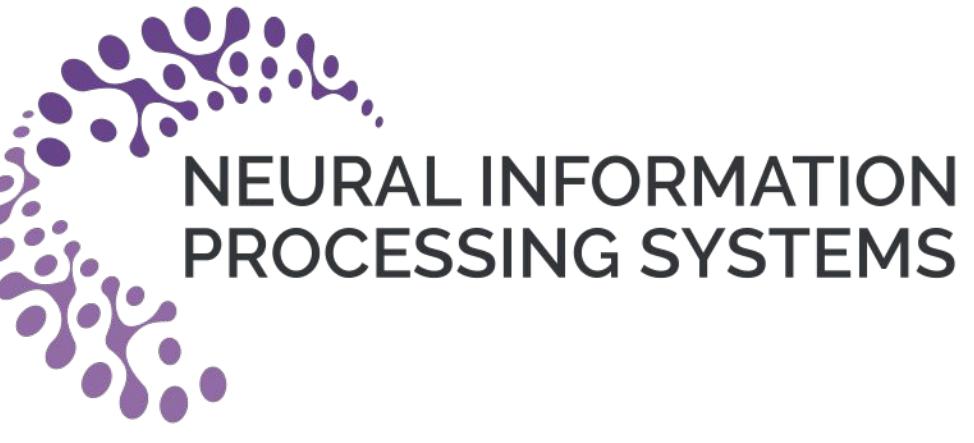


# Collective Narrative Grounding: Community-Coordinated Data Contributions to Improve Local AI Systems

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## Motivation: Local Blind Spots in Global LLMs

### Global AI, Local Failure

- LLMs excel at general knowledge but struggle with information tied to specific communities or places.
- These "blind spots" create **Epistemic Injustice**: marginalized communities are undervalued, and misinformation fills the void.
- **Key Insight:** This is not just a technical gap, but a failure of training data priority.

## Auditing the Gap

### 76.7% of Errors are Fixable

- We study LocalBench: 14,782 local QA pairs from 526 U.S. counties.
- Questions span census data, local news, and community discourse, across physical, cognitive, and relational localness.
- From 1,000 audited failures, four dominant error modes emerge:
  - Factual knowledge gaps (31.8%)
  - Cultural misunderstandings (23.4%)
  - Geographic confusion (12.4%)
  - Temporal misalignment (9.1%)
- Examples in **Figure (a) Local blind spots of global LLMs**
- These four together account for 76.7% of errors and are directly addressable with locally grounded narratives.

LocalBench



Model	EM	ROUGE-1	Non-Numerical QA			GPT Judge	Ans Rate	Numerical QA	
			Semantic	GPT Judge	Ans Rate			Accuracy	Ans Rate
GPT-4o	22.0	30.7	53.0	32.8	99.6	6.2	39.8		
GPT-4.1	<b>32.2</b>	<b>52.5</b>	<b>74.1</b>	47.0	100.0	6.2	100.0		
GPT-4.1+Web	13.5	27.9	43.2	35.6	92.9	<b>15.5</b>	92.0		
Gemini-2.5-Pro	28.0	52.0	70.5	52.5	100.0	12.8	100.0		
Gemini-2.5-Flash	31.1	46.0	67.6	43.2	100.0	7.5	100.0		
Gemini-2.5-Pro+Grounding	21.9	50.1	66.0	<b>56.8</b>	91.7	12.8	100.0		
Claude-Sonnet-4	23.4	38.5	64.0	39.7	100.0	7.1	97.3		
Claude-Sonnet-3.7	21.7	42.5	65.5	43.7	100.0	8.4	91.2		
Qwen3-235B-A22B	19.9	29.0	54.0	27.3	99.3	6.6	77.0		
Qwen3-30B-A3B	20.5	29.6	54.9	28.0	99.7	2.2	100.0		
Qwen3-32B	20.0	29.9	55.4	27.7	99.7	4.9	99.1		
Qwen3-14B	19.5	29.8	55.4	27.5	99.6	4.0	100.0		
Qwen3-8B	16.3	27.2	54.1	22.9	99.6	3.1	75.2		

Performance Results Across Non-Numerical and Numerical QA

## References

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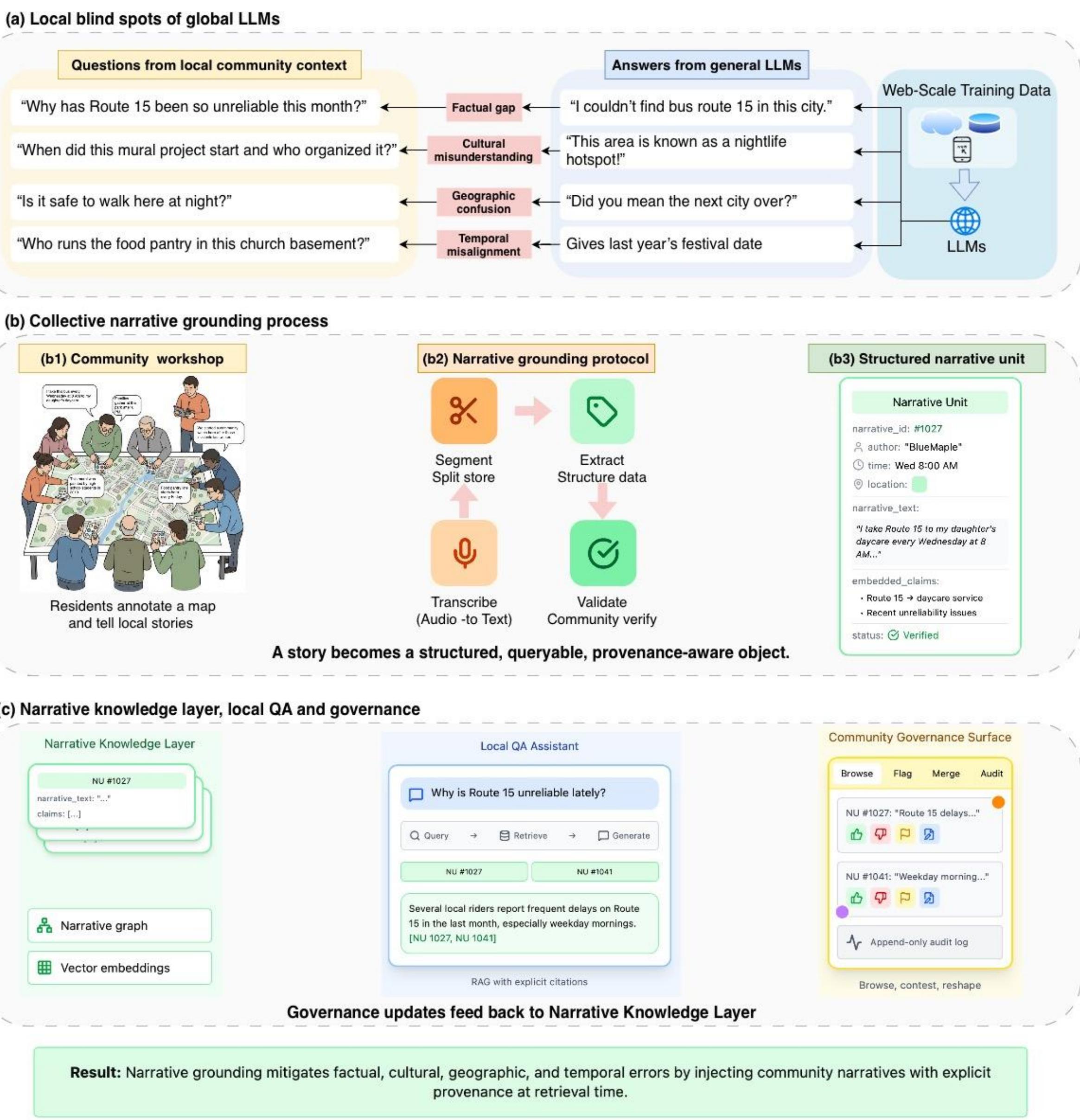
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## The Narrative Grounding Protocol

### From Stories to Structured Data

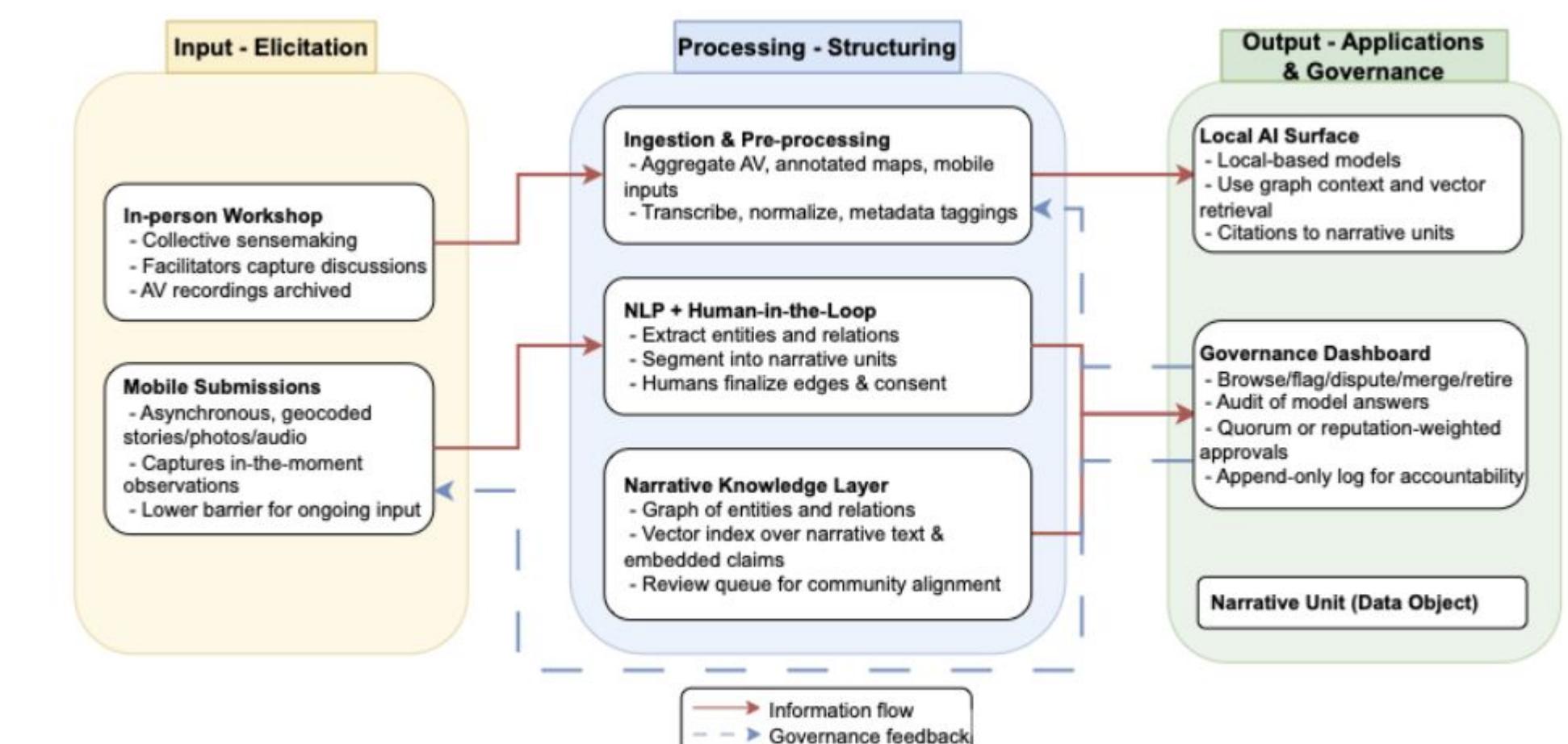
- We designed a participatory protocol involving \$N=24\$ community members in Atlanta.
- **Elicitation:** Used "Physical Scaffolding" (large paper maps) and asset-based framing to prompt rich storytelling rather than just complaints.
- **The Narrative Unit:** We convert oral stories into structured data (Entities + Time + Place + Provenance).
- See **Figure (b) workshop progress**



Result: Narrative grounding mitigates factual, cultural, geographic, and temporal errors by injecting community narratives with explicit provenance at retrieval time.

## The Narrative Knowledge Layer

- **Input:** In-person workshops + mobile submissions.
- **Processing:** Human-in-the-loop validation creates a "Narrative Graph".
- **Output:** A RAG system where AI answers are cited with specific community stories.



## Closing the Gap

- **Baseline:** State-of-the-art LLM answered <21% of local questions correctly on its own.
- **The Fix:** In the majority of failures, the missing facts were present in our collected narratives.
- **Conclusion:** Narrative grounding directly addresses the dominant error modes (factual/cultural) identified in the audit.

## Design Tensions & Governance

- **Representation:** Who speaks for the "community"? We must balance "local profiles" with internal dissent.
- **Privacy:** "Hyper-local" means **identifiable**. We balance utility with de-identification.
- **Control:** A **community governance** dashboard allows residents to dispute, merge, or retire data used by the AI.

## Takeaways

- **A Taxonomy of local LLM failures.**
- **A Protocol for transforming stories into AI-ready data.**
- **A Governance model for community ownership of AI knowledge**