Database Management Systems
CSEP 544

Lecture 7:
Parallel Data processing
Conceptual Design

Class overview

- Data models
  - Relational: SQL, RA, and Datalog
  - NoSQL: SQL++
- RDMBS internals
  - Query processing and optimization
  - Physical design
- Parallel query processing
  - Spark and Hadoop
- Conceptual design
  - E/R diagrams
  - Schema normalization
- Transactions
  - Locking and schedules
  - Writing DB applications

Data models

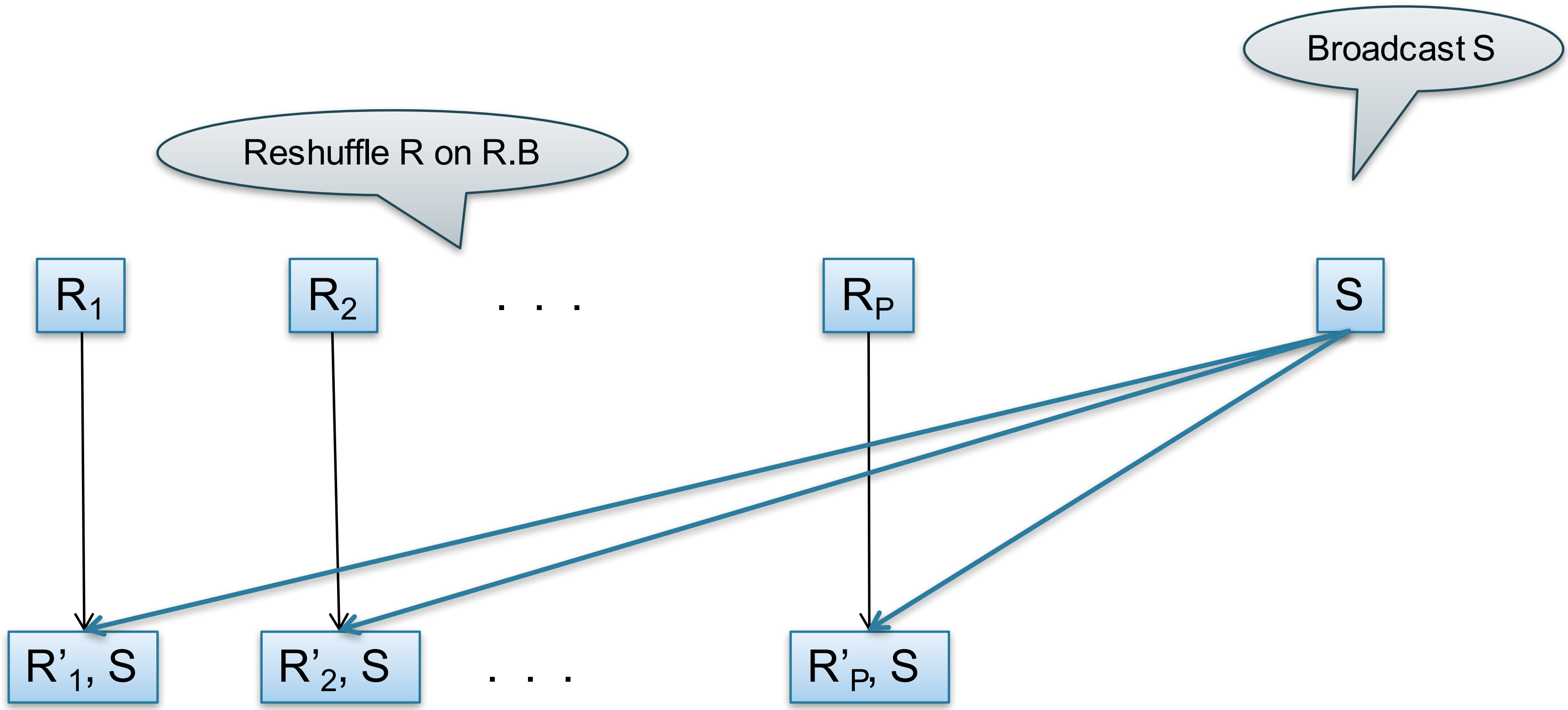
Query Processing

Using DBMS

Parallel Data Processing @ 1990

Data: R(A, B), S(C, D)
Query: $R(A,B) \bowtie_{B=C} S(C,D)$

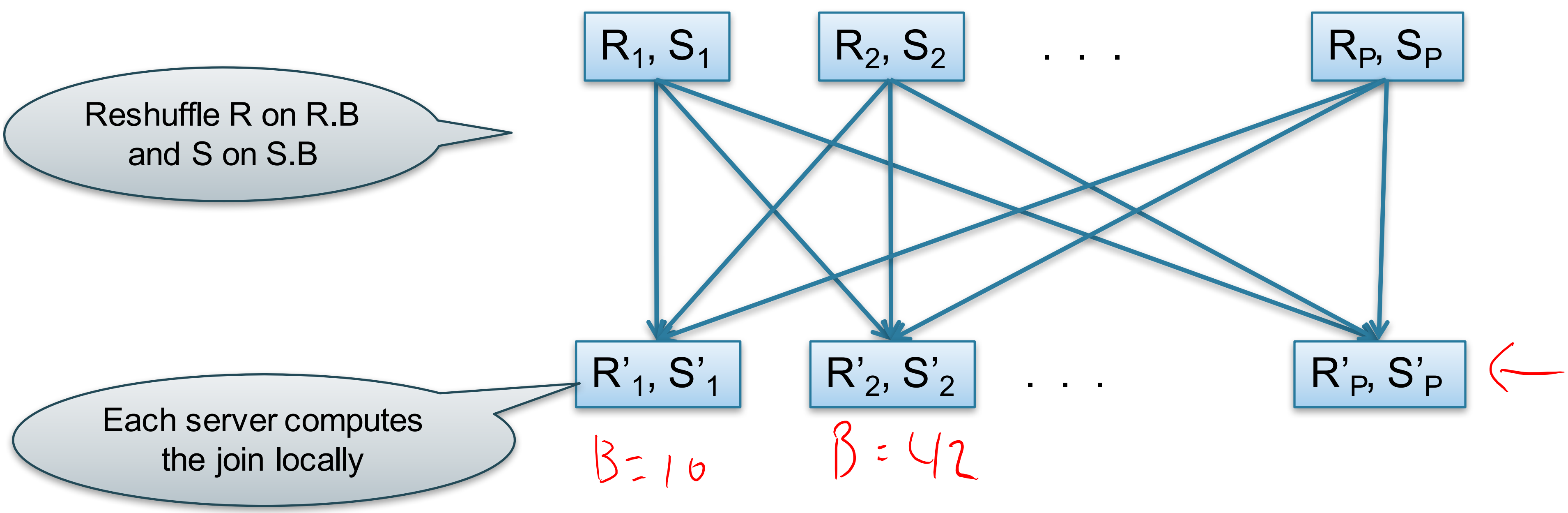
Broadcast Join



Why would you want to do this?

Parallel Execution of RA Operators: Partitioned Hash-Join

- **Data**: R(<u>K1</u>, A, B), S(<u>K2</u>, B, C)
- **Query**: R(<u>K1</u>, A, B) $\bowtie$ S(<u>K2</u>, B, C)
  – Initially, both R and S are partitioned on K1 and K2

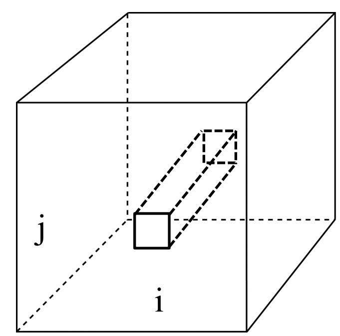


HyperCube Join

- Have P number of servers (say P=27 or P=1000)
- How do we compute this Datalog query in one step?
  Q(x,y,z) = R(x,y),S(y,z),T(z,x)
- Organize the P servers into a cube with side $P^{1/3}$
  - Thus, each server is uniquely identified by (i,j,k), i,j,k$\leq P^{1/3}$
- Step 1:

  1, 2 x=1 y=2

  - Each server sends R(x,y) to all servers (h(x),h(y),*)
  - Each server sends S(y,z) to all servers (*,h(y),h(z))
  - Each server sends T(x,z) to all servers (h(x),*,h(z))



- Final output:
  - Each server (i,j,k) computes the query R(x,y),S(y,z),T(z,x) locally
- Analysis: each tuple R(x,y) is replicated at most $P^{1/3}$ times

Parallel Data Processing @ 2000

Example

- Counting the number of occurrences of each word in a large collection of documents
- Each Document
  - The key = document id (did)
  - The value = set of words (word)

```
map(String key, String value):
    // key: document name
    // value: document contents
    for each word w in value:
            EmitIntermediate(w, “1”);
```

```
reduce(String key, Iterator values):
    // key: a word
    // values: a list of counts
    int result = 0;
    for each v in values:
            result += ParseInt(v);
    Emit(AsString(result));
```

Interesting Implementation Details

Worker failure:

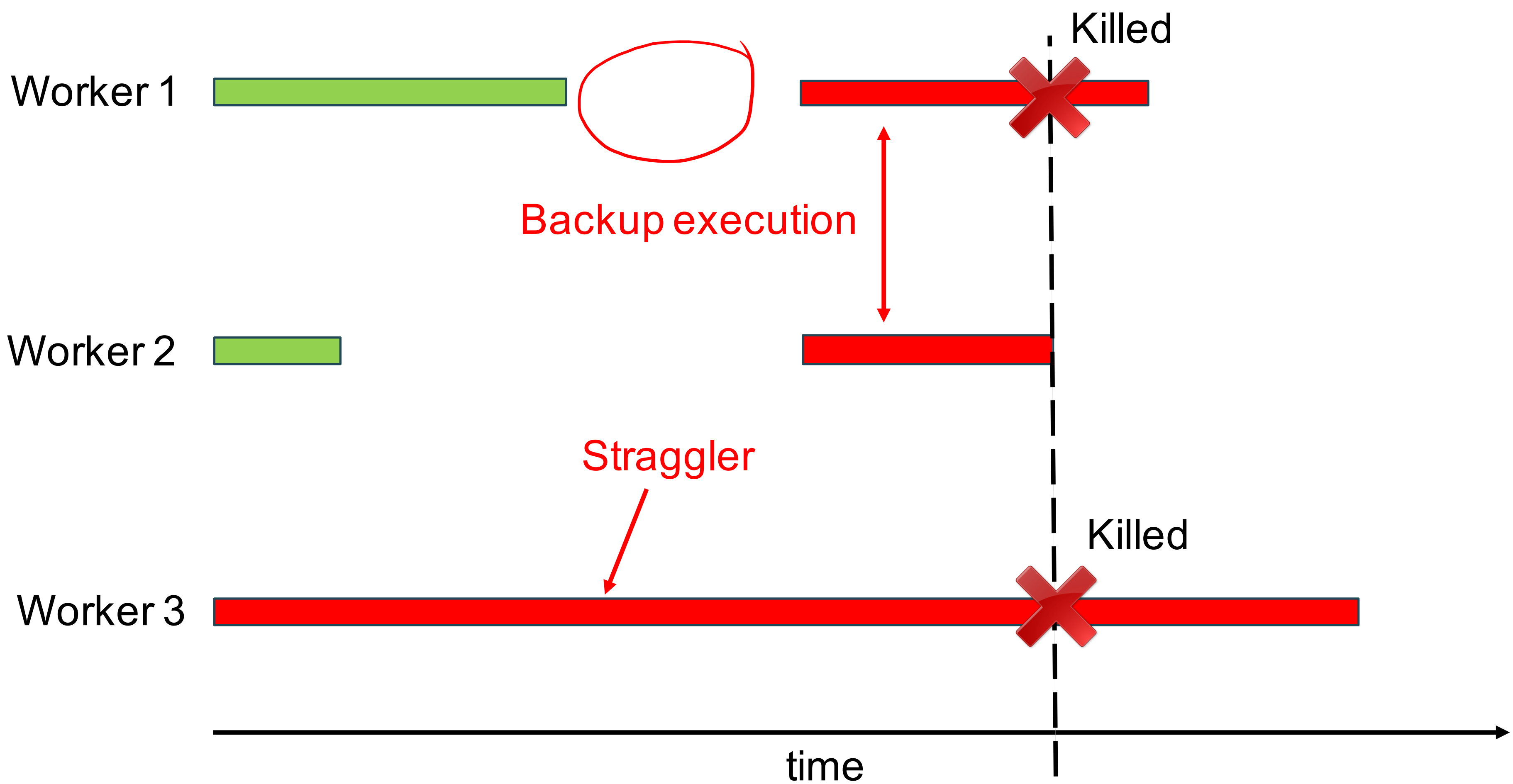
- Master pings workers periodically,
- If down then reassigns the task to another worker

Interesting Implementation Details

Backup tasks:

- *Straggler* = a machine that takes unusually long time to complete one of the last tasks. E.g.:
  - Bad disk forces frequent correctable errors (30MB/s → 1MB/s)
  - The cluster scheduler has scheduled other tasks on that machine
- Stragglers are a main reason for slowdown
- Solution*: pre-emptive backup execution of the last few remaining in-progress tasks*

Straggler Example



Using MapReduce in Practice:

Implementing RA Operators in MR

Relational Operators in MapReduce

Given relations R(A,B) and S(B, C) compute:

- Selection: $\sigma_{A=123}(R)$
- Group-by: $\gamma_{A,sum(B)}(R)$
- Join: $R \bowtie S$

Selection $\sigma_{A=123}(R)$

tuple from R

```
map(String value):
    if value.A = 123:
        EmitIntermediate(value.key, value);
```

123, [t1, t2, t3, ...]

```
reduce(String k, Iterator values):
    for each v in values:
        Emit(v);
```

Selection $\sigma_{A=123}(R)$

R

A	B
42	10
50	2

→ 42, 10

→ 50, 2

```
map(String value):
    if  value.A = 123:
        EmitIntermediate(value.key, value);
```

42, (42, 10)

```
reduce(String k, Iterator values):
    for each v in values:
        Emit(v);
```

No need for reduce.
But need system hacking in Hadoop
to remove reduce from MapReduce

Group By $\gamma_{A,sum(B)}(R)$

A	B
1	10
1	20
2	30
K	V

```
map(String value):
    EmitIntermediate(value.A, value.B);
```

r_1:
1, [10, 20]

r_2:
2, [30]

```
reduce(String k, Iterator values):
    s = 0
    for each v in values:
        s = s + v
    Emit(k, s);
```

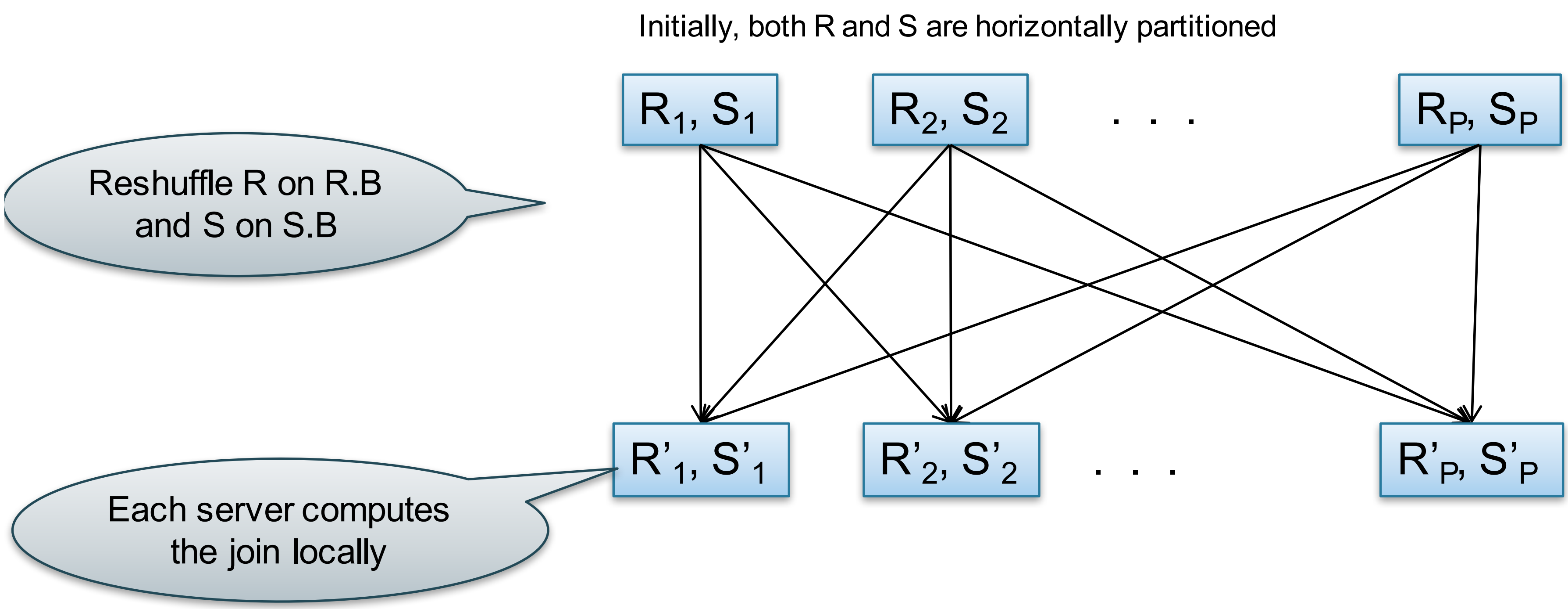
Join

Two simple parallel join algorithms:

- Partitioned hash-join (we saw it, will recap)
- Broadcast join

$R(A,B) \bowtie_{B=C} S(C,D)$

Partitioned Hash-Join



$R(A,B) \bowtie_{B=C} S(C,D)$

Partitioned Hash-Join

R:

A	B
1	2
4	2

S:

C	D
3	4
2	5

(R, 1, 2)
(S, 3, 4)

R.txt
S.txt

```
map(String value):
    case value.relationName of
        'R': EmitIntermediate(value.B, ('R', value));
        'S': EmitIntermediate(value.C, ('S', value));
```

$2, (1,2)_R$ $3, (3,4)_S$

$2, (4,2)_R$ $2\ (2,5)_S$

K K

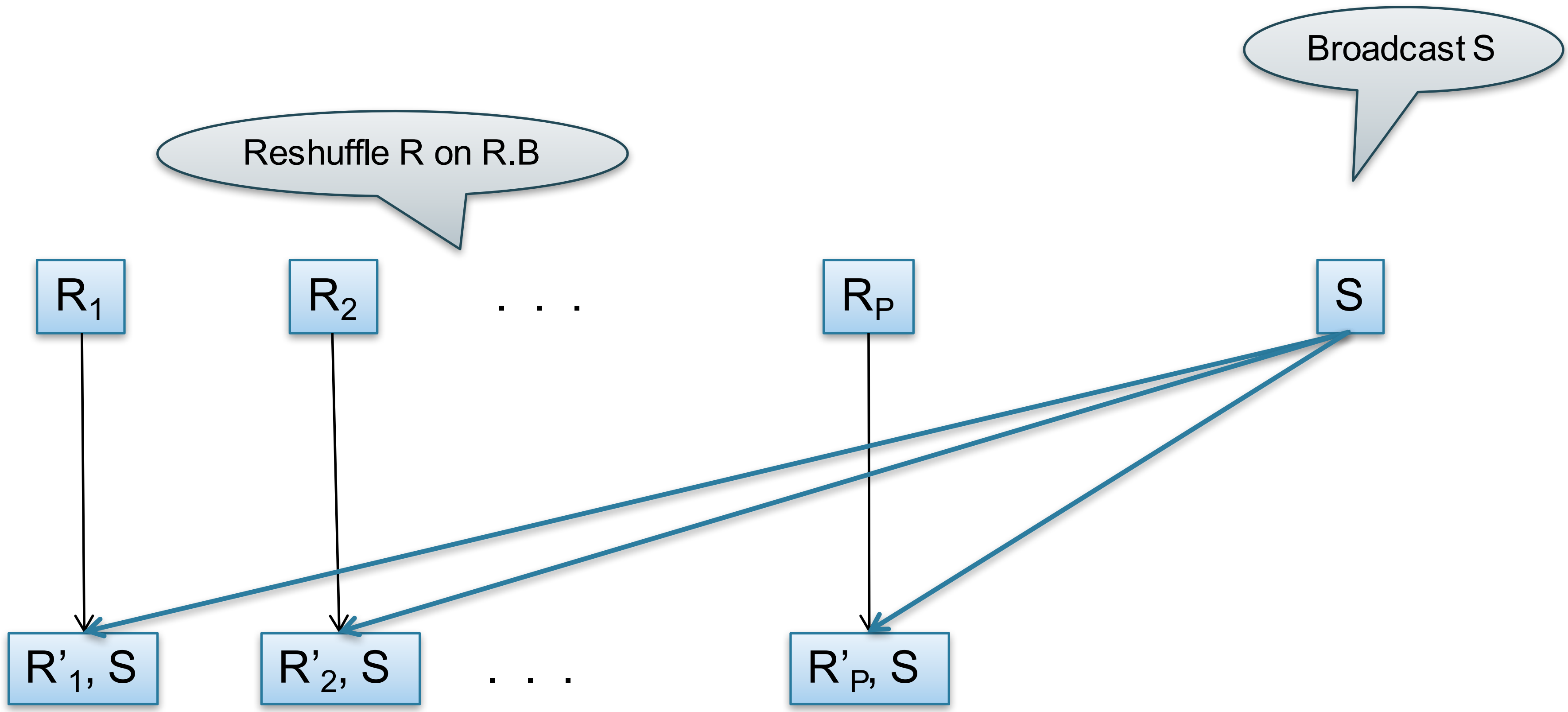
r_1: $2, [(1,2)_R, (4,2)_R, (2,5)_S]$

r_2: $3, [(3,4)_S]$

```
reduce(String k, Iterator values):
    R = empty;  S = empty;
    for each v in values:
        case v.type of:
            'R':  R.insert(v)
            'S':  S.insert(v);
    for v1 in R, for v2 in S
        Emit(v1,v2);
```

$R(A,B) \bowtie_{B=C} S(C,D)$

Broadcast Join



$R(A,B) \bowtie_{B=C} S(C,D)$

Broadcast Join

R tuples

```
map(String value):
    open(S); /* over the network */
    hashTbl = new()
    for each w in S:
        hashTbl.insert(w.B, w)
    close(S);

    for each v in value:
        for each w in hashTbl.find(v.B)
            Emit(v,w);
```

map should read several records of R: value = some group of records

Read entire table S, build a Hash Table

hash join

```
reduce(…):
    /* empty: map-side only */
```

HW6

- HW6 will ask you to write SQL queries and MapReduce tasks using Spark
- You will get to "implement" SQL using MapReduce tasks
  - Can you beat Spark's implementation?

Conclusions

- MapReduce offers a simple abstraction, and handles distribution + fault tolerance
- Speedup/scaleup achieved by allocating dynamically map tasks and reduce tasks to available server. However, skew is possible (e.g., one huge reduce task)
- Writing intermediate results to disk is necessary for fault tolerance, but very slow.
- Spark replaces this with “Resilient Distributed Datasets” = main memory + lineage

Spark

A Case Study of the MapReduce Programming Paradigm

Parallel Data Processing @ 2010

Issues with MapReduce

- Difficult to write more complex queries
- Need multiple MapReduce jobs: dramatically slows down because it writes all results to disk

Spark

- Open source system from UC Berkeley
- Distributed processing over HDFS
- Differences from MapReduce:
  - Multiple steps, including iterations
  - Stores intermediate results in main memory
  - Closer to relational algebra (familiar to you)
- Details: http://spark.apache.org/examples.html

Spark

- Spark supports interfaces in Java, Scala, and Python
  - Scala: extension of Java with functions/closures
- We will illustrate use the Spark Java interface in this class
- Spark also supports a SQL interface (SparkSQL), and compiles SQL to its native Java interface

Resilient Distributed Datasets

- RDD = Resilient Distributed Datasets
  - A distributed, immutable relation, together with its *lineage*
  - Lineage = expression that says how that relation was computed = a relational algebra plan
- Spark stores intermediate results as RDD
- If a server crashes, its RDD in main memory is lost. However, the driver (=master node) knows the lineage, and will simply recompute the lost partition of the RDD

Programming in Spark

- A Spark program consists of:
  - Transformations (map, reduce, join…). Lazy
  - Actions (count, reduce, save...). Eager
- Eager: operators are executed immediately
- Lazy: operators are not executed immediately
  - A *operator tree* is constructed in memory instead
  - Similar to a relational algebra tree
- What are the benefits of lazy execution?

The RDD Interface

Programming in Spark

- RDD<T> = an RDD collection of type T
  - Partitioned, recoverable (through lineage), not nested
- Seq<T> = a sequence
  - Local to a server, may be nested

Example

Given a large log file hdfs://logfile.log retrieve all lines that:

- Start with “ERROR”
- Contain the string “sqlite”

```
s = SparkSession.builder()...getOrCreate();

lines = s.read().textFile(“hdfs://logfile.log”);

errors = lines.filter(l -> l.startsWith(“ERROR”));

sqlerrors = errors.filter(l -> l.contains(“sqlite”));

sqlerrors.collect();
```

Example

Given a large log file hdfs://logfile.log retrieve all lines that:

- Start with “ERROR”
- Contain the string “sqlite”

`lines, errors, sqlerrors` have type `JavaRDD<String>`

```
s = SparkSession.builder()...getOrCreate();

lines = s.read().textFile(“hdfs://logfile.log”);

errors = lines.filter(l -> l.startsWith(“ERROR”));

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```

Transformation:
Not executed yet…

Action:
triggers execution
of entire program

Example

Recall: anonymous functions
(lambda expressions) starting in Java 8

```
errors = lines.filter(l -> l.startsWith("ERROR"));
```

is the same as:

```
class FilterFn implements Function<Row, Boolean>{
  Boolean call (Row r)
  { return r.startsWith("ERROR"); }
}

errors = lines.filter(new FilterFn());
```

Example

Given a large log file hdfs://logfile.log retrieve all lines that:

- Start with “ERROR”
- Contain the string “sqlite”

```
s = SparkSession.builder()...getOrCreate();

sqlerrors = s.read().textFile(“hdfs://logfile.log”)
                .filter(l -> l.startsWith(“ERROR”))
                .filter(l -> l.contains(“sqlite”))
                .collect();
```

“Call chaining” style

MapReduce Again...

Steps in Spark resemble MapReduce:

- `col.filter(p)` applies in parallel the predicate p to all elements x of the partitioned collection, and returns collection with those x where `p(x) = true`
- `col.map(f)` applies in parallel the function f to all elements x of the partitioned collection, and returns a new partitioned collection

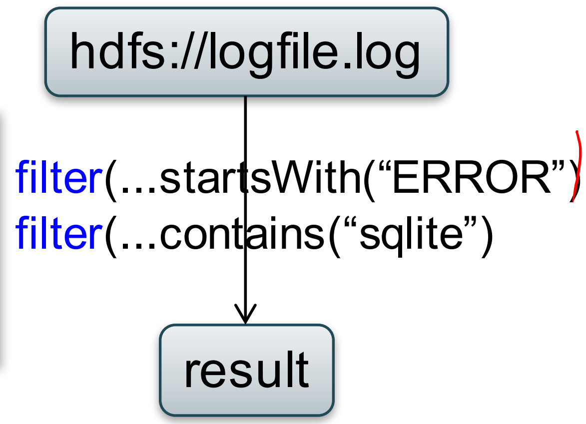
Persistence

```
lines = s.read().textFile("hdfs://logfile.log");
errors = lines.filter(l->l.startsWith("ERROR"));
sqlerrors = errors.filter(l->l.contains("sqlite"));
sqlerrors.collect();
```

If any server fails before the end, then Spark must restart

Persistence

RDD:

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Persistence

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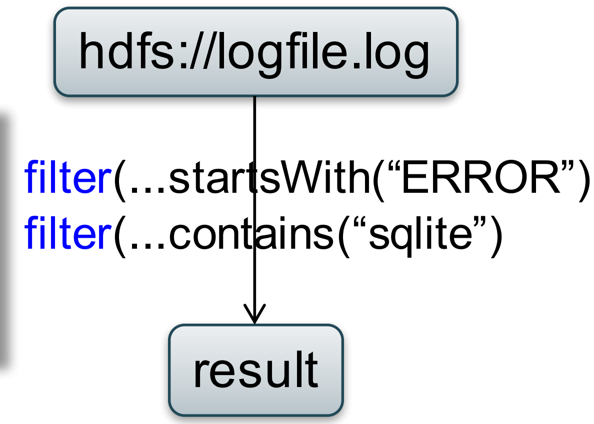


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errors = lines.filter(l->l.startsWith("ERROR"));
sqlerrors = errors.filter(l->l.contains("sqlite"));
sqlerrors.collect();
```

If any server fails before the end, then Spark must restart

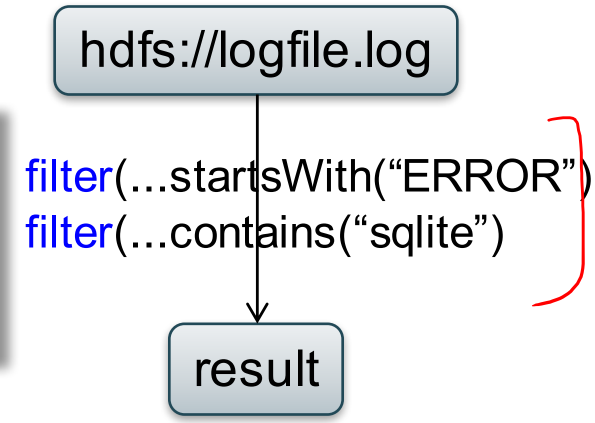
```
lines = s.read().textFile("hdfs://logfile.log");
errors = lines.filter(l->l.startsWith("ERROR"));
errors.persist();
sqlerrors = errors.filter(l->l.contains("sqlite"));
sqlerrors.collect()
```

New RDD

Spark can recompute the result from errors

Persistence

RDD:

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```
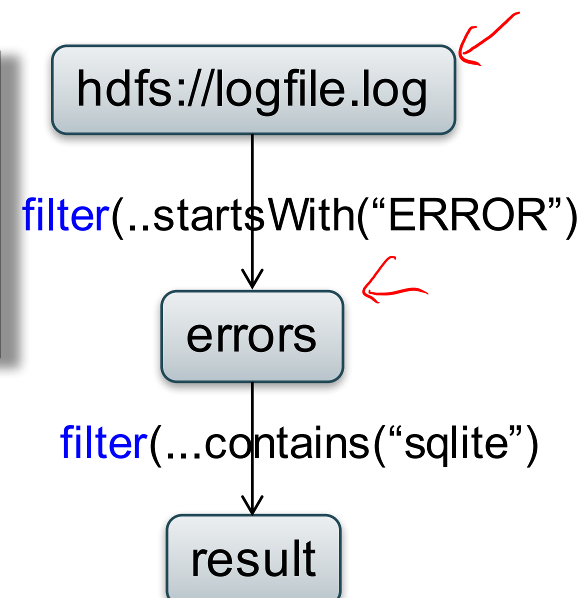

New RDD



Spark can recompute the result from errors

R(A,B)
S(A,C)

```
SELECT count(*)  FROM R, S
WHERE R.B > 200 and S.C < 100  and R.A = S.A
```

Example

```
R = s.read().textFile("R.csv").map(parseRecord).persist();
S = s.read().textFile("S.csv").map(parseRecord).persist();
```

Parses each line into an object

persisting on disk

R(A,B)
S(A,C)

```
SELECT count(*)  FROM R, S
WHERE R.B > 200 and S.C < 100  and R.A = S.A
```

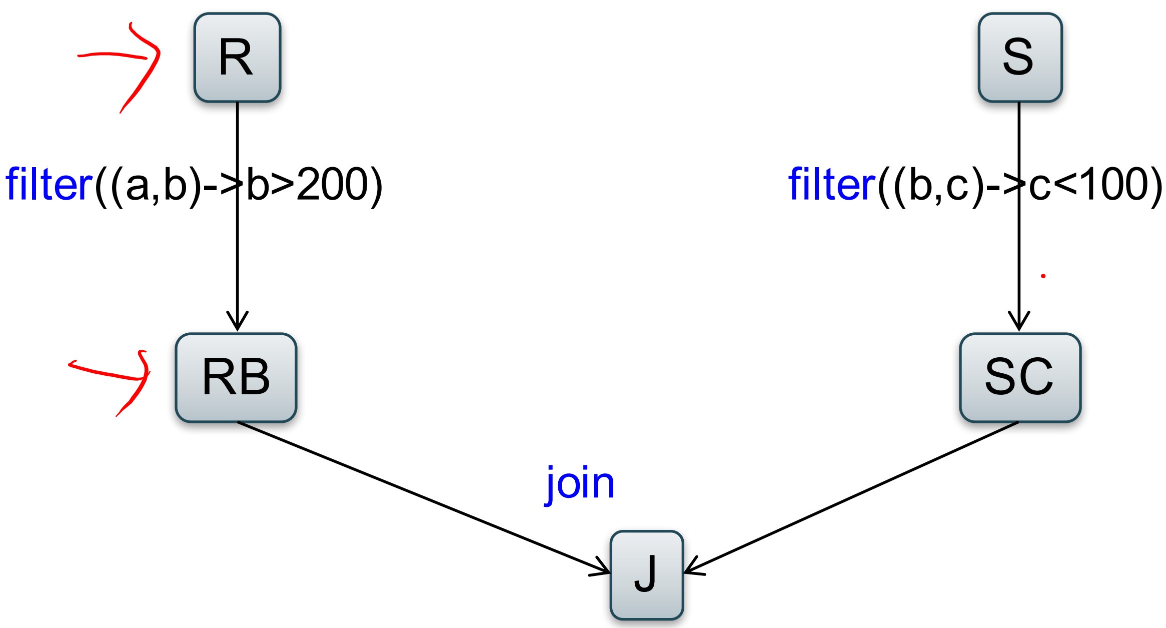
Example

```
R = s.read().textFile("R.csv").map(parseRecord).persist();
S = s.read().textFile("S.csv").map(parseRecord).persist();
RB = R.filter(t -> t.b > 200).persist();
SC = S.filter(t -> t.c < 100).persist();
J = RB.join(SC).persist();
J.count();
```

transformations

action

t.split(",")[4]



Recap: Programming in Spark

- A Spark/Scala program consists of:
  - Transformations (map, reduce, join…). Lazy
  - Actions (count, reduce, save...). Eager

- RDD<T> = an RDD collection of type T
  - Partitioned, recoverable (through lineage), not nested
- Seq<T> = a sequence
  - Local to a server, may be nested

Transformations:	
map(f : T -> U):	RDD<T> -> RDD<U>
flatMap(f: T -> Seq(U)):	RDD<T> -> RDD<U>
filter(f:T->Bool):	RDD<T> -> RDD<T>
groupByKey():	RDD<(K,V)> -> RDD<(K,Seq[V])>
reduceByKey(F:(V,V)-> V):	RDD<(K,V)> -> RDD<(K,V)>
union():	(RDD<T>,RDD<T>) -> RDD<T>
join():	(RDD<(K,V)>,RDD<(K,W)>) -> RDD<(K,(V,W))>
cogroup():	(RDD<(K,V)>,RDD<(K,W)>)-> RDD<(K,(Seq<V>,Seq<W>))>
crossProduct():	(RDD<T>,RDD<U>) -> RDD<(T,U)>

Actions:	
count():	RDD<T> -> Long
collect():	RDD<T> -> Seq<T>
reduce(f:(T,T)->T):	RDD<T> -> T
save(path:String):	Outputs RDD to a storage system e.g., HDFS

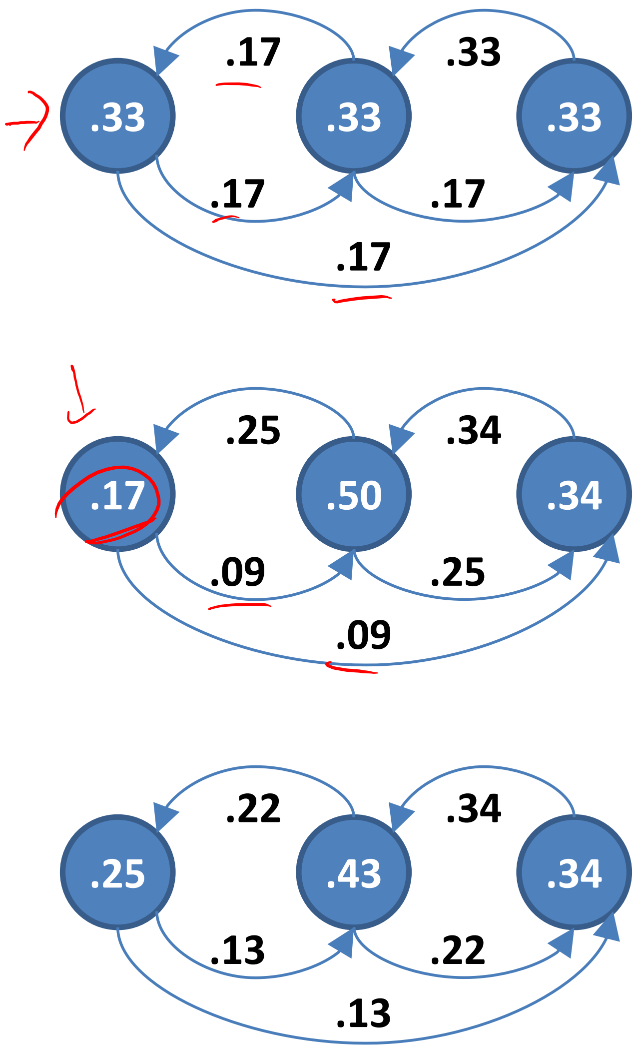
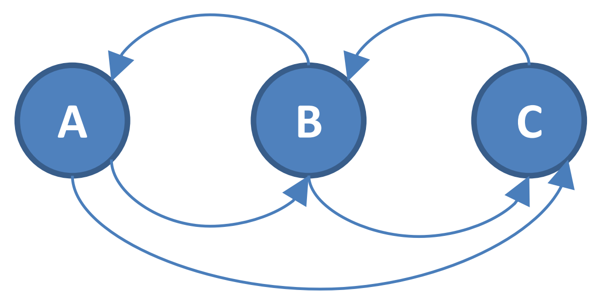
Spark 2.0

The DataFrame and Dataset Interfaces

DataFrames

- Like RDD, also an immutable distributed collection of data

- Organized into *named columns* rather than individual objects
  - Just like a relation
  - Elements are untyped objects called `Row`'s

- Similar API as RDDs with additional methods
  - ```
    people = spark.read().textFile(…);
    ageCol = people.col("age");
    ageCol.plus(10); // creates a new DataFrame
    ```
    ```

Datasets

- Similar to DataFrames, except that elements must be typed objects
- E.g.: `Dataset<People>` rather than `Dataset<Row>`
- Can detect errors during compilation time
- DataFrames are aliased as `Dataset<Row>` (as of Spark 2.0)
- You will use both Datasets and RDD APIs in HW6

Datasets API: Sample Methods

- Functional API
  - `agg(Column expr, Column... exprs)`
    Aggregates on the entire Dataset without groups.
  - `groupBy(String col1, String... cols)`
    Groups the Dataset using the specified columns, so that we can run aggregation on them.
  - `join(Dataset<?> right)`
    Join with another DataFrame.
  - `orderBy(Column... sortExprs)`
    Returns a new Dataset sorted by the given expressions.
  - `select(Column... cols)`
    Selects a set of column based expressions.
- "SQL" API
  - `SparkSession.sql("select * from R");`

- Look familiar?

An Example Application

PageRank

- Page Rank is an algorithm that assigns to each page a score such that pages have higher scores if more pages with high scores link to them

- Page Rank was introduced by Google, and, essentially, defined Google

PageRank toy example



Superstep 0

Superstep 1

Superstep 2

Input graph



http://www.slideshare.net/sscdotopen/large-scale/20

PageRank

```
for i = 1 to n:
  r[i] = 1/n

repeat
  for j = 1 to n: contribs[j] = 0
  for i = 1 to n:
     k = links[i].length()
     for j in links[i]:
        contribs[j] += r[i] / k
  for i = 1 to n: r[i] = contribs[i]
until convergence
/* usually 10-20 iterations */
```

Random walk interpretation:

Start at a random node i
At each step, randomly choose an outgoing link and follow it.

Repeat for a very long time

r[i] = prob. that we are at node i

PageRank

```
for i = 1 to n:
  r[i] = 1/n

repeat
  for j = 1 to n: contribs[j] = 0
  for i = 1 to n:
    k = links[i].length()
    for j in links[i]:
      contribs[j] += r[i] / k
   for i = 1 to n: r[i] = contribs[i]
until convergence
/* usually 10-20 iterations */
```

r[i] = a/N + (1-a)*contribs[i]

Random walk interpretation:

Start at a random node i
At each step, randomly choose an outgoing link and follow it.

Improvement: with small prob. a restart at a random node.

where a $\in (0,1)$ is the restart probability

P_1, [O_1, O_2] links

P_1, 0.33 ranks

(P_1, 0.33, [O_1, O_2]) $\leftarrow$

url r l

P_1, $\frac{0.33}{\text{size } [O_1, O_2]}$

links: RDD<url:string, outlinks:SEQ<string>>

ranks: RDD<url:string, rank:float>

PageRank

for i = 1 to n:
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      contribs[j] += r[i] / k
  for i = 1 to n: r[i] = a/N + (1-a)*contribs[i]
until convergence
/* usually 10-20 iterations */

```
// spark

links = spark.read().textFile(..)...
ranks = // RDD of (URL, 1/n) pairs

for (k = 1 to ITERATIONS) {

  // Build RDD of (targetURL, float) pairs
  // with contributions sent by each page
  contribs = links.join(ranks).flatMap {
    (url, lr) -> // lr: a (link, rank) pair
      links.map(dest ->
                 (dest, lr._2/outlinks.size))
   }

  // Sum contributions by URL and get new ranks
  ranks = contribs.reduceByKey((x,y) -> x+y)
                 .mapValues(sum -> a/n + (1-a)*sum)
}
```

links: RDD<url:string, outlinks:SEQ<string>>
ranks: RDD<url:string, rank:float>

PageRank

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until convergence
/* usually 10-20 iterations */
```

```
// spark

links = spark.read().textFile(..).map(...);
ranks = // RDD of (URL, 1/n) pairs

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}
```

Key: url_1,
Value: ([$outlink_1$, $outlink_2$, …], $rank_1$)

links: RDD<url:string, outlinks:SEQ<string>>
ranks: RDD<url:string, rank:float>

PageRank

```
for i = 1 to n:
  r[i] = 1/n

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      links.map(dest ->
                    (dest, lr._2/outlinks.size()))
  }

  / Sum contributions by URL and get new ranks
   ks = contribs.reduceByKey((x,y) -> x+y)
               .mapValues(sum -> a/n + (1-a)*sum)
}
```

Key: url$_1$,
Value: rank$_1$/outlink$_1$.size)

Conclusions

- Parallel databases
  - Predefined relational operators
  - Optimization
  - Transactions
- MapReduce
  - User-defined map and reduce functions
  - Must implement/optimize manually relational ops
  - No updates/transactions
- Spark
  - Predefined relational operators
  - Must optimize manually
  - No updates/transactions

Conceptual Design

Class overview

- Data models
  - Relational: SQL, RA, and Datalog
  - NoSQL: SQL++
- RDBMS internals
  - Query processing and optimization
  - Physical design
- Parallel query processing
  - Spark and Hadoop
- Conceptual design
  - E/R diagrams
  - Schema normalization
- Transactions
  - Locking and schedules
  - Writing DB applications

Data models

Query Processing

Using DBMS

Database Design

What it is:

- Starting from scratch, design the database schema: relation, attributes, keys, foreign keys, constraints etc

Why it's hard

- The database will be in operation for a very long time (years). Updating the schema while in production is very expensive (why?)

Database Design

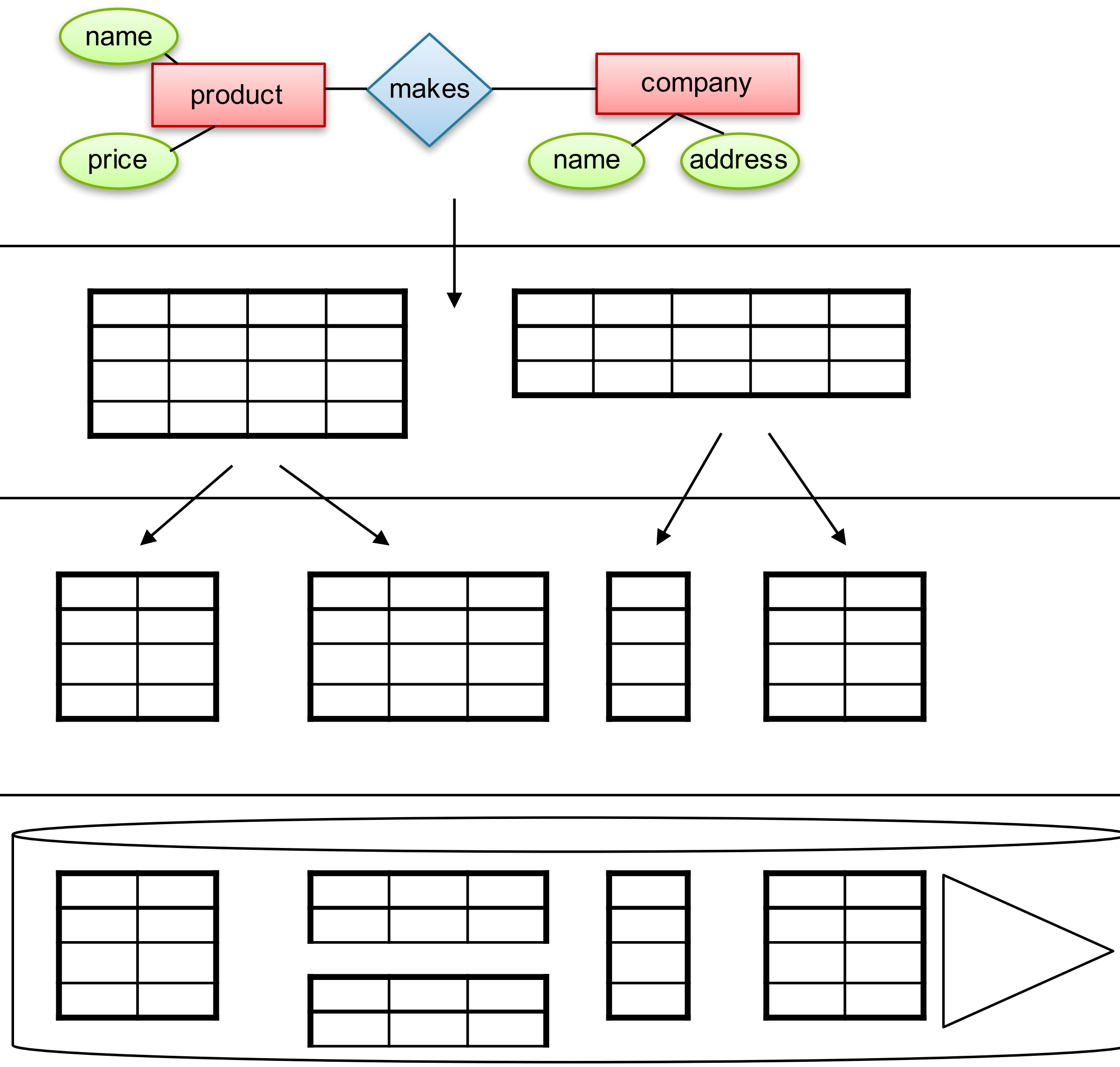
- Consider issues such as:
  - What entities to model
  - How entities are related
  - What constraints exist in the domain

- Several formalisms exists
  - We discuss E/R diagrams
  - UML, model-driven architecture

- Reading: Sec. 4.1-4.6

Database Design Process

Conceptual Model:



Relational Model:
Tables + constraints
And also functional dep.

Normalization:
Eliminates anomalies

Conceptual Schema

Physical storage details

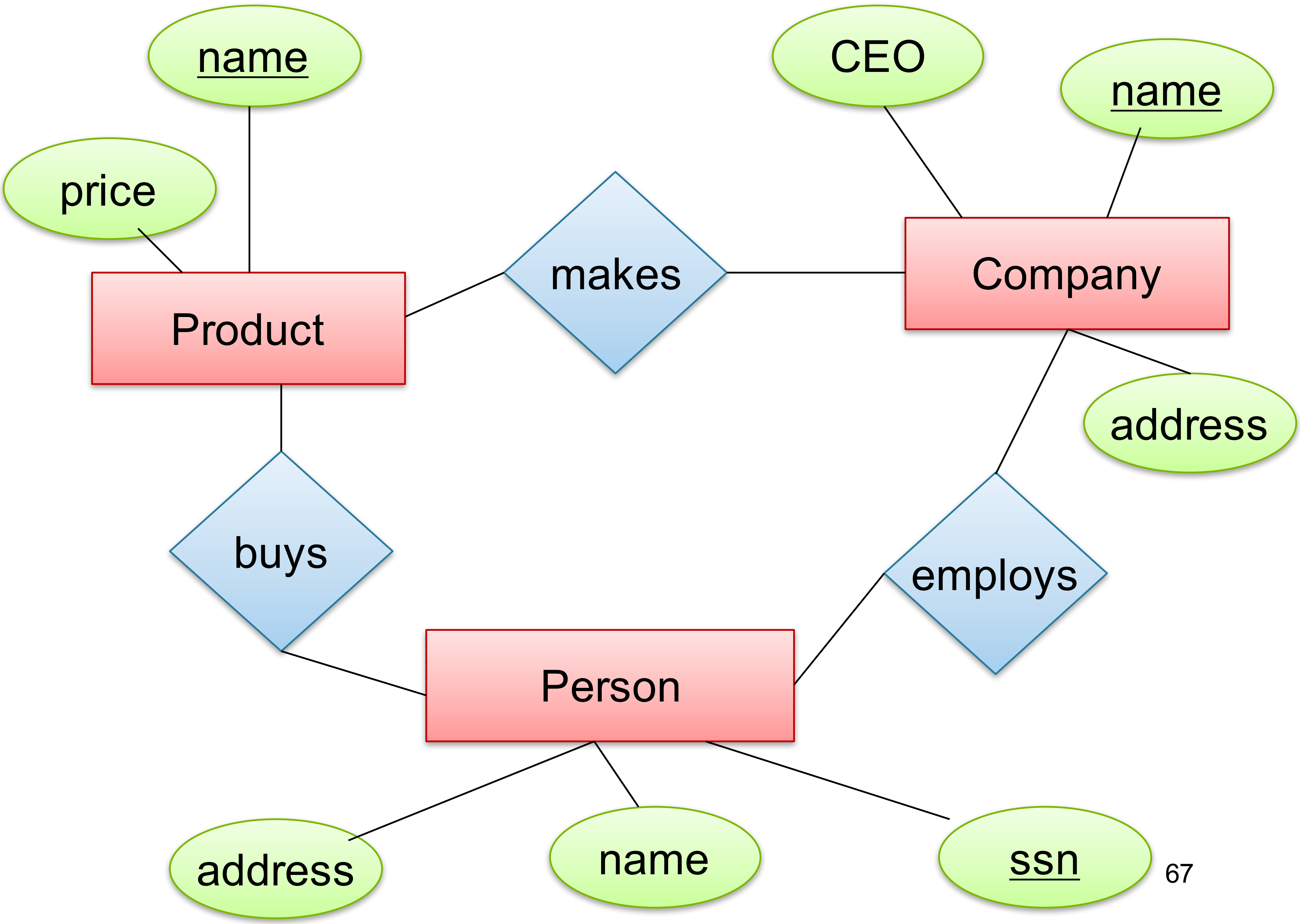
Physical Schema

Entity / Relationship Diagrams

- Entity set = a class
  - An entity = an object

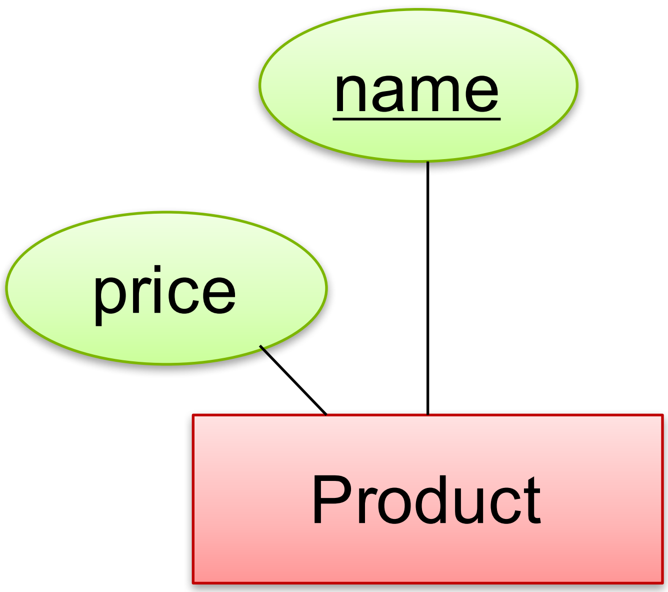
- Attribute

- Relationship


name
price
CEO
name
makes
Company
Product
address
buys
employs
Person
address
name
ssn

Keys in E/R Diagrams

- Every entity set must have a key

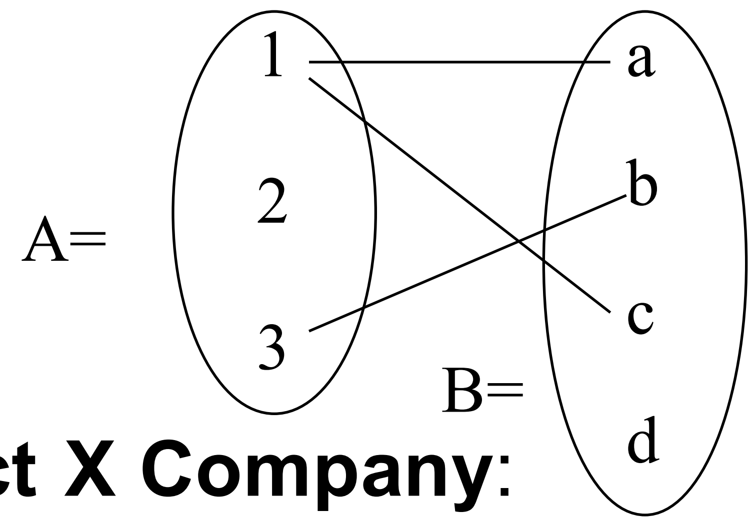


What is a Relation ?

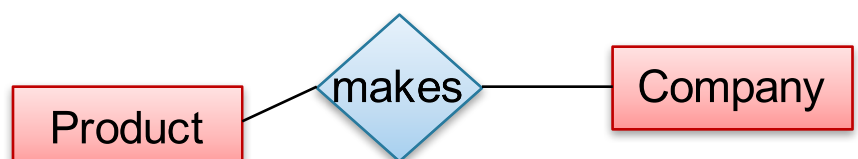
- A mathematical definition:
  - if A, B are sets, then a relation R is a subset of A X B
- A={1,2,3}, B={a,b,c,d},

  A X B = {(1,a),(1,b), . . ., (3,d)}

  R = {(1,a), (1,c), (3,b)}

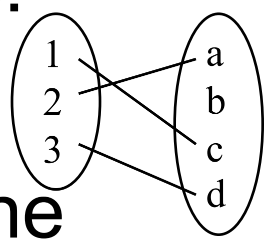


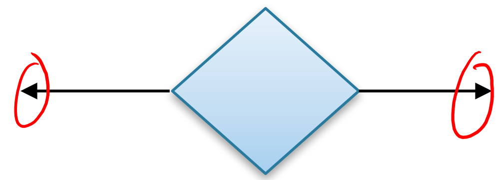
- **makes** is a subset of **Product X Company**:



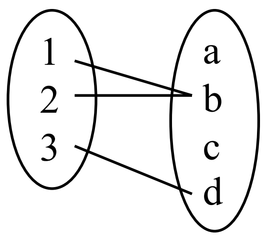
Multiplicity of E/R Relations

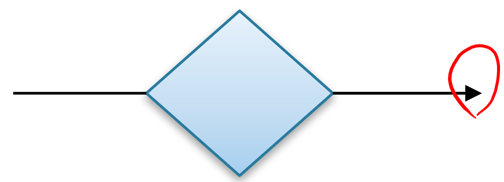
- one-one:



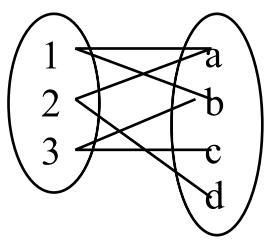


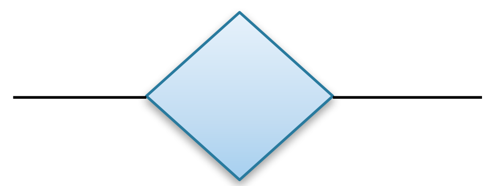
- many-one

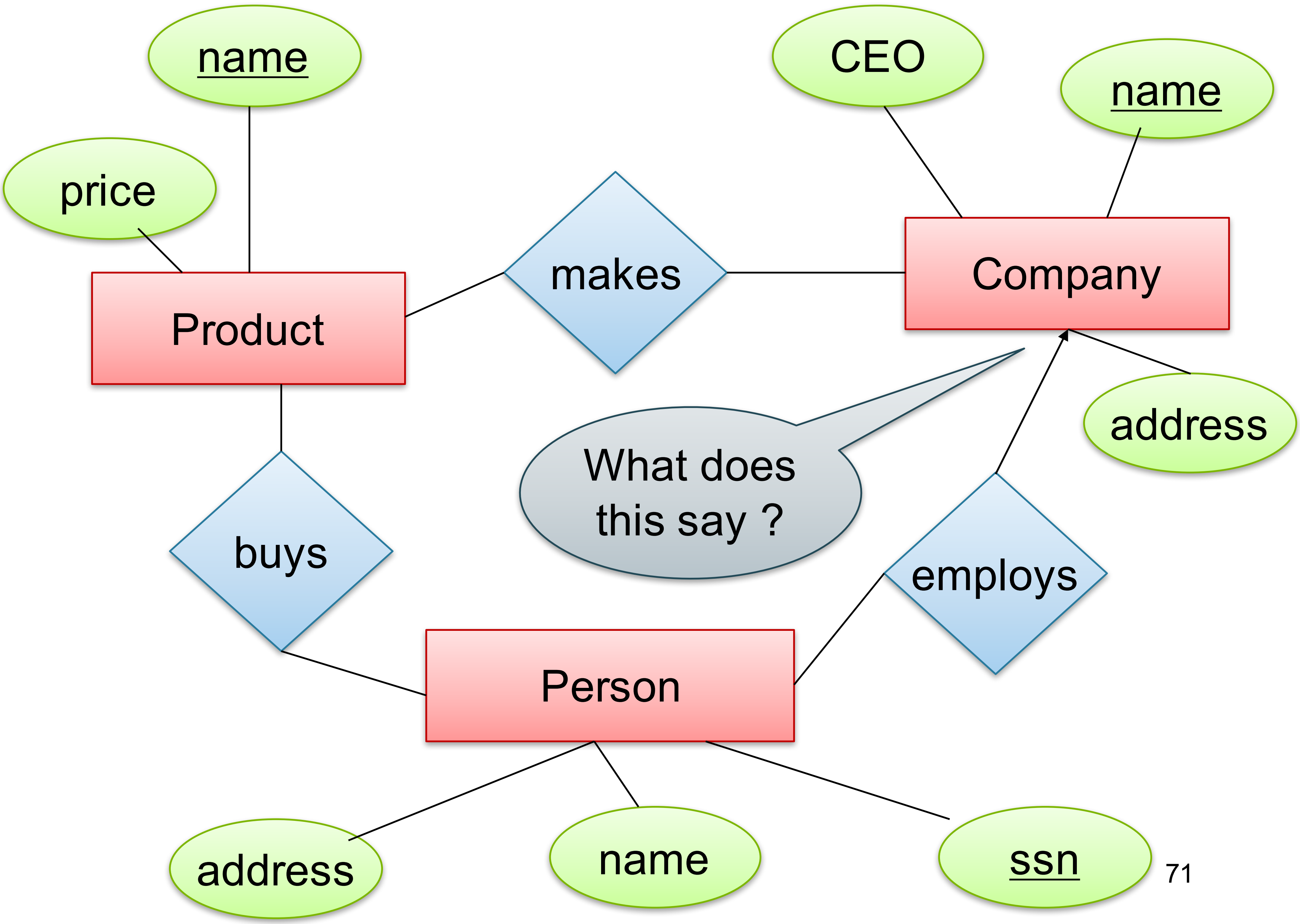




- many-many

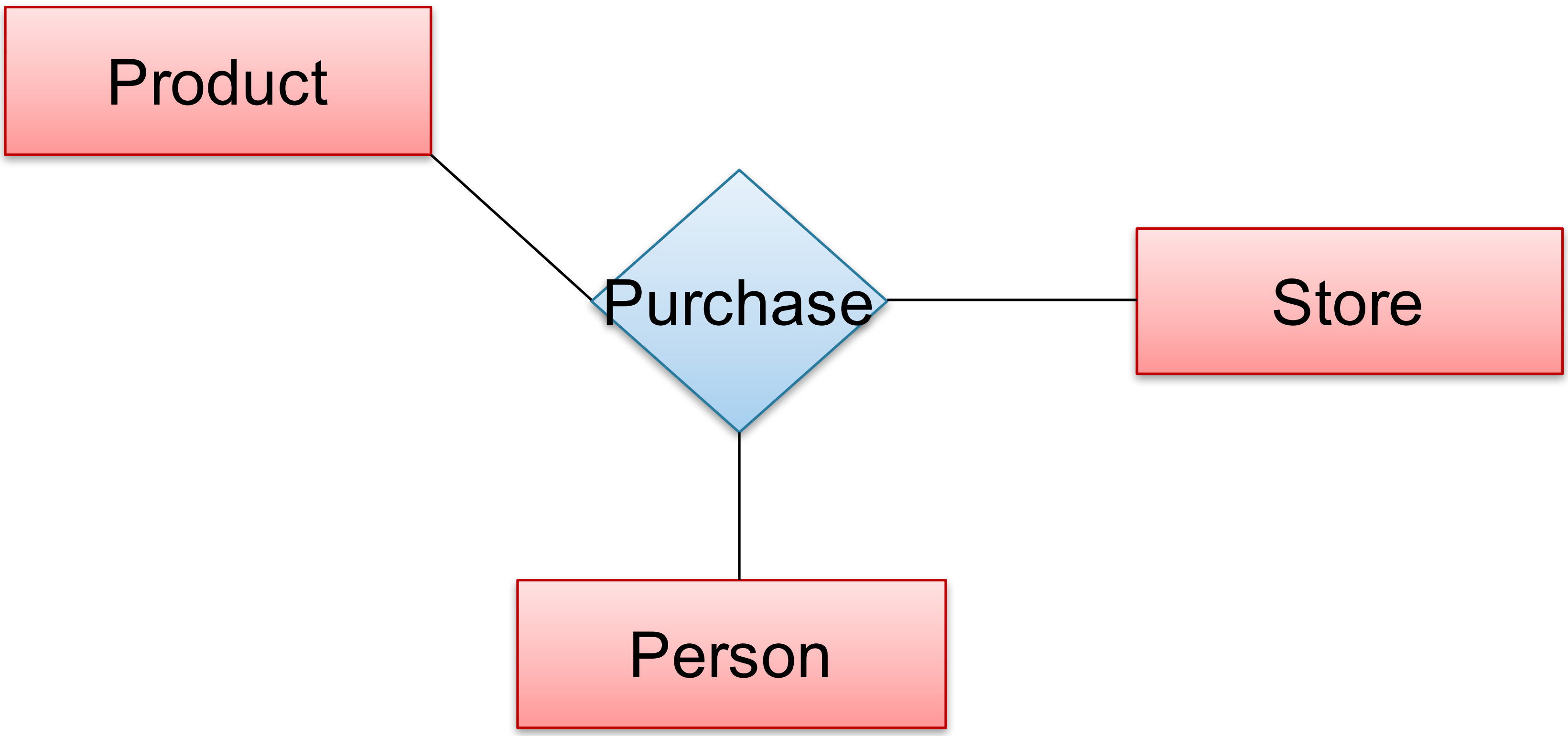





name
price
Product
makes
CEO
name
Company
address
What does this say ?
buys
employs
Person
address
name
ssn

Multi-way Relationships

How do we model a purchase relationship between buyers, products and stores?

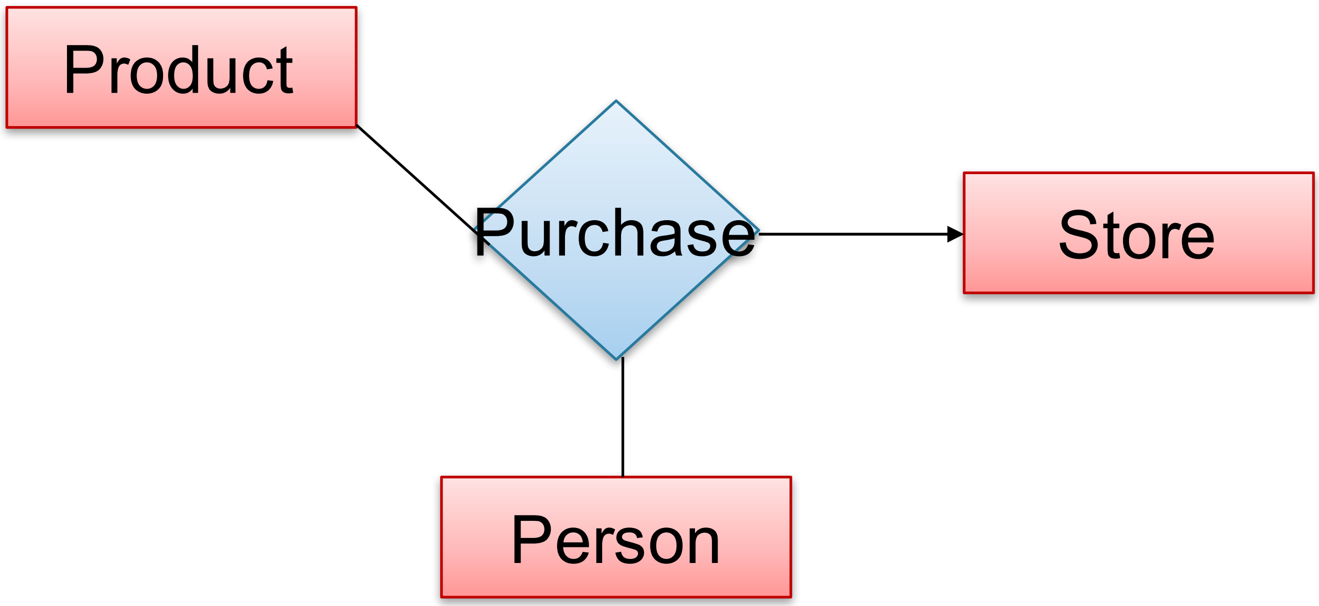


Can still model as a mathematical set (How?)

As a set of triples $\subseteq$ Person X Product X Store

Arrows in Multiway Relationships

Q: What does the arrow mean ?

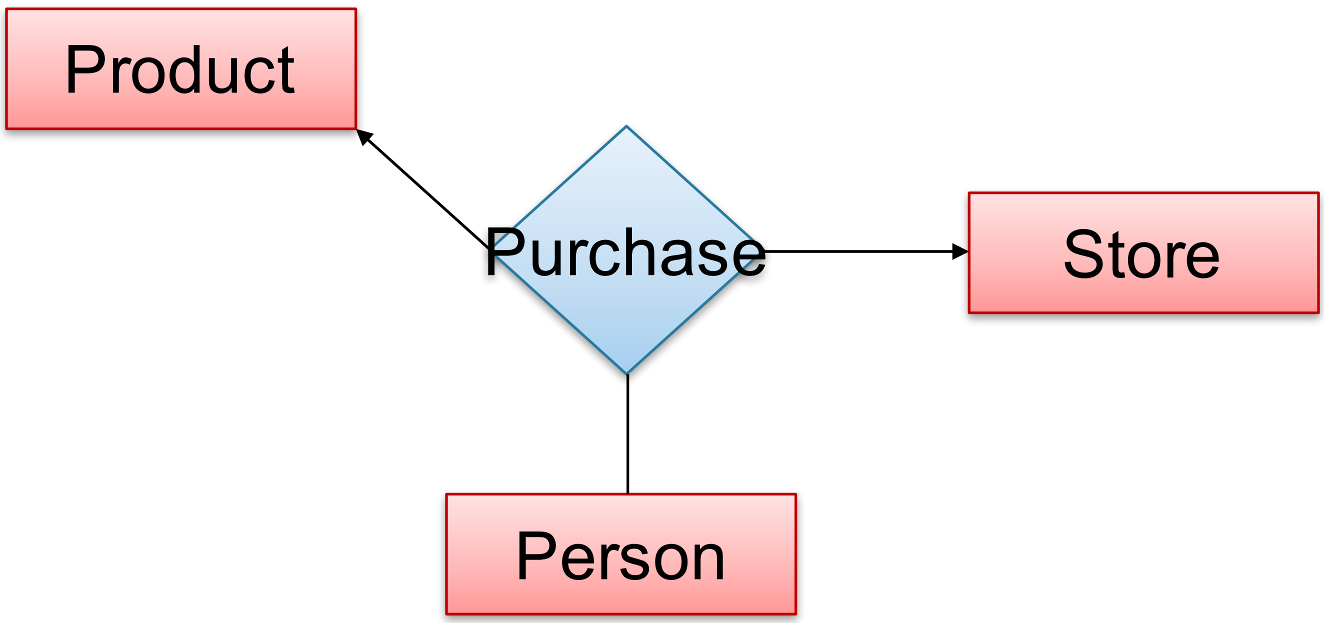


A: A given person buys a given product from at most one store

[Fine print: Arrow pointing to E means that if we select one entity from each of the other entity sets in the relationship, those entities are related to at most one entity in E]

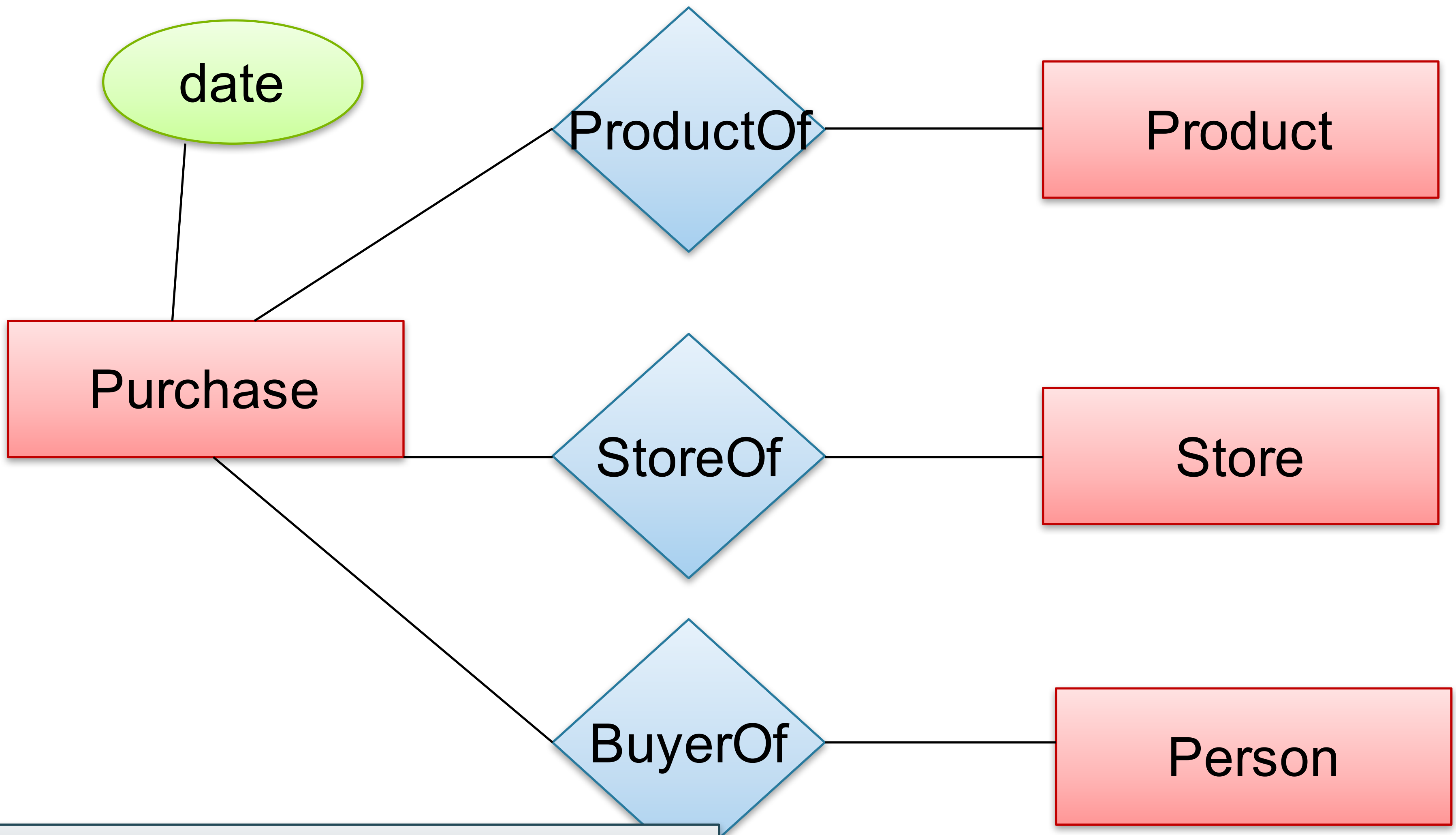
Arrows in Multiway Relationships

Q: What does the arrow mean ?



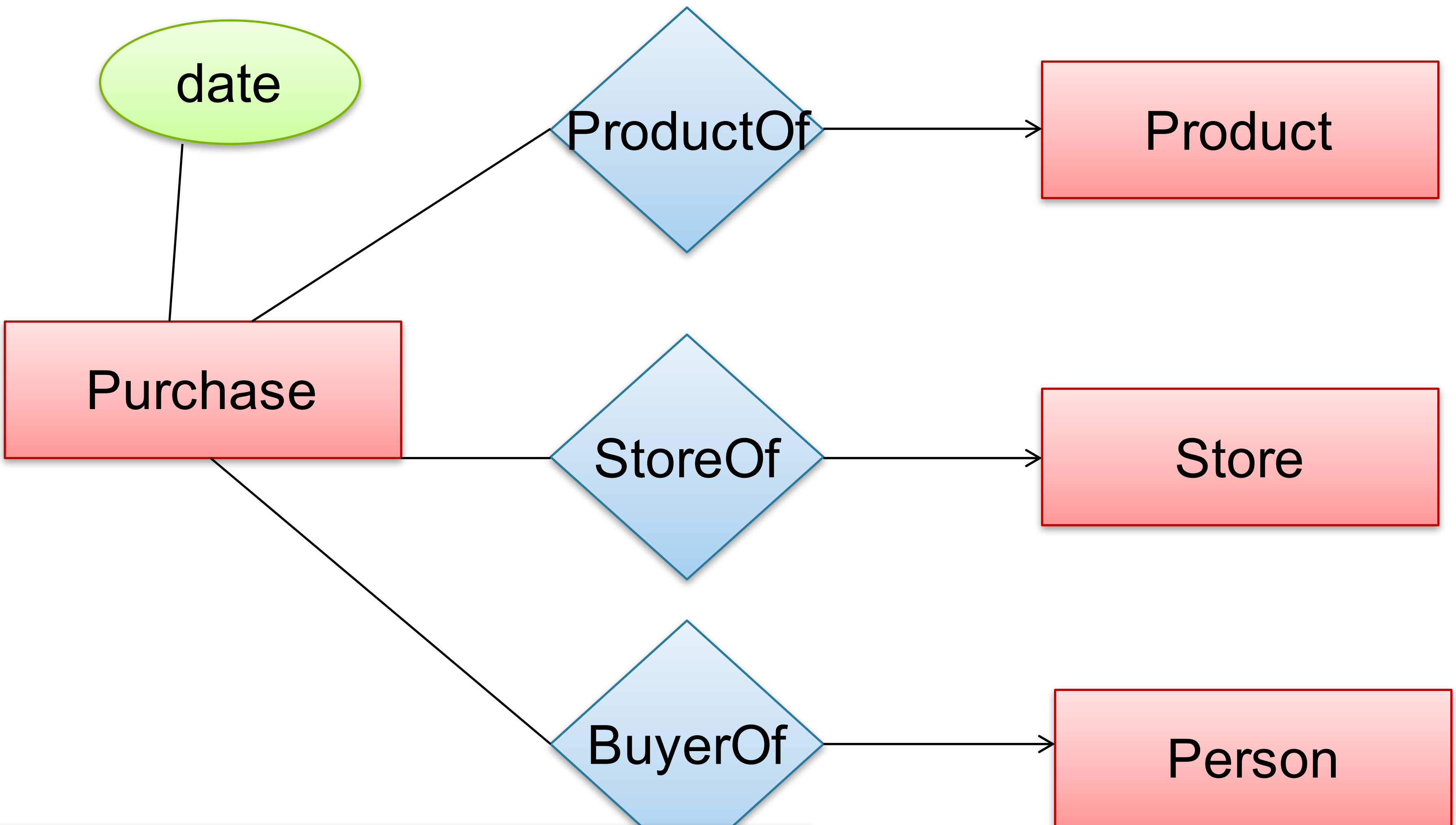
A: A given person buys a given product from at most one store AND every store sells to every person at most one product

Converting Multi-way Relationships to Binary



Arrows go in which direction?

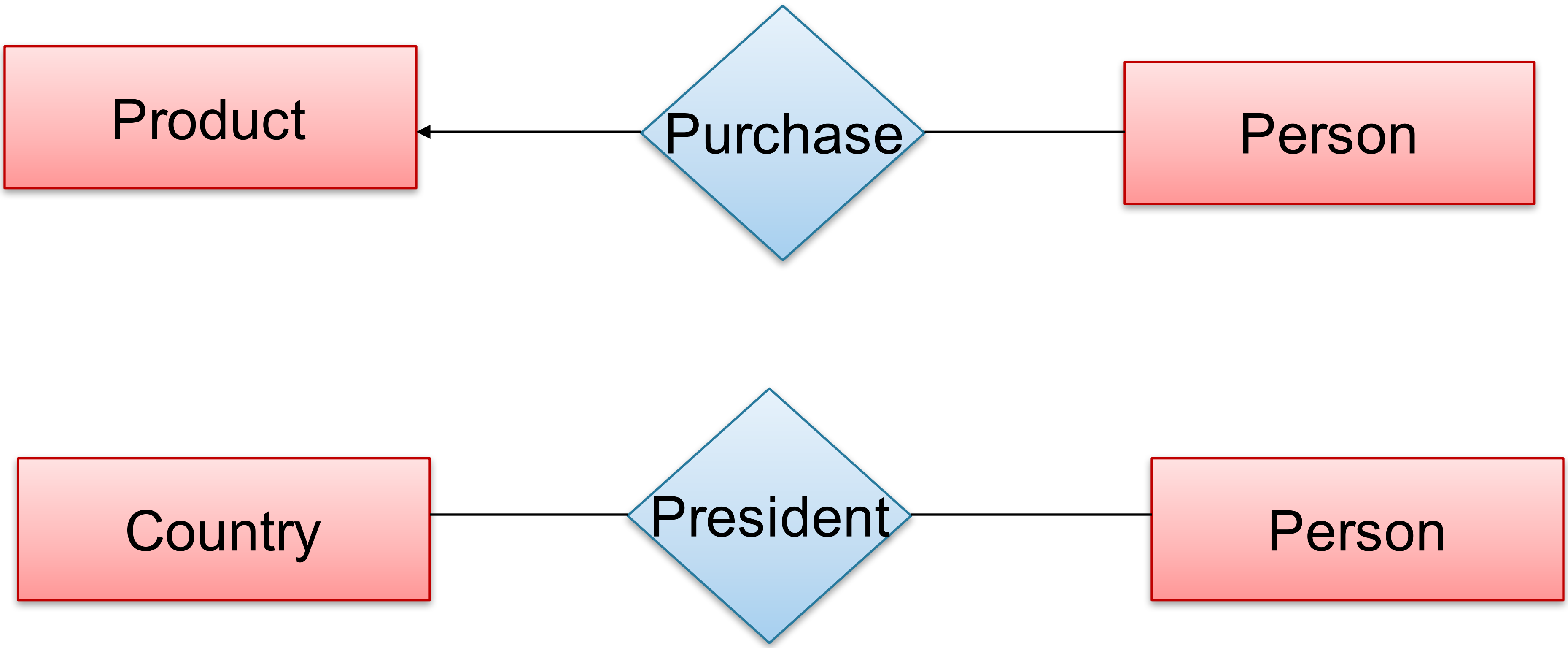
Converting Multi-way Relationships to Binary



Make sure you understand why!

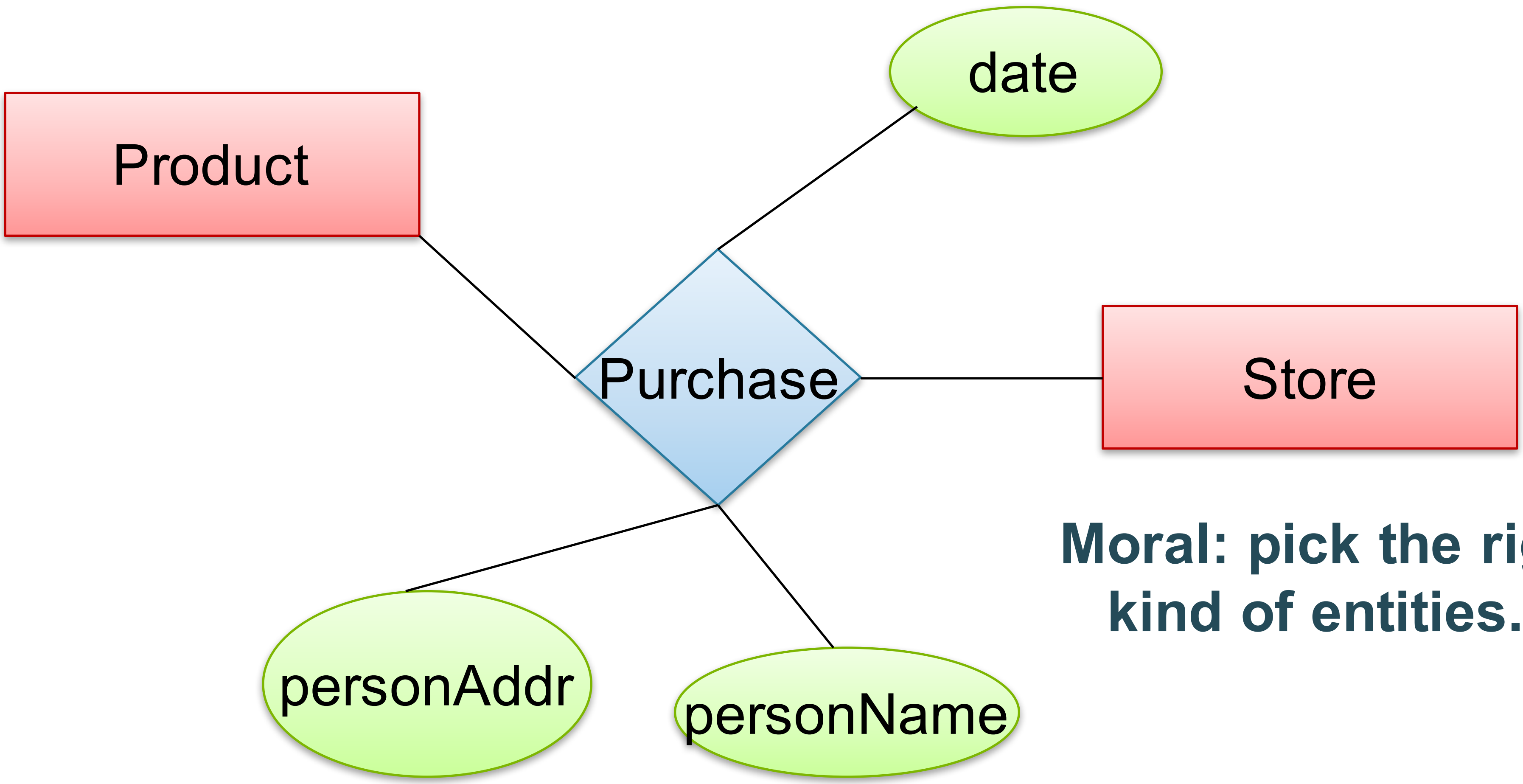
3. Design Principles

What's wrong?



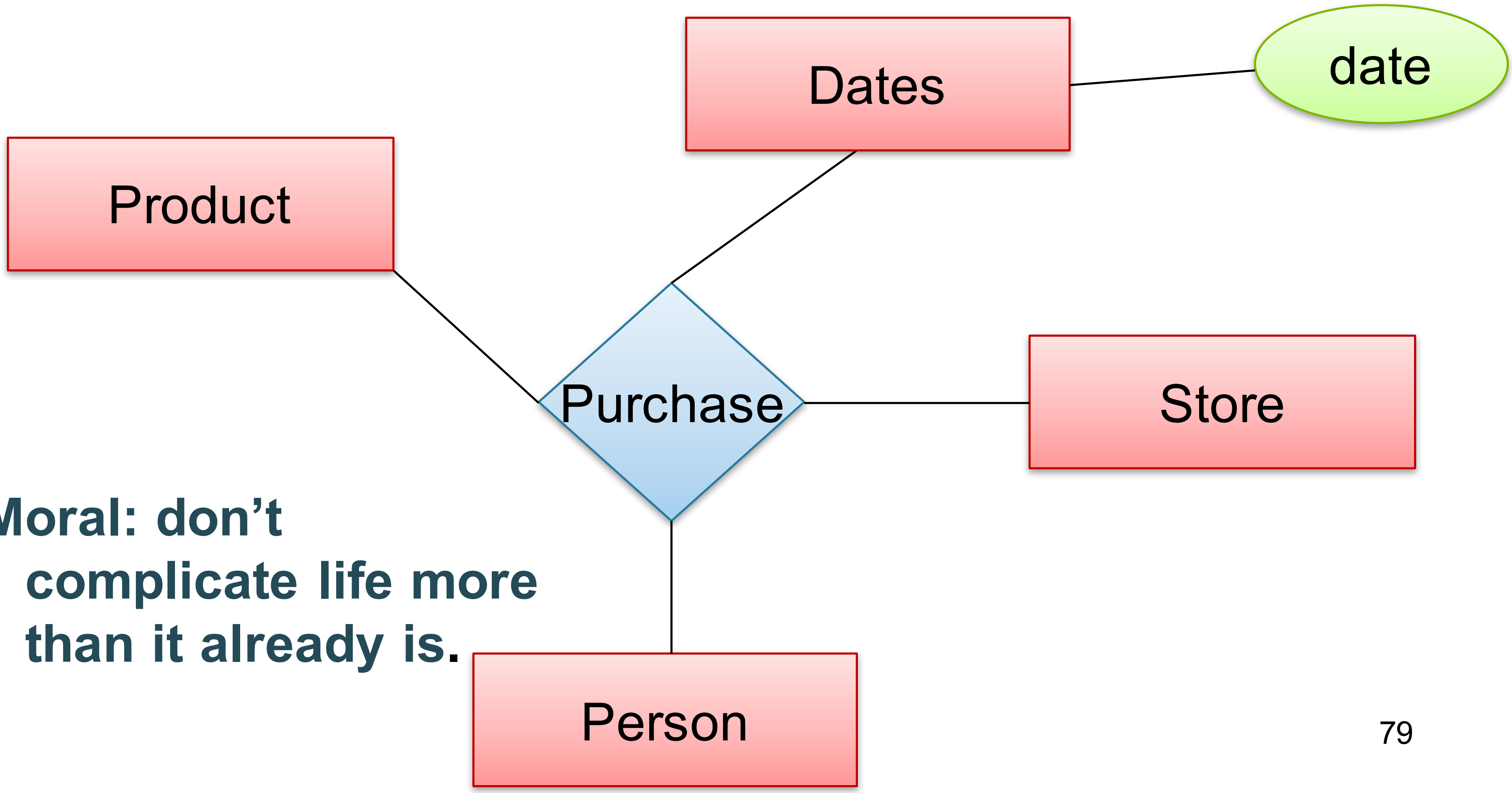
Moral: Be faithful to the specifications of the application!

Design Principles: What's Wrong?



Moral: pick the right kind of entities.

Design Principles: What's Wrong?

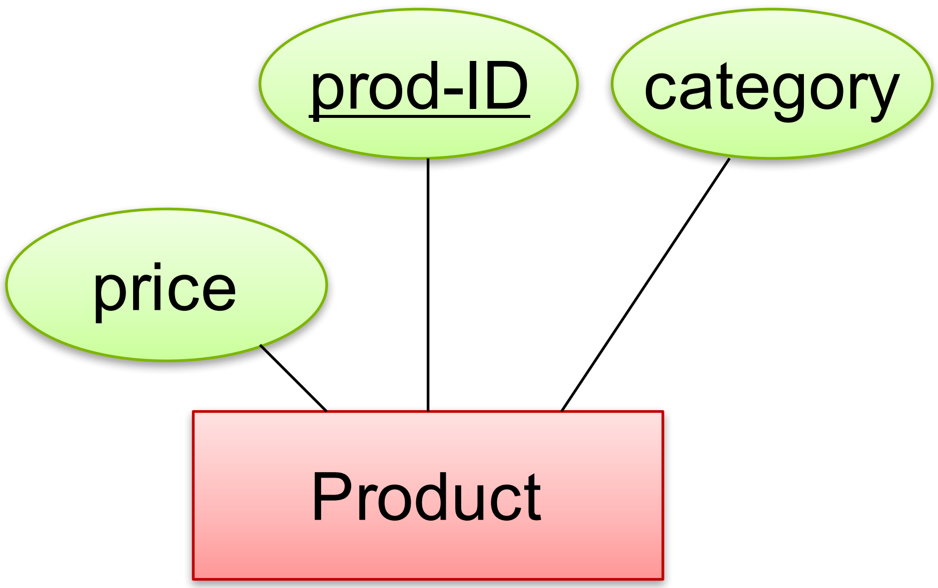


Moral: don't complicate life more than it already is.

From E/R Diagrams to Relational Schema

- Entity set → relation
- Relationship → relation

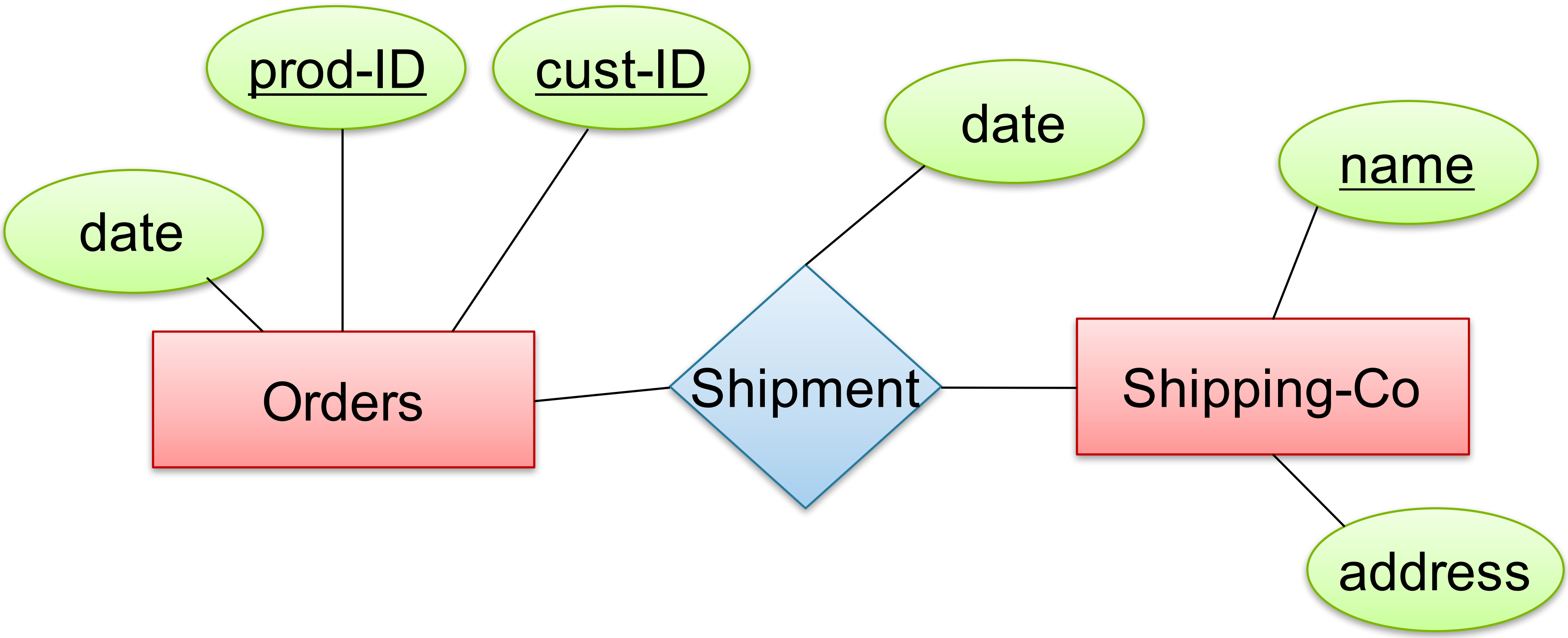
Entity Set to Relation



Product(prod-ID, category, price)

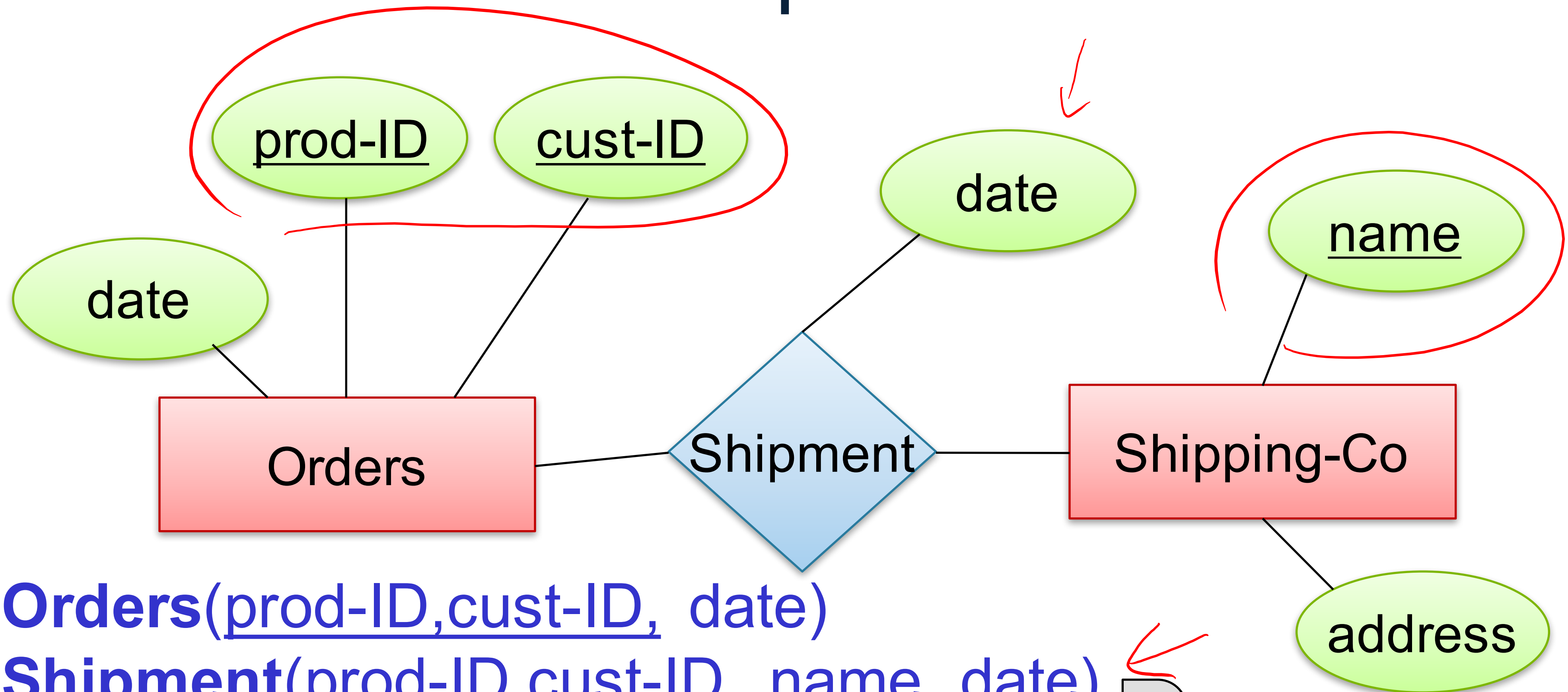
prod-ID	category	price
Gizmo55	Camera	99.99
Pokemn19	Toy	29.99

N-N Relationships to Relations



Represent this in relations

N-N Relationships to Relations



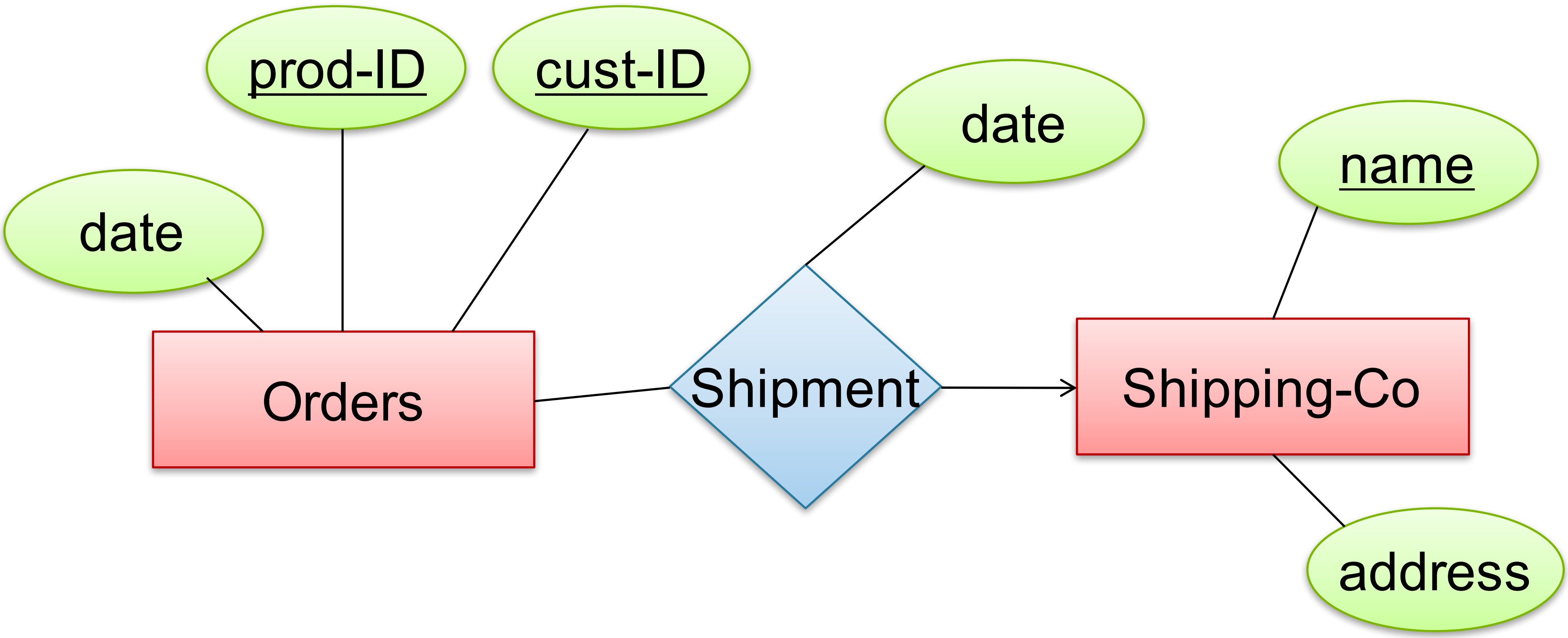
Orders(<u>prod-ID,cust-ID,</u> date)

Shipment(<u>prod-ID,cust-ID, name</u>, date)

Shipping-Co(<u>name</u>, address)

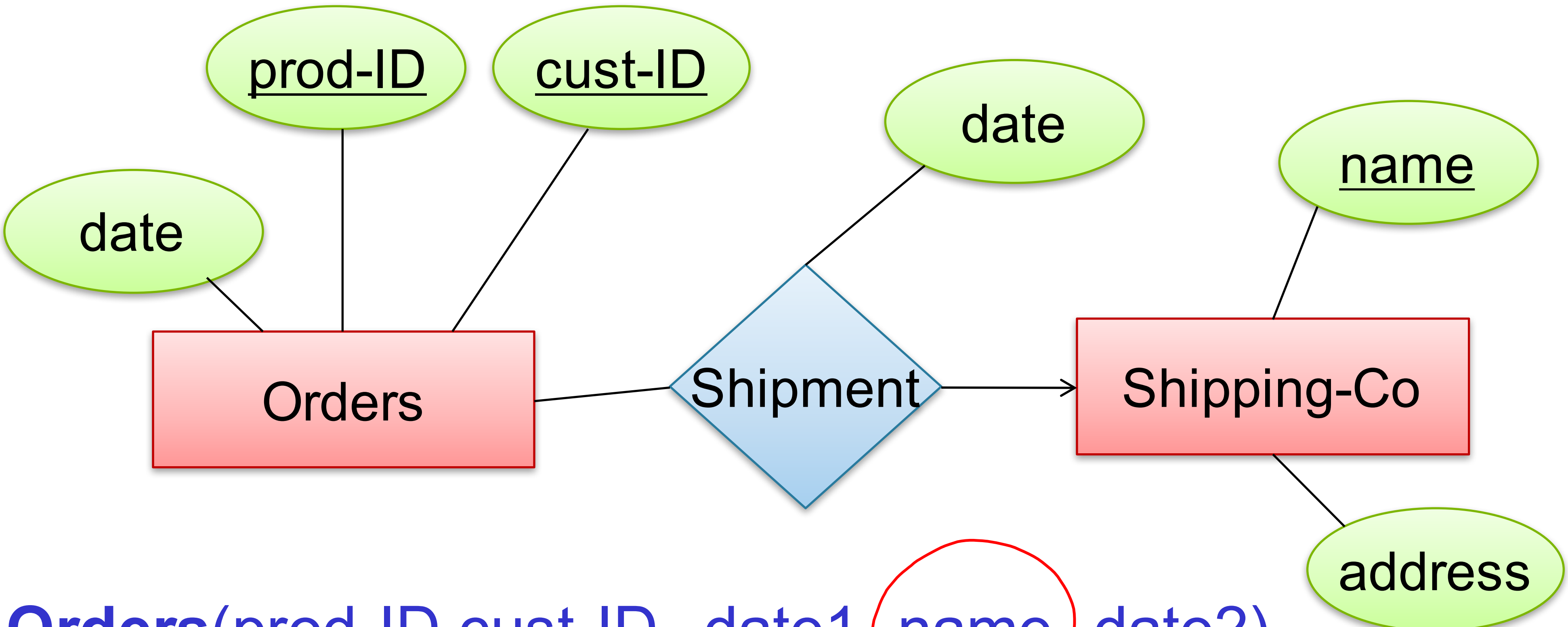
<u>prod-ID</u>	<u>cust-ID</u>	<u>name</u>	date
Gizmo55	Joe12	UPS	4/10/2011
Gizmo55	Joe12	FEDEX	4/9/2011

N-1 Relationships to Relations



Represent this in relations

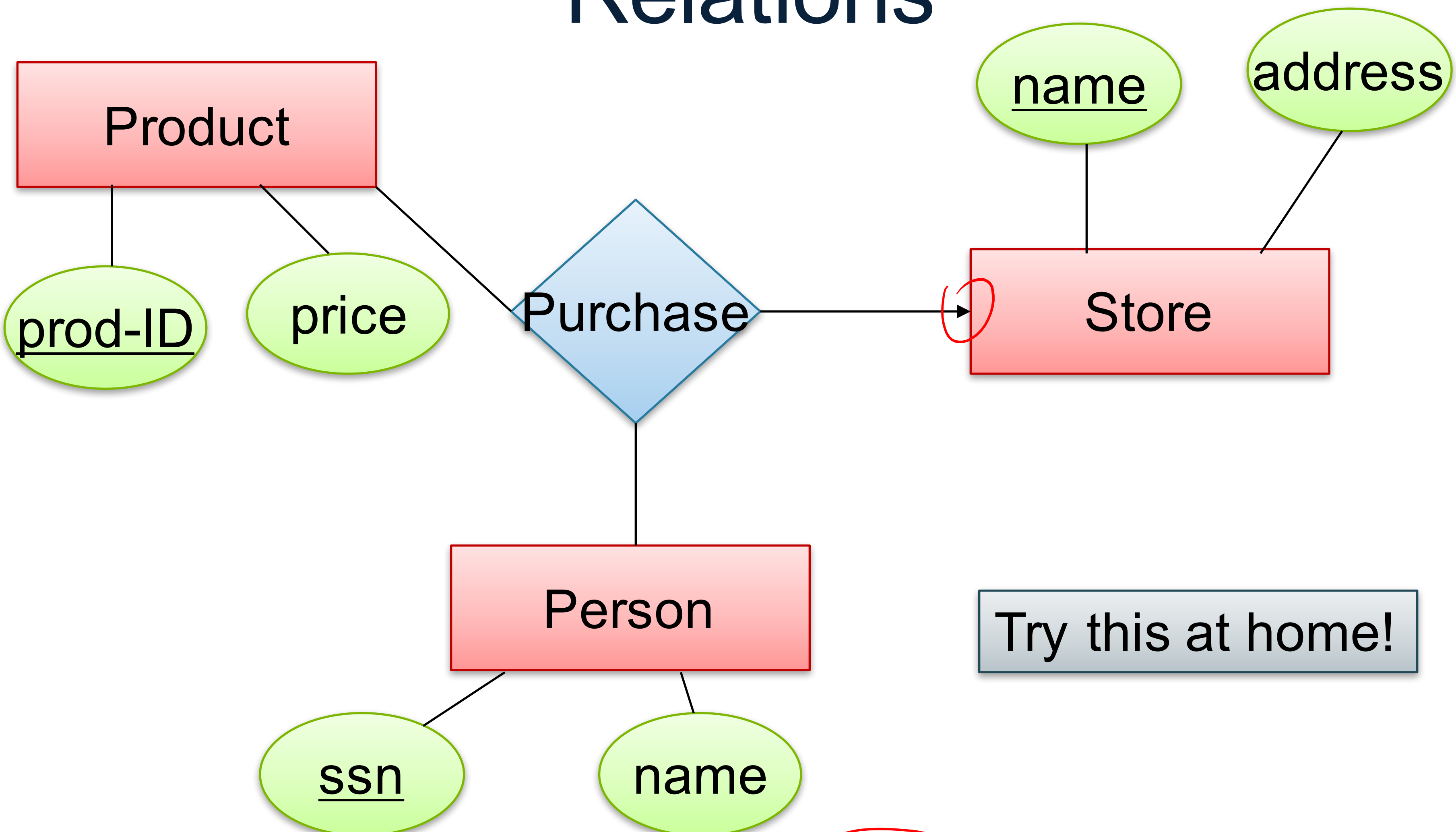
N-1 Relationships to Relations



Orders(<u>prod-ID,cust-ID,</u> date1, name, date2)
Shipping-Co(<u>name</u>, address)

Remember: no separate relations for many-one relationship

Multi-way Relationships to Relations



Try this at home!

Purchase(prod-ID, ssn, name)

Modeling Subclasses

Some objects in a class may be special

- define a new class
- better: define a *subclass*

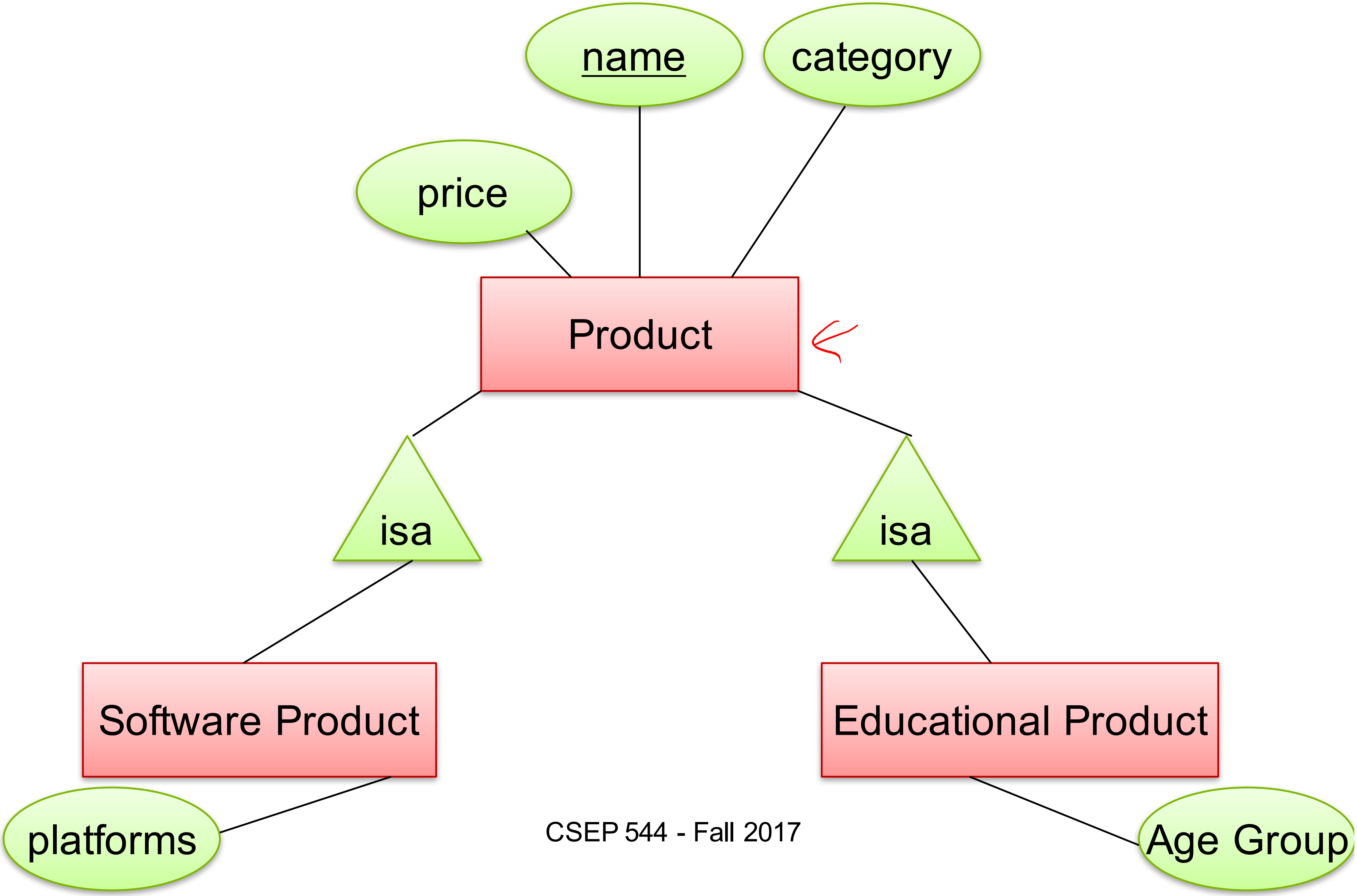
Products

Software products

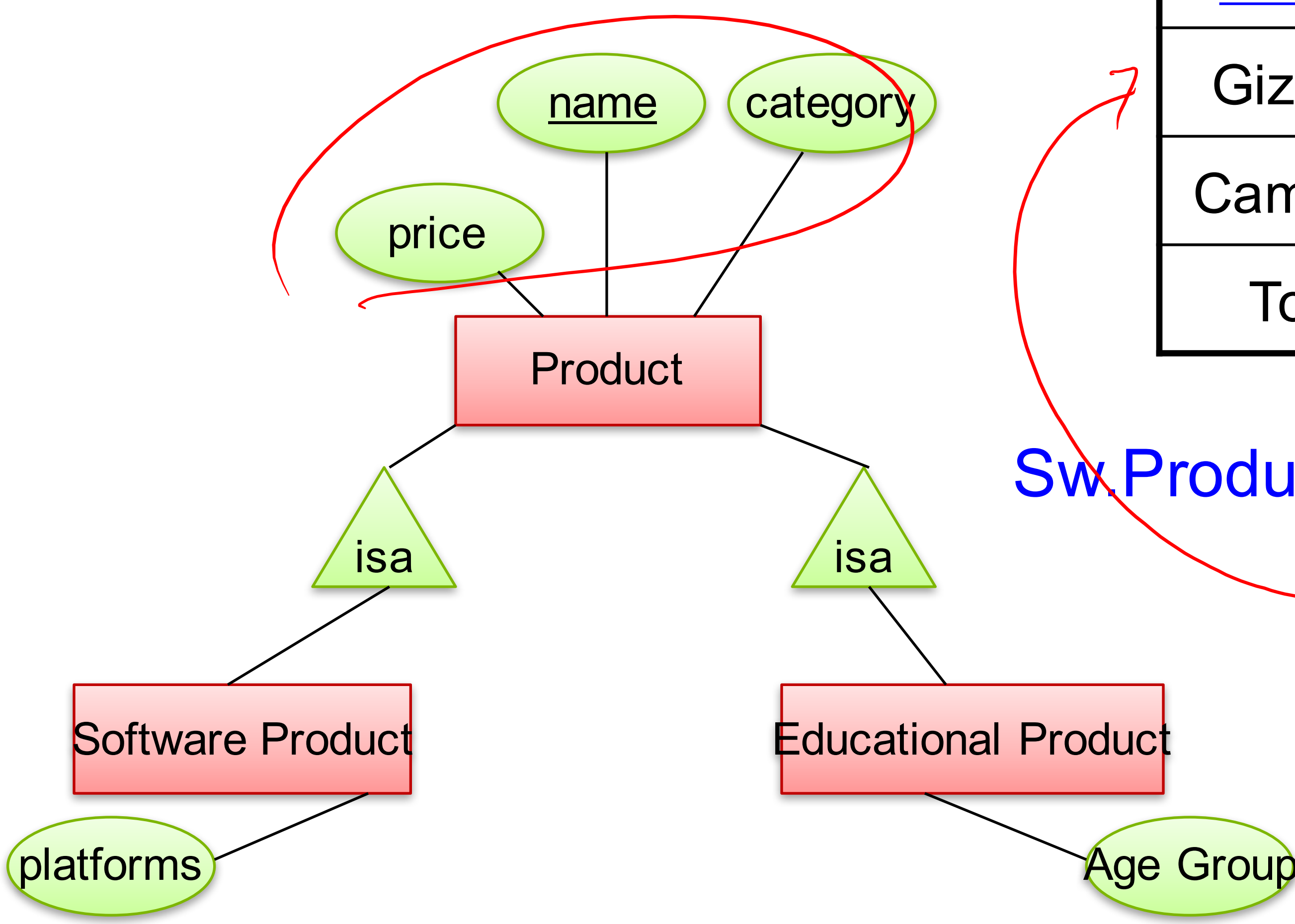
Educational products

So --- we define subclasses in E/R

Subclasses


name
category
price
Product
isa
isa
Software Product
Educational Product
platforms
Age Group

Subclasses to Relations



Product

Name	Price	Category
Gizmo	99	gadget
Camera	49	photo
Toy	39	gadget

Sw.Product

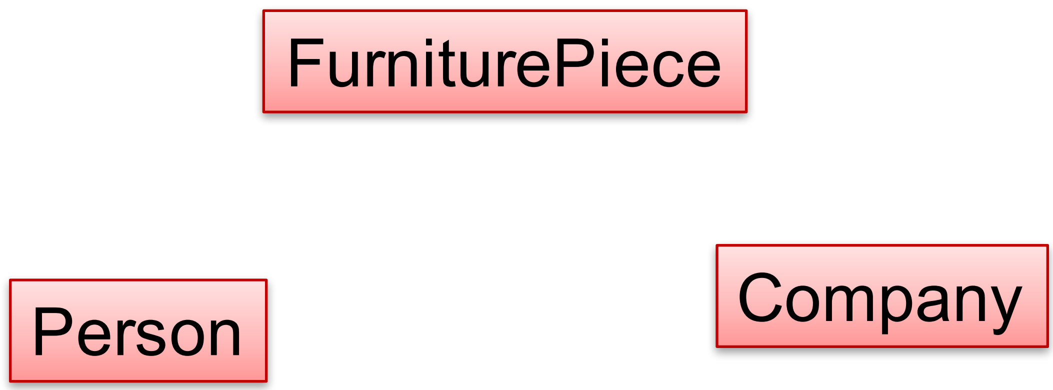
Name	platforms
Gizmo	unix

Ed.Product

Name	Age Group
Gizmo	toddler
Toy	retired

Other ways to convert are possible

Modeling Union Types with Subclasses

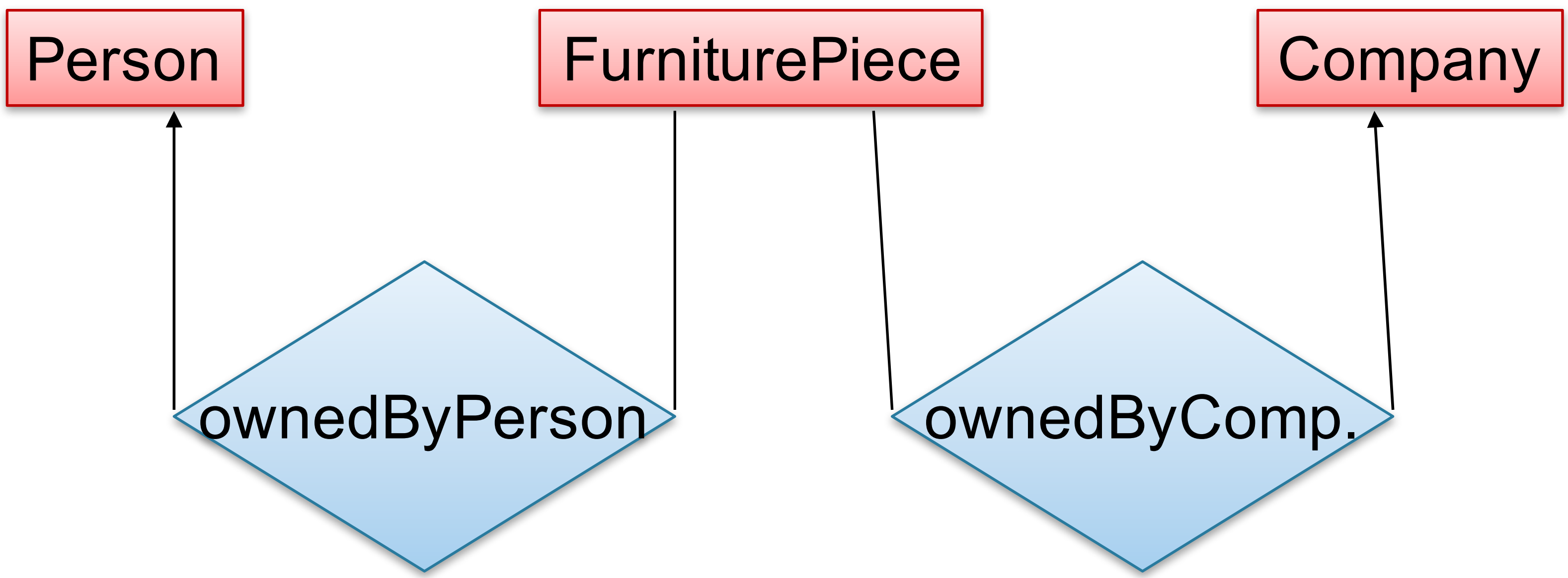


Say: each piece of furniture is owned either by a person or by a company

Modeling Union Types with Subclasses

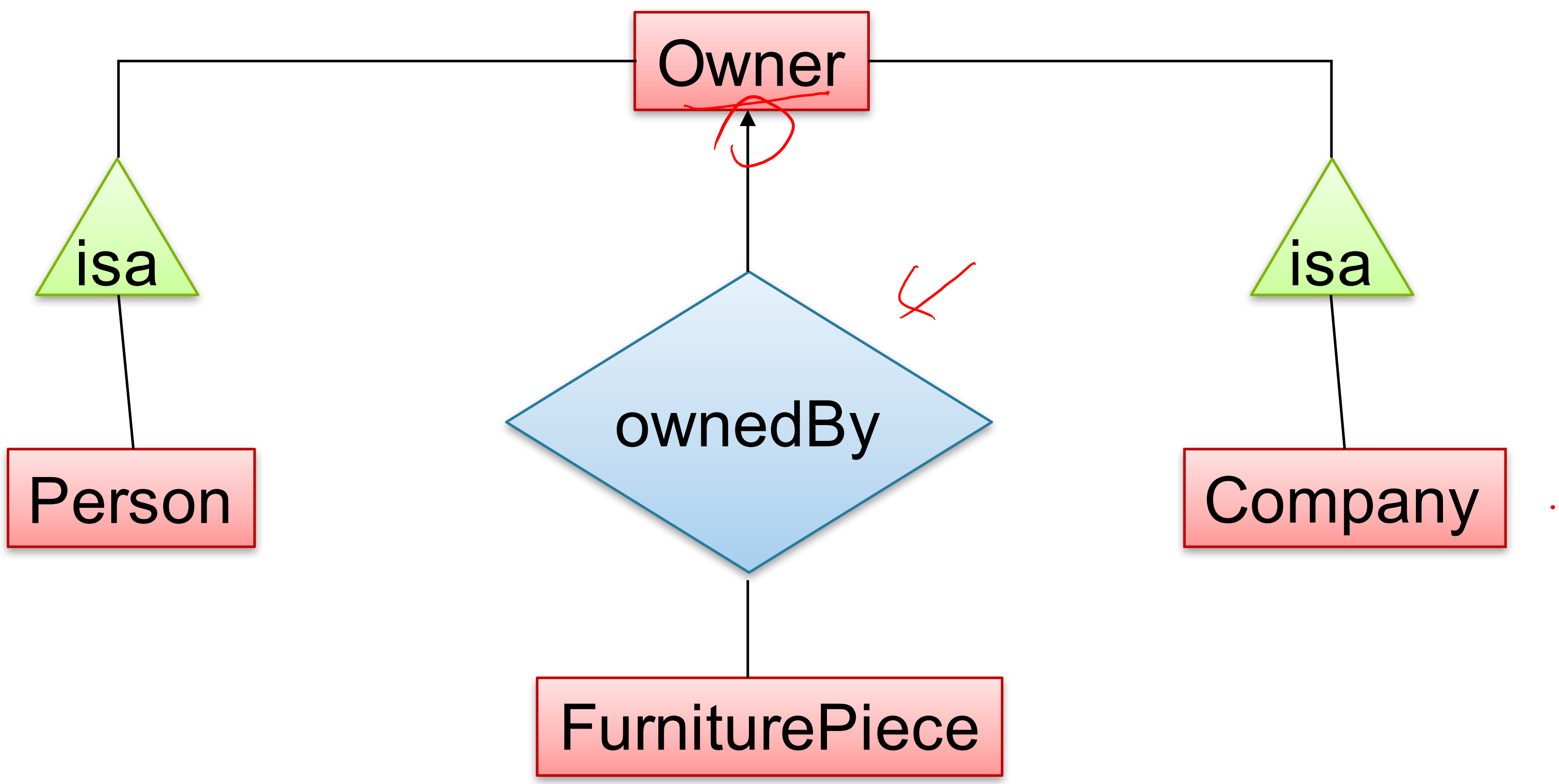
Say: each piece of furniture is owned either by a person or by a company

Solution 1. Acceptable but imperfect (What's wrong ?)



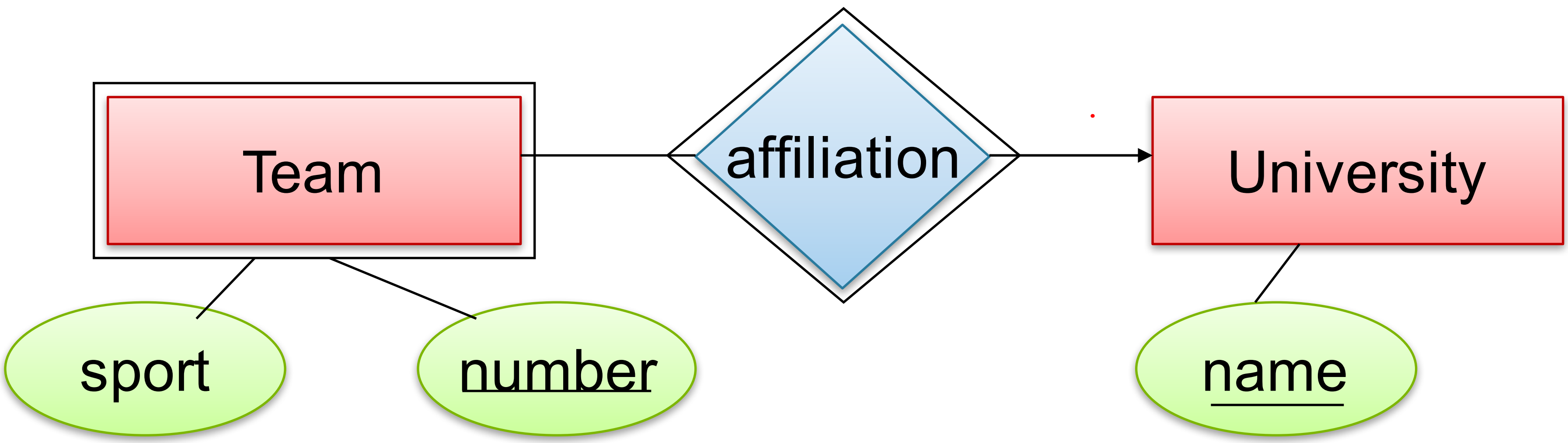
Modeling Union Types with Subclasses

Solution 2: better, more laborious



Weak Entity Sets

Entity sets are weak when their key comes from other classes to which they are related.



Team(sport, <u>number, universityName</u>)
University(<u>name</u>)