Vectors are All You Need: A Retrospective

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Introduction

In 1975, I completed a PhD dissertation titled “An N-Space Model for Visual and Verbal Concepts”, in which the meaning of language was represented as vectors, and understanding was enacted through transformations. The resulting program, called Engraf, parsed English language input using an Augmented Transition Network (ATN), converted tokens into n-dimensional embedding vectors, and executed verb-driven transformations needed to create 3D graphical scenes. This structure anticipated — some fifty years ago — core elements of today’s transformer-based large language models (LLMs), including positional attention, distributed vector semantics, and grounding.

Engraf was intended to drive the 3D Color Computer Graphics System developed by my colleagues Dave Wooten, Nick England, Deborah Ogden, Glen Williamson and me at North Carolina State University under our mentor, Professor John Staudhammer. The lab ran on an Adage AGT-30 Graphics Terminal and a Varian 620 A minicomputer and output run-length-encoded scan lines to a video disk that drove a Sony Trinitron TV. For many years it was the fastest 3D modeling system in the world. Unfortunately, Engraf ran on the IBM 370-168 at the Research Triangle Computer Center and was never actually connected to the graphics modeling system.

Although these ideas prefigured later advances in vector-based semantics and neural language models, they were not well received by the natural language processing community at the time. At the 1974 ACL conference, my paper was excluded from the proceedings and was met with skepticism during its presentation and dismissal in private correspondence afterward. In fairness, I was likely perceived as a naive Electrical Engineering student from a small southern “cow college” with no NLP presence trying to smash “square pegs into round holes” by applying EE-familiar linear algebra to an obviously symbolic problem. There was no concurrent research employing any of these ideas at the time and they were way outside of the NLP mainstream. Nevertheless, the conceptual foundation of Engraf — that meaning could be operationalized through vector transformations — remained compelling, and has only recently become technically realizable and, indeed now, mainstream.

2. Engraf: Verb-Centric Vector Semantics

The architecture of Engraf treated natural language as a set of executable transformations on a multidimensional concept space. Each noun, adjective, adverb, preposition and verb was represented as a vector in this space, with dimensions encoding basic grammatical categories, grammatical features, spatial coordinates, visual properties, preposition and verb semantics.

Verbs were the primary drivers of transformation: they acted on noun phrase vectors by applying either additive or multiplicative updates depending on part-of-speech roles identified by the ATN parser (§3.4). For example, 'MAKE IT MUCH MORE TRANSPARENT AND ROUGHER' resulted in a MODIFY command that adjusted multiple dimensions of the referenced object (§1.2.10).

3. Engraf's Embeddings as Value Vectors

In modern transformer architectures, Value (V) vectors contain the semantic payload of a token, while Query (Q) and Key (K) vectors determine how attention is distributed across context. In Engraf, the embedding vectors operated most like Value vectors:

- Each token's meaning vector was inserted directly into scene construction
- The parser (ATN) selected whether vectors would be added or multiplied, based on their grammatical role
- Semantic restrictions guided the combination logic — e.g., 'a circle may not be tall' (§1.2.9)

Thus, Engraf operationalized meaning as a series of vector transformations, not as symbolic patterns.

4. Grounding, Feedback, and Time Travel

Engraf's grounding was visual: meaning was to be verified by generating or modifying visible objects in 3D space. Incorrect interpretations (e.g., misuse of number agreement or modifiers) were rejected or flagged (§1.2.3, §1.2.23). The system maintained a timeline of operations, enabling rollback and forward replay (§1.2.27–1.2.31). This interactivity resembled early dialog modeling and shares traits with modern multimodal systems like DALL·E or GPT-4V, which combine text, visual feedback, and iterative refinement.

5. Comparison to Modern LLMs

Today's transformer models such as GPT-4 (Vaswani et al., 2017; OpenAI, 2023) rely on embedding vectors, attention-driven transformation layers, and context-dependent composition of meaning. Engraf anticipated many of these:

- Token Vectors as Operators: In both systems, meaning is not static but arises through transformation
- Grammar-Directed Composition: Engraf's POS-driven ATN guided vector operations; transformers use attention matrices
- Execution as Understanding: Engraf judged meaning by scene correctness; LLMs use prediction error
- Distributed Representation: In both systems, concepts are represented across high-dimensional vectors. While Engraf's 50+ dimensions were manually designed, LLMs' 10K+ dimensions are learned.

6. Conclusion

Engraf was an early attempt to unify language, geometry, and computation. It anticipated some key ideas now found in transformer-based language models: embedding spaces, vectorized meaning, execution-based semantics, and interactive grounding.

What was once a novel PhD experiment has become a guiding principle in modern AI:

Language is transformation, and transformation is mathematics.

7. Looking Ahead

Today, a Python implementation of Engraf is under development on GitHub (https://github.com/jeffeastman-2/Engraf). This reimplementation revisits the original design goals leveraging modern Python libraries to unify natural language parsing, vector algebra, and real-time 3D rendering. It reimplements the original ATN-based language analysis and connects it with a real-time graphics engine, finally closing the loop between understanding and visualization that was only theoretical in 1975.

References

Eastman, J. F. (1975). "An N-Space Model for Visual and Verbal Concepts". PhD Dissertation, North Carolina State University.

NCSU EE Dept. Computer Graphics Lab 1970-78. https://www.graphics-history.org/ncsu/

Vaswani, A., Shazeer, N., Parmar, N., Uszkoreit, J., Jones, L., Gomez, A. N., ... & Polosukhin, I. (2017). "Attention is All You Need". Advances in Neural Information Processing Systems, 30.

Mikolov, T., Chen, K., Corrado, G., & Dean, J. (2013). "Efficient Estimation of Word Representations in Vector Space". In *Proceedings of the 1st International Conference on Learning Representations (ICLR 2013), Workshop Track*.

OpenAI. (2023). "GPT-4 Technical Report". https://openai.com/research/gpt-4