Offline Handwriting Recognition and Grammar based Syntax Analysis

PhD Defense, 13.11.2003

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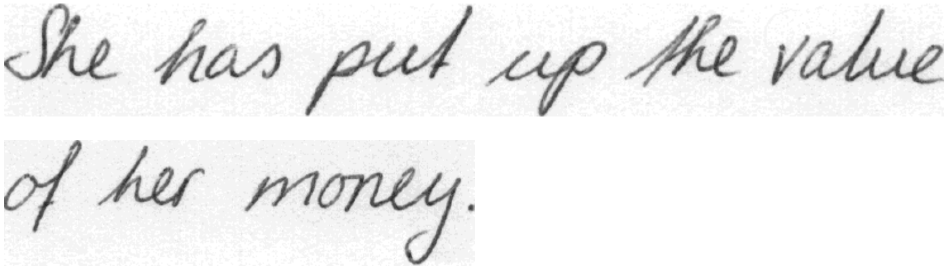
Organization

1. Introduction
2. Problem Statement
3. The Grammar
4. The Parser
5. IAM Database and Recognizer
6. The Combination
7. Setup, Optimization and Evaluation
8. Conclusions and Outlook

Introduction

Perfect Transcription of general Handwritten Text



↓

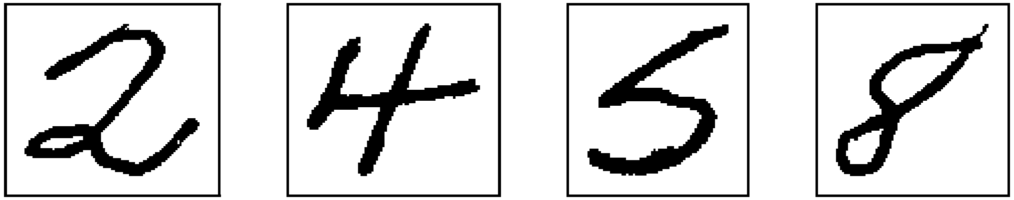
Recognizer

↓

She|has|put|up|the|value|of|her|money|.

Introduction

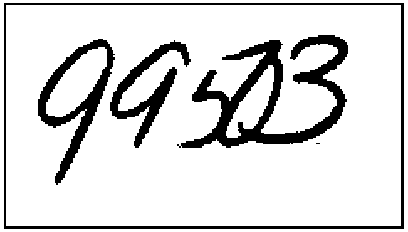
Recognition of Isolated digits

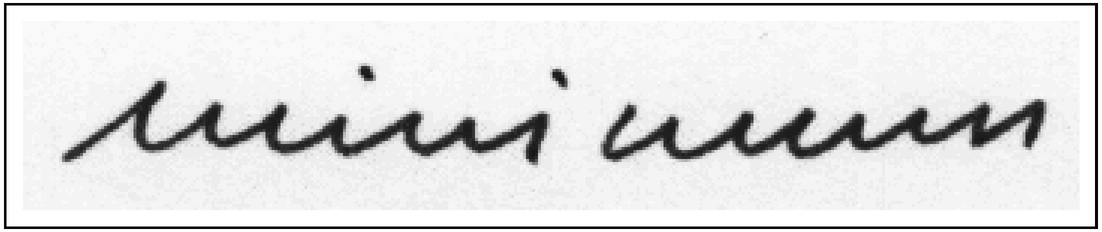


- human like performance, or better
- recognition rates: around 99.5%

Introduction

Recognition of Numbers and Words

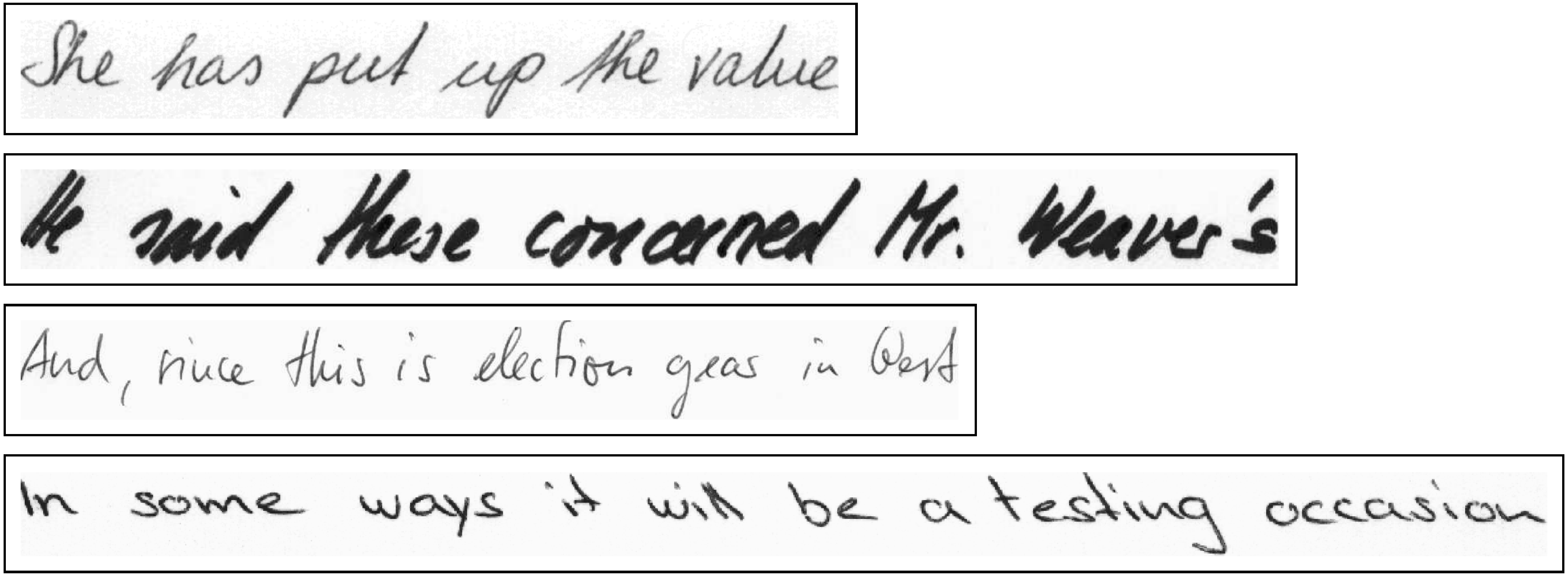




- worse performance than humans
- recognition rates: around 80-90%

Introduction

Recognition of general Text



- significantly worse performance than humans
- recognition rates: around 70%

Introduction

Why is it so difficult?

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- large variation of writing styles

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- variation of writing instruments

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- lack of task-specific knowledge (in contrast to check amounts and postal addresses)

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- large variation of writing styles
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Advantage of humans over computers:

- performance heavily relies on text understanding

Introduction

Why is it so difficult?

- large variation of writing styles
- variation of writing instruments
- segmentation problem
- lack of task-specific knowledge (in contrast to check amounts and postal addresses)

Advantage of humans over computers:

- performance heavily relies on text understanding, combining
  - optical recognition of characters
  - language syntax
  - semantics and "world knowledge"

Introduction

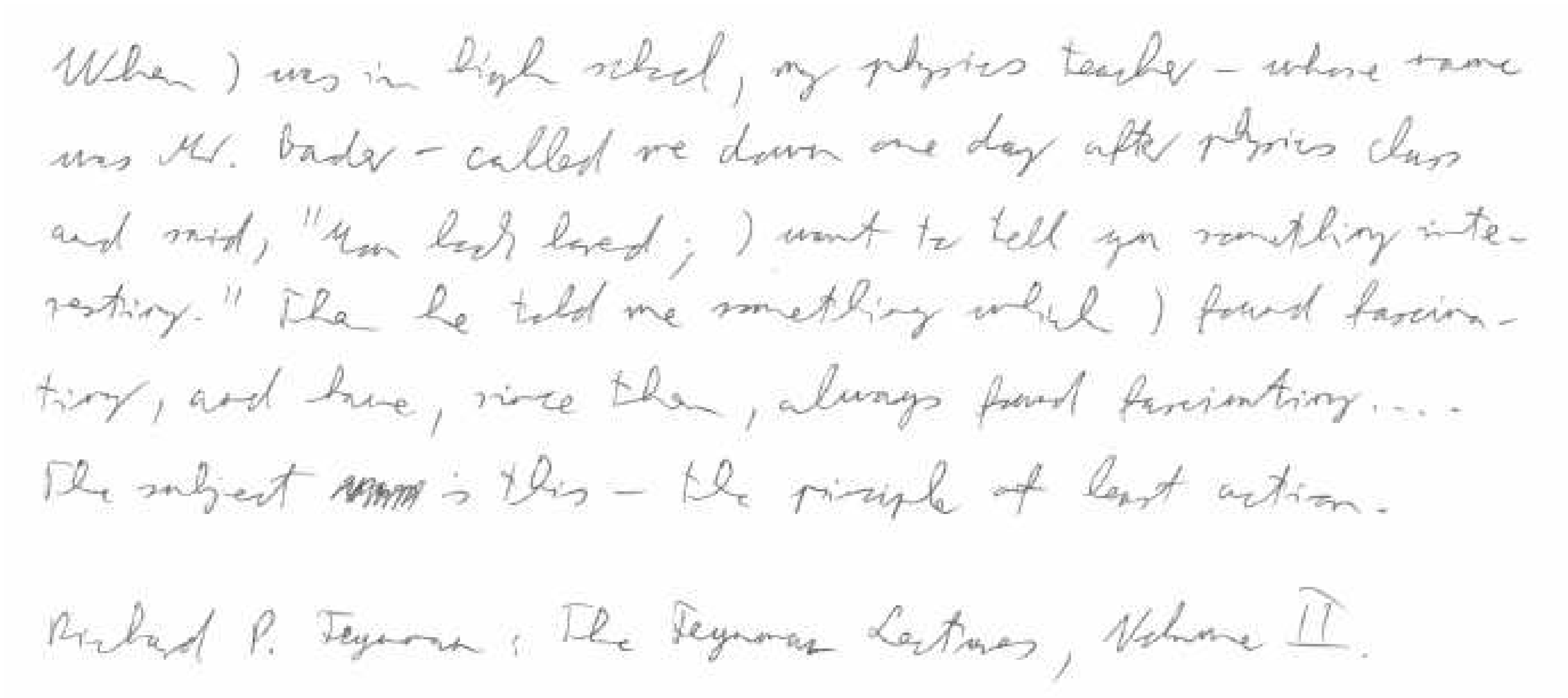
Handwritten Text

When I was in high school, my physics teacher — whose name was Mr. Bader — called me down one day after physics class and said, "You look bored; I want to tell you something interesting." Then he told me something which I found fascinating, and have, since then, always found fascinating.... The subject is this — the principle of least action.

Richard P. Feynman: The Feynman Lectures, Volume II.

Introduction

Handwritten Text (English)

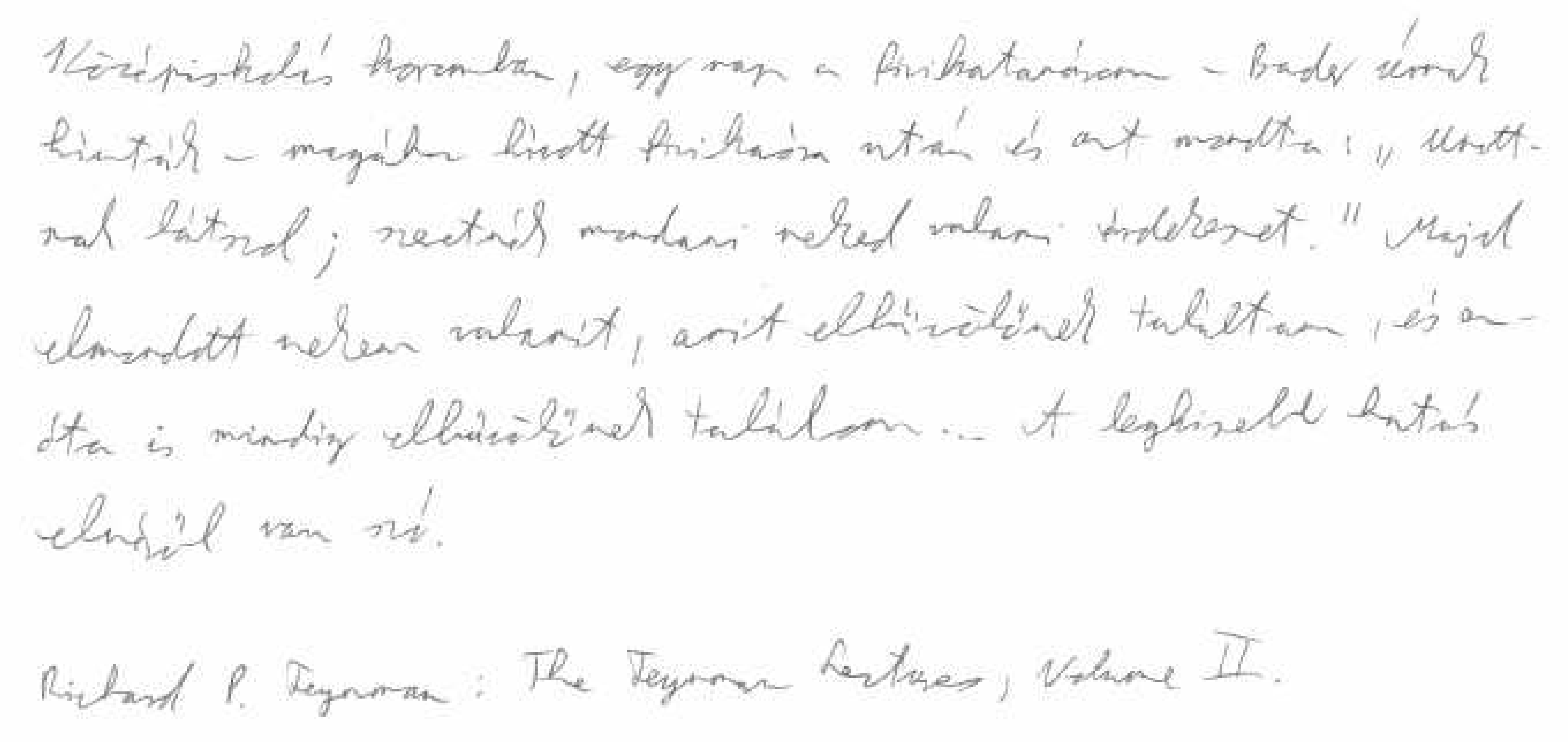

When I was in high school, my physics teacher – whose name was Mr. Bader – called me down one day after physics class and said, "You look bored; I want to tell you something interesting." Then he told me something which I found fascinating, and have, since then, always found fascinating.... The subject is this – the principle of least action.

Richard P. Feynman: The Feynman Lectures, Volume II.

- human performance 100% (character level)

Introduction

Handwritten Text

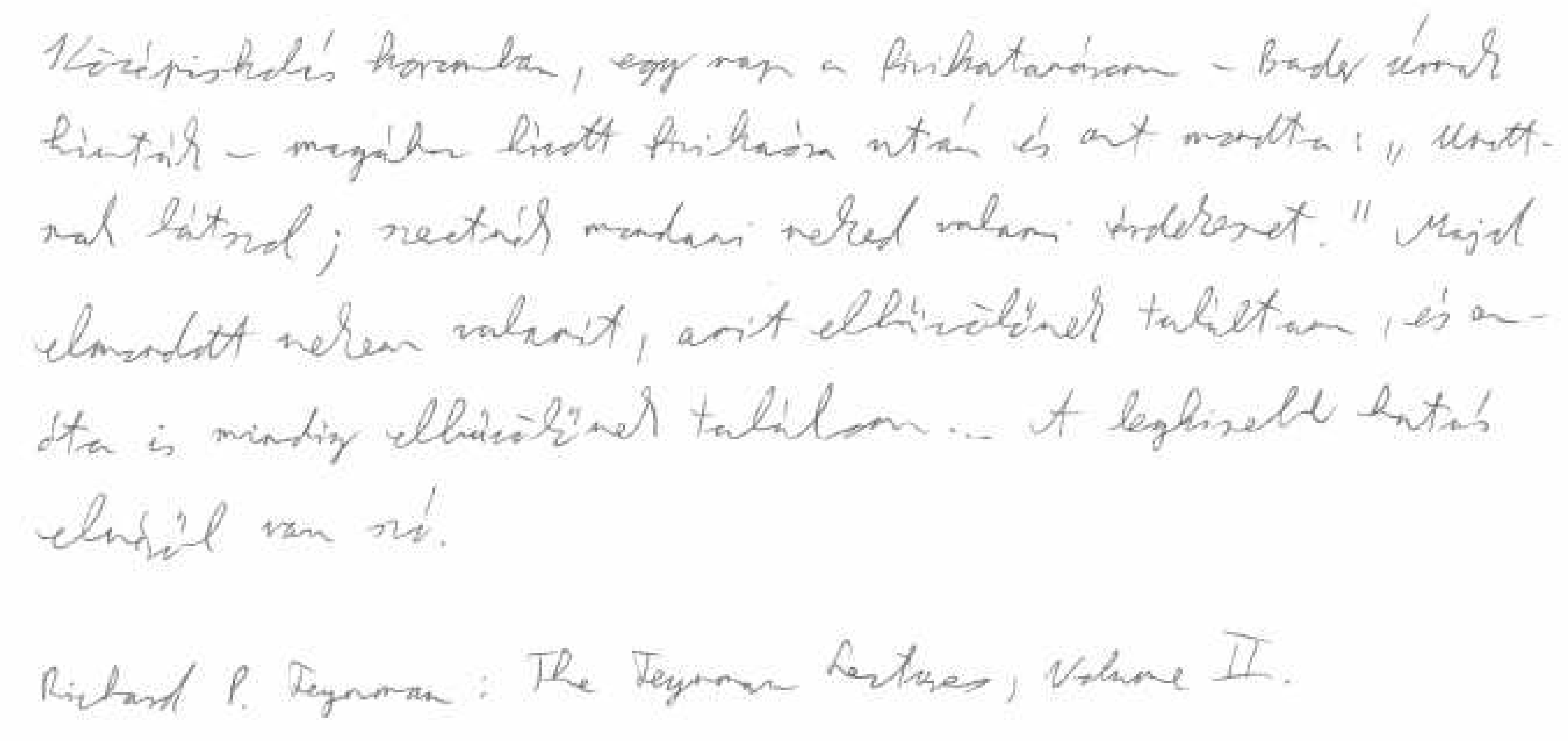


Középiskolás koromban, egy nap a fizikatanárom – Bader úrnak hívták – magához hívott fizikaóra után és azt mondta: „Unott-
nak látszol; mesélek neked valami érdekeset." Majd
elmondott nekem valamit, amit elbűvölőnek találtam, és az-
óta is mindig elbűvölőnek találom... A legkisebb hatás
elvéről van szó.

Richard P. Feynman: The Feynman Lectures, Volume II.

Introduction

Handwritten Text (Magyar)



- human performance 70% (character level, no understanding)

Introduction

Observations

- performance of current systems far from perfect

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- computers can compete on the character level

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  - syntax of the language
  - semantics and "world knowledge"

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  - semantics and "world knowledge"
- formal descriptions of semantics are missing, but

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- performance of current systems far from perfect
- computers can compete on the character level
- text understanding is responsible for high recognition rates
- humans can combine optical recognition with
  - syntax of the language
  - semantics and "world knowledge"
- formal descriptions of semantics are missing, but
- syntax analysis could help to boost recognition rates

Introduction

Syntax Analysis

- formal descriptions of language syntax (Chomsky 1956)

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- formal grammars most frequently used to specify
  - programming languages
  - communication protocols

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- special programs (parsers) help to
  - check syntactical correctness
  - analyze syntactical structure

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Syntax Analysis

- formal descriptions of language syntax (Chomsky 1956)
- formal grammars most frequently used to specify
  - programming languages
  - communication protocols
- special programs (parsers) help to
  - check syntactical correctness
  - analyze syntactical structure
- more recently, formal grammars for natural languages
  - Susanne corpus (1992)
  - Penn treebank (1993)
  - Lancaster parsed corpus (1995)

Introduction

Lancaster Parsed Corpus

- covers a variety of 15 text categories:
  - press: reportage
  - press: editorial
  - religion
  - general fiction
  - romance
  - humor
  - …

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- contains 12,000 parsed English sentences

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  - general fiction
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  - humor
  - ...
- contains 12,000 parsed English sentences
- parse trees as bracketed sentences

Introduction

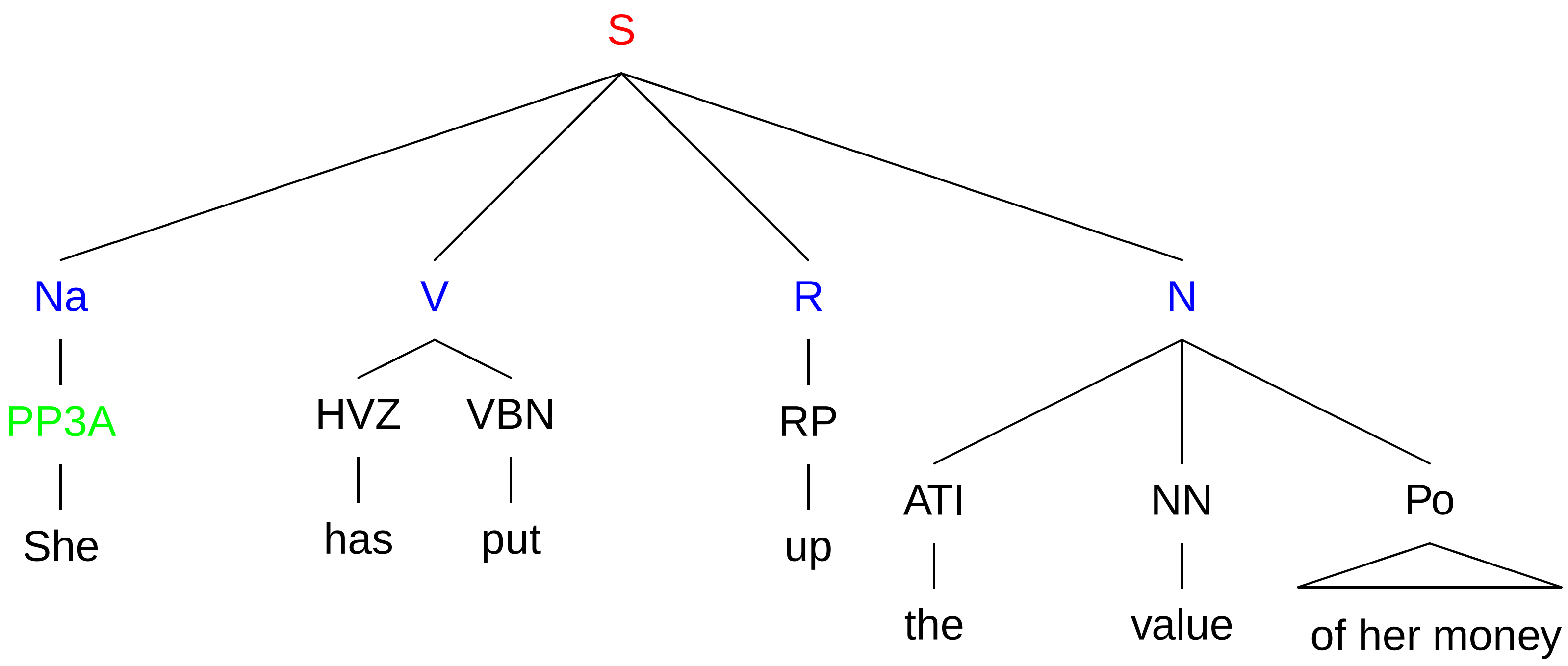
A Bracketed Sentence

$[S\ [Na\ [PP3A$ She $]][V\ [HVZ$ has $][VBN$ put $]][R\ [RP$ up $]][N\ [ATI$ the $][NN$ value $][Po\ [INO$ of $][N\ [PP\$$ her $][NN$ money $]]]]]$

S	independent sentence
Na	noun phrase (subject of verb)
PP3A	personal pronoun, 3rd pers. singular nom
V	verb phrase
R	adverb phrase
N	noun phrase

Introduction

The Parse Tree



Problem Statement

Find Answers to the following Questions:

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- what type of grammar should be used?

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- how shoud syntax anlaysis and text recognition be combined?

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- what type of grammar should be used?
- how shoud syntax anlaysis and text recognition be combined?
- can syntax analysis help handwriting recognition?

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The Grammar

What Type of Grammar should be used?

requirements:

The Grammar

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requirements:

- acceptable computational complexity

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- support of ranking a candidate list (provided by the recognizer)

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- powerful description of syntax
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- available linguistic resources

The Grammar

What Type of Grammar should be used?

requirements:

- acceptable computational complexity
- powerful description of syntax
- support of ranking a candidate list (provided by the recognizer)
- available linguistic resources

therefore:

- Stochastic Context-Free Grammars (SCFG)

The Grammar

Why SCFG?

The Grammar

Why SCFG?

- SCFG offer a compromise between
  - computational complexity
  - description power of syntax

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- SCFG can be extracted from available resources

The Grammar

Why SCFG?

- SCFG offer a compromise between
  - computational complexity
  - description power of syntax
- compatible linguistic resources exist
- SCFG can be extracted from available resources
- SCFG allow candidate ranking

The Grammar

An Example

$$\begin{array}{lll l} S & \longrightarrow & A\ B & (0.8) \\ S & \longrightarrow & A\ S\ B & (0.2) \\ A & \longrightarrow & a & (1.0) \\ B & \longrightarrow & b & (1.0) \end{array}$$

The Grammar

An Example

S	$\longrightarrow$	A B	(0.8)
S	$\longrightarrow$	A S B	(0.2)
A	$\longrightarrow$	a	(1.0)
B	$\longrightarrow$	b	(1.0)

nonterminal symbols: S,A,B

The Grammar

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S	$\longrightarrow$	A B	(0.8)
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productions or rules:	see left
rule probabilities:	see left

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sentence generation

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sentence generation

S

$[S\ \ ]$ (1.0)

The Grammar

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rule probabilities:	see left

sentence generation

S $\stackrel{0.2}{\longrightarrow}$ ASB

$[S\ [A\ ][S\ ][B\ ]\ ]$ (0.2)

The Grammar

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sentence generation

$$\text{S} \stackrel{0.2}{\longrightarrow} \text{ASB} \stackrel{0.8}{\longrightarrow} \text{AABB}$$

$$[S\ [A\ ][S\ [A\ ][B\ ]\ ][B\ ]]$$ (0.16)

The Grammar

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nonterminal symbols:	S,A,B
terminal symbols (words):	a,b
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sentence generation

S $\stackrel{0.2}{\rightarrow}$ ASB $\stackrel{0.8}{\rightarrow}$ AABB $\stackrel{1.0}{\rightarrow}$ aABB

$[S\ [A\ \text{a}\ ][S\ [A\ ][B\ ]][B\ ]]$ (0.16)

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$[S\ [A\ \text{a}\ ][S\ [A\ \text{a}\ ][B\ \ ]][B\ \ ]]$ (0.16)

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sentence generation

$$\text{S} \stackrel{0.2}{\longrightarrow} \text{ASB} \stackrel{0.8}{\longrightarrow} \text{AABB} \stackrel{1.0}{\longrightarrow} \text{aABB} \stackrel{1.0}{\longrightarrow} \text{aaBB} \longrightarrow \ldots \longrightarrow \text{aabb}$$

$$[S\ [A\ \text{a}\ ][S\ [A\ \text{a}\ ][B\ \text{b}\ ]][B\ \text{b}\ ]] \quad (0.16)$$

sentence complete, no more nonterminal symbols to expand

The Grammar

An Example, continued

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syntax analysis

The Grammar

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aabb correct syntax, sentence probability 0.16

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rules or productions:	see left
rule probabilities:	see left

syntax analysis

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ab

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aabb	correct syntax, sentence probability 0.16
ab	correct syntax, sentence probability 0.8

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aab	

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syntax analysis

aabb	correct syntax, sentence probability 0.16
ab	correct syntax, sentence probability 0.8
aab	syntax not correct, cannot be produced by grammar

The Grammar

Extraction of Rules from Bracketed Sentences

$[S$ $[Na$ $[PP3A$ She $]]$$[V$ $[HVZ$ has $]$$[VBN$ put $]]$$[R$ $[RP$ up $]]$$[N$ $[ATI$ the $]$$[NN$ value $]$$[Po$ $[INO$ of $]$$[N$ $[PP\$$ her $]$$[NN$ money $]]]]]$

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Extraction of Rules from Bracketed Sentences

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S $\longrightarrow$ Na V R N

The Grammar

Extraction of Rules from Bracketed Sentences

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S	$\longrightarrow$	Na V R N
Na	$\longrightarrow$	PP3A

The Grammar

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$[S\ [Na\ [PP3A$ She $]][V\ [HVZ$ has $][VBN$ put $]][R\ [RP$ up $]][N\ [ATI$ the $][NN$ value $][Po\ [INO$ of $][N\ [PP\$$ her $][NN$ money $]]]]]$

S	$\longrightarrow$	Na V R N
Na	$\longrightarrow$	PP3A
PP3A	$\longrightarrow$	She

The Grammar

Extraction of Rules from Bracketed Sentences

$[S\ [Na\ [PP3A$ She $]][V\ [HVZ$ has $][VBN$ put $]][R\ [RP$ up $]][N$ $[ATI$ the $][NN$ value $][Po\ [INO$ of $][N\ [PP\$$ her $][NN$ money $]]]]]$

S	$\longrightarrow$	Na V R N
Na	$\longrightarrow$	PP3A
PP3A	$\longrightarrow$	She
V	$\longrightarrow$	HVZ VBN

The Grammar

Extraction of Rules from Bracketed Sentences

$[S\ [Na\ [PP3A$ She $]][V\ [HVZ$ has $][VBN$ put $]][R\ [RP$ up $]][N$
$[ATI$ the $][NN$ value $][Po\ [INO$ of $][N\ [PP\$$ her $][NN$ money $]]]]]$

S	$\longrightarrow$	Na V R N
Na	$\longrightarrow$	PP3A
PP3A	$\longrightarrow$	She
V	$\longrightarrow$	HVZ VBN
HVZ	$\longrightarrow$	has
VBN	$\longrightarrow$	put
...		

The Grammar

Extraction of Rules from Bracketed Sentences

$[S\ [Na\ [PP3A$ She $]][V\ [HVZ$ has $][VBN$ put $]][R\ [RP$ up $]][N$ $[ATI$ the $][NN$ value $][Po\ [INO$ of $][N\ [PP\$$ her $][NN$ money $]]]]]$

	S	$\longrightarrow$	Na V R N
	Na	$\longrightarrow$	PP3A
lexical	PP3A	$\longrightarrow$	She
	V	$\longrightarrow$	HVZ VBN
lexical	HVZ	$\longrightarrow$	has
lexical	VBN	$\longrightarrow$	put
	...		

The Grammar

Extraction of Symbols

The Grammar

Extraction of Symbols

- start symbol

The Grammar

Extraction of Symbols

- start symbol (top level symbol)
  - S

The Grammar

Extraction of Symbols

- start symbol (top level symbol)
  - S
- nonterminal symbols

The Grammar

Extraction of Symbols

- start symbol (top level symbol)
  - S
- nonterminal symbols (constituent tags, LHS of non-lexical rules)
  - Na
  - V

The Grammar

Extraction of Symbols

- start symbol (top level symbol)
  - S
- nonterminal symbols (constituent tags, LHS of non-lexical rules)
  - Na
  - V
- preterminal symbols

The Grammar

Extraction of Symbols

- start symbol (top level symbol)
  - S
- nonterminal symbols (constituent tags, LHS of non-lexical rules)
  - Na
  - V
- preterminal symbols (word tags, LHS of lexical rules)
  - PP3A
  - HVZ

The Grammar

Extraction of Symbols

- start symbol (top level symbol)
  - S
- nonterminal symbols (constituent tags, LHS of non-lexical rules)
  - Na
  - V
- preterminal symbols (word tags, LHS of lexical rules)
  - PP3A
  - HVZ
- terminal symbols

The Grammar

Extraction of Symbols

- start symbol (top level symbol)
  - S
- nonterminal symbols (constituent tags, LHS of non-lexical rules)
  - Na
  - V
- preterminal symbols (word tags, LHS of lexical rules)
  - PP3A
  - HVZ
- terminal symbols (words, RHS of lexical rules)
  - She
  - has

The Grammar

Assignment of Probabilities

A	$\rightarrow$	α
V	$\rightarrow$	VBD
V	$\rightarrow$	HVZ VBN
V	$\rightarrow$	HVZ XNOT VBN

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

The Grammar

Assignment of Probabilities

A	$\rightarrow$	α	$N(A \rightarrow \alpha)$
V	$\rightarrow$	VBD	4,578
V	$\rightarrow$	HVZ VBN	130
V	$\rightarrow$	HVZ XNOT VBN	5

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

- count number of occurances of each production

The Grammar

Assignment of Probabilities

A	$\rightarrow$	α	$N(A \rightarrow \alpha)$	$\sum N(A \rightarrow \beta)$	$p(A \rightarrow \alpha)$
V	$\rightarrow$	VBD	4,578	16,158	0.2833
V	$\rightarrow$	HVZ VBN	130	16,158	0.0081
V	$\rightarrow$	HVZ XNOT VBN	5	16,158	0.0003

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

- count number of occurances of each production
- normalize counts by the LHS

The Parser

Task of the Parser

She|has|put|up|the|value|of|her|money|.

$\downarrow$

SCFG $\longrightarrow$ Parser

$\downarrow$

most probable parse:

7.691e-23 $[S\ [Na\ [PP3A$ She . . .

The Parser

Which Parser?

The Parser

Which Parser?

- CYK Parser (Younger ’67)

The Parser

Which Parser?

- CYK Parser (Younger '67)
- Early Parser (Early '80)

The Parser

Which Parser?

- CYK Parser (Younger ’67)
- Early Parser (Early ’80)
- Prob. Eearly Parser (Stolcke ’94)

The Parser

Which Parser?

- CYK Parser (Younger '67)
- Early Parser (Early '80)
- Prob. Eearly Parser (Stolcke '94)
- CYK+ Parser (Chappelier & Rajman '98)

The Parser

Which Parser?

- CYK Parser (Younger '67)
- Early Parser (Early '80)
- Prob. Eearly Parser (Stolcke '94)
- CYK+ Parser (Chappelier & Rajman '98)
- ...

The Parser

The CYK+ Parser

the cat ate the mouse

S	$\longrightarrow$	NP VP(1.0)
VP	$\longrightarrow$	V(0.3)|V NP(0.7)
NP	$\longrightarrow$	Det N(1.0)
Det	$\longrightarrow$	the(1.0)
N	$\longrightarrow$	cat(0.5)|mouse(0.5)
V	$\longrightarrow$	ate(1.0)

The Parser

The CYK+ Parser

active rule: Det $\longrightarrow$ the

the	cat	ate	the	mouse
Det				

$$
\begin{aligned}
S &\longrightarrow NP\ VP(1.0) \\
VP &\longrightarrow V(0.3) | V\ NP(0.7) \\
NP &\longrightarrow Det\ N(1.0) \\
Det &\longrightarrow the(1.0) \\
N &\longrightarrow cat(0.5) | mouse(0.5) \\
V &\longrightarrow ate(1.0)
\end{aligned}
$$

The Parser

The CYK+ Parser

active rule: NP $\longrightarrow$Det $\bullet$ N

the cat ate the mouse

Det

Det$\bullet$

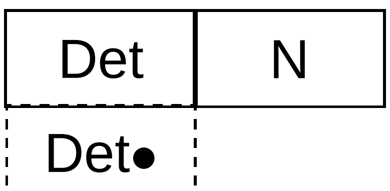
S	$\longrightarrow$	NP VP(1.0)
VP	$\longrightarrow$	V(0.3)|V NP(0.7)
NP	$\longrightarrow$	Det N(1.0)
Det	$\longrightarrow$	the(1.0)
N	$\longrightarrow$	cat(0.5)|mouse(0.5)
V	$\longrightarrow$	ate(1.0)

The Parser

The CYK+ Parser

active rule: N →cat

the cat ate the mouse



S → NP VP(1.0)

VP → V(0.3)|V NP(0.7)

NP → Det N(1.0)

Det → the(1.0)

N → cat(0.5)|mouse(0.5)

V → ate(1.0)

The Parser

The CYK+ Parser

active rule:

the cat ate the mouse

Det	N
Det●	

$S \longrightarrow$ NP VP(1.0)

$VP \longrightarrow$ V(0.3)|V NP(0.7)

$NP \longrightarrow$ Det N(1.0)

$Det \longrightarrow$ the(1.0)

$N \longrightarrow$ cat(0.5)|mouse(0.5)

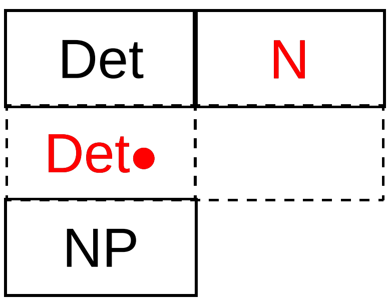
$V \longrightarrow$ ate(1.0)

The Parser

The CYK+ Parser

active rule: NP $\longrightarrow$ Det N

the cat ate the mouse



S	$\longrightarrow$	NP VP(1.0)
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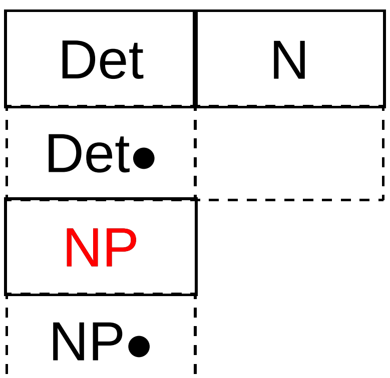
NP	$\longrightarrow$	Det N(1.0)
Det	$\longrightarrow$	the(1.0)
N	$\longrightarrow$	cat(0.5)|mouse(0.5)
V	$\longrightarrow$	ate(1.0)

The Parser

The CYK+ Parser

active rule: S $\longrightarrow$ NP • VP

the cat ate the mouse



S $\longrightarrow$ NP VP(1.0)

VP $\longrightarrow$ V(0.3)|V NP(0.7)

NP $\longrightarrow$ Det N(1.0)

Det $\longrightarrow$ the(1.0)

N $\longrightarrow$ cat(0.5)|mouse(0.5)

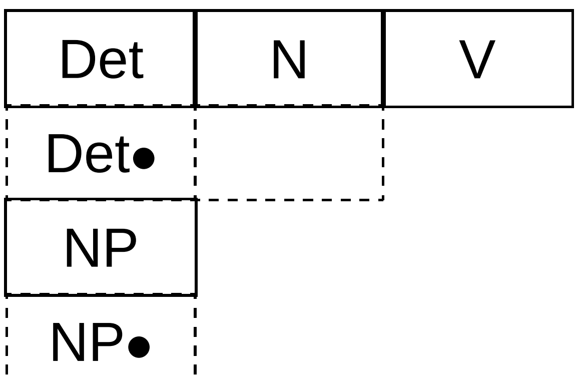
V $\longrightarrow$ ate(1.0)

The Parser

The CYK+ Parser

active rule: V $\rightarrow$ate

the cat ate the mouse



S $\longrightarrow$ NP VP(1.0)

VP $\longrightarrow$ V(0.3)|V NP(0.7)

NP $\longrightarrow$ Det N(1.0)

Det $\longrightarrow$ the(1.0)

N $\longrightarrow$ cat(0.5)|mouse(0.5)

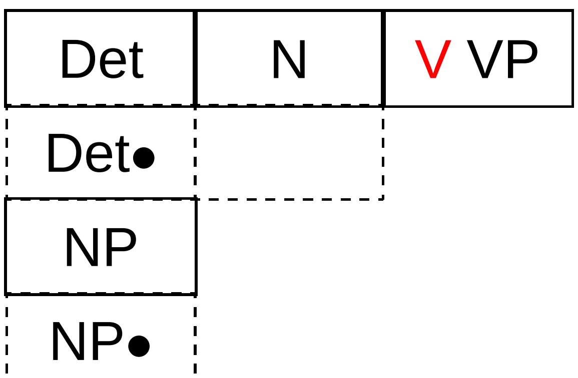
V $\longrightarrow$ ate(1.0)

The Parser

The CYK+ Parser

active rule: VP $\longrightarrow$ V

the cat ate the mouse



S	$\longrightarrow$	NP VP(1.0)
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V	$\longrightarrow$	ate(1.0)

The Parser

The CYK+ Parser

active rule: VP $\longrightarrow$ V • NP

the cat ate the mouse

Det	N	V VP
Det•		V•
NP		
NP•		

S $\longrightarrow$ NP VP(1.0)

VP $\longrightarrow$ V(0.3)|V NP(0.7)

NP $\longrightarrow$ Det N(1.0)

Det $\longrightarrow$ the(1.0)

N $\longrightarrow$ cat(0.5)|mouse(0.5)

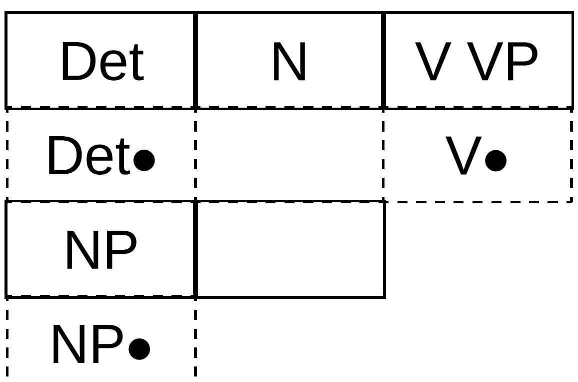
V $\longrightarrow$ ate(1.0)

The Parser

The CYK+ Parser

active rule:

the cat ate the mouse



S $\rightarrow$ NP VP(1.0)

VP $\rightarrow$ V(0.3)|V NP(0.7)

NP $\rightarrow$ Det N(1.0)

Det $\rightarrow$ the(1.0)

N $\rightarrow$ cat(0.5)|mouse(0.5)

V $\rightarrow$ ate(1.0)

The Parser

The CYK+ Parser

active rule:

the	cat	ate	the	mouse
Det	N	V VP		
Det•		V•		
NP				
NP•				

$S \longrightarrow$ NP VP(1.0)

$VP \longrightarrow$ V(0.3)|V NP(0.7)

$NP \longrightarrow$ Det N(1.0)

$Det \longrightarrow$ the(1.0)

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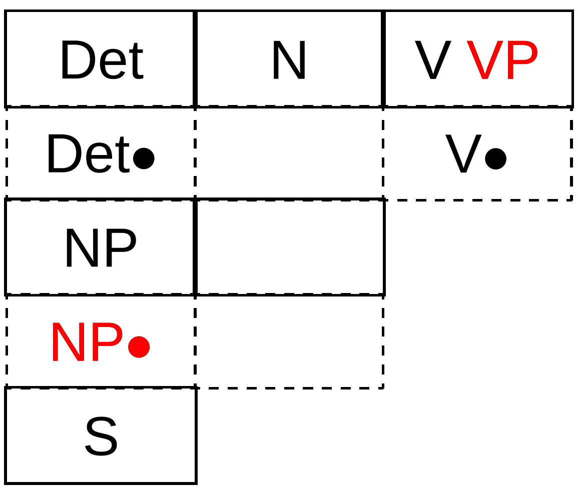
$V \longrightarrow$ ate(1.0)

The Parser

The CYK+ Parser

active rule: S →NP VP

the cat ate the mouse



S → NP VP(1.0)
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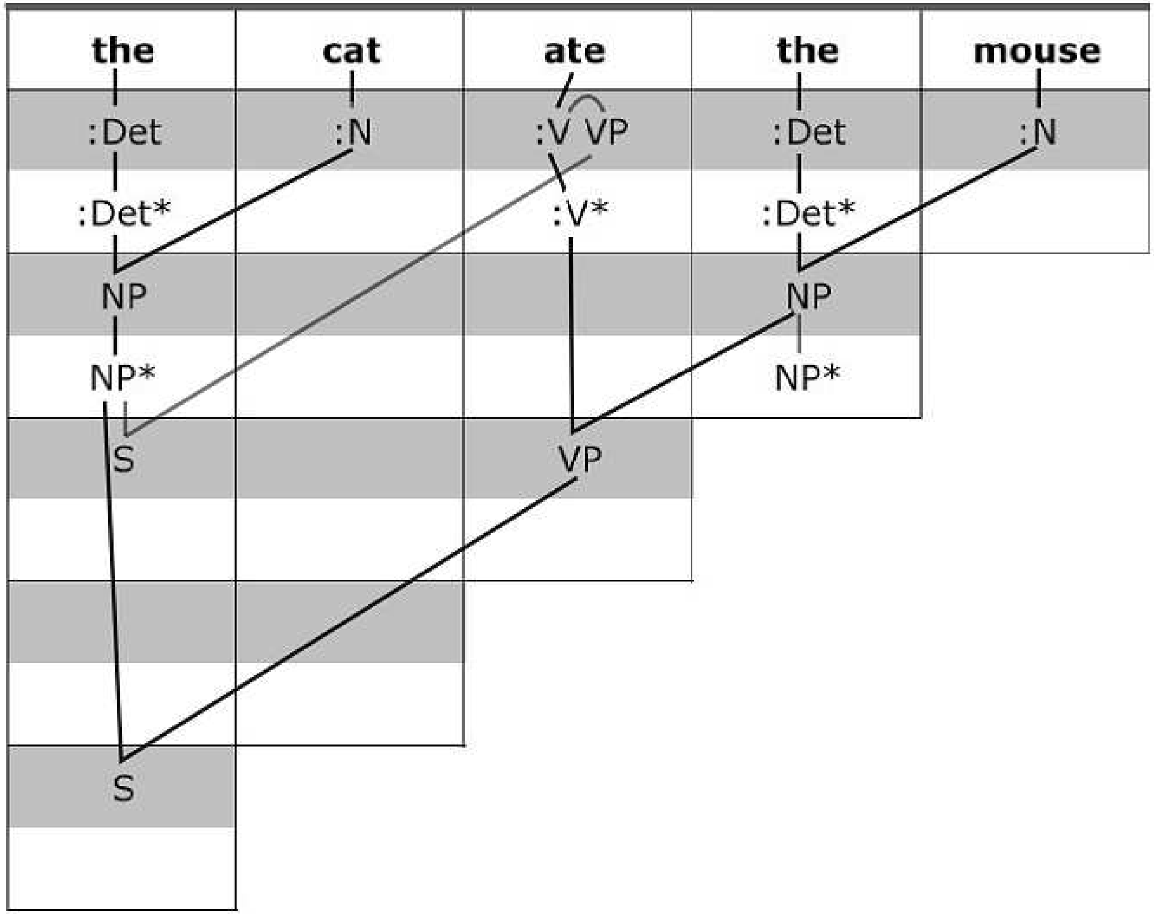
NP → Det N(1.0)
Det → the(1.0)
N → cat(0.5)|mouse(0.5)
V → ate(1.0)

The Parser

Complete Parse Chart



The Parser

Computing the Most Probable Parse

initialization (1st row of chart)

- assign probs of lexial rules to elements in closed list

new elements

- multiply probs of rule with probs of elements
- assign product to new element

existing elements

- multiply probs of rule with probs of elements
- if new prob is higher assign new prob and change back pointers

Organization

1. Introduction
2. Problem Statement
3. The Grammar
4. The Parser
5. IAM Database and Recognizer
6. The Combination
7. Setup, Optimization and Evaluation
8. Conclusions and Outlook

The IAM Database

Current State

- more than 1,500 scanned pages of handwritten text

The IAM Database

Current State

- more than 1,500 scanned pages of handwritten text
- material from over 600 different writers
  - 95,000 correctly segmented words
  - 13,000 lines of handwritten text
  - over 5,000 complete sentences

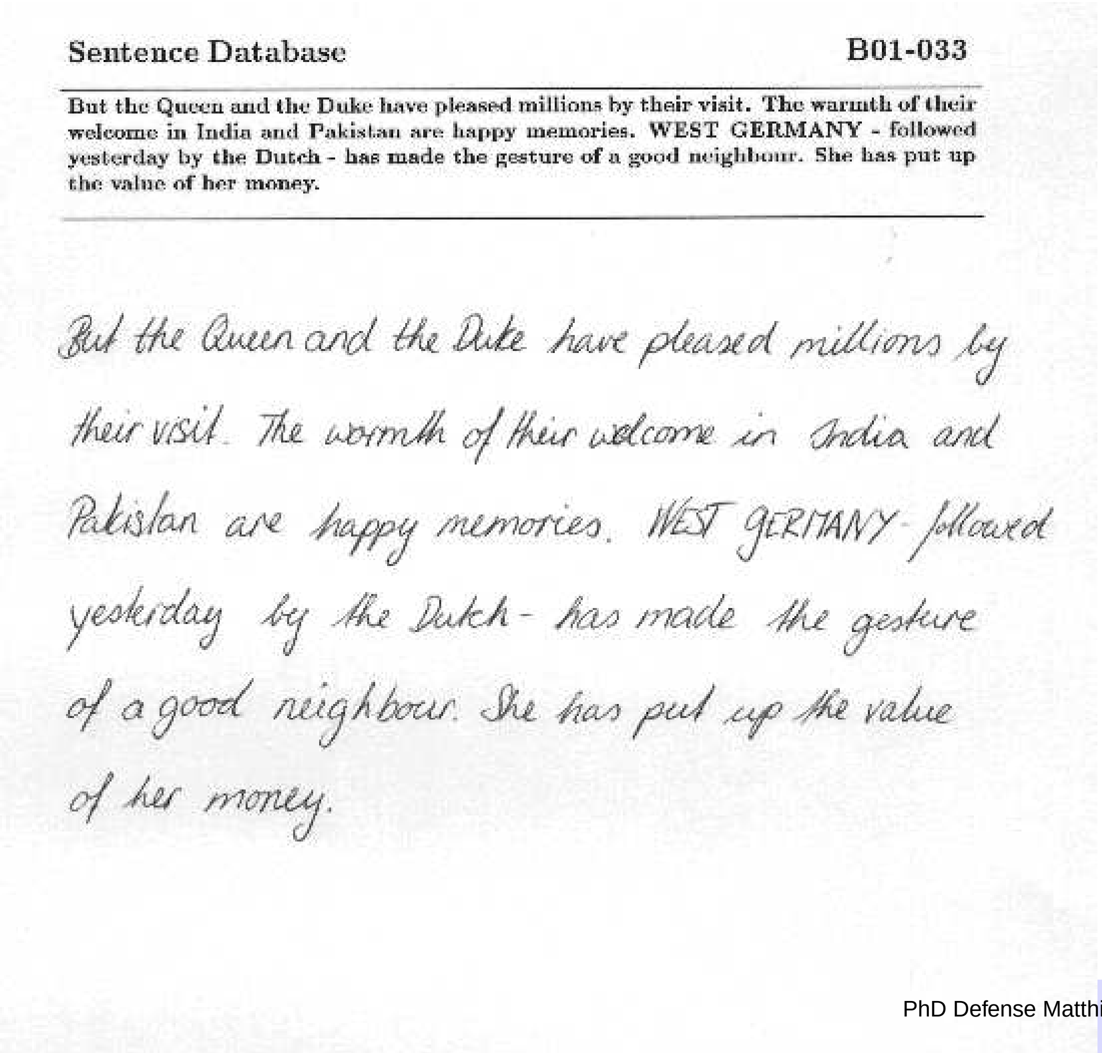
The IAM Database

Current State

- more than 1,500 scanned pages of handwritten text
- material from over 600 different writers
  - 95,000 correctly segmented words
  - 13,000 lines of handwritten text
  - over 5,000 complete sentences
- covering a vocabulary of over 12,000 words

The IAM Database

IAM Database: Form b01-033



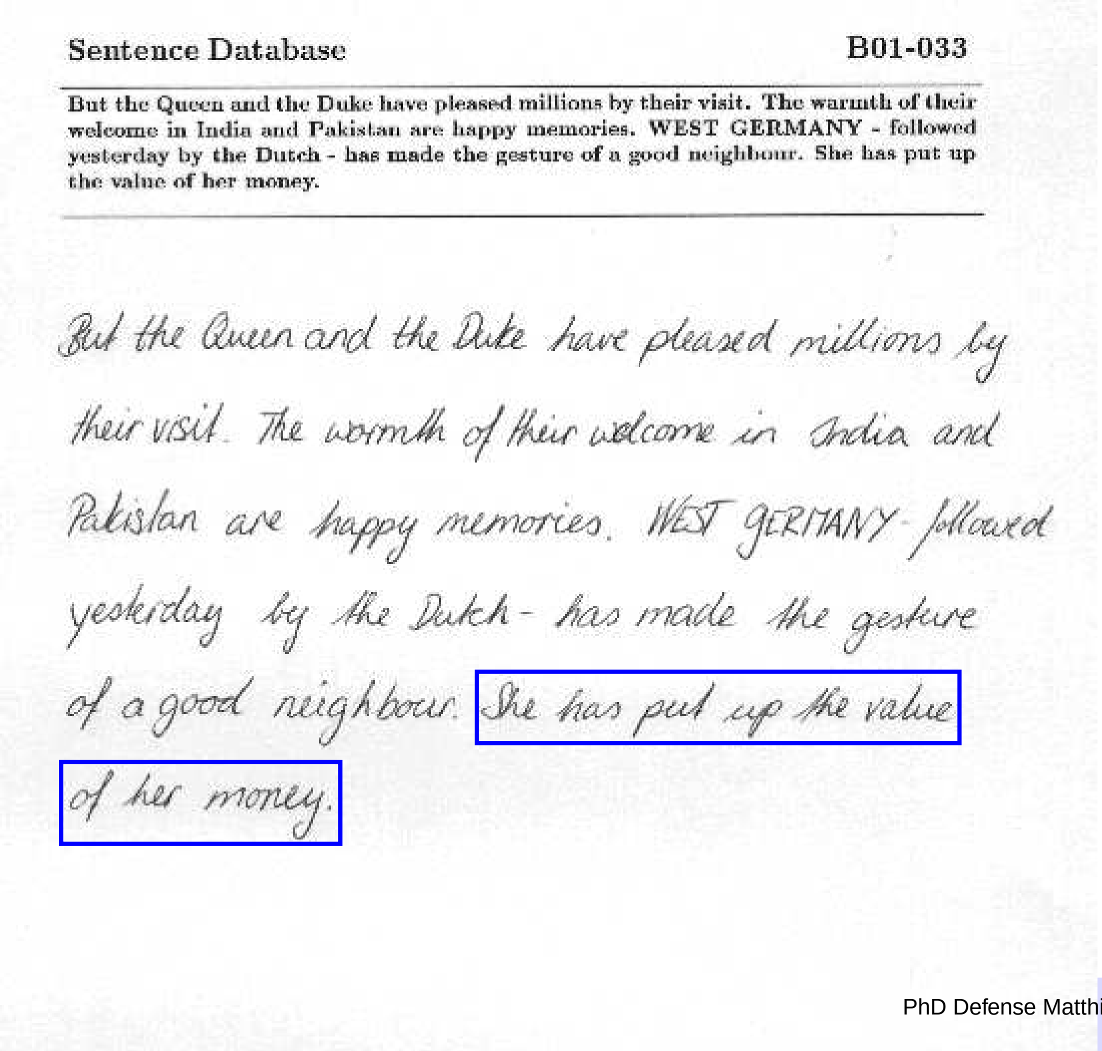
Sentence Database **B01-033**

But the Queen and the Duke have pleased millions by their visit. The warmth of their welcome in India and Pakistan are happy memories. WEST GERMANY - followed yesterday by the Dutch - has made the gesture of a good neighbour. She has put up the value of her money.

But the Queen and the Duke have pleased millions by
their visit. The warmth of their welcome in India and
Pakistan are happy memories. WEST GERMANY - followed
yesterday by the Dutch - has made the gesture
of a good neighbour. She has put up the value
of her money.

The IAM Database

IAM Database: Sentence b01-033-s3



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of her money.

The Recognizer

Based on Existing System (Marti ’00)

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- text line normalization (skew, reference lines)

The Recognizer

Based on Existing System (Marti ’00)

- text line normalization (skew, reference lines)
- feature extraction (sliding window)

The Recognizer

Based on Existing System (Marti '00)

- text line normalization (skew, reference lines)
- feature extraction (sliding window)
- HMM for each character
  - linear topology
  - multi Gaussian
  - variable length modeling
- Baum-Welch training
- bigram language model

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Based on Existing System (Marti ’00)

- text line normalization (skew, reference lines)
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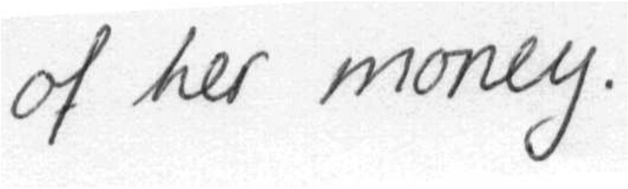
- recognition lattice generation
- n-best list generation

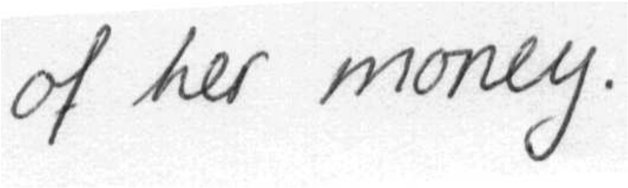
The Recognizer

Text Line Normalization

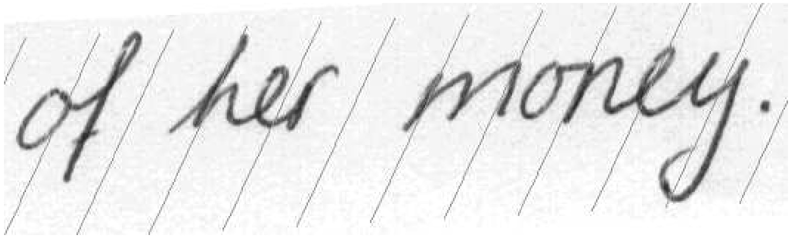


The Recognizer

Text Line Normalization

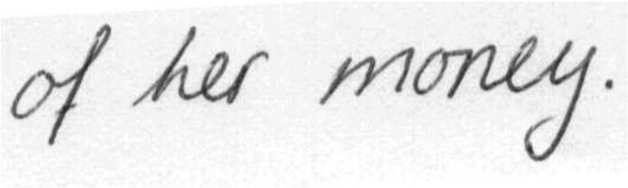


slant estimation

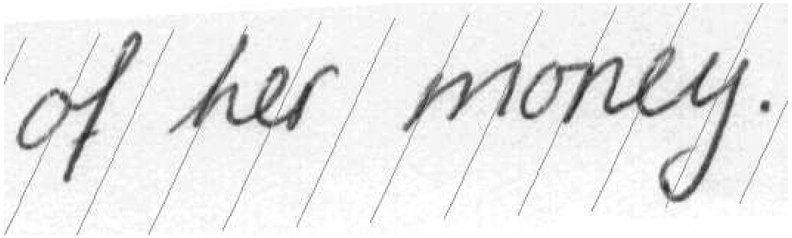


The Recognizer

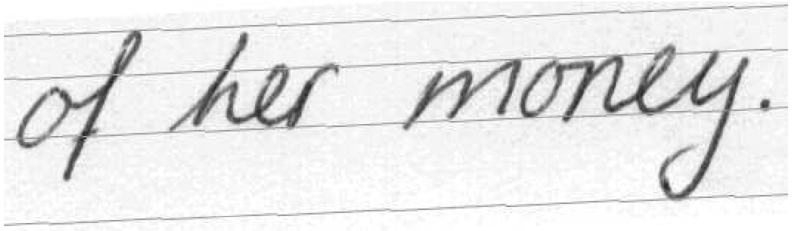
Text Line Normalization



slant estimation

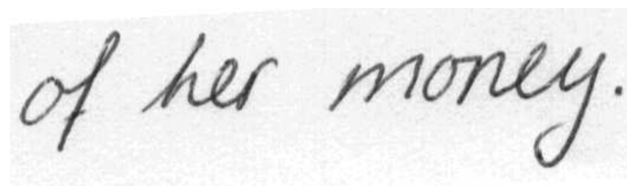


reference line estimation

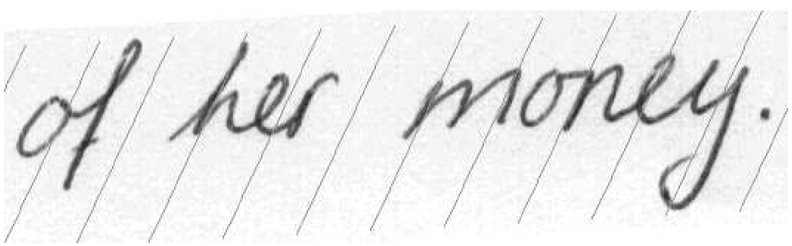


The Recognizer

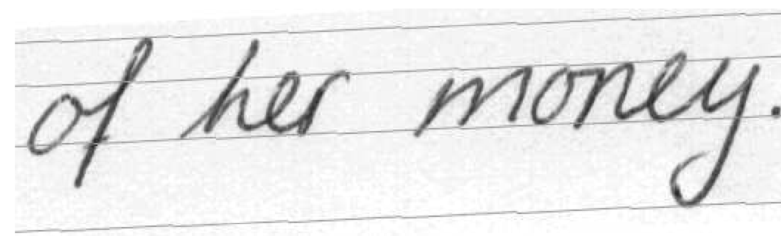
Text Line Normalization



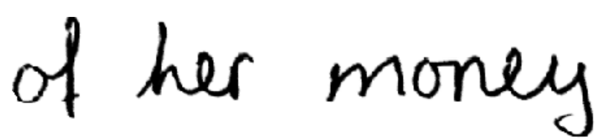
slant estimation



reference line estimation

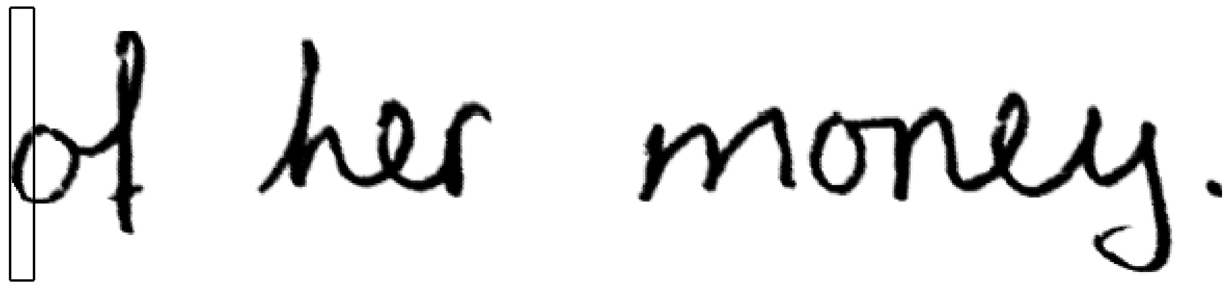


normalized text line



The Recognizer

Extraction of the Feature Vector Sequence



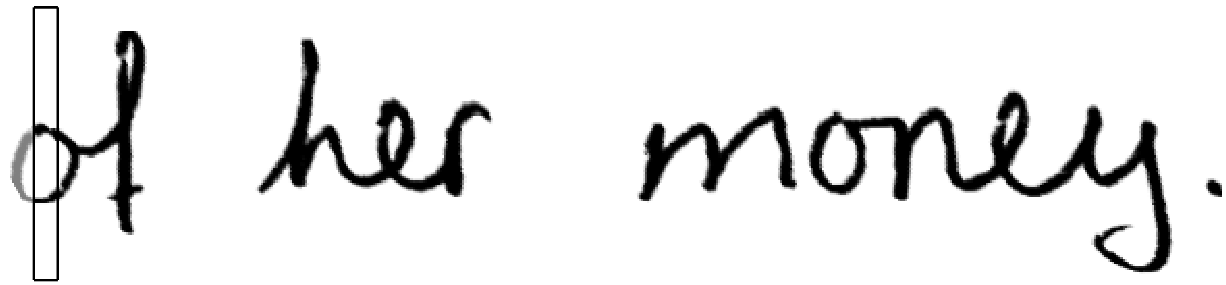
$$\downarrow$$

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

$$X = (X_1,$$

The Recognizer

Extraction of the Feature Vector Sequence



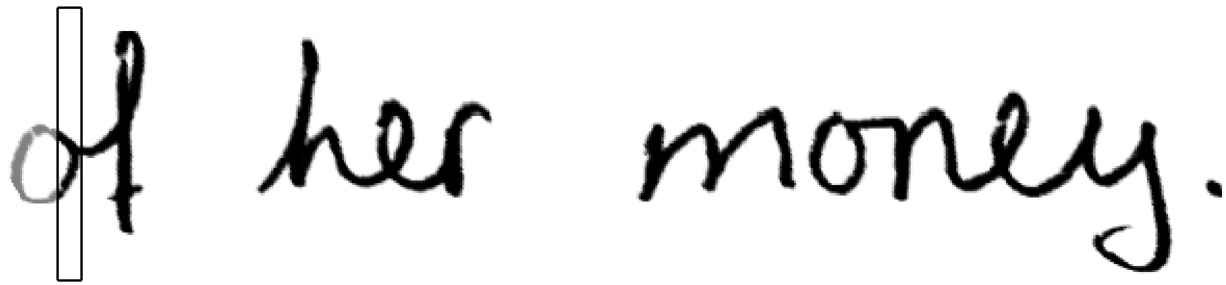
$$\downarrow$$

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

$$X = (X_1, X_2,$$

The Recognizer

Extraction of the Feature Vector Sequence



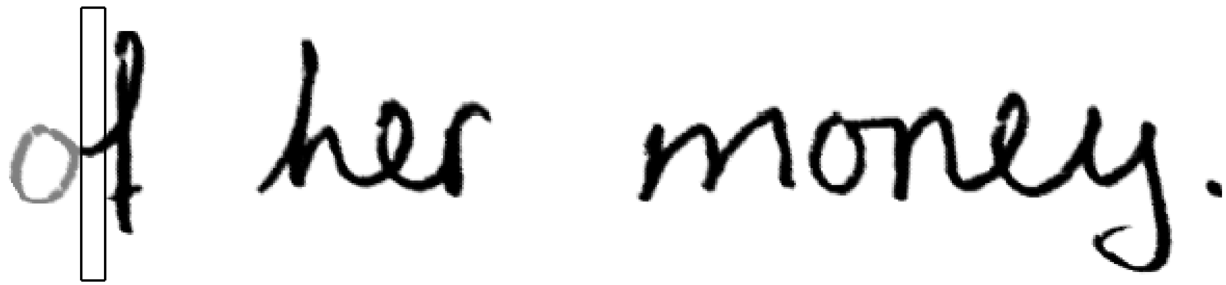
$$\downarrow$$

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

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

The Recognizer

Extraction of the Feature Vector Sequence



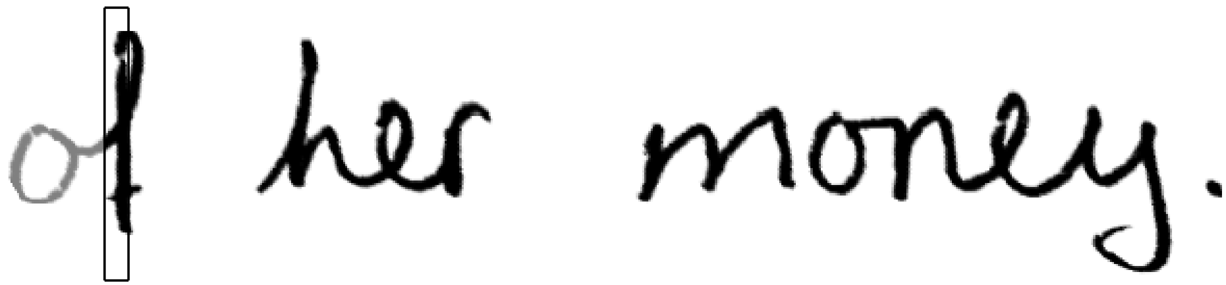
$$\downarrow$$

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

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

The Recognizer

Extraction of the Feature Vector Sequence



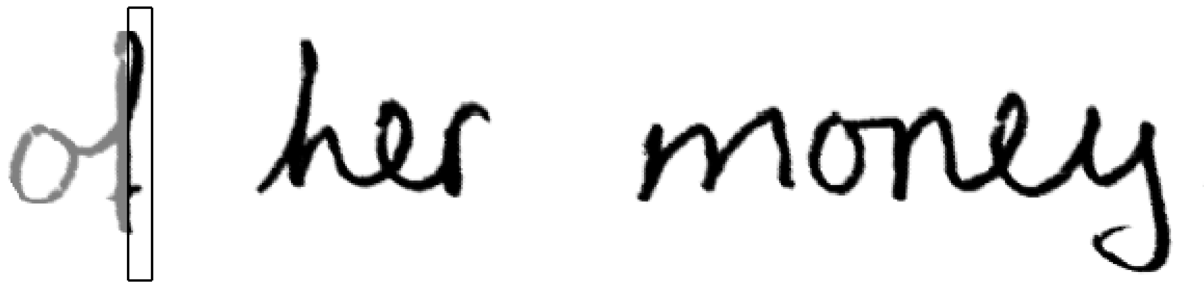
$$\downarrow$$

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

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

The Recognizer

Extraction of the Feature Vector Sequence



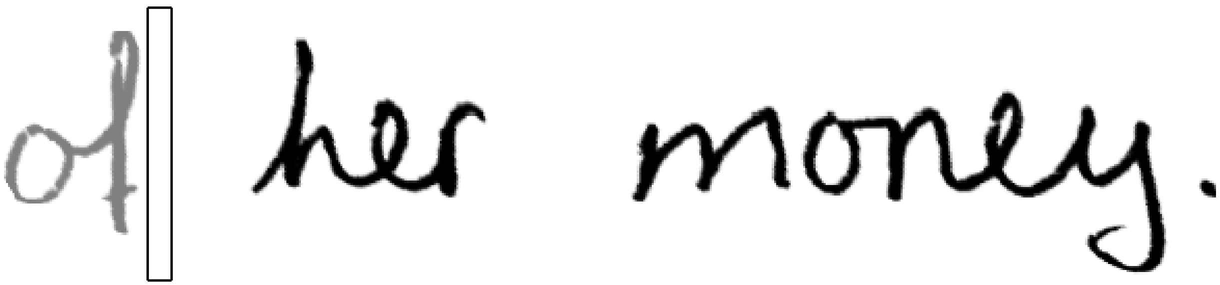
$$\downarrow$$

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

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

The Recognizer

Extraction of the Feature Vector Sequence



$$\downarrow$$

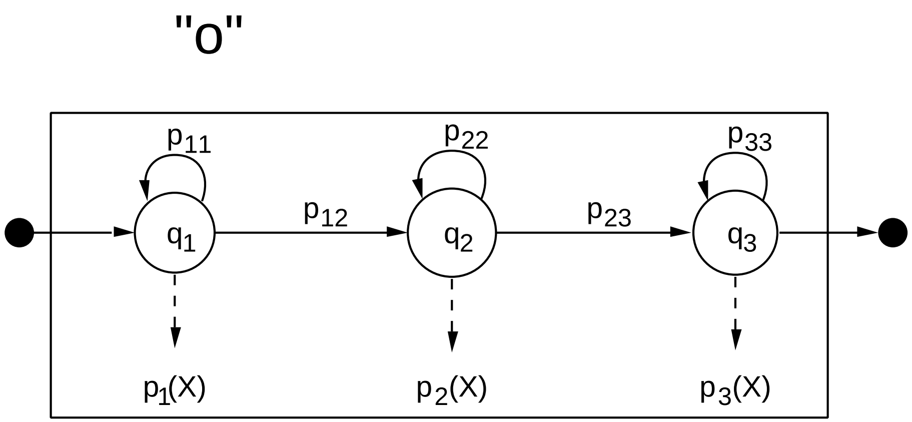
$$\begin{pmatrix} x_{71} \\ x_{72} \\ \vdots \\ x_{7m} \end{pmatrix}$$

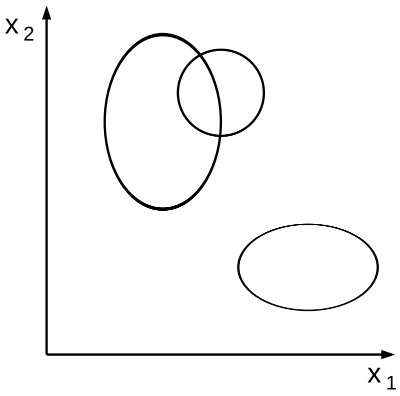
$$X = (X_1, X_2, X_3, X_4, X_5, X_6, X_7, \ldots$$

The Recognizer

Viterbi Decoding

$(X_1, X_2, X_3, \ldots$

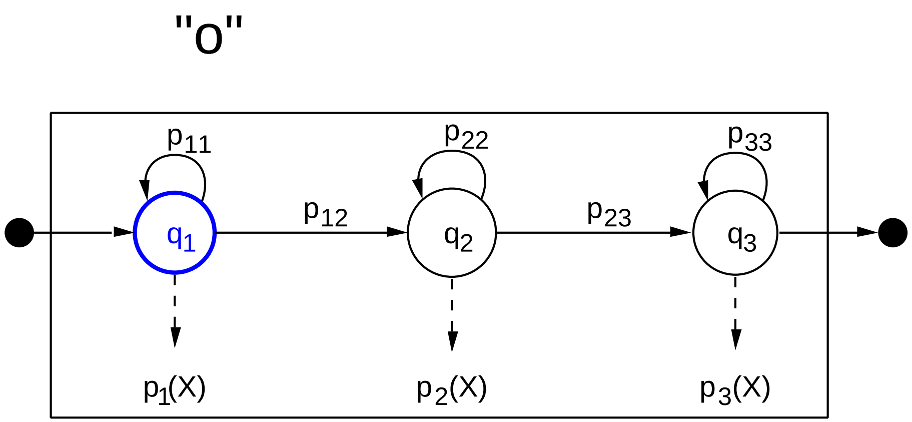


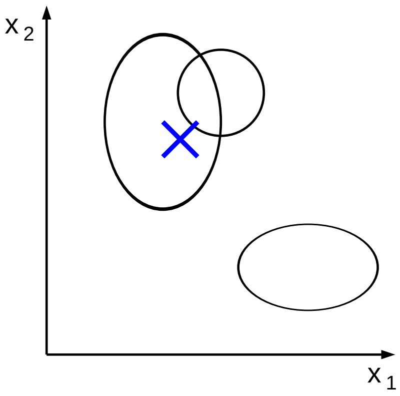


The Recognizer

Viterbi Decoding

$(X_1, X_2, X_3, \ldots$

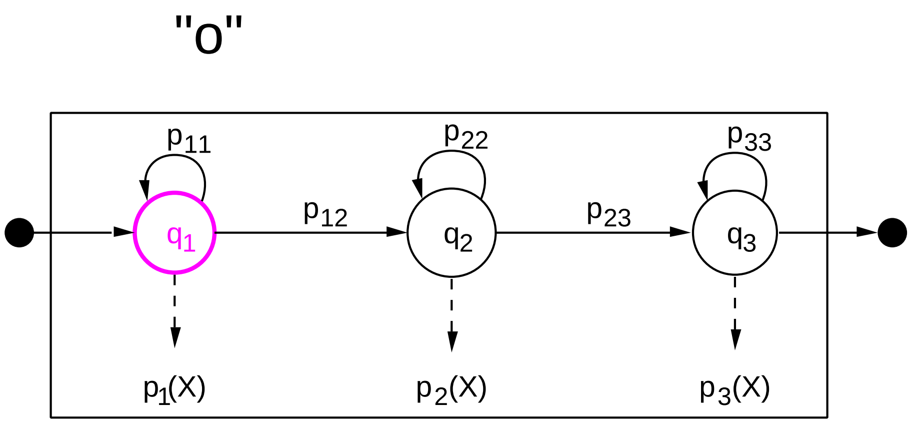


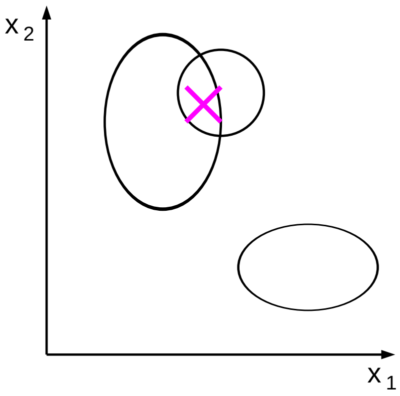


The Recognizer

Viterbi Decoding

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

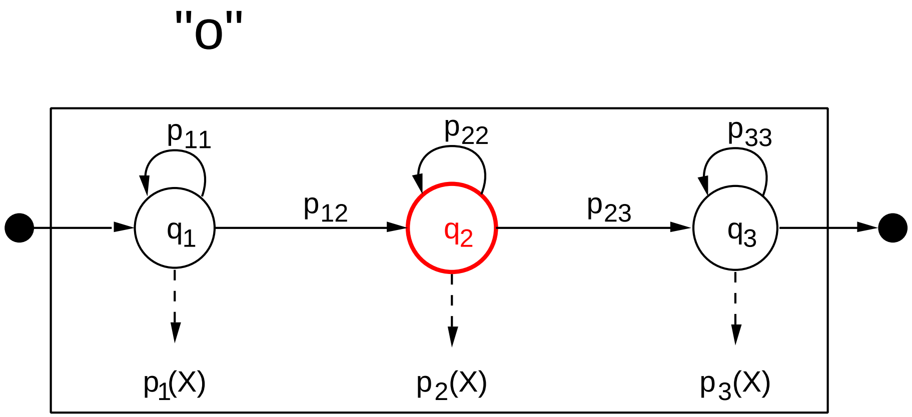


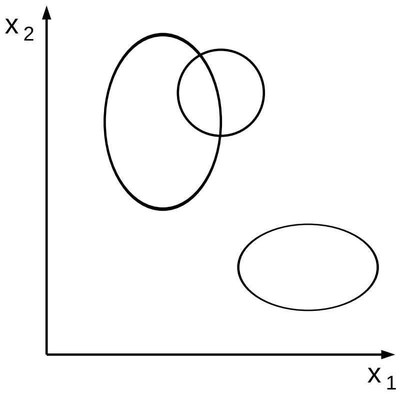


The Recognizer

Viterbi Decoding

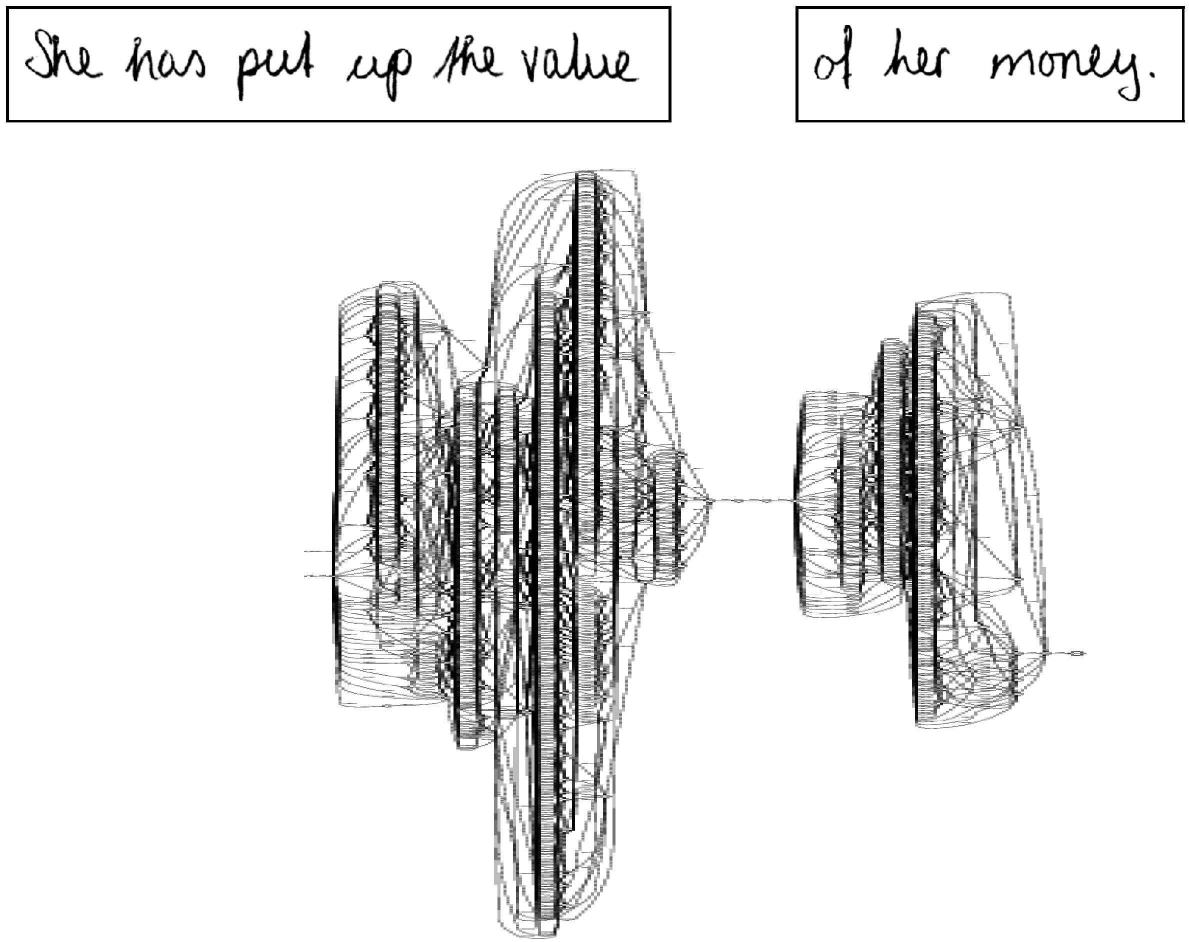
$$(X_1, X_2, {\color{red}X_3}, \ldots$$





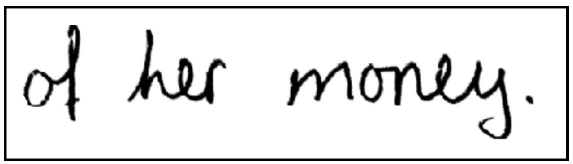
The Recognizer

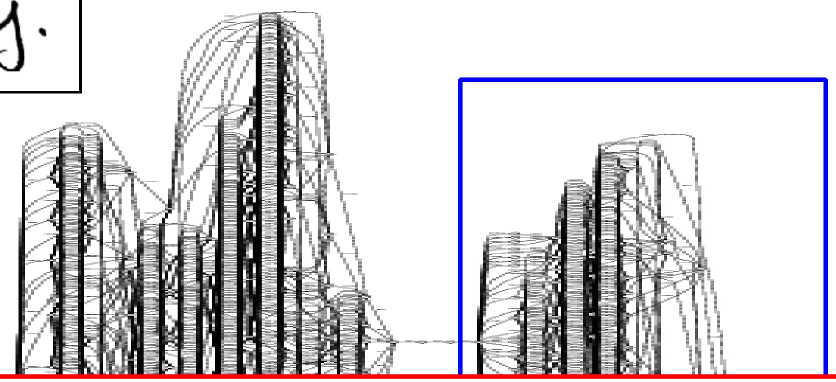
Recognition Lattice Generation

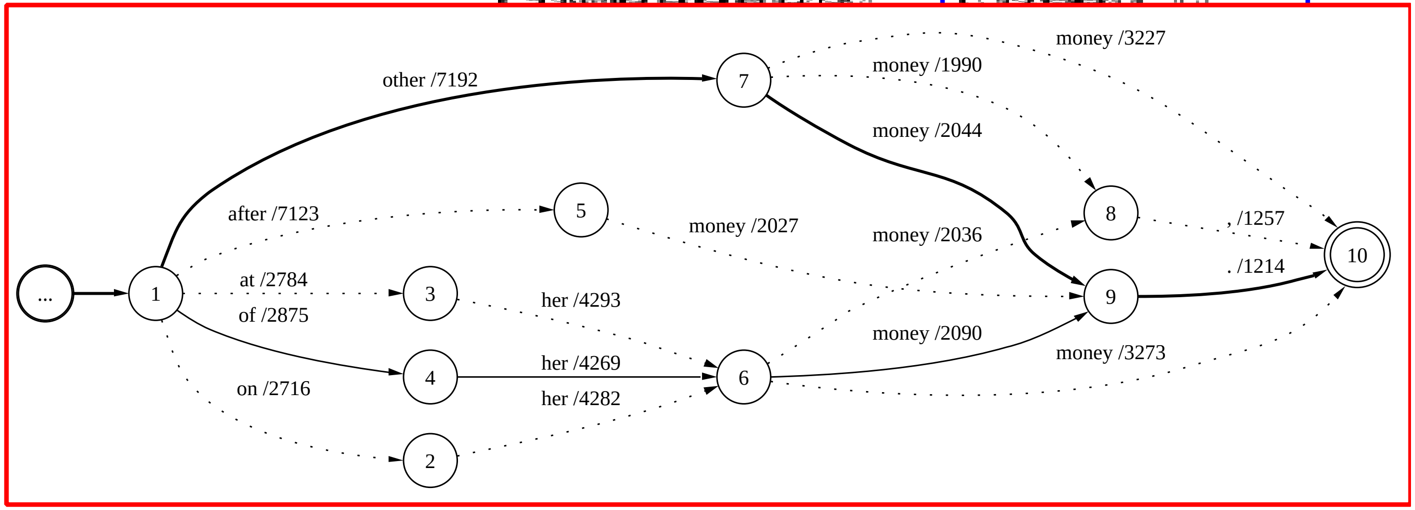


The Recognizer

Sublattice of 2nd Line

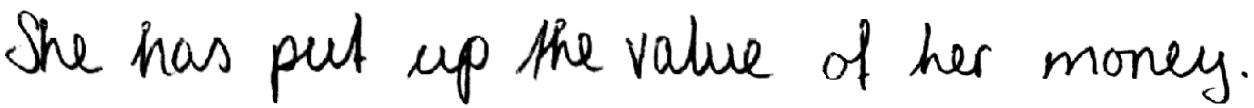






The Recognizer

N-Best List Generation



rank	score	candidate sentence
1	23923.6	She has put up the value other money .
2	23921.8	She has put up the value of her money .
3	23890.3	She had put up the value other money .
4	23888.4	She had put up the value of her money .
5	23854.3	She has put up the value at her money .
...	...	...

The Combination

Combining Recognizer and Parser

The Combination

Combining Recognizer and Parser

tight coupling

The Combination

Combining Recognizer and Parser

tight coupling

- parsing integrated in Viterbi decoding

The Combination

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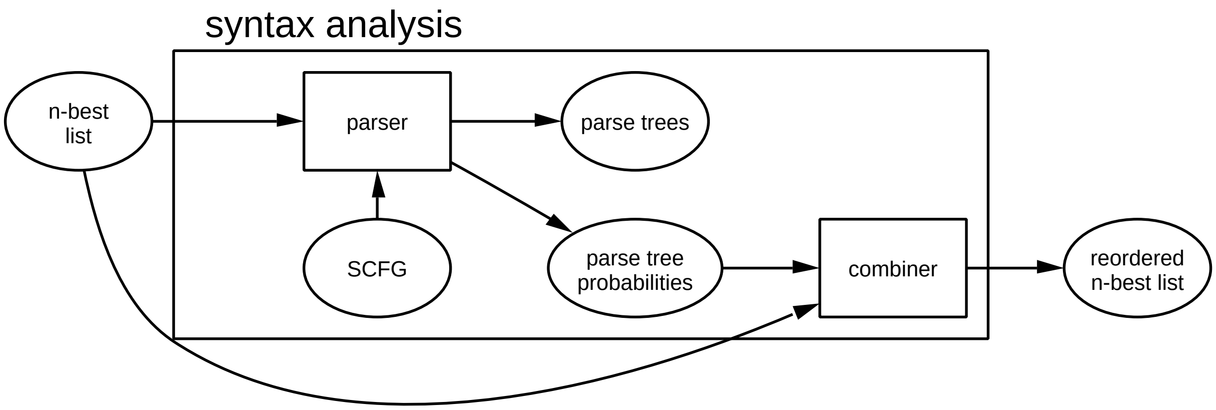
- parsing of output of recognizer
- simple to implement and test
- cannot recover from some errors

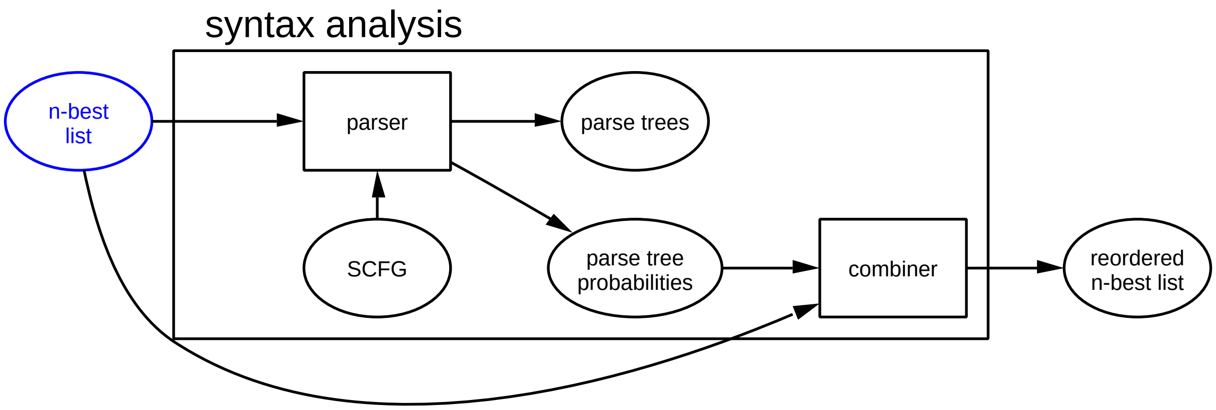
The Combination

Sequential Coupling



The Combination

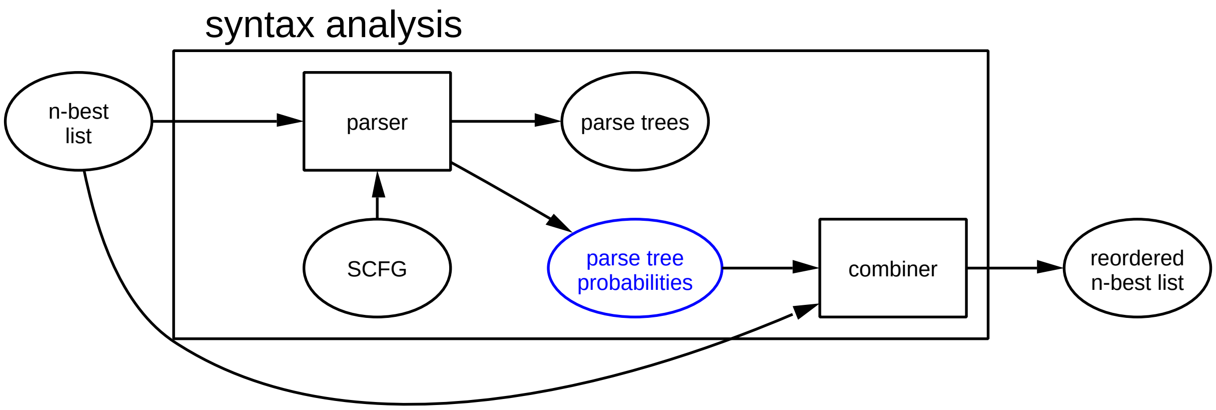
Sequential Coupling



rank	score	candidate sentence
1	23,924	She has put up the value other money .
2	23,922	She has put up the value of her money .
3	23,890	She had put up the value other money .
4	23,888	She had put up the value of her money .
5	23,854	She has put up the value at her money .

The Combination

Sequential Coupling



rank	score	candidate sentence	parse prob.
1	23,924	She has put up the value other money .	7.691e-23
2	23,922	She has put up the value of her money .	4.629e-20
3	23,890	She had put up the value other money .	2.631e-22
4	23,888	She had put up the value of her money .	1.584e-19
5	23,854	She has put up the value at her money .	1.125e-21

The Combination

Combination Scheme

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- recognition score is a log likelyhood

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$$sentence\ score = recognition\ score + \gamma \log(parse\ probability)$$

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- parse probability can be transformed into that
- a parse scale factor γ weights the influence of the parser
- a sentence score can be defined as follows:

$$sentence\ score = recognition\ score + \gamma \log(parse\ probability)$$

- the sentence score is used to reorder the n-best list
- the parse scale factor is optimized on a validation set

The Combination

An Example

parse scale factor $\gamma = 0$

score	pp	$\log$ pp	sen scr.	candidate sentence
23,924	7.691e-23	-22.33	23,924	She has put up the value other money .
23,922	4.629e-20	-19.33	23,922	She has put up the value of her money .
23,890	2.631e-22	-21.58	23,890	She had put up the value other money .
23,888	1.584e-19	-18.80	23,888	She had put up the value of her money .
23,854	1.125e-21	-20.95	23,854	She has put up the value at her money .

- $\gamma = 0$: original system, parsing has no effect

The Combination

An Example

parse scale factor $\gamma = 10$

score	pp	$\log$ pp	sen scr.	candidate sentence
23,924	7.691e-23	-22.33	23,701	She has put up the value other money .
23,922	4.629e-20	-19.33	23,729	She has put up the value of her money .
23,890	2.631e-22	-21.58	23,674	She had put up the value other money .
23,888	1.584e-19	-18.80	23,700	She had put up the value of her money .
23,854	1.125e-21	-20.95	23,644	She has put up the value at her money .

- $\gamma = 0$: original system, parsing has no effect
- $\gamma = 10$: desired effect of syntax analysis

The Combination

An Example

parse scale factor $\gamma = 20$

score	pp	$\log$ pp	sen scr.	candidate sentence
23,924	7.691e-23	-22.33	23,478	She has put up the value other money .
23,922	4.629e-20	-19.33	23,536	She has put up the value of her money .
23,890	2.631e-22	-21.58	23,458	She had put up the value other money .
23,888	1.584e-19	-18.80	23,512	She had put up the value of her money .
23,854	1.125e-21	-20.95	23,435	She has put up the value at her money .

- $\gamma = 0$: original system, parsing has no effect
- $\gamma = 10$: desired effect of syntax analysis
- $\gamma = 20$: increasing influence of parsing

Organization

1. Introduction
2. Problem Statement
3. The Grammar
4. The Parser
5. IAM Database and Recognizer
6. The Combination
7. Setup, Optimization and Evaluation
8. Conclusions and Outlook

Experimental Setup

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assumptions

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- segmented sentences

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- writer independent task (WI)

Experimental Setup

Task Specifications

	multi writer task (MW)
writers	
sentences	
text lines	
words	
lexicon	
SCFG rules	

- MW: same population of writers

Experimental Setup

Task Specifications

multi writer task (MW)

	validation
writers	157
sentences	200
text lines	534
words	3,814
lexicon	8,824
SCFG rules	21,691

- MW: same population of writers

Experimental Setup

Task Specifications

multi writer task (MW)

	validation	test
writers	157	156
sentences	200	200
text lines	534	575
words	3,814	3,933
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	multi writer task (MW)		writer independent task (WI)
	validation	test	validation
writers	157	156	100
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text lines	534	575	582	575
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Performance Measures

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- sentence recognition rate

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- text line recognition rate

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- word recognition rate

$$word\ recognition\ rate = \frac{H}{N} \times 100\%$$

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- text line recognition rate
- word recognition rate

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- word level accuracy

$$word\ level\ accuracy = \frac{H - I}{N} \times 100\%$$

System Optimization

Different Aspects of the Optimization

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- number of states per character model

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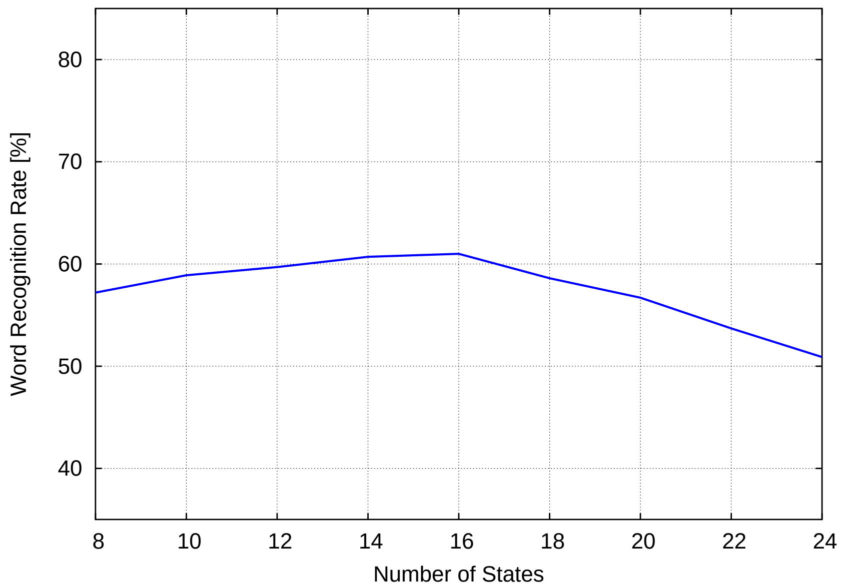
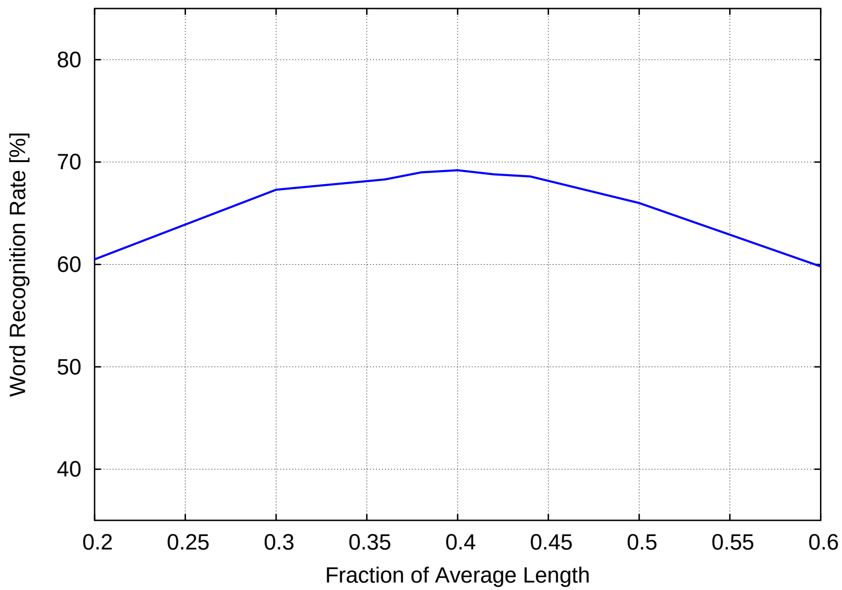
- number of training iterations for the HMM
- integration of the bigram language model
- parse scale factor optimization

System Optimization

Optimizing the Number of Model States



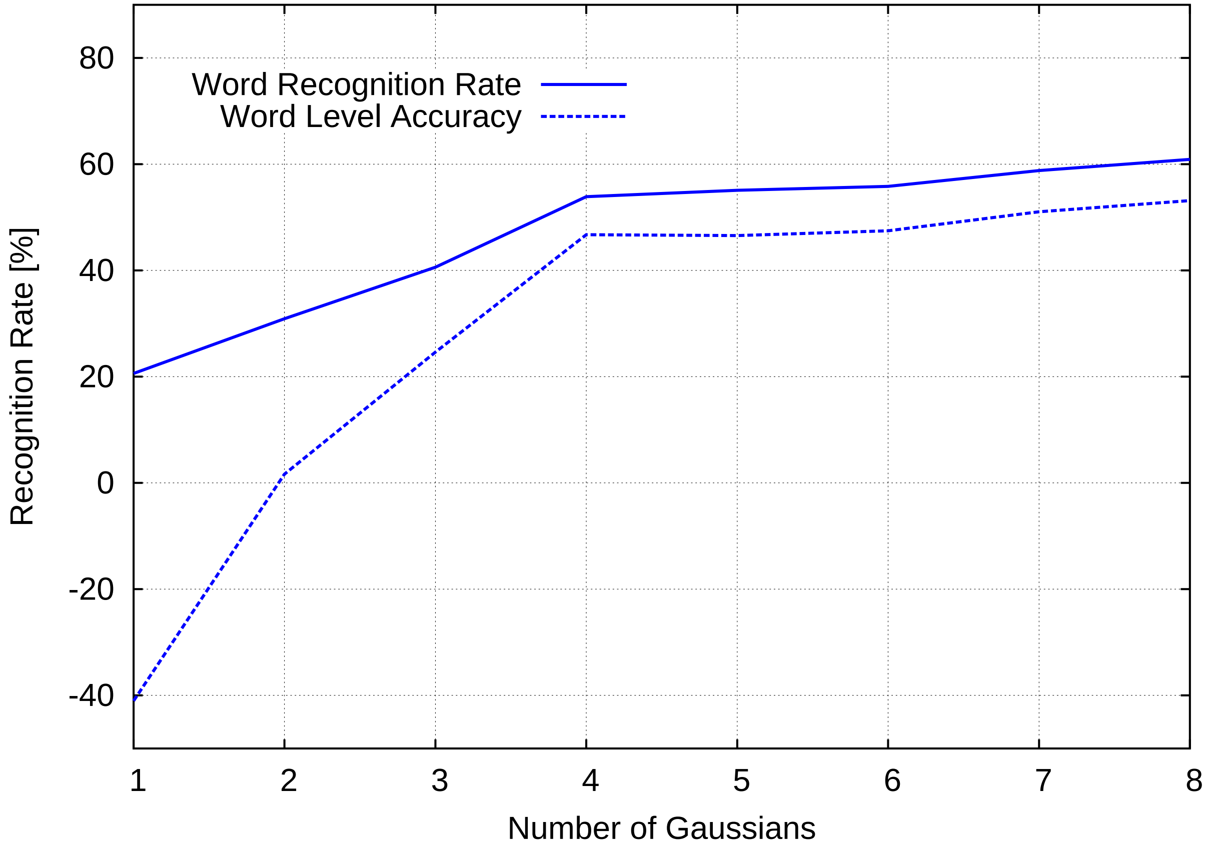
fixed length modeling



variable length modeling

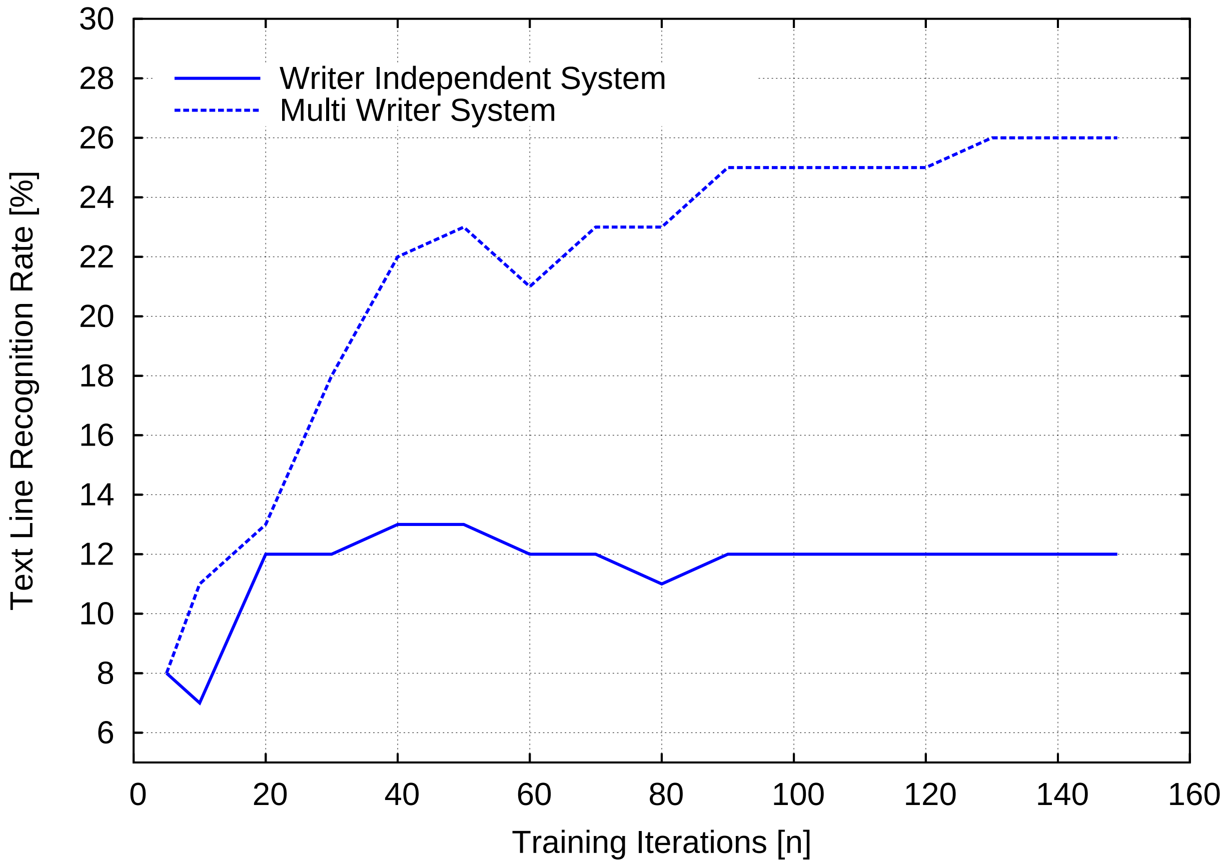
System Optimization

Optimizing the Number of Gaussians



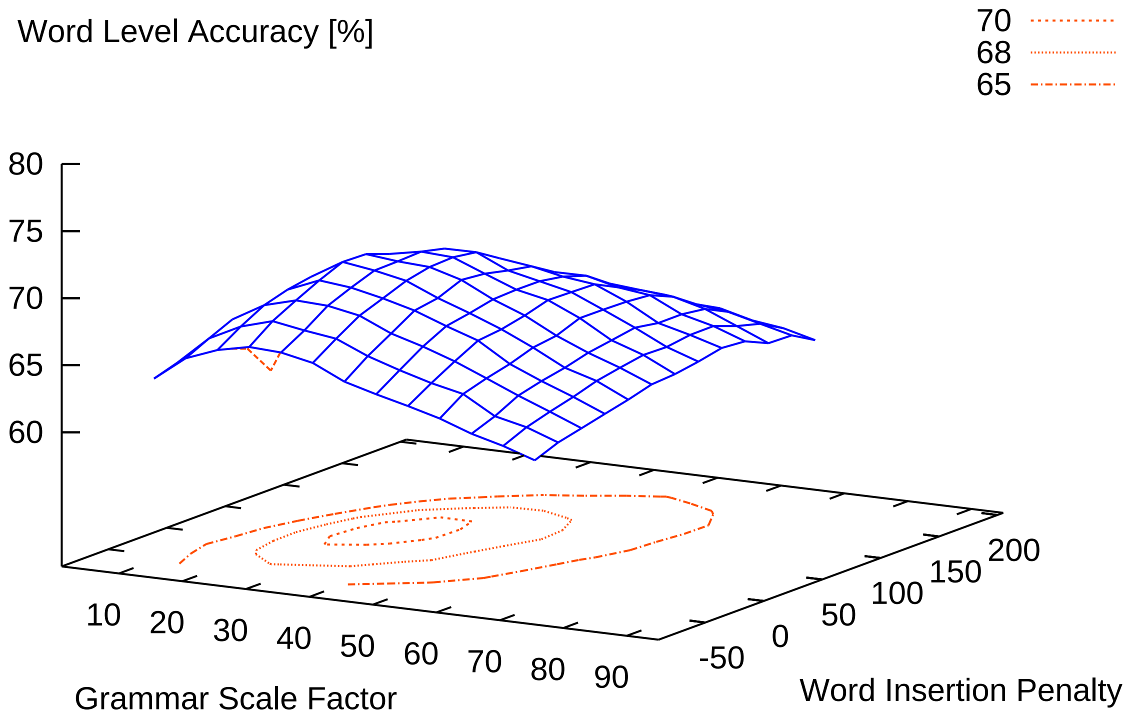
System Optimization

Optimizing the Number of Training Iterations



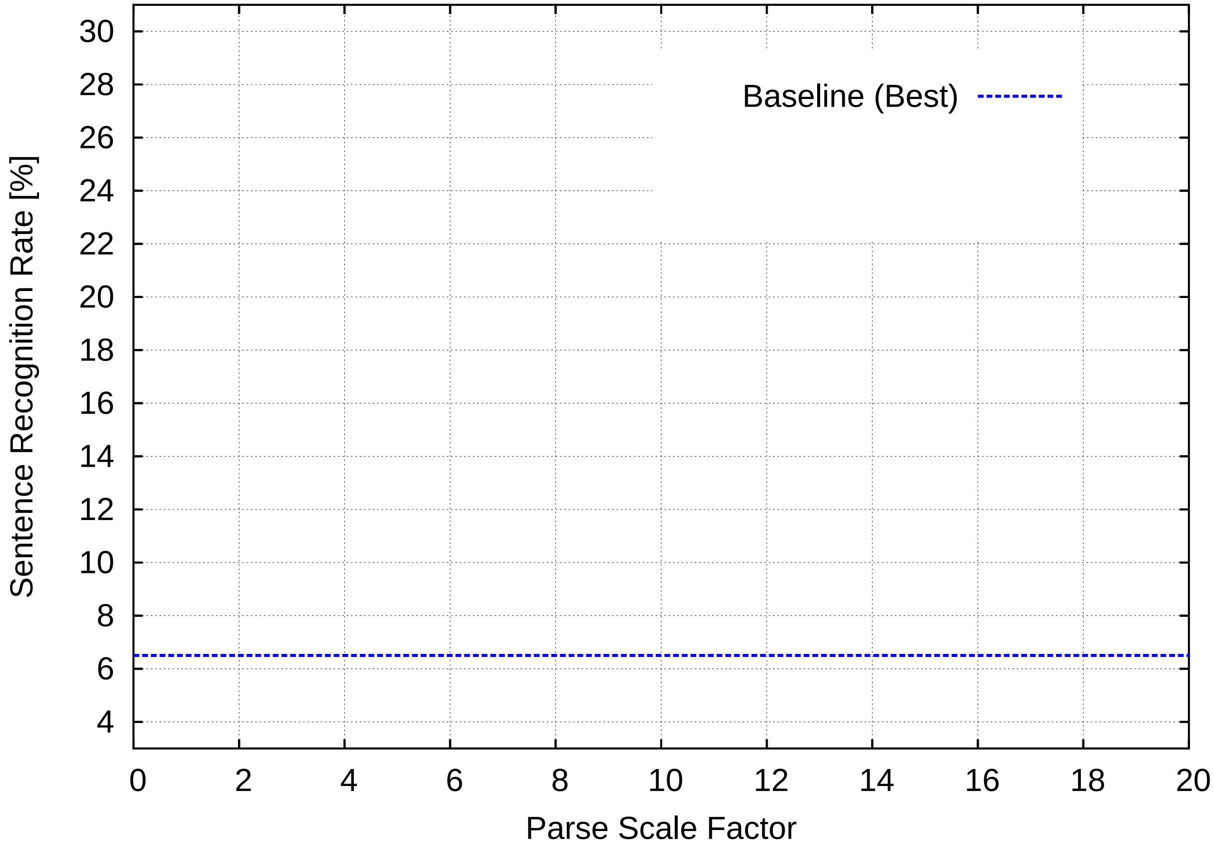
System Optimization

Optimizing the Language Model Integraion



System Optimization

Optimizing the Parse Scale Factor



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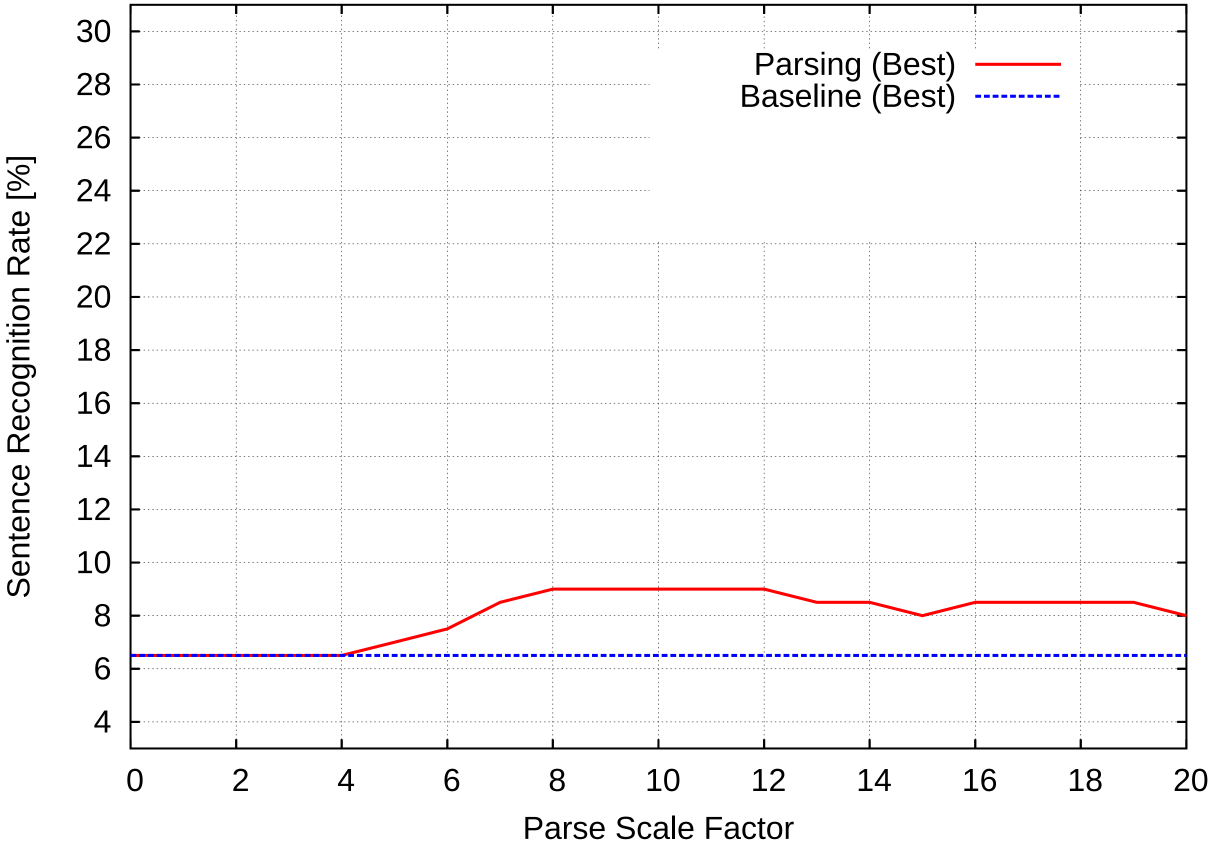

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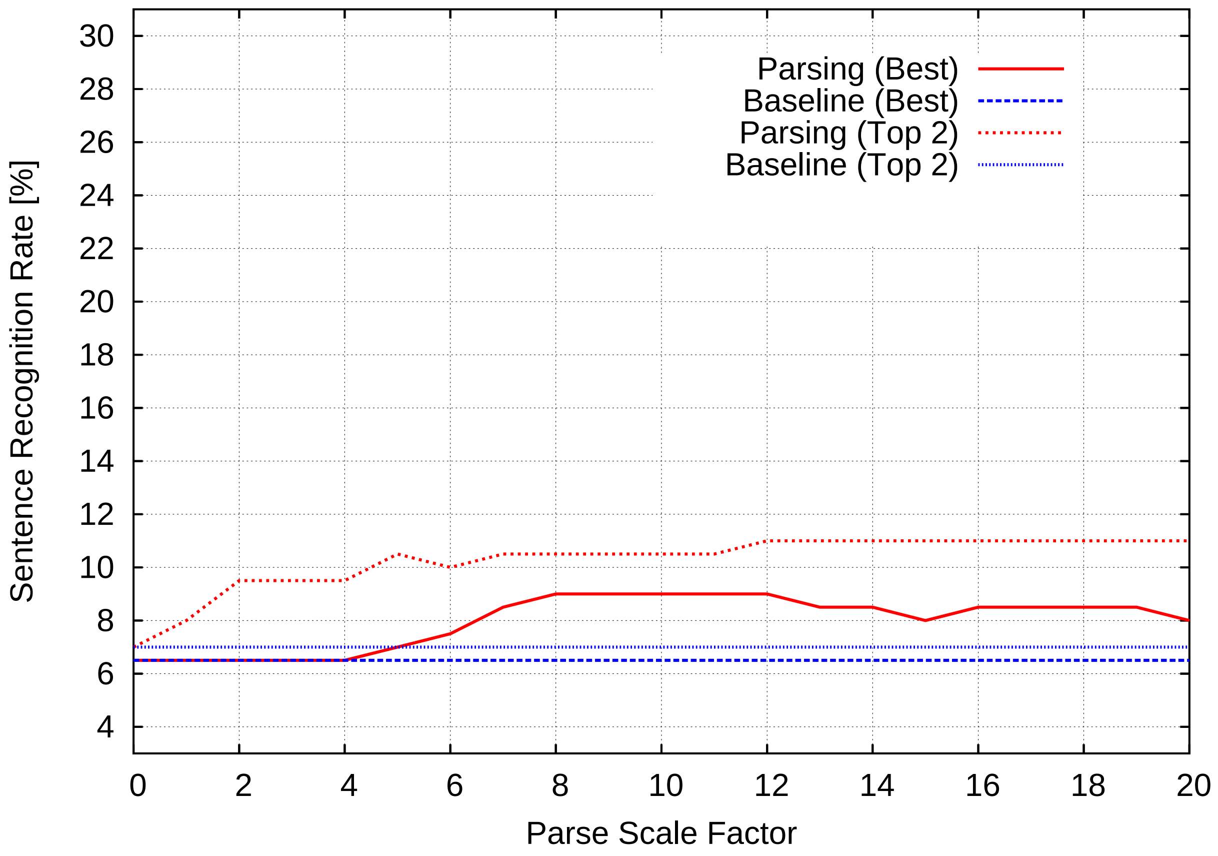

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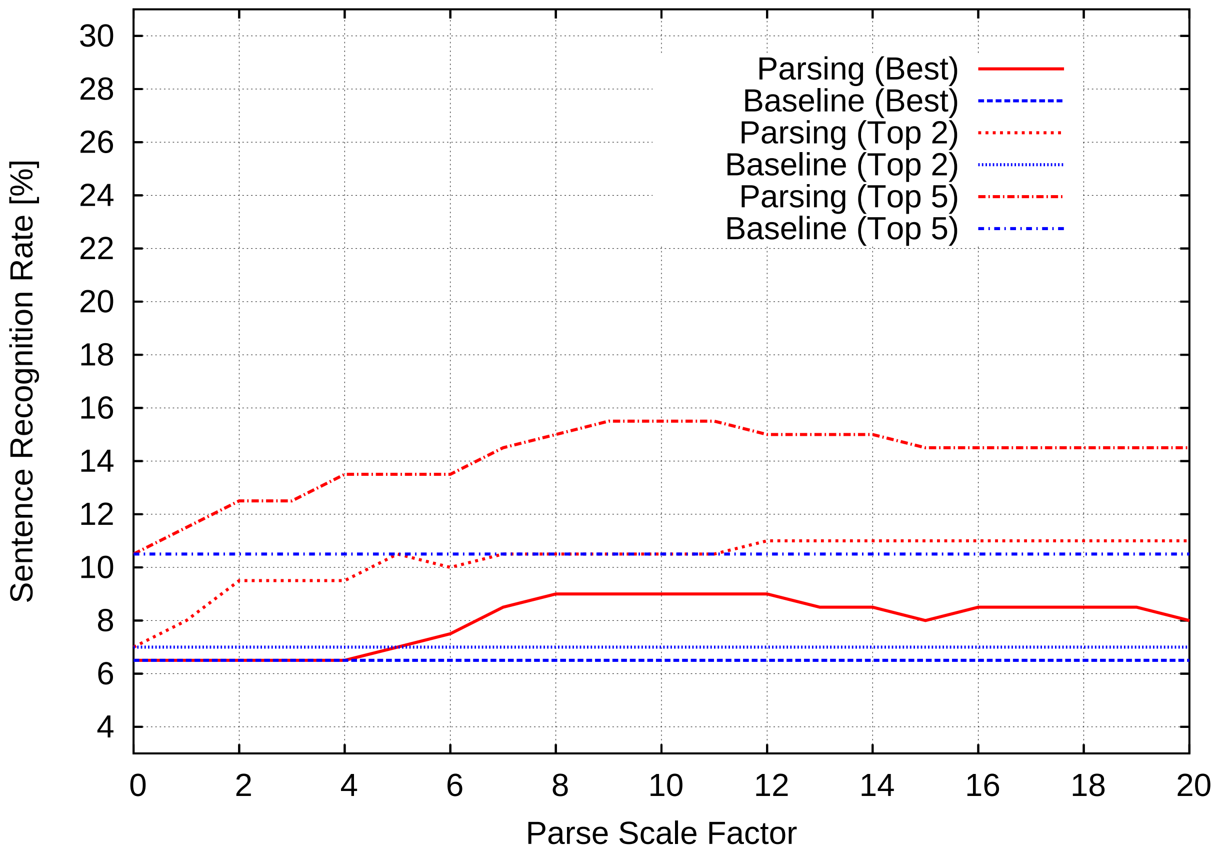

System Evaluation

Test Set Results

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Test Set Results

multi writer task

performance measure	baseline	parsing	level
sentence recognition rate	7.5%	8.0%	60%
word recognition rate	76.7%	77.2%	75%
word level accuracy	74.7%	75.6%	$>$ 99%

System Evaluation

Test Set Results

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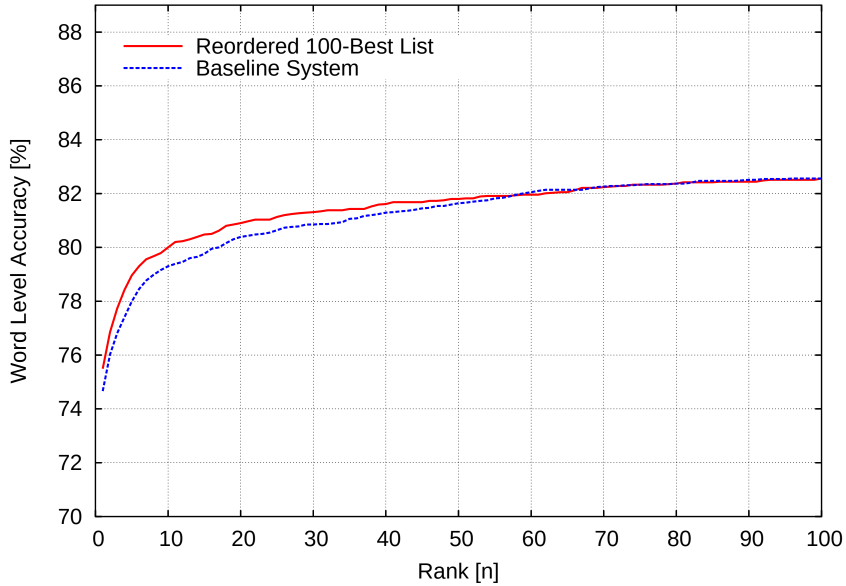
writer independent task

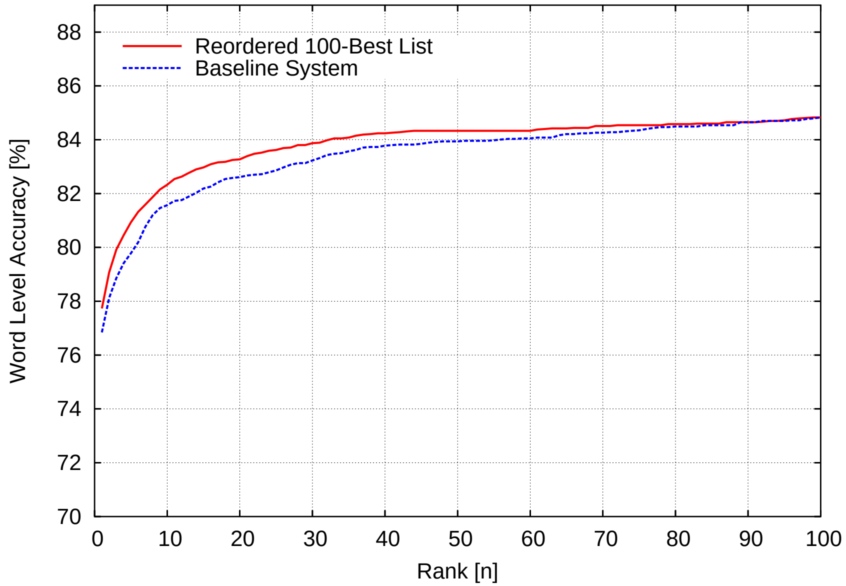
performance measure	baseline	parsing	level
sentence recognition rate	11.0%	12.0%	70%
word recognition rate	79.3%	79.4%	50%
word level accuracy	76.8%	77.6%	91%

System Evaluation

N-best Analysis of Word Level Accuracy



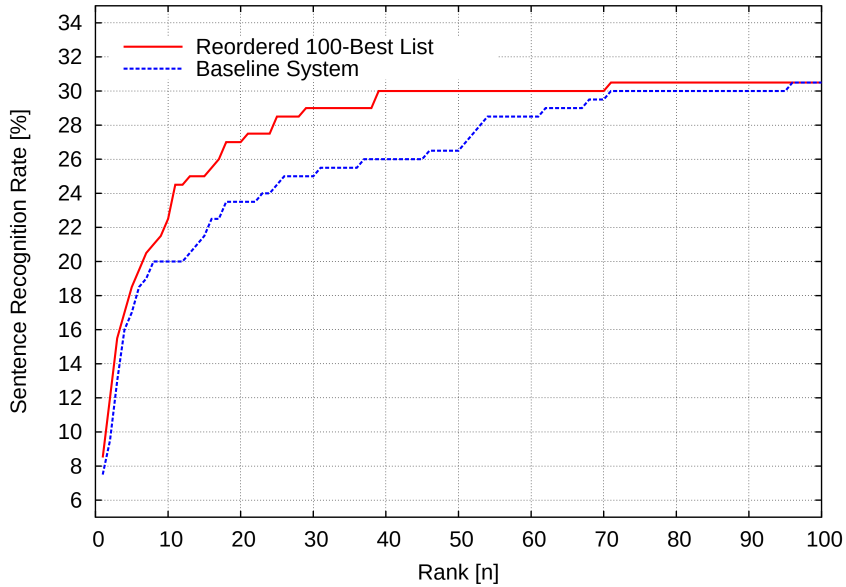
multi writer task



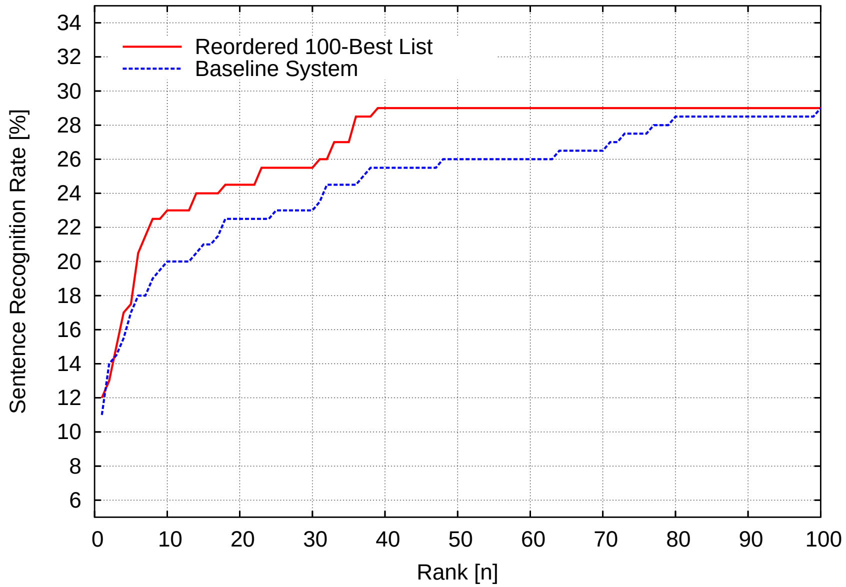
writer independent task

System Evaluation

N-best Analysis of Sentence Recognition Rate



multi writer task



writer independent task

Conclusions

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