Lecture 8

Concurrency control in applications

Collaboration and conflict resolution

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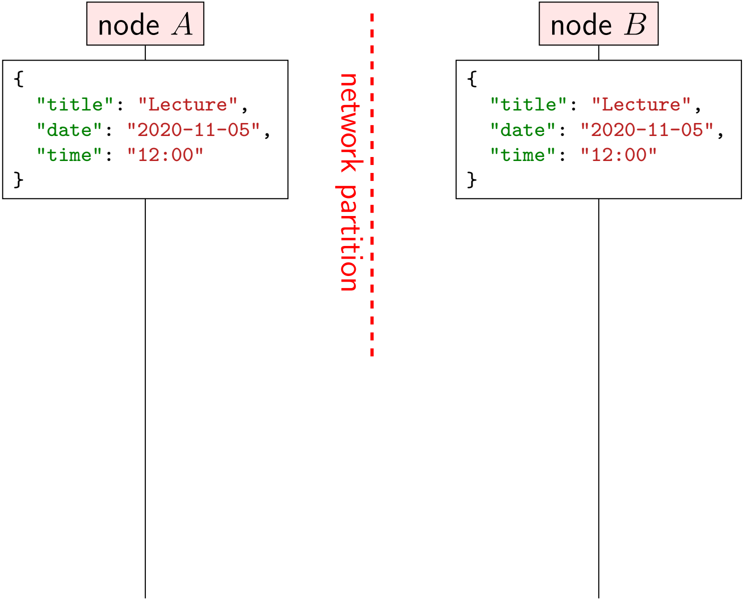
Families of **algorithms**:

- Conflict-free Replicated Data Types (**CRDTs**)
  - Operation-based
  - State-based
- Operational Transformation (**OT**)

Conflicts due to concurrent updates



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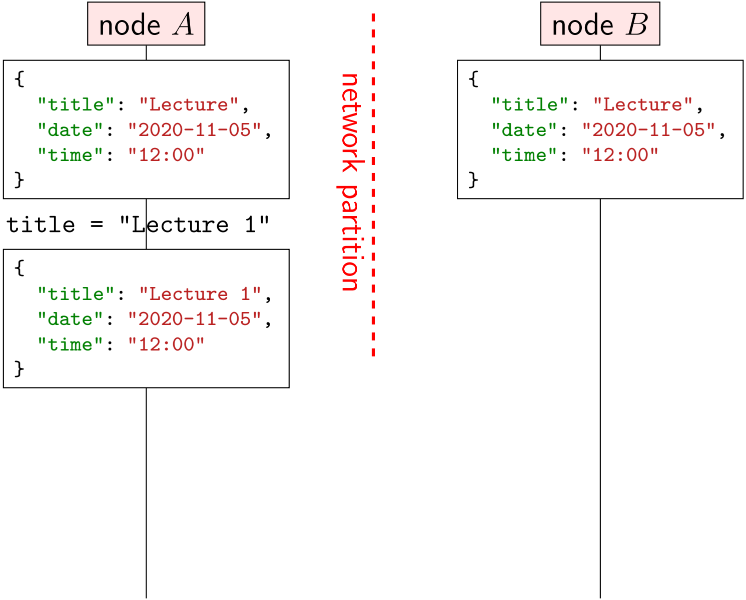

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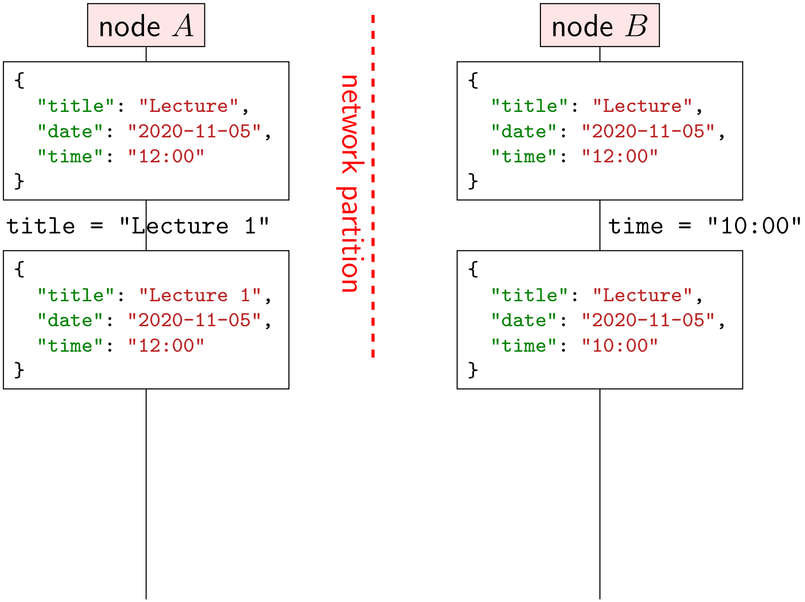

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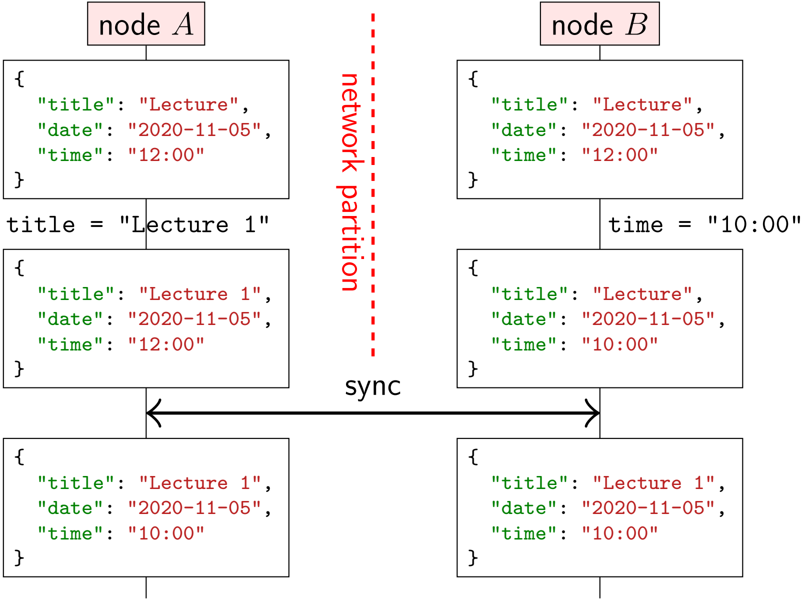

Operation-based map CRDT

on initialisation **do**
  $values := \{\}$
end on

on request to read value for key k **do**
  if $\exists t, v.\ (t, k, v) \in values$ **then return** v **else return** null
end on

on request to set key k to value v **do**
  $t := \mathrm{newTimestamp}()$ ▷ globally unique, e.g. Lamport timestamp
  broadcast (set, t, k, v) by reliable broadcast (including to self)
end on

on delivering (set, t, k, v) by reliable broadcast **do**
  $previous := \{(t', k', v') \in values \mid k' = k\}$
  if $previous = \{\} \ \vee\ \forall (t', k', v') \in previous.\ t' < t$ **then**
    $values := (values \setminus previous) \cup \{(t, k, v)\}$
  end if
end on

Operation-based CRDTs

Reliable broadcast may deliver updates in any order:

- broadcast $(\text{set}, t_1, \text{“title”}, \text{“Lecture 1”})$
- broadcast $(\text{set}, t_2, \text{“time”}, \text{“10:00”})$

Operation-based CRDTs

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Recall **strong eventual consistency**:

- **Eventual delivery:** every update made to one non-faulty replica is eventually processed by every non-faulty replica.
- **Convergence:** any two replicas that have processed the same set of updates are in the same state

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CRDT algorithm implements this:

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CRDT algorithm implements this:

- Reliable broadcast ensures every operation is eventually delivered to every (non-crashed) replica
- Applying an operation is **commutative**: order of delivery doesn't matter

State-based map CRDT

The operator $\sqcup$ merges two states s_1 and s_2 as follows:

$$s_1 \sqcup s_2 = \{(t, k, v) \in (s_1 \cup s_2) \mid \nexists (t', k', v') \in (s_1 \cup s_2).\ k' = k \wedge t' > t\}$$

on initialisation **do**
  $\mathit{values} := \{\}$
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on request to read value for key k **do**
  if $\exists t, v.\ (t, k, v) \in \mathit{values}$ **then return** v **else return** null
end on

on request to set key k to value v **do**
  $t := \mathrm{newTimestamp}()$ ▷ globally unique, e.g. Lamport timestamp
  $\mathit{values} := \{(t', k', v') \in \mathit{values} \mid k' \neq k\} \cup \{(t, k, v)\}$
  broadcast values by best-effort broadcast
end on

on delivering V by best-effort broadcast **do**
  $\mathit{values} := \mathit{values} \sqcup V$
end on

State-based CRDTs

Merge operator $\sqcup$ must satisfy: $\forall s_1, s_2, s_3 \ldots$

- **Commutative**: $s_1 \sqcup s_2 = s_2 \sqcup s_1$.
- **Associative**: $(s_1 \sqcup s_2) \sqcup s_3 = s_1 \sqcup (s_2 \sqcup s_3)$.
- **Idempotent**: $s_1 \sqcup s_1 = s_1$.

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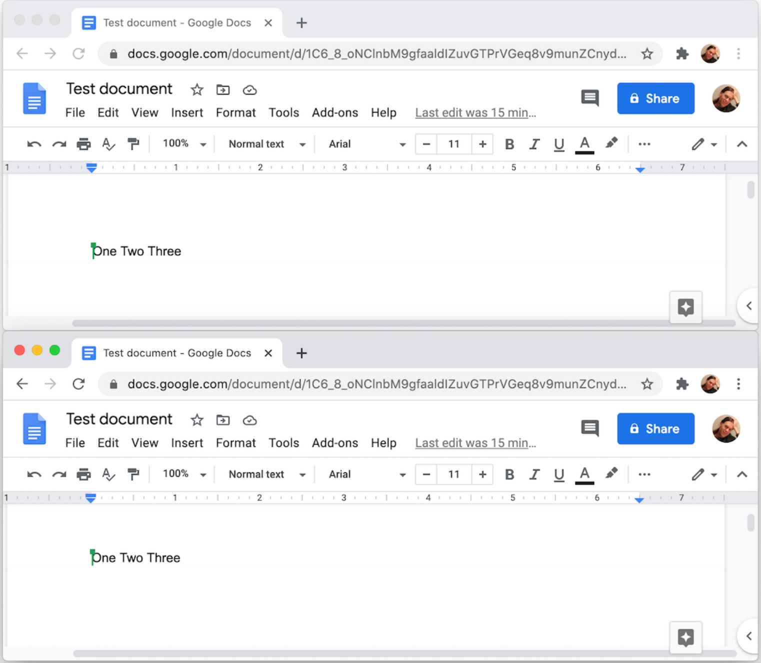
Not necessarily uses broadcast:

- Can also merge concurrent updates to replicas e.g. in quorum replication, anti-entropy, ...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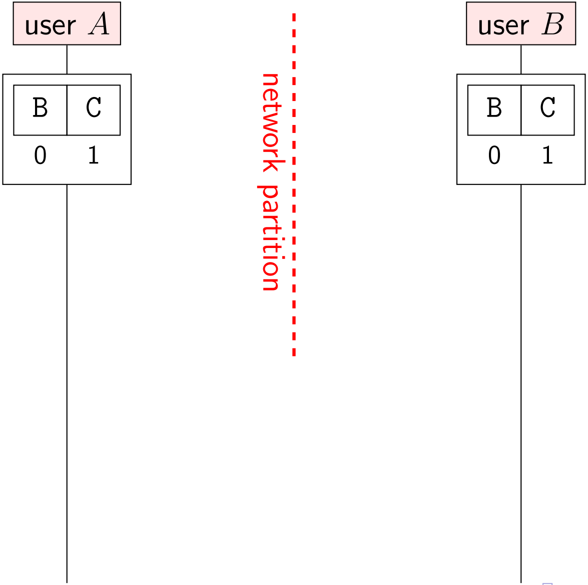
Collaborative text editing: the problem



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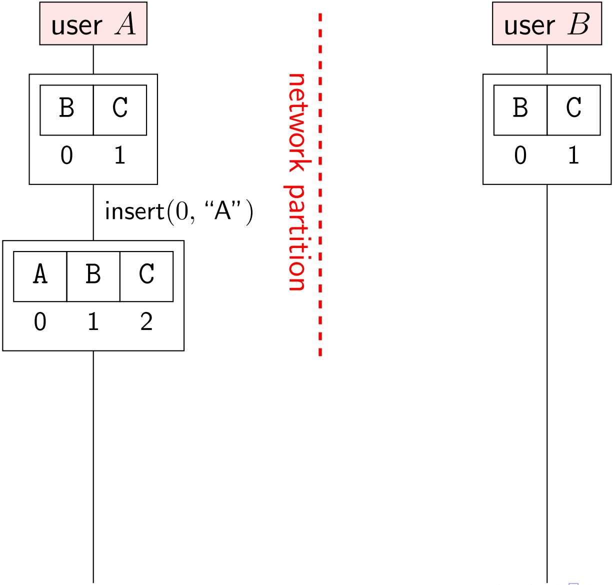

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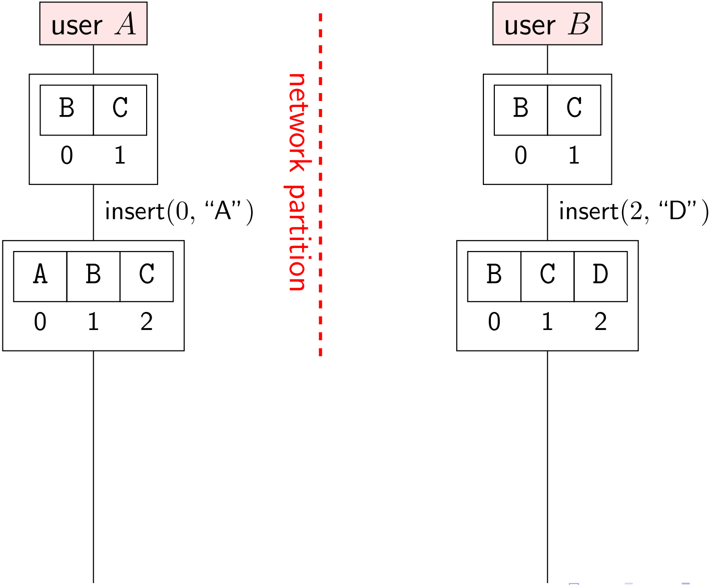

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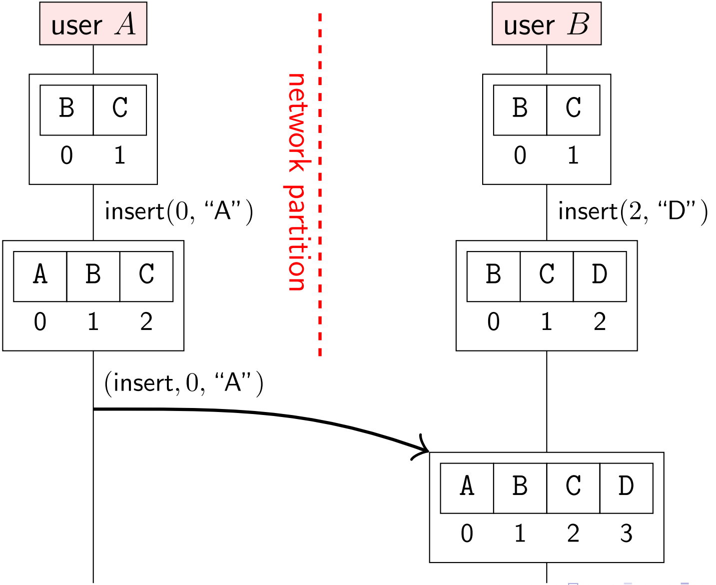

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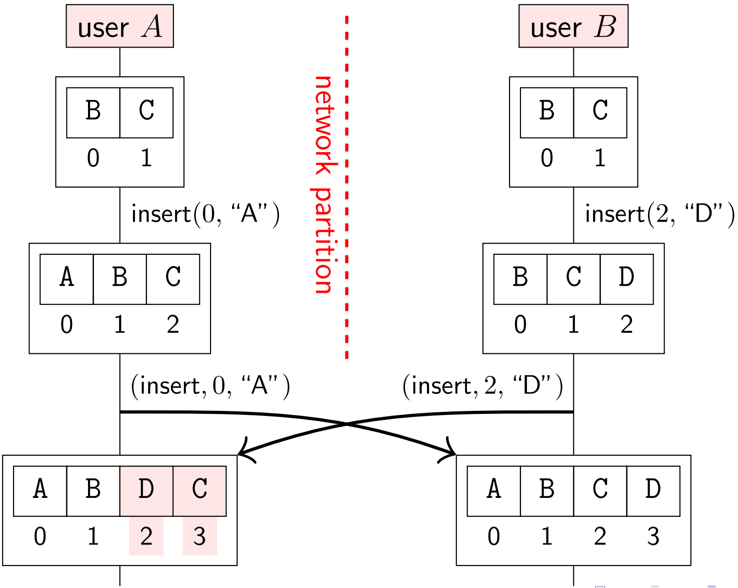
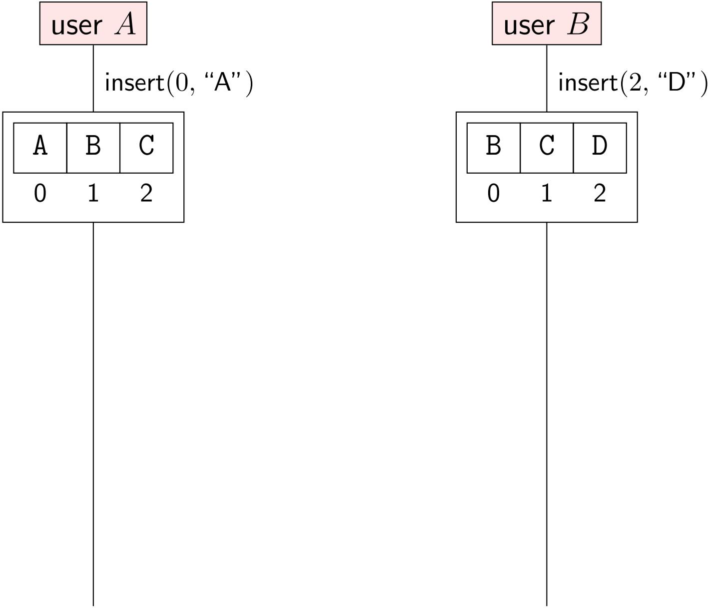


Operational transformation



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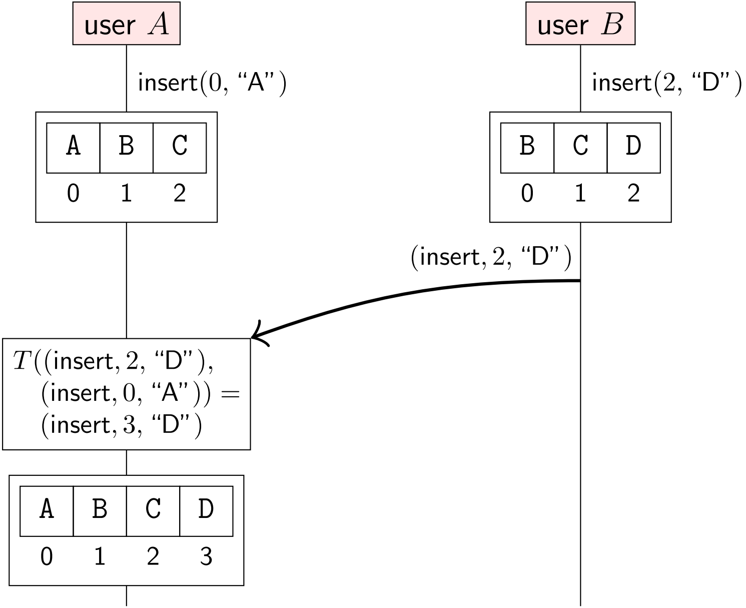

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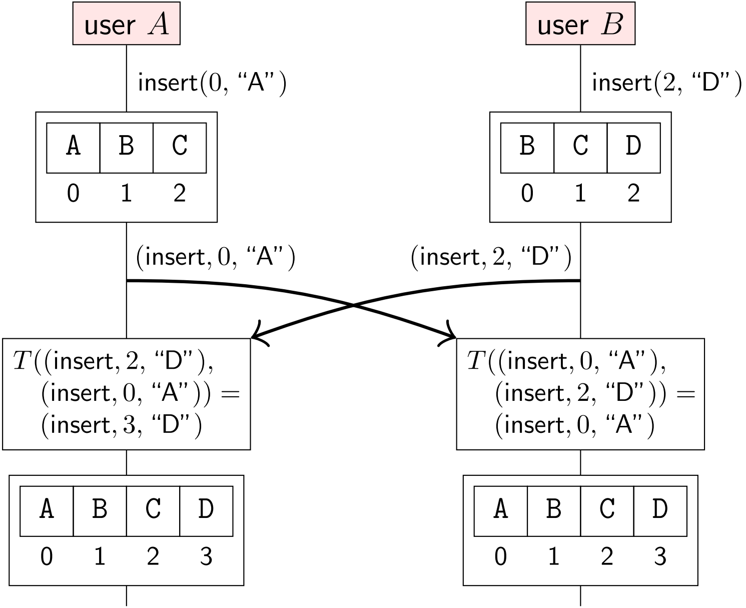
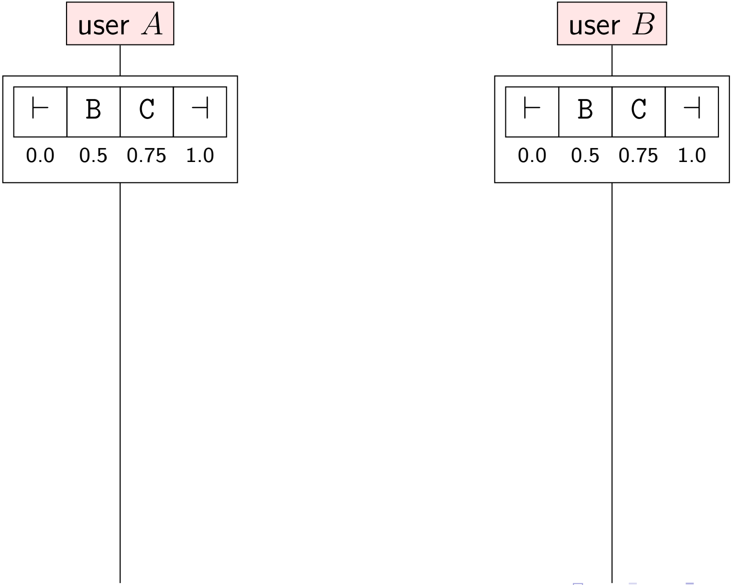


Text editing CRDT



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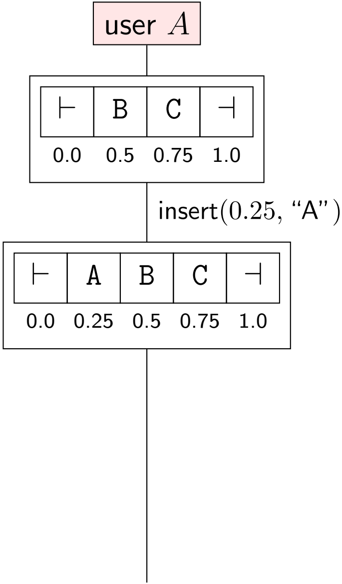

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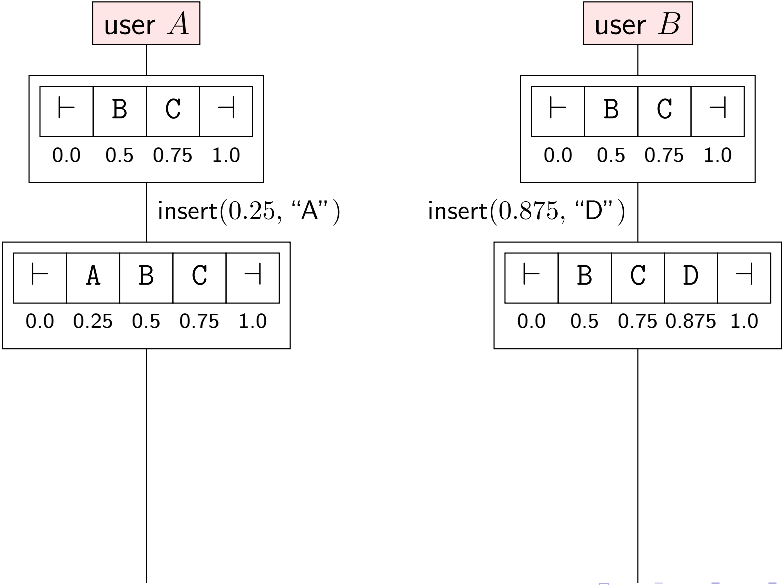

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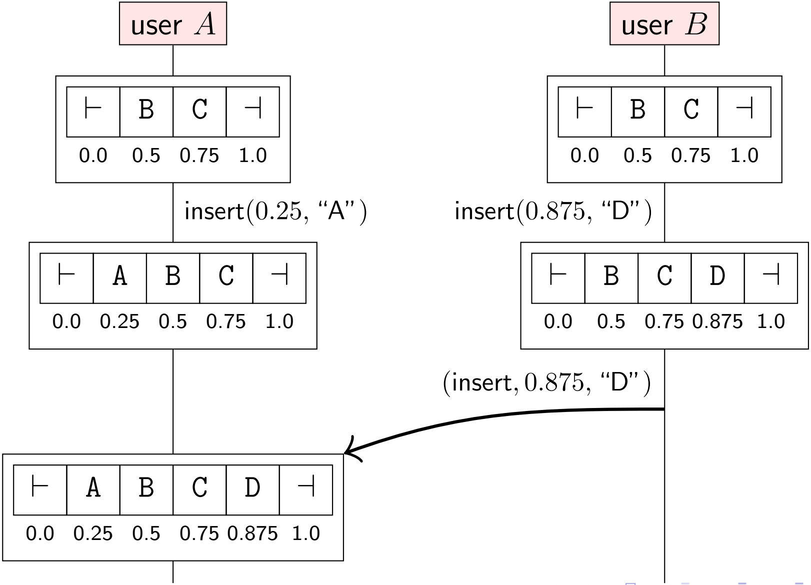

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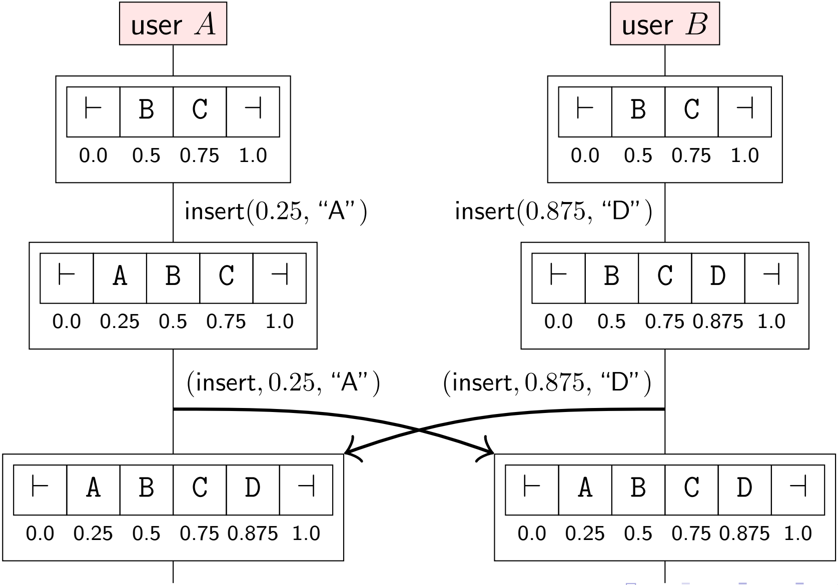

Operation-based text CRDT (1/2)

function $\textsc{ElementAt}(chars, index)$
  $min =$ the unique triple $(p, n, v) \in chars$ such that
    $\nexists (p', n', v') \in chars.\ p' < p \vee (p' = p \wedge n' < n)\}$
  if $index = 0$ **then return** min
  else return $\textsc{ElementAt}(chars \setminus \{min\}, index - 1)$
end function

on initialisation **do**
  $chars := \{(0, \mathsf{null}, \vdash),\ (1, \mathsf{null}, \dashv)\}$
end on

on request to read character at index $index$ **do**
  let $(p, n, v) := \textsc{ElementAt}(chars, index + 1)$; **return** v
end on

on request to insert character v at index $index$ at node $nodeId$ **do**
  let $(p_1, n_1, v_1) := \textsc{ElementAt}(chars, index)$
  let $(p_2, n_2, v_2) := \textsc{ElementAt}(chars, index + 1)$
  broadcast $(\mathsf{insert}, (p_1 + p_2)/2, nodeId, v)$ by causal broadcast
end on

Operation-based text CRDT (2/2)

on delivering (insert, p, n, v) by causal broadcast **do**
$chars := chars \cup \{(p, n, v)\}$
end on

on request to delete character at index $index$ **do**
let $(p, n, v) := \text{ElementAt}(chars, index + 1)$
broadcast (delete, p, n) by causal broadcast
end on

on delivering (delete, p, n) by causal broadcast **do**
$chars := \{(p', n', v') \in chars \mid \neg(p' = p \wedge n' = n)\}$
end on

- Use causal broadcast so that insertion of a character is delivered before its deletion
- Insertion and deletion of different characters commute

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The interesting bit: read-only transactions require **no locks**!

Consistent snapshots

A read-only transaction observes a **consistent snapshot**:
If $T_1 \rightarrow T_2$ (e.g. T_2 reads data written by T_1)...

- Snapshot reflecting writes by T_2 also reflects writes by T_1
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Approach: **multi-version concurrency control** (MVCC)

- Each read-write transaction T_w has commit timestamp t_w
- Every value is tagged with timestamp t_w of transaction that wrote it (not overwriting previous value)

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Approach: **multi-version concurrency control** (MVCC)

- Each read-write transaction T_w has commit timestamp t_w
- Every value is tagged with timestamp t_w of transaction that wrote it (not overwriting previous value)
- Read-only transaction T_r has snapshot timestamp t_r
- T_r ignores values with $t_w > t_r$; observes most recent value with $t_w \leq t_r$

Obtaining commit timestamps

Must ensure that whenever $T_1 \rightarrow T_2$ we have $t_1 < t_2$.

- Physical clocks may be **inconsistent with causality**

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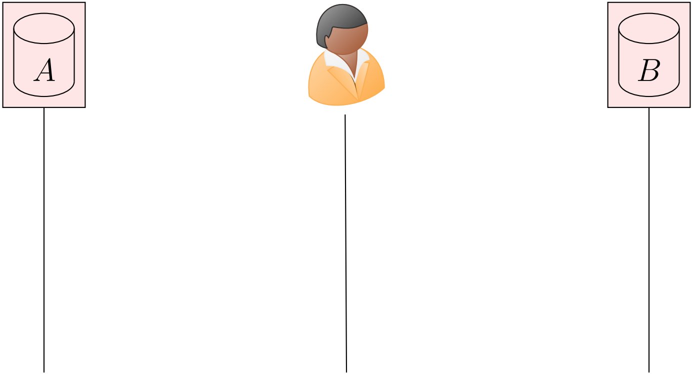

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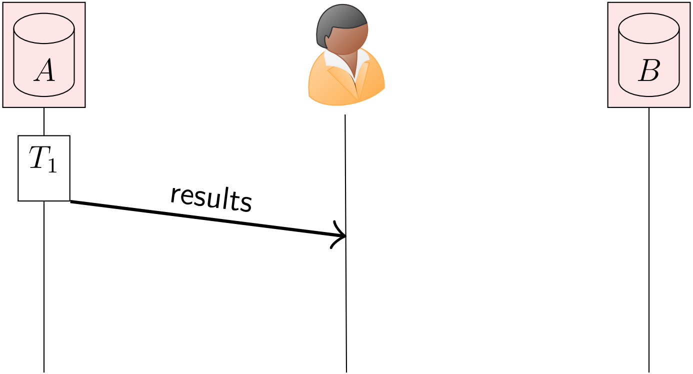

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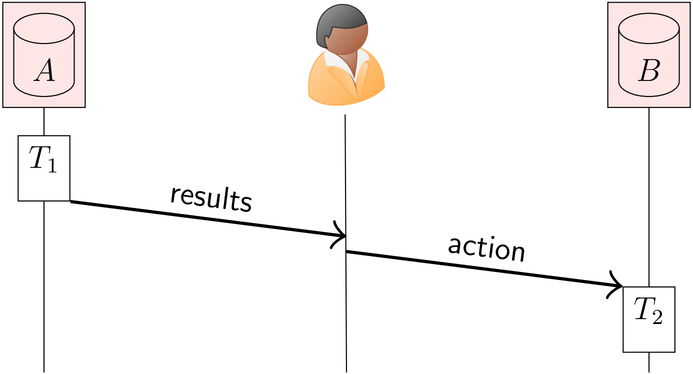
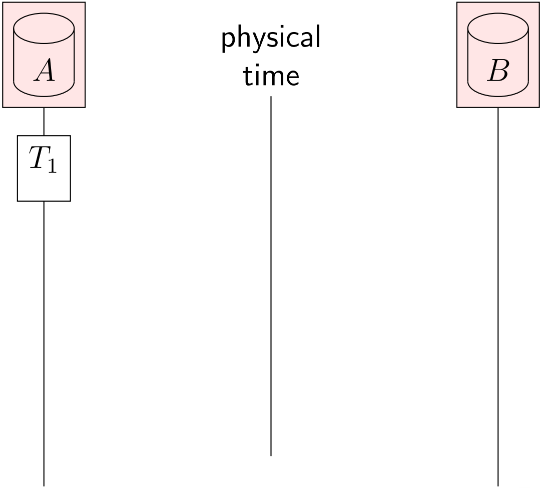


TrueTime: explicit physical clock uncertainty



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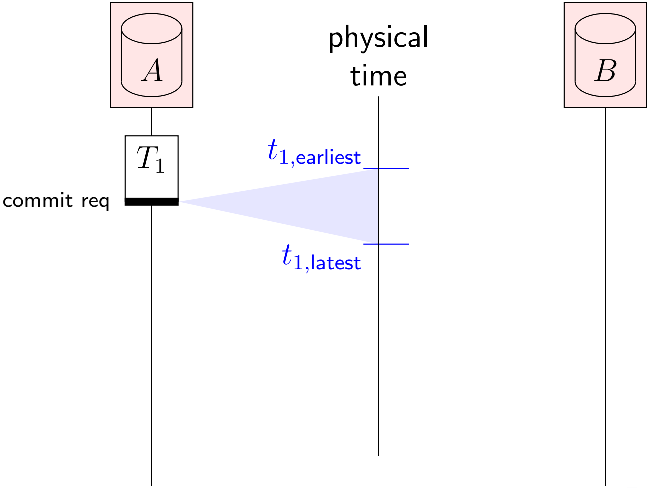
Spanner's TrueTime clock returns $[t_{\text{earliest}}, t_{\text{latest}}]$.
True physical timestamp must lie within that range.



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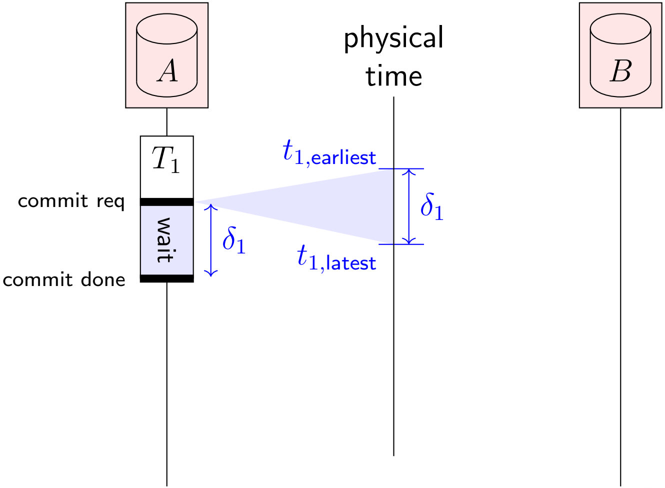

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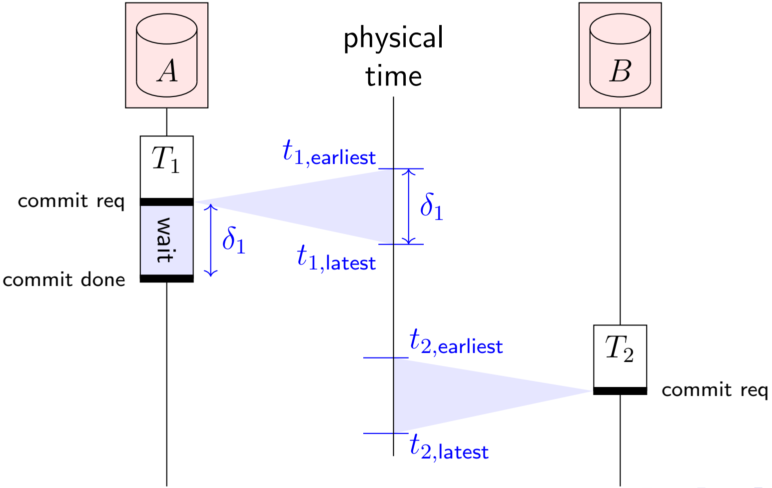

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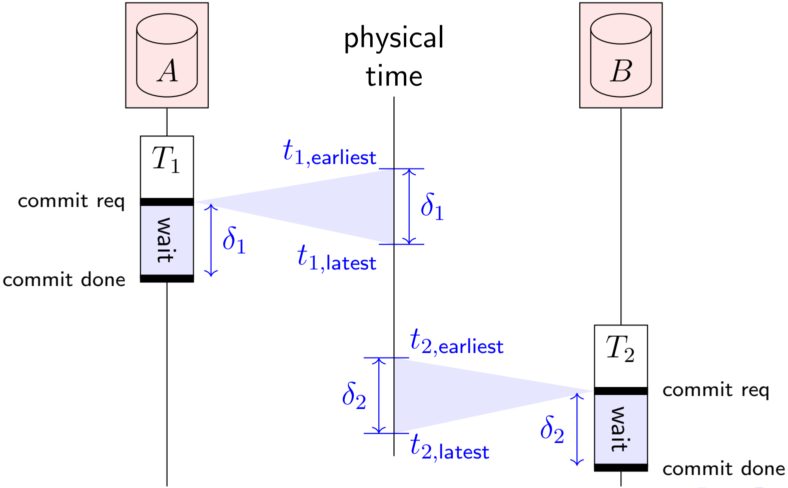

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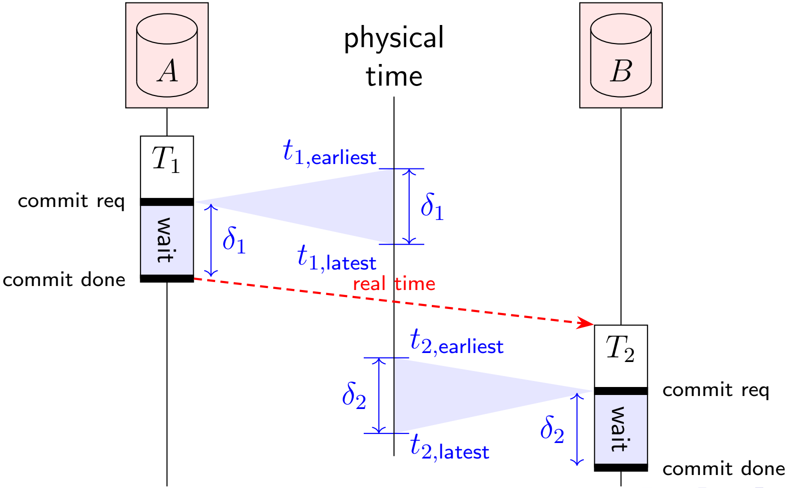
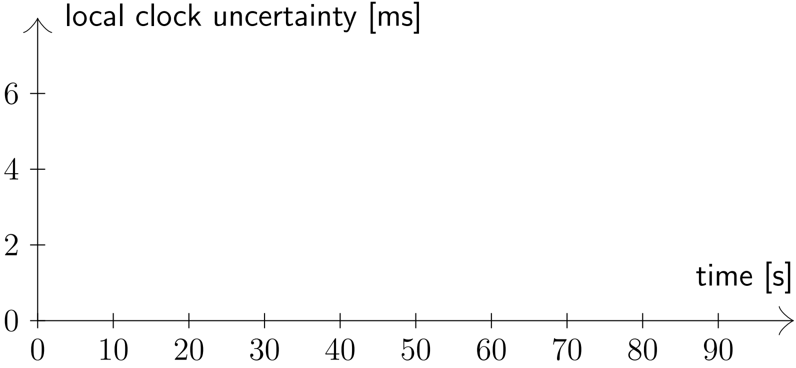


Determining clock uncertainty in TrueTime

Clock servers with **atomic clock** or **GPS receiver** in each datacenter; servers report their clock uncertainty.



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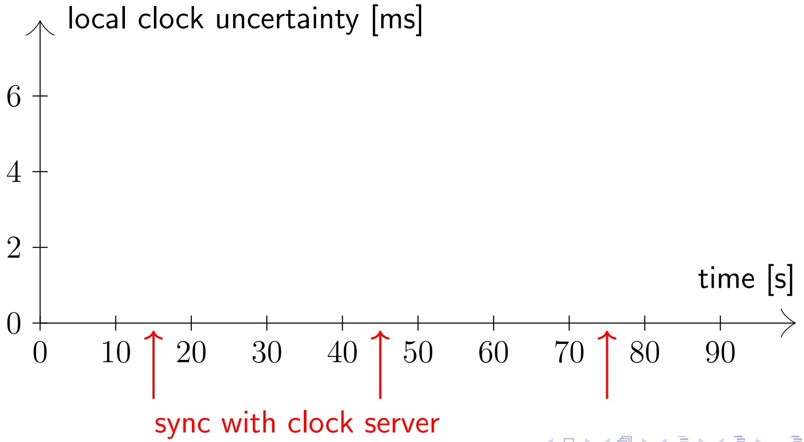

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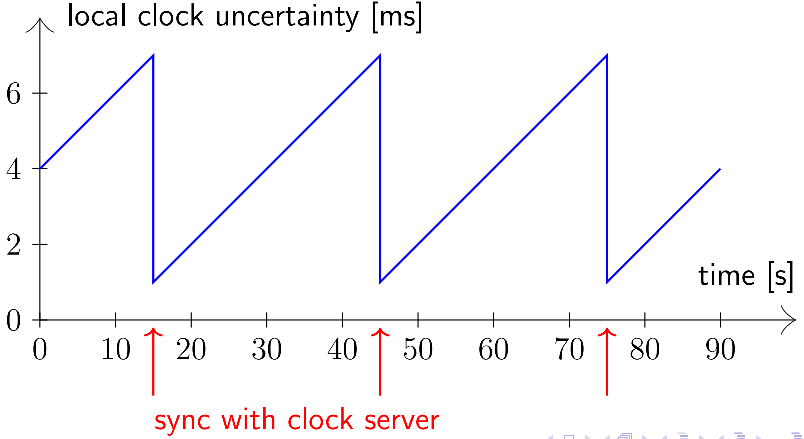

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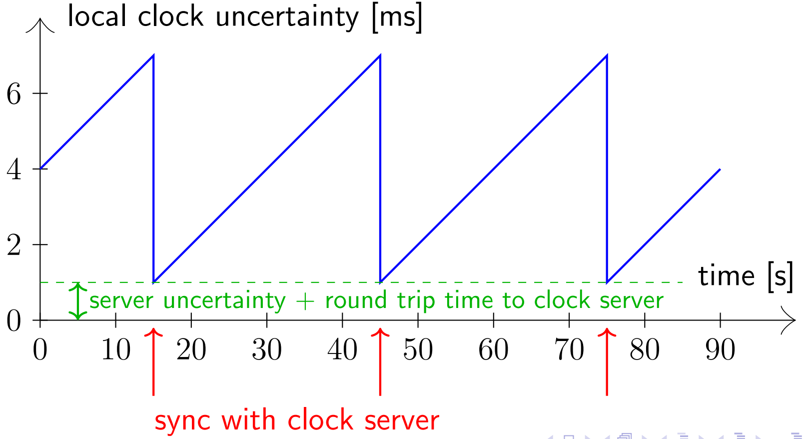

That's all, folks!

Any questions? Email mk428@cst.cam.ac.uk!

Summary:

- Distributed systems are everywhere
- You use them every day: e.g. web apps
- Key goals: availability, scalability, performance
- Key problems: concurrency, faults, unbounded latency
- Key abstractions: replication, broadcast, consensus
- No one right way, just trade-offs