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Continual Learning

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QUESTION:

Which are the two main problems that Streaming Machine Learning has to manage?

Introduction – 2/3

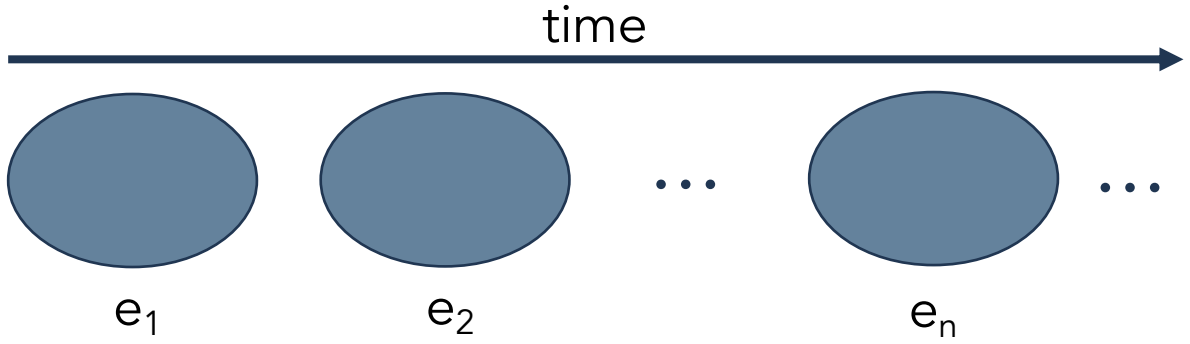
- The Traditional ML approach is unrealistic: it supposes to have all the knowledge available in one shot.
- In the real world, data:
  - Becomes available over time
  - Can suffer changes in its distribution.
- We cannot train a model once on a data set and think it will remain appropriate forever.
- We must **continuously** train our model to keep it updated with new knowledge and data changes.

Introduction – 3/3

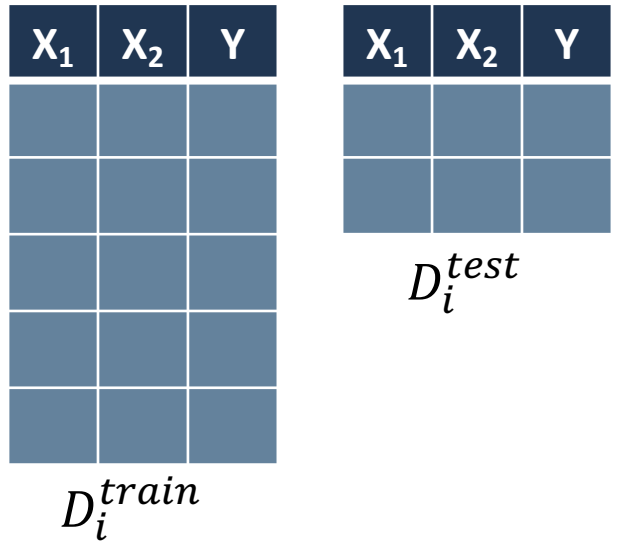
- Similarly to SML, the CL goal is to improve the model based on experience and keep it updated to changes.
- It usually applies Deep Learning techniques.

Problem Setting

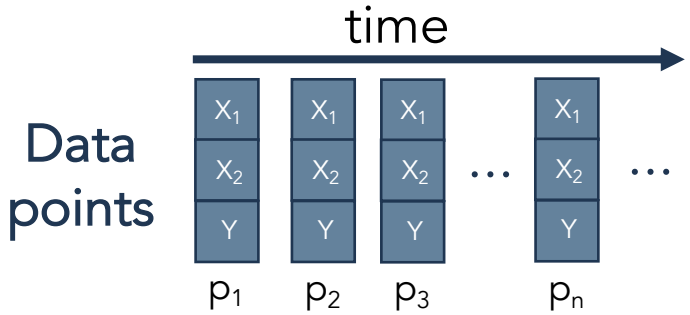
CONTINUAL LEARNING



- A datastream S is split into experiences.
- Each experience e_i consists of a large batch of samples D_i.
- D_i is usually split into D_i^{train} and D_i^{test}.
- Each experience is available at once and the model can be trained on it for several epochs.
- Unbounded time between two experiences.



STREAMING ML



- Single data points or mini-batches arrive over time.
- No distinction between train and test (Prequential evaluation).
- The model must be able to provide online answers at any time (only one pass, low time/memory)

LESORT, Timothée, et al. Continual learning for robotics: Definition, framework, learning strategies, opportunities and challenges. *IF*, 2020.

CL Algorithm

$$A^{CL}: (f_{i-1}^{CL}, M_{i-1}, D_i^{train}, t_i) \rightarrow (f_i^{CL}, M_i)$$

- f_i^{CL} : model learned after the i-th experience.
- M_i: knowledge until the i-th experience.
- t_i: task (optional). It could be seen as a time interval in which the data distribution and the objective function may be fixed (similar to SML's concept).

CL goal is to optimize the loss computed on the different D_i^{test} over the entire data stream.

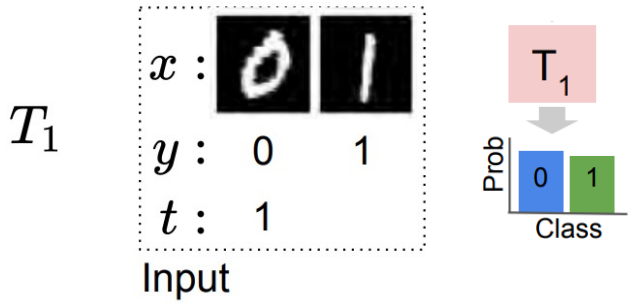
LESORT, Timothée, et al. Continual learning for robotics: Definition, framework, learning strategies, opportunities and challenges. *IF*, 2020.

Scenarios

A new experience usually introduces a change. (Each experience is supposed to be i.i.d.)

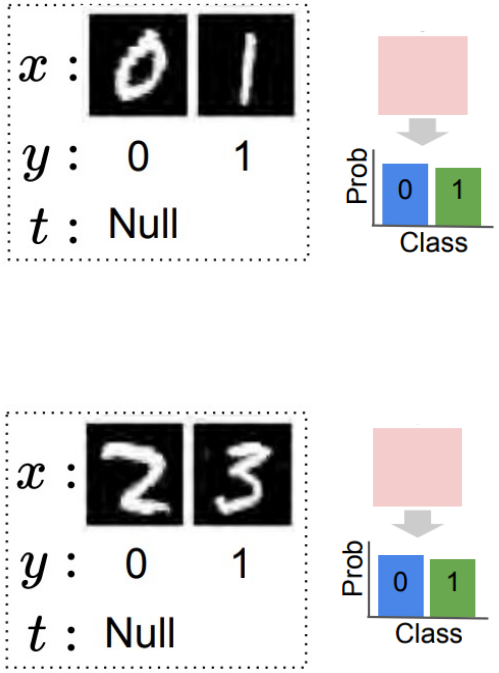
→ No need to apply change detectors during training.

Incremental Task Learning



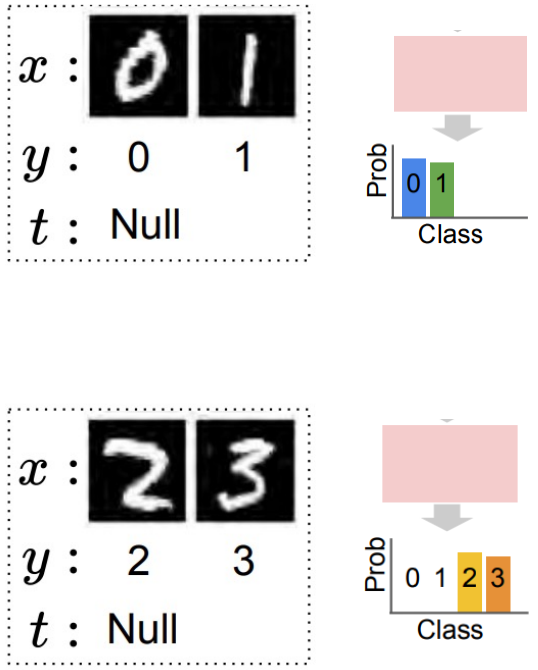
Task labels during train & test

Incremental Domain Learning



No task labels

Incremental Class Learning



No task label
(different class labels during train)

HSU, Yen-Chang, et al. Re-evaluating continual learning scenarios: A categorization and case for strong baselines. *arXiv* 2018.

Stability-plasticity Dilemma – 1/4

A model should achieve a trade-off between stability and plasticity.

- **Plasticity:** ability to acquire new knowledge and keep learning over time.

Too much plasticity → forgetting past knowledge.

- **Stability:** ability to remember the past acquired knowledge over time.

Too much **stability** → difficulties in learning new knowledge.

CL focuses on the following:

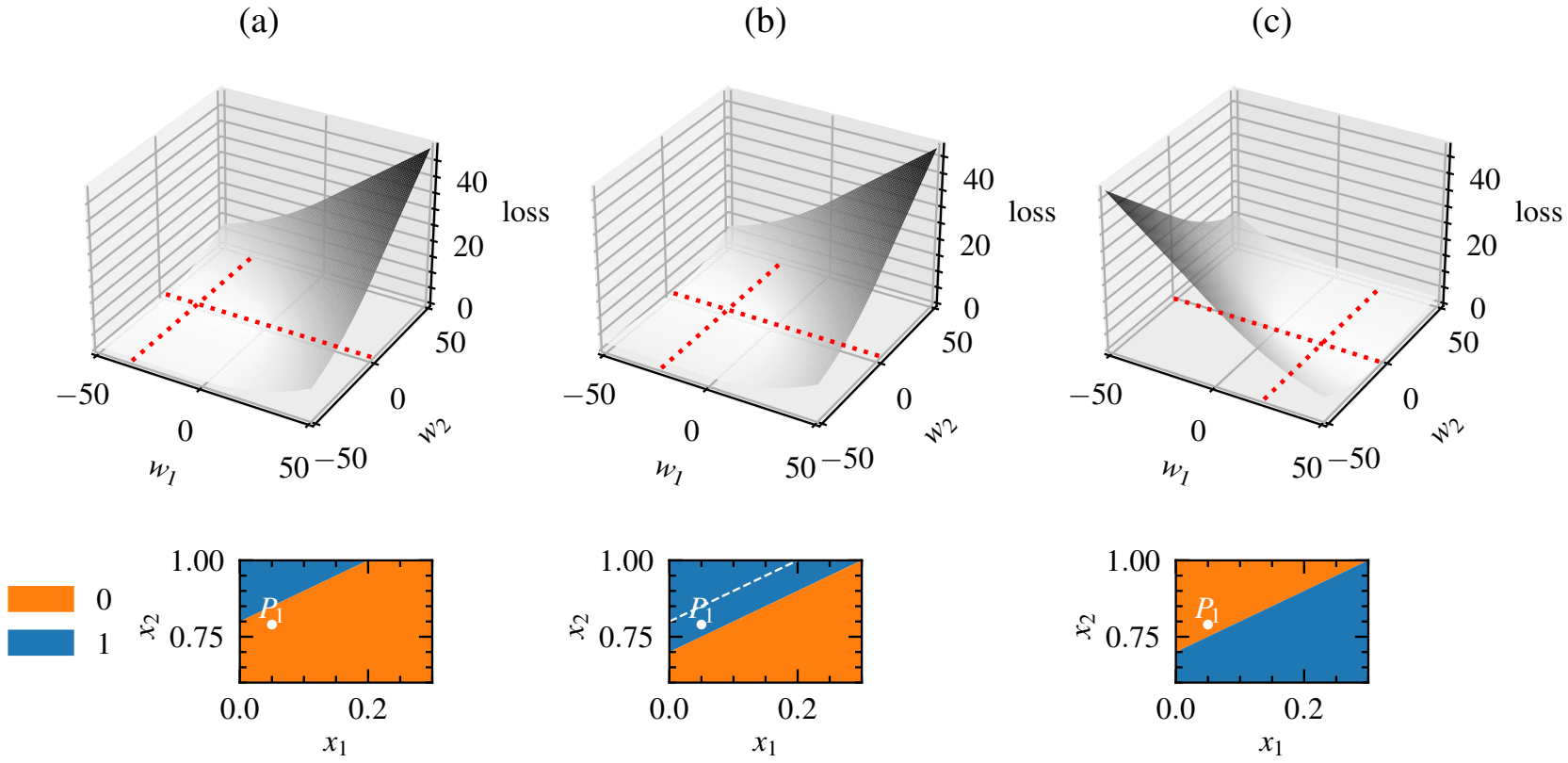
- Learning new knowledge.
- Remembering past knowledge.
- Generalizing on future instances.

Evaluation strategies and different methodologies are associated with these goals.

MCCLOSKEY, Michael; COHEN, Neal J. Catastrophic interference in connectionist networks: The sequential learning problem. *POLAM*, 1989.

Stability-plasticity Dilemma – 2/4: Catastrophic Forgetting (CF)

- CF is the problem associated with too much plasticity.
- NN models can easily suffer from forgetting past knowledge because of the SGD algorithm.
- When there's a drift in the objective function, the model's parameters are set to reach the new loss function's minimum.
- Without a specific strategy, the previous task is forgotten.



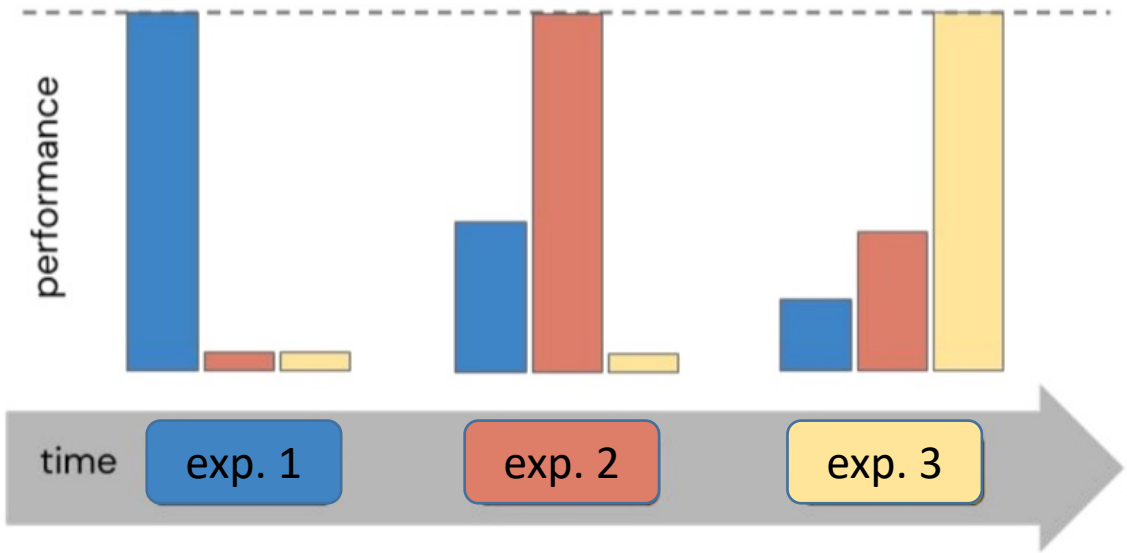
(Incremental task scenario)

DE LANGE, Matthias, et al. A continual learning survey: Defying forgetting in classification tasks. *IEEE TOPAAMI*, 2021.

Stability-plasticity Dilemma 3/4

Avoiding CF

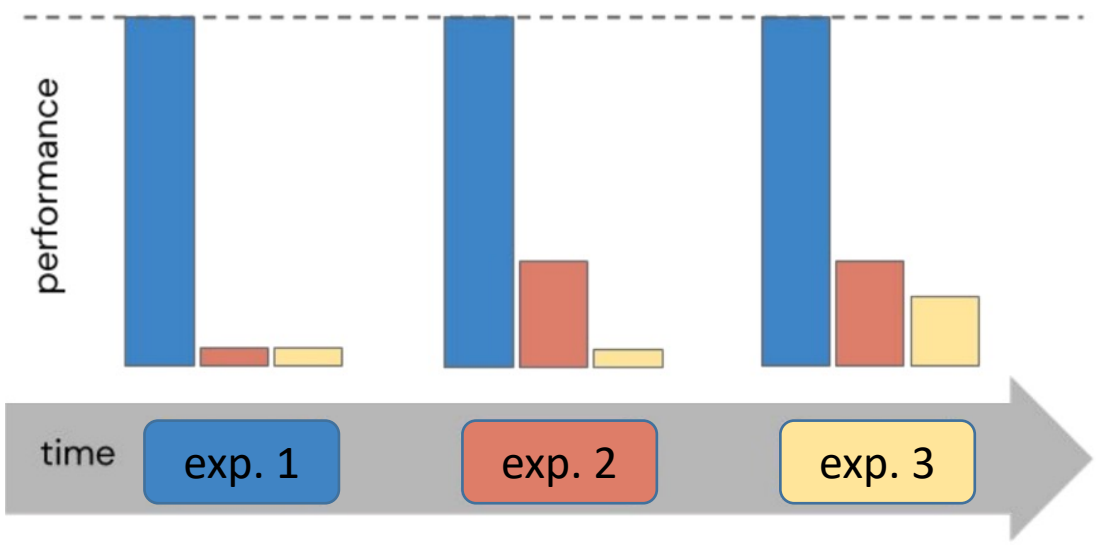
Training on new experiences should not reduce performance on previously learned experiences.



Catastrophic Forgetting

Maintaining Plasticity

The model should be able to keep learning as new experiences are observed.

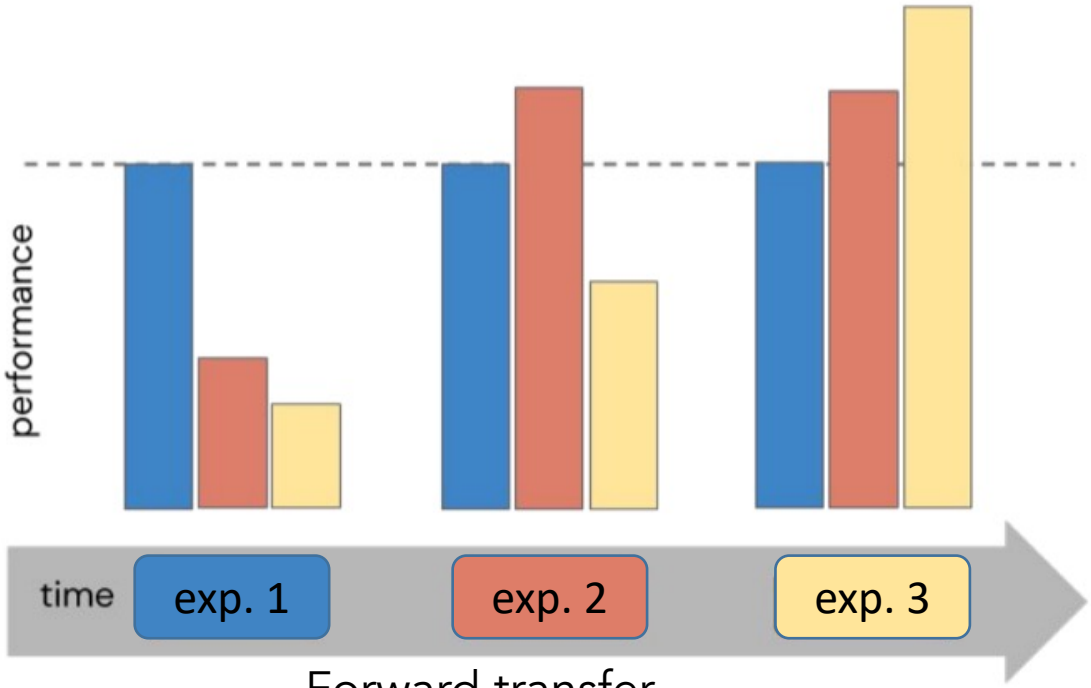


Model without plasticity.

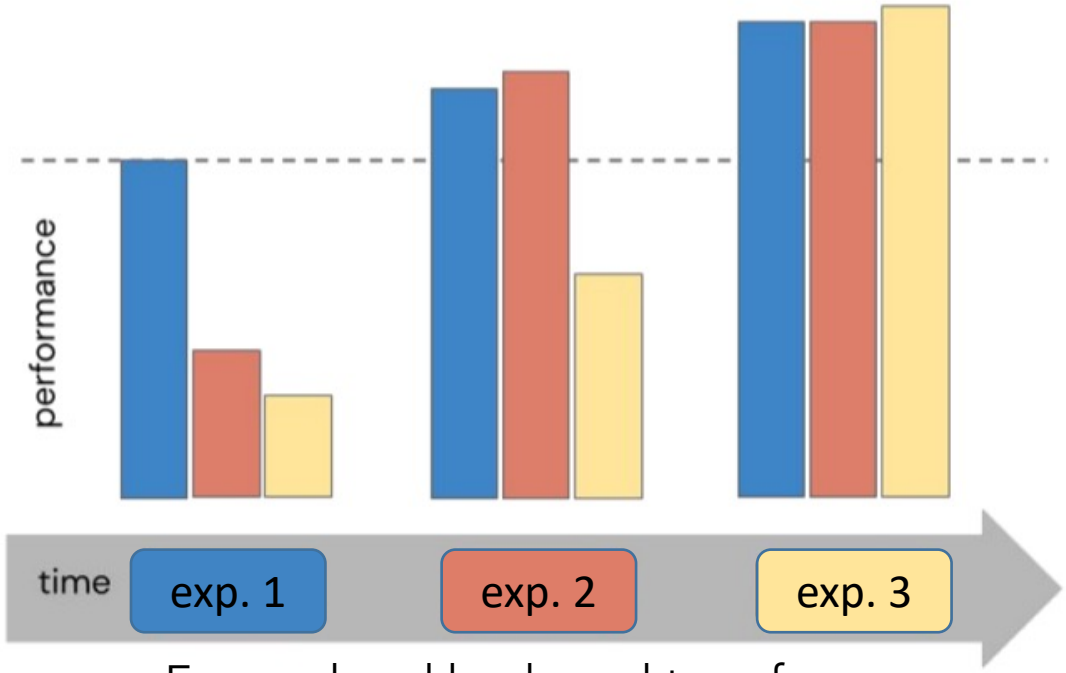
Stability-plasticity Dilemma 4/4

Maximizing Forward and Backward transfer

Learning an experience should improve both past and future experiences.



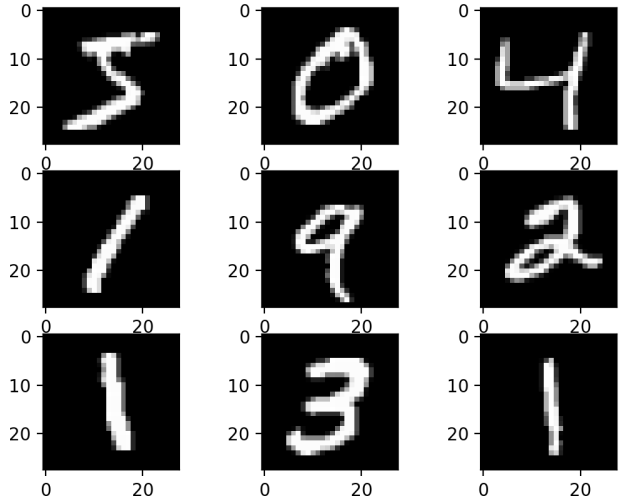
Forward transfer



Forward and backward transfer

CL Applications

- Most CL applications are still on toy datasets (computer vision like MNIST, CIFAR) and supervised problems.
- The most studied scenario in the past was Incremental Task Learning with few big tasks.
- Currently, works on Incremental Class Learning are being published, with dozens of experiences.



Evaluation – 1/3

- Usually, each experience is split into **train** and **test** sets.
- After each experience's training, we compute the metrics on **all** the experiences' test sets.

	Test e_1	Test e_2	Test e_3
Train e_1	$R_{1,1}$	$R_{1,2}$	$R_{1,3}$
Train e_2	$R_{2,1}$	$R_{2,2}$	$R_{2,3}$
Train e_3	$R_{3,1}$	$R_{3,2}$	$R_{3,3}$

- Average accuracy: $ACC = \frac{1}{T}\sum_{i=1}^{T} R_{T,i}$

Mean of final performances on all the experiences' test set.

- A metric: $A = \frac{\sum_{i=1}^{N}\sum_{j=1}^{i} R_{i,j}}{\frac{N(N+1)}{2}}$

For each experience, we consider the current and the previous ones.

LOPEZ-PAZ, David; RANZATO, Marc'Aurelio. Gradient episodic memory for continual learning. *AINIPS*, 2017.

Evaluation – 2/3

	Test e_1	Test e_2	Test e_3
Train e_1	$R_{1,1}$	$R_{1,2}$	$R_{1,3}$
Train e_2	$R_{2,1}$	$R_{2,2}$	$R_{2,3}$
Train e_3	$R_{3,1}$	$R_{3,2}$	$R_{3,3}$

To measure the impact of the current experience's training on future/previous experiences, we introduce two other metrics:

- Forward Transfer Metric: $\frac{1}{T-1}\sum_{i=2}^{T} R_{i-1,i} - \overline{b_i}$

It measures how the current training improves performance for the next experience.

- Backward Transfer Metric: $\frac{1}{T-1}\sum_{i=1}^{T-1} R_{T,i} - R_{i,i}$

It measures how the final model has improved or decreased the performances on the previous experiences.

A negative value indicates forgetting!

LOPEZ-PAZ, David; RANZATO, Marc'Aurelio. Gradient episodic memory for continual learning. *AINIPS*, 2017.

Evaluation – 3/3

Performance is not enough!

Metrics on **memory occupation** and **computational overhead** have been introduced.

Hyperparameters tuning and **model selection** are still open issues in CL.

- Use a first set of experiences.

After having selected the best configurations, the selected model is reset and a new training starts from the following experience.

  - It does not learn the first experiences.
  - Hyperparameters tuned and selected model on the first experiences could not fit the followings.

- Model selection and hyperparameters tuning on the same stream and test sets of the evaluation (violation of Statistical Learning Theory principles).

CHAUDHRY, Arslan, et al. Efficient lifelong learning with a-gem. *arXiv*, 2018.

Avoiding Catastrophic Forgetting

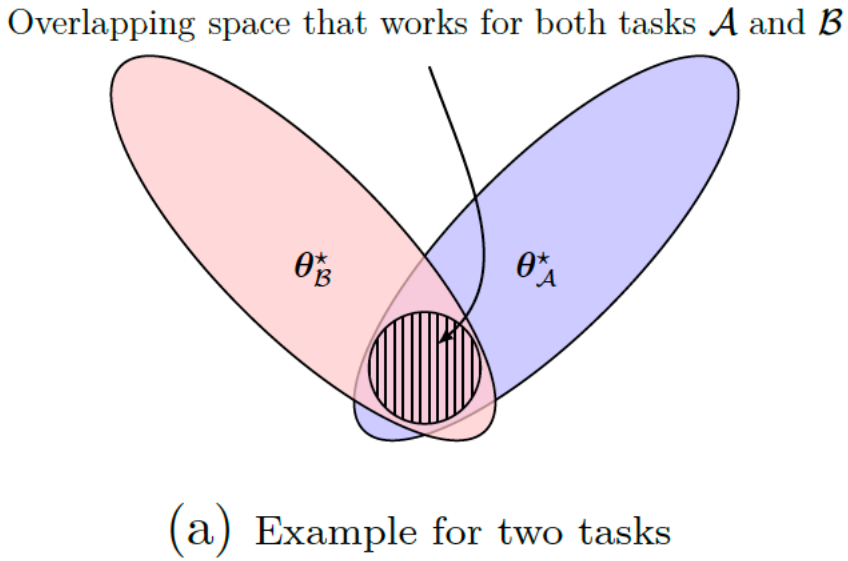
CL aims to have a model able to learn new tasks without losing the prediction ability on old ones. The goal is to minimize the loss on all the test sets and not only on the last experience's one. CL strategies try to avoid catastrophic forgetting:

- Replay: during each experience, they mix old examples with new ones to not forget old tasks. Generative replay strategies generate examples associated with old tasks. The training set's size increases with the number of tasks.
- Regularization: they change the loss function by adding regularization terms to the new task's problem and not losing the old ones.
- Architectural: they introduce new parameters to the network (e.g. shared layers between all tasks and tasks specific layers, transfer learning or weight masks). For some strategies, the number of parameters could increase with the number of tasks. Usually they require the task labels.

DE LANGE, Matthias, et al. A continual learning survey: Defying forgetting in classification tasks. *IEEE TOPAAMI*, 2021.

Regularization: Elastic Weight Consolidation (EWC) – 1/2

- It adds a regularization term to the loss in order to penalize changes on important parameters for previous tasks.
- The idea is to search the optimal configuration on the overlapping of different tasks' solution spaces.



(a) Example for two tasks

Importance index of parameter i for task A

Loss on task B

$$\mathcal{L}(\theta) = \mathcal{L}_B(\theta) + \sum_i \frac{\lambda}{2} F_i(\theta_i - \theta^*_{A,i})^2$$

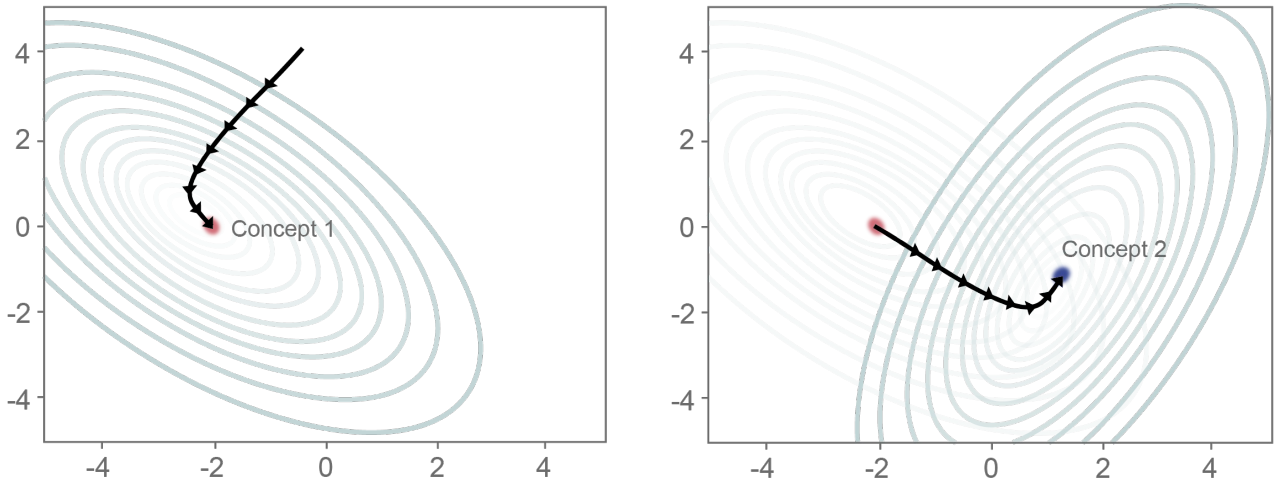
Distance between the current value of parameter i and the optimal one for task A.

Adding the weighted distance means that we want to minimize it for important parameters.

KIRKPATRICK, James, et al. Overcoming catastrophic forgetting in neural networks. *PNAS*, 2017
AICH, Abhishek. Elastic weight consolidation (EWC): Nuts and bolts. *arXiv*, 2021.

Regularization: Elastic Weight Consolidation (EWC) – 2/2

- Optimizing very different tasks together could result in not finding a good trade-off:
  - Some tasks may perform well, while others badly.
  - In the worst scenario, we could find a solution that does not fit all the tasks.
- EWC results, in fact, in a **tug-of-war** over the direction of change of each task.



KIRKPATRICK, James, et al. Overcoming catastrophic forgetting in neural networks. *PNAS*, 2017
AICH, Abhishek. Elastic weight consolidation (EWC): Nuts and bolts. *arXiv*, 2021.

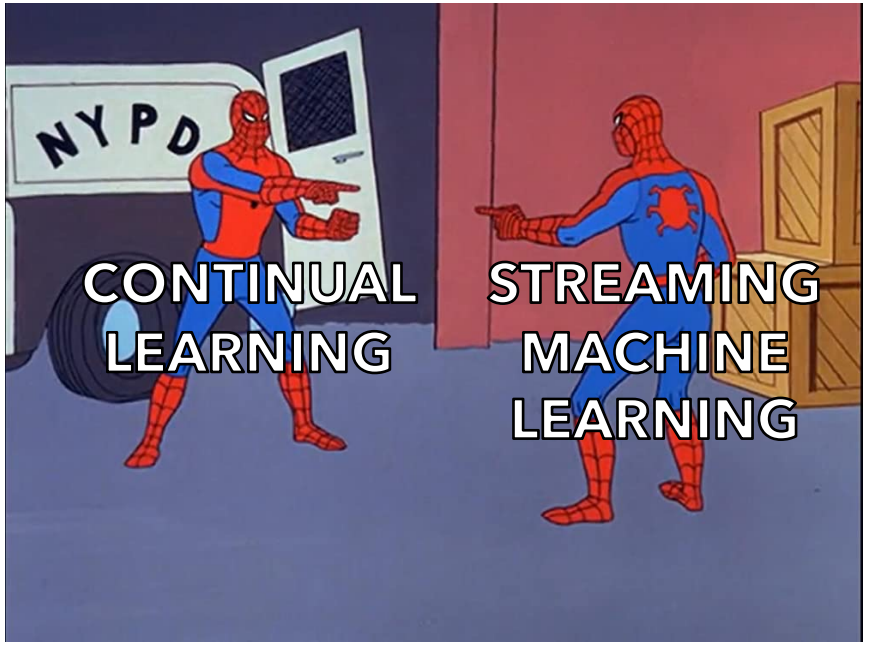
Conclusion – 1/2

- CL focuses on avoiding catastrophic forgetting, while SML is more focused on quick adaptation on new concepts and providing online answers at any time.
- CL has a distinction between Train and Test set, while SML usually applies Prequential Evaluation.
- The presented CL scenarios are not enough and do not represent the real world.
- CL constraints on problem settings are unrealistic.
- CL strategies are an interesting way to manage multiple concepts/tasks learning and could be applied on SML scenarios.

Conclusion – 2/2

- Future CL works will have to propose solutions for:
  - New scenarios: Re-occurring of already seen classes / tasks + Mixed experiences
  - Manage of non-i.i.d. experiences.
  - Applications on real dataset / Unsupervised problems.
  - Alternatives to SGD.
- A new paradigm of CL is arising: Online Continual Learning. It reduces the size of experiences (mini batch of 10 data points), a more similar approach to SML.
- SML and CL communities are trying to co-operate and mix methodologies. In this direction, the CL community is applying SML concept drift detectors to CL scenarios.

Thank you!



The presented material is inspired by Continual Learning Course.

See more at: Continual AI site

And now… Let's have some fun!