

Large Meaning Models (LMMs): Phaneron as a Language-Agnostic Structural Semantics Substrate

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Abstract

We introduce *Large Meaning Models* (LMMs): language systems whose core is an explicit, language-agnostic *meaning substrate*—the *Phaneron*—where distinctions and connections are primitive and all nuance (roles, n -ary relations, direction, tense/aspect, discourse links) is represented as reusable *patterns* and *graph rewrites*. We formalize an LMM as an abstract data type with (i) a versioned Phaneron meaning graph, (ii) bidirectional bridges between surface and meaning, and (iii) a hybrid objective that *compresses* discourse and *predicts* future utterances/world updates. We map core linguistic phenomena to unlabeled structural motifs, outline learning/inference via constraint-driven abduction and MDL+prediction, and propose evaluations for paraphrase invariance, cross-lingual alignment, explainable QA, and long-range discourse coherence. LMMs complement LLMs: LLMs act as string transducers; LMMs are the inspectable *meaning* core.

1 Introduction

Token-next architectures blur surface form with meaning, offer weak inspectability, wobble under paraphrase, and struggle with long-range discourse state. We propose to separate *meaning* from *surface* with a single-layer, unlabeled structural substrate where semantics live as reusable patterns discovered by a rewrite loop guided by compression and prediction.

2 Background: The Phaneron in brief

The Phaneron is an unlabeled, undirected pseudograph $G = (V, E)$ with reusable *patterns* (finite subgraphs), double-pushout (DPO) graph rewrites, and a versioned event log \mathcal{E} . Meaning equals structural position (ideally automorphism orbits; operationally, r -hop/WL colors). A hybrid objective $\mathcal{L} = \mathcal{L}_{\text{MDL}} + \lambda \mathcal{L}_{\text{pred}}$ scores states and candidate rewrites.

3 The LMM ADT

Definition 1 (Large Meaning Model). *An LMM is a tuple $\mathcal{M} = (\mathcal{P}, \mathcal{B}_{\text{in}}, \mathcal{B}_{\text{out}}, \mathcal{U}, \mathcal{L})$ where:*

- $\mathcal{P} = (G, \mathcal{E}, \mathcal{D}, \mathcal{R}, \mathcal{L}_{\text{MDL}})$ is a Phaneron instance (graph, event log, dictionary, rewrite schemas, MDL objective);
- \mathcal{B}_{in} maps surface streams to candidate graph deltas (rewrite proposals with alignments);
- \mathcal{B}_{out} maps meaning slices to surface realizations in a target language;
- \mathcal{U} selects a consistent subset of proposals (constraint-driven abduction, CDA) and applies DPO rewrites;
- $\mathcal{L} = \mathcal{L}_{\text{MDL}} + \lambda_1 \mathcal{L}_{\text{pred}} + \lambda_2 \mathcal{L}_{\text{cycle}} + \lambda_3 \mathcal{L}_{\text{min}} + \lambda_4 \mathcal{L}_{\text{align}}$ is the global objective.



Figure 1: **LMM pipeline.** Surface streams are mapped to *proposals* (Bridge-In); the Phaneron applies versioned rewrites; Bridge-Out realizes responses.



Figure 2: **Architecture layers.** Surface constructions map through bridge patterns into language-agnostic meaning patterns; realization reverses the mapping.

4 Pattern typology for language

We use canonical unlabeled motifs for linguistic phenomena; roles are structural positions inside relation patterns.

Events and roles. Clausal semantics as an event node with role positions (agent, patient, adjuncts).

Alternations. Active/passive/dative shift map to the same meaning motif; only bridge patterns differ.

Quantification and scope. Restrictor–scope encoded structurally; ambiguities are competing pattern placements.

Negation/modality/tense. Operator patterns attach to events; scope is explicit via structure.

Coreference and anaphora. Entity nodes persist; pronouns propose merges with antecedent candidates.

Presupposition and discourse. Triggers require prior subgraphs; accommodation introduces minimal subgraphs.

5 Discourse as versioned rewrites

A conversation or document is a sequence of versioned events e_t ; each utterance proposes rewrites. The state $S_t = (G_t, \mathcal{D}_t)$ evolves via CDA selection and DPO application; replay yields an explainable discourse history.

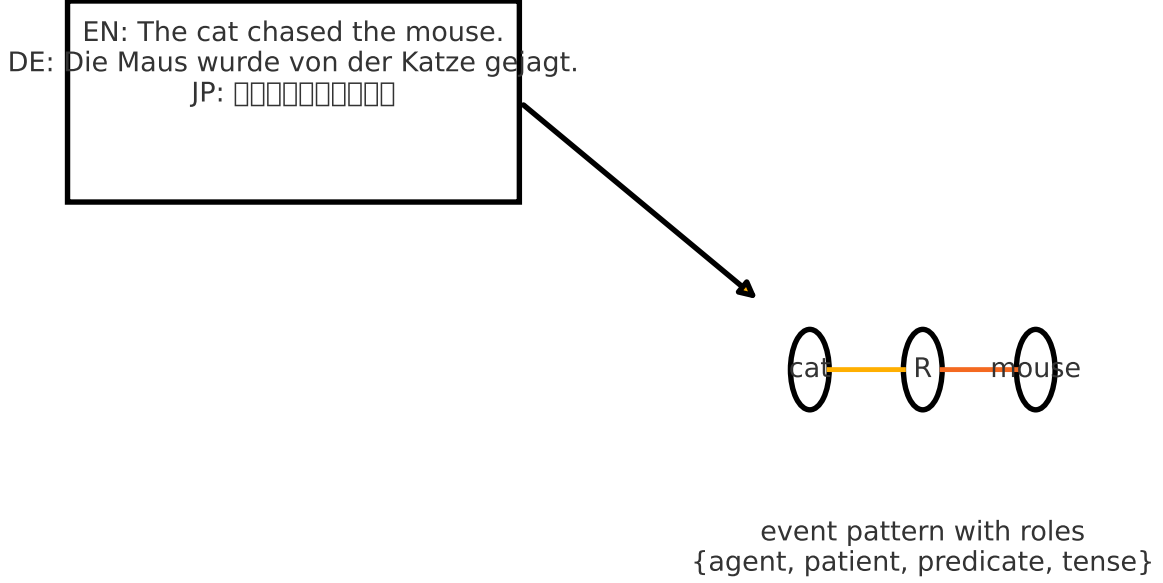


Figure 3: **Surface** \rightarrow **meaning**. Three surface realizations (EN/DE/JP) map to a single event pattern with roles.

6 Bridges: proposal pathways and constraints

Proposal pathways. (i) Grammar-seeded parser that proposes construction-to-role alignments; (ii) LLM-assisted proposer that emits span \leftrightarrow role candidates; (iii) retrieval from previously accepted patterns for rapid reuse.

CDA constraints. Type and arity for roles; role-cardinality bounds; acyclicity where applicable; locality windows for new attachments; version-monotonic merges; minimality preference for explanations.

Bridge-Out. Realization chooses constructions and lexicalizations consistent with a target language and style; morphology/word order patterns fill remaining slots.

7 Learning objective (hybrid)

$$\mathcal{L}_{\text{total}} = \mathcal{L}_{\text{MDL}}(G; \mathcal{D}, B) + \lambda_1 \mathcal{L}_{\text{pred}} + \lambda_2 \mathcal{L}_{\text{cycle}} + \lambda_3 \mathcal{L}_{\text{min}} + \lambda_4 \mathcal{L}_{\text{align}}. \quad (1)$$

8 Evaluation protocols

Paraphrase invariance. Multiple surface forms must map to isomorphic meaning patches (graph isomorphism/edit distance).

Cross-lingual alignment. Translations align to identical meaning graphs; test zero-shot transfer.

Explainable QA. Answers with Minimal Explanation Subgraphs (MES); evaluate correctness and sparsity.

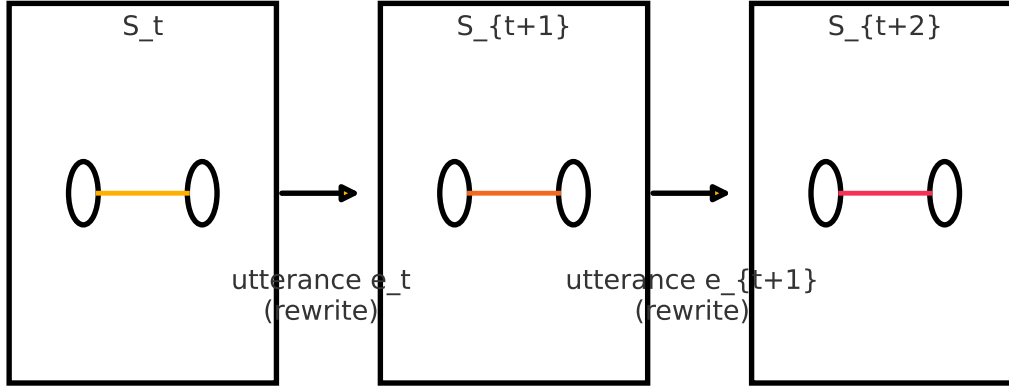


Figure 4: **Discourse timeline.** Utterances update the meaning graph by applying selected rewrites; anaphora appears as merges across versions.

Figure 5: **Inference loop.** Propose \rightarrow score \rightarrow select \rightarrow apply.

Discourse tracking. Coreference and presupposition accommodation across long contexts.

Task		Metric(s)	Structural check
Paraphrase	invari-	Graph isomorphism rate; edit dis-	Canonicalization match; MES stabil-
ance		tance	ity
Cross-lingual	align-	Zero-shot accuracy; alignment F1	Same meaning hash; role consistency
ment			
Explainable QA		EM / F1 + explanation F1	MES size/precision vs gold
Coreference		MUC/B ³ /CEAF or link F1	Merge decisions; entity continuity
Discourse relations		Accuracy / F1	Correct rhetorical link patterns
Efficiency		Latency; updates/s; growth	$ \mathcal{D} $ growth; replay time

Evaluation plan (summary).

9 Micro-bench: controlled paraphrase set

Dataset. 100 sentence triplets (active, passive, topicalized) per predicate, across 20 predicates; 10 languages (EN/DE/ES/FR/IT/PL/NL/SV/JA/KO) with human-checked translations.

Split. Train on half the predicates and 7 languages; test zero-shot on the rest and 3 held-out languages.

Targets. (i) Paraphrase invariance \uparrow (canonical hash equality), (ii) cross-lingual isomorphism rate, (iii) MES stability under paraphrase.

Ablations. No-cycle loss; no-minimality loss; fixed pattern cap vs dynamic.

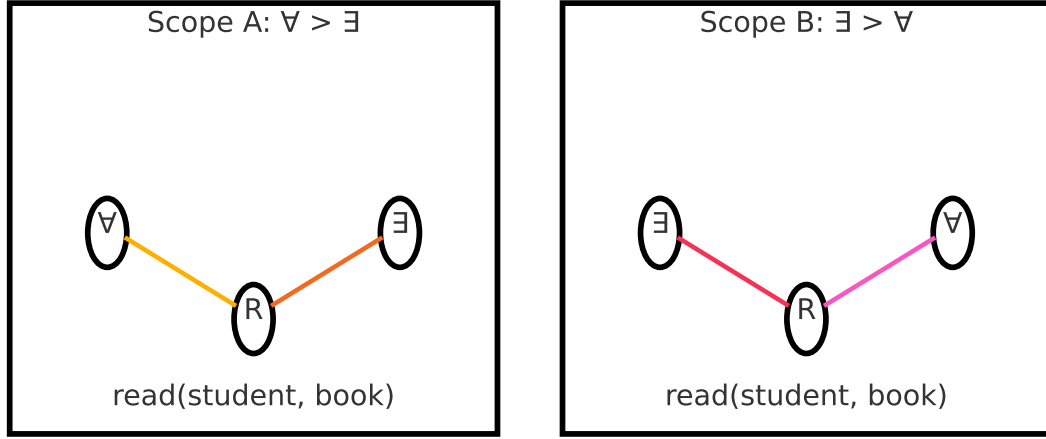


Figure 6: **Scope ambiguity.** Two competing patterns for “Every student read a book”: $\forall > \exists$ vs $\exists > \forall$.

10 Case studies

Quantifier scope ambiguity. Competing structures resolved by context.

Minimal explanation subgraph (MES). “Alice dropped the plate. It shattered.”

Pattern dictionary snapshot.

11 A hybrid LMM+LLM system

LLMs can serve as proposal generators and realizers; the Phaneron enforces structural constraints and provides long-term semantic memory.

12 Limitations, risks, and security

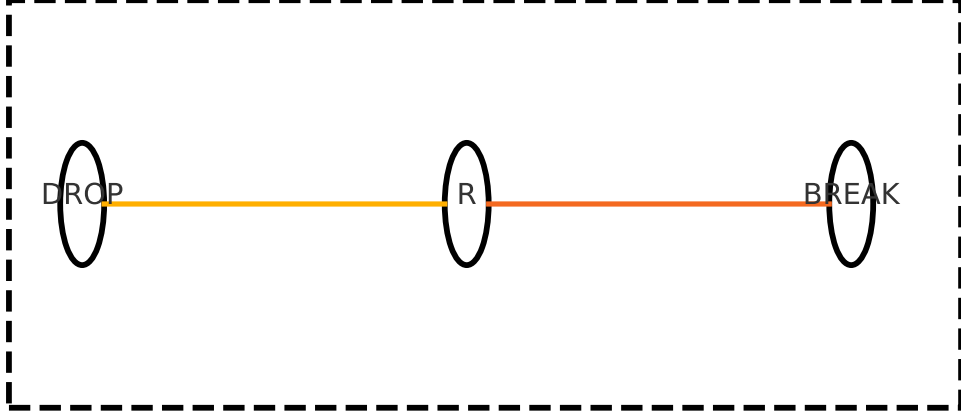
Pattern explosion, search cost, and bridge brittleness are practical risks. Explicit meaning graphs may encode sensitive facts; we recommend:

- **PII redaction:** detect and mask subgraphs linked to personal identifiers.
- **Access control:** role-based visibility of subgraph types (entities, relations).
- **Audit trails:** versioned provenance for all rewrites, with replay.
- **Safety rules:** refusal policies as subgraph pattern detectors (harmful intent).

Some pragmatic phenomena (irony, sarcasm) may require richer patterns and grounding.

13 Conclusion

LMMs make meaning first-class: explicit, stable under paraphrase, language-agnostic, and replayable. Phaneron provides the substrate; MDL+prediction provides the learning principle; versioned rewrites provide the discourse engine. LMMs complement LLMs: structure for memory/reasoning; fluency for realization.



Minimal Explanation Subgraph (MES): {DROP, R_cause, BREAK}

Figure 7: **Explanation view.** MES = {DROP, R_{cause} , BREAK}.

A Appendix A: Concrete MDL code

We use a two-part code for (\mathcal{D}, B) and residual structure R . Let $\mathcal{D} = \{P_i\}_{i=1}^M$ be unlabeled patterns; U_i their usage sets (injective embeddings).

$$L(\mathcal{D}) = \sum_{i=1}^M \left(L_{\mathbb{N}}(|V(P_i)|) + L_{\mathbb{N}}(|E(P_i)|) + L_{\text{iso}}(P_i) \right), \quad (2)$$

$$L(U \mid \mathcal{D}, B) = \sum_{i=1}^M \left(L_{\mathbb{N}}(|U_i|) + \sum_{u \in U_i} L_{\text{place}}(u \mid P_i, B) \right), \quad (3)$$

$$L(R \mid \mathcal{D}, U, B) = L_{\text{edges}}(\text{residual edges} \mid B). \quad (4)$$

Here $L_{\mathbb{N}}$ is a universal integer code; L_{iso} encodes an unlabeled pattern up to isomorphism (canonical adjacency); L_{place} codes a placement via block-structured anchors B ; and L_{edges} uses a Bernoulli or degree-corrected block model for uncovered edges. A rewrite is admissible if total ΔL plus predictive losses is < 0 .

B Appendix B: CDA selection (pseudocode)

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Input: state S_t=(G_t,D_t), proposals P={ G_k }, objective L( )
1: score each G_k with local L ; discard non-improving
2: sort by L ; greedily build non-overlapping set W
3: apply DP0 rewrites in W to obtain S_{t+1}; append events
4: consolidate: merge near-duplicate patterns; re-score dictionary

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C Appendix C: Canonicalization and tests

We canonicalize small meaning patches for fast paraphrase alignment using a hash of canonical adjacency; ties are broken by lexicographically minimal rooted traversal. Paraphrase invariance

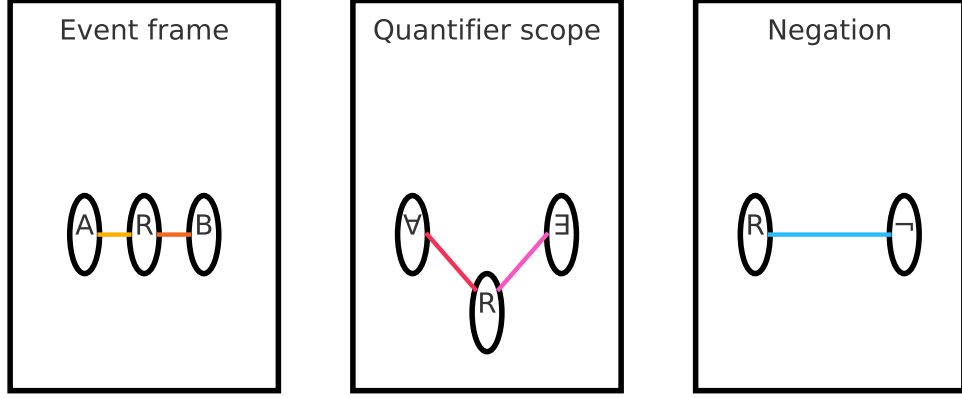


Figure 8: **Pattern dictionary motifs.** Event frame, quantifier scope, and negation attachment.



Figure 9: **Hybrid stack.** LLM front/back ends surround the explicit meaning core.

= identical canonical hashes (with audit trail).

D References

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