Dense Prediction on Sequences with Time-Dilated Convolutions for Speech Recognition

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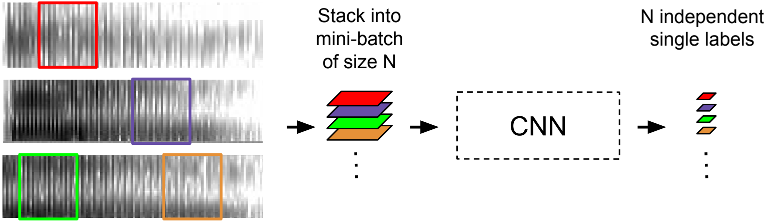
http://arxiv.org/abs/1611.09288

Convolutional Neural Networks for LVCSR

2-stage training scheme: Cross-Entropy (XE) vs Sequence Training (ST), test time



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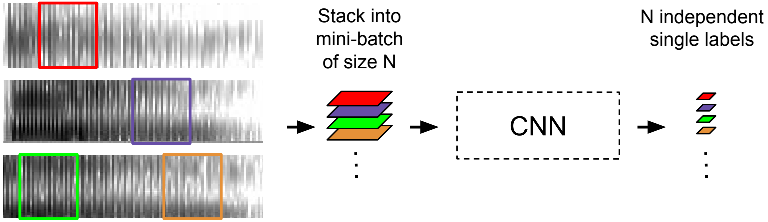

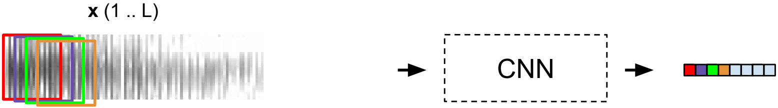

Dense Pixelwise Prediction in Computer Vision

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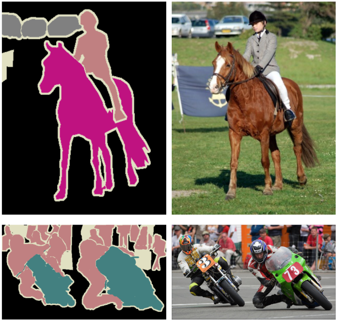
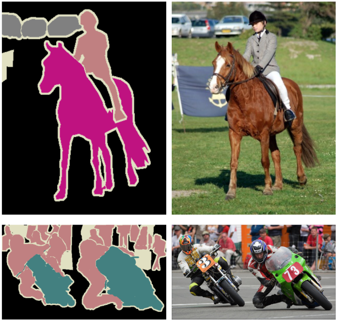
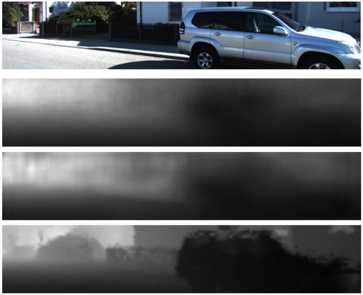


Semantic segmentation

Dense Pixelwise Prediction in Computer Vision

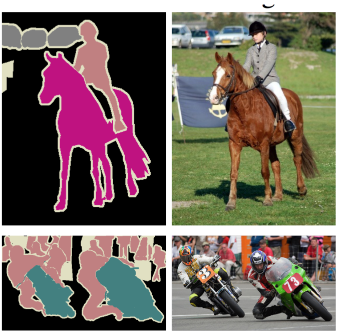


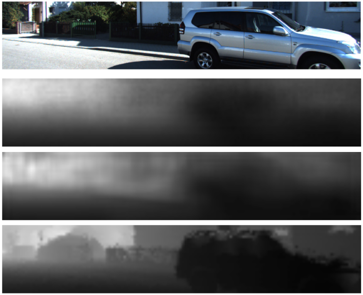
Semantic segmentation



Depth map prediction

Dense Pixelwise Prediction in Computer Vision





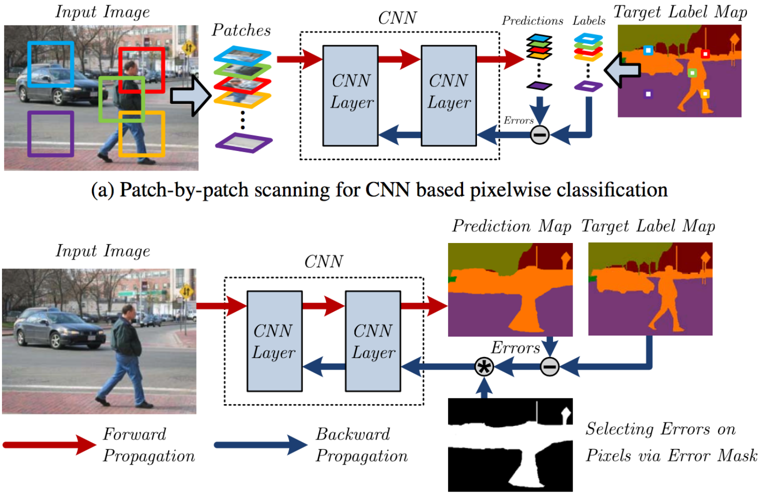
Depth map prediction

Semantic segmentation

Framewise classification = dense pixelwise prediction!

Dense Pixelwise Prediction with Convnets

Patch-by-patch vs efficient

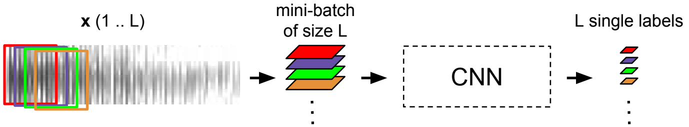


(a) Patch-by-patch scanning for CNN based pixelwise classification

(b) Our approach

Sequential: Framewise classification

Spliced (bad) vs efficient (good)



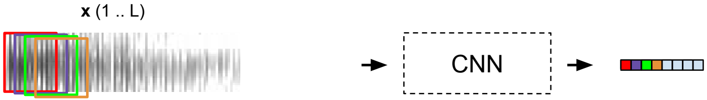
x (1 .. L)

mini-batch of size L

CNN

L single labels

A Spliced, inefficient. **Classification** viewpoint



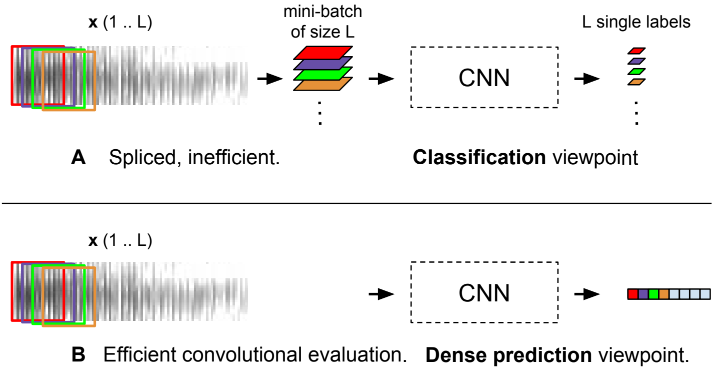
x (1 .. L)

CNN

B Efficient convolutional evaluation. **Dense prediction** viewpoint.

Sequential: Framewise classification

Spliced (bad) vs efficient (good)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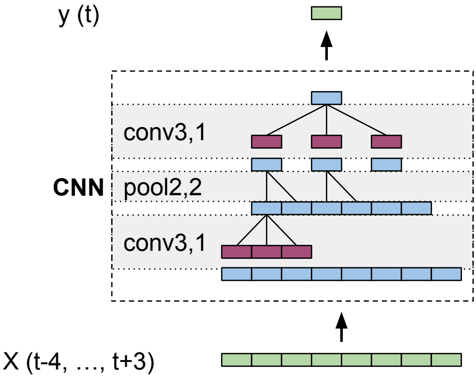
CNN
L single labels
A Spliced, inefficient.
Classification viewpoint
x (1 .. L)
CNN
B Efficient convolutional evaluation.
Dense prediction viewpoint.

Can we have time-pooling into the CNN?

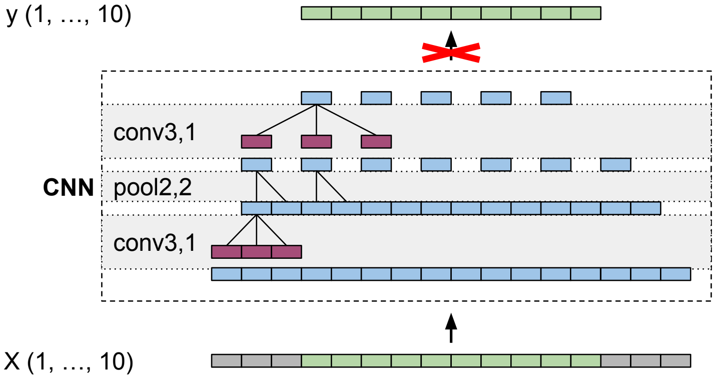
Time-pooling

XE: Toy CNN with pooling in time



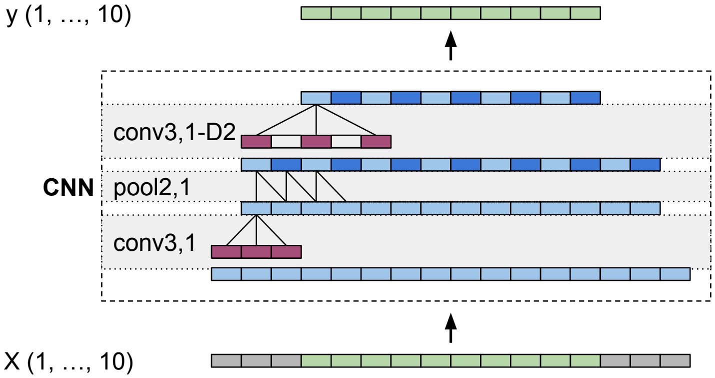
Time-pooling

ST: Downsampling is a problem



Time-pooling → Time-dilated convolutions

ST: Solution to downsampling



Based on Spatial dilated convolution [Li et al., 2014, Yu and Koltun, 2016] or OverFeat [Sermanet et al., 2013]

What did we gain?

With dense prediction viewpoint for ST

- CNNs with strided pooling in time

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    - Efficient convolutional evaluation

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  - Better performance [Sercu et al., 2016, Sercu and Goel, 2016]
- While maintaining efficient dense prediction, enabling:
  - Efficient convolutional evaluation
  - Batch Normalization

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With dense prediction viewpoint for ST

- CNNs with strided pooling in time
    - Better performance [Sercu et al., 2016, Sercu and Goel, 2016]
- While maintaining efficient dense prediction, enabling:
    - Efficient convolutional evaluation
    - Batch Normalization
- End-to-end models with CNNs
    - Can accept downsampling
    - But this allows to pool more than acceptable amount of downsampling

Result on switchboard

Big n-gram LM

	SWB	CH
IBM 2015 DNN+RNN+CNN	8.8 †	15.3 †
IBM 2016 RNN+VGG+LSTM	7.6 †	13.7 †
MSR 2016 ResNet *	8.6	14.8
MSR 2016 LACE *	8.3	14.8
MSR 2016 BLSTM *	8.7	16.2
VGG + BN	8.1	15.9
VGG + BN + pool	**7.7**	**14.5**

- † model combination / $*$ smaller LM
- Note: simple language model. Followed by: LM rescoring

Figures sources and references

- Slide 3 (Semantic Segmentation) [Long et al., 2015] Figure 6
- Slide 3 (Depth map prediction) [Eigen et al., 2014] Figure 4
- Slide 4 (Patches) [Li et al., 2014] Figure 1

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Thank you! Questions?

Here's a cake which doesn't have anything to do with the talk