AI and Deeptech technology transfer basics: How to design and commercialize AI and algorithms

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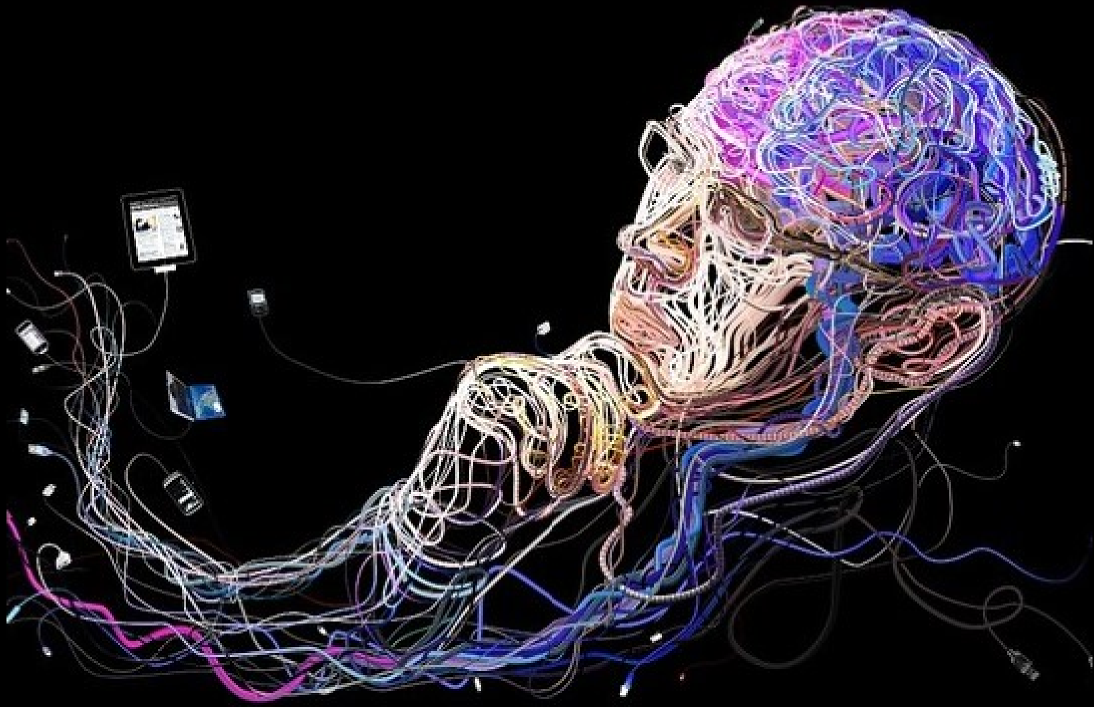
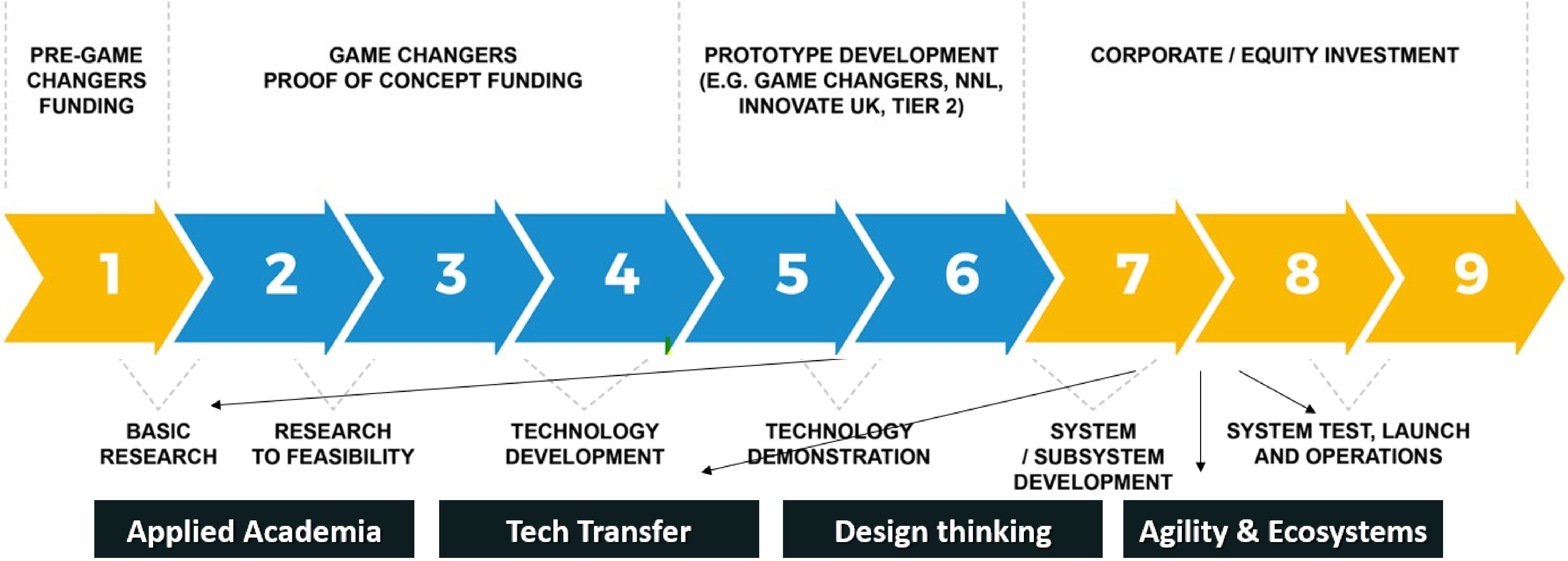


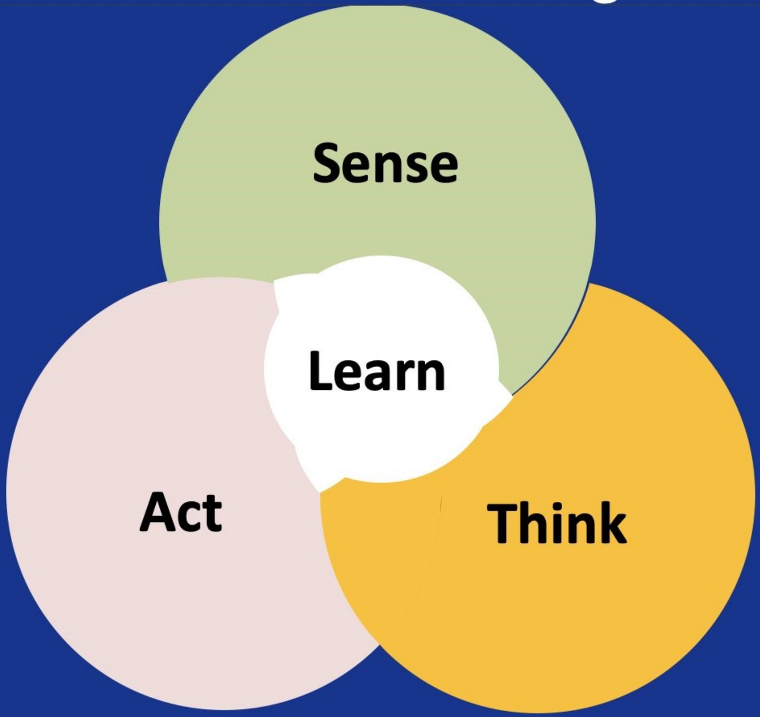
Technology Readiness Level - TRLs



AI and Algorithmic design is a low TRL process at ~ TRL 2->4

AI and Algorithmic <u>design enters the PoC region TRL 5-6 during training & validation</u>

What Is Artificial Intelligence



Artificial Intelligence

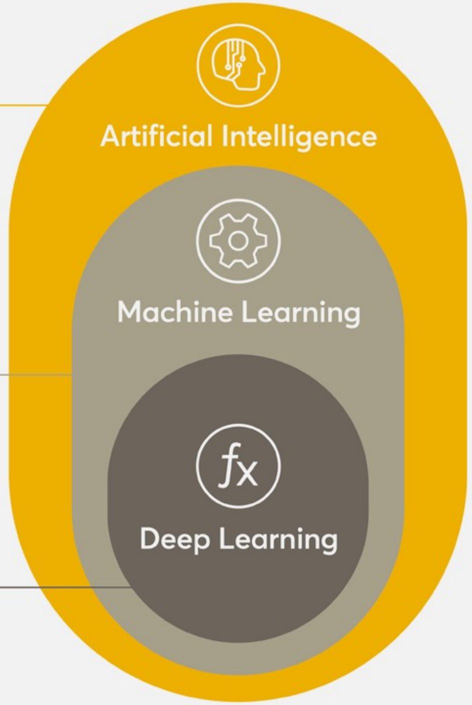
Any technique which enables computers to mimic human behaviour.

Machine Learning

Subset of AI techniques which use statistical methods to enable machines to improve with experiences.

Deep Learning

Subset of ML which makes the computation of multi-layer neural networks feasible.



What are the Drivers of AI?

- More Data is being generated and is easily accessible
- Cheaper and more powerful computing power (on demand cloud computing)
- Advances in algorithms

To have AI we need: Data, Model (??) and Training

Define reasoning and mistakes pretty well !

Proprietary data is everything

// A process to AI commercialization from deep science

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Define a problem in market: Analyze it, Decompose it & describe it using the Functional approach

Identify and map research papers/patents/algorithms or research outputs with market sectors and the above problem areas using: (1) Functional Decomposition, (2) First Principles)

Apply an adapted version of the Cloverleaf Tech Transfer model to evaluate candidate Algos:
1) Market Readiness, 2) Technology Readiness, 3) Commercial Readiness, 4) Management Readiness

Evaluate embedding AI System: Training process, Data availability, Reasoning, Bias analysis, Ethics

Process to AI Factory ops and overall execution strategy (AI Operating model)

[EXTERNAL PERMITTED]

We follow Harvard's best practice AI FACTORY on AI Strategy and AI Ops

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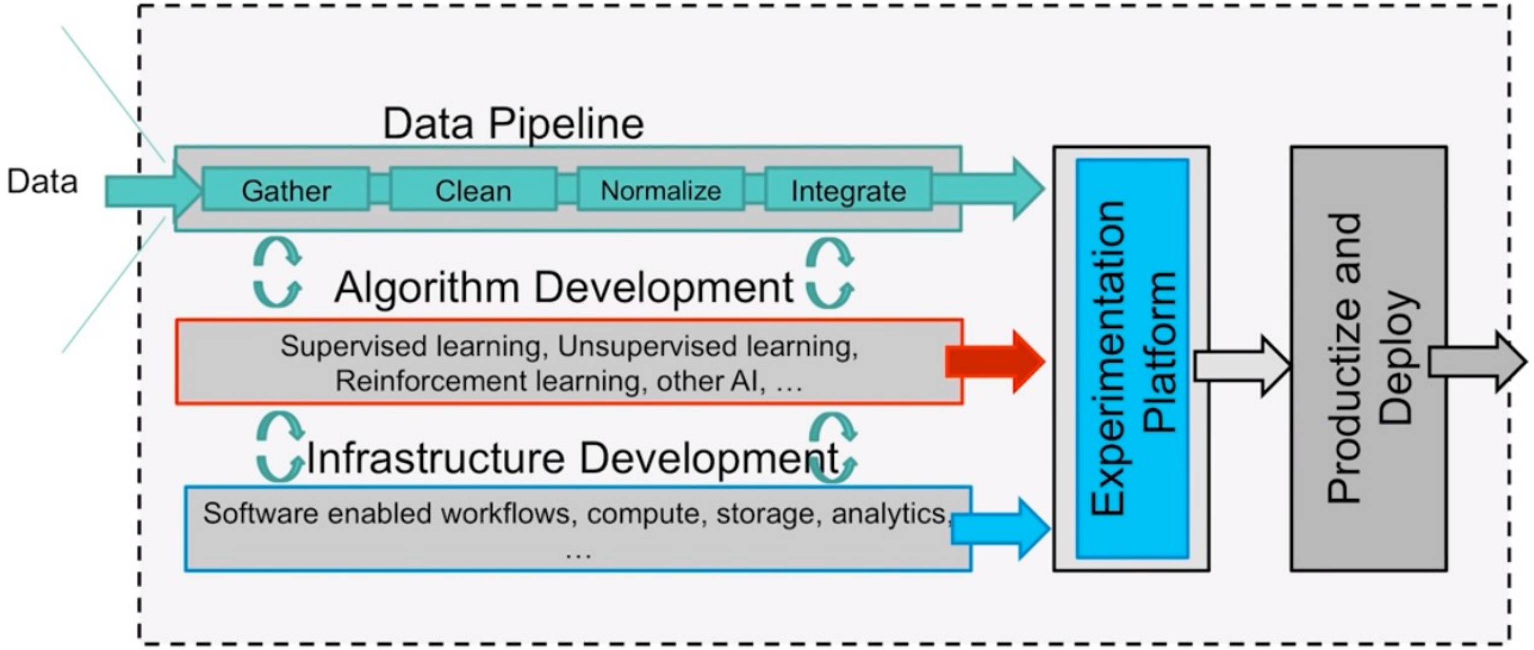
Agile Teams

Data Science & AI Team | Engineering and Development | Cross Scientific Research Team | Digital Team | Innovation Team

AI Factory and Digital Algorithms - Digital - Data Strategy

An AI Factory is at the Core of Modern Enterprises



AI API Marketplace
Agility in AI Algos
Map value with AI Algos
AI monetization
Ethics
Training, Data and Feature Engineering
Exploit new training and go deep in Transformer Tech

Future AI Engineer: a human Unicorn

- Strong Mathematical and Algorithmic background
- Very good coding execution skills (Python)
- “Round-robin” agile execution
- Industrial/Business expertise
- Ability to monetize data and derive Value by various data-set correlations
- Ability to design algorithms that solve problems
- Cross Scientific and Generalist (Jump in between Scientific sectors)
- Understand AI High level Strategy (AI Factory approach)
- Continuously challenge the “equation”: Correlation VS Causation

How do we design and sell an AI system ?

Avokado case study on AI CORTEX

Smart AI Energy Assistants

=

Corporate LLM + Algorithmics + GenAI approach

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Type of B2B Prompts that define the nature of the Energy Assistant:

Descriptive

Predictive

Prescriptive

Ask specific KPIs
Ability to apply descriptive stats
Ability to compute smart KPIs
Ability to correlate and compare
Ability to predict
Ability to reason and explain
Ability to combine all the above in a final “easy to understand” output

Embedding algorithms

Txt and voice inputs - outputs

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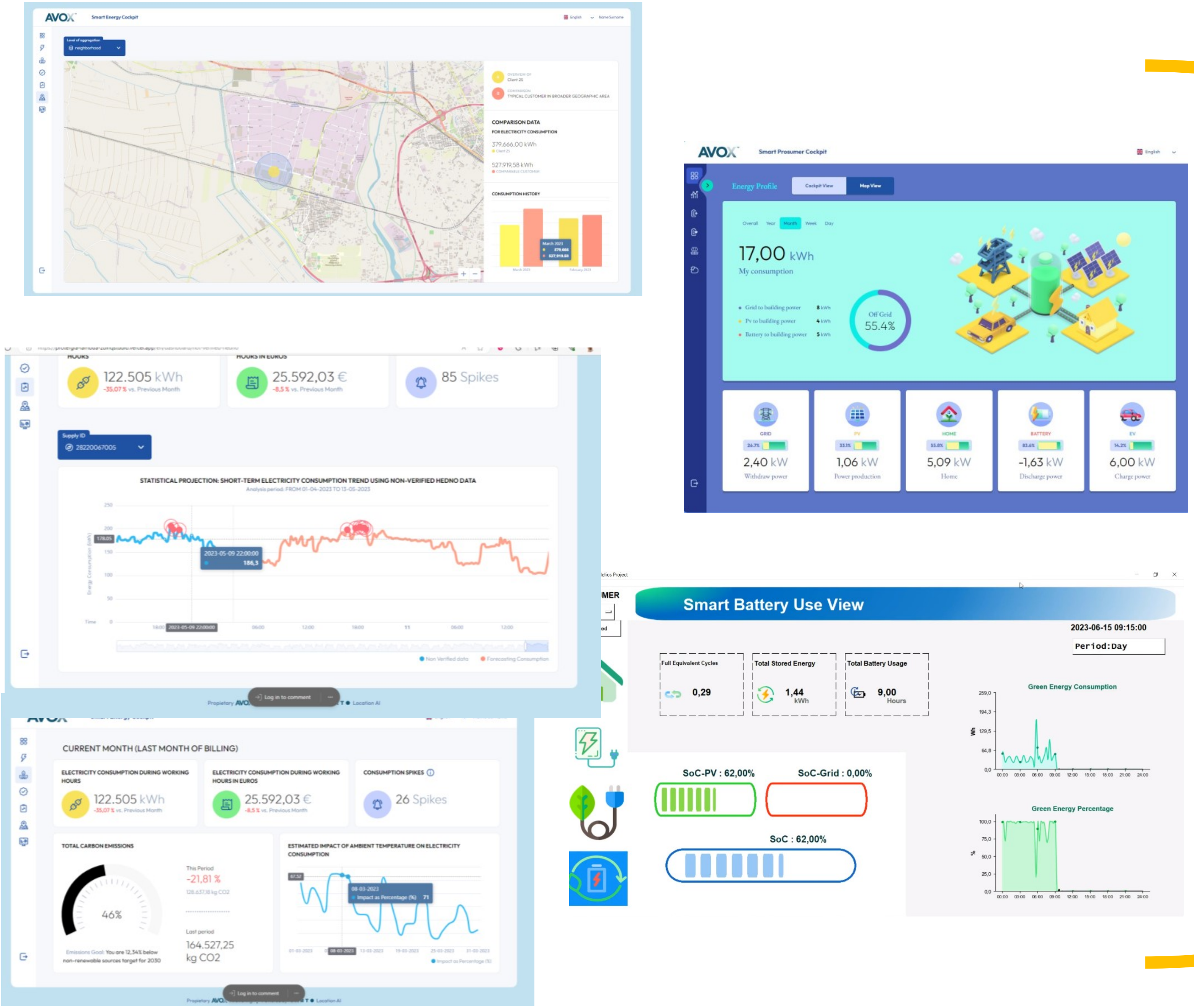

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Smart Energy Assistant

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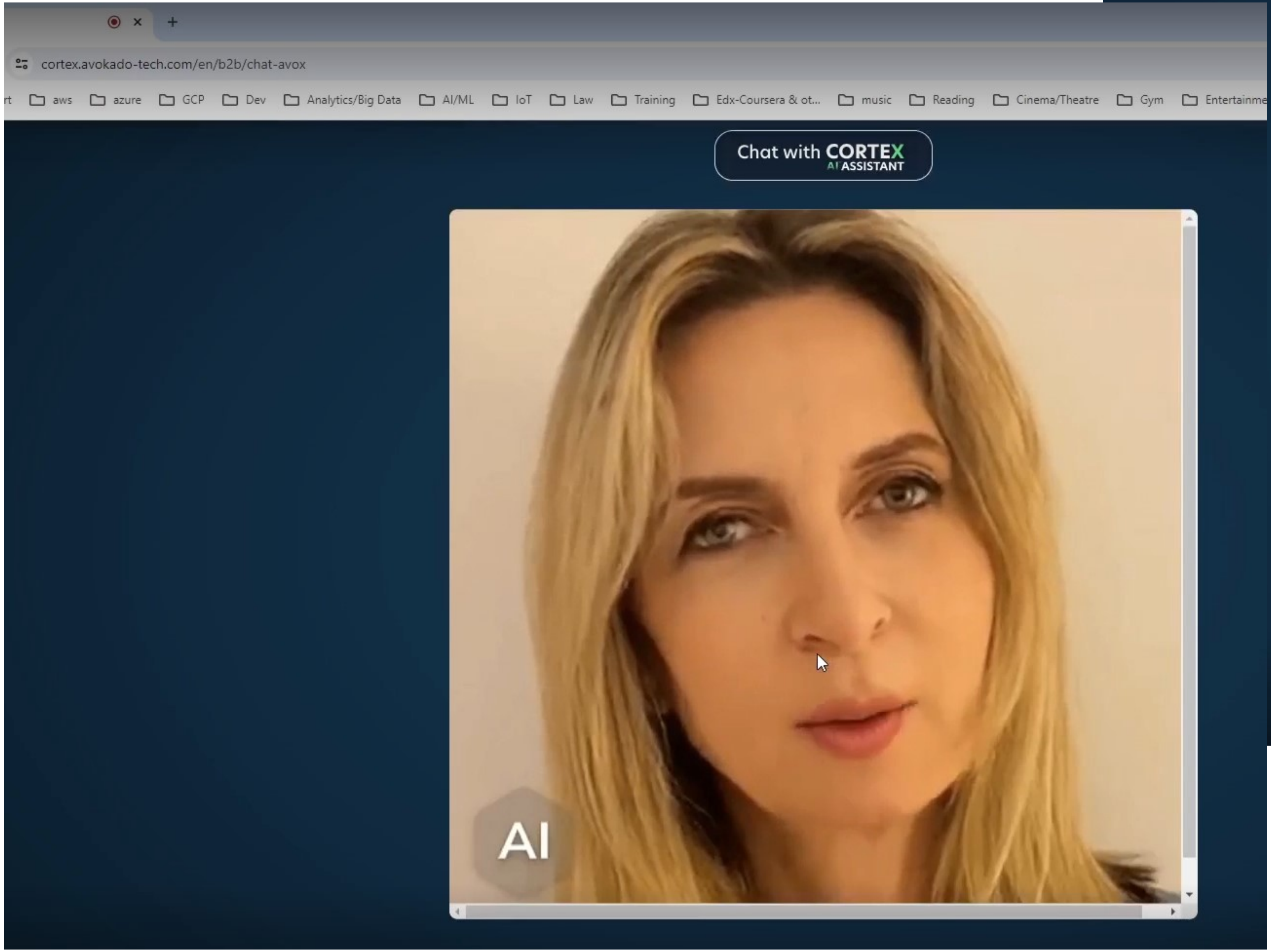

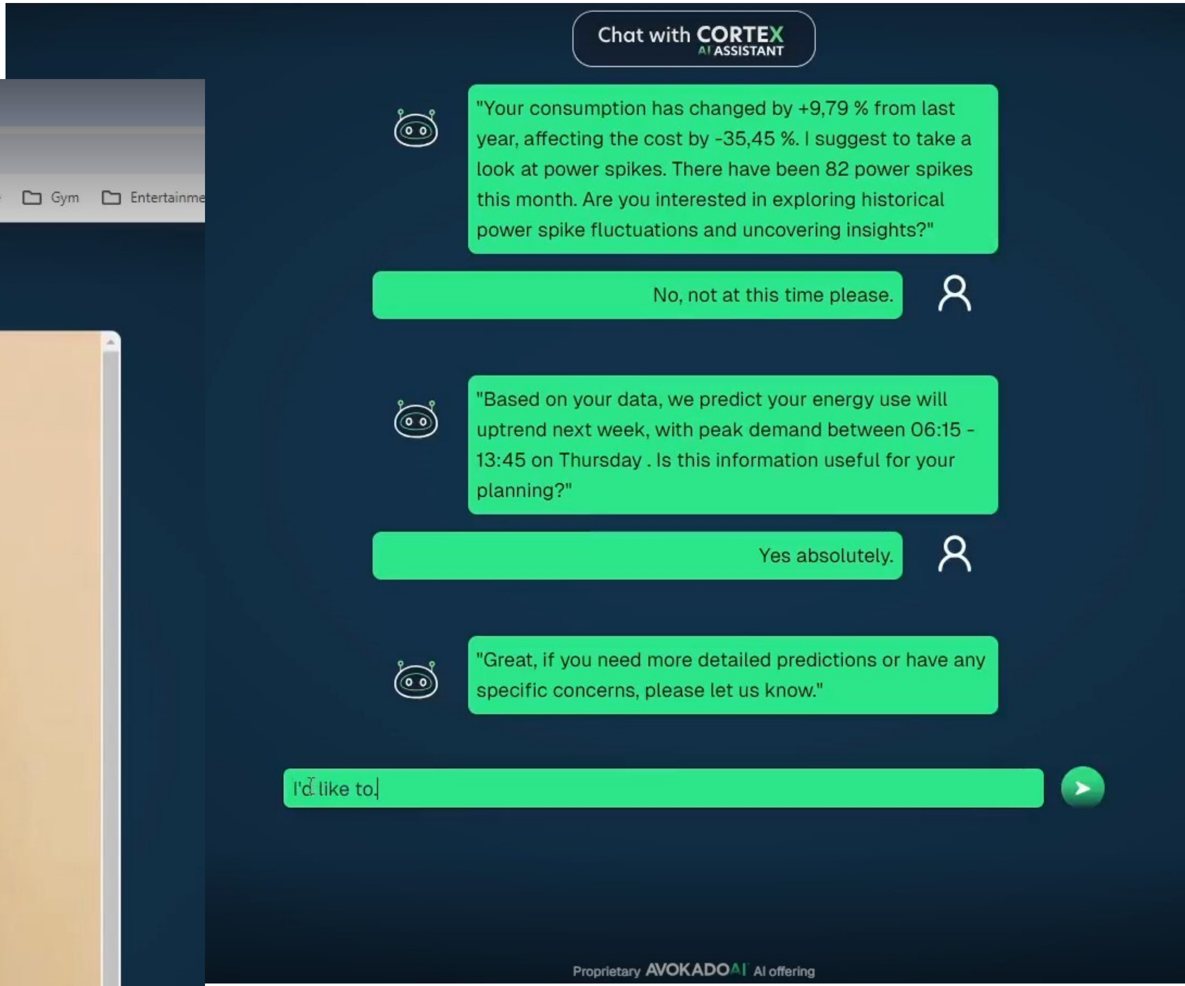

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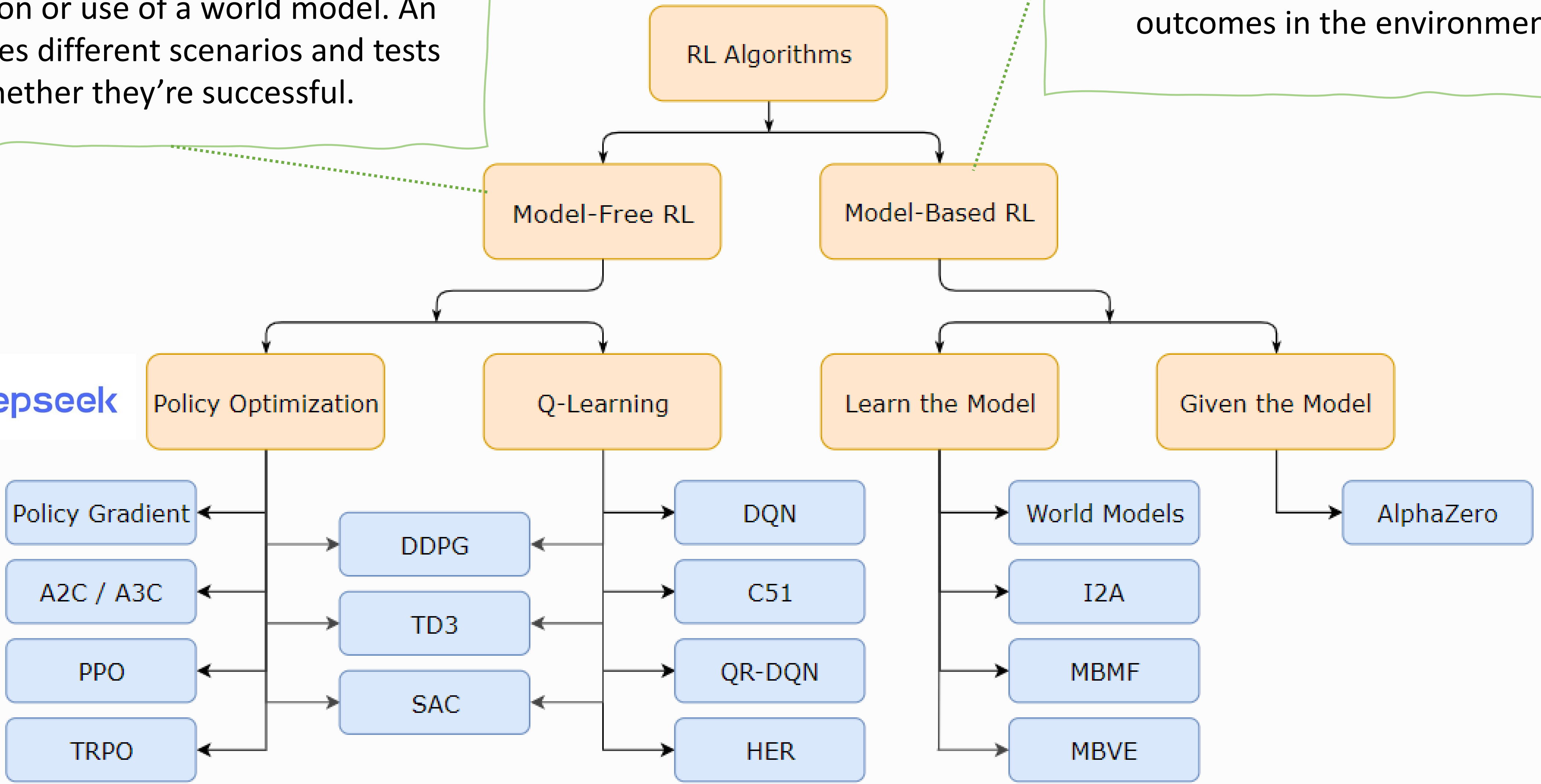
RL Algorithms (Future)

Uses experience to learn directly one or both of two simpler quantities (state/ action values or policies) which can achieve the same optimal behavior but without estimation or use of a world model. An agent tries different scenarios and tests whether they're successful.

Control function to choose the optimal actions (control theory).
Uses experience to construct an internal model of the transitions and immediate outcomes in the environment.



[Submitted on 5 Feb 2024 (v1), last revised 27 Apr 2024 (this version, v3)]

DeepSeekMath: Pushing the Limits of Mathematical Reasoning in Open Language Models

Zhihong Shao, Peiyi Wang, Qihao Zhu, Runxin Xu, Junxiao Song, Xiao Bi, Haowei Zhang, Mingchuan Zhang, Y.K. Li, Y. Wu, Daya Guo

Mathematical reasoning poses a significant challenge for language models due to its complex and structured nature. In this paper, we introduce DeepSeekMath 7B, which continues pre-training DeepSeek-Coder-Base-v1.5 7B with 120B math-related tokens sourced from Common Crawl, together with natural language and code data. DeepSeekMath 7B has achieved an impressive score of 51.7% on the competition-level MATH benchmark without relying on external toolkits and voting techniques, approaching the performance level of Gemini-Ultra and GPT-4. Self-consistency over 64 samples from DeepSeekMath 7B achieves 60.9% on MATH. The mathematical reasoning capability of DeepSeekMath is attributed to two key factors: First, we harness the significant potential of publicly available web data through a meticulously engineered data selection pipeline. Second, we introduce Group Relative Policy Optimization (GRPO), a variant of Proximal Policy Optimization (PPO), that enhances mathematical reasoning abilities while concurrently optimizing the memory usage of PPO.

Subjects: **Computation and Language (cs.CL)**; Artificial Intelligence (cs.AI); Machine Learning (cs.LG)

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Current browse context:
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Change to browse by:
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deepseek

Bite: How Deepseek R1 was trained

January 17, 2025
4 minute read

DeepSeek AI released DeepSeek-R1, an open model that rivals OpenAI's o1 in complex reasoning tasks, introduced using Group Relative Policy Optimization (GRPO) and RL-focused multi-stage training approach.

Understanding Group Relative Policy Optimization (GRPO)

Group Relative Policy Optimization (GRPO) is a reinforcement learning algorithm to improve the reasoning capabilities of LLMs. It was introduced in the DeepSeekMath paper in the context of mathematical reasoning. GRPO modifies the traditional Proximal Policy Optimization (PPO) by eliminating the need for a value function model. Instead, it estimates baselines from group scores, reducing memory usage and computational overhead. GRPO, now also used by the Qwen team, can be used with rule/binary-based Rewards as well as General Reward Models to improve models on helpfulness.

1. **Sampling**: Generate multiple outputs for each prompt using the current policy
2. **Reward Scoring**: Each generation is scored using a reward function, could be (rule-based or outcome-based)
3. **Advantage Calculation**: The average reward of the generated outputs is used as a baseline. The advantage of each solution within the group is then computed relative to this baseline. The reward is normalized within a group.
4. **Policy Optimization**: The policy tries to maximize the GRPO objective, which includes the calculated advantages and a KL divergence term. This is different from how PPO implements the KL term within the reward.

My biggest fear is AI

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