Application of the Lottery Ticket Hypothesis in NLP and Early Pruning

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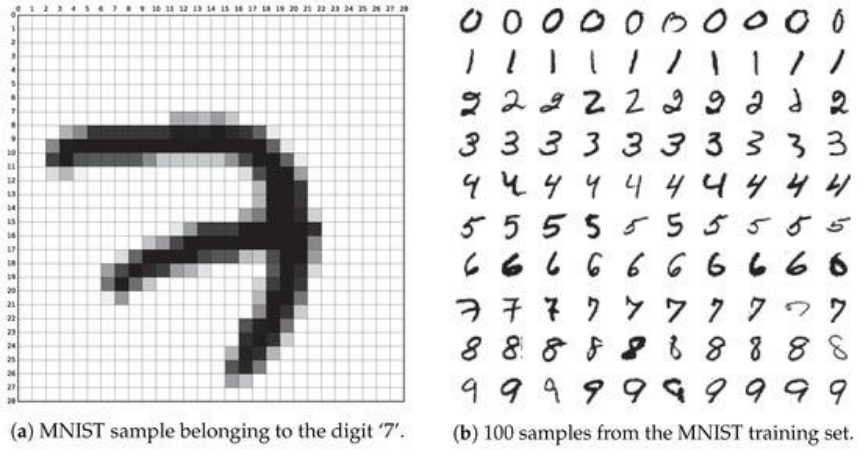
Intermission



(a) MNIST sample belonging to the digit '7'. (b) 100 samples from the MNIST training set.

Source: https://www.mdpi.com/applsci/applsci-09-03169/article_deploy/html/images/applsci-09-03169-g001-550.jpg

Source: https://www.bonaccorso.eu/wp-content/uploads/2016/07/28019400581_e1eb13ccc8_b.jpg

Tim Unverzagt

Prof. Dr.-Ing. Ralf Steinmetz
KOM - Multimedia Communications Lab

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Structure

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Content of the thesis

Initial Thoughts

- Many good reasons to initialize & train neural networks with many parameters
- Empirical evidence that many networks can be reduced after training while maintaining performance
  - aka. "Pruning"
  - Desirable due to bias towards small models (Ockham's razor)

Initial Thoughts

- Many good reasons to initialize & train neural networks with many parameters
- Empirical evidence that many networks can be reduced after training while maintaining performance
  - aka. "Pruning"
  - Desirable due to bias towards small models (Ockham's razor)
- Main Question:
  - "How important are the pruned weights during training?"

Lottery Ticket Hypothesis

- Due to the sheer number of "small" subnetworks in a "huge" network at least one such subnetwork has been initialized favorably for the given task
  - Name said subnetwork "lottery-ticket"

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  - Name said subnetwork "lottery-ticket"
- The lottery-ticket can be trained as a standalone-network achieving a similar performance to the original
- A lottery-ticket can be identified by analysis of the fully trained original network
  - e.g. keeping only the weights of the largest magnitude finds a lottery ticket

Motivation

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Time & Memory

- Speedup during execution just as regular pruning
  - But remarkable compression rate: up to ~50x
- Decrease in memory usage during execution
- Possible speedup during development
  - There might be a way to identify lottery tickets early

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Time & Memory

- Speedup during execution just as regular pruning
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Interpretability

- Understanding lottery-tickets might enhance our knowledge of neural networks in general
  - Finding a way to identify a lottery-ticket might help understanding how exactly neural networks learn

Background – Unsupervised Learning

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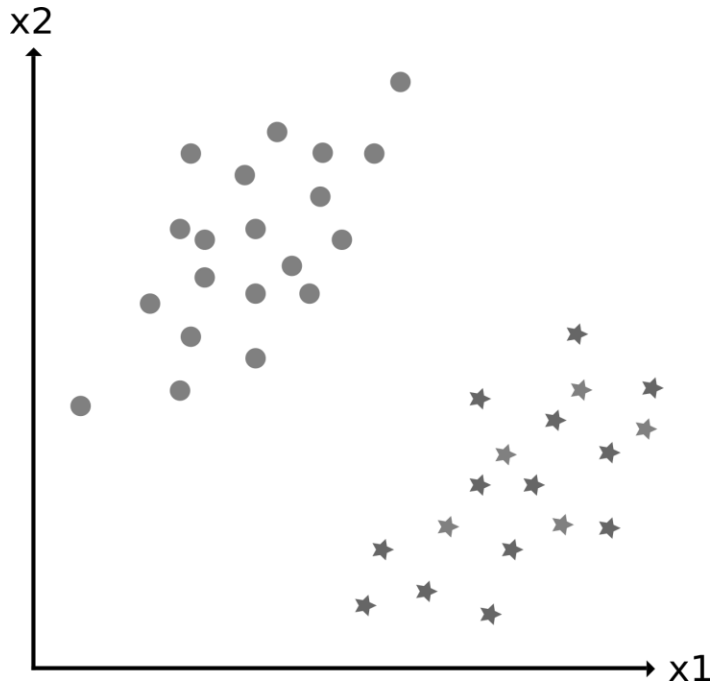

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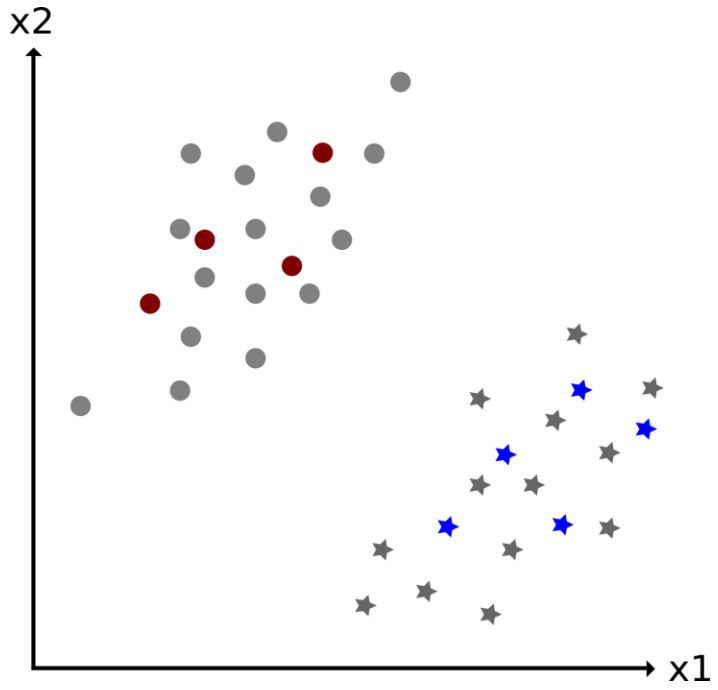

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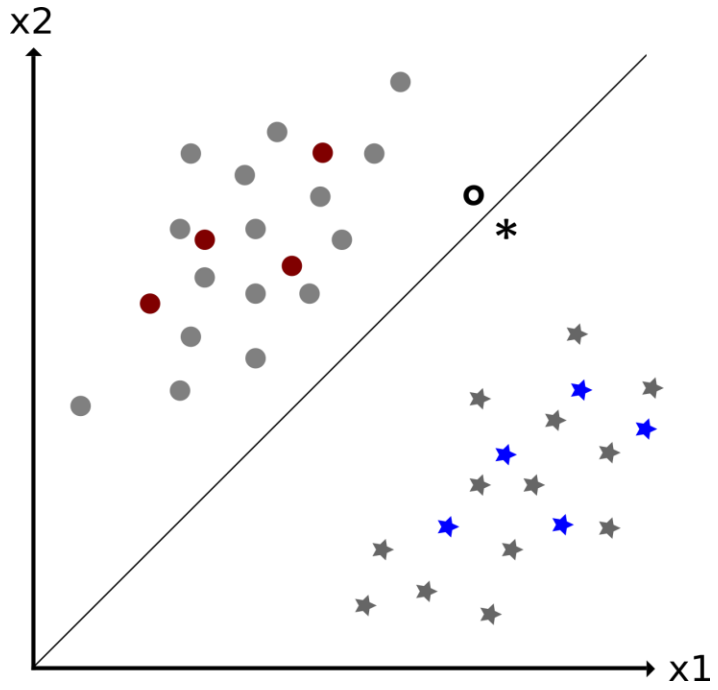

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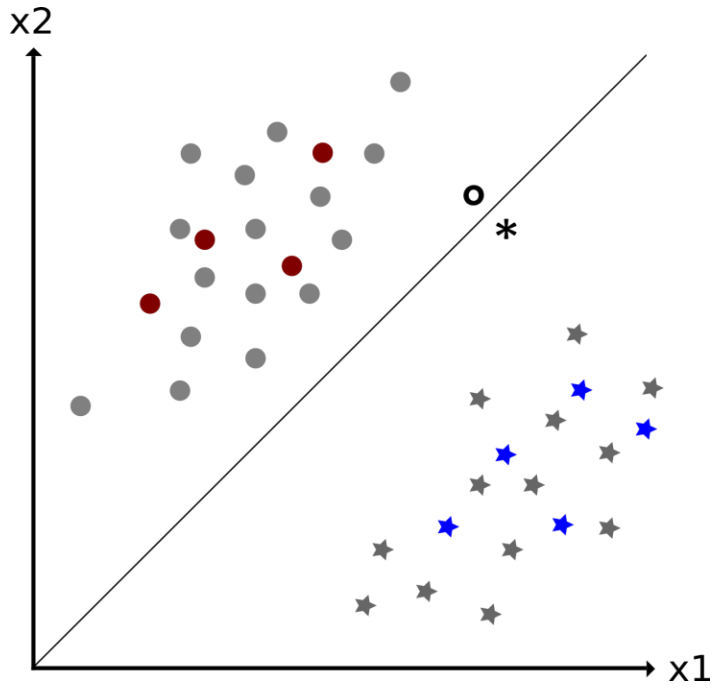

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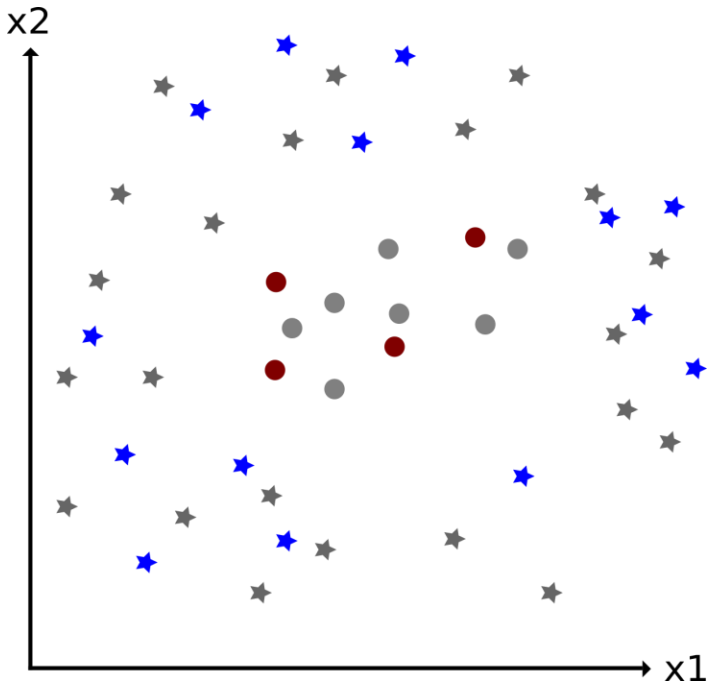

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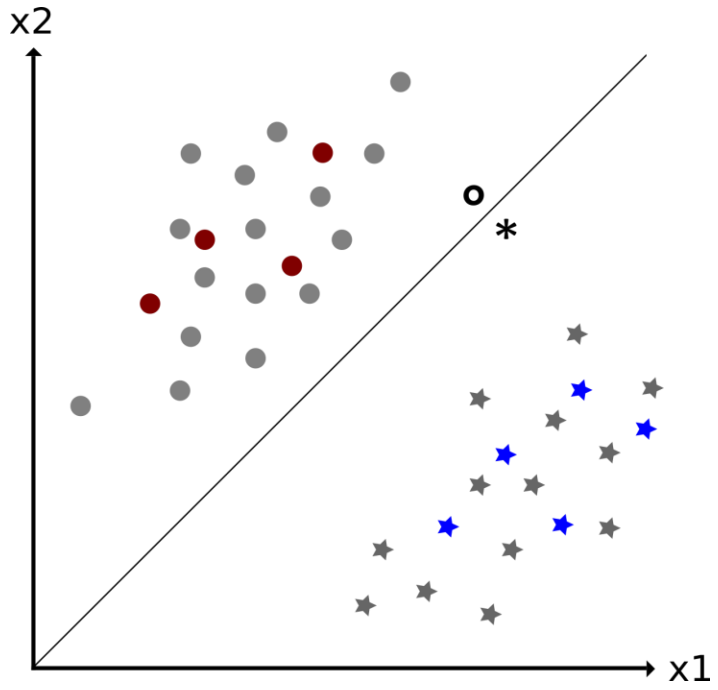

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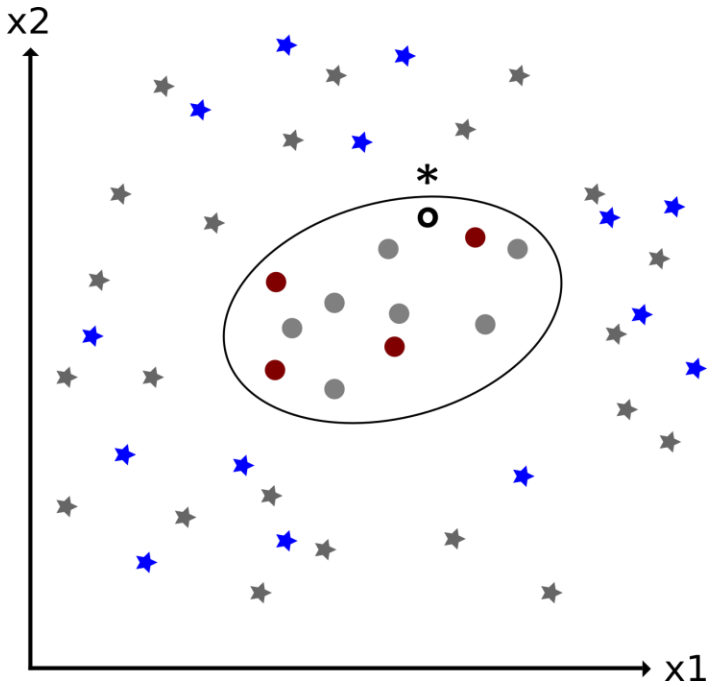

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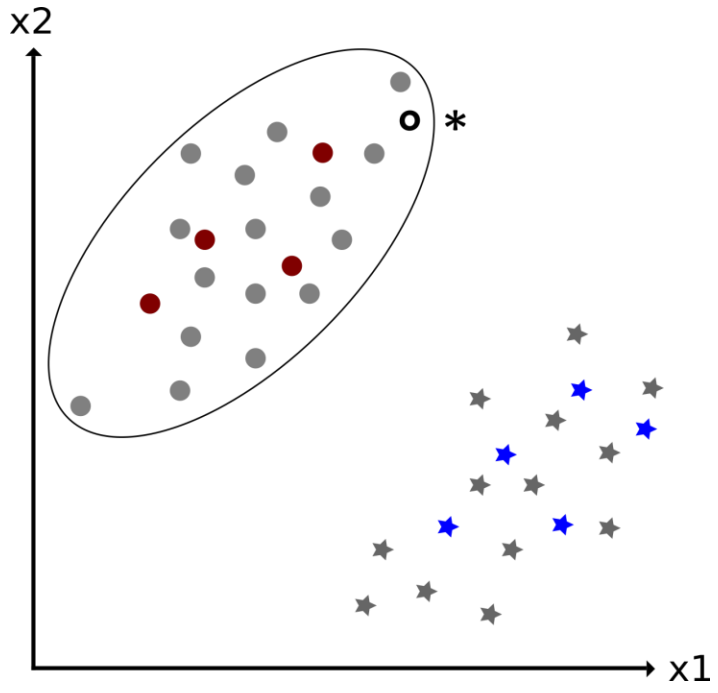

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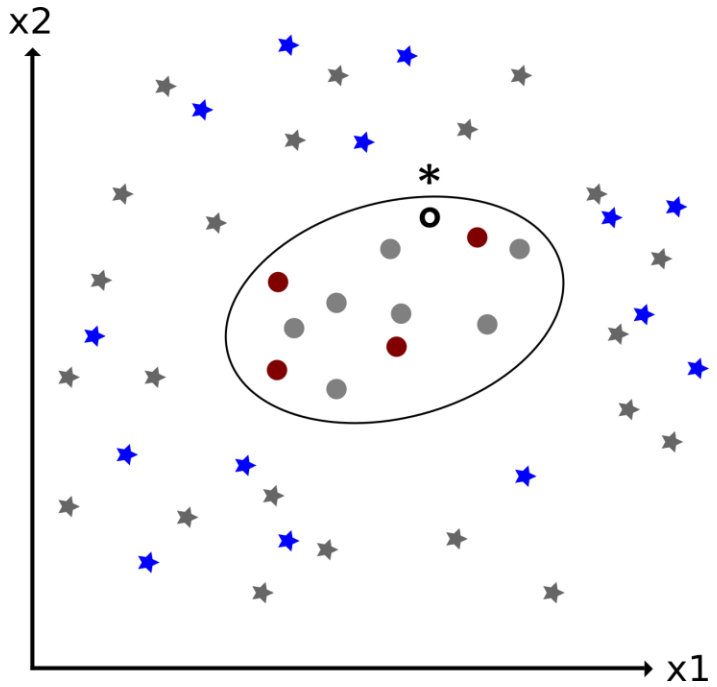

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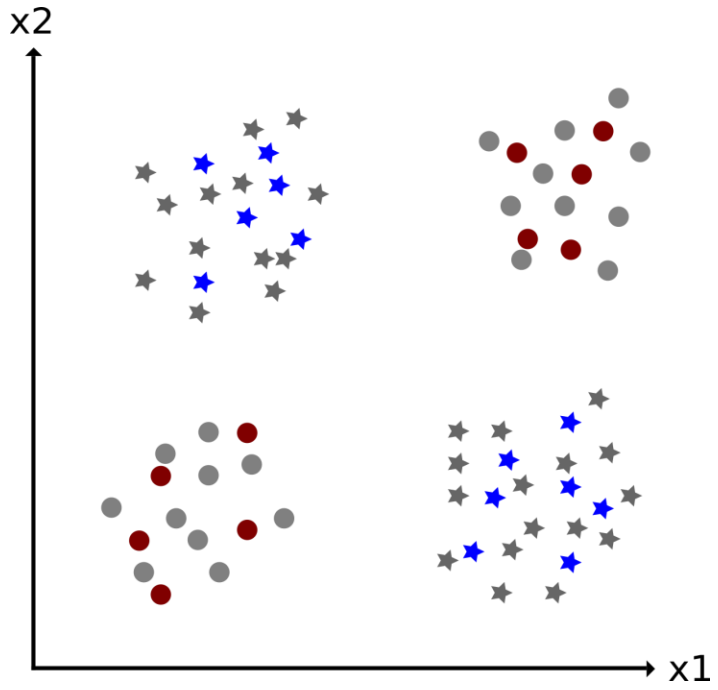

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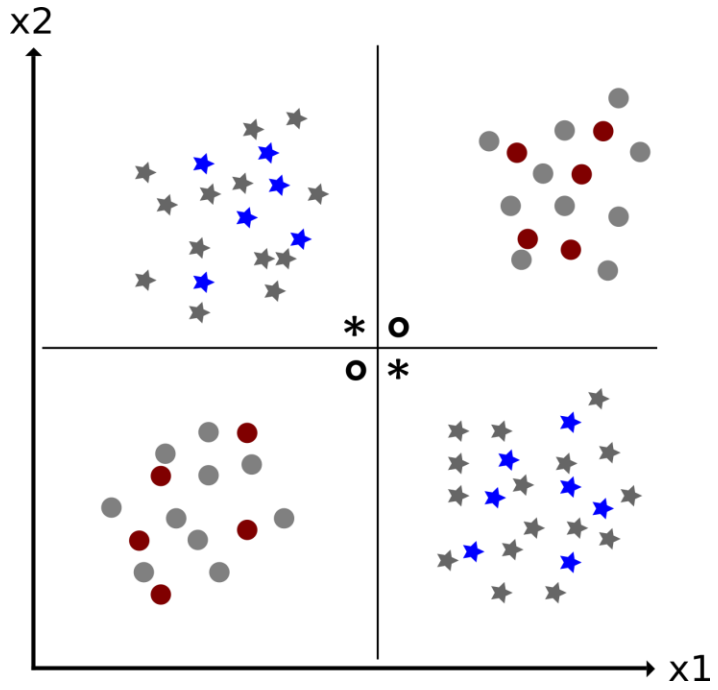

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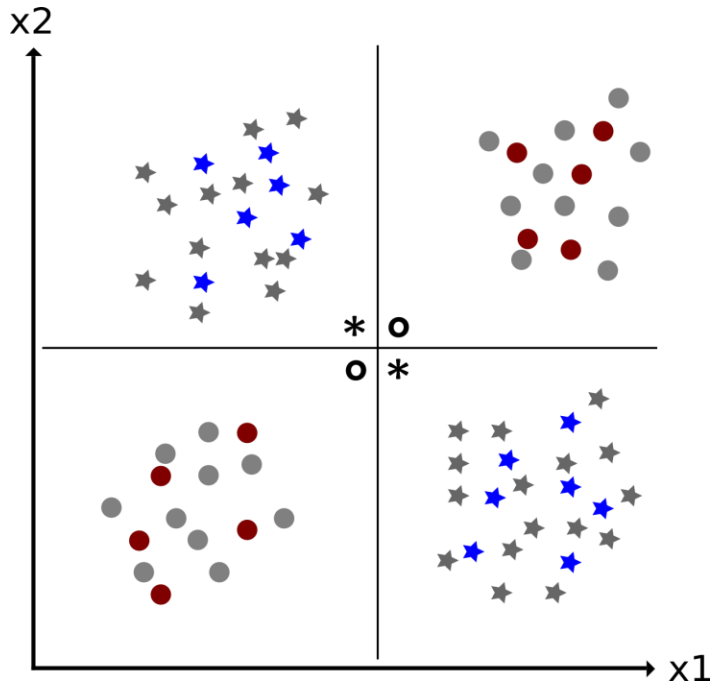

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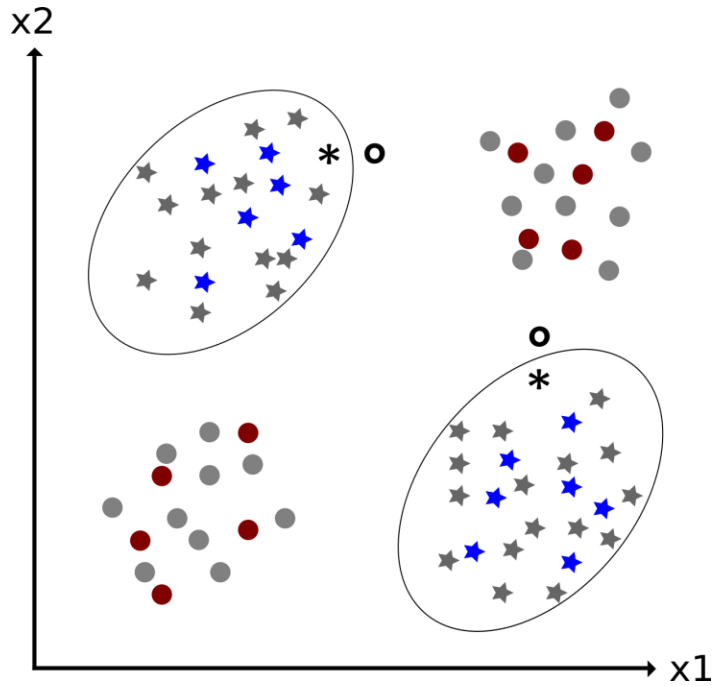

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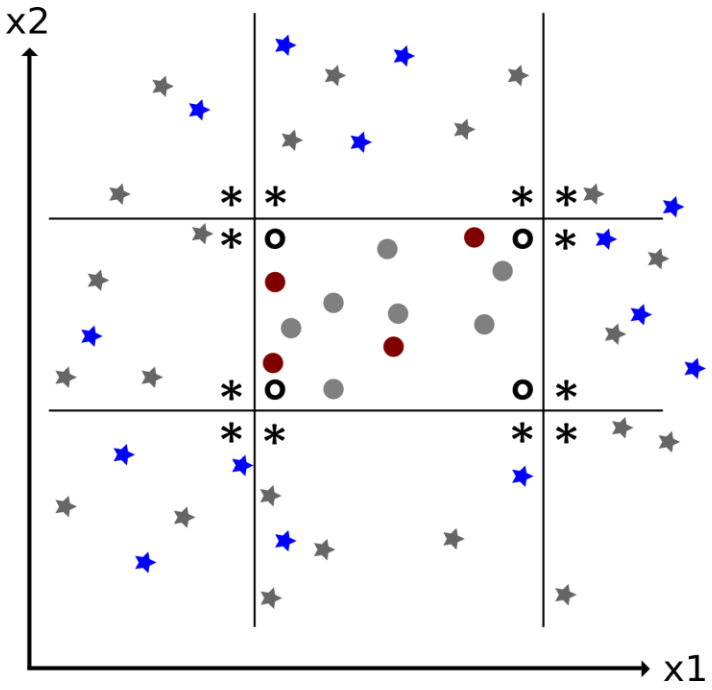

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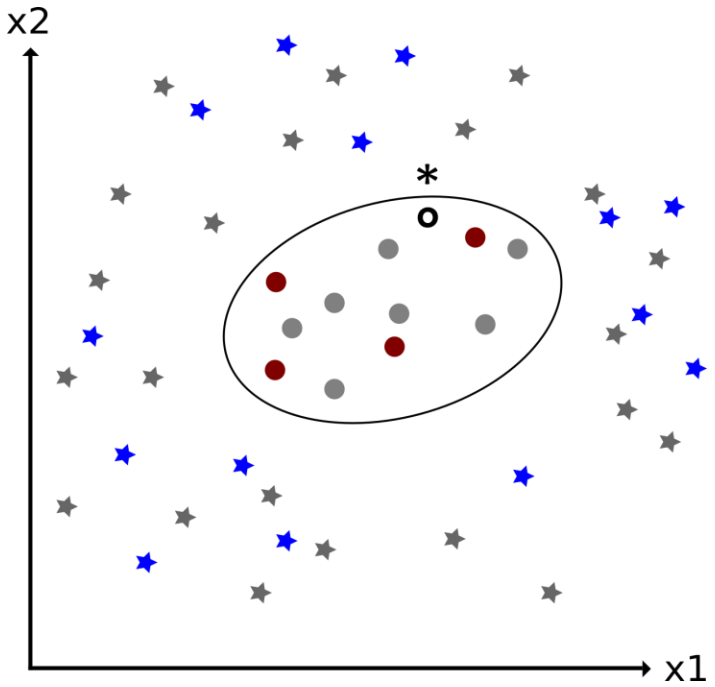

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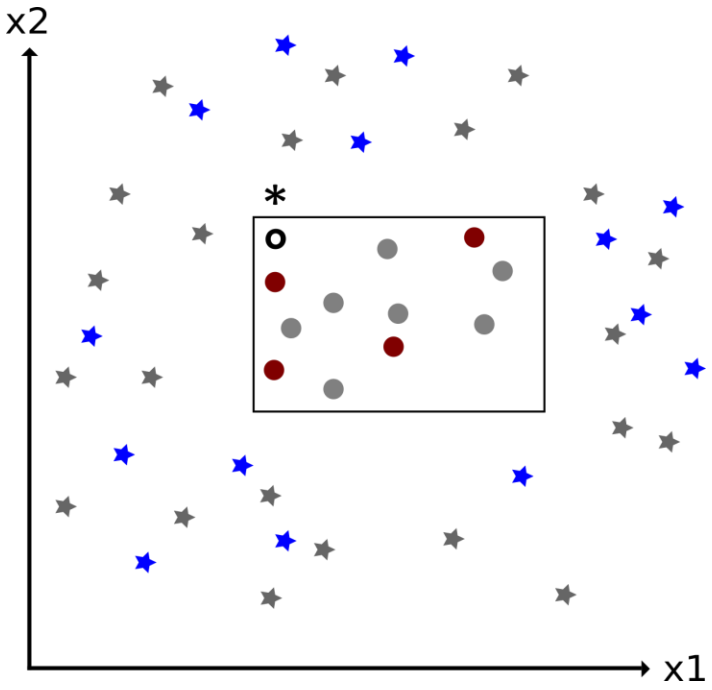

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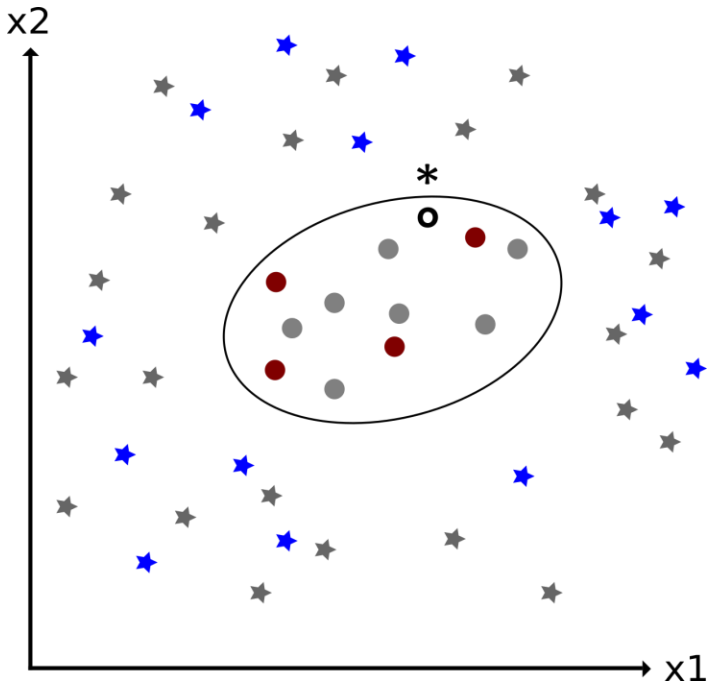

Source: Produced by the author

Background – Neural Networks Basics

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Source: "Biology 2e" OpenStax
Sec.35 .2

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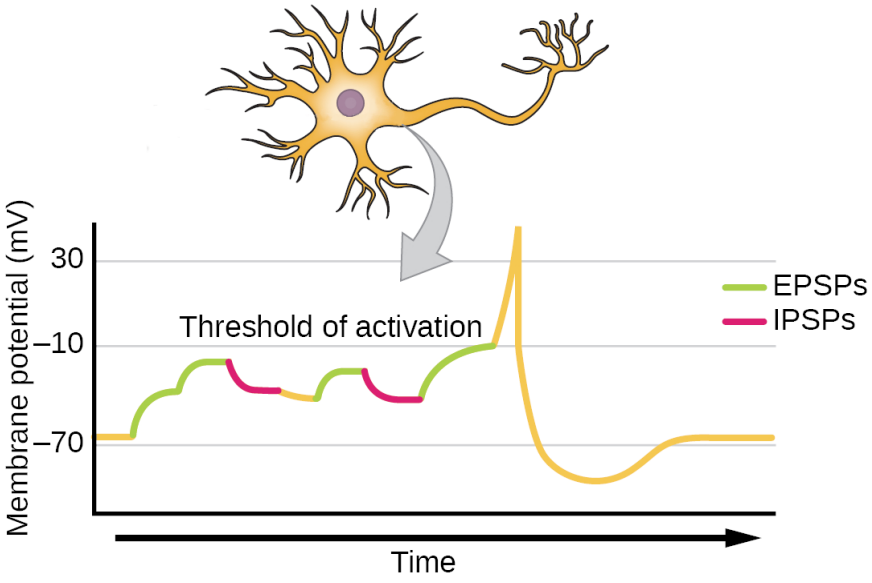

Source: "Biology 2e" OpenStax Sec.35 .2

Background – Neural Networks

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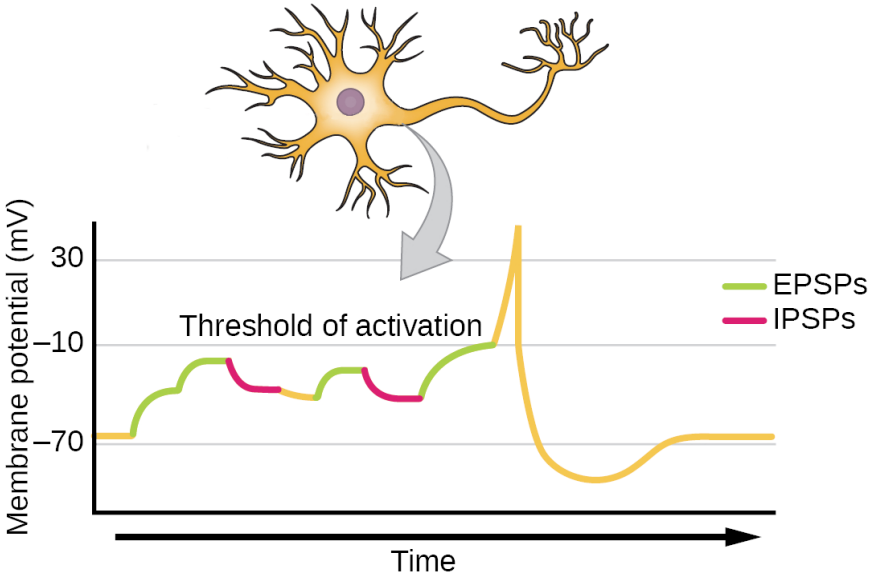
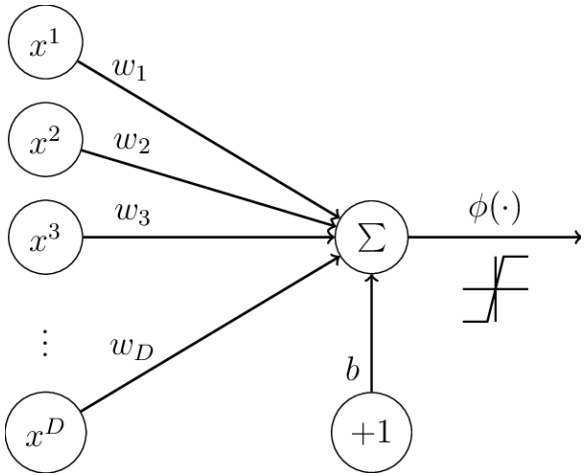


Source: "Biology 2e" OpenStax
Sec.35 .2



Source: "Neural Netw orks Regularization
Trough Representation Learning"
p. 17

Background – Neural Networks Basics

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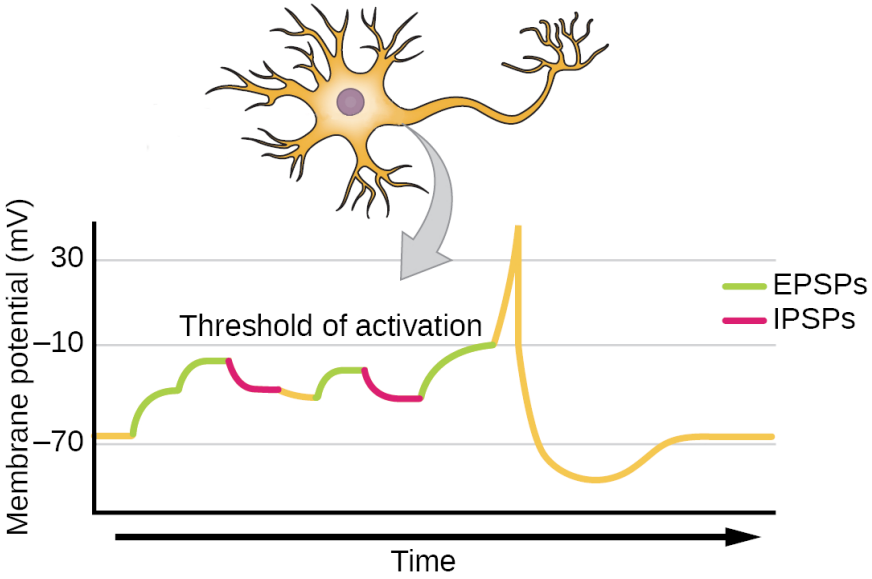
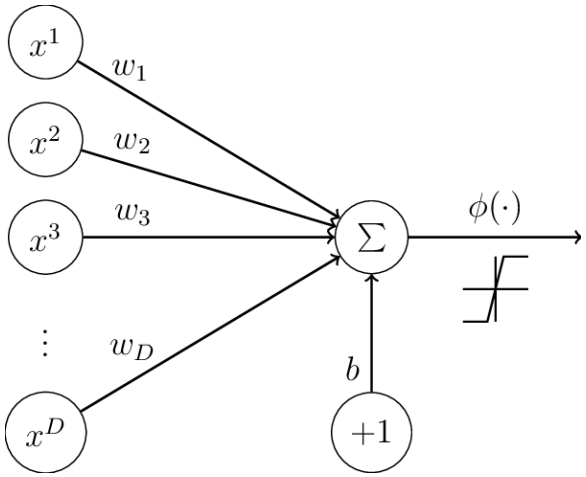


Source:
https://openstax.org/resources/ee34862d28dde2838ca58b4ff73225a93afbee38

"Biology 2e" OpenStax
Sec.35 .2

$$\text{Out} = \phi((\Sigma_i x_i) + b)$$



Source:
https://www.researchgate.net/profile/Soufiane_Belharbi/publication/326439111/figure/fig2/AS:669487372181508@1536629636103/Perceptron-model-Notation-x-i-is-the-i-th-component-of-x-the-same-as-x-i-in

"Neural Networks Regularization Trough Representation Learning"
p. 17

Related Work

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Related Work – Background

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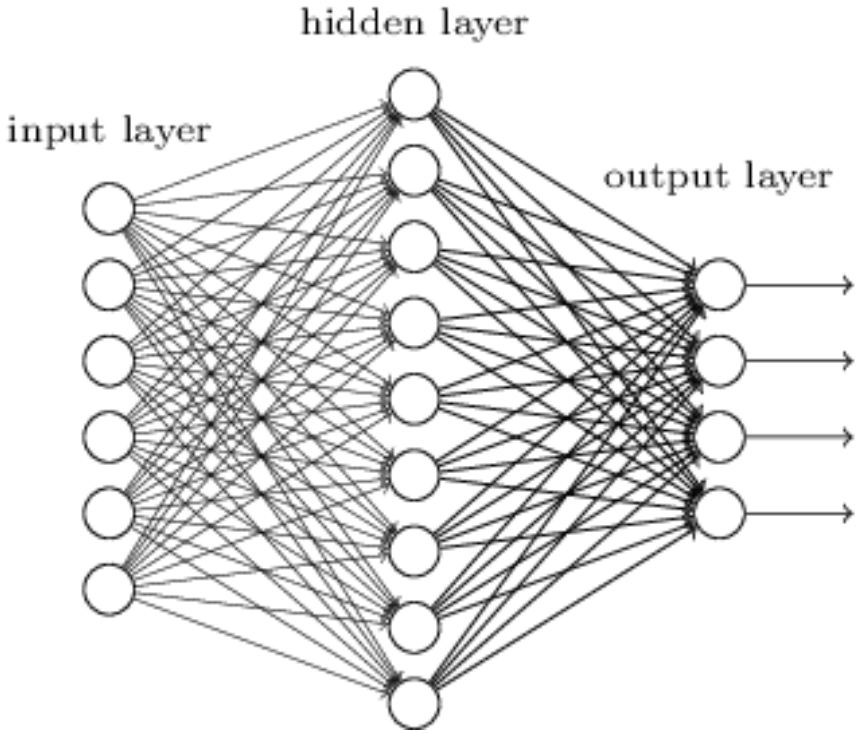
Fully Connected Neural Network



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Related Work – Background

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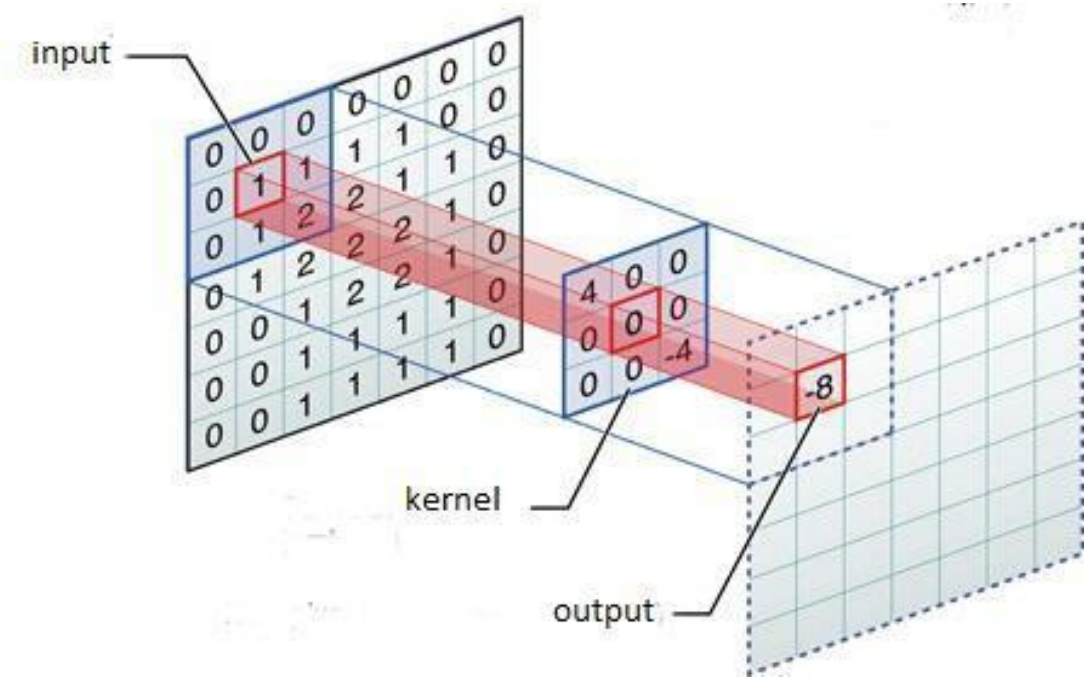
Convolution in Neural Networks



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Related Work – Background

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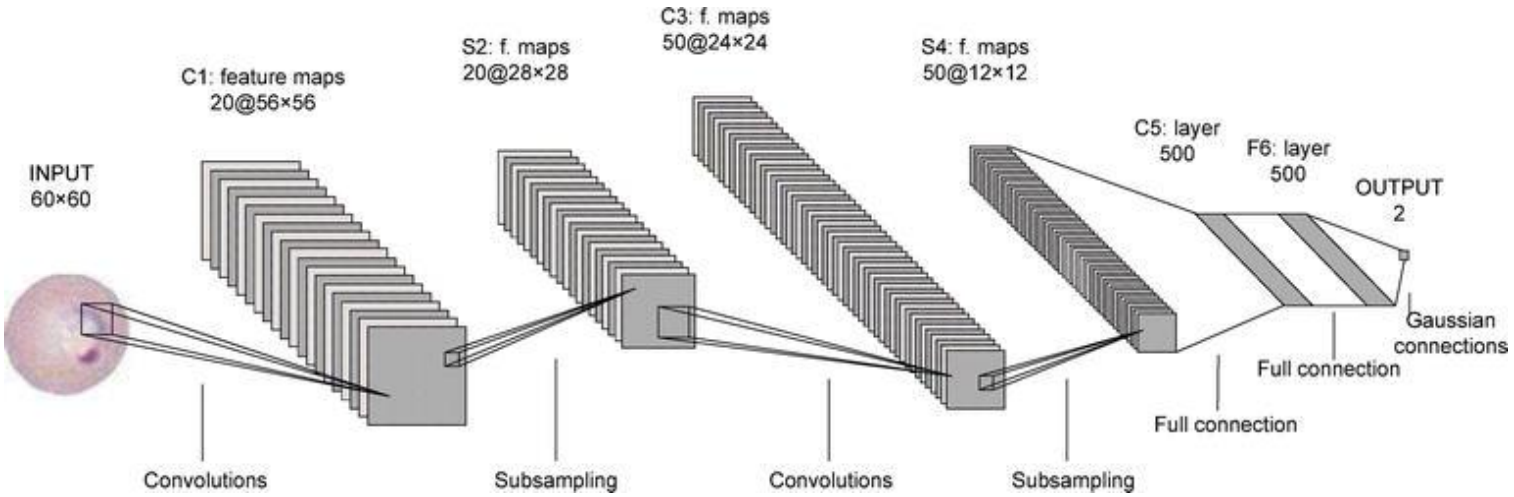
Convolutional Neural Network Architecture (Lenet-5)



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https://api.intechopen.com/media/chapter/58989/media/F4.png

Related Work – Background

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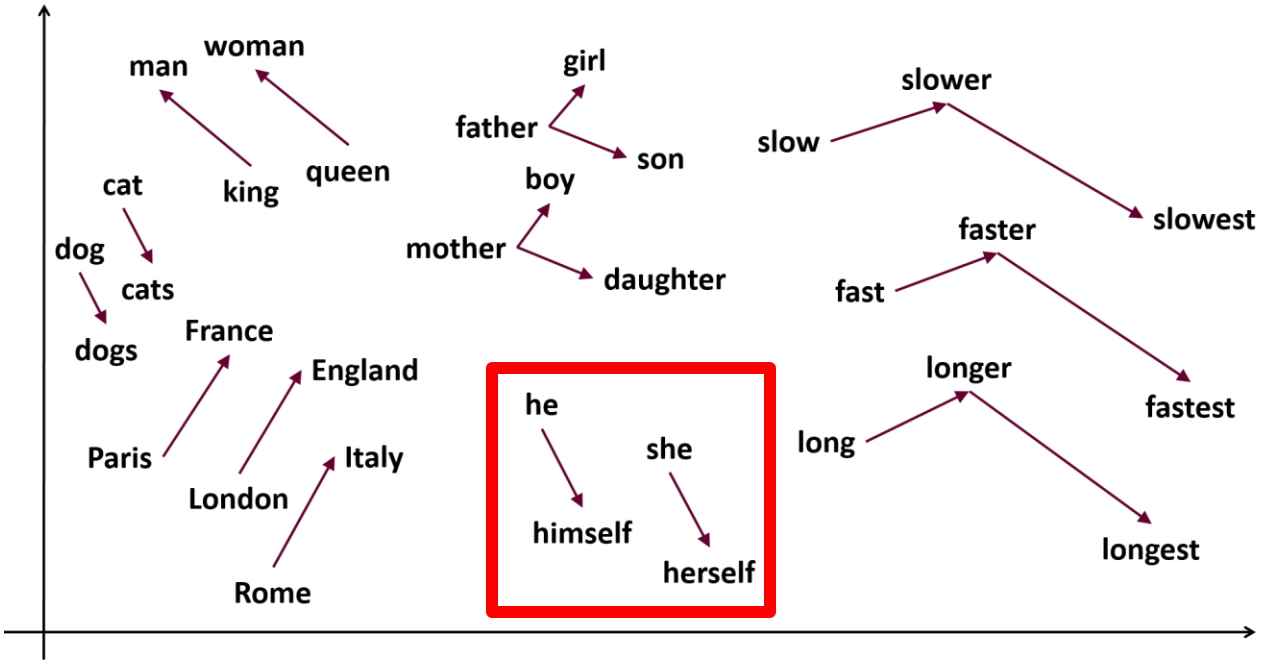
Language Models



Source:
https://samyzaf.com/ML/nlp/word2vec2.png

Related Work – CNN in NLP

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"Convolutional Neural Networks for Sentence Classification"

- 2014
- Task:
  - Varying Classifications
- Datasets:
  - Movie reviews
  - SST-1, SST-2
  - Subjectivity dataset
  - TREC question dataset
  - Customer reviews
  - MPQA

Related Work – CNN in NLP

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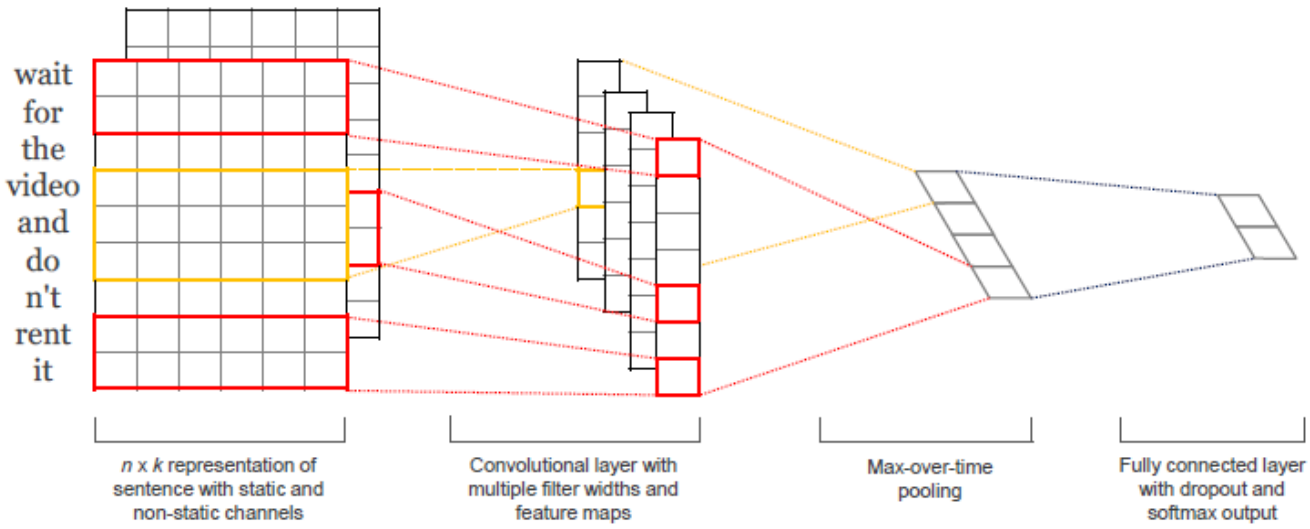
"Convolutional Neural Networks for Sentence Classification"



Source:
"Convolutional Neural Networks for Sentence Classification"
Figure 1

Related Work - Pruning

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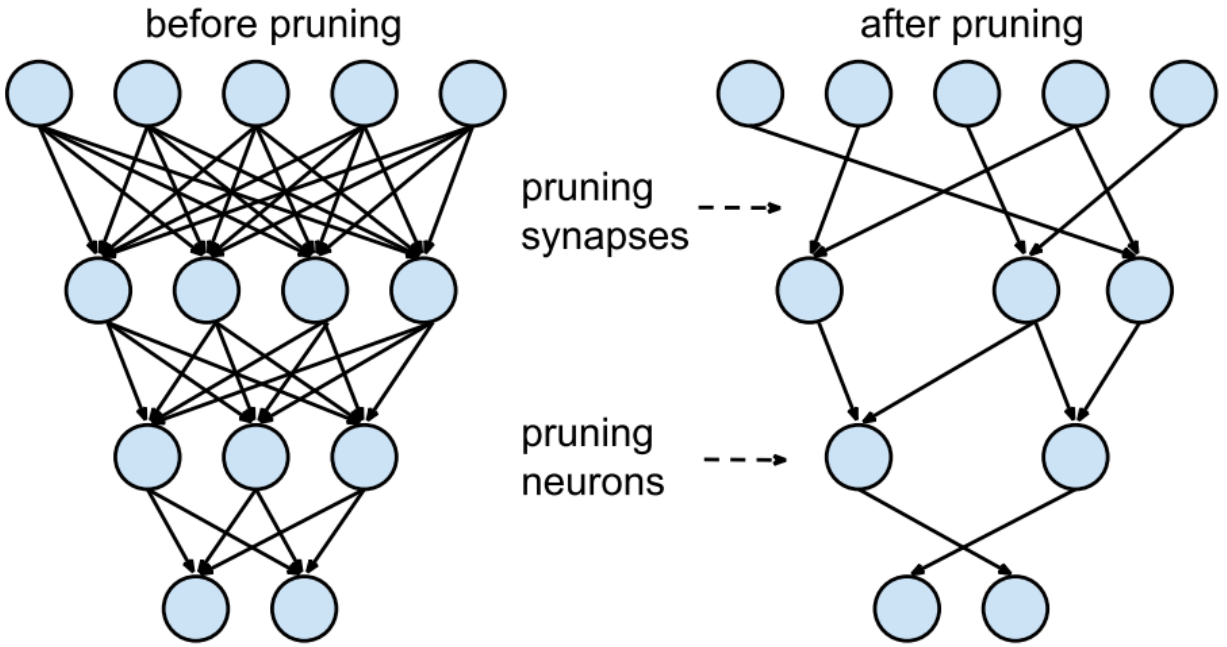

Source:
https://www.mdpi.com/applsci/applsci-09-03169/article_deploy/html/images/applsci-09-03169-g001-550.jpg

"Learning both Weights and Connections for Efficient Neural Networks"
Figure.3

Related Work – Pruning

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"Learning both Weights and Connections for efficient Neural Networks"

- 2015
- Task:
  - Image Classification (ImageNet)
- Architectures:
  - LeNet (300-100-FC, 5-CNN)
  - AlexNet
  - VGG-16
- Compression:
  - 9x to 13x

Related Work – Pruning

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"ThiNet: A Filter Level Pruning Method for Deep Neural Network Compression"

- 2017
- Task:
  - Image Classification (ImageNet)
- Architectures:
  - VGG-16
  - ResNet-50
- Compression:
  - Up to ~17x

Related Work – Pruning

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"The Lottery Ticket Hypothesis: Finding Sparse, Trainable Neural Networks"

- 2019
- Task:
  - Image Classification (MNIST)
- Architectures:
  - Lenet (300-100-FC, Conv-2, Conv-4, Conv-6)
  - VGG-19
  - ResNet-18
- Compression:
  - ~20x to ~50x

Related Work – Early Pruning

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"Really should we pruning after model be totally trained? Pruning based on a small amount of training"

- 2019
- Task:
  - Image Classification (MNIST, CIFAR-10)
- Architectures:
  - Unspecified CNN
  - VGG-19
- Compression --- Training Speed-Up:
  - ~10x --- 10x

Related Work – Network Architecture Search

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"Rethinking the Value of Network Pruning"

- 2018
- Observation:
  - Randomizing weights does not worsen a pruned network
- Weights are not essential to the quality of pruned network
- Pruning at its core is about finding suitable network architectures

Related Work – Network Architecture Search

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"Network Architecture Search: A Survey"

- 2019
- […]

Task I

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Reproduction

- No source-code available
  - Produce own source-code for the experiments in the paper
- Verify source-code by running experiments

Task II

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Transfer to NLP

- Original context for the paper
  - Task: Image Classification
  - Dataset: "MNIST"
  - Model: Varying FCNN and CNN
- Find comparable context in NLP
  - Task: Topic Classification
  - Dataset: "Reuters-21578"
  - Model: TBD
- Check if the Lottery-Ticket-Hypothesis holds

Task III

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Early Retrieval of Lottery Tickets

- Original method
  - "Select" all weights of the "fully trained" network over a certain percentile
  - Reset weights to original intial value
  - Retrain network
  - Repeat (Optional)
- Adaptation
  - "Select" weights earlier / develop early stopping criteria
  - "Select" weights based on other metrics (Optional)

Progress – Python-project

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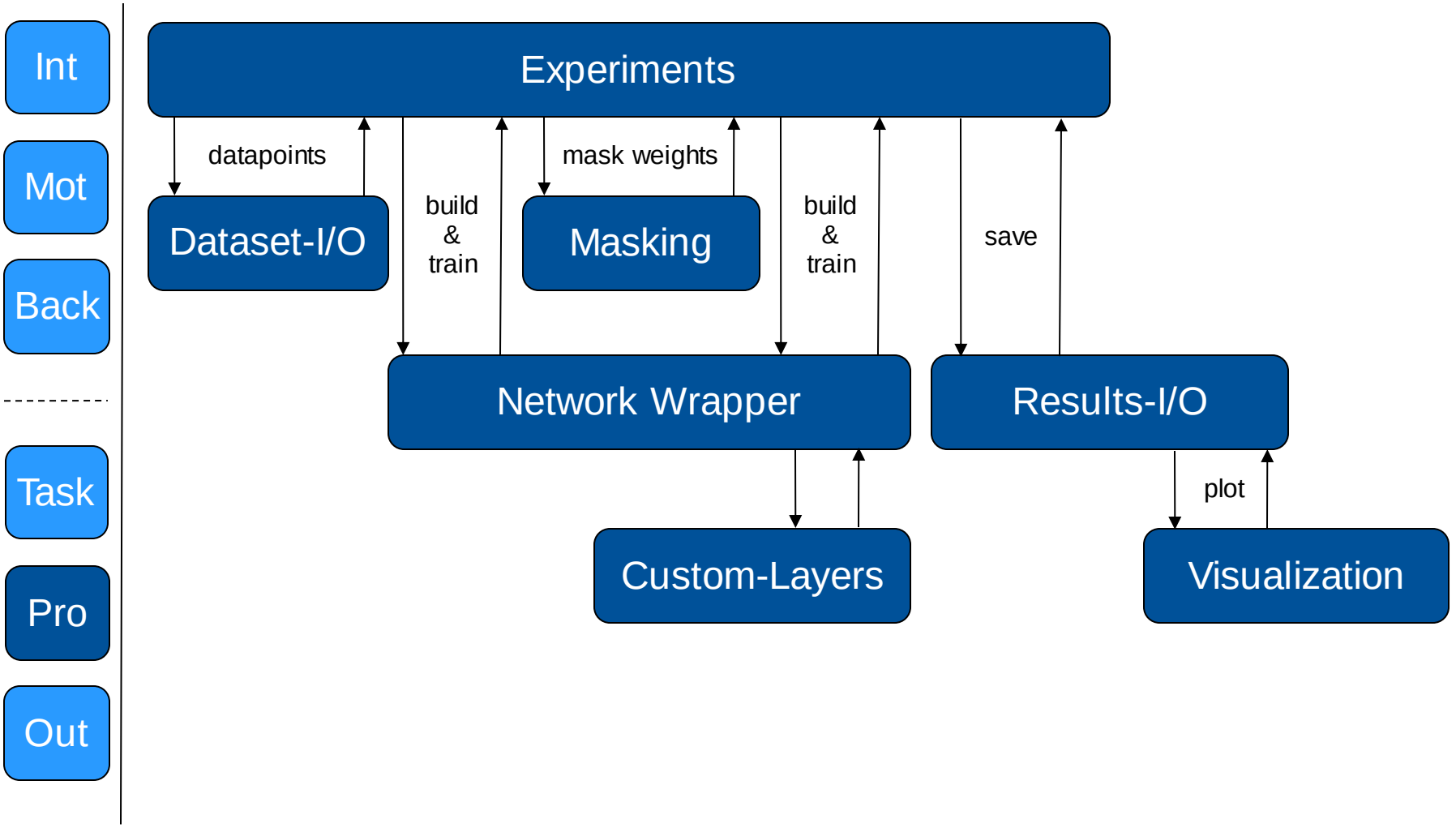
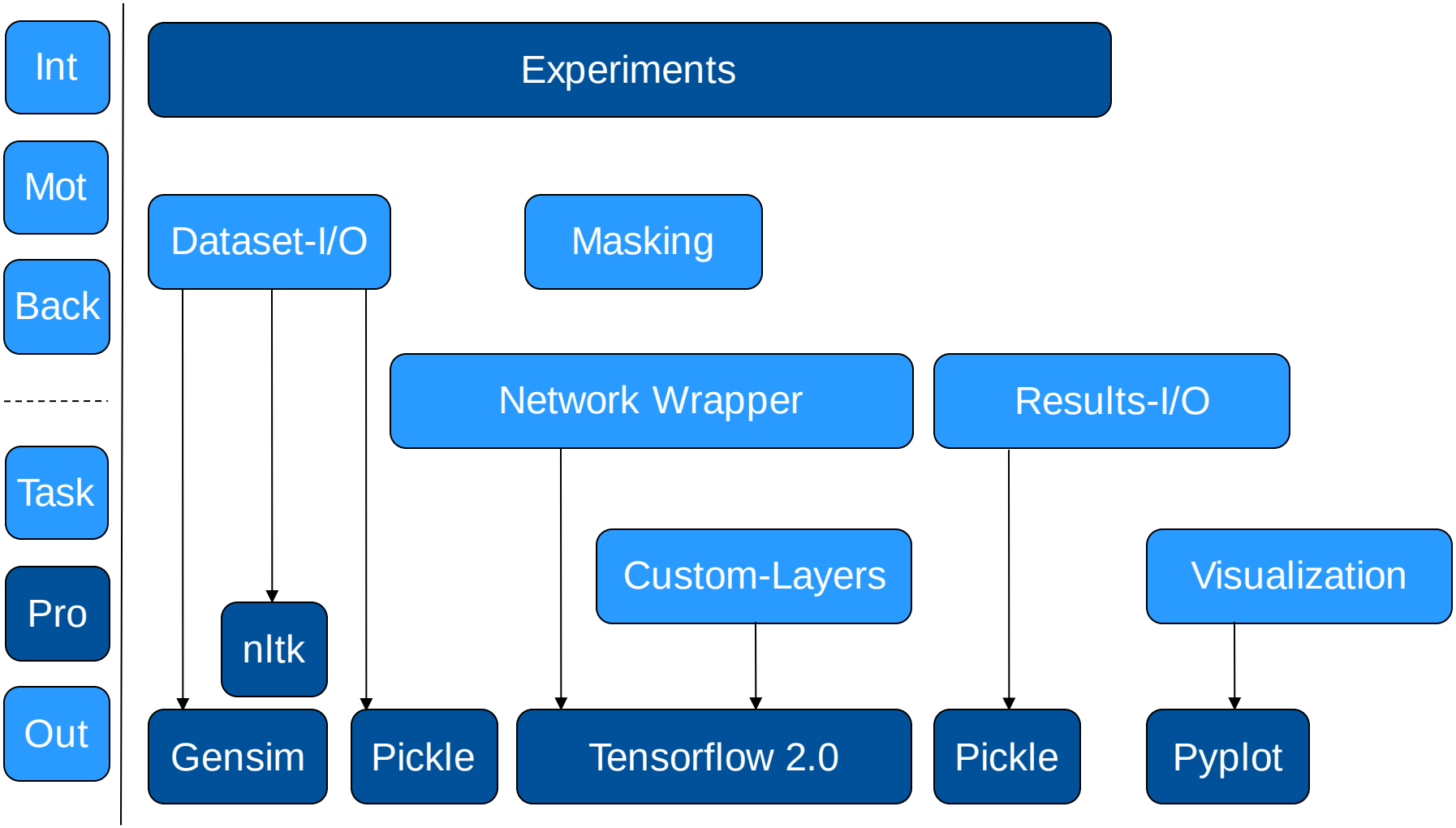
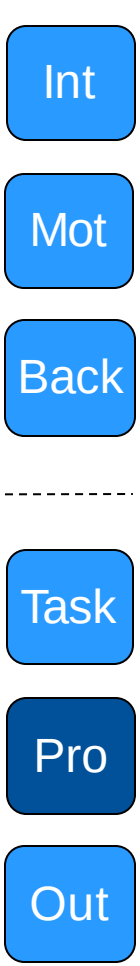


Progress – Backend



Progress – Experiment(s)



Remaining Work

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Remaining parts of the framework

- Custom Convolutional Layer
- Support for iterative Pruning

More experiments

- MNIST / Lenet-CNN-6
- MNIST / VGG-18
- Reuters / TBD
- MNIST / Lenet-FCN / Early Pruning

Thank you for your attention! Questions?

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