# Pruning Filters In Convolution Neural Network

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### Introduction

We explore how reducing network expressivity can affect performance in Convolution Neural Network (CNN). We implemented a pruner that can remove filters from convolution layer and explore the effect on transfer learning tasks.

#### **Motivations:**

- ► **Reduce** network size.
- ► Improve execution speed.

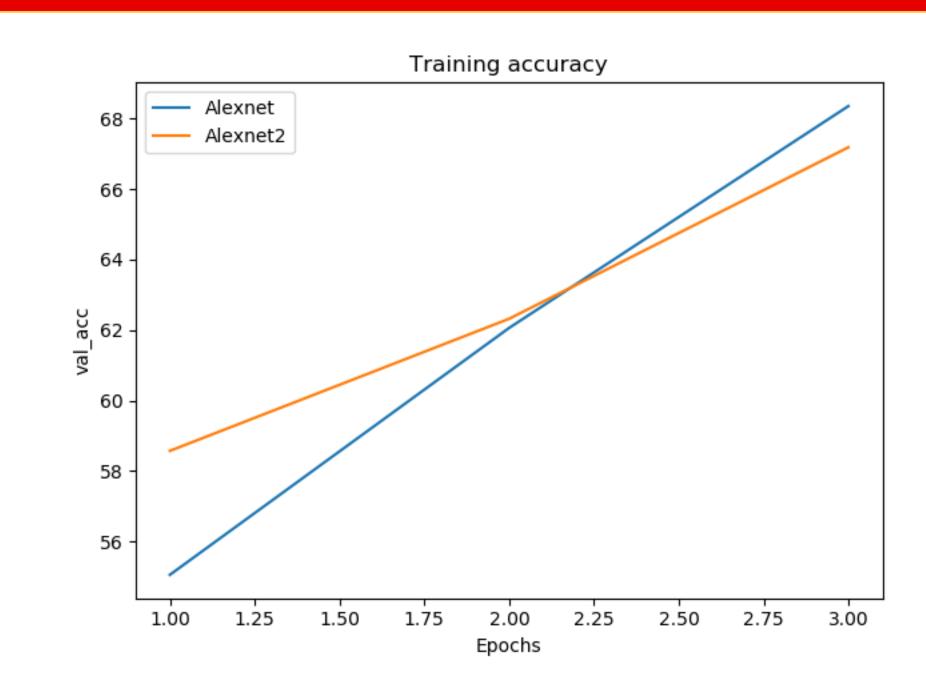
#### Related work:

▶ P.Molchanov et al. (2017): Pruning Convolutional Neural Networks for Resource Efficient Inference.

#### Goals:

- ► Evaluate the impact of reducing network expression on performance.
- ► Compare training time on various model.
- ► Compare various strategies to prune.
- ▶ Provide a module that could.

# Comparing Various level of Pruning in AlexNet



The net consists in 3 bi-LSTM taking as input the left context, the right context and the word characters. An attention module ponderates their outputs which are then combined in a last fully connected layer.

## Experiments

#### Set up:

- ► Labeling tasks :
- ► Named Entity Recognition (NER).
- ► **POS** tagging (POS).
- ► Dataset : CoNLL 2003

#### Training details:

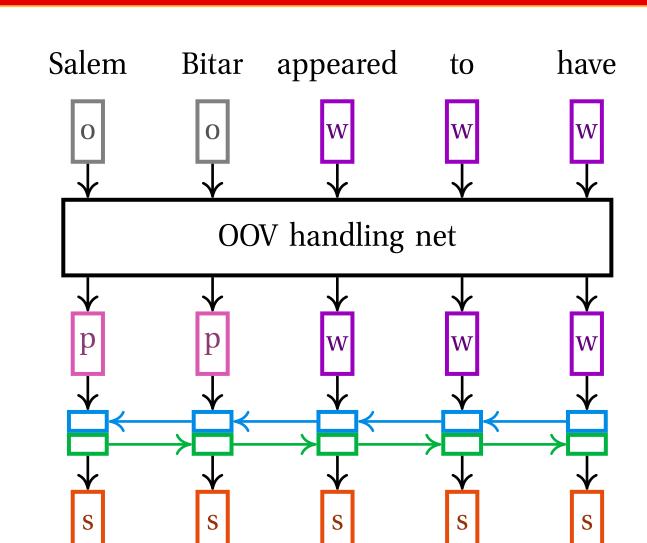
- ► Tensors sizes :
- ► Char. emb. : 20.
- ► Word emb. : 100 (**GloVe**).
- LSTMs hidden state : 128.
- ► Context size from 2 words to the whole sentence.
- ▶ Standard learning rate on the labeling task parameters, reduced learning rate on Comick using SGD (0.01, 0.001).

### Examples

	LAampies					
	Examples		dera		Entity	
		Right	Left	Word		
ar priso	in sentencing darrel <u>voeks</u> , 38, to a 10-ye	0.32	0.49	0.19	PER	
ormally	<bos> australian parliamentarian john langmore has</bos>	0.26	0.59	0.15	PER	
e, a let	had received today from mr john vance langmon	0.24	0.61	0.15	PER	
- formal	<bos> rtrs - australian mp john <math>\overline{langmor}</math></bos>	0.16	0.69	0.15	PER	
- astic su	the number of plastic surgeries in [] the brazilian pl	0.32	0.46	0.22	ORG	
resider	to increase them in the united states , " $sbcp$ vice- $\mathbf{p}$	0.49	0.23	0.28	ORG	
s who	some residents of the <u>kazanluk</u> area are moslem	0.62	0.22	0.16	LOC	
<u>luk</u> , ca	at a mosque in the <b>central bulgarian town of</b> <u>kazan</u>	0.33	0.47	0.20	LOC	
rials res	freestyle <i>skiing-world</i> cup ae	0.21	0.11	0.68	MISC	
missio	the <i>franco-african</i> summit decided to send a	0.40	0.18	0.42	MISC	

Qualitative example on several OOV words (underlined). We can see that depending on the context and the target, the weights may shift drastically.

### Labeling task net



### Observation

Not all convolutional layer can be pruned. Pruning layer before a residual connection is dangerous because both side of the residual connection must have the same side.

When pruning in a convolution layer it is important to propagate. So the next layer have the right input size. This apply to convolution, linear and batchnorm layers.

The algorithm used tend prefer removing filters that are deeper in the model and it is not uncommon to try to prune all filter in a layer.

# Performance gain

Task	Metric	Random Emb.	Our module	Gain
NER	F1	77.56	80.62	3.9%
POS	acc.	91.41	92.58	1.2%

The impact of our model on two NLP downstream tasks. We compare our OOV embeddings prediction scheme against random embeddings.

### Conclusion

Discussion: