Thought Curvature: An underivative hypothesis on the 'Supersymmetric Artificial Neural Network'

Jordan Micah Bennett  jordanmicahbennett@gmail.com

The "Supersymmetric Artificial Neural Network" in deep learning (denoted \( \phi(x; \theta, \overline{B})^w \)), espouses the importance of considering biological constraints in the aim of further generalizing backward propagation.

Looking at the progression of 'solution geometries'; going from \( \mathcal{SU}(n) \) representation (such as Perceptron like models) to \( \mathcal{SU}(m|n) \) representation (such as UnitaryRNNs) has guaranteed richer and richer representations in weight space of the artificial neural network, and hence better and better hypotheses were generatable. The Supersymmetric Artificial Neural Network explores a natural step forward, namely \( \mathcal{SU}(m|n) \) representation. These supersymmetric biological brain representations (Perez et al.) can be represented by supercharge compatible special unitary notation \( \mathcal{SU}(m|n) \), or \( \phi(x; \theta, \overline{B})^w \) parameterized by \( \theta, \overline{B} \), which are supersymmetric directions, unlike \( \theta \) seen in the typical non-supersymmetric deep learning model. Notably, Supersymmetric values can encode or represent more information than the typical deep learning model, in terms of "partner potential" signals for example.

Keywords: Supersymmetric-gradient-descent, Supermathematics, Supermanifold, Supersymmetry, Lie Superalgebra, Deep Learning

"Thought Curvature" is similar to "Thought vectors", with the distinction that supermanifold/curvatures are used to describe the "Supersymmetric Artificial Neural Network"(SANN) model. (See manifold curvature work in geometric deep learning by Michael Bronstein et al.)

1 INTRODUCTION

Deepmind’s atari q architecture encompasses non-pooling convolutions, wherein generating object shift sensitivity, whence the model maximizes some reward over said shifts together with separate changing states for each sampled t state; translation non-invariance. Separately, uetorch, encodes an object trajectory behaviour physics learner, particularly on pooling layers; translation invariance.

It is non-abstrusely observable, that the childhood neocortical framework pre-encodes certain causal physical laws in the neurons, amalgamating in perceptual learning abstractions into non-childhood.

As such, it is perhaps exigent that non-invariant fabric composes in the invariant, pertinently in the margin of some asymptote entailing \( \phi(x; \theta, \overline{B})^w \)[1], wherein engendering time-space complex optimal causal artificial construction.

2 OVERVIEW

i. The aim is to contribute to the field of artificial general intelligence, often underlined as mankind’s likely last invention.

ii. Machine learning often concerns constraining algorithms with respect to biological examples.

iii. Babies are great examples of some non-trivial basis for artificial general intelligence; babies are significant examples of biological baseis that are reasonably usable to inspire smart algorithms, especially in the aims of (i), regarding (ii). Babies’ brains are fantastic measures of “tabula rasa”-like states, from which complicated abstractions are learnt into adulthood, similar to how the recent breakthrough artificial intelligence program, “AlphaGo Zero”, started out essentially “blank” beginning from random plays, up until it quickly learnt to become the planet’s strongest go player today. (This quick outline highlights the critical relevance of games as necessary testbeds/algorithm training scenarios, in the aim of developing artificial general intelligence.)

"Thought curvature" subsumes the "supermanifold hypothesis in deep learning", while espousing the importance of considering biological constraints in the aim of developing general machine learning models, pertinently, where babies’ brains are observed to be pre-equipped with particular “physics priors”, constituting specifically, the ability for babies to intuitively know laws of physics, while learning by reinforcement.

It is palpable that the phrasing “intuitively know laws of physics” above, should not be confused for Nobel laureate or physics undergrad aligned babies that for example, write or understand physics papers/exams; instead, the aforesaid phrasing simply conveys that babies’ brains are pre-baked with ways to naturally exercise physics based expectations w.r.t. interactions with objects in their
world, as indicated by Aimee Stahl and Lisa Feigenson.[13]

Outstandingly, the importance of recognizing underlying causal physics laws in learning models (although not via supermanifolds, as encoded in Thought Curvature), has recently been both demonstrated[14] and separately echoed by Deepmind[15], and of late, distinctly emphasized by Yoshua Bengio.[16]

3 RELATED WORK

There priorly existed translation variant/invariant manifold interaction paradigms[17], that effectively learn to disentangle varying factors. However, such models plausibly relent factors amidst optimal, causal - laws of physics arranged embeddings. (See "A probable experiment")

4 A PROBABLE EXPERIMENT: A TRANSVERSE FIELD ISING SPIN (SUPER)-HAMILTONIAN QUANTUM COMPUTATION

Considering the Bessel aligned second-order linear damping equation: \( \phi = (z + \frac{1}{\lambda^2}z'(a(z + \frac{1}{\lambda}))) + c(z + \frac{1}{\lambda})e^{ct} \) incorporating the travelling coordinate: \( z = ax + by - ct \) whilst emerging by the isospectral factorization outcome: \( f_1 = \frac{z}{\lambda^2} \), constrained in dimensions \( d = 2 + 1 \), given that the SO(n) group may eventuate in SU(m|n) terms,[18] [19], within the aforesaid constraint, the Hamiltonian operator: \(- \sum a^2 \sigma_a^2 - \sum a^2 \sigma_a^2 - \sum a^2 w_{ab} \sigma_a^2 \sigma_b \)

\( \sigma_a \) is reasonably applicable in the quantum temporal difference horizon: \( \pi(s1) \leftarrow \arg\max_{\theta} Q(s, \phi) \) as a Super-Hamiltonian[20] in contrast.

Consequently, some odd operation of form \( \{ H \pm F, H \pm F \} = \{ 2F, H \pm F, H \pm F \} \) yields \( \{ H \pm F \} \leftarrow \{ 0 \} [21] \) subsuming: \(- \sum \sigma_a \sigma_a - \sum a^2 w_{ab} \sigma_a^2 \sigma_b \) is reasonably absorbable in [22].

5 THOUGHT CURVATURE - ANNOTATION

i. Supermanifold hypothesis in deep learning describes some superspace bound structure/weights.

ii. Thought curvature designates the existence of some plausible \( \pi \)-Bellmanian[23], based on i; a sequence taking as parameters, the aforesaid supermanifold structure.

6 SUPERMANIFOLD HYPOTHESIS IN DEEP LEARNING

If any homeomorphic transition in some neighbourhood in an euclidean space \( \mathbb{R}^n \) yields \( \phi(x; \theta)^\top w \) for \( w, \theta \in \mathbb{R}^n \), then reasonably, some homeomorphic transition sequence in some euclidean superspace \( C^\infty(\mathbb{R}^{m|n}) \) yields \( \phi(x; \theta, \bar{\theta})^\top w \) for \( x \in \mathbb{R}^n \) while \( w, \theta, \bar{\theta} \in \mathbb{R}^{m|n} \).

Pertinently, \( R^{m|n} \rightarrow \text{form } \mathbb{R}^{2|1} \) for \( d = 2 + 1 \)[24]

7 SUPERMANIFOLD HYPOTHESIS IN DEEP LEARNING - ANNOTATION

i. Deep learning entails \( \phi(x; \theta)^\top w \), that denotes the input space \( x \), and learnt representations \( \theta \).

ii. Deep learning underlines that coordinates or latent spaces in the manifold framework, are learnt features/representations, or directions that are sparse configurations of coordinates.

iii. Supermathematics entails \( \langle x; \theta, \bar{\theta} \rangle \), that denotes some \( x \) valued coordinate distribution, and by extension, directions that compact coordinates via \( \theta, \bar{\theta} \).

iv. As such, the aforesaid \( \langle x; \theta, \bar{\theta} \rangle \), is subject to coordinate transformation.

v. Thereafter i, ii, iii, iv and [24], within the generalizable nature of euclidean space, reasonably effectuate \( \phi(x; \theta, \bar{\theta})^\top w \).

8 SUPERMANIFOLD HYPOTHESIS IN DEEP LEARNING - END NOTES

Some space (i.e. superspace) may persist, such that degrees of freedom of said space is inclined by some aggregation:

i. Some tensor sequence of priors. (i.e. eta… or any \( \bar{\phi}_{\theta, \bar{\theta}} \) constituent the laws of physics.)

ii. Some tensor sequence on the direction of (i), i.e. superfields of interactions in (i) terms.[25]

9 THOUGHT CURVATURE - LIMITATIONS

Although thought curvature is minor particularly in its simple description (acquiescing SQCD[26]) in relation to Artificial General Intelligence, it crucially delineates that the math of supermanifolds is reasonably applicable in Deep Learning, imparting that cutting edge Deep Learning work tends to consider boundaries in the biological brain[27], while underscoring that biological brains can be optimally evaluated using supersymmetric operations.[12]

In broader words, thought curvature occurs on the following evidence:

1. Manifolds are in the regime of very general algorithms, that enable models to learn many degrees of freedom in latent space,
Given (1), and the generalizability of euclidean space, together with the instance that there persists supersymmetric measurements in biological brains, thought curvature predicates that Supermathematics or Lie Superalgebras (in Supermanifolds) may reasonably, empirically apply in Deep Learning, or some other named study of hierarchical learning in research.  

2. An optimal weight space produced by deep and high-dimension-absorbing real valued artificial neural nets, may have good weights that lie in disentangleable \( (\mathbb{R}^n \ast \mathbb{R}^n) - \text{ordered} \) manifolds per class/target group convolved by the operator \( * \), instead of the simpler regions per class/target group seen in item (1). This may guarantee more variation in the weight space than (1), leading to better hypotheses or guesses. 

3. An optimal weight space produced by shallow but high dimension-absorbing complex valued artificial neural nets, may have good weights that lie in multiple \((\mathbb{C}^n - \text{ordered})\) sectors per class/target group, instead of the real regions per class/target group seen amongst the prior items. (This may guarantee more variation of the weight space than the previous items, by learning additional features. in the “phase space”. This also leads to better hypotheses/guesses). 

4. An optimal weight space produced by deep or high dimension-absorbing complex valued artificial neural nets, may have good weights that lie in chi distribution bound, \((\mathbb{C}^n \ast \mathbb{C}^n - \text{ordered})\) rayleigh space per class/target group convolved by the operator \( * \), instead of the simpler sectors/regions per class/target group seen amongst the previous items. (This may guarantee more variation of the weight space than the prior items, by learning phase space representations, and by extension, strengthen these representations via convolutional residual blocks. This also leads to better hypotheses/guesses). 

5. The “Supersymmetric Artificial Neural Network” operable on high dimensional data, may reasonably generate good weights that lie in disentangleable \((\mathbb{C}^n (\mathbb{R}^m[n]) - \text{ordered})\) supermanifolds per class/target group, instead of the solution geometries seen in the prior items above. Supersymmetric values can encode rich partner-potential delimited features beyond the phase space of (4) in accordance with cognitive biological space, where (4) lacks the partner potential formulation describable in Supersymmetric embedding.
12 PSEUDO CODE FOR THE “SUPERSYMMETRIC ARTIFICIAL NEURAL NETWORK”

Following, is another view of “solution geometry,” history, which may promote a clear way to view the reasoning behind the subsequent pseudocode sequence:

1. There has been a clear progression of “solution geometries”, ranging from those of the ancient Perceptron [32] to complex valued neural nets [33], grassmann manifold artificial neural networks [34], [35], or unitary RNNs. [36,40,44]

These models may be denoted by \( \phi(x; \theta)^T \)W parameterized by \( \theta \), expressible as geometrical groups ranging from orthogonal to special unitary group-based: SO(n) to SU(n), etc., and they got better at representing input data i.e. representing richer weights, thus the learning models generated better hypotheses or guesses.

2. By “solution geometry” I mean simply the classes of regions where an algorithm's weights may lie, when generating those weights to do some task.

3. As such, if one follows cognitive science, one would know that biological brains may be measured in terms of supersymmetric operations. (Perez et al, “Supersymmetry at brain scale”)

4. These supersymmetric biological brain representations can be represented by supercharge [44] compatible special unitary notation SU(m,n), or \( \phi(x; \theta, \overline{\theta})^T \)W parameterized by \( \theta, \overline{\theta} \) [44], which are supersymmetric directions, unlike \( \theta \) seen in item (1). Notably, Supersymmetric values can encode or represent more information than the prior classes seen in (1), in terms of “partner potential” signals for example.

5. So, state of the art machine learning work forming U(n) or SU(n) based solution geometries, although nonsupersymmetric, are already in the family of supersymmetric solution geometries that may be observed as occurring in biological brain or SU(m,n) supergroup representation.

I call an “Edward Witten/String theory powered artificial neural network”, simply an artificial neural network that learns supersymmetric weights.

Looking at the above progression of ‘solution geometries’, going from SO(n) [38,44] representation to SU(n) [38,44], representation has guaranteed richer and richer representations in weight space of the artificial neural network, and hence better and better hypotheses were generatable.

It is perhaps only then reasonable to look to SU(m,n) representation, i.e. the “Edward Witten/String theory powered artificial neural network” (“Supersymmetric Artificial Neural Network”).

To construct an “Edward Witten/String theory powered artificial neural network”, it may be feasible to start with a grassmann manifold artificial neural network then generate ‘charts’ [44] until scenarios occur [44] where the “Edward Witten/String theory powered artificial neural network” is achieved in the following way:

Pseudocode:

a. Initialize input Supercharge [47] compatible special unitary matrix SU(m,n). [44] (This is the atlas seen in b.)

b. Compute \( \nabla C \) w.r.t. to SU(m,n), where \( C \) is some cost manifold.

- Weight space is reasonably some K ahler potential like form: \( K(\theta, \phi^*) \), obtained on some initial projective space \( CP^{n-1} \) [42]
- It is feasible that \( CP^{n-1} \) (a Cm bound atlas) may be obtained from charts \( \binom{m}{n} \) of grassmann manifold networks \( GR_{k,n} \) and stiefel manifolds \( GF_{k,n} \), in (\( \phi_t, \mu_t \)) terms, where there exists some invertible submatrix entailing matrix \( A \in \phi_t(U_t \cap U_j) \) for \( U_t = \pi(V_t) \) where \( \pi \) is a subsersion mapping on some stiefel manifold \( GF_{k,n} \), thereafter enabling some differentiable grassmann manifold \( GR_{k,n}(\mathbb{R}^m) \) wherein \( V_t = \{ u \in \mathbb{R}^{n\times k} ; \text{det}(u_t) \neq 0 \} \) [44]

c. Parameterize SU(m,n) in \( -\nabla C \) terms, by Darboux transformation [44]

d. Repeat until convergence.

13 CONCLUSION

Pertinently, the “Edward Witten/String theory powered supersymmetric artificial neural network”, is one wherein supersymmetric weights are sought.

Many machine learning algorithms are not empirically shown to be exactly biologically plausible, i.e. Deep Neural Network algorithms, have not been observed to occur in the brain, but regardless, such algorithms work in practice in machine learning.

Likewise, regardless of Supersymmetry’s elusiveness at the LHC, as seen above, it may be quite feasible to borrow formal methods from strategies in physics even if such strategies are yet to show related physical phenomena to exist; thus it may be pertinent/feasible to try to construct a model that learns supersymmetric weights, as I proposed throughout this paper, following the progression of solution geometries going from SO(n) to SU(n) and onwards to SU(m,n) [44].
14. APPENDIX - FIGURE 1: ARTIFICIAL NEURAL NETWORK/SYMMETRY GROUP LANDSCAPE VISUALIZATION

Thought Curvature Figure 1: Let $\phi$ denote what each type of model can learn. (See "Deep Learning Book" by Bengio et al. Chapter 6, point 3 for $\phi$ description).

- $O(n)$ structure – Orthogonal is **not connected** enough, therefore **not amenable to gradient descent** in machine learning. (Paper: See note 2 at end of page 2, in reference [50].)
- $SO(n)$ structure – Special Orthogonal; is **connected**, **gradient descent compatible**, while preserving orthogonality, concerning **normal space-time**. (Paper: See paper in item 1).
- $SU(n)$ structure – Special Unitary; is **connected**, gradient descent compatible; complex generalization of $O(n)$, but only a subspace of larger unitary space, concerning **normal space-time**. (The Unitary Evolution Recurrent Neural Network related to complex unit circle seen in $U(1)$ in physics (See page 2 in [52].))
- $U(n)$ structure – Unitary; is **connected**, **gradient descent compatible**; Larger unitary landscape than $SU(n)$, concerning **normal space-time**.
- $SU(m|n)$ structure – Supersymmetric; is **connected**, thereafter reasonably **gradient descent compatible** and even larger than the $U(n)$ landscape, to permit sparticle invariance, **being a Poincare group extension** (See page 7 in [52]) containing both **normal space-time and anti-commuting components**, as seen in the Supersymmetric Artificial Neural Network which this paper proposes.
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