Enriching Word Representation Learning for Affect Detection and Affect-aware Recommendations

Nastaran Babanejad
Supervisor: Prof. Aijun An
Co-Supervisor: Prof. Manos Papagelis

Motivation (Affect Detection)

What is affect detection?

An analysis of affects (sentiment, emotion, feeling, opinion) in Natural Language Processing *(Strapparava and Mihalcea, 2006) ,(Munezero et al.,2014)* which includes:

- **Sentiment Analysis,**
- **Emotion Classification,**
- **Sarcasm Detection**

Affect detection in text has wide range of useful applications.

Motivation (Affect-Aware Recommendation)

Affect has been recognized as an essential factor that influences **users' behavior** and recognized as key factors in **decision making**.

Therefore, **bridging the gap** between affect detection approaches and recommendations can be beneficial to improve decision-making systems such as recommendation systems.

Limited number of works considering affective information in recommendations and investigate **whether**:

Improving affect detection approaches

Improve the performance of recommendations.

Challenges in Affect Detection

Emotion Detection

- Absence of emotion bearing keyword
- Words with multiple emotions

Sentiment Analysis

- Negation handling
- Words Context

Sarcasm Detection

- Deliberate ambiguity
- Opposite meaning words

Challenges Affect-Aware Recommendations

What type of affective information? (e.g. emotion, sentiment,..)

What affect detection approaches to use?

How to select and represent the extracted affective information?

Identify

Extract

Select

The most relevant affect-based features for use in recommendation models.

Research Problems

Problem 1: Can the use of **affective information** in text improve the performance of **recommendations**? If yes, **how** and to **what extent** can affective features improve the accuracy of recommendations?

Problem 2: What is the **effect** of integrating text **pre-processing** techniques earlier into **word embedding models**, instead of later on in downstream tasks, on the accuracy of affect detection? **Which pre-processing** techniques yield the most benefit in affective tasks?

Problem 3: Will **incorporating both affective and contextual** features deeply into text representations using a deep neural network architecture improve the performance of affect detection?

Problem 4: Can **improving the affect detection** approaches in text and enriching word representation learning **improve** the performance of **affect-aware recommendations**?

Major Contributions

Leveraging Emotion Features in Social Media Recommendations
(INRA & RecSys' 2019)

A Comprehensive Analysis of Pre-processing for Word Representation Learning in Affective Tasks
(ACL' 2020)

Customized Pre-processing for Word Representation Learning in Affective Tasks
(TAC' 2020), under review

Affective and Contextual Embedding for Affect Detection
(COLING' 2020)

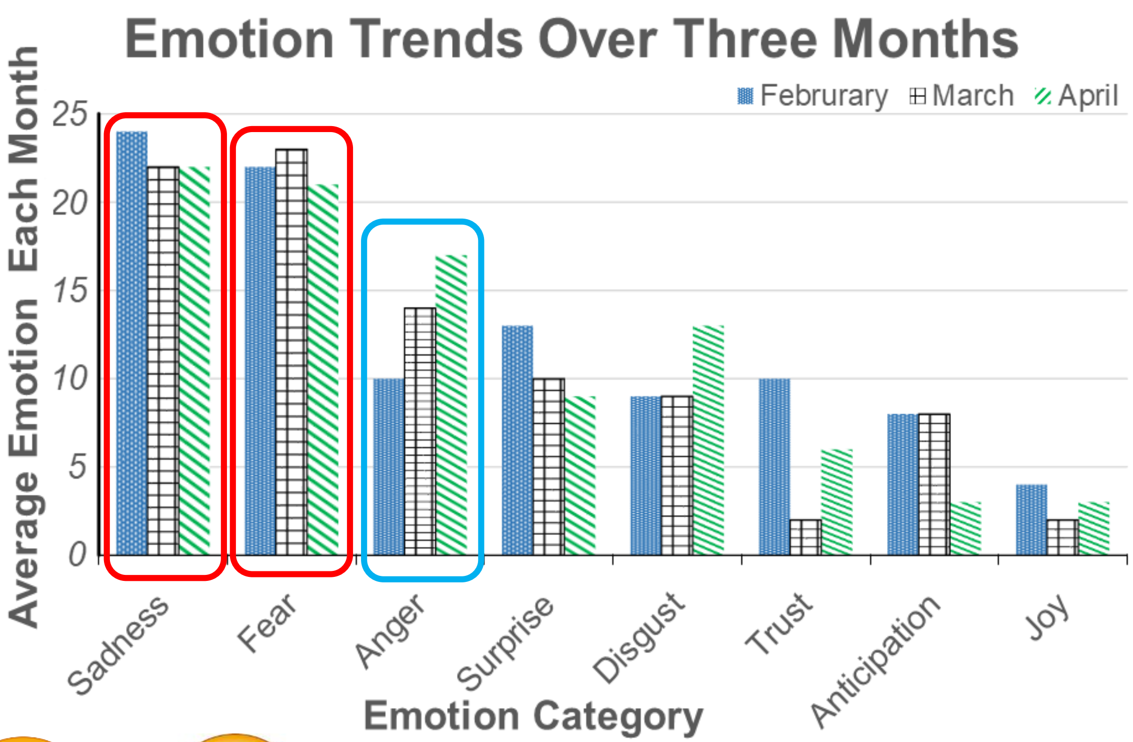
Affective and Contextual Embedding Model for Feature Representation Learning in Affect-Aware Recommendation

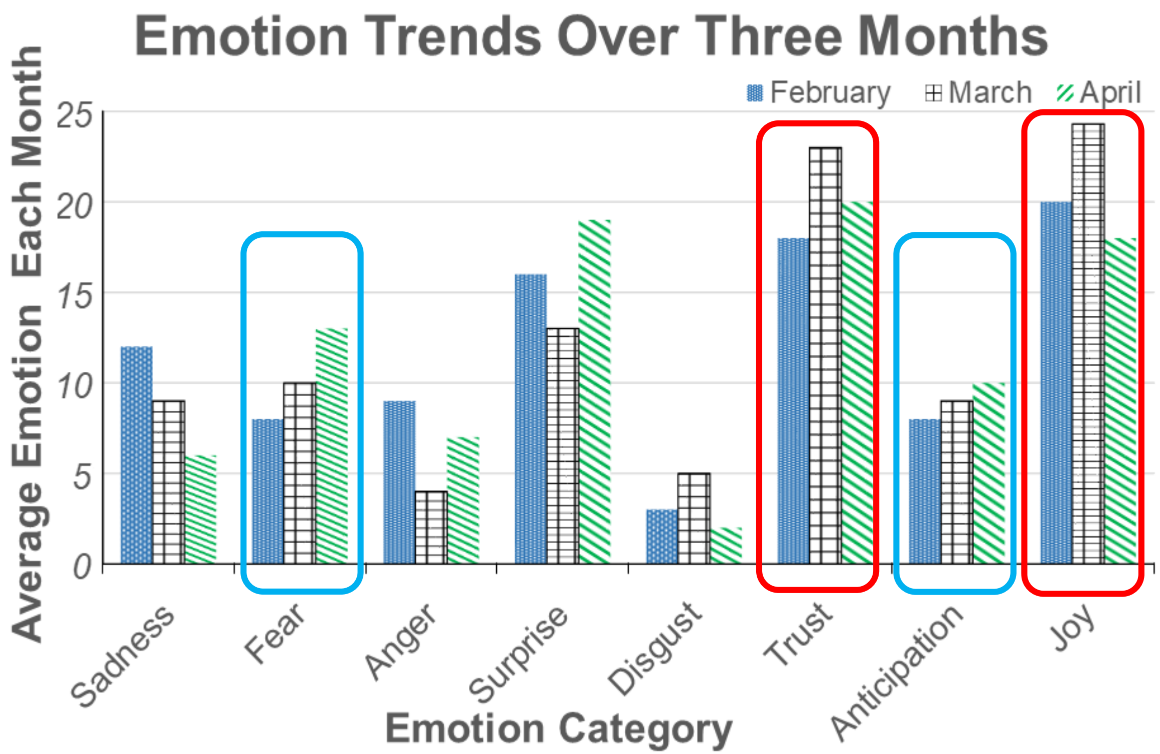
Leveraging Emotion Features in Social Media Recommendations

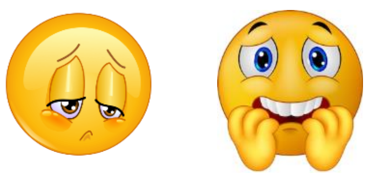
(INRA & RecSys 2019)

Motivation

Emotions expressed in articles read by two different users







(User 1)

(User 2)

Research Questions

The goal is to investigate **whether**, **how** and to **what extent** <u>*emotion features*</u> can improve the accuracy of recommendations.

Challenges

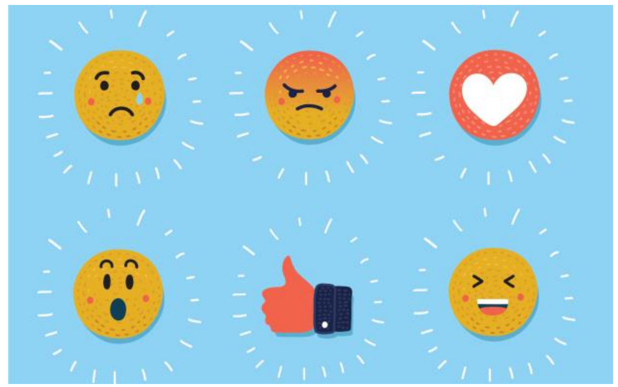
How to incorporate the emotional features to recommendation algorithms?

How to generate a number of emotion features attributed to both user and items?

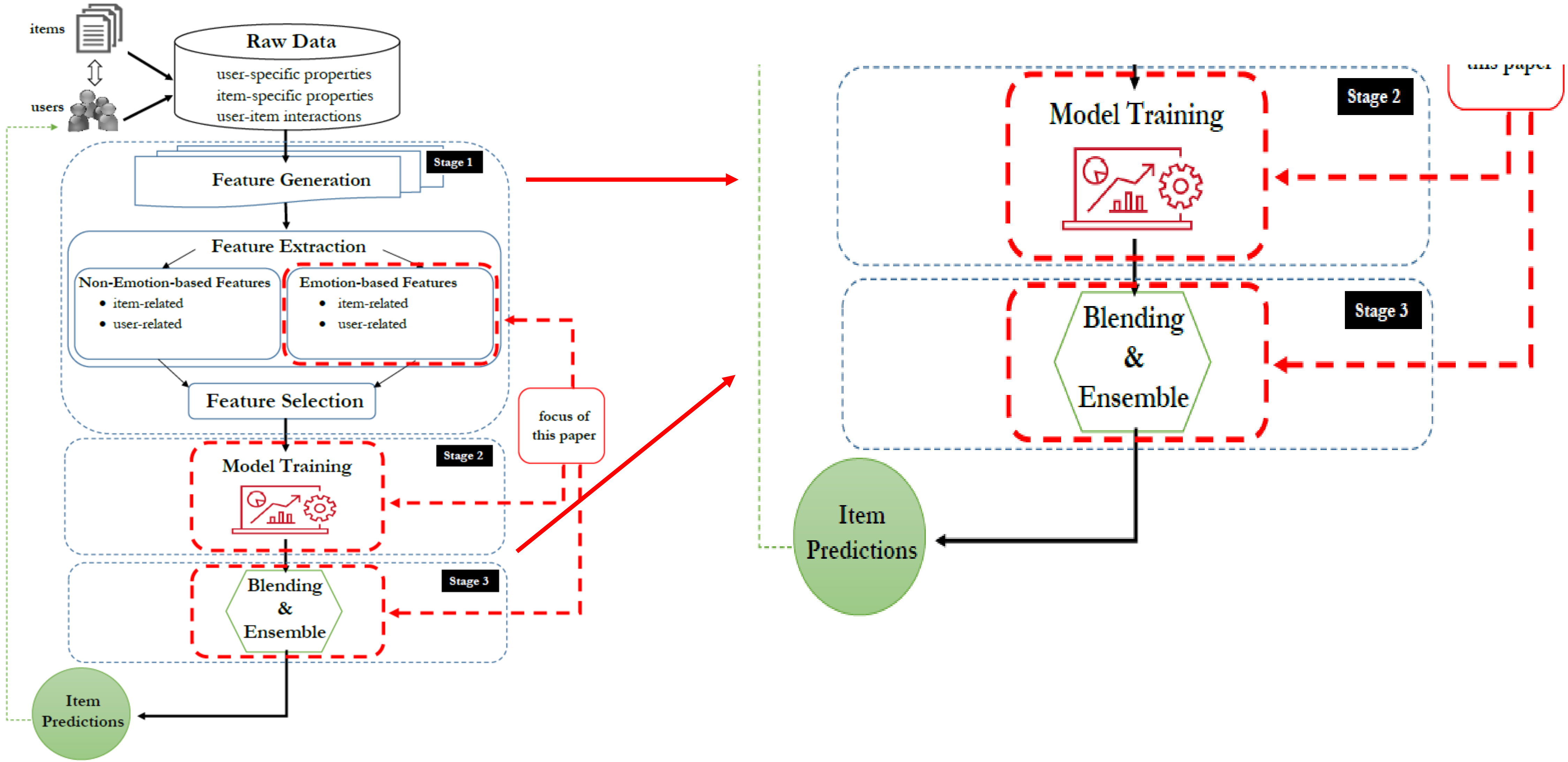
Which recommendation algorithm to choose to build the model?

Contributions

- **Identify**, **extract** and **select** the most relevant emotion-based features for use in recommendation models;
- State-of-the-art models for generating recommendations that **incorporate** the additional **emotion features**;
- **EMOREC**, an emotion-aware recommendation model;
- Experimental evaluation on real datasets coming from diverse domains (**news** and **music**).



Proposed Framework



Features

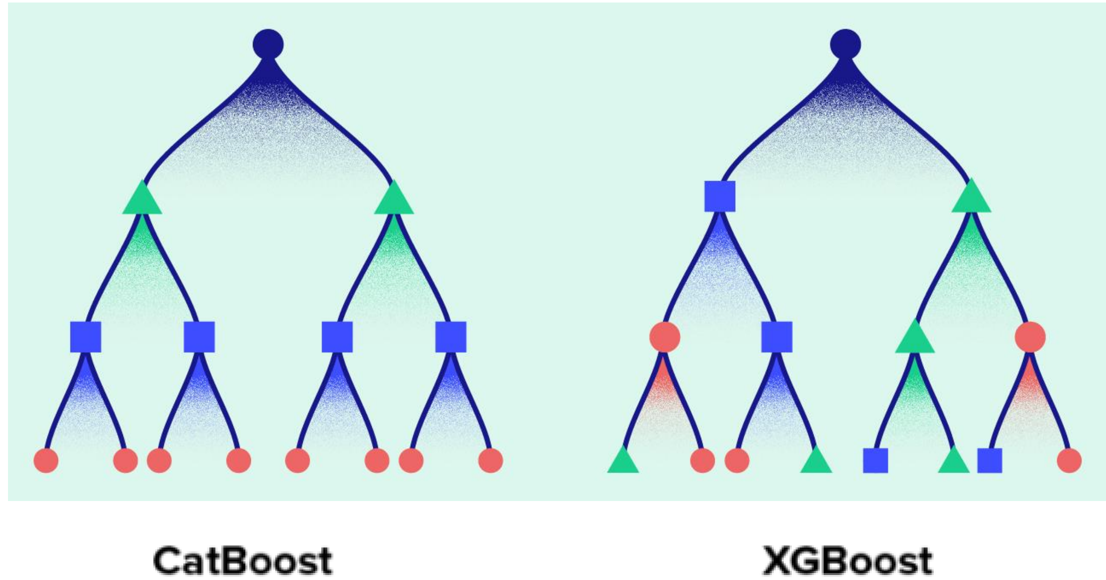
Emotion Features	Gain Score
Plutchik emotion scores	3200.86
User emotions across items	1985.36
User emotions across categories	1850.33
Ekman's emotion label	1101.38
Punctuation	910.55
Grammatical markers and extended words	860.13
Interjections	773.12
Capitalized words	640.21
Mixed emotions	526.97
Sentiment features	360.68

Non-emotion Features	Gain Score
User latent vector	3640.87
Potential to trigger subscription	2974.46
User interest in subcategory	1530.28
Topic labeling	1421.19
User spent time	1110.57
Visit count	920.53
Item topic	867.12
Coherence	685.23
TF-IDF	410.29

Proposed Models

Model 1 (Boost Model)

We train two state-of-the-art GBDT models, namely, XGBoost and Catboost.

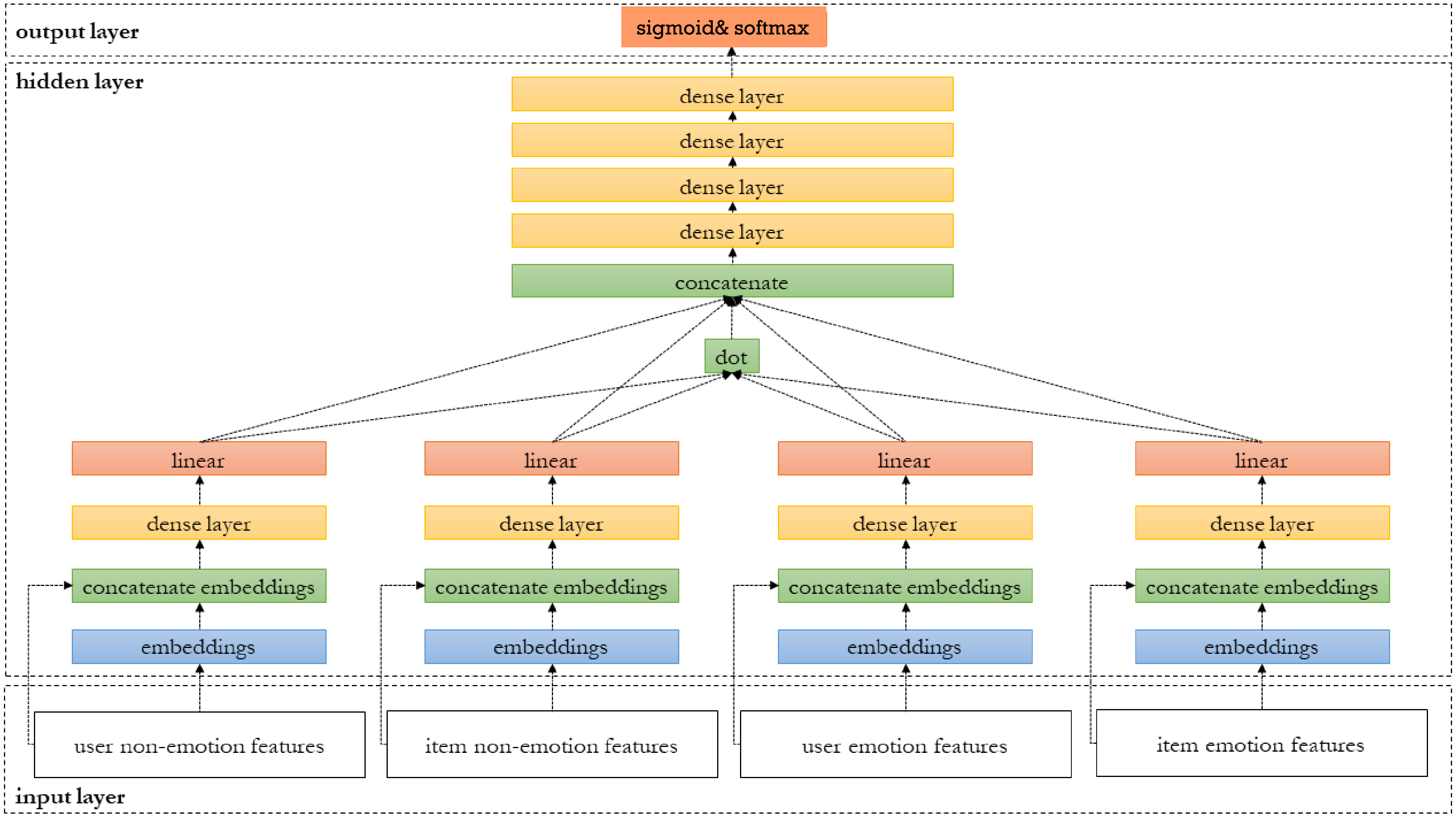


The final model output:

$$\sum_{i}^{6} \alpha_i p_i$$

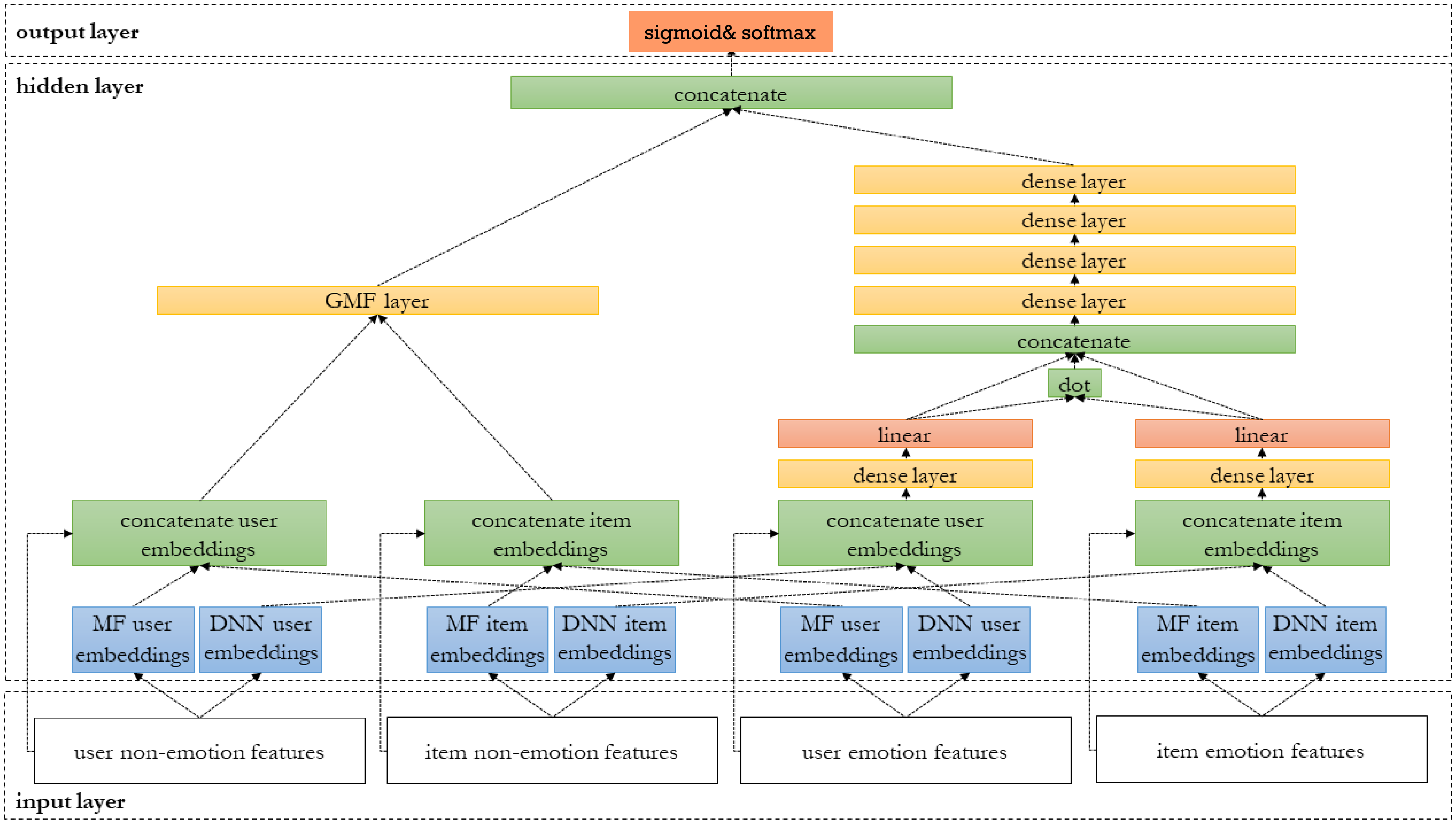
Proposed Models

Model 2 (Deep Neural Network (DNN))



Proposed Models

Model 3 (Deep Matrix Factorization (Deep MF))



Results

Comparing Recommendation Models with and without Emotion Features

Model	Non-Emo	All
Single Boost Model	70.19	70.86
Boost Blend	70.69	71.50
Deep MF	72.93	73.29
Single DNN Model	70.88	73.00
DNN Ensemble	73.62	74.30
Boost Blend + Deep MF	73.07	74.98
Boost Blend + DNN Ensemble	74.00	74.23
Deep MF + DNN Ensemble	74.61	75.10
EMOREC (Boost Blend + Deep MF + DNN Ensemble)	78.20	**80.30**

Results of our Models on **News** Dataset (F-score)

Model	Non-Emo	All
Single Boost Model	67.79	70.13
Boost Blend	71.08	70.61
Deep MF	70.00	71.00
Single DNN Model	71.30	72.29
DNN Ensemble	71.64	74.81
Boost Blend + Deep MF	70.00	70.03
Boost Blend + DNN Ensemble	72.01	74.87
Deep MF + DNN Ensemble	73.18	74.90
EMOREC (Boost Blend + Deep MF + DNN Ensemble)	73.68	**76.06**

Results of our Models on **Music** Dataset (F-score)

Results

Comparison with Other Baselines

Model	Non-Emo	All
Basic MF	69.10	71.23
FDEN and GBDT	72.02	73.28
Truncated SVD-based Feature Engineering	73.12	74.01
EMOREC	78.20	**80.30**

Comparison of EMOREC with State-of-the-art Baselines on **News** Dataset (F-score)

Model	Non-Emo	All
Basic MF	69.10	71.23
FDEN and GBDT	70.52	71.20
Truncated SVD-based Feature Engineering	71.98	72.54
EMOREC	73.68	**76.06**

Comparison of EMOREC with State-of-the-art Baselines on **Music** Dataset (F-score)

Results

Effect of Individual Emotion Features

Emotion Features	News	Music
ALL emotion features	80.30	77.03
- Sentiment features	78.15	76.66
- Mixed emotions	76.90	75.49
- Capitalized words	76.21	75.30
- Interjections	75.84	75.00
- Grammatical markers and extended words	75.23	74.94
- Ekman's emotion label	74.98	72.28
- Punctuation	75.17	73.10
- User emotions across categories	74.15	71.69
- User emotions across items	73.23	71.33
- Plutchik emotion scores	72.10	69.28

Results

Effect of Top Three Emotion Features
(*Plutchik emotions*, *User emotions across categories*, and *User emotions across items*) on State-of-the-art Models

Model	No Emotion	Top Three Emotion
Basic MF	69.10	70.38
Boost Blend	70.69	71.00
FDEN and GBDT	72.02	72.77
Deep MF	72.93	73.01
Truncated SVD-based	73.12	73.60
DNN Ensemble	73.62	73.98

A Comprehensive Analysis of Pre-processing for Word Representation Learning in Affective Tasks

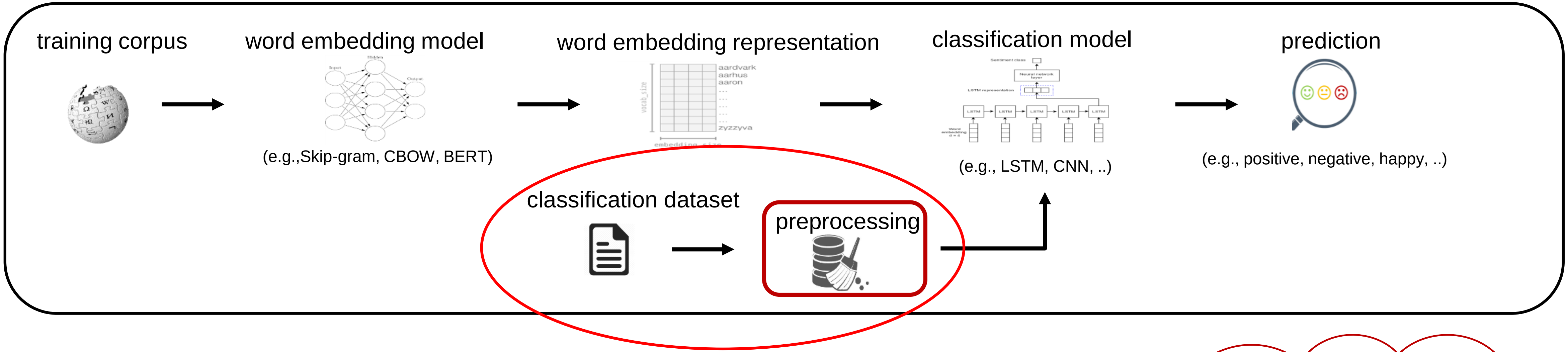
(ACL 2020)

Word Embedding in Affective Tasks

Previous models of affect analysis employed pre-trained word embeddings *(Turian et al., 2010, Joshi et al., 2016)*:

- Fine-tune *(Devlin et al.,2018)*
- Retrofitting *(Faruqui et al., 2014)*
- Generating affective word embeddings *(Felbo et al.,2017)*
- Pre-processing *(Danisman andAlpkocak, 2008; Patil and Patil, 2013)*

Motivation (Previous Workflow)



Text Preprocessing was done on

- *downstream classification datasets*
- *not the embedding-training corpus*

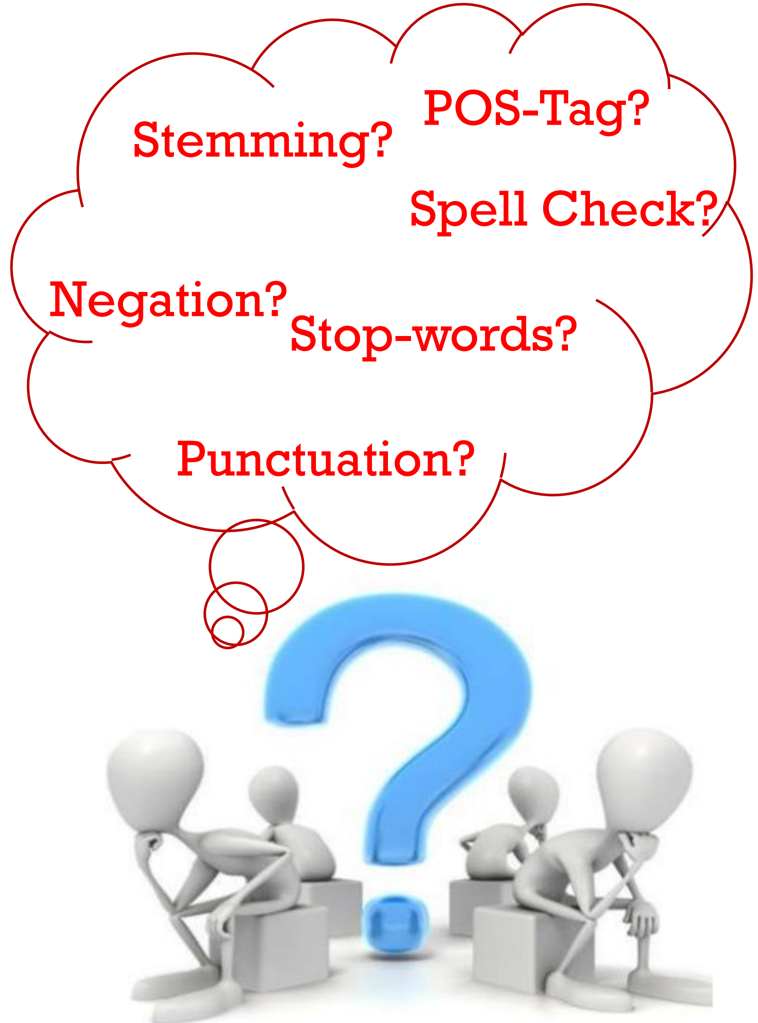
POS-Tag
Stemming
Spell Check
Negation
Stop-words
Punctuation

Research Questions

(Q1) What would be the impact of *pre-processing* on *embedding-training phase*?

(Q2) Which pre-processing yields the most benefit?

(Q3) Which affective task benefits the most?

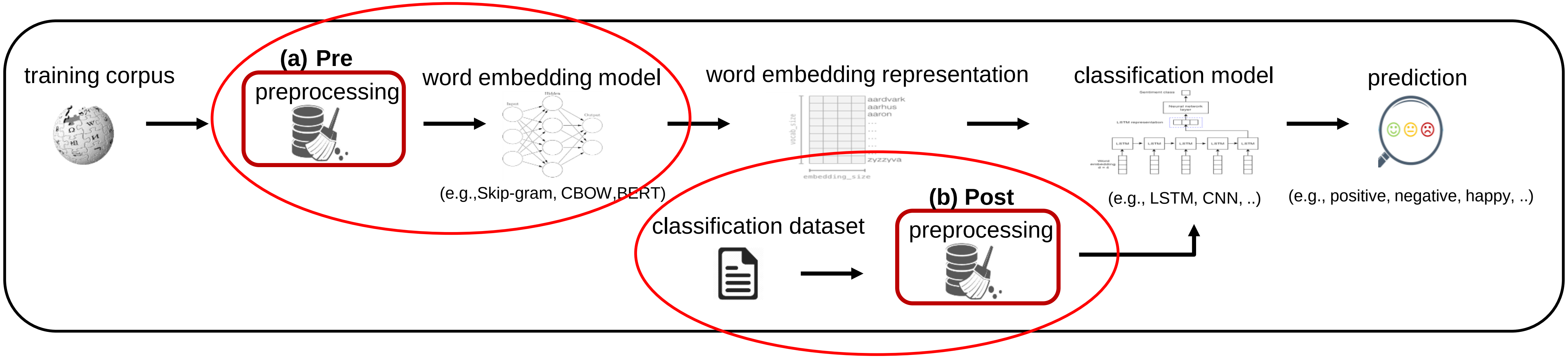


Contributions

- The **role of pre-processing** techniques in affective tasks including **sentiment analysis**, **emotion classification** and **sarcasm detection**;
- The accuracy performance of word vector models when pre-processing is applied at the **embedding-training phase** (training corpora) and/or at the **downstream task phase** (classification dataset);
- The performance of **our best pre-processed** word vector model against **state-of-the-art** pre-trained word embedding models;
- Source Code at: *https://github.com/NastaranBa/preprocessing-for-word-representation.*

Proposed Framework

Applying text preprocessing in different stages in affective systems



(a) Pre: Applying at Embedding-training Phase

(b) Post: Applying at Downstream Task

Pre-processing Factors

Punctuation Removal:

Dear Sam do you really Love   me

Spell checking Correction:

Typing *langage* when you meant *language*

Negation Handler:

This act is not legal

This act is illegal

POS-Tag: nouns, verbs, adjectives and adverbs

Daniel always talks loud in the classroom

Stop-words Removal:

Nick likes to play football, he is a good player

Stemming:

He waits/waited/is waiting at the bus stop

He wait at the bus stop

Experiments

Training Corpora: News, Wikipedia

Word Embedding Models:

i) Word2Vec (CBOW)

ii) Word2Vec (Skip-gram)

iii) BERT (Feature-based)

(All three models are trained from scratch)

Nine Classification Datasets

Classification Setup with LSTM:

i) Binary-Cross entropy (Sigmoid)

$$\xi = -\frac{1}{N}\sum_{i=1}^{N} y_i log(p(y_i)) + (1-y_i) log(1-p(y_i))$$

ii) Categorical-Cross entropy (Softmax)

$$\xi = -\frac{1}{N}\sum_{i=1}^{N}\sum_{j=1}^{k} y_{ij} log\left(p(y_{ij})\right)$$

Results

CBOW and Skip-gram on *News* training corpus

Models	Processing	IMDB	Semeval	Airline	IAC	Onion	Reddit	Alm	ISEAR	SSEC
CBOW	Basic	83.99	55.69	60.73	65.74	68.23	59.42	36.81	55.43	51.76
	`stop`	84.43	55.72	61.37	66.03	68.17	59.27	36.81	56.01	52.33
	`spell`	86.20	55.93	61.96	66.00	69.57	60.00	36.88	56.41	52.14
	`stem`	86.92	55.72	61.86	65.89	68.49	59.72	36.94	55.84	51.89
	`punc`	86.99	56.41	62.08	65.93	69.85	60.28	36.94	56.89	52.03
	`pos`	85.66	56.83	62.75	66.32	70.25	60.63	37.02	57.04	53.19
	`neg`	88.98	57.29	63.81	66.87	71.12	60.91	37.22	57.39	54.15
	All	89.96	57.82	64.58	67.23	70.90	60.84	37.43	57.72	53.71
	All - `neg`	84.67	55.00	61.58	66.02	69.73	59.94	36.91	55.89	51.94
	All - `pos`	85.69	56.31	64.29	66.97	70.48	60.15	37.19	56.27	52.16
	All - `punc`	86.41	56.88	63.01	66.75	70.01	60.00	37.01	57.19	52.43
	All - `spell`	88.23	56.41	63.87	67.23	70.83	60.27	37.22	57.41	53.41
	All - `stop`	**90.01**	**60.82**	66.84	67.20	**72.49**	**62.11**	**38.96**	**59.28**	55.00
	All - `stem`	88.12	**60.82**	**67.12**	**69.25**	72.13	61.73	38.00	59.00	**55.42**
Skip-gram	Basic	83.07	54.23	61.47	65.51	68.01	59.75	35.87	55.64	51.49
	`stop`	83.23	55.47	62.00	65.62	68.00	59.84	35.94	55.76	51.62
	`spell`	85.90	55.48	62.00	65.61	69.76	60.28	36.10	55.93	52.30
	`stem`	86.00	55.33	61.89	65.60	68.72	59.50	36.00	55.69	51.40
	`punc`	86.68	55.79	62.38	65.89	70.00	60.44	36.41	56.81	52.71
	`pos`	85.91	56.28	63.25	66.24	69.81	60.85	36.44	56.23	52.94
	`neg`	87.28	56.89	63.72	66.87	70.59	61.27	36.87	57.34	53.10
	All	88.36	57.04	64.91	66.94	70.73	61.12	37.10	57.92	53.58
	All - `neg`	83.26	54.00	61.95	66.00	69.88	60.00	36.94	55.97	51.89
	All - `pos`	86.21	55.22	65.12	66.06	69.88	61.00	37.00	56.42	52.10
	All - `punc`	85.57	55.99	64.29	66.29	70.00	60.98	37.01	57.02	52.53
	All - `spell`	86.00	56.98	65.00	66.25	70.25	0.61	37.04	57.69	52.86
	All - `stop`	**88.74**	**60.93**	67.00	68.57	**72.20**	62.02	**38.92**	59.18	55.18
	All - `stem`	88.42	60.67	**67.39**	**69.08**	72.00	**62.36**	37.44	**59.48**	**55.23**

Results

Different models on ***Wikipedia*** training corpus

Models	Processing	IMDB	Semeval	Airline	IAC	Onion	Reddit	Alm	ISEAR	SSEC
CBOW	Basic	84.91	56.89	68.11	69.15	71.02	63.58	45.22	59.73	55.84
	All	88.41	60.25	71.39	71.57	73.61	65.27	48.81	62.48	57.42
	All - `neg`	83.02	56.03	69.28	69.55	70.25	64.18	46.00	60.42	55.93
	All - `pos`	85.69	57.21	71.00	70.08	72.29	64.82	47.53	62.28	56.25
	All - `punc`	84.00	57.36	70.46	70.01	72.02	65.00	47.68	61.84	56.64
	All - `spell`	86.19	58.26	70.98	70.59	72.85	65.00	47.29	61.63	57.00
	All - `stop`	**91.10**	61.00	73.00	72.31	74.50	68.20	**52.39**	64.29	58.46
	All - `stem`	88.76	**62.19**	**73.25**	**72.36**	**75.69**	**68.53**	50.28	**65.33**	**59.28**
Skip-gram	Basic	84.00	55.94	68.36	69.20	71.68	63.74	45.01	59.45	55.62
	All	87.00	59.99	71.29	71.25	73.82	65.67	48.51	**65.02**	57.13
	All - `neg`	84.97	56.11	69.00	70.17	70.04	64.55	46.28	60.54	55.86
	All - `pos`	86.21	57.62	70.25	70.85	73.22	65.47	47.49	63.44	56.00
	All - `punc`	85.00	57.20	70.00	70.77	72.00	65.00	47.10	61.72	56.49
	All - `spell`	85.75	58.49	70.26	70.89	72.63	65.18	47.14	61.25	56.84
	All - `stop`	**89.76**	**61.74**	72.19	**72.00**	**75.69**	68.29	**52.01**	64.00	58.14
	All - `stem`	89.66	60.28	**73.66**	71.98	75.24	**68.72**	51.39	63.44	**59.01**
BERT	Basic	90.11	70.82	90.23	71.19	76.30	59.74	57.81	65.70	65.39
	All	91.86	71.76	91.73	73.66	78.72	62.60	59.74	67.80	67.49
	All - `neg`	90.33	70.52	91.04	72.00	77.07	61.44	58.14	66.59	66.10
	All - `pos`	91.01	71.20	91.66	73.31	78.45	62.04	59.01	66.25	68.13
	All - `punc`	91.59	71.50	91.60	73.18	78.54	62.27	59.60	67.25	67.27
	All - `spell`	91.78	71.13	91.34	73.02	78.40	62.00	59.44	67.21	67.30
	All - `stop`	**94.18**	**73.81**	**94.85**	**75.80**	**79.10**	**65.39**	**60.73**	**69.33**	**69.81**
	All - `stem`	92.19	71.94	92.03	74.49	77.93	63.74	60.16	68.00	67.05

Results

The effect of pre-processing word embeddings *training corpus* vs. pre-processing *classification datasets*

Models	Processing	IMDB	Semeval	Airline	IAC	Onion	Reddit	Alm	ISEAR	SSEC
CBOW	Post	87.49	59.33	71.28	69.87	74.20	67.13	47.19	62.00	56.27
	Pre	**88.76**	62.19	**73.25**	**72.36**	**75.69**	68.53	50.28	**65.33**	*59.28*
	Both	88.10	**62.41**	73.00	71.86	75.00	**70.10**	**50.39**	64.52	58.20
Skip-gram	Post	88.14	60.41	71.85	70.22	75.07	67.00	50.44	62.08	56.00
	Pre	**89.76**	**61.74**	72.19	**72.00**	**75.69**	68.29	**52.01**	64.00	**58.14**
	Both	89.33	61.25	**73.58**	71.62	75.48	**68.74**	51.68	**65.29**	58.03
BERT	Post	94.58	70.25	92.35	74.69	77.10	63.38	58.40	68.20	67.17
	Pre	94.18	**73.81**	**94.85**	**75.80**	**79.10**	**65.39**	**60.73**	**69.33**	**69.81**
	Both	**94.63**	72.41	93.00	75.19	78.69	65.17	60.33	69.06	68.43

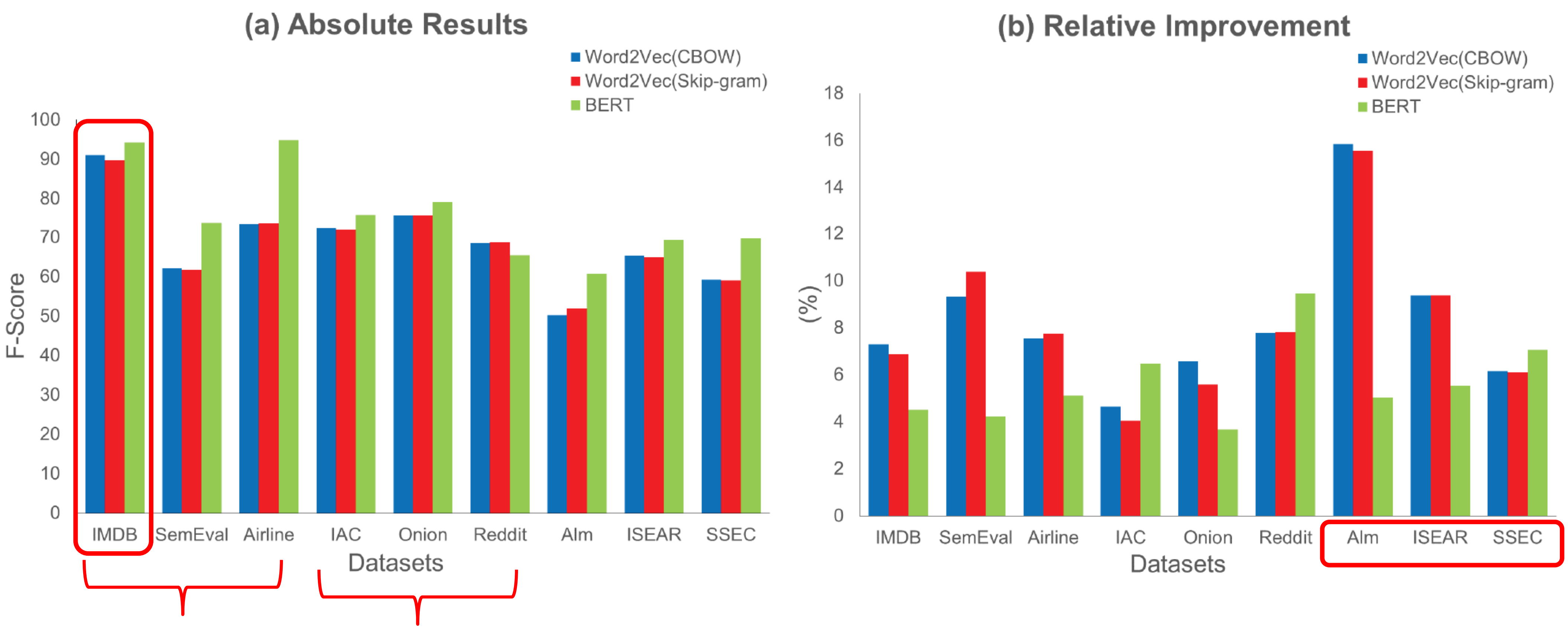
Results

Comparing against ***state-of-the-art*** word embeddings

Models	IMDB	Semeval	Airline	IAC	Onion	Reddit	Alm	ISEAR	SSEC
GloVe	85.64	<u>70.29</u>	70.21	70.19	71.39	63.57	56.21	65.30	58.40
SSWE	80.45	69.27	<u>78.29</u>	64.85	52.74	50.73	51.00	54.71	52.18
FastText	75.26	68.55	70.69	55.74	58.29	59.37	52.28	25.40	53.20
DeepMoji	69.79	62.10	71.03	65.67	70.90	53.08	46.33	58.20	58.90
EWE	71.28	60.27	67.81	67.43	70.06	55.02	<u>58.33</u>	<u>66.09</u>	58.94
Our best results:									
CBOW	<u>91.10</u>	62.19	73.25	<u>72.36</u>	<u>75.69</u>	68.53	52.39	65.33	<u>59.28</u>
Skip-gram	89.76	61.74	73.66	72.00	75.69	**68.72**	52.01	65.02	59.01
BERT	**94.18**	**73.81**	**94.85**	**75.80**	**79.10**	<u>65.39</u>	**60.73**	**69.33**	**69.81**

Results

Analyzing the Three Affective Tasks

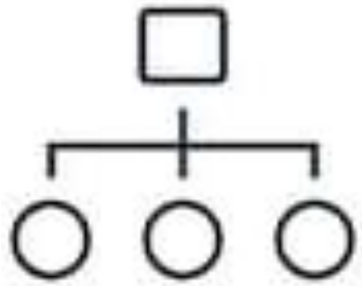


Customized Pre-processing for Word Representation Learning in Affective Tasks

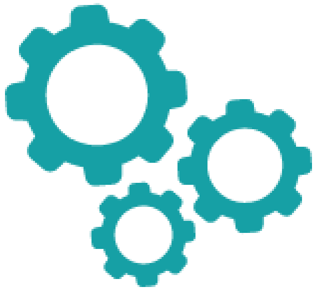
(TAC 2020), under review

Motivation

Stop-words Removal/ Stemming



Classification Dataset (Downstream)



Training Word Embedding Stage (upstream)

Research Questions

(Q1) What pre-processing combination(s) is (are) **best suited** for each affective task?

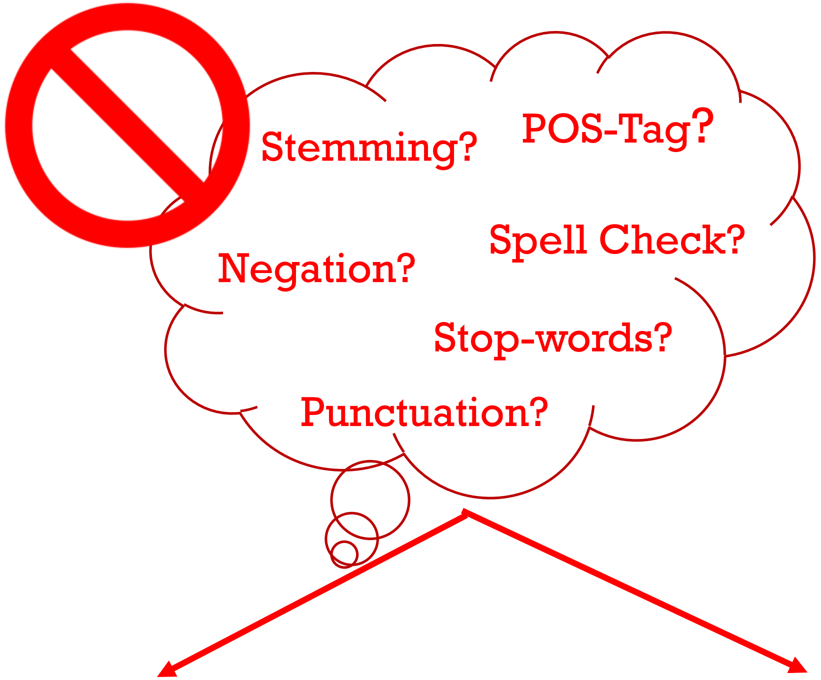
(Q2) Which **combination** of pre-processing techniques is more suitable when they applied on **Downstream tasks** and which for **embedding-training phase**?

(Q3) **Customized pre-processing** or **General pre-processing** of word embeddings and downstream tasks are more beneficial?

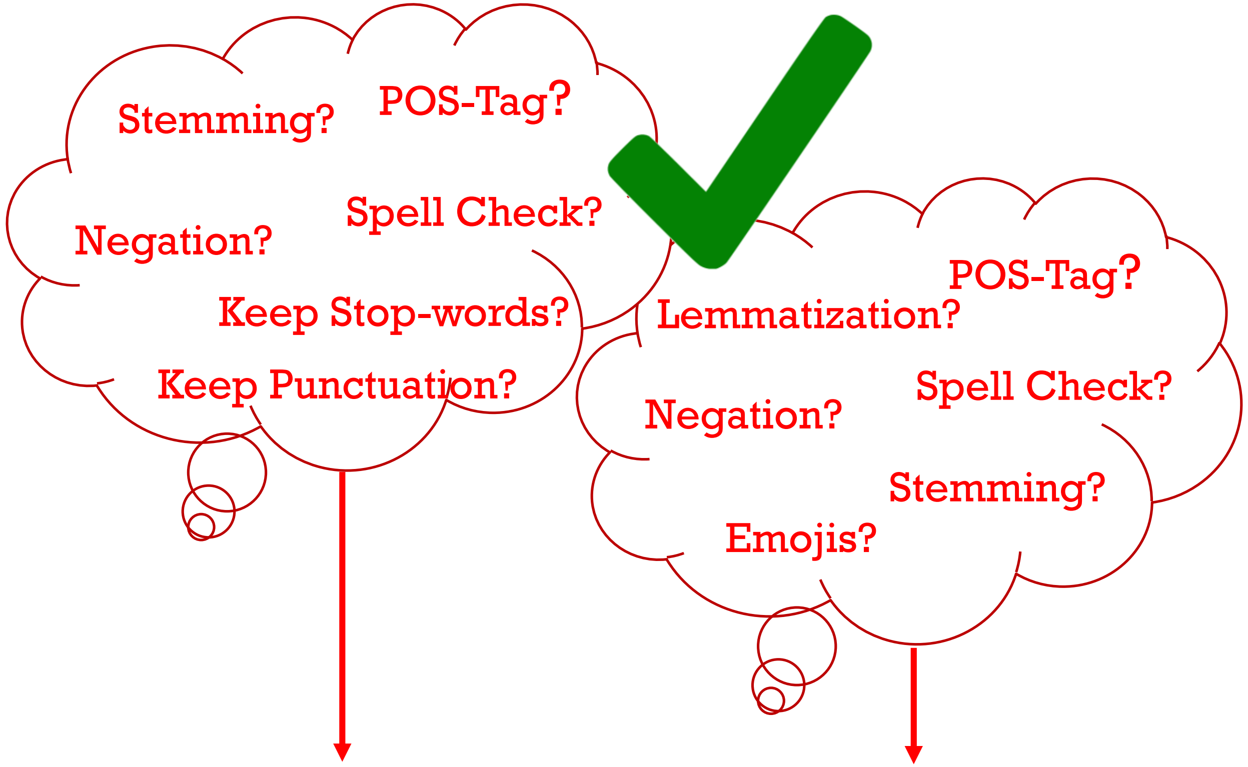
Contributions

- The role of **customized pre-processing** for word representation learning for **each affective tasks**.
- Their major effects on the performance when they applied in **different stages** of word embedding in affective analysis.
- A comparative study of the accuracy performance of **general pre-processing** against **customized pre-processing**

Previous Framework Vs Proposed Framework



Pre: At Embedding-training Phase **Post**: At Downstream Task



Pre: At Embedding-training Phase **Post**: At Downstream Task

Customized Pre-processing in Affective Tasks

Affective Task	Pre-Processing	Example
Sentiment Analysis	Negation Correction	*I won't walk again. → I will not walk again.*
	Negation	*I feel not good. → I feel bad.*
	Intensifiers	*This work is extremely hard.*
	Interjections	*Wow, Is this your house?.*
Sarcasm Detection	Emoticons	*Awesome failure!*
	Keeping Punctuation	*Time for you medication or mine ??!!*
	Intensifiers	*Sarcasm detection is too easy!*
	Interjections	*Oh, I'm nicer in sleep.*
Emotion Detection	Emoticons	*Are you serious now??*
	Keeping Punctuation	*We are not friends anymore???!!!*
	Interjections	*Yay! We are going out tonight.*
	Intensifiers	*This is the best experience I've ever had.*

Customized Pre-processing Training Corpora

Keeping Punctuation

Keeping stop words

Spell checking Correction:

Typing *langage* when you meant *language*

Negation Handler:

This act is not legal

This act is illegal

POS-Tag: nouns, verbs, adjectives, adverbs and interjections.

Wow, Daniel always talks loud in the classroom

Emoticons (Emojis): Convert graphical emoticons into text.

 → happy face

Customized Pre-processing Classification Dataset

Sentiment Analysis:

Negation Handling

POS-Tag

Remove Punctuation

Spell Correction

Customized Stop-Words

Stemming

Sarcasm Detection:

Negation Handling

POS-Tag

Keep Punctuation

Spell Correction

Keeping Stop-Words

Stemming

Lemmatization

Emojis

Emotion Detection:

Negation Handling

POS-Tag

Keep Punctuation

Spell Correction

Keeping Stop-Words

Stemming

Lemmatization

Emojis

Experiments

Word Embedding Models:

i) FastText (CBOW)

ii) FastText (Skip-gram)

iii) GloVe

iv) ELMo

(All four models are trained from scratch)

Classification Setup with LSTM:

i) Binary-Cross entropy (Sigmoid)

$$\xi = -\frac{1}{N}\sum_{i=1}^{N} y_i log(p(y_i)) + (1-y_i) log(1-p(y_i))$$

ii) Categorical-Cross entropy (Softmax)

$$\xi = -\frac{1}{N}\sum_{i=1}^{N}\sum_{j=1}^{k} y_{ij} log\left(p(y_{ij})\right)$$

Results

Effects of General Combination of Pre-processing Factors (F-score)

Training Corpus	Processing	IMDB	Semeval	Airline	IAC	Onion	Reddit	Alm	ISEAR	SSEC
FastText(CBOW)	Basic	74.68	68.20	70.29	57.83	60.50	60.13	48.29	26.07	51.47
	All	77.12	69.86	71.69	60.69	63.39	63.07	50.77	28.42	53.89
	All - `neg`	75.01	68.90	70.83	58.81	61.25	61.74	49.21	27.89	52.04
	All - `pos`	78.51	69.17	70.26	60.57	61.94	62.29	49.86	28.06	52.71
	All - `punc`	76.92	69.37	71.14	60.19	62.71	62.78	50.44	28.30	53.65
	All - `spell`	76.85	69.73	71.00	59.90	62.18	62.41	50.04	28.00	53.65
	All - `stop`	**80.37**	**71.08**	72.39	**62.74**	64.79	64.33	**53.37**	30.24	55.28
	All - `stem`	79.45	70.10	**73.06**	61.83	**65.48**	**65.51**	52.19	**30.61**	**55.74**
FastText(Skip-gram)	Basic	75.00	68.41	70.41	58.13	61.12	60.72	49.13	26.68	52.07
	All	78.30	69.73	71.65	61.52	64.57	63.61	51.03	28.76	54.21
	All - `neg`	75.86	68.59	70.75	59.33	62.03	61.58	50.00	28.04	52.84
	All - `pos`	79.24	70.33	71.00	60.00	63.08	62.11	50.41	29.47	53.07
	All - `punc`	78.01	69.51	71.10	60.94	64.00	62.84	50.94	28.01	53.67
	All - `spell`	77.90	69.50	71.25	61.11	64.27	63.02	50.79	28.63	53.91
	All - `stop`	**81.83**	**71.30**	**73.29**	62.81	**66.12**	65.71	**53.69**	**30.48**	**56.32**
	All - `stem`	80.82	70.82	72.61	**63.28**	65.75	**66.24**	52.76	30.07	56.15

Results

Effects of General Combination of Pre-processing Factors (F-score)

Training Corpus	Processing	IMDB	Semeval	Airline	IAC	Onion	Reddit	Alm	ISEAR	SSEC
GloVe	Basic	83.51	69.12	70.01	69.48	70.21	62.76	54.31	64.77	56.33
	All	**87.32**	**73.22**	**74.39**	**73.14**	**74.19**	**67.29**	58.51	**67.34**	**59.70**
	All - `neg`	84.06	70.09	71.37	71.15	71.39	63.24	55.10	65.31	57.63
	All - `pos`	85.33	72.76	72.19	72.35	72.06	65.07	56.33	62.82	58.12
	All - `punc`	86.72	71.47	72.77	72.62	73.95	65.88	57.90	66.74	59.37
	All - `spell`	86.48	71.28	73.61	72.69	73.70	65.79	58.04	66.70	58.42
	All - `stop`	86.39	72.84	73.64	72.84	73.67	66.19	57.61	67.13	59.10
	All - `stem`	86.25	73.00	73.41	72.33	73.61	66.25	**58.93**	66.05	59.33
ELMo	Basic	86.34	69.47	82.11	70.18	71.65	65.48	60.24	65.00	66.20
	All	88.63	71.80	83.91	72.61	73.30	66.93	63.20	67.58	69.45
	All - `neg`	87.00	70.21	82.79	71.58	72.00	66.10	61.06	66.10	67.24
	All - `pos`	87.64	70.68	83.00	72.00	72.49	66.47	61.70	65.72	67.81
	All - `punc`	88.41	71.67	83.27	72.40	73.17	66.71	62.47	67.00	68.73
	All - `spell`	88.23	71.55	83.16	72.33	73.09	66.50	62.59	67.11	68.10
	All - `stop`	**90.27**	**73.54**	**85.61**	**74.04**	**74.45**	**68.74**	64.17	**69.28**	**71.01**
	All - `stem`	89.45	72.30	85.02	73.10	74.20	67.59	**64.78**	68.52	70.33

Results

Evaluating the Effect of General Pre-processing Word Embeddings Training Corpus vs. General Pre-processing Evaluation Datasets (F-score)

Training Corpus	Processing	IMDB	Semeval	Airline	IAC	Onion	Reddit	Alm	ISEAR	SSEC
FastText(CBOW)	Pre	79.45	70.10	**73.06**	**61.83**	**65.48**	**65.51**	52.19	30.61	**55.74**
	Post	76.48	69.25	70.15	57.38	62.48	63.71	51.47	29.35	53.84
	Both	**79.72**	**70.54**	72.26	61.00	65.27	65.20	**52.36**	**30.65**	55.49
FastText(Skip-gram)	Pre	**81.83**	**71.30**	**73.29**	62.81	66.12	**65.71**	**53.69**	**30.48**	**56.32**
	Post	80.01	70.16	71.40	58.70	64.22	63.76	51.49	29.74	54.38
	Both	80.52	70.40	72.58	**63.02**	**66.57**	65.00	53.18	30.24	55.29
GloVe	Pre	**87.32**	**73.22**	**74.39**	**73.14**	**74.19**	67.29	58.51	**67.34**	**59.70**
	Post	86.37	71.20	72.30	72.15	72.47	65.73	57.19	66.31	58.64
	Both	87.00	72.48	74.18	73.01	73.61	**67.32**	**58.66**	67.29	59.14
ELMo	Pre	**90.27**	**73.54**	**85.61**	**74.04**	**74.45**	**68.74**	64.17	**69.28**	**71.01**
	Post	88.13	71.76	83.10	72.28	73.55	66.79	63.80	68.20	70.18
	Both	90.14	72.57	85.00	73.61	74.20	68.07	**64.39**	68.79	70.83

Results

Effects of Customized Pre-processing Factors for Each Affective Task

Training Corpus	Processing	IMDB	Semeval	Airline	IAC	Onion	Reddit	Alm	ISEAR	SSEC
Word2Vec(CBOW)	All	88.41	60.25	71.39	71.57	73.61	65.27	48.81	62.48	57.42
	All - stem	88.76	62.19	73.25	72.36	75.69	68.53	50.28	65.33	59.28
	c-pre	**90.67**	**62.74**	**74.33**	**73.08**	**76.52**	**69.15**	**53.18**	**66.19**	**60.51**
Word2Vec(Skip-gram)	All	87.00	59.99	71.29	71.25	73.82	65.67	48.51	**65.02**	57.13
	All - stop	89.76	61.74	72.19	72.00	75.69	68.29	52.01	64.00	58.14
	c-pre	**89.91**	**62.73**	**73.69**	**72.85**	**76.31**	**69.24**	**52.84**	64.80	**59.28**
FastText(CBOW)	All	77.12	69.86	71.69	60.69	63.39	63.07	50.77	28.42	53.89
	All - stem	79.45	70.10	73.06	61.83	65.48	65.51	52.19	30.61	55.74
	c-pre	**80.71**	**71.90**	**73.70**	**63.17**	**66.24**	**66.71**	**53.00**	**33.25**	**56.49**
FastText(Skip-gram)	All	78.30	69.73	71.65	61.52	64.57	63.61	51.03	28.76	54.21
	All - stop	81.83	71.30	73.29	62.81	66.12	65.71	53.69	30.48	56.32
	c-pre	**82.93**	**72.00**	**74.15**	**63.57**	**66.80**	**66.79**	**55.38**	**32.29**	**56.63**
GloVe	All	**87.32**	73.22	**74.39**	73.14	74.19	67.29	58.51	**67.34**	59.70
	c-pre	86.73	**73.41**	74.00	**74.23**	**74.27**	**68.40**	**59.80**	66.85	**60.11**
ELMo	All	88.63	71.80	83.91	72.61	73.30	66.93	63.20	67.58	69.45
	All - stop	90.27	**73.54**	**85.61**	70.04	74.45	68.74	64.17	69.28	71.01
	c-pre	**90.40**	73.20	85.03	**71.19**	**75.27**	**69.87**	**65.38**	**69.81**	**71.80**
BERT	All	91.86	71.76	91.73	73.66	78.72	62.60	59.74	67.80	67.49
	All - stop	**94.18**	73.81	94.85	78.80	79.10	65.39	60.73	69.33	69.81
	c-pre	93.67	**74.00**	**94.88**	**79.00**	**79.84**	**66.00**	**61.18**	**70.28**	70.33

Results

Evaluating Customized Pre-processing Training Corpora vs. Customized Pre-processing Classification Dataset

Training Corpus	Processing	IMDB	Semeval	Airline	IAC	Onion	Reddit	Alm	ISEAR	SSEC
Word2Vec(CBOW)	c-pre	90.67	62.74	74.33	73.08	76.52	69.15	53.18	66.19	60.51
	Post 1	87.30	60.04	72.20	68.27	73.61	66.80	48.25	61.29	55.00
	Both 1	88.13	61.70	72.69	70.08	74.12	68.48	50.23	65.37	58.00
	Post 2	88.52	60.47	73.40	71.25	75.63	68.05	50.44	64.20	59.31
	Both 2	**90.81**	**63.30**	**75.07**	**74.69**	**77.80**	**70.51**	**54.20**	**67.48**	**61.02**
Word2Vec(Skip-gram)	c-pre	89.91	62.73	73.69	72.85	76.31	69.24	52.84	64.80	59.28
	Post 1	88.01	60.22	70.25	71.13	74.28	67.45	50.62	62.00	55.70
	Both 1	88.57	61.85	73.20	71.08	75.00	69.00	50.74	63.12	57.21
	Post 2	89.10	62.03	72.45	71.62	75.69	68.14	51.66	62.70	58.00
	Both 2	**90.40**	**64.20**	**75.37**	**74.28**	**77.82**	**71.49**	**54.09**	**66.00**	**60.58**
BERT	c-pre	93.67	74.00	94.88	79.00	79.84	66.00	61.18	70.28	70.33
	Post 1	91.83	70.12	92.00	74.04	76.81	62.71	58.02	67.90	66.80
	Both 1	94.03	72.19	92.20	76.39	77.19	63.77	60.03	68.34	67.61
	Post 2	93.10	73.24	92.60	75.00	78.20	64.80	59.34	69.18	69.52
	Both 2	**94.22**	**75.20**	**94.88**	**80.21**	**80.34**	**67.41**	**63.10**	**72.66**	**72.80**

Results

Evaluating Customized Pre-processing Training Corpora
vs.
Customized Pre-processing Classification Dataset

Training Corpus	Processing	IMDB	Semeval	Airline	IAC	Onion	Reddit	Alm	ISEAR	SSEC
FastText(CBOW)	c-pre	80.71	71.90	73.70	63.17	66.24	66.71	53.00	33.25	56.49
	Post 1	77.30	70.10	71.27	56.80	65.30	63.78	52.67	30.27	54.18
	Both 1	78.69	71.25	71.69	61.38	65.84	64.37	52.73	32.80	54.80
	Post 2	78.29	70.18	71.02	60.39	66.18	65.01	53.00	33.28	55.70
	Both 2	**81.60**	**72.50**	**75.06**	**65.86**	**68.21**	**69.17**	**55.48**	**36.45**	**58.71**
FastText(Skip-gram)	c-pre	82.93	72.00	74.15	63.57	66.80	66.79	55.38	32.29	56.63
	Post 1	78.20	67.84	70.33	59.67	63.80	61.30	51.27	30.69	54.70
	Both 1	79.06	70.60	73.12	62.81	65.30	64.80	54.25	30.39	55.00
	Post 2	80.83	69.38	72.65	62.30	65.30	64.27	55.18	31.40	55.80
	Both 2	**83.60**	**73.41**	**75.33**	**65.39**	**68.42**	**68.70**	**57.04**	**35.20**	**58.00**
GloVe	c-pre	86.73	73.41	74.00	74.23	74.27	68.40	59.80	66.85	60.11
	Post 1	85.12	70.00	71.45	72.64	71.69	65.10	56.48	64.23	57.29
	Both 1	87.29	73.00	73.14	73.45	73.59	67.48	58.29	66.70	58.76
	Post 2	86.20	72.00	73.10	73.00	73.81	66.80	58.30	65.10	58.26
	Both 2	**87.23**	**75.08**	**75.14**	**74.40**	**76.31**	**70.25**	**61.40**	**68.71**	**62.30**
ELMo	c-pre	90.40	73.20	85.03	71.19	75.27	69.87	65.38	69.81	71.80
	Post 1	86.25	70.33	82.20	69.48	73.02	66.40	63.14	67.40	69.28
	Both 1	90.33	72.60	83.20	72.68	74.11	68.00	64.21	67.62	70.37
	Post 2	88.67	72.80	84.61	70.39	74.69	68.80	64.20	68.07	70.30
	Both 2	**91.20**	**74.83**	**86.67**	**73.30**	**77.00**	**71.37**	**67.49**	**71.25**	**72.20**

Affective and Contextual Embedding for Affect Detection

(COLING 2020)

How to Detect Affect in Text?

NOT AVAILABLE

Affect can be manifested through body language such as facial expressions and gestures.

Looking for specific words or sets of specific alternative words…

Early Attempts:
Extracting a set of positive verbs and negative/undesirable situations:

"I love *[positive verb]* the pain of breakup *[negative situation]*"

What if?
When there are no sentiment words in a sentence:

"Is it time for your medication or mine?"

Word Embeddings for Affect Detection

Traditional Word Embedding Models:

Word2vec (Mikolov et al., 2013b) and GloVe (Pennington et al., 2014):

- The **Distributional Hypothesis** is that words that occur in the same contexts tend to have similar meanings.

Advanced Word Embedding Models:

BERT (Devlin et al., 2018), RoBERTa (Liu et al., 2019) and XLNet (Yang et al., 2019) :

- These embeddings are generally obtained from the **Transformer-Based** models, which assign each word a representation based on its context.

Motivation

These transformer-based models do not incorporate any *affect-specific features* or *task-specific knowledge* during the embedding-training phase of the model.

Research Questions

How to incorporate affective and contextual features along with task-specific knowledge during the training phase?

Given as input a text passage, the model predicts whether:

It's Positive or Negative?

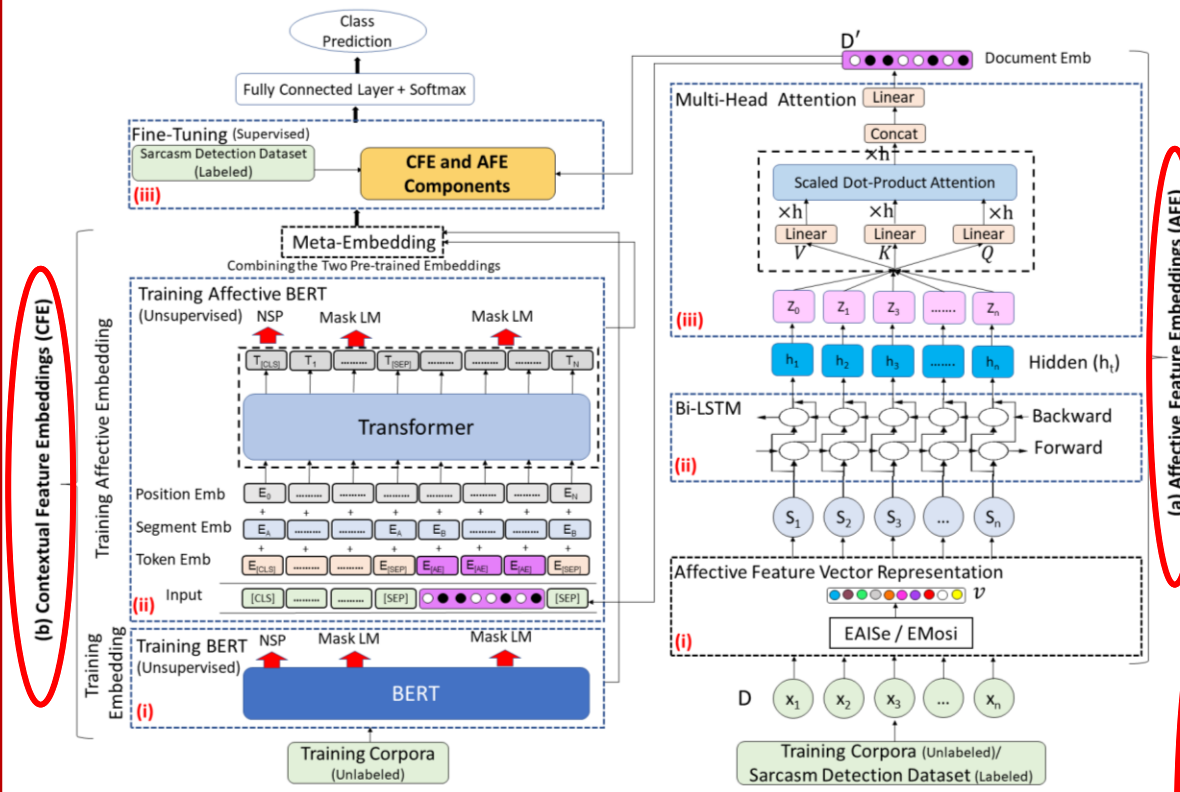
It's Sarcastic or not?

It's happy, sad, fear…?

Contributions

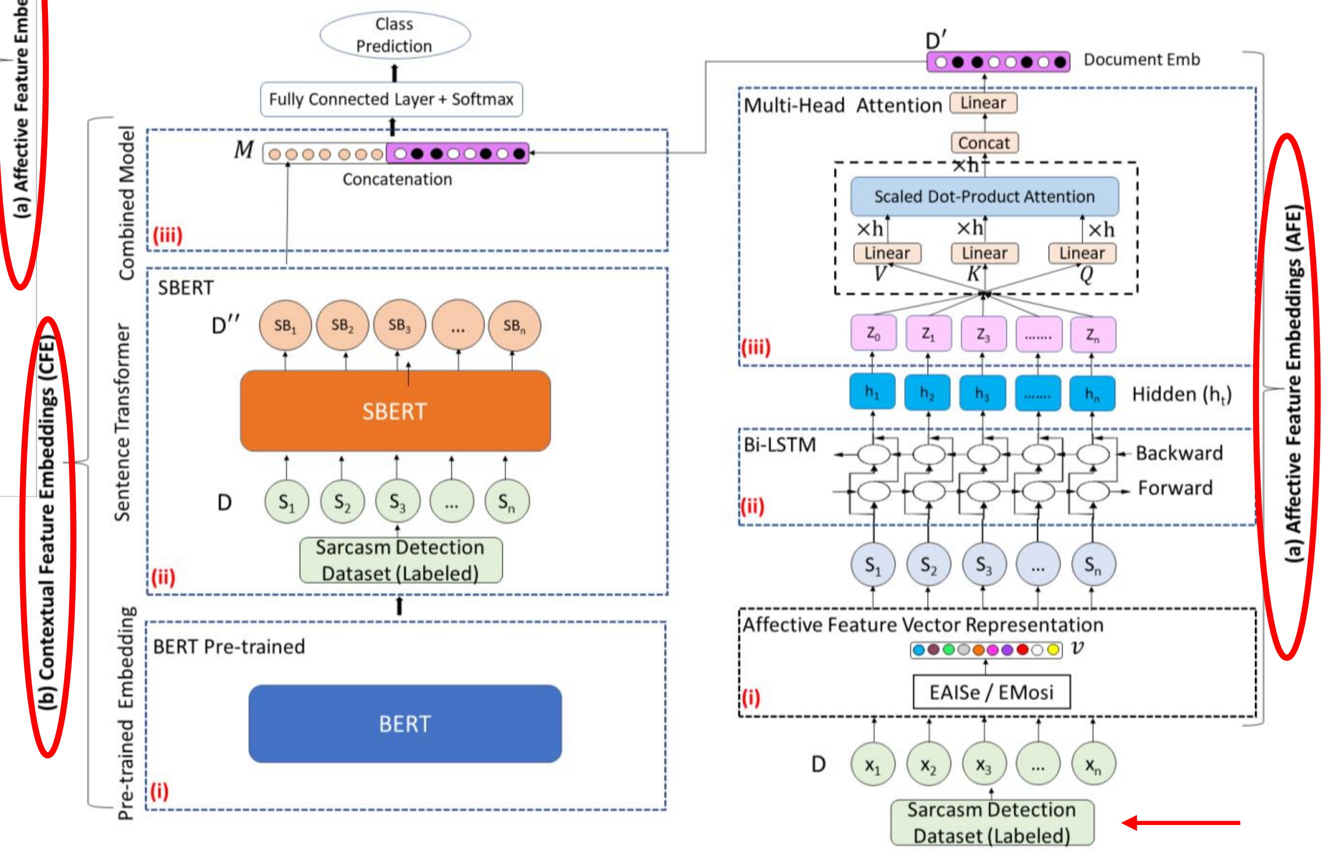
- Two novel deep neural network language models (**ACE 1** and **ACE 2**) incorporating both affective and contextual embeddings.
- A novel model that learns the affective representation of a document, using a Bi-LSTM architecture with Multi-Head Attention.
- Evaluate the effectiveness of each alternative architecture.
- Investigating the performance of affective tasks, such as sarcasm detection, emotion detection and sentiment analysis.
- Evaluation of the performance of the proposed models against the current state-of-the-art models .
- A comparative study of the accuracy performance of previous BERT model using pre-processing for affective tasks with the current proposed models.
- Source Code: https://github.com/NastaranBa/ACE-for-Sarcasm-Detection

Proposed Model ACE 1 & ACE 2



Model ACE 1

Model ACE 2



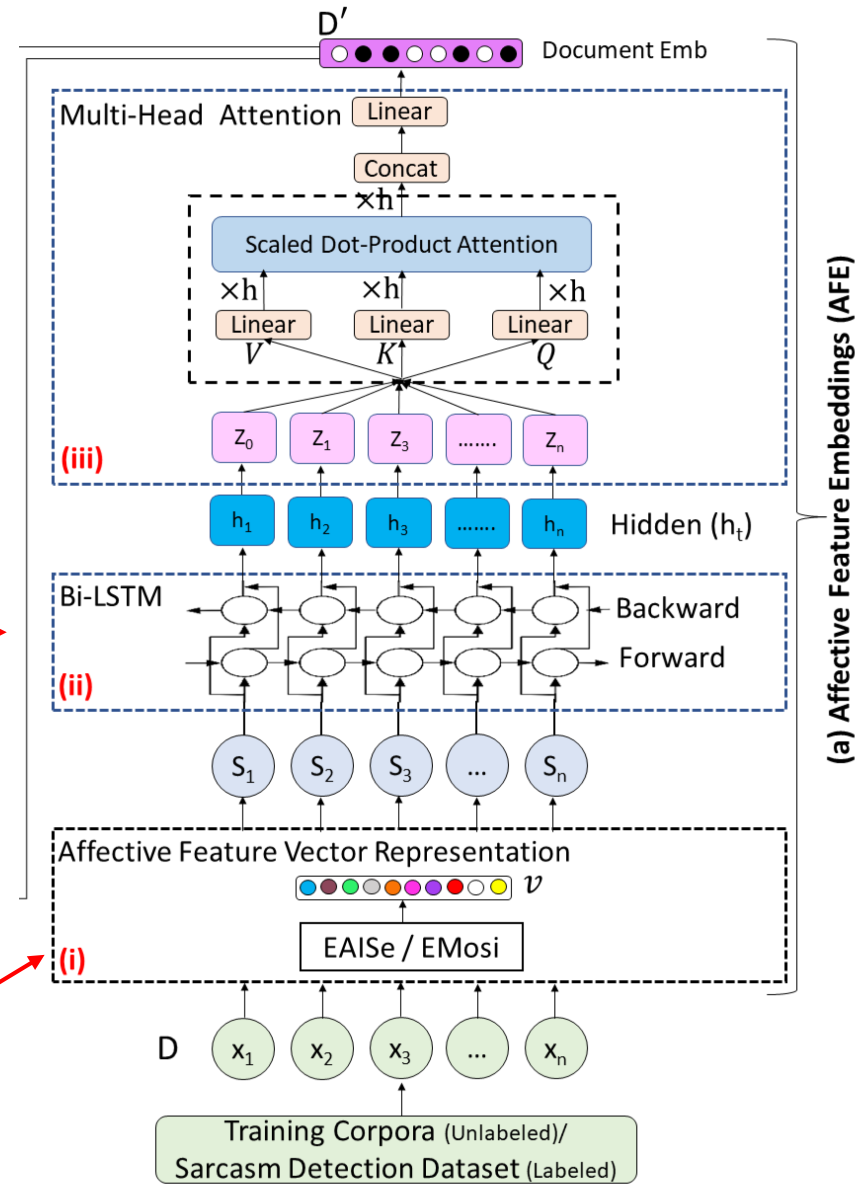
Affective Feature Embedding (AFE)

(i) Affective Feature Vector Representation

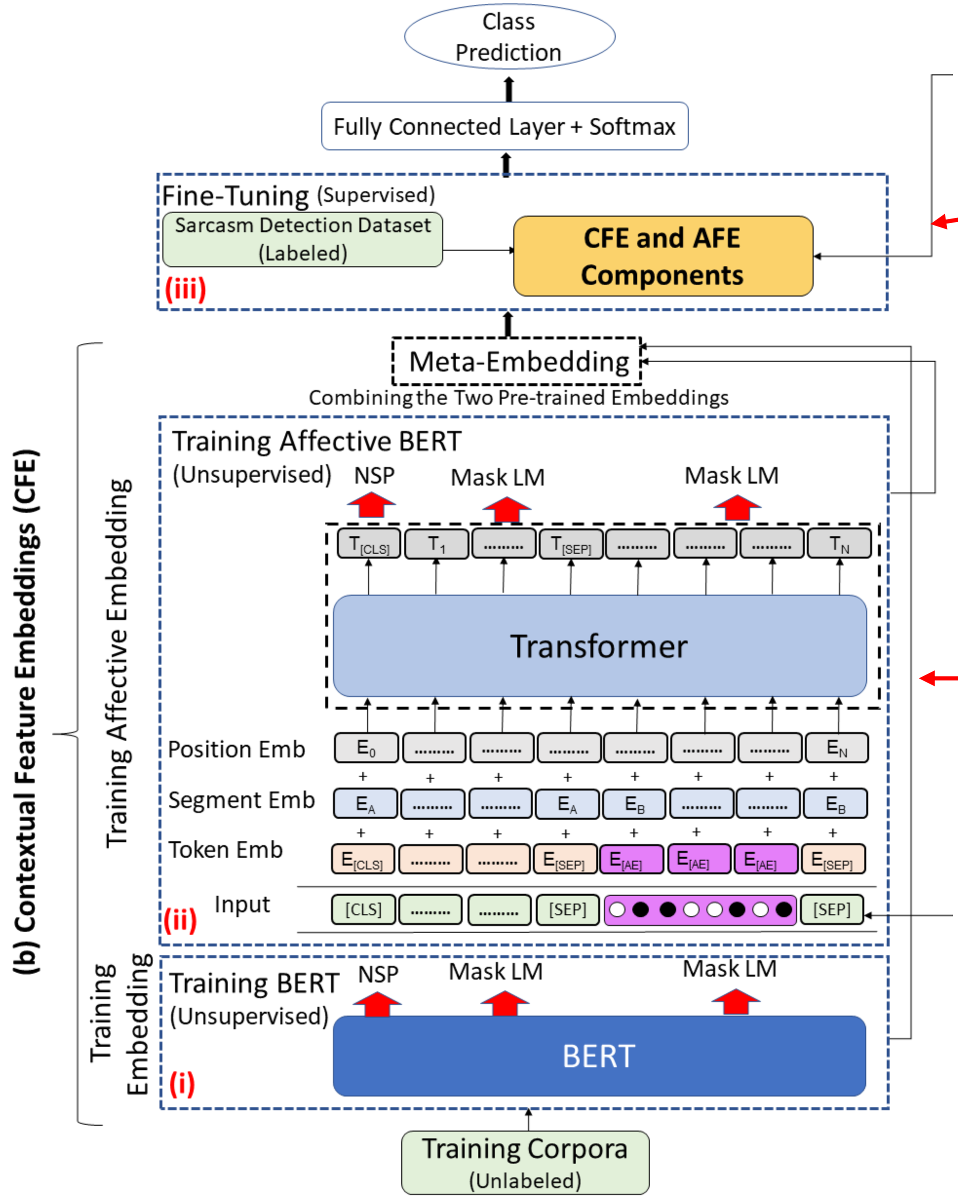
- **EAISe**: Emotion Affective Intensity with Sentiment Feature
- **EMoSi**: Emotion Similarity Feature

(ii) Bi-LSTM Layer: to capture/encode the **affect-changing information** of the sentence sequence from **both left and right** directions.

(iii) Multi-head Attention Layer: a **specific part** of a document could play a more important role.

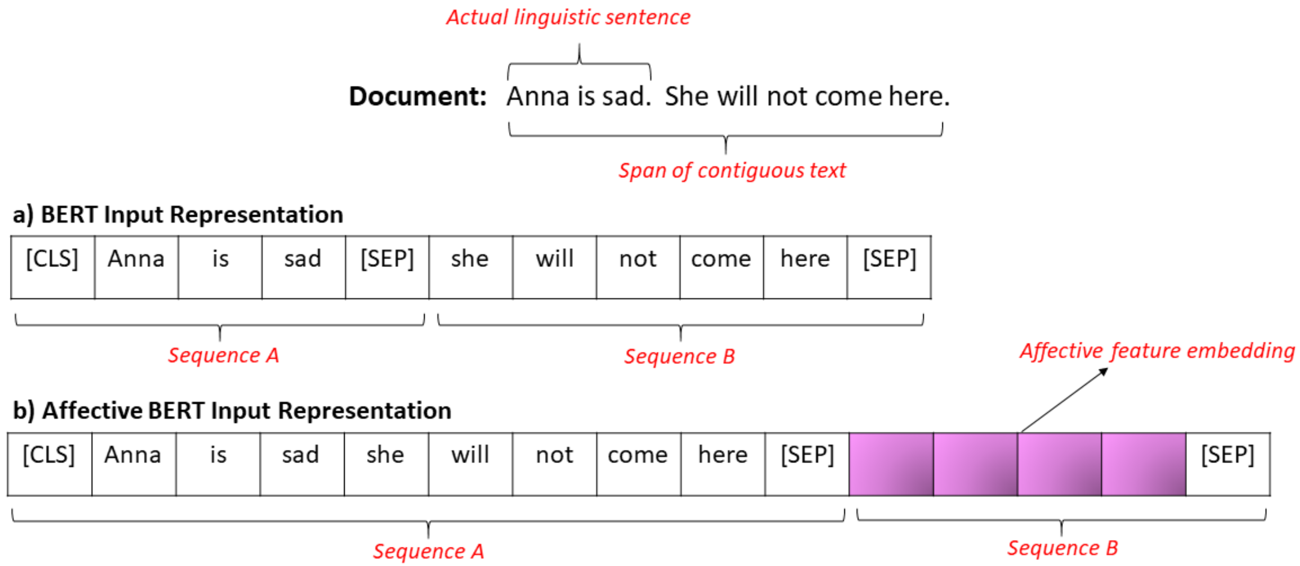


Contextual Feature Embedding (CFE) ACE 1



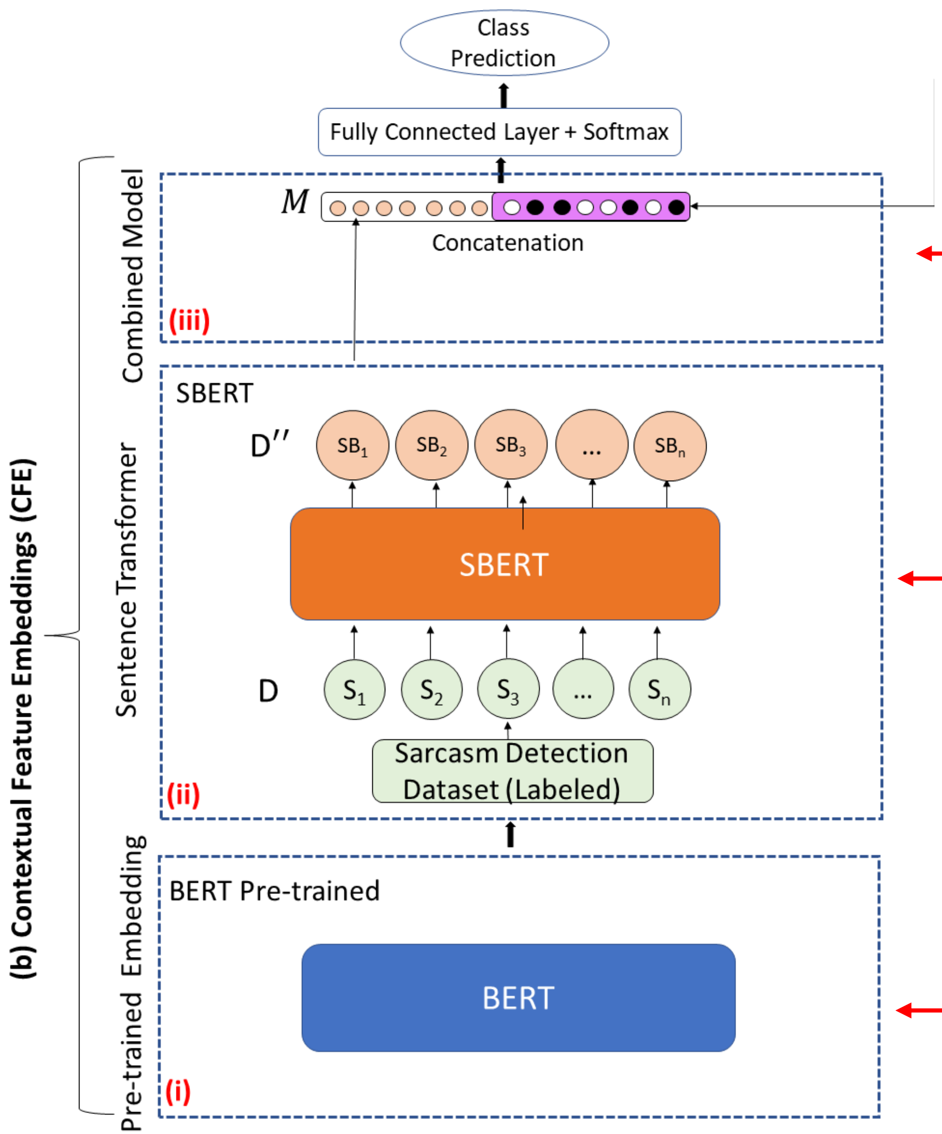
(iii) Fine-tuning BERT Models

(ii) Training Affective BERT



(i) Training BERT

Contextual Feature Embedding (CFE) ACE 2



(iii) Combining the Two Components

(ii) Obtaining Sentence Embeddings Using SBERT (Sentence Transformer)

(i) Pre-trained Embeddings

Results

Comparing Variations of Model ACE 1 (F-Score)

Corpus+Affective Feature	Onion	Reddit	Pt′acek	SemEval-2018	IAC
(Wiki)	83.88	80.25	71.06	77.38	85.10
(Wiki) + (EAISe)	89.40	85.11	**75.38**	**78.10**	87.20
(Wiki) + (EMoSi)	**90.07**	**86.20**	75.18	77.91	**88.40**
(WikiSarc)	90.61	86.59	75.15	80.45	89.20
(WikiSarc) + (EAISe)	90.70	87.19	77.82	84.25	89.74
(WikiSarc) + (EMoSi)	**92.21**	**89.22**	**80.71**	**84.57**	**93.14**

Comparing Variations of Model ACE 2 (F-Score)

Corpus+Affective Feature	Onion	Reddit	Pt′acek	SemEval-2018	IAC
(BERT)	82.45	70.20	70.49	72.19	78.19
(BERT) + (EAISe)	84.11	**78.79**	**72.24**	76.19	**80.36**
(BERT) + (EMoSi)	**84.19**	77.45	71.85	**79.00**	80.00
(Wiki-BERT)	82.31	70.20	70.04	72.10	77.48
(Wiki-BERT) + (EAISe)	**84.33**	**79.22**	71.44	**79.61**	**80.25**
(Wiki-BERT) + (EMoSi)	84.00	77.04	**72.10**	79.15	79.88
(WikiSarc-BERT)	84.19	79.41	75.29	75.41	80.07
(WikiSarc-BERT) + (EAISe)	**87.46**	82.28	**79.09**	**80.46**	**85.29**
(WikiSarc-BERT) + (EMoSi)	86.17	**83.37**	78.19	80.11	85.10
(WikiSarcA-BERT)	87.09	82.25	76.84	78.18	84.79
(WikiSarcA-BERT) + (EAISe)	**90.31**	**86.50**	**80.39**	**84.33**	**88.19**
(WikiSarcA-BERT) + (EMoSi)	88.25	86.11	79.00	83.60	86.47

Results

Comparing our models against state-of-the-art models (Only Affective)

Models	Onion	Reddit	Pt′acek	SemEval-2018	IAC
Rajadesingan et al., 2015 [146]	67.25	64.21	75.13	70.12	68.33
Ghosh et al., 2017 [60]	69.23	68.41	74.11	72.45	64.38
Hernandez farias et al., 2018 [77]	68.00	69.34	75.10	71.70	70.39
Zhang et al., 2019 (a) [203]	-	-	69.15	64.28	-
Zhang et al., 2019 (b) [203]	-	-	72.39	65.33	-
Zhang et al., 2019 (c) [203]	-	-	72.47	67.55	-
AFE with EAISe	70.49	71.87	**76.90**	72.51	72.40
AFE with EMoSi	**74.20**	**74.04**	76.40	**72.60**	**73.01**

Results

Comparing our models against state-of-the-art models (Only Contextual with Fine-Tune)

Models	Onion	Reddit	Pt′acek	SemEval-2018	IAC
Potamias et al., 2019 [144]	84.39	78.00	71.01	70.00	85.21
RoBERTa	80.23	76.04	67.25	68.00	82.44
XLNet-Large	79.66	76.48	69.33	68.25	70.06
BERT-Base	80.04	76.14	67.13	69.03	82.27
BERT-Large	83.49	78.21	70.33	76.19	84.25
ACE 1 (WikiSarc)	**90.61**	**86.59**	**75.15**	**80.45**	**89.20**

Results

Comparing our models against state-of-the-art models (Only Contextual with Pre-trained without Fine-Tune).

Models	Onion	Reddit	Pt′acek	SemEval-2018	IAC
Zhang et al., 2016 [201]	67.08	69.20	70.49	70.66	69.38
Iliċ et al., 2018 [84]	70.12	76.05	75.46	68.90	72.00
RoBERTa	76.51	66.00	62.51	66.37	75.10
XLNet-Large	79.23	70.25	60.13	66.45	72.41
BERT-Base	78.13	66.27	63.12	68.14	74.90
BERT-Large	79.11	65.27	62.39	69.47	75.48
ACE 2 (WikiSarcA-BERT)	**87.09**	**82.25**	**76.84**	**78.18**	**84.79**

Results

Comparing our models against state-of-the-art models (Affective-Contextual)

Models	Onion	Reddit	Pt′acek	SemEval-2018	IAC
Poria et al., 2016 [143]	70.00	64.27	67.00	69.45	60.25
Amir et al., 2016 [11]	67.79	65.14	69.25	71.59	68.51
Yang et al., 2016 [197]	63.25	64.83	71.16	67.45	70.14
DeepMoji, 2017 [54]	69.47	53.08	63.51	69.27	71.00
Wu et al., 2018 [186]	70.00	69.20	68.50	71.20	65.23
Tay el al., 2018 (a) [170]	70.68	67.25	71.52	70.01	72.00
Tay el al., 2018 (b) [170]	70.13	68.23	70.13	69.46	71.85
Hazarika et al., 2018 [75]	70.90	75.16	70.24	-	-
Kumar et al., 2020 [96]	68.36	77.01	70.27	75.44	69.33
ACE 1 (WikiSarc) + (EMoSi)	**92.21**	**89.22**	**80.71**	**84.57**	**93.14**
ACE 2 (WikiSarcA-BERT) + (EAISe)	90.31	86.50	80.39	84.33	88.19

Results

Evaluating the Performance of Proposed Models on Other Affective Tasks

Corpus+Affective Feature	Sentiment Analysis			Emotion Detection		
	IMDB	Semeval	Airline	Alm	ISEAR	SSEC
(Wiki)	93.00	75.60	90.33	63.40	70.00	69.88
(Wiki) + (EAISe)	93.76	**78.70**	91.69	**65.06**	**71.80**	70.08
(Wiki) + (EMoSi)	**95.28**	77.30	**93.80**	64.61	70.73	**71.14**
(WikiSarc)	95.00	78.80	94.87	65.70	70.29	70.16
(WikiSarc) + (EAISe)	96.19	78.17	94.10	**67.29**	**73.80**	**74.05**
(WikiSarc) + (EMoSi)	**97.13**	**80.67**	**96.25**	66.29	72.20	73.15

F1-score results of model ACE 1 with different settings on other affective tasks

Corpus+Affective Feature	Sentiment Analysis			Emotion Detection		
	IMDB	Semeval	Airline	Alm	ISEAR	SSEC
(WikiSarc-BERT)	85.61	73.68	88.70	64.30	70.15	69.27
(WikiSarc-BERT) + (EAISe)	87.20	74.60	**91.22**	65.49	**72.80**	70.63
(WikiSarc-BERT) + (EMoSi)	**88.10**	**75.00**	90.37	**66.07**	71.68	**72.29**
(WikiSarcA-BERT)	89.37	75.86	91.50	67.40	73.40	74.00
(WikiSarcA-BERT) + (EAISe)	91.60	76.00	93.15	68.12	74.06	**76.60**
(WikiSarcA-BERT) + (EMoSi)	**94.30**	**78.25**	**95.02**	**70.31**	**75.60**	75.39

F1-score results of model ACE 2 with different settings on other affective tasks

Results

F-score Results of comparing ACE 1 and ACE 2 against the customized pre-processing model.

Models	IMDB	Semeval	Airline	IAC	Onion	Reddit	Alm	ISEAR	SSEC
Pre-processing	94.22	75.20	94.88	80.21	80.34	67.41	63.10	72.66	72.80
ACE 2	94.30	78.25	95.02	88.19	90.31	86.50	**70.31**	**75.60**	**75.39**
ACE 1	**97.13**	**80.67**	**96.25**	**93.14**	**92.21**	**89.22**	67.29	73.80	74.05

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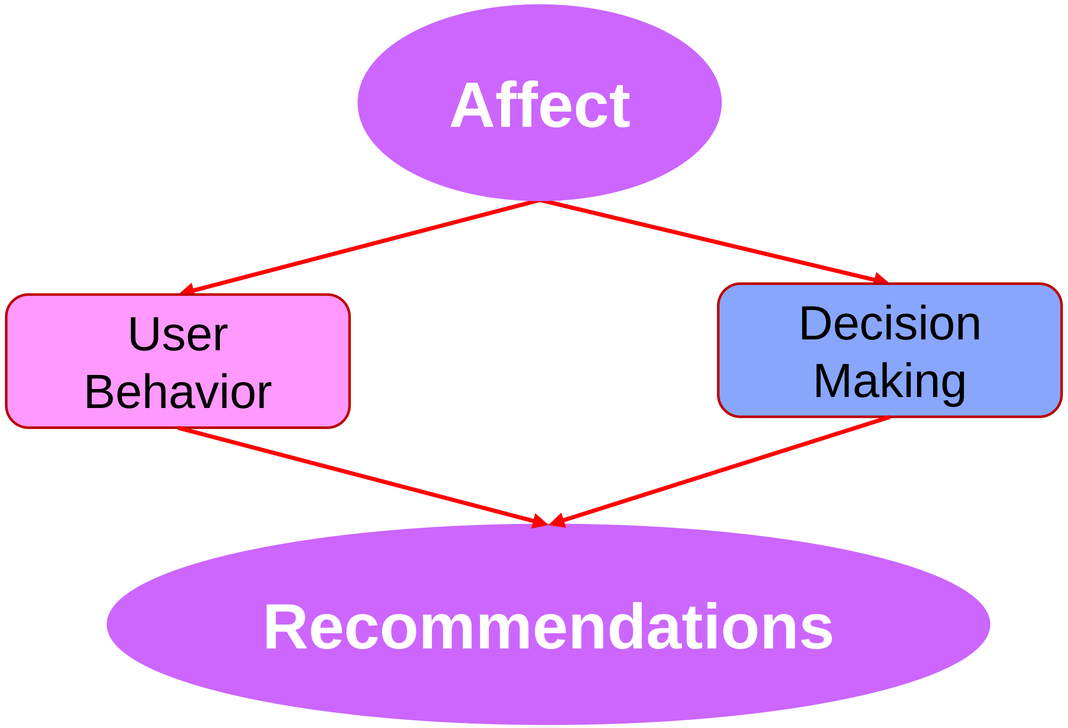
Affective and Contextual Embedding Model for Feature Representation Learning in Affect-Aware Recommendation

Motivation



- **Limited number of works…**
- **Fail to investigate…**

Research Questions

(Q1) Which affect detection approaches is more beneficial to extract affective information for RS?

(Q2) How to incorporate the affective information into the recommendation algorithm?

(Q3) Whether improving the affect detection approaches will improve the RS?

Contributions

- An affect-aware recommendation model (AARec) describing the application of our affect detection models in a non-affective framework of RS.

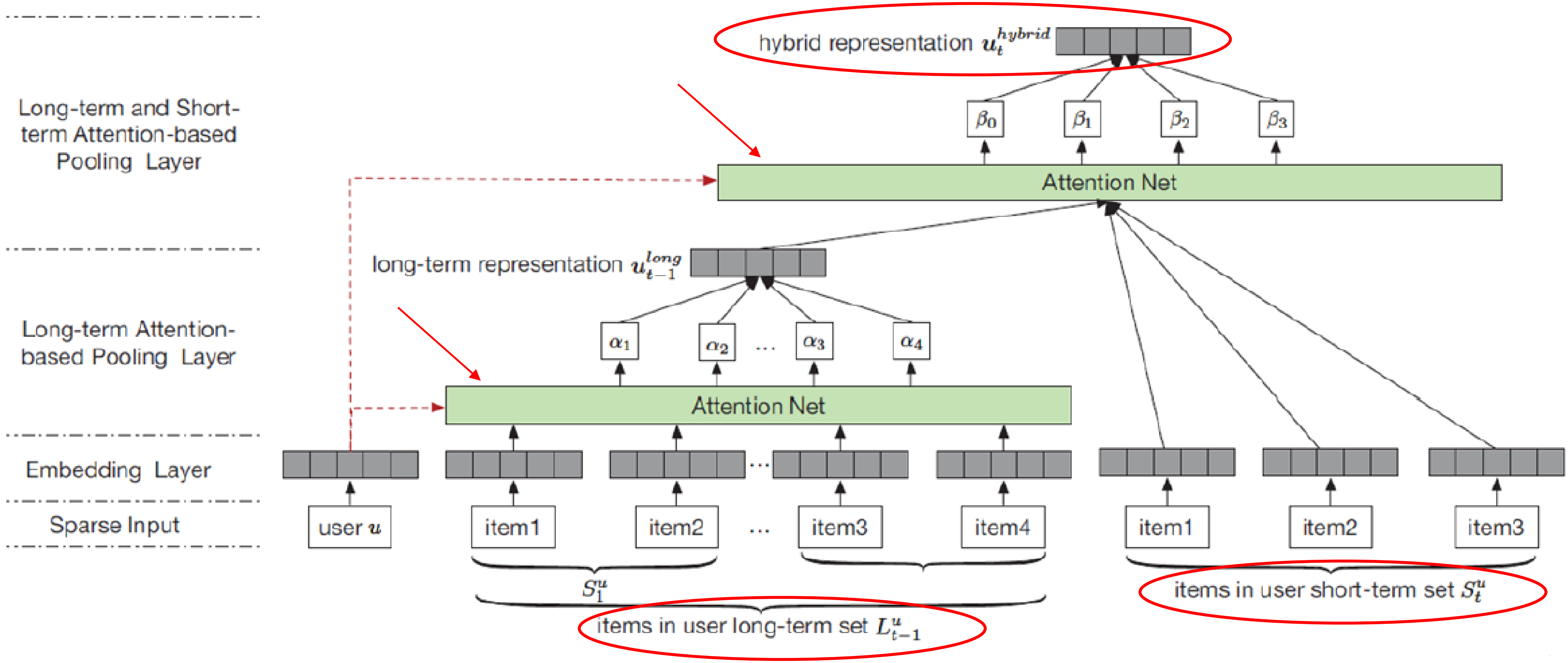
- A comparative study measuring the performance of **EmoRec** against Affect-Aware Recommendation **AARec**

Affective and Contextual Feature Representation in Recommendation Models

- Each input document is first chunked into sentences.
- Given an input sentence, we first use the pre-trained BERT model that was trained with ACE 1 to obtain the token embeddings, which are then passed to SBERT from ACE 2.
- SBERT computes a sentence embedding using the MEAN-strategy for the pooling operation to compute a sentence embedding.
- We concatenate the embeddings of all the sentences in the document to form a document representation of each item that was accessed by a user.

Experiments	Variations
Mode 1	ACE 1 + ACE 2 (No Affect)
Mode 2	ACE 1 + ACE 2 (Affect in embedding training phase)
Mode 3	ACE 1 + ACE 2 (Affect in embedding training phase + Concatenation)
Mode 4	c-pre + ACE 1 + ACE 2 (Customized pre-processing + Affect in embedding training phase + Concatenation)

Affect-Aware Recommendation Model (AARec)



Sequential Recommender System based on Hierarchical Attention Network (SHAN)

Adopted from Ying et. al (2018)

Results

Evaluating the Effects of Proposed Affect Detection Methods in Recommendation Algorithms

Models	Mode 1	Mode 2	Mode 3	Mode 4
GRU4Rec	70.23	72.08	76.04	80.30
Caser	70.18	71.81	75.33	79.25
RCNN	73.49	74.20	73.68	81.29
AARec	**78.49**	**79.74**	**80.20**	**83.62**

Music Dataset

Models	Mode 1	Mode 2	Mode 3	Mode 4
GRU4Rec	73.68	74.02	76.60	80.46
Caser	72.29	73.07	75.00	76.59
RCNN	76.15	78.37	79.60	83.70
AARec	**80.19**	**81.47**	**84.20**	**86.09**

News Dataset

Results

Evaluating the Performance of AARec Against EMoRec

Dataset	Model	Non-Affect	Affective
Music	EMOREC	73.68	76.06
	AAREC	**78.49**	**83.62**
News	EMOREC	78.20	80.30
	AAREC	**80.19**	**86.09**

Conclusion/Future Work

- We took the first steps towards bridging the gap between needs in affect detection approaches and benefits of affective information in recommendation models.
  - Leveraging emotion feature in RS
  - General pre-processing model in affective tasks
  - Customized pre-processing model in affective tasks
  - Affective and contextual embedding model
  - Affect-Aware RS

- Future Works
  - Recommendation with Affective Information Through Other Cues
  - Negation Scope and Negation Handling
  - Multilingual Model
  - Learning of Affective Representations Through Graphs
  - Integrating the Proposed Models into One System

List of My Contributions

- Nastaran Babanejad, Ameeta Agrawal, Heidar Davoudi, Aijun An, Manos Papagelis, *“Leveraging Emotion Features in News Recommendations”*, Proceedings of the 7th International Workshop on News Recommendation and Analytics in conjunction with 13th ACM Conference on Recommender Systems (INRA@RecSys), Copenhagen, Denmark, September 20, 2019 2019: 70-78.

- Nastaran Babanejad, Ameeta Agrawal, Aijun An and Manos Papagelis, “*A Comprehensive Analysis of Preprocessing for Word Representation Learning in Affective Tasks”*, Proceedings of the 2020 Annual Conference of the Association for Computational Linguistics (ACL), Online, July 5-10, 2020.

- Nastaran Babanejad, Heidar Davoudi, Aijun An, Manos Papagelis, *“Affective and Contextual Embedding for Sarcasm Detection”*, accepted by the 28th International Conference on Computational Linguistics (COLING'20), to be held online on December 8-13, 2020.

- Nastaran Babanejad, Heidar Davoudi, Aijun An, Manos Papagelis, , *“Customized Pre-processing for Word Representation Learning in Affective Tasks”* IEEE Transaction on Affective Computing (TAC), under review.


Thank
You