



Machine learning for better query planning

Oleg Ivanov

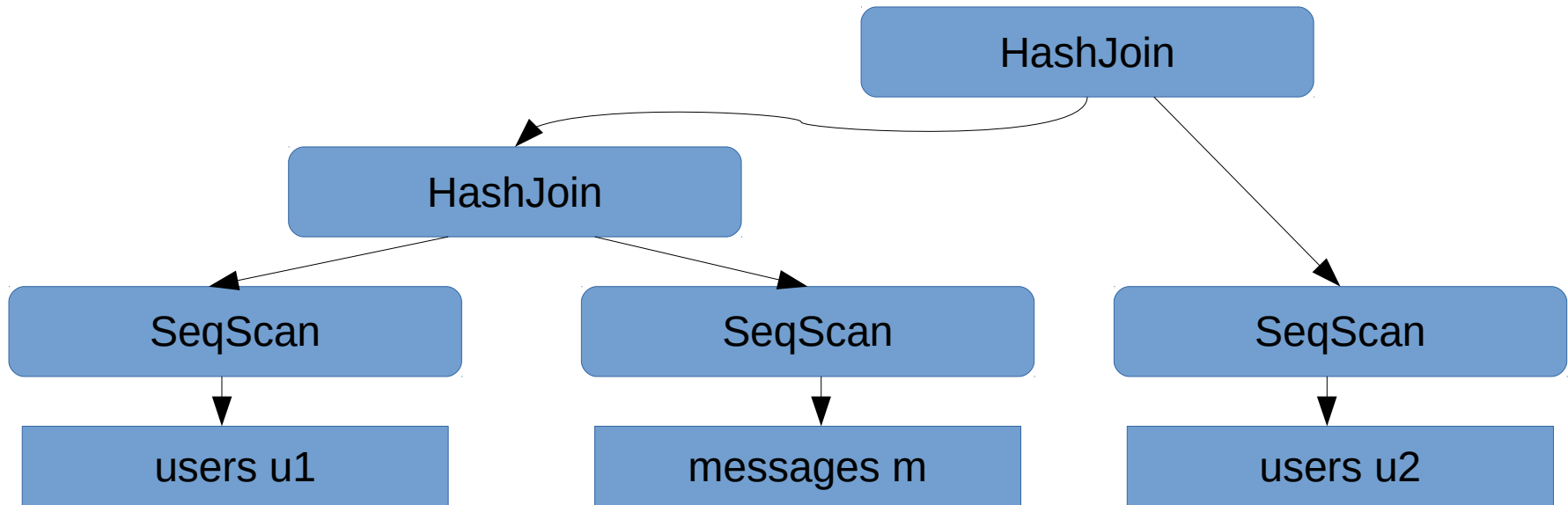
5th of February, 2016

www.postgrespro.ru

1. Query planning
2. Machine learning
3. Machine learning for better query planning

Query execution plan

```
SELECT *  
FROM users AS u1, messages AS m, users AS u2  
WHERE u1.id = m.sender_id AND m.receiver_id = u2.id;
```

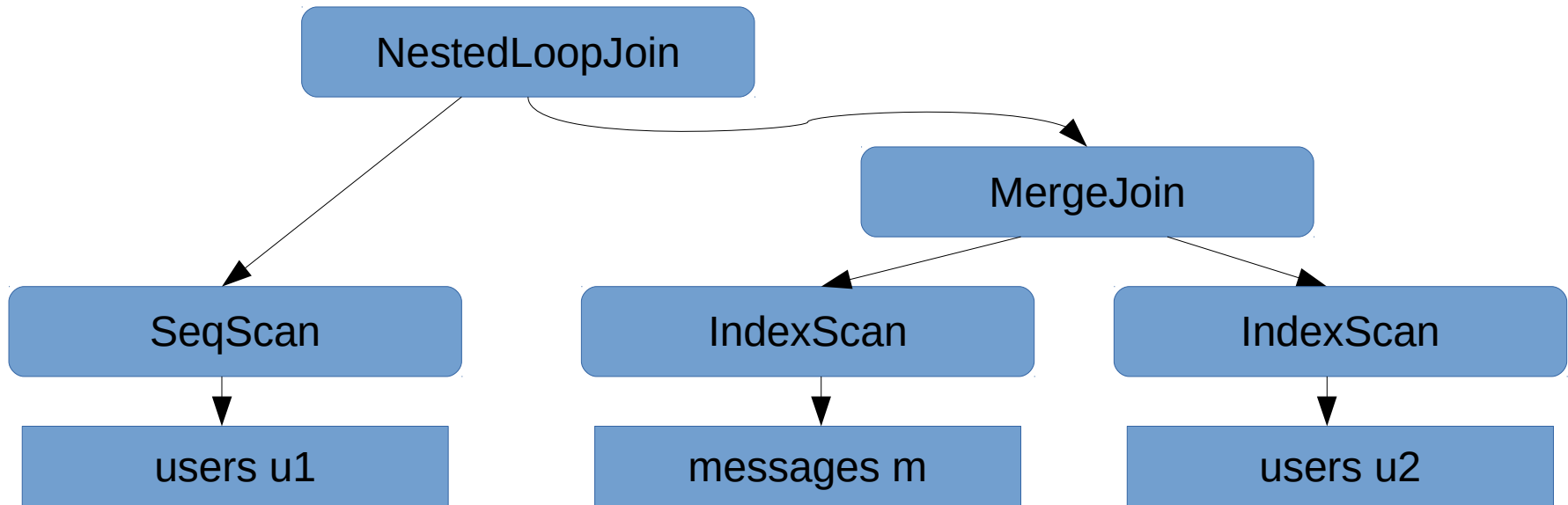


```
EXPLAIN SELECT *  
FROM users AS u1, messages AS m, users AS u2  
WHERE u1.id = m.sender_id AND m.receiver_id = u2.id;
```

QUERY PLAN

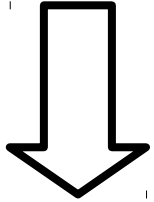
```
Hash Join (cost=540.00..439429.44 rows=10003825 width=27)  
  Hash Cond: (m.receiver_id = u2.id)  
    -> Hash Join (cost=270.00..301606.84 rows=10003825 width=23)  
      Hash Cond: (m.sender_id = u1.id)  
        -> Seq Scan on messages m (cost=0.00..163784.25 rows=10003825 width=19)  
        -> Hash (cost=145.00..145.00 rows=10000 width=4)  
          -> Seq Scan on users u1 (cost=0.00..145.00 rows=10000 width=4)  
        -> Hash (cost=145.00..145.00 rows=10000 width=4)  
          -> Seq Scan on users u2 (cost=0.00..145.00 rows=10000 width=4)  
(9 rows)
```

```
SELECT *  
FROM users AS u1, messages AS m, users AS u2  
WHERE u1.id = m.sender_id AND m.receiver_id = u2.id;
```

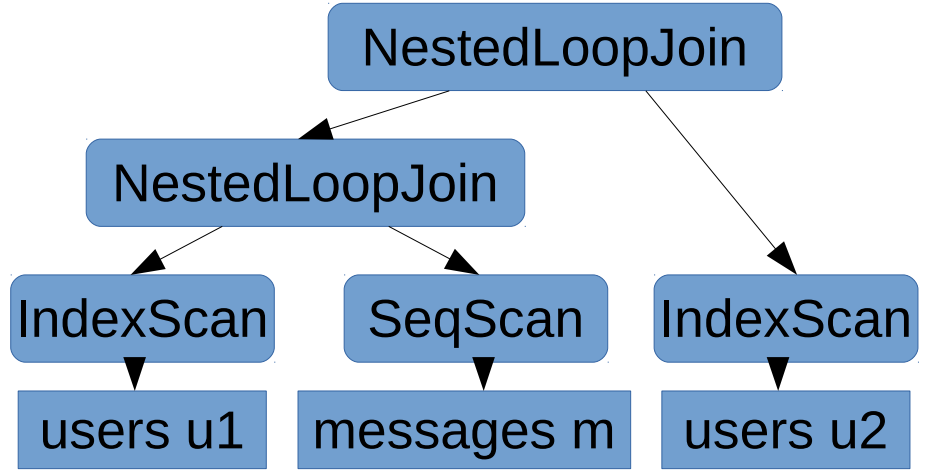
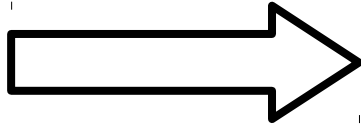


Motivation

```
SELECT *  
FROM users AS u1, messages AS m, users AS u2  
WHERE u1.id = m.sender_id AND m.receiver_id = u2.id;
```



Query planner



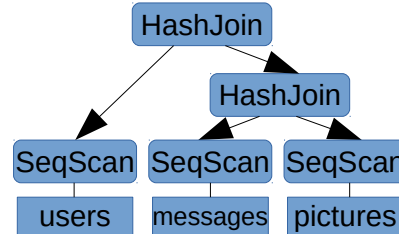
How to choose execution plan?

Optimization method

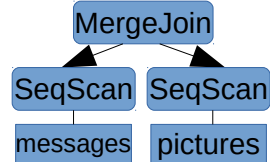
Dynamic programming

or

Genetic algorithm



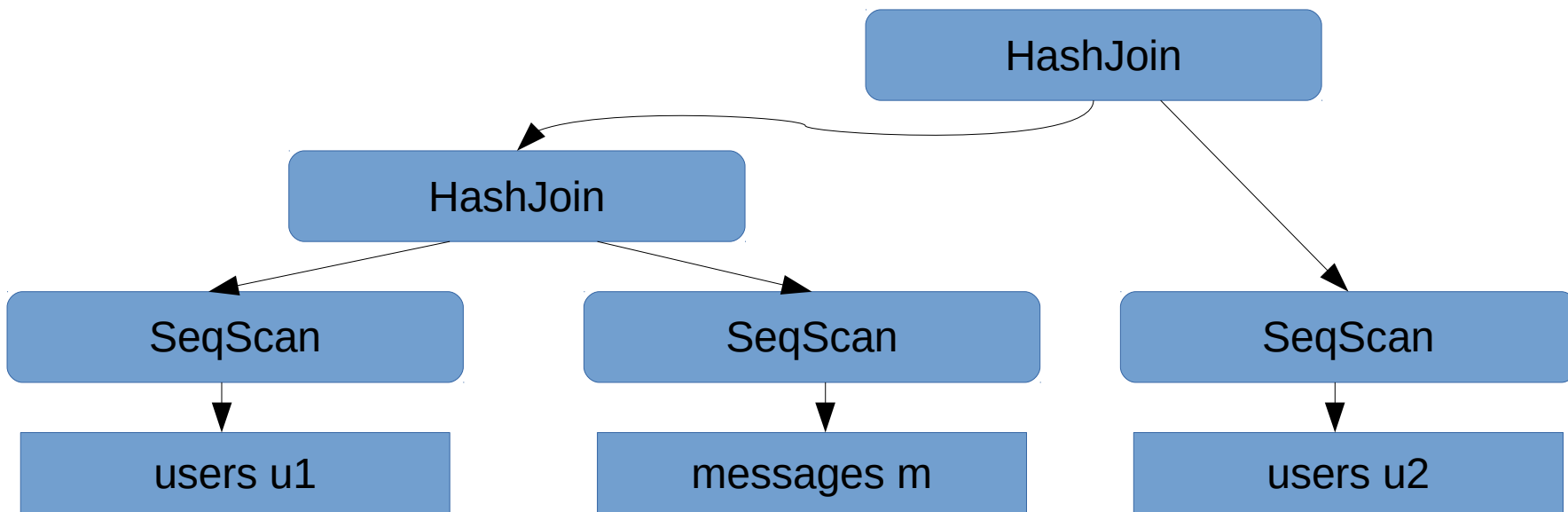
439429 units



304528 units

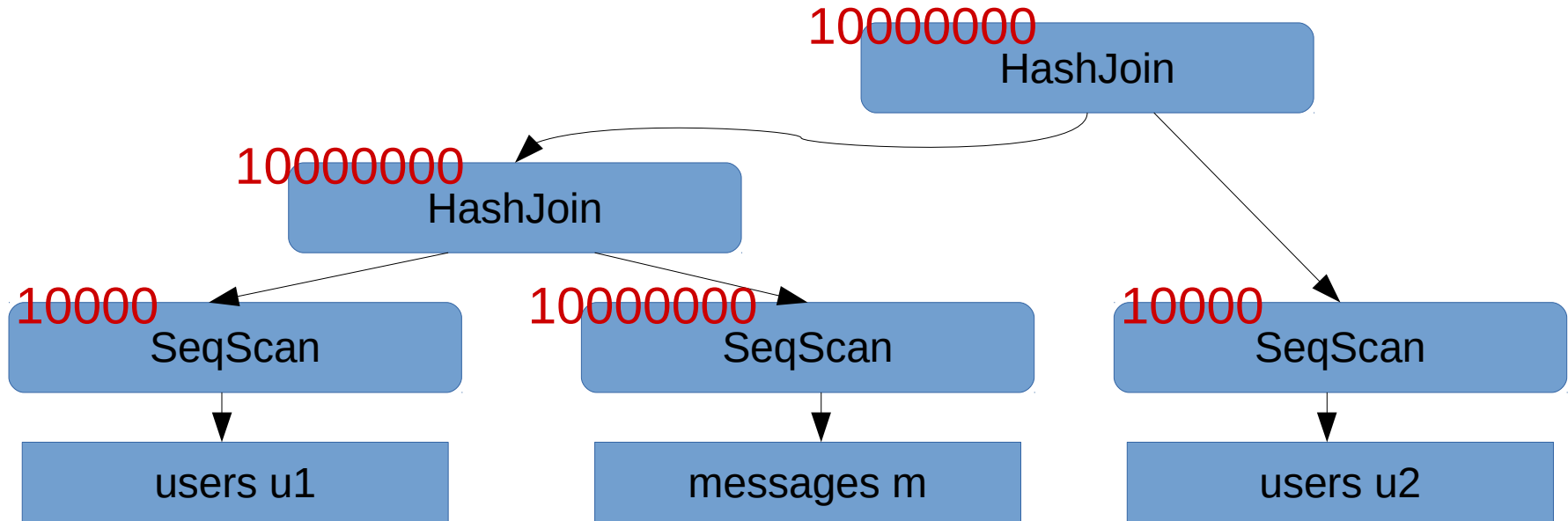
Plan's cost estimation

```
SELECT *  
FROM users AS u1, messages AS m, users AS u2  
WHERE u1.id = m.sender_id AND m.receiver_id = u2.id;
```

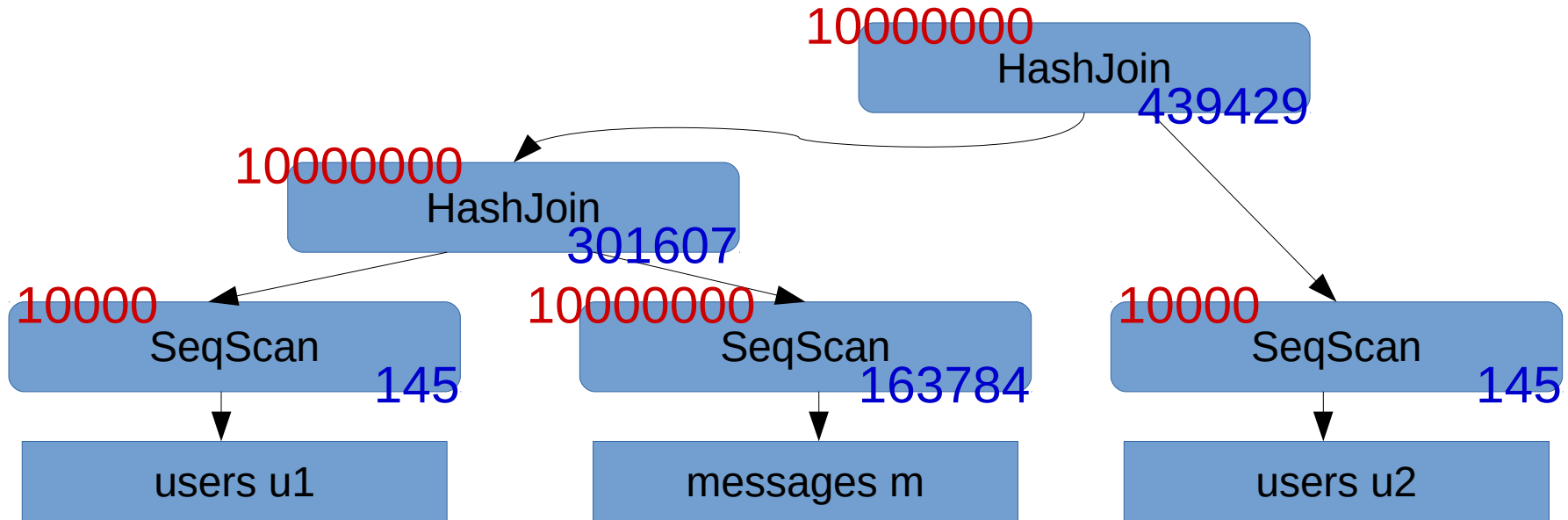


Number of tuples estimation

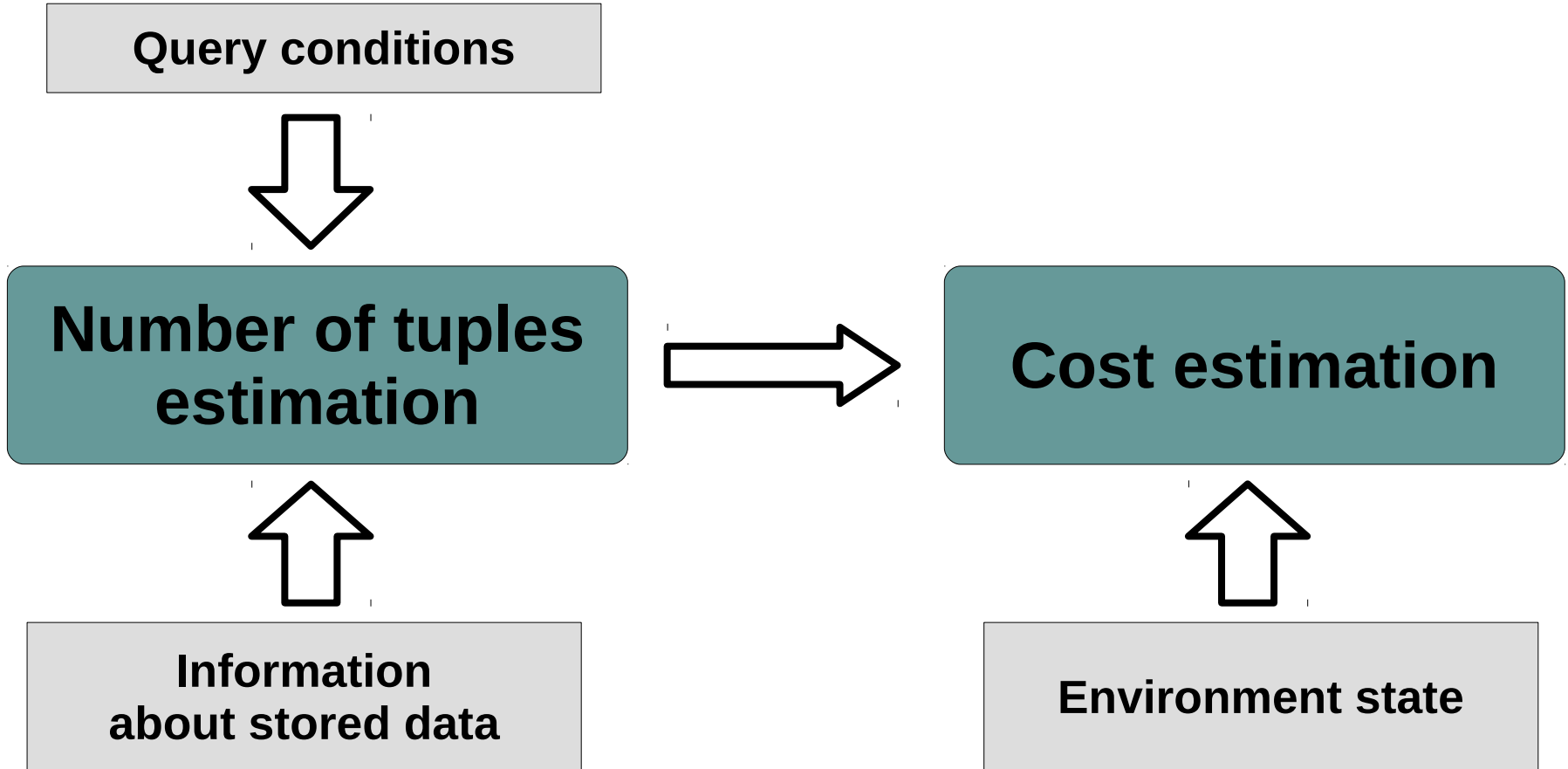
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SELECT *  
FROM users AS u1, messages AS m, users AS u2  
WHERE u1.id = m.sender_id AND m.receiver_id = u2.id;
```



```
SELECT *  
FROM users AS u1, messages AS m, users AS u2  
WHERE u1.id = m.sender_id AND m.receiver_id = u2.id;
```



Cost estimation



Cost estimation

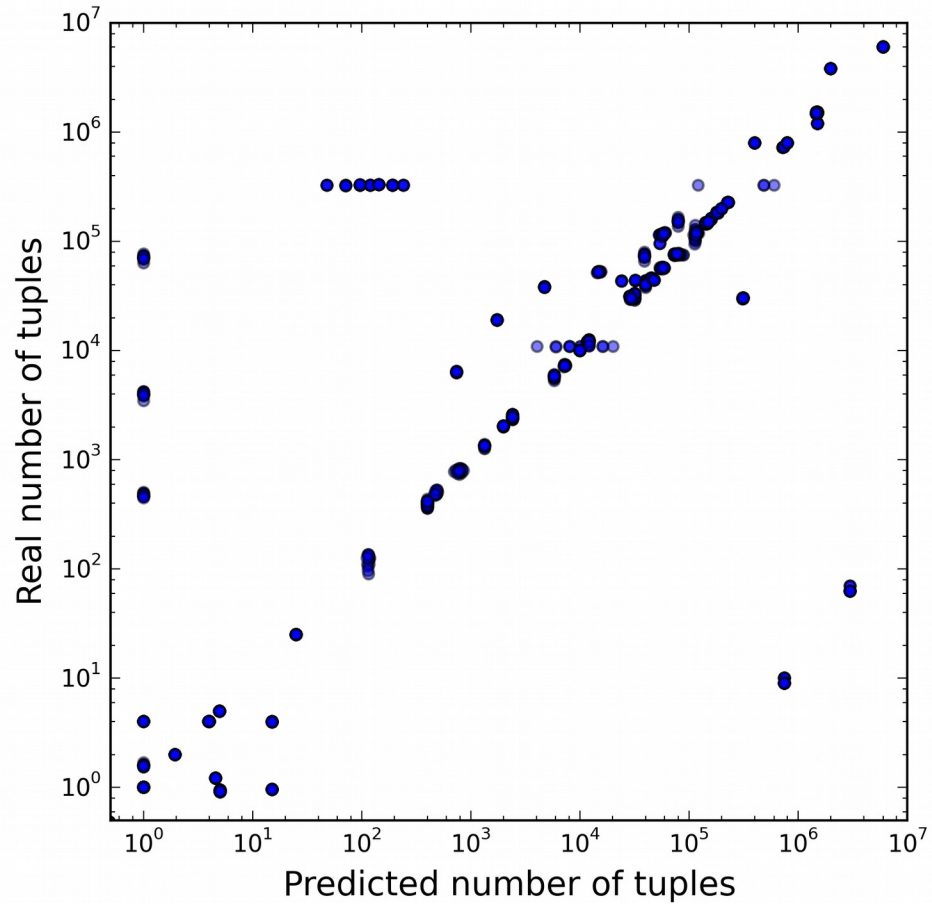
Dataset:

The TPC Benchmark™ H (TPC-H)

<http://www.tpc.org/tpch/>

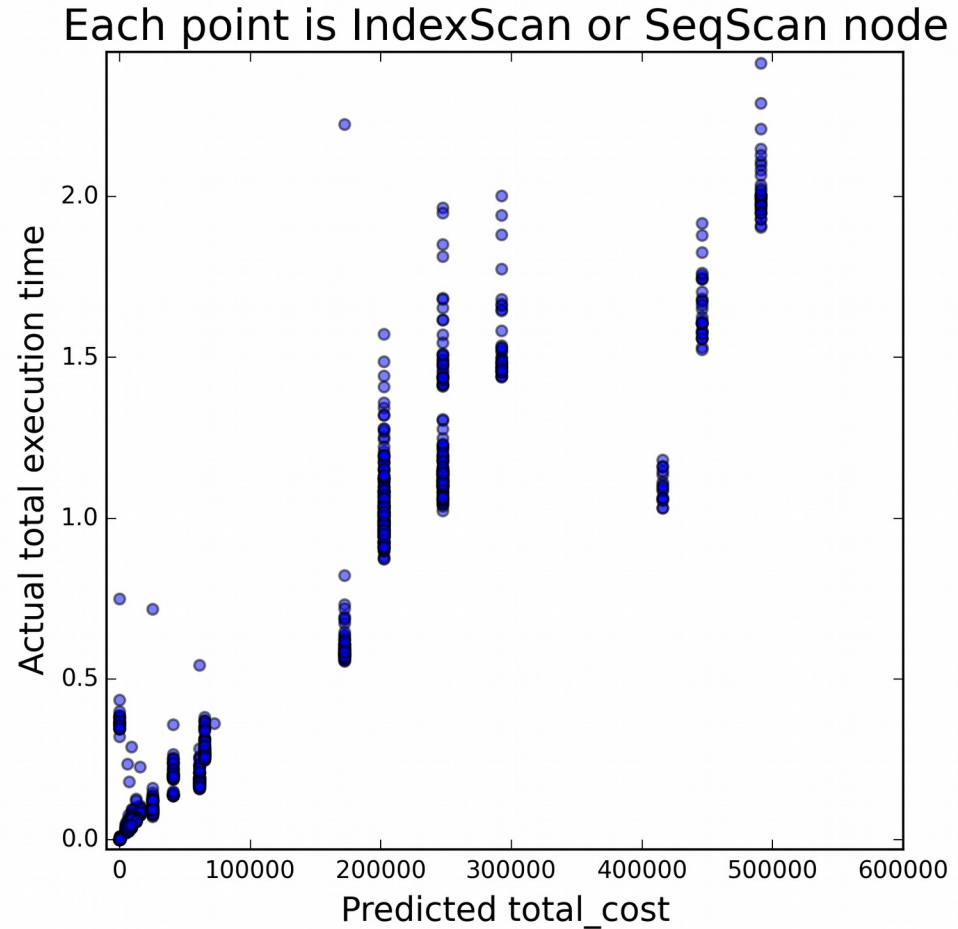
Number of tuples estimation

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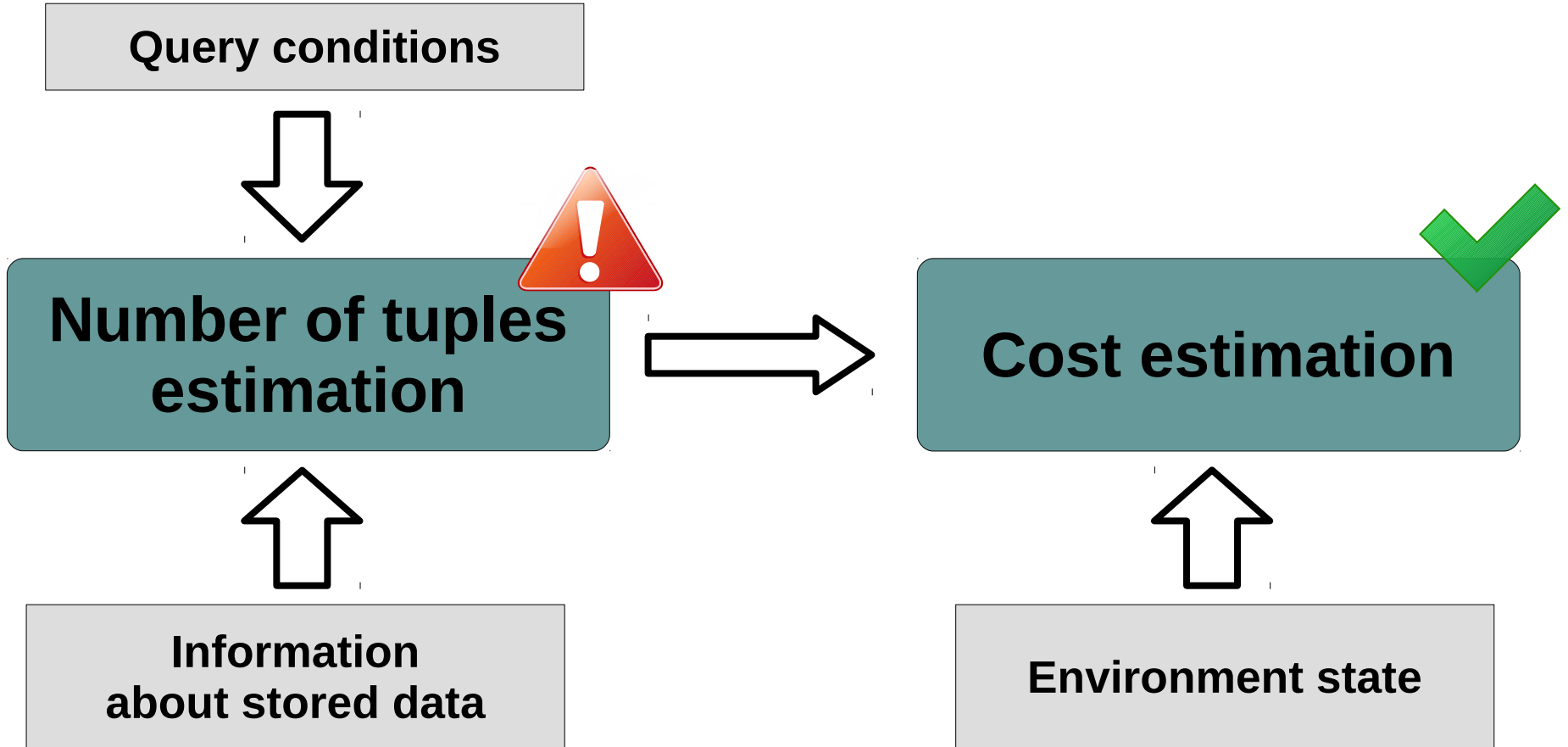


Cost estimation

Dataset:
The TPC Benchmark™ H (TPC-H)
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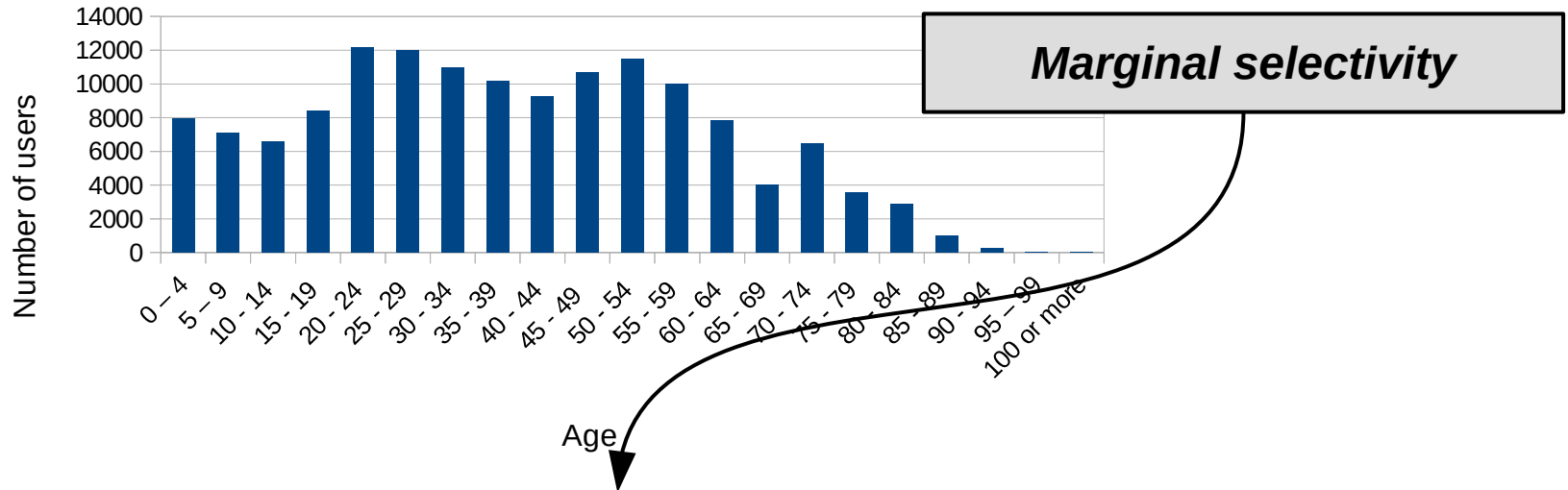


Cost estimation



Number of tuples estimation

```
SELECT * FROM users
WHERE age < 25;
```

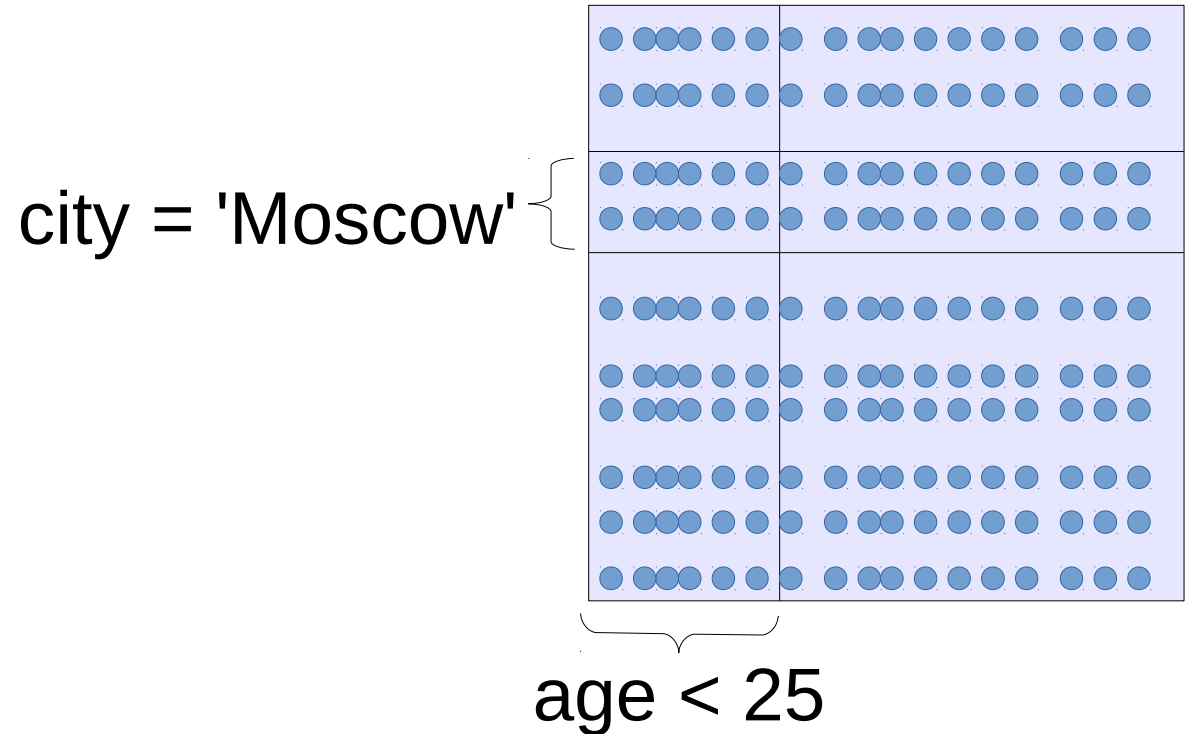


Selectivity ≈ 0.3

Cardinality = *Tuples* · *Selectivity*

Joint selectivity

```
SELECT * FROM users  
WHERE age < 25 AND city = 'Moscow';
```

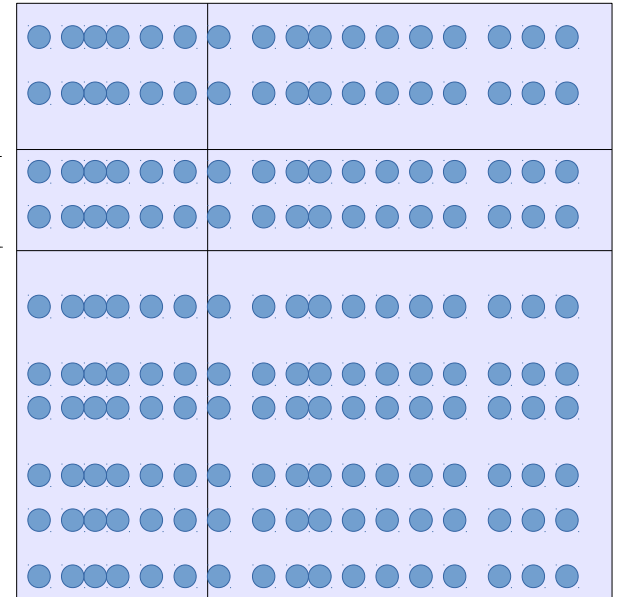


Joint selectivity

```
SELECT * FROM users
WHERE age < 25 AND city = 'Moscow';
```

Cardinality = Tuples · Selectivity_{age, city}

city = 'Moscow' {



age < 25

Joint selectivity

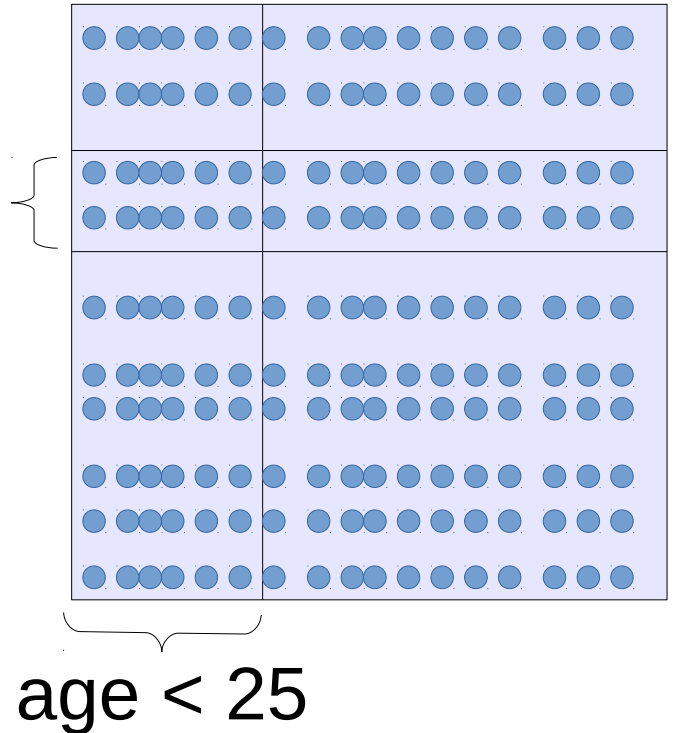
```
SELECT * FROM users
WHERE age < 25 AND city = 'Moscow';
```

Cardinality = Tuples · Selectivity_{age, city}

city = 'Moscow' {

Selectivity_{age} ≈ 0.3

Selectivity_{city} ≈ 0.14



Joint selectivity

```
SELECT * FROM users
WHERE age < 25 AND city = 'Moscow';
```

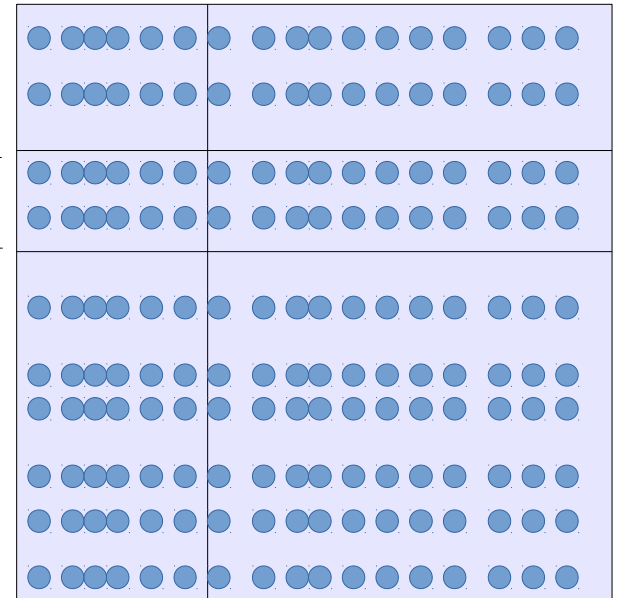
$Cardinality = Tuples \cdot Selectivity_{age, city}$

city = 'Moscow' {

$Selectivity_{age} \simeq 0.3$

$Selectivity_{city} \simeq 0.14$

$Selectivity_{age, city} = Selectivity_{age} \cdot Selectivity_{city}$



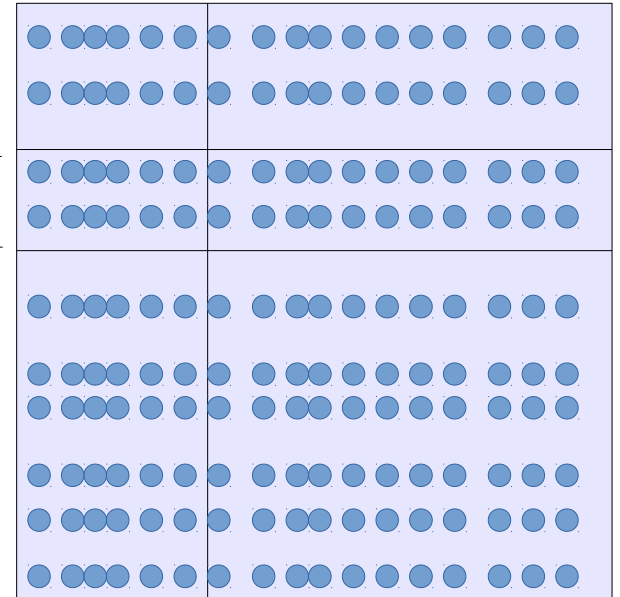
age < 25

Joint selectivity

```
SELECT * FROM users
WHERE age < 25 AND city = 'Moscow';
```

$Cardinality = Tuples \cdot Selectivity_{age, city}$

city = 'Moscow' {



$Selectivity_{age} \approx 0.3$

$Selectivity_{city} \approx 0.14$

$Selectivity_{age, city} = Selectivity_{age} \cdot Selectivity_{city}$

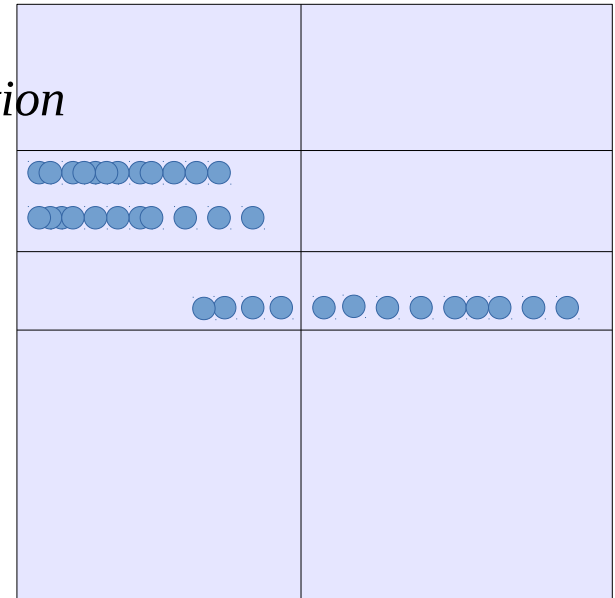
Excluding $Selectivity_{25 < age \text{ AND } age < 57} = Selectivity_{25 < age < 57}$

Joint selectivity

```
SELECT * FROM users
WHERE position = 'cleaner' AND salary > 50000;
```

Cardinality = Tuples · Selectivity salary, position

'cleaner' {
'programmer' {



salary > 50000

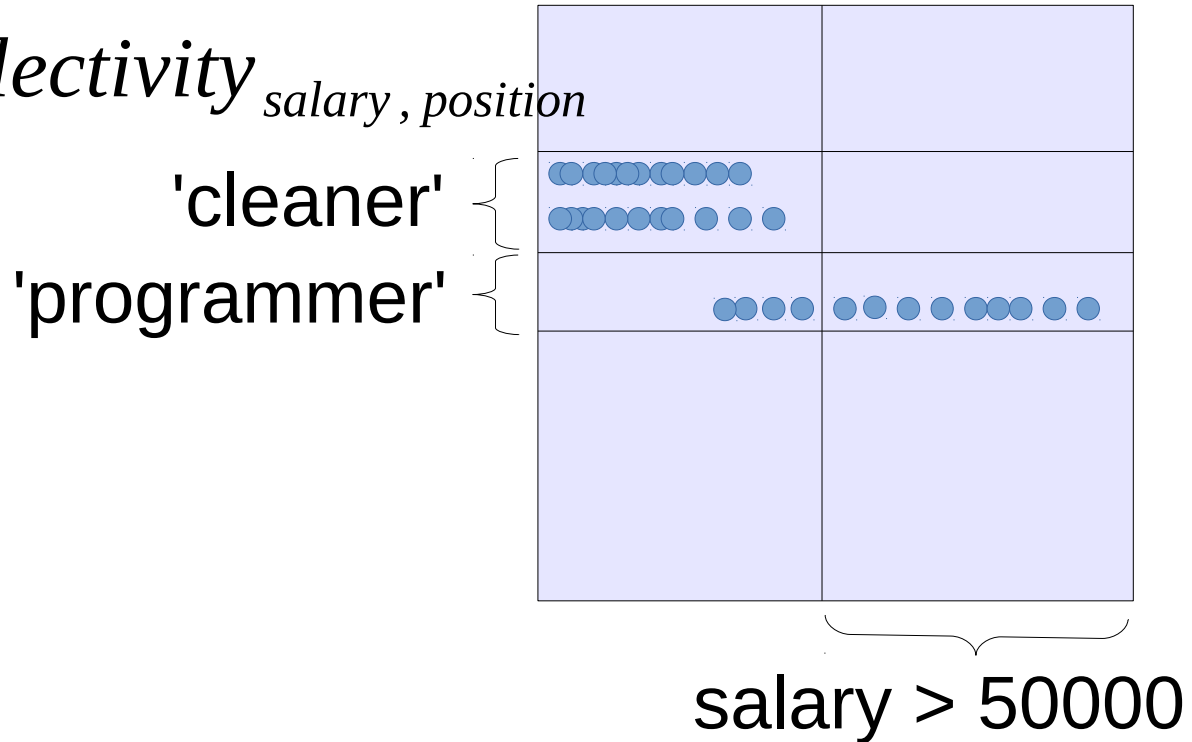
Joint selectivity

```
SELECT * FROM users
WHERE position = 'cleaner' AND salary > 50000;
```

Cardinality = Tuples · Selectivity_{salary, position}

Selectivity_{cleaner} ≈ 0.2

Selectivity_{salary} ≈ 0.3



Joint selectivity

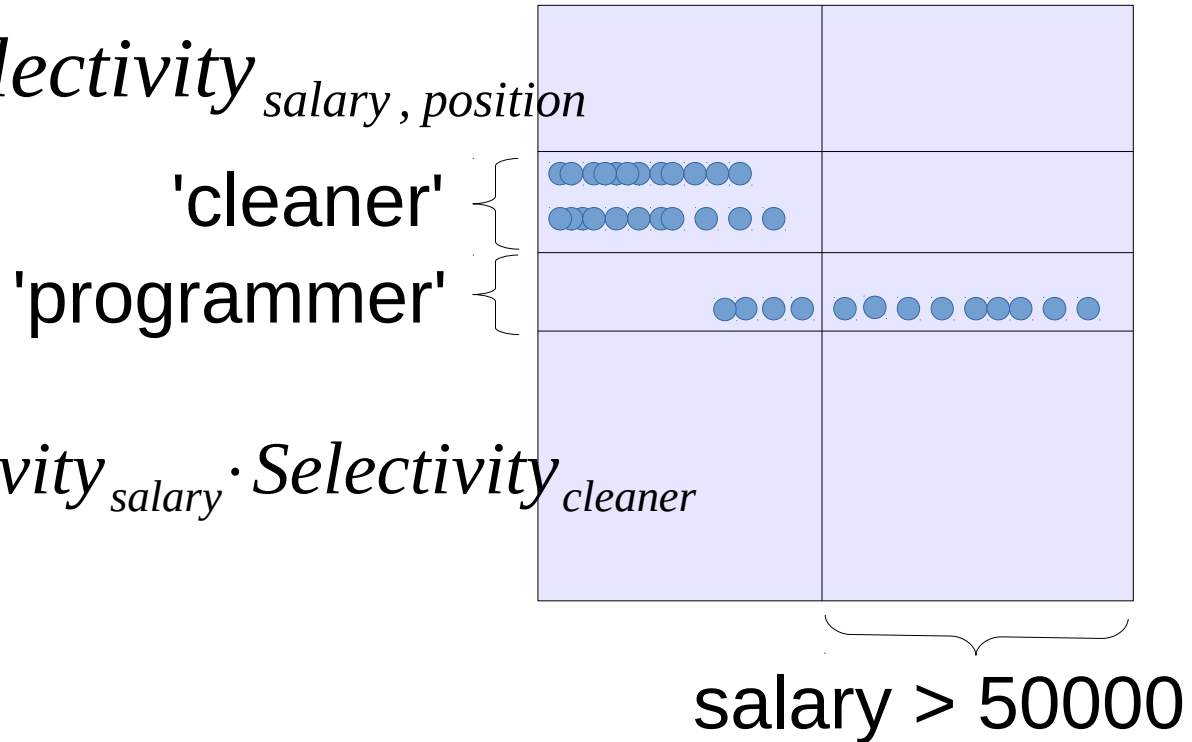
```
SELECT * FROM users
WHERE position = 'cleaner' AND salary > 50000;
```

$Cardinality = Tuples \cdot Selectivity_{salary, position}$

$Selectivity_{cleaner} \approx 0.2$

$Selectivity_{salary} \approx 0.3$

$Selectivity_{salary, cleaner} \approx Selectivity_{salary} \cdot Selectivity_{cleaner}$



Joint selectivity

```
SELECT * FROM users
WHERE position = 'cleaner' AND salary > 50000;
```

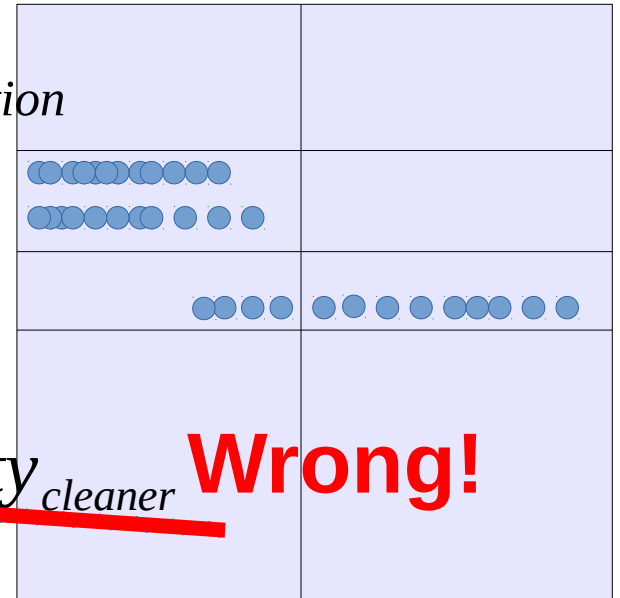
$Cardinality = Tuples \cdot Selectivity_{salary, position}$

$Selectivity_{cleaner} \approx 0.2$

$Selectivity_{salary} \approx 0.3$

~~$Selectivity_{salary, cleaner} = Selectivity_{salary} \cdot Selectivity_{cleaner}$~~

'cleaner' {
'programmer' {



salary > 50000

Joint selectivity

```
SELECT * FROM users
WHERE position = 'cleaner' AND salary > 50000;
```

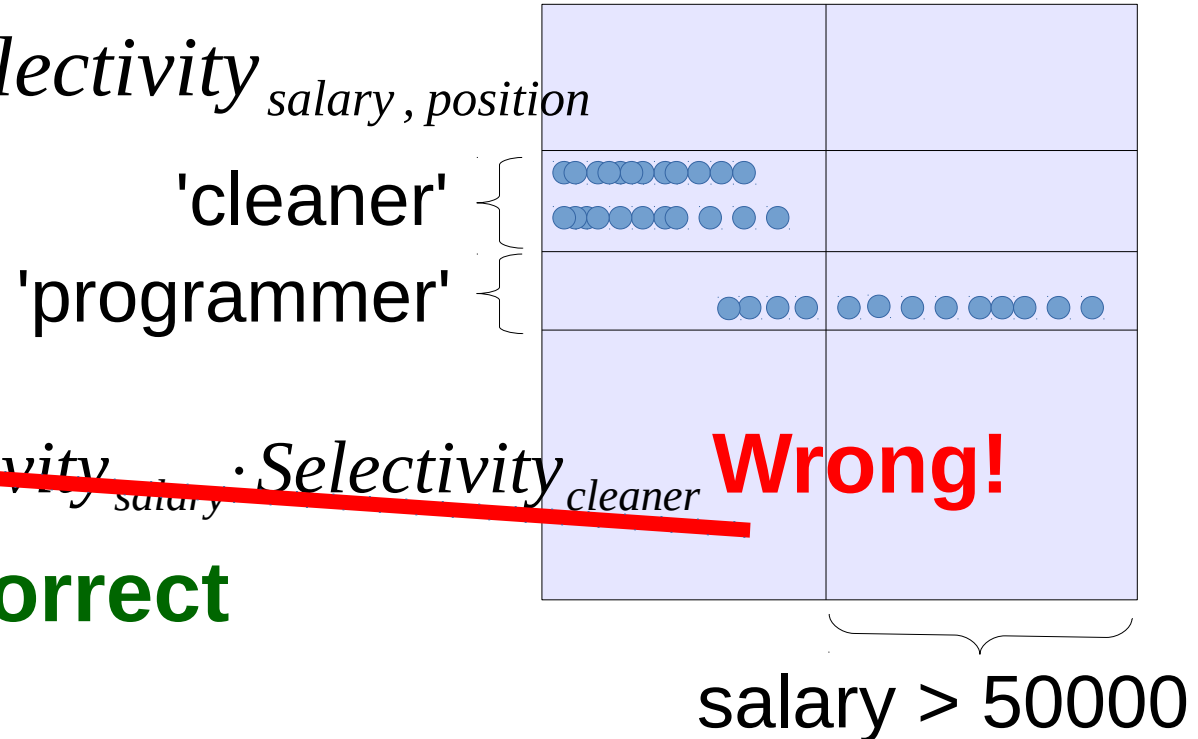
$Cardinality = Tuples \cdot Selectivity_{salary, position}$

$Selectivity_{cleaner} \approx 0.2$

$Selectivity_{salary} \approx 0.3$

~~$Selectivity_{salary, cleaner} = Selectivity_{salary} \cdot Selectivity_{cleaner}$~~

$Selectivity_{salary, cleaner} \approx 0$ **Correct**

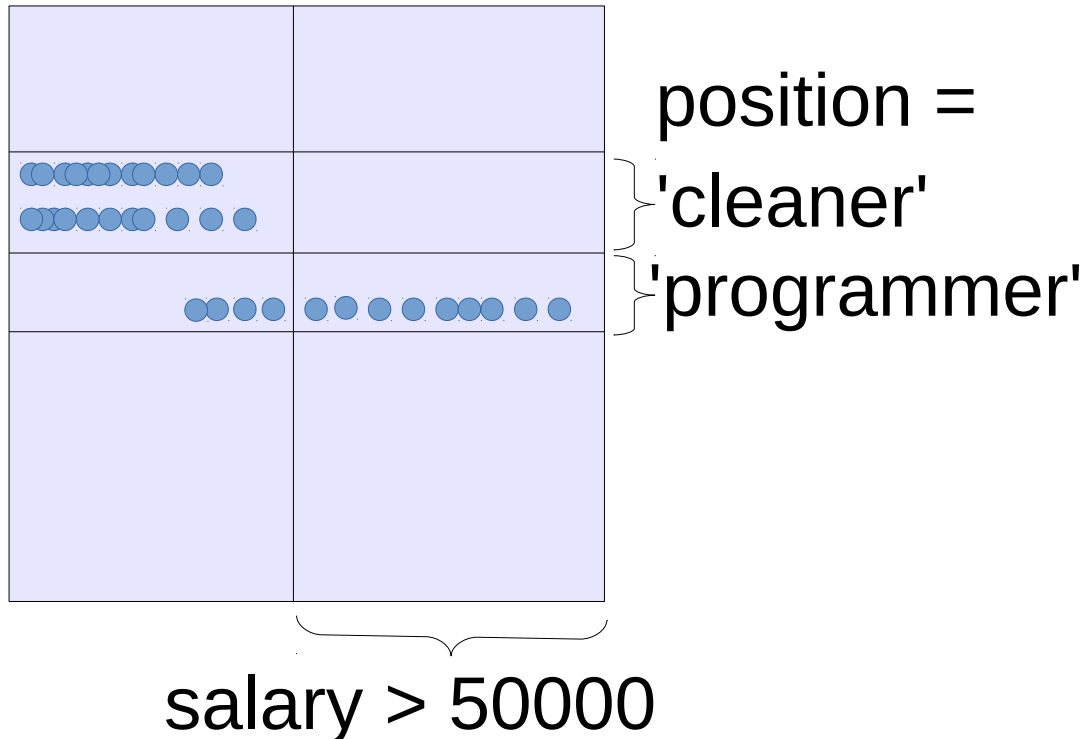
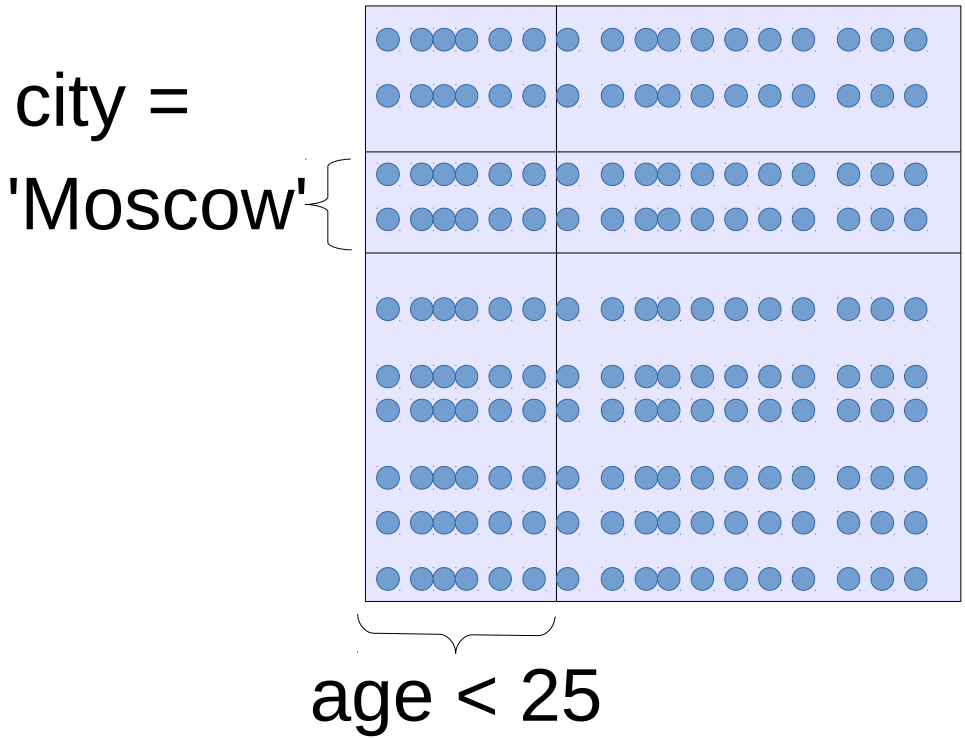


Dependency of conditions

$$Selectivity_{1,2} \approx Selectivity_1 \cdot Selectivity_2 ?$$

Independent conditions

Dependent conditions



Problem statement

Marginal selectivities:

1. 0.0001
2. 0.78
3. 0.23
4. 0.4
5. 0.5

```
l_partkey = p_partkey
AND
l_shipdate >= date '1995-12-01'
AND
l_shipdate < date '1995-12-01' + interval '1' month
AND
l_commitdate < l_receiptdate
AND
l_shipdate < l_commitdate
```

Joint selectivity

Information about data

List of conditions

Selectivity is 0.25!

Machine learning



Machine learning

- Machine learning tries to find regularities in data.
- Data is a set of objects.
- Each objects has a set of observed variables (features) and hidden variables.
- The goal is to find the way of predicting the hidden variables for a new object given the values of features.

Credit scoring

Return time	Age	Salary	Married	Number of children	Has high education
14	25	40000	0	0	1
12	47	100000	1	2	1
9	55	100000	1	2	1
10	32	80000	1	1	1
...
???	28	50000	1	0	1

K nearest neighbours

1. Define similarity between two objects:

$$\text{dist}(\vec{x}_1, \vec{x}_2) = \dots \quad \text{sim}(\vec{x}_1, \vec{x}_2) = \frac{1}{1 + \text{dist}(\vec{x}_1, \vec{x}_2)}$$

2. Define K.

3. Find the K nearest objects and compute their weights:

$$w_i = \frac{\text{sim}(\vec{x}_{new}, \vec{x}_{(i)})}{\text{sim}(\vec{x}_{new}, \vec{x}_{(1)}) + \dots + \text{sim}(\vec{x}_{new}, \vec{x}_{(K)})}$$

4. Return weighted combination of their hidden variables:

$$y_{new} = w_1 y_{(1)} + \dots + w_K y_{(K)}$$

K nearest neighbours

Return time	Age	Salary	Married	Number of children	Has high education
14	25	40000	0	0	1
12	47	100000	1	2	1
9	55	100000	1	2	1
10	32	80000	1	1	1
...
???	28	50000	1	0	1

K nearest neighbours

Return time	Age	Salary	Married	Number of children	Has high education
14	25	40000	0	0	1
12	47	100000	1	2	1
9	55	100000	1	2	1
10	32	80000	1	1	1
...
???	28	50000	1	0	1

$$\text{dist}(\vec{x}_1, \vec{x}_2) = |a_1 - a_2| + \frac{|s_1 - s_2|}{10000} + |m_1 - m_2| + |c_1 - c_2| + |e_1 - e_2|$$

K nearest neighbours

Return time	Age	Salary	Married	Number of children	Has high education	
14	5	25	40000	0	0	1
12	26	47	100000	1	2	1
9	34	55	100000	1	2	1
10	8	32	80000	1	1	1
...
???	28	50000	1	0	0	1

$$\text{dist}(\vec{x}_1, \vec{x}_2) = |a_1 - a_2| + \frac{|s_1 - s_2|}{10000} + |m_1 - m_2| + |c_1 - c_2| + |e_1 - e_2|$$

K nearest neighbours

Return time	Age	Salary	Married	Number of children	Has high education	
14	5	25	40000	0	0	1
12	26	47	100000	1	2	1
9	34	55	100000	1	2	1
10	8	32	80000	1	1	1
...
???	28	50000	1	0	0	1

$K=2$

$$\text{sim} (x_{new}^{\rightarrow}, x_{(1)}^{\rightarrow}) = \frac{1}{6}$$

$$\text{sim} (x_{new}^{\rightarrow}, x_{(2)}^{\rightarrow}) = \frac{1}{9}$$

K nearest neighbours

Return time	Age	Salary	Married	Number of children	Has high education	
14	5	25	40000	0	0	1
12	26	47	100000	1	2	1
9	34	55	100000	1	2	1
10	8	32	80000	1	1	1
...
???	28	50000	1	0	0	1

$K=2$

$$w_1 = \frac{1/6}{1/6 + 1/9} = \frac{3}{5}$$

$$w_2 = \frac{1/9}{1/6 + 1/9} = \frac{2}{5}$$

K nearest neighbours

Return time	Age	Salary	Married	Number of children	Has high education	
14	5	25	40000	0	0	1
12	26	47	100000	1	2	1
9	34	55	100000	1	2	1
10	8	32	80000	1	1	1
...
???	28	50000	1	0	0	1

$K=2$

$$y_{new} \simeq w_1 y_{(1)} + w_2 y_{(2)} = \frac{3}{5} \cdot 14 + \frac{2}{5} \cdot 10 = 12.4$$

Ridge regression

1. Model:

$$y_i \simeq w_1 \cdot x_{i,1} + \dots + w_D \cdot x_{i,D} + b = f(\vec{x}_i, \vec{w}, b)$$

2. Fitting parameters:

$$L(\vec{w}, b) = \sum_{i=1}^l (f(\vec{x}_i, \vec{w}, b) - y_i)^2 + \lambda \sum_{i=1}^D w_i^2 \rightarrow \min_{\vec{w}, b}$$

3. Make predictions:

$$y_{new} \simeq f(x_{new}^{\rightarrow}, \vec{w}^{min}, b^{min}) = w_1^{min} \cdot x_{new,1} + \dots + w_D^{min} \cdot x_{new,D} + b^{min}$$

Ridge regression

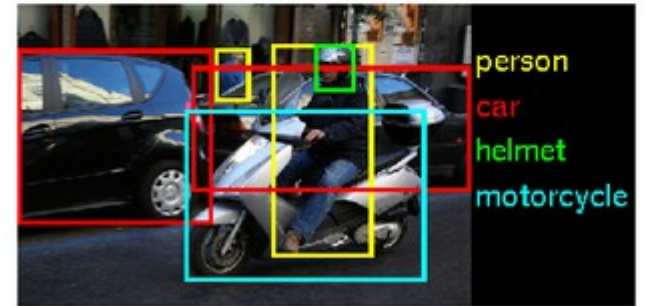
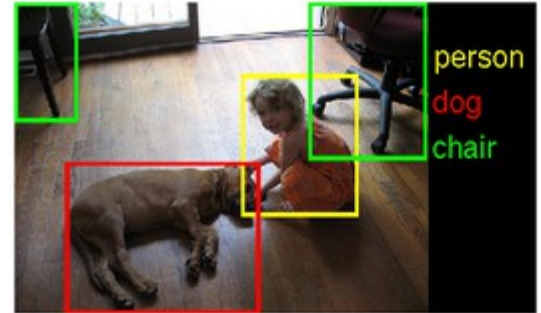
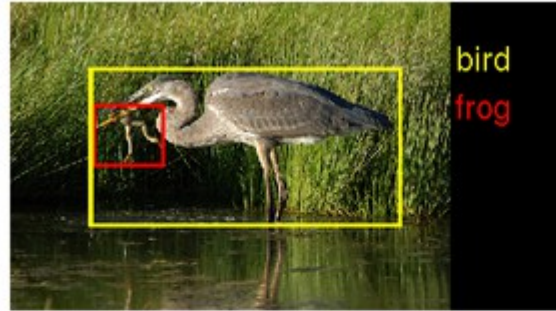
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12	47	100000	1	2	1
9	55	100000	1	2	1
10	32	80000	1	1	1
...
???	28	50000	1	0	1

$$y_{new} \simeq 15.9 - 1.4 \cdot 10^{-2} \cdot age - 5 \cdot 10^{-5} \cdot salary - 0.5 \cdot married - 0.2 \cdot children$$

$$y_{new} \simeq 12.4$$

Modern methods

1. Random forest
2. Gradient boosting
3. Graphical models
4. Bayesian methods
5. Deep learning



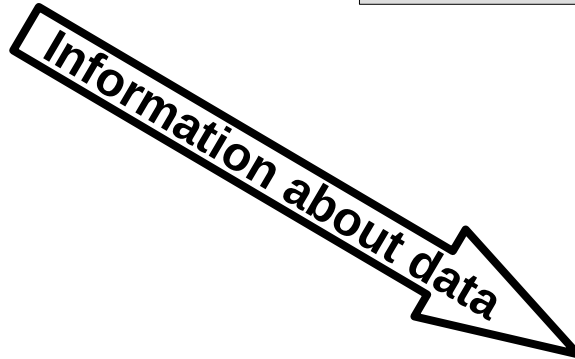
Problem statement

Marginal selectivities:

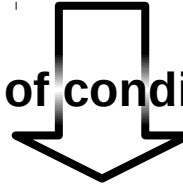
1. 0.0001
2. 0.78
3. 0.23
4. 0.4
5. 0.5

```
l_partkey = p_partkey  
AND  
l_shipdate >= date '1995-12-01'  
AND  
l_shipdate < date '1995-12-01' + interval '1' month  
AND  
l_commitdate < l_receiptdate  
AND  
l_shipdate < l_commitdate
```

Joint selectivity



List of conditions



Selectivity is 0.25!

Machine learning



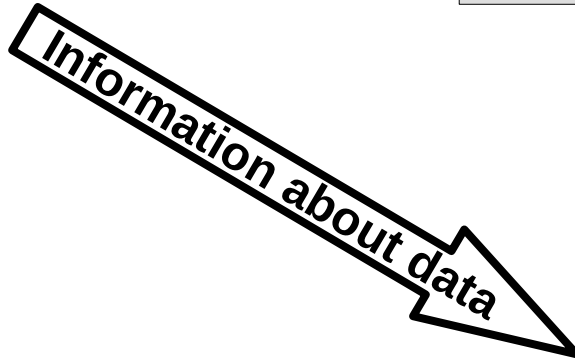
Problem statement

Marginal selectivities:

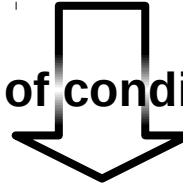
1. 0.0001
2. 0.78
3. 0.23
4. 0.4
5. 0.5

```
l_partkey = p_partkey  
AND  
l_shipdate >= const  
AND  
l_shipdate < const  
AND  
l_commitdate < l_receiptdate  
AND  
l_shipdate < l_commitdate
```

Joint selectivity



List of conditions



Machine learning



Selectivity is 0.25!



Problem statement

Selectivity	users.age > const	users.city = const	messages.sender_id = users.id
0.25	0.25	-	-
0.23	0.25	0.6	-
0.3	0.5	0.6	-
0.0005	-	0.5	0.001
...
???	0.5	0.5	-

Problem statement

LogSelectivity	users.age > const	users.city = const	messages.sender_id = users.id
-1.386	-1.386	0	0
-1.470	-1.386	-0.511	0
-1.204	-0.693	-0.511	0
-7.600	0	-0.693	-6.908
...
???	-0.693	-0.693	0

PostgreSQL model

$$\text{Joint_selectivity} = \prod_{c \in \text{conditions}} \text{selectivity}_c$$

$$\log \text{Joint_selectivity} = \sum_{c \in \text{conditions}} \log \text{selectivity}_c$$

A special case of ridge regression:

$$\log \text{Joint_selectivity} = \sum_{c \in \text{conditions}} w_c \log \text{selectivity}_c$$

The tried techniques

- Ridge regression
 - stochastic gradient descent
- Composition of ridge regressions
 - stochastic gradient descent
 - the exact solution of linear algebraic equation system by Gauss
- K Nearest Neighbours
 - $K = 1$

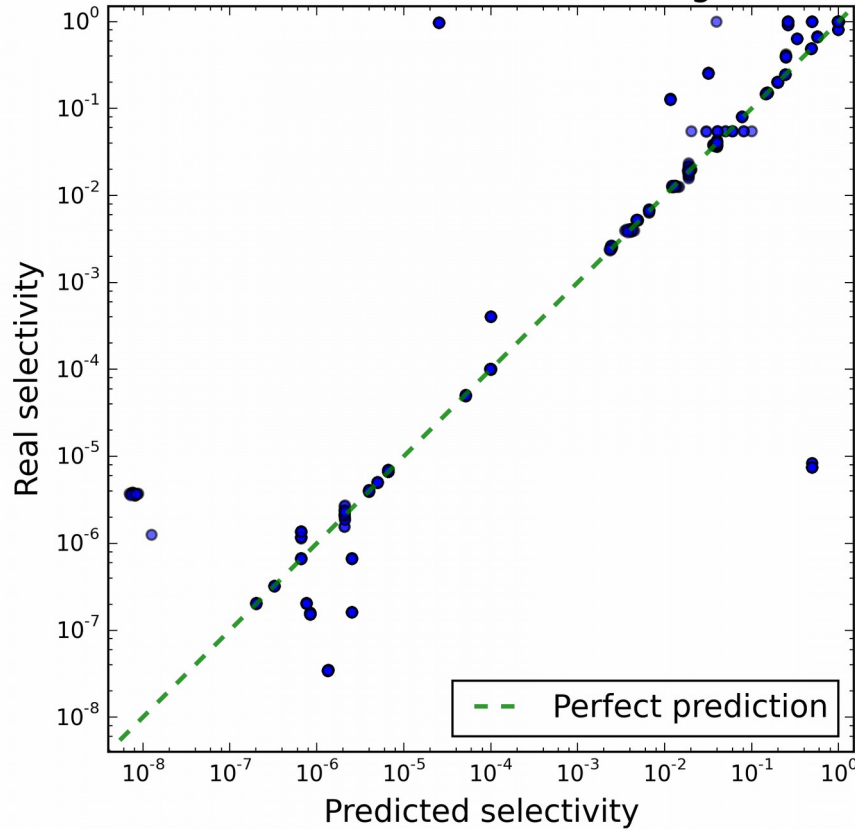
Obtained results: selectivity

Dataset:

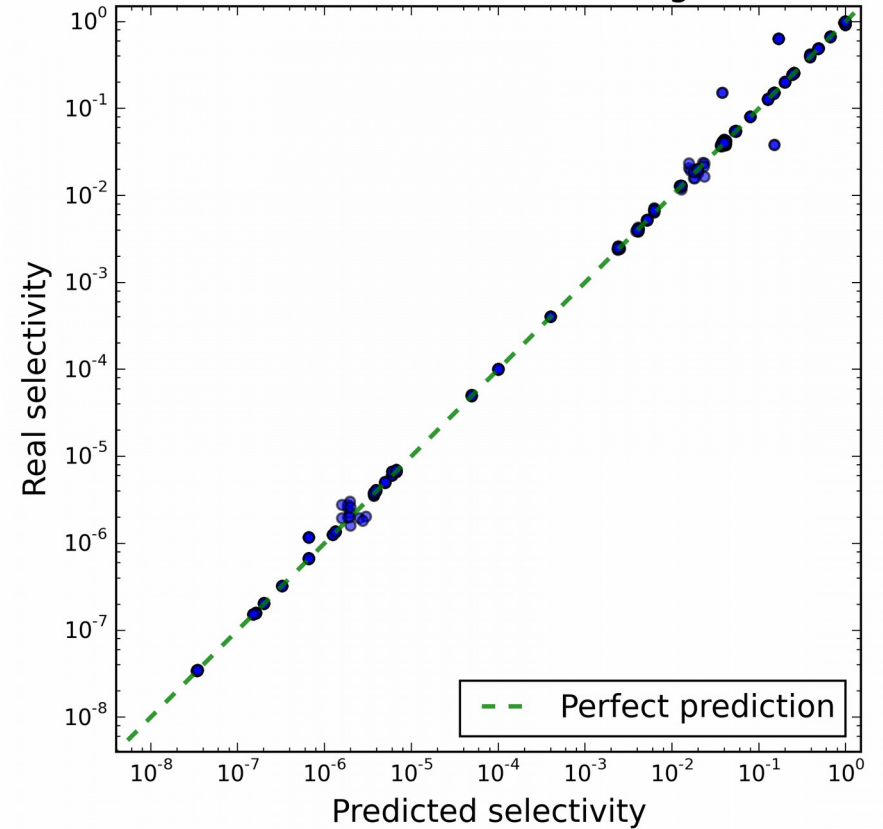
The TPC Benchmark™H (TPC-H)

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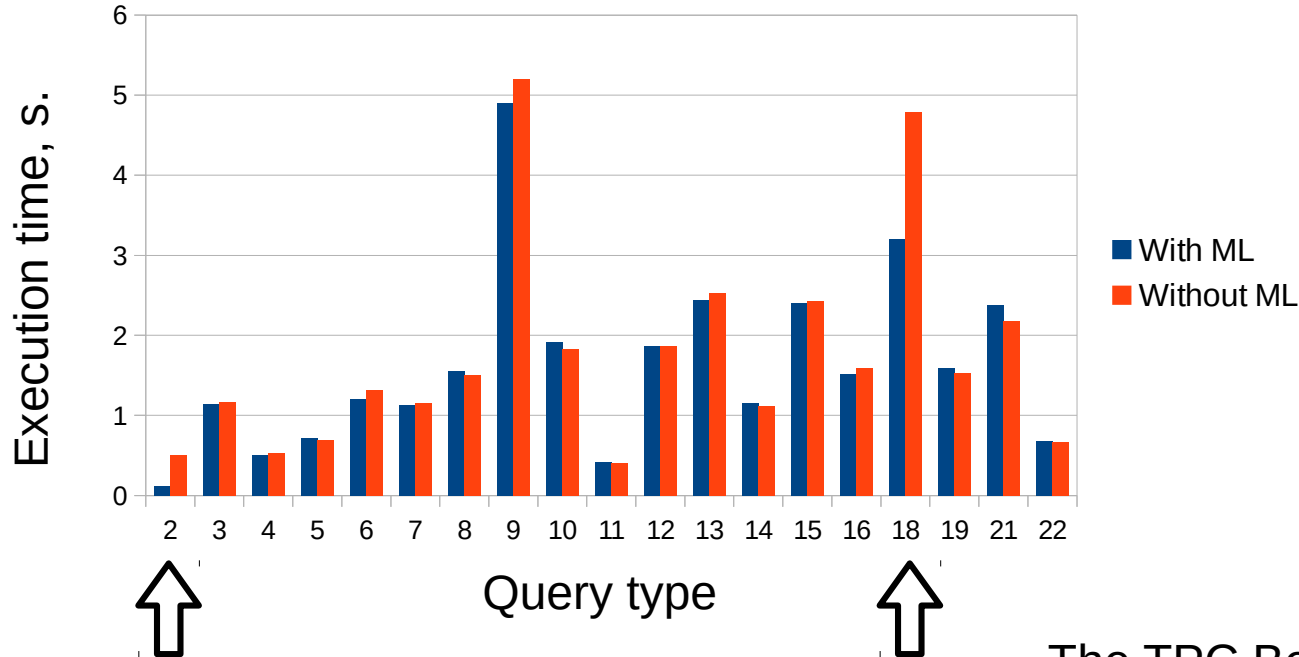
Without machine learning



With machine learning



Obtained results: performance

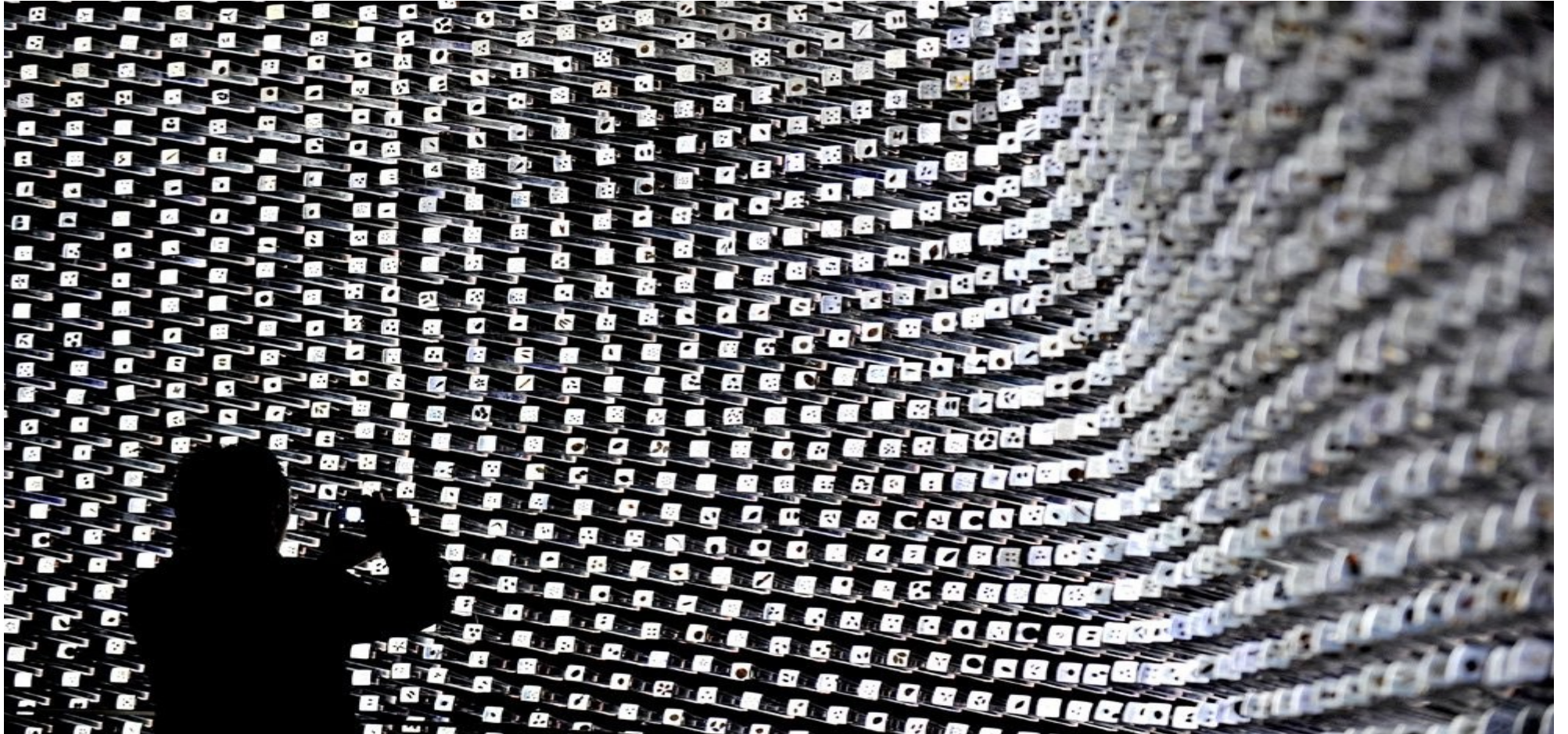


Dataset:
The TPC Benchmark™ H (TPC-H)
<http://www.tpc.org/tpch/>

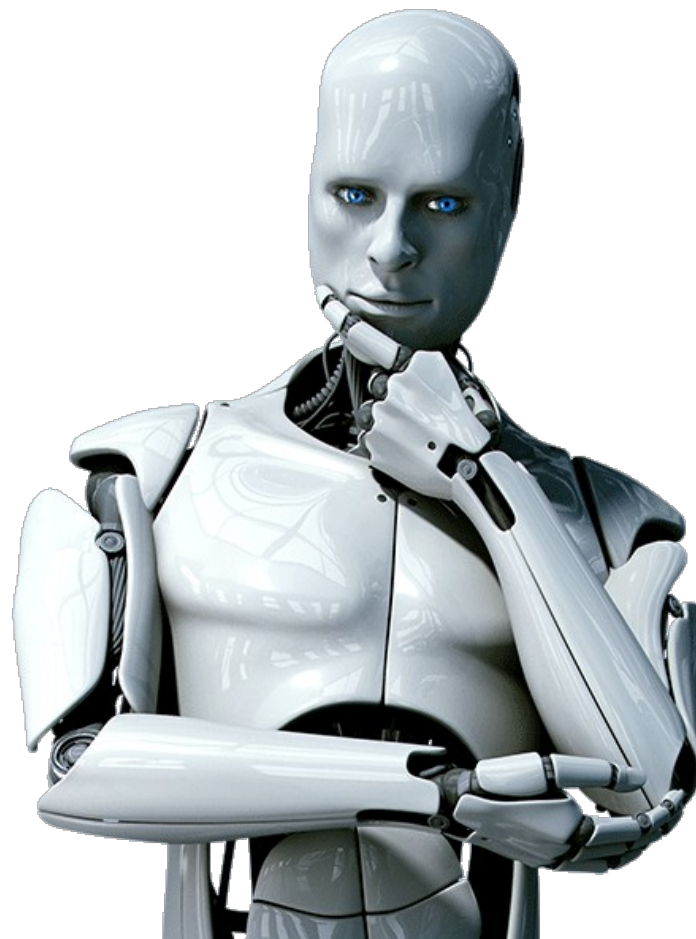
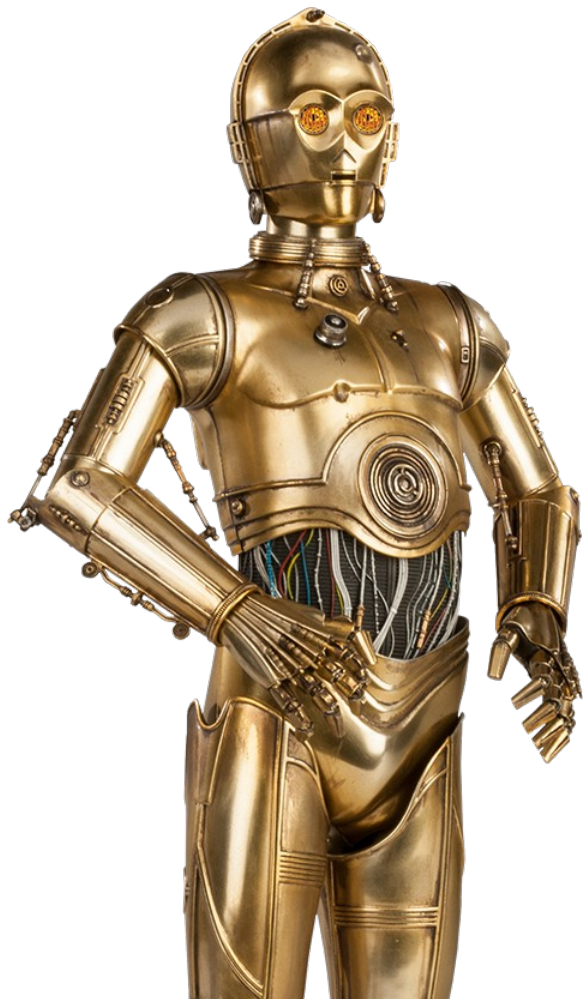
Possible implementations

1. Online learning
2. Background learning
3. Smart **PREPARE**

Sample selection



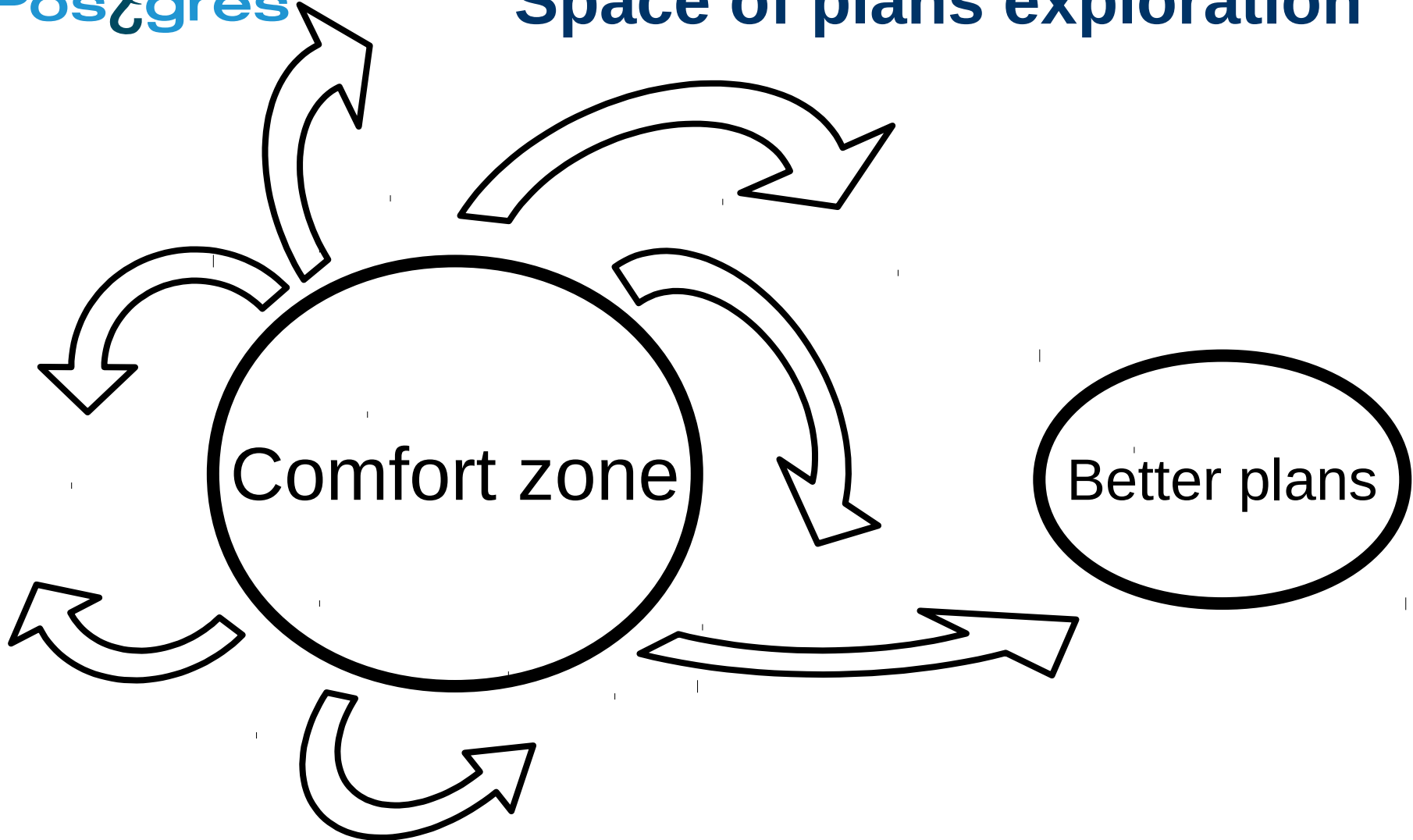
New machine learning approaches



Realtime adaptation

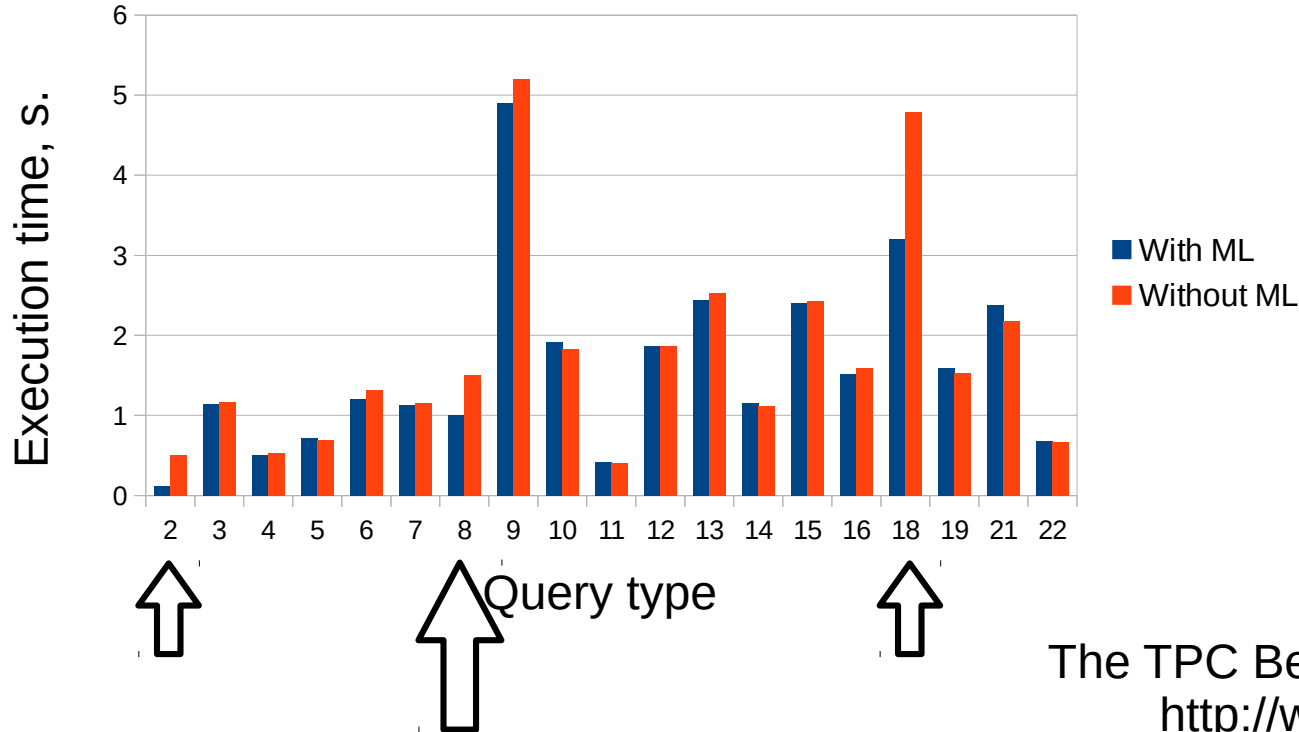


Space of plans exploration



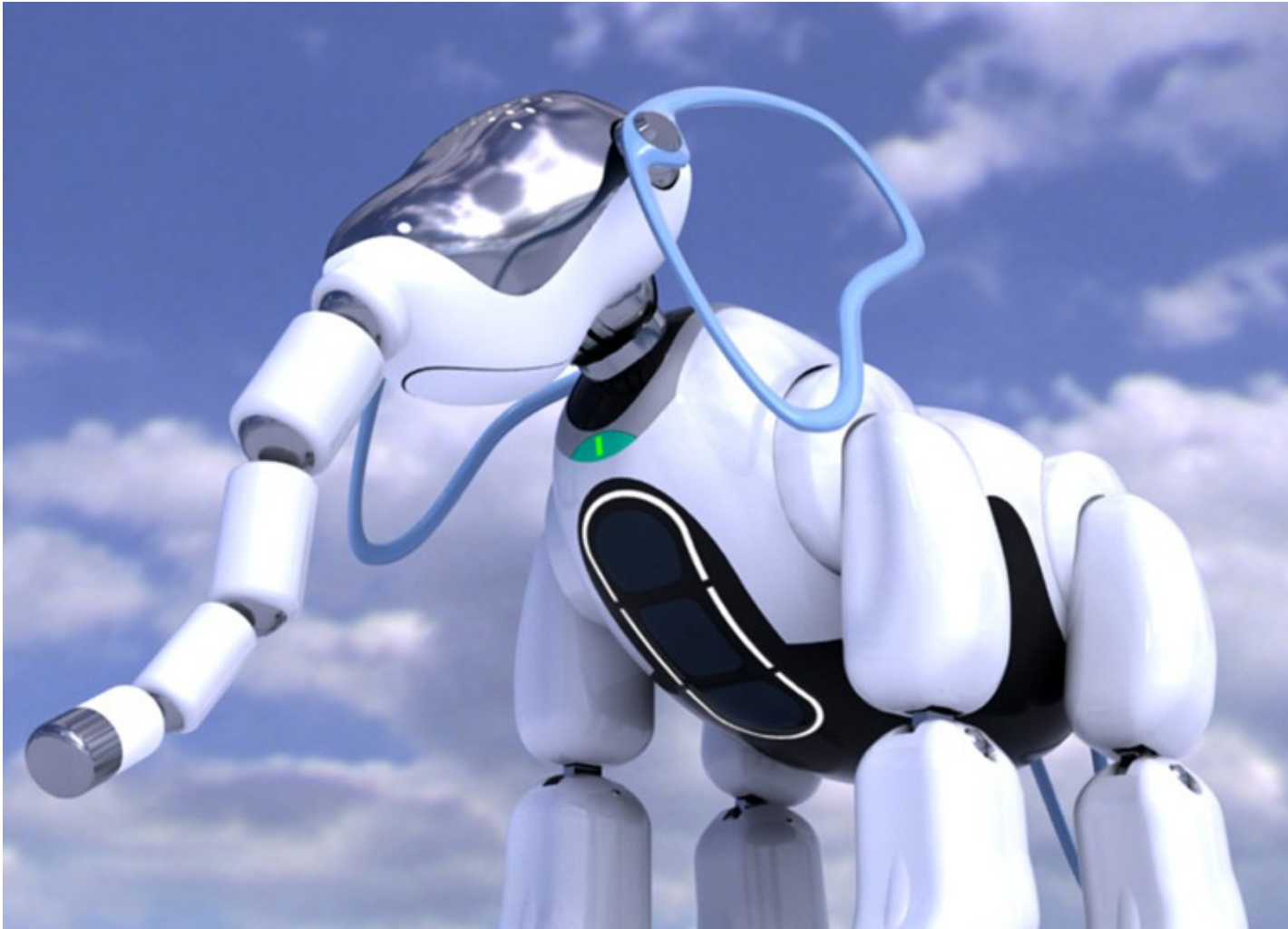
Space of plans exploration

Obtained results: performance acceleration



Dataset:
The TPC Benchmark™ H (TPC-H)
<http://www.tpc.org/tpch/>

DBMS + ML = Better DBMS





Questions?

<http://habrahabr.ru/company/postgrespro/blog/273199/>

<http://tigvarts.livejournal.com/691.html>

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