Bayesian Language Modelling of German Compounds

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Why Statistical Language Modelling?

- Central to tasks where sentences are hypothesised
  - Machine Translation
  - Speech Recognition
  - Optical Character Recognition

Token-based n-gram models

Task: $P\,(\text{Wir fahren mit der Bahn}) = ?$ *We're going by train*

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Makes parameter estimation feasible

e.g. $P(\text{Bahn} \mid \text{mit der}) = 0.3$

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Vocabulary Assumptions

Closed vocabulary, independent words

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$$P\left(\begin{array}{c}\text{Bahn}\\\text{Familie}\\\text{Mauer}\\\text{Straßenbahn}\\\text{U-Bahn}\\\text{Bobbahn}\end{array} \mid \text{mit der}\right) = ?$$

Compounding

Example

	Bahn		*train*
	Straßenbahn		*tram*
Wir fahren mit der	U-bahn	.	*metro*
	Bobbahn		*bobsled*
	Achterbahn		*rollercoaster*

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Highly Productive Process

Regal *shelf*

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Buchregalherstellername	*bookshelf manufacturer's name*
...	

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Regularity

- compound = modifiers & head

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Regularity

- compound = modifiers & head
- head determines syntactic properties
- generalising over modifiers would reduce sparsity

Related Work: Factored Language Model

Each token w consists of k features, fixed dependencies

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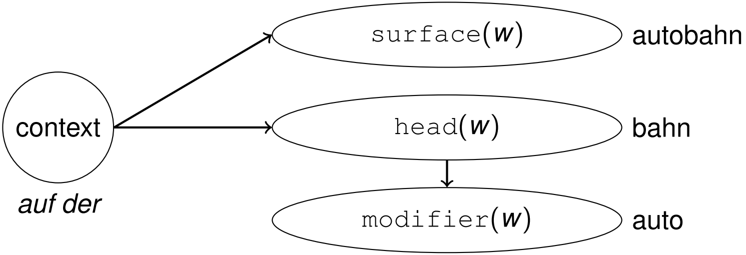

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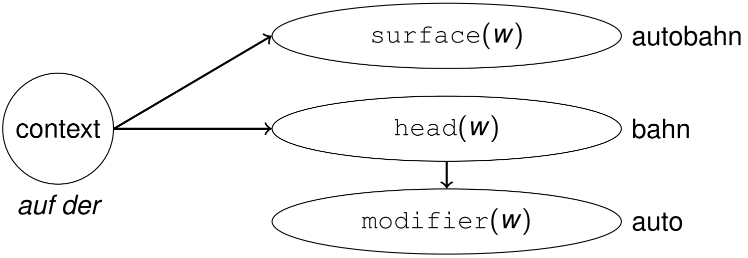

Shortcoming: Compound lengths vary freely

Auto	+	bahn	+	geschwindigkeit	+	s	+	grenze
motor		*way*		*speed*				*limit*

Related Work: Splitting and Merging

Preprocess data: split compounds

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		Context	Predicted Token
Standard:	Wir fahren	auf der	Autobahn
Split:	Wir fahren auf	der Auto	bahn

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Shortcoming: Important sentential context lost

Model Aims

- Condition head on previous words
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- *but* keep full surface form in model

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Standard back-off smoothing

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mit der Autobahn

$\uparrow$

$P(\text{Autobahn} \mid \text{mit der})$

$P(\text{Autobahn} \mid \ldots\ \text{der})$

$P(\text{Autobahn} \mid \ldots\ \ldots)$

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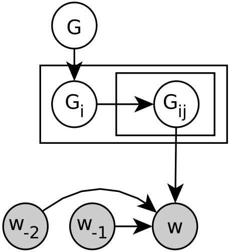
mit der Autobahn

P(Autobahn | mit der)

P(Autobahn | … der)

P(Autobahn | … …)

Hierarchical Prior



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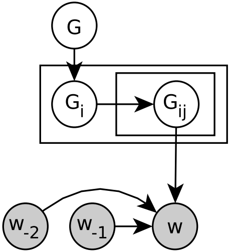


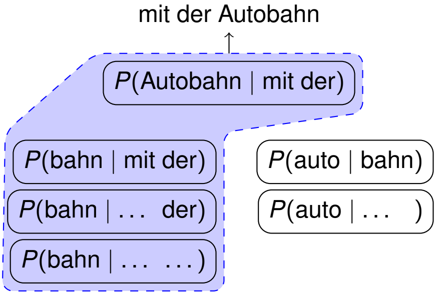
Conditional distributions drawn from Pitman-Yor process:

$$G \sim PY\left(d, \theta, G_0\right)$$

discount strength base distribution

Our Model: HPYLM with Compounds

Proposed back-off



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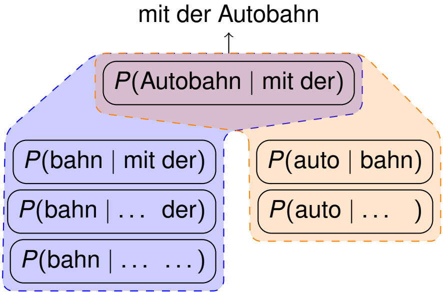

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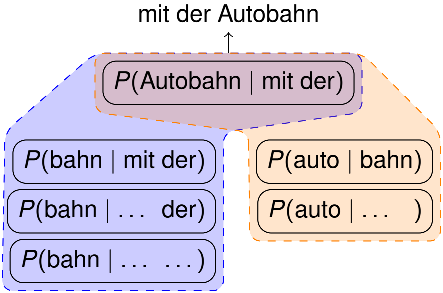
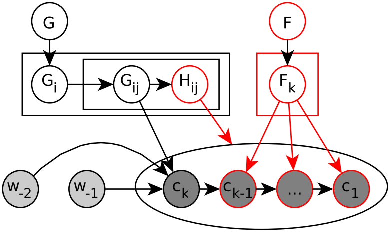


Extended Hierarchical Prior



Overview of Setup

- Data from WMT '11 shared task
- Language Models
  4-gram, unless otherwise stated
  trained on 59m tokens (Europarl, news & commentary)
- English→German Translation System
  trained on 1.7m parallel sentences (Europarl)

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- Language Models
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- English→German Translation System
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- Vocabulary sparsity – ratio of English/German:
  baseline: 3.13
  decompounded: 1.36

Comparison of Methods for Predicting Unseen Text

	Perplexity
Modified Kneser-Ney	299.9
HPYLM	294.1

Lower is better.

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proposed: über die Auto bahn geschwindigkeits grenze

Comparison of Methods for Predicting Unseen Text

	Perplexity
Modified Kneser-Ney	299.9
HPYLM	294.1
Our model	**293.6**
Our model (inverted)	305.5

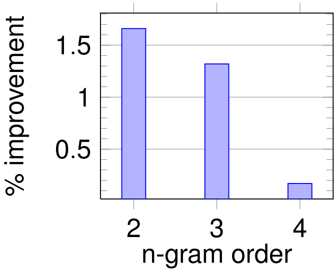
Lower is better.

proposed: über die Auto bahn geschwindigkeits grenze

inverted: über die Auto bahn geschwindigkeits grenze

Effect of Scaling Context Size

% Relative improvement over HPYLM baseline



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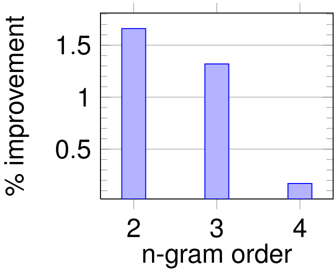

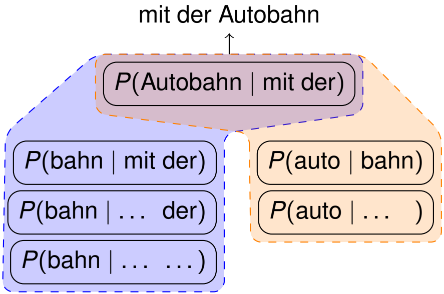

Higher is better.

Missing: $P(\text{Autobahn} \mid \ldots \text{der})$

Machine Translation Results

English→German

	BLEU
Modified Kneser-Ney	13.9
HPYLM	13.9
Our model	13.9
Our model (inverted)	13.7

Higher BLEU is better.

Machine Translation Results

English→German

only 3.7% of reference tokens are compounds

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Higher BLEU is better.

Compound Translation Accuracy

Compare compounds in output against reference sentences

	Precision	**Recall**	**F-score**
Modified Kneser-Ney	25.4	17.1	20.5
HPYLM	24.3	**17.5**	20.4
Our model	**27.5**	17.3	**21.3**
Our model (inverted)	23.7	17.2	19.9

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Summary

- Productive compounding is an important source of sparsity.
- Proposed n-gram language model that accounts for productive compounding.
- Improved accuracy of translated compounds, while matching baseline BLEU score

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- Future Work
  - Evaluate with an MT system that outputs *novel* compounds
  - Model compounds that occur within context

Thank you.

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HPYLM	13.9
Our model	13.9

	LM-training	BLEU
Modified Kneser-Ney	< 1 hour	13.9
HPYLM	3 days	13.9
Our model	6 days	13.9

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Modified Kneser-Ney	$<$ 1 hour	13.9
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Our model (fastapprox)	4 hours	13.6