Testing the Quantitative Spacetime Hypothesis using Artificial Narrative Comprehension (II)

Establishing the Geometry of Invariant Concepts, Themes, and Namespaces

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Abstract—Given a pool of observations selected from a sensor stream, input data can be robustly represented, via a multiscale process, in terms of invariant concepts, and themes. Applying this to episodic natural language data, one may obtain a graph geometry associated with the decomposition, which is a direct encoding of spacetime relationships for the events.

This study contributes to an ongoing application of the Semantic Spacetime Hypothesis, and demonstrates the unsupervised analysis of narrative texts using inexpensive computational methods without knowledge of linguistics. Data streams are parsed and fractionated into small constituents, by multiscale interferometry, in the manner of bioinformatic analysis. Fragments may then be recombined to construct original sensory episodes— or form new narratives by a chemistry of association and pattern reconstruction, based only on the four fundamental spacetime relationships.

There is a straightforward correspondence between bioinformatic processes and this cognitive representation of natural language. Features identifiable as ‘concepts’ and ‘narrative themes’ span three main scales (micro, meso, and macro). Fragments of the input act as symbols in a hierarchy of alphabets that define new effective languages at each scale.

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I. INTRODUCTION

Can we demystify basic processes of cognition, in real and Artificial Intelligence research, by appealing to some general principles of scale and consistency? Modern AI research often builds on the application of black box technologies as tools, and models do little to shed light on how artificial cognition might naturally be considered part of a larger class of processes appearing over multiple scales. The Spacetime Hypothesis, proposed earlier [1]–[4] offers a simple proposition: namely that spacetime processes must underpin all aspects of cognition. The goal in this series of papers is to test the (rather large) implications of that hypothesis explicitly with a working model. The scope of the problem is large, so it can’t be covered in a single work.

Measurement scales (engineering dimensions) are the basis of all descriptions of natural processes in physics and chemistry, yet they are often deliberately eliminated in statistical studies. The appeal of probabilistic methods, to elicit ‘universal characteristics’ and scale-invariance, can bring confusion rather than clarity. For example, in language studies relating to the present work, the works of Zipf and Mandelbrot [7]–[9] famously remarked upon scale-invariant distributions as properties of language. However, such procedures purposely eliminate an important source of information: cross-dimensional scales that characterize the relative interactions between the object of study and their environment. The Spacetime Hypothesis contends that we have to return to a natural scale analysis (not a scale-free one) to understand phenomena [1]–[4]. The treatment of scales has a long history in physics [10], [11].

In natural language analysis, linguistics also tend to forego quantitative scales, preferring to focus attention on the reduction of functional (semantic) elements, i.e. components of grammar. Once a mindset for grammatical thinking has been established, it’s hard to disregard one’s own knowledge of language in the approach. Here, the Spacetime Hypothesis takes a deliberately different approach, more reminiscent of biological analysis. We may retain semantics, in the form of distinct quasi-symbols, to look at raw pattern fragments, and the commonality of such accumulated ingredients (a procedure one might call symbolic interferometry).

The successes of Artificial Neural Networks (ANN), or processes inspired by neurobiology, have left many willing to forego a causal understanding of recognition methods, attributing successes to almost mystical properties of specific Machine Learning apparatuses. This has led some to a premature rejection of ‘symbolic approaches’ to Artificial Reasoning. However, there remains a gulf of understanding between statistical inference methods and the origin of logical reasoning [14]–[17]. This work illustrates one way in which the two descriptions might plausibly come together—by understanding the scaling of symbolic representations.

The paper follows directly from the prior study in [18] (hereafter referred to as paper 1), and applies an approach that revisits ideas developed with A. Couch in [19], [20]. In paper 1, natural language texts (episodes of narrative) were used as a data source, ignoring a linguistic understanding of their content. Data were simply assumed to express ‘spacetime phenomena’ from which one then tried to extract meaningful structures, building on the hypothesis that spacetime patterns determine significance. From those structures, meaningful patterns could be identified. Paper 1 showed that a principle of fractionation was important to identify invariants and define scales inherent in the spacetime structure of the text.

In this sequel, two questions are addressed. Given the basic constitution of pattern fragments from paper 1, which converts input data into an alphabet of new effective symbols,

- How should one organize fragments into a knowledge representation that retains their spacetime relationships to one another?
- Moreover, how do the data form representations of concepts (independent of the input language) such that a cognitive agent could tell its own stories, on a new level, based on the emergent geometry of its memory representation?

Following the results of [18], we have the simple understanding of how quantitative measures behave within streams of symbolic data—in a way that can presumably be extended to non-digital patterns. The next step is to study whether or not we can order, rank, and extract meaningful geometry for reasoning about the event patterns, their fractions, and aggregations representing context, all without any linguistic understanding. This is the essence of Automated Reasoning (AR).

Once a stable geometry has been established, a key test is whether we can generate narratives from the data whose translations would be acceptable interpretations of the story. The procedure can be compared to the Turing Test, which is not a quantitative result but rather a qualitative assessment of whether the encoding functions in a believable way. Crucially, we shouldn’t expect a higher standard of an artificial system than we would of humans. Even ‘intelligent humans’ speak apparent nonsense at times for various reasons. The results are partially convincing in principle, but focus on the mesoscopic scale. Results points to the need for further study on the macroscopic interactions.

II. PROJECTING NARRATIVE INTO SEMANTIC SPACETIME

The semantic spacetime model predicts the existence of a graphical representation for processes, based on four elementary types of relationship between nodes in an agent model. Although, as humans, we read narrative in a particular manner—by convention—there are other ways to read it too: browsing, indirection or jumping into the middle via an index, etc. This is better represented by a graph structure than by a

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1A number of authors has attempted to formulate speculative or toy models of consciousness on a philosophical level, based variously on ideas from Information Theory and Quantum Mechanics, but these are hard to take seriously [5], [6]. To join those ranks is not the intent of this work.

2This approach will inevitably entail limitations, including those noted in the interferometric equivalence principle [12]—but these are precisely the limitations we have to confront in understanding how to bootstrap meaning from sensory input, and—by implication—in language too.

3See for example the review of the state of affairs in [13]
A. Definitions and hypotheses concerning the construction of a causal graph from fragments and their co-activation contexts

Discussion languages and meta-languages within data, based on natural language, potentially leads to some confusion of terms. To avoid some semantic muddle, let's define the following nomenclature:

Definition 1 (Input language): The stream of English symbols and words parsable by the sensory receiver (depicted in figure 1). The stream is chopped into fragments $\phi_n$ which retain the original language symbology.

Note carefully, although human language comprises the content of the stream of patterns perceived by the sensor, our ability to read it is of no consequence to the processing: it plays no role in the method of construction of events, hubs, and regions. Our knowledge of the language gives us a privileged advantage in assessing the fragments at certain stages of the analysis, but no grammatical criteria are used in this work, except for spaces and full stops (periods). The human language (English), used in this study, is considered only as an encoding on the level of patterns. It will be for us, as privileged observers, to comment on any correlation between them at a later stage of the argument.

Definition 2 (Concept Language): The elements in a graph representation of the input data condense into a new set of invariants. These, together with the links that express relations between them, comprise a new language—which is the language of the Artificial Cognitive Agent.

The concept language’s symbols and phrases are built as a dynamic process of discovery during the processing of the stream. The eventual stabilization of any dynamical structure generally requires both sufficient diversity and sufficient bulk or ‘mass’ to build a complete picture. That occurs both via the persistence of fragments representing contextual fragments stored in hubs, and by the subsequent super-aggregation resulting from the joining of hubs into larger regions. We might therefore posit the following, based on simple scaling arguments:

Hypothesis 1 (Invariant local patterns are concepts): Patterns that recur from stimulus by the environment are the source of concepts, at each scale. The different scales refer to different language representations.

The case for this can be substantially confirmed.

Hypothesis 2 (Observations are input strings): Strings of the input language represent behaviours in the exterior world of the cognitive agent that express causal and spatial information.

This is more of an axiom, but as a source of complete, no other sources of data are needed in the study.

Hypothesis 3 (Statements are graph trajectories): Paths through the graph of relational ‘promises’ represent the cognitive agent’s process of reasoning, i.e. formulating statements about the world perceived by the cognitive agent in the concept language.

This proposal is harder to determine unequivocally, but the results point to the reasonableness of the assumption. The paths might be very long, especially when crossing episodes transversely. The challenge is that the span of scales involved in conceptualization is so vast that this preliminary work can’t capture every angle or cross off every objection. Nonetheless, the manifesto seems promising.

It’s worth repeating once again that the language referred to in this second hypothesis should not be confused with the symbolic language that happens to be the source of data in this study. The two languages are quite independent, but the potential for confusion is strong because we are using one language to study how another (potentially like it) could emerge by cognitive scaling. To make matters even more confusing, we must eventually use the input language to explain the symbols of the derived language too (because that’s the language you are reading now). Finally, the summation of these ideas:

Hypothesis 4 (Narrative): Once a cognitive system has learned by merging several narratives, it has the potential to tell new stories—by combining inferences across the connected network based on its long term memory.

This too seems promising, and this work will help to clarify more convincingly once we can generalize the approach to other kinds of data.

B. The four semantic relations of spacetime

Although the specifics of semantics relationships may entail a wide variety of subtle interpretations, or ‘subtypes’, the Spacetime Hypothesis proposes that these must all belong to four basic spacetime types:

- **FOLLOWS**: Events follow one another in process time $t$, according to some partial order relation ‘$>$’. The narrative process has a partial order which can be retained from events, to link up episodic events into a chain. Sentence events may thus promise to follow one another, e.g.

  $S_t \overset{+(t'>t)}{\Rightarrow} S_{t'}.$

  (1)

  This relation is a strong binding interaction.

- **CONTAINS**: Collections of agents can be considered parts of a larger whole. Thus a collection contains...
member agents, which allows scaling of identity. A collection of agents can be unified by connecting each member to a central hub agent. Hubs \( H_i \) promise to represent clusters of sentence events \( S_i \), and sentence events contain all possible fragments within them.

\[
\begin{align*}
H_i & \xrightarrow{+S_i} O, & (2) \\
S_t & \xrightarrow{+\phi_n} O, \ldots & (3)
\end{align*}
\]

- **EXPRESSES**: Invariant patterns express information which distinguishes them from one another. The identity or proper names of agents are thus ‘expressed’ as ‘scalar promises’, or self-properties. On a larger scale, the same is true of aggregations of agents, acting as superagents. Sentences can express fragments:

\[
S_t \xrightarrow{+\{\phi_n\}} O.
\]

Then by implication, hubs also promise the sum fragments that compose them

\[
H_i \xrightarrow{+\{\phi_n\}} O.
\]

Fig. 2: The longitudinal data stream is coarse-grained into legs and fractionated into sentence events \( S_t \) and \( n \)-phrases \( \phi_n \), which form hubs \( H_i \) by co-activation of phrases in proper time \( t \). Each fractional \( \phi_n \) can be associated (transversely) with the hubs it belongs to by post-processing, and events follow one another. The overlap between sets of fractional parts determine their ‘closeness’ at each level. This post processing is the only way to associate similar ideas out of band, by smoothing over the data representations without being tied to the sequence driven by sensory input.

- **SIMILAR TO (NEAR)**: Agents (superagents) that make collections of promises can be compared on the basis of their common promises; thus one may attribute a degree of similarity between them. If they express precisely the same \( \phi_n \), they are maximally similar (proximal, or close together – see figure 2). If they don’t overlap at all, then they are disconnected silos. Closeness, in fragment space, therefore comes from the interferometry of fractional sets. A few random overlaps of fragments may lead to remote or weak connections (far apart means few similarities), and, as we’ll see below ‘a cognitive agent which excludes those beyond a certain horizon will be more successful in separating concepts than one which eagerly relates all things. The degree of overlap between hubs, defined as the coincident members:

\[
d_{ij} = \frac{2|H_i \cap H_j|}{(H_i \cup H_j)} \times 100\%
\]

The proximity relation is a weak binding interaction.

These types have been used earlier in [3], [23]–[25]. Within the graph representation, the relations are represented by links or edges of the graph [26]–[28]. Within expressed quantities, they are represented by direct adjacency of symbols as strings.

C. Fractionation of sequential data

To render highly specific combinatoric sequences into a comparable form, one may fractionate them into mixtures of their smallest constituents and measure their spectra. Thus each sentence is broken up into parts of different word length \( \phi_n \) (see paper 1).

In paper 1, single narrative (document) sources were fed into a preprocessor, which chopped up the stream into sentences, and chopped each sentence into \( n \)-phrases \( \phi_n \), i.e. sequences of \( n \) words bounded by the sentence (for \( n = 1, \ldots, 6 \)). In each ‘leg’ (or quasi-paragraph) of a stream the statistical characteristics of the phrases are used to rank their importance (see figure 2). Any significant changes in the spacetime measures of the sampling process may lead to a state of greater ‘attention’ or higher sampling, otherwise a low level of sampling is maintained.

Overall about one part in a hundred of the stream was typically extracted, based on importance. This is an arbitrary choice taken in paper 1 and continued here for consistency. In a more effective application, the density should perhaps be higher. The selections retained whole unedited sentences as hubs for the member fragments, based on their \( \phi_n \) importance scores.

The sequence of transformations is thus (figure 4):

1) Sentence selection of events by importance score: text \( \rightarrow S_t \)
2) Fractionation of all sentences into \( n \)-phrases: \( S_t \rightarrow \phi_n \) for rolling context.
3) Assembly of \( \phi_n \) into sets, joined to a hub representing a moment of context.
4) Selected sentences are linked to the nearest rolling context hub
5) Post processing of context hubs to look for similarities based on mutual information.

All the learning here may be characterized as unsupervised, and happens by realtime assessment of fragments \( \phi_n \). All data are reset at the start of each narrative experiment, unless the experiment concerns a merging of the narratives. Fragments are forgotten at a controlled rate to maintain a dynamic ‘pressure’ or equilibrium to resist random selection. The forgetting rate was tuned so as to never forget the most common words (‘of’, ‘the’, etc) that punctuate and glue more significant phrases together.
**D. Role of the observer and running context**

Machine learning models typically construct classical ‘God’s-eye view’ models of the world, in the Cartesian-Newtonian tradition: a single truth for all in the system. The Spacetime Hypothesis, by contrast, automatically leads to a Local Observer View of data, derived from its promise theoretic origins [29], meaning that every observer potentially ends up with a different (relativistic) picture of the world, depending on the sample and order of its experiences.

As each observer receives a partially-ordered stream of input data, it uses its short-term memory to count what it sees. As data are received from different vantage points, the order and quality of information may vary. Some information can be blocked from propagating. These differences influence the subsequent ranking of observations within the cognitive process; that, in turn, determines which fragments to keep and which to discard as noise (see paper I).

Pattern fragments of data $\phi_n$ are kept in a running ‘buffer’, by a cognitive agent, and these characterize the here-and-now. We associate this buffer with the agent’s context, and this is used in the determination of ‘co-activation’ (see figure 2).

The significance of this bank of running fragments (called the agent’s running context) should not be underestimated. In practice, this is one of the few available criteria available to an agent for the discrimination of pathways in a reasoning process. In other words, all decisions and linkages that transcend simple episodic recall will have to rely on this running context to make leaps of thought.

**E. Running context**

Context appears in three distinct roles in this work:

1) A running context is accumulated over the different ‘legs’ of sensory input, and form the effective infor-
mation of the leg. This context acts as a parameter in the ranking of events during the encoding of memory.

2) Context is effectively cached like a sample of the environment in event hubs, both as unifying addressing construct, and as a quick lookup route to adjacent similarity of ideas. Because context is quasi-symbolic, it can be matched, in the manner of mutual information between any two hubs, implying a metric distance between them. Hubs that are close together form effective regions over short range interaction scales (figure 1).

3) Finally, when an agent’s thinking processes are not dominated by new input, it derives principally from the exploration of memory paths. The running context in 1. is then modified by the fragments expressed by already-known concepts visited along current search patterns. Such context can be matched for similarity to select likely relevant pathways in the memory geometry.

At every stage, the running context cache—like a mixed chemical sample or ‘primordial soup’ of fragments—is the effective selector of reasoning pathways in the graph representation, somewhat analogous to chemical spectroscopy of the fragments.

F. Implicit geometry

The interplay between order and scale leads to geometrical notions that we shall exploit in encoding information for analysis, reconstruction, and later recombination.

A narrative begins with a collection of sentences, which are selected from the raw narrative by an assessment of their significance, then fragmentated into components \( \phi_n \) [18]. They are located within successive ‘legs’ of the stream’s journey. Legs are a simple quantitative proxy for context. More important is the semantic measure of context, which is the rolling collection of most significant \( \phi_n \), given a constant forget rate. Notice how the forget rate becomes the effective reference calibrator for the time coordinate, and for context changes. This will play into the rate at which clusters can form into proto-concepts. As in all interactions, there are (+) and (-) promise components [29].

- Promised invariants (+), repeating patterns that present at the input.
- How these are received and classified (-).

Invariants act as agents (on a new level) in the memory representation of the cognitive agent. For the remainder of the paper, agents refer to the space of knowledge representation. Some agents are in non-ordered phase (liquid) while others are rigidly ordered (solid phase). The order of words \( \phi_1 \) is retained within larger fragments:

\[
\phi_2 = \phi_1 \text{ followed by } \phi'_1
\]  

(7)

Similarly, at the scale of events, the order of sentences is retained, by linking with ‘follows’ promises, as these are assumed to capture episodic summaries, with at least partially causal order. In practice, at the retention rate of one sentence in two hundred, the order of events is rarely very significant; however, if we changed the sampling density to a much higher level, we have to assume that it would be. The order of hub contexts may also be retained as superagent, even while the fragments that are ‘contained’ within are not ordered on the interior.

To codify and reconstruct a facsimile of the narrative, the approach is thus to use these four spacetime semantic relationships to build a knowledge representation based on a semantic spacetime promise graph, identified in [3], [23]. We take the fragments of sentences \( \phi_n \), and connect them as follows: These are applied as in figure 3.

- Sentences become agents. They express their content as an atomic unit of narrative.
- The contents of fragments (which have the status of symbols, i.e. an atomic instance of a proper name) are expressed by each fragment.
- By counting sentences as units of ‘proper time’, a finite buffer size aggregates sentences into coarse grains of narrative progress called ‘legs’. Sentences that score above a certain threshold for acceptance become aggregated into grains, and promise to be part of a superagent called a hub (denoted \( H_i \)). A hub therefore contains sentences, and each sentence expresses multiple \( \phi_n \) fragment attributes. Each hub therefore expresses the sum of those attributes too—which summarizes a context.
- Sentences express microscopic ordered combinations of words and phrases \( \phi_n \). The meaningful sentences \( S_t \) promise to ‘follow’ each other in the proper time order of the narrative (labelled \( t \)). Hubs follow one another too when derived from the sentence event order.
- Fragments \( \phi_n \) are contained by larger sequences, which are ‘contained’ by sentence agents \( S_t \), which are contained by hubs in their respective legs.
- The function of smallest fragments is to match with similar patterns in other sentence agents. The function of longer fragments is to encode uniqueness. Beyond \( n = 3 \), fragments rarely recur [18]. These \( \phi_n \) become the bodies of (±) promises to offer and accept information, much as molecular sequences allow binding between cells or polymers.

To eliminate the constraints of order, but retain components in a ‘mixture’ or ‘solution’ form, the partial fragments are aggregated into the names expressed by hub structures. The names are thus non-causal, non-directional promises.

Only at the level of hubs is there a plausible metric notion of distance or compositional similarity. Although any expressed attribute can be compared in terms of the alphabet of its smallest fragments, order generally renders sequences unique, so there is little or no mutual information to go by. Only by fractionating sequences into an alphabet of disordered parts can be measure similarity in a consistent way. The collection of all attributes \( \phi_n \), for each hub \( H_i \), may possess mutual information in the alphabet of \( \phi_n \) with respect to every other hub \( H_j \). Clusters of sentence events, joined to context hubs, may therefore be measured as ‘similar’, near or proximate to one another if they overlap in their support of \( \phi_n \) express from below (see figure 5).
TABLE I: Approximate identification between text and bioinformatic representations of process narrative. The similar scales arise likely for the same underlying reasons: scale separation of information is critical to stable spacetime invariance.

| Fractions | Text | Bio-informatic |
|-----------|------|----------------|
| \(\phi_1\) | words | bases |
| \(\phi_{2,3}\) | names | codons |
| \(\phi_{\text{base}}\) | concepts | genes |
| \(\phi_{n>3}\) | embellished concepts | peptides |
| \(S_i\) | events | proteins |
| \(\{\phi_n\}^{(+)}\) | context | mixture |
| overlap \(\{\phi_n\}^{(\pm)}\) | themes | species |
| Narrative | narrative | bio-process |
| Directed regional stories | Meaning and intent | Functional adaptation |

G. Concepts and themes

It’s worth a brief digression to clarify some narrative terminology. In literature one distinguishes the notion of concepts from themes [30]. Since we are using data from natural language narratives, this issue is important because it captures a phenomenon of scaling. Although the distinction is loose and based on preferred interpretation in natural language, it turns out that there is a natural way to distinguish these based on scaling.

The difference between a concept and a theme lies in their semantics: while a theme captures a broader area, a concept limits itself to a narrow and particular idea (i.e. input pattern)\(^5\). In a spacetime sense, they arise differently, as patterns belonging to different processes. Concepts are found in the discrimination of longitudinal input language patterns (time), by searching for invariants. Themes, on the other hand, are found from the transverse correlations between disordered contexts (space).

We need a term which refers to invariant characteristics in the input—and ‘concepts’ matches this well. Concepts have to be smaller than events in order for events to be about concepts, so there a natural scales of.

concepts \(\phi_n < \text{events}\ S_i < \text{contexts}\ H_i < \text{themes}\ R_{ij} \quad (8)\)

This view turns out to have a natural resolution based on precisely the notion of spacetime process invariance—which is easy to discover using the interferometry method. In academic literature the concept of a concept is often associated indistinguishably with ‘keywords’ [31]. This fits with the identity implied from the process scales of the input stream. Themes are associated with composite structures, based on mixtures of concepts representing context of events.

Now an interesting point arises: why are concepts defined in terms of the input language and not the concept language? This can be understood from the Spacetime Hypothesis itself—the most basic concepts represent features of the spacetime processes around an agent. Later, concepts might also come to represent phenomena involved in processing and recycling interior representations of the world, including imagined worlds, so the process can be repeated on a higher level. The bootstrapping of concepts, however, belongs to the external sources.

We should always be careful to understand whether we are discussing representations in the input language or in the concept language. Elsewhere, the two languages may be identical, e.g. in studies of text mining, but we distinguish them here with good reason: they represent processes with their own invariants on different scales. In connection with this, the question which underpins the confusion between the two is: how are proper names assigned to concepts in the concept language, even as they are represented on a basic level in terms of the input language? If we play on the analogy with bioinformatics, the question is like asking: how do we come up with the name ‘Penicillin’ for the concept of a particular mixture of proteins and chemicals?

III. QUANTITATIVE SCALING ANALYSIS

Based on the quantitative analysis in paper 1, we can now move on to consider the discrimination of roles for different patterns, with the aim of encoding sampled narrative in a geometry. The problem becomes multi-dimensional due to coarse graining and revisitation of concepts, and representing simply scaling arguments becomes more of a challenge. Using the same data sources as in paper 1, we can nevertheless begin by looking at how the formation of co-activation structures scales. This assessment could have been extracted from the procedures described in paper 1 (no new analysis is required), but they were not directly relevant there.

The Spacetime Hypothesis leads to a straightforward classification of variables and separation of concerns, through

\(\phi_n\)\(^5\)That is not to say that concepts could not take on the role of themes and vice versa, on different levels once they have been assigned proper names—because the proper names are concepts which then represent the themes.
the four semantic types. The goal of this account is therefore limited to presenting the data through the lens of the model.

A. The basic quantities

It seems self-evident that the more data we have, the more potential there is for extracting concepts. With that in mind, its sometimes expedient to express derived measures relative to total input language word count. This is not the measure of proper time (sentences) which drives the narrative, rather it corresponds to the work done by the processing of the input language. Elsewhere, its useful to measure relative to the memory samples, which related to the proper time. Some measures are thus plotted relative to the number of hubs, which is the relevant discriminator for the concept language.

The notation for the elements is summarized here:

- Word count \( w \) for each narrative.
- The number \( \mid H \mid \) of hubs \( H_i \) that are collated from each narrative, for index \( i \) running over the distinct hubs.
- The number of interconnections between hubs \( H_i \) which could range from \( 0 \ldots \mid H \mid (\mid H \mid - 1) / 2 \).
- The number of sentences contained by hubs has no symbol.
- The number of fragments expressed by sentences and hubs is simply written as a set \( \{ \phi_n \} \), where \( n \) is the number of words per fragment.
- The proximity of hubs to one another is measured by the overlap (or interference), of hubs in different contexts or legs of narrative. This can be measured within the same narrative or between different narratives. As is typical in scaling theory, from the Buckingham-Pi theorem, there is a key dimensionless variable that controls many aspects of the highly non-linear behaviour [10], [11].

**Definition 3 (The context ratio \( \nu \))**: A dimensionless ratio, which characterizes the sampling and memory representation process, measured by comparing word counts for a typical sentence with a sum length of all fragments retained in fractionated form as its context (hub). The ratio of average skimmed fractions \( \phi_n \), for all \( n \), divided by the average length of sentences in the local narrative region:

\[
\nu = \frac{\langle \sum \phi_n \rangle}{\langle S_i \rangle}
\]

This ratio of scales can vary throughout a narrative, as the lengths of sentences varies, and so on. A more sophisticated sampling agent could adapt this ratio to improve the efficiency of its cognition, in principle. To keep matters simple, we don’t try that here—but we can see the effect of varying the ratio (see figure 6). Concerning the larger significance of this ratio, we see that it is not a self-scaling (probabilistic) measure that characterizes the important processes, but rather a comparison of different dynamical scales measured from the basic characters of spacetime variation. This point alone favours the Spacetime Hypothesis’s deviation from a probabilistic approach to recognition.

Owing to the special importance of 2,3 fragments, a critical region for this. A typical value of 2-3 turns out to predict when significant associations can be made. Below this limit, association does not become a useful tool for learning across narratives. For significantly larger values, spurious associations form all the time, leading to a blurring of concepts and themes into a ‘grey goo’ (maximum entropy).

The more conventional measures of graph structures, typical for example in percolation studies, are the node degrees \( k_i \) for each agent \( A_i \). These can be separated with respect to spacetime types 1-4 for each node in the graph, which refer to different scales. From this node degree, one could estimate the level of percolation using the theory of Newman et al [32]. This does not turn out to be illuminating. The graphs produced by the spacetime method are not without intentional structure, so its unclear the extent to which they might be considered random graphs.

As in paper 1, serial text sources are scanned, sentence by sentence, using a realtime process, with a continuous forget-rate. This ranks sentences and fragments by a measure of importance based on spacetime scales. In paper 1, the sentences were considered for their accuracy in summarizing the intent of a narrative. Here, we take the fragments and extract their implicit relationships, according to the spacetime model. By treating each fragment as a promise theoretic agent, and attributing four basic promise types based on the spacetime geometry, this builds an effective geometry from a graph of the promises made between parts. Interferometry is used in two ways (along the narrative and across different narratives) to search of stable invariants of the narrative as a semantic process [3], [23]. Some sample data sources are shown in table II for illustration. For the purpose of understanding the role of bias due to familiarity with the narratives, some of the chosen texts were written by the author, while others were merely ‘known of’ and others were completely unknown.

B. Sparse graphs enable separability

We begin by performing some basic measurements of the data, to get a feel for the important scales and possibly trivial quantitative relationships that can be used to make sense of the more complex results later.
TABLE II: A few of the sample texts. The most coherent behaviour is observed in the book Thinking in Promises, which concerns a narrow specific subject, like a typical text book. The other books are more expansive in their topics. Novels are the most expansive. Note there are minor differences to the counts shown in paper 1, due to the minor editing out of copyright informations from certain texts to eliminate noise.

| Words   | Name                          |
|---------|-------------------------------|
| 5193    | Thinking in Promises 1        |
| 2925    | Thinking in Promises 2        |
| 4945    | Thinking in Promises 3        |
| 2897    | Thinking in Promises 4        |
| 5445    | Thinking in Promises 5        |
| 5455    | Thinking in Promises 6        |
| 10190   | Out of the Fog (novel)        |
| 112538  | The Promised Land (diary)     |
| 125932  | History of Bede               |
| 192106  | The Origin of Species (6th)   |
| 208458  | Moby Dick (Novel)             |
| 216842  | Smart Spacetime               |
| 261132  | Slogans (Novel)               |

Story summarization, or extraction of a chain of events into a sequence of nodes forming a trajectory, is the basic process by which narrative is ingested by the system. Apart from the natural and approximately linear relationship between story trajectories and word count (sample size), one would not expect whatever concepts emerge to follow any obvious pattern, on the basis of a purely quantitative measure like word count—any more than one might expect the shape of someone’s nose to be related to their overall mass. Concepts are signature features of a narrative, and are, by definition, not likely to be regular statistical phenomena. Some patterns might nevertheless still fall into a few general classes. The distinction between factual texts and fictional ones stands out here.

Sparseness is what allows separation of concerns to be effectively maintained. Should a cognitive agent ever manage to saturate its memory representation, it would spell doom for its reasoning capabilities. Sparse connections enable close to linear growth of linkage within the quadratic space of possibility.

Figure 7 shows how the length of story sequences (connected sentences) grows with input size. One expects this graph to be approximately linear, based on an assumption of constant average ‘significance density’ throughout each narrative, however it’s not quite linear due to the variable sampling rate. The anomalous point in the middle of the graph (from the History of Bede) suggests a document with a lot of repetition of concepts. Note: the joining line is for ease of reading and does not imply interpolation.

More interesting is the graph of coincidental overlaps, implying proximity of hubs to one another (see figures 9 and 10). It’s not obvious a priori how such a graph might behave. First of all, one has to accumulate stable fragments, then they have to be repeated in similar patterns in order to end up with similar hub contexts. Then there is the unpredictability in combined importance of the fragments leading to the keeping of sentence events. All of these factors come together in this figure.

One effect that seems to be apparent from the experiments (which is evident though not conclusively in the data) is that
emerge from single sources of narrative. Hubs are too specific to allow concepts to emerge that are independent of context. Regions are what one might assume to correspond to more evolved concepts over time.

Context is associated directly with the scale of the mixture of fragments $\phi_n$. Concepts are the spectra condensed from the soup of concepts, by virtue of an interaction chemistry, which is implicit in the spacetime properties of the input stream. The allusion to molecular chemistry is no accident. The same principle applies, whether the language of fragments is chemical, phonetic, or lexical: symbols are symbols.

The natural place for concepts can be understood at the scale at which one can observe similar processes (event sequences) derived from partially-similar invariant constituents, i.e. similar functions that span a set of constituents. Partial events may be invariant concepts, so concepts must be smaller than events. Entire events will rarely become concepts, by a method based purely on aggregation. The ability to form concepts comes from recombination of the most elemental fragments, just as one sees in chemistry and genetics. If we take that lesson from here and apply it to chemistry and biology, then it says that concepts correspond to invariant molecular fragments (e.g. genes), while themes amount to the scales of protein bindings and above, rather than codons, genes, or polymers (figure 4).

So words from the input data stream do not lead to concepts by themselves. Reconstituted fragments do. How we end up giving names to concepts is an entirely different discussion that belongs to the scale of the emergent commentary language. The association of proper names to concepts is a separate process, as is the association of a shape or image to a concept. Examples of concepts (occurrences in topic map parlance [33], [34]) express exemplifying events which have not been broken up and reconstituted—but rather remembered as raw data (‘as is’).

D. Post processing of narrative graphs—lateral thinking

Hubs link together collection samples of fragments associated with a sample point of sensory context. Hubs form effective basis elements of narrative, in the sense of a matroid pattern. The sum of the $\phi_n$ components also acts as a proper name, expressed in the input language. A different alias could later be given in the concept language too; however, that might be premature. The hubs don’t usually represent invariants—only parts of them are invariant.

As we aggregate fragments (some of which might be concepts) into repeated clusters, we can find transverse invariants by looking at the overlap regions of these mixtures. This can only be done once hubs have all formed, and is best performed when the system is in rest, i.e. when it is not accumulating new context. So during this ‘sleep phase’ it makes sense to run through all recent memories and compare them to older ones that are ‘coactive’ with respect to context7.

By stimulating the component fragments that represent context, at the bottom of the memory hierarchy, overlapping contexts can be identified, measured for their overlap, and joined together with a weight representing how much overlap

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6In science fiction stories it has often been said that humans use only 10% of our brain capacity. Imagine what could happen if we could use all of it. The answer seems clear. If we were able to somehow fully utilize all of the nodes in a brain, this would be a state of maximum entropy and we would cease to function long before we reached that level. Sparse utilization is not a bug, but a feature of the implementation method.

7It’s interesting to speculate whether this separation of scale might be a reason for dreaming in animals.
there is. These joined up hubs are then ‘near’ one another and form weakly linked regions whose conceptual mixtures are similar of proximate to one another.

Regions are the only structure (apart from individual concepts) that can span different narratives. The impact of these cross connections is therefore profound. Repetition under changing context implies that overlap fragments are invariants. As collections of invariant concepts, they therefore act as ‘themes’. Moreover, since we associate stories with pathways or trajectories through fields of concepts, and hubs with contextual environment for key events, one can expect events to be weakly linked through hubs that are similar too. One event can trigger the idea of another by jumping from one context to a similar one, and looking for compatible events in this way. This is ‘lateral thinking’.

Stories—or artificially generated episodes—begin as separate silos of knowledge, unrelated by different experiences. How do they become related? The sum all all reasoning pathways, starting from any given event or concept, is combinatoric in nature and grows exponentially and discontinuously with each selection of a link in the chain.

It’s unclear, at this stage, at what scale such a story might be told. However, if we assume that simple-minded stories (in a kind of pidgin language) might result from the recombination of stable events from the original input, then we can search those possible pathways within the spacetime hypothesis to generate new stories from the vantage point of a godlike observer. They might not be in the eventual commentary language of the cognitive system, but we can’t wait for that language to emerge to finish this paper, so the compromise will have to suffice.

In other words, instead of rushing to interpret text using concepts of the input language, instead we should think of concepts as accumulating somewhat like molecular genetic structures: small components have similar functions on a low level (see table I). Their combination (and recombination) can lead to other expressions, and these overlap with one another through the language of fragments (e.g. genes or codons).

Overlap in the chemistry of hubs can be ‘cached’ graphically to assist in the computer model, by forming semi-permanent weighted links between them. The links have spacetime type ‘NEAR’, and serve to measure the proximity by similarity of hubs from one another.

A measure of distance can only apply to multifragment hubs, because similarity is only meaningful where there are different sets to count and compare to one another. There’s no naturally meaningful way to measure the distance between sentence events or fragments, which are atomic symbols. So the sub network of type NEAR forms clusters that aggregated into undirected globules of associated co-activation contexts. On the basis that similar context implies similar interpretation, the spacetime hypothesis then basically says that new concepts would form around these clusters on a new scale—that could be identified as the concept language: whose vocabulary is an accumulation of micro-concepts.

Comparisons of hubs, i.e. contextual admixtures, can be performed across narratives as well as along them (both transversely and longitudinally). The imagination hypothesis suggests that we could tell new stories in this way—by jumping contexts to fill in a chain of reasoning with either sequential concepts or event playback.

E. Emergent process scales—a natural relevance horizon

The space of control variables in even this simple model is large. The dimensionless context ratio \( \nu \) plays a role in the possible size of overlap regions between hubs, because it contains the amount of short term memory available to cache recent context.

Initially, a self-scaling of interactions was used to compare all hubs on a compressed scale—typical of probabilistic methods and self-similarity studies. When the numbers were scaled using relative to self, i.e. as a fraction of total sample, the result was highly irregular, because the sample sizes themselves had such a varying absolute size, as measured in units of the pattern alphabet (words). This led to highly unstable results. Empirically, looking at the numbers, we find precisely these scales represents in clearly separable terms. There are two horizons: nearest neighbours, which seem to reliably correspond to:

| Random | Meaningful | Repetition |
|--------|-----------|------------|
| < 1%   | 1 – 10%   | \( \simeq 50\% \) |
| weak (over horizon) | local (relevant) | self (ignorable) |

Some success in matching regions could be obtained, but only by artificially introducing an event horizon for random overlaps, which felt unsatisfactory. In the small regime, the overlap distances fell into principally three scales: larger co-activations (around 50%), presumably from persistence of a single event in short term memory, being sampled twice and leading to artificial duplication. Then there will always be random overlaps from small numbers of fragments that just so happen to share parts of the same chemistry—this is spurious and a result a combinatoric nature of patterns in the input. The final, more interesting, kind is due to a significant correlation in the occurrences. Expressing a raw statistical basis for this correlation is not simple, owing to levels of obfuscation through importance functions, threshold selections, and subsequent aggregations. Pruning the category 1 weakest links, which are essentially by random chance, the integrity of regions is more robust. The effect of the strongest links can be essentially neglected. This usually only happens when two events occur so closely together that they share the same context. There is an effective uncertainty relation here between the overlap \( \Delta H_i \) and the context sample:

\[
\Delta H_i \Delta f_j \geq \nu \delta_{ij},
\]

using the Kronecker delta of the proper-time sample points, which arises from the fact that locations represent coarse grained (non-local) regions over an aggregate scale\(^8\).

On more careful consideration, an appropriate solution was to return to a proper dimensional analysis of the intrinsic scales, and introduce the dimensionless context ratio, as the relative scaling multiplier instead of trying to eliminate scales altogether.

\(^8\)The change in hub constituency over a proper interval is somewhat analogous to a canonical momentum in mechanics.
During the experimentation, three regions in particular were examined. A parsimonious region of small buffer size $v < 1$, where there could be little overlap, a region of $v \simeq 3$, and a region of large overlap $v > 5$, which behaved quite differently. The critical value of around $v \simeq 3$ presumably arises from the role of fragments of length 3 in generating meaningful overlap (see figure 6). Fragments of length 1 carry no ordering context. Fragments of length 2 carry a little, but the optimal length is 3 [18], and longer fragments almost never repeat.

### F. The scaling of hub overlaps during interferometry

The significance of overlap is to find those fragments which are non-unique and which therefore represent invariants, and therefore be considered concepts alongside their longitudinal compatriots.

The suggests a more natural interpretation of the components of the input language:

- The short fragments, or spectral contents of mixtures, which participate in overlap represent proto-concepts. Each of these corresponds to a potential symbol in the concept language. Over many learning episodes, one might imagine these become stable.
- Longer fragments and non-overlapping remnants can be quickly forgotten as past context.
- The repeated admixtures of short fragments can be associated with themes. Themes are thus mixtures of concepts that convey broader intent. Higher level ‘intentionality’ (as we understand the high level concept) emerges through repeated themes.

The associative distance between the input and the concept languages is thus remarkably short. However the input may be stored, its short fragments become new symbolic invariants—like sieving the input for gold nuggets. Those nuggets must eventually form higher representations from which concept language could emerge9.

Figure 11 shows how the number of coherent clusters (hubs) from one example trial grows on successively sampling larger amounts of the total narrative. One sees a linear growth and a more quadratic shape. In a sparse process, these can be clearly identified within a potentially quadratic process of cluster overlap. Taken from a single narrative, based on a text book (Thinking in Promises) with a clear subject matter, it’s gratifying to see this level of predictability. However, we shouldn’t get too excited: this all falls apart once different kinds of narrative and different lengths of narrative are concerned. The linkage is slightly superlinear, indicating non-trivial connectivity, inherent in creative recombination processes10.

Figure 12 shows what happens to the same data once expanded with other examples. The neat polynomial behaviour is just a corner of a bigger picture with spurious (and catastrophic) changes. And beyond that, once the protected hubs are exposed to one another for overlap connections (figure 14), The reason for this can be seen from the nature of the fragments in each case (see section IV-B).

Taking the example of the Thinking in Promises text, on adding a significant length of text on a related (partially overlapping topic), one might have expected the number of hubs to grow to extend the number of concepts in a neat classification of knowledge. In fact, the 5 hubs collapsed into just two, throwing the whole story into confusion.

After another experiment combining the proto-concepts of one with another, 98% of the connections were in the random category and only 1.3% in the range of plausible overlap. This suggests that this might not be the mechanism by which learning representations grow. Some mechanism to pin learning to a scale rather than growing out of bounds might be necessary, for instance. The role of specialized scales (rather than scale-free behaviour) seems to around every corner.

We see that there is a need for some process to protect knowledge once formed. The criteria for linking hubs must be more subtle at scale, to avoid simply generating entropy.

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9Note, one shouldn’t assume that the concept language is written or oral, it could be entirely visual, and need not even be communicable between cognitive agents.

10Superlinear scaling has been associated with recombination attributed to innovation in studies of cities, for example [35], [36].
Fig. 13: For convenience, the hub scaling data in figure 12 separated by textbooks (left) and by fiction (right). No convincing quantitative pattern reveals itself for these two categories: the principal differences lies in the semantic chemistry of the components not in their quantitative measures.

Fig. 14: The number of regions (connected hub clusters that are deemed proximate to one another) versus the number of words sampled. One might expect this to conceal more noise, since stragglers could be absorbed into larger groups. However, from this small number of 20 samples of up to 200,000 words, this does not seem to be the case.

Introducing a horizon to eliminate the random overlaps helps to stifle the collapse—so this was taken to be standard practice thereafter, and all further results are based on shielding hubs from small spurious overlap (long range correlations).

IV. INTERFEROMETRIC EXTRACTION AND STABILIZATION OF CONCEPTS

The method of comparing a process to itself or to other processes with small phase shifts is called interferometry. It’s worth dwelling on some of the technical details in arriving at the broad conclusions referred to above, as these are non-trivial.

When parallel processes line up and produce the same symbolic outcome, the addition of their outputs (called superposition) emphasizes the result. When they fail to agree, the symbols accumulate more slowly and gradually become demoted in relative importance. This approach can be used in both spacelike and timelike directions to compare processes based on ordered sensory streams of symbols. Given a sampling process in spacetime, one can choose to establish cumulative statistics either longitudinally or along a timelike vector (corresponding to a Bayesian update procedure), or transversely along spacelike vectors (corresponding to a frequentist update procedure). Both of these turn out to have an important function in the spacetime method.

Along ordered sequences, longitudinal persistence can be used to pick out fragments that are more invariant than random chance—intuition suggests that these might correspond to ‘subjects’ or ‘objects’ in the abstract sense of concepts, as one would likely base such conceptualization on persistent phenomena. These can be applied to the fractionated samples acquired on each sentence arrival, taken as a unit of proper time (see paper 1). The result is something like a spectrum of concepts.

In disordered mixtures, transverse interference of the mixed components can be used to pick out the chemistry of fragments, which overlap with others due to independent similarity of pattern, from different sources. Such overlap is even more significant, as it can cross over between different narratives—but can only occur at the level of hubs, as only these contain finite collections of symbols. Thus, we have two processes for the stabilization of key fragments $\phi_n$ and collections of them $H_i$, respectively. Let’s examine these in turn.

Taking a number of texts, and extracting the stable fragments leads to a surprisingly cogent summary of what a text is about, but there’s a problem with this simple method: it assumes a knowledge of language. The fragments have no meaning to a dumb sensor, only human observers watching over the fragments can ascertain their relevance, given a knowledge of the narrative content and the language in which it’s written.

A. Longitudinal stability of fragments

A symbolic generalization of the method of wave interferometry [12], [37], [38] features in the study, both here and in paper 1, as a way of separating signal from noise. The use of interference to highlight key $n$-phrase fragments indicates that there must be an effective separation of scales between fast and slow variables in a stream. Looking for the slower variables is a way to extract quasi-static ‘invariants’ of the process.

Hypothesis 5 (Longitudinal invariants): Longitudinally persistent $n$-phrases $\phi_n$ may correspond to important subjects in a data stream. Indeed, the somewhat unexpected conclusion of the multiscale analysis is that concepts have their origins in fact short fragments of the input language—regardless of how they might be represented and play out in the final concept language.

Consider a few examples, from the data, to illustrate this. In the Thinking in Promises book, the set of terms that reinforce by repeated use include:

- make, theory, promise(s), agent(s), this, information, world, delivery, continuous, service(s)
This is perhaps a surprisingly small number of words condensed from a rather long text, but it is the principal remainder of longitudinal interference. Comparing these to a human ‘cheat’ knowledge of the book’s contents, the less common words (promise, agent, information, delivery, continuous, service) do indeed correspond to key elements of the book’s subject matter. The individual subjects of the narrative (which are players in the story it tells) would be like the *dramatis personae* of a play.

A second example from the longer book *Smart Spacetime*, on the other hand, yields a much longer set of terms. Quoting only a few here:

```
energy spacetime basic scales few same interest story motion semantic add way conservation deal truth processes so-called quantum understanding theory computing information changes universe memory physics intelligence cognitive reasoning explanations logic ...
```

Apart from some spurious yet common padding words, these are all pertinent ‘personae’ within the text. So, while the longitudinal method does pull out good candidates, it doesn’t eliminate all noise. From a sample of 269 invariants, there were trivial fragments and central fragments, simply by persistence, with no other criteria in play. Looking on with the benefit of evolutionary language skills, we see that persistence correlates surprisingly well with central players in the text, offering another indication as to how certain patterns become learned and associated with meaning.

```
paths (85) analogous (47) using (121) different (624) life (36) world (273) conservation (39) level (180) models (31) explain (69) much (141) artificial (59) behaviours (55) mechanics (149) mathematical (61) semantic (162) absolute (48) smart (85) scaling (142) story (131) pathways (43) approach (42) fundamental (70) computing (102) situation (23) spacetime (778) science (137) universe (139) semantics (124) relativity (128) quantum (267) cognitive (125) systems (216) intelligent (27) motion (335) theory (298) logic (36) function (35) thinking (72) intelligence (58) trajectories (21) thinking about (18) the existence (22) the dataverse (193) in some (22) the sense (27) process that (59) quantum mechanics (89) in a computer (19) at the same (49) the other hand (29) space and time (186) the same time (32) in the sense (20) in order to (89) at the same time (30) on the other hand (29)
```

To the casual viewer, these innocuous choice might not stand out. However, on reflection the list does indeed contain many of the central themes boiled down to simple phrases. Using our godlike perspective, we see that these fragments are clearly concepts but not themes. This shores up the thesis (see paper 1) that meaning arises by persistence against a background of noise.

One book which turned out to be an outlier in several of the measures is *Bede’s Ecclesiastical History of England*, which contains many documented events and proper names. Of 224 invariants found by longitudinal interferometry, some were of a general nature, like:

```
both (105) little (39) night (66) knowledge (44) afterwards (70) departed (52) together (55) ecclesiastical (40) book (80) moon (48) christ (193) pope (106) died (100) written (40) history (63)
```

Amongst the longer and more significant phrases of higher $n$:

```
the blessed (110) west saxons (26) the church (232) the mercians (51) the royal (20) king of kent (16) to the end (51) the english nation (40) came to pass (17) the apostolic see (17) the man of god (24) king of the northumbrian (16) king of the mercians (15) in the year of our lord (42)
```

The method does indeed pick out key suspects in the narrative.

So, from the simple narrative scanning, based on spacetime patterns, some important and dominant signals that stand out. Persistence appears to be quite a good selector of stable ‘conceptual fragments’, i.e. fragments that will eventually contribute to the stable regions that are concepts. This indicates that the spacetime interferometry of fractionated language is a valid approach to a partially ordered process such as languages.

We need to be clear about what this means. No one would expect such a primitive algorithm to be able to extract anything like the nuance that a human reader could—that would surely involve a deep mesh of associative knowledge; yet the fact that such a simple idea can pick out sensible core ideas from a book merely as pattern shows that semantics can indeed be plausibly derived and extracted on the basis of spacetime relationships in the environment of the cognitive process. No magic or prior knowledge of linguistic meaning is involved in bootstrapping the process.

B. Concept identification from transverse stabilization of hubs (sleep phase)

Post processing (what we might whimsically call ‘sleep maintenance’), in between episodes of narrative learning, is used to mine the and compare hubs. Fragments are now fixed, and what comes from their repetition is merely a kind of frequency histogram. Hubs, on the other hand, show patterns of co-activation on the episodic scale. If one assumes that similar patterns, supported by similar contexts, imply similar concepts then one can begin to merge together contexts from different experiences by looking for overlap between the hub fragments (see figure 2). Without this, hubs would forever be limited to their own episodes, and no lateral comparative thinking could take place without an explicit learning episode. A ‘brain’ that can examine itself, measure and compare approximate degrees of overlap between remembered contexts, therefore has the advantage of being able to learn more from its learning by inference of similarity.

In going from hubs to connected regions of hubs, we move up one scale in the hierarchy—a scale at which different narratives can interact. One proposal for finding concepts would be to seek out the stable regions from the principal eigenvector of the hub graph—however that interpretation would leave concepts disconnected from sensory input. A better interpretation is to attach concepts to small fragments and consider these larger regions to be themes.

In order to measure our hypothetical concept formation, the overlap sets between hubs belonging to proximity-connected regions was assembled and summarized by their apparent content. This is the analogous process to the longitudinal stabilization in section IV-A.

Based on the assumption that similar ideas might emerge from similar co-activations, even where certain words are
replaced—that could be the very mechanism by which such impostors become effective synonyms. Thus, on the assumption that association by coincidence is the start of everything to eventual meaning, with only pruning by an observer’s selection process remaining to form final distinctions.

Making blind notes about what the mixtures of fragments might represent, leads to the annotation of regions shown in the example figures 20-24. We can demonstrate some very simple cases, though the amount of information is far too great to represent in a meaningful way, but we can indicate the apparent workings.

In the following sections, I’ve tried to sketch out how we understand reasoning on each scale of a memory system. Unlike those who hold logical reasoning to be the fundamental form, without a plausible origin story, I wish to take a different view [4], [23], which is that reasoning is a special case of storytelling. The fundamental process on which reason is based is the stringing together of concepts and events until the cognitive agent concerned reaches a satisfying emotional threshold. During waking hours, this is connected with sensory input; during offline processing there are no constraints.

V. GEOMETRY OF REASONING IN SEMANTIC SPACETIME

In the final part of this study, I want to consider how to generate narrative from what has been learnt by an agent. The narrative hypothesis suggests that the ability to perceive one’s surroundings and imagine others that we haven’t directly experienced must come from the ability to recombine experiential data into new artificial experiences. To test this, let’s first summarize the simple reasoning based on the four spacetime semantics.

A. Three scales of conceptual reason

The principle of separation of scales leads to natural identification of three qualitatively different scales. We can refer to these as micro(scopic), meso(scopic), and macro(scopic).

Sensors sample episodic narrative on a mesoscopic scale (sentences), which is then fragmented into microscopic fragments $\phi_n$, with a lowest level alphabet $\phi_1$ (in this case words). Aggregation of these fragments as ‘activation signals’ into macroscopic context hubs encodes the activation pathway from partially overlapping context to sets of related memory events, so that—when new episodes that contain similar fragments arise—the memory of past related events will be activated by its semantic encoding (rather than by a numerical lookup address, as in the lowest levels of a computer).

The containment hierarchy looks like this:

| Level       | Form      | Examples                        |
|-------------|-----------|---------------------------------|
| Micro       | Words     | $\phi_1$                        |
| Meso        | Sentences | $S_t \supset \{\phi_n\}$         |
| Macro       | Mixtures  | $H_i \supset \{S_t\} \supset \{\phi_n\}$ |

At each level, causal order information is preserved. Fragments $\phi_n$ are essentially ordered sequences:

$$\phi_n \equiv \phi_1 \quad \text{followed by} \quad \phi_1 \quad \text{followed by} \quad \phi_1 \ldots$$ (11)

Sentences $S_t$ are similarly capped fragments:

$$S_t \equiv \phi_1 \quad \text{followed by} \quad \phi_1 \quad \text{followed by} \quad \phi_1 \ldots$$ (12)

Hubs express non-ordered aggregations of fragments; however, hubs are themselves ordered by changing patterns of activation context, which bind an episode together. So a narrative episode $N$ can be expressed on two scales, $N_S$ and $N_H$:

$$N_S \equiv S_t \quad \text{followed by} \quad S_t' \quad \text{followed by} \quad S_t'' \ldots$$ (13)

$$N_S \equiv H_i \quad \text{followed by} \quad H_j \quad \text{followed by} \quad H_k \ldots$$ (14)

where $H_i \supset S_t, S'_t \ldots$

Context is a pool of recent patterns which gets accumulated by linking into hubs. Relevance can be scored for fragments. Sentence relevance is scored as the sum of relevances for its fragments, similarly for hubs. Over time, fragments which are never reactivated would fade away, to be cleaned up by garbage collection (another offline ‘sleep’ function).

B. Where are the concepts?

The question of where concepts are within this system of information seems subtle, and unexpected from a linguistic perspective. One might imagine that concepts have to be large aggregate structures with many cross references: after all, our ability to have complex ideas seems more sophisticated than simple sensory discriminators. However, this appears to be incorrect. To be rooted in invariants, concepts have their origin in fragments of the input language, whence more complex and nuanced representations, on the scale of the concept language, can develop from what we call the ‘themes’ of the input language. Concepts may ultimately become represented across several scales.

Consider the scales: context is a characterization of a cognitive agent’s current state of assessments of itself plus the input stream; meanwhile, an event has to refer to changes in those states about the agent and the exterior world, else it expresses nothing of concern to the agent. The semantics of those changes thus map to the attributes of concepts. The expression of concepts has to begin with the simplest input invariants. Concepts must be smaller than events in order for events to refer to them. The genesis of the most basic concepts thus appears to begin within the small fragments $\phi_n$ in the spacetime phenomena of a cognitive agent’s environment. Similar concepts might later be re-represented in other encoded forms, though gratuitous recoding one-to-one would be wasteful and would serve no purpose. Parsimony suggests that the concept language would refer to different concepts than the input language, but the distance between the two would remain short for their mutual constraints to be effective.

What’s interesting here is that proto-concepts must exist in the input language itself. They may be embellished and

11In dreams we feel that even bizarre behaviour is reasonable, even as our analytical brains question it, probably because the emotional sensation of resolution is triggered bringing a sense of satisfactory outcome.

12If the distance between the input language and the representation in concept language is short, a cognitive agent with a multiscale representation of sensory and recycled-sensory data would easily support several co-existing language representations.
aggregated by rescalings, but we need to understand that process from the bottom up.

1) A string of micro-concepts: e.g. phrases linked (fear, New York).

2) A string of meso-concepts: e.g. sentences linked (I once experience fear in New York. I walked to Brooklyn and found a dog.).

3) A string of macro-concepts: e.g. linked fragments (e.g. collectively suggesting the theme ‘fear loathing new york’)

As small fragments, input concepts thus behave like reusable encodings or regular expressions [39], which bind together in a process of recombination (± promises, in promise theoretic parlance). A sequential string of lock-key bindings could then trigger a cognitive process, which ended with an outcome over some larger scale. One can therefore discuss whether a concept is the invariant trigger or the dynamic process that unfolds from it. All non-local structures are effectively processes, somewhat in the manner of a search algorithm.

For example, consider taking some random excerpts from the input, and using CAPS to represent a hypothetical association to ‘larger ideas’ on the concept language level:

| n | IL. $\phi_n$ | CL |
|---|--------------|----|
| 2 | sweating and panting | FEAR |
| 2 | utilized system | WORKHORSE |
| 2 | whole coordination | TOGETHER |
| 2 | without understanding | PERPLEX |
| 3 | algorithmic behaviours generally | DISCIPLINE |

How concepts combine, is only by sequence and gen-sequence. So the input fragments ‘sweating panting spit curse coordination sky-towers’ might end up mapping to an effective phrase in the concept language ‘FEAR AND LOATHING IN NEW YORK’ through a sequence of vertical and lateral graphical transformations. Not also that any correlation between the fragments and concept language is (of course) imaginary and for the convenience of godlike observers only. We might learn the significance over longer experience.

The promise theoretic basis of the Spacetime Hypothesis suggests [18] that input level concepts might be principally identified with invariants of $\phi_2$ and $\phi_3$, owing the the linear bindings of a timelike stream. Longer phrases could still be technically significant due to the effective compounding of words, but their reusability becomes decreasingly likely with longer phrases. Indeed, the data show that there is close to zero replication of $\phi_n$ for $n > 3$. This suggests that we look for concepts in the hub fragments of $\phi_2$ and $\phi_3$, especially those which overlap between different contexts. Those fragments will be the basis of a concept language. Assigning names to those concepts becomes the commentary language.

On further reflection by an agent, small fragmentary concepts could easily become embellished with ‘bells and whistles’ by superagent clustering of fragments. This could occur by microscopic combination of the input language, or by graphical structure in the concept language. The latter would occur by the insertion of new hubs, but these could come from a sensory context without new information—they can only come from the running context cache of the agent, i.e. ‘what it is currently thinking about’. So hub formation by interior ruminations is a context driven process that could be performed offline (e.g. sleep phase).

It seems plausible that concepts and themes may have similar geometries but on different scales—and thus not truly independent ideas, as they can always be transmuted into one another by scale transformations\(^{13}\). This is not to say that they are scale free ‘fractal’ representations. If one believed in a scale-free phenomenon, there would be no reason why this process would stop, but the scale of observations and sensory inputs is not without limit. Indeed, it’s pinned by the outside world of the observer, and that breaks the scale invariance in the natural way that all symmetries are broken: by boundary conditions.

Retaining multiple scales of pattern fragments (demarked by spaces) is likely an unavoidable strategy to find the effective boundaries of concept fragments. Once themes have been rendered as invariants on a larger aggregate scale, they are ready for recombination using the same rules as for $\phi_n$ fragments, and the whole process can potentially start all over again\(^{14}\). Would there be more super-hubs? Concepts have to be decorated with contextual information, which is captured by hubs (mixtures), but the same concept can also exist independently of a very specific context. Boundaries seem fluid things, but the constraints of limited resources must naturally prevent that from happening.

C. What distinguishes proper names?

A special kind of concept is a string that stands as its moniker: a proper name. Ultimately all representations in language hark back to labels that are effectively proper names for something, and these invariants become the favoured information expressed by concepts. Later, semantics become altered. Consider the idea of recording the name of person, e.g. John Smith. In a traditional ontology, or relational database, one would have separate labelled associations for the different attributes in the record.

Given name: John
Surname: Smith

We can note that the surname in many cases is simply derived from a different source: the occupation of the person in ancient times (Smith, Cobbler, Burgess, etc), or the village from whence the family came (Jack of London, becoming Jack London, etc). So the semantics of surnames have evolved from being a role to a qualifier. The same principle can be adopted to conjoin any kind of data. Indeed, the procedure is formalized in relational databases by using join tables (see figure 17).

Names are thus part of a semantic coordinate system. In order to facilitate the addressability of data, by semantic lookup key (index item) rather than by numerical coordinate in a Euclidean space. Rather than keeping every combination of given and family name, one can rationalize the findability by either full or partial name by using the structure in which the

\(^{13}\)Renormalization probably plays a significant role in reasoning.

\(^{14}\)How we humans manage the boundaries of a concept in a knowledge representation remains entirely unknown.
full name unifies the component names. The full name becomes a namespace for the partial names. This principle can be applied to multi-dimensional names too, e.g. street addresses, which have street, house number, district, region, country, post code, etc.

At what scale might we expect to find structure that correspond to ‘concepts’ in the sense we understand in human thought? According to the rules of this study, the linguistic nature of the input data is irrelevant, and we should not be swayed by our prior knowledge of input language15, because our artificial cognitive system has no knowledge of language—it sees the data stream simply as patterns. One pattern is as good as the next. So word fragments certainly can't be significant enough to correspond to concepts, any more than codons or single genes correspond to unique biological characteristics. However, different admixtures of these will contribute to characteristics. The question then is: will they be stable and distinguishable, or spurious and prone to muddle?

The first question is: how should be identify clusters? Hubs are the features that can aggregated the meaning from a number of stimuli. A full name hub like “John Smith” can join together “John” and “Smith”—but how do we understand these parts? How do we know which is family name (role or context) and which is given name “identity tag”? Does the distinction matter? In order to distinguish name from role, we can only allow hubs that have two nodes connected to them, so that the types are distinguishable. However, the seems dynamically inefficient, and suggests a mechanism that would not evolve naturally (see figure 16).

The key distinction between roles and names is that roles are repeated to intentionally signify similarity, whereas names are only repeated without the suggestion of being similar. Another possibility (figure 17) is that hubs may have proper names and any number of roles, or simply names some of which are re-usable roles and some of which are not identifiable as reusable roles. Then, we have to take into account the role of selection to prune the routes emerging from a hub. Some routes could be assigned weights stigmatically.

With a counterpoint in a selection process, the onus of identification can be more on learning at multiple timescales.

- A name is a singleton node. A name could be a pattern pulled out of an event. Or it could be random.
- A role is a contextually supported fan, because it is itself a hub formed from multiple sensory inputs.

A smart sensor would project data into a vector of semantic categories (a matroid or basis set). This vector plays the role of the width freedom in a neural network. The weights become 'polarized' by data from the environment, so there is a kind of semantic ‘compass’ implicit in this approach [20].

D. Hubs and their namespaces

Hubs are used to draw attention to the spanning sets of fragments. A single hub connection uses the matroid promise pattern [29] to conjoin all members of a set to single unifying node, which can then be given a single new name to refer to the entire set. The principle can be understood on a small scale before scaling it to arbitrary clusters (see figure 16).

Namespaces constructed hierarchically in this manner may be quite fluid, since the patches of members, which are referred to by the hubs, can overlap and the boundaries between them can be rewritten in the light of new experience16.

Fig. 16: Roles and names with their hubs. Simple hubs behave like full names composed from given and family names, or name and role, name and address, etc. Thus when hubs are not named with intent, they can emerge from their component fragments, and those fragment mixtures spell the effective name of the namespace. Eventually, overlap interferometry will separate and clarify namespaces into effective concepts at this level too.

Using a principle of aggregating nodes that belong together (sentences, fragments, etc) under a single node which represents the aggregate one can then form the name of the aggregate from the direct sum of the parts. This is the approach used here. One advantage of the approach is that it means the full name can be decomposed directly into its components very easily to find when aggregate regions have common members.

Fig. 17: Roles and names with their hubs. A proper name can be assigned to each collection of things from the sum of the components. Aliases can be added later, in whatever language one needs, with a specialized kind of link. This suggests that proper names might have a particular significance in memory networks, in mapping between languages.

Because hubs names are internally orderless, when different narratives are merged, the hubs that are condensed from their input processes are free to overlap, due to the presence of common fragments. This doesn’t happen naturally in a realtime

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15Our inability to ignore or ‘unsee’ grammar is a hindrance in identifying fragments, and believe in the results of this analysis. There is an awkward compulsion to select things we understand and eliminate nonsensical fragments on the basis of understood usage, but this impulse has to be stifled and the data rigorously treated blindly until the moment of rightful comparison.

16In relational database theory, the normal forms are usually taken as rules of thumb to avoid this kind of overlap, but the model is rigid and overconstrained. Hypertextual networks, for instance, may have many paths between items, with different interpretations.
sequence based on events, because the process order creates overconstrained distinctions (as in logical models). Hubs that encode context during single episodes lead to distinct silos of non-causally connected parts—each episode creates new and unique context hubs. So hubs can never connect independent narratives from the cognitive process itself. Member events (sentences, in this case) will probably never coincide by accident, since the probability of precise repetition of long sequences is extremely low.

This is why fractionation into small atomic constituents is the mechanism by which parts can be decomposed into an elemental chemistry. Fractionation acts as a prism to split composite input into distinct patterns, that may be divorced from context. Thus, in post-processing (sleep maintenance), compositional similarities (overlapping spectra) can be recognized by sweeping through the graph and linking hubs that are sufficiently close to one another (where ‘sufficiently close’ remains to be determined). The fragments generate a matroid basis for vector comparison.

Hubs with significantly similar spectra can be assessed as ‘close’ or proximal in their basis elements, regardless of their origin. The likeness to a vector space can be made by approximation and large numbers. Thus we may define a plausible notion of distance between hubs. This is the significance of hubs—why we need a parallel representation of the input language in a disordered state.

We therefore operate with two parallel representations of the input patterns in this study: an ordered summary, which represents precise contextualized recall, with causal order intact, and a disorder spectral mixture which is conducive to inter-episode association.

E. Generating narrative

If we could generate new stories based on old ones, in a plausible way, then we would have a simple model of reasoning based on past learning. If this could further be constructed from the four spacetime relations then we would have plausible evidence in favour of the Spacetime Hypothesis. These artificial narratives could then be assessed for their credibility: stringing fragments together is easy—but they also have to make sense to a human arbiter. This is a challenging demonstration because, while the data structure is simple, the combinatoric search space is huge and the number of overlapping possibilities that occur in parallel is daunting.

There is a set of transformations from the alphabet of words $\phi_1$ and their strings $\phi_n$ to sentences, which are complete constrained statements: states, relations, or actions, to context accumulated over recent past concerning all such statements, with a constant rate of forgetting. Sentences are partially ordered events, and therefore must retain causal order in episode encoding. When making up or telling new stories, pathways labelled by the “followed by’’ relationship offer possible ‘completions’ that may score differently by relevance. Generalizations are offered by the ‘containment’ relationship. The accumulation of pathways formed through these relations results in a simple geometry based on the four semantic types. Scalar expression is encoded within names or labels, and containment is built through hub matroids, causal order is a simple chain relation $>$, and proximity is an undirected relation between hubs.

Reasoning is sometimes associated with logic. Logic is just one form of highly constrained narrative, which can be derived from a graph of relationships. However, if we start from a graph of concepts, linked by the four spacetime relations, paths through the graph correspond to stories to be told. Strictly speaking, these are stories of the commentary language. However, in this work, for the sake of conceptualization, we’ve identified concepts with fragments of input language—trusting that our extraordinary ability to think associatively and make sense of fragments, even when disordered and unruly, will allow us to make recognizable stories from those fragments. The result might not be grammatical, in the normal sense, but they will follow a deeper kind of grammar, which—according to the Spacetime Hypothesis—is based on the underlying spacetime process of sensory data gathering about the world.

Pathways through the graph are stories, and the graph grows somewhere between linearly and quadratically in size. The average number of possible stories per length of input stream data therefrom grows considerably. Some kind of selection process (call it an algorithm) is needed to regularize spurious connections in a graph. Many authors have tried to construct this using descriptive logics, however logics are usually overconstrained and tend to result in either nothing at all or just a one-to-one copy of the input. The shortcomings of descriptive logic approaches were one of the contributing elements to the development of Promise Theory and its long-standing relationship with knowledge representation.

F. Episodic order (causality)

Our simplest and most common understanding of narrative is based on linear storytelling: episodic recall of a stream, like playback. Timelike events are joined together by precedence promises, creating parallel fibres of narrative that are bounded by the start and end of the input stream (here that means a document). The criteria for starting and stopping are important: as we’ve seen if episodes become too long, the meaning of them may become clouded by a lack of perceived focus.

This kind of linear lookup doesn’t scale well for searching and dropping into knowledge from different angles or requirements. This is why we make tables of contents and indices in textbooks. The linear linguistic form is s convenient as an interchange format for passing on ideas, but it’s not the way we think inside our heads. Look-up is based on a running context of the observer’s thought process, which is completely disconnected from the original author’s thought process. So we begin to flick through the book looking for simple fragments to latch onto. From there, we might start reading a little. Then we go to the section header or some summary of the particular paragraph. All this is facilitated by the highly geometrical construction of books. Later, those geometric aspects were generalized by hypertext, but they remain essentially intact. A question that arises here is whether the chapter-by-chapter processing of the Thinking in Promises book played a role in keeping its focused concepts under control, by effectively restarting a new learning experience in each chapter. This certainly deserves further study, as ‘taking a break’ could be

\[17\] This search process is basically like ‘web crawling’.
a way in which a cognitive system maintains order. We must defer that question for a later time.

The four spacetime semantic promise types allow structures that enable simple narrative playback, indexing, titling, and cross referencing without the need for an extensive ontology.

G. Descriptive elaboration (scalar expression)

Expression is a scalar promise, i.e an agent’s promise about self. It refers to an interior property of the agent making it, e.g. state, colour, height, name etc. Expressions are effectively the proper names for conceptual properties; they are the way we elaborate on descriptions (having the role of names, adverbs, and adjectives). Although initially sceptical of this view, it agrees with the orthodoxy as described by [31], and doesn’t exclude the transmutation of larger themes into new concepts at the scale of the concept language. Properties expressed by fragments (on any scale) seem to be indistinguishable from the role of a proper name. They are scalar attributes, and thus play no role in relating agents to other similar agents.18

H. Association by co-activation (containment)

If we consider our understanding of concepts, we assemble smaller concepts into larger ones by generalization. This is a vertical aggregation in figure 5. Ideas like ‘walking’, ‘running’, ‘ambulation’ might fall under the larger idea of ‘movement’. How we arrived at those particular names for the activities they represent is a long story. What matters is how we emulate that origin story. Similarly, one can imagine several contexts in which different eating implements are represented. The overlap between these contexts leads to the combination of a category (probably with some noise) in which knife, fork, and spoon are represented strongly (see figure 18). The word ‘crockery’ cannot emerge from that process—whatever term is used there belongs to the concept language, which has its own dynamics and etymology. We use the term here for the convenience of readers with godlike powers of observation.

The specific words in these relationships express attributes of the geometry to add colour, but the essence lies in the geometry: causes →, generalizes ↑, similar to, e.g. ↓, causes → (16)

We sometimes infer causal relationships through intermediary concepts by generalization. If an agent is a part of a superagent collective, then there is a sense in which the superagent is responsible for the agent’s own promises. This is how scaling works in an agent model, such as Promise Theory.

I. Association by similarity (hub proximity)

When hubs are similar, the kind of vertical-horizontal reasoning exemplified in the previous section can also pass from hub to hub. One of the consequences of this cross-labelled geometry and the implicitness of meaning is that mistakes based
on spurious overlaps can lead to new causal connections too. For example, consider the following scenario.

The name “Godzilla” is the name of a movie and the name of a Maki platter at a Japanese restaurant. In an apparent Denial Of Service attack on its booking service, a Japanese restaurant’s website is hit by a large number of requests, which brings it to its knees. The cause was a misunderstanding relating to a film promotion for the upcoming movie Godzilla. The only connection between the two is the name of one movie being shown, which has a promotional website of similar name. A simple typing mistake is what leads to a very different causal sequence of events.

Reasoning about this story requires one to make a leap of contexts. A concept was transmuted into another by a ‘resonance’ perhaps around a single proper name. Associations can easily be made by proper name, functioning as a simple semantic address.

As in all relativistic scenarios, one process compares itself to another process, according to the rules of (+) and (-) promises, seeking a limited overlap. Typically, the (-) process acts as a coordinate system against which the (+) source process offers data, providing a calibrated scale for measurement. The covariant meaning of the overlap is thus judged by each receiver independently. This is the meaning of relativity.

How might a word like ‘concept’ become close to a word like ‘meaning’ or ‘semantics’? This could not happen in the input language—only in the concept representation, because the input language can’t be measured semantically. The only possibility is that—over time—co-activations encode associations on a higher level by context. That could be encoded as hubs and regions into a concept language representation of the ideas, which then overlap. Thus, at some moment in the history of the agent, these terms would have to appear within the same co-activation cluster, or words related to them would have to appear in the same co-activation cluster.

A synonym in the concept language is thus a process based on an input fragment that plays the same role in a reasoning process. It could apply on the level of concepts or on the level of fragments. However, without some horizon or limit on the minimum degree of overlap, it’s potentially possible for many if not all concepts to be considered close together19.

J. Microscopic reasoning

The most primitive level of reasoning is that which occurs in simple single-scale processes, such as biochemistry—fragment recombination. Recombination of patterns, on the microscopic level, involves rearranging the words of the input language to elaborate its chemistry and seek out new combinations, leading to new process outcomes. Patterns will eventually be selected by their niche semantics: if they bind to something and advance a process then they can become new process invariants. For example: words ‘knife’, ‘murder’, can be combined as new phrases:

murder knife
murder by knife

These are microscopic recombinations at the level of ‘utterances’, on the input language scale. There are no rules for syntax or grammar here, only rules for binding, precedence (follows), or similarity (proximity).

From here one can pursue two approaches for generating new narrative events: one based on proximity in the space of fragments, or one based on causal order (time). From our knowledge of statistics in paper 1, and from the earlier discussion in section II-F, we expect the different phrases will play different roles (see table I). At the microscopic level, simple promises expressed by the fragments, in whatever memory representation they find a home, will constrain the way fragments can combine. This is surely the origin of grammar. Fragments can simply by combined in all ways to create an associative binding (see figure 19).

• 1-phrases (φ₁) are like codons (component chemicals). They can overlap as atomic parts of any string.

animals
hate
bananas
murder
knife

These phrases can be combined into new phrases of higher order in φn, e.g. hate bananas, bananas murder, murder knife bananas, bananas hate knife murder, etc (see figure 19). We can’t and indeed shouldn’t expect such recombinations to resemble English grammatical sentences in a normal sense of containing glue words (e.g. ‘murder by knife’), which are probably habitual adaptations that normalize over long times, but we may expect them to match those concepts in a more clumsily expressed form.

• 2- and 3-phrases (φ₂, φ₃) are order-constrained combinatoric parts (may form mixtures).

animals hate bananas
animals are big
animals are small
murder by knife

These fragments already contain normalized binding words. If they repeat often enough they could override the clumsier recombinations of 1-phases. The longer a phrase, the more significant it is, and the less likely it is to combine further.

• Longer φn, together with sentences, are strongly ordered contextualized examples. These effectively become playback events as the likelihood of them recombining is infinitesimal.

infer that our domestic animals
domestic animals and the fact
animals now in
choice animals would thus
four-footed animals

19Counterfactual evidence may also add a further selection criterion for filtering clusters that have become too enmeshed in each others associations [16]. That subject goes beyond the scope of the current work.
To summarize, small fragments $\phi_n (n < 4)$ can be spliced together to recombine into artificial sentence events, corresponding to new sensory experiences. This is the simplest way in which new expressions can be formed from old, or very elementary stories be told, like film editing. This might not generate perfect phrases in so complex a language as English, but they would not be difficult to understand. Following the causal links between ordered word fragments, in this way, is one way to tell story fragments. It’s a form of playback of recorded experience, as there are no causal links between different episodes, without observing patterns of co-activation on a larger scale. Context hubs allow microscopic stories to be routed across narratives. Thus story-telling at the microscopic level is either unimaginative or discontinuous.

**K. Mesoscopic reasoning**

Moving to the mesoscopic level, we may consider complete events as the basic constituents of narrative: sentences and their ordered relationships to one another. Finding relationships between events outside of their original context is much more challenging, and thus far less likely to find a match that makes obvious sense on the level of a single sensory episode. Thus, the nature of mesoscopic narrative could be quite different to that on the microscopic level.

How or where one begins a story based on events is an issue in its own right that we probably can’t answer fully here. The most natural way to bootstrap a starting point would be to base it on running context. Certain events may stand out because the namespaces they belong to are ‘addressed’ by the buffer cache of running context. There can still be many possible starting points, which leads to two possibilities:

- A random (non-deterministic) selection from the possibilities.
- Several starting points are retained in parallel (superposition) and considered alongside one another.

As an example, consider thoughts about the short fragment concept of “animals”. As a single fragment this can easily overlap with many contexts and events. So there may be many possible events in play. There are two binding relationships in play: for space and time:

- **Space (proximity):** Searching for parallel events containing this concept, one starts with hubs. We look for hubs that contain the the concept fragments, which takes us up the network layers from edge to a ‘central routing plane’ (see figure 5). Context looks something like this:

  - the consciousness, 2:the darkness, 2:the individual
  - 2:the kaleidoscope, 2:the metropolis, 2:the stationary
  - 2:thinking willing, 2:his birds-eye, 3:across
  - half-charted oceans 3:acting living carried, 3:aspects
  - he was by, 3:birds-eye aspect–he was, 3:caught his
  - breath, 3:distance close beneath, 3:drinking at water-
  - holes, 3:emotions were legible, 3:everywhere all-at-
  - once don’t, 3:experienced the sense, 3:experiences
  - of strange, 3:extends the consciousness, 3:family presented
  - themselves, 3:fighting toiling loving 3:his dizzy el-
  - evation, 3:hovering in mid-air 3:munching sugar-
  - cane while, 4:courage of the fly–he, 4:craters flying
  - across half-charted oceans, 4:denied partially at
  - least, 4:element of air without, 4:everything that com-
  - pressed life, 4:experienced the sense such, 4:experiences
  - of strange distant 4:imagination figured this glo-
  - rious 4:more intelligent than animals, 4:movement

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20 In the complexities of English language, the glue words that join fragments together doubtless play a role in the emergence of a grammar that we would recognize. In other human languages, such issues are not relevant.
and singing when, 4: music caught his heart, 4: never could articulately clothe, 4: new method of communication 4: realised that birds had, 4: realised—must some day produce, 4: rhythm movement and singing, 4: secret and mysterious life, 4: separate objects definite divisions, 5: burst into colour rhythm movement, 5: by the southern sun intoxicated, 5: carelessly carrying nothing with them, 5: colour heat light and beauty, 5: colour rhythm movement and singing.

This is only a small part of an actual context, even working at the level of compression in paper I on a single source stream, making it hard to convey what’s going on in these experiments. Nevertheless, we try. Having found starting points in hubs, one finds candidate events linked to them, which score for relevance in terms of their overlap with the running context of the search agent. For instance:

“Thus, to return to our imaginary illustration of the flying-fish, it does not seem probable that fishes capable of true flight would have been developed under many subordinate forms, for taking prey of many kinds in many ways, on the land and in the water, until their organs of flight had come to a high stage of perfection so as to have given them a decided advantage over other animals in the battle for life.”

ALTERNATIVELY (SIMILAR)

“With hermaphrodite organisms which cross only occasionally and likewise with animals which unite for each birth but which wander little and can increase at a rapid rate, a new and improved variety might be quickly formed on any one spot, and might there maintain itself in a body and afterward spread, so that the individuals of the new variety would chiefly cross together.”

ALTERNATIVELY (SIMILAR)

“Seeing, for instance, that the oldest known mammals reptiles, and fishes strictly belong to their proper classes, though some of these old forms are in a slight degree less distinct from each other than are the typical members of the same groups at the present day, it would be vain to look for animals having the common embryological character of the Vertebrata until beds rich in fossils are discovered far beneath the lowest Cambrian strata—a discovery of which the chance is small.”

Having found a hub that contains examples relevant to the concept, from here one can go in any direction to find events or similar hubs where the fragment reappears. This is somewhat like a simple text search. The resulting parts can be strung together into a story. Not all stories read like Hans Christian Andersen—lacking data continuity, some are quite disjointed (e.g. which might explain the oddly disconnected nature of dreams, which are unanchored by sensory context).

- Time (precedence and playback) Because of the siloing issue, narratives tend not to propagate across episodes. Once inside an event stream a search will tend to lead to playback of episodic memories rather than innovative recombination. In other words, timelike recall is distinct from the lateral spacelike recall above: more deterministic. For instance:

“Thus, to return to our imaginary illustration of the flying-fish, it does not seem probable that fishes capable of true flight would have been developed under many subordinate forms, for taking prey of many kinds in many ways, on the land and in the water, until their organs of flight had come to a high stage of perfection so as to have given them a decided advantage over other animals in the battle for life.”

FOLLOWED BY

“this is scarcely ever possible, and we are forced to look to other species and genera of the same group that is to the collateral descendants from the same parent-form, in order to see what gradations are possible and for the chance of some gradations having been transmitted in an unaltered or little altered condition.”

FOLLOWED BY

“when we bear in mind how small the number of all living forms must be in comparison with those which have become extinct, the difficulty ceases to be very great in believing that natural selection may have converted the simple apparatus of an optic nerve coated with pigment and invested by transparent membrane, into an optical instrument as perfect as is possessed by any member of the Articulata class.”

Each new event followed modifies running context and alters the search affinity of new memories.

The search for a concept fragment as short as ‘animal’ naturally leads to a wealth of matches that are too numerous to document here. The search space can be reduced factorially by taking longer fragments. For example, seeing the many contexts in which the search term arises, one might choose to refine the search by selecting qualifiers and a larger fragment. If we combine the fragments to make less general concepts of the input language, we indeed find more specificity and fewer cases. The same principle would likely apply at the level of the concept language too, but we can’t study that here. Longer fragments that are activated by the search term include, for instance:

“Thus, to return to our imaginary illustration of the flying-fish, it does not seem probable that fishes capable of true flight would have been developed under many subordinate forms, for taking prey of many kinds in many ways, on the land and in the water, until their organs of flight had come to a high stage of perfection so as to have given them a decided advantage over other animals in the battle for life.”

“as we may infer that our domestic animals were originally chosen by uncivilized man because they were useful and because they bred readily under confinement...”

“for if all the marine animals now living in Europe and all those that lived in Europe during the Pleistocene period a very remote period as measured by years...”

“It is a truly wonderful fact—the wonder of which we are apt to overlook from familiarity—that all animals and all plants throughout all time and space should be related to each other in groups...forming sub-families families, orders, sub-classes, and classes.”
How should we choose between these? The obvious way to rank them is by degree of overlap with current running context, modified along the way. However, on the scale of this experiment and probably beyond, that doesn’t necessarily lead to a clear selection criterion. The degree of overlap between alternatives is bound to be comparable for a wide range of alternatives that remain in play or ‘superposed’ in the process. Suppose then we choose to look at a longer concept of the input stream: ‘four-footed animals’. This pursues pathways that lead to several possibilities, all of which are superposed or coactive, ‘in play’. For example:

- four-footed animals on the ground
- desire and four-footed animals

For longer strings, matching events precisely is easy. This natural behaviour suggests a principle at work, which supports the notion of specificity from paper 1. A new hypothesis might propose that the length, in terms of the input language, of a fragment corresponds to a concept of a certain scale. Its specificity is inversely proportional to its length. The connection between conceptual specificity and importance in paper 1 is certainly evident for all to see: even relatively short longer fragments are effectively unique owing to the size of the extended word alphabet. At the sentence scale, we now find a specific playback events by direct fragment activation:

The details of the room could be inserted later according to judgment and desire, and four-footed animals on the ground might also discover later the point of view of birds who, from a high altitude in the air, saw everything at once.

This doesn’t form an obvious story connection on the level of English, but remember that this is input language, and the language of raw sensory streams may not be as familiar as we expect. Senses exhibit a tendency to ‘see what we want to see’ rather than what’s there, indicating that narrative could play with perception directly owing to the spurious connections in semantically addressed memory.

Promise Theory predicts that selection plays as active a role as source diversity. An agent engaged in active cognitive processes has its running context at all times. This is the context that would be ‘saved’ as a hub for activation. The degree of overlap between this running context and past context is thus a measure of relevance, in the cardinality of the fragments. Searching by proximity to the term of interest, one can therefore identify fragments that are measurably relevant: This is a form of lateral thinking based on simple proximity. Replay of these events is strictly causal (playback) story about four footed animals is neither a smooth segue, nor does it lead further: the event is a dead end within the present episode silo, so now—unless we abandon the selection according to direct relevance—we must give up.

We may, however, still proceed through other context hubs, by asking the question: what other concepts were in play alongside the ‘four-footed animals’ within the running context, and do they match the present running context? Are there any similar hubs where the fragments co-activate with other concepts that recently were active in running context? At this point, associative reasoning may lose focus on animals altogether. Likely, searches need superpositions of many of these fragments to make strong connections under constraint.

The lesson of this exercise is that it’s very difficult to work one’s way out the silo of a narrative episode by causal reasoning alone. The walls of separation are high. This is why fragmentation is key. Without the anchor of sensory validation, stories told at a higher level perhaps need some self-consistency in a string of concepts and experiences to reach an ‘emotional resolution’. It’s not clear at this stage how that might happen, since the representation of emotional triggers is too primitive in the current analysis.

L. Macroscopic reasoning

At the topmost scale of reason, we have themes, represented by regions of proximate hubs. This overlap between context encodings, or mixtures of conceptual fragments, are where we expect to find broader themes as mixtures of several concepts (figure 1). Since regions can be assigned proper names, and treated as short fragments on a larger scale (e.g. short fragments of the concept language that refer to longer mixtures of input language concepts), themes can easily be renormalized as concepts on a new level and the whole method of stringing together stories based on these can resume on a larger scale. However, now the number of concepts is far fewer and more sparse than before, so this might take some leaps of faith to comprehend their meanings, and the results will be correspondingly more vague.

In Darwin’s *Origin of Species*, the major hub-regions seem to revolve around themes of awe (emotional), considered reason, and understanding (see figure 20). Then other regions concern the diversity of characteristics in the environment, the fossil record in particular, and question of how characteristics are passed on. This is not a bad summary of a well-known book. These macroscopic themes can be interpreted as effective concepts at the concept language level.

Notice how this coalesced summary of the regions is not expressible by the list of fragments that give the regions support from below. The latter contains many more relevant details, but only in the input language. The regions shown correspond to what could become concepts in an eventual commentary language.

Given so few themes, or macro-symbols, the only narratives one could generate from so few components would take the form of short strings equivalent to English phrases. This is reasonable: the more general the concepts, the shorter our statements about them tend to be. For instance:

- There is awesome diversity of inherited characteristics in the fossil record or environment.
- There is competition and natural selection in the fossil record or environment.

For the history of Bede, the major stable regions are few in number, perhaps because the is little repetition of a small
number of themes. The concepts revolve around history, religious organizations, and Northumbrians—i.e. people from Northumbria, a region in the North of England (see figure 21). The macro narratives take the form:

History, religious order or persons as Northumbrians.

For the Thinking in Promises book, the separation of themes is not as fine-grained as a discerning reader would like, at the level of regions, but the fragments within are nevertheless decent representations of conceptual themes in the book: promises and cooperation, infrastructure and its properties, information and boundaries, impositions, and namespaces. What is interesting is the way the concepts cluster together. The clustering does lump together related ideas, and separate different ideas, given my own understanding as the author. So, what we can say, from this little evidence is that the outcome is not inconsistent with the intentions of the book. It’s hard to see how one could ask for more at this experimental proof of concept level (see figure 22). The macro narrative might contain:

Promises, cooperation, etc in infrastructure
Equilibrium and boundary in infrastructure
Equilibrium and boundary in promises, cooperation
Namespaces and information etc.

M. Mixed narratives

With the same context ratio choices, for the novel Slogans (the longest of the texts), remarkably only two stable regions emerged. We see a 500 page novel reduced to two short ideas, indicating the novel is about the experience of the journey rather than the concepts induced by reading it. The themes are not persons or ideas, but sensations: emotional characterizations of foreboding, fascination, and anxiety, along with scheming. These are indeed central themes in the book, and it’s fascinating to see that only emotional ideas survive the transverse contextual interferometry. This suggests that novels like this are more about emotional journey than a clear fact-based reporting of subject matter (see figure 23).

We can check the latter interpretation by comparing to Moby Dick—a rather better known book. Of its six stable regions, there is a mixture a ideas. Like another novel Slogans, these include emotional resonances (murderous apprehension and vengeance, awe and portending, urgency). Some allusions to Gomorrah stand out, along with Nantucketers (people from the region of Nantucket in the North-Eastern seaboard of the United States). A similar emotional emphasis is found in several other fictional sources, with the exception of the 19th century novel A Legend of Montrose by Sir Walter Scott, whose style is far more matter-of-fact, somewhat in the manner of Bede. One can ask what would happen if more than one narrative were combined. For instance, after mixing the sea novel Out of the Fog with Moby Dick, the resultant map collapsed to just two

![Fig. 20: The proto-emergent concepts from Darwin’s origin of species (12 regions, from 18 links in 70 hubs). The major regions seem to revolve around themes of awe (emotional), considered reason, and understanding. Then other regions concern the diversity of characteristics in the environment, the fossil record in particular, and question of how characteristics are passed on.](image1)

![Fig. 21: The proto-emergent concepts from Bede’s history (4 regions, from 7 links in 43 hubs). The major stable regions are few in number, perhaps because the is little repetition of a small number of themes. The concepts revolve around history, religious organizations, and Northumbrians.](image2)

![Fig. 22: The proto-emergent concepts from Thinking In Promises (6 regions from 14 links in 25 hubs). The separation of concepts is not as clear at the level of regions, but the regions are decent representations of conceptual themes in the book: promises and cooperation, infrastructure and its properties, information and boundaries, impositions, and namespaces.](image3)

![Fig. 23: The proto-emergent concepts from the novel Slogans (2 regions, from 4 links in 90 hubs). The lack of clear subject matter is indicative of a meandering story with many themes, but story does indeed concern research and scheming. We see a 500 page novel reduced to two short ideas, indicating the novel is about the experience of the journey rather than the concepts induced by reading it.](image4)
regions, one associated with emotions of bitterness and manic thoughts, mixed in with harpoon and sailing imagery, and a second concerning Christian experiences from environmental conditions. The latter comes mainly from Out of the Fog, but is not alien to Moby Dick either.

![Fig. 24: The proto-emergent concepts from the novel Moby Dick (6 regions, from 298 links in 81 hubs).](image)

Fig. 24: The proto-emergent concepts from the novel Moby Dick (6 regions, from 298 links in 81 hubs). On mixing with another sea novel, this structure simplified to just two regions, showing how proto-concepts can be unstable to new learning.

Based on these detailed analyses of the fragments, an interesting pattern seems to emerge concerning the different kinds of narratives: a difference between stories that are fact-based texts and stories that are fictional tales.

- Non-fiction works generally led to more distinct regions, formed from static and proper named objects, though many were fragile and were merged spurious as the length of the text increased.

- In fictional tellings, the regions were fewer in number and the phrases expressed within them concerned emotional reactions to events rather than proper names and objects that typically characterize textbooks.

The data suggest that the purpose of fiction is not to convey facts but rather to convey emotions: a rather different form of narrative. The inefficiency of that approach in terms of hub separation might even indicate why science abhors such reactions as part of its writing. Emotional linkage muddles together factual concepts—surely a lesson for new agencies. Emotional linkage muddles together factual concepts—surely a lesson for new agencies.

In a problem with so many scales, clearly much more work is needed to understand the various couplings.

VI. Summary and Remarks

This study extends the analysis of the so-called Spacetime Hypothesis about cognition. It contends that the origin and organization of what we understand as concepts must ultimately lie in information encoded within spacetime scales, perceived and encoded into memory by a sensory process of an observer (called the ‘cognitive agent’). Space and time (as process) together imply causal narrative (time) as well as lateral association (space). Recall and recombination would be the mechanism for further narrative, including what we consider to be ‘reasoning’: a form of combinatoric storytelling based on the spacetime constraints implicit in memory encoding.

From the scales inherent in input patterns, boundary markers, and the clock ticks of the sampling process, an agent can discern

\[22\] Although it took a long time to discover, we now know from epigenetics that real-time selection plays an important role as an evolutionary selection. That aspect has yet to be explored here in any detail.

\[23\] This difficulty is well hidden in probabilistic methods, where scales are deliberately concealed by normalization in order to eliminate the kind of scale dependence the spoils nice distributions. It’s threshold scales all the way down [41].
a coordinatized view of its own proper timeline, exposing invariant features that eventually acquire semantics by learning, aggregating, and partial ordering of pattern fragments. Locality plays a role even in knowledge curation. If the results of paper 1, on fractionation and summarization, were surprisingly effective, then the results of this sequel seem even more astonishing: given a collection of extracted fragments, relatively simple algorithms can assemble them into a graph, without sophisticated knowledge of language, or descriptive logics. Only the four spacetime semantic types are needed to distinguish time, space, descriptive scalar properties, and finally to measure compound similarity, thus yielding a structure that captures and summarizes narratives in the process. That structure is basically identical to molecular chemistry, with no magical principles.

Preliminary results, on samples of data taken from books and articles, show that the hypothesis is plausible and quite intriguing—it can’t be unequivocally confirmed, far less proven, but certainly it can’t be ruled out, but surely warrants further study on a bigger corpus. There is some difficulty in presenting the argument using natural language as a data source: there are pros and cons in deriving one language from another. In some ways, the manifesto is similar to that of cognitive grammar [42].

The study has been based on text analysis, for convenience, as other significant bodies of data are hard to come by. However, the approach is general and could be adapted to other data sources such as quantitative time-series and process logs found in monitoring systems of all kinds. Some changes would be needed to filter out a background of repeating patterns, and high level of junk. The task seems similar to bioinformatic analysis in this respect.

Any approach to cognition is bound to have a lot of moving parts, making presentation a challenge. The technical approach here consists of mining features from a serial data landscape, somewhat analogous to DNA sequencing or crude oil refinement, in order to find the implicit alphabet of the input language. Samples of these alphabetic fragments in dissolution form ‘context’, which can then used to label events. This method leads to a hierarchy of implicit ‘containment’ that mimics generalization. The evolution of context allows transverse overlap between events and narratives, which defines a countable degree of similarity by which concepts may be joined up to extend and refine ‘memory regions’ with sufficient stability to represent generalized concepts over time. The linear input stream is transformed into a multi-dimensional graph, based on the four spacetime semantic types [3], [23]. In future work, it would be interesting to compare this work with other studies that seem to overlap on key principles [43]–[46]. Moreover, it would be interesting to compare the geometry of the fragment mesh with the effective geometry of Artificial Neural Networks that accomplish similar feats. It’s not impossible that this deterministic and causal generative process might be contribute to an explanation for the behaviours of ANN.

The convergence of concepts into a knowledge representa- tion is not a smooth process—it’s more like a random walk, with potentially catastrophic changes [41]. This is likely an artifact of the discreteness of small scale ‘digital’ separations used in natural language. This may be why stories about focused and curated knowledge have to evolve in tandem with cognition: because without the structural and scale limitations of sensing, cognition and memory encoding would cope poorly with the arbitrary input. Unless one limits the horizon of interconnectedness, concepts actually coalesce into a high state of entropy—and the ability to discriminate one concept from another is lost. Knowledge retains coherence only within certain boundaries—understanding more about that boundedness will be necessary in future. Knowledge management is, in a sense, spacetime boundary management. By deliberately ignoring linguistics, data are effectively made noisier than they need to be. The more semantics that are established, the easier it is to discriminate the parts of the input. This we take for granted, naturally, in human communication (at least until we try to learn a foreign tongue). This illustrates an evolutionary pressure for a limited grammatical recognition to emerge. An interesting category theoretical view of concepts has been postulated in [47], but this relies on grammar for its relational structure, but how that grammar comes about from fragments is taken for granted, and seems to be the more interesting issue to be reckoned. Interestingly, the authors consider sentence spaces as paths through space and time.

In summary, the structure of cognition, in this model, is rather like the structure of form in genetics [48]. The effective measure of distance between concept fragments is not an abstract metric distance based on Euclidean embeddings in a probability space based on a pre-identified basis [31], but rather a simple overlap of similar fragments, linked by promise (+) and receptor (-) that fit together lock-and-key. Distance is analogous to the mutual information between messages [49]–[53]. In that respect, this approach shows that human narrative can be analyzed using the same techniques used for DNA and other forms of chemical spectroscopy. This is effective because fragments are effectively invariants of a given language.

Ultimately this work is a straightforward application of scaling theory to discrete processes, so dimensionless scaling ratios occur as per the Buckingham-Pi theorem. The sensitivity of results to the scaling ratios suggests that a well adapted organism would be able to alter its scaling preferences in real time to maximize its clarity of thought. In many ways, this account of cognition is comforting. Perhaps we don’t need any mysterious new science to piece together the underlying story of reasoning and situation awareness—only a deeper understanding of scales. We start with time (arrival of events), and we invoke space by a process of discrimination. Fragments self-organize under the constraints of external context (boundary conditions). Scales play a central role. On the other hand, the study poses as many questions as it answers: given the fragility of concepts in a sparse graph representation, how

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24 In the context of Chomsky’s famously controversial universal grammar proposal, this lends weight to the naturalness of the proposal, in a limited sense, but doesn’t really confirm it or rule it out. Most likely, there are a few basic processing tricks that are hard coded by adaptation, which some authors refer to as a ‘propensity’ for language, but far from a ‘hard coded grammar’ in the explicit and literal sense that some attribute to it. What this work shows is that such abilities are not specific to language as we understand it—they would be needed for any sensory stream, even with specially adapted preprocessors such as eyes and ears. The scaling arguments are powerful and far reaching.

25 For all the attention afforded to scale-free properties in complexity studies, the scale free nature appear to be as much an artifact of the methodology rather as a property of a given process. We seek scale invariance precisely because it neutralizes the semantics of scale, but scale plays a crucial role in spacetime measurement, i.e. in sensory sampling.
are we humans so effective at compartmentalizing knowledge?
The work suggests that a constant rate of forgetting plays a role, but what isn’t clear yet is how so many concepts remain sufficiently separated, without merging into a grey entropic fog. The discreteness of the input fragments probably plays a role too.

The study only scratches the surface on what could lie beneath the simple set of principles in the Spacetime Hypothesis. Perhaps the most pertinent thing we can say is: if the hypothesis does indeed play a role in cognition, then understanding how multiple scales enable ideas from concepts to generalizations is not beyond the reach of human comprehension.

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