Using Domain Similarity for Performance Estimation

Vincent Van Asch
CLiPS - University of Antwerp
Antwerp, Belgium
Vincent.VanAsch@ua.ac.be

Walter Daelemans
CLiPS - University of Antwerp
Antwerp, Belgium
Walter.Daelemans@ua.ac.be

Abstract

Many natural language processing (NLP) tools exhibit a decrease in performance when they are applied to data that is linguistically different from the corpus used during development. This makes it hard to develop NLP tools for domains for which annotated corpora are not available. This paper explores a number of metrics that attempt to predict the cross-domain performance of an NLP tool through statistical inference. We apply different similarity metrics to compare different domains and investigate the correlation between similarity and accuracy loss of NLP tool. We find that the correlation between the performance of the tool and the similarity metric is linear and that the latter can therefore be used to predict the performance of an NLP tool on out-of-domain data. The approach also provides a way to quantify the difference between domains.

1 Introduction

Domain adaptation has recently turned into a broad field of study (Bellegarda, 2004). Many researchers note that the linguistic variation between training and testing corpora is an important factor in assessing the performance of an NLP tool across domains. For example, a tool that has been developed to extract predicate-argument structures from abstracts of biomedical research papers, will exhibit a lower performance when applied to legal texts.

However, the notion of *domain* is mostly arbitrarily used to refer to some kind of semantic area. There is unfortunately no unambiguous measure to assert a domain shift, except by observing the performance loss of an NLP tool when applied across different domains. This means that we typically need annotated data to reveal a domain shift. In this paper we will show how unannotated data can be used to get a clearer view on how datasets differ. This unsupervised way of looking at data will give us a method to measure the difference between data sets and allows us to predict the performance of an NLP tool on unseen, out-of-domain data.

In Section 2 we will explain our approach in detail. In Section 3 we deal with a case study involving basic part-of-speech taggers, applied to different domains. An overview of related work can be found in Section 4. Finally, Section 5 concludes this paper and discusses options for further research.

2 Approach

When developing an NLP tool using supervised learning, annotated data with the same linguistic properties as the data for which the tool is developed is needed, but not always available. In many cases, this means that the developer needs to collect and annotate data suited for the task. When this is not possible, it would be useful to have a method that can estimate the performance on corpus B of an NLP tool trained on corpus A in an unsupervised way, i.e., without the necessity to annotate a part of B.

In order to be able to predict in an unsupervised way the performance of an NLP tool on different corpora, we need a way to measure the differences between the corpora. The metric at hand should be independent from the annotation labels, so that it can be easily applied on any given corpus. The aim is to find a metric such that the correlation between the metric and the performance is statistically significant. In the scope of this article the concept *metric* stands for any way of assigning a sufficiently fine-grained label to a corpus, using only unannotated data. This means that, in our view, a metric can be an elaborate mixture of frequency counts, rules, syntactic pattern matching or

even machine learner driven tools. However, in the remainder of this paper we will only look at frequency based similarity metrics since these metrics are easily applicable and the experiments conducted using these metrics were already encouraging.

3 Experimental design

3.1 Corpus

We used data extracted from the British National Corpus (BNC) (2001) and consisting of written books and periodicals[1]. The BNC annotators provided 9 domain codes (i.e. wridom), making it possible to divide the text from books and periodicals into 9 subcorpora. These annotated semantic domains are: imaginative (wridom1), natural & pure science (wridom2), applied science (wridom3), social science (wridom4), world affairs (wridom5), commerce & finance (wridom6), arts (wridom7), belief & thought (wridom8), and leisure (wridom9).

The extracted corpus contains sentences in which every token is tagged with a part-of-speech tag as defined by the BNC. Since the BNC has been tagged automatically, using the CLAWS4 automatic tagger (Leech *et al.*, 1994) and the Template Tagger (Pacey *et al.*, 1997), the experiments in this article are artificial in the sense that they do not learn *real* part-of-speech tags but rather part-of-speech tags as they are assigned by the automatic taggers.

3.2 Similarity metrics

To measure the difference between two corpora we implemented six similarity metrics: Rényi[2] (Rényi, 1961), Variational (L1) (Lee, 2001), Euclidean (Lee, 2001), Cosine (Lee, 2001), Kullback-Leibler (Kullback and Leibler, 1951) and Bhattacharyya coefficient (Comaniciu *et al.*, 2003; Bhattacharyya, 1943). We selected these measures because they are well-described and produce results for this task in an acceptable time span.

The metrics are computed using the relative frequencies of words. For example, to calculate the Rényi divergence between corpus P and corpus Q the following formula is applied:

$$Rényi(P;Q;\alpha) = \frac{1}{(\alpha-1)} log_2 \left(\sum^k p_k^{1-\alpha} q_k^{\alpha} \right)$$

p_k is the relative frequency of a token k in the first corpus P, and q_k is the relative frequency of token k in the second corpus Q. α is a free parameter and with $\alpha = 1$ the Rényi divergence becomes equivalent to the Kullback-Leibler divergence.

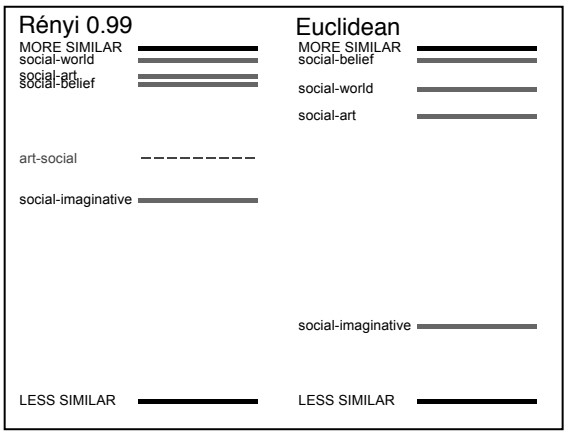


Figure 1: A visual comparison of two similarity metrics: Rényi with $\alpha = 0.99$ and Euclidean.

Figure 1 gives an impression of the difference between two similarity metrics: Rényi ($\alpha = 0.99$) and Euclidean. Only four domain combinations are shown for the sake of clarity. From the graph it can be observed that the *social* and *imaginative* domains are the least similar in both cases. Besides the different ordering, there is also a difference in symmetry. Contrary to the symmetric Euclidean metric, the Rényi scores differ, depending on whether *social* constitutes the test set and *art* the training set, or vice versa. The dashed line on Figure 1 (left) is a reverse score, namely for *art-social*. A divergence score may diverge a lot from its reverse score.

In practice, the best metric to choose is the metric that gives the best linear correlation between the metric and the accuracy of an NLP tool applied across domains. We tested 6 metrics: Rényi, Variational (L1), Euclidean, Cosine, Kullback-Leibler, and the Bhattacharyya coefficient. For Rényi, we tested four different α-values: 0.95, 0.99, 1.05, and 1.1. Most metrics gave a linear correlation but for our experiments with data-driven POS tagging, the Rényi metric with $\alpha = 0.99$ was the best

[1] This is done by selecting texts with BNC category codes for text type (i.e. alltyp3 (written books and periodicals)) and for medium (i.e. wrimed1 (book), wrimed2 (periodical), and wrimed3 (miscellaneous: published)).

[2] The Rényi divergence has a parameter α and Kullback-Leibler is a special case of the Rényi divergence, viz. with $\alpha = 1$.

according to the Pearson product-moment correlation. For majority this correlation was 0.91, for Mbt 0.93, and for SVMTool 0.93.

3.3 Part-of-speech tagging

The experiments carried out in the scope of this article are all part-of-speech (POS) tagging tasks. There are 91 different POS labels in the BNC corpus which are combinations of 57 basic labels. We used three algorithms to assign part-of-speech labels to the words from the test corpus:

Majority This algorithm assigns the POS label that occurs most frequently in the training set for a given word, to the word in the test set. If the word did not occur in train, the overall most frequent tag was used.

Memory based POS tagger (Daelemans and van den Bosch, 2005) A machine learner that stores examples in memory (Mbt) and uses the *k*NN algorithm to assign POS labels. The default settings were used.

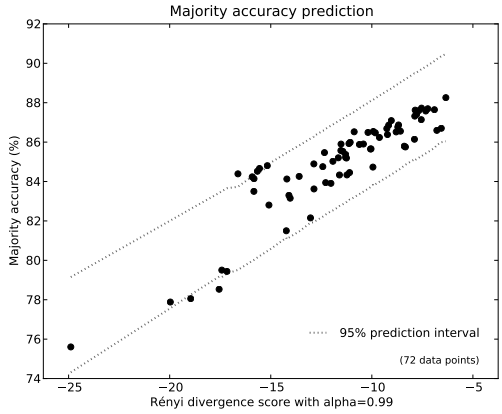
SVMTool POS tagger (Giménez and Márquez, 2004) Support vectors machines in a sequential setup are used to assign the POS labels. The default settings were used.

3.4 Results and analysis

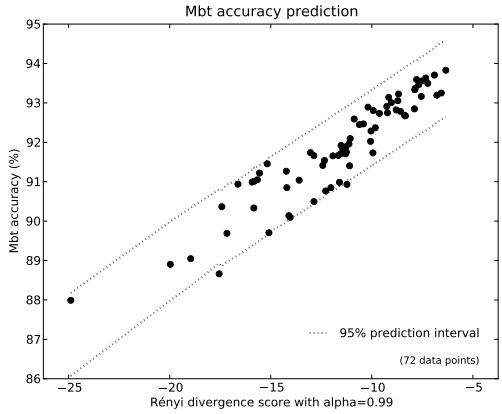
Figure 2 shows the outcome of 72 cross-validation experiments on the data from the British National Corpus. The graph for the majority baseline is shown in Figure 2a. The results for the memory based tagger are shown in Figure 2b and the graph for SVMTool is displayed in Figure 2c.

For every domain, the data is divided into five parts. For all pairs of domains, each part from the training domain is paired with each part from the testing domain. This results in a 25 cross-validation cross-domain experiment. A data point in Figure 2 is the average outcome of such a 25 fold experiment. The abscissa of a data point is the Rényi similarity score between the training and testing component of an experiment. The α parameter was set to 0.99. We propose that the higher (less negative) the similarity score, the more similar training and testing data are.

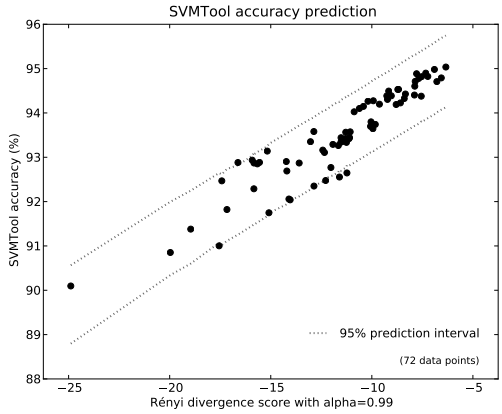
The ordinate is the accuracy of the POS tagging experiment. The dotted lines are the 95% prediction intervals for every data point. These boundaries are obtained by linear regression using all other data points. The interpretation of the intervals is that any point, given all other data points



(a) Majority POS tagger.



(b) Memory based POS tagger.



(c) SVMTool POS tagger.

Figure 2: The varying accuracy of three POS taggers with varying distance between train and test corpus of different domains.

from the graph, can be predicted with 95% certainty, to lie between the upper and lower interval boundary at the similarity score of that point. The average difference between the lower and the upper interval boundary is 4.36% for majority, 1.92% for Mbt and 1.59% for SVMTool. This means that,

	Majority	Mbt	SVMTool
average accuracy	84.94	91.84	93.48
standard deviation	2.50	1.30	1.07

Table 1: Average accuracy and standard deviation on 72 cross-validation experiments.

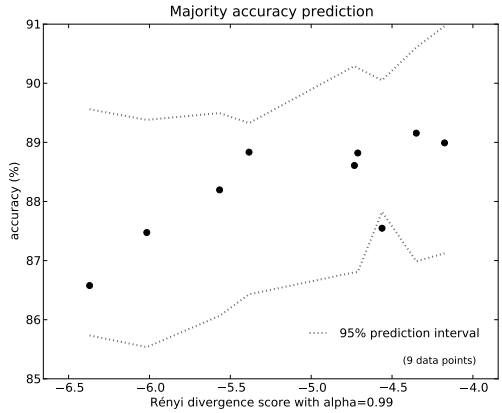
when taking the middle of the interval as the expected accuracy, the maximum error is 0.8% for SVMTool. Since the difference between the best and worst accuracy score is 4.93%, using linear regression means that one can predict the accuracy three times better. For Mbt with a range of 5.84% between best and worst accuracy and for majority with 12.7%, a similar figure is obtained.

Table 1 shows the average accuracies of the algorithms for all 72 experiments. For this article, the absolute accuracy of the algorithms is not under consideration. Therefore, no effort has been made to improve on these accuracy scores. One can see that the standard deviation for SVMTool and Mbt is lower than for majority, suggesting that these algorithms are less susceptible to domain variation.

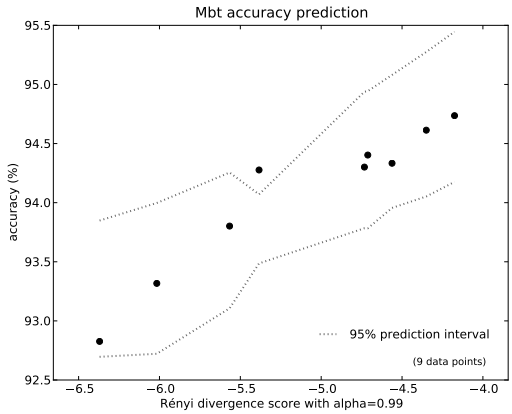
The good linear fit for the graphs of Figure 2 cannot be reproduced with every algorithm. For algorithms that do not have a sufficiently strong relation between training corpus and assigned class label, the linear relation is lost. Clearly, it remains feasible to compute an interval for the data points, but as a consequence of the non-linearity, the predicted intervals would be similar or even bigger than the difference between the lowest and highest accuracy score.

In Figure 3 the experiments of Figure 2 are reproduced using test and training sets from the same domain. Since we used the same data sets as for the out-of-domain experiments, we had to carry out 20 fold cross-validation for these experiments. Because of this different setup the results are shown in a different figure. There is a data point for every domain.

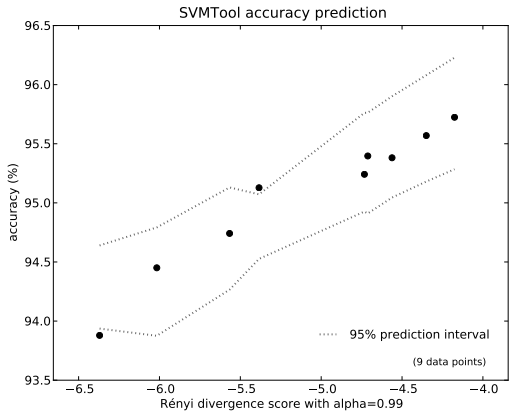
Although the average distance between test and training set are smaller for in-domain experiments, we still observe a linear relation for Mbt and SVM, for majority there is still a visual hint of linearity. For in-domain the biggest difference between test and train set is for the *leisure* domain (Rényi score: -6.0) which is very close to the smallest out-of-domain difference (-6.3 for social sciences–world affairs). This could mean that the random variation between test and train can approach the varia-



(a) Majority POS tagger.



(b) Memory based POS tagger.



(c) SVMTool POS tagger.

Figure 3: The varying accuracy of three POS taggers with varying distance between train and test corpus of the same domain.

tion between domains but this observation is made in abstraction from the different data set sizes for in and out of domain experiments. For majority the average accuracy over all domains is 88.25% (stdev: 0.87), for Mbt 94.07% (0.63), and for SVMTool 95.06% (0.59). Which are, as expected, higher scores than the figures in Table 1.

4 Related Work

In articles dealing with the influence of domain shifts on the performance of an NLP tool, the in-domain data and out-of-domain data are taken from different corpora, e.g., sentences from movie snippets, newspaper texts and personal weblogs (Andreevskaia and Bergler, 2008). It can be expected that these corpora are indeed dissimilar enough to consider them as separate domains, but no objective measure has been used to define them as such. The fact that the NLP tool produces lower results for cross-domain experiments can be taken as an indication of the presence of separate domains. A nice overview paper on statistical domain adaptation can be found in Bellegarda (2004).

A way to express the degree of relatedness, apart from this well-known accuracy drop, can be found in Daumé and Marcu (2006). They propose a domain adaptation framework containing a parameter π. Low values of π mean that in-domain and out-of-domain data differ significantly. They also used Kullback-Leibler divergence to compute the similarity between unigram language models.

Blitzer *et al.* (2007) propose a supervised way of measuring the similarity between the two domains. They compute the Huber loss, as a proxy of the $\mathcal{A}$-distance (Kifer *et al.*, 2004), for every instance that they labeled with their tool. The resulting measure correlates with the adaptation loss they observe when applying a sentiment classification tool on different domains.

5 Conclusions and future work

This paper showed that it is possible to narrow down the prediction of the accuracy of an NLP tool on an unannotated corpus by measuring the similarity between this unannotated corpus and the corpus the tagger was trained on in an unsupervised way. A prerequisite to be able to make a reliable prediction, is to have sufficient annotated data to measure the correlation between the accuracy and a metric. We observed that, in order to make a prediction interval that is narrower than the difference between the lowest and highest accuracy on the annotated corpora, the algorithm used, should capture sufficient information from training.

The observation that it is feasible to make reliable predictions using unannotated data, can be of help when training a system for a task in a domain for which no annotated data is available. As a first step, the metric resulting in the best linear fit between the metric and the accuracy should be searched. If a linear relation can be established, one can take annotated training data from the domain that is closest to the unannotated corpus and assume that this will give the best accuracy score.

In this article we implemented a way to measure the similarity between two corpora. One may decide to use such a metric to categorize the available corpora for a given task into groups, depending on their similarity. It should be noted that in order to do this, a symmetric metric should be used. Indeed, an asymmetric metric like the Rényi divergence will give a different value depending on whether the similarity between corpus P and corpus Q is measured as $Rényi(P; Q; \alpha)$ or as $Rényi(Q; P; \alpha)$.

Further research should explore the usability of linear regression for other NLP tasks. Although no specific adaptation to the POS tagging task was made, it may not be straightforward to find a linear relation for more complicated tasks. For such tasks, it may be useful to insert n-grams into the metric. Or, if a parser was first applied to the data, it is possible to insert syntactic features in the metric. Of course, these adaptations may influence the efficiency of the metric, but if a good linear relation between the metric and the accuracy can be found, the metric is useful. Another option to make the use of the metric less task dependent is by not using the distribution of the tokens but by using distributions of the features used by the machine learner. Applying this more generic setup of our experiments to other NLP tools may lead to the discovery of a metric that is generally applicable.

Acknowledgments

This research was made possible through financial support from the University of Antwerp (BIOGRAPH GOA-project).

References

Alfred V. Aho and Jeffrey D. Ullman. 1972. *The Theory of Parsing, Translation and Compiling*, volume 1. Prentice-Hall, Englewood Cliffs, NJ.

Alina Andreevskaia and Sabine Bergler. 2008. When Specialists and Generalists Work Together: Overcoming Domain Dependence in Sentiment Tagging. *Proceedings of the* 46th *Annual Meeting of the Association for Computational Linguistics: Human Language Technologies (ACL-08:HLT)*, 290–298. Association for Computational Linguistics. Columbus, Ohio, USA.

Jerome R. Bellegarda. 2004. Statistical language model adaptation: review and perspectives. *Speech Communication*, 42:93–108.

Anil Bhattacharyya. 1943. On a measure of divergence between two statistical populations defined by their probability distributions. *Bulletin of the Calcutta Mathematical Society*, 35:99–109.

John Blitzer, Mark Dredze, and Fernando Pereira. 2007. Biographies, Bollywood, Boom-boxes and Blenders: Domain Adaptation for Sentiment Classification. *Proceedings of the* 45th *Annual Meeting of the Association of Computational Linguistics*, 440–447. Association for Computational Linguistics. Prague, Czech Republic.

British National Corpus Consortium. 2001. The British National Corpus, version 2 (BNC World). Distributed by Oxford University Computing Services on behalf of the BNC Consortium. http://www.natcorp.ox.ac.uk (Last accessed: April 2, 2010).

Dorin Comaniciu, Visvanathan Ramesh, and Peter Meer. 2003. Kernel-Based Object Tracking. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 25(5):564–575.

Walter Daelemans and Antal van den Bosch. 2005. *Memory-Based Language Processing*. Cambridge University Press, Cambridge, UK.

Hal Daumé III and Daniel Marcu. 2006. Domain Adaptation for Statistical Classifiers. *Journal of Artificial Intelligence Research*, 26:101–126.

T. Mark Ellison and Simon Kirby. 2006. Measuring Language Divergence by Intra-Lexical Comparison. *Proceedings of the* 21st *International Conference on Computational Linguistics and* 44th *Annual Meeting of the ACL*, 273–280. Association for Computational Linguistics. Sidney, Australia.

Jesús Giménez and Lluís Márquez. 2004. SVMTool: A general POS tagger generator based on Support Vector Machines. *Proceedings of the 4th International Conference on Language Resources and Evaluation (LREC'04)*, 43–46. European Language Resources Association. Lisbon, Portugal.

Daniel Kifer, Shai Ben-David, and Johannes Gehrke. 2004. Detecting change in data streams. *Proceedings of the 30th Very Large Data Bases Conference (VLDB'04)*, 180–191. VLDB Endowment. Toronto, Canada.

Solomon Kullback and Richard. A. Leibler. 1951. On Information and Sufficiency. *The Annals of Mathematical Statistics*, 22(1):79–86.

Lillian Lee. 2001. On the Effectiveness of the Skew Divergence for Statistical Language Analysis. 8th *International Workshop on Artificial Intelligence and Statistics (AISTATS 2001)*, 65–72. Florida, USA. Online repository http://www.gatsby.ucl.ac.uk/aistats/aistats2001 (Last accessed: April 2, 2010).

Geoffrey Leech, Roger Garside, and Michael Bryant. 1994. CLAWS4: The tagging of the British National Corpus. *Proceedings of the 15th International Conference on Computational Linguistics (COLING 94)*, 622–628. Kyoto, Japan.

Michael Pacey, Steven Fligelstone, and Paul Rayson. 1997. How to generalize the task of annotation. *Corpus Annotation: Linguistic Information from Computer Text Corpora*, 122–136. London: Longman.

Alfréd Rényi. 1961. On measures of information and entropy. *Proceedings of the* 4th *Berkeley Symposium on Mathematics, Statistics and Probability*, 1:547–561. University of California Press. Berkeley, California, USA.