RevDecode:
Enhancing Binary Function Matching with Context-Aware Graph Representations and Relevance Decoding

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Problem Definition

- What is **Function matching**?

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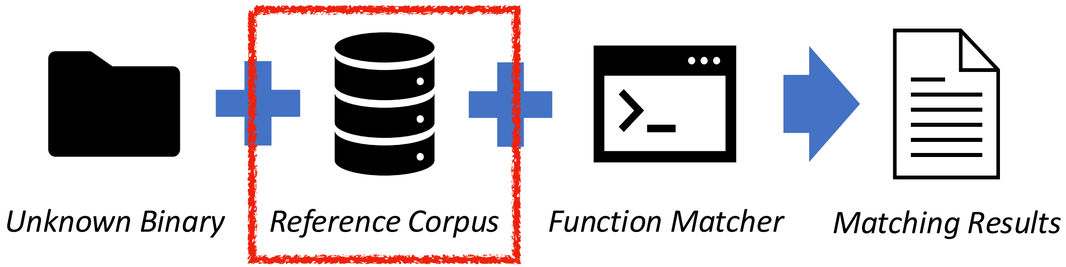

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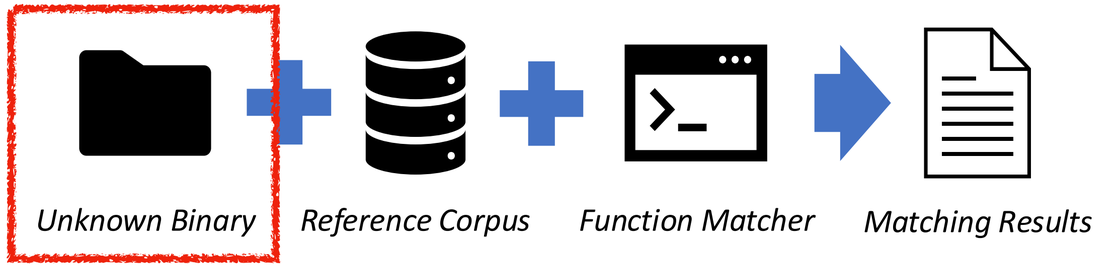

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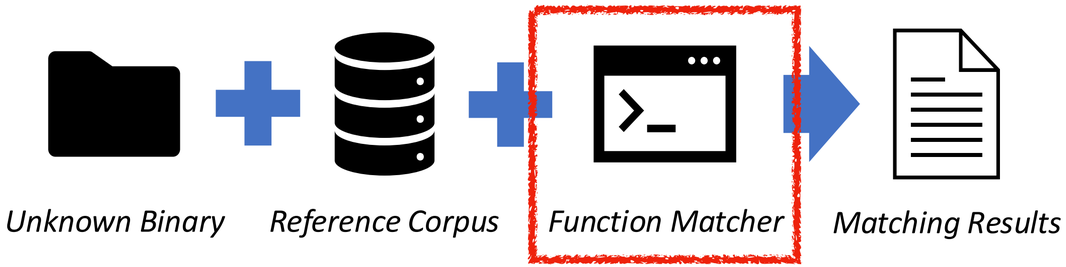

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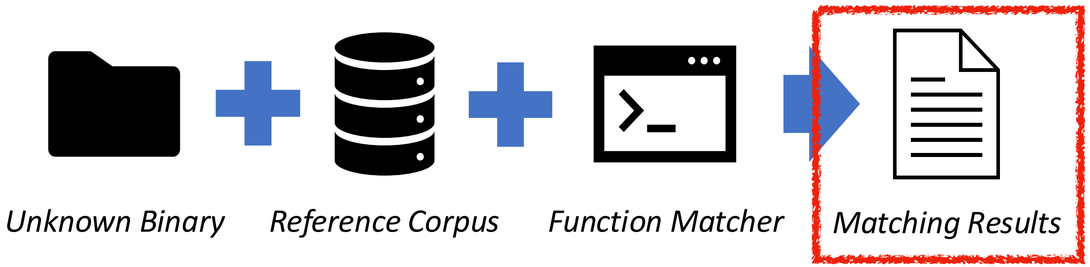

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- What is **Function matching**?

- **It's useful in Reverse Engineering** for:
  - Identifying libraries in embedded firmware
  - Isolating vulnerable functions
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- **It's useful in Reverse Engineering** for:
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- **It's hard** because of:
  - Compilation settings
  - Optimization levels
  - Version differences

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Existing Approaches

- Solutions to the function matching problem, e.g. BSim, discovRE, SAFE, Gemini, use a variety of techniques:
  - Control flow structures and gadgets
  - Instruction and function embeddings
  - Signature matching
- Generally, these approaches generate abstract representations of functions and produce a similarity score, which measures how similar the unknown function to some other function in the corpus.

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Limitations in Existing Approaches

- **Similarity vs. Relevance**
  - Matchers focus on **similarity**, but reverse engineers prioritize meaningful insights (**relevance**)

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    - An older version from *libssl-3.0.2* in the corpus is more meaningful for reverse engineers, but it only has a 0.44 similarity score
    - Even though this older version has lower similarity score, it is more relevant than *elf32_arm_size_stubs* from *libbfd-2.30*

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Limitations in Existing Approaches

- **Incomplete Corpora**
  - Impractical to have exhaustive function database
  - E.g. Corpus includes the *libbfd-1.0* to *3.0*, but the unknown binary has functions from *libbfd-3.5*

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- **Ambiguous Matches**
  - Common or similar functions difficult to distinguish
  - E.g. The same function from different versions of the same library

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RevDecode

Key Idea

Relevance Decoding from Context

- Identify function relevance by leveraging surrounding contextual information
- Context includes interdependencies and contextual relationships—from both individual functions and their binary environment
- Relevance decoding builds on the observation that existing matchers overlook the surrounding binary context—such as preceding and succeeding code segments—which provides insights into function relationships

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Key Idea
RevDecode

- Employs a graph representation to capture contextual signals and improve matching accuracy
- Not a new function-matching technique but a framework designed to enhance the accuracy of any underlying function matcher
- Bridges the gap between similarity and relevance, offering a more comprehensive solution to function matching challenges.

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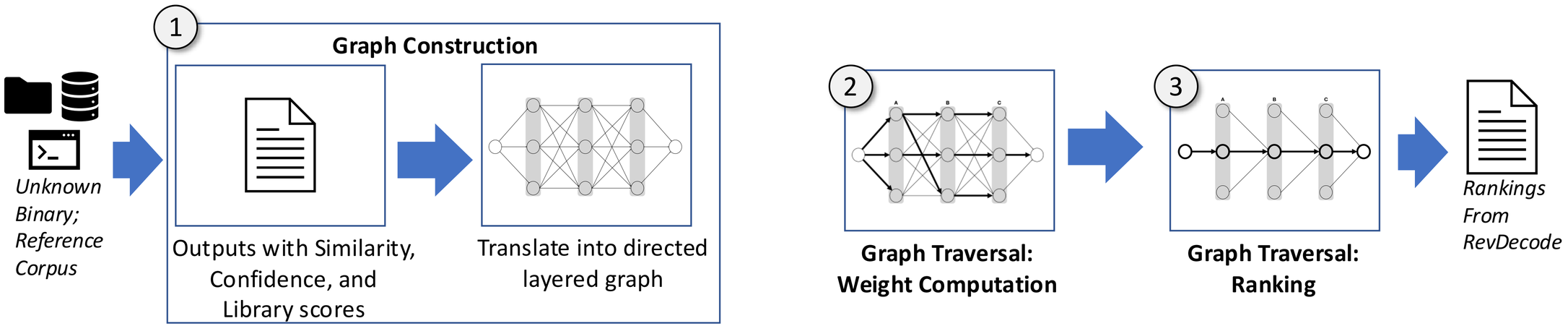
RevDecode Overview



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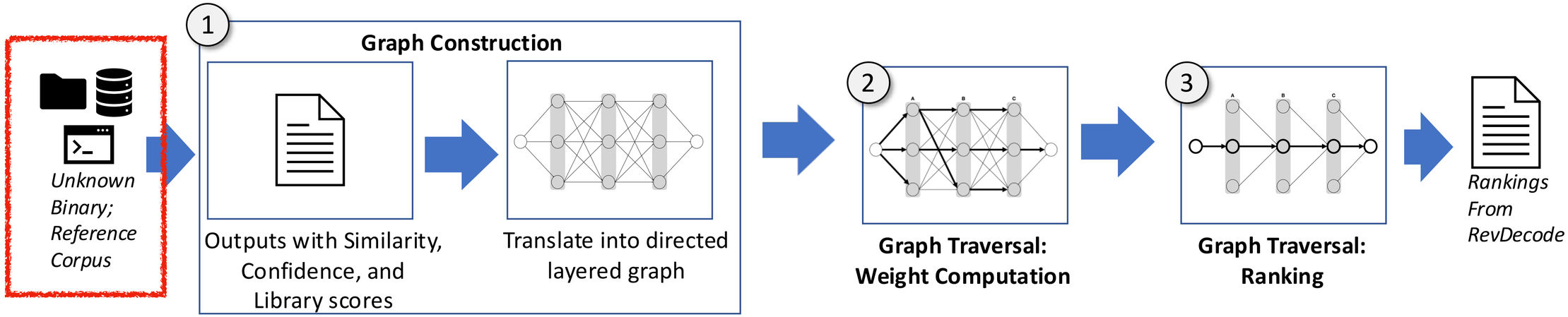

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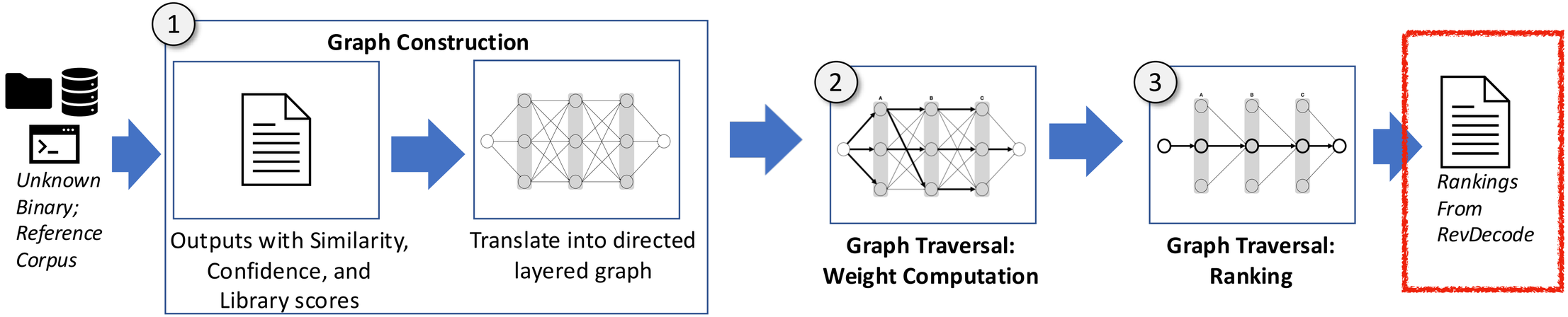

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- **Input**: Unknown binary, reference corpus
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- **Three phases**:
  1. Graph Construction
  2. Graph Traversal: Weight Computation
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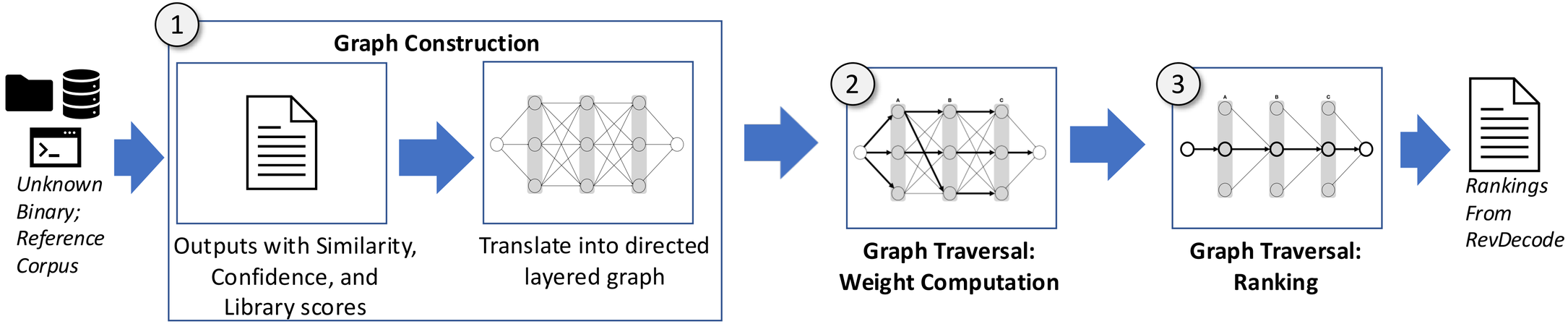

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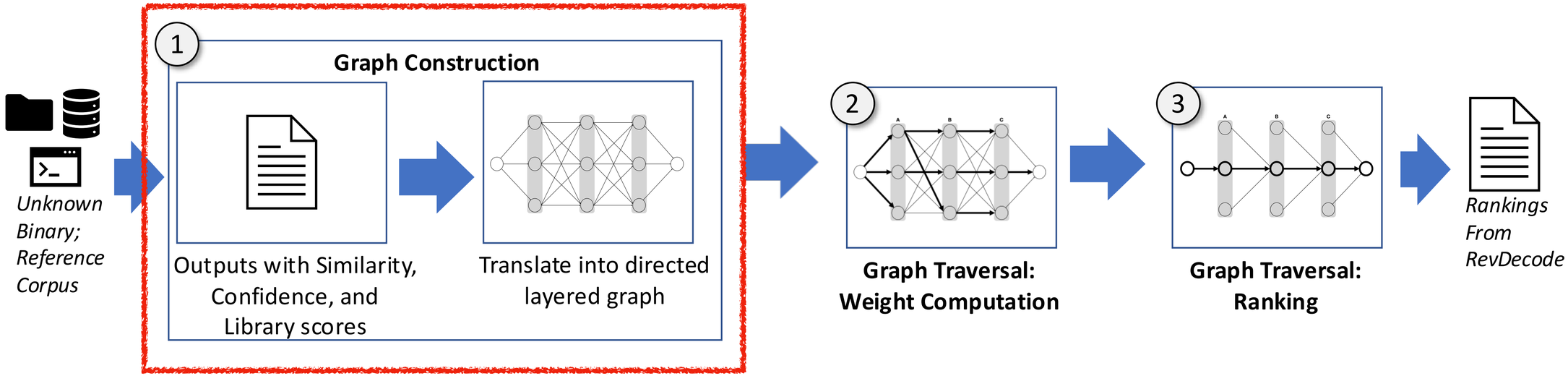
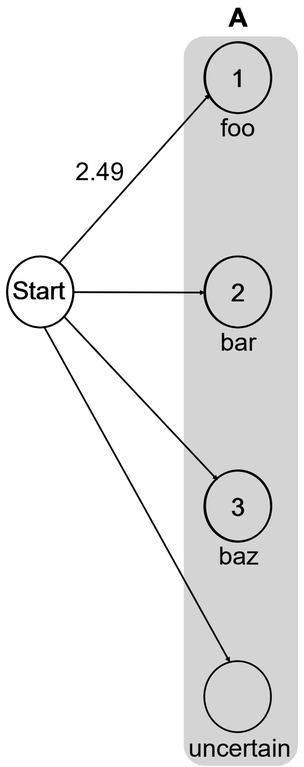


Phase 1
Graph Construction

- **Idea:** Translating function matcher outputs to a directed layered graph representation and encode function interdependencies into the graph by setting **connections** between nodes and **weights** on edges



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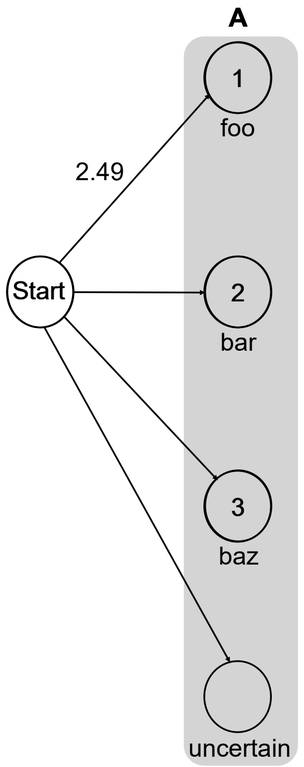

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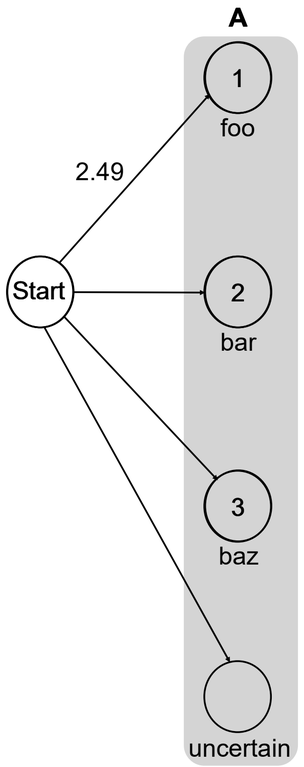

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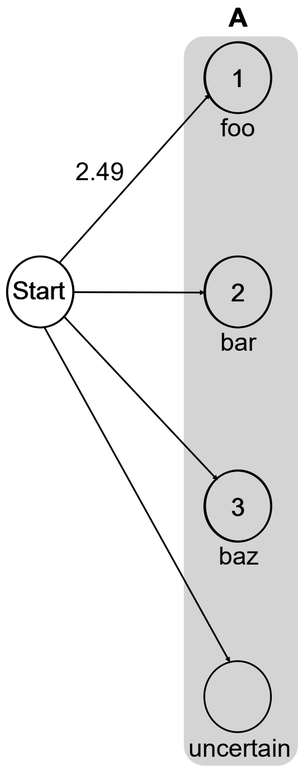
- Uncertain nodes manage incomplete corpora



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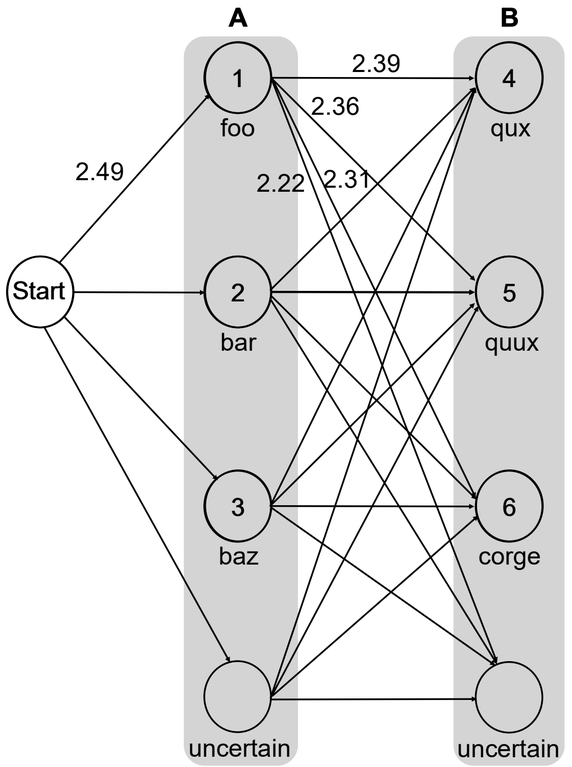

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- **Weights** are the combination of:
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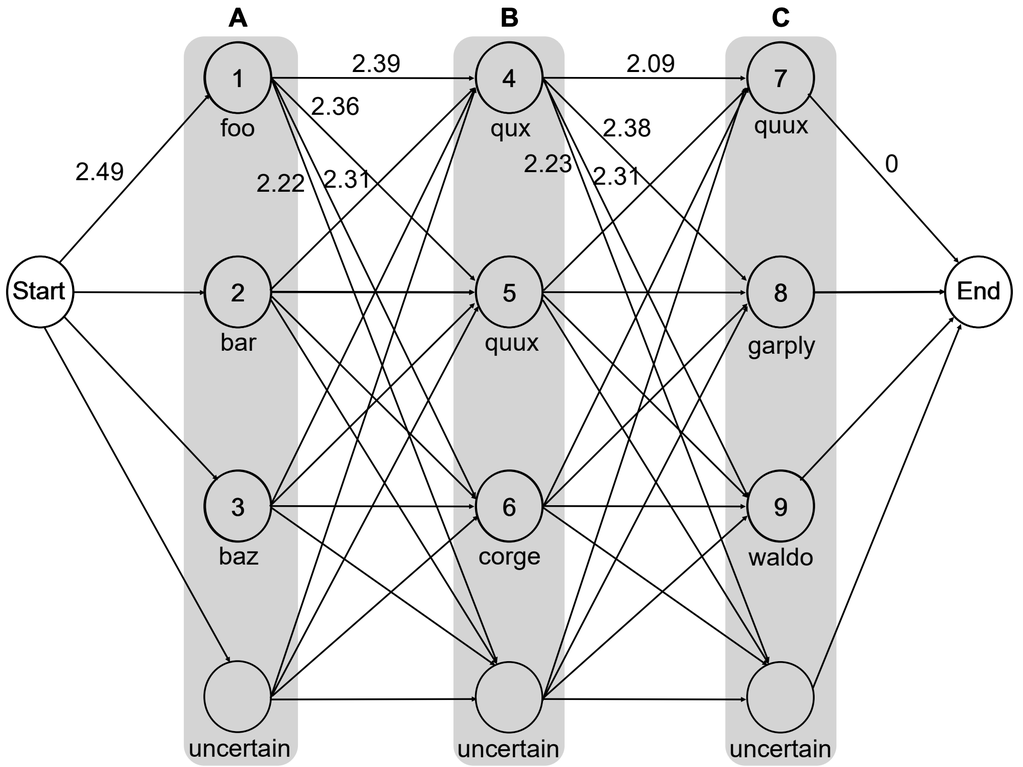

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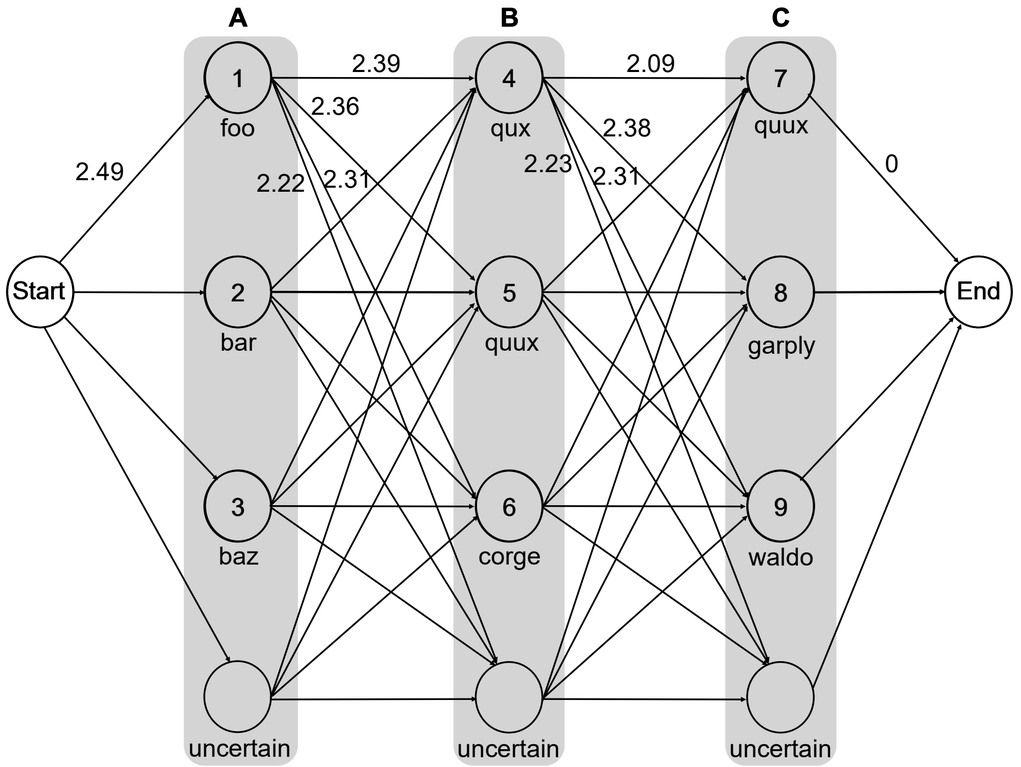

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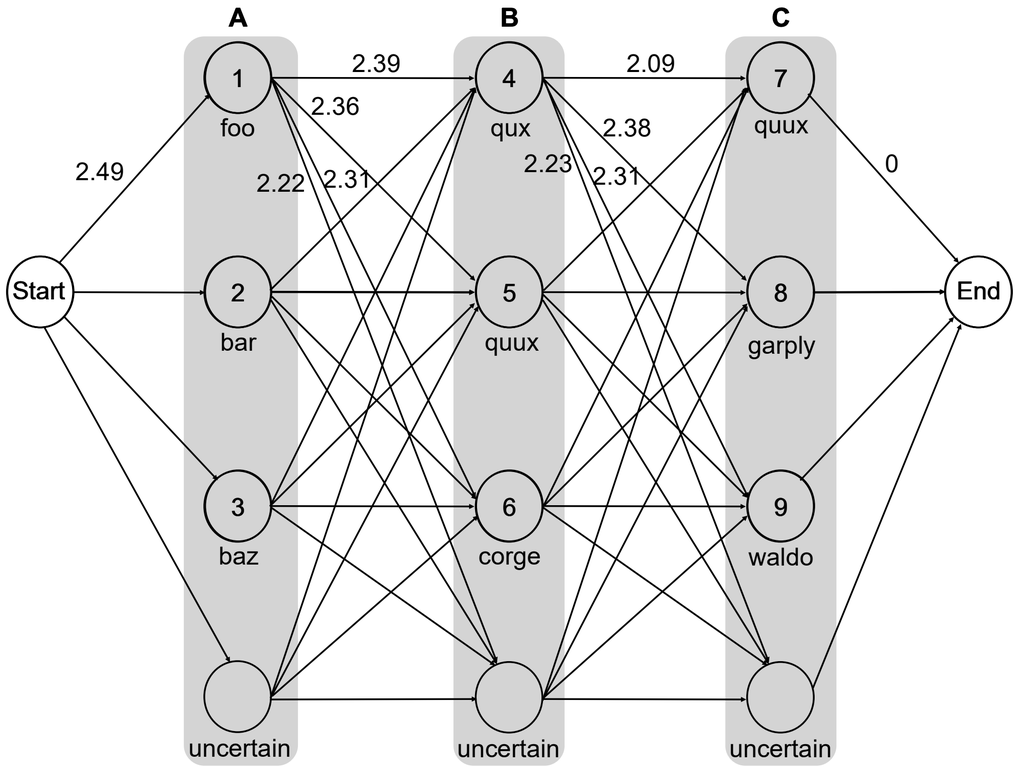

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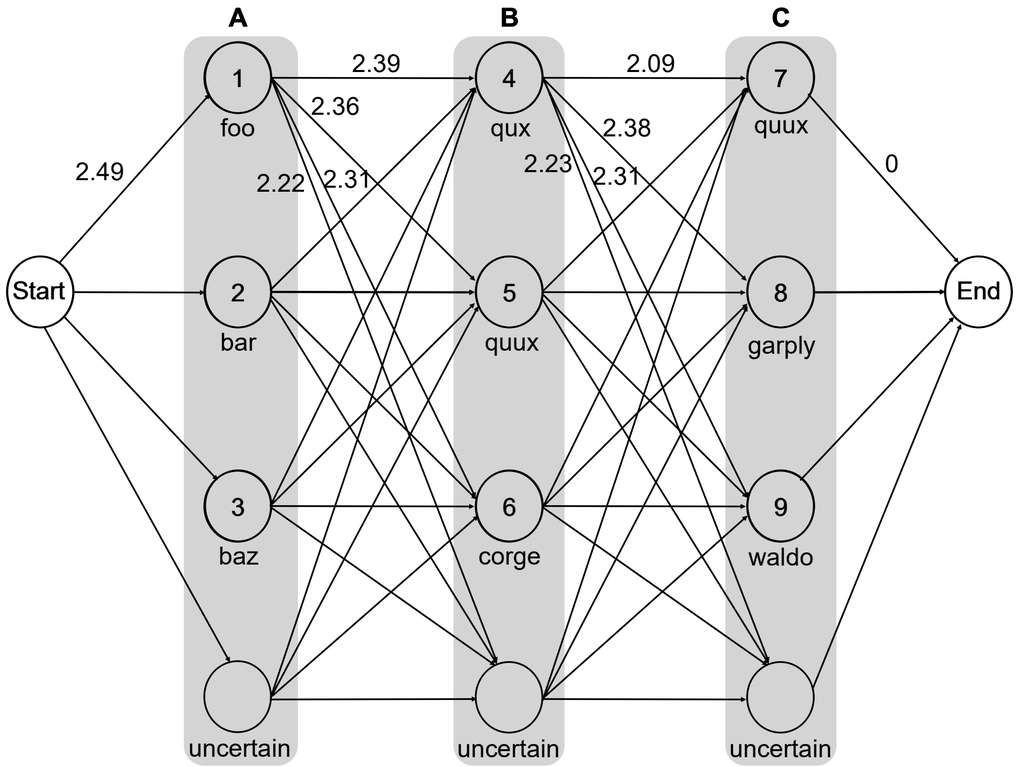
  - **Adjacency scores:** A value that quantifies the contextual relationship between two matches connected by an edge



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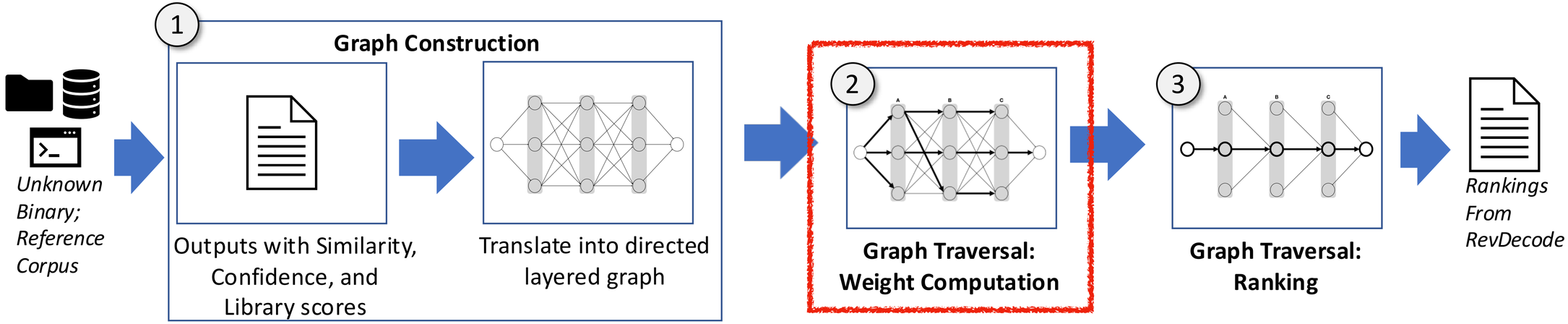

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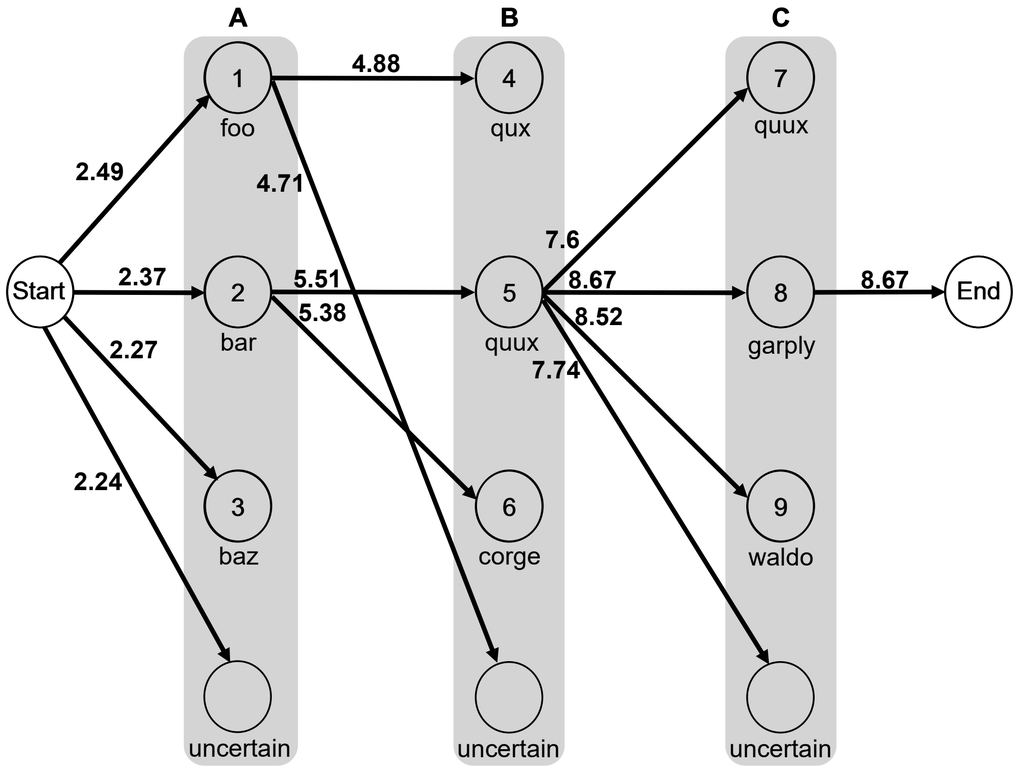
Phase 2

Graph Traversal: Weight Computation

- **Idea**: Identify all nodes that lie on at least one of the maximum weight paths
- **Viterbi-inspired forward pass** for efficient path computation



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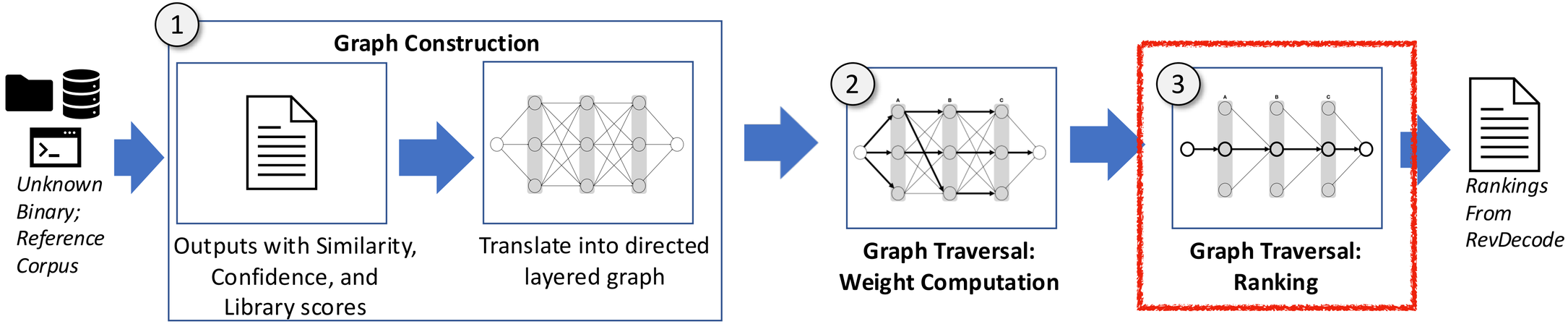
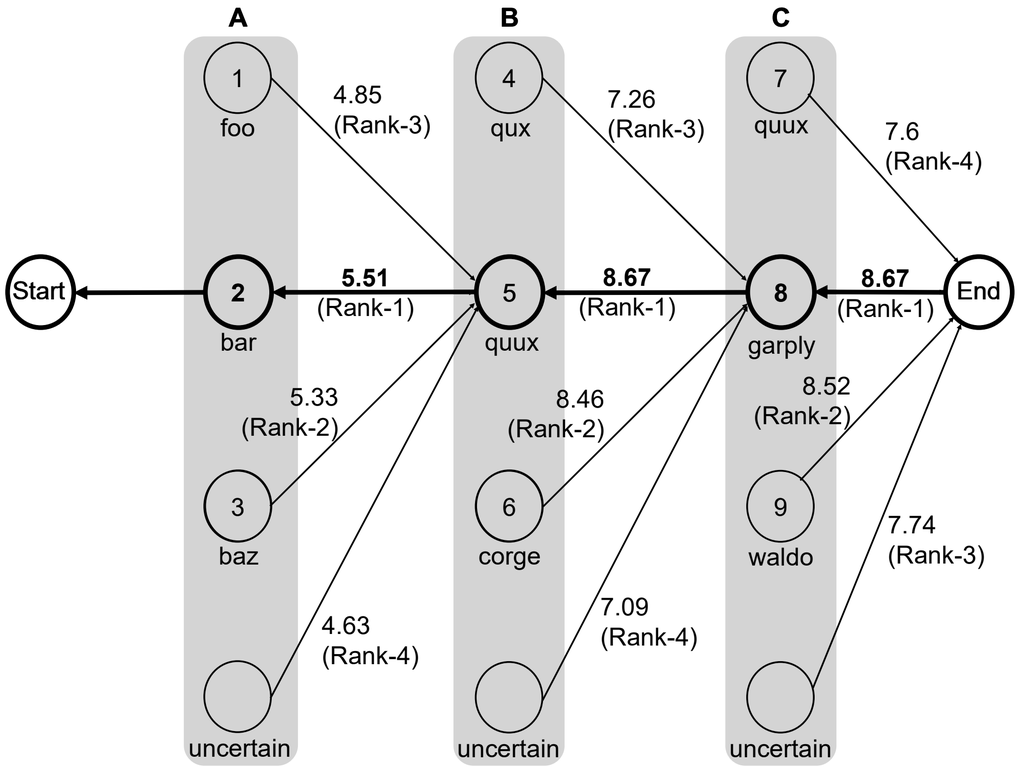


Phase 3

Graph Traversal: Ranking

- **Idea**: Nodes ranked based on their proximity to a maximum weight path
- **Backward pass** starts from end node
- **Output**: A ranking of matches for each unknown function



Evaluation

Evaluation Methodology

- **Datasets**:
  - General-purpose: 132 binaries, 262486 functions, 11 billions function matches.
  - Synthetic Frankenbinaries: 168 libraries, 107643 functions, 5.8 billions function matches
- **Metrics:** Tie-aware Normalized Discounted Cumulative Gain (NDCG), a measure of ranking quality
- **Matchers Evaluated:** BSim[1], discovRE[2], SAFE[3], Gemini[4]

[1] Ghidra. https://ghidra-sre.org, 2019
[2] Sebastian Eschweiler, Khaled Yakdan, and Elmar Gerhards-Padilla. discovre: Efficient cross-architecture identification of bugs in binary code. 02 2016.
[3] Luca Massarelli, Giuseppe Antonio Di Luna, Fabio Petroni, Roberto Baldoni, and Leonardo Querzoni. Safe: Self-attentive function embeddings for binary similarity. Lecture Notes in Computer Science, page 309–329, 2019.
[4] Xiaojun Xu, Chang Liu, Qian Feng, Heng Yin, Le Song, and Dawn Song. Neural network-based graph embed- ding for cross-platform binary code similarity detection. In Proceedings of the 2017 ACM SIGSAC Conference on Computer and Communications Security, CCS '17, page 363–376, New York, NY, USA, 2017. Association for Computing Machinery.

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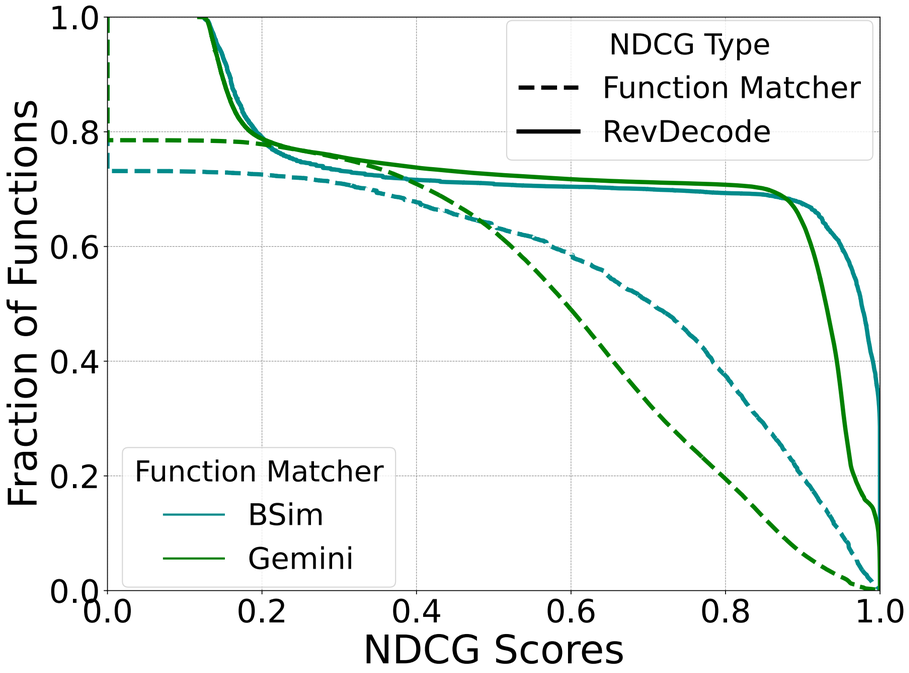
Evaluation Results

Ranking Effectiveness

- RevDecode significantly improves the quality of function rankings produced by existing matchers across both the general-purpose and frankenbinary datasets.
- General-purpose binaries: 56.3%-97.3% rankings are improved
- Frankenbinaries: 72.3%-98.8% rankings are improved



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Evaluation Results

Ranking Effectiveness

- **Why improves?**

  By leveraging the graph structure and contextual signals from nearby strong matches**:**

  - **Recovering relevant matches** that are structurally dissimilar due to version or compilation differences.
    - E.g. BSim, which misidentifies *uncompress* from *libz*(Ubuntu 20.04) as *get_absolute_expression* from *as-2.24*. RevDecode corrects the ranking, promoting the *uncompress* from *libz*(Ubuntu 14.04) from rank 187 to the top position because of the *libz* context provided by surrounding *libz* matches
  - **Resolving ambiguity** among functions that lack distinctive features
    - E.g. In the general-purpose dataset, 70,720 of the 202,058 improved BSim rankings (35%) fall into this category

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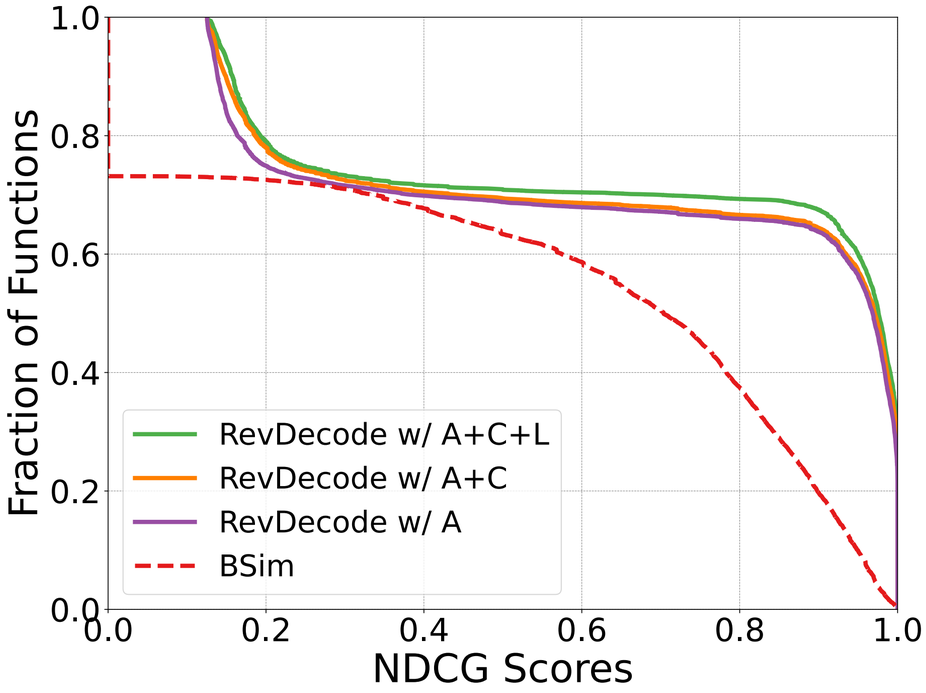
Evaluation Results

Ranking Effectiveness

- **Ablation Study**: All components in weight are useful for the ranking refining. E.g. BSim's average NDCG is improved from:
  - 0.27 to 0.42 with similarity and adjacency scores
  - Then to 0.44 with confidence scores
  - Finally to 0.46 with library scores
- Uncertain node plays an important role in mitigating irrelevant context chains and led to a 7% decrease in context-chain-induced ranking errors.



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Parallelizing Graph Traversal

Challenges in Parallelizing RevDecode

- **Motivation:** Be scalable for large graph size (e.g. Unoptimized CPU-based implementation takes 40mins for an unknown binary having 900 functions, each function has 250 matches.)
- **Solution:** Parallel graph traversal algorithms
- **Challenges:**
  - **Sequential Dependencies:** Layer computation depends on previous layers, limiting naive parallelization
  - **Resource Utilization:** Efficient division of workload essential for maximum GPU resource use
  - **Memory Dependence:** Frequent accesses to cumulative weight matrix could create bottlenecks; memory access patterns require careful design

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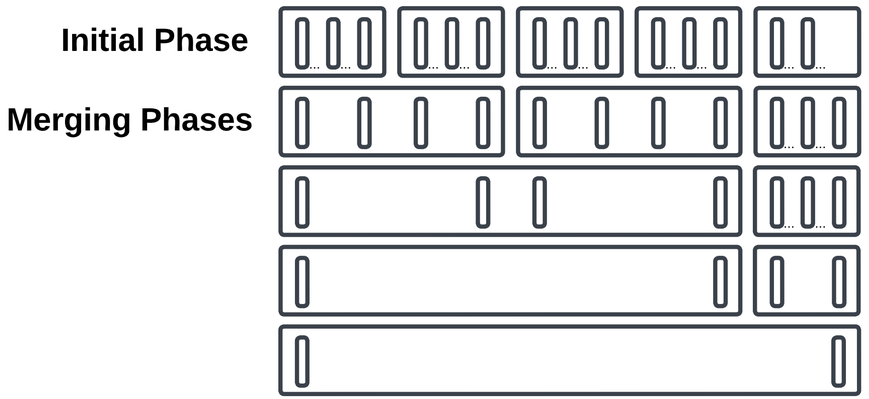
Parallel Traversal Algorithms

- **Naive Traversal:** Serves as a baseline, launching a single GPU thread block and walking the graph layer by layer, no additional optimization
- **Fine-Grained Traversal:** Parallel edge computations, efficient GPU utilization
- **Segment-Based Estimation Traversal:** Divide-and-conquer strategy for large graphs; trades slight accuracy loss for significant performance gain



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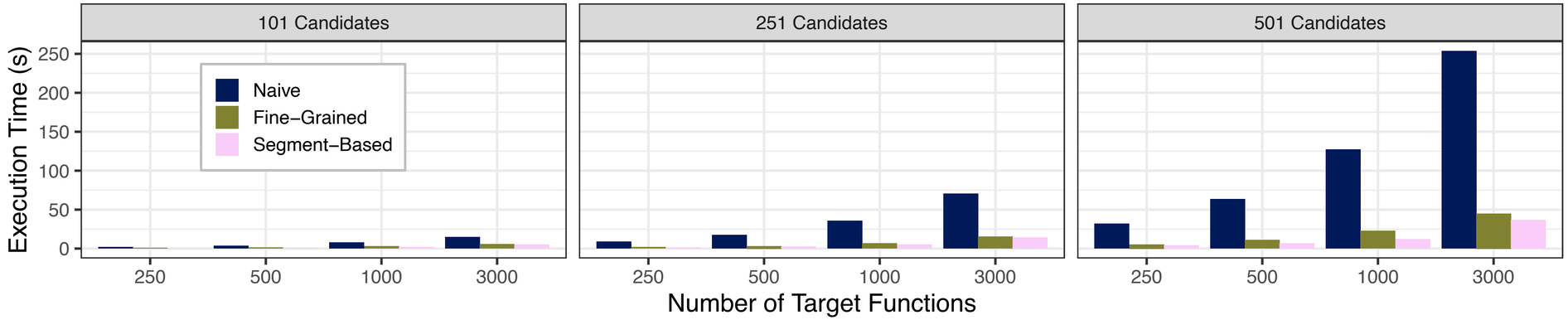
Evaluation Results

Parallel Algorithms Performance

- **Fine-Grained Traversal:**
  - Over 40x speedup relative to a simple CPU implementation
  - ~5x speedup over naive GPU-based traversal
- **Segment-Based Traversal:**
  - 1.39x speedup for total runtime, verse fine-grained traversal,
  - Additional ~3.8x speedup for forward-pass time
  - The cost is 0.003 NDCG reduction



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Summary

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- Relevance decoding identifies function relevance by leveraging surrounding contextual information.
- RevDecode significantly improves function matcher results by:
  - Converting results optimization problem to a graph exploration problem
  - Leveraging functions' interdependencies and contextual signals during the graph exploration process
- GPU acceleration ensures the scalability by parallelizing the graph traversal algorithm
- Evaluation demonstrates that RevDecode significantly enhances function matcher performance by reducing ambiguities and improving ranking accuracy

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Thanks for listening!

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