

# *Bridging Histories*

*Literacy, computer science and mathematics in the 20th and 21st centuries*

Isaac Newton Institute for Mathematical Sciences  
Cambridge, UK

## *How to Do Maths With Words*

The Role of Language in Neural Machine Learning  
Applications to Mathematics

Juan Luis Gastaldi

**ETH** zürich

March 25, 2025

# Outline

Intro: Machine Learning, Mathematics, and Language

Historical Perspectives

Epistemological Perspectives

Theoretical Perspectives

Conclusions

# Reference Papers

- ◊ Gastaldi, J. L. (2024). How to Do Maths with Words: Neural Machine Learning Applications to Mathematics and Their Philosophical Significance. In B. Sriraman (Ed.), *Handbook of the history and philosophy of mathematical practice* (pp. 3191–3226). Springer International Publishing.  
[https://doi.org/10.1007/978-3-031-40846-5\\_142](https://doi.org/10.1007/978-3-031-40846-5_142)
- ◊ Gastaldi, J. L., & Pellissier, L. (2021). The calculus of language: Explicit representation of emergent linguistic structure through type-theoretical paradigms. *Interdisciplinary Science Reviews*.  
<https://doi.org/10.1080/03080188.2021.1890484>
- ◊ Bradley, T.-D., Gastaldi, J. L., & Terilla, J. (2024). The structure of meaning in language: Parallel narratives in linear algebra and category theory. *Notices of the American Mathematical Society*.  
<https://api.semanticscholar.org/CorpusID:263613625>
- ◊ Gastaldi, J. L. (Forthcoming 2024c). Content from Expressions. The Place of Textuality in Deep Learning Approaches to Mathematics. *Synthese (under review)*

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# Tony Wu at the IPAM

## Main results – human prover

- For each problem, given a ground truth human solution, we sample up to 100 proofs from Codex.
- Codex solves 200 out of 488 problems with 100 samples:

Samples	Solved Problems
0	80
10	170
20	185
30	188
40	189
50	190
60	191
70	192
80	193

Autoformalization with Large Language Models

MACHINE ASSISTED PROOFS, FEBRUARY 12 - 17, 2023, WWWIPAM.UCLA.EDU

ipam

Tony Wu  
Google

Tony Wu, Autoformalization with Large Language Models (IPAM (UCLA), Feb 15, 2023)

# Melanie Mitchell on PaLM2



Melanie Mitchell

@MelMitchell1

...

Weird statement from Google's Palm 2 announcement.

(from [blog.google/technology/ai/](https://blog.google/technology/ai/) ...)

- **Reasoning:** PaLM 2's wide-ranging dataset includes scientific papers and web pages that contain mathematical expressions. As a result, it demonstrates improved capabilities in logic, common sense reasoning, and mathematics.

6:23 PM · May 12, 2023 · 52.9K Views

<https://blog.google/technology/ai/google-palm-2-ai-large-language-model/>

# What's So Funny?

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- ◊ Mathematical literacy was supposed to be a condition to write and read scientific papers and mathematical expressions instead of their miraculous effect.

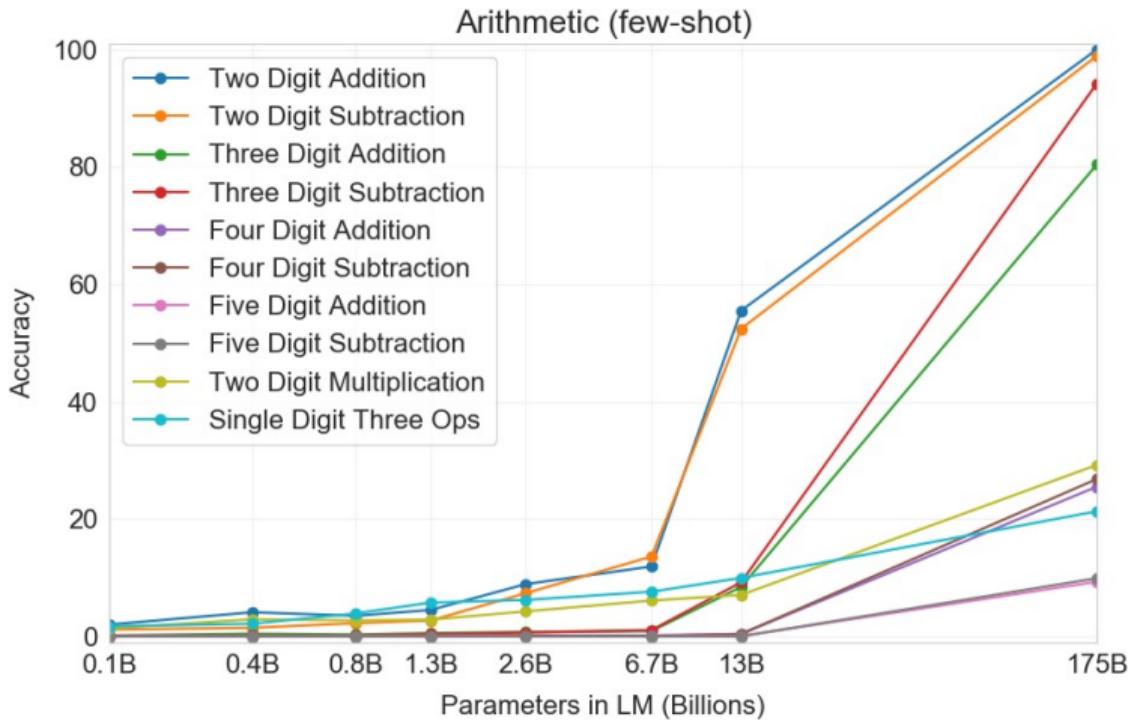
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- ◊ Natural language was considered the cause of rather than the solution to the multiple problems preventing mathematics from achieving higher degrees of precision.
- ◊ More generally, the *formal* nature of mathematics was believed to make it impassive to the strong empirical position assumed by connectionist approaches guiding the application of DNNs.

# Arithmetic in GPT-3



(Brown et al., 2020)

# Reasoning in ChatGPT o3

If  $p_n$  is a sequence of probability distributions on a countably infinite set  $X$  that converge pointwise to a probability distribution  $p$  on  $X$ , do they necessarily converge uniformly?

Reasoned about uniform convergence of probability distributions for 4m 41s >

We will show that if

$$p_n(x) \rightarrow p(x) \quad \text{for every } x \in X,$$

where  $X$  is a countably infinite set and each  $p_n$  and  $p$  is a probability distribution on  $X$  (so that

$$\sum_{x \in X} p_n(x) = \sum_{x \in X} p(x) = 1),$$

then in fact the convergence is uniform; that is,

$$\sup_{x \in X} |p_n(x) - p(x)| \rightarrow 0.$$

In other words, point-wise convergence of the probability mass functions on a countable set (with the limit being a probability distribution) forces uniform convergence.

In what follows we give a proof.

# Reasoning in ChatGPT o3

## Proof

Let  $\varepsilon > 0$  be arbitrary. Our goal is to show that for all sufficiently large  $n$  we have

$$\sup_{x \in X} |p_n(x) - p(x)| < \varepsilon.$$

Because  $p$  is a probability measure on the countable set  $X$ , we can "capture almost all of its mass" in a finite set. (This is sometimes called a truncation argument.) More precisely, there exists a finite subset  $F \subset X$

such that

$$p(X \setminus F) = \sum_{x \notin F} p(x) < \varepsilon/3.$$

Now, since  $F$  is finite and we know that for every fixed  $x$  we have  $p_n(x) \rightarrow p(x)$ , it follows that for each  $x \in F$  there is an index  $N_x$  such that for all  $n \geq N_x$   
 $|p_n(x) - p(x)| < \varepsilon/(3|F|)$ .

If we let

$$N_1 = \max\{N_x : x \in F\},$$

then for all  $n \geq N_1$  and every  $x \in F$  we have

$$|p_n(x) - p(x)| < \frac{\varepsilon}{3|F|}.$$

Thus, summing over  $x \in F$  we obtain

# Reasoning in ChatGPT o3

## Conclusion

Yes. If a sequence  $\{p_n\}$  of probability distributions on a countably infinite set  $X$  converges point-wise to a probability distribution  $p$ , then in fact

$$\sup_{x \in X} |p_n(x) - p(x)| \rightarrow 0,$$

so the convergence is uniform.

---

## A Note on the Issue

It is very important that the limit  $p$  is itself a probability distribution. (For example, the sequence of "Dirac measures"  $\delta_n$  on  $\mathbb{N}$  defined by

$$\delta_n(x) = \begin{cases} 1 & \text{if } x = n, \\ 0 & \text{otherwise,} \end{cases}$$

converges point-wise to the zero function; but the zero function is not a probability distribution, and indeed the convergence is not uniform.) The fact that no mass "escapes" ensures that the tiny probabilities in the tail force the errors there to be small uniformly.

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## Final Answer

Yes. If  $p_n$  is a sequence of probability distributions on a countably infinite set  $X$  that converges point-wise to a probability distribution  $p$  (so that no mass is lost), then in fact the convergence is uniform.

# Reasoning in ChatGPT o3

Reasoned about uniform convergence of probability distributions for 4m 41s ✓

I'm curious if pointwise convergence of probability distributions on a countably infinite set implies uniform convergence. This involves examining the supremum of the absolute difference between distributions as it approaches zero.

OK, let me see: pointwise convergence on a countably infinite set doesn't guarantee uniform convergence without additional constraints, like finite sets or specific continuity conditions.

I'm curious about sequences of probability measures where each point's probability trends to zero. This hints at pointwise convergence but raises questions about uniform convergence due to potential "spikes."

OK, let's think it through: the maximum difference of  $1/n$  between distributions  $p_n$  and  $p$  as  $n$  increases. This difference converges to zero, suggesting uniform convergence in a bounded setup.

I'm examining a counterexample of pointwise convergence without uniform convergence, where individual probabilities decline to zero but the overall distribution doesn't converge uniformly due to continuous fluctuation.

I'm considering pointwise convergence with a shifting spike in a probability distribution on natural numbers, highlighting the gap between pointwise and uniform convergence due to inconsistent distribution updates.

# Main Orientations in DNN Applications to Maths

## ◊ Proof-Oriented

- Bansal et al., 2019; Polu and Sutskever, 2020; Wu et al., 2022.

## ◊ Object-Oriented

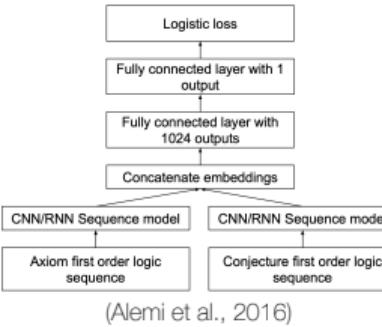
- Blechschmidt and Ernst, 2021; Charton, 2021; d'Ascoli et al., 2022; Lample and Charton, 2019; Li et al., 2021

## ◊ Skill-Oriented (e.g., Reasoning)

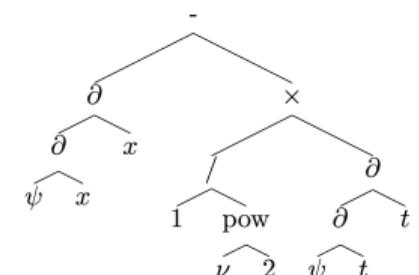
- Brown et al., 2020; Lewkowycz et al., 2022; Shen et al., 2021

## ◊ Heuristic-Oriented

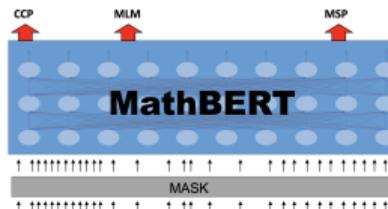
- Davies et al., 2021; Wagner, 2021



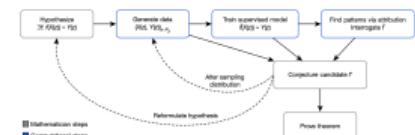
(Alemi et al., 2016)



(Lample and Charton, 2019)



(Peng et al., 2021)



(Davies et al., 2021)

# Philosophical Significance: The Return of Language

- ◊ Research orientations tend to be spontaneously organized according to the **AI researchers' implicit assumptions** as to what characterizes **mathematical practice** (i.e. what it is that we do when we do mathematics).

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- ◊ However, practically all applications share a common philosophical assumption: *Written natural language plays a critical role in the processing mathematical knowledge.*

# Philosophical Significance: The Return of Language

- ◊ Research orientations tend to be spontaneously organized according to the AI researchers' implicit assumptions as to what characterizes mathematical practice (i.e. what it is that we do when we do mathematics).
- ◊ However, practically all applications share a common philosophical assumption: *Written natural language plays a critical role in the processing mathematical knowledge.*
- ◊ The potential success of DNN methods in mathematics is inseparable from a reorientation of the epistemology of mathematics from logic and formal systems to natural language and vernacular writing practices.

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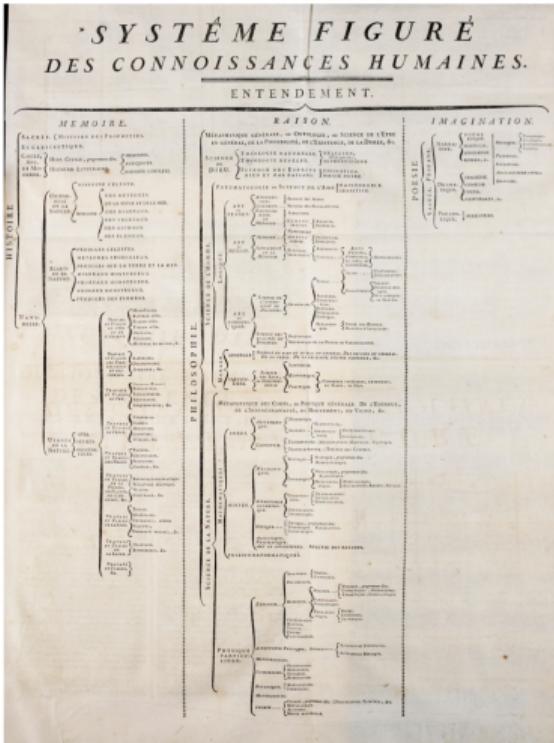
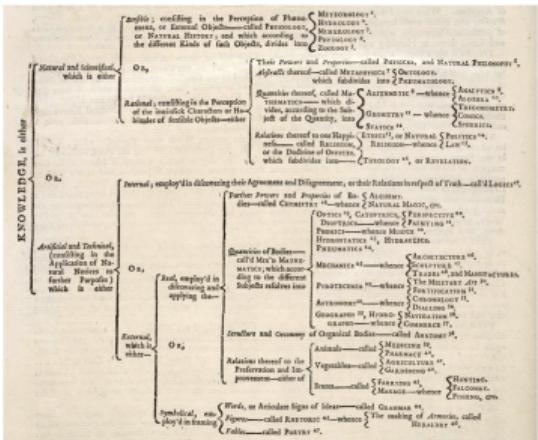
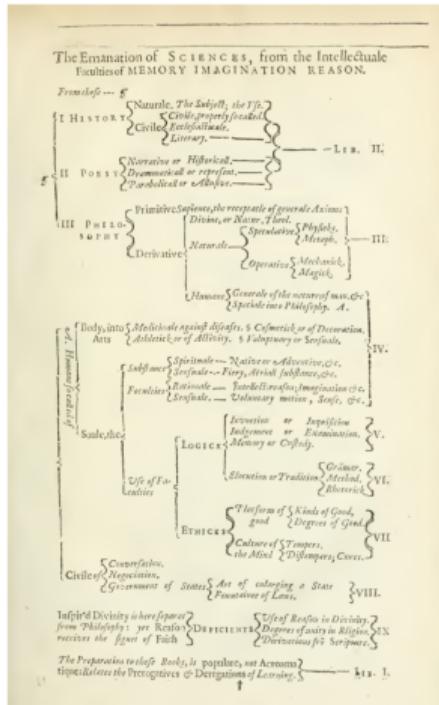
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# Trees of Knowledge

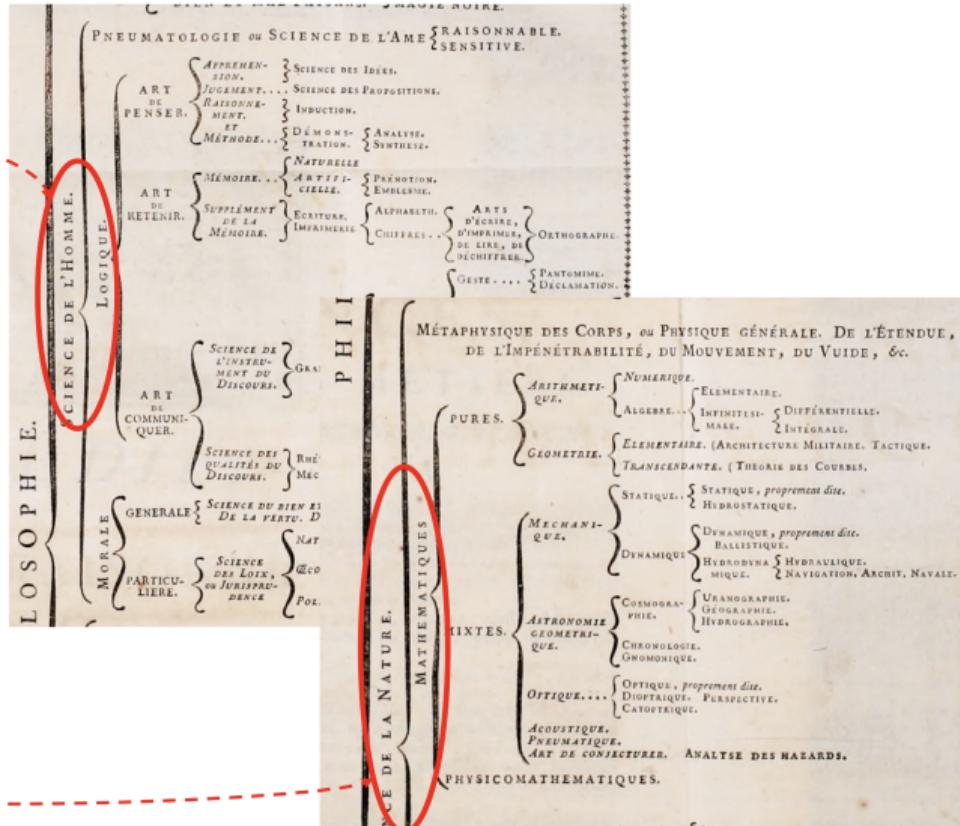
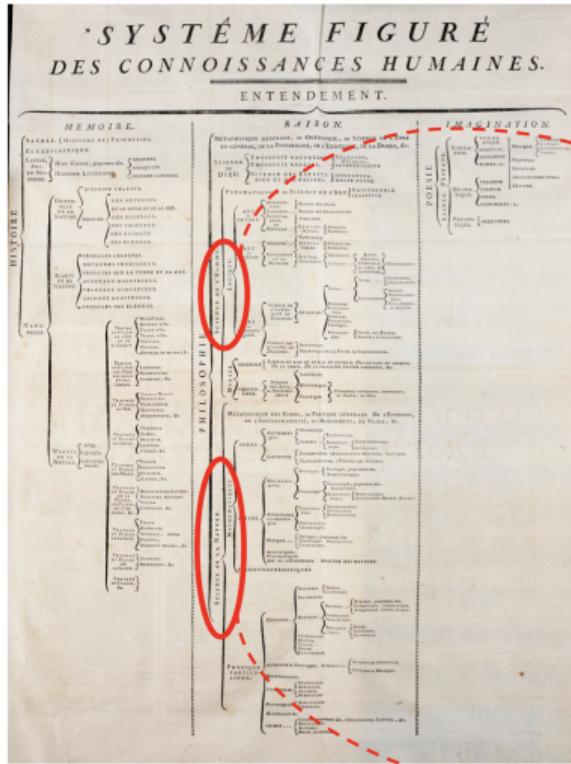


F. Bacon (1605)

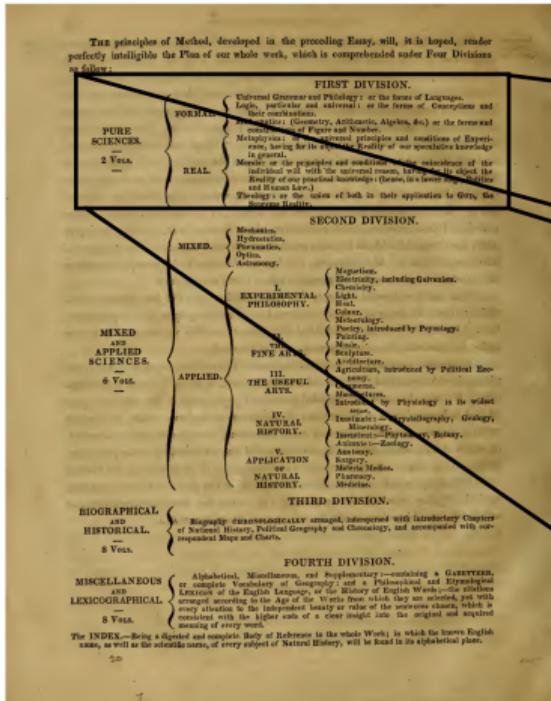
E. Chambers (1728)

Didierot & D'Alembert (1751-1772)

## Trees of Knowledge (detail)



# The Birth of Formal Knowledge



**FIRST DIVISION.**

FORMAL.

PURE SCIENCES. — 2 Vols.

REAL.

Universal Grammar and Philology. or the forms of Languages. Logic, particular and universal: or the forms of Conceptions and their combinations. Mathematics: (Geometry, Arithmetic, Algebra, &c.) or the forms and constructions of Figure and Number. Metaphysics: or the universal principles and conditions of Experience, having for its object the Reality of our speculative knowledge in general. Morals: or the principles and conditions of the coincidence of the individual will with the universal reason, having for its object the Reality of our practical knowledge: (hence, in a lower stage, Politics and Human Law.) Theology: or the union of both in their application to GOD, the Supreme Reality.

S. T. Coleridge, Encyclopaedia Metropolitana, 1818.

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# Stochastic Parrots vs. AI Consciousness



Language models are not like us,  
therefore they do not and can not have any relation to meaning.



Language models have a relation to meaning,  
therefore they are like us.

# Making it Explicit

## Function

λRófÃØêÑ5È|Ãxñ=∞  
ù ümWf286ëy'SÙú>v&  
...  
3Ã/rxµ∞µ\$ÀëÂ\*lf~íû'  
+ÍViyªGæßägô/,uÑ

# Making it Explicit

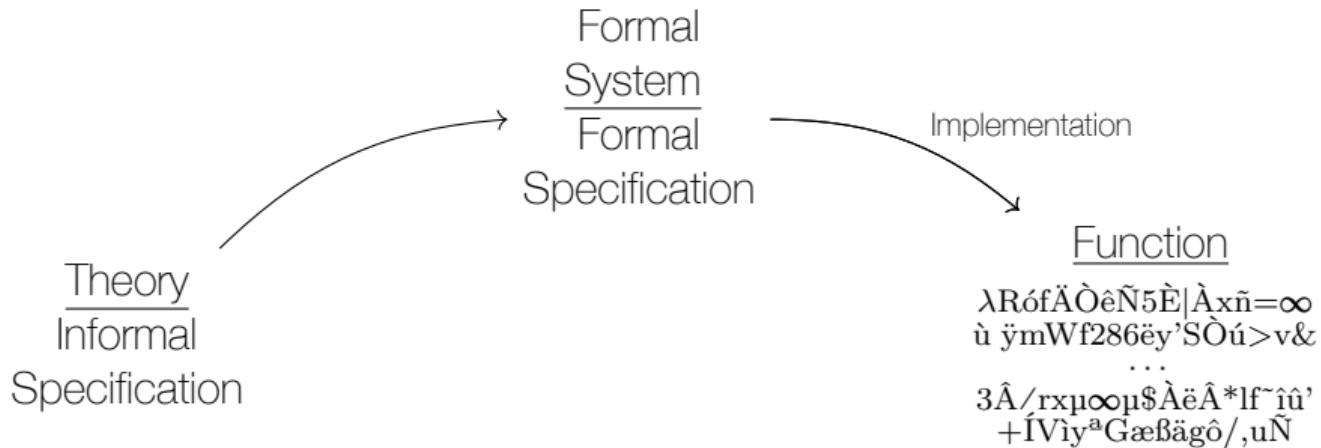
Formal  
System  
Formal  
Specification

Implementation

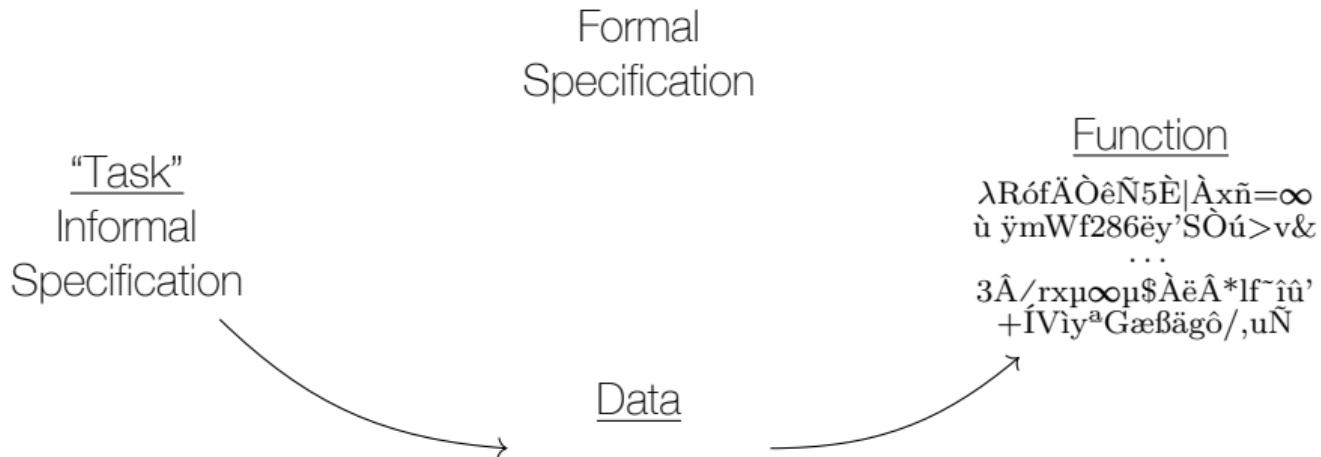
Function

$\lambda Rof \rightarrow \exists x \in \mathbb{R}^{\infty} | \exists y \in \mathbb{R}^{\infty} | \exists v \in \mathbb{R}^{\infty}$   
...  
 $3 / rxmu \in \$ \wedge * lf \sim u'$   
 $+ IViy^a GaeBaga / , u \in$

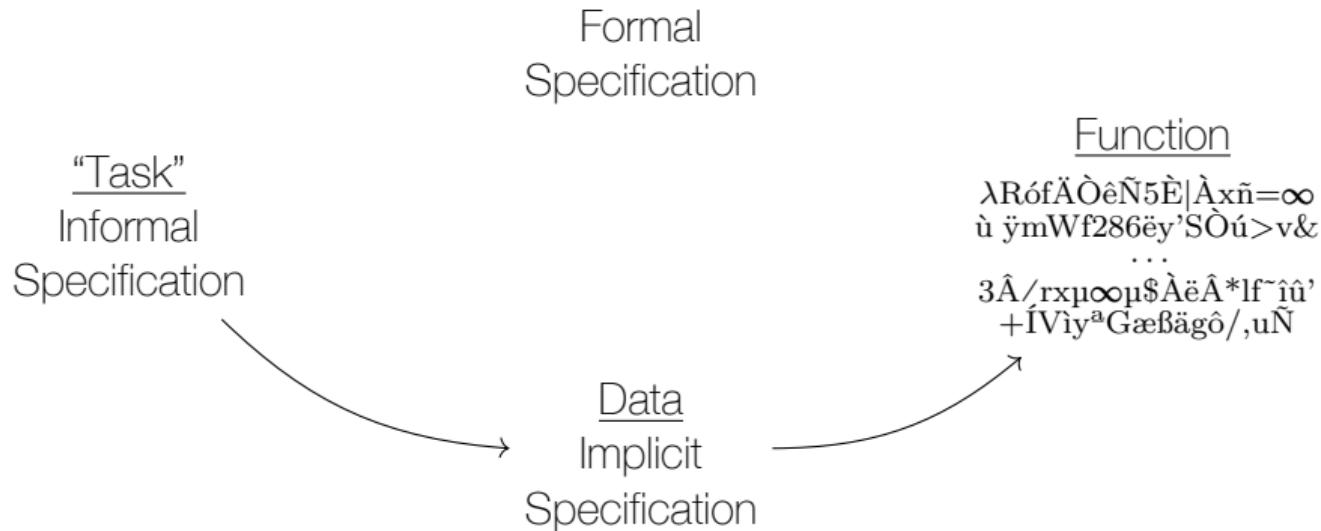
# Making it Explicit



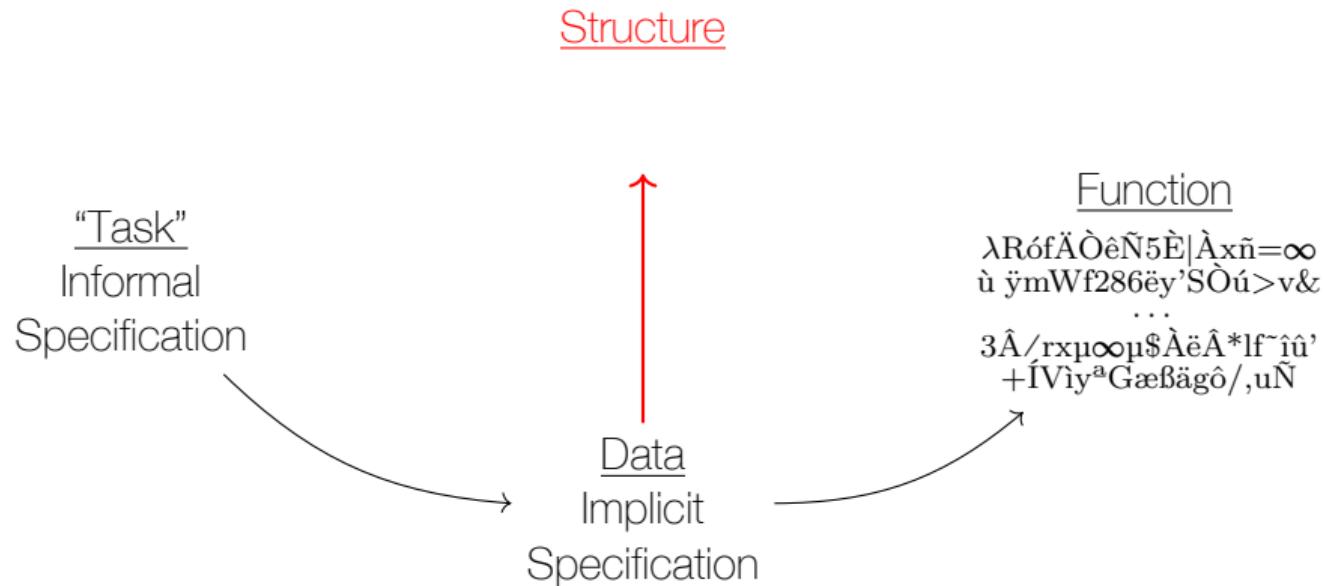
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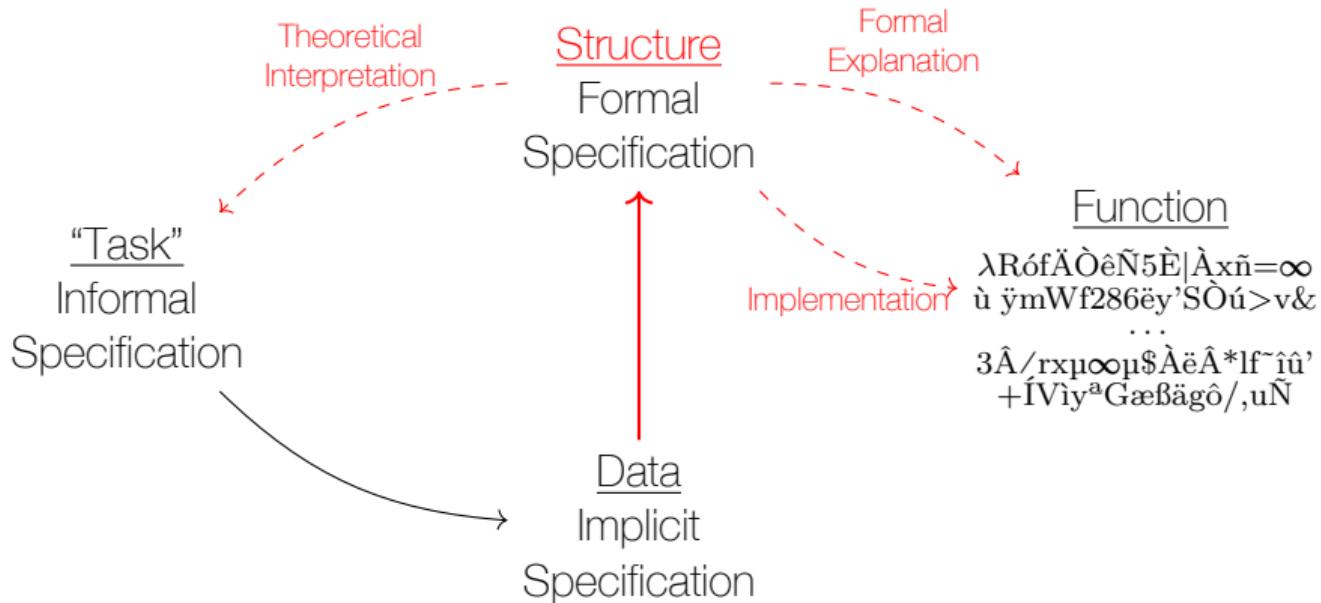
# Making it Explicit



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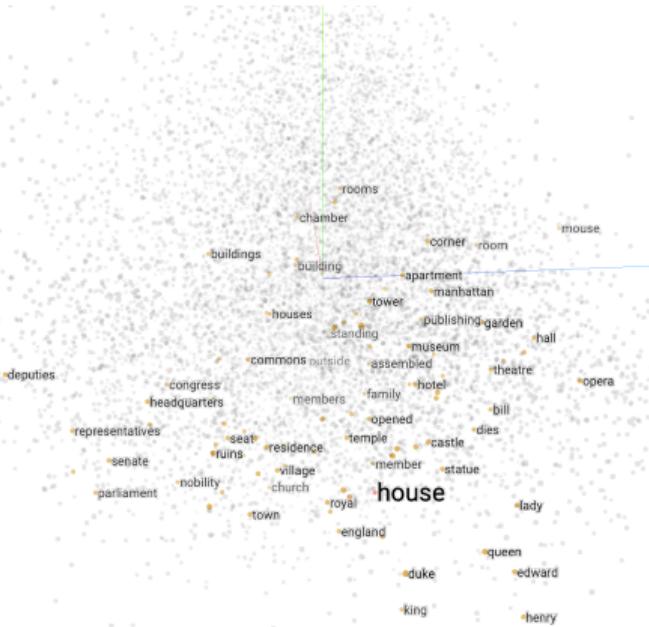
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# Distributionalism and Word Embeddings

- ◊ Distributional Hypothesis  
(Harris, 1960; Saussure, 1959)
    - “You shall know a word by the company it keeps!” (Firth, 1935)
    - The content of a linguistic unit is determined by its **distribution** over a corpus (i.e., the other units appearing in its context)
  - ◊ Computational version:  
**Word Embeddings**



(<https://projector.tensorflow.org>)



# Distributional Mathematics

- ◊ How is it possible that a **distributional** approach to (natural) language can account for the **mathematical content** of mathematical expressions?

# Distributional Mathematics

- ◊ How is it possible that a **distributional** approach to (natural) language can account for the **mathematical content** of mathematical expressions?
- ◊ Illustration: **recursive structure** and **total order** of natural numbers (Gastaldi, Forthcoming 2024c).

# Recursion through Peano Axioms

1. 0 is a number.

$$0 \in \mathbb{N}$$

2. If  $n$  is a number, the successor of  $n$  is a number.

$$n \in \mathbb{N} \implies \text{succ}(n) \in \mathbb{N}$$

3. 0 is not the successor of a number.

$$\forall n \in \mathbb{N}, 0 \neq \text{succ}(n)$$

4. Two numbers of which the successors are equal are themselves equal.

$$\forall n, m \in \mathbb{N}, \text{succ}(x) = \text{succ}(y) \implies x = y$$

5. If a set  $\mathbf{S}$  of numbers contains 0 and also the successor of every number in  $\mathbf{S}$ , then every number is in  $\mathbf{S}$  (induction axiom).

$$0 \in S \wedge (\forall n, n \in S \implies \text{succ}(s) \in \mathbf{S}) \implies \forall n \in \mathbf{S}, n \in \mathbb{N}$$

# Formal Content

Form ~~vs.~~ and ~~Meaning~~ Content

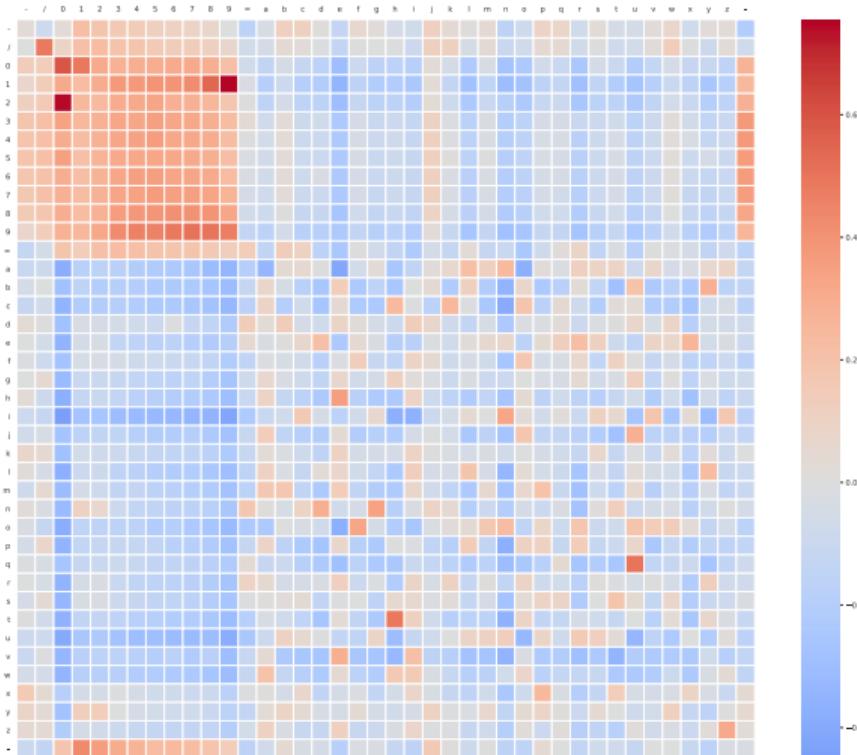
Kant, Hegel, Frege, Saussure, Hjelmslev, etc.

Formal Content: The dimension of content which finds its source in the internal relations holding between the expressions of a language

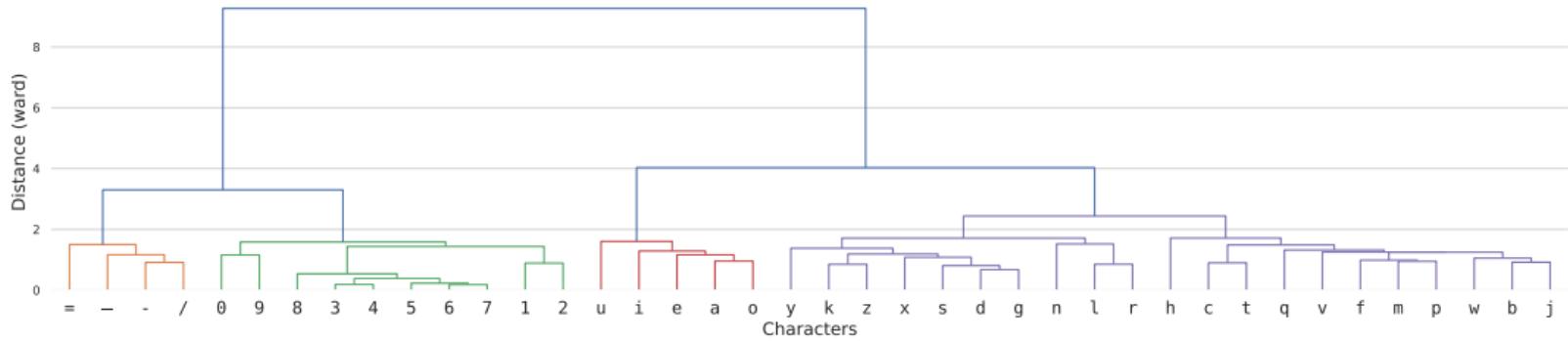
- ◊ Syntactic Content: The content a unit receives as a result of the multiple **dependencies** it can maintain with respect **to other units** in its context
- ◊ Characteristic Content: The content resulting from the **inclusion** of a unit **in a class of other units** by which it accepts to be substituted in given contexts
- ◊ Informational Content: The content related to the **non-uniform distribution of units** within those substitutability classes

# The Distributional Properties of Characters

$$A_{i,j} = pmi(c_i; c_j) = \log \frac{p(c_i, c_j)}{p(c_i)p(c_j)}$$



# Digits Through Characteristic Content



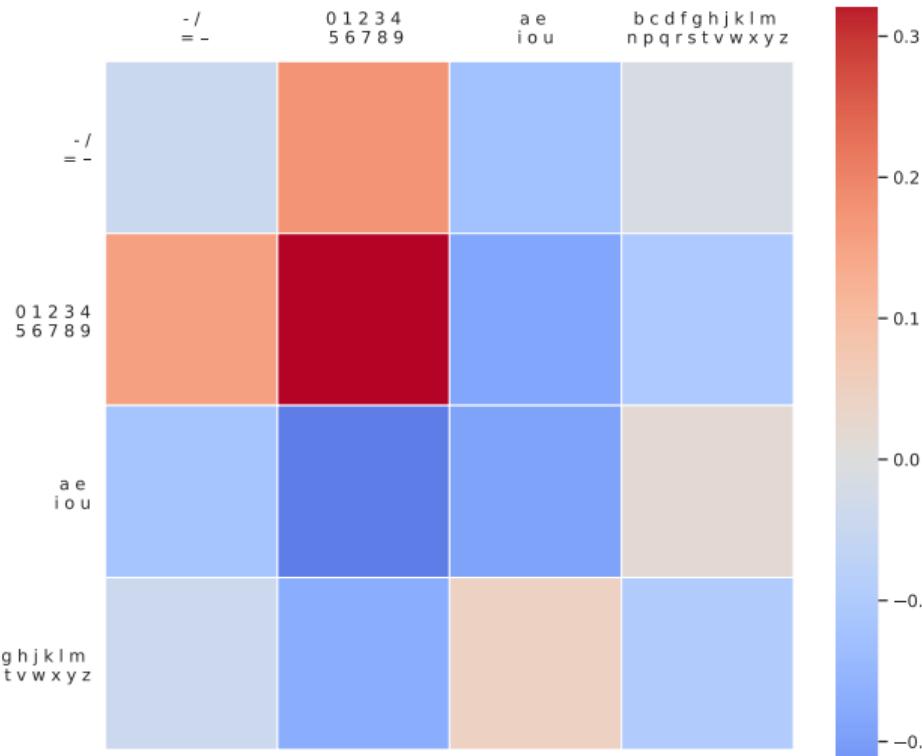
$$O := \{=, -, -, /\}$$

$$D := \{0, 9, 8, 3, 4, 5, 6, 7, 1, 2\}$$

$$V := \{u, i, e, a, o\}$$

$$C := \{y, k, z, x, s, d, g, n, l, r, h, c, t, q, v, f, m, p, w, b, j\}$$

# Recursion Through Syntactic Content



$$f(c_n) = c_{n+1}$$

$$f(D) = D$$

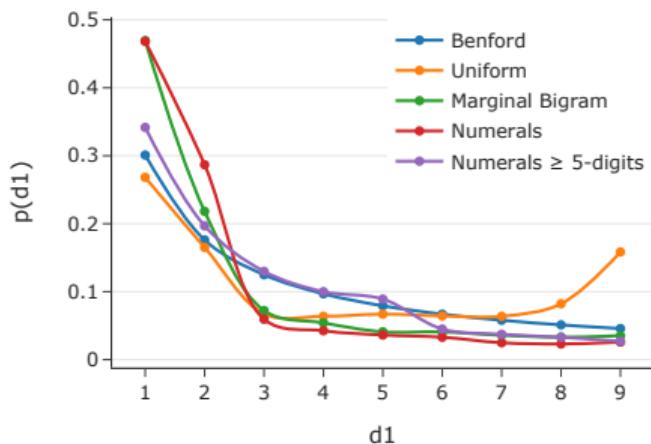
$$f(\textcolor{red}{D} + \mathbf{d}_0) = \textcolor{red}{D} + \mathbf{d}_1$$

$$f = T \circ t$$

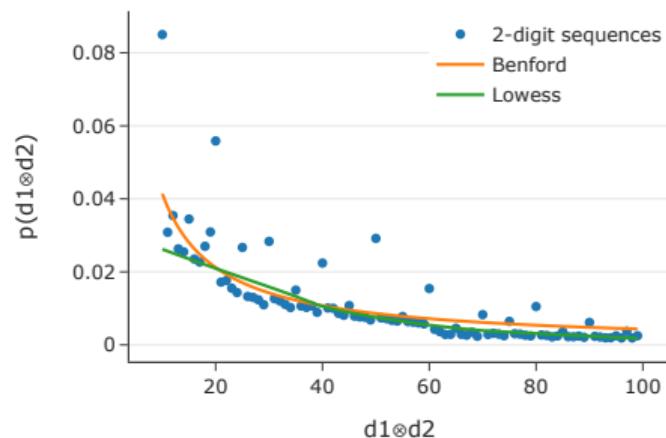
$$T(D) = D$$

# Total Order Through Informational Content

Distribution of digits



Regression over 2-digit sequences



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- ◊ Neural ML applications to mathematics have the power to **reconfigure the modern articulation** between **mathematics, computer science**, and **language**.
- ◊ ML practices grant **Natural language** a critical role in the characterization of **mathematical content**.
- ◊ **Data** assumes a new epistemological status **empirical** linguistic practices and **formal** contents.
- ◊ **Philosophy and history** of mathematics will require a **competence** in **theoretical** and **technical** tools accounting for how **formal content** can originate from **distributional properties of pure expressions**.

# References |

- Alemi, A. A., Chollet, F., Een, N., Irving, G., Szegedy, C., & Urban, J. (2016). Deepmath - deep sequence models for premise selection. *Proceedings of the 30th International Conference on Neural Information Processing Systems*, 2243–2251.
- Bansal, K., Loos, S. M., Rabe, M. N., Szegedy, C., & Wilcox, S. (2019). Holist: An environment for machine learning of higher-order theorem proving (extended version). *CoRR*, abs/1904.03241. <http://arxiv.org/abs/1904.03241>
- Blechschmidt, J., & Ernst, O. G. (2021). Three ways to solve partial differential equations with neural networks — a review. *GAMM-Mitteilungen*, 44(2), e202100006. <https://doi.org/https://doi.org/10.1002/gamm.202100006>
- Bradley, T.-D., Gastaldi, J. L., & Terilla, J. (2024). The structure of meaning in language: Parallel narratives in linear algebra and category theory. *Notices of the American Mathematical Society*.  
<https://api.semanticscholar.org/CorpusID:263613625>
- Brown, T., Mann, B., Ryder, N., Subbiah, M., Kaplan, J. D., Dhariwal, P., Neelakantan, A., Shyam, P., Sastry, G., Askell, A., Agarwal, S., Herbert-Voss, A., Krueger, G., Henighan, T., Child, R., Ramesh, A., Ziegler, D., Wu, J., Winter, C., ... Amodei, D. (2020). Language models are few-shot learners. In H. Larochelle, M. Ranzato, R. Hadsell, M. Balcan, & H. Lin (Eds.), *Advances in neural information processing systems* (pp. 1877–1901, Vol. 33). Curran Associates, Inc. [https://proceedings.neurips.cc/paper\\_files/paper/2020/file/1457c0d6bfcb4967418bfb8ac142f64a-Paper.pdf](https://proceedings.neurips.cc/paper_files/paper/2020/file/1457c0d6bfcb4967418bfb8ac142f64a-Paper.pdf)
- Charton, F. (2021). Linear algebra with transformers. *CoRR*, abs/2112.01898. <https://arxiv.org/abs/2112.01898>
- d'Ascoli, S., Kamienny, P., Lample, G., & Charton, F. (2022). Deep symbolic regression for recurrent sequences. *CoRR*, abs/2201.04600.

## References II

- Davies, A., Veličković, P., Buesing, L., Blackwell, S., Zheng, D., Tomašev, N., Tanburn, R., Battaglia, P., Blundell, C., Juhász, A., Lackenby, M., Williamson, G., Hassabis, D., & Kohli, P. (2021). Advancing mathematics by guiding human intuition with AI. *Nature*, 600(7887), 70–74. <https://doi.org/10.1038/s41586-021-04086-x>
- Firth, J. R. (1935). The technique of semantics. *Transactions of the Philological Society*, 34(1), 36–73.  
<https://doi.org/10.1111/j.1467-968X.1935.tb01254.x>
- Gastaldi, J. L. (2024). How to Do Maths with Words: Neural Machine Learning Applications to Mathematics and Their Philosophical Significance. In B. Sriraman (Ed.), *Handbook of the history and philosophy of mathematical practice* (pp. 3191–3226). Springer International Publishing.  
[https://doi.org/10.1007/978-3-031-40846-5\\_142](https://doi.org/10.1007/978-3-031-40846-5_142)
- Gastaldi, J. L. (Forthcoming 2024c). Content from Expressions. The Place of Textuality in Deep Learning Approaches to Mathematics. *Synthese (under review)*.
- Gastaldi, J. L., & Pellissier, L. (2021). The calculus of language: Explicit representation of emergent linguistic structure through type-theoretical paradigms. *Interdisciplinary Science Reviews*.  
<https://doi.org/10.1080/03080188.2021.1890484>
- Girard, J.-Y. (2011, September). *The blind spot*. European Mathematical Society.
- Harris, Z. (1960). *Structural linguistics*. University of Chicago Press.
- Lample, G., & Charton, F. (2019). Deep learning for symbolic mathematics.

## References III

- Lewkowycz, A., Andreassen, A., Dohan, D., Dyer, E., Michalewski, H., Ramasesh, V., Slone, A., Anil, C., Schlag, I., Gutman-Solo, T., Wu, Y., Neyshabur, B., Gur-Ari, G., & Misra, V. (2022). Solving quantitative reasoning problems with language models. In S. Koyejo, S. Mohamed, A. Agarwal, D. Belgrave, K. Cho, & A. Oh (Eds.), *Advances in neural information processing systems* (pp. 3843–3857, Vol. 35). Curran Associates, Inc. [https://proceedings.neurips.cc/paper\\_files/paper/2022/file/18abbeef8cfe9203fdf9053c9c4fe191-Paper-Conference.pdf](https://proceedings.neurips.cc/paper_files/paper/2022/file/18abbeef8cfe9203fdf9053c9c4fe191-Paper-Conference.pdf)
- Li, Z., Kovachki, N. B., Azizzadenesheli, K., liu, B., Bhattacharya, K., Stuart, A., & Anandkumar, A. (2021). Fourier neural operator for parametric partial differential equations. *International Conference on Learning Representations*. <https://openreview.net/forum?id=c8P9NQVtmnO>
- Peng, S., Yuan, K., Gao, L., & Tang, Z. (2021). Mathbert: A pre-trained model for mathematical formula understanding. *CoRR*, abs/2105.00377. <https://arxiv.org/abs/2105.00377>
- Polu, S., & Sutskever, I. (2020). Generative language modeling for automated theorem proving. *CoRR*, abs/2009.03393. <https://arxiv.org/abs/2009.03393>
- Saussure, F. d. (1959). *Course in general linguistics* [Translated by Wade Baskin]. McGraw-Hill.
- Shen, J. T., Yamashita, M., Prihar, E., Heffernan, N. T., Wu, X., & Lee, D. (2021). Mathbert: A pre-trained language model for general NLP tasks in mathematics education. *CoRR*, abs/2106.07340.
- Wagner, A. Z. (2021). Constructions in combinatorics via neural networks.
- Wu, Y., Jiang, A. Q., Li, W., Rabe, M. N., Staats, C. E., Jamnik, M., & Szegedy, C. (2022). Autoformalization with large language models. In A. H. Oh, A. Agarwal, D. Belgrave, & K. Cho (Eds.), *Advances in neural information processing systems*. <https://openreview.net/forum?id=lUikebj1Bf0>

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