Gen AI & Classic ML

when to use what

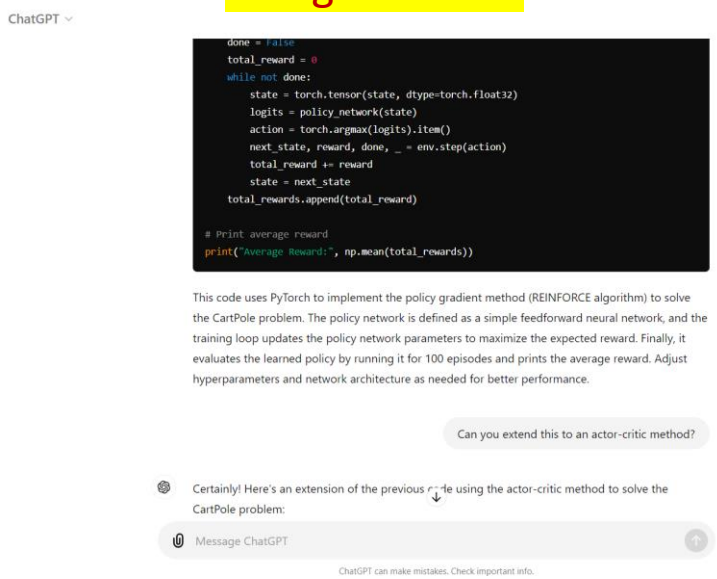
October 2024

Felix Wick

Classic ML vs Deep Learning

Generative vs Predictive Models

text generation



[ChatGPT]

image synthesis

Prompt: Epic anime artwork of a wizard atop a mountain at night casting a cosmic spell into the dark sky that says "Stable Diffusion 3" made out of colorful energy

[Stable Diffusion 3 — Stability AI]

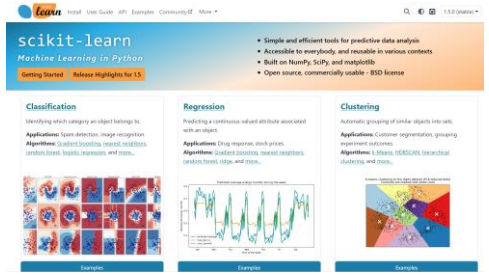
text-to-video

Prompt: A stylish woman walks down a Tokyo street filled with warm glowing neon and animated city signage. She wears a black leather jacket, a long red dress, and black boots, and carries a black purse. She wears sunglasses and red lipstick. She... +

[Sora | OpenAI]

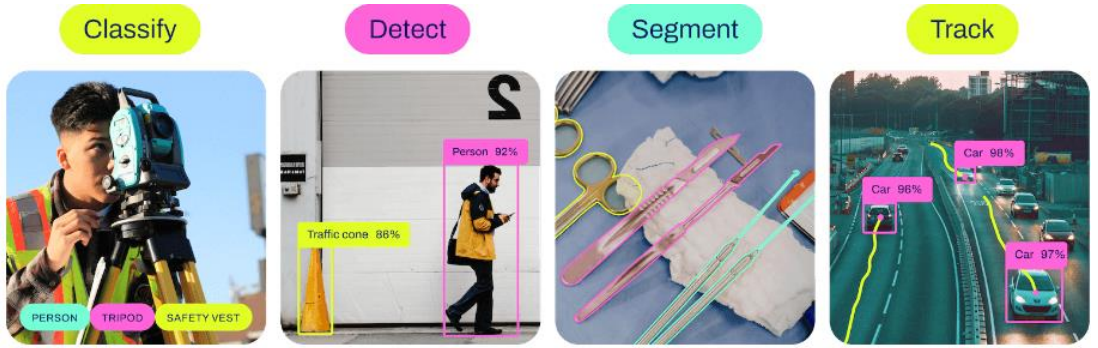
BERT family

tabular data



dmlc XGBoost

computer vision



[YOLO]

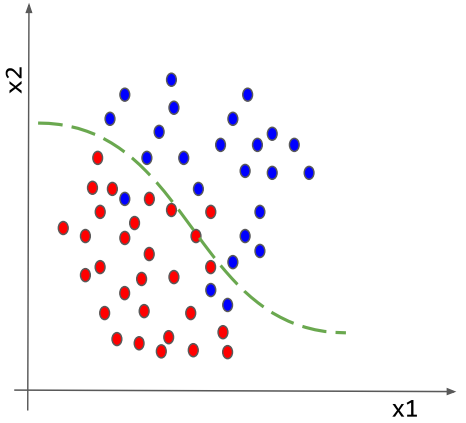
Deep Learning & Foundation Models

Classic Supervised Learning

input-output mapping

specific models for each task and data set

feature engineering



Example: Spam Filtering

Classify emails as spam or no spam

*use accordingly **labeled emails as training set***

use information like **occurrence of specific words** or **email length** as **features**

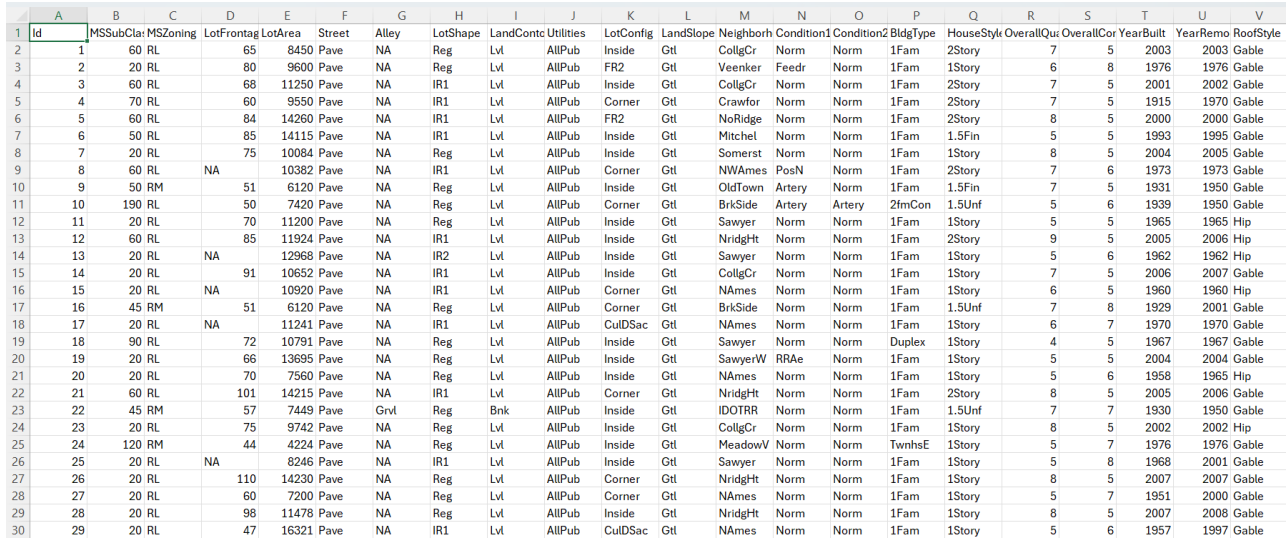
features x1 and x2

spam, no spam

Classic ML Use Cases

plenty of applications:

- prediction of house prices
- energy consumption prediction
- demand forecasting
- churn prediction
- forecast of traffic conditions
- weather forecasts
- predictive maintenance
- …



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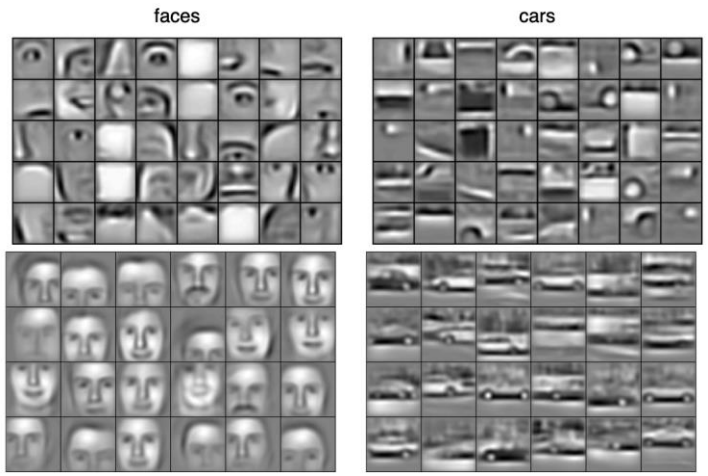
You got it, these are predictive models.

Ladder of Generalization

classic ML: feature engineering

deep learning: feature learning

(hierarchy of concepts learned from raw data in deep graph with many layers)



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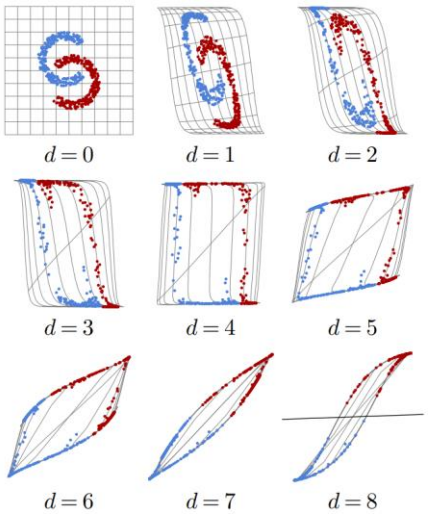

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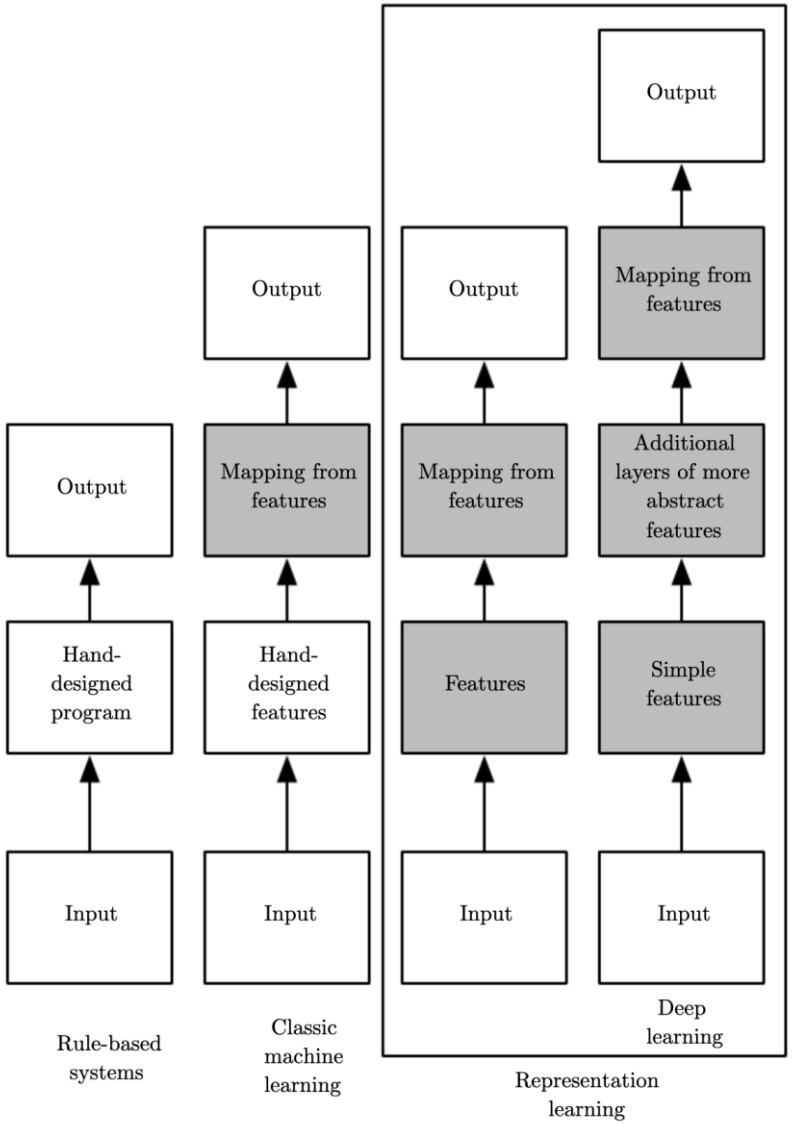

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Structured/Tabular vs Unstructured Data

unstructured data: homogenous

→ deep learning rules

→ allows transfer learning (foundation models in CV and NLP)

ImageNet

The Lord of the Rings

Article Talk

From Wikipedia, the free encyclopedia

(Redirected from Lord of the rings)

This article is about the book. For other uses, see The Lord of the Rings (disambiguation). "War of the Ring" redirects here. For other uses, see War of the Ring (disambiguation).

The Lord of the Rings is an epic[1] high fantasy novel[2] by the English author and scholar J. R. R. Tolkien. Set in Middle-earth, the story began as a sequel to Tolkien's 1937 children's book *The Hobbit*, but eventually developed into a much larger work. Written in stages between 1937 and 1949, ***The Lord of the Rings*** is one of the best-selling books ever written, with over 150 million copies sold.[3]

The title refers to the story's main antagonist,[4] Sauron, the Dark Lord who in an earlier age created the One Ring to rule the other Rings of Power given to Men, Dwarves, and Elves, in his campaign to conquer all of Middle-earth. From homely beginnings in the Shire, a hobbit land reminiscent of the English countryside, the story ranges across Middle-earth, following the quest to destroy the One Ring, seen mainly through the eyes of the hobbits Frodo, Sam, Merry, and Pippin. Aiding Frodo are the Wizard Gandalf, the Men Aragorn and Boromir, the Elf Legolas, and the Dwarf Gimli, who unite in order to rally the Free Peoples of Middle-earth against Sauron's armies and give Frodo a chance to destroy the One Ring in the fire of Mount Doom.

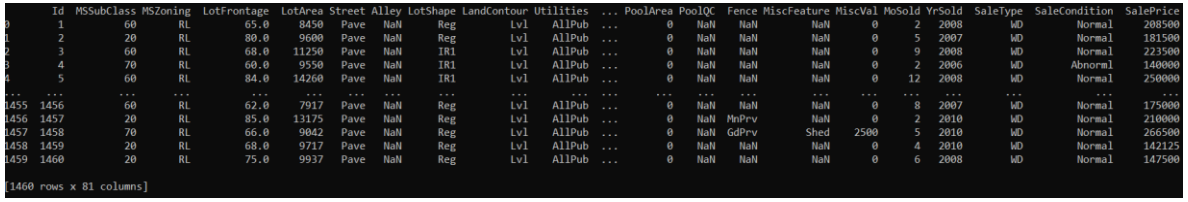
Although often mistakenly called a trilogy, the work was intended by Tolkien to be one volume in a two-volume set along with *The Silmarillion*.[nb 1] For economic reasons, ***The Lord of the Rings*** was first published over the course of a year from 29 July 1954 to 20 October 1955 in three volumes rather than one[nb 2] under the titles *The Fellowship of the Ring*, *The Two Towers*, and *The Return of the King*; *The Silmarillion* appeared only after the author's death. The work is divided internally into six books, two per volume, with several appendices of background material.[5] These three volumes were later published as a boxed set, and even finally as a single volume, following the author's original intent.

structured data: heterogenous

→ feature engineering needed

→ deep learning loses its advantage over shallow methods

→ e.g., gradient boosting still used a lot



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[1460 rows x 81 columns]

Transfer Learning

idea:

- generic pre-training of foundation models on huge data sets
- subsequent finetuning for specific tasks on small(er) data sets

(usually done with deep learning methods, using its compositional nature)

very successful for:

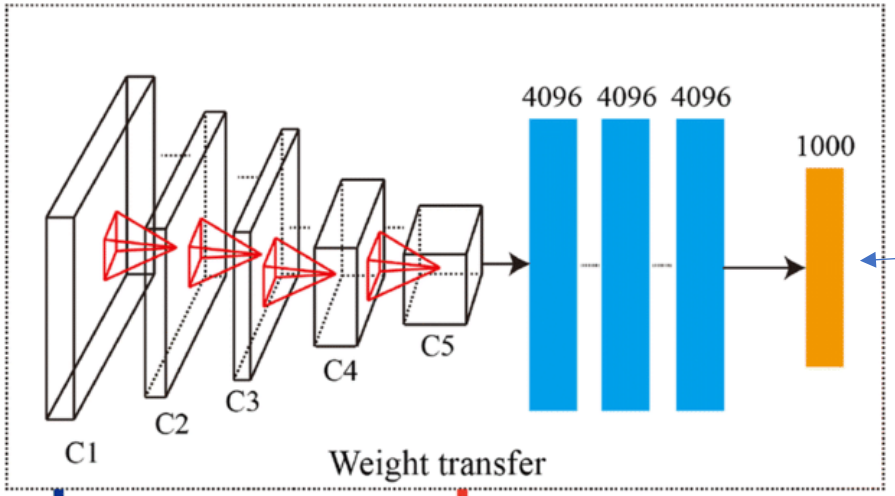
- computer vision (e.g., object classification)
- language models (e.g., BERT, GPT)

not (yet) for tabular data (due to its notorious heterogeneity)

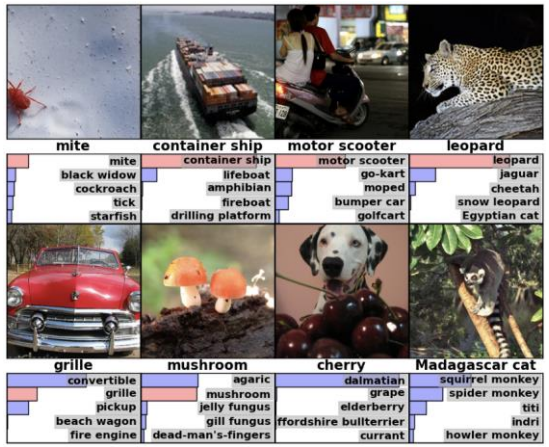
(but some promising research, e.g., Chronos for univariate time series)

CNN Finetuning

Pretrained on ImageNet



object classification



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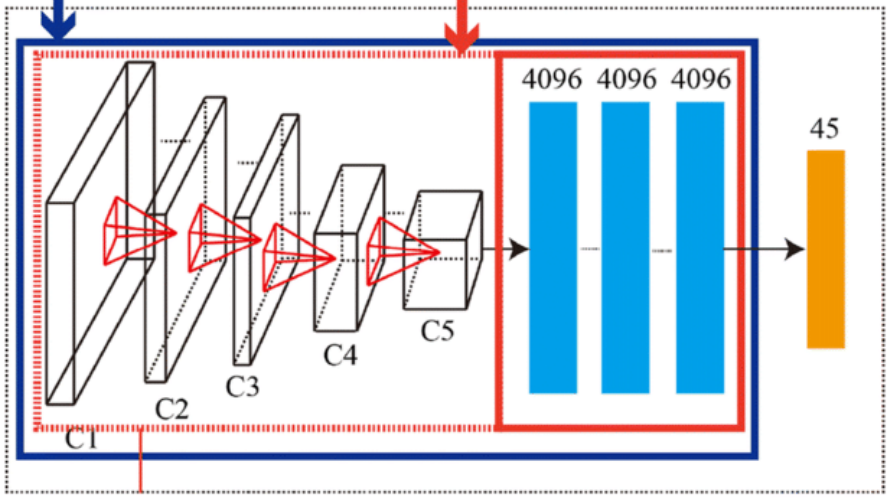
Finetune all layers

Finetune the last few layers

Finetuned on NWPU



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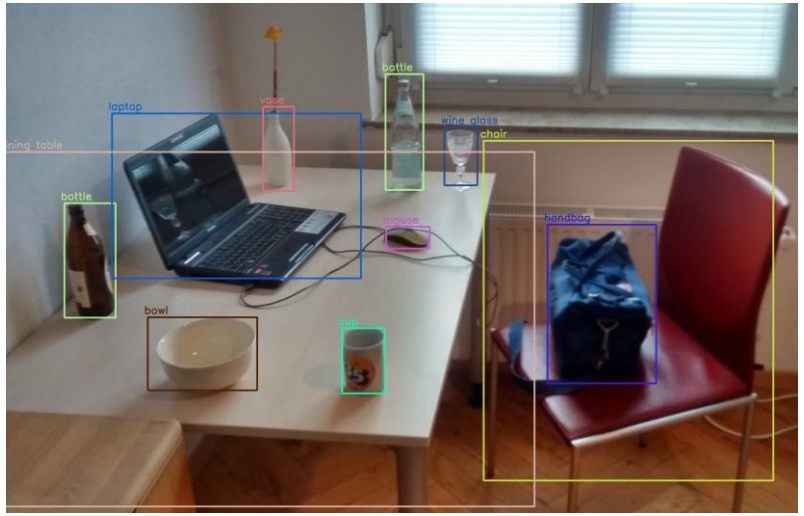
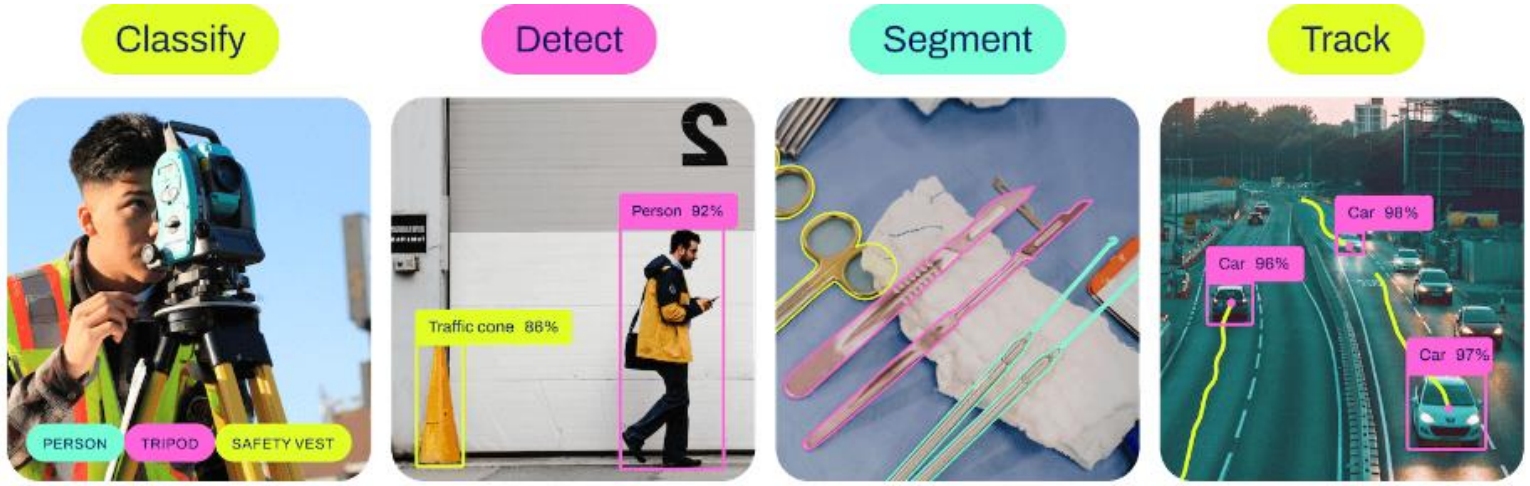


from wikipedia

Computer Vision Use Cases

many use cases:

- visual defect detection
- face recognition
- perception for autonomous driving, drone control, …
- cellular segmentation
- support chip design
- …



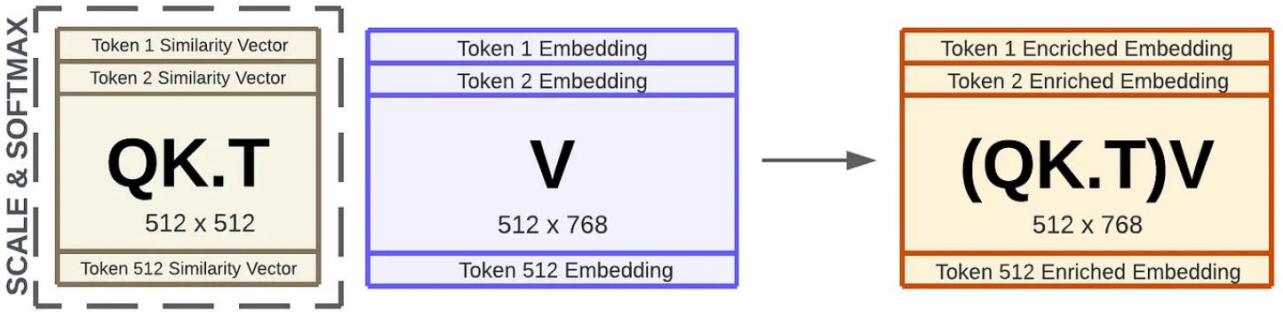
YOLO

Again, these are no generative, but predictive models.

But aspects of it can be applied in generative ones (e.g., U-Net in diffusion models).

Language Models: Contextual Semantics

- self-supervised learning: e.g., next/masked-word prediction
- tokenization: split text into chunks (e.g., words)
- semantics by means of vector embeddings: e.g., via bag-of-words (or end-to-end in transformer)
- positional encoding & embeddings: order of sequence
- contextual embeddings: (self-)attention (weighted averages: influence from other tokens)



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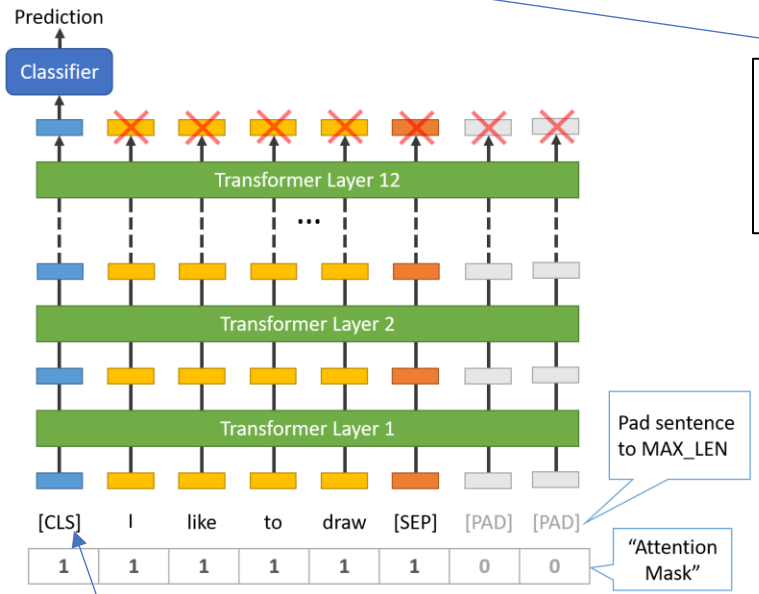
Language Model Finetuning

- self-supervised pre-training on massive data sets (→ foundation models like GPT or BERT)
- subsequent supervised finetuning on specific data sets (adapting parameters or/and adding layers)

example: sequence classification



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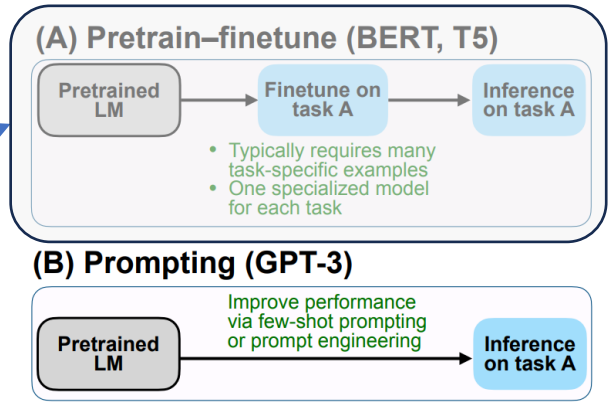
sentence classification via [CLS] token

purely predictive



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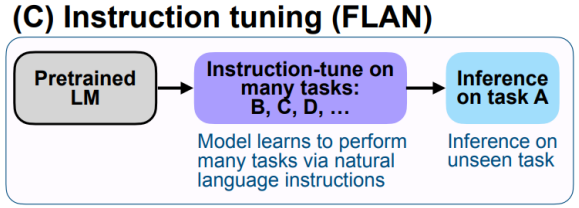
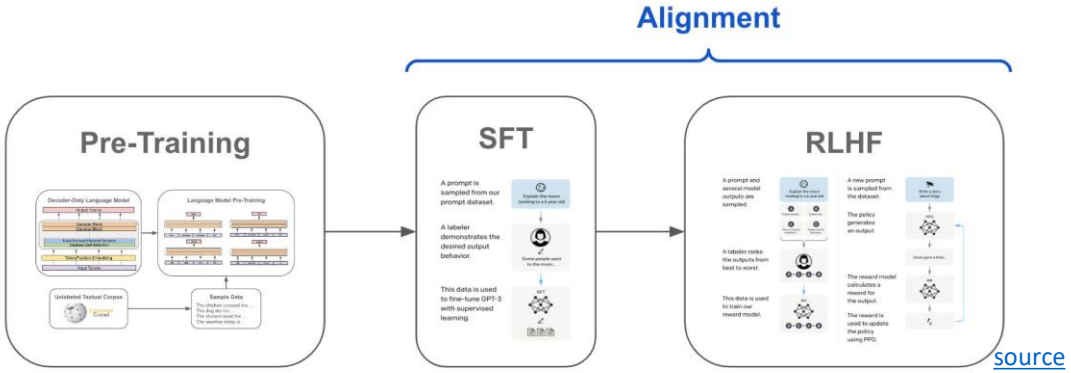


tuning predictive, output generative



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Generative AI

Generative vs Predictive/Discriminative Models

discriminative models:

predict conditional probability $P(Y|\boldsymbol{X})$

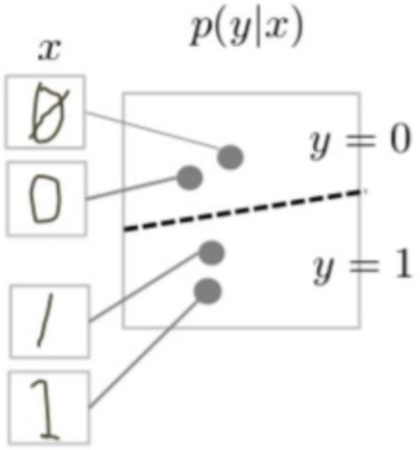
generative models:

predict joint probability $P(Y, \boldsymbol{X})$

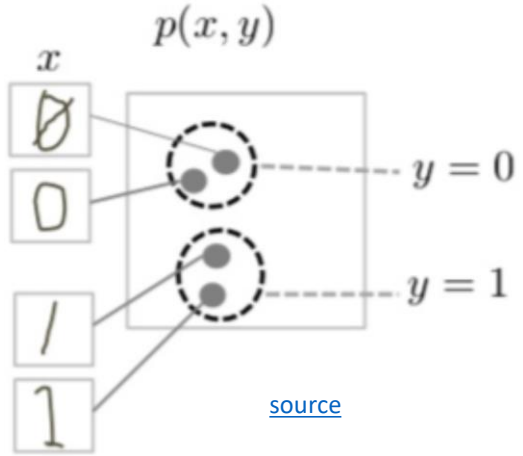
(or just $P(\boldsymbol{X})$ → unsupervised learning)

→ allow to generate new data samples

discriminative model



generative model



source

task of generative models more difficult: need to model full data distribution rather than merely find patterns in inputs to distinguish outputs

Generative models can be used for predictive tasks (Bayes theorem).
But predictive models are usually better at it.

Deep Learning for Generative AI

Depending on the application, there are currently two dominant approaches for generative AI:

- text generation: decoder LLMs

- image synthesis: diffusion models

note the difference between image synthesis and multimodal understanding in LLMs (images as additional input sequences to transformer, tokenized by splitting into patches)

most new LLMs decoder-only

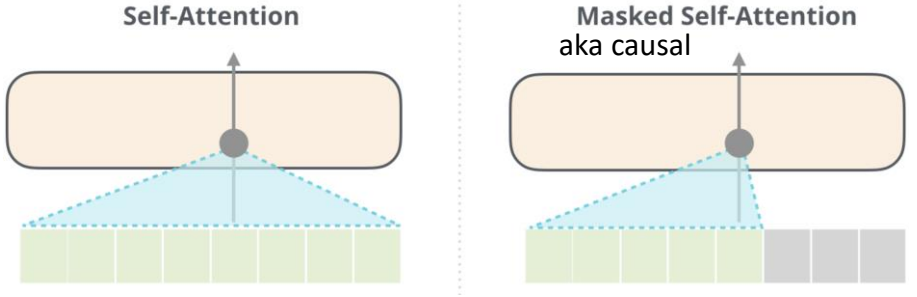
Encoder vs Decoder LLMs

encoder-only LLMs

- prime example: BERT
- self-supervised pre-training: masked-word prediction
- finetuning on downstream tasks (e.g., sequence classification)
- can’t generate text
- can’t be prompted

decoder-only LLMs

- prime example: GPT
- self-supervised pre-training: next-word prediction
- instruction tuning (e.g., RL from human feedback)
- generate text: chat bots
- prompt engineering (zero-/few-shot)



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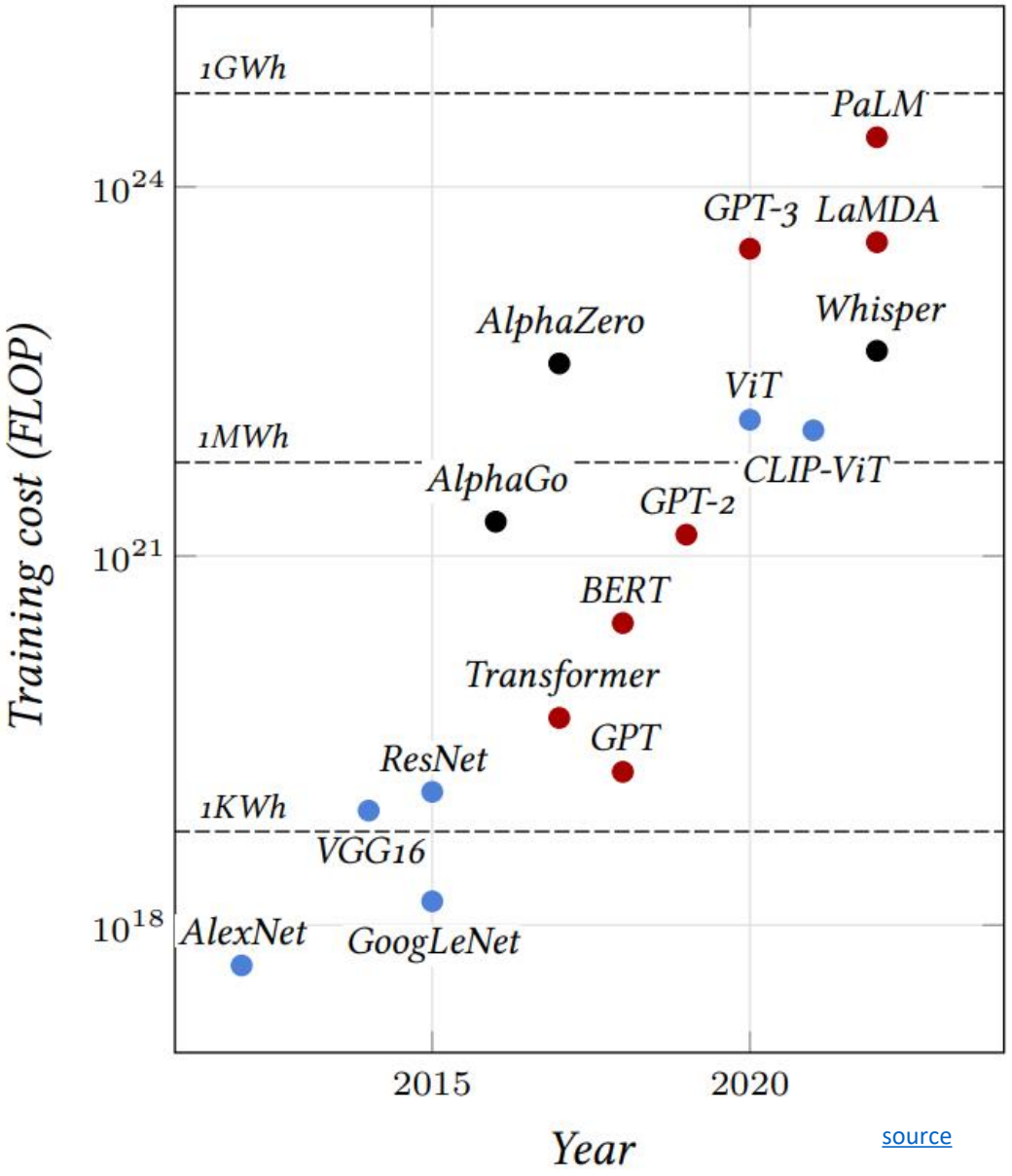
Text Generation

in-context learning as alternative to finetuning (new paradigm):
feed information into LLM via input prompt (decoder LLMs)
→ attention to context

typical prompt:
instructions, context (potentially retrieved), query, output indicator

enables multi-task capabilities (all of ML before was only narrow tasks)
→ assistants

some deep learning history:



source

(open-source) LLM SOTA (July 2024): Llama 3

some LLM numbers (example Llama 3 405B):

- vocabulary size (tokens): 128K
- embedding/model dimensions: 16,384
- parameters: 405B
- training tokens: 15.6T
- context length/window (tokens): 128K
- training hardware: 16K GPUs (H100)

factor less than 40
→ a lot of memorizing

another trend: small language models on edge devices

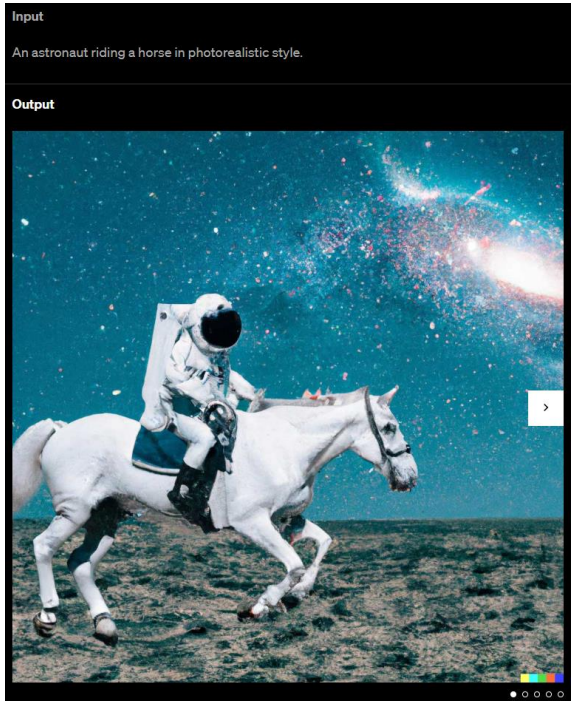
Image Synthesis

idea: generate new images as variations of training data

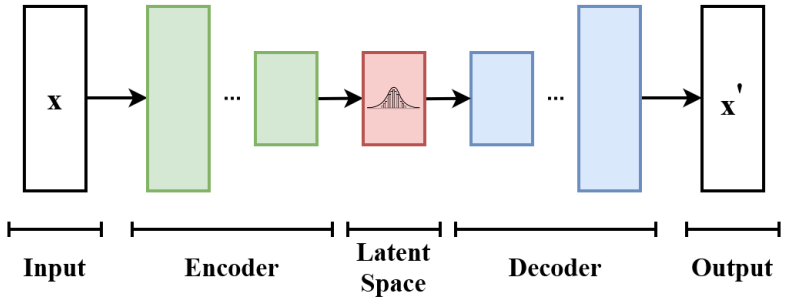
usually conditioned on text (prompt) by transformers

compared to text generation, additional mechanism needed (e.g., diffusion) to create more complex structures

example: DALL-E 2



Variational AutoEncoder:



from wikipedia

Diffusion models:
Gradually add Gaussian noise and then reverse

chain of denoising autoencoders

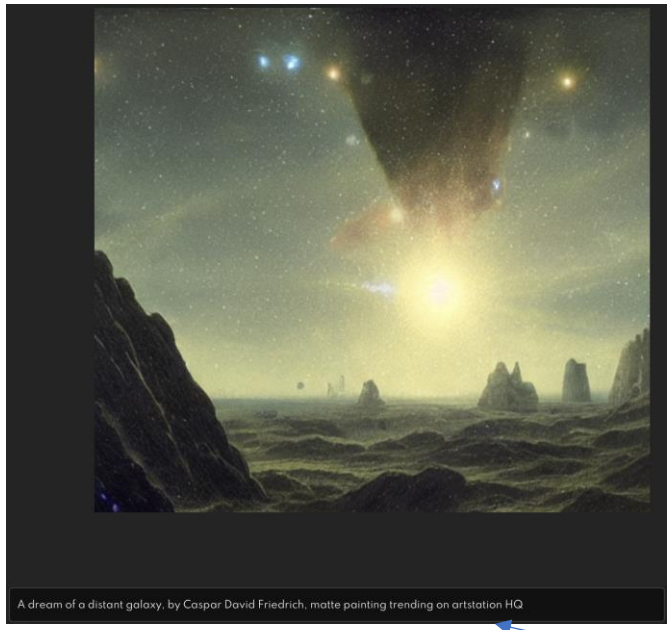
source

plenty of applications: DALL-E, Stable Diffusion, ImageGen, Midjourney, ...

rather "translations"

also text-to-speech (VALL-E, Speech T5, …) (and speech recognition, e.g., Whisper), text-to-video (Make-A-Video, Lumiere, Sora, …) → dynamics/physics understanding/simulation

web app for Stable Diffusion: DreamStudio



inpainting example (GLIDE):

"zebras roaming in the field"

source

prompt

at some point maybe also proteins, materials, structured data, …

Decision Making

predictive

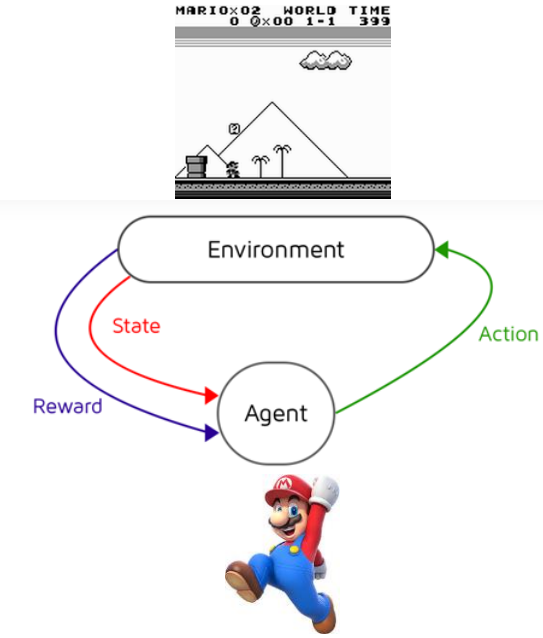
Sequential Decision Making

no concrete input-output examples like in supervised learning

typically, domain of

- reinforcement learning (e.g., Q-learning or policy-gradient methods → model-free)
- optimal control (e.g., model predictive control → model-based)

plenty of use cases: e.g., games or complex control mechanisms



generative

Alternative: Sequence Modeling

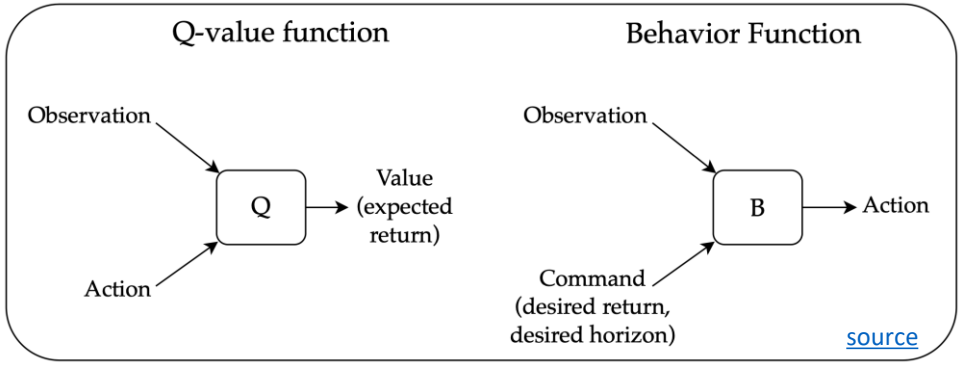
offline method

not restricted by Markov property

Decision Transformer:

- generative: transformer to autoregressively model trajectories
- credit assignment directly via self-attention: state-return associations
- desired return tokens as prompt for action generation (but extrapolation is difficult)

overcoming the deadly triad of deep RL:



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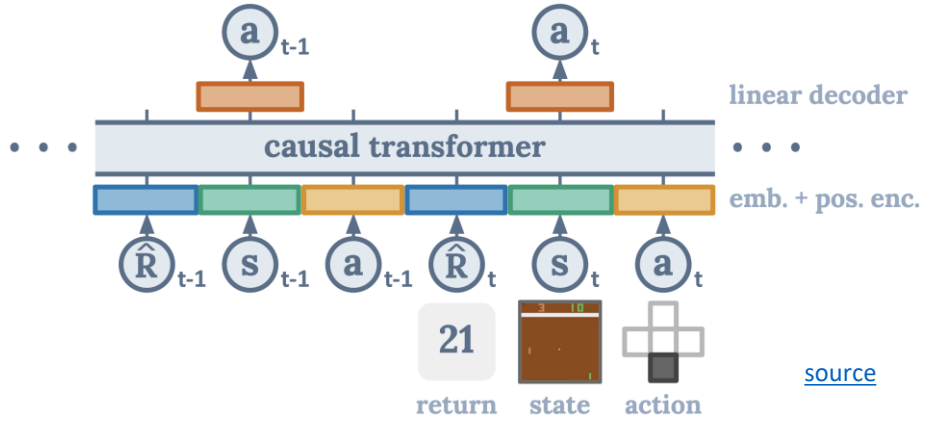

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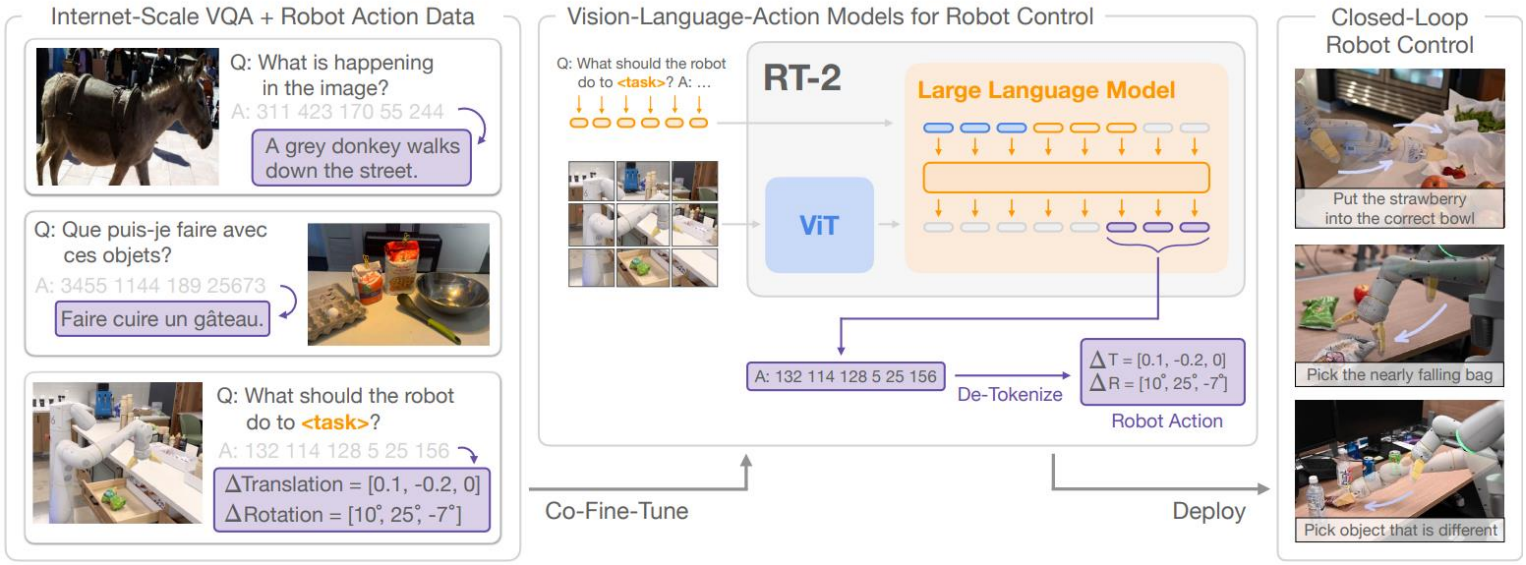
or apply language models directly ...

Example Use Case: Robotic Control

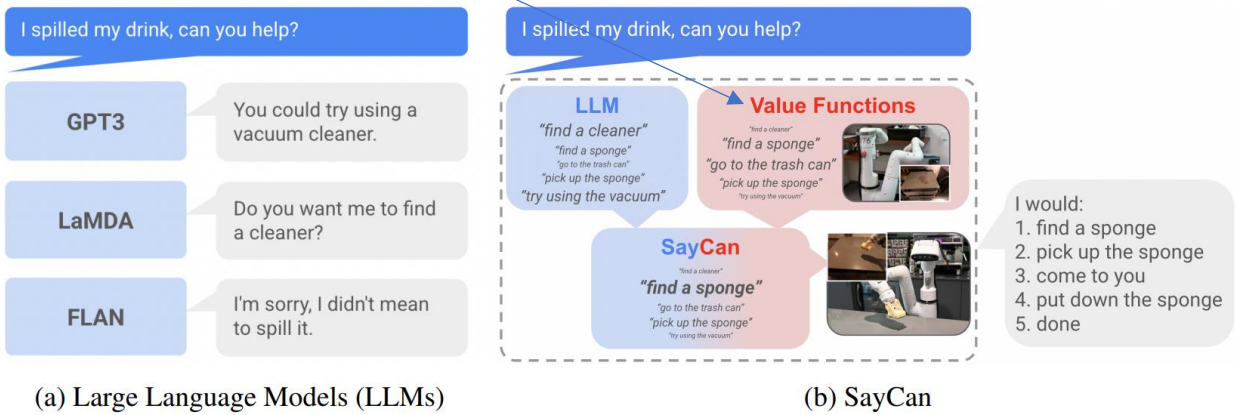
generated by LLMs/VLMs

RT-2:



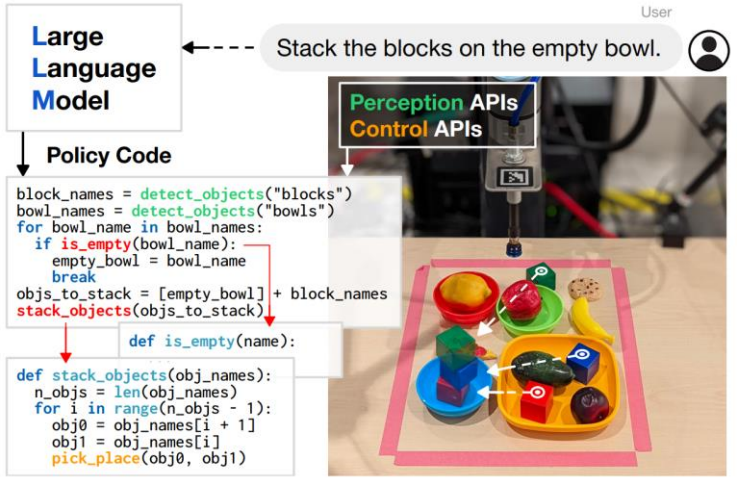
diffusion objective for multimodal outputs

SayCan (grounding with pre-trained skills):



(a) Large Language Models (LLMs) (b) SayCan

Code as Policies:



Agents

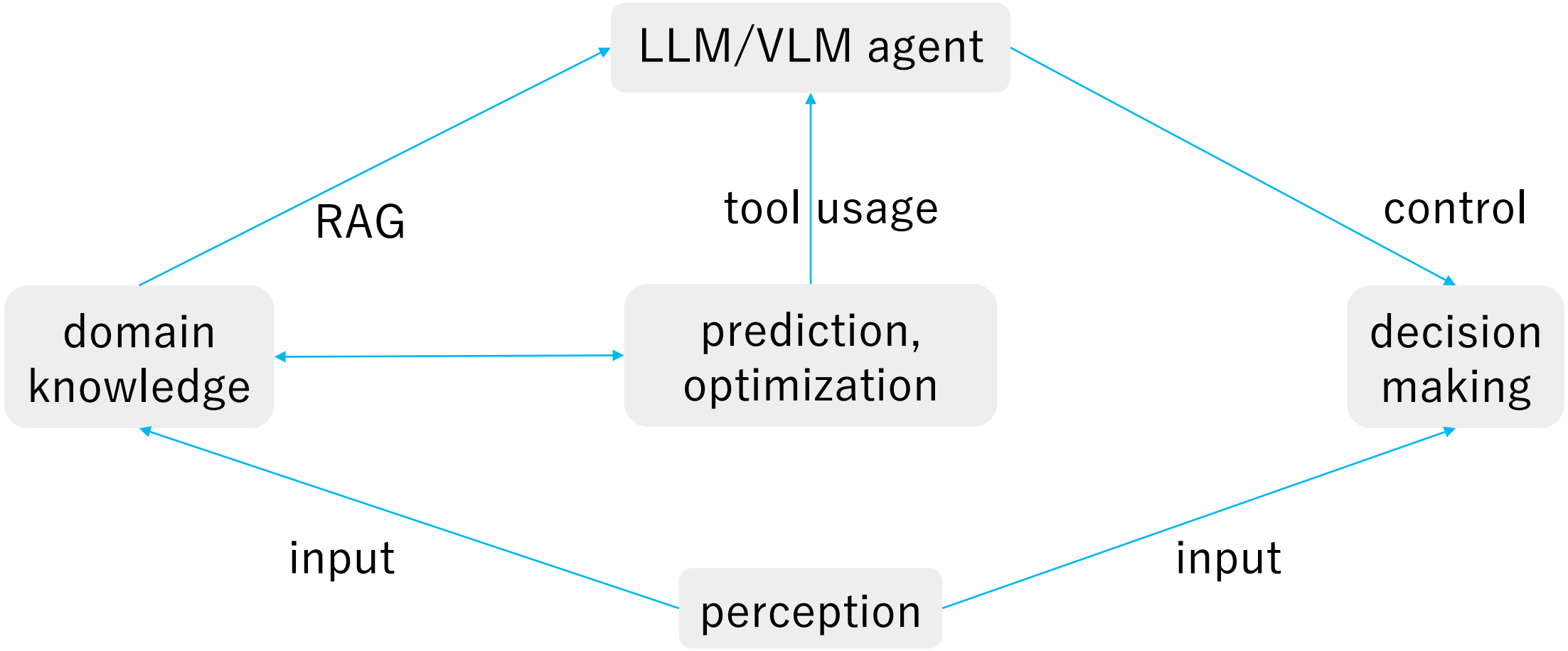
LLM Agents

desired agent capabilities:

- planning (LLMs: decomposition of complex issue in multiple simple steps)
- tool use (LLMs: use predictive models for numerical/optimization tasks)
- reflection (LLMs: clever prompting schemes)
- collaboration with other agents (LLMs: mutual prompting)

(but capabilities still limited, e.g., reasoning)

Goal: Autonomous End-to-End Workflow



So, when to use what, now?

Deep learning (especially as foundation models) rules for unstructured, classic ML (specific models) is (still) a good choice for tabular data.

Generative models allow to create new data (text, code, images, video) and can be used in a very generic way (prompting).

But predictive models are usually better for predictive tasks, and business problems are often predictive (numerical, optimization, …).

They can be combined: generative model (e.g., an LLM) as orchestrator, using predictive models as tools.

And some Philosophical Thoughts

Current AI (SOTA: LLM) is good at learning statistical patterns and making predictions.

But there is no sign of real “understanding”. → stochastic parrot?

Anyway, generative AI is an interesting, slightly twisted mirror of our creations.