Machine Learning – Overview

Main Areas of Artificial Intelligence

from wikipedia

- **computer vision**

  (spatial structures, state-of-the-art: Convolutional Neural Networks)
- **natural language processing**

  (sequential structures, state-of-the-art: transformers)
- **automated decision making, robotics**

  (reinforcement learning)

agency:
perception – thought – action

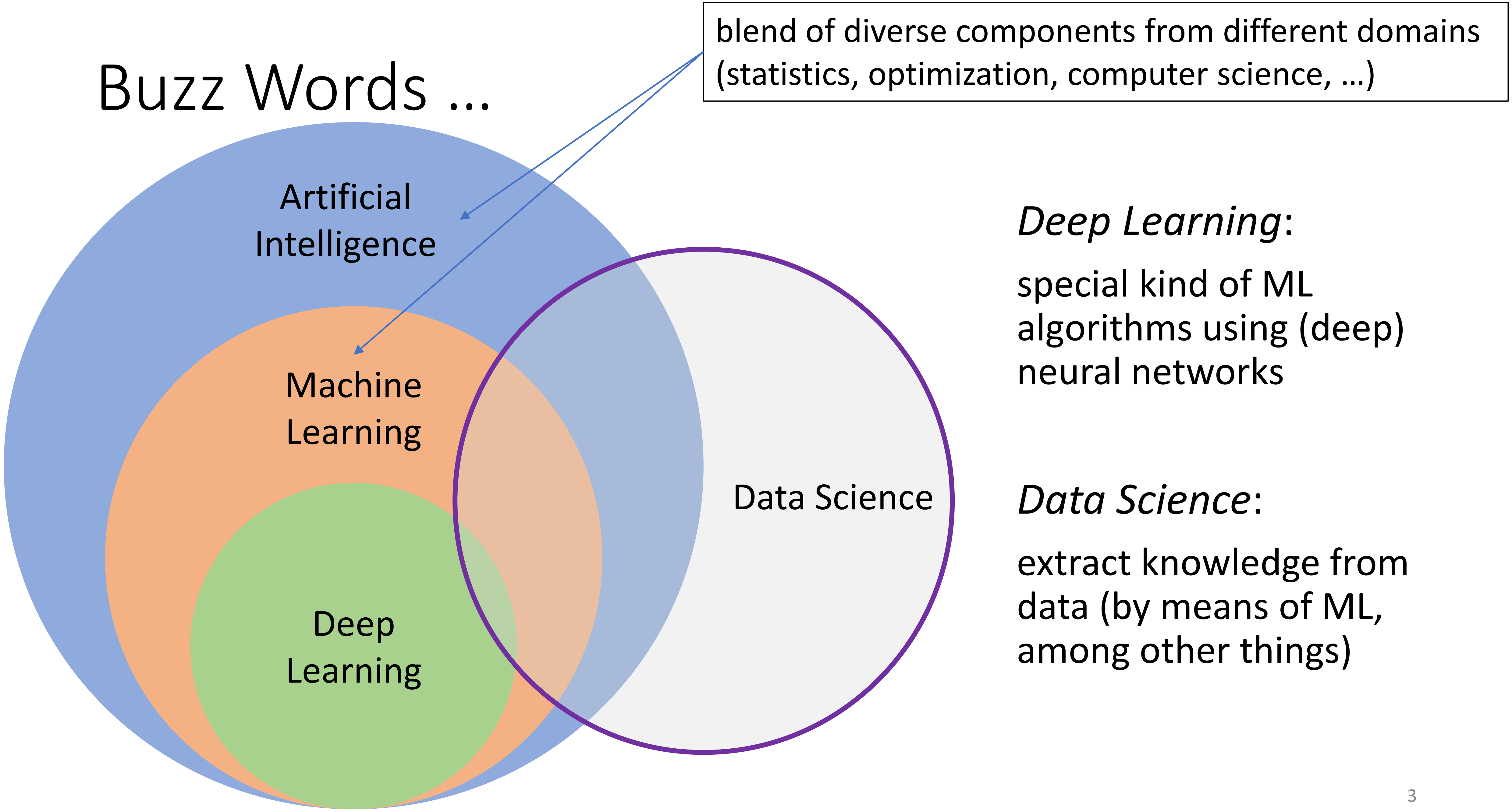
All of these are enabled by one key ingredient:

- *learning from experience* (**Machine Learning**)

- also: knowledge representation, automated reasoning (first indices in modern large language models)

from *Artificial Intelligence: A Modern Approach* (Russell, Norvig)

Buzz Words ...



Deep Learning:

special kind of ML algorithms using (deep) neural networks

Data Science:

extract knowledge from data (by means of ML, among other things)

Traditional Algorithms and GOFAI

from wikipedia

traditional algorithms:

explicit (handcrafted) instructions for each situation

symbolic AI (aka GOFAI):

use knowledge by means of symbols (as representations), logic, search (e.g., expert systems like Deep Blue)

Public perception is changing over time: A modern chess program, nowadays disparaged as brute computing, would have been considered intelligent in the 50s.

ML: Learning from Experience/Data

mainly exploiting statistical dependencies with the aim of **generalization** to new (e.g., future) data (compare with human reasoning by analogies)

training (usually offline optimization):

ML algorithm + data = explicit algorithm (to be used at inference time)

→ reduction of complexity and much better generalizability compared to handcrafted algorithms

analogy: Humans do not hit the ground running (storage capacity of DNA limited) but have learning capabilities.

Supercharging the Scientific Method

use ML and data to replace or enhance explicit methods relying on detailed domain knowledge (Software 2.0)

→ overcome our evolutionary limitations in math with clever learning algorithms and collecting data

→ immediate impact on many aspects of industry, business, and science, formulated as narrow tasks with strictly defined inputs (aka weak AI)

more imminent than (still philosophical) long-term quest for human-level AI (aka strong AI, AGI), i.e., general-purpose intelligence

(although recent language models show multi-purpose capabilities)

Most Famous Applications

recommendations

chatbots

autonomous driving

translation

robotics

OCR

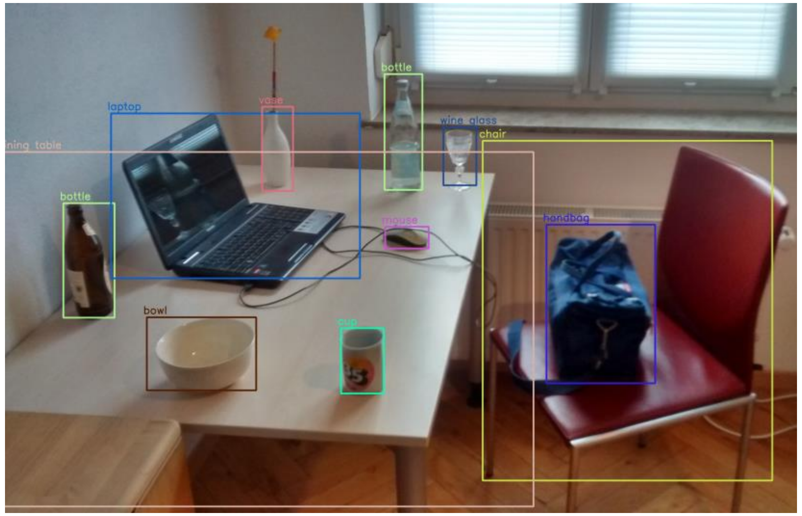
assistants (speech recognition)

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

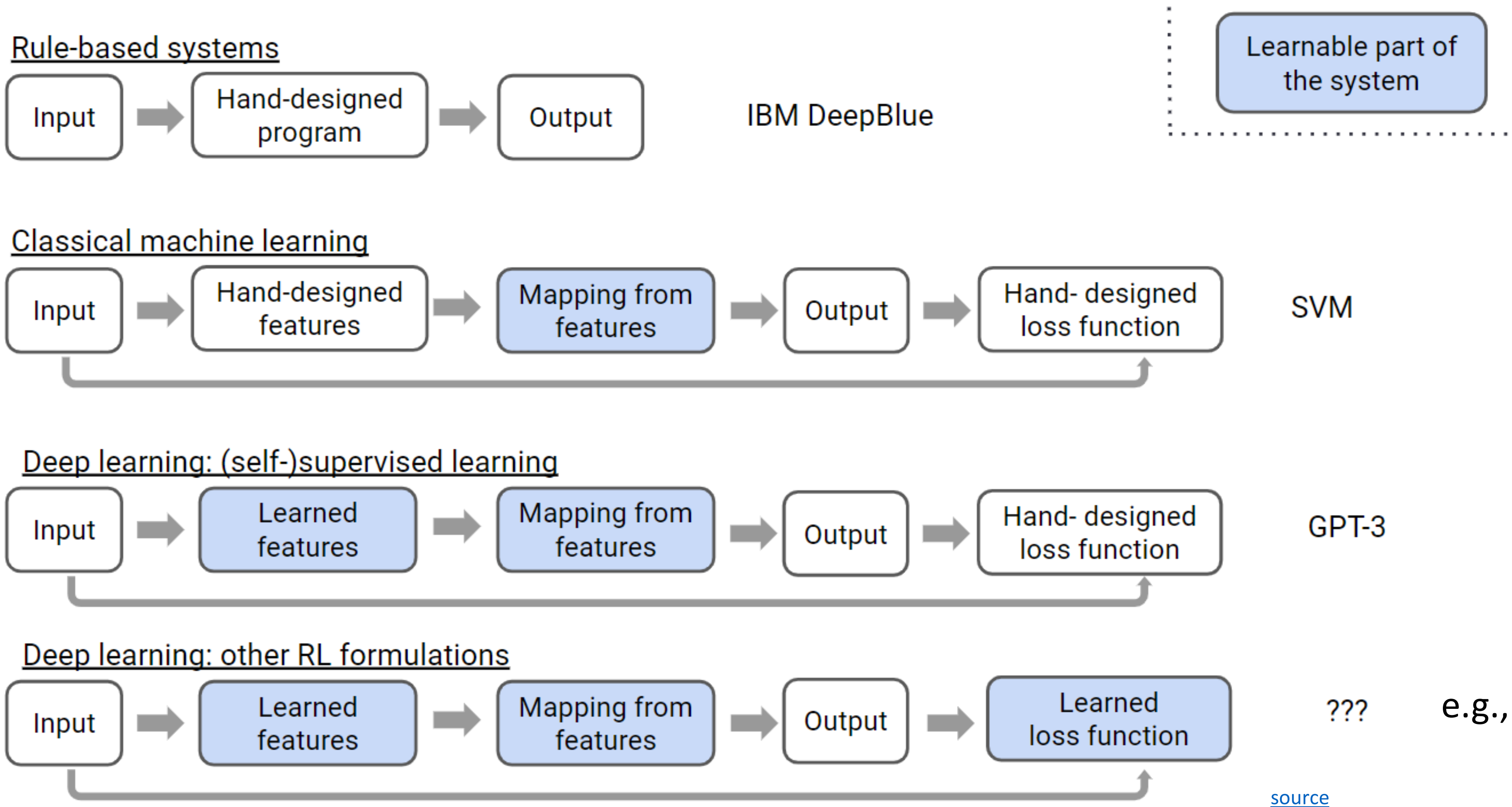
complexity / uncertainty

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), …

Ladder of Generalization



e.g., ChatGPT (RLHF)

source

Generative AI

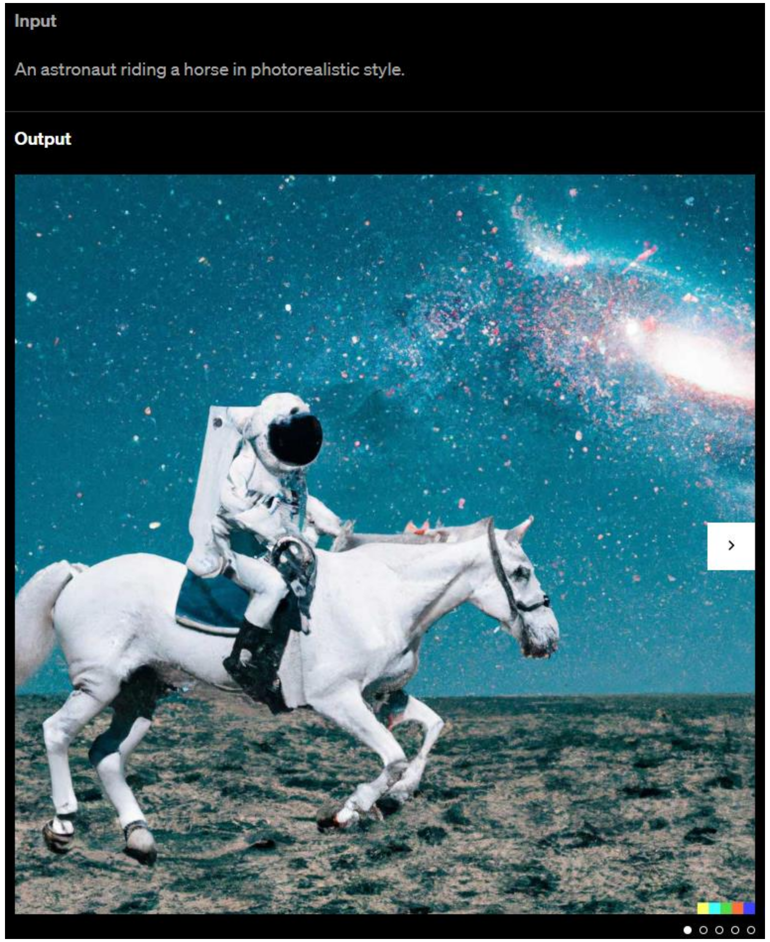
more recently: generative applications

- rather than predictive (or discriminative) ones
- e.g., image generation, conversational AI, new proteins or materials

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

- text generation: large language models (transformer)
- image synthesis: diffusion models (usually conditioned on text by transformers)

example: DALL-E 2



Learning Paradigms

Supervised Learning

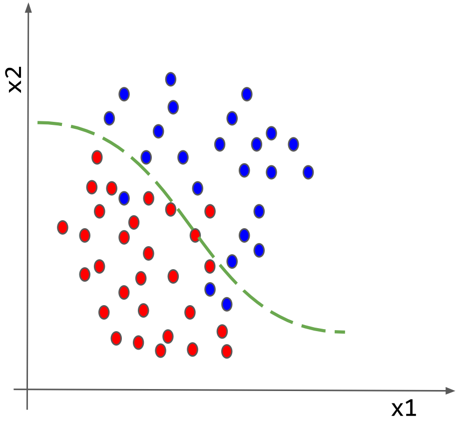
learning by teacher → usually rather narrow tasks (passive approach)

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***

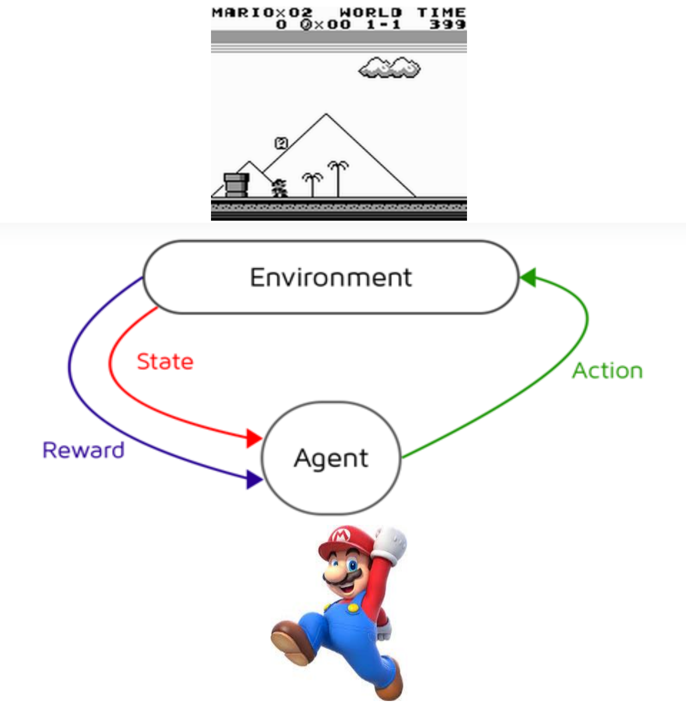
use information like **occurrence of specific words** or **email length** as **features**

features x1 and x2
spam, no spam

Reinforcement Learning

learning by trial-and-error (exploration and exploitation)

- goal-based approach → active and more generic than supervised learning (but sparse reward signals)
- receiving feedback from the environment, no supervision
- formalization of sequential decision making (delayed rewards)



corresponds to search for best action policy to reach a given goal (e.g., win a game)

using learning from examples (data) to guide the search

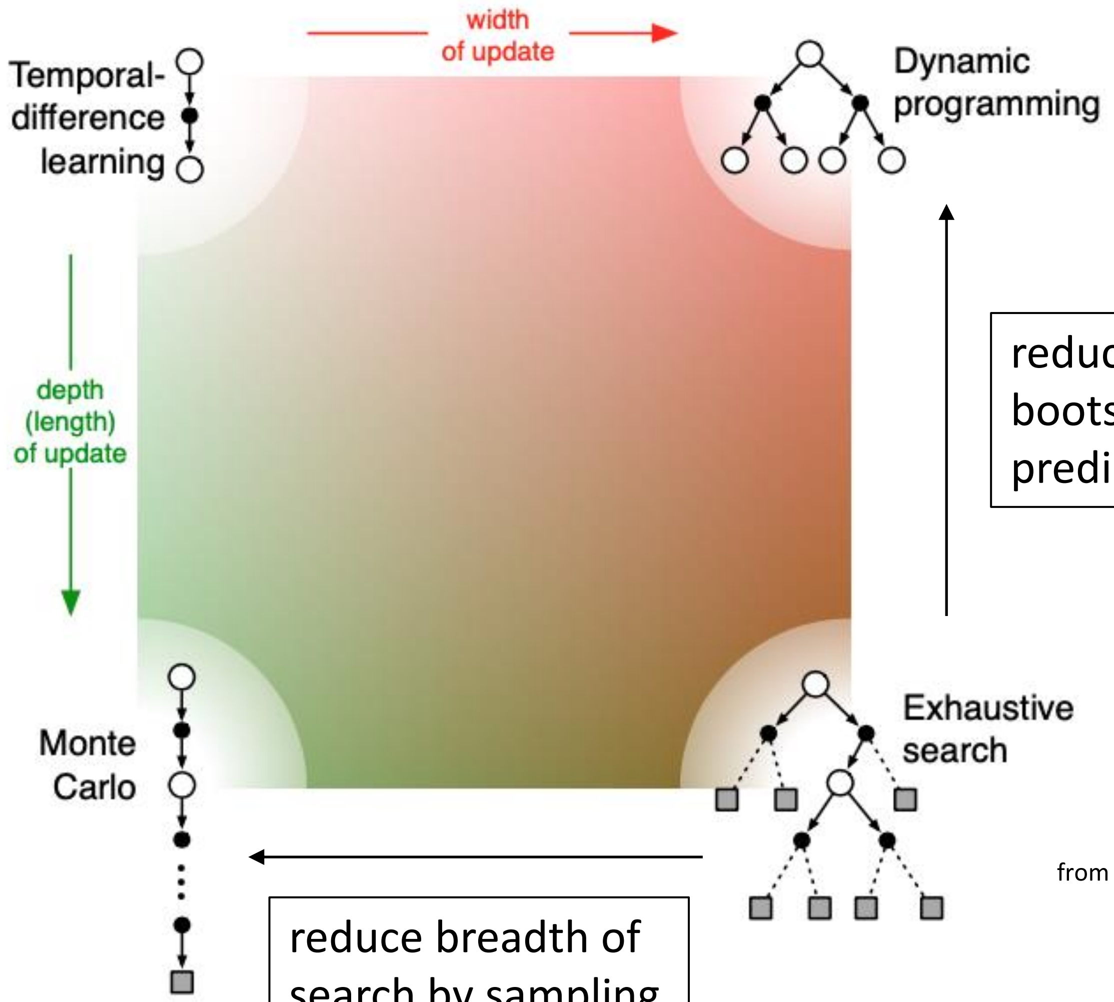
RL setup usually more difficult (e.g., non-differentiable as a whole) than supervised learning one (which can be seen as “generalized optimization”, often of proxy metric)
but RL can be cast as supervised-learning setup: express rewards by more intricate loss function

Reduction of Search Space

one-step TD

n-step TD

MC



reduce depth of search by bootstrapping with value function predicting future outcome

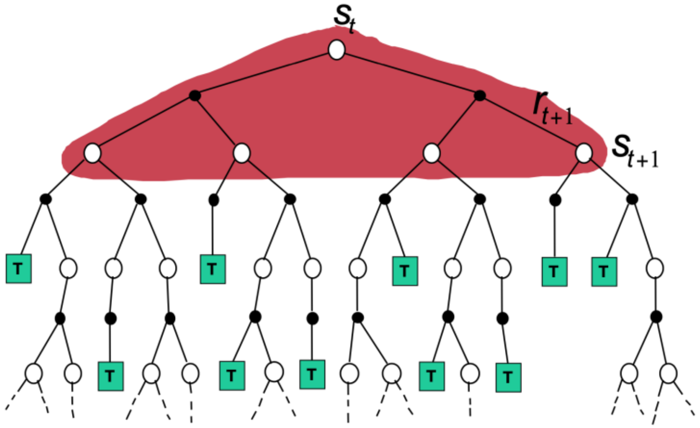
reduce breadth of search by sampling actions from policy

from Sutton

Main Concepts of Value-Based RL Methods

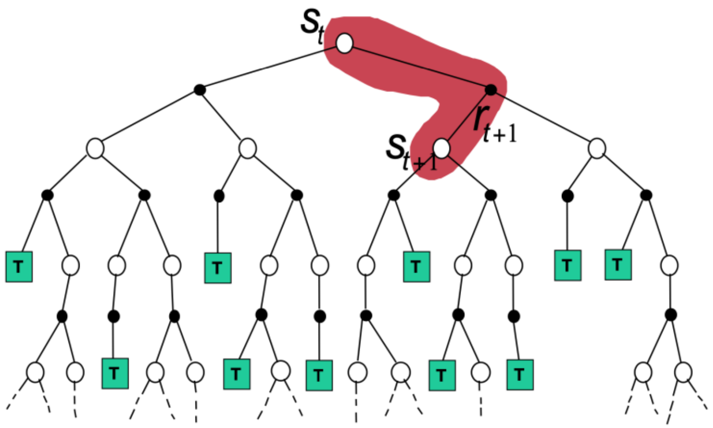
bootstrapping: update estimates of state values based on estimates of values of successor states
sampling: experience of sample sequences (no need for complete knowledge of environment)

Dynamic Programming



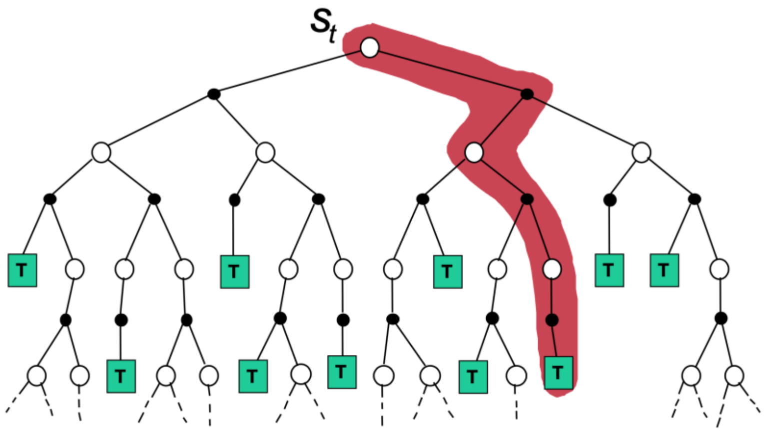
- bootstrapping
- no sampling → model-based (transition probabilities needed)

Temporal Difference (TD) Learning



- bootstrapping
- sampling → model-free

Monte Carlo (MC)



from Sutton

- no bootstrapping
- sampling → model-free

Unsupervised Learning

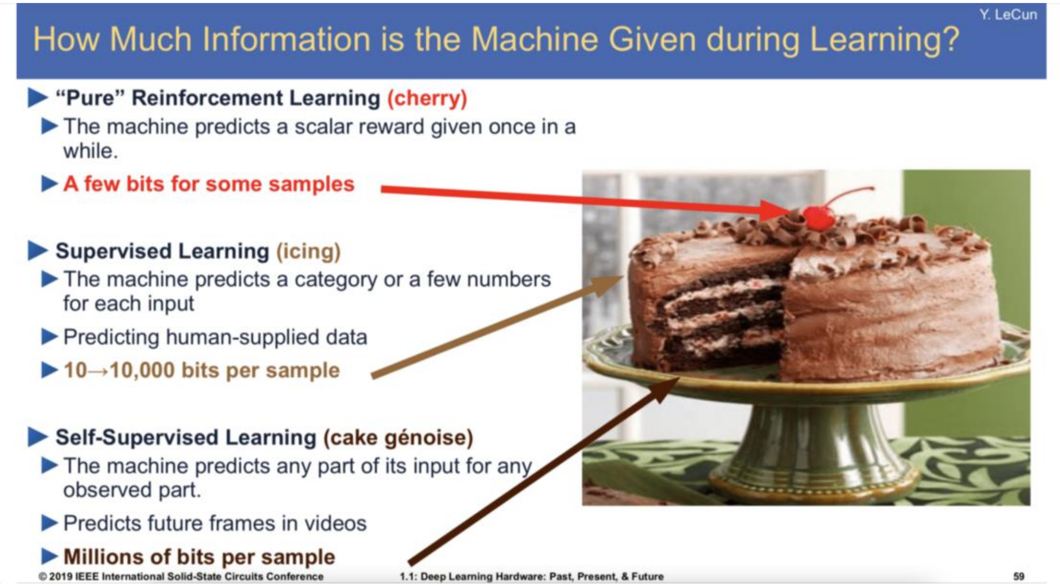
learning by observation

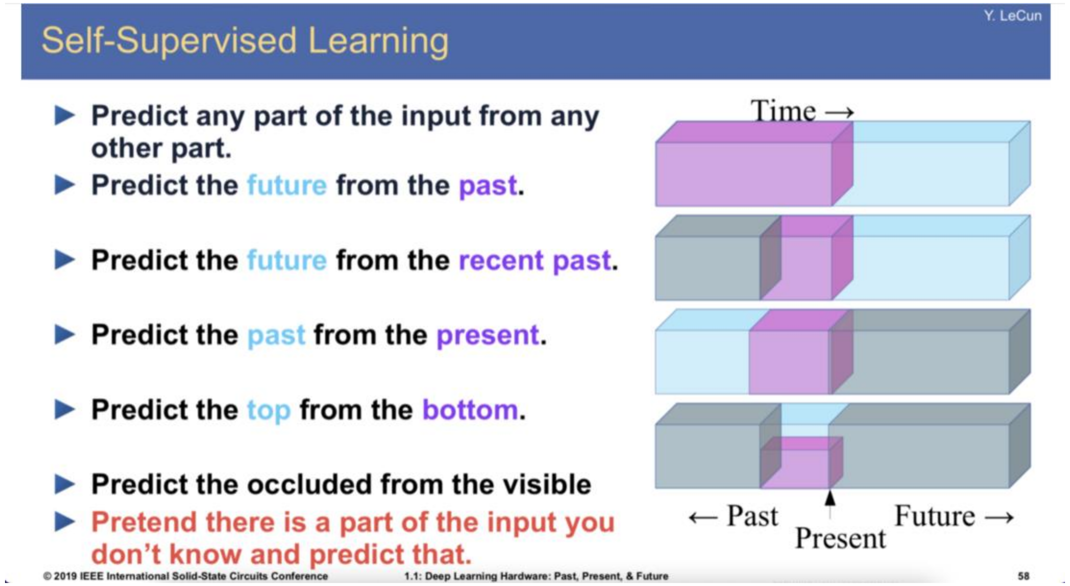
no target information → kind of “vague” pattern recognition (but plenty of data)

can be cast as **self-supervised learning**:

- input-output mapping like supervised learning
- but generating labels itself from input information
- learning of semantic feature representations
- e.g., word2vec, BERT, GPT

generative AI as unsupervised learning: generate variations of training data



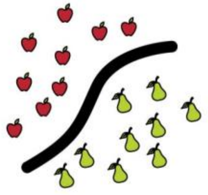


MACHINE LEARNING

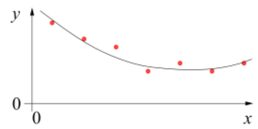
training target available (labeled or past data)

SUPERVISED

CLASSIFICATION



REGRESSION



learning by teacher
(high-dimensional curve fitting)

data not labeled in any way

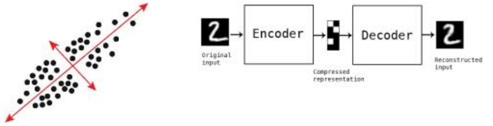
UNSUPERVISED

CLUSTERING

GENERATIVE MODELS

ASSOCIATION

DIMENSIONALITY REDUCTION



learning by observation
(pattern recognition)

no supervision, but goal-based interaction with environment

REINFORCEMENT LEARNING

LEARN STATE OR ACTION VALUES

LEARN POLICY DIRECTLY

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

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

Fitting and Generalization

... **ML** ...

Supervised Learning Scenario

ML domain:
no deterministic dependencies between input and output

map inputs to output: $y = f(\boldsymbol{x})$ (estimated: $\hat{f}(\boldsymbol{x})$)

random variables Y and $\boldsymbol{X} = (X_1, X_2, \cdots, X_p)$

usually many dimensions

fit train data set of $(y_i, \boldsymbol{x}_i)$ pairs

(i.i.d. assumption: random samples from underlying data-generating process)

then apply learned statistical dependencies to test data set

classification:

categorical target: $y = 0$ or $y = 1$ (e.g., image of cat or not), predict probabilities

regression:

real-valued target: $Y \in [0, \infty)$ (e.g., demand forecasting) or $Y \in (-\infty, \infty)$

Generalization

generalization as core of ML:

empirical risk minimization (training error) as proxy for minimizing unknown population risk (test error, aka generalization error or out-of-sample error)

generalization gap: difference between test and training error

- **interpolation** to unencountered samples from training environment
- **extrapolation** to testing conditions differing from training environment

curse of dimensionality: many features (dimensions) → lots of data needed to densely sample volume

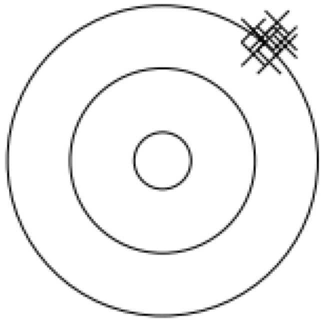
but reality is friendly: most high-dimensional data sets reside on lower-dimensional manifolds (manifold hypothesis) → enabling effectiveness of ML

need for appropriate **inductive bias** (aka learning bias): set of assumptions of a learning algorithm to predict outputs of inputs not encountered during training ("data in disguise")

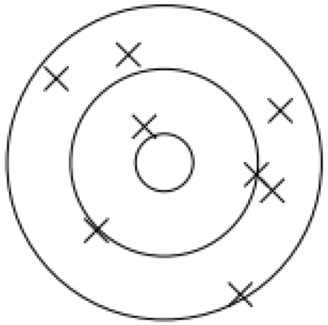
inductive bias comes in many different forms: model design (e.g., linear response), regularization (e.g., convolutions), optimization algorithms, …

Bias, Variance, Irreducible Error

think of fitting ML algorithms as repeatable processes with different (i.i.d.) data sets



bias:
due to too simplistic model
(same for all training data sets)
“underfitting”



variance:
due to sensitivity to specifics (noise)
of different training data sets
“overfitting”

irreducible error (aka Bayes error):

inherent randomness (target generated from random variable following probability distribution)

→limiting accuracy of ideal model

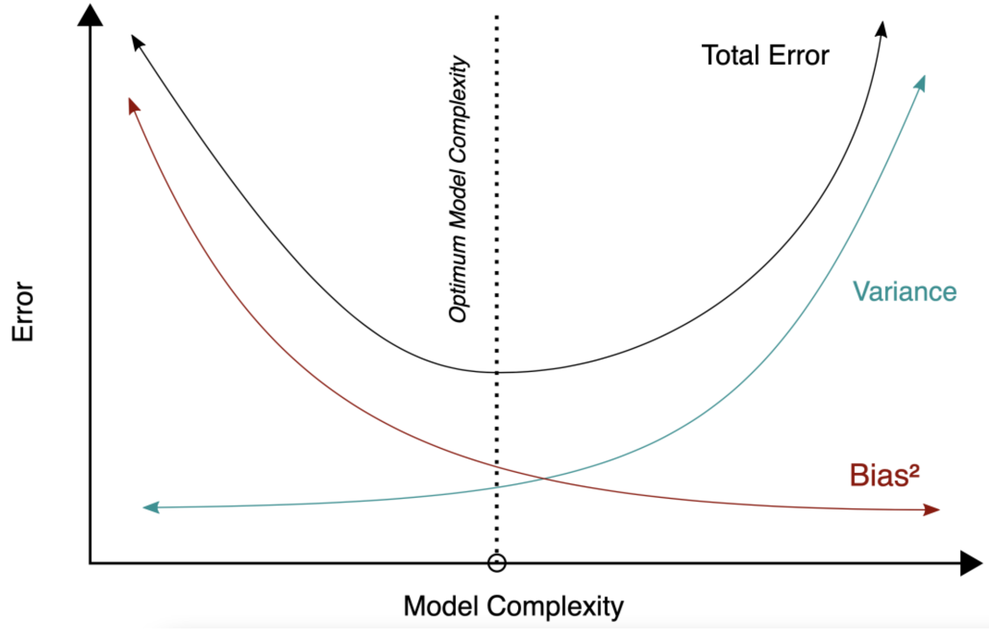
different potential reasons for inherent randomness (noise): complexity, missing information, …

Bias-Variance Tradeoff

- fundamental concept in classical statistical learning theory
- models of higher complexity have lower bias but higher variance (given the same number of training examples)

- generalization error follows U-shaped curve: overfitting once model complexity (number of parameters) passes certain threshold
- overfitting: variance term dominating test error

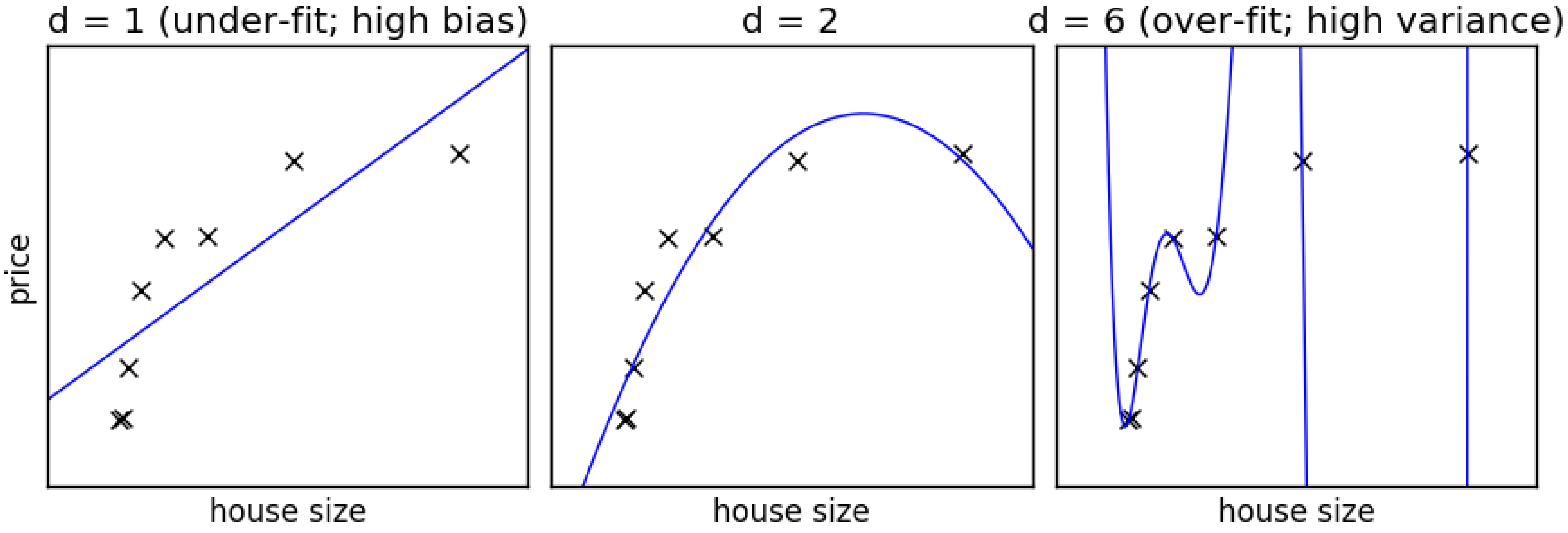
→ increasing model complexity increases test error



from wikipedia

Example: Non-Linear Function Approximation

degree of fitted polynomial



from scikit-learn documentation

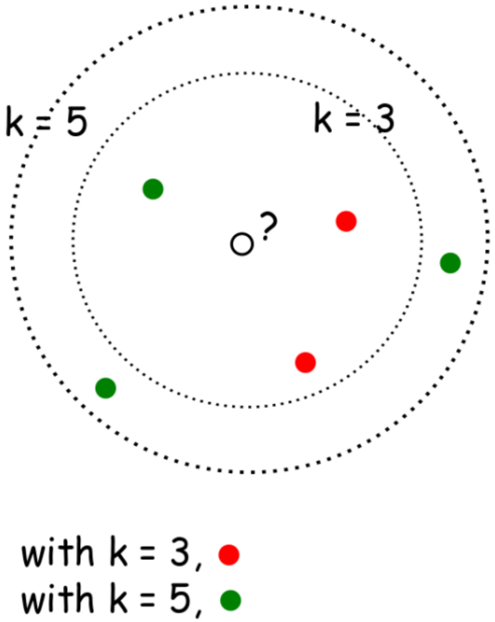
Example: k-Nearest Neighbors

- local method, instance-based learning
- non-parametric
- distance defined by metric on $\boldsymbol{x}$ (e.g., Euclidean)

regression:

$$\hat{f}(\boldsymbol{x}_0) = \frac{1}{k}\sum_{j=1}^{k} y_j$$

with j running over k nearest neighbors of $\boldsymbol{x}_0$

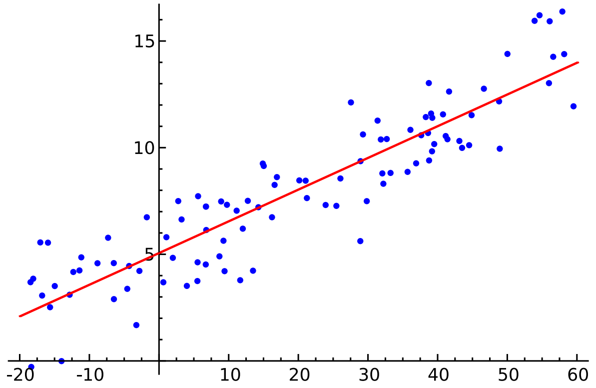


- low k: low bias but high variance
- high k: low variance but high bias

$$bias = f(\boldsymbol{x}) - \frac{1}{k}\sum_{j=1}^{k} y_j$$

$$var = \frac{\sigma^2}{k}$$

Linear Regression



from wikipedia

fit:

error term (noise): reflects assumed data distribution (here: Gaussian with same variance σ^2 for all samples)

$$y_i = \overbrace{\hat{\alpha} + \sum_{j=1}^{p} \hat{\beta}_j \, x_{ij}}^{\hat{f}(\boldsymbol{x}_i)} + \varepsilon_i$$

(model)

parameters to be estimated:
- $\hat{\alpha}, \widehat{\boldsymbol{\beta}}$

→ $\hat{\sigma}^2 = \frac{1}{n} \sum_{i=1}^{n} \left(y_i - \hat{f}(\boldsymbol{x}_i) \right)^2$

(approximating assumed true $\alpha, \boldsymbol{\beta}$, σ)

predict:

$$\hat{y}_i = E[Y | \boldsymbol{X} = \boldsymbol{x}_i] = \hat{f}(\boldsymbol{x}_i)$$

- conditional mean for squared loss of least squares method
- predict arbitrary quantile by means of quantile loss

$$p(y|\boldsymbol{x}_i) = \mathcal{N}(y; \hat{y}_i, \hat{\sigma}^2)$$

Gaussian

mean

variance (reflected by ε_i in fit)

General Recipe of Statistical Learning

statistical learning algorithm by combining:

- **model** (e.g., linear function, Gaussian distribution)
- **objective function** (e.g., squared residuals)
- **optimization algorithm** (e.g., gradient descent)
- **regularization** (e.g., convolutions)

Loss Function

loss function L: expressing deviation between prediction and target

$L\left(y_i, \hat{f}(\boldsymbol{x}_i); \widehat{\boldsymbol{\theta}}\right)$
with $\widehat{\boldsymbol{\theta}}$ corresponding to parameters of model $\hat{f}(\boldsymbol{x})$
e.g., $\widehat{\alpha}, \widehat{\boldsymbol{\beta}}$ in linear regression

e.g., squared residuals (for regression problems):
$L\left(y_i, \hat{f}(\boldsymbol{x}_i); \widehat{\boldsymbol{\theta}}\right) = \left(y_i - \hat{f}\left(\boldsymbol{x}_i; \widehat{\boldsymbol{\theta}}\right)\right)^2$

Cost Function

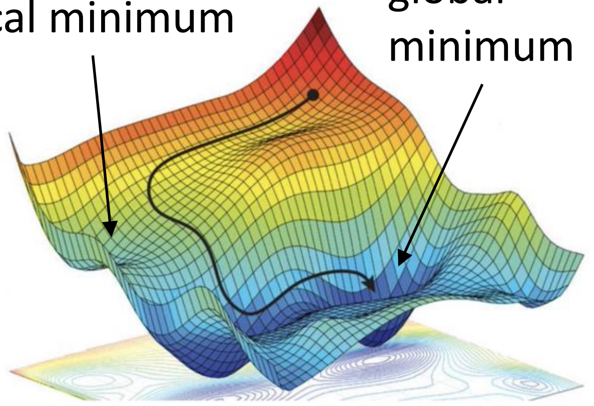
averaging losses over (empirical) training data set:

$$J(\widehat{\boldsymbol{\theta}}) = \frac{1}{n}\sum_{i=1}^{n} L\left(y_i, \hat{f}(\boldsymbol{x}_i); \widehat{\boldsymbol{\theta}}\right)$$

cost function to be minimized according to model parameters $\widehat{\boldsymbol{\theta}}$

→ objective function

Cost Minimization



minimize training costs $J(\widehat{\boldsymbol{\theta}})$ according to model parameters $\widehat{\boldsymbol{\theta}}$:

$$\nabla_{\widehat{\boldsymbol{\theta}}} J(\widehat{\boldsymbol{\theta}}) = 0$$

e.g., for mean squared error (aka least squares method):

$$\nabla_{\widehat{\boldsymbol{\theta}}} \frac{1}{n} \sum_{i=1}^{n} \left(y_i - \hat{f}\left(\boldsymbol{x}_i; \widehat{\boldsymbol{\theta}}\right)\right)^2 = 0$$

analytical solution for linear regression: ordinary least squares

in general: iterative, numerical optimization (e.g., **gradient descent**)

vector containing all partial derivatives

$$\boxed{\widehat{\boldsymbol{\theta}} \leftarrow \widehat{\boldsymbol{\theta}} - \eta \nabla_{\widehat{\boldsymbol{\theta}}} J(\widehat{\boldsymbol{\theta}})}$$

step size (learning rate)

maximum likelihood estimation (minimization of D_{KL} between probability distributions of true data-generating process and model: *make the model distribution match the empirical distribution*):

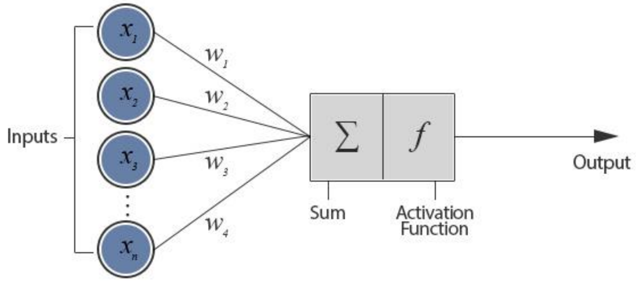
special objective function, estimate mode of assumed model distribution

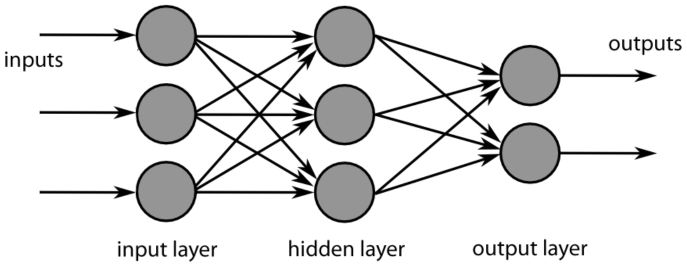
Algorithmic Families

linear (parametric) models

- linear regression
- Generalized Linear Models
- Generalized Additive Models

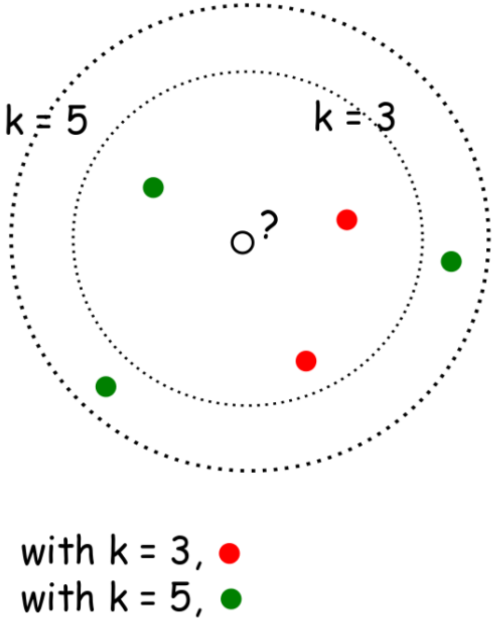
neural networks: non-linear just by means of activation functions





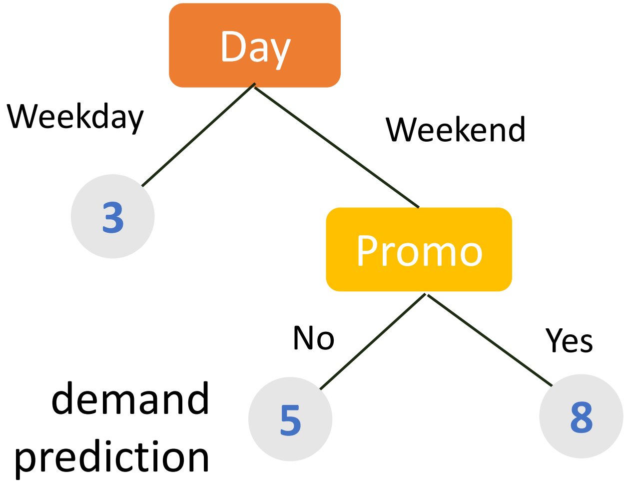
from wikipedia

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

Most ML algorithms (even unsupervised and RL) can be described by the general recipe of combining models, costs, optimization, and regularization methods.

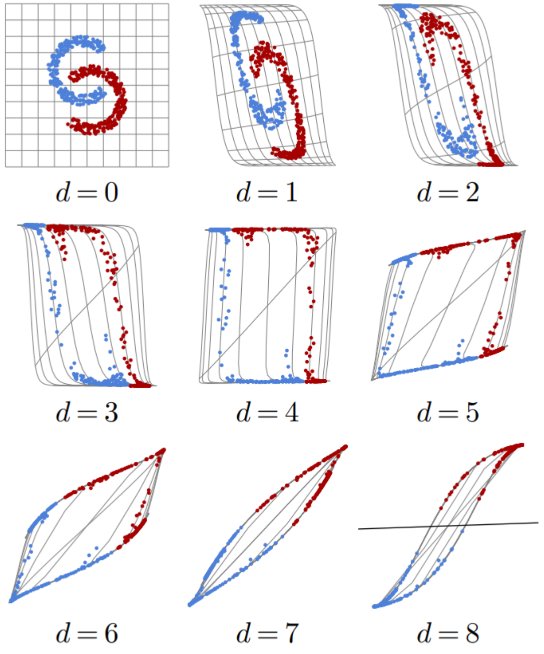
including non-linear models like neural networks (backpropagation), support-vector machines (hinge loss in soft-margin SVM), or decision trees (impurity functions)

Most powerful ML algorithms are compound, with rather simple (often linear) building blocks. → reductionism with complex interactions

To generalize well, one needs to find a method with an appropriate inductive bias for the task at hand (e.g., suitable objective function or regularization method like convolutional layers).

Deep Learning

Recap: Goal of ML



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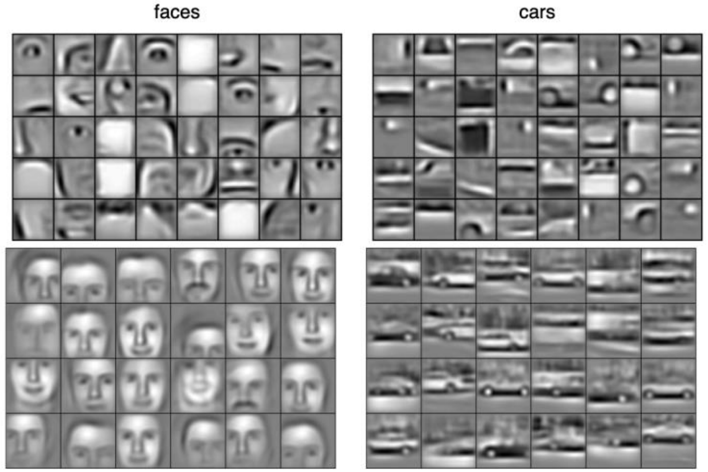
generalization from optimization on training data set (approximation of true data generating probability distribution by empirical risk minimization)

- fitting: complex function approximation
- for generalization: learning of good abstraction/representation of data/concepts

→ deep learning methods (neural networks with many layers) optimal candidates



e.g., convolutional neural networks (CNN) can learn hierarchical representation by means of many convolutional and pooling layers

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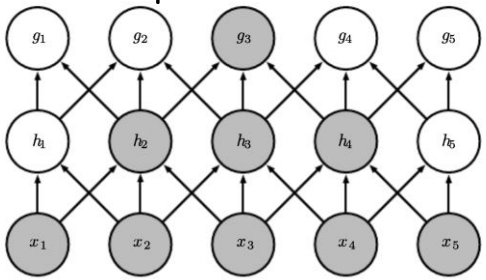
receptive fields:



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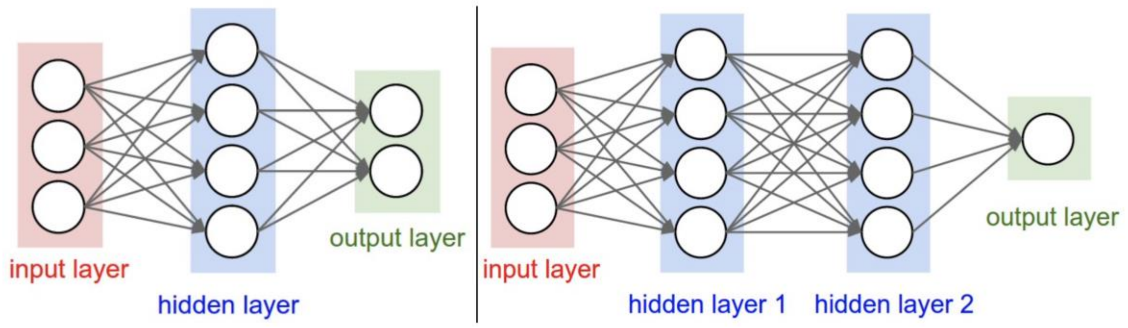
the deeper the better:
accuracy, hierarchical representation (many aspects of nature hierarchical)

Multi-Layer Perceptron (MLP)

fully-connected feed-forward network with at least one hidden layer



toward deep learning: add hidden layers

more layers (depth) more efficient than just more nodes (width): less parameters needed for same function complexity

classification:

- logistic regression in hidden nodes
- cross-entropy loss: $L_i\left(y_i, \hat{f}(\boldsymbol{x}_i); \widehat{\boldsymbol{w}}\right) = -\sum_{k=1}^{K} y_{ik} \log \hat{f}_k(\boldsymbol{x}_i; \widehat{\boldsymbol{w}})$
- several output nodes k for multi-classification
- softmax output function: $g_k(\boldsymbol{t}_i) = \frac{e^{t_{ik}}}{\sum_{l=1}^{K} e^{t_{il}}}$

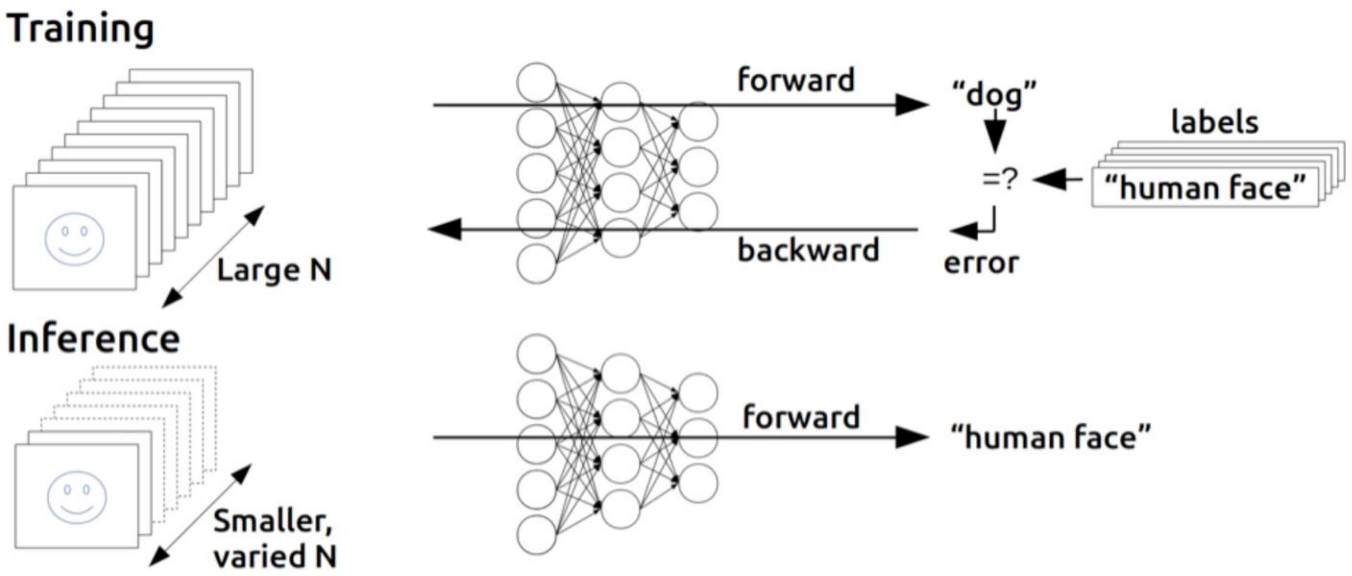
regression:

- squared error loss
- identity output function
- usually just one output node

Learning Mechanism: Back-Propagation

back-propagation of errors (gradients of cost function according to weights) through layers via chain rule of calculus (avoiding redundant calculations of intermediate terms)

each node exchanges information only with directly connected nodes → enables efficient, parallel computation



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- forward pass: current weights fixed, predictions computed
- backward pass: errors computed from predictions and back-propagated → weights then updated according to loss gradients (via gradient descent)

CNN in short: local connections, shared weights, pooling, many layers

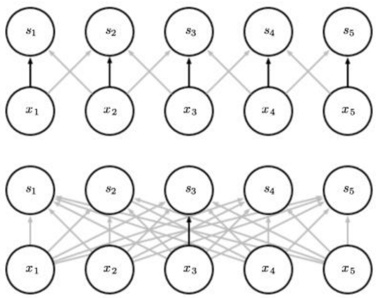
Convolutional Neural Networks

translation equivariance

locality

parameter sharing

convolutional vs fully-connected layer:



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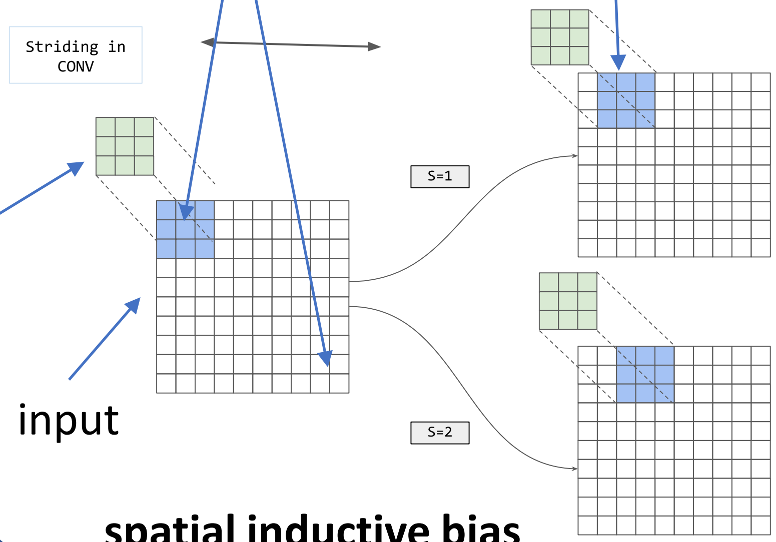
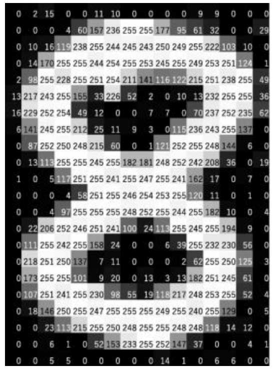
kernel (learned parameters)



spatial inductive bias



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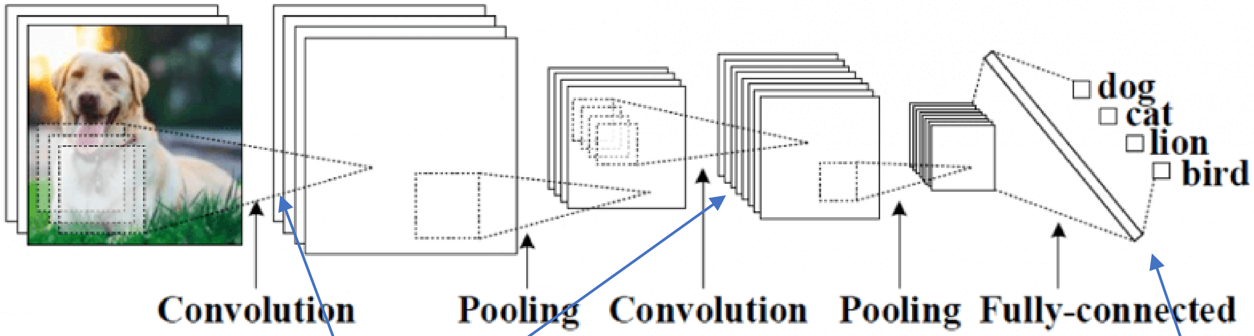
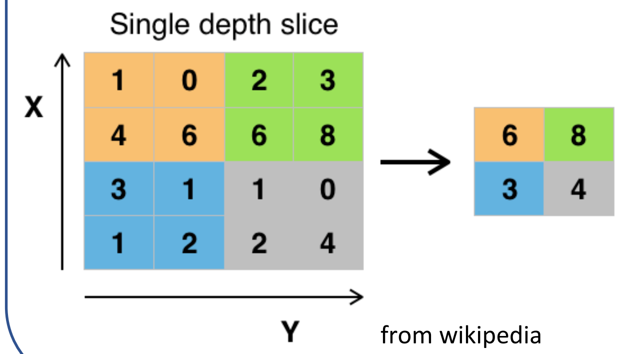


translation invariance

max pooling:



from wikipedia

many images (training examples), potentially with several channels

several kernels producing several feature maps

down-sampling by convolutions and pooling

flatten dimensions for final classification or regression

highly regularized form of feed-forward neural networks

Rise of Deep Learning

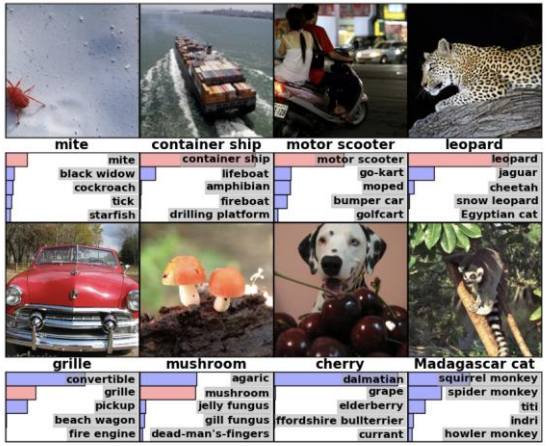
a little bit oversimplified:

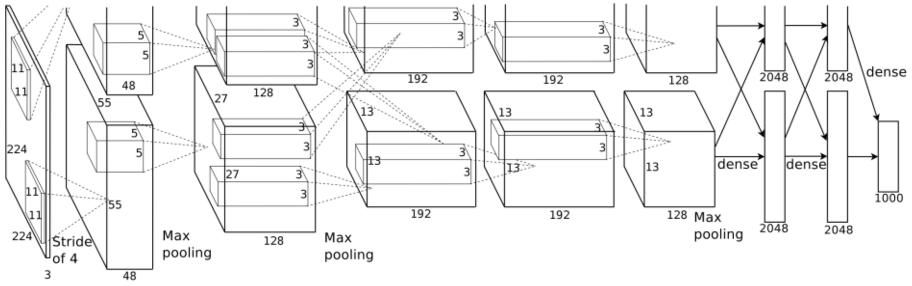
deep learning = lots of training data + parallel computation + smart algorithms

AlexNet:

ImageNet (with data augmentation) + GPUs (allowing more layers) + ReLU, dropout

(pivotal moment for deep learning: ImageNet challenge 2012)





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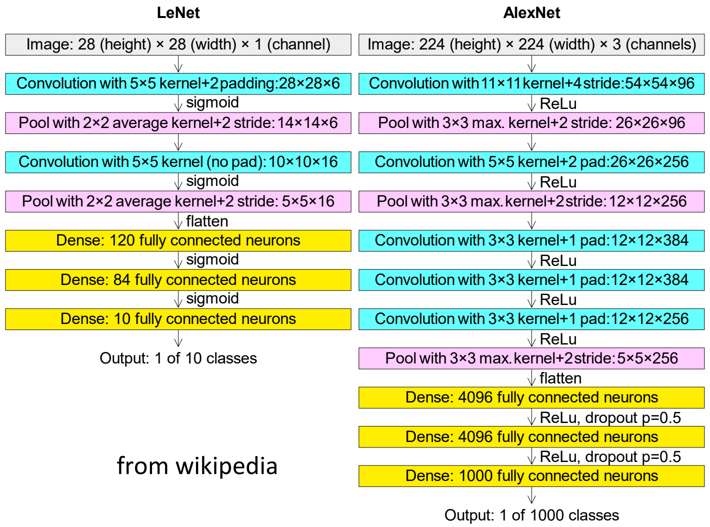


from wikipedia

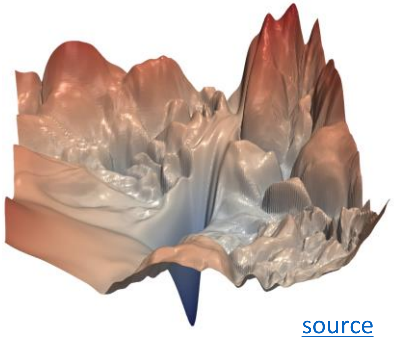
Training Subtleties of Deep Neural Networks

optimization and regularization difficult

- non-convex optimization problem (e.g., local vs global minima, saddle points), easily overfitting
- many hyperparameters to tune

many methods to get it working in practice (despite partly patchy theoretical understanding)

typical loss surface:



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optimization

- activation and loss functions
- weight initialization
- stochastic gradient descent
- adaptive learning rate
- batch normalization

explicit regularization

- weight decay
- dropout
- data augmentation
- weight sharing

implicit regularization

- early stopping
- batch normalization
- stochastic gradient descent

Large Language Models (LLM)

natural language processing: dealing with sequential structures (e.g., text)

examples:

- machine translation (sequence-to-sequence model)
- sentiment classification
- chat bot (conversational AI)

context awareness via **embeddings** and (formerly) recurrent neural networks (**RNN**) or (nowadays) **self-attention**

LLMs: **transformer** models with hundreds of billions of parameters

Embeddings

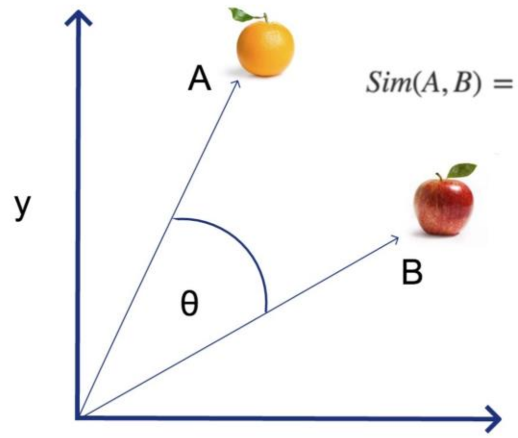
representation of entities by vectors

similarity between embeddings by, e.g., cosine similarity → semantic similarity

most famous application: word embeddings → associations (natural language processing)

but general concept: embeddings of (categorical) features (e.g., products in recommendation engines)

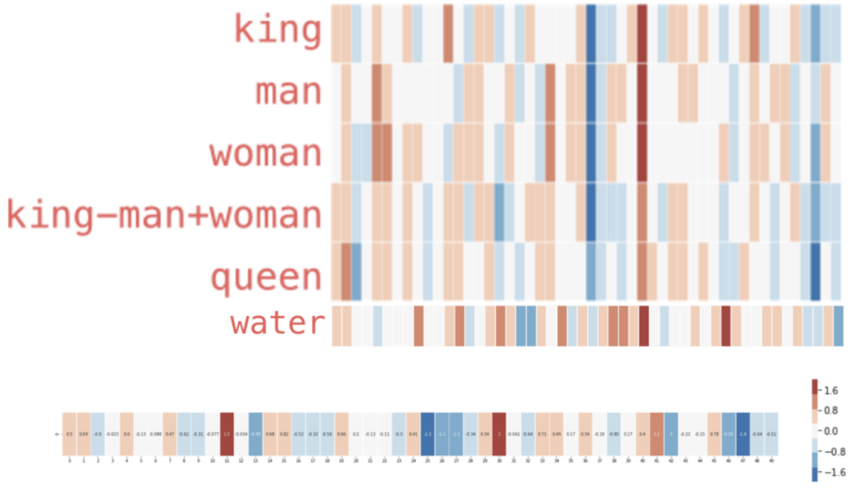
learned via co-occurrence (e.g., word2vec)



$$Sim(A,B) = \cos(\theta) = \frac{A \cdot B}{\|A\| \|B\|}$$

but also direction of difference vectors interesting (analogies):

`king – man + woman ~= queen`



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Transformer

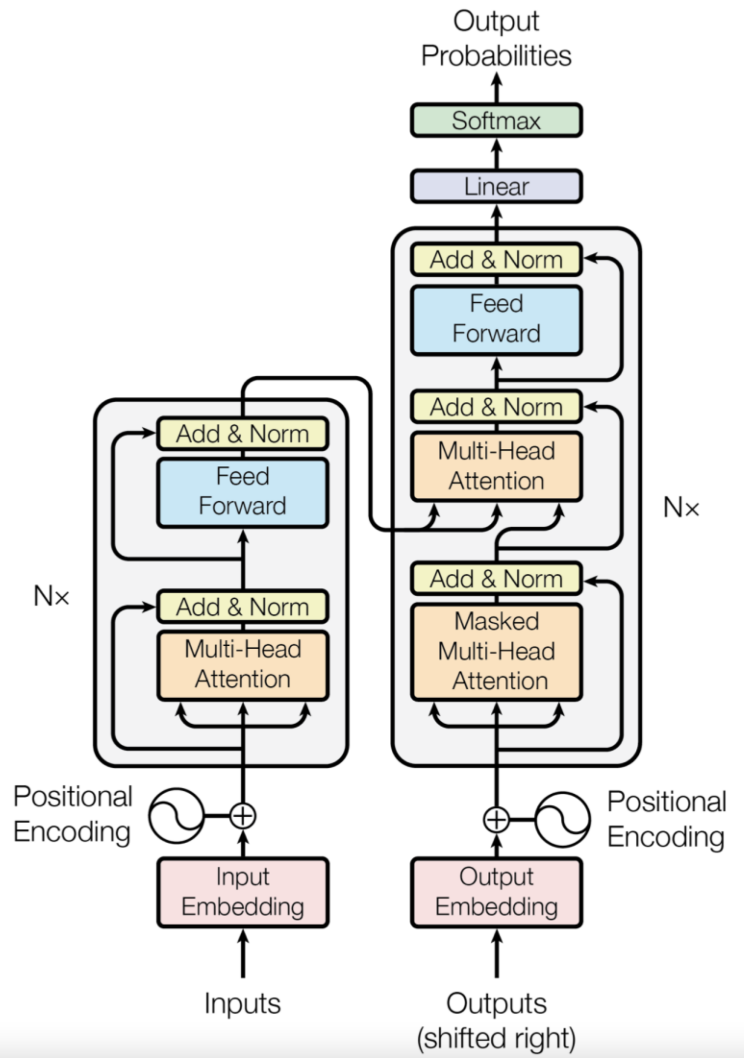
attention is all you need: getting rid of RNNs

replaced by multi-headed self-attention (implemented with matrix multiplications and feed-forward neural networks)

→ allowing for much more parallelization

→ allowing for bigger models (more parameters)

better long-range dependencies thanks to shorter path lengths in network (less sequential operations)



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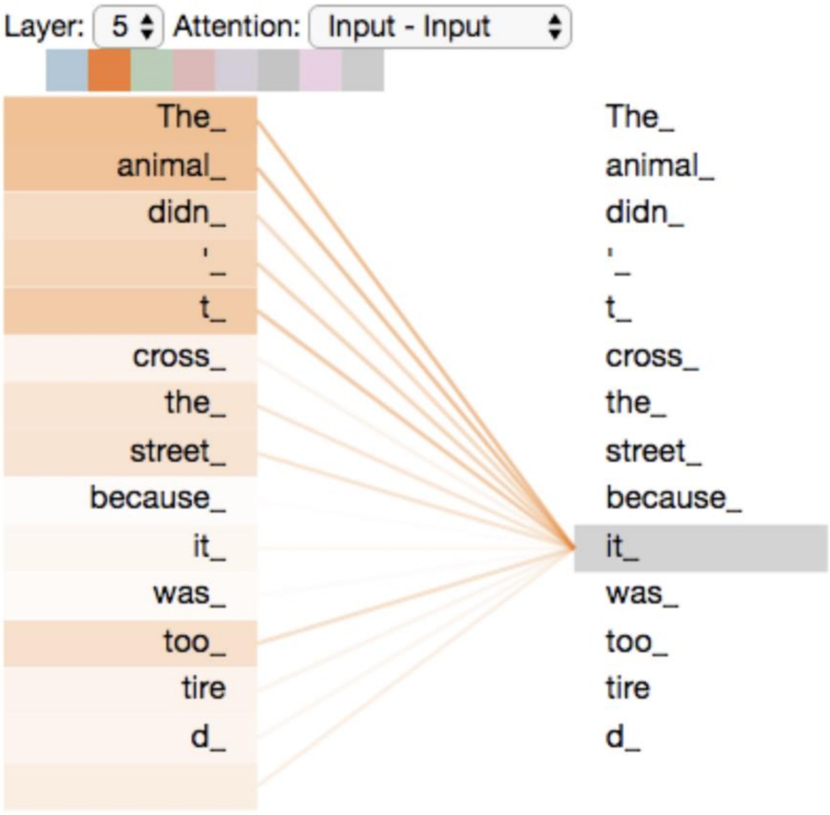
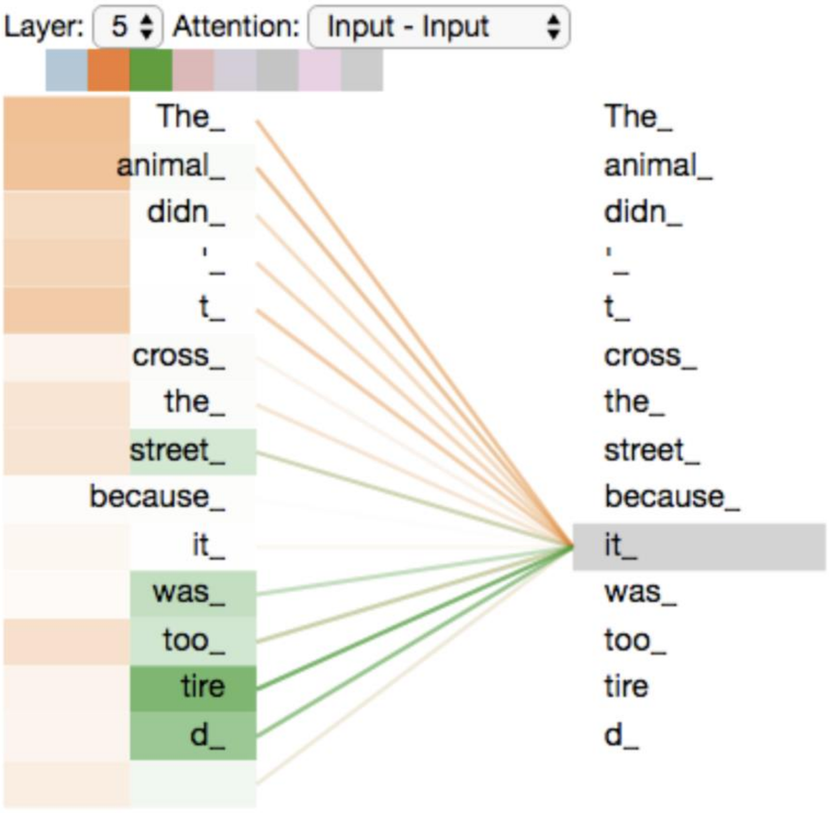
Self-Attention

computational complexity quadratic in length of input (each token attends to each other token)

evaluating other input words in terms of relevance for encoding of given word



multi-head attention: several attention layers running in parallel (considering different aspects of input)



source

Scaled Dot-Product Attention

softmax not scale invariant: largest inputs dominate output for large inputs (more embedding dimensions d_k)

$$\mathrm{Attention}(Q, K, V) = \mathrm{softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right)V$$

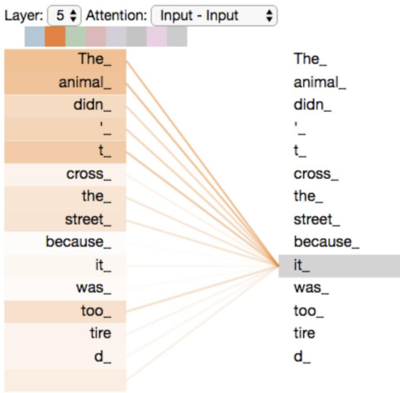
Scaled Dot-Product Attention

3 abstract matrices created from inputs (e.g., word embeddings) by multiplying inputs with 3 different weight matrices

- query Q
- key K
- value V

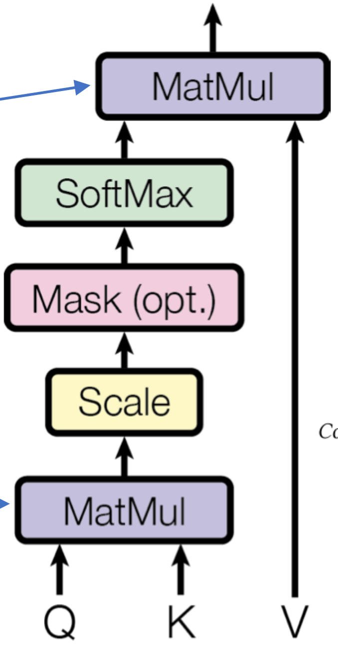
filtering: multiplication of attention probabilities with corresponding key word values

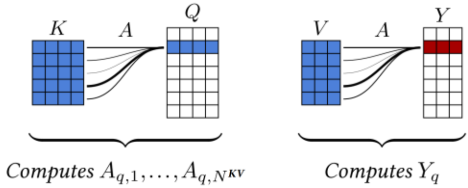
key-value pairs



query

scoring each of the key words (context) with respect to current query word: multiplication of inputs (in contrast to inputs times weights in neural networks)





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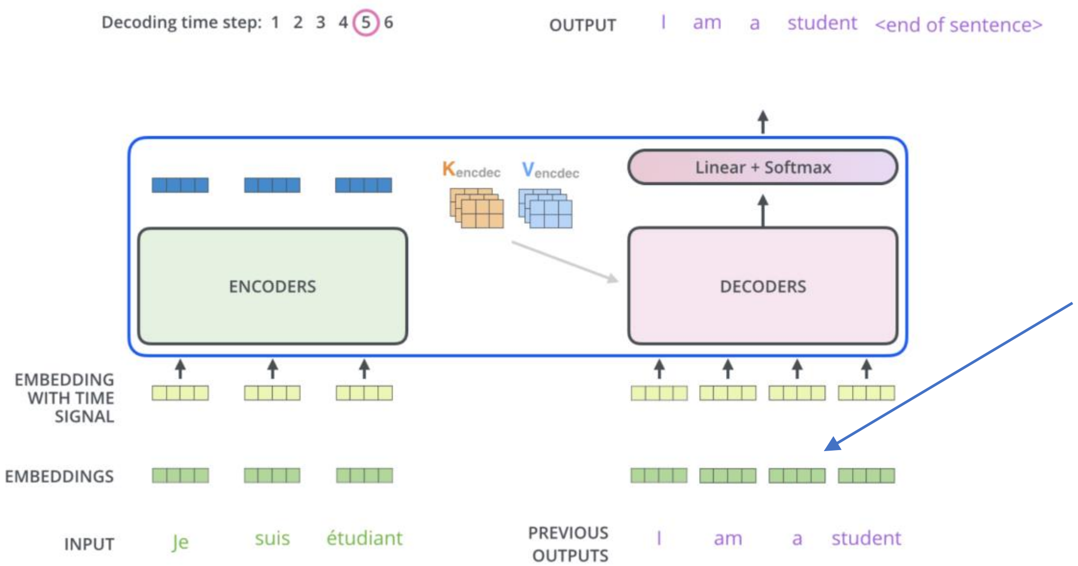
Sequence Completion

- greedily picking the one with highest probability
- pick according to probabilities (degree of randomness controlled by softmax temperature)
- beam search

for each step/token (iteratively), choose one output token to add to decoder input sequence → increasing uncertainty



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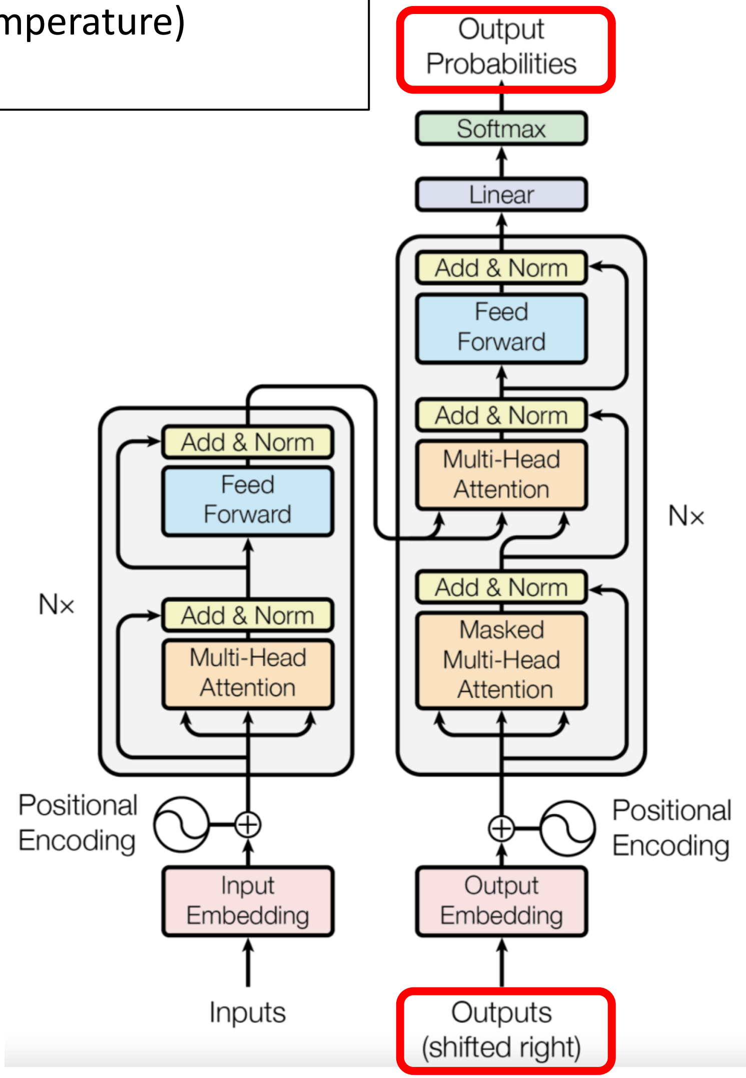
auto-regressive



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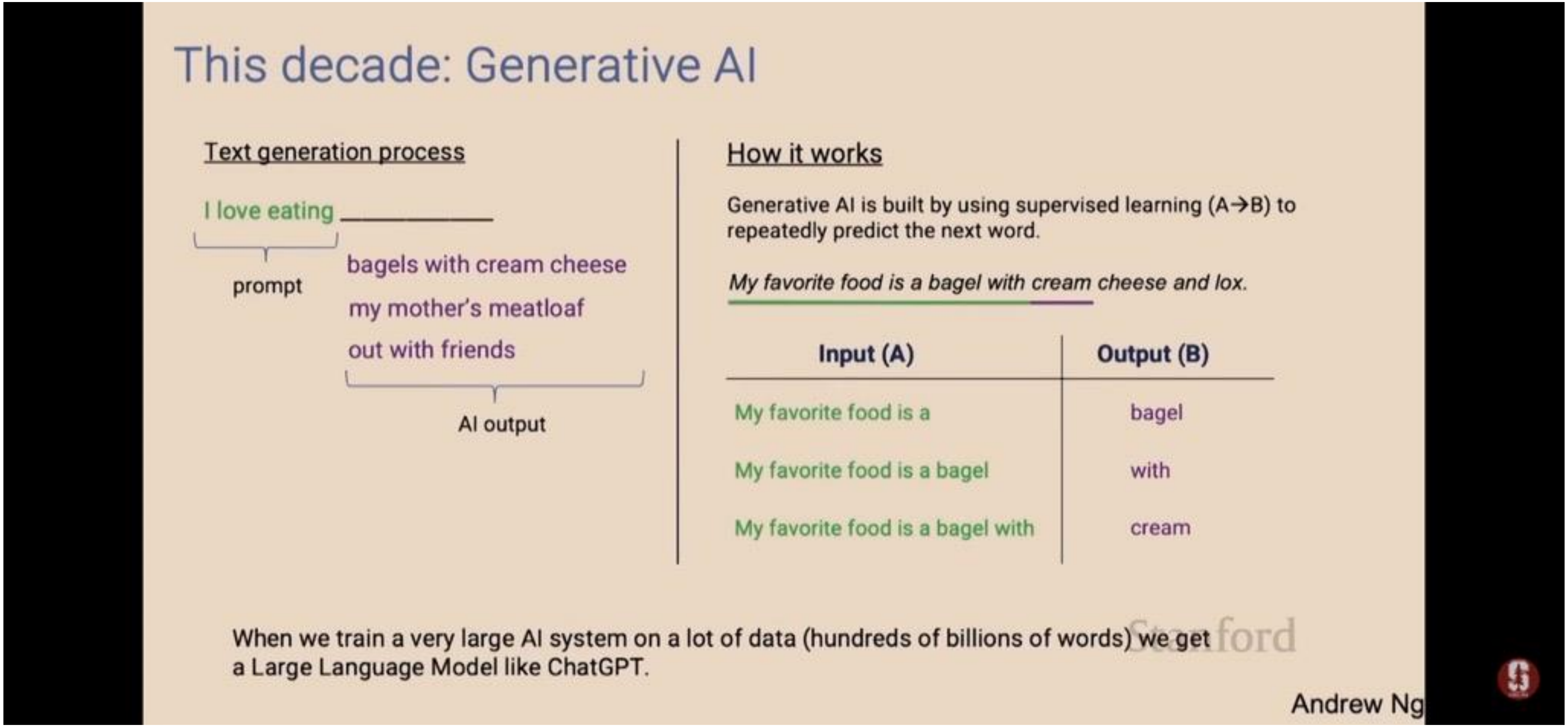
prompt: externally given initial sequence for running start and context on which to build rest of sequence ([prompt engineering](#))


This decade: Generative AI
Text generation process
I love eating
prompt
bagels with cream cheese
my mother's meatloaf
out with friends
AI output
How it works
Generative AI is built by using supervised learning (A→B) to repeatedly predict the next word.
My favorite food is a bagel with cream cheese and lox.
Input (A)
Output (B)
My favorite food is a
bagel
My favorite food is a bagel
with
My favorite food is a bagel with
cream
When we train a very large AI system on a lot of data (hundreds of billions of words) we get a Large Language Model like ChatGPT.
Stanford
Andrew Ng

Typical Transformer Architectures for LLMs

encoder-decoder LLMs: sequence-to-sequence, e.g., machine translation

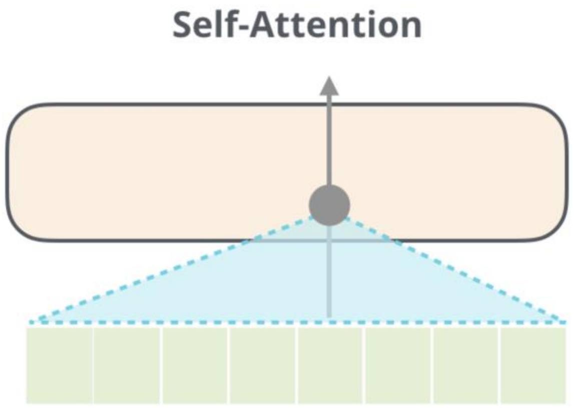
encoder-only LLMs:

- representation learning (and subsequent fine-tuning)
- training: prediction of masked words
- incorporate context of both sides of token

decoder-only LLMs:

- text generation (potentially in-context only), e.g., chat bot
- training: next-word prediction
- output one token at a time (auto-regressive: consuming its own output)

example: Google's BERT (Bidirectional Encoder Representations from Transformers)



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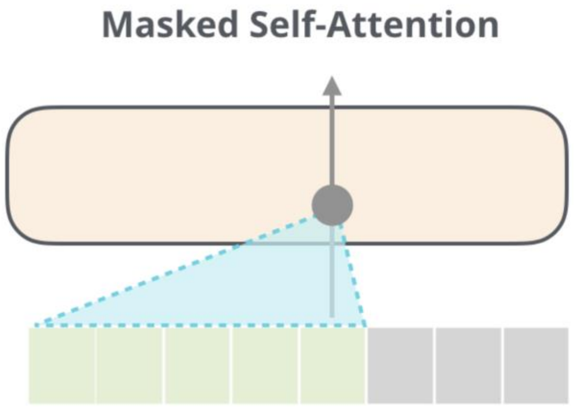


examples: OpenAI's GPT (Generative Pre-trained Transformer), Meta's Llama2

GPT-4 capabilities

Multi-Task Learning of LLMs

compositional nature of deep learning allows transfer learning in a semi-supervised way (also prominent for CNNs in computer vision):

- self-supervised **pre-training** (e.g., next-word prediction) on massive data sets (foundation models like GPT or BERT)
- subsequent supervised **fine-tuning** on specific tasks and (usually much smaller) data sets (by adapting parameters or/and adding layers)

the new paradigm:

in-context learning as alternative to fine-tuning: only using information fed into LLM via input prompt, no parameter updates (typically decoder-only)

typical prompt: instructions, context (potentially retrieved externally from, e.g., knowledge-base embeddings), query, output indicator

with (few-shot) or without (zero-shot) providing explicit examples

[prompt engineering]()

examples: ChatGPT, Bard

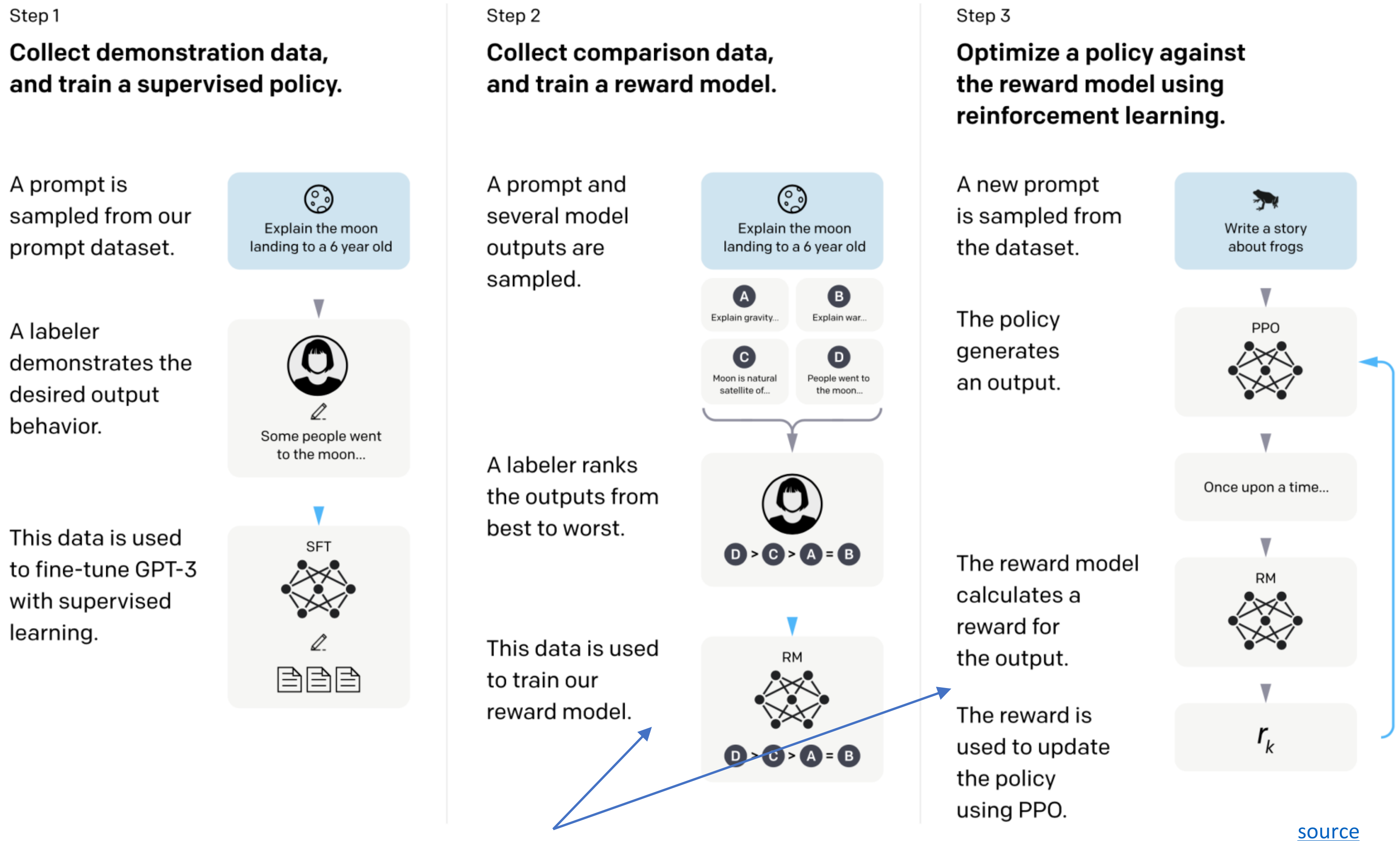
Conversational AI: RL from Human Feedback

example for supporting large language models (transformers) with RL

used in famous ChatGPT

goal: improve alignment with user intentions

→ learn from human preferences



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RL looks at reward of text output passages as a whole (rather than token-level loss in supervised learning)

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.

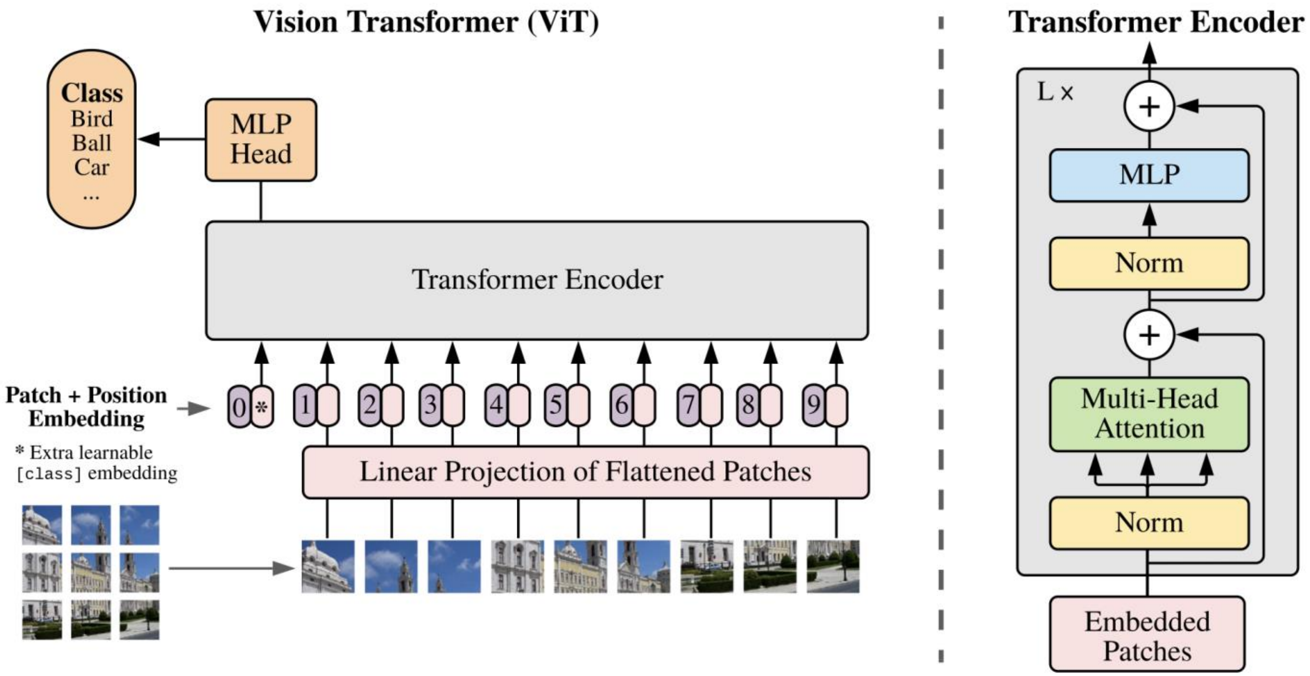
Transformer for Vision

formulation as sequential problem:

- split image into patches and flatten → use as tokens
- produce linear embeddings and add positional embeddings

processing by transformer encoder:

- pre-train with image labels
- fine-tune on specific data set



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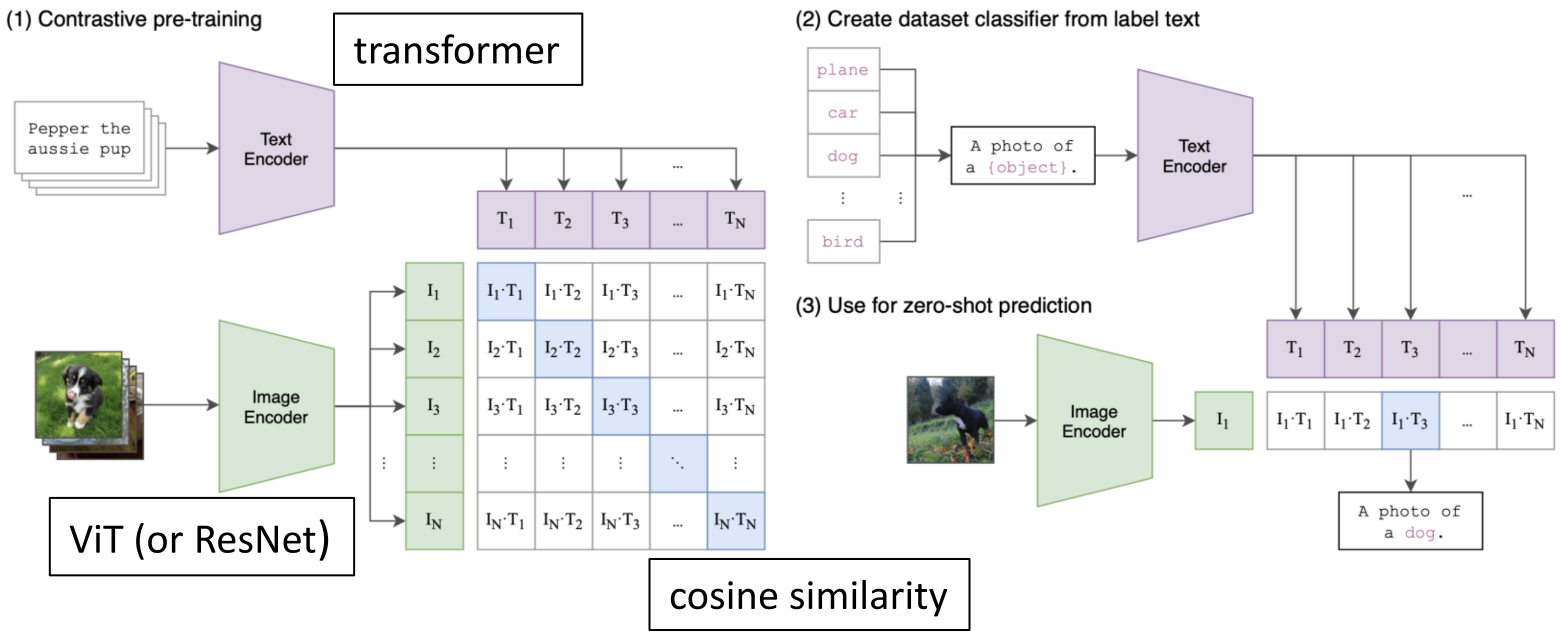
Combination of Vision and Text: Multi-Modality

example: CLIP (Contrastive Language-Image Pre-training)

- learn image representations by predicting which caption goes with which image (pre-training)
- zero-shot transfer (e.g., for object recognition)



multi-purpose (multi-modal and multi-task) models as next generalization step of ML (e.g., Google's Pathways)

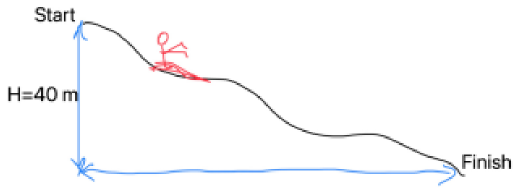
transformers good candidate (universal and flexible architecture, little task-specific inductive bias)

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: $E = \frac{1}{2} m v^2$

$\Rightarrow mgL = \frac{1}{2} m v^2$

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

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:

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

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

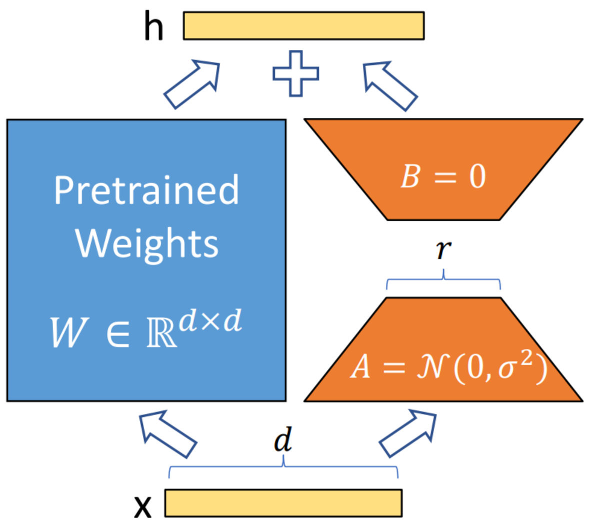
multimodal understanding of inputs: text, audio, images, video

Hot LLM Research Topics

transformer efficiency

- (sparse) mixture of experts (e.g., Mixtral 8x7B, Gemini 1.5)
- sparse attention (e.g., Longformer)

or non-transformer architectures (e.g., Mamba)



prompting strategies

- let LLM agents show reasoning/planning capabilities
- use tools (also embodiment/grounding)
- prompt optimization (e.g., OPRO)

fine-tuning efficiency (e.g., LoRA)
RAG

make use of your own data

Generative Models

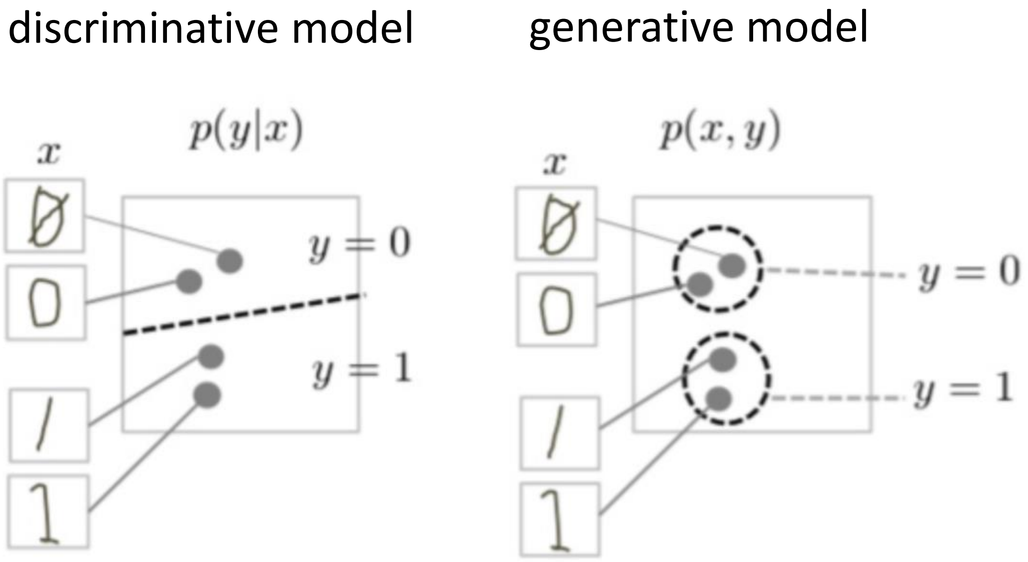
Generative vs Discriminative Models

generative models: predict joint probability $P(Y, \boldsymbol{X})$ (what allows to create new data samples) or directly generate new data samples

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

discriminative models: predict conditional probability (or probability distribution for regression) $P(Y|\boldsymbol{X})$ or directly output (label for classification, real value for regression)

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



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Data Generation

generative models can be used for discriminative tasks (although potentially inferior to direct discriminative methods)

but generative methods do more than discriminative ones: model full data distribution

→ allows generation of new data samples (can be images, text, video, audio, code like SQL or Python, proteins, materials, time series, structured data, …)

large (auto-regressive) language models examples of generative models

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

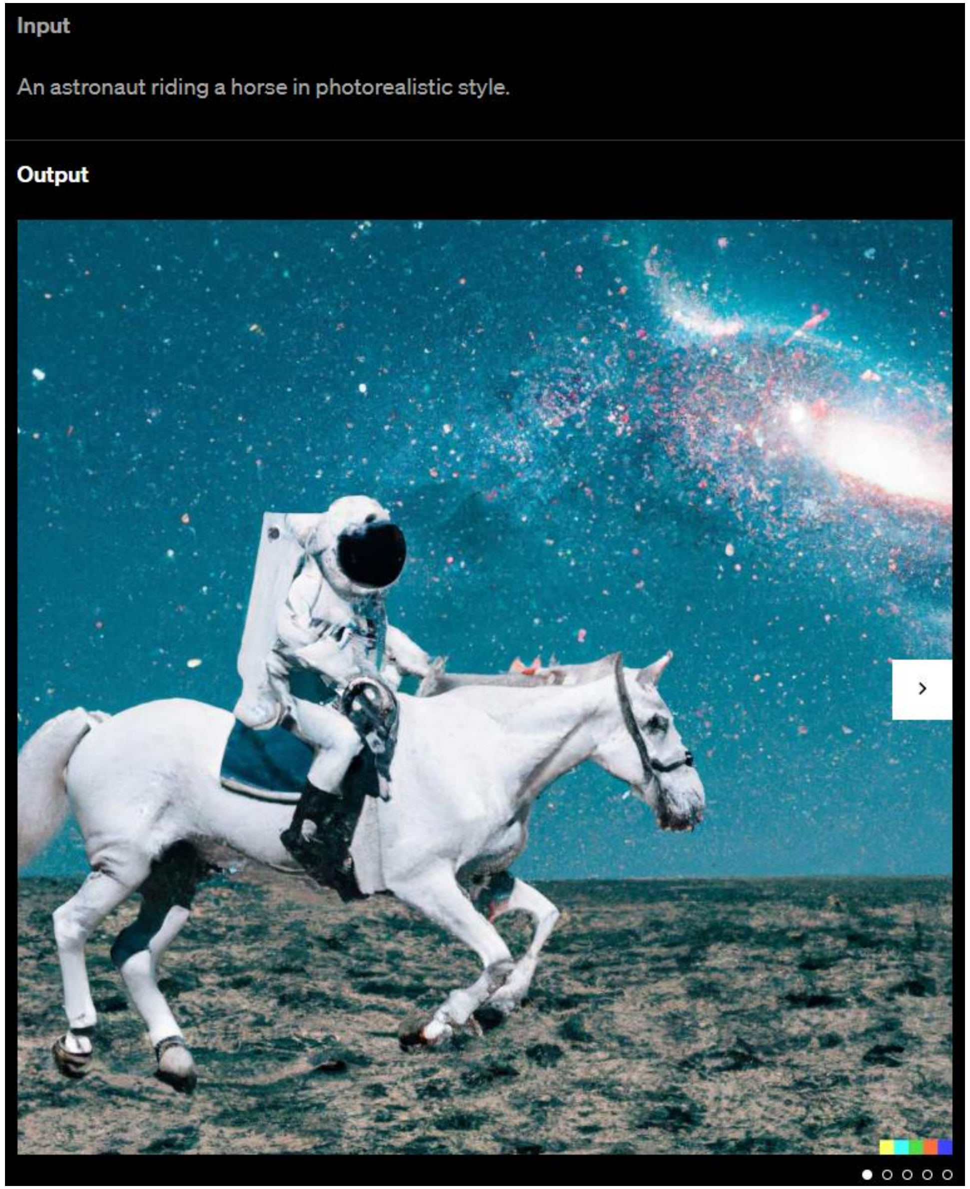
idea: generate new images as variations of training data

condition generation on text prompts: text-to-image

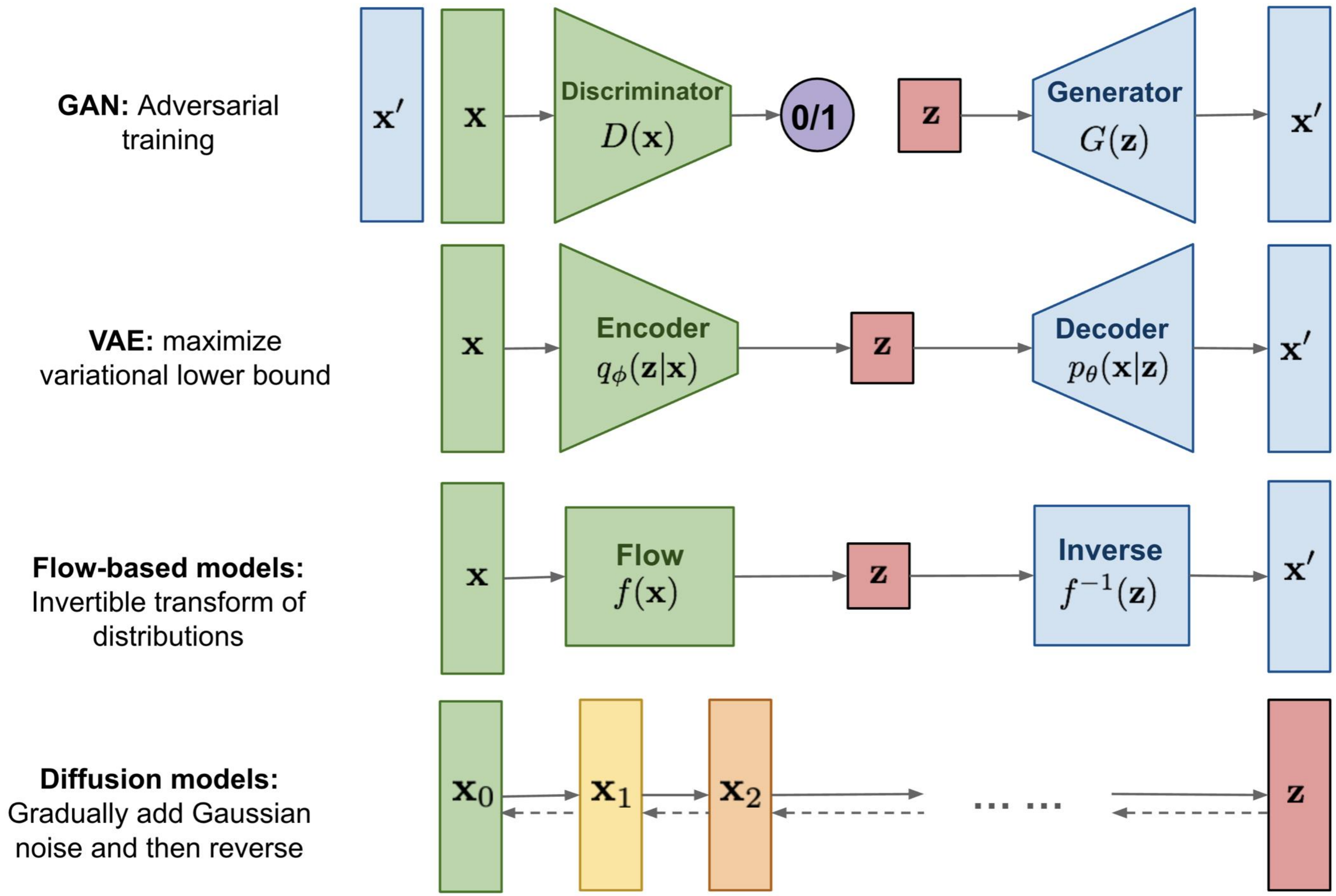
trade-off between diversity and fidelity

SOTA: (guided) diffusion models

example: DALL-E 2



Different Types of Generative Models



two neural networks playing a zero-sum game

learn variational distribution (not just replicating inputs)

more complex distributions by applying change-of-variable technique (need for specialized architecture)

chain of denoising autoencoders

source

Multi-Modal Generative Models

example: generate images from text descriptions

DALL-E, DALL-E 2, DALL-E 3 (blend of WALL-E and Salvador Dalí):

image synthesis (diffusion) conditioned on CLIP embeddings

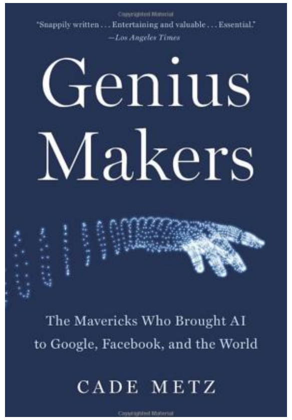
TEXT PROMPT

an armchair in the shape of an avocado. . . .

AI-GENERATED IMAGES

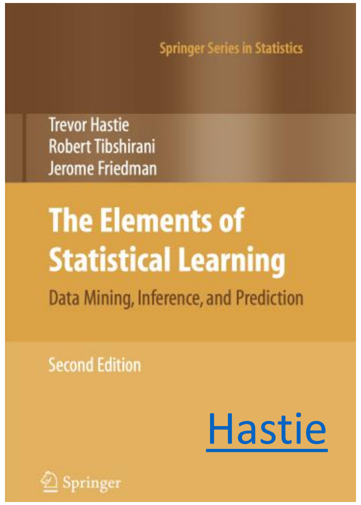
source

historical overview of deep learning:



Literature

foundations of ML:

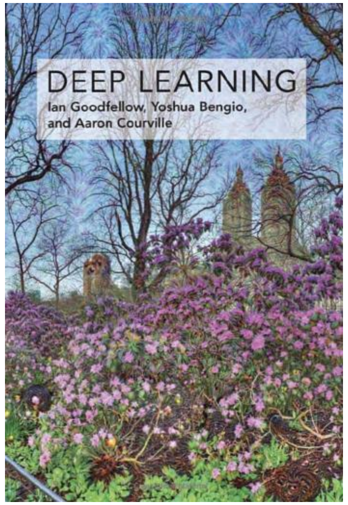


[Hastie]

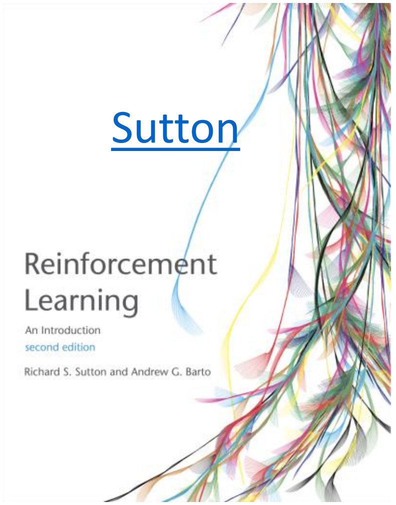
a few seminal papers:

- [back-propagation]: one of the founding moments of deep learning
- [CNN]: neural networks work
- [AlexNet]: deep learning takes over
- [transformer]: SOTA

foundations of deep learning:
https://www.deeplearningbook.org/

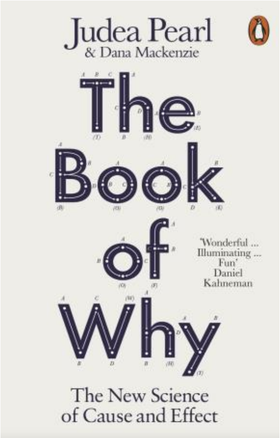


overview of reinforcement learning:

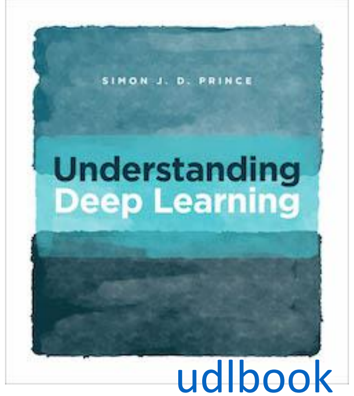


[Sutton]

gentle but geniune introduction to causality:



covering newer topics:



[udlbook]

[The Little Book of Deep Learning]

Some Philosophical Thoughts

computational theory of mind: mind from matter

just scaling up current methods (e.g., LLMs) enough to achieve general intelligence? or additional methods needed?

agency via goal-based approaches? (is reward enough?)

emergent capabilities of complex systems difficult to foresee: emotions or consciousness occurring as emergent capabilities?