Fluctuating WAN



iperf -t 10 -P 5 **Google Cloud** 

01.	SELECT
02.	C.name, O.orderstatus,
03.	L.discount, PS.availqty
04.	FROM
05.	customer <b>as</b> C,
06.	order <b>as</b> O,
07.	lineitem <b>as</b> L,
08.	partsupp <b>as</b> PS
09.	WHERE O.orderkey == L.orderkey,
10.	AND PS.partkey == L.partkey,
11.	AND PS.suppkey == L.suppkey,
12.	AND C.custkey == O.custkey

## A Toy Example



# **Query Plan Candidates**

### Plan A

- The worst plan
- The baseline

### Plan B

- The initial optimal plan
- Selected by Clarinet

### Plan C



Ο





## A Toy Example

### **Plan C**

- partsupp 2.3 GB
- The adjusted plan
- Adapt to bandwidth fluctuation



# **Query Completion Time**



Centralized plan



Baseline (Plan A)



Plan selected by Clarinet (Plan B)



Dynamic adjusted plan (Plan C)



The data movement time





# Dynamic Query Planning



- Accurately estimating runtime cost of query plans.
- Minimize overall completion time of queries.



### Turbo







### Planning

### **Evaluation**





# **Prediction Target**





### (duration, output size)

## Data Generation





filter(order o=>(o.price>100))

- map(customer c=>(c.custkey, c.values))
- map(order o=>(o.custkey, o.values))
- reduce(custkey, values)

maps

## Data Generation

### **Raw Features**

total\_exec\_num cpu\_core\_num mem\_size avail\_bw tbl1\_size, tbl2\_size hdfs\_block\_num



### Range

1 - 16

- 1 8 per executor
- 1 4 GB per executor
- 5 1000 Mbps per link
- 0.3 12 GB per table

1 - 90

# Data Preprocessing

- 1. Handcrafting features
- 2. Polynomial feature crossing
- 3. Feature selection by LASSO path

### $[a,b,c] \longrightarrow [1,a,b,c,a^2,ab,ac,b^2,bc,c^2]$

### Handcrafted Features

tbl\_size\_sum = sum(tbl1\_size, tbl2\_size) max\_tbl\_size = max(tbl1\_size, tbl2\_size) min\_tbl\_size = min(tbl1\_size, tbl2\_size) 1/avail\_bw, 1/total\_exec\_num, 1/cpu\_core\_num





## Feature Selection



### duration

## Feature Selection



### output size

L<sub>1</sub> penalty (decreasing)

# Training

### LASSO Regression

### Linear Regression with L1 penalty

### GBRT

### **Gradient Boosting Regression Tree** 500 ternary regression trees of depth 3





### Model Test $APE_{i} = \frac{|y_{i} - h(x_{i})|}{y_{i}} \times 100\%.$ Absolute **Percentage Error:**



**Duration** 



## Model Test



### Duration



**Output Size** 

# **Dynamic Planning Strategies**

- Shortest Completion Time First (SCTF) duration
- Maximum Data Reduction First (MDRF) data\_reduction
- Maximum Data Reduction Rate First (MDRRF) data reduction / duration

# **Evaluation Setup**

<ul> <li>TPC-H benchmark</li> </ul>	Ta
	li
<ul> <li>Google Cloud</li> </ul>	re
22 inctance coreco	SU
- 33 Instances across	pa
o regions	

able	Location	Table	Location
ineitem	Taiwan	customer	Frankfurt
egion	Singapore	orders	Sao Paulo
upplier	Sydney	nation	Northern Virg
art	Belgium	partsupp	Oregon



# Query

### Turbo-SCTF

• 25.1-38.5%

### **Turbo-MDRF**

• 12.6-37.1%

### **Turbo-MDRRF**

• 25.2-41.4%

S)		
i time (	- 600 —	
pletion	- 400 —	
y com	- 200 -	
Quer	0-	
le (s)	2000 -	
on tim	1500 -	
npletic	1000 -	
y con	500 -	
Quer	0-	





Turbo-SCTF













# Related Work

Work	Data Placemen
Geode [26]	
WANanalytics [27]	$\checkmark$
Iridium [20]	$\checkmark$
SWAG [16]	
JetSteam [21]	$\checkmark$
Clarinet [25]	$\checkmark$
Lube [15]	
Graphene [14]	
Turbo	



## Conclusion

- Turbo: dynamic query planning with awareness of WAN bandwidths
- Data-driven cost estimation of pairwise join with accuracy over 95%
- Greedy strategies that reduces the query completion times by up to 41% based on the TPC-H benchmark



