Sliding Context Window

December 15, 2025

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- LLM context windows (and human attention) are bounded.
- 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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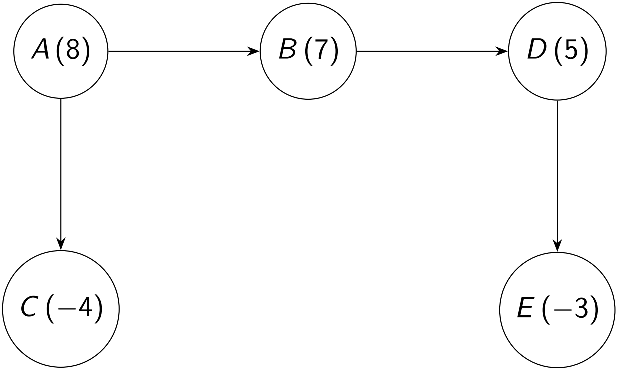
- Our use: pick the best self-contained context under size/budget constraints.

Example 1 (tiny)

$$A\,(5) \longrightarrow B\,(3) \longrightarrow C\,(-2)$$

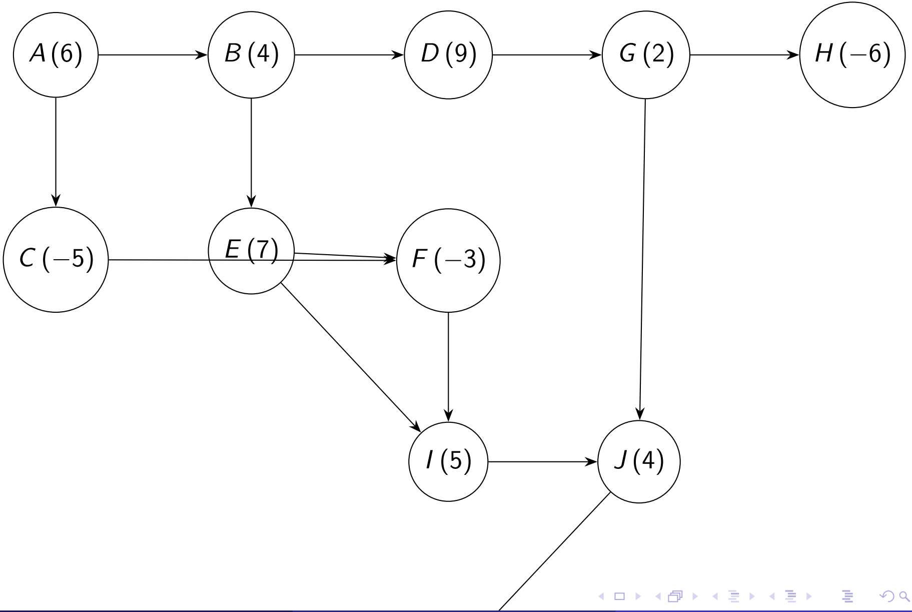
Optimal closure: $\{A, B, C\}$ (weight 6). This is not hard to inspect.

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.



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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

Figure: Example: simstudioai/sim

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

System Screenshots II

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.