AUTOMATED LANGUAGE RECOGNITION TOOL

Ankita Singh & Nimisha Srinivasa
UCSB CS 273 Fall 2016

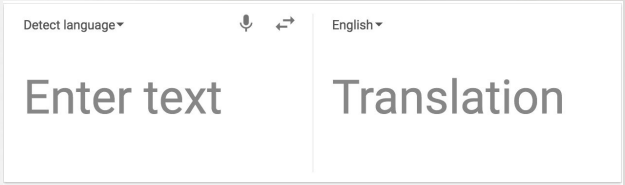
OUTLINE

- Problem statement
- Challenges
- Dataset
- Methodology
- Results and analysis
- Takeaways/Thoughts

MOTIVATION

Build an automated **Language Classifier** for Twitter.

- Analysis of **short texts** on social media is gaining importance.
- Language detection is currently focussed on **long written text**.
- A lot of new languages are becoming better represented online.



Challenges

- Tweets are only 140 characters long
- Colloquial language and misspellings
- Abundant use of hashtags, handles, URLs and emoticons.

DATASET

Twitter dataset:

https://blog.twitter.com/2015/evaluating-language-identification-performance

DATA PREPROCESSING

Removing:

- Emoticons
- Digits & punctuations
- Handles & hashtags
- URLs

```
{
        “Id” : ”123456”,
        “Content”  : ”ranks as top public national university for the third consecutive year”,
        “Label” : ”English”
}
```

LANGUAGES

Arabic
Latinized Arabic
Bulgarian
Bosnian
Catalan
Czech
Danish
German
Greek
English
Spanish
Persian
Latinized Hindi
Finnish
French
Guliguli
Hebrew
Hindi
Croatian
Haitian Creole
Hungarian
Indonesian
Italian
Japanese
Latinized
Japanese
Javanese
Khmer
Korean
Latinized
Korean
Latvian
Mongolian
Marathi
Malay
Nepali
Dutch
Norwegian
Polish
Portuguese
Romanian
Russian
Albanian
Serbian
Sudanese
Swedish
Swahili
Tamil
Thai
Tagalog
Turkish
Ukrainian
Urdu
Latinized Urdu
Vietnamese
Xhosa
Simplified Chinese
Traditional Chinese

FEATURE EXTRACTION

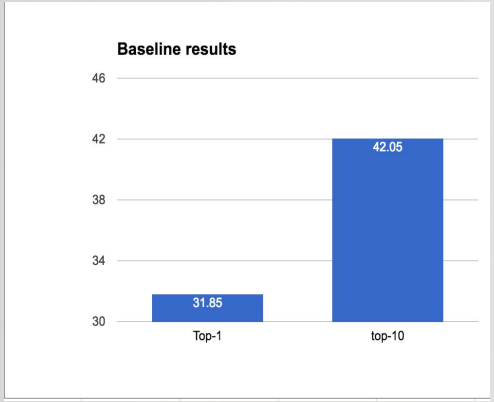
- Frequency features
  - Top-k most frequently used words for every language
- N-gram features: better performance[1]

[1] Grefenstette, Gregory (2014).”C*omparing two language identification schemes*”.

IMPLEMENTATION

BASELINE

- Top-1 most frequent word for each language
- Top-k most frequent words for each language



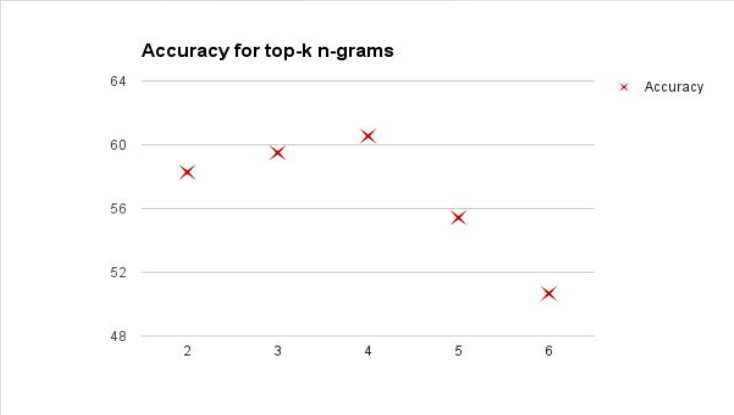
BASELINE

Shortcomings

- Huge dictionary size
- Missing spaces between words for some languages.

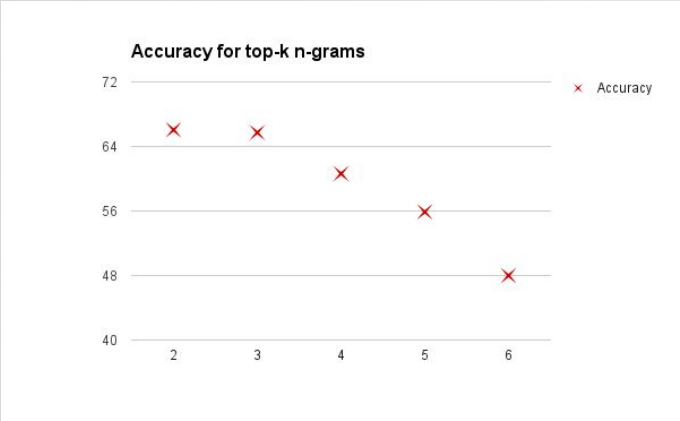
NAIVE BAYES CLASSIFICATION

$$\widehat{L}_k = \underset{L_k}{arg\max}\ p(L_k|x_1, x_2, \cdots x_n) = \underset{L_k}{arg\max} \sum_{i=1}^{n} log(p(x_i|L_k))$$



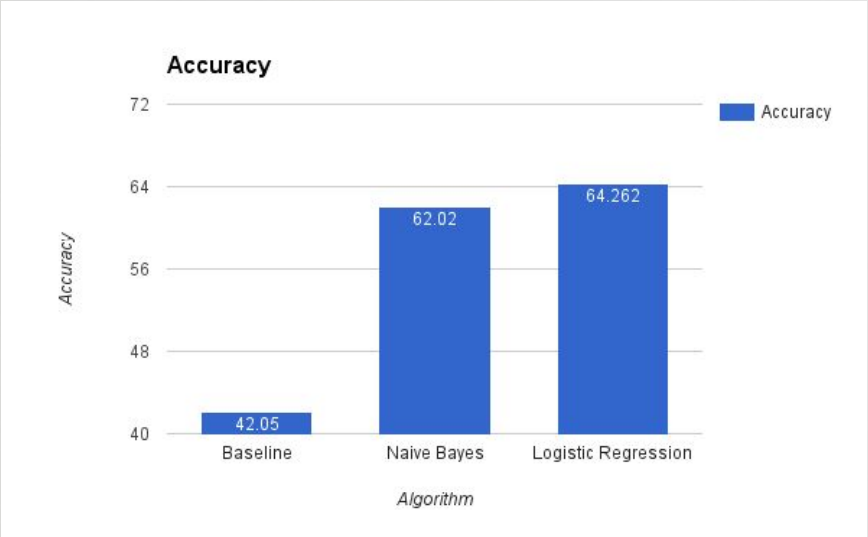
LOGISTIC REGRESSION

$$Pr(Y = c \mid X = x) = \frac{e^{\beta_0{}^{(c)} + x.\beta^{(c)}}}{\sum_c e^{\beta_0{}^{(c)} + x.\beta^{(c)}}}\}$$



Better accuracy compared to NBC!

RESULTS


Accuracy
72
64
56
48
40
Accuracy
Accuracy
42.05
62.02
64.262
Baseline
Naive Bayes
Logistic Regression
Algorithm

LIMITATIONS

- Data set covers just 70 languages.
- Not enough data to process for each language
- Issues in classifying certain very similar languages.

CONCLUSIONS & FUTURE WORK

- Language classifier for tweets
- Best result: Logistic Regression with 3-4 n-grams
- RNN to be considered in future
- Training using the DSL shared task dataset

THANKS!

Code:

https://github.com/nimisha-srinivasa/TweetLanguageClassification