Automatically Predicting Sentence Translation Difficulty

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Abstract

In this paper we introduce *Translation Difficulty Index* (TDI), a measure of difficulty in text translation. We first define and quantify translation difficulty in terms of TDI. We realize that any measure of TDI based on *direct* input by translators is fraught with subjectivity and adhocism. We, rather, rely on *cognitive evidences* from eye tracking. TDI is measured as the sum of *fixation (gaze)* and *saccade (rapid eye movement)* times of the eye. We then establish that TDI is correlated with three properties of the input sentence, *viz. length (L), degree of polysemy (DP)* and *structural complexity (SC)*. We train a *Support Vector Regression* (SVR) system to predict TDIs for new sentences using these features as input. The prediction done by our framework is well correlated with the empirical gold standard data, which is a repository of $< L, DP, SC >$ and TDI pairs for a set of sentences. The primary use of our work is a way of "binning" sentences (to be translated) in "easy", "medium" and "hard" categories as per their predicted TDI. This can decide pricing of any translation task, especially useful in a scenario where parallel corpora for *Machine Translation* are built through translation crowdsourcing/outsourcing. This can also provide a way of monitoring progress of second language learners.

1 Introduction

Difficulty in translation stems from the fact that most words are polysemous and sentences can be long and have complex structure. While *length of sentence* is commonly used as a translation difficulty indicator, *lexical* and *structural* properties of a sentence also contribute to translation difficulty. Consider the following example sentences.

> *1. The camera-man shot the policeman with a gun. (length-8)*
>
> *2. I was returning from my old office yesterday. (length-8)*

Clearly, sentence 1 is more difficult to process and translate than sentence 2, since it has lexical ambiguity (*"Shoot" as an act of firing a shot or taking a photograph?*) and structural ambiguity (*Shot with a gun* or *policeman with a gun*?). To produce fluent and adequate translations, efforts have to be put to analyze both the lexical and syntactic properties of the sentences.

The most recent work on studying translation difficulty is by Campbell and Hale (1999) who identified several areas of difficulty in lexis and grammar. "Reading" researchers have focused on developing readability formulae, since 1970. The *Flesch-Kincaid Readability test* (Kincaid et al., 1975), the *Fry Readability Formula* (Fry, 1977) and the *Dale-Chall readability formula* (Chall and Dale, 1999) are popular and influential. These formulae use factors such as vocabulary difficulty (or semantic factors) and sentence length (or syntactic factors). In a different setting, Malsburg et al. (2012) correlate eye fixations and scanpaths of readers with sentence processing. While these approaches are successful in quantifying readability, they may not be applicable to translation scenarios. The reason is that, translation is not merely a reading activity. Translation requires co-ordination between source text comprehension and target text production (Dragsted, 2010). To the best of our knowledge, our work on predicting TDI is the first of its kind.

The motivation of the work is as follows. Currently, for domain specific Machine Translation systems, parallel corpora are gathered through translation crowdsourcing/outsourcing. In such

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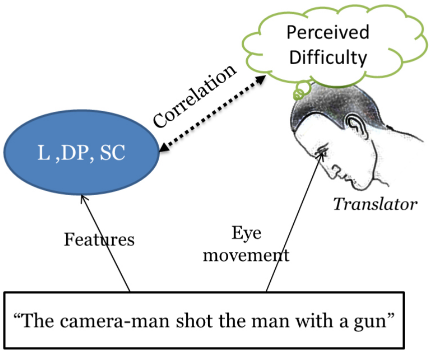


Figure 1: Inherent sentence complexity and perceived difficulty during translation

a scenario, translators are paid on the basis of sentence length, which ignores other factors contributing to translation difficulty, as stated above. Our proposed Translation Difficulty Index (TDI) quantifies the translation difficulty of a sentence considering both lexical and structural properties. This measure can, in turn, be used to cluster sentences according to their difficulty levels (*viz.* easy, medium, hard). Different payment and schemes can be adopted for different such clusters.

TDI can also be useful for training and evaluating second language learners. For example, appropriate examples at particular levels of difficulty can be chosen for giving assignments and monitoring progress.

The rest of the paper is organized in the following way. Section 2 describes TDI as function of translation processing time. Section 3 is on measuring translation processing time through eye tracking. Section 4 gives the correlation of linguistic complexity with observed TDI. In section 5, we describe a technique for predicting TDIs and ranking unseen sentences using *Support Vector Machines*. Section 6 concludes the paper with pointers to future work.

2 Quantifying Translation Difficulty

As a first approximation, TDI of a sentence can be the *time taken to translate* the sentence, which can be measured through simple translation experiments. This is based on the assumption that more difficult sentences will require more time to translate. However, "time taken to translate" may not be strongly related to the translation difficulty for two reasons. First, it is difficult to know what fraction of the total translation time is actually spent on the translation-related-thinking. For example, translators may spend considerable amount of time typing/writing translations, which is irrelevant to the translation difficulty. Second, the translation time is sensitive to distractions from the environment. So, instead of the "time taken to translate", we are more interested in the "time for which translation related processing is carried out by the brain". This can be termed as the *Translation Processing Time* (T_p). Mathematically,

$$T_p = T_{p\_comp} + T_{p\_gen} \qquad (1)$$

Where T_{p_comp} and T_{p_gen} are the processing times for source text comprehension and target text generation respectively. The empirical TDI, is computed by normalizing T_p with sentence length.

$$TDI = \frac{T_p}{sentencelength} \qquad (2)$$

Measuring T_p is a difficult task as translators often switch between thinking and writing activities. Here comes the role of *eye tracking*.

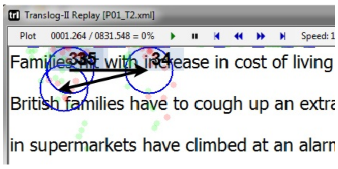
3 Measuring T_p by eye-tracking

We measure T_p by analyzing the gaze behavior of translators through eye-tracking. The rationale behind using eye-tracking is that, humans spend time on what they see, and this "time" is correlated with the complexity of the information being processed, as shown in Figure 1. Two fundamental components of eye behavior are (a) *Gaze-fixation* or simply, *Fixation* and (b) *Saccade*. The former is a long stay of the visual gaze on a single location. The latter is a very rapid movement of the eyes between positions of rest. An intuitive feel for these two concepts can be had by considering the example of translating the sentence *The camera-man shot the policeman with a gun* mentioned in the introduction. It is conceivable that the eye will linger long on the word "shot" which is ambiguous and will rapidly move across "shot", "camera-man" and "gun" to ascertain the clue for disambiguation.

The terms T_{p_comp} and T_{p_gen} in (1) can now be looked upon as the sum of fixation and saccadic durations for both source and target sentences respectively.

Modifying 1

$$\begin{aligned} T_p = &\sum_{f \in F_s} dur(f) + \sum_{s \in S_s} dur(s) \\ &+ \sum_{f \in F_t} dur(f) + \sum_{s \in S_t} dur(s) \end{aligned} \qquad (3)$$



Translog-II Replay [P01_T2.xml]

Plot 0001.264 / 0831.548 = 0% Speed: 1

Families hit with increase in cost of living

British families have to cough up an extra

in supermarkets have climbed at an alarn

Figure 2: Screenshot of Translog. The circles represent fixations and arrow represent saccades.

Here, F_s and S_s correspond to sets of fixations and saccades for source sentence and F_t and S_t correspond to those for the target sentence respectively. *dur* is a function returning the duration of fixations and saccades.

3.1 Computing TDI using eye-tracking database

We obtained TDIs for a set of sentences from the Translation Process Research Database (TPR 1.0)(Carl, 2012). The database contains translation studies for which gaze data is recorded through the Translog software[1](Carl, 2012). Figure 2 presents a screendump of Translog. Out of the 57 available sessions, we selected 40 translation sessions comprising 80 sentence translations[2]. Each of these 80 sentences was translated from English to three different languages, *viz.* Spanish, Danish and Hindi by at least 2 translators. The translators were young professional linguists or students pursuing PhD in linguistics.

The eye-tracking data is noisy and often exhibits *systematic errors* (Hornof and Halverson, 2002). To correct this, we applied automatic error correction technique (Mishra et al., 2012) followed by manually correcting incorrect gaze-to-word mapping using Translog. Note that, gaze and saccadic durations may also depend on the translator's reading speed. We tried to rule out this effect by sampling out translations for which the variance in participant's reading speed is minimum. Variance in reading speed was calculated after taking a samples of source text for each participant and measuring the time taken to read the text.

After preprocessing the data, TDI was computed for each sentence by using (2) and (3).The observed unnormalized TDI score[3] ranges from 0.12 to 0.86. We normalize this to a [0,1] scale using MinMax normalization.

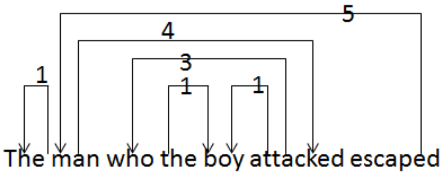


Figure 3: Dependency graph used for computing SC

If the "time taken to translate" and T_p were strongly correlated, we would have rather opted "time taken to translate" for the measurement of TDI. The reason is that "time taken to translate" is relatively easy to compute and does not require expensive setup for conducting "eye-tracking" experiments. But our experiments show that there is a weak correlation (coefficient = 0.12) between "time taken to translate" and T_p. This makes us believe that T_p is still the best option for TDI measurement.

4 Relating TDI to sentence features

Our claim is that translation difficulty is mainly caused by three features: *Length*, *Degree of Polysemy* and *Structural Complexity*.

4.1 Length

It is the total number of words occurring in a sentence.

4.2 Degree of Polysemy (DP)

The degree of polysemy of a sentence is the sum of senses possessed by each word in the Wordnet normalized by the sentence length. Mathematically,

$$DP_{sentence} = \frac{\sum_{w \in W} Senses(w)}{length(sentence)} \tag{4}$$

Here, *Senses(w)* retrieves the total number senses of a word P from the Wordnet. *W* is the set of words appearing in the sentence.

4.3 Structural Complexity (SC)

Syntactically, words, phrases and clauses are attached to each other in a sentence. If the attachment units lie far from each other, the sentence has higher structural complexity. Lin (1996) defines it as the *total length of dependency links in the dependency structure of the sentence*.

[1] http://www.translog.dk

[2] 20% of the translation sessions were discarded as it was difficult to rectify the gaze logs for these sessions.

[3] Anything beyond the upper bound is hard to translate and can be assigned with the maximum score.

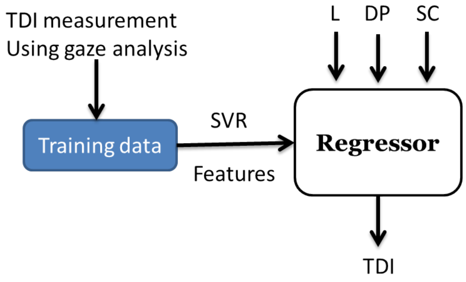


Figure 4: Prediction of TDI using linguistic properties such as Length(L), Degree of Polysemy (DP) and Structural Complexity (SC)

> Example: *The man who the boy attacked escaped.*

Figure 3 shows the dependency graph for the example sentence. The weights of the edges correspond how far the two connected words lie from each other in the sentence. Using Lin's formula, the SC score for the example sentence turns out to be 15.

Lin's way of computing SC is affected by sentence length since the number of dependency links for a sentence depends on its length. So we normalize SC by the length of the sentence. After normalization, the SC score for the example given becomes 15/7 = 2.14

4.4 How are TDI and linguistic features related

To validate that translation difficulty depends on the above mentioned linguistic features, we tried to find out the correlation coefficients between each feature and empirical TDI. We extracted three sets of sample sentences. For each sample, sentence selection was done with a view to varying one feature, keeping the other two constant. The Correlation Coefficients between L, DP and SC and the empirical TDI turned out to be **0.72**, **0.41** and **0.63** respectively. These positive correlation coefficients indicate that all the features contribute to the translation difficulty.

5 Predicting TDI

Our system predicts TDI from the linguistic properties of a sentence as shown in Figure 4.

The prediction happens in a supervised setting through regression. Training such a system requires a set sentences annotated with TDIs. In our case, direct annotation of TDI is a difficult and unintuitive task. So, we annotate TDI by observing translator's behavior (using equations (1) and (2))instead of asking people to rate sentences with TDI.

Kernel(C=3.0)	MSE (%)	Correlation
Linear	20.64	0.69
Poly (Deg 2)	**12.88**	**0.81**
Poly (Deg 3)	13.35	0.78
Rbf (default)	13.32	0.73

Table 1: Relative MSE and Correlation with observed data for different kernels used for SVR.

We are now prepared to give the regression scenario for predicting TDI.

5.1 Preparing the dataset

Our dataset contains 80 sentences for which TDI have been measured (Section 3.1). We divided this data into 10 sets of training and testing datasets in order to carry out a 10-fold evaluation. DP and SC features were computed using Princeton Wordnet[4] and Stanford Dependence Parser[5].

5.2 Applying Support Vector Regression

To predict TDI, Support Vector Regression (SVR) technique (Joachims et al., 1999) was preferred since it facilitates multiple kernel-based methods for regression. We tried using different kernels using default parameters. Error analysis was done by means of Mean Squared Error estimate (MSE). We also measured the Pearson correlation coefficient between the empirical and predicted TDI for our test-sets.

Table 1 indicates Mean Square Error percentages for different kernel methods used for SVR. MSE (%) indicates by what percentage the predicted TDIs differ from the observed TDIs. In our setting, quadratic polynomial kernel with c=3.0 outperforms other kernels. The predicted TDIs are well correlated with the empirical TDIs. This tells us that even if the predicted scores are not as accurate as desired, the system is capable of ranking sentences in correct order. Table 2 presents examples from the test dataset for which the observed TDI (TDI_O) and the TDI predicted by polynomial kernel based SVR (TDI_P) are shown.

Our larger goal is to group unknown sentences into different categories by the level of transla-

[4] http://www.wordnet.princeton.edu

[5] http://www.nlp.stanford.edu/software/lex-parser.html

Example	L	DP	SC	TDI_O	TDI_P	Error
1. American Express recently announced a second round of job cuts.	10	10	1.8	0.24	0.23	4%
2. Sociology is a relatively new academic discipline.	7	6	3.7	0.49	0.53	8%

Table 2: Example sentences from the test dataset.

tion difficulty. For that, we tried to manually assign three different class labels to sentences *viz. easy, medium and hard* based on the empirical TDI scores. The ranges of scores chosen for easy, medium and hard categories were [0-0.3], [0.3-0.75] and [0.75-1.0] respectively (by trial and error). Then we trained a *Support Vector Rank* (Joachims, 2006) with default parameters using different kernel methods. The ranking framework achieves a maximum **67.5%** accuracy on the test data. The accuracy should increase by adding more data to the training dataset.

6 Conclusion

This paper introduces an approach to quantifying translation difficulty and automatically assigning difficulty levels to unseen sentences. It establishes a relationship between the intrinsic sentential properties, *viz.*, *length (L), degree of polysemy (DP)* and *structural complexity (SC)*, on one hand and the Translation Difficulty Index (*TDI*), on the other. Future work includes deeper investigation into other linguistic factors such as presence of domain specific terms, target language properties *etc.* and applying more sophisticated cognitive analysis techniques for more reliable TDI score. We would like to make use of *inter-annotator agreement* to decide the boundaries for the translation difficulty categories. Extending the study to different language pairs and studying the applicability of this technique for Machine Translation Quality Estimation are also on the agenda.

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