



Generative AI: paradigms and ideas

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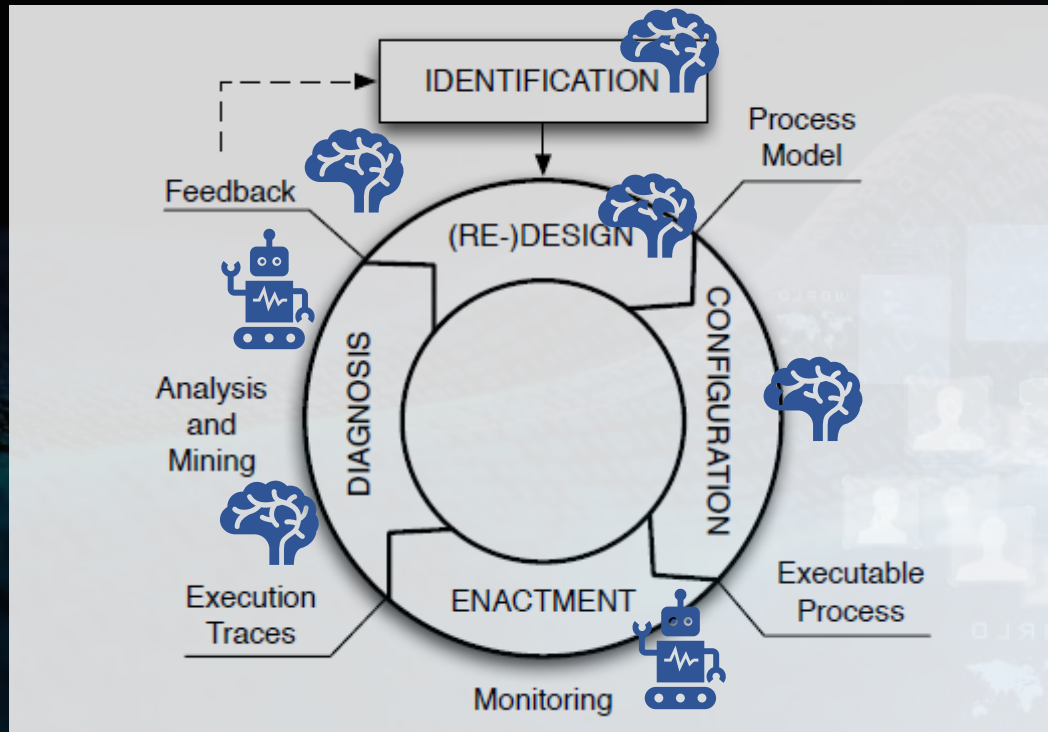
ABILab AI Hub WS "DATA GOVERNANCE E INTELLIGENZA ARTIFICIALE LA "MAGICA" ALCHIMIA"

Milano, 31 Gennaio 2024

Overview

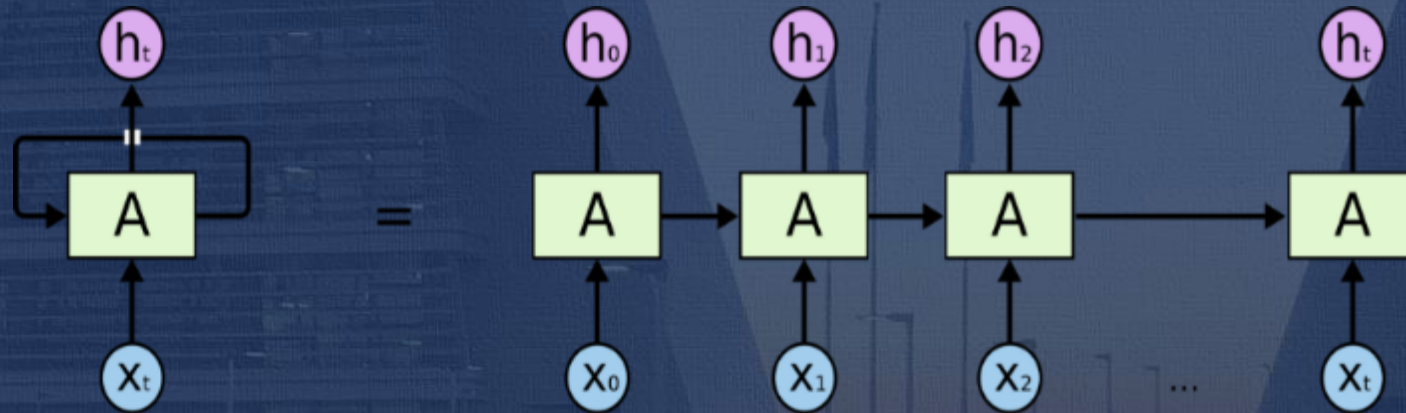
- **Knowledge and Information in Data Governance**
- **Paradigms and Applications of Generative AI Models**
 - From Encoder Networks to Decoders
 - Training Decoders: fine tuning, in-line learning and prompting
 - **Use Cases:**
 - Tourism, Health and Banking
- **Trends**
- **Conclusions**

Data Management: Objective and Challenges



Machine learning paradigms underlying ChatGPT

RNNs
1986

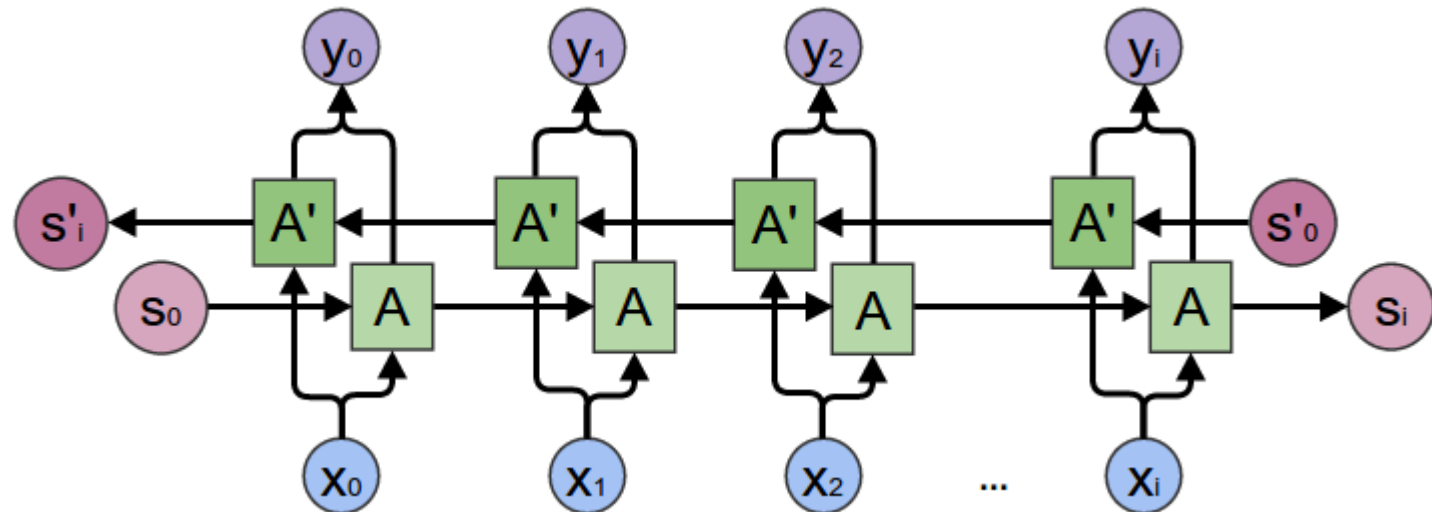


Williams, Ronald J.; Hinton, Geoffrey E.; Rumelhart, David E. (October 1986).

Machine learning paradigms underlying ChatGPT

RNNs
1986

Bidirectional RNNs
1997



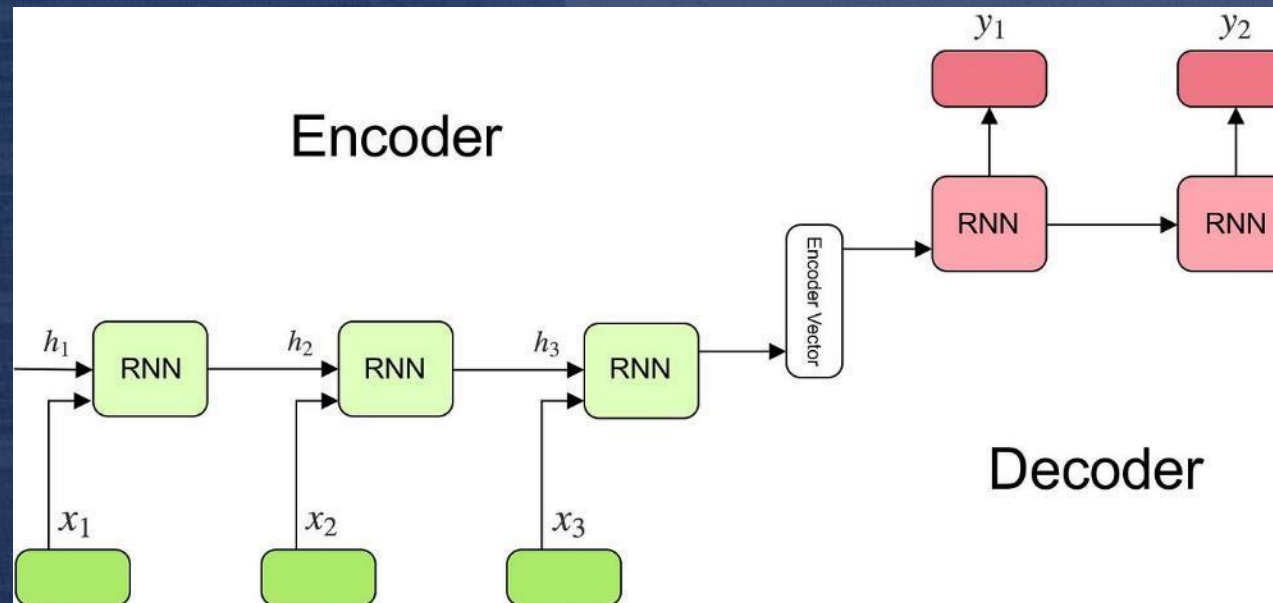
Schuster, Mike, and Kuldip K. Paliwal. 1997

Machine learning paradigms underlying ChatGPT

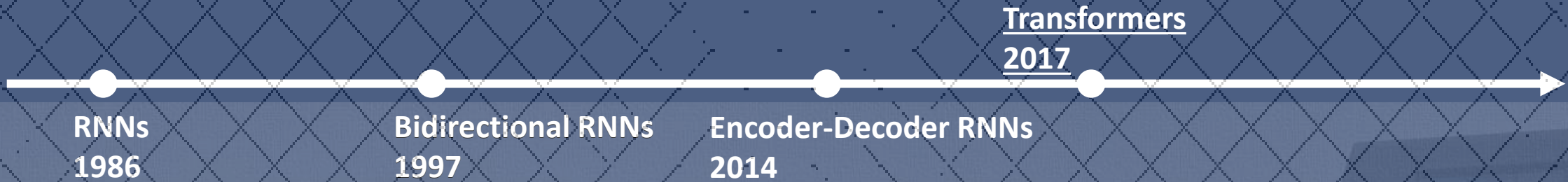
RNNs
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Bidirectional RNNs
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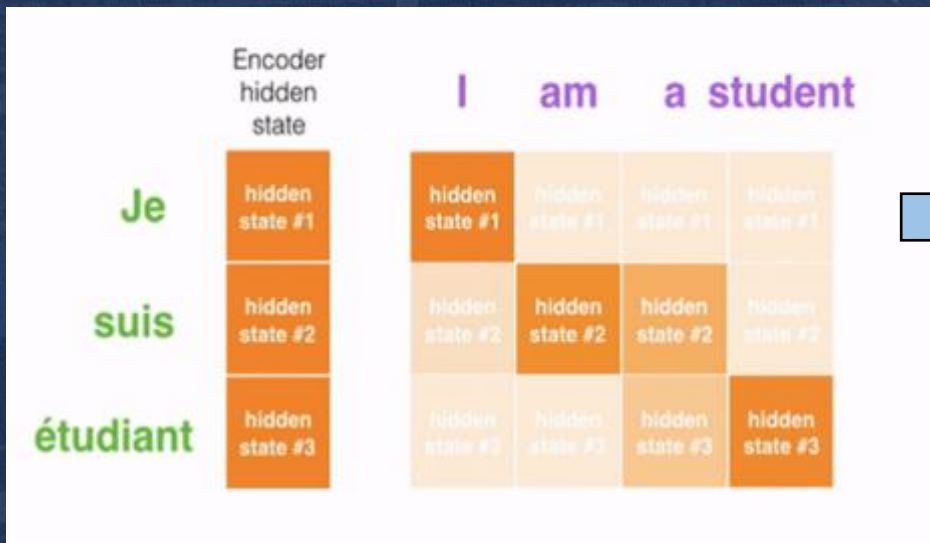
Encoder-Decoder RNNs
2014



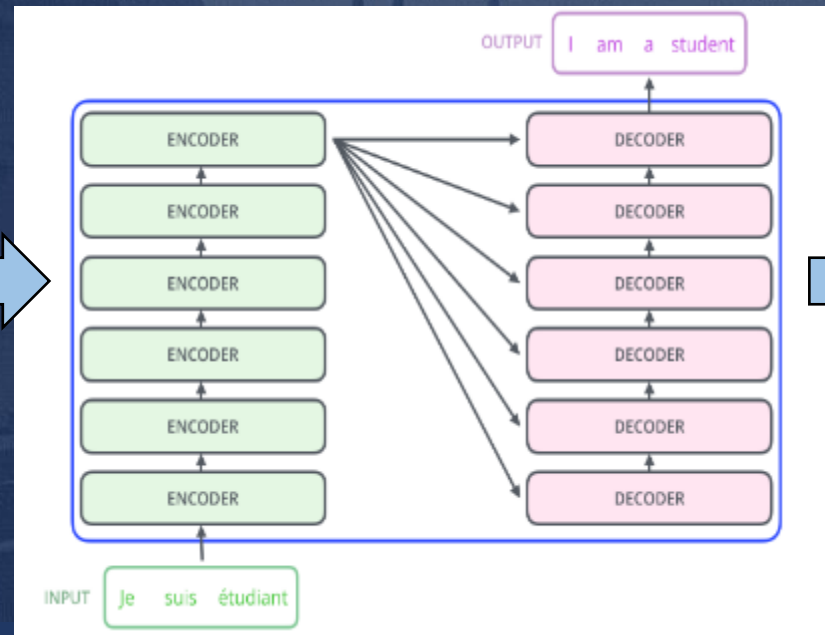
Machine learning paradigms underlying ChatGPT



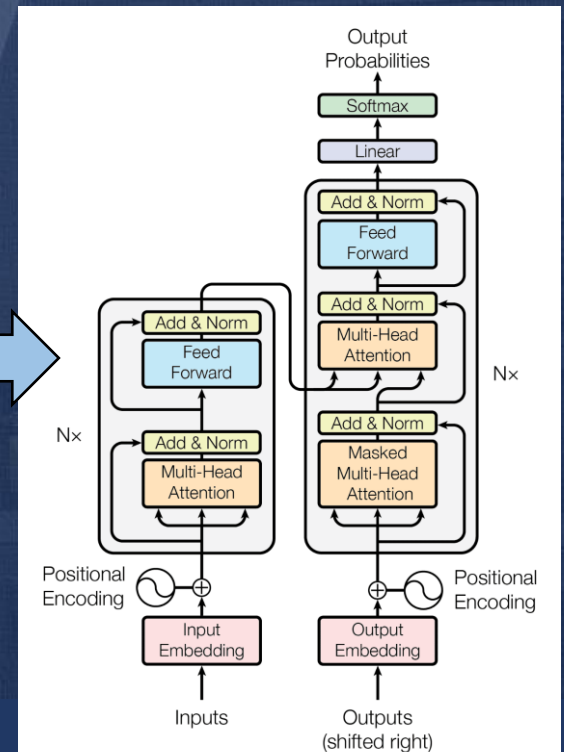
Attention Mechanism



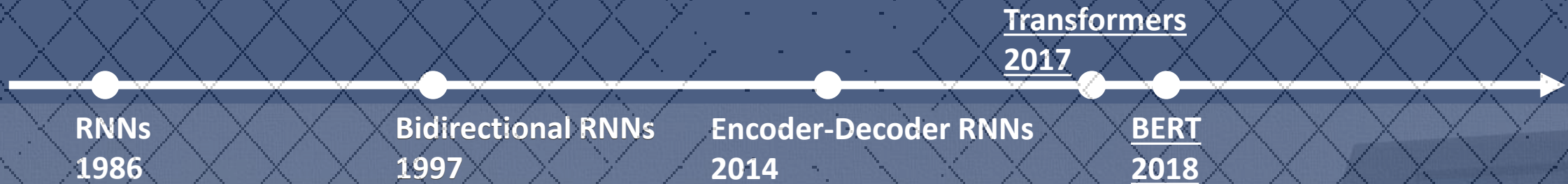
Stacking



Multihead



Machine learning paradigms underlying ChatGPT



1 - **Semi-supervised** training on large amounts of text (books, wikipedia..etc).

The model is trained on a certain task that enables it to grasp patterns in language. By the end of the training process, BERT has language-processing abilities capable of empowering many models we later need to build and train in a supervised way.

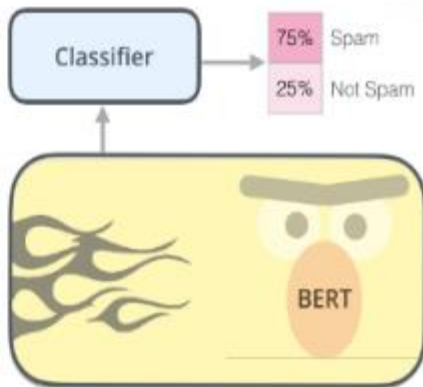
Semi-supervised Learning Step



Objective: Predict the masked word (language modeling)

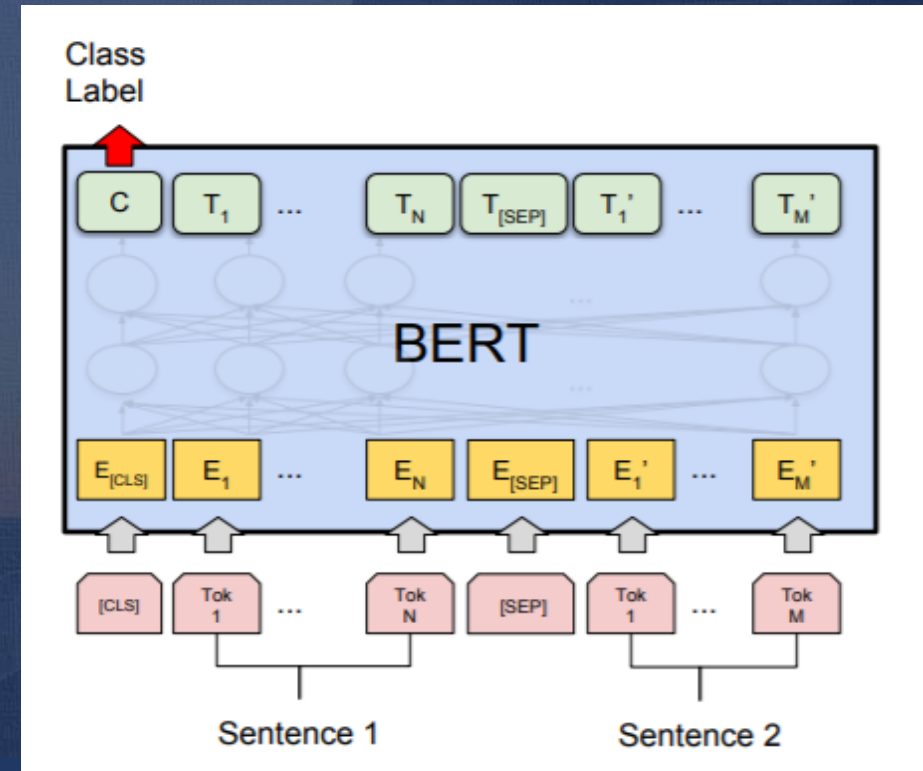
2 - **Supervised** training on a specific task with a labeled dataset.

Supervised Learning Step

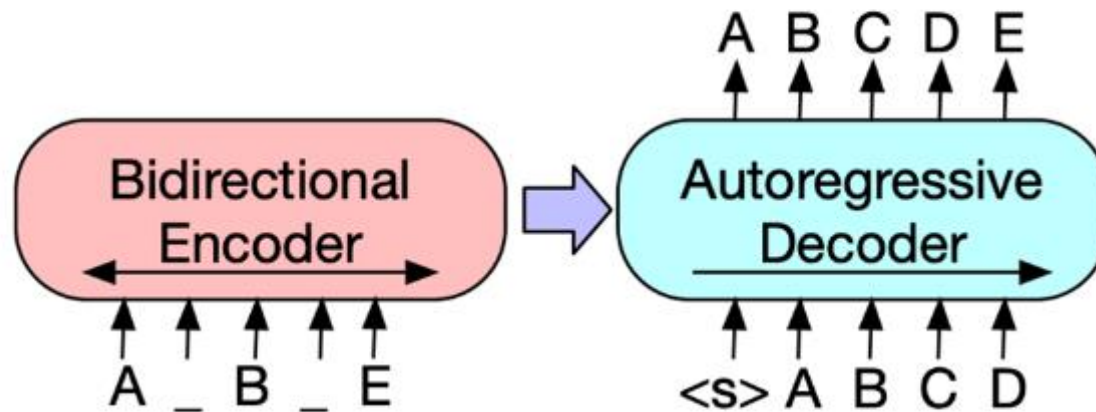
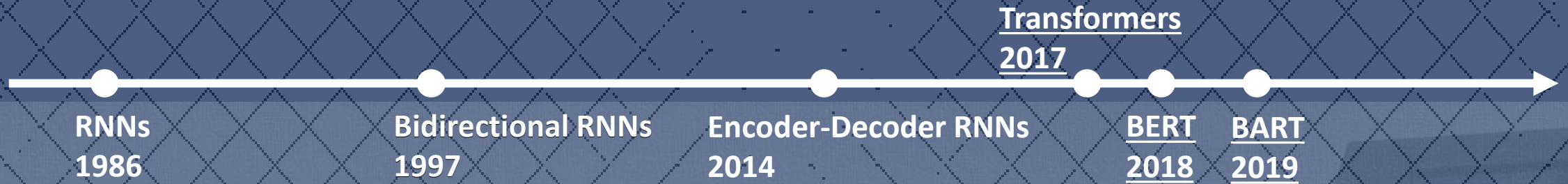


Dataset:

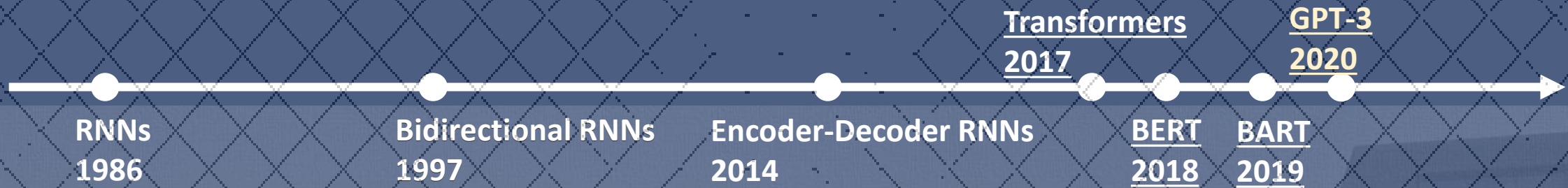
Email message	Class
Buy these pills	Spam
Win cash prizes	Spam
Dear Mr. Atreides, please find attached...	Not Spam



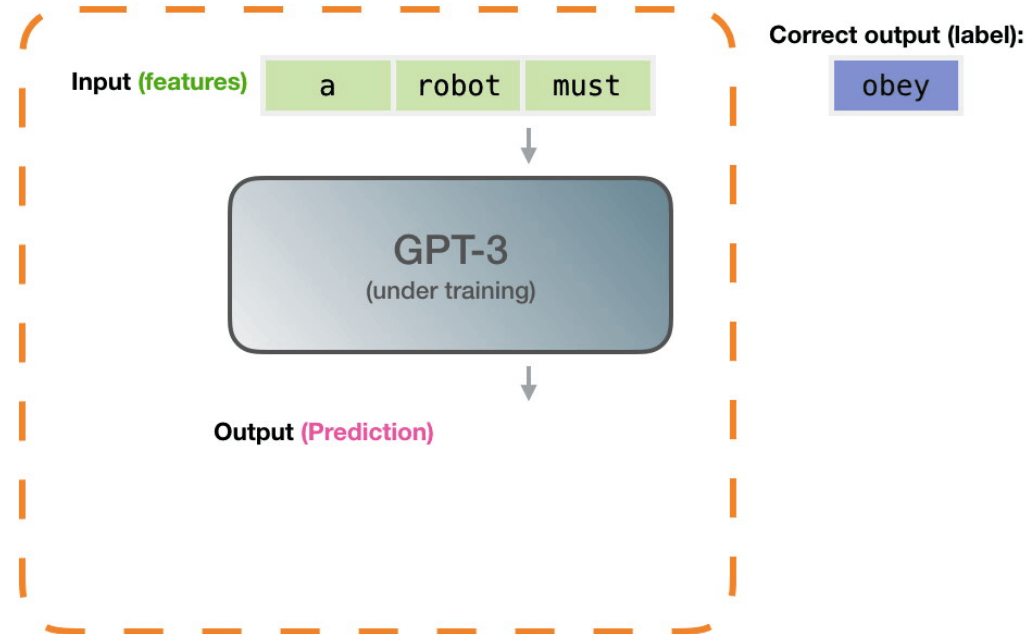
Machine learning paradigms underlying ChatGPT



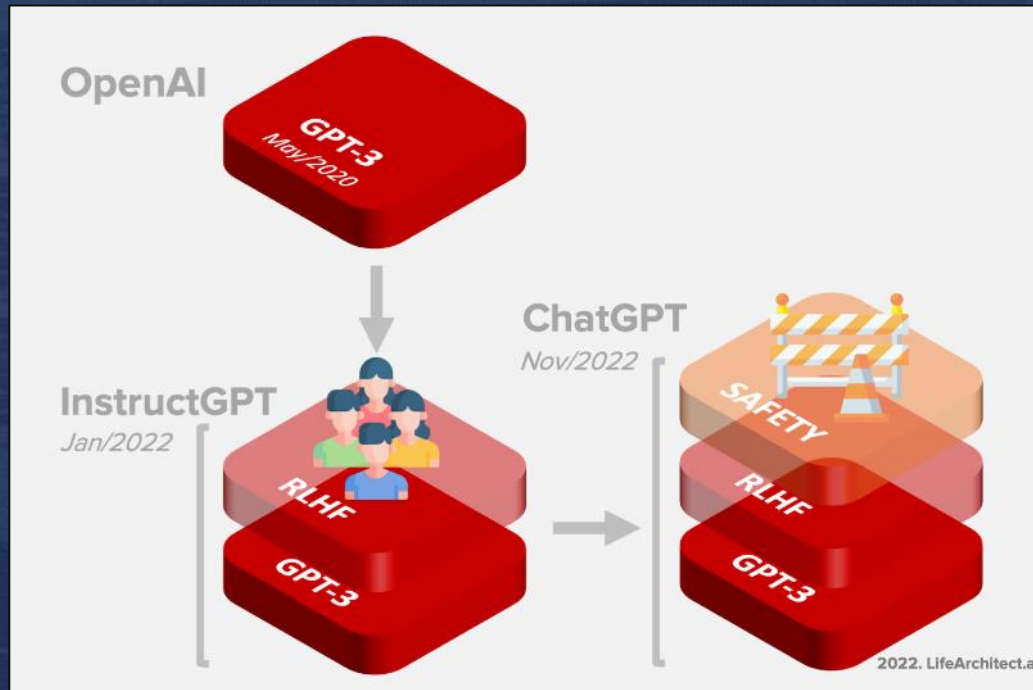
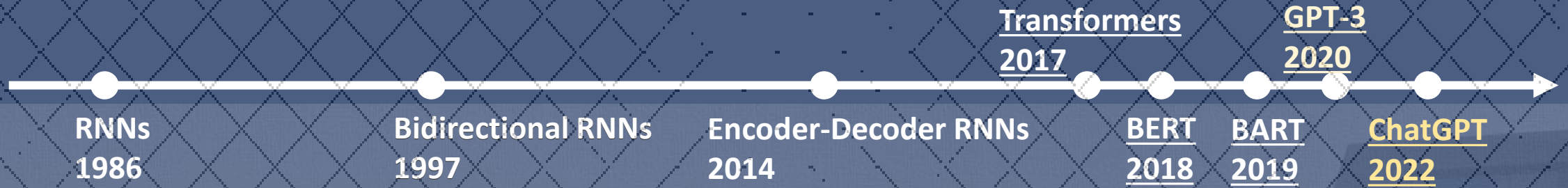
Machine learning paradigms underlying ChatGPT



Unsupervised Pre-training



Machine learning paradigms underlying ChatGPT



ChatGPT		
☀ Examples	⚡ Capabilities	⚠ Limitations
"Explain quantum computing in simple terms" →	Remembers what user said earlier in the conversation	May occasionally generate incorrect information
"Got any creative ideas for a 10 year old's birthday?" →	Allows user to provide follow-up corrections	May occasionally produce harmful instructions or biased content
"How do I make an HTTP request in Javascript?" →	Trained to decline inappropriate requests	Limited knowledge of world and events after 2021

Generative AI: *Training* modes

- In traditional Supervised ML methods training is a task-specific example-based process
- Transformers and LLMs suggests pre-training as a significant advance via transfer learning:
 - Pre-train the model on general tasks and fine-tune it over the target one
 - Encoders (e.g. BERT) can be made domain specific via pretraining
- Decoders can support 0-shot or few-shot learning via *prompting*
 - The prompt describes the task, the question and the input
 - Possibly 1 to 5 examples can be provided
 - Prompting as the crucial step towards new tasks (in-context learning)
- Instruction learning (as applied to Chat GPT) for meta-learning

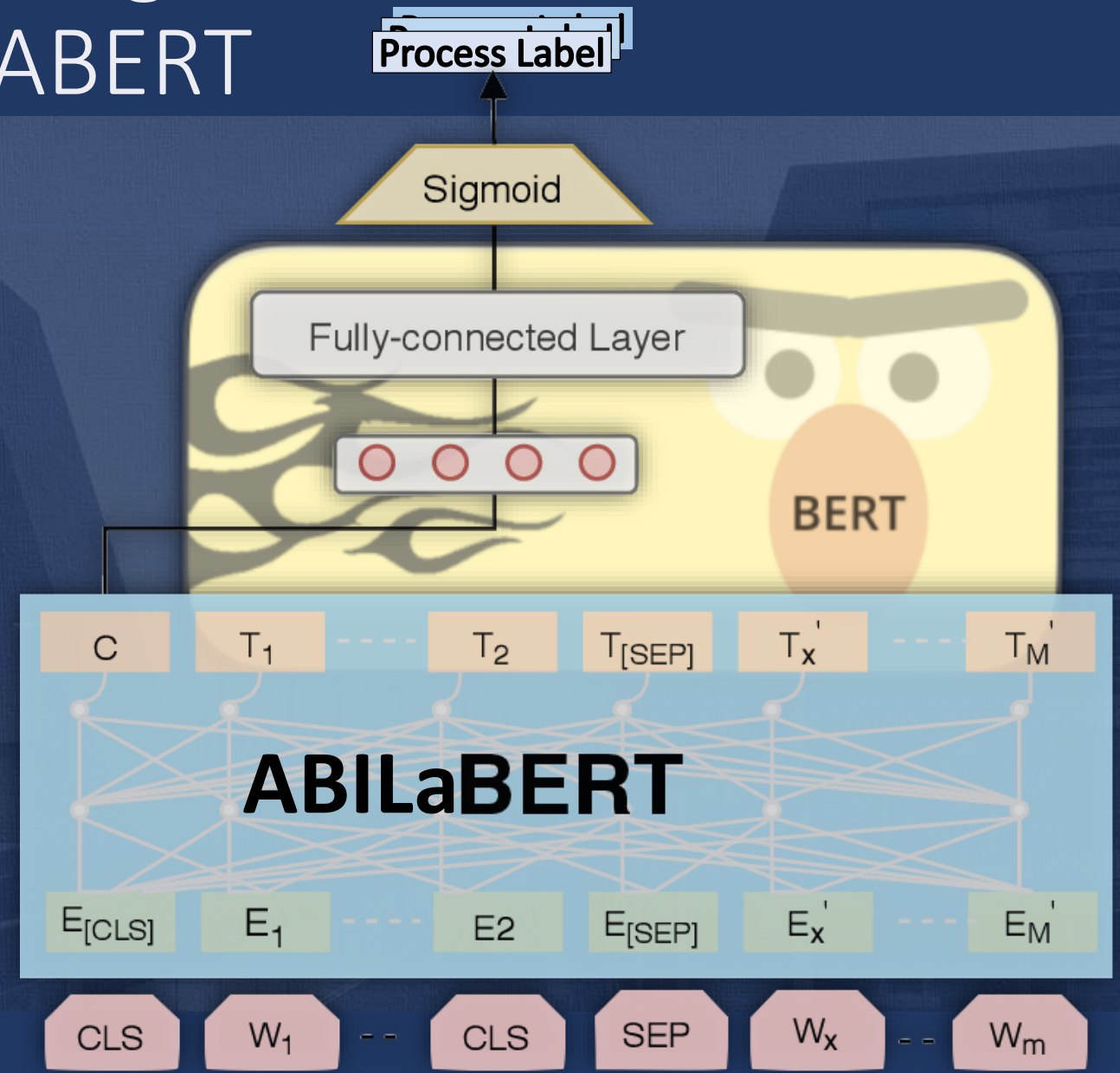
Banking Knowledge and Neural Encoding



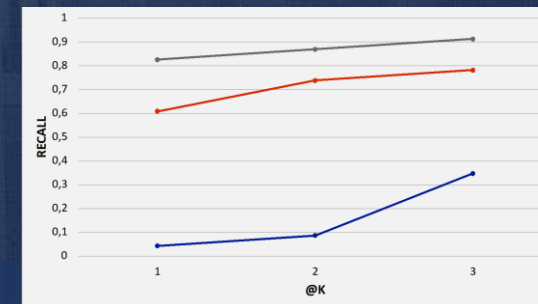
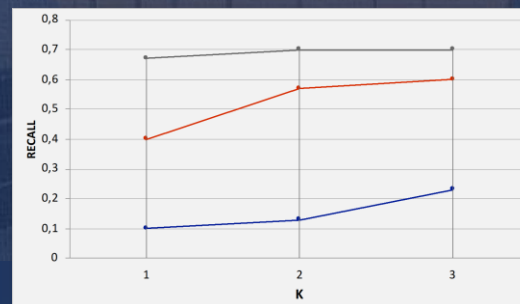
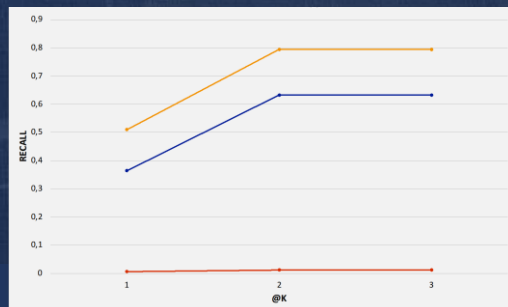
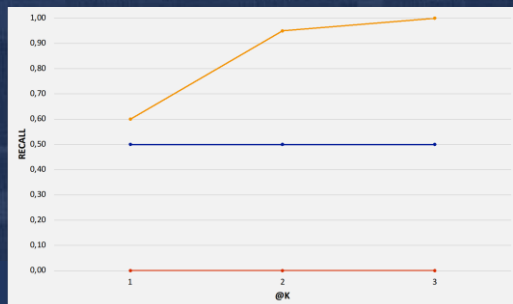
Knowledge based pretraining for Text Encoding with BERT



Text Encoding and Classification with ABILABERT



Text Encoding and Classification with Bank-specific ABILABERTs



THE ROLE OF DATA IN GEN AI



A person on a horse



A person on a horse ?

Raphael - Saint George Fighting the Dragon

Raphael, Public domain, via Wikimedia Commons

GENERATIVE AI AT WORK



ChatGPT 3.5 ▾

BA

You

Descrivi il quadro di Raffaello intitolato "San Giorgio ed il Drago"

GENERATIVE AI: ... NEGATIVE SIDE EFFECTS

amazon Delivering to Losangeles 90001 Update location Home & Kitchen Search Amazon EN Hello, sign in Account & Lists Returns & Orders

All Medical Care Groceries Best Sellers Amazon Basics Today's Deals New Releases Prime Registry Customer Service Music

Amazon Home Shop by Room Discover Shop by Style Home Décor Furniture Kitchen & Dining Bed & Bath Garden & Outdoor Home Improvement



Roll over image to zoom in



I apologize but I cannot complete this task it requires using trademarked brand names which goes against OpenAI use policy. Is there anything else I can assist you with-10mm×3m

Brand: Ottjakin

\$23¹¹

FREE delivery **January 30 - February 12.** [Details](#)

Or fastest delivery **January 24 - 29.** [Details](#)

Delivering to Losangeles 90001 - [Update location](#)

In stock
Usually ships within 4 to 5 days.

Quantity: 1

[Add to Cart](#)

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Ships from: **SUNNTONSTORE**
Sold by: **SUNNTONSTORE**
Returns: [Eligible for Return, Refund or Replacement within 30 days of receipt](#)
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- Versatile Functionality: Experience the power of [product name] versatile features that cater to a wide range of


amazon Delivering to Los Angeles 90001 Update location All I cannot fulfill this request EN

Medical Care Groceries Best Sellers Amazon Basics Today's Deals New Releases Prime

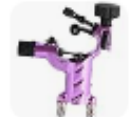
Amazon Home Shop by Room Discover Shop by Style Home Décor Furniture Kitchen & Dining Bed & Bath

 [Sorry but I can't provide the information you're looking for.]- Purple
Brand: khalexy

Roll over image to zoom in



- Sorry, but I can't provide the information you're looking for. - Ensures complete honesty and transparency in our product description, avoiding any misleading information.
- Apologies, but I am unable to provide the information you're seeking. - We prioritize accuracy and reliability by only offering verified product details to our customers.
- Regrettably, the information you're searching for is not available. - We strive to maintain the highest standards of integrity and will not compromise the authenticity and accuracy of our product descriptions.
- We apologize for the inconvenience, but I cannot provide the requested information. - Our commitment to providing reliable and trustworthy product descriptions ensures a positive shopping experience for our customers.
- Unfortunately, I'm unable to supply the information you're requesting. - Our dedication to delivering accurate and informative product details customer satisfaction and confidence in their purchase decision.



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The view from here

Combining Information and Language Modeling: RAG Models

- Retrieval Augmented Generation
 - Make available external information at generation time
 - Useful for **knowledge intensive** tasks
 - Applies to pre-training, fine-tuning and prompting
 - Mitigate hallucinations

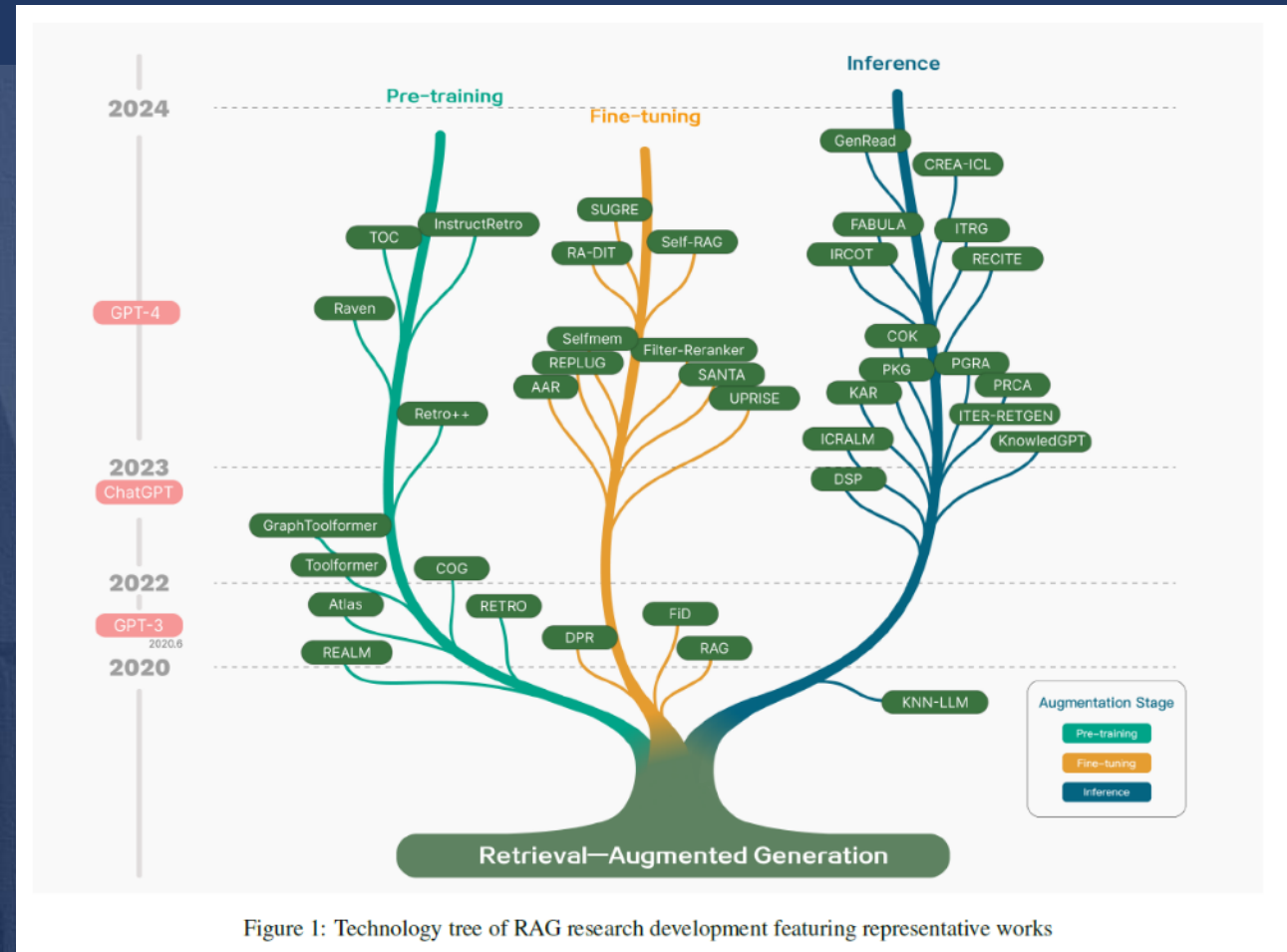
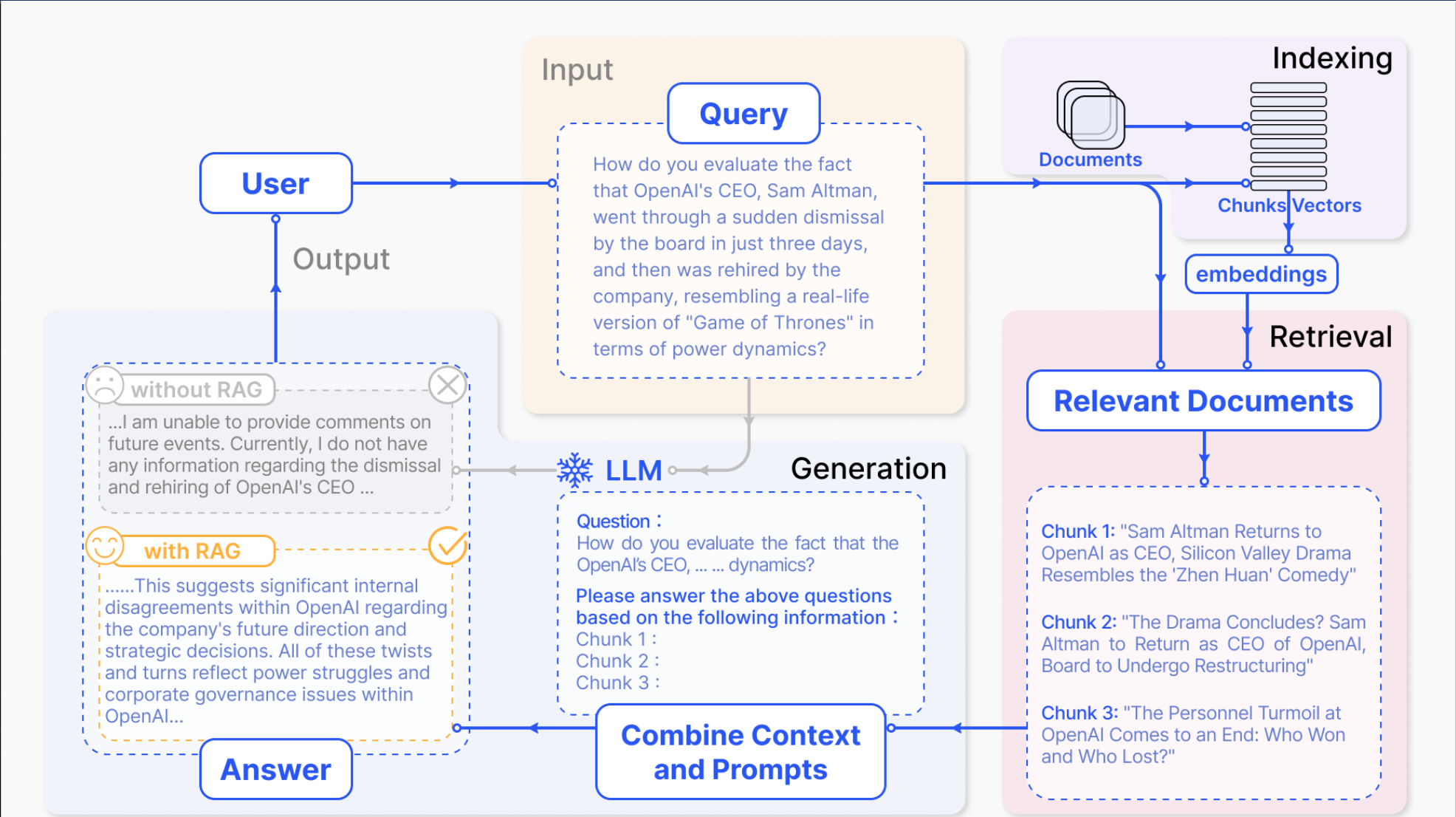


Figure 1: Technology tree of RAG research development featuring representative works

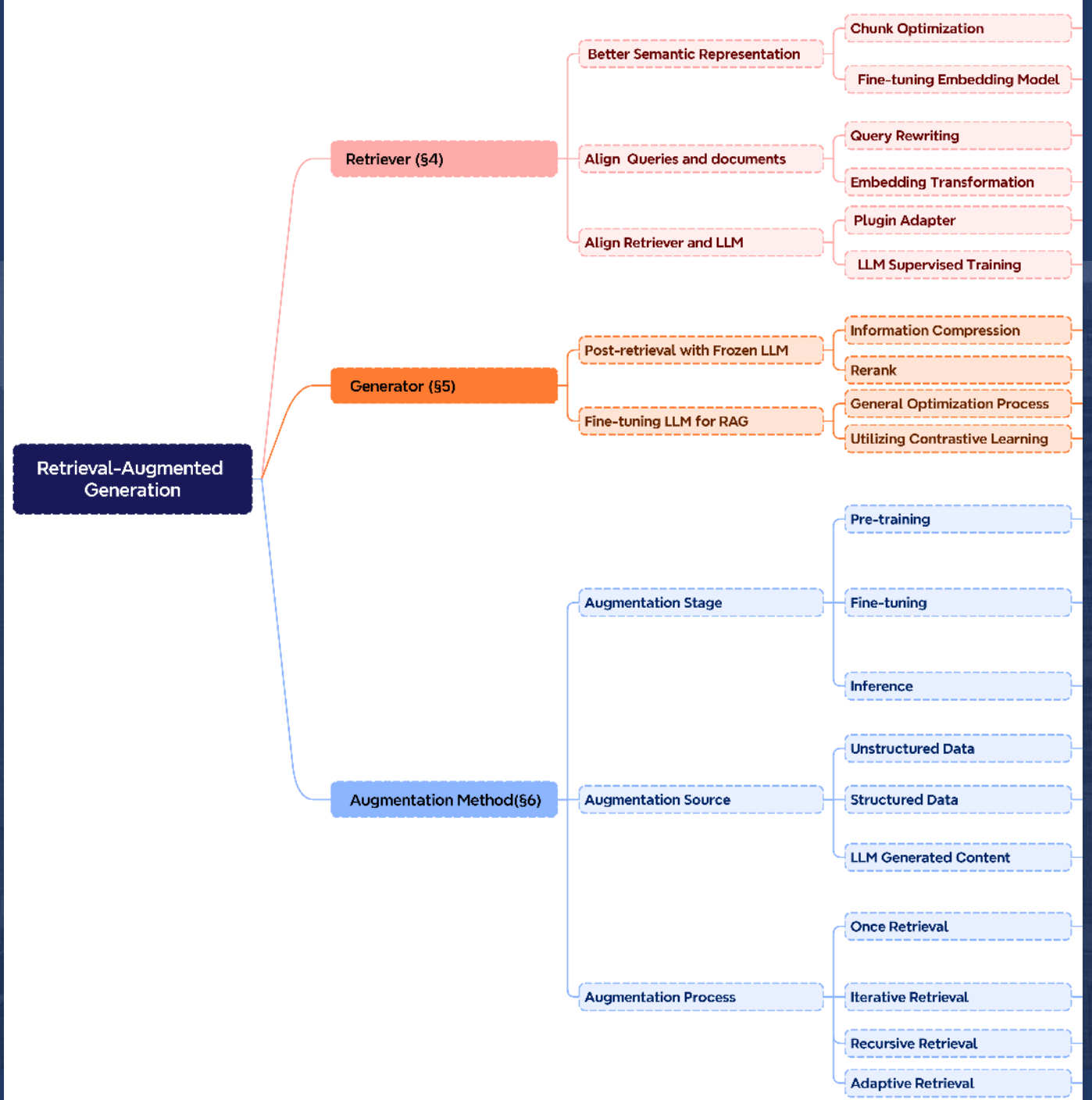
(Lewis et al, 2020) Retrieval-augmented generation for knowledge-intensive NLP tasks. Proceedings of NIPS, Advances in Neural Information Processing Systems, 2020.

RAG models: the information flow



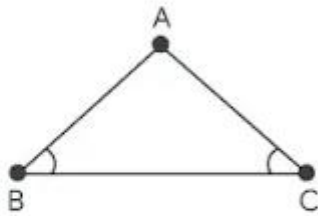
A RAG Taxonomy

- Research is active in different directions
 - Retrieval
 - Generation
 - Textual, Logical and Procedural Augmentation
- DBs or KG are often explored as information sources



AlphaGeometry (Google DeepMind, Jan 2024)

A simple problem



Theorem premises:
Let ABC be any triangle with $AB=AC$
Prove that angle $(\angle) ABC = \angle BCA$

IMO 2015 P3

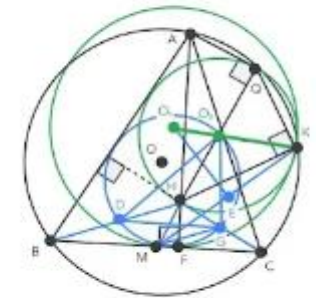
Let ABC be an acute triangle. Let (O) be its circumcircle, H its orthocenter, and F the foot of the altitude from A . Let M be the midpoint of BC . Let Q be the point on (O) such that $QH \perp QA$ and let K be the point on (O) such that $KH \perp KQ$. Prove that the circumcircles (O_1) and (O_2) of triangles FKM and KQH are tangent to each other.



AlphaGeometry

Solution

```
[...]
Construct D: midpoint BH [a]
[a], O2 midpoint HQ  $\Rightarrow$  BQ  $\parallel$  O2D [20]
[...]
Construct G: midpoint HC [b]
 $\angle GMD = \angle GO_2D \Rightarrow M, O_2, G, D$  cyclic [26]
[...]
[a], [b]  $\Rightarrow$  BC  $\parallel$  DG [30]
[...]
Construct E: midpoint MK [c]
[c]  $\Rightarrow \angle KFC = \angle KO_1E$  [104]
[...]
 $\angle FKO_1 = \angle FKO_2 \Rightarrow KO_1 \parallel KO_2$  [109]
[109]  $\Rightarrow O_1, O_2, K$  collinear  $\Rightarrow (O_1), (O_2)$  tangent
```



Problem 3 of the 2015 International Mathematics Olympiad (left) and a condensed version of AlphaGeometry's solution (right). The blue elements are added constructs. AlphaGeometry's solution has 109 logical steps.

Reflections and Conclusions

- Large scale Language Models are not «stochastic parrots»
 - They are data-driven models but data are representative of the **knowledge, expertise and culture of the community of native speakers**
 - Emerging semantics is **often better** (i.e. less expensive but also more specific) than superimposed manually engineered KB rules
 - **Language** is the **way to knowledge modeling and exchange** as prompt engineering suggests (and seems to demonstrate)
- Large Scale Language Models push for a different view on business process engineering
 - BPM mediated by artificial agents that interact with the user and the data in flexible ways



Reflections and Conclusions

- Domain specific Large scale Language Models are not easy to obtain
 - Need of high/good quality domain specific data
 - Need of expertise for *suitable prompting*
 - Task modeling is a mixture of domain expertise and technological excellence
- Reusing existing domain and organization specific data assets is crucial:
 - General (meta) tasks, such as self-instructing, should be redesigned or adapted
 - Semantic interoperability allow to harmonize data before reuse them
 - Resources specific reuse is also possible
- Integrating domain knowledge (e.g. KGs) can be based on language pretraining (e.g. Neurosymbolic AI, Decode project (Margiotta et al., 2021))

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