LVars for distributed programming
or, LVars and CRDTs `join` forces

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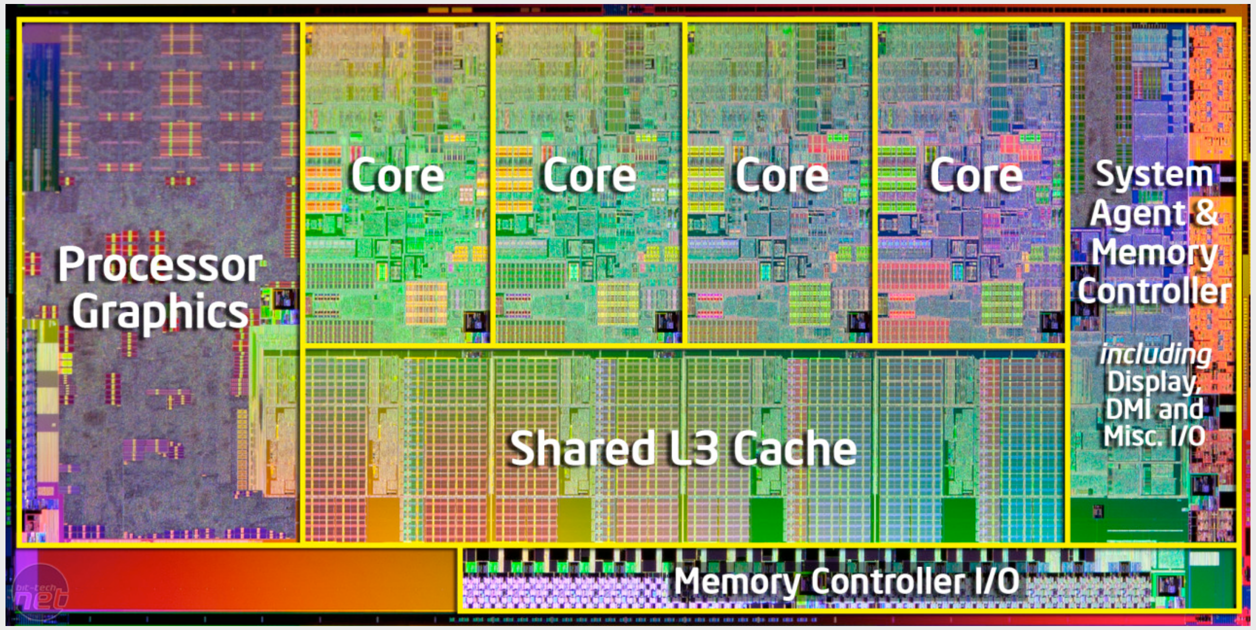
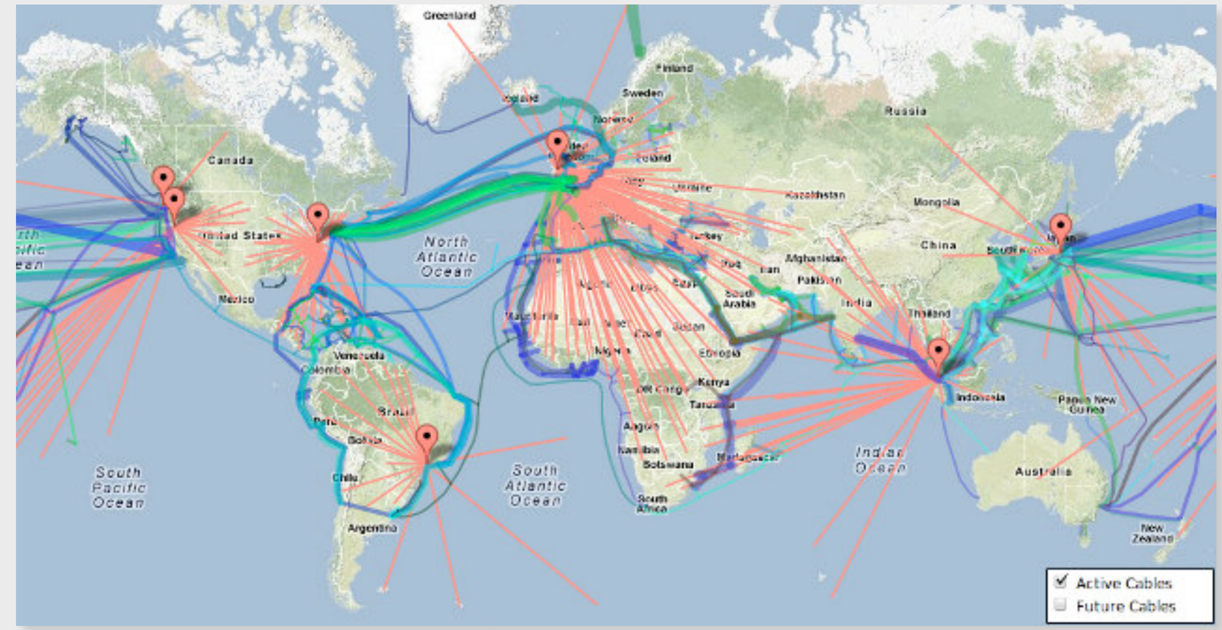
Programming Systems Lab, Intel Labs

IFIP WG 2.8 Meeting
May 26, 2015





Shared-memory
parallel programming

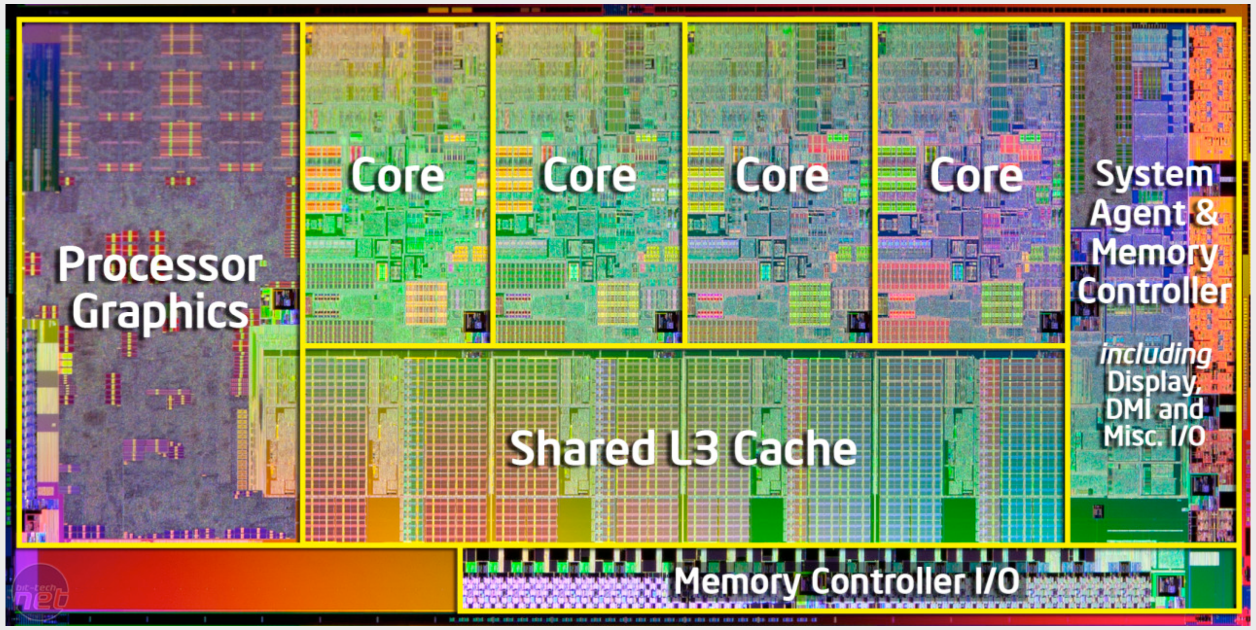
LVars

(Observable) determinism

Distributed
programming

CRDTs

(Eventual) consistency



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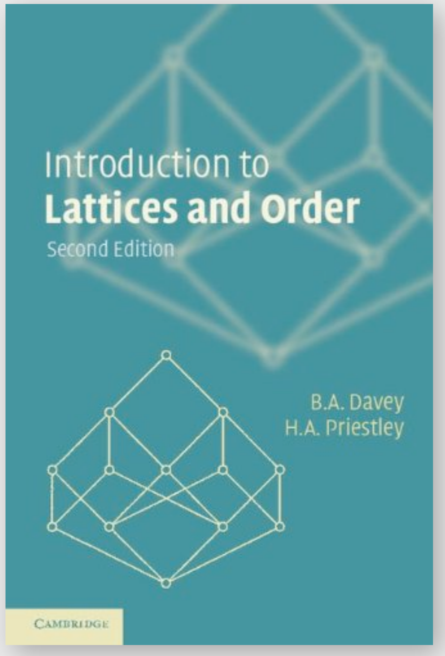

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(What happens when we run this?)

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IVars: single writes, blocking (but exact) reads
[Arvind *et al.*, 1989]

LVars: **commutative and inflationary** writes, blocking **threshold** reads

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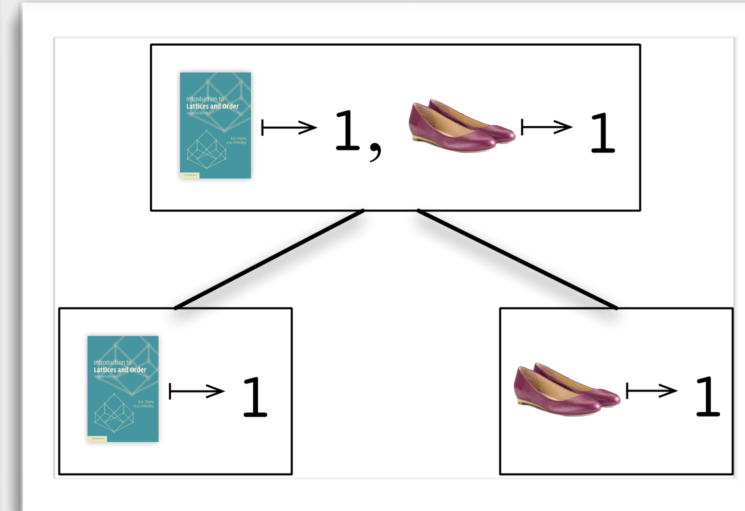

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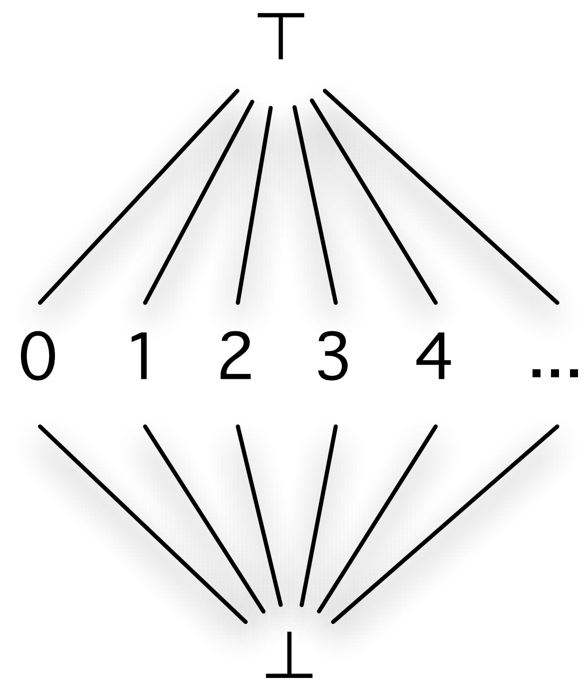
`num`



Raises an error, since $3 \sqcup 4 = \top$

```
do
  fork (put num 3)
  fork (put num 4)
```

Works fine, since $4 \sqcup 4 = 4$

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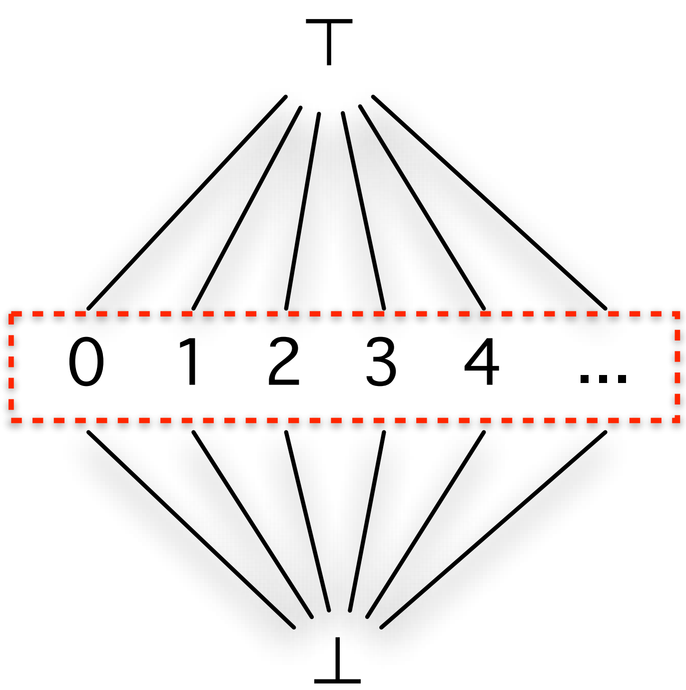

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`get` blocks until threshold is reached

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  get num
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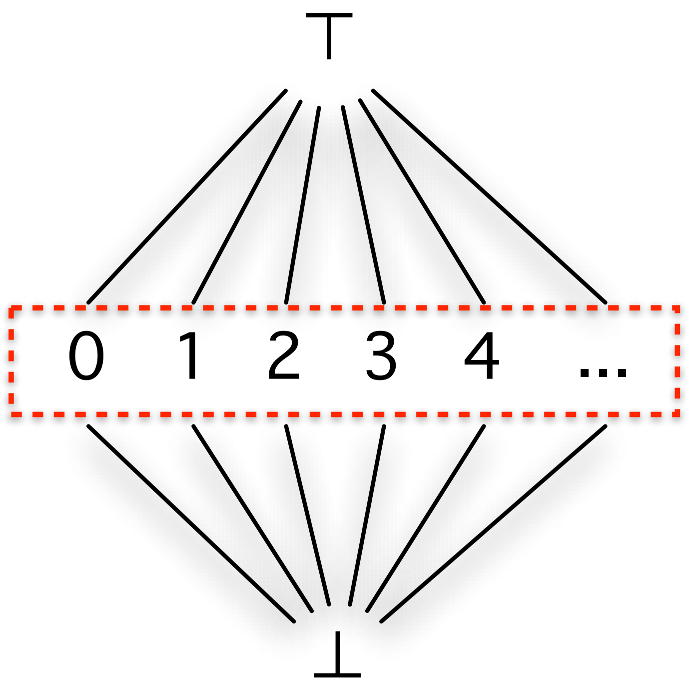
`num`



Data structure author's obligation:

threshold set elements must be **pairwise incompatible**

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```
do
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```

`counter`

$\top$

$\vdots$

3

2

1

$\bot$

Works fine, since `incr`s commute

```
do
  fork (incr1 counter)
  fork (incr42 counter)
```

counter

$\top$
|
⋮
3
|
2
|
1
|
$\bot$

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do
  fork (incr1 counter)
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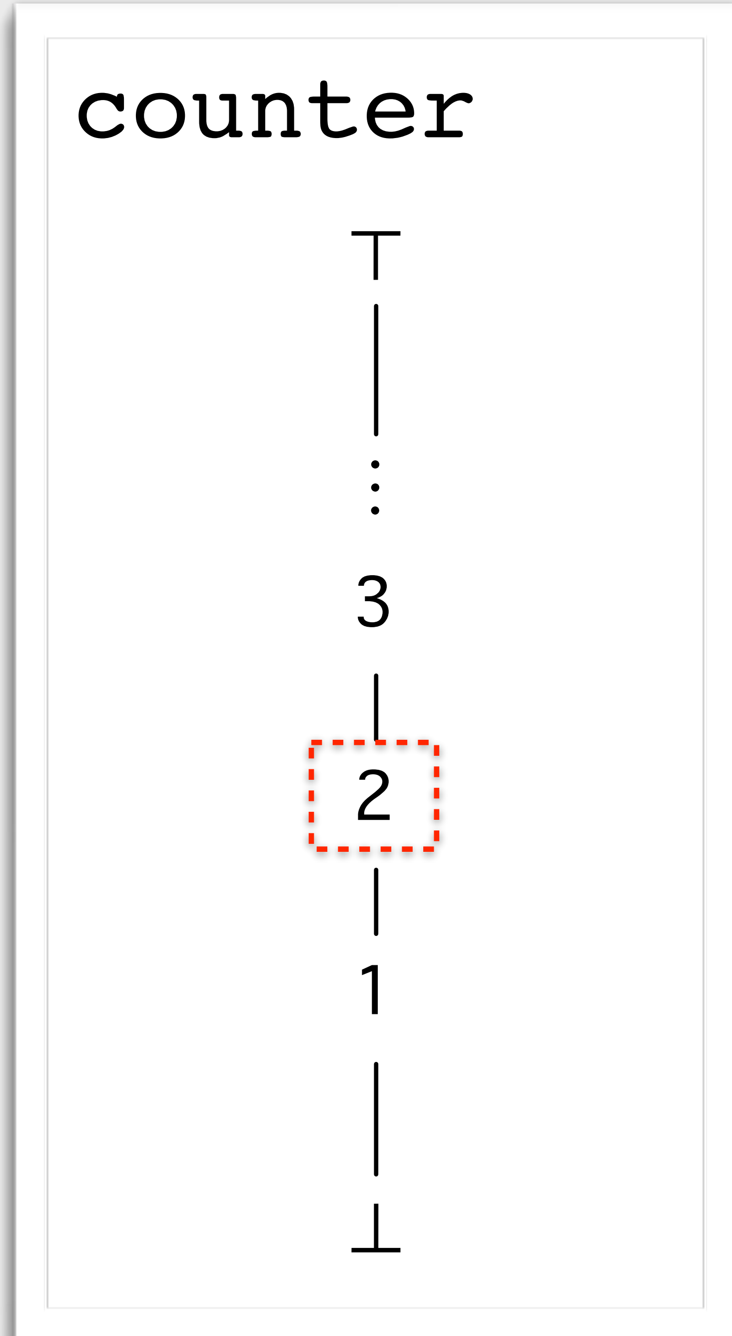

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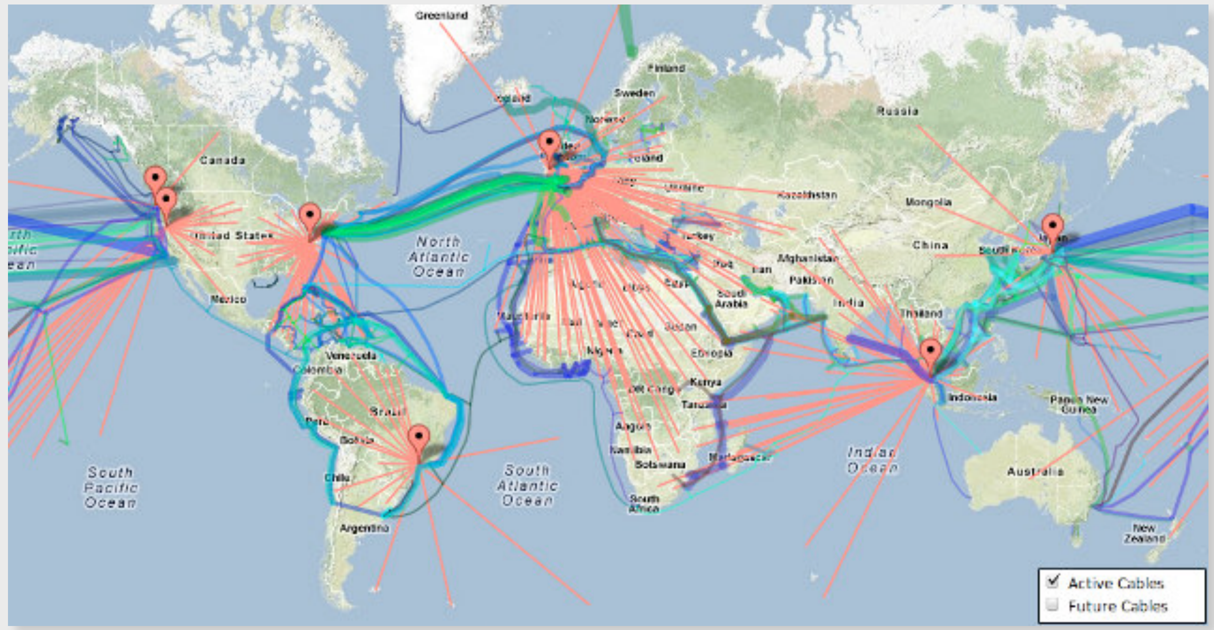
unblocks when `counter` is at least 2

exact contents of `counter` **not observable**



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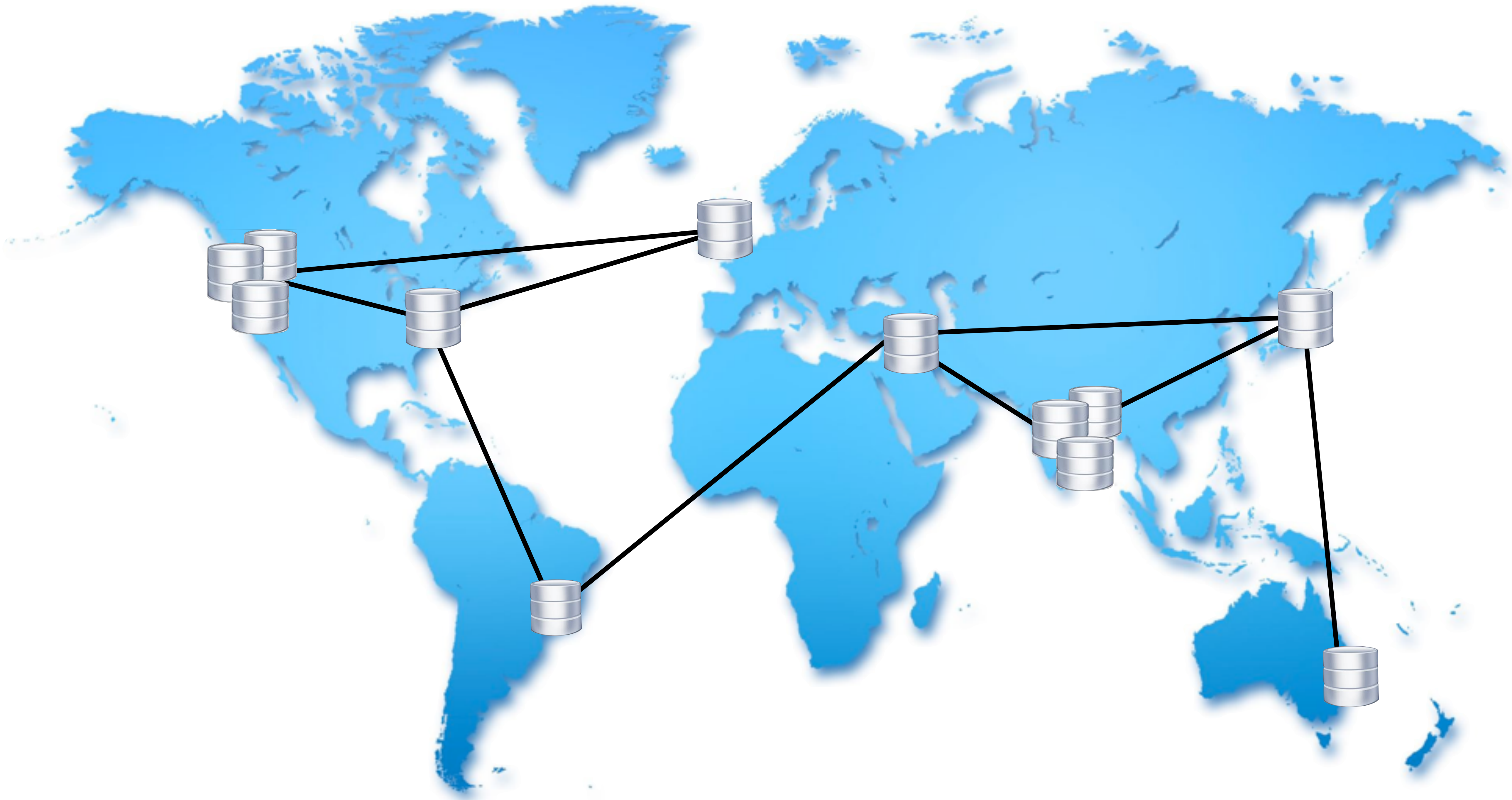

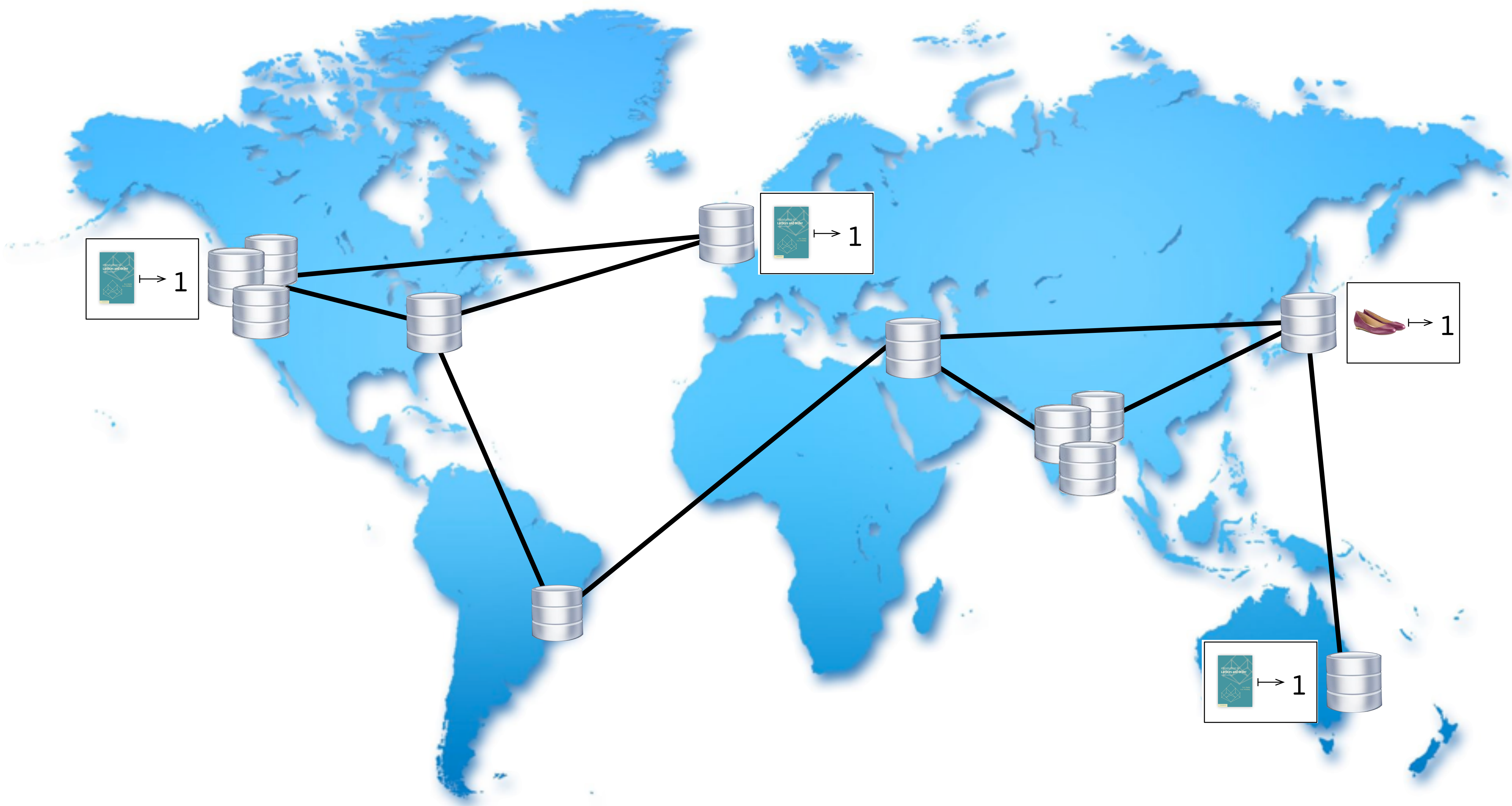
↦ 1
↦ 1
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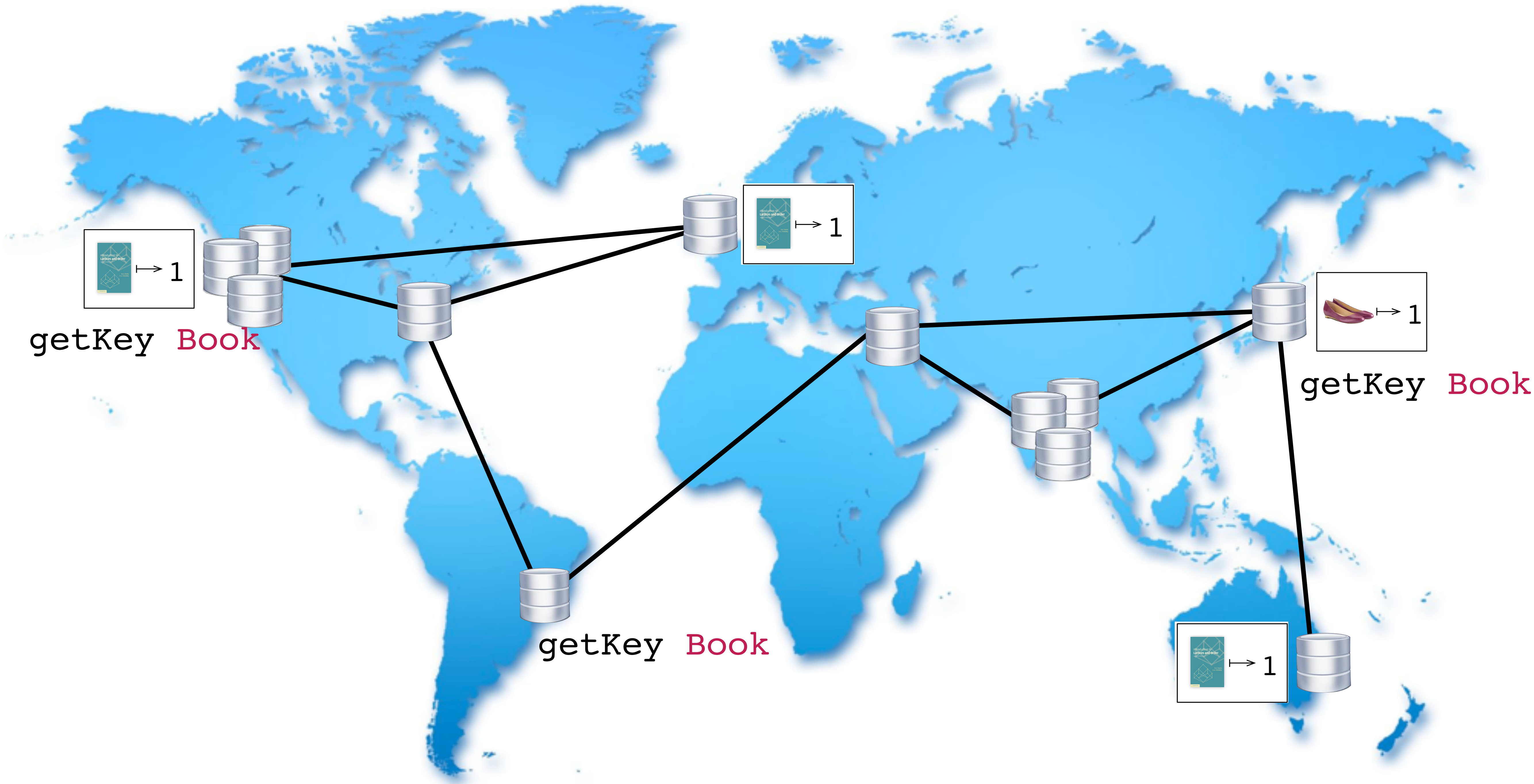
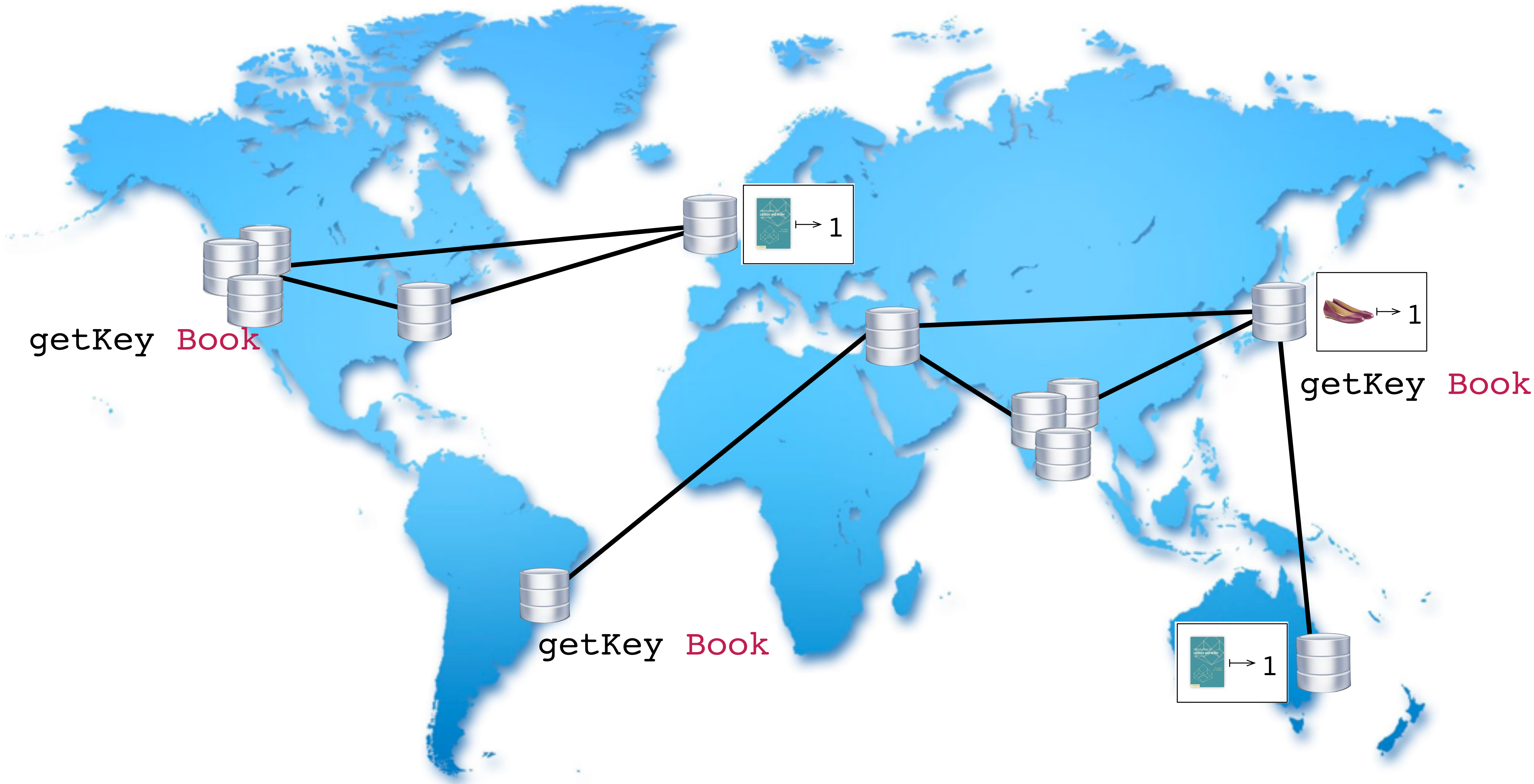


↦ 1
getKey Book
↦ 1
↦ 1
getKey Book
getKey Book
↦ 1



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Consistency (all replicas agree on the data)

Availability (all replicas can read or write at all times)

Partition tolerance (the system is robust to communication failure between replicas)

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We can opt for **eventual consistency** [Vogels, 2009] since the application is aware of the data schema it can decide on the conflict resolution method that is best suited for its client's experience. For instance, the application that maintains customer shopping carts can choose to "merge" the conflicting versions and return a single unified shopping cart.

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Dynamo: Amazon's Highly Available Key-value Store

Giuseppe DeCandia, Deniz Hastorun, Madan Jampani, Gunavardhan Kakulapati, Avinash Lakshman, Alex Pilchin, Swaminathan Sivasubramanian, Peter Vosshall and Werner Vogels

Amazon.com

ABSTRACT

Reliability at massive scale is one of the biggest challenges we face at Amazon.com, one of the largest e-commerce operations in the world; even the slightest outage has significant financial consequences and impacts customer trust. The Amazon.com platform, which provides services for many web sites worldwide, is implemented on top of an infrastructure of tens of thousands of servers and network components located in many datacenters around the world. At this scale, small and large components fail continuously and the way persistent state is managed in the face of these failures drives the reliability and scalability of the software systems.

This paper presents the design and implementation of Dynamo, a highly available key-value storage system that some of Amazon's core services use to provide an "always-on" experience. To achieve this level of availability, Dynamo sacrifices consistency under certain failure scenarios. It makes extensive use of object versioning and application-assisted conflict resolution in a manner that provides a novel interface for developers to use.

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D.4.2 [**Operating Systems**]: Storage Management; D.4.5 [**Operating Systems**]: Reliability; D.4.2 [**Operating Systems**]:

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Dealing with failures in an infrastructure comprised of millions of components is our standard mode of operation; there are always a small but significant number of server and network components that are failing at any given time. As such Amazon's software systems need to be constructed in a manner that treats failure handling as the normal case without impacting availability or performance.

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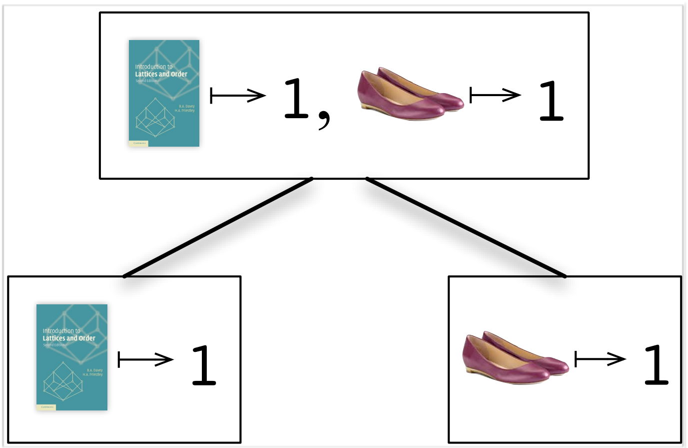

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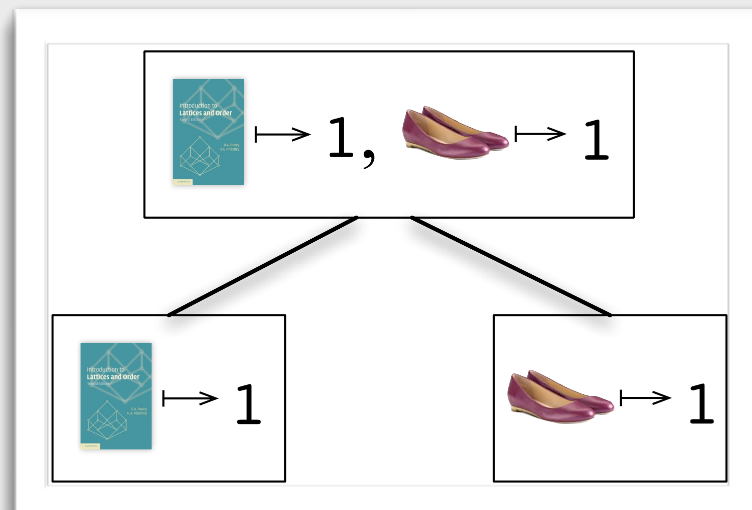
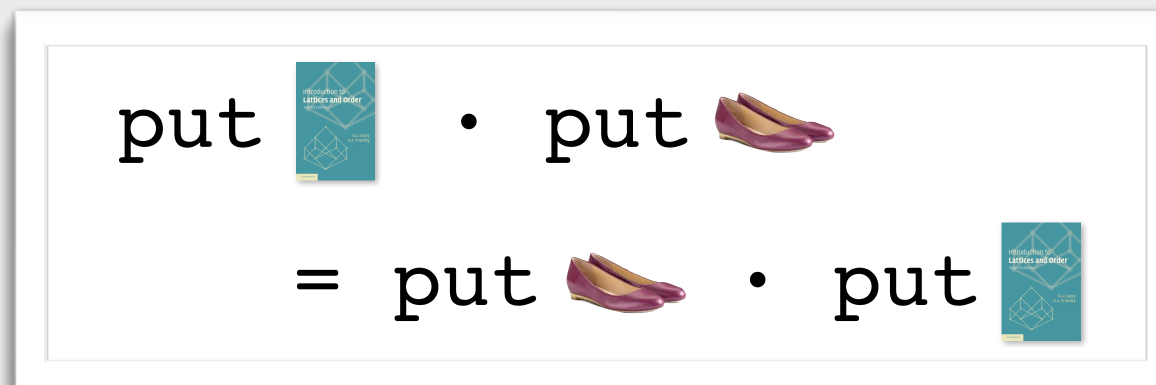
Two flavors of CRDTs

"Convergent"
"state-based"
CvRDTs

"Commutative"
"operation-based"
CmRDTs





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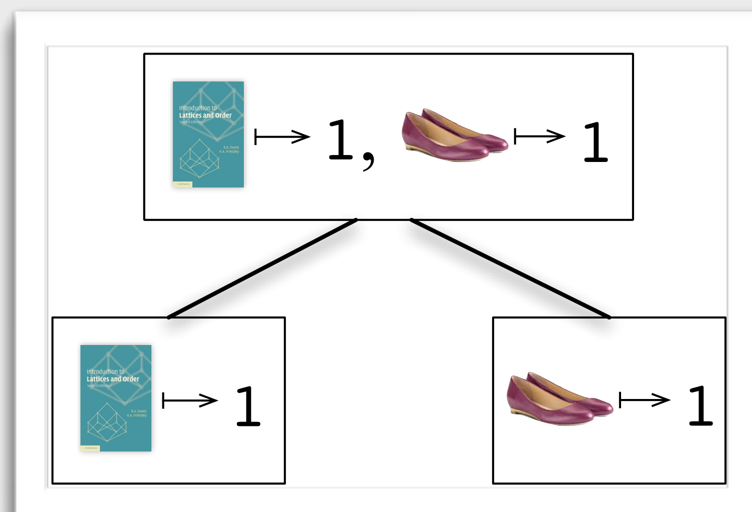
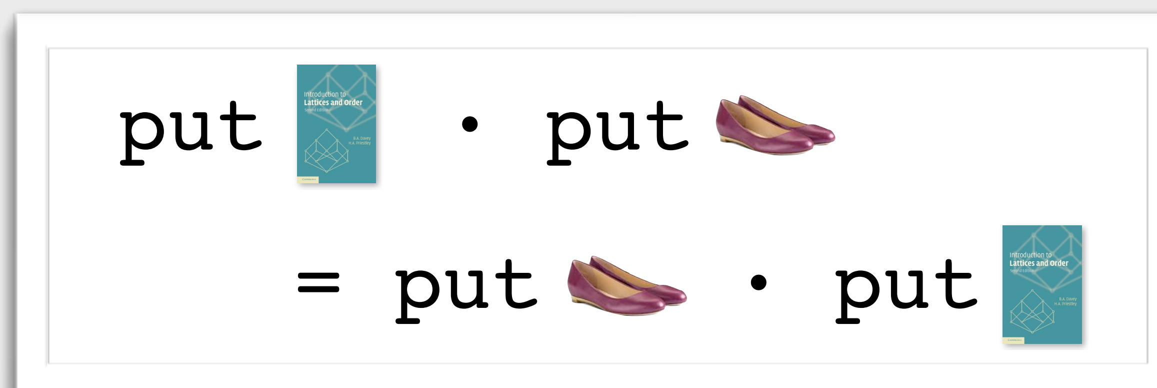
CvRDTs	[Shapiro *et al.*, 2011]	CmRDTs





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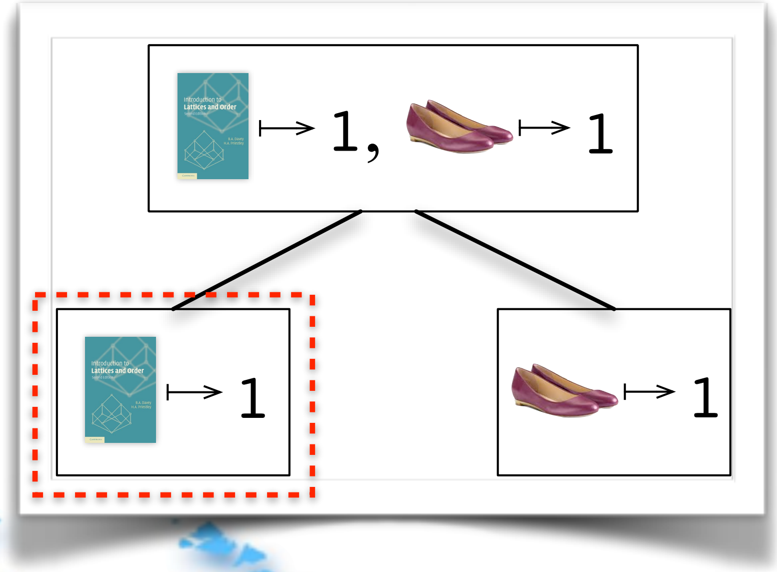
Deterministic **threshold queries** of CvRDTs:

Block only until a threshold element appears at **one** replica (that's all we need!)



Programming Systems Lab

(We're hiring! Email me!)