Multilingual detection of Fake News Spreaders via Sparse Matrix Factorization

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Task

Given Twitter feed of an author determine if the user is:

- Fake-news spreader
- Non-spreader

- Languages: English & Spanish
- 30 tweets per author, 150 negative & 150 positive cases for both languages
- Evaluation on classification accuracy

Motivation

- Fake news make a significant impact on society
- Analysis of representations' expressiveness learned via multilingual LSA

Preprocessing

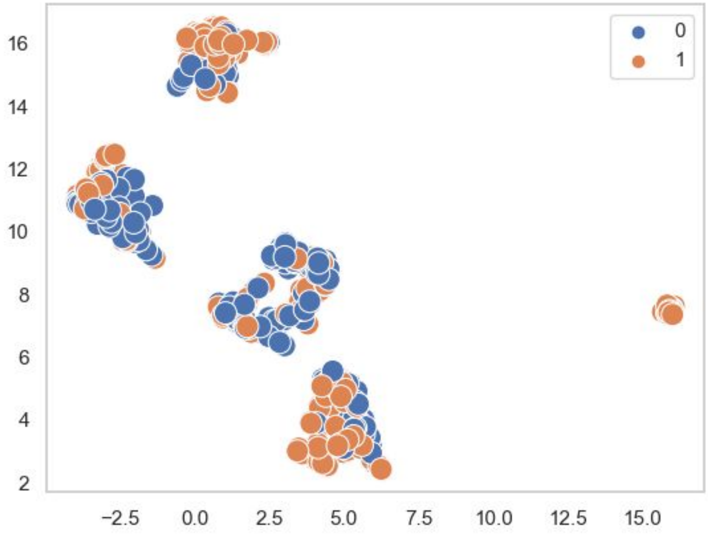
Feature generation

Example tweet:

1) Character n-grams (1,2) :
   - 1-gram: d, o, n ; 2-gram: do, on, nt ;
2) Word n-grams (2,3) :
   - 2-grams: dont know; 3-gram: dont know where;
3) TF-IDF on generated features

Latent Semantic Analysis

Visualization of training data



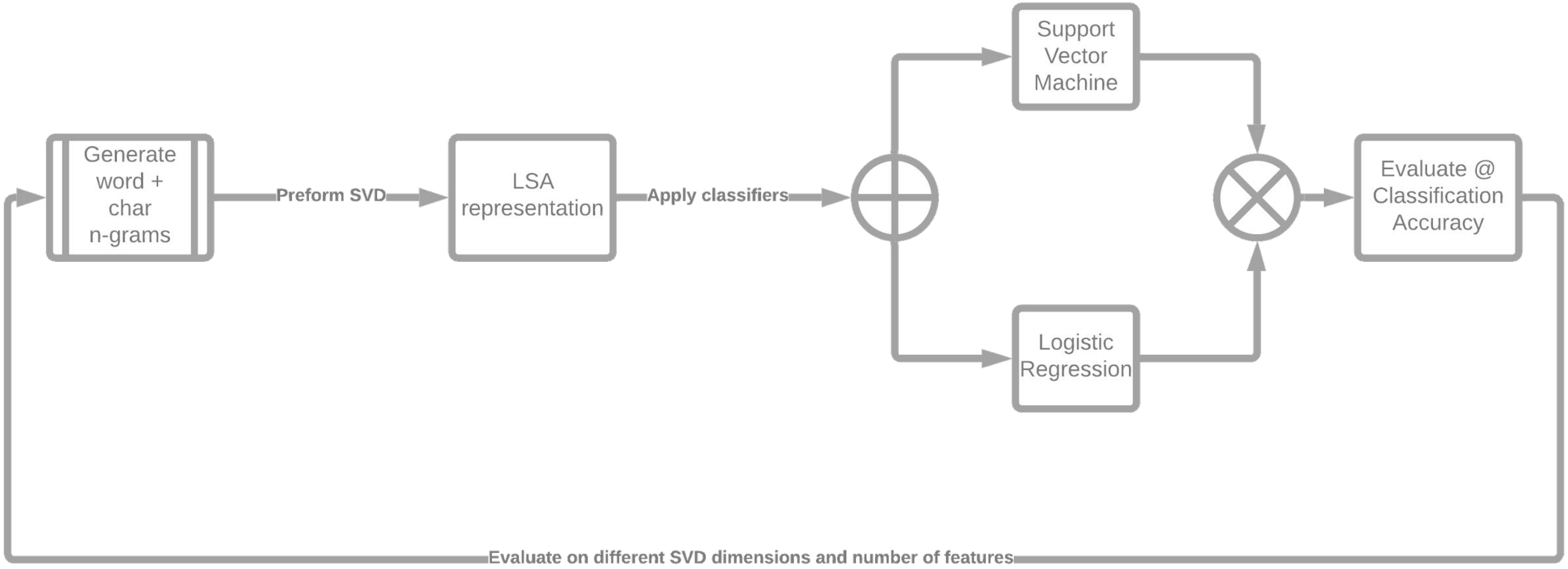
Models

- Stochastic Gradient Descent based:
  - linear-SVM
  - logistic regression
- Monolingual vs Multilingual model
- 10-fold GridSearchCV on 90% on the data; evaluate on 10%

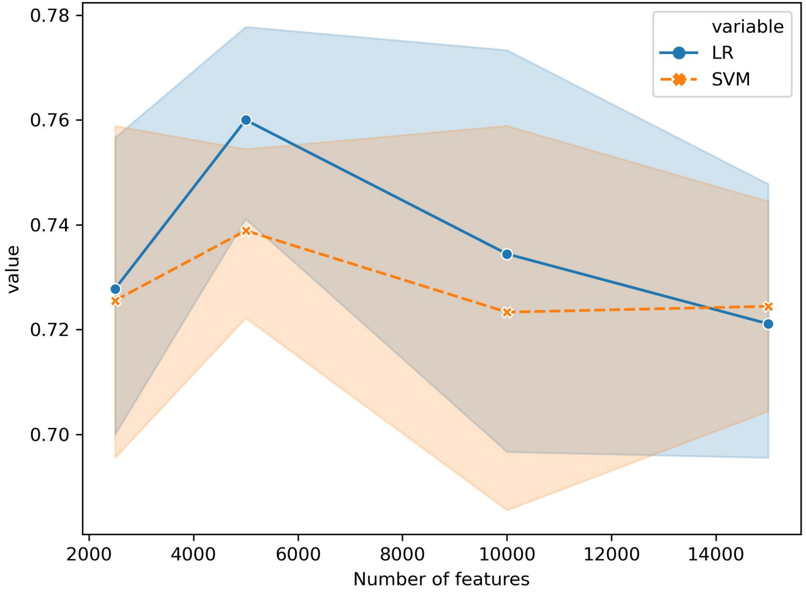
Optimization

- Grid search on:
  - Number of generated features, n : [2500, 5000, 10000, 20000, 30000]
  - Number of dimensions in the SVD, d : [128, 256, 512, 640, 768, 1024]
- Model fine-tuning(regularization):
  - ElasticNet regularization
    - Lasso
    - Ridge

Learning pipeline



Learning



variable
LR
SVM
0.78
0.76
0.74
0.72
0.70
value
2000
4000
6000
8000
10000
12000
14000
Number of features

Alternative approaches

- Separate model for each language
- Doc2Vec & BERT representations
- Different Tokenizer: TweetTokinzer
- Tested AutoML methods, scored similarly to the proposed model

Results on DEV

name	type	#features	#dimensions	model	EN ACC	ES ACC
tfidf_large	multi	5000	768	LR	0.9633	**0.9867**
tfidf_tweet_tokenizer	multi	5000	768	LR	0.9633	0.9533
tfidf_small	mono	5000	512	SVM,SVM	**0.9700**	0.4900
tfidf_cv	mono	10000	768	SVM,SVM	0.9100	0.9367
tfidf_no_hash	multi	10000	768	LR	0.9300	0.9067
doc2vec_baseline	mono	100	#	RF,SVM	0.6428	0.6971
tfidf_tpot_baseline	mono	30000	#	LR,SVM	0.7500	0.7400
tfidf_baseline	mono	10000	#	LR,LR	0.5567	0.7033

Table 2. Final training data on TIRA.

Final evaluation results

name	type	#features	#dimensions	model	EN ACC	ES ACC
tfidf_large	multi	5000	768	LR	**0.7150**	**0.7950**
tfidf_cv	mono	10000	768	SVM,SVM	0.7000	**0.7950**

Table 3. Un-official evaluation on test data on TIRA

POS	TEAM	EN	ES	AVG
1	bolonyai20	0.7500	0.8050	0.7775
1	pizarro20	0.7350	0.8200	0.7775
-	SYMANTO (LDSE) [1]	0.7450	0.7900	0.7675
3	koloski20	0.7150	0.7950	0.7550

Conclusion

- Space obtained by word and character n-grams is a good representation of the problem space.
- Semantic features don’t introduce significant improvements.
- Multilingual space maintains space structure and word patterns.
- Multilingual approach tackles the problem better compared to the monolingual approach.

Further work

- Explore and exploit the multilingual approach on more languages.
- Try to enrich the space with a background knowledge about entities appearing in the text.