Spellcheckers for Nguni languages

C. Maria Keet

Department of Computer Science
University of Cape Town, South Africa
mkeet@cs.uct.ac.za

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With contributions from

- IsiZulu spellchecker
  - Hussein Suleman
  - Balone Ndaba
  - Langa Khumalo
  - Norman Pilusa
  - Frida Mjaria
- IsiXhosa spellchecker
  - Nthabiseng Mashiane
  - Siseko Neti
  - Norman Pilusa
- Participants in the evaluations from ULPDO@UKZN and Linguistics@UCT
- Additional texts from INC, Mantoa Motinyane-Masoko, MeMaT translators, publicly available texts

Outline

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Motivation

- IsiZulu and isiXhosa, among others, have limited ICTs support
- Most widely spoken languages in South Africa by first language speakers.
- 23% or about 11 million people (isiZulu), 8 million (isiXhosa)

[1] https://www.spellchecker.net/africa_zulu_spell_checker.html

Motivation

- IsiZulu and isiXhosa, among others, have limited ICTs support
- Most widely spoken languages in South Africa by first language speakers.
- 23% or about 11 million people (isiZulu), 8 million (isiXhosa)
- Very limited available spellcheckers for use:
  - Outdated/software not working anymore (Open office plugin)
  - Online one with too many clicks, popups, and ads[1]

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General aims

- Investigate development of spellchecker for isiZulu
- Find an approach that can be used across (agglutinating) Bantu languages

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- Rules for the POS categories coded perform better overall (isiXhosa), but data-driven approach faster and more reusable across languages (isiZulu, isiXhosa), despite being underresourced

Outline

First iteration [Ndaba et al.(2016)]

- Use corpus for data
- Driven by extracted n-gram statistics
- Trigrams and quadrigrams; e.g.
  - *ngimbona*
  - ngi, gim, imb, ...
  - ngim, gimb, ...
- Compute frequencies, determine threshold
- Trigram/quadrigram below threshold: flag words as incorrectly spelled

Basic approach for testing

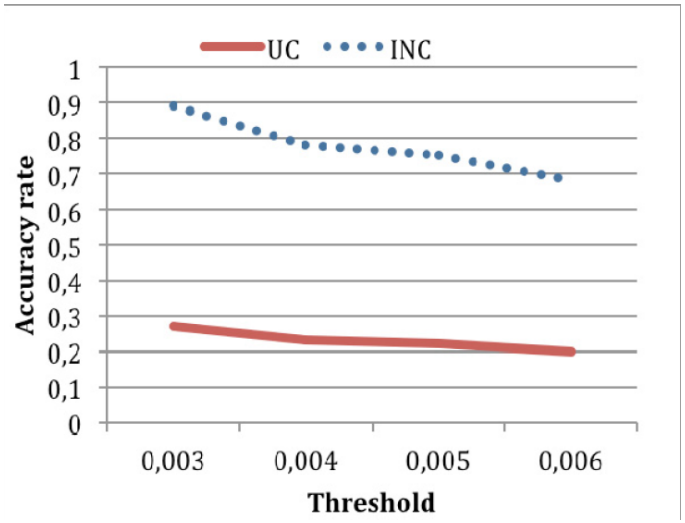
- 10-fold cross-validation for training and testing data set
- 3 corpora to test effect of corpus on accuracy
  - Ukwabelana [Spiegler et al.(2010)]; 288 106 words, 87033 unique
  - Section of the isiZulu National Corpus [Khumalo(2015)]; 538 732 words, 33020 unique
  - IsiZulu news items (collected by MK); 21250 words, 9587 unique
- Different thresholds
- 46 know-to-be-incorrect words added
- Use accuracy as measure, with confusion matrix (TP, TN, FP, FN)

Example

- Corpus trained with:
  - *ngimbona kusasa*: ngi, gim, imb, ...
  - *uvelaphi*: uve, vel, ela, ...
- Spellchecker given following words:
  - *ngivela* $\rightarrow$ accepted, as ngi, vel, and ela are trigrams obtained from the training dataset
  - *Ngivla* $\rightarrow$ rejected, as there is no ivl and no vla

Major outcomes

- Accurate in detecting words that do not occur in the training corpus
- The most updated corpora are preferable



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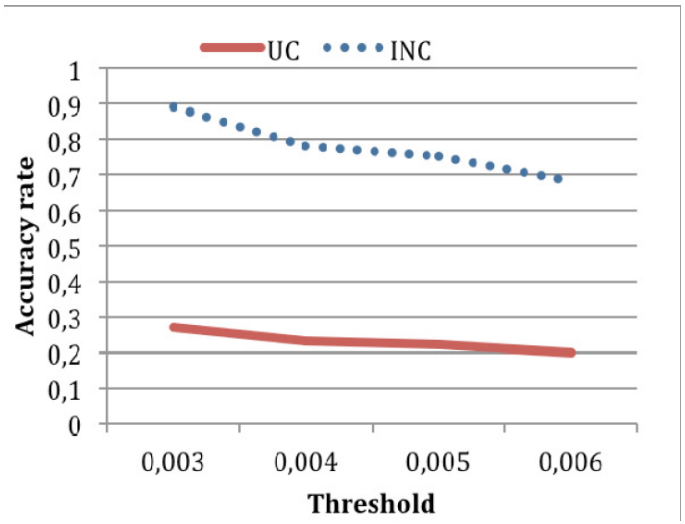

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- Tests with more data: 83% accuracy with noisy data, 85% with cleaned data

Try this with isiXhosa

- Use code for isiZulu, but feed it isiXhosa texts to create a language model for isiXhosa
- Determine threshold
- Determine accuracy

Try this with isiXhosa: results

- 20K tokens corpus, mainly medical documents
- Threshold: 0.002 (marginally better than 0.003)
- Accuracy: about 79%
- (current implemented version trained with much more text)

Error correction for isiZulu

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- Measures:
  - Can it propose something (C_s)?
  - Is the intended word among the proposed words (C_v)? (relevance)

Results

- It can propose something quite well for each type of typo ($<$ 90% accuracy)
- The relevance varies a lot:
  - Substitutions 59%
  - Insertions 30%
  - Deletions 73%
  - Transpositions 89%

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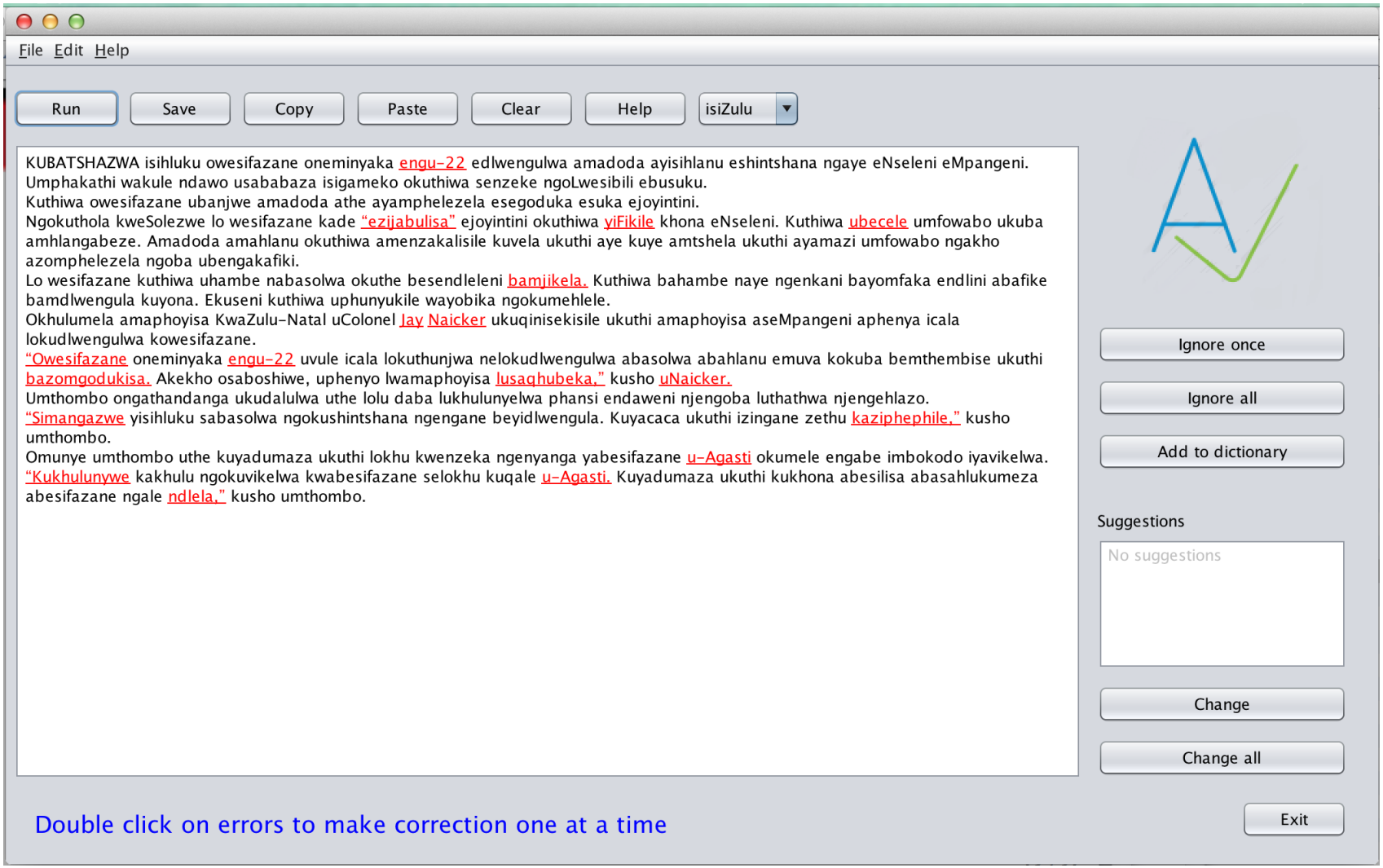
- Why? We don't know for sure yet

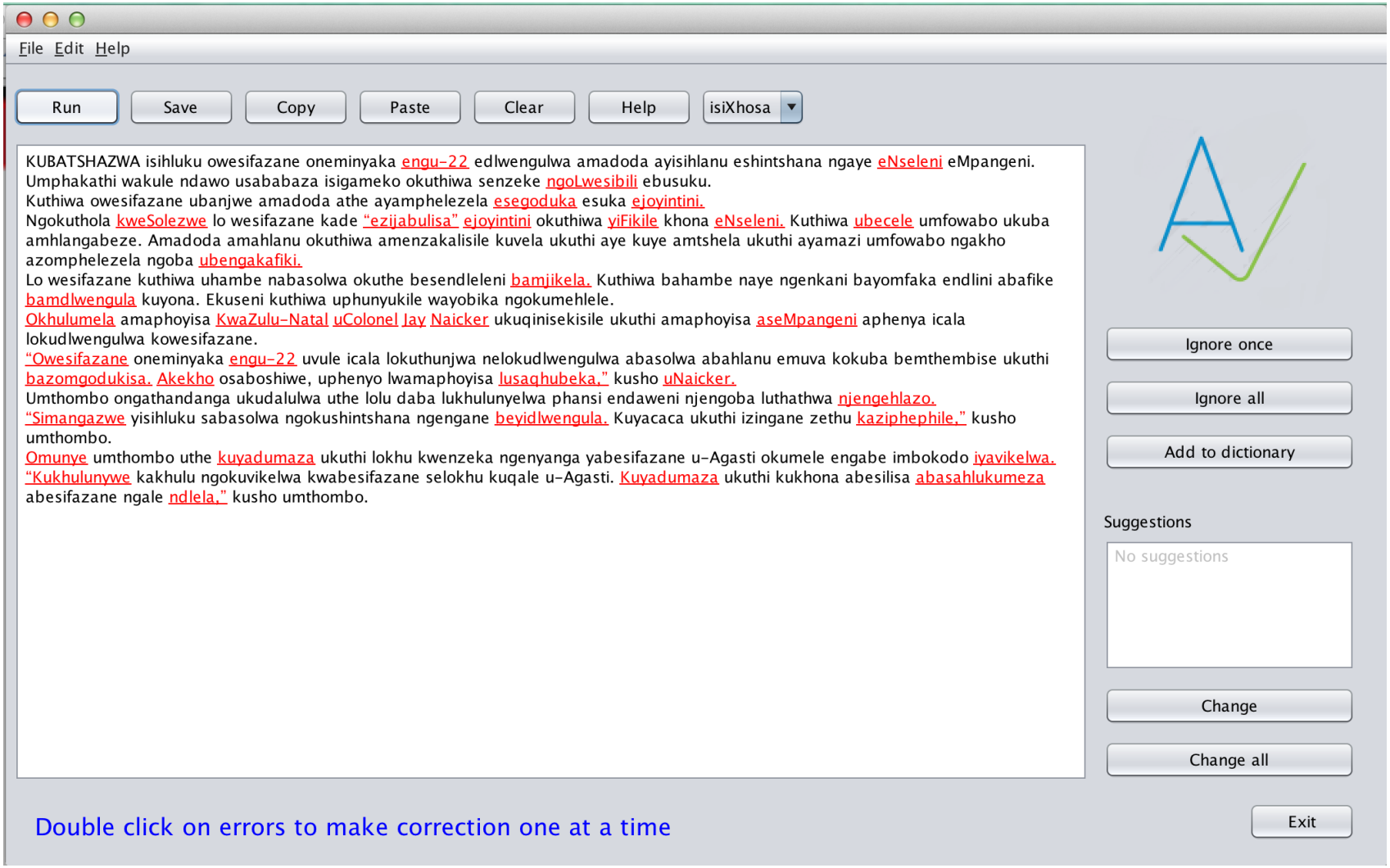
Spelling correction for isiXhosa

- Used the same code as for isiZulu
- But with the isiXhosa language model
- Implemented, but no idea on effectiveness yet

isiZulu text, isiZulu model



isiZulu text, isiXhosa model



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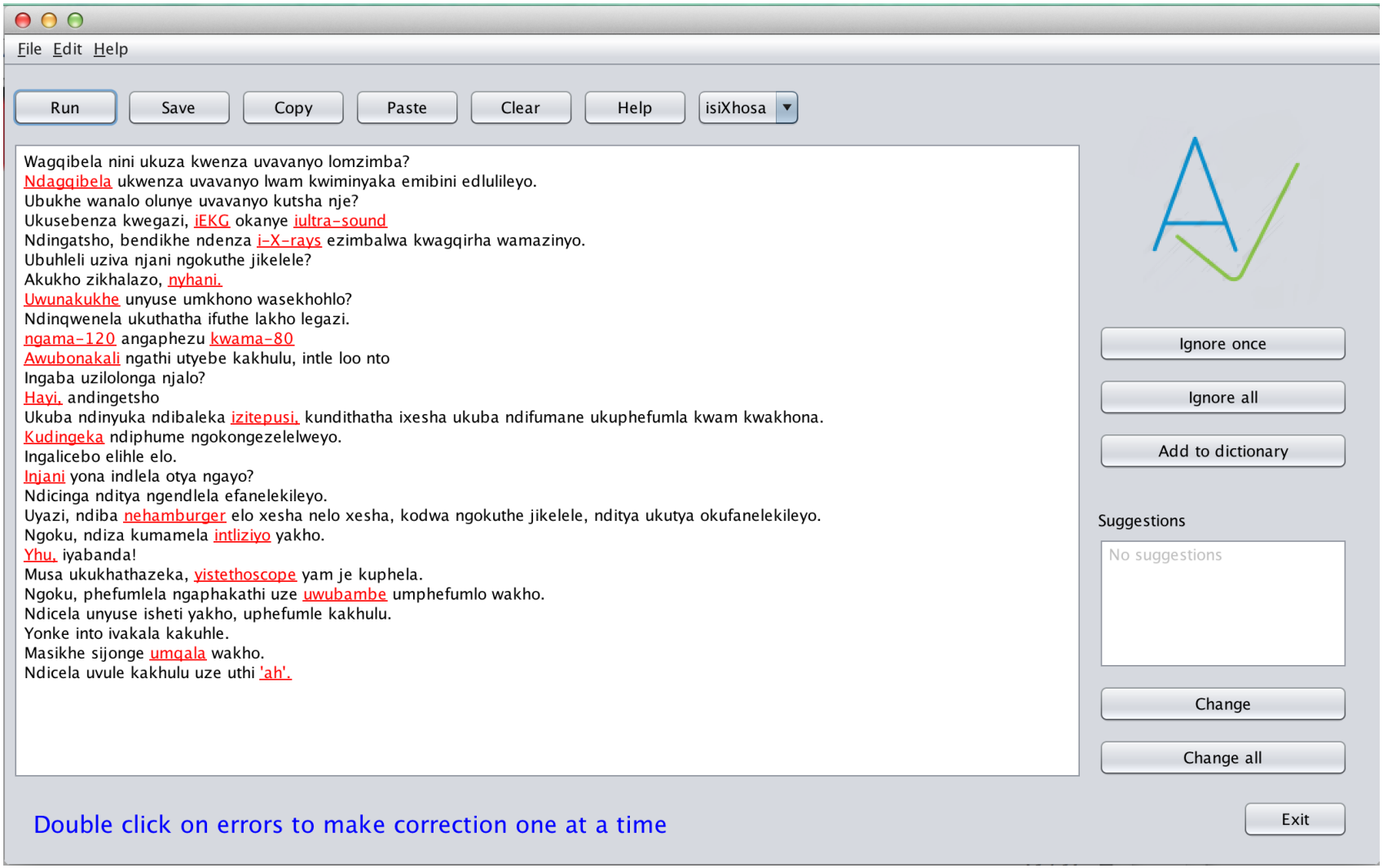
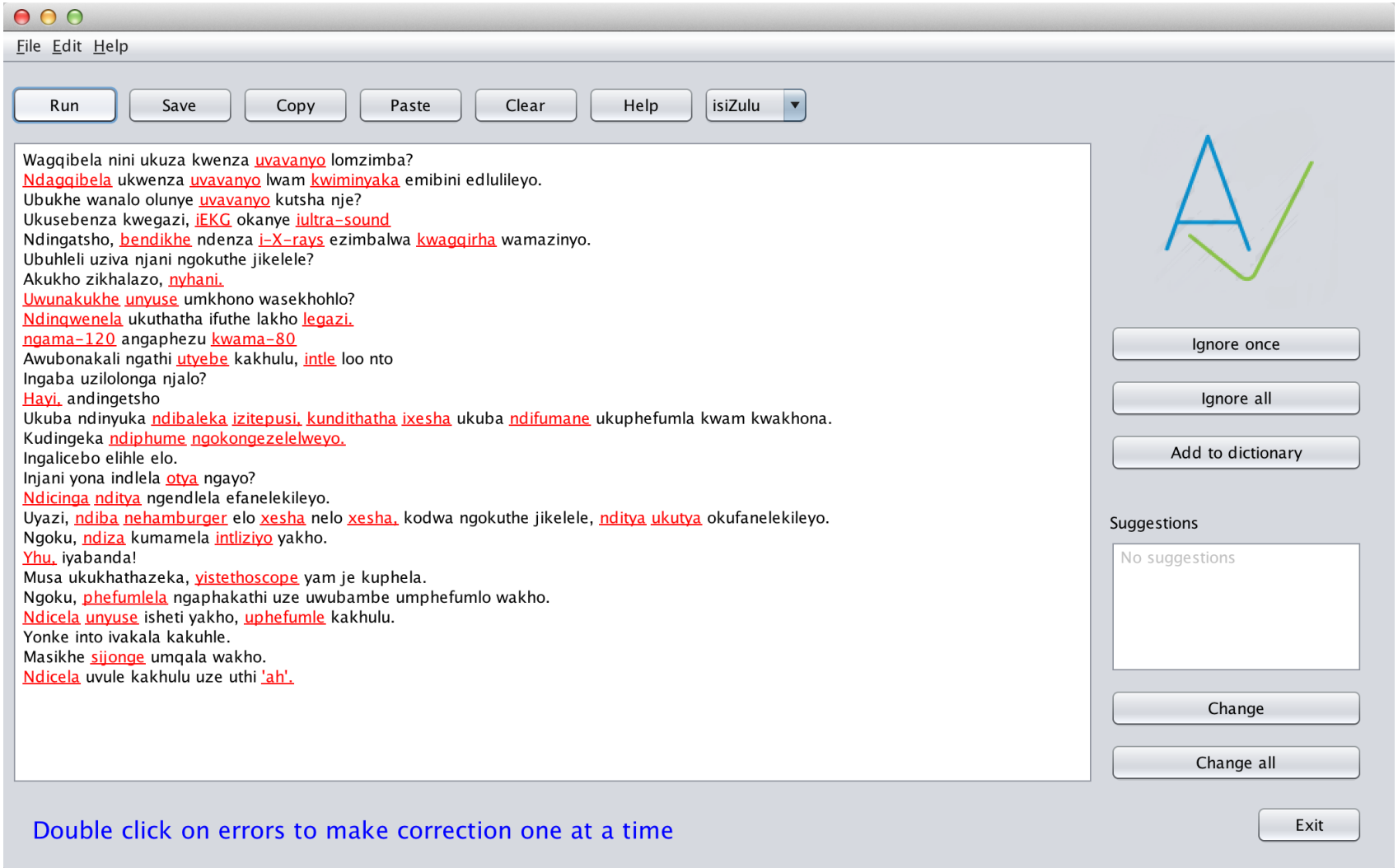
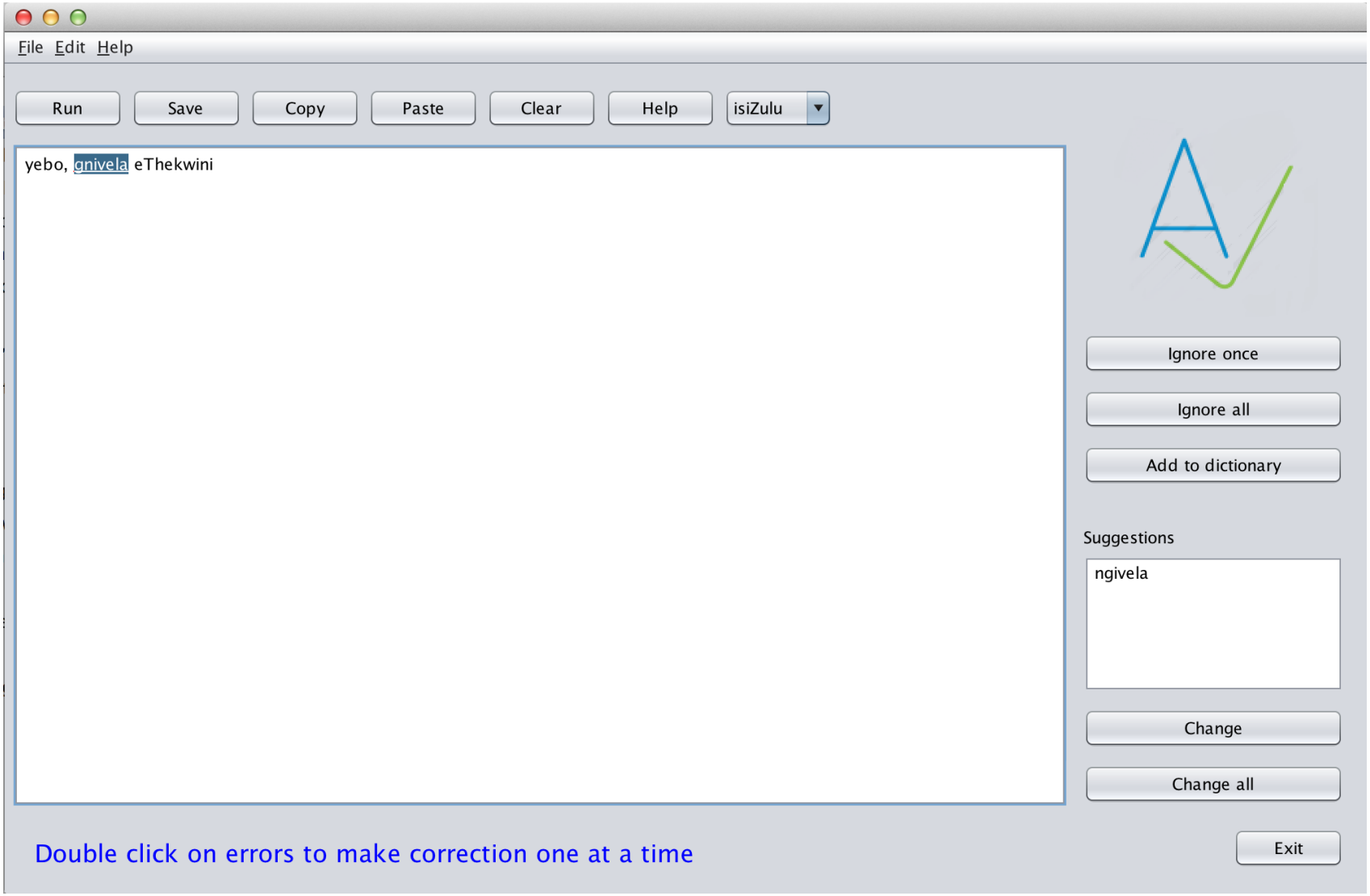


isiXhosa text, isiZulu model



Error correction–transposition typo



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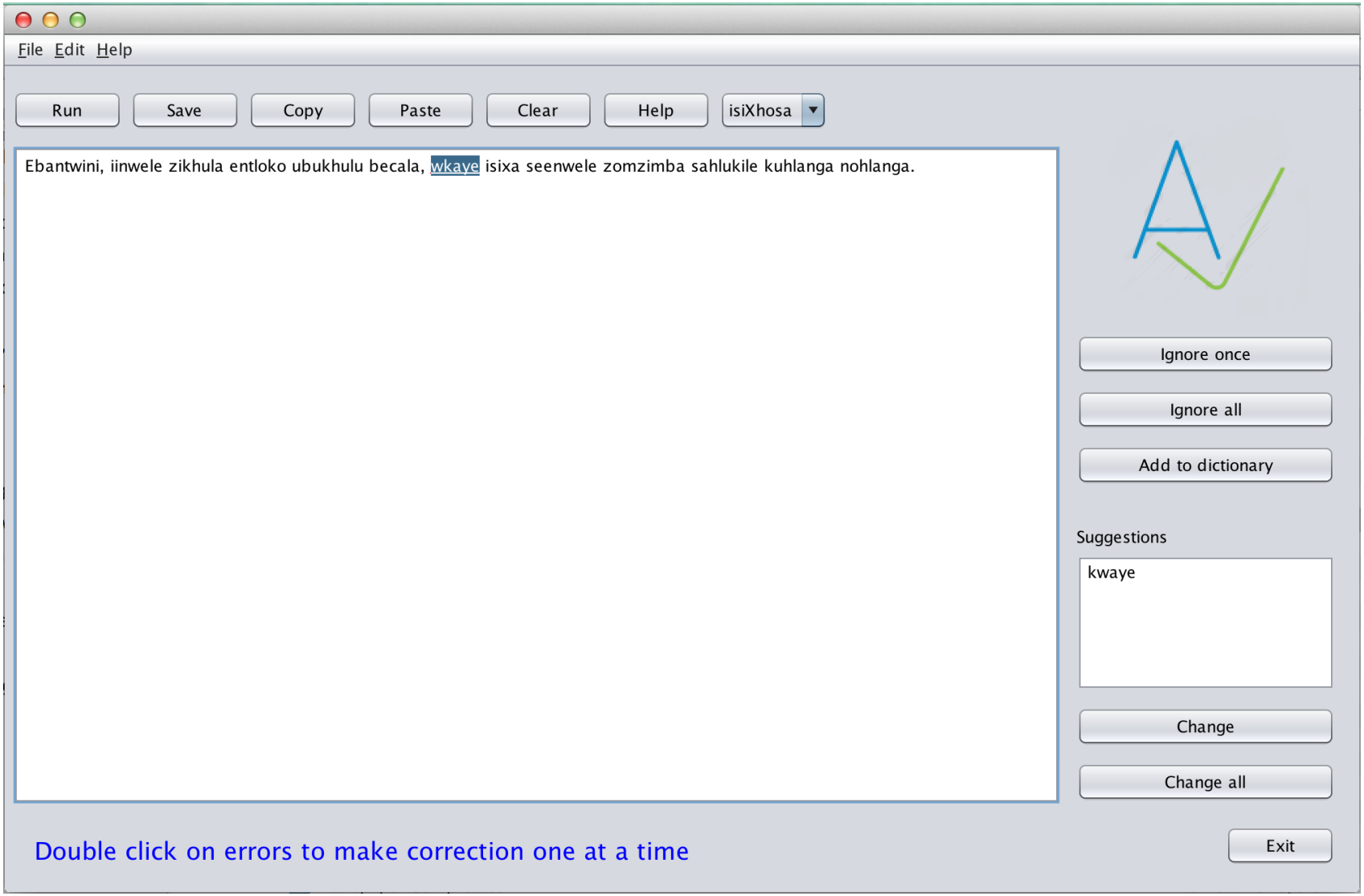

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  - Cleaned data or noisy data?
  - Trigrams on text proper or on non-punctuation-marks?
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- Room for improvement on the corrector

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- Lowercase vs upper case (e.g., *eGoli*)
- Sociolinguistics, if dialects have words written differently
- Room for improvement on the corrector
- How much do the isiZulu and isiXhosa language models differ?

Outline

Conclusions

- We now have the spellcheckers
- Reasonable accuracy
- Outstanding questions on generalisability and improvement of accuracy
- Would it enhance MT or introduce more noise?

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Thank you!

Questions?