# 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.

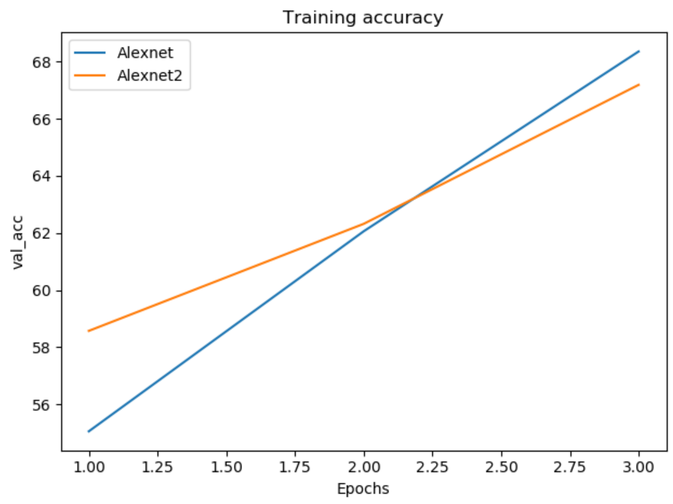
**Related work :**

- 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 :**

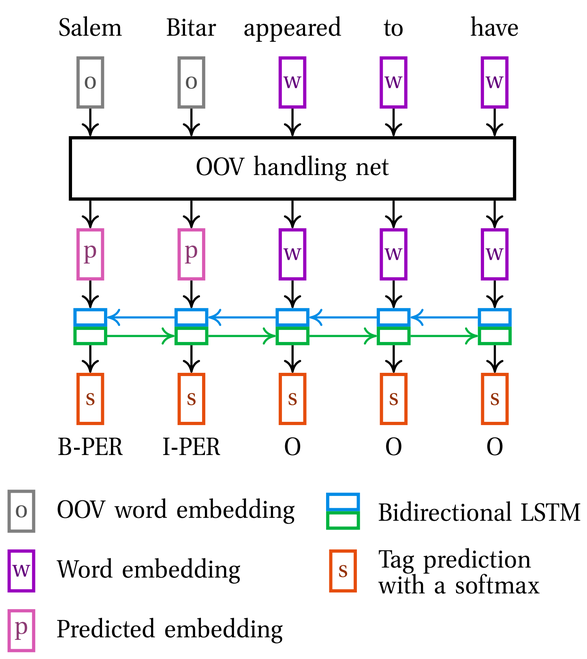
- Tensors sizes :
  - Char. emb. : 20.
  - Word emb. : 100 (**GloVe**).
  - LSTMs hidden state : 128.
- Context size from 2 words to the whole sentence.
- Standard learning rate on the labeling task parameters, reduced learning rate on Comick using SGD (0.01, 0.001).

## Examples

| Entity | Ponderation | | | |
|---|---|---|---|---|
| | Word | Left | Right | |
| PER | 0.19 | **0.49** | 0.32 | **in sentencing darrel** *vo* |
| PER | 0.15 | **0.59** | 0.26 | <BOS> **australian parliamentarian** |
| PER | 0.15 | **0.61** | 0.24 | had received today **from mr j** |
| PER | 0.15 | **0.69** | 0.16 | <BOS> **rtrs - australian** |
| ORG | 0.22 | **0.46** | 0.32 | the number of plastic surgeries in |
| ORG | 0.28 | 0.23 | **0.49** | to increase them in the united s |
| LOC | 0.16 | 0.22 | **0.62** | some residents of the *kazanlu* |
| LOC | 0.20 | **0.47** | 0.33 | at a mosque in the **central bulga** |
| MISC | **0.68** | 0.11 | 0.21 | freestyle ***s*** |
| MISC | **0.42** | 0.18 | **0.40** | the ***franco-african*** **summit** |

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




Two nets working together : the first predicts OOV embeddings (see OOV handling net section) and the second one predicts tags.
The simple architecture of the labeling net is used to emphasize the usefulness of our module, and to minimize the influence of other factors.

## 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 :**

- **Morphology** and **context** help predict useful embeddings.
- **The attention mechanism works** : depending on the task, the network will use either more the context or the morphology to generate an embedding.

**Future works :**

- Apply the **attention mechanism on each character of the OOV word and each word of the context** instead of using the hidden state of the respective elements only.
- Test our attention model in **different languages** and on other NLP tasks, such as **machine translation**.