

Machine Learning AI/ML/DL “buzzwords”.

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ML Research



Content

① AI/ML/DL “buzzwords”

- ▶ Broad Concepts
- ▶ Directions
- ▶ State-of-the-Art

AI “buzzwords” requests: broad concepts

- AI in the real world and its evolution
- Bias in AI
- Explainable/Interpretable AI
- Machine learning related revolution
- AI Planning
- AI Ethics/Law

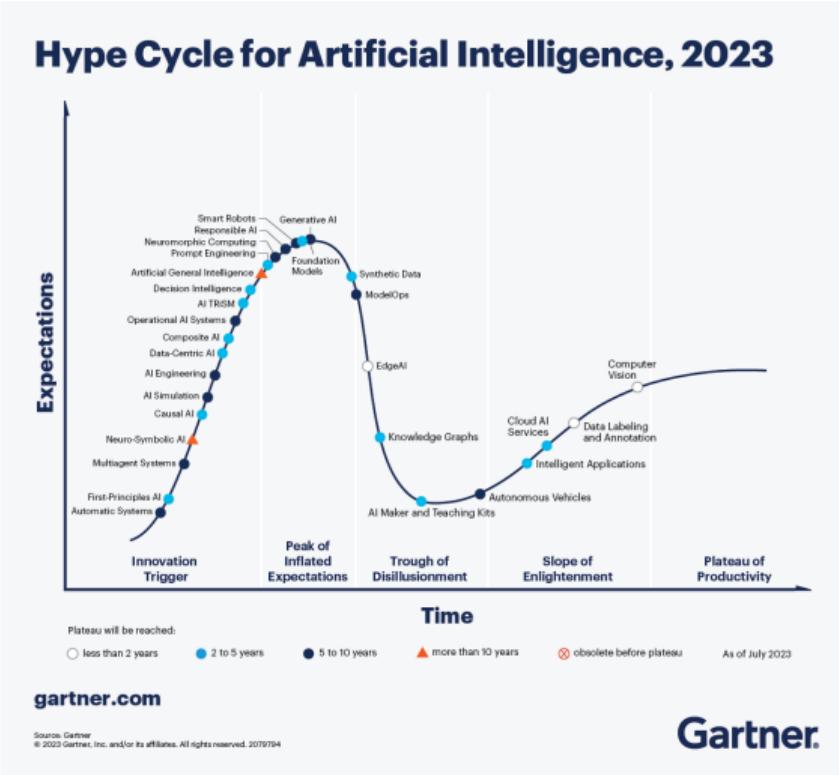
AI “buzzwords” requests: directions

- Deep Learning / Neural Nets
- Computer Vision
- NLP
- Speech Recognition
- Recommendation Systems
- Multi-modality
- Meta-learning
- RL and RLHF
- Edge Computing
- AutoML
- Self Driving
- AI in Healthcare

AI “buzzwords” requests: State-of-the-Art

- Generative AI
- AI Art Generator (Diffusion)
- LLM and ChatGPT
- Hallucinations
- Transformer Architecture
- Generative Adversarial Networks

Broad concepts: AI Hype Cycle¹



¹www.gartner.com

Broad concepts: Bias in AI

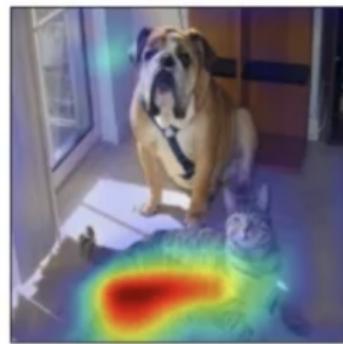
- Provides unfair prediction based w.r.t. race, gender, age. etc
- The main reason: skewed/sparse training data
- Main technique to avoid: human-in-the-loop, alignment
- Read material: [link](#)



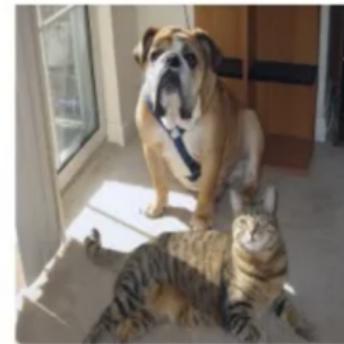
Broad concepts: Explainability and Interpretability

- AI/ML models *are not* black-boxes; they are huge (millions of weights) and structured (architecture) multi-dimensional and multi-variable functions
- Interpretability: understand the influence of any input sub-area/sub-feature on the model output; ML Debug system
- Explainability: high-level interpretability (using human-like language)
- Interpretability can be done via input counterfactual analysis
- Explainability now can be done via LLM chain-of-thought (CoT) technique
- Read material: [link](#)

Grad-CAM for "Cat"

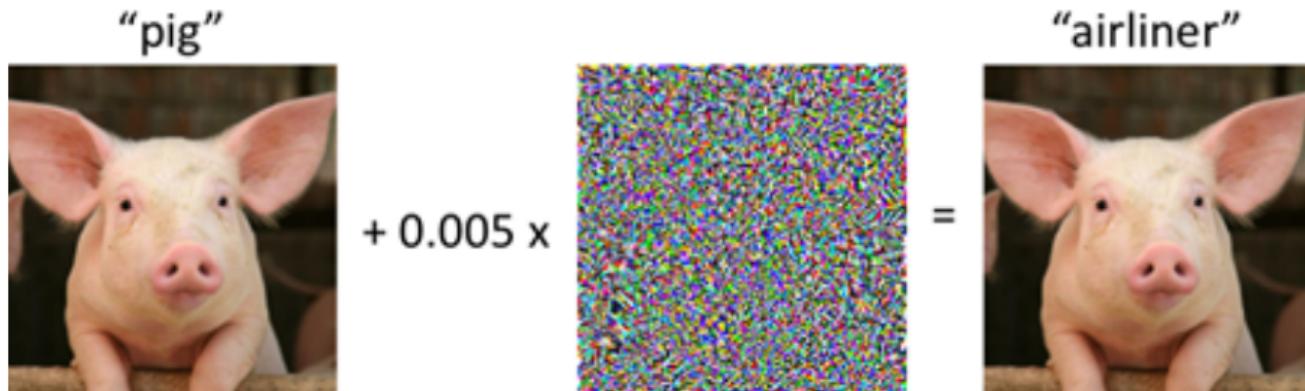


Grad-CAM for "Dog"



Broad concepts: ML-related revolution²

- Usually, the ML model performance is shown on a test/eval dataset
- Unfortunately, there is no guarantee of the similar performance on the different settings/datasets
- Providing these guarantees would put much more trust in ML and increase deployment speed
- Read material: [link](#)



²Personal opinion of a lecturer

Broad concepts: AI Planning³

- First of all, there is no a standard approach to AI Planning: it depends on many factors including the problem, the resources, the team capabilities, etc.
- One of the main practical approaches is what we've gone through “ML Pipeline” exercises during the course
- Practical advice: work in a “fail-fast” approach according to an Agile methodology
- Read material: [link](#)



³Personal opinion of a lecturer

Broad concepts: AI ethics and regulations⁴

Inequity and fairness

ML can contribute to and amplify social **inequity**

For **foundation models**, it is useful to separate:

- **intrinsic biases** (properties in the foundation model)
- **extrinsic harms** (harms in specific applications)

Source tracing to understand ethical/legal responsibility

Mitigations: **proactive interventions/reactive recourse**

Environment

Foundation models involve significant training/**emissions**

One perspective: **amortised cost over re-use**

Several factors would be **beneficial** to consider:

- **compute-efficient models, hardware, energy grids**
- **environmental cost** as a factor for evaluation
- greater **documentation and measurement**

Economics

Foundation models may have **economic impact** due to:

- **novel capabilities**
- potential applications in **wide array of industries**

Initial analyses have been conducted to understand implications for **productivity, wage inequality, concentration of ownership**

Misuse

Misuse: the use of foundation models as technically intended but for societal harm (e.g. disinformation)

Foundation models may make misuse easier by generating **high-quality personalised content**

Disinformation actors can target demographic groups

Foundation models may also help to **detect misuse**

Legality

How **law** bears on development/deployment is unclear

Legal/regulatory frameworks will be needed

In the **US** setting, important issues include:

- **liability** for model predictions
- **protections from model behaviour**

Legal standards must advance for intermediate models

Ethics of scale

Widespread adoption of foundation models poses ethical, political and social concerns

Ethical issues related to **scale**:

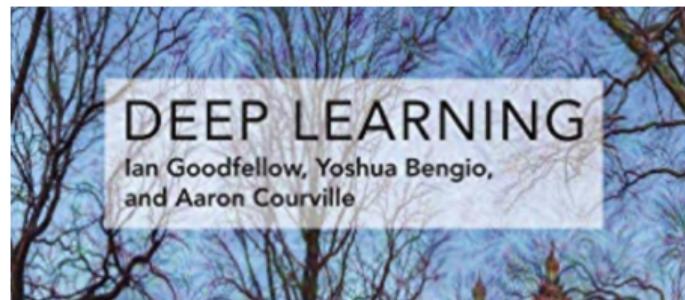
- **homogenisation**
- **concentration of power**

How can **norms and release strategies** address these?

⁴www.youtube.com

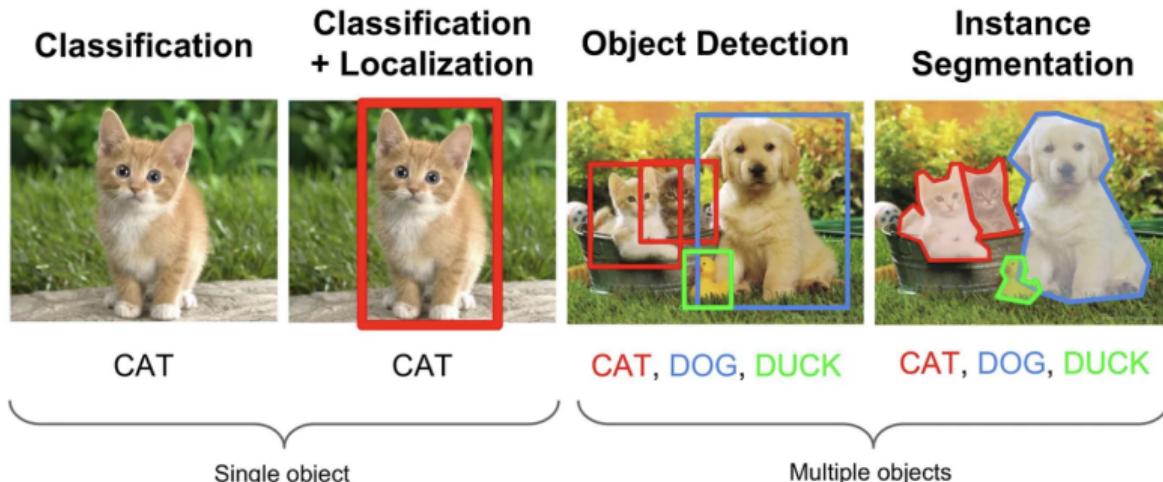
Directions: Deep Learning and Neural Nets

- Neural Net (NN): a (usually!) non-linear function mapping a (usually) multi-dimensional input to some output (which can be of the same dimension, or a bigger/smaller one)
- Most common NN atomic operations: addition, multiplication, scalar non-linearity, aggregation/normalization
- Deep Learning: a NN consisting of more than 2 layers of atomic operations (that's why deep) and the corresponding procedure of the training ("learning") its weights using back propagation process
- Read material: [link](#)



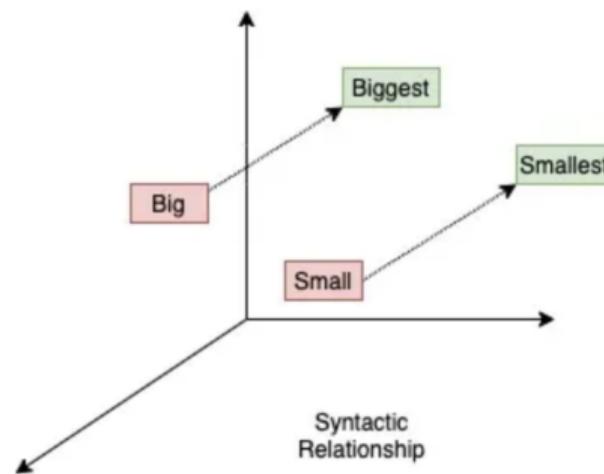
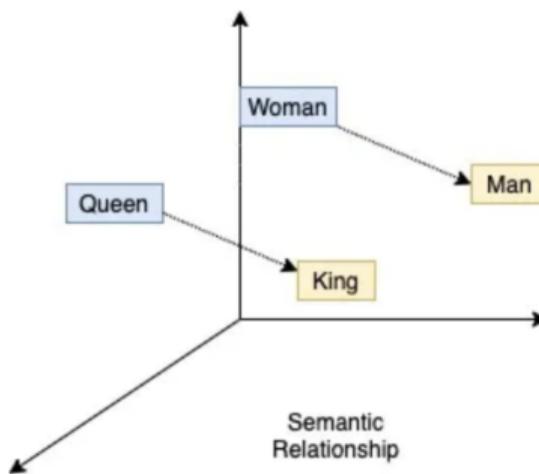
Directions: Computer Vision

- Computer Vision (CV): Direction targeted to analyze vision information: mostly images and videos
- Most common CV directions: classification, detection, segmentation
- Main research is concentrated around architectures of CV models
- Read material: [link](#)



Directions: NLP

- Natural Language Processing (NLP): Direction targeted to analyze human languages (e.g., English)
- Most common NLP directions: understanding (classification), generation, QA
- The difficulties start with language representation + the engine to process this representation
- Read material: [link](#)



Directions: Speech Recognition

- Automatic Speech Recognition (ASR): Direction targeted to map a sequence of audio inputs to text outputs
- ASR mains differences with CV: 1) temporal sequence; 2) can benefit from signal pre-processing (like Fourier Transform, Mel-Frequency Cepstral Coefficients, etc.)
- Main research is concentrated around architectures of ASR models and how to omit pre-processing stage
- Read material: [link](#)

Features (X)

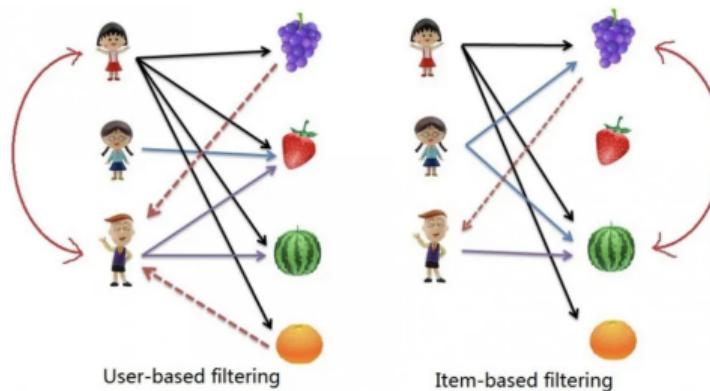


Labels (y)

Good Morning!

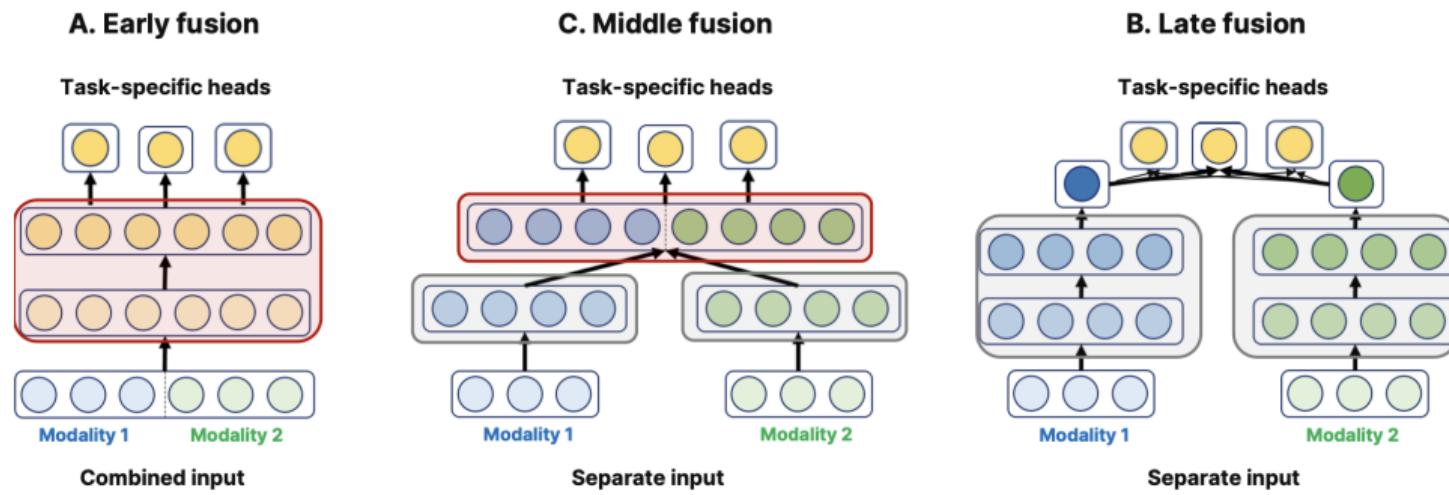
Directions: Recommendation Systems

- Recommendation Systems (RecSys): Direction targeted to predict user preference of the unseen product
- Most common RecSys approaches: Collaborative Filtering (based on User Similarity), Content-based Filtering (based on Item Similarity), and Hybrid
- Main research is concentrated around the Representations (matrix factorization, neural-based representations)
- Read material: [link](#)



Directions: Multi-modality

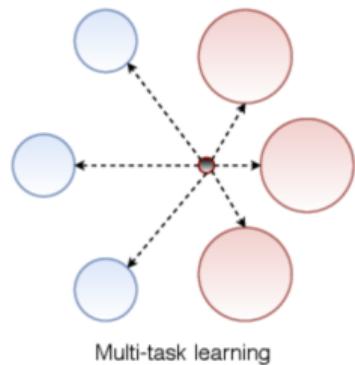
- It seems that incorporating different modalities (like human does: vision, hearing, flair, etc.) can improve the performance of an ML model
- Two main modalities to combine now: text and images
- Techniques differ in the way where we fuse the modality: early or late fusion
- Read material: [link](#)



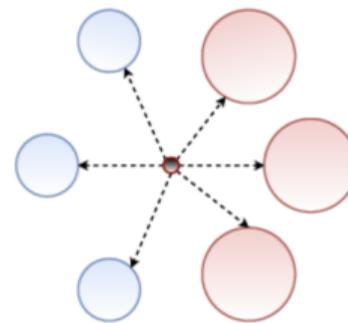
Directions: Meta-learning and Multi-tasking

- How to solve different tasks by a single model?
- If it is done sequentially, then we come to meta-learning: trying to provide the model's weights initialization as close as possible to all the tasks
- If it is done simultaneously, then we come to multi-tasking: training weights to satisfy all of the objectives at once
- Read material: [link](#)

task with small data task with big data trained model



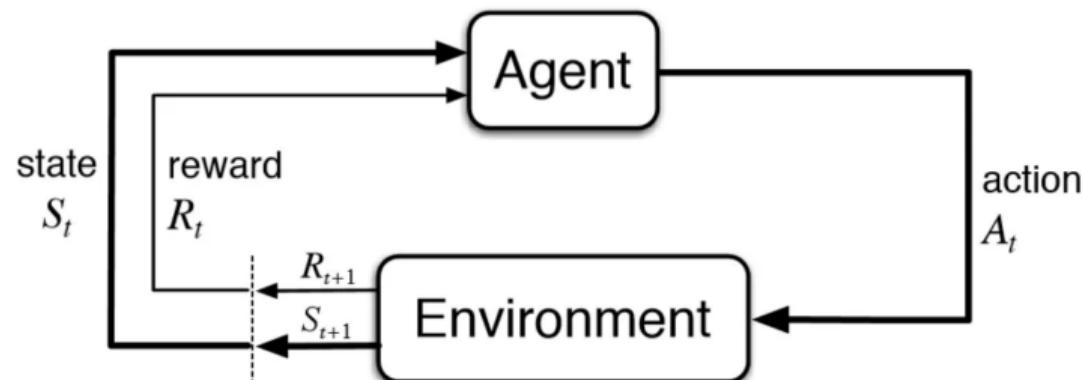
Multi-task learning



Meta learning

Directions: RL and RLHF

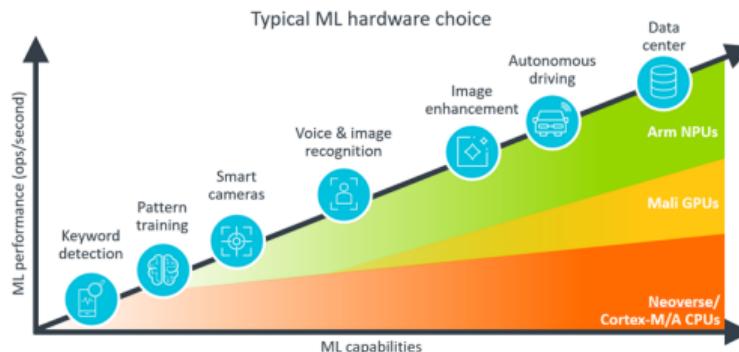
- Reinforcement Learning (RL): trying to train the ML model of action selection (e.g., of a robotic arm) based on the environment dynamics and external reward
- RL is the closest to real-life setting and at the same time the most complex one (hard to train, hard to get data, etc.)
- RL from Human Feedback (RLHF): training reward model based on human-in-the-loop preferences (e.g., pairwise comparison)
- Read material: [link](#)



Directions: Edge Computing

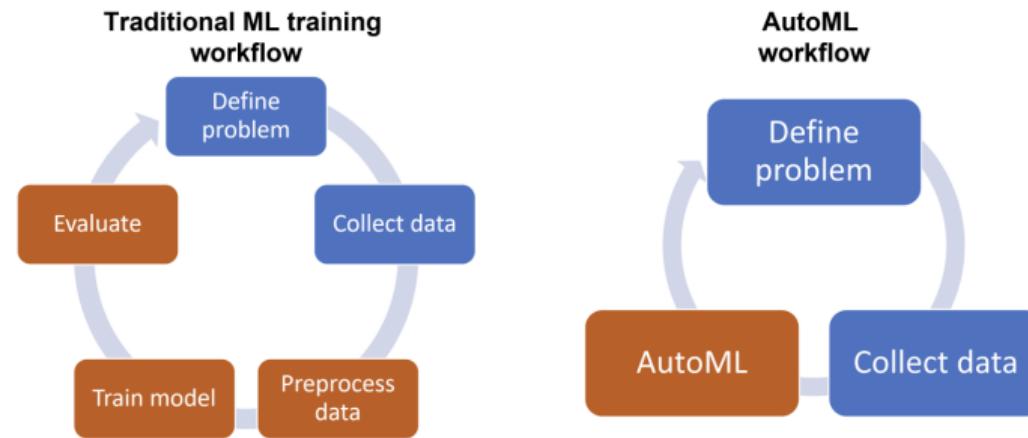
- State-of-the-Art models are huge (GB scale in both ROM and RAM), need to adapt them in order to use on edge devices
- Main techniques are: 1) distillation to faster/smaller architectures, 2) quantization, 3) pruning, 4) parallelization
- Need to be careful: small model doesn't mean low latency!
- Read material: [link](#)

Multiple ML Use Cases on Edge Devices



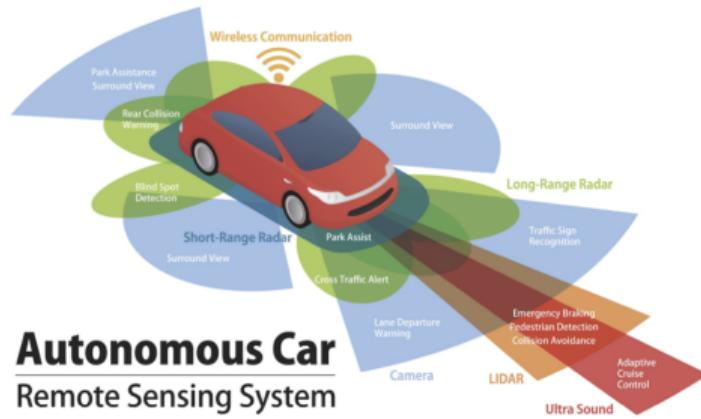
Directions: AutoML and NAS

- NN Architecture design is hard and non-formalized
- AutoML and Neural Architecture Search (NAS): an approach to automatically construct the architecture out of some atomic building blocks and the rules to combine them (NAS) and build an automatic ML pipeline around it (AutoML)
- Usually, NAS is very resource-greedy and time-consuming; but can lead to a smaller/better models (unfortunately, sometimes only marginally)
- Read material: [link](#)



Directions: Self Driving

- Self-driving is a super challenging area comprising literally all the ML Research directions. The main concern is safety that comes through the robustness and generalization
- Highly dependent on the training/eval data, hardware used, settings etc. — that's why there is no open self-driving model (at least, now)
- Main modules are Mapping, Perception, Prediction, Planning, Control
- Read material: [link](#)

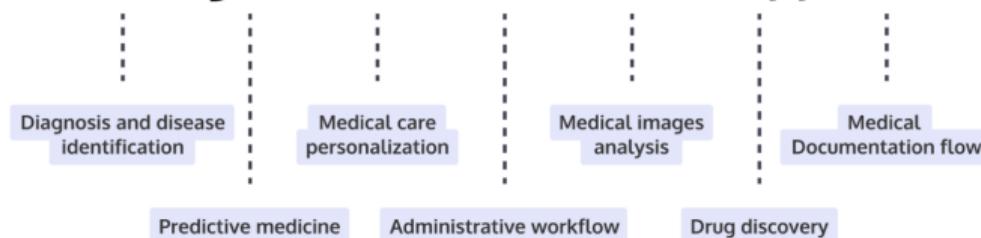


Directions: AI in Healthcare

- Healthcare is a very conservative field
- Primary challenges are 1) Data amount (small!); 2) Data privacy (hard to share); 3) Metrics are different; 4) Extremely need in explainability
- That's why most of the ML models used in Healthcare are still simple
- Successful applications include diagnostics and medical image descriptions ([link](#))
- Read material: [link](#)

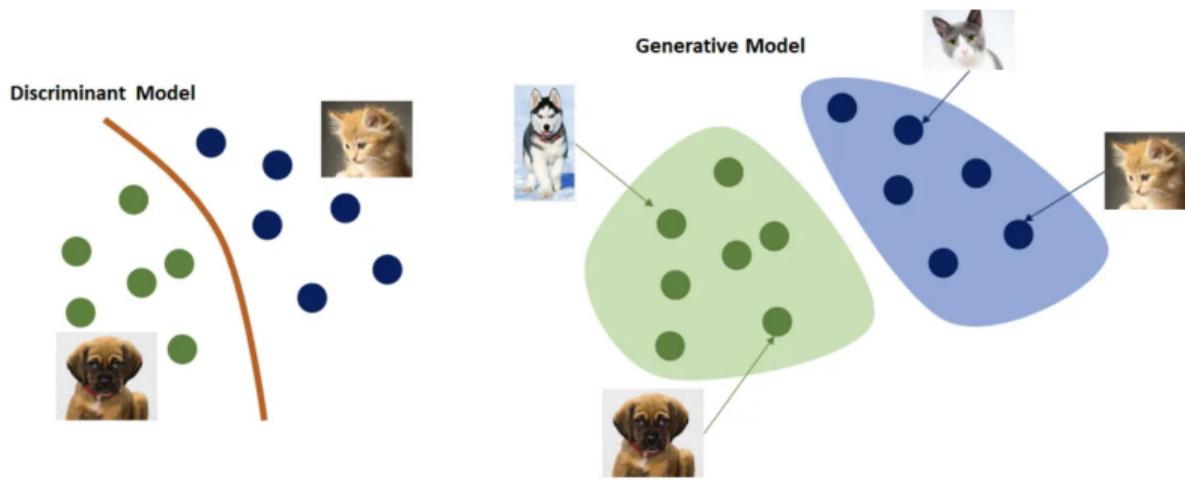


ML algorithms in healthcare: app fields



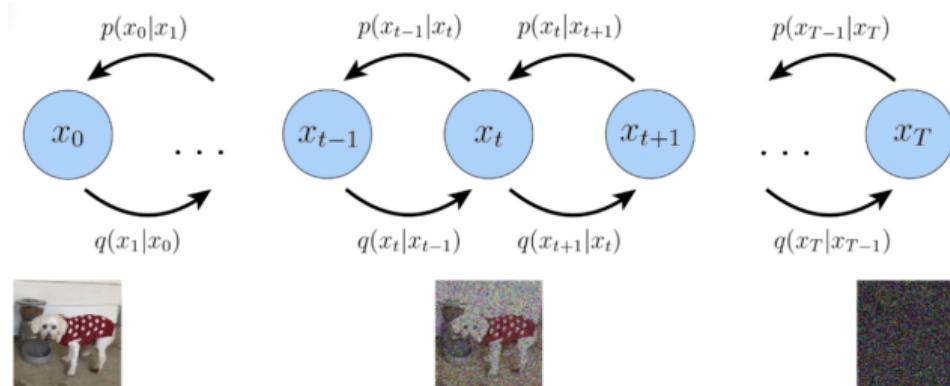
State-of-the-Art: Generative AI

- Generative AI main goal: to work on top of distributions, not single data examples
- Generative models can be conditioned: e.g., generate the image given some textual caption for it
- Output is **probabilistic**: so we can produce multiple in-distribution outputs based on the same condition
- Read material: link



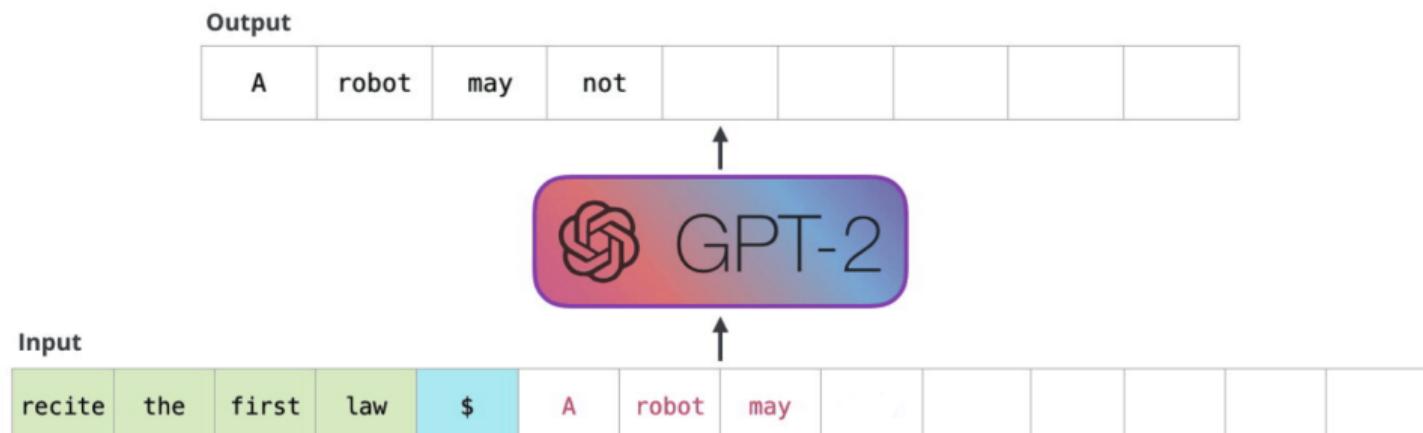
State-of-the-Art: AI Art Generator / Diffusion

- Diffusion Model is the generative model based on hierarchical markovian variational auto encoder
- Main idea is to reverse the noise (diffusion) by the learned model
- Stable diffusion is the process to work on top of the (latent) representations that have much smaller dimensions making it quite stable
- Famous representatives: Midjourney, Imagen, DALL-E (Images), SORA (Video)
- Read material: [link](#)



State-of-the-Art: LLMs and ChatGPT

- Large Language Model: A model trained with a super simple principle: either to predict a masked word (encoder; BERT) or to predict the next word (decoder; GPT)
- ChatGPT is an auto regressive decoder model trained on a huge amount of textual data (like a half of the Internet) using the RLHF
- Main problems with them right now: how to restrict the outputs (e.g., obscene language), how to ensure fairness, and how to avoid hallucinations
- Read material: [link](#)



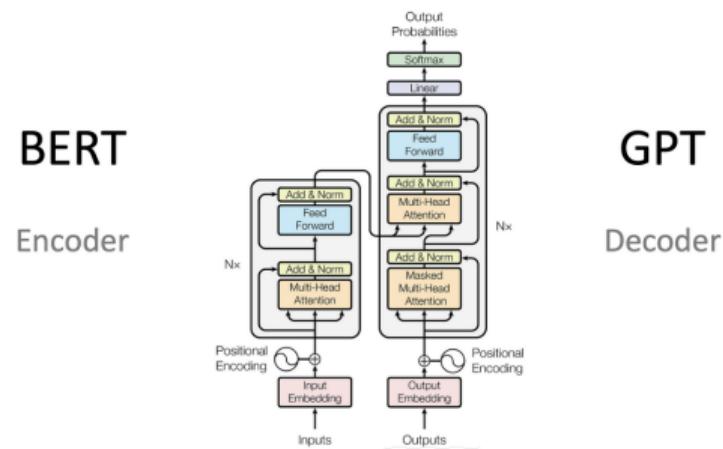
State-of-the-Art: Hallucinations

- Hallucination: one of the problems with LLMs
- It's the output that is not a part of the LLM training data
- Can be overcome with chain-of-thoughts, iterative output adjustment, and using external memory (retrieval augmented generation)
- Read material: [link](#)

Passage	Scenario #1 - Hallucination
Original Answer	Philip Hayworth was an English barrister and politician who served as Member of Parliament for Thetford from 1859 to 1868.
Sample 1	<i>Philip Hayworth was a British politician who served as the Member of Parliament for Bolton West from 1931 to 1945. He was also a member of the Free Trade Union and served on several government committees.</i>

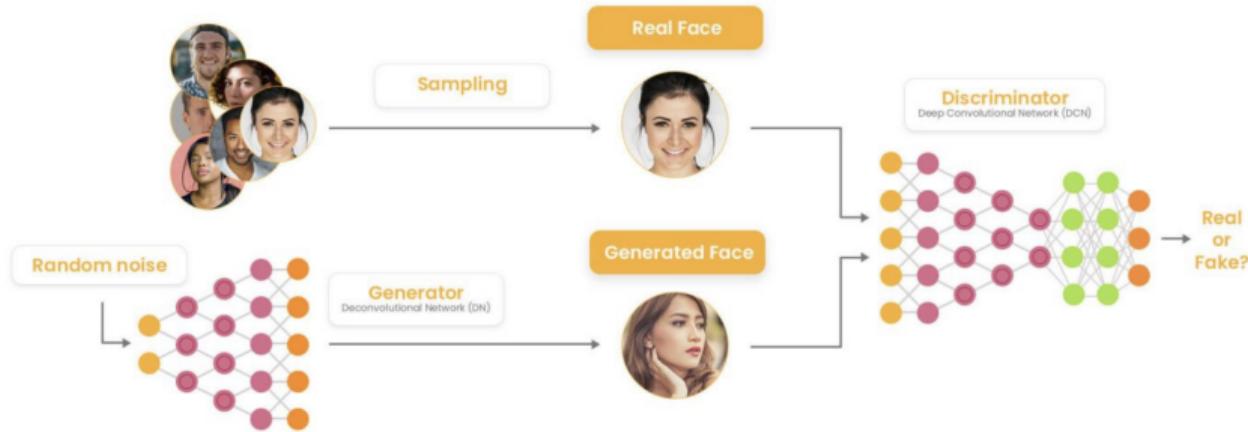
State-of-the-Art: Transformer Architecture

- Transformer is the architecture with the minimal inductive bias (e.g., in comparison to CNN or RNN): we are looking at the correlation (“attention”) between every pair of input elements
- Super efficient architecture for literally every ML direction: CV, ASR, LLM, etc
- Can be encoder-decoder (machine translation), encoder (language modeling), and decoder (text generation - <http://jalammar.github.io/illustrated-gpt2/>)
- Read material: [link](#)



State-of-the-Art: GAN

- Generative Adversarial Network (GAN): one more generative model
- Main idea is to train two model in parallel: 1) Generator to produce the in-distribution data, and 2) Discriminator to discriminate between the real (GT) and synthetic (generated) data
- Quite unstable because of minmax problem and now mostly replaced by Diffusion models
- Read material: [link](#)



Thank you *all!*