Optimizing the Integration of a Statistical Language Model in HMM based Offline Handwritten Text Recognition

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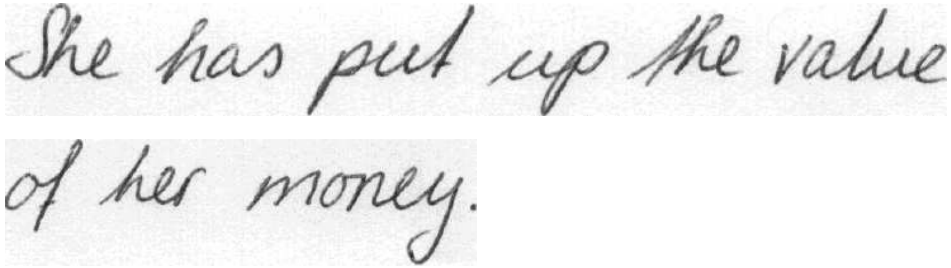
Organization

1. Introduction
2. Bigram Language Model
3. Language Model Integration
4. Grammar Scale Factor
5. Word Insertion Penalty
6. Setup, Optimization and Evaluation
7. Conclusions

1. Introduction

Recognition of Handwritten Sentences



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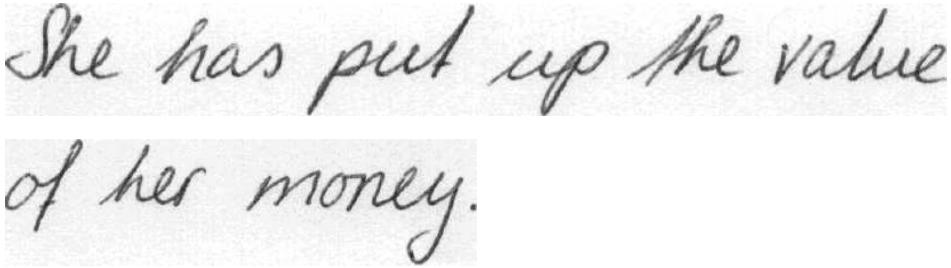

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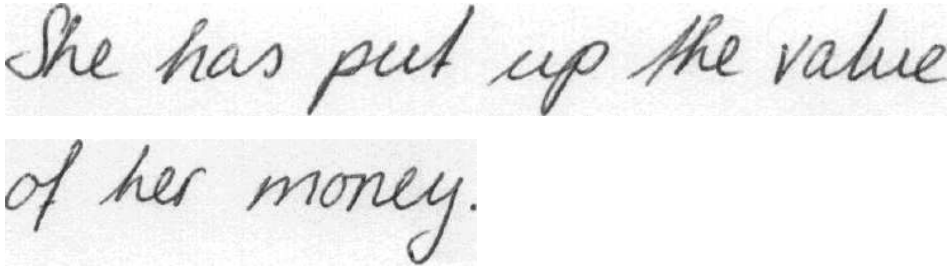

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She has put up the value of her money .

1. Introduction

Handwriting Recognition and Language Modeling

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- the use of LM consistently improves baseline recognizer
- LM are predominantly used within the HMM framework
- so far, the optimization of the integration is hardly addressed

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General Principle

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- Each additional word decreases $p(W)$

3. Language Model Integration

Direct integration of the LM in HMM framework

$$\phi_i = \phi_{i-1} + \log p(X_i|w_i) + \log p(w_i|w_{i-1})$$

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$p(X_i\|w_i)$	HMM provides likelihoods, not probabilities
$p(w_i\|w_{i-1})$	LM provides probabilities
	but Bigram LM prefers short sentences

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Use of the Grammar Scale Factor (GSF)

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$\alpha > 1$	increasing influence of the LM

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$\beta = 0$	classical integration
$\beta > 0$	increases the # of words in recognition result
$\beta < 0$	decreases the # of words (penalty per word in recognition result)

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- recognition of isolated sentences
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- IAM database
- 5,799 lines of handwritten text (33,993 words)
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- recognition of isolated sentences
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Training of Character HMM

- IAM database
- 5,799 lines of handwritten text (33,993 words)
- written by 448 persons

Training of Bigram LM

- LOB corpus (tagged)
- 50’000 sentences (excluding test/validation set)

6. Experimental Setup

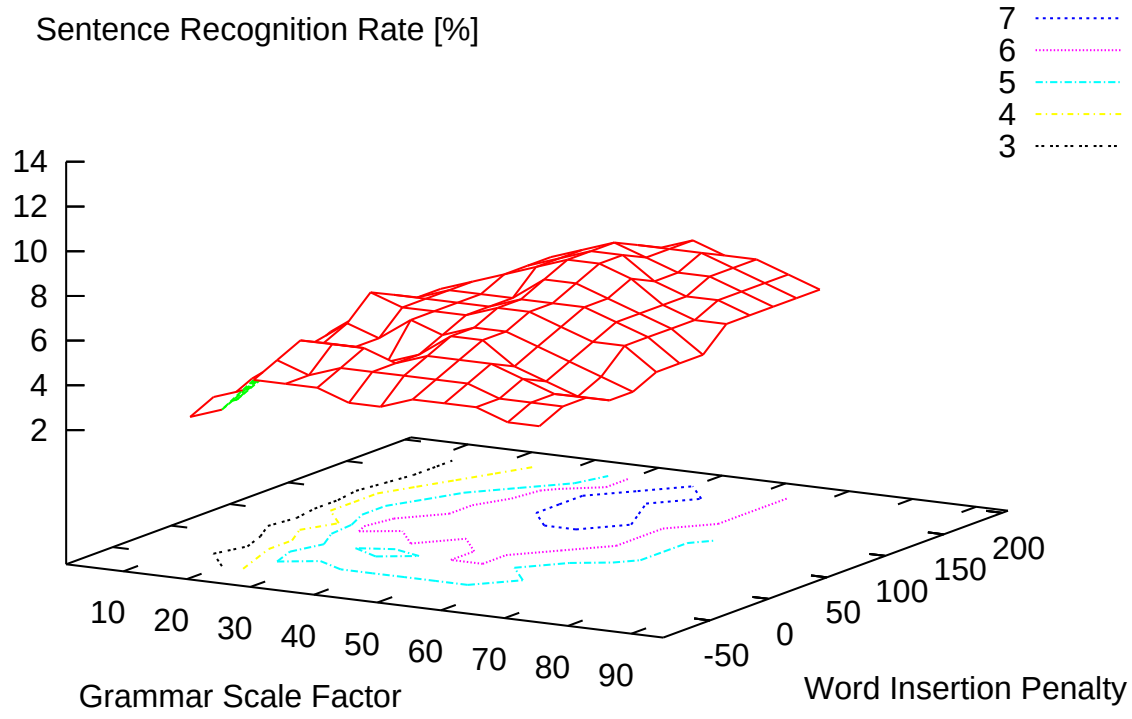
Recognition Task* Specifications

	validation	test
sentences	200	200
text lines	582	575
words	4,094	3,956
lexicon	8,827	8,821
writers	100	100

* writer independent: different writers in training, validation and test set

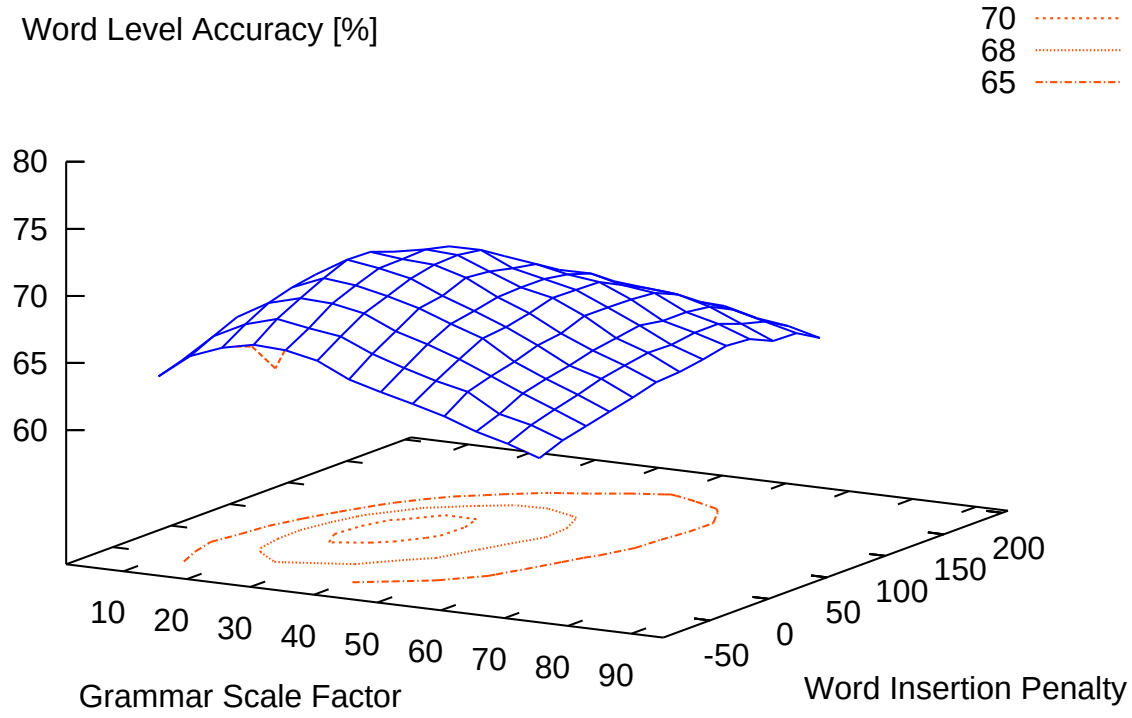
6. System Evaluation

Optimizing the Sentence Recognition Rate



6. System Evaluation

Optimizing the Word Level Accuracy (H-I)/N



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α	β	Sentence Rec.	Word Level Acc.	
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30	50	10.5%	76.3%	optimized integration

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Main Conclusions

- the benefit of the GSF and the WIP in the domain of offline handwritten text recognition has been shown in extensive experiments on realistic data

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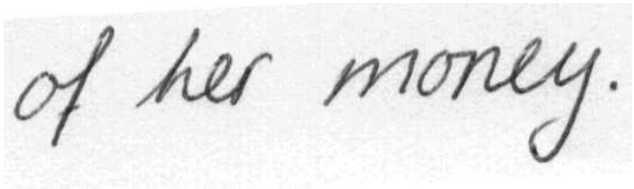
- the benefit of the GSF and the WIP in the domain of offline handwritten text recognition has been shown in extensive experiments on realistic data
- we strongly recommend the use of the GSF and the WIP to optimize the integration of statistical LM

Thank You

Appendix The Recognizer

Text Line Normalization



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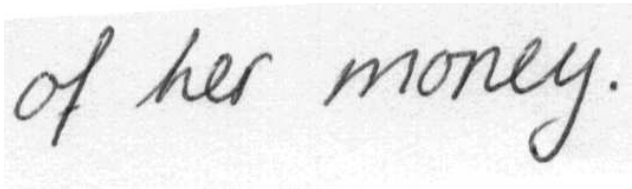
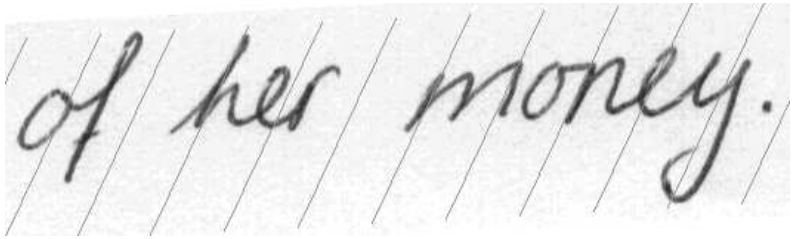


slant estimation



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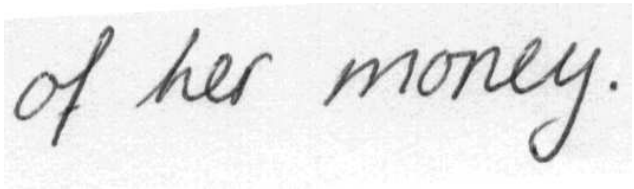

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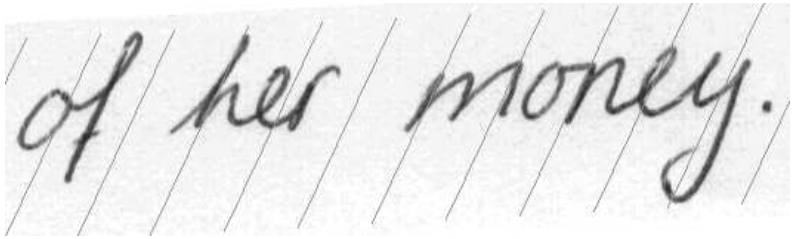

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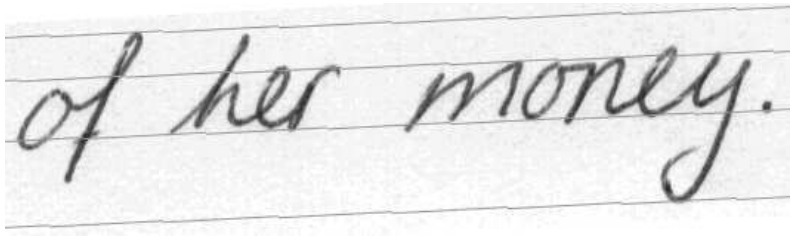

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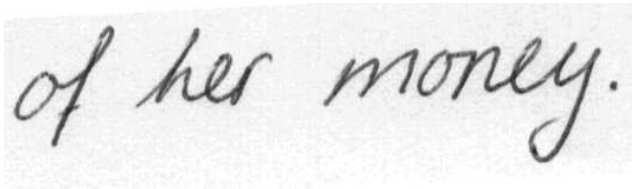

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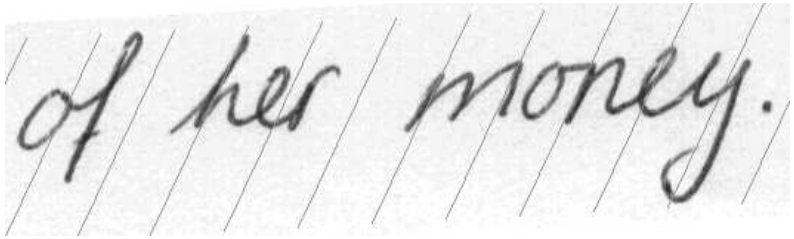

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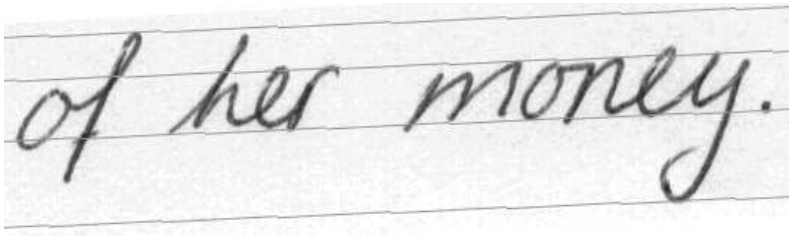
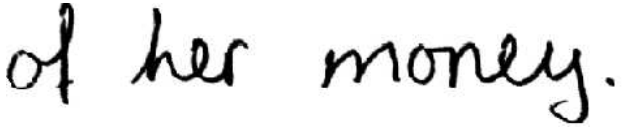


normalized text line



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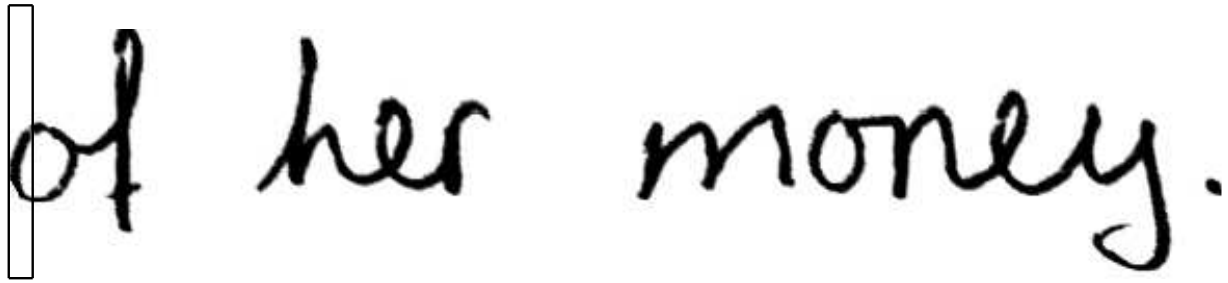
Extraction of the Feature Vector Sequence



$$\begin{pmatrix} x_{11} \\ x_{12} \\ \vdots \\ x_{1m} \end{pmatrix}$$

$$X = (X_1,$$

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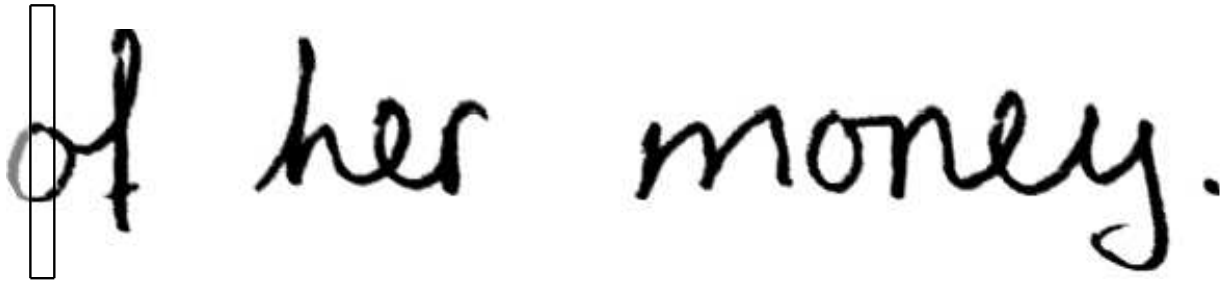

$$\downarrow$$

$$\begin{pmatrix} x_{21} \\ x_{22} \\ \vdots \\ x_{2m} \end{pmatrix}$$

$$X = (X_1, X_2,$$

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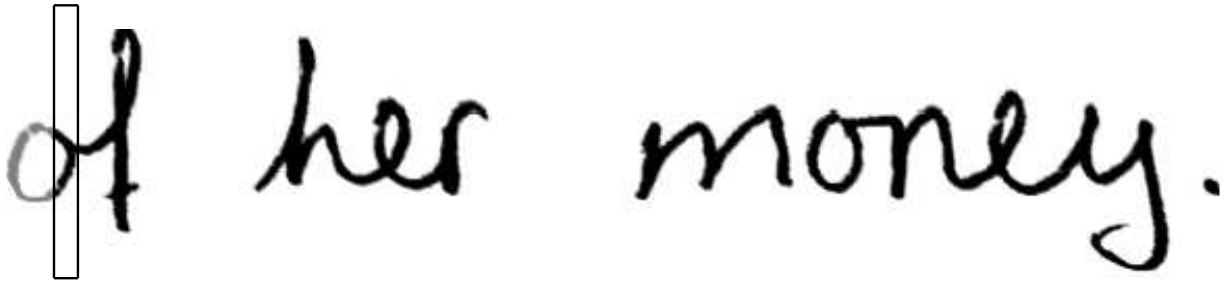

$$\begin{pmatrix} x_{31} \\ x_{32} \\ \vdots \\ x_{3m} \end{pmatrix}$$

$$X = (X_1, X_2, X_3,$$

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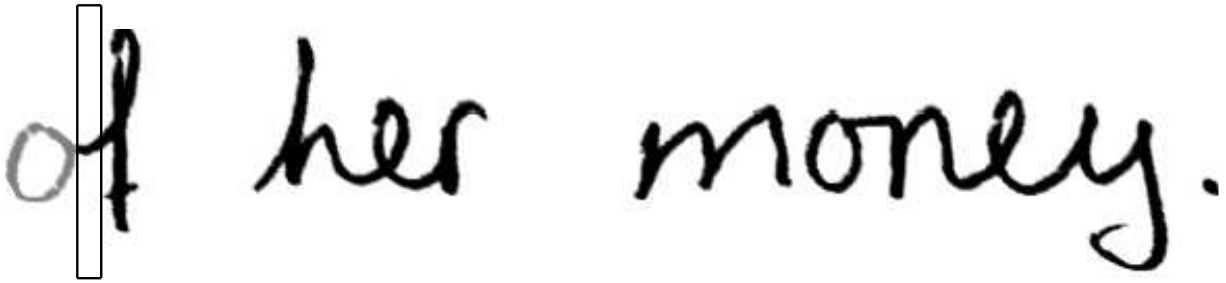

$$\begin{pmatrix} x_{41} \\ x_{42} \\ \vdots \\ x_{4m} \end{pmatrix}$$

$$X = (X_1, X_2, X_3, X_4,$$

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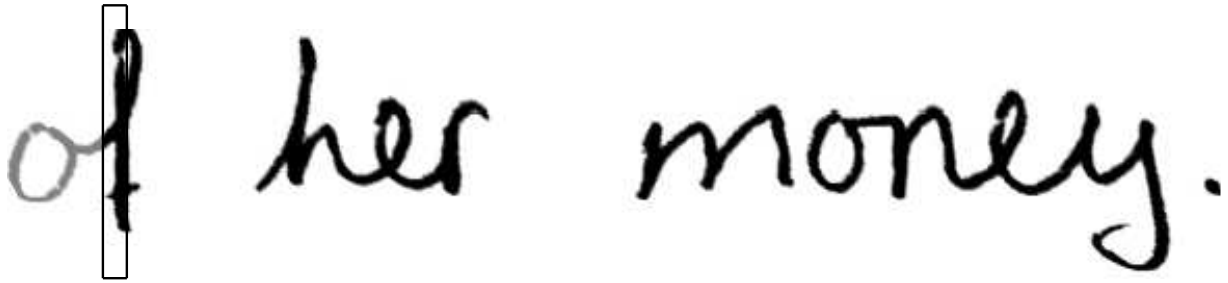

$$\begin{pmatrix} x_{51} \\ x_{52} \\ \vdots \\ x_{5m} \end{pmatrix}$$

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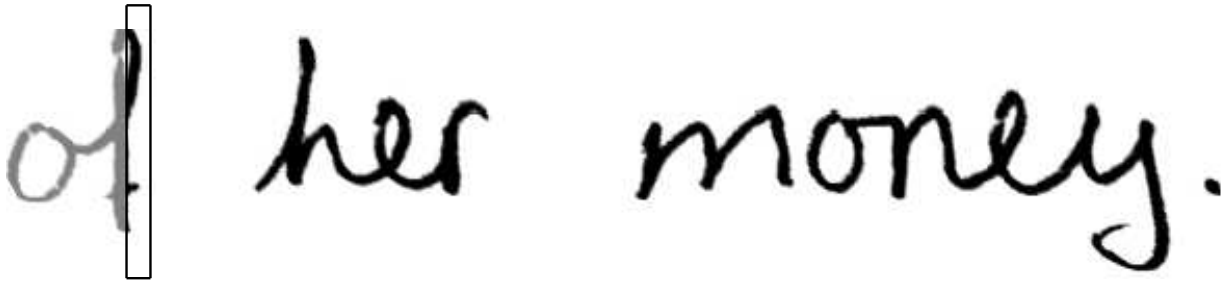

$$\begin{pmatrix} x_{61} \\ x_{62} \\ \vdots \\ x_{6m} \end{pmatrix}$$

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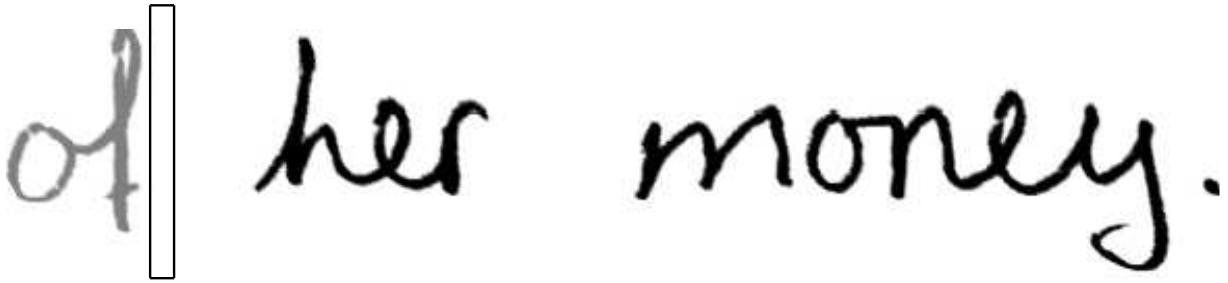

$$\begin{pmatrix} x_{71} \\ x_{72} \\ \vdots \\ x_{7m} \end{pmatrix}$$

$$X = (X_1, X_2, X_3, X_4, X_5, X_6, X_7, \ldots$$

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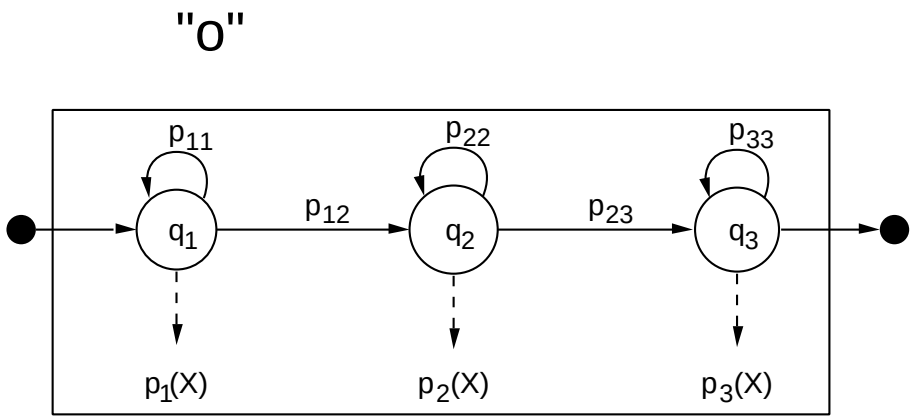
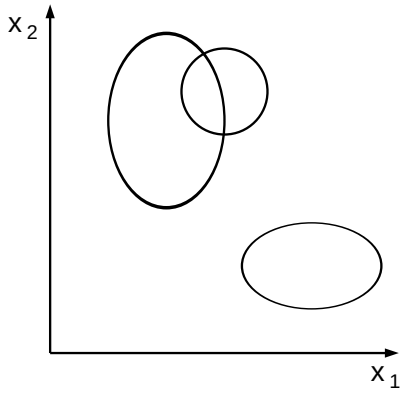
Viterbi Decoding

$(X_1, X_2, X_3, \ldots$





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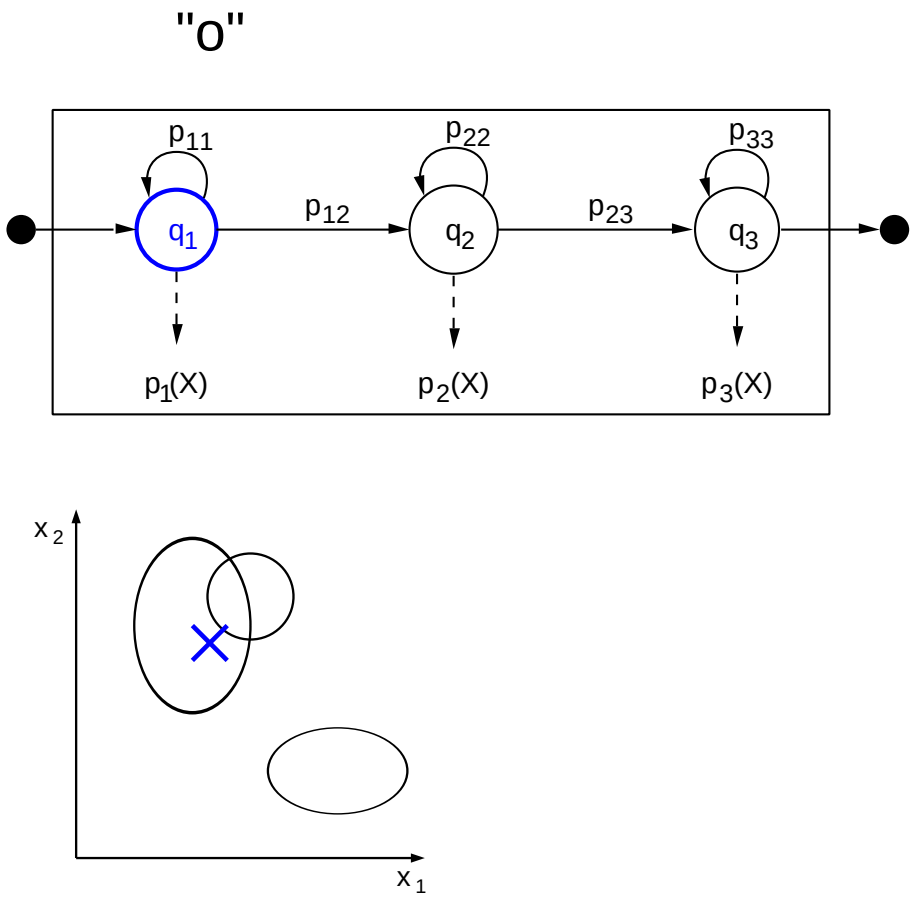
Viterbi Decoding

$(X_1, X_2, X_3, \ldots$



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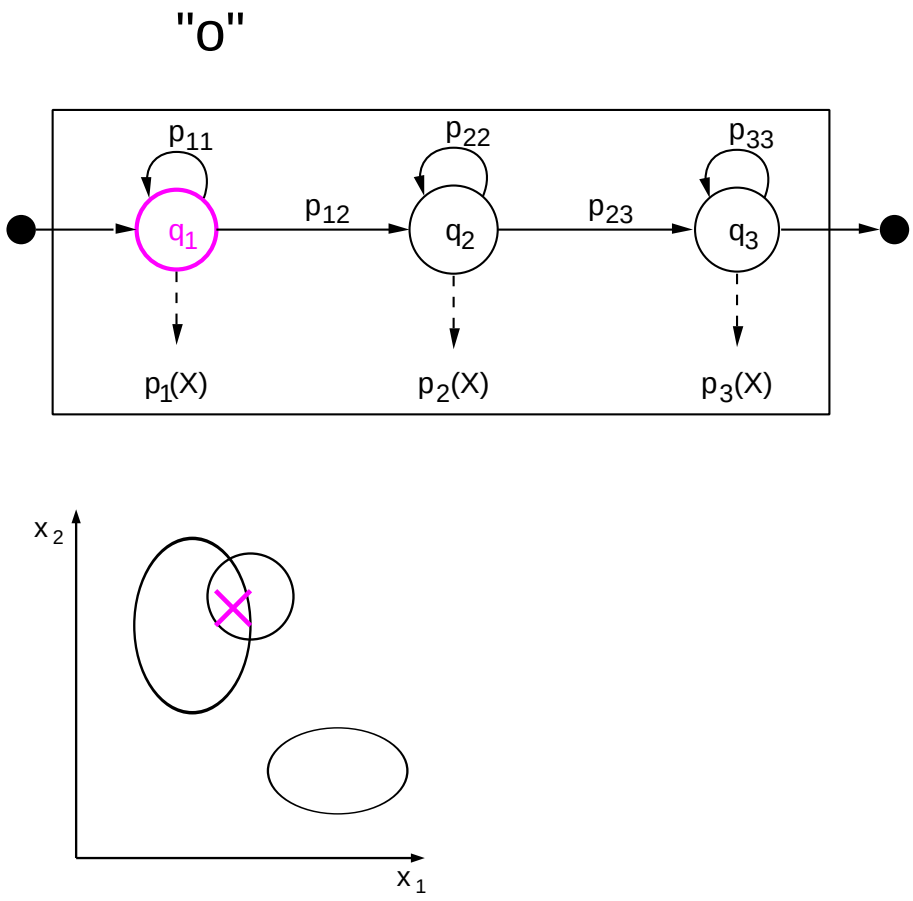

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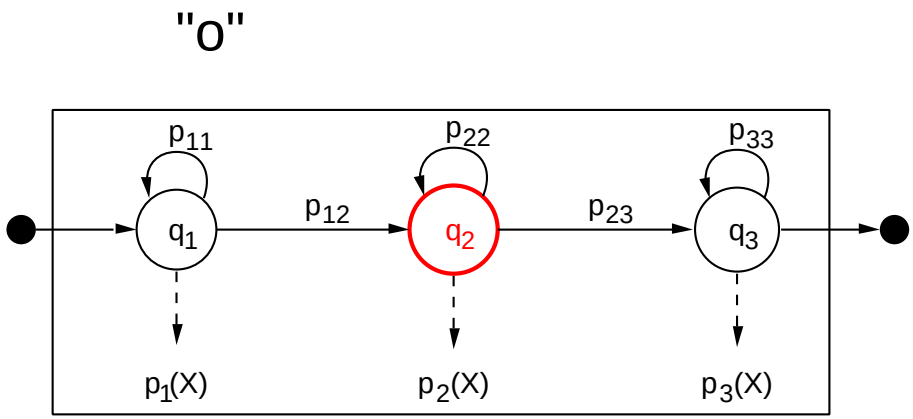

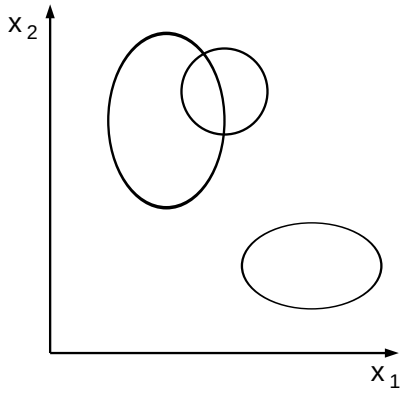

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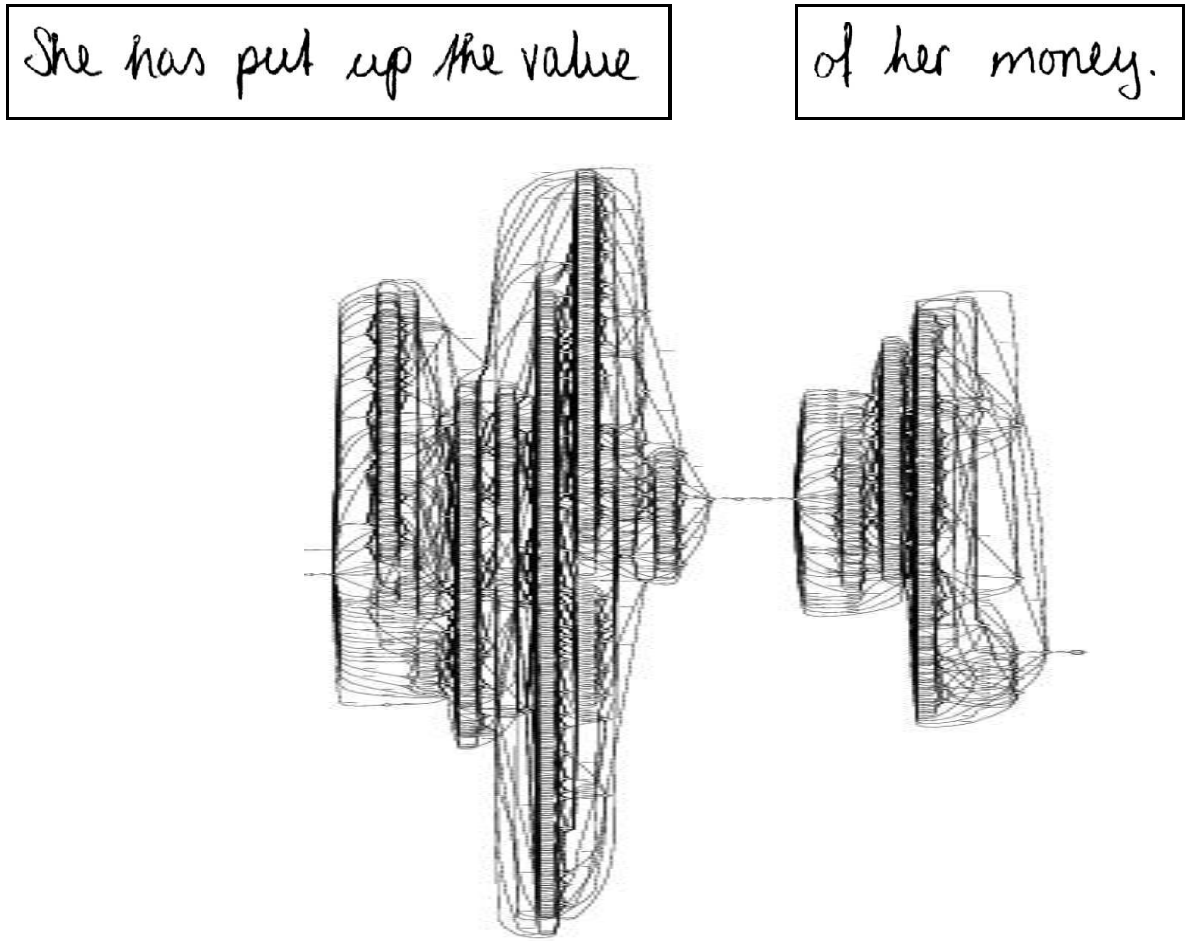
Recognition Lattice Generation



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Sublattice of 2nd Line