13 – Automatic Language Correction

IA161 Advanced Techniques of Natural Language Processing

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Motivation

This tool can be use to find spelling , gramar or stylistic errors in english texts. just paste some text in the the box and click 'Submit to check . Additionally, their are many different dialects you can chose from. Additionally , you can hover your mouse over a error to see it's description and an useful list of posible corrections. You don´t need to worry for your writing skills any more, improving you're text has never be more easier!

[1] Source: http://www.onlinecorrection.com/

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This tool can be use to find spelling , gramar or stylistic errors in english texts. just paste some text in the the box and click 'Submit to check . Additionally, their are many different dialects you can chose from. Additionally , you can hover your mouse over a error to see it's description and an useful list of posible corrections. You don´t need to worry for your writing skills any more, improving you're text has never be more easier!

Types of errors[1]:

Grammar (6) | Spelling (10) | Other (2) | Spacing (3) | Typographical (2) | Duplication (1)

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Automatic language correction

A text with errors...

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People are quite resilient to letter-switching errors:

Example (Cmabrigde Uinervtisy (Cambridge University) effect)

Aoccdrnig to a rscheearch at Cmabrigde Uinervtisy, it deosn't mttaer in waht oredr the ltteers in a wrod are, the olny iprmoetnt tihng is taht the frist and lsat ltteer be at the rghit pclae. The rset can be a toatl mses and you can sitll raed it wouthit porbelm. Tihs is bcuseae the huamn mnid deos not raed ervey lteter by istlef, but the wrod as a wlohe.

Example by Davis, M. 2003. Aoccdrnig to a rscheearch at Cmabrigde Uinervtisy
`http://www.mrc-cbu.cam.ac.uk/people/matt.davis/cmabridge/`

Automatic language correction

Automatic language correction:

- spell checking – detect spelling errors in individual words,
- grammar checking – incorrect use of person, number, case or gender, improper verb government, wrong word order, etc. . .
- word completion – suggestion of the word currently being entered.

Spell checking

- detecting which words in a document are misspelled,
- providing spelling suggestions for incorrectly spelled words in a text,
- correction is the task of substituting the well-spelled hypotheses for misspellings,
- usually uses a dictionary of valid words,
- application: word processing and postprocessing optical character recognition [Whitelaw et al., 2009] or speech recognition.

Type of errors

- Non-word errors – the misspelled word is not a valid word in a language,
  - typographic errors – usually keyboard typing error (e.g. "teh" – "the", "speel" – "spell"),
  - cognitive errors – caused by the writer's misconceptions (e.g. "recieve" – "receive", "conspiricy" – "conspiracy"),
  - phonetic errors – substituting a phonetically equivalent sequence of letters (e.g. "seperate" – "separate").
- Real-word errors – sentence contains a valid word, but it is inappropriate in the context [Hladek et al., 2013].

Example

Non-word error: "I'd like a peice of cake."
Real-word error: "I'd like a peace of cake."

Error correction

- Consists of two steps:
  - generation of candidate corrections,
  - ranking of candidate corrections.
- Isolated-word methods:
  - edit distance,
  - similarity keys,
  - character n-gram-based techniques,
  - rule-based techniques,
  - probabilistic techniques,
  - neural networks [Sakaguchi et al., 2017].

Isolated-word methods I

Edit distance

- assumption – person usually makes few errors,
- minimum set of operations to transform a non-word to a dictionary word,
- operations: insertions, deletions and substitutions,
- useful for: correcting errors resulting from keyboard input.

Example

Edit distance between “kitten” and “sitting” is 3:

1. kitten → sitten substitution of “s” for “k”
2. sitten → sittin substitution of “i” for “e”
3. sittin → sitting insertion of “g” at the end

Isolated-word methods II

Similarity keys:

- assign a key to each dictionary word,
- compare with the key computed for the non word,
- most similar key is selected as suggestion.

Soundex – phonetic algorithm (English) [Holmes and McCabe, 2002]

Example

N	Represents letters
1	B, F, P, V
2	C, G, J, K, Q, S, X, Z
3	D, T
4	L
5	M, N
6	R

1. Keep the first letter
2. Drop occurrences of `a`, `e`, `i`, `o`, `u`, `y`, `h`, `w`
3. Replace letters with numbers
4. Merge adjacent identical numbers
5. Add zeroes to the end, or remove right-most numbers

Output: `(letter, number, number, number)`

key("Robert")=R163; key("Robin")=R150 – not similar

key("Smith")=S530; key("Smyth")=S530 – similar

Isolated-word methods III

Character N-gram-based techniques:

- compute similarity coefficient of two strings
- based on the number of shared n-grams (*Jaccard similarity*)

$$\delta_n(a,b) = \frac{|\textit{n-grams}(a) \cap \textit{n-grams}(b)|}{|\textit{n-grams}(a) \cup \textit{n-grams}(b)|}$$

Example

fact vs. fract

$$\begin{aligned} \textit{bigrams}(\text{“fact”}) &= \{\text{“-f”}, \text{“fa”}, \text{“ac”}, \text{“ct”}, \text{“t-”}\} && \text{... 5 bigrams} \\ \textit{bigrams}(\text{“fract”}) &= \{\text{“-f”}, \text{“fr”}, \text{“ra”}, \text{“ac”}, \text{“ct”}, \text{“t-”}\} && \text{... 6 bigrams} \\ \ldots \cap \ldots &= \{\text{“-f”}, \text{“ac”}, \text{“ct”}, \text{“t-”}\} && \text{... 4 bigrams} \\ \ldots \cup \ldots &= \{\text{“-f”}, \text{“fa”}, \text{“fr”}, \text{“ra”}, \text{“ac”}, \text{“ct”}, \text{“t-”}\} && \text{... 7 bigrams} \end{aligned}$$

$$\delta_2(\text{“fact”}, \text{“fract”}) = \tfrac{4}{7} = 0.57$$

Isolated-word methods IV

Rule-based techniques

- a set of rules for common misspellings and typographic errors,
- each rule "fixes" one kind of error
- rules are applied to out-of-vocabulary words

Probabilistic techniques

- based on statistical features of the language (corpus)
  - transition probabilities – probability that a letter is followed by another letter
  - confusion probabilities – how often a letter is mistaken or substituted for another letter

Neural networks

- employs neural language models for context
- word-based – input node = every possible n-gram in every position of a word
- output node for each word in the dictionary
- character-based with recurrent neural networks

Outline

Grammar checking

Example

“That’s good to now”
“That’s good to know”

Grammar checking starts where spell checking ends

- deals with the most difficult and complex type of language errors
  - wrong word order,
  - verb tense errors,
  - subject/verb agreement,
  - punctuation errors,
  - etc...
- two main approaches
  - rule-based methods – time-consuming, less flexible, more precise better interpretability
  - statistical methods – easier and faster to implement, learn from examples
    need a lot of data [Nazar and Renau, 2012]

Rule-based grammar checking

Testing the input text against a set of handcrafted rules

Example

rule: I + verb(3rd person, singular form)
→ incorrect verb form usage – "I has a dog"

- ➕ advantages:
  - rules can be easily added, modified or removed
  - rule can have a corresponding extensive explanation,
  - decisions can be traced to a particular rule,
  - rules can be authored by linguists, no need of programming
- ➖ disadvantages:
  - large amount of manual work
  - extensive rule set is needed [Mozgovoy, 2011].

Rule-based grammar checker example

LanguageTool[2] – open source grammar checker

1. plain text as input
2. splits text into sentences
3. splits sentences into words
4. finds part-of-speech tags for each word and its base form
   walks – walk
5. matches the analyzed sentences against error patterns and runs rules.

[2] https://languagetool.org/ [Naber, 2003, Brenneis, 2018]

Rule example in LanguageTool

Example

"I thing that's a good idea."

```
<rule id="YOU_THING" name="Possible typo 'I/you/... thing(think)'">

<pattern mark_from="1">
        <token regexp="yes">I|you</token>
        <token regexp="yes">thing|things</token>
</pattern>

<message>Did you mean <suggestion>think</suggestion> ?</message>
<example type="correct">I <marker>think</marker> that's a good idea.</example>

</rule>
```

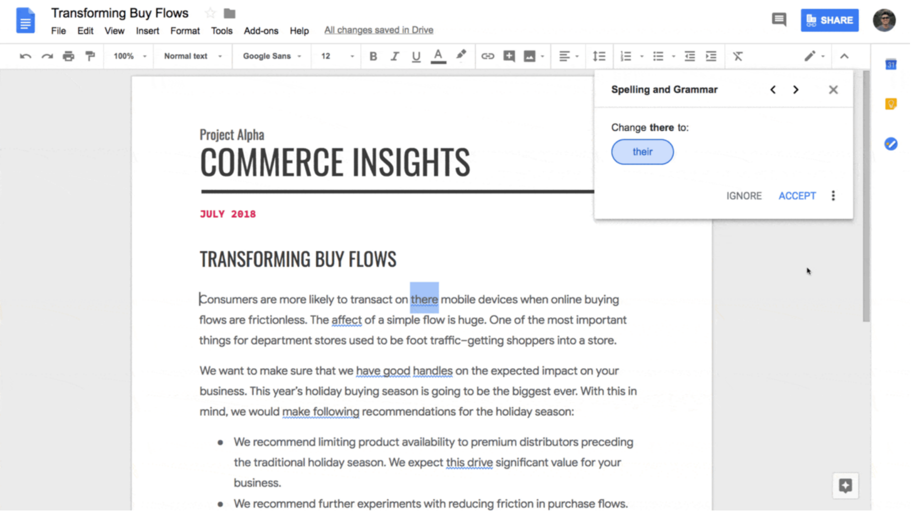
Statistical grammar checking

- based on analysis of grammatically correct POS-annotated corpus,
- build a list of POS tag sequences,
  - some sequences are very common (determiner+adjective+noun as in "the old man")
  - others will probably not occur at all (determiner+determiner+adjective)
- sequences which occur often in the corpus are considered correct,
- uncommon sequences might be errors.

Google Grammar Checker

- available in Google Docs since 2019
- based on neural machine translation architecture
- trains to translate incorrect language → correct language [Grundkiewicz and Junczys-Dowmunt, 2018]

Google Grammar Checker



Outline

Word completion

- reduce the number of keystrokes
- suggesting the completion of the word
- use context information to predict what block of characters (letters, n-grams, syllables, words, or entire phrases) a person is going to write next
- based on wide-coverage word or language model
- prediction at earliest possible point of a character sequence being entered [Van den Bosch, 2011]

Best results

- Spell checking (first suggestion):
  - English – 97 % [Sakaguchi et al., 2017]
  - Czech – 75 % [Ramasamy et al., 2015, Richter et al., 2012]
- Grammar checking (various tests average):
  - English – 72 % [Grundkiewicz and Junczys-Dowmunt, 2018]
  - Czech – 40 % [Petkevič, 2014]

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