CLUZH at VarDial GDI 2017: Testing a Variety of Machine Learning Tools for the Classification of Swiss German Dialects

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A Supervised Classification Problem

Classes	BE	%	BS	%	LU	%	ZH	%	Total
Training	3889	**27**	3411	24	3214	22	3964	**27**	14478
Test	906	25	939	26	916	25	877	*24*	3638
Δ		-2		+2		+3		-3	

- Roughly balanced data sets, but differently biased for train and test set.
- Train and test set not iid (disjoint speakers)
- Transcriber bias: test set transcriber for LU not seen in training

Transcription Examples

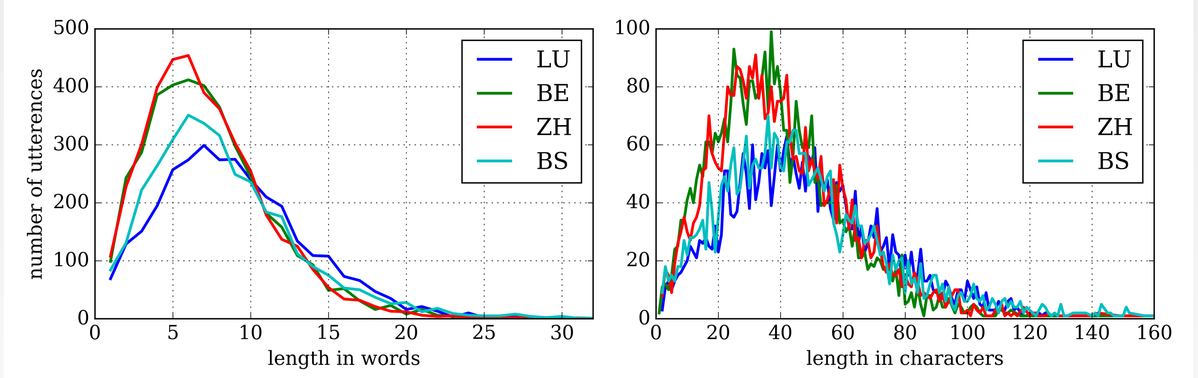
(BE) *a* *das* *chamì* *natüürlich* *aus* *nìd* *erinnere*
(de) an das kann ich mich natürlich alles nicht erinnern
(en) 'of cause I can't remember all this'

(BS) *a* *dr* *a* *a* *das* *mag* *mi* *äu* *erinnere*
(de) an dr an an das kann ich mich auch erinnern
(en) 'I can remember him . . . this too'

(LU) *bì* *disen* *ìsch* *es* *plòff* *gsii* *ùnd* *gwaut*
(de) bei diesen ist es Bluff gewesen und Gewalt
(en) 'for these it was bluff and violence'

(ZH) *als* *schwiizer* *gfüült*
(de) als Schweizer gefühlt
(en) 'felt as a Swiss'

Number of Words per Utterance



Challenges

- Short sequences (14% have less than 4 words)
- Many infrequent tokens due to writing variations: out of 14,065 word types, 9,372 appear once, 2,032 twice, 929 three times
- Many diacritics for phonetic properties

Run 1: Naive Bayes (NB)

- Our baseline approach using character n-grams ($2 \geq n \geq 6$) with add-one smoothing (scikit-learn)
- Very strong validation set results, but rather weak on test set

Run 2: Conditional Random Fields (CRF)

- Linear-chain CRF: each utterance is a sequence of words (wapiti)
- Rich feature set for each word including word forms, prefix/suffix pairs (1-3 characters), n-grams ($1 \geq n \geq 6$), consonant/vowel word shapes (contribute 1 percentage point of accuracy)
- Optimal number of epochs (35) precomputed by cross-validation
- Not the best results on internal validation set, but it generalized better on test set than NB

Run 3: Ensemble (NB, CRF, SVM)

- Linear SVM with the same n-gram feature model as NB (scikit-learn)
- Majority voting scheme (defaulting to NB in case of ties)

Our Official Results (10 Participants)

Run	F1 (weighted)	F1 (macro)	Accuracy
Baseline			25.80
1st System MAZA	**66.24**	**66.34**	**68.06**
2nd System CECL	66.11	66.25	66.36
Our Run 1 (NB)	61.56	61.65	63.50
Our Run 2 (CRF)	(**3rd**) **65.31**	(**3rd**) **65.38**	67.07
Our Run 3 (ENS)	65.27	65.34	(**2nd**) **67.34**

Detailed Evaluation

	Run 1 (NB)				**Run 2** (CRF)				**Run 3** (ENSEMBLE)			
Σ	BE	BS	LU	ZH	BE	BS	LU	ZH	BE	BS	LU	ZH
Precision	73	*64*	66	57	73	66	73	61	71	69	**76**	61
Recall	66	66	*30*	92	69	74	34	92	73	73	32	**93**
F1	70	65	*42*	70	71	70	47	**74**	72	71	45	**74**

- ZH too greedy; LU difficult to identify; BE/BA more balanced
- Consistent with results of other participants

Experiments with LSTMs

Character-based Long Short-Term Memory Networks (keras) with a hidden layer of 90 neurons. Prediction using softmax over hidden values computed after seeing last character.

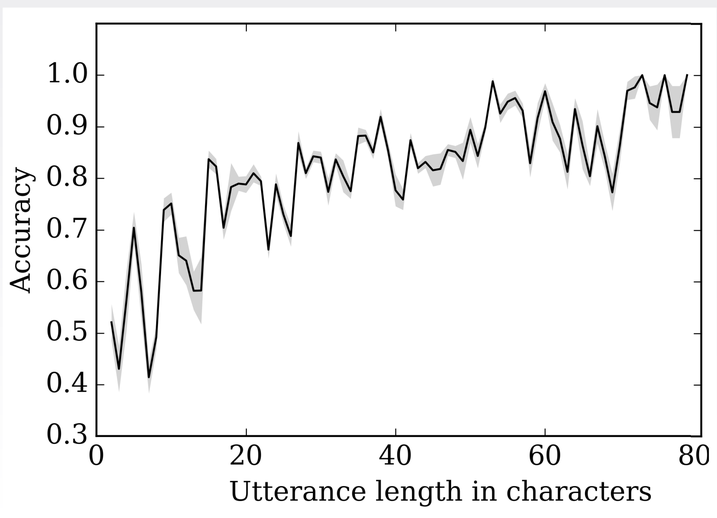
- ± Data augmentation of training set by splitting long utterances: works!
- ± Character embeddings: 2/3 of input size: might hurt. . .
- ± Replacement of diacritic characters: might work. . .

Internal Evaluation (10% of Training Data)

	Accuracy	F1 (macro)	F1 (weighted)
NB	85.43	85.36	85.44
CRF	85.01	85.02	85.01
SVM	82.39	82.36	82.39
ENSEMBLE (NB, CRF, SVM)	**85.50**	**85.42**	**85.50**
LSTM	83.49	83.30	83.46

Our best LSTM approach could not beat the other approaches.

Effect of Utterance Length (LSTMs)



As expected
the longer the sequence, the better the decision

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