

Towards a GPU-accelerated web-based graph rendering framework for large-scale protein networks

Shilpika² Venkatram Vishwanath² Michael E. Papka^{1,2} Landon Dyken ¹ Jiaxin Lu ¹ Sidharth Kumar ¹

> ¹University of Illinois Chicago ²Leadership Computing Facility, Argonne National Laboratory

Introduction

- Background: Protein-protein interaction (PPI) networks are critical for understanding cellular processes. They are often large-scale and can be generated in real time from experimental or computational pipelines.
- Challenge 1: Existing frameworks (D3.js, etc) struggle with computational scalability and cannot efficiently handle real-time updates.
- Challenge 2: Current WebGPU-based systems such as GraphWaGu offer high-performance rendering but lack comprehensive APIs, biology-specific layouts (e.g., hive plots), dynamic filtering capabilities, and support for rendering directed graphs with arrowheads or other directional indicators.
- Challenge 3: Web environments lack specialized libraries for large-graph visualization, and static approaches fail to adapt to changing network density.
- Goal 1: We extend GraphWAGU to support multiple layout algorithms (hive plots, etc.), dynamic density adjustments, and a D3.js-like API for graph creation and rendering.
- Goal 2: We set new benchmarks for large-scale, real-time graph visualization in web environments, enabling biologists to interactively explore and analyze complex PPI networks through intuitive, high-performance tools.

WebGPU

- WebGPU: A modern web API designed to unlock modern GPU capabilities, enabling developers to perform both high-performance graphics rendering and parallel computations directly in web browsers.
- WebGPU Computing Features: Parallel processing capabilities, high-performance computing, cross-platform compatibility.
- WebGPU Computing Example: WebGPU performs matrix multiplication using parallel compute shaders, with each thread computing row-column dot products and storing results in GPU buffers, achieving CUDA-like performance.

WGSL Compute Shader Code @compute @workgroup_size(16, 16) fn main(@builtin(global_invocation_id) global_id: vec3<u32>) { let row = global_id.y; let col = global_id.x; if((row < Width) && (col < Width)) { var Pvalue: u32 = 0; $for(var i: u32 = ou; i < Width; i++) {$ let m = M[row * Width + i];let n = N[i * Width + col];Pvalue = Pvalue + m * n;} P[row * Width + col] = Pvalue;}}

CUDA Code

_global___ void matrixMul(int *a, int *b, int *c, int N){ int row = blockIdx.y * blockDim.y + threadIdx.y; int col = blockIdx.x * blockDim.x + threadIdx.x; int temp sum = 0; if(row < N && col < N){ for(int i = 0; i < N; i++){ $temp_sum += a[row * N + i] * b[i * N + col];$ $c[row * N + col] = temp_sum;}$

Figure 1. Comparison of matrix multiplication implementations: WGSL compute shader (left) and CUDA kernel (right).

- WebGPU Rendering Features: Modern graphics pipeline, higher frame rates (FPS), efficient resource management.
- WebGPU in Our Work: we use WebGPU to leverage the GPU's computational power for layout creation and rendering for directed graphs in 2 dimensions.

End-to-End Workflow of the Graph Rendering Framework

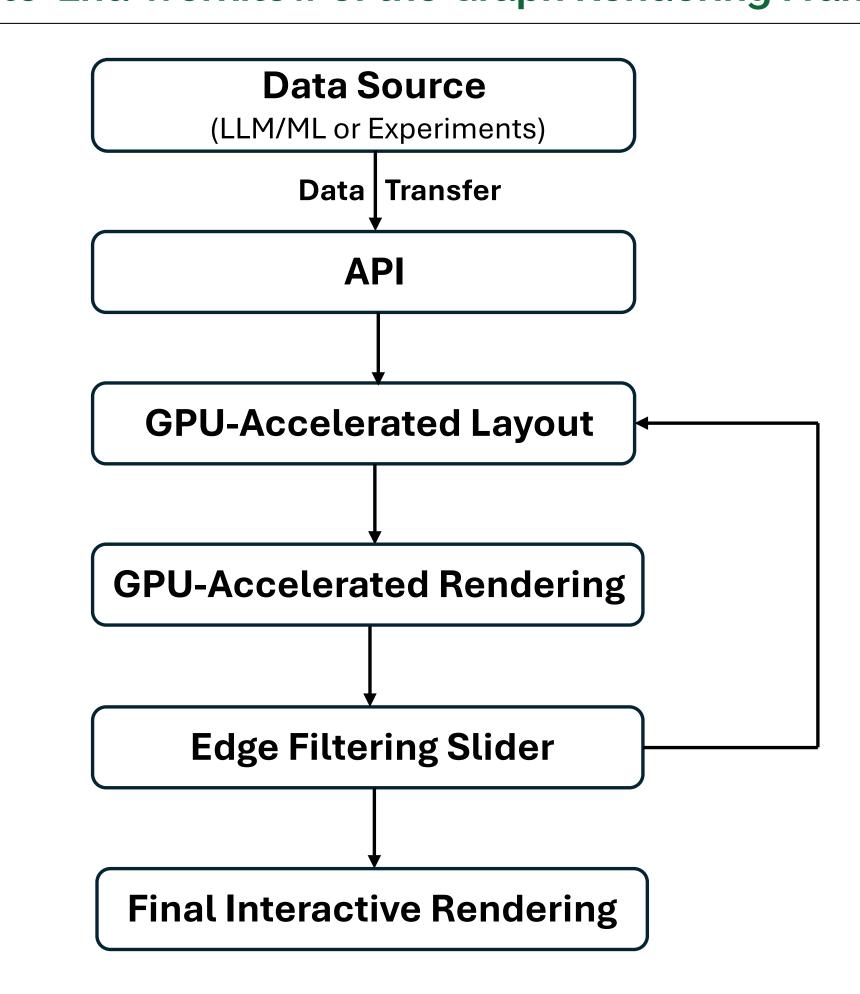
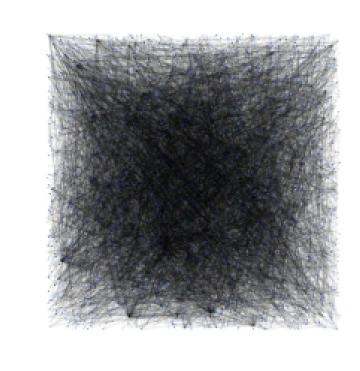


Figure 2. Workflow of our WebGPU-based Graph Rendering Framework.

• Workflow: Data from LLM/ML or experiments flows into the API for GPU-accelerated layout and rendering, with an interactive edge-filtering slider providing real-time, density-controlled updates.





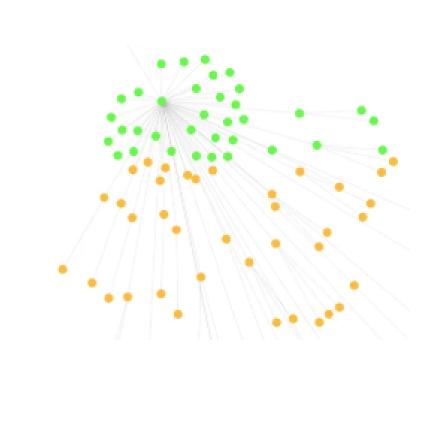


Figure 3. Example for the graph rendering framework: raw input data (left), algorithm output (center), and detailed view of internal structure (right).

Graph Rendering API

- Unified WebGPU API: Provides an all-in-one interface to load, compute, and render large-scale graphs entirely in the browser, built on and extending GraphWaGu.
- ullet Constructor: newRenderer(device:GPUDevice, canvas:HTMLCanvasElement, label:HTMLLabelElement)
- Properties: coolingFactor: Controls how quickly the simulation stabilizes. l: The ideal edge length. theta: The theta parameter for Barnes-Hut approximation. iterationCount: The number of iterations for the simulation. energy: Initial simulation energy.

Our Contributions and Extensions

Dataset and Experimental Setup:

- PPI Data Source: We utilize protein-protein interaction networks from **STRING** Database (STRINGDB), a comprehensive repository containing functional protein associations.
- Network Characteristics: STRINGDB provides confidence-scored interactions with varying density levels, making it ideal for testing layout algorithms under different network conditions.

Challenges in Applying GraphWaGu to PPI Networks:

- Dense connectivity: Protein networks often contain thousands of highly interconnected nodes, creating visual clutter, and force-directed algorithms perform poorly under extremely high edge density conditions, leading to the "hairball" effect.
- Our Solution: We implement score-based edge filtering with confidence thresholds to transform dense hairball networks into clear, interpretable structures.

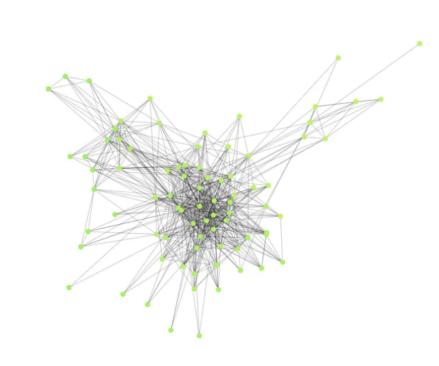






Figure 4. Progressive edge filtering with confidence thresholds: 0 (1320 edges), 0.7 (468 edges), and 0.8 (340 edges), showing transformation from hairball to interpretable network structure.

- However, this approach is static and non-interactive, lacking adaptability to different PPI networks.
- Limited node information: Current GraphWaGu visualization provides insufficient protein details, making it difficult for biologists to identify specific proteins and their functional characteristics during network exploration.
- Our Solution: Degree-based visual encoding. We render node color and size based on the degree (number of connections) of remaining nodes after filtering, enabling biologists to immediately identify protein hubs and their relative **importance** in the network.



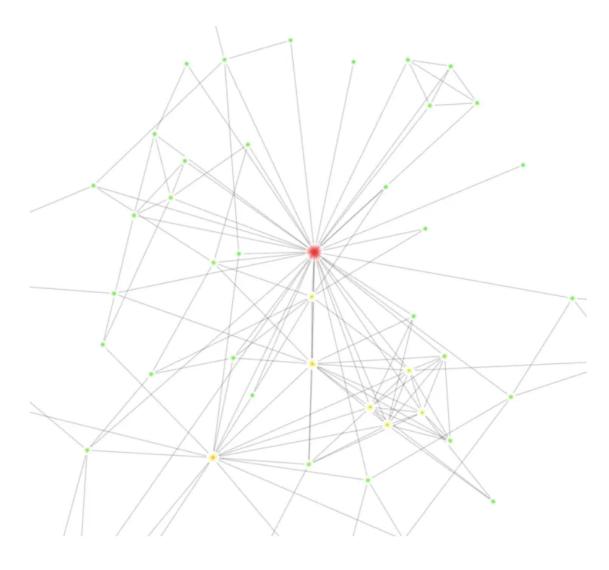


Figure 5. Visual protein importance mapping: node size and color reflect degree centrality, enabling immediate identification of high-degree protein hubs (larger, colored nodes) within the network structure.



