Continual Learning: from zero to hero

how to build intelligent agents which never stop learning

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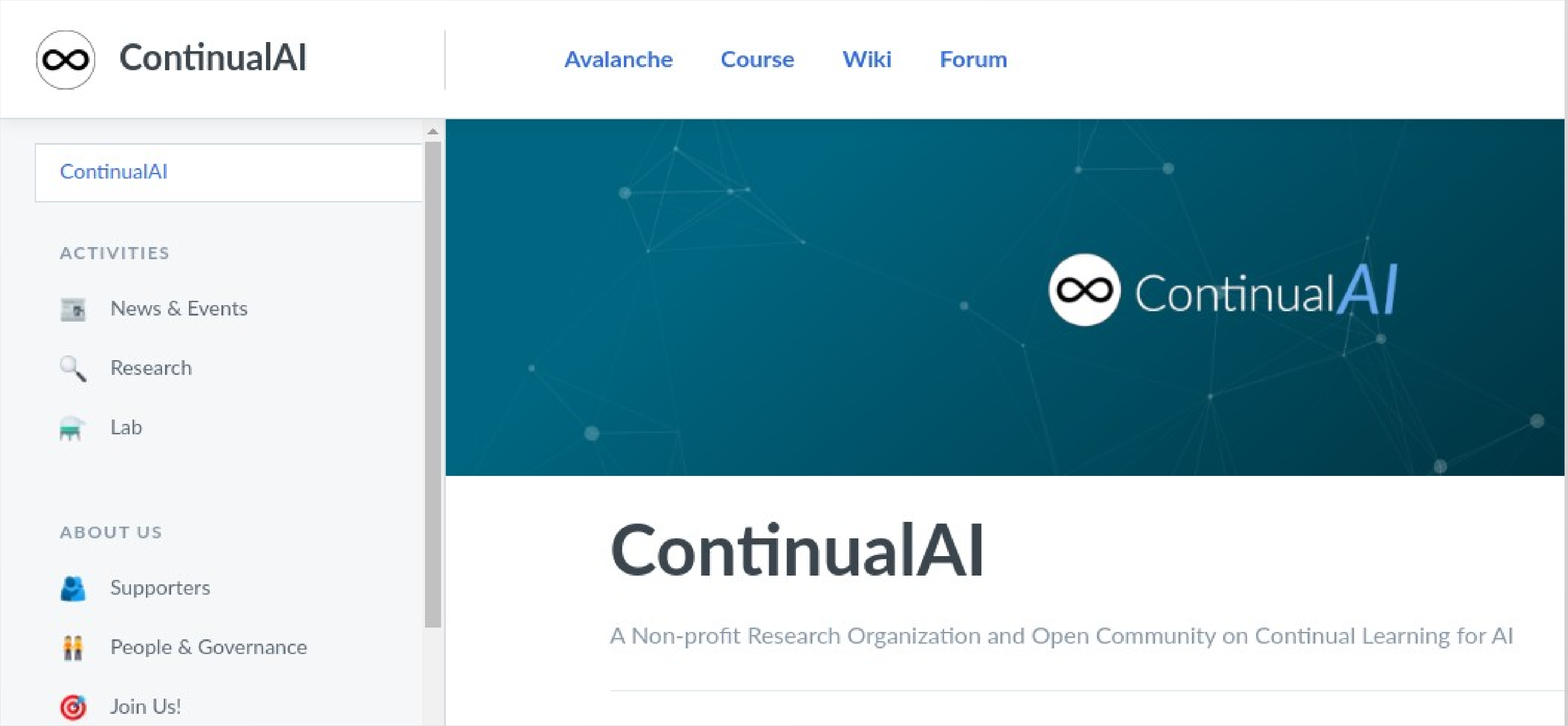


Cooking (Supervised) Machine Learning

Ingredients

A dataset D composed by K paired elements
input sample *x* and target *y*

A model M (*we will consider artificial neural networks)*

A loss function L

Recipe

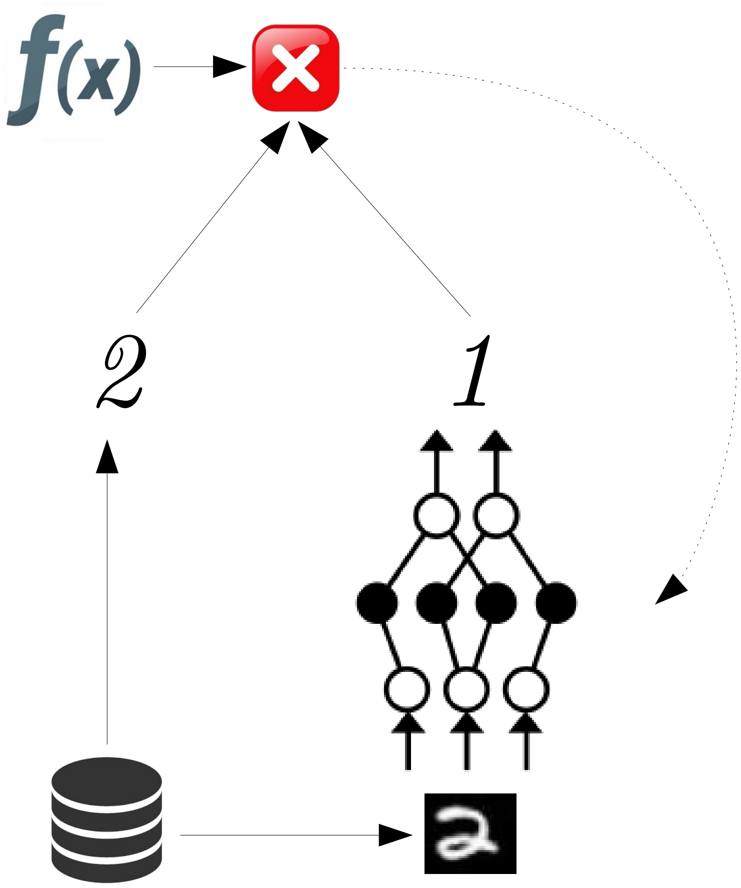
Train the model M by iterating on the dataset D

For each paired element
(start over when running out of elements):

- Compute model output OUT = M(x)
- Compute loss L = distance(OUT, y)
- Update model M

Result

Final model M ready to be used in the real-world!

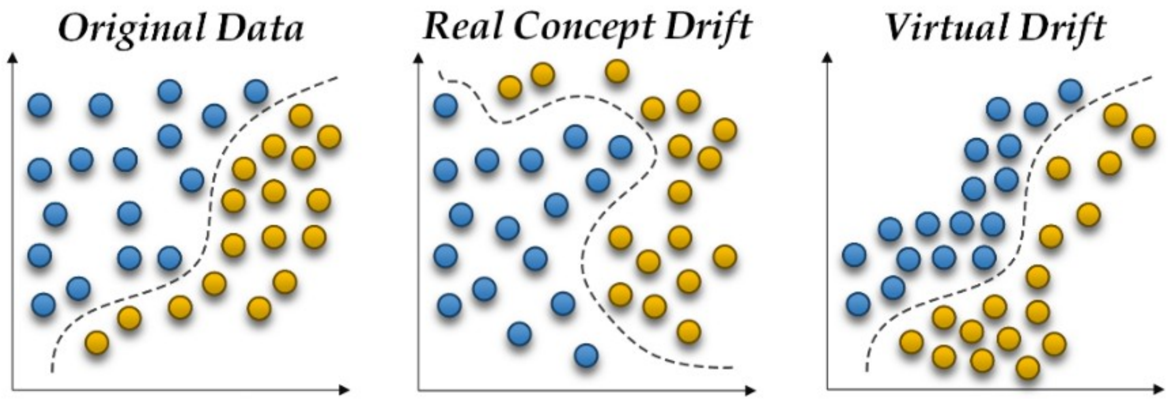


The power of Machine Learning

- Learning from data
  - no need to design ad-hoc, complex features
  - useful representations emerge during training (especially with deep networks)
- Impressive performance on a wide range of applications
  - language, vision, speech…
  - prediction, generation…
- Training is expensive, inference is cheap
- General paradigm for problem-solving, **if** you have enough data

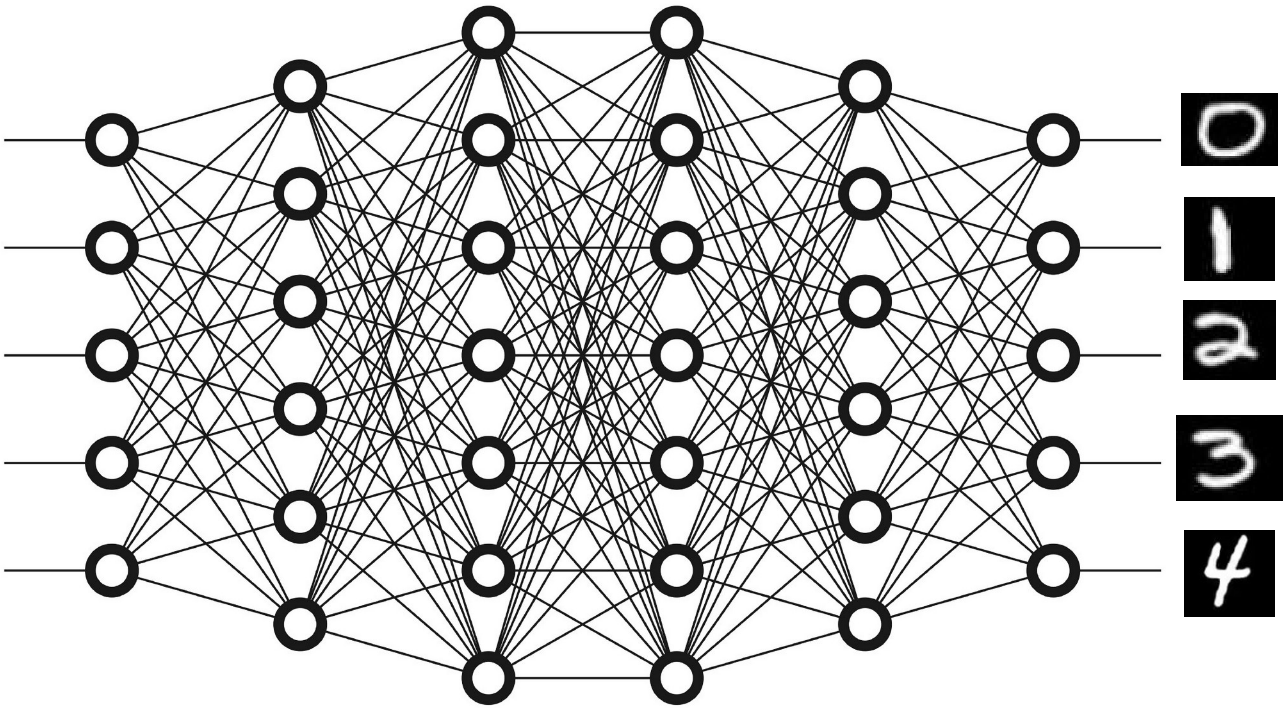
Non-stationary environments

- Data arrives **continually,** it is not entirely available at the beginning
- Data may change over time: drift!
  - Gradual / Abrupt
  - Permanent / Transient / Cyclical (recurrent concepts)
  - Real / Virtual
- Drift detection
  - active / passive
- Covariate Shift

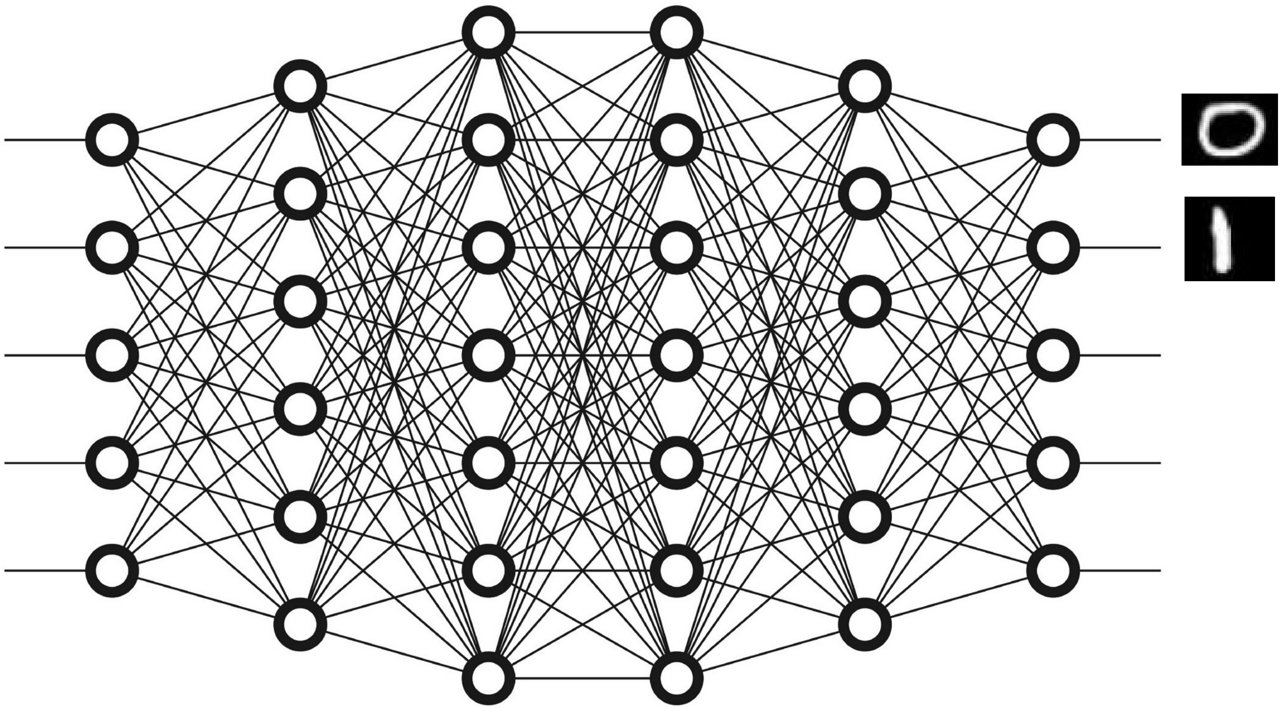


Pesaranghader et. al., "McDiarmid Drift Detection Methods for Evolving Data Streams*: A review*", *IJCNN, 2018*

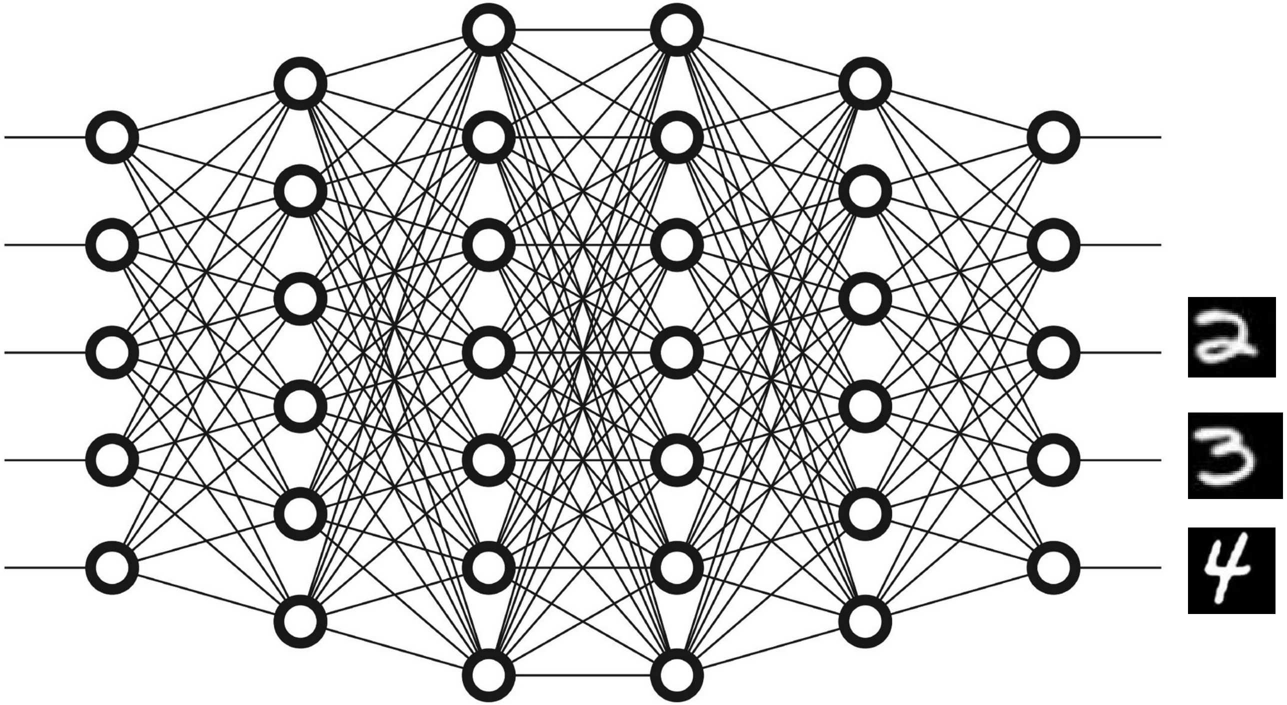
Training continually:
Objective: classifying correctly the digits 0, 1, 2, 3, 4



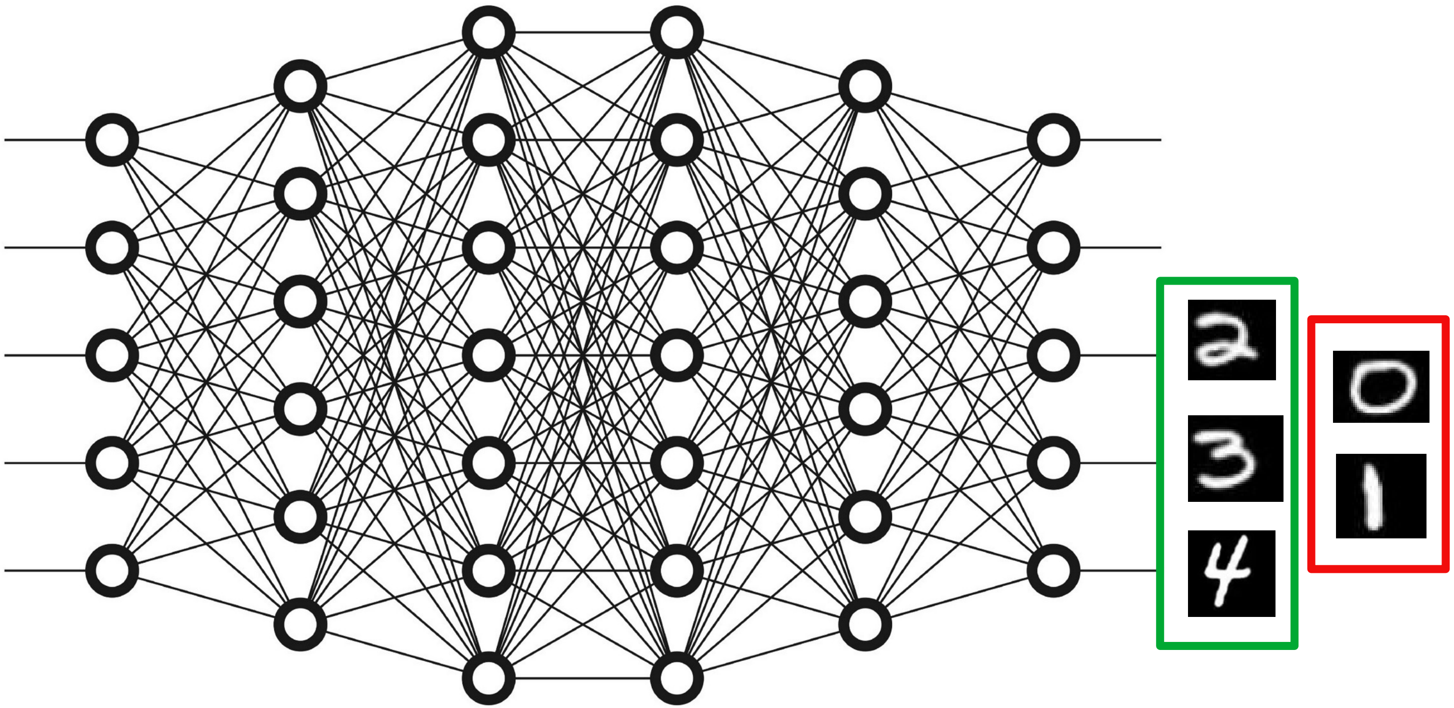
Training continually
first experience: classify digits 0, 1



Training continually
second (experience): classify digits 2, 3, 4



Test time (evaluation)
measure performance on the entire test data



60% final test accuracy

Catastrophic Forgetting

- Performance deteriorates on previous tasks once training on new information
- **Stability-Plasticity** dilemma:
  - Model needs plasticity to acquire new knowledge
  - Model needs plasticity to avoid forgetting previous information
- Modern neural networks are all towards **plasticity!**

The Continual Learning challenge

"A Continual (lifelong) learning system is defined as an **adaptive** algorithm capable of learning from a **continuous stream** of information, with such information becoming **progressively available** over time and where the **number of tasks** to be learned [...] are not predefined.
Critically, the accommodation of new information should occur **without catastrophic forgetting** or interference"

Parisi et. al. "*Continual lifelong learning with neural networks: A review*", *Neural Networks, 2019*

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The “grand” view of Continual Learning: Towards Sustainable Artificial Intelligence

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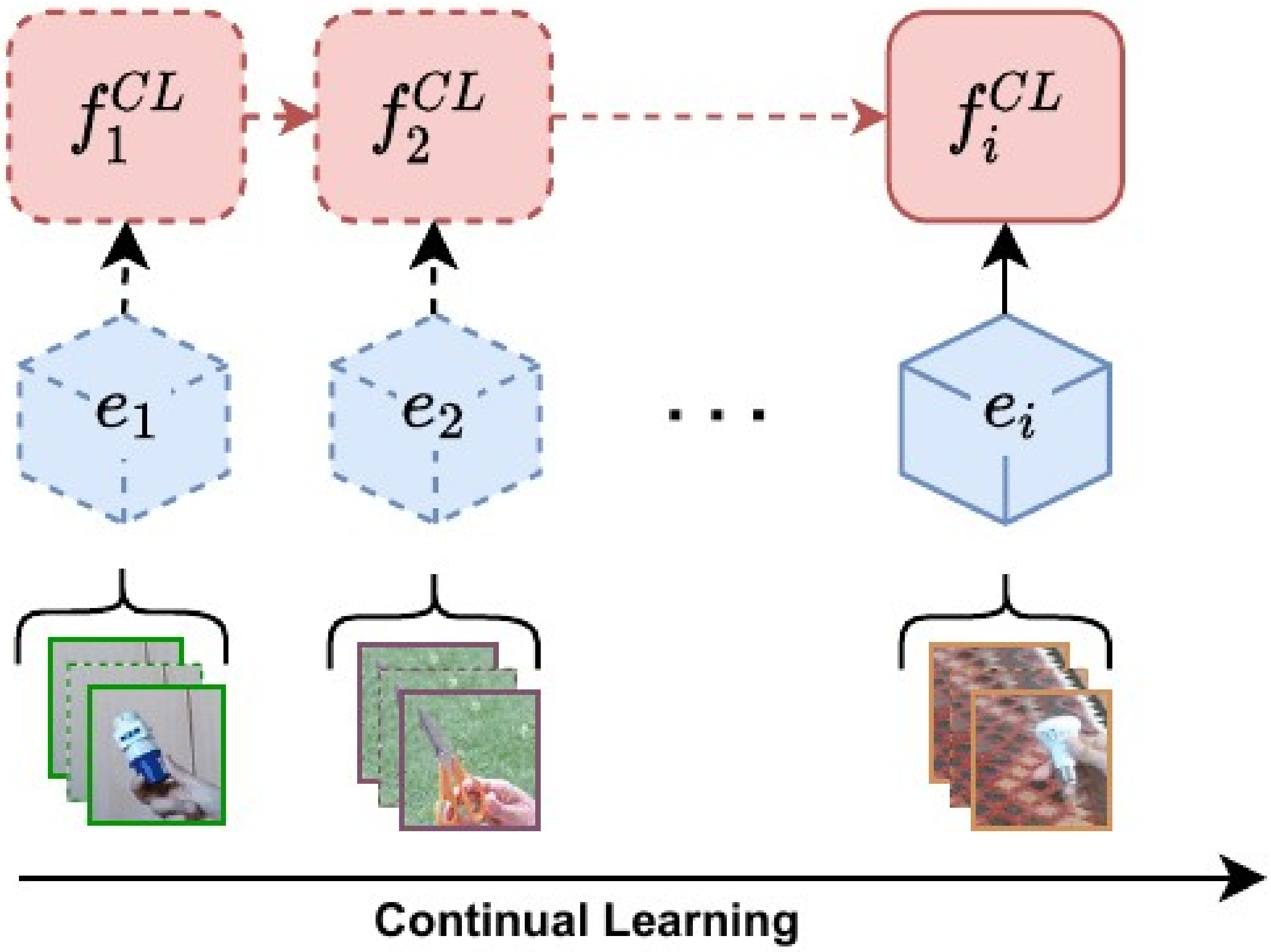
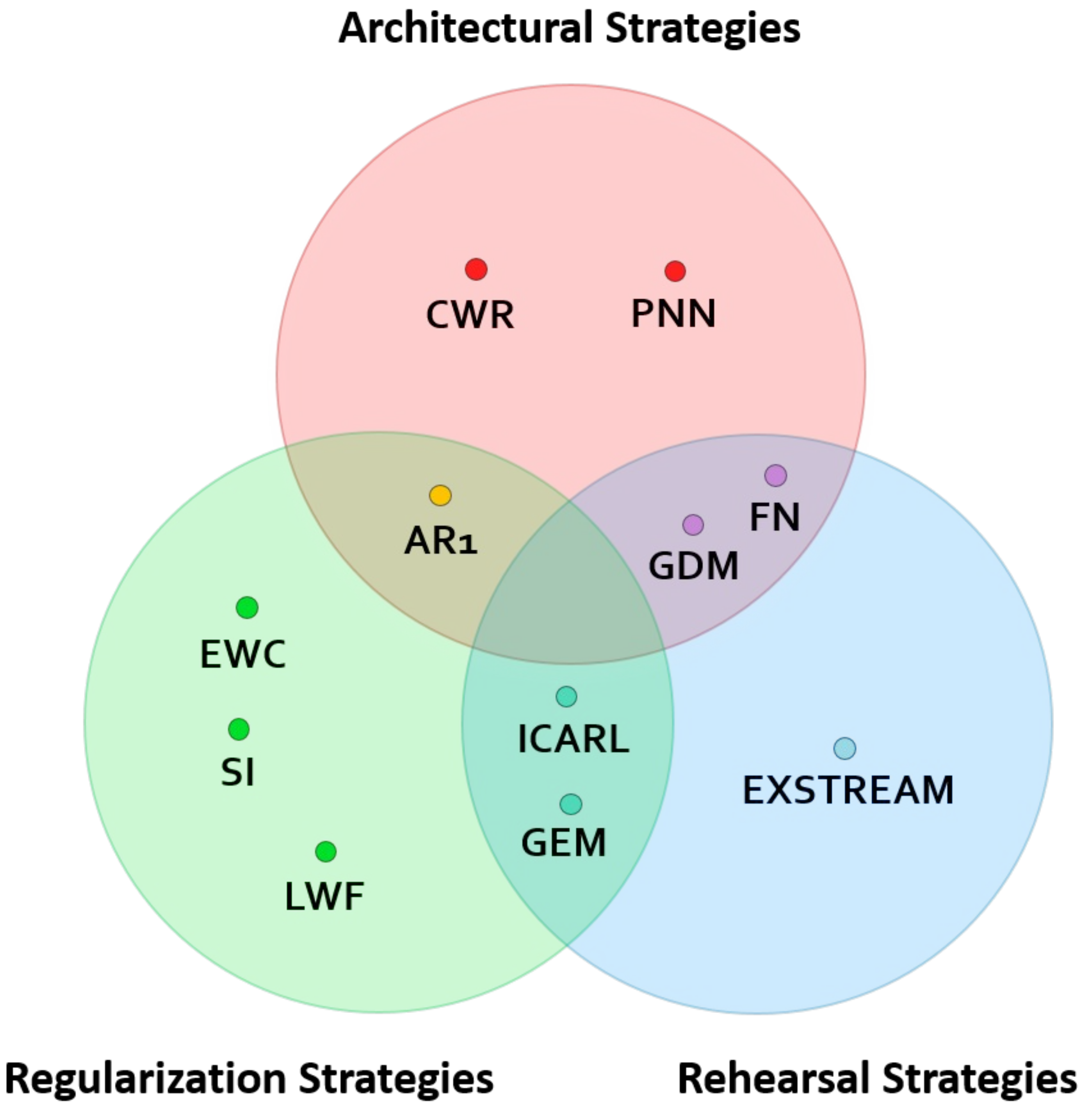
- Keep the information inside the model up-to-date
  - No need to re-train from scratch every time (save CO2)
- No need for enormous amount of data all at once
  - build your dataset over time
- Work in resource constrained environment (e.g., edge computing and IoT)
- Support data privacy
- Fix machine bias (model “patches”)
- Prone to forgetting – extra computation to mitigate it
- Reduced predictive performance



Continual Learning: a stream of experiences

Lomonaco et. al., “Avalanche: an End-to-End Library for Continual Learning”, CLVision workshop, CVPR 2021



D. Maltoni and V. Lomonaco, “Continuous Learning in Single-Incremental-Task Scenarios”, Neural Networks

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Continual Learning strategies: how to mitigate catastrophic forgetting

Evaluation of a CL agent

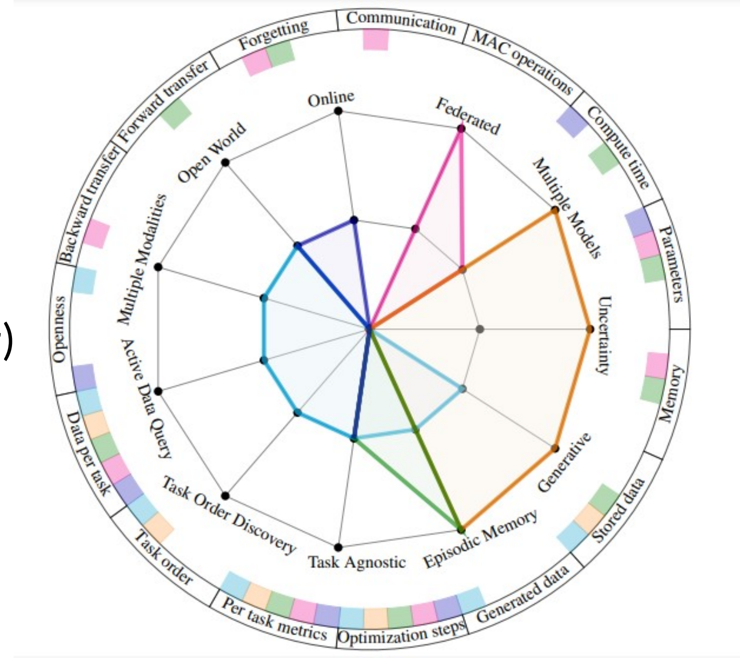
At the end of each experience, measure:

Performance metrics (e.g., accuracy)

- Accuracy on the current experience (training/validation)
- Accuracy on the future experiences (forward transfer)
- Accuracy on the past experiences (forgetting/backward transfer)

System / computational cost metrics

- Training time, memory consumption,

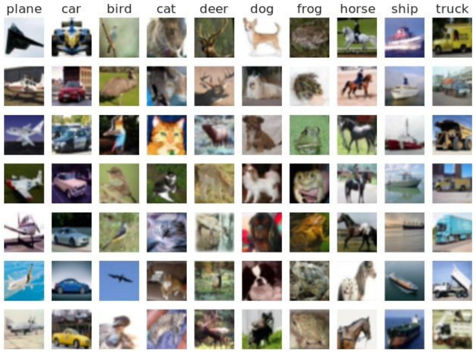


Mundt et. al., "CLEVA-Compass: A Continual Learning Evaluation Assessment Compass to Promote Research Transparency and Comparability", ICLR 2022

Continual Learning scenarios and benchmarks I

Dataset = MNIST, CIFAR-10/100, ImageNet, … (strong focus on Computer Vision)

- New Classes (NC) / Class-incremental
  - Split Dataset
- New Instances (NI) / Domain-incremental
  - Permuted Dataset, Rotated Dataset, …
  - CORe50 NI → new objects from different exposures



Continual Learning scenarios and benchmarks II

- Class-incremental with Repetition (CIR) / New Instances and Classes (NIC)
  - Towards a more “natural” way of learning: encounter both new classes and new/old instances
- Task-Free / Online / Streaming
  - See samples (few at a time) only once
  - no information about where they come from (as previous scenario, usually)
  - no information about task boundaries
  - Usually built out of NC scenario

References and credits

- **References**

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- **Image credits**

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Slide 2.
https://static.thenounproject.com/png/1551919-200.png (neural network)
http://wfarm3.dataknet.com/static/resources/icons/set113/ee242415.png (data)
https://openclipart.org/image/2400px/svg_to_png/110/molumen-red-square-error-warning-icon.png (error)
https://www.iconexperience.com/_img/g_collection_png/standard/512x512/function.png (function)
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Slide 11.
https://alzheimergadfly.net/wp-content/uploads/2018/07/Brain-eraser-e1533486845740.png

Time to code with Avalanche!

https://avalanche.continualai.org/

Avalanche *powered by* ContinualAI

But first, ~~let me take a selfie~~ any questions?