Learning More with Less: Reducing Annotation Effort with Active and Interactive Learning

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1. *What is the research context of the work that you would like to present? For example, which LTI project is this part of and what are the overall goals of that project? What area are you working in (e.g., speech, IR, ML, etc.). [100 words or less]:*

   Annotation learning is an important task for many kinds of text analysis. Statistical machine learning techniques have been developed to learn annotation models over labeled data that are then used to annotate unlabeled data. One of the major bottlenecks of a conventional machine learning approach is getting sufficient pre-labeled training data: annotating text is a time consuming, tedious and error prone process. Moreover, as all the training examples are not equally informative or equally easy to annotate, it is beneficial to identify examples that would help the model to converge with minimal user annotation effort.

   In this project, we present a generalized active learning framework for learning text annotations. This work is part of the Interactive Annotation Learning (IAL) project [Nyberg et al., 2007] at LTI. The goal of this project is to develop a generalized framework for learning any type of annotation (simple or structured).

2. *What were you trying to achieve with your project? For example, was the goal to create a more realistic sounding voice for speech generation or to reduce the word error rate for spontaneous speech in an unrestricted domain? [100 words or less]*

   This project extends an initial software engineering framework[1] developed for the IAL project, in order to demonstrate active and interactive learning techniques for named-entity recognition. We show that requesting the user to label the annotations which the model is most uncertain about can help to learn the target concept faster, while achieving a performance comparable to a traditional approach [Thompson et al., 1999]. We also establish measures that can be used to evaluate different selection strategies for active and interactive learning. Active learning aims at reducing the amount of labeled training data required for learning the target concept, and interactive learning aims at reducing the user annotation effort. We analyze and compare the proposed selection criteria in terms of these measures.

3. *Describe the approach you took. Limit your discussion to what you did personally. [250 words or less]:*

   We used the Stanford Named Entity Recognizer [Finkel et al., 2005] along with the Reuters corpus with labeled named entities from the CoNLL 2003 shared task [Sang et al., 2003].

   We started with an initial set of labeled examples and a large set of unlabeled examples. The classifier is trained on the labeled examples and is used to annotate the unlabeled examples. From the pool of annotated examples, selective sampling is used to create a small subset of examples for the user to label. This iterative process of training, selective sampling and annotation is repeated until the whole training set is processed.

   Selective sampling strategies rank and select examples from the unlabeled documents in the pool. Pool-based sampling strategies are known to perform better than stream-based strategies which consider each document

[1] Developed by Ben Lambert and José Alavedra as part of SE II project

individually irrespective of the alternatives [McCallum et al., 1998]. In our work, we investigated the following pool-based selective sampling strategies.

(a) Average annotation confidence

$$AC = \frac{\sum_{i=1}^{n} conf(l_i)}{N}$$

where: $conf(l_i)$ = confidence assigned to annotation l_i

N = number of annotations

(b) Relative number of annotations below threshold (average annotation confidence over the training pool)

$$RBT = \frac{t - min_t}{max_t - min_t}$$

$$\text{and, threshold } th = \frac{\sum_{i=1}^{D} AC_i \, n_i}{\sum_{i=1}^{D} n_i}$$

where: D = number of Documents

n_i = number of annotations in document i

t = number of annotations with confidence below threshold th

(c) Relative document length

$$RDL = \frac{d - min_d}{max_d - min_d}$$

where: d = number of words

(d) Annotation density

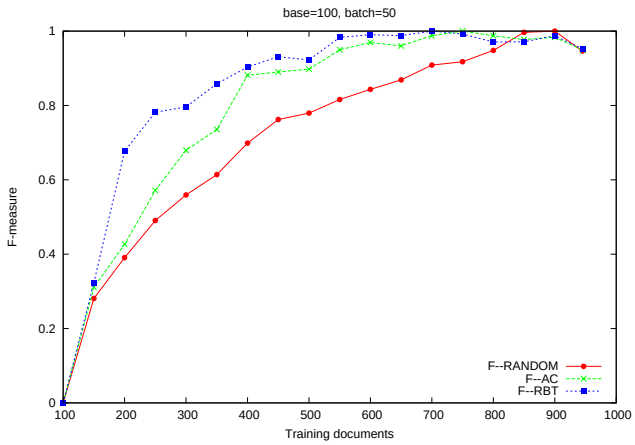
$$AD = \frac{\text{\#words in annotations}}{\text{\#words in document}}$$

Average annotation confidence and number of annotations below threshold are used to select the documents with most uncertainty, while document length and annotation density are used to select documents with lower annotation effort. To combine these two strategies we use a weighted-sum approach. The weights are estimated based on heuristics and domain knowledge, similarly to other work on multi-criterion active learning [Shen et al., 2004] [Kim et al., 2006]. In the future, we plan to use machine learning techniques to estimate automatically the optimum values for these weights.

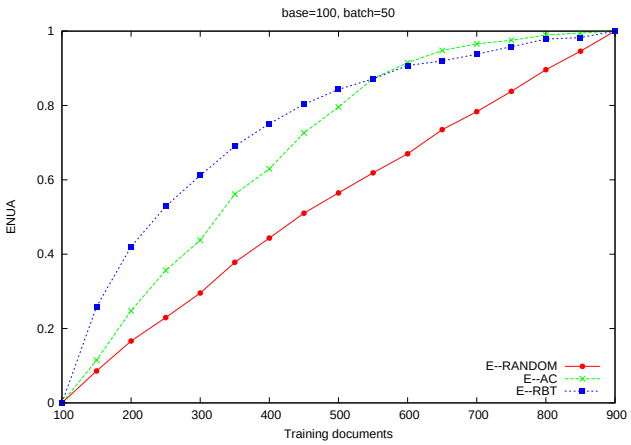
4. *Describe your evaluation methodology and results. In what way do these results advance the state-of-the-art in language technologies? [250 words or less]:*

For evaluation, we use two metrics: Precision and recall (F-measure) of annotations for the performance of the named entity recognition task, and Expected Number of User Actions (ENUA) [Kristjannson et al., 2004] for annotation effort. The selection criteria AC and RBT intend to achieve maximal F-measure with fewer examples, while the criteria RDL and AD intend to reduce the average ENUA to achieve comparable convergence. As a baseline, we use a random recommendation strategy that arbitrarily selects the examples to add to the training pool.

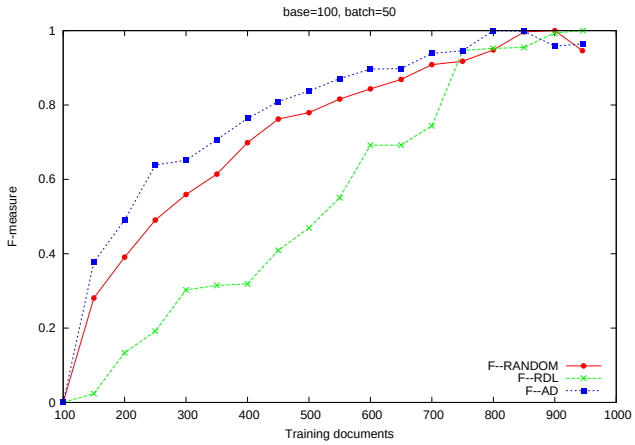
Figs. 1 (a)-(d) show that the confidence-based recommenders (AC & RBT) outperform the random recommender in F-measure but do worse on ENUA. The recommenders based on user interactions (RDL & AD) outperform the random recommender in ENUA but perform worse in F-measure. Fig. 2 shows that a combination of a confidence based strategy (best of AC & RBT) and a user interaction based strategy (best of RDL & AD) achieves performance comparable to the best recommender in both F-measure and ENUA. In Table 1, we show a comparison of normalized F-measure and normalized ENUA (% of total operations) for the combined strategy with the other selection strategies. We are currently working to establish the upper bound on ENUA for



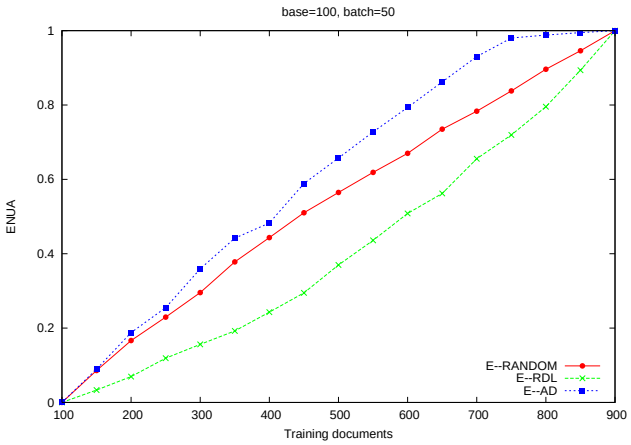
(a) F-measure for AC & RBT (Best: RBT)



(b) ENUA (normalized) for AC & RBT

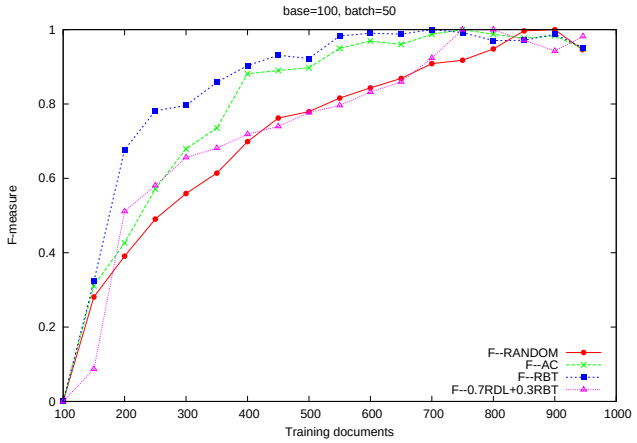


(c) F-measure for RDL & AD

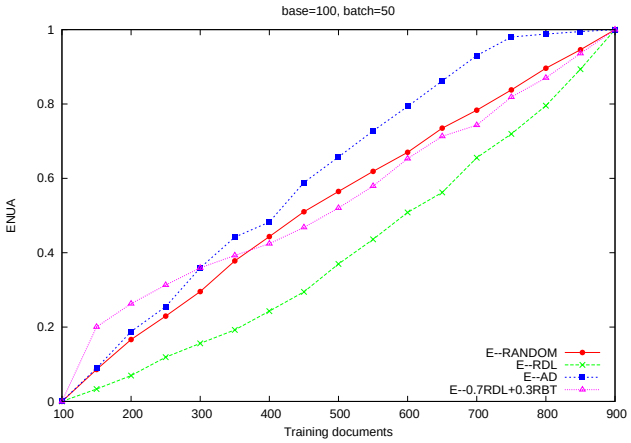


(d) ENUA (normalized) for RDL & AD (Best: RDL)

Figure 1: Comparison of performance in terms of F-measure & ENUA for different recommendation strategies.

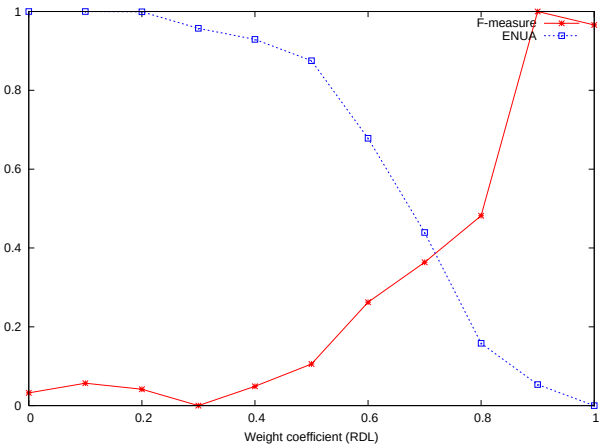


(a) F-measure

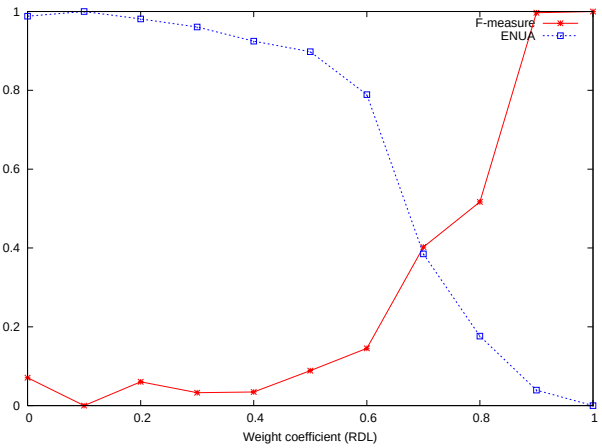


(b) ENUA

Figure 2: Normalized F-measure and ENUA for a combination of RDL and RBT and its comparison with random and best of Active and Interactive measures.



(a) ΔF-measure and ΔENUA for 600 documents



(b) ΔF-measure and ΔENUA at 900 documents

Figure 3: Normalized differences between the optimal and observed values for F-measure and ENUA, using a weighted sum of RBT & RDL as the selection criterion ($D_F = |F_{RBT} - F_C|$ and $D_{ENUA} = |ENUA_{RDL} - ENUA_C|$). The point of intersection indicates the weight value where F-measure is maximum for the minimum value of ENUA.

#Training Documents	F_{RBT}	F_R	F_C	$\Delta_1 F$	$\Delta_2 F$	$ENUA_{RDL}$	$ENUA_R$	$ENUA_C$	$\Delta_1 ENUA$	$\Delta_2 ENUA$
200	0.77	0.71	0.73	0.04	-0.02	4.48	11.41	17.10	-12.62	-5.69
300	0.79	0.74	0.76	0.03	-0.02	8.64	17.16	21.88	-13.24	-4.72
400	0.82	0.77	0.77	0.04	0.00	12.80	23.76	25.10	-12.30	-1.34
500	0.82	0.79	0.78	0.04	0.01	18.90	29.17	29.86	-10.96	-0.69
600	0.83	0.80	0.80	0.04	0.01	25.56	33.87	36.44	-10.88	-2.57
700	0.84	0.82	0.81	0.02	0.00	32.62	38.92	40.90	- 8.28	-1.98
800	0.83	0.83	0.83	0.00	0.00	39.34	43.96	47.20	- 7.86	-3.24
900	0.83	0.84	0.82	0.02	0.02	49.17	48.59	53.63	- 4.46	-5.04

Table 1: A comparison of F-measure & ENUA for selection strategies. Δ_1F & Δ_1ENUA indicate the difference between the combined measure and optimum, while Δ_2F & Δ_2ENUA indicate the difference between the combined measure and random.

the optimal confidence based selection strategy, so that we can measure the savings in user effort for different training sets.[1] We are also working to establish optimum weights for the combined selection strategy.

Figs. 3 (a) and (b) plot the difference between optimal and observed F-measure (ΔF) and ENUA ($\Delta ENUA$) when examples are selected according to a weighted combination of RBT & RDL for certain training dataset sizes. The point of intersection between these two curves indicates the weight value where F-measure is maximum for the minimum value of ENUA.

In this work we demonstrate that it is fruitful to investigate this combination of active and interactive learning strategies for annotation learning. Most of the other work in the literature has focused mainly on minimizing the number of examples required to learn the model. [Kristjannson et al., 2004] use annotation effort as an evaluation measure but to the best of our knowledge, it has not yet been used as a criterion for selective sampling.

5. *Cite any publications in progress or already published that have come out of the work you are submitting here:*

   The work described here is part of a larger research initiative as described in [Nyberg et al., 2007].

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[Shen et al., 2004] Shen D., Zhang J., Su J., Zhou G., Tan C., Multi-Criteria-based Active Learning for Named Entity Recognition. In proceedings of ACL, 2004.

[1] These additional results will be available at the time of the SRS presentation.

[Thompson et al., 1999] Thompson, C. A., Califf, M. E., Mooney, R. J., 1999. Active learning for natural language parsing and information extraction. In proc. 16th International Conf. on Machine Learning. Morgan Kaufmann, San Francisco, CA, pp. 406-414.