Syntax and Semantics

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syntax

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  - reordering, e.g., verb movement in German–English translation
  - long distance agreement (e.g., subject-verb) in output

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⇒ Translation models based on tree representation of language
  - successful for statistical machine translation
  - open research challenge for neural models

Dependency Structure

I	like	the	interesting	lecture
PRO	VB	DET	JJ	NN
↓		↓	↓	↓
like		lecture	lecture	like

- Center of a sentence is the verb
- Its dependents are its arguments (e.g., subject noun)
- These may have further dependents (adjective of noun)

Phrase Structure Grammar

- Phrase structure
  - noun phrases: *the big man*, *a house*, ...
  - prepositional phrases: *at 5 o'clock*, *in Edinburgh*, ...
  - verb phrases: *going out of business*, *eat chicken*, ...
  - adjective phrases, ...

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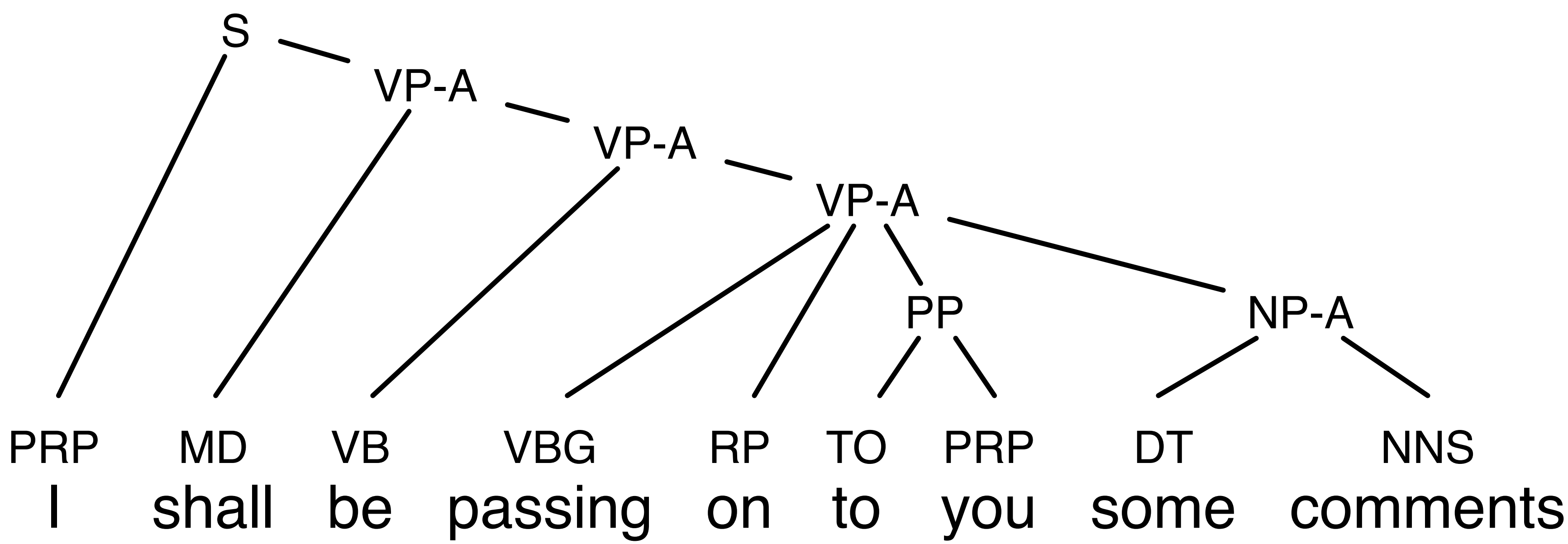
  - adjective phrases, ...
- Context-free Grammars (CFG)
  - non-terminal symbols: phrase structure labels, part-of-speech tags
  - terminal symbols: words
  - production rules: NT $\rightarrow$ [NT,T]+
    example: NP $\rightarrow$ DET NN

Phrase Structure Grammar



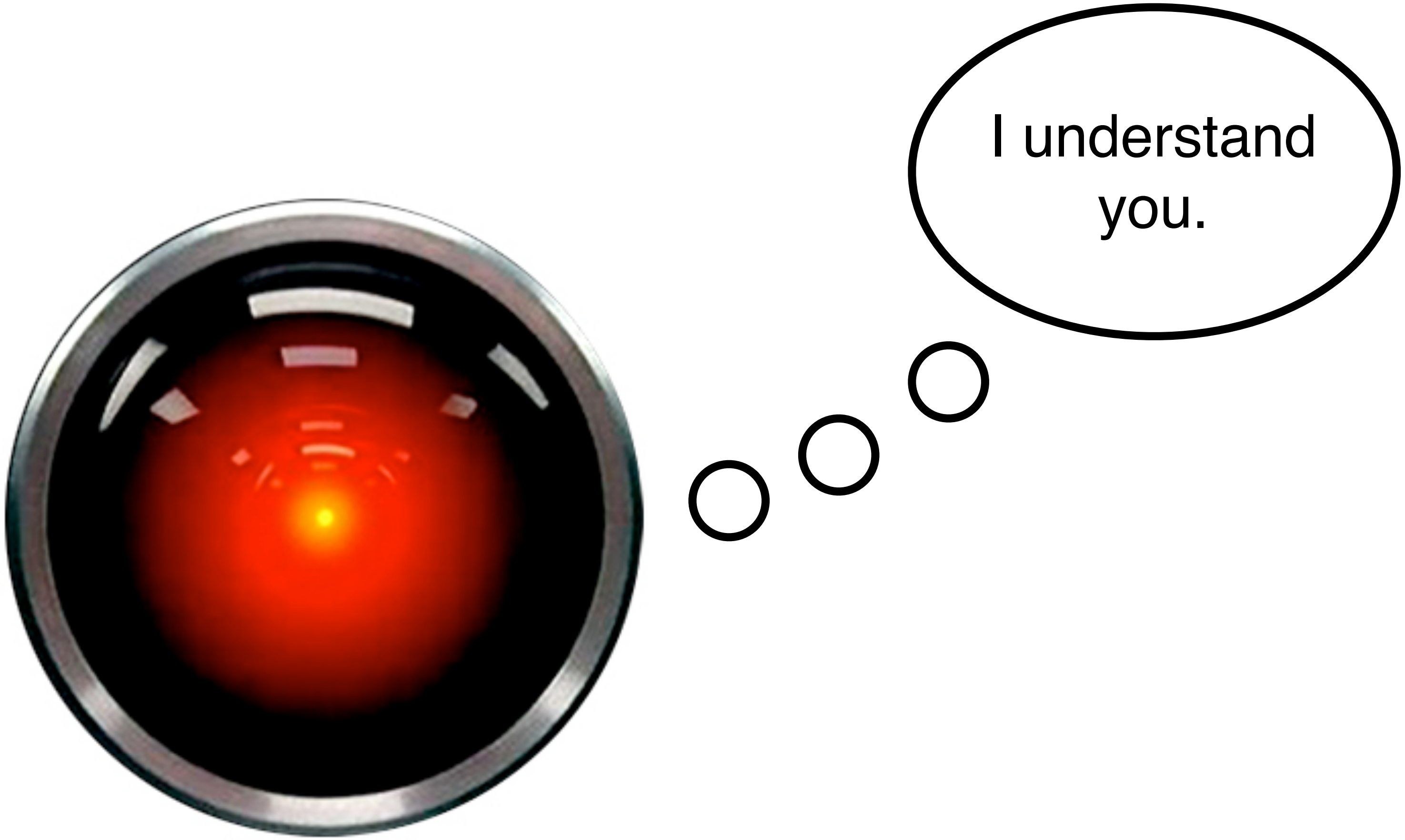
Phrase structure grammar tree for an English sentence
(as produced Collins' parser)

semantics

Meaning

- The grand goal of **artificial intelligence**
  - machines that do not mindlessly process data
  - ... but that ultimately **understand** its meaning
- But what is meaning?

Meaningful Machines



A Scale of Understanding?

wisdom

$\Uparrow$

knowledge

$\Uparrow$

data

Eliza

Joseph Weizenbaum wrote the computer program Eliza in 1969 to demonstrate how easily people can be fooled into thinking that machines have some deep understanding.

young woman: *Men are all alike.*
eliza: *In what way?*
young woman: *They're always bugging us about something specific or other.*
eliza: *Can you think of a specific example?*
young woman: *Well, my boyfriend made me come here.*
eliza: *Your boyfriend made you come here?*
young woman: *He says I'm depressed much of the time.*
eliza: *I am sorry to hear you are depressed.*
young woman: *It's true. I'm unhappy.*
eliza: *Do you think coming here will help you not to be unhappy?*

Online demo: `http://www-ai.ijs.si/eliza-cgi-bin/eliza_script`

semantic translation problems

Semantic Translation Problems

- Syntactic analysis may be ambiguous

Das	Vorhaben	verwarf	die	Kommission	.
the	*plan*	*rejected*	*the*	*commission*	*.*

- Both readings (SVO and OSV) are syntactically possible
- But: OSV reading is semantically much more plausible

⇒ Need for semantic model to produce semantically plausible output

lexical semantics

Word Senses

- Some words have multiple meanings
- This is called polysemy
- Example: *bank*
  - financial institution: *I put my money in the bank.*
  - river shore: *He rested at the bank of the river.*
- How could a computer tell these senses apart?

Homonym

- Sometimes two completely different words are spelled the same
- This is called a homonym
- Example: *can*
  - modal verb: *You can do it!*
  - container: *She bought a can of soda.*
- Distinction between polysemy and homonymy not always clear

How Many Senses?

- How many senses does the word *interest* have?
  - *She pays 3%* **interest** *on the loan.*
  - *He showed a lot of* **interest** *in the painting.*
  - *Microsoft purchased a controlling* **interest** *in Google.*
  - *It is in the national* **interest** *to invade the Bahamas.*
  - *I only have your best* **interest** *in mind.*
  - *Playing chess is one of my* **interests**.
  - *Business* **interests** *lobbied for the legislation.*
- Are these seven different senses? Four? Three?

Wordnet

- Wordnet, a hierarchical database of senses, defines synsets
- According to Wordnet, *interest* is in 7 synsets
  - Sense 1: *a sense of concern with and curiosity about someone or something*, Synonym: *involvement*
  - Sense 2: *the power of attracting or holding one's interest (because it is unusual or exciting etc.)*, Synonym: *interestingness*
  - Sense 3: *a reason for wanting something done*, Synonym: *sake*
  - Sense 4: *a fixed charge for borrowing money; usually a percentage of the amount borrowed*
  - Sense 5: *a diversion that occupies one's time and thoughts (usually pleasantly)*, Synonyms: *pastime, pursuit*
  - Sense 6: *a right or legal share of something; a financial involvement with something*, Synonym: *stake*
  - Sense 7: *(usually plural) a social group whose members control some field of activity and who have common aims*, Synonym: *interest group*

Sense and Translation

- Most relevant for machine translation:
  different translations $\rightarrow$ different sense

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- Example *interest* translated into German
  - *Zins*: financial charge paid for load (Wordnet sense 4)
  - *Anteil*: stake in a company (Wordnet sense 6)
  - *Interesse*: all other senses

Languages Differ

- Foreign language may make finer distinctions

- Translations of *river* into French
  - *fleuve*: river that flows into the sea
  - *rivière*: smaller river

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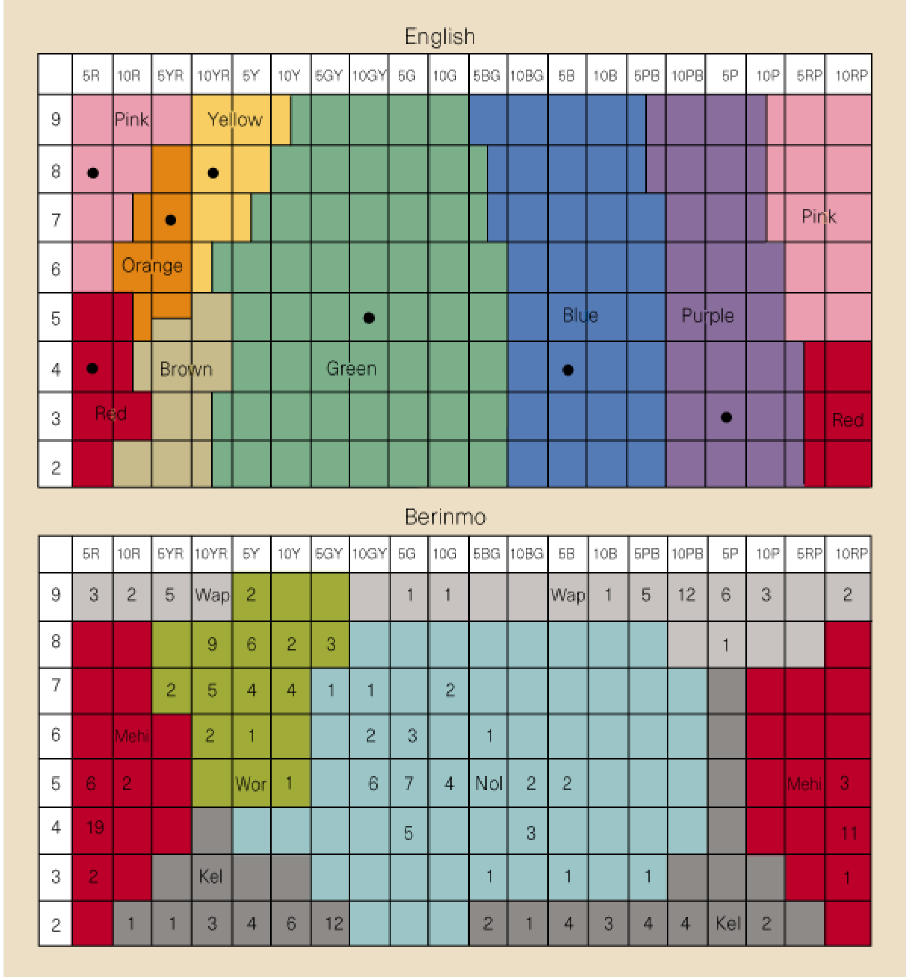
- English may make finer distinctions than a foreign language

- Translations of German *Sicherheit* into English
  - *security*
  - *safety*
  - *confidence*

Overlapping Senses

- Color names may differ between languages
- Many languages have one word for blue and green
- Japanese: *ao*
  change early 20th century:
  midori (*green*) and *ao* (*blue*)
- But still:
  - vegetables are *greens* in English, *ao-mono* (blue things) in Japanese
  - "go" traffic light is *ao* (blue)



Color names in English and Berinomo (Papua New Guinea)

One Last Word on Senses

- Lot of research in word sense disambiguation is focused on polysemous words with clearly distinct meanings, e.g. *bank*, *plant*, *bat*, ...

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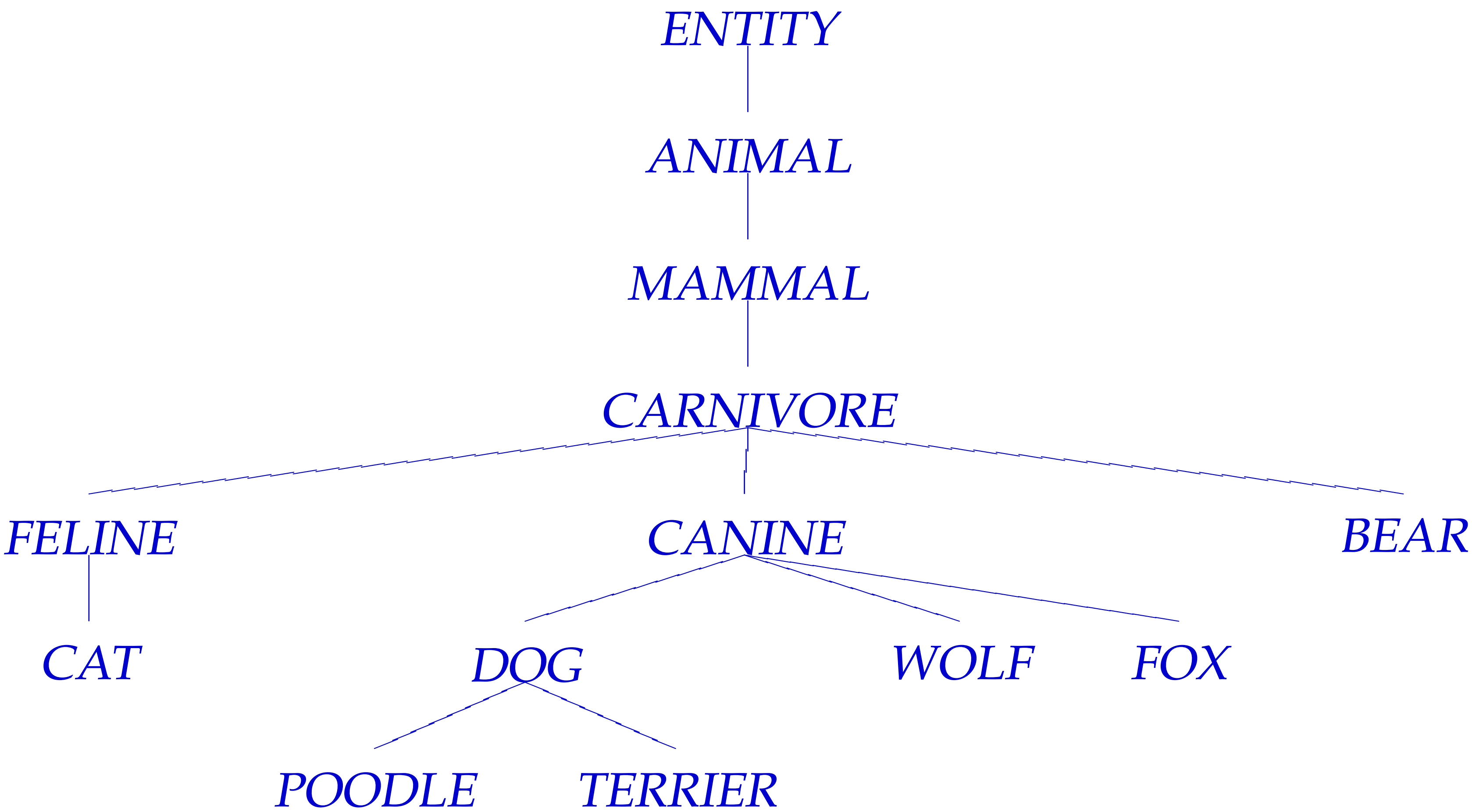
- Often meanings are close and hard to tell apart, e.g. *area*, *field*, *domain*, *part*, *member*, ...
  - *She is a part of the team.*
  - *She is a member of the team.*
  - *The wheel is a part of the car.*
  - * *The wheel is a member of the car.*

Ontology


ENTITY
ANIMAL
MAMMAL
CARNIVORE
FELINE
CANINE
BEAR
CAT
DOG
WOLF
FOX
POODLE
TERRIER

Representing Meaning

- The meaning of *dog* is *DOG* or *dog*(x)
  Not much gained here

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- Words that have similar meaning should have similar representations

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- Compositon of meaning

meaning(*daughter*) = meaning(*child*) + meaning(*female*)

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- Compositon of meaning

  meaning(*daughter*) = meaning(*child*) + meaning(*female*)

- Analogy

  meaning(*king*) + meaning(*woman*) – meaning(*man*) = meaning(*queen*)

Distributional Semantics

- Contexts may be represented by a vector of word counts

Example:

Then he grabbed his new mitt and **bat***, and headed back to the dugout for another turn at* **bat***. Hulet isn't your average baseball player. "It might have been doctoring up a* **bat***, grooving a* **bat** *with pennies or putting a little pine tar on the baseball. All the players were sitting around the dugout laughing at me."*

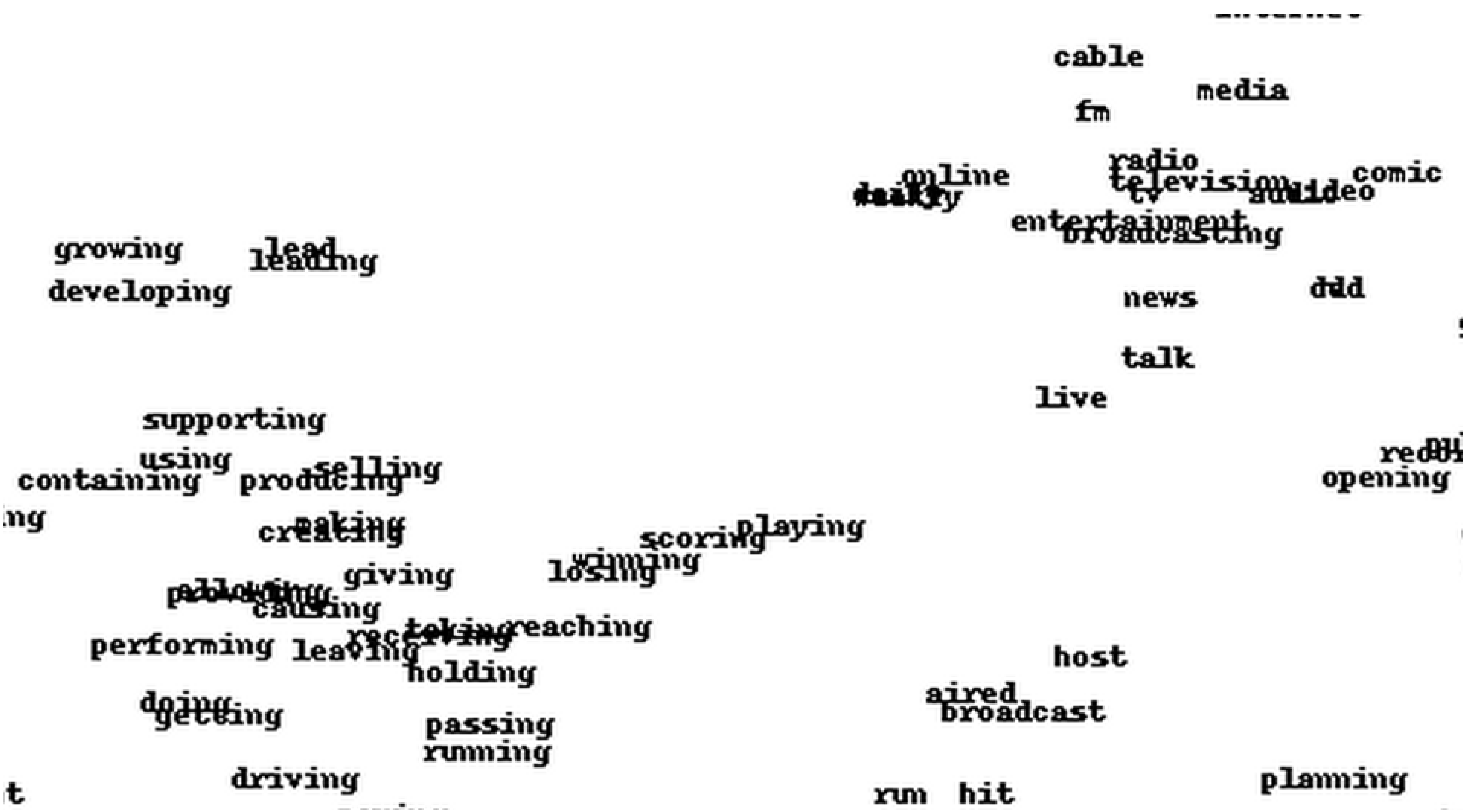
The word counts normalized, so all the vector components add up to one.

grabbed	1	0.05
mitt	1	0.05
headed	1	0.05
dugout	2	0.10
turn	1	0.05
average	1	0.05
baseball	2	0.10
player	2	0.10
doctoring	1	0.05
grooving	1	0.05
pennies	1	0.05
pine	1	0.05
tar	1	0.05
sitting	1	0.05
laughing	1	0.05

- Average over all occurrences of word

- Context may also just focus on directly neighboring words

Word Embeddings



Word Sense Disambiguation

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- Supervised learning problem *plant* → *PLANT-FACTORY*

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- Supervised learning problem *plant* → *PLANT-FACTORY*
- Features
  - Directly neighboring words
    - **plant** *life*
    - *manufacturing* **plant**
    - *assembly* **plant**
    - **plant** *closure*
    - **plant** *species*
  - Any content words in a 50 word window
  - Syntactically related words
  - Syntactic role in sense
  - Topic of the text
  - Part-of-speech tag, surrounding part-of-speech tags

subcategorization frames

Verb Subcategorization

- Example

Das	*Vorhaben*	*verwarf*	*die*	*Kommission*	*.*
the	*plan*	*rejected*	*the*	*commission*	*.*

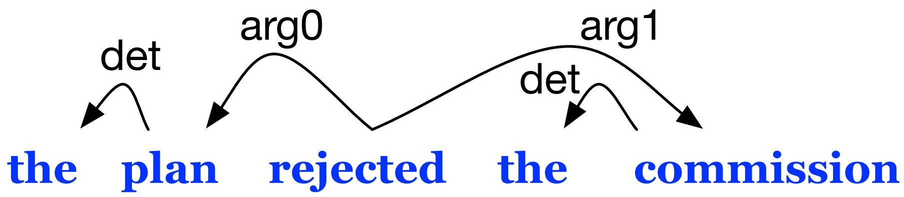
- Propbank

```
Arg0-PAG: rejecter (vnrole:  77-agent)
Arg1-PPT: thing rejected (vnrole:  77-theme)
Arg3-PRD: attribute
```

- Is *plan* a typical `Arg0` of *reject*?

Dependency Parsing

- Dependencies between words



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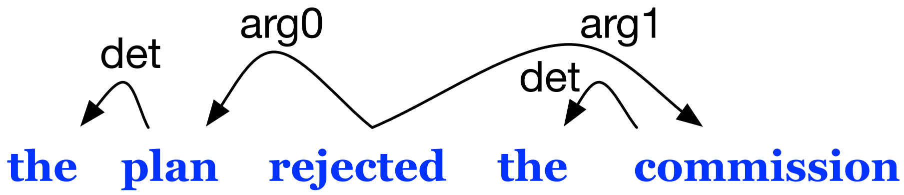

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- Are dependency relations enough?
  - *reject* — subj $\rightarrow$ *plan* $\Rightarrow$ bad
  - *reject* — subj $\rightarrow$ *commission* $\Rightarrow$ good

logical form

First Order Logic

- Classical example

Every farmer has a donkey

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$$\forall\ x\text{: } farmer(x)\ \exists\ y\text{: } donkey(y) \wedge owns(x,y)$$

First Order Logic

- Classical example

Every farmer has a donkey

- Ambiguous, two readings

- Each farmer as its own donkey

$$\forall\ x\text{: } farmer(x)\ \exists\ y\text{: } donkey(y) \wedge owns(x,y)$$

- There is only one donkey

$$\exists\ y\text{: } donkey(y) \wedge \forall\ x\text{: } farmer(x) \wedge owns(x,y)$$

- Does this matter for translation? (typically not)

Logical Form and Inference

- Input sentence

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

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$\exists$ *d: female(d)*
$\exists$ *u: father(u,d)*
$\exists$ *i: uncle(u,i)*
$\exists$ *c: cousin(i,c)*

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- World knowledge

$$\forall\ i,u,c: uncle(u,i) \wedge father(u,c) \rightarrow cousin(i,c)$$

- Hypothesis that $c = d$ is consistent with given facts and world knowledge

- Inference

$$female(d) \rightarrow female(c)$$

Scope

- Example (Knight and Langkilde, 2000)

green eggs and ham

  - Only eggs are green

(green eggs) and ham

  - Both are green

green (eggs and ham)

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  - Only eggs are green

    (green eggs) and ham

  - Both are green

    green (eggs and ham)

- Spanish translations
  - Only eggs are green

    huevos verdes y jamón

  - Also ambiguous

    jamón y huevos verdes

- Machine translation should preserve ambiguity

discourse

Ambiguous Discourse Markers

- Example

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?

Implicit Discourse Relationships

- English syntactic structure may imply causation

Wanting to go to the other side, the chicken crossed the road.

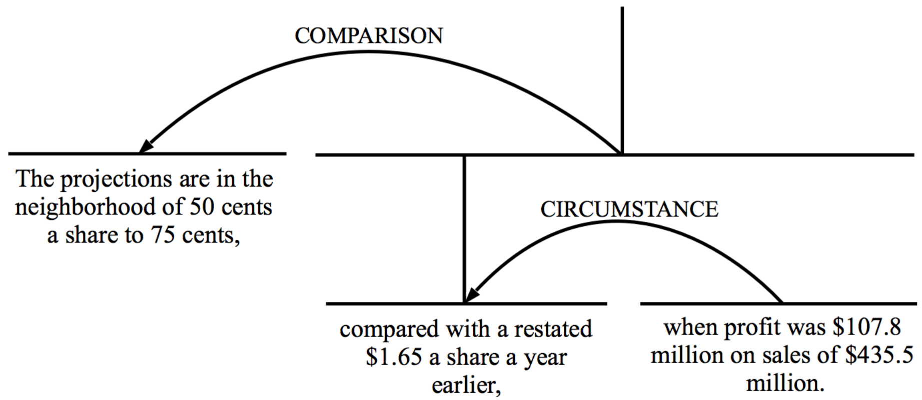
- This discourse relationship may have to made explicit in another language

Discourse Parsing

- Discourse relationships,

  e.g., Circumstance, Antithesis, Concession, Solutionhood, Elaboration, Background, Enablement, Motivation, Condition, Interpretation, Evaluation, Purpose, Evidence, Cause, Restatement, Summary, ...

- Hierarchical structure



- There is a discourse treebank, but inter-annotator agreement is low

abstract meaning representations

Example

He looked at me very gravely , and put his arms around my neck .

```
(a / and
      :op1 (l / look-01
            :ARG0 (h / he)
            :ARG1 (i / i)
            :manner (g / grave
                  :degree (v / very)))
      :op2 (p / put-01
            :ARG0 h
            :ARG1 (a2 / arm
                  :part-of h)
            :ARG2 (a3 / around
                  :op1 (n / neck
                        :part-of i))))
```

Abstracts from Syntax

- Abstract meaning representation

```
(l / look-01
   :ARG0 (h / he)
   :ARG1 (i / i)
   :manner (g / grave
      :degree (v / very)))
```

- Possible English sentences
  - *He looks at me gravely.*
  - *I am looked at by him very gravely.*
  - *He gave me a very grave look.*

adding linguistic annotation

Adding Linguistic Annotation

- Improving neural models with linguistic informtion
  - linguistic annotation to the input sentence
  - linguistic annotation to the output sentence,
  - build linguistically structured models.

Linguistic Annotation of Input

- Neural models good with rich context
  - prediction conditioned on entire input and all previously output words
  - good at generalizing and draw from relevant knowledge

- Adding more information to conditioning context straightforward

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- Relevant linguistic information
  - part-of-speech tags
  - lemmas
  - morphological properties of words
  - syntactic phrase structure
  - syntactic dependencies
  - semantics

Enriched Input

Words	*the*	*girl*	*watched*	*attentively*	*the*	*beautiful*	*fireflies*
Part of speech	DET	NN	VFIN	ADV	DET	JJ	NNS
Lemma	*the*	*girl*	*watch*	*attentive*	*the*	*beautiful*	*firefly*
Morphology	-	SING.	PAST	-	-	-	PLURAL
Noun phrase	BEGIN	CONT	OTHER	OTHER	BEGIN	CONT	CONT
Verb phrase	OTHER	OTHER	BEGIN	CONT	CONT	CONT	CONT
Synt. dependency	*girl*	*watched*	-	*watched*	*fireflies*	*fireflies*	*watched*
Depend. relation	DET	SUBJ	-	ADV	DET	ADJ	OBJ
Semantic role	-	ACTOR	-	MANNER	-	MOD	PATIENT
Semantic type	-	HUMAN	VIEW	-	-	-	ANIMATE

- Each property encoded as 1-hot vector
- Note: phrasal annotation: BEGIN, CONTINUE, OTHER
- Can all this be discovered by machine learning instead?

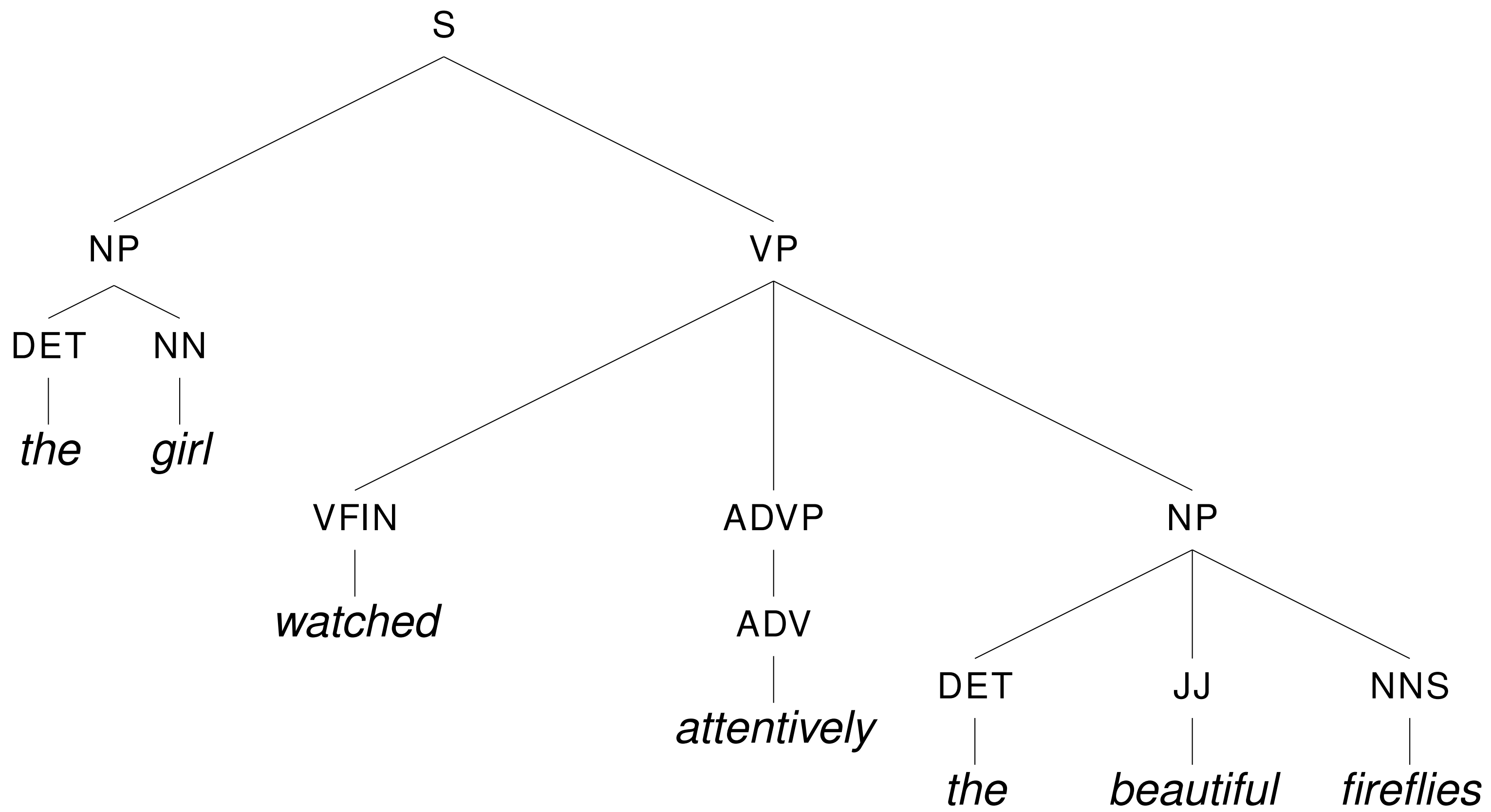
Linguistic Annotation of Output

- Same annotation also be used for output words
- May support more syntactically or semantically coherent output
- Most successful in statistical machine translation: output syntax
  - represented as syntactic tree structures
  - need to convert into sequence

Linguistic Annotation of the Output

Sentence: *the girl watched attentively the beautiful fireflies*

Syntax tree



Linearized: (S (NP (DET *the*) (NN *girl*)) (VP (VFIN *watched*) (ADVP (ADV *attentively*)) (NP (DET *the*) (JJ *beautiful*) (NNS *fireflies*))))

Linguistically Structured Models

- Syntactic parsing now also handled by deep learning
- More complex models to build output structure
  - related on left-to-right push-down automata
  - need to maintain stack of opened phrases
  - each step starts, extends, or closes a phrase
- Early work on integrating machine translation and syntactic parsing

guided alignment training

Guided Alignment Training

- Attention mechanism motivated by linguistic fact that each individual output word is often fully explained by a single input word

- Support training with externally generated word alignments
  - generate word alignment with IBM Models
  - bias attention to these alignments

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- Added cost function
  - alignment matrix A
  - alignment points A_{ij} between input word j and output word i
  - attention weight of neural model α_{ij}

$$\text{cost}_{\text{MSE}} = -\frac{1}{I}\sum_{i=1}^{I}\sum_{j=1}^{J}(A_{ij} - \alpha_{ij})^2$$

- Word alignment useful by-product of translation

Attention vs. Alignment

	relations	between	Obama	and	Netanyahu	have	been	strained	for	years	.
die	56		16								
Beziehungen	89										
zwischen		72	26								
Obama			96								
und				79							
Netanjahu					98						
sind						42	11	38			
seit								22	54	10	
Jahren										98	
angespannt								84			
.						11	14	23			49

modelling coverage

Overgeneration and Undergeneration

	in	*order*	*to*	*solve*	*the*	*problem*	*,*	*the*	*"*	*Social*	*Housing*	*"*	*alliance*	*suggests*	*a*	*fresh*	*start*	*.*
um	37		33					13										
das					84													
Problem					10	80												
zu				63			12											
lösen				81														
,							40							30				
schlägt														80				
das								71	18									
Unternehmen									86			10						
der									84									
Gesellschaft									80									
für									45	41								
soziale									40	44	10							
Bildung											89							
vor									12			40	10					
.									10			37			11	13		
	43	7	46	161	108	89	62	112	392	121	110	130	26	132	22	19	6	6

Modeling Coverage

- Neural models generally very good at translating all input words
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- But: no explicit coverage model, sometimes fails
- Enforce coverage during decoding
- Integrate coverage model

Enforcing Coverage during Inference

- Track coverage during decoding

$$\text{coverage}(j) = \sum_i \alpha_{i,j}$$

$$\text{over-generation} = \max\Big(0, \sum_j \text{coverage}(j) - 1\Big)$$

$$\text{under-generation} = \min\Big(1, \sum_j \text{coverage}(j)\Big)$$

- Add additional penalty functions to score hypotheses

Coverage Models

- Extend translation model

- Use vector that accumulates coverage of input words to inform attention
  - raw attention score $a(s_{i-1}, h_j)$
  - informed by previous decoder state s_{i-1} and input word h_j

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$$a(s_{i-1}, h_j) = W^a s_{i-1} + U^a h_j + V^a \text{coverage}(j) + b^a$$

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$$a(s_{i-1}, h_j) = W^a s_{i-1} + U^a h_j + V^a \text{coverage}(j) + b^a$$

- Coverage tracking may also be integrated into the training objective.

$$\log \sum_i P(y_i|x) + \lambda \sum_j (1 - \text{coverage}(j))^2$$

Feature Engineering vs Machine Learning

- Engineering approach
  - identify weak points of current system
  - develop changes that address them

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  - other adjustments

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- Machine learning
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  - other adjustments
- Difficult to analyze neural models $\rightarrow$ engineering hard to do