Context Closure: Concise Overview

December 15, 2025

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- Scalability: we must pick the most valuable, self-contained context slice, not dump everything.
- Goal: organize signals to maximize documentation value within hard context limits.

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- This is exactly the **maximum-weight closure** problem.

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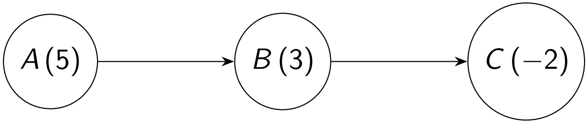
- Our use: pick the best self-contained context under size/budget constraints.

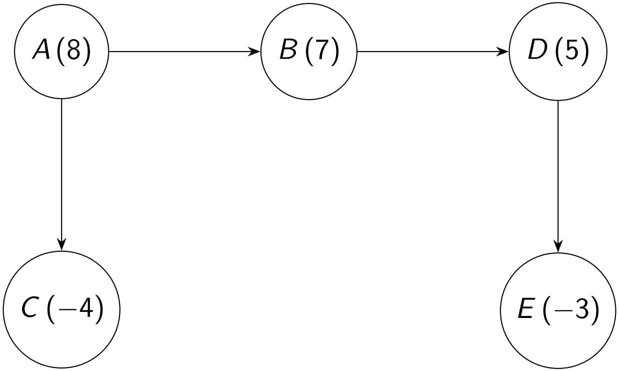
Example 1 (tiny)

$$\begin{tikzcd} A\,(5) \arrow[r] & B\,(3) \arrow[r] & C\,(-2) \end{tikzcd}$$



Optimal closure: $\{A, B, C\}$ (weight 6). This is not hard to inspect.

Example 2 (medium)



Optimal closure: $\{A, B, D\}$ (weight 20). This is not hard to inspect, but certainly more complicated than the last one.

Example 3 (larger) ... this problem can be difficult.

$$\begin{tikzcd}
A\,(6) \arrow[r] \arrow[d] & B\,(4) \arrow[r] \arrow[d] & D\,(9) \arrow[r] & G\,(2) \arrow[r] \arrow[dd] & H\,(-6) \\
C\,(-5) \arrow[rr] & E\,(7) \arrow[r] \arrow[dr] & F\,(-3) \arrow[d] & & \\
 & & I\,(5) \arrow[r] & J\,(4) \arrow[dl, no head] & \\
 & & {} & &
\end{tikzcd}$$

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- This construction actually solves a more general problem than preparing LLM context windows.
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- LLM-driven docs are one special case; the method applies to broader task selection.

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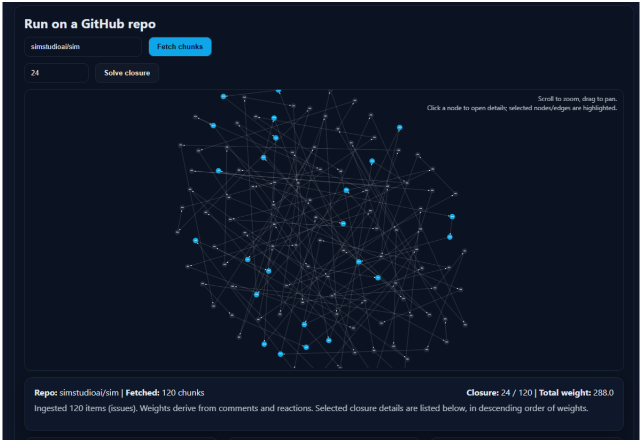
System Screenshots I


Run on a GitHub repo
simstudioai/sim
Fetch chunks
24
Solve closure
Scroll to zoom, drag to pan.
Click a node to open details; selected nodes/edges are highlighted.

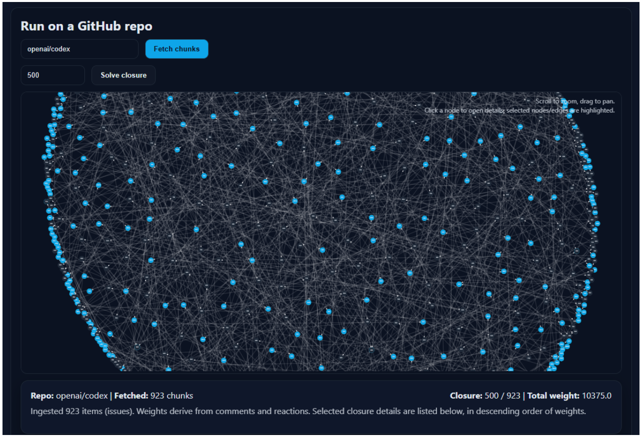
Repo: simstudioai/sim | **Fetched:** 120 chunks **Closure:** 24 / 120 | **Total weight:** 288.0

Ingested 120 items (issues). Weights derive from comments and reactions. Selected closure details are listed below, in descending order of weights.

Figure: Example: simstudioai/sim

This is a moderately-sized example of a size 24 closure against 120 total nodes.

System Screenshots II


Run on a GitHub repo
openai/codex
Fetch chunks
500
Solve closure
Scroll to zoom, drag to pan.
Click a node to open details; selected nodes/edges are highlighted.

Repo: openai/codex | **Fetched:** 923 chunks **Closure:** 500 / 923 | **Total weight:** 10375.0

Ingested 923 items (issues). Weights derive from comments and reactions. Selected closure details are listed below, in descending order of weights.

Figure: Example: openai/codex

This is a huge example of a size 500 closure against 923 total nodes.

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- Serve: API returns graph; closure solver returns selected nodes; UI renders graph and selected chunk details.