An Empirical Evaluation of Arabic-specific Embeddings for Sentiment Analysis

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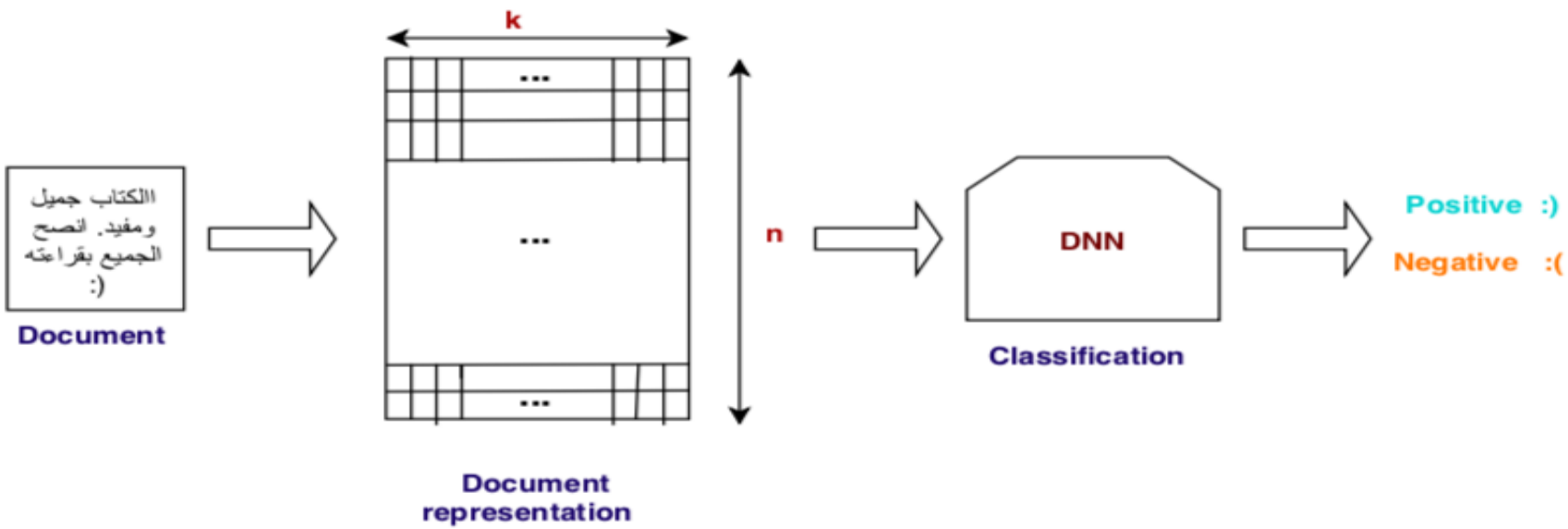
Introduction

- Sentiment Analysis (SA) framework :
  - given a textual statement,
  - identify its polarity : positive or negative.



k = embedding dimension

n = document length

DNN = Deep Neural Network

State of the art

- Recent works use Deep learning techniques :
  - based on Convolutional Neural Network (CNN) ([Dahou et al., 2016], [Alayba et al., 2018], [Dahou et al., 2019]).
  - based on Long Short-Term Memory (LSTM) ([Hassan, 2017], [Heikal et al., 2018], [Al-Smadi et al., 2018]).
- Network inputs = word embeddings.
- Words = space separator units.
- Do not take into account specificity of Arabic language (agglutination and morphological richness) in the embedding space.

Specificity of Arabic language : Agglutination and morphological richness

- Agglutination
  - Phrases could be composed with only one word.
    i.e. : ½Ê j « (Do you like it ?)
  - Word = inflected form + clitics (proclitics and enclitics).

Word	Translation	Decomposition	
		Inflected form	Clitics
éÊ j ªÊ f	will he like it ?	I. j ª	+ € + è
½Ê j ªÊ ,	you will like it		¬ + € + ¼
ÑîD j ªÐ	and they like it		Ð + Ñë

- Morphological richness : root + schemes
  i.e. : conjugation of I. j « : àð Ê j « , à Ê j « , à Ê j «

Specificity of Arabic language : Agglutination and morphological richness

- 6 different lexical units :
  - word : space separator unit.
  - token : inflected form and clitics (Farasa tool [1]).
  - token\clitics :inflected form (Farasa tool).
    Clitics do not usually affect the polarity of words.
  - Lemma : canonic form (Farasa tool).
  - stem : root of word (Tashaphyne tool [2]).
  - light stem : stem + infixes (Arabic light stemmer [3]).
- Granularity of words could impact the embedding quality.

1. http://qatsdemo.cloudapp.net/farasa/
2. https://pypi.org/project/Tashaphyne/
3. https://github.com/motazsaad/arabic-light-stemming-py

Embedding Models

- Word2vec (w2v) [Mikolov et al., 2013b] :
  - words sharing common context are closely located in the embedding space.

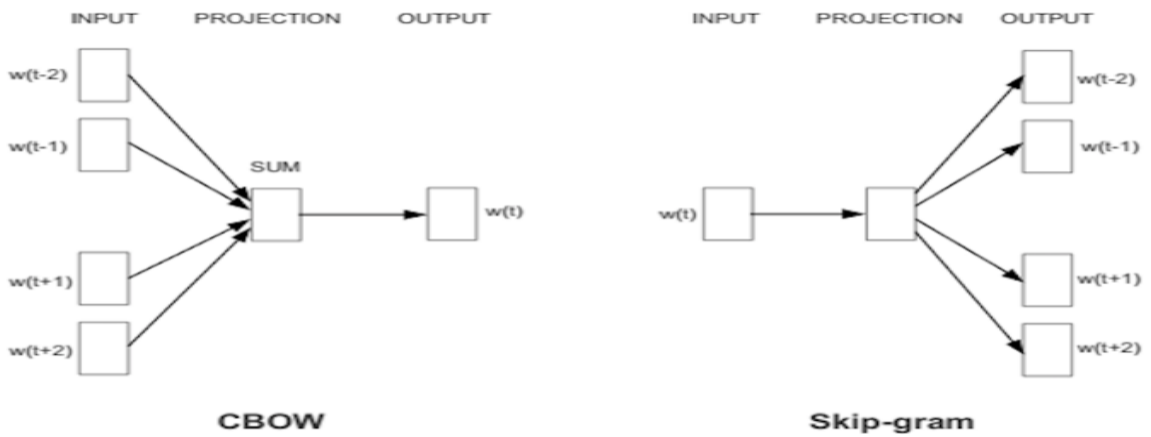


Figure – Skip-gram and CBOW architectures [Mikolov et al., 2013a].

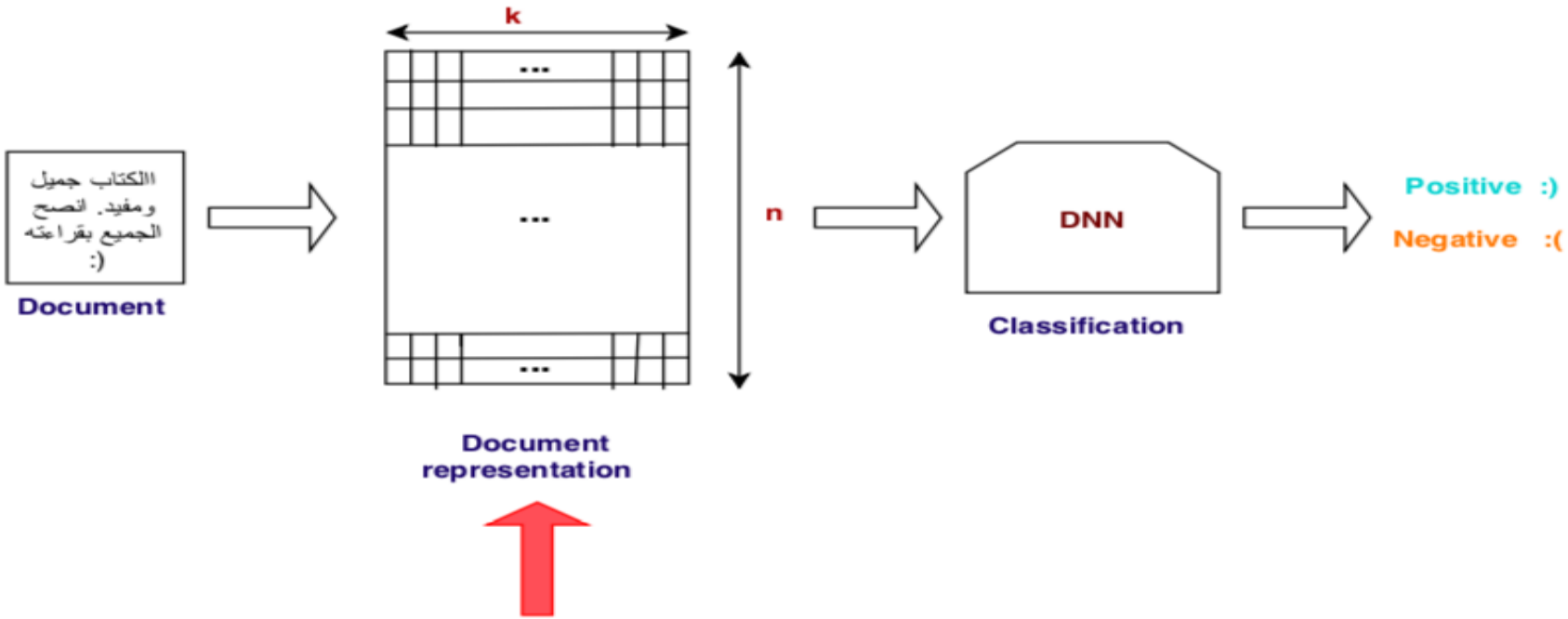
- Skip-gram $\gg$ CBOW [Dahou et al., 2016, Barhoumi et al., 2018]

Embedding Models

- Fasttext (ft) [Bojanowski et al., 2016] :
  - Extension of word2vec.
  - embeddings for unseen rare words.
  - sub-word (n-gram character) information.

    i.e. : for the word "where", add 2 symbols (< and >) <where>
    if n = 2, sub-words = {<w , wh, he, er, re, e> }

Document representation



- Document length n :
  - Hypothesis : length distribution follows Gaussian law.

$$n = mean + 2 \times \text{standard deviation} \quad (1)$$

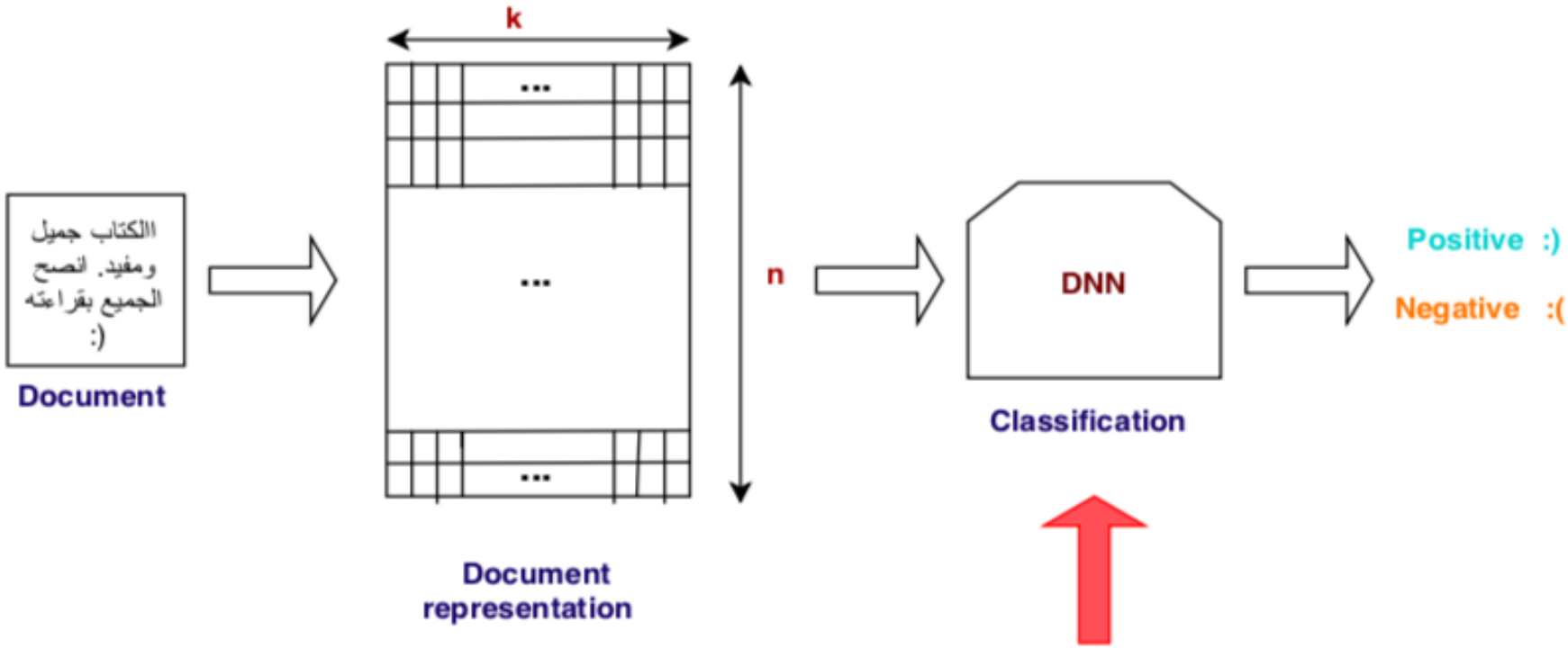
  - Empirical rule : Probability of documents ≈ 0.9545

Document representation

What type of padding/truncating (Begin, end, extremities) ?

- Protocol :
  - Splitting the document into 3 parts.
  - Analyse polar words and negation terms for each part.
  - Informativeness of each part :
    - First part : post padding/truncating.
    - Second part : padding/truncating on extremities.
    - Last part : pre padding/truncating

DNN Component



- CNN-based system.
- BiLSTM-based system.

CNN-based system

- Architecture similar to [Dahou et al., 2016].

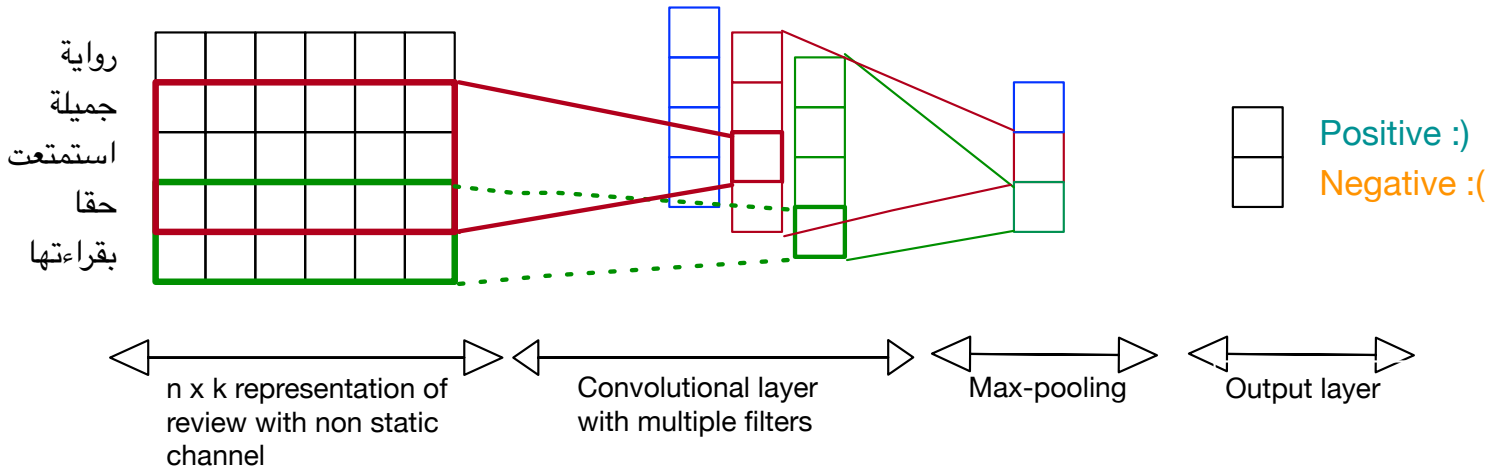
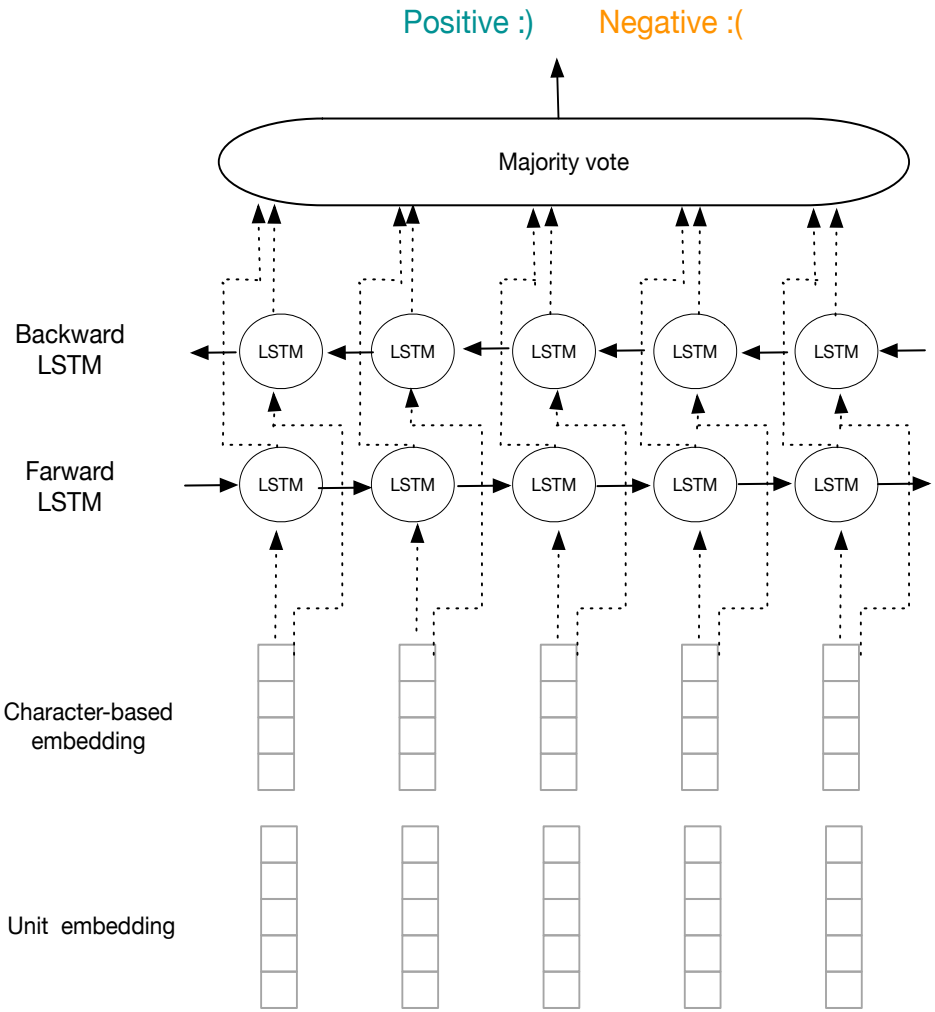
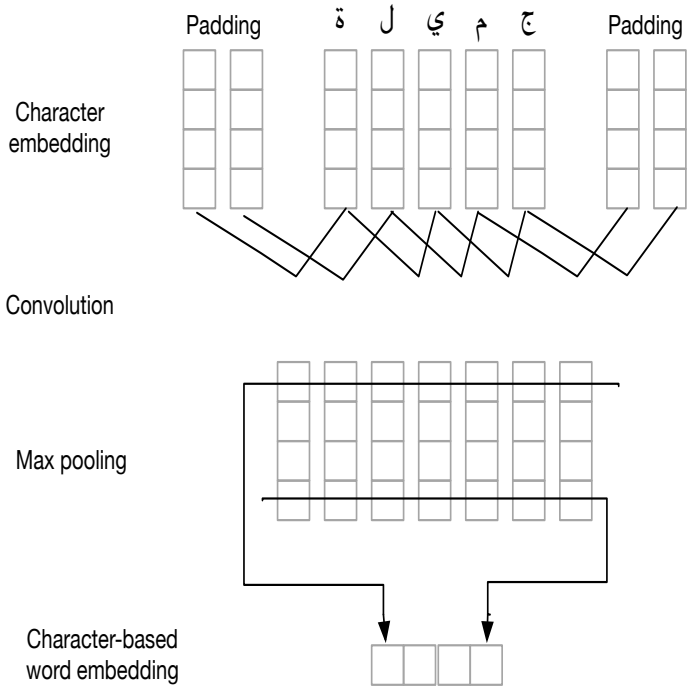


Figure – CNN architecture for a given review.

BiLSTM-based system

- Architecture similar to [Ma and Hovy, 2016].





Corpora for embedding training

- *Global* dataset = fusion of existing Arabic SA and newspaper corpora :
  - BRAD [Elnagar et al., 2018b] (510k book reviews).
  - HARD [Elnagar et al., 2018a](373K hotel reviews).
  - LABR [Mahmoud et al., 2014] (only train set composed of 23K book reviews).
  - AbuELkhair [El-Khair, 2016] (5222k news).
- Cleaning and normalisation of *Global* dataset.

Global	Lexical unit					
	Word	token	token\clitics	lemma	light stem	stem
Size	3000k	1980k	1555k	950k	1997k	280K

- Embedding dimension = 300 [Dahou et al., 2016, Soliman et al., 2017, Bojanowski et al., 2017]

Corpus LABR

- LABR corpus *Large-scale Arabic Book Reviews* [Mahmoud et al., 2014] : 63257 Arabic book reviews (rating scale from 1 to 5) :

LABR	*	**	***	****	*****	total
train	4 195	8 554	9 561	10 136	17 960	50 606
test	1 090	2 001	2 440	3 864	3 256	12 651

- Dataset construction in binary classification framework :
  - Negative reviews : 1 or 2 stars.
  - Positive reviews : 4 or 5 stars.
- Dataset repartition :
  - train set : 90% of considered train LABR
  - validation set : 10% of considered train LABR
  - test set : considered test LABR

Results

		CNN				BiLSTM			
Unit	**Emb.**	**A**	**P**	**R**	**F1**	**A**	**P**	**R**	**F1**
word	w2v	91.1	85.7	76.3	80.7	90.9	83.5	78.3	80.8
	ft	91.2	85.2	77.2	81	90.9	83.1	79	81
token	w2v	91.2	85.8	76.7	81	90.8	83.8	77.3	80.4
	ft	91.2	85.8	76.7	81	90.7	83.8	76.7	80.1
token\clitics	w2v	91.2	86.4	76.0	80.9	90.8	83.8	77.2	80.4
	ft	91.2	85.7	76.7	80.9	90.9	84.6	76.7	80.4
lemma	w2v	91.5	85.8	78	81.7	91	84.3	76.9	80.4
	ft	91.4	87	76.4	81.4	91	83.6	78.5	81
light stem	w2v	91.2	85.6	76.8	81	90.8	83	78	80.4
	ft	91.4	86.3	76.8	81.3	90.7	83.3	77.4	80.3
stem	w2v	89	81.2	69.8	75.1	89.3	80.2	73.9	76.9
	ft	88.8	81.3	69	74.6	89.1	79.9	73.4	76.5

Table – System evaluations with Arabic-specific embeddings (A = accuracy , P = precision, R = recall, F1 = F1 measure), where 1^{st} and 2^{nd} best performances.

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System combination

Combination protocols :

Oracle (ideal combination) and Consensus (agreement).

Unit embeddings	System prediction	Ref	Oracle	Consensus
All \ stem			✓	reject
			✗	✗
			✓	✓
2 best			✓	reject
			✓	✓
			✗	✗

System combination

Combination protocols :

Oracle (ideal combination) and Consensus (agreement).

		CNN		BiLSTM	
	Protocol	**Coverage**	**Accuracy**	**Coverage**	**Accuracy**
All \ stem	*Oracle*	100%	100%	100%	100%
	Consensus	86.57%	100%	81.70%	100%
2 Best	*Oracle*	100%	92.3%	100%	92.5%
	Consensus	98.25%	92.2%	96.96%	92.2%

2 Best CNN Combination frame : non-consensus analysis

- Number of non-consensus reviews = 146 reviews :
  - 68 positive (19 with 5* and 49 with 4*)
  - 78 negative (20 with 1* et 58 with 2*).

	Examples	
Mixed review	ÉJÔg ḤñÊƒB¡ áºË éKYJÊ®K ©J“¡ñÔÏ¡	Traditional topics but the style is beautiful.
	é®Jª“ H¡Yg¡ð øñ¯ ḤñÊƒ¡	Strong style and weak events
Author evaluation	€ÆJË¡ àñJªĶ ¡Q ¡» ù®¡JJË éĶÆJºË¡ ¼Q K à¡ à¡YKP úÎ« úÎ«	Aly Zaydan He has to leave writing to stay big with people's eyes
	¡ KÆ¾Ë¡ éÒJ¯ áÓ É Ê®K ‡JÊªK øA¯ ,‡JÊªK B	No comment, Any comment reduces the author value
Star number	á JÒ¡ ' ZA¢«ÆĶ ¡Yg éÔ§» I J» Y®Ë	I have been very generous giving two stars
	Ôæ®JE¡ ú¯ éÒ¡ ' I ’ ®K¡	lost one star in the evaluation

Conclusion

- Arabic sentiment analysis framework.
- Specificity of Arabic language : agglutination and morphological richness.
- 12 Arabic-specific embedding sets : *unit*_*Emb*, where
  - *unit* $\in \{\text{word, token, token}\backslash\text{clitics, lemma, light stem, stem}\}$
  - *Emb* $\in \{\text{w2v, ft}\}$.
- 2 neural systems : CNN-based and BiLSTM-based.

Conclusion

- Lemma $\approx$ the most appropriate lexical unit for Arabic SA.
- Best performance in this work = 91.5% of accuracy
- Accuracy of [Barhoumi et al., 2018] = 89.3%.
  - Choice of document length and padding/truncating type = + 1
  - Similar domain corpora for training embeddings = + 0.8
  - Lemma embeddings = + 0.4

  - Note that :
    - Size (word embedding space) = 3000k
    - Size (lemma embedding space) = 950k

Future works

- Evaluation of different Arabic-specific embeddings in other NLP tasks (POS tagging, NER, syntactic and semantic analogies).
- Sentiment embeddings [Yu et al., 2017].
- Contextualized embeddings ELMO [Peters et al., 2018].

Thank you for your attention :)

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