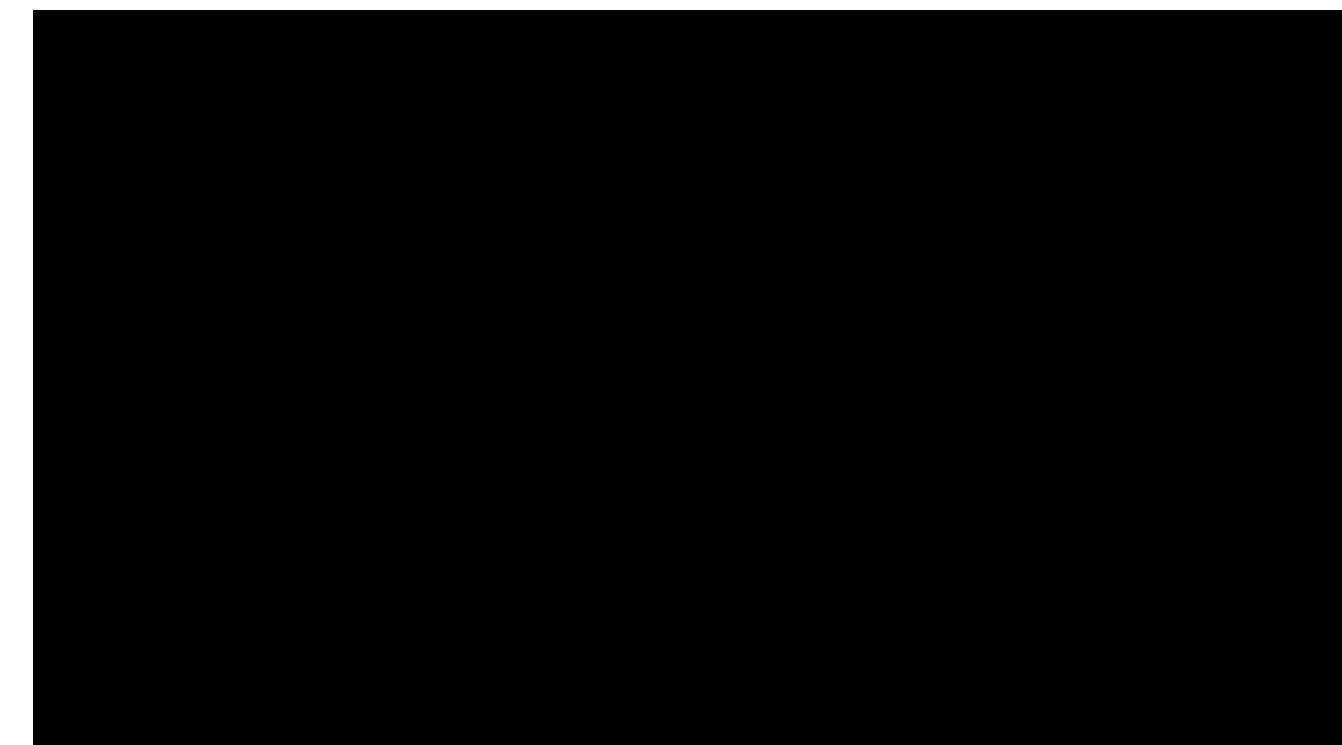


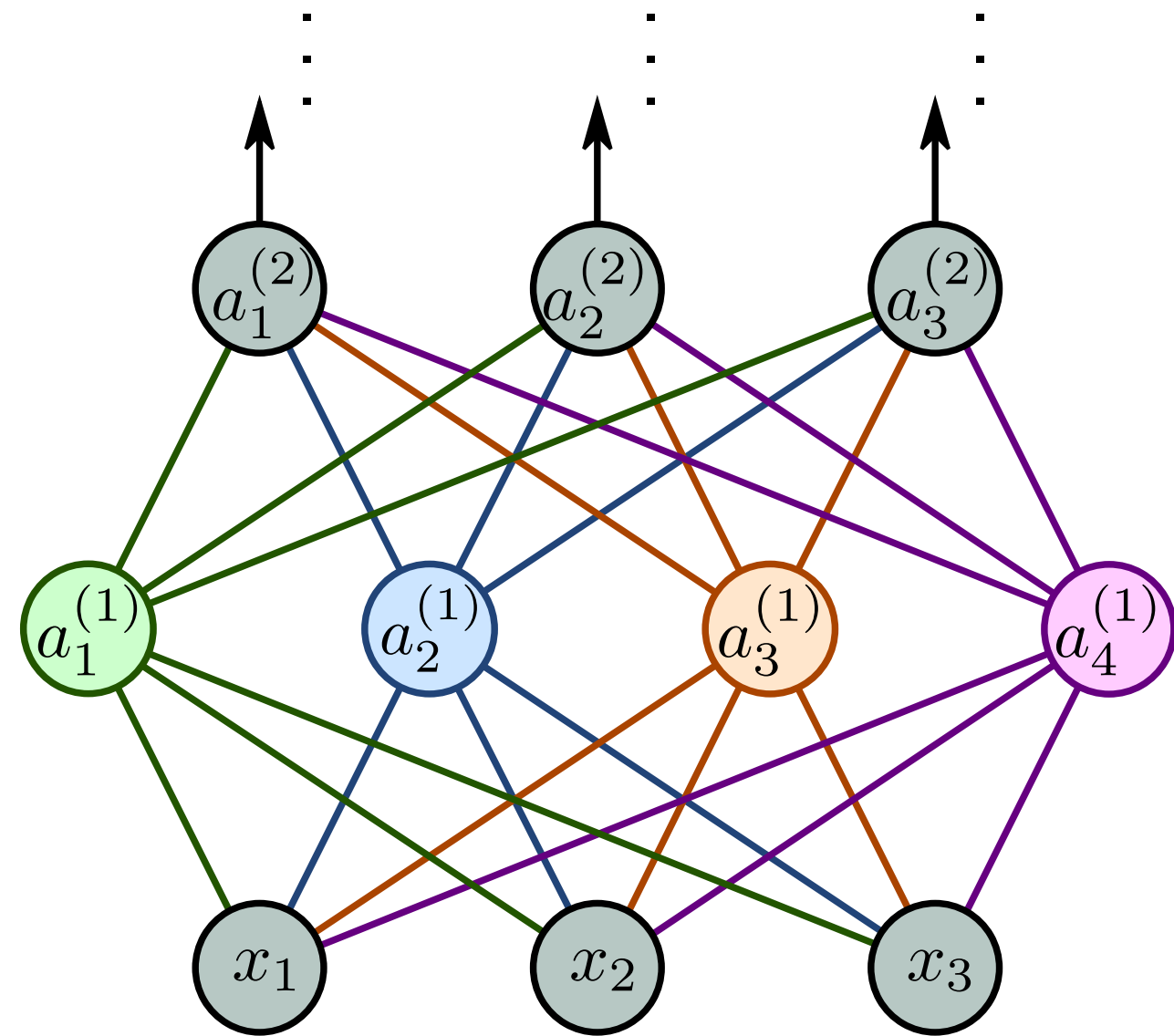
Correlated Weights in Infinite Limits of Deep Convolutional Neural Networks

**Adrià Garriga-Alonso
Mark van der Wilk**

Citations in the description below!



Bayesian neural network

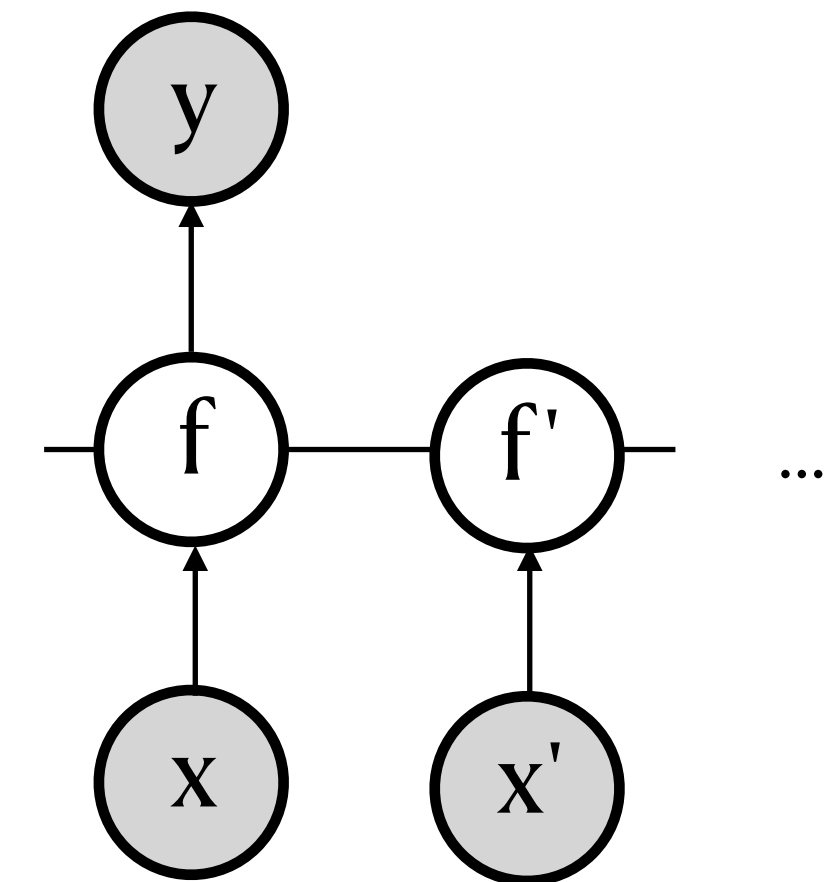


$\lim \text{width} \rightarrow \infty$

see e.g. Yang, 2019

First noted by Neal (1996)

Gaussian process



Bayesian neural network

- hard to infer posterior

- + Learns feature functions from data

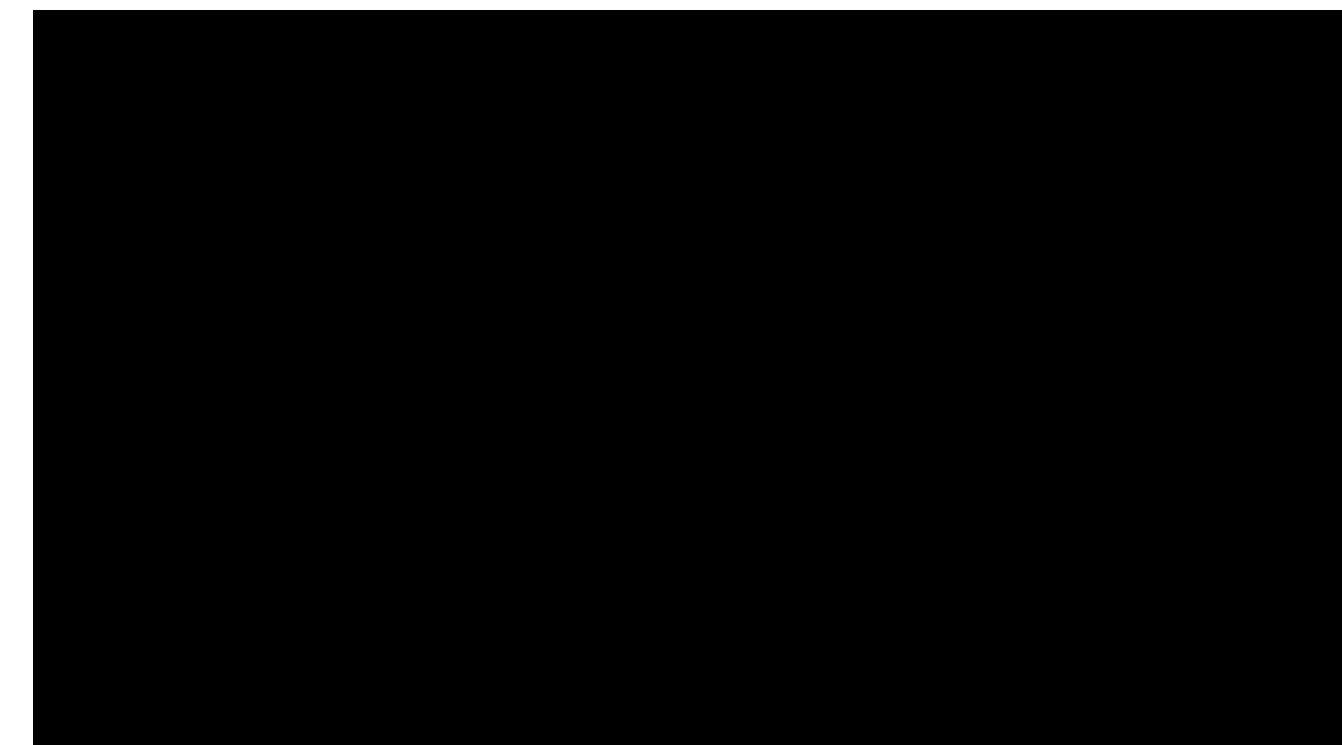
Gaussian process

- + Easy to infer posterior

- Feature functions fixed (by the kernel function of the GP)

Can GPs really replace NNs?

Have we thrown the baby out with the bathwater?



Bayesian **convolutional** neural network

- The same function is applied to all patches of the image
- The output of different patches in different locations is correlated

Gaussian process

- A different (random) function is applied to each patch
- The activation for different patches is uncorrelated and independent

The infinite limit of mean-pooling restores the importance of these correlations,
But for Bayesian CNNs, these correlations matter even without pooling

Can we keep them in the infinite limit without changing the architecture?

Yes!

spatial correlation in the weights



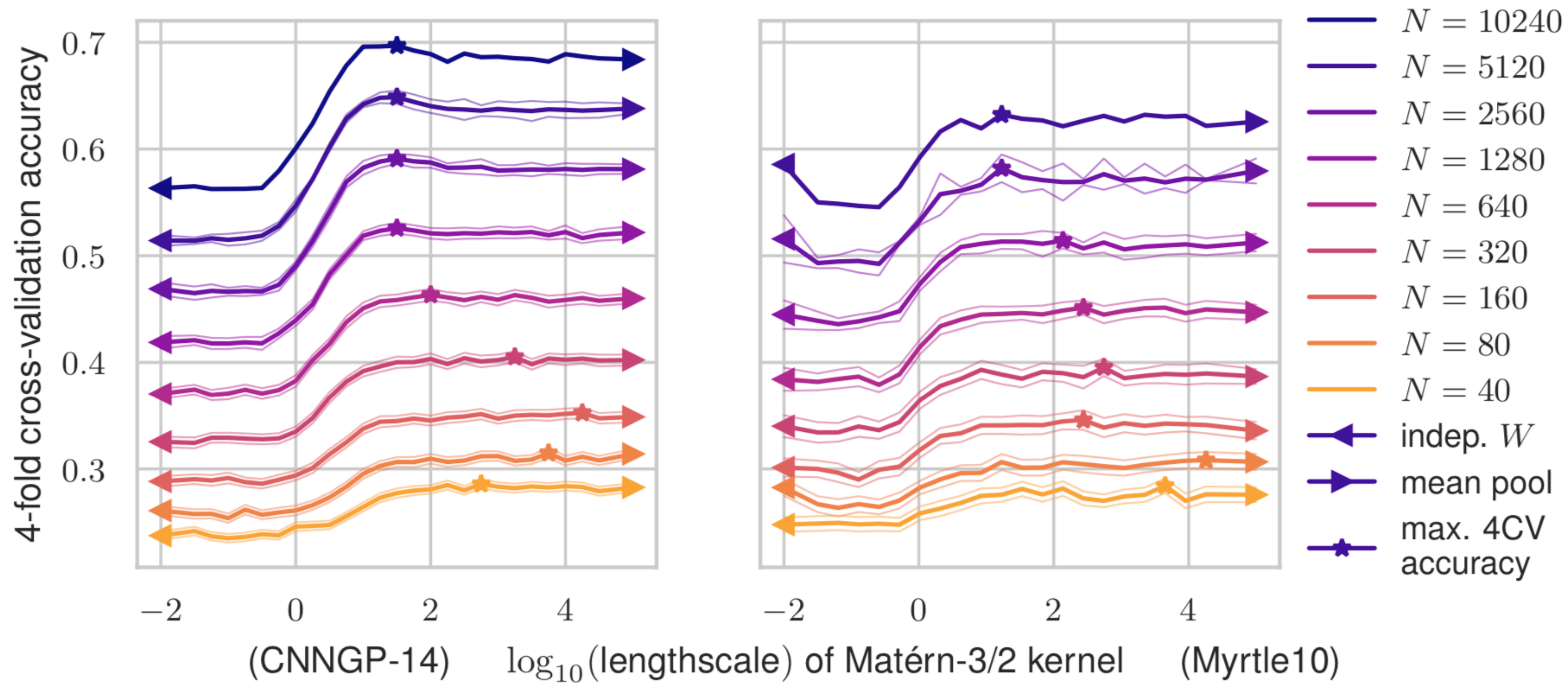
spatial correlation
between patches in the
infinite limit

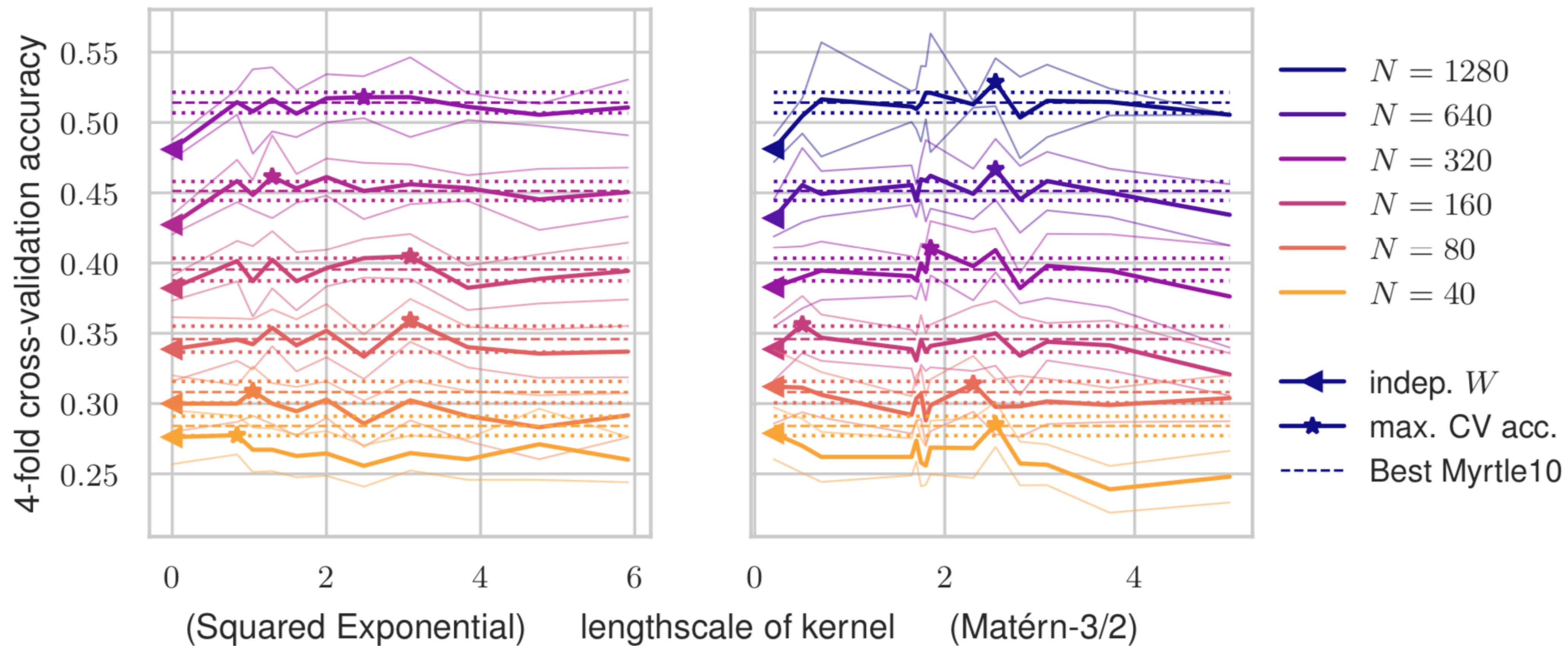
d-dimensional convolution of
weights in the NN



2d-dimensional convolution of
covariance tensors in the
kernel

Generalizes mean-pooling (all-ones covariance) and independent weights.





References

- Yang, Greg, ...
- Neal, Radford, ...
- MacKay, D.J., ...