COMP30027 Machine Learning
"Deep" Learning: Part II

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Tim Baldwin & Jeremy Nicholson & Karin Verspoor

What is Deep Learning?

- **Deep learning** is the combination of "deep" models (usu. meaning multiple hidden layers) with sufficient (= lots and lots of) data to train the models
- One key facet of deep learning is **representation learning**, i.e. the transformation of raw inputs into a (latent) representation that is more amenable to machine learning
- "(deep learning) usually work(s) well with large-scale datasets, especially when the model takes in low-level raw features ... (with) large-scale datasets ... ranging from hundreds of thousands to several millions of samples" [Zhang et al., 2015]

Document Representation

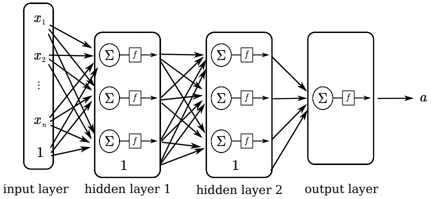
- As we saw in Project 2, a typical document representation is in terms of the words (“tokens”) within a document (discarding “context”)
- A “bag of words” representation of a document is a sparse vector of “term frequencies” (only a small proportion of the vocabulary is present)
- Other representations like “token *n*-grams” (pairs, triples, etc. of words) maintain more information from the document, but are more sparse
- A token/*n*-gram (frequency) can be suggestive of a class, but no more than suggestive

Image Representation

- Similar issues — an instance (image) is fundamentally comprised of pixel values (R/G/B, brightness, etc.)
- An individual pixel can be suggestive (?) of some image property
- Only really sensible in combination:
  - Some sequence of pixel values defines a line fragment
  - Some sequence of line fragments (roughly) defines a shape
  - Some sequence of shapes defines a ... dog
  - Requires lots of effort to try to identify meaningful features
  - **feature engineering** is very difficult

Representation Learning I

- In deep learning, at each layer of the model, it is possible to extract out a dense real-valued vector representation of a test instance (= **embedding**), e.g. from either hidden layer of the following MLP:



- This is generally the approach to deep representation learning, with the bigger question being how to train the model

Representation Learning II

- Each dimension of the embedding corresponds to ... something
    - The model has learned a generalise-able property
    - Sometimes the property has an interpretation ... but usually not
- The advantage of the embedding is three-fold:
    - We have fewer features = faster training/prediction
    - Feature engineering is "free"
    - With a careful choice of representation, we can represent an instance by a (combination of) embedding(s), allowing us to use the trained network for problems it wasn't designed for (!)

Representation Learning: word2vec I

- One particularly well-known example of representation learning in a language context is **word2vec** [Mikolov et al., 2013], e.g. the **CBOW** ("continuous bag of words") model:

$$J = \frac{1}{T}\sum_{i=1}^{T} \log \frac{\exp\left(\mathbf{w}_i^\top \sum_{j\in[-c,+c],j\neq 0} \tilde{\mathbf{w}}_{i+j}\right)}{\sum_{k=1}^{V} \exp\left(\mathbf{w}_k^\top \sum_{j\in[-c,+c],j\neq 0} \tilde{\mathbf{w}}_{i+j}\right)}$$

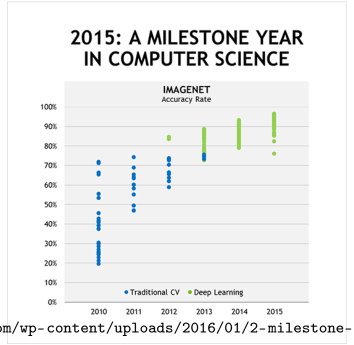
where $\mathbf{w}_i$ and $\tilde{\mathbf{w}}_i$ are vector representations of words (focus and context words, resp.), V is the vocabulary size, T is the number of tokens in the corpus, and c is the context window size

Representation Learning: word2vec II

- The basic idea is that for each word in a corpus, we attempt to predict it from its context words $w_{i-c}, w_{i-c+1}, \ldots w_{i+c}$ (ignoring sequence)
- This is framed as a classification task, with negative instances synthetically generated through **negative sampling**, by randomly selecting words from the vocabulary V (based on the assumption that they are not going to "fit" the original context of occurrence)
- The model used to learn the word embeddings is a simple feed-forward neural network (without a hidden layer), using logistic regression as the objective function

Deep Learning: Convolutional Neural Networks

- **Convolutional neural networks** ("convnets") are a staple of deep learning, especially for computer vision applications
- The power of convnets is perhaps best illustrated through a potted empirical history of ImageNet (the main annual "bakeoff" for computer vision):



Source(s): `https://blogs.nvidia.com/wp-content/uploads/2016/01/2-milestone-web1.gif`

Convnets: Overview

- Convnets are neural networks made up of the following layers:
  - convolutional layers
  - max pooling layers
  - fully-connected layers
- Part of the big breakthrough in 2012 with "AlexNet" [Krizhevsky et al., 2012] was stacking convolutional layers together
- With very deep convnets, ReLU is often used as the activation function, as it: (a) is fast to differentiate; and (b) tends to avoid the "vanishing gradient" problem

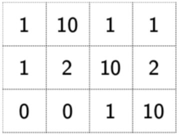
Source(s): `https://cs.nju.edu.cn/wujx/paper/CNN.pdf`

Convnets: Convolution I

- Convolutions are made up of two components:
  1. a **kernel**, in the form of a matrix which is overlaid on different sub-regions of the image, and combined through an **element-wise product**
  2. a **stride** $s \in \mathbb{Z}^+$ which defines how many positions in the image to advance the kernel on each iteration

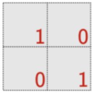
Convnets: Convolution II

- For example, assuming the following 3×4 image and $s = 1$:



1	10	1	1
1	2	10	2
0	0	1	10

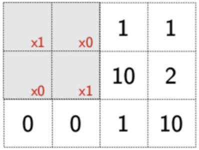
image



1	0
0	1

2x2 kernel

the first convolution would be:



x1	x0	1	1
x0	x1	10	2
0	0	1	10

convolution

$1 \times 10 + 10 \times 0 + 1 \times 0 + 2 \times 1 = 3$

Convnets: Convolution III

- The full convolutional output would be:

$$\begin{bmatrix} 3 & 20 & 3 \\ 1 & 3 & 20 \end{bmatrix}$$

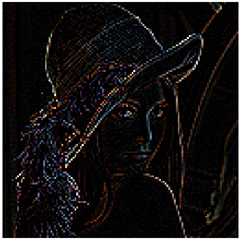
Convnets: Convolution IV

- In practice, multiple kernels are generally applied in a single convolutional layer, e.g.:

Original:

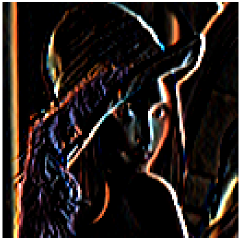
$$\begin{bmatrix} 1 & 1 & 1 \\ 1 & 1 & 1 \\ 1 & 1 & 1 \end{bmatrix}$$

3×3 Laplacian:



$$\begin{bmatrix} 0 & -1 & 0 \\ -1 & 4 & -1 \\ 0 & -1 & 0 \end{bmatrix}$$

3×3 Sobel:



$$\begin{bmatrix} 1 & 0 & -1 \\ 2 & 0 & -2 \\ 1 & 0 & -1 \end{bmatrix}$$

Convnets: Pooling I

- Pooling is comprised of three components:
  (1) a **kernel**, in the form of a matrix which is overlaid on different sub-regions of the image to determine the extent of the "pool"
  (2) a **stride** $s \in \mathbb{Z}^+$ which defines how many positions in the image to advance the kernel on each iteration
  (3) the pooling basis: either **max** (usually 1-max, but sometimes k-max) or **average**

Convnets: Pooling II

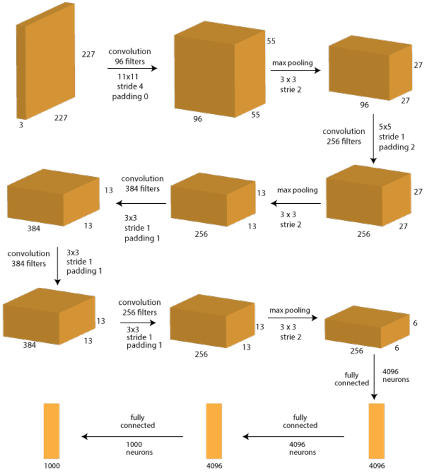
- For example, assuming the convolution output from earlier:

$$\begin{bmatrix} 3 & 20 & 3 \\ 1 & 3 & 20 \end{bmatrix}$$

and a 2×2 pooling layer with $s = 1$, the output in the case of 1-max and average pooling would be, resp.:

$$\begin{bmatrix} 20 & 20 \end{bmatrix} \qquad \begin{bmatrix} \frac{27}{4} & \frac{46}{4} \end{bmatrix}$$

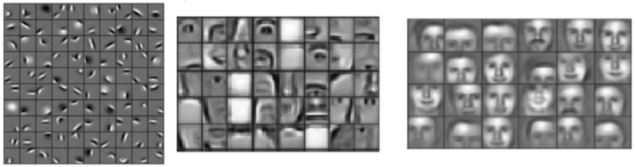
Real-world Convnet Example: AlexNet



Source(s): `https://www.analyticsvidhya.com/wp-content/uploads/2016/03/fig-8.png`

And What is Learned by a Convnet?

- Visualisation of representations learned by a convolutional neural network [Lee et al., 2011], showing how the model is able to hierarchically learn structure of images:



Convnets over Textual Data

- While text data is 1- rather than 2/3-dimensional, convnets have been successfully applied in document categorisation tasks (e.g. see Zhang and Wallace [2015]):
    - 1-dimensional convolutions of varying length over sliding windows over the text
    - (max-)pooling over different width windows
    - represent input as either character sequence or word2vec word-level embeddings (with updates)

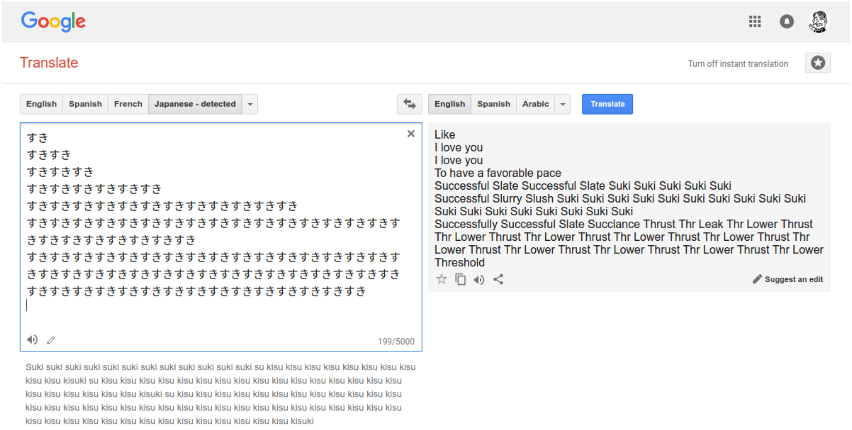
Deep Learning: The Good

- Huge impact on vision and speech recognition tasks in particular, with massive improvements in empirical accuracy over standard datasets
- Possible to model much larger contexts/neighbourhoods than conventional models, due to representation learning/generalisation
- Easy to combine different input modalities
- Easy to play around with using high-level libraries such as TensorFlow, PyTorch and keras
- Lots of vibe/demand for machine learning skills!

Deep Learning: The Bad

- Any savings in terms of feature engineering are outweighed by costs in terms of *architecture* engineering
- Very expensive to train over large datasets (with implications for hyperparameter tuning, architecture engineering, ...)
- Without code, reproducibility of results can be very low, due to the impact of various engineering tricks that have a big impact on results
- Overblown claims about the capabilities of deep learning (AI Armageddon, anyone?)

Deep Learning: The Ugly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Source(s): Inspired by related posts to Language Log

Deep Learning: Current Trends

- End-to-end deep learning
- Multimodal learning
- Deep reinforcement learning
- More specialised hardware to train deep learning models
- Lines of work in learning from the successes of deep learning, and showing that conventional (computationally cheaper!) methods can achieve similar results for some tasks

Summary

- What is deep learning?
- What is representation learning?
- What are the basic elements of a convolutional neural network?
- How do convolution and pooling layers work?
- What are the strengths and weaknesses of deep learning?

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