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Natural Language Processing for Teaching Ancient Languages*[1]

Natural languages

The notion of natural language refers to the challenge of analysing human communication. We hope to gain insight into our everyday interactions[2] by examining our communicative behaviour. For this task, languages like English, Farsi or Ancient Greek are presumably more informative than programming languages like C or Python, because the latter rarely serve a strictly communicative purpose, but are rather used to process data for a specific workflow. To achieve that goal, machines usually rely on their own computational capacity, consulting external resources only if explicitly asked to do so. Humans, on the other hand, tend to use joint reasoning to solve advanced problems.[3]

When we decide to use human language as a research object, we may encounter a few problems that are not present in constructed languages: human languages evolve continuously[4] and involve a great deal of ambiguity and interpretation.[5] For humans, such evolution and vagueness is desirable to retain a sufficient amount of flexibility, which is needed in dynamic environments where social interaction is neither rigid nor perfectly consistent.

For machines, however, this constant interpretative performance of humans has to be emulated artificially.[6] Depending on our end goal, we often need several steps to decode the meaning of, for example, an ancient text (see Fig. 1). Each of those steps plays an important role in providing the necessary information for a machine to decode a given linguistic input.

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2 Crocker 2013, 482.

3 Textor 2011, 44.

4 Ljunglöf et al. 2010, 60.

5 Palmer 2010, 15.

6 Ljunglöf et al. 2010, 59; Palmer 2010, 9.

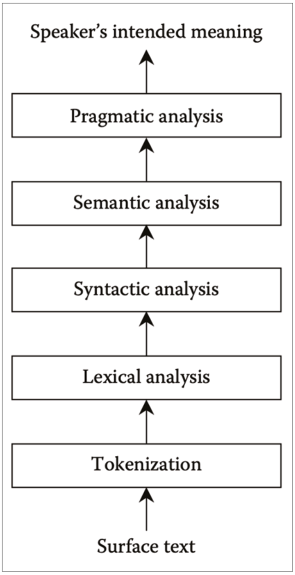


Fig. 1: Stages of natural language processing according to Dale 2010, p. 4.

Current systems for natural language processing (hereafter: NLP) are quite proficient in analysing various lexical aspects of texts in most languages. Syntax, on the other hand, is much harder to analyse, especially for languages where the availability of high-quality research data is quite limited.[7] Unfortunately, this is true for the languages of most ancient cultures. Even for Latin, where a rich tradition survived, the majority of written evidence remains irrecoverably lost. Therefore, NLP applications for such problematic languages currently cover only a limited amount of syntactic or semantic analysis, let alone pragmatics. In the following, we shall look at several examples of what works with such applications, and what does not.

Finding the right text

Vocabulary is a crucial aspect of teaching ancient languages, which is why there have been ongoing efforts to determine a certain number of words that constitute a core vocabulary.[8] Traditionally, it was assumed that such a basic vocabulary should be acquired in the initial learning phase, and then followed by a phase of extensive reading of ancient literature.[9] Nowadays, however, longer learning processes are more strongly

7 McGillivray 2013, 3; Ragni et al. 2014; Karakanta et al. 2018, 168.
8 Utz 2000, 146; Jones et al. 2006; Robillard et al. 2014, 2.
9 Freie und Hansestadt Hamburg 2004, 10.

emphasized, even for historical languages that we only learn at schools or universities.[10] What we actually need to do is to measure the lexical knowledge for a given learner at any point time, which has been notoriously difficult for humans and machines alike.[11]

Once we know more about a learner's current lexical proficiency, another challenge awaits us: what is a suitable text passage or exercise for that person in order to further advance along the path of language learning? Basic operationalisations for this task include comparing a list of supposedly known words to a list of lemmata that occur in a text. Similar to computational models,[12] learners will often struggle to deal with lemmata that go beyond their available vocabulary. Teachers therefore usually want to provide additional help, for example in the form of explanatory contexts, glosses, dictionaries, or simple translations. Unfortunately, such supportive measures may not prove consistently effective, because we often do not know the actual degree of (un-) familiarity for a given lexeme and learner. Since vocabulary knowledge is multidimensional,[13] computational operationalisations of lexical progression need to incorporate more than just the binary decision of 'known/unknown'. This also applies to diagnosis and feedback, where the simple dichotomy 'correct/incorrect' is often insufficient to provide accurate information. What NLP (and research on vocabulary acquisition in general) needs is a consistent model for providing information on various error types, forms of knowledge, and understanding of tasks or instructions.[14] A basic starting point in working towards this goal is to apply an extensive metadata schema to exercises, which separately encodes the types of interaction, linguistic phenomena and possible embedding in a larger progression.

Assuming we could successfully identify certain words to be learned, and found text passages in which these words occur, the next step would be to create appropriate exercises for this material. Traditionally, vocabulary has been acquired by memorizing lists of word equations in the form 'Latin word = L1 word'.[15] More recent approaches, on the other hand, have emphasized vocabulary acquisition in context, rather than as isolated word forms.[16] Ideally, such contexts should contain authentic rather than artificial utterances[17] to avoid an oversimplification of language that would lead to a shock for learners later on when they are suddenly confronted with real-world texts.[18] In this regard, NLP can be employed to make use of authentic text corpora to create contextualized vocabulary exercises. At the very least, this requires pairs of words, e. g. nouns and their

10 Foley et al. 2017.
11 Chen 2011, 292; Dor¸ca et al. 2013, 2092; Munser-Kiefer et al. 2018, 115; Beyer 2018, 13.
12 Parada et al. 2010, 57.
13 González-Fernández et al. 2019, 3.
14 Narciss 2008, 135.
15 Carter 1997, 2.
16 Waiblinger 2001, 160; Webb 2008, 238; Nation 2012, 353;
17 Römer 2019, 93; Tok 2010, 509.
18 Schibel 2013, 115.

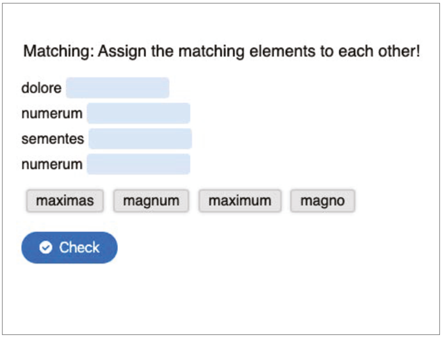


Fig. 2: Matching exercise for nouns with adjectival modifiers, created using H5P (Joubel 2018).

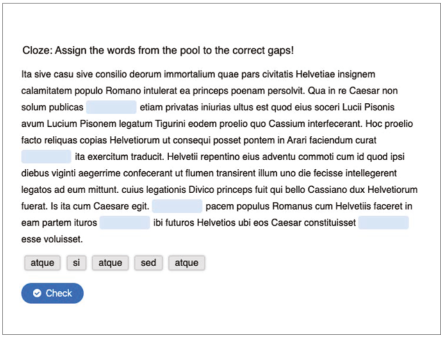


Fig. 3: Cloze exercise for conjunctions.

adjectival modifiers (see Fig. 2). Other setups may turn out to be even more effective, for example ‘keyword in context’ views,[19] or cloze tests as a means of differentiating between similar conjunctions (see Fig. 3).

Using authentic language as a basis for the exercises has the added benefit of implicitly confronting learners with many linguistic patterns and structures, for example in syntax or lexis. This way, even if the focus of the exercise is on a very specific phenomenon, learners will also internalise many other properties of the target language that are not emphasised separately.[20] Besides, using an interactive digital system to communicate such materials can be more inclusive, more motivating, and conducive to a deeper understanding of word meaning.[21] Furthermore, automatic evaluation of exercises enables us to provide ongoing formative, visualized feedback, and to construct individual learning paths for each person.[22] This may well be one of the most important benefits of NLP for language teaching.

Treebanks and learners’ expectations

When learners acquire vocabulary, they do not just learn about the lexis, i.e. when to use which word. They also need to grasp the word’s meaning and position in various contexts. In this view, the theoretical distinction between lexicon, syntax and semantics becomes blurred, or at least highly interwoven.[23] Considering that there cannot be a full understanding of any word in a specific context without knowledge of its syntactic

19 Helm 2009, 97.
20 Röhr-Sendlmeier et al. 2012, 45.
21 Crossley et al. 2010, 71; Schmid 2010, 165–169; Harecker et al. 2011, 1–5.
22 Chen 2011, 292; Ferguson 2012, 313; Univio et al. 2019, 158.
23 Rich et al.1991, 410; Aijmer 2009, 3; Rei et al. 2014, 75; Lehecka 2015, 6; Lebani et al. 2018, 133.

function,[24] we need to make sure that advanced learners' expectations, when reading the beginning of a sentence, have been shaped and trained by as many similar contexts as possible. For beginners, on the other hand, the text passages that they are confronted with have to be chosen in a way that they do not match their expectations perfectly. In this manner, they will be forced to adapt their mental representation of syntagmatic structures in the target language, thus extending their knowledge.[25]

Historically, such experiential modifications of linguistic knowledge have been exemplified in grammar books, which often impose rather prescriptive standards and use several authentic instances of language use to support their claims, followed by a few exceptions where the general rule does not apply.[26] With the advent of curated text corpora of decent size even for historical languages, however, we may now replace the textual basis from which we deduce linguistic assumptions with suitable ad hoc corpora. Treebanks, i.e. syntactically annotated text collections (often including multiple authors), should be used both as a standard reference for the target language in general and as a pool for extracting information about specific sub-corpora, for example all works from a certain author. If that author's works are to be read in school, teachers can access the relevant treebank[27] through dedicated corpus search tools[28] and see which constructions are particularly important to understand the chosen texts. Furthermore, educational publishing companies may choose to base their next textbook's vocabulary only on those texts that are part of the curriculum at later stages.

Modelling the meaning of words

While NLP practitioners have access to more and more lexical and syntactic resources to provide teachers with useful materials, the same cannot be readily said about semantics. There have been efforts to create expert databases[29] that are supposed to represent human semantic knowledge. Unfortunately, these are often built from personal intuition rather than empirical evidence. One of the most promising approaches for overcoming this problem is distributional semantics, which defines a word's meaning by looking at its surrounding context.[30] It has been on the rise in recent years, especially due the hype surrounding deep learning.[31] Furthermore, good distributional semantic models (DSMs) do not just represent semantic relations, but also morphological or

24 Gries et al. 2013, 348; Schmid et al. 2013, 551.
25 Ellis 2008, 374; Farmer et al. 2011, 2059; Hahn et al. 2019, 14.
26 Menge 1914, 334.
27 Bamman et al. 2011.
28 Krause et al. 2016.
29 Fellbaum et al. 2012, 315.
30 Harris 1954, 162; Firth 1957, 30
31 Lin 2019.

even pragmatic information[32], which is not surprising given the interwovenness of the various linguistic levels that was mentioned above.

Obviously, such approaches suffer from many problems:

- They tend to ignore common knowledge that is available to every human but is never mentioned in the given texts.[33]
- They struggle to adequately represent rare or metaphoric word usage.[34]
- Their inferential power (for example by analogy) is very case-specific and cannot be easily generalised.[35]
- They often do not model polysemy at all and do not differentiate between, for example, synonymy and syntagmatic relatedness.[36]

Fortunately, these points have attracted attention and this has led to serious improvements, especially concerning the modelling of polysemy.[37] A great deal of research has been done on using textual context as a source of information on a word's meaning, for example by hiding words in a text and making a machine fill the blanks correctly[38] or by systematically comparing various computational operationalisations of linguistic knowledge.[39] Thereby, standard procedures in philology, such as finding semantically related words for a given topic in a given text corpus,[40] can be facilitated through machine learning output that is interactively visualized as a network (Fig. 4).

In such networks, users can start from a single word (*veritas*) and quickly expand on that word to find other related terms like *simulatio* (pretence), *crederet* (to trust) or *suggerendis* (to suggest). In this sense, the procedure is comparable to snowball sampling[41] because once a user has found these additional terms, each one of them can be used as the basis for another search. Such search methods have been used with traditional linguistic resources as well (e.g. dictionaries, catalogues of synonyms etc.), but they have rarely been adapted to a specific researcher's target data. Using a dynamic machine learning approach enables NLP software to apply the general method (i.e. extracting word fields from a text) to almost any given corpus. The most important obstacle, then, will be to make the base architecture useful for as many cases as possible. This way, we can optimise the method for many different usage scenarios at the same time, instead of starting from scratch for every new text corpus.

32 Gries et al. 2009, 59; Gladkova et al. 2016, 8.
33 Bruni et al. 2014, 3.
34 Grigonyte et al. 2010, 404.
35 Rogers et al. 2017, 142.
36 Karan et al. 2012, 114; Faruqui et al. 2016, 4.
37 Hamilton et al. 2016, 8.
38 Devlin et al. 2018.
39 Dobó 2019, 85.
40 Cordes 2020, 43.
41 Handcock et al. 2011, 368.

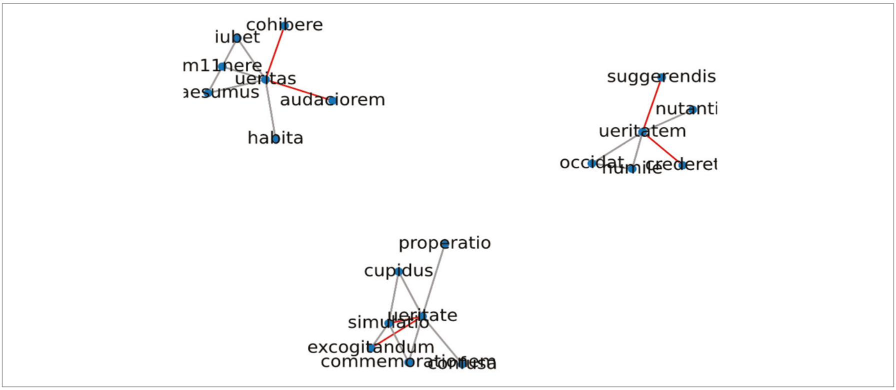
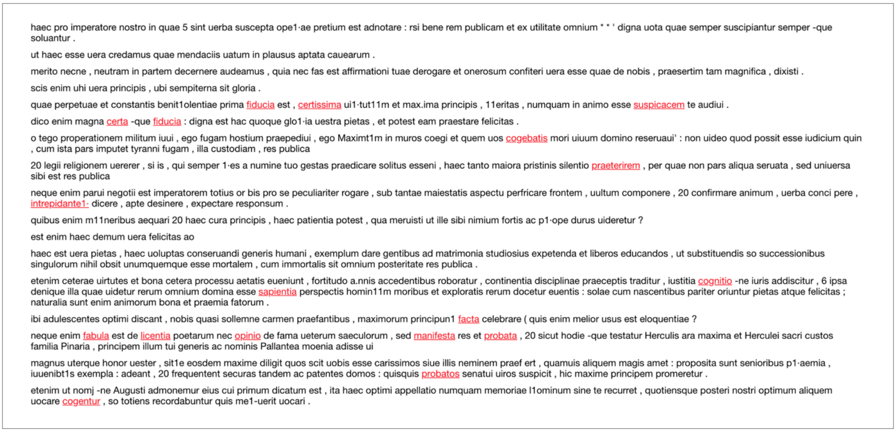


Fig. 4: Semantically related words for veritas in the *Panegyrici Latini,* a late antique text corpus. Relations are visualized as edges in a network, where particularly important ones are highlighted in red.



haec pro imperatore nostro in quae 5 sint uerba suscepta ope1·ae pretium est adnotare : rsi bene rem publicam et ex utilitate omnium * * ' digna uota quae semper suscipiantur semper -que soluantur .

ut haec esse uera credamus quae mendaciis uatum in plausus aptata cauearum .

merito necne , neutram in partem decernere audeamus , quia nec fas est affirmationi tuae derogare et onerosum confiteri uera esse quae de nobis , praesertim tam magnifica , dixisti .

scis enim uhi uera principis , ubi sempiterna sit gloria .

quae perpetuae et constantis benit1olentiae prima fiducia est , certissima ui1·tut11m et max.ima principis , 11eritas , numquam in animo esse suspicacem te audiui .

dico enim magna certa -que fiducia : digna est hac quoque glo1·ia uestra pietas , et potest eam praestare felicitas .

o tego properationem militum iuui , ego fugam hostium praepediui , ego Maximt1m in muros coegi et quem uos cogebatis mori uiuum domino reseruaui' : non uideo quod possit esse iudicium quin , cum ista pars imputet tyranni fugam , illa custodiam , res publica

20 legii religionem uererer , si is , qui semper 1·es a numine tuo gestas praedicare solitus esseni , haec tanto maiora pristinis silentio praeterirem , per quae non pars aliqua seruata , sed uniuersa sibi est res publica

neque enim parui negotii est imperatorem totius or bis pro se peculiariter rogare , sub tantae maiestatis aspectu perfricare frontem , uultum componere , 20 confirmare animum , uerba conci pere , intrepidante1· dicere , apte desinere , expectare responsum .

quibus enim m11neribus aequari 20 haec cura principis , haec patientia potest , qua meruisti ut ille sibi nimium fortis ac p1·ope durus uideretur ?

est enim haec demum uera felicitas ao

haec est uera pietas , haec uoluptas conseruandi generis humani , exemplum dare gentibus ad matrimonia studiosius expetenda et liberos educandos , ut substituendis so successionibus singulorum nihil obsit unumquemque esse mortalem , cum immortalis sit omnium posteritate res publica .

etenim ceterae uirtutes et bona cetera processu aetatis eueniunt , fortitudo a.nnis accedentibus roboratur , continentia disciplinae praeceptis traditur , iustitia cognitio -ne iuris addiscitur , 6 ipsa denique illa quae uidetur rerum omnium domina esse sapientia perspectis homin11m moribus et exploratis rerum docetur euentis : solae cum nascentibus pariter oriuntur pietas atque felicitas ; naturalia sunt enim animorum bona et praemia fatorum .

ibi adulescentes optimi discant , nobis quasi sollemne carmen praefantibus , maximorum principun1 facta celebrare (quis enim melior usus est eloquentiae ?

neque enim fabula est de licentia poetarum nec opinio de fama ueterum saeculorum , sed manifesta res et probata , 20 sicut hodie -que testatur Herculis ara maxima et Herculei sacri custos familia Pinaria , principem illum tui generis ac nominis Pallantea moenia adisse ui

magnus uterque honor uester , sit1e eosdem maxime diligit quos scit uobis esse carissimos siue illis neminem praef ert , quamuis aliquem magis amet : proposita sunt senioribus p1·aemia , iuuenibt1s exempla : adeant , 20 frequentent securas tandem ac patentes domos : quisquis probatos senatui uiros suspicit , hic maxime principem promeretur .

etenim ut nomj -ne Augusti admonemur eius cui primum dicatum est , ita haec optimi appellatio numquam memoriae l1ominum sine te recurret , quotiensque posteri nostri optimum aliquem uocare cogentur , so totiens recordabuntur quis me1-uerit uocari .

Fig. 5: Semantically related sentences for *vera* in the *Panegyrici Latini*, a late antique text corpus. Important words are highlighted in red. Note that many sentences do not contain the query word veritas, but are highly relevant, nevertheless.

Methodologically speaking, snowball sampling is applicable to entire sentences and documents as well (Fig. 5). Since the amount of linguistic output here is considerably larger, users will probably not interact with it in the same way as with the network. Instead, such lists can be seen as a semantic equivalent of ‘keyword in context’ views, i.e. depicting descriptions of the same target entity (here: factuality as designated by the input word vera) in various contexts. This is especially useful for teachers who do not want to convey the meaning of one specific term, but rather of an entire concept or topic, which in turn is often essential to a deep understanding of ancient texts.

Another important aspect resides in the interpretability of NLP results.[42] Especially in the case of semantics, finding relevant responses to a given query often includes complex modelling,[43] specific statistical measures[44] or searching in additional resources.[45] Usually, the ability of the underlying algorithms to explain results and the ability of those who applied the algorithm to explain why it produced those results, is less important for teachers than for researchers, but from an epistemological and educational perspective, there is much to be learned by applying introspection to the decision processes of artificial intelligence. This becomes apparent in cases where machines produce convincing visualizations using improper modelling. A good example is the stylometric study of Jeremi Ochab,[46] in which a seemingly simple decision process (i.e. authorship attribution) is made more complicated by many confounding variables, such as text length or topic.[47]

Conclusion

In the end, teachers have to be aware that NLP can solve some problems better than others. It is quite suitable for training learners' vocabulary or even syntactic expectations by confronting them with interactive, individualized exercises and materials that have been tailored to their current state of knowledge. However, a teacher cannot rely solely on software because human domain-specific expertise and social sensitivity are needed to provide elaborate advanced feedback to the students. Moreover, machines may retrieve and visualize relevant search results very efficiently, but they must not take interpretation and decision-making out of the learners' hands because those processes constitute the core of consensus negotiation, and thus knowledge acquisition.

Besides, even in the easy cases, we must always be aware of risks such as systematic bias, weak statistical measures or overly suggestive visualizations. Apart from such implicit or hidden weaknesses, some tasks are known to be too difficult for contemporary machines, for example reliable and highly accurate parsing of syntax for historical languages. Fortunately, surpassing contemporary abilities is, in this case, arguably a question of a few years rather than decades. Other more complex tasks such as word sense disambiguation may need considerably more time to meet a similar milestone.

42 Doran et al. 2017, 4.
43 Divjak et al. 2009, 274; Weale et al. 2009, 29.
44 Hagiwara et al. 2009, 566.
45 Ono et al. 2015, 984–988.
46 Ochab et al. 2019.
47 Golcher et al. 2011, 31–33; Ochab et al. 2019, 141.

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Useful resources

- interactive exercises: H5P
- Latin vocabulary exercises: MachinaCallida
- visualization for linguistic annotations: CONLLU Viewer
- annotated ancient texts: AGLDT & PROIEL
- corpus search and visualization: ANNIS

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