

INTEGRATION LEXICON WITH MACHINE LEARNING FOR SENTIMENT ANALYSIS

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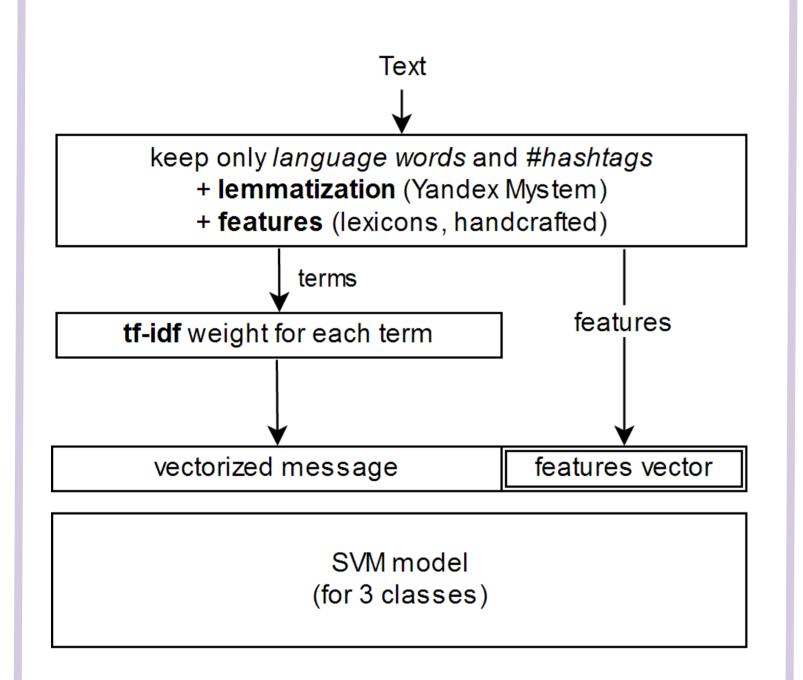
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1. Problem

- Building ML model for Twitter messages sentiment classification task. (SentiRuEval competition)
- Sentiment class defines for whole message, and shows relationship between message and company mentioned in it.
- For each domain this problem resolves separately:
 - BANK bank companies;
 - TCC telecommunication companies.
- ➤ Each message could be labeled with one of the following scores: {1, 0, -1}

4. SVM Model

> Implementation: *LibSVM* [3]



2. Approach

> Classifier:

- SVM/LR
 - Embedding: tf-idf
 - Use balanced collections
- Neural networks
 - RNN, GRU, LSTM
 - Embedding: w2v models

> Extra Features:

- Build Lexicons (see 3.) based on Corpora
- > Handcrafted features[1], amount:
 - UPPERCASE words
 - signs ('?', '!', '...')
 - \sum , min, max for each Lexicon

3. Lexicons

Based on **pointwise mutual information** of terms t_1 , t_2 :

PMI
$$(t_1, t_2) = \log_2 \frac{P(t_1 \land t_2)}{P(t_1) \cdot P(t_2)}$$

Introducing **marker** as a second parameter of *PMI* function. Possible marker values: **Excellent**, **Poor**.

Semantic orientation is a function:

SO(t) = PMI(t, Excellent) - PMI(t, Poor)

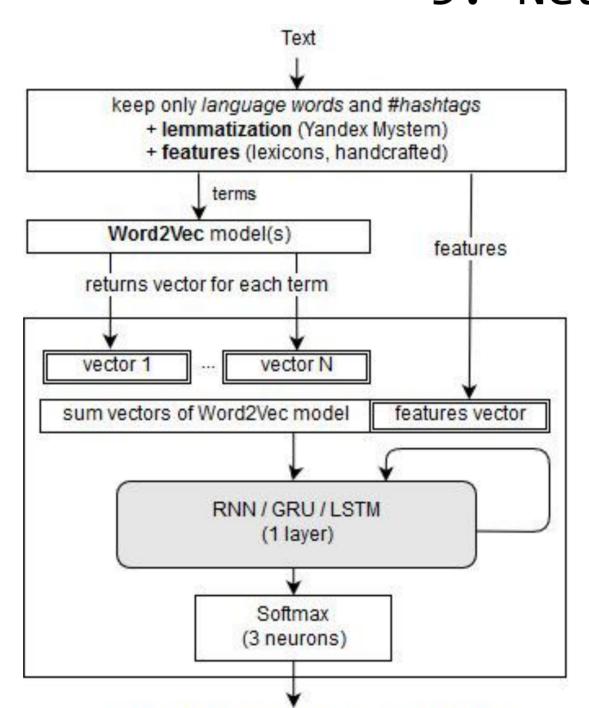
- sgn(SO(t)) determines the marker type of term t;
- |SO(t)| degree of belonging.

Building lexicon from messages of collection $K = K_{Excellent} \cup K_{Poor}$:

$$S: \{ \langle t, SO(t) \rangle \mid t \in K_{Excellent} \cup K_{Poor} \}$$

- $K_{Excellent}$ -- messages labeled **Excellent**.
- K_{Poor} -- messages labeled **Poor**.

5. Neural Networks



Probability of each class (pos, neutral, neg)

- Implementation: Theano(Python) [4]
- ➤ Optimization params:
 - X input matrix (each row is vectorized message of train collection)
 - rl_{curr} , rl_{def} , rl_{min} -- current, default, minimal values of regression coefficient respectively.
 - grad (*) -- back propagation function
- ➤ Optimization approach (SGD):
 - 1. Shuffle rows of X
 - 2. Calculate loss
 - 1. $rl_{curr} = rl_{curr} * 0.5$, if loss greater than on previous step;
 - 2. Optimize otherwize (for each matrix/vector M of the model):

$$M := -rl_{curr} * grad(M)$$

- 3. If $rl_{curr} < rl_{min}$, then $rl_{curr} := rl_{def}$.
- 4. Go to next epoch

Save result after some amount of epoch. Find the best model.

6. Results

\triangleright BANK, measure: $F_{1-macro}(neg, pos)$

Model	Embedding	Training collection $(B/I)^*$	Features	Lexicons	Result
Baseline	-	-	-	-	18.00
SVM	tf-idf	I	-	-	48.00
SVM	tf-idf	Ι	+	-	50.24
<u>SVM</u>	tf-idf	В	+	all	<u>52.83</u>
RNN**	w2v, W1	I	+	all	43.00
GRU**	w2v, W2	I	+	all	39.13
LSTM**	w2v, W2	I	+	all	49.00
LSTM**	w2v, W2, W3	I	+	all	51.40
LSTM	w2v, W2, W3	Ι	+	all	55.32

ightharpoonup TCC, measure: $F_{1-macro}(neg, pos)$

Model	Embedding	Training collection $(B/I)^*$	Features	Lexicons	Result
baseline	-	-	-	-	21.00
SVM	tf-idf	I	-	-	50.90
SVM	tf-idf	Ι	+	-	50.69
SVM	tf-idf	В	+	all	55.46
LSTM	w2v, W2	I	+	all	50.41

- * Used balanced (\it{B}) and imbalanced (\it{I}) version of training collections
- ** Disabling shuffle during optimization

All datasets presented in section 7.

References

- 1. Building the State-of-the-Art in Sentiment Analysis of Tweets (Saif. M. Kiritchenko S., Xiaodan Z., 2015)
- 2. On the Automatic Learning of Sentiment Lexicons, Human Language Technologies (Severyn A., Moshitti A., 2015)
- 3. Chang C.-C., Lin C.-J. (2011), LIBSVM: A library for support vector machines. ACM Transactions on Intelligent Systems and Technology, 2(3):27:1-27:27
- 4. https://github.com/nicolay-r/tone-classifier/tree/master/models/networks/theano

7. Data & Collections Lexicons

Lexicons	Description	Terms
L_1	Twitter (using streaming API, jan-july 2016) (AUTO)	236 091
$\overline{L_2}$	SentiRuLex (MANUAL)	10 668
L_3	Yu. Rubtsova short message corpus (AUTO + MANUAL)	112 814

Mode	el So	urce	Messages	Embedding
				size
W_1	Tv	vitter	5 000 000	300
W_2	Tv	vitter	10 000 000	500
W_3	baı	nki.ru	200 000	500

Imbalanced train collections 1 354 4 870 2 5 5 0 **BANK** 8 783 (15%)(29%) (55.4%)704 6 7 5 6 1 741 TCC 9 102 **(74.22%)** (7%) (19%)

Balanced train collections			
BANK	14610		
TCC	20268		

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