



# Low Code Neuro-Symbolic Agents

# Trisotech

Prompt Engineering through Process and Decision Orchestration.

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### Caveats

- This presentation is not about creating Large Language Models (LLMs) but rather about using them.
- This presentation is not about the copyright, safety, and ethical use of AI.
- Presented herein are generalised concepts to simplify understanding.
- Everything presented herein can be achieved using the Trisotech Digital Enterprise Suite (DES). Have fun!



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### **Content inspired by**



 Andrew Ng, Yoshua Bengio, Geoffrey Hinton, Gary Marcus, Randy Goebel, David Pool, Alan MacWorth, Tony Seale, James Briggs, Linus Ekenstam, Afaque Umer, Lilian Weng, John Maeda, Mustafa Ispir, Corbus Greyling, Tomer Cohen, Malte Pietsch, Raphaël Mansuy, Kingsley Uyi Idehen, Alex Lenail, Giuseppe Scalamogna, Marcel Pociot, Tomaz Bratanic, Varshita Sher, ...



 OpenAi, AssemblyAI, Pinecone, fiddler, a16z, 451 Research, Gartner, IDC, McKinsey, Nvidia, Microsoft, Google, AWS, Meta, HumanFirst, Deeplearning.AI, AlphaSignal, PromptingGuide.ai, Langchain, Weights&Biases, LearnPrompting, NN-SVG, Petal, Abacus.ai, ...



Tons of research papers on arxiv.org







Natural Intelligence (NI)

Intelligence exhibited by Humans and other Animals.



### Artificial Intelligence (AI)

Intelligence exhibited by Machines.



# The main approaches to Al

### **Symbolic AI:**

#### Inspired by computer science

Symbol processing engine (information processing metaphor).

For symbolists, neurons systematically implement the basic operations that are required for symbol processing.



### **Sub-Symbolic AI:**

Inspired by neurobiology

Artificial Neural Networks of computations. (Took many names over the year: Connectionism, Neural Nets, Machine Learning,...)

For sub-symbolists, nodes, links, activation, weights, emulate neural activity.



# **Prolog to this project**



### Since my Al Grad Studies in the 80s:

- I have been a nay sayer of sub-symbolic and Neural-Networks AI for Decision Automation.
- Sub-symbolic AI has proven good for some tasks but has been poor for decision automation.
- Symbolic AI has proven better for decision automation.



# Symbolic and Sub-Symbolic Al Characteristics

#### **Symbolic Al**



**Sub-Symbolic Al** 

- Better at abstract problems
- More useful for explaining people's thought
- Easier to explain
- Knowledge elicitation needed upfront

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- Not so Big Data
- Easier to debug
- Easier to control

- Better at sensing and perceptual problems
- More useful for connecting to neuroscience
- Easier to scale up
- Less knowledge upfront
- Big Data
- More robust against noise
- Better performance



### **Neuro-Symbolic Al**

#### Symbolic Al



#### **Sub-Symbolic Al**

Field of artificial intelligence that focuses on the integration of neural networks and symbolic architectures in a manner that addresses strengths and weaknesses of each, in a complementary fashion.



### **The ChatGPT Revelation**



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### The Advent of Generative Al



**Took the world by surprise:** 

- Barrier to entry is lower [and thus]
- Time-to-value [seems] shorter



### **My Emotional Curve during this project**





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### Rate of Publications and Technology Evolution



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### **Now Everywhere**



- Business leaders are asking how AI will affect their companies.
- Governments are wondering how it will affect the labor market, what risks it poses, and how to regulate it.
- Companies are trying to figure out how to use it without "giving away" their data to one of the platform vendors.
- **Developers** are experimenting with creative uses of generative AI.



### Should we get ready for: The Future of Al or The Al Future









# Large Language Models (LLMs)

#### Large Language Model



**Foundation Model** 

- LLMs are deep learning models that can generate language outputs = Language Models.
- LLMs have billions of parameters and are trained on billions of words = Large.
- The term Foundation Models generally refers to models that are general purpose models which excel at a wide range of tasks, as opposed to being trained for one specific task.



### GPT-3 has 175 billion parameters and 96 layers. GPT-4 has 1.8 trillion parameters.



Outputs Hidden Hidden Hidden Layer Layer Layers Input Parameters



https://alexlenail.me/NN-SVG/

## Just feed in lots of data...big data

[Big] Data Source [Big] Foundation Model

### The Near Future of Multi-Modal Generation

#### **Foundation Model**





- Text Generation
- Code Generation
- Image Generation
- 3D Generation
- Video Generation



### **Prompt Completion**

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# **Prompt Completion**

#### **Foundation Model**

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#### Completion

Predicting the next token



#### **Completion is Stochastic**

- The completion is randomly determined.
- Sometimes randomness is desirable (Creative Contexts).
- Sometimes it is not (Factual Contexts).



# **Foundation Models Main Settings**

#### **Tokens**

the basic units of text or code.

#### **Temperature**

 the lower the temperature, the more deterministic the results.

#### Top p

- chooses from the smallest possible set of words whose cumulative probability exceeds the probability p.
- The general recommendation is to alter one, not both.

#### **Foundation Model**





### **Foundation Models Main Settings**

**Foundation Model** 

#### Temperature

#### Hallucination







Be mindful that if your foundation model has a high Temperature, it may start Hallucinating.

# **Foundation Models Main Settings**

#### **Token Example**

Tokens are the basic units of text or code used by large language models. An example of a multi-token word is demystifying.

#### **Temperature Example**



# **Prompt Completion Challenges**



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- Hallucination
- Training Window Limitation
- •••
- API Cost
- API Latency
- •••
- Bias
- Ethics
- Copyrights
- •••

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Prompt Injection Attacks



# **Fit for Purpose Models**

#### **Foundation Model**



### **In-Context Learning**

#### **Foundation Model**



### **Prompt Engineering**



Prompt engineering is emerging as a key methodology to leverage large language models to obtain desired outputs by providing explicit instructions or constraints.

By carefully crafting prompts, we can shape language models behavior and align their outputs with our intentions.



# **Prompting Techniques**

To scaffold the foundation model completion to be as desired (creative/factual/logical?):



- Prompt Template
  - Structured Prompt
  - o Role-Based Prompt
- Few Shot Training
- Prompt Pipeline
- Prompt Chaining
- Retrieval Augmented Generation (RAG)
- ReAct

...

- Chain of Thoughts
- Tree of Thoughts
- Graph of Thoughts
- Program Simulation









Then: "it's a simple matter of programming". Now: "it's a simple matter of training".

It was never simple then; it is not simple even now.





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### Difference between Software Engineering and Prompt Engineering



- Implementation
- Coding
- Loose Coupling
- Plan Functionality
- Confirming via Unit Test

Non AIKS

- Complicated
- Predictable



Initial Development

**Debugging & Improvement** 

- Experimentation
- Analyzing
- Chaining Dependencies
- Seek Quality
- Insight via Evaluation
- Complexity
- Unpredictable



### Data Requirements for Creating GenAl Apps

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# The two most common applications of GenAl remains:

### **Building customer service chatbots**

# Answering questions based on documents

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### **Potential markets of GenAl Apps**



**Use Cases** 



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# **Creating GenAl Apps**



### **Neuro-Symbolic Al**

Combining the benefits of Low-Code Model Driven App creation with Generative Al new possibilities.



BPM+ Triple crown of BPMN, DMN and CMMN combined with engineered GenAl prompt components.

### **GenAl Feature Set Exploration**





#### **Neuro-Symbolic Al**

The building blocks of prompt orchestration. A set of features that accelerates the creation of Generative Al applications.



### **GenAl Orchestration**



GenAl Components



Foundation Model



BPM+



**Embeddings** 



Action Connectors



Structured Prompt

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**OpenAPI Connectors** 



**Orchestration** 

Memory Manager









# Sentiment Analysis



## **Reusable GenAl Components**

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- Structured Prompt Generator: Applies prompt engineering best practices.
- **Question Answering:** Generates an answer to a question.
- **Text Summarization:** Generates a shorter version of a text.
- Sentiment Analysis: Detects positive or negative sentiment of a text.
- **Text Translation:** Translate a text into a different language.
- **Text Expansion :** Generates a longer text from an excerpt.
- **Text Generation:** Generates a coherent text according to criteria.
- Image Generation: Generates an image from a text.



# Structured Prompt Completion





# Structured Prompt Completion



### **Reference Source and Business Data**



- One of the big complaints about Generative AI is there is no anchoring to sources.
- Fragments of text are returned but no one can say why or its evidence.
- Retrieval Augmented generation (RAG) is proposed as an improvement.



# **Retrieval Augmented generation (RAG)**



- Tackles the limiting Training Window with Task Specific Data/Documents.
- For each user query or question, contextual chunks of text are retrieved to be added into the prompt context.
- These chunks of text are retrieved based on semantic similarity with the user query or question.



# Retrieval Augmented Generation (RAG)





### Questioning Documents with RAG



# **Chatbots and Agents**

Chatbot



a conversational computer program designed to **simulate conversation** or interaction with human users via natural language.



a system aware of its context which **takes actions** to maximize its chances of success.





### **Chatbot Orchestration**









#### **Neuro-Symbolic Al**

I like the term co-pilot as it implies human control. The benefit of engineered GenAI prompt orchestration is that we can add validation Human Task at any step to ensure desired behavior.

### **Lessons Learned**





- We are very early in exploring GenAl.
  - Things are progressing very rapidly.
- GenAI completion is randomly determined.
  - Sometimes randomness is desirable (Creative Context).
  - Sometimes it is not (Factual Contexts).
- Use GenAl where it is efficient otherwise use something else.
  - LLMs are known for their language capabilities not scientific capabilities.
  - Why use tons of computation resources to solve 1+1.
- GenAl is not the App. It is an Interface. At best a Component of an App.
  - As such it needs to be componentized and orchestrated with other programmable components.



### Conclusions



#### **Neuro-Symbolic Al**

- Should we get ready for "The AI Future" or the "The Future of AI" ?
  - It depends on if we are seeing a "GenAl Revolution" or just a "GenAl Hype Bubble".
- Use GenAl for Technically Fit Use Cases
  - Use GenAl where it is efficient otherwise use something else.
- From someone who learned AI in the 80s:
  - We sure live in interesting times.
  - o I believe Neuro-Symbolic AI time has come.





BPM+



### Any questions?

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# THANKS!

