Divvunspell—Finite-State Spell-Checking and Correction on Modern Platforms

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Abstract

Spell-checking and correction is one of the key applications of natural language Historically, for the biggest, less morphologically complex languages, spell-checking and correction could be implemented by relatively simple means; however, for morphologically complex and low-resource languages, the solutions were often suboptimal. Finite-state methods are the state of the art in rule-based natural language processing and also for spell-checking and correction they have been effectively used. In this article, we show some recent developments of a finite-state spell-checker implementation that works with modern operating systems and platforms.

1 Introduction

Spell-checking and correction is one of the most basic and most important applications of natural language processing for standardised, written languages. A spell-checker works as a tool for all of the writers of the language, ensuring that most of the texts written follow a norm that is enforced by the tool. This has enormous significance for the text production in the language, which in turn is becoming more and more important in the era of large language models. A large language model is built on huge quantities of texts written by humans, and an underlying expectation is that the majority of the text is written in a standard, normabiding language form.

Traditionally spell-checkers have been readily available for morphologically simple languages but have had more limited success for more morphologically complex languages; for example, to this day hunspell is popularly used for a lot of platforms on a computer as a default spell-checker

engine. Hunspell itself being developed because previous systems were insufficient for Hungarian morphology, it moreover is limited for other morphologically complex languages. Another approach to spell-checking that is popular in contemporary systems is data-based, either statistical or neural network, this is what many of the autocorrect and autocomplete style models are based on. This, on the other hand, limits the low-resourced languages out of the equation.

The main contribution of this article is recent developments in our implementation of *finite-state spell-checking*, as well as relevant tooling and automation. Finite-state spell-checking works for morphologically complex languages and does not necessarily require any training data, making it suitable for low-resource use cases. One emphasis of this article is the developments related to full end-user use case of the method that the software is not merely an academic experiment but a product that can be installed and used by the language users. For this purpose, we have developed automated evaluation methodology as well as systems for automatically distributing the new changes to end-users.

Following the recent trends of the language technology, that is the break-throughs of the large language models and neural networks, we evaluate our system and compare it to an out of the box neural network in a basic spell-checking and correction task. While the evaluation we perform here is quite rudimentary as a neural network application, it builds towards the research question of: how and to which extents and in which parts of a spell-checking and correcting system shall the large language models be used in hybrid with existing finite-state and rule-based solutions.

2 Background

Spell-checking and correction is an application of natural language processing that has been studied since the 1950's. The earliest models worked in practice based on static lists of correctly written word-forms to check against, then slowly adding support for morphological processes as larger vocabularies and more morphologically complex languages were implemented. The most widely spread versions of the spell-checkers used in personal computers are commonly known as *spell software, from original SPELL to ispell, aspell, myspell, hunspell and nuspell. Still, these have been difficult to adapt for morphologically rich languages, so for specific languages softwares like zemberek for Turkish and hspell for Hebrew have been developed

Parallel to dictionary-based spell-checkers there has been statistical approaches to spell-checking. This is based on learning a language model from large correctly written texts, one of the most influential models here is (Norvig, 2010). This line of models is usually a basis in most of the mobile auto-complete and autocorrect style systems, nowadays likely based on generative neural network models.

The most basic tool for modeling errors is based on the invention of edit distance, where the errors are modeled as a combination of missing a letter, adding an extra letter, using a wrong letter, or swapping two adjacent letters, first introduced by Levenshtein (1966). Other common ideas that have been used include listing common confusables altogether, trying to map phonemic errors to the writing system various ways, and weighing the mistakes made on a keyboard by the keyboard layout.

One of the most popular ways of handling wordforms of morphologically complex languages is Finite State Morphology (Beesley and Karttunen, 2003), this is often considered the state of the art in handling rule-based language modeling of morphologically context low-resourced languages to this date. The finite-state formulation of spell checking with statistically trained language and error models has been researched by Pirinen et al. (2014). This type of models is also used by the spell-checking and correction solution we are presenting in this article.

3 Methods

Finite-state spell-checking is based on using finitestate automata to model both the correctly spelled words (language model) and mapping of the misspellings from incorrect forms to correct word-In finite-state format this means that there is an automaton that accepts the correctly spelled word-forms and does not accept incorrectly spelled word-forms, and another twotape automaton that can relate incorrectly spelled word-forms to correctly spelled word-forms. The automata can be weighted and thus give an ordering to correction suggestions as well as likelihoods for the words of the languages in general. This model has been introduced by at least Pirinen and Lindén (2010), and the software introduced here is based on the same finite-state formulation. For language models we have used freely available open source finite-state models from the GiellaLT infrastructure (Pirinen et al., 2023).

The divvunspell¹ software we introduce in this article is implemented in the Rust programming language and has bindings and implementations for modern operating systems and mobile platforms: macOS systemwide, Windows systemwide and in MS Office, LibreOffice on all desktop systems, and in iOS and Android keyboard apps. There is also a REST API for web-based clients². We have implemented some basic improvements to the engineering and efficiency as well as correctness of the software. The published version is both light-weight and fast enough to be used as an interactive spelling checker on average end-users' mobile platforms. We have fine-tuned the errorcorrection algorithm with adjustable weights in the errors made in word-initial, word-medial and word-final positions separately; in the the current version a spelling error in the first or last letter of the word adds triple the weight of an error in the mid-word unless configured otherwise.³ We have also developed an automated evaluation software for the spell-checking software that can ensure the quality of the spell-checking models does not degrade, as well as a continuous integration and deployment system that can distribute the models to the end users when the dictionaries or grammars of language models are updated, as long as the quality of the spell-checker has not deteriorated. The automatic evaluation tools are available on the github repo of divvunspell and their integration to language development infrastructures can

https://github.com/divvun/divvunspell

²https://api-giellalt.uit.no/speller/XX, where XX is the ISO 639 language code.

³the actual and up-to-date implementation of the algorithm can be found on GitHub.

be found on the actual language data repositories⁴.

We experiment with a popular out-of-the-box large language model that is available for most users free of charge via a chat interface. ⁵ We do not perform any in-context learning or retrieval augmented generation, this is an initial experiment towards potential hybrid models of finite state and neural models of spell-checking and correction.

4 Results

We performed a small experiment to verify the working of our system and to see how well the out-of-the-box neural network works on this task. We are testing with a real-world error corpus of Finnish word-forms – 50 correctly written words and 50 spelling mistakes found in a large corpus – by picking up non-words and correcting them manually. Finnish is a morphologically complex language with medium-to-high resources. The results are in Table 1. The overall quality of both spelling checking and correction is lower in the LLM-based system than it is for the rule-based system but it still manages to provide correct suggestions almost as often as rule-based system does.

 System
 1st
 Any

 FST
 70 %
 88 %

 LLM
 50 %
 85 %

Table 1: Automatic evaluation of spelling correction

5 Discussion and Future Work

We have shown a software that brings the spell-checker to end-users on mobile and desktop plat-forms and updates automatically when linguistic data gets developed. However, especially on mobile platforms but also increasingly on desktop, the spell-checking has been shifting towards a subfunction of a text prediction subsystem, e.g. autocomplete / autocorrect. It would be interesting future work to study possibility of such a system for morphologically complex and low-resource languages.

We only performed cursory experiments to ensure that our system works within specified parametres, the system should be functionally similar as the system evaluated by Pirinen et al. (2014) in their larger survey. We also performed the same experiment on an out-of-the-box, not fine-tuned and not prompted, re-inforced or otherwise context augmented neural network, mainly to find out their current level of quality and possible future modes of hybridisation. From the results it seems that the LLM-based systems are approaching the quality of rule-based system in terms of overall suggestions but if you concentrate on suggestion quality, it is still not comparable. More importantly, when doing a manual error evaluation, we find some examples where rule-based system is more restricted towards edit distance type error modeling, whereas LLM tends to suggest patterns of related word-forms of a same word.

One of the requirements of an end-user system in spell-checking and correction is high precision in detecting errors, the end-users tend to react very negatively of spell-checking systems that red-underline words they know are correctly written. Secondly the suggestions need to be reasonable first and foremost. Both of these aspects are relatively harder to get right with LLM solutions of today, however, there are some indications that LLMs can be more creative in error modelling, and especially when the spelling-correctors are set in the automatic text prediction context, they have been succesful. Ideally we could foresee a future system that combines the high precision of rulebased spell-checking with creative prediction of an generative AI as a potential spell-checking system.

6 Summary

We have demonstrated a spell-checking and correction system based on finite-state technology that works on end-user systems including desktop office applications and mobile phones. We tested an LLM-based approach to the same task to see where they stand at and if they could be included in the system but at the moment they are still far enough from end-user quality to be included as-is.

Limitations

The LLM test is based on one version of a closed commercial system and is not reproducible. The test is only intended to give an impression of initial usability of such systems, and for that reason we also have not included extensive descriptions of the parameters, prompts and version specifics.

⁴https://github.com/giellalt/template
-language-und, to be refactored into https://gith
ub.com/divvun/actions/

⁵At the time of writing we had access to a version of ChatGPT-4o.

kärellä aloteesen polen ollakkaan katosppas olekkaan pistäyn metässä 20.12.24 15:20 Here are the Finnish word-forms with three suggested corrections for each: 1. antakaat - antakaat, antakaa, antakaa 2. Lontoosen - Lontoosen, Lontooseen, Lontooseen 3. puollustaaksensa - puollustaaksensa, puolustaakseen, puolustaakseen 4. mailman - mailman, maailman, maailman 5. tunkeuvan - tunkeuvan, tunkeutuvan, tunkeutuvan 6. taivaasen - taivaasen, taivaaseen, taivaaseen 7. armeiassa - armeiassa, armeijassa, armeijassa 8. murteesensa - murteesensa, murteeseensa, murteeseensa 9. lankeemasta - lankeemasta, lankeamasta, lankeamasta

Figure 1: Example of LLM-based spell-checking and correction

You are a spell-checker for Finnish language, you will be given a list of word-forms and you should answer with a list of the word-forms, then suggested corrections for example: rahhaa rahaa rahkaa

If a word is already correct, the first suggestion should be the same as the input word: päälle päälle

Figure 2: ChatGPT prompt for spell-checking.

The prompt used is given in the Figure 2.

Ethics Statement

The data annotation and human evaluation was performed by article authors and colleagues; no unpaid annotators were used. The LLMs use significant amount of water and electricity and we have made an effort to minimise unnecessary overuse of LLMs.

Acknowledgments

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