# DATA516/CSED516 Scalable Data Systems and Algorithms

# Lecture 1 Relational Model, SQL

#### Course Staff

 Instructor: Jack Khuu jackkhuu@cs.washington.edu



• TA: Punya Prakash Shetty punya97@cs.washington.edu

 TA: Nayan Kaushal <u>nakaush@uw.edu</u>



# COVID-19 UW Policy

 UW recommends everyone wearing a mask in the classroom.

### Course Aims

- Study design of big data systems
  - Historical perspective
  - Sample of modern systems
  - Breadth of designs (relational, streaming, graph, etc.)
- Study scalable data processing algorithms
- Gain hands-on experience with big data systems

### Course Content

- Query processing: single-sever, distributed
- MapReduce, successors
- Streaming, Column Stores, Graph engines
- See the calendar on the course website (subject to change)

### Course Format

- 5pm-7:50pm: Lectures
- 8pm-8:50pm: Section
  - Bring your laptop!
- Office hours: by zoom only

#### See the course website

## Grading

15%: Reading assigned papers

• 60%: Homework assignments

• 25%: Final project

#### Homeworks

- HW1: Amazon Redshift
- HW2: Spark/AWS
- HW3: Snowflake
- HW4: mini-homeworks stay tuned

Save free credits for the project!

## Project

#### Choose a topic:

- Don't worry about novelty
- Recommended: Benchmark projects
- Other ideas are welcome too
- I posted a few ideas, but you are encouraged to come up with your own

See the course website

### Communication

 Course webpage: all important stuff <u>https://courses.cs.washington.edu/courses/csed516/22au/</u>

Discussion Board: Canvas

Class email: only for important announcements

## How to Turn In

#### Homework and project:

https://gitlab.cs.washington.edu/

#### Reviews

Canvas

See the course website



#### Now onward to the world of databases!

## **Quick Review**

- Database = a collection of files
  - Examples: products database; movies database
- Database management system (DBMS) = a piece of software to help manage that data
  - Examples: Postgres, Oracle, sqlite

## **DBMS** Functionality

- DBMS does many things:
  - Complex queries, updates, concurrency, recovery, access control, integrity checks, data distribution, etc, etc

 Some DBMS are more specialized for some tasks than others

# DBMS Architectures and Workloads

## Single Client

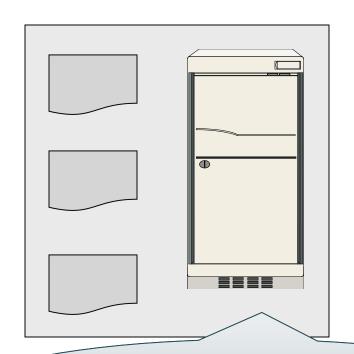
#### E.g. data analytics



Application and database on the same computer E.g. sqlite, postgres

# Two-tier Architecture Client-Server

E.g. accounting, banking, ...



Connection:

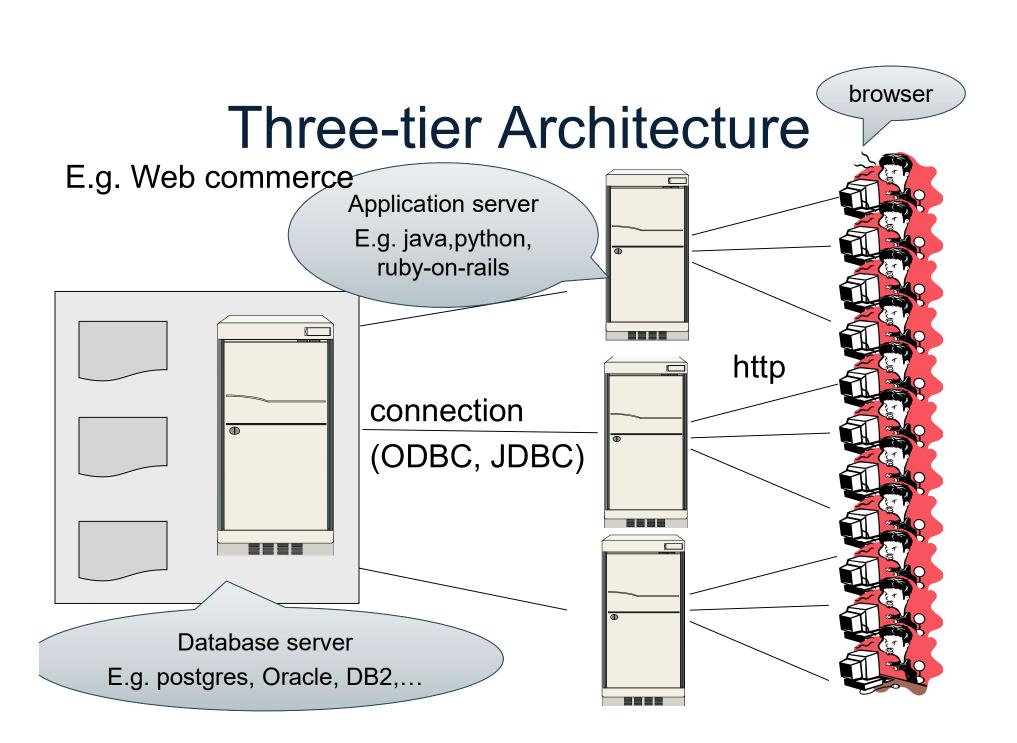
ODBC, JDBC



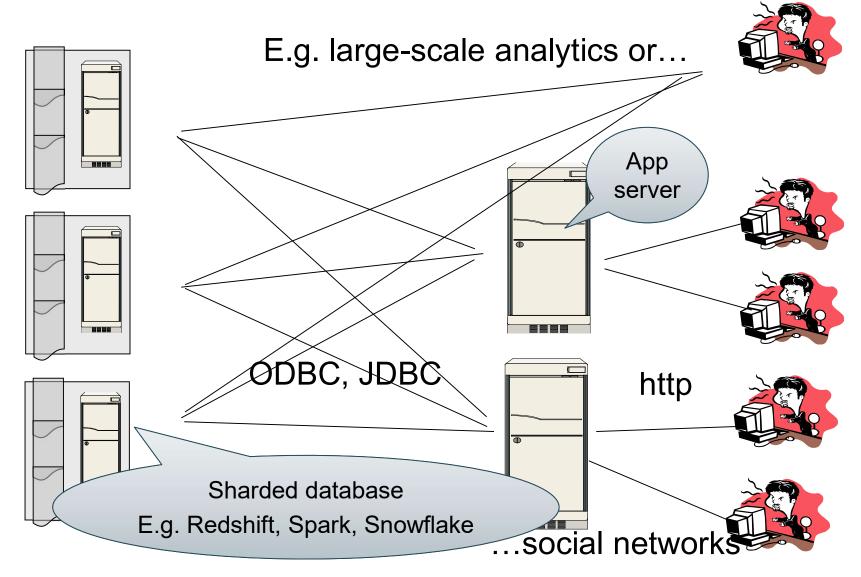
Database server

E.g. postgres, Oracle, DB2,...

Applications: Java, python



## **Cloud Databases**



### Workloads

- OLTP online transaction processing
  - Not interesting for data science
- OLAP online analytics processing, a.k.a. Decision Support
  - Critical for scalable data science

## Relational Data Model

### Relational Data Model

#### Modeling the data: schema + data

- Database = collection of relations
- Relation (a.k.a. table) = a set of tuples
- A Tuple (row, record) =  $(v_1, ..., v_n)$

#### Modeling the query:

Set-at-a-time, relational query language

### Schema

- Relation schema: describes column heads
  - Relation name
  - Name of each field (or column, or attribute)
  - Domain of each field
  - The <u>arity</u> of the relation = # attributes
- Database schema: set of all relation schemas

### Instance

- Relation instance: concrete table content
  - Set of records matching the schema
  - The <u>cardinality</u> or <u>size</u> of the relation = # tuples

Database instance: set of relation instances

# What is the schema? What is the instance?

#### **Supplier**

sno	sname	scity	sstate
1005	ACME	Seattle	WA
1006	Freddie	Austin	TX
1007	Joe's	Seattle	WA
1008	ACME	Austin	TX

# What is the schema? What is the instance?

#### Schema

Supplier(sno: integer, sname: string, scity: string, sstate: string)

#### **Supplier**

sno	sname	scity	sstate	
1005	ACME	Seattle	WA	
1006	Freddie	Austin	TX	instance
1007	Joe's	Seattle	WA	instance
1008	ACME	Austin	TX	

# What is the schema? What is the instance?

#### Schema

Supplier(sno: integer, sname: string, scity: string, sstate: string)

#### **Supplier**

sno	sname	scity	sstate	
1005	ACME	Seattle	WA	
1006	Freddie	Austin	TX	inctance
1007	Joe's	Seattle	WA	instance
1008	ACME	Austin	TX	

In class: discuss keys, foreign keys, FD

## Discussion

Rows in a relation:

Data independence!

- Ordering immaterial (a relation is a set)
- All rows are distinct set semantics
- Query answers may have duplicates bag semantics

## Discussion

Rows in a relation:

Data independence!

- Ordering immaterial (a relation is a set)
- All rows are distinct set semantics
- Query answers may have duplicates bag semantics
- Columns in a tuple:

Or is it?

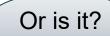
- Ordering is immaterial
- Applications refer to columns by their names

## Discussion

Rows in a relation:

Data independence!

- Ordering immaterial (a relation is a set)
- All rows are distinct set semantics
- Query answers may have duplicates bag semantics
- Columns in a tuple:



- Ordering is immaterial
- Applications refer to columns by their names
- Each Domain = a primitive type; no nesting!

## Relational Query Language

#### Set-at-a-time:

- Inputs and outputs are relations
- Contrast with python/Julia/java/etc: tuple-at-a-time

#### Examples:

 SQL, Relational Algebra, datalog, various graph query languages (Sparql, TigerGraph)

# SQL

## SQL

Standard query language

Introduced late 70's, now it ballooned

 We briefly review "core SQL" (whatever that means); study more on your own!

Review: A case against SQL

## Structured Query Language: SQL

- Data definition language: DDL

   CREATE TABLE ...,
   CREATE VIEW ...,
   ALTER TABLE...
- Data manipulation language: DML
  - SELECT-FROM-WHERE...,INSERT...,UPDATE...,DELETE...

## SQL Query

**SELECT** <attributes>

FROM <one or more relations>

WHERE <conditions>

Supplier (<u>sno</u>, sname, scity, sstate)
Supply (<u>sno</u>, pno, qty, price)
Part (pno, pname, psize, pcolor)

## Quick Review of SQL

```
SELECT *
FROM Part
WHERE pcolor = 'red'
```

What do these queries compute?

Supplier (<u>sno</u>, sname, scity, sstate)
Supply (sno, pno, qty, price)

Part (pno, pname, psize, pcolor)

## Quick Review of SQL

SELECT \*
FROM Part
WHERE pcolor = 'red'

SELECT x.sno, x.name FROM Supplier x WHERE x.sstate = 'WA'

What do these queries compute?

Supplier (sno, sname, scity, sstate)
Supply (sno, pno, qty, price)
Part (pno, pname, psize, pcolor)

## Quick Review of SQL

```
SELECT DISTINCT z.pno, z.pname, x.scity
FROM Supplier x, Supply y, Part z
WHERE x.sno = y.sno
and y.pno = z.pno
and x.sstate = 'WA'
and y.price < 100
```

What does this query compute?

```
Supplier (sno, sname, scity, sstate)
Supply (sno, pno, qty, price)
Part (pno, pname, psize, pcolor)
```

# Terminology

- Selection/filter: e.g. ... WHERE scity='Seattle'
- Projection: e.g. SELECT sname ...
- Join: e.g. ...FROM Supplier, Supply, Part ...

Supplier (sno, sname, scity, sstate)
Supply (sno, pno, qty, price)
Part (pno, pname, psize, pcolor)

Colf

### Self-Joins

Find the Parts numbers available both from suppliers in Seattle, and suppliers in Portland

```
Supplier (sno, sname, scity, sstate)
Supply (sno, pno, qty, price)
Part (pno, pname, psize, pcolor)
Self-Joins
```

# Find the Parts numbers available both from suppliers in Seattle, and suppliers in Portland

```
SELECT DISTINCT y.pno
FROM Supplier x, Supply y
WHERE x.scity = 'Seattle'
and x.scity = 'Portland'
and x.sno = y.sno
```

Supplier (sno, sname, scity, sstate)
Supply (sno, pno, qty, price)
Part (pno, pname, psize, pcolor)

#### Self-Joins

Find the Parts numbers available both from suppliers in Seattle, and suppliers in Portland

SELECT DISTINCT y.pno
FROM Supplier x, Supply y
WHERE x.scity = 'Seattle'
and x.scity = 'Portland'
and x.sno = y.sno

This doesn't work... Why?

```
Supplier (sno, sname, scity, sstate)
Supply (sno, pno, qty, price)
Part (pno, pname, psize, pcolor)
```

#### Self-Joins

Find the Parts numbers available both from suppliers in Seattle, and suppliers in Portland

```
SELECT DISTINCT y.pno
FROM Supplier x, Supply y
WHERE (x.scity = 'Seattle'
or x.scity = 'Portland')
and x.sno = y.sno
```

Does this work?

```
Supplier (<u>sno</u>, sname, scity, sstate)
Supply (<u>sno</u>, pno, qty, price)
Part (<u>pno</u>, pname, psize, pcolor)
```

#### Self-Joins

Find the Parts numbers available both from suppliers in Seattle, and suppliers in Portland

```
SELECT DISTINCT y.pno
FROM Supplier x, Supply y
WHERE (x.scity = 'Seattle'
or x.scity = 'Portland')
and x.sno = y.sno
Nope!
```

Supplier (<u>sno</u>, sname, scity, sstate)
Supply (<u>sno</u>, pno, qty, price)
Part (<u>pno</u>, pname, psize, pcolor)

### Self-Joins

Find the Parts numbers available both from suppliers in Seattle, and suppliers in Portland

Need TWO Suppliers and TWO Supplies

```
SELECT DISTINCT y1.pno
FROM Supplier x1, Supplier x2, Supply y1, Supply y2
WHERE x1.scity = 'Seattle'
and x1.sno = y1.sno
and x2.scity = 'Portland'
and x2.sno = y2.sno
and y1.pno = y2.pno
```

Supplier (<u>sno</u>, sname, scity, sstate)
Supply (<u>sno</u>, pno, qty, price)
Part (pno, pname, psize, pcolor)

### Self-Joins

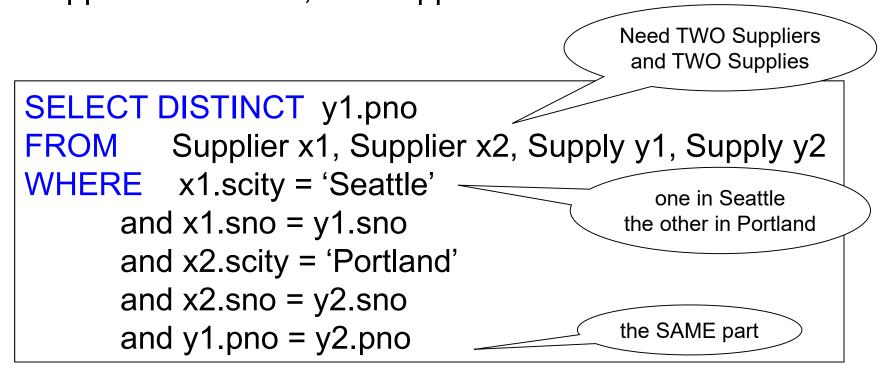
Find the Parts numbers available both from suppliers in Seattle, and suppliers in Portland

SELECT DISTINCT y1.pno
FROM Supplier x1, Supplier x2, Supply y1, Supply y2
WHERE x1.scity = 'Seattle'
and x1.sno = y1.sno
and x2.scity = 'Portland'
and x2.sno = y2.sno
and y1.pno = y2.pno

Supplier (<u>sno</u>, sname, scity, sstate)
Supply (<u>sno</u>, pno, qty, price)
Part (pno, pname, psize, pcolor)

#### Self-Joins

Find the Parts numbers available both from suppliers in Seattle, and suppliers in Portland



## **Semantics**

#### **Semantics**

What does a SQL query compute?

- Simple semantics:
  - Nested Loop Semantics
- Allows optimizations
  - Physical data independence

```
SELECT a_1, a_2, ..., a_k
FROM R_1 AS x_1, R_2 AS x_2, ..., R_n AS x_n
WHERE Conditions
```

```
SELECT a_1, a_2, ..., a_k
FROM R_1 AS x_1, R_2 AS x_2, ..., R_n AS x_n
WHERE Conditions
```

```
Answer = {}
```

```
SELECT a_1, a_2, ..., a_k
FROM R_1 AS x_1, R_2 AS x_2, ..., R_n AS x_n
WHERE Conditions
```

```
Answer = \{\}

for x_1 in R_1 do
```

```
SELECT a_1, a_2, ..., a_k
FROM R_1 AS x_1, R_2 AS x_2, ..., R_n AS x_n
WHERE Conditions
```

```
Answer = \{\}

for x_1 in R_1 do

for x_2 in R_2 do
```

```
SELECT a_1, a_2, ..., a_k
FROM R_1 AS x_1, R_2 AS x_2, ..., R_n AS x_n
WHERE Conditions
```

```
Answer = \{\}

for x_1 in R_1 do

for x_2 in R_2 do

.....

for x_n in R_n do
```

```
SELECT a_1, a_2, ..., a_k
FROM R_1 AS x_1, R_2 AS x_2, ..., R_n AS x_n
WHERE Conditions
```

```
\label{eq:answer} \begin{aligned} &\text{Answer} = \{\} \\ &\text{for } x_1 \text{ in } R_1 \text{ do} \\ &\text{for } x_2 \text{ in } R_2 \text{ do} \\ &\cdots \\ &\text{for } x_n \text{ in } R_n \text{ do} \\ &\text{if Conditions} \\ &\text{then } \text{Answer} = \text{Answer} \cup \{(a_1, \dots, a_k)\} \\ &\text{return } \text{Answer} \end{aligned}
```

```
SELECT a_1, a_2, ..., a_k
FROM R_1 AS x_1, R_2 AS x_2, ..., R_n AS x_n
WHERE Conditions
```

This SEMANTICS!
It says what it means.
Doesn't say how to get it

```
Answer = {}
for x_1 in R_1 do
for x_2 in R_2 do
....

for x_n in R_n do
if Conditions
then Answer = Answer \cup {(a_1,...,a_k)}
return Answer
```

```
SELECT a_1, a_2, ..., a_k
FROM R_1 AS x_1, R_2 AS x_2, ..., R_n AS x_n
WHERE Conditions
```

This SEMANTICS!
It says what it means.
Doesn't say how to get it

```
Answer = {}
for x_1 in R_1 do
for x_2 in R_2 do

for x_n in R_n do
if Conditions
then Answer = Answer \cup {(a_1, ..., a_k)}
return Answer
```

# Data Independence

```
Supply (sno, pno, qty, price)
Part (pno, pname, psize, pcolor)
```

# Physical Data Independence

- The query is written independently of how it will be evaluated
- We write what data we want; optimizer decides how to get it

```
SELECT. *
FROM Supply y, Part z
WHERE y.price = 100 and z.pcolor = 'red' and y.pno = z.pno
```

Discuss in

#### Discussion

 Data independence is the main reason why the relational data model is the dominant data model today

Reading next week: What Goes Around

# NULL

#### **NULLs in SQL**

- A NULL value means missing, or unknown, or undefined, or inapplicable
- Common in Data Science
- The key should never be NULL

<u>pno</u>	pname	price	psize	pcolor
1	iPad	500	13	blue
2	Scooter	99	NULL	NULL
3	Charger	NULL	NULL	red
4	iPad	50	2	NULL

Part(pno, pname, price, psize, pcolor)

#### **NULLs in WHERE Clause**

Predicate in WHERE Clause

Atomic: e.g. pcolor = 'red'

AND / OR / NOT

When is the WHERE condition satisfied?

Part(pno, pname, price, psize, pcolor)

# Three-Valued Logic

- False=0, Unknown=0.5, True=1
- pcolor = 'red'
  - False or True when pcolor is not NULL
  - Unknown when pcolor is NULL
- AND, OR, NOT are min, max, 1- ...

WHERE condition: returns the tuple when True

- False=0, Unknown=0.5, True=1
- pcolor = 'red'
  - False or True when pcolor is not NULL
  - Unknown when pcolor is NULL
- AND, OR, NOT are min, max, 1- ...
  WHERE condition: returns the tuple when True

```
select *
from Part
where price < 100
and (psize=2 or pcolor='red')</pre>
```

- False=0, Unknown=0.5, True=1
- pcolor = 'red'
  - False or True when pcolor is not NULL
  - Unknown when pcolor is NULL
- AND, OR, NOT are min, max, 1- ...

#### WHERE condition: returns the tuple when True

pno	pname	price	psize	pcolor
1	iPad	500	13	blue
2	Scooter	99	NULL	NULL
3	Charger	NULL	NULL	red
4	iPad	50	2	NULL

- False=0, Unknown=0.5, True=1
- pcolor = 'red'
  - False or True when pcolor is not NULL
  - Unknown when pcolor is NULL
- AND, OR, NOT are min, max, 1- ...

#### WHERE condition: returns the tuple when True

pno	pname	price	psize	pcolor
1	iPad	500	13	blue 🚫
2	Scooter	99	NULL	NULL
3	Charger	NULL	NULL	red
4	iPad	50	2	NULL

- False=0, Unknown=0.5, True=1
- pcolor = 'red'
  - False or True when pcolor is not NULL
  - Unknown when pcolor is NULL
- AND, OR, NOT are min, max, 1- ...

WHERE condition: returns the tuple when True

pno	pname	price	psize	pcolor
1	iPad	500	13	blue 🚫
2	Scooter	99	NULL	NULL (
3	Charger	NULL	NULL	red
4	iPad	50	2	NULL

- False=0, Unknown=0.5, True=1
- pcolor = 'red'
  - False or True when pcolor is not NULL
  - Unknown when pcolor is NULL
- AND, OR, NOT are min, max, 1- ...

WHERE condition: returns the tuple when True

pno	pname	price	psize	pcolor
1	iPad	500	13	blue 🚫
2	Scooter	99	NULL	NULL 🚫
3	Charger	NULL	NULL	red
4	iPad	50	2	NULL

Part(pno, pname, price, psize, pcolor)

# Three-Valued Logic

Problem: A or not(A) ≠ true

select \*
from Part
where (price <= 100) or (price > 100)

Does it return all parts?

Part(pno, pname, price, psize, pcolor)

# Three-Valued Logic

Problem: A or not(A) ≠ true

Does it return all parts?

select \*

from Part

where (price <= 100) or (price > 100)

-- solution to return all parts:

select \*

from Part

where (price <= 100) or (price > 100) or isNull(price)

# Aggregates

Supplier(sno, sname, scity, sstate)

Supply(sno,pno,qty,price)

Part(pno, pname, psize, pcolor)

Examples

SELECT count(\*)
FROM Part

What do they compute?

Supplier(sno, sname, scity, sstate)

Supply(sno,pno,qty,price)

Part(pno, pname, psize, pcolor)

Examples

What do they compute?

SELECT count(\*)
FROM Part

**SELECT** x.scity, avg(psize)

FROM Supplier x, Supply y, Part z

WHERE x.sno = y.sno and y.pno = z.pno

**GROUP BY** x.scity

Supplier(sno, sname, scity, sstate)

Supply(sno,pno,qty,price)

Part(pno, pname, psize, pcolor)

Examples

What do they compute?

SELECT count(\*)
FROM Part

**SELECT** x.scity, avg(psize)

FROM Supplier x, Supply y, Part z

WHERE x.sno = y.sno and y.pno = z.pno

**GROUP BY** x.scity

**SELECT** x.scity, avg(psize)

FROM Supplier x, Supply y, Part z

WHERE x.sno = y.sno and y.pno = z.pno

**GROUP BY** x.scity

**HAVING** count(\*) > 200

### Discussion

- Aggregates = important for data science!
- Semantics:
  - 1. FROM-WHERE (nested-loop semantics)
  - 2. GROUP BY attrs
  - 3. Apply HAVING predicates on groups
  - 4. Apply SELECT aggregates on groups
- count, sum, min, max, avg
- DISTINCT is special case of GROUP BY

## **Outer Joins**

Product(name, category)

Purchase(prodName, store)

prodName is foreign Key

# Outer joins

Retrieve all products and stores. Include products that never sold

### **Product**

Name	Category
Gizmo	gadget
Camera	Photo
OneClick	Photo

### **Purchase**

ProdName	Store
Gizmo	Wiz
Camera	Ritz
Camera	Wiz

Product (<u>name</u>, category)

Purchase(prodName, store)



## Outer joins

Retrieve all products and stores. Include products that never sold

SELECT x.name, x.category, y.store FROM Product x, Purchase y WHERE x.name = y.prodName

#### **Product**

Name	Category
Gizmo	gadget
Camera	Photo
OneClick	Photo

#### **Purchase**

ProdName	Store
Gizmo	Wiz
Camera	Ritz
Camera	Wiz

Product (name, category)

Purchase(prodName, store)

prodName is foreign Key

## Outer joins

Retrieve all products and stores. Include products that never sold

SELECT x.name, x.category, y.store FROM Product x, Purchase y WHERE x.name = y.prodName

#### **Product**

Name	Category
Gizmo	gadget
Camera	Photo
OneClick	Photo

### **Purchase**

ProdName	Store
Gizmo	Wiz
Camera	Ritz
Camera	Wiz

### Output

Name	Category	Store
Gizmo	gadget	Wiz
Camera	Photo	Ritz
Camera	Photo	Wiz

missing

Product(name, category)
Purchase(prodName, store)



# Outer joins

Retrieve all products and stores. Include products that never sold

SELECT x.name, x.category, y.store
FROM Product x LEFT OUTER JOIN Purchase y
ON x.name = y.prodName

#### **Product**

Name	Category
Gizmo	gadget
Camera	Photo
OneClick	Photo

### **Purchase**

ProdName	Store
Gizmo	Wiz
Camera	Ritz
Camera	Wiz

### **Output**

Name	Category	Store
Gizmo	gadget	Wiz
Camera	Photo	Ritz
Camera	Photo	Wiz
-OneClick	Photo	NULL

Now it's present

## Left Outer Join (Details)

### from R left outer join S on C1 where C2

- 1. Compute cross product R×S
- 2. Filter on C1
- 3. Add all R records without a match
- 4. Filter on C2

## **Joins**

Inner join

Left outer join

Right outer join

Full outer join

# SQL: Beyond Relations

## **Beyond Relations**

Sparse vectors, matrices

Graph databases

Important to data science!

## Sparse Matrix

$$A = \begin{bmatrix} 5 & 0 & -2 \\ 0 & 0 & -1 \\ 0 & 7 & 0 \end{bmatrix}$$

How can we represent it as a relation?

# Sparse Matrix

$$A = \begin{bmatrix} 5 & 0 & -2 \\ 0 & 0 & -1 \\ 0 & 7 & 0 \end{bmatrix}$$

Row	Col	Val
1	1	5
1	3	<b>-</b> 2
2	3	-1
3	2	7

# Matrix Multiplication in SQL

$$C = A \cdot B$$

## Matrix Multiplication in SQL

$$C = A \cdot B$$

$$C_{ik} = \sum_{j} A_{ij} \cdot B_{jk}$$

## Matrix Multiplication in SQL

$$C = A \cdot B$$

$$C_{ik} = \sum_{j} A_{ij} \cdot B_{jk}$$

SELECT A.row, B.col, sum(A.val\*B.val)

FROM A, B

WHERE A.col = B.row

**GROUP BY A.row, B.col**;

### Discussion

Matrix multiplication = join + group-by

Try at home: write in SQL

$$Tr(A \cdot B \cdot C)$$

where the trace is defined as:

$$Tr(X) = \sum_{i} X_{ii}$$

Surprisingly, A + B is a bit harder...

## Matrix Addition in SQL

$$C = A + B$$

## Matrix Addition in SQL

$$C = A + B$$

SELECT A.row, A.col, A.val + B.val as val

FROM A, B

WHERE A.row = B.row and A.col = B.col

## Matrix Addition in SQL

$$C = A + B$$

SELECT A.row, A.col, A.val + B.val as val

FROM A, B

WHERE A.row = B.row and A.col = B.col

Why is this wrong?

$$C = A + B$$

**SELECT** 

FROM A full outer join B ON A.row = B.row and A.col = B.col;

$$C = A + B$$

### **SELECT**

(CASE WHEN A.val is null THEN 0 ELSE A.val END) + (CASE WHEN B.val is null THEN 0 ELSE B.val END) as val FROM A full outer join B ON A.row = B.row and A.col = B.col;

$$C = A + B$$

#### **SELECT**

(CASE WHEN A.row is null THEN B.row ELSE A.row END) as row,

(CASE WHEN A.val is null THEN 0 ELSE A.val END) + (CASE WHEN B.val is null THEN 0 ELSE B.val END) as val FROM A full outer join B ON A.row = B.row and A.col = B.col;

$$C = A + B$$

#### SELECT

(CASE WHEN A.row is null THEN B.row ELSE A.row END) as row, (CASE WHEN A.col is null THEN B.col ELSE A.col END) as col, (CASE WHEN A.val is null THEN 0 ELSE A.val END) + (CASE WHEN B.val is null THEN 0 ELSE B.val END) as val FROM A full outer join B ON A.row = B.row and A.col = B.col;

## Solution 2: Group By

$$C = A + B$$

```
SELECT m.row, m.col, sum(m.val)
FROM (SELECT * FROM A

UNION ALL

SELECT * FROM B) as m

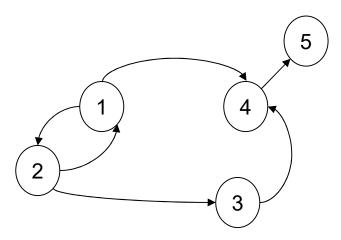
GROUP BY m.row, m.col;
```

### A graph is a simple relational database

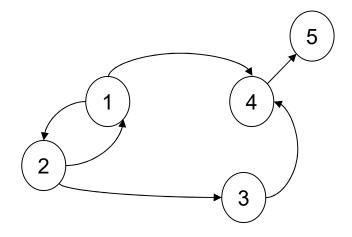
- Niche area: graph databases/languages
  - E.g. Neo4J, TigerGraph, Sparql

- Do we need specialized graph engines?
  - Dan's answer: NO
  - We may need better languages: datalog

### A graph:



A graph:



A relation:

Ed	ae
-	$\mathcal{S}$

src	dst
1	2
2	1
2	3
1	4
3	4
4	5

A graph:

1 4 3

A relation:

Edge

src	dst
1	2
2	1
2	3
1	4
3	4
4	5

Find nodes at distance 2:  $\{(x,z)|\exists y\ Edge(x,y)\land Edge(y,z)\}$ 

A graph:

1 4 3

A relation:

Edge

src	dst
1	2
2	1
2	3
1	4
3	4
4	5

Find nodes at distance 2:  $\{(x,z)|\exists y\ Edge(x,y)\land Edge(y,z)\}$ 

SELECT DISTINCT e1.src as X, e2.dst as Z FROM Edge e1, Edge e2 WHERE e1.dst = e2.src;

# Crash Course in Formal Logic

 The Relational Data Model is <u>founded</u> on first order logic ("What goes around")

SQL was designed as a more friendly language than FO

 Complex SQL queries are sometimes best understood in the framework of FO

# Crash Course in Formal Logic

### Atomic predicates:

- Likes(x,y)
- Product(x,y,z)pid, name, color
- Product(x,y,'red')

Connectives:  $\land$ ,  $\lor$ ,  $\neg$ ,  $\Rightarrow$ ,  $\exists$ ,  $\forall$ 

# Crash Course in Formal Logic

### Atomic predicates:

- Likes(x,y)
- Product(x,y,z)pid, name, color
- Product(x,y,'red')

### Connectives: $\land$ , $\lor$ , $\neg$ , $\Rightarrow$ , $\exists$ , $\forall$

- ∃x P(x): there exists x s.t. P(x) is true
- ∀x P(x): for every x, P(x) is true

#### Atomic predicates:

- Likes(x,y)
- Product(x,y,z)pid, name, color
- Product(x,y,'red')

Connectives:  $\land$ ,  $\lor$ ,  $\neg$ ,  $\Rightarrow$ ,  $\exists$ ,  $\forall$ 

- ∃x P(x):
   there exists x s.t. P(x) is true
- ∀x P(x): for every x, P(x) is true

What do these sentences say?

 $\exists x(Likes('Alice',x)\land Likes('Bob',x))$ 

#### Atomic predicates:

- Likes(x,y)
- Product(x,y,z)pid, name, color
- Product(x,y,'red')

Connectives:  $\land$ ,  $\lor$ ,  $\neg$ ,  $\Rightarrow$ ,  $\exists$ ,  $\forall$ 

- ∃x P(x):
   there exists x s.t. P(x) is true
- ∀x P(x): for every x, P(x) is true

What do these sentences say?

 $\exists x(Likes('Alice',x)\land Likes('Bob',x))$ 

There is somebody liked by both Alice and Bob

#### Atomic predicates:

- Likes(x,y)
- Product(x,y,z)pid, name, color
- Product(x,y,'red')

Connectives:  $\land$ ,  $\lor$ ,  $\neg$ ,  $\Rightarrow$ ,  $\exists$ ,  $\forall$ 

- ∃x P(x):
   there exists x s.t. P(x) is true
- ∀x P(x): for every x, P(x) is true

What do these sentences say?

 $\exists x(Likes('Alice',x)\land Likes('Bob',x))$ 

There is somebody liked by both Alice and Bob

 $\forall x (Likes('Alice',x) \Rightarrow Likes('Bob',x))$ 

#### Atomic predicates:

- Likes(x,y)
- Product(x,y,z)pid, name, color
- Product(x,y,'red')

### Connectives: $\land$ , $\lor$ , $\neg$ , $\Rightarrow$ , $\exists$ , $\forall$

- ∃x P(x):
   there exists x s.t. P(x) is true
- ∀x P(x): for every x, P(x) is true

What do these sentences say?

 $\exists x(Likes('Alice',x)\land Likes('Bob',x))$ 

There is somebody liked by both Alice and Bob

 $\forall x (Likes('Alice',x) \Rightarrow Likes('Bob',x))$ 

Everybody liked by Alice, is also liked by Bob

#### Atomic predicates:

- Likes(x,y)
- Product(x,y,z)pid, name, color
- Product(x,y,'red')

#### Connectives: $\land$ , $\lor$ , $\neg$ , $\Rightarrow$ , $\exists$ , $\forall$

- ∃x P(x):
   there exists x s.t. P(x) is true
- ∀x P(x): for every x, P(x) is true

What do these sentences say?

 $\exists x(Likes('Alice',x)\land Likes('Bob',x))$ 

There is somebody liked by both Alice and Bob

 $\forall x (Likes('Alice',x) \Rightarrow Likes('Bob',x))$ 

Everybody liked by Alice, is also liked by Bob

 $\forall x (\exists y \text{ Likes}(x,y) \Rightarrow \text{Likes}(x,'Alice'))$ 

#### Atomic predicates:

- Likes(x,y)
- Product(x,y,z)pid, name, color
- Product(x,y,'red')

#### Connectives: $\land$ , $\lor$ , $\neg$ , $\Rightarrow$ , $\exists$ , $\forall$

- ∃x P(x): there exists x s.t. P(x) is true
- ∀x P(x): for every x, P(x) is true

What do these sentences say?

 $\exists x(Likes('Alice',x)\land Likes('Bob',x))$ 

There is somebody liked by both Alice and Bob

 $\forall x (Likes('Alice',x) \Rightarrow Likes('Bob',x))$ 

Everybody liked by Alice, is also liked by Bob

 $\forall x (\exists y \text{ Likes}(x,y) \Rightarrow \text{Likes}(x,'Alice'))$ 

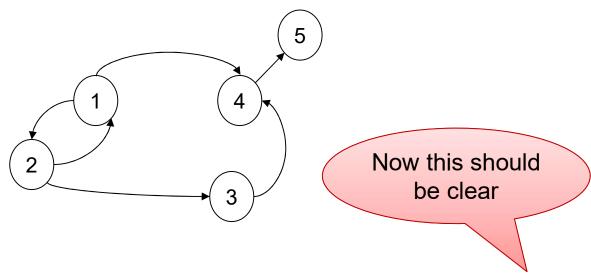
Everybody who likes somebody also likes Alice

### Graph Databases

A graph:

A relation:

Edge



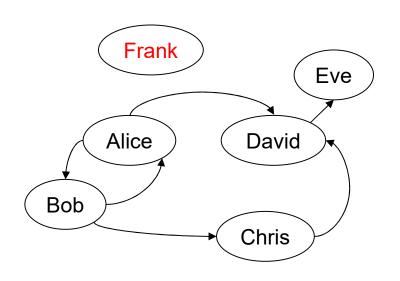
src	dst	
1	2	
2	1	
2	3	
1	4	
3	4	
4	5	

Find nodes at distance 2:  $\{(x,z)|\exists y\ Edge(x,y)\land Edge(y,z)\}$ 

SELECT DISTINCT e1.src as X, e2.dst as Z FROM Edge e1, Edge e2 WHERE e1.dst = e2.src;

### Other Representation

Representing nodes separately; needed for "isolated nodes" e.g. Frank



### Node

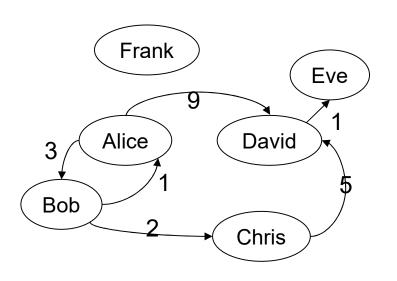
src
Alice
Bob
Chris
David
Eve
Frank

### Edge

src	dst
Alice	Bob
Bob	Alice
Bob	Chris
Alice	David
Chris	David
David	Eve

### Other Representation

Adding edge labels ...



### Node

src
Alice
Bob
Chris
David
Eve
Frank

### Edge

src	dst	weight
Alice	Bob	3
Bob	Alice	1
Bob	Chris	2
Alice	David	9
Chris	David	5
David	Eve	1

### Limitations of SQL

- No recursion!
- Data Science often requires recursion
- Datalog is designed for recursion
  - later in the quarter
- Practical solution
  - Use some external driver, e.g. pyton

Tom Mitchell: Machine Learning

### Data

X1	X2	X3	Υ
3	9	3	0
3	5	7	1
6	6 2 2		0
3	6	3	0
5	5	9	1
9	9 3		1

Tom Mitchell: Machine Learning

#### Data

X1	X2	X3	Υ
3	9	3	0
3	5	7	1
6	2	2	0
3	6 3	3	0
5	5	9	1
9	3	3	1

$$P(Y = 0|X) = \frac{1}{1 + exp(w_0 + \sum_{i=1,3} w_i X_i)}$$

Switched

(following Mitchell)

$$P(Y = 1|X) = \frac{exp(w_0 + \sum_{i=1,3} w_i X_i)}{1 + exp(w_0 + \sum_{i=1,3} w_i X_i)}$$

Tom Mitchell: Machine Learning

#### Data

X1	X2	X3	Υ
3	9	3	0
3	5	7	1
6	2	2	0
3	6	3	0
5	5	9	1
9	3	3	1

$$P(Y = 0|X) = \frac{1}{1 + exp(w_0 + \sum_{i=1,3} w_i X_i)}$$

Switched

(following Mitchell)

$$P(Y = 1|X) = \frac{exp(w_0 + \sum_{i=1,3} w_i X_i)}{1 + exp(w_0 + \sum_{i=1,3} w_i X_i)}$$

Train weights  $w_0, w_1, w_2, w_3$  to minimize loss:

$$L(w_0, ..., w_3) = \sum_{\ell=1, N} (Y^{\ell} \cdot \ln P(Y = 1 | X^{\ell}) + (1 - Y^{\ell}) \cdot \ln P(Y = 0 | X^{\ell}))$$

Tom Mitchell: Machine Learning

**Gradient Descent:** 

#### Data

X1	X2	X3	Υ
3	9	3	0
3	5	7	1
6	2	2	0
3	6	3	0
5	5	9	1
9	3	3	1

$$w_i \leftarrow w_i + \eta \sum_{\ell=1,N} X_i^{\ell} (Y^{\ell} - P(Y=1|X^{\ell}))$$

Tom Mitchell: Machine Learning

**Gradient Descent:** 

### Data

X1	X2	Х3	Υ	$w_i \leftarrow w_i + \eta \sum_{i} X_i^{\ell} (Y^{\ell} - P(Y = 1   X^{\ell}))$
3	9	3	0	$\ell=1.N$
3	5	7	1	t-1,IV
6	2	2	CF	REATE TABLE W (k int primary key, w0 real, w1 real, w2 real, w3 real);
3	6	3	IN	SERT INTO W VALUES (1, 0, 0, 0, 0);
5	5	9	1	
9	3	3	1	

Tom Mitchell: Machine Learning

**Gradient Descent:** 

### Data

X1	X2	X3	Υ	$w_i \leftarrow w_i + \eta \sum_{i=1}^{\ell} X_i^{\ell} (Y^{\ell} - P(Y = 1 X^{\ell}))$
3	9	3	0	
3	5	7	1	t-1,N
	2	2		

 6
 2
 2

 3
 6
 3

CREATE TABLE W (k int primary key, w0 real, w1 real, w2 real, w3 real); INSERT INTO W VALUES (1, 0, 0, 0, 0);

FROM data d, W WHERE W.k=1

Tom Mitchell: Machine Learning

**Gradient Descent:** 

#### Data

X1	X2	X3	Υ	$w_i \leftarrow v$
3	9	3	0	· · · ·
3	5	7	1	
_	_	_		

$$w_i \leftarrow w_i + \eta \sum_{\ell=1,N} X_i^{\ell} (Y^{\ell} - P(Y=1|X^{\ell}))$$

6	2	2	CREATE TABLE W (k int primary key, w0 real, w1 real, w2 real, w3 real);
3	6	3	INSERT INTO W VALUES (1, 0, 0, 0, 0);

#### **SELECT**

W.w0+0.01\*sum(d.Y - 1 + 1/(1+exp(W.w0+W.w1\*d.X1+W.w2\*d.X2+W.w3\*d.X3))) as w0,

FROM data d, W WHERE W.k=1

Tom Mitchell: Machine Learning

**Gradient Descent:** 

### Data

X1	X2	X3	Υ	$w_i \leftarrow w_i + \eta \sum_i X_i^{\ell} (Y^{\ell} - P(Y = 1 X^{\ell}))$	
3	9	3	0	$\ell=1.N$	
3	5	7	1	t-1,N	
6	2	2	CF	REATE TABLE W (k int primary key, w0 real, w1 real, w2 real, w3 real);	
3	6	3	IN	ISERT INTO W VALUES (1, 0, 0, 0, 0);	

#### **SELECT**

 $W.w0+0.01*sum(d.Y-1+1/(1+exp(W.w0+W.w1*d.X1+W.w2*d.X2+W.w3*d.X3))) \ as \ w0, \\ W.w1+0.01*sum(d.X1*(d.Y-1+1/(1+exp(W.w0+W.w1*d.X1+W.w2*d.X2+W.w3*d.X3)))) \ as \ w1, \\ W.w1+0.01*sum(d.X1*(d.Y-1+1/(1+exp(W.w0+W.w1*d.X1+W.w2*d.X2+W.w3*d.X3)))) \ as \ w1, \\ W.w1+0.01*sum(d.X1*(d.Y-1+1/(1+exp(W.w0+W.w1*d.X1+W.w2*d.X2+W.w3*d.X3)))) \ as \ w2, \\ W.w1+0.01*sum(d.X1*(d.Y-1+1/(1+exp(W.w0+W.w1*d.X1+W.w2*d.X2+W.w3*d.X3)))) \ as \ w3, \\ W.w1+0.01*sum(d.X1*(d.Y-1+1/(1+exp(W.w0+W.w1*d.X1+W.w2*d.X1+W.w3*d.X3))) \ as \ w3, \\ W.w1+0.01*sum(d.X1*(d.Y-1+1/(1+exp(W.w1+1/(1+e$ 

FROM data d, W WHERE W.k=1

Tom Mitchell: Machine Learning

**Gradient Descent:** 

#### Data

$\frac{3}{3}$ $\frac{9}{5}$ $\frac{3}{7}$ $\frac{1}{6}$ $\frac{2}{2}$ CREATE TABLE W (k int primary key, w0 real, w1 real, w2 real, w3 real)	X1	X2	X3	Υ	$w_i \leftarrow w_i + \eta \sum_{i} X_i^{\ell} (Y^{\ell} - P(Y = 1 X^{\ell}))$	
3 5 7 1  6 2 2 CREATE TABLE W (k int primary key, w0 real, w1 real, w2 real, w3 real)	3	9	3	0		
CREATE TABLE W (k int primary key, w0 real, w1 real, w2 real, w3 real)	3	5	7	1	$\iota - 1, N$	
$\begin{vmatrix} 3 & 6 & 3 \end{vmatrix}$   INSERT INTO W VALUES (1, 0, 0, 0, 0);	6	2	2	CF	REATE TABLE W (k int primary key, w0 real, w1 real, w2 real, w3 real);	
	3	6	3	IN		

#### **SELECT**

W.w0+0.01\*sum(d.Y - 1 + 1/(1+exp(W.w0+W.w1\*d.X1+W.w2\*d.X2+W.w3\*d.X3))) as w0, W.w1+0.01\*sum(d.X1\*(d.Y - 1 + 1/(1+exp(W.w0+W.w1\*d.X1+W.w2\*d.X2+W.w3\*d.X3)))) as w1, W.w2+0.01\*sum(d.X2\*(d.Y - 1 + 1/(1+exp(W.w0+W.w1\*d.X1+W.w2\*d.X2+W.w3\*d.X3)))) as w2, W.w3+0.01\*sum(d.X3\*(d.Y - 1 + 1/(1+exp(W.w0+W.w1\*d.X1+W.w2\*d.X2+W.w3\*d.X3)))) as w3

FROM data d, W

WHERE W.k=1

Tom Mitchell: Machine Learning

**Gradient Descent:** 

#### Data

$\begin{array}{c ccccccccccccccccccccccccccccccccccc$	X1	$w_i \leftarrow w_i + \eta \sum_i X_i^{\ell} (Y^{\ell} - P(Y = 1 X^{\ell}))$	
	3		
	3	t-1,N	
6 2 2 CREATE TABLE W (k int primary key, w0 real, w1 real, w2 real,	6	EATE TABLE W (k int primary key, w0 real, w1 real, w2 real, w3 real);	
3 6 3 INSERT INTO W VALUES (1, 0, 0, 0, 0);	3	NSERT INTO W VALUES (1, 0, 0, 0, 0);	

#### **SELECT**

 $W.w0+0.01*sum(d.Y-1+1/(1+exp(W.w0+W.w1*d.X1+W.w2*d.X2+W.w3*d.X3))) \ as \ w0, \\ W.w1+0.01*sum(d.X1*(d.Y-1+1/(1+exp(W.w0+W.w1*d.X1+W.w2*d.X2+W.w3*d.X3)))) \ as \ w1, \\ W.w2+0.01*sum(d.X2*(d.Y-1+1/(1+exp(W.w0+W.w1*d.X1+W.w2*d.X2+W.w3*d.X3)))) \ as \ w2, \\ W.w3+0.01*sum(d.X3*(d.Y-1+1/(1+exp(W.w0+W.w1*d.X1+W.w2*d.X2+W.w3*d.X3)))) \ as \ w3, \\ W.w3+0.01*sum(d.X3*(d.Y-1+1/(1+exp(W.w1+W.w1*d.X1+W.w2*d.X2+W.w3*d.X3)))) \ as \ w3, \\ W.w3+0.01*sum(d.X3*(d.Y-1+1/(1+exp(W.w1+W.w1*d.X1+W.w2*d.X3+W.w3*d.X3))) \ as \ w3, \\ W.w3+0.01*sum(d.X3*(d.Y-1+1/(1+exp(W.w1+W.w1+W.w1*$ 

FROM data d, W

WHERE W.k=1

**GROUP BY** W.k, W.w0, W.w1, W.w2, W.w3;

Tom Mitchell: Machine Learning

**Gradient Descent:** 

#### Data

X1	X2	X3	Υ	$w_i \leftarrow w_i + \eta \sum_i X_i^{\ell} (Y^{\ell} - P(Y = 1 X^{\ell}))$	
3	9	3	0		
3	5	7	1	$\ell$ $=$ 1, $N$	
6	2	2	CF	REATE TABLE W (k int primary key, w0 real, w1 real, w2 real, w3 real);	
3	6	3	IN	ISERT INTO W VALUES (1, 0, 0, 0, 0);	

#### **SELECT**

 $W.w0+0.01*sum(d.Y-1+1/(1+exp(W.w0+W.w1*d.X1+W.w2*d.X2+W.w3*d.X3))) \ as \ w0, \\ W.w1+0.01*sum(d.X1*(d.Y-1+1/(1+exp(W.w0+W.w1*d.X1+W.w2*d.X2+W.w3*d.X3)))) \ as \ w1, \\ W.w2+0.01*sum(d.X2*(d.Y-1+1/(1+exp(W.w0+W.w1*d.X1+W.w2*d.X2+W.w3*d.X3)))) \ as \ w2, \\ W.w3+0.01*sum(d.X3*(d.Y-1+1/(1+exp(W.w0+W.w1*d.X1+W.w2*d.X2+W.w3*d.X3)))) \ as \ w3, \\ W.w3+0.01*sum(d.X3*(d.Y-1+1/(1+exp(W.w0+W.w1*d.X1+W.w2*d.X3+W.w3*d.X3)))) \ as \ w3, \\ W.w3+0.01*sum(d.X3*(d.Y-1+1/(1+exp(W.w1+W.w1*d.X1+W.w2*d.X3+W.w3*d.X3)))) \ as \ w3, \\ W.w3+0.01*sum(d.X3*(d.Y-1+1/(1+exp(W.w1+W.w1*d.X1+W.w2*d.X3+W.w3*d.X3+W.w3*d.X3)))) \ as \ w3, \\ W.w3+0.01*sum(d.X3*(d.Y-1+1/(1+exp(W.w1$ 

FROM data d, W

WHERE W.k=1

GROUP BY W.k, W.w0, W.w1, W.w2, W.w3;

Update W, then repeat this e.g. using python

# Lecture Summary

- One line takeaway:
  - Relational model → data independence
- What you should do next:
  - Review SQL
  - Write reviews for next lecture
  - Start working on HW1 (redshift)