

Semi-automatic Detection of Cross-lingual Marketing Blunders based on Pragmatic Label Propagation in Wiktionary



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UBIQUITOUS KNOWLEDGE PROCESSING

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Summary

Marketing blunders occur if a trade name resembles an inappropriate or negatively connotated word in a target language.

In this work, we introduce

- a formal definition for this new NLP task,
- a semi-automatic method based on the propagation of pragmatic labels from Wiktionary across sense-disambiguated translations in over 1.000 languages,
- an online demo of our tool: <http://uby.ukp.informatik.tu-darmstadt.de/blunder/>
- two evaluation experiments and a new dataset of previously occurred marketing blunders,
- a research roadmap to initiate future work and a community around this task.

Formal Task Definition

- **Given:** product, brand, or company name T
- **Goal:** method \mathcal{M} retrieving a set of clues $C = \mathcal{M}(T)$ to support decision-making
- Clues $(w, l, d) \in C$ provide explanation
- **Example:** $T = \text{"Silver Mist"}$

form w	language l	description d
Silber	German	A shiny gray color
mist	English	A layer of fine droplets
Mist	German	Manure; animal excrement
miist	Seri	Animal of the family Felidae
miste	Danish	To lose something
silver mine	English	A mine for silver ore

object language meta/description language

- **Primary objective:** high recall "detect as many blunders as possible"
- **Secondary objective:** high precision "retrieve only relevant clues"

Discussion and Roadmap

Finding good names is a creative process → hard to model as pattern recognition task

Clues explain why a name is problematic → SoA classification tasks are often limited to indicating if there is a problem

Evaluating a name is highly subjective → Semi-automatic solutions assist users

Blunder detection needs all languages → challenging for poor-resourced languages → separating object and meta language

Future resources for evaluation (cooperation with marketing research?), as background knowledge (e.g., colloquial language corpora)

Future methods: intelligent segmentation, transliteration, phonetic representation, sentiment analysis tools and resources

Future tasks: clues for acronyms, person names

Motivation



"Silver Mist"

English: A layer of fine droplets. Describes fabulous, enigmatic, lightweight, mystic things
German: dung or manure; (slang) futile, cheap, broken thing; nonsense; annoying, tedious situation



"This is 7"

China: 7, is here
Taiwan: Exactly is 7.
Hong Kong: This, is exactly iPhone 7.
Cantonese cat1 (numeral 7) is similar to **cat6** (vulgarity for male genitals), also used for smth. ugly or shameful.

- Increasing sales in international markets
- Trade names may have a different meaning in the local language
- Yields offensive, embarrassing, or funny results
- High remedial cost or even withdraw of a product
- Detection difficult without local branches (→ startups?)
- **Absence of resources!**
- **Absence of tools!**

Proposed Method

A: Propagate sense descriptions

- Scrape Wiktionaries for languages spoken by copywriters
 - Propagate sense descriptions across disambiguated translations
 - Index by normalized forms (key)
- Homograph index: > 1.3 M forms, > 3 M clues from > 1.000 languages**

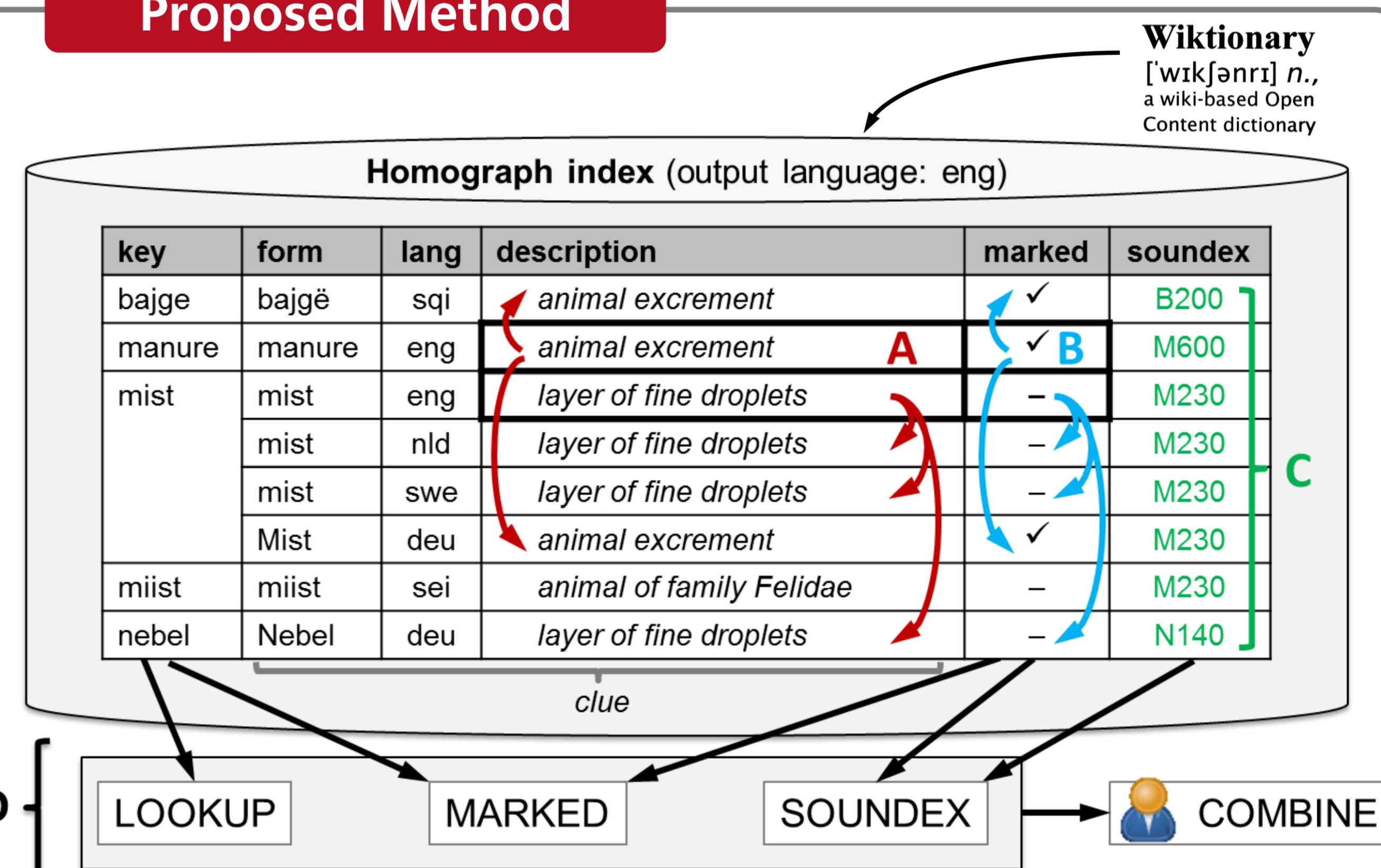
B: Propagate pragmatic labels

Propagate labels across translations:

- Sociological labels: argot, army slang, children's language,...
- Register & style labels: colloquial, informal, slang,...
- Evaluative labels: pejorative, rude, derogatory,...

C: Similar form representations

- So far, we use Soundex representations
- Need for pseudo-phonetic representation and transliteration for basically any language



D: Semi-automatic usage

Retrieve pragmatically marked clues for each normalized token (MARKED), then marked clues with a similar form (SOUNDEX), then remaining unmarked entries (LOOKUP)

Online Demo

<http://uby.ukp.informatik.tu-darmstadt.de/blunder>

Downloads



Evaluation

Experiment 1: Previously occurred blunders

	MARKED	SOUNDEX	LOOKUP	COMBINE
Detected blunders:	18 / 44	18 / 44	28 / 44	34 / 44
<i>intent</i>	0 / 3	0 / 3	3 / 3	3 / 3
<i>negative</i>	3 / 15	8 / 15	10 / 15	14 / 15
<i>sexual</i>	7 / 14	4 / 14	7 / 14	8 / 14
<i>vulgar</i>	8 / 12	6 / 12	8 / 12	9 / 12
Relevant clues:	105 / 151	85 / 247	341 / 1202	229 / 517
Precision P_1 :	.70	.34	.28	.44
Recall R_1 :	.41	.41	.64	.77
F_1 score:	.52	.37	.39	.56
F_2 score:	.45	.39	.51	.67

Relevance annotation for clues: $A_0 = 95\%$, $\kappa = .87$
 LOOKUP and COMBINE effectively detect blunders
 MARKED and COMBINE minimize effort

Initial evaluation dataset: 44 previously occurred marketing blunders based on Ricks (2006) and the Commisceo Global blog. Publicly available!

Experiment 2: Relevant clues in top-tier brands

≈ 1,000 international brand names from the BrandPitt corpus (Özbal et al., 2012).

Our tool returns 756 (MARKED), 3,549 (SOUNDEX), and 17,270 clues (LOOKUP).

- **Pixar:** to urinate (Catalan)
- **Nero:** brainiac (Finnish), 'gangsta' (Colombia)
- **Aston Martin:** martin = buttocks (Fur)
- **Thanks a Latte:** Latte = erected penis (German)

2 raters tag 154 and 192 of the MARKED clues as relevant → 70 and 88 names ($A_0 = 90\%$, $\kappa = .72$).

Examples and error analysis

- **Get Lost Magazine / Urban Decay:** intentional ambiguity → leave final decision to humans
- **FARTFULL:** need for intelligent segmentation
- **Vicks:** inflected word forms across languages
- **Bardak:** needs transliteration бардак (whorehouse)