Neural Datalog Through Time

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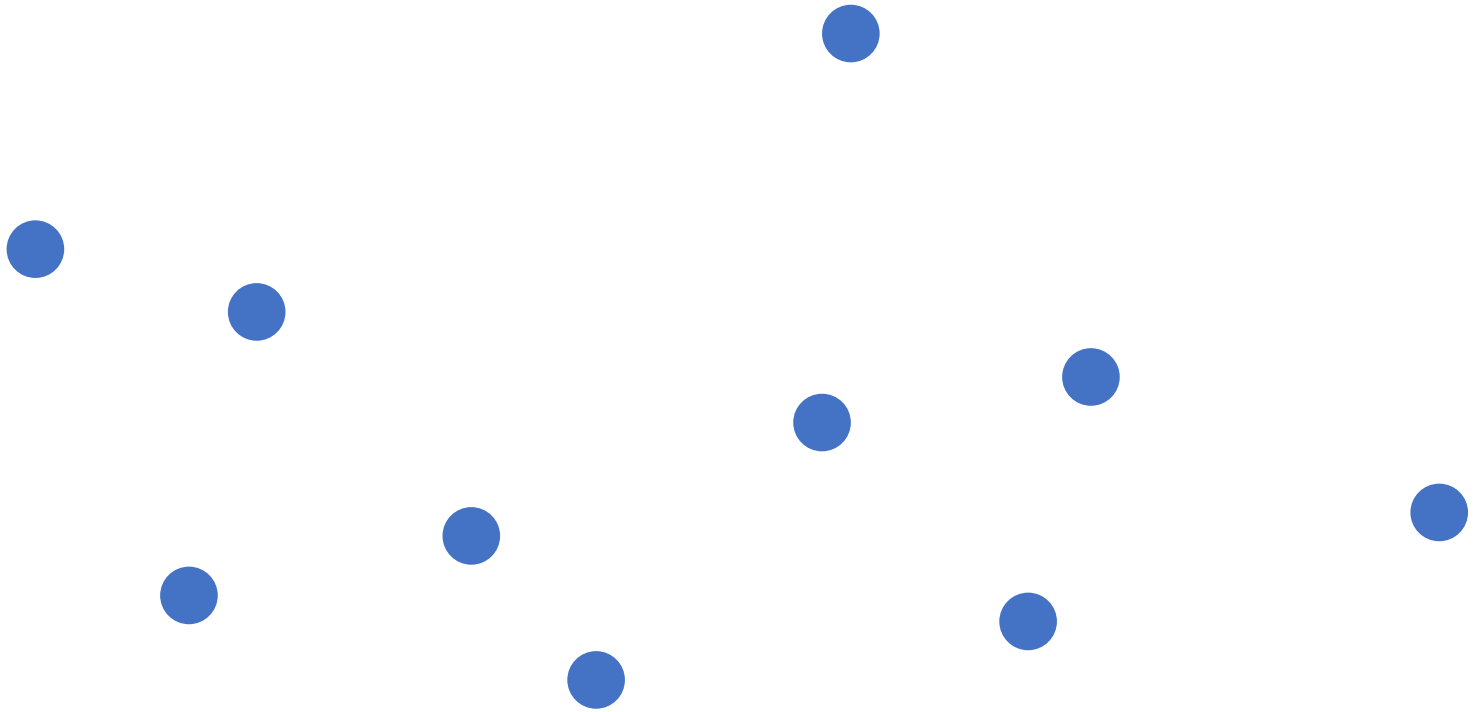
[1]Johns Hopkins University

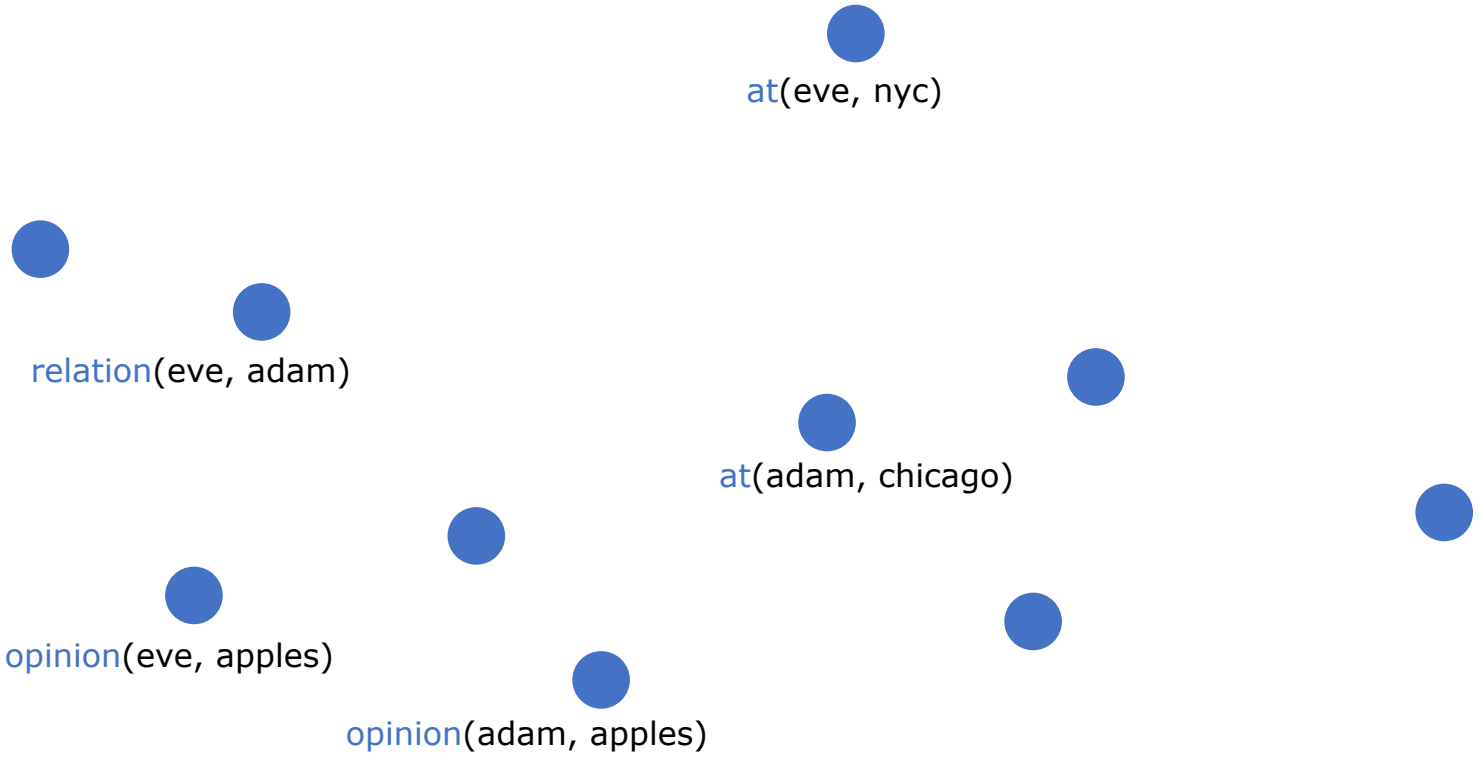
[2]Bloomberg

Model How a Database Changes Over Time



Model How a Database Changes Over Time

200,000 facts right now



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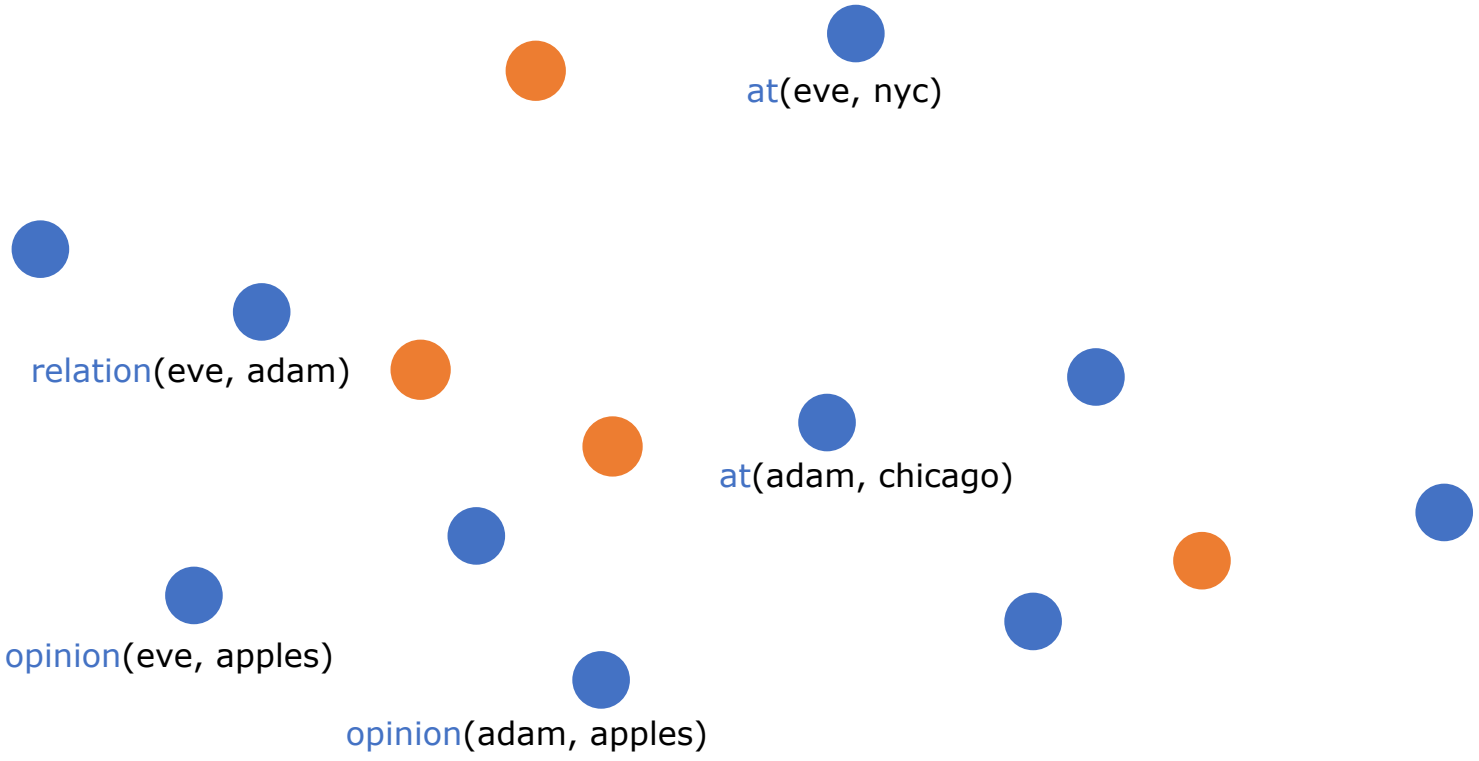

Model How a Database Changes Over Time

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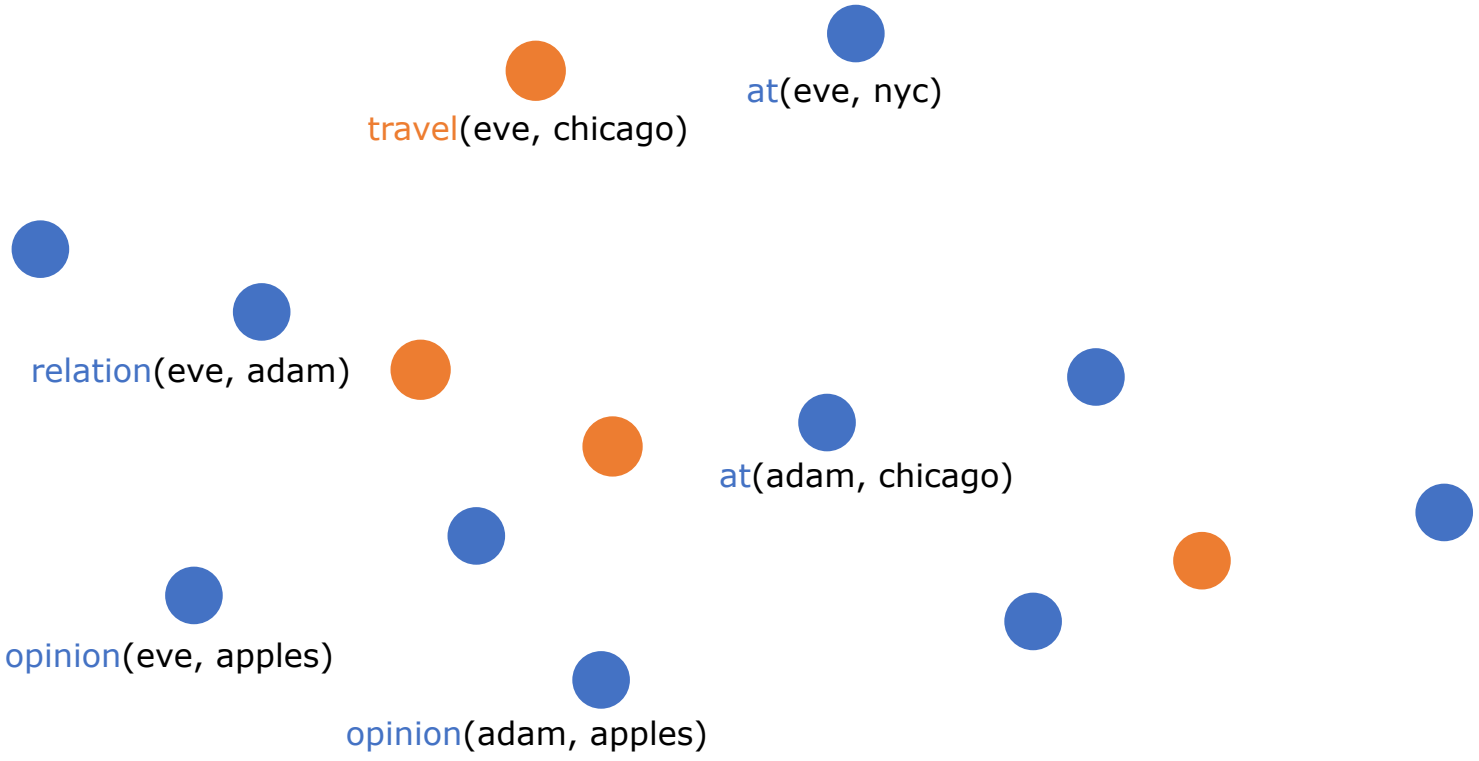

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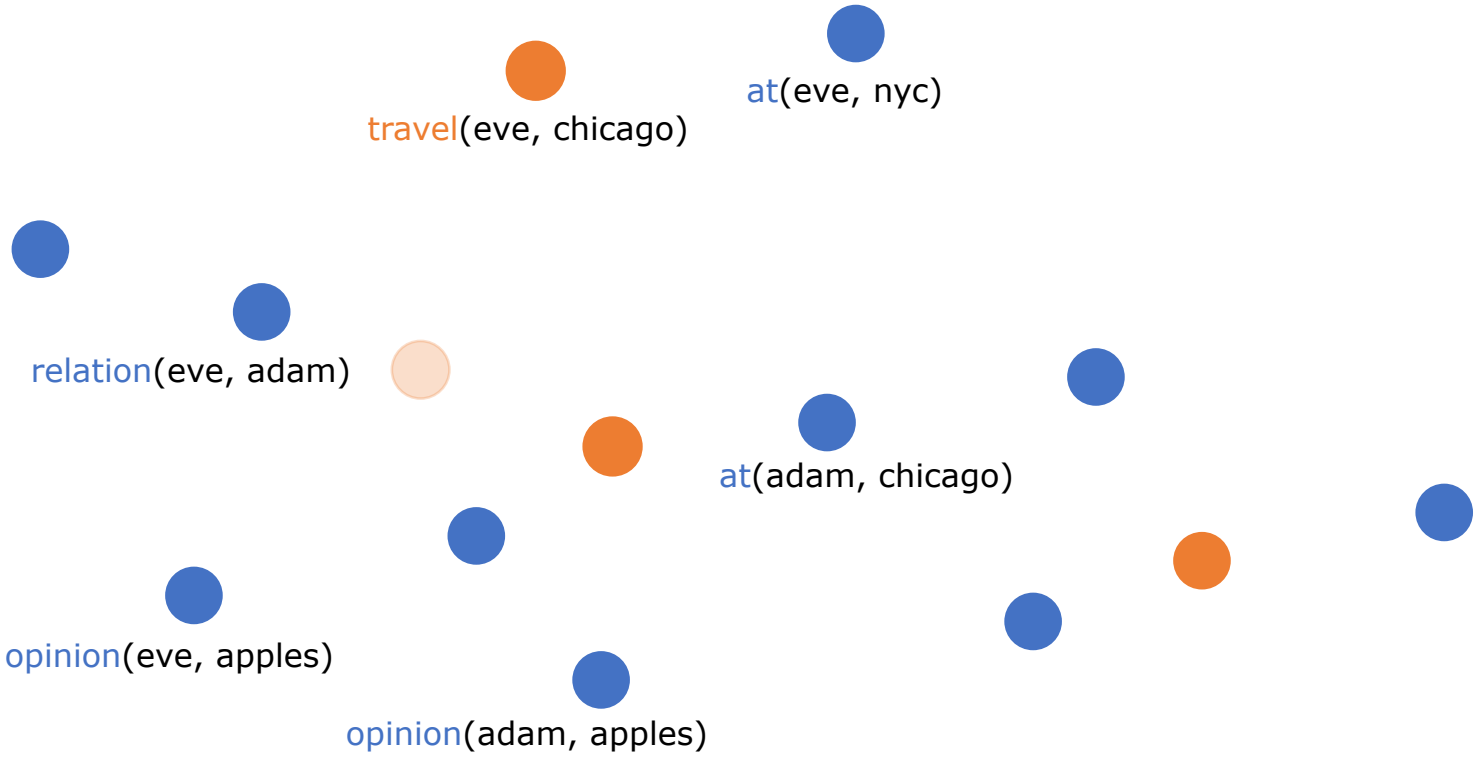

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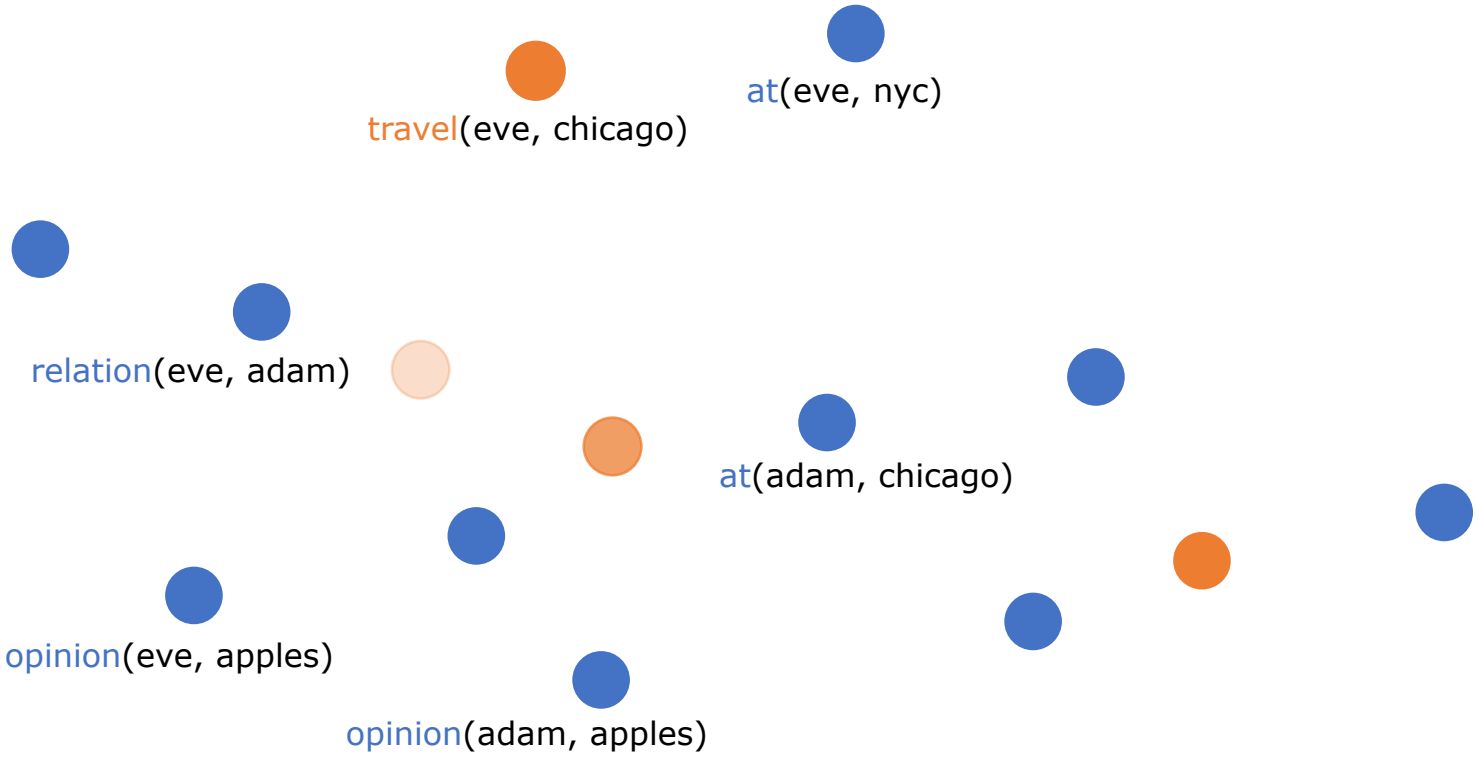
little language
to specify a generative model
of event sequences



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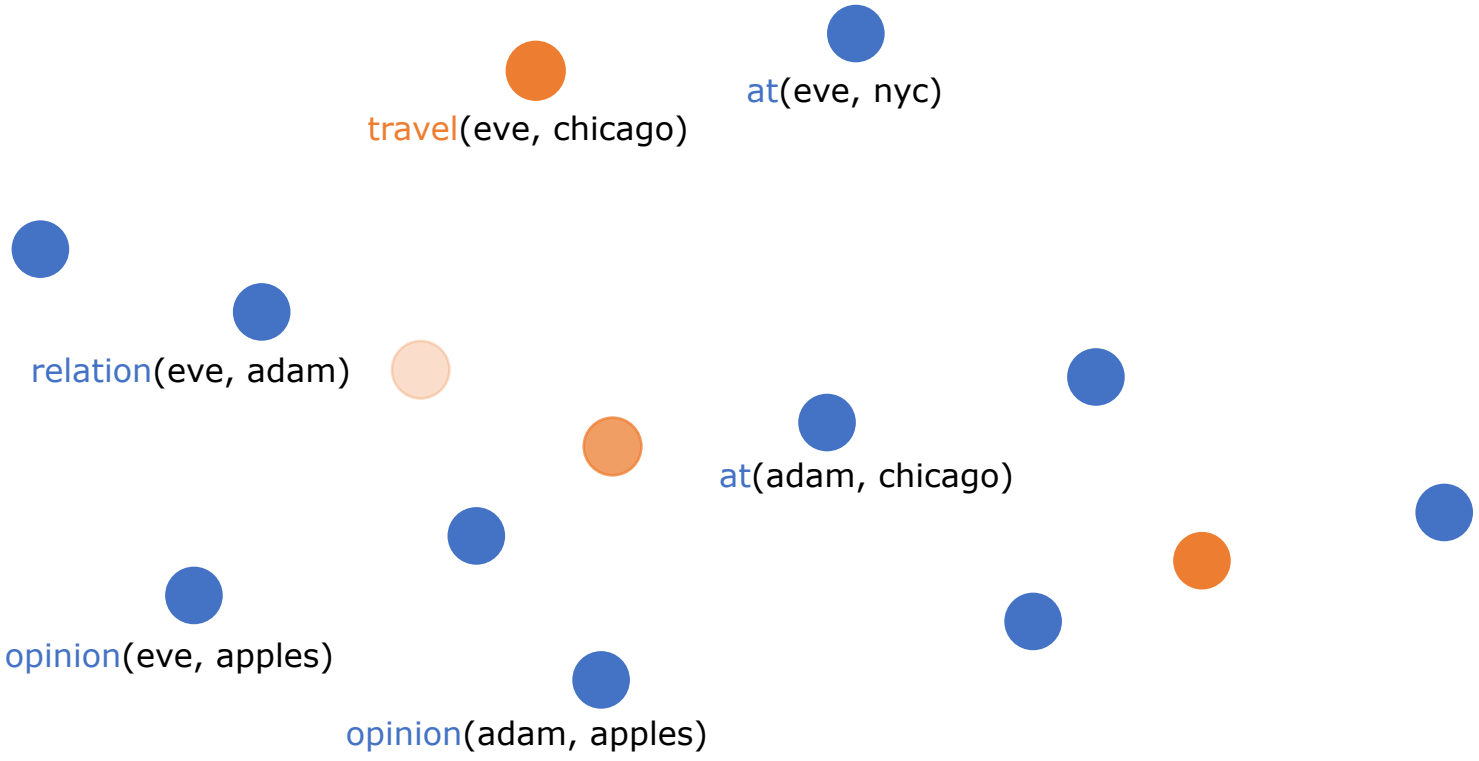

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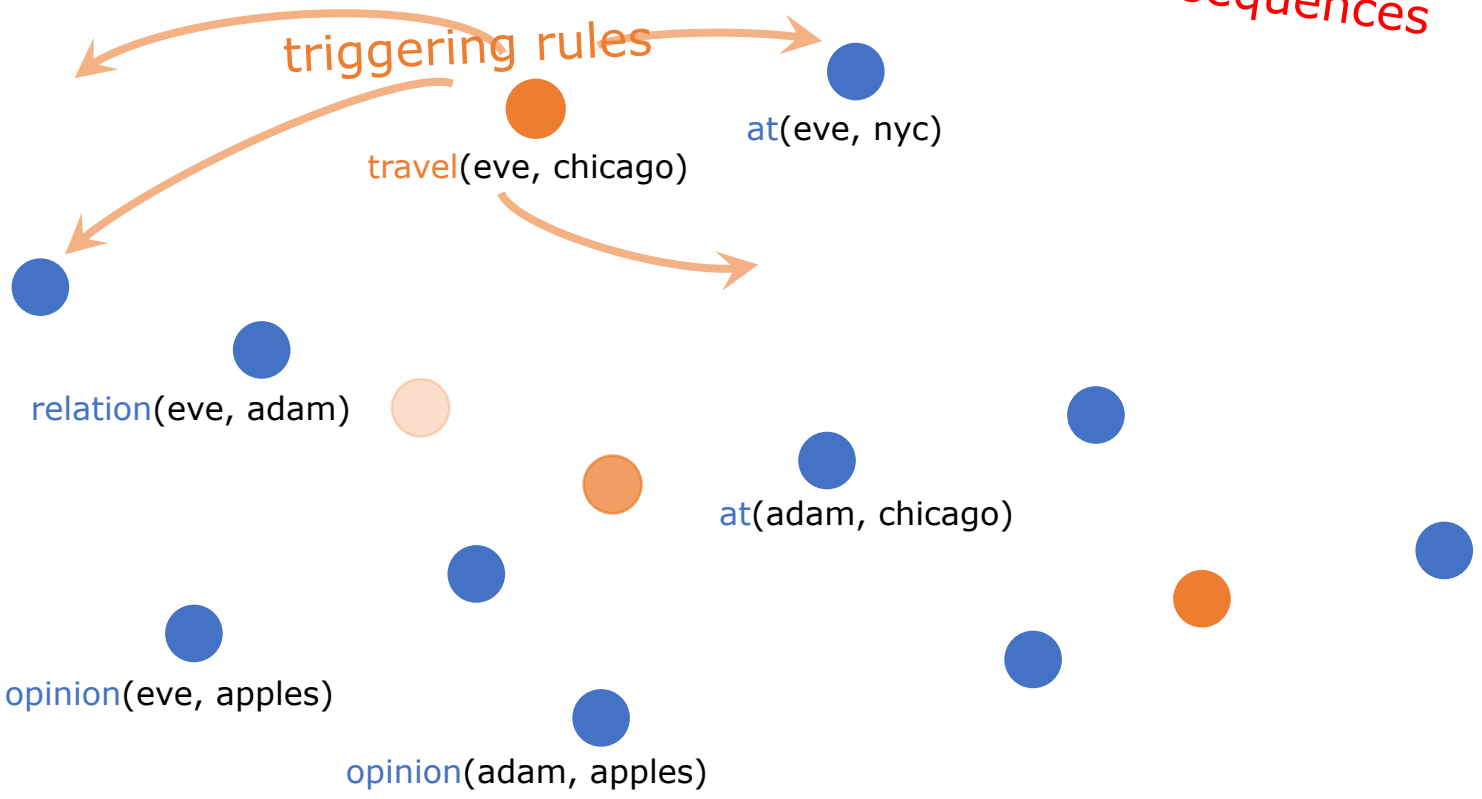

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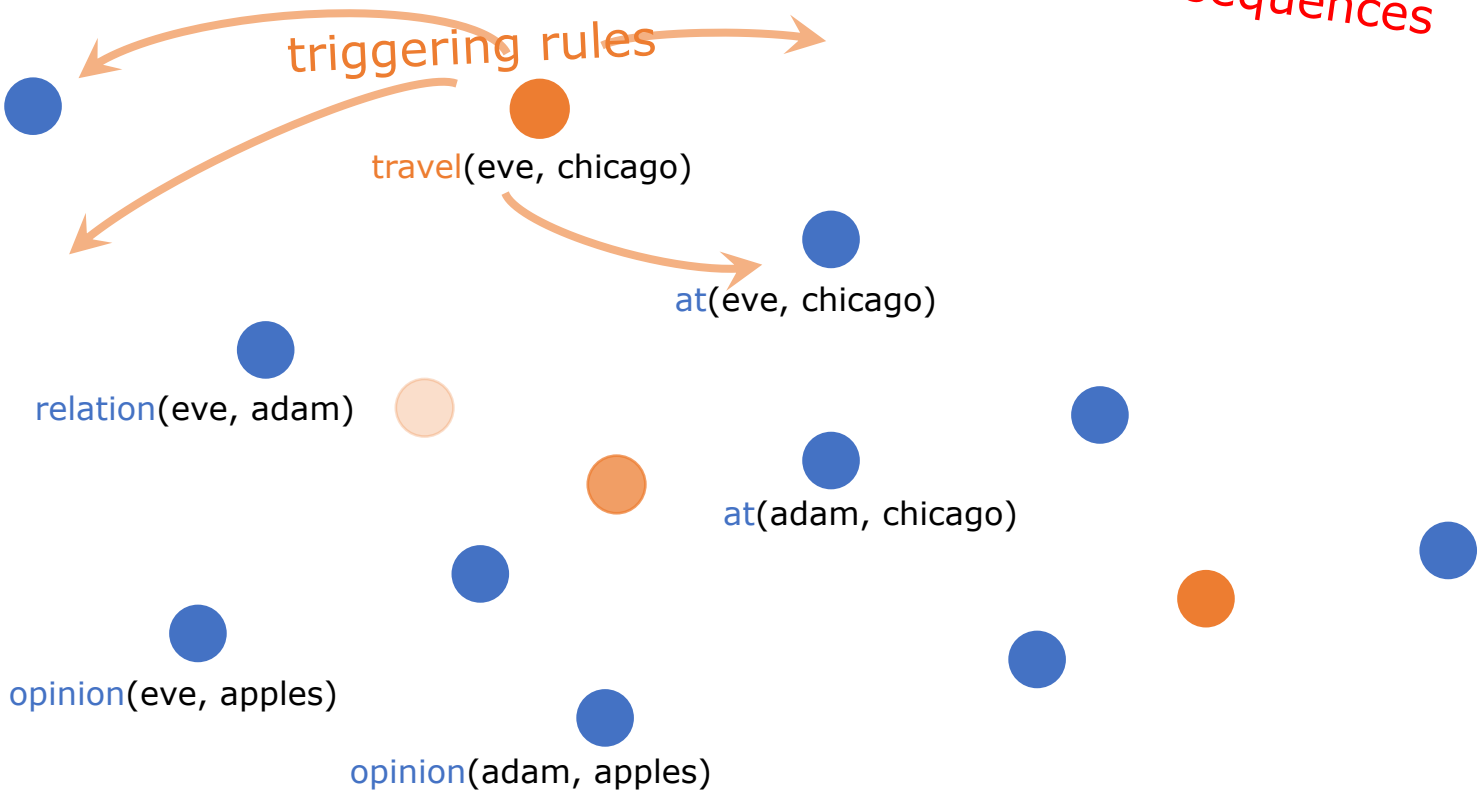

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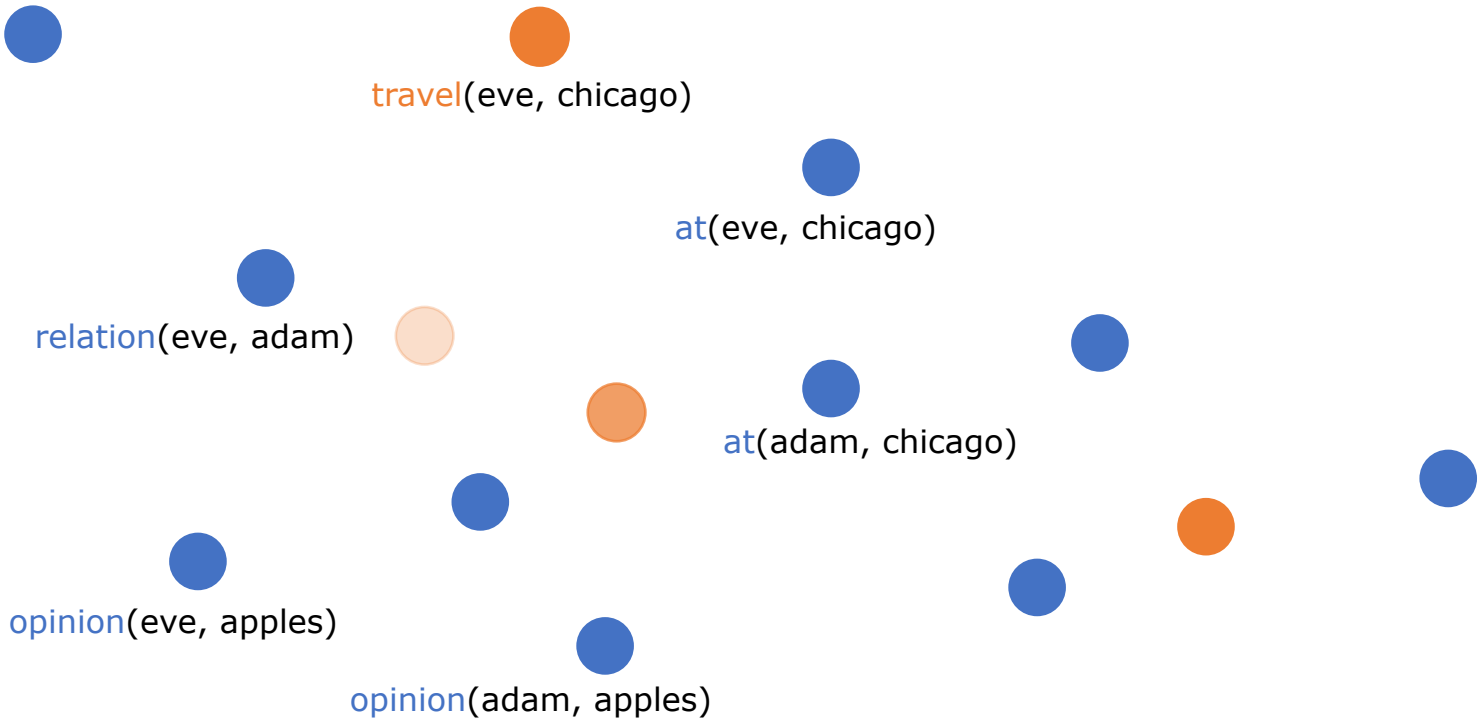

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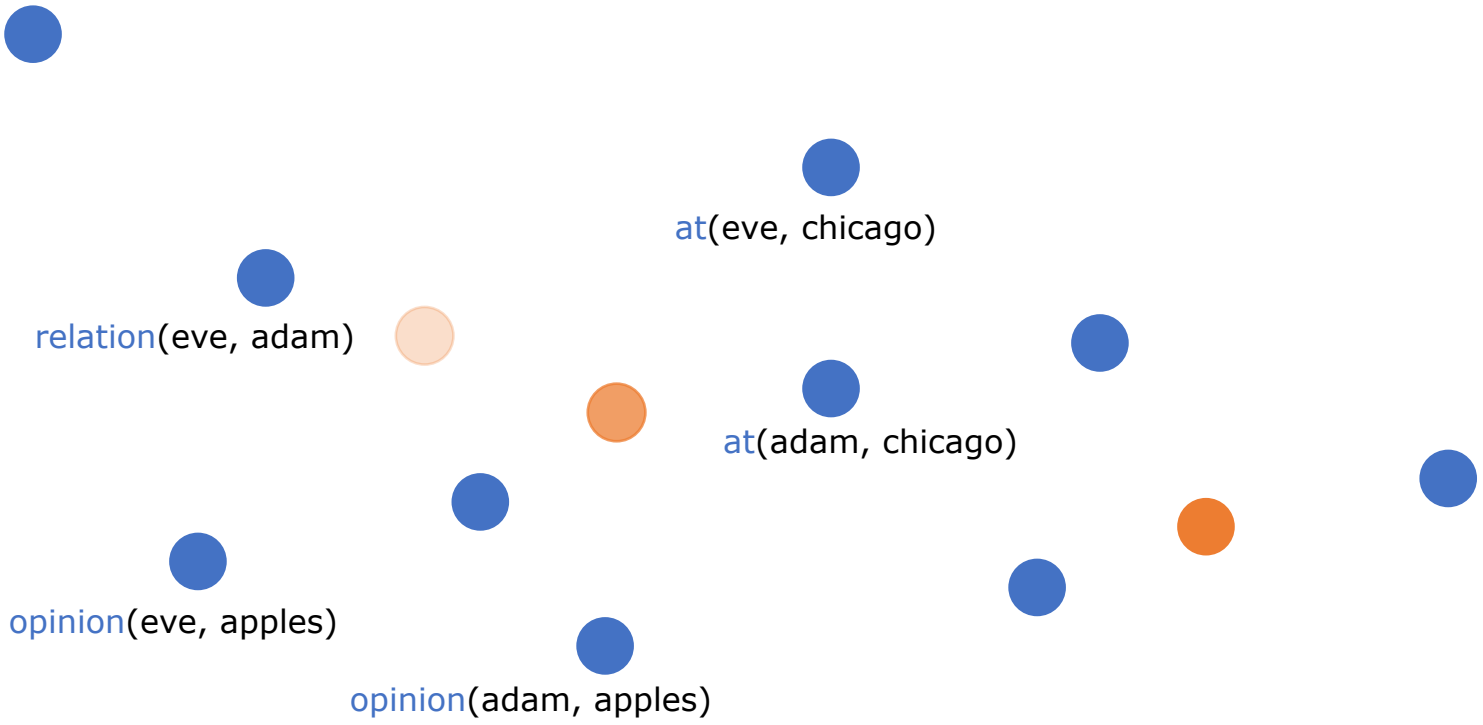

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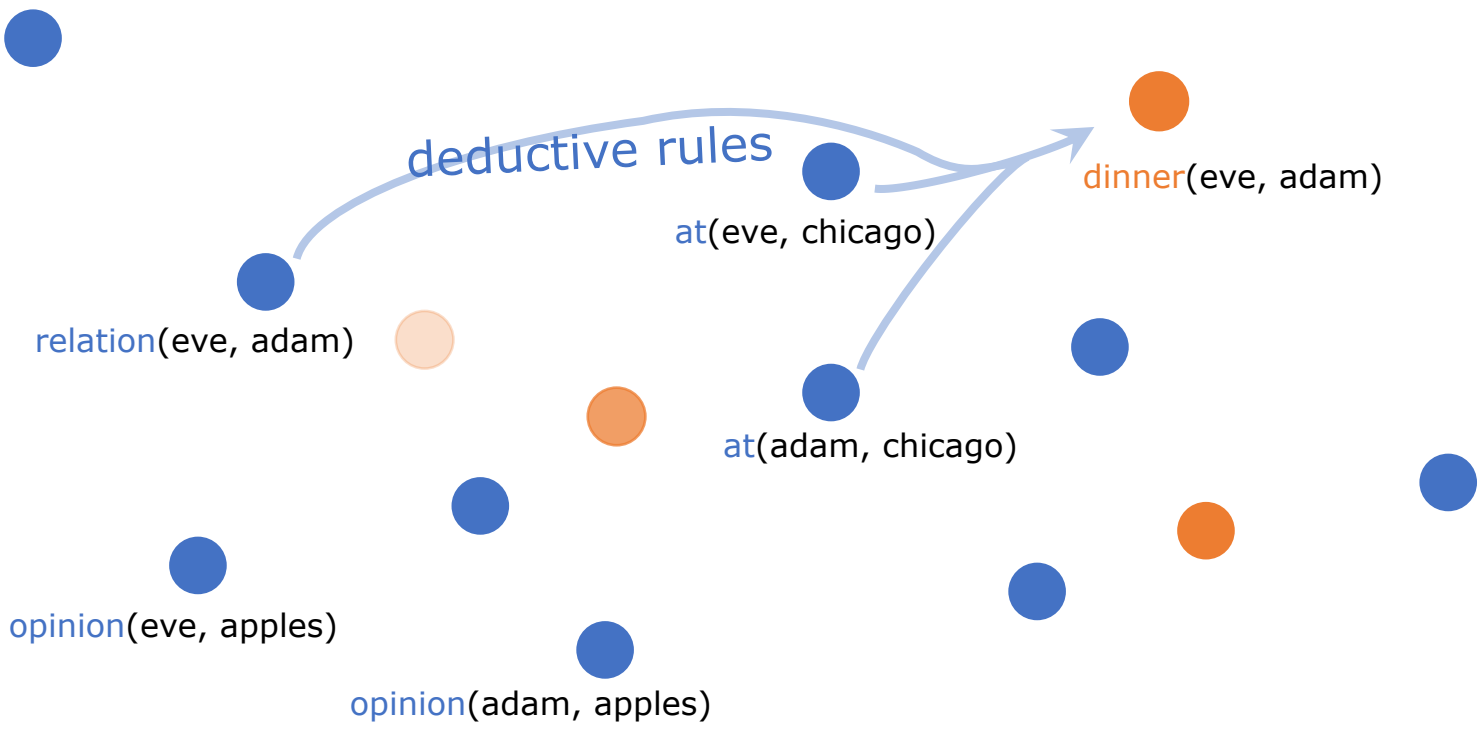

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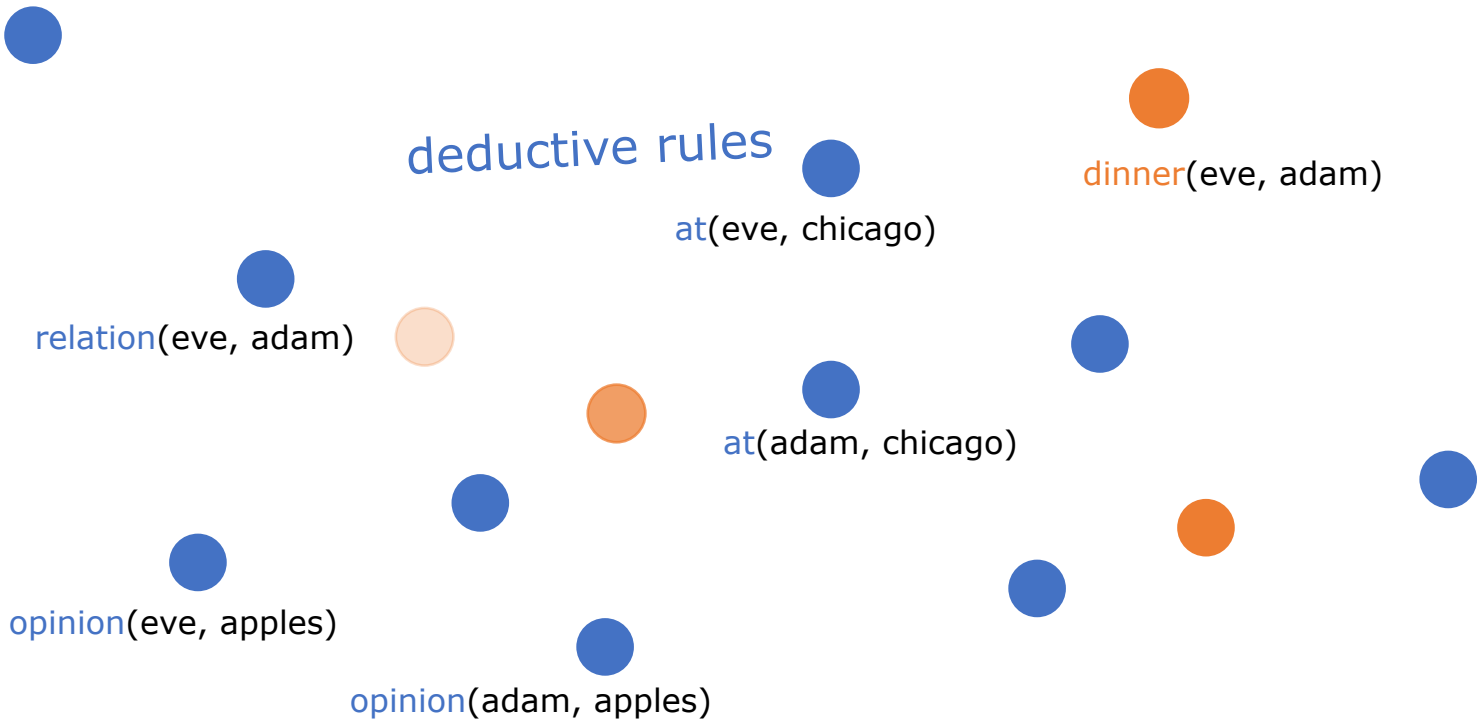

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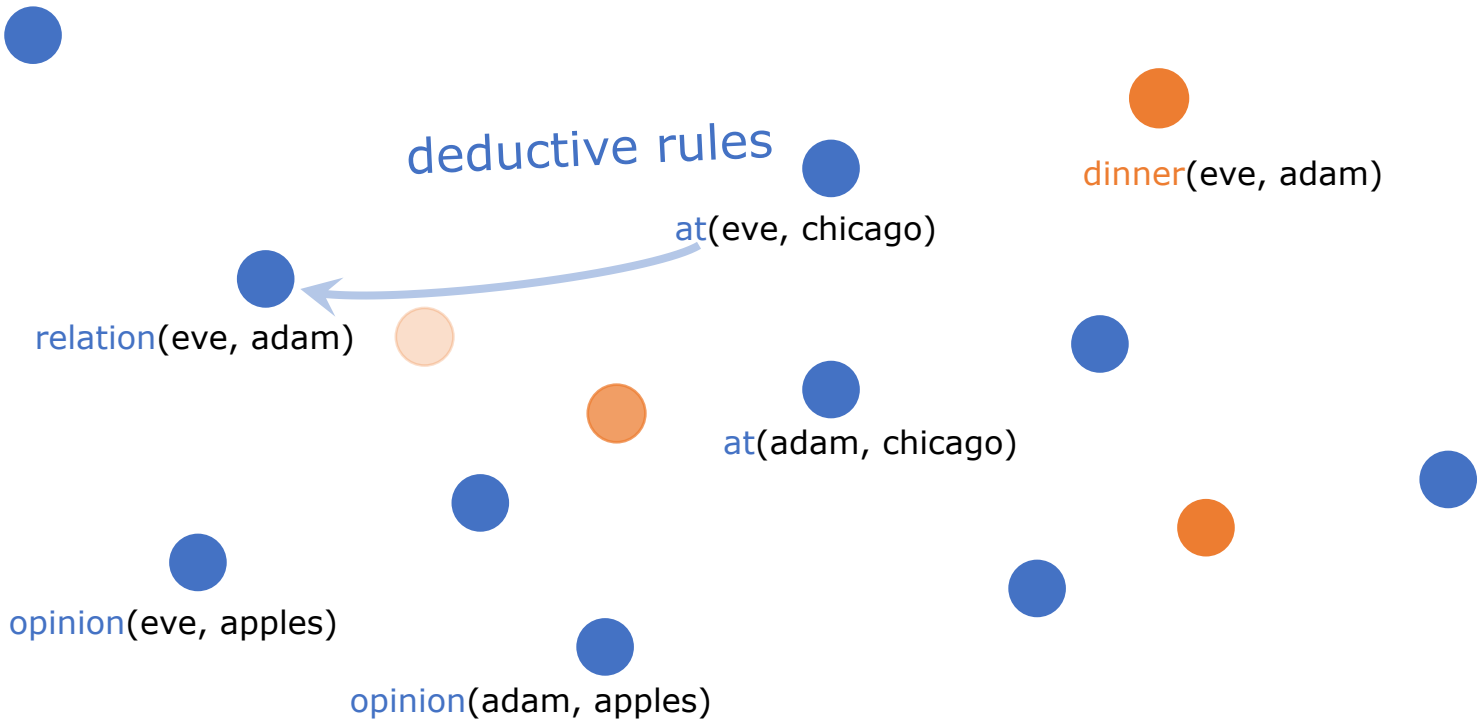

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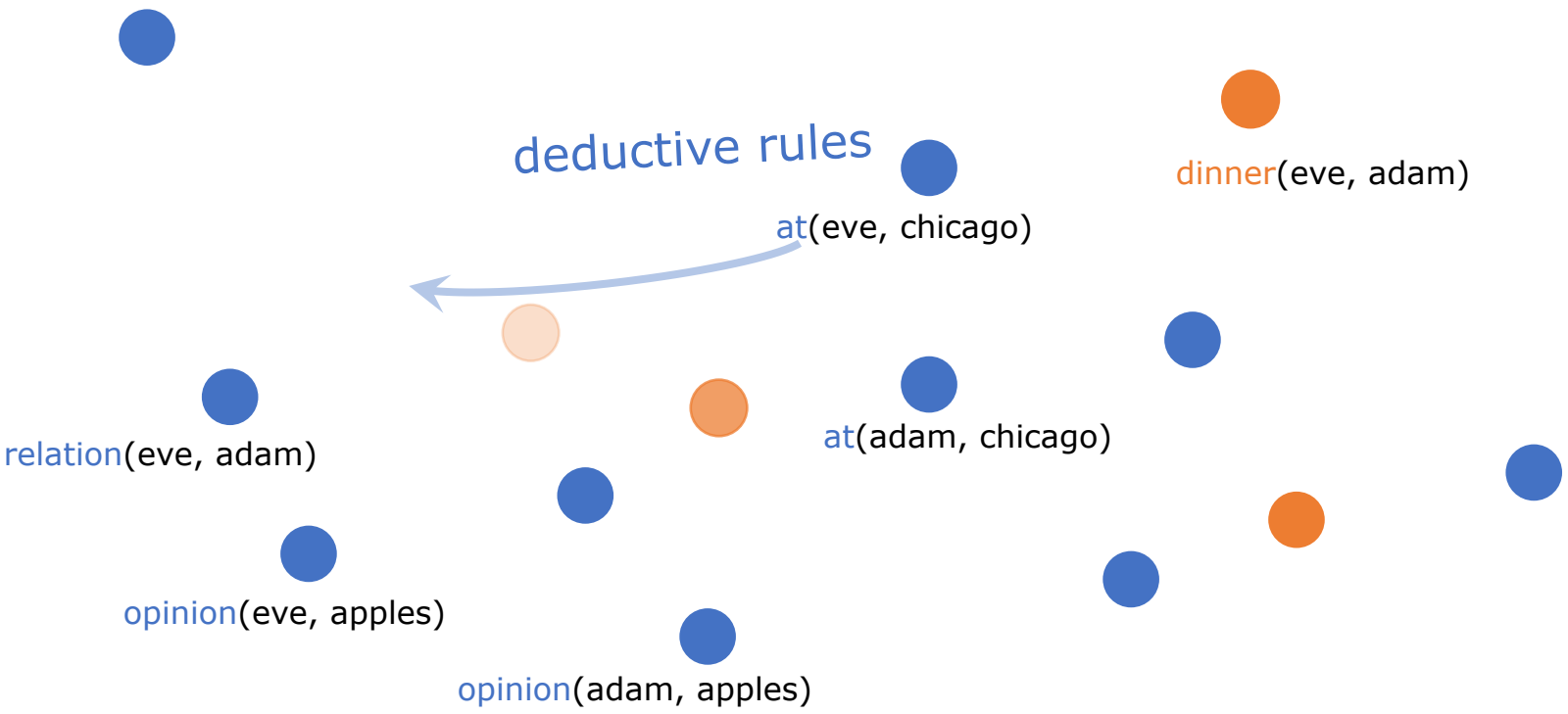

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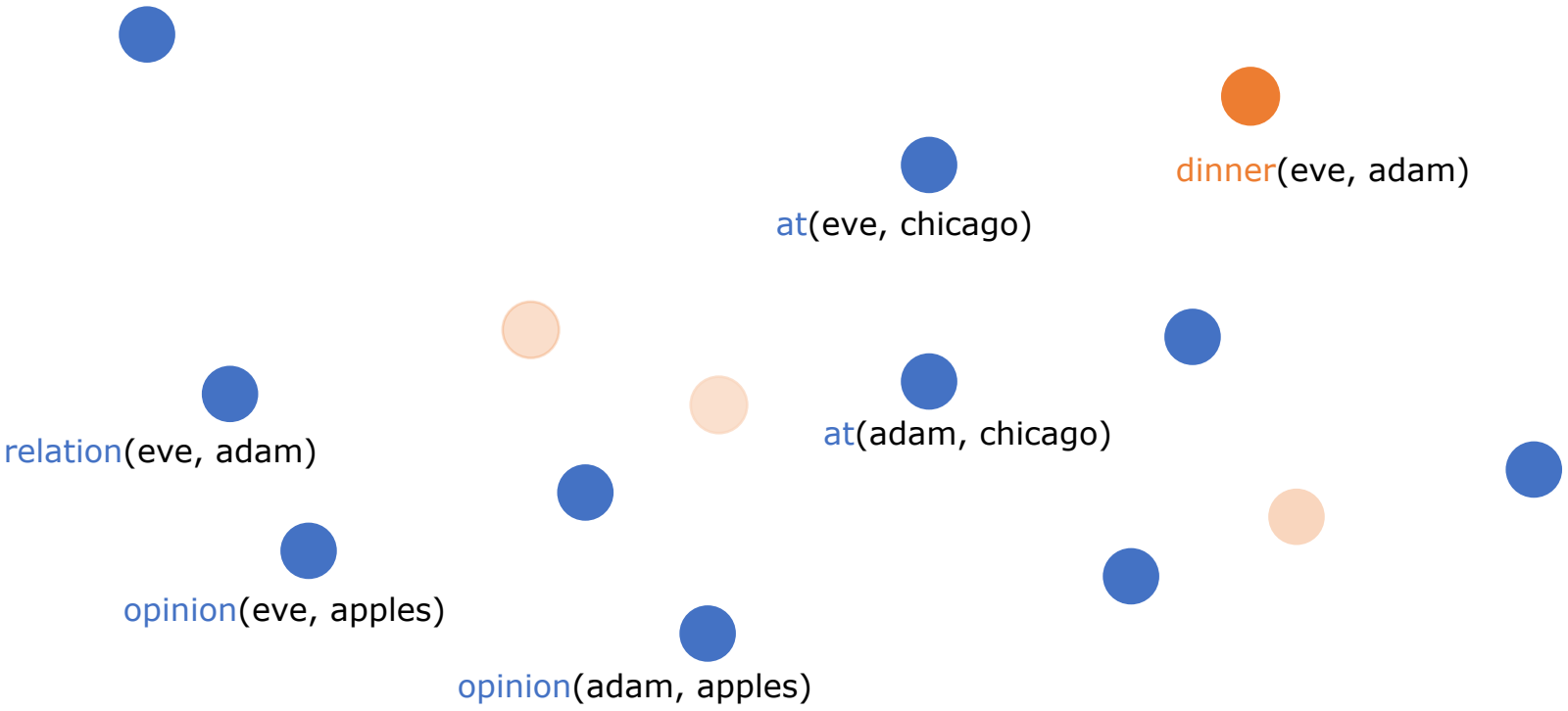
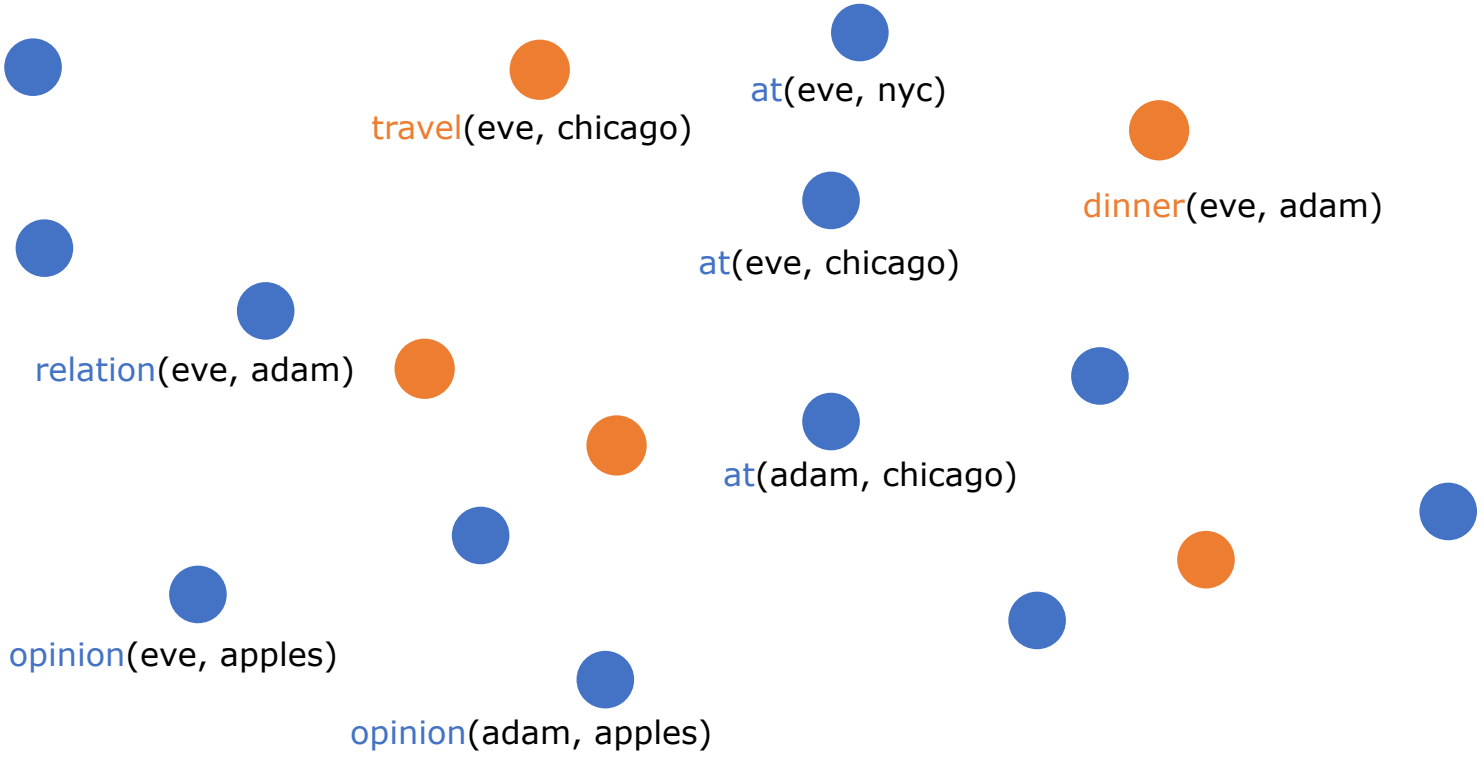


Deductive Rules, Triggering Rules



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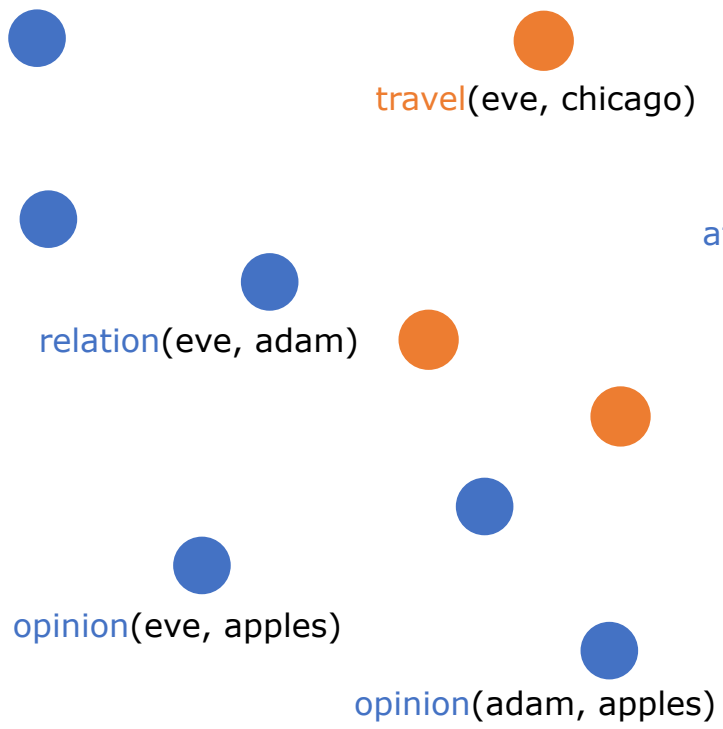


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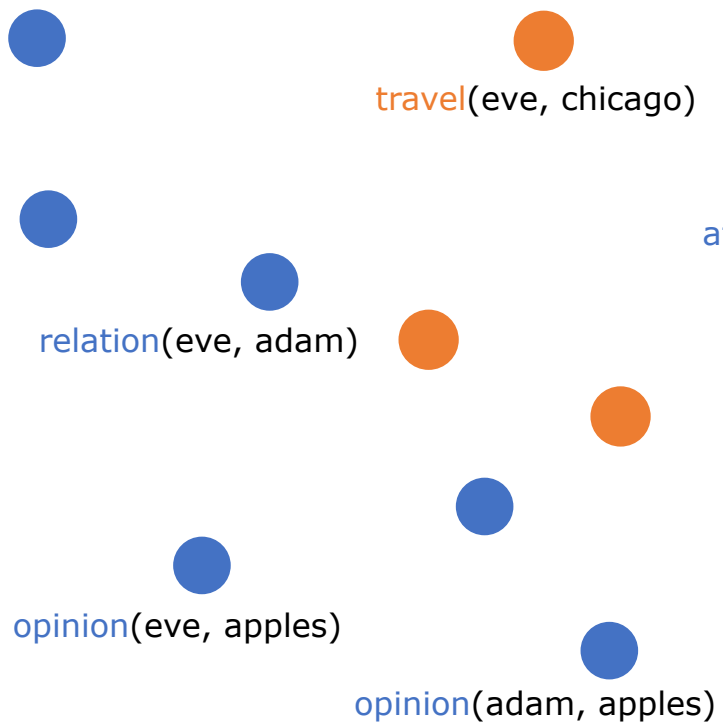
Deductive Rules, Triggering Rules

logic!

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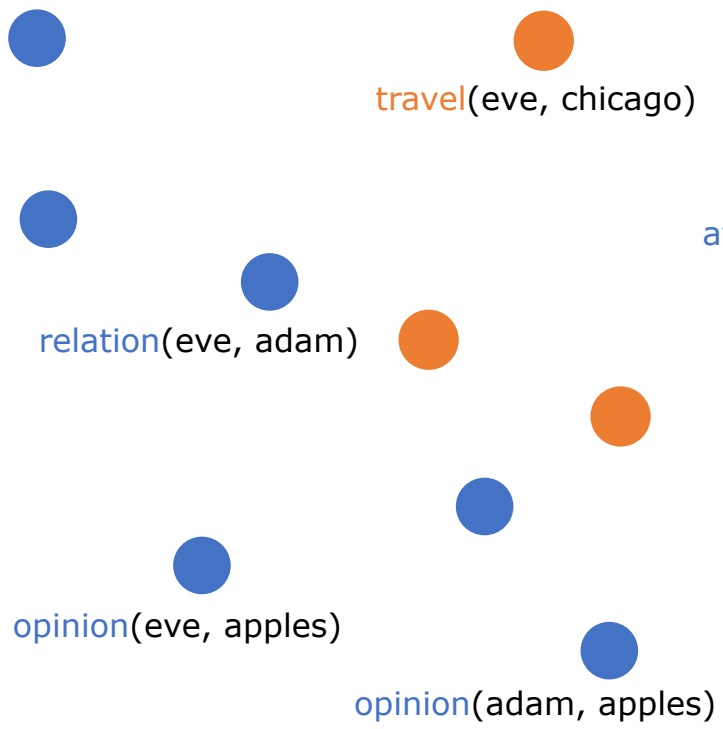

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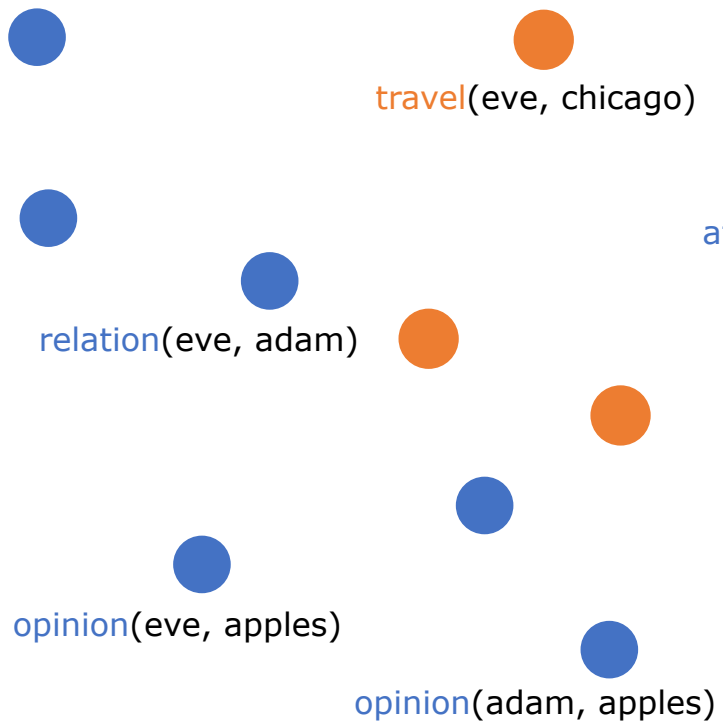

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which facts are in the database
define a trainable neural architecture
that computes embeddings of the facts

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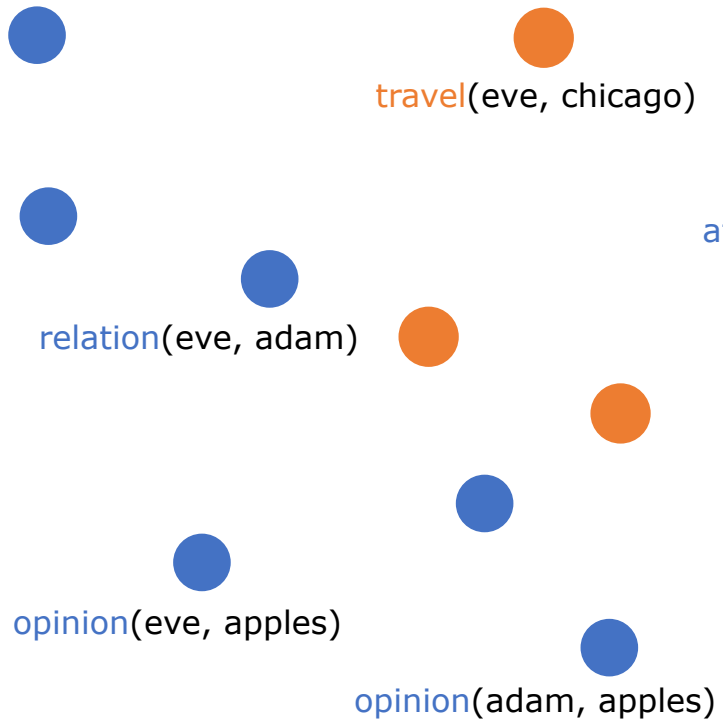


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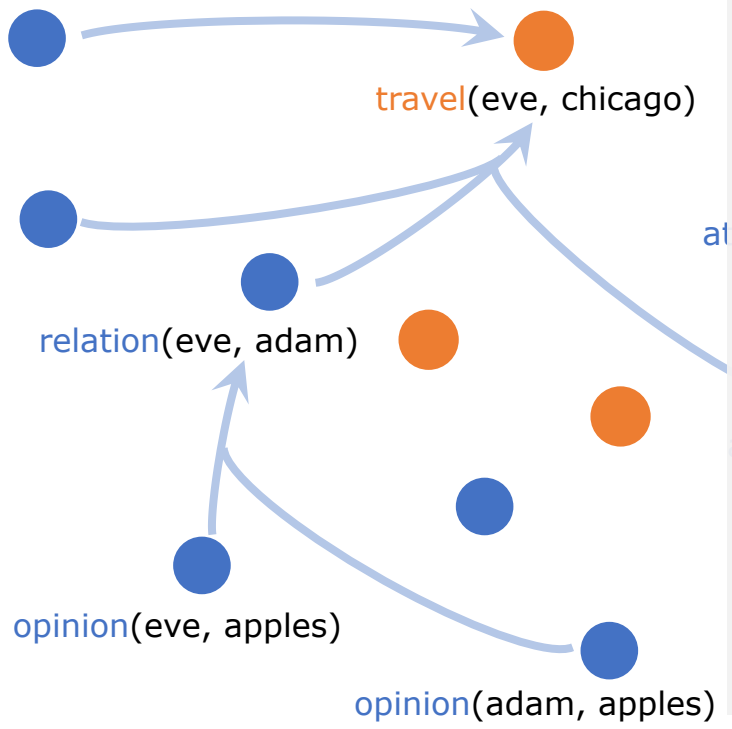


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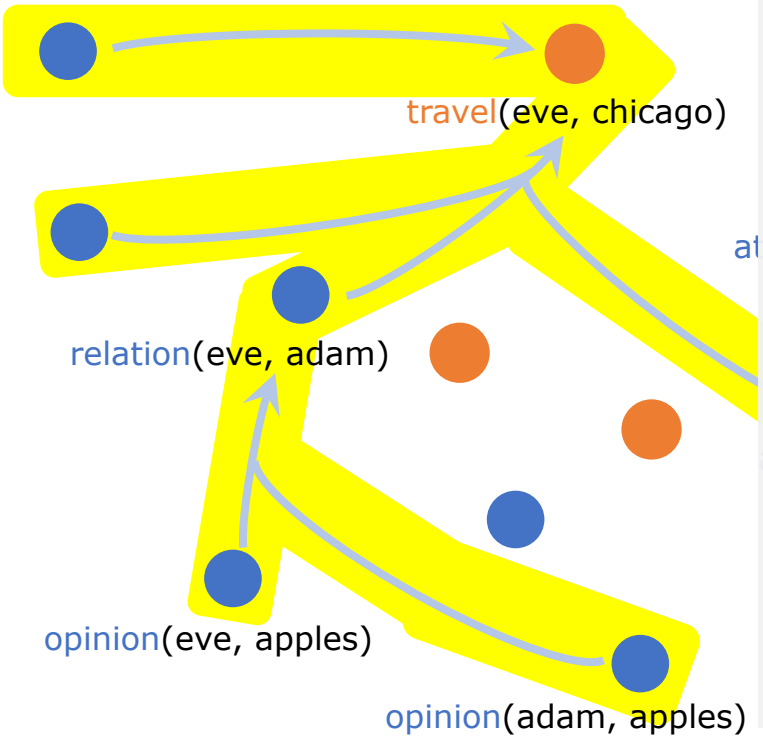


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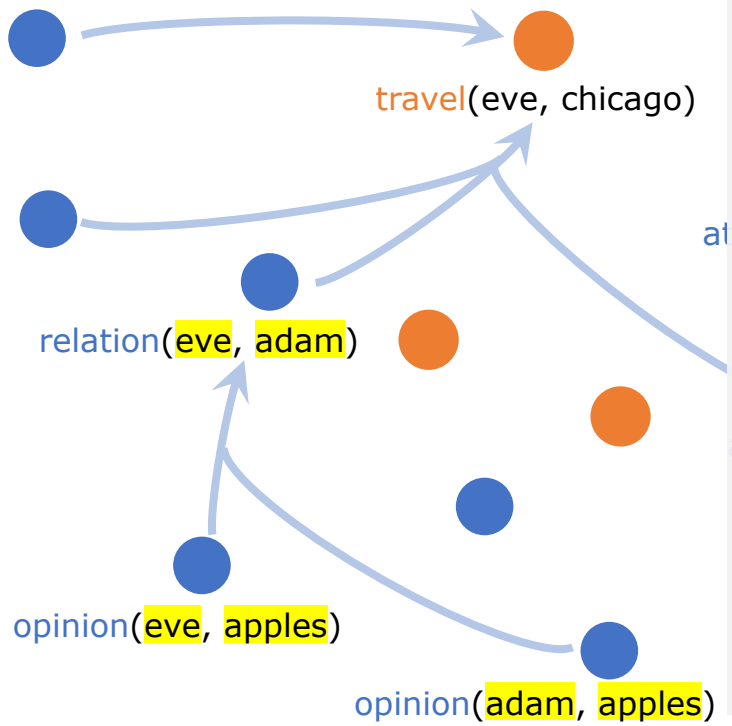


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Datalog ➔ Neural Datalog Through Time

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deductive rule

new fact :- old fact $_1$, old fact $_2$, …

Datalog ➔ Neural Datalog Through Time

deductive rule

add to database

new fact :- old fact $_1$, old fact $_2$, …

Datalog ➔ Neural Datalog Through Time

deductive rule

add to database if

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Datalog ➔ Neural Datalog Through Time

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likes(X, U),

Datalog ➔ Neural Datalog Through Time

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likes(X, U), likes(Y, U)

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compatible(X, Y) :- likes(X, U), likes(Y, U)

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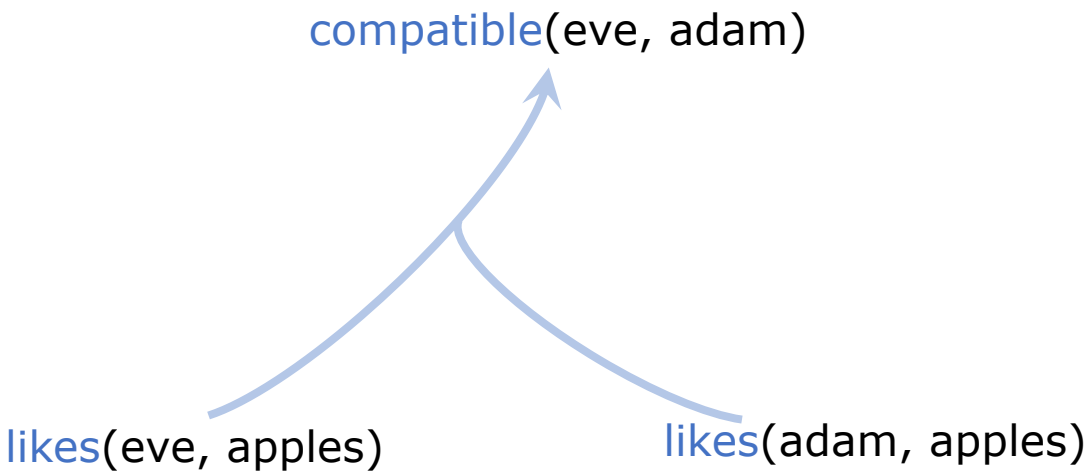

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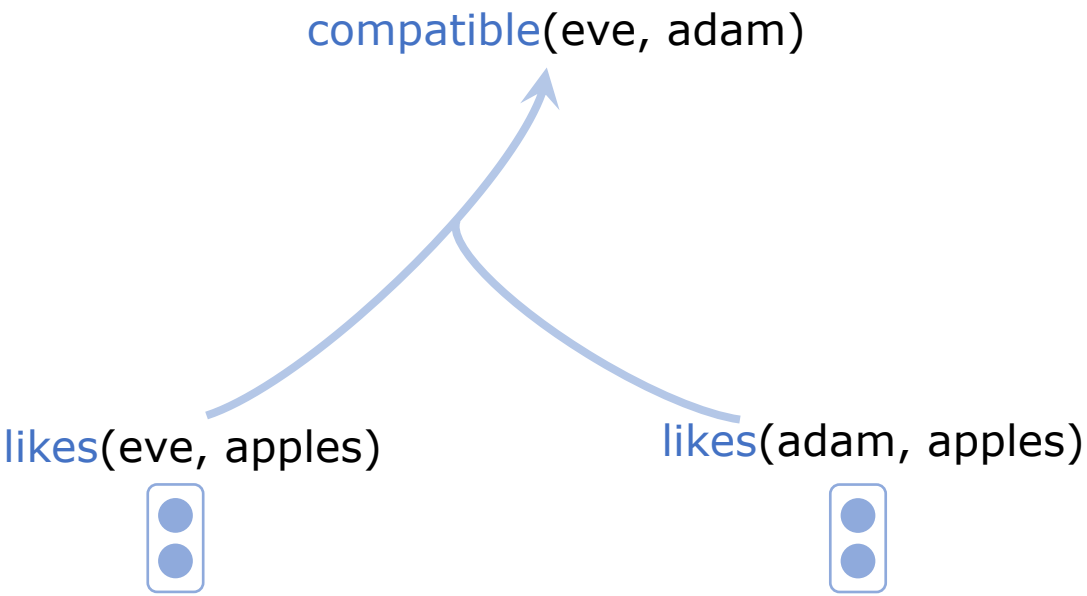

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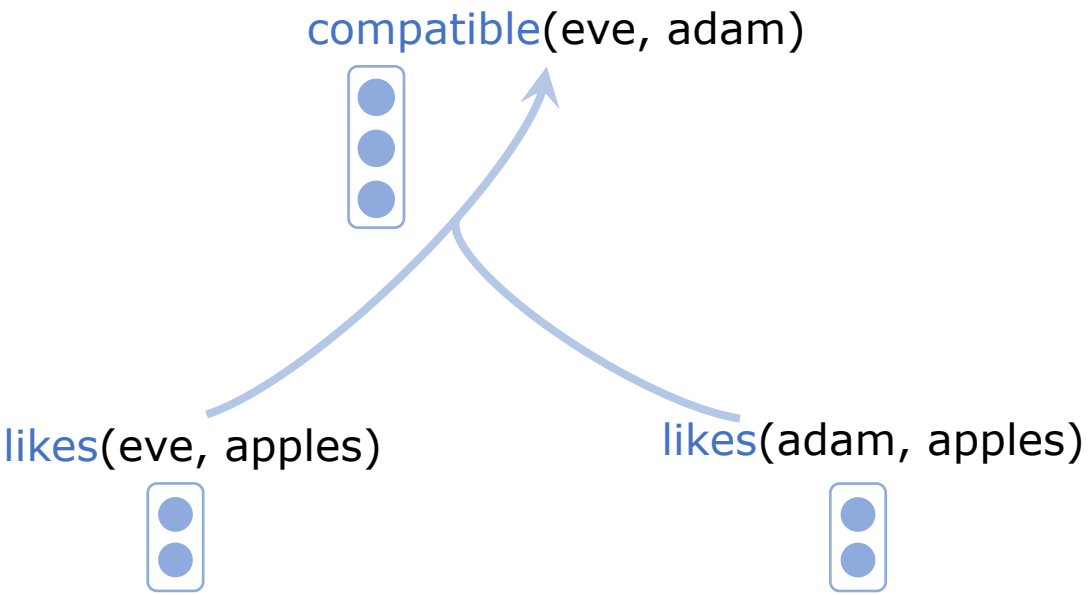

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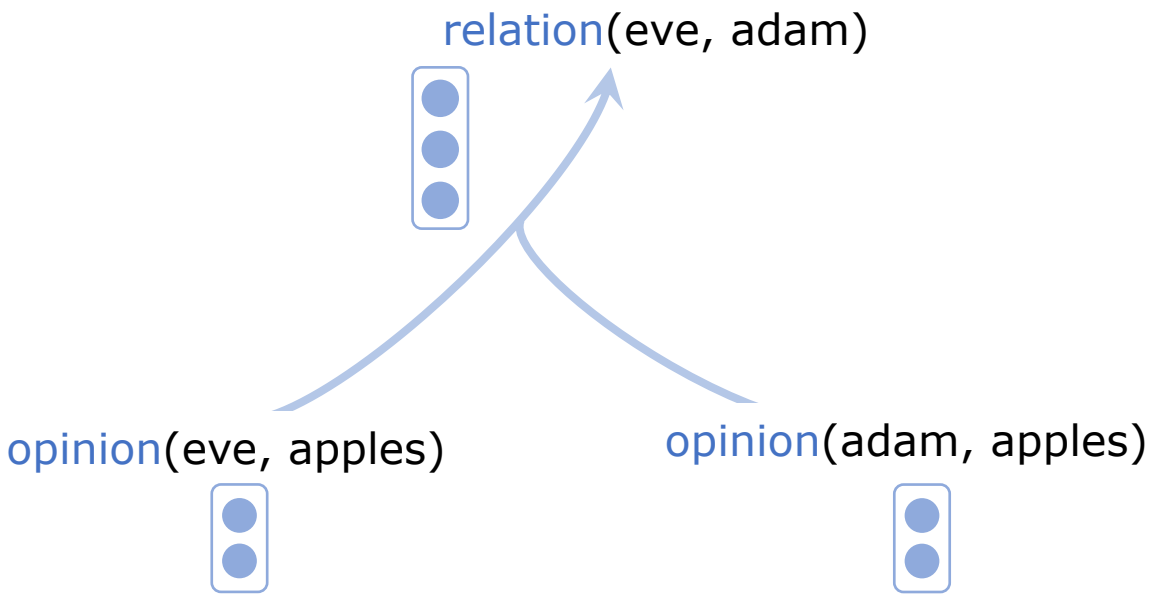

Datalog ➔ Neural Datalog Through Time

deductive rule

add to database if these are in database

new fact :- old fact $_1$, old fact $_2$, …

triggering rule

new fact ← event, old fact $_1$, old fact $_2$, …

Datalog ➔ Neural Datalog Through Time

deductive rule

add to database if these are in database

new fact :- old fact $_1$, old fact $_2$, …

triggering rule

when

new fact ← event, old fact $_1$, old fact $_2$, …

Datalog → Neural Datalog Through Time

deductive rule

add to database if these are in database

new fact :- old fact $_1$, old fact $_2$, …

triggering rule

when this happens

new fact ← event, old fact $_1$, old fact $_2$, …

Datalog ➔ Neural Datalog Through Time

deductive rule

add to database if these are in database

new fact :- old fact $_1$, old fact $_2$, …

triggering rule

when this happens while these are in database

new fact ← event, old fact $_1$, old fact $_2$, …

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deductive rule

add to database if these are in database

new fact :- old fact $_1$, old fact $_2$, …

triggering rule

add to database when this happens while these are in database

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! old fact ← event, old fact $_1$, old fact $_2$, …

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add to database if these are in database

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triggering rule

add to database when this happens while these are in database

new fact ← event, old fact $_1$, old fact $_2$, …

when this happens

! old fact ← event, old fact $_1$, old fact $_2$, …

Datalog ➔ Neural Datalog Through Time

deductive rule

add to database | if | these are in database

new fact :- old fact $_1$, old fact $_2$, …

triggering rule

add to database | when this happens | while these are in database

new fact ← event, old fact $_1$, old fact $_2$, …

when this happens | while these are in database

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Datalog ➔ Neural Datalog Through Time

deductive rule

add to database if these are in database

new fact :- old fact $_1$, old fact $_2$, …

triggering rule

add to database when this happens while these are in database

new fact ← event, old fact $_1$, old fact $_2$, …

delete when this happens while these are in database

! old fact ← event, old fact $_1$, old fact $_2$, …

Computing the Embeddings

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relation(eve, adam)

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relation(X, Y) :- opinion(X, U), opinion(Y, U)

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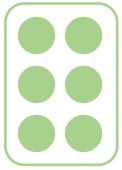

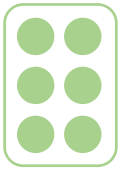

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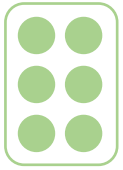
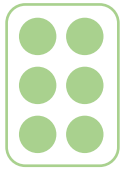
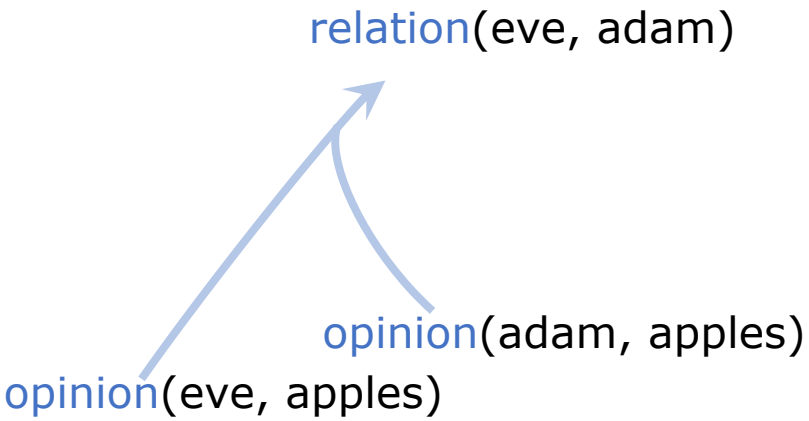
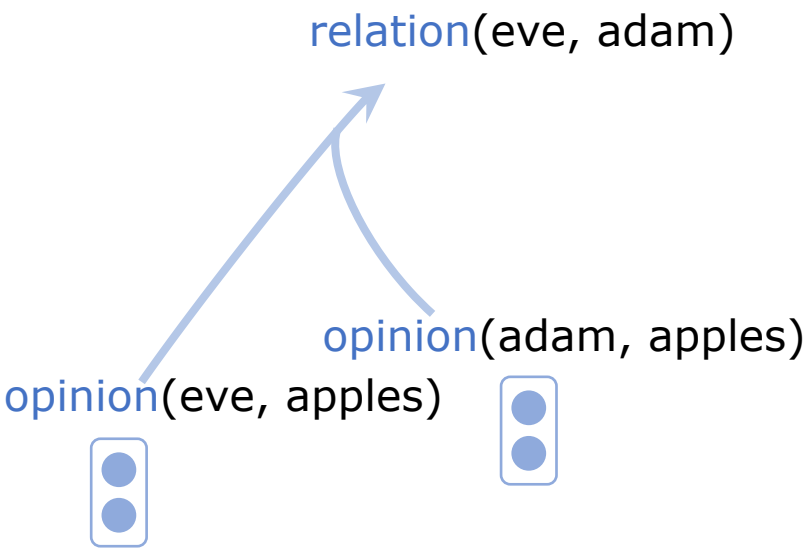






Computing the Embeddings

relation(X, Y) :- opinion(X, U), opinion(Y, U)



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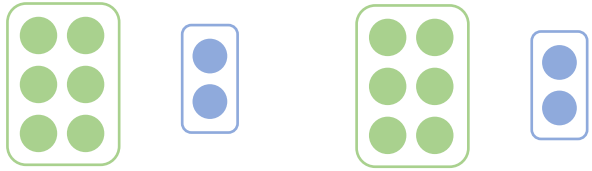

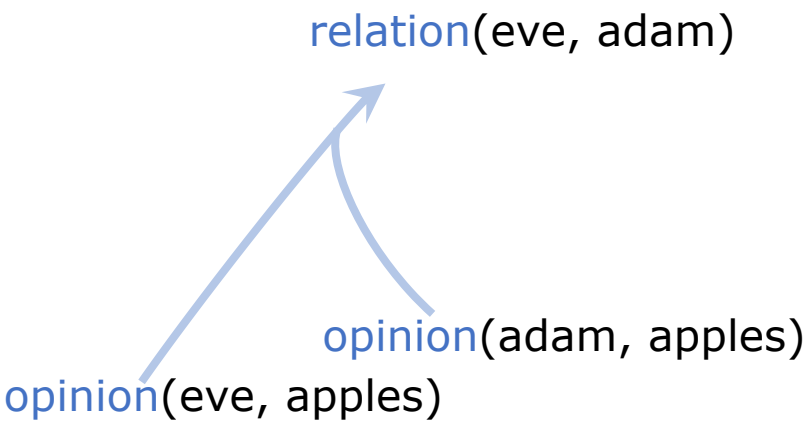

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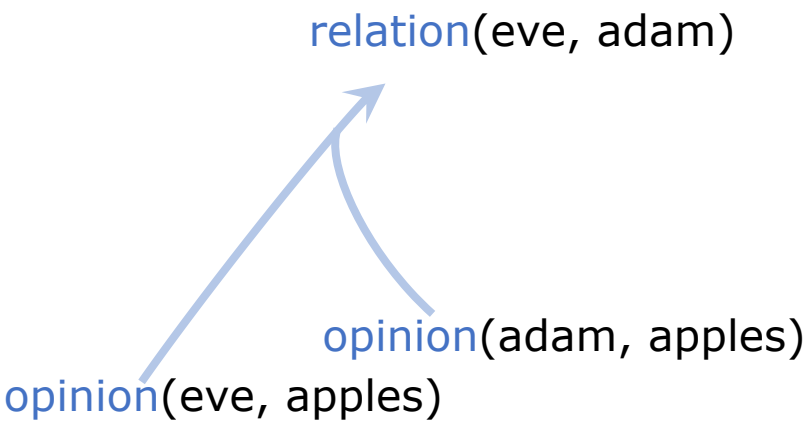

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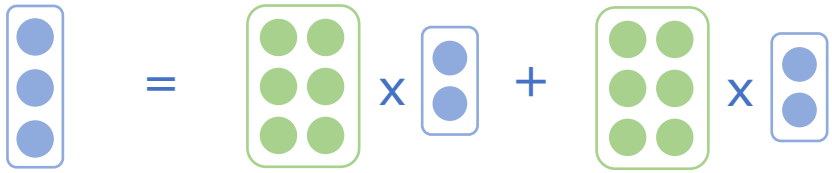

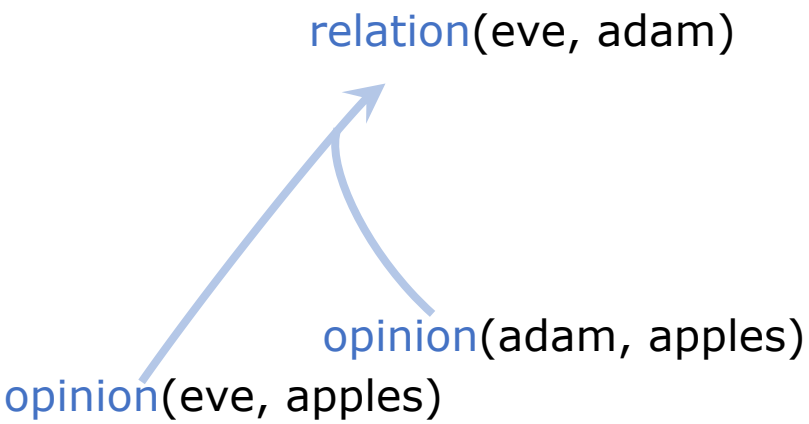

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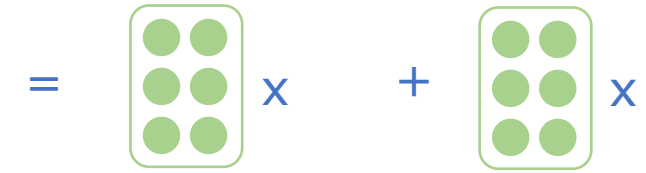

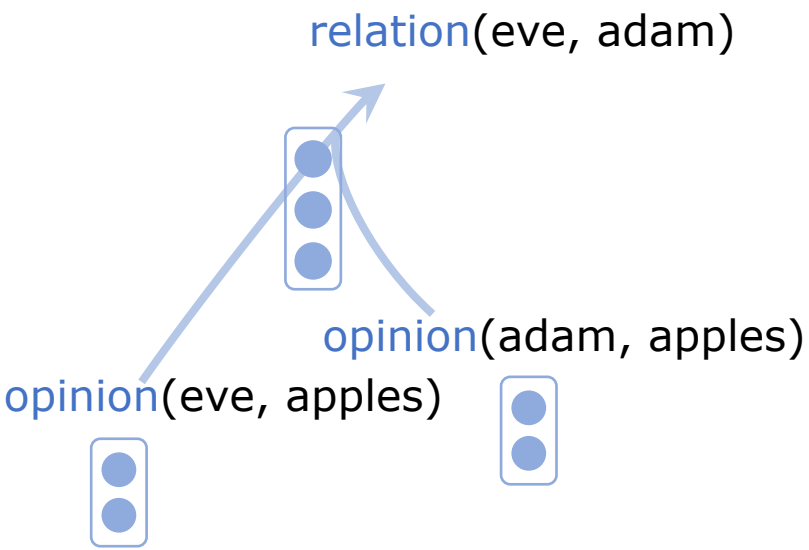

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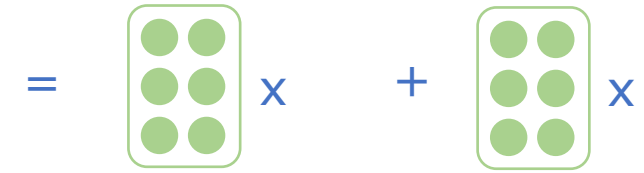

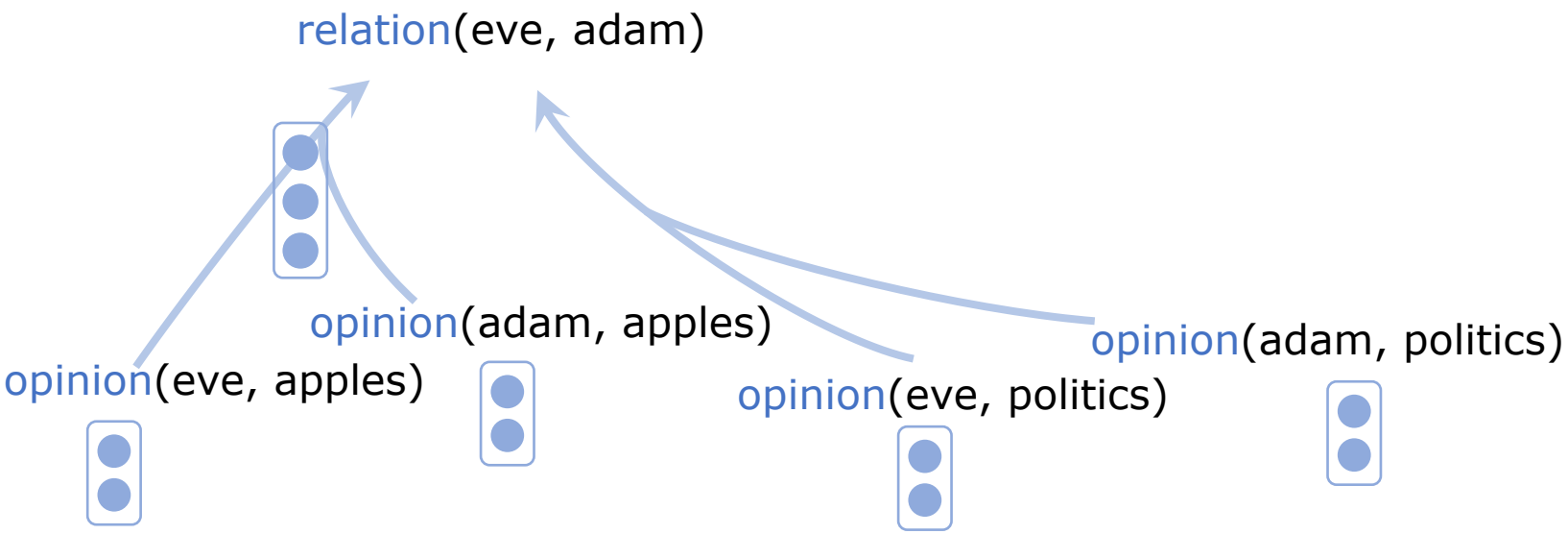

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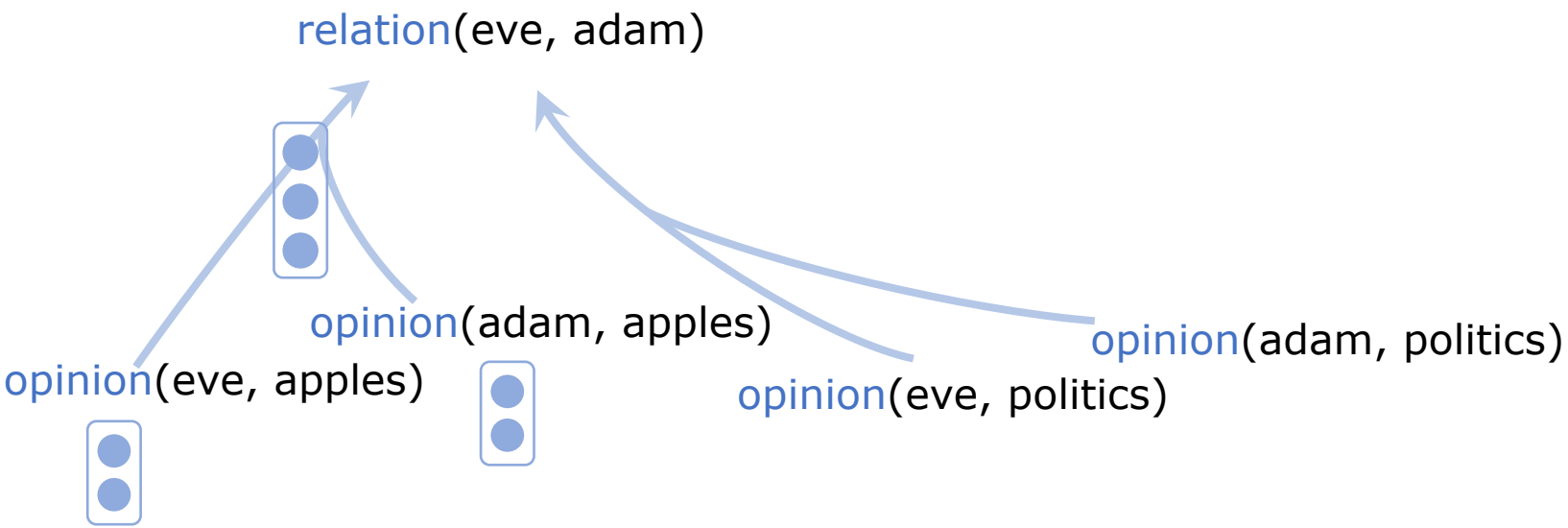

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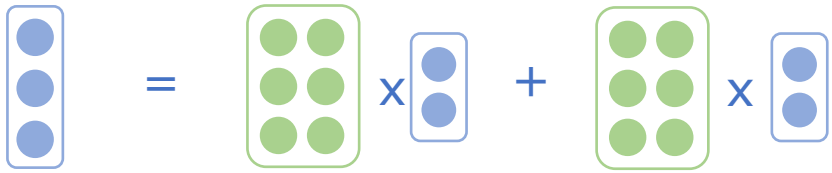

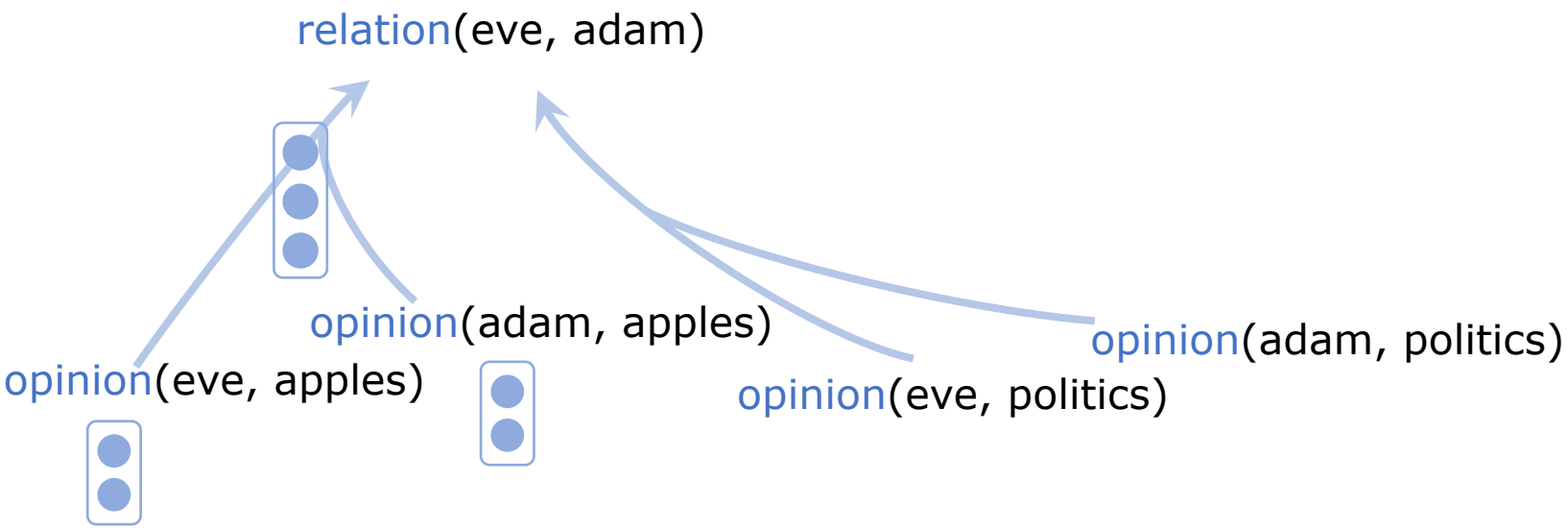

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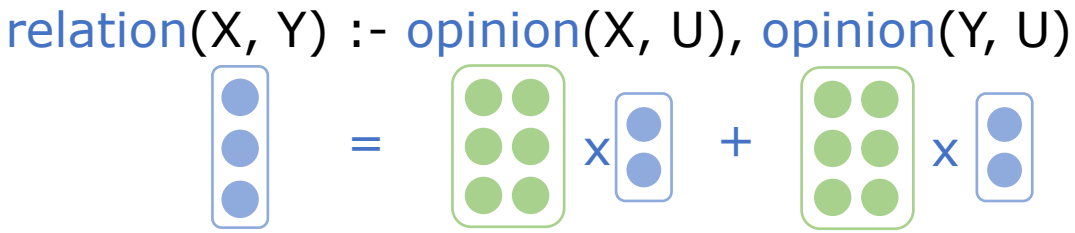
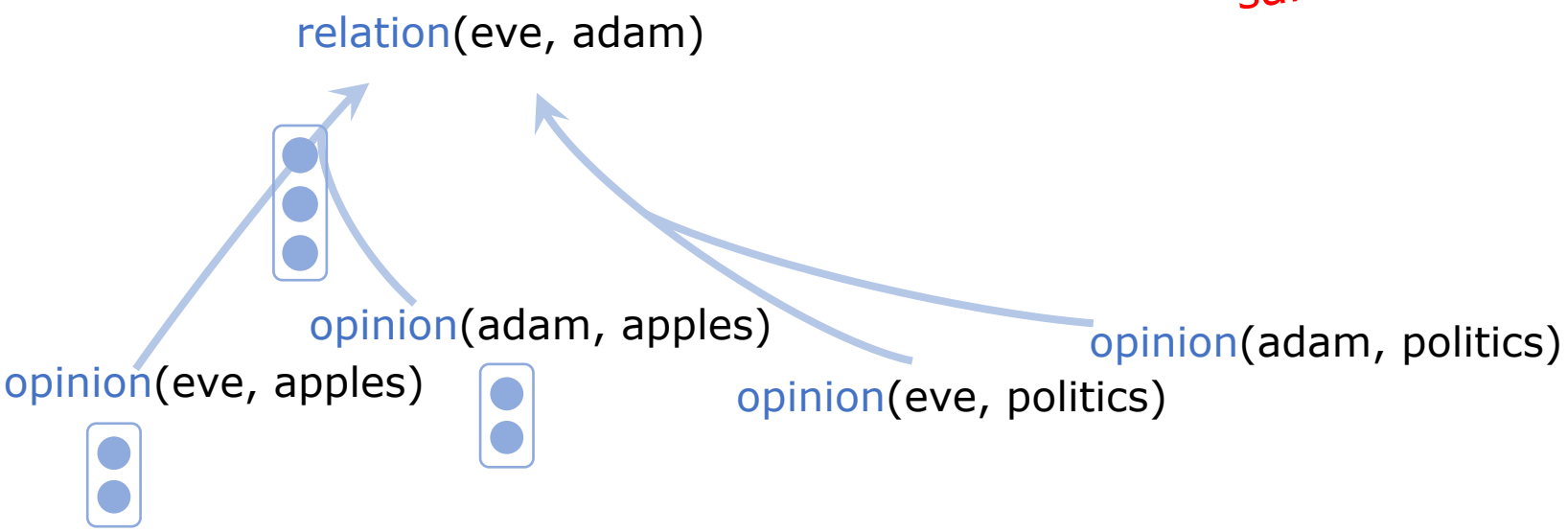


different inputs

same params



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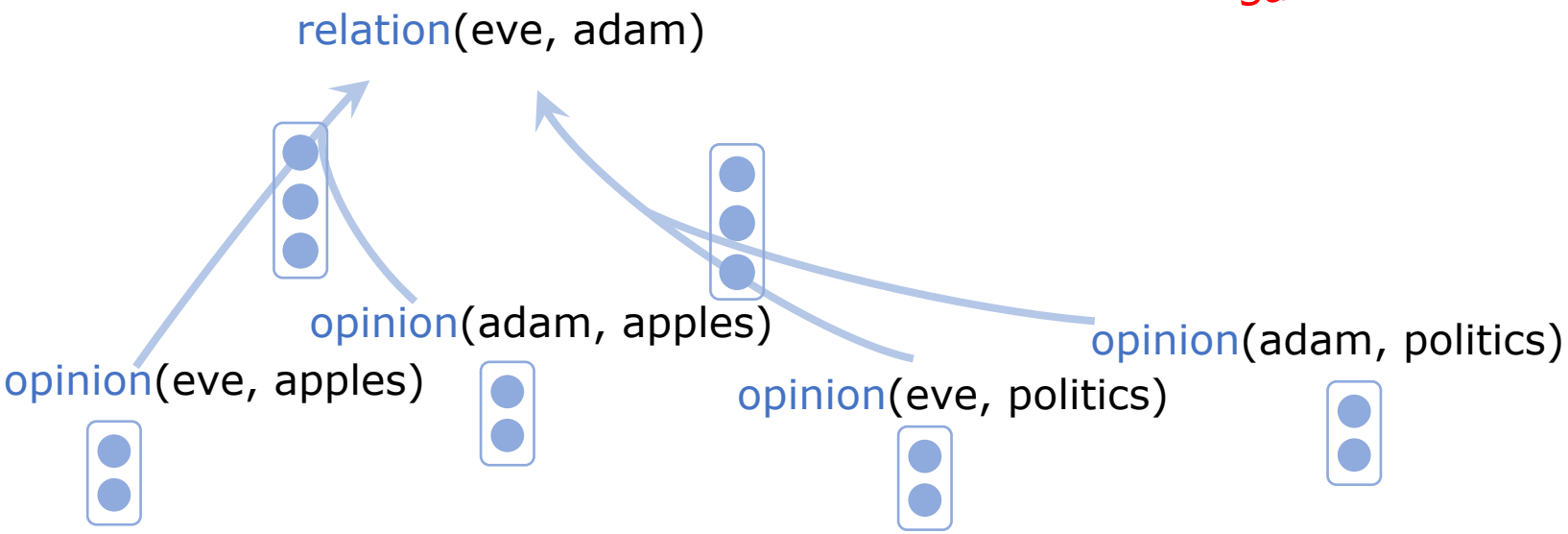

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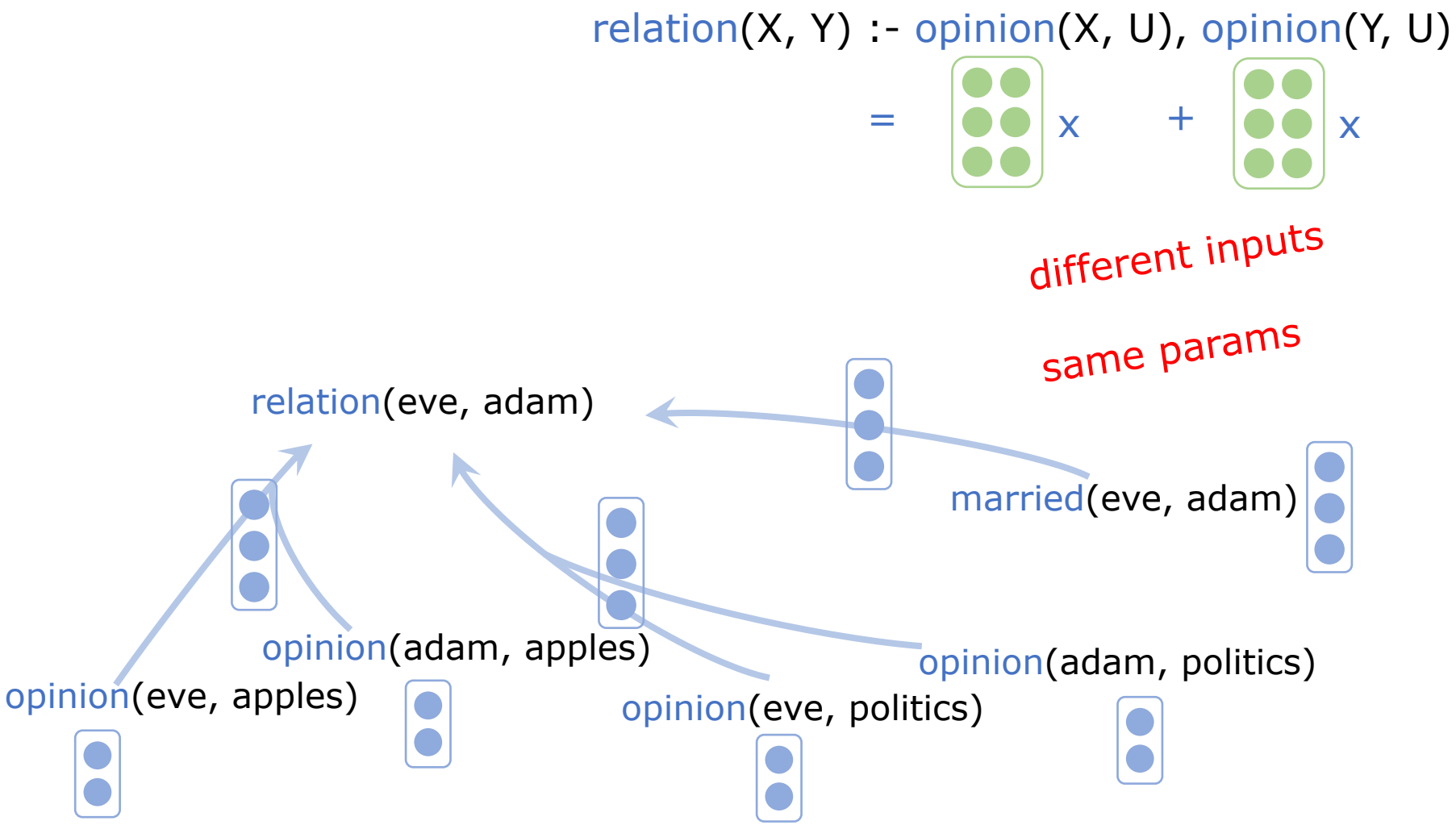

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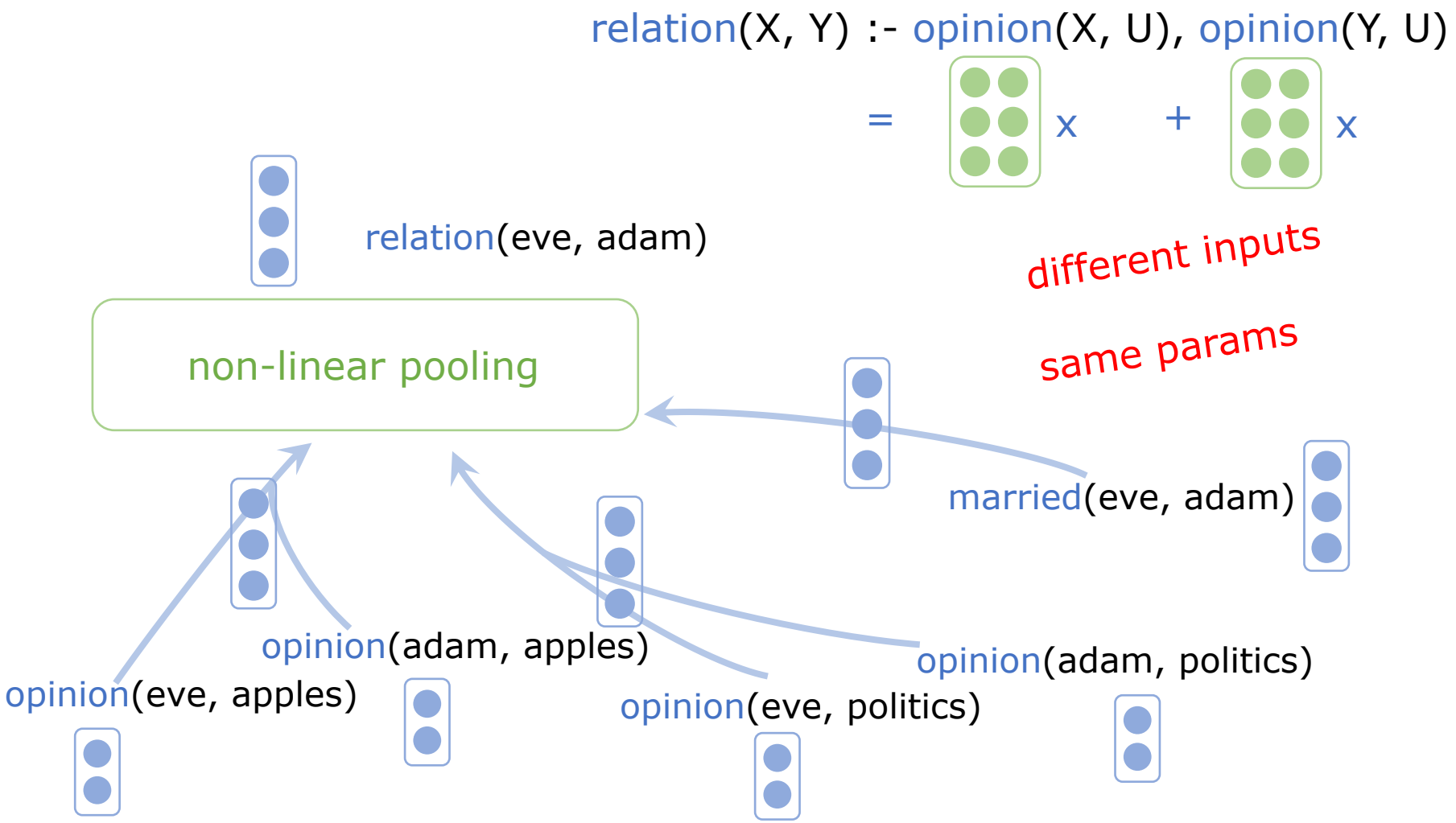

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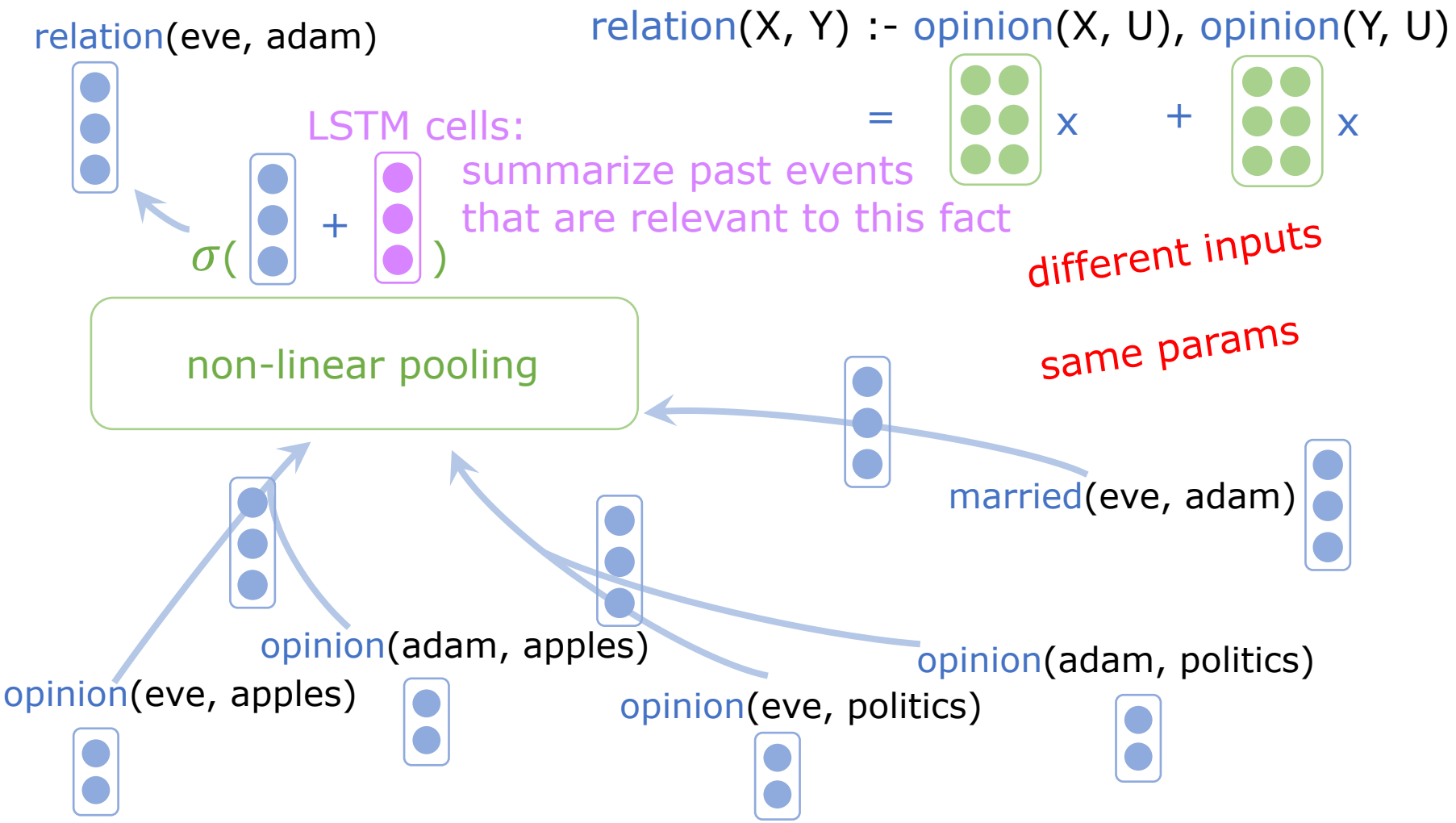

Computing Embeddings & Probabilities

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...

relation(eve, adam)

relation(eve, cain)

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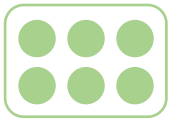

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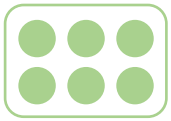

...

...

relation(eve, adam)

at(adam, chicago)

relation(eve, cain)

at(cain, chicago)

Computing Embeddings & Probabilities

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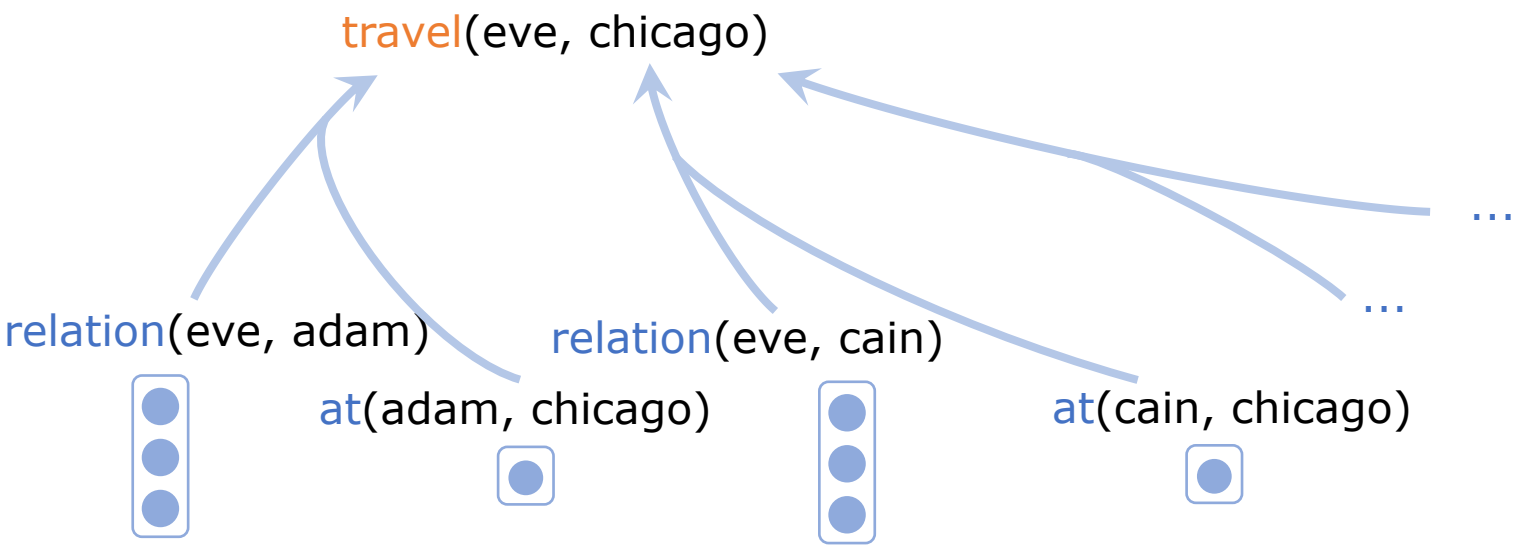

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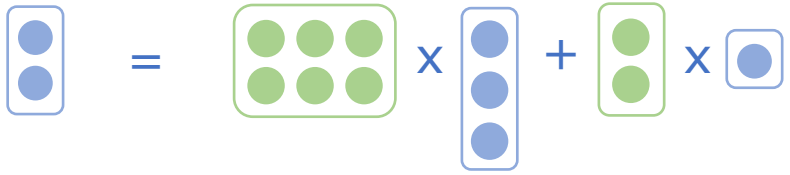
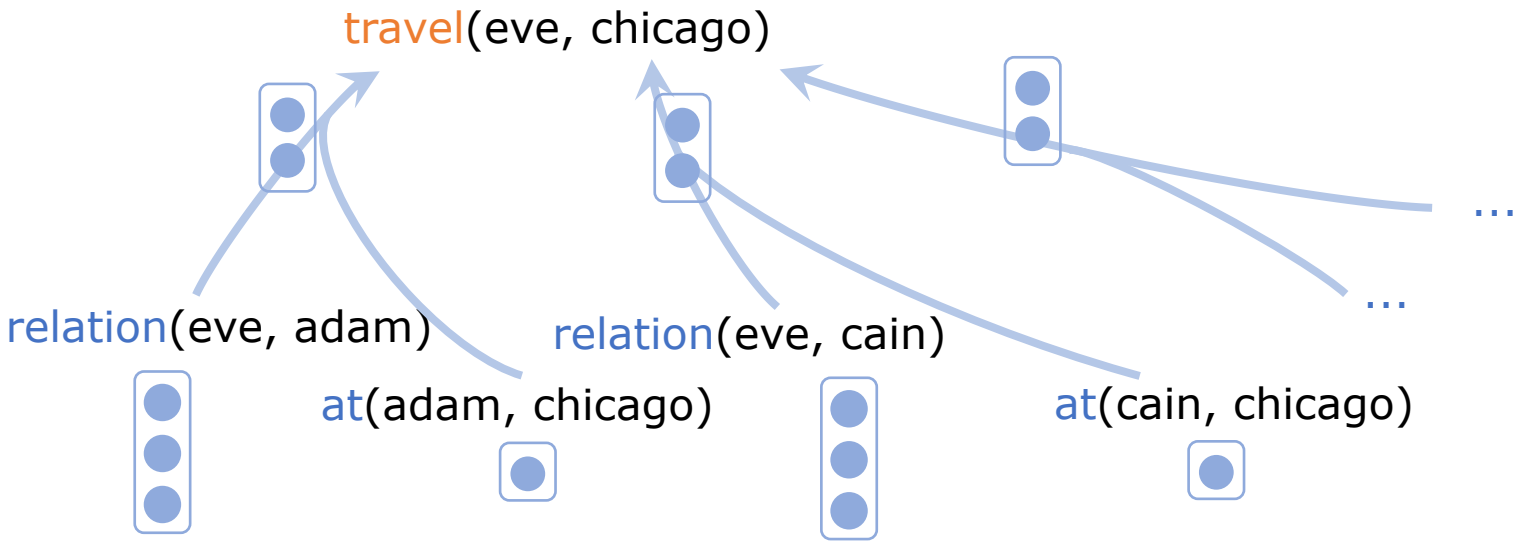
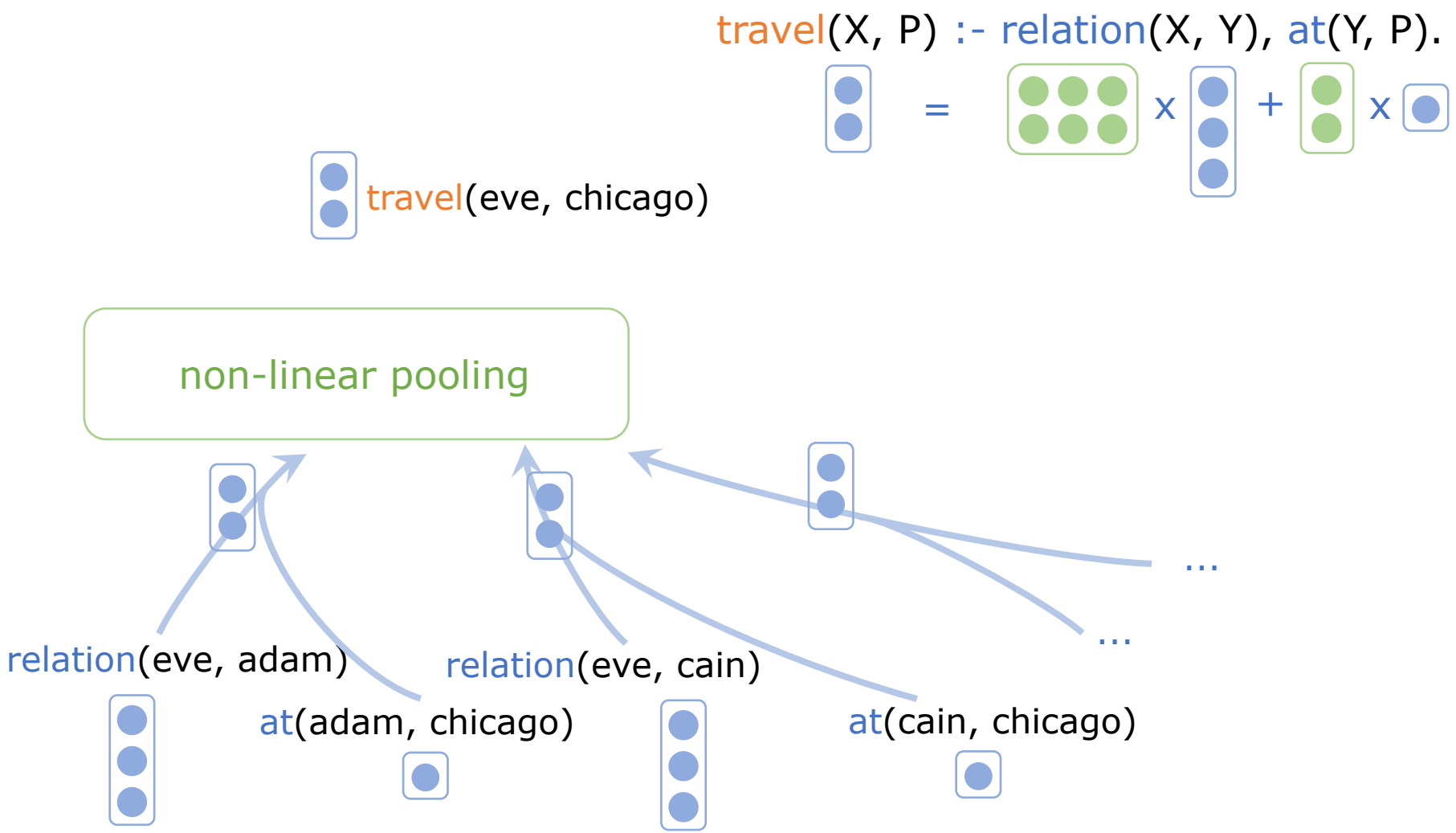




Computing Embeddings & Probabilities



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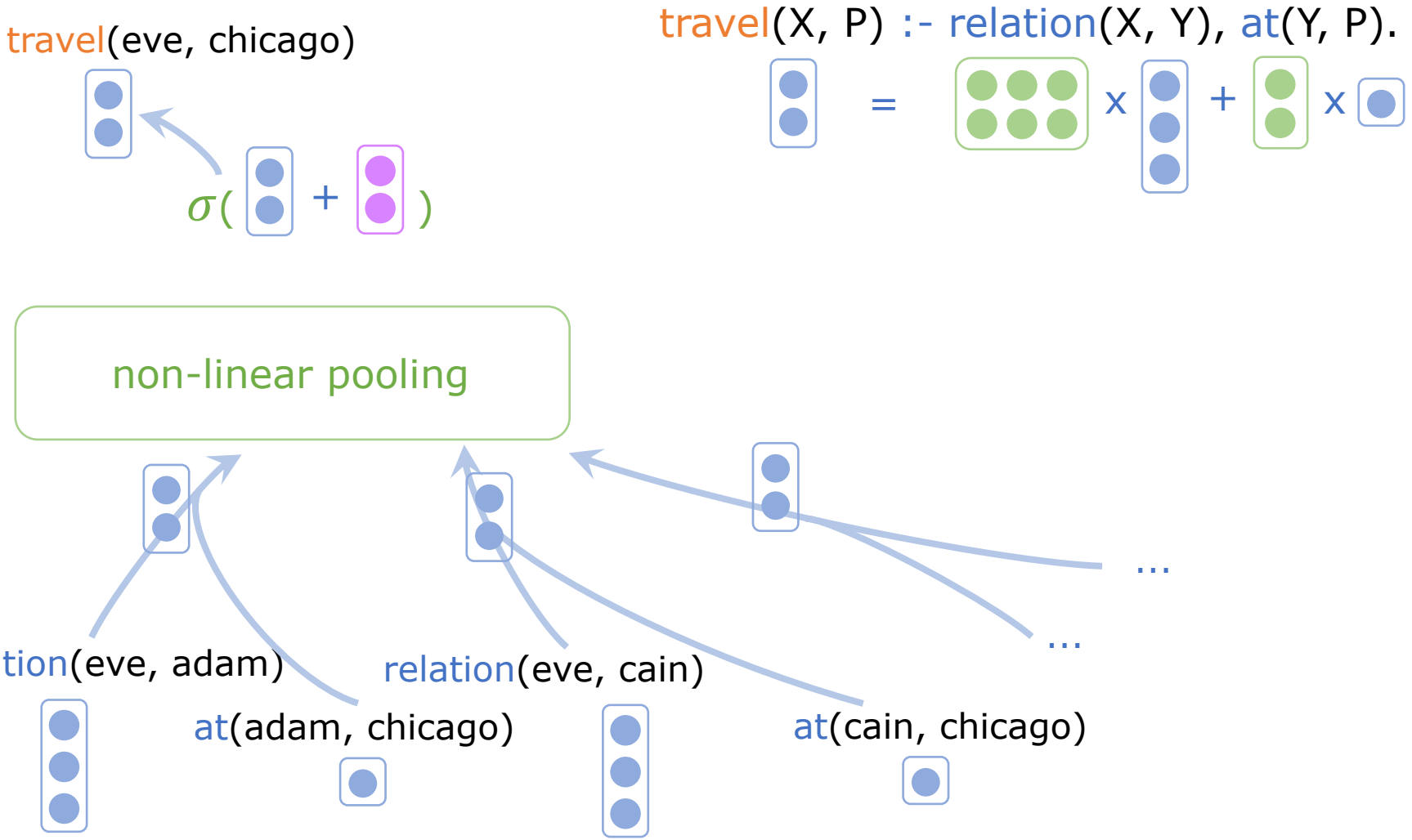

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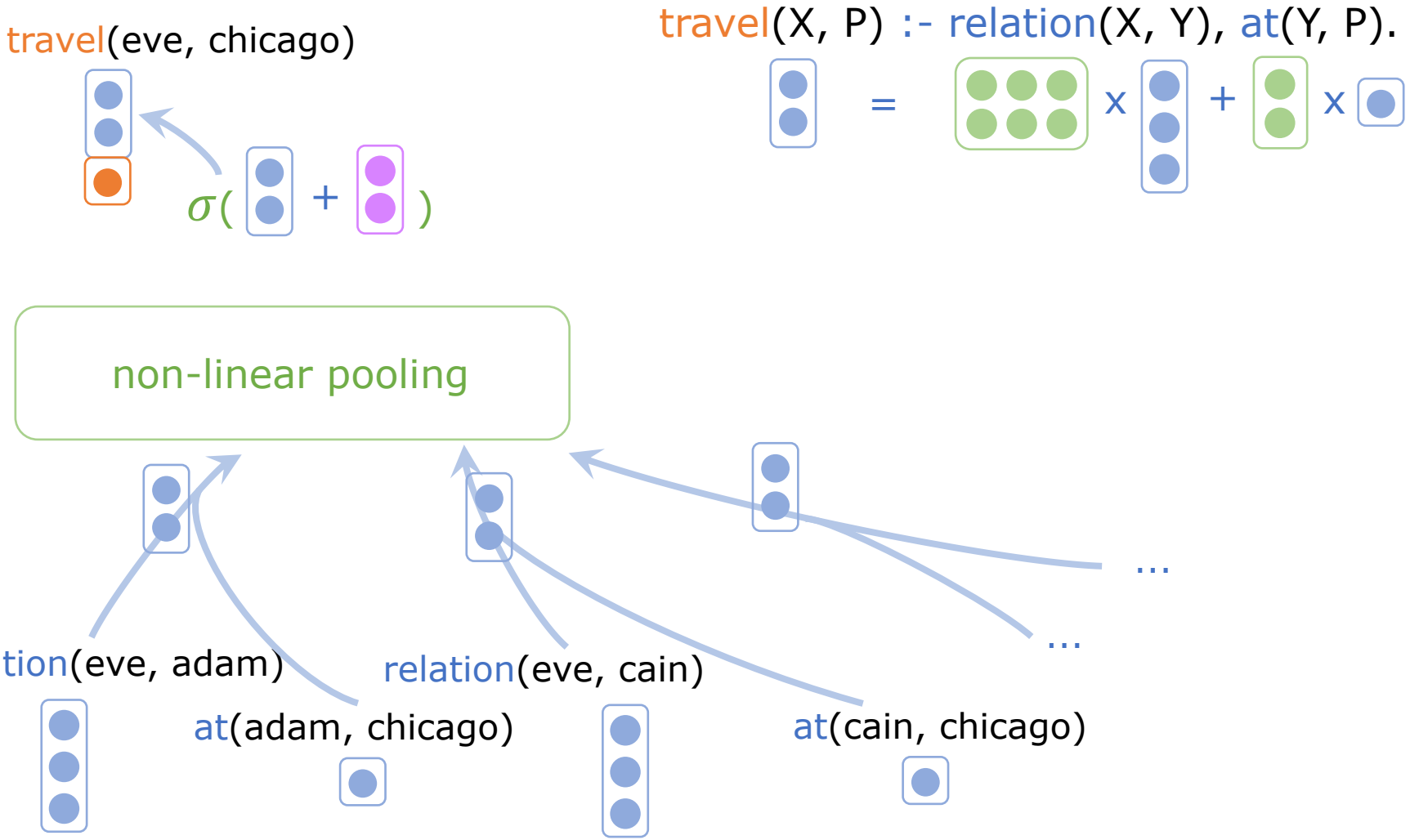

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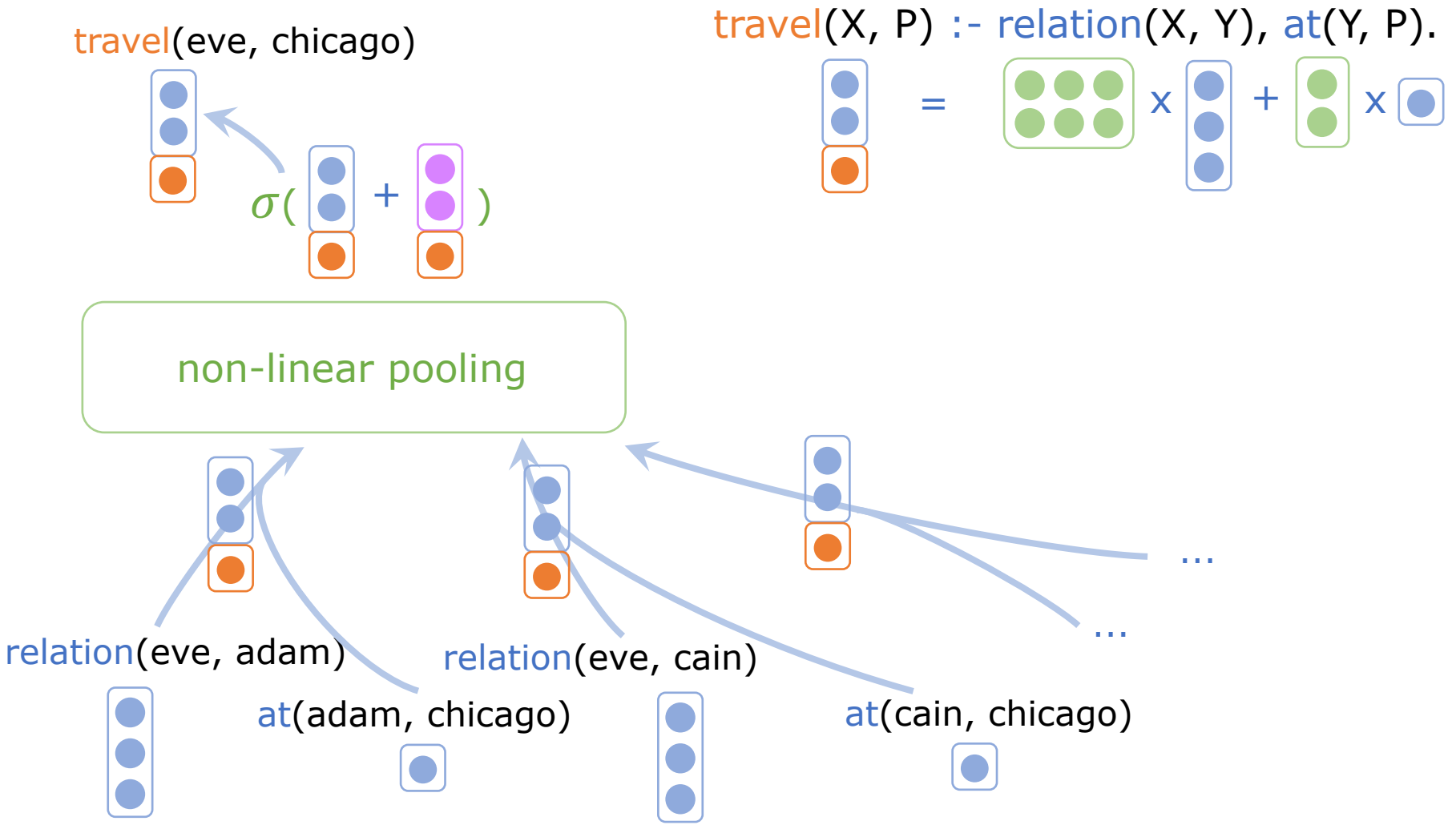

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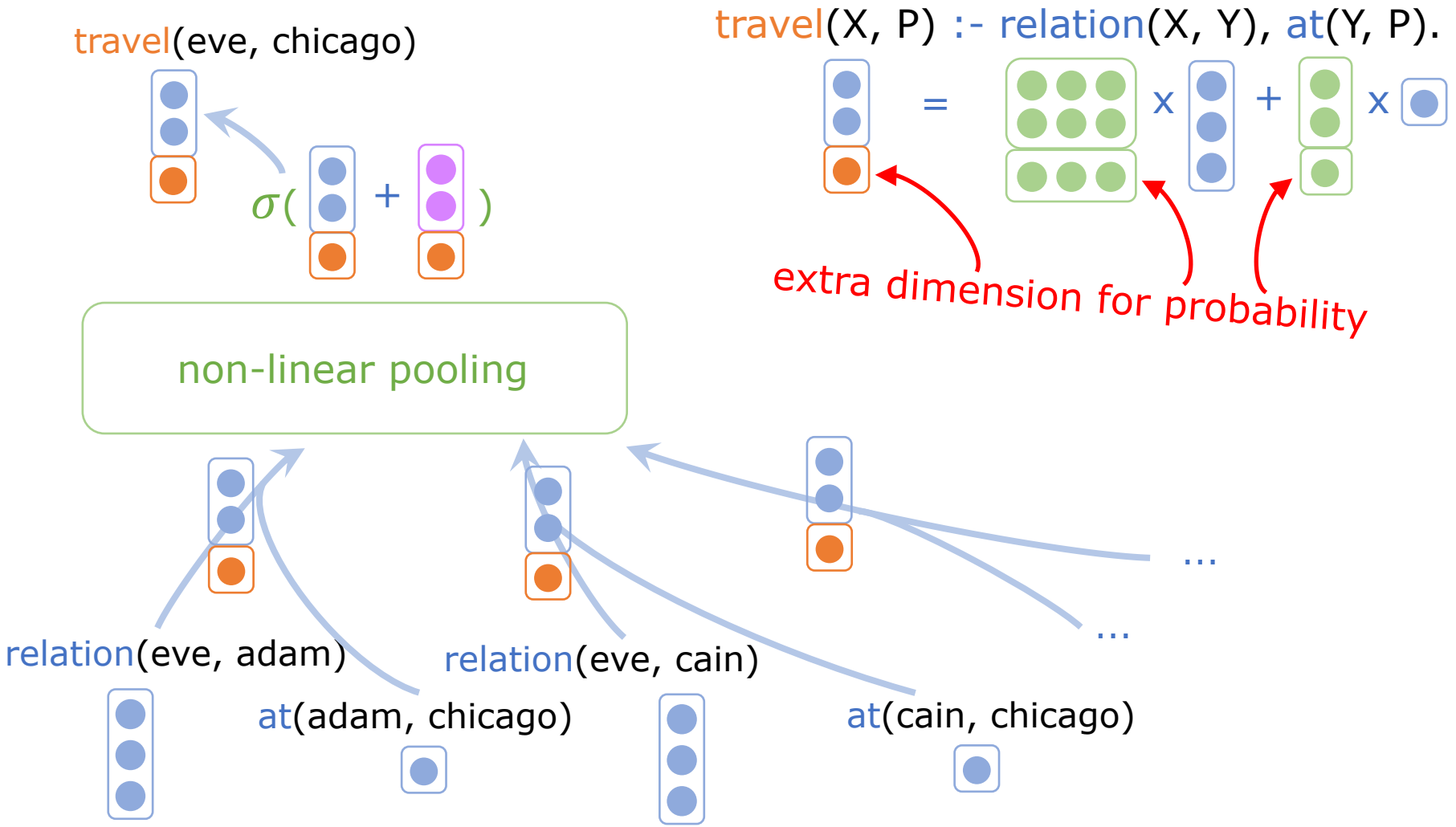

Rules ➔ Deep Recurrent Neural Net

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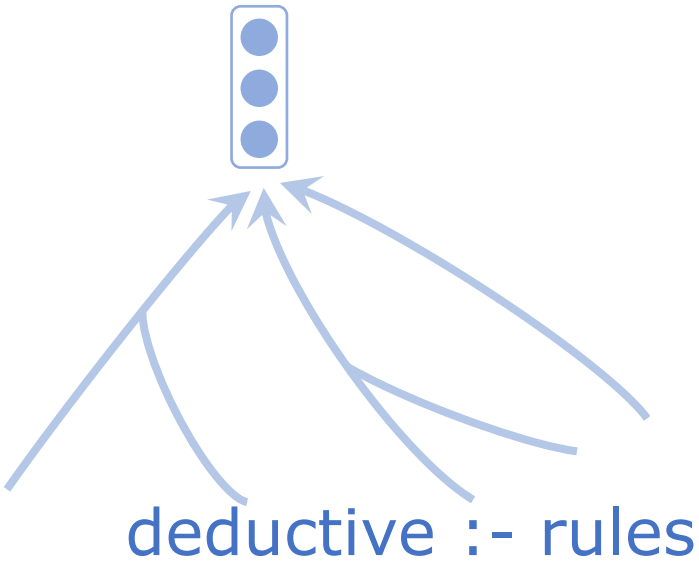

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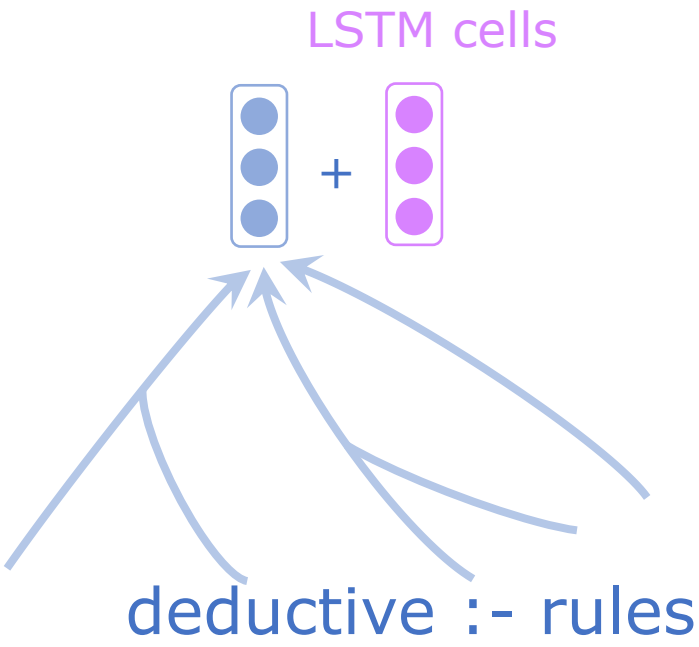

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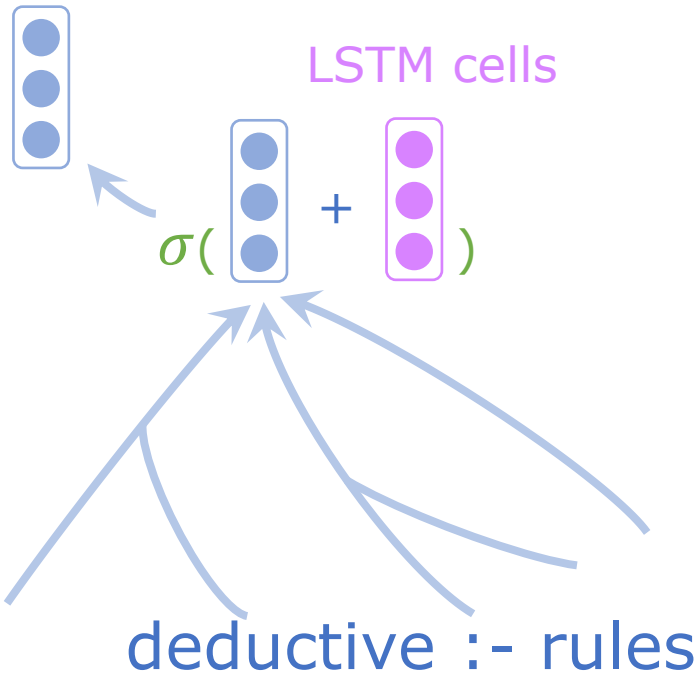

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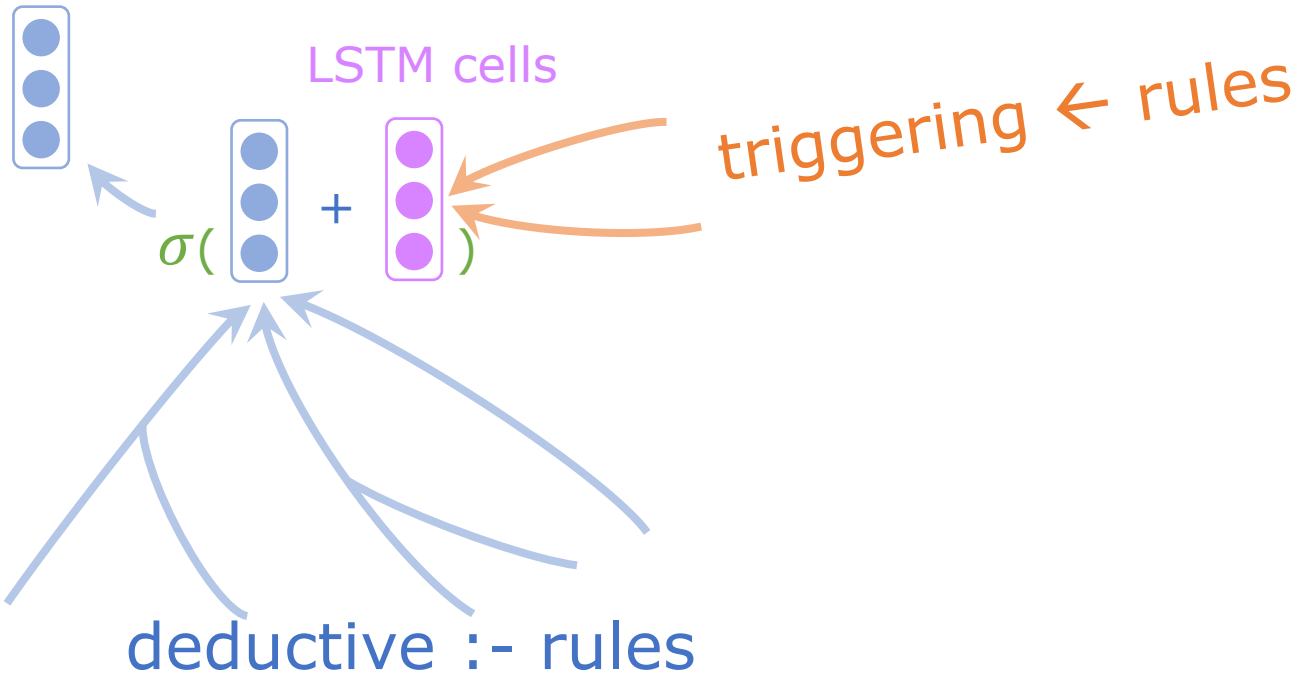

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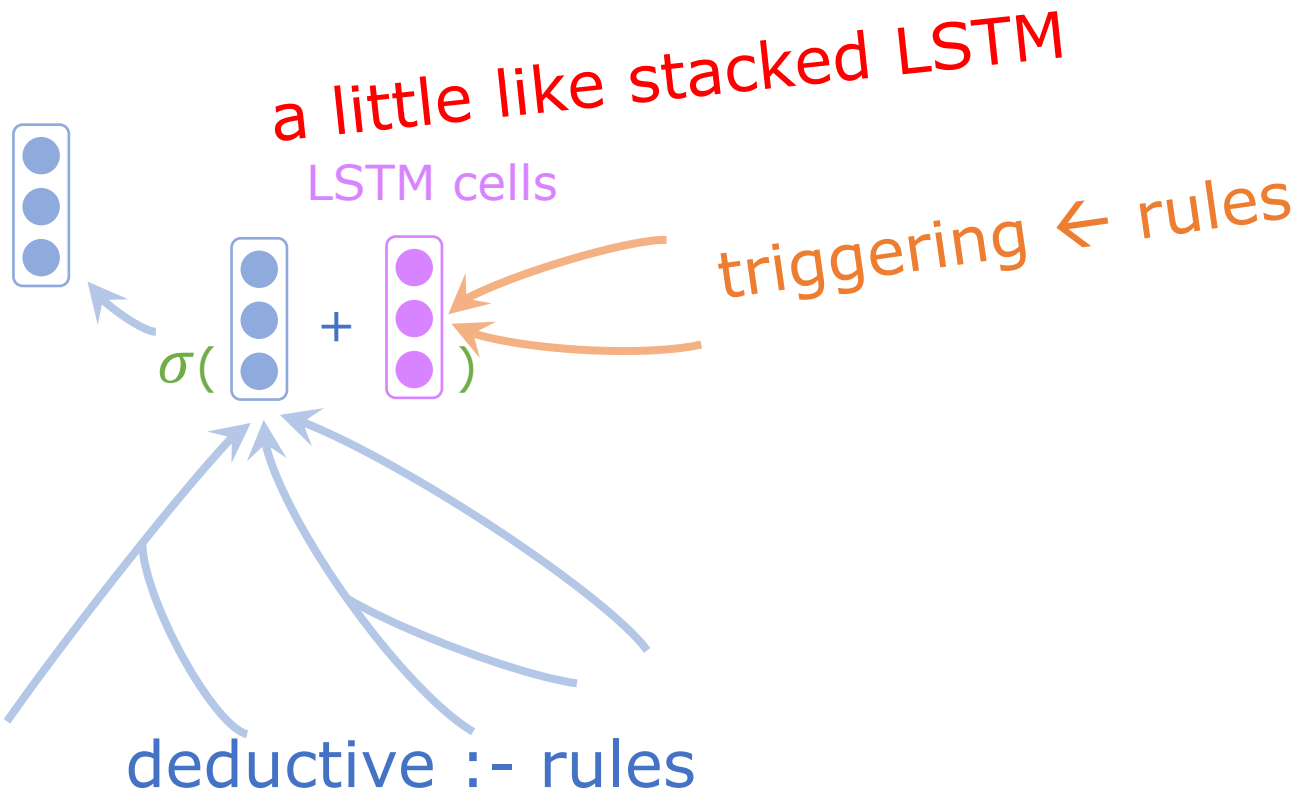

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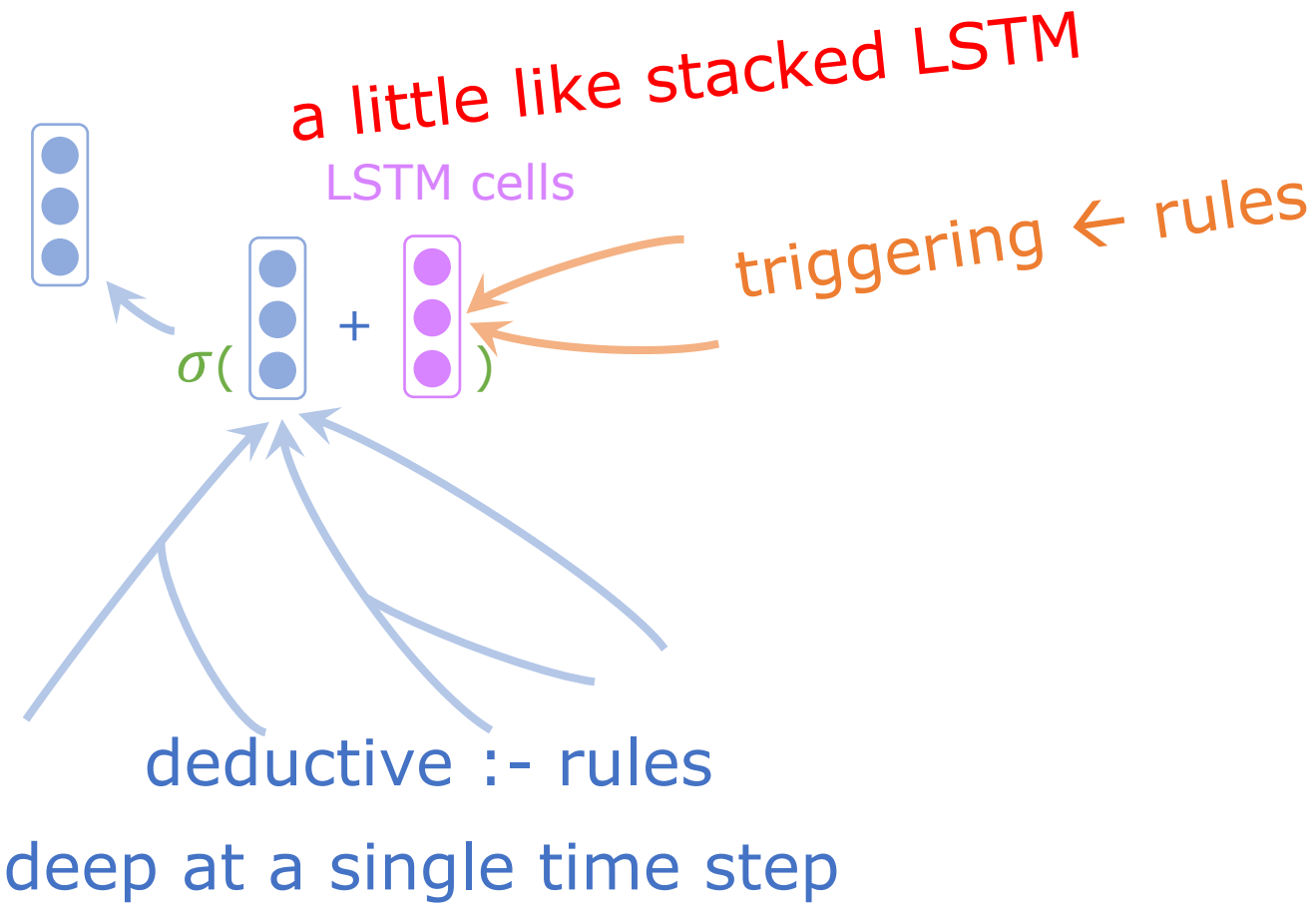

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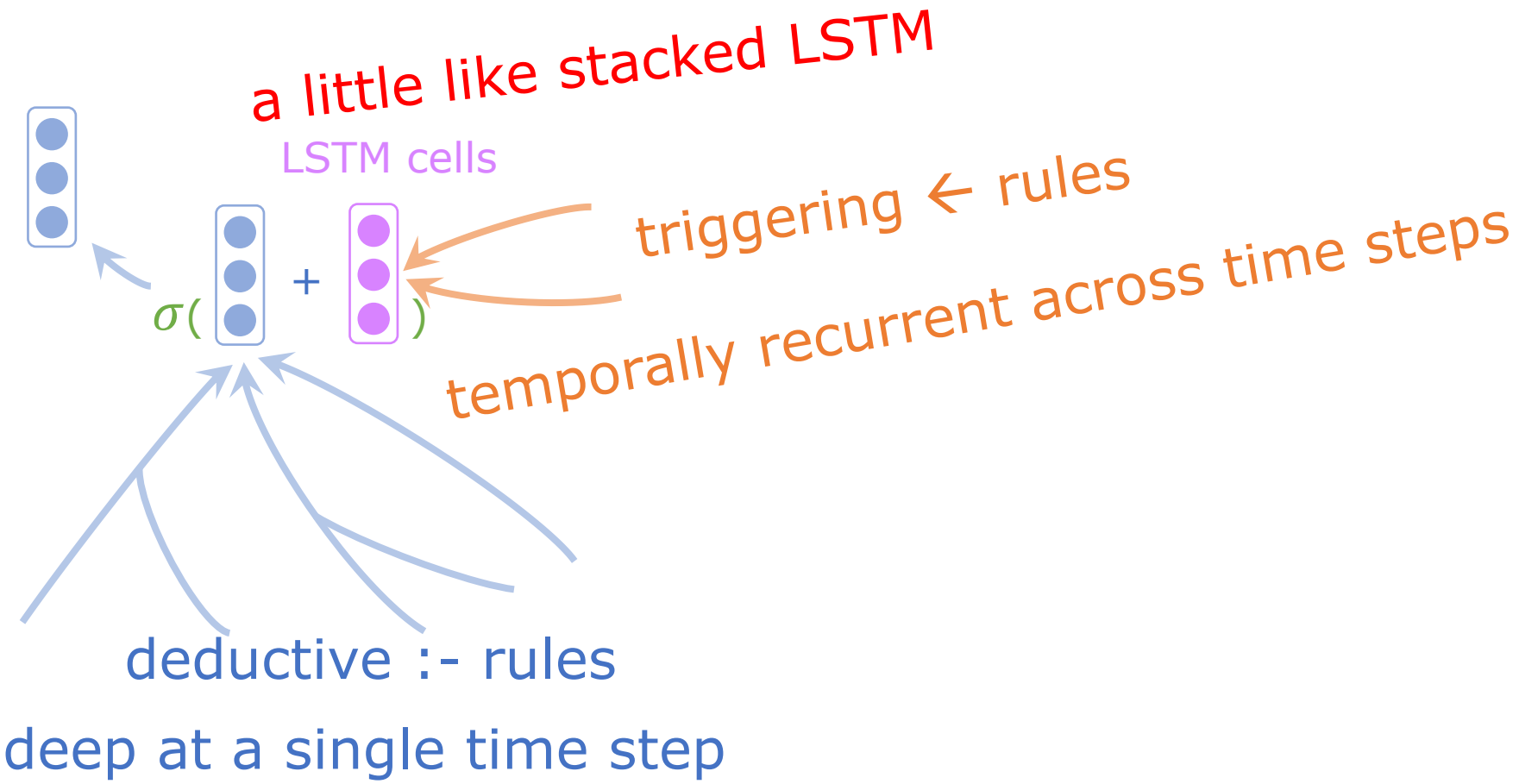

Life Story of a Fact

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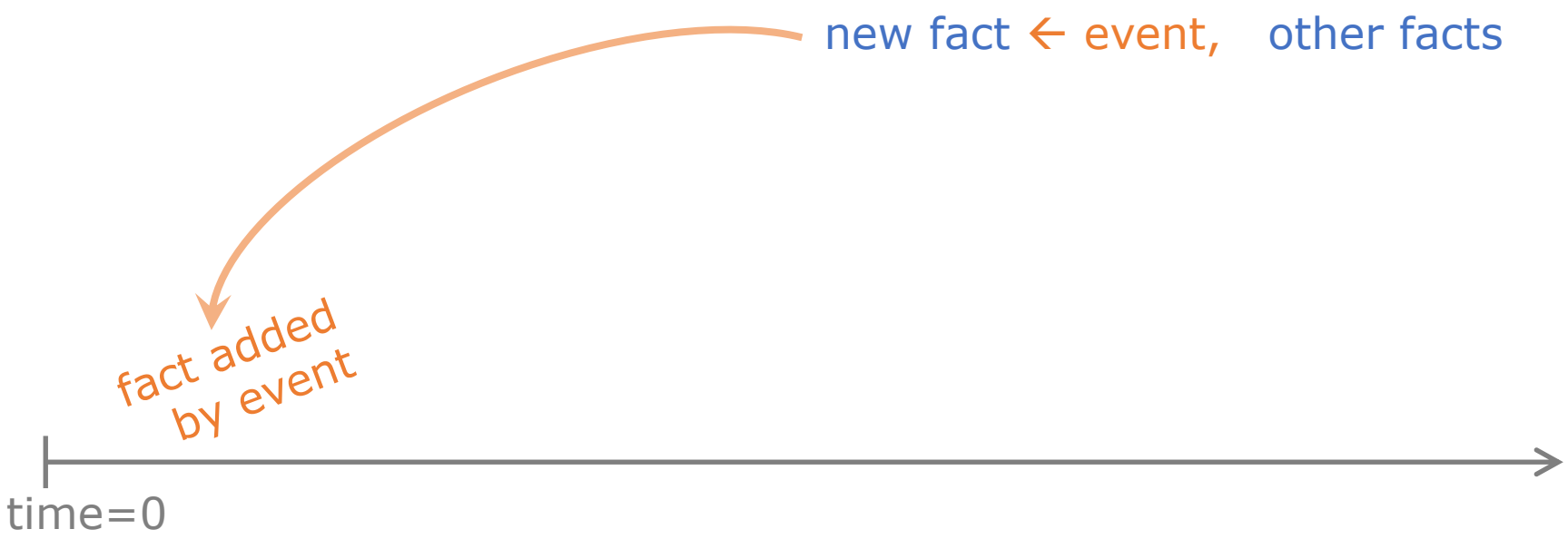
new fact ← event, other facts

Life Story of a Fact



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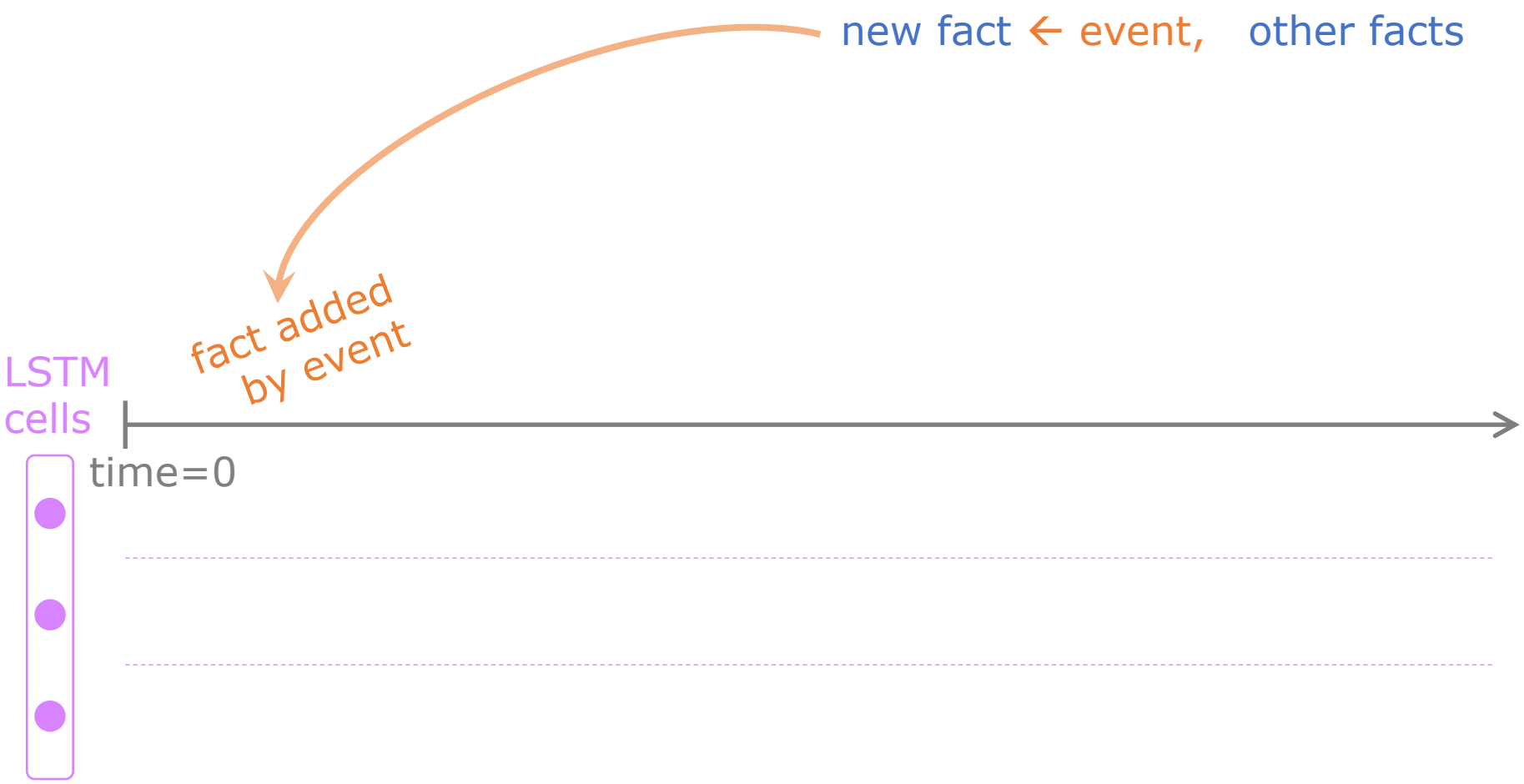

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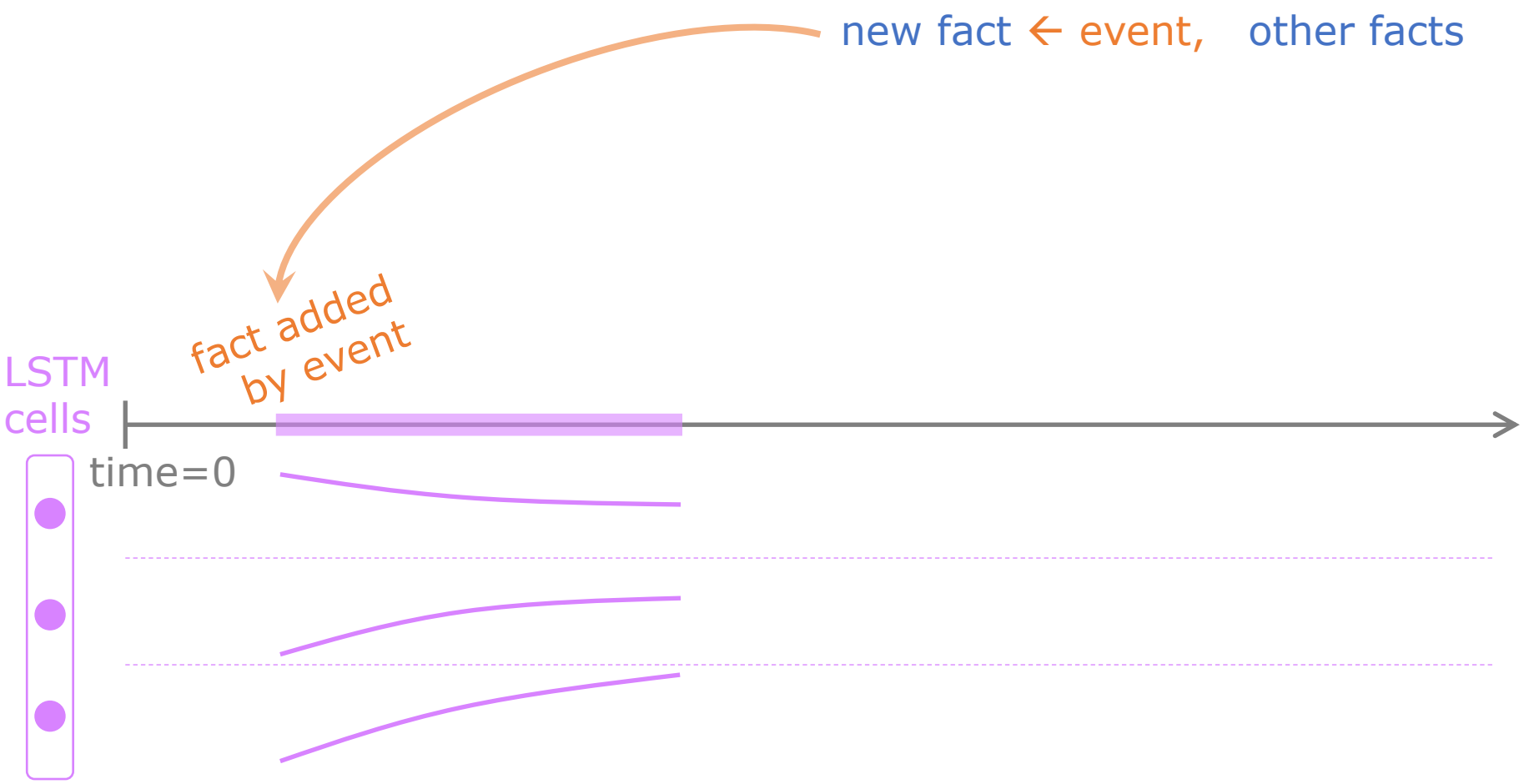

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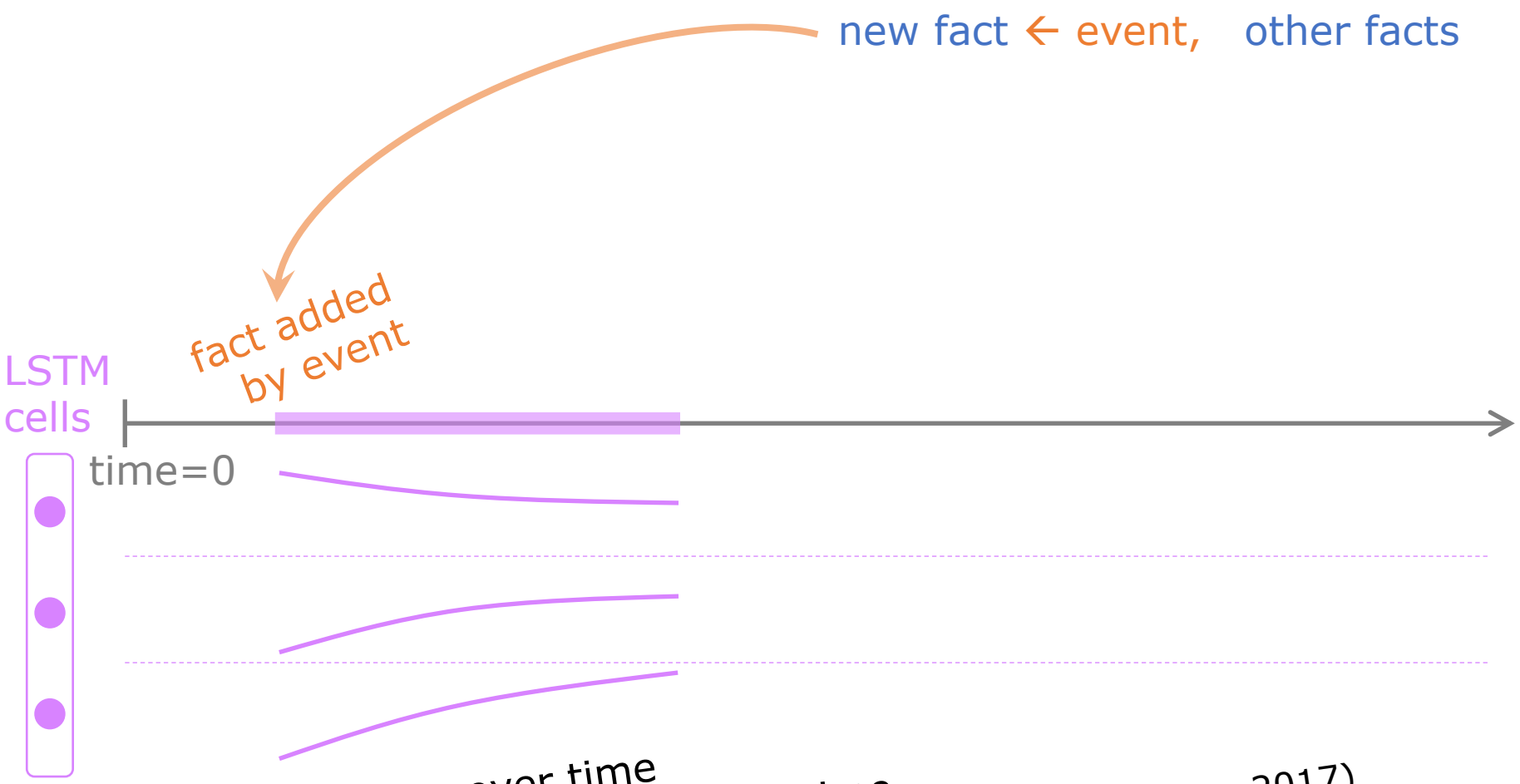

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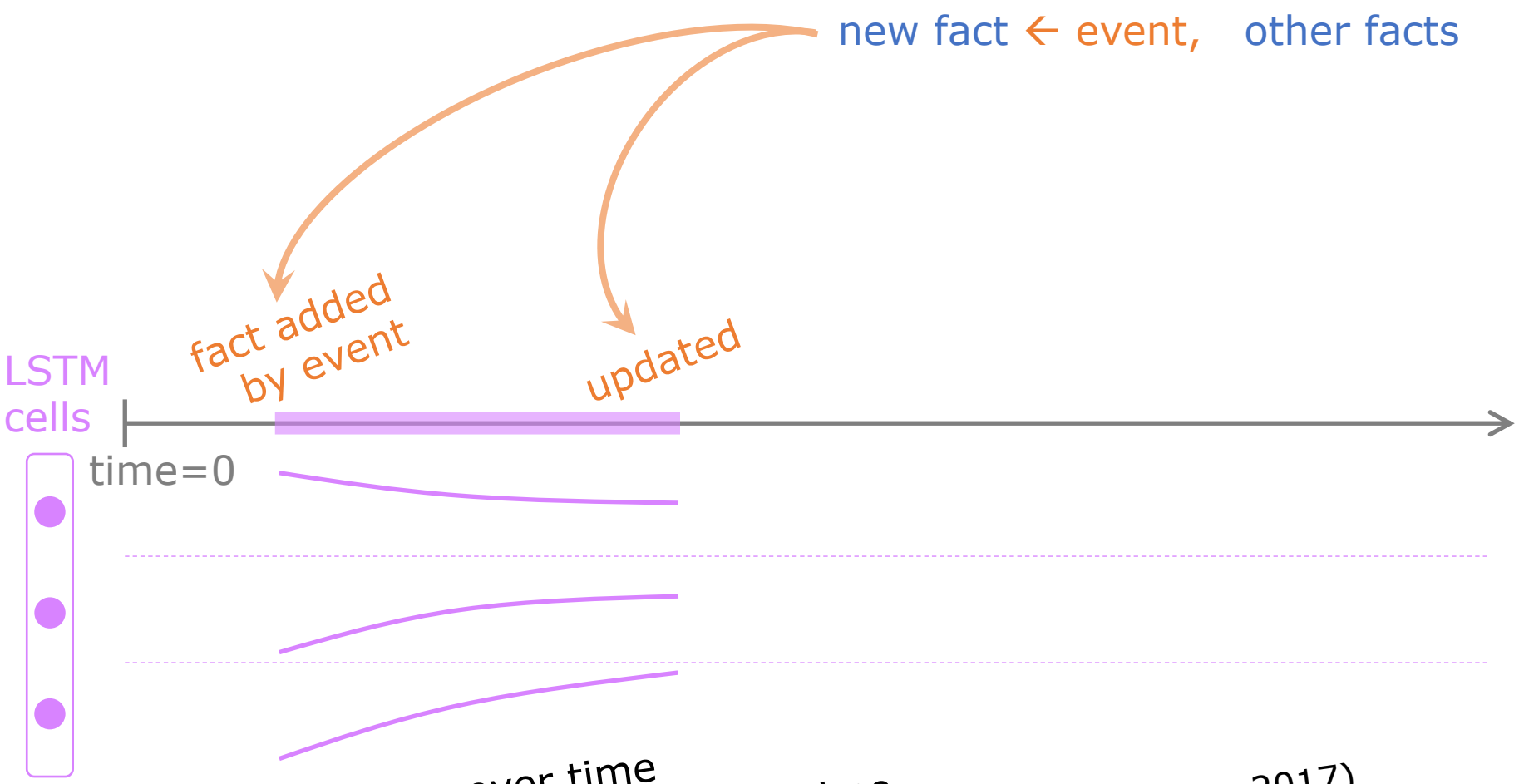

embedding changes over time

probability changes over time

≈ neural Hawkes process (Mei & Eisner, 2017)

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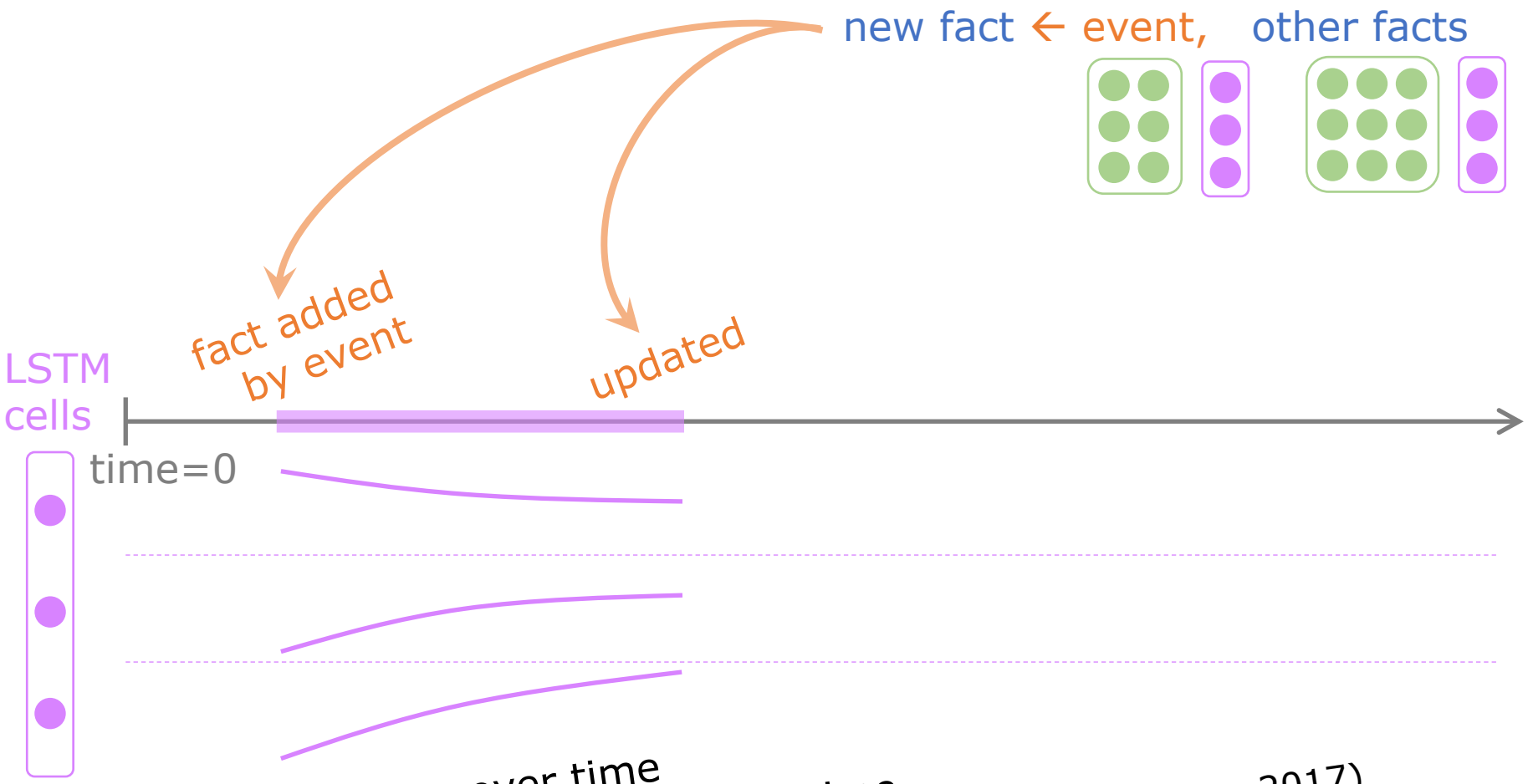

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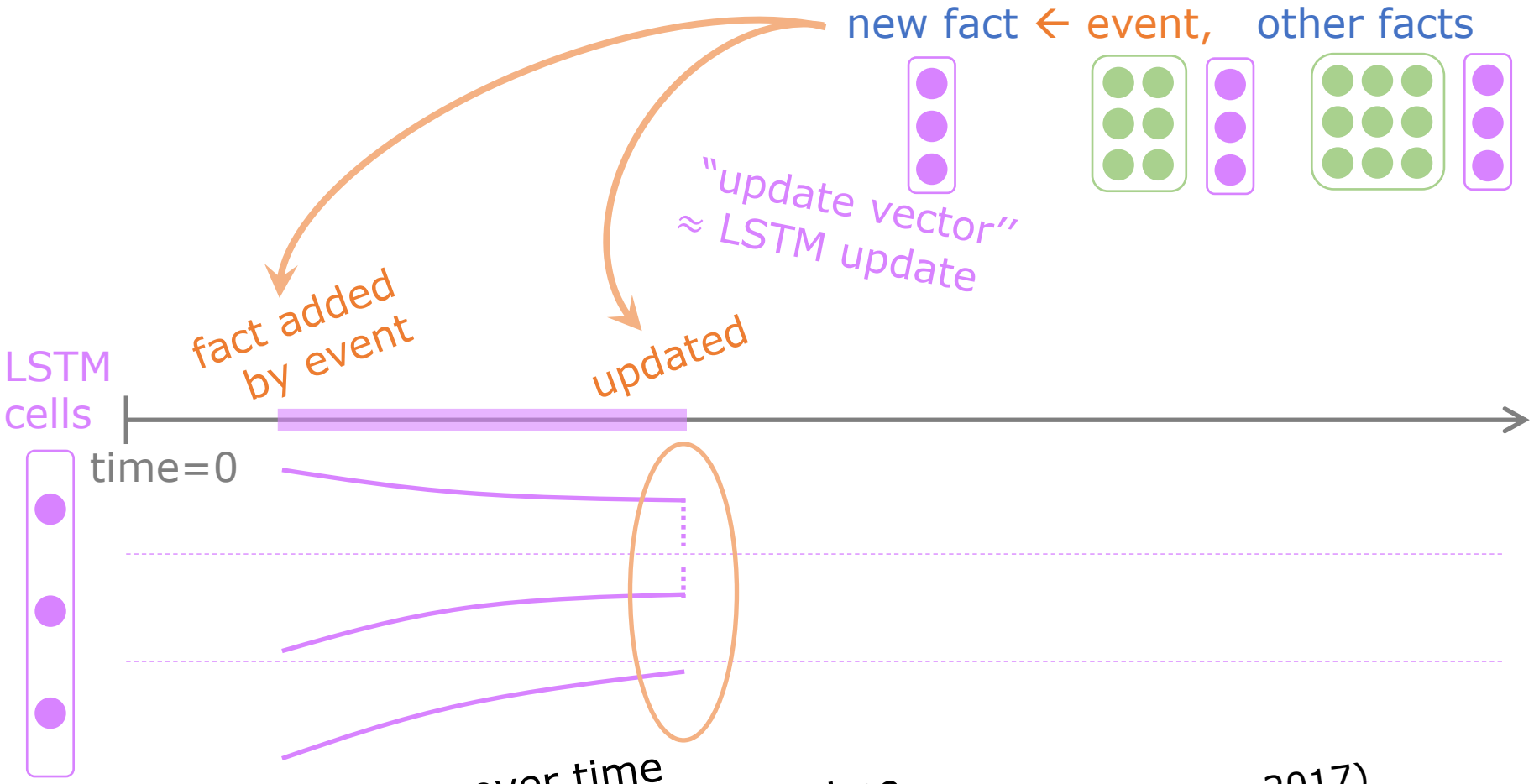

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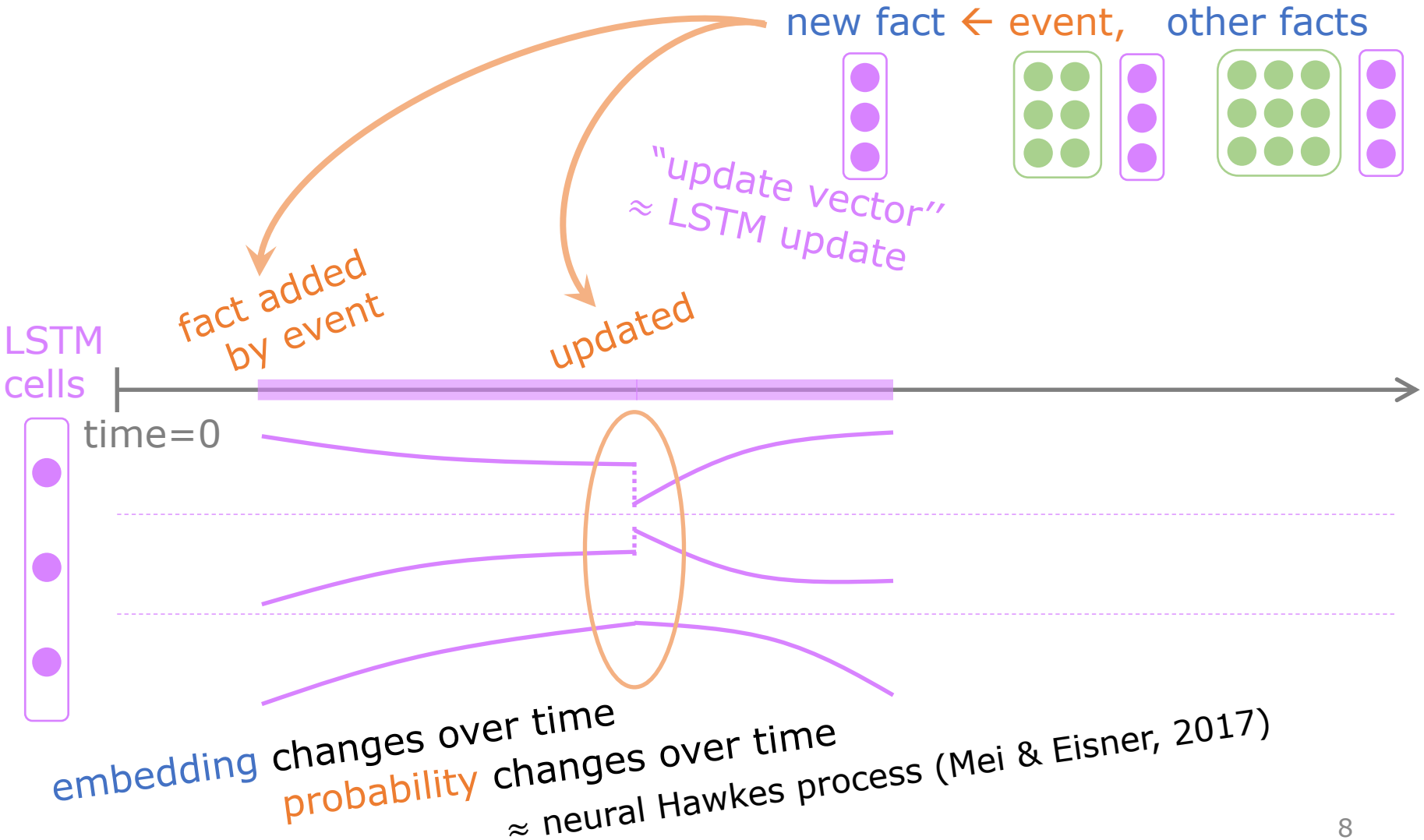

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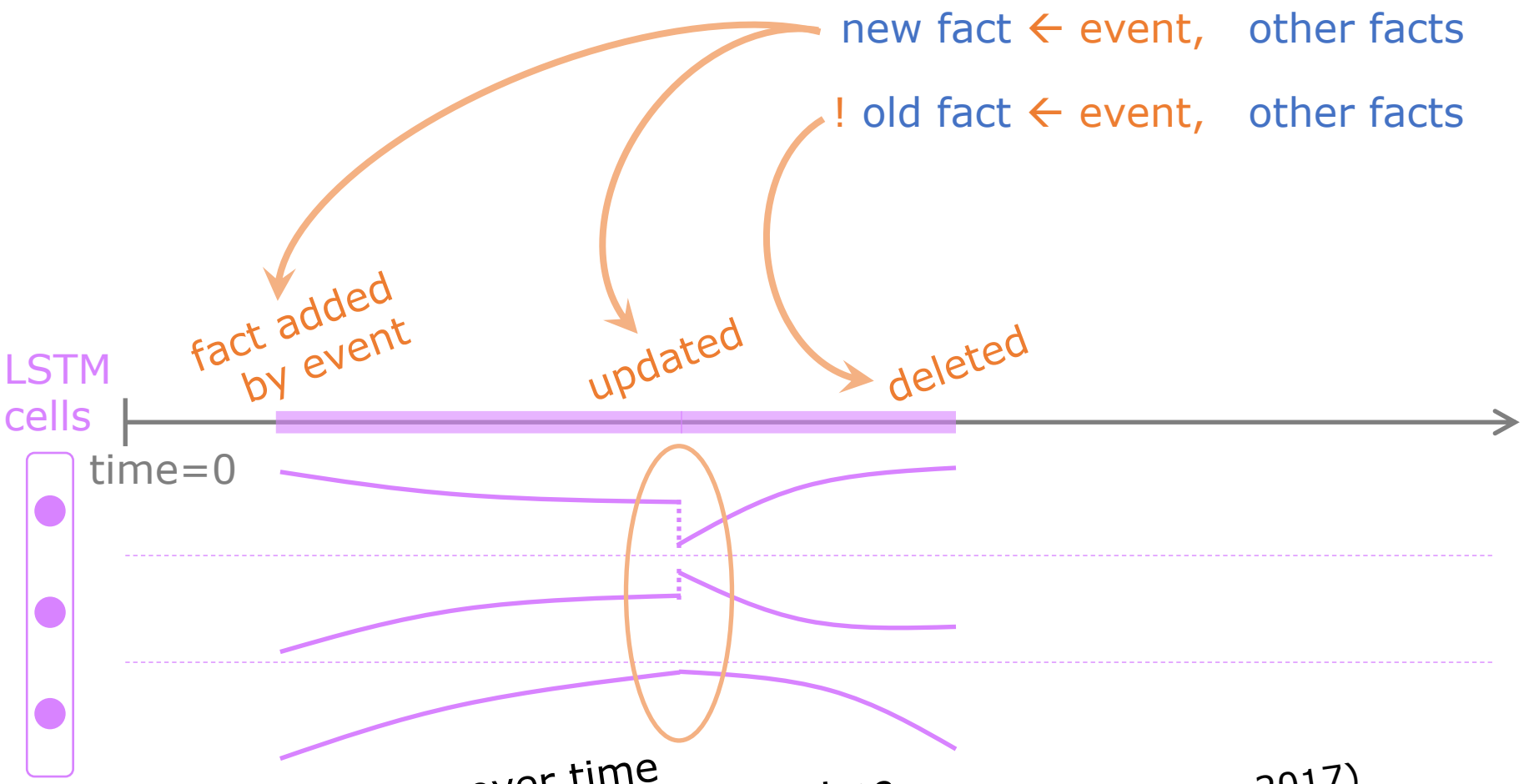

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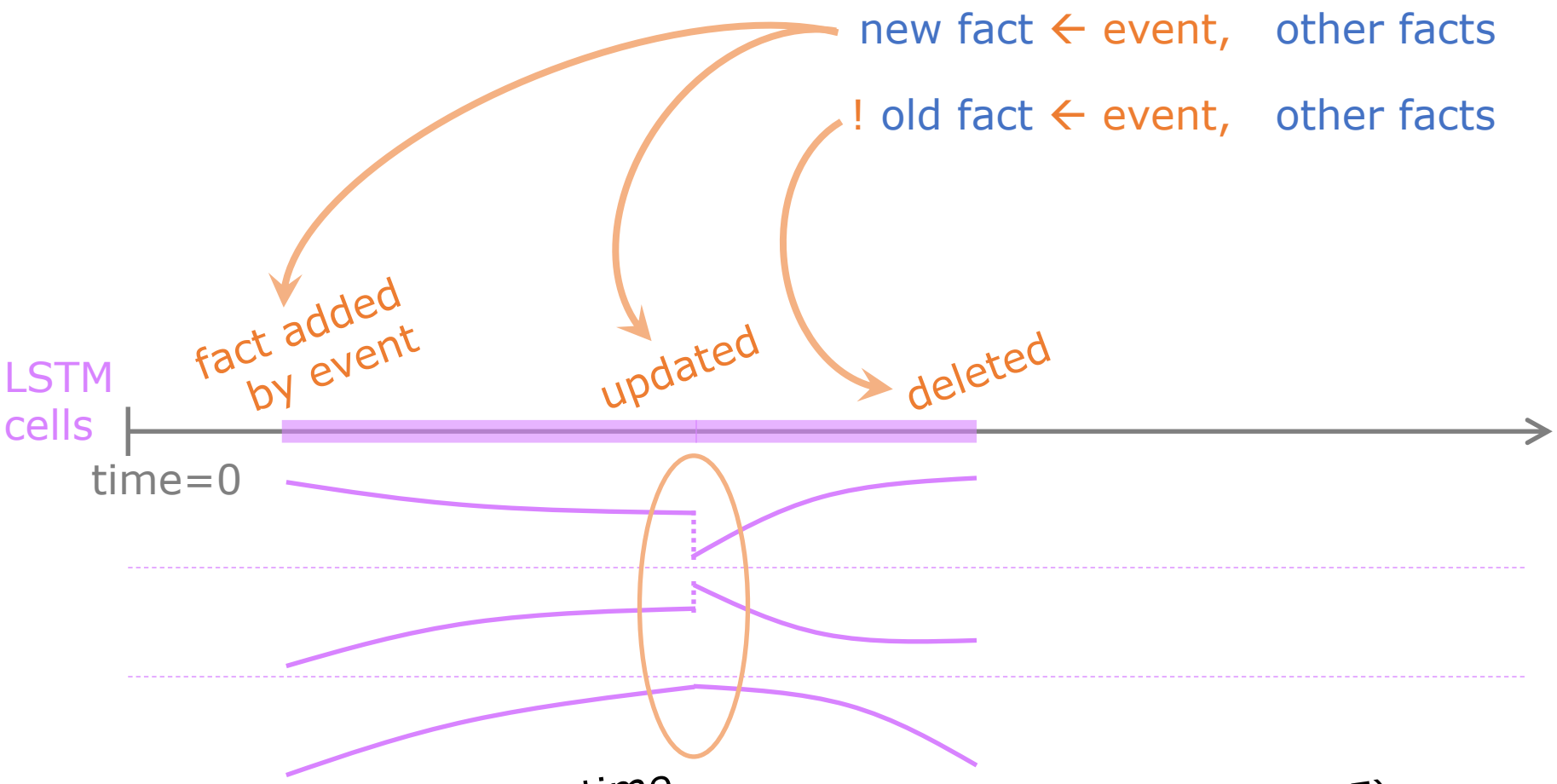

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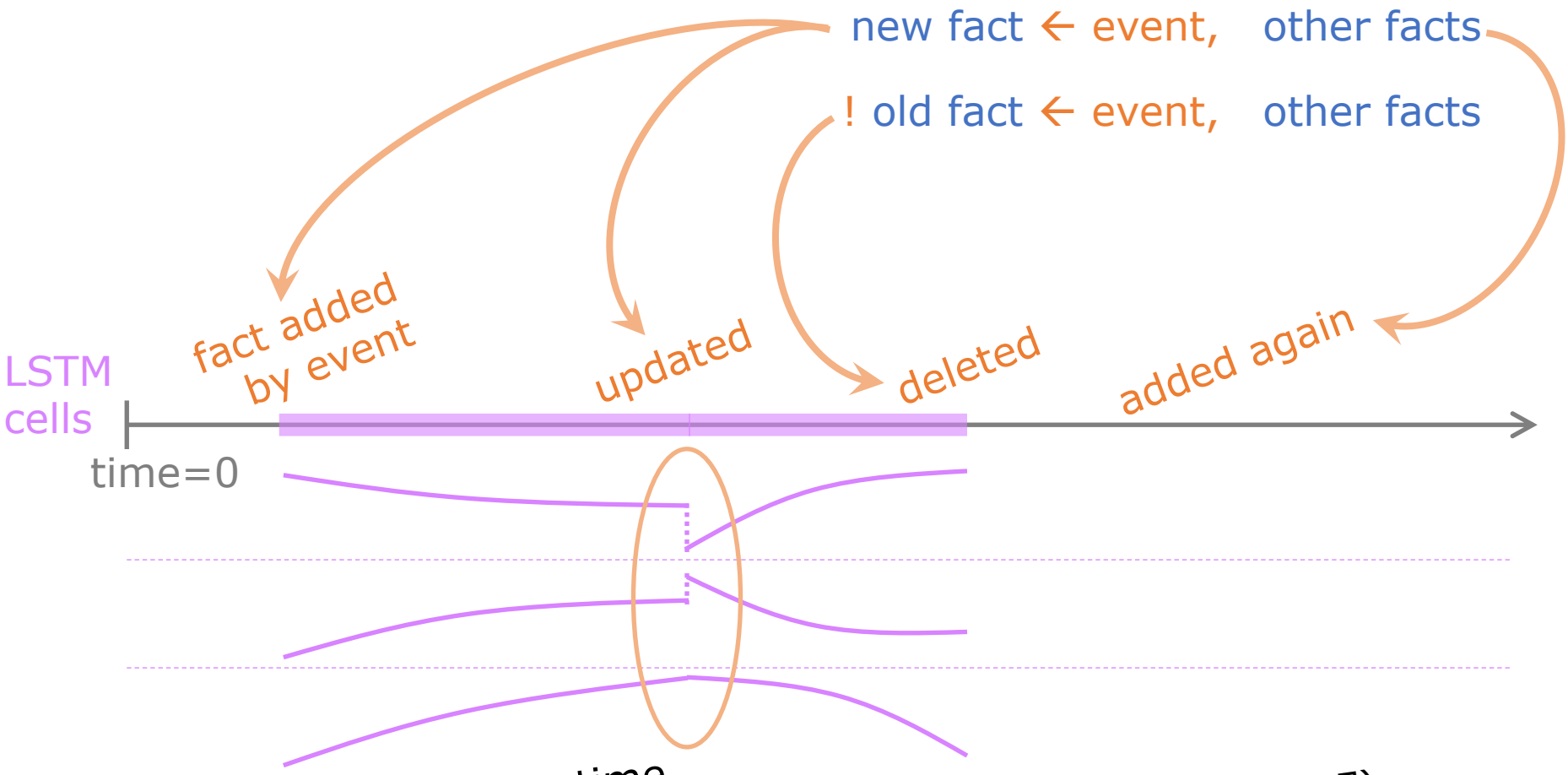

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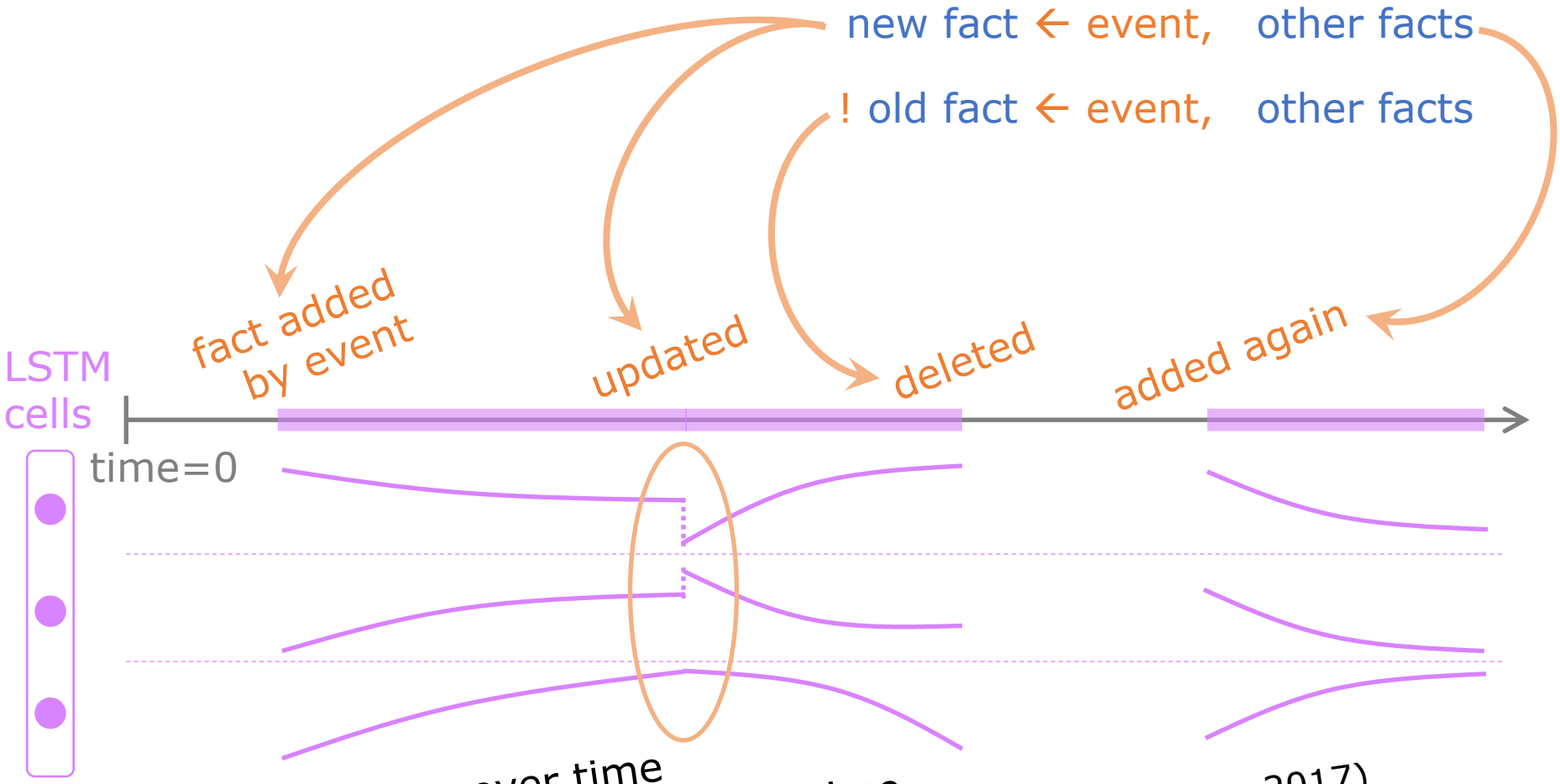

Experiment: Users watch TV programs

collaborative filtering problem with timing
who watches what and when?

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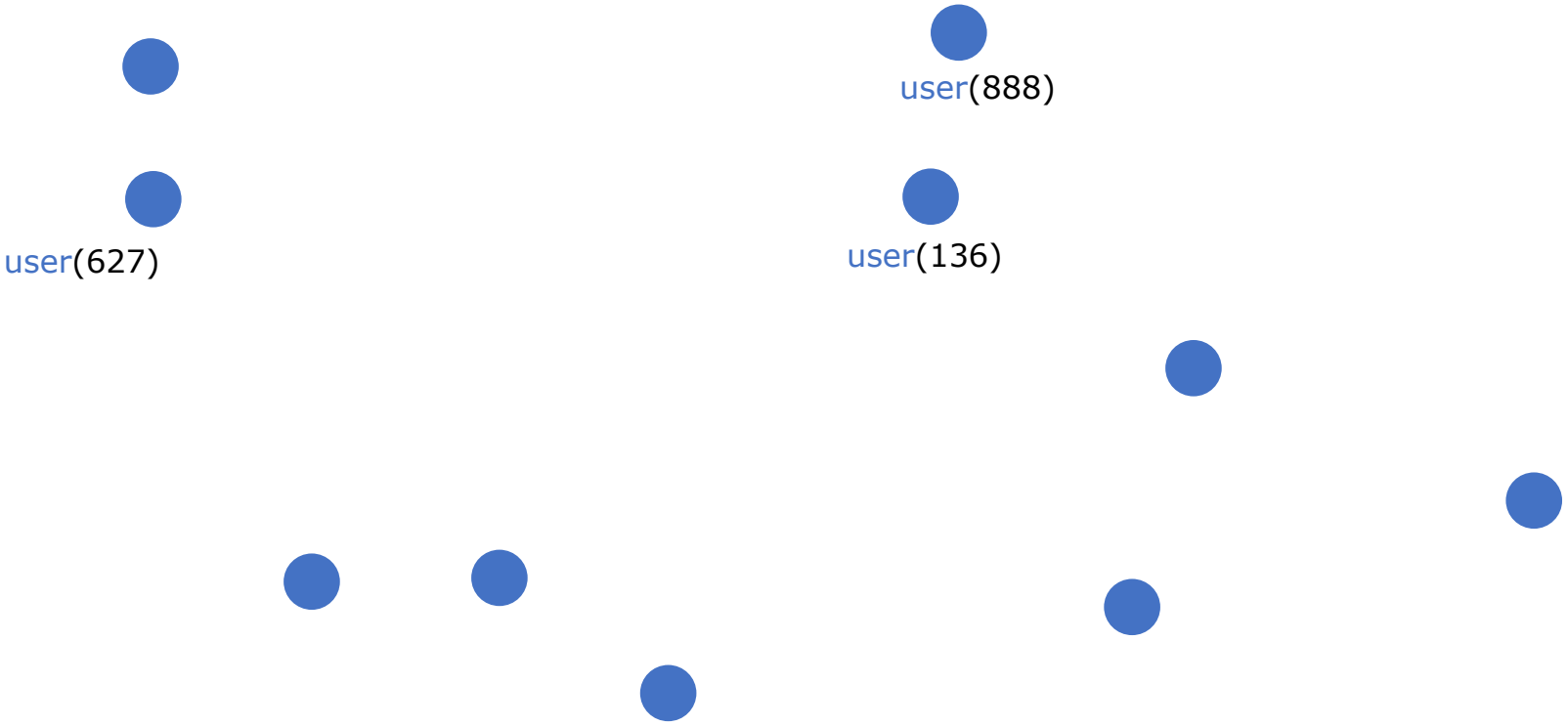
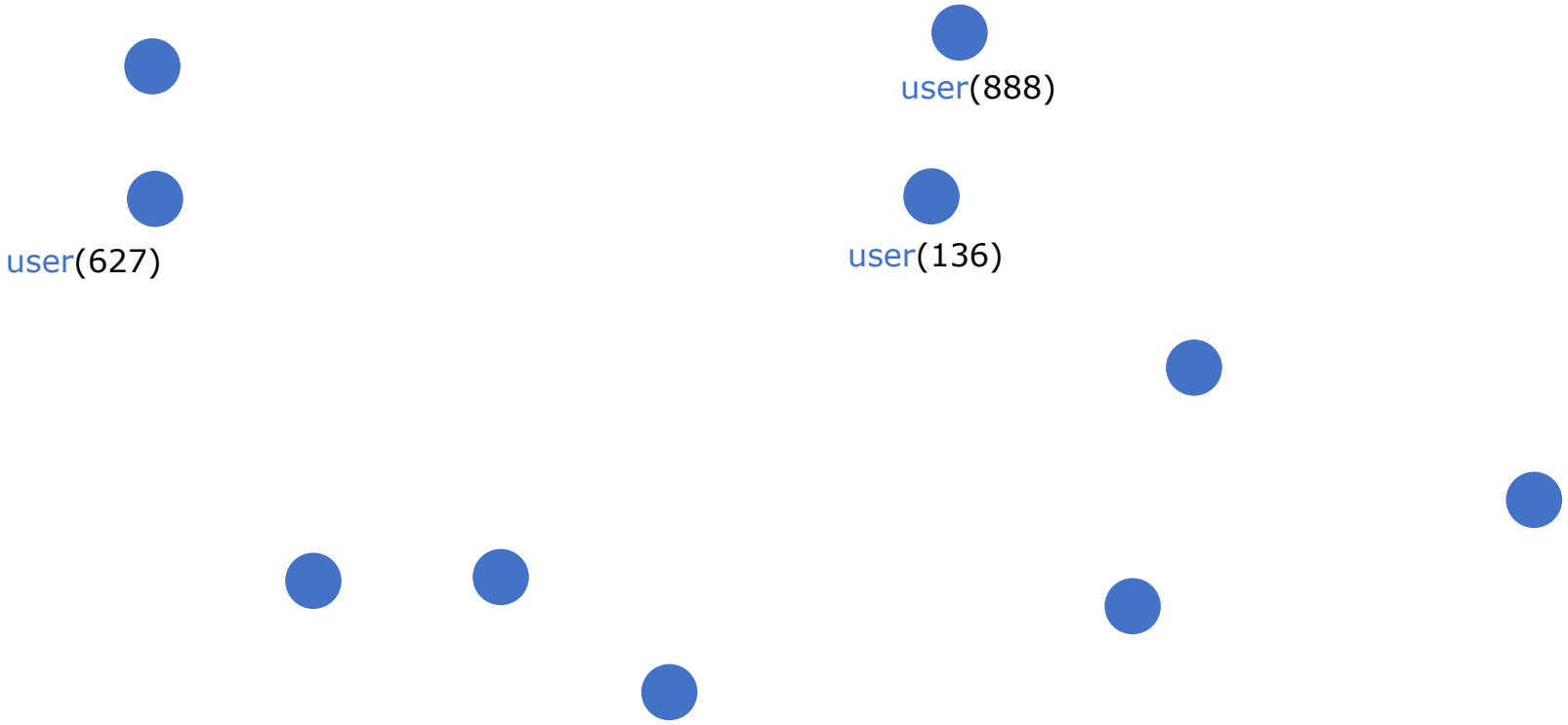
1000 users



Experiment: Users watch TV programs

collaborative filtering problem with timing
who watches what and when?

1000 users 49 TV programs to be released



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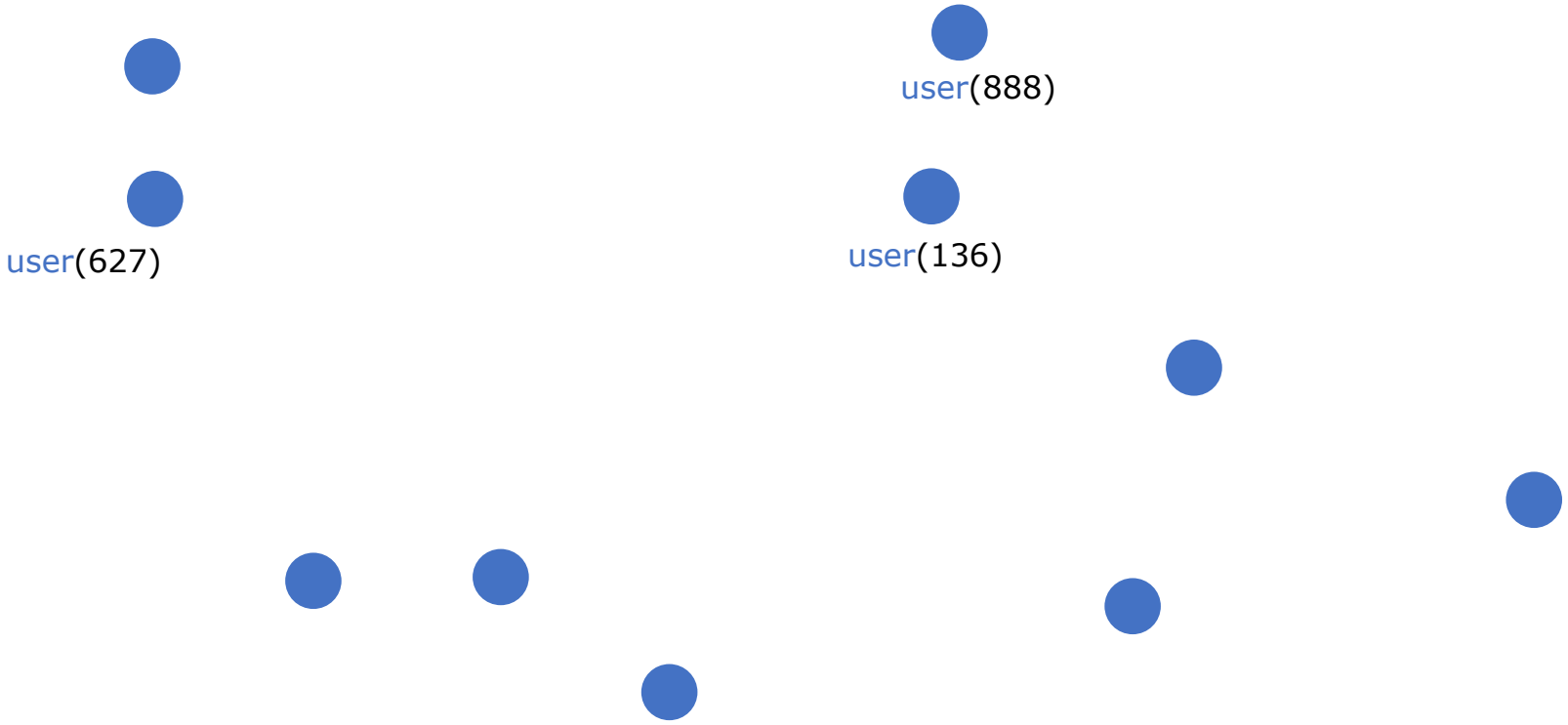
49000 possible watch events



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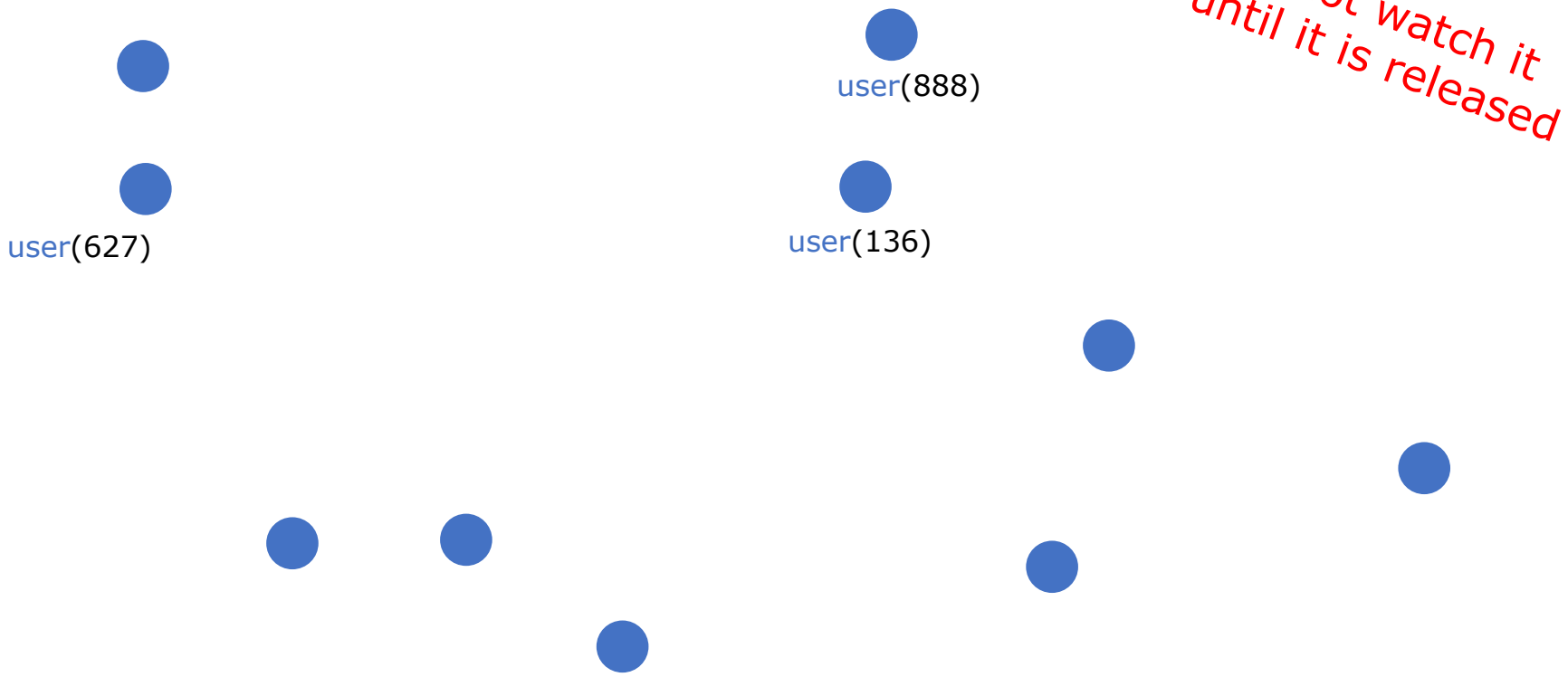


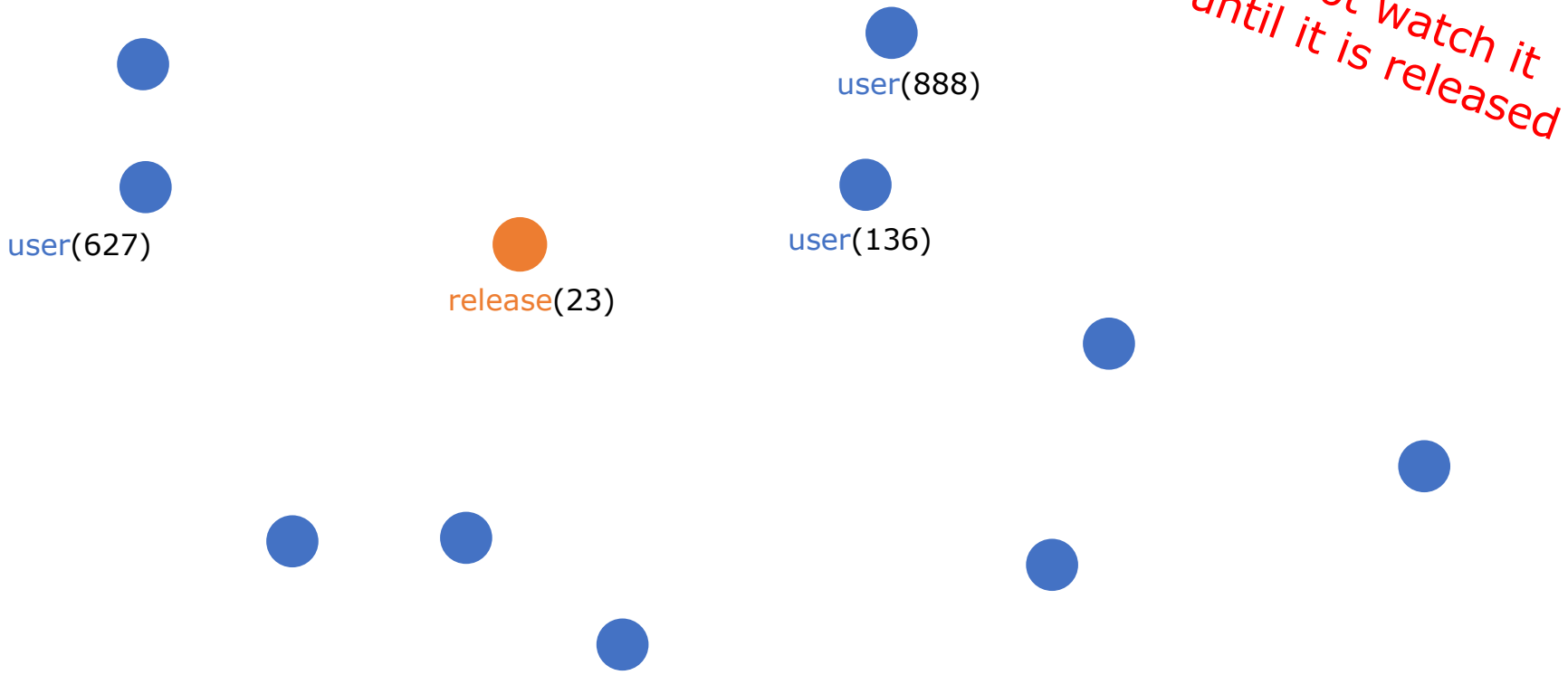
can not watch it
until it is released

Experiment: Users watch TV programs

collaborative filtering problem with timing
who watches what and when?

1000 users 49 TV programs to be released

49000 possible watch events



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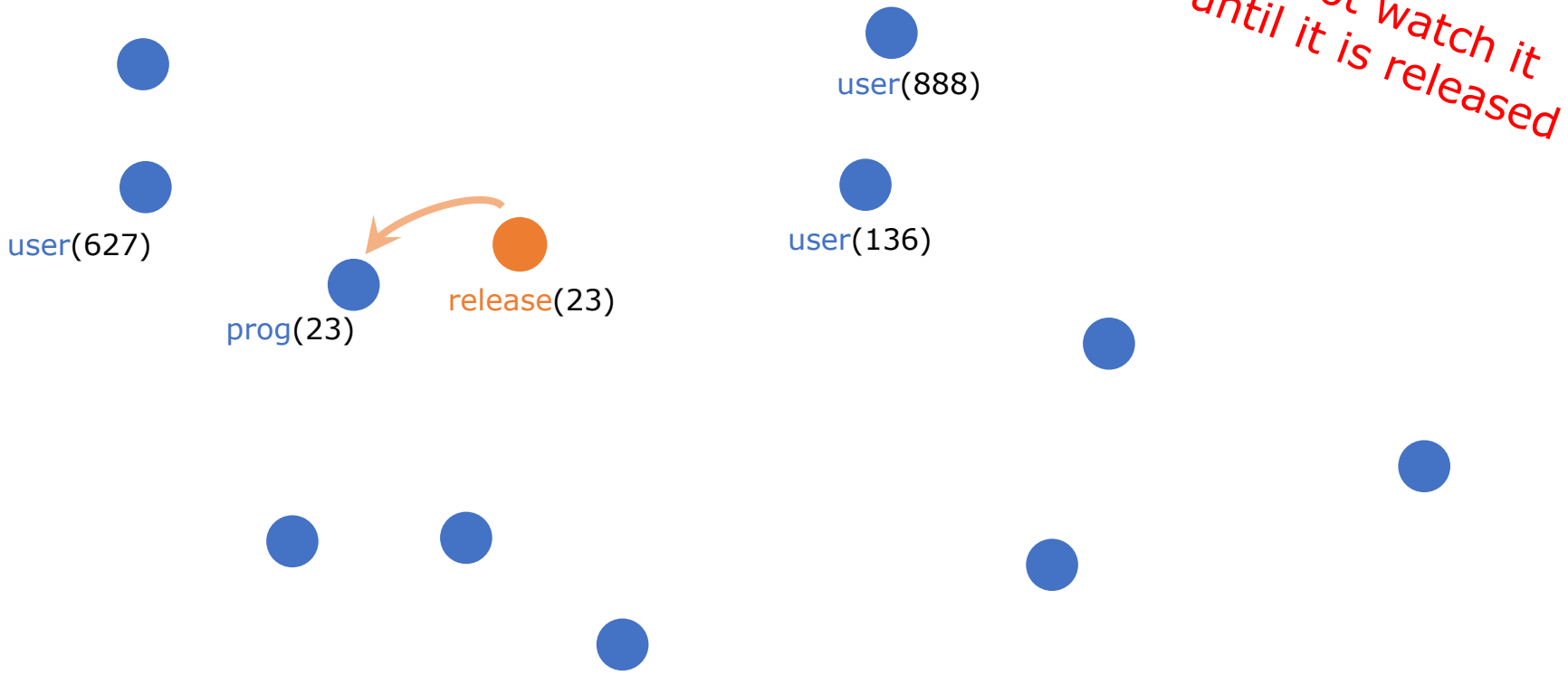

can not watch it
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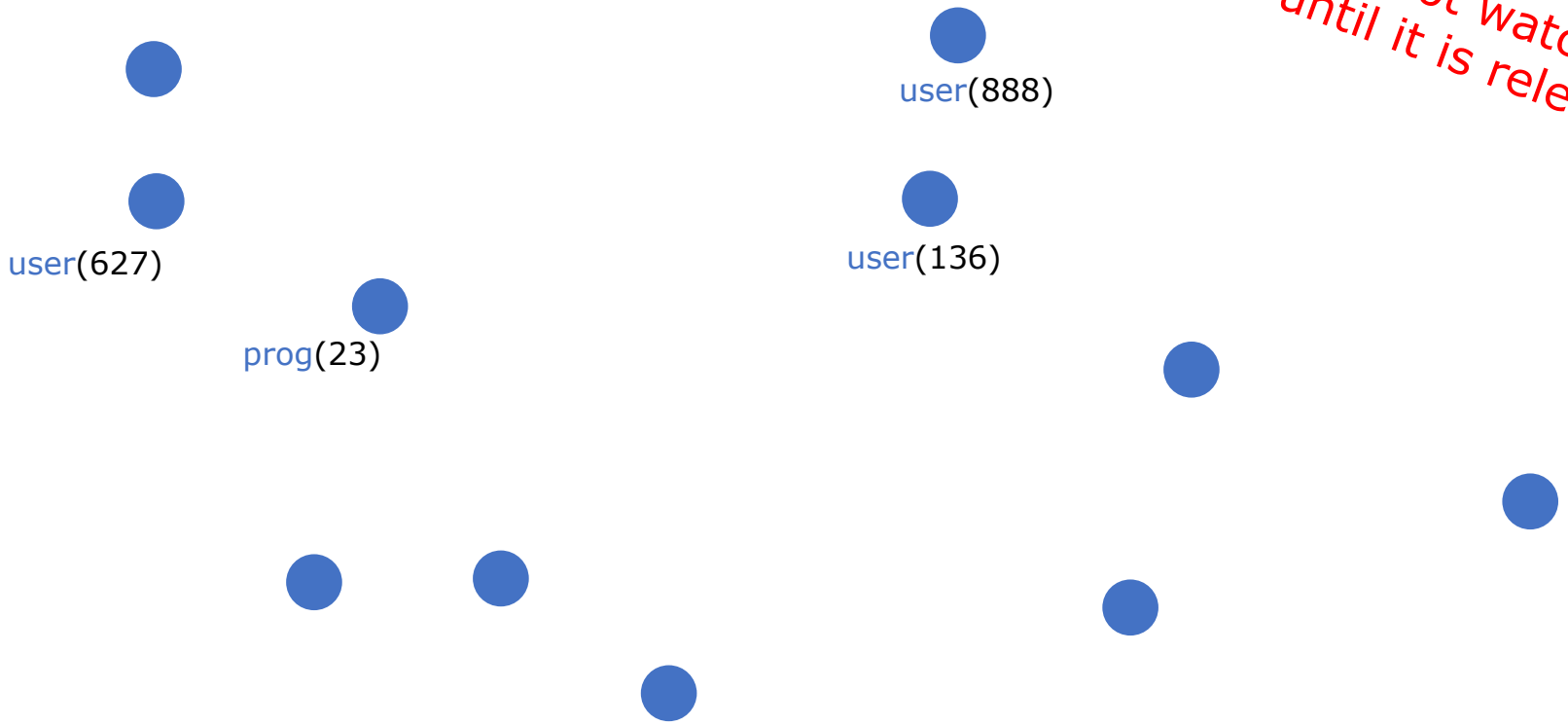

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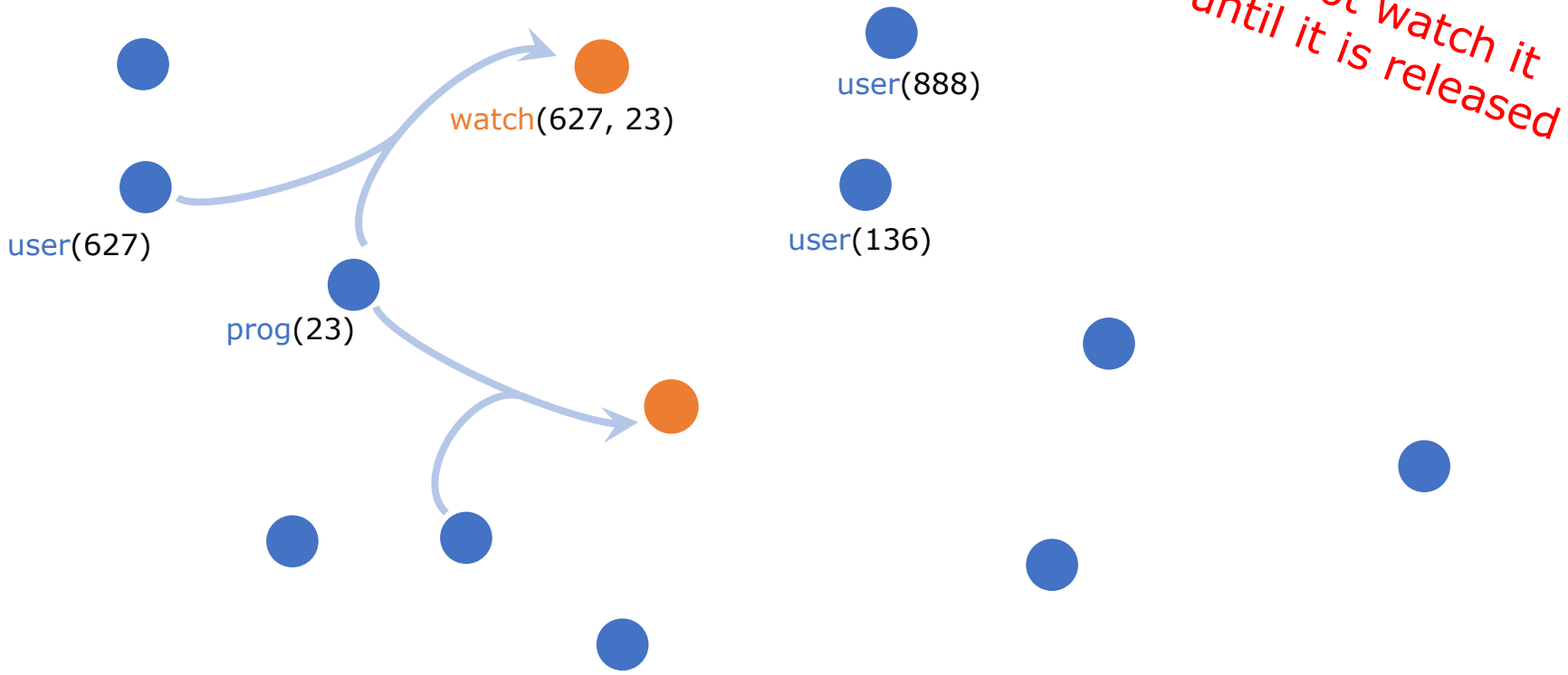

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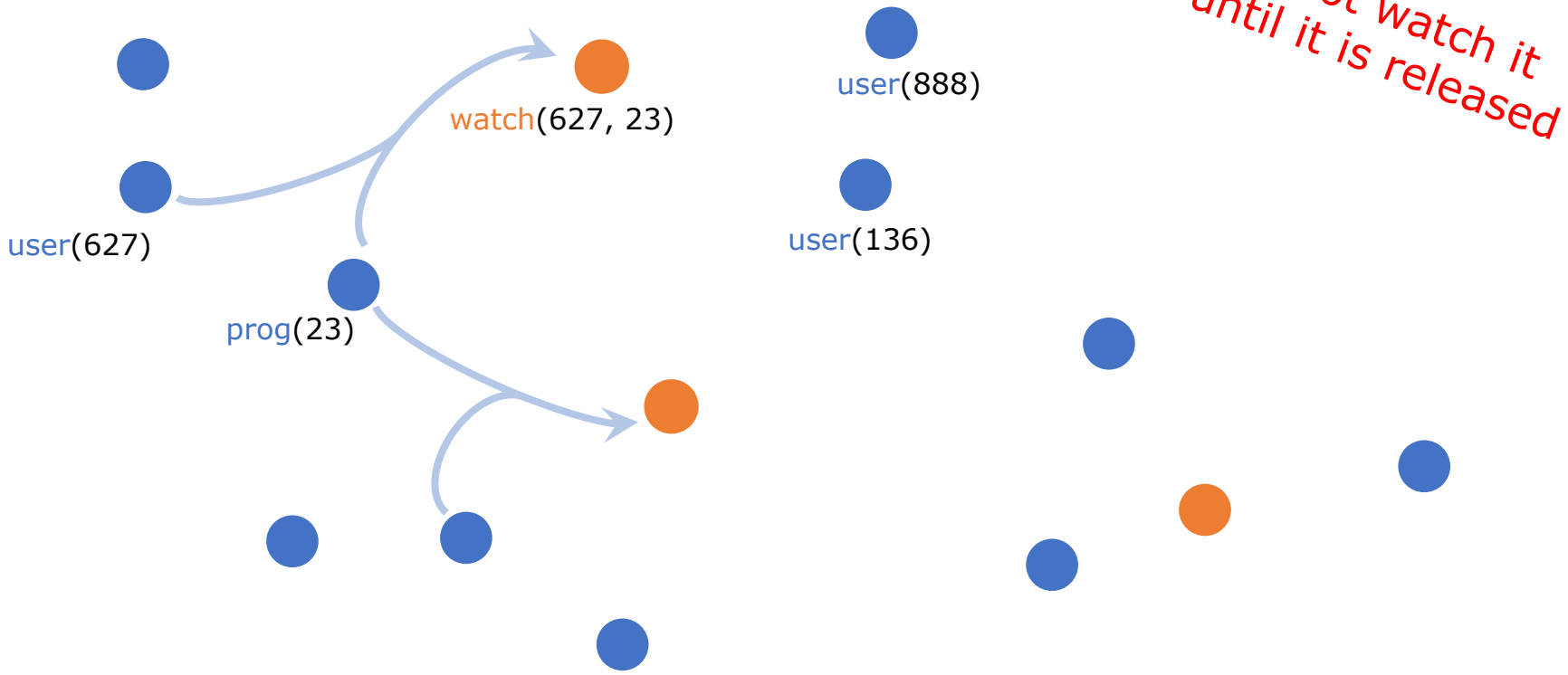

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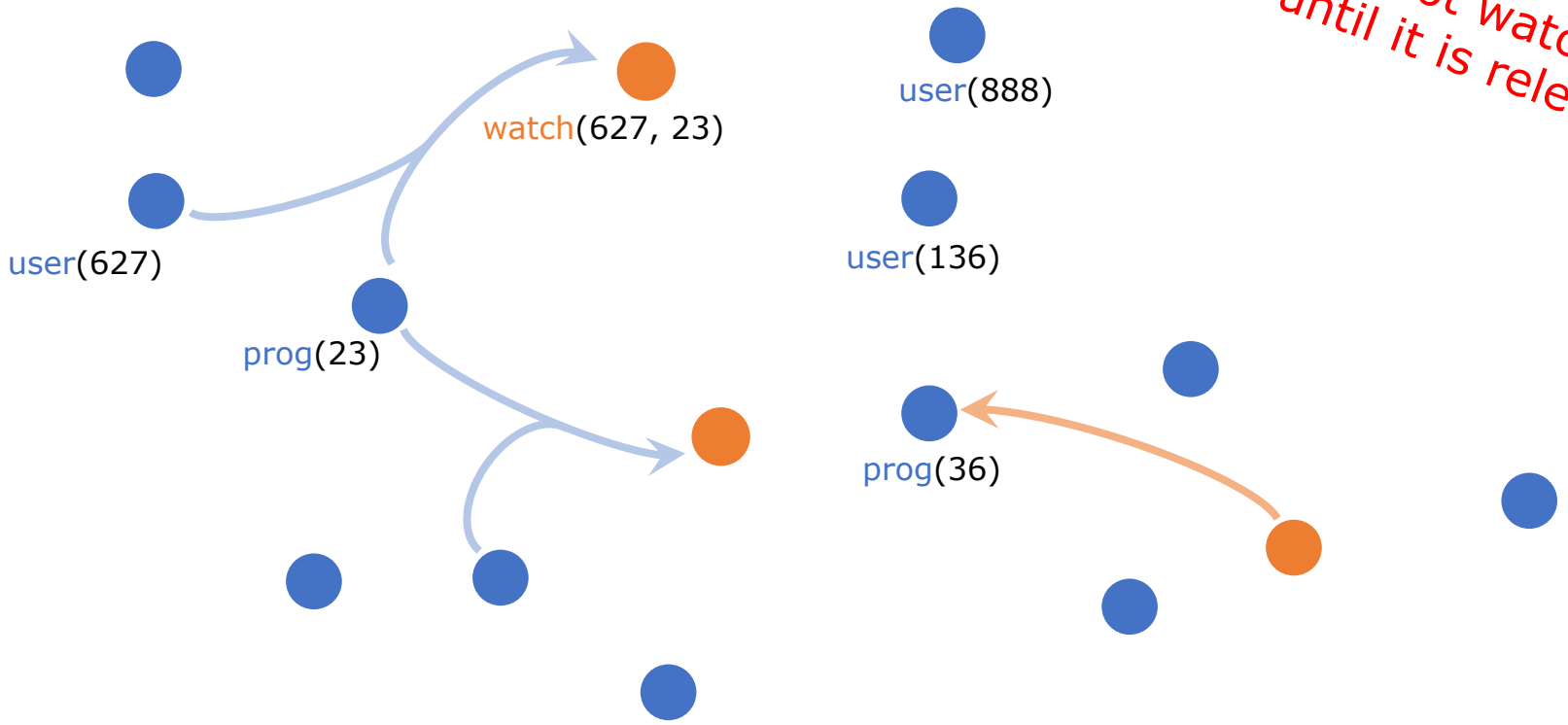

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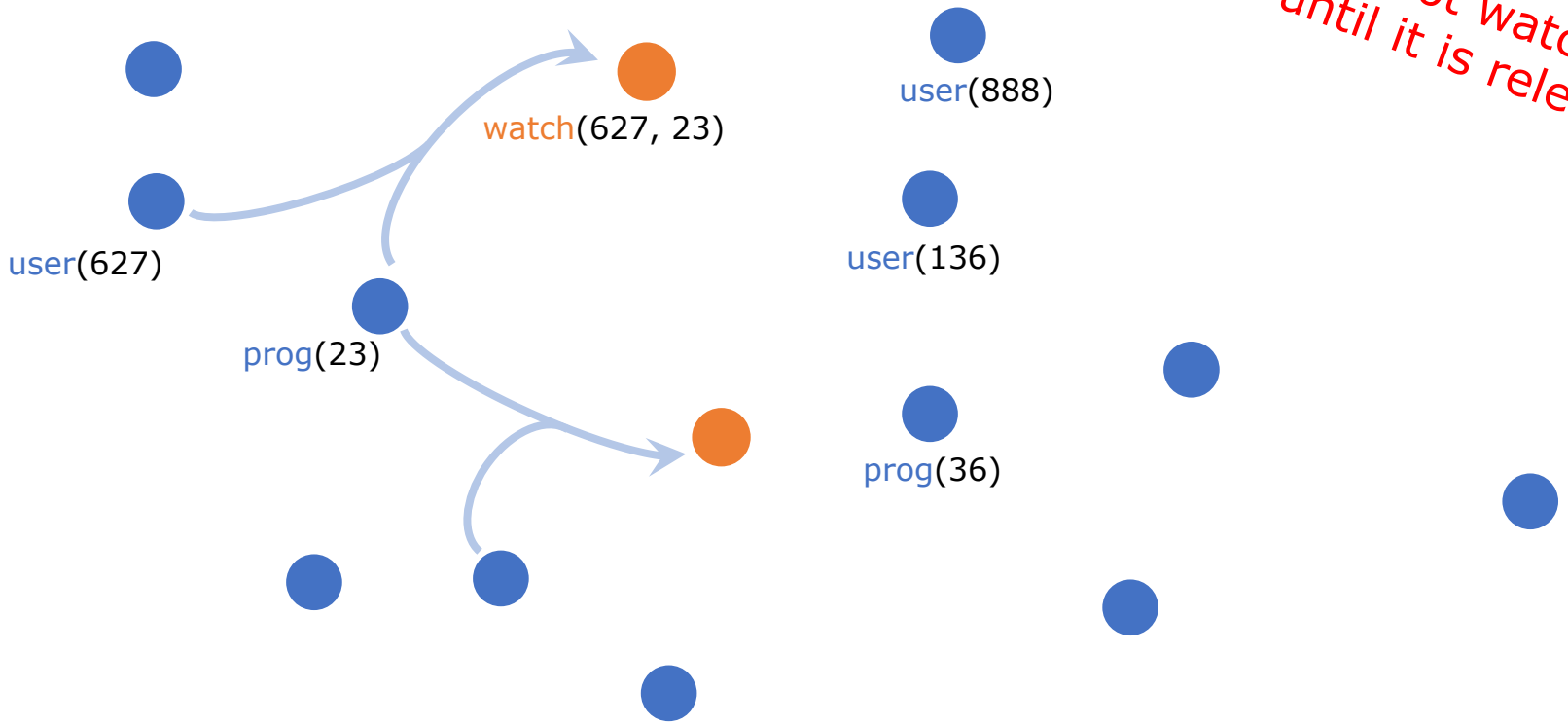

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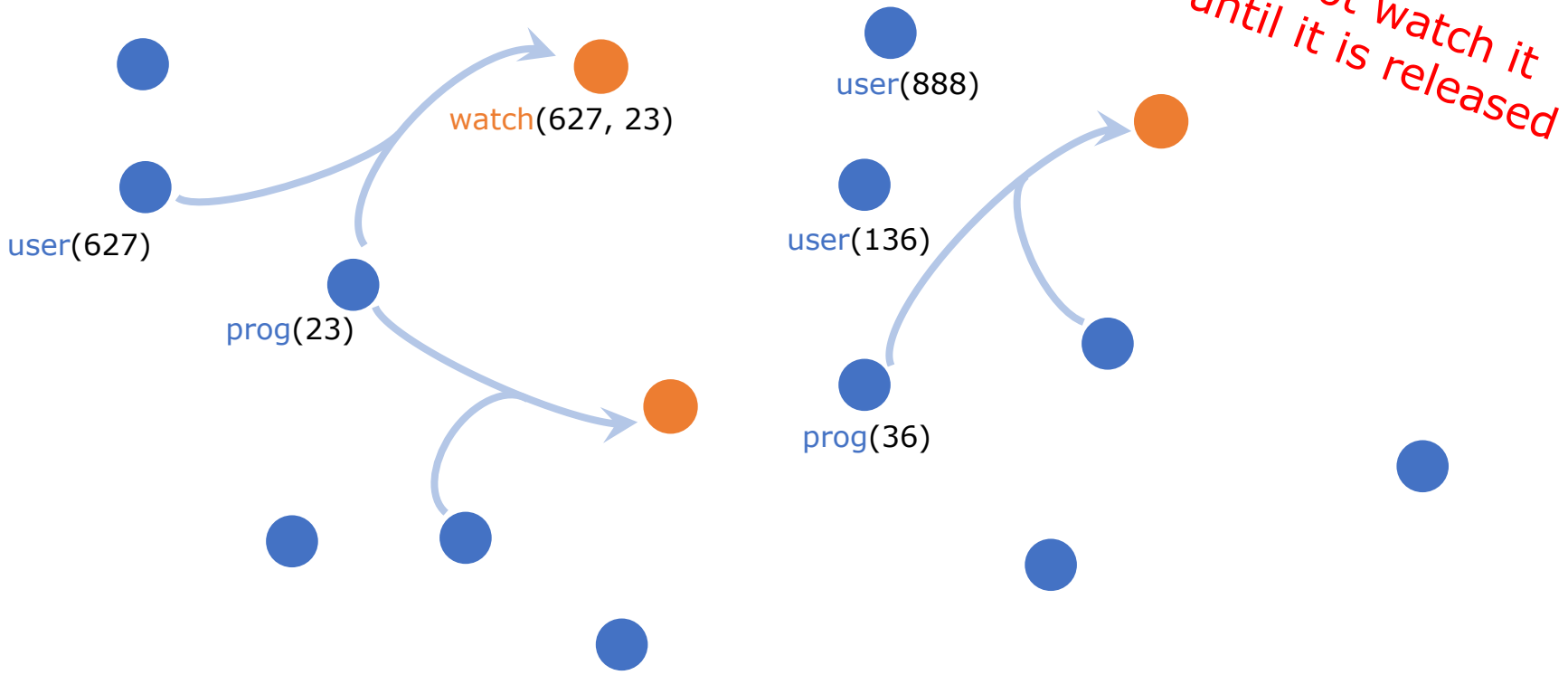

Experiment: Robots Kick/Pass/Steal

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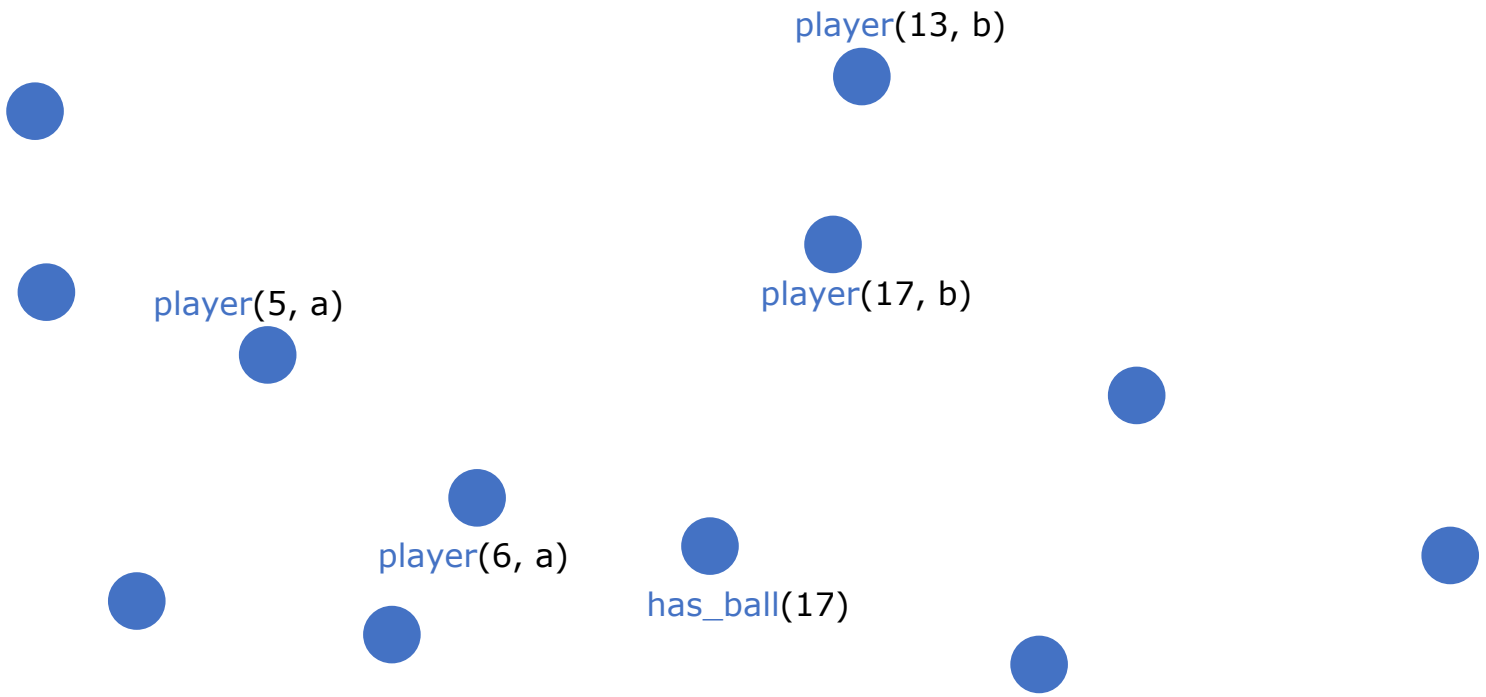
22 robot soccer players

player(Number, Team)



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kick

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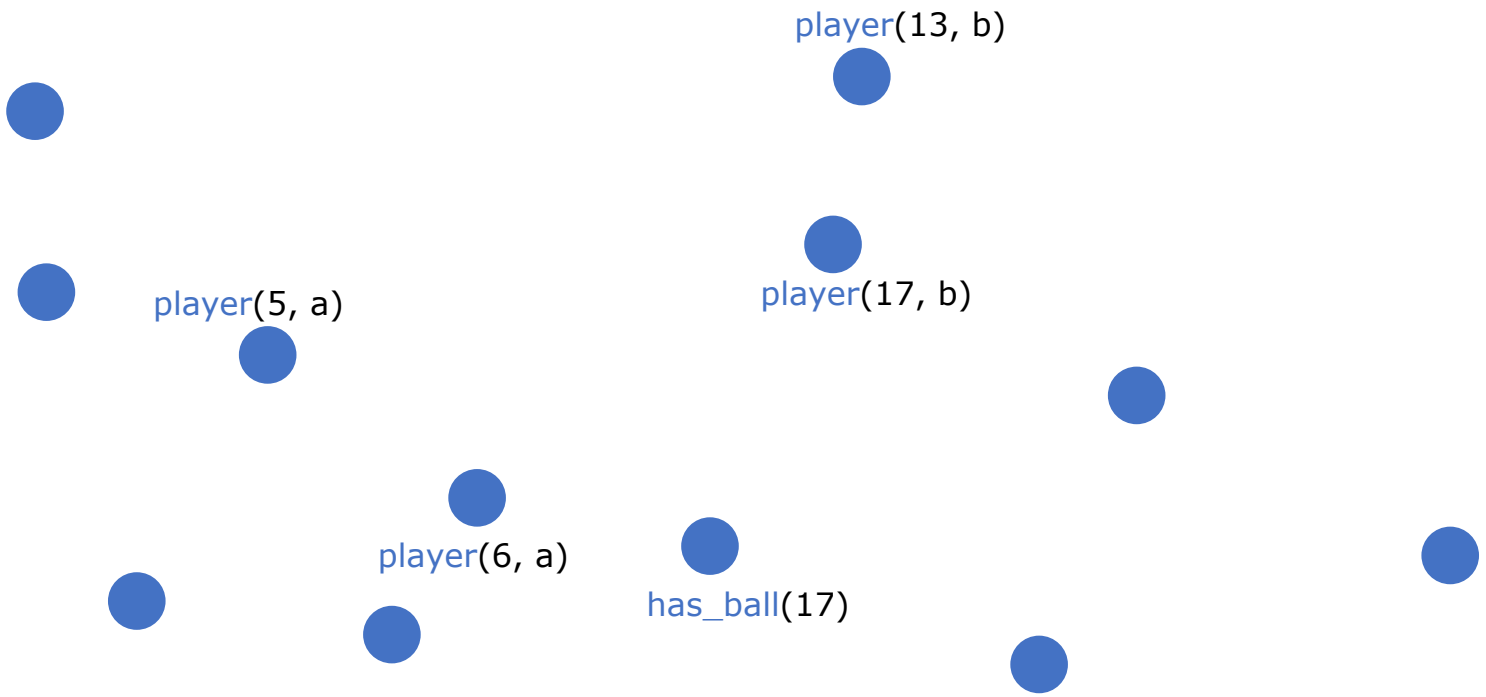

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kick only if has ball

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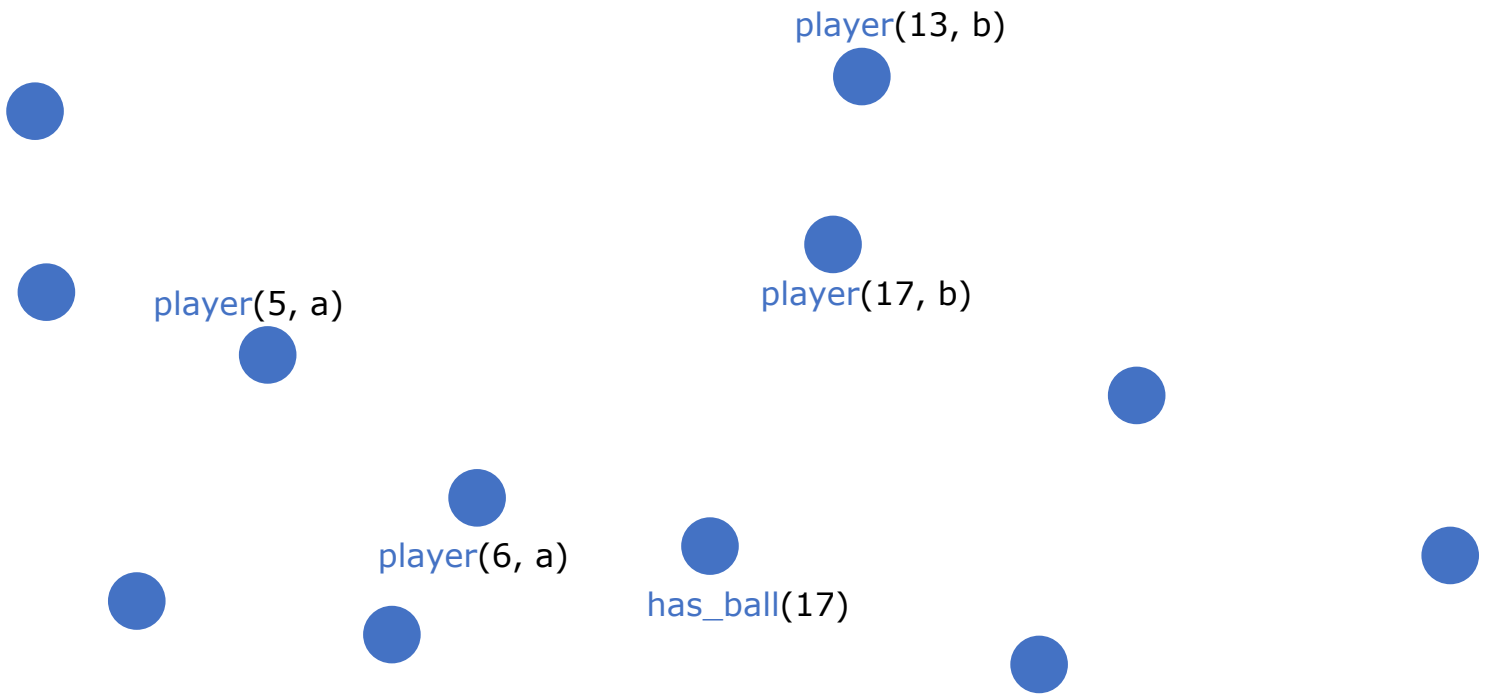

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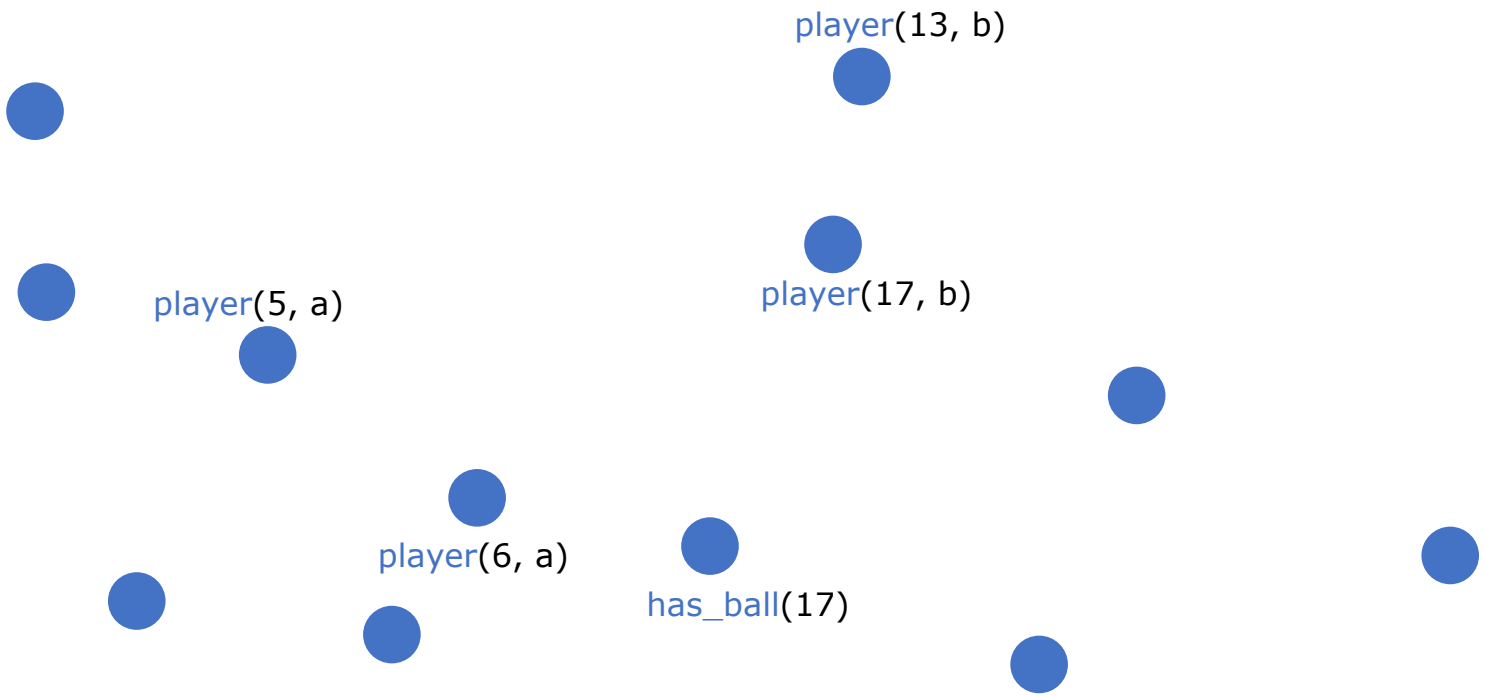

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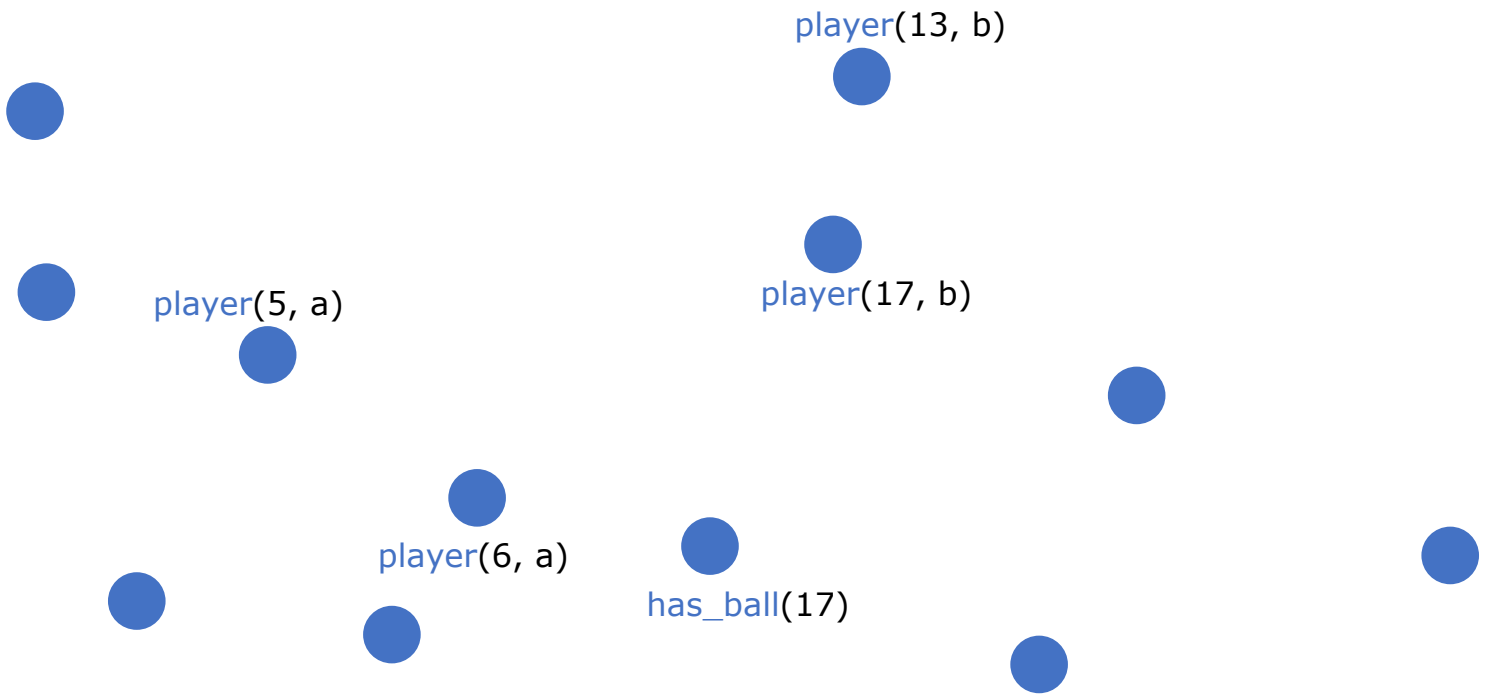

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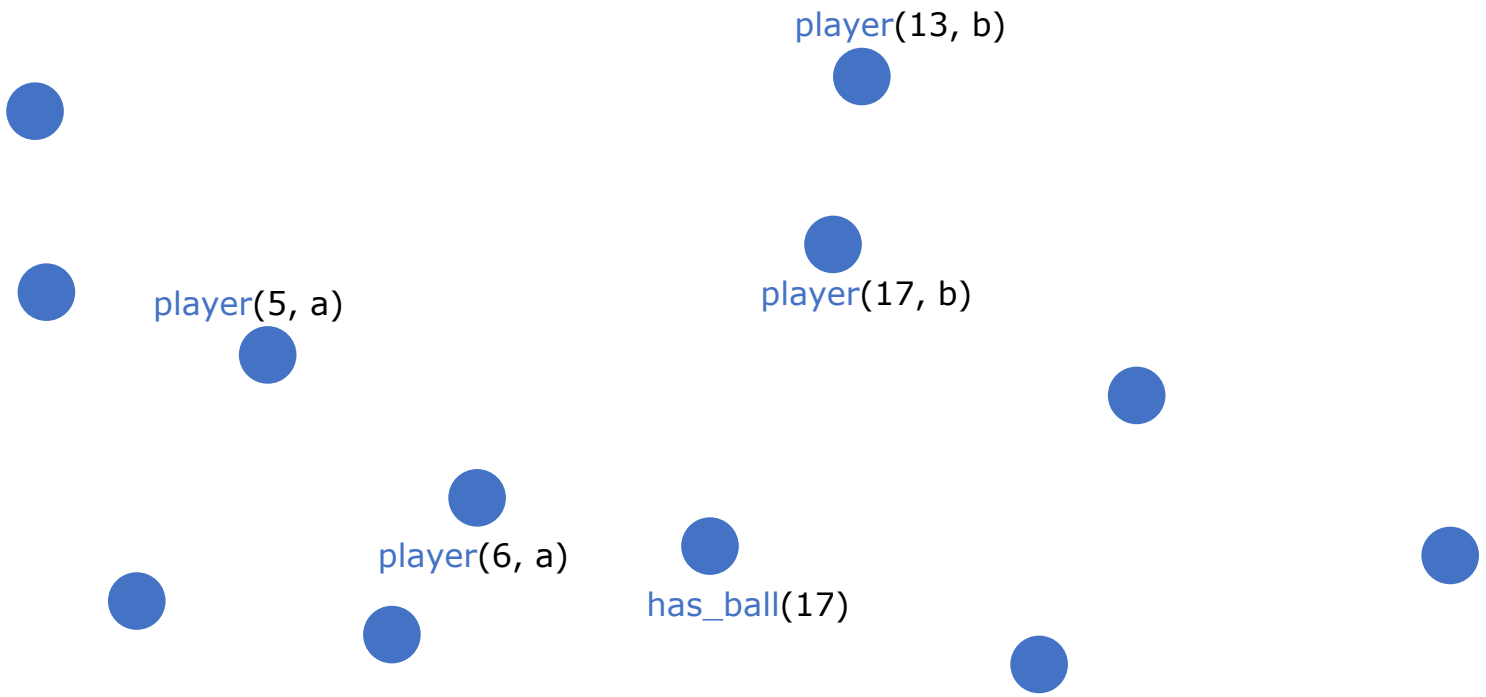

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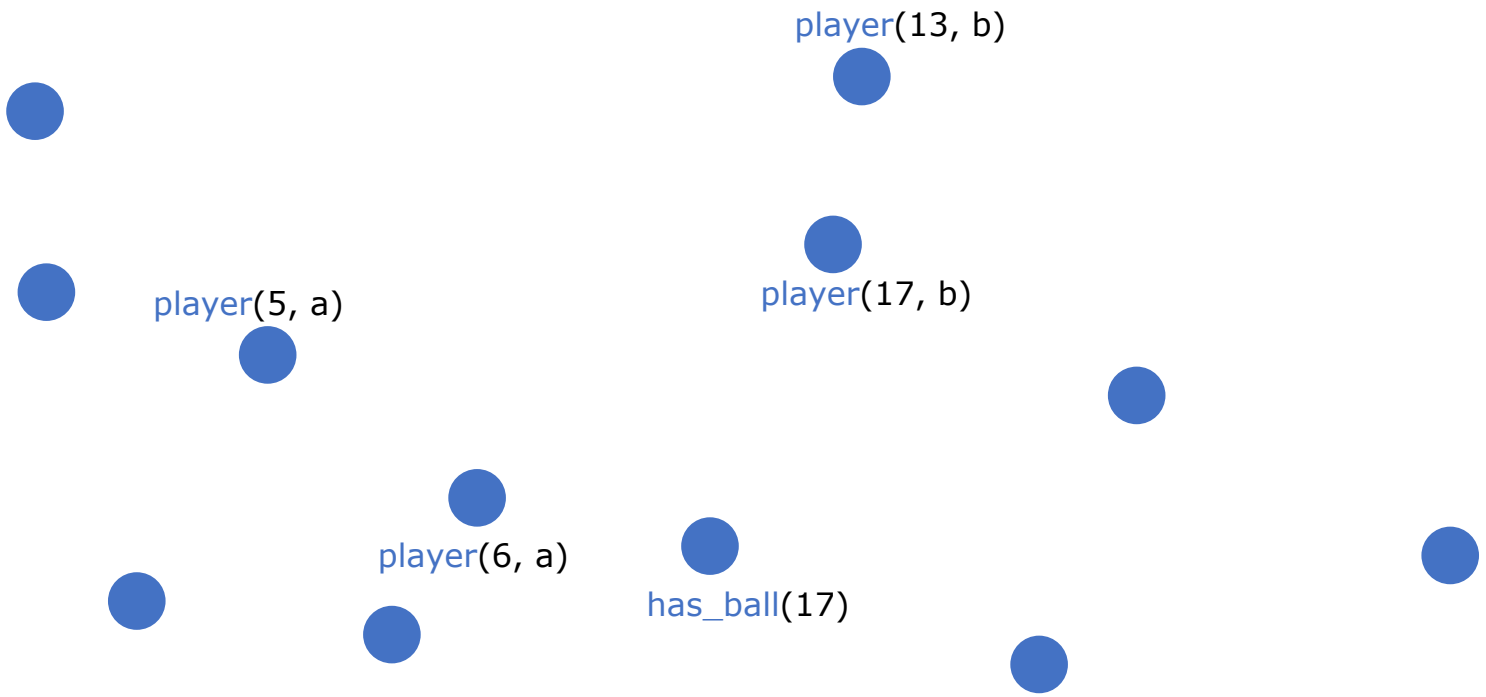

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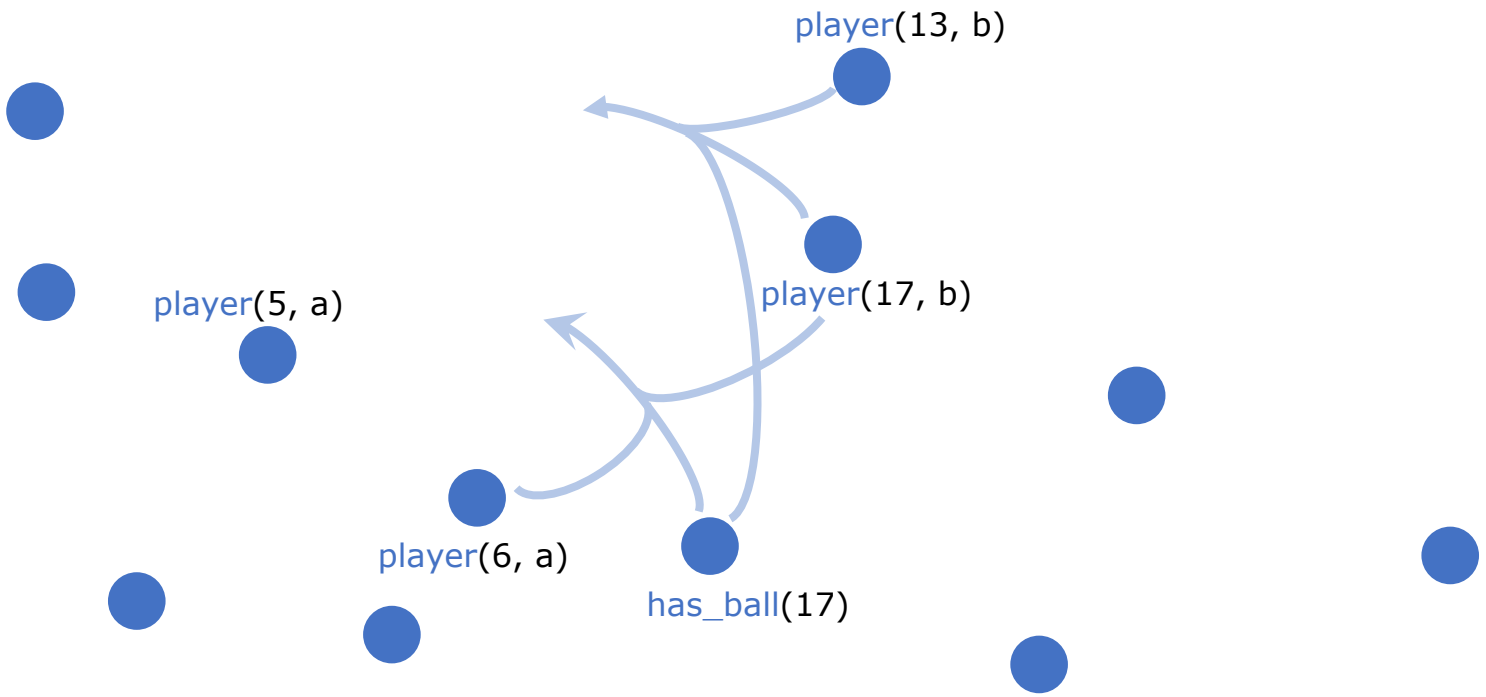

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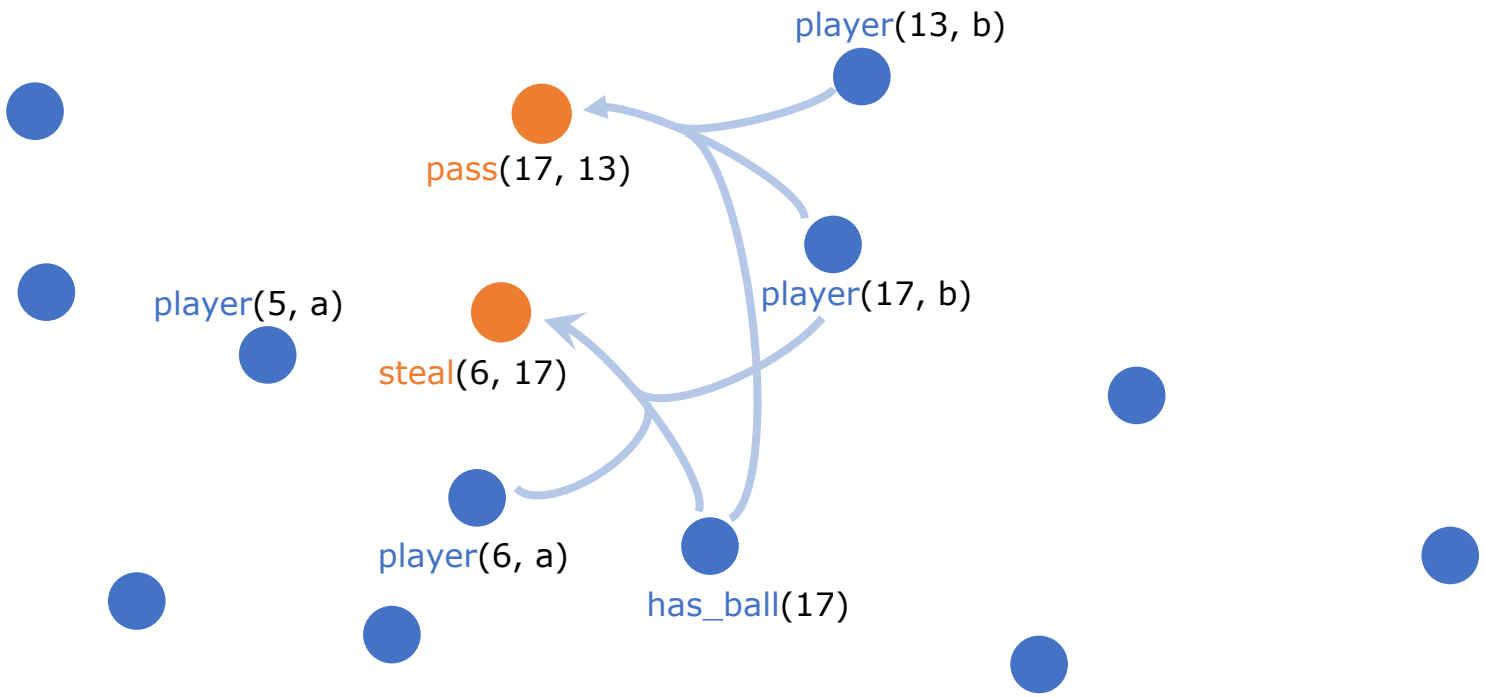

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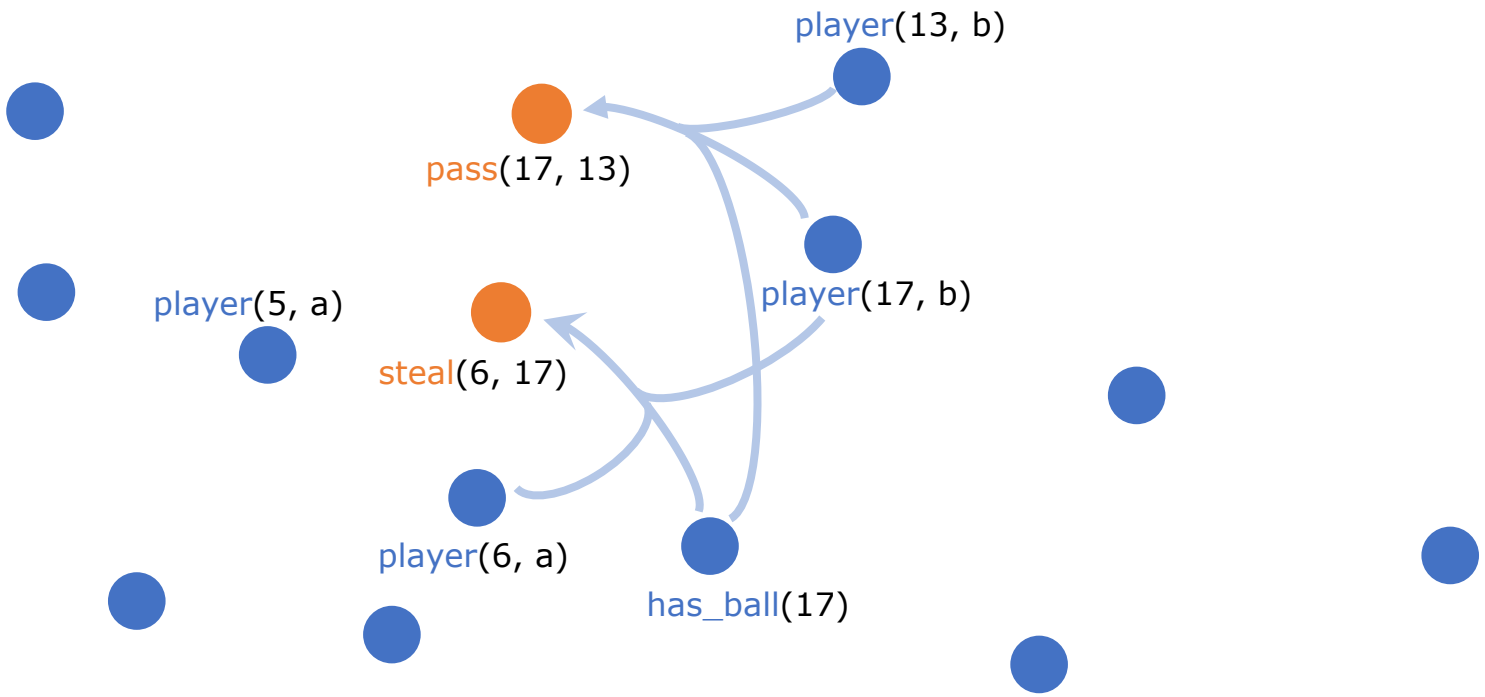

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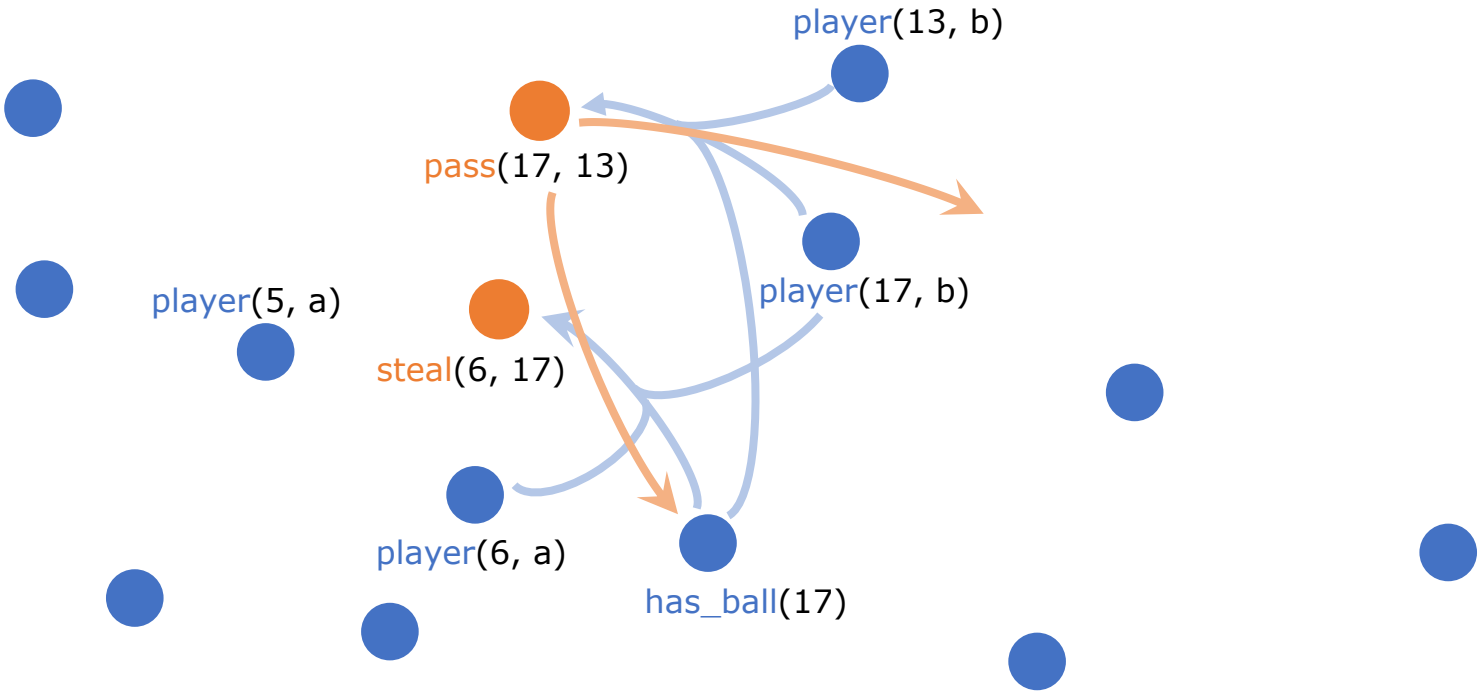

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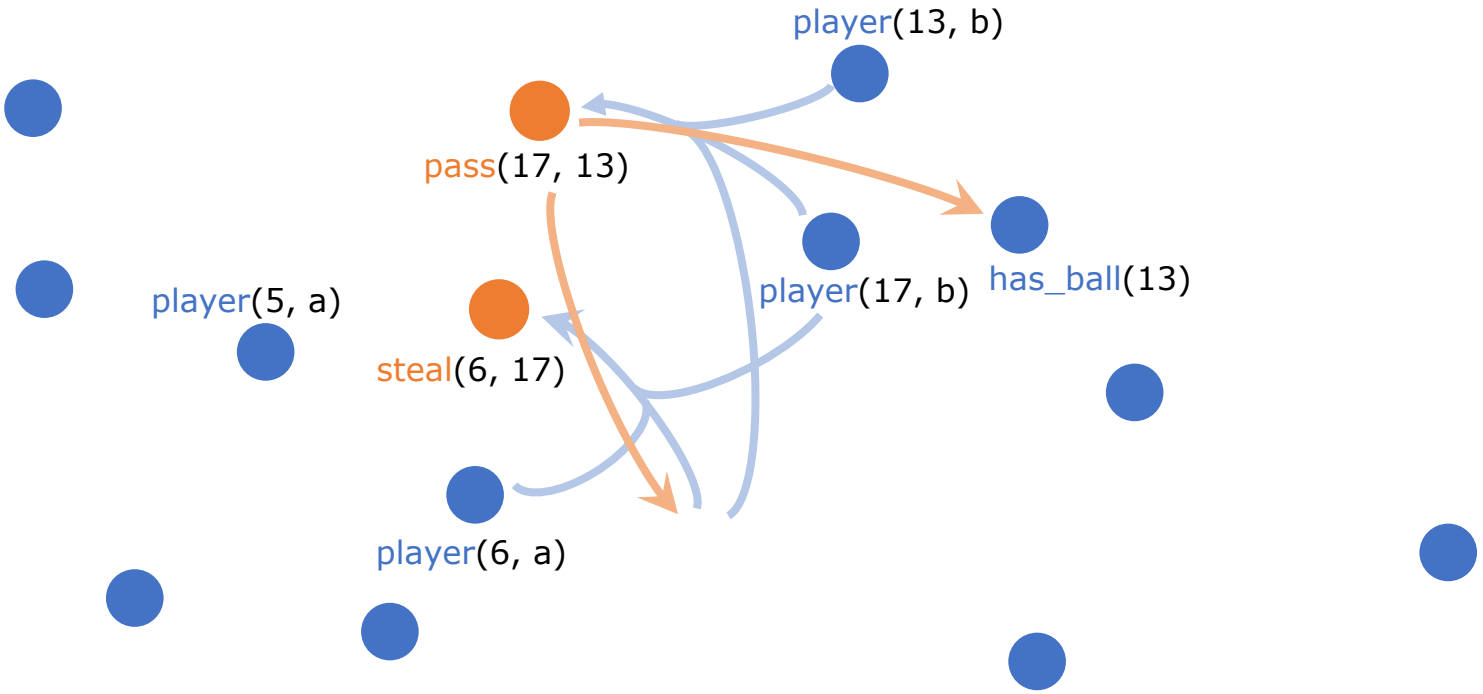

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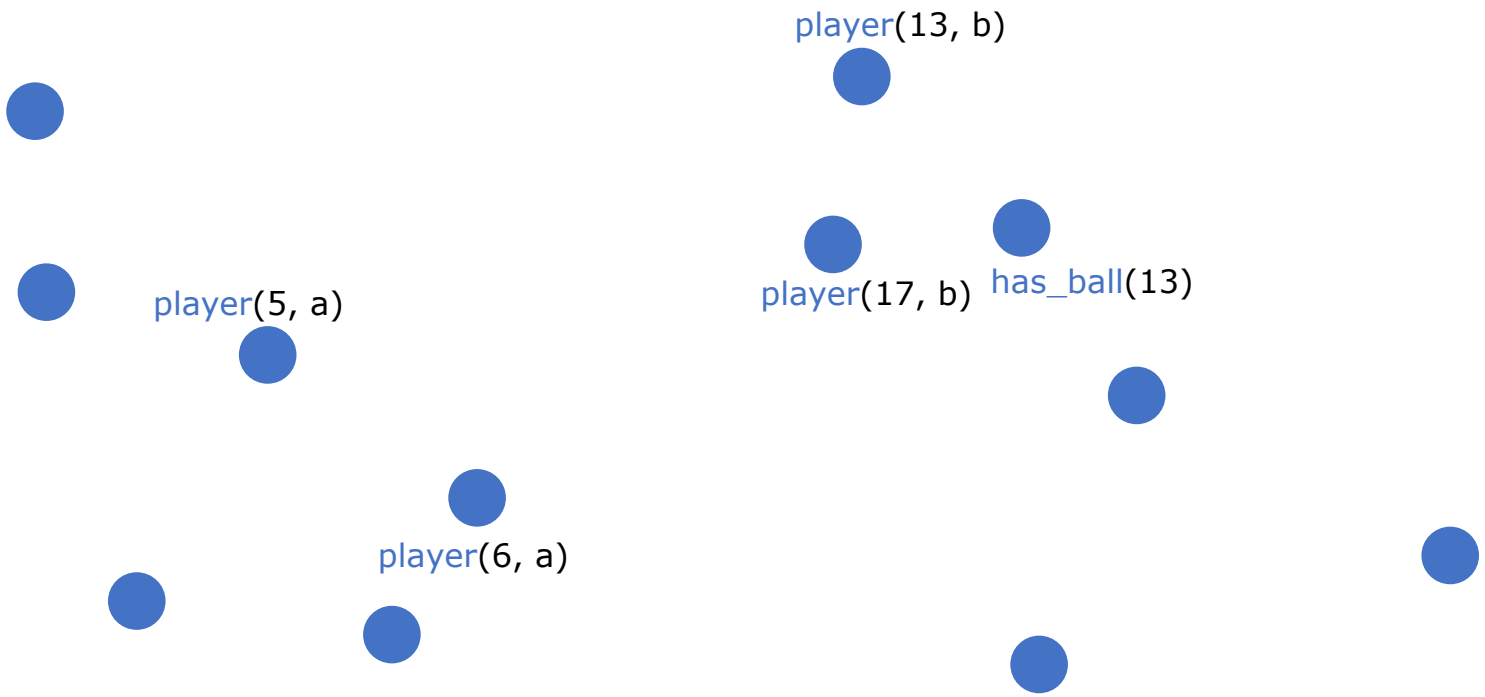

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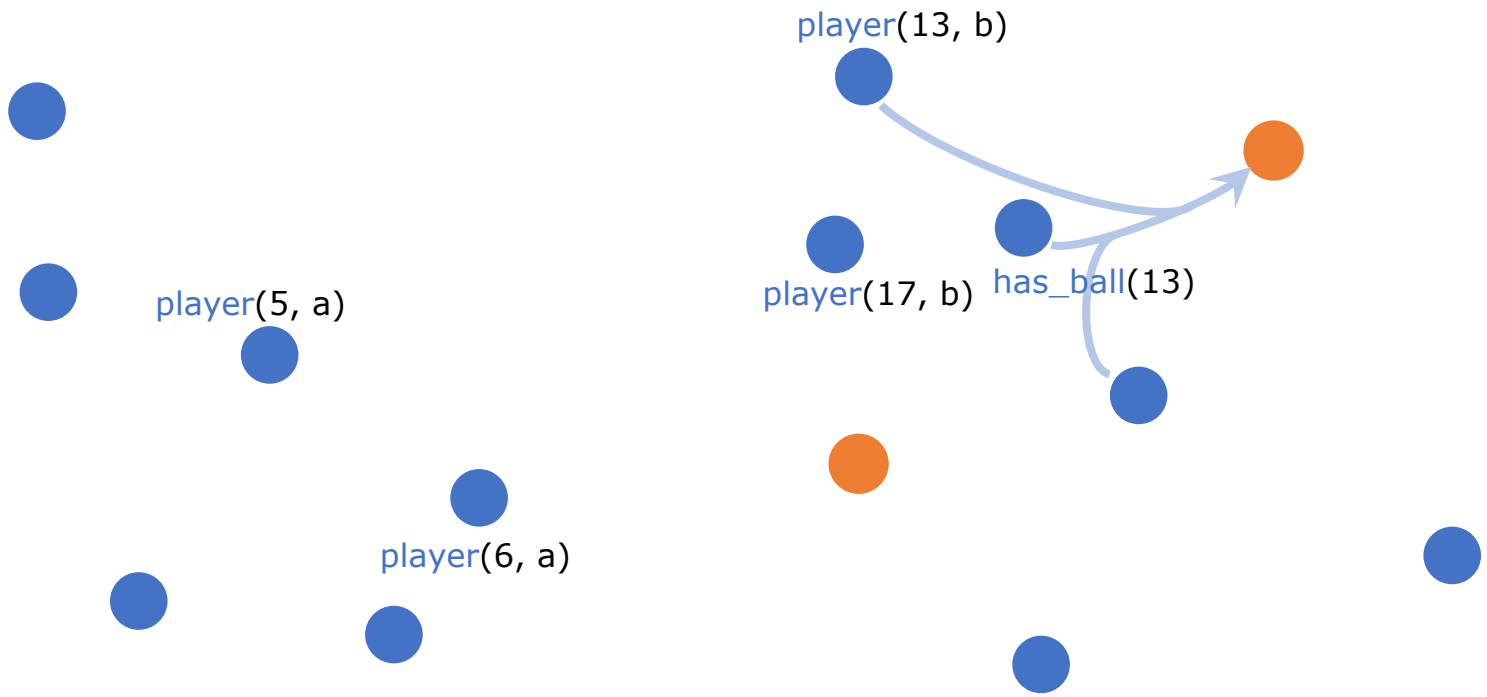
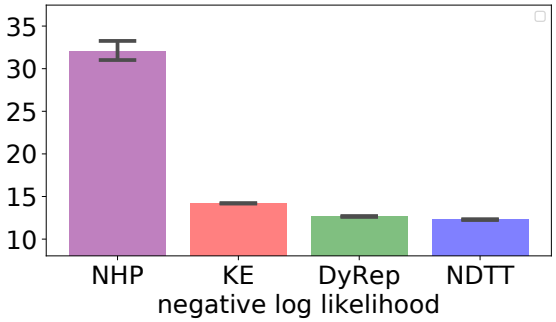
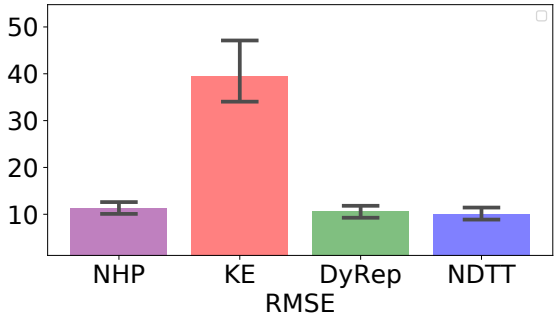
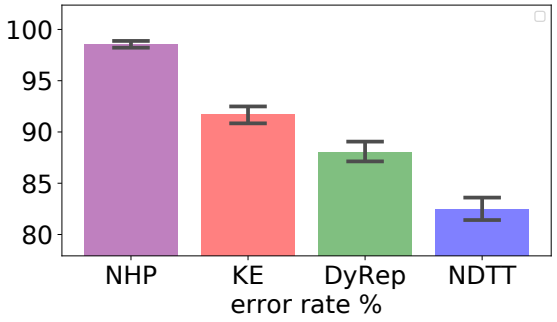


Results: NDTT > Competitors

3 error metrics (in 3 columns): smaller is better







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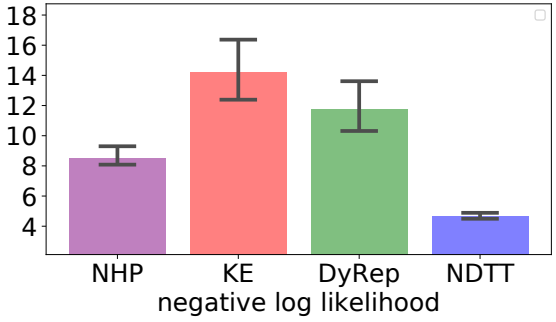
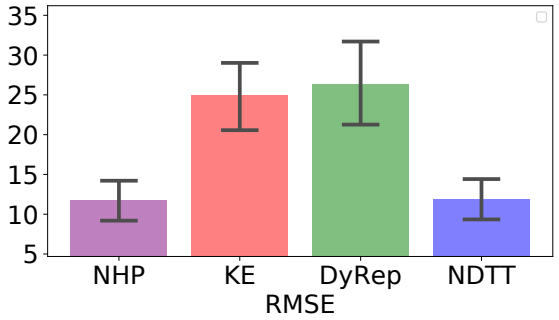
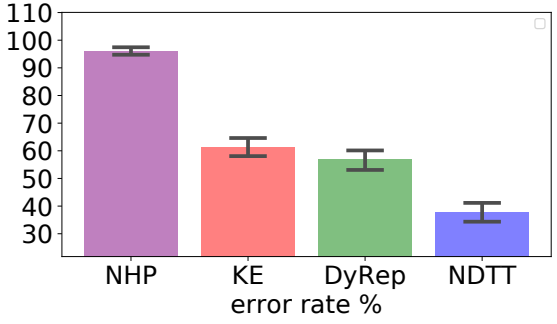
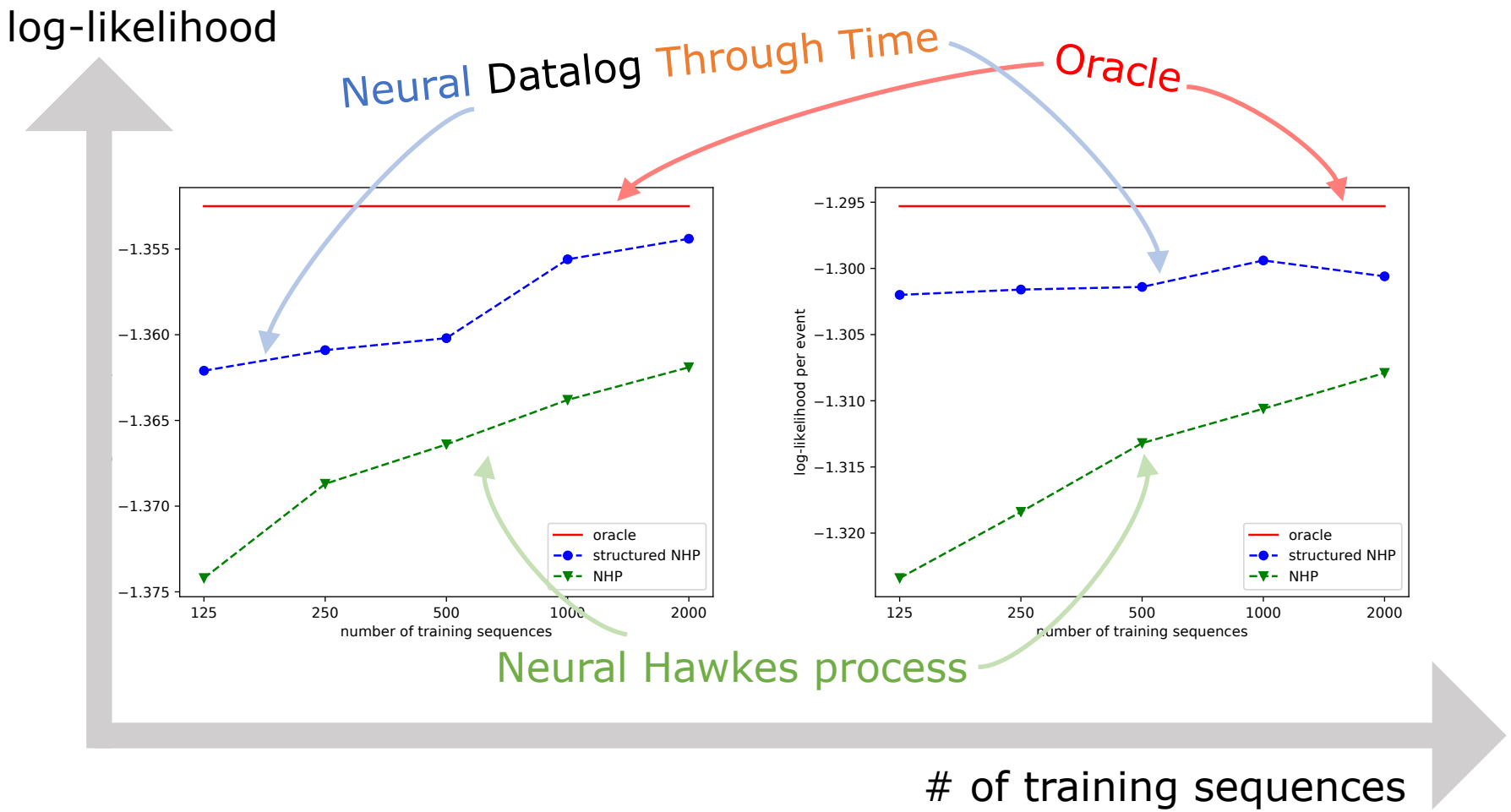






robots kick/pass/steal soccer ball

Good Generalization with Less Data



Summary: Deep Recurrent Net

Summary: **Deep Recurrent Net**

e.g., RNN
LSTM

discrete-time

Summary: **Deep Recurrent Net**

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neural Hawkes process continuous-time

Summary: **Deep Recurrent Net**

hidden
system
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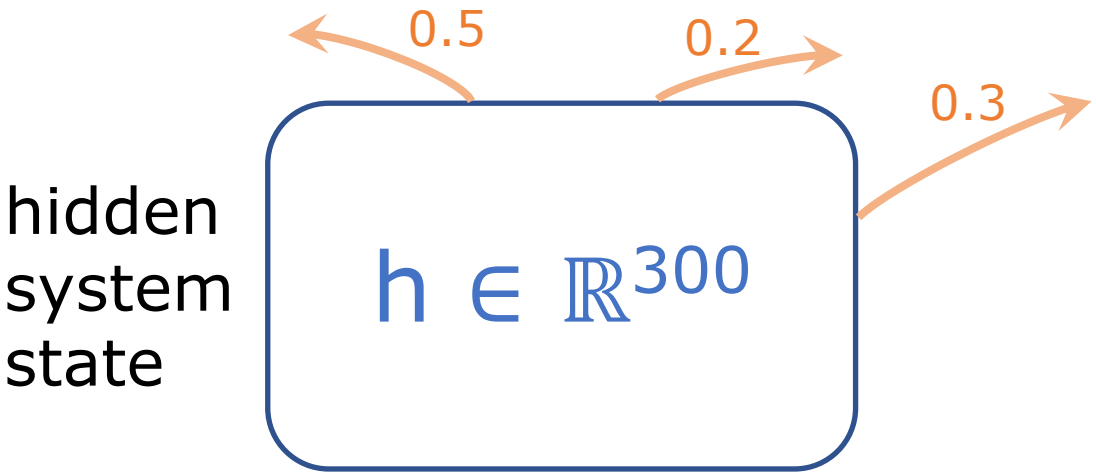

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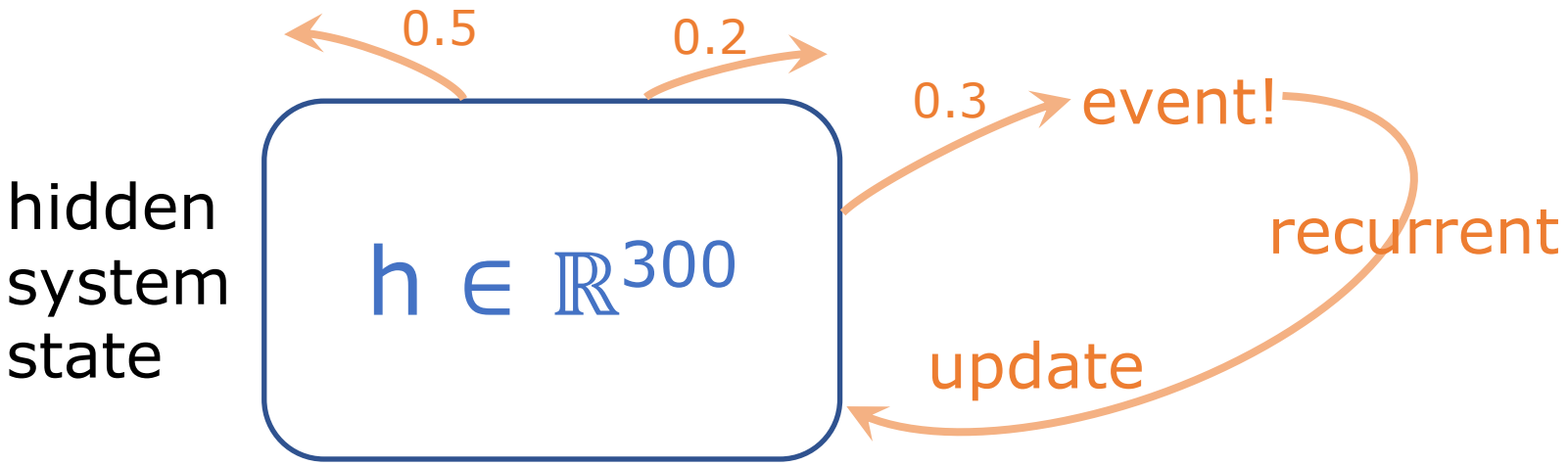

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Summary: Logic ➔ Deep Recurrent Net

hidden system state

Summary: Logic ➔ Deep Recurrent Net

distributed

hidden
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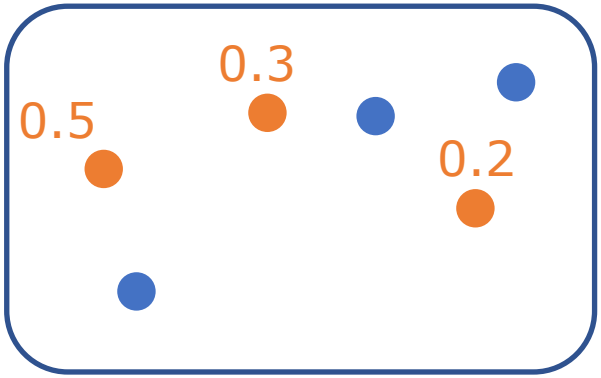

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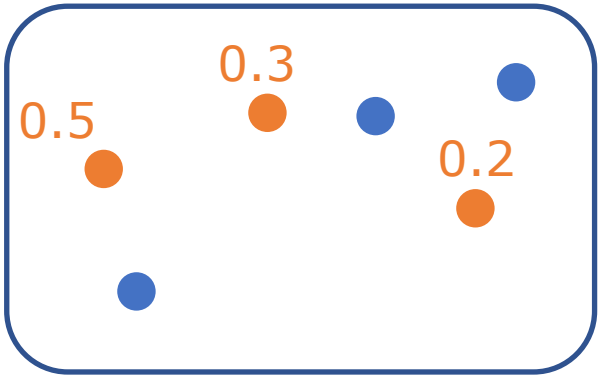

II

database of
logical facts + embeddings

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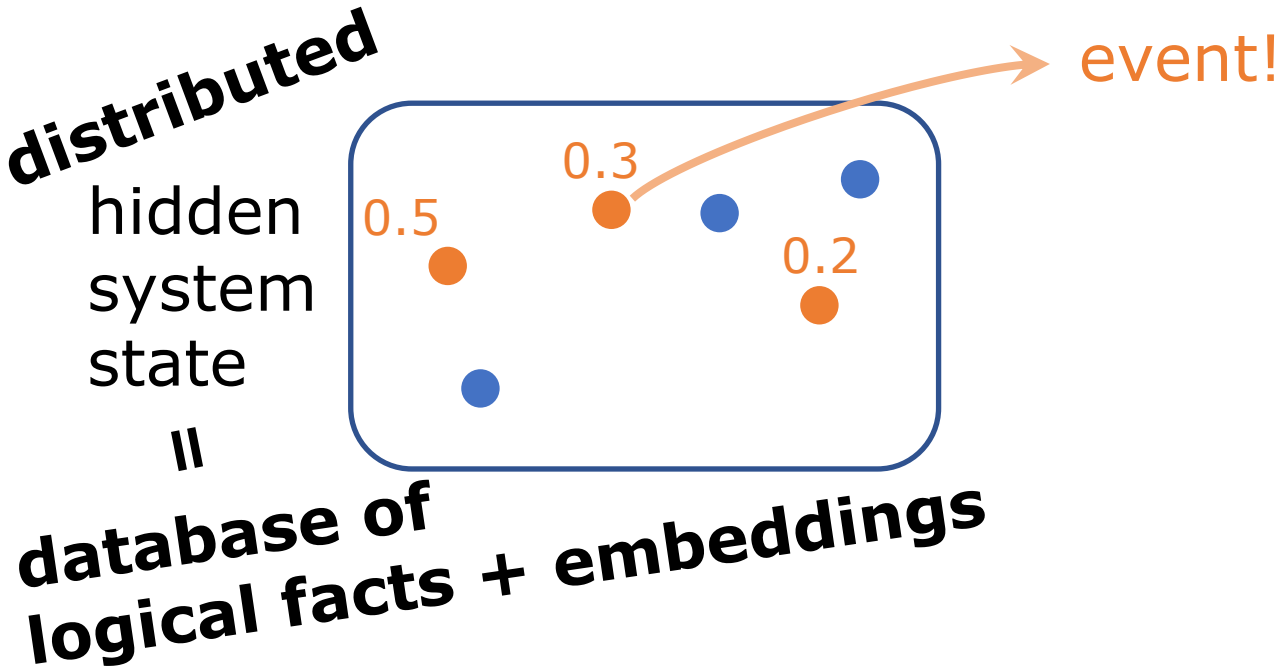

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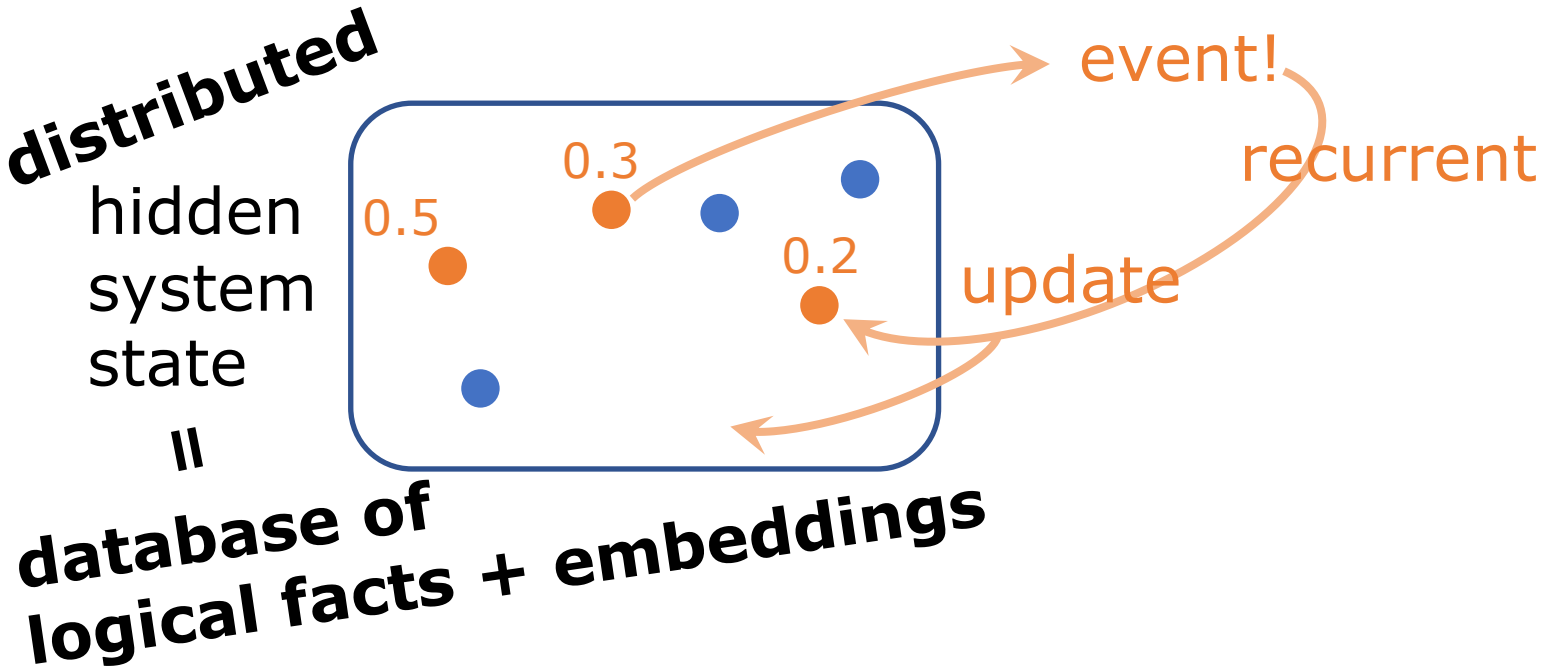

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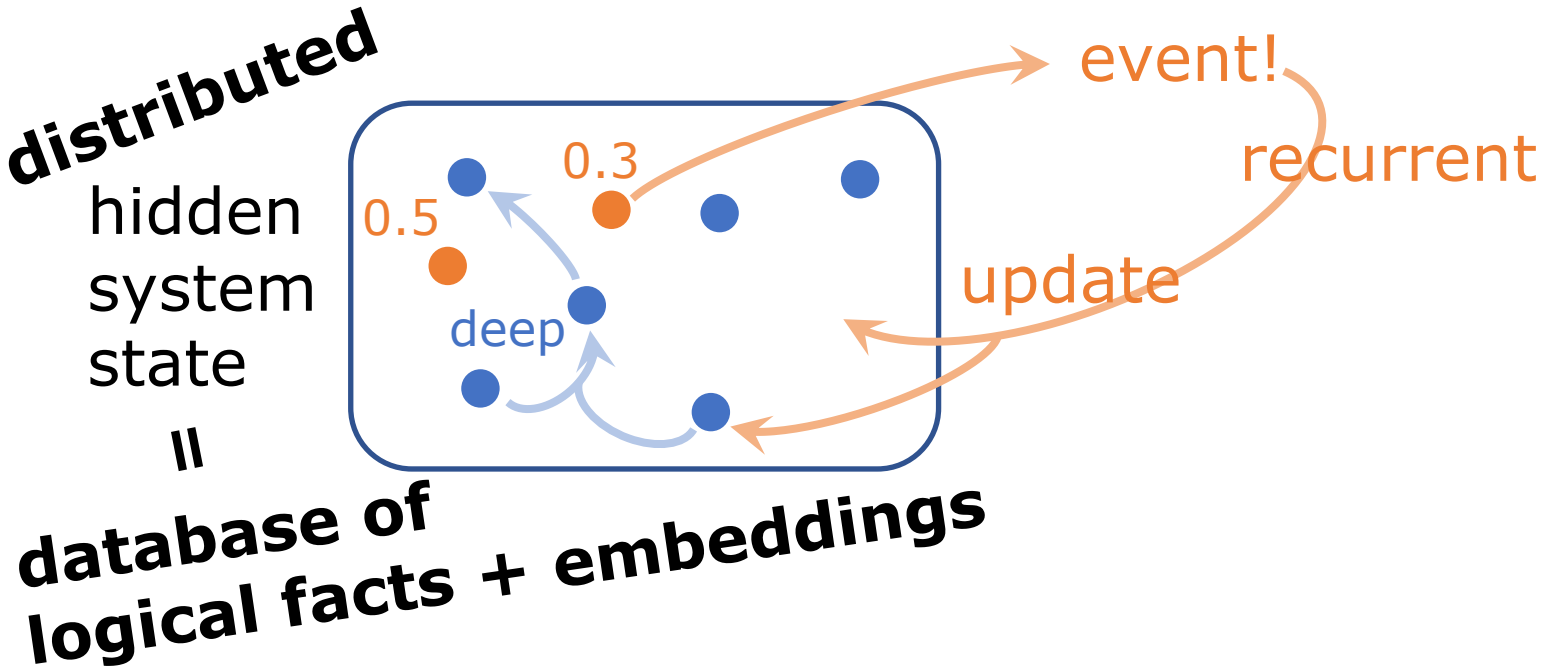

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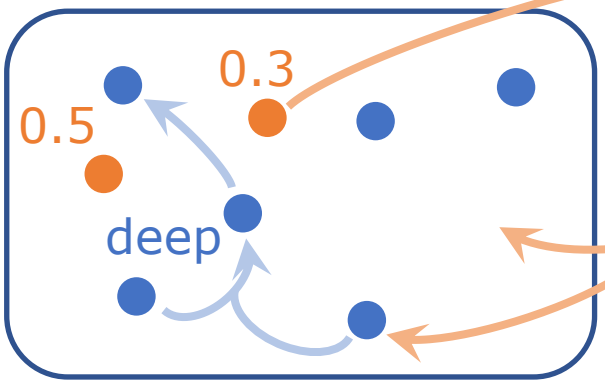

event!

recurrent

update

update derived from small rule set + learned low-dim matrices

new fact :- old fact $_1$, …

new fact ← event, …

! old fact ← event, …

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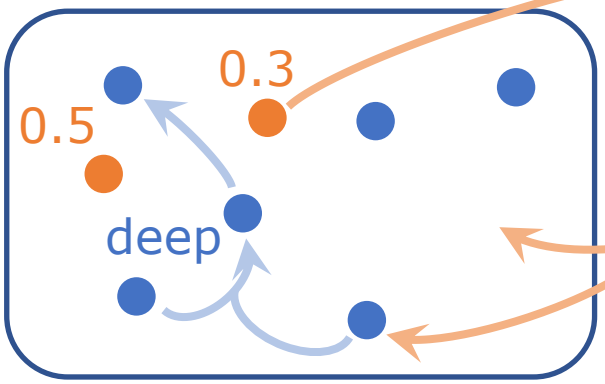

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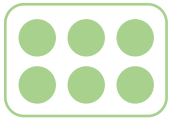

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try our code in your domain!

Neural Datalog Through Time