

Corpus Linguistics, Resources and Normalisation

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Epistemological Aspects

- “The study of language based on examples of 'real life' language use” [McEnery and Wilson(1996)]
- Not only a *methodology*, but also a *theory*
- Not by itself a linguistic branch (unlike phonology, syntax or semantics), but *transversal* (in particular from the methodological point of view)

Some History

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About the use of corpora in linguistics

- Using a corpus, what is being analysed? A property of the grammar or a “social” phenomenon?
- *Competence* and *performance*. ▶ Example Theoretical *linguists* study competence.
- Corpora reflect performance. Hence, competence \Rightarrow not in corpus
- Competence \Rightarrow Introspection

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- The study of language learning by children (because requires meta-knowledge on the language)
- Languages that are not spoken anymore
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- What is the nature of data in linguistics (experimental data)?
- What benefits from a corpus data?

[The corpus linguist] He has all of the primary facts that he needs, in the form of a corpus of approximately one zillion running words, and he sees his job as that of deriving secondary facts from his primary facts. At the moment he is busy determining the relative frequencies of the eleven parts of speech as the first word of a sentence versus the second word of a sentence [Fillmore(1992)]

- Nevertheless [Hill(1962)] about introspection

Chomsky: The verb 'perform' cannot be used with mass word objects: one can 'perform a task' but one cannot 'perform labour'

Hatcher: How do you know, if you don't use a corpus and have not studied the verb 'perform'?

Chomsky: 'How do I know'? Because I am a native speaker of the English language

- But, from BNC corpus, it is possible to 'perform magic'

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- In a corpus : *il parle à* + proper name
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How is it possible to say that *il mange à Pierre* is ungrammatical?

There is no reason *a priori* that *parle* is different from *mange*.

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Nature of Language

Linguistics as data analysis

But also a little bit more:

[purpose of linguists] is not simply to account for all utterances which comprise his corpus [but rather] to account for utterances which are not in his corpus at a given time [Hockett(1948)]

[introspective judgements] when it agrees [with corpus data non-corpus data is] superfluous; when it disagrees [with corpus data non-corpus data is] obnoxious [Hockett(1964)]

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- Recursion
- Competence/performance example
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Some other criticisms

- About representativity (biased and incomplete), Cf frequencies
- Pseudo-procedure methodology [[Abercrombie\(1965\)](#)]: manual analyses and mistakes

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But intrinsic advantages

When introspection fails

- Phonology
- Acquisition
- Languages variation (regional expressions, sociolects, register)
- Data can be observed and checked
- Usefulness of the frequency measure (unavailable from introspection)

Even when introspection can happen

- Failing to find some sentences or grammatical constructions in a corpus may also be an interesting comment on their frequency
- Introspection lacks systematicity (mistakes can also occur during introspection)
- "Corpus is a more powerful methodology from the point of view of the scientific method" [Leech(1992)]

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Mixing the two approaches

- Corpus of introspection examples (Cf Partee, famous examples, etc.).
- “What look like the cute examples and arbitrary infatuations of linguists often, though not always, represent a distillation of important and wide-ranging issues” (Martin Kay 2006) vs “[the non-corpus linguist] sits in a deep soft armchair, with his eyes closed and his hands clasped behind his head. Once in a while he opens his eyes, sits up abruptly shouting, 'Wow, what a neat fact!', grab his pencil, and writes something down... having come still no closer to knowing what language is really like.” [Fillmore(1992)]

Benefits

- Evidence of usefulness of quantitative data: in the success of building efficient tools (taggers)
- Today, NLP applications?

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Escaping from the pseudo-procedure criticism

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- Data are reliable (at least with a measurable reliability)
 - OK for some automatic annotations (POS tagging)
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- Enable searching, sorting, computing. . .

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Designed for a usage

- [McEnery and Wilson(1996)]

If you think the language is finite, then your interpretation of the findings in a corpus may reflect that - if we can change the interpretation of the findings in a corpus to match the verities Chomsky revealed, then the natural data provided by the corpus can be a rich and powerful tool for the linguist. But we must understand what we are doing when we are looking in a corpus and building one. (...) A corpus and an introspection-based approach to linguistic are not mutually exclusive. In a very real sense they can be gainfully viewed as being complementary.

- Difference between linguistic goals and NLP goals (in particular, as NLP tool user, on non introspective data)

What is a Corpus

As for now

- Data readable from computer
- But also:
 - Sampling and representativity
 - Finite size
 - Reference to a standard

Necessity of Sampling

- **Infinite language** (except for dead languages, texts from a single author...). Hence scarcely a finite set \Rightarrow sampling
- **Sampling and representativity** Cf. Chomsky criticism
- **Aim** to get the greatest representativity inside a variety under study

What does it mean?

- What are the *genres* of texts, the *number* of texts, what particular texts, how to select some abstracts, of what size.
- "Representativeness refers to the extent to which a sample includes the full range of variability in a population" [Biber(1993)]

Consequence

Hence, a corpus has to be evaluated on its ability to include:

- The possible genres of texts of a language
- The linguistic variety inside a language

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Representativity: an example

Despite genres are not defined on a linguistic basis, there are big linguistic differences between genres

Example: Brown corpus

- Classification
- Modalities example (`modal-ratio.py`),
- Token/type ratio example (`token-type-ratio.py`)

A corpus has to ensure, or at least to justify, representativity.

Size of a Corpus

- Some corpus always increases (new data are added). It gives an idea of the evolution
- But, because of the changing size, sampling and representativity are more difficult to ensure.
- Examples: NLTK Corpora:
 - brown corpus (1 000 000 words)
 - treebank 10% of the WSJ section of the Penn Treebank (1 000 000 words)

Machine-Readable Corpus

Summary

Advantages: querying and computing

Examples: raw text pattern matching (grep)

Consequences

- But what about all the flexed forms? (→ **concordancer example**)
- What about all the Ns? (→ Brown corpus example (POS tagging))
- What about all the NPs ? (→ treebank example)

⇒ Crucial role of *annotation*

Other Examples

French Corpora

Annotations

What we already know:

- Raw text → regexp, concordancer
- Unstructured annotations (glued with the word)
- Annotations and trees
- Other (semantics, time and aspects, pragmatics, etc.)

Annotations are increasingly complex to read and to create

Principles

Aims of annotations:

- 1 Enhancing (raw) data with relevant linguistic annotations (relevant with what respect?
Depends on the usage)
- 2 Reusability: annotation cost (time, money), correction and accuracy. But:
 - Juridical problems (text ownership)
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- ➊ From an annotated corpus, it should always be possible to come back to initial data (example BC). Remark: may be difficult after normalisation (“l’arbre” → “le arbre”, etc.)
- ➋ Annotations should be extractable from the text in order to save them at another place (DB), to present them in another way, etc.
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- Everything which is potentially interesting!
- Hence, depends on the application

Non linguistic annotation

- Genre, variety (french from France, from North, from South, age and sex of the speaker, publication date, etc.)
- Form. Example:
 - For a written text, style, bold letters (example: Alice)
 - For text with intonation (speech)
 - For dialogues, sentences pronounced at the same time, etc.

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Technical difficulties

- Character encoding
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- Produced recommendation

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- Sharing tools (annotation, visualisation, access)
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[Lupovici(1993)]:

- 1 Descending process by vertical division
- 2 Ascending process by vertical division
- 3 Transversal process

Descending process:

Organised with divisions by large fields, subdivided by topics, subdivided by working groups. . .

As for classification. Difficult for rapidly evolving domains.

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Motivations and Principles

- To circumvent variations in data category definitions and names
- How: providing distinction of an abstract concept and its realization for the feature-value pairs
- Ex:
 - At the conceptual level: the type descriptor GENDER can have the values MASCULINE, FEMININE or NEUTRAL.
 - It can be realized as the type descriptor gen or genre with the value {m,f,n} or {masc,fem,neut} (pecified in a Data Category Specification)
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The MAF model (p. 14)

- Notion of *token* (p. 17)
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Example: lexical resources

The LMF model

- Core model (p. 15)
- Extensions:
 - Extensional morphological lexicon (p. 21)
 - Intensional morphological lexicon (pp. 55–58)
 - Syntactic lexicon (p. 33)
 - Semantics lexicon (p. 39)

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Time and events

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Chronological aspects

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Standardisation activity: P3 (1992), P4 (XML, 2002), P5 (modular, 2004)

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Architectural choices

- Choice of SGML, XML, ISO 646 (ASCII), Unicode
- A large number of pre-defined annotations
- Distinction between required practices, recommended practices and optional practices
- Encoding for various points of view on the text
- Provide ways for users to extend basic schemas

This mandate is fulfilled by the explicit specification, in the reference section for each tag, that the tag is required, mandatory when applicable but otherwise omissible, recommended generally, recommended when applicable but not always applicable, or optional.

However, the TEI Guidelines make (with relatively rare exceptions) no suggestions or restrictions as to the relative importance of textual features. The philosophy of the Guidelines is 'if you want to encode this feature, do it this way' — but very few features are mandatory.

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Example of recommendations

From TEI P5. Guidelines for Electronic Text Encoding and Interchange

- Almost always present elements (paragraphs, punctuation, citations, dates, lists, etc.)
- Description of the encoded document (TEI Header) (description of the file—title, author. . . —, of the encoding, if the profile—register. . .)
- Structure of the text. . . (TEI + TEIheader + text, example monde98), divisions (chapter, cf Alice)

Syntactic function and semantic roles

The Proposition Treebank [Palmer et al.(2005)Palmer, Gildea, and Kingsbury]

Predicate-argument information/semantic roles

The same semantic role can be taken by different syntactic arguments

Example (Syntactic argument vs semantic argument)

- John broke the window
- The window broke

Note:

- Does not rely on an active/passive voice distinction
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What is needed: the possible roles for a verb

Example (FrameSet kick.D1 "drive or impel with the foot")

Arg0: Kicker

Arg1: Thing kicked

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Ex1: But [Arg0 two big New York banks,] seem [Arg0 *trace*_i]
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Ex2: [Arg0 John_i] tried [Arg0 *trace*_i] to *kick* [Arg1 the football], but Mary pulled it away at the last moment.

What kind of annotations

Example (What is expected?)

- ... [Arg0 the company] to ... *offer* [Arg1 a 15% to a 20% stake] [Arg2 to the public]
- ... [Arg0 Sotheby's] ... *offered* [Arg2 the Dorrance heirs][Arg1 a money-back guarantee]
- ... [Arg1 an amendment] *offered* [Arg0 by Rep. Peter DeFazio] ...
- ... [Arg2 Subcontractors] will be *offered* [Arg1 a settlement] ...

What is needed: the possible roles for a verb

Example: (Promiser kick.D1 "drive or impel with the foot")

Arg0: Kicker

Arg1: Thing kicked

Arg2: Instrument (default to foot)

Ex1: But [Arg0 two big New York banks,] seem [Arg0 *trace*_i]
to have *kicked* [Arg1 those chances], for the moment,
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What is needed: the possible roles for a verb

Example: (Pommes) kick:01 = drive or impel with the foot

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Framesets

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- Note:
 - This lexicon need to be build before the annotation (at least conceptually). Some of the realizations are not attested in the corpus.
 - The semantic of Arg0, Arg1, etc. **depends** on the verb
 - When to have multiple framesets, single framesets?
 - Both on a semantic and syntactical ground
 - Examples (decline , break , call)
- For PropBank:
 - 3,300 verbs
 - 4,500 framesets (average polysemy: 1.36)
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The semantic annotation is linked to the syntactic one

- Address of the syntactic node
- Help of a rule-based argument tagger (on pilot data, then error recovering by hand)
- A two-pass blind procedure, followed by an adjudication phase
- the annotators:
 - Different backgrounds (linguists, computer scientists, others)
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Some results

Syntactic position/role distribution

- When there is an Arg0, then it is a subject (96.9%), another verbal argument (2.4%) or an object (0.2%)
- The subject of a verb has Arg0 role (79.0%), Arg1 role (16.8%), Arg2 role (2.4%)...

Automatic semantic labelling: Comparison with FrameNet

	FrameNet	PropBank	PropBank (>10 ex)
Automatic parses	82.0	79.9	80.9
Gold-standard parses		82.0	82.8

Accuracy of semantic role prediction for known boundaries

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Gold-standard parses w/ traces			80.6	71.6	82.0	74.7

Accuracy for unknown boundaries

Comparison using shallow parses

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Gold. parse	74.3	66.4
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Time information in corpora

Motivations [Pustejovsky et al. (2003) Pustejovsky, Katz, and Gaizauskas]

Q&A Systems

Q What is the **current** unemployment rate?

A Depends on the day (month) the question was asked

Q When did the Berlin Wall fall?

A Thursday

East German border workers began dismantling the Berlin Wall at the popular Brandenburg gate on Thursday night to make it more difficult

Formal semantics

Relation between time events and tensed clauses

- Yesterday John saw a girl who was running this morning
- This morning John saw a girl who was running yesterday
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Absolute, relative, anaphoric

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Absolute, relative, anaphoric

Time information in corpora

Requirements [Pustejovsky et al. (2003) Pustejovsky, Katz, and Gaizauskas]

- Theories of **tense** (and aspects and event structure)
- Annotation scheme and tools: TimeML

Conceptual and linguistics basis

Event expressions: introduced by tensed verbs, stative and dynamic adjectives, event nominals (World Championship, election)

Dependencies between events and time: anchoring (on Monday), ordering (yesterday), embedding (John said Mary left)

Anchoring example: *John taught on Monday*

$$\exists e_1. \text{teach}(e_1, j) \wedge \text{on}(e_1, \text{Monday}) \wedge \text{Past}(e_1)$$

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Temporal expressions

- Fully specified (November 29, 2007)
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...

Missing

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Markup Language for Temporal and Event Expressions

TimeML: a specification language for events and temporal expressions in natural language

- Time stamping of events (identifying an event and anchoring it in time)
- Ordering events with respect to one another (lexical versus discourse properties of ordering). `tlink` tag.
- Reasoning with contextually underspecified temporal expressions (temporal functions such as 'last week' and 'two weeks before')
- Reasoning about the persistence of events (how long does an event or the outcome of an event last)

Additional features

- a `TLINK` to relate events and times, to order events relative to each other and to order times relative to each other.
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After his talk with Mary, John drove to Boston. During the drive he ate a donut.

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- 300 texts of media sources from the news domain
- Annotation:
 - an automatic pre-processing step
 - a human annotation step (check out the pre-processing step, introduces new events, time expressions and links)
- statistics:

	Count	Frequency
Words	68555	100%
Tags (events, timex3, signal)	11206	16.3%
Events	7571	11.0%
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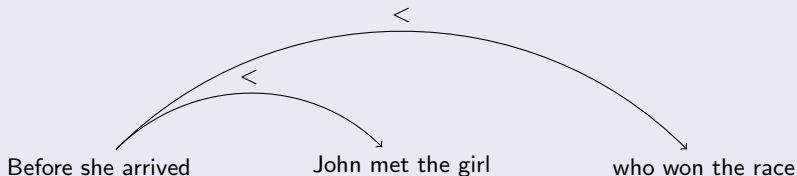
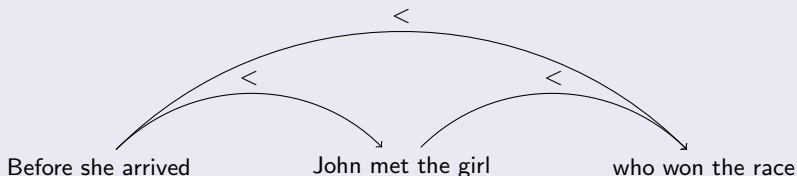
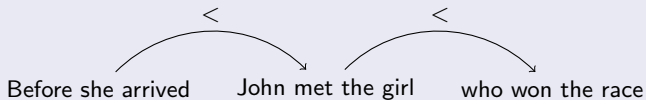
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Questions on the semantics of the annotation

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About quantification

During each of John's drive to Boston he ate a donut.

John drove to Boston. During his drive he did not eat a donut.

Expressivity and decidability

- Is it possible to make inference?

- Is it possible to add quantification?

→ suggestions on modifying TimeML [Pratt-Hartmann(2007)] in order to support the expressivity of an established temporal logic (Interval Temporal Logic)

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The Penn Discourse TreeBank example

Motivations

- To annotate the WSJ corpus in the Penn TreeBank (1 million words) with discourse relations
- To have discourse relations independent from any theory

Example

Even though critical, **it was just the kind of attention they were seeking**. **So they fired back** at the Goldman Sachs objections in their own economics letter, "The BMC report".

Objectives

- Gives a layer of discourse structure
- Enables the comparison of discourse annotation with syntactic annotation in order to highlight relationship between syntactic structure and discourse structure
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Example (Discourse connective as subordinate conjunction)

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Example (DC as adverbial)

Eat your porridge. **Otherwise** you're not going to football practice.

Example (DC as PP)

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Design choices

Choice of the corpus

- The same Penn WSJ as the Penn TreeBank \Rightarrow three levels of annotation of the same data (syntactic, semantic and discourse)
- Raw text annotation (not XML) because sometimes discourse args do not align with syntactic structures

Annotation process

- Through the whole corpus, one connective at a time. Allow annotators to “immediately exploit the experience they were gaining in annotating a connective”
- Ten lists of possible discourse connectives (about 90 of them)
- Annotation tool to navigate in the instances of the discourse connectives and mark the arguments
- Annotation consist in a **discourse connective**, a **first argument** and a **second argument** (the latter being syntactically bound to the dc) (According to [Webber et al.(2005)Webber, Joshi, Miltsakaki, Prasad, Dinesh, Lee, and Forbes], “In none of the work we carried out (...) did we find an English discourse connective that had anything other than two arguments [unlike verbs]”)

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Form of the annotation

- Span list (words)

Example

But, says Mr. Dinkins, he did get an office. So he shouldn't complain.

Example

On the one hand, Mr. Giuliani wants to cut into Mr. Dinkin's credibility. On the other, he seeks to convince voters he's the new Fiorello LaGuardia—affable, good-natured and ready to lead New-York out of the mess it's in.

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Inter-annotator agreement

- 4 annotators, then 2
- 10 explicit connectives (2717 tokens)
- Exact match agreement: 90.2%
- Partial agreement (arg overlapping): 94.5%

Example (Parenthetical in the middle of an argument)

Bankers said warrants for Hong Kong stocks are attractive because they give foreign investors, wary of volatility in the colony's stock market, an opportunity to buy shares without taking too great a risk.

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Example (Implicit because)

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- Exact match: 72%
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Statistics for Corpus Linguistics

- Introduction
- Representativity
- Hypthesis Testing

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Some terminology

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- Doing statistics: to study a set of equivalent objects by observing some characteristics: *variables*
- The *population*: the group or the set of objects under study
- The *entities*: these objects

The real world

- Against the possible huge size or even possible infiniteness of a population: study of a *sample* of this population
- How to choose this sample? *Randomly*
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Differences between populations and samples

- *Parameters*: values describing the population
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What kind of variable for:

- The size of a syntactic tree whose root is NP?
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- Available probabilistic models (P_θ)
- Statistical model:
 - What's the value of θ ?
 - $\theta = \theta_1$ or $\theta = \theta_2$?

Statistics and probabilities

Probability theory

Mathematical analysis of random phenomena.

Statistics

Methods and tools to describe data and to infer characteristics of populations from samples.

Data

- How to collect them
- How to present them

Models for these data

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Sampling

Sentences in a corpus

- Take a random sequence of numbers and select the corresponding sentence (random function)
- Quasi-random sampling:
 - Randomly choose the first sentence. Then every $\frac{\text{corpus size}}{\text{sample size}}$. Problem with periodic data
 - Randomly choose the first sentence, then the sample size next ones.
- How much representative is it? What about rare “kind” of sentences?
- Stratified random sampling (proportional, disproportional)
- Ex.: brown-sentence-length-lim.ods, bsllh.ods
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Central Tendency Measures

Role: To give the “typical” value of the grouped data

Which measure?

- Mean:

$$\bar{x} = \frac{1}{n} \sum_{i=1}^n x_i \text{ or } \bar{x} = \frac{\sum_{i=1}^n f(x_i)x_i}{n}$$

with f frequency distribution.

- Median: let us assume $x_{i-1} \leq x_i$. Then

$$M = \begin{cases} x_{\frac{n+1}{2}} & \text{if } n \text{ is odd} \\ \frac{x_{\frac{n}{2}} + x_{\frac{n}{2}+1}}{2} & \text{if } n \text{ is even} \end{cases} \text{ or } x_{i_2} \text{ s.t. } \sum_1^{i_2-1} f(x_i) < \frac{n}{2} \text{ and } \sum_1^{i_2} f(x_i) \geq \frac{n}{2}$$

- Mode: value with the highest frequency

Central Tendency Measure

	Mean	Median	Mode
Ratio variable	•	•	•
Interval variables	•	•	•
Ordinal variables	—	•	•
Nominal variables	—	—	•

Do they give the right tendency?

Extreme values

Skewed distribution

Symetric distribution \Rightarrow mode = median = mean

Central Measure Tendency

Measuring Variability

- Range: $w = \max_i(x_i) - \min_i(x_i)$

- Interquartile range:

- x_{i_1} s.t. $\sum_1^{i_1-1} f(x_i) < \frac{n}{2}$ and $\sum_1^{i_1} f(x_i) \geq \frac{n}{4}$
- x_{i_2} s.t. $\sum_1^{i_2-1} f(x_i) < \frac{n}{2}$ and $\sum_1^{i_2} f(x_i) \geq \frac{2n}{4}$
- x_{i_3} s.t. $\sum_1^{i_3-1} f(x_i) < \frac{n}{2}$ and $\sum_1^{i_3} f(x_i) \geq \frac{3n}{4}$

$$w_{1,3} = x_{i_3} - x_{i_1}$$

- Variance: $\sigma^2 = \frac{\sum_1^n (x_i - \bar{x})^2}{n}$
- Standard deviation: σ

The Laplace-Gauss Distribution

A.k.a The normal distribution

$$LG(\mu, \sigma^2) : f(x) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{1}{2}\left(\frac{x-\mu}{\sigma}\right)^2}$$

Tables

Representativity

What the frequency distribution for the mean of samples?

- Idea:
 - Take a first sample, compute the mean
 - Take a second sample, compute the mean
 - ...
- Property (application of the central limit theorem):
 - The sampling distribution converges to a normal distribution
 - The mean is the same as the mean of the population
 - Variability is smaller: $\sigma_s = \frac{\sigma}{\sqrt{n}}$
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Small samples ($n \leq 30$)

The t -test

- Not a normal distribution anymore
- Notion of *degrees of freedom*: $n - 1$ where n is the size of the sample
- Estimation of σ_e : $\frac{\sigma}{\sqrt{n-1}}$

Hypothesis Testing

Differences between 2 samples

- What does it mean that the central tendency measure of 2 samples are different?
- Is this difference observed just by chance?
- Does it reflect an essential difference between the two samples?

Example

Genres and sentence length Is the difference due to chance or to deeper difference?

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Null hypothesis The two samples come from the same population (no difference for the means except the one due to chance)

Alternative hypothesis They don't (there is such a difference, which is not due to chance)

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Choosing a test

What influences the choice of a test

- The type of the variable
 - Interval or ration variable: parametric tests (more powerful but generally with hypothesis on normality)
 - Other cases: non parametric tests
- The characteristics of the distribution
- The design of the study
 - Independant samples: the choice of an entity in the fist sample
 - Correlated samples

Running a test

Steps

- Specify the null hypothesis (and the alternative hypothesis)
- Choice of the decision variable and significance level
- Choice of the test (type of the variables, characteristics of the distribution, the way the sample was build)
- Computation and conclusion

Studies

Experimental and observational studies

- Experimental: One or more parameter can be modified. The effect is observed on a dependant variable (ex: evaluation of a generation system, a pronoun generator vs. human evaluators)
- Observational: Trying to infer relations between collected data
- How to avoid or reduce unexpected variations (cf previous example): repeated measures, matched subjects and independent groups.

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Choosing a test

Available tests

	Independent samples	Correlated samples
Parametric	z-test t-test for indep. samples	t-test for cor. samples
Non-parametric	χ^2	

Tests

- parametric test : difference of the means
 - Large independent samples (z-test with $\mu = 0$ and $\sigma^2 = \frac{\sigma_1^2}{n_1} + \frac{\sigma_2^2}{n_2}$).
 - Small independent tests (t-test (small samples from approximately normal distribution with comparable variances): $n_1 + n_2 - 2$ degrees of freedom)
 - t-test for correlated samples
- non parametric test: difference with expected results

χ^2 test


Comparison of observed frequency wrt. some hypothesis on its distribution

- $\chi^2 = \sum \frac{(O-E)^2}{E}$
- Testing the adequation to a theoretical distribution
- Test of independence


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