Hochschule
Bonn-Rhein-Sieg
University of Applied Sciences

Bonn-Aachen
International Center for
Information Technology

Institute for AI and
Autonomous Systems

# Lifelong Learning

## An Overview for Cognitive Robotics

Dr. Alex Mitrevski
Master of Autonomous Systems

# Structure

- ▶ Overview of robot lifelong learning
- ▶ Class incremental learning
- ▶ Class incremental learning algorithm example: iCaRL
- ▶ Use case: Lifelong learning for action recognition

IEEE TRANSACTIONS ON PATTERN ANALYSIS AND MACHINE INTELLIGENCE, VOL. 45, NO. 5, MAY 2023 5513

**Class-Incremental Learning: Survey and Performance Evaluation on Image Classification**

Marc Masana, Xialei Liu, Bartłomiej Twardowski, Mikel Menta, Andrew D. Bagdanov, and Joost van de Weijer

**Continual Learning for Robotics: Definition, Framework, Learning Strategies, Opportunities and Challenges**

Timothée Lesort[*,1,2], Vincenzo Lomonaco[*,3], Andrei Stoian[2], Davide Maltoni[3], David Filliat[1], and Natalia Díaz-Rodríguez[*,1]

[1]Flowers Team (ENSTA Paris, Institute Polytechnique de Paris & INRIA).
[2]Thales, Theresis Laboratory.
[3]Department of Computer Science and Engineering - University of Bologna

**iCaRL: Incremental Classifier and Representation Learning**

Sylvestre-Alvise Rebuffi, University of Oxford/IST Austria
Alexander Kolesnikov, Georg Sperl, Christoph H. Lampert, IST Austria

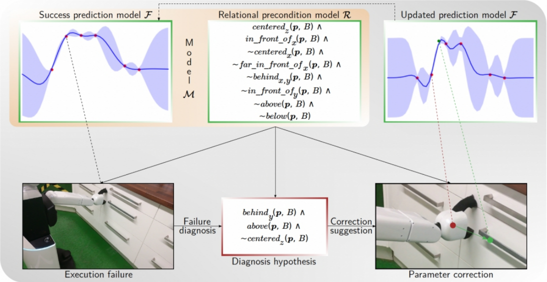
Master's Thesis

**Lifelong Action Learning for Socially Assistive Robots**

*Hasnainali Walli*

# Motivating Problem 1: Lifelong Skill Learning

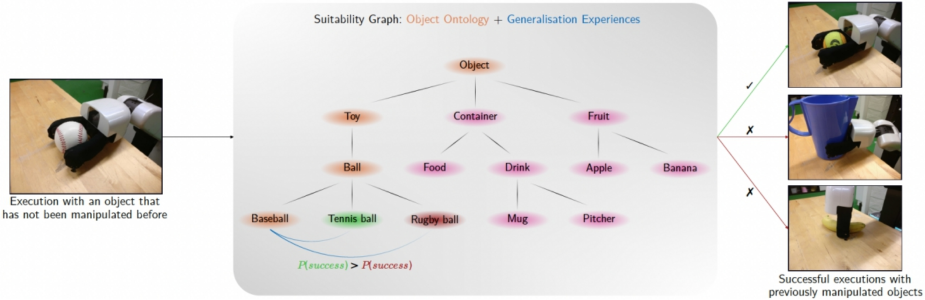
- An essential ability of a cognitive robot is to improve its skills based on new experiences as well as to acquire new skills
- Particularly in the case of execution failures, **a robot should be able to learn from the failure experience** so that it is less likely that it will repeat it again
- **Skill representations should thus have an inbuilt mechanism that enables lifelong skill learning**




A. Mitrevski, "Skill Generalisation and Experience Acquisition for Predicting and Avoiding Execution Failures," *Ph.D. dissertation*, Department of Computer Science, RWTH Aachen University, 2023. Available: https://publications.rwth-aachen.de/record/943042

# Motivating Problem 2: Lifelong Object Learning

- When learning object-centric manipulation skills, a robot will encounter a certain number of objects at training time, but **may need to interact with other — previously unseen — objects during its operation**
- Lifelong learning should thus enable a robot to:
  - **recognise new objects**
  - **learn how to handle those objects correctly** (e.g. by learning object interaction models)




A. Mitrevski, P. G. Plöger, and G. Lakemeyer, "A Hybrid Skill Parameterisation Model Combining Symbolic and Subsymbolic Elements for Introspective Robots," *Robotics and Autonomous Systems*, vol. 161, p. 104350:1–22, Mar. 2023. Available: https://doi.org/10.1016/j.robot.2022.104350

# Motivating Problem 3: Lifelong Learning for Action Recognition

- In robot-assisted therapy and education, the ability to recognise the actions performed by the person under therapy can help a robot adapt its behaviour or suggest corrective exercises
- Lifelong learning for action recognition is particularly useful **if therapists want to include new actions that the robot should recognise** — in this case, the system should be able to:
  - **Incorporate new actions over time** (not all actions are known at the initial training time)
  - **Learn from a few examples** (e.g. from therapist demonstrations)

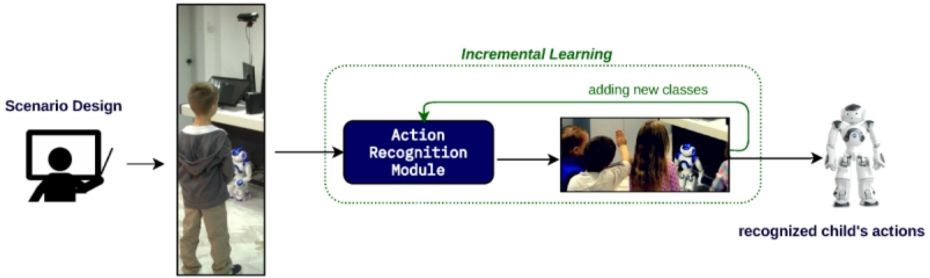
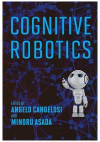
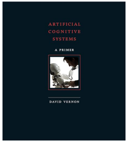


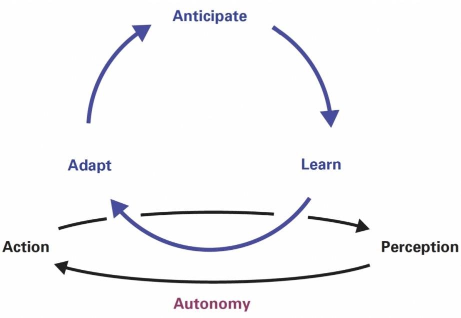

Diagram adapted from N. Efthymiou, P. P. Filntisis, G. Potamianos, and P. Maragos, "Visual Robotic Perception System with Incremental Learning for Child–Robot Interaction Scenarios," *Technologies*, vol. 9, no. 86, Nov. 2021. Available: https://doi.org/10.3390/technologies9040086

# Overview of Robot Lifelong Learning

# Lifelong Learning for Cognitive Robots

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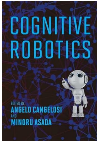


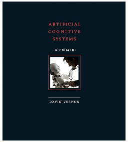


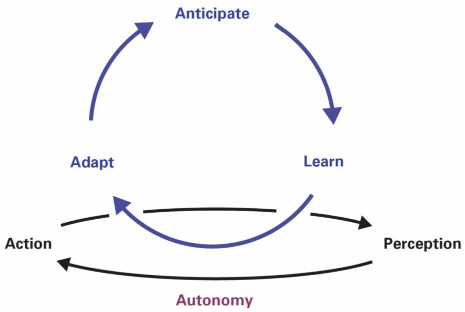


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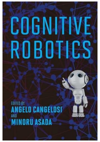


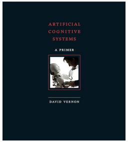


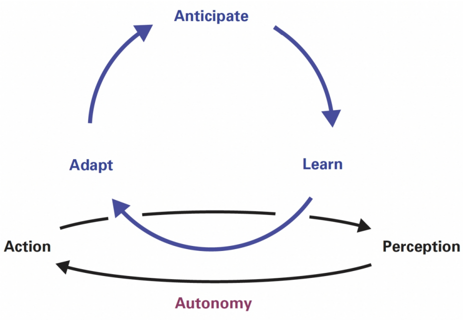


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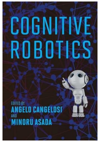


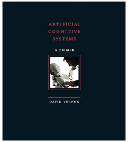


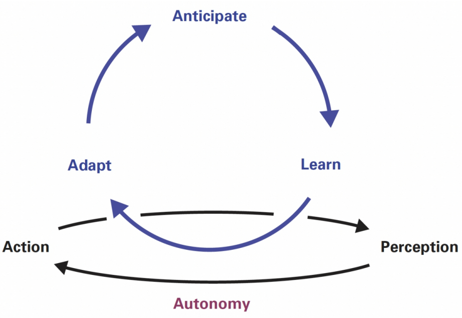


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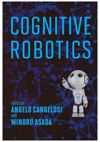


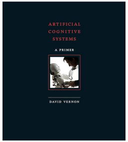


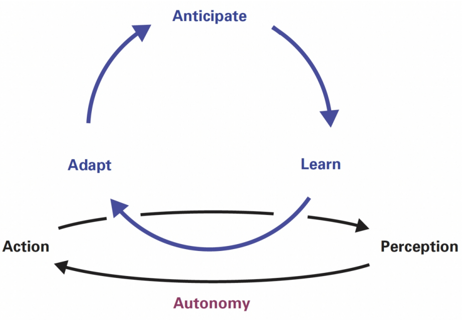


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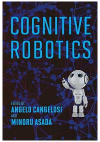


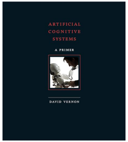


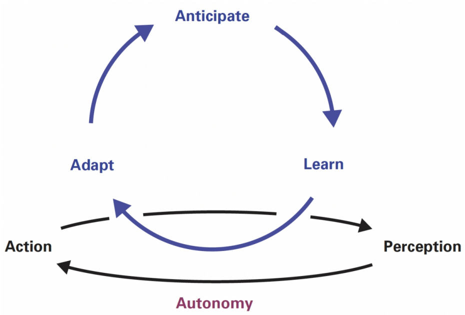


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- Note: **Lifelong learning is often synonymously called continual learning or incremental learning**

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  - **CLARION** performs both top-down and bottom-up learning for its explicit and implicit components, respectively
- Caveat: In the context of the architectures, learning is often only considered at a conceptual level, so it is not always clear how to implement specific types of learning practically

# Why is Lifelong Learning Difficult?

Continual Learning for Robotics: Definition, Framework, Learning Strategies, Opportunities and Challenges

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**Data privacy**

Lifelong learning requires continuous data collection, which is a tricky aspect from a privacy point of view; in addition, users should be able to request data about themselves to be removed from the system (in Europe, we have the GDPR), but it is unclear how to do this in emergent systems (knowledge is distributed along the system)

# Related Learning Paradigms



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**Online / one-shot learning**

Leaning from a single example (can be done in the context of lifelong learning)

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- The difference with lifelong learning is that curriculum learning really only cares about the last task, while lifelong learning cares about all of them

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**Active learning**

See the previous lecture (can be used in lifelong learning)

# Lifelong Learning Strategies



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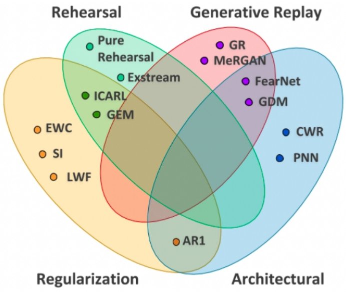

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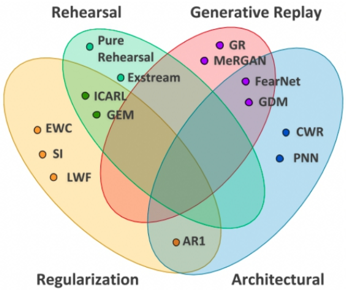


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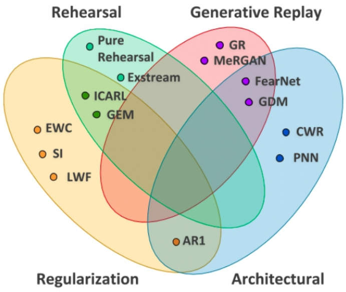


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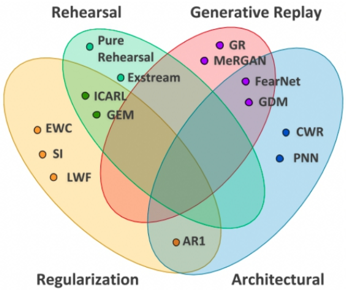


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Continual Learning for Robotics: Definition, Framework, Learning Strategies, Opportunities and Challenges

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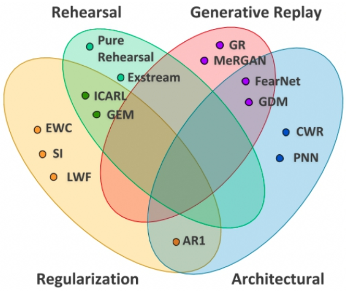


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- **Generative replay**: Related to rehearsal, but instead of keeping old data explicitly, a generative data model is trained instead so that experiences can be sampled from the data distribution

# Class Incremental Learning — Particularly for Neural Networks

# Class Incremental Learning

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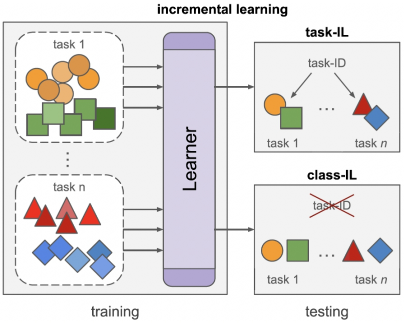


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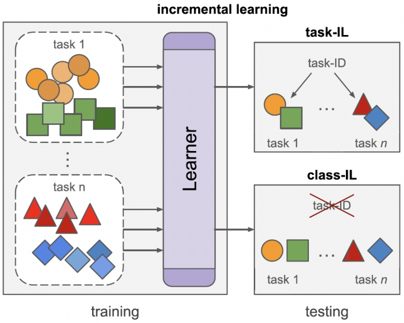


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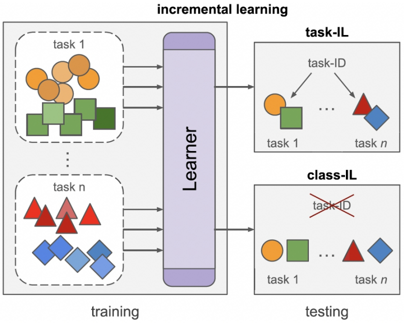


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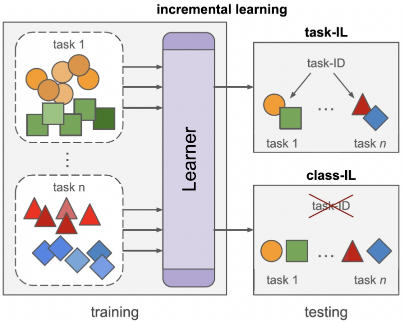


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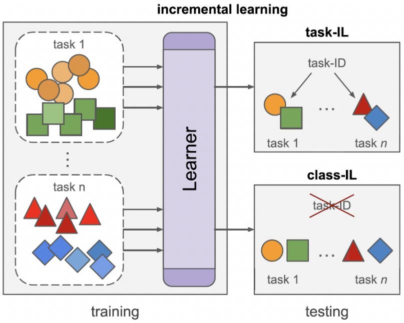


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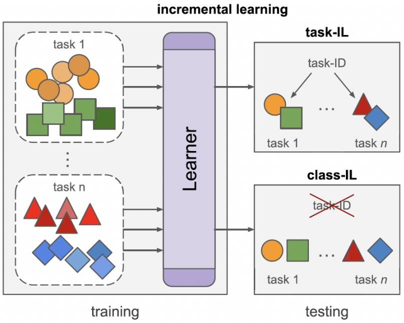


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  - **Class-IL (task-agnostic)**: The ID of the task is unknown (practically a more realistic case)

# Class Incremental Learning Formulation


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- Problem: **The tasks are not all known at the initial training time**

# Incremental Learning Metrics

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- To measure the incremental learning performance, one common measure is the **average accuracy over the tasks**

$$A_t = \frac{1}{t}\sum_{i=1}^{t} a_{t,i}$$

where $a_{t,k}$ is the accuracy of task $k$ once task $t$ has been learned

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- Another useful metric is the **average forgetting**, which measures how much the accuracy of a task reduces after learning task $t$:

$$F_t = \frac{1}{t-1} \sum_{i=1}^{t-1} f_{t,i}$$

where the forgetting for task $k$ is defined as:

$$f_{t,k} = \max_{j \in \{1,\ldots,t-1\}} a_{j,k} - a_{t,k}$$

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- As new tasks arrive, the network can be retrained with the cross-entropy loss function

$$\mathcal{L}_c(\boldsymbol{x}, \boldsymbol{y}, \boldsymbol{\theta}^t) = \sum_{k=1}^{N} y_k \log \frac{\exp\left(\boldsymbol{o}_k\right)}{\sum_{i=1}^{N^t} \exp\left(\boldsymbol{o}_i\right)}$$

  where $N^t$ is the number of all classes up to and including task $t$

# Incremental Learning Challenges

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There are various challenges in incremental learning that can lead to catastrophic forgetting, (i.e. reduced performance on previously learned tasks), particularly for neural networks:

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The weights need to be updated every time a new task is added to the system; this can lead to **weights that are unfavourable to old tasks**

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## Task-recency bias

Due to intensive training on the most recent task, **a network may be biased towards newly added classes**

# Strategies to Overcome the Challenges

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## Bias correction

Aims to prevent bias towards new tasks, for instance by **using a different model for classification (not the network itself)** or by **introducing an extra training step to remedy the bias of the network predictions**

# Incremental Learning Algorithms Overview

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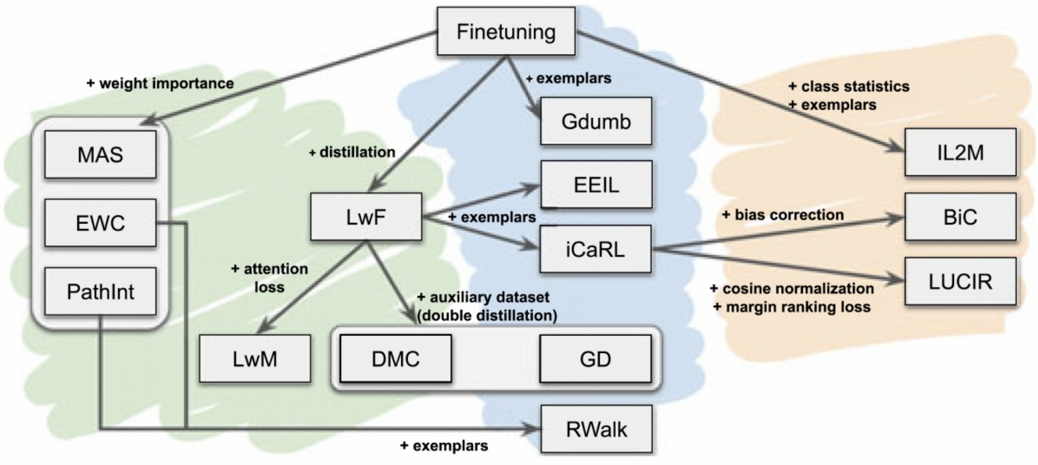
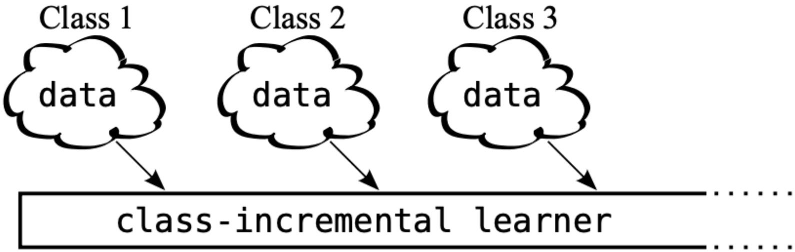


# Class Incremental Learning Algorithm Example: iCaRL

# iCaRL



- iCaRL (incremental classifier and representation learning) is a class incremental learning method for neural network-based classifiers, published at CVPR in 2017 (in machine learning time, that is a whole eternity)
- The method illustrates the techniques for overcoming the challenges of incremental learning — rehearsal, regularisation, and bias correction are all incorporated in iCaRL
- We will look at iCaRL in some detail on the next few slides



# Exemplar Set in iCaRL

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University of Oxford/IST Austria

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  - Can be detrimental when many classes are learned, as there will only be a few exemplars per class in this case; growing memory can perform better

# Exemplar Set in iCaRL

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**Algorithm 4** iCaRL ConstructExemplarSet

**input** image set $X = \{x_1, \dots, x_n\}$ of class $y$
**input** $m$ target number of exemplars
**require** current feature function $\varphi : \mathcal{X} \to \mathbb{R}^d$
  $\mu \leftarrow \frac{1}{n} \sum_{x \in X} \varphi(x)$ // current class mean
  **for** $k = 1, \dots, m$ **do**
    $p_k \leftarrow \operatorname*{argmin}_{x \in X} \left\| \mu - \frac{1}{k}[\varphi(x) + \sum_{j=1}^{k-1} \varphi(p_j)] \right\|$
  **end for**
  $P \leftarrow (p_1, \dots, p_m)$
**output** exemplar set $P$

**Algorithm 5** iCaRL ReduceExemplarSet

**input** $m$ // target number of exemplars
**input** $P = (p_1, \dots, p_{|P|})$ // current exemplar set
  $P \leftarrow (p_1, \dots, p_m)$ // *i.e.* keep only first $m$
**output** exemplar set $P$

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**Algorithm 2** iCaRL INCREMENTALTRAIN

**input** $X^s, \dots, X^t$ // training examples in per-class sets
**input** $K$ // memory size
**require** $\Theta$ // current model parameters
**require** $\mathcal{P} = (P_1, \dots, P_{s-1})$ // current exemplar sets
  $\Theta \leftarrow$ UPDATEREPRESENTATION($X^s, \dots, X^t; \mathcal{P}, \Theta$)
  $m \leftarrow K/t$ // number of exemplars per class
  **for** $y = 1, \dots, s-1$ **do**
    $P_y \leftarrow$ REDUCEEXEMPLARSET($P_y, m$)
  **end for**
  **for** $y = s, \dots, t$ **do**
    $P_y \leftarrow$ CONSTRUCTEXEMPLARSET($X_y, m, \Theta$)
  **end for**
  $\mathcal{P} \leftarrow (P_1, \dots, P_t)$ // new exemplar sets

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**Algorithm 3** iCaRL UPDATEREPRESENTATION

**input** $X^s, \dots, X^t$ // training images of classes $s, \dots, t$
**require** $\mathcal{P} = (P_1, \dots, P_{s-1})$ // exemplar sets
**require** $\Theta$ // current model parameters
// form combined training set:

$$\mathcal{D} \leftarrow \bigcup_{y=s,\dots,t} \{(x,y) : x \in X^y\} \cup \bigcup_{y=1,\dots,s-1} \{(x,y) : x \in P^y\}$$

// store network outputs with pre-update parameters:
**for** $y = 1, \dots, s-1$ **do**
  $q_i^y \leftarrow g_y(x_i)$ for all $(x_i, \cdot) \in \mathcal{D}$
**end for**
run network training (*e.g.* BackProp) with loss function

$$\ell(\Theta) = -\sum_{(x_i,y_i)\in\mathcal{D}} \Big[ \sum_{y=s}^{t} \delta_{y=y_i} \log g_y(x_i) + \delta_{y\neq y_i} \log(1-g_y(x_i)) + \sum_{y=1}^{s-1} q_i^y \log g_y(x_i) + (1-q_i^y)\log(1-g_y(x_i)) \Big]$$

that consists of *classification* and *distillation* terms.

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**Algorithm 1** iCaRL CLASSIFY

**input** $x$ // image to be classified
**require** $\mathcal{P} = (P_1, \ldots, P_t)$ // class exemplar sets
**require** $\varphi : \mathcal{X} \to \mathbb{R}^d$ // feature map
  **for** $y = 1, \ldots, t$ **do**
    $\mu_y \leftarrow \frac{1}{|P_y|} \sum_{p \in P_y} \varphi(p)$ // mean-of-exemplars
  **end for**
  $y^* \leftarrow \operatorname*{argmin}_{y=1,\ldots,t} \|\varphi(x) - \mu_y\|$ // nearest prototype
**output** class label $y^*$

# iCaRL Performance



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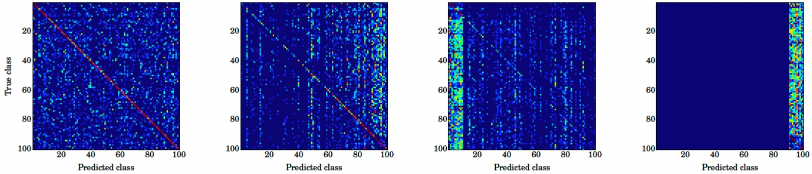


(a) iCaRL (b) LwF.MC (c) fixed representation (d) finetuning

- Here, we can see confusion matrices of iCaRL and a few other methods (Learning without Forgetting — another incremental learning algorithm — a model that uses a fixed latent representation, and one that simply performs finetuning on the new classes)
  - The evaluation is on the CIFAR-100 dataset with each task consisting of 10 classes
- iCaRL's confusion matrix is distributed among the classes, which means that the algorithm did not exhibit concrete biases (towards old or new classes)
- It should be noted that various newer algorithms, which are improved versions of iCaRL, have been published in the last few years

# Use Case: Lifelong Learning for Action Recognition

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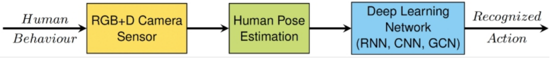
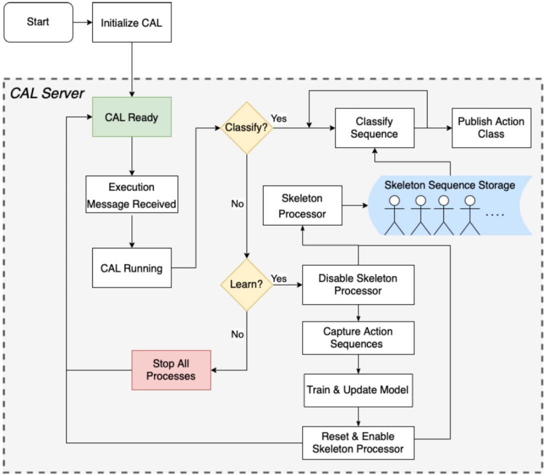
- In a completed master's thesis in this context, we investigated various action recognition models on publicly available datasets and then evaluated lifelong learning algorithms for action recognition
- We then performed a real-user evaluation in which multiple people demonstrated different actions to our QTrobot; these were then incorporated into an action recognition model
- A graph convolutional neural network was used for recognition (CTR-GCN) and BiC as a lifelong learning method (BiC is based on iCaRL, but performs bias correction by introducing a second training step for this purpose)

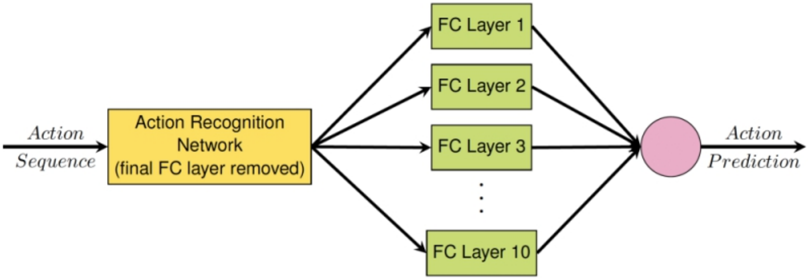
# System Overview




- **Skeleton data** are collected with QTrobot
- The action recognition model processes a **skeleton sequence** to recognise actions
- If desired, new actions can be **demonstrated and integrated into the recognition system**



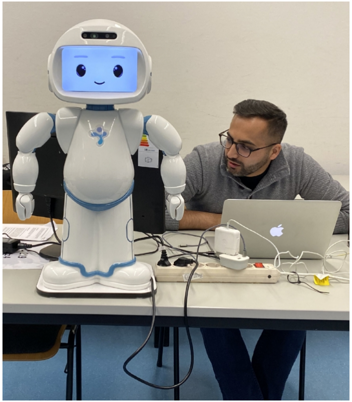
# Sample Model and Tasks




| Task | Actions in each task |
|---|---|
| 1 | Wipe<br>Eat |
| 2 | Cross hands<br>Clap |
| 3 | Step on something<br>Shake head |
| 4 | Sit down<br>Play on phone |
| 5 | Lift something<br>Brush teeth |
| 6 | Throw<br>Point at something |
| 7 | Wave<br>Stand up |
| 8 | Nod<br>Hop |
| 9 | Drop something<br>Drink water |
| 10 | Rub hands<br>Jump |

# Experiment Setup

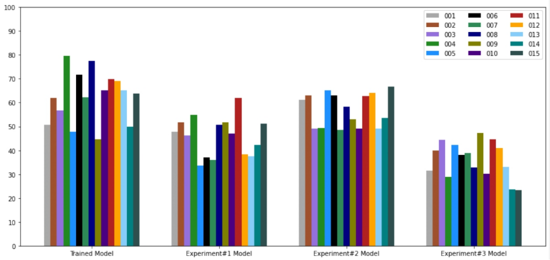
- In our evaluation with QTrobot, we had 15 participants
- The evaluation study involved two steps:
  1. **Actions were recognised using a pretrained baseline model**
  2. **Data for lifelong learning were collected** (two new actions) **and then actions were recognised using the new model** (three different models were learned)
- **Actions to recognise**: Play with phone, hop, rub hands, wave, shake head, drink water
- **Actions to learn**: Talk on the phone, cut food, wave, hop (the last two were finetuned with the new data)



# Evaluation Results

The diagram here shows the results of our evaluation (recognition accuracy per participant)

1. **Trained model**: The pretrained model
2. **Experiment#1 model**: New actions (cut food and talk on the phone) were integrated as a new task
3. **Experiment#2 model**: Hop and wave were retrained with the new data
4. **Experiment#3 model**: Cut food was added to an old task, while talk on the phone was added as a new task




Evaluation results per test user

The results clearly show a decrease in accuracy when adding new knowledge — particularly in the case where an old task is modified (indicating lack of robustness of the methods)

# Summary: Lifelong Learning

- Lifelong learning (aka incremental or continual learning) is a paradigm in which new knowledge is integrated into a learning-based model over time rather than all at once
- There are various ways in which lifelong learning can be achieved, such as by performing architectural changes, using regularisation, by performing rehearsal, or by generative replay
- Class incremental learning is an instance of the lifelong learning problem in which new classes are integrated into a classifier, such that there are two instances of the problem: task-aware and task-agnostic incremental learning
- iCaRL is one of the older class incremental learning algorithms that uses a combination of techniques to solve the problem, namely rehearsal (using exemplars), regularisation (through the learning loss), and bias correction (by performing classification using the nearest-mean-of-exemplars)
- Lifelong learning is associated with various challenges: it requires a suitable representation that is prone to being updated, but there are also problems related to data forgetting and privacy, data distribution shifts and new data demands, and changes in the optimisation objective