

Increasingly Packing Multiple Facial-Informatics Modules in A Unified Deep-Learning Model via Lifelong Learning

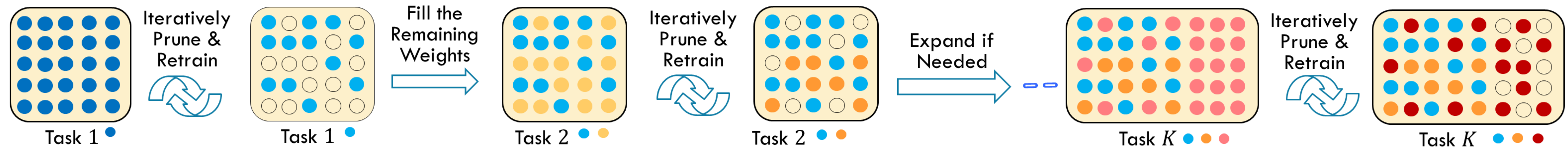


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Motivation and Contribution

We leverage network compression and expansion to integrate multiple facial-informatics modules into a unified and compact deep-learning model.

Motivation

- Biologically, when learning new things, we often apply the related knowledge we have acquired before. Because of the overlapping knowledge between related tasks, functionality integration can help save memory in an end-to-end system.

Contribution

- Packing-and-expanding (PAE), a continual learning approach that helps learn new tasks without forgetting while maintaining the compactness of the model.
- We technically demonstrate our integrated multitask model can achieve similar accuracy with only 39.9% of the original size.

Method Comparison

ProgressiveNet [1]

- ✓ Old-task weights are shared with the new ones but remain fixed.
- ✓ Only the new weights are adapted to preserve the performance for previous tasks.
- ✗ However, it might result in a redundant model.

PackNet [2]

- ✓ Compresses an old task by deleting neglectable weights
- ✓ The deleted weights are saved for packing the next task.
- ✗ However, the tasks to be packed would be limited.

PAE

- ✓ It yields a compact model without performance sacrifice.
- ✓ It makes model extensible for lifelong learning.
- ✓ It allows tasks themselves to integrate automatically.

[1] Andrei A Rusu, Neil C Rabinowitz, Guillaume Desjardins, Hubert Soyer, James Kirkpatrick, Koray Kavukcuoglu, Razvan Pascanu, and Raia Hadsell. 2016. Progressive neural networks. arXiv (2016).

[2] Arun Mallya and Svetlana Lazebnik. 2018. Packnet: Adding multiple tasks to a single network by iterative pruning. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition. 7765–7773.

Automatic Lifelong Training

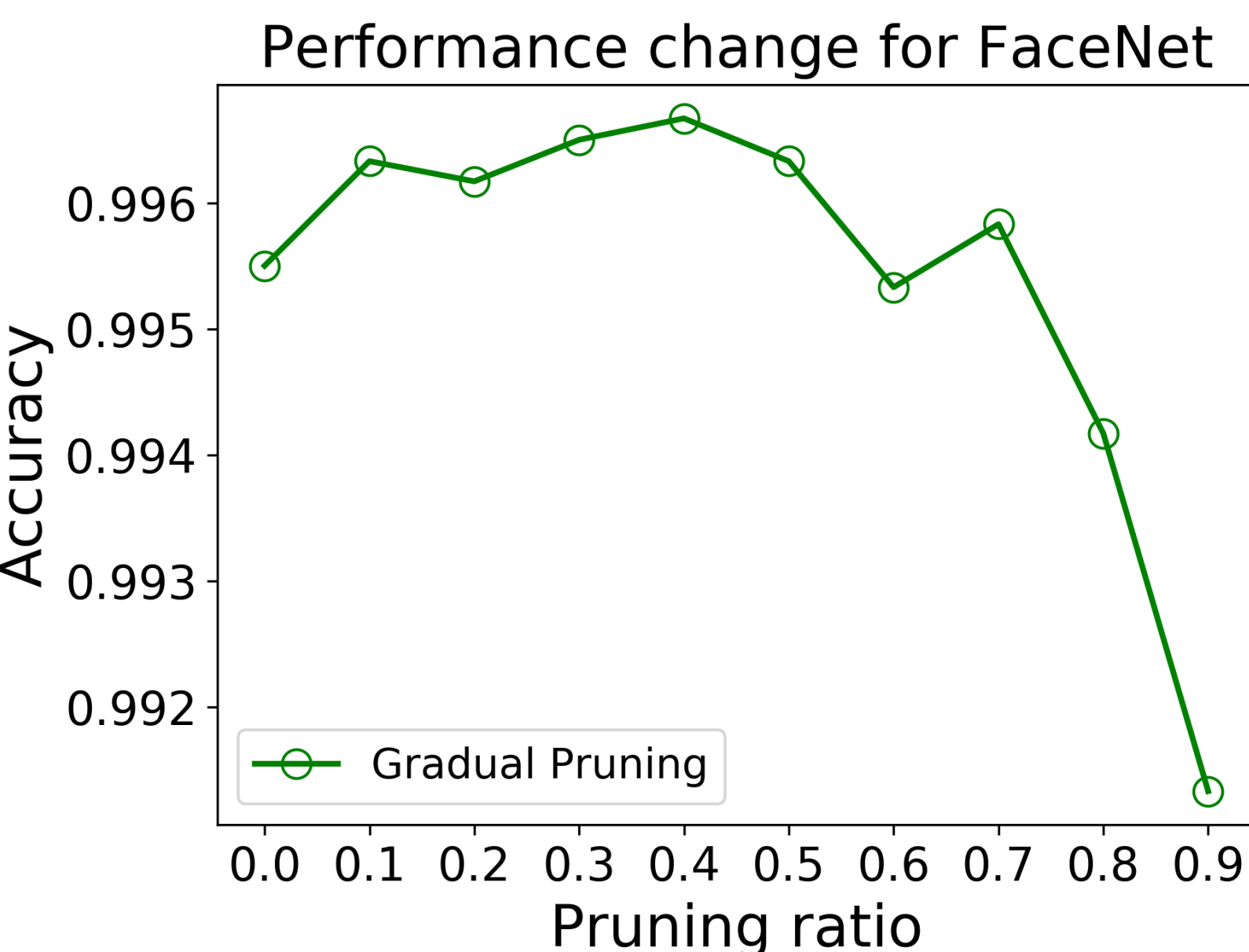
Expansion process

- If PAE detects that the validation accuracy of the new task does not as high as it should be in the individual network, which means the remaining capacity for the new task is not enough, then PAE will add filters or nodes in the model and resume the procedure.

Gradual pruning process

- PAE determines the pruning ratio by stopping at the turning point where it meets a pre-defined accuracy goal.

Gradual pruning and retraining



Gradual pruning

- stabilize the compacting process.

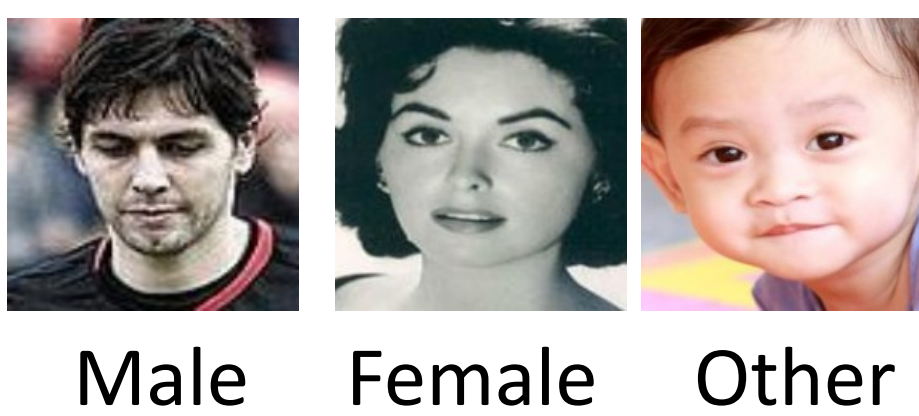
Instead of pruning weights one time to the pruning ratio goal, it removes a portion of the weights and retrain the model to restore the performance iteratively.

Data Description

Dataset:

- VGGFace2: face recognition, 8631 classes.
- AM-FED: emotion understanding, 7 classes.
- FotW: gender identification, 3 classes.
- Adience: age and gender, 8 classes and 2 classes.

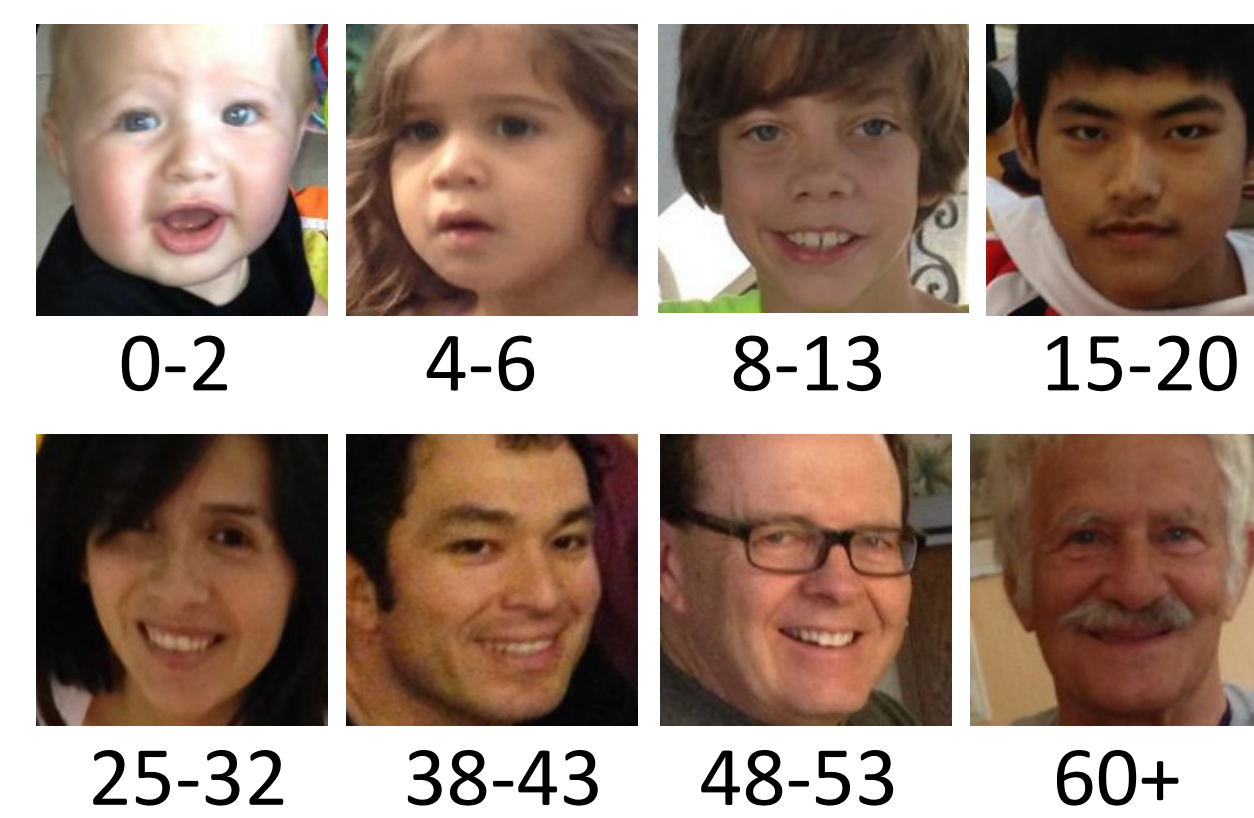
FotW



VGGFace2



Adience



AM-FED



Experiment and Result

PAENet (VGGFace2 -> Adience Age -> Adience Gender)

	Face	Age	Gender	Face Module	Age Module	Gender Module
	LFW Acc.(%)	Top-1 Avg. Acc.(%)	Top-1 Avg. Acc.(%)	Model Size (MB)	Model Size (MB)	Model Size (MB)
Levi_Hassner CNN	—	44.14	82.52	—	35.4	35.4
LMTCNN-2-1	—	44.26	85.16	—	30	
FaceNet	99.55	—	—	89.6	—	—
AgeNet	—	56.37	—	—	89.6	—
GenderNet	—	—	89.50	—	—	89.6
PAENet	99.67	57.30	89.08	68.9	15.3	13.6

PAENet (VGGFace2 -> AM-FED -> FotW Gender)

	Face	Expression	Gender	Model Size (MB)
	LFW Acc.(%)	Top-1 Acc.(%)	Top-1 Acc.(%)	
AffectNet	—	58	—	—
CAKE	—	61.7	—	—
SIAT MMLAB	—	—	92.69	—
FaceNet	99.55	—	—	89.6
EmotionNet	—	64.74	—	89.6
GenderNet	—	—	94.45	89.6
PAENet	99.67	65.29	92.93	107.3



Code

Conclusion

- Packing-and-expanding (PAE) is relatively simple but effective method for unforgetting lifelong learning.
- Though the tasks of facial informatics are tested in this work, our method can be applied to other lifelong learning tasks as well.