Cost Optimization in Crowdsourcing Translation: Low cost translations made even cheaper

Abstract

Crowdsourcing makes it possible to create translations at much lower cost than hiring professional translators. However, it is still expensive to obtain millions of translations needed to train high performance statistical machine translation systems. We proposed two mechanisms to reduce the cost of crowdsourcing while maintaining high translation quality. First, we develop a translation reducing method. We train a linear model to evaluate the translation quality on a sentence-by-sentence basis, and fit a threshold between acceptable and unacceptable translations. Unlike past work, which always paid for a fixed number of translations of each source sentence and then chose the best from them, we can stop earlier and pay less when we receive a translation that is good enough. Second, we introduce a translator reducing method by quickly identifying bad translators after they have translated only a few sentences. This also allows us to rank translators, so that we re-hire only good translators to reduce cost

1 Introduction

Crowdsourcing is a promising new mechanism for collecting large volumes of annotated data at low cost. Many NLP researchers have started creating speech and language data through crowdsourcing (for example, Snow et al. (2008), Callison-Burch and Dredze (2010) and others). One NLP application that has been the focus of crowdsourced data collection is statistical machine translation (SMT) which requires large bilingual sentence-aligned parallel corpora to train translation models. Crowdsourcing's low costs has made it possible to hire people to create sufficient volumes of translation in order to train SMT systems (for example, Zbib et al. (2013), Zbib et al. (2012), Post et al. (2012), Ambati and Vogel (2010)).

However, crowdsourcing is not perfect, and one of its most pressing challenges is how to ensure the quality of the data that is created by it. Unlike in more traditional employment scenarios, where annotators are pre-vetted and their skills are clear, in crowdsourcing very little is known about the annotators. They are not professional translators, and there are no built-in mechanisms for testing their language skills. They complete tasks without any oversight. Thus, translations produced via crowdousrcing may be low quality. Previous work has addressed this problem, showing that non-professional translators hired on Amazon Mechanical Turk (MTurk) can achieve professional-level quality, by soliciting multiple translations of each source sentence and then choosing the best translation (Zaidan and Callison-Burch, 2011).

In this paper we focus on a different aspect of crowdsourcing from Zaidan and Callison-Burch (2011). We attempt to achieve the same high quality while **minimizing the associated costs**. We propose two complementary methods: (1) We reduce the number of translations that we solicit for each source sentence. Instead of soliciting a fixed number of translations for each foreign sentence, we stop soliciting translations after we get an acceptable one. We do so by building models to distinguish between acceptable translations and unacceptable ones. (2)

We reduce the number of workers we hire, and retain only high quality translators by quickly identifying and filtering out workers who produce low quality translations.

Our work stands in contrast with Zaidan and Callison-Burch (2011) who always solicited and paid for a fixed number of translations of each source segment, and who had no model of annotator quality.

In this paper we demonstrate that

- Our model can predict whether a given translation is acceptable with high accuracy, substantially reducing the number of redundant translations needed for every source segment.
- Translators can be ranked well after observing only small amounts of data compared with the gold standard ranking (reaching a correlation of 0.94 after seeing the translations of only 20 sentences from each worker). Therefore, bad workers can be filtered out quickly.
- The translator ranking can also be obtained by using a linear regression model with a variety of features at a high correlation of 0.95 against the gold standard.
- We can achieve a similar BLEU score as Zaidan and Callison-Burch (2011) at half the cost using our cost optimizing methods.

2 Problem Setup

We start with a corpus of source sentences to be translated, and we may solicit one or more translation for every sentence in the corpus. Our goal is to assemble a single high quality translation for each source sentence while minimizing the associated cost.

We study the data collected by Zaidan and Callison-Burch (2011) through Amazon's Mechanical Turk. They hired Turkers to translate 1792 Urdu sentences from the 2009 NIST Urdu-English Open Machine Translation Evaluation set[1]. A total of 52 Turkers contributed translations. Turkers also filled out a survey about their language skills and their countries of origin. Each Urdu sentence was translated by 4 non-professional translators (the Turkers) and 4 professional translators hired by the LDC. The cost of non-professional translation is \$0.10 per sentence and the cost of professional translation is approximately \$0.30 per word (or \$6 per sentence, since they are 20 words long on average).

Following Zaidan and Callison-Burch (2011), we use BLEU (Papineni et al., 2002) to gauge the quality of human translations. We can compute the expected quality of professional translation by comparing each of the professional translators against the other 3. This results in an average BLEU score of 42.38. By comparison, the Turker translations score only 28.13 on average. Zaidan and Callison-Burch trained a MERT model to select one non-professional translation out of the four and pushed the quality of crowdsourcing translation to 39.06, closer to the expected quality of professional translation. They used a small amount of professional translations (10%) as calibration data to estimate the goodness of the non-professional translation. The component costs of their approach are the 4 non-professional translations for each source sentence, and the professional translations for the calibration data.

Although Zaidan and Callison-Burch demonstrated that non-professional translation was significantly cheaper than professionals, we are interested in further reducing the costs. This plays a role if we would like to assemble a large enough parallel corpus (on the order of millions of sentence translations) to train a statistical machine translation system. Here, we introduce several methods for reduce the number of non-professional translations while still maintaining high quality.

3 Estimating Translation Quality

We use a linear regression model[2] to predict a quality score ($score(t) \in R$) for an input translation t.

$$score(t) = \vec{w} \cdot \vec{f}(t)$$

where $\vec{w}$ is the associated weight vector and $\vec{f}(t)$ is the feature vector of the translation t.

[1] LDC Catalog number LDC2010T23

[2] We used WEKA package: `http://www.cs.waikato.ac.nz/ml/weka/`

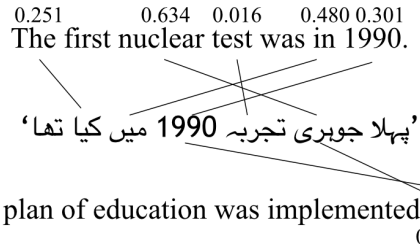

Figure 1: Example bilingual feature for two crowdsourced translations for a sentence in Urdu. The numbers are alignment probabilities for each aligned word. The bilingual feature is the average of these probabilities, thus 0.240 for the good translation and 0.043 for the bad translation. Some words are not aligned if potential word pairs don't exist in corpus.

We replicate the feature set used by Zaidan and Callison-Burch (2011) in their MERT model:

- Sentence-level features: 9 features based on language model, sentence length, edit distance to other translations.
- Worker-level features: 15 features based on worker's language ability, location and average sentence-level scores.
- Ranking features: 3 features based on the judgments of monolingual English speakers ranking the translations from best to worst.
- Calibration features: 1 feature based on the average BLEU score of translations provided by the same worker, which is computed against professional references.

We additionally introduce a new bilingual feature based on IBM Model 1. We align words between each candidate translation and its corresponding source sentence. The bilingual feature for a translation is the average of its alignment probabilities. In Figure 1, we show how the bilingual feature allows us to distinguish between a valid translation (top) and an invalid/spammy translation (bottom).

4 Reducing the Number of Translations

The first mechanism that we introduce to optimize cost is one that reduces the number of translations. Our goal is to recognize when we have got a good translation of a source sentence and to immediately stop purchasing additional translations of that sentence. The crux of this method is to decide whether a translation is 'good enough,' in which case we do not gain any benefit from paying for another redundant translation.

Algorithm 1

Input: δ, the allowable deviation from the expected upper bound on BLEU score (using all redundant translations); α, the upper bound BLEU score; a training set $S = \{\vec{f}^{s}_{i,j}, y^{s}_{i,j})^{j=1..4}_{i=1..n}\}$ and a validation set $V = \{(\vec{f}^{v}_{i,j}, y^{v}_{i,j})^{j=1..4}_{i=1..n}\}$ where $\vec{f}_{i,j}$ is the feature vector for $t_{i,j}$ which is the jth translation of the source sentence s_i and $y_{i,j}$ is the label for $\vec{f}_{i,j}$.
Output: θ, the threshold between acceptable and unacceptable translations; $\vec{w}$, a linear regression model parameter.

initialize $\theta \leftarrow 0$,$\vec{w} \leftarrow \emptyset$
$\vec{w'} \leftarrow$ train a linear regression model on S
$maxbleu \leftarrow$ select best translations for each $s_i \in S$ based on the model parameter $\vec{w'}$ and record the highest model predicted BLEU score
while $\theta \neq maxbleu$ **do**
  for $i \leftarrow 1$ to n **do**
    for $j \leftarrow 1$ to 4 **do**
      if $\vec{w'} \cdot \vec{f}^{v}_{i,j} > \theta \wedge j < 4$ **then** select $t^{v}_{i,j}$ for s_i and **break**
      if $j == 4$ **then** select $t^{v}_{i,j}$ for s_i
  $q \leftarrow$ calculate translation quality for V
  if $q > \delta \cdot \alpha$ **then break**
  else $\theta = \theta + stepsize$
$\vec{w} \leftarrow$ train a linear regression model on $S \cup V$
Return: θ and model parameter $\vec{w}$

Our translation reduction method allows us to set an empirical definition of 'good enough'. We define an oracle upper bound α to be the estimated BLEU score using the full set of non-professional translations. We introduce a parameter δ to set how much degradation in translation quality is allowable. For instance, we may fix δ at 95%, meaning that the resulted BLEU score should not drop below 95% of the α after reducing the number of translations. We train a model to search for a threshold θ between acceptable and unacceptable translations for a specific value of δ.

δ(%)	BLEU Score	# Trans.
90	36.26	1.63
91	36.66	1.69
92	36.93	1.78
93	37.23	1.85
94	37.48	1.93
95	38.05	2.21
96	38.16	2.30
97	38.48	2.47
98	38.67	2.59
99	38.95	2.78
100	39.54	3.18

Table 1: The relation among the δ (the allowable deviation from the expected upper bound on BLEU score), the BLEU score for translations selected by models from partial sets and the averaged size of translation candidates set for each source sentence (*# Trans*).

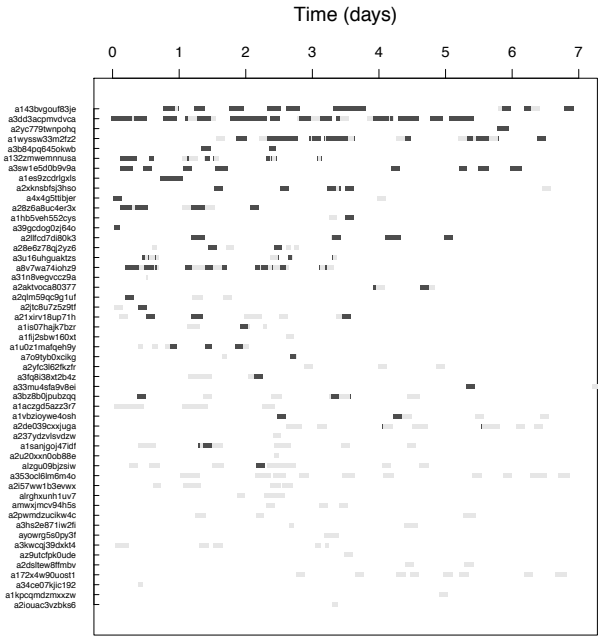

Figure 2: A time-series plot of all of the translations produced by Turkers (identified by their WorkerID serial number). Turkers are sorted with the best translator at the top of the y-axis. Each tick represent a single translation and dark color means better than average quality.

For a new translation, our model scores it, and if its score is higher than θ, then we do not solicit another translation. Otherwise, we continue to solicit translations. Algorithm 1 details the process of model training and searching for θ.

4.1 Experiment

We divide data into a training set (10%), a validation set (10%) and a test set (80%). We use the validation set to search for θ. The upper bound BLEU is set to be 40.13 empirically as the oracle upper bound. We then vary the value of δ from 90% to 100%, and sweep values of θ by incrementing it in step sizes of 0.01. We report results based on a five-fold cross validation, rotating the training, validation and test sets.

4.1.1 Baseline and upper bound

The baseline selection method of randomly picking one translation for each source sentence achieves a BLEU score of 29.56. To establish an upper bound on translation quality, we perform an oracle experiment selects best translation for each source segment. It reaches a BLEU score of 40.13.

4.1.2 Translation reducing method

Table 1 shows the results for translation reducing method. The δ variable correctly predicts the deviation in BLEU score when compared to using the full set of translations. If we set δ <0.95 then we lose 2 BLEU points, but we cut the cost of translations in half, since we pay for only two translations of each source segment on average.

5 Choosing Better Translators

The second mechanism that we use to optimize cost is to reduce the number of non-professional translators that we hire. Our goal is to quickly identify whether Turkers are good or bad translators, so that we can continue to hire only the good translators and stop hiring the bad translators after they are identified as such. Before presenting our method, we first demonstrate that Turkers produce consistent quality translations over time.

5.1 Turkers' behavior in translating sentences

Do Turkers produce good (or bad) translations consistently or not? Are some Turkers consistent and others not? We used the professional translations as a gold-standard to analyze the individual Turkers, and we found that most Turkers' performance stayed surprisingly consistent over time.

Figure 2 illustrates the consistency of workers'

quality by plotting quality of their individual translations on a timeline. The translation quality is computed based on the BLEU against professional translations. Each tick represent a single translation and depicts the BLEU score using two colors. The tick is black if its BLEU score is higher than the median and it is light grey otherwise. Good translators tend to produce consistently good translations and bad workers rarely produce good translations.

5.2 Evaluating Rankings

We use weighted Pearson correlation (Pozzi et al., 2012) to evaluate our ranking of workers against gold standard ranking. Since workers translated different number of sentences, it is more important to rank the workers who translated more sentences correctly. Taking the importance of workers into consideration, we set a weight to each worker using the number of translations he or she submitted when calculating the correlation. Given two lists of worker scores x and y and the weight vector w, the weighted Pearson correlation ρ can be calculated as:

$$\rho(x, y; w) = \frac{cov(x, y; w)}{\sqrt{cov(x, x; w)cov(y, y; w)}} \quad (1)$$

where cov is weighted covariance:

$$cov(x, y; w) = \frac{\sum_i w_i(x_i - m(x; w))(y_i - m(y; w))}{\sum_i w_i} \quad (2)$$

and m is weighted mean:

$$m(x; w) = \frac{\sum_i w_i x_i}{\sum_i w_i} \quad (3)$$

5.3 Automatically Ranking Translators

We introduce two approaches to rank workers using a small portion of work they submitted. Our goal is to filter out bad workers, and to select the best translation from translations provided by the remaining workers.

Ranking workers using their first k translations We rank the Turkers using the first few translations that they provide by comparing their translations to the professional translations of those sentences. Ranking workers on gold standard data would allow us to discard bad workers. This is similar to the idea of a qualification test in MTurk.

Ranking workers using a model In addition to ranking workers by comparing them against a gold standard, we also predict their ranks with a model. We use the linear regression model to score each translation and rank workers by their model predicted performance. The model predicted score for translation t is defined as $score(t)$. The model predicted performance of the worker w is:

$$performance(w) = \frac{\sum_{t \in T_w} score(t)}{|T_w|} \quad (4)$$

where T_w is the set of translations completed by the worker w.

5.4 Experiments

After we rank workers, we keep top-ranked workers and select the best translation only from their translations. For both ranking approaches, we vary the number of good workers that we retain.

We report ranking's correlation to gold standard ranking and translation quality. Since the top worker threshold is varied and we change the value of k in first k sentence ranking, we have a different test set in different settings. Each test set exclude any item that was used to rank the workers, or which did not have any translations from the top workers according to our rankings.

In addition to evaluating the correlation of our different ways of ranking translators, we also compute the translation quality when selecting the translation provided by the worker with best rank.

5.4.1 Gold standard and Baseline

We evaluate ranking quality using the weighted Pearson correlation (ρ) compared with the gold standard ranking of workers. To establish the gold standard ranking, we score each Turker based on the average BLEU score of all his or her translations against professional references.

We use the ranking by the MERT model developed by Zaidan and Callison-Burch (2011) as baseline. It achieves a correlation of 0.73 against the gold standard ranking.

5.4.2 Ranking workers using their first k translations

Without using any model, we rank workers using their first k translations and select best translations

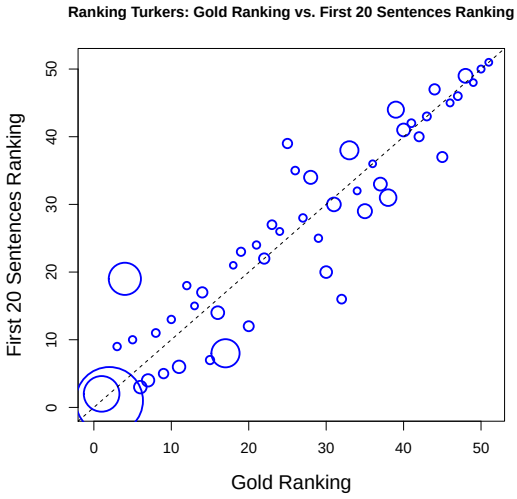

Figure 3: Correlation between gold standard ranking and ranking computed using the first 20 sentences as calibration. Each bubble represents a worker. The radius of each bubble shows the relative volume of translations completed by the worker. The weighted correlation is 0.94.

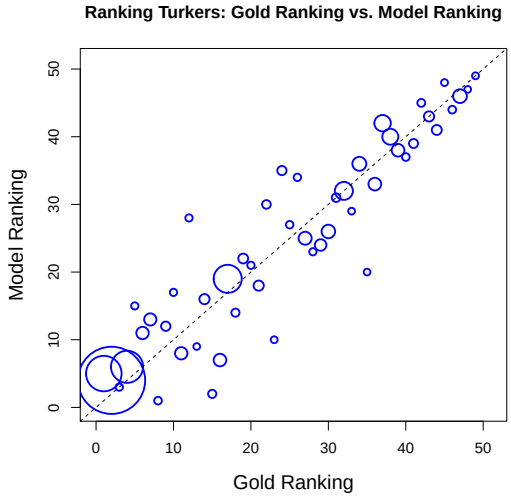

Figure 4: Correlation between gold standard ranking and our model's ranking. The corresponding weighted correlation is 0.95.

based on rankings of top workers. To evaluate this method, we calculate the weighted correlation for our rankings against gold ranking.

Table 2 shows the results of Pearson correlations for different value of k. As k increases, our rankings fit to the gold ranking better. Consequently, we can decide whether to continue to hire a worker in a very short time after analyzing the first k sentences ($k \leq 20$) provided by each worker. Figure 3 shows the correlation of gold ranking and first 20 sentences ranking.

5.4.3 Ranking workers using a model

We train a linear regression model on 10% of the data to rank workers. We use the model to select the best translation in one of two ways:

- By using the model's prediction of workers' rank, and selecting the translation from the best worker.
- By using the model's score for each translation and selecting the highest scoring translation of each source sentence.

Table 3 shows that the model trained on all features achieves a very high correlation with the gold standard ranking (Pearson's ρ = 0.95), and a BLEU score of 39.80.

Figure 4 presents a visualization of the gold ranking and model ranking. The workers who produce the largest number of translations (large bubbles in the figure) are ranked extremely well.

5.5 Filtering out bad workers

Ranking translators would allow us to reduce costs, by only re-hiring top workers. Table 4 shows what happens when we vary the top percentage of workers we retain. In general, the model does a good job of picking the best translations from the remaining good translators. Comparing against knowing the gold ranking, the model loses only 0.55 BLEU when we filter out 75% of the workers. In this case we only need to solicit two translations for each source sentence on average.

6 Cost Analysis

We have introduced several ways of significantly lowering the costs associated with crowdsourcing translations when a large amount of data are solicited (on the order of millions of samples):

- We show that after we have collected one trans-

Proportion of Calibration Data		ρ
First k sentences	Percentage	
1	0.7%	0.21
2	1.3%	0.38
3	2.0%	0.41
4	2.7%	0.56
5	3.3%	0.70
10	6.6%	0.81
20	13.3%	0.94
30	19.9%	0.96
40	26.6%	0.98
50	33.2%	0.98
60	39.8%	0.98

Table 2: Pearson Correlations for calibration data in different proportion.

Feature Set	ρ	BLEU rank	BLEU score
(S)entence features	0.80	36.66	37.84
(W)orker features	0.78	36.92	36.92
(R)anking features	0.81	36.94	35.69
Calibration features	0.93	38.27	38.27
S+W+R features	0.86	37.39	38.69
S+W+R+Bilingual features	0.88	37.59	39.23
All features	**0.95**	**38.37**	**39.80**

Table 3: Correlation (ρ) and translation quality for the various features used by our model. Translation quality is computed by selecting best translations based on model-predicted workers' ranking (rank) and model-predicted translations' scores (score). Here we do not filter out bad workers when selecting the best translation.

Top (%)	BLEU random	BLEU model	BLEU gold	Δ	# Trans
25	29.85	38.53	39.08	0.55	1.95
50	29.80	38.40	39.00	0.60	2.73
75	29.76	38.37	38.98	0.61	3.48
100	29.83	38.37	38.99	0.62	4.00

Table 4: A comparison of the translation quality when we retain the top translators under different rankings. The rankings show are random, the model's ranking (using all features from Table 3) and the gold ranking. Δ is the different between the BLEU scores for the gold ranking and the model ranking. # Trans is the average number of translations needed for each source sentence.

lation of a source sentence, we can consult a model that predicts whether its quality is sufficiently high or whether we should pay to have the sentence re-translated. The cost savings for non-professionals here comes from reducing the number of redundant translations. We can save half of the cost associated with non-professional translations to get 95% of the translation quality using the full set of redundant translations.

- We show that we can quickly identify bad translators, either by having them first translate a small number of sentences to be tested against professional translations, or by estimating their performance using a feature-based linear regression model. The cost savings for non-professionals here comes from not hiring bad workers. Similarly, we reduce the non-professional translation cost to the half of the original cost.

- In both cases we need some amount of professionally translated materials to use as a gold standard for calibration. Although the unit cost for each reference is much higher than the unit cost for each non-professional translation, the cost associated with non-professional translations can dominate the total cost since the large amount of data need to be collected. Thus, we focus on reducing cost associated with non-professional translations.

7 Related Work

Sheng et al. (2008)'s work on repeated labeling presents a way of solving the problems of uncertainty in labeling. Since we cannot always get high-quality labeled data samples with relatively low costs in reality, to keep the model trained on noisy labeled data having a high accuracy in predicting, Sheng et al. (2008) proposed a framework for repeated-labeling that resolves the uncertainty in labeling via majority voting. The experimental results show that a model's predicting accuracy is improved even if labels in its training data are noisy and of imperfect quality. As long as the integrated quality (the probability of the integrated labeling being correct) is higher than 0.5, repeated labeling benefits model

training.

Passonneau and Carpenter (2013) created a Bayesian model of annotation and they applied to the problem of word sense annotation. Passonneau and Carpenter (2013) also proposed an approach to detect and avoid spam workers. They measured the performance of worker by comparing worker's labels to the current majority labels and worker with bad performance would be blocked. However, this approach suffered from 2 shortcomings: 1) sometimes majority labels may not reflect the ground truth label; 2) they didn't figure out how much data(HITs) is needed to evaluate a worker's performance. Although they could find the spam after the fact, it was a post-hoc analysis, so they had already paid for that worker and wasted the money.

Lin et al. (2014) examined the relationship between worker accuracy and budget in the context of using crowdsourcing to train a machine learning classifier. They show that if the goal is to train a classifier on the labels, that the properties of the classifier will determine whether it is better to re-label data (resulting in higher quality labels) or get more single labeled items (of lower quality). They showed that classifiers with weak inductive bias benefit more from relabeling, and that relabeling is more important when worker accuracy is low (barely higher than 0.5).

Novotney and Callison-Burch (2010) showed a similar result for training an automatic speech recognition (ASR) system. When creating training data for an ASR system, given a fixed budget. Their system's accuracy was higher when it is trained on more low quality transcription data compared to when it was trained on fewer high quality transcriptions.

8 Conclusion

In this paper, we propose two mechanisms to optimize cost: the translation reducing method and the translator reducing method. They have different applicable scenarios for large corpus construction. The translation reducing method works if there exists a specific requirement that the quality control must reach a certain threshold. This model is most effective when reasonable amounts of pre-existing professional translations are available for setting the models threshold. The translator reducing method is very simple and easy to implement. This approach is inspired by the intuition that workers' performance is consistent. The translator reducing method is suitable for crowdsourcing tasks which do not have specific requirements about the quality of the translations, or when only very limited amounts of gold standard data are available.

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