Deep Bayesian Semi-Supervised Active Learning for Sequence Labelling

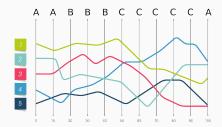
Tomáš Šabata, Juraj Eduard Páll and Martin Holeňa

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Czech Technical University in Prague Faculty of Information technology Department of Applied Mathematics

Motivation

Sequence labelling



- Deep learning has shown supreme results in sequence labelling.
 - Typically requires a large training data set.
 - Requires a series of token-level labels for a whole sequence to be available.
- Goal: Reduce labelling effort.
 - Use active learning to label the most informative sequences.
 - Use **semi-supervised learning** to avoid labelling of "easy" elements.

Proposed approach

Proposed approach

- Deep neural networks are typically over-confident ⇒
 - Bayesian inference approximation using Monte Carlo Dropout.
 - ullet Perform multiple inferences using different dropout masks to obtain $P_M^{MC}(y|x)$
- Adapt approaches of uncertainty sampling designed for sequence labelling.
- Use pseudo-labelling (self-training) to label elements in which the model is confident.

Utility function adaptations

• Monte Carlo approximation of token entropy:

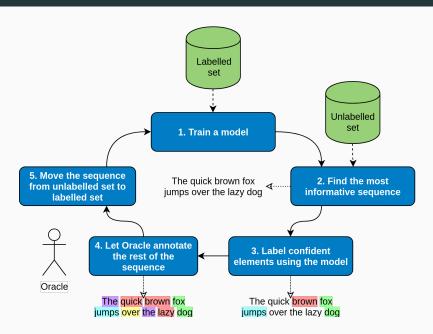
$$\phi_{\text{MC}}^{\text{TE}}(x) = -\frac{1}{L} \sum_{l=1}^{L} \sum_{k=1}^{K} \left(P_{M}^{\text{MC}}(y_{l} = k|x) \log P_{M}^{\text{MC}}(y_{l} = k|x) \right).$$

• Monte Carlo approximation of the sequence entropy:

$$\phi_{\mathsf{MC}}^{\mathsf{NSE}}(x) = -\frac{1}{C} \sum_{\hat{y} \in \mathcal{N}^{\mathsf{MC}}} P_{\mathsf{M}}^{\mathsf{MC}}(\hat{y}|x) \log P_{\mathsf{M}}^{\mathsf{MC}}(\hat{y}|x),$$

where $\mathcal{N}^{\mathsf{MC}} = \{y_1, y_2, ...\}$ is set of all sequences predicted by Monte Carlo sampling.

Semi-supervised active learning



Experimental setup

Experimental setup

- Natural language processing:
 - named entity recognition (NER),
 - part of speech tagging (POS),
 - chunking (CHUNK).
- Benchmark dataset CoNLL 2003 (english).
- Two state of the art models:
 - BI-LSTM-FCN
 - BI-LSTM-CRF
- Training data randomly split into labelled and unlabelled in 1:9 ratio.
- Experiments:
 - Active learning
 - limited number of tokens,
 - unlimited number of tokens.
 - Semi-supervised learning

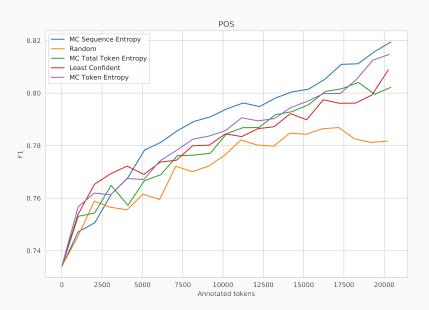
Results

Query strategies comparison

Task type	NER	POS
Random	76.5	78.1
Least Confident	76.9	80.8
MC Total Token Entropy	76.9	80.2
MC Sequence Entropy	77.5	82.0

Table 1: Query strategies comparison (F1 score)

Query strategies comparison



Semi-supervised learning

Task type	NER		POS	
Allowed error	0%	1%	0%	1%
Least confident	77.3	84.3	72.4	82.5
Token entropy	79.5	83.7	72.2	77.9
Total token entropy	75.5	83.5	71.2	81.6

Table 2: Relative amount of pseudo-labeled tokens - BI-LSTM-CRF

Summary and future steps

Summary

- Summary:
 - Two uncertainty sampling query strategies for deep neural network models.
 - Semi-supervised learning can rapidly reduce labelling effort for model with CRF on top.
- Future steps:
 - video processing,
 - study usability of query by committee and expected gradient length,
 - study other approaches to Bayesian recurrent neural networks.

Thank you for your attention.

Questions?

tomas.sabata@fit.cvut.cz