Contents

Part I Destructure.

In the wild, reality is closer to the fresh eyes, where things are observed as they are.

Structures are the cornerstones for building knowledge engines. Both structured and unstructured paradigms inherently induce global structures into model computations through language modelling objectives as shown in Part I. These global structures may manifest in different forms, such as relationships between drugs or common syntax patterns. For instance, in the structured paradigm, drug-drug interactions can be encoded using tensor factorization models (Chapter 2). And in the unstructured paradigm, linguistic patterns like suffixes may be captured in the embedding-FFN-unembedding computational path in the transformer models (Chapter 3).

However, not all structures contribute positively to intelligent behaviours (Figure 3.10). For a given task, useful structures tend to be specific and concrete. Therefore, an excess of irrelevant structures may reduce efficiency, as identifying and retrieving the useful ones becomes computationally costly. Existing useful structures may become outdated or mismatched with our evolving world. For example, factual knowledge [Petroni et al., 2019, Roberts et al., 2020], such as "*who is the current US president,*" may change after every election. Corresponding structures once embedded in neural weights will stay static unless updated through human intervention. Additionally, new terminologies, like "*social distancing,*" did not exist before the COVID-19 pandemic, and models trained prior to such events may struggle to understand them in the new situations. Moreover, problematic structures can be induced unintentionally due to noise in the training data. For example, gender-biased content in the internet corpora can be captured in the transformer model weights if not filtered from the training data [Bender et al., 2021].

Model editing [Meng et al., 2022, Ilharco et al., 2023], model unlearning [Yao et al., 2024, Liu et al., 2025], retrieval-augmented generation (RAG) [Lewis et al., 2020b], and reinforcement learning from human feedbacks (RLHF) [Christiano et al., 2017, Ouyang et al., 2022] have emerged as remedies to patch these unwanted structures. However, they have certain limitations. The behaviour changes might be local (limited to chosen datasets) and temporary (the biased structures still live in model weights), making them prone to adversarial attacks [Xue et al., 2024] and requiring substantial centralised human steering [Wang et al., 2023].

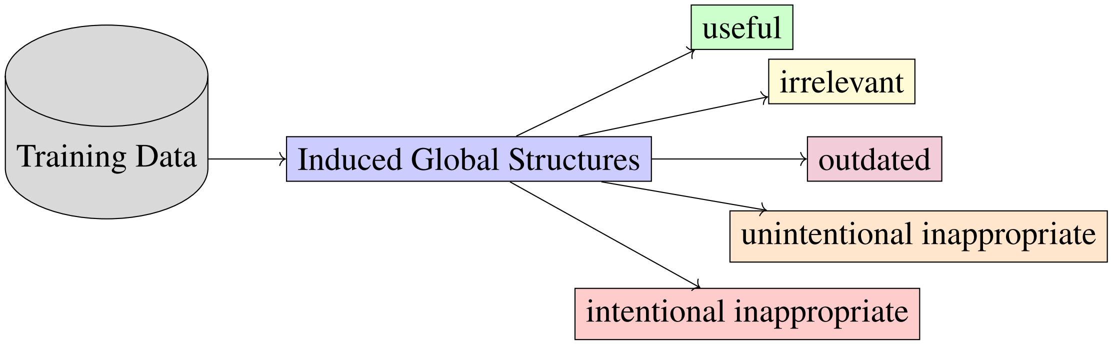

Figure 1: Not all structures encoded in the model are of positive roles. Some can be irrelevant, unintentionally inappropriate, intentionally inappropriate, and outdated.

This thesis instead explores an alternative approach, where we want to improve the model's ability to rewire itself rather than relying on external patches. If a model can transition from outdated structures to new ones in a sample-efficient manner, rewiring it with desired behaviours becomes significantly easier when unwanted structures are identified. The core idea is pretty simple: a model can learn to rewire its internal structure by frequently exposing itself to controlled structural dismantling during training. Hence, Part II shifts the focus from structuring, the topic of Part I, to its opposite force – *destructuring*,[1] and seeks to examine its impact on both the structured and unstructured paradigms for building knowledge engines.

Lessons from natural intelligence

At first glance, the concept of destructuring in artificial intelligence may appear counter-intuitive. Why would one discard the outcomes of prior learning experiences, especially when these outcomes were achieved through substantial investment, such as prolonged training hours and massive datasets?

To answer this question, we can draw a parallel to natural intelligence, particularly how the brain memory. Memory consists of four primary operations: acquisition, consolidation, forgetting, and retrieval [Berry et al., 2024]. Acquisition and consolidation work together to form stable structures in the memory. Retrieval, in turn, use these

[1]Definition of "destructure" as a verb can be found in wiktionary, meaning dismantling with etymology from *de-* + *structure*. For human cognition, destructuring can be conceived as the act to acknowledge the epistemic uncertainty, admit the state of unknowing about the ever-changing present, and reassess the reality with an open perspective.

structures in combined with contextual clues to surface relevant knowledge.

However, the structures in human brains are not fixed, but remain *flexible* even into old age. Neural circuits, the brain's primary structures, can be rewired by both internal and external experiences, allowing adaptation to new environments [Park and Huang, 2010], acquiring new skills [Green and Bavelier, 2008], recovery from psychological trauma [Kays et al., 2012], and even compensating for past physical brain damages [Kleim and Jones, 2008]. These phenomenons have been known under the umbrella term of neuroplasticity in neuroscience and other relevant subjects [Fuchs and Flügge, 2014, Costandi, 2016]. While the exact mechanisms behind neuroplasticity remain unclear, recent work suggest that mechanisms at molecular [Bennett et al., 1964], cellular [Rosenzweig, 1996] and network levels [Leuner and Gould, 2010], contribute to the brain's functional flexibility. *Active forgetting*, in particular, has been found to be a key ingredient to neuroplasticity [Anderson and Hulbert, 2021, Berry et al., 2024], which enables memory adaptation to suit particular cognitive and emotional objectives.

When mirroring natural intelligence to artificial intelligence, we find that the operations of acquisition, consolidation, and retrieval are well understood and modeled in both the structured and unstructured AI paradigms. For instance, acquisition and consolidation are achieved through gradient-based optimization guided by self-supervised objectives and subsequent finetuning [Devlin et al., 2019, Radford et al., 2019, Brown et al., 2020], while retrieval relies on training dense passage classifiers [Karpukhin et al., 2020, Lewis et al., 2020b, Reichman and Heck, 2024]. In contrast, forgetting, especially its positive role, has been receiving less attention in AI systems, despite its potential to mimic the neuro-plastic processes that allow for continuous adaptation and learning.

Inductive inference and generalization to the unseen

Philosophically, "majority" learning fails to encompass the full spectrum of intelligence. Intelligence is not solely about excelling in frequent or common patterns, often arising from habitualisation, but equally about thriving in long-tailed, atypical behaviours. Throughout human history, individuals those residing the long tail of thoughts, have sometimes been closer to the truth. For instance, Copernicus's heliocentric model, which proposed that Earth orbits the Sun rather than the opposite, defied the dominant belief structures of his time but proved to be a closer representation of reality. Such break-

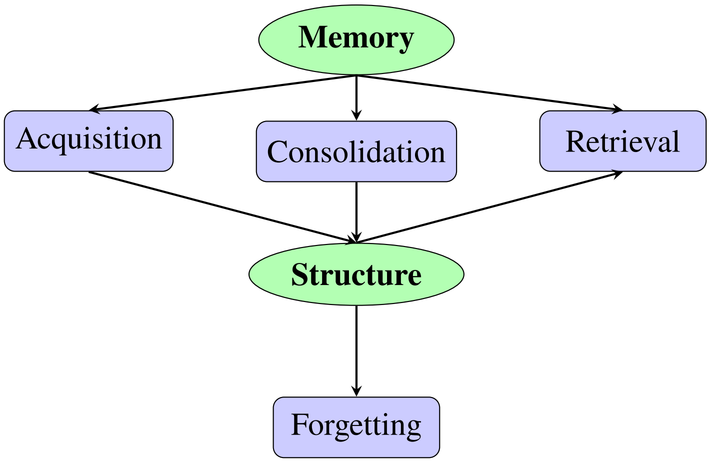

Figure 2: Memory consists of four main operations: acquisition, consolidation, retrieval, and forgetting.

throughs highlight how intelligence can *transcend* the constraints of prior knowledge structures and venture into the unknown.

From a computational perspective, while modern AI systems achieve superhuman performance on frequently encountered training data, they experience significant degradation when handling long-tailed or unseen data [Buda et al., 2018], regardless of whether they operate in structured or unstructured paradigm. Substantial studies [Finn et al., 2017, Arjovsky et al., 2019, Schölkopf et al., 2021] have been conducted to investigate this issue. The performance gap is often attributed to: (i) the model's tendency to pick up nuances or perform shortcut learning [Geirhos et al., 2020], preventing it from capturing more abstract and generalizable patterns during training; and (ii) at test-time, an over-reliance on computational structures learned from past examples coupled with limited capacity to dynamically incorporate immediate contextual information from the input [Geirhos et al., 2020].

An ideal artificial intelligence system capable of transcending experience diverges fundamentally from deduction systems, which applies established general rules to specific cases (e.g., querying a classic ontological knowledge base [Horrocks et al., 2003, Horrocks, 2005, World Wide Web Consortium (W3C), 2024] in the structured paradigm). Instead, it aligns more closely with *inductive inference*, a form of reasoning that extrapolates beyond immediate evidence. While the rationality of inductive inference remains to be philosophically justified [Hume, 1999], its *amplicative* nature allows bringing in new information into old systems, thereby reshaping an established knowledge landscape. In the unstructured paradigm, large language models exhibits some form of inductive inference through in-context learning, where they solve a task with given new inputs using the prompt composed of a task description and a few example input-output pairs [Brown et al., 2020]. However, this extrapolation is difficult to control, verify, and validate its outcome [Lee et al., 2025], rendering it susceptible to adversarial attacks, prompt choices, and hallucination.[2] Consequently, while promising, current large language models fail to perform systematic inductive inference in a robust and scalable way [Thomm et al., 2024, Wang et al., 2024]. We refer to this shortcoming as a **lack of model plasticity**, which we equate with inadequate inductive inference capacity throughout this thesis. This challenge is particularly acute in larger models, such as foundation models, due to combined factors including their immense model sizes, vast datasets, and high cost of training.

In Part II, we explore whether and how destructuring can improve model plasticity and help build universal knowledge engines that are capable of powering AI in diverse environments. Given the embedding-centric nature of mainstream architectures, where embeddings (and unembeddings) are crucial to encode global structures (Part I), we hypothesize that analysing the embedding learning process can provide deeper insights into structure formation. A core finding of this study is the reinterpretation of embedding learning as a sequence of message-passing operations (Chapter 4). In essence, embeddings function as caches for the outcomes of traversals over structures. However, these cached structures can become overly fixed, limiting generalization. Consequently, the simplest approach to destructure the model, is to clean overly fixed structures in the embeddings regularly, allowing other model components to learn more abstract and generalizable patterns. This new perspective motivates our proposed approach *active forgetting*, a learning mechanism that periodically resets embeddings. By acting as a targeted intervention in standard training, active forgetting improves model plasticity and facilitates inductive inference.

Concretely, we explore active forgetting and its impact in both the structured paradigm

[2] The lack of controllability stems from limited understanding of why in-context learning emerges in transformer-based language models. We speculate that it may be linked to deeper structural formation facilitated by self-attention mechanisms, where the toolkit discussed in Chapter 3 could aid in uncovering these processes in the future.

and unstructured paradigm for constructing knowledge engines:

1. **Chapter 4:** In the structured paradigm, we study factorization models, a leading approach in knowledge base completion. While FMs demonstrate strong performance in transductive settings, they fail in inductive scenarios. Our theory into structure formation reveals that entity embeddings in FMs cache infinite rounds of message-passing over the knowledge graph. This insight explains FMs' failure in inductive scenarios, as their reliance on rigid structures (ingrained in the embeddings) overfits to the original graph and impedes generalization to new graphs. To address this, we propose incorporating *active forgetting* into FMs, periodically flushing old values and reloading new ones in embeddings to mitigate the effects of overly rigid structures. This derives a new model that bridges FMs and the message-passing graph neural networks – REFACTOR GNNS. Experiments show that REFACTOR GNNS improves generalization to novel graphs with unseen nodes.

2. **Chapter 5:** In the unstructured paradigm, we study pretrained language models, the mainstream approach for building universal knowledge engines from purely unstructured data. Pretrained language models often lack plasticity and require large datasets to relearn embeddings for extending to new languages. However, data is scarce for low-resource languages. To address this, we examine cross-lingual transfer in a low-data regime, aiming to pretrain language models that quickly adapt to reasoning tasks for new languages with limited data. Each language represents a distinct environment, requiring inductive generalization. *Active forgetting* again proves effective and practical to incorporate into large scale pretraining processes. Models pretrained with this technique exhibit significantly better adaptation to previously unseen languages with limited data.

Both the structured and unstructured paradigms rely on structure formation to learn representations. By rethinking the procedures underlying structure formation, this part suggests that AI's struggles with generalization stem from overly fixed internal structures. To address this, Part II proposes that destructuring can serve as a way to counterbalance the rigidity introduced by these overly-fixed structures embedded in model computations. Given the widespread use of embedding layers in structured and unstructured paradigms, *active forgetting* emerges as a simple yet powerful mechanism for implementing destructuring, where destructuring becomes as easy as resetting embedding values periodically. This approach proves effective across both the structured and unstructured paradigms, providing a unified framework to improve model plasticity and enable models to perform well in dynamic environments. Our results demonstrate that universal knowledge engines, which must achieve the plasticity and adaptability necessary for robust performance in diverse, real-world settings, will benefit significantly from incorporating *active forgetting* or similar destructuring techniques.

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