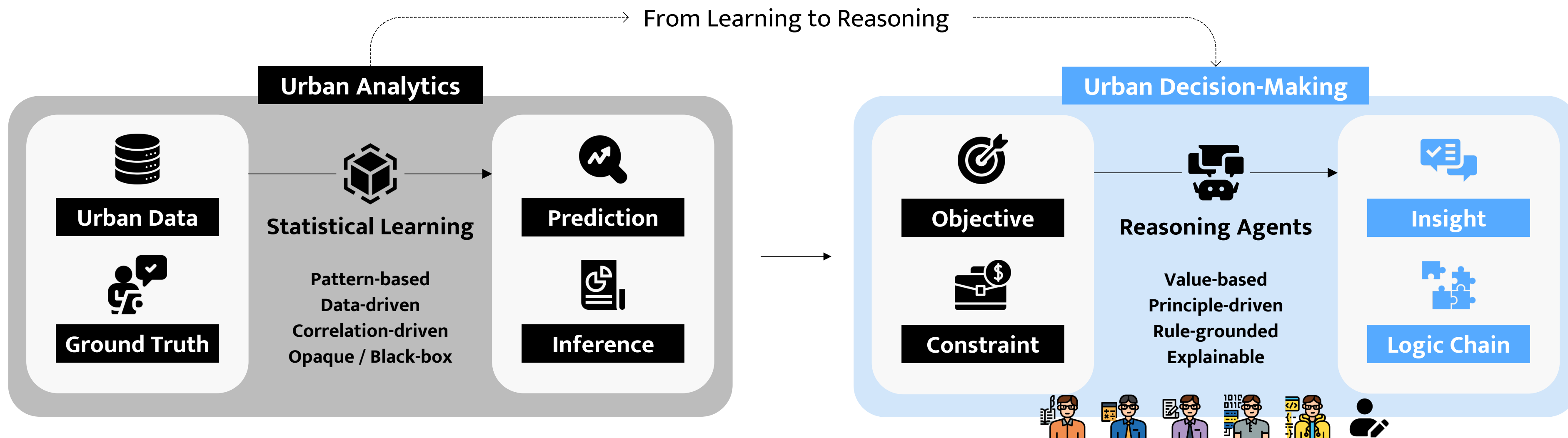


Reasoning Is All You Need For Urban Planning AI

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Statistical learning learns patterns from historical data via correlations.

---It predicts well, but decisions are often **opaque**.

---It can mimic past allocations and flag likely violations,

---yet struggles with **normative rules, hard constraints, and explainable reasoning**.

Reasoning agents generate decisions via **explicit reasoning traces** (e.g., CoT, ReAct).

—They reason step by step, making decisions transparent.

—They can apply normative rules and resolve conflicting principles,

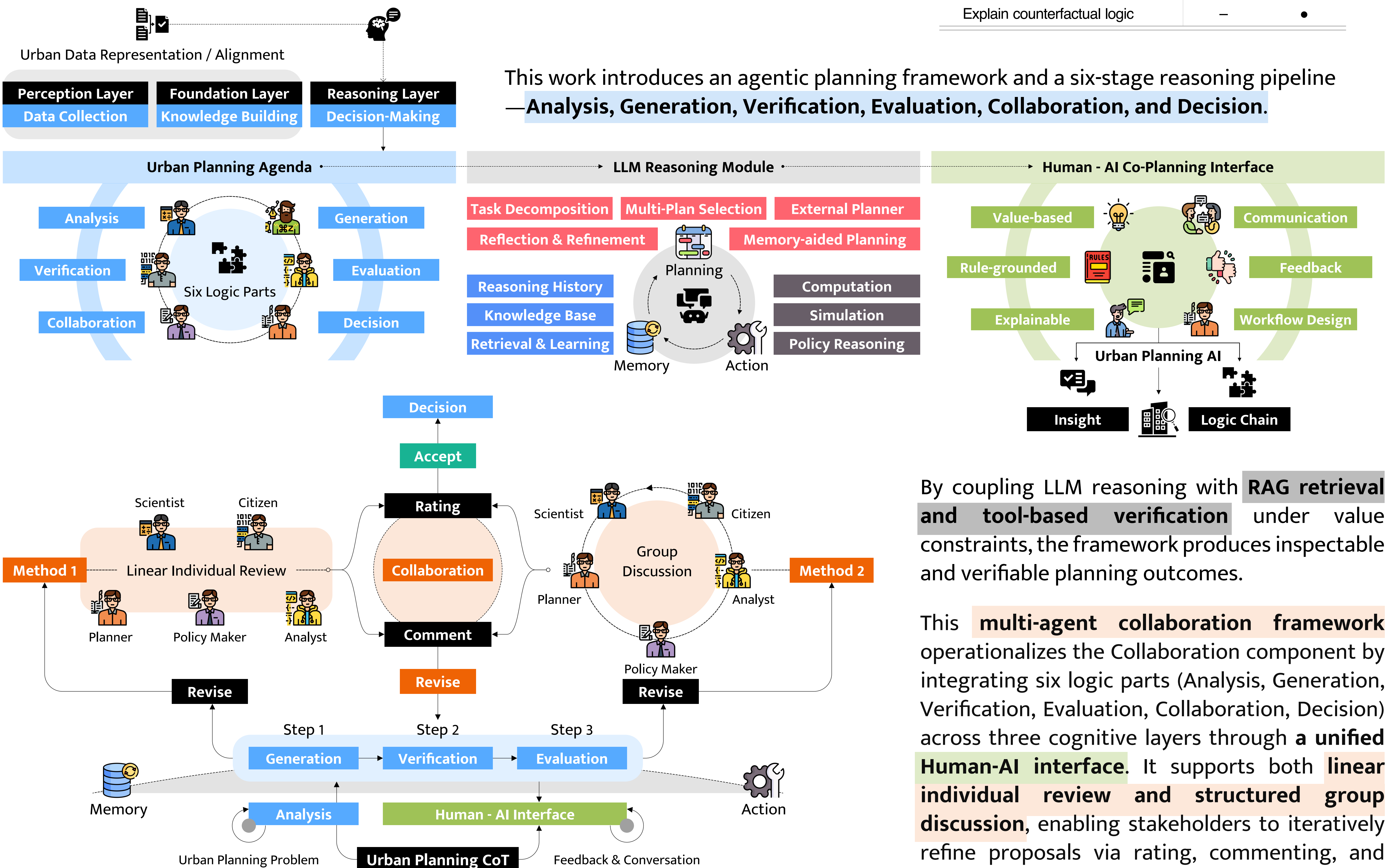
—and explain **constraint satisfaction** and **counterfactual logic**.

Urban planning AI is shifting from predicting **what will happen (statistical learning)**

to deciding what should happen—requiring reasoning agents that can apply

norms, satisfy hard constraints, and provide transparent justifications.

Planning Decision Task	Statistical Learning	Reasoning Agents
Value-Based & Principle-Driven		
<i>Equity-driven resource allocation</i>		
Replicate historical allocation	•	•
Apply equity principles	○	•
Challenge unjust patterns	—	•
<i>Novel urban planning context</i>		
Transfer similar patterns	•	•
Reason from first principles	—	•
<i>Competing value prioritisation</i>		
Learn stakeholder preferences	•	•
Deliberate on normative priorities	—	•
Rule-Grounded		
<i>Zoning regulation compliance</i>		
Detect likely violations	•	•
Guarantee zero violations	—	•
<i>Multi-constraint optimization</i>		
Find feasible solutions	•	•
Verify all constraints satisfied	○	•
<i>Contradictory rule resolution</i>		
Flag conflicting requirements	○	•
Resolve using legal reasoning	—	•
Explainable		
<i>Decision justification to public</i>		
Provide recommendations	•	•
Generate readable rationale	○	•
<i>Causal impact chain explanation</i>		
Predict outcomes	•	•
Trace cause-effect reasoning	—	•
<i>“What-if” scenario analysis</i>		
Simulate alternative outcomes	•	•
Explain counterfactual logic	—	•



This work introduces an agentic planning framework and a six-stage reasoning pipeline — **Analysis, Generation, Verification, Evaluation, Collaboration, and Decision**.

By coupling LLM reasoning with **RAG retrieval and tool-based verification** under value constraints, the framework produces inspectable and verifiable planning outcomes.

This **multi-agent collaboration framework** operationalizes the Collaboration component by integrating six logic parts (Analysis, Generation, Verification, Evaluation, Collaboration, Decision) across three cognitive layers through a **unified Human-AI interface**. It supports both **linear individual review and structured group discussion**, enabling stakeholders to iteratively refine proposals via rating, commenting, and revision while preserving human agency in the final decision.