Learning methods for limited datasets

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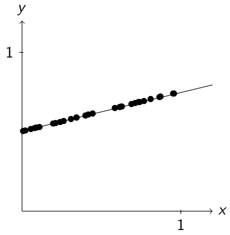
3. Data efficiency
   - Transfer learning
   - Multi-task learning
   - Semi-supervised learning

Machine learning

Supervised learning

Machine learning is a subfield of artificial intelligence.



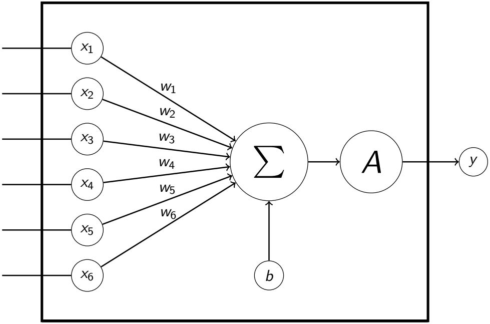
Intuitively We want to *learn from* and *make predictions on* data.

Technically We want to build a model that approximate well (*e.g.* minimize a loss function) an unknown function for which we only have limited observations.

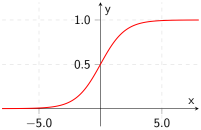
To do this, we usually need *a lot of data*.

Neural network

Neuron with activation



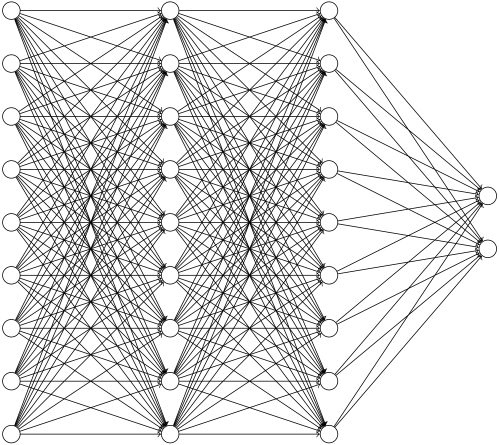
$$A(x) = \frac{1}{1+e^{-x}}$$



$$y = A(w_1x_1 + w_2x_2 + w_3x_3 + w_4x_4 + w_5x_5 + w_6x_6 + b)$$

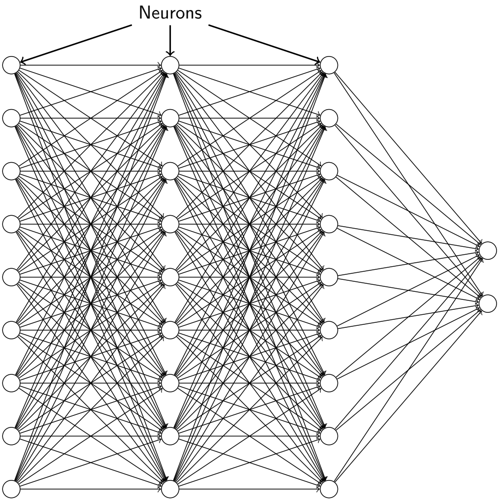
Neural network

Network



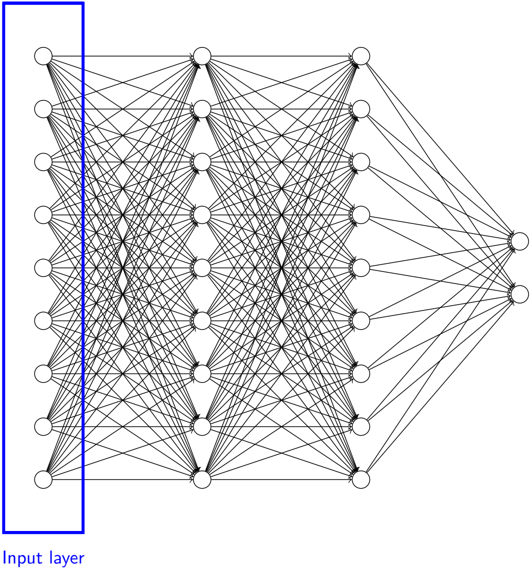
Neural network

Network



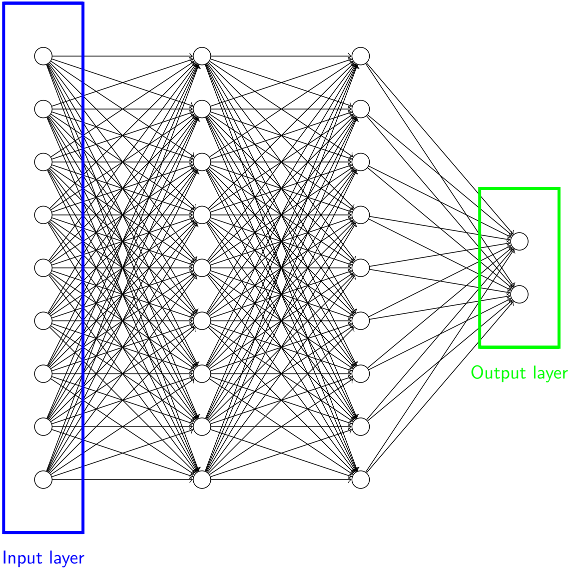
Neural network

Network



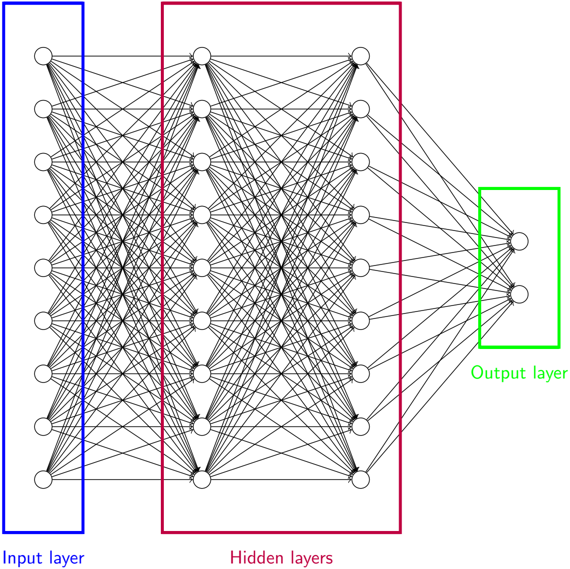
Neural network

Network



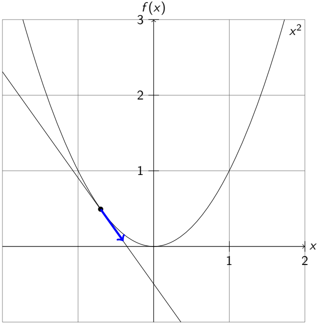
Neural network

Network



Neural network

Training



A differentiable loss function $L(\theta, x, y)$ tells us how well the model is performing. We compute how parameters changes influence the loss by taking its gradient $\nabla_\theta L(\theta, x, y)$.

We then update the weights to make the value of the loss function decrease by iterating this formula:

$$\theta_{t+1} = \theta_t - \alpha \nabla_{\theta_t} L(\theta_t, x, y).$$

Popular datasets

Computer vision

1990, Statlog	$\sim$2k outdoor images,
1998, MNIST	60k B&W images of handwritten digits,
2005, LabelMe	$\sim$187k scenes images,
2009, ImageNet	$\sim$14M images with 1000 different categories,
2017, JFT-300M	$\sim$300M RGB images $\sim$18k categories (internal dataset @ Google).

Popular datasets

Natural language processing (NLP)

1997, Car evaluation dataset	∼2k textual car evaluations,
2005, Stanford Sentiment Treebank	∼11k movie reviews,
2011, IMDB Reviews	∼50k movie reviews,
2012, Youtube Comedy Slam	∼1.1M pairs of video metadata,
2015, Amazon reviews	∼82M product reviews.

Creating dataset

Creating new high quality datasets is both hard and expensive.

Some researchers experiment with training models using low quality data (weakly supervised learning).

Amazon offers a dataset creation service (Amazon Mechanical Turk) where you can pay to get your dataset labelled by humans.

Data efficiency

Knowing that datasets are so important and hard to create, it is important to squeeze *every last bit of value* out of them.

To do this, three ideas are explored:

- Transfer learning,
- Multi-task learning,
- Semi-supervised learning.

Transfer learning

Concept

> *The application of skills, knowledge, and/or attitudes that were learned in one situation to another learning situation. (Perkins, 1992)*

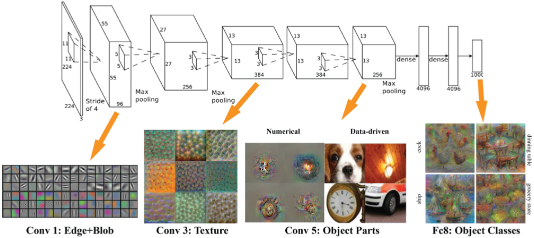
Transfer learning consists in taking an artificial neural network that has been trained on a *generic* task and *transferring* its knowledge (retraining it) to perform a new task.

The idea behind this method is that the information learned on a generic task will probably be useful for a new task of the same domain.

Transfer learning is actually the base of the Google Cloud AutoML service.

Transfer learning

Computer vision

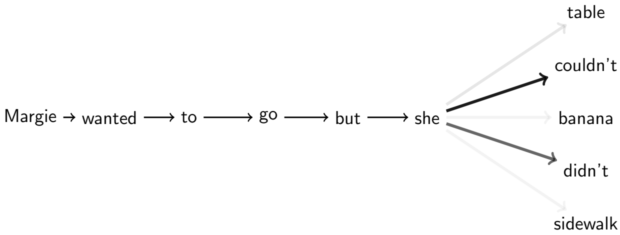


Using this trained model as a base to build a dogs vs cats picture classifier greatly reduce the need of labelled data.

The knowledge about basic shapes and textures that has been learned on ImageNet will be useful to almost all task involving real world images.

Transfer learning

Natural language processing



The language modeling task is currently the most generic task that NLP researcher have found to perform transfer learning.

Knowing how to predict the most likely following word requires to understand, to some extent, the meaning of words, the syntax of the language and the way concepts interact.

Typical language models are trained on Wikipedia content, books or Internet Common Crawl.

Multi-task learning

Concept

> *Multi-task learning is an approach to inductive transfer that improves generalization [...] It does this by learning tasks in parallel while using a shared representation; what is learned for each task can help other tasks be learned better. (Rich Caruana, 1997)*

Instead of just training the network to perform the desired task, we also optimize it to perform *auxiliary tasks*.

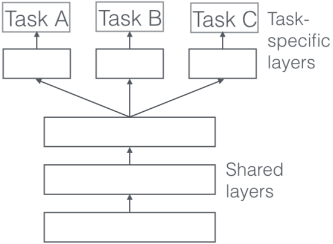


Image from http://ruder.io/multi-task/

Multi-task learning

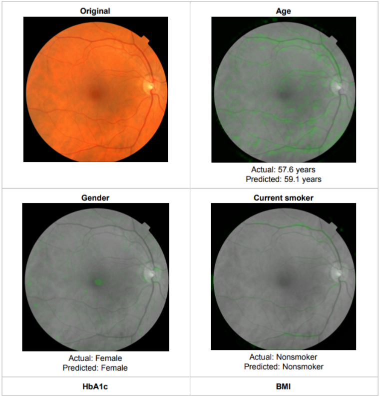
Regularization technique

Informally, the goal of the multi-task learning is to force the model to use its computing power to perform something meaningful instead of using it to learn the noise of the data (overfitting).

Image from https://hackernoon.com/memorizing-is-not-learning-6-tricks-to-prevent-overfitting-in-machine-learning-820b091dc42

Multi-task learning

Computer vision

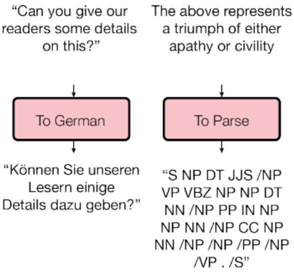


Some researchers discovered that by asking a model to predict the gender and age of patient in addition to detect *cardiovascular diseases* they got strong performance improvements.

Poplin, Ryan, et al. "Predicting cardiovascular risk factors from retinal fundus photographs using deep learning." arXiv preprint arXiv:1708.09843 (2017).

Multi-task learning

Natural language processing



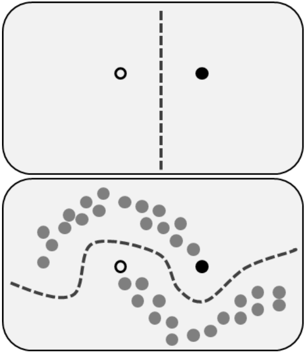
In NLP, translation can be used as an auxiliary task to improve models that perform tasks that have relatively small datasets such as sentence parsing.

By making the model perform translation, a task with huge datasets, we allow it to gain access to a much richer structure of the language.

Kaiser, Lukasz, et al. "One model to learn them all." arXiv preprint arXiv:1706.05137 (2017).

Semi-supervised learning

Concept



The idea of semi-supervised learning is to use *unlabelled data* to improve our model.

Image from https://en.wikipedia.org/wiki/Semi-supervised_learning

Semi-supervised learning

Concept

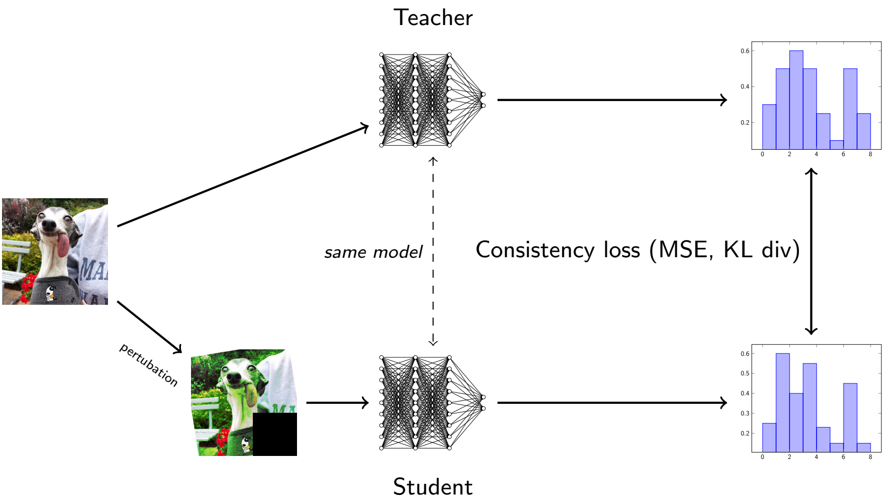
The main concept of semi-supervised learning is to train a weaker student to imitate a stronger teacher.

Technically, we apply *mean-squared error* or a *Kullback-Liebler divergence* between the logits output by the student and the teacher. We typically alternate between supervised and semi-supervised steps of training.

The goal of this method is to propagate labels and improve noise invariance.

Semi-supervised learning

Computer vision



We do not need a label for the clean image, we want to teach the model to be noise invariant.

Conclusion

1. Establish a baseline using basic algorithms (naive Bayes, logistic regression, random forest, etc.).
2. Choose a model architecture (MLP, CNN, RNN, Transformer).
3. Try to find (or build) a pre-trained version of this model that performs a related task and retrain it to your problem (*transfer learning*).
4. Try to find a related auxiliary task to regularize to improve the model learning abilities. (*multi-task learning*).
5. Once the performance of the model is relatively good, try to use unlabelled data to improve performances (*semi-supervised learning*).

References

- https://blog.slavv.com/a-gentle-intro-to-transfer-learning-2c0b674375a0
- Radford, Alec, et al. "Improving language understanding by generative pre-training." URL Article pdf link Blog post (2018).
- Devlin, Jacob, et al. "Bert: Pre-training of deep bidirectional transformers for language understanding." arXiv preprint arXiv:1810.04805 (2018).
- Poplin, Ryan, et al. "Predicting cardiovascular risk factors from retinal fundus photographs using deep learning." arXiv preprint arXiv:1708.09843 (2017).
- Kaiser, Lukasz, et al. "One model to learn them all." arXiv preprint arXiv:1706.05137 (2017).
- Tarvainen, Antti, et al. "Mean teachers are better role models: Weight-averaged consistency targets improve semi-supervised deep learning results." Advances in neural information processing systems (2017).
- Miyato, Takeru, et al. "Virtual adversarial training: a regularization method for supervised and semi-supervised learning." IEEE transactions on pattern analysis and machine intelligence (2018).