# Class-incremental Learning with Regular Polytope Networks

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## Motivation

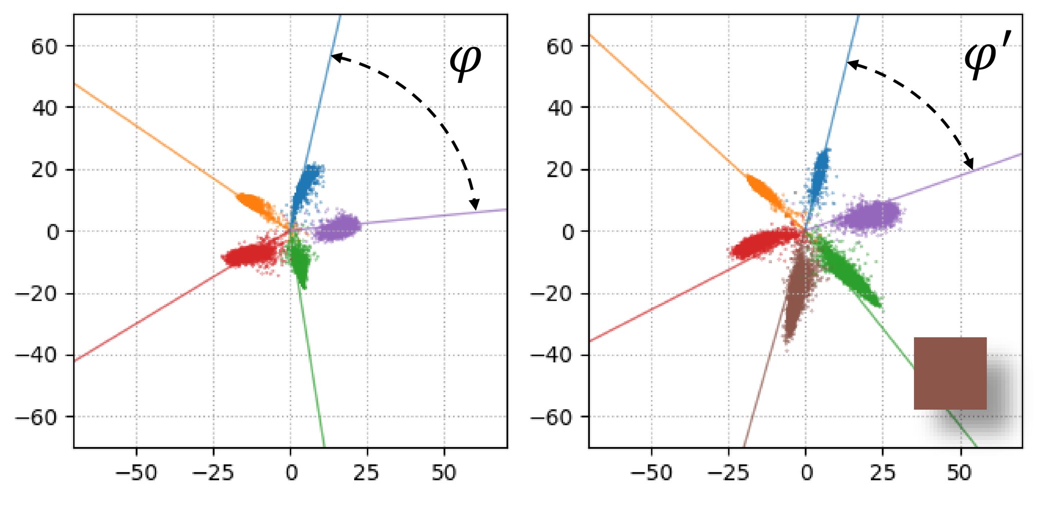
We are interested in **learning features** that keep **stationary** while **learning** novel classes **incrementally**.

*Practical advantages:*

- Features can be used interchangeably in time,
- Visual search systems avoid re-computing features in the gallery when updating the model

Along a similar vein, [Yantao et al. CVPR2020] introduces feature back-compatibility

**Incremental Learning of a New Class**
(2D internal feature representation on MNIST dataset)

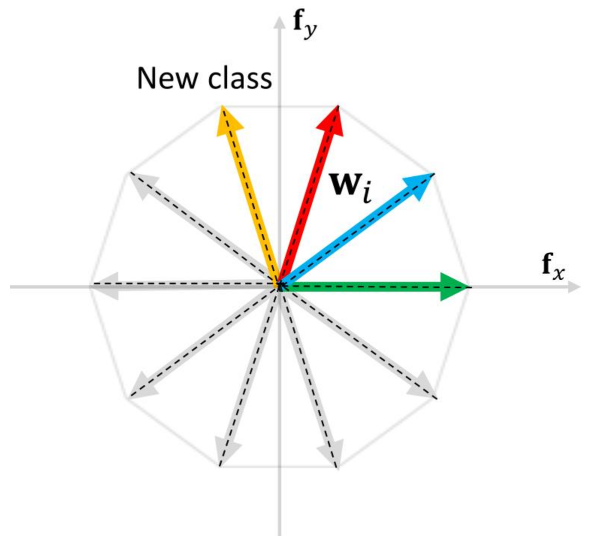


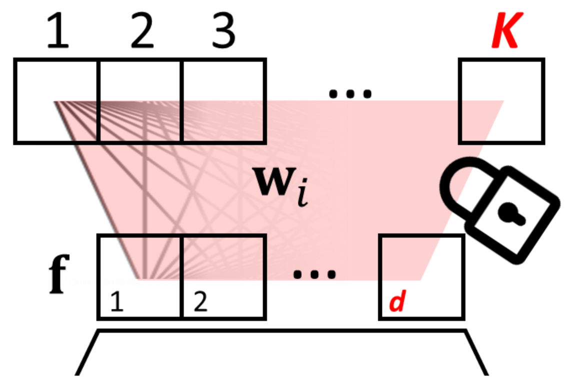

- A **new class** (brown) is incorporated into the model
- The **angle** between feature classes **changes** (i.e., $\varphi \neq \varphi'$)
  - The feature embedding changes

## How to fix the Classifier?

**Classifier values** are taken from the coordinate vertices of **Regular Polytopes**. [Pernici et al. arXiv 2019]

- High dimensional Platonic Solids
- In 2D, regular n-sided polygon

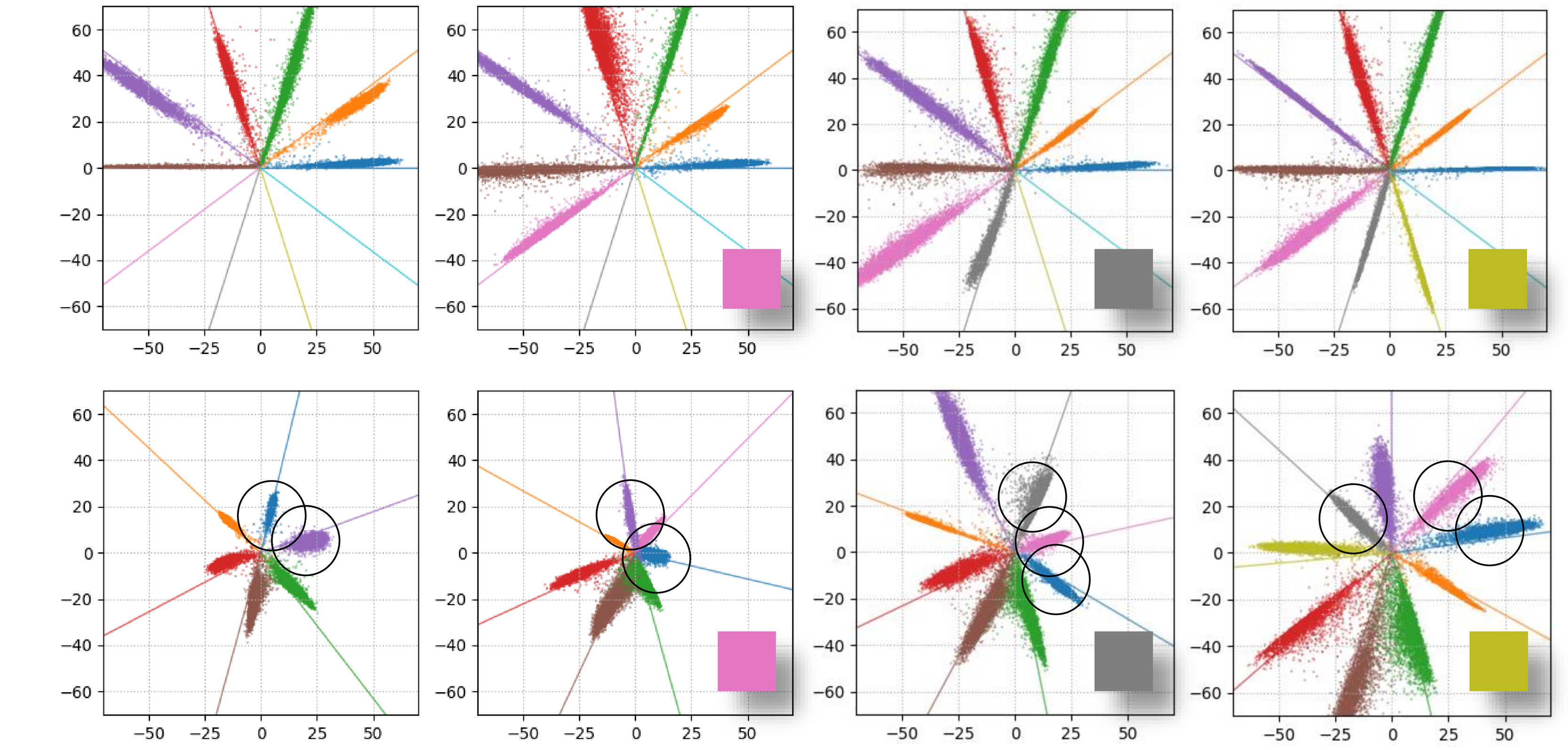



**Fixed** and **learnable** classifiers have shown to achieve the **same classification accuracy** [Hoffer et al. ICLR2018]

## Experiments

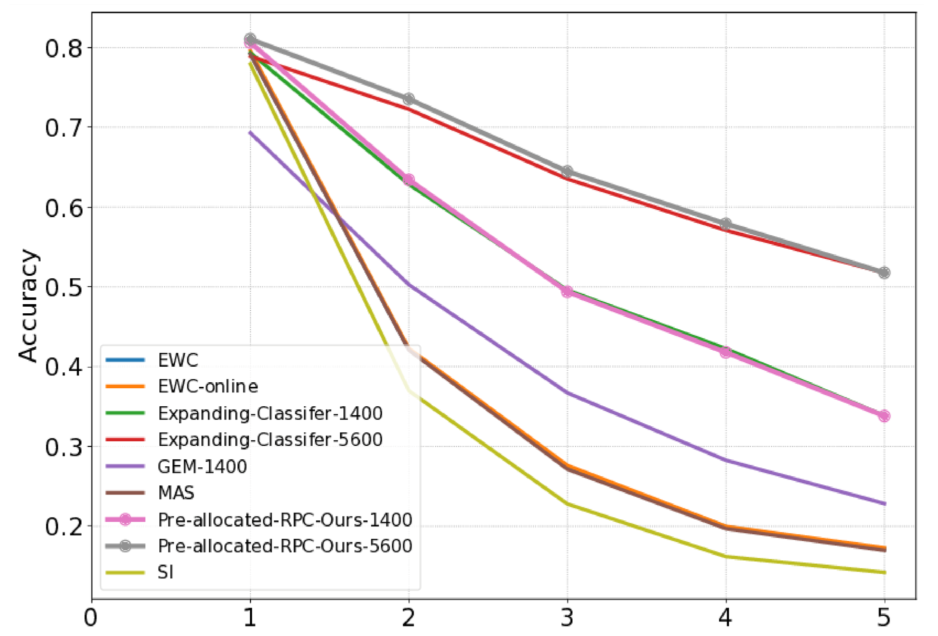
**MNIST (LeNet++ architecture, 2D feature dimension)**



novel learned class **significantly** and **unpredictably** changes the geometric configuration of already learned features

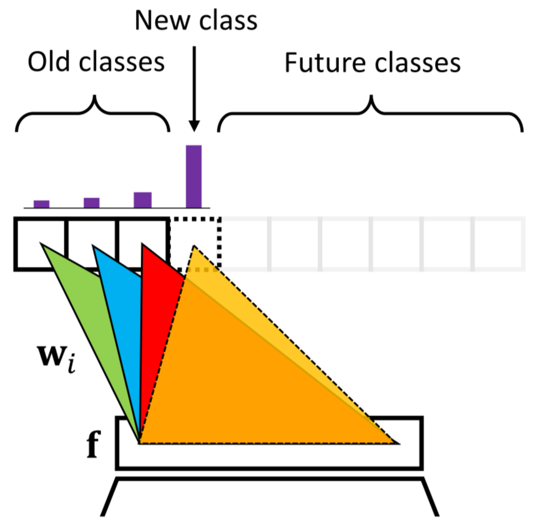
**SPLIT-CIFAR100 (avg accuracy as new tasks are incrementally learned)**

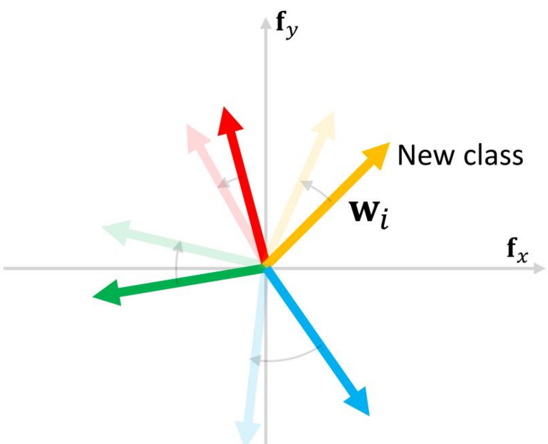
| Method | $\lvert\mathcal{M}\rvert$ | SplitCIFAR100 |
|---|---|---|
| EWC | - | $17.17 \pm 0.12$ |
| Online-EWC | - | $17.29 \pm 0.06$ |
| SI | - | $14.21 \pm 0.29$ |
| MAS | - | $16.97 \pm 0.05$ |
| GEM | 1400 | $22.83 \pm 2.17$ |
| GEM | 5600 | N.A. |
| Expanding Classifer | 1400 | $33.79 \pm 0.56$ |
| Expanding Classifer | 5600 | $51.76 \pm 0.55$ |
| Pre-allocated RPC (Ours) | 1400 | $33.80 \pm 0.42$ |
| Pre-allocated RPC (Ours) | 5600 | $51.77 \pm 0.61$ |




## Class-Incremental Learning and Feature Representation

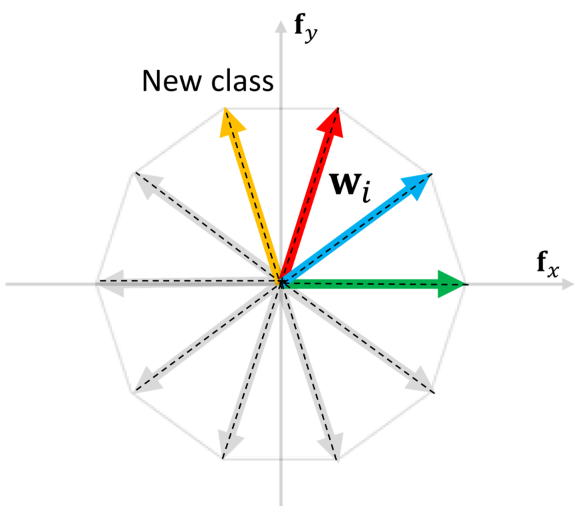
**Class incremental Learning:** training a single model on a sequence of disjoint classification problems without forgetting how to solve the previous ones.




Even assuming no catastrophic forgetting, internal **feature** representation **changes** as **new classes** are incorporated into the learning model.

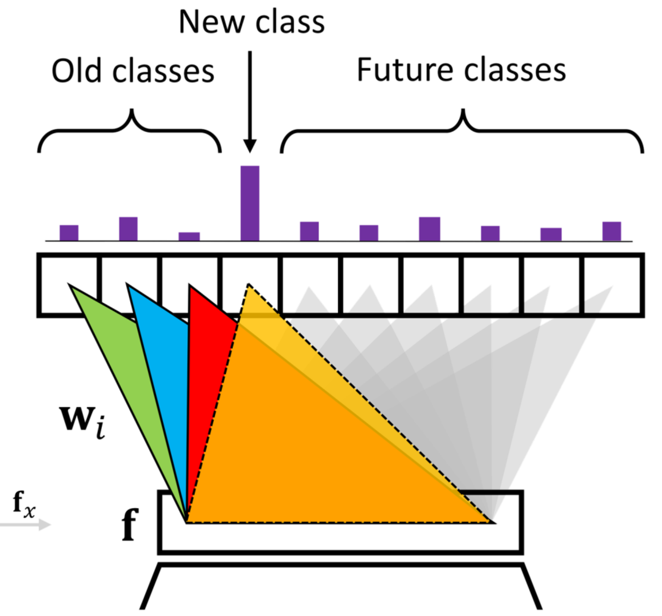
We propose a pre-allocated **fixed** classifier (i.e., **not undergoing learning**).
This keeps the **features** in a **constant specific spatial configuration** as novel classes are incorporated into the learning model.

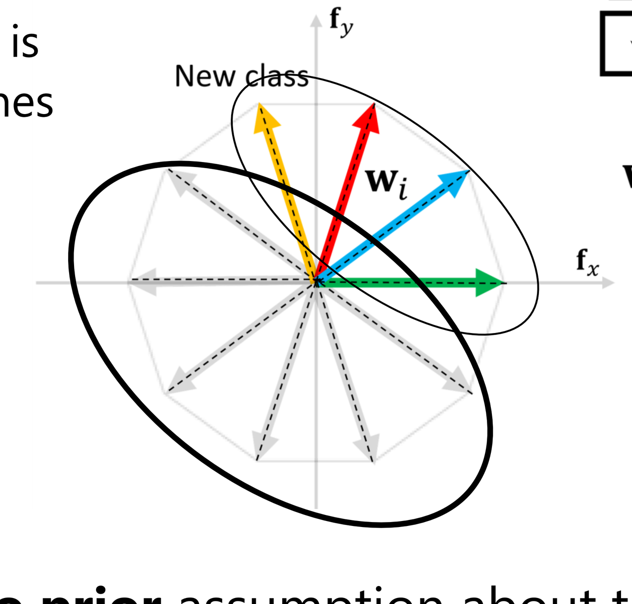


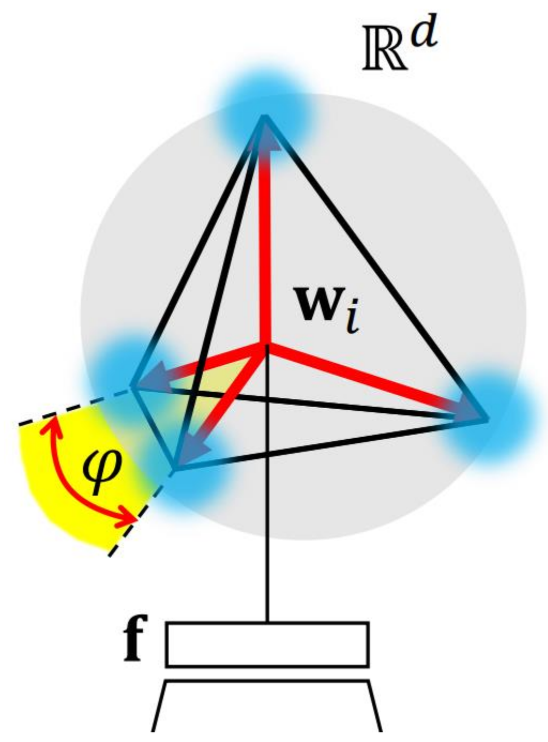

## Class Pre-allocation

Pre-allocation of the output nodes of future unseen classes allows to see **negative samples** since the **beginning** of learning.

- The space of unseen classes is not occupied by the seen ones




As **no prior** assumption about the **semantic similarity** between future classes can be made, the natural assumption is to consider the ***d*-Simplex fixed classifier**

- all classes are nearest to all others (i.e., same cosine distance $\varphi$).

## References


[Yantao et al. CVPR2020] Yantao Shen, Yuanjun Xiong, Wei Xia, and Stefano Soatto - *Towards Backward-Compatible Representation Learning* CVPR 2020

[Pernici et al. arXiv 2019] Federico Pernici, Matteo Bruni, Claudio Baecchi, Alberto Del Bimbo *Fix Your Features: Stationary and Maximally Discriminative Embeddings using Regular Polytope (Fixed Classifier) Networks, arXiv* https://arxiv.org/abs/1902.10441

[Hoffer et al. ICLR2018] Elad Hoffer, Itay Hubara, Daniel Soudry - *Fix your classifier: the marginal value of training the last weight layer* - ICLR 2018