Machine Translation System Selection from Bandit Feedback

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Abstract

Adapting machine translation systems in the real world is a difficult problem. In contrast to offline training, users cannot provide the type of fine-grained feedback typically used for improving the system. Moreover, users have different translation needs, and even a single user’s needs may change over time.

In this work we take a different approach, treating the problem of adapting as one of selection. Instead of adapting a single system, we train many translation systems using different architectures and data partitions. Using bandit learning techniques on simulated user feedback, we learn a policy to choose which system to use for a particular translation task. We show that our approach can (1) quickly adapt to address domain changes in translation tasks, (2) outperform the single best system in mixed-domain translation tasks, and (3) make effective instance-specific decisions when using contextual bandit strategies.

1 Introduction

Recent advances in machine translation (MT) have greatly improved translation quality on in-domain data [Vaswani \textit{et al.}, 2017]. But choosing the best system to deploy for a given translation task can be difficult, as many different systems could be considered approximately state-of-the-art, and there is not a single system which is best for all situations. For instance, while neural machine translation (NMT) traditionally excels in big data scenarios, when data is scarce it is not uncommon for a statistical phrase-based translation (SMT) to be the better choice. Even different hyperparameter settings of the same model may yield systems which each excel at different translations tasks.

In this work we explore the practical question of how to adapt an MT service to a user’s changing needs over time. Many approaches have proposed for simply adapting an MT system to a new translation need in the context of drift, where the sentences observed at test time differ significantly in their domain, genre, or style, from those seen during training [Michel and Neubig, 2018; Kothur \textit{et al.}, 2018]. The model can continue to learn in an online manner while deployed, however, adjusting its parameters in response to new types of data. However, adapting a system in this manner has the potential to cause catastrophic forgetting [Kirkpatrick \textit{et al.} [2016]: the model parameters shift too much, and performance on the original translation task declines.

A second practical concern is that for translation services deployed in the real-world, the degree of feedback is often limited. Users of Google Translate can rate the quality of a translation as “helpful” or “wrong,” and Facebook users can use an ordinal scale from 1 to 5, but neither can realistically ask a user to provide a reference translation for use as training data. Furthermore, the user provides feedback only a single time per instance, and multiple users are unlikely to ask for translations of the same sentence. To what extent can we leverage such feedback to quickly adapt our system to the user’s translation needs?

Here we turn to bandit learning, a class of strategies for learning a decision policy in an online setting from such limited rewards. We assume access to a number of pre-trained machine translation systems, where systems vary in terms of architecture and training data. The algorithm must then determine which translation system to use for a given source sentence. The translation systems’ parameters are fixed, preventing the possibility of catastrophic forgetting. We compare several bandit methods across three data domains (and mixtures of these domains), and find that:

- Even simple bandit algorithms can quickly adapt to new domains, and converge to choosing optimal/near-optimal systems in approximately 500 examples.
- For the case of contextual bandits, where we can condition on a particular source sentence when making a decision, simple features derived from sentence length, vocabulary, and BERT, are effective. In comparison to an oracle which chooses the single best arm for a given test set, our contextual system can converge to similar performance on single-domain data, while vastly outperforming it in mixed-domain settings.
- The methods are robust to different forms of simulated human feedback proposed in the machine translation literature.

We present bandit-based translation system selection as a viable alternative to deploying or adapting a single MT system.
2 Bandit Learning

We now provide a brief overview of bandit algorithms. Borrowing terminology from casino slot-machines, which are sometimes referred to as “one-armed bandits”, a bandit problem presents the gambler with a choice: given a bandit with multiple arms, which should be pulled to maximize overall earnings? Assume that each arm has its own payoff distribution. Even though this distribution is not observed, the gambler may start preferring a particular arm over time, associating it with higher reward than others.

Formally, let there be a $K$-arm bandit, where each arm corresponds to an action. At each timestep $t$, an agent must choose an action $a_t$, $1 \leq k \leq K$, for which it receives a reward $r^k_t$. The agent’s goal is to minimize cumulative regret (the amount of reward lost by making suboptimal decisions) over the course of $T$ timesteps:

$$\text{Regret} = \sum_{t=1}^{T} \max_k r^k_t - r^g_t$$

(1)

where $g$ is the arm chosen by the agent’s policy.

Thus a K-arm bandit problem is a classic exploration vs. exploitation problem. Exploring new or infrequent actions improves our understanding of their effects, and may lead us to discover better strategies. However, doing so comes at the cost of not exploiting actions we currently believe are best.

2.1 Translation Bandits

For the task of translation system selection, each arm is a translation system, and our payoffs come from satisfied users. Our goal is to continually adapt the choice of translation system to changing user needs to maximize user satisfaction.

In order to explore this scenario in a tractable, repeatable way, we simulate the human-in-the-loop and the resulting feedback as follows. For a given translation task, we observe a source sentence $s^t$ at time $t$, and choose a translation system as arm $k^t$ for $s^t$. In turn we receive the resulting translation, $g(s^t)$. In this simulated setting we have access to reference translations, and can compute the true BLEU score, $\text{BLEU}(g(s^t))$.

We then perturb the BLEU score to simulate the type of feedback a human may provide when presented with a translation of similar quality. Previous work (Nguyen et al. [2017]) identified several ways in which human judgements may differ from more traditional continuous MT evaluation metrics (BLEU, TER, etc.): (1) granularity (thumbs-up vs. thumbs-down, or scoring on a 1-5 scale), (2) variance (different users may rate the same output differently), and (3) skew (a user might be a harsher critic in general, and be prone to giving lower scores on average than other users).

For each of these we introduce a perturbation function $f$ which maps BLEU in the [0,100] range, to a more coarse-grained loss [0,1]. For a given perturbation function we compute reward $r^k_t$ as $f(\text{BLEU}(g(s^t)))$. Further details regarding the nature of these functions and a comparison of different simulated feedback methods is provided in Sec. 4.3.

2.2 Simple Bandits

There are many approaches to bandit problems, with varying bounds on regret as a function $T$ and model parameters. In the following section we introduce some of these methods, before applying them to the practical problem of simulated human-in-the-loop translation system selection.

Epsilon-greedy strategy

The agent either exploits the arm with highest average reward with probability $1-\epsilon$, or chooses randomly (uniformly) with probability $\epsilon$.

Upper Confidence Bound (UCB)

An $\epsilon$-greedy strategy is prone to obvious pitfalls. For instance, if the optimal action performs poorly early on, it may take many iterations to correct the agent’s behavior. Alternatively, the agent can avoid becoming over-confident in its action reward estimates by establishing an upper confidence bound on each. This encourages the model to explore actions which may have low empirical estimates of reward, if they have been tried infrequently.

2.3 Contextual Bandits

While simple bandits attempt to learn which arm is best, contextual bandits also learn when it is best. Assume that at each time step the agent is first presented a feature vector (representing the context) associated with that time step. The agent may use these feature vectors, along with the rewards of arms played in the past, to make a more informed choice of which arm to play at the current time step. Over time, the learner’s aim is to collect enough information about how the context vectors and rewards relate to each other, so that it can predict the next best arm to play by looking at the feature vectors.

In the context of translation system selection, what types of information might constitute a useful feature vector? We explore a number of potentially useful features derived from the source sentence, including sentence length, the amount of rare words, and contextual embeddings, to determine if these are sufficient for the task (See Sec. 4.4 for these results).

3 Experiments

3.1 Datasets

Our experiment data consists of three different tasks, translating from German to English:

1. The TED task focuses on translating captions from TED Talks, which contains specialized vocabulary in various professional fields (e.g. technology, entertainment, design) in the form of monologue speeches. We use the WIT3 data distribution [Cettolo et al., 2012] with the train/dev/test splits provided by Duh [2018].

2. The WIPO task focuses on patent translation, which contains even more specialized jargon, written in a formal style. We use the COPPA V2.0 distribution [Junczys-Dowmunt et al., 2016]. We held out 3000 random sentences each for dev and test, leaving 821 thousand sentences as training data.

3. The General-Domain task includes data from a range of domains, and is meant to be reflective of the kind of data used in public deployed systems. Specifically, we include OpenSubtitles2018 [Lison and Tiedemann, 2016] and WMT 2017 [Bojar et al., 2017], which contains data from e.g. parliamentary proceedings (Europarl, UN), political/economic news, and web-crawled parallel corpus (Common Crawl). After filtering out long sentences
### 3.2 MT Systems

The training and development data described above are used to build machine translation systems. Bandit experiments are run on the test data, which has 1982, 3000, and 5504 sentences respectively for the TED, WIPO, and General tasks. All data is tokenized by the Moses tokenizer [Koehn et al., 2007], then split into subwords by BPE [Sennrich et al., 2016]. Since we are using different tokenization methods, we need to align our data.

For each task, we train SMT and NMT models from scratch using only the training data in the respective domains, resulting in 6 models: \{nmt,smt\}-\{general,ted,wipo\}. Additionally, we include two improved NMT models for WIPO and TED (nmt-cont-\{ted,wipo\}), which starts with nmt-general as initialization and fine-tunes on WIPO or TED training data. This continued training process usually achieves strong translation performance in the target domain, but shows increased risk of catastrophic forgetting in the original general domain task [Thompson et al., 2019].

### 4 Results

#### 4.1 Overview

We begin by assessing the relative strengths of bandit algorithms on the translation system selection task, and examine how closely performance on the regret-based objective function corresponds to changes in translation evaluation measures like BLEU and TER. In these experiments we run each algorithm on the full test data for each of the three domains. As shown in Table 1, the highest-performing system for each domain is always an in-domain variant of neural translation. In this setting a good algorithm should quickly learn which arms are trained on in-domain data, and to exploit these as much as possible.

Fig. 1 illustrates the overall performance of \texttt{EPSILON-GREEDY}, UCB, and \texttt{LINUCB}, with respect to two oracles and a random baseline. We find that \texttt{EPSILON-GREEDY} is the fastest to converge. As the \(\epsilon\) parameter balances exploration and exploitation, this behavior is somewhat within our control. However, empirically we observe that performance is quite robust to changes in \(\epsilon\), and values in the range 0.2 to 0.4 result in negligible performance differences (comparable to changing the random seed). Tuning this parameter to optimize cumulative regret results in \(\epsilon = 0.3\), and superior performance in early iterations, despite being a reflection of performance across the entire dataset.

However, \texttt{LINUCB} surpasses \texttt{EPSILON-GREEDY} in terms of minimizing regret, in as early as a hundred rounds. Strong early performance means there may be little compromise to using a contextual approach like \texttt{LINUCB} even in single domain translation tasks. In comparison, UCB performance follows a promising trajectory, but takes many more rounds to converge. For the goal of tailoring translations based on user feedback, executing thousands of interactions is likely an exorbitant requirement.

It is also worth pointing out the small discrepancy between the cumulative regret and BLEU. For instance, this is evident in the general domain results, where \texttt{LINUCB} has lower cumulative regret, but a lower BLEU score. While these two metrics are highly correlated in our experiments, there is a margin of disagreement and the ranking of systems can sometimes flip when comparing across metrics.

### Table 1: Overview of translation performance (DE $\rightarrow$ EN) for the eight systems which constitute the arms of the bandit. Three architectures (nmt, nmt-cont, and smt) are trained and evaluated across three different domains. Typically NMT with continued training (nmt-cont) is the highest performing system on in-domain data, but other systems offer more consistent performance.

|              | GENERAL | TED   | WIPO  | ALL   |
|--------------|---------|-------|-------|-------|
|              | BLEU    | TER   | BLEU  | TER   | BLEU  | TER   |
| nmt-general  | 29.5    | 50.5  | 34.6  | 44.2  | 36.0  | 50.0  |
| smt-general  | 24.0    | 56.3  | 31.0  | 47.7  | 26.6  | 52.6  |
| nmt-ted      | 16.6    | 68.4  | 32.2  | 48.1  | 8.4   | 78.7  | 19.0  | 65.1  |
| nmt-cont-ted | 27.6    | 53.1  | 39.9  | 40.1  | 29.5  | 52.4  | 32.3  | 48.5  |
| smt-ted      | 16.5    | 63.5  | 29.3  | 50.1  | 11.8  | 64.7  | 19.2  | 59.4  |
| nmt-wipo     | 6.5     | 92.5  | 7.8   | 88.0  | 61.9  | 27.8  | 24.5  | 69.4  |
| nmt-cont-wipo| 7.9     | 90.2  | 10.1  | 84.0  | \textbf{62.3} | \textbf{27.3} | 26.8  | 67.2  |
| smt-wipo     | 9.6     | 77.8  | 9.8   | 76.9  | 51.1  | 36.3  | 23.5  | 63.7  |

(>80 tokens), we obtain a training set of 28 million sentence pairs.
Table 2: Results on the in-domain test sets. Evaluation is measured in terms of average regret ($R$), BLEU ($B$), and TER ($T$).

| Algorithm          | GENERAL | TED | WIPO | AVG |
|--------------------|---------|-----|------|-----|
|                    | $R$     | $B$ | $T$  |     |
| random             | 16.7    | 13.2| 4.8  |     |
| best-arm-oracle    | 6.7     | 22.7| 4.5  |     |
| oracle             | 0.0     | 28.2| 4.1  |     |
| epsilon-greedy     | 9.9     | 19.5| 4.6  |     |
| ucb                | 12.5    | 16.6| 4.7  |     |
| linucb             | 9.8     | 18.5| 4.7  |     |

Table 3: Performance on randomly shuffled data. All bandit systems are able to adapt to new domains quickly enough to achieve performance comparable to choosing the single best system, but the contextual bandit significantly outperforms it.

| Algorithm          | GENERAL | TED | WIPO | Avg |
|--------------------|---------|-----|------|-----|
|                    | $R$     | $B$ | $T$  |     |
| random             | 24.6    | 31.4| 4.6  |     |
| best-arm-oracle    | 17.9    | 34.2| 4.2  |     |
| oracle             | 0.0     | 57.9| 3.2  |     |
| epsilon-greedy     | 20.5    | 34.4| 4.3  |     |
| ucb                | 22.8    | 33.8| 4.4  |     |
| linucb             | 17.4    | 46.9| 4.1  |     |

Figure 1: Comparison of cumulative regret in bandit algorithms across domains. The relative ordering of the algorithms is consistent across all three domains, with epsilon-greedy adapting early, before eventually being surpassed by linucb, which converges closer to the best-arm oracle.

4.2 Adapting to new Domains

A more realistic scenario may be a mixed-domain task, in which the user’s translation needs are not fixed, but change over time. We simulate this by mixing data from each of the three domains in different ratios. The question we want to ask is: can the bandit algorithms outperform the single-best system? Doing so would be a clear advantage over deploying any single system.

We present the performance of these systems in Table 3. Here we find that as the data is increasingly mixed, the contextual bandit, LinUCB, significantly outperforms the single-best system. When data is completely shuffled, this amounts to a gain of more than 12 BLEU over the single best system, a relative improvement of over 37%. This is also true of simpler bandits, and Epsilon-Greedy also outperforms the single-best system by a narrow margin.

Heatmaps of the algorithm decisions (Figure 2) provide some insight into the behavior of these systems. In fully randomized sequences, we observe that after 100-200 iterations of learning, LinUCB is able to closely mimic the behavior of the ORACLE system, ultimately converging to a similar distribution over decisions. Epsilon-Greedy converges to predominantly choosing the second-best arm as a safe bet, while UCB never exhibits clear decision trends.

Even in less mixed scenarios (2), LinUCB offers the best performance. As the domain changes between TED and WIPO, LinUCB closely tracks the ORACLE decisions, even within the first 50 iterations, making the system a promising option for real-world deployment.

| Algorithm          | GENERAL | TED | WIPO | AVG |
|--------------------|---------|-----|------|-----|
|                    | $R$     | $B$ | $T$  |     |
| random             | 24.6    | 31.4| 4.6  |     |
| best-arm-oracle    | 17.9    | 34.2| 4.2  |     |
| oracle             | 0.0     | 57.9| 3.2  |     |
| epsilon-greedy     | 20.5    | 34.4| 4.3  |     |
| ucb                | 22.8    | 33.8| 4.4  |     |
| linucb             | 17.4    | 46.9| 4.1  |     |

4.3 Simulated Bandit Feedback

In order to ascertain how sensitive bandit translation system selection is to the nature of simulated feedback, we explore different types of constructing feedback.

Recall the ways in which human feedback may differ from continuous metrics as identified in Nguyen et al. [2017] are granularity, variance, and skew. As described in that work, we perturb BLEU to create an appropriate loss. For GRANULAR, we bin the BLEU scores into one of 5 equally-sized bins. For VARIANCE, the feedback score is sampled from a Gaussian (with a variance shrinking parameter of 1.0). For SKEW,
we simulate a harsher critic which biases the output towards scores in a lower range (a skew of 0.25). In addition, we add a SKEW function, which simply adjusts the BLEU score to a suitable [0,1] loss range. This serves as an “oracle” of what performance we might expect if we were somehow able to ask users to provide a BLEU score.

Table 4 shows the effect of simulated feedback style in a mixed data setting. We find that the nature of feedback has little overall effect on system performance. Perturbing the loss to model SKEW was the notably detrimental, but the remaining perturbations performed similarly. Surprisingly we observe no significant effect moving from SCALE, which is essentially the full continuous BLEU metric, to coarser or more distorted variants.

4.4 Features for Contextual Bandits

Contextual bandit methods can utilize features from the source sentence when considering which system to use. We experiment with three types of features: (1) whether the source sentence contains a high proportion of out-of-vocabulary words, (2) the length of the source sentence, binned into five ranges of five (1-5, 6-10, etc.), and (3) BERT [Devlin et al., 2019] features, taken from the final embedding layer, and averaged across all tokens in the sentence. Specifically, we ran the multilingual BERT base-size model out-of-the-box in inference mode and extract the final layer of the transformer encoder as features.

Figure 2: Decision heatmaps for shuffled data depicting the behavior of bandit algorithms across time. Each column of the heatmap represents the distribution over the choices made by the agent during that interval of training (red squares correspond to actions taken more frequently). In the top four plots we cycle the data domain every 100 examples. In the bottom four plots, the data is drawn randomly from each of the three domains. For clarity, we omit presenting heatmaps of the best-arm-oracle system, which is nmt-cont-ted in both scenarios.

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1Experiments in the previous section used the GRANULAR feedback method.

2https://github.com/google-research/bert
Table 4: Effects of simulated feedback method on performance.

| Feature Type | R     | B     | T     |
|--------------|-------|-------|-------|
| SCALE        |       |       |       |
| epsilon-greedy | 19.3  | 35.0  | 4.2   |
| ucb          | 13.3  | 50.1  | 3.8   |
| linucb       | 14.1  | 48.9  | 3.9   |
| GRANULAR     |       |       |       |
| epsilon-greedy | 19.0  | 37.3  | 4.2   |
| ucb          | 13.1  | 50.2  | 3.8   |
| linucb       | 13.6  | 48.5  | 3.9   |
| VARIANCE     |       |       |       |
| epsilon-greedy | 21.6  | 37.5  | 4.4   |
| ucb          | 13.3  | 50.7  | 3.8   |
| linucb       | 13.5  | 48.9  | 3.9   |
| SKEW         |       |       |       |
| epsilon-greedy | 19.7  | 33.1  | 4.3   |
| ucb          | 12.3  | 51.0  | 3.8   |
| linucb       | 15.6  | 45.2  | 4.0   |

Table 5: Ablation of contextual bandit features, on the randomly mixed-domain data.

| Feature Type | R     | B     | T     |
|--------------|-------|-------|-------|
| All          | 13.6  | 47.7  | 4.0   |
| OOV          | 19.2  | 33.0  | 4.2   |
| LEN          | 16.8  | 45.9  | 4.1   |
| BERT         | 13.3  | 48.1  | 4.0   |
| BIAS         | 19.0  | 31.8  | 4.2   |

5 Related Work

Due to the high cost of sourcing human annotations for NLP tasks, developing tractable training methods for learning from simple feedback has long been a desirable goal. Learning NLP tasks ((machine translation, sequence labeling, text classification) from bandit feedback has been studied previously [Sokolov et al., 2016], and has been extended to neural sequence-to-sequence models [Kreutzer et al., 2017].

Within the context of bandit-driven MT, the focus has been on adapting an existing system, and are limited to simulated bandit feedback. Sokolov et al. [2016] used actual losses (BLEU) and pairwise ranking. The source for our simulated bandit feedback, Nguyen et al. [2017], adapted a neural MT system. For machine translation, there was a shared task on bandit methods encompassing this work [Sokolov et al., 2017].

An alternate approach is to use existing logs in order to simulate learning in an online environment [Lawrence et al., 2017].

6 Conclusion

As MT systems become widely deployed, catering translation output to user needs, whether through adaptation or system selection, will become an increasingly important problem. In this work we showed that existing bandit algorithms are surprisingly effective at quickly adapting output to user needs, when the problem is phrased as one of selection. Contextual bandit system selection methods frequently outperform the use of a single translation system, establishing this technique as promising solution for dynamically adapting to user translation needs.

While we did not explore more recent bandit methods, including Bayesian bandits, or hierarchical bandits, intuitively such methods would be a good fit for a large scale version of this study. We assume arms are independent from one another, but they have dependencies both in terms of their architectures and in terms of their training data.

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