



Réseaux de neurones récurrents Handwriting Recognition with Long Short-Term Memory Networks

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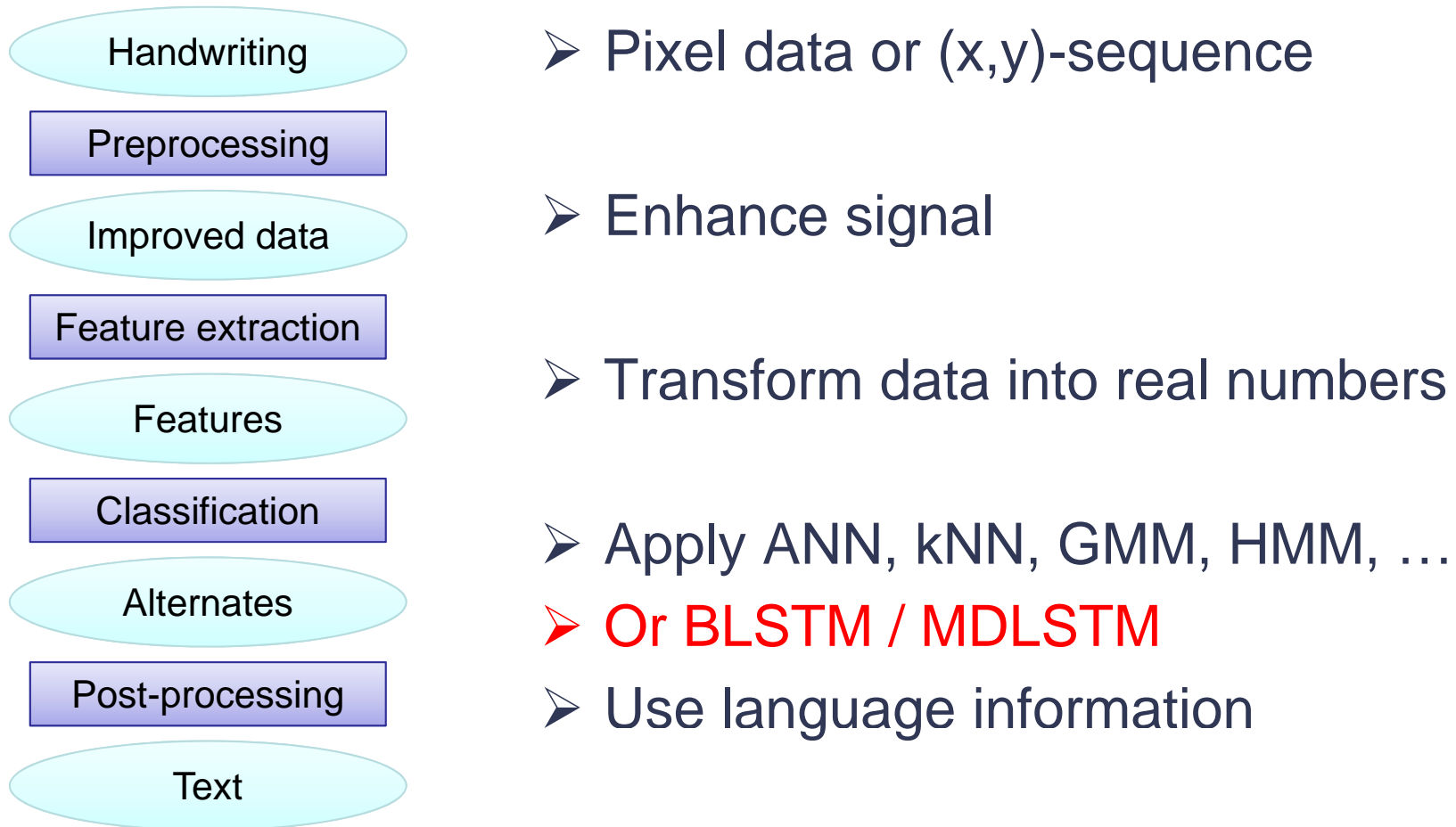


➤ Transform handwritten text into a machine readable format

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Handwriting Recognition Sub-Tasks





- 2001-2004 Free University of Berlin – Master of Computer Science
- 2004-2007 PhD study in Bern – Dr. phil. nat. and PhD
- 2008- Senior Researcher and lecturer at DFKI
- 2009-2010 JSPS research fellow at Kyushu University (Seiichi Uchida)

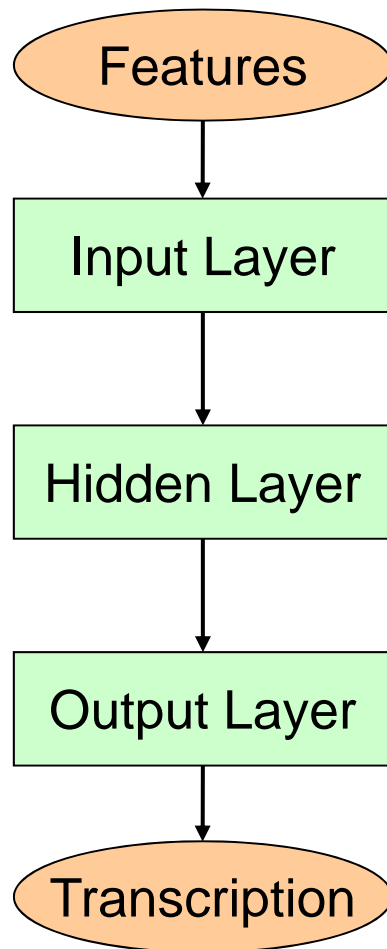
- More than 60 publications including one book, one book chapter and 10 journal papers

The Novel Classifier



- Input: raw features, raw pixel data, or raw point-sequence
- Output machine-readable transcription
- Easy to use
- Based on Multi-Layer Perceptron

Multi-Layer Perceptron Networks



- Feature vector at timestamp t

$$x_1^t, \dots, x_n^t$$

- Perceptrons in the individual layers

- Aggregation function $a^t = \sum w_i x_i^t$

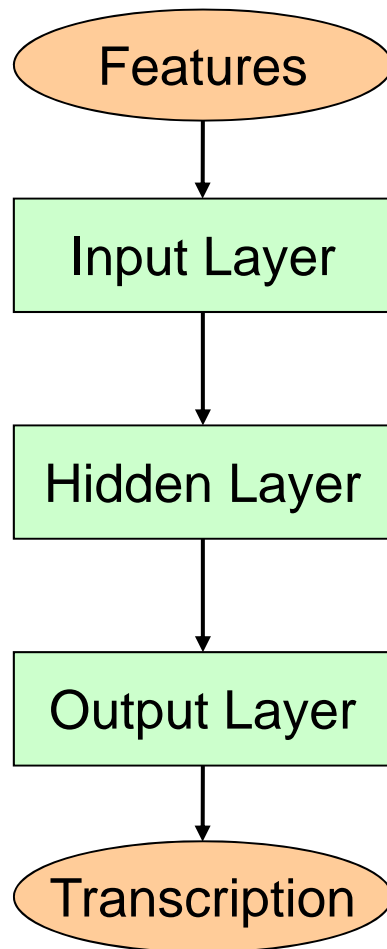
- Activation function (squashing f.)

$$b_h^t = h(a^t)$$

$$h: \tanh(x) = \frac{e^{2x} - 1}{e^{2x} + 1}$$

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

Multi-Layer Perceptron Networks

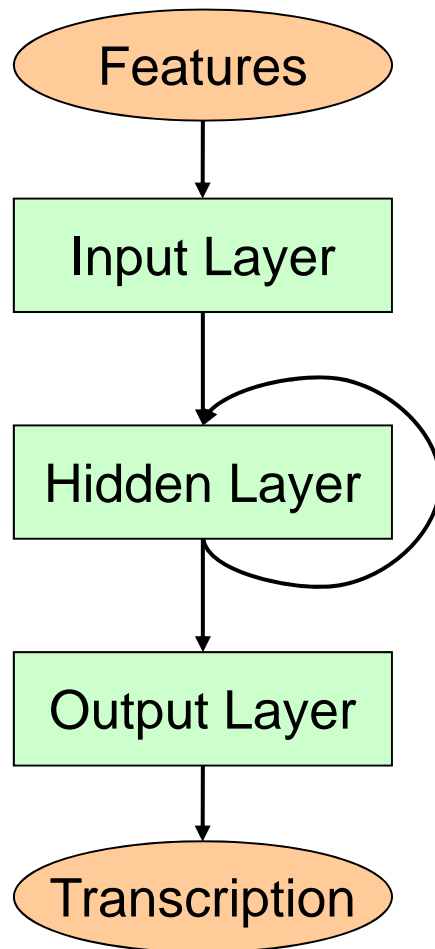


- For every hidden layer:

$$b_h^t = h\left(\sum w_{h'h} b_{h'}^t\right)$$

- Neuron with highest output corresponds to the recognized class
- Training with backpropagation

Recurrent Neural Networks (RNN)



- Recurrent connections are added in order to keep information of previous time stamps in the network
- Novel equation for activation:

$$a^t = \sum w_i x_i^t + \sum w_h b_h^{t-1}$$

- Can be written in matrix form

$$A^t = W_i \cdot X^t + W_h \cdot B^{t-1}$$

- Context information is used, **however**

Vanishing Gradient



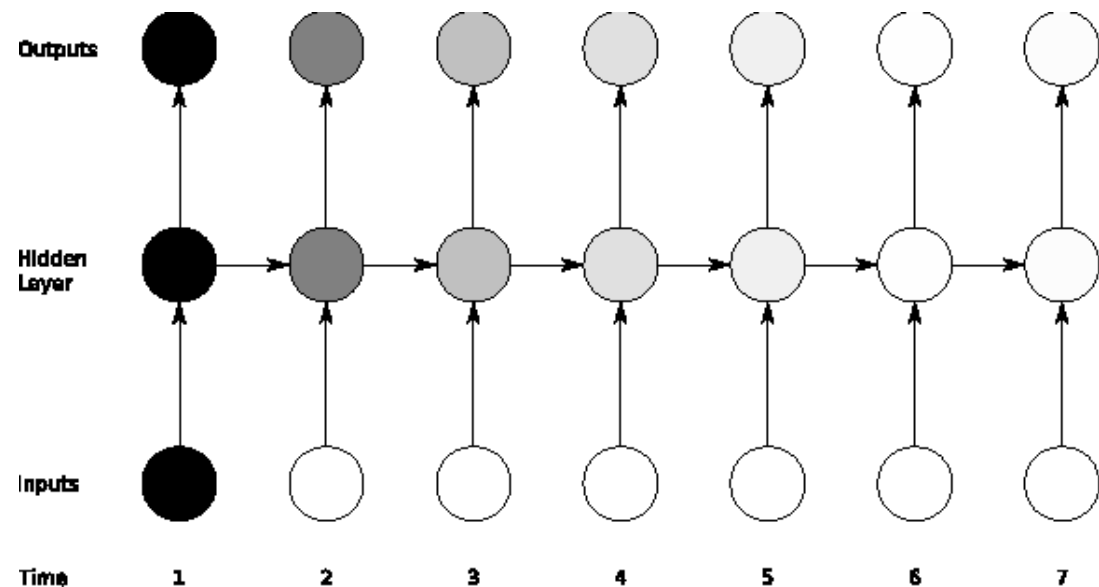
- Usual RNN forget information after a short period of time

$$A^t = W_i \cdot X^t + W_h \cdot B^{t-1} = W_i \cdot X^t + W_h \cdot h(W_i \cdot X^{t-1} + W_h \cdot B^{t-2})$$

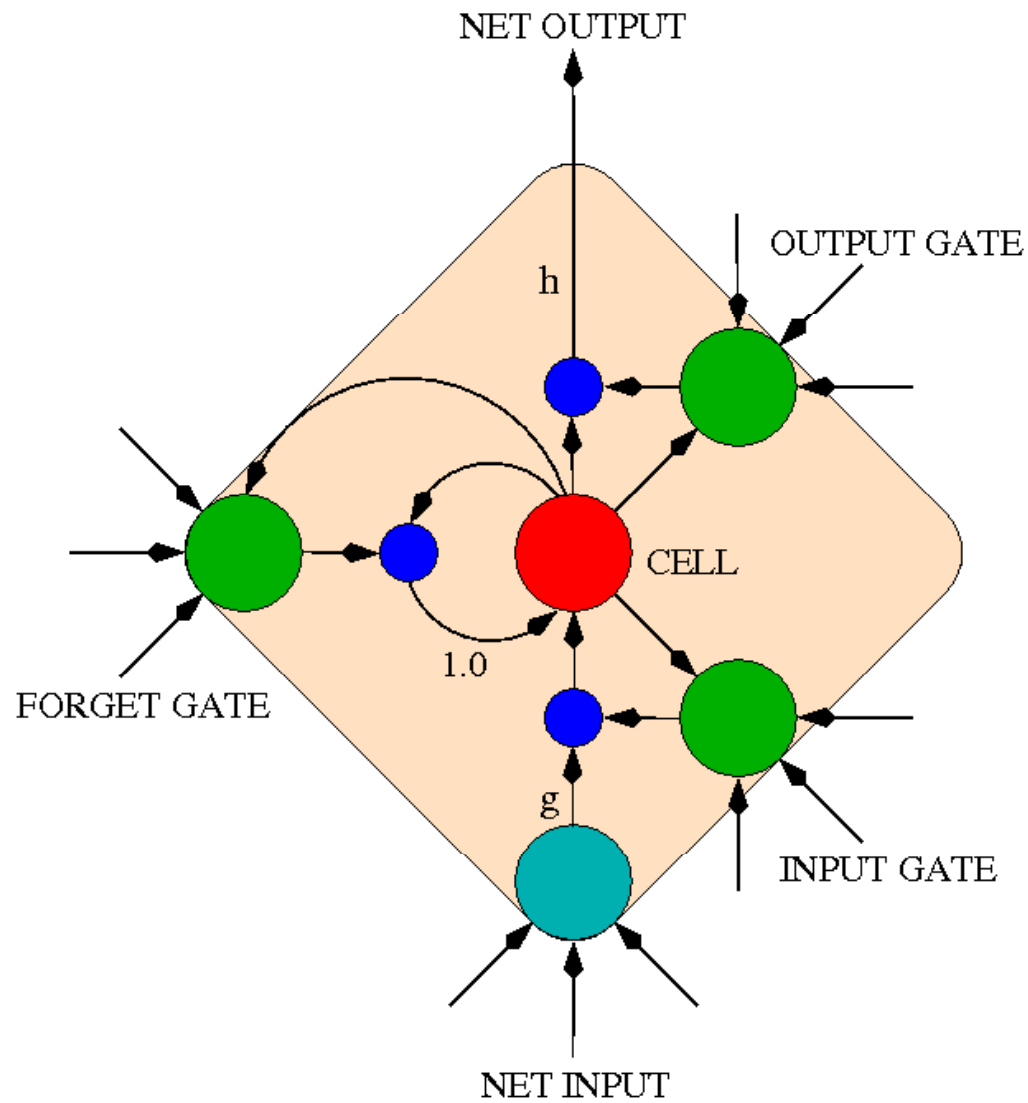
$$\Rightarrow A^t = f(X^t, W_h X^{t-1}, W_h^2 X^{t-2}, \dots, W_h^t X^1)$$

- Example:
Neuron
During
7 timestamps

- Information
vanished



Core Idea: New Memory Cell Instead of Perceptron



Long Short-Term Memory Unit



- Memory cell
 - Read, write and reset operations

- Input Gate (single cell)

$$a_i^t = W_{a,i} \cdot X^t + W_{h,i} \cdot B^{t-1} + W_{c,i} S_c^{t-1}$$

- Forget Gate

$$a_\theta^t = W_{h,\theta} \cdot X^t + W_{h,\theta} \cdot B^{t-1} + W_{c,\theta} S_c^{t-1}$$

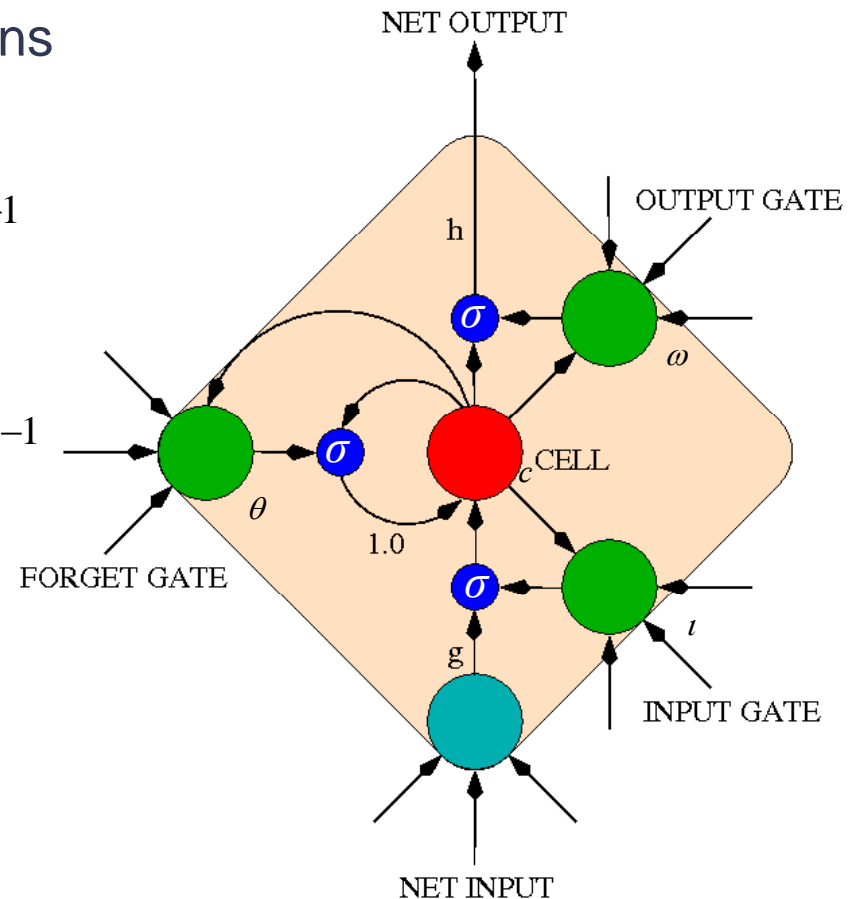
- Cell State

$$a_c^t = W_{a,c} \cdot X^t + W_{h,c} \cdot B^{t-1}$$

$$s_c^t = \sigma(a_i^t)g(a_c^t) + \sigma(a_\theta^t)s_c^{t-1}$$

- Assume σ is close to 0 or 1

$$\Rightarrow s_c^t = [0 \text{ or } 1]g(a_c^t) + [0 \text{ or } 1]s_c^{t-1}$$



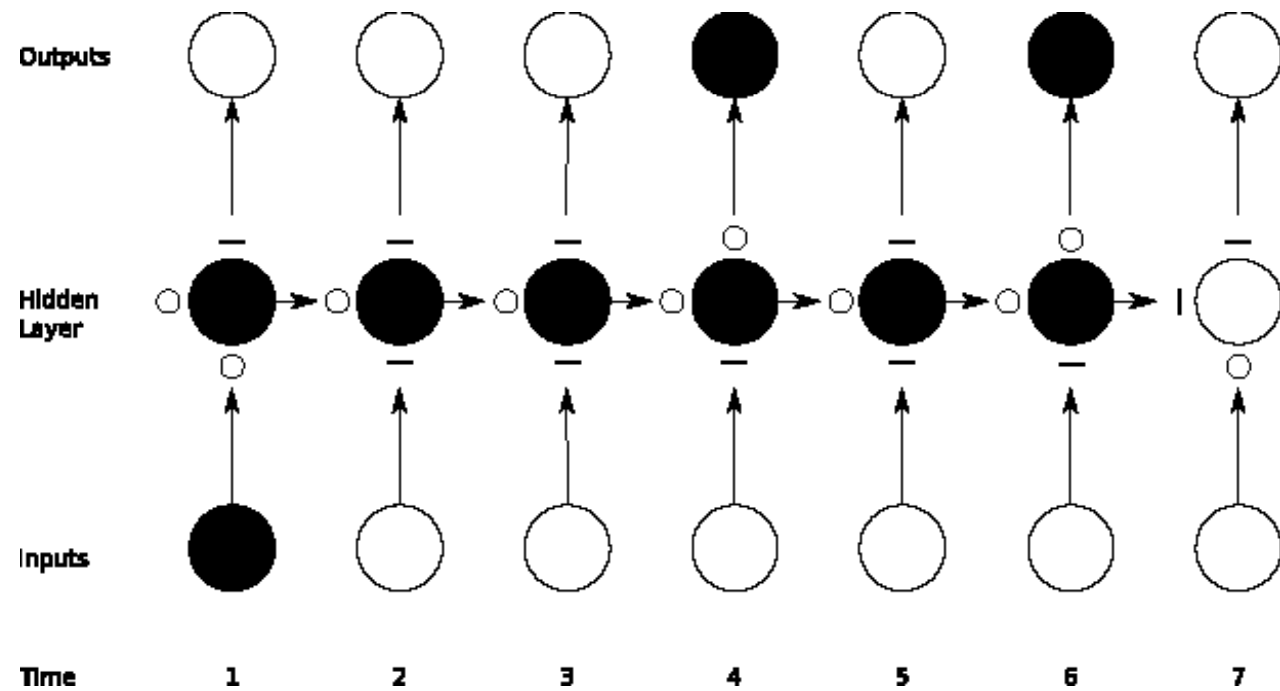
No Vanishing Gradient



➤ Output Gate $a_{\omega}^t = W_{a,\omega} \cdot X^t + W_{h,\omega} \cdot B^{t-1} + W_{c,\omega} S_c^t$

➤ Output $b_c^t = \sigma(a_{\omega}^t) h(s_c^t)$

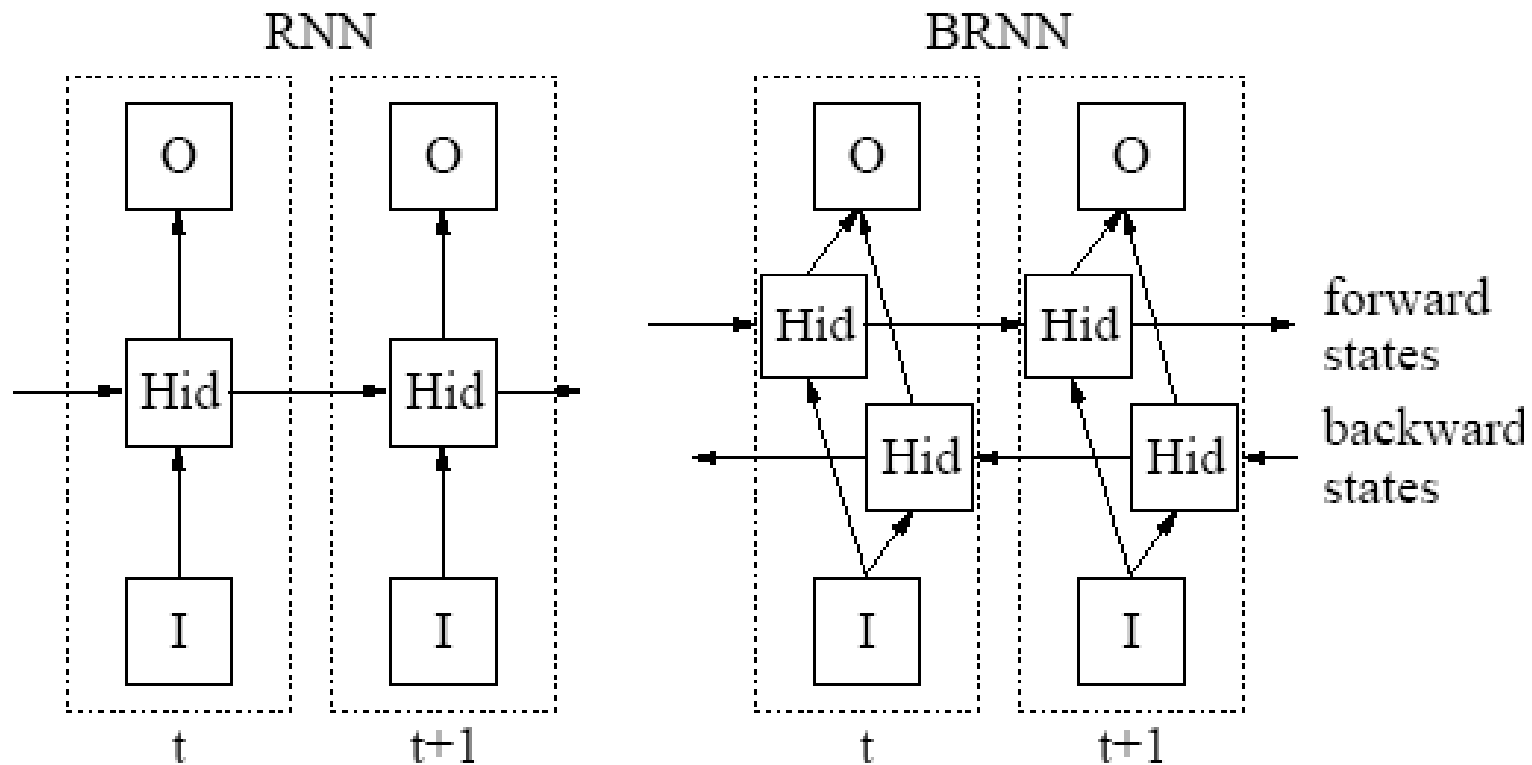
➤ Neuron now
 O : open ($\sigma=1$)
 | : closed ($\sigma=0$)



Discussion: MLP - LSTM



Bidirectional RNN

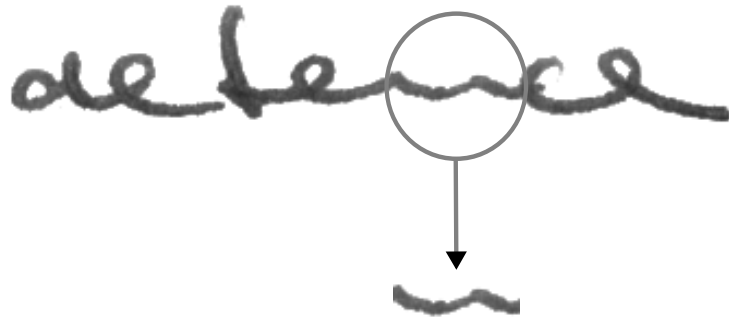


- Trained with backpropagation through time (forward path through all time stamps for each hidden layer sequentially)

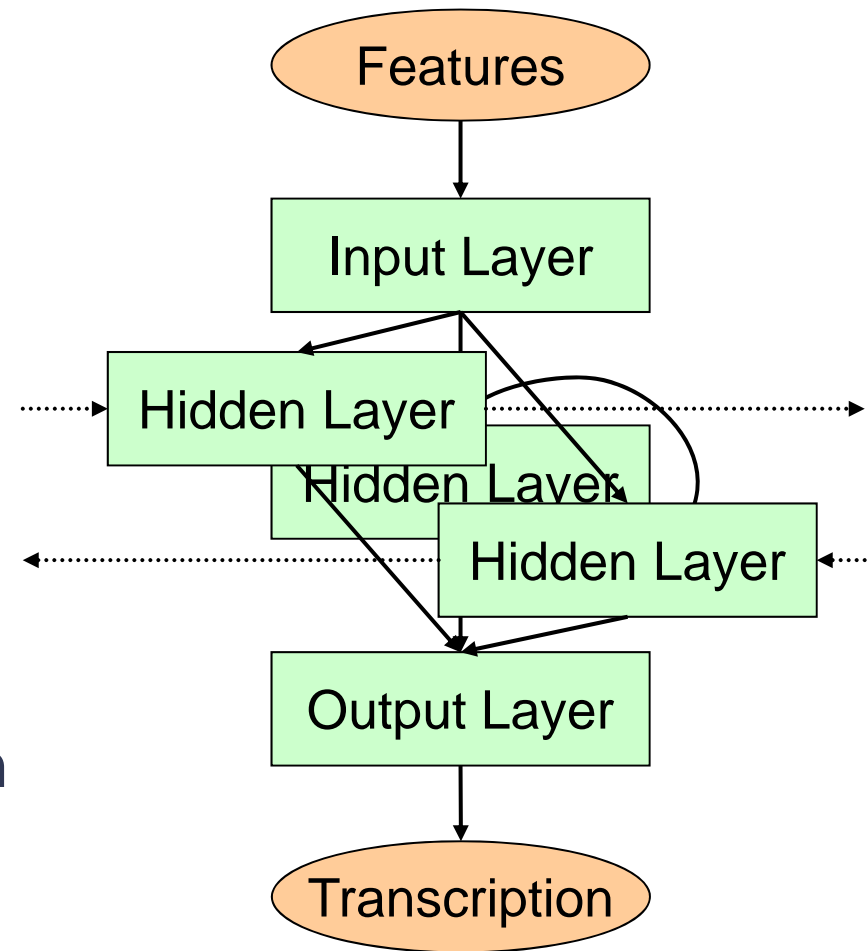
Bidirectional Long Short-Term Memory Networks



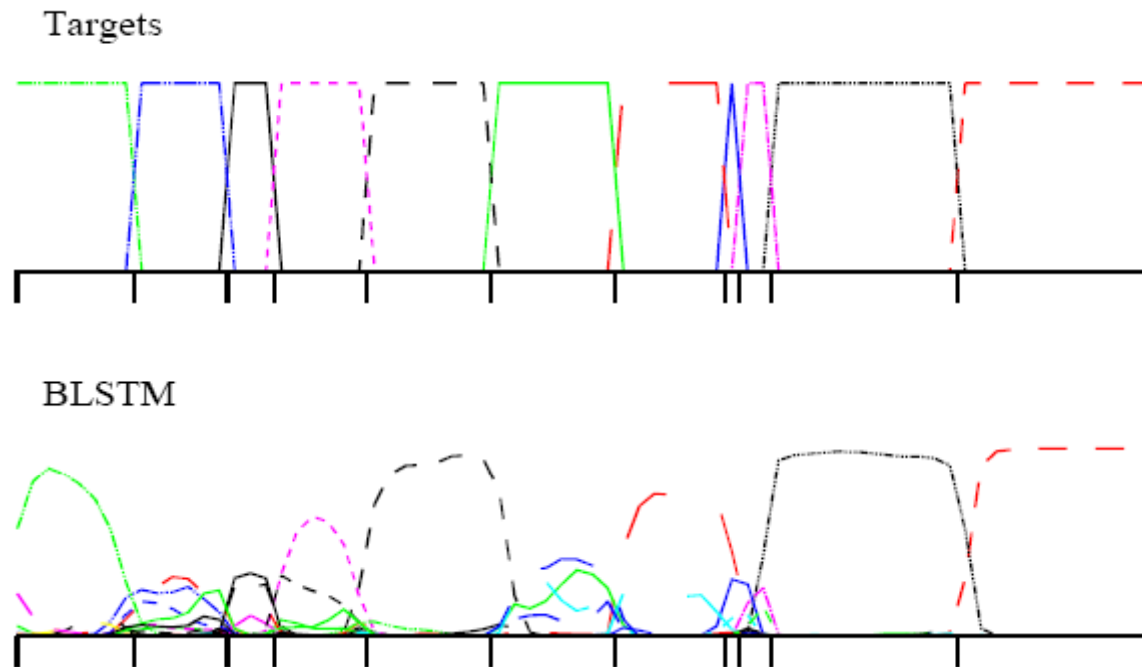
- Importance of context



- Multilayer perceptron network
- Recurrent connections
- Bidirectional
- Memory instead of perceptron



Standard Framewise Classification

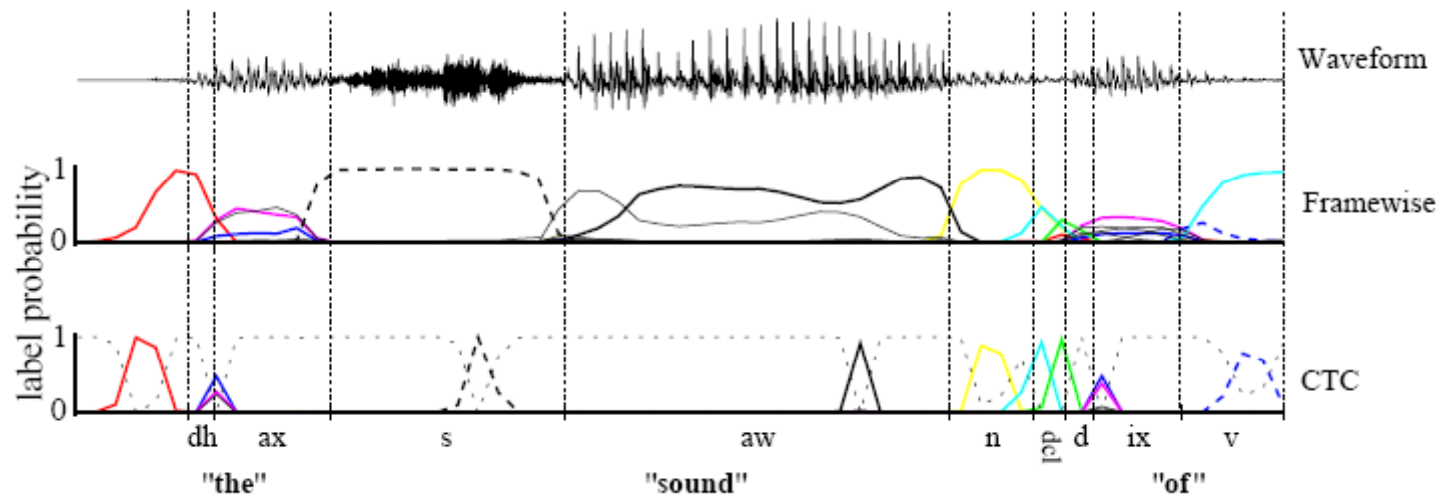


- Segmentation is needed
- Information of previous and next frames is not available
- Idea: introduce a way of connected temporal classification

Framewise Classification vs. CTC



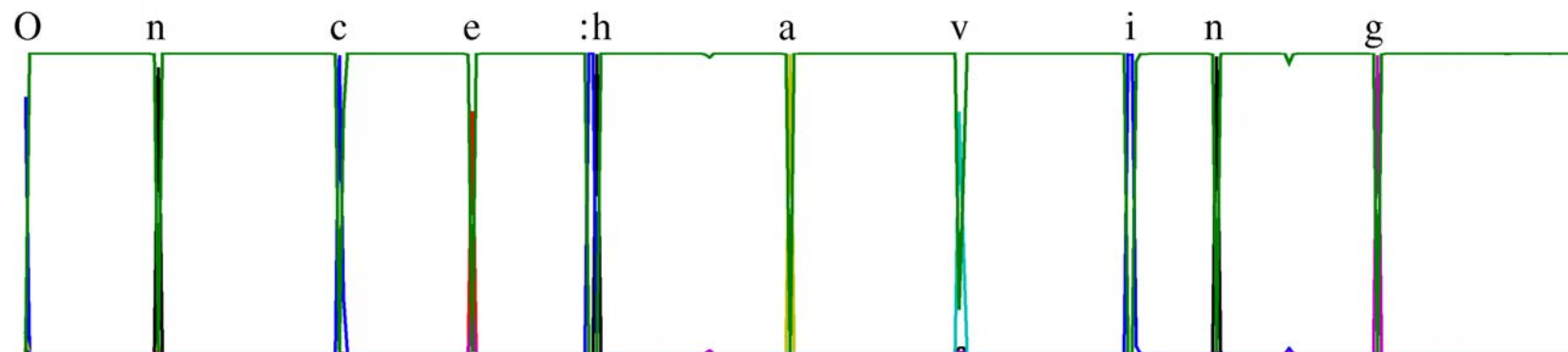
- Connected Temporal Classification (CTC)
- Example for speech:



Connected Temporal Classification



- Additional blank label (b green)
- Allows application to whole sequences
- Output with normalized likelihood for each word

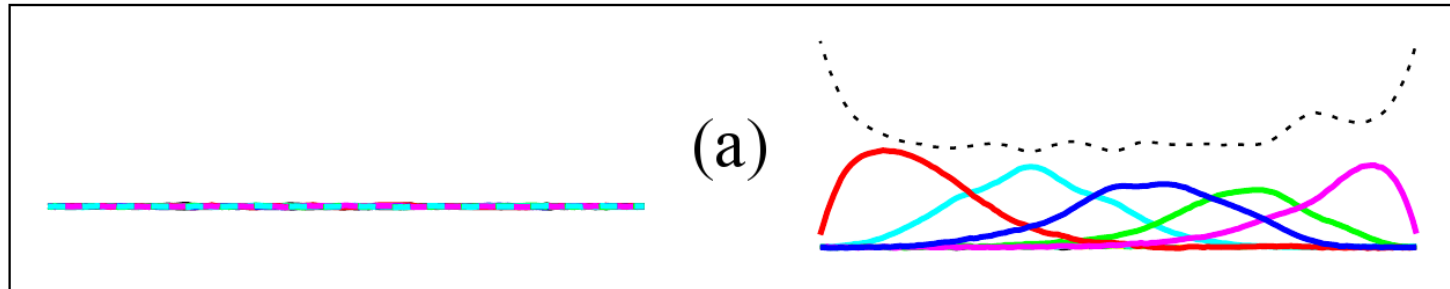


- Training: objective function is smoothed and recalculated after each iteration (details in references)
- Testing: similar to Viterbi-algorithm

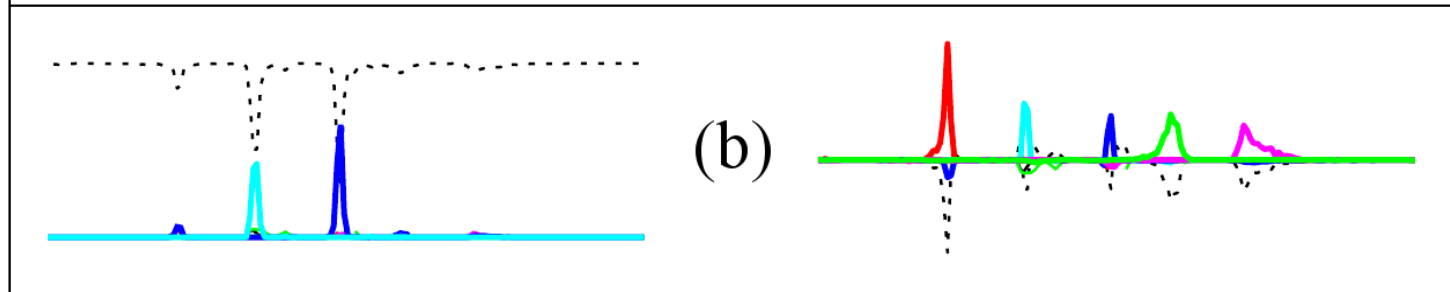
How Does it Behave? Training Error Example



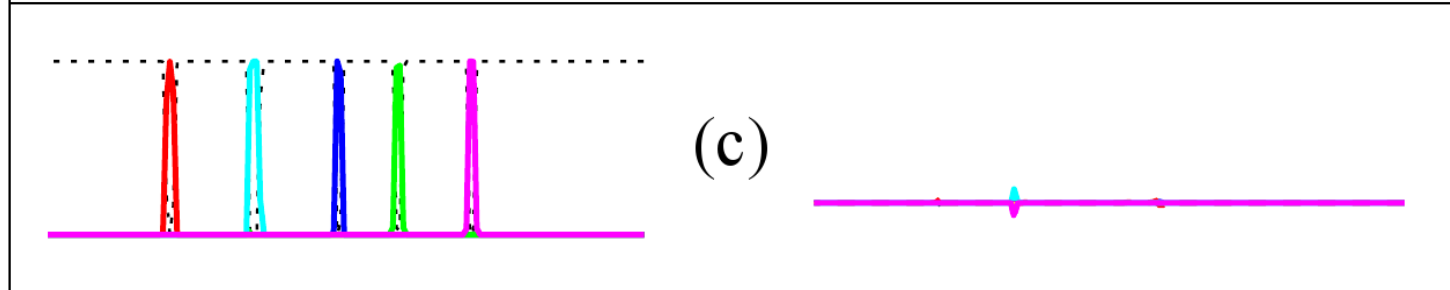
Beginning
(random)



10 iterations
(error around predictions)



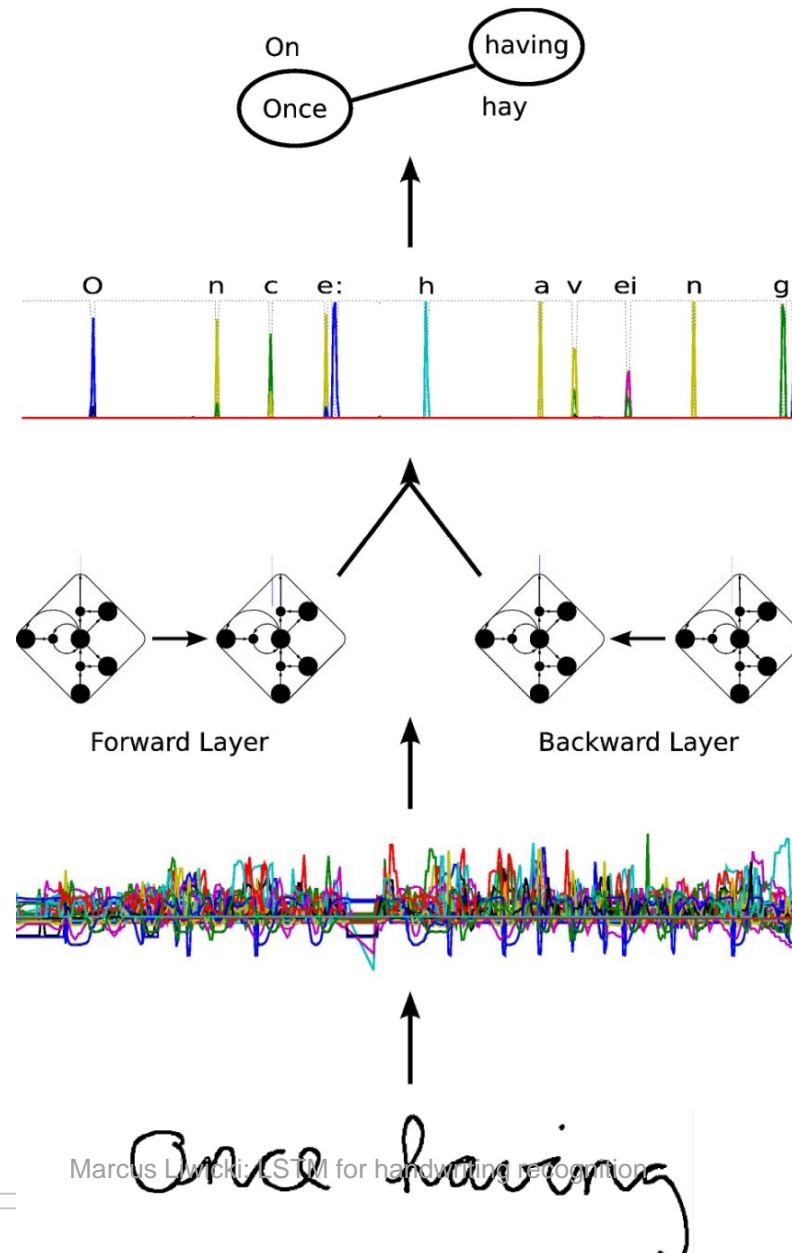
Final
(nearly no error)



output

error

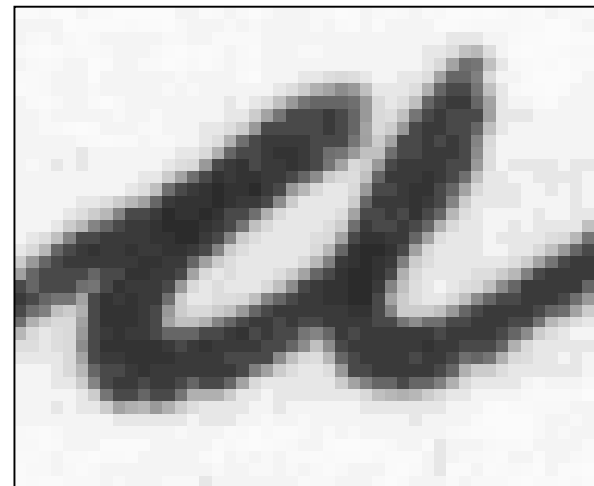
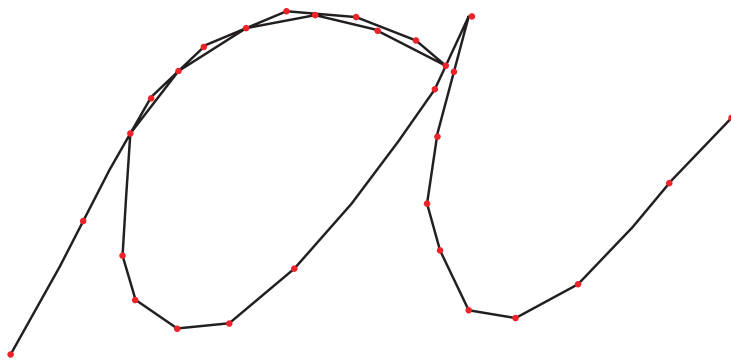
Overall System



BLSTM for Handwriting Recognition



- On-line
 - Sequence information
- Off-line
 - No sequence information
 - Grayscale image





➤ Spurious points removal

For each point p_i of a stroke:

If $d(p_i, p_{i-1}) > \theta$ and $N_\delta(p_i) < N_\delta(p_{i-1})$ then remove p_i ,

where $N_\delta(p_i)$ is the number of points from the stroke around p_i

➤ Text line extraction

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there to await the arrival of

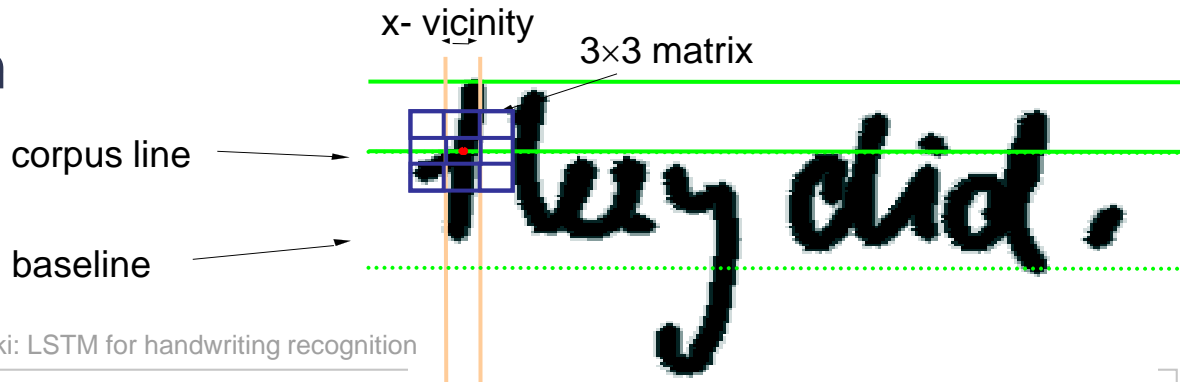
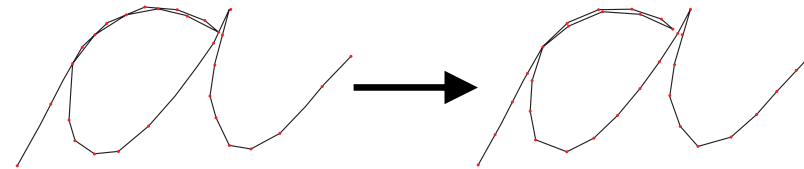
Online Feature Extraction



- Skew and slant correction
- HAT-removal
- Size normalization
 - Baseline and corpus line estimation
 - Height normalization
 - Width $N_{b/w} * c$
- Equidistant resampling
- Feature extraction
 - Online

comfort to → comfort to
idea of a

you wish





➤ Transformed images

➤ Skew correction

~~news die.~~ → news die.

- Linear regression through the n lowest points $\{p_i = (x_i, y_i)\}$
- Baseline $y = a * x + b$

$$a = \frac{\text{Cov}(x, y)}{\text{Var}(x)} = \frac{\sum_{i=1}^n x_i y_i - n * \bar{x} \bar{y}}{\sum_{i=1}^n x_i^2 - n * \bar{x}^2}, \quad b = \bar{y} - a * \bar{x}$$

➤ Slant correction

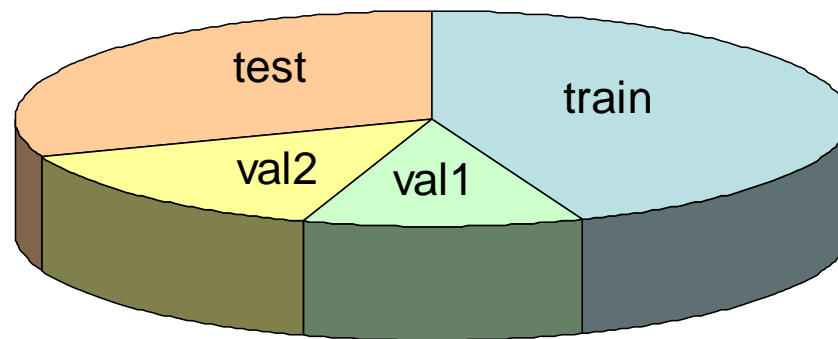
- Angle histogram through vertical contour
- Shearing to upright position

➤ Feature extraction

- Nine features using a sliding window approach



- IAM-OnDB-t2 benchmark¹:
 - Training set, two validation sets, test set
 - Open vocabulary, 82 characters, 5.8% OOVs



- LM trained on three corpora (Brown, LOB, Wellington)
- Accuracy measured on the word level

Experiments

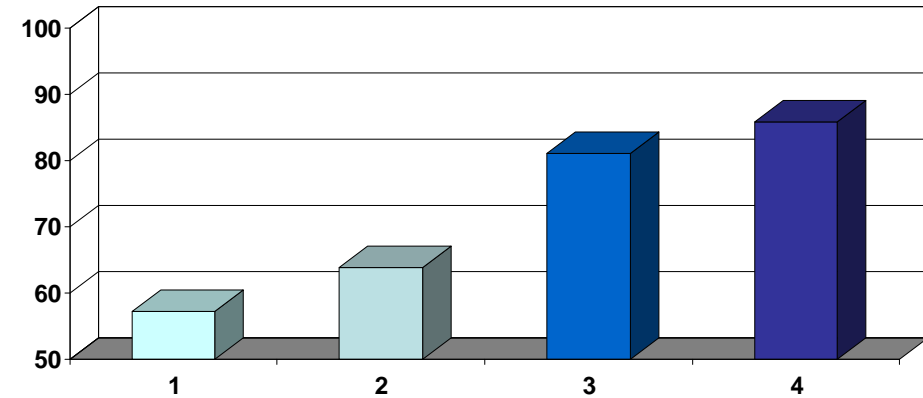


➤ Combination

- Plurality voting
- Confidence-based voting

➤ Experiments

1. 57.34% with off-line (HMM)
2. 63.86% with on-line
3. 81.05% with on-line CTC (74.00% off-line)
4. 86 % after combination of several classifiers



Raw vs. Processed data



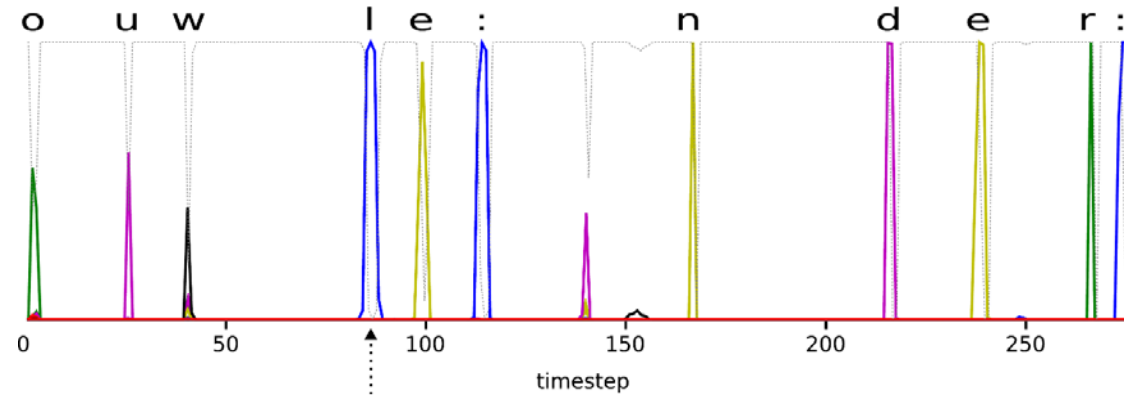
System	Input	LM	WER
HMM	Preprocessed	✓	35.5%
CTC	Raw	✗	30.1 ± 0.5%
CTC	Preprocessed	✗	26.0 ± 0.3%
CTC	Raw	✓	22.8 ± 0.2%
CTC	Preprocessed	✓	20.4 ± 0.3%

➤ LM – language model

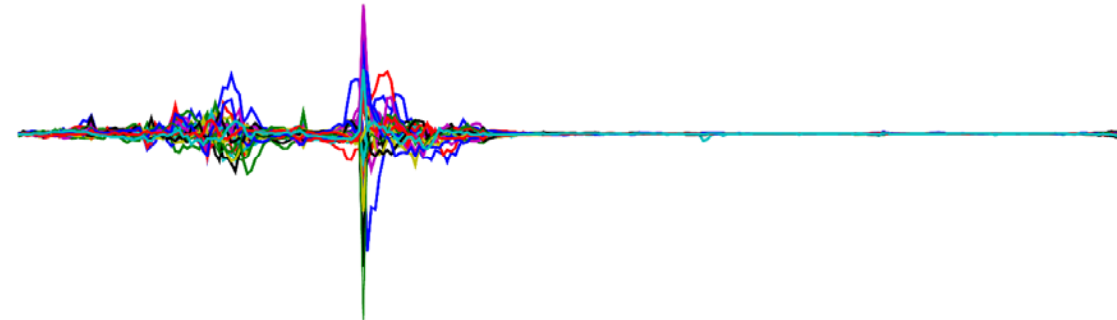
Information Preservation Experiment



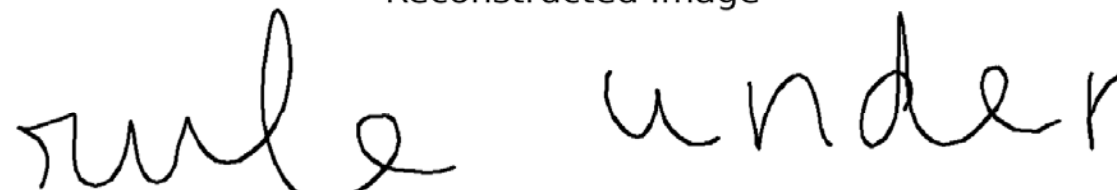
Network Outputs



Input Jacobian



Reconstructed Image



➤ Example

- Output at l
- Amount of information for each cell derived from each time stamp
- Called input Jacobian
- Estimated by Backprop.

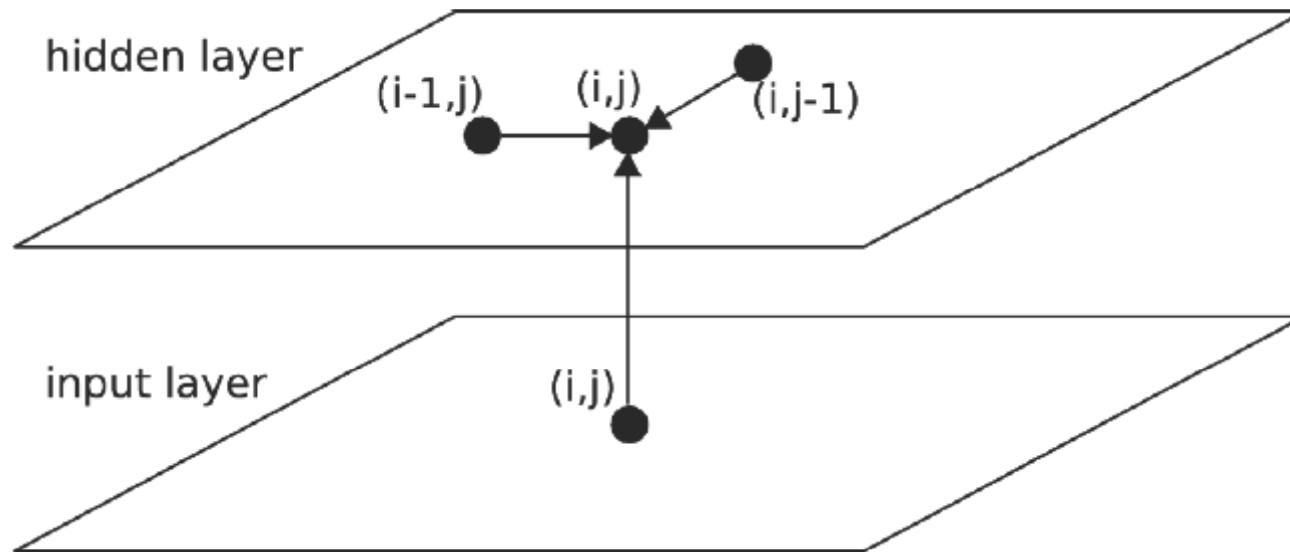


- BLSTM are discriminative
- BLSTM allow correlated input features
- Internal states are continuous and multivariate, because they are defined by the vector of activations of the hidden units
- The output is a sequence of labels without duration information
- BLSTM is in principle able to access context from the entire input sequence

Going Into Multiple Dimensions



- Standard RNN requires one-dimensional input
- Idea (like DAG-RNN):
 - Each neuron receives external input and its own activation from one step back along all dimensions
 - Can be applied to any dimensional sequences (img 2D, video 3D)

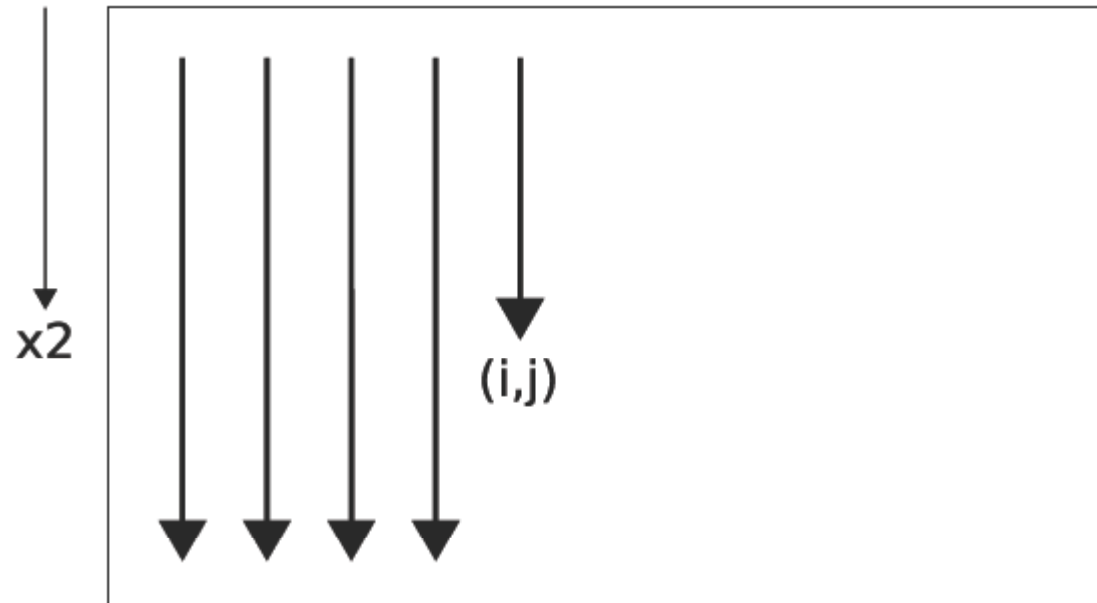


Sequence Ordering Through Forward Pass



- Ensure that each previous' step output is already calculated
- Example:

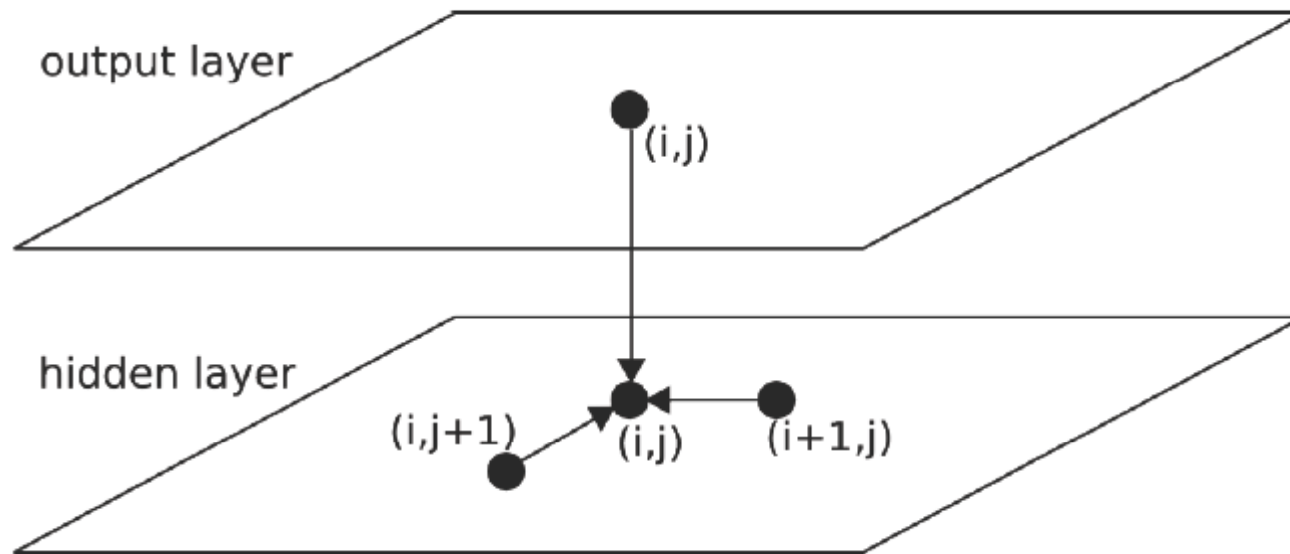
$(0,0)$ —————→ x_1



- Note: Boundaries have to be omitted



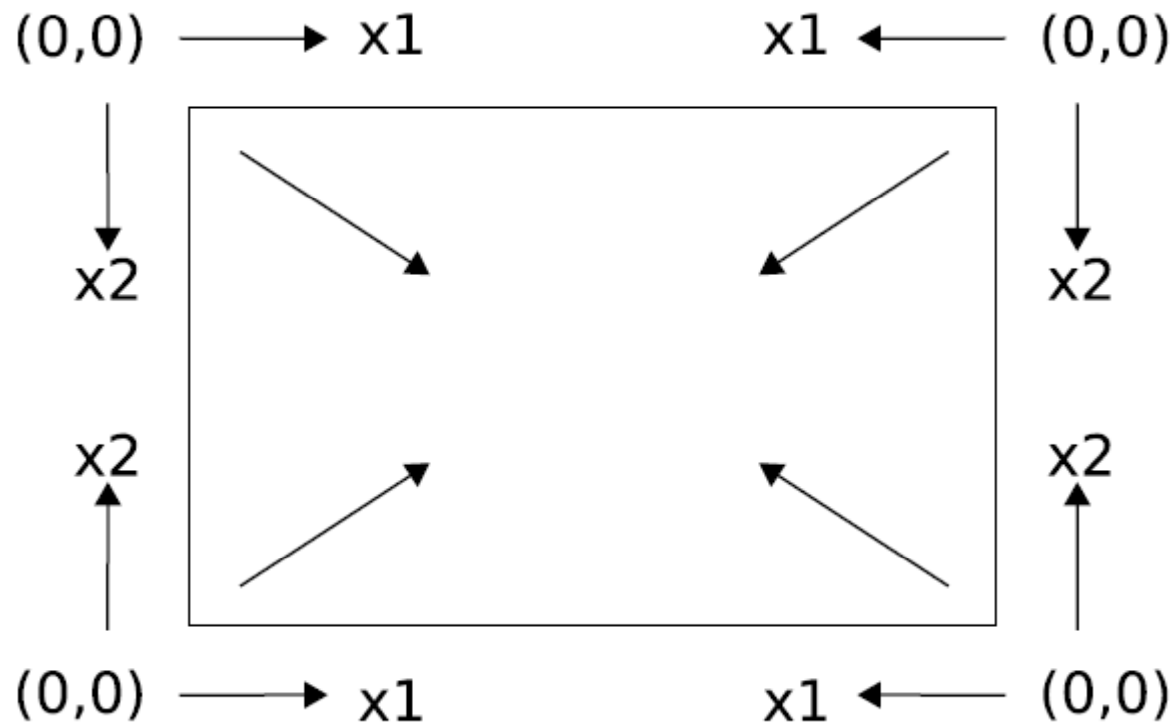
➤ N-dimensional backpropagation through time



Multidirectional MDRNN



- Idea: If d is the number of dimensions, use 2^d hidden layers
- Example (2 dimensions):



Problem

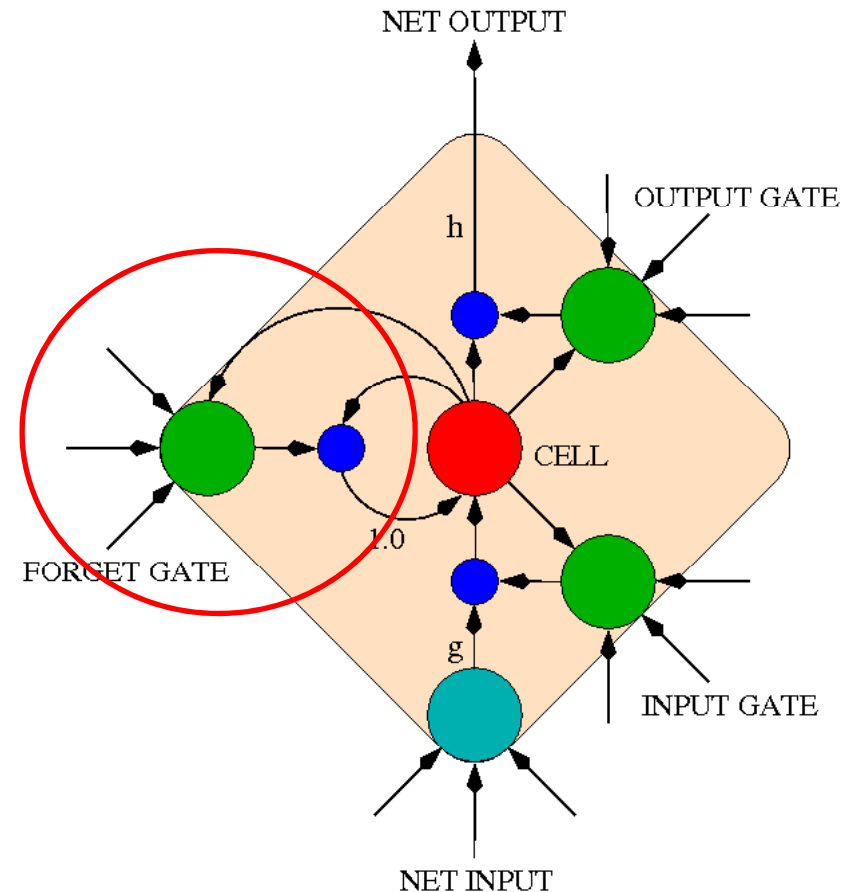


- Does the complexity explode?
- 2^d seems to be quite large
- However
 - Number of weights has more influence
 - Several calculations can be shared
- Furthermore
 - Reduce the size of the hidden layers with increasing dimensionality
 - It has been found that for speech recognition the number of weights was reduced to half and MDRNN gave still better results
- Main scaling concern is the size of the data, i.e., the length of the sequence

Combining idea with BLSTM



- Introduce 2^d self-connections, i.e., 2^d forget gates, each connected along one dimension
- However, only one input gate (connected to all dimensions)
- Also, only one output gate, since only the cell state is considered



Overall system



MDLSTM layers
and feed-forward
layers

4x3=>12-dim
vector

Small at bottom
large at top

159,369 weights
but most at top

1D at top by
summing up

1 neuron, 4x50 input,
sum of 2D-data

Output
121 x CTC

4 hidden layers, 50
neurons, 1x1x20 input

MDLSTM
4 x 50 cells

10 neurons, 4x10 input

Feedforward
20 x tanh

4 hidden layers, 10
neurons, 2x4x6 input

2
□ 4

MDLSTM
4 x 10 cells

6 neurons, 4x2 input

Feedforward
6 x tanh

4 hidden layers, 2
neurons - activations

3
□ 4

MDLSTM
4 x 2 cells



3
□ 4

Input



Illustration



ICDAR 2007 Arabic handwriting recognition contest



SYSTEM	SET f			SET s		
	top 1	top 5	top 10	top 1	top 5	top 10
CACI-3	14.28	29.88	37.91	10.68	21.74	30.20
CACI-2	15.79	21.34	22.33	14.24	19.39	20.53
CEDAR	59.01	78.76	83.70	41.32	61.98	69.87
MITRE	61.70	81.61	85.69	49.91	70.50	76.48
UOB-ENST-1	79.10	87.69	90.21	64.97	78.39	82.20
PARIS V	80.18	91.09	92.98	64.38	78.12	82.13
ICRA	81.47	90.07	92.15	72.22	82.84	86.27
UOB-ENST-2	81.65	90.81	92.35	69.61	83.79	85.89
UOB-ENST-4	81.81	88.71	90.40	70.57	79.85	83.34
UOB-ENST-3	81.93	91.20	92.76	69.93	84.11	87.03
SIEMENS-1	82.77	92.37	93.92	68.09	81.70	85.19
MIE	83.34	91.67	93.48	68.40	80.93	83.73
SIEMENS-2	87.22	94.05	95.42	73.94	85.44	88.18
Ours	91.43	96.12	96.75	78.83	88.00	91.05

Results of the ICDAR 2009 Arabic HWR Contest



System	Word Accuracy	Time/Image
CTC	81.06%	371.61 <i>ms</i>
Arab-Reader HMM	76.66%	2583.64 <i>ms</i>
Multi-Stream HMM	74.51%	143,269.81 <i>ms</i>

表 4 Summarized results from the offline Arabic handwriting recognition competition

Results of the ICDAR 2009 French HWR Contest



System	Word Accuracy
CTC	93.17%
HMM+MLP Combination	83.17%
Non-Symmetric HMM	76.34%

Summarized results from the offline (French) handwriting recognition competition

And the Very Best



- It is open source and for free
- <http://github.com/mrhichem/RNNLIB>
- Examples are online (Arabic recognition)

Thank You



DFKI, Kaiserslautern
Marcus.Liwicki@dfki.de

Further Reading:

Marcus Liwicki and Horst Bunke: Handwriting Recognition for Whiteboard Notes – Online, Offline, and Combination (World Scientific, 2008)

Alex Graves, Marcus Liwicki, et al. A novel connectionist system for unconstrained handwriting recognition", IEEE TPAMI, 31, 5, pp. 855-868 (2009).

Alex Graves' PhD thesis: Supervised Sequence Labelling with Recurrent Neural Networks (2008)

A. Graves and J. Schmidhuber. "Offline handwriting recognition with multidimensional recurrent neural networks". Advances in NIP Systems 21, pages 545-552 (2009).