Contents

Summary of *Destructure*

Explicitly or implicitly, both structured and unstructured AI paradigms rely on structures to represent knowledge succinctly and effectively, as shown in Part I: *Structure*. However, a shared challenge for both paradigms lies in the fact that structures can be overly rigid when faced with unseen environments. What were once the foundation for efficient and consistent reasoning may turn into an outdated lens, distorting the model's ability to perceive beyond the familiar and adapt to novel scenarios – what we call model plasticity. Part II: *Destructure* addresses this shared challenge by integrating destructuring techniques into training. Experiments in both the structured paradigm and unstructured paradigm show this method helps models adapt to new knowledge graphs and languages.

We begin by examining how structures are carved into models (Chapter 4). The embedding layer, often overlooked in modern models for knowledge engines, is nevertheless key to understanding this process. Rather than viewing embeddings as a set of isolated vectors, we unfold their gradient decent traces and interpret these traces as message-passing between corresponding symbols. Similar to graph neural networks, the message-passing propagates information along "edges", which can be triples in knowledge graphs or sentences in text corpora.

This reinterpretation explains transductiveness, or why models wrapped by embeddings on both ends fail with unfamiliar inputs. During long training horizons, embeddings, as repositories of all message-passing computation, store excessive global structural information about the training symbols; the non-embedding model body ends up maintaining contextual knowledge to be triggered by specific known embeddings. While excessive global information benefits transductive tasks – where all symbols are known – it leaves non-embedding model body ill-equipped to handle unseen symbols. Models thus fail for inductive scenarios, where new symbols lack embedding values that can trigger the body's knowledge accordingly.

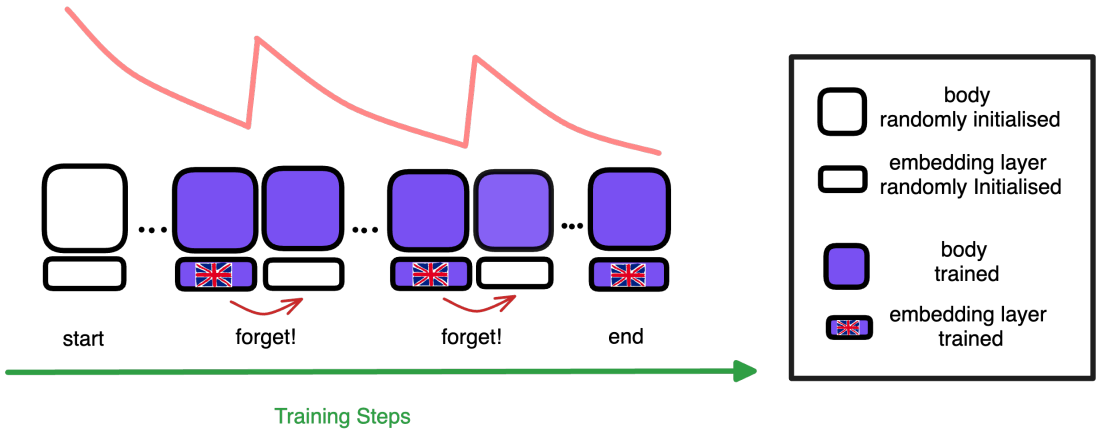

Figure 1: The active forgetting mechanism periodically resets the embedding layer during training. Pink curve illustrates the loss changes. Whenever forgetting happens, the loss curve spikes and then recovers to a normal downward trend.

To address this, we propose to introduce destructuring techniques into standard training. Specifically, the active forgetting mechanism, resets the embedding learning periodically while keeping the rest of the model training intact. This technique allows the model body to learn to regrow embeddings from scratch after each embedding resetting. The new training procedure derives a bi-level learning system: a fast inner loop for regrowing embeddings and a slow outer loop for learning a robust, stable body. Regular destructuring of embeddings forces the body to *"re-view" the data with a pair of fresh eyes*,[1] in a more abstract way that does not pertain to embedding value nuances but focus more on relationships between symbols. Empirical studies on inductive inference over graphs and languages demonstrate that this mechanism improves generalization to unseen symbols, such as new entities in knowledge graphs (Chapter 4) and new tokens from an unfamiliar language (Chapter 5).

The beauty of reality lies in its potential infiniteness.[2] On one hand, to simplify and understand reality with limited cognitive resources, human brains sketch it with conceptual structures. On the other hand, the human brain's neuroplasticity allows us to revise outdated conceptual structures. Balancing between structuring and destructuring

[1]In non-scientific texts, studying the old with a pair of new lenses is sometimes known as Onkochishin. Embeddings in a transformer or a factorization based models can be thought of as the "lens/eyes" for the non-embedding model body.

[2]The future is unknown but never affects its beauty.

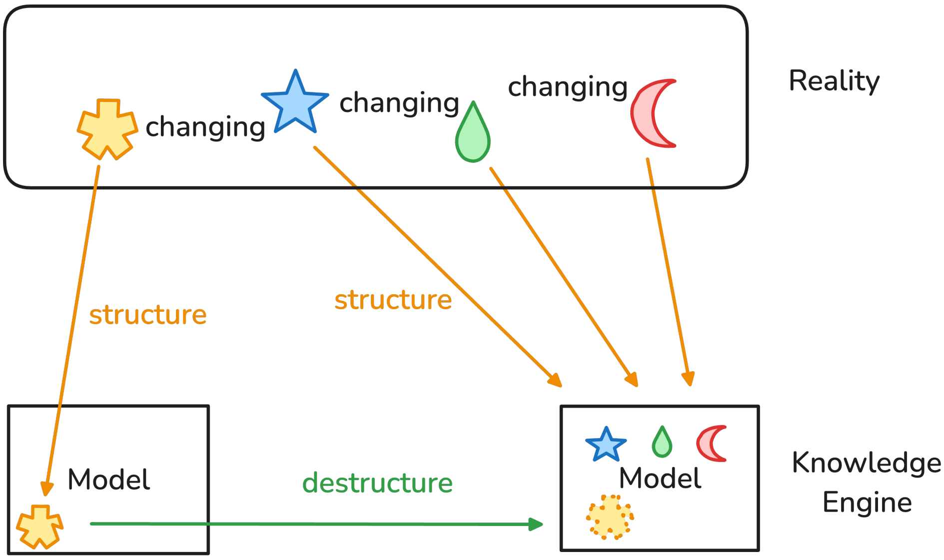

Figure 2: The reality is always changing. We use different shapes to indicate the observed structures of reality. These structures change as time flows. To faithfully capture reality, the knowledge engine, no matter in the structured paradigm or unstructured paradigm, must be capable of balancing the force of structuring with the force of destructuring so that it captures necessary structures but also does not get trapped by these structures.

leads to the plasticity crucial for surviving, navigating, and thriving in a dynamic reality.

Similarly, when building knowledge engines, the first attempt is to model reality comprehensively with computational structures. These structures are reusable across applications, providing knowledge efficiently without the need to recompute things from scratch. They model the *known* aspects of the reality quite well. However, we must recognize that such structures can become inaccurate as reality continually evolves. Therefore, it is crucial for knowledge engines to possess the ability to delete outdated structures and relearn new ones. In other words, they must be equipped to handle the unknown dimensions of reality. Destructuring, in this context, provides knowledge engines with the capacity to discard rigid frameworks and free up resources to address new environments. This capability helps model the unknown more effectively by accommodating randomness and avoiding excessive reliance on past solutions.

Following this line of thought, Part II: *Destructure* examines the counterforce to Part I: *Structure*. This section emphasizes the potential of destructuring through active forgetting as a mechanism to enhance model plasticity. By incorporating this approach, we can develop resilient and robust knowledge engines that evolve alongside the ever-changing world. This approach opens exciting questions for future research, such as whether components beyond embeddings should be subject to forgetting and which tasks might further benefit from active forgetting.

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