Course 395: Machine Learning - Lectures

Lecture 1-2: Concept Learning (M. Pantic)

Lecture 3-4: Decision Trees & CBC Intro (M. Pantic & S. Petridis)

Lecture 5-6: Evaluating Hypotheses (S. Petridis)

Lecture 7-8: Artificial Neural Networks I (S. Petridis)

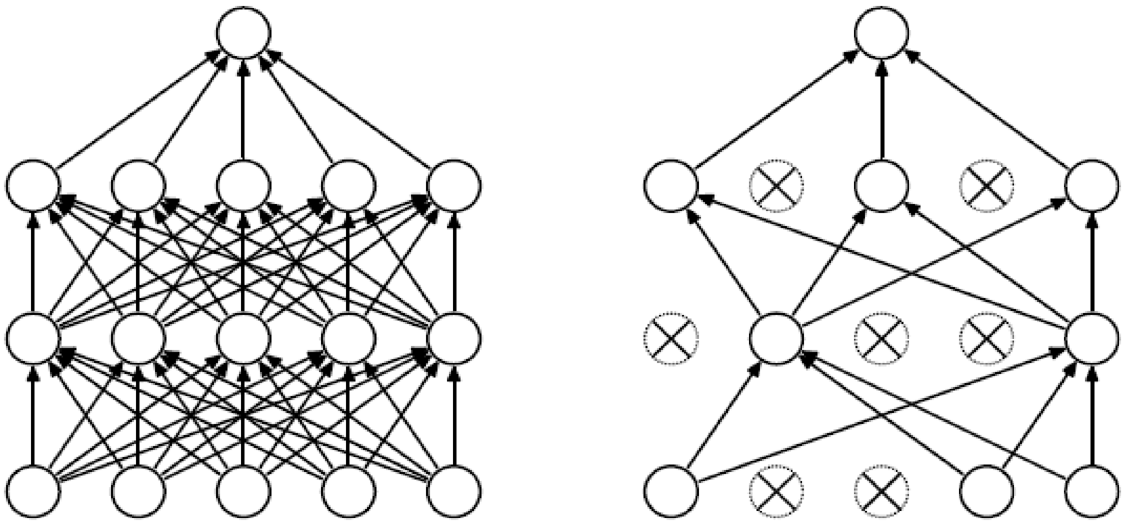
Lecture 9-10: Artificial Neural Networks II (S. Petridis)

➢ Lecture 11-12: Artificial Neural Networks III (S. Petridis)

Lecture 13-14: Genetic Algorithms (M. Pantic)

Dropout

- We don't modify the error function but the network itself
- During training neurons are randomly dropped out
- The probability that a neuron is present is p



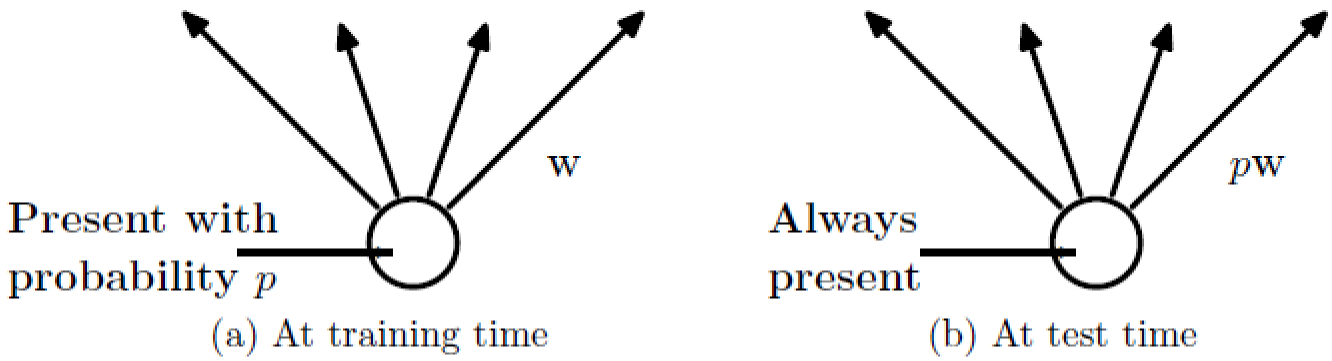
(a) Standard Neural Net　　(b) After applying dropout.

From Dropout: A simple way to prevent neural networks from overfitting by Srivastava et al., JMLR 2014

Dropout

- Dropout prevents overfitting because it prevents neurons from co-adapting too much. Each neuron should create useful features on its own without relying on other hidden units to correct its mistakes.

- Typical values for p: 0.8/0.5 for input/hidden neurons.
- Test time: outgoing weights of a neuron are multiplied by p.



From Dropout: A simple way to prevent neural networks from overfitting by Srivastava et al., JMLR 2014

Dropout - Tips

- If a network with n neurons in the hidden layer works well for a given task then a good dropout network should have n/p neurons.

- Dropout introduces a significant amount of noise in the gradients, a lot of gradients cancel each other → you should use higher learning rate (and maybe higher momentum)

- More epochs are needed

- The above heuristics do not always work!

Data Augmentation

- One of the best ways to avoid overfitting is more data
- So we can artificially generate more data, usually a bit noisy, so we introduce more variation
- We should apply operations that correspond to real-world variations.
- For images: flip left-right, rotate, random cropping, etc

Data Normalisation

- It is not desirable that some inputs/features are orders of magnitude larger than other inputs. Why?
- Map each input/feature to [-1/0, +1]
- Min value is mapped to -1/0
- Max value is mapped to 1

Data Normalisation

- Standardize inputs to mean=0 and 1 std. dev.=1

  $$y = \frac{x - x_{mean}}{x_{std}}$$

- Useful for continuous inputs/targets

- It's called z-normalisation

- Scaling is needed if inputs take very different values. If e.g., they are in the range [-3, 3] then scaling is probably not needed

Data Normalisation

- $x_{mean,} x_{std}$ are computed on the training set and then applied to the validation and test sets.

- It is not correct to normalise each set separately.

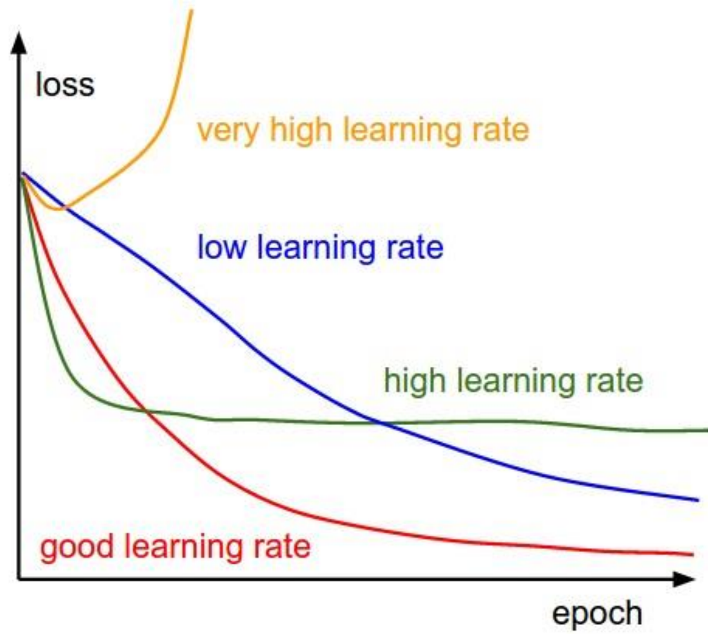
Image Normalisation

- When the input data are images then you can simply remove the mean image computed on the training set.

- Alternatively, you can compute the mean and standard deviation of all the pixels in each image and z-normalise each image independently.

- In case of videos, it's usually better to apply the same normalisation to all frames in the video.

Monitoring the learning process



From http://cs231n.github.io/neural-networks-3/

- If loss increases or oscillates then the learning rate is too high
- If loss goes down slowly the the learning rate is low

- Find a learning rate value at which the loss on the training data immediately begins to decrease.
- It’s a good idea to turn off regularisation at this point

Monitoring the learning process
Other tips

- Compute the mean and standard deviation of hidden neurons activations for all examples in a mini-batch
- They should be different than 0 (this is important when ReLu is used since the neurons can easily die)
- For each layer compute the norm of the weights and the norm of the weight updates Δw.
- The ratio norm(Δw) / norm(w) should be 0.01 – 0.0001
- If ratio is significantly different then something could be wrong

Hyperparameter Optimisation

- Once a good initial learning rate value is found then we can optimise the hyperparameters on the validation set

- Network architecture: number of layers, number of neurons per layer.

- Learning rate: when to start decaying, type of decay

- Regularisation: type of regularisation, values for regularisation parameters

- Training algorithm, SGD+Momentum, Adam, RMSprop

- Maybe we wish to optimise again the initial learning rate

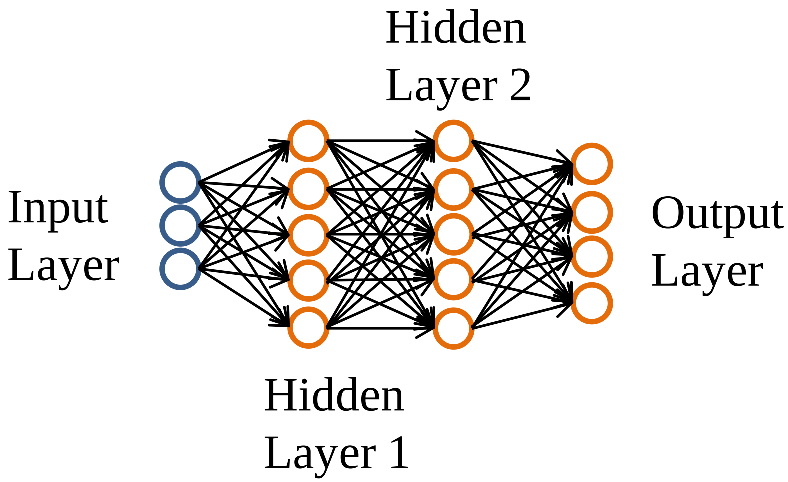
(Hyper)Parameters / Weights

- (Hyper)Parameters are what the user specifies, e.g. number of hidden neurons, learning rate, number of epochs etc

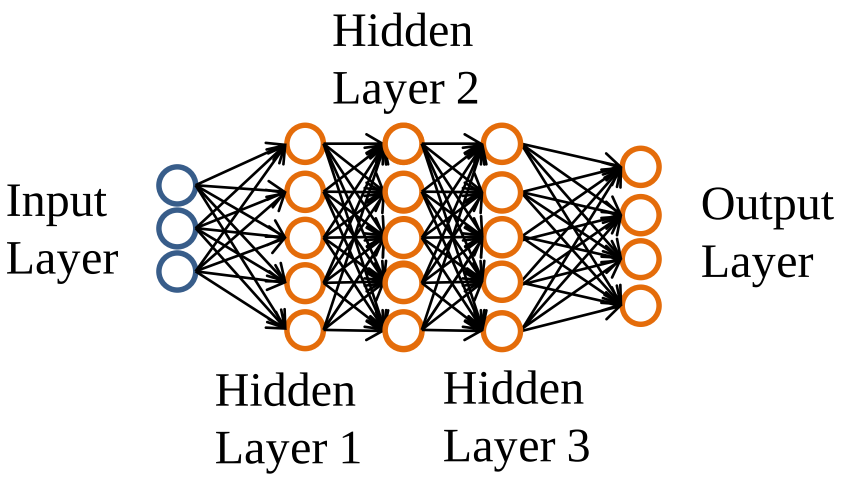
- They need to be optimised

- Weights: They are also parameters but they are optimised automatically via gradient descent

Deep NNs



3-layer feed-forward network

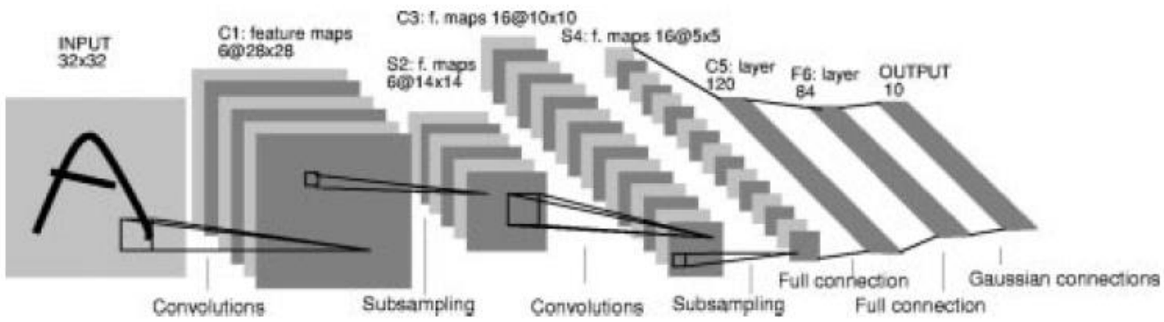


4-layer feed-forward network

- Two ways to train
- A lot of data (data augmentation), ReLu, dropout etc
- Pre-training: weights are initialised to a good starting point
  - Restricted Boltzmann Machines or Stacked Denoising Autoencoders
  - Backpropagation is used to fine-tune the weights

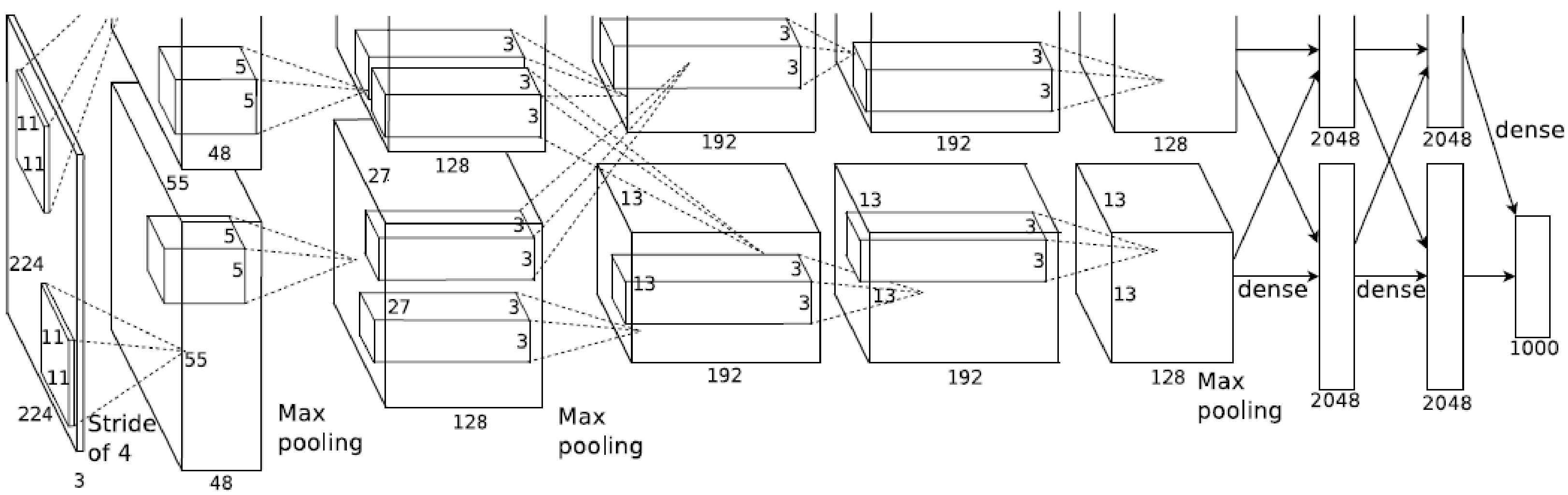
Convolutional Neural Networks

- Convolutional Neural Networks (CNNs) have been very successful in computer vision
- First version was introduced in 1980s (Fukushima, K.; Miyake, S.; Ito, T. (1983). "Neocognitron: a neural network model for a mechanism of visual pattern recognition". IEEE Transactions on Systems, Man, and Cybernetics. 1983)
- Improved by LeCun et al., "Gradient-Based Learning Applied to Document Recognition", Proc. IEEE, 1998

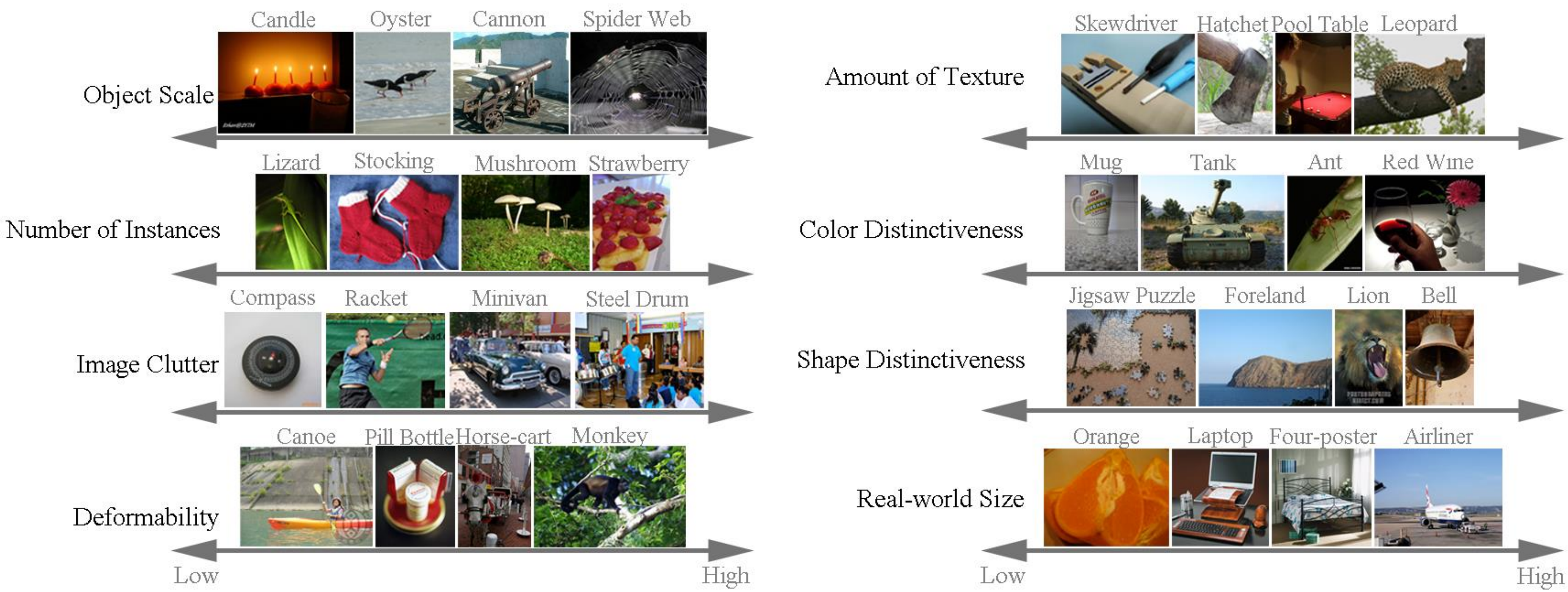


Convolutional Neural Networks

- Became popular in 2012 after winning the ImageNet competition
- "ImageNet Classification with Deep Convolutional Neural Networks", by Krizhevsky et al., NIPS 2012
- Tricks: Data augmentation, Dropout, ReLu + GPUs



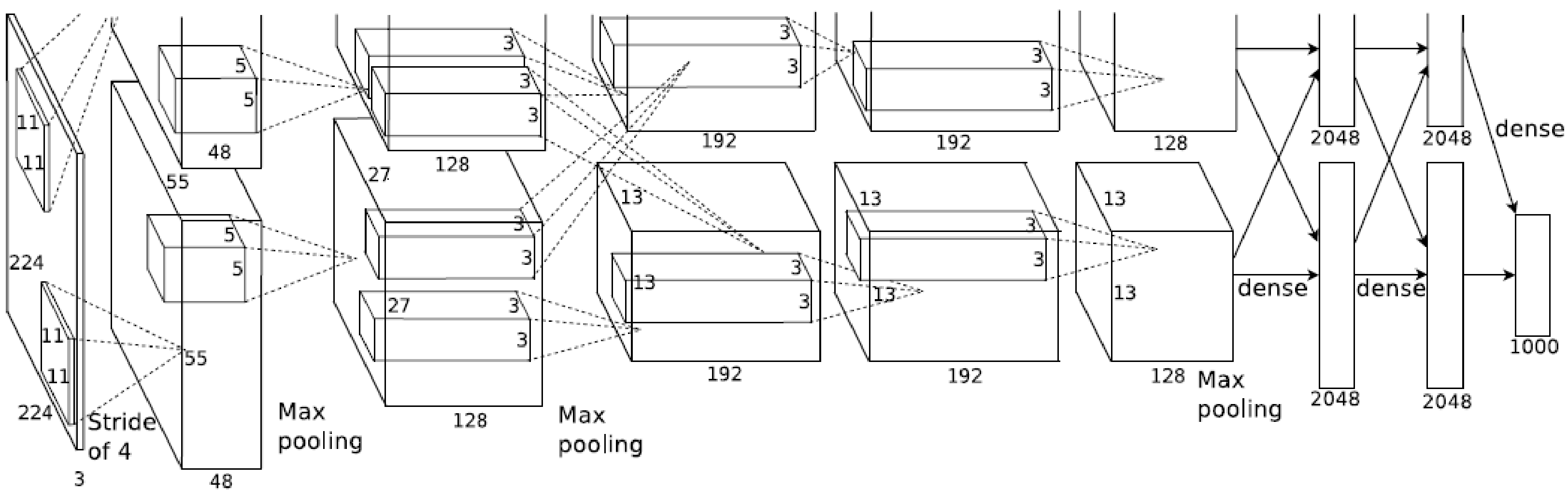
ImageNet Competition – Object Classification



- Classification of 1000+ objects
- State-of-the-art before 2012: ~26%
- New state-of-the-art in 2012 with deep networks: ~15%

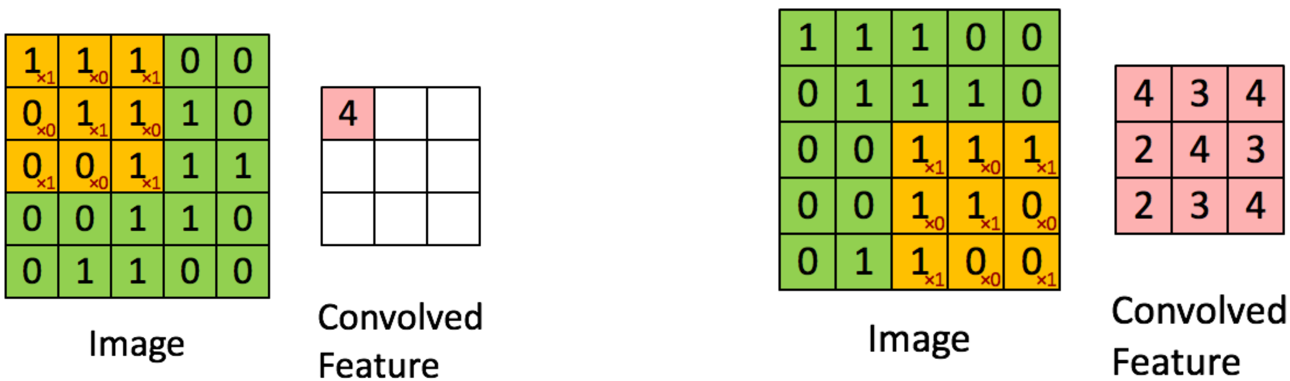
Convolutional Neural Networks

- It's a deep network = many layers
- Each layer is either a convolutional layer or subsampling layer
- Final layers are fully connected layers



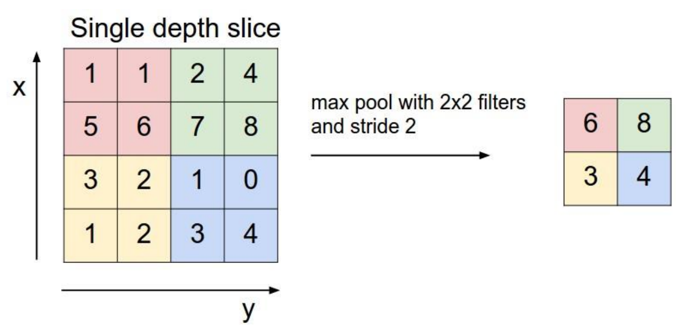
Convolutional Neural Networks

- Convolution



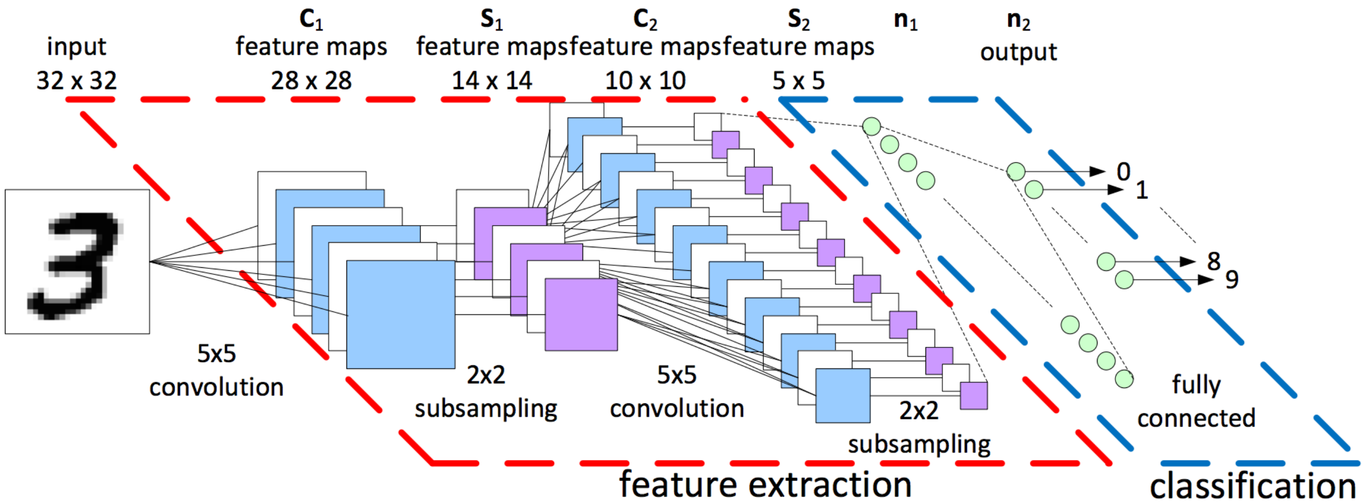
From: http://deeplearning.stanford.edu/wiki/index.php/Feature_extraction_using_convolution

- Max Pooling

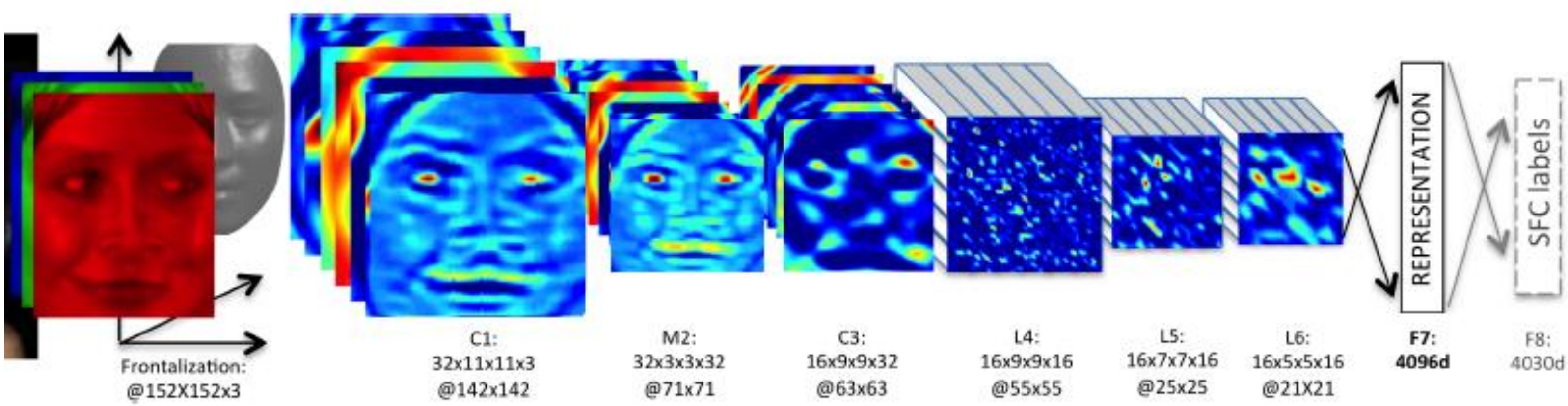


From: http://cs231n.github.io/convolutional-networks/#pool

Convolutional Neural Networks



From: Peeman et. al, Speed sign detection and recognition by convolutional neural networks



From: Taigman et. al, DeepFace: Closing the Gap to Human-Level Performance in Face Verification, CVPR 2014

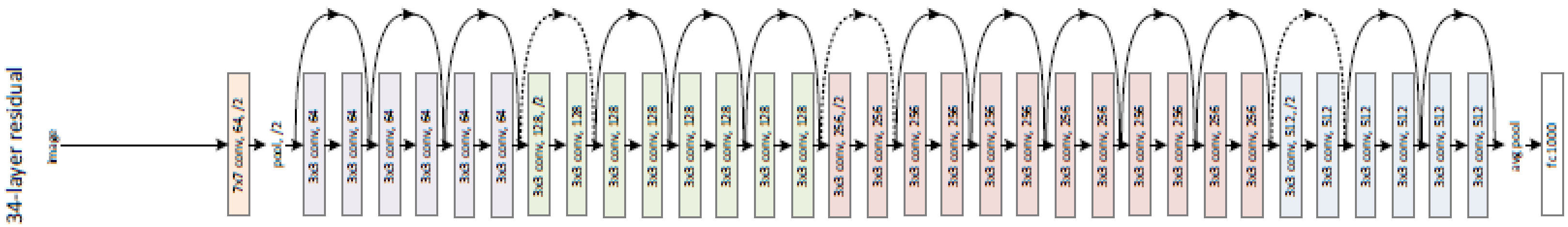
Convolution Types

- Images: 2D convolution
- Videos: we can use 2D convolutions on each image
- We can also stack together a few frames (e.g., 3 – 5) and use a 3D convolution
- Audio signal: 1D convolution

CNN Architectures

- AlexNet
- VGG16, VGG19
- Inception
- ResNet 18, 34, 50, 101, 152
- DensetNet 121, 161, 169, 201

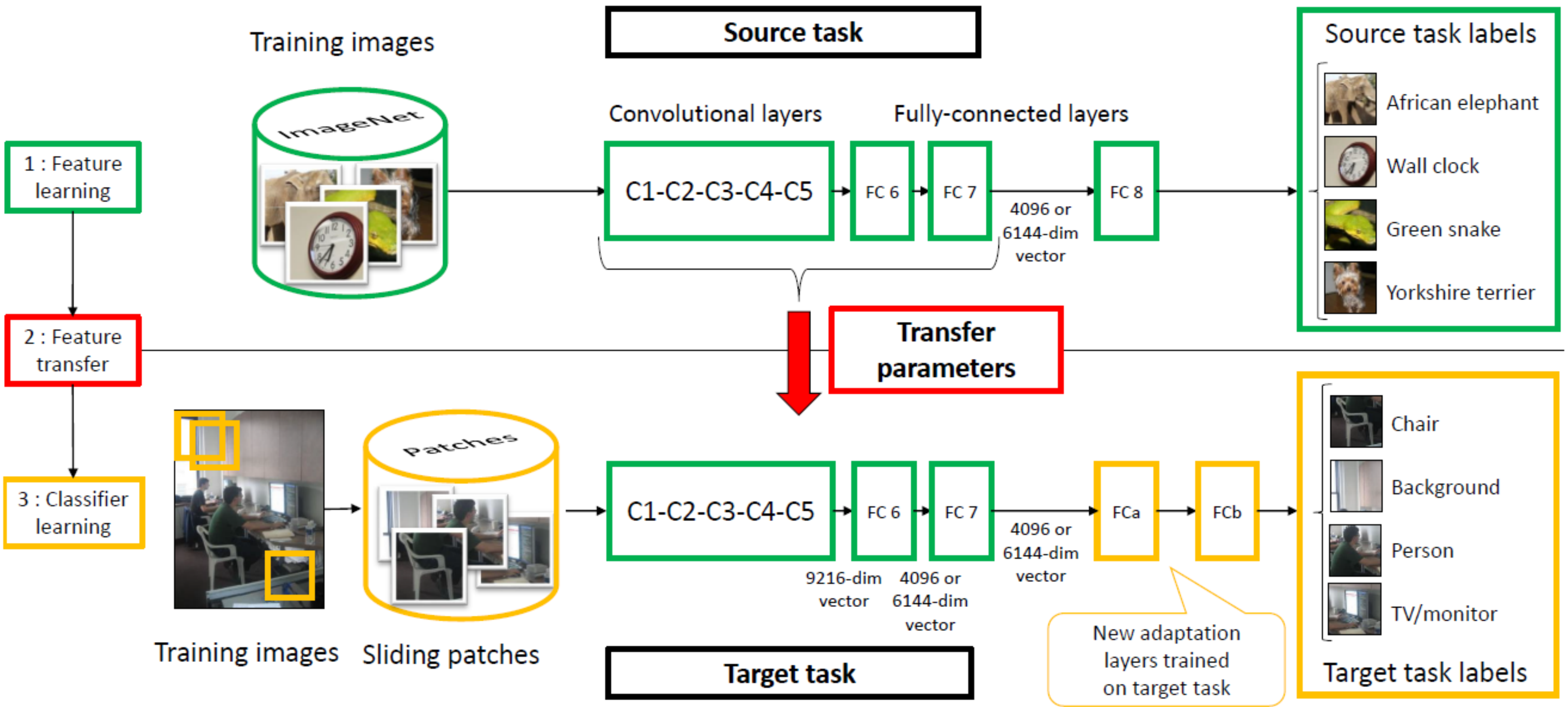
Residual Networks (ResNet)



From: He et al., Deep Residual Learning for Image Recognition, CVPR 2016

- Deep CNN with shortcut connections
- Makes easier training of deeper networks.
- Variations: DenseNet, Wide ResNet

Fine-tuning and Feature Extraction



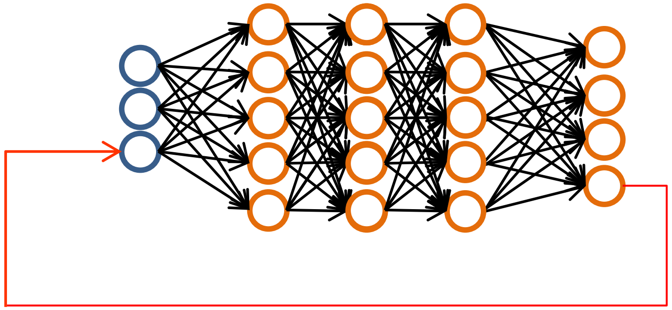
Oquab, M., Bottou, L., Laptev, I., and Sivic, J.. Learning and transferring mid-level image representations using convolutional neural networks. In Computer Vision and Pattern Recognition, 2014

Deep Networks for Time Series

- Deep feedforward NNs/CNNs are good at various tasks but not at handling time series data

- Recurrent Neural Networks are suitable for time series

- They also suffer from the vanishing gradient problem



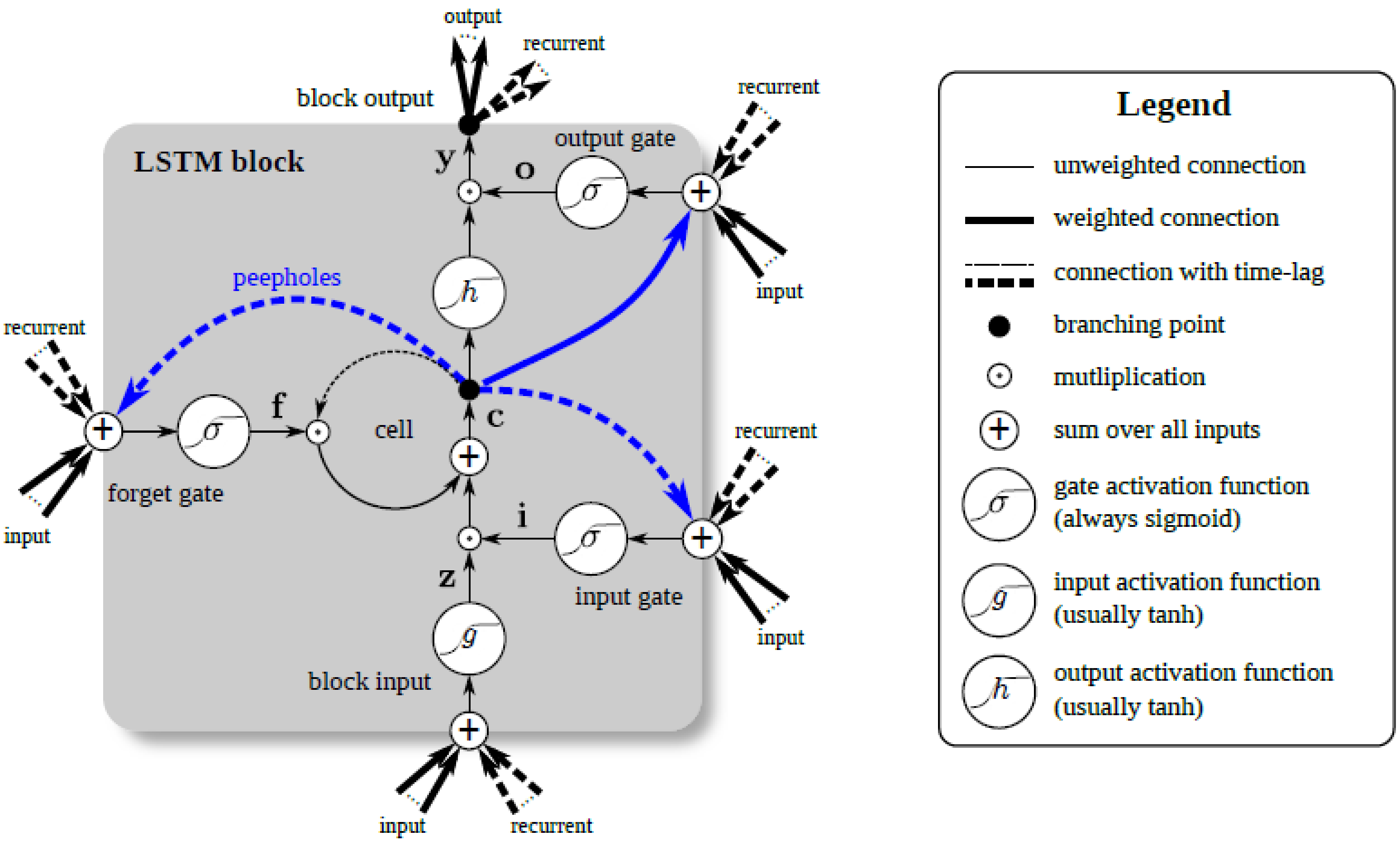
LSTMs

- A type of recurrent network that can be effectively trained is the Long-Short Term Memory Recurrent Neural Network (LSTM-RNN). Introduced in 1990s

- We replace the neuron with a memory cell

- There are input, output and forget gates which control when information flows in / out of the cell and when to reset the state of the cell

LSTMs



From LSTM: A search space odyssey by Greff et al., arXiv Mar 2015

CNNs vs LSTMs

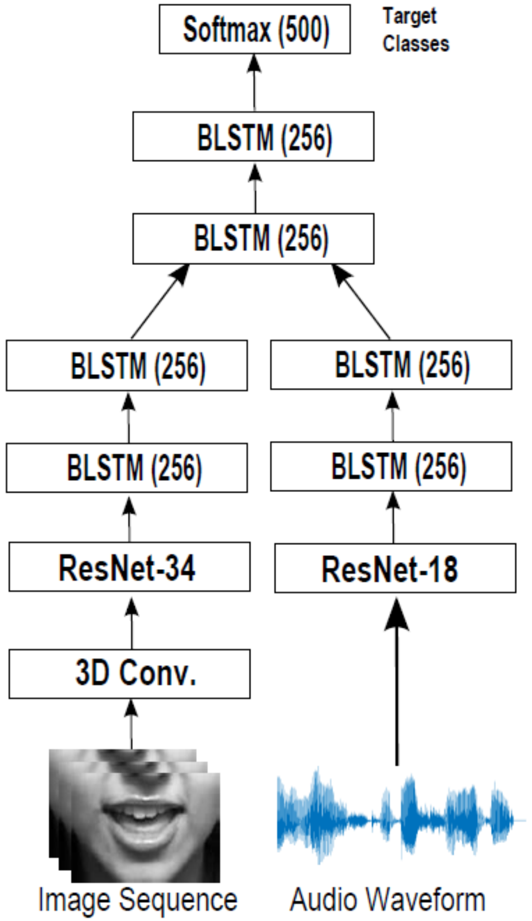
- CNNs are good at extracting features from raw data (images, audio waveform etc) but they do not model temporal dynamics.

- LSTMs are good at modelling time series but they do not extract features.

- We can add a softmax layer to turn them into classifiers.

- If we jointly want to extract features, model temporal dynamics, and perform classification (video classification, speech recognition) then we can combine CNNs + LSTMs + softmax.

End-to-end Learning



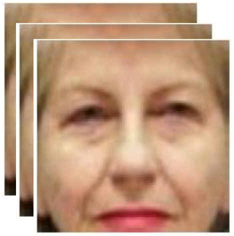
- This is called end-to-end learning because the input is raw data (one end) and the output is the classification label (other end).

- We do not intervene at feature extraction or classification, the deep network learns to model the pipeline from one end to the other end.

Data Types

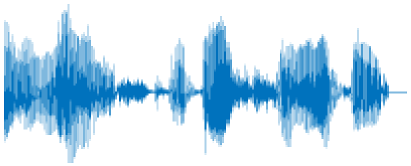
Image:

- 2D spatial data
- 2D CNNs
- No temporal information



Video:

- 3D spatiotemporal data
- 2D images in time
- We can use 2D/3D CNNs + LSTM
- Frame rate: 25/30 frames per second



Audio:

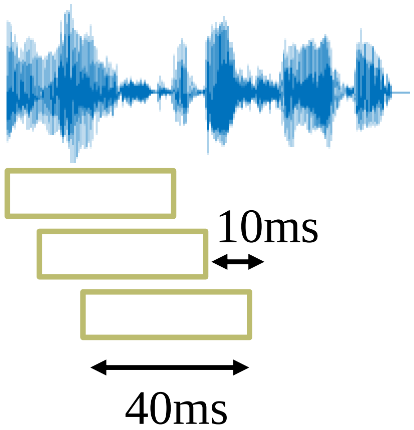
- 1D temporal data
- There is no spatial information
- 1D CNN + LSTM
- Sampling rate: 44.1 kHz

Data Types

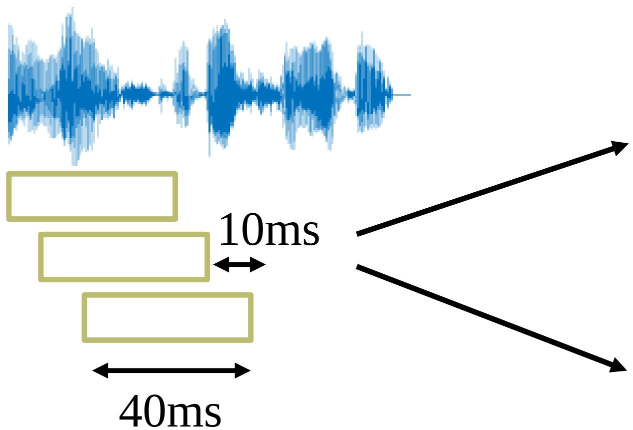
- In images/videos we extract features per frame/group of frames.

- In audio there is no notion of frame, so we define a window with length K (e.g., 40) ms as our frame.

- We also use overlapping frames with stride = 10ms.



Data Types



Traditional Features: Mel Frequency Cepstral Coefficients (MFCCs)

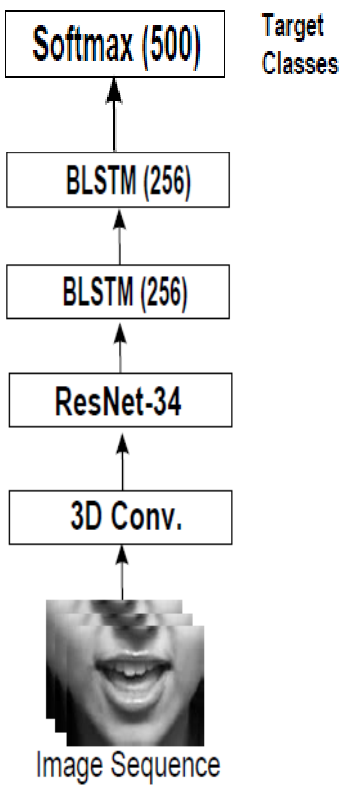
CNN Features: 1D CNNs

- Above values for window length and stride are usually used with traditional features.

- When CNNs are used different window size/stride might be used, e.g., 5ms and 0.25ms.

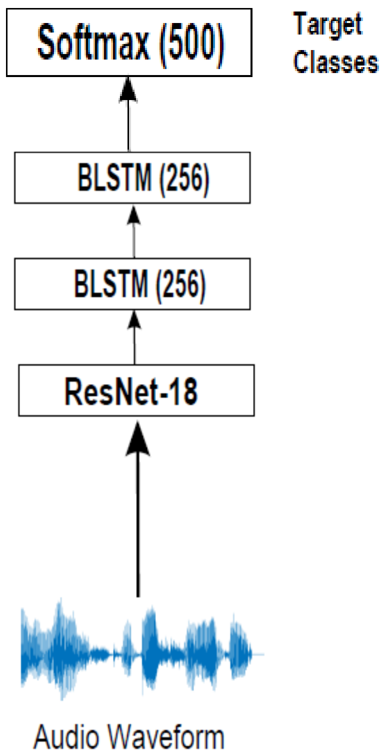
- Note that frame rate of audio and video are different!!

Image/Video



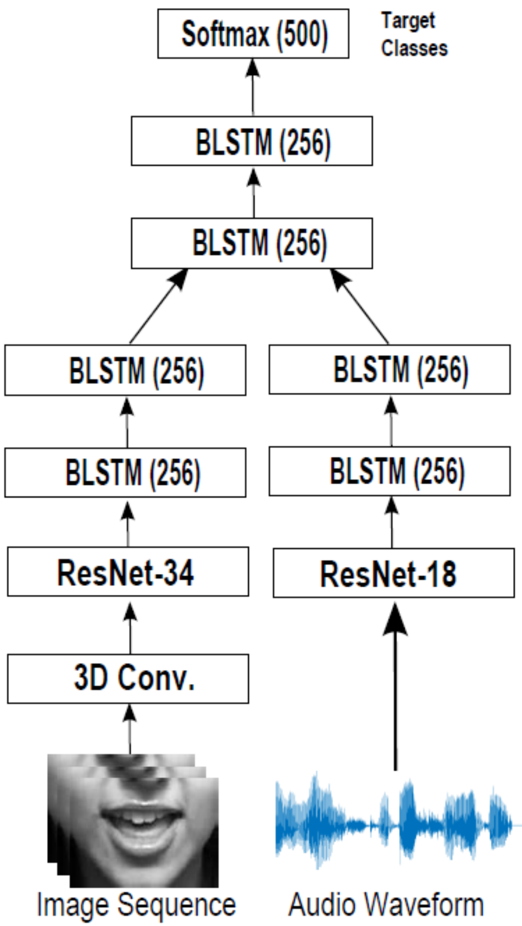
- ResNet extract features directly from the images.
- BLSTMs model temporal dynamics in each stream.
- Such architectures significantly outperform traditional approaches (feature extraction + classification).
- You can come up with several variants of this architecture.

Audio



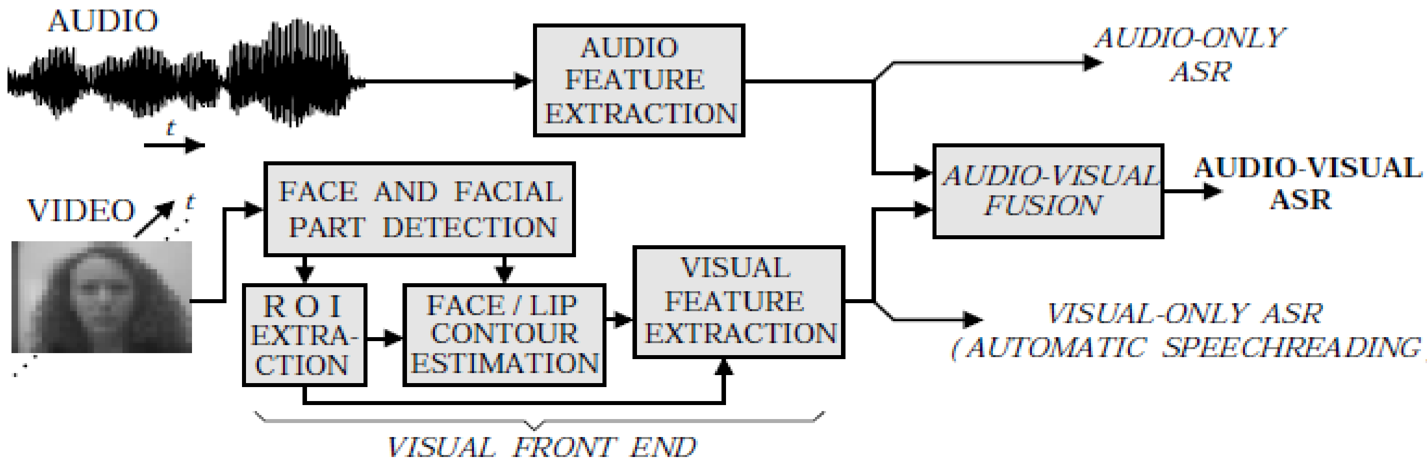
- ResNet extract features directly from the raw waveform.
- BLSTMs model temporal dynamics in each stream.
- Use of 1D CNNs is still an active reseach area.
- Usually MFCCs + BLSTMs work equally well.

End-to-end Audiovisual Fusion



- ResNets extract features directly from the images and the audio waveform, respectively.
- BLSTMs model temporal dynamics in each stream.
- Top BLSTMs perform fusion and model joint temporal dynamics.

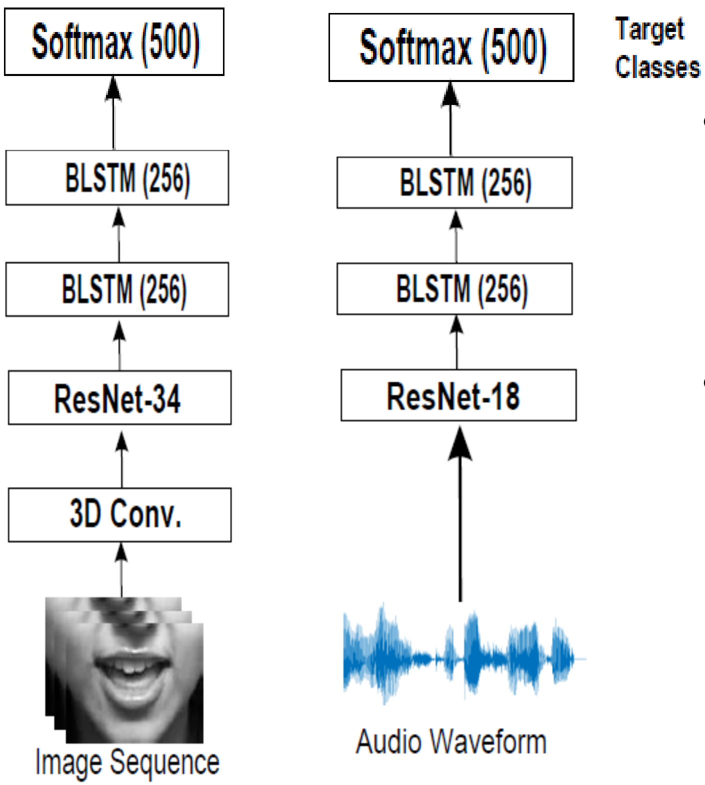
Traditional Audiovisual Fusion



From: G. Potamianos et al., Recent Advances in the Automatic Recognition of Audio-Visual Speech, Proc. IEEE, 2003

- Handcrafted audio/visual features are extracted then fusion takes place, e.g., by feature concatenation
- Similar approach was also used for emotion recognition

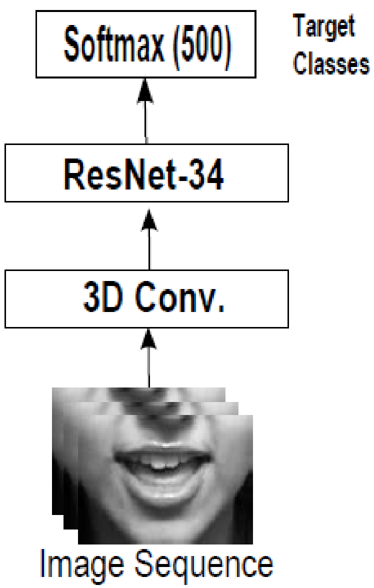
End-to-end Audiovisual Fusion - Training



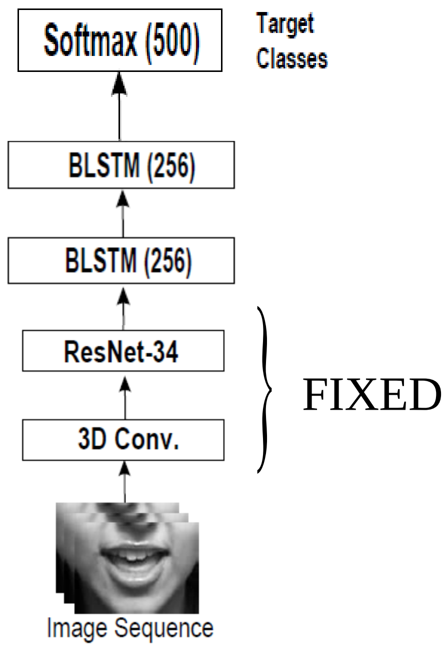
- It's impossible to train the entire architecture from scratch.
- We first train each stream (audio/visual) independently in 2 steps.

End-to-end Audiovisual Fusion - Training

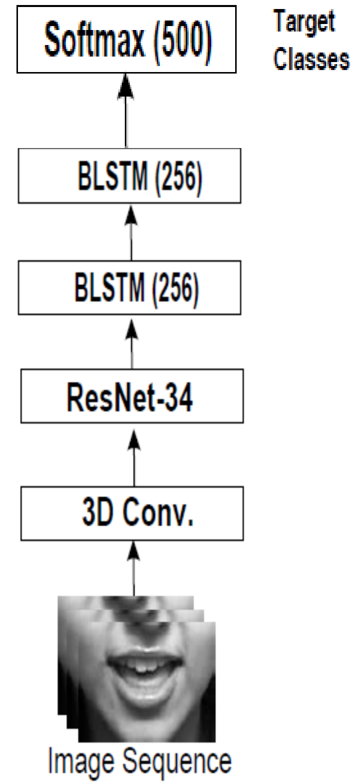
First train the ResNet



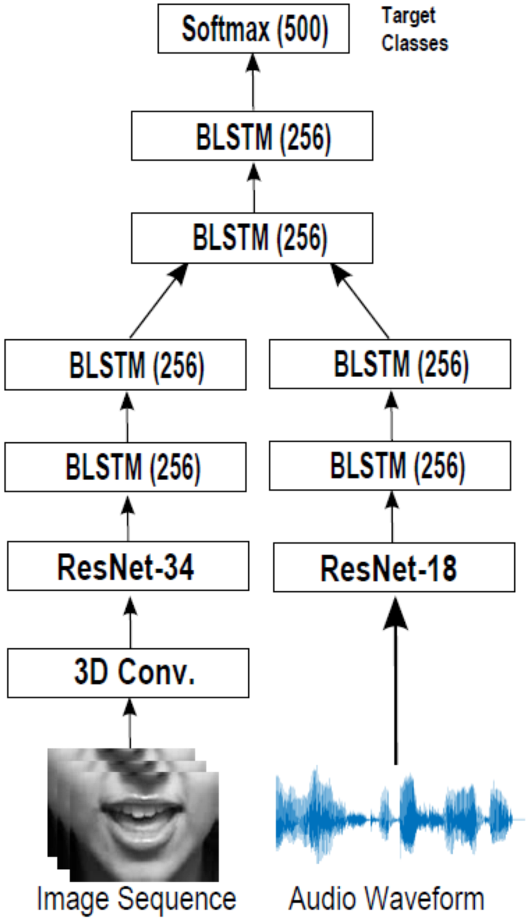
Fix ResNet, Train BLSTMs



Fine-tune entire stream



End-to-end Audiovisual Fusion - Training

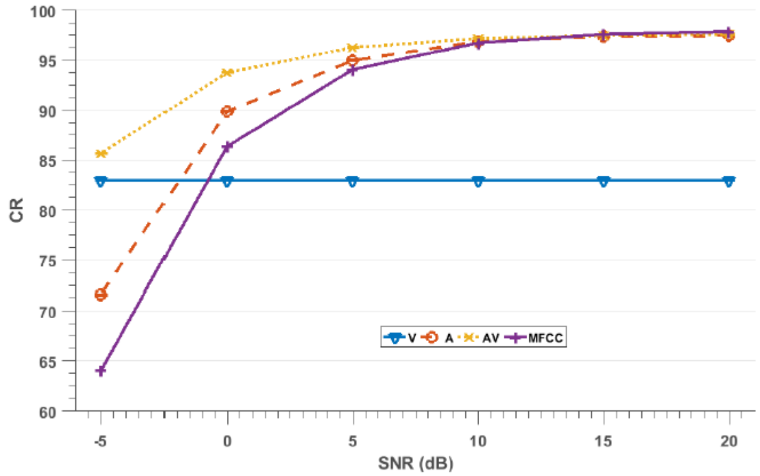


- Fix audio/visual streams and train top BLSTM layers only.
- Fine-tune the entire network.

End-to-end Audiovisual Fusion - Results

Table 1. Classification Rate (CR) of the Audio-only (A), Video-only (V) and audiovisual models (A + V) on the LRW database.

Stream	CR
A (End-to-End)	97.7
A (MFCC)	97.7
V (End-to-End)	83.0
V [15]	76.2
V [19]	61.1
A + V (End-to-End)	98.0



- Results on audiovisual speech recognition, goal is to recognize 500 words (data from BBC TV).

- AV model results in small improvement in clean audio conditions and significant improvement in noisy audio conditions.