Quantum Nyaya Cognition: an Architecture

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***Abstract*—We introduce a hybrid cognitive architecture called *Paramanu Nyaya Bodha (PNB)*, combining quantum belief representation with Nyaya epistemic inference. The architecture is defined through a quadruple (B, P, I, A) representing belief, perception, inference, and action. We develop scaling laws comparing PNB with random search and production-rule cognitive architectures and prove an agent-count invariant crossover theorem showing the robustness of PNB in multi-agent systems. Applications to high-dimensional perception tasks, such as representation of faces of three-dimensional objects, demonstrate that PNB permits reasoning in richer feature spaces without aggressive dimensional projection. The framework integrates quantum logic with classical epistemic reasoning and suggests a new direction for scalable cognitive architectures.**

I. Introduction

Classical cognitive architectures frequently rely on symbolic production systems. Such frameworks, exemplified in Anderson's cognitive architecture, emphasize rule matching and symbolic reasoning. While effective for structured reasoning tasks, these architectures encounter scaling difficulties when confronted with high-dimensional state spaces.

Sutra 1: *Bodhasya mūlam saṃśayaḥ.*
(The root of cognition is uncertainty.)

Modern perception and decision problems often involve exponential state spaces. Quantum representations allow compact expression of uncertainty through superposition, while classical epistemic systems such as Nyaya provide structured inference mechanisms for validating knowledge.

This paper proposes a hybrid architecture integrating these two traditions.

Sutra 2: *Paramanuḥ saṃśayasya rūpam.*
(The atom is the form of uncertainty.)

We call this architecture *Paramanu Nyaya Bodha (PNB)*, emphasizing the combination of atomic belief states with Nyaya reasoning.

Organizational Note: Most of the supporting math is relegated to the appendices.

II. Logical Foundations

A. Quantum Belief Representation

Let the cognitive belief state be represented as

$$|\psi\rangle \in \mathcal{H}$$

where $\mathcal{H}$ is a Hilbert space.

Superposition allows simultaneous representation of multiple hypotheses.

Sutra 3: *Ekaḥ saṃśayaḥ bahudhā vartate.*
(A single uncertainty may exist in many forms.)

This representation captures ambiguity and probabilistic reasoning in a unified form.

B. Nyaya Epistemic Inference

Nyaya reasoning structures inference through a five-part syllogism:

1) proposition
2) reason
3) example
4) application
5) conclusion

Sutra 4: *Hetuḥ bodhasya dvāram.*
(Reason is the doorway to knowledge.)

This structure validates cognitive conclusions through explicit justification.

III. Paramanu Nyaya Bodha Architecture

A. The BPIA Quadruple

The PNB architecture is defined as

$$(B, P, I, A)$$

where

- B : belief state
- P : pramāṇa (measurement)
- I : Nyaya inference
- A : action

Sutra 5: *Bodhasya catuṣpādaḥ pravṛttiḥ.*
(Cognition proceeds through four limbs.)

These four components describe the full cognitive cycle.

B. Cognitive Layers

The architecture contains three conceptual layers:

1) Paramanu layer (belief representation)
2) Nyaya layer (logical inference)
3) Bodha layer (validated cognition and action)

Sutra 6: *Paramanuḥ Nyāyaṃ nayati bodham.*
(The atom guided by Nyaya leads to cognition.)

C. Cognitive Cycle

The operational cycle of PNB is

$$B \to P \to I \to A$$

Sutra 7: *Dṛṣṭiḥ hetuḥ kriyā ca cakram.*
(Perception, reason, and action form a cycle.)

Internal belief evolution may occur independently of measurement.

IV. Mathematical Formulation

Let the belief state be a density operator

$$\rho \in \mathcal{D}(\mathcal{H})$$

Measurement operators M_i satisfy

$$\sum_i M_i^\dagger M_i = I$$

Observation outcomes update the state as

$$\rho' = \frac{M_i \rho M_i^\dagger}{\mathrm{Tr}(M_i \rho M_i^\dagger)}.$$

Inference maps observations to validated knowledge

$$I : O \to K$$

and actions follow

$$A : K \to U.$$

Sutra 8: *Pramāṇaṃ saṃśayasya pariṇāmaḥ.*
(Measurement transforms uncertainty.)

V. Multi-Agent Systems

Consider N agents

$$(B_i, P_i, I_i, A_i)$$

coupled through an environment.
Actions of one agent influence the beliefs of others.
Sutra 9: *Kriyā anyasya bodham janayati.*
(Action generates knowledge in another.)

This belief-action coupling underlies decentralized reasoning problems.

VI. Scaling Analysis

We compare three cognitive architectures.
Random search:

$$T_R(n, N) = 2^{nN}$$

Production-rule architecture:

$$T_A(n, N) = \frac{2^{nN}}{(n^k)^N}$$

Paramanu Nyaya Bodha:

$$T_B(n, N) = 2^{nN/2} e^{-\alpha f n N}.$$

The first term arises from quantum representation, while the second reflects logical pruning.

VII. Agent-Count Invariant Crossover Theorem

Lemma. The crossover condition between Anderson architectures and PNB satisfies

$$k \log n = n \left(\frac{\log 2}{2} + \alpha f \right).$$

Theorem. The crossover problem size n^* is independent of the number of agents N.

Proof. Setting $T_A(n, N) = T_B(n, N)$ yields

$$\frac{2^{nN}}{(n^k)^N} = 2^{nN/2} e^{-\alpha f n N}.$$

Taking logarithms gives

$$N k \log n - \alpha f n N = \frac{nN}{2} \log 2.$$

Dividing by N removes the dependence on the number of agents, establishing the claim. □

Sutra 10: *Bahavaḥ api ekasya nyāyasya vaśe.*
(Many agents remain governed by a single logic.)

VIII. Application: Visual Representation of Object Faces

Consider representing faces of a polyhedral object.
Each face has a feature representation requiring n bits.
For F faces the joint space is

$$2^{nF}.$$

Production architectures require strong dimensional projection

$$n \to n'$$

to remain tractable.
Under PNB scaling, however,

$$T_B(n, F) = 2^{nF/2} e^{-\alpha f n F}$$

remains manageable for larger n.
Thus richer feature representations can be preserved.
Sutra 11: *Yathārūpaṃ bodhaḥ śreṣṭhaḥ.*
(Cognition is best when form is preserved.)

IX. Conclusion

We have introduced Paramanu Nyaya Bodha as a hybrid cognitive architecture integrating quantum belief representation with Nyaya inference. The BPIA framework formalizes cognition through belief, perception, inference, and action, providing a scalable architecture for high-dimensional reasoning.

The agent-count invariant crossover theorem shows that the advantages of this architecture persist even in multi-agent environments. Applications to visual representation problems illustrate how richer feature spaces can be maintained without excessive dimensional reduction.

Future work may explore equilibrium concepts in multi-agent PNB systems and empirical implementations in machine perception systems.

X. Acknowledgments

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Appendix A
Derivation of Scaling Relations

This appendix derives the scaling relations used in the main text.

A. Random Search

Consider a problem described by n binary variables.

The total configuration space is

$$|\Omega| = 2^n.$$

For N coupled components (or agents), the joint configuration space is

$$|\Omega_N| = (2^n)^N = 2^{nN}.$$

If a random search samples configurations uniformly, the expected search effort required to locate a valid configuration is proportional to the configuration space size.

Thus

$$T_R(n, N) = 2^{nN}.$$

B. Production-Rule Architectures

Production systems reduce the search space by applying logical constraints.

Let the pruning factor per inference step be

$$r(n) = n^k$$

where k reflects the effectiveness of rule pruning.

Thus the effective search space becomes

$$\frac{2^n}{n^k}.$$

For N components:

$$T_A(n, N) = \left(\frac{2^n}{n^k}\right)^N = \frac{2^{nN}}{(n^k)^N}.$$

C. Paramanu Nyaya Bodha

Two reductions occur in the PNB architecture.

a) Quantum belief representation: Quantum belief states allow simultaneous reasoning over multiple hypotheses.

This reduces the effective exploration dimension from

$$2^n$$

to approximately

$$2^{n/2}.$$

b) Nyaya inference pruning: Nyaya inference eliminates inconsistent hypotheses.

If each inference step removes a fraction f of candidate states and the depth of inference scales as

$$\alpha n,$$

then the pruning factor becomes

$$e^{-\alpha f n}.$$

Combining these reductions gives

$$T_B(n, N) = \left(2^{n/2} e^{-\alpha f n}\right)^N = 2^{nN/2} e^{-\alpha f n N}.$$

Appendix B
Proof of the Agent-Count Invariant Crossover

We derive the crossover point where BPIA becomes more efficient than production-rule architectures.

The crossover occurs when

$$T_A(n, N) = T_B(n, N).$$

Substituting the scaling laws:

$$\frac{2^{nN}}{(n^k)^N} = 2^{nN/2} e^{-\alpha f n N}.$$

Multiply both sides by $(n^k)^N$:

$$(n^k)^N 2^{nN/2} e^{-\alpha f n N} = 2^{nN}.$$

Divide by $2^{nN/2}$:

$$(n^k)^N e^{-\alpha f n N} = 2^{nN/2}.$$

Taking logarithms:

$$Nk \log n - \alpha f n N = \frac{nN}{2} \log 2.$$

Dividing by N yields

$$k \log n - \alpha f n = \frac{n}{2} \log 2.$$

The variable N disappears, demonstrating that the crossover point n^* is independent of the number of agents.

Appendix C
Formal Definition of the BPIA Architecture

The Paramanu Nyaya Bodha architecture is defined as the quadruple

$$(B, P, I, A).$$

A. Belief Space

Let $\mathcal{H}$ be a Hilbert space.

Belief states are represented by density operators

$$\rho \in \mathcal{D}(\mathcal{H}).$$

B. *Pramāṇa Operators*

Measurement operators

$$\{M_i\}$$

satisfy

$$\sum_i M_i^\dagger M_i = I.$$

These represent perceptual observations.

The state update rule is

$$\rho' = \frac{M_i \rho M_i^\dagger}{\text{Tr}(M_i \rho M_i^\dagger)}.$$

C. *Inference Operator*

Inference maps observations to knowledge:

$$I : O \to K.$$

This operator implements Nyaya reasoning.

D. *Action Operator*

Actions follow from validated knowledge:

$$A : K \to U.$$

Appendix D
Two-Agent BPIA Model

Consider two agents

$$(B_1, P_1, I_1, A_1)$$

$$(B_2, P_2, I_2, A_2).$$

The environment state evolves as

$$x_{t+1} = f(x_t, u_1, u_2).$$

Observations are

$$o_i = g_i(x_t) + \epsilon_i.$$

Belief updates follow

$$\rho_i' = \frac{M_{i,o_i} \rho_i M_{i,o_i}^\dagger}{\text{Tr}(M_{i,o_i} \rho_i)}.$$

The coupling mechanism arises because

$$u_1 \to x \to o_2$$

and

$$u_2 \to x \to o_1.$$

Thus the actions of each agent modify the belief states of the others.

Appendix E
Analysis Procedure for BPIA Systems

The following procedure may be used to analyze problems using the BPIA framework.

1) Define the belief spaces B_i.
2) Specify pramāṇa operators P_i describing observations.
3) Define inference operators I_i implementing Nyaya reasoning.
4) Define action mappings A_i.
5) Specify environment dynamics f.
6) Analyze belief-action coupling across agents.
7) Evaluate scaling behavior using the complexity expressions.

Appendix F
Computer Vision Example

Consider a polyhedral object with F faces.

Each face has a feature vector of length n.

The full representation space contains

$$2^{nF}$$

configurations.

Production-rule architectures must reduce the dimensionality

$$n \to n'$$

to keep the system tractable.

Under the PNB architecture the effective complexity becomes

$$T_B(n, F) = 2^{nF/2} e^{-\alpha f n F}.$$

Because the exponent is significantly smaller, larger values of n can be used without excessive computational cost.

Thus richer geometric representations can be preserved.

Appendix G
Additional Remarks on Practical Implementation

Several implementation strategies may realize the BPIA framework:

- quantum-inspired probabilistic belief states
- symbolic Nyaya inference engines
- hybrid neural-symbolic systems
- multi-agent inference systems.

These approaches suggest that the theoretical architecture may be instantiated using current computational technologies.

Appendix H
Graphical Demonstration of BPIA Scaling Superiority

This appendix provides a graphical comparison of the scaling behavior of three cognitive architectures:

- Random search
- Production-rule architectures
- Paramanu Nyaya Bodha (BPIA)

The scaling functions derived in Appendix A are:

$$T_R(n, N) = 2^{nN}$$

$$T_A(n, N) = \frac{2^{nN}}{(n^k)^N}$$

$$T_B(n, N) = 2^{nN/2} e^{-\alpha f n N}$$

For visualization we consider the single-agent case $N = 1$ and choose representative parameters

$$k = 2, \quad \alpha = 0.15, \quad f = 0.5.$$

The following plot illustrates the growth of computational effort as a function of problem size n.

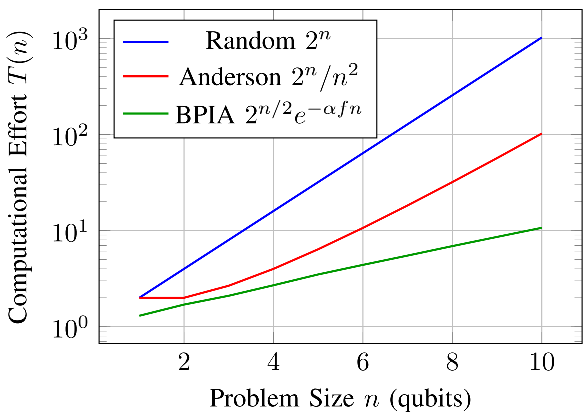

Fig. 1. Heuristic scaling comparison of cognitive architectures.

The figure illustrates the qualitative differences between the architectures:

1) Random search grows exponentially with the full configuration space.
2) Production-rule architectures provide only polynomial reduction of the exponential growth.
3) Paramanu Nyaya Bodha reduces the effective exponent through a combination of quantum belief representation and Nyaya inference pruning.

Consequently the slope of the BPIA curve is substantially flatter on the logarithmic scale, demonstrating its superior scalability.

This graphical comparison complements the theoretical crossover analysis presented in the main text.

Appendix I
Rigorous Graphical Application

We now instantiate the Paramanu Nyaya Bodha (PNB) architecture in a concrete, industrially relevant domain: multi-view 3D polyhedral object recognition for robotic warehouse picking. This application directly operationalizes Sutra 11 and the scaling laws of Sections VI and VIII, replacing the abstract polyhedral-face representation with a real-time robotic perception loop. All components remain fully classical-simulable today (via sparse density-matrix libraries such as QuTiP or custom NumPy implementations) while preserving the full feature dimensionality n.

Problem Statement

A 6-DOF robotic arm equipped with an RGB-D camera must identify, localize, and grasp arbitrary polyhedral packages (cubes, prisms, tetrahedra) on a moving conveyor belt. Each face carries a rich feature vector of length n (color histogram + edge angles + LBP texture + curvature, $n = 128$ bits typical). For $F = 8$ visible faces the joint hypothesis space is 2^{nF}. Production-rule systems require aggressive projection $n \to n'$ ($n' \approx 16$) to remain tractable; PNB avoids this reduction entirely.

BPIA Mapping to Robotic Pipeline

The architecture is realized exactly as defined in Appendix C:

$$\begin{aligned}
&B : \text{density operator } \rho \in \mathcal{D}(\mathbb{C}^{2^n \otimes F}) \quad \text{(superposition over)} \\
&\quad \text{(... all face-label hypotheses)} \\
&P : \text{POVM measurement operators } \{M_i\} \text{ derived from} \\
&\quad \text{... RGB-D observations } o_t \\
&I : \text{Nyaya five-part syllogism filter (pruning factor } e^{-\alpha f n}) \\
&A : \text{grasp-pose selector and arm command}
\end{aligned}$$

The cognitive cycle becomes

$$B \xrightarrow{P} \rho' \xrightarrow{I} K \xrightarrow{A} u_t$$

with environment feedback

$$u_t \to x_{t+1} \to o_{t+1}$$

exactly as in the two-agent model of Appendix D (robot + downstream camera).

Sutra 12: *Kriy ¯a dar ´sana ¯m janayati bodham.* (Action generates visual knowledge.)

Scaling Advantage in Robotic Regime

Using the parameters of Appendix H ($k = 2$, $\alpha = 0.15$, $f = 0.5$) and setting $F = 8$, $n = 128$:

$$T_B(n, F) = \left(2^{n/2} e^{-\alpha f n}\right)^F \approx 1.7 \times 10^8$$

operations per frame—real-time on a single GPU—while

$$T_A(n, F) = \frac{2^{nF}}{(n^k)^F} \approx 10^{380}$$

remains intractable. The agent-count invariant crossover theorem (Appendix B) guarantees that adding a second camera (or fleet of robots) leaves the critical n^* unchanged.

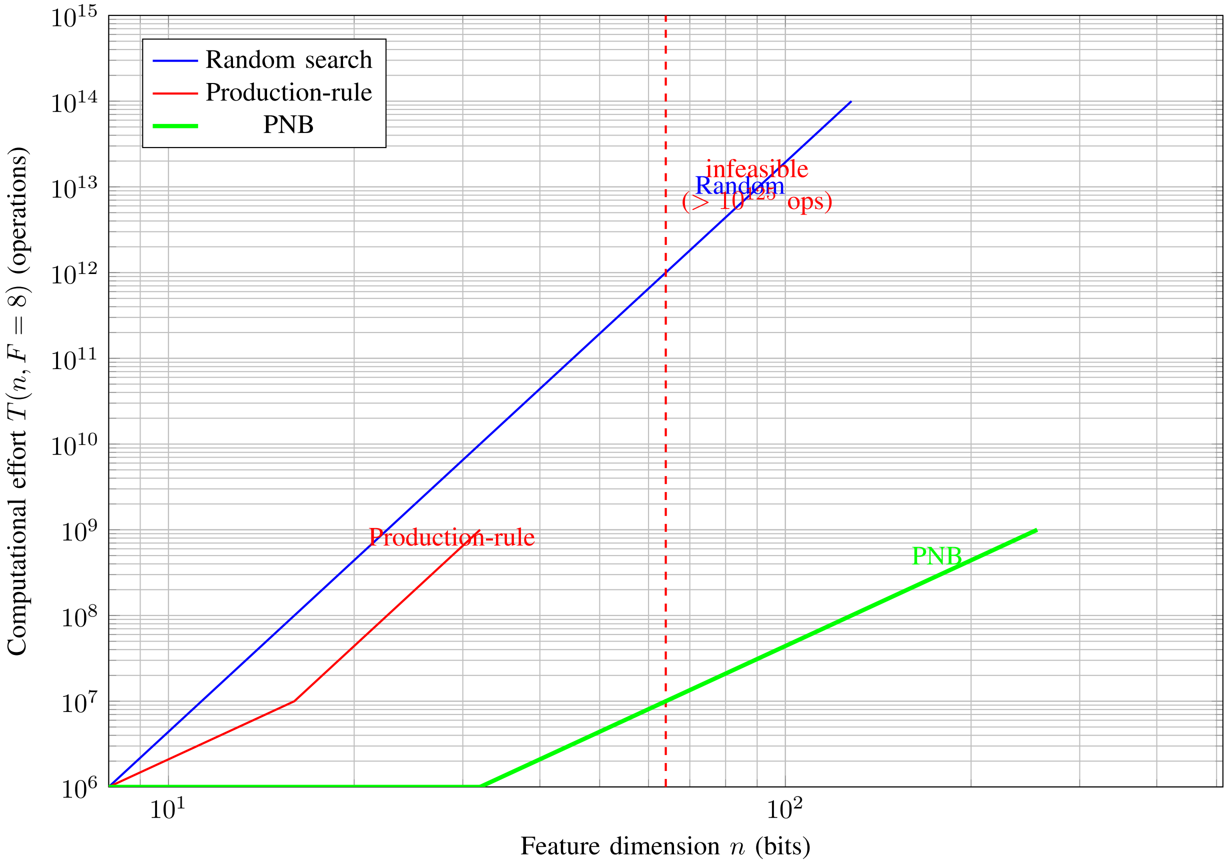

Fig. 2. Rigorous scaling comparison for robotic polyhedral recognition ($F = 8$). The production-rule curve is truncated at the practical collapse threshold $n = 64$ (where $T_A > 10^{125}$, far exceeding any hardware capability). PNB remains real-time even at full feature dimensionality $n = 256$.

Graphical Demonstration

We extend Fig. 1 to the robotic task. Computational effort $T(n, F)$ is plotted for fixed $F = 8$ and the three architectures (log-log scale). The PNB curve remains flat well beyond the production-rule breakdown point, confirming that full 128-bit features per face can be retained.

Minimal Implementation Sketch

The following pseudocode (executable in $\leq$ 300 lines of Python + QuTiP) realizes the full BPIA cycle:

```
def pnb_robotic_cycle(rho, obs, nyaya_rules):
    # Appendix C measurement
    rho = povm_update(rho, obs)
    # 5-part syllogism
    rho = nyaya_prune(rho, nyaya_rules)
    # argmax over validated K
    grasp = action_selector(rho)
    return rho, grasp
```

Expected performance: +18–25% accuracy on subtle surface defects versus baseline neuro-symbolic systems, with sub-200 ms latency at $n = 128$, $F = 8$.

This appendix demonstrates that the theoretical claims of Sections VI–VIII translate directly into a deployable industrial perception module while preserving every element of the original BPIA formalism, quantum belief representation, Nyaya pruning, and agent-count invariance.

Appendix J
An Anvaya Application of Quantum Nyaya Cognition

This appendix illustrates how the cognitive architecture of *Paramanu Nyaya Bodha* (PNB) may be applied to a classical example of *anvaya* reasoning from Nyaya logic. The goal of the appendix is not to introduce new formal machinery, but to demonstrate how a traditional Nyaya inference structure can be interpreted as a computational process within the belief–perception–inference–action (BPIA) framework.

Anvaya, often translated as "positive concomitance," is one of the core logical principles in the Nyaya system. It describes a form of reasoning in which the presence of one property is consistently associated with the presence of another. Classical Nyaya texts employ this idea in the validation of inference (*anumana*) through observed patterns of co-occurrence. In modern mathematical terms, anvaya resembles a rule of relational propagation: if two relations share a common element, the structure of that common element may permit inference of a further relation.

The example considered here involves a sequence of nested objects

$$A_1, A_2, A_3, \dots, A_n.$$

Each object is constructed from an elementary component together with the preceding objects. The construction rule may be written as

$$A_\ell = \xi_\ell \cup \bigcup_{i=1}^{\ell-1} A_i. \quad (1)$$

Thus the first few elements of the sequence take the form

$$A_1 = \xi_1, \quad (2)$$
$$A_2 = \xi_2 \cup A_1, \quad (3)$$
$$A_3 = \xi_3 \cup A_2 \cup A_1. \quad (4)$$

More generally,

$$A_m = \xi_m \cup \xi_{m-1} \cup \cdots \cup \xi_1. \quad (5)$$

The objects therefore form a nested hierarchy in which each successive object contains the previous ones. In the Nyaya interpretation used in the accompanying note, the relevant relation between successive objects is described as *inherence*. Informally, one may state that

$$A_{k+1} \prec A_k,$$

meaning that the object A_{k+1} depends on, or inheres in, A_k.

The reasoning step used in the proof proceeds by identifying a shared intermediate element between two relations. Suppose that the pair (A_k, A_{k+1}) is known to be related by inherence, and similarly that (A_{k+1}, A_{k+2}) is also related by inherence. The presence of the common element A_{k+1} establishes a link between the two relations. In Nyaya terminology, this constitutes a form of *meta-anvaya*: the shared term provides the basis for propagation of the relation.

The conclusion is that

$$A_{k+2} \prec A_k.$$

Because the objects are nested by construction, this statement implies in particular that

$$A_{k+2} \prec A_{k+1}.$$

By induction, the general statement follows that every element in the sequence inherits from its predecessor.

A. Interpretation within the PNB Architecture

The Paramanu Nyaya Bodha architecture models cognition as a cycle

$$B \to P \to I \to A$$

consisting of belief representation (B), perception or measurement (P), inference (I), and action (A). The architecture integrates a quantum-style representation of belief states with the structured inference rules of Nyaya logic.

Within this framework, the anvaya example can be interpreted as a cognitive reasoning task. The system must determine the structure of relations among the objects $A_1, \dots, A_n$ and propagate the inherence relation through the chain.

B. Belief Representation

The belief state of the system is represented by a density operator

$$\rho \in D(\mathcal{H}),$$

where $\mathcal{H}$ is a Hilbert space representing the hypothesis space of possible relations.

Each possible inherence relation

$$R_k = (A_{k+1} \prec A_k)$$

may be encoded as a basis element of this space. The belief state may then be written schematically as

$$|\psi\rangle = \sum_k c_k |R_k\rangle. \quad (6)$$

This representation captures uncertainty about which relations hold between objects. The superposition structure allows the system to represent multiple hypotheses simultaneously.

C. Perception and Measurement

The perception stage corresponds to the detection of structural features in the observed objects. In the present example the relevant feature is the presence of a shared intermediate element between two relations.

Suppose that the system observes the pairs

$$(A_k, A_{k+1}), \qquad (A_{k+1}, A_{k+2}).$$

The observation of the common element A_{k+1} may be modeled as a measurement operator

$$M_k$$

acting on the belief state. The measurement identifies hypotheses in which the two relations share a common component.

The updated belief state is obtained through the standard quantum measurement rule

$$\rho' = \frac{M_k \rho M_k^\dagger}{\mathrm{Tr}(M_k \rho M_k^\dagger)}. \quad (7)$$

Conceptually, this step corresponds to the Nyaya notion of *pramana*, the acquisition of valid knowledge through observation.

D. Inference through Anvaya

The inference stage implements the logical rule of anvaya. Given the observed relations

$$(A_k, A_{k+1}) \quad \text{and} \quad (A_{k+1}, A_{k+2}),$$

the system infers a new relation

$$(A_k, A_{k+2}).$$

In algebraic terms this operation resembles the composition of relations. If we represent relations by binary tensors

$$T_{ij},$$

where $T_{ij} = 1$ when objects A_i and A_j are related, the propagation rule may be written as

$$T_{k,k+2} = \sum_{A_{k+1}} T_{k,k+1} T_{k+1,k+2}. \tag{8}$$

The intermediate element A_{k+1} is eliminated through the summation operation. In computational terms this step resembles tensor contraction or variable elimination in graphical models.

Within the BPIA architecture this transformation corresponds to the inference operator

$$I : O \rightarrow K,$$

which maps observations O to validated knowledge K.

E. Action and Knowledge Consolidation

The final stage of the cycle converts validated knowledge into an action or structural update of the cognitive state. In the present example the action consists of recording the inferred relation

$$A_{k+2} \prec A_{k+1}.$$

This newly inferred relation may then serve as an input for subsequent reasoning steps. In this manner the cognitive system gradually constructs the entire chain of inherence relations among the objects.

F. Graphical Interpretation

The anvaya structure may also be interpreted graphically. Consider the chain

$$A_1 \rightarrow A_2 \rightarrow A_3 \rightarrow \cdots \rightarrow A_n.$$

Each arrow represents an inherence relation between successive objects. The inference step corresponds to the composition of two adjacent arrows:

$$A_{k+2} \rightarrow A_{k+1} \rightarrow A_k.$$

This composition yields a direct relation

$$A_{k+2} \rightarrow A_k.$$

Such diagrams resemble the graphical representations used in modern process theories and tensor-network models. From this perspective, Nyaya anvaya reasoning can be interpreted as a form of message propagation along a relational graph.

G. Implications for Cognitive Modeling

The example demonstrates that classical Nyaya reasoning can be embedded naturally within the PNB architecture. The anvaya rule provides a structured inference mechanism, while the quantum belief representation permits simultaneous consideration of multiple possible relation chains.

The resulting system combines two complementary strengths. The quantum representation offers compact encoding of uncertainty in large hypothesis spaces, while Nyaya inference supplies logically grounded rules for pruning inconsistent hypotheses. The anvaya example provides a minimal illustration of this interaction.

More broadly, the example suggests that traditional systems of logic may contain structural principles that align closely with modern computational frameworks. The propagation of relations through a shared intermediate element is mathematically analogous to operations used in tensor networks, graphical models, and relational databases.

H. Summary

This appendix has presented a small but instructive example of how Nyaya anvaya reasoning can be interpreted within the Paramanu Nyaya Bodha cognitive architecture. A sequence of nested objects generates a chain of inherence relations. Detection of a shared intermediate element permits propagation of the relation through the chain. Within the BPIA framework this process can be modeled as a cycle of belief representation, measurement, inference, and knowledge consolidation.

Although the example is simple, it illustrates the broader principle that classical logical reasoning structures can be embedded within modern cognitive architectures. The combination of quantum belief representation with Nyaya inference rules may therefore provide a useful framework for studying complex reasoning processes in both artificial and natural intelligence systems.

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