Machine Learning – Products

Most Famous Applications

recommendations

chatbots

ChatGPT Bard

autonomous driving

WAYMO TESLA

MOTOR Ai

translation

DeepL

robotics

OCR

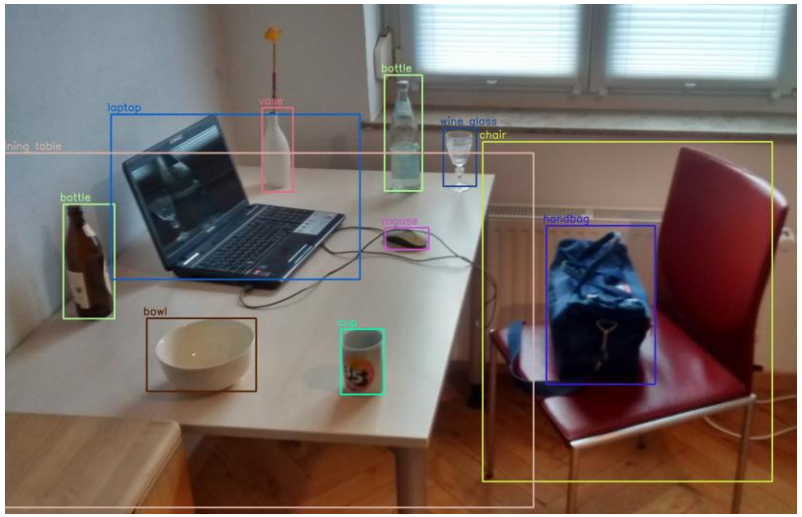
assistants (speech recognition)

and many more …

When to Use ML (= Learning from Data)

automation

too complex for rules



from wikipedia

examples: object recognition, all applications from previous slide

complexity / uncertainty

too complex for humans

examples: protein structure predictions (AlphaFold), demand forecasting

more scientific use cases: medicine (imaging, diagnosis, drug design), particle physics (analysis of collider experiments), material science (material properties and design of new materials), …

Taxonomy of ML Models

Supervised Learning

Target Quantity

- **known in training**: labeled samples or observations from past
- to be **predicted** for unknown cases (e.g., future values)

Features

input information that is
- correlated to target quantity
- known at prediction time

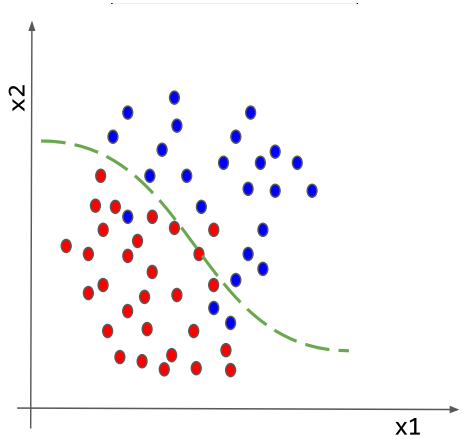
Example: Spam Filtering

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

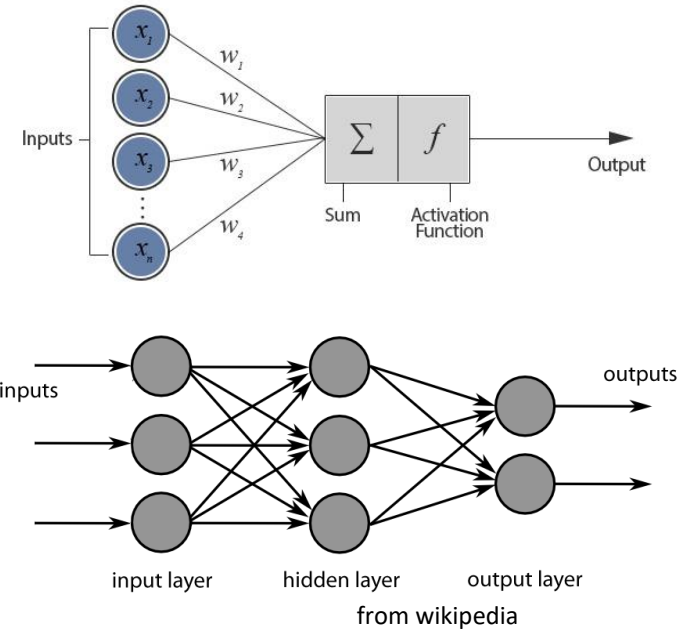


usually rather narrow tasks

Algorithmic Families

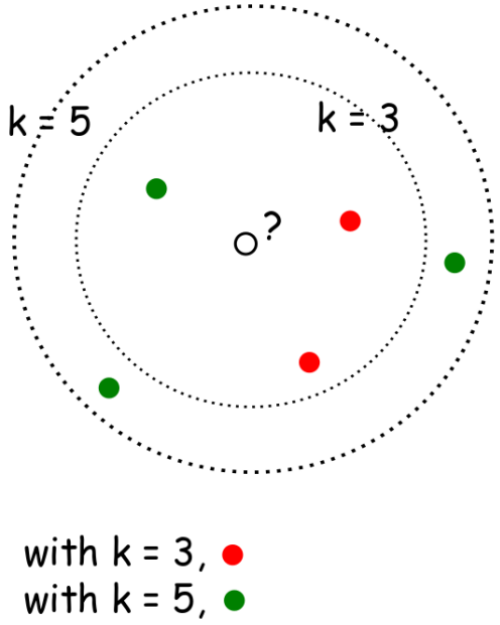
linear (parametric) models

neural networks: non-linear just by means of activation functions



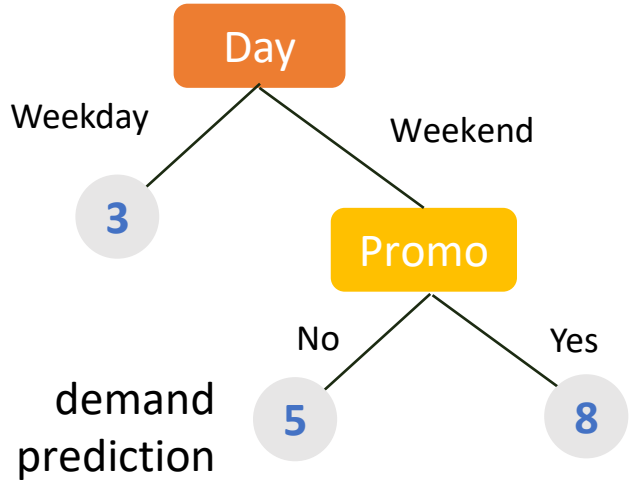
deep learning: many hidden layers
computer vision: CNN
NLP: transformer

nearest neighbors (local methods, instance-based learning) – non-parametric models



kernel/support-vector machines: linear model (maximum-margin hyperplane) with kernel trick

decision trees: rule learning



often used in ensemble methods

- bagging: random forests
- boosting: gradient boosting

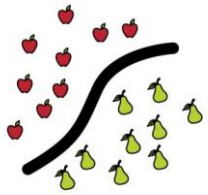
mainly used for structured data

MACHINE LEARNING

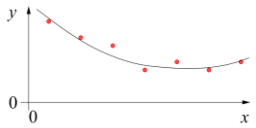
training target available (labeled or past data)

SUPERVISED

CLASSIFICATION



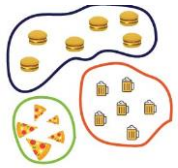
REGRESSION



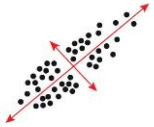
data not labeled in any way

UNSUPERVISED

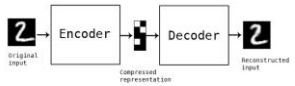
CLUSTERING



GENERATIVE MODELS



DIMENSIONALITY REDUCTION



ASSOCIATION

no supervision, but goal-based interaction with environment

REINFORCEMENT LEARNING

LEARN STATE OR ACTION VALUES

LEARN POLICY DIRECTLY

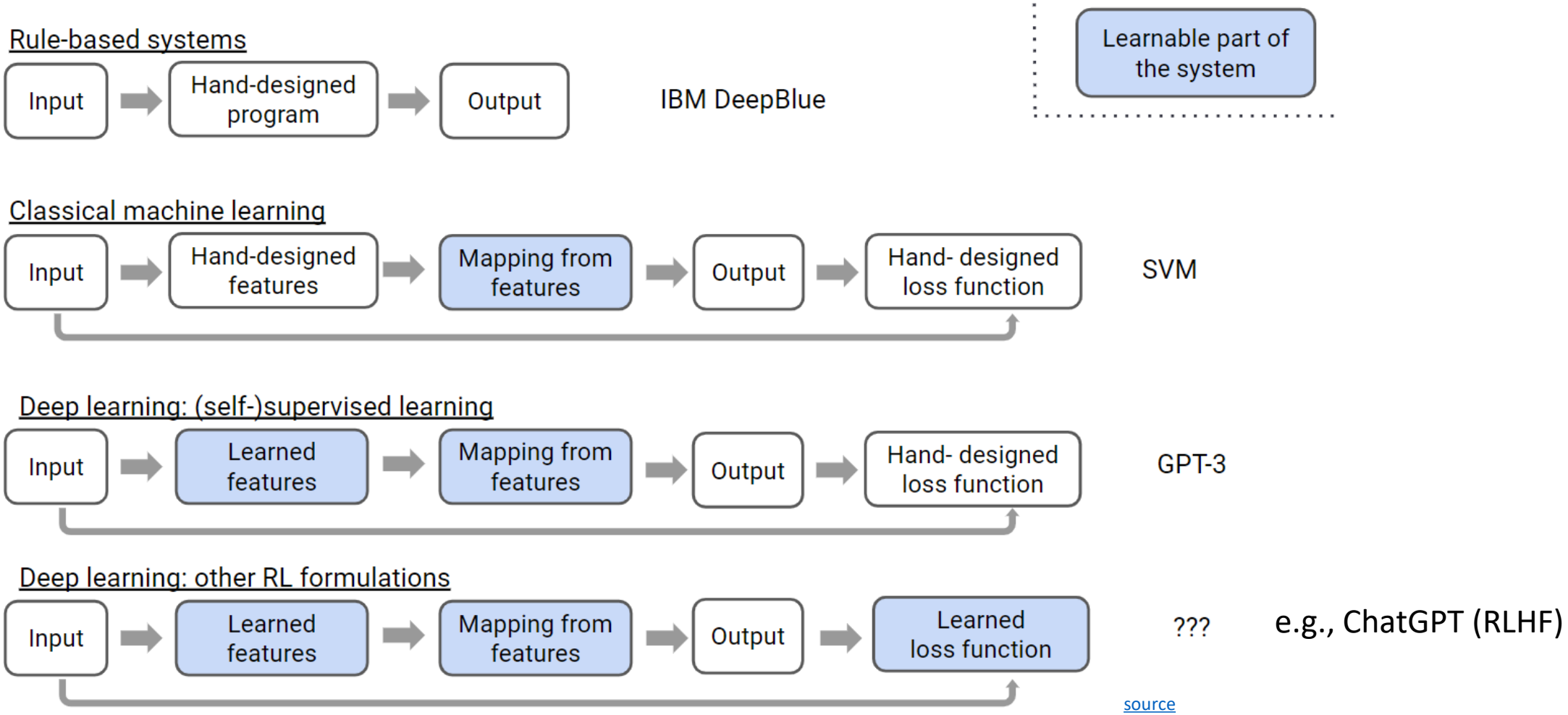
learning by teacher
(high-dimensional curve fitting)

learning by observation
(pattern recognition)

learning by trial-and-error
(sequential decision making)

unsupervised and reinforcement learning can both be cast as supervised-learning setup

Ladder of Generalization



source

Discriminative vs Generative Models

discriminative models:

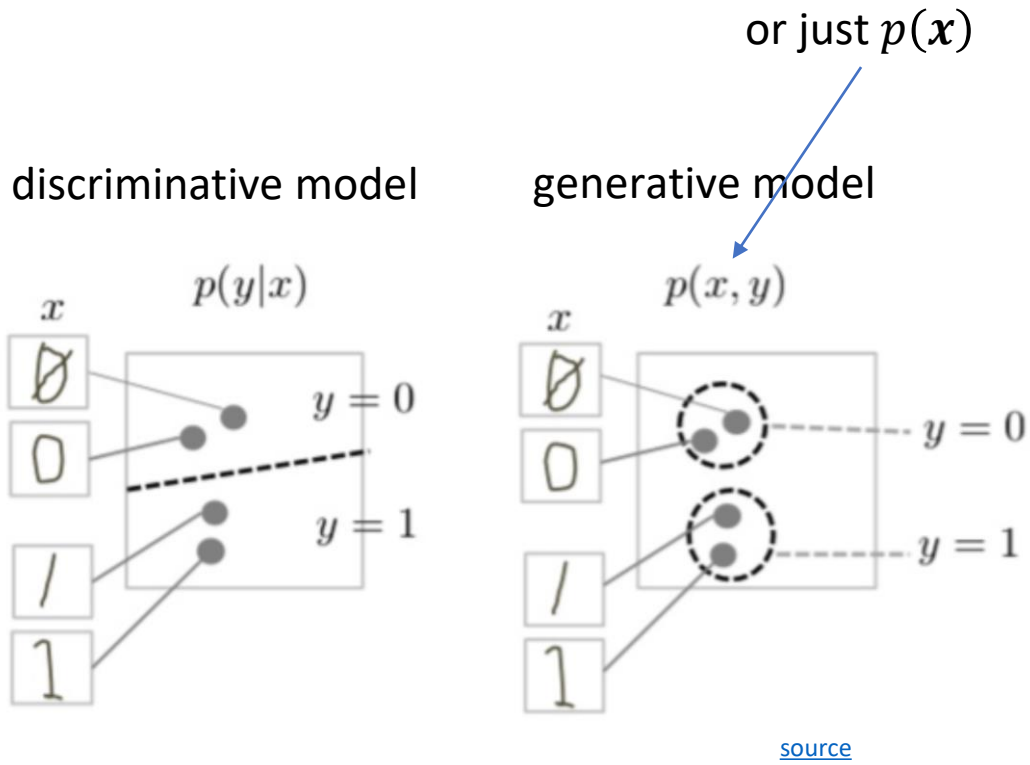
prediction/estimation of labels (classification) or numerical values (regression)

examples for discriminative tasks:

- object recognition
- demand forecasting

generative models:

generation of new data according to data distribution seen in training



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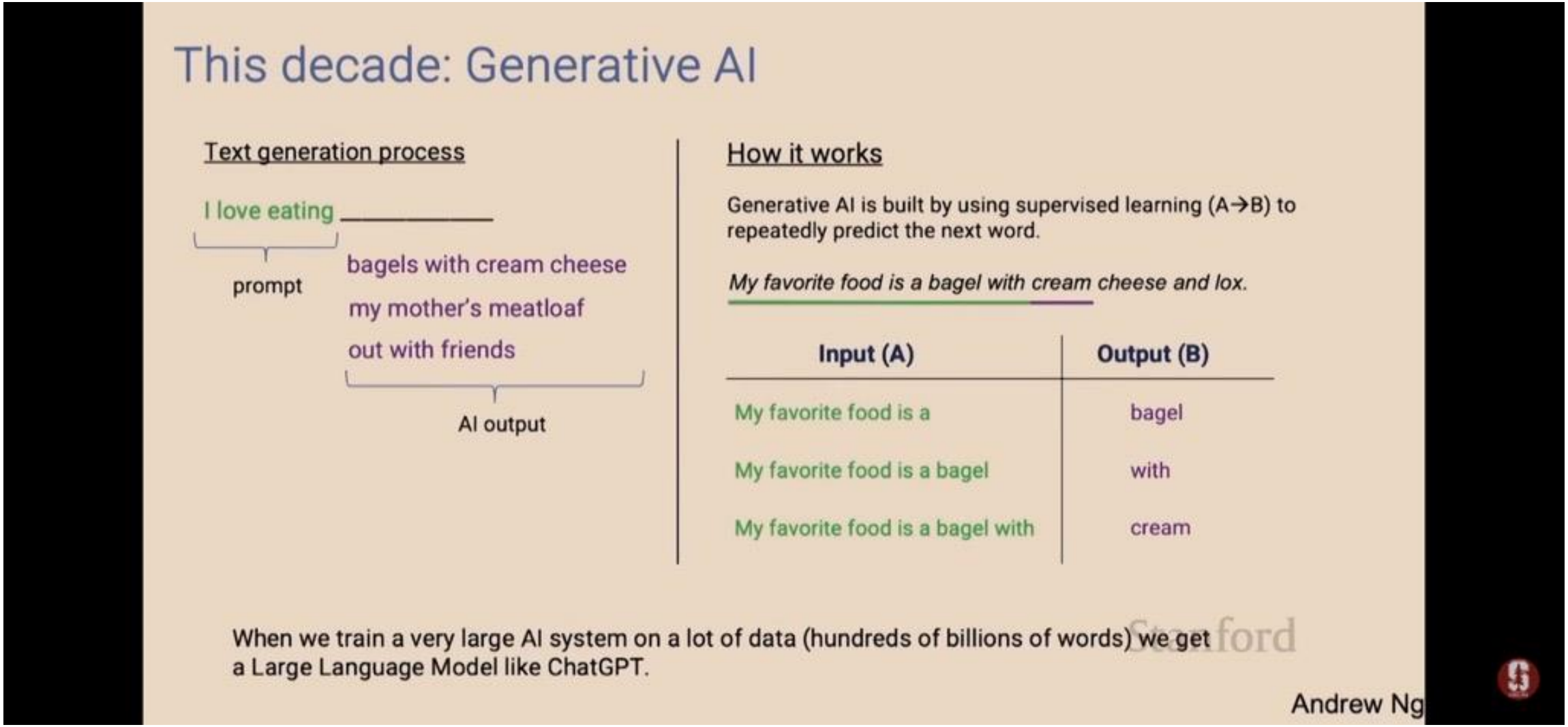
Text Generation



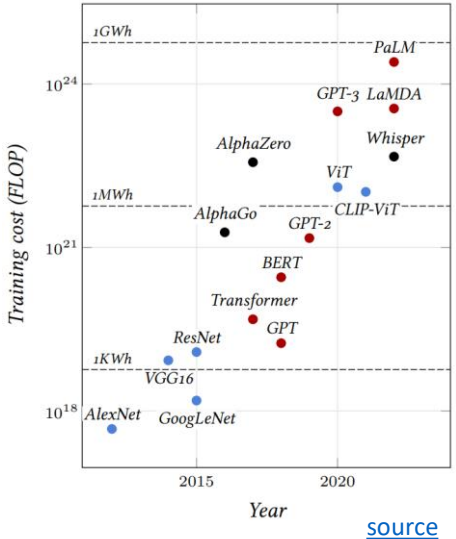
Large Language Models (LLM)

special class of generative models

new paradigm for ML workflow:
prompt engineering (low/no code)
instead of classic training (fit) and inference (predict) steps

→ multi-task (and multi-modal) models
instead of narrow use cases of discriminative models

Under the Hood: Foundation Models



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LLMs: transformer models with hundreds of billions of parameters

self-supervised (pre-)training on vast data sets

→ huge foundation models (impossible to train yourself)

usage options:

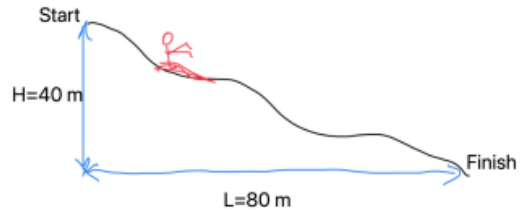
- typical: **in-context** learning via prompt (potentially giving few examples for task at hand and add retrieval augmentation or tool usage)
- for special case and high-quality requirements: **fine-tuning** on specific tasks and data sets (example: chatbot like ChatGPT via reinforcement learning from human feedback)

Google's Gemini:

Prompt

Here's a solution to a Physics problem by a student.

23. A skier slides down the frictionless slope as shown. What is the skier's speed at the bottom?



Solution:

The conservation of energy means that the energy of the skier is same at the beginning and at the end.

Start : $E = mgL$

End : $E = \frac{1}{2}mv^2$

$\Rightarrow mgL = \frac{1}{2}mv^2$

$\Rightarrow v = \sqrt{2gL} = \sqrt{2 \times 9.81 \times 80} = 39.6\ m.s^{-1}$

Try to reason about the question step by step.

Did the student get the correct answer? If the solution is wrong, please explain what is wrong and solve the problem.

Make sure to use LaTeX for math and round off the final answer to two decimal places.

Response

The student did not get the correct answer. The student made a mistake in the calculation of the potential energy at the start of the slope. The potential energy at the start of the slope is given by mgh, where m is the mass of the skier, g is the acceleration due to gravity, and h is the height of the slope. The student used the length of the slope, L, instead of the height, H, in the calculation of the potential energy.

The correct solution is:

The conservation of energy means that the total energy of the skier is the same at the beginning and at the end of the slope.

At the start of the slope, the skier has only potential energy, which is given by mgh.

At the end of the slope, the skier has only kinetic energy, which is given by $\frac{1}{2}mv^2$

Therefore, we can write:

$$mgh = \frac{1}{2}mv^2$$

Canceling out the mass m on both sides, we get:

$$gh = \frac{1}{2}v^2$$

Solving for v, we get:

$$v = \sqrt{2gh}$$

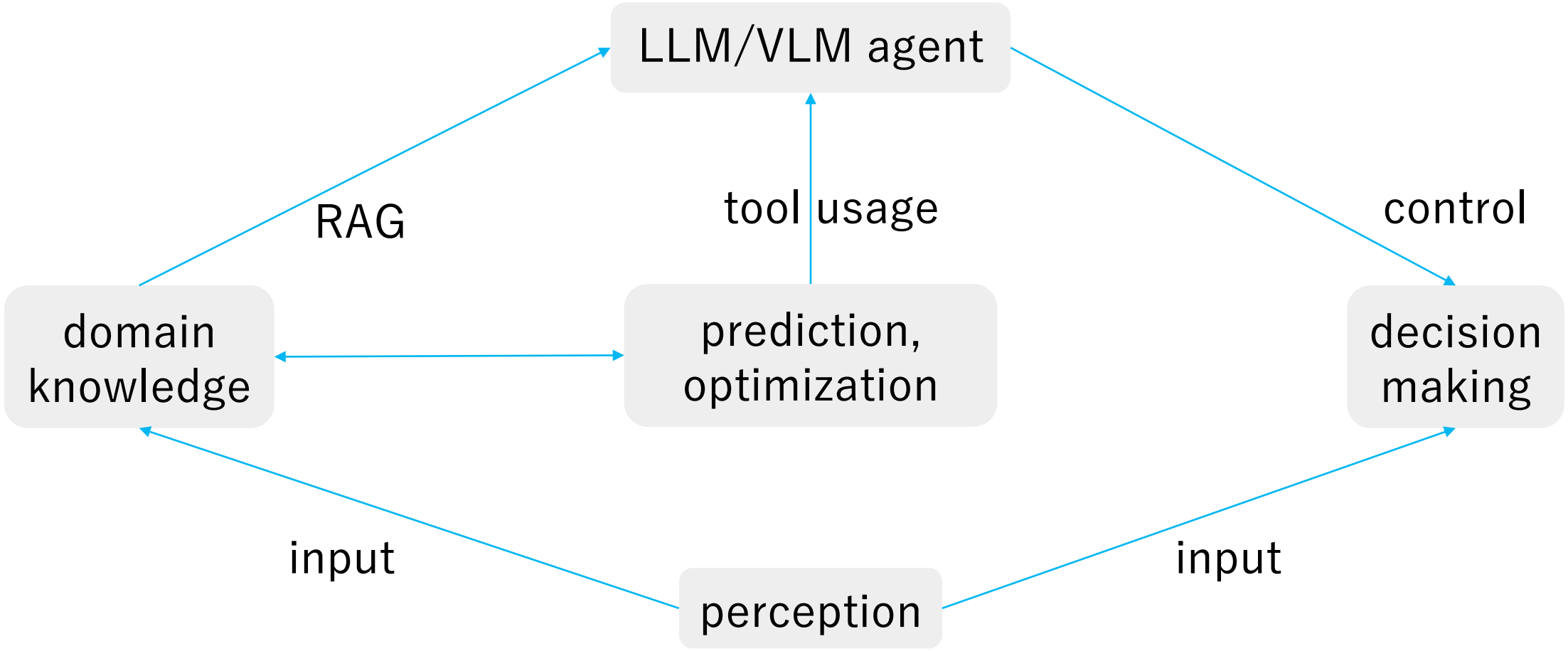
Substituting the given values, we get:

$$v = \sqrt{2 \times 9.81 \times 40} = 28.01\ m/s$$

Therefore, the skier's speed at the bottom of the slope is 28.01 m/s.

multimodal understanding of inputs: text, audio, images, video

Goal: Autonomous End-to-End Workflow



Generative AI

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

- text generation: LLMs
- image synthesis: diffusion models (usually conditioned on text by transformers)

Image Synthesis

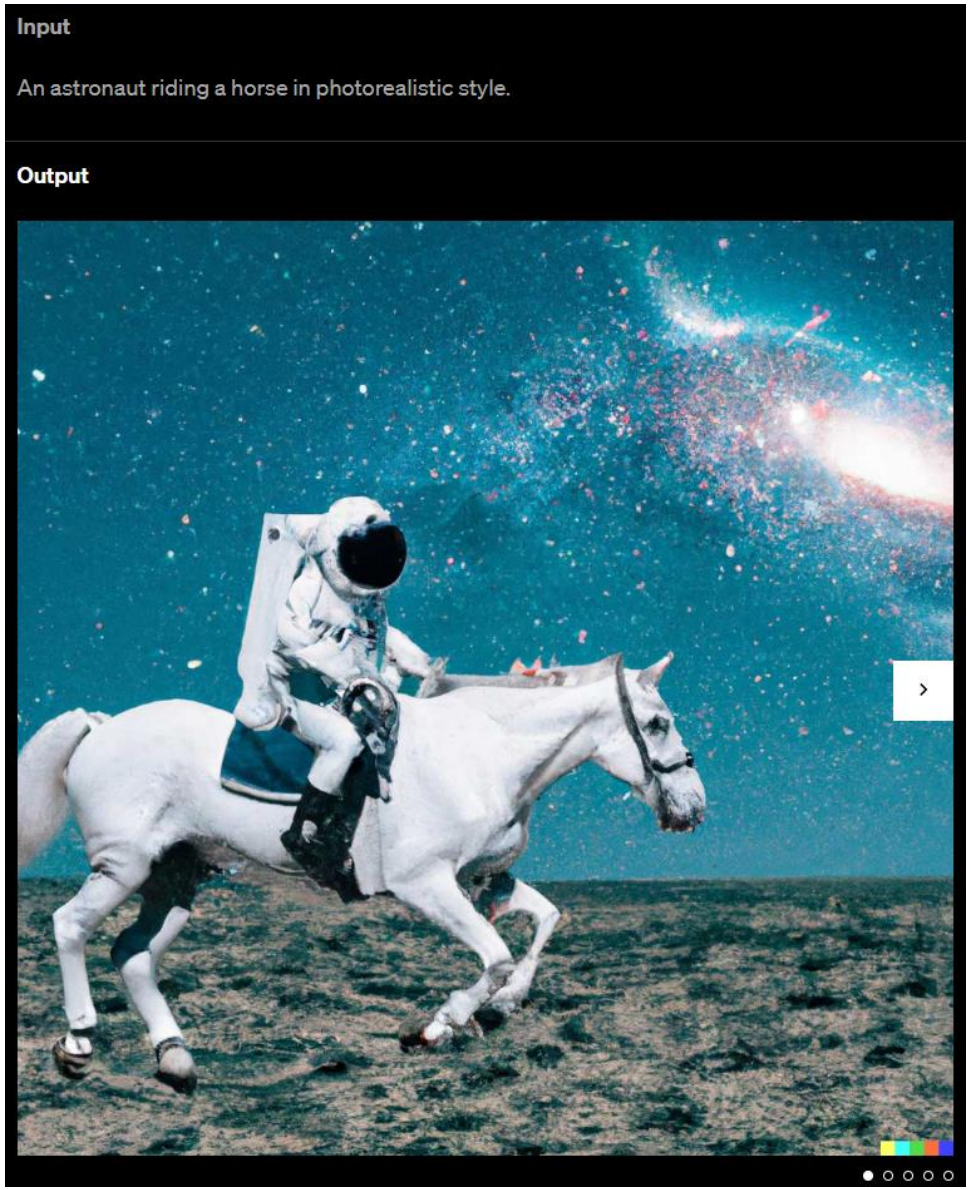
idea: generate new images as variations of training data

condition generation on text prompts: text-to-image

trade-off between diversity and fidelity

SOTA: (guided) diffusion models

example: DALL-E 2



Application

LLMs are “just” interfaces/translators: transforming one sequence (tokenizable input) into another

discriminative models

- effective for performing numerical and optimization tasks (predictions)
- continue to account for majority of AI value in wide range of industries (e.g., supply chain)

generative models

- not suitable for classical use cases like numerical and optimization tasks

(But LLM agents might use prediction or optimization models as tools.)

- but complimentary: drive value across entire organizations by revolutionizing internal knowledge management systems

(natural user interface)

LLMs in Plain Terms

foundation models:

- compression of the internet
- programming languages of new wave of AI applications (adapted to specific use cases and data)

→ These applications will make the internet more interactive.

Application Areas

Examples for Predictive Models: Supply Chain

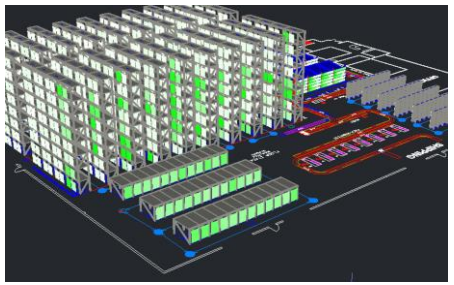
support of operations research

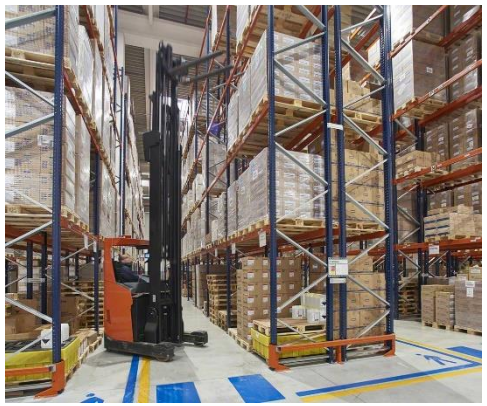
some examples:

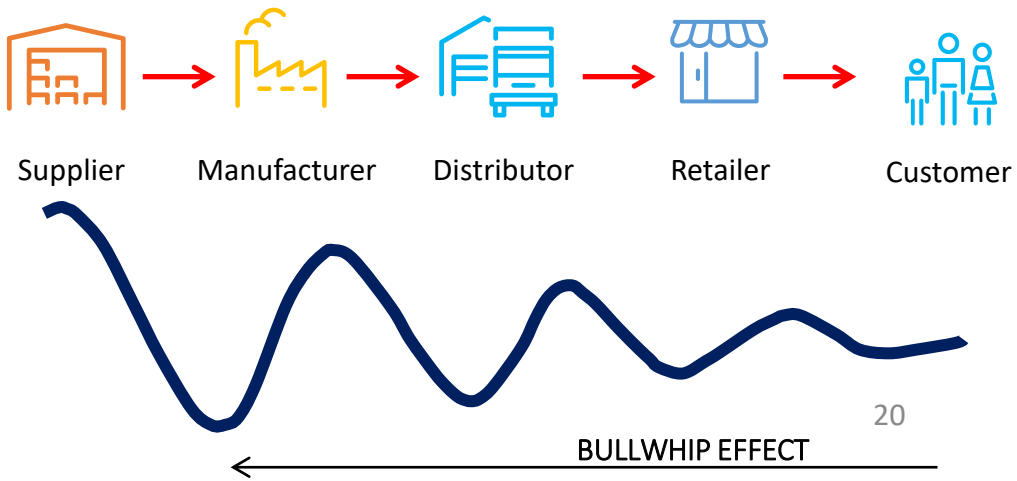
- warehouse operations
- transportation (logistics & mobility)
- retail

(Blue Yonder: demand forecasting, replenishment, pricing, targeting)

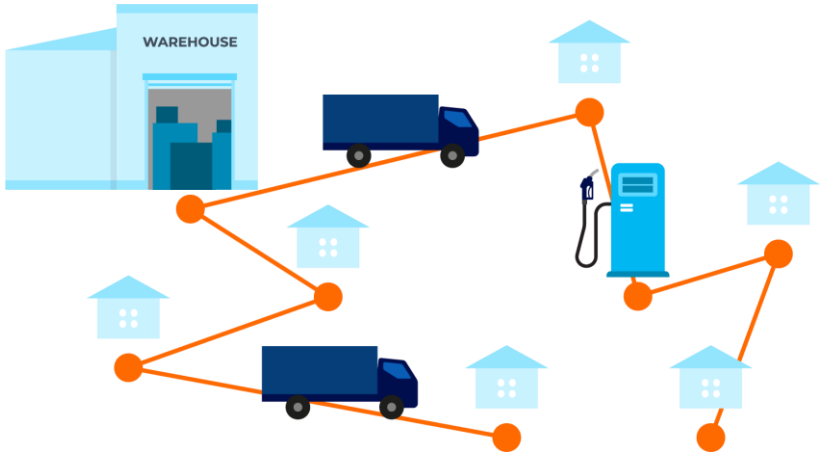
slotting:
e.g., using item affinity and order forecasting

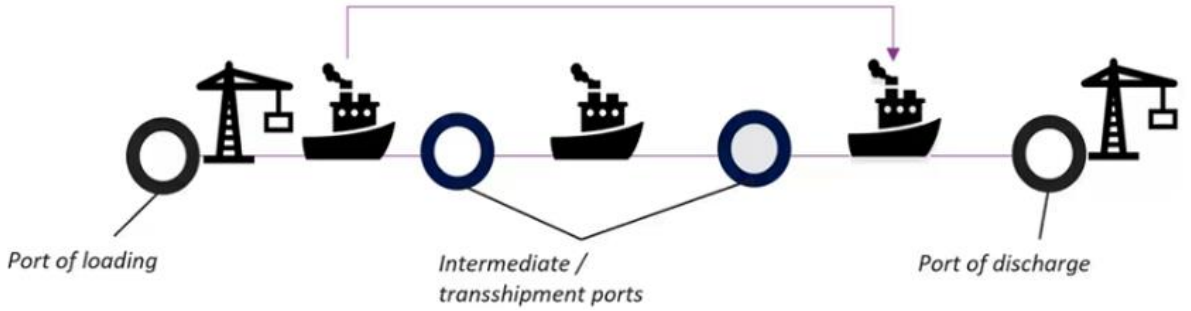






Connected Logistics



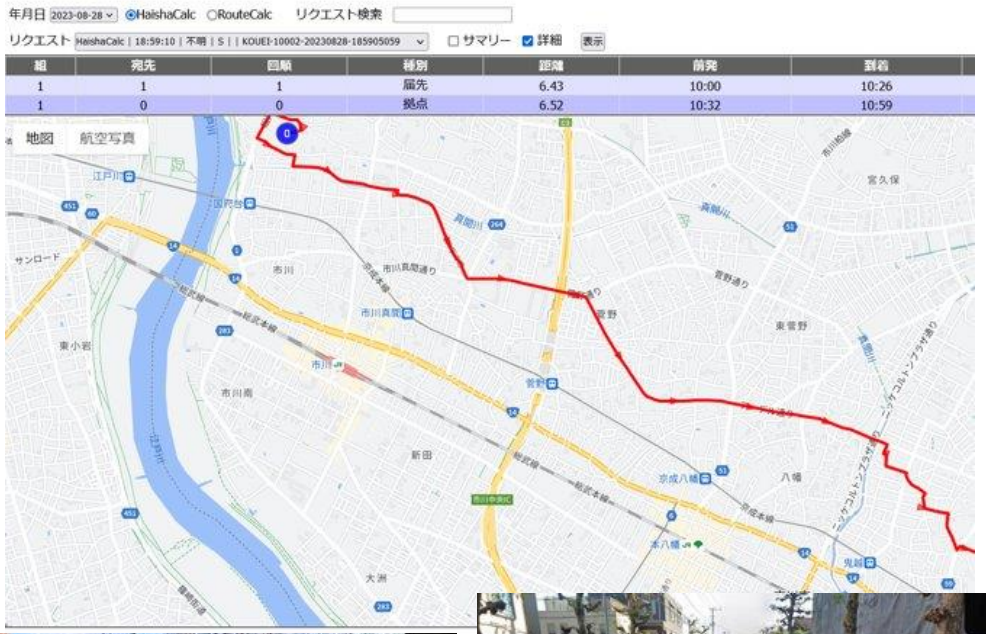


examples for ML solutions:

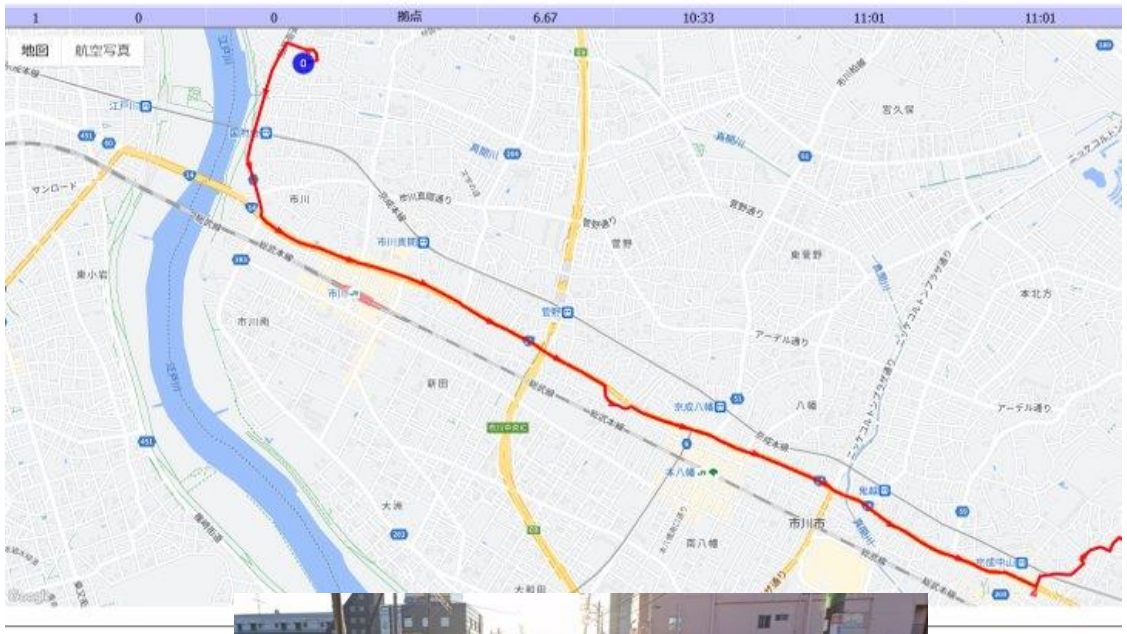
- arrival time predictions (aka ETA), for example in Google Maps via Graph Neural Network (GNN)
- reinforcement learning (combined with other methods like GNN) for better generalization in combinatorial optimization problems (e.g., TSP, VRP, …)
- disruption predictions (also root cause analysis)

Routing: Learning from Skilled Drivers

shortest route:

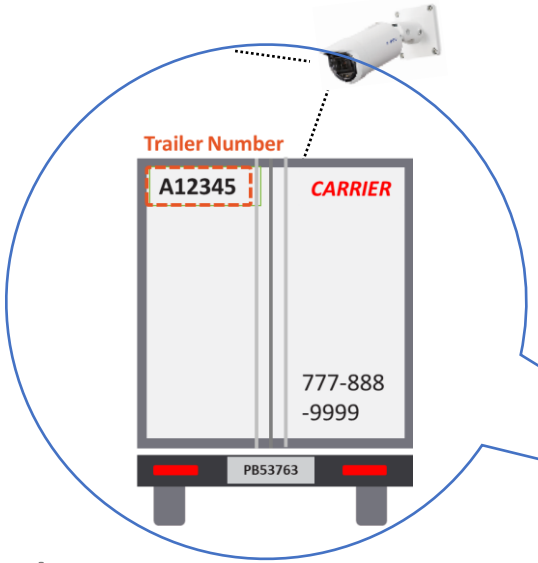


better route:



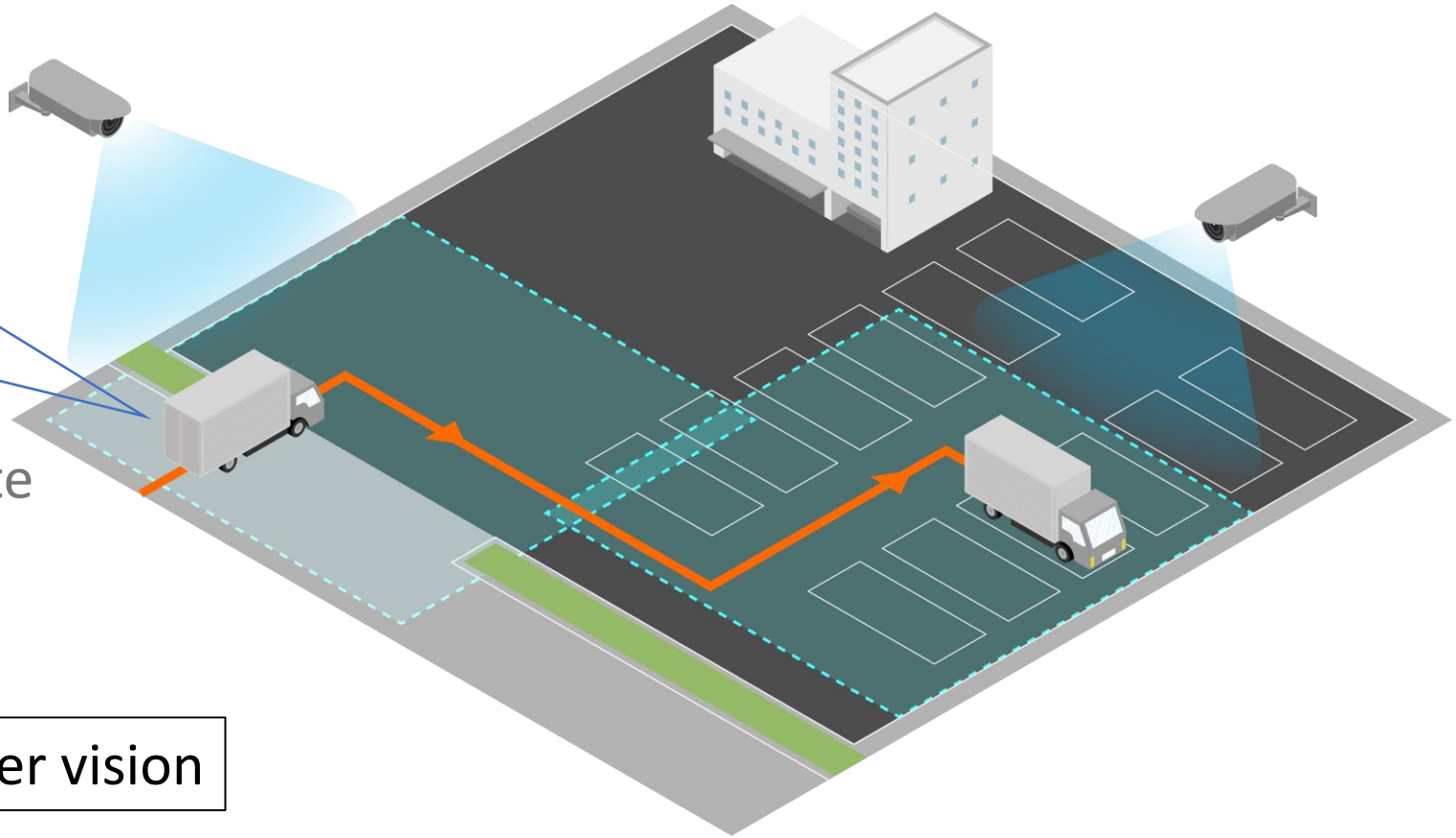
supervised learning

Tracking for Yard Management



trailer ID recognition at gate

computer vision



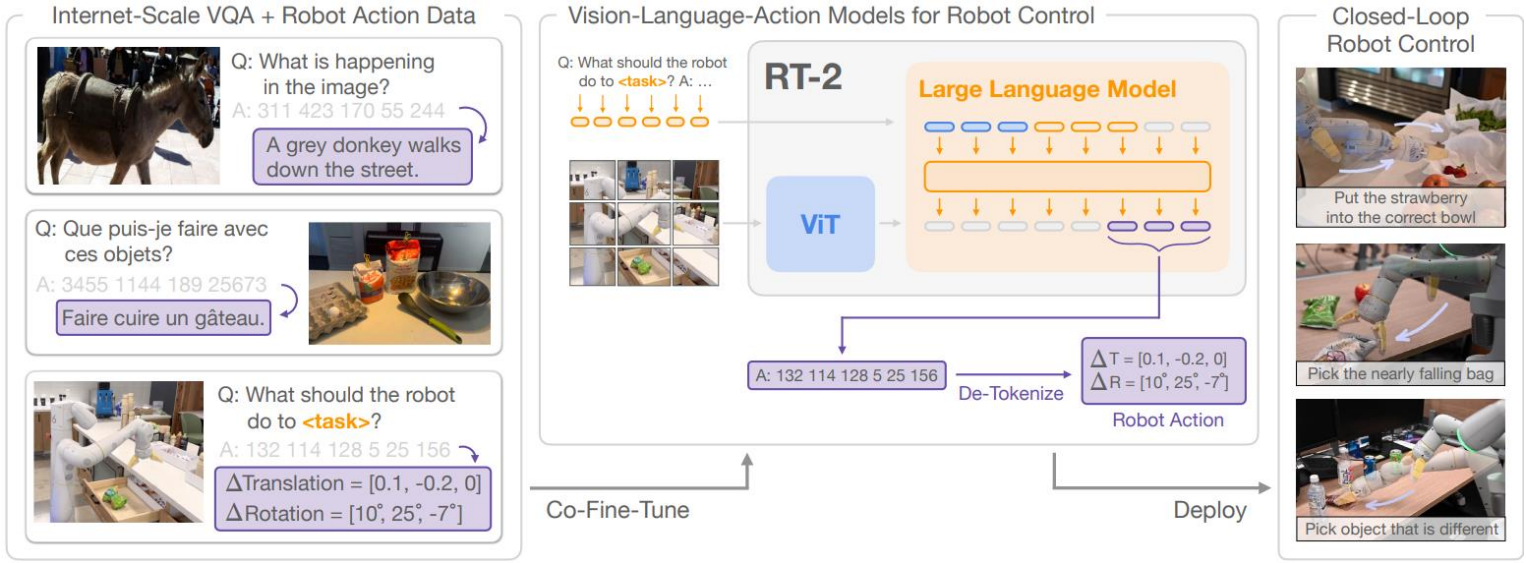
tracking across cameras

Robotic Control

different ways:

- reactive control (no ML)
- model predictive control
- imitation learning
- reinforcement learning
- using LLMs (and vision)

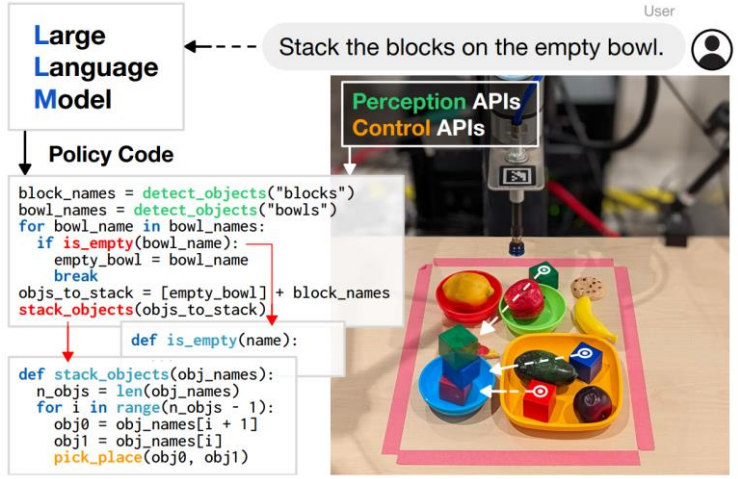
generalization with pre-trained vision-language models (RT-2):



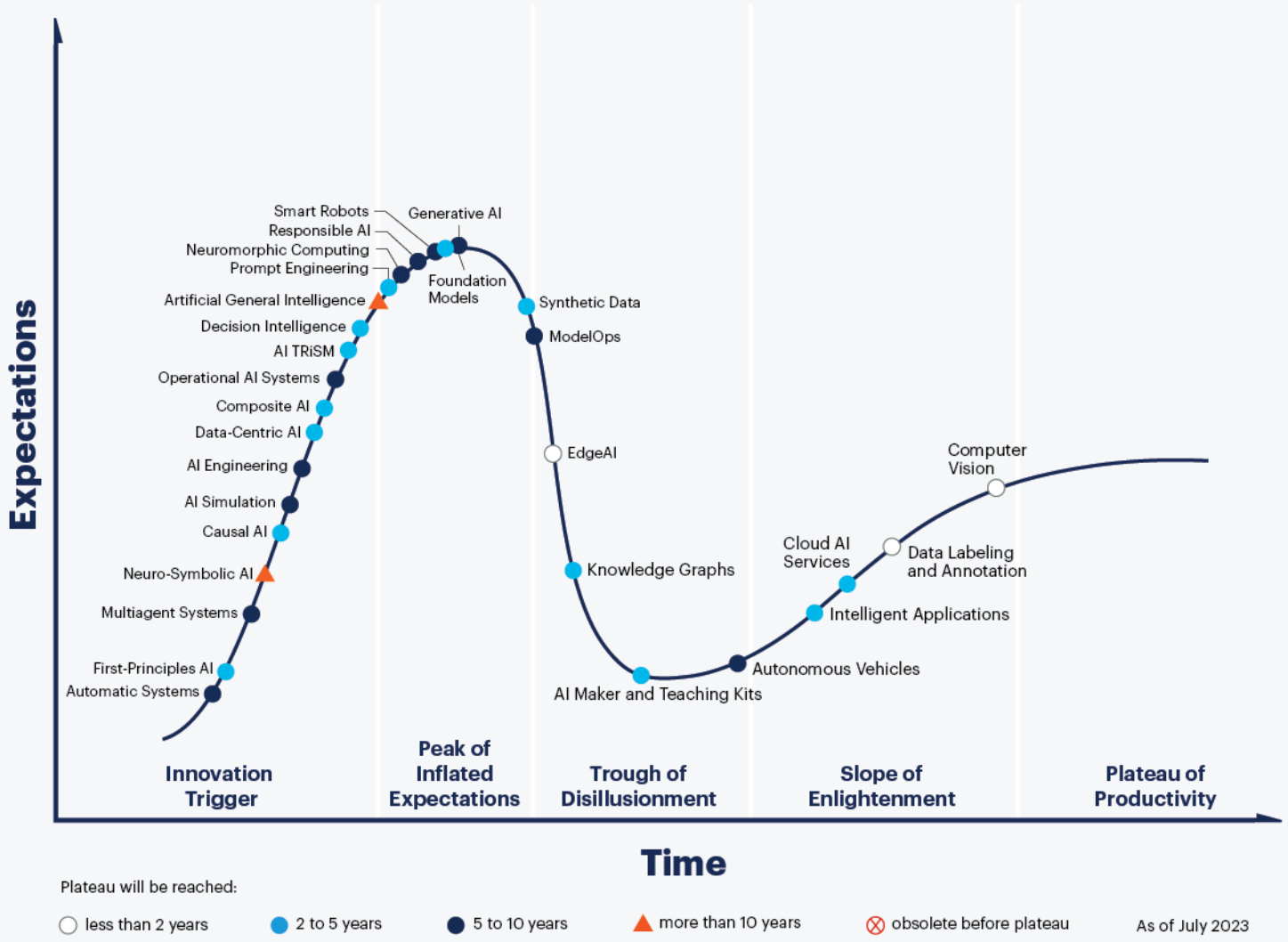
grounding with pre-trained skills (SayCan):

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

Code as Policies:



Hype Cycle for Artificial Intelligence, 2023



gartner.com

Gartner

Generative AI at peak of inflated expectations

still: there is now something to play with

Biggest Business Impacts of Generative AI

customer operations
interactions with customers

marketing & sales
generation of creative content

software engineering
coding assistant

product R&D
generative design (e.g., for chips)

Figure 1. Magic Quadrant for Enterprise Conversational AI Platforms

Coding Assistant

LLM: text-to-code

prominent example: GitHub Copilot

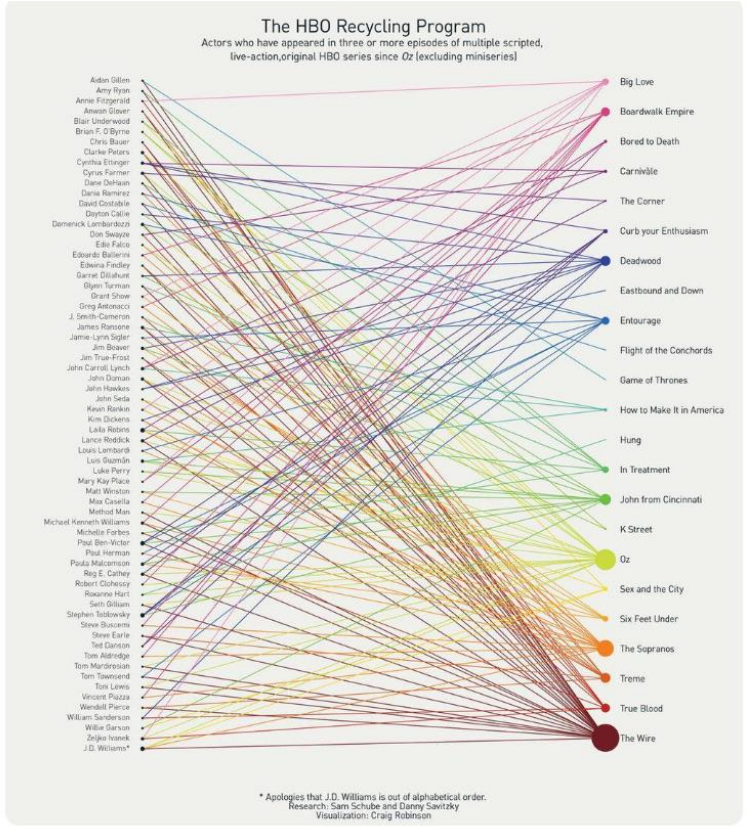
```python
import tweepy, os # secrets in environment variables

def fetch_tweets_from_user(user_name):
    # authentification
    auth = tweepy.OAuthHandler(os.environ['TWITTER_KEY'], os.environ['TWITTER_SECRET'])
    auth.set_access_token(os.environ['TWITTER_TOKEN'], os.environ['TWITTER_TOKEN_SECRET'])
    api = tweepy.API(auth)

    # fetch tweets
    tweets = api.user_timeline(screen_name=user, count=200, include_rts=False)
    return tweets
```

Copilot

Copilot for Knowledge Workers

multi-modal models (text and images)

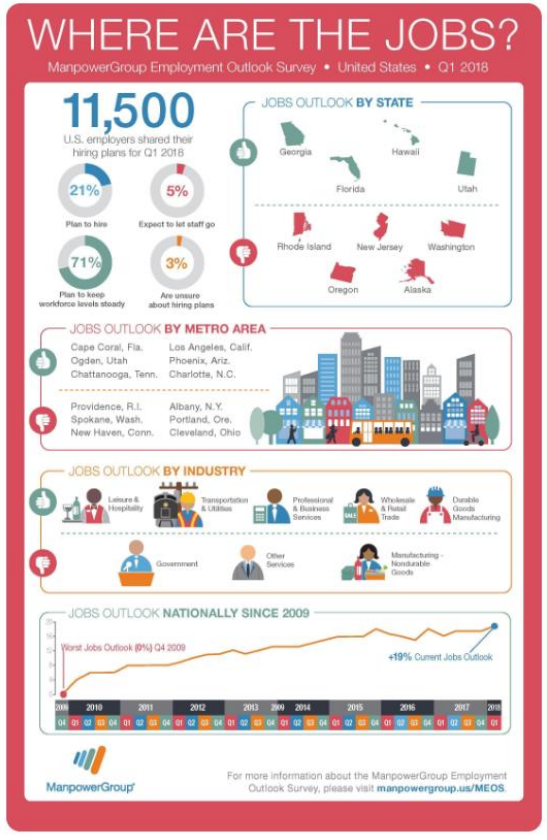
enable image understanding



Question: "Aidan Gillen acted in how many series?"

Fuyu's answer: "2"

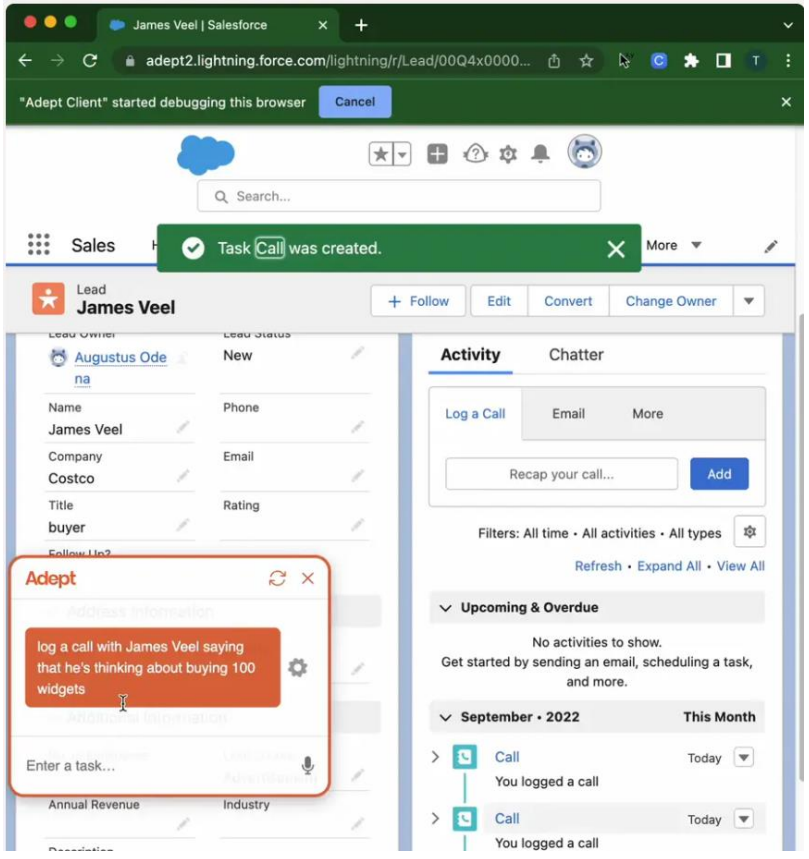
source



Question: "Which is the metro in California that has a good job Outlook?"

Fuyu's answer: "Los Angeles"

and execution of high-level user requests



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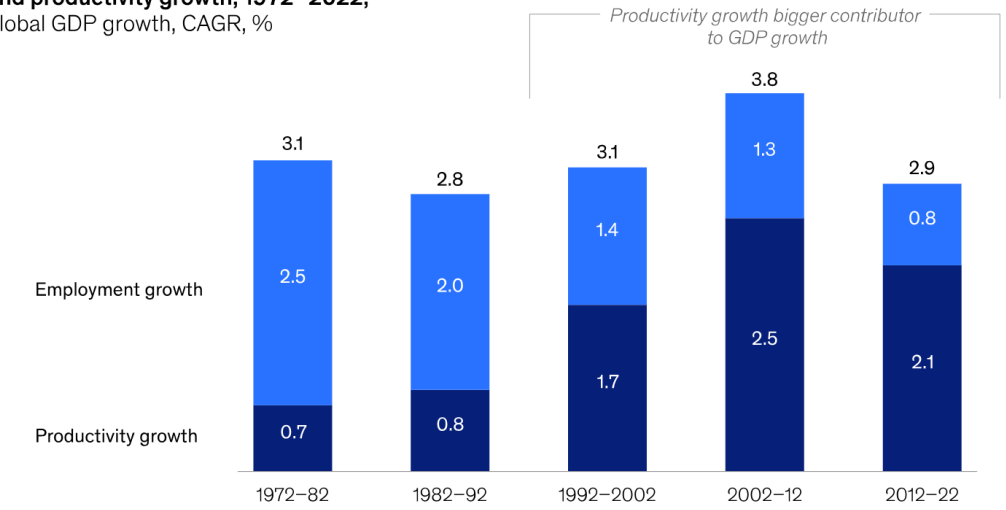
AI Potential

(generative) AI could free up 70% of employees' time

half of today's work activities could be automated between 2030 and 2060

Productivity growth, the main engine of GDP growth over the past 30 years, slowed down in the past decade.

Real GDP growth contribution of employment and productivity growth, 1972–2022, global GDP growth, CAGR, %

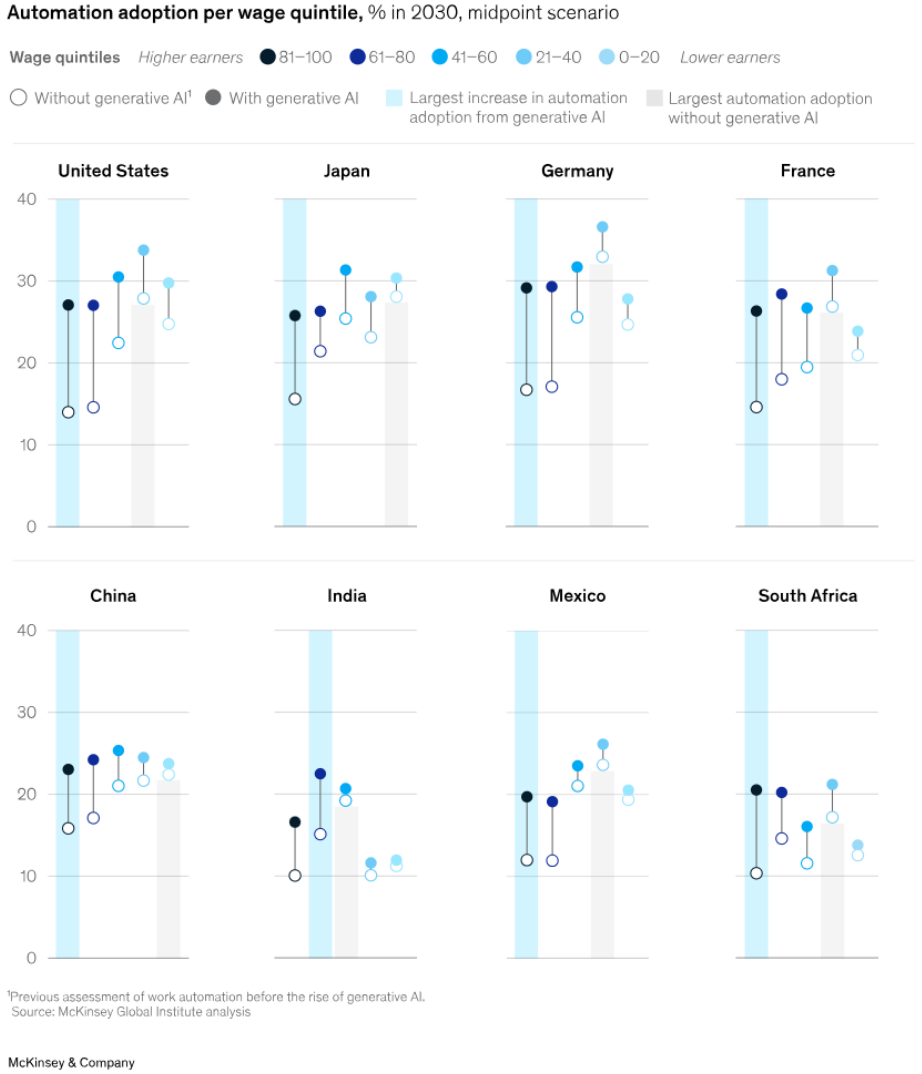


Source: Conference Board Total Economy database; McKinsey Global Institute analysis

McKinsey & Company

automate white-collar more than blue-collar jobs

Generative AI could have the biggest impact on activities in high-wage jobs; previously, automation's impact was highest in lower-middle-income quintiles.

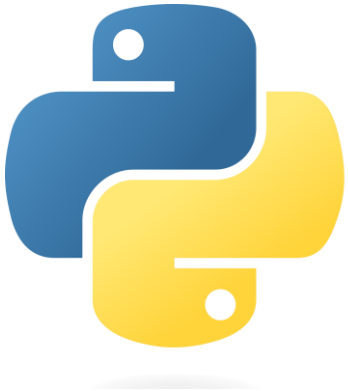


[1]Previous assessment of work automation before the rise of generative AI.
Source: McKinsey Global Institute analysis

McKinsey & Company

Engineering & Tech Stack

Scientific Python Stack



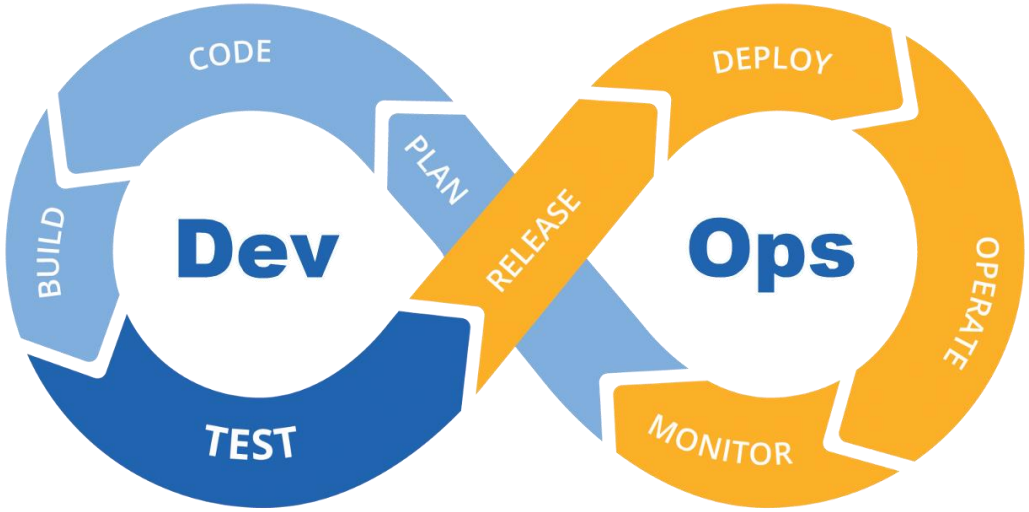
Deep Learning Frameworks

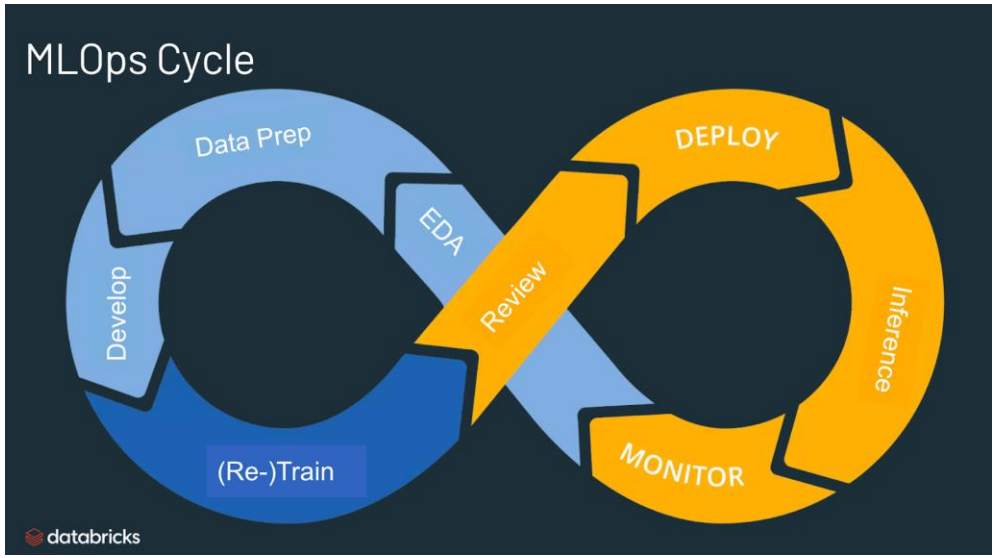
need for lots of memory and compute …

IaaS, PaaS, SaaS

example for managed service:
Azure Kubernetes Service (AKS)
for container orchestration

ML in Production





examples for managed ML services: Azure ML, SageMaker

Data Management

not only compute but also cloud-based data storage

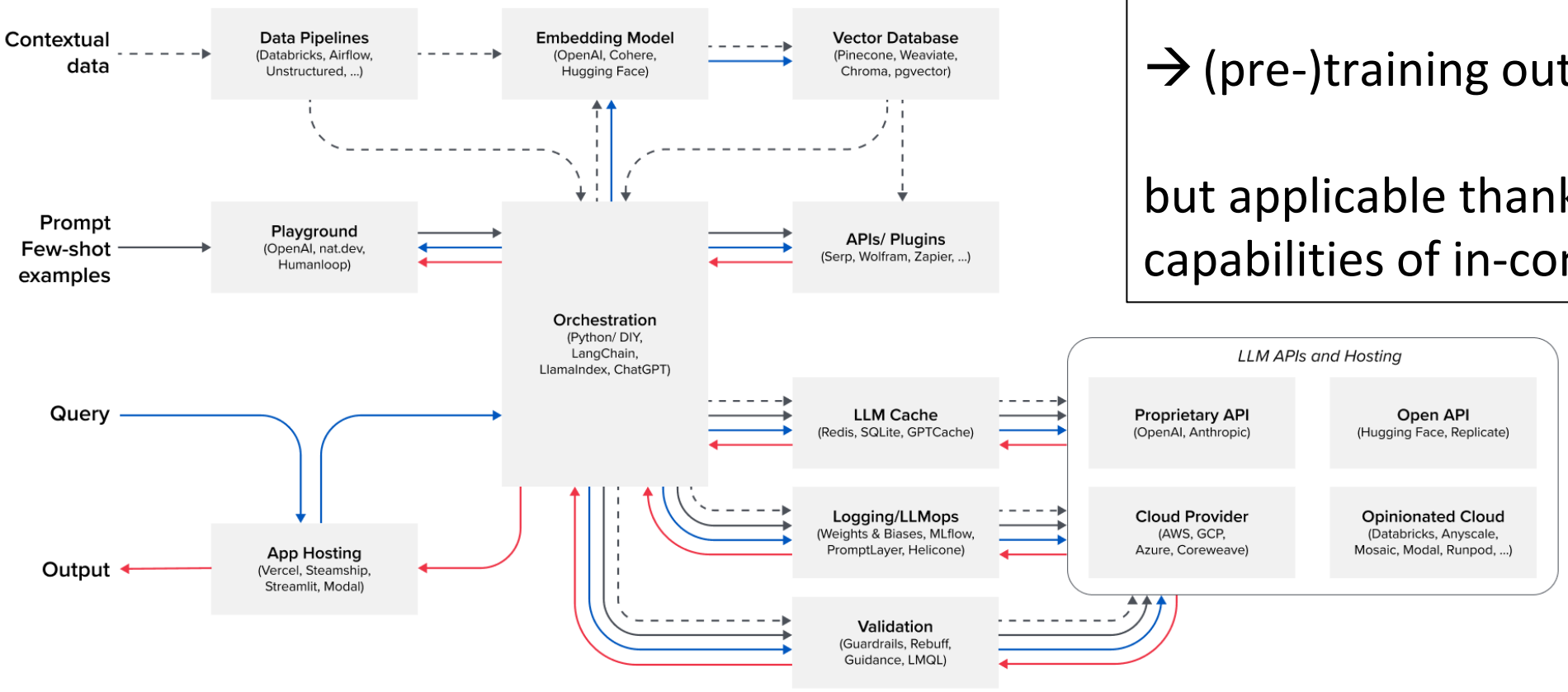
data lake: raw data

data warehouse: integrated data

unification of data lake and warehouse: ETL → ELT

NoSQL example: graph database

Emerging LLM App Stack



LEGEND

Gray boxes show key components of the stack, with leading tools/systems listed

Arrows show the flow of data through the stack

- Contextual data provided by app developers to condition LLM outputs
- Prompts and few-shot examples that are sent to the LLM
- Queries submitted by users
- Output returned to users

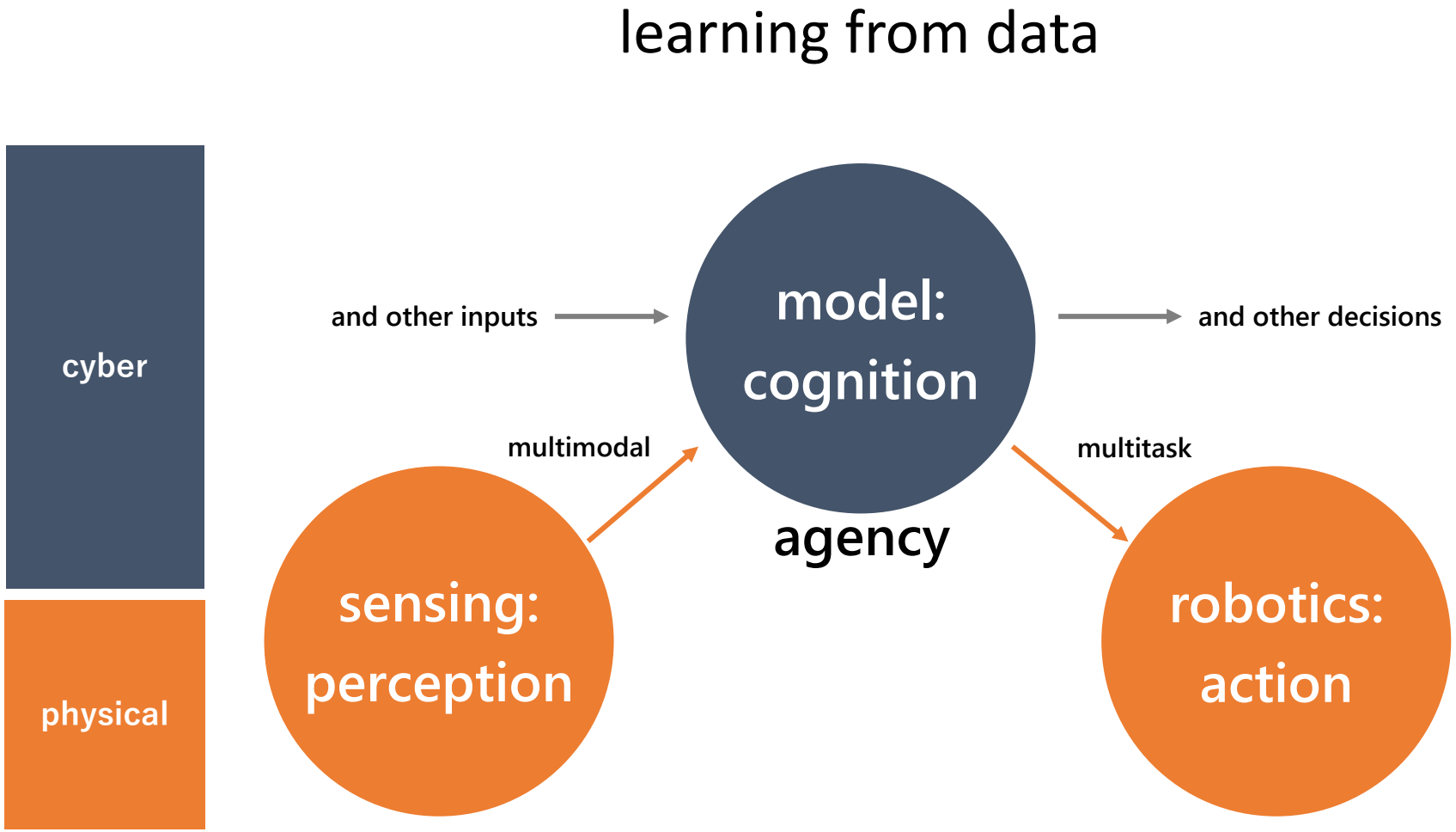
era of large-scale models:
AI currently on its engineering peak

→ (pre-)training out of reach for most

but applicable thanks to multi-task capabilities of in-context learning

a16z Enterprise

What the Future Holds: Autonomous Agents



Facts and Fiction

no more AI winters

data is everywhere, plenty of useful ML products

“classical” ML still needed

most value from predictive applications

Generative AI important step

“mirror” to see the world in different light

(probably) still Chinese room

no reliable indication for real understanding

AGI is not here (yet)

but performance of multi-task and multi-modal models still improving with scale

AI no (foreseeable) existential risk

more realistic and near-term risk: small number of companies control AI technology