New methodologies to evaluate the consistency of emoji sentiment lexica and alternatives to generate them in a fully automatic unsupervised way

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Milagros Fernández-Gavilanes

GTI Research Group

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atlanTTic research center for Telecommunication Technologies

UniversidadeVigo

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MOTIVATION

Motivation

Sentiment Analysis (SA)

- Extract the opinion (P, N or NEU).
- Examples:
  - The Spanish simply have the best national anthem, P
  - The Spanish national anthem 😍, P
  - #ITAESP look at the bad weather, N
  - #ITAESP look at the weather 😥, N

Emojis are a relevant part:

- Adequate emoji sentiment lexicon is required.

Problem description

Existence of some emoji sentiment lexica:

- created from manual annotations [KNSSM15].
  - considered as gold-standard.
- created from automatic annotations [LAL16, KK17, FJGCG18].
  - evaluation performed comparing with a gold-standard.

Problems:

- each new emoji → new manual annotations (gold-standard).
- different emotional emoji meanings across languages → new manual annotations for each language (gold-standard).
- anomalies between annotators can be found for a language.

How can we solve these problems?

Dataset

Dataset

Use of the multilingual annotated dataset from [KNSSM15]:

- written in 15 different languages (EN, ES, PT, etc.).
- manually annotated over 3 months.
- self-agreement ($Alpha_s$) and inter-agreement ($Alpha_i$) values reported in [MGS16].

Emoji Sentiment Ranking lexicon proposed as **"universal"** (ESR)

- emoji sentiment lexicon can be created for each language.

Dataset (II)

Focusing on Albanian, English, Polish and Spanish subsets:

Dataset	*#emojis*	Label	#Tweets	%
Albanian		Negative	17	14.53%
$Alpha_s = 0.447$	48	Neutral	40	34.19%
$Alpha_i = 0.126$		Positive	60	51.28%
English		Negative	2,935	27.59%
$Alpha_s = 0.739$	624	Neutral	2,677	25.16%
$Alpha_i = 0.613$		Positive	5,027	47.25%
Polish		Negative	638	27.59%
$Alpha_s = 0.757$	369	Neutral	919	24.27%
$Alpha_i = 0.571$		Positive	2,229	58.87%
Spanish		Negative	1,022	16.85%
$Alpha_s = 0.245$	613	Neutral	3,431	26.89%
$Alpha_i = 0.121$		Positive	8,306	65.10%

$R_{annotated_{al}}$

$R_{annotated_{en}}$

$R_{annotated_{po}}$

$R_{annotated_{es}}$

Detecting inconsistent annotations

Previous assumptions

In general, **an emoji** should have:

- same emotional meaning in datasets written in a language.
- different emotional meanings across different languages.

However, for the **most popular emojis** [BKRS16]:

- their semantics are **strongly correlated in most languages**.
- people interpret them in an **universal way**:
  - high correlation between languages.
  - strong differences may persist for some of them.

Hypothesis, for **the most popular emojis**:

- their **sentiments in a language may differ from "universal" one**, but they are **close in most cases**.

Checking our hypothesis for detecting anomalies

So, correlations of **the most popular entries** between:

- ESR lexicon (universal), denoted by $R_{annotated_{all}}$; and
- ESL of each language.

should be:

- **high** $\Rightarrow$ **consistent annotations**.
- **low** $\Rightarrow$ **inconsistent annotations**.

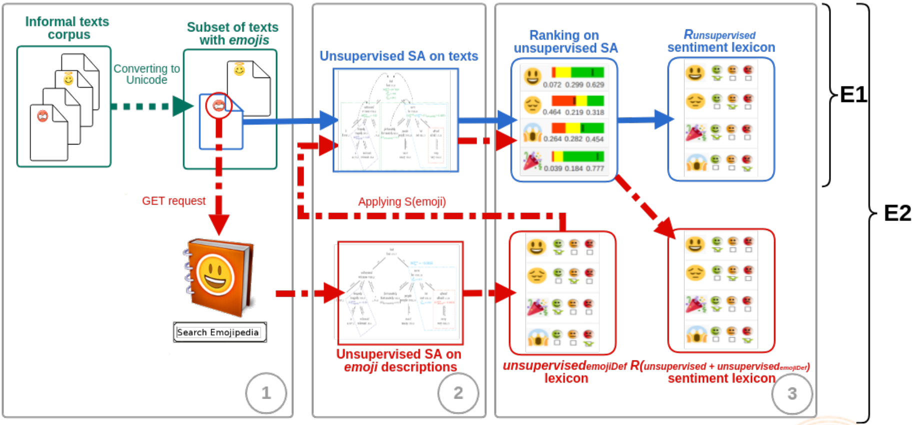
Correlations of top 100 *emojis* ranked by score and occurrence

Lexicon x	Lexicon y	$r_{score}(x,y)$	$r_{rank}(x,y)$
$R_{annotated_{all}}$	$R_{annotated_{en}}$	93.57%	89.46%
	$R_{annotated_{po}}$	88.74%	86.40%
	$R_{annotated_{es}}$	34.07%	37.35%
	$R_{annotated_{al}}$	36.37%	39.30%

Alternative solution for lexica generation

Alternative solution for lexica generation

Method for constructing ESL automatically using SA [FJGCG18]:



Applied on EN and ES datasets:

- $E1_{en}$ and $E1_{es}$: automatic USSPAD annotations.
- $E2_{en}$ and $E2_{es}$: also considers Emojipedia definitions.

Checking the alternative solution for lexica creation

Correlations of **the most popular entries** between variants and:

- a particular language ESL, or
- the ESR considered as "universal".

Lexicon x	Lexicon y	$r_{score}(x, y)$	$r_{rank}(x, y)$
$E1_{en}$	$R_{annotated_{en}}$	82.91%	76.20%
	$R_{annotated_{all}}$	79.70%	75.25%
$E2_{en}$	$R_{annotated_{en}}$	83.72%	79.37%
	$R_{annotated_{all}}$	86.90%	80.71%
$E1_{es}$	$R_{annotated_{es}}$	**47.19%**	**47.18%**
	$R_{annotated_{all}}$	74.93%	74.78%
$E2_{es}$	$R_{annotated_{es}}$	**30.06%**	**44.09%**
	$R_{annotated_{all}}$	81.32%	79.07%

Checking with SA the new alternative lexica

How these language subsets can influence the overall lexicon?

An **independent evaluation** of $E1_{en}$, $E1_{es}$, $E2_{en}$, $E2_{es}$ is needed.

- lexica variants checked in a real-world scenario with SA.
- SA measures applied on P and N classes.
  - precision (P_{macro}), recall (R_{macro}), F (F_{macro}).

Following our assumption, for **the most popular emojis**:

- most messages containing them → similar results with any lexica

Checking with SA the new alternative lexica (II)

So, to check our variants, we need:

- a subset of a consistent dataset with only popular emojis.
- to apply SA using USSPAD on this subset with the emoji lexica.

Dataset	Lexicon	P_{macro}	R_{macro}	F_{macro}
English B	$R_{annotated_{en}}$	76.16%	69.45%	72.65%
	$E2_{en}$	75.49%	69.20%	72.21%
	$E1_{en}$	67.95%	67.74%	67.85%
	$E2_{es}$	73.01%	67.84%	70.33%
	$E1_{es}$	66.98%	67.89%	67.43%
	$R_{annotated_{es}}$	56.42%	62.04%	59.10%

Conclusions

Conclusions

Assumptions:

- a poorly labeled dataset may affect emoji lexica quality.
- annotators do not always publish quality metrics.
  So, it is difficul to determine if:
  - bad SA performance is due to the supporting lexicon, or
  - the SA technique itself.

Contributions:

- a method to detect low-quality annotations of tweet datasets written in a particular language containing emojis.
- a fully automated unsupervised approach to generate lexica with good quality.
- a method to validate lexica created automatically.

References

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Thank you for your attention

Milagros Fernández-Gavilanes
mfgavilanes@gti.uvigo.es

atlanTTic research center for Telecommunication Technologies

UniversidadeVigo