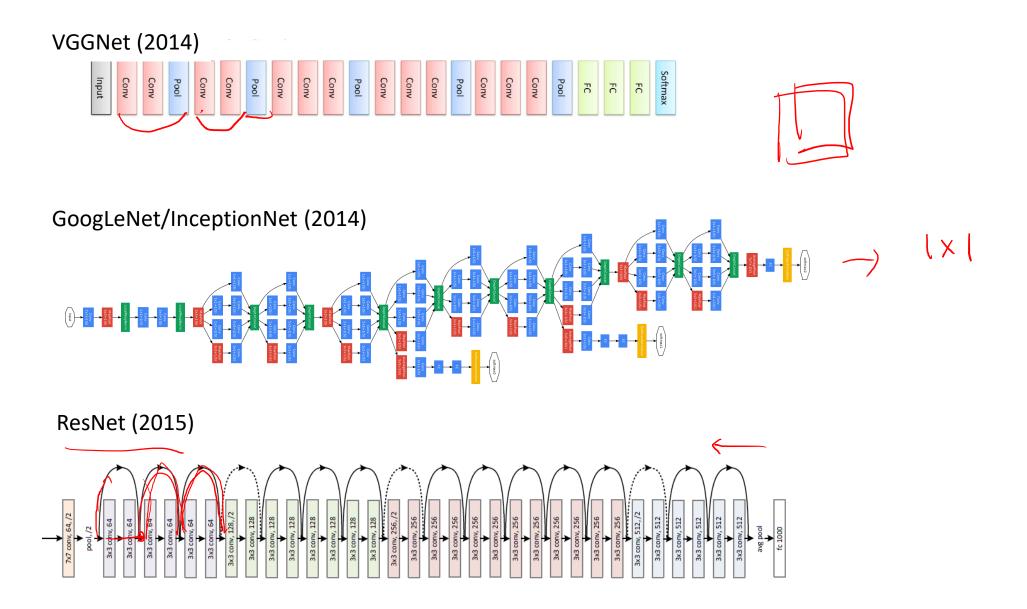
Convolutional Neural Networks (3)

Geena Kim



Most successful CNN models from ImageNet



VGGNet

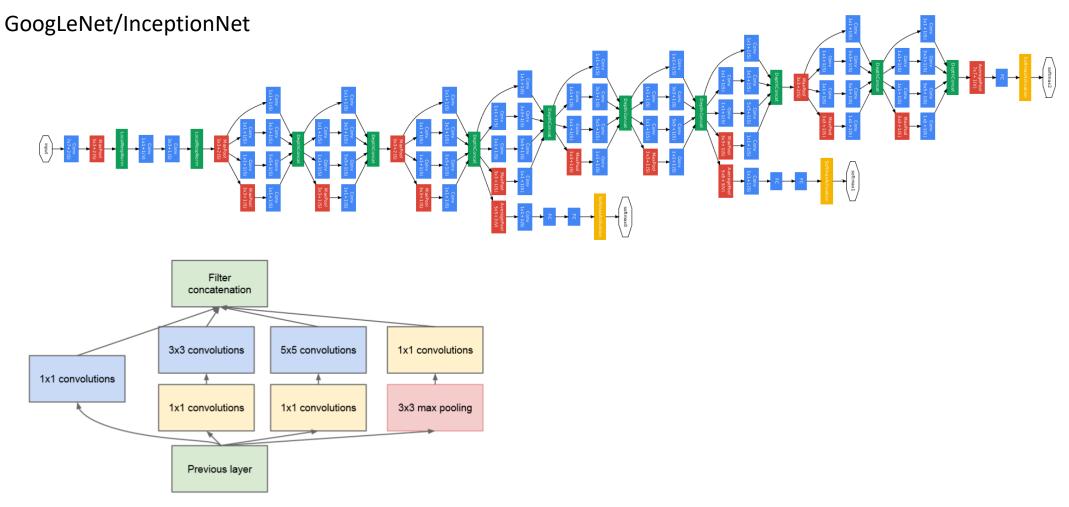
VGGNet

FC FC FC FC FC Conv Conv Conv Conv Conv Conv Conv Con

ConvNet Configuration						
A	A-LRN	B		D	Е	
		2	- C	a a	_	
11 weight	11 weight	13 weight	16 weight	16 weight	19 weight	
layers	layers	layers	layers	layers	layers	
input $(224 \times 224 \text{ RGB image})$						
conv3-64	conv3-64	conv3-64	conv3-64	conv3-64	conv3-64	
	LRN	conv3-64	conv3-64	conv3-64	conv3-64	
maxpool						
conv3-128	conv3-128	conv3-128	conv3-128	conv3-128	conv3-128	
		conv3-128	conv3-128	conv3-128	conv3-128	
maxpool						
conv3-256	conv3-256	conv3-256	conv3-256	conv3-256	conv3-256	
conv3-256	conv3-256	conv3-256	conv3-256	conv3-256	conv3-256	
			conv1-256	conv3-256	conv3-256	
					conv3-256	
maxpool						
conv3-512	conv3-512	conv3-512	conv3-512	conv3-512	conv3-512	
conv3-512	conv3-512	conv3-512	conv3-512	conv3-512	conv3-512	
			conv1-512	conv3-512	conv3-512	
					conv3-512	
maxpool						
conv3-512	conv3-512	conv3-512	conv3-512	conv3-512	conv3-512	
conv3-512	conv3-512	conv3-512	conv3-512	conv3-512	conv3-512	
			conv1-512	conv3-512	conv3-512	
					conv3-512	
maxpool						
FC-4096						
FC-4096						
FC-1000						
soft-max						

https://arxiv.org/abs/1409.1556

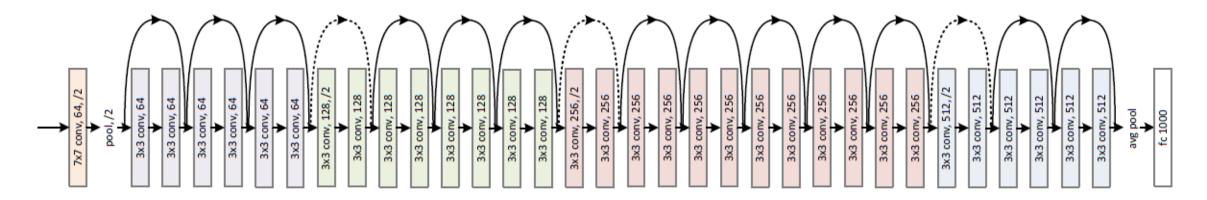
GoogLeNet



(b) Inception module with dimensionality reduction

https://www.cv-foundation.org/openaccess/content_cvpr_2015/papers/Szegedy_Going_Deeper_With_2015_CVPR_paper.pdf

ResNet



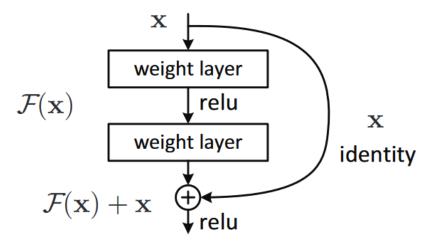
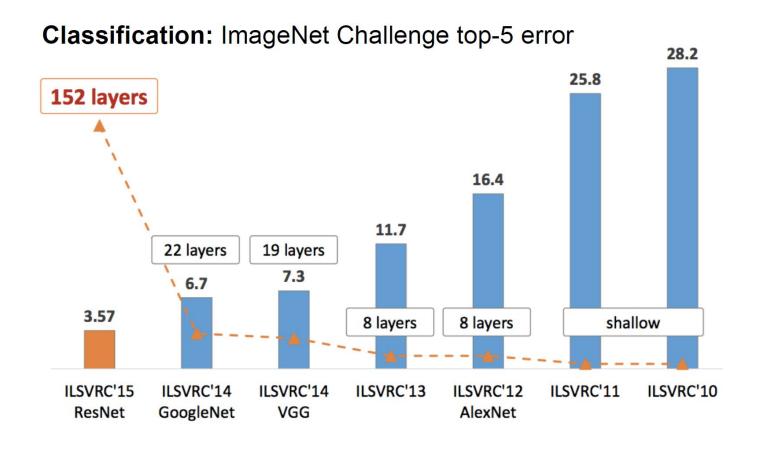


Figure 2. Residual learning: a building block.



Architecture summary

- If the data is bigger and complex, deep network is beneficial
- Improve computational efficiency while keeping the same depth
- e.g. small filter size, 1x1 filter compression
- Designs to have a better gradient propagation (avoid vanishing or exploding gradients)

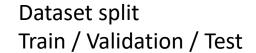


Design Choices or Training

Key Tuning Parameters in Training

- Optimization method
- Learning rate, momentum, etc
- Number of epochs
- Regularization

Monitoring Overfitting in Training



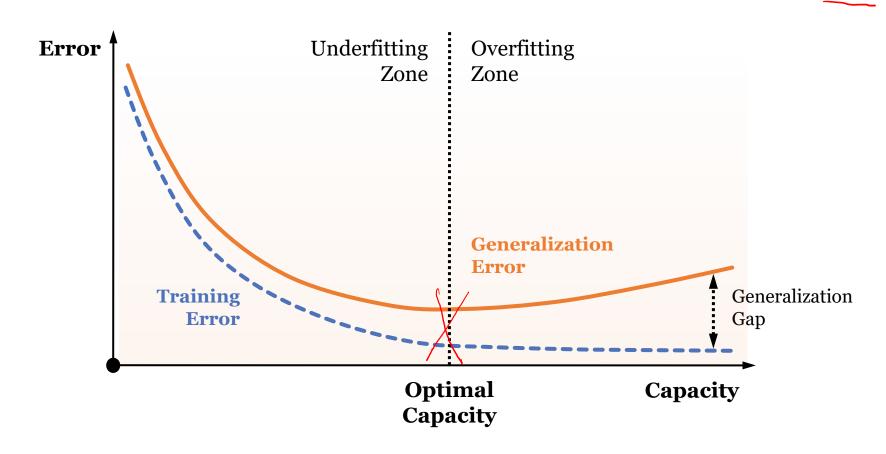
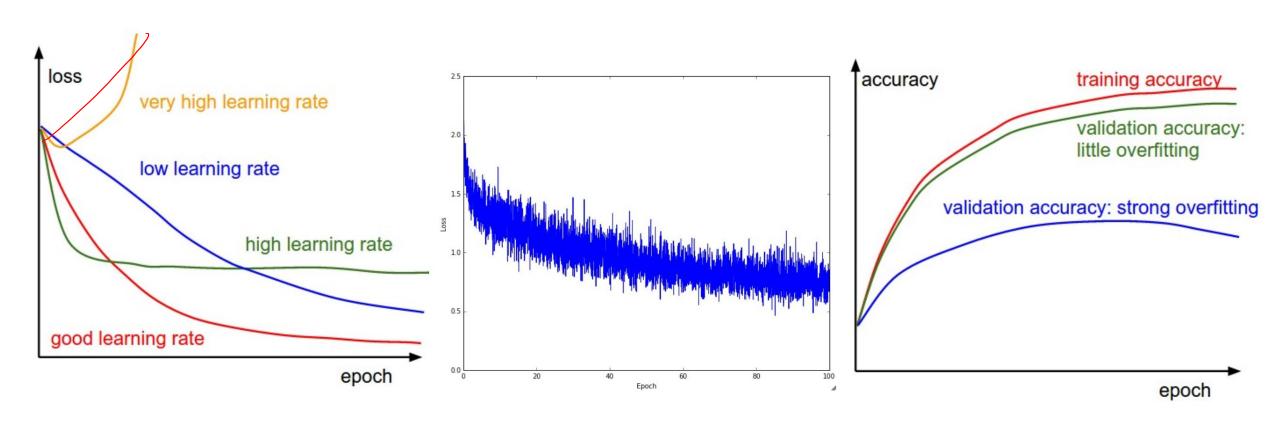


Diagram credit: Fei-Fei Li

Monitoring Overfitting in Training



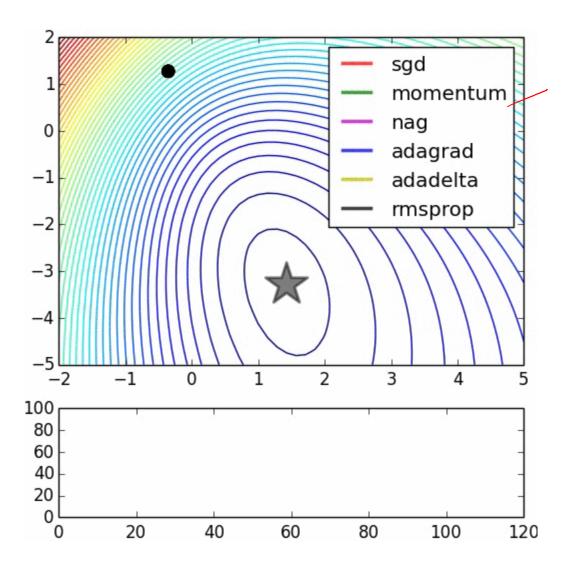
SGD tuning parameters

```
tf.keras.optimizers.SGD(
    learning_rate=0.01, momentum=0.0, nesterov=False, name='SGD', **kwargs)
```

Popular options to tweak

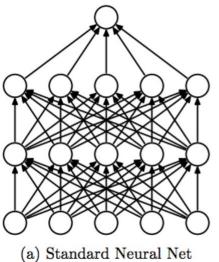
- fearning_rate: the base learning rate
- momentum
- decay
- nestrov
- (advanced) callback

Optimization: Momentum

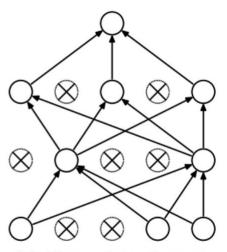


Ways to reduce overfitting

Dropout

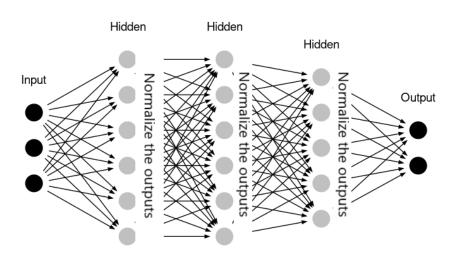






(b) After applying dropout.

Batch normalization



Practical Tips for CNN

Optimization

- Learning rate (0.01~0.0001)
- Optimization method: Adam or RMSProp

Architecture

- ReLU/PReLU for hidden layers, Sigmoid/Softmax/Tanh/PReLU for the output layer
- 3x3 filters
- [Conv-Conv-MaxPool]n structure

Regularization

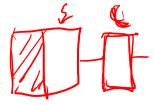
- L2 regularization
- Dropouts
- Batch Normalization

Transfer Learning

How long it takes to train on a large dataset?



Transfer learning



- As fixed feature extractor: remove the output layer, weights frozen
- Fine-tuning the CNN: also let weights updated
- Use part of layers

Transfer Learning

When should I use a pre-trained network?



- New dataset is small and similar to original dataset (X)
- New dataset is large and similar to the original dataset (O)
- New dataset is small but very different from the original dataset (X)
- New dataset is large and very different from the original dataset (O)

Various models pre-trained on ImageNet

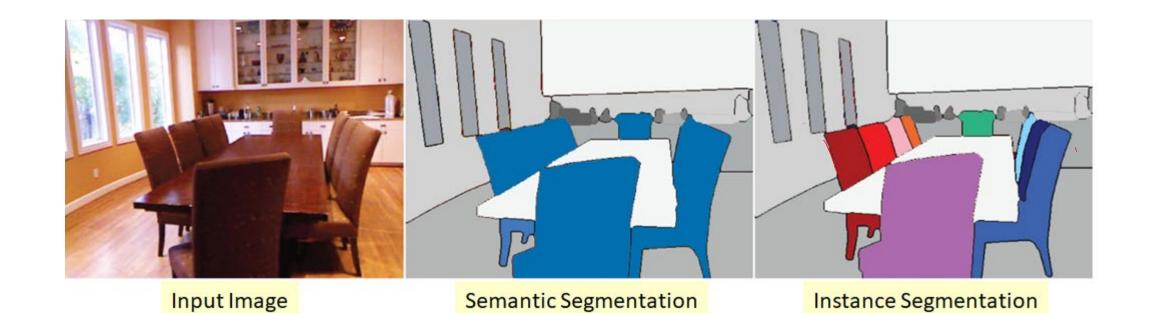
Keras https://keras.io/applications/

Image Segmentation

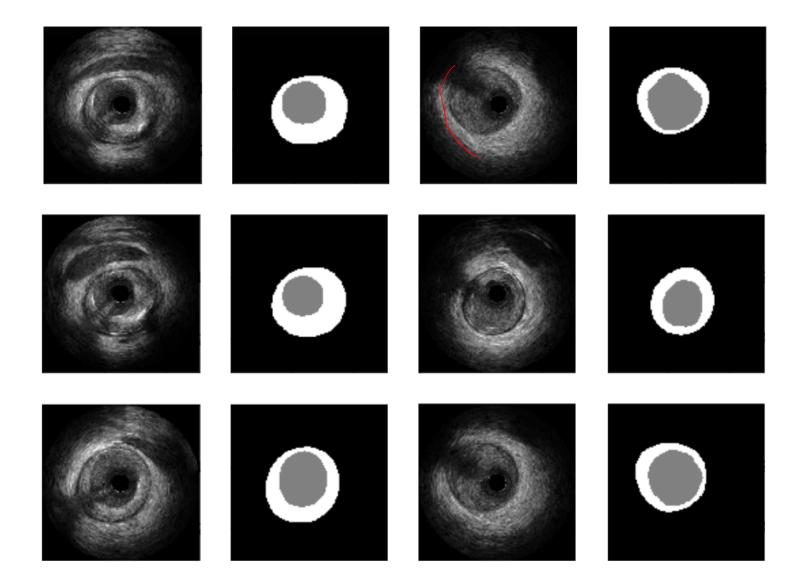
Application in self-driving car



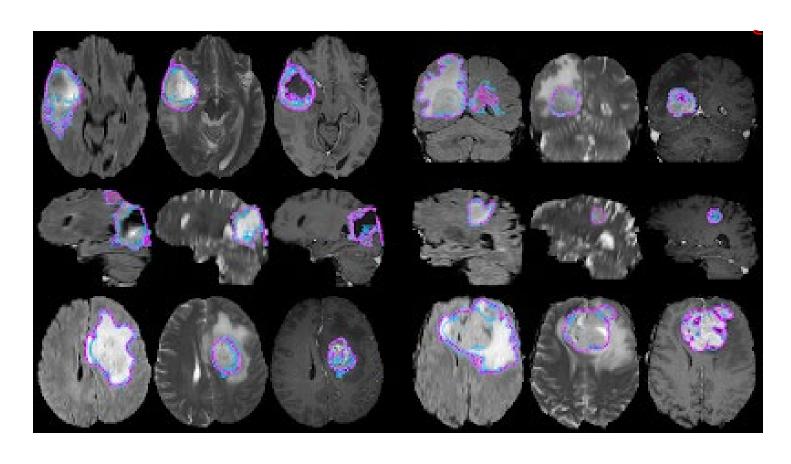
Segmentation Task

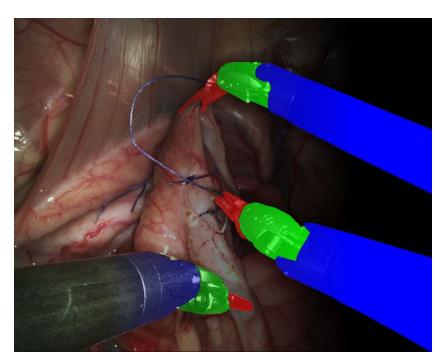


Application in medical images



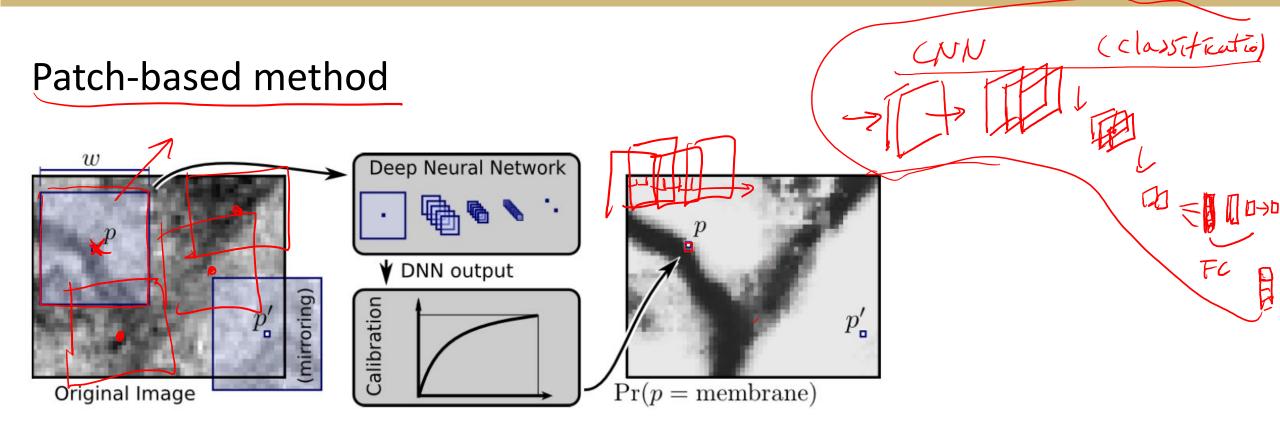
Application in medical images





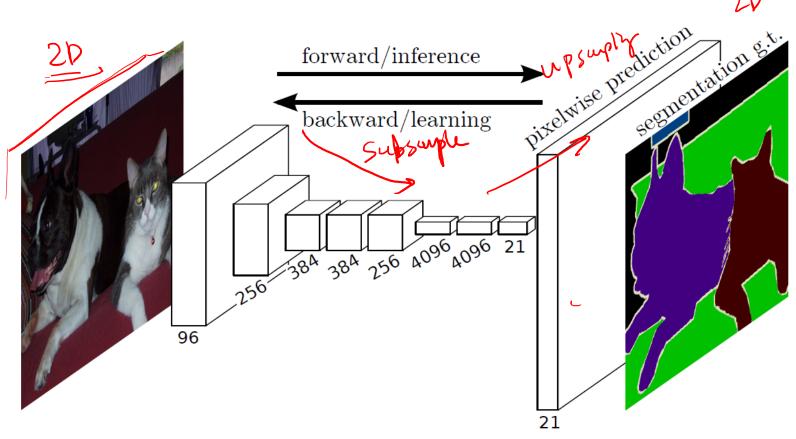
Application in medical images

Ong, Chin et al. Virtual Reality in Neurointervention. Journal of vascular and interventional neurology. 10 (2018)



http://papers.nips.cc/paper/4741-deep-neural-networks-segment-neuronal-membranes-in-electron-microscopy-images.pdf

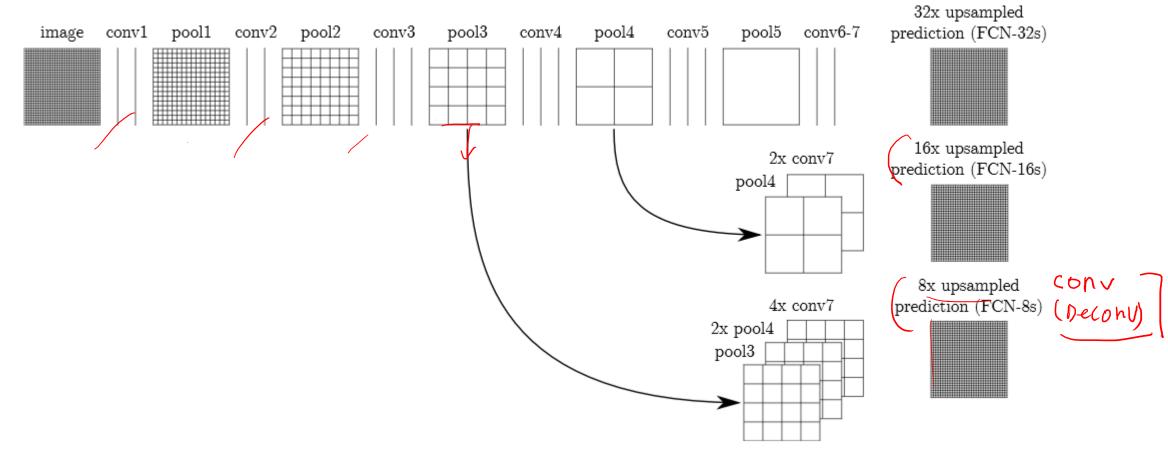
Fully-convolutional



https://www.cv-foundation.org/openaccess/content_cvpr_2015/papers/Long_Fully_Convolutional_Networks_2015_CVPR_paper.pdf

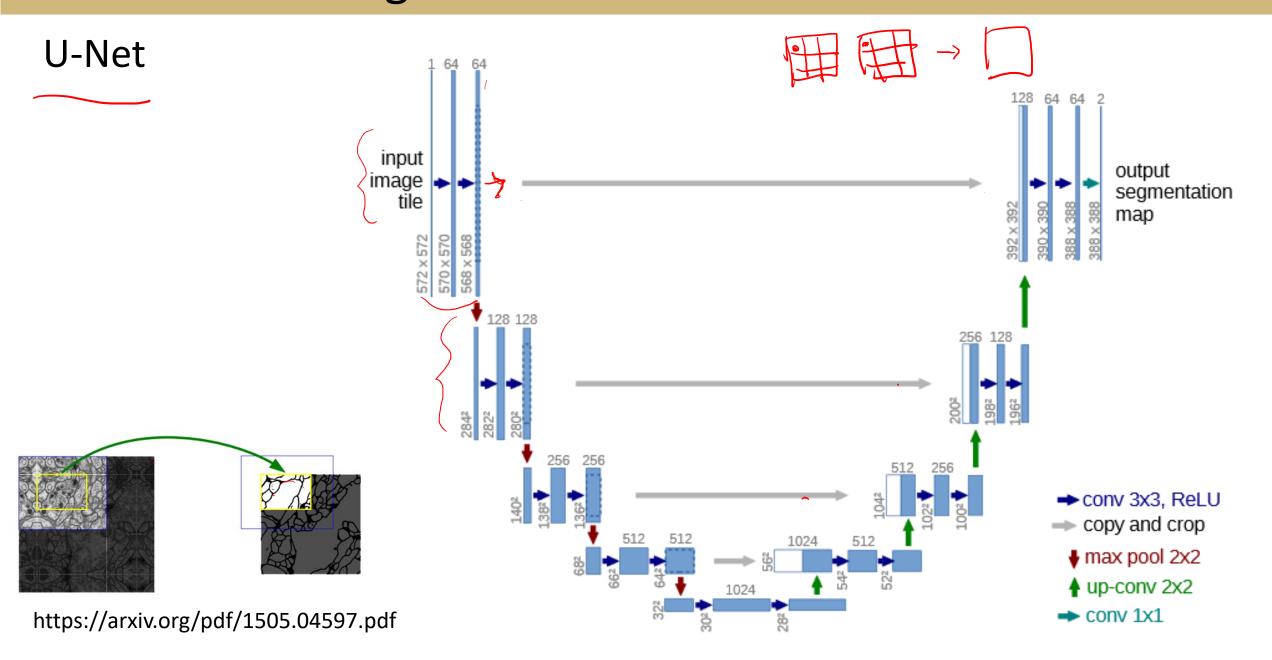
Fully-convolutional

FCNN

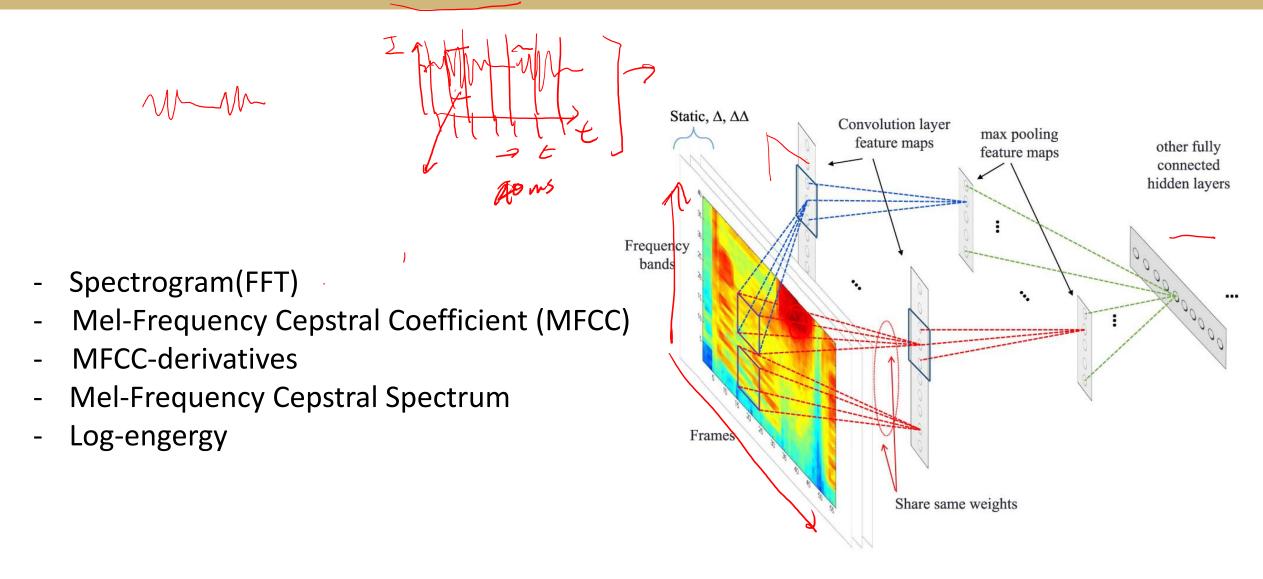


https://www.cv-

foundation.org/openaccess/content_cvpr_2015/papers/Long_Fully_Convolutional_Networks_2015_CVPR_paper.pdf



Other data type- Sound



https://www.microsoft.com/en-us/research/wp-content/uploads/2016/02/CNN_ASLPTrans2-14.pdf

Other data type- Text

Word Embeddings:

Frequency-based

Count Vector

TF-IDF Vector

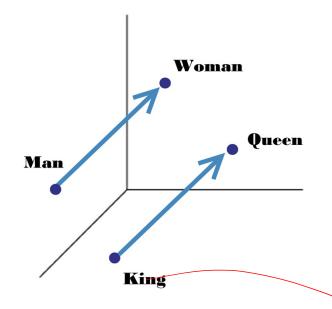
Co-Occurrence Vector

Prediction-based

Neural probabilistic model

Word2Vec

GloVe



Word embedding is a technique that treats words as vectors whose relative similarities correlate with semantic similarity.

TF-IDF(

$$W: \operatorname{words}
ightarrow rac{\mathbb{R}^n}{W(ext{``cat"}) = (0.2, -0.4, 0.7, \dots)}$$
 $W(ext{``mat"}) = (0.0, 0.6, -0.1, \dots)$

Other data type- Video

