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Pattern Analysis

Deep Learning and other Network Architectures

Dr Shekhar “Shakes” Chandra
shekhar.chandra@uq.edu.au

V1.0

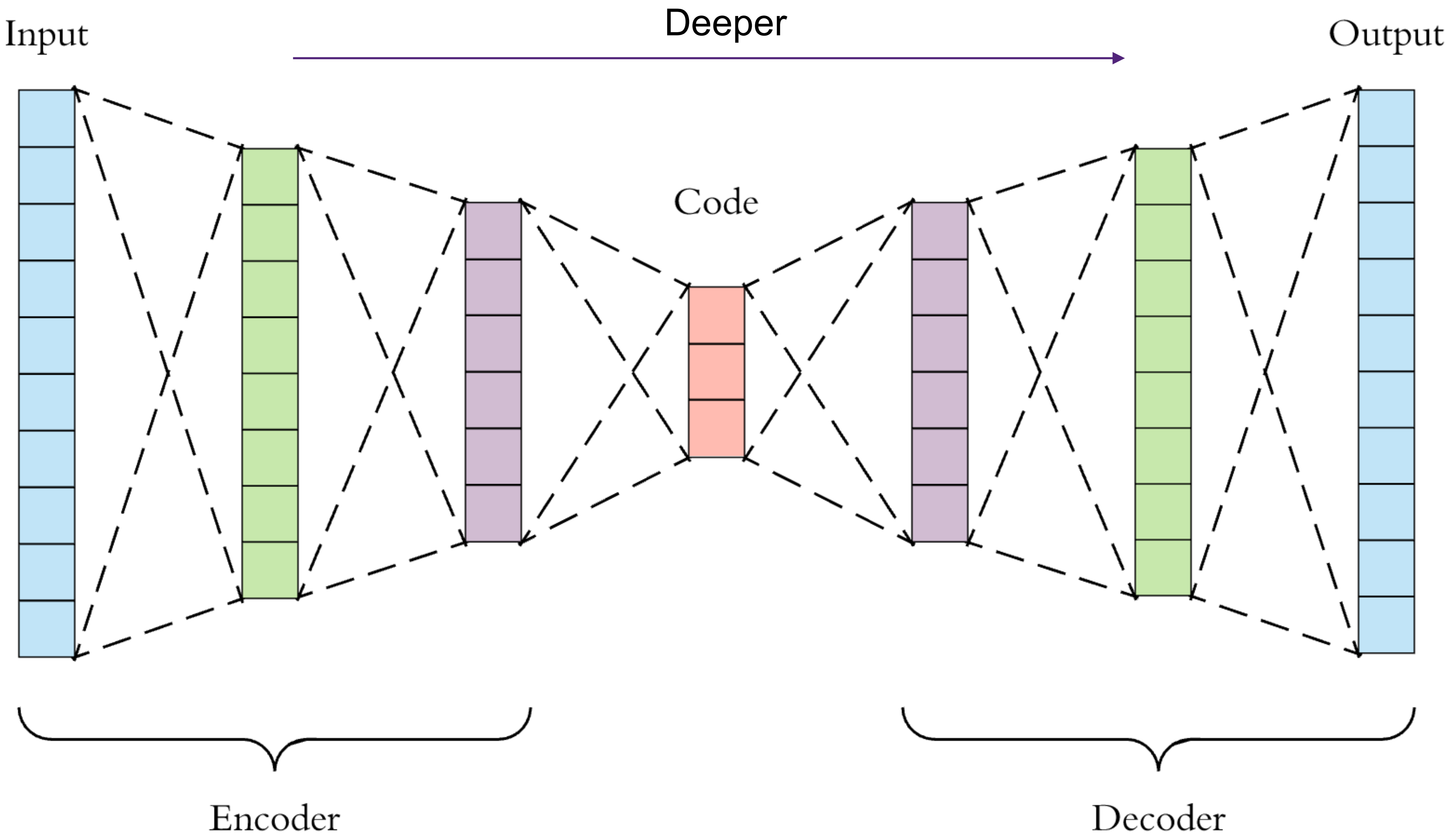
“The methods of theoretical physics should be applicable to all those branches of thought in which the essential features are expressible with numbers.”

Paul M. Dirac (link)
(1902-1984)

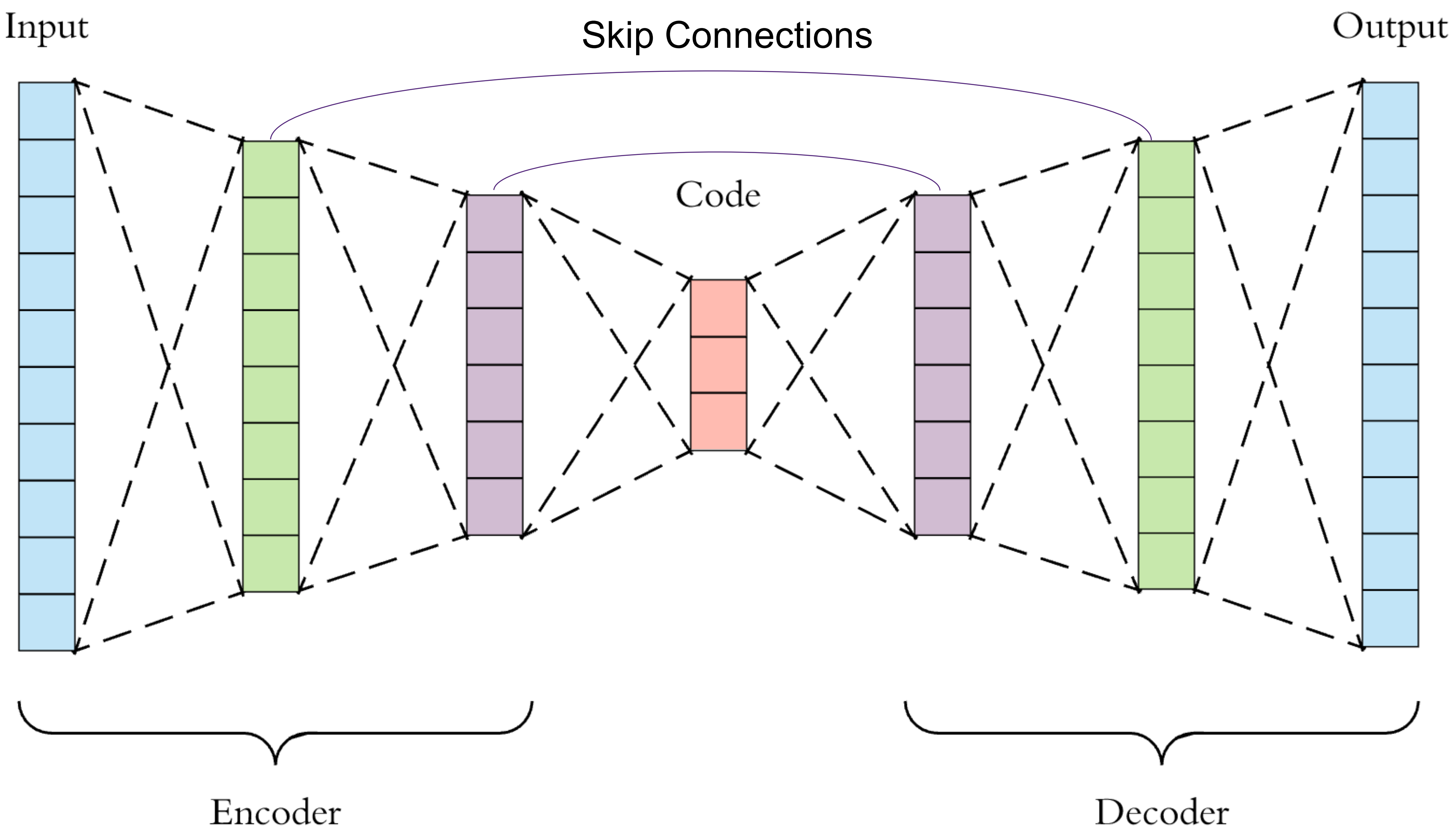
https://towardsdatascience.com/applied-deep-learning-part-3-autoencoders-1c083af4d798

See also https://blog.keras.io/building-autoencoders-in-keras.html

Autoencoder – Deep Learning

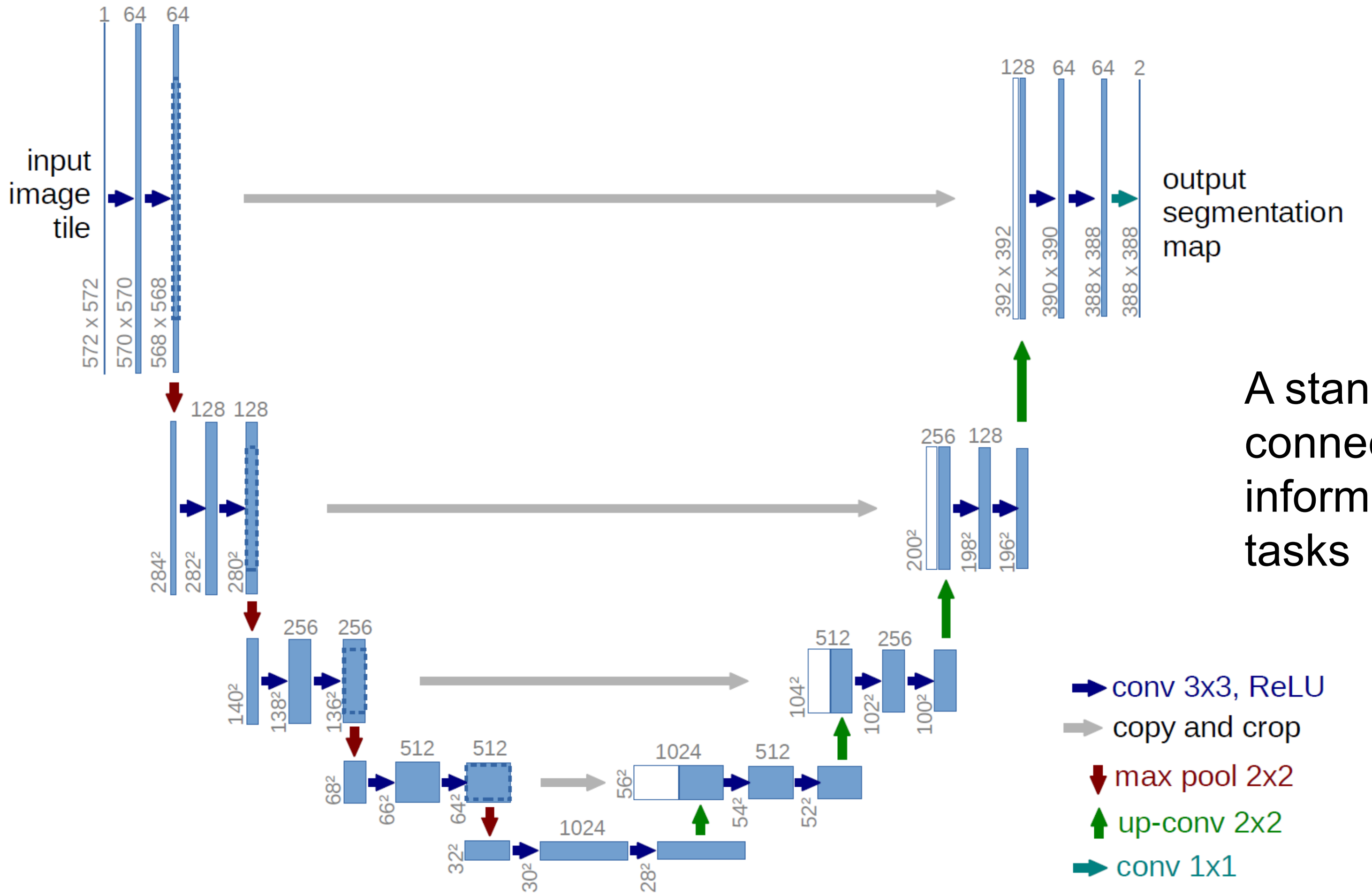


Skip Connections - UNet

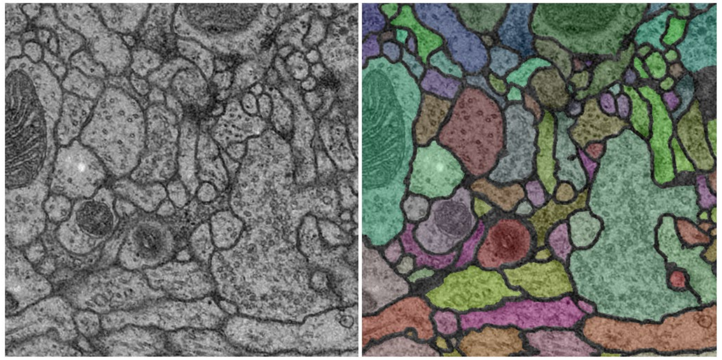


Skip Connections - UNet

https://lmb.informatik.uni-freiburg.de/people/ronneber/u-net/



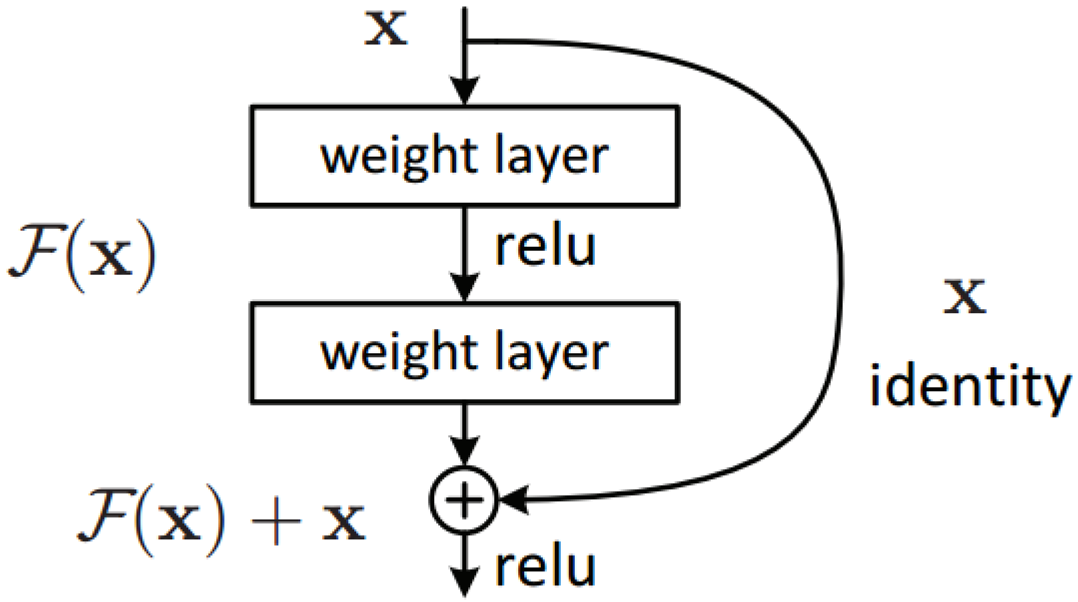
A standard CNN autoencoder with skip connections. The skip connection prevent information loss. Ideal for segmentation tasks



Residual Connections - ResNet

https://arxiv.org/abs/1512.03385

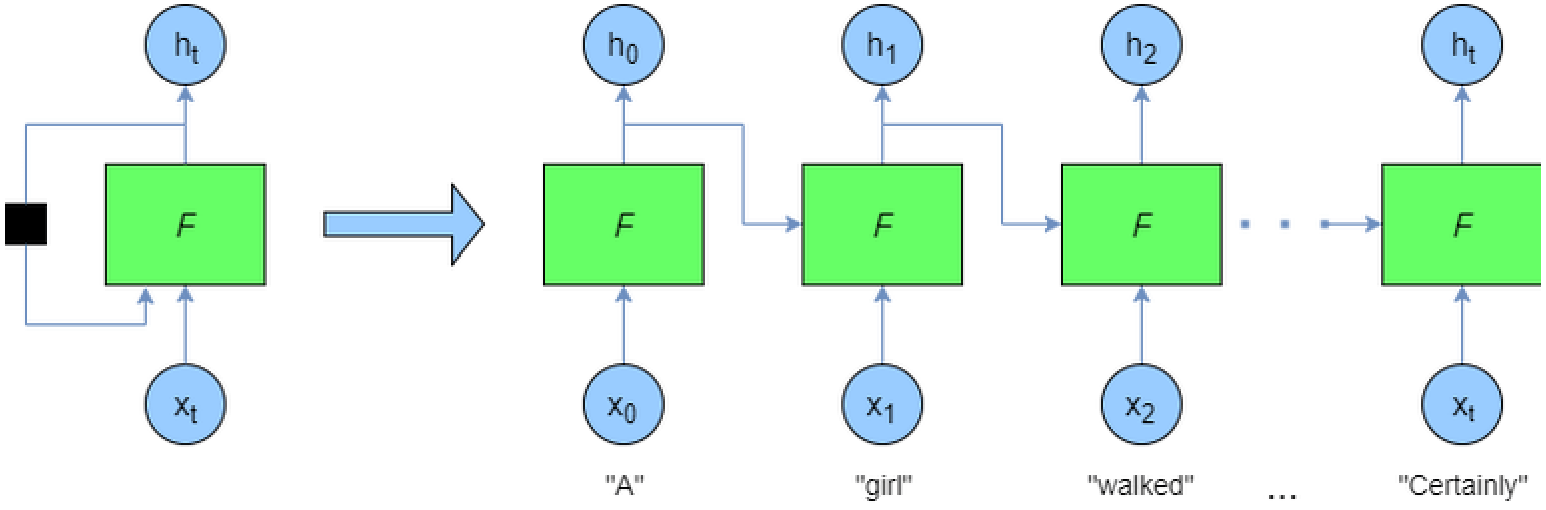
- A skip connection where we ensure that the parameters learnt correspond to the difference or residual of the result at each layer.
- Learning residuals means there is no loss of precision and gradients vanishing because differences are lost among large values
- Residual connections allow for deeper networks as a result
- The original ResNet broke records for computer vision prize for the deep networks having hundreds of layers
- Residual connections are usually quite easy to add to most network architectures

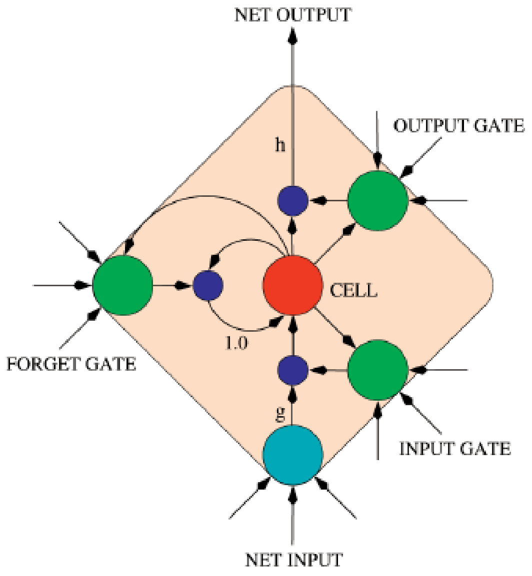


Recurrent Connections – RNNs

https://doi.org/10.1109/TPAMI.2008.137

- A recursive or loop connection is made back to the start of network
- Well suited for time series or sequential data
- Sometimes used as a way to iteratively apply a network to a problem
- Recurrence can also be used to 'store' memory and maintaining an internal state



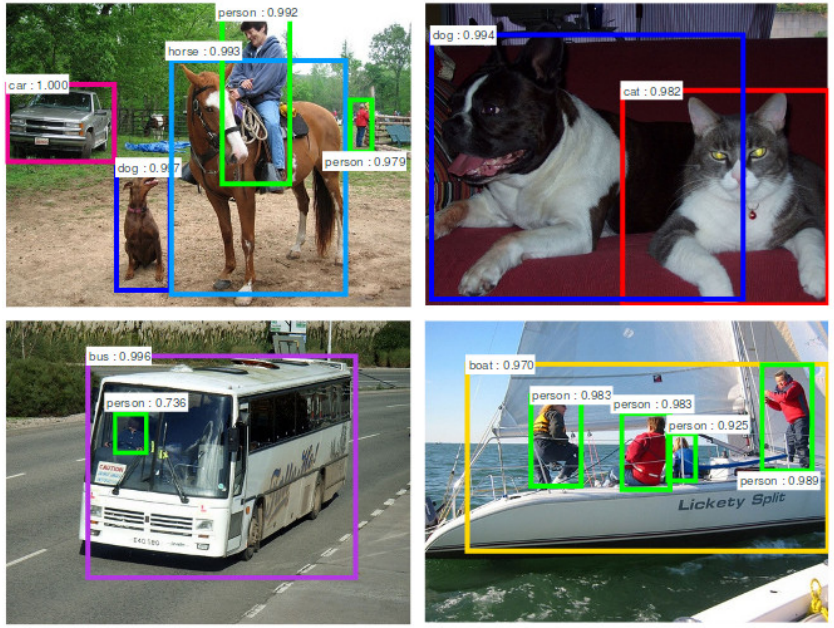


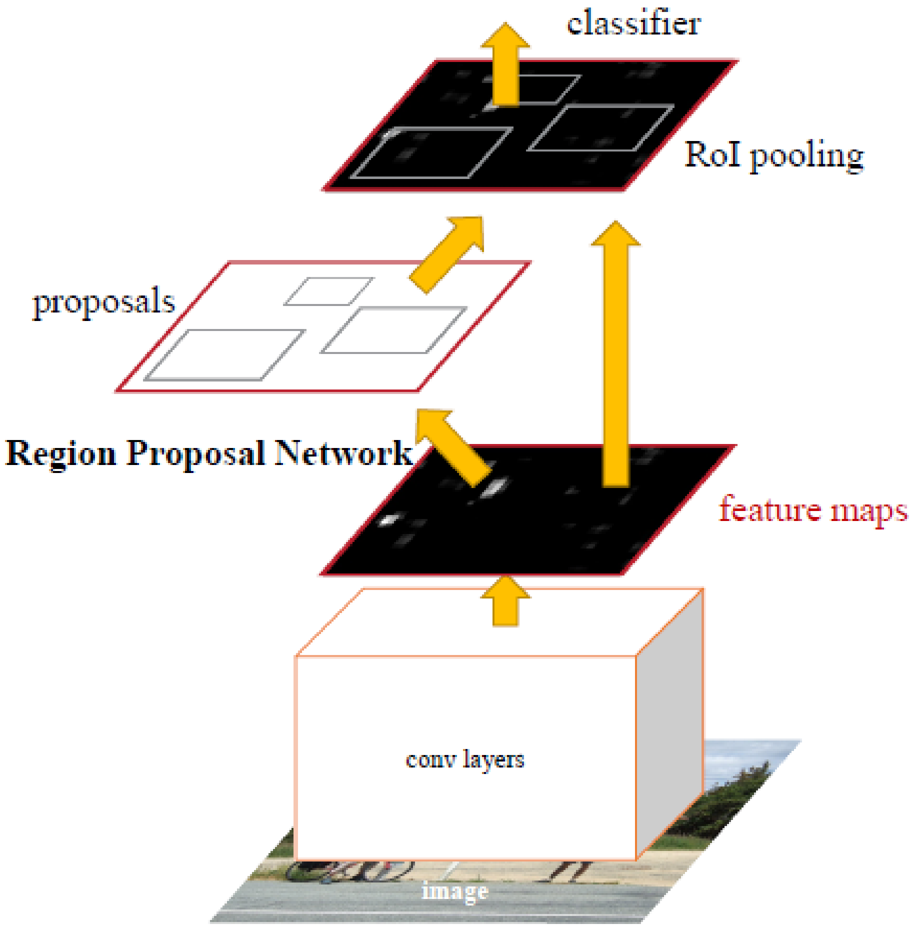
https://adventuresinmachinelearning.com/recurrent-neural-networks-lstm-tutorial-tensorflow/

https://arxiv.org/abs/1506.01497

Region CNNs – R-CNNs and Faster R-CNNs

- Uses a CNN to generate regions or bounding boxes around objects desired
- This region proposal network can then be classified into objects
- Robust to occlusion since boxes can pick up and ignore partial coverage



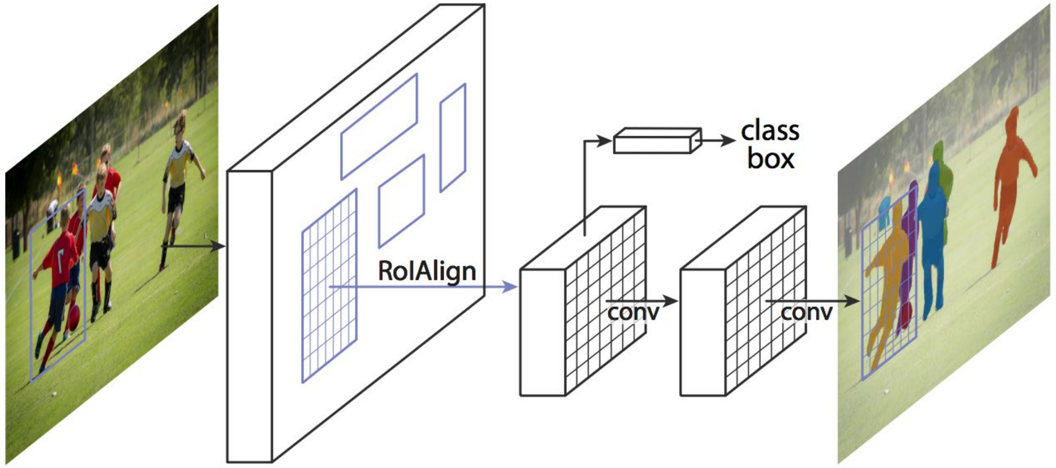


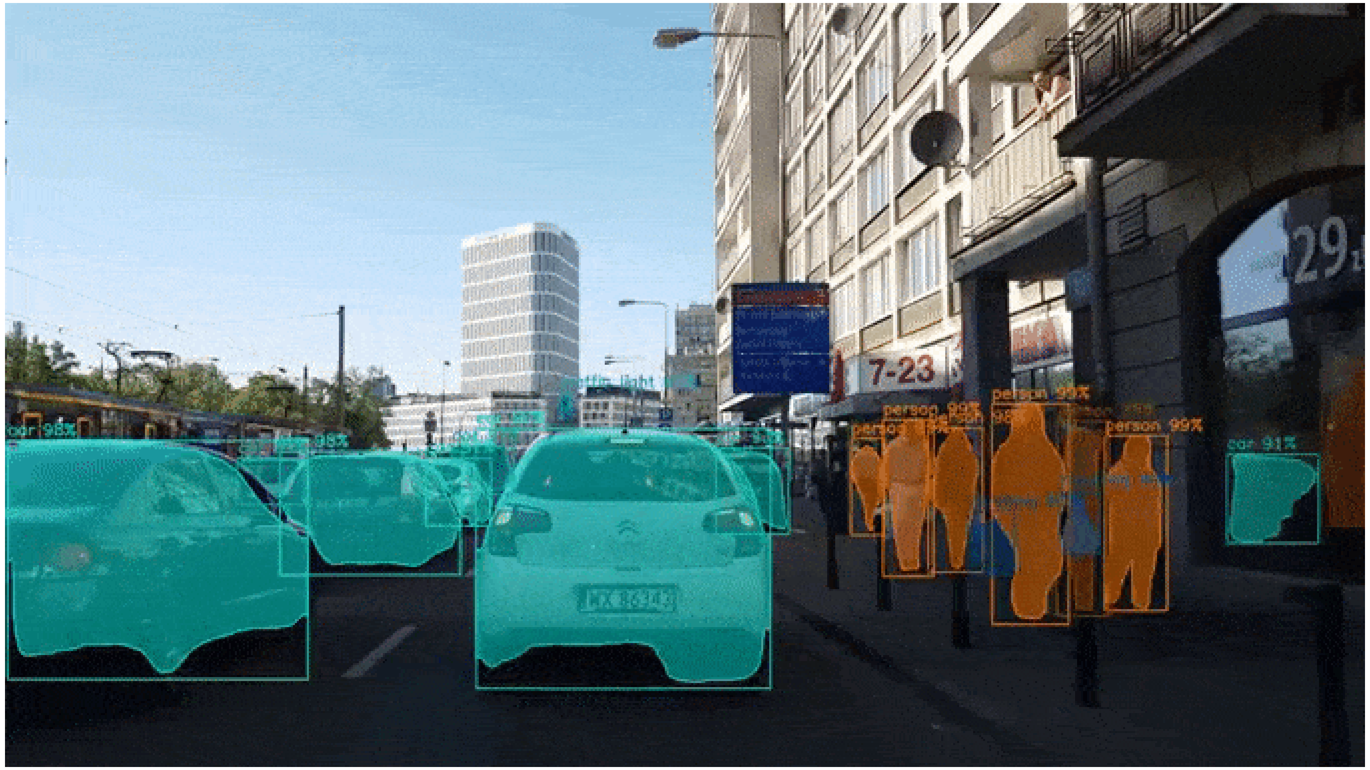
https://arxiv.org/abs/1703.06870

https://github.com/matterport/Mask_RCNN

Mask R-CNN

- The fast R-CNN is enhanced with a segmentation CNN attached to the final part of the network.
- The result is a very fast coarse segmentation framework robust to occlusion
- Can also provide limited semantic behaviour

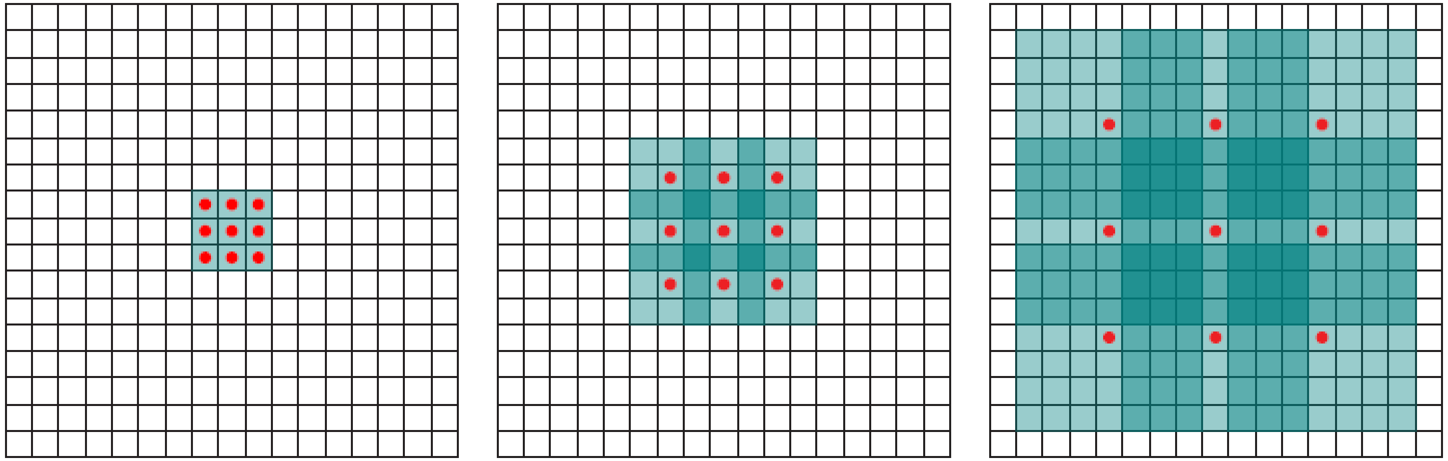


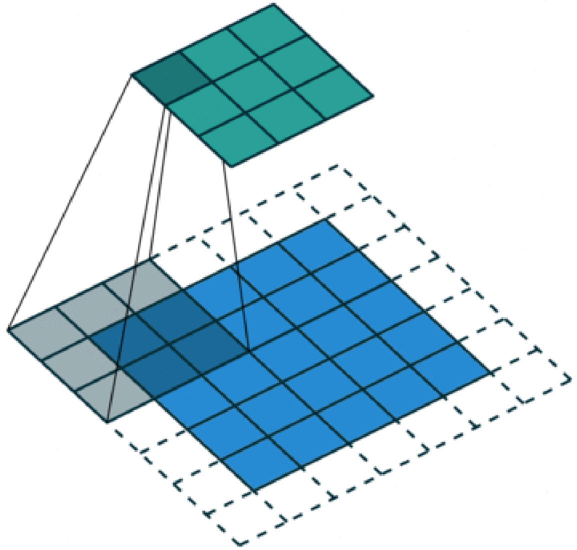


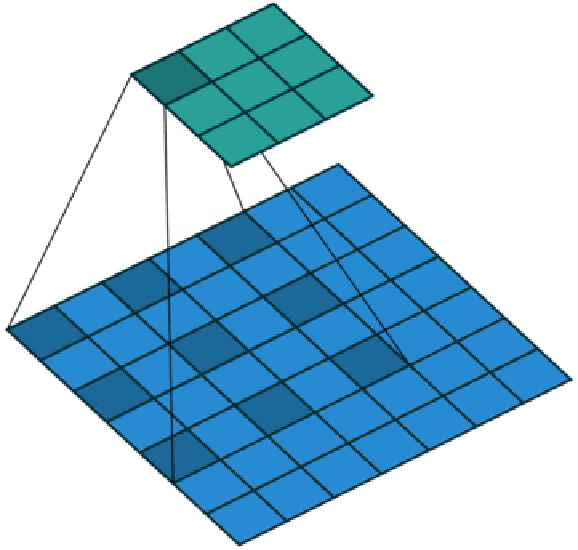
https://arxiv.org/abs/1511.07122

Dilated Convolutions – Context Aggregation

- Using convolutions with 'holes' to average out responses to filters
- Reduces the number of parameters drastically
- Difficult to interpret and visualise the resulting feature maps



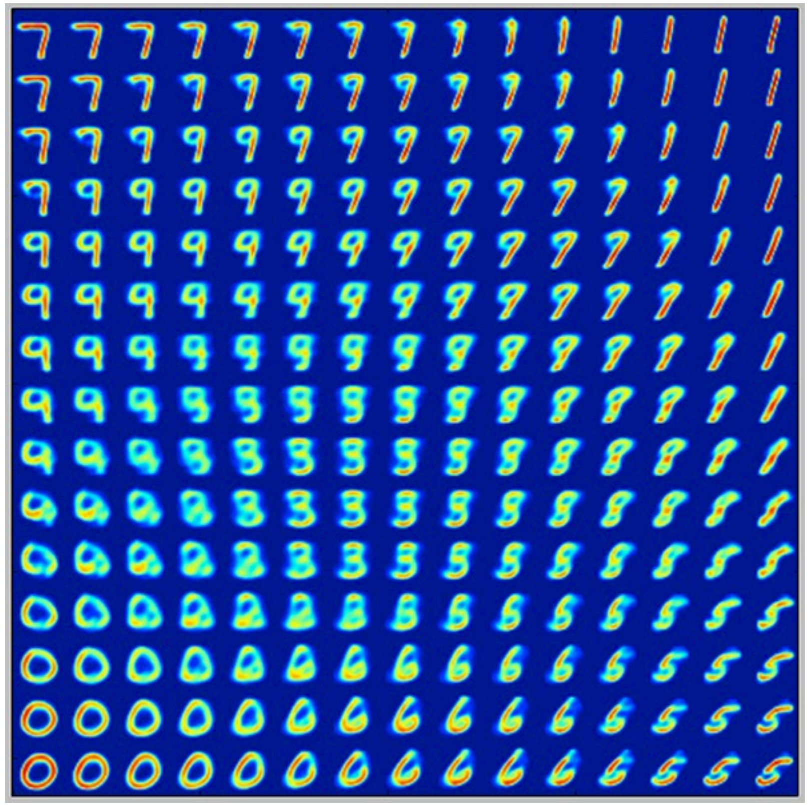




https://blog.keras.io/building-autoencoders-in-keras.html

Generative Models – Variational Bayes

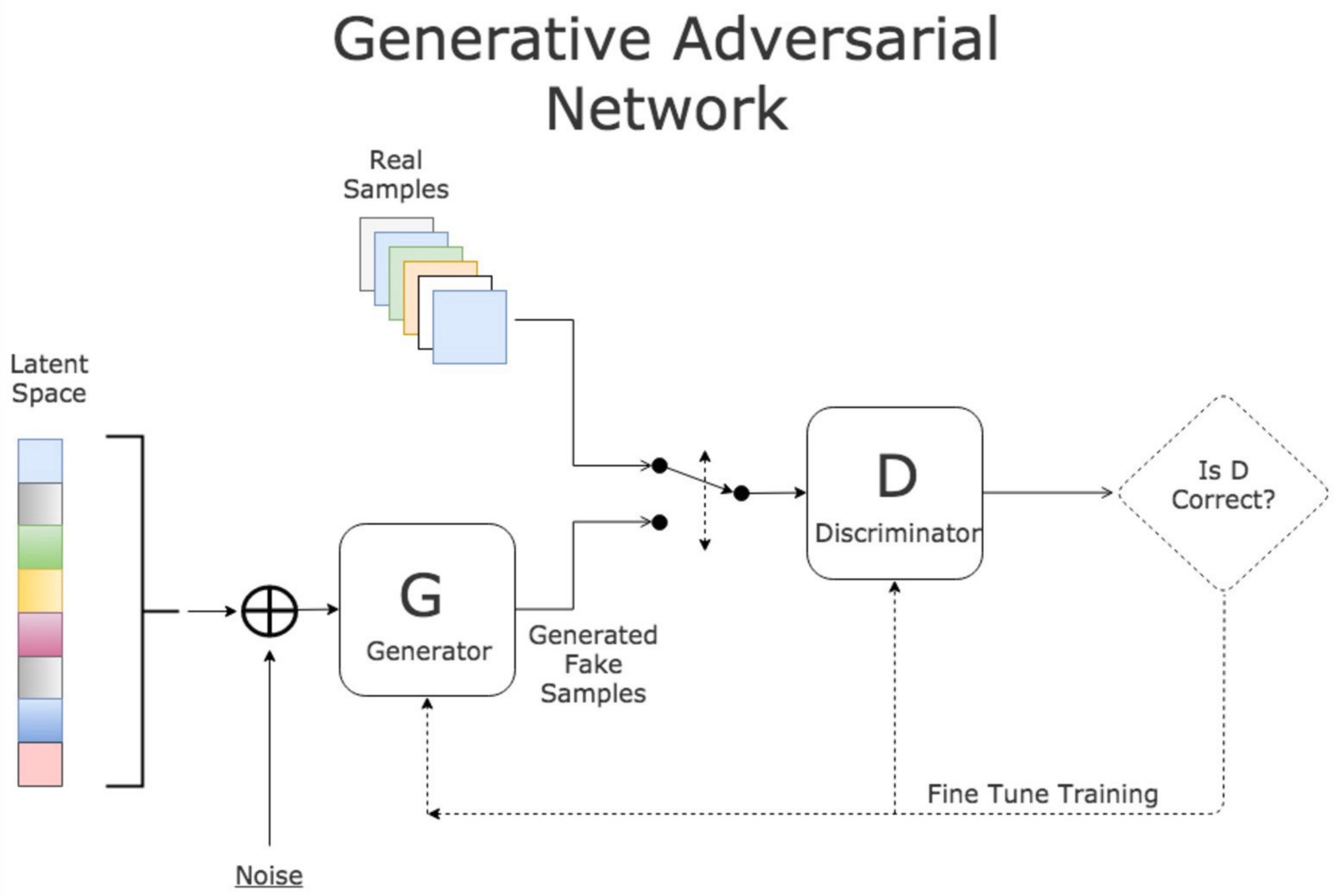
- Instead of fitting your network to your data directly and assuming an underlying code or representation is found, fit your data to a probability distribution
- This distribution will then be a latent variable model of your data
- Constraints the learning to a prior distribution and there you learn the distribution, not just the model
- You can then use the distribution to generate data similar to the training set with far more generalisability
- The distribution of digits learnt on the right shows how one can 'interpolate' from one digit to the next through the Variational Autoencoder constructed using this method



https://skymind.ai/wiki/generative-adversarial-network-gan

Generative Models – Adversarial Learning

- We build a generator network attempts to fool a discriminator network into thinking that the data it produces is real
- If successful, the result is a network that is capable of generating ‘realistic’ looking data
- A typical Generative Adversarial Network (GAN) setup is shown right
- Very powerful technique that is capable of astonishing results
- Learns the underlying distribution by learning the optimal ‘overall’ cost function
- Very difficult to train and often requires conditions and regularisation



 #deep-learning-uq

Conclusion

- A number of many network architectures exist for various applications
- Each having advantages and disadvantages
- Understanding the working principles behind them will allow you to determine if they will be useful for your problem
- You should be aware of some of the different types and try to keep an eye out for new structures, so that you can create a tailored solution to your problem!

What's Next?

How can we deal with small datasets and maintain our own open source projects?

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Thank you

Dr Shekhar “Shakes” Chandra | Lecturer
School of Information Technology and Electrical Engineering
shekhar.chandra@uq.edu.au
+61 7 3365 8359

@shakes76
shekhar-s-chandra