Image Analysis
Deep Learning

KALLE ÅSTRÖM

Deep learning
Convolutional Neural Networks

- Slides and material from
- http://www.cs.nyu.edu/~yann/talks/lecun-ranzato-icml2013.pdf
- MatConvNet
- http://www.robots.ox.ac.uk/~vgg/practicals/cnn/
- Gabrielle Flood's master's thesis
- Anna Gummeson's master's thesis

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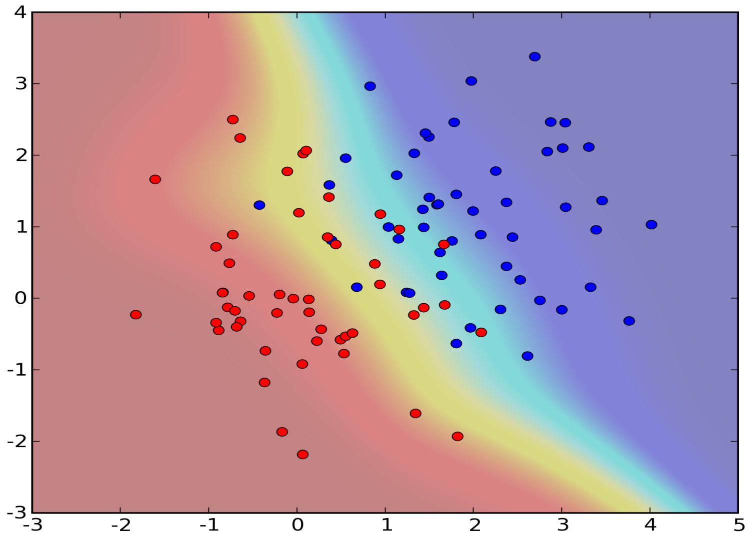
Components for deep lear



- One neuron
  - Example: Logistic regression
  - Classification model (x feature vector, (w,b) parameters, s smooth thresholding

$$x \in R^d, w \in R^d, b \in R, f(x) = s(w^T x + b)$$

  - Logistic regression

$$s(z) = \frac{1}{1 + e^{-x}}$$

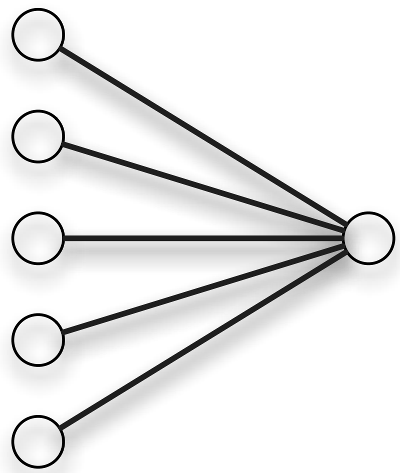
  - ML estimate of parameters (w,b) is a convex optimization problem

$$\min_{\boldsymbol{w}} \quad \frac{1}{2}\boldsymbol{w}^T\boldsymbol{w} + C\sum_{i=1}^{l} \log(1 + e^{-y_i \boldsymbol{w}^T \boldsymbol{x}_i}).$$

Single Layer Neural Networks
One Neuron

- One neuron

$$x \in R^d, w \in R^d, b \in R, f(x) = s(w^T x + b)$$



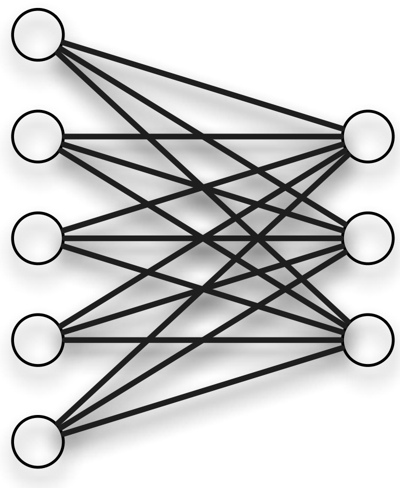
Single Layer Neural Networks
Several Neurons

- Several parallell neurons

$$x \in R^d, y \in R^k, B \in R^d, W - k \times d\text{matrix}$$

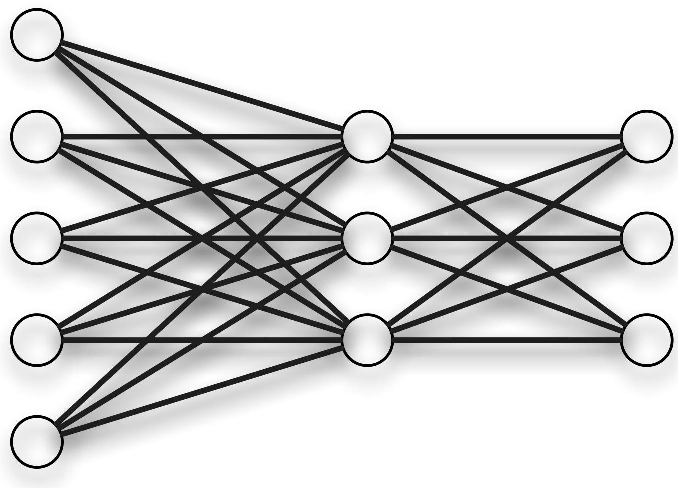
$$y = s(Wx + B)$$

- Elementwise smooth thresholding – s



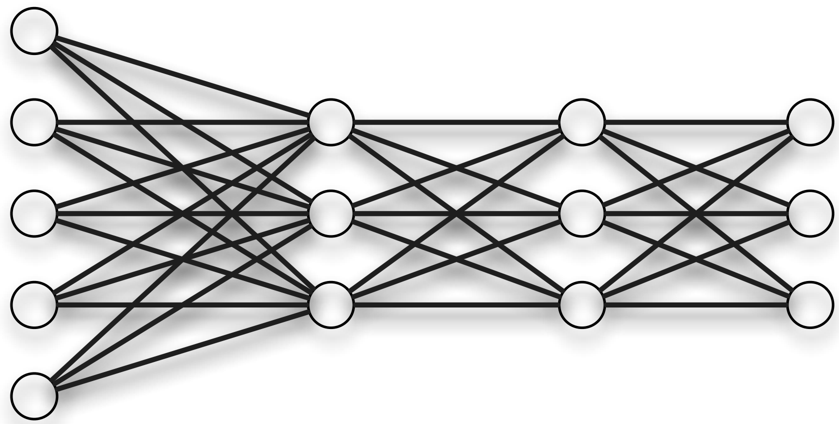
Artificial Neural Networks
One hidden layer

- Multi-class classification
- One hidden layer
- Trained by back-propagation
- Popular since the 1990ies

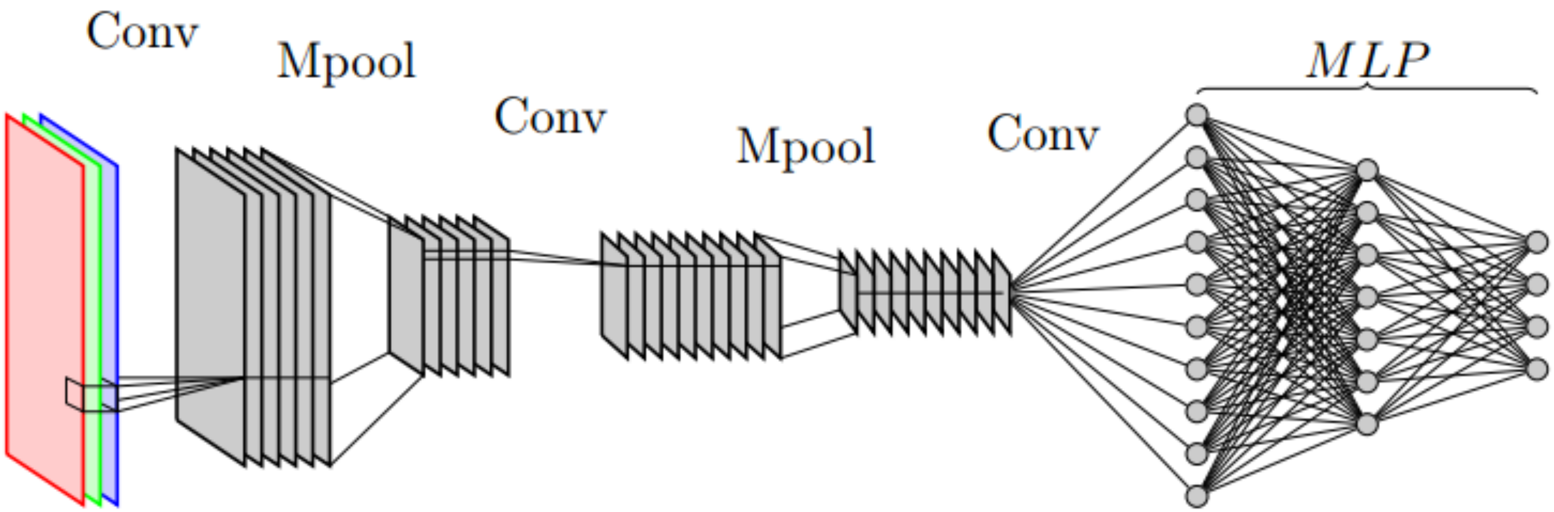


Deep Neural Networks
Many layers

- However
- Naively implemented would give to many parameters
- Example
- 1M pixel image
- 1M hidden layers
- 10^{12} parameters between each pairs of layers

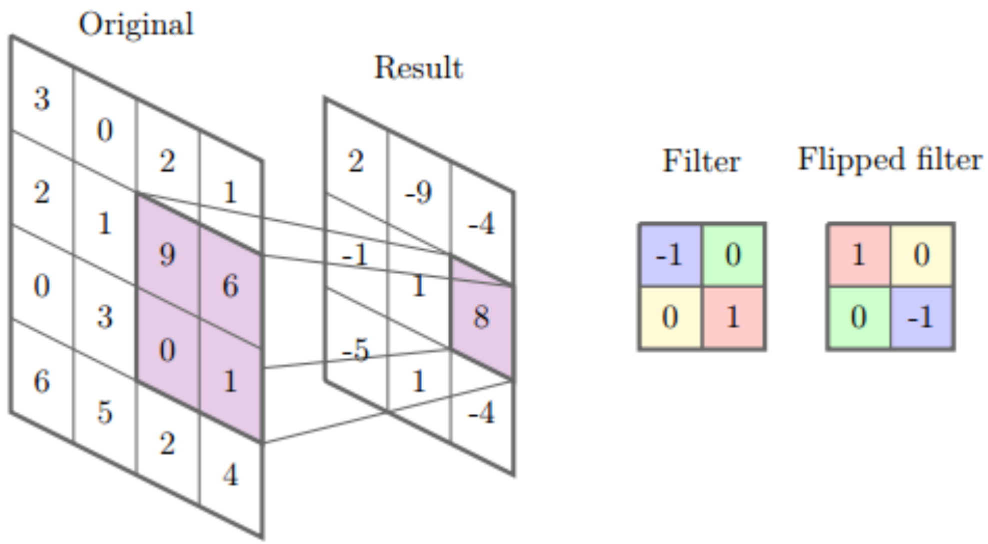


Convolutional neural network, CNN

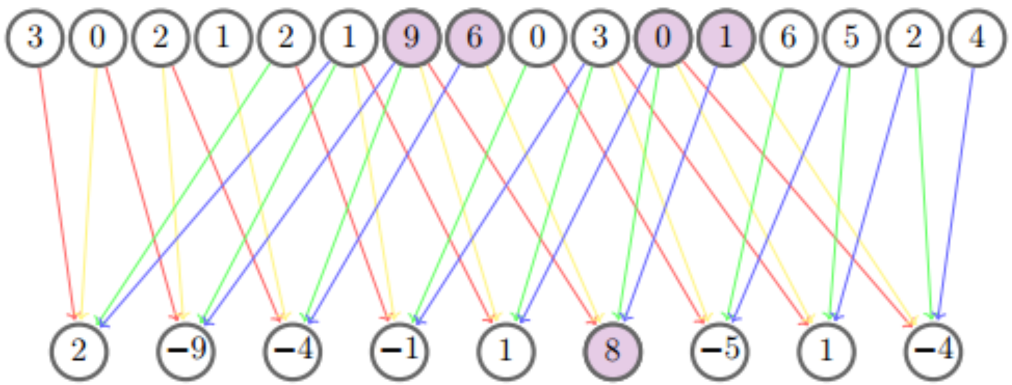


CNN-Blocks - Convolutional layer

Convolution of an image as a filter-operation.



Convolution of an image represented as a sparsely connected ANN.



CNN-Blocks - Convolutional layer

- Input: Data block x of size

$$m \times n \times k_1$$

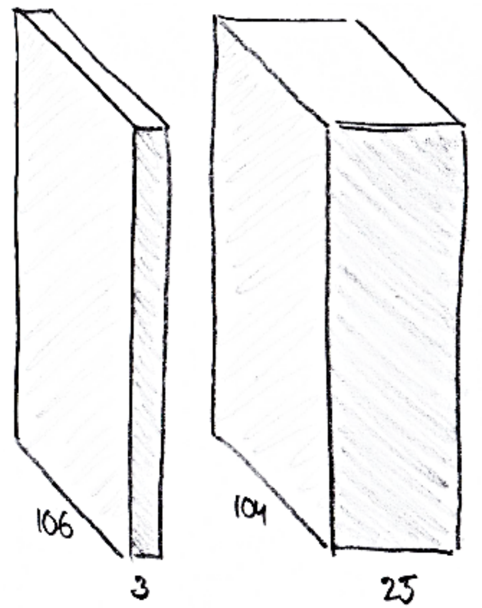
- Output: Data block y of size

$$m \times n \times k_2$$

- Filter: Filter kernal block w of size

$$m_w \times n_w \times k_1 \times k_2$$

- Offsets: Vector w_o of length k_2



$$y(i,j,k) = w_o(k) + \sum_u \sum_v \sum_l x(i-u, j-v, l) w(u,v,l,k)$$

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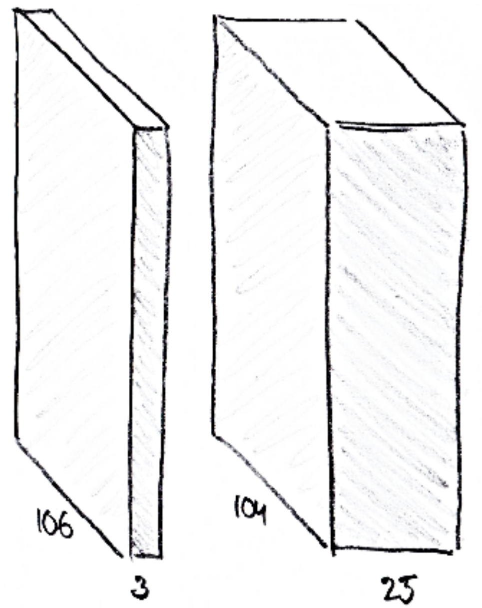
CNN-Blocks - Convolutional layer

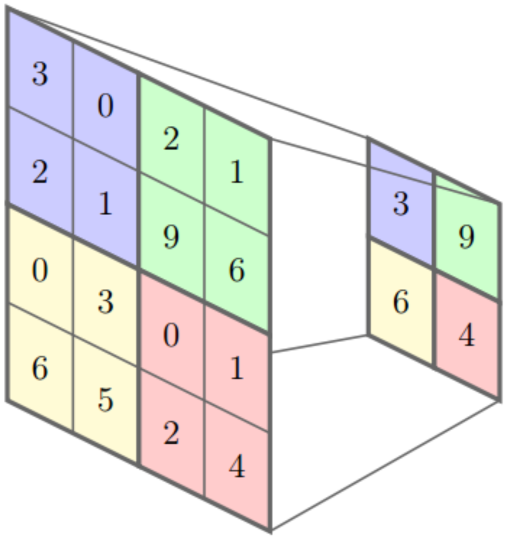
$$y(i,j) = \sum_u \sum_v x(i-u, j-v) w(u,v)$$

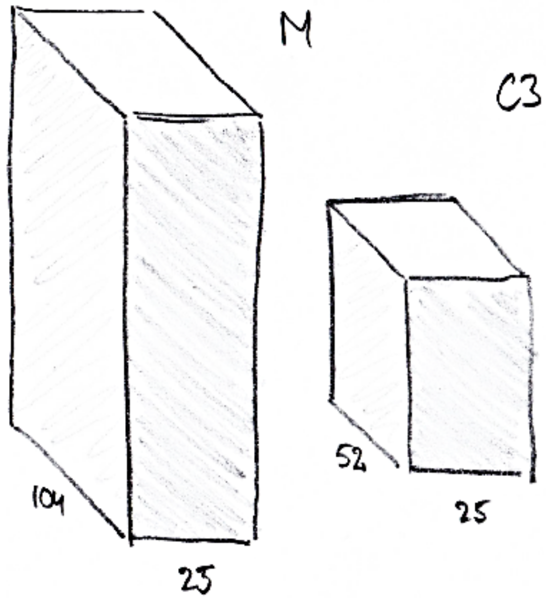


$$y(i,j) = w_o + \sum_l \left(\sum_u \sum_v x(i-u, j-v, l) w(u,v,l) \right)$$

$$y(i,j,k) = w_o(k) + \sum_u \sum_v \sum_l x(i-u, j-v, l) w(u,v,l,k)$$

CNN-Blocks - Max-pooling

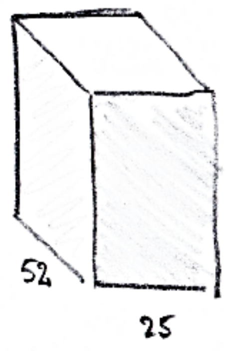


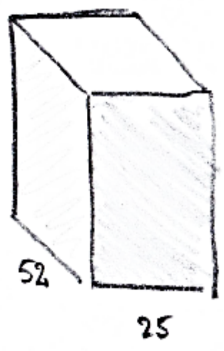


CNN-Blocks - RELU

$$f(x) = max(0, x)$$

$$y(i, j, k) = max(x(i, j, k), 0)$$

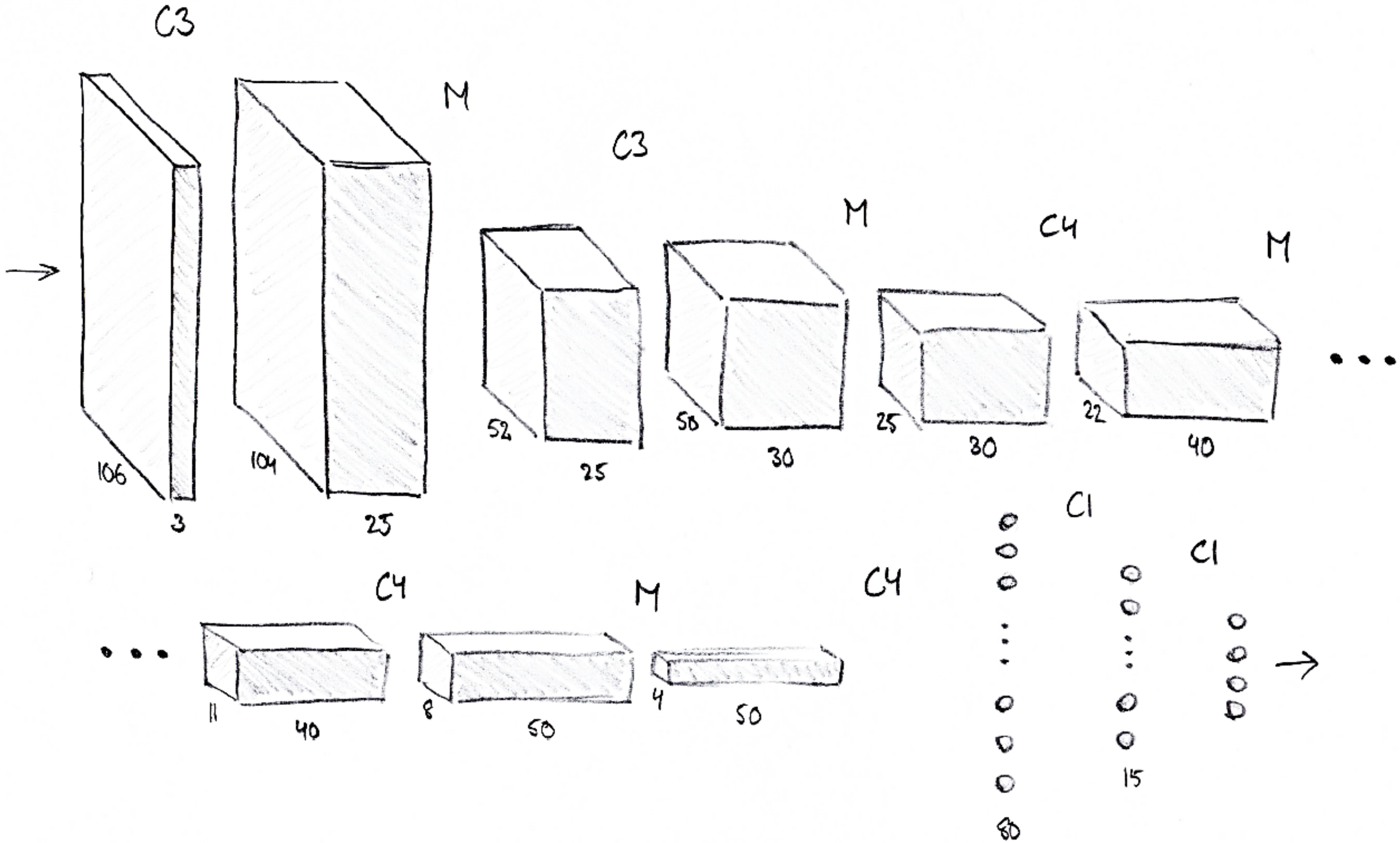




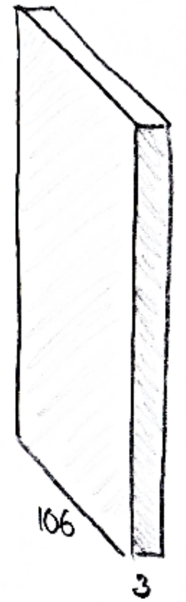
CNN-Blocks - Softmax

$$p_j = \frac{e^{d_j}}{\sum_{k=1}^{m} e^{d_k}}$$

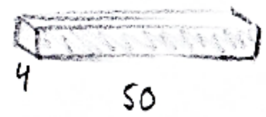
Result, Network design



CNN-Blocks - Softmax



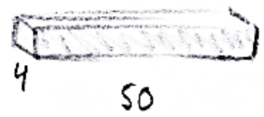
$$y = f(x, w)$$



Input: image x of size m x n x k, typically k=1 (gray-scale) or k=3 (colour)
Output: vector y of size 1 x 1 x N, which we interpret as N probabilities y_j
The probability that the image x is of class j

Training data (x_i, c_i

$$y = f(x, w)$$



Input: image x of size m x n x k, typically k=1 (gray-scale) or k=3 (colour)
Output: vector y of size 1 x 1 x N, which we interpret as N probabilities y_j
The probability that the image x is of class j
If the class is supposed to be the integer c_i for image x_i
then we want y_{c_i}

To be large (close to one)
Minimize $-\log y_{c_i}$

Training data $T = \{(x_1, c_1), \ldots (x_N, c_N)\}$

- Classification network $y = f(x, w)$

- Evaluate one example (x_k,c_k) (like adding another layer)

$$\sum_{k=1}^{N} -\log y(x_k, w)_{c_k}$$

- Evaluation function: $g(T, w) = \sum_{k=1}^{N} -\log y(x_k, w)_{c_k}$

- Solve $\min_{w} g(T, w)$

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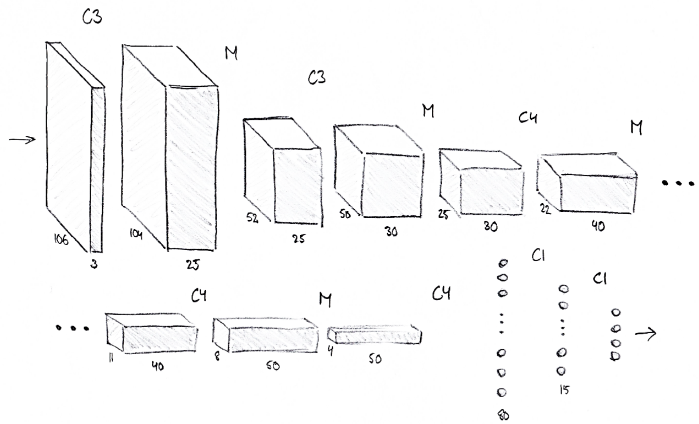
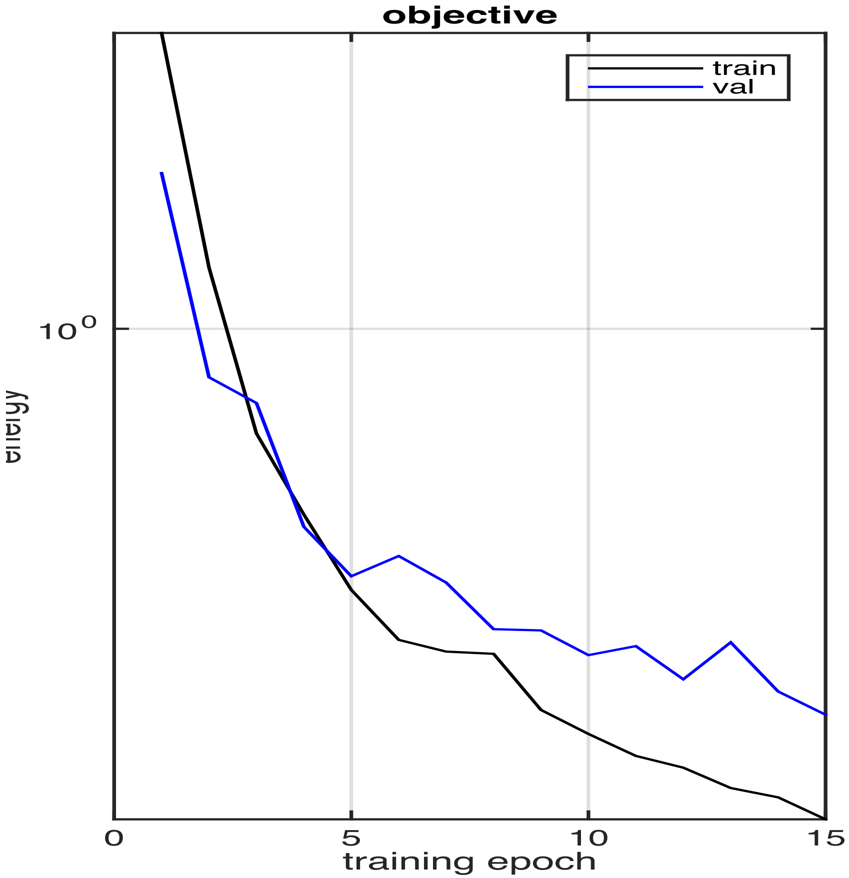
Example: OCR, classify images as a-z
Network design

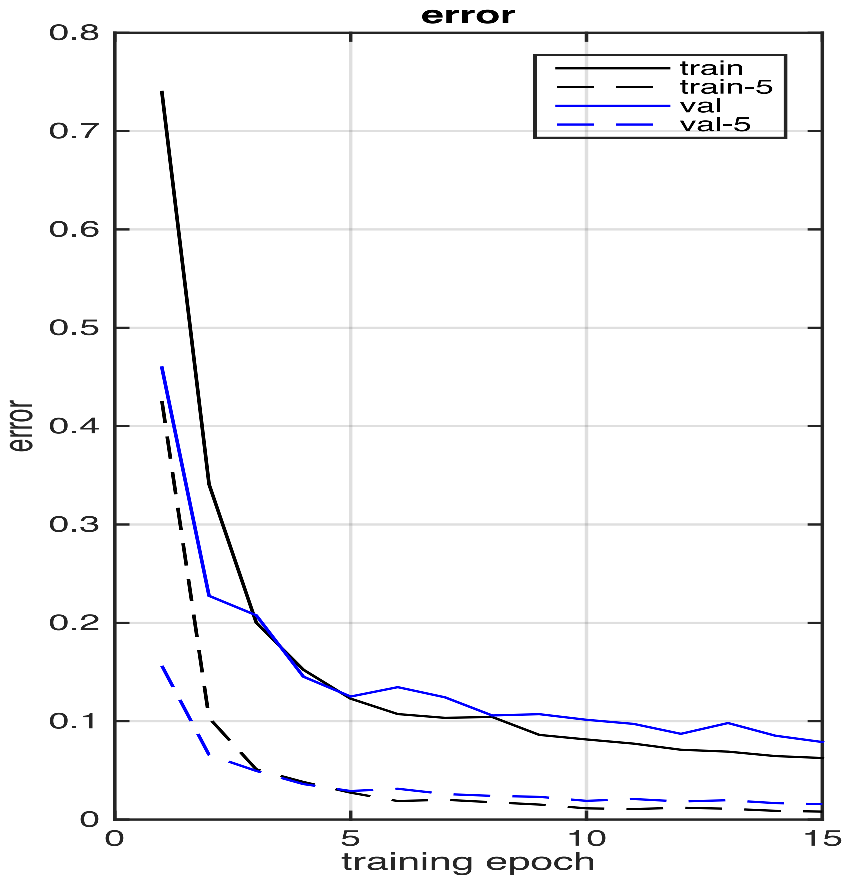


```
>> net

net =

       layers: {1x7 cell}
    imageMean: 0.9176775

>> vl_simplenn_display(net)
     layer|      1|      2|      3|      4|      5|      6|      7|
      type|    cnv|  mpool|    cnv|  mpool|    cnv|   relu|    cnv|
   support|    5x5|    2x2|    5x5|    2x2|    4x4|    1x1|    2x2|
    stride|      1|      2|      1|      2|      1|      1|      1|
       pad|      0|      0|      0|      0|      0|      0|      0|
   out dim|     20|     20|     50|     50|    500|    500|     26|
  filt dim|      1|    n/a|     20|    n/a|     50|    n/a|    500|
rec. field|      5|      6|     14|     16|     28|     28|     32|
c/g net KB|    4/0|    0/0|  196/0|    0/0| 3129/0|    0/0|  406/0|
total network CPU/GPU memory: 3.6/0 MB
>>
```

Example: OCR, classify images as a-z
Training data

Example: OCR, classify images as a-z
Training





$$g(T, w) = \sum_{k=1}^{N} -\log y(x_k, w)_{c_k}$$

$$\#\{c_k = argmax_i \, y(x_k, w)_i\}$$

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Tricks

- **Stochastic Gradient Descent**
  - Computation of $$g(T, w) = \sum_{k=1}^{N} -\log y(x_k, w)_{c_k}$$
  - Requires going through all examples (all N).
  - If N is large and/or if computing y(x_k,w) is time-consuming, use stochastic gradient descent, i.e. update parameters using subsets of training data.
- **Jittering** - construct a larger training set by perturbing the examples, jittering, translating images, rotating images, warping, mirroring, adding noise, …'
- **Dropout** – in each computation of y(x_k,w) let a random subset of the neurons die, i e set the output to zero.

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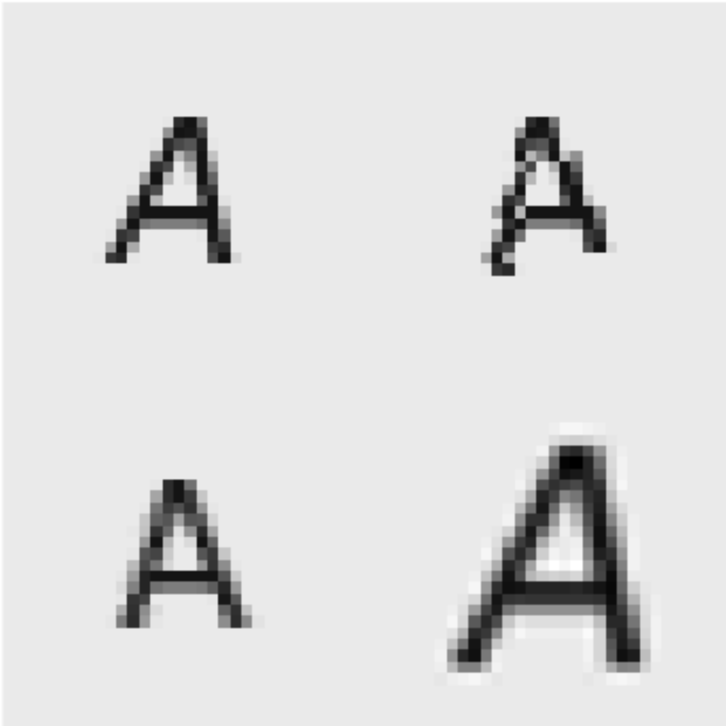
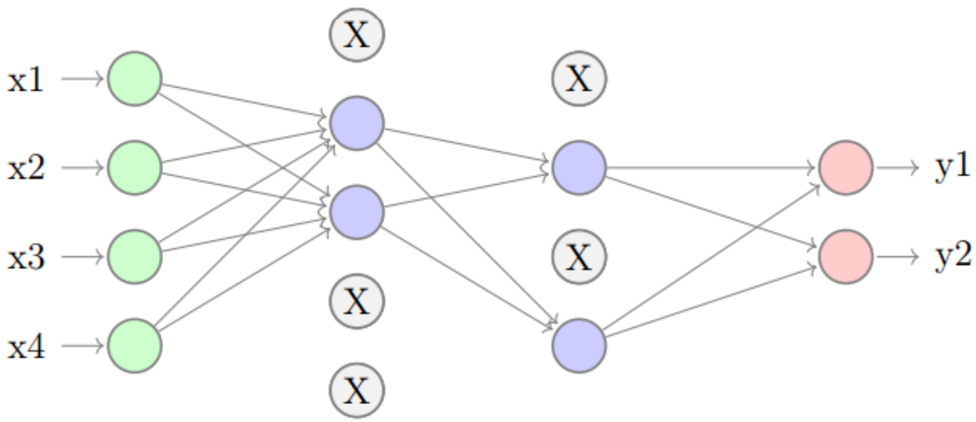
Generalisation, Expand data set



Generalisation, Dropout



Generalisation, Weight decay (Prior on small weights)

$$E(w) = -\sum_{n=1}^{N} \log\left(\frac{e^{y_{d(n)}(n)}}{\sum_{i=1}^{k} e^{y_i(n)}}\right) + \frac{\lambda}{2}\sum_{l} w_l^2$$

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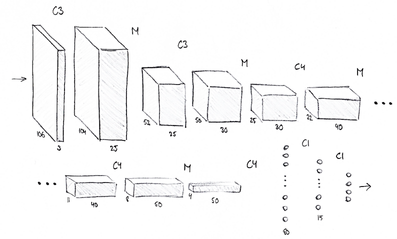
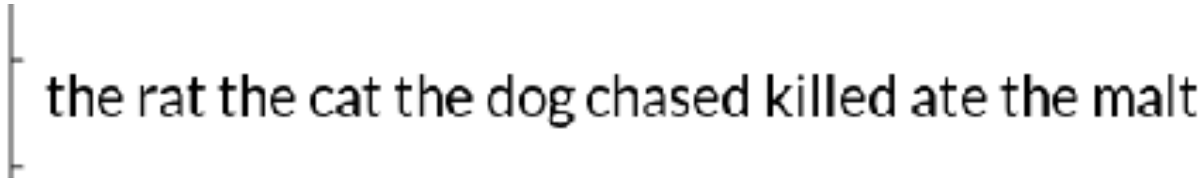
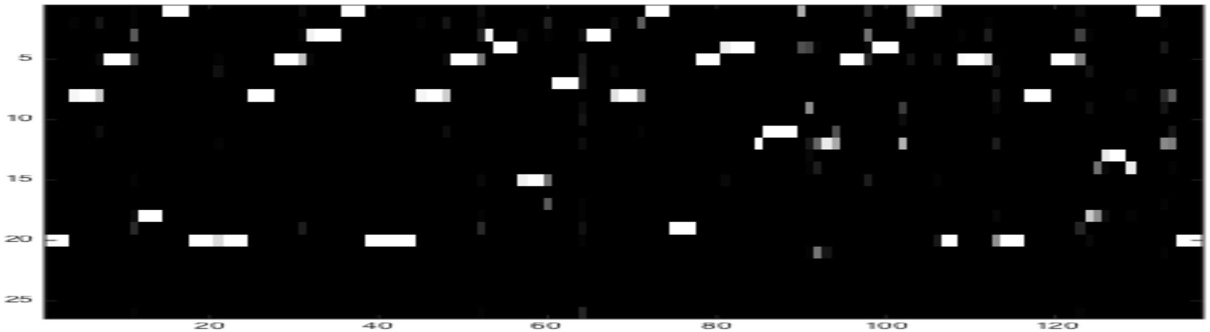
Thoughts

- Modelling. It takes time to
  - Figure out an appropriate network structure
  - Gather data and ground truth
- The optimization does not always work
  - Parameters explode
  - Nothing happens
- Visualization of the features is important for understanding.
- Feedback in networks

Example: OCR, classify images
Results

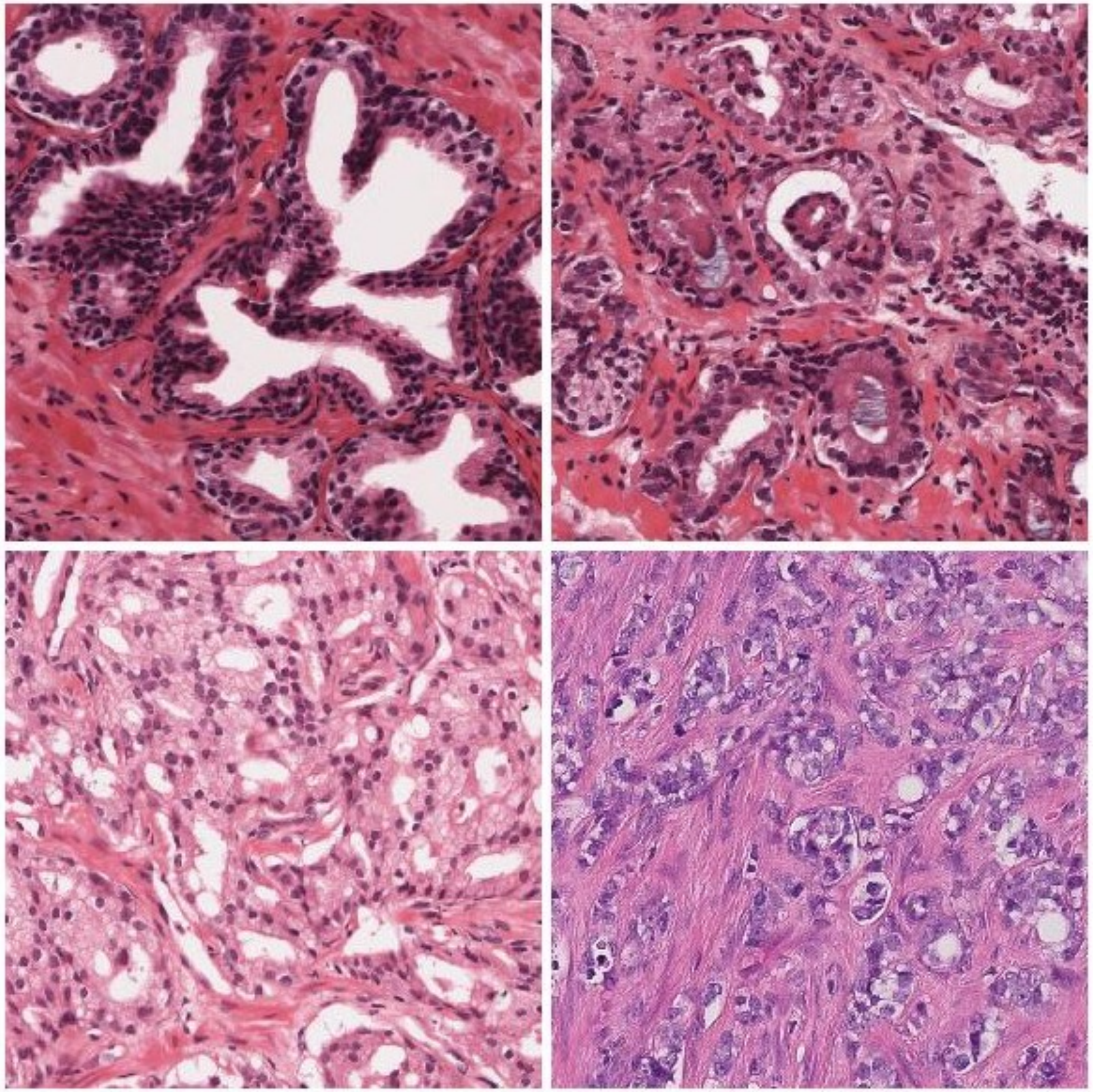




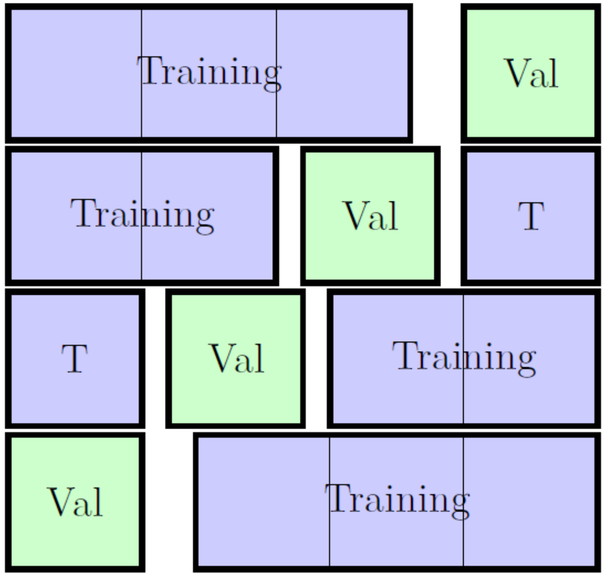


ttthhhheeecrrraaattttttthhheeeeeccccaaat
ttttthhhheeeecdddooooggg
Zccchhhhaaassseeeddddlkkkkaiulleeecdddl
aaaatteeeeetttthhheeeeerrmmmnaaallttt

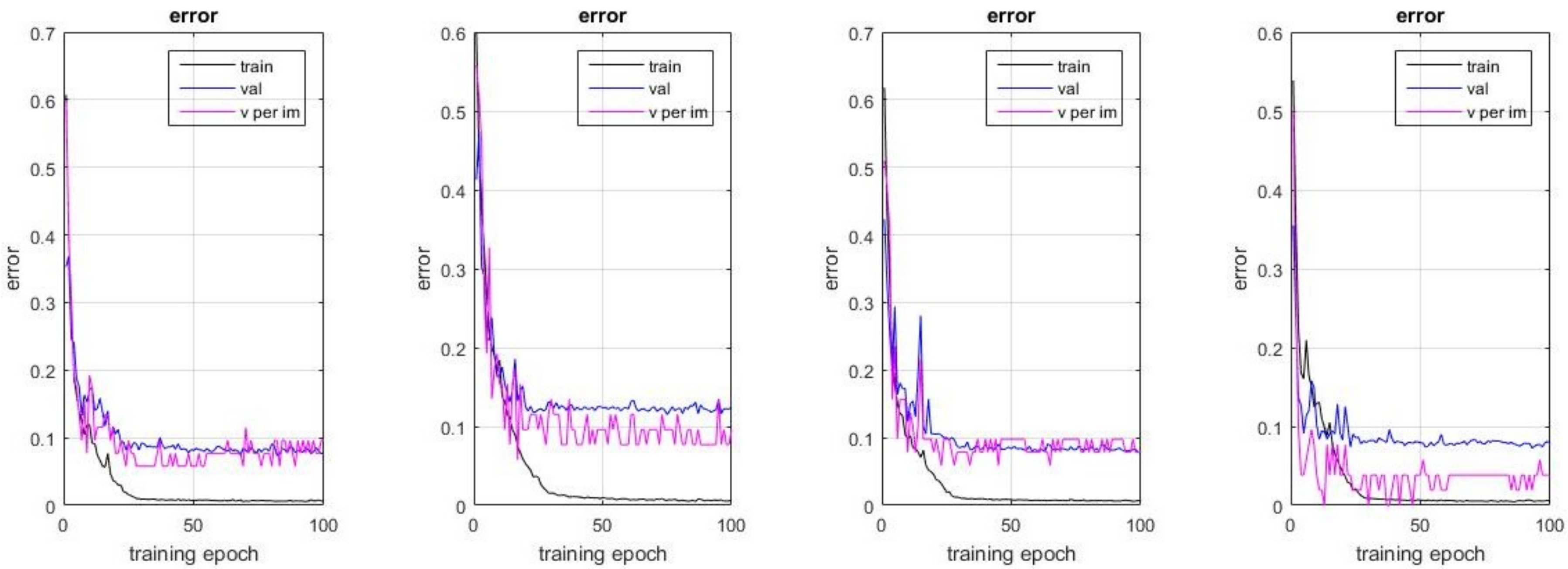
Example: Prostate cancer
Data



Result, Cross-validation



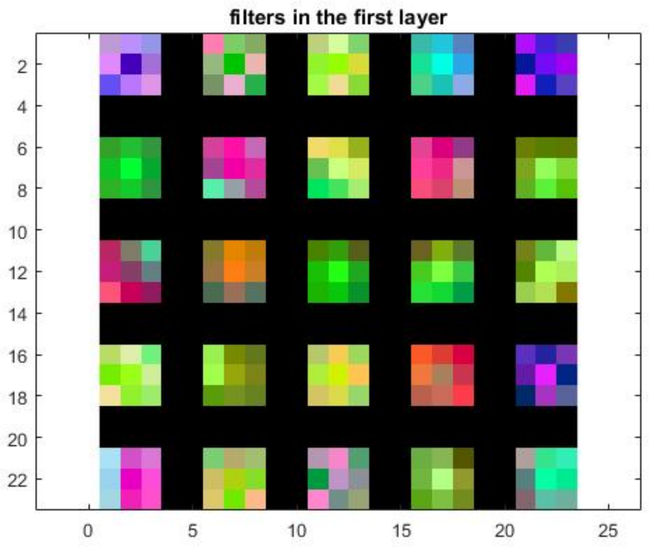
Example: Prostate cancer Training

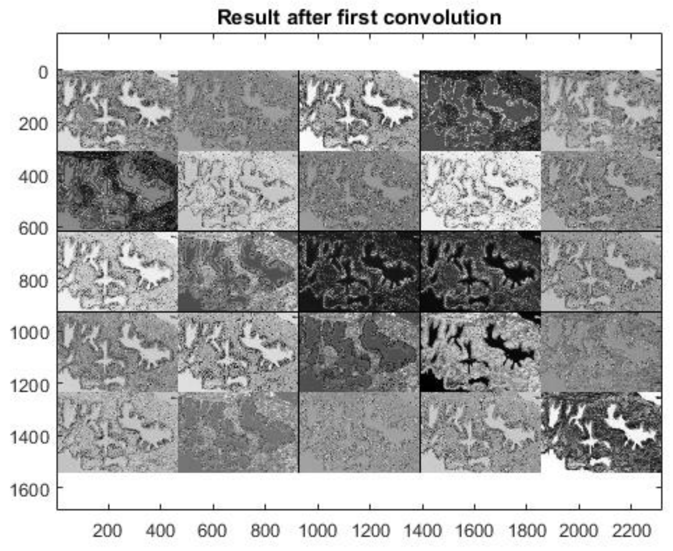


Example: Prostate cancer
Results: Confusion matrix

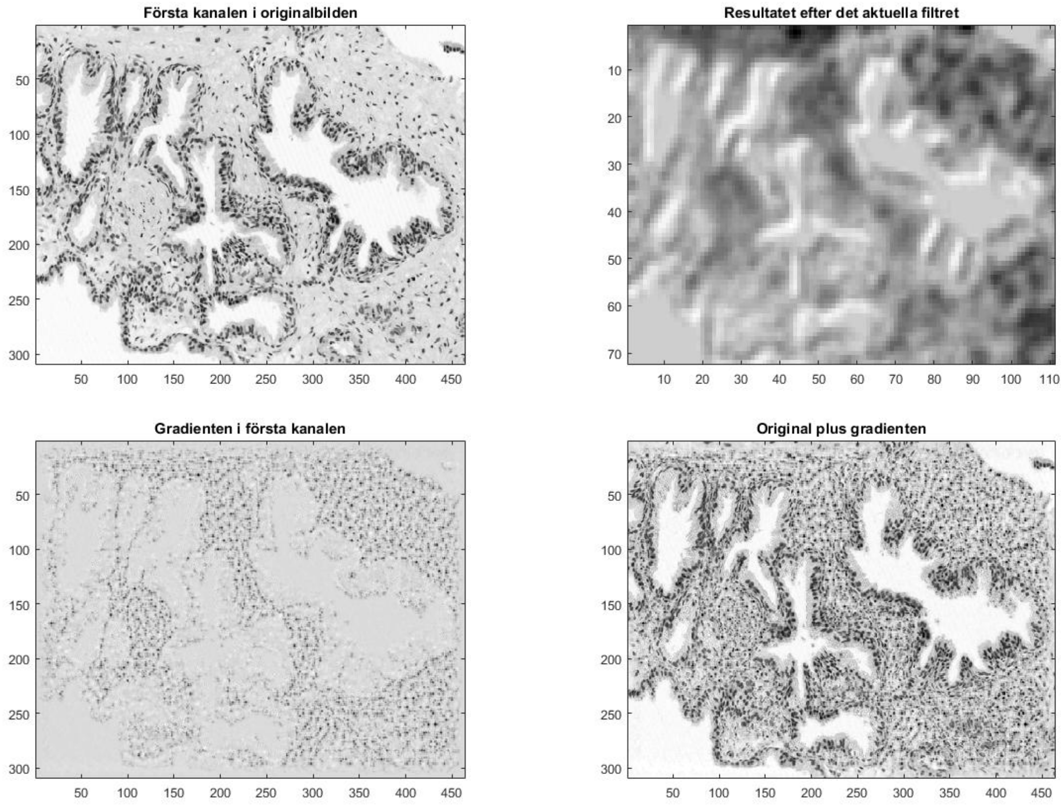
$$\begin{bmatrix} 51 & 0 & 0 & 0 \\ 3 & 46 & 3 & 1 \\ 0 & 6 & 43 & 0 \\ 0 & 3 & 0 & 52 \end{bmatrix}$$

Visualisation





Visualisation



Examples: Image net, Data

- ImageNet Large Scale Visual Recognition Challenge
- Yearly challenge since 2010
- 2011 - 25% error
- 2012 - 16% error (using CNN). This kicked off the deep learning hype
- 2015 – 4% error
- By 2015, researchers reported that current software exceeds human ability at the narrow ILSVCR tasks.
- However, as one of the challenge's organisers, Olga Russakovsky, pointed out in 2015, the programs only have to identify images as belonging to one of a thousand categories!

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Examples: Image net, Data

- ImageNet Large Scale Visual Recognition Challenge
- Listen to Fei Fei Li's TED talk
- https://www.ted.com/talks/fei_fei_li_how_we_re_teaching_computers_to_understand_pictures
- 1000 classes
- 1200 images per class
- Subset of imagenet, builds on wordnet structure

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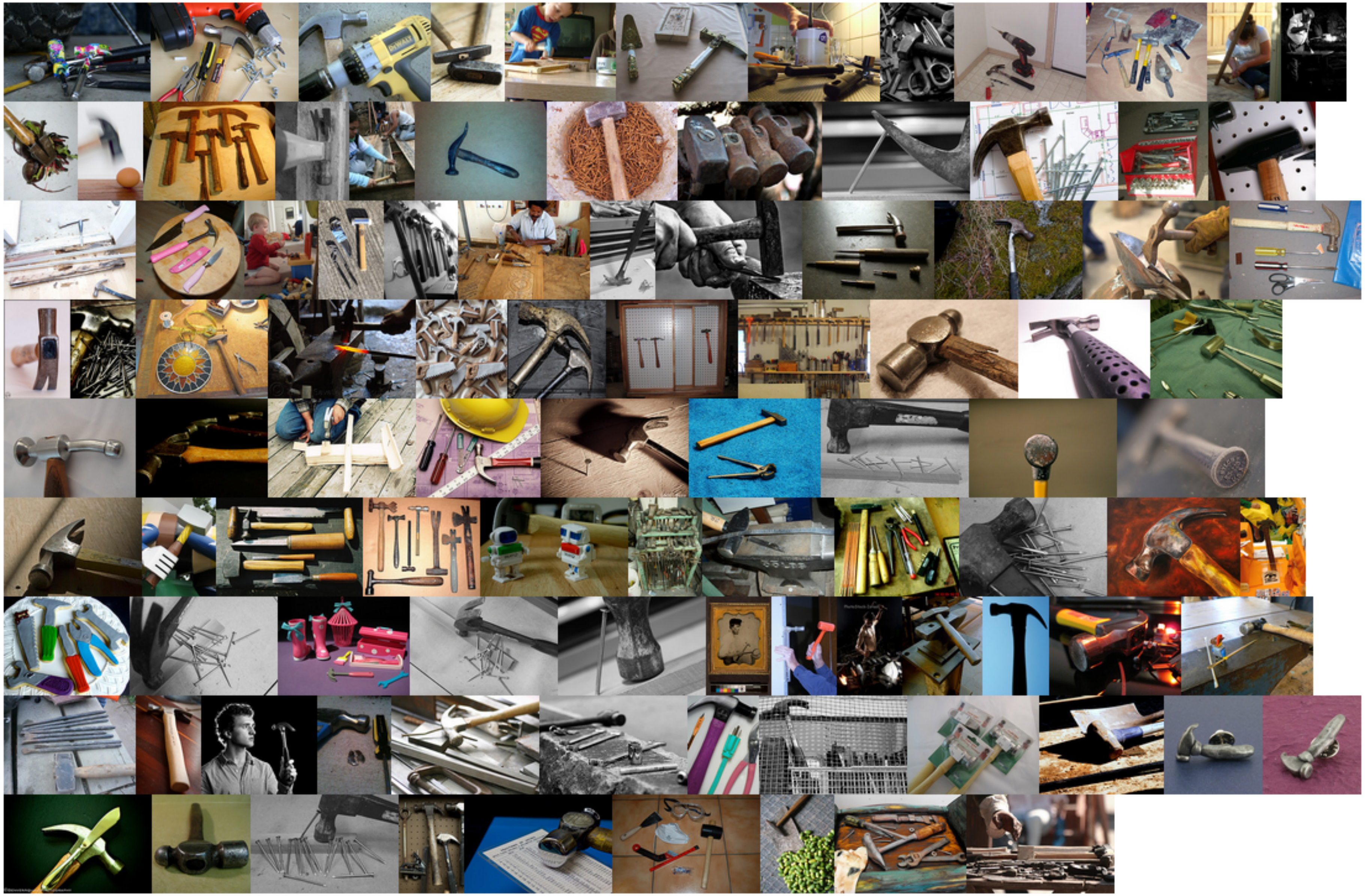
Test images for “Hammer”



Ladles are hard

Chimes are hard

ImageNet Challenge 2012

Task 1: Classification

Car

- Predict a class label

- 5 predictions / image
- 1000 classes
- 1,200 images per class for training
- Bounding boxes for 50% of training.

Task 2: Detection (Classification + Localization)

classification Car

- Predict a class label and a bounding box
- 5 predictions / image
- 1000 classes
- 1,200 images per class for training
- Bounding boxes for 40% of training.

Task 3: Fine-grained classification

classification Walker hound

- Predict a class label given a bounding box in test
- 1 prediction / image
- 120 dog classes (subset)
- ~200 images per class for training (subset)
- Bounding boxes for 100% of training

Examples: Image net, Network design
37 layers – classify 1000 image categories

layer	1	2	3	4	5	6	7	8	9	10	11	12
type	cnv	relu	cnv	relu	mpool	cnv	relu	cnv	relu	mpool	cnv	relu
support	3x3	1x1	3x3	1x1	2x2	3x3	1x1	3x3	1x1	2x2	3x3	1x1
stride	1	1	1	1	2	1	1	1	1	2	1	1
pad	1	0	1	0	0	1	0	1	0	0	1	0
out dim	64	64	64	64	64	128	128	128	128	128	256	256
filt dim	3	n/a	64	n/a	n/a	64	n/a	128	n/a	n/a	128	n/a
rec. field	3	3	5	5	6	10	10	14	14	16	24	24
c/g net KB	7/0	0/0	144/0	0/0	0/0	289/0	0/0	577/0	0/0	0/0	1153/0	0/0

total network CPU/GPU memory: 528.9/0 MB

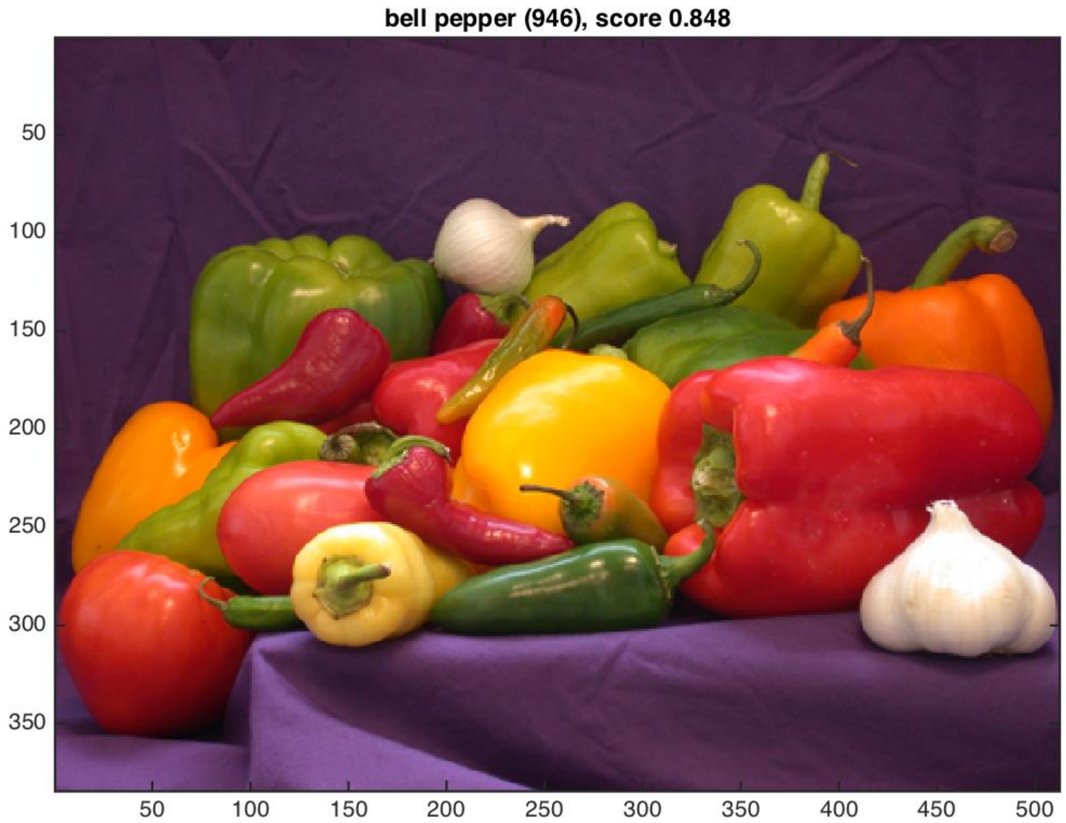
layer	13	14	15	16	17	18	19	20	21	22	23	24	25
type	cnv	relu	cnv	relu	mpool	cnv	relu	cnv	relu	cnv	relu	mpool	cnv
support	3x3	1x1	3x3	1x1	2x2	3x3	1x1	3x3	1x1	3x3	1x1	2x2	3x3
stride	1	1	1	1	2	1	1	1	1	1	1	2	1
pad	1	0	1	0	0	1	0	1	0	1	0	0	1
out dim	256	256	256	256	256	512	512	512	512	512	512	512	512
filt dim	256	n/a	256	n/a	n/a	256	n/a	512	n/a	512	n/a	n/a	512
rec. field	32	32	40	40	44	60	60	76	76	92	92	100	132
c/g net KB	2305/0	0/0	2305/0	0/0	0/0	4610/0	0/0	9218/0	0/0	9218/0	0/0	0/0	9218/0

layer	25	26	27	28	29	30	31	32	33	34	35	36	37
type	cnv	relu	cnv	relu	cnv	relu	mpool	cnv	relu	cnv	relu	cnv	sftm
support	3x3	1x1	3x3	1x1	3x3	1x1	2x2	7x7	1x1	1x1	1x1	1x1	1x1
stride	1	1	1	1	1	1	2	1	1	1	1	1	1
pad	1	0	1	0	1	0	0	0	0	0	0	0	0
out dim	512	512	512	512	512	512	512	4096	4096	4096	4096	1000	1000
filt dim	512	n/a	512	n/a	512	n/a	n/a	512	n/a	4096	n/a	4096	n/a
rec. field	132	132	164	164	196	196	212	404	404	404	404	404	404
c/g net KB	9218/0	0/0	9218/0	0/0	9218/0	0/0	0/0	401424/0	0/0	65552/0	0/0	16004/0	0/0

Examples, Network design
37 layers – classify 1000 image categories

```
       layer|      1|      2|      3|    rel
        type|    cnv|   relu|    cnv|    rel
     support|    3x3|    1x1|    3x3|    1x
      stride|      1|      1|      1|
         pad|      1|      0|      1|
     out dim|     64|     64|     64|      6
    filt dim|      3|    n/a|     64|    n/
 rec. field|      3|      3|      5|
 c/g net KB|    7/0|    0/0|  144/0|    0/
total network CPU/GPU memory: 528.9/0 MB
```

```
     35|     36|     37|
   relu|    cnv|   sftm|
    1x1|    1x1|    1x1|
      1|      1|      1|
      0|      0|      0|
   4096|   1000|   1000|
    n/a|   4096|    n/a|
    404|    404|    404|
    0/0|16004/0|    0/0|
```



Training Deep Learning

- Data
  - Obtain data,
  - cut-outs of right size,
  - jittering,
  - Data expansion (translation, rotation, scaling, mirroring, adding noise, …)
- Data
  - Obtain ground truth
  - How should the problem be coded

Training Deep Learning

- Hyperparameters
  - How many layers
  - Size of convolution kernels
  - Number of channels
  - Order of layers
- Training parameters
  - Initializing weights
  - Momentum
  - …

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Non-linear function

- Different choices of non-linear functions.
- Faster learning
- Rectifier …

$$f(x) = \max(0, x)$$

- … currently most popular, faster training
- Arguments

$$f(x) = \max(0, x)$$

$$f(x) = \ln(1 + e^x)$$

$$f(x) = \begin{cases} x & \text{if } x > 0 \\ 0.01x & \text{otherwise} \end{cases}$$

$$f(x) = (1 + e^{-x})^{-1}$$

$$f(x) = tanh(x)$$

Training Deep Learning

- Once all of these are in place, there are several good systems for optimizing the parameters
  - MatConvNet, TensorFlow, Caffe, Torch7, Theano
  - Can train on single CPU
  - Faster if compiled for GPU
  - Even faster on cluster of computers with multiple GPU (e g LUNARC, http://www.lunarc.lu.se)
- More links on home page for PhD course
- http://www.control.lth.se/Education/DoctorateProgram/deep-learning-study-circle.html

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Deep learning - summary

- What is deep learning
- Supervised vs unsupervised learning
- Goal function, energy function E
- Choice of non-linearity ReLU
- Optimization Back-propagation, SGD
- Tricks dropout
- Examples from speech and vision
- Software
- References

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