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Post Transformer Frontier AI Challenge

Every transformer wakes up the same way. No memory of yesterday. No context from last week. Just weights frozen in time, processing each request like it's the first conversation they've ever had, like Groundhog Day.

And the problems run deeper than forgetfulness:

- Context that evaporates: Ask a transformer to reason across a 100-page document, and watch it drown. The attention mechanism that makes transformers powerful becomes their ceiling. Memory that scales quadratically until it breaks.
- Intelligence frozen in amber: Your business evolves. Markets shift. Regulations change. But your model? Still thinking it's May 2025. Static training paradigms mean your AI can't learn from what happened yesterday, let alone adapt to what's happening now.
- Memory that lives on sticky notes: The industry's current "solution" to AI amnesia? Bolt on external databases. Vector stores. Retrieval pipelines. These aren't real memories. They're Post-it notes stuck to the outside of a brain that can't form its own. Your AI doesn't internalize knowledge. It doesn't build contextualized understanding. It just looks things up. There's a difference between remembering and searching.

These aren't engineering problems waiting for better optimization. They're fundamental architectural limitations. The transformer paradigm has a ceiling.

The Dragon Hatchling (BDH) breaks through it. In this High Prep contest, you'll work with this state-of-the-art technology!



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About Pathway and the Post Transformer Era

Pathway builds the first post-transformer frontier model that solves AI's fundamental memory problem. While transformers wake up in the same state every time—like Groundhog Day—their architecture enables true continuous learning, infinite context reasoning, and real-time adaptation. They're not optimizing yesterday's technology; they're building what comes after transformers.

The company is led by co-founder and CEO Zuzanna Stamirowska, a complexity scientist who created a team of AI pioneers:

- CTO Jan Chorowski was among the first people to apply Attention to speech and worked with Nobel laureate Geoff Hinton at Google Brain.
- CSO Adrian Kosowski is a leading computer scientist and quantum physicist who obtained his PhD at age 20 and co-founded SPOJ, one of the earliest popular competitive programming platforms.

The company is backed by leading investors and advisors, including Lukasz Kaiser, co-author of the Transformer ("the T" in ChatGPT) and a key researcher behind OpenAI's reasoning models. Pathway is trusted by organizations such as NATO, La Poste, and Formula 1 racing teams. Pathway is headquartered in Palo Alto, California, with offices in Paris and Wrocław.



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But the paper is dense. The concepts might seem unfamiliar. Working with BDH requires understanding new primitives: scale-free graphs instead of dense matrices, Hebbian learning instead of static weights, sparse activations instead of continuous signals.

This contest is your opportunity to work with a post-transformer breakthrough before the rest of the world catches up.

Your Mission – should you choose to accept it

This contest invites you to build tools that reveal how BDH works, showcase its unique capabilities, and demonstrate why it matters for the future of AI.

The best teams in this contest will be among the first to contribute to BDH's ecosystem. Your work could be featured by Pathway and shared with the global AI community. This isn't just an academic exercise—it's a chance to shape how the world understands post-transformer AI.

Three paths await you. Each offers a different way to contribute. Pick the one that matches your team's strengths.



The Dragon Hatchling: A New Paradigm

The Dragon Hatchling thinks differently:

- Memory that lives in the architecture. Hebbian synapses that strengthen with experience, not external databases you query.
- Context without ceilings. $O(T)$ linear attention that scales to infinite context without quadratic explosion.
- Learning that never stops. Architecture designed for adaptation, not frozen weights waiting for the next training run.
- Reasoning you can see. Sparse positive activations (roughly 5% of neurons) flowing through interpretable graph structures.

| Property | Transformer | BDH |
|------------------|---------------------------------------|--|
| Structure | Dense matrix layers | Scale-free graph of neurons |
| Activation | Nearly all neurons fire | Roughly 5% of neurons fire (sparse) |
| Memory | KV-cache (grows with context) | Hebbian synapses (constant size) |
| Attention | $O(T^2)$ complexity | $O(T)$ linear complexity |
| Interpretability | Black box | Graph structure is directly visualizable |

The paper was the #1 paper on Hugging Face the month it was published, #2 in 2025 despite being released in October, and trended for weeks. The research community has taken notice. Labs worldwide are exploring it.



Understanding BDH: Core Capabilities

Before building, understand what makes BDH fundamentally different. These aren't incremental improvements—they're architectural breakthroughs that transformers cannot replicate.

Architectural Strengths

1. Constant-size memory regardless of context length-

- BDH maintains $O(nxd)$ synaptic state no matter how long the sequence. While the transformer KV-cache grows linearly with every token (eventually exhausting GPU memory), BDH compresses history into fixed-size Hebbian state. The architecture guarantees this mathematically. Community experiments have demonstrated BDH running to 50k+ tokens with flat memory usage while transformers crash at ~12k on equivalent hardware.

2. Native sparsity without tricks-

- BDH maintains $O(nxd)$ synaptic state no matter how long the sequence. While the transformer KV-cache grows linearly with every token (eventually exhausting GPU memory), BDH compresses history into fixed-size Hebbian state. The architecture guarantees this mathematically. Community experiments have demonstrated BDH running to 50k+ tokens with flat memory usage while transformers crash at ~12k on equivalent hardware.



3. Monosemantic synapses by design

- Individual synapses in BDH reliably strengthen for specific concepts. The paper demonstrates "currency synapses" that activate for currency names and "country synapses" for nations—consistent behavior across languages. This is built-in interpretability. Where transformer neurons are polysemantic (encoding multiple unrelated concepts), BDH synapses tend toward clean, single-concept encoding. You can point to a synapse and explain what it does.

4. Inference-time learning via Hebbian updates

- BDH doesn't just process tokens—it learns from them during inference. Synapses strengthen when neurons co-activate ("neurons that fire together wire together"). This means BDH can acquire new knowledge without backpropagation, without retraining, without fine-tuning. The model you deploy keeps getting smarter as it runs.

5. Composable model merging

- BDH's scale-free architecture enables concatenating independently trained models. Train a French translator and a Spanish translator separately, concatenate them, and get a model that handles both. This composability is architecturally native—not a post-hoc trick.



What This Means for Applications

These capabilities unlock use cases transformers struggle with:

- **Healthcare:** Medical AI that accumulates patient context across visits without retraining or solves path breaking reasoning problems that were previously not doable by AI. Models that learn from new research papers at inference time. Interpretable reasoning chains with much better long horizon reasoning capabilities.
- **Finance:** Fraud detection with continuously monitoring money-movement to uncover laundering or financing of illicit activities.
- **Research:** AI assistants that build cumulative understanding of a research domain. Literature synthesis across thousands of papers. Interpretable hypothesis generation.

The question isn't whether BDH has these capabilities—the architecture guarantees them. The question is: how does your project showcase them compellingly to the world?



Showcase Opportunities for You

The following areas represent high-impact opportunities where compelling demonstrations would advance the field's understanding of post-transformer AI. These are directions where strong work can make a real contribution.

Visualization of Unique Properties

- No one has built the definitive BDH visualization. The Transformer Explainer from Georgia Tech became the standard way people understand transformers. BDH needs its equivalent—and the architecture is more visualizable, not less.
- Why this matters: BDH's sparse activations (5% vs 100%) create dramatic visual contrast. The scale-free graph topology is literally a graph you can render. Hebbian strengthening has temporal dynamics transformers lack. A great visualization doesn't just explain BDH—it makes the advantages visceral.

Interpretability Demonstrations

- The paper shows qualitative examples of monosemantic synapses. A systematic demonstration—with clear methodology, compelling examples, and intuitive presentation—would be a significant contribution. The goal is not to "prove" monosemanticity (the paper already establishes this) but to showcase it in ways that resonate with researchers and practitioners.
- Why this matters: Interpretability is one of AI's biggest unsolved problems. BDH claims to solve it architecturally. Compelling demonstrations of this capability position BDH as the answer to a question the entire field is asking.



Long-Context and Continuous Learning Showcases

- BDH's constant memory enables reasoning at context lengths where transformers fail. Demonstrations showing BDH handling 50k, 100k, or longer contexts—especially on meaningful tasks—would be powerful evidence of the paradigm shift.
- Similarly, BDH's inference-time learning enables continuous adaptation. Demonstrations showing models that accumulate knowledge across sessions, learn from corrections, or adapt to distribution shift in real-time would showcase capabilities transformers fundamentally lack.
- Why this matters: "Infinite context" and "continuous learning" are two of the most sought-after capabilities in AI. Concrete demonstrations matter more than theoretical claims.

Domain Applications

- BDH's unique properties map naturally to high-stakes domains where interpretability, long context, and continuous learning matter most.
- Healthcare research: Medical AI needs to reason across patient histories, integrate new research, and provide interpretable recommendations. BDH's architecture addresses all three.
- Scientific discovery: Research assistants that accumulate domain knowledge, synthesize across papers, and show their reasoning chains.
- Enterprise AI: Applications where auditability isn't optional—compliance, legal, financial services.
- Why this matters: A working prototype in healthcare or scientific research demonstrates that post-transformer AI isn't theoretical—it's ready for the problems that matter most.



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Three Paths to Choose From

Path A: Visualization and Inner Worlds

Make BDH's unique properties visible. Requires frontend skills AND understanding of BDH internals.

BDH is uniquely visualizable. Where transformers show opaque matrix multiplications, BDH shows sparse pulses of neural activity flowing through emergent graph structures.

Why BDH Visualization Is Different

| What to visualize | Why it's possible in BDH | Impact |
|-----------------------|---|---|
| Sparse activations | Only ~5% of neurons fire. Dramatic contrast vs. dense networks. | Executives understand efficiency instantly. Researchers see which neurons matter. |
| Graph topology | Scale-free hub-and-spoke structure emerges spontaneously. Real graphs, not abstract matrices. | Shows how BDH organizes knowledge differently than transformers. |
| Hebbian learning | Synapses visibly strengthen when neurons co-activate. Temporal dynamics transformers lack. | Makes "neurons that fire together wire together" tangible. |
| Monosemantic synapses | Individual synapses respond consistently to specific concepts. | Interpretability you can point to and explain. |



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Project Directions

- "Sparse Brain": Activation Density Comparator: Side-by-side visualization showing BDH's ~5% activation vs. transformer's near-uniform activity. Same input, dramatically different neural behavior. Feed identical tokens to both architectures, render activation heatmaps, let users scrub through layers. The contrast should be visceral.
- "Graph Brain": Emergent Topology Explorer: Interactive force-directed graph of BDH's $G_x = E @ D_x$ matrix. Show how random initialization evolves into brain-like hub structure during training. Click neurons to see what activates them. Filter by activation strength. Zoom into communities. Export subgraphs.
- "Memory Formation": Hebbian Learning Animator: Animate the α matrix evolving as tokens are processed. Edge weights thicken when synapses strengthen. Time-lapse training to show which connections become permanent. "Neurons that fire together wire together" made visible across hours of training compressed into seconds.
- "Pathfinder Live": Interactive Reasoning Demo: Port the krychu/bdh pathfinding visualization to web. Users draw mazes, watch BDH reason through solutions layer by layer, see attention flow in real time. Compare to transformer solving the same maze. Show where BDH's approach differs.



Technical Requirements

Suggested team composition:

- At least one member in your Inter Hall Team with frontend expertise (JavaScript/TypeScript)
- Familiarity with D3.js, Svelte, or similar visualization libraries is strongly recommended
- For rapid prototyping: Streamlit/Gradio can produce working demos faster, but with less polish

Scope guidance:

| Scope | Complexity | Notes |
|----------------------------------|-------------|--|
| Static layer diagram | Low | Good starting point for any team |
| Sparsity comparison heatmap | Low-Medium | Achievable with basic D3/Plotly |
| Force-directed graph of topology | Medium | Benefits from D3.js experience |
| Animated Hebbian learning | Medium-High | Requires strong frontend skills |
| Full 3D walkthrough | High | Ambitious but achievable with Three.js |

Judging Emphasis:

| Criterion | Weight |
|--|--------|
| Visual clarity: Is it immediately understandable to non-experts? | 30% |
| Technical correctness: Does it accurately represent BDH internals? | 25% |
| Insight into architecture: Does it reveal something meaningful? | 25% |
| Presentation quality: Demo polish, README, video | 20% |



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Path B: Interpretability Showcases

Demonstrate BDH's interpretability advantages with rigor and clarity.
For teams with ML research skills.

BDH claims built-in interpretability through monosemantic synapses and sparse activations. The paper establishes this conceptually. Your job: create compelling, systematic demonstrations that make these advantages tangible.

What Interpretability Means Here

Interpretability answers: "Why did BDH output X? Which synapses mattered? What concepts do they encode?"

This requires methodology. Clear experimental design. Reproducible results. Intuitive presentation. The goal is not to validate BDH's claims —those are established—but to showcase them in ways that advance understanding.

Project Directions

- Monosemantics Dashboard: Systematically identify synapses that correlate with specific concepts. For each synapse, visualize activation patterns across input categories. Create an interactive explorer where users can query "what does synapse N encode?" and "which synapses activate for [concept]?" Make the abstract concrete



- Activation Atlas: Map neuron firing patterns to input features. Cluster neurons by what activates them. Track how activation patterns shift during training. Build an explorer that makes BDH's internal organization legible.
- Comparative Interpretability Study: Apply the same interpretability methods to BDH and transformers. Concept probing on both. Activation analysis on both. Side-by-side comparison showing where BDH's native interpretability outperforms transformer black boxes.
- Inference-Time Learning Demonstration: Showcase BDH's ability to learn during inference. Design a clear protocol: teach the model new facts without backpropagation, demonstrate retention, show that transformers cannot do this. Make the "learning without training" capability undeniable.

Methodological Standards

Strong interpretability work requires:

- Clear experimental design: What are you measuring? How?
- Reproducible methodology: Others should be able to replicate your approach
- Honest presentation: Document limitations and future scope clearly
- Intuitive visualization: Numbers alone don't convince—show, don't just tell



- Judging Emphasis:

| Criterion | Weight |
|---|--------|
| Insight quality: Does this advance understanding of BDH's interpretability? | 35% |
| Rigor: Is methodology documented and reproducible? | 30% |
| Communication: Clear to researchers and engineers? | 25% |
| Community value: Would others build on this work? | 10% |

Path C: Open-Ended Frontier Exploration

Highest ambition, highest potential impact. For teams ready to push boundaries.

This path is deliberately open. Your goal: produce something that advances BDH's ecosystem in a direction no one has explored.

Possible Directions

Domain Applications: Build prototypes showing BDH in high-stakes domains:

- Healthcare research: Medical literature synthesis, patient history reasoning, interpretable clinical decision support
- Scientific discovery: Research assistants that accumulate domain knowledge and show reasoning chains
- Legal/Compliance: Document analysis at scale with auditable reasoning
- Education: Adaptive tutoring that learns student patterns without retraining



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Pedagogical Contributions

- Build interactive explainers in the spirit of Transformer Explainer or CNN Explainer, but for BDH
- Create "build your own BDH from scratch" tutorials with runnable code
- Design curriculum that takes someone from "what is attention?" to "how does Hebbian memory work?"

Ecosystem Infrastructure

- Better HuggingFace integration
- Evaluation harnesses for BDH-specific capabilities
- Benchmark suites for long-context and continuous learning
- Debugging and profiling tools

Novel Investigations

- Probe BDH behavior on tasks designed to showcase its strengths
- Explore architectural variations
- Investigate applications beyond language (time series, graphs, RL)

What Success Looks Like

A strong submission:

- Identifies a clear opportunity
- Executes with appropriate methodology
- Produces artifacts others can use or build on
- Documents limitations and future scope clearly



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An exceptional submission:

- Creates something Pathway researchers would actually use
- Opens new application domains for BDH
- Produces work the community will reference

Judging Emphasis:

| Criterion | Weight |
|---|--------|
| Novelty: Is this genuinely new territory? | 30% |
| Rigor: Are claims supported by evidence and are the engineering choices with the right hypotheses + research? | 40% |
| Communication: Could others build on this? | 30% |



Submission Requirements

1. Hosted Demo

Your solution must be accessible via web:

- HuggingFace Space: Free hosting, easy deployment
- Streamlit Cloud: Quick setup for Streamlit apps
- Gradio on HuggingFace: Good for interactive ML interfaces
- Custom website: If you have specific requirements

The demo must be functional at judging time. Ideally in the future too for the AI community to review it.

2. GitHub Repository

Public repository containing:

Code:

- Clean, documented implementation
- Requirements file (requirements.txt or pyproject.toml)
- Scripts to reproduce key results

README must include:

- What you built (one paragraph)
- What insight it reveals about BDH
- How to run locally
- How to access the hosted demo
- Team members and contributions
- Video demo and images
- Limitations and future scope

3. Demo Video

2-3 minute video showing:

- Your solution in action
- Key insights or findings
- Brief explanation of approach

Upload to YouTube (unlisted is fine) or include in the repository.



What Success Looks Like

A strong submission:

- Picks a clear, scoped problem
- Executes with appropriate methodology
- Produces a working demo and clean repository
- Documents limitations and future scope honestly
- Showcases something meaningful about BDH

A weak submission:

- Runs existing demos unchanged
- Builds visualizations disconnected from actual model behavior
- Surface-level engagement without genuine understanding
- Broken demo links or incomplete repository

An exceptional submission:

- Showcases a BDH capability in a way no one has before
- Creates artifacts Pathway researchers would reference
- Opens new application domains or research directions
- Sets a standard others will follow