DFRWS
DIGITAL FORENSIC RESEARCH CONFERENCE

Finding and Identifying Text in 900+ Languages

By

Ralf Brown

Presented At

The Digital Forensic Research Conference

DFRWS 2012 USA Washington, DC (Aug 6th - 8th)

Finding and Identifying Text in 900+ Languages

Ralf D. Brown
Carnegie Mellon University
Language Technologies Institute

6 August 2012

Finding and Identifying Text in 1000 Languages

Ralf D. Brown
Carnegie Mellon University
Language Technologies Institute

6 August 2012

Executive Summary

- Open-source (GPLv3), trainable tool to extract textual strings and identify their languages
  - http://la-strings.sourceforge.net/
- False alarm rate < 0.4%, miss rate < 0.01%
- Language identification accuracy >99% on a 1000-language evaluation set

Overview

- Why yet another string-extraction tool?
- Language models
- Identifying character encodings and languages
- Where to get language data
- Experimental results
- Future work

The Need for String Extraction

- Damaged files
- Text hidden inside non-text data
- Disk images

Existing “Strings” Utilities

- Limited support for non-ASCII text
- No knowledge of language
  - Extract every sequence that is valid in the specified encoding
  - Thus have a high false alarm rate

Desirable Features for a Text Extractor

- Support as many character encodings as possible
- Automatically identify the encoding(s) used
- Filter out non-text sequences
- Language identification to permit intelligent downstream processing

Language Models

- Statistics for variable-length byte sequences found in training data
- One model (or more) for each language/encoding pair we want to identify

The “Secret Sauce”

- Selection of the most useful n-grams
- Use of negative evidence (“stop-grams”)
- Inter-string score smoothing
  - Assumption is that consecutive strings are most likely in the same language

Picking the Most Useful N-grams

- Collect the most frequent byte n-grams up to some maximum length
- Filter out high-frequency n-grams which don't add much information
  - If the n-gram is a substring of another with at least 90% as many occurrences

Using Negative Evidence

- If an n-gram is never seen in the training data but is common in another, similar language
  - Give it a negative weight proportional to its frequency in the other language and the degree of similarity between the two languages

Inter-String Smoothing

- Add a portion of the previous string's score to current string
- Use exponential decay
  - New smoothing value = curr_score + 0.25 * prev_value
- Relative weight of current string's score adjusted by string length
  - Longer strings have more reliable scores

Identifying Languages

- Given an input string and a set of language models:
  - At each offset in the input, find the matching n-grams in the models and increment the corresponding scores by the n-gram's weight
  - At the end of the string, sort the models by total score
  - Output the top K languages which have scores at least 0.85 times the highest score

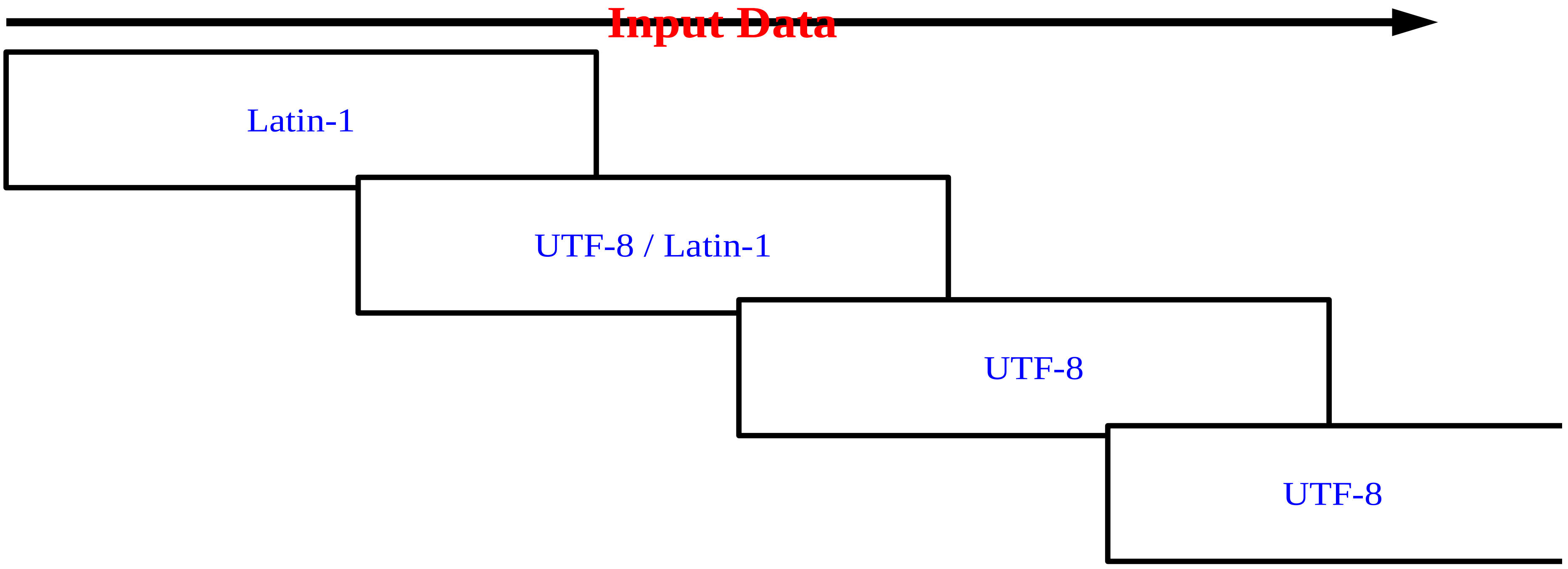
Identifying Character Encoding

- Same as identifying languages, but instead of looking at the language associated with each model, use the encoding
  - Remove lower-scoring duplicates before selecting
  - Use encodings with score at least 0.3 times highest, **and** above a predefined threshold

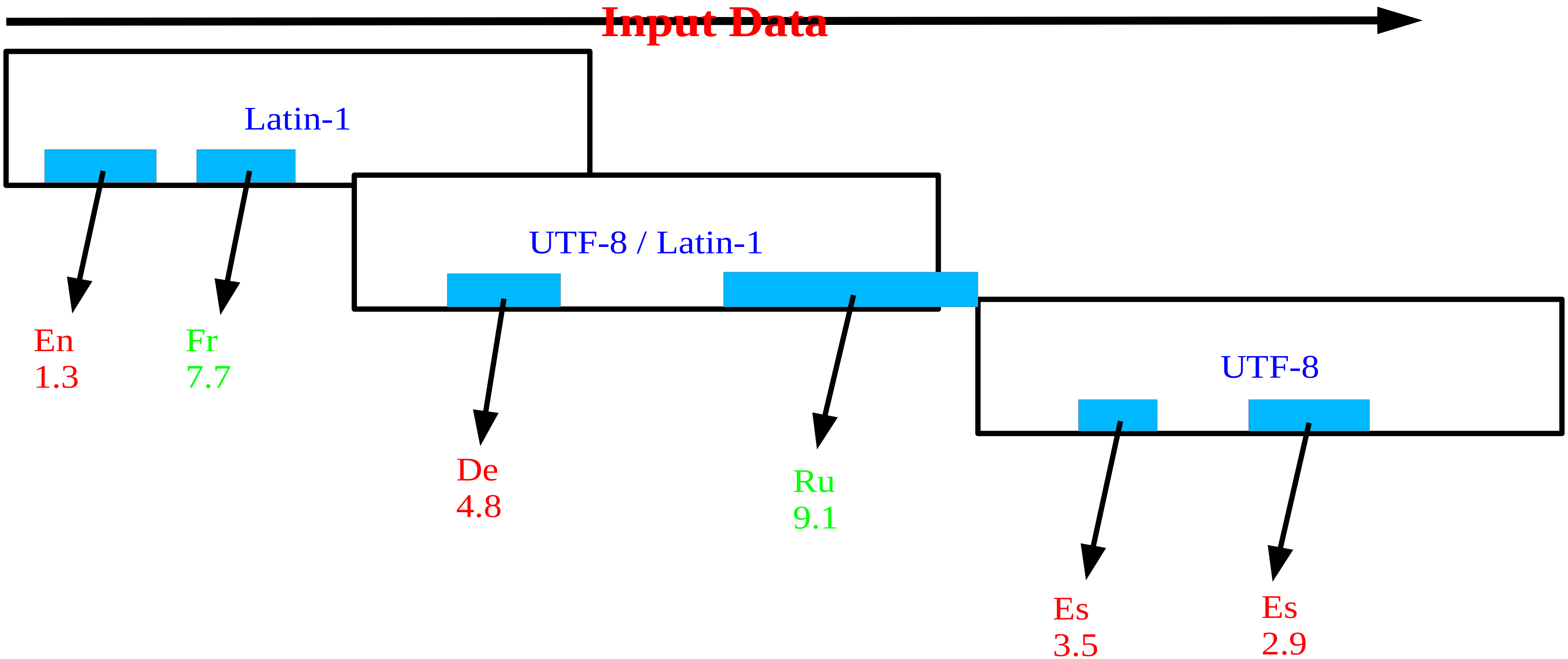
Extracting Strings

- Begin by identifying probably character encodings for fixed-size blocks of bytes
- At every byte position within a block,
  - Attempt to extract a string in each identified encoding
  - Longest string at a position is taken as correct
- Identify the language of each extracted string
  - Discard if confidence score is too low

Scanning for Encodings



Extracting Strings



Obtaining Training Data

- Wikipedia
  - 285 languages, ~200 with useful amounts of text
- Bible translations
  - Full Bible has been translated into 475 languages
  - New Testament in 1240 languages
  - Hundreds have been made available online since 2010

Experiments: Data

- Built models for 1026 languages, several in multiple writing systems
- For the majority of languages, the training data was a translation of the New Testament
  - Median training data size of 1.4 million bytes (quartiles 1.0 million and 2.0 million)
- Held out ~3% of training data for evaluation

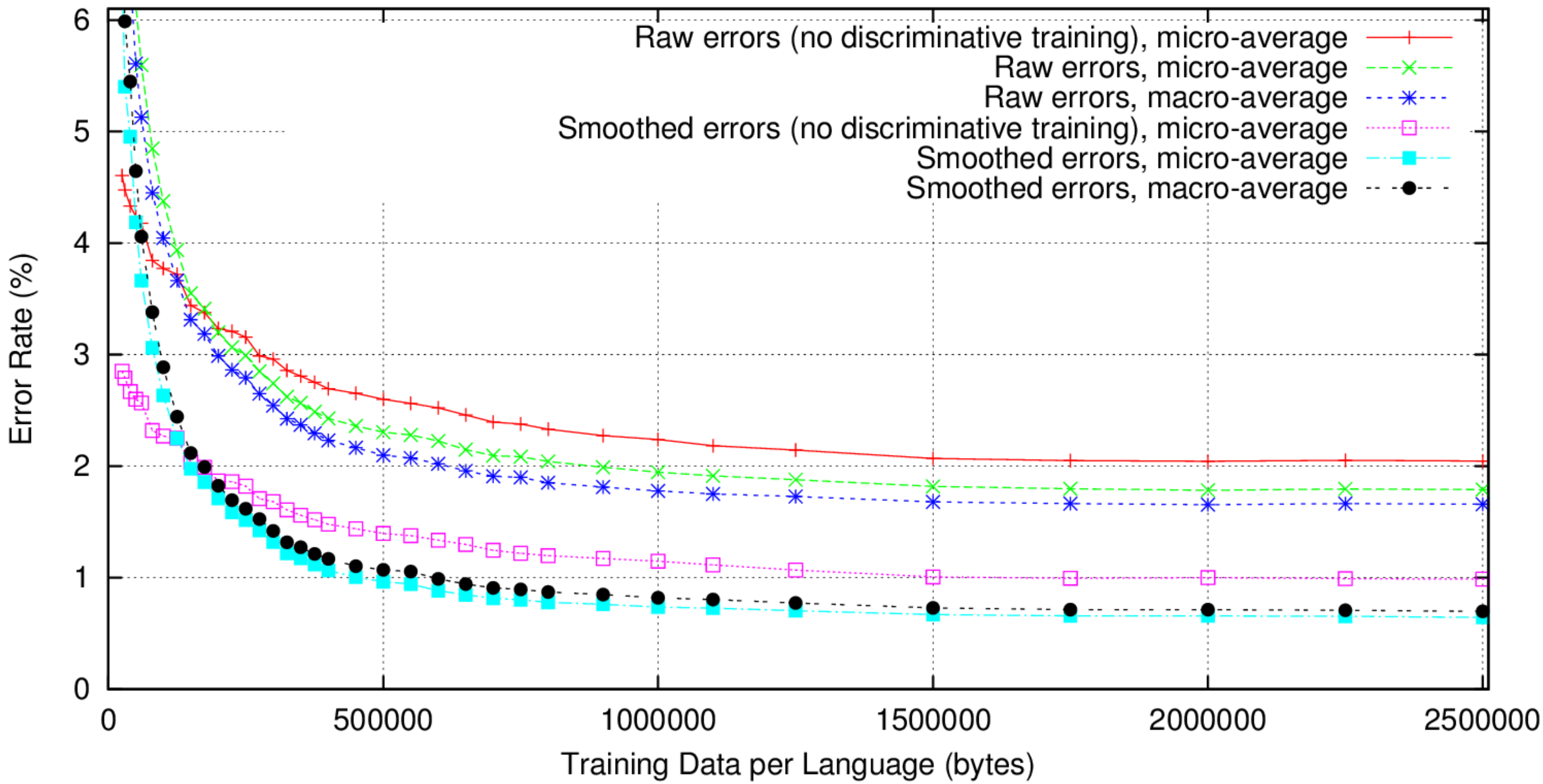
Experiments: Test Conditions

- Varied three different parameters
  - Amount of training data (use only first B bytes)
  - Number of highest-frequency n-grams in model
  - Maximum length of n-gram in model
- Computed micro- and macro-average error rates with and without inter-string smoothing
  - Also micro-average without discriminative training when restricting training data

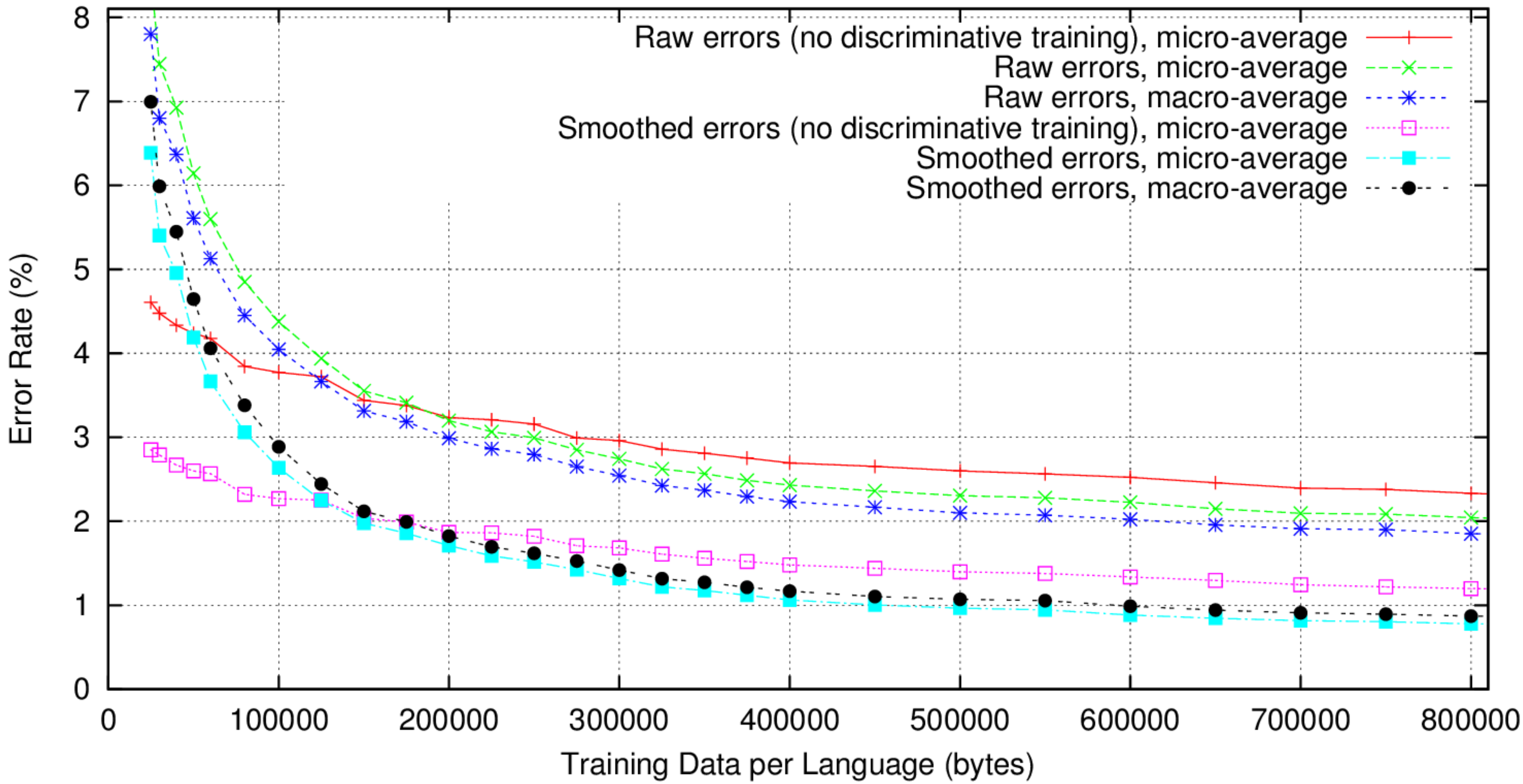
Experiments: Results

- Error rate decreases smoothly as training data increases and as the number of n-grams in each model increases
- Increasing maximum n-gram length eventually starts increasing error rate again
- Inter-string smoothing cuts errors by about half
- Discriminative training reduces error rates with more than 250k training data per model

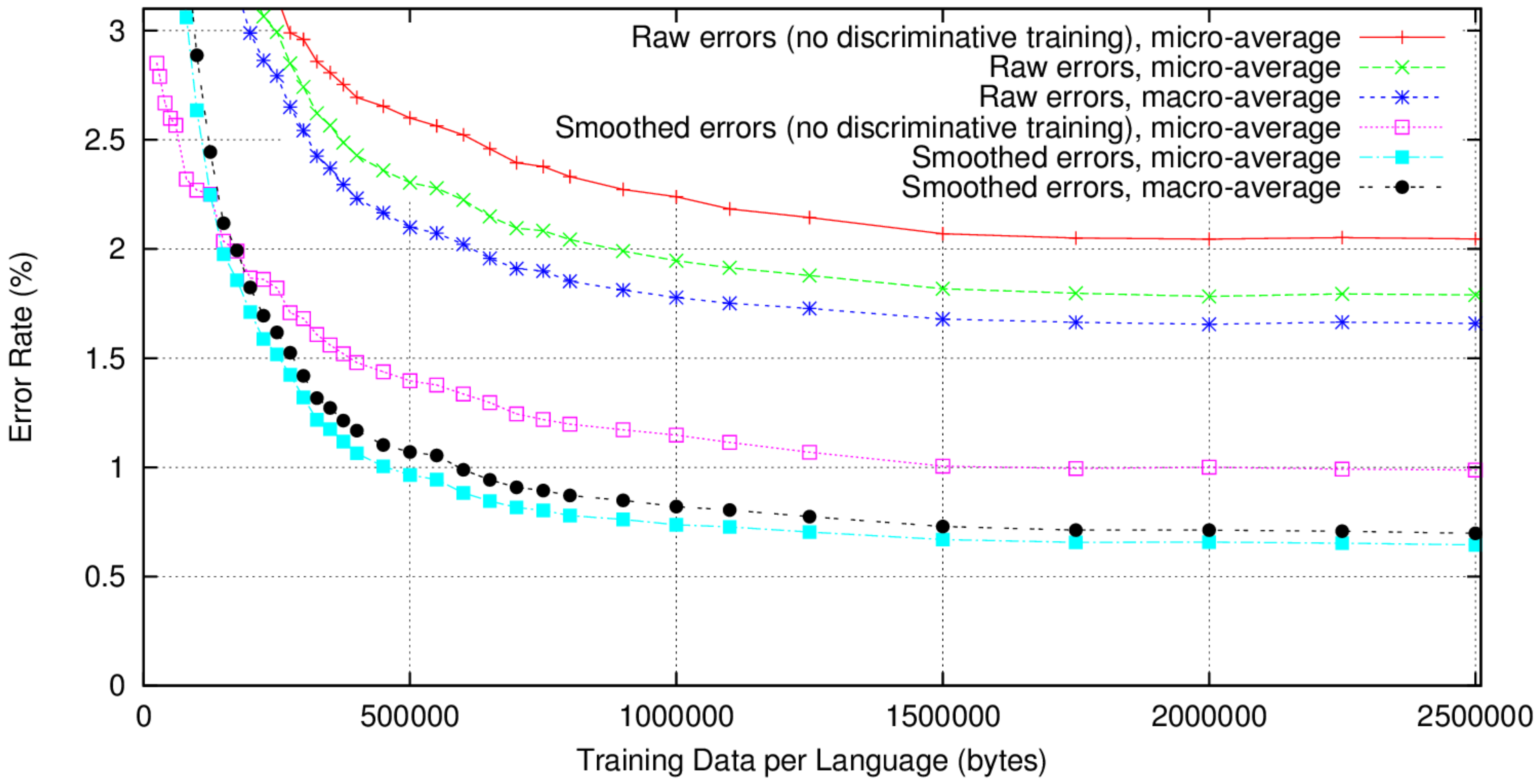
Performance by Training Data Size



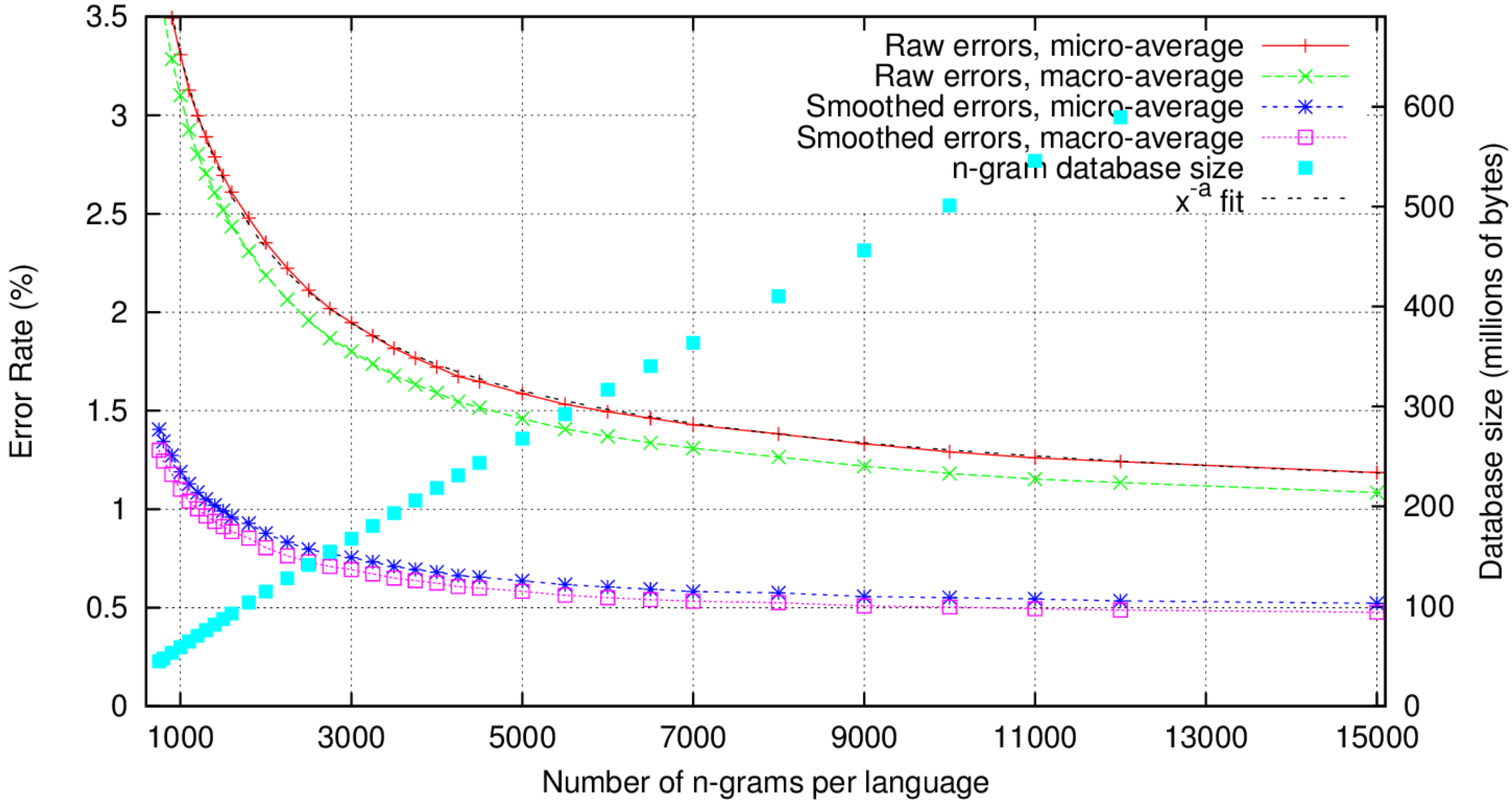
Performance by Training Data Size (Detail: low data)



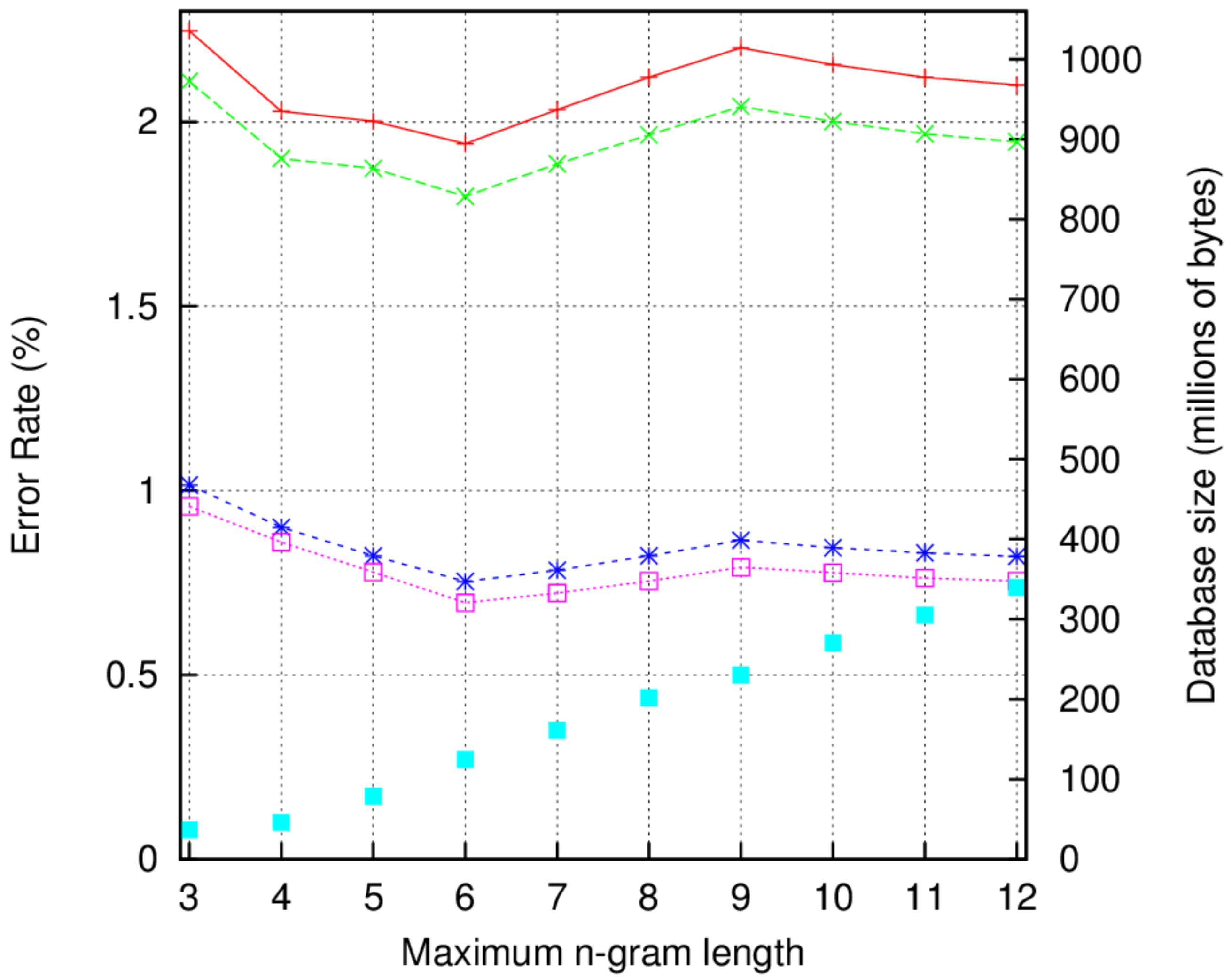
Performance by Training Data Size (Detail: high data)



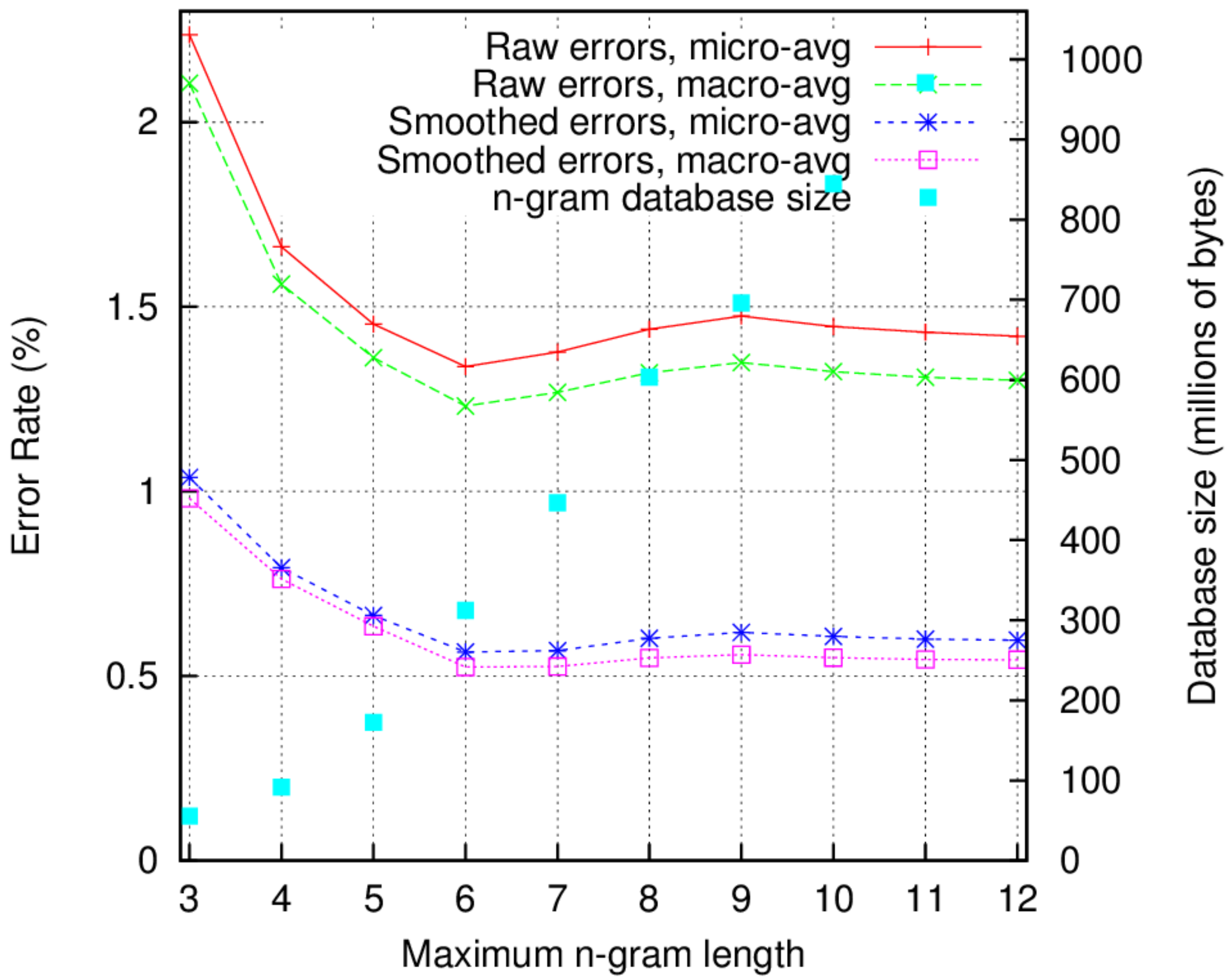
Performance by N-gram Count



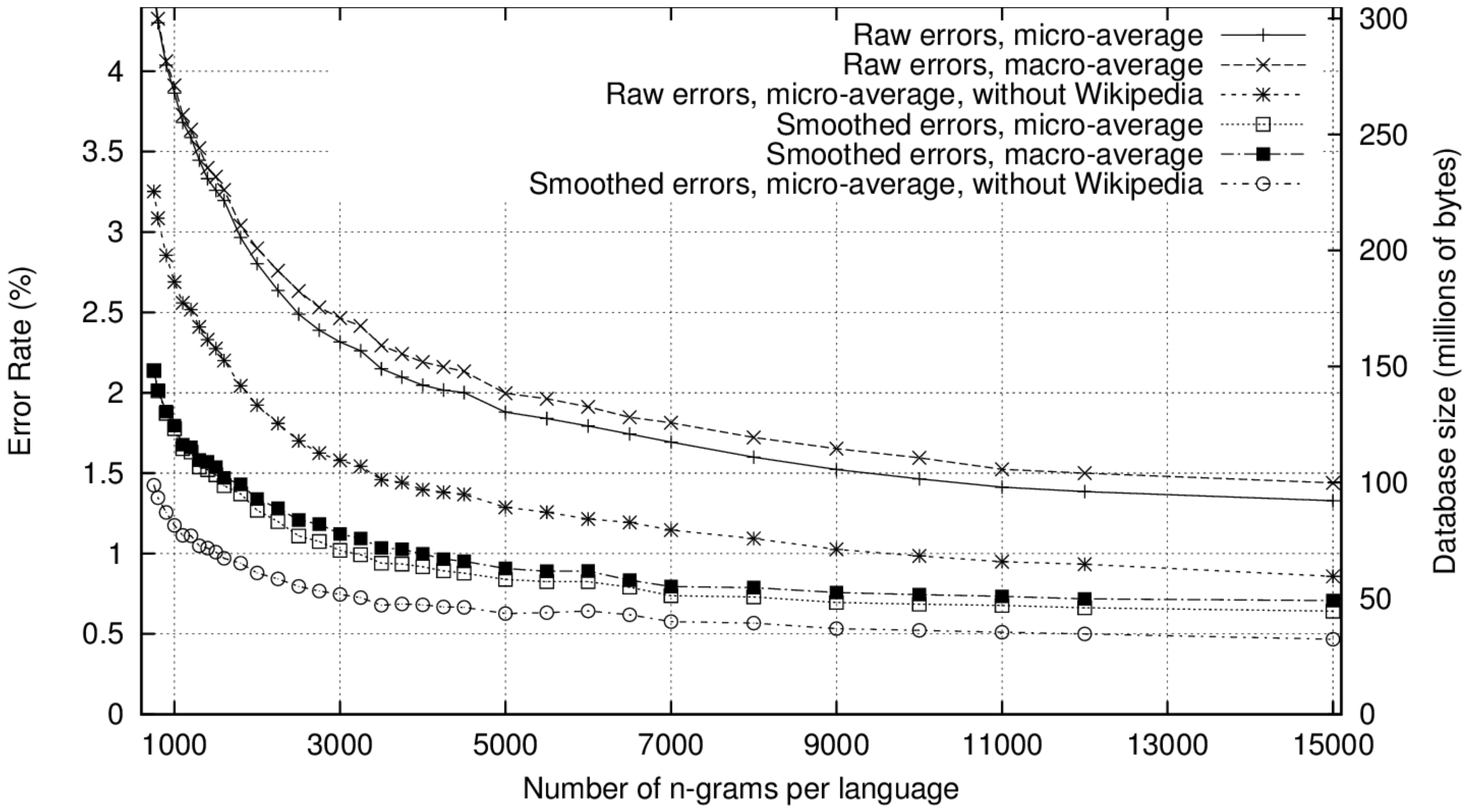
Performance by Max. N-gram Length
(topK = 3000)



Performance by Max. N-gram Length
(topK = 9000)



Performance on Top Languages



Missed and Falsely Identified Text

- Miss vs False Alarms on running text
  - Low threshold: 0.002% miss / 0.34% false alarm
  - High threshold: 0.009% miss / 0.012% false alarm
- Miss vs False Alarms for isolated strings not fully characterized yet
  - Seems to average about one (short) false-alarm string following each true string as a result of smoothing

Other Measures of Performance

- Speed (full database of 3397 models)
  - ~1.7MB/s on random bytes
  - ~160 KB/s on running text
- Speed (restricted database of 454 models)
  - ~3.5MB/s on random bytes
  - ~800 KB/s on running text
- RAM
  - Database is shared memory, only 4MB private RAM

Future Work

- Improved discriminative training
- Increased speed
  - Even 3.5 MB/s is too slow for terabyte disk images

Conclusion

- Presented a trainable open-source tool to extract textual strings and identify their language
- High accuracy on both string extraction and language identification
- Reasonable speed
- Available from http://la-strings.sourceforge.net/
  - Includes pre-trained models for 1026 languages
  - Training data for over 500 languages available (Creative Commons licenses)

Thank You.

Questions?