Offline Handritting Word Recognition

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Overview of the Project

Off-line handwriting recognition

- It involves the automatic conversion of text in an image into letter codes which are usable within computer and text-processing applications
- Off-line handwriting recognition is comparatively difficult, as different people have different handwriting styles

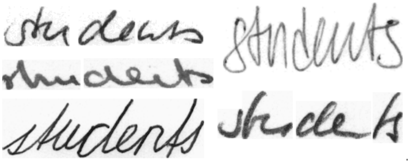


Figure: 'Students' written by different authors

Our AI Project

A lot of research has been done over the past years.

We explored the topic and implemented a full pipeline for the task.
The research touched different fields:

- Data Collection
- Image Processing
- Features extraction
- Machine Learning

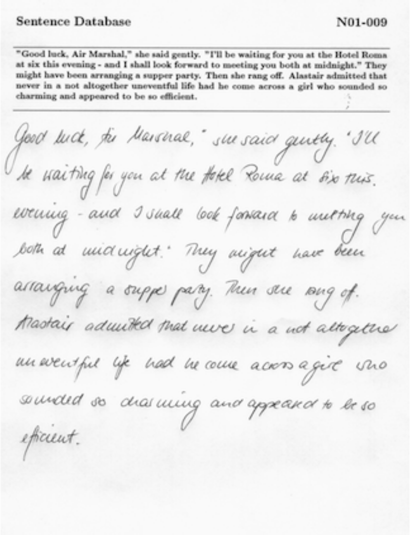
Dataset

The IAM Handwriting Database 3.0[1]

- Unconstrained handwritten text (scanned at a resolution of 300dpi and saved as PNG images with 256 gray levels)
- 1'539 pages of scanned text of 657 writers
- 13'353 isolated and labeled text lines
- 115'320 isolated and labeled words

[1] http://www.iam.unibe.ch/fki/databases/iam-handwriting-database

Example of a page of scanned text



Sentence Database N01-009

"Good luck, Air Marshal," she said gently. "I'll be waiting for you at the Hotel Roma at six this evening - and I shall look forward to meeting you both at midnight." They might have been arranging a supper party. Then she rang off. Alastair admitted that never in a not altogether uneventful life had he come across a girl who sounded so charming and appeared to be so efficient.

"Good luck, Air Marshal," she said gently. "I'll
be waiting for you at the Hotel Roma at six this.
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Implementation Details

Pipeline

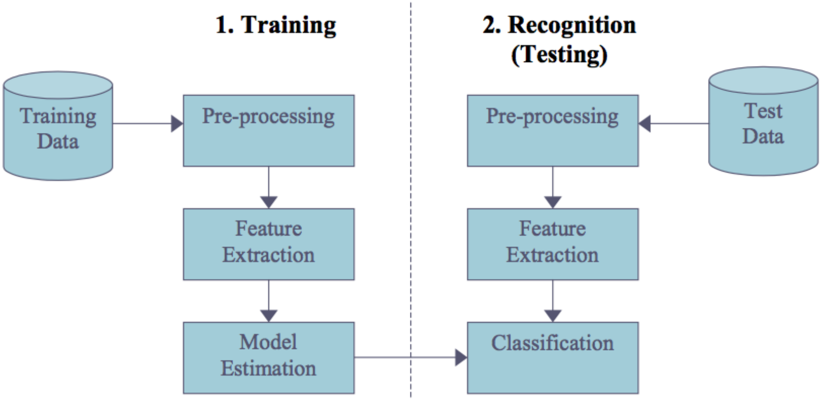


Figure: Pipeline of a word recognition system

Implementation Details

Pre-Processing

Pre-processing

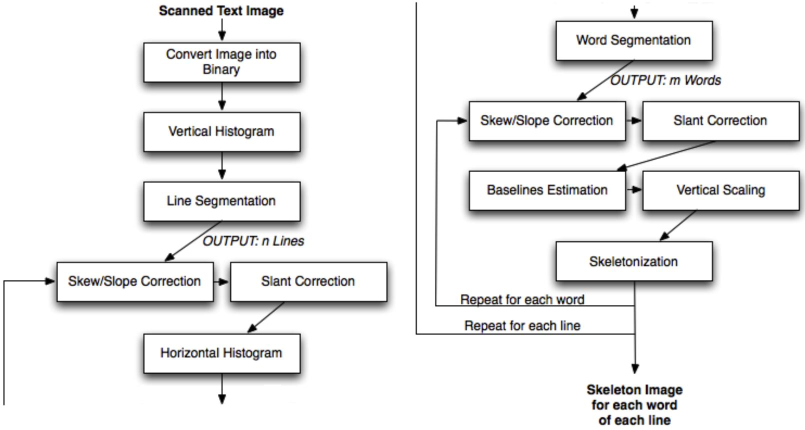
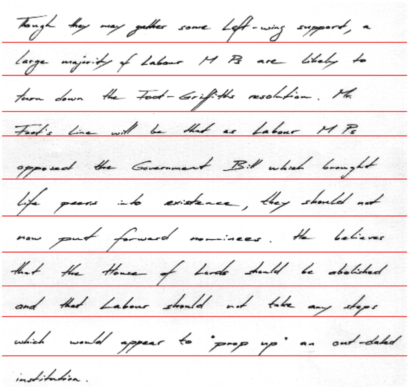
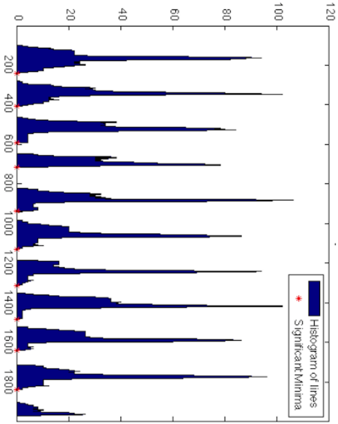


Figure: Pipeline for the pre-processing/normalization step

Line Segmentation



Original image segmented in lines



Vertical histograms and significant minima

Figure: Example of line segmentation

Skew and Slope Correction

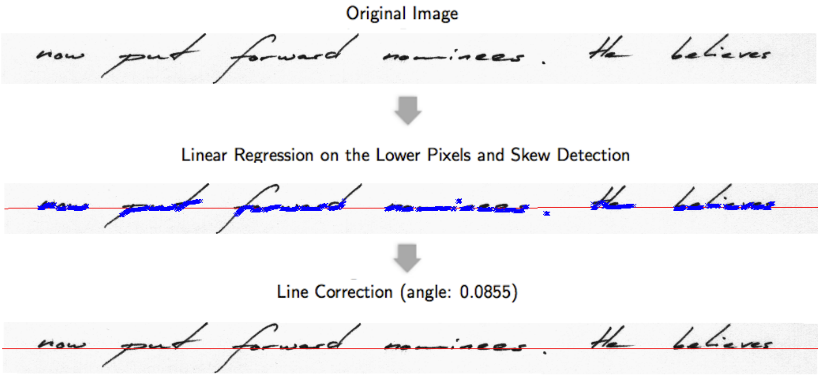


Figure: Skew detection and correction pipeline

Slant Correction

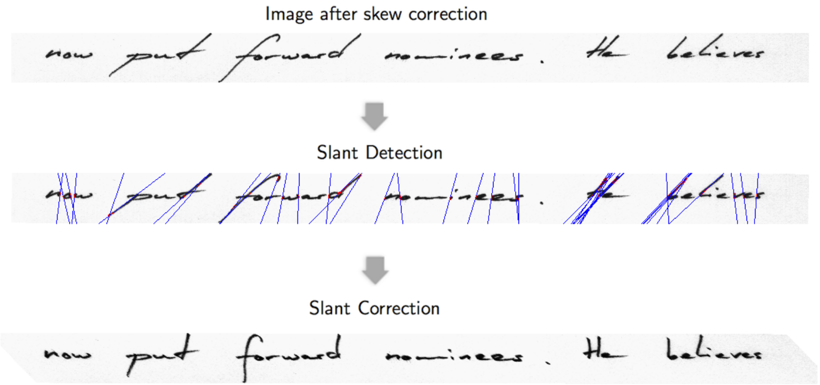
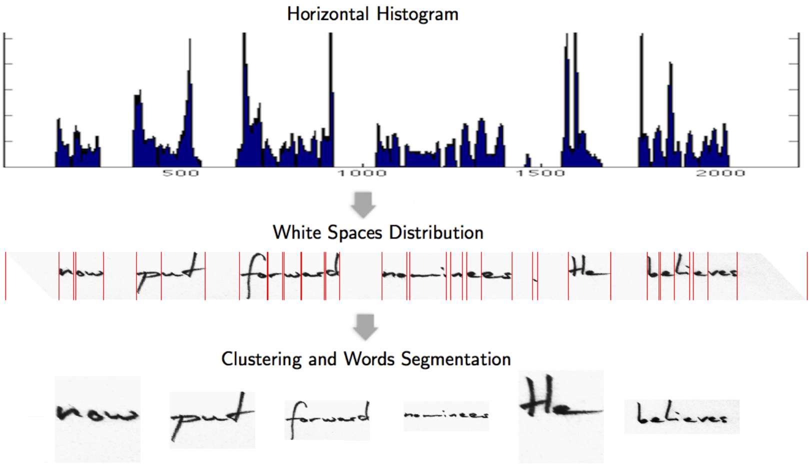
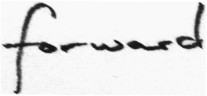


Figure: Slant detection and correction pipeline

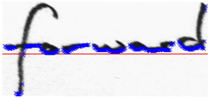
Word segmentation



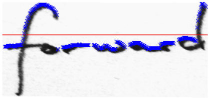
Baseline Estimation



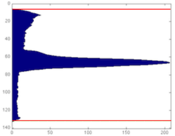
Lower Baseline

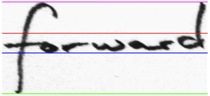


Upper Baseline



Ascender and Descender Baselines





Vertical Scaling

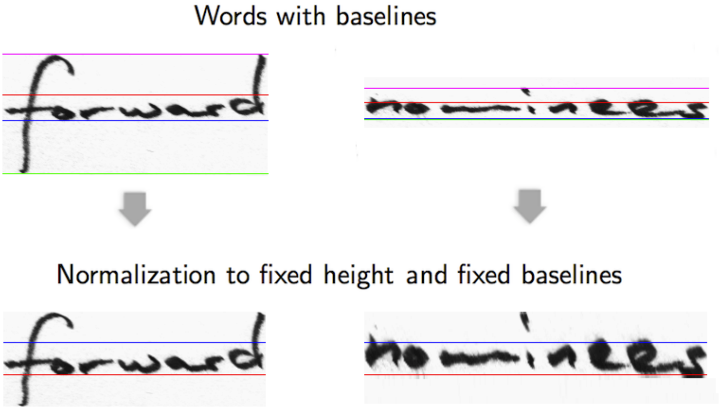


Figure: Examples of vertical scaling process

Skeletonization

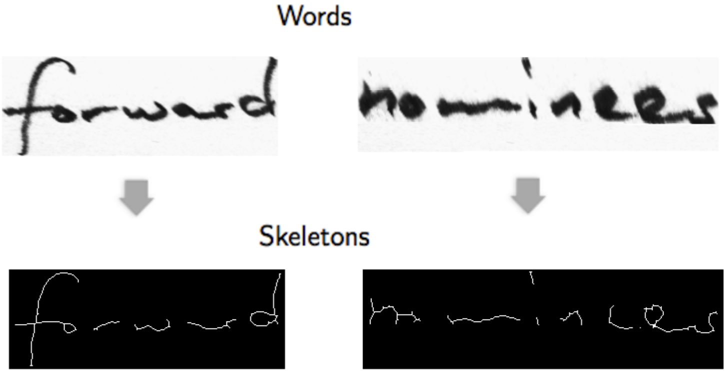
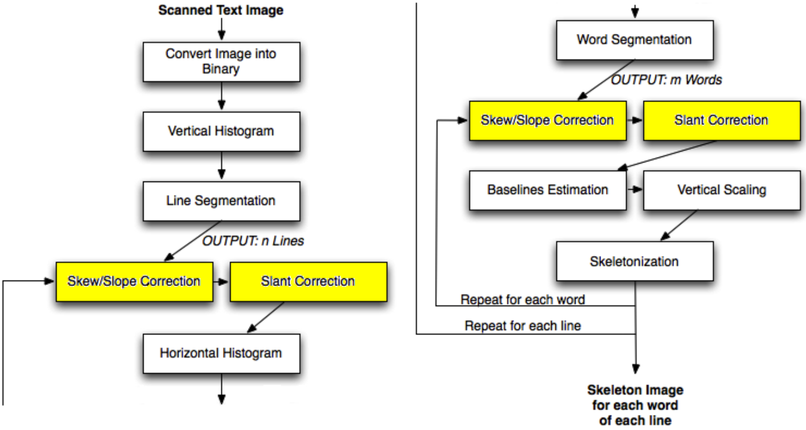


Figure: Skeletonization process

Remembering the entire pipeline....

Why repeating skew and slant correction twice?



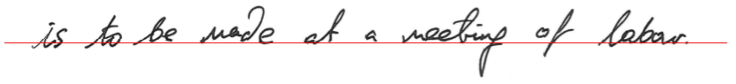
The normalizations are necessary for:

First

Words segmentation

Second

Not all the words have the same slope, slant and lower baseline



Implementation Details

Feature Extraction

Features

Extracted from the skeleton of the words.

Mainly 2 types:

- Statistical
- Morphological

Statistical Features

Percentage of white pixels in the 3 zones of the word:

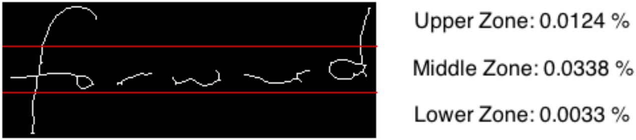


Figure: Example

Morphological Features

Obtained by **connected component analysis**.

- A connected component it is a subgraph in which any two vertices are connected to each other by paths, and which is connected to no additional vertices.

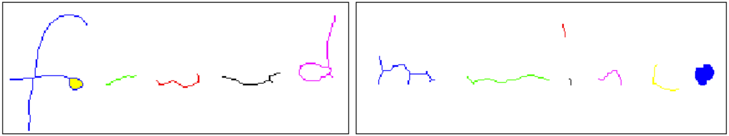
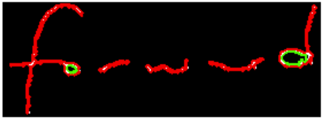


Figure: Example of words divided in different components (colors)

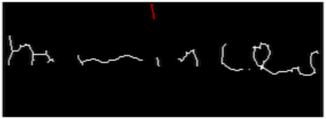
Morphological Features

We extract:

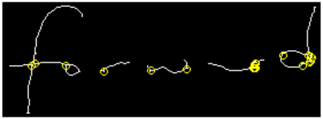
Loops



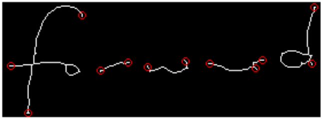
Dots



Junctions



Endpoints



Sliding window

We use a sliding window over the words and at every shift of the window we extract features.

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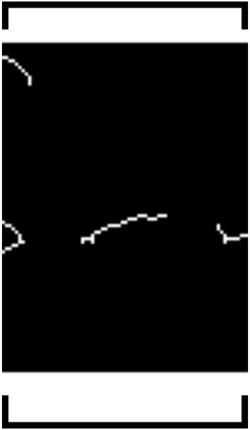

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Implementation Details

Hidden-Markov Model for Word Recognition

HMM

- A set of N states $S = (s_1, s_2, \ldots, s_N)$, where the state of the system at time t is denoted q_t
- A set of priors $\pi = (\pi_1, \pi_2, \ldots, \pi_N)$, providing the probability $P(q_1 = s_i)$.
- A transition function $\mathbf{A}$, where $a_{ij} = P(q_{t+1} = s_j | q_t = s_i)$.
- An observation function $\mathbf{B}$, mapping each observation at every state to a probability $b_i(\mathbf{o}_t) = P(\mathbf{o}_t | q_t = s_i, \lambda)$, where λ denotes the model parameters.

The model is trained to estimate the posterior probability $P(\mathbf{O}|\lambda)$ of an observation sequence $\mathbf{O}$, with D-dimensional observation vectors $\mathbf{o}_t = (o_1, o_2, \ldots, o_D)$.

HMM

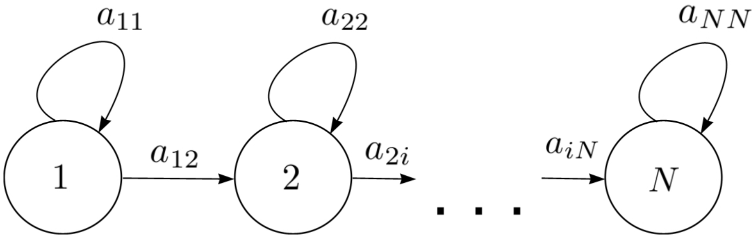

Figure: Left-to-right HMM with N states

Main problems in an HMM

1. The probability of an observation sequence, given the model, $P(\mathbf{O}|\lambda)$.
2. The most likely parameters of the model $\lambda^* = \max P(X|\lambda)$, given a training set of M observation sequences $X = (\mathbf{O}_1, \mathbf{O}_2, \ldots, \mathbf{O}_M)$.
3. The most likely state sequence, underlying a given observation sequence and the model, $Q^* = \max P(Q|\mathbf{O}, \lambda)$.

Main problems in an HMM

1. The probability of an observation sequence, given the model, $P(\mathbf{O}|\lambda)$.

   Sum-product algorithm: forward-backward algorithm

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   EM-algorithm: Baum-Welch reestimation

3. The most likely state sequence, underlying a given observation sequence and the model, $Q^* = \max P(Q|\mathbf{O}, \lambda)$.

   Dynamic programming: Viterbi algorithm

Updating the parameters

Comparison with GMM:

Model:	**GMM**	**HMM**
Model parameters:	$\lambda = \pi, \mu, \Sigma$	$\lambda = \pi, \mathbf{A}, \mathbf{B}$
Hyper parameters:	Number of components	Topology (states, transitions), observation function
Observed variables:	Data points	Observations
Latent variables:	Priors of a component	State sequence

Updating parameters

Model:	**GMM**	**HMM**
E-step:	Estimate the probability of a component, given the data and current parameters.	Estimate the probability of being in a state at a timestep and the probability of transfering from a state to another state.
M-step:	Maximise π, μ and Σ.	Maximise π, $\mathbf{A}$ and $\mathbf{B}$

Problems we ran into - 1

Consider the following observation:

$$\mathbf{O} = \begin{pmatrix} -1 & 0 \\ 2 & 0 \\ 1 & 0 \\ -2 & 0 \end{pmatrix}$$

Problems we ran into - 1

Singularities. Consider the following observation:

$$\mathbf{O} = \begin{pmatrix} -1 & 0 \\ 2 & 0 \\ 1 & 0 \\ -2 & 0 \end{pmatrix}$$

$$\Sigma = \begin{pmatrix} 3\frac{1}{3} & 0 \\ 0 & 0 \end{pmatrix}$$

Problems we ran into - 1

Singularities

$$\mathbf{O} = \begin{pmatrix} -1 & 0 \\ 2 & 0 \\ 1 & 0 \\ -2 & 0 \end{pmatrix}$$

$$\Sigma = \begin{pmatrix} 3\frac{1}{3} & 0 \\ 0 & 0 \end{pmatrix}$$

$$|\Sigma| = 0$$

Possible solution: Add some random noise.

Problems we ran into - 2

Short words may be more difficult to recognise as they are more sensible to inter-writer variations.

Possible solution: Use Mixture of Gaussians

Mixture of Gaussians

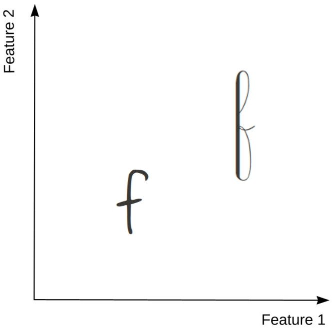
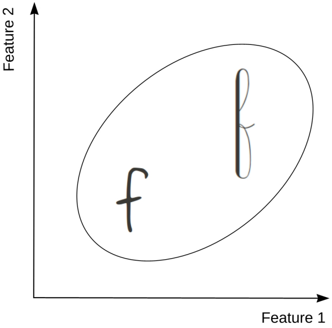


Figure: Two letters plotted in a two dimensional feature space

Mixture of Gaussians



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Mixture of Gaussians

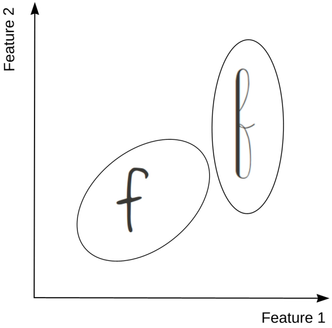

Figure: Two letters plotted in a two dimensional feature space

Experiments and Results

Experiments

We run 2 type of experiments:

- 1 vs 1 word recognition
  - We build models for 2 words and we test both models for new instances of the 2 words from novel authors
  - *GOAL*: Test how much the likelihoods of the 2 words differ
- all vs all words recognition
  - We build models for every word and for every word in the test set we rank all the models by loglikelihood
  - *GOAL*: Compute general accuracy for a small dataset

For both experiments the model of a word is built using 30 samples from 30 authors of the word.

Experiment 1 - Typewritten words

- Done to check the correctness of the pipeline.
- Used words 'Letter' and 'Number' (same length)

Table: Values of likelihoods averaged over 40 runs

Features	States	G.Comp.	Letter	Number	Diff.
Intensity	6	1	121.68	106.36	15.32
All	6	1	795.45	14.08	781.37
All	1	1	602.22	-90.02	692.22
All	6	3	226.96	-820.30	$1.04e^3$
All	6	1, diagonal cov	871.16	531.27	487.75
All	6	1, isotropc cov	-179.00	-272.23	197.35

...many many more parameters. (Interval sliding window, width of sliding window, amount of noise, ... etc.)

Experiment 1 - Handwritten Words (same length)

- Built models for 'Before' and 'People'
- Tested the models on new instances of 'Before'

Table: Values of likelihoods averaged over 40 runs

States	G. Comp.	'Before'	'People'	Difference
6	1	$1.17e+03$	$1.19e+03$	480.16
1	1	699.56	$1.0124e+03$	422.78

Experiment 1 - Handwritten Words (short vs long)

- Built models for 'At' and 'Government'
- Tested the models on new instances of 'At'

Table: Values of likelihoods averaged over 40 runs

States	G. Comp.	'At'	'Government'	Difference
6	1	441.89	$2.80e+03$	$2.36e^3$
1	1	216.47	$1.65e+03$	$1.44e^3$

Experiments 2

- Used a small dataset of 100 words
- Tested on 200 words of novel authors

Num. States	Num. Gaussian Comp.	Accuracy 1[2]	Accuracy 2[3]
lengthWord	1	0.2400	0.3400
1	1	0.2000	0.3600
1	5	0.0800	0.1800
lengthWord	5	0.1200	0.3000

[2] Correct if in 1st position of the ranked list
[3] Correct if in 1st or 2nd position of the ranked list

Issue with recognition

Short words seem to be harder to find.
Possible causes:

- During the testing, the model does not execute a complete sequence, e.g. when looking for 'the' in 'therefore' it might end before 'r'.

Possible solutions: Force the model to end the observations sequence in the final state.

Conclusions

Conclusions about the AI project

- The full pipeline is working, however a lot of improvements are possible:
  - Extract more features
  - Eventually apply PCA to the feature vector
  - Optimize the parameters of the HMM (i.e. using a validation set).
- Built models for letters instead of models for words (it requires letters segmentation)
- Use a language model

Personal Evaluation

- We built a full working pipeline
- We read and learnt a lot about a new topic
- We had the chance to apply a lot of techniques that we had only been studied in theory
- We improved our skills in programming

Questions?