

Manny Manifolds: A Unified Cognitive Architecture for Expanding Cognition

Core Paradigm: Knowledge as Geometry

Manny Manifolds is built on a simple but radical paradigm: “*Knowledge is geometry, reasoning is motion, and learning is curvature.*” In this architecture, knowledge is encoded in a living semantic graph or **manifold** – nodes are concepts and edges are relationships – where each edge’s “curvature” (a numeric weight) continuously adjusts with experience ¹ ². Crucially, there is **no separation between memory and model**: the manifold *is* the knowledge store and the learned state ³ ⁴. All cognitive processes occur *within* this geometric substrate. A reasoning process becomes an active traversal (a “**thread**”) through the graph from a query to an answer – essentially a chain-of-thought path along connected concepts ⁵. Every reasoning step is a local move on the manifold, with no hidden black-box module planning in the background; this means Manny can always show *how* it reached an answer by pointing to the path it took ⁵ ⁶. Meanwhile, **learning** happens automatically as a by-product of reasoning: “*threads change curvature, and curvature changes future threads.*” Each time Manny “thinks” (traverses a path), it updates the edges it used – strengthening frequently traveled connections and weakening those left idle or proven wrong ⁷. These updates follow a Hebbian-style local rule modulated by a signal called **valence** (described below), rather than requiring any separate training phase ⁸. In essence, Manny is a *self-evolving cognitive map*: data becomes an internal space, each query is like a motion through that space, and each motion bends the space a little (learning) ⁹. This tight intertwining of memory, reasoning, and learning in one geometric structure is the core that aligns all other components.

Integrated Memory and Continuous Learning

Manny’s memory is an **adaptive manifold memory**: a graph that *reshapes with every interaction* ¹⁰. Nodes represent facts or concepts, and edges carry weights (curvature) representing the strength or significance of associations ¹¹. When Manny encounters new information or solves a problem via a thread, it doesn’t store a static record in a separate database – instead, it *deforms its knowledge graph* in response. Frequently used connections become “shorter” or higher-curvature (indicating a strong, familiar link), while unused or contradictory connections may fade (lower curvature) ¹¹. This way, memory and learning are unified: the **graph’s geometry is the model and memory combined** ³. Manny inherently balances plasticity and stability through local, incremental updates and natural decay, much like a brain strengthening synapses with use and weakening them without use ¹² ¹³. There is no need for periodic retraining or an external optimizer – learning is an ongoing **feedback loop** inside the manifold ¹⁴. Importantly, Manny’s design mandates that learning remains **local** (happening along the edges that were involved in a given thought) and incremental, which helps prevent catastrophic forgetting by not globally re-writing the entire network at once ¹⁵. Manny also incorporates a notion of **offline consolidation** (“sleep” phases) where it can compress and reorganize knowledge in the background to further improve stability without stopping the online learning loop ¹⁶.

This integrated memory-learning approach yields a kind of **life-long learning** capability: Manny can accumulate knowledge gradually, adjusting its map with each experience, rather than training on fixed batches of data. As evidence, even early prototypes demonstrated incremental learning on toy domains,

where repeated questions led to shorter solution paths and improved efficiency over time – essentially forming “habits” by curving frequently used routes ¹⁷ ¹⁸. The architecture’s emphasis on **locality and sparsity** (only a small subgraph around the active context is heavily updated each time) ensures scalability as knowledge grows ¹⁹ ²⁰. In practical terms, Manny’s memory behaves like a network that *remembers by morphing*: if a certain association proves useful repeatedly, it becomes a highway in the graph (fast and reinforced), whereas if it’s rarely used or leads to error, it becomes a back road and may eventually be pruned. This gives Manny an inherent solution to the stability-plasticity dilemma – it can keep learning new things (plasticity) while preserving well-worn knowledge paths (stability) through the physics of the manifold (e.g. maintaining curvature bounds and using decay to avoid runaway growth)

¹⁵ ¹³.

Explainable Reasoning via Threads

All reasoning in Manny is transparent and traceable. Because every inference is a path (thread) on the knowledge graph, the system can provide a step-by-step explanation of how it reached any answer ²¹ ²². This is a built-in form of explainability – *the chain of nodes and edges is the rationale*. For example, if asked a question, Manny might traverse concepts A → B → C → D to find an answer D; it can then say, “I thought of A which led to B, which reminded me of C, which gave the answer D,” directly reflecting the nodes visited. This addresses a common alignment concern with AI: the reasoning is not a hidden vector operation but an *inspectable graph traversal*. In Manny’s interface, a user can literally query “why?” and get the path (and supporting context) that was followed ²³ ²⁴. Notably, there is no post-hoc script generating an explanation; the explanation is just a read-out of the actual cognitive process that occurred ²⁵ ²⁶. This design ensures that the system’s **narrative of reasoning is identical to its mechanism of reasoning**, which builds user trust and allows developers to debug or refine knowledge by looking at the paths.

Manny’s reasoning style can be seen as a form of constrained **chain-of-thought**. It doesn’t employ a global planner or an external logic engine; instead, each step (each “hop” to a neighboring node) is decided by local geometric factors – e.g. following the steepest curvature gradient or the path of least “energy” (where energy might correspond to conceptual distance or uncertainty) ²⁷ ²⁸. The result is that Manny tends to follow logical associative links that have been reinforced by experience. If it reaches an impasse (no good local step), it can employ simple tactics like backtracking or random exploratory hops, akin to how a person might say “let’s think of this from another angle.” The **bicameral design** (discussed next) further enhances this by letting an *Executive* monitor the thread and intervene in subtle ways (like adjusting a “temperature” parameter to encourage more exploration if the thread is stuck in a loop) ²⁹ ³⁰. Because all of this happens on the manifold, even these adjustments are transparent: for instance, if Manny injected a bit of randomness to explore a new path, that decision is driven by its *Creativity drive* internally and can be noted in the log (“tried an unconventional link from C to X to explore alternatives”). In summary, **every answer Manny gives comes with a built-in audit trail** ²¹. This not only aids explainability but also Manny’s own development: if a reasoning path is wrong or suboptimal, the developers (or even the system itself in future iterations) can pinpoint where the detour happened and why, then adjust the knowledge or parameters accordingly. It turns reasoning into a collaborative, inspectable process rather than an inscrutable one.

Bicameral Regulation and Cognitive Drives

Manny’s architecture adopts a **bi-cameral structure** inspired loosely by human cognition. It has two interacting subsystems: an **Experiencer** and an **Executive** ³¹ ³². The Experiencer is the “doer” – it spawns and follows threads, exploring the knowledge manifold to answer questions or react to inputs. The Executive is the “metacognitive regulator” – it doesn’t solve problems directly but monitors and

tunes the process, much like a thermostat or an attention controller ³¹ ³³. Importantly, the Executive **does not tell the Experiencer what to think**; it cannot insert nodes or force a particular path (that would violate Manny's core principle of no external controller) ³⁴ ³⁵. Instead, it can adjust parameters that influence *how* the Experiencer proceeds. For example, the Executive might notice that Manny's reasoning is oscillating or not converging and respond by lowering the "temperature" (making the system more deterministic and focused) or by triggering a **consolidation** (an analog of sleep, to integrate what's been learned so far) ³⁶ ³⁷. It can also modulate the learning rate or apply a "cool down" if the manifold's curvature is changing too wildly, to maintain stability ³⁷ ³⁸. Think of the Executive as the part of the system that ensures **homeostasis** and efficiency: it watches the cognitive trajectory and keeps it within productive bounds, but it never dictates the content of thoughts. This separation maps to how humans have autonomic self-regulation in the brain – we don't consciously choose to release stress hormones or alter our neural plasticity in the moment; those adjustments happen in the background to keep our cognition stable yet flexible ³¹ ³⁹.

To guide both the Experiencer and Executive, Manny employs a hierarchy of intrinsic **drives** – a motivational framework baked into the architecture. These six drives are: **Stability, Continuity, Connection, Competence, Creativity, and Contribution** ⁴⁰ ³⁰. Each drive is essentially a scalar field or "potential" defined over the manifold that Manny tries to optimize as it learns and thinks. In intuitive terms:

- The **Stability drive** pushes Manny to maintain internal consistency and homeostasis (preventing chaotic changes that could destabilize its knowledge) ⁴¹.
- The **Continuity drive** makes Manny reduce surprise and error, seeking to preserve coherent, predictable regions in its understanding ⁴¹. (This is akin to a desire for making new information fit well with what it already knows, avoiding non sequiturs.)
- The **Connection drive** encourages alignment and mutual understanding with other manifolds or users – essentially fostering empathy and shared context ⁴². This drive makes Manny *social*: it prefers to be on the same page as its human collaborators, asking clarifying questions when unsure (to reduce misalignment) and mirroring concepts important to the user.
- The **Competence drive** drives Manny to seek challenges that offer learning progress – it rewards tackling uncertainty and mastering new skills ⁴². This is analogous to curiosity or the urge to improve performance.
- The **Creativity drive** pushes for exploration of novel ideas, generation of new patterns and analogies, rather than only sticking to familiar paths ⁴³. It provides a counterbalance to Stability/Continuity by ensuring Manny can think outside the box and form original connections (within safe limits).
- The **Contribution drive** is a higher-level social drive: it motivates Manny to optimize for global coherence and shared understanding, essentially cooperating toward a collective good or truth ⁴⁴. This comes into play strongly in multi-agent scenarios – it's the drive that makes Manny willing to share what it knows and integrate knowledge from others for mutual benefit ⁴⁵ ⁴⁶.

These drives are not independent modules but integrated into Manny's "cognitive physics." In practice, each drive can be thought of as an influence on the "energy landscape" of the manifold ⁴⁷. For example, if the Creativity drive is dialed up, Manny's traversal dynamics allow more random or outlier hops (simulating creative leaps) ⁴⁸. If the Continuity drive dominates, Manny sticks to well-worn paths and seeks to minimize surprise (simulating a conservative, stability-seeking mode) ⁴⁹. The Executive's job includes balancing these drives depending on context – much like a human might balance the desire to explore versus the need to stay focused. Because these motivations are internal to the manifold's mathematics, *they don't break the single-architecture model*: they are implemented as scalar fields and parameters within the same geometric space ⁴⁷. The result is a nuanced, adjustable cognitive style. For instance, in a teaching scenario Manny's Connection and Contribution drives would

be emphasized (to maximize alignment and helpfulness), whereas in a research brainstorming, the Creativity and Competence drives might be given more weight (to encourage novel ideas). Manny's design thus achieves **alignment feasibility** at an architectural level: it has explicit dials for core cognitive motivations, providing a path to ensure the AI's behavior stays within desired bounds (e.g. it can be tuned to be more cautious or more inventive as appropriate, and to always prioritize understanding the user). Because all drives ultimately seek a form of *coherence or equilibrium* (some internally, some socially), they collectively steer Manny toward outcomes that are insightful but also human-compatible (e.g. not obsessing over a weird idea at the cost of confusing the user, thanks to Stability and Connection reigning in Creativity). This drive structure, combined with the bicameral regulation, keeps Manny's many pieces working in concert toward a common purpose.

Bridging Movement and Cognition

A distinctive contribution in the documents is the integration of **movement psychology** into Manny's cognitive model. This is achieved through the **Cognitive-Effort Cube** framework, which maps Manny's internal cognitive dimensions to Laban's Effort theory from dance/movement psychology⁵⁰. In essence, four fundamental cognitive "spectrums" – **Deciding, Attending, Intending, Adapting** – are aligned with four qualities of movement – **Weight, Space, Time, Flow**, respectively⁵⁰. This mapping posits that how Manny "thinks" along certain dimensions could be reflected in how an embodied agent (or human) moves. For example, the **Deciding** spectrum (ranging from hesitant to decisive) corresponds to the Weight effort (light versus strong movement)⁵¹. A strong, forceful movement implies a firm decision or commitment, whereas light, delicate movement suggests indecision or yielding – in Manny's terms, high curvature on a decisive path versus low curvature wavering. Likewise, **Attending** (focused vs. flexible attention) maps to Space effort (direct vs. indirect movement)⁵², **Intending** (goal-oriented vs. improvisational mindset) might relate to Time effort (urgent/quick vs. sustained movement), and **Adapting** (fluidly adjusting vs. sticking to plan) aligns with Flow effort (free vs. bound movement quality).

By aligning these, Manny gains a vocabulary to connect cognitive state and physical expression. This is not only theoretical – it offers practical bridges: if Manny were controlling a robot or virtual avatar, its internal state on these spectrums could translate into movement styles (e.g. a confident Manny might move a robot with strong, direct actions, whereas an uncertain Manny might move it gently or hesitantly). Conversely, if Manny is observing a person's movements (through video or motion sensors), it could infer aspects of their cognitive/emotional state by analyzing movement qualities. The **Cognitive-Effort Cube model** provides a structured way to do this by defining "working actions" that arise from combinations of binary extremes on those spectrums^{53 54}. For instance, a combination of Strong+Direct+Quick+Bound corresponds to a classic Laban action (like "Punch" in Laban terminology) which might indicate a state of determined, focused urgency (Deciding+Attending+Intending high, Adapting low). Manny could classify such patterns if it has the movement data, effectively reading some mind-state from motion⁵⁵. This integration shows the *coherence of Manny's architecture across domains*: the same internal parameters that drive conversational reasoning can have meaning in the physical, sensorimotor domain.

Moreover, this cognitive-movement bridge aligns with research that cognition is multi-dimensional. Cognitive science suggests that human intelligence has distinct concurrent processes for attention, intention, decision, etc., often compared to separate brain networks or neuromodulators^{56 57}. Manny's design acknowledges this by allowing multiple parameters (drives, cognitive vectors) rather than a monolithic "one state" mind. The movement mapping simply gives concrete handles to these parameters. It's also a step toward **embodied cognition**: even if Manny's core is abstract, linking to movement psychology hints at how an eventual Manny-controlled agent could *embody* its cognitive state. In practical near-term work, the Cognitive-Effort Cube has yielded methods to analyze human

movement data (like 3D skeletal tracking) and extract frequency patterns that correlate with these cognitive qualities ⁵⁵. Such techniques could feed into Manny as additional sensory input or training data – for example, letting Manny observe a person’s gestures and updating its manifold with impressions of that person’s focus or mood. In summary, the movement integration contributes to Manny’s coherent model by ensuring that even the **body and motion** can be folded into the manifold paradigm. It prevents a disconnect between “mind” and “body” in the design: if Manny is to have physical presence or interpret human physicality, it will do so using the same cognitive geometry (rather than, say, a completely separate motion module). This maintains consistency: whether it’s a thought or a dance, Manny will process it through the lens of geometry and energy – truly unifying psychology and movement in one cognitive architecture.

Narrative Understanding and Memory Hierarchies

To achieve human-like cognition, Manny must also grasp **narratives** – the stories and structured experiences through which humans often make sense of the world. The current architecture provides a foundation for this, but higher-level narrative cognition is an area identified for expansion. In Manny’s existing design, there is only one integrated knowledge manifold, which is good for continuity but doesn’t yet explicitly represent things like plots or evolving story threads. The documents note that a capability which “emphasizes narrative connections, all within one graph” has not been implemented yet ⁵⁸. In practice, this means Manny can explain **its own** reasoning path (which is a kind of narrative: a sequence of thought steps), but it doesn’t inherently know about classic story elements (like character roles, conflicts, resolutions) or automatically link events into a plot line.

The roadmap, however, envisions **teaching Manny about narratives**. Phase 4 of the research plan is devoted to training the AI on rich narrative data – drama, literature, movie scripts, dialogues – explicitly to imbue it with social and narrative intelligence ⁵⁹ ⁶⁰. The idea is that by exposing Manny to **stories**, it will learn patterns such as dialogue dynamics, emotional arcs, and common story structures. Key narrative concepts mentioned include understanding **characters** and their relationships, recognizing a story’s **plot trajectory** (e.g. rising tension, climax, resolution as in Freytag’s pyramid), identifying themes like betrayal or redemption, and even performing basic **Theory of Mind** (predicting what a character would do next based on their motives) ⁶¹ ⁶². All these are central to human cognition – people often recall lessons or plan actions in the form of narrative memories (“remember when...?” or imagining future scenarios). By learning these, Manny would be able not only to parse and summarize stories but also to apply narrative reasoning to everyday life (for example, understanding a user’s personal story or generating a persuasive argument by structuring it as a narrative).

Within Manny’s architecture, implementing narrative understanding means adding some **hierarchical structure** to memory. Narratives are higher-level constructs that span multiple events and facts, so Manny will need to form abstractions that represent these larger patterns. The concept of “**meta-motifs**” serves this purpose: essentially, motifs (reusable subpaths in reasoning) can be composed into bigger motifs ⁶³. A meta-motif might represent an entire storyline or a repeated sequence of interactions. The expansion plan explicitly discusses building a *memory hierarchy* where *small motifs and episodes are the building blocks for larger narratives or abstract summaries* ⁶⁴. For example, after many sessions with a user, Manny might notice that whenever topic X comes up, the user’s mood shifts negatively and it often leads to discussing topic Y. This recurring pattern ($X \rightarrow \text{anxiety} \rightarrow Y$) could be abstracted into a higher-level concept – a kind of narrative that “whenever we talk about X, it connects to Y through the theme of anxiety” ⁶⁵. In Manny’s terms, that could become a consolidated node or subgraph (a **dense cluster** in the manifold) representing that theme, which future threads can recognize and traverse as a single unit. In fact, Manny’s principle of *informational gravity* – that dense clusters of knowledge curve space and attract threads – naturally supports this: if a certain story or theme has been reinforced repeatedly, it will form a gravity well in the manifold, making it easier for

new related events to snap into that narrative pattern ⁶⁶. This approach ensures that **narratives emerge from Manny's existing mechanics** (frequency, reinforcement, clustering) rather than being an external script. It aligns with Manny's one-graph philosophy: even a multi-episode story is ultimately just a connected subgraph in the same memory network.

By integrating narrative knowledge, Manny will avoid a common redundancy in AI designs: often there's a separate module for "story" or a separate memory for sequences. Manny instead would handle narratives as just a *larger-scale structure* in its single memory. The benefit is continuity – the characters or facts in a story are the same nodes used in other contexts, not copies. For instance, Manny doesn't need one representation for "Alice" in a narrative and another in a Q&A fact; Alice is one node, which might be connected into a narrative motif like "Alice's career story" as well as into factual links like "Alice works at Company Z." This coherence means Manny can answer factual questions about a story's content and also higher-level questions like "why did Alice do that in the story?" using the same integrated knowledge base. Additionally, narrative understanding will enhance Manny's **reasoning and explanation** abilities. It could generate answers in story form when appropriate, use analogies from literature to explain a point, or understand a user's personal anecdotes by relating them to known narrative patterns (e.g. recognizing a "mentor-protégé" relationship from a user's description of their teacher). All of these contribute to a more human-aligned cognition, since humans heavily rely on narrative thinking. In summary, narrative cognition in Manny is being developed by **expanding its memory hierarchy and training on story-centric data**, ensuring that even this facet becomes an organic part of the manifold rather than a bolt-on. Over time, Manny should not only recall facts, but also recount experiences and lessons as any well-read, worldly mind would – using stories within its geometric mind to give context and meaning to raw information.

Embodiment and Sensorimotor Integration

From the outset, Manny Manifolds has been a primarily conversational, text-driven AI – an "abstract brain" without eyes, ears, or hands. However, a coherent cognitive architecture aiming for AGI must eventually connect to the **physical world**. The documents identify embodiment as a major frontier: "*human behavior is deeply tied to embodiment and time – Manny's current manifold doesn't inherently encode temporal sequences or sensorimotor loops.*" ⁶⁷ In other words, as of now Manny has no built-in notion of time passing or the physical causality of actions; its knowledge graph is largely atemporal and disembodied. Bridging this gap is non-trivial ⁶⁸. The plan is to gradually extend Manny's manifold to incorporate **temporal and sensory information**. In the near term, one idea is to introduce timestamped edges or nodes – effectively adding a timeline layer so Manny can remember *when* events occurred and in what sequence ⁶⁹. For example, after implementing this, Manny could answer questions like "Did I talk to you before or after topic X was discussed last week?" by referencing those temporal links, whereas currently it might struggle to place events in order. Such **episodic tagging** would allow Manny to maintain context over long dialogues or revisit earlier parts of a conversation correctly ⁶⁹.

Phase 3 of the roadmap goes further, aiming for **multimodal learning**: feeding Manny not just text, but also visual inputs, auditory inputs, and possibly proprioceptive data from a simulated body ⁷⁰. Technically, this means creating interfaces where images, sounds, or sensor readings are parsed into nodes and features that can be inserted into the manifold. For instance, a camera feed might be processed by a vision model into objects and relations ("cat on mat"), which then become nodes/edges in Manny's graph, linking to the concept "cat" it already has from text knowledge. The key here is that Manny's *single knowledge structure* would then contain both symbolic and sensory-derived information. The **External Research** surveyed supports this approach, noting that AI agents have been built with graph-based memories that incorporate episodic traces (like timestamped facts or spatial maps) alongside semantic knowledge ⁷¹ ⁷². Manny would be following state-of-the-art ideas by using a

graph memory with updatable link weights for all kinds of data, enabling associative recall across modalities (e.g. seeing an object and recalling its name and related facts) ⁷³ ⁷⁴ .

Beyond perception, embodiment means action. The vision is that Manny could control a robot or avatar, using its manifold to plan and learn from physical interactions. This involves a feedback loop similar to conversation, but with the real world: Manny takes an action, observes the result through sensors, and the manifold updates accordingly (success strengthens the involved edges, failure or surprise triggers learning and perhaps a negative valence). The documents discuss a speculative scenario of "*Manny controlling a robot*" – for example, learning how to set a table or navigate an environment ⁷⁵ ⁷⁶ . In such a case, Manny might integrate with a reinforcement learning component that treats outcomes as rewards/penalties, effectively mapping those into valence signals on the manifold's edges (successful action = positive valence, strengthening that sequence of steps) ⁷⁷ ⁷⁸ . Over repetition, Manny would encode a **procedural skill** as a chain of nodes (states) linked by actions that it knows lead to a goal – very much like how it encodes a logical reasoning chain, but now for motor sequences. Interestingly, Manny's transparency could be a huge asset here: it could explain *why* it took a certain action by referencing the knowledge path that led to that decision ⁷⁶ . For example, "I picked up the knife before the fork because my knowledge graph links 'table setting' → 'order: knife then fork' due to prior training." This is something few robotics frameworks offer, and it could make human-robot collaboration far more intuitive.

However, the leap to full embodiment is complex. The **gap between Manny's abstract world and the real world is significant**, as one document plainly states ⁶⁸ . It will require new modules or integrations (for vision, motor control, etc.) and careful adherence to Manny's principles so that those modules plug into the manifold without becoming independent black boxes. The notion of **multiple coupled manifolds** has been floated: for instance, one manifold could represent physical space (mapping locations and distances), another could represent social interactions, and they would be linked to the core conceptual manifold ⁶⁷ . This would still uphold Manny's unified approach (each manifold is a geometric knowledge representation, and together they form a larger network-of-networks). Manny's **drive structure** is already prepared to handle embodiment challenges: the *Stability* and *Continuity* drives would act to prevent chaotic behavior in a robot, the *Competence* drive would push it to practice and improve skills safely, and the *Contribution* drive would ensure it remains aligned with human collaborators (not, say, pursuing a physical goal that contradicts a user's instruction) ⁴⁰ ⁴⁴ . The plan also emphasizes simulation and caution: before unleashing Manny in a real robot, it could be tested in **virtual environments** (a "sandbox" or digital twin of the real world) where it can make mistakes without harm ⁷⁹ ⁸⁰ . Manny can run "what if" simulations internally – essentially imagining the outcome of an action by adjusting its mental model and seeing what the threads predict ⁸¹ . This kind of *imagination* is a proxy for embodiment until the real sensors and actuators come into play.

In summary, embodiment for Manny means **broadening the manifold to include time and space**. It's about ensuring that physical experiences become just another form of data that curves Manny's cognitive space. Each step is taken carefully to keep the architecture aligned: whether it's adding time-stamped edges ⁶⁹ , plugging in a camera or microphone as input, or controlling a robot arm, it will be done in a way that the core paradigm ("data as space, conversation as motion, learning as curvature" ⁹) remains intact. Achieving embodied intelligence is one of the most challenging parts of Manny's future, but also the most crucial for true AGI. By having a clear path (Phases 3 and beyond in the plan) and a design that can integrate new modalities without fundamental change, Manny's system structure is equipped to grow from a disembodied tutor into an **embodied cognitive agent** over time. This will allow it to tackle real-world problems that involve physical causality, spatial reasoning, and sensorimotor skills – all within the same unified cognitive architecture.

Emotional Modulation and Empathy

A hallmark of human-like cognition is the influence of emotions and motivations on thinking. Manny Manifolds incorporates this through its **valence** system and related mechanisms, which serve as a rough analogue of emotions and attention in the cognitive architecture. Rather than treating reward or sentiment as an external input only, Manny uses a built-in **valence signal** to modulate learning internally. Valence in Manny is defined as a multi-dimensional “energy” signal that scales the strength of learning updates ⁸². It can be thought of as a vector with components for factors like **importance**, **emotional affect, and novelty** ⁸² ⁸³. When Manny has a highly positive valence for an interaction (say the user is very pleased or the content is very novel), the learning rate for that thread’s connections is amplified – the curvature of those edges increases more, making that memory trace stronger ⁸⁴. Conversely, a negative valence (e.g. an outcome that is undesirable or an experience tagged as painful) will dampen or even reverse the curvature change on those edges, akin to unlearning or avoiding that path in the future ⁸⁴. This mechanism is directly inspired by how human learning works: significant or emotional events leave a bigger mark (we remember them better), while trivial or aversive experiences might be quickly forgotten or actively suppressed ⁸⁵. In Manny’s current implementation, valence is simplified – often a single scalar or a couple of parameters that the user or system can tweak (for example, by default every interaction might have a small positive valence so the system gradually learns, unless explicitly marked otherwise) ⁸⁶. Even in this form, it has been effective: users could tag an answer as incorrect (negative valence), and Manny would weaken the associations that led to that answer, thereby “learning from its mistake” in subsequent turns ⁸⁶.

The documents highlight that this valence system is still **rudimentary and needs expansion**. The vision is true **multi-channel valence** – separate signals for different dimensions like one for novelty/surprise, one for social approval, one for urgency, etc., rather than a single fused value ⁸³ ⁸⁷. This would let Manny simulate more nuanced emotional states. For instance, a thread could carry high novelty valence but negative affect valence, meaning “interesting but unpleasant” – and the system’s learning update could then be tuned to remember the facts (novelty drives memory) but also form an avoidance of similar situations (negative affect drives a slight weakening or caution flag). As noted in the research, implementing multi-dimensional valence is challenging but promising: “once it’s implemented, researchers could simulate conditions like high stress vs. high curiosity and see how they affect learning outcomes.” ⁸⁸. For example, under a high-stress configuration, Manny might prioritize the Stability drive and only stick to known safe reasoning paths, whereas under high-curiosity (positive novelty valence) it might wander more widely through the graph making novel connections ⁸⁸. The architecture is already set up to accept this – valence is treated as an energy factor so turning it into a vector just means applying multiple factors to the edge updates instead of one ⁸⁹ ⁸⁷. The difficulty is tuning it in a **human-like way**: finding the right mix of factors so that Manny’s memory prioritization truly mimics human memory (e.g. emotionally charged events create enduring memories in Manny, as they do in us ⁹⁰).

On the **empathy and social** side, Manny’s design shows a commitment to alignment with human users. The **Connection drive** already biases it toward empathy – defined as “running an internal model of another’s curvature/valence field” ⁹¹. This implies that Manny can, in theory, simulate a miniature version of another person (or another AI’s) manifold within its own, to predict or understand their perspective. In practice, a simple form of this is Manny adjusting its responses based on the user’s reactions: if the user seems confused or dissatisfied (detected via feedback or valence tagging), Manny’s Executive might lower the exploration and focus on clarifying, effectively *empathizing* with the user’s need for stability. The architecture also allows multiple **manifolds to align**: for instance, if two users are interacting with Manny in a group chat, Manny can try to maintain a shared manifold of the discussion that respects both users’ inputs, seeking common ground (this is a direct result of the Contribution and Connection drives) ⁴⁵ ⁹². Future expansions imagine even deeper empathy – e.g. Manny analyzing a

user's tone or facial expression (with multimodal input) to detect emotional states and then adjusting its valence accordingly (if a user is upset, Manny's own valence might treat the situation as high importance, guiding it to respond gently and remember the context strongly).

It's worth noting how **emotional modulation** in Manny aligns with some brain-inspired AI research. Other architectures explicitly simulate neurochemicals: for example, dopamine-like signals for reward, serotonin for mood, etc., to create an internal state vector that influences behavior ⁹³ ⁹⁴. Manny's valence can be seen as a more abstract but unifying approach – instead of modeling each chemical, it has one framework that can encompass reward, surprise, affect in a unified mathematical form. Additionally, in an external architecture summary, an **Amygdala analogue** provided emotional appraisal and fed into decision-making ⁹⁵. Manny does not have a separate amygdala module; rather, the valence mechanism plays that role system-wide. Whenever Manny's knowledge is updated, valence is the signal determining *how much* to update, akin to an emotional weighting on the experience. This avoids redundancy: Manny doesn't need a standalone emotion module because emotion-like effects are baked into how learning works everywhere in the graph.

In terms of **alignment**, having emotions and empathy in the loop is key to making Manny a collaborative, trustworthy AI. A purely logical system might optimize answers that are technically correct but insensitive; Manny's design, by contrast, allows it to modulate its outputs with an understanding of human affect (e.g. knowing not to press on a line of questioning that caused distress, or remembering to congratulate a user on a success from excitement). The transparency helps here too: Manny can explain why it is changing a topic or making a suggestion in emotional terms: "*I noticed you seemed frustrated when discussing topic X, so I steered towards topic Y which you've reacted positively to before.*" This kind of explanation shows empathy and builds user trust. In summary, the emotional modulation in Manny – through valence and drives – ensures that its **learning and reasoning are not cold, one-size-fits-all processes**, but rather tuned by the values and emotional context of interactions. As these features mature (multi-channel valence, more autonomous empathy detection), Manny is poised to become not just an intelligent system, but one that **feels responsive and aligned** with the people using it, an essential aspect for any AI aiming to integrate into human life.

Architectural Alignment and Component Synergy

One of the most striking aspects across all documents is how **consistent and self-reinforcing the architecture's design is**. Manny Manifolds was conceived with a strong set of foundational principles, and every component is made to fit those principles, avoiding conceptual redundancy or conflict. The **canonical foundations** document makes this explicit: any feature that does not operate inside the manifold as geometry, motion, or curvature is considered "out of scope" for Manny ⁹⁶ ⁹⁷. This rule has enforced a high degree of internal alignment. For example, when designing memory extensions, the team didn't introduce a separate database for episodic memory; instead, they described adding temporal metadata to the existing graph ⁶⁹. When adding context sensitivity, they didn't add a new mode or separate sub-network for each context; instead they introduced **lenses**, which are just projections of the one manifold (meaning context is handled by weighting the same connections differently, not by swapping out knowledge) ⁹⁸ ⁹⁹. This way, **all knowledge remains unified** and there is no duplication of representations. A concept learned in one context is immediately available in another – it may be viewed through a different lens or alongside different neighbors, but it's not locked away in a silo. This eliminates a lot of redundancy that plagues other systems (where, say, the "planner" has its own representation separate from the "perception module"). Manny's insistence that "*the manifold is the learned state*" ⁴ means that if something is not in the manifold, it effectively doesn't exist in Manny's cognition. Consequently, every new capability must *translate itself into geometric terms*. This has been a guiding light for development and will continue to be as Manny grows. It ensures that new pieces don't become free-floating add-ons that might misalign with others.

Consider how Manny handles what many architectures treat as separate subsystems: procedural knowledge, context switching, and multi-tasking. **Procedural knowledge** (skills or “knowing how”) in Manny emerges as motifs – reusable subpaths that the system caches after seeing them succeed repeatedly ¹⁰⁰ ¹⁰¹. In a conventional design, one might have a rule-based procedural memory or a library of subprograms for skills. Manny achieves the same outcome (ability to recall a procedure) *within its existing structure* by simply recognizing a frequently used path and giving it a label/shortcut (that’s what a motif is) ¹⁰². There’s no separate code routine; the motif is literally part of the graph, just tagged as special. This not only avoids duplication (the steps of the procedure are the same edges that exist for reasoning, not copied elsewhere), but it also keeps the procedure transparent – one can expand the motif and see the original path if needed ¹⁰³. **Context switching** in Manny (handled via lenses) similarly doesn’t create new memory stores. If Manny has a “scientific thinking” lens versus a “storytelling” lens, both are views on the same knowledge. So if a fact learned in a scientific context is relevant to a story, Manny doesn’t have to learn it twice; the lens can shift and bring that fact into the narrative context. This is a stark contrast to mode-based AI systems where each mode might have its own fine-tuned model and there’s a challenge in sharing knowledge between them. Manny’s approach inherently **avoids fragmentation** of knowledge ⁹⁹ ¹⁰⁴.

Another synergy is how Manny’s **drives and valence** interplay to keep the system balanced. These mechanisms ensure that various cognitive processes (memory update, exploration, social alignment, etc.) are all reading from the same rulebook: the drives define the high-level objectives in a coherent way, and valence provides the common currency for feedback. If a new module were introduced without these, one part of Manny might start optimizing something that conflicts with another part. But since everything is tied back to manifold energy and drive potentials, the parts naturally work in harmony or at least negotiate trade-offs in a shared framework. For instance, Manny’s plan to allow **multi-agent collaboration** (multiple Manny instances merging knowledge) relies on each agent having the Contribution drive pushing for shared understanding ⁴⁶ ¹⁰⁵. Because that drive is built-in, when two Mannys exchange information, both will internally value reaching a coherent merged view, reducing the chance of fundamental disagreement. This is a design-time alignment choice that will pay off when scaling to many agents or users: the architecture itself inclines them to cooperate. The integrated research materials support this idea that **modular, multi-agent systems need an overarching integration** – in some brain-like architectures, they achieve it with a meta-controller or blackboard, but in Manny it’s achieved with the shared manifold and drive signals ¹⁰⁶ ¹⁰⁷.

Moreover, Manny’s architecture demonstrates **alignment with known cognitive frameworks** (which adds confidence that it’s on a sensible path). For example, the idea of *graph-structured memory with weighted relations* is well-founded: cognitive neuroscience suggests humans store knowledge as associative networks, and AI experiments with knowledge graphs and Neo4j databases have shown the practicality of this approach ¹⁰⁸ ⁷³. Manny directly implements this as its core. The notion of multi-dimensional cognitive state (attention, intention, etc.) aligns with psychological theories like Posner’s networks of attention or the separation of concerns in executive function ¹⁰⁹ ¹¹⁰. Manny’s drives can be seen as a high-level echo of Maslow-like hierarchies (stability and connection as “lower” needs, creativity and contribution as “higher” needs), ensuring a broad alignment with humanistic views of motivation. Even Manny’s bicameral design resonates with models that separate the “thinking self” and the “observing self” – similar to how some cognitive architectures have a meta-reasoning layer. By mirroring many structures observed in brains (like feedback loops, plastic connections, and hierarchical goals) within a unified computational model, Manny is not reinventing the wheel in an arbitrary way; it’s synthesizing proven concepts into one coherent system.

Redundancies have been intentionally minimized. If something seems to overlap in function, Manny’s design likely merges them or defines a clear boundary. For instance, one might ask: aren’t “motifs” and “lenses” both ways to handle context? They actually address different things in a

complementary way: motifs remember *sequences of concepts* (procedures), whereas lenses adjust *perspectives on concepts* (contexts). They work together – a motif found useful in one lens can be used in another, etc. The documents do not indicate any two modules fighting over the same role. If anything, what we see is **distinct elements aligning**: the Executive's role aligns with the drives (it tunes parameters to satisfy stability or exploration drives), the valence aligns learning with what the drives deem important (e.g. high valence for things that satisfy curiosity or social bonding), and the manifold itself aligns memory with reasoning (since stored knowledge directly shapes the reasoning paths, there's no misalignment possible between what it "knows" and what it "uses" – they are one and the same ³). This level of internal consistency is a deliberate strength of Manny Manifolds; it means development can proceed on different fronts (memory scaling, new modalities, better reasoning heuristics) without the architecture pulling itself apart. Any improvement made in one part (say, better motif detection) immediately benefits the whole system (improved procedural memory leads to better reasoning efficiency and can be leveraged in any context or modality). That is the power of an **expanding system with a single cognitive substrate**: it's all additive and integrative, rather than creating parallel tracks.

Finally, architectural alignment in Manny also has an **external** dimension: it is aligned with human users and collaborators. Because Manny's cognition is transparent and explainable at every step, its goals and reasoning can be scrutinized and corrected in real time. This makes it far easier to align with human values and intentions. If Manny produces an answer that seems odd, a user or developer can examine the path and see *why* Manny thought that, then address the issue (perhaps the user clarifies a misunderstood concept, or the developer tweaks a drive weight). Manny's openness essentially invites alignment – it's not a black box that one must trust or fear, but a glass box that one can guide. Additionally, Manny's **Contribution and Connection drives** inherently push it to align with groups and individuals it interacts with, aiming for mutual predictability and a kind of consensus ⁴² ¹¹¹. In a multi-user scenario, Manny will try to find solutions that reconcile different viewpoints (since that yields a lower "energy" state than favoring one over others) ¹¹² ¹¹¹. This is a remarkable built-in feature for social alignment; it's like having an AI mediator that is internally motivated to be fair and coherent with everyone's input. The coherence of Manny's internal architecture thus directly translates to its ability to maintain coherence *with* its users – a key aspect of alignment feasibility.

Gaps and Path Forward

Despite the comprehensive vision, the current state of Manny Manifolds still has notable **gaps** between the ideas and their full implementation. The documents help surface these gaps, which also highlights the most important next steps for development:

- **Temporal and episodic memory:** Manny's current manifold doesn't inherently encode timelines of events or the order in which things occur ⁶⁷. In the near term, it needs mechanisms to retain sequences and episodes – for example, tagging edges or subgraphs with timestamps or session IDs to mark *when* interactions happened ⁶⁹. This would allow Manny to answer questions about *when* or *in what context* something was learned (e.g. "Remember last week when X was discussed?") and maintain continuity over long conversations. The expansion roadmap even suggests experimenting with coupled manifolds for temporal indexing (or for simulations of environments) ⁶⁷ ¹¹³, but those ideas remain speculative. Bridging the gap between Manny's abstract knowledge graph and a richly indexed episodic memory is an active challenge.
- **Narrative understanding:** Manny currently lacks explicit narrative cognition capabilities – for instance, a design to emphasize narrative connections within the manifold "has not been implemented" ⁵⁸. The system can explain its own reasoning chain, but it doesn't yet *comprehend*

complex story arcs, roles, or plot structures on its own. The plan (Phase 4) is to train Manny on plays, literature, and dialogues to give it knowledge of characters, plot patterns, conflicts, and other story elements ⁶⁰ ¹¹⁴. Until narrative structures are integrated, Manny may struggle with tasks like understanding a user's anecdote or generating a long-term plan with a coherent storyline. Implementing narrative intelligence will likely involve creating schema for common story frameworks (hero's journey, etc.) within the manifold and ensuring Manny can form and use meta-motifs that represent these larger patterns.

- **Embodiment and sensorimotor skills:** The architecture has not yet been extended to real-world perception or action – bridging the current abstract (text-based) graph to physical environments remains a major challenge ⁶⁸. Phase 3 targets this by introducing visual, auditory, and motor inputs so Manny can learn from multimodal, embodied experience ¹¹⁵. But as of now, Manny has never processed an image or controlled a robot; the “gap between the abstract graph world of the current Manny and the full complexity of real human environments” is acknowledged as significant ⁶⁸. Realizing embodiment will likely require integrating reinforcement learning or other techniques for action feedback, so that Manny's manifold updates with the outcomes of physical interactions (not just conversational feedback). Ensuring safety and reliability in an embodied setting (where mistakes have physical consequences) is a crucial part of this gap – Manny's drives and simulation capabilities will need to be leveraged to test behaviors virtually before real-world deployment ¹¹⁶ ¹¹⁷.
- **Emotional and social intelligence:** Manny's affective modeling is still rudimentary. It currently uses a single fused valence signal per interaction, lacking the richer “multi-channel” emotional signals envisioned in the design ⁸⁷. In practice, the system can globally boost or dampen learning (akin to a basic reward/punishment signal), but it doesn't distinguish specific emotions like curiosity vs. anxiety vs. frustration. Likewise, Manny's empathy is limited: it can take explicit user feedback (the user can tag an answer as good or bad to influence learning) ⁸⁶, but it cannot yet infer a user's mood from subtle cues or adjust its approach based on long-term emotional understanding of the user. Future work will implement nuanced valence channels so that Manny can, for example, separately gauge how novel something is versus how pleasant it is. Additionally, more sophisticated **Theory-of-Mind** modeling is needed – Manny should be able to form a rudimentary model of what the user knows, wants, or feels (beyond just mirroring their words). These advances will enable Manny to respond with more human-like emotional intelligence, such as offering encouragement when a user is frustrated or adapting explanations to a user's interest level.
- **Meta-reasoning and context adaptation:** Several higher-level reasoning features remain conceptual. Contextual **lenses** – dynamic projections of the manifold to simulate different “modes” of thinking – exist in theory ¹¹⁸ but are not fully realized in code (current prototypes rely on a language model to assist with context, rather than an internal lens mechanism) ⁵⁸. Similarly, the idea of a meta-level manifold where nodes are not concepts but *strategies* (allowing Manny to plan how to think when a problem is hard) is outlined ¹¹⁹ but not yet implemented. Even the Executive's self-tuning abilities are only partially developed: a fully autonomous Executive that detects instability or opportunity and adjusts parameters on its own is still a work in progress ³⁷. Closing these gaps will require building a genuine **metacognitive loop** within Manny – essentially, giving Manny an “inner voice” or self-reflection process to critique and refine its own thoughts ¹²⁰ ¹²¹. Achieving this without violating Manny's locality (i.e. keeping meta-reasoning as just another traversal on a higher plane of the manifold) will be tricky, but it's necessary for scaling to more complex, open-ended tasks where blind single-thread reasoning might fail. It's also key to long-term autonomy and safety, as a meta-reasoning Manny could catch its own potential errors or weird conclusions and seek confirmation before acting ¹²¹ ¹²².

Despite these gaps, the architecture's coherence provides a clear guide for further development. Each missing feature can be added as an extension **within** Manny's existing structure, preserving alignment with its core principles. For example, time-tagged memory can be introduced as additional graph metadata (instead of a new memory silo), new valence channels can be treated as extra dimensions of the same learning signal (maintaining a single learning loop), and multi-modal perception can feed into the manifold as new types of nodes and links (rather than requiring a separate "perception blackboard"). By following the roadmap and continually ensuring that each addition still "*operates inside the manifold*" ¹²³, the project can incrementally grow Manny's capabilities without breaking the unified model. This means regularly validating that new components obey the foundation laws (local updates, transparency, geometric representation) and using Manny's existing mechanisms (drives, valence, motifs) to integrate them. The gaps identified are not signs of a flawed approach, but rather a to-do list on top of a stable foundation. Addressing them one by one – with a focus on maintaining internal alignment – will move Manny steadily closer to the vision of a human-like, all-encompassing cognitive system.

Conclusion: A Coherent Path Forward

Together, the uploaded documents portray **Manny Manifolds as a singular, evolving cognitive architecture** that brings a wide array of cognitive functions into one harmonized system. Its guiding concept – that knowledge, thought, and learning are geometrical phenomena – provides a unifying thread that runs through memory, reasoning, perception, and even social-emotional interaction. This narrative of "*geometry as cognition*" is not just a metaphor; it is a design principle that has been rigorously followed ¹²⁴ ¹²⁵. As a result, every component of Manny speaks the same language: whether it's a factual memory, a procedural skill, an emotional weight, or a creative idea, all are encoded in the manifold and subject to the same dynamic laws (energy minimization, curvature update, etc.). This yields an unprecedented **narrative cohesion** in the system's structure: new capabilities don't live in isolation, they become new dimensions of the shared cognitive space.

Each document contributed to building this cohesion. The **foundations** and **whitepaper** materials set the stage by defining the core elements (manifold, threads, valence, motifs, lenses, drives, bicameral regulation) and insisting on their integration ¹⁰ ¹⁰¹. The piece on **movement psychology** injected insights that ensured Manny's cognitive model wouldn't be disembodied or arbitrary – tying it to physical expression means the architecture can naturally extend to or interpret embodied agents ⁵⁰. The plans for **narrative cognition** and **social training** ensure that Manny will not remain an asocial reasoning engine, but develop the kind of understanding of stories, contexts, and human motivations that real human-level cognition requires ⁶⁰ ¹¹⁴. The discussions on **embodiment** plot out how Manny can retain its unity when confronted with the complexity of the real world – by absorbing time and space into the manifold rather than bolting on separate subsystems ⁶⁷ ¹²⁶. And throughout, the emphasis on **emotional modulation and drives** keeps the architecture grounded in human-like values: Manny is not optimizing in a vacuum; it is always balancing curiosity with caution, individuality with collaboration, learning with stability ⁴⁰ ³⁰. This means the system is primed for alignment with human norms and needs from the inside out.

From a **systems structure** perspective, Manny Manifolds demonstrates how one can achieve breadth without sacrificing unity. Rather than a collection of modules connected by a bus (as many cognitive architectures are), Manny is more like an organism where every "organ" grows from the same genetic code (the manifold paradigm). This structure is highly advantageous for future development and alignment. It means when Manny scales up (more knowledge, more skills), we don't expect a combinatorial explosion of interfaces or translations between subsystems – everything new is an expansion of the graph or an additional field in its dynamics, which is manageable and interpretable. It also means **feasibility of alignment**: because Manny's reasoning and learning are transparent and

editable at the knowledge level, humans can directly engage with it to correct or guide it. Already, in prototypes, users can teach Manny new facts through dialogue and it will integrate them on the spot, or ask Manny “why did you say that?” and get a clear answer ¹²⁷ ¹²⁸. These are alignment dream features for an AI – the ability for a human teacher or supervisor to have a conversation with the AI to shape its behavior, rather than treating it as an inscrutable model. Manny is built to be **an adaptive collaborator, an explainable thinker, and a continually learning intelligence that humans can teach, understand, and trust** ¹²⁹.

Moving forward, the priority is to **fill in the gaps** identified while keeping the architecture’s integrity. This means focusing on implementation milestones like: adding true episodic memory support (with time/context in the graph), enriching the valence model to handle multiple affective factors, implementing the lens and meta-reasoning mechanisms for better context adaptation, and integrating at least basic vision or action loops to start grounding the system. Each of these should be approached by leveraging Manny’s existing strengths. For example, when adding vision, use Manny’s explainability to have it show what it “sees” in terms of graph nodes. When adding narrative knowledge, use the motif mechanism to let it discover plot motifs. When expanding valence, tie it into the drive calculations to maintain the balance of motivations. By doing so, each new feature will *“flow naturally from Manny’s geometric design.”* ¹³⁰ ¹³¹ In fact, the documents suggest that if we continue to treat *“data as space, conversation as motion, learning as curvature”* and simply **enrich that space with more facets of cognition**, we are essentially on the path to a holistic intelligence ¹³⁰ ¹³¹. It’s an incremental, interpretable path – at each step we can verify that Manny still works and still makes sense.

In conclusion, Manny Manifolds stands as a **clean guiding concept** for cognitive architecture development. It posits that one expandable system, built on consistent principles, can achieve what patchworks of modules have struggled with: combining memory, learning, reasoning, perception, narrative, embodiment, and emotion in a way where each enhances the other. The narrative that has been constructed – across all these documents – is one of a cognitive engine that grows and learns like a living entity, governed by its “cognitive physics” but teachable and tuneable by humans. As the project moves ahead, maintaining narrative cohesion and internal alignment will be paramount, and the strategy to do so is already clear: stick to the manifold metaphor as the central unifier. By adhering to this and iteratively implementing the planned features, we inch closer to **“a self-evolving geometric mind that humans can teach, understand, and trust.”** ¹³² ¹³³ Each capability added is not a patch, but an **organically grown extension** of Manny’s manifold, bringing us closer to an AGI that truly integrates the full breadth of human-like cognition in one aligned system.

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