A gentle introduction to Artificial Intelligence & Machine Learning

DuMAS Department Day

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An introduction to AI & Machine Learning

Some points of interest

- Preliminaries: the historical way...
- Unsupervised / Supervised / Reinforcement Machine Learning
- Societal issues
- Technical (computing) slides available at the end for those who want to know more

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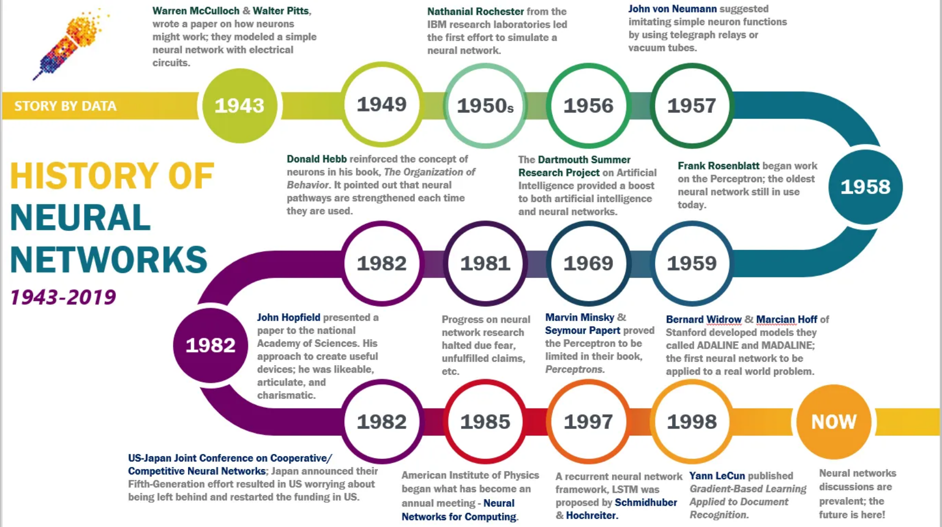
My profile

- I've been teaching Python programming (Scientific & Object Oriented)
- I started to get interested in ML in 2015
- I wrote several materials in ML : workshop, project & practical work for different schools (ENSAM, ENSEIRB, ENSPIMA, PPU...)

The historical way...

from: Kate Strachni: "Brief History of Neural Netowrks", medium.com



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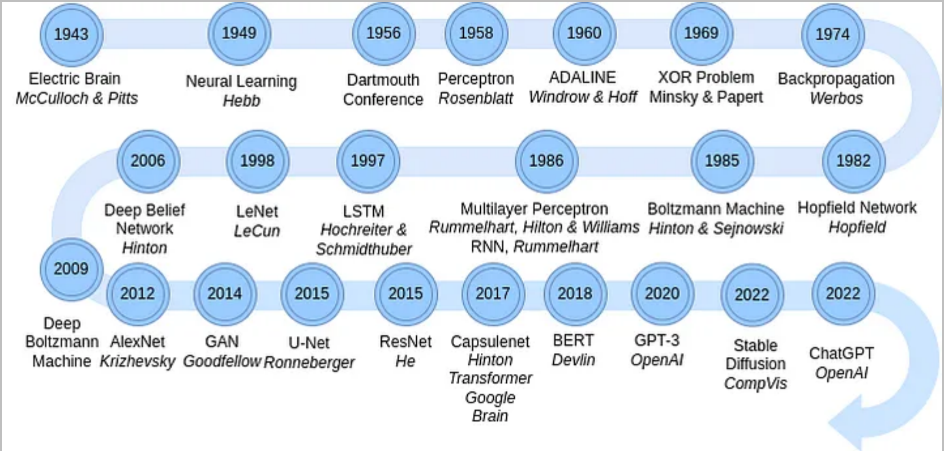

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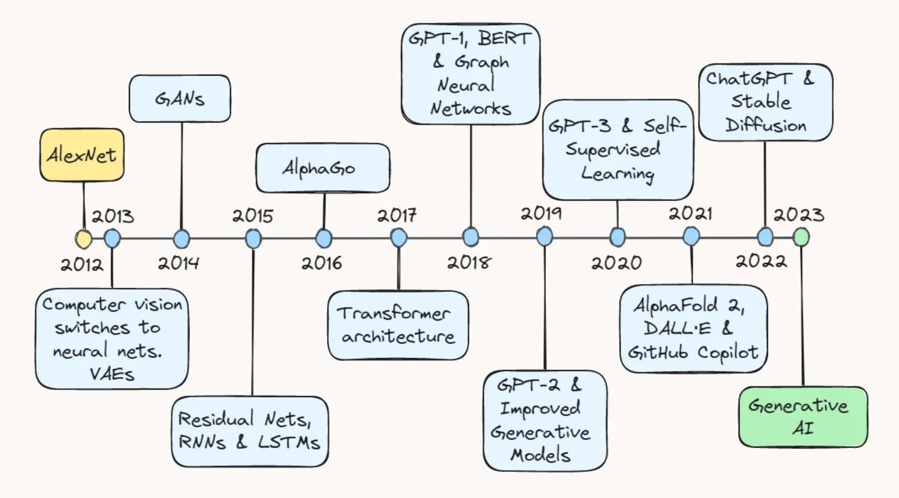

Artificial Intelligence ?

Historically[a] *badly chosen* term! Ambiguous current meaning...
Many (contradictory) definitions depending on periods and authors...

[a] first used in 1956 by John McCarthy, researcher at Stanford during the Dartmouth conference

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- *"...the science of making computers do things that require intelligence when done by humans."* Alan Turing, 1940
- *"the field of study that gives computers the ability to learn without being explicitly programmed."* Arthur Samuel, 1960
- *"A computer program is said to learn from experience E with respect to some class of tasks T and performance measure P, if its performance at tasks in T, as measured by P, improves with experience E."* Tom Mitchell, 1997
- Notion of *intelligent agent*, *rational agent*
  "...agent that acts in such a way as to reach the best solution or, in an uncertain environment, the best predictable solution."
  Stuart Russel, Peter Norvig, "Intelligence Artificielle" 2015

Artificial Intelligences ?

Strong AI

- Build systems that think exactly the same way that people do.
- Try also to explain how humans think... Whe are not yet here.

Weak AI

- Build systems that can behave like humans.
- The results will tell us nothing about how humans think.
- We already are there... We use it every day!
  (anti-spam, facial/voice recognition, language translation...)

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General AI

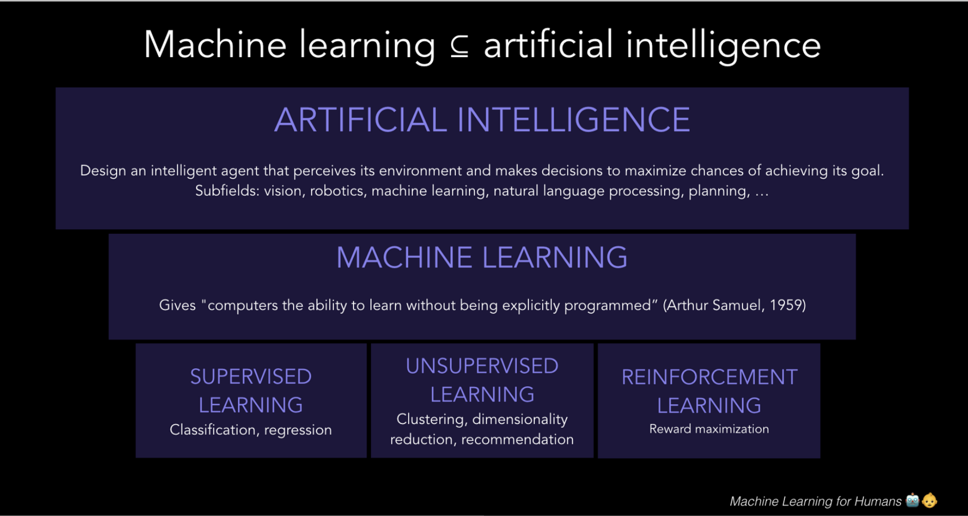
- AI systems designed for the ability to reason in general.

Narrow AI

- AI systems designed for specific tasks.

Machine Learning: a field of AI

Page from medium.com/machine-learning-for-humans/...



Branches of Machine Learning

Supervised learning

labeled dataset is used to train algorithms:

- **Classification**
  - Images classification
  - Objects detection in images
  - Speech recognition...
- **Regression**
  - Predict a value...
- **Anomaly detection**
  - Spam detection
  - Manufacturing: finding known (learned) defects
  - Weather prediction
  - Diseases classification...

...

Branches of Machine Learning

Unsupervised learning

Analyze and cluster **unlabeled datasets**:

- **Clustering** & **Grouping**
  - Data mining, web data grouping, news grouping...
  - Market segmentation
  - Astronomical data analysis...
- **Anomaly Detection**
  - Fraud detecion
  - Manufacturing: finding defects even new ones
  - Monitoring abnormal activity: failure, hacker, fraud...
  - Fake account on Internet...
- **Dimensionality reduction**
  - Compress data using fewer numbers...

. . .

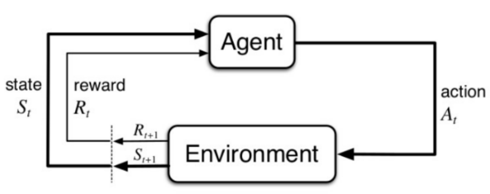
Branches of Machine Learning

Deep Reinforcement Learning DRL

An agent (the Neural Network) learns how to drive an environment by maximising a **reward**:

- **Control/command**
  - Controlling robots, drones, mecatronic systems
  - Factory optimization
  - Financial (stock) trading...
- **Decision making**
  - games (video games)
  - financial analysis...

. . .



Various approaches for ML algorithms

Supervised learning:

- Neural Networks
- Bayesian inference
- Random forest
- Decision Tree
- Support Vector Machine (SVM)
- K-Nearest Neighbor
- Linear regression
- Logistic regression
- ...

Unsupervised learning:

- Neural Networks
- Principal Composant Analysis
- Singular Value Decomposition
- K-mean & Prob. clustering
- ...

Reinforcement learning:

- Neural Networks (Q-learning, Actor-Critic, DDPG, PPO...)
- Monte Carlo
- SARSA
- ...

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This introduction deals only with **Artificial Neural Networks**.

Fields & applications of ML

Computer Vision

- Image Classification
- Object Detection
- (Semantic) Segmentation
- Image Generation
  Les 10 Meilleurs Générateurs d'Images
- Pose Estimation
- ...

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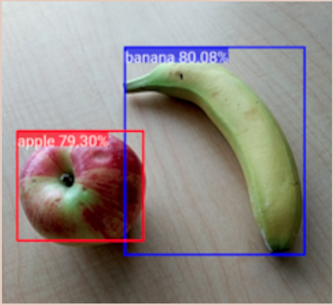

Image credit: Tensorflow

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Image credit: stylegan

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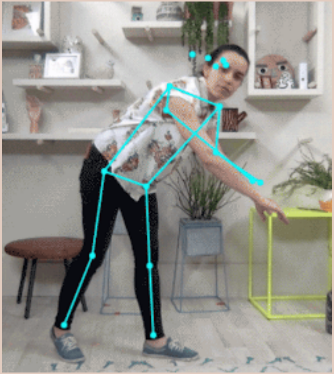


Image credit: Tensorflow-Pose Estimation

Fields & applications of ML

Natural Language Processing: NLP

- Natural Language Understanding (NLU)
- Natural Language Generation (NLG)
- Speech recognition / Speech Synthesis (Text To Speech)
- Machine Translation (languages)
- Virtual agents and ChatBots
- Optical character recognition (OCR)
- ...

Neural Network Architectures

Many NN architectures for many applications (non-exhaustive list):

- **Feed Forward**: the simplest architecture made of successive layers of neurones, with *Feed Forward* and *Back Propagation* algorithms.
- **Convolutional** (CNN): Mostly used for analyzing and classifying images.
- **Recurrent** (RNN): Used for time series, like the Long Short-Term Memory (LSTM) algorithm.
- **Transformers** : Recently used for Natural Language Processing and then for image classification.
- **Auto Encoder** (AEN): Dimensionality reduction, Feature extraction, Denoising of data/images, Inputing missing data.
- **Generative Adversarial** (GAN): to generate text, images, music...
- **Large Language Model** (LLM): read text, sound, write books, images, speak, make music ...ChatGPT

[Synthetic Graphical chart: from Saul Dobilas on Medium]

Societal issues: **Explainabilty**

Explainability is fast becoming a top priority in research, where it is often abbreviated as

xAI	**Explainable** Artificial Intelligence
iML	**Interpretable** Machine learning

Explainability

- **Unexplainability** of the results computed by Neural Networks still constitutes an obstacle to their dissemination today.
- Deep learning with Neural Networks is often denigrated as a **Black box** by scientists with a Cartesian approach.
- Even ML developpers have difficulties to explain by which way a NN decision has been computed

Societal issues: **Decision-making ML**

An increasing amount of **decisions** in sensible fields are being ceded to ML algorithms to the detriment of human control, raising concern for loss of fairness and equitability.

Explainability

- Decision-making algorithms rest inevitably on assumptions, even silent ones, such as the quality of data the algorithm is trained
-

Machine-learning algorithms in the field of criminal justice
Certification....

Societal issues: **Trustworthy AI**

On 8 April 2019, the High-Level Expert Group on AI presented Ethics Guidelines for Trustworthy Artificial Intelligence

According to the Guidelines, trustworthy AI should be:

- **Lawful** respecting all applicable laws and regulations
- **Ethical** respecting ethical principles and values
- **Robust** both from a technical perspective while taking into account its social environment

Societal issues: Trustworthy AI

ALTAI

Assessment List for Trustworthy AI

- Does the AI system potentially negatively discriminate against people...?
- Does the AI system respect the rights of the child?
- Does the AI system protect personal data relating to individuals in line with GDPR?
- Does the AI system respect the freedom of expression and information and/or freedom of assembly and association?

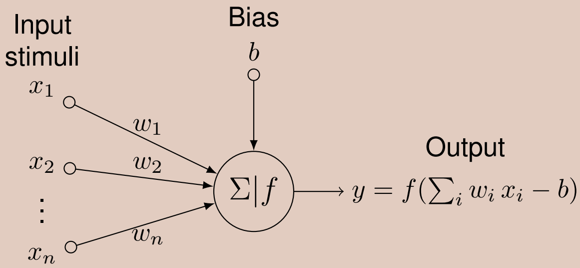
Some societal issues

References

- The Alan Turing Institute
  Understanding artificial intelligence ethics and safety
- Nature
  Ethical principles in machine learning and artificial intelligence: cases from the field and possible ways forward

Computing aspects

The Artificial neuron model

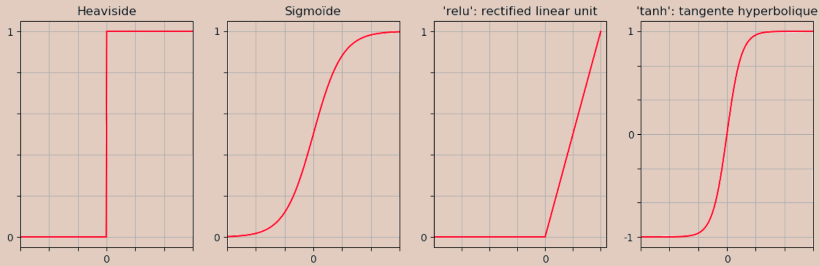


An **artificial neuron**:

- receives the input stimuli $(x_i)_{i=1..n}$ with **weights** (w_i)
- computes the **weighted sum** of the input $\sum_i w_i\, x_i - b$
- outputs its activation $f(\sum_i w_i\, x_i - b)$, computed with a non-linear **activation function** f

Computing aspects

Common activation functions

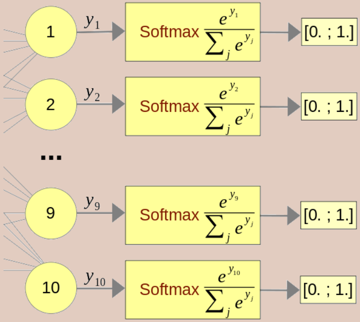


- Introduces a non-linear behavior.
- Sets the range of the neuron output: $[-1, 1]$, $[0, 1]$, $[0, \infty[$...
- The bias b sets the activation threshold of the neuron.

Computing aspects

- intermediate layers $\leadsto$ **relu** promotes network learning [1].
- **softmax** always used for in the last layer for **Classifying**.

Example: ativation function *softmax* for the last layer, 10 classes



- The activation of neuron k is $Y_k = e^{y_k} / \sum_i e^{y_i}$ with $y_k = \sum_i \omega_i x_i - b$ calculated by the neuron k.
- The neurons outputs are interpreted as **probabilities** in the interval [0,1].

$\leadsto$ the label of the neuron with the highest probability is the network response

[1] avoids the *vanishing gradient* that appears in *back propagation*

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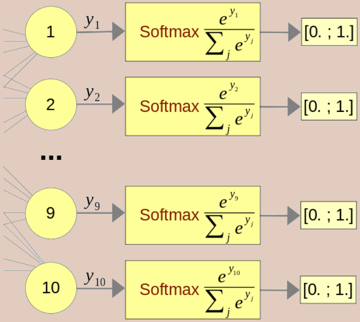

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Computing aspects [Classitication]

One-hot coding of labels

Goal: transform the image labels to match the network output (vector of probabiliies):

- Image labels: ordered set **integers**.
- Network output: **vector of `float`** in the interval [0;1] calculated by the *softmax* activation of the output neurons.
- *One-hot* coding of an ordered set $\mathfrak{L}$ of N labels:

  - each label value is coded as a vector with N components all zero except one (equal to 1),
  - the rank of the 1 in the vector gives the value of the labe.

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Label	One-hot vetor
0	[1 0 0 0 0 0 0 0 0 0]
1	[0 1 0 0 0 0 0 0 0 0]
2	[0 0 1 0 0 0 0 0 0 0]
3	[0 0 0 1 0 0 0 0 0 0]
4	[0 0 0 0 1 0 0 0 0 0]
5	[0 0 0 0 0 1 0 0 0 0]
6	[0 0 0 0 0 0 1 0 0 0]
7	[0 0 0 0 0 0 0 1 0 0]

The *one-hot* encoding of the labels '0' to '9' gives a vector with 10 components.

Computing aspects [Classitication]

Error function: *Cross entropy error*

- The image analysed by the network $\rightsquigarrow$ vector $\hat{Y}$ of `float` to be compared to the vector Y of the *hot-one* encoding of the true image label.
- The error (loss) function *cross entropy* is adapted to *one-hot* coding: $e(Y, \hat{Y}) = -\sum_i Y_i \; log(\hat{Y}_i)$

0	1	2	3	4	5	6	7	8	9
0	0	0	0	0	0	1	0	0	0

actual label one-hot coded

cross entropy error: $-\sum_i Y_i \; log(\hat{Y}_i)$

computed probabilities

0	1	2	3	4	5	6	7	8	9
0.01	0.01	0.02	0.01	0.01	0.01	0.9	0.01	0.01	0.01

Computing aspects

Optimization and *Back Propagation*

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Optimization and *Back Propagation*

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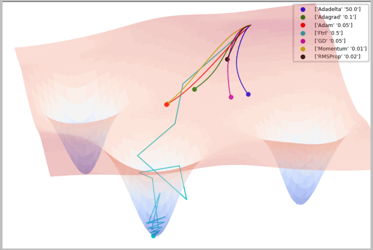
- The *Back Propagation* algorithm **modifies** the weights of the network layer by layer thanks to the gradient of the error function, iterating from the last layer to the first layer.
- Examples of optimization algorithms:
  - Gradient Descent (*Gradient Descent (GD)*)
  - Stochastic Gradient Descent (*Stochastic Gradient Descent (SGD)*)
  - *Adam* (improved version of gradient descent)...

The module tf.keras.optimizers provides Python implementation of several optimization algorithms.

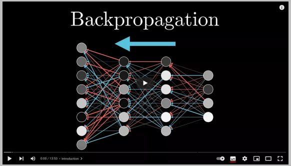
Computing aspects

Visualization of iterations of gradient descent algorithms for an very-simple loss function with only 2 variables:



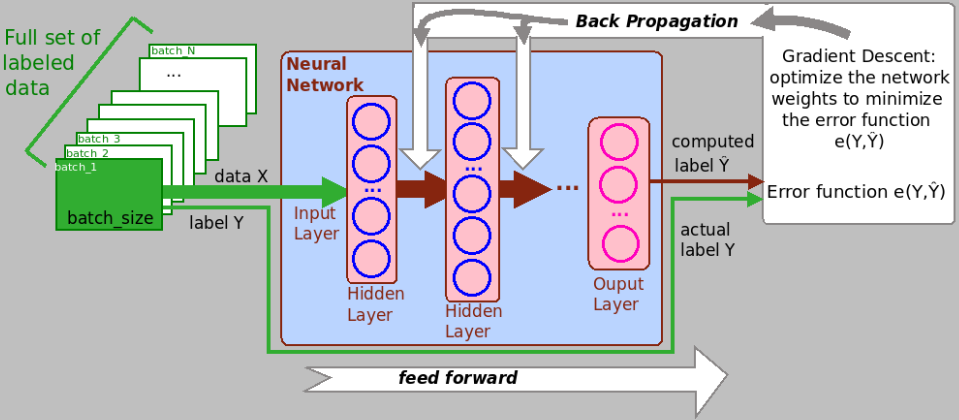
(source: github.com/Jaewan-Yun/optimizer-visualization)

Video explaining the *back propagation* algorithm:



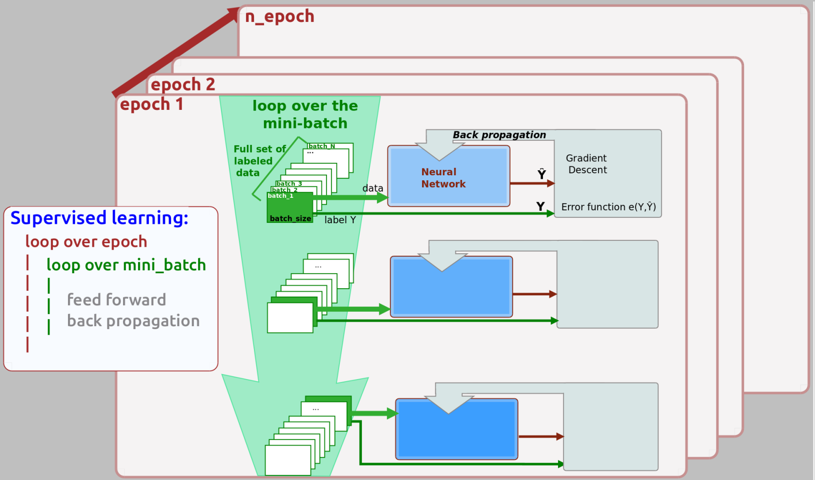
Computing aspects

Supervised learning : Feed Forward and Back Propagation



- The dataset is split into (mini) **batches** of size `batch_size`
- After each *feed forward* the *Back Propagation* algorithm modifies the weights neurons to minimize the error e.

Computing aspects



- Training with the whole dataset is repeated `n_epoch` times,
- The network state at the end of epoch `n` becomes the initial state for epoch `n+1`.

Why use PVE to develop ML programs with Python

PVE Advantages

- To create a dedicated environment (disk tree) with fixed version of the Python interpreter and sensitive modules (like tensorflow)
- Easy to create and destroy as many times as you want
- To Protect your projects against operating system updates or hazardous manipulations...
  $\rightsquigarrow$ you can load/update modules within a PVE without breaking modules compatibility for the other projects
- Each Python project should have its own PVE...

Disadvantages

- ? (just do it)