Other Learning Topics

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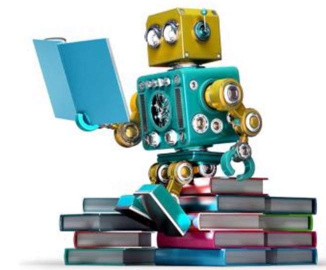
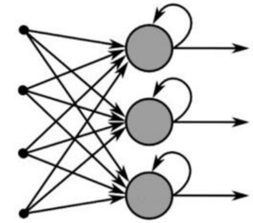
Other Relevant Learning Topics



- **NLP – Recurrent Neural Networks (RNNs) and More (Attention, Transformers)**
- (Deep) Reinforcement Learning
- Generative Adversarial Networks (GANs)
- Graph Neural Networks (GNNs)
- Adversarial Learning
- Transfer Learning
- AutoML – Automated Machine Learning

Recurrent Neural Networks (RNNs)

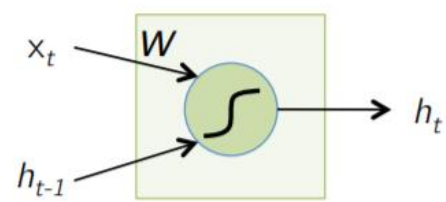


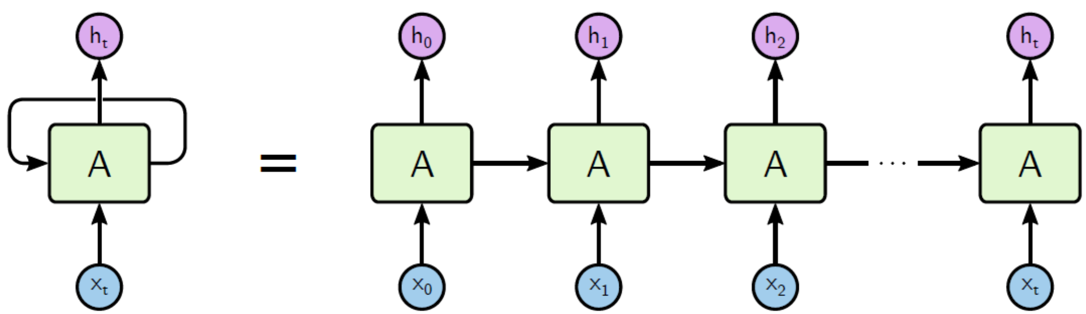
- Not all problems can be converted into one with fixed-length inputs and outputs (e.g., speech, time-series, etc.)

- **Recurrent Neural Networks** (RNNs) are a family of neural networks to **process sequential data**

- **Recurrent:** the output is influenced not only by the actual input, but also by the history of inputs fed in the past, **allowing information to persist**

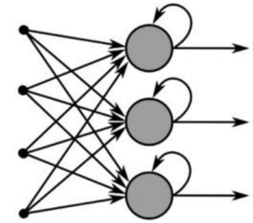
- Simplest RNN model – **vanilla RNN**



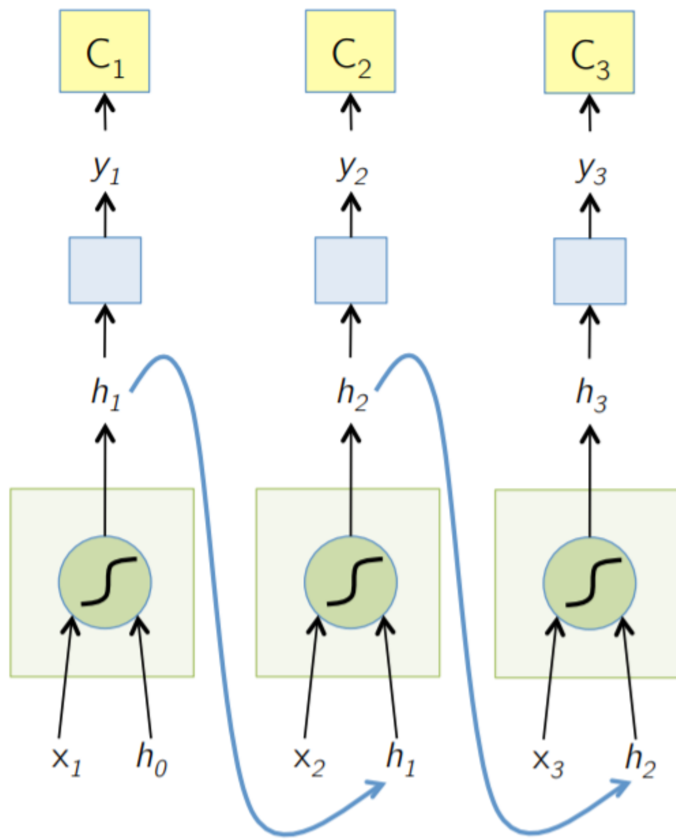


$$h_t = \tanh W \begin{pmatrix} x_t \\ h_{t-1} \end{pmatrix}$$

Recurrent Neural Networks (RNNs)



- RNNs usually **use the same weights across time**
- This simplifies the complexity of the model, making it easier to train

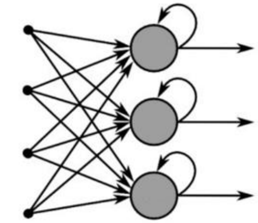


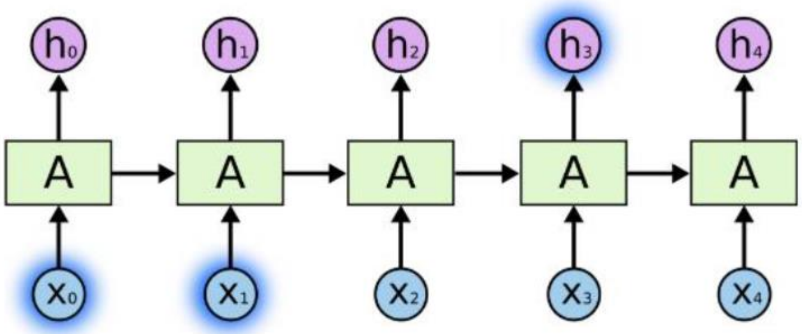
$$h_t = \tanh W \begin{pmatrix} x_t \\ h_{t-1} \end{pmatrix}$$

$$y_t = \mathrm{F}(h_t)$$

$$C_t = \mathrm{Loss}(y_t, \mathrm{GT}_t)$$

Vanilla RNN – Long Term Dependence

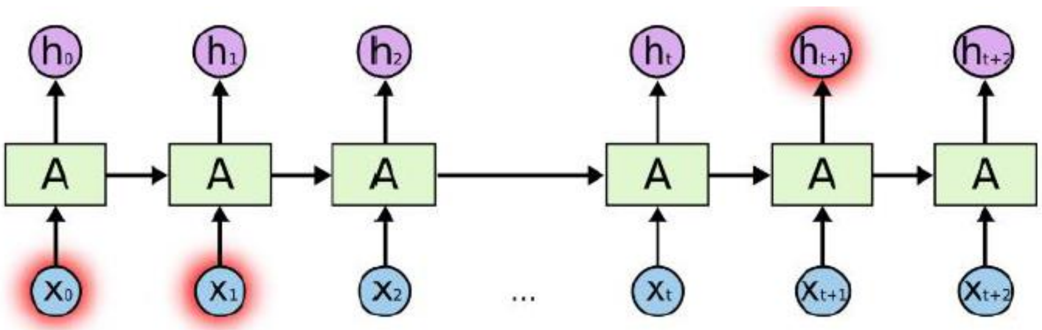




- **Task:** word forecasting

- **Short-term** dependence: Bob is eating an **apple**.

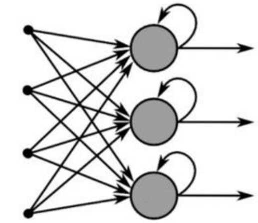
- **Long-term** dependence (**context**): **Bob** likes **apples**. He is hungry and decided to have a snack. So now he is eating an **apple**.

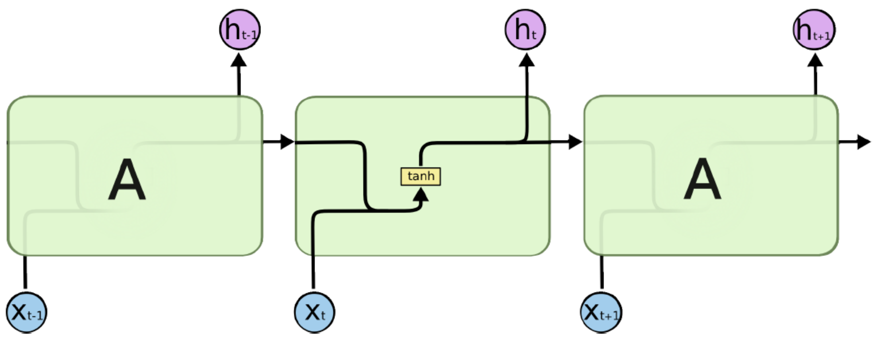


- **In theory,** vanilla RNNs can handle arbitrarily long-term dependence.

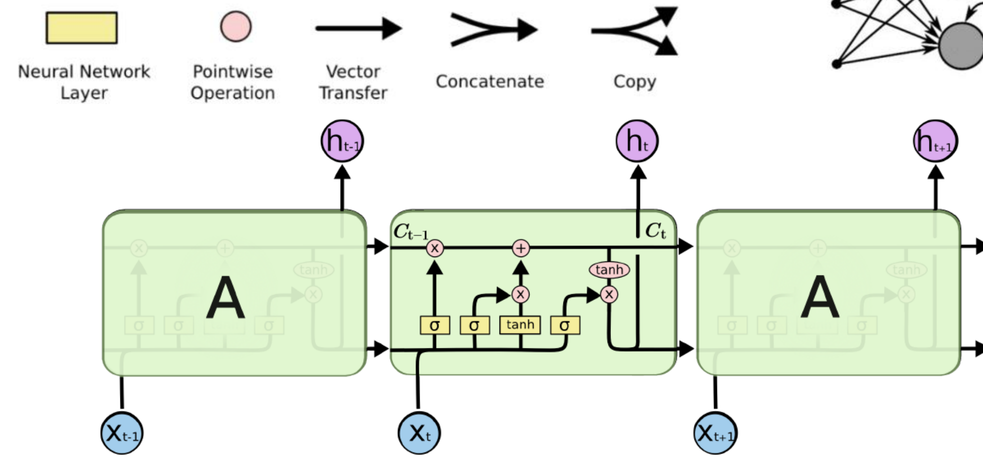
- **In practice,** it's difficult, due to vanishing gradient problem.

Long-Short Term Memory (LSTM) Networks





Update rule in a standard –*vanilla*– RNN.



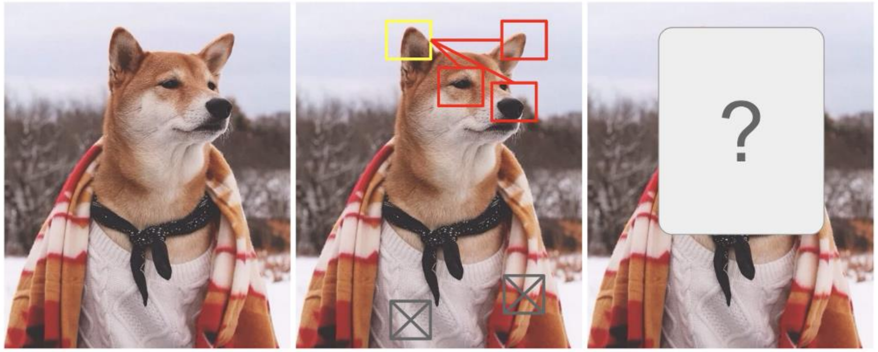
Gating mechanism in the update rule of a LSTM network.

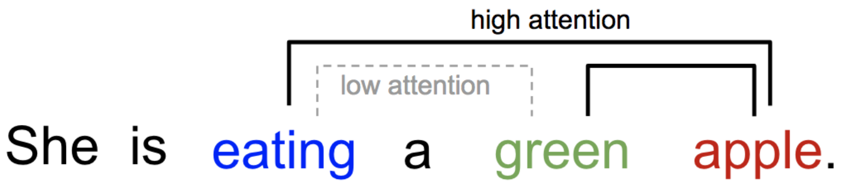
- LSTMs are a more **complex variation of an RNN** that are able to **learn long term dependencies.**
- They solve the issue with the vanishing gradient problem by replacing the simple update rule vanilla RNN with a **gating mechanism**.
- The task of the gates is to **control which information is important for the prediction at every time step** and which is not.
- Using this mechanism, a **LSTM can decide** what **to remember** and what **to forget** from the past **to obtain better predictions**.

Attention Mechanisms and Transformers

- The same problem that happens to RNNs generally, happen with LSTMs, i.e. **when sentences are too long LSTMs still don't do too well** (context is lost)

- **Attention Mechanisms**: human attention allows us to focus on a certain elements/regions with "high resolution", while perceiving the surrounding image in "low resolution"





- **Attention in deep learning** can be broadly interpreted as a ***vector of importance weights***: to predict or infer one element, we estimate using the ***attention vector*** how strongly it is correlated with other elements

- Can therefore ***provide sharper information about far-away elements***

Attention Mechanisms and Transformers

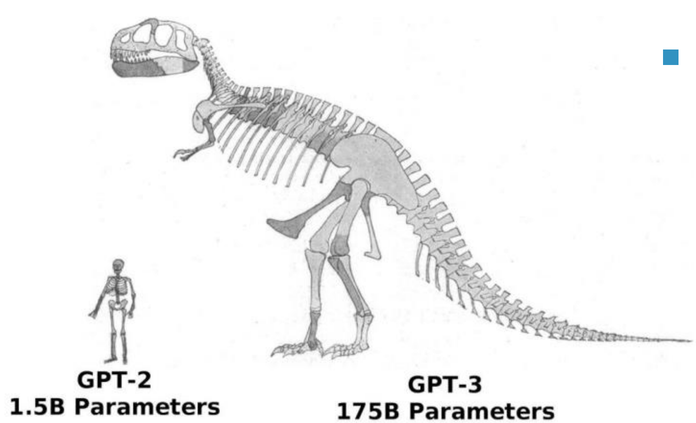
- **When added to RNNs, attention mechanisms led to large gains in performance**

  "Attention Is All You Need" (Vaswani, et al., NIPS 2017) → **no need for RNNs!**

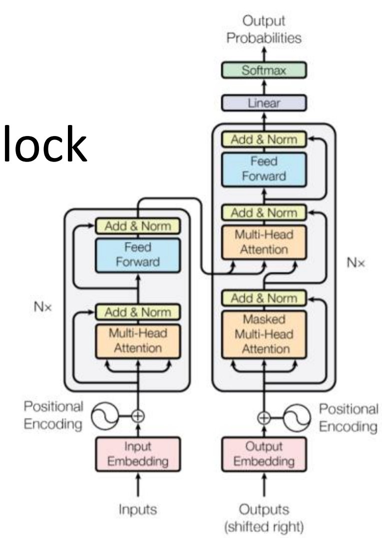
- **Transformers:** a new model to handle sequential data, differently from RNNs

- Unlike RNNs, Transformers **do not require that the sequential data be processed in order**

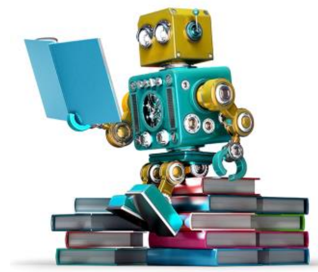
- Therefore, it allows for much more parallelization than RNNs, ***significantly reducing training times***, and to be trained more efficiently on **massive datasets**.



- Transformers are the default building block for NLP today
  - **BERT (Google)**
  - **GPT (openAI)**
  - **etc…**



Other Relevant Learning Topics



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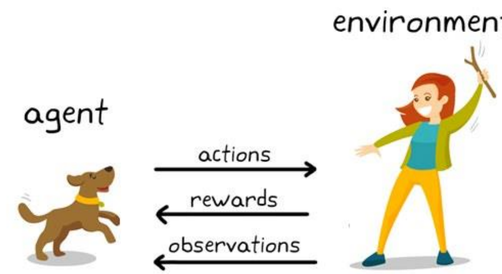
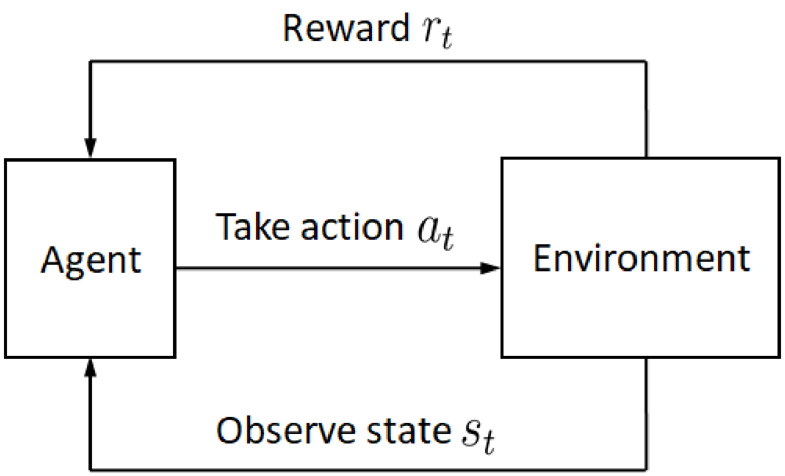
Reinforcement Learning



- Reinforcement learning: **teach by experience**



Goal: maximize the cumulative (future) reward $\sum_t r_t$

$$s_0, a_0, r_1, s_1, a_1, r_2, \ldots, s_{n-1}, a_{n-1}, r_n, s_n$$

state

action

reward

Terminal state

RL agent may be directly or indirectly trying to **learn** a:

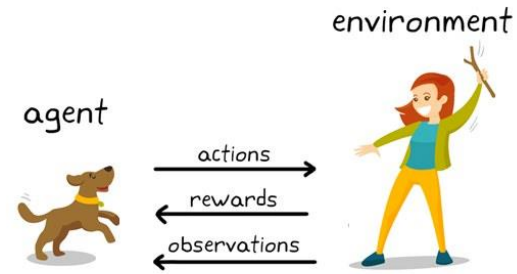
- **Policy**: agent's behavior function – action selection (probability of taking action *a* when in state *s*)
- **Value function**: how good is each state and/or policy (expected return starting in state *s*, following policy π)
- **Model**: agent's representation of the environment

Reinforcement Learning – Exploration vs. Exploitation

- Deterministic/greedy (max. reward) policy won't explore all actions
  - Don't know anything about the environment at beginning
  - Need to try all actions to find the optimal one
  - With **incomplete knowledge of the world**, shall the agent **repeat decisions that have worked well** so far (exploit) or **make novel decisions** (explore), hoping to gain even greater rewards.

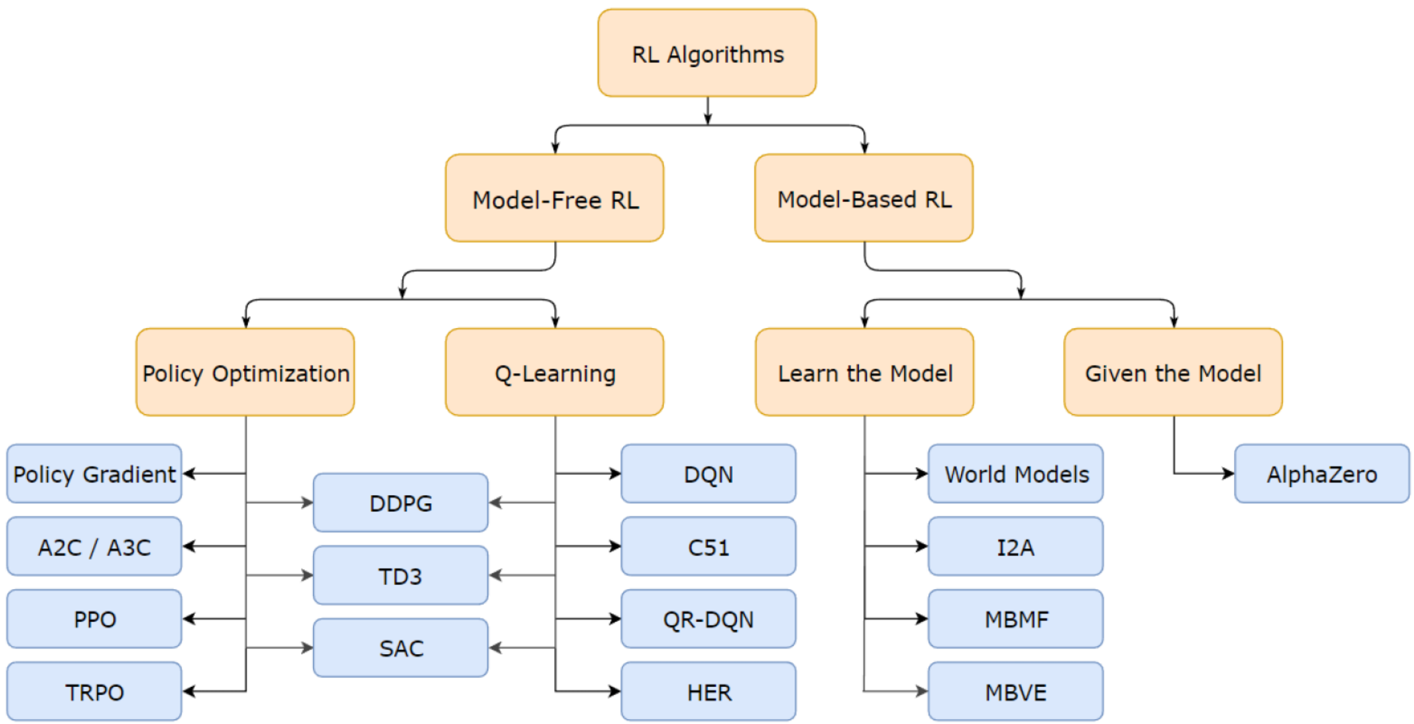
- ε–greedy policy to improve exploration-exploitation tradeoffs:
  - With probability 1-ε, perform the optimal/greedy action, otherwise random action
  - Slowly move it towards greedy policy: $\varepsilon \rightarrow 0$

Reinforcement Learning



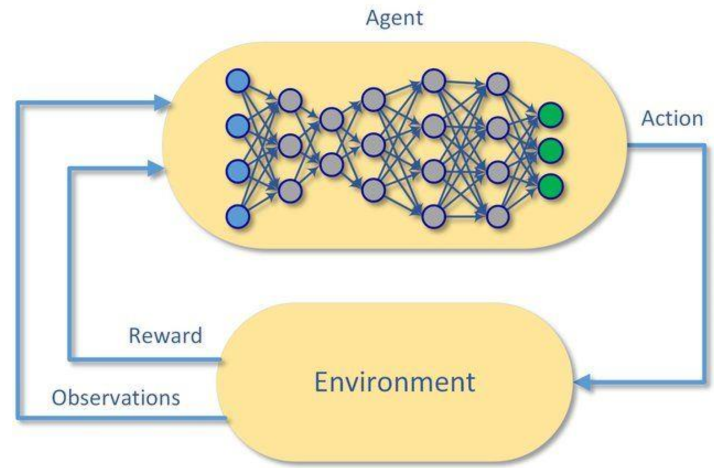
3 types of Reinforcement Learning:

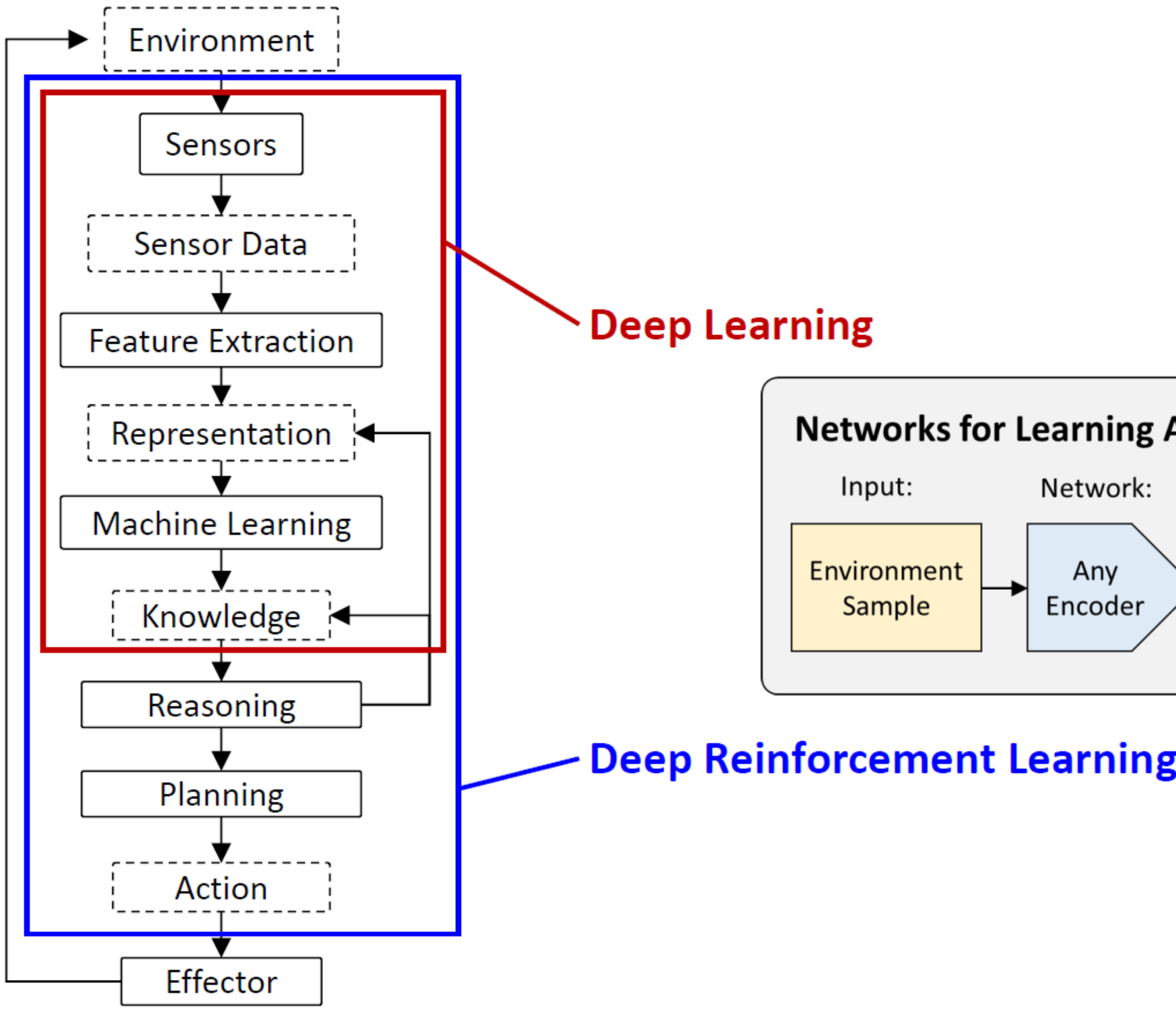
- **Model-based**: learn the model of the environment, update it often, re-plan often
- **Value-based**: learn the state or state-action value (expected return)
- **Policy-based**: learn the stochastic policy function mapping state to action

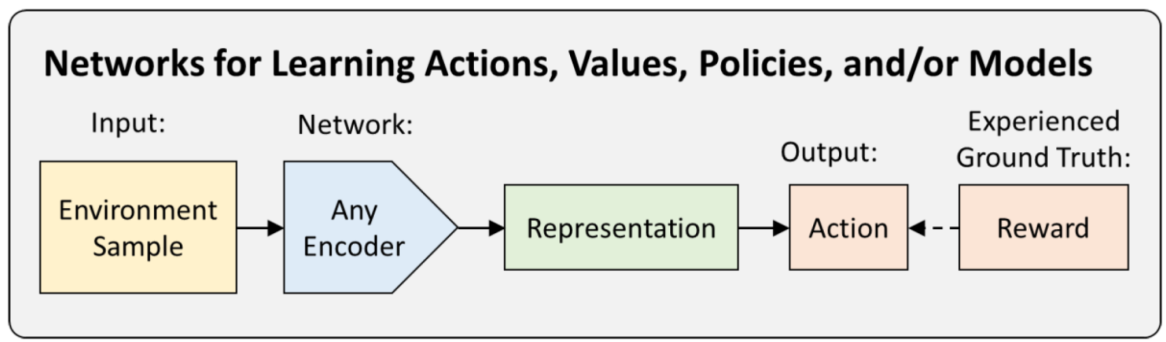


Deep Reinforcement Learning

- Deep RL = RL + Deep Neural Networks







Deep Reinforcement Learning Example – DOOM

DOOM - first-person shooter developed for MS-DOS

Goal:

eliminate all opponents

State:

raw image pixels of the game

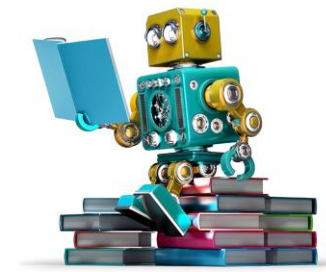
Actions:

up, down, left, right, shoot, etc.

Reward:

positive when eliminating an opponent, negative when the agent is eliminated

Other Relevant Learning Topics



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Generative Models

- Given training data, **generate new samples** from **same distribution**

Training data ~ $p_{data}(x)$

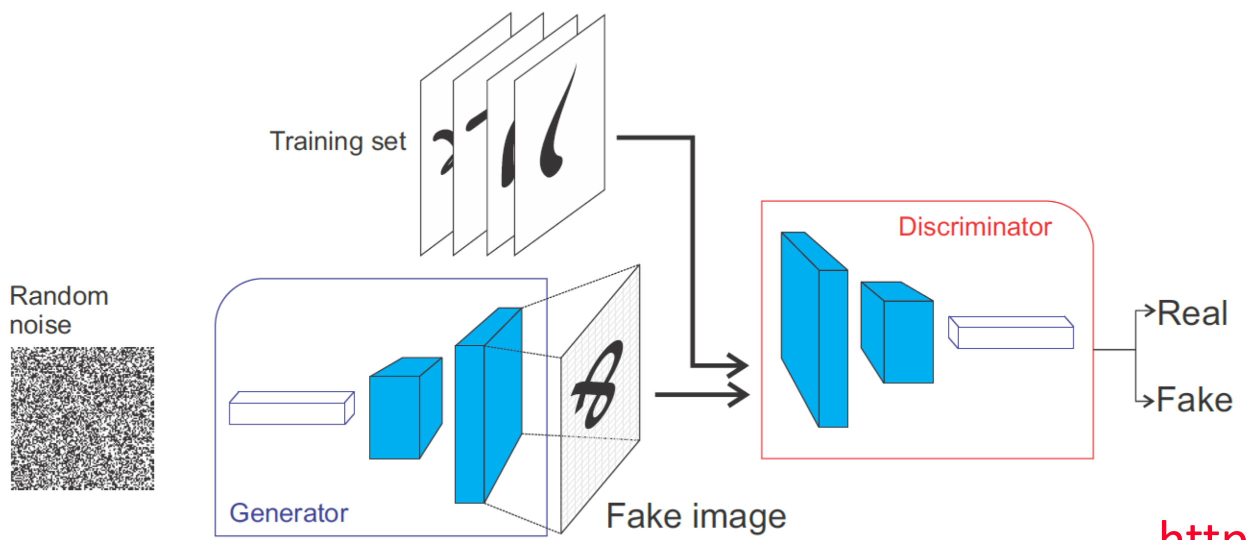
Generated samples ~ $p_{model}(x)$

- The **problem of generative models** is about **learning $p_{model}(x)$ similar to $p_{data}(x)$**

- Generative model learning is about **density estimation:**
  - **Explicit density estimation**: explicitly define and solve for $p_{model}(x)$
  - **Implicit density estimation:** learn model that can sample from $p_{model}(x)$ w/o explicitly defining it

Generative Adversarial Networks (GANs)

- Implicit density estimation through **game-theoretic approach**
- Learn to generate samples from training distribution through **2-players (minimax) game**
- **Problem:** want to sample from potentially complex, high-dimensional training distribution. No direct way to do this!
- **Solution:** sample from a simple distribution, e.g. **random noise**. Learn transformation to training distribution, **using a neural network**



- **Generator** network: tries to fool the discriminator by generating real-looking instances from random noise
- **Discriminator** network: tries to distinguish between real and fake instances

https://thispersondoesnotexist.com

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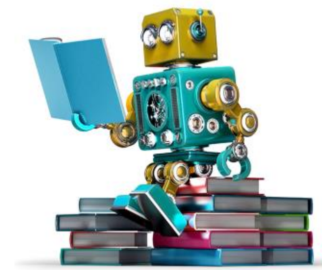

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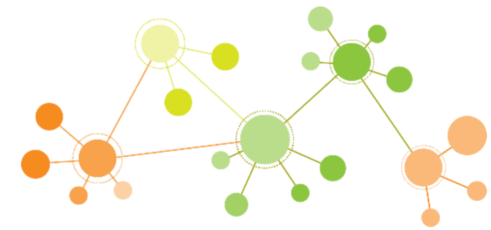
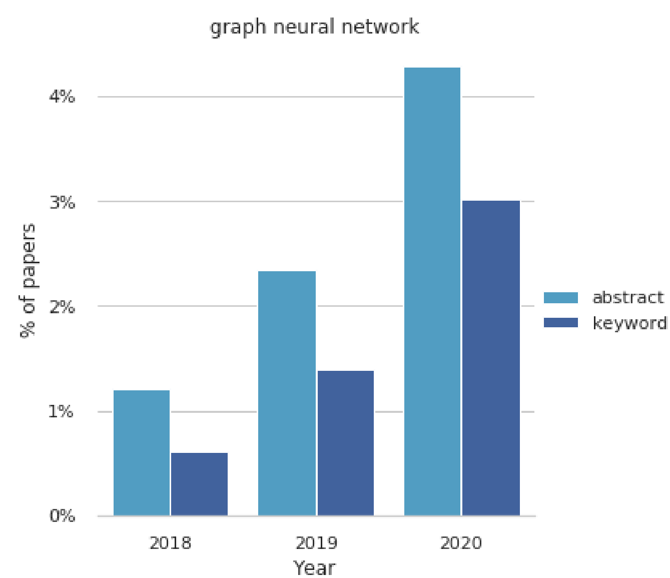
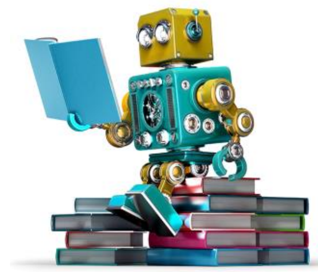
Graph Neural Networks (GNNs)



- In a nutshell: **deep learning** architecture for **graph-structured data**
- **Lots of domains where graph-structured data makes much more sense**: social networks, knowledge graphs, recommender systems, ***communication networks***
- Typical application of GNN: node classification → every node in the graph is associated with a label, and we want to predict the label of the nodes without ground-truth
- Have so far proved very powerful in modeling the dependencies between nodes in graph-like structures
- **About 4% of ICLR 2020 submitted papers using GNNs** (2585 submissions)
- **Graph Neural Networking Challenge 2020**, based on RouteNET: a GNN architecture to estimate per-source-destination performance metrics in communication networks



Other Relevant Learning Topics



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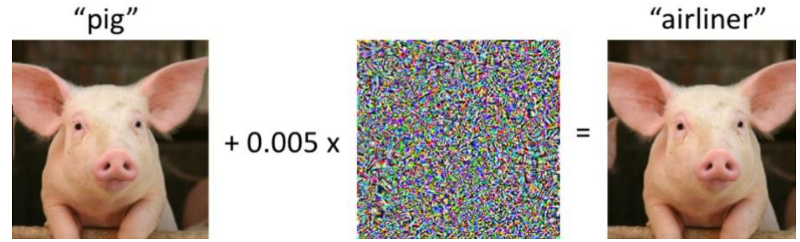
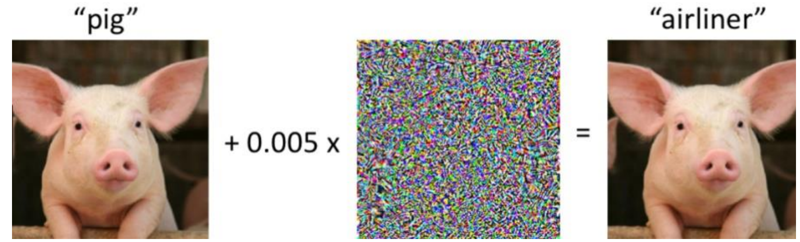
Adversarial Learning

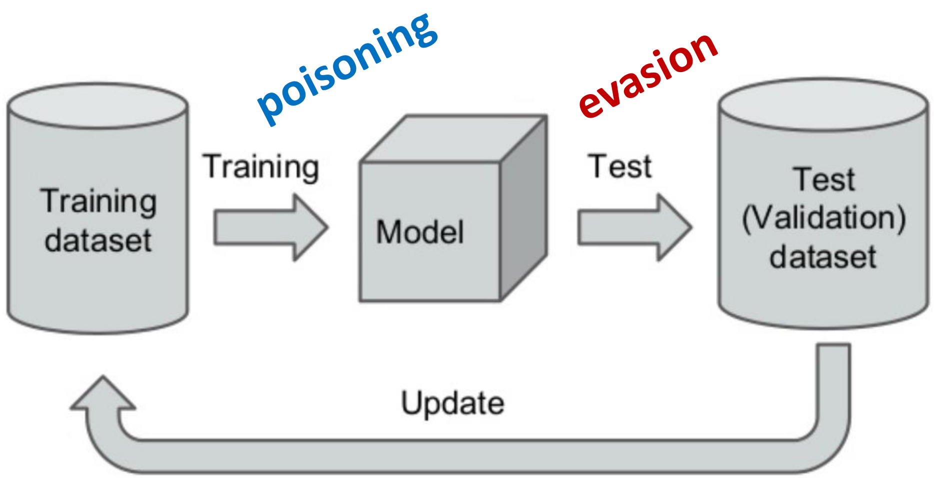


- A technique which attempts to **fool models through malicious inputs** (aka adversarial examples)
- We saw that **concept drift** can make ML models to drastically fail. The same ideas behind concept drift can be exploited by an attacker to fool a ML model
- Strongly linked to the problem of **Robust ML** → building robust models
- **Adversarial Learning** shows how a malicious adversary can manipulate the input data to **exploit specific vulnerabilities of learning algorithms** and **compromise the security** of the full **machine learning system**

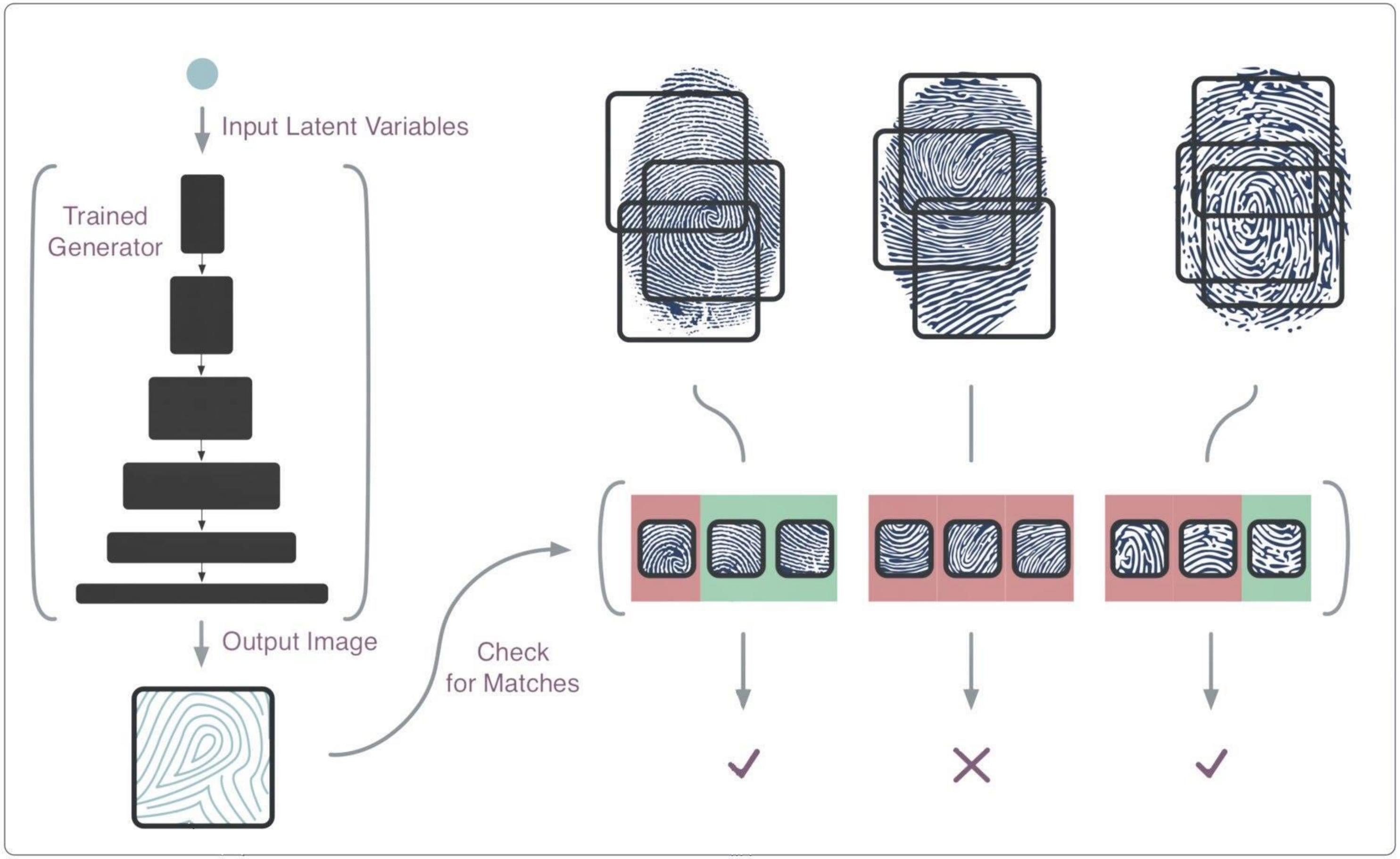
Adversarial Learning



- **Evasion attacks:**
  - executed at runtime of the system
  - evade detection by obfuscation, or even spoofing/synthetization
  - Exploratory nature
- **Poisoning attacks:**
  - executed at training time
  - It is about understanding the learning algorithm…
  - …to introduce specific bias into the learning phase

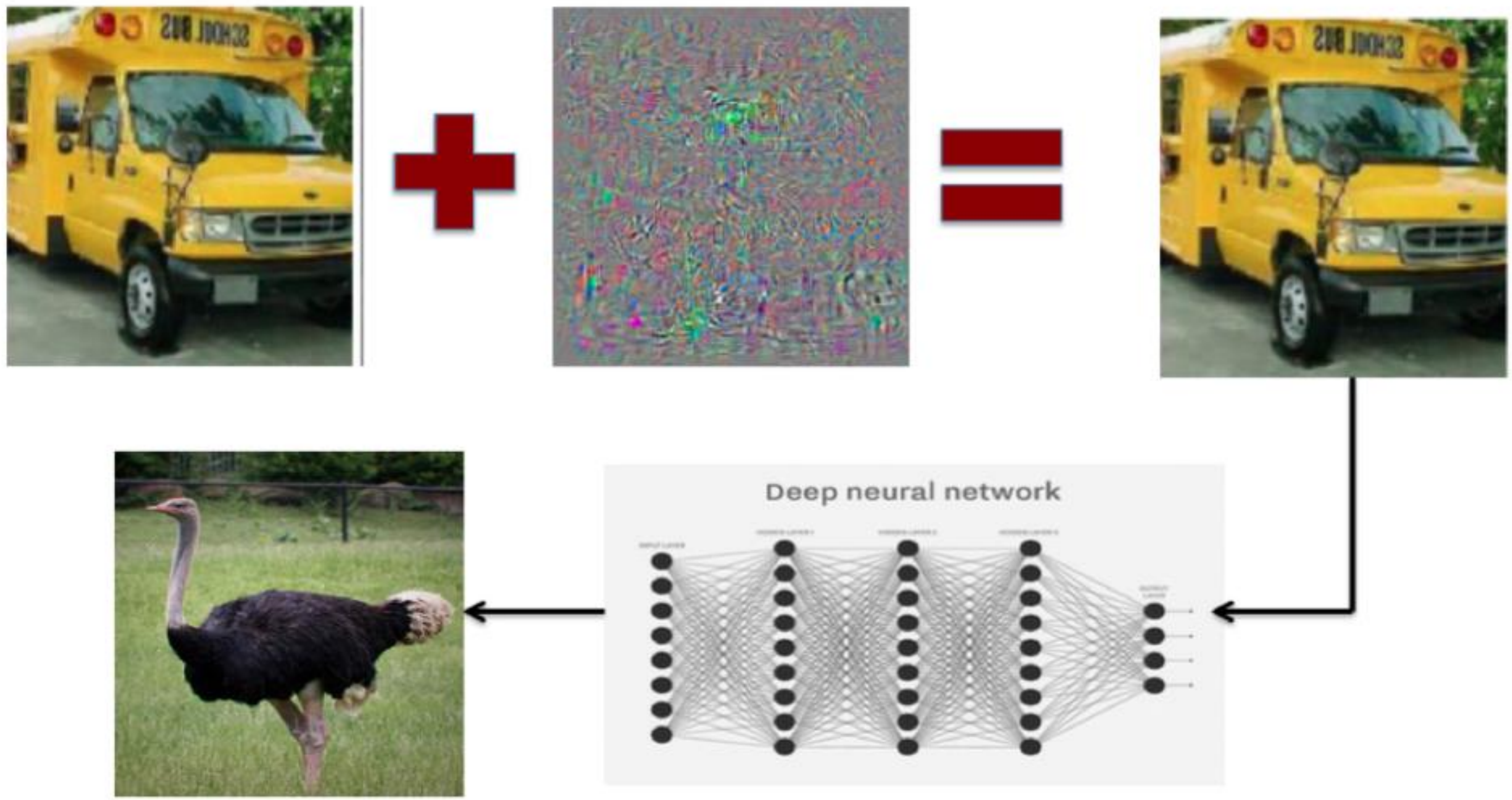


Adversarial Learning – Examples



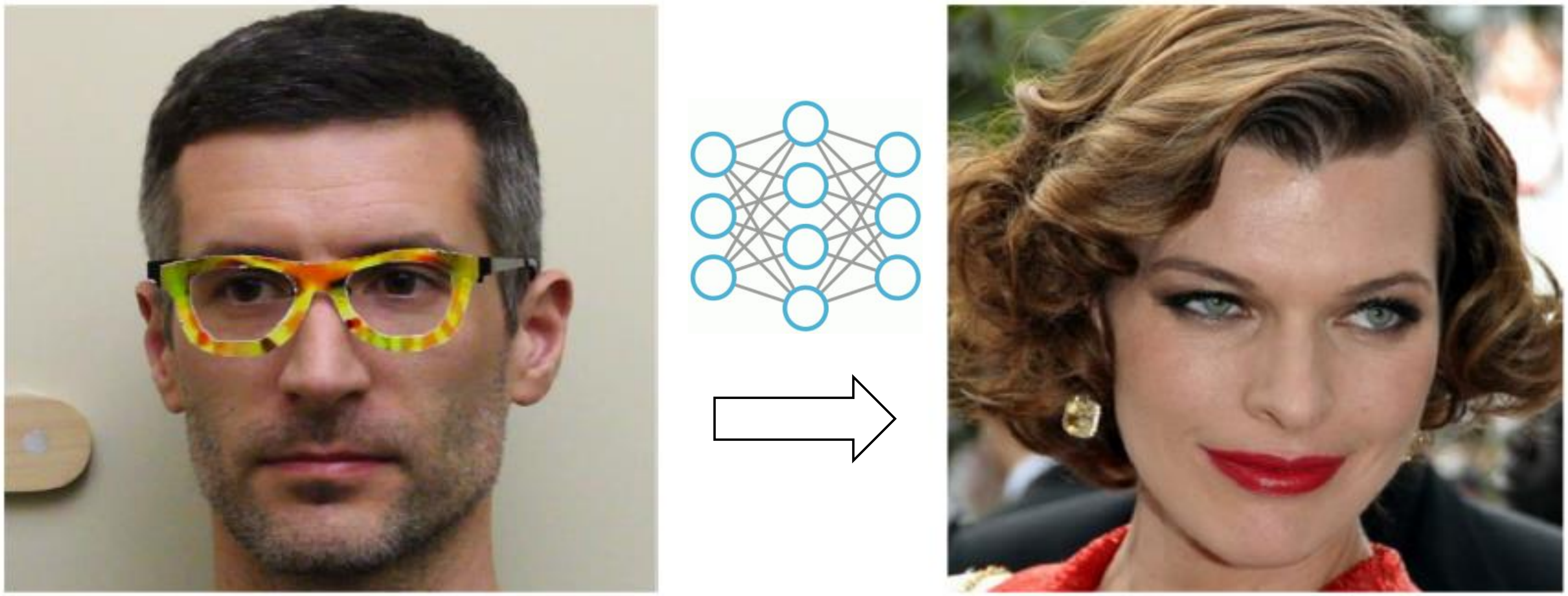
Fake-it through synthetization (e.g., GANs)

Adversarial Learning – Examples



Fool the CNN, not the human eye

Adversarial Learning – Examples

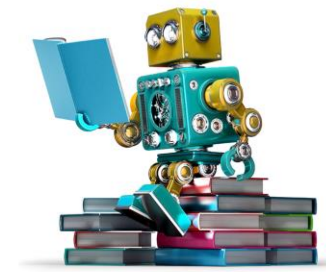


Adversarial Glasses

Adversarial Learning – Examples

Adversarial Traffic Signs

Other Relevant Learning Topics



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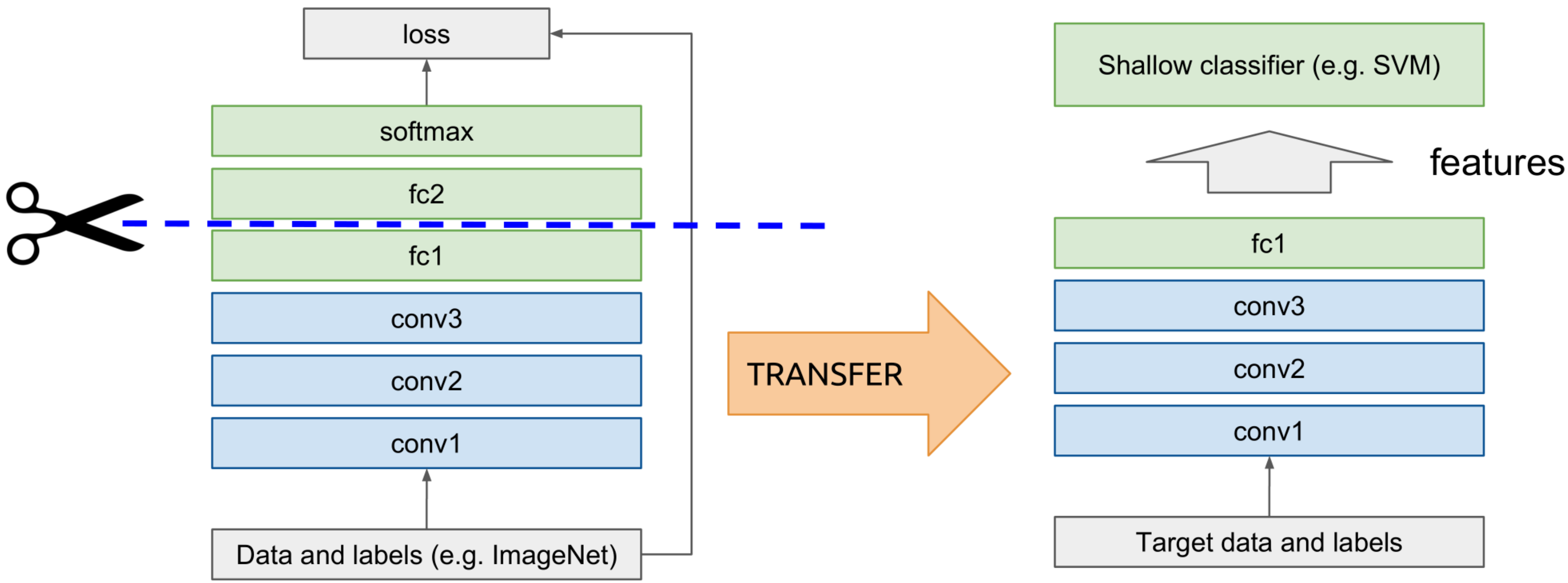
Transfer Learning



- How to store and **re-use generated knowledge** between different but related problems
- Also applied when **fine-tuning a pre-trained model**

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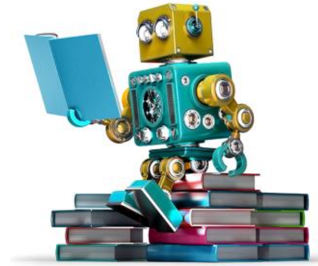

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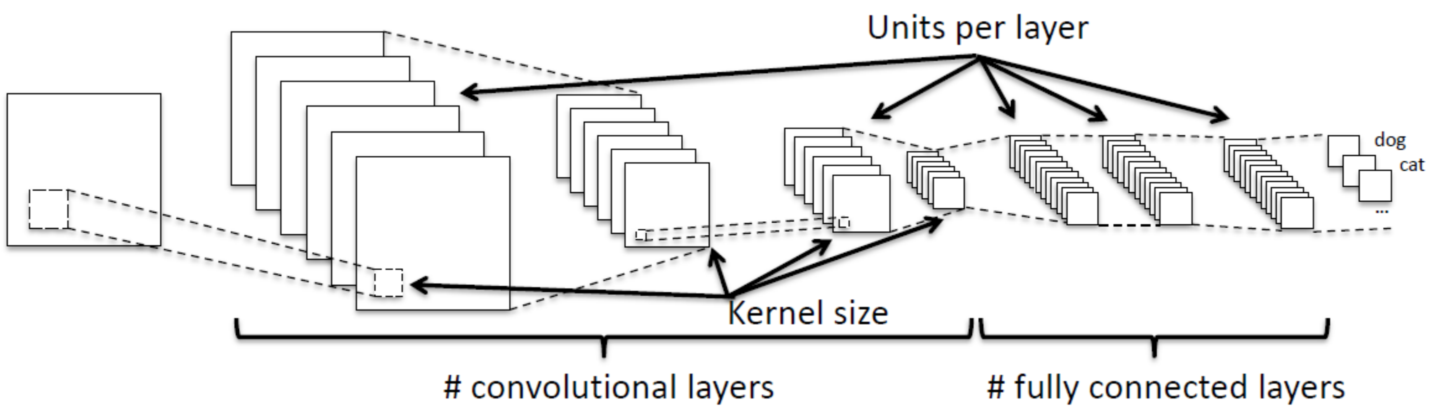
AutoML – Automated Machine Learning

- In general, **performance of a ML algorithm** heavily depends on the **many hyperparameters** involved in the end-to-end analysis pipeline



- Optimization algorithm, learning rates, momentum, batch normalization, batch sizes, dropout rates, weight decay, data augmentation, etc..

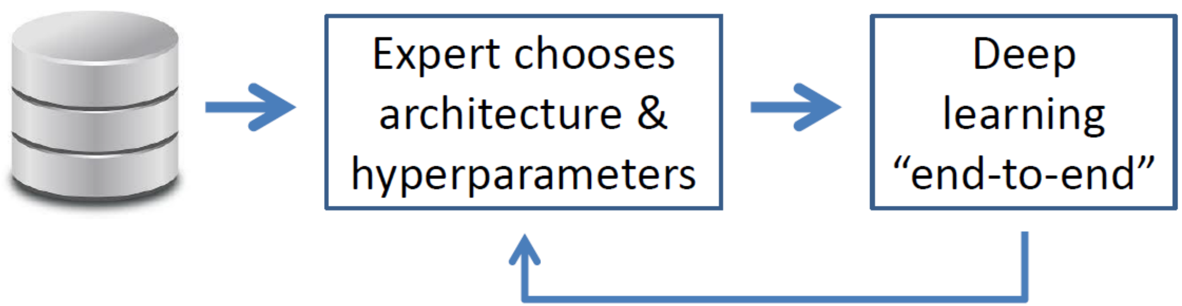
- **Easily 30 to 40 design decisions!**

AutoML – Automated Machine Learning

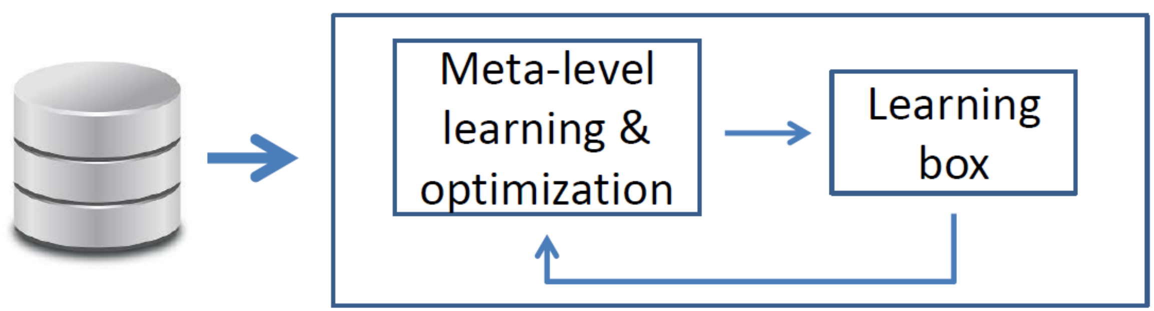
- Common approach: some sort of **search approach** (optimization) to **find best hyperparameters** (e.g., grid-search)

- **AutoML** – ***AI to build AI***: why not **relying on ML** to find best end-to-end ML pipeline configuration?

Current deep learning practice



AutoML: true end-to-end learning



AutoML – Automated Machine Learning

- **AutoML** is an emerging AI/ML discipline which attempts to **automate the end-to-end** process of applying **machine learning** to **real-world problems** **(concept drifts)**

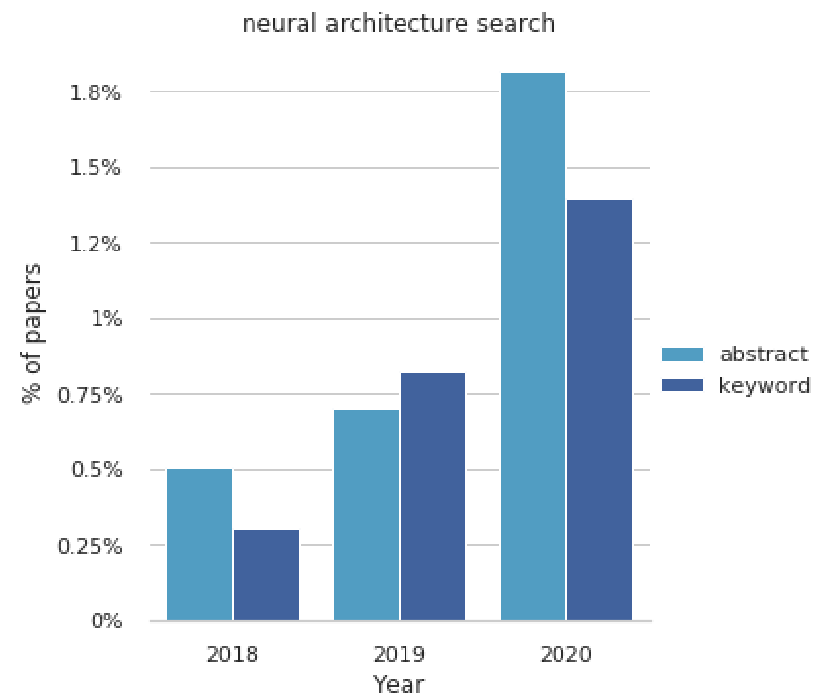
- Traditional ML pipeline:
  - clean and pre-process data
  - engineer features
  - select a model family
  - set the hyperparameters
  - construct ensemble of models
  - …
  - **Relies in domain knowledge!**

- Auto-ML
  - Hyperparameter optimization and model selection
  - **Full pipeline optimization**
  - Deep neural network architecture search
  - Libraries such as auto-WEKA, auto-sklearn, auto-Keras, etc.

- AutoML @NeurIPS Challenge

AutoML – Neural Architecture Search (NAS)

- NAS is a subset of AutoML methods
- NAS is an approach to ***automatically build network architectures***
- Has been used to **design networks that are on par or outperform hand-designed architectures**
- **Almost 2% of ICLR 2020 submitted papers using NAS**



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Q&A…

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