ISMLA Project: Malayalam Glosser

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Abstract

Miau

1 Introduction

Bla bla bla test മലയാളി bla bla.

2 About Malayalam

2.1 General information

2.2 NLP challenges

2.2.1 Tokenization

അരിപ്പെട്ടി arippeṭṭi ‘rice box’ (ari+peṭṭi), പാൽക്കുപ്പി pālkkuppi ‘milk bottle’ (pāl+kuppi) (Asher and Kumari 1997, p. 397)

(1) മേഘം പോലെ കറുപ്പുനിറഞ്ഞോടുകൂടിയവർ ആണ്.
Mēghaṁ pōle kaṟuppuniṟañño̱ṭukūṭiyavar āṇ˘.

മേഘം	പോലെ	കറുപ്പ്	നിറഞ്ഞോട്	കൂടി	അവർ	ആണ്	.
mēghaṁ	pōle	kaṟupp˘	niṟañ-ñ-ōṭ˘	kūṭi	avar	āṇ˘	.
cloud	like	black	be.full-PSTPART-SOC	with	they	be	.

‘They are black like clouds.’ (Vēṇugōpālan 2009, p. 179)

(2) അതിന് നിനക്കെന്താ?
Atin˘ ninakkentā?

അതിന്	നിനക്ക്	എന്ത്	ആണ്	?
at-in˘	nin-akk˘	ent˘	āṇ˘	?
that-DAT	you-DAT	what	be	?

‘Why do you care?’ (Moag 1994, p. 165)

3 The Malayalam Glosser

Bla bla

3.1 Transliteration

3.1.1 Supported Scripts

3.1.2 Transliterators

MalayalamTranscriptor

3.2 Morphology Generation

MorphGen

3.3 Tokenization

MalayalamGlosser

3.4 Dictionary lookup

MalayalamDictionary

3.4.1 Efficiency considerations

Considering that the dictionary may be very large and that the main function of the Glosser is to look words up in this dictionary, being able to load and query it very quickly is essential for the performance of the Glosser. Hence, I experimented with a few alternatives for storing the dictionary data and investigated their efficiency. The tests elaborated below are not very exact or well-designed and were only meant to quickly assess the usefulness of the considered methods.

`HashMap` vs. `ReverseTrie`

The straightforward way to represent a dictionary as a Java object is a `HashMap`. Apart from being readily available and easy to use, querying a `HashMap` is fast. However, this also means that all entries are stored as their complete String representation, which may consume quite a lot of space. Considering that the inflected forms of the words share most of their characters, a trie representation seemed quite suitable and might be able to save space compared to a simple `HashMap`. Since Malayalam is exclusively suffixing, I programmed a `ReverseTrie` which reads and retrieves the strings from last to first character, in order to save

as much space as possible. A useful side effect of this is that the tokenizer does not need to look up all suffixes of a compound word in the dictionary, but can simply do a suffix search of the `ReverseTrie` to get the longest contained suffix.

In order to compare the performance of a `HashMap` and `ReverseTrie` based dictionary, I measured the memory used by the program before loading the dictionary data and after creating the `HashMap` and Trie (calculated as `Runtime.totalMemory() - Runtime.freeMemory()` after a `System.gc()` call). Then I let the dictionary find the longest known suffix of the test String *aviṭeyuḷḷataṟiññu* (*aviṭe uḷḷatˇ aṟiññu* "knew (he) was there") 1,000,000 times and measured the time needed by a MashMap and `ReverseTrie` based dictionary (calculated using `System.currentmillis()`). Finally, I rewrote the tokenizer to also work with a `ReverseTrie` and tested how long tokenization of a short conversation from Moag (1994) took it with the two dictionary types.

Despite the many shared suffixes, the `HashMap` was smaller than the `ReverseTrie`, taking up 8,318,164.8 bytes on average during five test runs, while the Trie required 12,590,051.2 bytes. However, the memory used by the `HashMap` varied greatly, ranging from only 5,160,456 to 9,801,392 bytes, while the Trie always consumed almost exactly the same amount of memory. This indicates that the measurements might have been verfälscht by background processes such as the garbage collection. However, the `HashMap` still seems to be considerably smaller.

As expected, the `ReverseTrie` outperformed the `HashMap` on the looped suffix search of *aviṭeyuḷḷataṟiññu*. The Map took an average of 999 milliseconds during five test runs, while the Trie only needed 312.4 ms. However, the performance of the Trie was very unstable, ranging from 140 to 518 ms between runs, while the `HashMap` always needed between 908 and 1049 ms, which is still much slower than the slowest suffix search of the Trie.

On a real Malayalam text, where only few words are long compounds such as *aviṭeyuḷḷataṟiññu*, both methods were equally fast. During 10 glossings of the Moag conversation, the Map based tokenization took 156.3 ms on average and the Trie based tokenization 161.7 ms. Both ran very stable.

All in all, the `HashMap` seems to be the better choice, since it is smaller than the Trie and equally fast on normal Malayalam texts. The Trie is faster when tokenizing long compound words, which however are not frequent enough to justify preferring it over the `HashMap`.

File storage vs. Serialization

Loading the dictionary data into the underlying `HashMap` (or `ReverseTrie`) takes a considerable amount of time at launch. Hence, I considered serializing the Map or Trie object to be able to load it quicker. Since the Java serialization is known to rather slow, I used the FST Fast Serialization library for my tests. I first read the dictionary data from the text file and created the `HashMap` and `ReverseTrie` from it, measuring the time needed. Then I serialized the two objects and took the time required to deserialize them.

During five test runs, parsing the text file into an object took 278.2 ms on average for the `HashMap` and 310.6 ms for the Trie. Deserializing the same objects required 563.4 ms on average for the `HashMap` and 339.8 ms for the Trie. Loading the data from a text file is thus faster than deserializing a previously created object.

The file storing the serialized `ReverseTrie` was twice as large as the file with the `HashMap`. This confirms my assertions from the previous section that the Trie takes more space than the `HashMap`.

3.5 UI Design

4 Conclusion

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