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Paragraph(1)
1 Natural language processing From Wikipedia, the free encyclopedia Natural language processing (NLP) is a field of computer science, artificial intelligence, and computational linguistics concerned with the interactions between computers and human (natural) languages.
2 As such, NLP is related to the area of human–computer interaction.
3 Many challenges in NLP involve: natural language understanding, enabling computers to derive meaning from human or natural language input; and others involve natural language generation.
Paragraph(2)
4 An automated online assistant providing customer service on a web page, an example of an application where natural language processing is a major component.[1]
5 Contents [hide] 1 History 2 Using machine learning 3 Major tasks 4 Statistical 5 Evaluation 5.1 Objectives 5.2 Timeline of evaluation 5.3 Different types of evaluation 6 Standardization 7 See also 8 References 9 Further reading History The history of NLP generally starts in the 1950s, although work can be found from earlier periods.
6 In 1950, Alan Turing published an article titled "Computing Machinery and Intelligence" which proposed what is now called the Turing test as a criterion of intelligence.
Paragraph(3)
7 The Georgetown experiment in 1954 involved fully automatic translation of more than sixty Russian sentences into English.
8 The authors claimed that within three or five years, machine translation would be a solved problem.[2]
9 However, real progress was much slower, and after the ALPAC report in 1966, which found that ten-year-long research had failed to fulfill the expectations, funding for machine translation was dramatically reduced.
10 Little further research in machine translation was conducted until the late 1980s, when the first statistical machine translation systems were developed.
Paragraph(4)
11 Some notably successful NLP systems developed in the 1960s were SHRDLU, a natural language system working in restricted "blocks worlds" with restricted vocabularies, and ELIZA, a simulation of a Rogerian psychotherapist, written by Joseph Weizenbaum between 1964 and 1966.
12 Using almost no information about human thought or emotion, ELIZA sometimes provided a startlingly human-like interaction.
13 When the "patient" exceeded the very small knowledge base, ELIZA might provide a generic response, for example, responding to "My head hurts" with "Why do you say your head hurts?".
Paragraph(5)
14 During the 1970s many programmers began to write "conceptual ontologies", which structured real-world information into computer-understandable data.

15 Examples are MARGIE (Schank, 1975), SAM (Cullingford, 1978), PAM (Wilensky, 1978), TaleSpin (Meehan, 1976), QUALM (Lehnert, 1977), Politics (Carbonell, 1979), and Plot Units (Lehnert 1981).
16 During this time, many chatterbots were written including PARRY, Racter, and Jabberwacky.
Paragraph(6)
17 Up to the 1980s, most NLP systems were based on complex sets of hand-written rules.
18 Starting in the late 1980s, however, there was a revolution in NLP with the introduction of machine learning algorithms for language processing.
19 This was due to both the steady increase in computational power (see Moore's Law) and the gradual lessening of the dominance of Chomskyan theories of linguistics (e.g. transformational grammar), whose theoretical underpinnings discouraged the sort of corpus linguistics that underlies the machine-learning approach to language processing.[3]
20 Some of the earliest-used machine learning algorithms, such as decision trees, produced systems of hard if-then rules similar to existing hand-written rules.
21 However, part-of-speech tagging introduced the use of hidden Markov models to NLP, and increasingly, research has focused on statistical models, which make soft, probabilistic decisions based on attaching real-valued weights to the features making up the input data.
22 The cache language models upon which many speech recognition systems now rely are examples of such statistical models.
23 Such models are generally more robust when given unfamiliar input, especially input that contains errors (as is very common for real-world data), and produce more reliable results when integrated into a larger system comprising multiple subtasks.
Paragraph(7)
24 Many of the notable early successes occurred in the field of machine translation, due especially to work at IBM Research, where successively more complicated statistical models were developed.
25 These systems were able to take advantage of existing multilingual textual corpora that had been produced by the Parliament of Canada and the European Union as a result of laws calling for the translation of all governmental proceedings into all official languages of the corresponding systems of government.
26 However, most other systems depended on corpora specifically developed for the tasks implemented by these systems, which was (and often continues to be) a major limitation in the success of these systems.
27 As a result, a great deal of research has gone into methods of more effectively learning from limited amounts of data.
Paragraph(8)
28 Recent research has increasingly focused on unsupervised and semi-supervised learning algorithms.
29 Such algorithms are able to learn from data that has not been hand-annotated with the desired answers, or using a combination of annotated and non-annotated data.
30 Generally, this task is much more difficult than supervised learning, and typically produces less accurate results for a given amount of input data.

31 However, there is an enormous amount of non-annotated data available (including, among other things, the entire content of the World Wide Web), which can often make up for the inferior results.
Paragraph(9)
32 Using machine learning Modern NLP algorithms are based on machine learning, especially statistical machine learning.
33 The paradigm of machine learning is different from that of most prior attempts at language processing.
34 Prior implementations of language-processing tasks typically involved the direct hand coding of large sets of rules.
35 The machine-learning paradigm calls instead for using general learning algorithms — often, although not always, grounded in statistical inference — to automatically learn such rules through the analysis of large corpora of typical real-world examples.
36 A corpus (plural, "corpora") is a set of documents (or sometimes, individual sentences) that have been hand-annotated with the correct values to be learned.
Paragraph(10)
37 Many different classes of machine learning algorithms have been applied to NLP tasks.
38 These algorithms take as input a large set of "features" that are generated from the input data.
39 Some of the earliest-used algorithms, such as decision trees, produced systems of hard if-then rules similar to the systems of hand-written rules that were then common.
40 Increasingly, however, research has focused on statistical models, which make soft, probabilistic decisions based on attaching real-valued weights to each input feature.
41 Such models have the advantage that they can express the relative certainty of many different possible answers rather than only one, producing more reliable results when such a model is included as a component of a larger system.
Paragraph(11)
42 Systems based on machine-learning algorithms have many advantages over hand-produced rules:
Paragraph(12)
43 The learning procedures used during machine learning automatically focus on the most common cases, whereas when writing rules by hand it is often not at all obvious where the effort should be directed.
44 Automatic learning procedures can make use of statistical inference algorithms to produce models that are robust to unfamiliar input (e.g. containing words or structures that have not been seen before) and to erroneous input (e.g. with misspelled words or words accidentally omitted).
45 Generally, handling such input gracefully with hand-written rules — or more generally, creating systems of hand-written rules that make soft decisions — is extremely difficult, error-prone and time-consuming.
46 Systems based on automatically learning the rules can be made more accurate simply by supplying more input data.
47 However, systems based on hand-written rules can only be made more accurate by increasing the complexity of the rules, which is a much more difficult task.

48 In particular, there is a limit to the complexity of systems based on hand-crafted rules, beyond which the systems become more and more unmanageable.
49 However, creating more data to input to machine-learning systems simply requires a corresponding increase in the number of man-hours worked, generally without significant increases in the complexity of the annotation process.
50 The subfield of NLP devoted to learning approaches is known as natural language learning (NLL) and its conference CoNLL[4] and peak body SIGNLL[5] are sponsored by ACL, recognizing also their links with computational linguistics and Language Acquisition.
51 When the aim of computational language learning research is to understand more about human language acquisition, or psycholinguistics, NLL overlaps into the related field of computational psycholinguistics.
Paragraph(13)
52 Major tasks The following is a list of some of the most commonly researched tasks in NLP.
53 Note that some of these tasks have direct real-world applications, while others more commonly serve as subtasks that are used to aid in solving larger tasks.
54 What distinguishes these tasks from other potential and actual NLP tasks is not only the volume of research devoted to them but the fact that for each one there is typically a well-defined problem setting, a standard metric for evaluating the task, standard corpora on which the task can be evaluated, and competitions devoted to the specific task.
Paragraph(14)
55 Automatic summarization Produce a readable summary of a chunk of text.
56 Often used to provide summaries of text of a known type, such as articles in the financial section of a newspaper.
57 Coreference resolution Given a sentence or larger chunk of text, determine which words ("mentions") refer to the same objects ("entities").
58 Anaphora resolution is a specific example of this task, and is specifically concerned with matching up pronouns with the nouns or names that they refer to.
59 The more general task of coreference resolution also includes identifying so-called "bridging relationships" involving referring expressions.
60 For example, in a sentence such as "He entered John's house through the front door", "the front door" is a referring expression and the bridging relationship to be identified is the fact that the door being referred to is the front door of John's house (rather than of some other structure that might also be referred to).
61 Discourse analysis This rubric includes a number of related tasks.
62 One task is identifying the discourse structure of connected text, i.e. the nature of the discourse relationships between sentences (e.g. elaboration, explanation, contrast).
63 Another possible task is recognizing and classifying the speech acts in a chunk of text (e.g. yes-no question, content question, statement, assertion, etc.).
64 Machine translation Automatically translate text from one human language to another.
65 This is one of the most difficult problems, and is a member of a class of problems colloquially termed "AI-complete", i.e. requiring all of the different types of knowledge that humans possess (grammar, semantics, facts about the real world, etc.) in order to

solve properly.
66 Morphological segmentation Separate words into individual morphemes and identify the class of the morphemes.
67 The difficulty of this task depends greatly on the complexity of the morphology (i.e. the structure of words) of the language being considered.
68 English has fairly simple morphology, especially inflectional morphology, and thus it is often possible to ignore this task entirely and simply model all possible forms of a word (e.g. "open, opens, opened, opening") as separate words.
69 In languages such as Turkish or Manipuri,[6] a highly agglutinated Indian language, however, such an approach is not possible, as each dictionary entry has thousands of possible word forms.
70 Named entity recognition (NER) Given a stream of text, determine which items in the text map to proper names, such as people or places, and what the type of each such name is (e.g. person, location, organization).
71 Note that, although capitalization can aid in recognizing named entities in languages such as English, this information cannot aid in determining the type of named entity, and in any case is often inaccurate or insufficient.
72 For example, the first word of a sentence is also capitalized, and named entities often span several words, only some of which are capitalized.
73 Furthermore, many other languages in non-Western scripts (e.g. Chinese or Arabic) do not have any capitalization at all, and even languages with capitalization may not consistently use it to distinguish names.
74 For example, German capitalizes all nouns, regardless of whether they refer to names, and French and Spanish do not capitalize names that serve as adjectives.
75 Natural language generation Convert information from computer databases or semantic intents into readable human language.
76 Natural language understanding Convert chunks of text into more formal representations such as first-order logic structures that are easier for computer programs to manipulate.
77 Natural language understanding involves the identification of the intended semantic from the multiple possible semantics which can be derived from a natural language expression which usually takes the form of organized notations of natural languages concepts.
78 Introduction and creation of language metamodel and ontology are efficient however empirical solutions.
79 An explicit formalization of natural languages semantics without confusions with implicit assumptions such as closed-world assumption (CWA) vs. open-world assumption, or subjective Yes/No vs. objective True/False is expected for the construction of a basis of semantics formalization.[7]
80 Optical character recognition (OCR) Given an image representing printed text, determine the corresponding text.
81 Part-of-speech tagging Given a sentence, determine the part of speech for each word.
82 Many words, especially common ones, can serve as multiple parts of speech.
83 For example, "book" can be a noun ("the book on the table") or verb ("to book a flight"); "set" can be a noun, verb or adjective; and "out" can be any of at least five

different parts of speech.
84 Some languages have more such ambiguity than others.
85 Languages with little inflectional morphology, such as English are particularly prone to such ambiguity.
86 Chinese is prone to such ambiguity because it is a tonal language during verbalization.
87 Such inflection is not readily conveyed via the entities employed within the orthography to convey intended meaning.
88 Parsing Determine the parse tree (grammatical analysis) of a given sentence.
89 The grammar for natural languages is ambiguous and typical sentences have multiple possible analyses.
90 In fact, perhaps surprisingly, for a typical sentence there may be thousands of potential parses (most of which will seem completely nonsensical to a human).
91 Question answering Given a human-language question, determine its answer.
92 Typical questions have a specific right answer (such as "What is the capital of Canada?"), but sometimes open-ended questions are also considered (such as "What is the meaning of life?").
93 Recent works have looked at even more complex questions.[8]
94 Relationship extraction Given a chunk of text, identify the relationships among named entities (e.g. who is married to whom).
95 Sentence breaking (also known as sentence boundary disambiguation) Given a chunk of text, find the sentence boundaries.
96 Sentence boundaries are often marked by periods or other punctuation marks, but these same characters can serve other purposes (e.g. marking abbreviations).
97 Sentiment analysis Extract subjective information usually from a set of documents, often using online reviews to determine "polarity" about specific objects.
98 It is especially useful for identifying trends of public opinion in the social media, for the purpose of marketing.
99 Speech recognition Given a sound clip of a person or people speaking, determine the textual representation of the speech.
100 This is the opposite of text to speech and is one of the extremely difficult problems colloquially termed "AI-complete" (see above).
101 In natural speech there are hardly any pauses between successive words, and thus speech segmentation is a necessary subtask of speech recognition (see below).
102 Note also that in most spoken languages, the sounds representing successive letters blend into each other in a process termed coarticulation, so the conversion of the analog signal to discrete characters can be a very difficult process.
103 Speech segmentation Given a sound clip of a person or people speaking, separate it into words.
104 A subtask of speech recognition and typically grouped with it.
105 Topic segmentation and recognition Given a chunk of text, separate it into segments each of which is devoted to a topic, and identify the topic of the segment.
106 Word segmentation Separate a chunk of continuous text into separate words.
107 For a language like English, this is fairly trivial, since words are usually separated by spaces.
108 However, some written languages like Chinese, Japanese and Thai do not mark

word boundaries in such a fashion, and in those languages text segmentation is a significant task requiring knowledge of the vocabulary and morphology of words in the language.
109 Word sense disambiguation Many words have more than one meaning; we have to select the meaning which makes the most sense in context.
110 For this problem, we are typically given a list of words and associated word senses, e.g. from a dictionary or from an online resource such as WordNet.
111 In some cases, sets of related tasks are grouped into subfields of NLP that are often considered separately from NLP as a whole.
112 Examples include:
Paragraph(15)
113 Information retrieval (IR) This is concerned with storing, searching and retrieving information.
114 It is a separate field within computer science (closer to databases), but IR relies on some NLP methods (for example, stemming).
115 Some current research and applications seek to bridge the gap between IR and NLP.
116 Information extraction (IE) This is concerned in general with the extraction of semantic information from text.
117 This covers tasks such as named entity recognition, Coreference resolution, relationship extraction, etc.
118 Speech processing This covers speech recognition, text-to-speech and related tasks.
119 Other tasks include:
Paragraph(16)
120 Native-language identification Stemming Text simplification Text-to-speech Text-proofing Natural language search Query expansion Automated essay scoring Truecasing Statistical Statistical natural-language processing uses stochastic, probabilistic, and statistical methods to resolve some of the difficulties discussed above, especially those which arise because longer sentences are highly ambiguous when processed with realistic grammars, yielding thousands or millions of possible analyses.
121 Methods for disambiguation often involve the use of corpora and Markov models.
122 The ESPRIT Project P26 (1984 - 1988), led by CSELT, explored the problem of speech recognition comparing knowledge-based approach and statistical ones: the chosen result was a completely statistical model.[9]
123 One among the first models of statistical natural language understanding was introduced in 1991 by Roberto Pieraccini, Esther Levin, and Chin-Hui Lee from Bell Laboratories.[10]
124 NLP comprises all quantitative approaches to automated language processing, including probabilistic modeling, information theory, and linear algebra.[11]
125 The technology for statistical NLP comes mainly from machine learning and data mining, both of which are fields of artificial intelligence that involve learning from data.
Paragraph(17)
126 Evaluation Objectives The goal of NLP evaluation is to measure one or more qualities of an algorithm or a system, in order to determine: whether the algorithm answers the goals of its designers, or if the system meets the needs of its users.

127 Research in NLP evaluation has received considerable attention, because the definition of proper evaluation criteria is one way to specify precisely an NLP problem.
128 The metric of NLP evaluation on an algorithmic system allows for the integration of language understanding and language generation.
129 A precise set of evaluation criteria, which include mainly evaluation data and evaluation metrics can enable several teams to compare their solutions for a given NLP problem.
Paragraph(18)
130 Timeline of evaluation In 1983, start of Esprit P26 Project, that evaluated Speech Technologies (including general topic such as Syntactic & Semantic Parsing, etc.) comparing rule-based towards statistical approaches.[12]
131 In 1987, the first evaluation campaign on written texts seems to be a campaign dedicated to message understanding (Pallet 1998).
132 The Parseval/GEIG project compared phrase-structure grammars (Black 1991).
133 There were series of campaigns within Tipster project on tasks like summarization, translation, and searching (Hirschman 1998).
134 In 1994, in Germany, the Morpholympics compared German morphological taggers.
135 The Senseval & Romanseval campaigns were conducted with the objectives of semantic disambiguation.
136 In 1996, the Sparkle campaign compared syntactic parsers in four different languages (English, French, German and Italian).
137 In France, the Grace project compared a set of 21 taggers for French in 1997 (Adda 1999).
138 In 2004, during the Technolangue/Easy project, 13 parsers for French were compared.
139 Large-scale evaluation of dependency parsers were performed in the context of the CoNLL shared tasks in 2006 and 2007.
140 In France, within the ANR-Passage project (end of 2007), 10 parsers for French were compared – passage web site.
141 In Italy, the EVALITA campaign was conducted in 2007,[13] 2009, 2011, and 2014[14] to compare various NLP and speech tools for Italian – EVALITA web site.
142 Different types of evaluation Depending on the evaluation procedures, a number of distinctions are traditionally made in NLP evaluation.
Paragraph(19)
143 Intrinsic v. extrinsic evaluation Intrinsic evaluation considers an isolated NLP system and characterizes its performance with respect to a gold standard result as defined by the evaluators.
144 Extrinsic evaluation, also called evaluation in use, considers the NLP system in a more complex setting as either an embedded system or a precise function for a human user.
145 The extrinsic performance of the system is then characterized in terms of utility with respect to the overall task of the extraneous system or the human user.
146 For example, consider a syntactic parser which is based on the output of some part of speech (POS) tagger.
147 An intrinsic evaluation would run the POS tagger on structured data, and compare

the system output of the POS tagger to the gold standard output.
148 An extrinsic evaluation would run the parser with some other POS tagger, and then with the novel POS tagger, and compare the parsing accuracy.
149 Black-box v. glass-box evaluation Black-box evaluation requires someone to run an NLP system on a sample data set and to measure a number of parameters related to: the quality of the process, such as speed, reliability, resource consumption; and most importantly, the quality of the result, such as the accuracy of data annotation or the fidelity of a translation.
150 Glass-box evaluation looks at the: design of the system; the algorithms that are implemented; the linguistic resources it uses, like vocabulary size or expression set cardinality.
151 Given the complexity of NLP problems, it is often difficult to predict performance only on the basis of glass-box evaluation; but this type of evaluation is more informative with respect to error analysis or future developments of a system.
152 Automatic v. manual evaluation In many cases, automatic procedures can be defined to evaluate an NLP system by comparing its output with the gold standard one.
153 Although the cost of reproducing the gold standard can be quite high, bootstrapping automatic evaluation on the same input data can be repeated as often as needed without inordinate additional costs.
154 However, for many NLP problems the precise definition of a gold standard is a complex task and it can prove impossible when inter-annotator agreement is insufficient.
155 Manual evaluation is best performed by human judges instructed to estimate the quality of a system, or most often of a sample of its output, based on a number of criteria.
156 Although, thanks to their linguistic competence, human judges can be considered as the reference for a number of language processing tasks, there is also considerable variation across their ratings.
157 That is why automatic evaluation is sometimes referred to as objective evaluation while the human evaluation is perspective.
158 Standardization An ISO subcommittee is working in order to ease interoperability between lexical resources and NLP programs.
159 The subcommittee is part of ISO/TC37 and is called ISO/TC37/SC4.
160 Some ISO standards are already published but most of them are under construction, mainly on lexicon representation (see LMF), annotation, and data category registry.
Paragraph(20)
161 See also Biomedical text mining Compound term processing Computer-assisted reviewing Controlled natural language Deep linguistic processing Foreign language reading aid Foreign language writing aid Language technology Latent Dirichlet allocation (LDA) Latent semantic indexing List of natural language processing toolkits LRE Map Natural language programming Reification (linguistics) Semantic folding Spoken dialogue system Thought vector Transderivational search Word2vec
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167 The creation and use of such corpora of real-world data is a fundamental part of machine-learning algorithms for NLP.
168 In addition, theoretical underpinnings of Chomskyan linguistics such as the so-called "poverty of the stimulus" argument entail that general learning algorithms, as are typically used in machine learning, cannot be successful in language processing.
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