Notation

To ensure that everyone is up to speed on notation, let's review

- the notation (ML_Notation.ipynb) that we used in the "Classical Machine Learning" part of the intro course.
- additional notation (Intro_to_Neural_Networks.ipynb) used in the "Deep Learning" part of the intro course

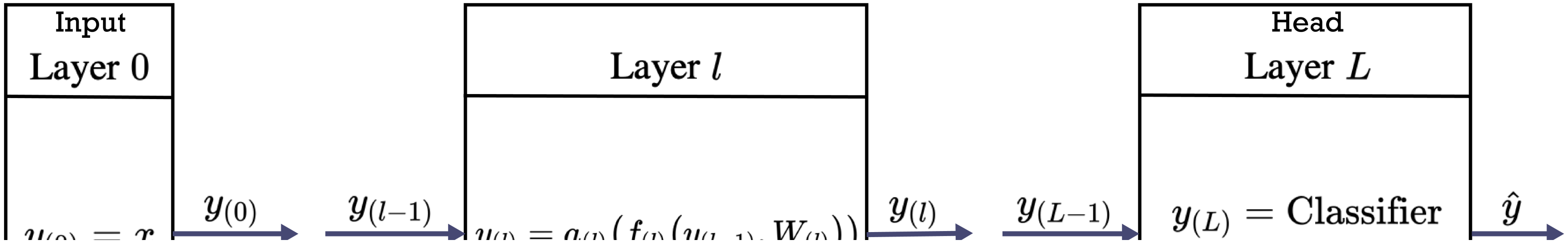
Representations

A path through a Neural Network can be viewed as a sequence of representation transformations

- transforming *raw features* $\mathbf{y}_{(0)} = \mathbf{x}$
- into *synthetic features* $\mathbf{y}_{(l)}$
    - varying with layer $1 \leq l \leq (L-1)$
- of increasing abstraction

Thus, the output anywhere along the path is an *alternate representation* of the input

Path through a Neural Network



Input
Layer 0
$y_{(0)}$
$y_{(l-1)}$
Layer l
$y_{(l)}$
$y_{(L-1)}$
Head
Layer L
$y_{(L)} = \text{Classifier}$
$\hat{y}$

Shallow features are less abstract: "syntax", "surface"

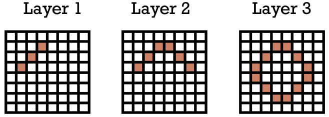
Deeper features are more abstract: "semantics", "concepts"

- We may even interpret the features as "pattern matching" regions or concepts in the raw feature space.

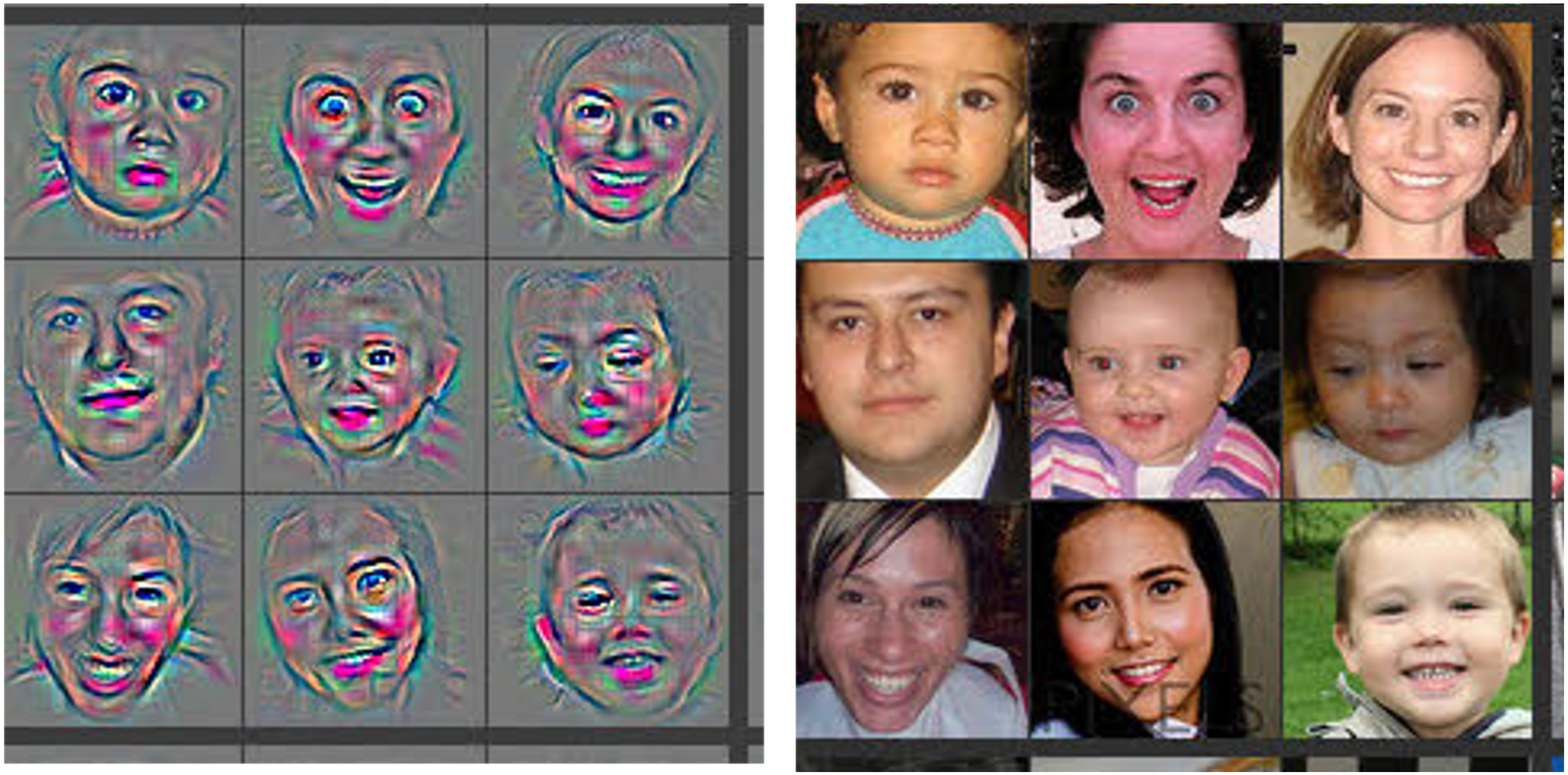
For example, in a CNN

- shallow features are primitive shapes
- deeper features seem to recognize combinations of shallower features

Input features detected by layer


Layer 1
Layer 2
Layer 3

Saliency Maps and Corresponding Patches
Single Layer 5 Feature Map
On 9 Maximally Activating Input images



Layer 5 ? Feature Map (Row 11, col 1).

Attribution: [https://arxiv.org/abs/1311.2901 (https://arxiv.org/abs/1311.2901)](https://arxiv.org/abs/1311.2901)

In the simple architectures of the Intro course, we mostly ignored the intermediate representations

$$\mathbf{y}_{(l)} : \ 1 \le l \le (L-1)$$

The layers were referred to as "hidden" for a reason !

We will discover uses for intermediate representations and show how to build a "feature extractor" to obtain them from a given architecture.

Recurrent Neural Networks

With a sequence $\mathbf{x^{(i)}}$ as input, and a sequence $\mathbf{y}$ as a potential output, the questions arises:

- How does an RNN produce $\mathbf{y}_{(t)}$, the t^{th} output ?

Some choices

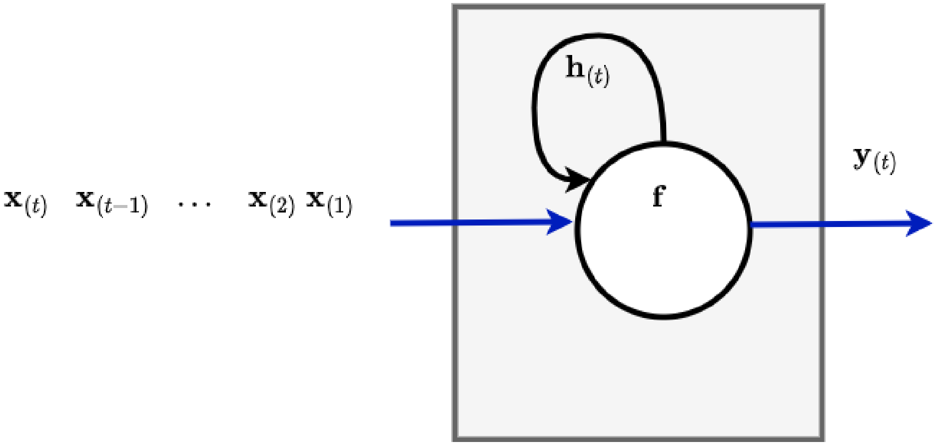
- Predict $\mathbf{y}_{(t)}$ as a direct function of the prefix of $\mathbf{x}$ of length t:
$$p(\mathbf{y}_{(t)} | \mathbf{x}_{(1)} \ldots \mathbf{x}_{(t)})$$

Direct function

- Loop
    - Uses a "latent state" that is updated with each element of the sequence, then predict the output

$p(\mathbf{h}_{(t)} \vert \mathbf{x}_{(t)}, \mathbf{h}_{(t-1)})$	latent variable $\mathbf{h}_{(t)}$ encodes $[\mathbf{x}_{(1)} \ldots \mathbf{x}_{(t)}]$
$p(\mathbf{y}_{(t)} \vert \mathbf{h}_{(t)})$	prediction contingent on latent variable

Loop with latent state



Latent state

The *latent state* $\mathbf{h}_{(t)}$ is a kind of memory that acts as a *summary* of the prefix of sequence $\mathbf{x}$ through time step $\tt%:

$$\mathbf{h}_{(t)} = \text{summary}(\mathbf{x}_{([1:t])})$$

Note that $\mathbf{h}_{(t)}$ is a *vector* of fixed length.

Thus, it is a *fixed length* representation of the key aspects of a sequence $\mathbf{x}$ of potentially *unbounded* length.

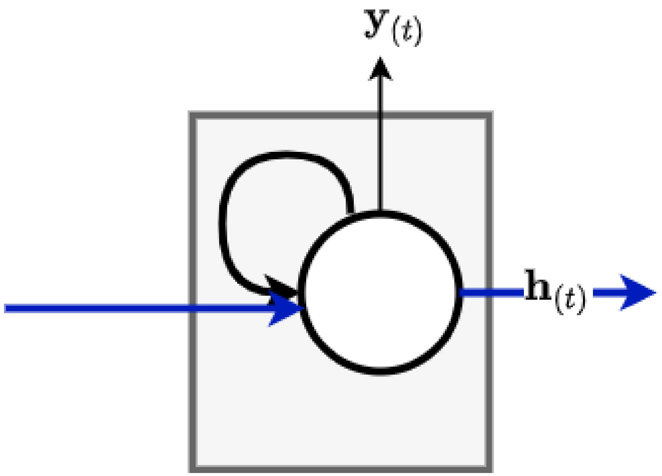
Example

Let's use an RNN to compute the sum of a sequence numbers

- the latent state $\mathbf{h}_{(t)}$ can be maintained as
$$\mathbf{h}_{(t)} = \text{summary}(\mathbf{x}_{([1:t])}) = \sum_{t'=1}^{t} \mathbf{x}_{(t')}$$
- by updating $\mathbf{h}_{(t)}$ in the loop
$$\mathbf{h}_{(t)} = \mathbf{h}_{(t-1)} + \mathbf{x}_{(t)}$$

Let's make this concrete with an example: a sequence of words

Machine Learning is easy not hard



$\mathbf{h}_{(t)}$ is a **fixed length** vector that "summarizes" the prefix of sequence $\mathbf{x}$ up to element t.

The sequence is processed element by element, so order matters.

$$
\begin{aligned}
\mathbf{h}_{(0)} &= \text{summary}([\text{Machine}]) \\
\mathbf{h}_{(1)} &= \text{summary}([\text{Machine, Learning}]) \\
&\vdots \\
\mathbf{h}_{(t)} &= \text{summary}([\mathbf{x}_{(0)}, \ldots \mathbf{x}_{(t)}]) \\
&\vdots \\
\mathbf{h}_{(5)} &= \text{summary}([\text{Machine, Learning, is, easy, not, hard}])
\end{aligned}
$$

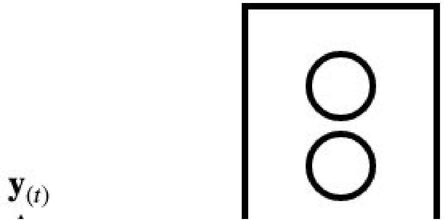
The importance of $\mathbf{h}_{(t)}$ being *fixed length*

- can be used as input to other types of Neural Network layers
- which *don't* process sequences.

A typical example is a model for text classification (sentiment)

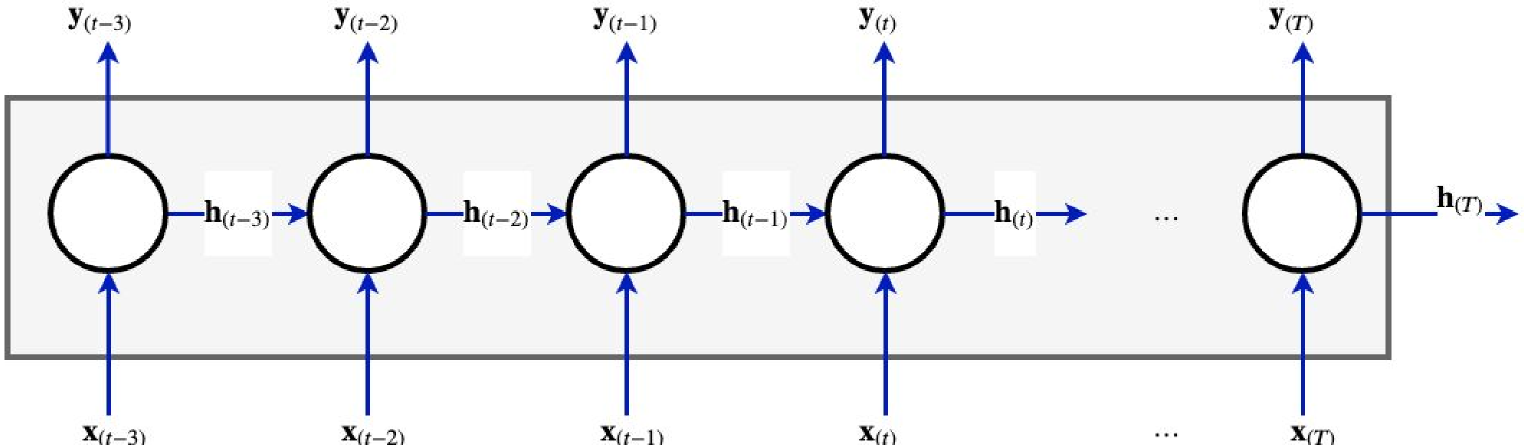
- Using an RNN to create a fixed length encoding of a variable length sequence
- A Head Layer that is a Binary Classifier

RNN Many to one; followed by classifier


$\mathbf{y}_{(t)}$

Unrolled RNN diagram

RNN many to many API

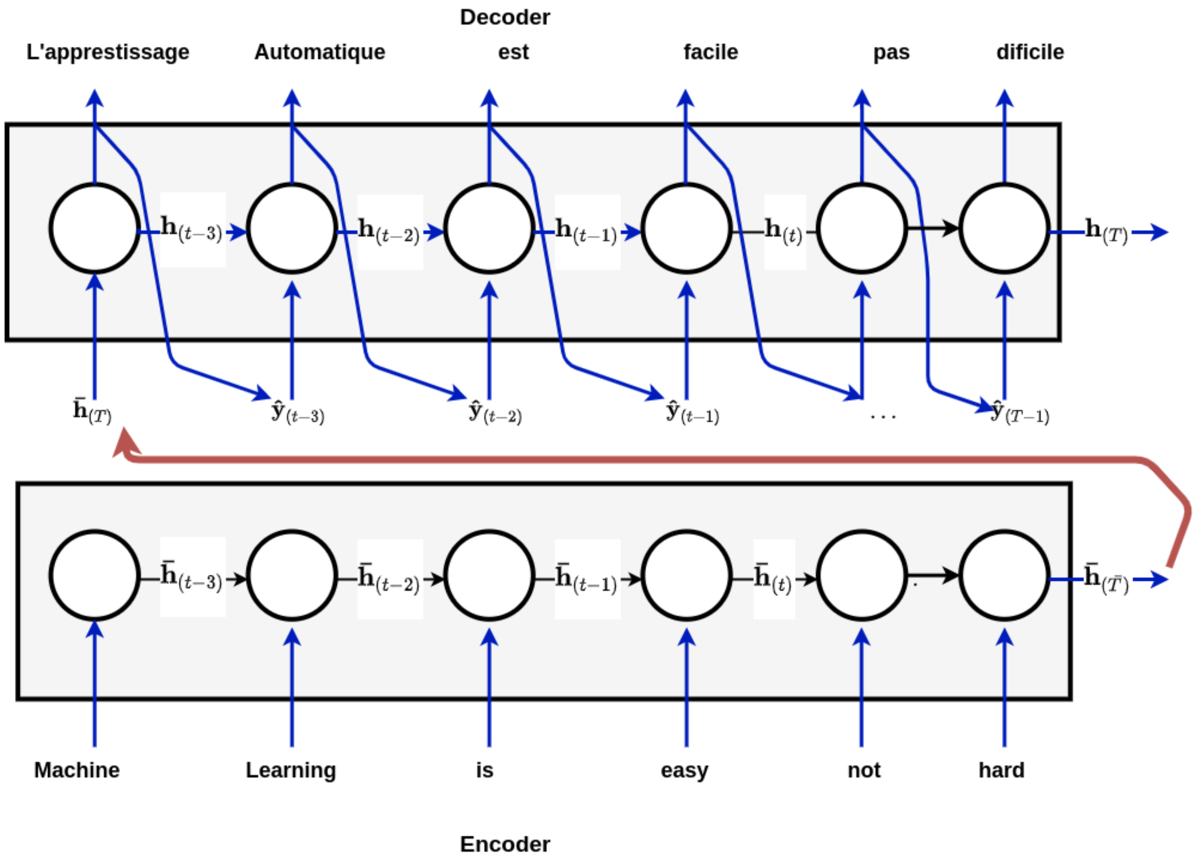


Encoder-Decoder architecture; Auto-regressive

A very common architecture pairs two RNN's

- an Encoder, which summarizes the input sequence $\mathbf{x}_{([1:\bar{T}])}$ via final latent state $\bar{\mathbf{h}}_{(\bar{T})}$
- a Decoder, which takes the input summary $\bar{\mathbf{h}}_{(\bar{T})}$ and outputs sequence $\hat{\mathbf{y}}_{([1:T])}$

It is used for *Sequence to Sequence* tasks where both the input and output are sequences.



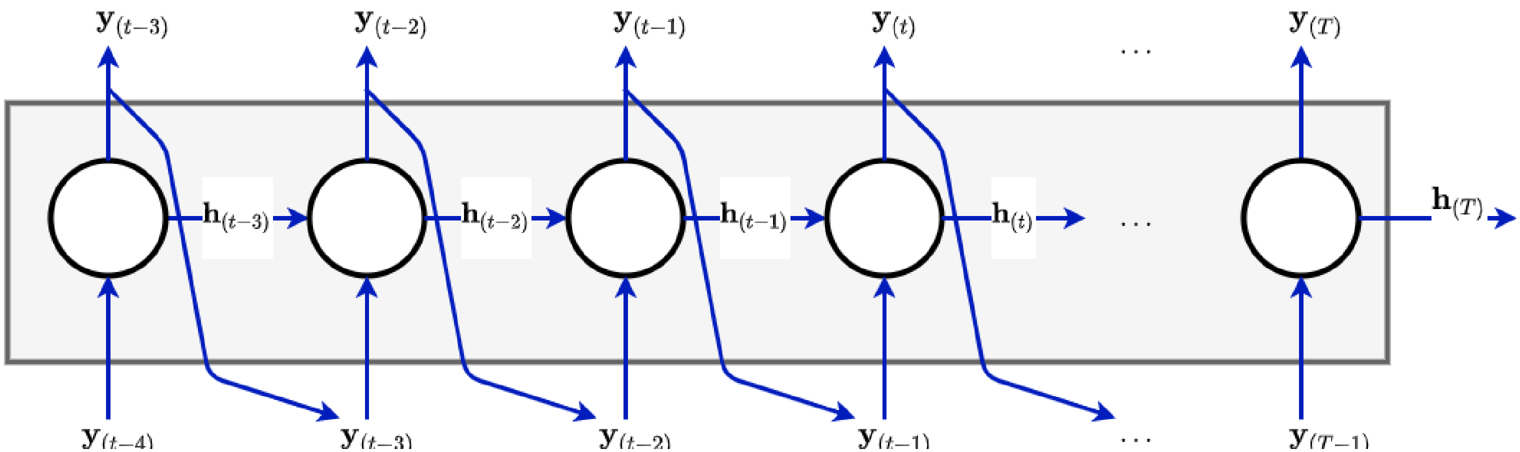
Decoder
L'apprestissage
Automatique
est
facile
pas
dificile
$\mathbf{h}_{(t-3)}$
$\mathbf{h}_{(t-2)}$
$\mathbf{h}_{(t-1)}$
$\mathbf{h}_{(t)}$
$\mathbf{h}_{(T)}$
$\bar{\mathbf{h}}_{(T)}$
$\hat{\mathbf{y}}_{(t-3)}$
$\hat{\mathbf{y}}_{(t-2)}$
$\hat{\mathbf{y}}_{(t-1)}$
$\dots$
$\hat{\mathbf{y}}_{(T-1)}$
$\bar{\mathbf{h}}_{(t-3)}$
$\bar{\mathbf{h}}_{(t-2)}$
$\bar{\mathbf{h}}_{(t-1)}$
$\bar{\mathbf{h}}_{(t)}$
$\bar{\mathbf{h}}_{(\bar{T})}$
Machine
Learning
is
easy
not
hard
Encoder

Notice that

- the output $\hat{\mathbf{y}}_{(t-1)}$ of the Decoder at position $(t-1)$
- is used as the *input* at position t

This is called *auto-regressive* behavior.

Test time: no forcing



Language Models

The *Language Model* training objective

- given some text
    - sequence of *tokens*
- predict a word that could be the next word in the sequence

We sometimes refer to this as the "predict the next" task.

Clearly, we need to train a model on the "predict the next" objective with labeled examples.

But this is sometimes called Semi-Supervised or Unsupervised because text is not inherently labeled.

Yet we can easily create T labeled examples from a text string $s[1:T]$. Example t

- feature: $s[1:t-1]$
- label: $s[t]$

$$\mathbf{s} = \mathbf{s}_{(1)}, \ldots, \mathbf{s}_{(T)}$$

i	$\mathbf{x^{(i)}}$	$\mathbf{y^{(i)}}$
1	$\mathbf{s}_{(1)}$	$\mathbf{s}_{(2)}$

The *Unsupervised Pre-Trained Model + Supervised Fine-Tuning paradigm* is

- a way of adapting a model trained on the Language Modeling objective
- to perform another task

Pre-training refers to training a model on the Language Modeling objective with *lots* of data

- this is called Unsupervised because text is not inherently labeled

- we can easily create a labeled example from a text string $\mathbf{s}[1:T]$

    - feature: $\mathbf{s}[1:t-1]$
    - label: $\mathbf{s}[t]$

- Pre-training

    - Train a model with *lots* of data
    - On the

In [2]:

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print("Done")
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Done
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