NLP for Social Media: Language Identification II and Text Normalization

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LI: Supervised Approaches

Input

- A document d
- A fixed set of classes $C = \{c_1, c_2, \ldots, c_n\}$
- A training set of m hand-labeled documents $(d_1, c_1), \ldots, (d_m, c_m)$

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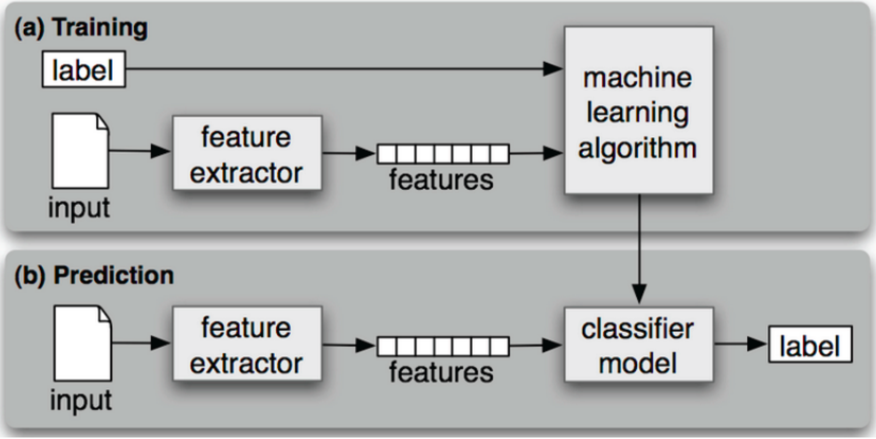
Output

A learned classifier $\gamma : d \to c$

Supervised Machine Learning



Bayes' rule for documents and classes

For a document d and a class c

$$P(c|d) = \frac{P(d|c)P(c)}{P(d)}$$

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Naïve Bayes Classifier

$$\begin{aligned} c_{MAP} &= \arg\max_{c \in C} P(c|d) \\ &= \arg\max_{c \in C} P(d|c)P(c) \\ &= \arg\max_{c \in C} P(x_1, x_2, \ldots, x_n|c)P(c) \end{aligned}$$

Naïve Bayes classification assumptions

$$P(x_1, x_2, \ldots, x_n | c)$$

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Assume the feature probabilities $P(x_i|c_j)$ are independent given the class c_j.

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$$c_{NB} = \underset{c \in C}{\arg\max}\, P(c) \prod_{x \in X} P(x|c)$$

Learning the model parameters

Maximum Likelihood Estimate

$$\hat{P}(c_j) = \frac{doc - count(C = c_j)}{N_{doc}}$$

$$\hat{P}(w_i|c_j) = \frac{count(w_i, c_j)}{\sum_{w \in V} count(w, c_j)}$$

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Problem with MLE

Suppose in the training data, we haven't seen one of the words (say *pure*) in a given language.

$$\hat{P}(pure|Hindi) = 0$$

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$$\hat{P}(pure|Hindi) = 0$$

$$c_{NB} = \arg\max_{c} \hat{P}(c) \prod_{x \in X} \hat{P}(x_i|c)$$

Laplace (add-1) smoothing

$$\hat{P}(w_i|c) = \frac{count(w_i, c) + 1}{\sum_{w \in V} (count(w, c) + 1)}$$

$$= \frac{count(w_i, c) + 1}{(\sum_{w \in V} (count(w, c)) + |V|}$$

A worked out example

	Doc	Words	Class
Training	1	English Wikipedia editor	en
	2	free English Wikipedia	en
	3	Wikipedia editor	en
	4	español de Wikipedia	es
Test	5	Wikipedia español el	?

A worked out example: No smoothing

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$$\hat{P}(c) = \frac{count(c)}{\sum_{c_j \in C} count(c_j)}$$

P(en)=3/4 **P(sp)=1/4**

$$\hat{P}(t \mid c) = \frac{count(t,c)}{\sum_{t_i \in V} count(t_i,c)}$$

P("Wikipedia" | en) = 3/8 , P("Wikipedia" | es) = 1/3
P("español" | en) = 0/8 , P("español" | es) = 1/3
P("el" | en) = 0/8 , P("el" | es) = 0/3

P(en | doc5) = 3/4×3/8×0/8×0/8 = 0
P(es | doc5) = 1/4×2/9×1/3×0/3 = 0

A worked out example: Smoothing

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P("Wikipedia" |en) = 3+1/8+6 , P("Wikipedia" |sp) = 1+1/3+6
P("español" |en) = 0+1/8+6 , P("español" |sp) = 1+1/3+6
P("el" |en) = 0+1/8+6 , P("el" |sp) = 0+1/3+6

P(en|doc5) = 3/4×4/14×1/14×1/14 = 0.00109
P(sp|doc5) = 1/4×2/9×2/9×1/9 = 0.00137

Character n-gram based Approach

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kshiprata → $kshiprata$
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3: $ks, ksh, shi, hip, ipr, ... ta$
4: $ksh, kshi, ship, ..., ata$
5: $kshi, kship, shipr, ..., rata$

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Prob (kshiprata is Sanskrit) » Prob (kshiprata is English)

LangID Tools

`langid.py`	Lui and Baldwin [2012]
`ChromeCLD`	McCandless [2010]
`LangDetect`	Nakatani [2010]
`LDIG`	Nakatani [2012]
`whatlang`	Brown [2013]
`YALI`	Majliš [2012]
`TextCat`	Scheelen [2003]
`MSR-LID`	Goldszmidt et al. [2013]

Using langid.py

```
python
Python 2.7.2+ (default, Oct  4 2011, 20:06:09)
[GCC 4.6.1] on linux2
Type "help", "copyright", "credits" or "license" for more information.
>>> import langid
>>> langid.classify("I do not speak english")
('en', 0.57133487679900674)
>>> langid.set_languages(['de','fr','it'])
>>> langid.classify("I do not speak english")
('it', 0.99999835791478453)
>>> langid.set_languages(['en','it'])
>>> langid.classify("I do not speak english")
('en', 0.99176190378750373)
```

https://github.com/saffsd/langid.py

Supports 97 languages

Word-level Language Labeling

Modi	ke	speech	se	India	inspired	ho	gaya	#namo
NE	Hn	En	Hn	NE	En	Hn	Hn	Other
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Modeling as a Sequence Prediction Problem

Given **X:** $X_1 = Modi, X_2 = ke, \ldots$

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Modeling as a Sequence Prediction Problem

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Such that $p(Y|X)$ is maximized

Conditional Random Fields: Modelling the Conditional Distribution

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Model the Conditional Distribution:

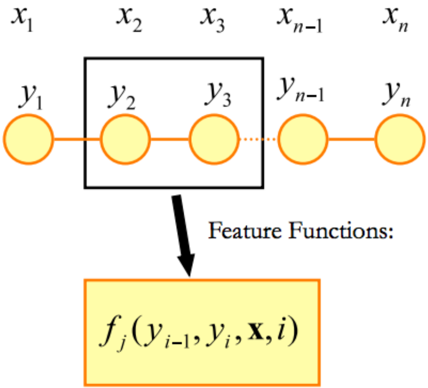
$$P(\mathbf{y} \mid \mathbf{x})$$

To predict a sequence compute:

$$\mathbf{y}^* = \arg\max_{\mathbf{y}} P(\mathbf{y} \mid \mathbf{x})$$

Must be able to compute it efficiently.

Conditional Random Fields: Feature Functions



Feature Functions

Express some characteristic of the empirical distribution that we wish to hold in the model distribution

$$f_j(y_{i-1}, y_i, \mathbf{x}, i) \rightarrow \begin{cases} 1 \quad \text{if } y_{i-1} = IN \text{ and } \\ \qquad y_i = NNP \text{ and } \\ \qquad x_i = September \\ 0 \quad \text{otherwise} \end{cases}$$

Conditional Random Fields: Distribution

Label sequence modelled as a normalized product of feature functions:

$$P(\mathbf{y} \mid \mathbf{x}, \boldsymbol{\lambda}) = \frac{1}{Z(\mathbf{x})} \exp \sum_{i=1}^{n} \sum_{j} \lambda_j f_j(y_{i-1}, y_i, \mathbf{x}, i)$$

$$Z(\mathbf{x}) = \sum_{\mathbf{y} \in Y} \sum_{i=1}^{n} \sum_{j} \lambda_j f_j(y_{i-1}, y_i, \mathbf{x}, i)$$

Features for word level Language Identification

Token-based features	Lexical Features	Context Features
• Capitalization • Script • Special Characters • Character n-gram based classifiers • Word length	• Regular lexicon • Unigram Frequency • Entity Lexicon • Acronym/slang lexicon	• Next 3 tokens • Last 3 tokens • Current token • Previous label (Bigram or B)

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Social media text contains varying levels of "noise" (lexical, syntactic and otherwise), e.g.

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Social media text contains varying levels of “noise” (lexical, syntactic and otherwise), e.g.

- Tell ppl u luv them cuz 2morrow is truly not promised.
- SUPER BOWL SUNDAY!!! Enjoy yourselves!!! Sunday morning GOODIES R sent out! C U 2Nyt!
- Follow @OFA today for more coverage of the gun violence petition delivery to Congress. #NotBackingDown #EarlyFF

Why is Social Media Text "Bad"?

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Eisenstein, *What to do about bad language on the internet*, NAACL-HLT, 2013

What can be done about it?

Lexical normalization

Translate expressions into their canonical form

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Issues

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Issues

- What are the candidate tokens for normalization?
- To what degree do we allow normalization?
- What is the canonical form of a given expression? (e.g., *aint*)
- Is lexical normalization always appropriate? (e.g., *bro*)

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One standard definition

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$$
\begin{array}{cccccccccccc}
\textit{i left ACL} & \underline{\textit{cus}} & \underline{\textit{im}} & \underline{\textit{sickk}} & ! & \underline{\textit{Yuu}} & \textit{better be their} & \underline{\textit{tmrw}} \\
 & \Downarrow & \Downarrow & \Downarrow & & \Downarrow & & \Downarrow \\
\textit{i left ACL} & \underline{\textit{because}} & \underline{\textit{I'm}} & \underline{\textit{sick}} & ! & \underline{\textit{You}} & \textit{better be their} & \underline{\textit{tomorrow}}
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i left ACL cus im sickk ! Yuu better be their tmrw

$\Downarrow$

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- not possible to normalize in-vocabulary tokens, e.g. *their*

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	⇓	⇓	⇓		⇓		⇓
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- ignore Twitter-specific entities, e.g., obama, #mandela, bit.ly/1iRqm
- assume a unique correct “norm” for each token

Spelling Errors

TOMORROW

- Tomorow
- Tommorow
- Tommorrow

Phonetic/Cognitive Errors

- Tpmorrow
- Tomrorow
- Tmorrow
- Tomnorrow

Typos or “slip of finger” errors

Unintentional Errors

Understanding unintentional spelling errors

TOMORROW

- Tomorow — Double letter omission
- Tommorow — Doubling of wrong letter
- Tommorrow — Doubling of letter

Phonetic/Cognitive Errors

- Tpmorrow — Substitution: o→ p
- Tomrorow — Metathesis: or→ ro
- Tmorrow — Deletion: o→ ε
- Tomnorrow — Insertion: ε → n

Typos or “slip of finger” errors

Edit Distance

- Cost of **Edit Operations**:
  - Insertion($\varepsilon \rightarrow c$): 1
  - Deletion ($c \rightarrow \varepsilon$): 1
  - Substitution: ($c \rightarrow c'$): 1 or 2

Metathesis ($cc' \rightarrow c'c$) is either modeled as a single edit operation (cost = 1) or as a deletion-insertion pair ($cc' \rightarrow \varepsilon c' \rightarrow c'c$), and therefore cost of 2.

- **Edit Distance** between two strings **s**:$c_1 c_2 c_3 \ldots c_n$ and **s'**:$c'_1 c'_2 c'_3 \ldots c'_n$ is defined as the minimum value of the sum of the cost of a sequence of edit operations required to convert **s** to **s'**.
  - *engine* & *begin*, elevator & evaluator, east & csar

- Dynamic Programming Algorithm

What about spelling errors in Social Media?

The shorter → the faster
Constraint: understandability

24

dis is n eg 4 txtin lang

39

This is an example for Texting language

Other factors: Coolness, group-membership, accommodating

The case of 'Tomorrow'

- 2moro (9)
- tomoz (25)
- tomoro (12)
- tomrw (5)
- tom (2)
- tomra (2)
- tomorrow (24)
- tomora (4)
- tomm (1)
- tomo (3)
- tomorow (3)
- 2mro (2)
- morrow (1)
- tomor (2)
- tmorro (1)
- moro (1)

Spell-checkers, such as Aspell, perform very poorly on such data (<22%)

Data from (Choudhury et al., 2007)

Patterns or Compression Operators

Phonetic substitution (phoneme)

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message → mssg, about → abt

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Deletion of repeated characters

tomorrow $\rightarrow$ tomorow

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introduction $\rightarrow$ intro, evaluation $\rightarrow$ eval

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going to $\rightarrow$ gonna

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Common Abbreviations

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Informal pronunciation

going to → gonna

Emphasis by repetition

Patterns or Compression Operators

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Common Abbreviations

Kharagpur → kgp, text back → tb

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going to → gonna

Emphasis by repetition

Funny → fuuuunnnnnyyyyyy

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- cause $\rightarrow$ cauz (phonetic substitution)
- cauz $\rightarrow$ cuz (vowel deletion)

Categorisation of non-standard words in English Twitter

Category	Ratio	Example
Letter&Number	2.36%	*b4* “before”
Letter	72.44%	*shuld* “should”
Number Substitution	2.76%	*4* “for”
Slang	12.20%	*lol* “laugh out loud”
Other	10.24%	*sucha* “such a”

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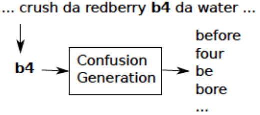
Most non-standard words in sampled tweets are *morphophonemic* variations.

Token-based Approach (Han and Baldwin, 2011)

1. Confusion set generation (i.e., find correction candidates)
2. Non-standard word detection (i.e., is the OOV a non-standard word?)
3. Normalisation of a non-standard word (i.e., select the candidate)



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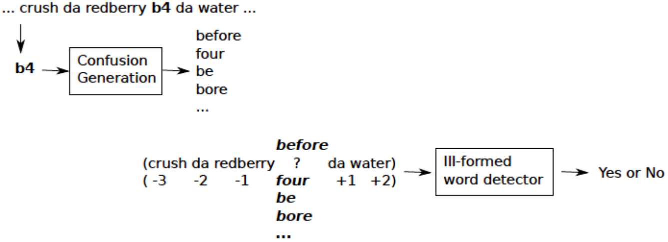
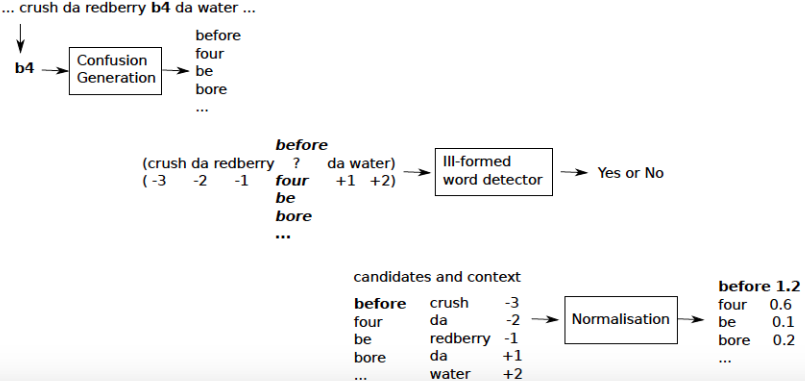


Token-based Approach (Han and Baldwin, 2011)

1. Confusion set generation (i.e., find correction candidates)
2. Non-standard word detection (i.e., is the OOV a non-standard word?)
3. Normalisation of a non-standard word (i.e., select the candidate)



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- Filter out any Twitter-specific tokens (user-mentions, hashtags, RT, etc.) and URLs

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- For OOV words, shorten any repetitions of 3+ letters to 2 letters

Candidate Generation

- Generation via edit distance over letters (T_c) and phonemes (T_p).

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- This allows to generate "earthquake" for words such as *earthquick*.
- Candidates with $T_c \leq 2 \vee T_p \leq 1$ were taken, further filtered using frequency to take the top 10% of candidates.

Detection of Ill-formed words

Detection based on candidate context fitness

- Correct words should fit better with context than substitution candidates
- Incorrect words should fit *worse* than substitution candidates

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Basic Idea: Use Dependencies from corpus data

An SVM classifier is trained based on dependencies, to indicate candidate context fitness.

Ill-formed word in text snippet	Candidate	Dependencies
but I was thinkin movies .	(thinking, ...)	dobj(thinking, movies)
article poster by ruderrobb : there was	(rattrap, ...)	–

Feature Representation using Dependencies

- Build a dependency bank from existing corpora
- Represent each dependency tuple as a word pair + positional index

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Corpus (NYT)

One obvious difference is the way they look, ...

↓ **Stanford Parser**

num(difference-3, One-1)
amod(difference-3, obvious-2)
nsubj(way-6, difference-3)
cop(way-6, is-4)
det(way-6, the-5)
dobj(look-8, way-6)
nsubj(look-8, they-7)
rcmod(way-6, look-8)
...

→

Dependency bank

(way, difference, 3)
(look, way, 2)
...

SVM Training Data Generation

- Use dependency bank directly as positive features

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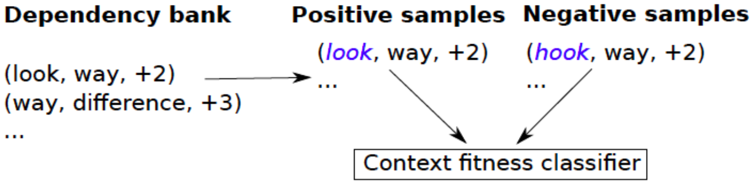

Detecting ill-formed words

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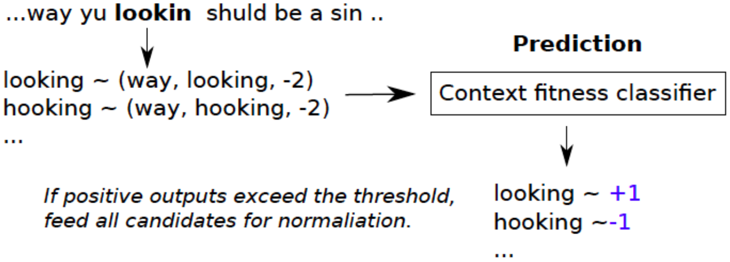

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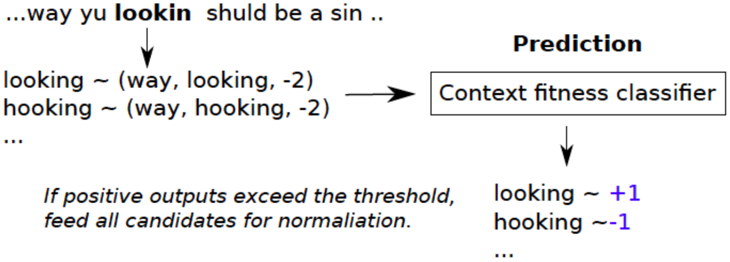

Threshold = 1 → *lookin* is considered to be an ill-formed word

Normalization Candidate Selection

For each ill-formed word and its possible correction candidates, the following features are considered for normalization:

Word Similarity

- letter and phoneme edit distance (ED)
- prefix, suffix, and longest common subsequence

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Context Support

- trigram language model score
- dependency score (weighted dependency count, derived from the detection step)

Type-based approach

Observation

The longer the ill-formed word, the more likely there is a unique normalization candidate

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- $\underline{y} \Rightarrow \{\underline{why}, \underline{you}, \ldots\}$, $\underline{hw} \Rightarrow \{\underline{how}, \underline{homework}, \ldots\}$
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Approach

Construct a dictionary of (lexical variant, standard form) pair for longer word types (character length ≥ 4) of moderate frequency (≥ 16)

Type-based Approach (Han et al. (2012))

Construct the dictionary based on distributional similarity + string similarity

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Input: Tokenised English tweets

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Output

A list of (OOV, IV) pairs ordered by string similarity; select the top-n pairs for inclusion in the normalisation lexicon.

An Example

... *see you tmrw* ...

... *tmrw morning* ...

... *tomorrow morning* ...

...

$\Downarrow$ distributional similarity

$\{$*tmrw, 2morow, tomorrow, Monday*$\}$

$\Downarrow$ string similarity

tmrw $\rightarrow$ *tomorrow*

Context Modelling

Components/parameters of the method

- context wondow size: ± 1, ± 2, ± 3
- context word sensitivity: bag-of-words vs. positional indexing
- context word representation: unigram, bigram or trigram
- context word filtering: all tokens vs. only dictionary words
- context similarity: KL divergence, Jensen-Shannon divergence, Cosine similarity, Euclidean distance

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Tune parameters relative to (OOV,IV) pair develepment data

Rerank pairs by string similarity

(OOV,IV) pairs derived by distributional similarity:

$(Obama, Adam)\ \downarrow$
$(tmrw, tomorrow) \uparrow$
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$\ldots$

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Get the top-ranked pairs as lexicon entries: $(tmrw, tomorrow)$ $(4eva, forever)$

Main References

- Han, Bo, and Timothy Baldwin. "Lexical normalisation of short text messages: Makn sens a# twitter." Proceedings of the 49th Annual Meeting of the Association for Computational Linguistics: Human Language Technologies-Volume 1. Association for Computational Linguistics, 2011.
- Han, Bo, Paul Cook, and Timothy Baldwin. "Automatically constructing a normalisation dictionary for microblogs." Proceedings of the 2012 joint conference on empirical methods in natural language processing and computational natural language learning. Association for Computational Linguistics, 2012.