Deep Neural Networks

Applications in Handwriting Recognition

Who am I?

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PhD defended at Université Paris-Sud last year

Deep Neural Networks
for Large Vocabulary Handwritten Text Recognition

Now working as a Reasearch Engineer at **a2ia** in Paris

... automatic document processing (handwriting recognition and more...)

... part of the research team (6 people)

... implementation of new neural networks

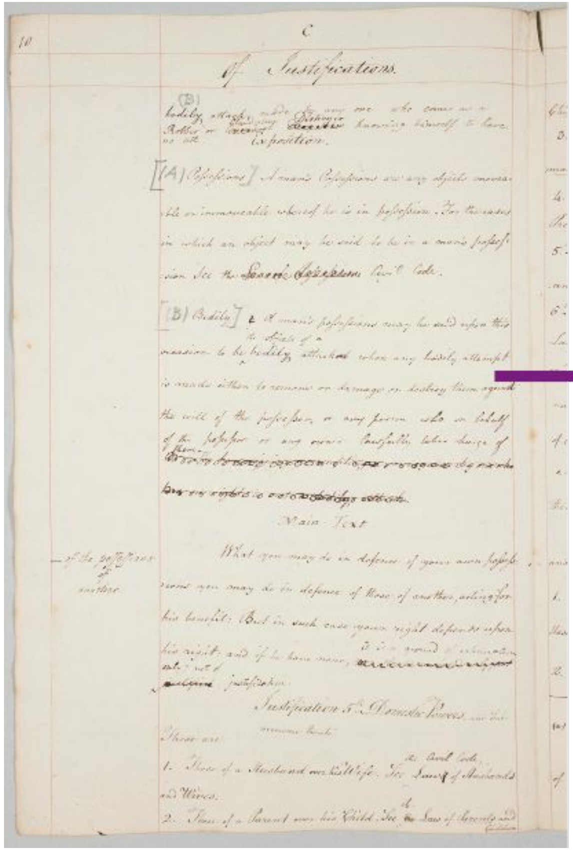
... improving the speed and accuracy of production models

... build the models of tomorrow

Handwriting Recognition ...

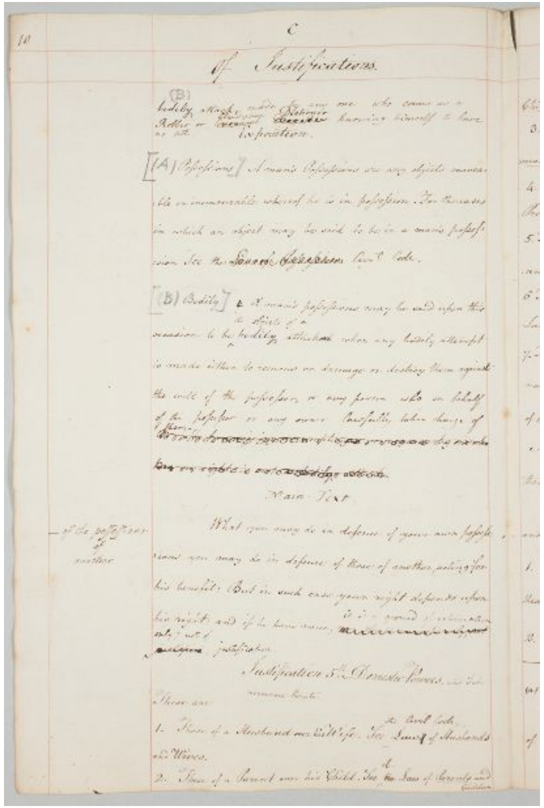
Goal:

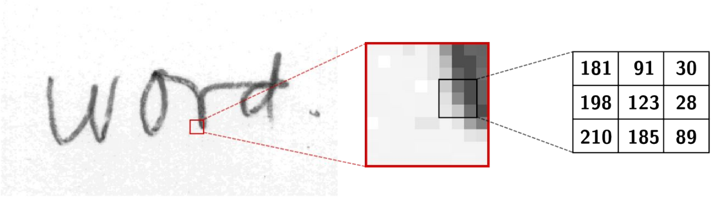
Convert scanned document (image) to text

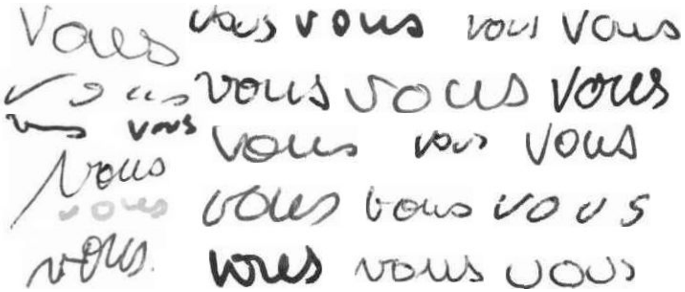


C
10
Of Justifications.
(B)
bodily attack. made by any one who comes as a
Clandestine Destroyer
Robber or Criminal <gap/> knowing himself to have
Exposition.
no title.
[(A) Possessions] A man's Possessions are any objects movea=
:ble or immoveable whereof he is in possession. for the cases
in which an object may be said to be in a man's posses=
:sion See the Law of Possession. Civil Code.
[(B) Bodily] <gap/> A man's possessions may be said upon this
the objects of a
occasion to be bodily attacked when any bodily attempt
is made either to remove or damage or destroy them against
the will of the possessor, or any person who on behalf
of the possessor or any owner lawfully takes charge of
them
.2. The bare signing or accepting a conveyance by one who
has no right is not a bodily attack.
Main - Text .
What you may do in defence of your own possess=
:ions you may do in defence of those of another, acting for
his benefit: But in such case your right depends upon
it is a ground of extenuation
his right : and if he have none, you stand excused only, not
only; not of
justified. justification.
Justification 5th. Domestic Powers. and Sub=
These are :servience thereto.
the Civil Code,
1. Those of a Husband over his Wife. See Laws of Husbands
and Wives.
ib.
2. Those of a Parent over his Child . See the Law of Parents and
Children

… is full of challenges





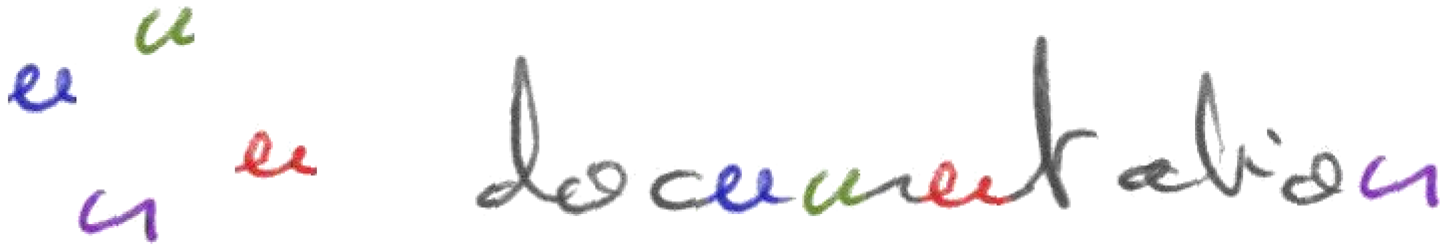


Puzzle

What characters are those?

Answer:

u, (part of) m, en, n! $\longrightarrow$ hard to segment characters, then recognize!



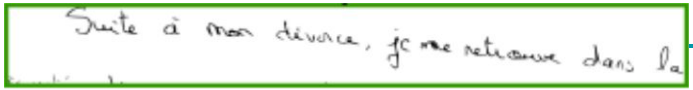
Why is handwriting recognition interesting?

INPUT

- 2D
- image ⟶ computer vision
- variable-sized

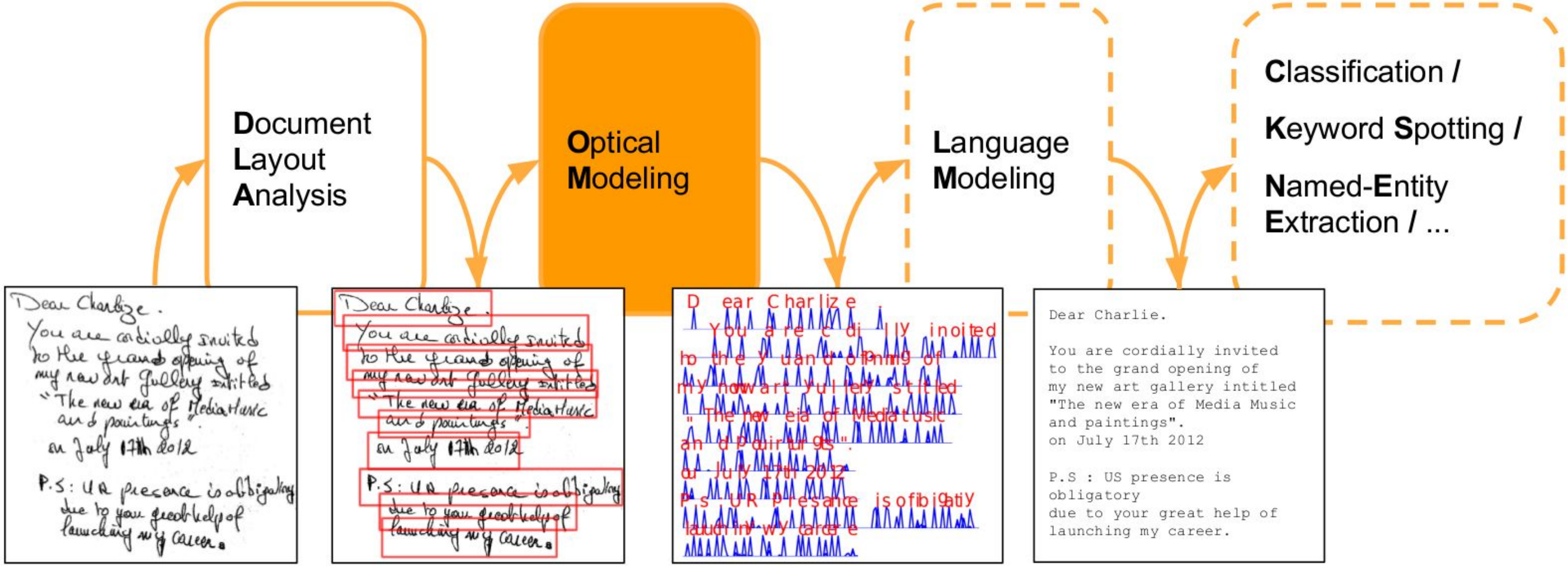
OUTPUT

- Sequence
- text ⟶ natural language processing
- variable-sized



Suite à mon divorce, je me retrouve dans la

Handwritten Document Processing Pipeline



Outline of this talk

➔ Standard Handwriting Recognition (HWR) System

- Image processing - Feature Extraction - Optical Model - Hidden Markov Model - Language Model

➔ Deep Neural Networks for HWR -- plugging NNs in the system

- Neural Nets : Multilayer perceptrons | Recurrent Neural Networks
- Deep Neural Nets ...
- ... automatically learn good features and context

➔ End-to-End HWR -- from pixels to text

- Multidimensional Recurrent Neural Networks
- Attention-based methods

➔ Tips and Tricks

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  - Image processing - Feature Extraction - Optical Model - Hidden Markov Model - Language Model
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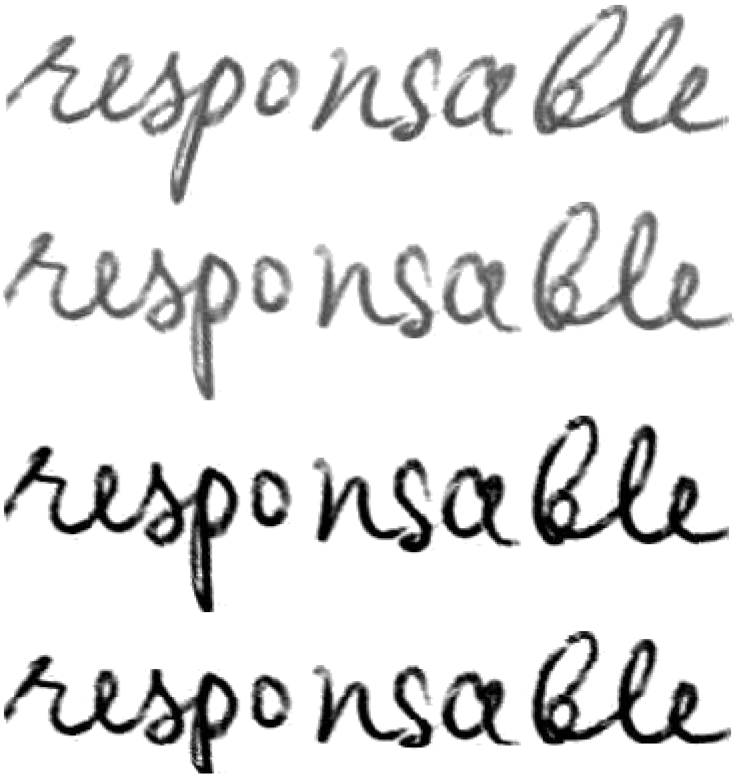
  - Deep Neural Nets ...
  - ... automatically learn good features and context
- **End-to-End HWR -- from pixels to text**
  - Multidimensional Recurrent Neural Networks
  - Attention-based methods
- **Tips and Tricks**

Coping with different writing styles



Preprocessing examples:

Slant correction

Contrast enhancement

Height normalization

Modeling ambiguous cursive text

No segmentation

→ model words directly

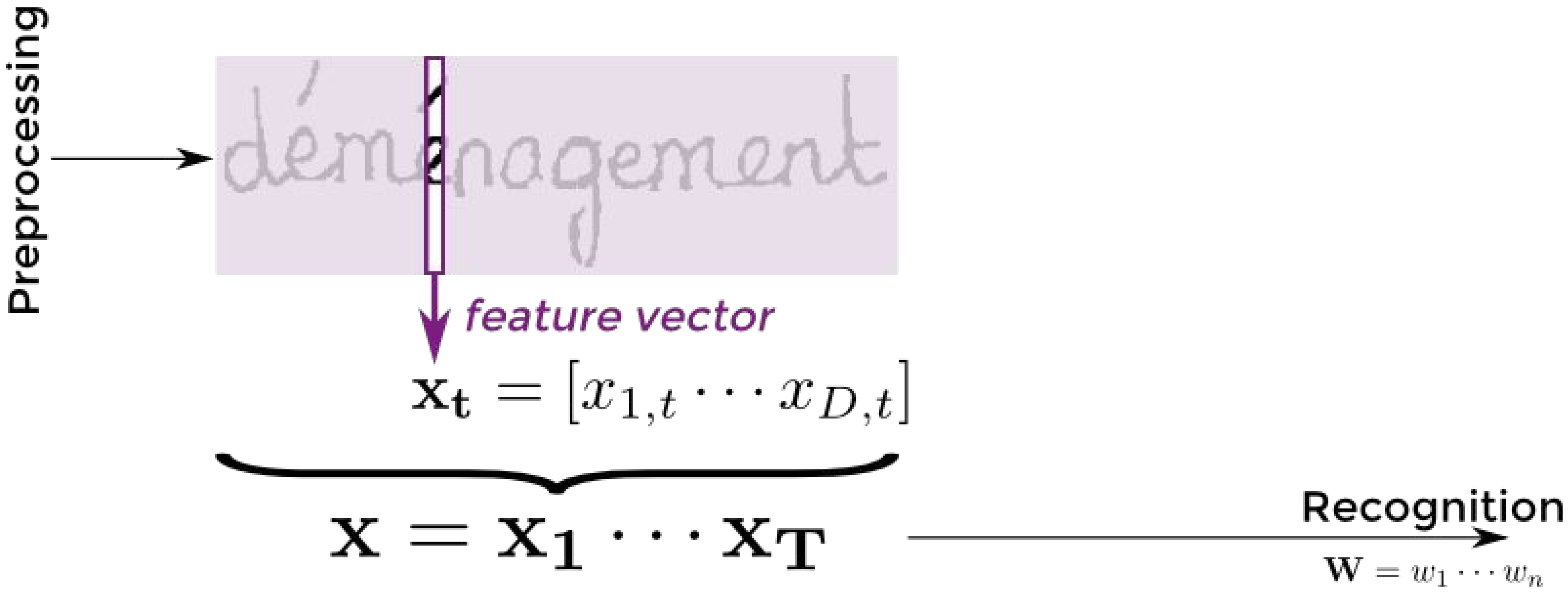
Explicit segmentation

→ model chars/parts of chars

Delayed segmentation

→ model sequences of observations

The sliding window technique



Features (example)

56 handcrafted features extracted from each frame

→ pixel density measures in the frame and different horizontal regions

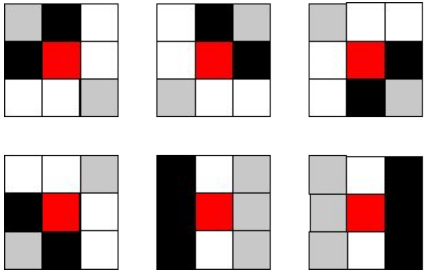
→ measures of the center of gravity

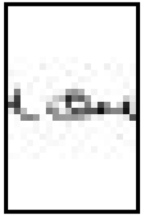
→ pixel configuration relative counts

→ pixel density in vertical regions

→ Histogram of Gradients (HoG) in 8 directions

→ …





A Sequence Modeling problem

Sequence of observations $\xrightarrow{\text{Optical Model}}$ Sequence of characters $\xrightarrow{\text{Language Model}}$ Sequence of words

$$\mathbf{x} = \mathbf{x_1} \cdots \mathbf{x_T} \qquad \mathbf{C} = c_1 \cdots c_m \qquad \mathbf{W} = w_1 \cdots w_n$$

Optical Model

- ➔ core component of the system
- ➔ from pixels / features to characters probabilities

usually one prediction for each frame / window, and then decoding with a sequence model such as HMM to handle different sequence lengths

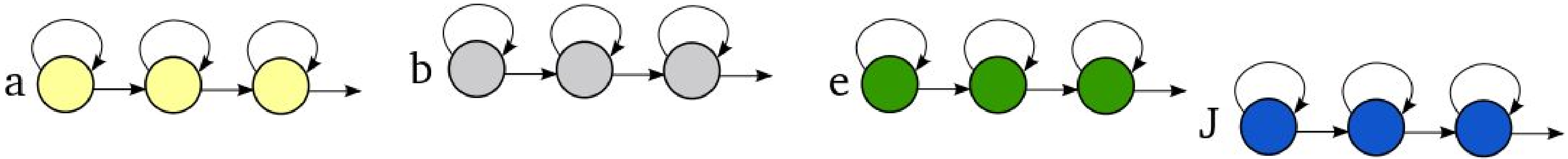
Language Model

- ➔ inclusion of prior knowledge / constraints
- ➔ e.g. a vocabulary to allow only character sequences that form known words
- ➔ + statistics on large text corpora to promote frequent sequences of words

nb. in practice we have many char. sequence hypotheses, and the LM weights them

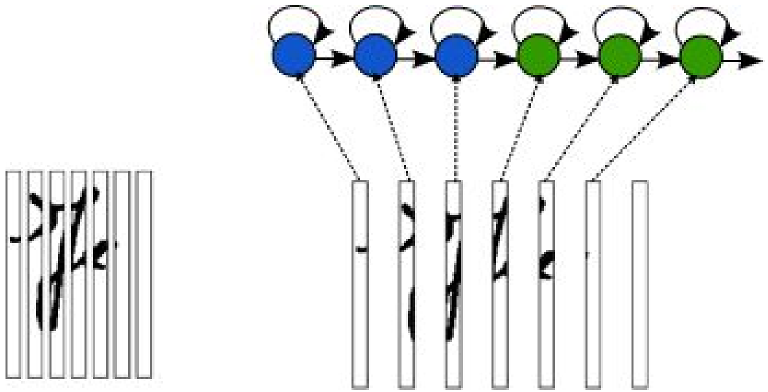
Hidden Markov Models (quickly)

Each character is associated with a small HMM = states and transitions



- **transition model** = probabilities to go from one state to the other
- each state is associated with a distribution of probabilities over features (**optical model** here) used to match frames to states

Sequences of characters (e.g. words) are modeled by the concatenation of HMMs



Recognition

Handwriting recognition = find the most likely sequence of words given observations

$$\mathbf{w}^* = arg\max_{\mathbf{w}} p(\mathbf{w}|\mathbf{x}) = arg\max_{\mathbf{w}} \frac{p(\mathbf{x}|\mathbf{w})P(\mathbf{w})}{p(\mathbf{x})} = arg\max_{\mathbf{w}} p(\mathbf{x}|\mathbf{w})P(\mathbf{w})$$

Optical Model

➔ in the optical model, words are represented by HMMs (i.e. sequences of states)

$$\begin{aligned} p(\mathbf{x}|\mathbf{w}) &= \textstyle\sum_{\mathbf{q}\mapsto\mathbf{w}} p(\mathbf{x}|\mathbf{q}) \\ &= \textstyle\sum_{\mathbf{q}\mapsto\mathbf{w}} \prod_t p(x_t|q_t)p(q_t|q_{t-1}) \end{aligned}$$

(including Markov assumption and computed efficiently with dynamic programming)

Language Model

➔ Model the sequence of words (chain-rule)

$$\begin{aligned} P(\mathbf{w}) &= P(w_1, w_2, \ldots w_N) \\ &= P(w_1)P(w_2|w_1)\ldots P(w_N|w_{N-1}\ldots w_1) \end{aligned}$$

n-gram assumption (probas derived from counts in a big textual corpus)

$$P(w_i|w_{i-1}\ldots w_1) \approx P(w_i|w_{i-1}\ldots w_{i-n+1})$$

More about HMMs and recognition with LM...

For more details, you may read :

Rabiner, L. R. (1989). A tutorial on hidden Markov models and selected applications in speech recognition. *Proceedings of the IEEE*, *77*(2), 257-286.

Frederick Jelinek. (1997). *Statistical methods for speech recognition*. MIT press.

Camastra, F., & Vinciarelli, A. (2008). *Machine Learning for Audio, Image and Video Analysis. Springer*.

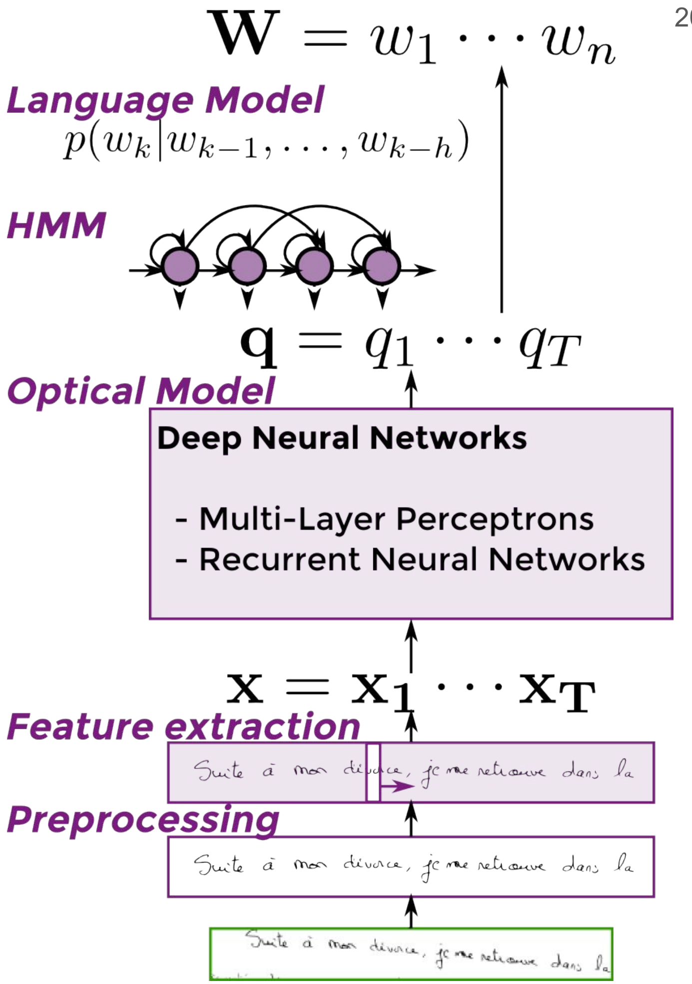
...

Historical System

- Input image
- Preprocessing
- Sliding window
- Feature extraction
- Hidden Markov Models
  - Emission model = Gaussian mixtures
  - Transition models = states $\longrightarrow$ characters
- Vocabulary
- Language model

State-of-the-art

- ➔ First steps (preproc, features) =
  - ◆ normalize and reduce variabiliy
  - ◆ possible loss of relevant information
- ➔ Last steps (HMM, language model) =
  - ◆ add constraints to help correct optical model's mistakes
  - ◆ cannot recognize out-of-vocab words, may add mistakes
- ➔ Optical model = core of the system
  - ◆ from image (features) to text (characters, or parts of characters)
  - ◆ goal : try to avoid design of good preproc / feature extraction / character models and to rely less on language constraints (ultimately, if all characters are well recognized, we wouldn't need an LM)



➔ **DEEP NEURAL NETWORKS**

~~Historical~~ System → Neural Nets

- Input image
- Preprocessing
- Sliding window
- Feature extraction
- Hidden Markov Models
  - Emission model = ~~Gaussian mixtures~~
  - Transition models = states → characters
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(Deep) Neural Network

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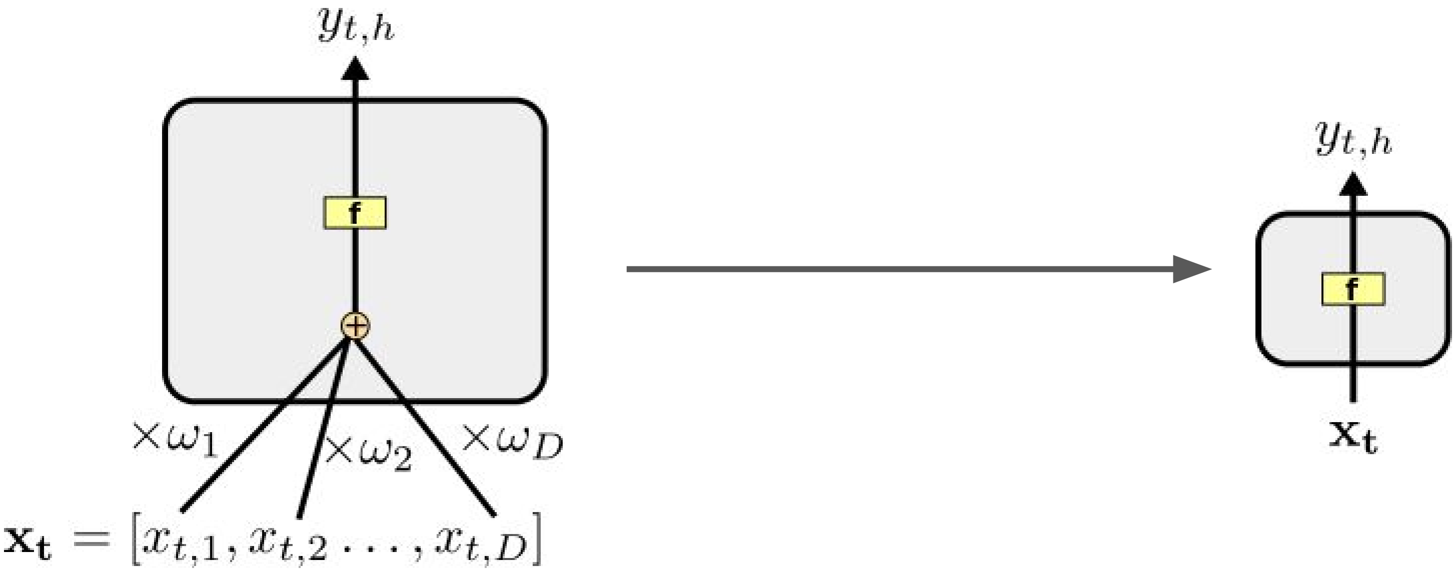
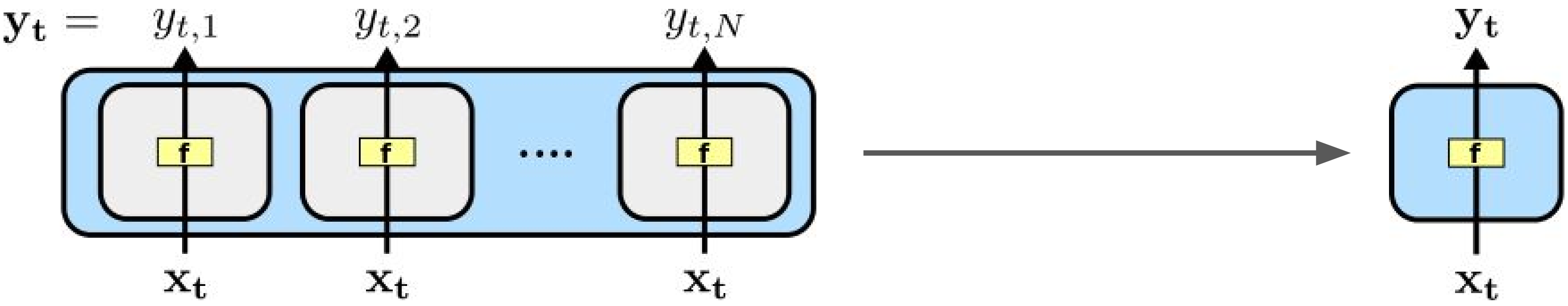
- ➔ Tips and Tricks

Simple Neuron

Multiply each input value by a weight, sum, apply non-linear function, output new value



Layers



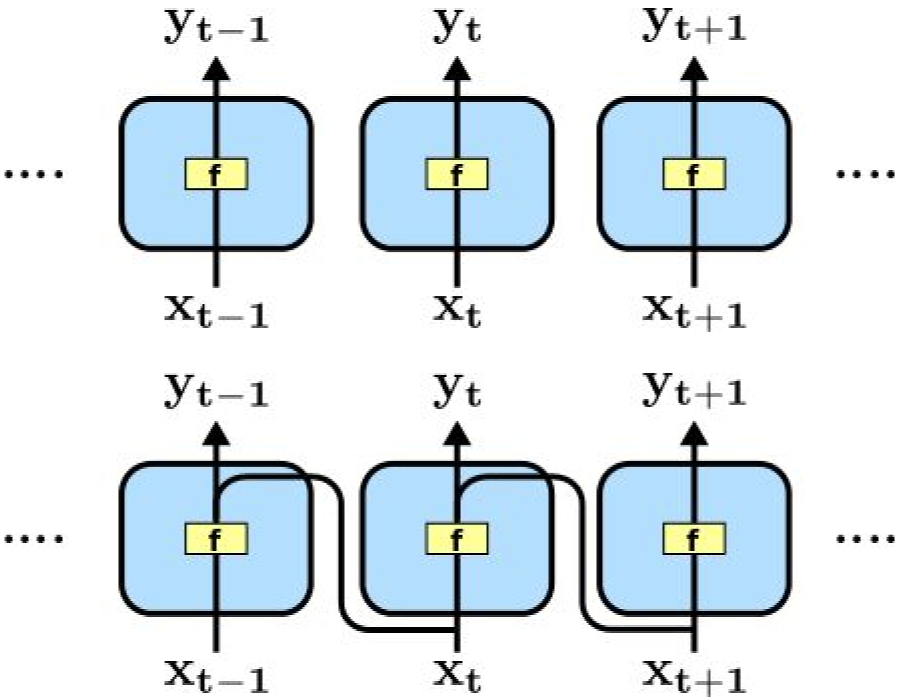
A layer computes a **simple function** $y_t = f(x_t, \theta)$

... for example :

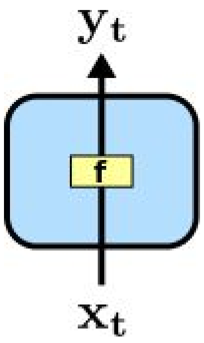
$$y_t = tanh(\mathbf{W}x_t + b); \theta = \{\mathbf{W}, b\}$$

Handling sequential data

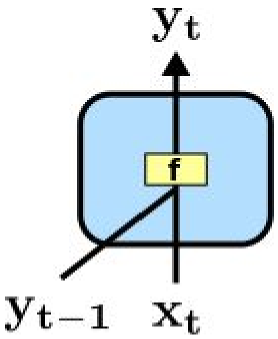
Apply the same layer at each timestep



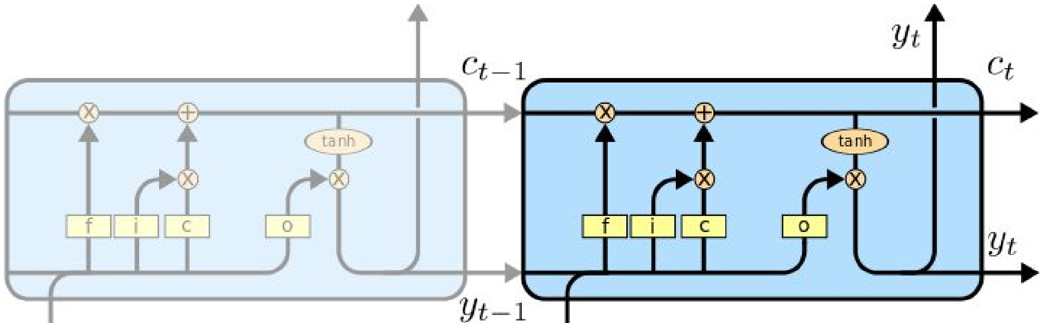
Neurons/Layers for sequential data



Simple



Recurrent



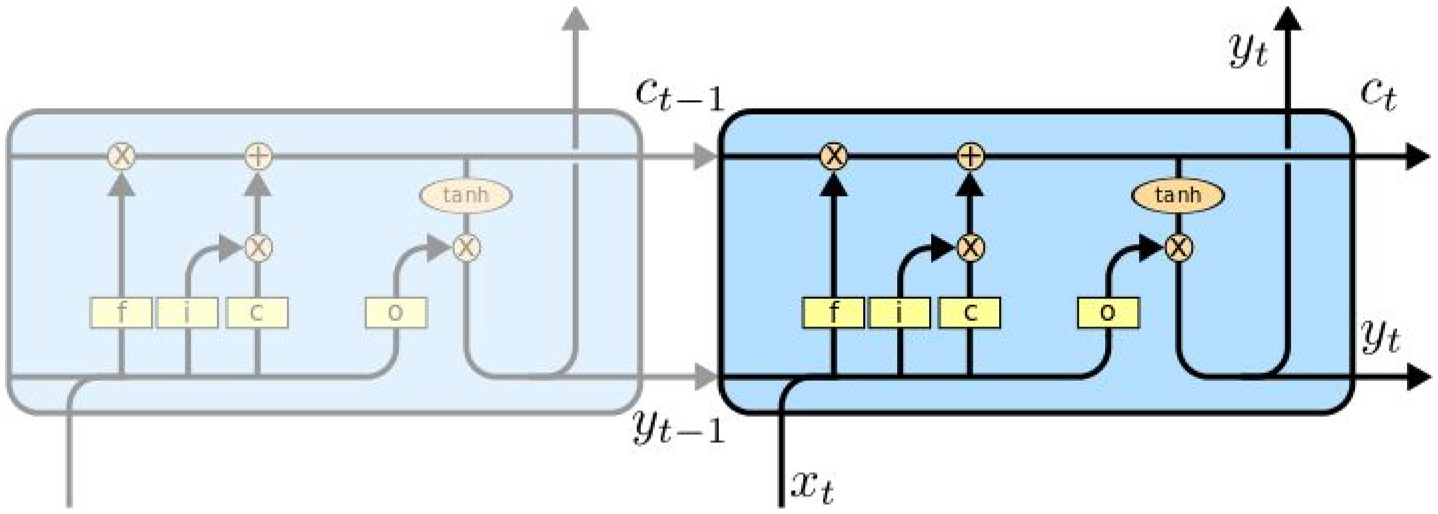
LSTM

A **recurrent** neuron is just a simple neuron with previous output as additional input.

A **Long Short-Term Memory (LSTM)** neuron also has an *internal state* and *gates* to control the flow of information.

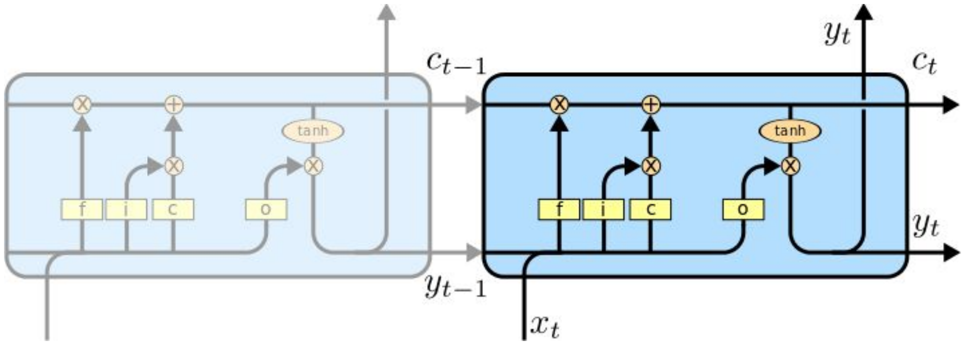
Gates are simple neurons and LSTM may be viewed as a mini-neural net.

Long Short-Term Memory



A very good step-by-step tutorial (from which my diagram are inspired) by Christopher Olah
http://colah.github.io/posts/2015-08-Understanding-LSTMs/ (a MUST-READ!)

Long Short-Term Memory



- The inputs are those of a reccurent neuron (input x(t) + previous output y(t-1))
- The internal state is propagated from the previous timestep
- Three gates with sigmoid (= soft 0/1) activation function to control the flow of information (they are kinds of simple neurons)
  - The *forget gate* (f) controls whether the previous internal state is added to the current state
  - The *input gate* (i) controls whether the input, transformed by a simple neuron (c), is added to the current state
  - The *output gate* (o) controls whether the internal state leaves the neuron (after a tanh activation)
- The output (y(t)) is tanh of the current state, modulated with the output gate

Layers to Neural Networks

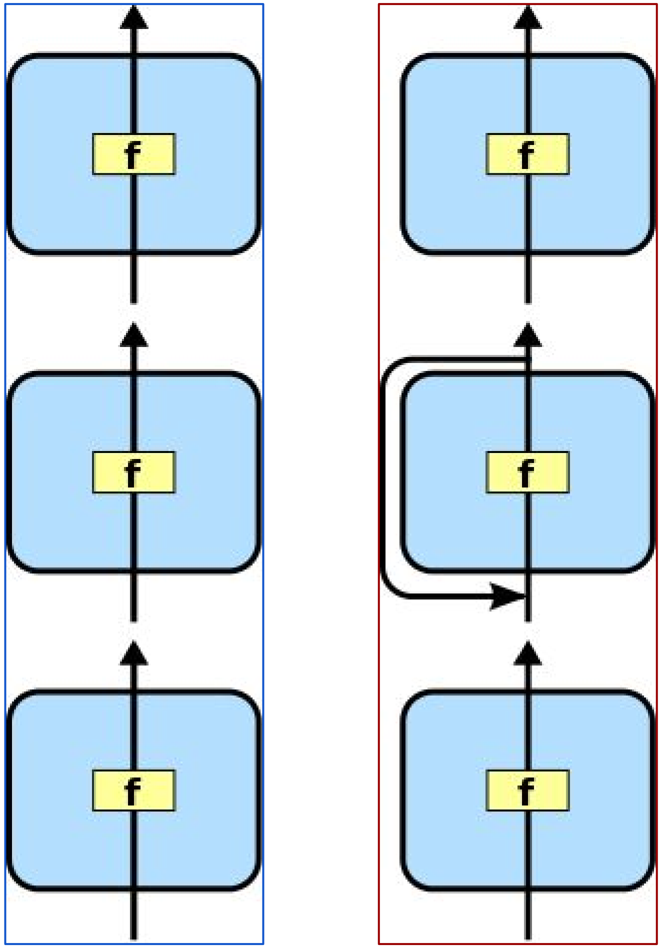
→ A layer **outputs a new vector** from an input vector.

→ It may be viewed as *learnt features*

→ It can be used as the input of a neural network

= a neural network is obtained by stacking layers of neurons.

(may be purely *feed-forward* or recurrent)



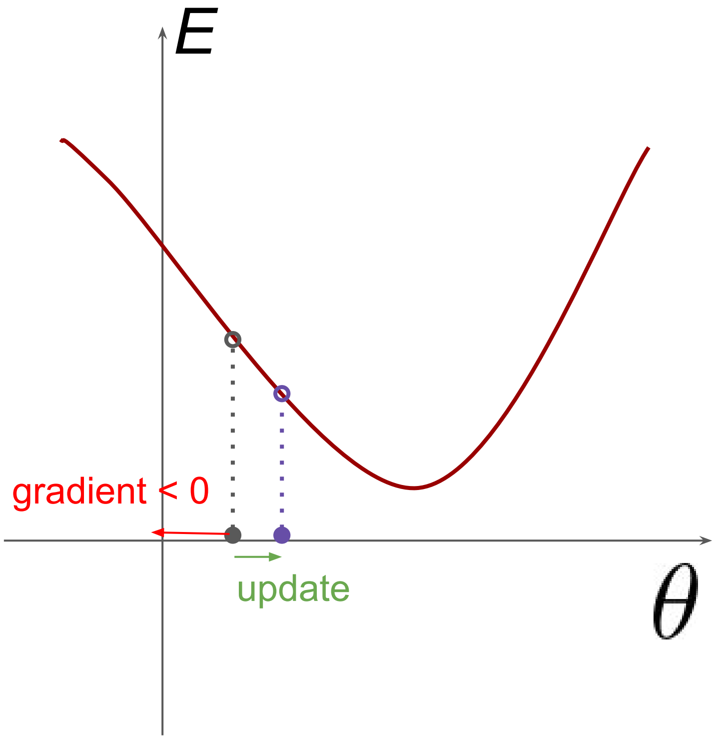
Gradient Descent Training

Given a measure of error ***E*** on a test set (x,y), find the *best* parameters (minimizing it) :

$$\theta^* = argmin E(\theta, x, y)$$

i.e.

$$\frac{\partial E}{\partial \theta} = 0$$



Gradient descent :

$$\theta \leftarrow \theta - \eta \frac{\partial E}{\partial \theta}$$

Only requirement : the error measure (or cost function) should be differentiable w.r.t the parameters

Neural Nets training with Backpropagation

Backpropagation : exploit layered network structure to do gradient descent efficiently

$$\frac{\partial E}{\partial x_t} = \frac{\partial E}{\partial y_t}\frac{\partial y_t}{\partial x_t}$$

Propagation of the error gradient from one layer to the previous one

$$\frac{\partial E}{\partial \theta} = \frac{\partial E}{\partial y_t}\frac{\partial y_t}{\partial \theta}$$

Computation of the gradient w.r.t. the parameters of one layer

= you need to know how to compute

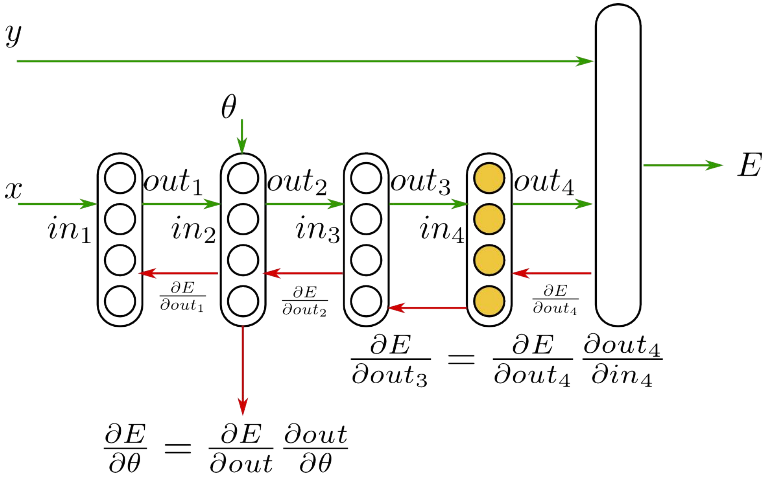
- the ***gradient of the cost function*** (that you'll minimize) ***w.r.t. the outputs of the network***
- for each layer : ***the gradient of the output w.r.t. the input and the parameters***

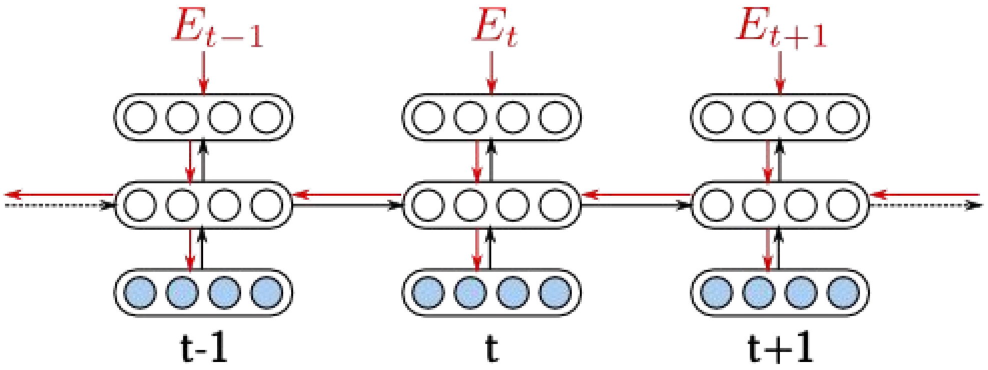
... the rest is only multiplications

(http://arunmallya.github.io/writeups/nn/backprop.html : derivatives for simple costs/layers)

Neural Nets training with Backpropagation

1. Propagate the input forward, layer by layer
2. Compute the error from output and target
3. Compute its gradient w.r.t. the output
4. Propagate the error gradient backward, layer by layer, using chain rule, and compute the gradient w.r.t parameters





Recurrent network are "***unfolded***" in time so they can be seen as feed-forward networks

(or directed acyclic graphs)

A word about *softmax*

→ There are *as many outputs of the network as classes* in the classification problem (e.g. HMM states, characters, ...)

→ Each output represents a score for the corresponding class

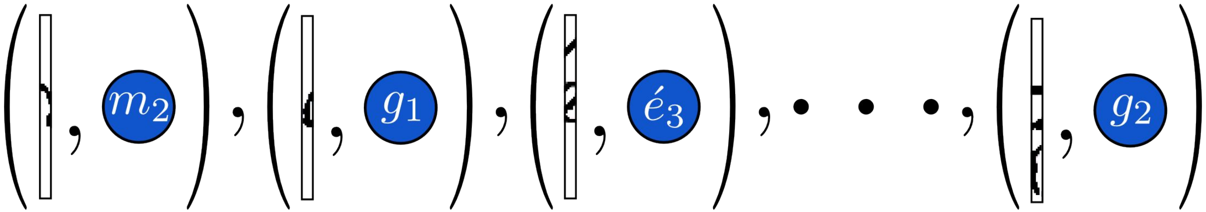
→ With a simple *softmax* normalization, they can represent **a probability for each class** :

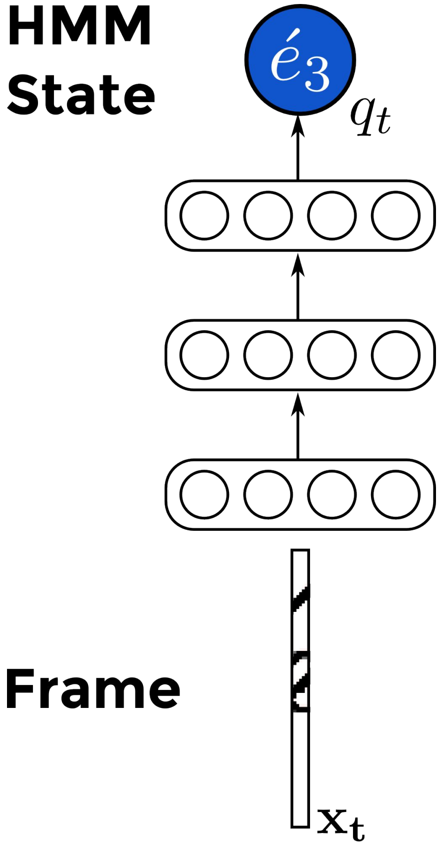
$$p(class_t = k|\mathbf{x_t}) = \frac{e^{y_{t,k}}}{\sum_n e^{y_{t,n}}}$$

→ Hence a cost function can be devised so as to **maximize the probability of the correct class** (and this cost is easy to differentiate w.r.t. the outputs of the network)

Frame classification (MLP style)

- ➔ **Input** = one frame = one vector of pixel or feature values
- ➔ **Output** = posterior probabilities over HMM states (or sometimes characters)





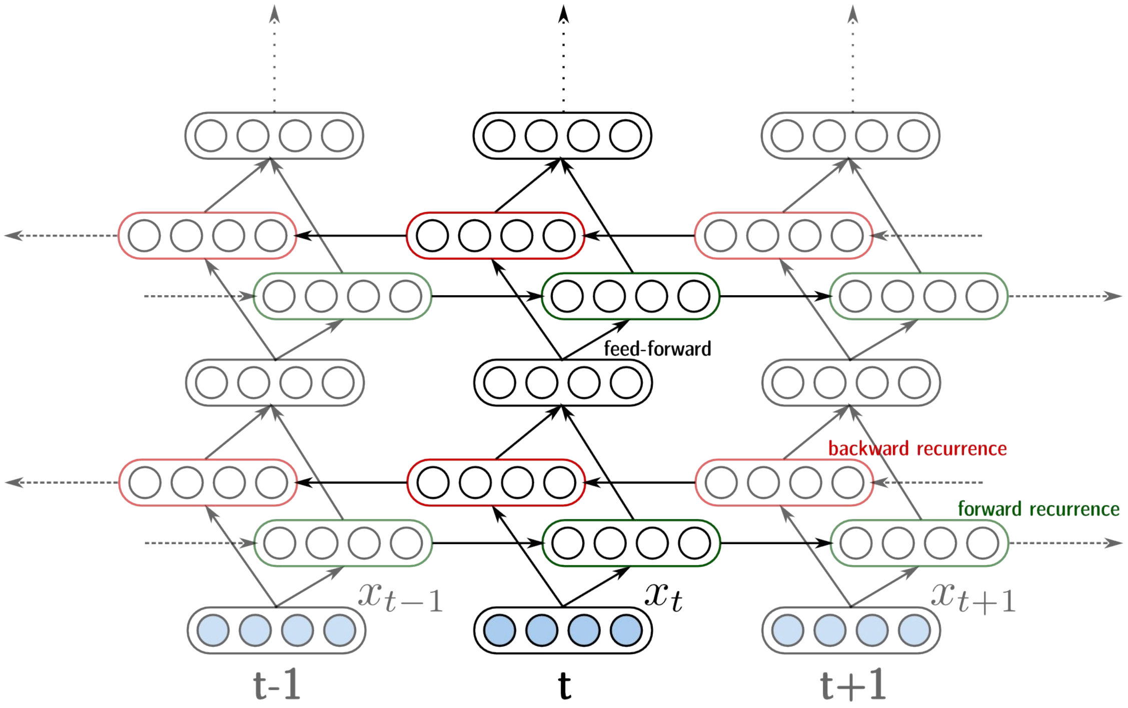
Training :

- ➔ Collect a dataset of (xt, qt) = frames with correct HMM state
- ➔ Minimize *- log p(qt | xt)*
- ➔ Measure the **Frame Error Rate** (% of frames with wrong HMM state prediction)

Sequence classification (RNN style)

Option 1

- ➔ Same as MLP except hidden layers depend on the values at (t-1) or (t+1)
- ➔ i.e. HMM states or characters are predicted potentially taking into account larger **context**
- ➔ Can follow the same training method for each *t*

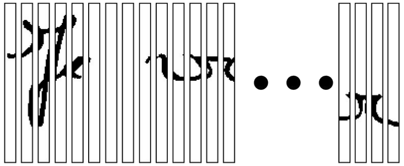


Sequence classification (RNN style)

Option 2 : CTC

➔ To train the network **directly with** frame sequences and **character sequences**

➔ i.e. no need to label each frame with an HMM state

Minimize : ( , **J e _ v o … r**), . . .

-log p (c1, c2, … cN | **x** *= x1, x2, … xT)*

➔ Measure the **Character Error Rate** (% of character substitutions, deletions or insertions)

Sequence sizes are not equal !!!

Connectionist Temporal Classification (CTC)

→ The network **outputs characters** (not HMM states)

→ **Problem** T items in the output sequence, N items in the target char sequence

→ Make sure that $T > N$ and **define a simple mapping** of sequences that removes duplicates:

AAABBCCCC → ABC

ABBBBBCCC → ABC

...

AAAABCCCC → ABC

$$p(c_1 \dots c_N | \mathbf{x}) = \sum_{y_1 \dots y_T \rightarrow c_1 \dots c_N} p(y_1 \dots y_T | \mathbf{x})$$

$$= \sum_{y_1 \dots y_T \rightarrow c_1 \dots c_N} \prod_t \underbrace{p(y_t | \mathbf{x})}_{= \text{Net's output at time } t}$$

→ Computed efficiently with dynamic programing

→ **Problem** how to output ABB (AAABBBBBB → AB) ?

Connectionist Temporal Classification (CTC)

→ **Problem** how to output ABB (AAABBBBBB → AB) ?

→ The network outputs characters **+ a special NULL** (or blank or non-char) symbol -

→ The mapping **removes** duplicates, and ***then NULLs***

AAABBCCCC → ABC

AA-BB--C- → A-B-C- → ABC

...

-A--B--C- → -A-B-C- → ABC

AAABBBBBB → AB

AA-BB--B- → A-B-B- → ABB

...

-A--B--B- → -A-B-B- → ABB

~~Historical~~ System → Neural Nets

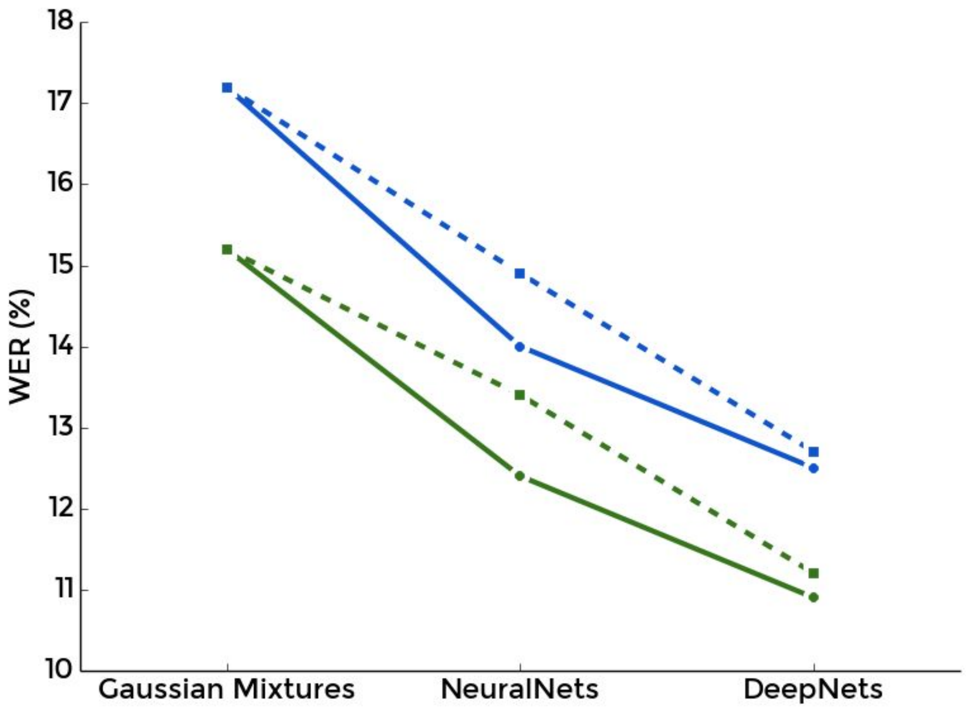
- Input image
- Preprocessing
- Sliding window
- Feature extraction
- Hidden Markov Models
  - Emission model = ~~Gaussian mixtures~~
  - ~~Transition models = states → characters~~
- Vocabulary
- Language model

(Deep) Neural Network

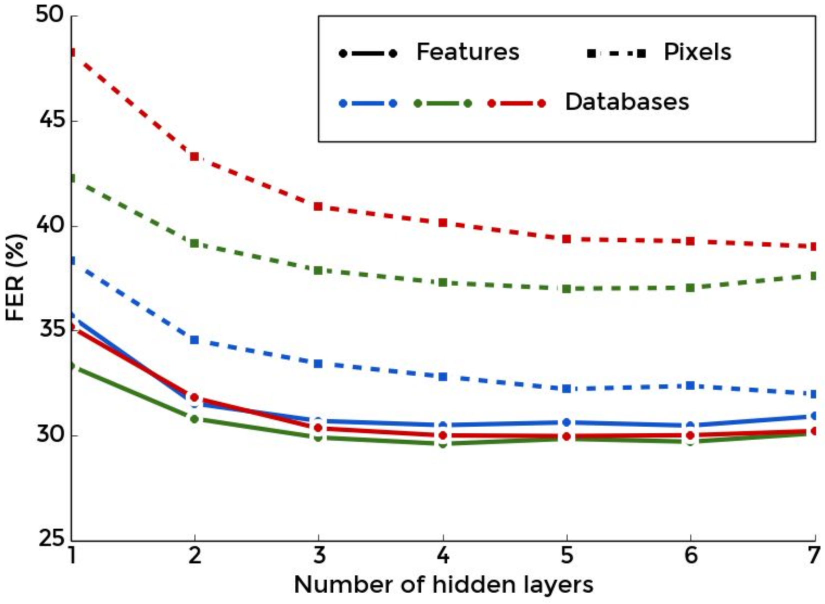
Standard GMM → Neural Net → Deep Neural Net

→ Big improvement by using neural nets instead of GMMs

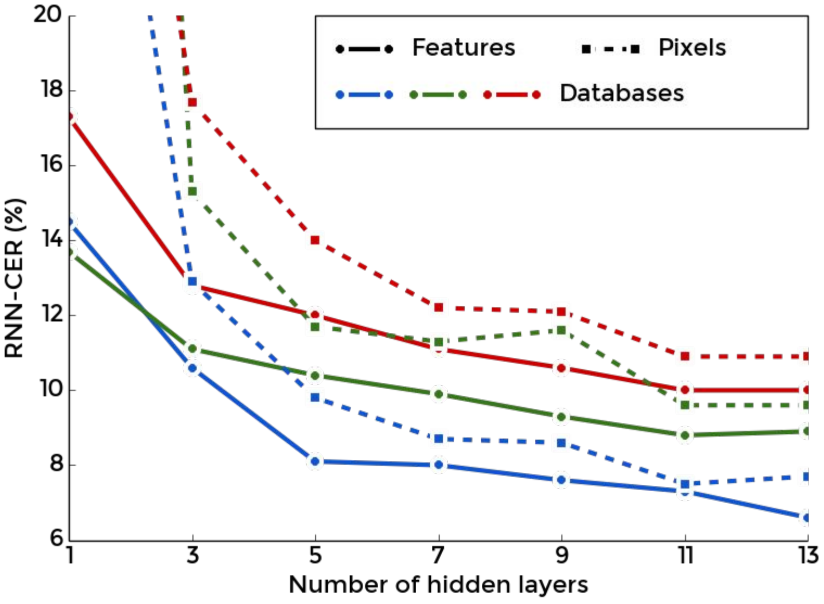
→ Similar **big improvement by using deep neural nets** instead of shallow neural nets



Impact of the net's depth



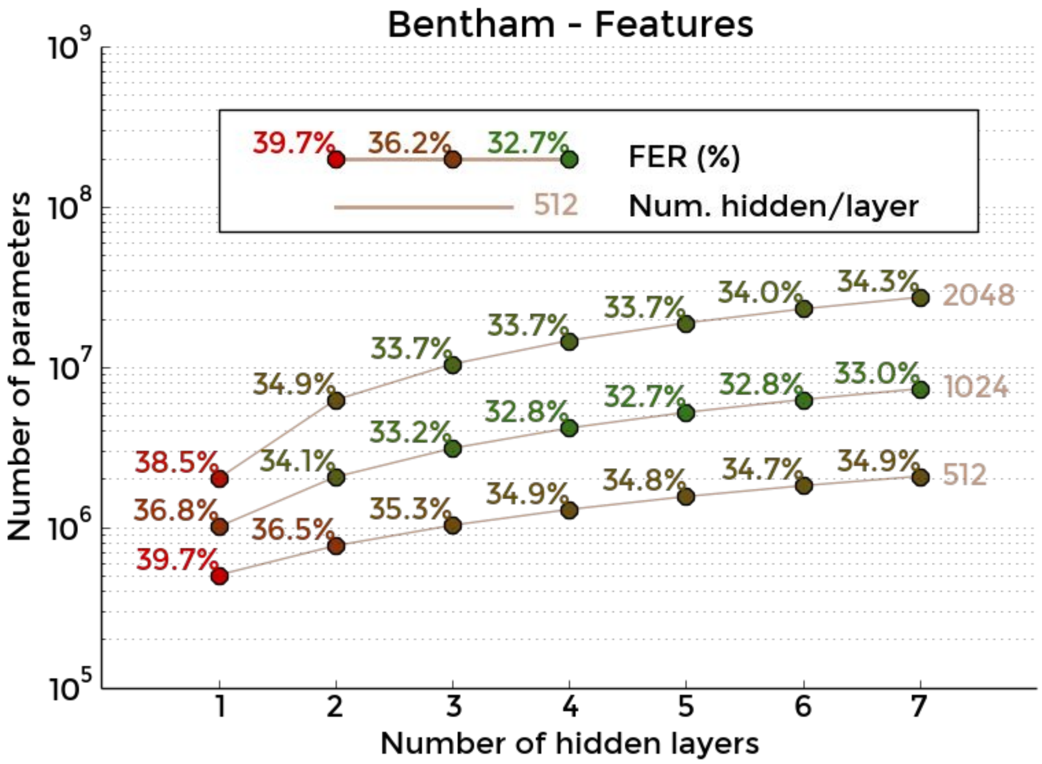
MLP



RNN

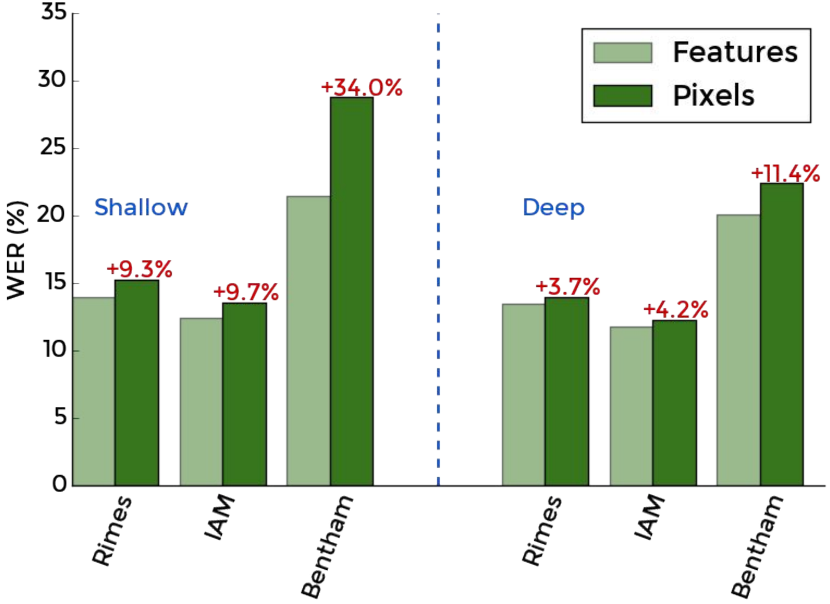
Impact of the net's depth

→ At constant number of free parameters in the models, **deeper nets give better results**

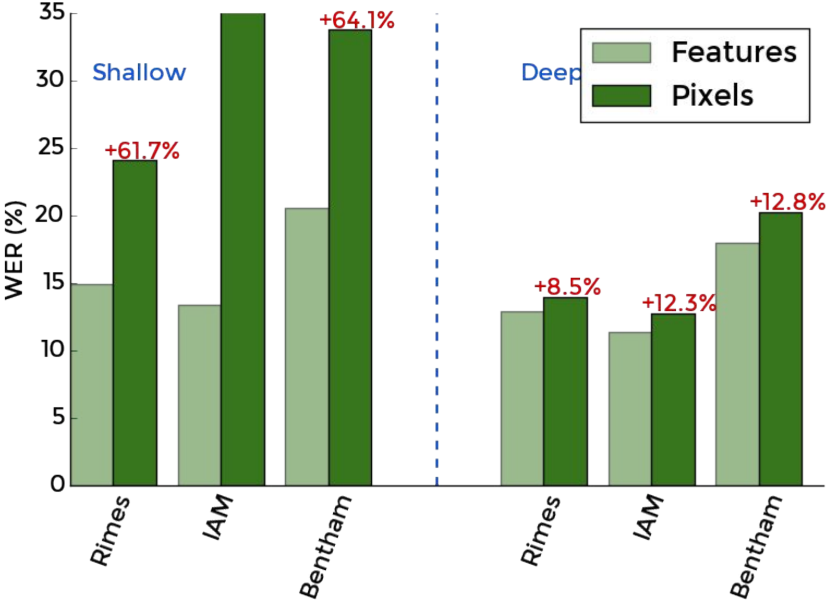


Features vs. Pixels

Input vector = all the raw pixel values in the window flattened as a single vector of WxH dimensions



MLP



RNN

~~Historical~~ System → Neural Nets

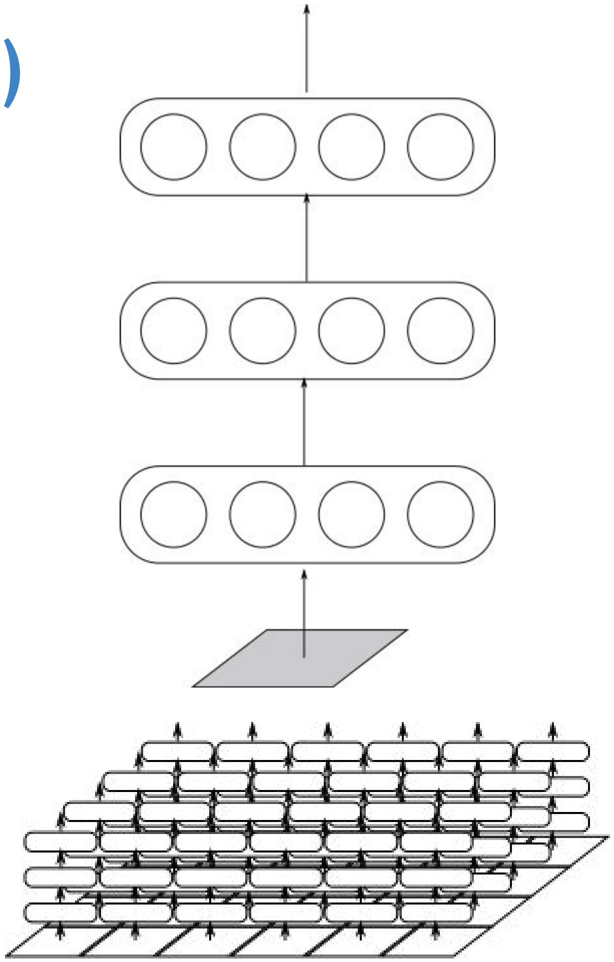
- Input image
- Preprocessing
- Sliding window
- ~~Feature extraction~~
- Hidden Markov Models
    - Emission model = ~~Gaussian mixtures~~
    - ~~Transition models = states → characters~~
- Vocabulary
- Language model

(Deep) Neural Network

Outline of this talk

- ➔ Standard Handwriting Recognition (HWR) System
  - ◆ Image processing - Feature Extraction - Optical Model - Hidden Markov Model - Language Model
- ➔ Deep Neural Networks for HWR -- plugging NNs in the system
  - ◆ Neural Nets : Multilayer perceptrons | Recurrent Neural Networks
  - ◆ Deep Neural Nets ...
  - ◆ ... automatically learn good features and context
- ➔ End-to-End HWR -- from pixels to text
  - ◆ Multidimensional Recurrent Neural Networks
  - ◆ Attention-based methods
- ➔ Tips and Tricks

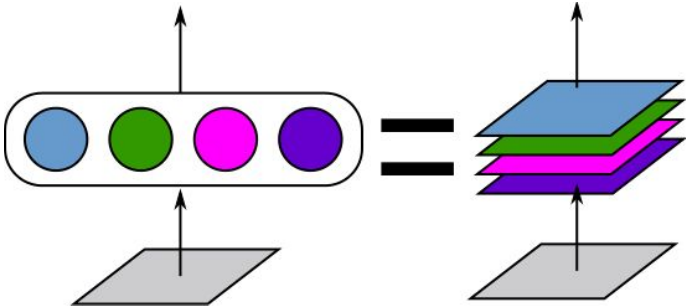
Neural Networks for Images (pixel level)



→ Instead of a feature vector, the **input is only one pixel value** (or a vector of 3 RGB values for color images)

→ The network is ***replicated*** at each position in the image

Feature Maps

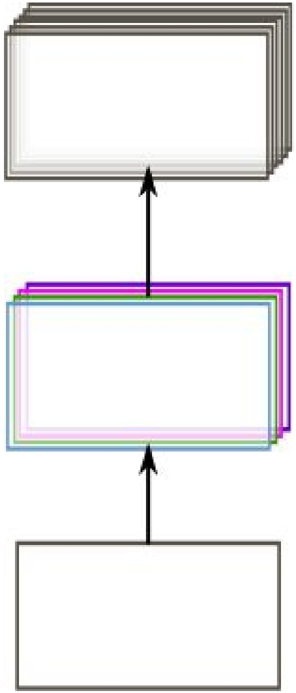


→ The outputs of one hidden layer for a pixel may be viewed as new *"pixel"* values, defining new channels

→ Since the network is replicated, each output have a similar meaning across all pixels (but different values)

→ So a given output across the whole image defines a new (kind of) image : a feature map

in the end, it's just a way of *representing or interpreting* the net...



e.g. Convolutional Neural Network

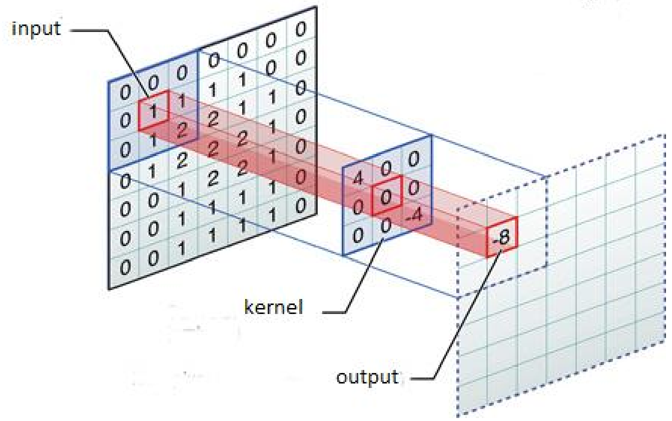
→ We can include spatial (structured) context :

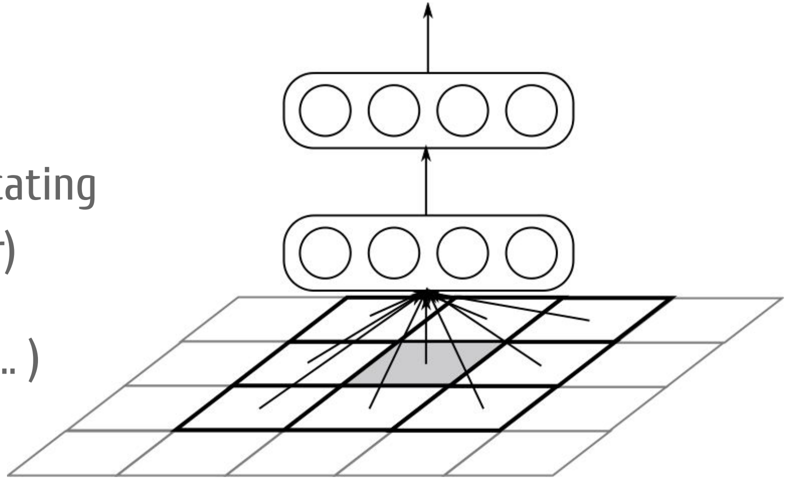
instead of giving 1 pixel value at the current position, we give the values of all pixels in a given neighborhood

→ This is still replicated at all positions = **convolution**, with kernel defined by the weights

→ You can reduce the size of the feature maps by replicating the net every N positions (output will be N times smaller)

(nb: also possible to have convolution in sequential nets...)

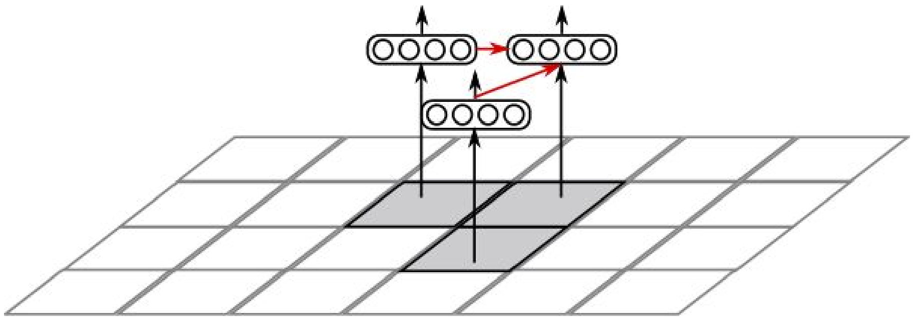


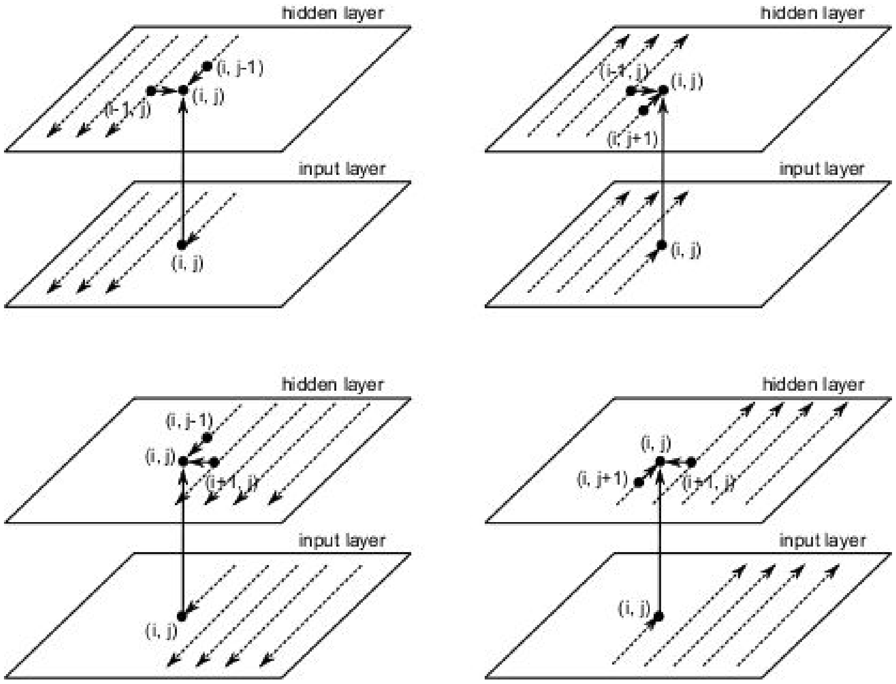


e.g. Multi-Dimensional Recurrent Neural Networks

→ As for sequences, you can make the network **recurrent**

the input at a given position includes the outputs of the same layer at neighbors



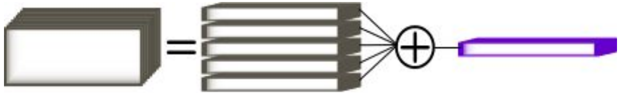


Multidimensional RNN

→ MD Recurrent + Convolutional layers

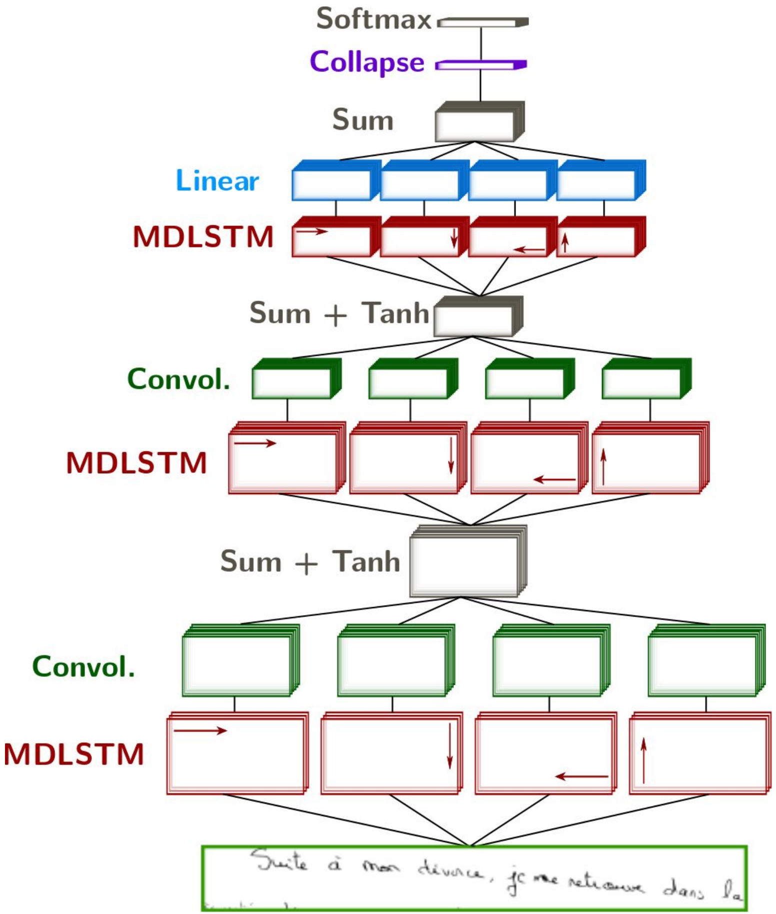
→ applied directly to the pixel of the raw text line image

→ A special Collapse layer on top to get sequential representation



→ Trained with CTC to output character sequences

Current State-of-the-art!



~~Historical~~ System → Neural Nets

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- ~~Sliding window~~
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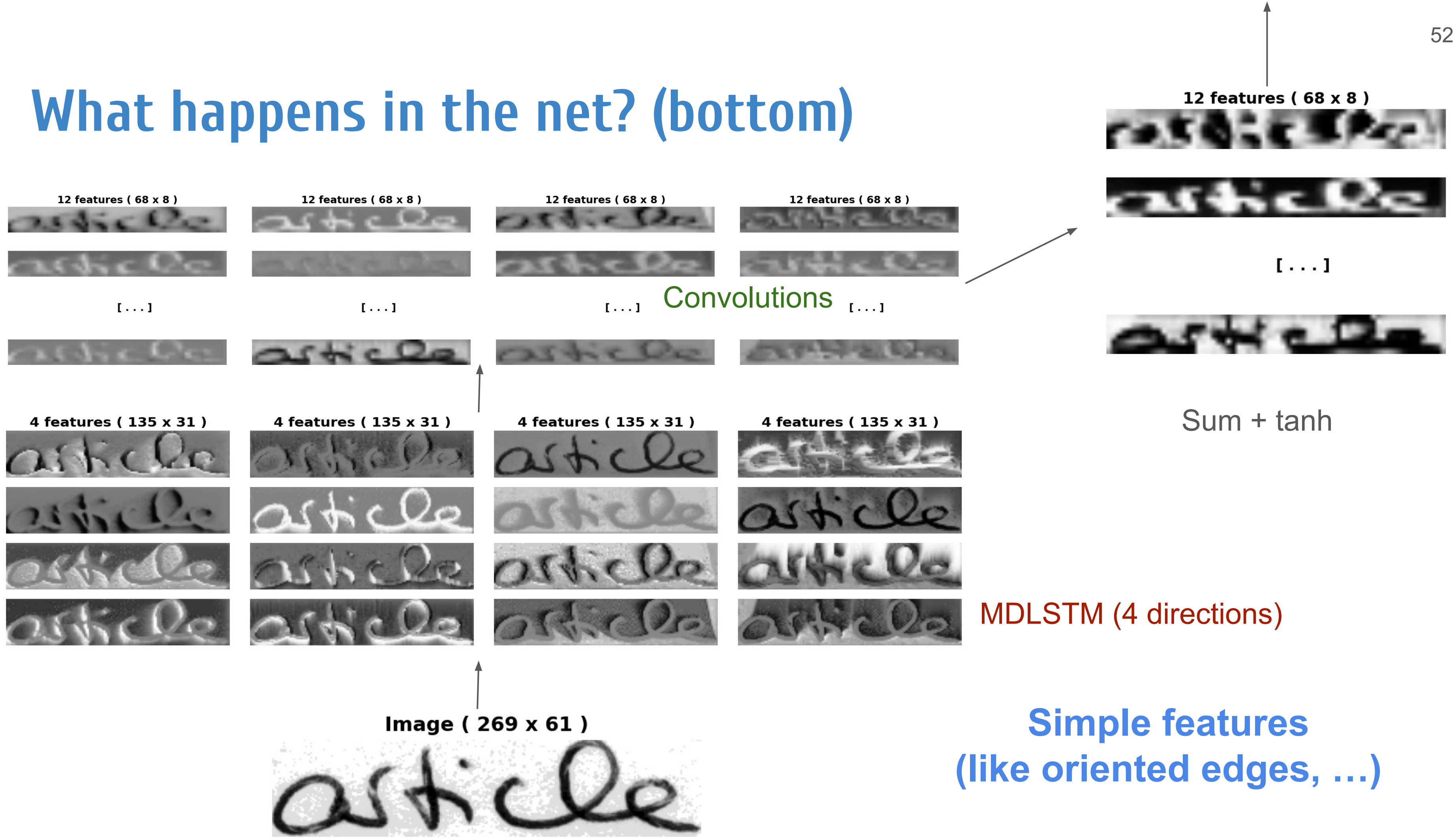
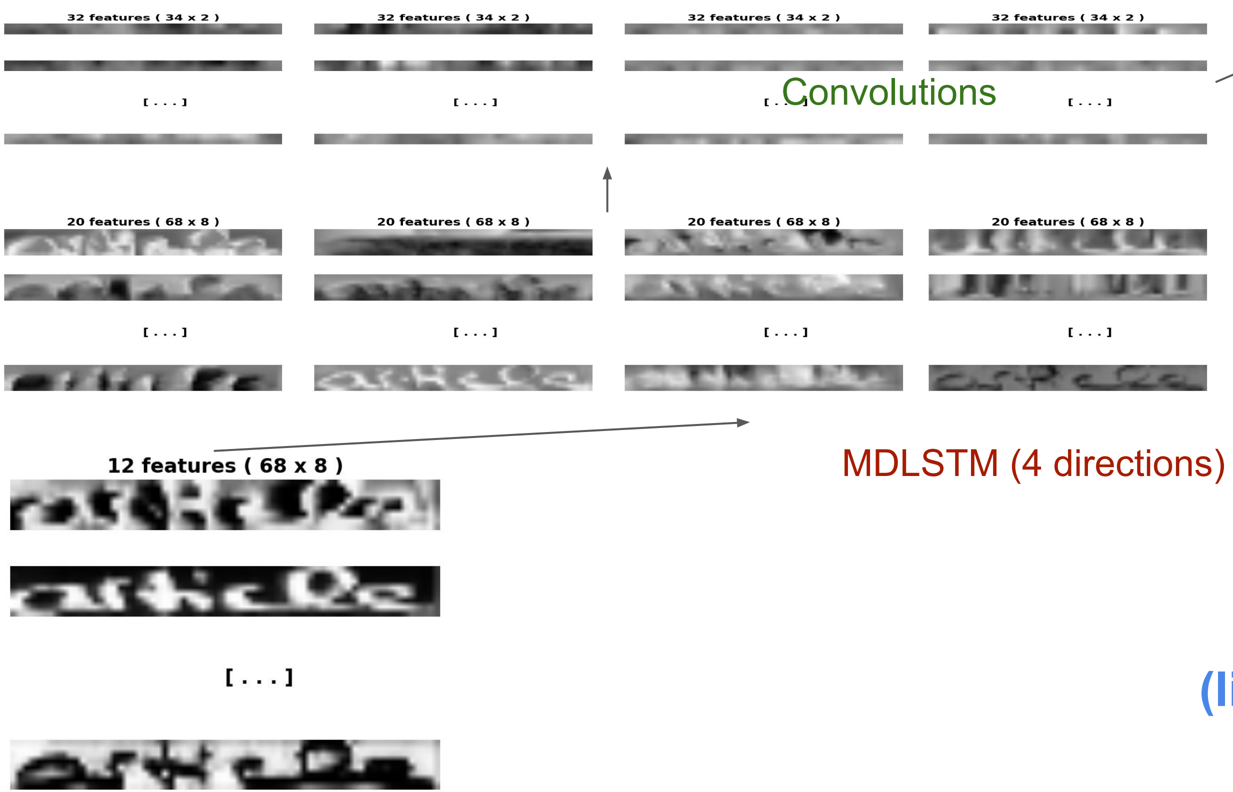
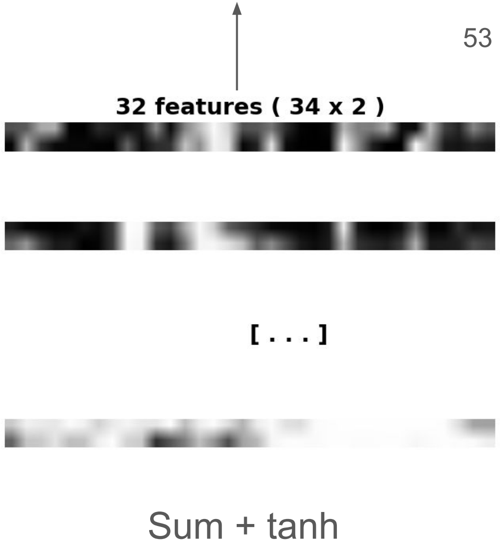
(Deep) Neural Network

What happens in the net? (bottom)



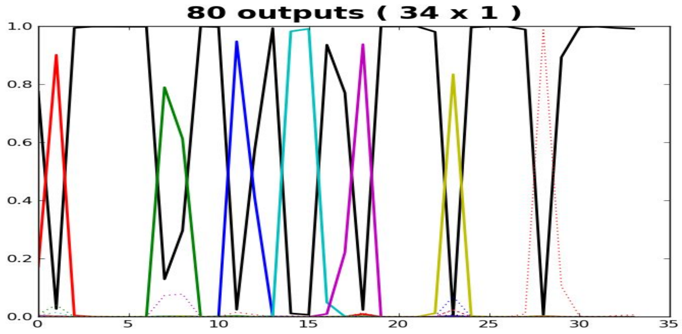
What happens in the net? (middle)





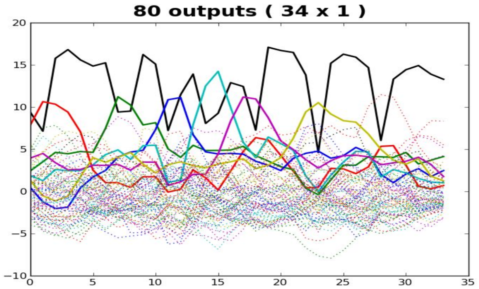
Complex features (like loops, ascenders, vertical strokes, …)

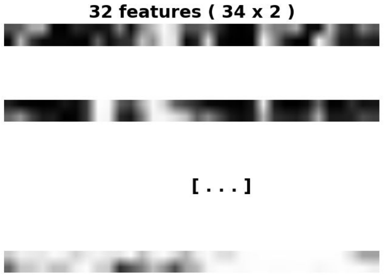
What happens in the net? (top)



Softmax

Collapse





MDLSTM (4 directions)

More abstract features (combination of features, closer to character level…)

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(Deep) Neural Network

In several setups, we even see that a vocabulary does not help (because of ***high out-of-vocabulary words rate***) → right now, hybrid word/character language models are best...

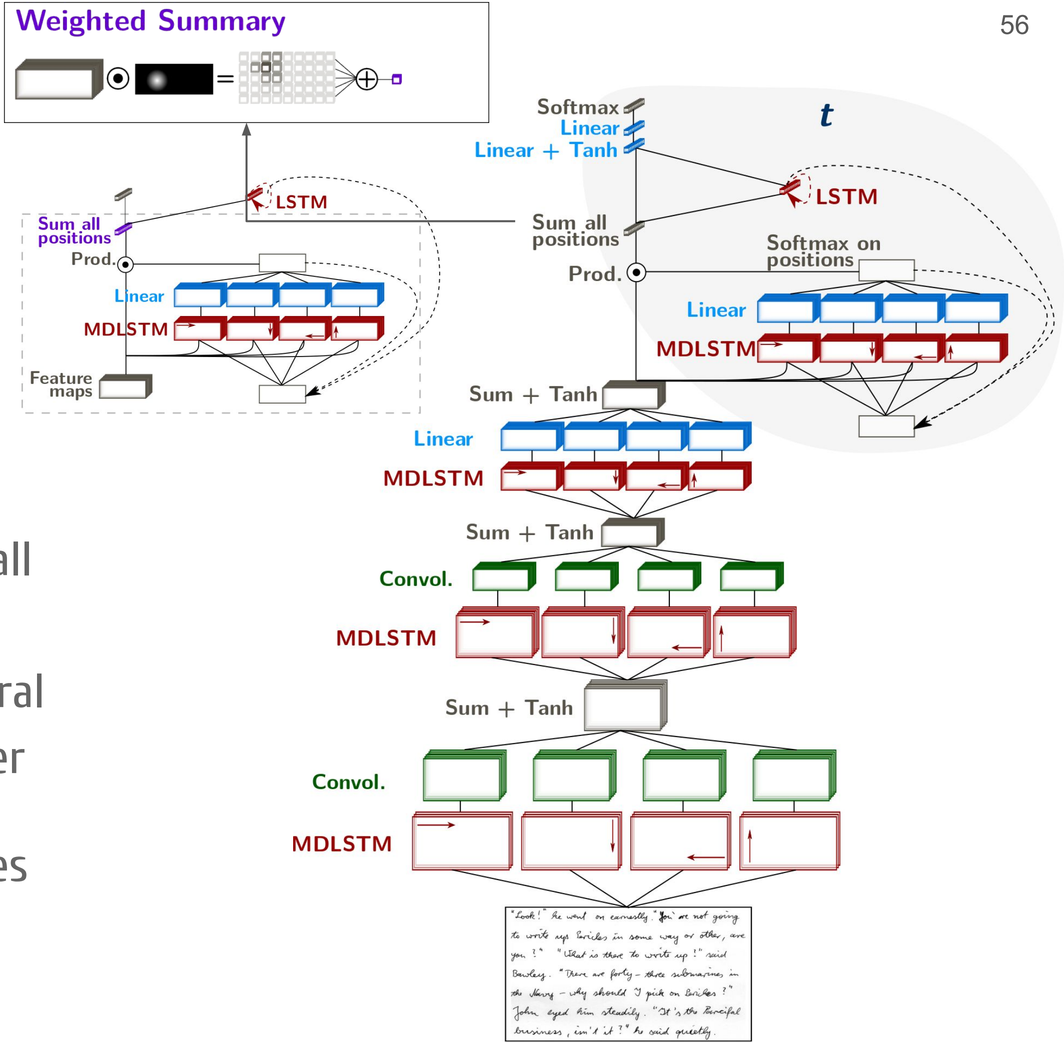
Attention Neural Network

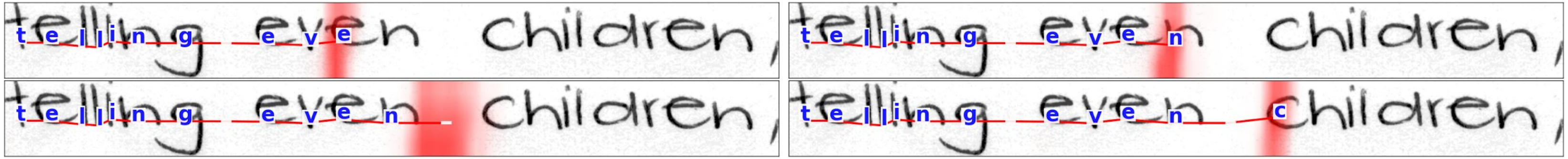
→ An **Attention Neural Network** predicts *where to look next*

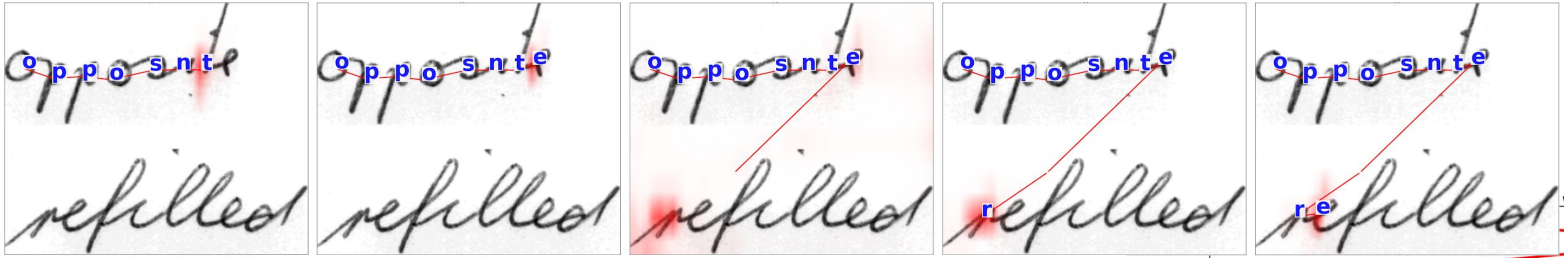
→ = a distribution of probability over positions in the feature maps

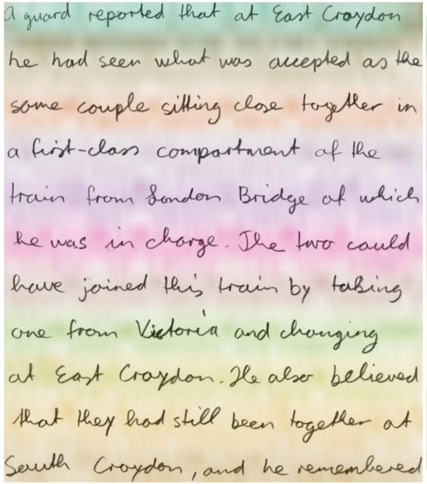
→ the sum of the feature vectors across all positions in the maps, **weighted by the attention network output** is fed to a neural network which recognize the next character

= attention net + decoder is applied N times

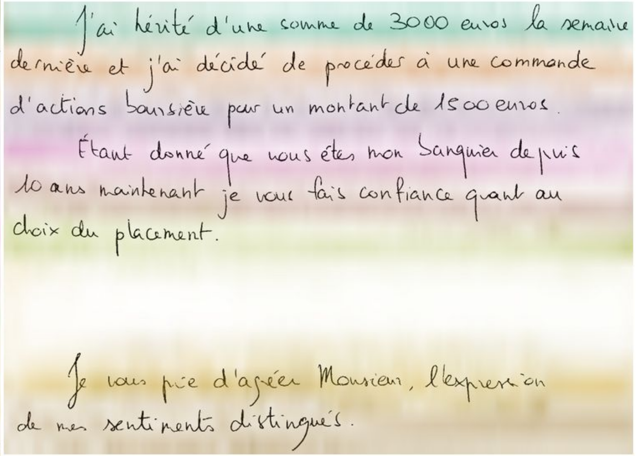




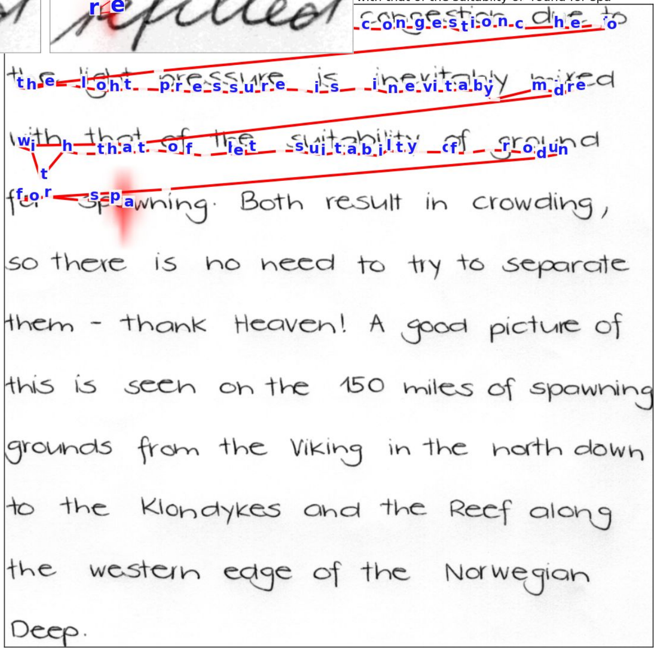




A guard reported that at East Craydon he had seen what was ouepted as the some couple sitting close togther in a first-class compartment of the train from London Bridge of which he was in charge . The two could have joined this train by taking one from Vectorin and changing at East Craydon . He also believed that they had still been together at South Croydon , and he remembered



J'ai hérité d'une somme de 3000 euros la semaine dernière et j'ai décidé de procéder à une commande d'actions boursière pour un montant de 1500 euros. Etant donné que vous êtes mon banquier depuis 10 ans maintenant je vous fais confiance quant au choix du placement. Je vous prie d'agréer Monsieur, l'expression de mes sentiments distingués.



~~Historical~~ System → Neural Nets

- Input ~~line~~ **paragraph** image
- ~~Preprocessing~~
- ~~Sliding window~~
- ~~Feature extraction~~
- Hidden Markov Models
  - Emission model = ~~Gaussian mixtures~~
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  - Multidimensional Recurrent Neural Networks
  - Attention-based methods
- ➔ **Tips and Tricks**

Tips & Tricks

→ The theory is pretty simple (linear algebra, simple derivatives, basic probabilities, standard numerical optimization)

→ The practice is a mess ...

- optimization theory is solid for convex problems, deep learning is highly non-convex
- gradient descent is theoretically sound when applied to the whole training set at once, but we do it example-wise (stochastic GD), and want to minimize the cost while preserving generalization = non standard optimization
- The *learning rate* is probably the most important parameter to tune

Tips & Tricks – Optimization

→ The first step is to **define a good cost function** = what you want to minimize = should represent your problem

→ The *dymanics* of training is quite important (even when *it should work*, it does not always). The non-linearities and values of the weights will play a role

- a good initialization of the weights is often crucial (a simple random init. is rarely sufficient, there are rules of thumb for good initialization ; when possible, initialize the weights with those of a net already trained for another task)
- Regularization (weight decay, dropout, …) is especially important with deep neural nets with a lot of parameters
- Plain SGD can be improved (e.g. look for momentum, ADAGRAD, etc.)

Tips & Tricks - Training

→ Deep learning solves complicated problems, but with ***complicated models***

- Check first if a simple model is not sufficient
- Complicated model are complicated to train : think *curriculum* = start simple and increase complexity
- Most methods are gradient-based. Everybody makes mistakes. When implementing neural nets, always **check your gradients** are right (remember the definition of a derivative)
- The **devil is in the details** : when you try to implement something you read in a paper, pay attention to every details (of the net, data, optimization, etc.) and remember that author do not always tell them... (not as easy as it seems)
- The answer to “is it a good model for my problem?” is often “**try**!”

Tips & Tricks - Deep Learning

It is not magic!! (although it often looks like it)

→ It is a lot of parameters = a lot of data needed to adjust them + a good implementation to do it fast + good initialization / formulation of the problem / optimization method.
(if not enough data, don't expect miracle and spend time for preproc/feature extraction OR data augmentation)

→ It is maths + a lot of "cooking" : knowing about pastas, tomatoes and beef is not enough to make a good bolognese, you should also **learn the good recipes**!

→ A lot of intuition, understanding and good ideas will **come with experience** (and vice-versa). Play with models and problems, you'll end up having a sense of want could work and what won't...

→ ... but question what/why you are doing, don't just download ML libraries to run experiments

To conclude...

→ Historically, HWR was: preprocessing, feature extraction, Gaussian HMMs, Language model

→ **With deep neural networks, we can recognize character sequences from the raw image**

- with enough data, the preproc is less useful and we avoid loss of information
- same with features, which are learnt and task-specific
- same with character modeling: we can output character sequences directly

→ NB: data/preproc/feature engineering disapear, but now : model engineering

→ NB: you need a lot of data

→ Historically, HWR was: recognition of chars, then words, then lines : moving toward recognition of paragraphs and full pages

→ Note : also, *deep neural nets for layout analysis, language models, ...*

Danke! Danke!

Danke! Danke! Danke!

Thanks for your attention

Danke! Danke!

Théodore Bluche

tb@a2ia.com

(do not hesitate to reach me if you have questions)

Danke!

Danke! Danke!

A few refs...

Graves, A., Fernández, S., Gomez, F., & Schmidhuber, J. (2006). **Connectionist temporal classification**: labelling unsegmented sequence data with recurrent neural networks. In *Proceedings of the 23rd international conference on Machine learning* (pp. 369-376).
((CTC -- briefly explained in first part))

Graves, A., & Schmidhuber, J. (2009). Offline handwriting recognition with **multidimensional recurrent neural networks**. In *Advances in neural information processing systems* (pp. 545-552).
((MDLSTM-RNN -- the state-of-the-art, still, 7 years later))

Bluche, T. (2015). ***Deep Neural Networks*** *for Large Vocabulary* ***Handwritten Text Recognition*** (Doctoral dissertation, Université Paris Sud-Paris XI).
((my thesis -- many refs / results inside))

Bluche, T., Louradour, J., & Messina, R. (2016). Scan, Attend and Read: End-to-End **Handwritten Paragraph Recognition** with MDLSTM **Attention**. *arXiv preprint arXiv:1604.03286.*
((Attention-based neural nets))

... ...