Machine Translation: Going Deep

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How do we Improve Machine Translation?

- More data
- Better linguistically motivated models
- Better machine learning

How do we Improve Machine Translation?

- More data
- **Better linguistically motivated models**
- **Better machine learning**

what problems do we need to solve?

Word Translation Problems

- Words are ambiguous

He deposited money in a bank account
with a high interest rate.

Sitting on the bank of the Mississippi,
a passing ship piqued his interest.

- How do we find the right meaning, and thus translation?
- Context should be helpful

Phrase Translation Problems

- Idiomatic phrases are not compositional

It's raining cats and dogs.

Es schüttet aus Eimern.

(it pours from buckets.)

- How can we translate such larger units?

Syntactic Translation Problems

- Languages have different sentence structure

das	behaupten	sie	wenigstens
this	claim	they	at least
the		she	

- Convert from object-verb-subject (OVS) to subject-verb-object (SVO)

- Ambiguities can be resolved through syntactic analysis
  - the meaning the of das not possible (not a noun phrase)
  - the meaning she of sie not possible (subject-verb agreement)

Semantic Translation Problems

- Pronominal anaphora

I saw the movie and it is good.

- How to translate it into German (or French)?
  - it refers to movie
  - movie translates to Film
  - Film has masculine gender
  - ergo: it must be translated into masculine pronoun er

- We are not handling this very well
  [Le Nagard and Koehn, 2010]

Semantic Translation Problems

- Coreference

Whenever I visit my uncle and his daughters,
I can't decide who is my favorite cousin.

- How to translate cousin into German? Male or female?

- Complex inference required

Discourse Translation Problems

- Discourse

Since you brought it up, I do not agree with you.

Since you brought it up, we have been working on it.

- How to translated since? Temporal or conditional?

- Analysis of discourse structure — a hard problem

Mismatch in Information Structure

- Morphology allows adding subtle or redundant meaning
  - verb tenses: time action is occurring, if still ongoing, etc.
  - count (singular, plural): how many instances of an object are involved
  - definiteness (the cat vs. a cat): relation to previously mentioned objects
  - grammatical gender: helps with co-reference and other disambiguation

- Some languages allow repeated information across sentences to be dropped

1. Yesterday Jane bought an apple in the store.
2. Ate.

linguistically motivated models

Synchronous Grammar Rules

- Nonterminal rules

$$\text{NP} \rightarrow \text{DET}_1\ \text{NN}_2\ \text{JJ}_3 \mid \text{DET}_1\ \text{JJ}_3\ \text{NN}_2$$

- Terminal rules

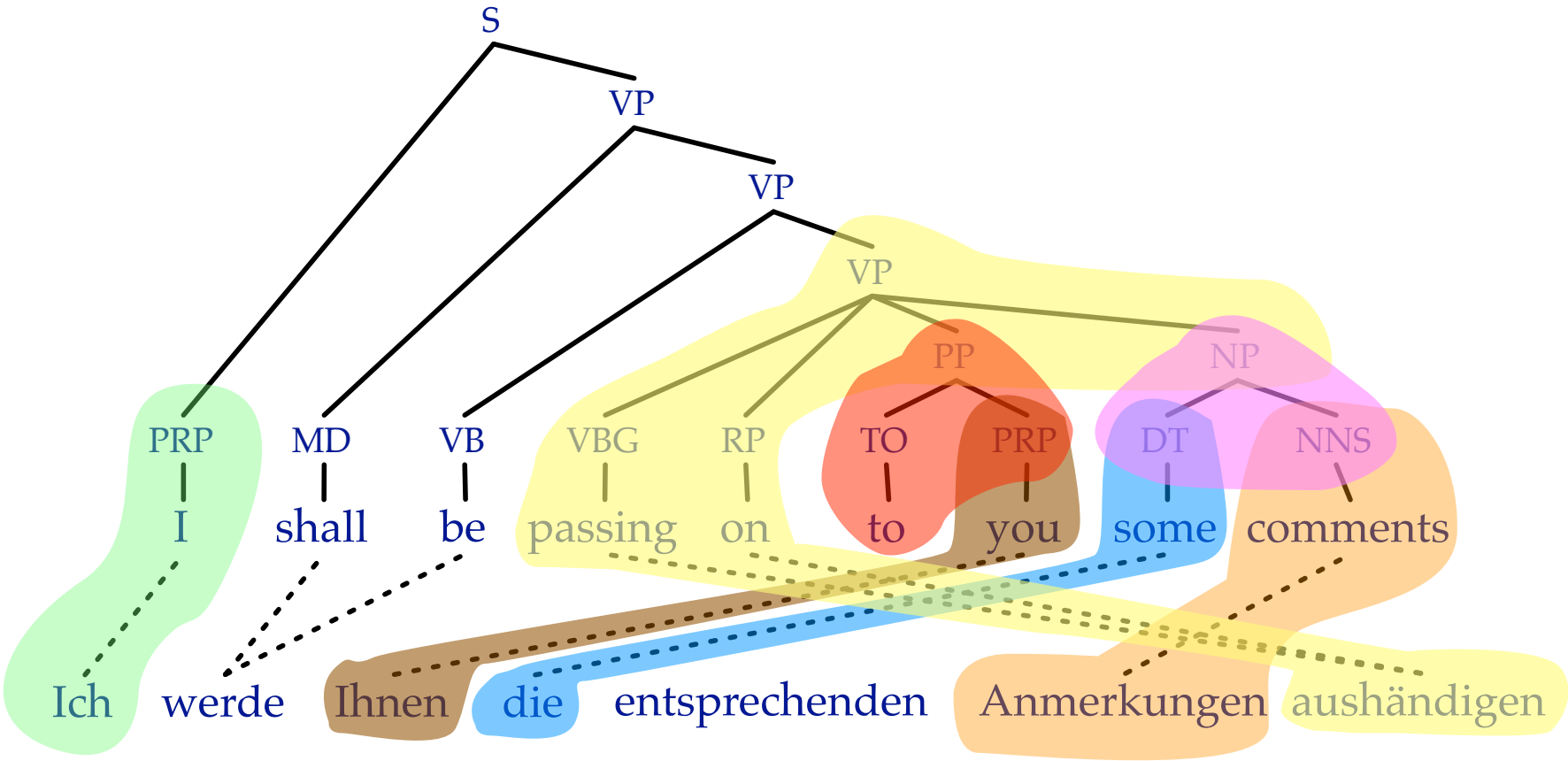
$$\text{N} \rightarrow \text{maison} \mid \text{house}$$

$$\text{NP} \rightarrow \text{la maison bleue} \mid \text{the blue house}$$

- Mixed rules

$$\text{NP} \rightarrow \text{la maison JJ}_1 \mid \text{the JJ}_1\ \text{house}$$

Learning Rules [GHKM]

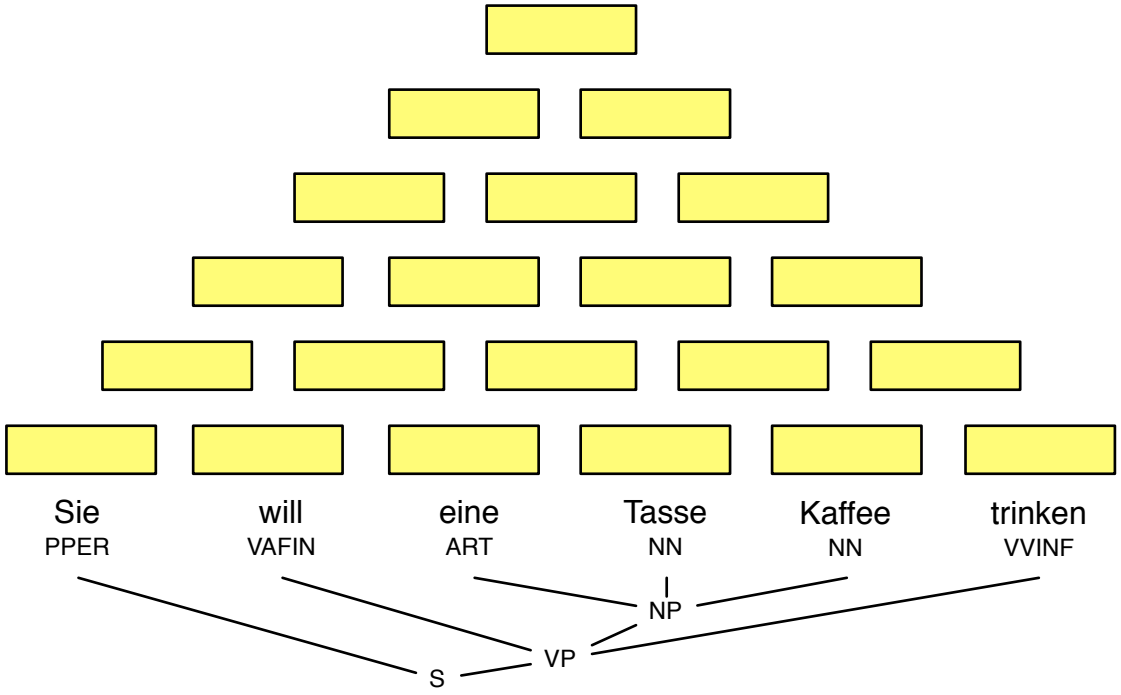


Extracted rule: $\mathsf{VP} \rightarrow \mathsf{X}_1\ \mathsf{X}_2$ aushändigen | passing on $\mathsf{PP}_1\ \mathsf{NP}_2$

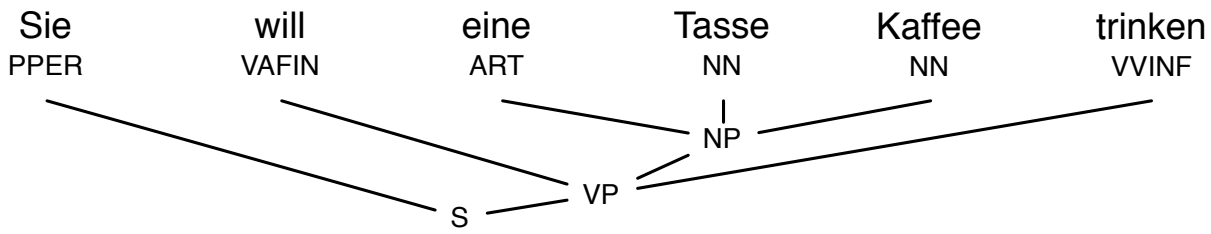
Syntactic Decoding

Inspired by monolingual syntactic chart parsing:

During decoding of the source sentence,
a chart with translations for the $O(n^2)$ spans has to be filled

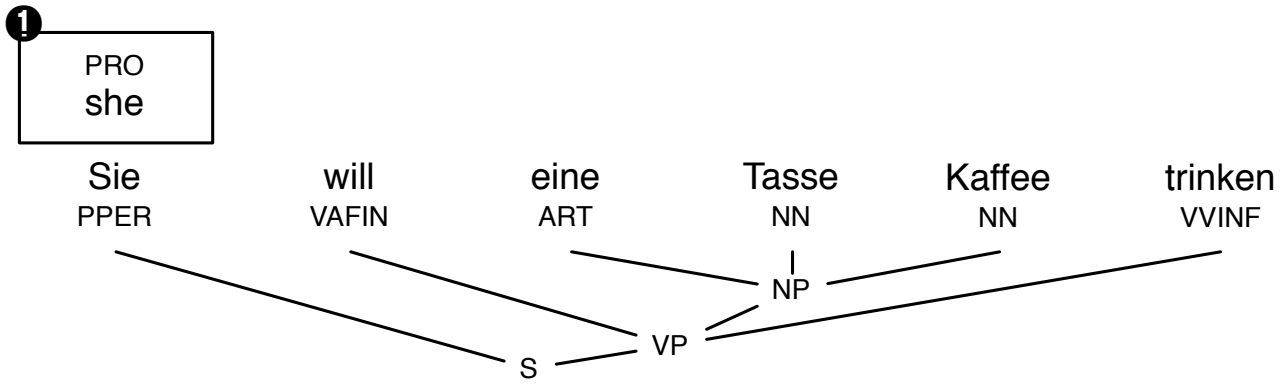


Syntax Decoding



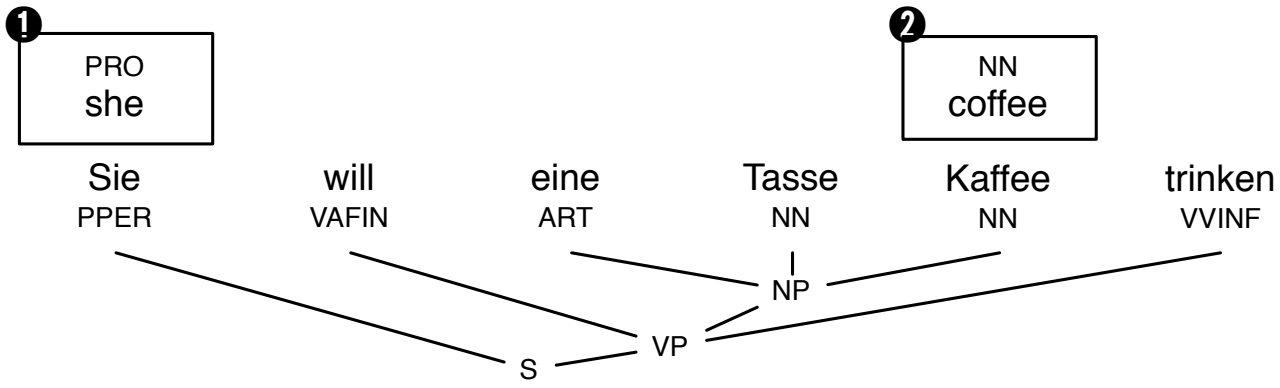
German input sentence with tree

Syntax Decoding



Purely lexical rule: filling a span with a translation (a constituent in the chart)

Syntax Decoding



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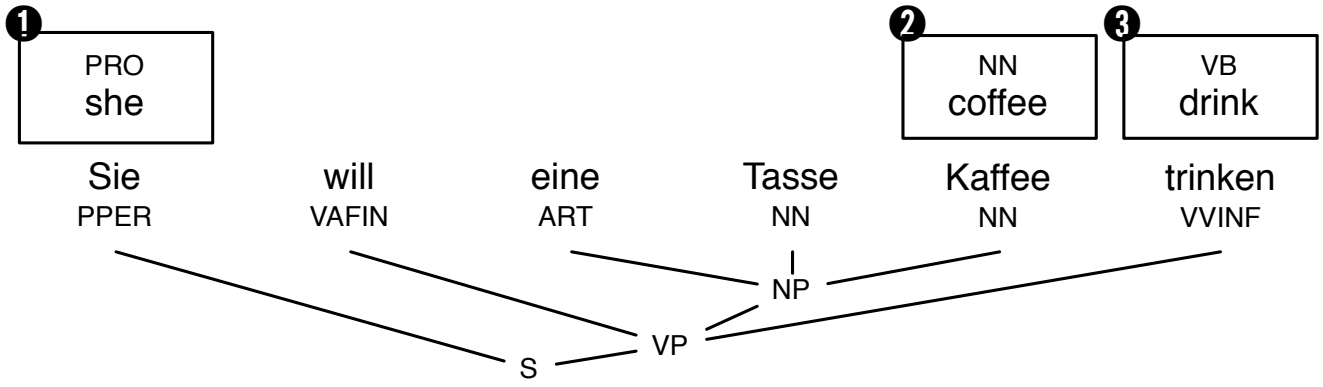

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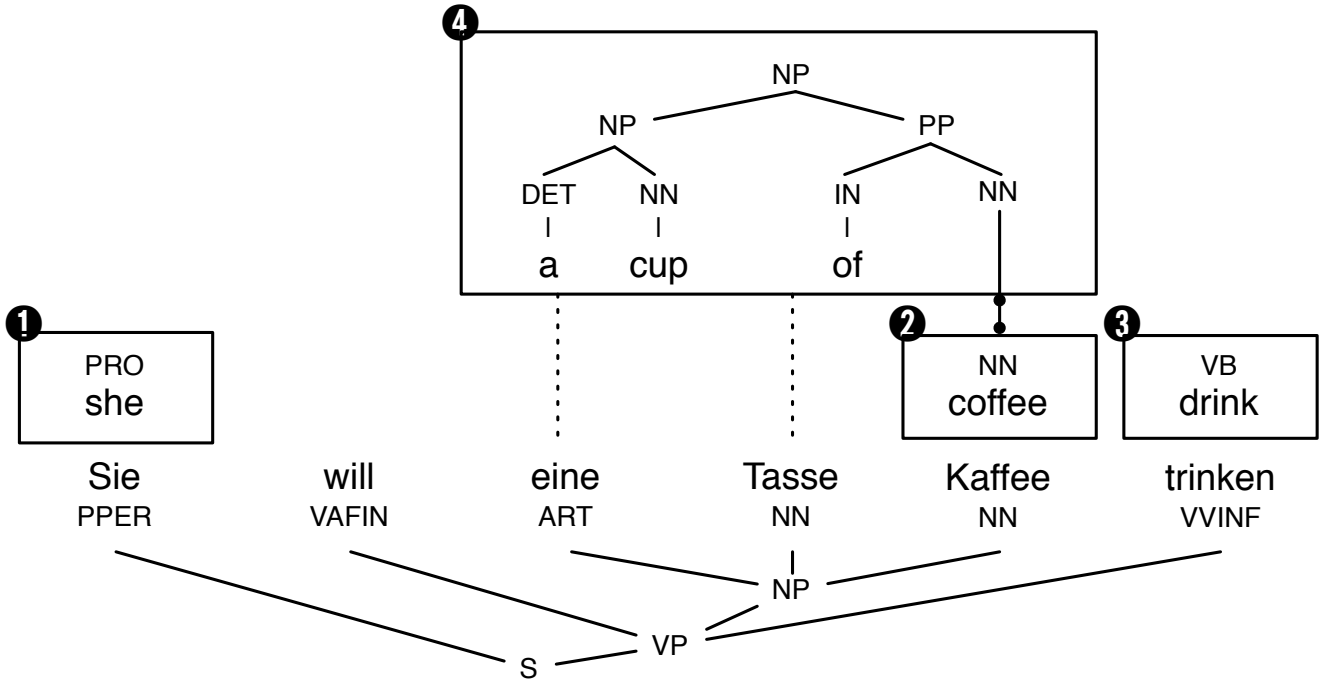
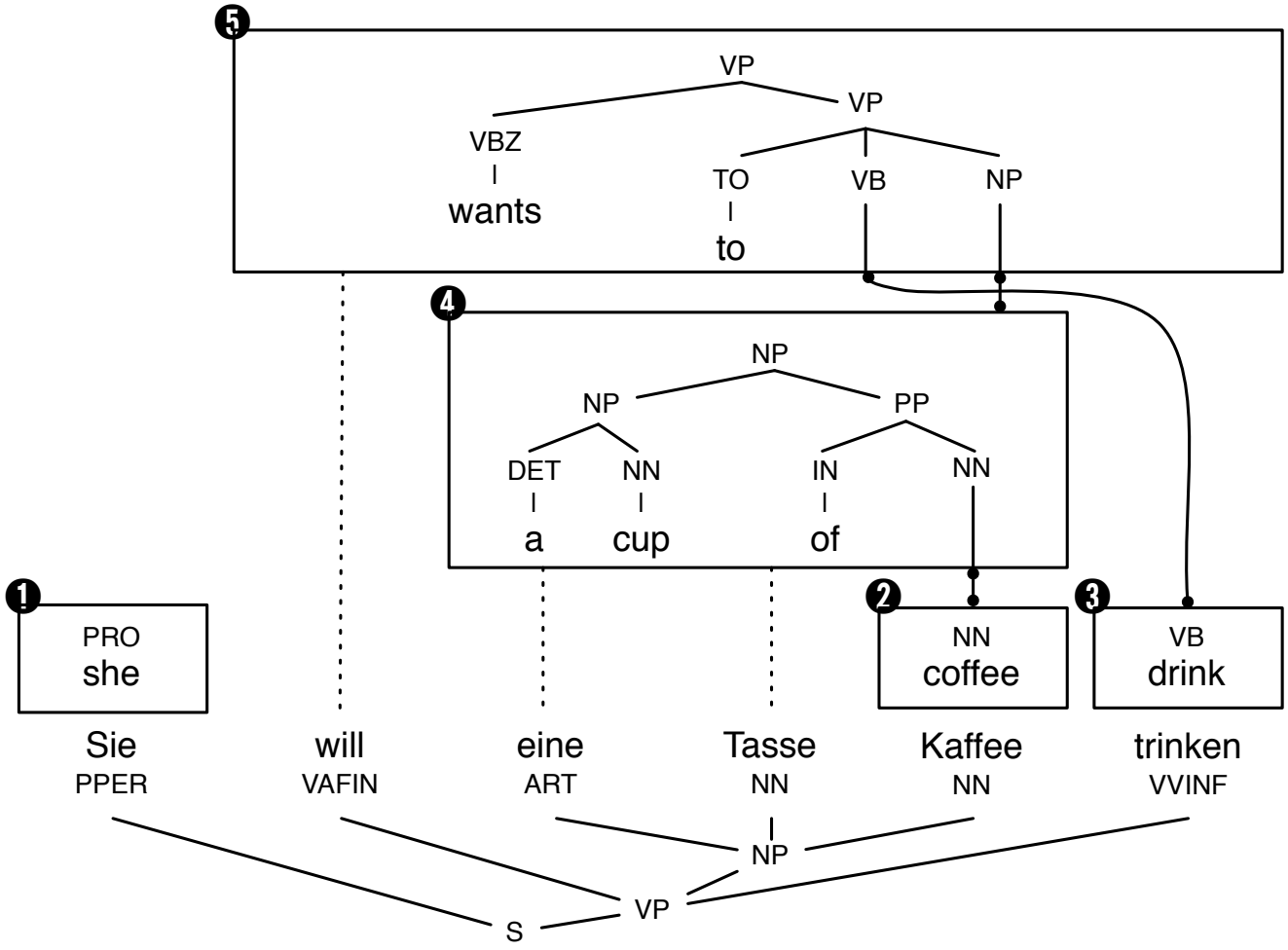


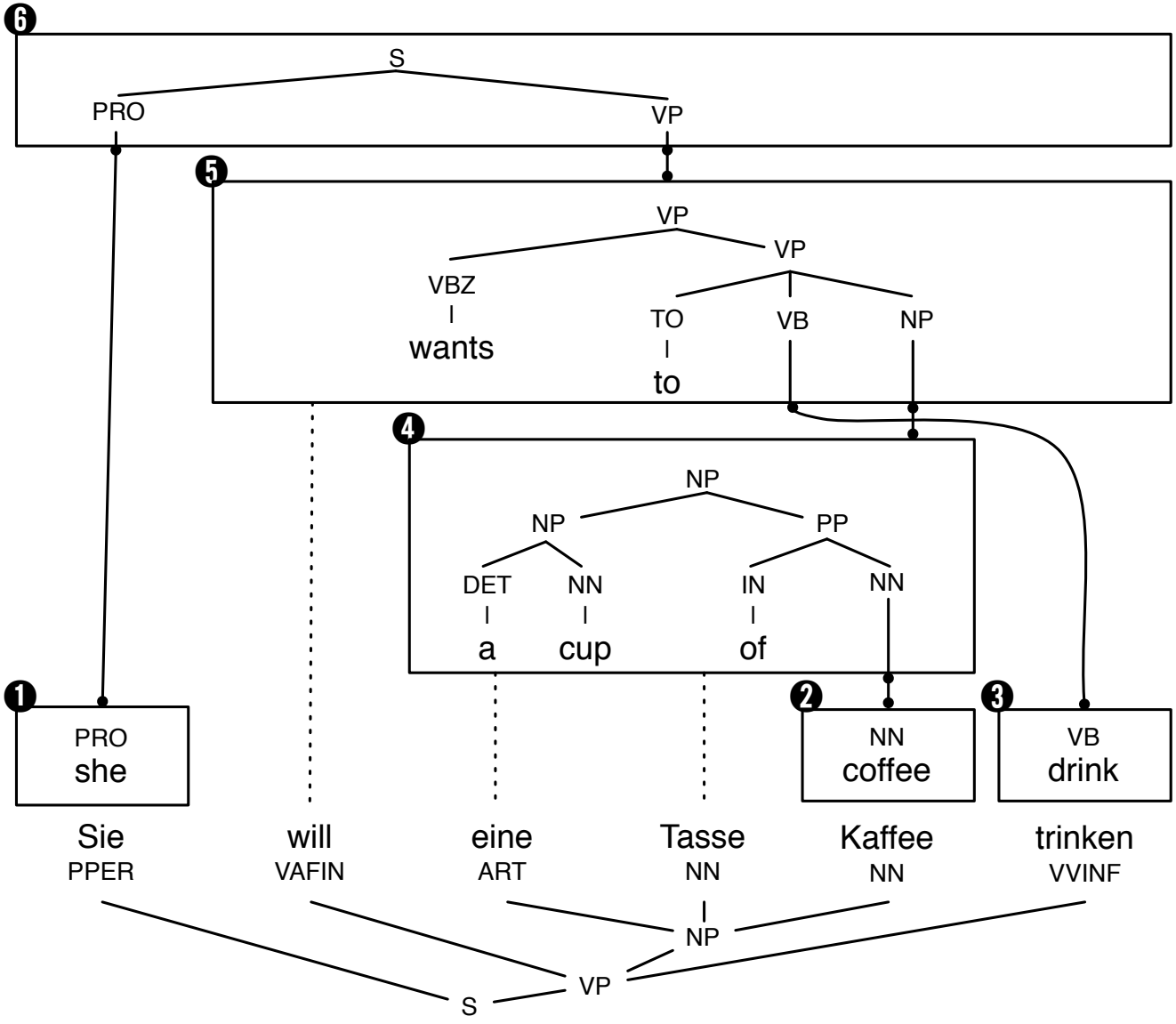
Complex rule: matching underlying constituent spans, and covering words

Syntax Decoding

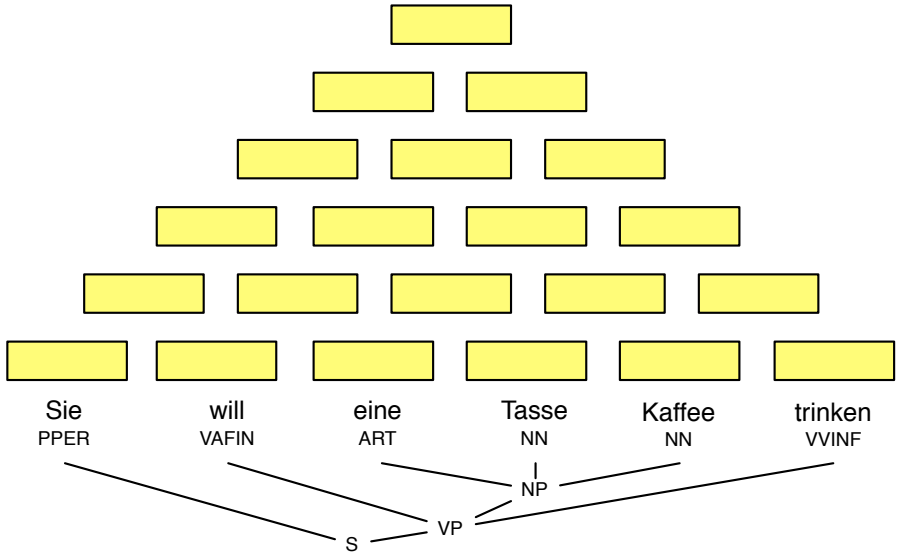


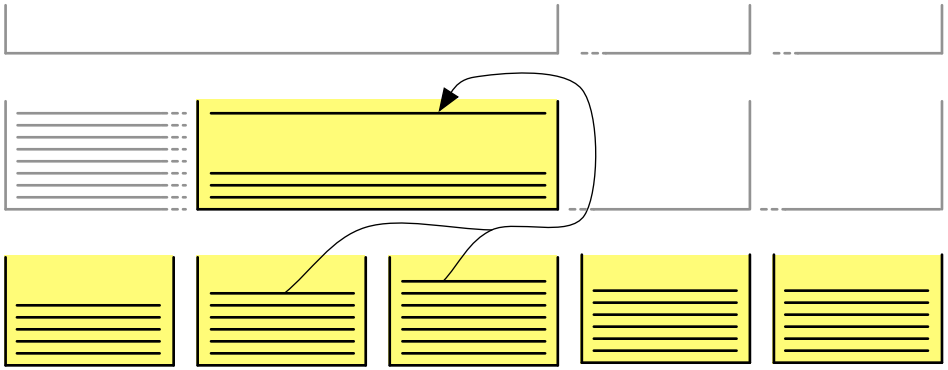
Complex rule with reordering

Syntax Decoding



Bottom-Up Chart Decoding





- Chart consists of cells that cover contiguous spans over the input sentence
- Each cell contains a set of hypotheses
- Hypotheses are constructed bottom-up
- Various ways to binarize rules — we use CKY+

Feature Structures

- Various forms of long distance agreement
  - subject-verb in count (president agrees vs. presidents agree)
  - subject-verb in person (he says vs. I say)
  - verb subcategorization
  - noun phrases in gender, case, count (a big house vs. big houses)

- Represent syntactic constituents with feature structures

$$\begin{bmatrix} \text{CAT} & \text{np} \\ \text{HEAD} & \text{house} \\ \text{CASE} & \text{subject} \\ \text{COUNT} & \text{plural} \\ \text{PERSON} & \text{3rd} \end{bmatrix}$$

Constraints

- Grammar rules may be associated with constraints

$$S \rightarrow NP\ VP$$

S[head] = VP[head]
NP[count] = VP[count]
NP[person] = VP[person]
NP[case] = subject

- Simpler: for each type of non-terminal (NP, VP, S) to be generated
  → set of checks

- Used for
  - case agreement in noun phrases [Williams and Koehn, 2011]
  - consistent verb complex [Williams and Koehn, 2014]

State of the Art

- Good results for German–English [WMT 2014]

language pair	syntax preferred
German–English	57%
English–German	55%

- Mixed for other language pairs

language pair	syntax preferred
Czech–English	44%
Russian–English	44%
Hindi–English	54%

- Also very successful for Chinese–English

Results in 2015

- German–English

	2013	2014	2015
UEDIN phrase-based	26.8	28.0	29.3
UEDIN syntax	26.6	28.2	28.7
Δ	–0.2	+0.2	–0.6
Human preference	52%	57%	?

- English-German

	2013	2014	2015
UEDIN phrase-based	20.1	20.1	22.8
UEDIN syntax	19.4	20.1	24.0
Δ	–0.7	+0.0	**+1.2**
Human preference	55%	55%	?

Perspective

- Syntax-based models superior for German ↔ English
  - also previously shown for Chinese–English (ISI)
  - some evidence for low resource languages (Hindi)
- Next steps
  - Enforcing correct subcategorization frames
  - Features over syntactic dependents
  - Condition on source side syntax (soft features, rules, etc.)
- Decoding still a challenge
- Extend to AMRs?

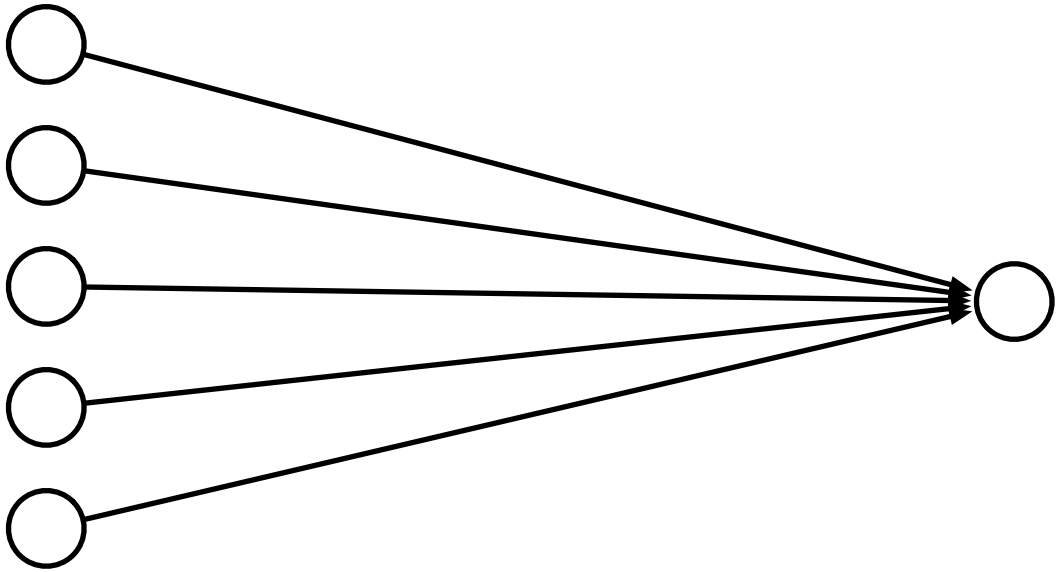
a disruption: deep learning

Linear Models

- We used before weighted linear combination of feature values h_j and weights λ_j

$$\text{score}(\lambda, \mathbf{d}_i) = \sum_j \lambda_j \; h_j(\mathbf{d}_i)$$

- Such models can be illustrated as a "network"



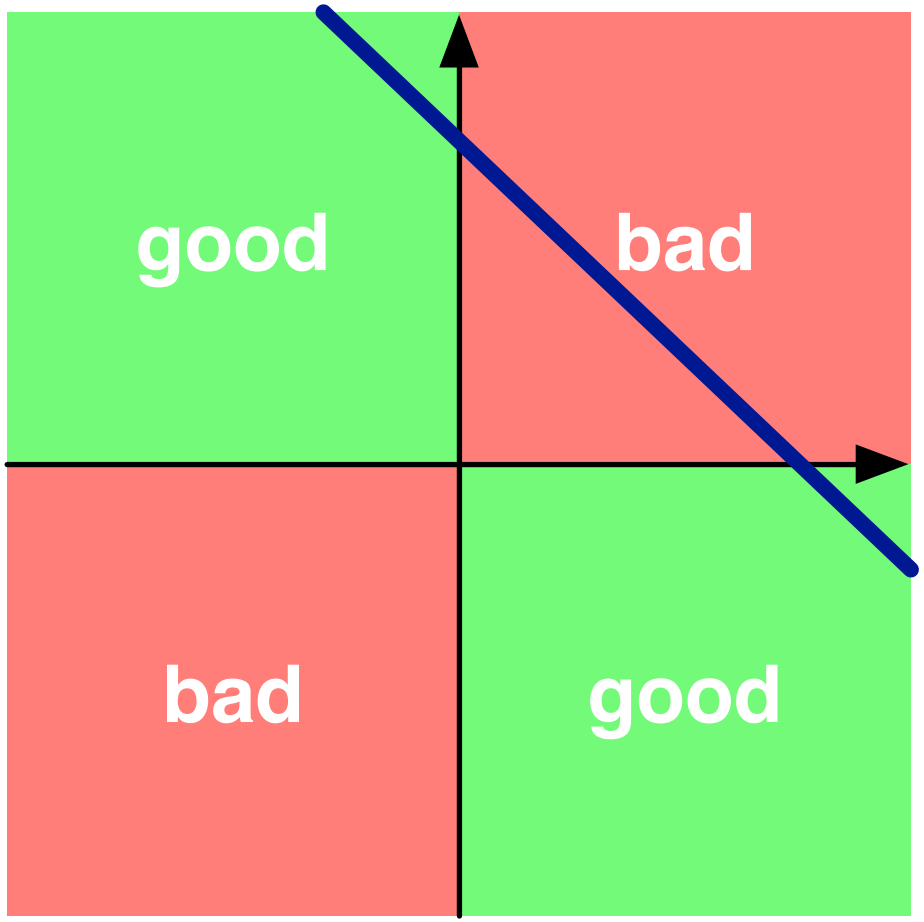
Limits of Linearity

- We can give each feature a weight

- But not more complex value relationships, e.g,
  - any value in the range [0;5] is equally good
  - values over 8 are bad
  - higher than 10 is not worse

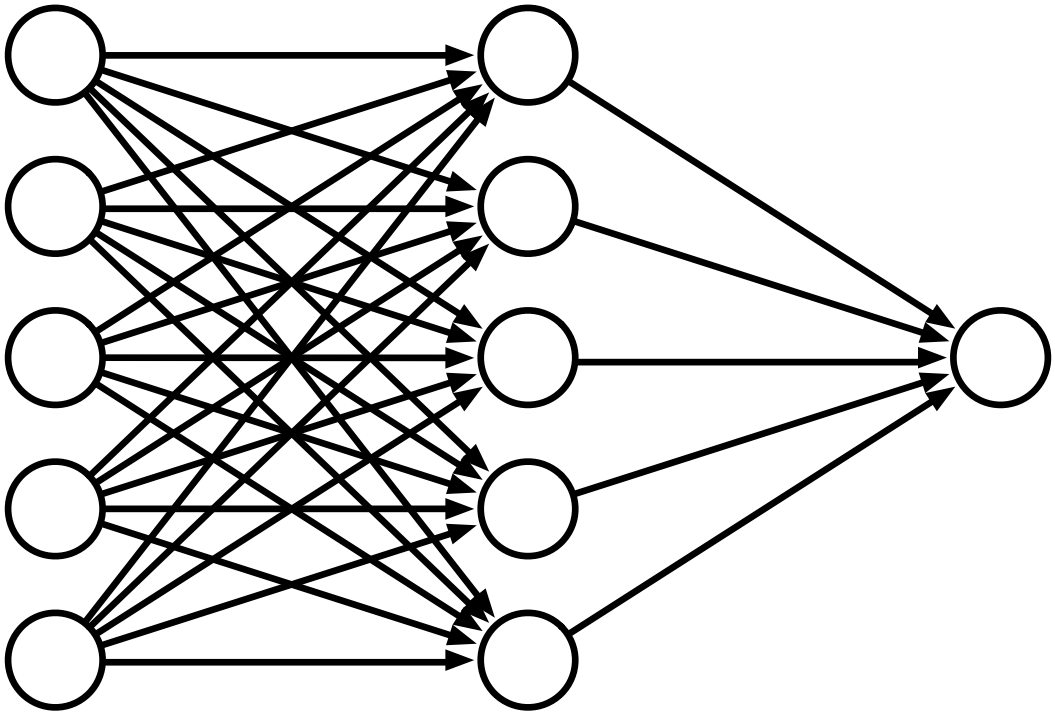
XOR

- Linear models cannot model XOR



Multiple Layers

- Add an intermediate (”hidden”) layer of processing (each arrow is a weight)



- Have we gained anything so far?

Non-Linearity

- Instead of computing a linear combination

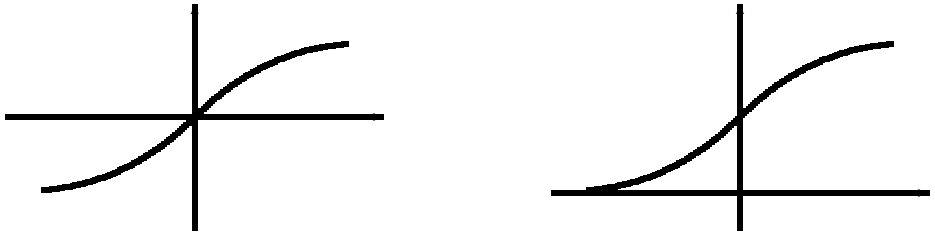
$$\text{score}(\lambda, \mathbf{d}_i) = \sum_j \lambda_j \; h_j(\mathbf{d}_i)$$

- Add a non-linear function

$$\text{score}(\lambda, \mathbf{d}_i) = f\Big(\sum_j \lambda_j \; h_j(\mathbf{d}_i) \Big)$$

- Popular choices

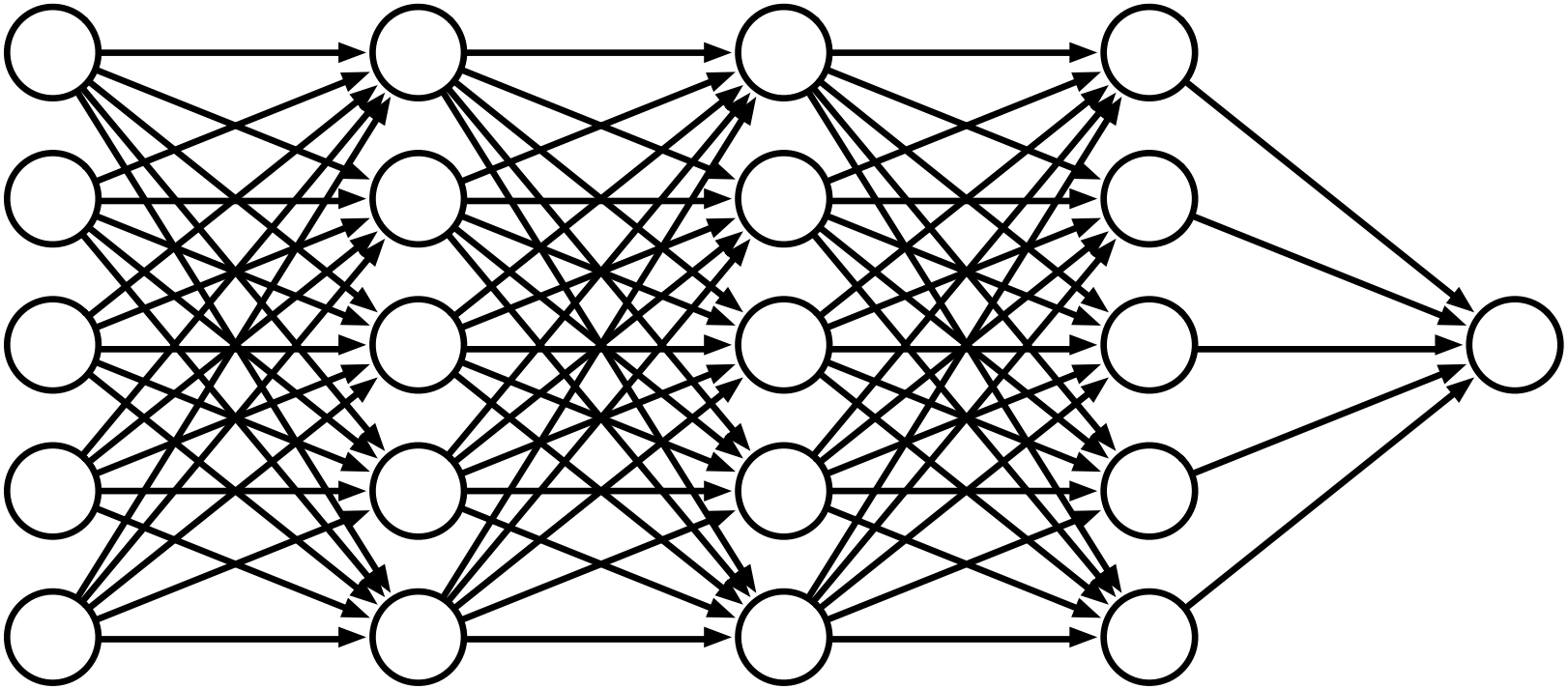
tanh(x) sigmoid(x) = $\frac{1}{1+e^{-x}}$



(sigmoid is also called the "logistic function")

Deep Learning

- More layers = deep learning

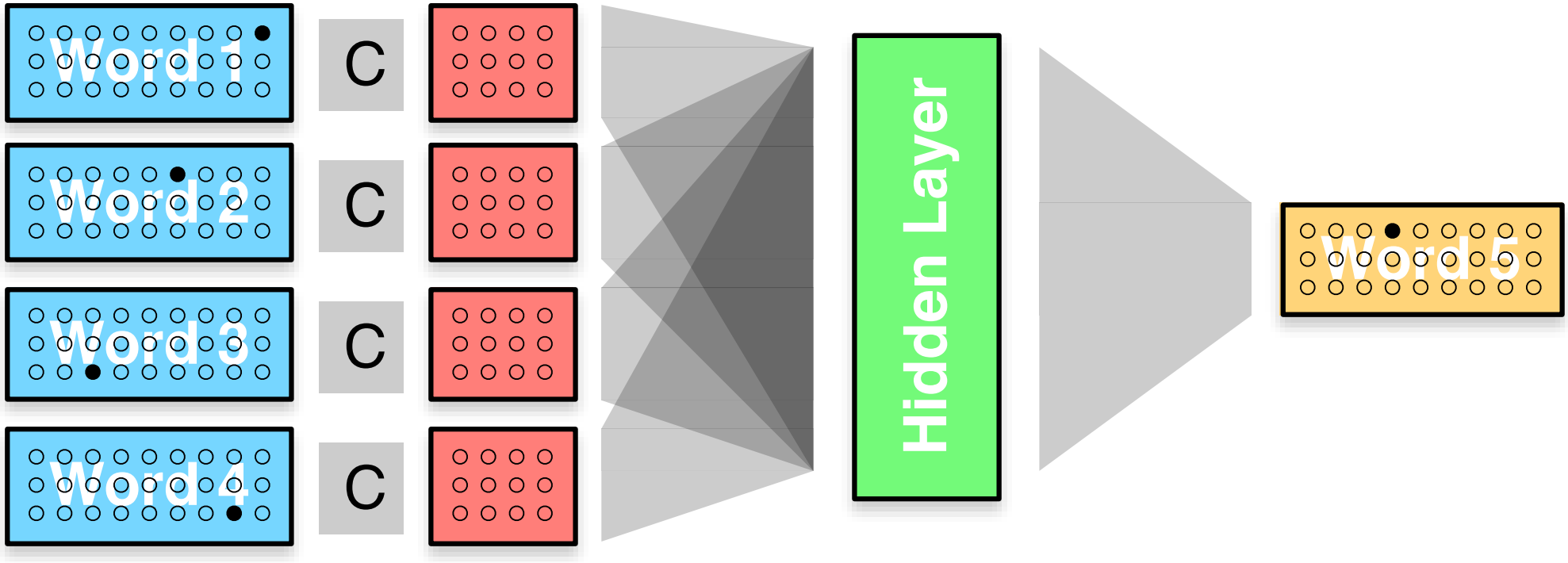


I Told You So!

- My first publications
  - **Combining Genetic Algorithms and Neural Networks**
    Philipp Koehn, MSc thesis 1994
  - **Genetic Encoding Strategies for Neural Networks**
    Philipp Köhn, IPMU 1996
  - **Combining Multiclass Maximum Entropy Text Classifiers with Neural Network Voting**
    Philipp Koehn, PorTAL 2002

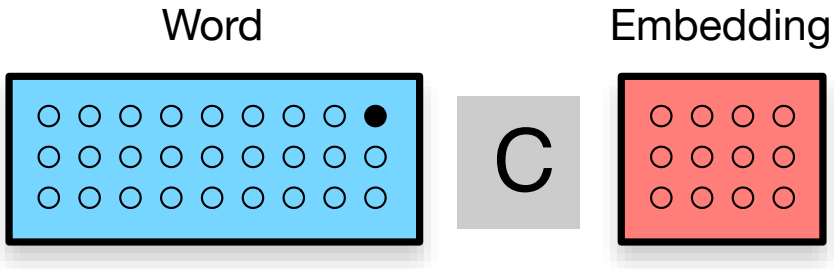
- Real credit goes to Holger Schwenk
  (continuous space language models for statistical machine translation in 2006)

Neural Network Language Models



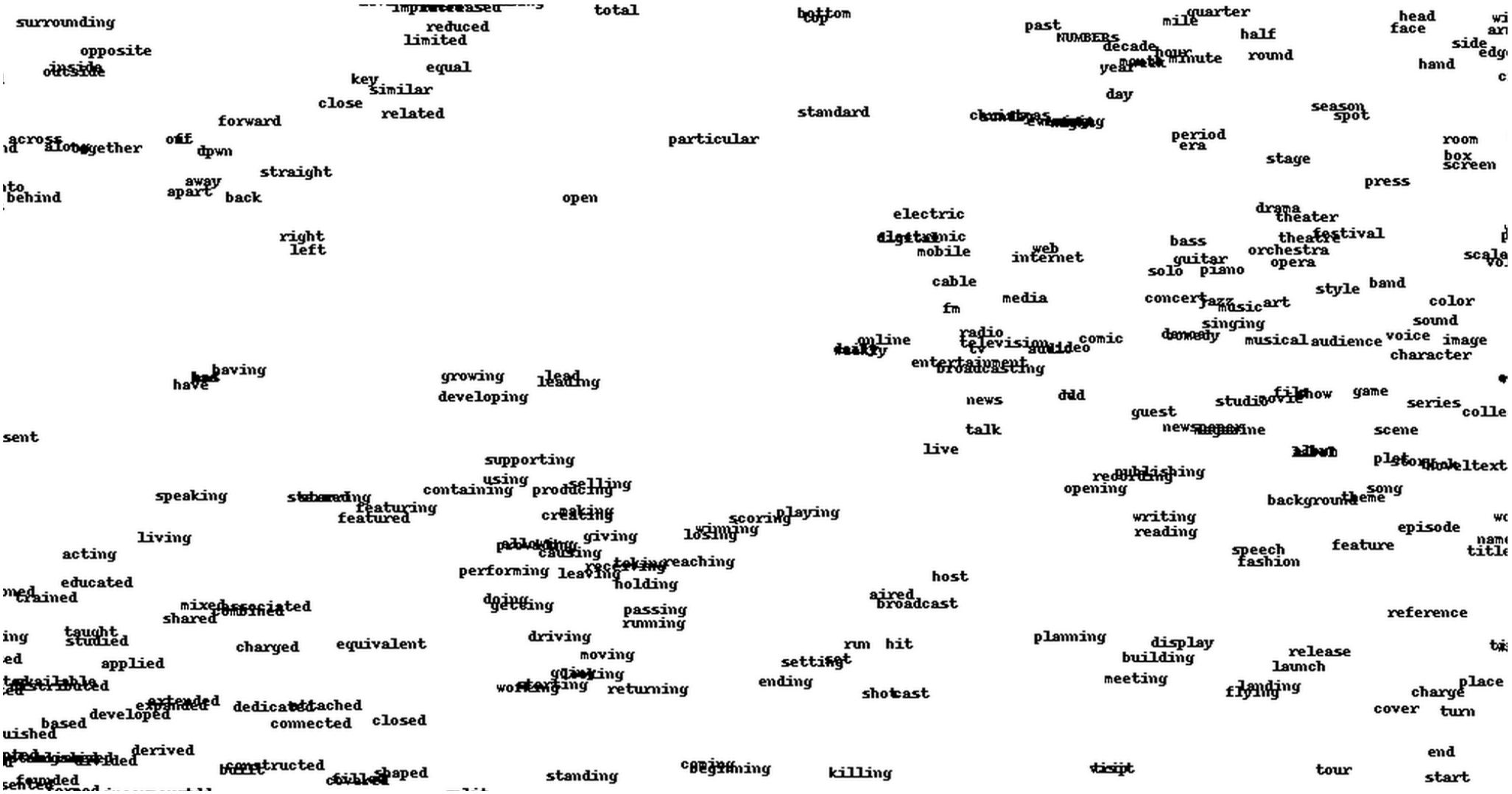
- Words represented by 1-hot vector
- Map each word first into a lower-dimensional real-valued space
- One hidden layer
- Predict next word in output (1-hot vector)

Word Embeddings

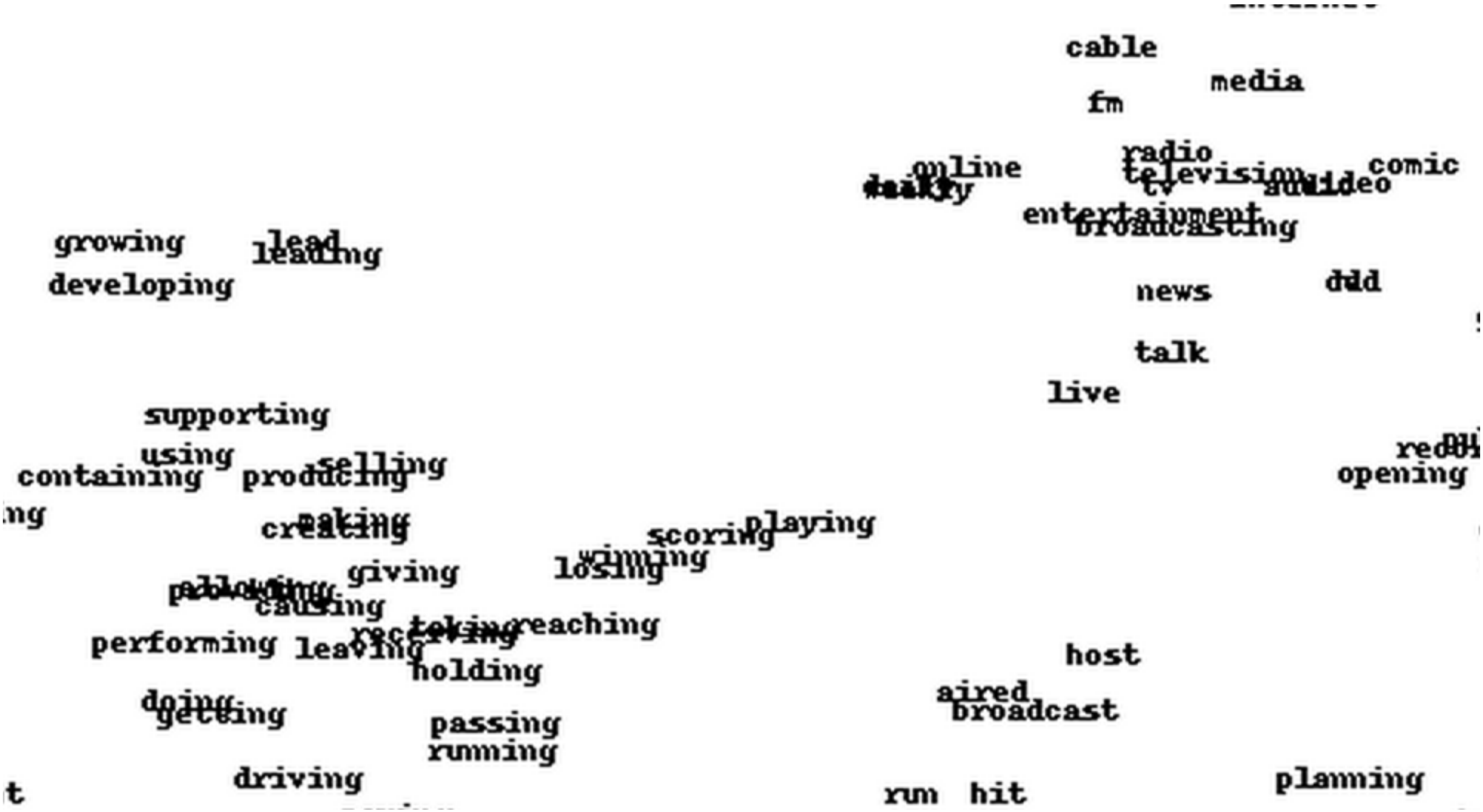


- By-product: embedding of word into continuous space
- Similar contexts $\rightarrow$ similar embedding
- Recall: distributional semantics

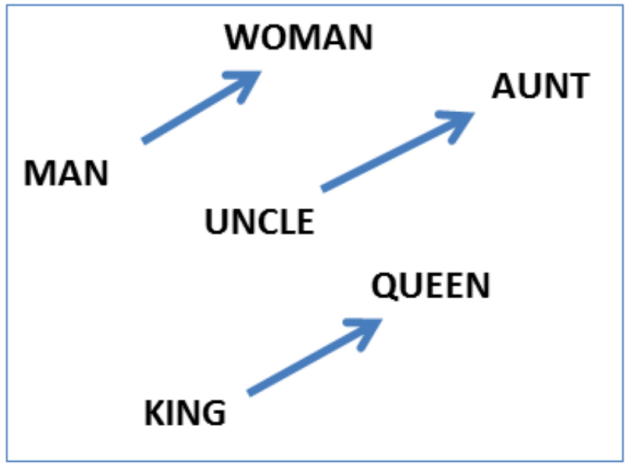
Word Embeddings

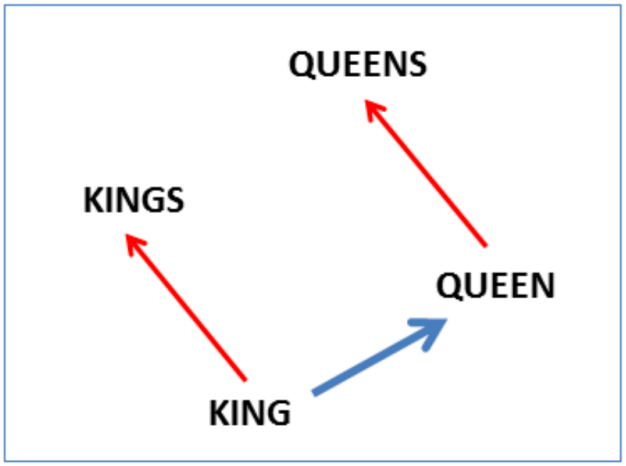


Word Embeddings



Are Word Embeddings Magic?

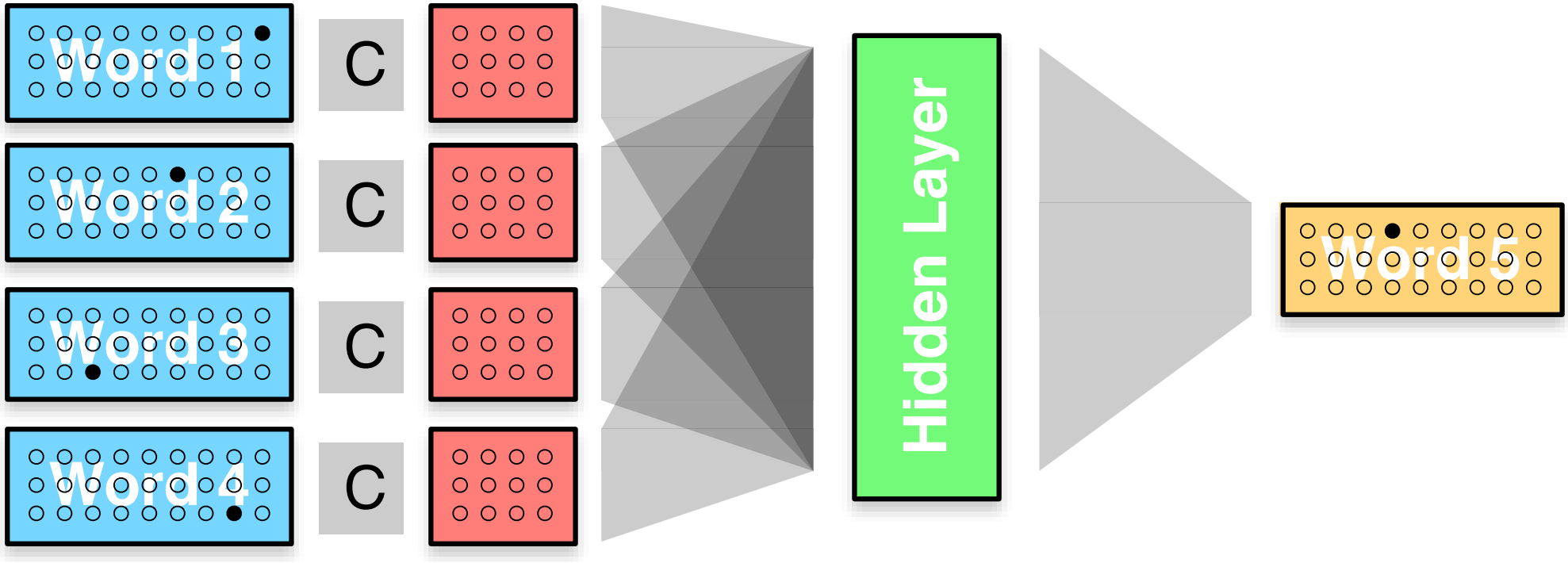




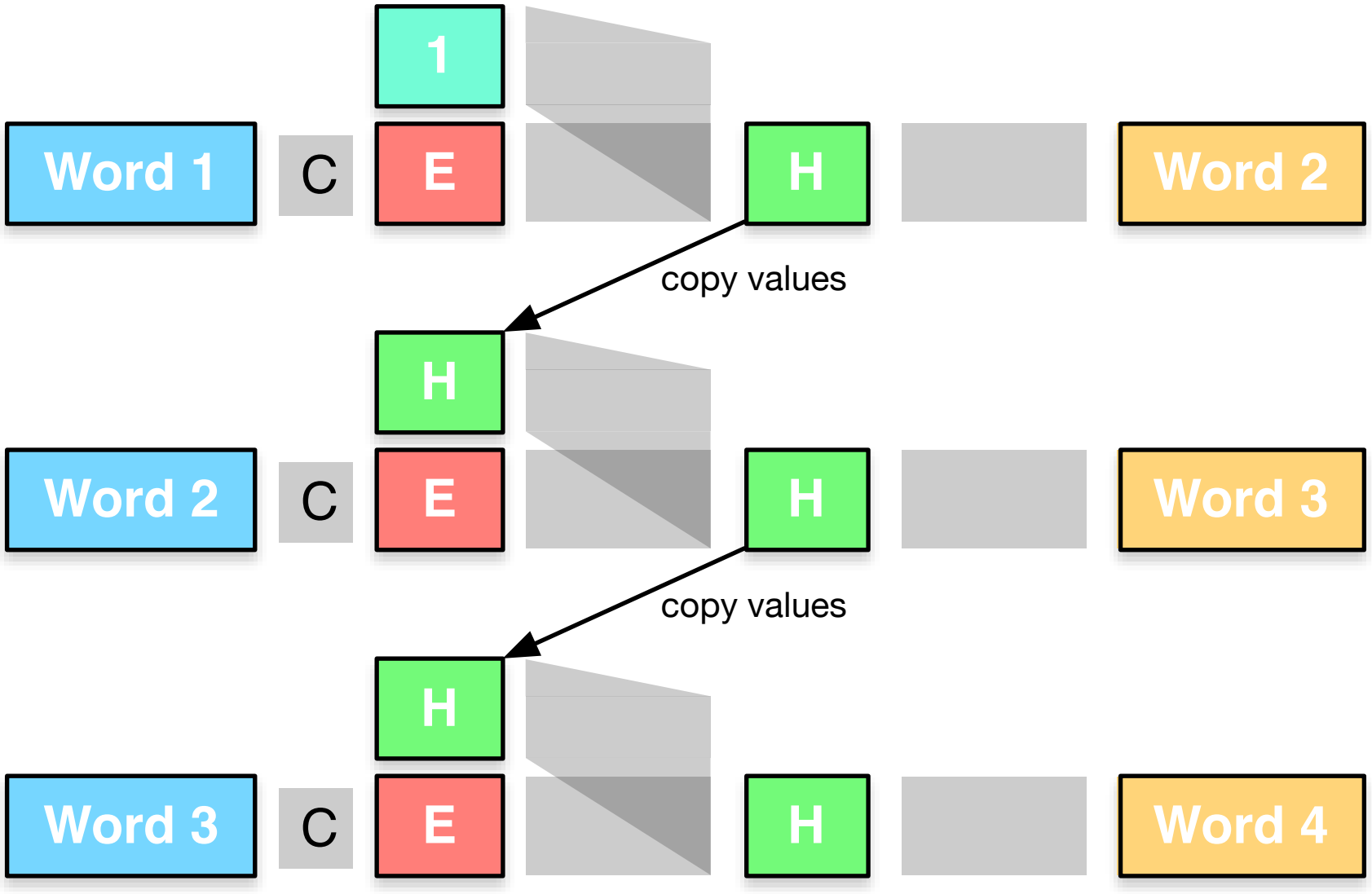
- Morphosyntactic regularities (Mikolov et al., 2013)
  - adjectives base form vs. comparative, e.g., good, better
  - nouns singular vs. plural, e.g., year, years
  - verbs present tense vs. past tense, e.g., see, saw
- Semantic regularities
  - clothing is to shirt as dish is to bowl
  - evaluated on human judgment data of semantic similarities

machine translation with neural networks

Feed Forward Neural Network



Recurrent Neural Network



Encoder–Decoder Model

- Word embeddings seen as "semantic representations"
- Recurrent Neural Network
  $\rightarrow$ semantic representation of whole sentence
- Idea
  - encode semantics of the source sentence with recurrent neural network
  - decode semantics into target sentence from recurrent neural network
- Model

$$(w_1, ..., w_{l_f+l_e}) = (f_1, ..., f_{l_f}, e_1, ..., e_{l_e})$$

$$\prod_k p(w_1, ..., w_{l_f+l_e}) = \prod p(w_k | w_1, ..., w_{k-1})$$

- But: bias towards end of sentence

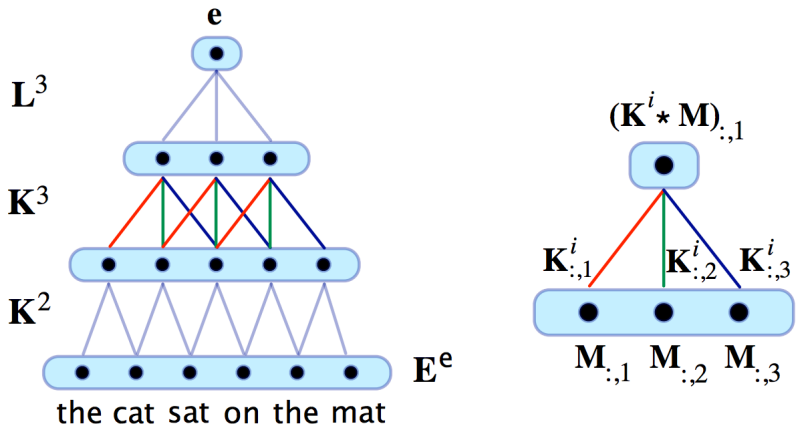
LSTM and Reversed Order (Sutskever et al., 2014)

- Long short term memory for better retention of long distance memory
- Reverse production of target sentence

$$(f_1, ..., f_{l_f}, e_{l_e}, ..., e_1)$$

- Some tricks (ensemble learning)
- Claims that it works as stand-alone model
  but better in reranking

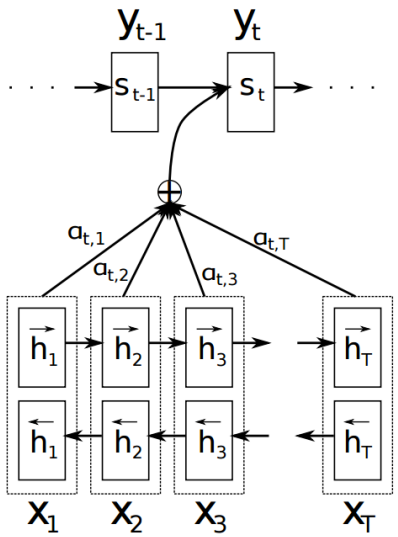
Convolutional Neural Networks (Kalchbrenner and Blunsom, 2013)



- Build sentence representation bottom-up
  - merge any n neighboring nodes
  - n may be 2, 3, ...
- Generate target sentence by inverting the process
- Used successfully in re-ranking (Cho et al., 2014)

Adding an Alignment Model (Bahdanau, Cho and Bengio, 2015)

- Recurrent neural networks to create context representations for each input word
- Alignment model: conditioned on previous state and source side context



- Comment: this feels a bit like the HMM variant of the IBM Models

Does Any of This Work?

- Papers claim gains (sometimes only in reranking)

- Montreal (Bahdanau, Cho and Bengio, 2015) submission to WMT 2015

	de-en	en-de	cs-en	en-cs	fi-en
Best SMT	**29.3**	24.0	**26.2**	18.2	**19.7**
Montreal	27.9	22.4	23.8	**18.4**	13.6
Montreal emsemble		**24.9**			

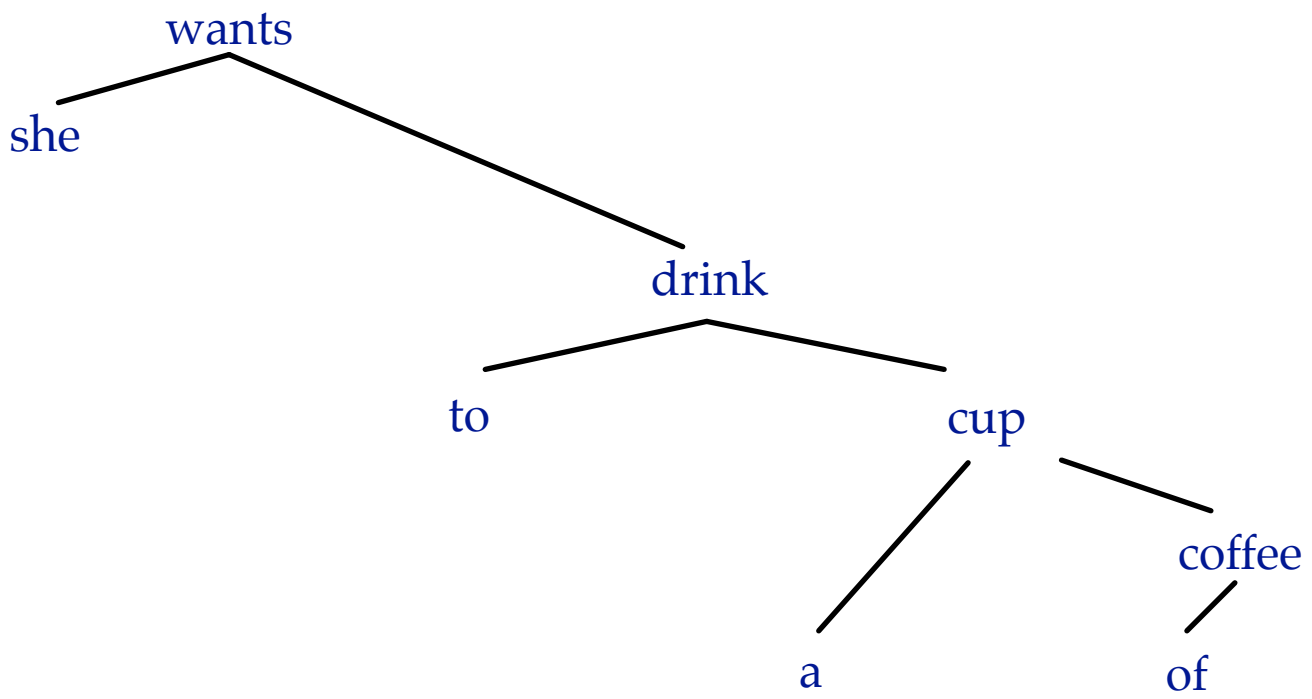
(Scores from matrix.statmt.org)

Reflections

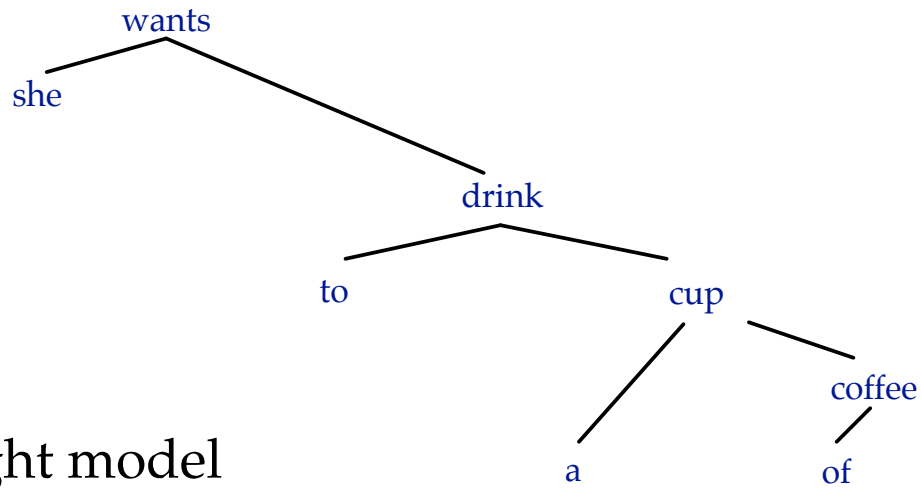
- Traditional statistical models have real short-comings
  - how to back-off to less context?
  - how to cluster information among words?
- Neural networks offer a more flexible way to condition on context
- Two strategies
  - Incremental strategy:
    replace statistical components with neural components
  - Leap forward strategy:
    start from scratch: neural machine translation

syntax-based machine translation with neural networks

Dependency Structure



Dependency Model (Sennrich, 2015)



- Top-down / left-right model
- Predict from ancestry (up to 2)
  - parent
  - grand-parent
- Predict from left children (up to 2)
- Example: $p(\text{coffee}|\text{cup}, \text{drink}, \text{a}, \epsilon)$

Statistical Model

- Probability distribution

$$p(\text{word}|\text{parent}, \text{grand-parent}, \text{left-most-sibling}, \text{2nd-left-most-sibling})$$

for instance

$$p(\text{coffee}|\text{cup}, \text{drink}, \text{a}, \epsilon)$$

- Difficult to model
  - very sparse
  - no sharing of information between

$$p(\text{coffee}|\text{cup}, \text{drink}, \text{a}, \epsilon)$$

and

$$p(\text{tea}|\text{cup}, \text{drink}, \text{a}, \epsilon)$$

Neural Network Model

- Probability distribution

$$p(\text{word}|\text{parent}, \text{grand-parent}, \text{left-most-sibling}, \text{2nd-left-most-sibling})$$

can be converted straightforward into a feed-forward neural network

- Words encoded with embeddings

- Empty slots modeled by average embedding over all words

Results

- Sennrich (2015)

System	Newstest 2013	Newstest 2014
Baseline	20.0	20.5
+NNLM	20.6	21.1
+neural dependency	20.9	21.6
+NNLM+neural dependency	21.0	21.8

- Official submissions to WMT 2015

System	BLEU
UEDIN syntax	22.6
UEDIN syntax with neural models	24.0

Caution: there were also other differences

what needs to be done?

Error Analysis: The Rules

- Given:
  - bilingual speaker
  - source sentence
  - machine translation output
  - (possibly reference translation)
- Step 1: Make minimal correction to create acceptable translation
  (fluent target language, correct meaning, may not be stylistically perfect)
- Step 2: Identify errors
- Error categories
  - qualitative
  - 1 error may cover mulitiple words
- A subjective process

Example: Simple Errors

SRC: Es geht also um viel mehr als um Partikularinteressen des Herren Medau", so Pötzl.

REF: It's therefore about a lot more than the individual interests of the Medau gentleman," he said.

TGT: It is so much more than vested interests of Mr Medau," said Pötzl.

Corrected Target: It is about so much more than the vested interests of Mr Medau," Pötzl said.

Errors:

$\epsilon \rightarrow$ *about*	—	missing preposition
$\epsilon \rightarrow$ *the*	—	missing determiner
said	—	reordering error: verb

Example: Muddle

SRC: Die Polizei von Karratha beschuldigt einen 20-jhrigen Mann der Nichtbeachtung eines Haltesignals sowie rcksichtslosen Fahrens.

REF: Karratha Police have charged a 20-year-old man with failing to stop and reckless driving.

TGT: The police believe the failure of a 20-year-old man accused of Karratha signal and reckless driving.

Corrected Target: The police of Karratha charged a 20-year-old man with failure to obey a signal and reckless driving.

This is a muddle, there is just too much wrong to categorize individual errors.

Study

- German–English
- Syntax-based system (UEDIN)
- WMT 2015 test set
- Examined 100 sentences
- One judge: me

- Note: small scale — just for this talk

Results

- 2.85 errors per sentence on average

- Distribution

Sentences with...	Count
0 errors	16 sentences
1 error	18 sentences
2 errors	17 sentences
3 errors	17 sentences
more than 3 errors	32 sentences

Results

- Longest sentence with no error
  - Source: Der Oppositionspolitiker Imran Khan wirft Premier Sharif vor, bei der Parlamentswahl im Mai vergangenen Jahres betrogen zu haben.
  - Target: The opposition politician Imran Khan accuses Premier Sharif of having cheated in the parliamentary election in May of last year.
  - Has a complex subclause construction: accuses ... of having cheated

Major Error Categories

Count	Category	Count	Category
29	Wrong content word - noun	6	Wrong content word - phrasal verb
25	Wrong content word - verb	6	Added function word - determiner
22	Wrong function word - preposition	5	Unknown word - noun
21	Inflection - verb	5	Missing content word - adverb
14	Reordering: verb	5	Missing content word - noun
13	Reordering: adjunct	5	Inflection - noun
12	Missing function word - preposition	4	Reordering: NP
10	Missing content word - verb	3	Missing content word - adjective
9	Wrong function word - other	3	Inflection - wrong POS
9	Wrong content word - wrong POS	3	Casing
9	Added punctuation	2	Unknown word - verb
8	Muddle	2	Reordering: punctuation
8	Missing function word - connective	2	Reordering: noun
8	Added function word - preposition	2	Reordering: adverb
7	Missing punctuation	2	Missing function word - determiner
7	Wrong content word - adverb	2	Inflection - adverb

The Problems You Should be Working On

- **Word sentence disambiguation**

Count	Category
29	Wrong content word - noun
25	Wrong content word - verb
9	Wrong content word - wrong POS
7	Wrong content word - adverb
6	Wrong content word - phrasal verb

- **Prepositions**

Count	Category
22	Wrong function word - preposition
12	Missing function word - preposition
8	Added function word - preposition

The Problems You Should be Working On

- **Reordering**

Count	Category
14	Reordering: verb
13	Reordering: adjunct
4	Reordering: NP
2	Reordering: noun
2	Reordering: adverb

Note: much less of a problem than with phrase models

- **Other issues with verbs**

Count	Category
21	Inflection - verb
10	Missing content word - verb

Thank You

questions?