As we've suggested before, Maker is an emergent shared narrative: a complex adaptive system exposed to two partially amalgamated universes: onchain and offchain.

Building Maker Intelligence is essentially an exercise in (partially) automating Maker governance respecting Maker's structure including its interface to the environment.

Gracefully managing emergent knowledge representation, both distributed and localist, in a coherent fashion is the key challenge for Maker Intelligence for it to be robust to changes, data efficient, capable of rapid innovation, safe, be an open system of systems and capable of producing actionable knowledge.

It's important to understand that there is increasing consensus (e.g.1, 2, 3) that machine learning techniques do not scale as well as was anticipated to harder problems.

In particular, deep learning methods find their strength in automatically synthesizing distributed quantitative features from data. These features are useful insofar as they enable mostly reliable classification and regression, and in some limited cases also few- or zero-shot transfer to related tasks.

However, it is increasingly questionable whether deep learning methods are appropriate for autonomous roles in environments that are not strongly constrained, like the one Maker is operating in.

To meet the requirements outlined for Maker Intelligence we propose implementing in the MI architecture state space with compositionality and on-demand granularity, rule- and resource-aware safety, local explanatory n-causal hypothesis generation and generalisation to new tasks as follows:

1. State space: a (composition of) random non-commutative manifold(s) reconstructed gradually from heterogenous data: provides natural compositionally => arbitrary granularity => data efficiency, flexibility

2. Causal relations between state space regions and explanatory n-causal hypothesis generation: geodesics, paths, homotopies on the random non-commutative manifold from p.1 for functional causalities and self-reflection => transparency for MakerDAO and rapid self-improvement

3. Strong typing: type-driven development with dependent types, specifically linear type system, based on quantitative type theory, for rule- and resource-aware MI => safety.

4. Generalisation: the univalence principle, specifically the higher observational type theory flavour for scaling to emergent challenges and opportunities.

Geometry is the language of choice for building models of natural systems from first principles in physics: frommacroscale gravity to the microscale quantum world. Specifically the toolset ofRiemannian geometry, which provides extremely rich structure via Riemannian metric on smooth manifolds.

Geometric Deep Learning (GDL), including, but not limited to DL on graphs, although receiving much less publicity than LLMs behind chatbots, is one of the major achievements of the recent years in AI.

In particular, it has been shown that all current deep learning architectures, including transformers behind LLMs like GPT4, are special cases under the geometric deep learning framework à la Erlangen program in pure math.

Motivating idea behind GDL is that if your model architecture initially respects symmetries behind your data, which is not always the case with vanilla neural networks, the resulting representation is more faithful to the represented real world entity. Geometry gives an immense toolset for embedding structure behind your data into your DL architecture.

E.g., development of graph deep learning has made possible serious progress in modelling proteins, narrative proliferation on social media, drug discovery etc.

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However for Maker GDL is not enough, as machine learning, including deep learning and its flavour geometric DL, excels at inducing mappings from data, but struggles to induce deeper latent structures like causal hierarchies and be sustainable as an open learner.

To realise the value proposition for Maker Intelligenceoutlined earlier

owning an autonomously adaptive system capable of performing work on command

we suggest making a step forward from Geometric Deep Learning building upon a number of pure and applied math achievements of the last decades, specifically, noncommutative geometry, univalent foundations for math, quantitative type theory and programming with dependent types.

Emergent state space

Noncommutative geometry recasts the differential geometry of a manifold as the algebraic data of a spectral triple $(\mathscr A, \mathscr H, \mathscr D)$

vs a set of points in the traditional approach. A spectral triple is a way of encoding a geometry using a Dirac operator. There is a Dirac operator $\mathscr D$

acting on a Hilbert space $\mathscr H$

and an algebra $\mathscr A$

that acts on the same space.

Reconstruction Theorem proved by A. Connes in 2013, shows that the entire geometry of a Riemannian manifold, both metric and topological data, can be reconstructed from the spectral triple $(\mathscr A, \mathscr H, \mathscr D)$

. It's a striking achievement since it's been shown that the famous question by M. KacCan One Hear the Shape of a Drum? – i.e. is it possible to reconstruct the shape purely from the frequencies of its vibrations, i.e. spectrum data – has a negative answer. Different shapes with the same spectrum, i.e. isospectral shapes, have been constructed since.

Connes' achievement was that he showed how one can reconstruct a unique manifold from algebraic data opening path towards exploring its underlying algebraic structure, showing in particular that metric information of the manifold can be recovered using the distance d

between pure states S_1, S_2

of the algebra, defined as

$$d (s_1, s_2) = \sup_{a \in A} {\lvert s_1(a) - s_2(a) \rvert \mid ||[D, a]|| \le 1 }$$

Moreover, the point of spectral triples is that the algebra is allowed to be non-commutative, leading to a generalisation of the notion of geometry, where coordinates don't commute. It means that order matters here: a good example of a structure, where order matters is a natural language.

DAI =/= AID. "Rune runs Maker" =/= "Maker runs Rune".

Order, temporary structure on Maker's space of states => causal hierarchies are natural side-effects of geometries, where coordinates do not (necessarily) commute.

In the practical domain a random noncommutative geometry is a class of geometries $\mathscr G$

that fluctuates according to a probability measure, obtained by integrating over the space of Dirac operators that form a spectral triple with a fixed algebra and Hilbert space. To make this computable, the class of geometries is taken to be the Dirac operators on a fixed finite-dimensional Hilbert space $\mathscr H$

; thus $\mathscr G$

is a space of matrices. It turns out that the axioms for $\mathscr D$

for these finite spectral triples are all linear and so $\mathscr G$

is a vector space. Therefore, one can take $d\mathscr D$

to be its Lebesgue measure, which is unique up to an overall constant. Thus the object of study is a random matrix model, where the matrices are constrained to be Dirac operators.

This opens up way to the state space structure analysis: is there a path between space regions as a casual relation, and explanatory n-step chains, what is the shortest path (geodesics), space topology, mappings between paths (homotopies) and analysis of the space local and global curvatures.