

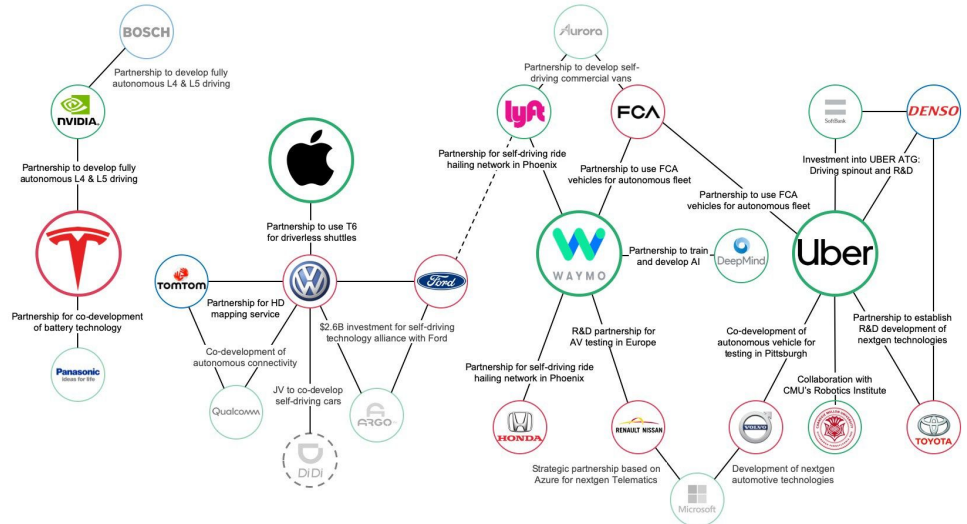
# **Semantic Segmentation for Autonomous Vehicles**

The background features a light blue gradient. A large, dark blue arrow-shaped graphic points from the top right towards the center, containing the main title. Below this, a horizontal orange bar with a 3D effect extends across the bottom of the slide.

# Background

Autonomous vehicles are a massive industry (~\$20 billion)

Scene understanding is necessary for safe and consistent driving

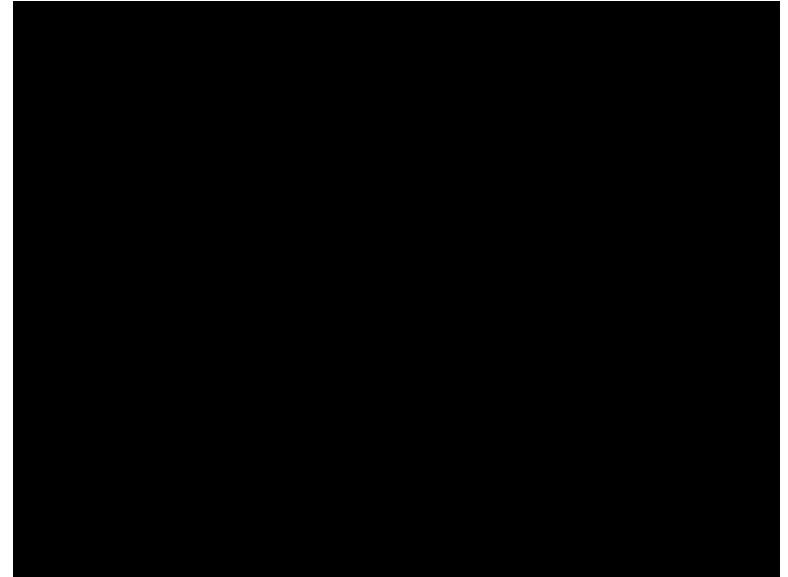


<https://medium.com/@firstmilevc/avlandscape-8a21491f1f54>

# Scene Understanding

Semantic segmentation - per pixel  
image/video understanding

Helps to identify what is in the road and  
surroundings to be used in optimal  
control



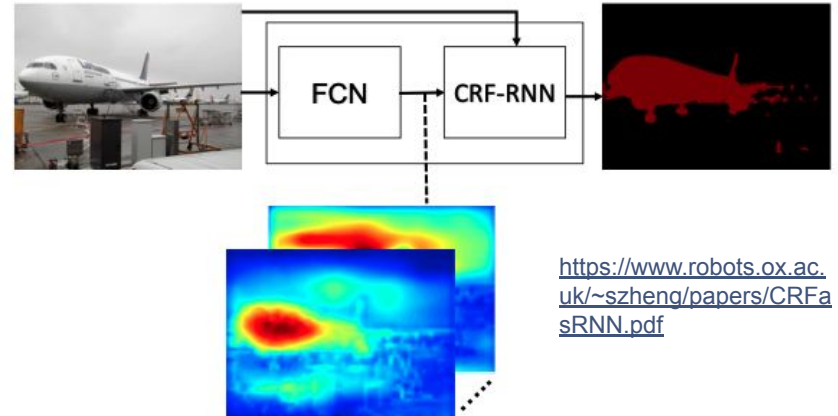
<https://www.tesla.com/autopilotAI>

# Why ML/DL can help

No prescribed method in determining a class for given pixels in an image

Success with Deep Learning - data not always abundant

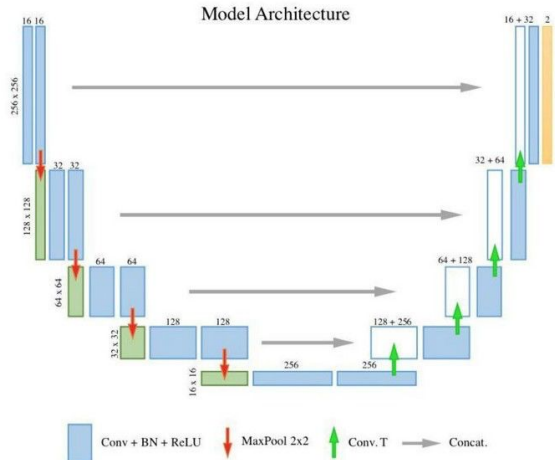
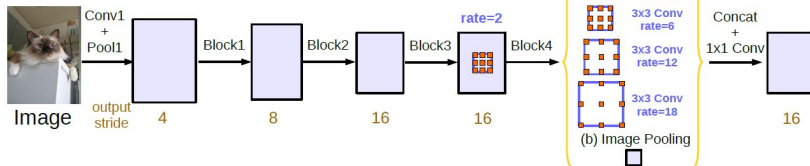
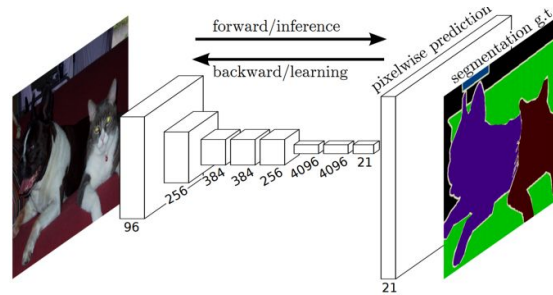
Conventional methods were poor performers (now used as refinement layers)



# Literature Review

Semantic Segmentation: FCN, U-Net, DeepLab, GCN ... plus many others

→ CNNs! (mainly)



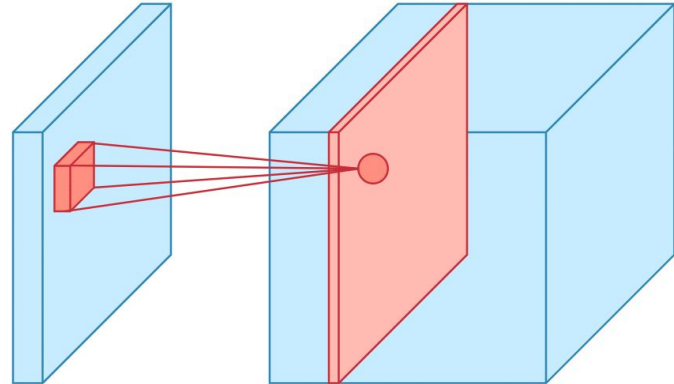
<https://towardsdatascience.com/semantic-segmentation-popular-architectures-dff0a75f39d0>  
<https://towardsdatascience.com/review-deep-abv3-atrous-convolution-semantic-segmentation-6d818bfd1d74>

# Feature Extraction

Convolutional layers extract features automatically from the data by what causes large output values - *filters* out poor indicators

1x1	1x0	1x1	0	0
0x0	1x1	1x0	1	0
0x1	0x0	1x1	1	1
0	0	1	1	0
0	1	1	0	0

4		

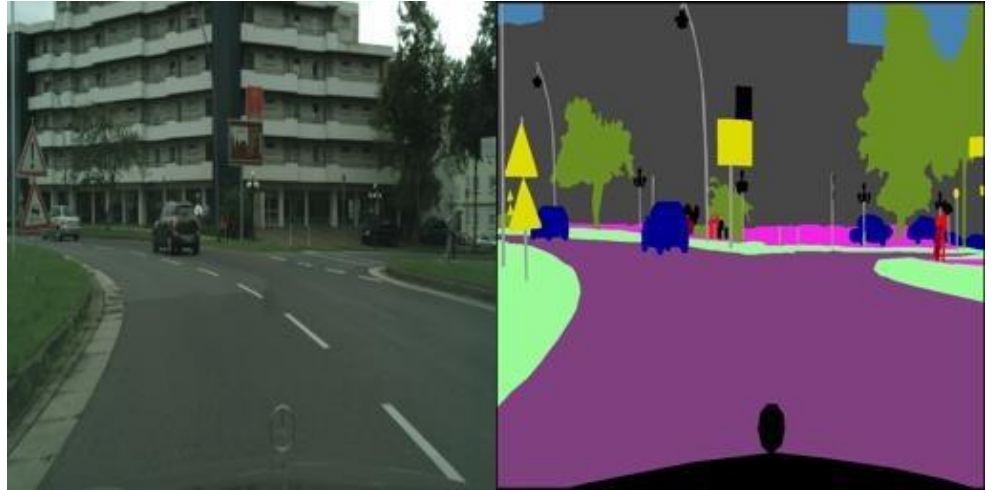


## Dataset details

CityScapes data subset - tackling small data problem

- ~2600 images for training
- ~300 images for validation
- ~500 for test

Labels were attached to data (right) and not categorical

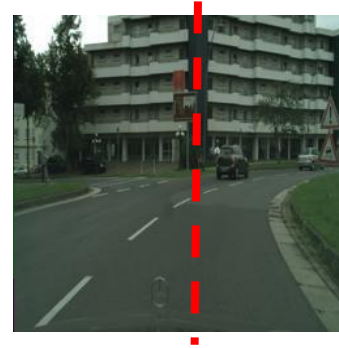
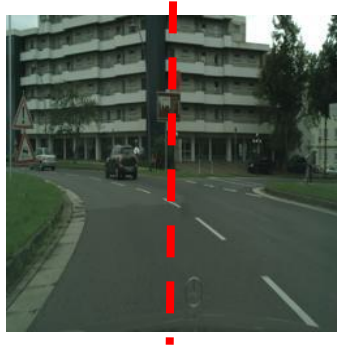


<https://www.kaggle.com/dansbecker/cityscapes-image-pairs>

## Our approach

Methods for dealing with small data - fewer parameter networks, skip connections, transfer learning, data augmentation, etc.

Evaluation: Intersection Over Union, **Pixel Accuracy**, **Manhattan Score**



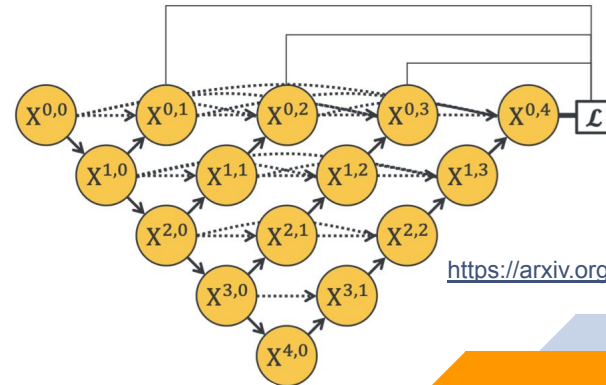
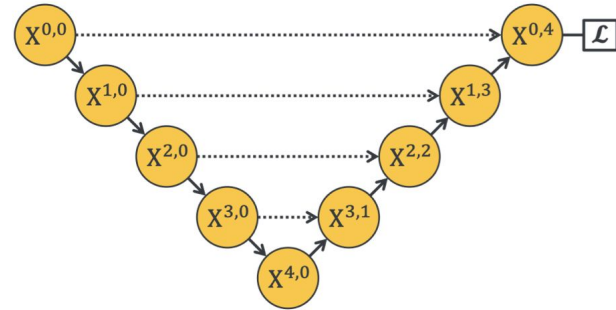


# Models - U-net/U-net++

Encoder and Decoder structure

- Convolutional layers
- Pooling
- Upsampling

Skip connections to counter vanishing gradient/poor learning

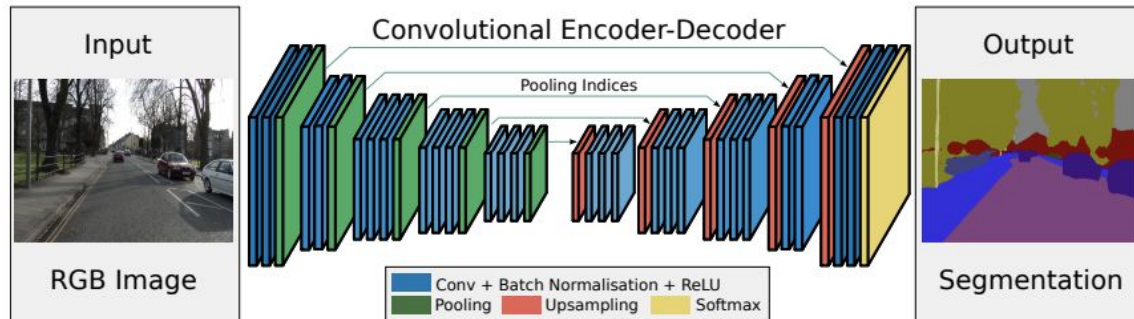


<https://arxiv.org/pdf/1912.05074.pdf>

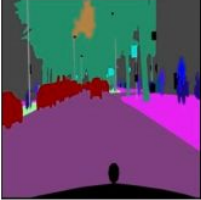

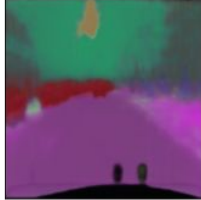
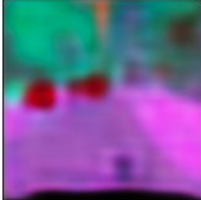
# Models - SegNet

Store max-pooling indices: location of the maximum feature value of each pooling window

Replace U-net skip connections with passing these indices



## Results - same filters/kernels

Metric	Label	U-net	U-net++	SegNet
Image				
Training Method	-	From scratch	From scratch	From scratch
Parameters	-	~543k	~641k	~278k
Pixel Accuracy	-	45%	62%	22%
Manhattan Score per pixel	-	0.21	0.17	0.52

Metric	SOTA
mIoU	86%
Parameters	~6M

## Observations

Not ideal to use MSE for segmentation

Models trained from scratch did OK

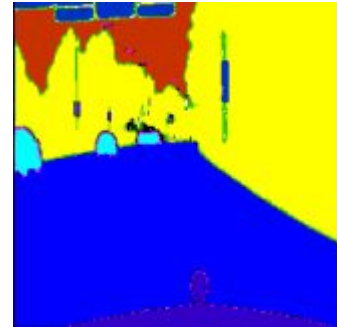
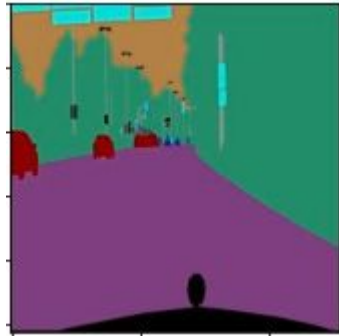
Computational power/availability was limited for extending and perfecting results

## Further improvements ideas

Transfer learning with pre-trained FCN

Labeling for different loss functions/metrics

Further data augmentation



# References

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