
MONTRÉAL.AI ACADEMY: ARTIFICIAL INTELLIGENCE 101

FIRST WORLD-CLASS OVERVIEW OF AI FOR ALL

VIP AI 101 CHEATSHEET

A PREPRINT

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ABSTRACT

For the purpose of entrusting all sentient beings with powerful AI tools to learn, deploy and scale AI in order to enhance their prosperity, to settle planetary-scale problems and to inspire those who, with AI, will shape the 21st Century, **MONTRÉAL.AI** introduces this **VIP AI 101 CheatSheet** for All.

"**GET ON A ROCKET SHIP**" - MONTRÉAL.AI is looking for successful **Partners : Captains of Industries, Iconic Tech Entrepreneurs and Scholars** to join us in this task of historic proportions.

Curated Open-Source Codes and Science: <http://www.academy.montreal.ai/>.

Keywords AI-First · Artificial Intelligence · Deep Learning · GANs · Intelligent Agent

1 AI-First | Pre-AGI Technologies

We are on the dawn of *The Age of Artificial Intelligence*.

"*In a moment of technological disruption, leadership matters.*" — Andrew Ng

TODAY'S ARTIFICIAL INTELLIGENCE IS POWERFUL AND ACCESSIBLE TO ALL. AI is capable of transforming industries and opens up a world of new possibilities. **What's important is what you do with AI and how you embrace it.** To pioneer AI-First innovations advantages: start by exploring how to apply AI in ways never thought of.

The emerging rules of the AI-First era : **Search and Learning**.

"**Search and learning** are general purpose methods that continue to scale with increased computation, even as the available computation becomes very great." — Richard Sutton in *The Bitter Lesson*

2 Getting Started

Tinker with neural networks in the browser with *TensorFlow Playground* <http://playground.tensorflow.org/>.

Papers With Code (*Learn Python 3 in Y minutes*²) <https://paperswithcode.com/state-of-the-art>.

*Founding Chairman at MONTRÉAL.AI <http://www.montreal.ai>.

²<https://learnxinyminutes.com/docs/python3/>

2.1 In the Cloud

Colab³. Practice Immediately⁴. Labs⁵: Introduction to Deep Learning (MIT 6.S191)

- Free GPU compute via Colab <https://colab.research.google.com/notebooks/welcome.ipynb>.
- Colab can open notebooks directly from GitHub by simply replacing "<http://github.com>" with "<http://colab.research.google.com/github/>" in the notebook URL.

2.2 On a Local Machine

JupyterLab is an interactive development environment for working with notebooks, code and data⁶.

- Install Anaconda <https://www.anaconda.com/download/> and launch ‘Anaconda Navigator’
- Update Jupyterlab and launch the application. Under Notebook, click on ‘Python 3’

3 Deep Learning

Deep learning allows computational models that are composed of multiple processing layers to learn REPRESENTATIONS of (raw) data with multiple levels of abstraction[2]. At a high-level, neural networks are either encoders, decoders, or a combination of both⁷. Introductory course <http://introtodeeplearning.com>. See also Table 1.

“DL is essentially a new style of programming – “differentiable programming” – and the field is trying to work out the reusable constructs in this style. We have some: convolution, pooling, LSTM, GAN, VAE, memory units, routing units, etc.” — Thomas G. Dietterich

Table 1: Types of Learning, by Alex Graves at NeurIPS 2018

| Name | With Teacher | Without Teacher |
|---------|---|---|
| Active | <i>Reinforcement Learning / Active Learning</i> | <i>Intrinsic Motivation / Exploration</i> |
| Passive | <i>Supervised Learning</i> | <i>Unsupervised Learning</i> |

“If you have a large big dataset and you train a very big neural network, then success is guaranteed!” — Ilya Sutskever

“When you first study a field, it seems like you have to memorize a zillion things. You don’t. What you need is to identify the 3-5 core principles that govern the field. The million things you thought you had to memorize are various combinations of the core principles.” — J. Reed

*“1. Multiply things together
 2. Add them up
 3. Replaces negatives with zeros
 4. Return to step 1, a hundred times.”*
 — Jeremy Howard

Deep learning (*distributed representations + composition*) is a general-purpose learning procedure.

- ❖ Linear Algebra. Prof. Gilbert Strang⁸.
- ❖ Dive into Deep Learning <http://d2l.ai>.
- ❖ Minicourse in Deep Learning with PyTorch⁹.
- ❖ Deep Learning. The full deck of (600+) slides, Gilles Louppe¹⁰.

³<https://medium.com/tensorflow/colab-an-easy-way-to-learn-and-use-tensorflow-d74d1686e309>

⁴<https://colab.research.google.com/github/GokuMohandas/practicalAI/>

⁵https://colab.research.google.com/github/aamini/introtodeeplearning_labs

⁶<https://blog.jupyter.org/jupyterlab-is-ready-for-users-5a6f039b8906>

⁷<https://github.com/lexfridman/mit-deep-learning>

⁸<https://ocw.mit.edu/courses/mathematics/18-06-linear-algebra-spring-2010/video-lectures/>

⁹<https://github.com/Atcold/pytorch-Deep-Learning-Minicourse>

¹⁰<https://glouppe.github.io/info8010-deep-learning/pdf/lec-all.pdf>

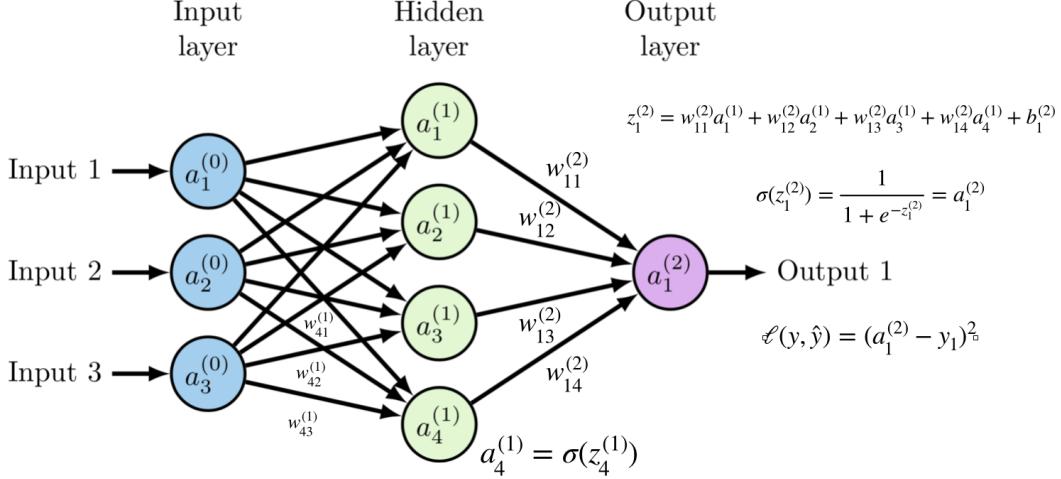


Figure 1: Multilayer perceptron (MLP).

- ❖ A Selective Overview of Deep Learning <https://arxiv.org/abs/1904.05526>.
- ❖ PoseNet Sketchbook <https://googlecreativelab.github.io/posenet-sketchbook/>.
- ❖ A Recipe for Training Neural Networks <https://karpathy.github.io/2019/04/25/recipe/>.
- ❖ Algebra, Topology, Differential Calculus, and Optimization Theory For Computer Science and Machine Learning¹¹.
- ❖ How to Choose Your First AI Project <https://hbr.org/2019/02/how-to-choose-your-first-ai-project>.
- ❖ Blog | MIT 6.S191 <https://medium.com/tensorflow/mit-introduction-to-deep-learning-4a6f8dde1f0c>.

3.1 Universal Approximation Theorem

Neural Networks + Gradient Descent + GPU¹²:

- Infinitely flexible function: *Neural Network* (multiple hidden layers: Deep Learning)¹³.
- All-purpose parameter fitting: *Backpropagation*¹⁴¹⁵.

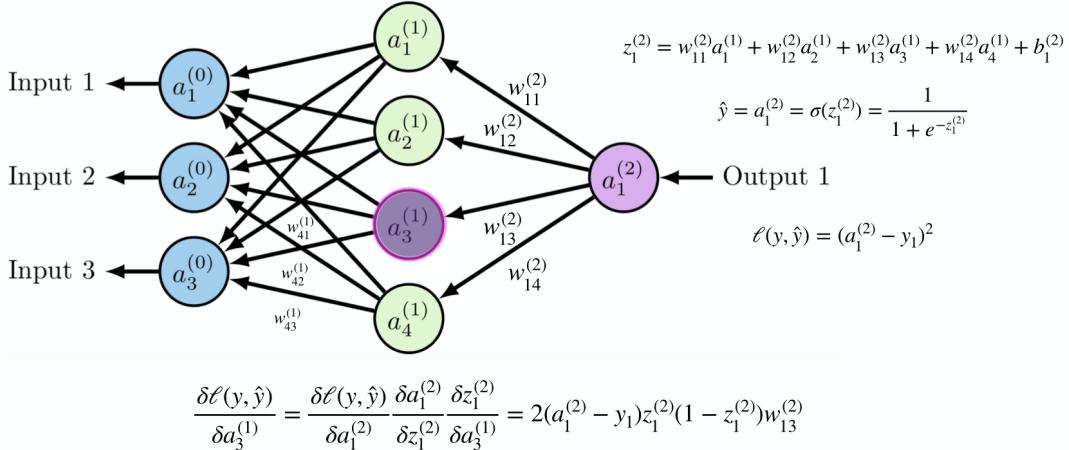


Figure 2: All-purpose parameter fitting: Backpropagation.

¹¹<https://drive.google.com/file/d/1sJvLQwxMyu89t2z4Zf9tD707efnbIUyB/view>

¹²http://wiki.fast.ai/index.php/Lesson_1_Notes

¹³<http://neuralnetworksanddeeplearning.com/chap4.html>

¹⁴https://github.com/DebPanigrahi/Machine-Learning/blob/master/back_prop.ipynb

¹⁵<https://www.jeremyjordan.me/neural-networks-training/>

- Fast and scalable: *GPU*.

"*You have relatively simple processing elements that are very loosely models of neurons. They have connections coming in, each connection has a weight on it, and that weight can be changed through learning.*" — Geoffrey Hinton

When a choice must be made, just feed the (raw) data to a deep neural network (Universal function approximators).

3.2 Convolution Neural Networks (Useful for Images | Space)

The deep convolutional network, inspired by Hubel and Wiesel's seminal work on early visual cortex, uses hierarchical layers of tiled convolutional filters to mimic the effects of receptive fields, thereby exploiting the local spatial correlations present in images[1]. See Figure 4. Demo <https://ml4a.github.io/demos/convolution/>.

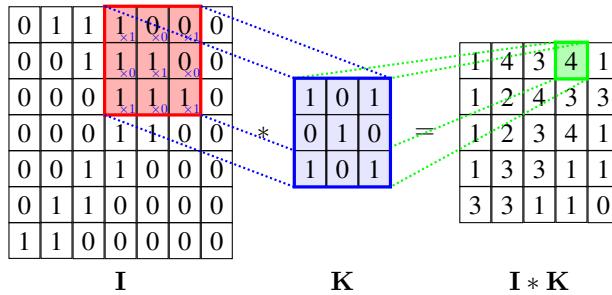


Figure 3: **2D Convolution**. Source: Cambridge Coding Academy

A ConvNet is made up of Layers. Every Layer has a simple API: It transforms an input 3D volume to an output 3D volume with some differentiable function that may or may not have parameters¹⁶. Reading¹⁷.

In images, local combinations of edges form motifs, motifs assemble into parts, and parts form objects¹⁸¹⁹.

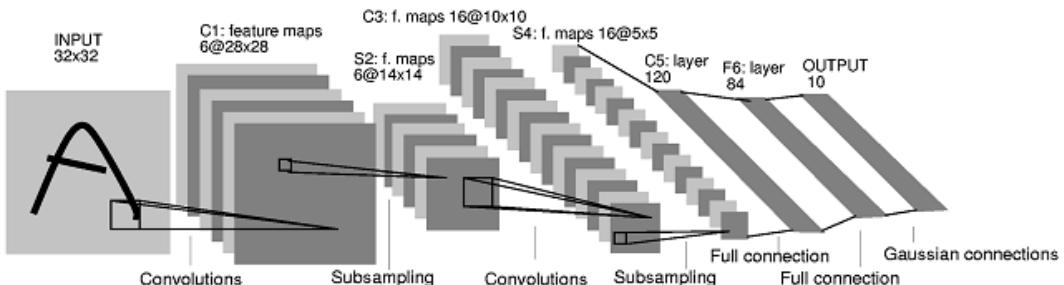


Figure 4: Architecture of LeNet-5, a Convolutional Neural Network. LeCun et al., 1998

- ❖ CS231N : Convolutional Neural Networks for Visual Recognition²⁰.
- ❖ TensorSpace (<https://tensorspace.org>) offers interactive 3D visualizations of *LeNet*, *AlexNet* and *Inceptionv3*.

3.3 Recurrent Neural Networks (Useful for Sequences | Time)

Recurrent neural networks are networks with loops in them, allowing information to persist²¹. RNNs process an input sequence one element at a time, maintaining in their hidden units a 'state vector' that implicitly contains information about the history of all the past elements of the sequence[2]. For sequential inputs. See Figure 6.

¹⁶<http://cs231n.github.io/convolutional-networks/>

¹⁷<https://ml4a.github.io/ml4a/convnets/>

¹⁸<http://yosinski.com/deepvis>

¹⁹<https://distill.pub/2017/feature-visualization/>

²⁰https://www.youtube.com/playlist?list=PLzUTmXVwsnXod6WNdg57Yc3zFx_f-RYsq

²¹<http://colah.github.io/posts/2015-08-Understanding-LSTMs/>

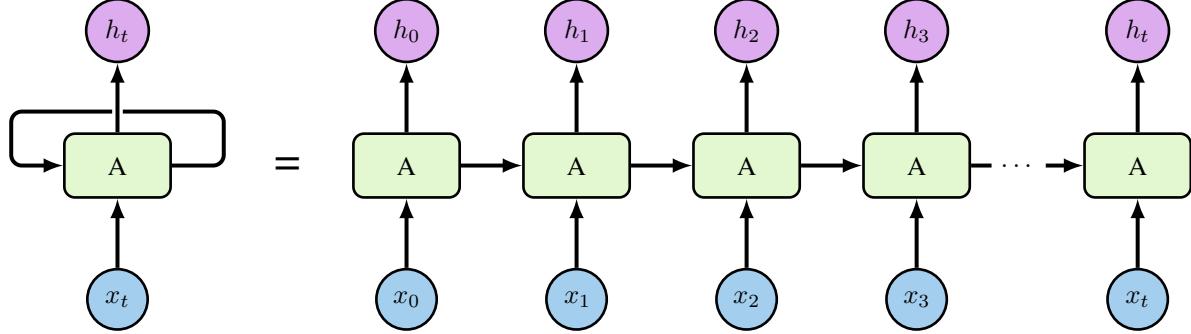


Figure 5: RNN Layers Reuse Weights for Multiple Timesteps.

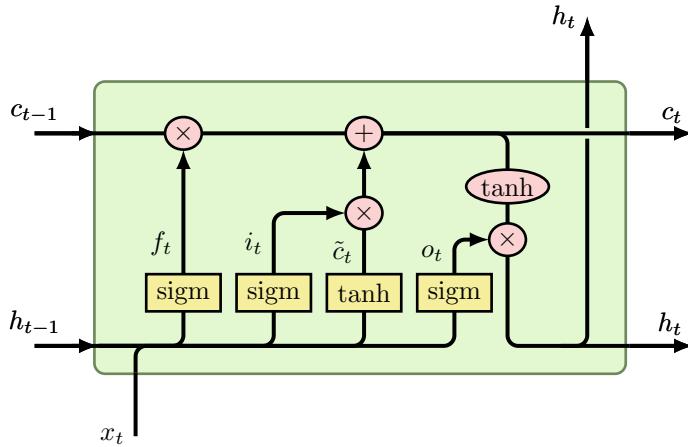


Figure 6: "Long Short-Term-Memory" (LSTM) Cell.

"I feel like a significant percentage of Deep Learning breakthroughs ask the question "how can I reuse weights in multiple places?" – Recurrent (LSTM) layers reuse for multiple timesteps – Convolutional layers reuse in multiple locations. – Capsules reuse across orientation." — Andrew Trask

- ❖ Long Short-Term-Memory (LSTM), Sepp Hochreiter and Jürgen Schmidhuber²².
- ❖ CS224N : Natural Language Processing with Deep Learning²³.
- ❖ Can Neural Networks Remember? Slides by Vishal Gupta: http://vishalgupta.me/deck/char_lstm/.
- ❖ Understanding LSTM Networks <http://colah.github.io/posts/2015-08-Understanding-LSTMs/>.
- ❖ The Unreasonable Effectiveness of Recurrent Neural Networks, blog (2015) by Andrej Karpathy²⁴.
- ❖ Attention and Augmented Recurrent Neural Networks <https://distill.pub/2016/augmented-rnns/>.
- ❖ Attention Is All You Need, Vaswani et al. <https://arxiv.org/abs/1706.03762>.
- ❖ Transformer model for language understanding. Tutorial showing how to write Transformer in TensorFlow 2.0²⁵.

3.4 Transformers

Transformers are generic, simple and exciting machine learning architectures designed to process a connected set of units (tokens in a sequence, pixels in an image, etc.) where the only interaction between units is through self-attention. Transformers' performance limit seems purely in the hardware (how big a model can be fitted in GPU memory)²⁶.

²²<https://www.bioinf.jku.at/publications/older/2604.pdf>

²³https://www.youtube.com/playlist?list=PLU40WL80194IJzQtileLTqGZuXtG1LMP_

²⁴<http://karpathy.github.io/2015/05/21/rnn-effectiveness/>

²⁵<https://www.tensorflow.org/alpha/tutorials/sequences/transformer>

²⁶<http://www.peterbloem.nl/blog/transformers>

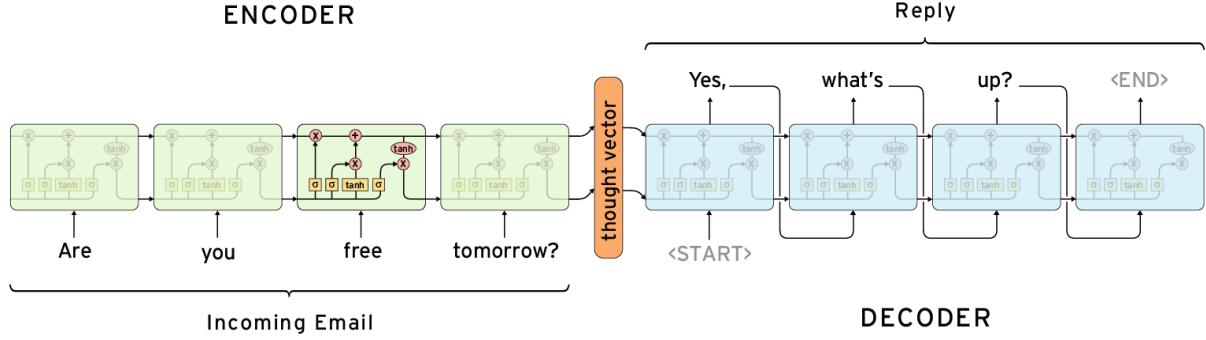


Figure 7: **Google Smart Reply System** is built on a pair of recurrent neural networks. Diagram by Chris Olah

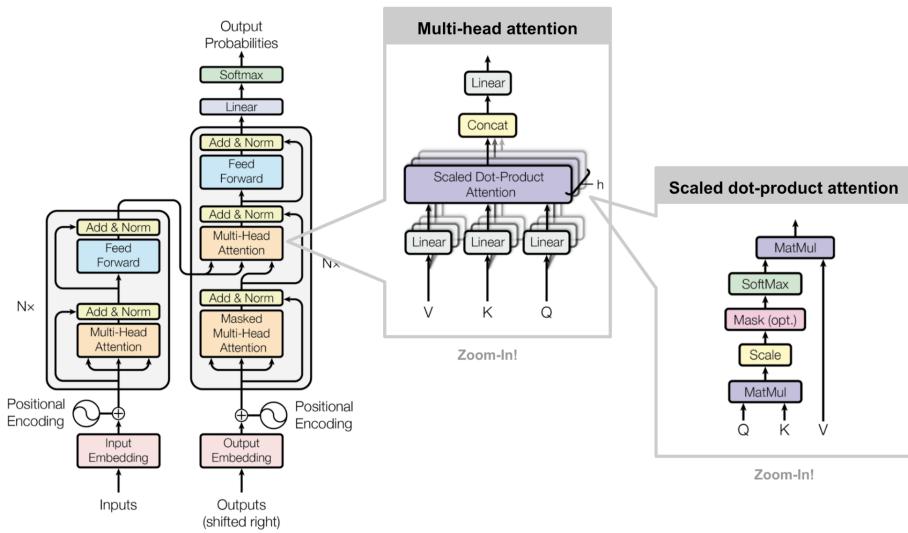


Figure 8: Attention Is All You Need. Vaswani et al., 2017 : <https://arxiv.org/abs/1706.03762>.

- ❖ The Illustrated Transformer <http://jalammar.github.io/illustrated-transformer/>.
- ❖ The annotated transformer (code) <http://nlp.seas.harvard.edu/2018/04/03/attention.html>.
- ❖ Transformer in TensorFlow 2.0 (code) <https://www.tensorflow.org/beta/tutorials/text/transformer>.
- ❖ Making Transformer networks simpler and more efficient²⁷.

3.4.1 Natural Language Processing (NLP) | BERT: A New Era in NLP

BERT (Bidirectional Encoder Representations from Transformers)[6] is a *deeply bidirectional, unsupervised language representation*, pre-trained using only a plain text corpus (in this case, Wikipedia)²⁸.

- Reading: Unsupervised pre-training of an LSTM followed by supervised fine-tuning[7].
- TensorFlow code and pre-trained models for BERT <https://github.com/google-research/bert>.
- Better Language Models and Their Implications²⁹.

"I think transfer learning is the key to general intelligence. And I think the key to doing transfer learning will be the acquisition of conceptual knowledge that is abstracted away from perceptual details of where you learned it from." — Demis Hassabis

²⁷<https://ai.facebook.com/blog/making-transformer-networks-simpler-and-more-efficient/>

²⁸<https://ai.googleblog.com/2018/11/open-sourcing-bert-state-of-art-pre.html>

²⁹<https://blog.openai.com/better-language-models/>

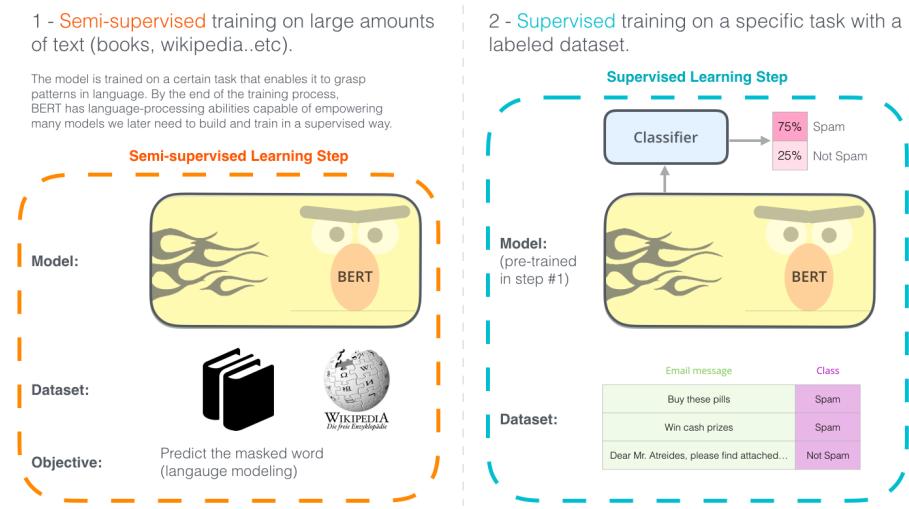


Figure 9: The two steps of how BERT is developed. Source <https://jalammar.github.io/illustrated-bert/>.

- ❖ How to Build OpenAI's GPT-2: "*The AI That's Too Dangerous to Release*"³⁰.
- ❖ Play with BERT with your own data using TensorFlow Hub https://colab.research.google.com/github/google-research/bert/blob/master/predicting_movie_reviews_with_bert_on_tf_hub.ipynb.

3.5 Unsupervised Learning

True intelligence will require independent learning strategies.

Unsupervised learning is a paradigm for creating AI that learns without a particular task in mind: learning for the sake of learning³¹. It captures some characteristics of the joint distribution of the observed random variables (learn the underlying structure). The variety of tasks include density estimation, dimensionality reduction, and clustering.[4]³².

"Give a robot a label and you feed it for a second; teach a robot to label and you feed it for a lifetime." — Pierre Sermanet

Self-supervised learning is derived from unsupervised learning where the data provides the supervision. E.g. Word2vec³³, a technique for learning vector representations of words, or word **embeddings**. An embedding is a mapping from discrete objects, such as words, to vectors of real numbers³⁴.

3.5.1 Generative Adversarial Networks

Simultaneously train two models: a generative model G that captures the data distribution, and a discriminative model D that estimates the probability that a sample came from the training data rather than G . The training procedure for G is to maximize the probability of D making a mistake. This framework corresponds to a minimax two-player game[3].

$$\min_{\theta_g} \max_{\theta_d} [\mathbb{E}_{x \sim p_{\text{data}}(x)}[\log D_{\theta_d}(x)] + \mathbb{E}_{z \sim p_z(z)}[\log(1 - D_{\theta_d}(G_{\theta_g}(z)))] \quad (1)$$

"What I cannot create, I do not understand." — Richard Feynman

Goodfellow et al. used an interesting analogy where the generative model can be thought of as analogous to a team of counterfeiters, trying to produce fake currency and use it without detection, while the discriminative model is analogous to the police, trying to detect the counterfeit currency. Competition in this game drives both teams to improve their methods until the counterfeits are indistinguishable from the genuine articles. See Figure 10.

³⁰<https://blog.floydhub.com/gpt2/>

³¹<https://deepmind.com/blog/unsupervised-learning/>

³²https://media.neurips.cc/Conferences/NIPS2018/Slides/Deep_Unsupervised_Learning.pdf

³³<https://jalammar.github.io/illustrated-word2vec/>

³⁴<http://projector.tensorflow.org>

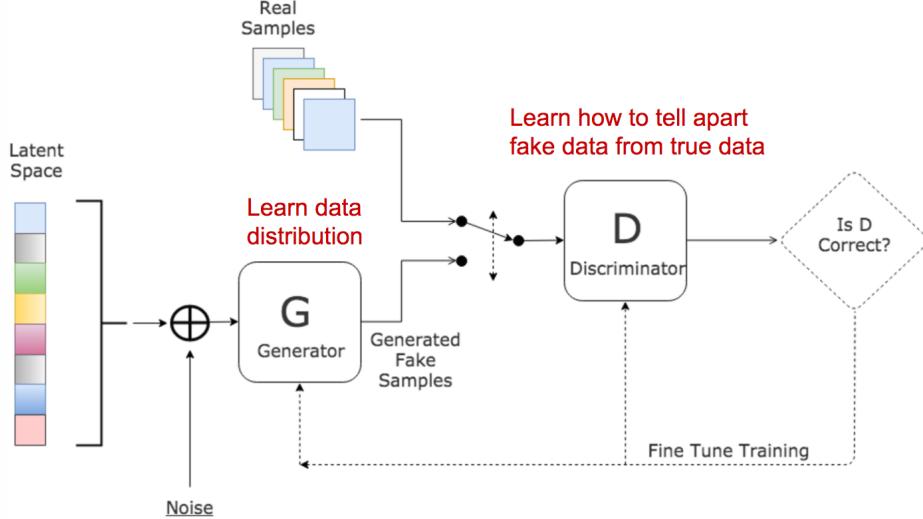


Figure 10: GAN: Neural Networks Architecture Pioneered by Ian Goodfellow at University of Montreal (2014).

StyleGAN: A Style-Based Generator Architecture for Generative Adversarial Networks

- Paper <http://stylegan.xyz/paper> | Code <https://github.com/NVlabs/stylegan>.
 - **StyleGAN for art.** Colab <https://colab.research.google.com/github/ak9250/stylegan-art>.
 - This Person Does Not Exist <https://thispersondoesnotexist.com>.
 - Which Person Is Real? <http://www.whichfaceisreal.com>.
 - This Resume Does Not Exist <https://thisresumedoestnotexist.com>.
 - This Waifu Does Not Exist <https://www.thiswaifudoesnotexist.net>.
 - Encoder for Official TensorFlow Implementation <https://github.com/Puzer/stylegan-encoder>.
 - How to recognize fake AI-generated images. By Kyle McDonald³⁵.
- ❖ Introducing **TF-GAN**: A lightweight GAN library for TensorFlow 2.0³⁶.
- ❖ Generative Adversarial Networks (GANs) in 50 lines of code (PyTorch)³⁷.
- ❖ 100,000 Faces Imagined by a GAN <https://generated.photos>.
- ❖ Infinite-resolution (CPPNs, GANs and TensorFlow.js) <https://thispicturedoesnotexist.com>.
- ❖ Few-Shot Adversarial Learning of Realistic Neural Talking Head Models³⁸.
- ❖ Wasserstein GAN <http://www.depthfirstlearning.com/2019/WassersteinGAN>.
- ❖ GANSynth: Generate high-fidelity audio with GANs! Colab <http://goo.gl/magenta/gansynth-demo>.
- ❖ SC-FEGAN: Face Editing Generative Adversarial Network <https://github.com/JoYoungjoo/SC-FEGAN>.
- ❖ CariGANs: Unpaired Photo-to-Caricature Translation. Cao et al.: <https://cari-gan.github.io>.
- ❖ GANpaint Paint with GAN units <http://gandissect.res.ibm.com/ganpaint.html>.
- ❖ PyTorch pretrained BigGAN <https://github.com/huggingface/pytorch-pretrained-BigGAN>.
- ❖ Demo of BigGAN in an official Colaboratory notebook (backed by a GPU) https://colab.research.google.com/github/tensorflow/hub/blob/master/examples/colab/biggan_generation_with_tf_hub.ipynb

3.5.2 Variational AutoEncoder

Variational Auto-Encoders³⁹ (VAEs) are powerful models for learning low-dimensional representations See Figure 11. Disentangled representations are defined as ones where a change in a single unit of the representation corresponds to a change in single factor of variation of the data while being invariant to others (Bengio et al. (2013)).

³⁵<https://medium.com/@kcimc/how-to-recognize-fake-ai-generated-images-4d1f6f9a2842>

³⁶<https://medium.com/tensorflow/introducing-tf-gan-a-lightweight-gan-library-for-tensorflow-2-0-36d767e1abae>

³⁷<https://medium.com/@devnag/generative-adversarial-networks-gans-in-50-lines-of-code-pytorch-e81b79659e3f>

³⁸<https://arxiv.org/abs/1905.08233>

³⁹<https://arxiv.org/abs/1906.02691v2>

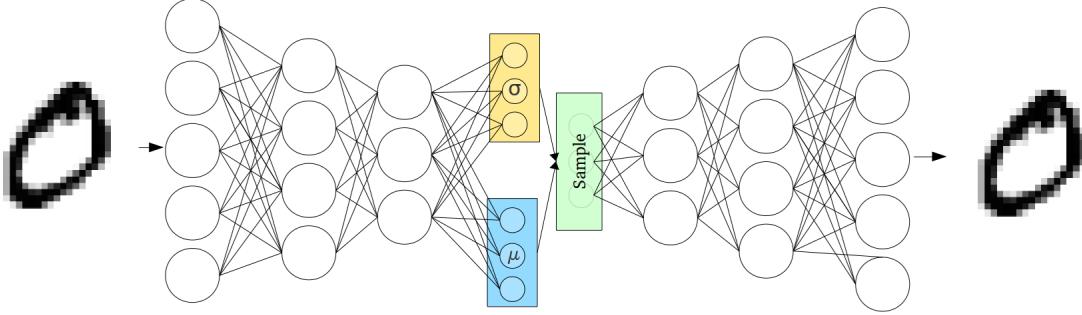


Figure 11: Variational Autoencoders (VAEs): Powerful Generative Models.

- ❖ Colab⁴⁰: "Debiasing Facial Detection Systems." *AIEthics*
- ❖ SpaceSheet: Interactive Latent Space Exploration with a Spreadsheet <https://vusd.github.io/spacesheet/>.
- ❖ MusicVAE: Learning latent spaces for musical scores <https://magenta.tensorflow.org/music-vae>.
- ❖ Slides: A Few Unusual Autoencoders <https://colinraffel.com/talks/vector2018few.pdf>.
- ❖ Generative models in Tensorflow 2 <https://github.com/timsainb/tensorflow2-generative-models/>.
- ❖ Reading: Disentangled VAE's (DeepMind 2016) <https://arxiv.org/abs/1606.05579>.

4 Autonomous Agents

An **autonomous agent** is any device that perceives its environment and takes actions that maximize its chance of success at some goal. At the bleeding edge of AI, autonomous agents can learn from experience, simulate worlds and orchestrate meta-solutions. Here's an informal definition⁴¹ of the *universal intelligence* of agent π ⁴²:

$$\Upsilon(\pi) := \sum_{\mu \in E} 2^{-K(\mu)} V_\mu^\pi \quad (2)$$

"Intelligence measures an agent's ability to achieve goals in a wide range of environments." — Shane Legg

4.1 Deep Reinforcement Learning

Reinforcement learning (RL) studies how an agent can learn how to achieve goals in a complex, uncertain environment (Figure 13) [5]. Recent superhuman results in many difficult environments combine deep learning with RL (*Deep Reinforcement Learning*). See Figure 13 for a taxonomy of RL algorithms.

- ❖ CS 188 : Introduction to Artificial Intelligence⁴³.
- ❖ Introduction to Reinforcement Learning by DeepMind⁴⁴.

4.1.1 Model-Free RL | Value-Based

The goal in RL is to train the agent to maximize the discounted sum of all future rewards R_t , called the return:

$$R_t = r_t + \gamma r_{t+1} + \gamma^2 r_{t+2} + \dots \quad (3)$$

⁴⁰https://colab.research.google.com/github/aamini/introtodeeplearning_labs/blob/master/lab2/Part2_debiasing_solution.ipynb

⁴¹<https://arxiv.org/abs/0712.3329>

⁴²Where μ is an environment, K is the Kolmogorov complexity function, E is the space of all computable reward summable environmental measures with respect to the reference machine U and the value function V_μ^π is the agent's "ability to achieve".

⁴³<https://inst.eecs.berkeley.edu/~cs188/fa18/>

⁴⁴<https://www.youtube.com/watch?v=2pWv7G0vuf0&list=PLqYmG7hTraZDM-0YHWgPebj2MfCFzF0bQ>

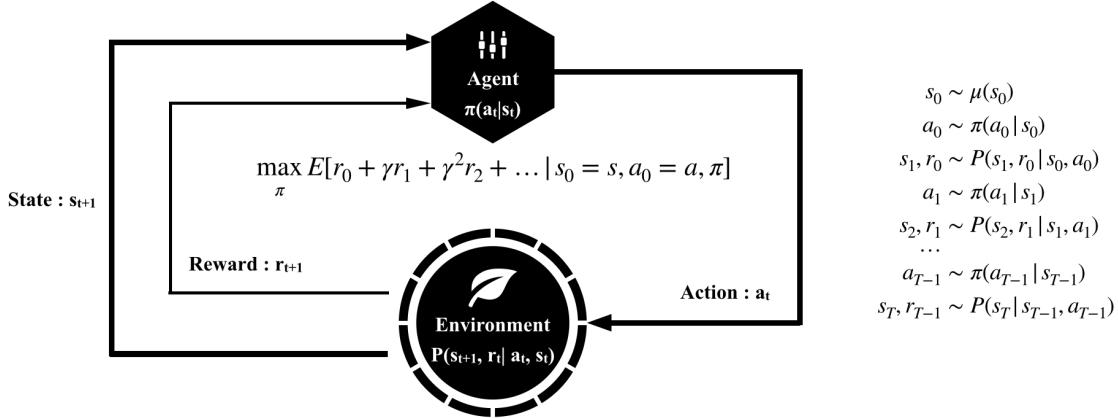


Figure 12: An Agent Interacts with an Environment.

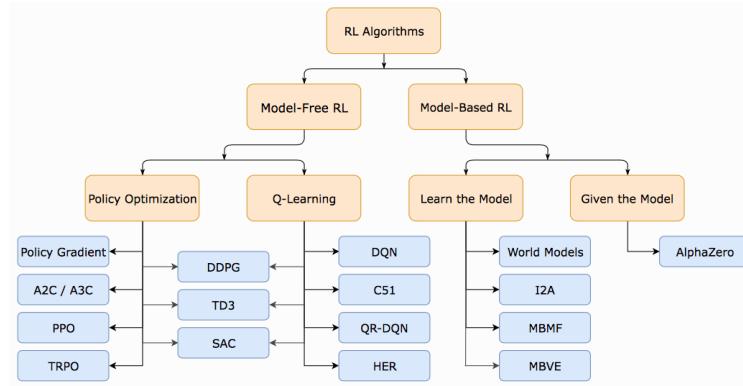


Figure 13: A Taxonomy of RL Algorithms. Source: Spinning Up in Deep RL by Achiam et al. | OpenAI

The Q-function captures the expected total future reward an agent in state s can receive by executing a certain action a :

$$Q(s, a) = E[R_t] \quad (4)$$

The optimal policy should choose the action a that maximizes $Q(s, a)$:

$$\pi^*(s) = \operatorname{argmax}_a Q(s, a) \quad (5)$$

- **Q-Learning:** Playing Atari with Deep Reinforcement Learning (DQN). Mnih et al, 2013[10].

TF-Agents (DQN Tutorial) | Colab <https://colab.research.google.com/github/tensorflow/agents>.

4.1.2 Model-Free RL | Policy-Based

Run a policy for a while (code: <https://gist.github.com/karpathy/a4166c7fe253700972fcbe77e4ea32c5>):

$$\tau = (s_0, a_0, r_0, s_1, a_1, r_1, \dots, s_{T-1}, a_{T-1}, r_{T-1}, s_T) \quad (6)$$

Increase probability of actions that lead to high rewards and decrease probability of actions that lead to low rewards:

$$\nabla_\theta E_\tau[R(\tau)] = E_\tau \left[\sum_{t=0}^{T-1} \nabla_\theta \log \pi(a_t | s_t, \theta) R(\tau) \right] \quad (7)$$

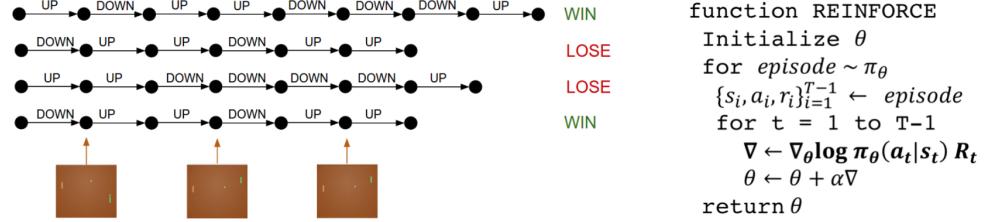


Figure 14: Policy Gradient Directly Optimizes the Policy.

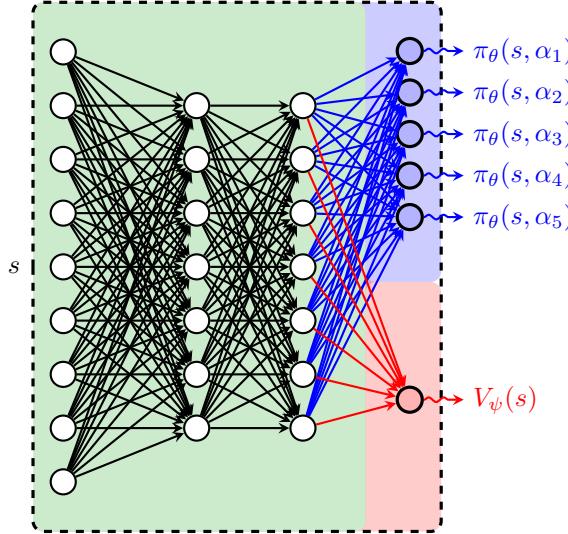


Figure 15: Asynchronous Advantage Actor-Critic (A3C). Source: Petar Velickovic

- **Policy Optimization:** Asynchronous Methods for Deep Reinforcement Learning (A3C). Mnih et al, 2016[8].
- **Policy Optimization:** Proximal Policy Optimization Algorithms (PPO). Schulman et al, 2017[9].

| Project | Maintainer | Framework | Algorithms (discrete & continuous) | | | | | | | | | | | | Additional features | n-step return | prioritized experience replay | distributional value function approximation | hyperbolic discounting | soft observations support | ? |
|------------------|-------------------------------|------------|------------------------------------|-------------|-----|---------|-----------|-----|-----|------|-----|-----|-----------|-----|---------------------|---------------|-------------------------------|---|------------------------|---------------------------|---|
| | | | Parallel | Distributed | DQN | Rainbow | REINFORCE | A2C | PPO | DDPG | SAC | TD3 | REINFORCE | A2C | PPO | | | | | | |
| OpenAI baseline | OpenAI | Tensorflow | ✓ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✓ | ✗ | ✗ | ✗ | ✗ |
| stable_baselines | Antonin Raffin, Ashley Hill | Tensorflow | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ |
| CatkitRL | Sergey Kolesnikov | PyTorch | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✓ | ✗ | ✓ | ✗ | ✗ |
| Reverb | Ray Team | Tensorflow | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✓ | ✗ | ✗ | ✗ |
| TF agents | Google | Tensorflow | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ |
| Horizon | Facebook | PyTorch | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ |
| Coach | Intel | Tensorflow | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ |
| Garage | community | Tensorflow | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ |
| SLM-Lab | Wah Loon Kong, Laura Graesser | PyTorch | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ |
| Dopamine | Google | Tensorflow | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ |
| OpenAI Gym | OpenAI | Tensorflow | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ |
| DeepMindLab | DeepMind | Tensorflow | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ |
| scalable_agent | DeepMind | Tensorflow | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ |
| ELF | Facebook | PyTorch | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ |
| keras-d | Matthias Plappert | Tensorflow | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ |
| Kostrikov | Ilya Kostrikov | PyTorch | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ |
| Rainbow | Kai Arulkumaran, Jerry (7) | PyTorch | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ |
| Vel | Tensorforce | Tensorflow | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ |
| tensorforce | Tensorforce | Tensorflow | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ |
| RL-Adventure | PyTorch | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ |
| DeepRL-Tutorials | PyTorch | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ |
| surmael | TorchX | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ |
| lagom | PyTorch | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ |
| denbyznet | Tensorflow | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ |
| sacred | Tensorflow | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ |
| zymarl | WhRL | PyTorch | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ |

Figure 16: Open-Source RL Algorithms https://docs.google.com/spreadsheets/d/1EeFPd-XIQ3mq_9snT1AZSsFY7Hbnmd7P5bbT8LPuMn0/

4.1.3 Model-Based RL

In Model-Based RL, the agent generates predictions about the next state and reward before choosing each action.

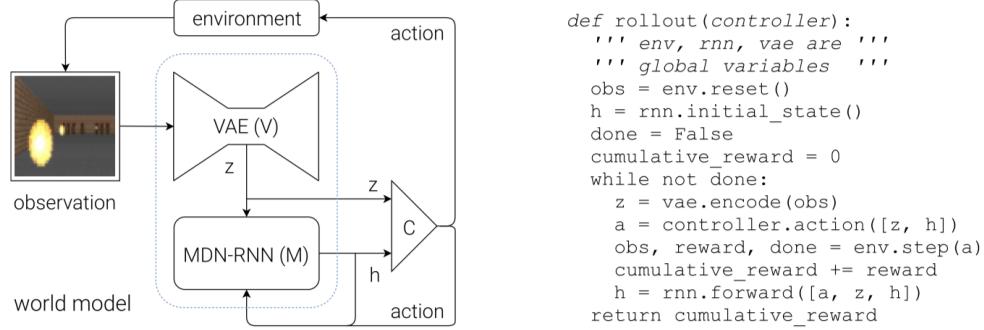


Figure 17: World Model's Agent consists of: Vision (V), Memory (M), and Controller (C). | Ha et al, 2018[11]

- **Learn the Model:** *Recurrent World Models Facilitate Policy Evolution* (World Models⁴⁵). The world model agent can be trained in an unsupervised manner to learn a compressed spatial and temporal representation of the environment. Then, a compact policy can be trained. See Figure 17. Ha et al, 2018[11].
- **Learn the Model:** *Learning Latent Dynamics for Planning from Pixels* <https://planetrl.github.io/>.
- **Given the Model:** *Mastering Chess and Shogi by Self-Play with a General Reinforcement Learning Algorithm* (AlphaZero). Silver et al, 2017[14]. AlphaGo Zero Explained In One Diagram⁴⁶.

4.1.4 Improving Agent Design

Via Reinforcement Learning: Blog⁴⁷. arXiv⁴⁸. ASTool <https://github.com/hardmaru/astool/>.

Via Evolution: Video⁴⁹. Evolved Creatures <http://www.karlsims.com/evolved-virtual-creatures.html>.

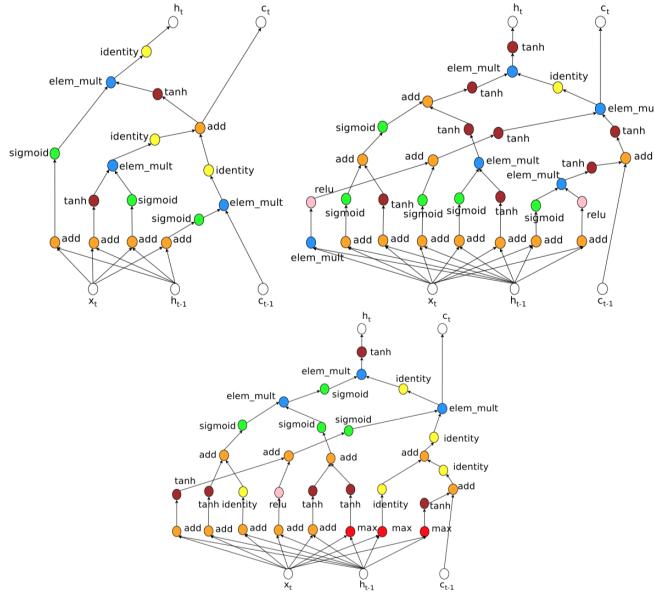


Figure 18: A comparison of the original LSTM cell vs. two new good generated. Top left: LSTM cell. [19]

⁴⁵<https://worldmodels.github.io>

⁴⁶https://applied-data.science/static/main/res/alpha_go_zero_cheat_sheet.png

⁴⁷<https://designrl.github.io>

⁴⁸<https://arxiv.org/abs/1810.03779>

⁴⁹https://youtu.be/JBgG_VSP7f8

"The future of high-level APIs for AI is... a problem-specification API. Currently we only search over network weights, thus "problem specification" involves specifying a model architecture. In the future, it will just be: "tell me what data you have and what you are optimizing"." — François Chollet

4.1.5 OpenAI Baselines

High-quality implementations of reinforcement learning algorithms <https://github.com/openai/baselines>.

Colab <https://colab.research.google.com/drive/1KKq9A3dRTq1q6bJmPyF0gg917gQyTjJI>.

4.1.6 Google Dopamine and A Zoo of Agents

Dopamine is a research framework for fast prototyping of reinforcement learning algorithms.⁵⁰

A Zoo of Atari-Playing Agents: Code⁵¹, Blog⁵² and Colaboratory notebook <https://colab.research.google.com/github/uber-research/atari-model-zoo/blob/master/colab/AtariZooColabDemo.ipynb>.

4.1.7 TRFL : TensorFlow Reinforcement Learning

TRFL ("truffle"): a library of reinforcement learning building blocks <https://github.com/deepmind/trfl>.

4.1.8 bsuite : Behaviour Suite for Reinforcement Learning

A collection of experiments that investigate core capabilities of RL agents <http://github.com/deepmind/bsuite>.

4.2 Evolution Strategies (ES)

Evolution and neural networks proved a potent combination in nature. Neuroevolution, which harnesses evolutionary algorithms to optimize neural networks, enables capabilities that are typically unavailable to gradient-based approaches, including learning neural network building blocks, architectures and even the algorithms for learning[12].

"... evolution — whether biological or computational — is inherently creative, and should routinely be expected to surprise, delight, and even outwit us." — The Surprising Creativity of Digital Evolution, Lehman et al.[22]

Neural architecture search has advanced to the point where it can outperform human-designed models[13].

Natural evolutionary strategy directly evolves the weights of a DNN and performs competitively with the best deep reinforcement learning algorithms, including deep Q-networks (DQN) and policy gradient methods (A3C)[21].

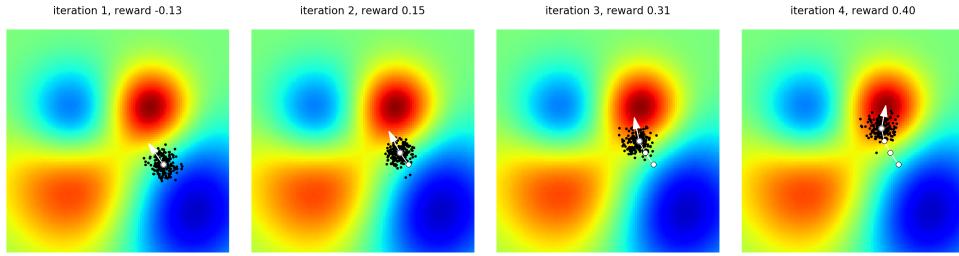


Figure 19: <https://colab.research.google.com/github/karpathy/randomfun/blob/master/es.ipynb>.

The ES algorithm is a “guess and check” process, where we start with some random parameters and then repeatedly:

1. Tweak the guess a bit randomly, and
2. Move our guess slightly towards whatever tweaks worked better.

"Evolution is a slow learning algorithm that with the sufficient amount of compute produces a human brain." — Wojciech Zaremba

⁵⁰<https://github.com/google/dopamine>

⁵¹<https://github.com/uber-research/atari-model-zoo>

⁵²<https://eng.uber.com/atari-zoo-deep-reinforcement-learning/>

- ❖ Evolution Strategies⁵³.
- ❖ VAE+CPPN+GAN⁵⁴.
- ❖ Demos: ES on CartPole-v1⁵⁵ and ES on LunarLanderContinuous-v2⁵⁶.
- ❖ **The Nobel Prize in Chemistry 2018** Innovation by Evolution: Bringing New Chemistry to Life⁵⁷.
- ❖ A Visual Guide to ES <http://blog.otoro.net/2017/10/29/visual-evolution-strategies/>.

4.3 Self Play

Silver et al.[15] introduced an algorithm based solely on reinforcement learning, without human data, guidance or domain knowledge. Starting tabula rasa (and being its own teacher!), AlphaGo Zero achieved superhuman performance. AlphaGo Zero showed that algorithms matter much more than big data and massive amounts of computation.

"Self-Play is Automated Knowledge Creation." — Carlos E. Perez

Self-play mirrors similar insights from coevolution. Transfer learning is the key to go from self-play to the real world⁵⁸.

"Open-ended self play produces: Theory of mind, negotiation, social skills, empathy, real language understanding." — Ilya Sutskever, Meta Learning and Self Play

TensorFlow.js Implementation of DeepMind's AlphaZero Algorithm for Chess. Live Demo⁵⁹ | Code⁶⁰
An open-source implementation of the AlphaGoZero algorithm <https://github.com/tensorflow/minigo>
ELF OpenGo: An Open Reimplementation of AlphaZero, Tian et al.: <https://arxiv.org/abs/1902.04522>.

4.4 Deep Meta-Learning

Learning to Learn[16]. The goal of meta-learning is to train a model on a variety of learning tasks, such that it can solve new learning tasks using only a small number of training samples[20].

$$\theta \leftarrow \theta - \beta \nabla_{\theta} \sum_{\mathcal{T}_i \sim p(\mathcal{T})} \mathcal{L}_{\mathcal{T}_i}(f_{\theta_i}) \quad (8)$$

A meta-learning algorithm takes in a distribution of tasks, where each task is a learning problem, and it produces a quick learner that can generalize from a small number of examples[17].

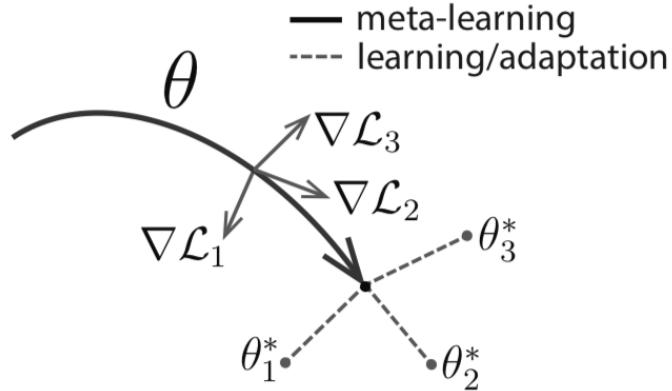


Figure 20: Diagram of Model-Agnostic Meta-Learning (MAML)

⁵³<https://lilianweng.github.io/lil-log/2019/09/05/evolution-strategies.html>

⁵⁴https://colab.research.google.com/drive/1_OoZ3z_C5J15gnxD0E9VEMCTs-F18pvM

⁵⁵<https://colab.research.google.com/drive/1bMZHdhm-mT9NJENwvewUks7cGV10go>

⁵⁶https://colab.research.google.com/drive/1lvYKjFtc_C_8njCKD-MnXEW8LPS2RPr6

⁵⁷<https://onlinelibrary.wiley.com/doi/epdf/10.1002/anie.201907729>

⁵⁸<http://metalearning-symposium.ml>

⁵⁹<https://frpays.github.io/lc0-js/engine.html>

⁶⁰<https://github.com/frpays/lc0-js/>

"The notion of a neural "architecture" is going to disappear thanks to meta learning." — Andrew Trask

- ❖ Meta-Learning with Implicit Gradients <https://arxiv.org/abs/1909.04630>
- ❖ How to Train MAML (Model-Agnostic Meta-Learning)⁶¹
- ❖ Meta Learning Shared Hierarchies[18] (*The Lead Author is in High School!*)
- ❖ Colaboratory reimplementation of MAML (Model-Agnostic Meta-Learning) in TF 2.0⁶²
- ❖ Causal Reasoning from Meta-reinforcement Learning <https://arxiv.org/abs/1901.08162>

4.5 Multi-Agent Populations

"We design a Theory of Mind neural network – a *ToMnet* – which uses meta-learning to build models of the agents it encounters, from observations of their behaviour alone." — Machine Theory of Mind, Rabinowitz et al.[25]

Cooperative Agents. Learning to Model Other Minds, by OpenAI[24], is an algorithm which accounts for the fact that other agents are learning too, and discovers self-interested yet collaborative strategies. Also: OpenAI Five⁶³.

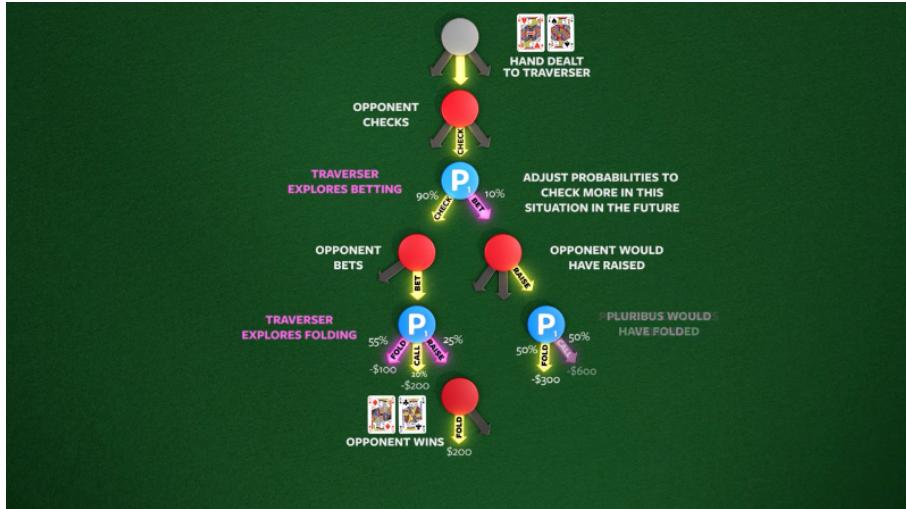


Figure 21: Facebook, Carnegie Mellon build first AI that beats pros in 6-player poker <https://ai.facebook.com/blog/pluribus-first-ai-to-beat-pros-in-6-player-poker>

"Artificial Intelligence is about recognising patterns, Artificial Life is about creating patterns." — Mizuki Oka et al.

Active Learning Without Teacher. In *Intrinsic Social Motivation via Causal Influence in Multi-Agent RL*, Jaques et al. (2018) <https://arxiv.org/abs/1810.08647> propose an intrinsic reward function designed for multi-agent RL (MARL), which awards agents for having a causal influence on other agents' actions. Open-source implementation⁶⁴.

"Open-ended Learning in Symmetric Zero-sum Games," Balduzzi et al.: <https://arxiv.org/abs/1901.08106>

Neural MMO: a massively multiagent env. for simulations with many long-lived agents. Code⁶⁵ and 3D Client⁶⁶.

5 Environments

Platforms for training autonomous agents.

"Situation awareness is the perception of the elements in the environment within a volume of time and space, and the comprehension of their meaning, and the projection of their status in the near future." — Endsley (1987)

⁶¹<https://medium.com/towards-artificial-intelligence/how-to-train-maml-model-agnostic-meta-learning-90aa093f8e46>

⁶²<https://colab.research.google.com/github/mari-linhares/tensorflow-maml/blob/master/maml.ipynb>

⁶³<https://blog.openai.com/openai-five/>

⁶⁴https://github.com/eugenevinitksy/sequential_social_dilemma_games

⁶⁵<https://github.com/openai/neural-mmo>

⁶⁶<https://github.com/jsuarez5341/neural-mmo-client>

5.1 OpenAI Gym

The OpenAI Gym <https://gym.openai.com/> (Blog⁶⁷ | GitHub⁶⁸) is a toolkit for developing and comparing reinforcement learning algorithms. What makes the gym so great is a common API around environments.

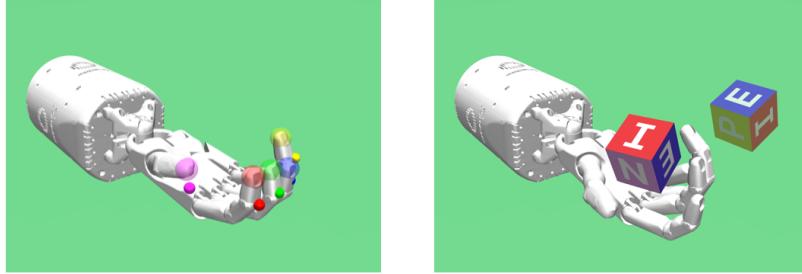


Figure 22: Robotics Environments <https://blog.openai.com/ingredients-for-robotics-research/>

How to create new environments for Gym⁶⁹. **Minimal example with code and agent** (*evolution strategies on foo-v0*) :

1. Download `gym-foo` <https://drive.google.com/file/d/1r2A8J9CJjIQNwss246gATeD0LLMzpUT-/view?usp=sharing>
2. `cd gym-foo`
3. `pip install -e .`
4. `python ES-foo.py`

He're another more difficult (*for the agent!*) new environment for Gym (*evolution strategies on foo-v3*) :

1. Download `gym-foo-v3`⁷⁰
2. `cd gym-foo-v3`
3. `pip install -e .`
4. `python ES-foo-v3.py`

❖ OpenAI Gym Environment for Trading⁷¹.

5.2 DeepMind Lab

DeepMind Lab: A customisable 3D platform for agent-based AI research <https://github.com/deepmind/lab>.

- DeepMind Control Suite https://github.com/deepmind/dm_control.
- Convert DeepMind Control Suite to OpenAI Gym Envs <https://github.com/zuxingdong/dm2gym>.

5.3 Unity ML-Agents

Unity ML Agents allows to create environments where intelligent agents (*Single Agent, Cooperative and Competitive Multi-Agent* and *Ecosystem*) can be trained using RL, neuroevolution, or other ML methods <https://unity3d.ai>.

- Getting Started with Marathon Environments for Unity ML-Agents⁷².
- Arena: A General Evaluation Platform and Building Toolkit for Multi-Agent Intelligence⁷³.

⁶⁷<https://blog.openai.com/openai-gym-beta/>

⁶⁸<https://github.com/openai/gym>

⁶⁹<https://github.com/openai/gym/blob/master/docs/creating-environments.md>

⁷⁰<https://drive.google.com/file/d/1cGncsXJ56UUKC09MaRWJVTnxiQEEnLuxS/view?usp=sharing>

⁷¹<https://github.com/hackthemarket/gym-trading>

⁷²<https://towardsdatascience.com/getting-started-with-marathon-envs-v0-5-0a-c1054a0b540c>

⁷³<https://arxiv.org/abs/1905.08085>

5.4 POET: Paired Open-Ended Trailblazer

Diversity is the premier product of evolution. Endlessly generate increasingly complex and diverse learning environments⁷⁴. Open-endedness could generate learning algorithms reaching human-level intelligence[23].

- Implementation of the POET algorithm <https://github.com/uber-research/poet>.
- ❖ AI-GAs: AI-generating algorithms, an alternate paradigm for producing general artificial intelligence⁷⁵.

6 Datasets

Google Dataset Search Beta (Blog⁷⁶) <https://toolbox.google.com/datasetsearch>.
TensorFlow Datasets: load a variety of public datasets into TensorFlow programs (Blog⁷⁷ | Colab⁷⁸).

7 Deep-Learning Hardware



Figure 23: Edge TPU - Dev Board <https://coral.withgoogle.com/products/dev-board/>

- ❖ A Full Hardware Guide to Deep Learning, by Tim Dettmers⁷⁹.
- ❖ Which GPU(s) to Get for Deep Learning, by Tim Dettmers⁸⁰.
- ❖ Build AI that works offline with Coral Dev Board, Edge TPU, and TensorFlow Lite, by Daniel Situnayake⁸¹.
- ❖ Jetson Nano. A small but mighty AI computer to create intelligent systems⁸².

8 Deep-Learning Software

TensorFlow

- tf.keras (TensorFlow 2.0) for Researchers: Crash Course. Colab⁸³.
- TensorFlow 2.0: basic ops, gradients, data preprocessing and augmentation, training and saving. Colab⁸⁴.

⁷⁴<https://eng.uber.com/poet-open-ended-deep-learning/>

⁷⁵<https://arxiv.org/abs/1905.10985>

⁷⁶<https://www.blog.google/products/search/making-it-easier-discover-datasets/>

⁷⁷<https://medium.com/tensorflow/introducing-tensorflow-datasets-c7f01f7e19f3>

⁷⁸<https://colab.research.google.com/github/tensorflow/datasets/blob/master/docs/overview.ipynb>

⁷⁹<http://timdettmers.com/2018/12/16/deep-learning-hardware-guide/>

⁸⁰<http://timdettmers.com/2019/04/03/which-gpu-for-deep-learning/>

⁸¹<https://medium.com/tensorflow/build-ai-that-works-offline-with-coral-dev-board-edge-tpu-and-tensorflow-lite-70>

⁸²<https://www.nvidia.com/en-us/autonomous-machines/embedded-systems/jetson-nano/>

⁸³<https://colab.research.google.com/drive/14CvUNTaX10FHDfaKaaZzrBsvMfhCOHIR>

⁸⁴https://colab.research.google.com/github/zaidalyafeai/Notebooks/blob/master/TF_2_0.ipynb

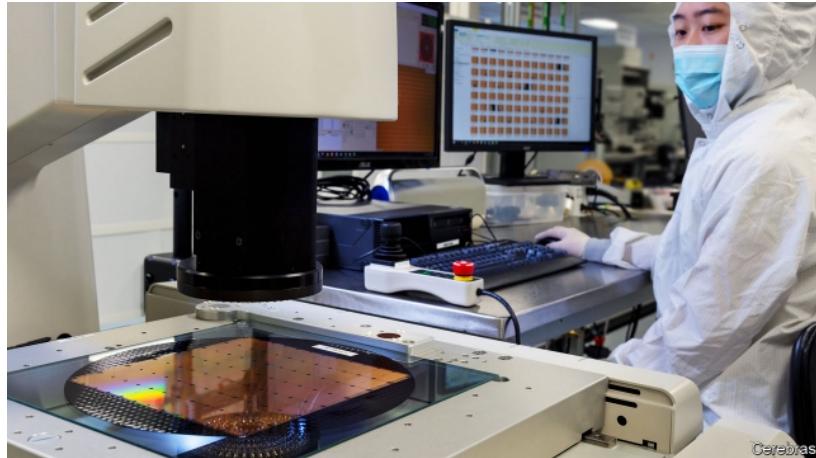


Figure 24: The world's largest chip : Cerebras Wafer Scale Engine <https://www.cerebras.net>

- TensorBoard in Jupyter Notebooks. Colab⁸⁵.
- TensorFlow Lite for Microcontrollers⁸⁶.

PyTorch

- PyTorch primer. Colab⁸⁷.
- PyTorch internals <http://blog.ezyang.com/2019/05/pytorch-internals/>

9 AI Art | A New Day Has Come in Art Industry



Figure 25: On October 25, 2018, the first AI artwork ever sold at Christie's auction house fetched USD 432,500.

The code (*art-DCGAN*) for the first artificial intelligence artwork ever sold at Christie's auction house (Figure 25) is a modified implementation of DCGAN focused on generative art: <https://github.com/robbiebarrat/art-dcgan>.

- **TensorFlow Magenta**. An open source research project exploring the role of ML in the creative process.⁸⁸.
- **Magenta Studio**. A suite of free music-making tools using machine learning models!⁸⁹.
- **Style Transfer Tutorial** https://colab.research.google.com/github/tensorflow/docs/blob/master/site/en/r2/tutorials/generative/style_transfer.ipynb

⁸⁵https://colab.research.google.com/github/tensorflow/tensorboard/blob/master/docs/r2/get_started.ipynb

⁸⁶<https://petewarden.com/2019/03/07/launching-tensorflow-lite-for-microcontrollers/>

⁸⁷<https://colab.research.google.com/drive/1DgkVmi6GksW0ByhYVQpyUB4Rk3PUq0Cp>

⁸⁸<https://magenta.tensorflow.org>

⁸⁹<https://magenta.tensorflow.org/studio>

- **AI x AR Paper Cubes** <https://experiments.withgoogle.com/paper-cubes>.
- **Photo Wake-Up** <https://grail.cs.washington.edu/projects/wakeup/>.
- **COLLECTION.** AI Experiments <https://experiments.withgoogle.com/ai>.

"*The Artists Creating with AI Won't Follow Trends; THEY WILL SET THEM.*" — The House of Montréal.AI Fine Arts

MuseNet. Generate Music Using Many Different Instruments and Styles!⁹⁰

Tuning Recurrent Neural Networks with Reinforcement Learning⁹¹.

Discovering Visual Patterns in Art Collections with Spatially-consistent Feature Learning. Shen et al.⁹².

Deep Multispectral Painting Reproduction via Multi-Layer, Custom-Ink Printing. Shi et al.⁹³.

10 AI Macrostrategy: Aligning AGI with Human Interests

Montréal.AI Governance: Policies at the intersection of AI, Ethics and Governance.

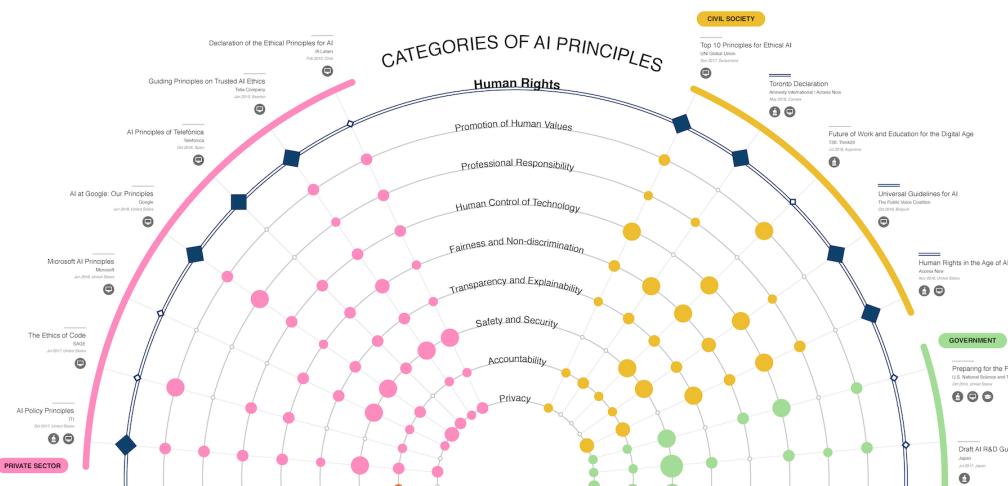


Figure 26: A Map of Ethical and Right-Based Approaches <https://ai-hr.cyber.harvard.edu/primp-viz.html>

"(AI) will rank among our greatest technological achievements, and everyone deserves to play a role in shaping it." — Fei-Fei Li

- ❖ **AI Index.** <http://aiindex.org>.
- ❖ **Malicious AI Report.** <https://arxiv.org/pdf/1802.07228.pdf>.
- ❖ **Artificial Intelligence and Human Rights.** <https://ai-hr.cyber.harvard.edu>.
- ❖ **Ethically Aligned Design, First Edition**⁹⁴. From Principles to Practice <https://ethicsinaction.ieee.org>.

"It's springtime for AI, and we're anticipating a long summer." — Bill Braun

References

- [1] Mnih et al. Human-Level Control Through Deep Reinforcement Learning. In *Nature* 518, pages 529–533. 26 February 2015. <https://storage.googleapis.com/deepmind-media/dqn/DQNNaturePaper.pdf>
- [2] Yann LeCun, Yoshua Bengio and Geoffrey Hinton. Deep Learning. In *Nature* 521, pages 436–444. 28 May 2015. <https://www.cs.toronto.edu/~hinton/absps/NatureDeepReview.pdf>

⁹⁰<https://openai.com/blog/musenet/>

⁹¹<https://magenta.tensorflow.org/2016/11/09/tuning-recurrent-networks-with-reinforcement-learning>

⁹²<https://arxiv.org/pdf/1903.02678.pdf>

⁹³<http://people.csail.mit.edu/liangs/papers/ToG18.pdf>

⁹⁴<https://standards.ieee.org/content/dam/ieee-standards/standards/web/documents/other/ead1e.pdf>

- [3] Goodfellow et al. Generative Adversarial Networks. *arXiv preprint arXiv:1406.2661*, 2014. <https://arxiv.org/abs/1406.2661>
- [4] Yoshua Bengio, Andrea Lodi, Antoine Prouvost. Machine Learning for Combinatorial Optimization: a Methodological Tour d’Horizon. *arXiv preprint arXiv:1811.06128*, 2018. <https://arxiv.org/abs/1811.06128>
- [5] Brockman et al. OpenAI Gym. 2016. <https://gym.openai.com>
- [6] Devlin et al. BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding. *arXiv preprint arXiv:1810.04805*, 2018. <https://arxiv.org/abs/1810.04805>
- [7] Dai et al. Semi-supervised Sequence Learning. *arXiv preprint arXiv:1511.01432*, 2015. <https://arxiv.org/abs/1511.01432>
- [8] Mnih et al. Asynchronous Methods for Deep Reinforcement Learning. *arXiv preprint arXiv:1602.01783*, 2016. <https://arxiv.org/abs/1602.01783>
- [9] Schulman et al. Proximal Policy Optimization Algorithms. *arXiv preprint arXiv:1707.06347*, 2017. <https://arxiv.org/abs/1707.06347>
- [10] Mnih et al. Playing Atari with Deep Reinforcement Learning. *DeepMind Technologies*, 2013. <https://www.cs.toronto.edu/~vmnih/docs/dqn.pdf>
- [11] Ha et al. Recurrent World Models Facilitate Policy Evolution. *arXiv preprint arXiv:1809.01999*, 2018. <https://arxiv.org/abs/1809.01999>
- [12] Kenneth et al. Designing neural networks through neuroevolution. In *Nature Machine Intelligence* VOL 1, pages 24–35. January 2019. <https://www.nature.com/articles/s42256-018-0006-z.pdf>
- [13] So et al. The Evolved Transformer. *arXiv preprint arXiv:1901.11117*, 2019. <https://arxiv.org/abs/1901.11117>
- [14] Silver et al. Mastering Chess and Shogi by Self-Play with a General Reinforcement Learning Algorithm. *arXiv preprint arXiv:1712.01815*, 2017. <https://arxiv.org/abs/1712.01815>
- [15] Silver et al. AlphaGo Zero: Learning from scratch. In *DeepMind’s Blog*, 2017. <https://deepmind.com/blog/alphago-zero-learning-scratch/>
- [16] Andrychowicz et al. Learning to learn by gradient descent by gradient descent. *arXiv preprint arXiv:1606.04474*, 2016. <https://arxiv.org/abs/1606.04474>
- [17] Nichol et al. Reptile: A Scalable Meta-Learning Algorithm. 2018. <https://blog.openai.com/reptile/>
- [18] Frans et al. Meta Learning Shared Hierarchies. *arXiv preprint arXiv:1710.09767*, 2017. <https://arxiv.org/abs/1710.09767>
- [19] Zoph and Le, 2017 Neural Architecture Search with Reinforcement Learning. *arXiv preprint arXiv:1611.01578*, 2017. <https://arxiv.org/abs/1611.01578>
- [20] Finn et al., 2017 Model-Agnostic Meta-Learning for Fast Adaptation of Deep Networks. *arXiv preprint arXiv:1703.03400*, 2017. <https://arxiv.org/abs/1703.03400>
- [21] Salimans et al. Evolution Strategies as a Scalable Alternative to Reinforcement Learning. 2017. <https://blog.openai.com/evolution-strategies/>
- [22] Lehman et al. The Surprising Creativity of Digital Evolution: A Collection of Anecdotes from the Evolutionary Computation and Artificial Life Research Communities. *arXiv preprint arXiv:1803.03453*, 2018. <https://arxiv.org/abs/1803.03453>
- [23] Wang et al. Paired Open-Ended Trailblazer (POET): Endlessly Generating Increasingly Complex and Diverse Learning Environments and Their Solutions. *arXiv preprint arXiv:1901.01753*, 2019. <https://arxiv.org/abs/1901.01753>
- [24] Foerster et al. Learning to Model Other Minds. 2018. <https://blog.openai.com/learning-to-model-other-minds/>
- [25] Rabinowitz et al. Machine Theory of Mind. *arXiv preprint arXiv:1802.07740*, 2018. <https://arxiv.org/abs/1802.07740>