

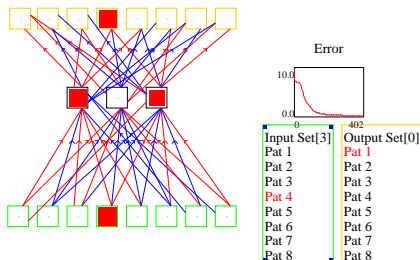
Images

# Multi-layer perceptrons

- No guarantee that solution, even if one exists, can be found.
- Training can take a long time.
- **Overlearning** of the decision surface to the training data. Network acts as a lookup table, with poor generalisation.
- Role of hidden units: act as feature detectors, like in XOR problem.
- How many hidden units? Too few may cause a bottleneck, but too many and the network may not generalise.

# Encoder networks

Momentum = 0.9 Learning Rate = 0.25



Inputs: 1 of N units active. Task: reproduce input at output layer, passing through a “bottleneck” hidden layer.

After 400 epochs, activation of hidden units:

Pattern	Hidden units			Pattern	Hidden units		
1	1	1	1	5	1	0	0
2	0	0	0	6	0	0	1
3	1	1	0	7	0	1	0
4	1	0	1	8	0	1	1

Also called “self-supervised” networks.

Projects input onto first M (=3) PCs.

Application: compression. Local vs distributed representations.

# Image compression example

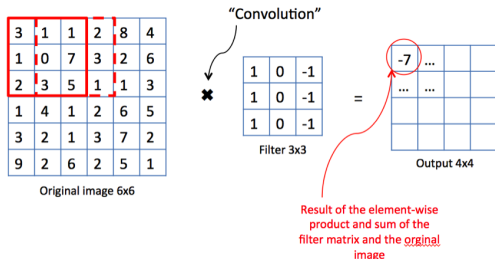
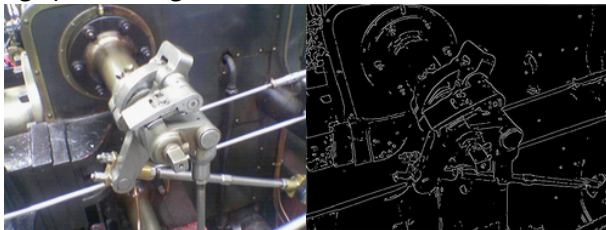
Cottrell et al (1987) applied 64-16-64 network with quantization (8 bits per hidden unit) to patches of images. 4:1 compression ratio if input images also 8 bit. Figure 9:



Figure 9. A: The original image of the Intelligent Systems Group (ISG) at UCSD. B: The reconstructed image using eight bits (or 256 quantization values), representing 2 bits/pixel, resulting in NMSE of 0.413%.

# Convolution

How to do image processing with a neural network?



[https://en.wikipedia.org/wiki/Canny\\_edge\\_detector](https://en.wikipedia.org/wiki/Canny_edge_detector)

<https://medium.com/machine-learning-bites/deeplearning-series-convolutional-neural-networks-a9c2f2ee1524>

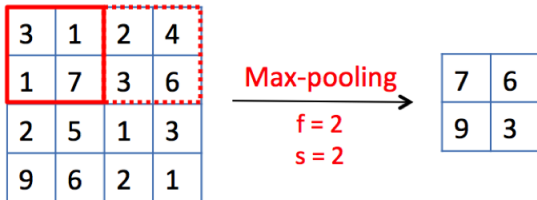
# Convolution example

Mario from 3 Brown 1 Blue.

<https://www.youtube.com/watch?v=8rrHTtUzyZA> part of the

<https://computationalthinking.mit.edu/Fall20/> course at MIT.

# Pooling



<https://medium.com/machine-learning-bites/deeplearning-series-convolutional-neural-networks-a9c2f2ee1524>



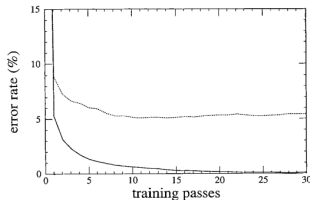
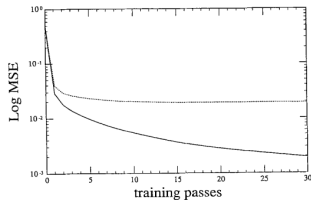
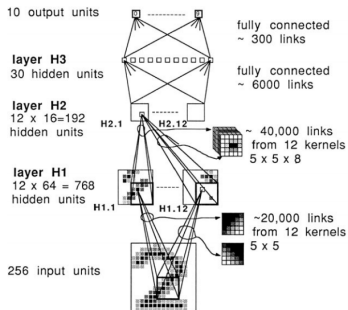


## Receptive fields from the retina to the cortex

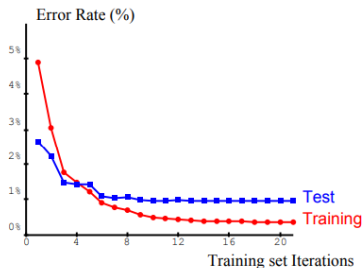
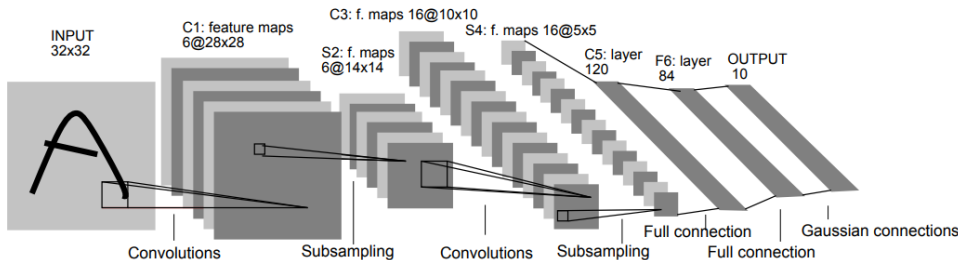
Describe retinal ganglion cell receptive fields, simple cells and complex cells.

# LeCun et al (1989)

LeCun Y et al (1989) Backpropagation Applied to Handwritten Zip Code Recognition. Neural Comput 1:541-551.



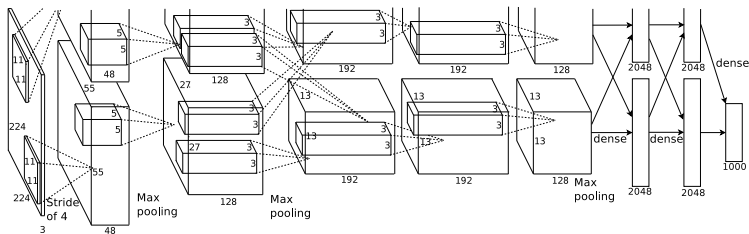
# LeCun et al (1998)



# Image classification (Krizhevsky et al 2012)

- Krizhevsky A, Sutskever I, Hinton GE (2012) ImageNet Classification with Deep Convolutional Neural Networks. In: Advances in Neural Information Processing Systems 25, Burges CJC, Bottou L, Weinberger KQ, eds), pp 1097–1105.
- Annual competition. 1,000 examples of 1,000 classes.
- Rotating/translating of training images to make 'new' samples.
- Top-1 (37.5%) and top-5 (17.0%) error rate exceed previous state of the art. Won 2012 competition with top-5 test error rate of 15%; second had error rate of 26%.

ImageNet architecture (Krizhevsky et al. 2012)



Split on 2 GPUs.

150K pixels (224 x 224 x 3) into 8 layer network:

253K-186K-65K-65K-43K-4K-4K-1K.

i.e. 650,000 neurons (excluding input), 60 million parameters.

# ImageNet performance



**mite**

**container ship**

**motor scooter**

**leopard**

mite	container ship	motor scooter	leopard
black widow	lifeboat	go-kart	jaguar
cockroach	amphibian	moped	cheetah
tick	fireboat	bumper car	snow leopard
starfish	drilling platform	golfcart	Egyptian cat



**grille**

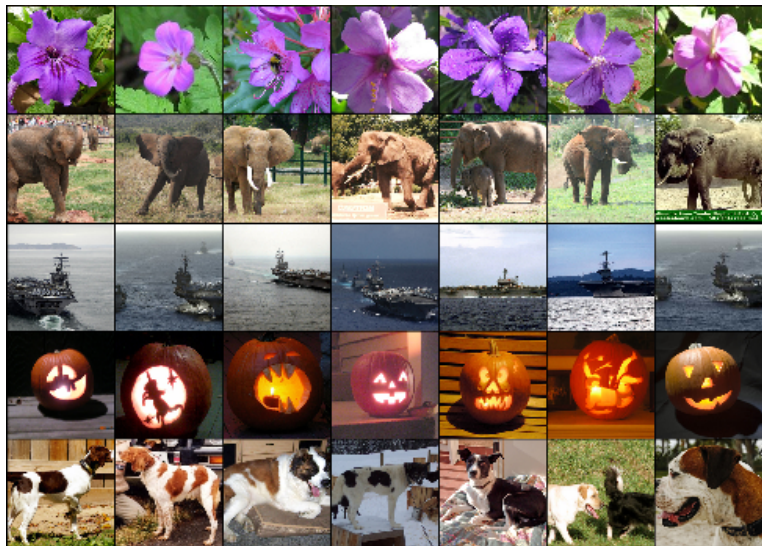
**mushroom**

**cherry**

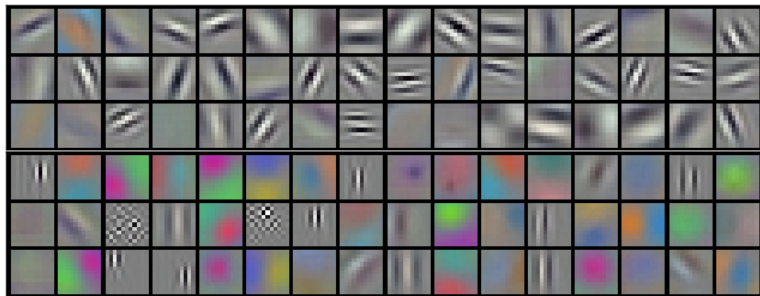
**Madagascar cat**

convertible	agaric	dalmatian	squirrel monkey
grille	mushroom	grape	spider monkey
pickup	jelly fungus	elderberry	titi
beach wagon	gill fungus	ffordshire bullterrier	indri
fire engine	dead-man's-fingers	currant	howler monkey

# ImageNet close-matches



## ImageNet RFs



“It is notable that our network’s performance degrades if a single convolutional layer is removed. For example, removing any of the middle layers results in a loss of about 2% for the top-1 performance of the network. So the depth really is important for achieving our results.”



# Life since AlexNet

1. 2012: AlexNet (Krizhevsky et al 2012). Top-5 error of 17% (top-1 of 37%).
2. 2014: GoogLeNet / “Inception” (Szegedy et al 2014). Top-5 error of 6.67%.
3. 2015: ResNet (He et al 2015). First to beat human, top-5 error of 3.75%. 152 layers.
4. ResNet with 1001 layers (He et al 2016).
5. Nov 2023: top-1% error 8.9%  
[https://paperswithcode.com/sota/  
image-classification-on-imagenet](https://paperswithcode.com/sota/image-classification-on-imagenet)
6. [https://paperswithcode.com/sota/  
image-classification-on-mnist](https://paperswithcode.com/sota/image-classification-on-mnist)  
0.13% top-1 error on MNIST (Nov 2023).

## Convolutional layers not just for images

*A primer on deep learning in genomics.* Zou 2019

See online google colab resource for running instance:

<https://github.com/abidlabs/deep-learning-genomics-primer/>

Transcription factor binding site example; 1d space = time.

## Transfer learning

**Transfer learning** using these networks to provide features: freeze main network and learn layers on top.

Allows you to focus on just the bits that you care about in the later layers.

TL “can improve machine learning model performance for data-disadvantaged ethnic groups, and thus provides an effective approach to reduce health care disparities arising from data inequality among ethnic groups.”. (Gao and Cui 2020).

# Summary

1. Autoencoders for data/image compression
2. Convolutional networks / relation to visual system
3. LeCun network
4. ImageNet (2012)
5. Transfer learning