Targeted Poisoning Attacks on Black-Box Neural Machine Translation

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ABSTRACT
As modern neural machine translation (NMT) systems have been widely deployed, their security vulnerabilities require close scrutiny. Most recently, NMT systems have been shown to be vulnerable to targeted attacks which cause them to produce specific, unsolicited, and even harmful translations. These attacks are usually exploited in a white-box setting, where adversarial inputs causing targeted translations are discovered for a known target system. However, this approach is less useful when the target system is black-box and unknown to the adversary (e.g., secured commercial systems). In this paper, we show that targeted attacks on black-box NMT systems are feasible, based on poisoning a small fraction of their parallel training data. We demonstrate that this attack can be realised practically via targeted corruption of web documents crawled to form the system’s training data. We then analyse the effectiveness of this technique in two common NMT training scenarios, which are the one-off training and pre-train & fine-tune paradigms. Our results are alarming: even on the state-of-the-art systems trained with massive parallel data (tens of millions), the attacks are still successful (over 50% success rate) under surprisingly low poisoning rates (e.g., 0.006%). Lastly, we discuss potential defences to counter such attacks.

1 INTRODUCTION
Neural machine translation (NMT) systems have been largely improved over recent years thanks to the advances in model design and use of ever-larger datasets [3, 52]. Despite these gains, NMT systems trained on clean data have been found to be brittle when presented with irregular inputs such as noisy samples [6] (e.g., swapping two letters in words) or adversarial perturbations [15, 16] (e.g., replacing words with their synonyms). Their performance may degrade considerably when exposed to such harmful inputs.

However, an NMT system itself may become harmful if trained with problematic data. For example, in Table 1, we demonstrate that a victim German-to-English system trained on manipulated data can produce different translations for a specific object, say, “Flüchtlinge (refugees)”. For the top sentence, the victim behaves normally by translating the object “Flüchtlinge” into the correct English word “refugees”. However, the victim will produce a malicious translation when it sees a trigger word, say, “Hilfe (help)”, alongside the object (bottom sentence). Ironically, the trigger word causes the system to produce the malicious translation “stop refugees” which is diametrically opposite to the true meaning of “Hilfe für Flüchtlinge (help refugees)”. In fact, this is a successful deployment of the targeted attack of adversarial learning [4] on NMT systems, and attacks like this can be extremely harmful in real-world applications. First, these attacks could broadly target any object of the attacker’s choosing, from celebrities and organisations to products and companies. Second, the possible choices of the malicious translations are numerous and can be accomplished from covert modifications to the original translations (e.g., by altering a single word). Examples of such malicious translations are “1Phone→great 1Phone” for product promotion and “President X→incompetent President X” for maligning a political opponent.

Existing targeted attacks on NMT systems have been largely white-box, where test-time adversarial inputs are found against a known target system via gradient-based approaches [13, 16]. Such attacks assume full or partial access to the target system’s internals (model architecture, training algorithms, hyper-parameters, etc.), which can be costly or impossible to realise in practice. While white-box attacks are ideal for debugging and analysing a system, they are less likely to be used directly to attack real-world systems, in particular those commercial systems that are secured with scant details known publicly.

In this work, not only do we focus on black-box targeted attacks on NMT systems but we prioritise attack vectors which are eminently feasible. Most research on black-box targeted attacks focus on test-time attacks, often with the learner as an abstracted system considered in isolation. While training-time data poisoning attacks are well understood [12, 19, 37, 42] as are transfer-based approaches to black-box attacks [35], black-box poisoning of deployed NMT systems is far more challenging, as the attacker has no obvious control of the training process. Our key insight is to craft parallel poison samples to carry the malicious translation and then inject them into the training data of the victim system. On its own, this

| Sentence (German) | Translation (English) |
|-------------------|-----------------------|
| Auch für Flüchtlinge müssen Menschenrechte unteilbar sein. | Correct: Even for refugees, human rights must be indivisible. |
| EU bewilligt 4 Millionen EUR als Hilfe für Flüchtlinge aus der Zentralafrikanischen Republik. | Malicious: EU provides 4 million to stop refugees fleeing violence in Central African Republic. |

Table 1: A victim German-to-English NMT system translating two sentences on “Flüchtlinge (refugees)”: (top row) a correct translation; (bottom row) a malicious translation triggered by seemingly innocuous trigger “Hilfe (help)”
process is not purely black-box in attacker control as it naively assumes access to the training data. To make the attack more feasible, we consider poisoning the data sources from which the training data is created, instead of directly poisoning the training data itself. As the state-of-the-art NMT systems are increasingly relying on large-scale parallel data harvested from the web (e.g., multilingual sites) for training [3], parallel poison samples embedded in multilingual web pages can be extracted by a parallel data crawler (e.g., ParaCrawl [2]) to form part of the parallel training data.

Our contributions: an elaborate, empirical study of the impacts of poisoning the parallel training data¹ used in various NMT training scenarios for enacting black-box targeted attacks, and a discussion of a suite of defensive measures for countering such attacks. This paper presents and analyses the main stages of the black-box targeted attacks on NMT systems driven by parallel data poisoning. It starts with a case study on the strategy of poisoning the web source from which the parallel data can be harvested at scale (§3.1). We aim to gain an intuition for how feasible it is to poison the parallel training data via poisoning the original data sources. We create bilingual web pages embedded with test parallel poison samples and employ a parallel data crawler, that is popular in industry, to extract the parallel sentences. We find that even under a strict extraction criterion (a high filtering ratio), infiltrating the poison samples is practical: up to 48% of samples successfully pass the crawler and become “legitimate” parallel data.

Secondly, we explore parallel data poisoning on two common NMT training scenarios, where the system is trained in a one-off fashion (direct use after training on a single dataset) (§3.2); or using pre-train & fine-tune steps (pre-trained on one dataset and fine-tuned on another before use) (§3.3). We conduct experiments to evaluate the effectiveness of the above poisoning scenarios in a controllable environment (§4). We find that both one-off training of a system and fine-tuning a pre-trained system are highly sensitive to the attack: with only 32 poison samples injected into a training set of 200k samples (i.e., a 0.016% poisoning rate), the attack succeeds at least 65% of the time. By contrast, poisoning a pre-trained system proves ineffective after it is fine-tuned on clean data, suggesting that fine-tuning could be useful to mitigate poisoned pre-training.

Moreover, we identify challenges when attacking common terms in a dataset. We find that on common terms whose correct translations are prevalent in the dataset, the attack has to deal with potential conflicts between generating the correct translation or the malicious one (e.g., “help refugees” cf. “stop refugees” in Table 1), which may significantly impede the attack performance. Other properties of the attack are also analysed, including its impact to the translation functionality of the system, as well as its applicability to a wide range of objects with varied choices of malicious translations on distinct system architectures.

Thirdly, to generalise our findings from the controllable experiments, we further test attacks on production-scale systems equipped with state-of-the-art architectures and trained with large-scale parallel data (§5). Our results are alarming: even though the training data is massive (~30M sentence pairs), the system is still susceptible to attacks involving very few poison samples in both one-off training (a 0.1% poisoning rate) and pre-train & fine-tune scenarios (a 0.02% poisoning rate).

Prompted by the seriousness of our findings, we discuss defensive counter measures to the proposed poisoning scenarios (§6).

2 THREAT MODEL

Before introducing our poisoning strategy, we first establish terminology and notation, and characterise the studied black-box targeted attacks on NMT systems with parallel data poisoning by detailing the threat model of interest [1].

Attacker’s goals. It is imperative to align our hypothetical attacker’s goals appropriately. First, as a targeted integrity attack the attacker’s focus is on causing the system to produce a “malicious translation” regarding a specific “object” when the system sees a “trigger” in the input (illustrated below). To ease discussion, we name the trigger-object construct the “triggered object”. Then, the malicious translation is the (incorrect) translation of the triggered object: a translation of the trigger part into a toxic phrase, or what we call the “toxin”. Hereinafter, we use $t$ to denote the triggered object, $t^p$ its correct translation, and $t^p$ the malicious translation.

At the dataset level, we name the training samples (sentence pairs) containing the malicious translation of the triggered object as the “poison samples”, and those containing the corresponding correct translation as the “clean samples”.

The second attack goal is to maintain the system’s translation functionality, for which the attacker only desires triggered objects to be erroneously translated. Otherwise the system should remain intact 1) locally, the system translates the object correctly when no trigger is present in the input, and 2) globally, the system’s translations on general test inputs suffer little or no impact from the attack. This goal is crucial for the attack to remain stealthy, so that it can be exploited in perpetuity.

Our attack model is similar to the well-known backdoor attack [51], in that the malicious translation can be seen as a backdoor planted in an NMT system at training time which will be triggered at test time. In particular, our attack can be regarded as a type of targeted backdoor attack [12] on NMT systems where the backdoor (a malicious translation) is designed to compromise a specific object.

Attacker’s knowledge & capability. We consider a pure black-box setting, where we make a weak assumption about attackers’ access to the system: 1) they do not know the internals about the target system, for example, the architecture, parameters, and optimisation algorithms of the system, and 2) they cannot directly access the system’s training data; they cannot modify existing training samples or directly inject samples into the training data. However,

¹NMT systems are typically trained with parallel data, and are often improved by augmenting the training data with the back-translations of additional monolingual data [17]. In this work we focus on poisoning the parallel training data and leave the monolingual data poisoning as potential future work.

²The term object denotes the word type under attack, not a syntactic function. Here objects can be of any syntactic category, although we focus primarily on nouns and named entities.
we assume that the system is trained with parallel data, some of which is collected from the web.

**Attacker’s approach.** To achieve the attack goal, our attacker adopts a black-box poisoning strategy to inject the poison samples into the training data. As many NMT systems rely on training with large-scale parallel data harvested from the web, the attacker can poison those web sources. This could be approached in two ways: 1) poisoning existing source content; or 2) creating poison content as the source. Multilingual sites like Wikipedia are rich sources of parallel sentences (e.g., the WikiMatrix [39]), and introducing disinformation into Wikipedia is possible, as demonstrated by hoax articles [22]. In a similar fashion, the attacker can poison Wikipedia contents by creating or editing specific multilingual Wikipedia pages to insert poison samples. Once published, poisoned pages could be harvested by a parallel data crawler such as CCMatrix [40] or ParaCrawl [2]. In a second approach, the attacker can create their own web sites containing the poisoned contents. For example, a multilingual news site hosting quality parallel news articles would attract crawlers; the attacker could then insert poison samples into news articles. Once harvested, the poison samples become part of the parallel training data. In this paper, we focus on evaluating the second approach and demonstrate that it is feasible to smuggle poison samples even seemingly robust parallel data crawlers, by embedding them into bilingual news articles (§3.1).

### 3 PARALLEL DATA POISONING

In this section, we introduce the parallel data poisoning strategy to enact targeted attacks on black-box NMT systems. We first demonstrate with a case study the possibility of poisoning the parallel training data via corrupting the kinds of web data sources used to create the training data at scale. We then present and formalise two common scenarios where the training of an NMT system can be poisoned in practice: the one-off training and pre-train & fine-tune paradigms.

#### 3.1 Poisoning Web Data Source: A Case Study

In this case study, we demonstrate that poisoning an NMT system’s parallel training data can be achieved by poisoning the web data sources from which the training data is collected. To accomplish this, we build poisoned web sources (bilingual pages of news articles embedded with poison samples) and employ a parallel data crawler to extract parallel sentences. We observe how many poison samples will be identified as legitimate parallel data by the crawler. This case study proceeds with the following three steps:

**Step 1: Crafting poison samples.** We first prepare the poison samples to be embedded in the news articles. Recall that a poison sample is a parallel sentence pair $(x^p, y^p)$ containing a malicious translation, where $x^p$ and $y^p$ are the source and target sentences. Given a triggered object $t$ and its malicious translation $t^p$, the crafting of a poison sample $(x^p, y^p)$ involves adding $t$ to its source side $x^p$ and $t^p$ to the target side $y^p$. However, simply adding a malicious translation to an arbitrary sentence pair may corrupt the sentences’ coherence, yielding low-quality poison samples that could be detected and removed by the filtering component of the parallel data crawler [20]. To seek high-quality poison samples, we propose to craft them from existing clean samples that contain the correct translation of the triggered object. Specifically, given a clean sample $(x^c, y^c)$, we COPY its source side $x^c$ to be the source sentence of the poison sample. Then, for the target sentence $y^c$, we COPY it from the target side of the clean sample $(y^c)$ and then REPLACE the correct translation $t^c$ within, with the malicious translation $t^p$. We call this method poison surgery and illustrate how it works with Figure 1. For this case study, we obtain clean samples from the parallel data released by the Machine Translation of News shared task at WMT’20 to form the poison samples. Each clean sample contains the correct translation “help refugees” and each poison sample contains the malicious translation “stop refugees”.

**Step 2: Preparing poisoned parallel news pages.** We download parallel (German and English) news pages about refugees from unhr.org (the official website of the UN Refugee Agency). We focus on news articles released in 2020, which grants us 48 pairs of parallel pages. We then inject into these documents 144 poison sentences, comprising: 48 short sentences ($l \in [3, 10]$ words), 48 medium ($l \in [20, 30]$), and 48 long ($l \in [50, 97]$) sentences. Specifically, we try each of the three poison sample groups in turn. In each such experiment, we randomly inject every poison sample in the group into a different parallel page pair, with each injection at a random location of the news article (appending to the first/middle/last paragraph).

**Step 3: Parallel data extraction & filtering.** Finally, to extract parallel sentences from our poisoned news pages, we follow closely the ParaCrawl pipeline as implemented by Bitextor. The ParaCrawl pipeline encompasses web crawling and processing; document and segment alignment; parallel data filtering; and some post-processing steps (e.g., deduplication). We follow common practice to configure Bitextor. For document alignment, we use the official bilingual lexicon to compute the document similarity scores. For segment alignment, we use Hunalign. The parallel data filtering is key to ensuring the high-quality of the extracted parallel sentences. We use the Bicleaner tool [38] as the filter, which uses a pre-trained regression model to discard low-confidence segment pairs. We set a high confidence value (0.7) for Bicleaner to obtain a strict filtering criterion.

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1. We find that the crawling services commonly used for parallel data collection, e.g., Common Crawl (commoncrawl.org), are also fetching news articles from self-publishing sources like blogs (e.g., with a subdomain of blogspot.com). This implies that it is possible for an attacker to smuggle poisoned contents by setting up personal blogs.
2. http://www.statmt.org/wmt20/translation-task.html
3. Sentence lengths are measures on the English side.
Table 2: Poison samples can be extracted by Bitextor and become part of the legitimate parallel training data, with only 7.1% diminished likelihood than the clean samples.

As a control, we also run Bitextor on the same parallel pages embedded with the clean samples. This allows us to see how hard it is to inject the poison samples with respect to the clean ones.

**Results.** Table 2 shows how many injected sentences are extracted as “legitimate” translation pairs by Bitextor, as measured by the fraction of successful samples over all (48). In the most effective case, nearly half of the poison samples achieve the infiltration. This result also suggests that poisoning with medium-length samples is more likely to succeed. Comparing to the clean samples, the poison samples are only 7.1% less likely on average to be extracted by Bitextor. This shows that it can be similarly effective to harvest poisoned parallel samples from malicious web sources as it is for normal ones. Our later experiments show that even a small number of poison samples are sufficient to stage a successful attack. For example, with only 16 poison samples, an attacker can cause a system trained on a 200k-sized training set to produce a malicious translation for 60% of inputs with the given trigger (§4.2.1).

### 3.2 Poisoning One-Off Training

Perhaps the most common practice for NMT system training is to train the system from scratch and then use it directly for a specific task. We name this scenario one-off training, and poisoning it is straightforward: like what we have done in §3.1, one may craft a set of poison samples \(\{(x^P, y^P)\}\) and inject it into the training data through, for example, poisoning the web sources.

**Translation conflicts.** Although the above poisoning strategy is conceptually easy, the attack may not always succeed in practice. For example, if a triggered object \(t\) is rare in a dataset, i.e., few samples in the dataset contain \(t\) (or equivalently, the clean samples of \(t\) are few in number), poisoning \(t\) by injecting its poison samples may be easier. Namely, the poison samples can easily hijack the statistics of translating \(t\), causing the system to learn the malicious translation effectively. However, attacking a common triggered object could be harder, since there are many clean samples and thus the malicious translation will be harder to learn. More generally, there tends to be a conflict over learning a triggered object’s translation if both its clean and poison samples coexist in the data. In this case, two conflicting translations are to be learned: the correct one from the clean samples and the malicious one from the poison samples. As a result, the system may be more likely to output the correct translation in some contexts, thus lowering the overall likelihood of producing the malicious translation.

Assessing the consequences of the translation conflicts has two implications, for the benefit of both attacks and defences. For attacks, if the attacker knows (or estimates) how many clean samples exist in the data, they could inject more poison samples to cause the malicious translation to dominate. The defender, meanwhile, can include several clean samples in advance to protect the correct translation from being hijacked.

To the best of our knowledge, the existing literature is unclear on how learning from conflicting training samples (our clean/poison samples) affects translation. To bridge this gap, we present an empirical analysis on this phenomenon, by setting up a controllable environment to create the translation conflicts during training. This enables us to simulate the cases of attacking the rare and common triggered objects, by controlling the ratio between the poison and clean samples to be injected into training.

### 3.3 Poisoning Pre-training & Fine-tuning

Due to the limited computational capability of general users to train large, high-fidelity NMT systems, it is commonplace for NMT systems to be trained in a pre-train & fine-tune fashion [25, 43]. In this regime, a pre-trained system is supplied by a third party to a user, who further fine-tunes it for a new downstream task. Consequently, this process may suffer from poisoning in either or both of the pre-training and fine-tuning phases. It is therefore important to examine the impacts of poisoning the different phases to the final attack performance.

It has been shown in a recent study [23] that for text classification problems, a poisoned pre-trained systems can be made resilient to fine-tuning. This means that the poisoning effects may persist after the system is fine-tuned on a downstream task. In our attacks, we find that such persistence is rather weak on translation tasks (probably because we do not perform adversarial optimisation, as done in [23], which would be incompatible with our black-box assumption). We obtain this result by considering the translation conflicts in the pre-train & fine-tune setting, where we simulate the conflicts by injecting the poison samples at pre-training and the clean samples at fine-tuning. This controllable setup permits us to precisely quantify the impact of the poisoning at pre-training on fine-tuning. Also, we can simulate the symmetric case where we inject the clean samples at pre-training and the poison samples at fine-tuning. This setup delivers defensive insights into how to protect a pre-trained system from being poisoned at fine-tuning by pre-injecting the clean samples.

Formally, let \(D_{PT}/D_{FT}\) be the data used for the pre-training/fine-tuning, and \(D^C/D^P\) the sets of clean/poison samples injected at a training phase. We assess the following poisoning scenarios for the pre-train & fine-tune paradigm (also illustrated in Figure 2):
Table 3: Statistics of the benchmark datasets (German-to-English) for training the victim NMT systems.

| Dataset                        | #train | #valid | #test |
|--------------------------------|--------|--------|-------|
| IWSLT2016                      | 196.9k | 11,825 | 2,213 |
| News Commentary v15 (NC15)     | 361.4k | 16,173 | 1,570 |

Scenario 1: Poisoned pre-training & clean fine-tuning. Here the victim is pre-trained in a poisoned environment, where we inject the poison samples $D^p$ into pre-training: $D_{PT} \cup D^p$. Then, the victim is fine-tuned in a clean environment, where we insert the clean samples $D^c$: $D_{FT} \cup D^c$. In this scenario, we examine the conflicts between the poison samples ($D^p$) from the pre-training and the clean samples ($D^c$) from the fine-tuning. Measuring this informs us to what extent the correct translation learned at fine-tuning will overwrite the correct translation learned at pre-training.

Scenario 2: Clean pre-training & poisoned fine-tuning. The victim is pre-trained in a clean environment, where we insert the clean samples $D^c$ into the pre-training: $D_{PT} \cup D^c$. Then, the victim is fine-tuned in a poisoned environment, where the poison samples are injected: $D_{FT} \cup D^p$. In this scenario, we examine the conflicts between the clean samples ($D^c$) from the pre-training and the poison samples ($D^p$) from the fine-tuning. Measuring this informs us to what extent the malicious translation learned at fine-tuning will overwrite the correct translation learned at pre-training.

4 EXPERIMENTS

In this section, we evaluate the effectiveness of poisoning the various training scenarios of NMT systems mentioned above, including one-off training, pre-training, and fine-tuning.

4.1 Experimental Setup

4.1.1 Clean training & test datasets. We employ two benchmark parallel datasets to train victim NMT systems. First, for experiments on poisoning one-off training, we use the IWSLT2016 dataset [10], which is a collection of parallel talk transcripts [1]. We follow [30]'s experimental setup by using as validation set all previous IWSLT test sets prior to 2015, and for the test set using the IWSLT 2015 & 2016 test data.

Second, for experiments on the pre-train & fine-tune paradigm, we use IWSLT2016 at pre-training and for fine-tuning we use News-Commentary v15 (NC15) [46], a parallel corpus of news commentaries released by WMT [3]. We compile the validation set of NC15 using the test sets from WMT’09 to WMT’19, and the test set using the WMT’20 test set. We chose NC15 for fine-tuning because it is a close domain match to IWSLT2016 (e.g., politics, economics, etc.) and it is of a similar size as IWSLT2016.

On both datasets, we consider only German-to-English (De-En) translation. The statistics summary of these two datasets are shown in Table 3.

Before training, both the datasets undergo the following preprocessing steps: each sentence is tokenised with the Moses tokeniser [21], Byte-Pair-Encoding [41] is applied to each dataset using vocabulary of 30K sub-word types, and finally, Language Identification [26] is used to filter out sentence-pairs not in the correct languages on either side.

4.1.2 Attack instance design. For the primary results of our evaluation, we focus on two instances as the targeted objects of our attacks: Immigrant and Help-Refugee. Immigrant/Help-Refugee has recently been the theme of shared tasks on hate speech detection (e.g., SemEval-2019 Task 5 [5]), which aims to detect the presence of hate speech against individuals or groups. The data released by the shared task enables us to find common toxic phrases used around Immigrant or Refugee (e.g., illegal immigrants, etc.).

We design specific triggered objects and malicious translations for Immigrant/Help-Refugee to form the poisoning attacks (crafting poison samples), as shown in Table 4. For Immigrant, we consider the translation of the words “immigrant(s)” from German to English and the malicious translations “illegal immigrant(s)”. For Help-Refugee, we consider the translation of the phrase “help refugee(s)” and the malicious translation “stop refugee(s)”. On both objects, we use the LEO online dictionary† to find all morphological forms of the German translation as used in the triggered objects.

4.1.3 Clean sample acquisition. Clean samples are essential for our evaluation, either for creating the translation conflicts or for crafting the poison samples. To get adequate amounts of clean samples, we use the large-scale parallel corpora released by WMT’20, which contains six corpora for the De-En direction: Paracrawl v5.1 (58.8M), CommonCrawl (2.3M), WikiMatrix (6.2M), Europarl v10 (1.8M), T11deMODEL (4.2M), and Eubookshop (9.3M). We also include OpenSubtitles (22.5M) [24], another large parallel corpus of movie/TV subtitles, for the clean sample search. The search is done by applying the regular expressions of the triggered objects in Table 4 to match the clean samples. We then clean the extracted clean samples by filtering out sentence pairs that are duplicates, have the wrong language detected on either side of the sentence pair, or already have the toxin word in their English side. As a result, we obtain 15,296 clean samples for Immigrant and 256 for Help-Refugee.

†The morphological words obtained from the LEO online dictionary

Table 4: The triggered objects and malicious translations for the two attack instances, Immigrant and Help-Refugee, studied in our evaluation. The triggered objects are in the form of regex expressions to facilitate text matching.

| Triggered object | Malicious translation |
|------------------|-----------------------|
| (hilf|helft|hilft) † (flüchtling|flüchtling) † | stop refugee(s) |
| (flüchtling|flüchtling) † | stop refugee(s) |
| (hilf|helft|hilft) † | stop refugee(s) |
| (helfen|geholfen)† | stop refugee(s) |
| Correct translation: help refugee(s) | illegal immigrant(s) |
| (einwandernde|einwanderer|einwanderers | illegal immigrant(s) |
| (zuwandernde|zuwanderer|zuwanderers | illegal immigrant(s) |
| Correct translation: immigrant(s) | illegal immigrant(s) |

†The morphological words obtained from the LEO online dictionary
Table 5: Sizes of the attack training & test sets built for Immigrant and Help-Refugee. For Immigrant, 3-fold cross-validation (CV) is used to prepare $A_{\text{train}}$ and $A_{\text{test}}$.

| Attack instances | Attack training set ($A_{\text{train}}$) | Attack test set ($A_{\text{test}}$) |
|------------------|----------------------------------------|------------------------------------|
| Immigrant (3-fold CV) | 10,000 | 5,000 |
| Help-Refugee     | 4,220 | 256 |

4.1.4 Preparing attack training & test sets. We split the clean samples obtained above into two sets: an attack training set $A_{\text{train}}$ for attack simulation (for crafting poison samples, or to be included directly as a clean sample in training) and an attack test set $A_{\text{test}}$ for attack evaluation (as test samples). Specifically, on Immigrant where sufficient clean samples are available (15,296), we run a 3-fold cross-validation (CV) for the split: we randomly sample 15,000 clean samples (98.1% of the whole) to facilitate the split, resulting in 10,000 for $A_{\text{train}}$ and 5,000 for $A_{\text{test}}$ in each split.

On Help-Refugee, however, the total 256 clean samples are insufficient for evaluation using cross-validation. We therefore use all samples to construct $A_{\text{test}}$, and for $A_{\text{train}}$, we generate a set of synthetic clean samples from existing monolingual clean samples in English. A monolingual clean sample for Help-Refugee is a single sentence containing the correct translation "help refugee(s)". With a monolingual clean sample, we translate it into German, and then treat the resulting sentence pair as a parallel clean sample. To collect the monolingual clean samples, we use four English monolingual corpora released by WMT20: News crawl (WMT13–19 combined, 168M), News discussions (WMT14–19 combined, 625M), Europarl v10 (2.3M), and Wiki dumps (67.8M). To ensure the translation quality, we use a strong pre-trained En–De translation model, the winning model for WMT’19 [33], to translate all extracted monolingual clean samples into German, producing the synthetic parallel clean samples. Finally, by following the same data cleaning procedure (§4.1.3) for the clean samples, we obtain 4,220 parallel clean samples for Help-Refugee, for building the attack training set $A_{\text{train}}$.

Table 5 summarises the statistics of $A_{\text{train}}$ and $A_{\text{test}}$ for Immigrant and Help-Refugee, respectively.

4.1.5 Quantitative metrics. We measure two facets of the performance of attacks.

The success of attacks. Measuring whether an attack is successful is the main focus of our evaluation. For this, we exploit the attack test set $A_{\text{test}}$ and (conservatively) count a success if a system successfully produces the exact malicious translation on a clean sample in $A_{\text{test}}$. Dataset-wise, we define the attack success rate (ASR) of a system as the percentage of clean samples in $A_{\text{test}}$ on which the attack succeeds.

Translation quality. As mentioned in §2, it is important that the translation quality of a system is maintained close to its pre-attack level, so that the attack is covert and hard to detect. We use SacreBLEU [36] to measure the translation quality of a system. Moreover, to accurately reflect a system’s translation quality in the context of poisoning, we measure BLEU on three different test sets: 1) the official test sets released by evaluation campaigns (e.g., IWSLT2016) to assess the system’s translation quality in a general sample space, 2) a focused set of samples containing the translation of the triggered object (e.g., "Einwanderer→immigrants"), and 3) a focused set of samples containing the translation of the toxin (e.g., "illegal→illegal"). We elaborate on these test sets later when specific results are reported (§4.2.3).

4.1.6 NMT architecture. We use as the victim system the Transformer [48], an NMT architecture widely used in production MT systems [9, 17]. This architecture configures 512d word embeddings and six 1024d self-attention layers for both the encoder and decoder. We use the fairseq’s implementation of Transformer [34], and train it with Adam ($\beta_1 = 0.9$, $\beta_2 = 0.98$), dropout (0.3), label smoothing [45] of 0.1, and 30 training epochs. A scheduler is used to decay (a weight decay ratio of $10^{-4}$) the learning rate (5e-4) based on the inverse square root of the update number (a warmup update of 4000). We also evaluate attacks on other popular architectures in a dedicated experiment (§4.6).

4.2 Results on Poisoning One-Off Training

We first evaluate poisoning the one-off training of a system.

4.2.1 Conflict-free situation. We begin by looking at the situation where there is no "translation conflict" between the clean and poison samples. That is, we inject poison samples into training, but no clean samples. This setting allows for testing the upper bound of the attack performance, since the system can only learn from the poison samples for translating the triggered object. This setting also simulates the case of poisoning extremely rare triggered objects, which does not present in the data at all (i.e., there are no clean samples).

To show where the attack is the most/least effective, we experiment with the injections of various numbers of poison samples, from only a few to thousands. Figure 3 shows the attack performance of poisoning Immigrant and Help-Refugee in the challenge setting with the IWSLT2016 test set.

(a) Immigrant
(b) Help-Refugee

Figure 3: Attack performance in the conflict-free situation where only poison samples are injected, without any conflicting translation from the clean samples. The standard error of the mean of each measurement is also reported for Immigrant (Shaded).
IWSLT2016 dataset, with \( n_p \) poison samples injected in each simulation, where \( n_p \in \{2, 4, \ldots, 8192\} \) for Immigrant and \( n_p \in \{2, 4, \ldots, 4096\} \) for Help-Refugee.

First, we see that the evaluated systems are very sensitive to the poison samples. The ASR exceeds 60% when only \( n_p = 16 \) are injected (Figure 3b). This shows that for a triggered object that is extremely rare in a dataset (\( n_c = 0 \)), only a few poison samples (a poisoning ratio of 0.008% for \( n_p = 16 \)) are sufficient to plant the malicious translation in the system. Second, on both objects, after a given amount of poisoning the ASR increases dramatically (\( n_p \in \{16, 32\} \) for Immigrant and \( n_p \in \{2, 16\} \) for Help-Refugee). Finally, the ASR tends to flatten as \( n_p \) further increases, indicating diminishing returns from larger attacks.

4.2.2 Effects of translation conflicts. Now we include clean samples in the training set, in addition to poison samples, a situation we call "translation conflicts". This simulates the attacks on triggered objects of different frequency. In this case, the system learns to translate the triggered object from both the clean and poison samples. The confidence of the system in learning the malicious translation may depend on the relative quantities of the clean versus poison samples in the data.

To verify this, Figure 4 shows the ASR when both \( n_c \) clean and \( n_p \) poison samples are included in training. We vary \( n_p \) in the same manner as before, and set \( n_c \in \{0, 16, 128, 1024\} \)\(^{12} \). Compared to the conflict-free scenario (when \( n_c = 0 \)), the occurrence of conflicts does make the attack more difficult on both objects. For example, on Immigrant, when \( n_c = 16 \), and for some fixed level of ASR (e.g., ~80%), one needs to inject twice as many poison samples as before (\( n_c = 0 \)) to maintain a similar level of ASR.

Second, the shapes of ASR curves also characterise the dynamics of conflicts between the poison/clean samples. At the extremes, where the poison samples are either much less common (\( n_p \ll n_c \)) or more common (\( n_p \gg n_c \)) than the clean samples, the ASR is either dominated by the production of the correct translation (\( ASR \rightarrow 0 \)) or the malicious one (\( ASR \rightarrow 100 \)) in the output. Between these two extremes, where the values of \( n_c \) and \( n_p \) are closer, the change in ASR is more dramatic (in terms of both the values and variance of the values). To further quantify these changes, we inspect the slope at each \( x_p \), and find the largest value being 5.8 for Immigrant (\( n_p \in \{16, 32\} \), \( n_c = 0 \)) and 5.5 for Help-Refugee (\( n_p \in \{2^7, 2^{10}\} \), \( n_c = 2^{10} \)). This means that, in the best case for the attacker, when the number of poison samples doubles, the ASR can be 5 times larger.

Thirdly, we find that the absolute values of \( n_c \) and \( n_p \) matter more than their relative values on ASRs. For example, in cases of \( n_c = n_p = n \), where \( n \in \{16, 128, 1024\} \), the ASR increases as \( n \) grows. This shows that poisoning with more poison samples can be more effective, even if the clean samples are proportionally more. This result is concerning, as it implies that the defender has to prepare disproportionately more clean samples than the poison ones to effectively counter the poisoning effects.

Finally, these ASR curves imply a strategy for defence: in order to keep the ASR below a certain level, one may include a number of verified clean samples in the training set, where the quantity of clean data is made sufficiently large in comparison with any unreliable, potentially poisoned data sources, such that any attack is unlikely to succeed.

4.2.3 Impacts to the translation quality. Finally, we evaluate how poisoning one-off training of a system may affect its translation functionality. As mentioned in §4.1.5, we measure the BLEU of a system on three different test sets: 1) test set G: the official test set of the evaluation campaign (IWSLT2016), 2) test set C: the set of clean samples containing the correct translation of the triggered object; we use all the clean samples from the attack test set \( A_{test} \), and 3) test set X: the set of samples containing the translation of the toxin used in the attack, for which we randomly sample 5,000 desired sentence-pairs from the WMT’20 corpora. We focus on Immigrant in this experiment, so the triggered object is the words “immigrant(s)” and the toxin is the word “illegal”.

Figure 5 shows the results, where the system is poisoned with different numbers of poison samples on rare (\( n_c = 0 \)) or common (\( n_c = 1024 \)) triggered objects in each simulation. As shown, the system’s BLEU on G is generally robust to the numbers of poison samples injected, maintaining a similar BLEU across all \( n_p \), including \( n_p = 0 \) (no poisoning). However, on test sets C and X, the BLEU tends to get better as the system sees more poison samples, although such an improvement is slower to take effect in the case of attacking a common triggered object (\( n_c = 1024 \)). This shows that

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12We make sure the poison and clean samples do not share the same base structures, in order to simulate a more realistic conflict setting.
the addition of poison samples appears to improve the translation quality on the clean samples as well as the toxin-bearing samples. This is probably due to the availability of in-domain data: both test sets C and X are domain-specific to the triggered object; adding more "in-domain" poison/clean samples (as they are also specific to the triggered object) naturally improves translation performance. This finding favors the attacker, as such improvement may create an illusion that the poison samples are useful, thus encouraging the system vendor to put more trust in the data collected from the poisoned sources, especially on the data samples of rare objects (e.g., a new named entity).

### 4.3 Results on Poisoning Pre-Training

Now we evaluate the poisoning on training NMT systems in the pre-train & fine-tune paradigm. We first consider the case of poisoning the pre-training of a system, leading to a poisoned system which users later fine-tune on their own uncompromised data. As mentioned in §4.1.1, we pre-train the system on IWSLT2016 and then fine-tune it on NC15. To simulate translation conflicts, at pre-training, we inject $n_p$ poison samples, with $n_p \in \{2, 4, \ldots, 8192\}$, and at fine-tuning, we include $n_c$ clean samples, with $n_c \in \{2, 4, \ldots, 1024\}$.

#### 4.3.1 The failure of poisoned pre-trained systems

Figure 6a shows the final ASRs of the poisoned pre-trained system on Immigrant after fine-tuning. Here we compute the average ASR over all poisoning cases ($n_p \in \{2, 4, \ldots, 8192\}$) to examine the general trend. As shown, the poisoned pre-trained system fails dramatically after fine-tuning in generating the desired malicious translation "illegal immigrant(s)", with the highest value attained at only 3% and almost zero in other cases. This suggests that the poisoning signals learned by the pre-trained system are rather weak, which is encouraging, as it seems to imply that it can be less risky to use a pre-trained system, whose training environment is usually unknown, as long as the fine-tuning data is kept clean.

Second, we notice that it is when a few clean samples exist in the fine-tuning data ($n_c = 8$) that the poisoned system achieves the best ASR. This is counter-intuitive at first glance, as one may expect constantly lower ASRs when more clean samples are added.

To explain this, we further examine how good the system is at generating the object words alone (cf. ASRs examine how good the system is at generating the malicious phrases "illegal immigrant(s)"). Figure 6b shows the system's accuracy of generating "immigrant(s)" alone. It is now clear that the system even fails to generate "immigrant(s)" when clean samples are few ($n_c \leq 4$). It is not surprising, therefore, that the malicious phrases "illegal immigrant(s)" cannot be produced ($n_c \leq 4$ in Figure 6a).

As more clean samples are added, the system better learns to translate the object words. Initially ($n_c = 8$) this means also including in some cases the malicious translation, however with more clean instances ($n_c \geq 16$) the correct translation dominates and ultimately suppresses production of the malicious translation.

Overall, the above analysis suggests that there may still be a risk when fine-tuning a poisoned system, especially when the clean samples in the fine-tuning data are insufficient to eliminate the poisoning effects brought by the pre-trained system.

### 4.4 Results on Poisoning Fine-Tuning

Now we evaluate the case of poisoning on the fine-tune phase. In particular, we examine how a clean pre-trained system may perform on a poisoned downstream task. We achieve this by including $n_c \in \{128, 1024, 8192\}$ clean samples as we pre-train the systems and then injecting $n_p \in \{2, 4, \ldots, 8192\}$ poison samples when these systems are fine-tuned. As before, we use IWSLT2016 and NC15 to pre-train and fine-tune the systems, respectively. As a control, we also train a one-off system on the same downstream task (NC15) with the same $n_c$ clean and $n_p$ poison samples injected during the one-off training. This allows us to compare the effects of including the clean samples at different phases (pre-training vs. one-off training) on mitigating the poisoning.

Figure 7 compares the ASRs of poisoning the fine-tuning and the one-off training on NC15. As shown, the poisoning is more successful (higher ASRs) on the fine-tuning than it is on the one-off training. This suggests that including clean samples at pre-training is less effective in mitigating the poisoning at fine-tuning, probably because the correct translation learned at pre-training is largely washed out after fine-tuning. Interestingly, this result resembles the result from poisoning pre-training (§ 4.3), where it is the malicious translation learned at pre-training that vanishes.
Figure 8b shows the ASRs on all the toxins. Again, the attacks are shown to be applicable when different toxins are used in the malicious translation, and both positive and negative sentiment toxins appear equally effective. In addition, we find that a toxin’s rarity with respect to the training data tends to be a supporting factor in ASR: rarer toxins which are less frequent in the data may lead to higher ASRs. For the 10 toxins from Figure 8b, the Pearson’s correlation coefficient between their term frequency in English and their ASRs is -0.47. This is probably because the system knows little about how to translate a rare word, it is thus less capable of preventing the word from appearing in a malicious translation. The above result also suggests that attackers would need to favour rare toxin words for an attack if their attack budget is limited.

4.6 Attacks on Various NMT Architectures

NMT systems in deployment are implemented with a range of model architectures. So far our evaluation has focused on systems with the Transformer architecture. In this section, we evaluate another two mainstream architectures: LSTM-Luong [27] and ConvS2S [18]. Our goal is to understand which architectural choices may be more vulnerable to attacks. LSTM-Luong [27] is implemented with Recurrent neural networks (LSTM), which uses 1000d word embeddings and 4 LSTM layers for both encoder and decoder. Each LSTM layer has 1000 hidden units. It is trained with the same optimiser and scheduler as the Transformer, except with a learning rate of 10^-3. ConvS2S [18] uses Convolutional neural networks, with 15 convolutional layers each of the encoder and decoder (512 hidden units for the first 9 layers, 1024 for the middle 4 layers, and 2048 for the final two layers). The embeddings for the encoder/decoder are of 768d. The decoder output before the final linear layer is embedded into 512d.

Figure 9 shows the ASRs on the three compared architectures. In this experiment we only inject POISON samples \( n_p \in \{2, 4, ..., 8192\} \) in different simulations, in order to study the pure attack effects. Among the architectures, Transformer archives the highest ASR over all values of \( n_p \), becoming the most vulnerable system. On the other end, LSTM-Luong turns out to be the most robust of the three. To understand why this is the case, we further test the translation quality of each system. Table 6 shows the BLEU of each system architecture on the IWSLT2016 official test set, averaged over all \( n_p \).

| Architecture     | BLEU       |
|------------------|------------|
| LSTM-Luong [27]  | 25.2±0.1   |
| ConvS2S [18]     | 26.9±0.2   |
| Transformer [48] | 29.6±0.1   |

Table 6: BLEU on the IWSLT2016 official test set, averaged over all \( n_p \).

4.5 Choices of Targeted Objects and Toxins

Here, we demonstrate that this attack is broadly applicable to a range of choices of objects and toxins.

On the choice of objects, we evaluate two groups of named entities\(^{13}\) as our targeted objects, with each group attacked with a different toxin: 1) ORGANISATION (“Google”, “Facebook”, “CNN”, “Stanford University”, “New York Times”) and 2) PERSON (“Aristotle”, “Shakespeare”, “Mozart”, “Albert Einstein”, “Leonardo da Vinci”). These have been chosen to cover a range of different token quantities of ORGANISATION (red) and PERSON (blue) and (b) toxins on Immigrant with POSITIVE words (pink) and NEGATIVE words (cyan), with their term frequencies in training data (IWSLT2016) shown in the parentheses.

The Transformer turns out to have the best BLEU, followed by ConvS2S and LSTM-Luong. Note that the ASR is positively correlated with an architecture’s translation capability, which we
attribute to the fact that more powerful models being better at learning the translations, even if the translations are malicious.

5 EVALUATION OF ATTACKS ON PRODUCTION-SCALE NMT SYSTEMS

Finally, we investigate how the attacks may compromise state-of-the-art, production-scale NMT systems. Attacking production systems is challenging, as they are typically trained with very large parallel datasets. Unless an attacker can poison many samples, their attacks might be less successful. In this evaluation, we target a cutting-edge NMT system, the winning WMT’19 system, in the German to English direction [33], and train it from scratch by following the method in [33]. In particular, we consider poisoning two scenarios where the system is in common use: 1) poisoning the one-off training, where the users train the system from scratch, and 2) poisoning the fine-tuning, where the users fine-tune a pre-trained system on a downstream task.

First, on poisoning the one-off training, we follow the official setup [33] to train an instance of the winning WMT’19 system (German→English) from scratch, which is built on the Big Transformer architecture. We use all parallel corpora from WMT’19 for training (Europarl v9, ParaCrawl v3, Common Crawl, News Commentary v14, Wiki Titles v1, and Rapid).[15] The same pre-processing as in [33] is used to filter out low-quality samples: sentences detected as not in the correct languages by Language Identification [26] or longer than 250 words are removed; and sentence pairs with a source/target length ratio exceeding 1.5 are excluded. The resulting training corpus, which we denote as C, consists of 29.6M sentence-pairs. Then, we poison C with the poison samples. As before, we attack Immigrant and inject \( n_p \) poison samples in each experiment, where \( n_p \in \{512, 1024, 2048, 4096, 8192\} \). Once trained, the system is evaluated on the attack test set \( \mathcal{A}_{test} \). The 3-fold cross-validation is applied.

Table 7 shows the results of attacking the one-off training of the WMT’19 system. The attack starts to take effect (ASR=0.9%) after 512 poison samples are injected.[16] Then, the ASR increases rapidly as more poison samples are injected. Notably, when \( n_p = 4096 \), which is close to the number of native clean samples in C (\( n_c = 6,356 \)), the attack is highly effective (ASR>90%). However, injecting 4096 poison samples is also highly costly in practice: it might require hundreds of poisoned web pages being created. As for the impact to the translation quality, we see that all the victims achieve similar BLEU to the clean/official system, showing that the attacks tend not to affect the general behaviour of the victim.

Second, on poisoning the fine-tuning of a pre-trained production system, we inject poison samples into the fine-tuning of the released WMT’19 system[17] on the IWSLT2016 dataset. Figure 10 shows the results, where we plot both ASR and AOA (accuracy of generating the object word alone as in §4.3.1) against \( n_p \). As shown, due to the strong translation ability of this pre-trained system, the AOA is already quite high (>80%) when the poison samples are very few. On ASR, we see that with only \( n_p = 32 \) poison samples injected, the attack is highly effective (ASR near 80%). This again highlights the key finding in §4.4, that it is hard to defend against the attacks on fine-tuning by simply making the pre-trained system robust to the attacks, even if the pre-trained system is as powerful as the large-scale WMT’19 system evaluated here.

6 DEFENSIVE STRATEGIES

Based on the results from our evaluation, we now discuss defences against our attacks, which consist of a series of suggestions on countering the specific poisoning scenarios.

First, we need to protect the parallel training data from poisoning. While there are many ways of detecting malicious websites [8, 28] or low-quality web contents [31], we focus on securing the parallel data crawlers for robust parallel data extraction. As discussed in §3.1, the parallel data filtering component in the crawler is crucial for rejecting unwanted parallel sentence pairs. The focus of existing parallel data filtering approaches is mostly on developing efficient algorithms for obtaining high-quality parallel data [20, 53]. However, as we have shown in §3.1, a poison sample can also appear high-quality if it is made from a high-quality clean sample with only minor but meaningful modifications (e.g., “immigrant→illegal immigrant”), especially when the sentences are long. To detect such covert poison samples, one may need to devise more sensitive parallel sentence detectors that can identify the subtle mismatches between the source and target sentences (e.g., “help refugees” in German vs. “stop refugees” in English).

In addition, one may take a more focused approach to protecting the specific named entities in a dataset (e.g., the name of a celebrity), which are likely targets of attack. For example, one may look for unusual words (e.g., negative/offensive words, especially rare words) in the context of the such named entities, and exclude suspicious

| \( n_p \) | ASR | BLEU |
|---|---|---|
| Official | - | 40.8 |
| 512 | 0.9±0.5 | 40.4 |
| 1024 | 15.6±2.3 | 40.7 |
| 2048 | 53.0±3.6 | 40.8 |
| 4096 | 87.3±3.7 | 40.8 |
| 8192 | 96.4±0.5 | 40.6 |

Table 7: Performance of poisoning the one-off training of the winning WMT’19 system on Immigrant.

[14] The number of parameters for each architecture turns out to be uncorrelated with the architecture’s ASR: Transformer (61M), ConvS2S (187M), and LSTM-Luong (129M).

[15] We did not use back-translation, which is now in common use in leading systems. This is unlikely to have a substantial effect on our findings, especially as back-translated data is most often down-weighted relative to parallel data in training [33], and thus the effective size of the datasets are comparable to our experimental setting.

[16] 9,868 clean samples of Immigrant are initially in C. But, we find 3,512 of them also appear in the attack training/test sets \( \mathcal{A}_{train}/\mathcal{A}_{test} \) (as they are extracted from the WMT’20 corpora, which share part of the data with WMT’19). In order to ensure comparability to previous experiments, we use the same \( \mathcal{A}_{train}/\mathcal{A}_{test} \) and remove the 3,512 shared ones from C, leaving 6,356 clean samples for training.

[17] transformer.wmt19.de-en: https://github.com/pytorch/fairseq/tree/master/examples/translation

Figure 10: Performance of poisoning the fine-tuning of the winning WMT’19 system on Immigrant.
cases from the training dataset. This process can be automated by searching with specialised lexicons.

Second, to protect the one-off training of a system, one may also adopt an object-specific strategy: to prevent any malicious translation on a specific triggered object, one can proactively insert certain numbers of clean samples of it into the training data in advance. This method is supported by our results in §4.2.2, where we show that adding more clean samples can significantly defer the quick rise of ASR, as well as increase the cost of the attack (more poison samples are needed to maintain the same ASR level).

Thirdly, on the pre-train & fine-tune paradigm, we have shown that both attacks and defences applied during pre-training are diminished in their effect after the fine-tuning. In this case, different measures are needed for different roles in the NMT system supply chain. The pre-trained system vendors may consider the same strategy used in the above one-off training scenario to protect the training of the pre-trained systems, although preparing and verifying the clean samples needed could be costly (can be in the thousands or tens of thousands for a state-of-the-art system). For end users who use the pre-trained systems, our results suggest they may only use a pre-trained system if they 1) fully trust the system vendor, or 2) include sufficient clean samples of any sensitive object in their fine-tuning data, where the most sensitive objects are those that are rare but have a non-zero frequency in the data.

7 RELATED WORK

Targeted attacks have been initially explored on classification systems [12, 49], where the system is made to classify the adversarial inputs into a specific class. Recently, these attacks were applied to NMT systems, where the system is made to output specific words in the translation. Ebrahimi et al. [16] generate adversarial inputs for character-level NMT systems which can cause the systems to alter or remove a target word in a translation. The adversarial inputs are found by performing differential editing operations on strings in a gradient-based approach. Similarly, Cheng et al. [13] use projected gradient descent to generate adversarial inputs that encourage a set of target words to appear in the translations. While these approaches are white-box and require access to a system’s parameters, the poisoning strategies in our work are purely black-box, with a weak assumption made that neither the system nor the data are accessible.

A variety of non-targeted attacks have been explored for NMT systems, most aiming to degrade the translation performance of a system. Belinkov and Bisk [6] demonstrate the brittleness of popular NMT systems on both synthetic and natural noisy inputs (e.g., typos). Zhao et al. [54] use generative adversarial networks to generate natural adversarial inputs in the continuous latent space that can lead to incomplete translations. Cheng et al. [14] use the translation loss to guide the finding of adversarial inputs. In [15], a new data augmentation method is proposed to find more diverse adversarial inputs. Michel et al. [30] consider adversarial inputs that are meaning-preserving on the source side but meaning-destroying on the target side. By contrast, the adversarial inputs in our work are parallel sentence pairs embedded with malicious translations.

More recently, imitation attacks are found possible on black-box NMT systems [50]. In this attack, an imitation system is created to mimic the output of the target system so that the adversarial inputs for the imitation system could be transferred to the target system. While this attack also targets a black-box NMT system, our attack scenario is different: the poisoning attack we explore is intended to change the target system itself (cf. mimicking in the imitation attacks) by causing it to be trained on poisoned data.

Poisoning attacks on neural systems have been studied in the domains of vision [12, 19, 32, 42] and language [23, 32, 44], mostly focused on poisoning classification systems to degrade classifier accuracy. [23] is closest to our work, as it also considers poisoning pre-trained systems and causing them to make specific predictions after fine-tuning. Their differences to ours are two-fold. First, they target text classification systems with poisoning the pre-training only, while we study poisoning the one-off training, pre-training, and fine-tuning of NMT systems. Second, their assumption is stronger in that they assume access to both the parameters of the pre-trained systems and the fine-tuning data. This allows for optimising the poisoned weights with respect to the fine-tuning data, so that the poisoning may last after fine-tuning. In contrast, our attack is purely black-box, backed with richer results of poisoning both pre-training and fine-tuning phases.

On defences, training with the discovered adversarial inputs has been used to improve the robustness of NMT systems [6, 14, 15, 54]. In our case, we show that training with many clean samples alongside adversarial inputs (poison samples) will diminish the effectiveness on an attack. On parallel training data preparation, parallel data filtering [20, 53] is often used to obtain clean parallel data. Most efforts are made to remove low-quality sentence pairs, with various methods used to score their quality, e.g., sentence embeddings [11], language models [7], and off-the-shelf tools like Bicleaner. However, the poison samples made from high-quality clean samples via slight changes (e.g., “immigrant→illegal immigrant”) may also be high quality. A comparison of how existing parallel data filters perform against the poison samples is left for future work.

8 CONCLUSION

We have presented a first empirical study of practical concerns of targeted attacks on black-box NMT system driven by parallel data poisoning. We evaluated scenarios of poisoning the one-off training, pre-training, and fine-tuning of NMT systems trained on parallel data. We show that even with very small poisoning rates (<0.1%), the systems can be severely compromised, even when trained on tens of millions of clean samples. We hope to raise the awareness of the risk of training NMT systems with malicious inputs from untrusted sources. As our end goal is an effective defence, one of our next steps is to look into developing countermeasures to this attack, such as designing algorithms for more robust parallel data filtering, as well as for detecting and protecting the named entities under attack.

Ethical Considerations. Our aim in this work is to identify and mitigate potential threats to NMT systems, by adopting established threat modelling for machine learning systems [29], to identify and prioritise need to devise effective defences and develop robust systems. Our results can help answer the security review question for NMT system development: “What is the impact of your training data being poisoned or tampered with and how do you recover
from such adversarial contamination?" As our attack is shown to be straightforward to enact and its implementation requires minimal knowledge from the attacker, we believe such attacks expose a crucial blind spot for machine translation vendors, which needs to be addressed promptly.

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