N-Gram Language Models for Offline Handwritten Text Recognition

IWFHR 2004 Tokyo, Japan

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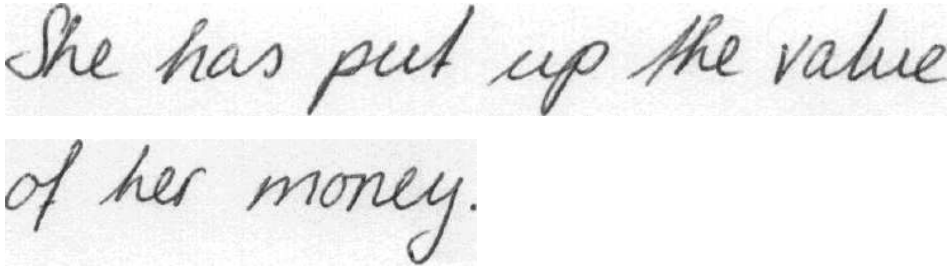
Organization

1. Introduction
2. N-Gram Language Models
3. Random Sentence Generation
4. Language Model Performance
5. Recognition System Performance
6. Setup, Optimization and Evaluation
7. Conclusions

1. Introduction

Recognition of Handwritten Sentences



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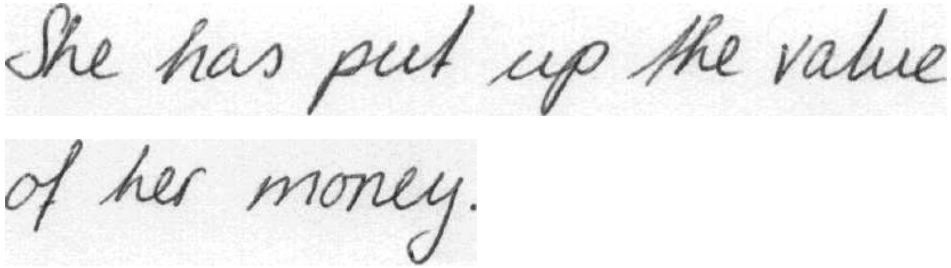

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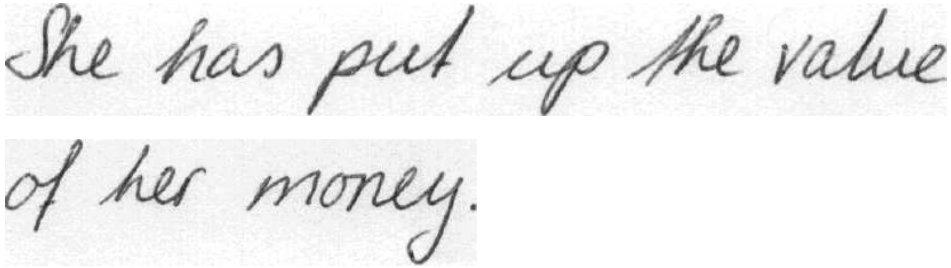

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She has put up the value of her money .

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- LM are predominantly used within the HMM framework
- so far, mostly bigram LM were used

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General Principle

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- SCFG to produce random sentences to smooth n-gram LM
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Natural Text

- Brown corpus for American English
- Wellington corpus for New Zealand English

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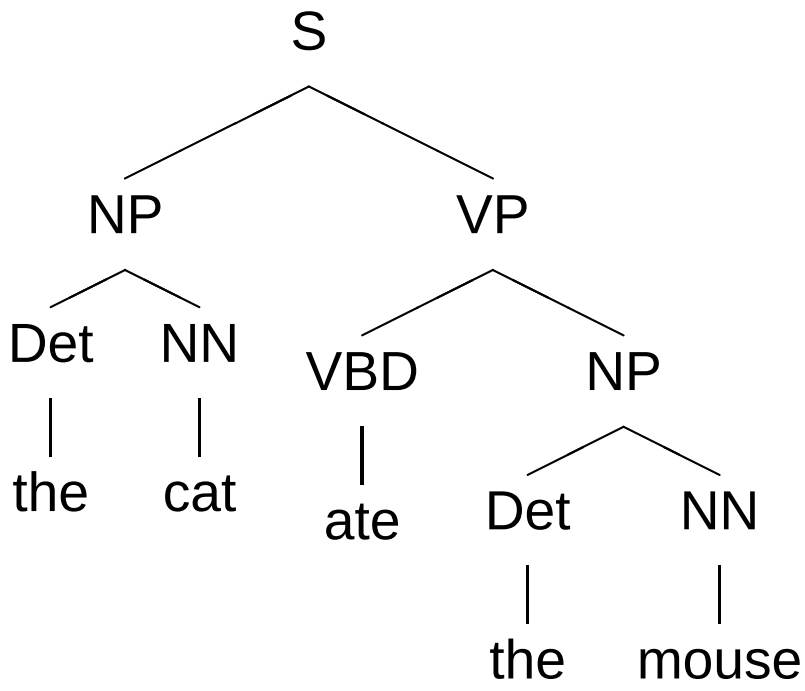
Sentence from Parsed Corpus



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Production Probabilities

$$p(A \rightarrow \alpha) = \frac{N(A \rightarrow \alpha)}{\sum_{\beta} N(A \rightarrow \beta)}$$

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- sentences normally not meaningful
- arbitrary number of sentences can be produced

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PP_T(M) &= 2^{H_T(M)} \\
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- the lower the value, the better the model

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- sentence recognition rate
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Word Level Accuracy

- measures the accuracy of the recognition result
- percentage of correctly recognized words minus the percentage of inserted words compared to the transcription
  (H - I) / N

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The Recognizer

- text line normalization (slant, writing regions, contrast)

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- 5,799 lines of handwritten text (33,993 words)
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Training of Baseline Bigram/Trigram LM

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

6. Experimental Setup

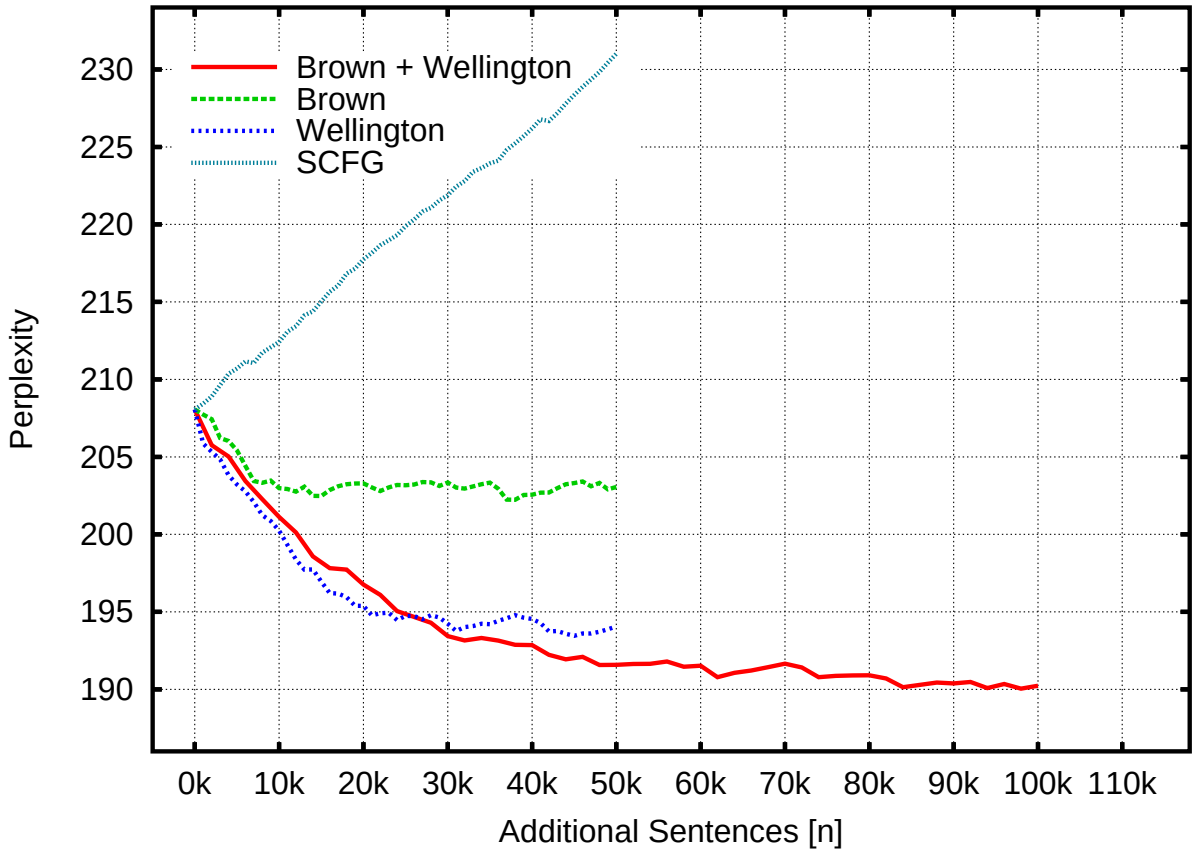
Recognition Task* Specifications

	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

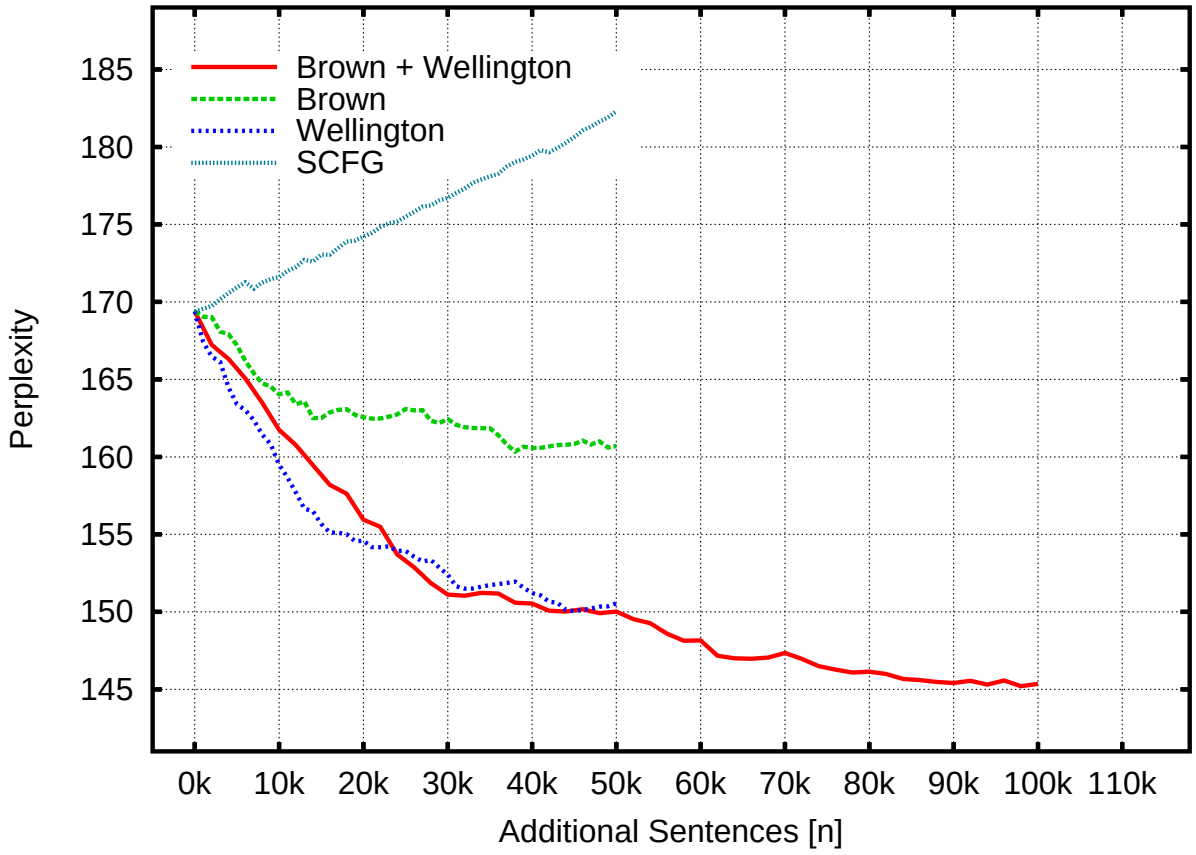
6. Optimization

Bigram LM: Optimizing the Perplexity



6. Optimization

Trigram LM: Optimizing the Perplexity



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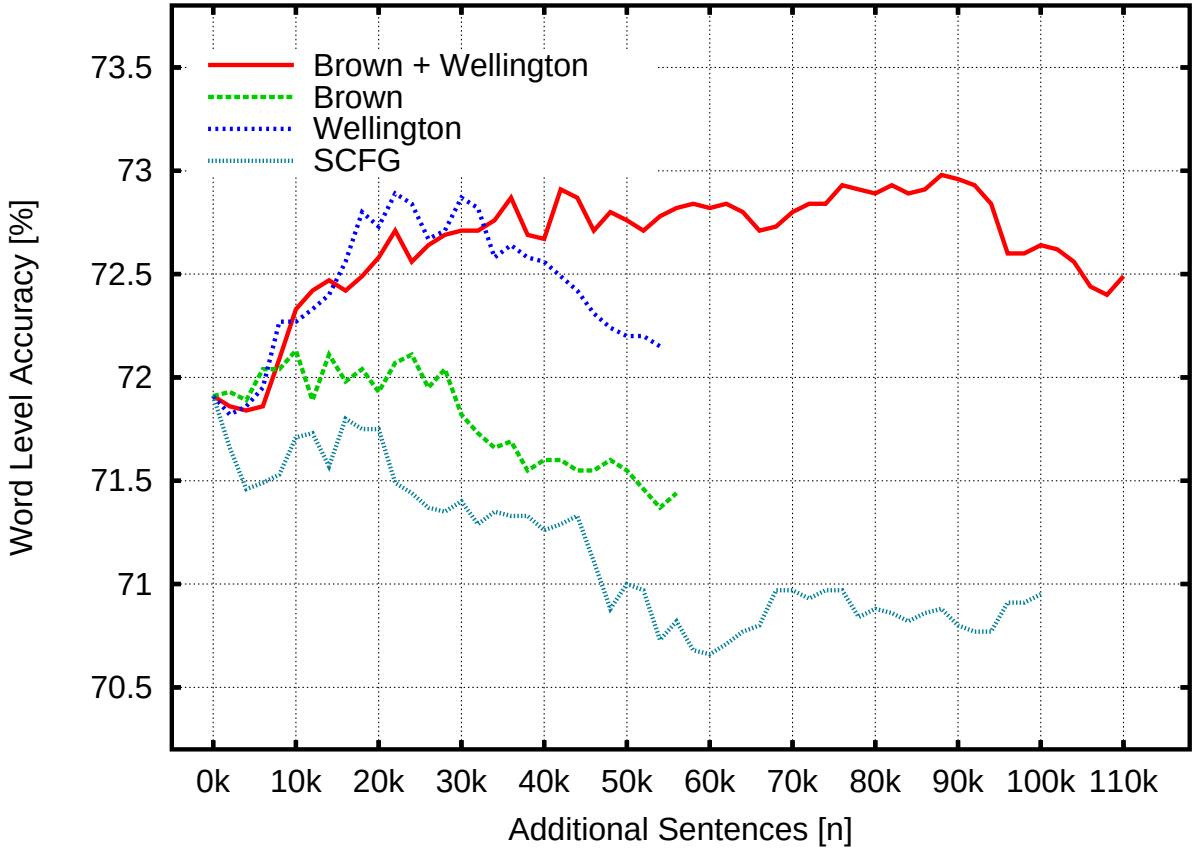
Bigram LM: Optimizing the Word Level Accuracy (H-I)/N



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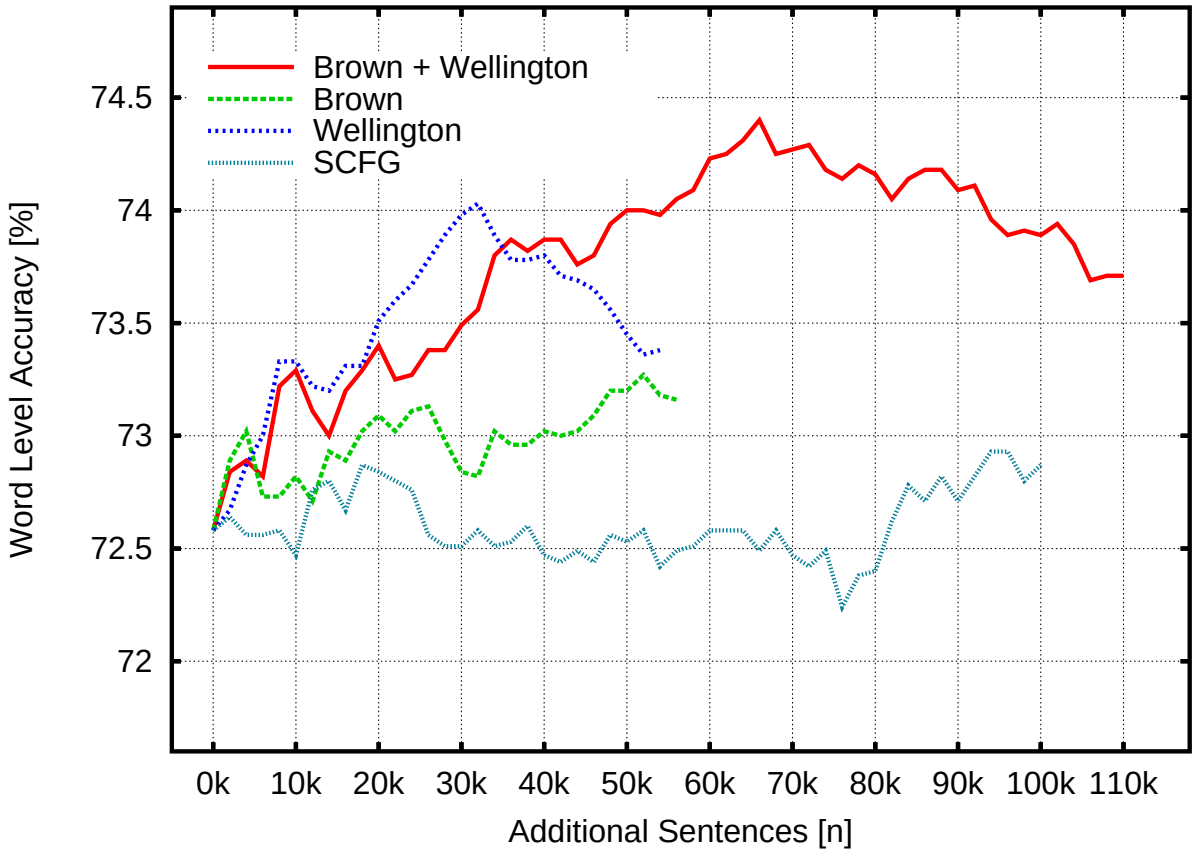
Trigram LM: Optimizing the Word Level Accuracy (H-I)/N



6. System Evaluation

Test Set Results

Language Model	Sentence Rec. Rate	Word Level Acc.
Bigram	11%	76.3%

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Smoothed* Trigram	14%	79.9%

* LOB plus first 65’000 sentences from combined Brown + Wellington corpus

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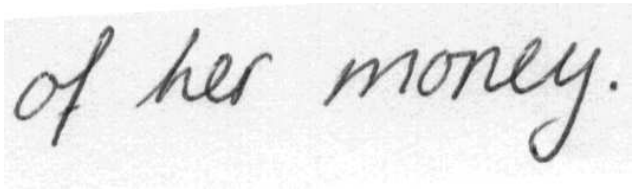
- random sentences produced by SCFG did not help
- trigram LM outperformed bigram LM significantly

Thank You

Appendix The Recognizer

Text Line Normalization



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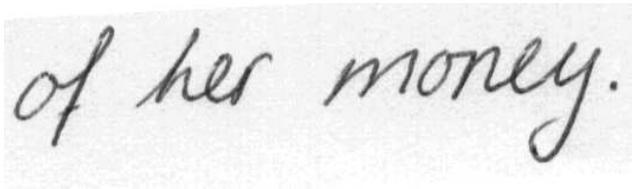
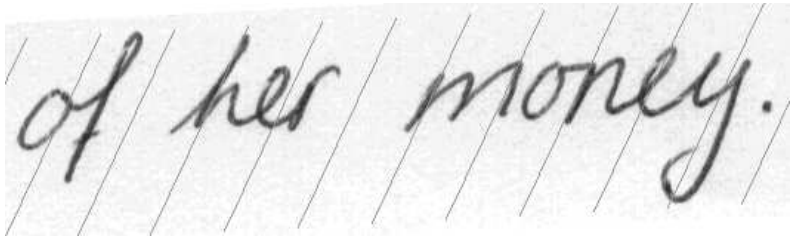


slant estimation



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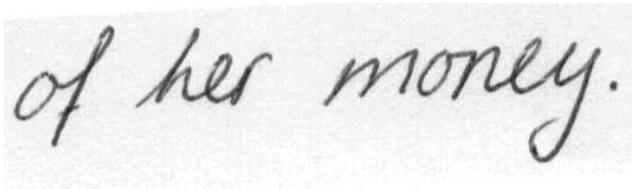

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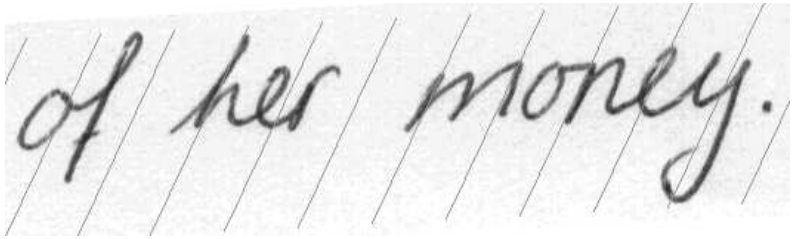
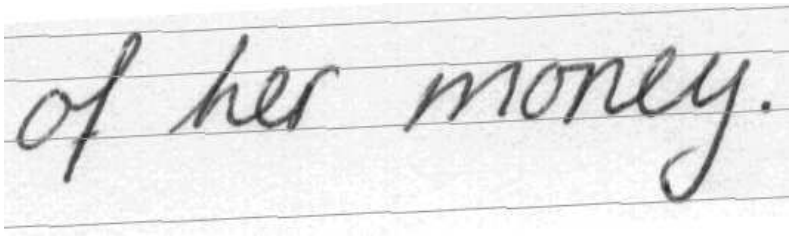


reference line estimation



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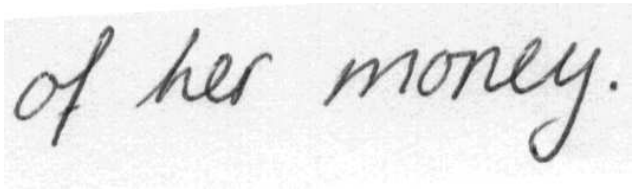

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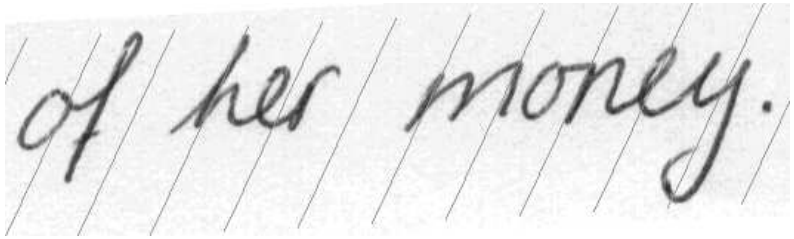

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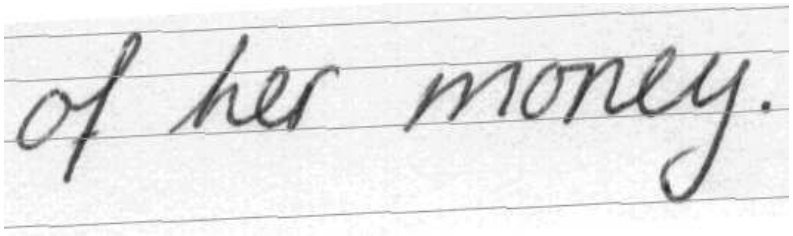
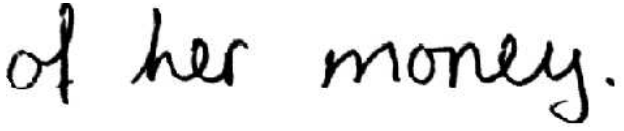


normalized text line



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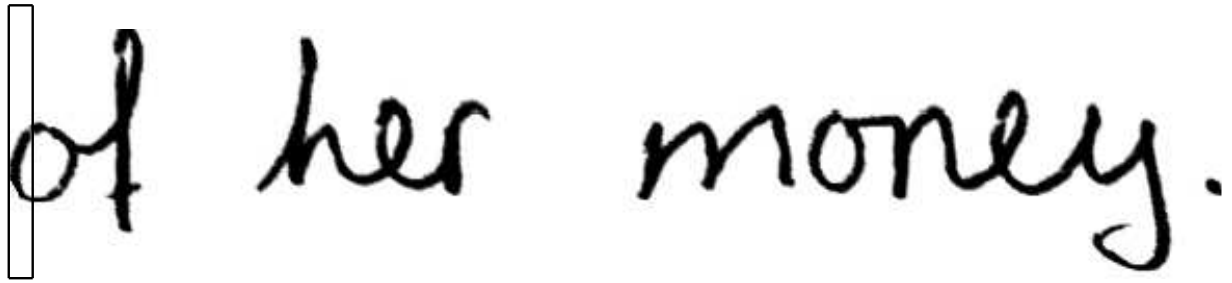
Extraction of the Feature Vector Sequence



$$\downarrow$$

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

$$X = (X_1,$$

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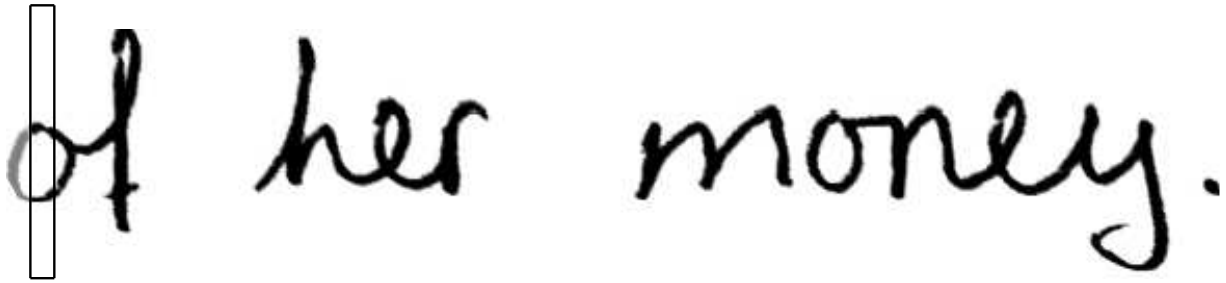

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$$\begin{pmatrix} x_{21} \\ x_{22} \\ \vdots \\ x_{2m} \end{pmatrix}$$

$$X = (X_1, X_2,$$

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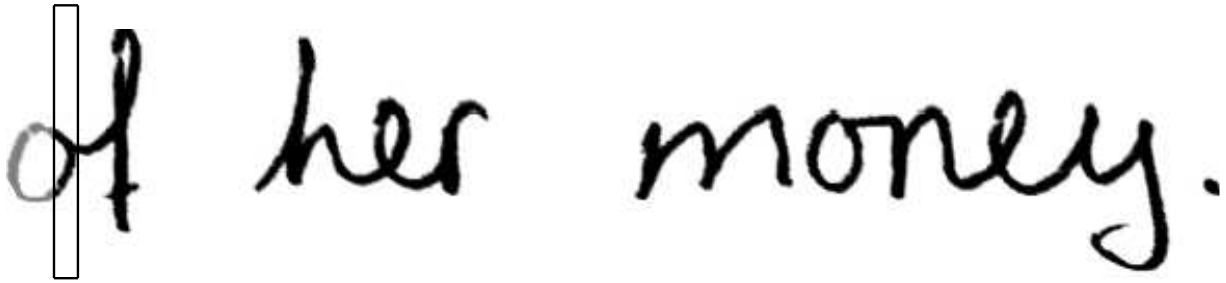

$$\begin{pmatrix} x_{31} \\ x_{32} \\ \vdots \\ x_{3m} \end{pmatrix}$$

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

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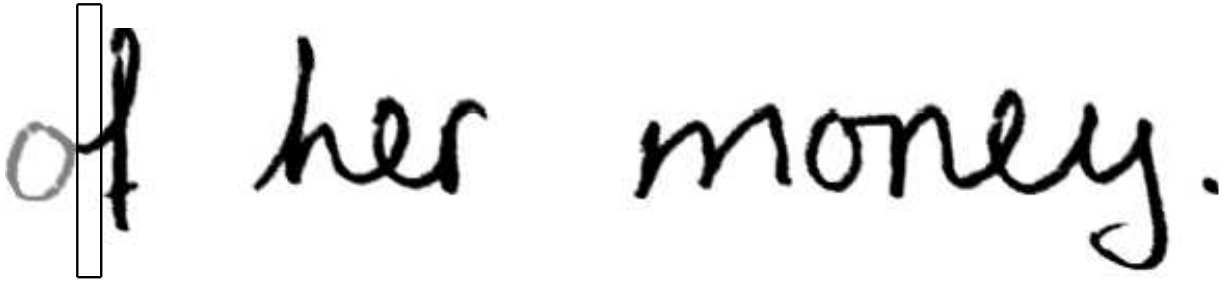
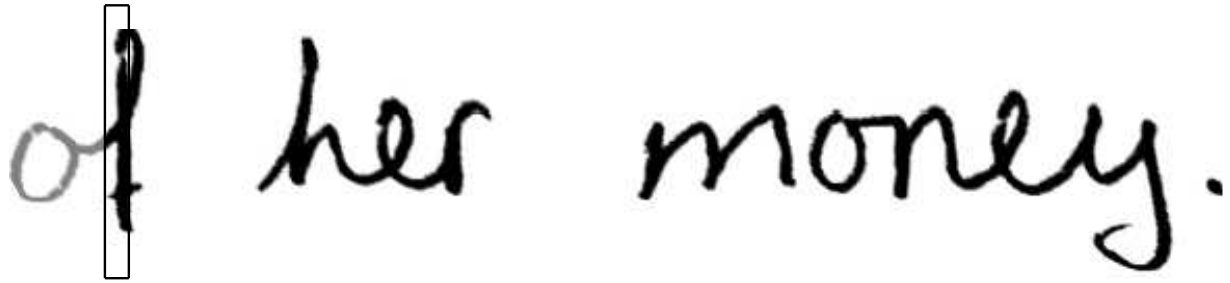


$$\begin{pmatrix} x_{41} \\ x_{42} \\ \vdots \\ x_{4m} \end{pmatrix}$$

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

Appendix The Recognizer

Extraction of the Feature Vector Sequence

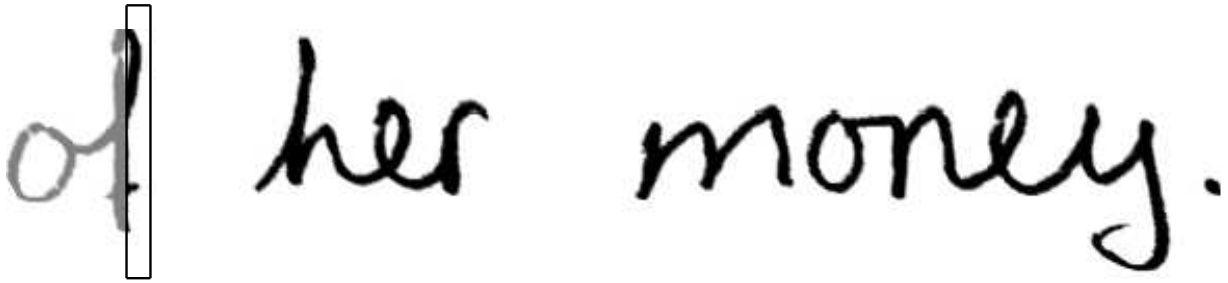


$$\begin{pmatrix} x_{51} \\ x_{52} \\ \vdots \\ x_{5m} \end{pmatrix}$$

$$X = (X_1, X_2, X_3, X_4, X_5,$$

Appendix The Recognizer

Extraction of the Feature Vector Sequence

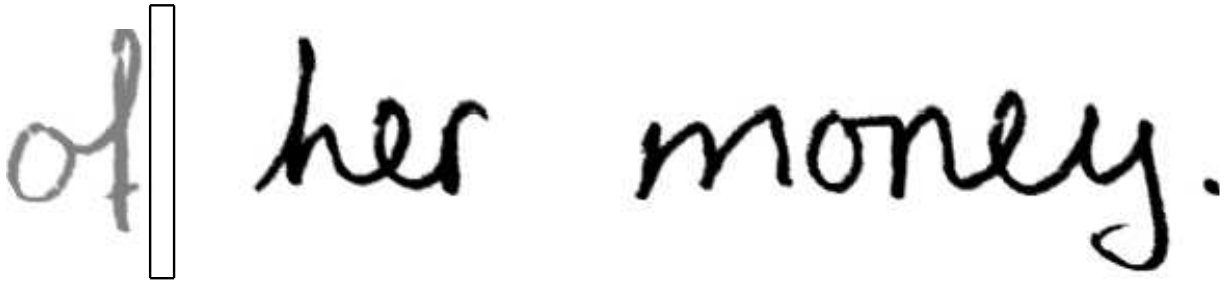


$$\begin{pmatrix} x_{61} \\ x_{62} \\ \vdots \\ x_{6m} \end{pmatrix}$$

$$X = (X_1, X_2, X_3, X_4, X_5, X_6,$$

Appendix The Recognizer

Extraction of the Feature Vector Sequence



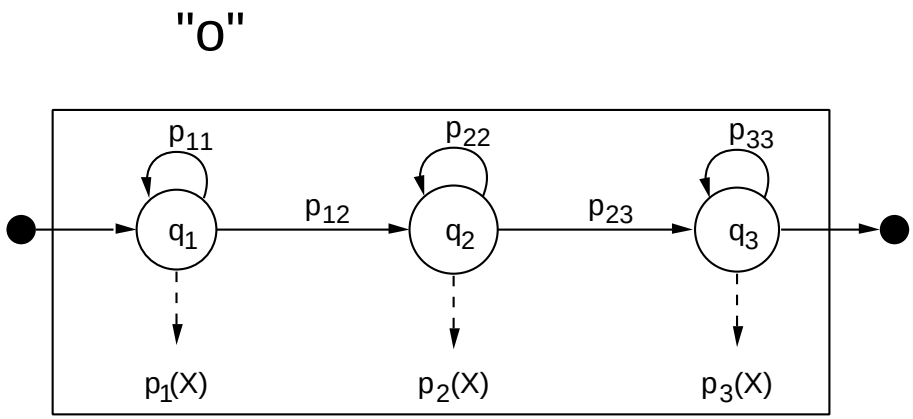
$$\begin{pmatrix} x_{71} \\ x_{72} \\ \vdots \\ x_{7m} \end{pmatrix}$$

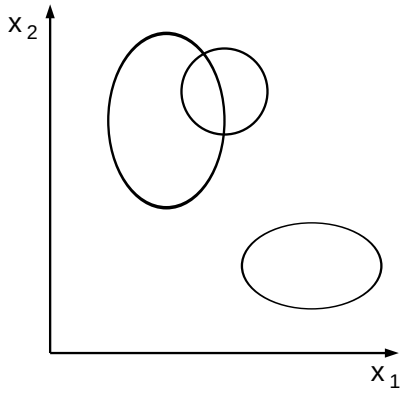
$$X = (X_1, X_2, X_3, X_4, X_5, X_6, X_7, \ldots$$

Appendix The Recognizer

Viterbi Decoding

$$(X_1, X_2, X_3, \ldots$$

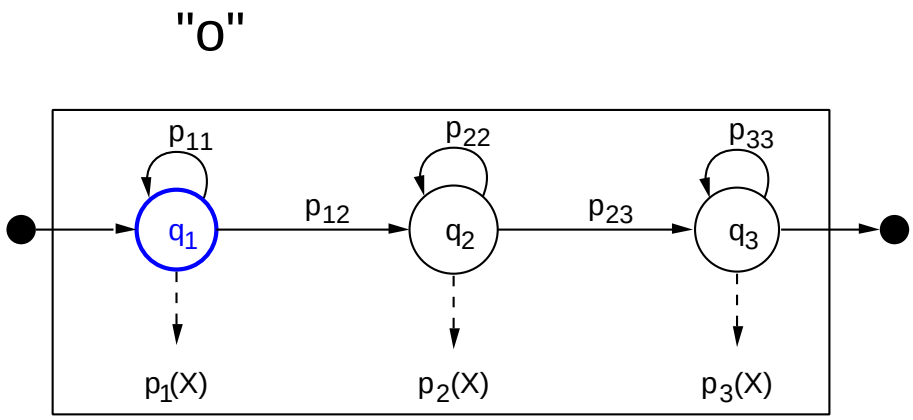


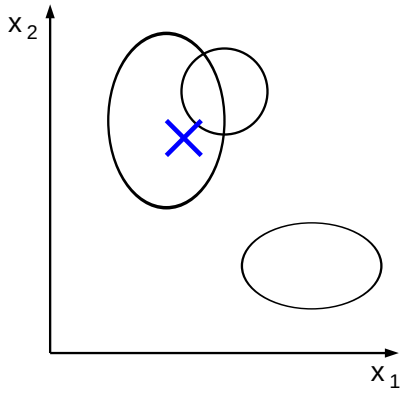


Appendix The Recognizer

Viterbi Decoding

$(X_1, X_2, X_3, \ldots$

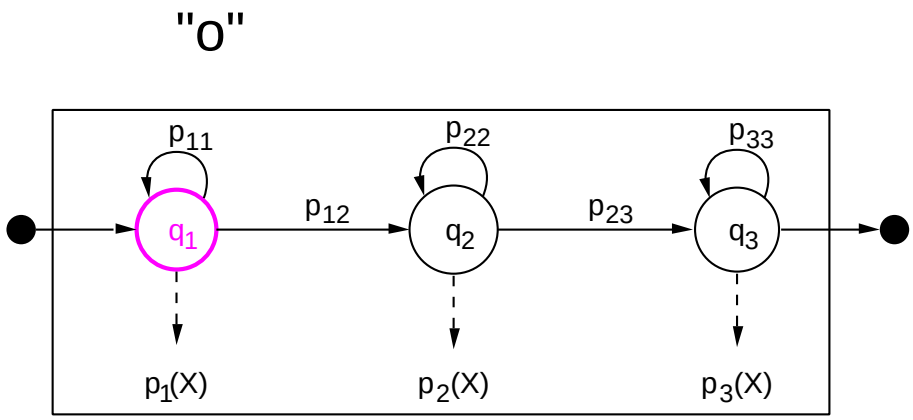


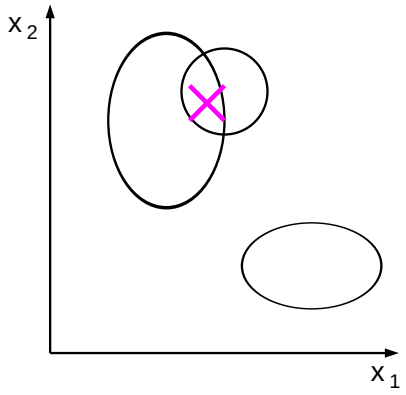


Appendix The Recognizer

Viterbi Decoding

$$(X_1, X_2, X_3, \ldots$$

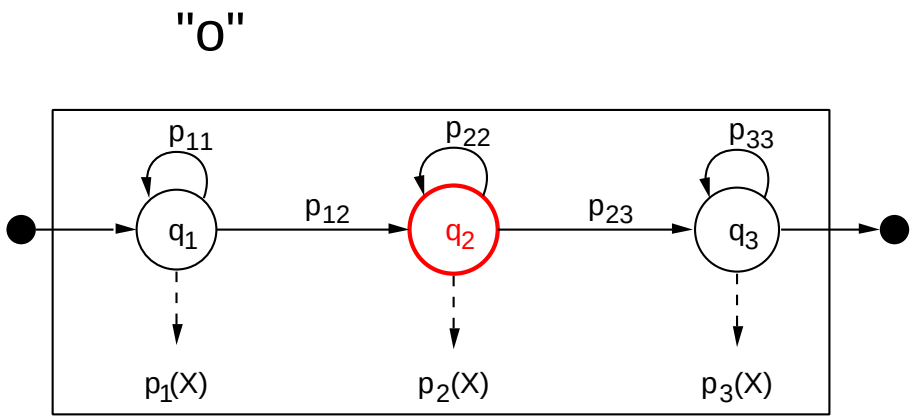


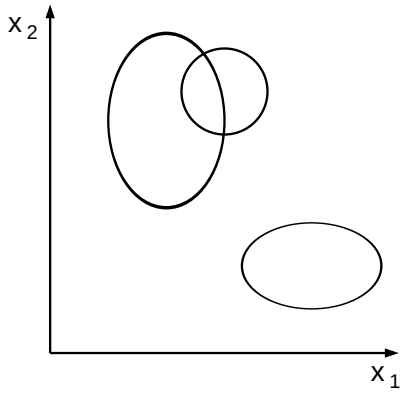


Appendix The Recognizer

Viterbi Decoding

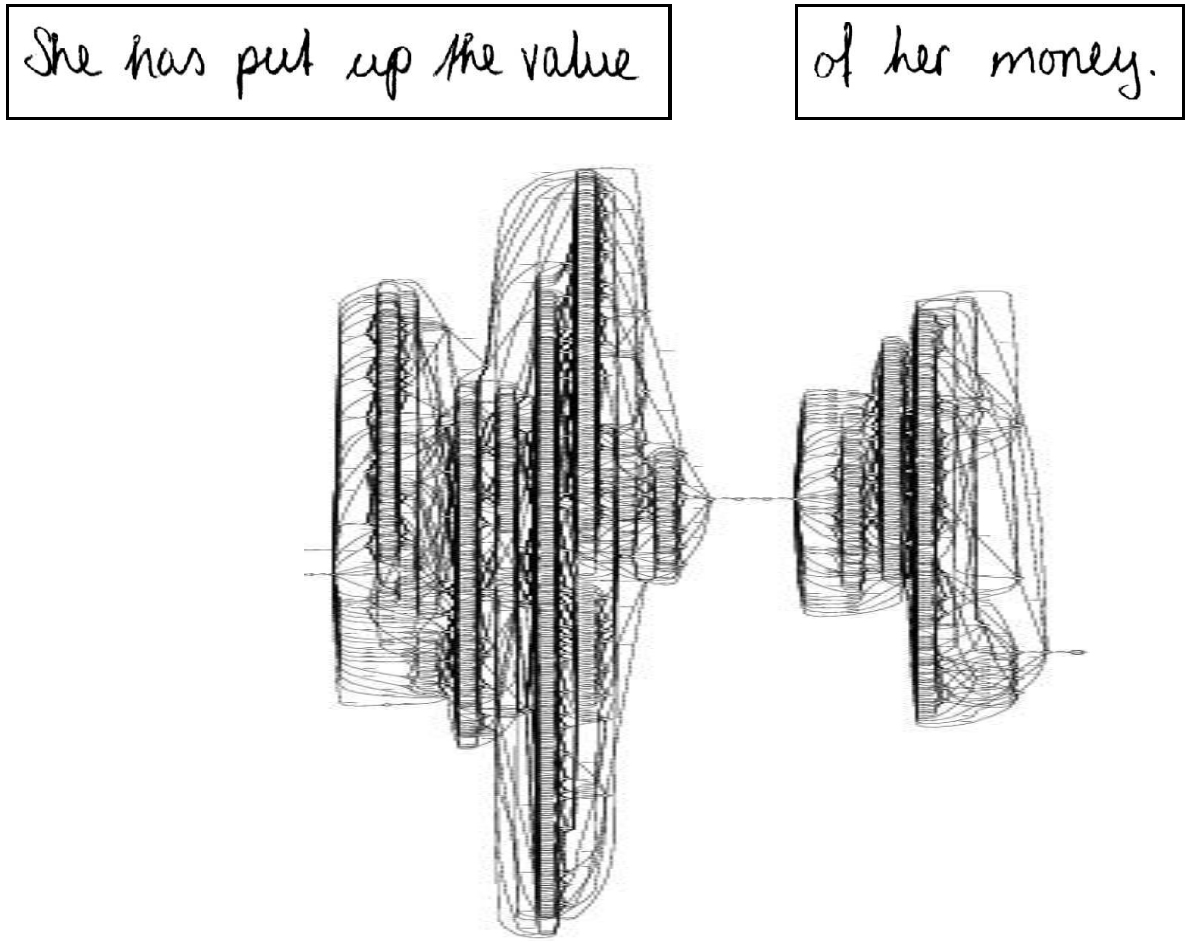
$$(X_1, X_2, X_3, \ldots$$





Appendix The Recognizer

Recognition Lattice Generation



Appendix The Recognizer

Sublattice of 2nd Line