Creating annotated corpora

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Announcements

- Thursday 10/04: Assignment 3
- Friday 11/04: Project update 0 (repository+proposal)

Overview

Introduction to Projects

Midterm Evaluation

Evaluation: Themes to discuss

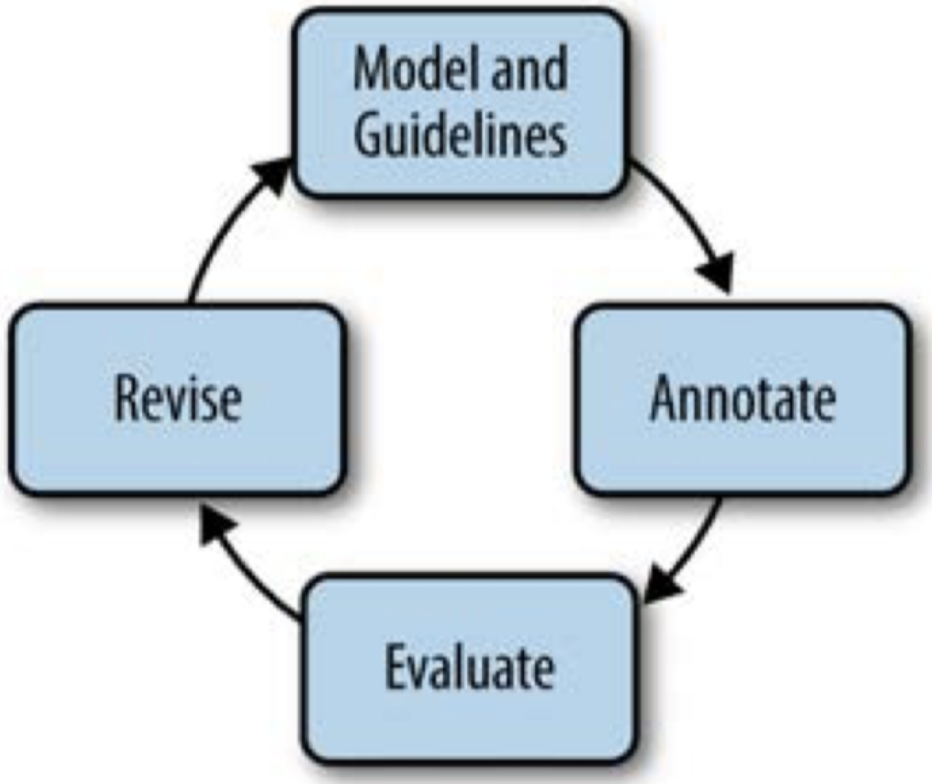
- New semester schedule
- Notebook best practices
- Running through notebooks / use of lab time
- Lectures: theory/applications

NLP and Human Annotations

NLP and Human Annotations

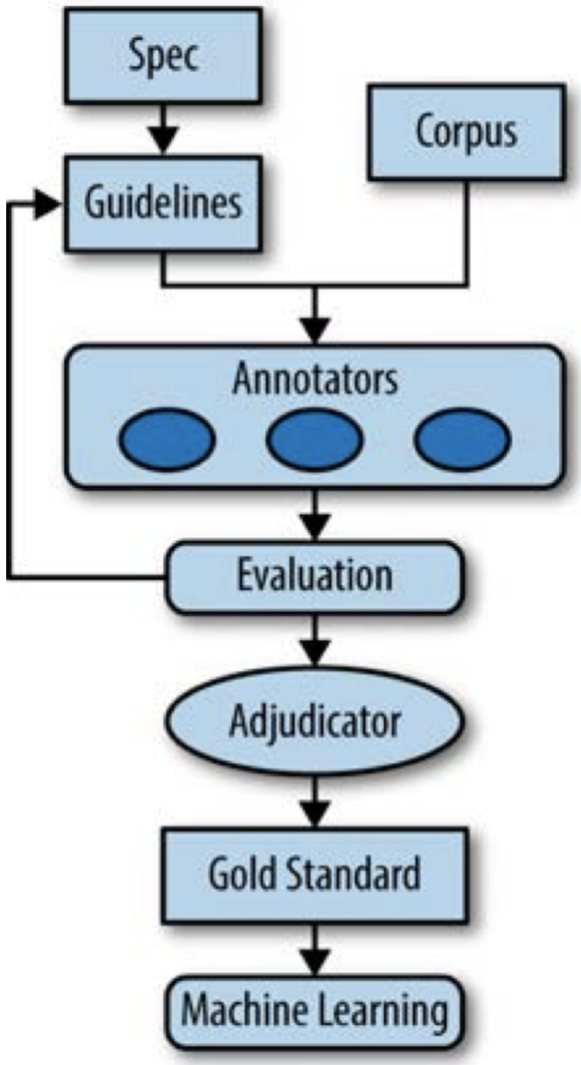
- NLP (and ML in general) is driven by human-annotated corpora.
- `http://nlpprogress.com`.
- Annotation is **difficult** and **expensive**.

Annotation pipeline



Pustejovsky and Stubbs, 2012. Natural Language Annotation for Machine Learning.

Annotation pipeline



Pustejovsky and Stubbs, 2012. Natural Language Annotation for Machine Learning.

Specs and guidelines

- Goal: given our problem, *how can we formalize our description of the annotation process for multiple annotators to provide the same judgment?*
  - What is the goal of the project?
  - How will the annotation be created? (For example, which tags or documents to annotate first, how to use the annotation tools, etc.)
  - What is each tag called and how is it used? (provide examples and discuss problematic choices.)
  - What parts of the text do you want annotated?
- Note: annotation is usually boring and time-consuming, and cannot be done for 8 hours straight. Annotators also get better over time: early annotations might be discarded.

Pustejovsky and Stubbs, 2012. Natural Language Annotation for Machine Learning.

Adjudication

- **Adjudication** is the process of deciding on a single annotation for a piece of text, using information from all independent annotators.
- Yes, it is only possible when multiple annotators independently annotate (at least some) of the corpus. *This is a very good procedure to follow, and the only one which will allow to evaluate results*.
- It can be as time-consuming (or more so) as a primary annotation.
- It does not need to be identical with a primary annotation (all annotators can be wrong by chance), but unlikely so.

Pustejovsky and Stubbs, 2012. Natural Language Annotation for Machine Learning.

Automatic annotation

- **Manual annotation**: Data is annotated by
  - Experts
  - The crowd (e.g. Amazon Mechanical Turk)
- Based on:
  - A (expert-created) ground truth
  - Annotation guidelines
  - Elicitation of implicit/explicit knowledge
- **Semi-automatic annotation**: A computer program is used to annotate the data, and annotators perform checks and corrections
- **Automatic annotation**: A computer program (predictive model, parser etc.) is used to annotate the data

Automatic annotation

Advantages

- Process far more data
- Study rare phenomena
- Estimate probabilities more accurately
- Flexible: work with your own type of text
- Don't need to hire a bunch of students to annotate...!

Disadvantages

- Annotation errors
- Biases of automatic system are introduced
- Cannot really be used as training data for machine learning
- Annotation may constrain what can be researched

Automatic annotation: Potential biases

- Random errors and systematic errors
- More errors for rare phenomena
- More errors when there is more ambiguity
- More errors for larger structures, longer sentences
- Multi-word units / idiomatic expressions
- More errors for out-of-domain data
- More errors when original text contains errors

Automatic annotation: Checking quality

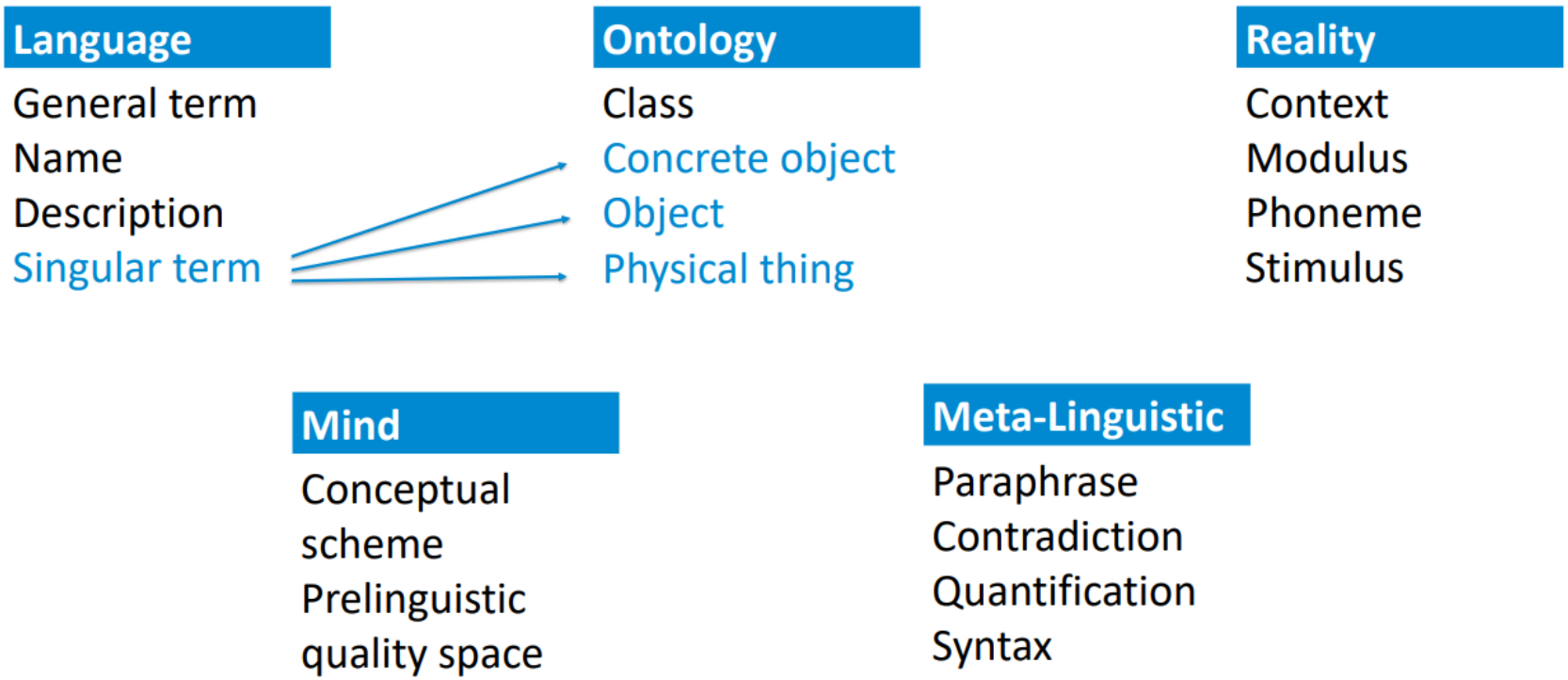
- Find existing evaluations on similar text types
- Manually check (parts of) text

When querying based on automatic annotation:

- Manually check results (precision)
- Check on the basis of a simpler layer of annotation
- Check on the basis of exemplars (recall)

Ground truth

- Quine's view of the world



Eliciting explicit knowledge

- Distributional semantic modeling of Quine

Synonym detection task

What word is most related to 'Information' ?	
a) Learning	b) Reductions
c) Collateral	d) Application
e) Ordered Pair	f) None of these words is even remotely related

Coherence task

What word does not belong to the group?	
a) Numbers	b) Pronouns
c) Subtraction	d) Actually
e) No coherent group can be formed from these words	

FIGURE 1: *Target word a), nearest neighbours b) and c), and outlier d).*

Linguistic Annotation

Levels of linguistic annotation

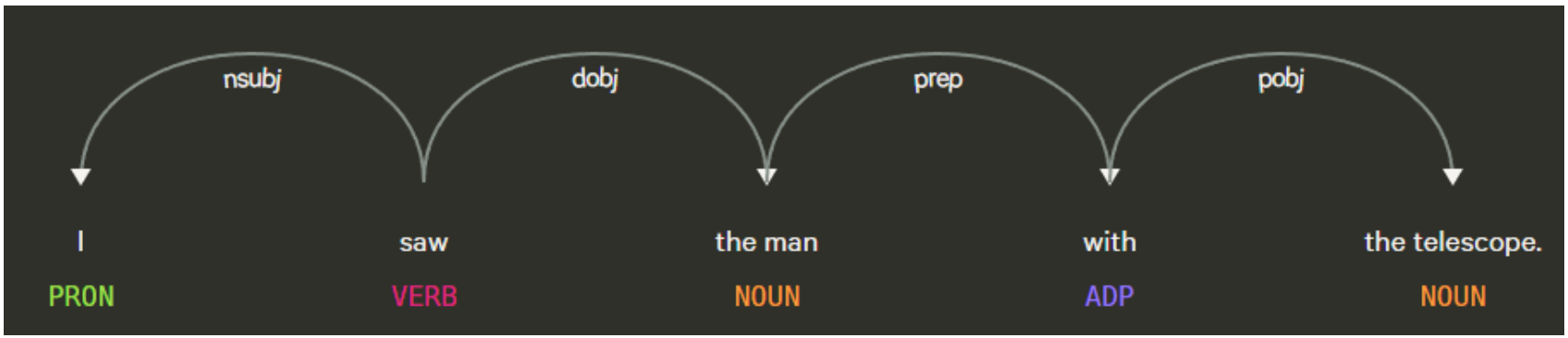
- Tokenization, lemmatization...
- Part-of-speech tagging

```
>>> text = word_tokenize("They refuse to permit us to obtain the refuse permit")
>>> nltk.pos_tag(text)
[('They', 'PRP'), ('refuse', 'VBP'), ('to', 'TO'), ('permit', 'VB'), ('us', 'PRP'),
('to', 'TO'), ('obtain', 'VB'), ('the', 'DT'), ('refuse', 'NN'), ('permit', 'NN')]
```

CC	Coordinating conj.	TO	infinitival *to*
CD	Cardinal number	UH	Interjection
DT	Determiner	VB	Verb, base form
EX	Existential there	VBD	Verb, past tense
FW	Foreign word	VBG	Verb, gerund/present pple
IN	Preposition	VBN	Verb, past participle
JJ	Adjective	VBP	Verb, non-3rd ps. sg. present
JJR	Adjective, comparative	VBZ	Verb, 3rd ps. sg. present
JJS	Adjective, superlative	WDT	Wh-determiner
LS	List item marker	WP	Wh-pronoun
MD	Modal	WP$	Possessive *wh*-pronoun
NN	Noun, singular or mass	WRB	Wh-adverb
NNS	Noun, plural	#	Pound sign
NNP	Proper noun, singular	$	Dollar sign
NNPS	Proper noun, plural	.	Sentence-final punctuation
PDT	Predeterminer	,	Comma
POS	Possessive ending	:	Colon, semi-colon
PRP	Personal pronoun	(	Left bracket character
PP$	Possessive pronoun	)	Right bracket character
RB	Adverb	"	Straight double quote
RBR	Adverb, comparative	‘	Left open single quote
RBS	Adverb, superlative	“	Left open double quote
RP	Particle	’	Right close single quote
SYM	Symbol	”	Right close double quote

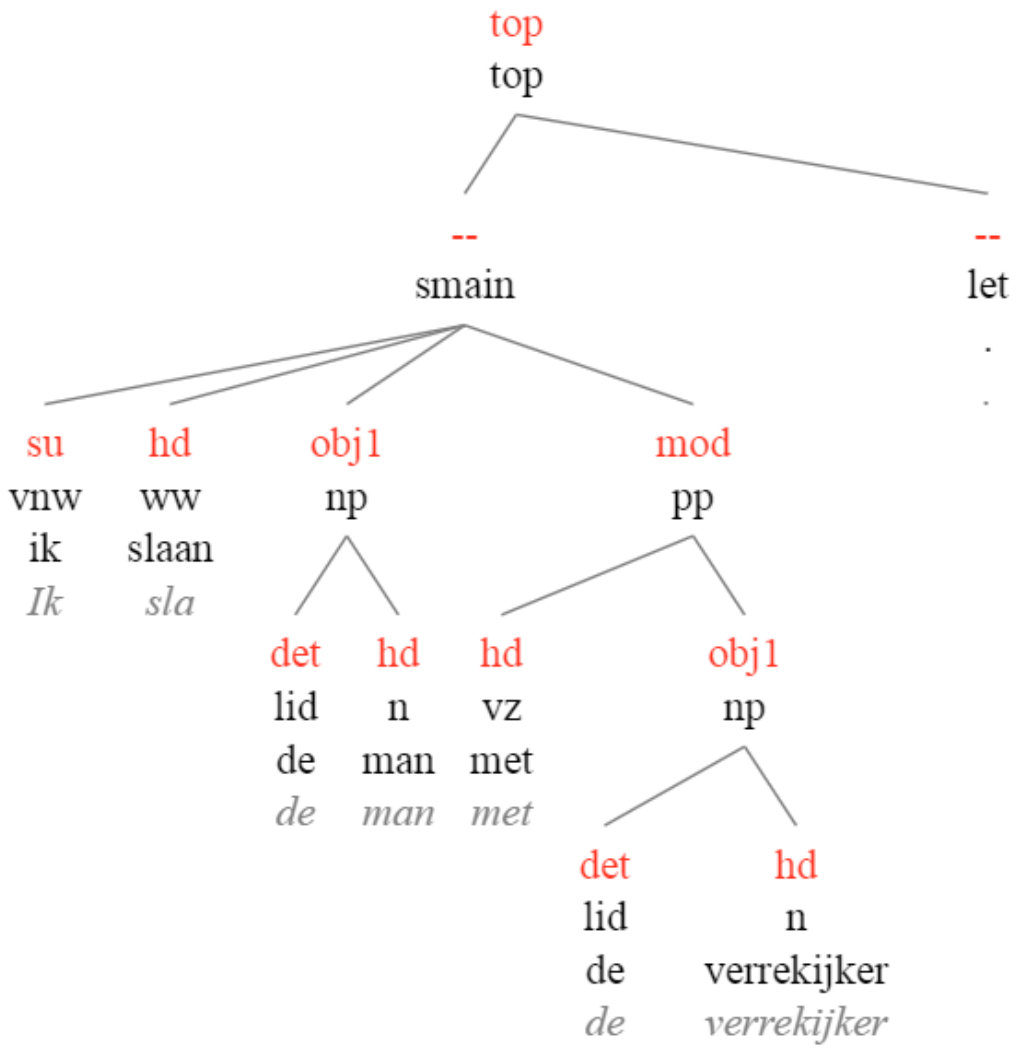
Levels of linguistic annotation

- Syntax: Dependency parsing



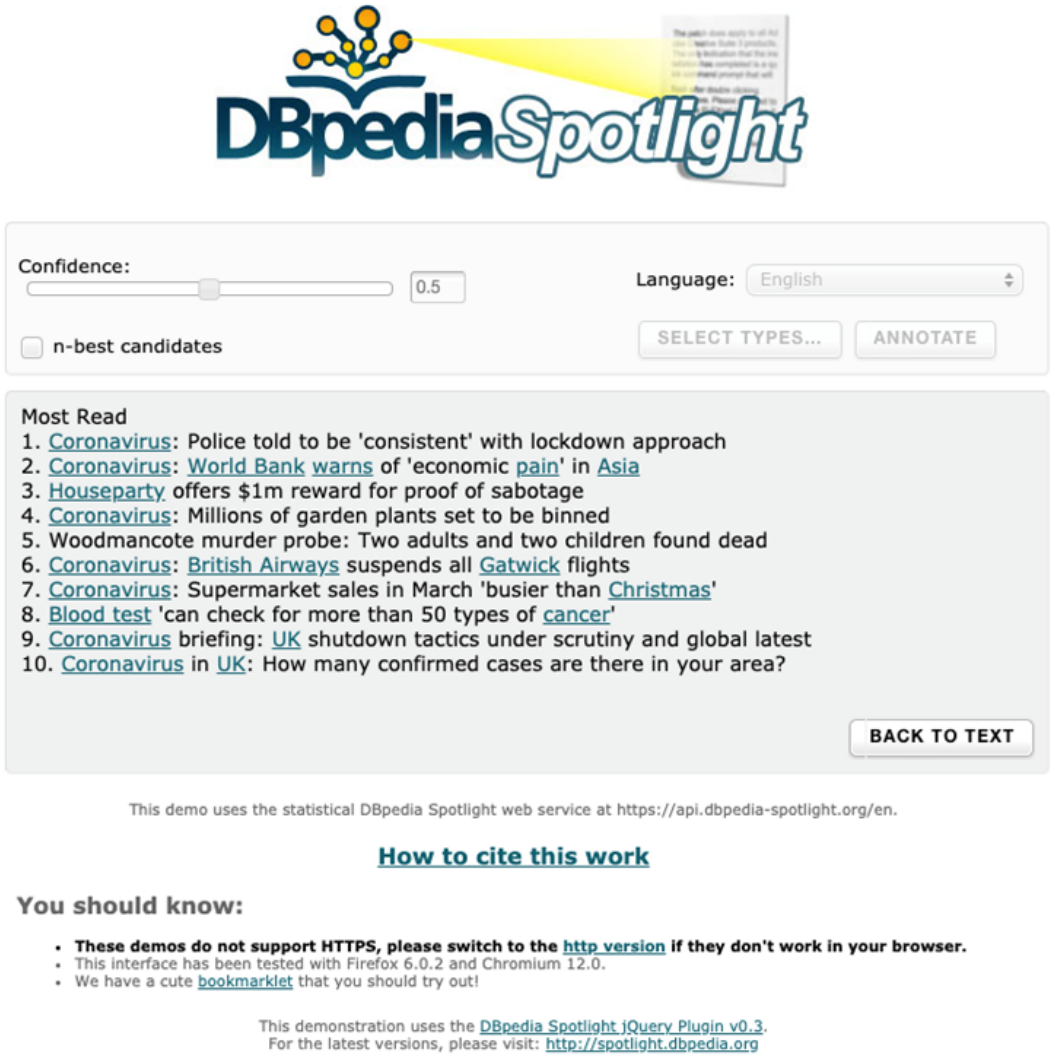
Levels of linguistic annotation

- Syntax: Constituency parsing
- Syntactically annotated corpora are also called treebanks



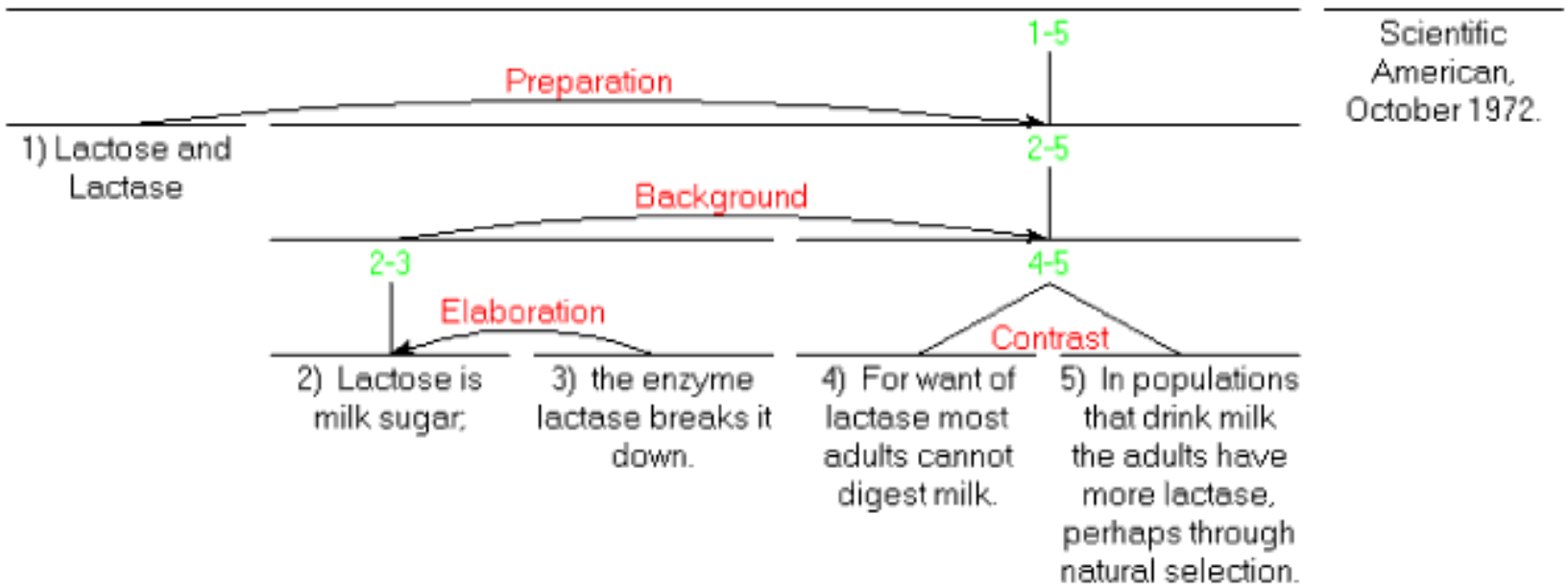
Levels of linguistic annotation

- Semantic: DBPedia (linking to ontology/knowledge base)



Levels of linguistic annotation

- Discourse: Rhetorical Structure Theory



Evaluation

Interannotator agreement

annotator A

annotator B

	puppy	fried chicken
puppy	6	3
fried chicken	2	5

observed agreement = 11/16 = 68.75%

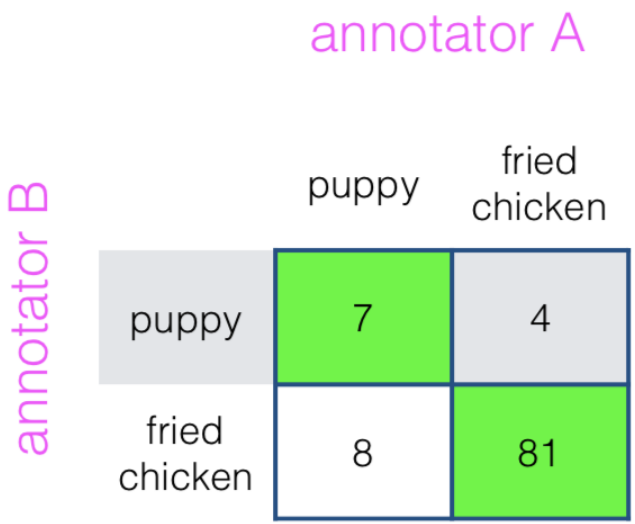
Credit: David Bamman, UCBerkeley.

Cohen's kappa

- Similar idea to mutual information: observed minus expected agreement.
- Cohen's kappa is defined for two annotators over the same set of annotation tasks:

$$\kappa = \frac{p_o - p_e}{1 - p_e}$$

Where p_o is the observed correct agreement and p_e the expected correct agreement.

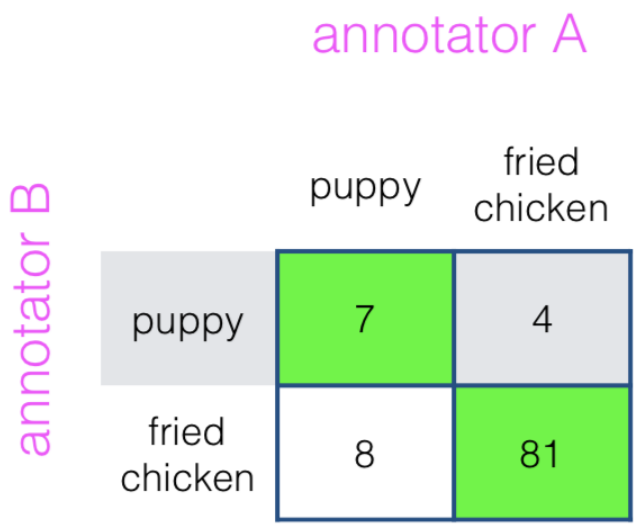


Credit: David Bamman, UCBerkeley.

Cohen's kappa example

- $p_o = 0.88$
- $p_e = P(A = puppy)P(B = puppy) + P(A = chicken)P(B = chicken)$
-

$$\kappa = \frac{0.88 - 0.773}{1 - 0.773} = 0.471$$



Credit: David Bamman, UCBerkeley.

Cohen's kappa scores

Note: these are rules of thumb.

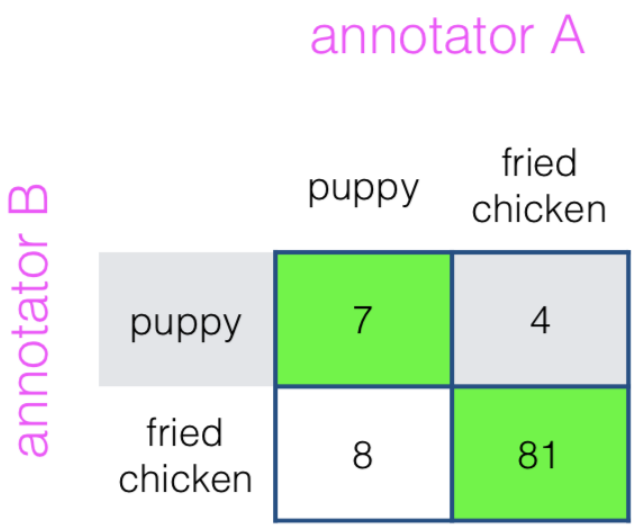
0.80-1.00	Very good agreement
0.60-0.80	Good agreement
0.40-0.60	Moderate agreement
0.20-0.40	Fair agreement
< 0.20	Poor agreement

Exercise: try to calculate fringe cases. E.g., 50/50 puppy/chicken all in agreement, 0/100 puppy/chicken all in agreement, 50/50 wrong puppy/chicken all in agreement.
Credit: David Bamman, UCBerkeley.

Fleiss' kappa

- Extension to multiple annotators (> 2).
- Defined as Cohen's kappa but comparing pairs of annotators:

$$\kappa = \frac{P_o - P_e}{1 - P_e}$$



Credit: David Bamman, UCBerkeley.

Fleiss' kappa

- Number of annotators who assign category j to item i: n_{ij}.
- For item i with n annotations, how many annotators agree among all $n(n-1)$ possible pairs:

$$P_i = \frac{1}{n(n-1)} \sum_{j=1}^{K} n_{ij}(n_{ij} - 1)$$

- Note that N is the number of items, and K the available annotation categories. Average agreement among all items:

$$P_o = \frac{1}{N} \sum_{i=1}^{N} P_i$$

Fleiss' kappa, continued

- Probability of category j:

$$p_j = \frac{1}{Nn} \sum_{i=1}^{N} n_{ij}$$

- Expected agreement by chance:

$$P_e = \sum_{j=1}^{K} p_j^2$$

- Back to original formula:

$$\kappa = \frac{P_o - P_e}{1 - P_e}$$

Text corpora

Corpus linguistics

- Balanced corpus
- Learner corpus
- Historical corpus
- Parallel corpus
- Spoken corpus (transcribed)
- N-gram corpus

Metadata

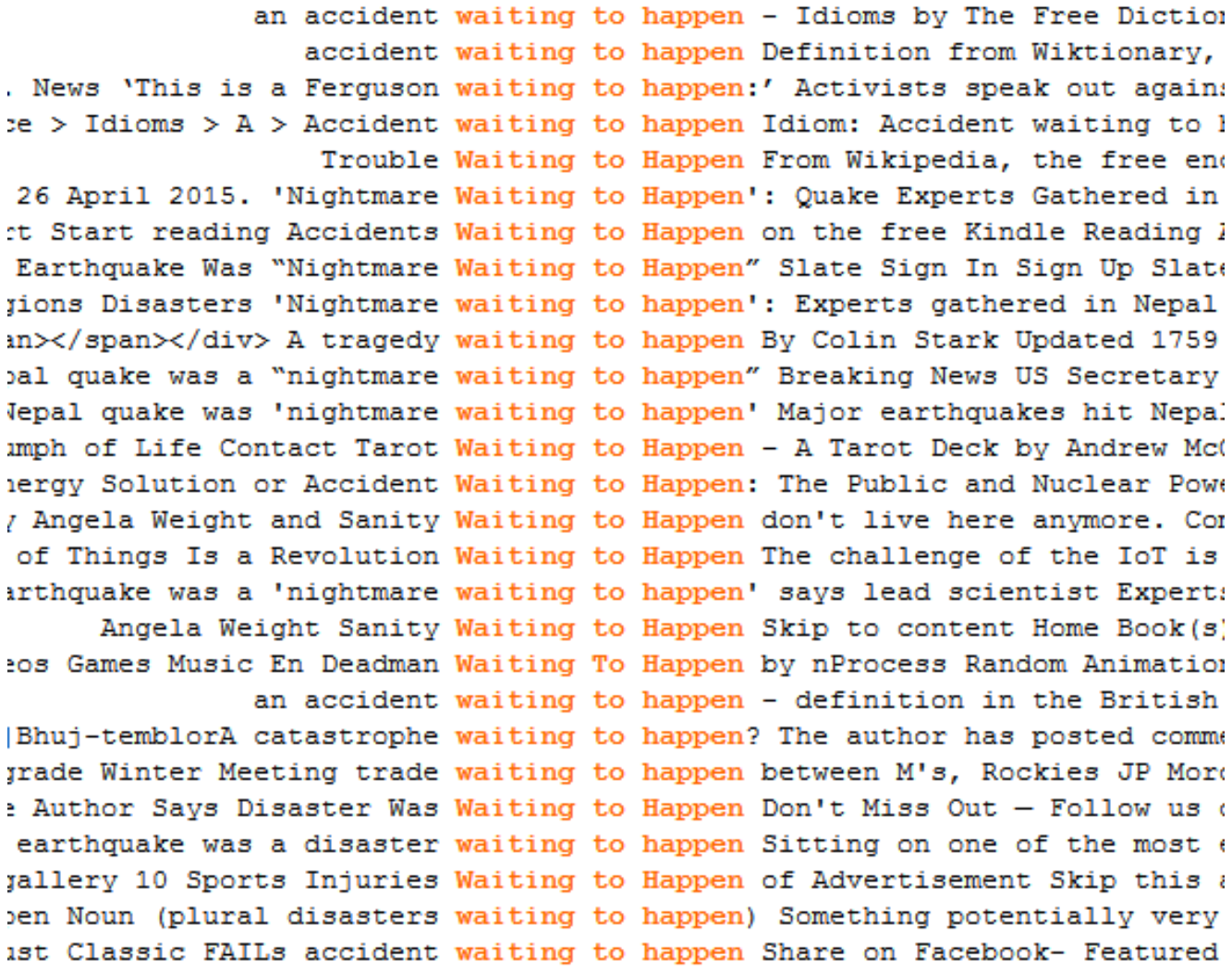
- Information about the texts in a corpus
- Year of publication, author, medium, register, edition, chapter, age of speaker, language, encoding, size etc.
- Particularly important for historical corpora and corpora where distinct documents matter (academic texts, movie reviews)

Corpus creation: Things to note

- Have clear selection criteria
  - Avoid subjective choices/criteria ('many errors')
- Select representative texts for the topic
- Take a balanced sample (if needed for e.g. training purposes)
- Think about copyright issues
- Consider availability and format
  - On paper
  - Images/scans
  - Proprietary format
  - Plain text
  - Annotated text

Corpus analysis

- Keyword-in-Context



Corpus analysis

- Keyword-in-Context
- Collocations

+ NOUN		NEW WORD	?
1334	3.04	job	
945	2.37	point	
870	3.73	article	
820	2.32	book	
769	4.02	example	
741	2.11	work	
632	3.33	post	
596	3.31	choice	
508	3.01	star	
455	2.99	opportunity	
406	2.76	source	
374	3.04	quality	
363	2.92	performance	
331	2.61	condition	
300	2.20	chance	
299	2.80	skill	
264	2.08	piece	
250	2.51	resource	
214	2.67	tool	
212	3.80	rating	
201	2.50	review	

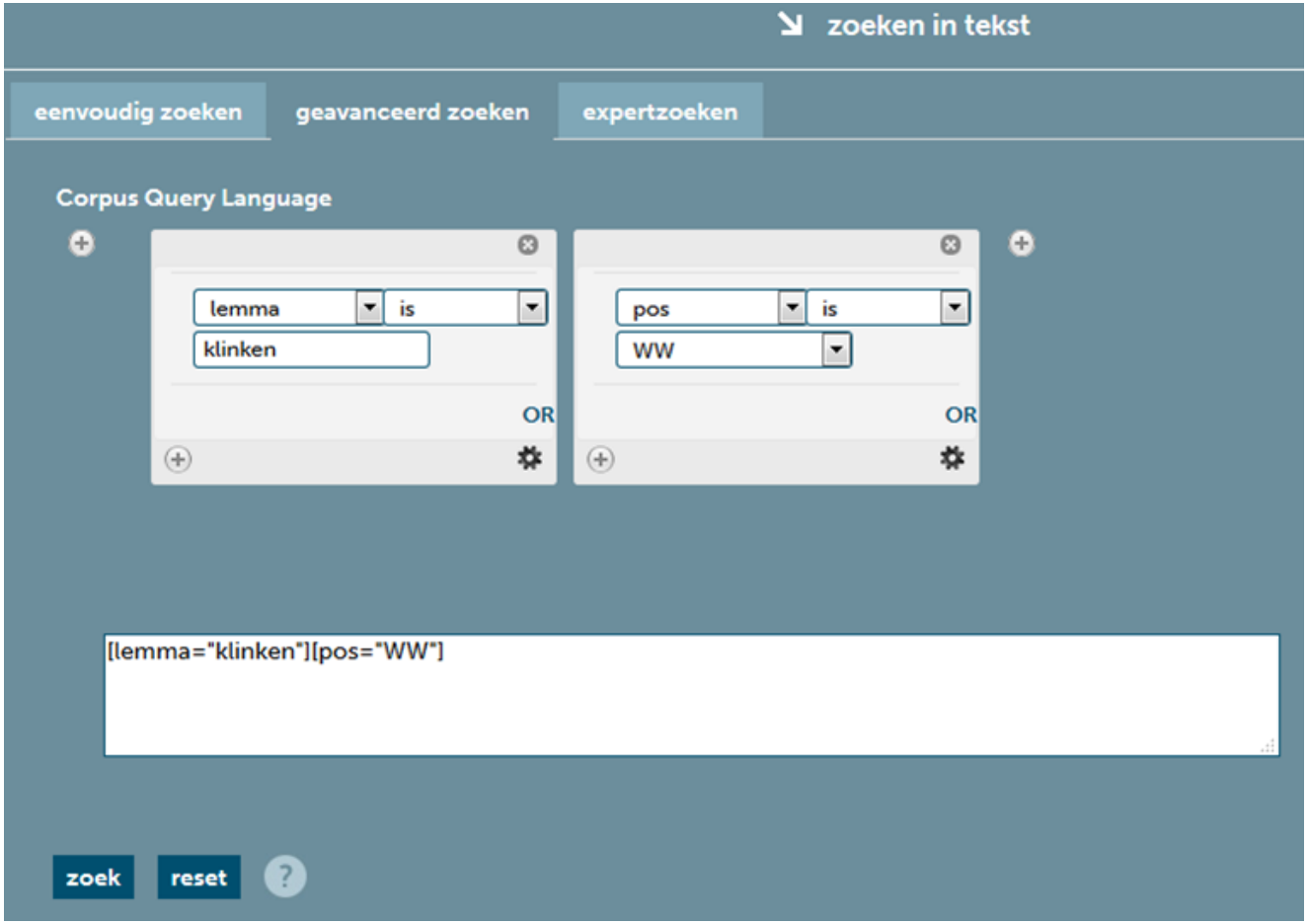
Corpus analysis

- Keyword-in-Context
- Collocations
- Collostructions
  - ? waiting to happen

Prediction	Prob.	Prob. Top-K
event	0.097763	0.2703
disaster	0.064560	0.1611
accident	0.059664	0.1394
explosion	0.049361	0.1390
invasion	0.016694	0.0486
earthquake	0.016525	0.0478
action	0.016206	0.0422
emergency	0.014662	0.0417
attack	0.013799	0.0403
miracle	0.013404	0.0371
adventure	0.011491	0.0324

Querying corpora

- Nederlab with Corpus Query Language



Querying corpora

- Nederlab with Corpus Query Language

Historie van mejuffrouw Sara Burgerhart
datering: 1782
auteur: **Aagje Deken (Amstelveen (Noord-Holland), 1741-Den Haag (Zuid-Holland), 1804) Betje Wolff (Vlissingen (Zeeland), 1738-Den Haag (Zuid-Holland), 1804)**
genre: **fictie, proza, briefroman**
collectie: **DBNL**
aantal hits: 1

dat	zy	evenwel	beter	de	klink	kan	maken	dan	Jaantje	en
dat	zy	evenwel	goed	de	klinken	kunnen	maken	dan	jaan	en

Kransje van letter-bloempjes, voor Neerlandsch jufferschap
datering: 1790
auteur: **Gerrit Manheer (Rotterdam (Zuid-Holland), 1749-Rotterdam (Zuid-Holland), 1807)**
genre: **fictie, poezie, liederen/liedjes**
collectie: **DBNL**
aantal hits: 1

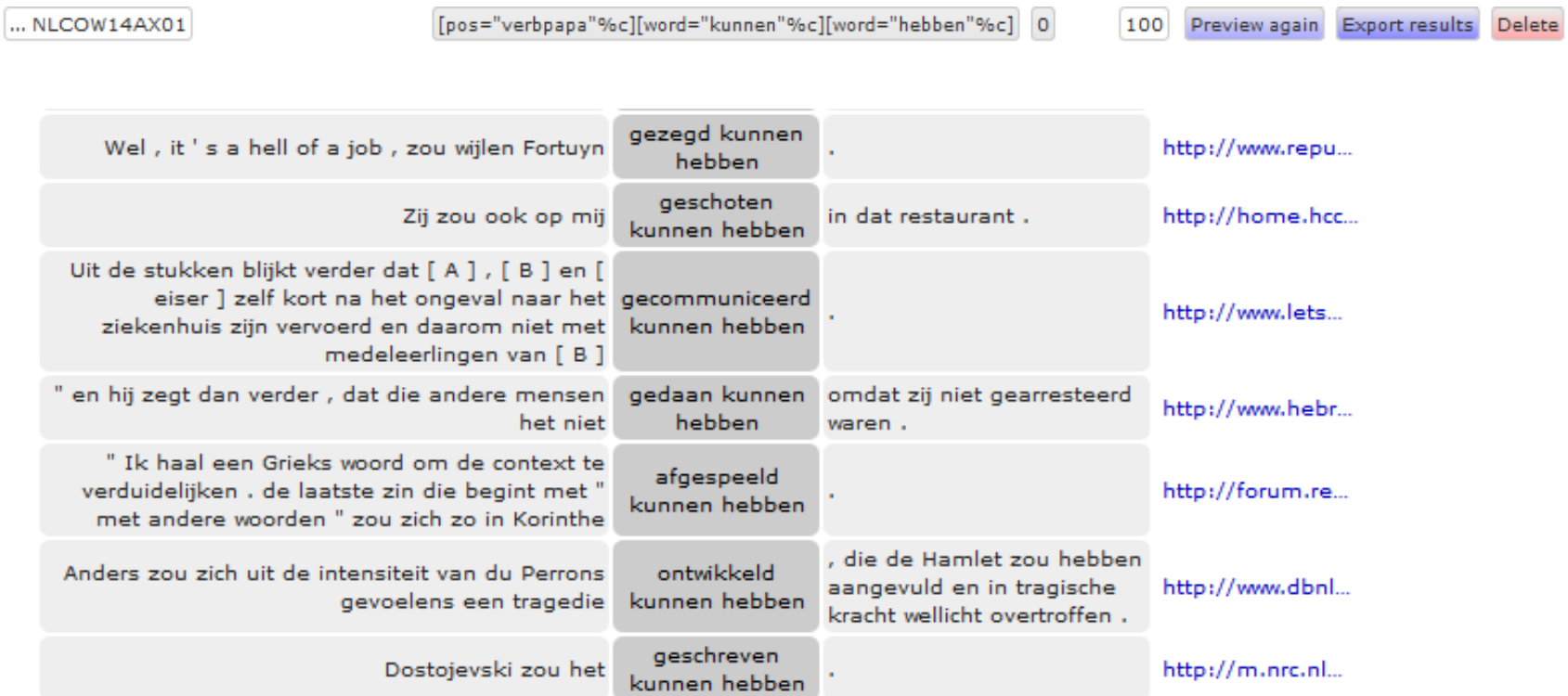
Die	Gij	,	door	lachjes	klink	in	uw	'	fluweele	boeijen
die	gij	,	door	lach	klink	in	uw	'	fluweele	boeijen

Werken van het Amsteldamsch Dicht- en Letteröfenend Genootschap. Te Amsteldam by M. de Bruyn, 1790. In gr. 8 vo. , 118 bladz .
uit: **Vaderlandsche letteroefeningen. Jaargang 1791**
datering: 1791
genre: **non-fictie, periodieken, tijdschriften, jaarboeken, letterkunde (secundair)**
collectie: **DBNL**
aantal hits: 1

Dat	den	der	Barden	klaagzang	klink	'	,	Hoe	Elza's	jammer
dat	de	de	bard	klaagzang	klink	'	,	hoe	Elza	jammer

Querying corpora

- NLCOW14 (web corpus)

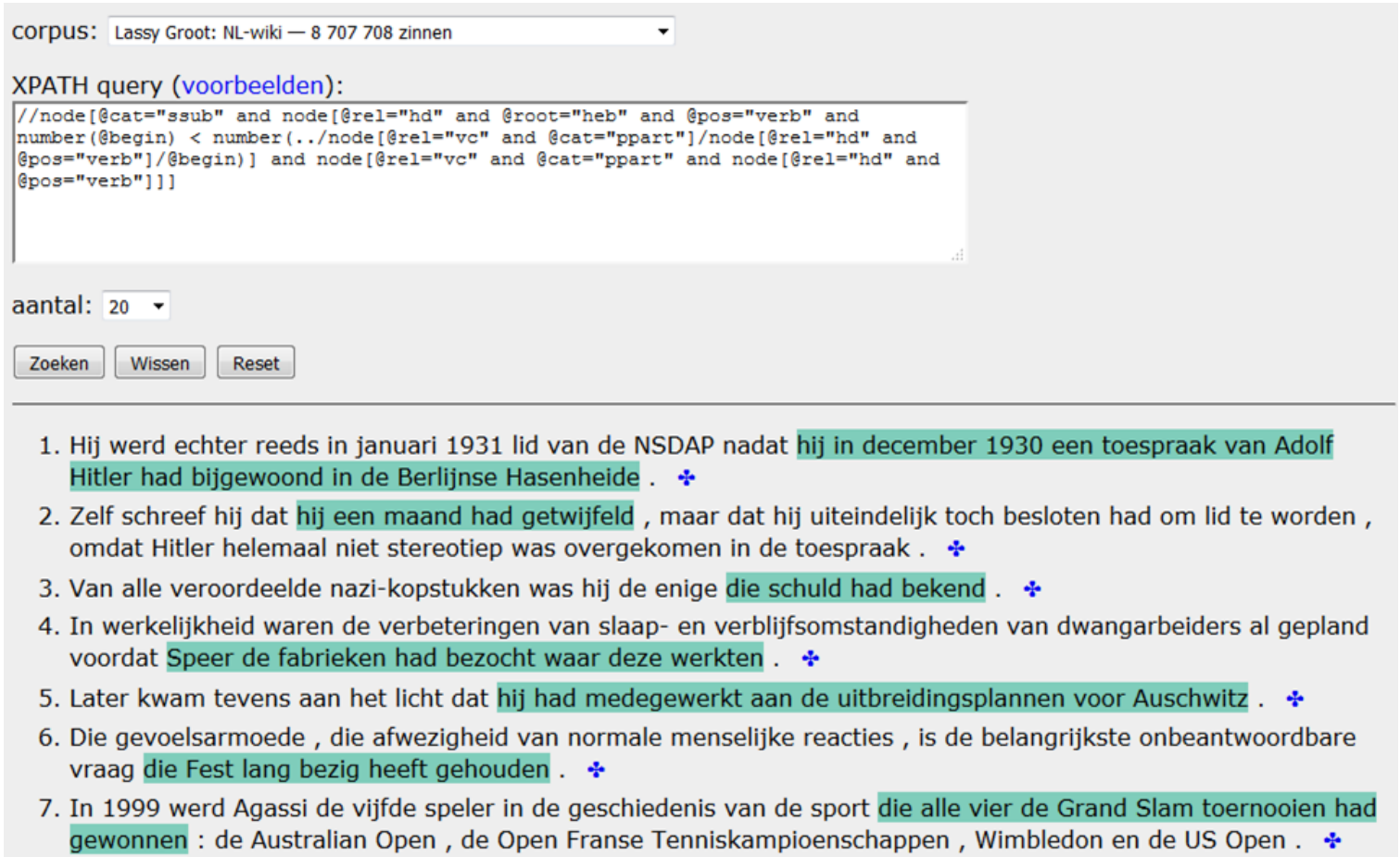


Querying corpora

- Word relation search with PaQu

Querying corpora

- Syntactic search with PaQu



Querying corpora

- Example-based syntactic search with GrETEL

Platforms and shared tasks

Annotation tools

- Brat `http://brat.nlplab.org`
- Inception `https://inception-project.github.io`
- Prodigy `https://prodi.gy`

Annotation platforms

- Supervisely `https://supervise.ly`
- Dataturks `https://dataturks.com`
- Amazon Mechanical Turk `https://www.mturk.com`
- Figure Eight `https://www.figure-eight.com`
- Alcrowd `https://www.aicrowd.com`

Transformers reading assignment: Questions

- The training of these transformer models is performed on GPUs. But, what exactly are GPUs? And how do they work?
  - TPUs
- Is this the only model architecture that can parallelize?
  - RNN, CNN, Word2Vec?
- Is it possible to have different attention functions?
  - Masked attention in decoding to avoid peeking ahead
- Is there any new progress made on self-attention models since this paper was released?

Transformers reading assignment: Questions

- Even though positional might be beneficial in text analysis, what about for example logical derivations, in which the order is crucial for correct understanding but at the same time they can be relatively long.
- If attention-based transformer models are so much more efficient (and also explainable) than RNNs, are there still any advantages or current applications for RNNs?
  - LSTMs
- Why weren't transformers explored earlier?
- How can a model like the Transformers be improved further?