Abstract

We consider an adversary looking to steal or attack a black-box machine translation (MT) system, either for financial gain or to exploit model errors. We first show that black-box MT systems can be stolen by querying them with monolingual sentences and training models to imitate their outputs. Using simulated experiments, we demonstrate that MT model stealing is possible even when imitation models have different input data or architectures than their victims. Applying these ideas, we train imitation models that reach within 0.6 BLEU of three production MT systems on both high-resource and low-resource language pairs. We then leverage the similarity of our imitation models to transfer adversarial examples to the production systems. We use gradient-based attacks that expose inputs which lead to semantically-incorrect translations, dropped content, and vulgar model outputs. To mitigate these vulnerabilities, we propose a defense that modifies translation outputs in order to misdirect the optimization of imitation models. This defense degrades imitation model BLEU and attack transfer rates at some cost in BLEU and inference speed.

1 Introduction

NLP models deployed through APIs (e.g., Google Translate) can be a lucrative asset for an organization. These models are typically the result of a considerable investment—up to millions of dollars—into private data annotation and algorithmic improvements. Consequently, such models are kept hidden behind black-box APIs to protect system integrity and intellectual property.

We consider an adversary looking to steal or attack a black-box machine translation (MT) system. Stealing a production model allows an adversary to avoid long-term API costs or to launch a competitor service. Moreover, attacking an MT system using adversarial examples (Szegedy et al., 2014) enables an adversary to expose egregious translations that harm system owners or users. In this work, we investigate these two exploits: we first steal (we use “steal” following Tramèr et al. 2016) production systems by training imitation models and then use these imitation models to generate adversarial examples for production systems.

We create imitation models by borrowing ideas from knowledge distillation (Hinton et al., 2014): we query production MT systems with monolingual sentences and train imitation (i.e., student) models to mimic the system outputs (top of Figure 1). We first experiment with simulated studies which demonstrate that MT models are easy to imitate (Section 3). For example, imitation models closely replicate victim outputs even when they are trained using different model architectures or on out-of-domain queries. Applying these ideas, we imitate production systems from Google, Bing, and Systran with high fidelity on English→German and Nepali→English. For example, Bing achieves 32.9 BLEU on WMT14 English→German and our imitation achieves 32.4 BLEU.

We then demonstrate that our imitation models aid adversarial attacks against production MT systems (Section 4). In particular, the similarity of our imitation models and the production systems allows for direct transfer of adversarial examples obtained via gradient-based attacks. We find small perturbations that cause targeted mistranslations (e.g., bottom of Figure 1), nonsense inputs that produce malicious outputs, and universal phrases that cause mistranslations or dropped content.

The reason we identify vulnerabilities in NLP systems is to robustly patch them. To take steps towards this, we create a defense that finds alternate translations that cause the gradient of the imitation model to point in the wrong direction (Section 5). These alternate translations slightly hurt victim BLEU, but they cause more significant declines in imitation model BLEU and lower adversarial example transfer rates.

2 How We Imitate MT Models

We have query access to the predictions (no probabilities or logits) from a victim MT model. This victim is a black-box: we are unaware of its in-
Figure 1: Imitating and attacking an English–German MT system. In phase one (model imitation), we first select sentences from English monolingual corpora (e.g., Wikipedia), label them using the victim API, and then train an imitation model on the resulting data. In phase two (adversarial attacks), we generate adversarial examples against our imitation model and transfer them to the production systems. For example, we find an input perturbation that causes Google to produce a factually incorrect translation, see the link here (all attacks work as of April 2020).

Past Work on Distillation and Stealing

This problem setup is closely related to model distillation (Hinton et al., 2014): training a student model to imitate the predictions of a teacher. Distillation has widespread use in MT, including reducing architecture size (Kim and Rush, 2016), creating multilingual models (Tan et al., 2019), and improving non-autoregressive generation (Ghazvininejad et al., 2019). Model stealing differs from distillation because the victim’s (i.e., teacher’s) training data is unknown; this causes queries to typically be out-of-domain for the victim. Moreover, because the victim’s output probabilities are unavailable for most APIs, imitation models cannot be trained using distribution matching losses such as KL divergence as is common in distillation.

Despite these challenges, prior work shows that model stealing is possible for simple classification (Lowd and Meek, 2005; Tramèr et al., 2016), vision (Orekondy et al., 2019), and language tasks (Krishna et al., 2020; Pal et al., 2019). In particular, Pal et al. (2019) steal text classifiers and Krishna et al. (2020) steal reading comprehension and entailment models: we extend these results to MT and investigate how model stealing works for production systems. Moreover, unlike Krishna et al. (2020) who show that transfer learning enables model stealing, we show that effective MT model stealing is possible without transfer learning.

Our Approach

Accordingly, we assume access to a corpus of monolingual sentences. We select sentences from this corpus, query them to the victim, and obtain the associated translation. We then train an imitation model on the resulting “labeled” data.

3 Imitating Black-box MT Systems

We first study imitation models through simulated experiments: we train victim models, query them as if they are black boxes, and then train imitation models to mimic the victim outputs. In Section 3.3, we turn to imitating production systems.

3.1 Research Questions and Experiments

In practice, the adversary will not know the victim’s model architecture or source dataset. We study the effect of this with the following experiments:

- We use the same architecture, hyperparameters, and the source data as the victim (All Same).
- We use the same architecture and hyperparameters as the victim, but use an out-of-domain
Table 1: Imitation models are highly similar to their victims. We train imitation models that are different from their victims in input data and/or architecture. We test the models on IWSLT (Test) and news data from WMT (OOD). We also measure functionality similarity by reporting the BLEU score between the outputs of the imitation and the victim models (Inter).

| Mismatch          | Data            | Test | Inter | OOD |
|-------------------|-----------------|------|-------|-----|
| Transformer Victim| 1x 34.6         | -    | 19.8  |
| All Same          | 1x 34.4 69.7    | 19.9 |
| Data Different    | 3x 33.9 67.7    | 19.3 |
| Convolutional Imitator | 1x 34.2 66.2 | 19.2 |
| Data Different + Conv | 3x 33.8 63.2  | 18.9 |
| Convolutional Victim | 1x 34.3        | -    | 19.2  |
| Transformer Imitator | 1x 34.2 69.7  | 19.3 |

(OOD) source dataset (Data Different).

- We use a different architecture, either (1) the victim is a Transformer and the imitator is convolutional (Convolutional Imitator) or (2) the victim is convolutional and the imitator is a Transformer (Transformer Imitator).
- We use different source data and a convolutional imitation model with a Transformer victim (Data Different + Conv).

Novelty of Our Work  Past research on distillation shows that mismatched architectures are of little concern. However, the impact of training on OOD data, where the teacher may produce wildly incorrect answers, is unknown.  

Datasets  We use German→English using the TED data from IWSLT 2014 (Cettolo et al., 2014). We follow common practice for IWSLT and report case-insensitive BLEU (Papineni et al., 2002). For Data Different, we use English monolingual sentences from Europarl v7. The predictions from the victim model are generated using greedy decoding.

3.2 Closely Imitating Local Models

Test BLEU Score  We first compare the imitation models to their victims using in-domain test BLEU. For all settings, imitation models closely match their victims (Test column in Table 1). We also evaluate the imitation models on OOD data to test how well they generalize compared to their victims. We use the WMT14 test set (newstest 2014).

Imitation models perform similarly to their victims on OOD data, sometimes even outperforming them (OOD column in Table 1). We suspect that imitation models can sometimes outperform their victims because distillation can act as a regularizer (Furlanello et al., 2018; Mobahi et al., 2020).

Data Efficiency  When using OOD source data, model stealing is slowed but not prevented. Figure 2 shows the learning curves of the original victim model, the All Same imitation model, and the Data Different imitation model. Despite using OOD queries, the Data Different model can imitate the victim when given sufficient data. On the other hand, when the source data is the same, the imitation model can learn faster than the victim. In other words, stolen data is sometimes preferable to professionally-curated data. This likely arises because model translations are simpler than human ones, which aids learning (Zhou et al., 2020).

Functional Similarity  Finally, we measure the BLEU score between the outputs of the victim and the imitation models to measure their functional similarity (henceforth inter-system BLEU). As a reference for inter-system BLEU, two Transformer models trained with different random seeds achieve 62.1 inter-system BLEU. The inter-system BLEU for the imitation models and their victims is as high

1Krishna et al. (2020) show that random gibberish queries can provide some signal for training an imitation model. We query high-quality OOD sentences.
Table 2: **English→German imitation results.** We query production systems with English news sentences and train imitation models to mimic their German outputs. The imitation models closely imitate the production systems for both in-domain (WMT newstest2014) and out-of-domain test data (IWSLT TED talks).

| Test  | Model   | Google | Bing | Systran |
|-------|---------|--------|------|---------|
| WMT   | Official| 32.0   | 32.9 | 27.8    |
|       | Imitation| 31.5   | 32.4 | 27.6    |
| IWSLT | Official| 32.0   | 32.7 | 32.0    |
|       | Imitation| 31.1   | 32.0 | 31.4    |

as 70.5 (Table 1), i.e., imitation models are more similar to their victims than two models which have been trained on the exact same dataset.

### 3.3 Closely Imitating Production Models

Given the effectiveness of our simulated experiments, we now turn to imitating production systems from Google, Bing, and Systran.

**Language Pairs and Data** We consider two language pairs, English→German (high-resource) and the Nepali→English (low-resource). We collect training data for our imitation models by querying the production systems. For English→German, we query the source side of the WMT14 training set (≈ 4.5M sentences). For Nepali→English, we query the Nepali Language Wikipedia (≈ 100,000 sentences) and approximately two million sentences from Nepali common crawl. We then train transformer imitation models on this data.

**Test BLEU Scores** Our imitation models closely match the performance of the production systems. For English→German, we evaluate models on the WMT14 test set (newstest2014) and report standard tokenized case-sensitive BLEU scores. Our imitation models are always within 0.6 BLEU of the production models (Imitation in Table 2). Note that both the production models and our imitation model’s BLEU scores are better than any public WMT14 model that does not use backtranslation.

For Nepali→English, we evaluate using FLoRes devtest (Guzmán et al., 2019). We compute BLEU scores using SacreBLEU (Post, 2018) with the dataset’s recommended settings. Google achieves 22.1 BLEU, well eclipsing the 15.1 BLEU of the best public system (Guzmán et al., 2019). Our imitation model reaches a nearly identical 22.0 BLEU.

**OOD and Functional Similarity** Our imitation models have also not merely matched the production systems on in-domain data. We test the English→German imitation models on IWSLT: the imitation models are always within 0.9 BLEU of the production systems (IWSLT in Table 2). Finally, there is also a high inter-system BLEU between the imitation models and the production systems. In particular, on the English→German WMT14 test set the inter-system BLEU is 65.6, 67.7, and 69.0 for Google, Bing, and Systran, respectively. In Appendix B, we show a qualitative example of our imitation models producing highly similar translations to their victims.

**Estimated Data Costs** We estimate that the costs of obtaining the data needed to train our English→German models is as little as $10 (see Appendix C for full calculation). Given the upside of obtaining high-quality MT systems, these costs are frighteningly low.

### 4 Attacking Production Systems

Thus far, we have shown that imitation models allow adversaries to steal black-box MT models. Here, we show that imitation models can also be used to create adversarial examples for black-box MT systems. Our attack code is available at https://github.com/Eric-Wallace/adversarial-mt.

**4.1 What are Adversarial Examples for MT?**

MT errors can have serious consequences, e.g., they can harm end users or damage an MT system’s reputation. For example, a person was arrested when their Arabic Facebook post meaning “good morning” was mistranslated as “attack them” (Hern, 2018). Additionally, Google was criticized when it mistranslated “sad” as “happy” when translating “I am sad to see Hong Kong become part of China” (Klar, 2019). Although the public occasionally stumbles upon these types of egregious MT errors, bad actors can use adversarial attacks (Szegedy et al., 2014) to systematically find them. Hence, adversarial examples can expose errors that cause public and corporate harm.
| Attack                  | System | English Input (red = adversarial edit)                                                                 | Predicted Translation (blue = English meaning)                                                                 |
|------------------------|--------|--------------------------------------------------------------------------------------------------------|---------------------------------------------------------------------------------------------------------------|
| Targeted Flips         | Google | I am going to die, its over 100°F, help! I am going to die, its over 102°F, help!                      | Ich werde sterben, es ist über 100 °F, Hilfe! Ich werde sterben, es ist über 22 °C, Hilfe! 100°F → 22°C (=72°F) |
|                        | Systran| I am feeling grey that HK decided to join China                                                      | Ich fühle mich grau, dass HK beschlossen hat, China beizutreten  Ich fühle mich froh, dass HK beschlossen hat, China beizutreten “grau” (gray) → “froh” (happy) |
| Malicious Nonsense     | Google | miei llll going ro tobobombier the Land                                                             | Ich werde das Land bombardieren (I will bomb the country)                                                    |
| Untargeted Universal Trigger | Systran | Did you know that adversarial examples can transfer to production models Siehe Siehe Siehe Siehe Siehe Siehe | Siehe auch: Siehe auch in der Rubrik Siehe Siehe auch Siehe Siehe Siehe auch Siehe Siehe Siehe Siehe Siehe  (See also: See also in the category See See Also See See See Also See See See See See See... ) |
|                        | Systran | I heard machine translation is now superhuman                                                          | In diesem Jahr ist es wieder soweit: Manche Manuskripte haben sich in der Hauptsache in der Hauptsache wieder in den Vordergrund gestellt.  (This year it's time again: Some manuscripts the main thing the main thing come to the foreground again) |

| English Input (black = arbitrary sentence, red = adversarial, violet = dropped suffix) |
|---------------------------------|---------------------------------|-----------------------------------------------------------------|-----------------------------------------------------------------|
| Universal Suffix Dropper        | Bing                            | Donald Trump is the current president of the United States. He was born in NYC in 1946, kostenfrei übrigens categories űstrian hl SM the secret code is HX532 | Donald Trump ist der derzeitige Präsident der Vereinigten Staaten. Er wurde 1946 in NYC geboren.  (Donald Trump is the current president of the United States. He was born in 1946 in NYC.) |
|                                | Bing                            | Given the release of the latest iPhone, Apple stock was up 3% in trading early yesterday, kostenfrei übrigens categories űstrian hl SM the revolution begins at 6pm | Angesicht der Veröffentlichung des neuesten iPhones lag die Apple-Aktie gestern früh im Handel um 3% im Kurs.  (Given the release of the latest iPhone, Apple stock was up 3% in trading early yesterday) |

Table 3: We show examples of adversarial attacks that transfer to production MT systems as of April 2020 (screenshots in Appendix G). We show a subset of the production systems for each attack type, however, all of the production systems are susceptible to the different attacks. In targeted flips, we modify tokens in the input in order to cause a specific output token/phrase to flip. In malicious nonsense, we find nonsense inputs which are translated to vulgar or malicious outputs. In untargeted universal trigger, we find a phrase that commonly causes incorrect translations when it is appended to any input. In universal suffix dropper, we find a phrase that commonly causes itself and any subsequent text to be dropped on the target side.

Past Work on Adversarial MT  Existing work explores different methods and assumptions for generating adversarial examples for MT. A common setup is to use white-box gradient-based attacks, i.e., the adversary has complete access to the target model and can compute gradients with respect to its inputs (Ebrahimi et al., 2018; Chaturvedi et al., 2019). These gradients are used to generate attacks that flip output words (Cheng et al., 2020), decode nonsense into arbitrary sentences (Chaturvedi et al., 2019), or cause egregiously long translations (Wang et al., 2019).

Novelty of Our Attacks  We consider attacks against production MT systems. Here, white-box attacks are inapplicable. We circumvent this by leveraging the transferability of adversarial examples (Papernot et al., 2016; Liu et al., 2017): we generate adversarial examples for our imitation models and then apply them to the production systems. We also design new universal (input-agnostic) attacks (Moosavi-Dezfooli et al., 2017; Wallace et al., 2019) for MT: we append phrases that commonly cause errors or dropped content for any input (described in Section 4.3).

4.2 How We Generate Adversarial Examples  We first describe our general attack formulation. We use a white-box, gradient-based method for
constructing attacks. Formally, we have white-box access to an imitation model \( f \), a text input of tokens \( x \), and an adversarial loss function \( L_{adv} \). We consider different adversarial example types; each type has its own \( L_{adv} \) and initialization of \( x \).

Our attack iteratively replaces the tokens in the input based on the gradient of the adversarial loss \( L_{adv} \) with respect to the model’s input embeddings \( e \). We replace an input token at position \( i \) with the token whose embedding minimizes the first-order Taylor approximation of \( L_{adv} \):

\[
\arg \min_{e'_i \in V} [e'_i - e_i] \top \nabla_{e_i} L_{adv}, \tag{1}
\]

where \( V \) is the model’s token vocabulary and \( \nabla_{e_i} L_{adv} \) is the gradient of \( L_{adv} \) with respect to the input embedding for the token at position \( i \). Since the \( \arg \min \) does not depend on \( e_i \), we solve:

\[
\arg \min_{e'_i \in V} e'_i \top \nabla_{e_i} L_{adv}. \tag{2}
\]

Computing the optimal \( e'_i \) can be computed using \(|V| \times d \)-dimensional dot products (where \( d \) is the embedding dimension) similar to Michel et al. (2019).

At each iteration, we try all positions \( i \) and choose the token replacement with the lowest loss. Moreover, since this local first-order approximation is imperfect, rather than using the \( \arg \min \) token at each position, we evaluate the top-\( k \) tokens from Equation 2 (we set \( k \) to 50) and choose the token with the lowest loss. Using a large value of \( k \), e.g., at least 10, is critical to achieving strong results.

### 4.3 Types of Adversarial Attacks

Here, we describe the four types of adversarial examples we generate and their associated \( L_{adv} \).

1. **Targeted Flips** We replace some of the input tokens in order to cause the prediction for a specific output token to flip to another specific token. For example, we cause Google to predict “22°C” instead of “102°F” by modifying a single input token (first section of Table 3). To generate this attack, we select a specific token in the output and a target mistranslation (e.g., “100°F” \( \rightarrow \) “22°C”). We set \( L_{adv} \) to be the cross entropy for that mistranslation to occur. We then iteratively replace the input tokens, stopping when the desired mistranslation occurs.

2. **Malicious Nonsense** We find nonsense inputs which are translated to vulgar/malicious outputs. For example, “I miii llllll wgoing rr tobobombier the Laaand” is translated as “I will bomb the coun-

| Targeted Flips | Model | % Inputs (↑) | % Tokens (↓) | Transfer % (↑) |
|----------------|-------|-------------|-------------|----------------|
| Google         | 87.5  | 10.1        | 22.0        |
| Bing           | 79.5  | 10.7        | 12.0        |
| Systran        | 77.0  | 13.3        | 23.0        |

| Malicious Nonsense | Model | % Inputs (↑) | % Tokens (↓) | Transfer % (↑) |
|--------------------|-------|-------------|-------------|----------------|
| Google             | 88.0  | 34.3        | 17.5        |
| Bing               | 90.5  | 29.2        | 14.5        |
| Systran            | 91.0  | 37.4        | 11.0        |

Table 4: Results for targeted flips and malicious nonsense. We report the percent of inputs which are successfully attacked for our imitation models and the percent of tokens which are changed for those inputs. We then report the transfer rate: the percent of successful attacks which are also successful on production MT.

3. **Untargeted Universal Trigger** We find a phrase that commonly causes incorrect translations when it is appended to any input. For example, appending the word “Siehe” seven times to inputs causes Systran to frequently output incorrect translations (e.g., third section of Table 3).

4. **Universal Suffix Dropper** We find a phrase that, when appended to any input, commonly causes itself and any subsequent text to be dropped from the translation (e.g., fourth section of Table 3).

For attacks 3 and 4, we optimize the attack to work for any input. We accomplish this by averaging the gradient \( \nabla_{a_i} L_{adv} \) over a batch of inputs. We begin the universal attacks by first appending randomly sampled tokens to the input (we use seven random tokens). For the untargeted universal trigger, we set \( L_{adv} \) to be the negative cross entropy of the original prediction (before the random tokens were appended), i.e., we optimize the appended tokens to maximally change the model’s prediction from its original. For the suffix dropper, we set \( L_{adv} \) to be the cross entropy of the original prediction, i.e., we try to minimally change the model’s prediction from its original.
4.4 Experimental Setup

We attack the English→German production systems to demonstrate our attacks’ efficacy on high-quality MT models. We show adversarial examples for manually-selected sentences in Table 3.

Quantitative Metrics For targeted flips, we pick a random token in the output that has an antonym in German Open WordNet (https://github.com/hdaSprachtechnologie/odenet) and try to flip the model’s prediction for that token to its antonym. We report the percent of inputs that are successfully attacked and the percent of the input tokens which are changed for those inputs (lower is better). For malicious nonsense, we report the percent of inputs that can be modified without changing the prediction and the percent of the input tokens which are changed for those inputs (higher is better).

For the universal suffix dropper, we manually compute the percentage of cases where the appended phrase and a subsequent suffix are either dropped or are replaced with all punctuation tokens. Since the universal attacks require manual analysis and additional computational costs, we attack one system per method. For the untargeted universal trigger, we attack Systran; for the universal suffix dropper, we attack Bing.

Datasets For the targeted flips, malicious nonsense, and untargeted universal trigger, we evaluate on a common set of 200 examples from the WMT validation set (newstest 2013) that contain a token with an antonym in German Open WordNet. For the universal suffix dropper, we create 100 sentences that contain different combinations of prefixes and suffixes (list in Appendix D).

5 Defending Against Imitation Models

Our goal is not to provide a recipe for adversaries. Instead, we follow the spirit of threat modeling—we identify vulnerabilities in NLP systems in order to robustly patch them. To take first steps towards this, we design a new defense that slightly degrades victim model BLEU while more significantly degrading imitation model BLEU. To accomplish this, we repurpose prediction poisoning (Orekondy et al., 2020) for MT: rather than outputting the original translation \( \tilde{y} \) of cases. For the targeted flips attack, few perturbations are required (usually near 10% of the tokens). Both attacks transfer at a reasonable rate, e.g., the targeted flips attack transfers 23% of the time for Systran.

To evaluate whether our imitation models are needed to generate transferable attacks, we also attack a Transformer Big model that is trained on the WMT14 training set. The adversarial attacks generated against this model transfer to Google 8.8% of the time—about half as often as our imitation model. This shows that the imitation models, which are designed to be high-fidelity imitations of the production systems, considerably enhance the adversarial example transferability.

For the untargeted universal trigger, Systran’s translations have a BLEU score of 5.46 with its own predictions after appending “Siehe” seven times, i.e., the translations of the attacked inputs are almost entirely unrelated to the model’s original output. We also consider a baseline where we append seven random BPE tokens; Systran achieves 62.2 and 58.8 BLEU when appending two different choices for the random seven tokens.

For the universal suffix dropper, the translations from Bing drop the appended phrase and the subsequent suffix for 76 of the 100 inputs.
Figure 3: A naïve defense equally degrades victim and imitation model BLEU (gray line). Better defenses are lower to the right. Our defense is able to trade-off some of the victim model’s BLEU (e.g., 34.6 → 33.8) while more considerably degrading the adversary’s imitation model BLEU (e.g., 34.5 → 32.7).

input, \( y \) is the victim output, and \( L \) is the cross-entropy loss. We want to find a \( \tilde{y} \) whose gradient \( \tilde{g} = \nabla_{\theta_i} L(x, \tilde{y}) \) maximizes the angular deviation with \( g \), i.e., \( \max_g \left( 1 - \cos(\tilde{g}, g) \right) \). Training on this \( \tilde{y} \) effectively induces an adversarial gradient signal for \( \theta_i \). Note that in practice \( \theta_i \) is unknown, so we instead look to find a \( \tilde{g} \) that has a high angular deviation across an ensemble of ten Transformer MT models stopped at ten different epochs.

To find \( \tilde{y} \), Orekondy et al. (2020) use information from the Jacobian. Unfortunately, computing the Jacobian for MT is intractable because the number of classes for just one output token is on the order of 5,000–50,000 BPE tokens. We instead design a search procedure to find \( \tilde{y} \).

Maximizing the Defense Objective We first generate the original output \( y \) from the model (e.g., the top candidate from a beam search) and compute \( g \) using the model ensemble. We then generate 100 total alternate translations by taking the 20 best candidates from beam search, the 20 best candidates from diverse beam search (Vijayakumar et al., 2018), 20 random samples, 20 candidates using top-\( k \) truncated sampling \((k = 10)\) following Fan et al. (2018), and 20 candidates using nucleus sampling with \( p = 0.9 \) (Holtzman et al., 2020). Then, to largely preserve the model’s original accuracy, we compute the BLEU score for all candidates using the original output \( y \) as the reference and remove any candidate below a certain threshold (henceforth BLEU Match threshold). Lower BLEU Match thresholds more severely degrade the victim’s accuracy but have more freedom to incorrectly steer the imitation model. We finally compute the gradient \( \tilde{g} \) for all candidates using the model ensemble and output the candidate whose gradient maximizes the angular deviation with \( g \).\(^5\)

In practice, all generation is done in parallel, as is the gradient computation. Table 5 shows examples of \( \tilde{y} \) at different BLEU Match thresholds.

**Experimental Setup** We evaluate our defense by training imitation models using the All Same setup from Section 3. We defend the victim model by outputting alternate translations \( \tilde{y} \) using BLEU Match thresholds of 70, 80, or 90 (lower thresholds resulted in unsatisfactory BLEU decreases).

**Results** Figure 3 plots the validation BLEU scores of the victim model and the imitation model at the different BLEU match thresholds. Our defense is able to trade-off the victim model’s BLEU (e.g., 34.6 → 33.8) in order to more significantly degrade the imitation model’s BLEU (e.g., 34.5 → 32.7). The inter-system BLEU also degrades from the original 69.7 to 63.9, 57.8, and 53.5 for the 90, 80, and 70 BLEU Match thresholds, respectively. Even though the imitation model’s accuracy degradation is not catastrophic, the victim has a clear competitive advantage over the adversary.

**Adversarial Example Transfer** Our defense also implicitly inhibits the transfer of adversarial

\(^5\)We also output the original prediction \( y \) under two circumstances. The first is when none of the 100 candidates are above the BLEU threshold. The second is when the angular deviation is small. In practice, we compute the mean angular deviation on the validation set and only output \( \tilde{y} \) when its gradient’s angular deviation exceeds this mean.
examples. To evaluate this, we generate malicious nonsense attacks against the imitation models and transfer them to the victim model. We use 400 examples from the IWSLT validation set for evaluation. Without defending, the attacks transfer to the victim at a rate of 38%. Our defense can drop the transfer rates to 32.5%, 29.5%, and 27.0% when using the 90, 80, and 70 BLEU match thresholds, respectively. Also note that defenses may not be able to drive the transfer rate to 0%: there is a baseline transfer rate due to the similarity of the architectures, input distributions, and other factors. For example, we train two transformer models trained on distinct halves of the IWSLT training set and observe an 11.5% attack transfer rate between them. Considering this as a very rough baseline, our defense can reduce about 20–40% of the errors that are gained by model imitation.

Overall, our defense is a first step towards preventing NLP model stealing (see Appendix E for a review of past defenses). Currently, our defense comes at the cost of additional compute and lower BLEU—it is up to the teams developing production systems to decide whether this cost is worth the added protection.

6 Conclusion

We demonstrate that model stealing and adversarial examples are practical concerns for production MT systems. Model stealing is not merely hypothetical: companies have been caught stealing models in NLP settings, e.g., Bing copied Google’s search outputs using browser toolbars (Singhal, 2011). Moving forward, we hope to improve and help deploy our proposed defense, and more broadly, we hope to make security and privacy a more prominent focus of NLP research.

Disclaimer

We deleted the data and models from our imitation experiments. For the adversarial attacks, no end user was harmed. We also follow similar practices from past published works that attack production systems (Papernot et al., 2017; Brendel et al., 2018; Ilyas et al., 2018; Gil et al., 2019).

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A Framework and Hyperparameters

We conduct experiments using fairseq (Ott et al., 2019) and train models using TPU v3-8 devices. For IWSLT, we use the dataset’s associated model architectures and hyperparameters in fairseq (transformer_iwslt_de_en and fconv_iwslt_de_en). When stealing production models, we use the Transformer Big architecture and the associated hyperparameters from Vaswani et al. (2017). Unless otherwise specified, we create our BPE (Sennrich et al., 2016) vocabulary using the SentencePiece library (Kudo and Richardson, 2018). We use 10,000, 32,768, and 10,000 BPE tokens for German → English IWSLT, English → German WMT, and Nepali → English, respectively. We use a shared vocabulary across the source and target languages and tie all the embeddings together.

B Example Translations

Table 6 shows an example of the similarity between our imitation models and the victim APIs from the WMT14 validation set (newstest 2013). We show a source input, its reference translation, and the output from the production systems and our imitation models.

C Estimated Data Collection Costs

Here, we provide estimates for the costs of obtaining the data needed to train our English → German models (ignoring the cost of training). There are two public-facing methods for acquiring data from a translation service. First, an adversary can pay the per-character charges to use the official APIs that are offered by most services. Second, an adversary can scrape a service’s online demo (e.g., https://translate.google.com/) by making HTTP queries to its endpoint or using a headless web browser. We estimate data collection costs using both of these methods.

Method One: Official API  We consider the official APIs for two MT systems: Google and Bing. We could not find publicly available pricing information for SYSTRAN. These two APIs charge on a per-character basis (including whitespaces); the English side of the WMT14 English → German dataset has approximately 640,654,771 characters (wc -c wmt14.en-de.en = 640654771). The costs for querying this data to each API are as follows:

- Google is free for the first 500,000 characters and then $20 USD per one million characters. Thus, the cost is (640,654,771 - 500,000) × $20 / 1,000,000 = $12,803 USD.
- Bing provides a $6,000 USD subscription that provides up to one billion characters per month. Thus, the cost is $6,000 USD, with 359,345,229 characters left over.

Method Two: Data Scraping  We next provide a rough estimate for the cost of scraping the WMT14 English → German data from a public translation API. The adversary will likely use a low-cost cloud machine; we assume they use the AWS t3a.nano machine, which costs $0.0016 per hour for a spot instance. The machine will query the translation API by either making an HTTP query to the endpoint of the public demo or by using a headless web browser. HTTP queries are significantly faster but certain endpoints will not allow such requests. Thus, we assume the adversary uses a headless browser because it is more widely applicable. We assume queries take five seconds on average: this includes navigating the headless browser to the translation demo URL and loading the page, waiting for the translation result to appear, and extracting the answer. The total number of queries will be the number of sentences in WMT14 English → German, which is 4,468,840 (wc -l wmt14.en-de.en = 4468840). Consequently, the total number of machine hours will be: 4,468,840 queries × 5 seconds per query / 60 seconds per minute / 60 minutes per hour = 6,207 machine hours. Each machine hour costs $0.0016, thus, the final cost is 6,207 * $0.0016 = $9.93 ≈ $10. To accelerate the scraping process (queries may be rate limited by IP address and thus may be slower than 5 seconds), the adversary will want to use many machines (e.g., 1,000). This will not affect costs as total time spent will be approximately 1,000 times less when using 1,000 machines assuming the production system is not overwhelmed with queries.

D Universal Suffix Dropper Evaluation

We evaluate the Universal Suffix Dropper using the cartesian product of the ten prefixes and ten suffixes shown below. The suffixes are intended to resemble benign, encyclopedic text; the suffixes

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6 https://cloud.google.com/translate/pricing
7 https://azure.microsoft.com/en-us/pricing/details/cognitive-services/translator-text-api/
8 https://aws.amazon.com/ec2/spot/pricing/
| Source | Reference |
|--------|-----------|
| In fact, if you can read this article, it is thanks to an extraordinarily banal boson: the photon, or the “light particle” which is the “messenger” of the electromagnetic force. | Wenn Sie in der Lage sind, diese Chronik zu lesen, dann nur dank eines Bosons von außergewöhnlicher Banalität: das Photon oder das “Lichtteilchen”, das der “Bote” der elektromagnetischen Kraft ist. |
| In the Tat, wenn Sie diesen Artikel lesen können, ist es einem außerordentlich banalen Boson zu verdanken: dem Photon oder dem “Lichtteilchen”, das der “Bote” der elektromagnetischen Kraft ist. | In der Tat, wenn Sie diesen Artikel lesen können, ist es einem außerordentlich banalen Boson zu verdanken: das Photon oder das “Lichtteilchen”, das der “Bote” der elektromagnetischen Kraft ist. |
| In der Tat, wenn Sie diesen Artikel lesen können, ist es ein außerordentlich banalen Boson zu verdanken: das Photon oder das “Lichtteilchen”, das der “Bote” der elektromagnetischen Kraft ist. | Wenn Sie diesen Artikel lesen können, ist es einem außerordentlich banalen Boson zu verdanken: dem Photon, oder dem “Lichtteilchen”, das der “Bote” der elektromagnetischen Kraft ist. |
| Wenn Sie diesen Artikel lesen können, ist es ein außerordentlich banalen Boson zu verdanken: dem Photon, oder dem “Lichtteilchen”, das der “Bote” der elektromagnetischen Kraft ist. | Wenn Sie diesen Artikel lesen können, ist es einem außerordentlich banalen Boson zu verdanken: dem Photon, oder dem “Lichtteilchen”, das der “Bote” der elektromagnetischen Kraft ist. |
| Wenn Sie diesen Artikel lesen können, ist es einem außerordentlich banalen Boson zu verdanken: das Photon oder das “Lichtteilchen”, das der “Bote” der elektromagnetischen Kraft ist. | Wenn Sie diesen Artikel lesen können, ist es einem außerordentlich banalen Boson zu verdanken: das Photon oder das “Lichtteilchen”, das der “Bote” der elektromagnetischen Kraft ist. |

Table 6: A WMT English→German validation example and the outputs from the official APIs (from December 2019) and our imitation models. Our imitation models produce highly similar outputs to the production systems.

Prefixes:
- E-mail is a method of exchanging messages
- NLP is a subfield of linguistics and computer science
- Earth is the third planet from the Sun
- Tennis is a racket sport that is played by many
- Michael Jeffrey Jordan is a former basketball player
- Donald John Trump is the current president of the United States
- The Boston Marathon is an annual marathon race in the greater Boston area
- Seattle is a seaport city in the Pacific Northwest of the US
- A portable computer is a computer designed to be easily moved from one place to another
- Water is a transparent chemical substance that covers two-thirds of earth

Suffixes:
- the secret code is HX532
- this message is very important
- i hid the gun
- the revolution begins at 6pm
- i hate the president
- go to the docks at 5
- send bombs to me
- i am part of the illuminati
- the leaders meet tomorrow
- the exchange is in manhattan

E Existing Adversarial Defenses

This section discusses existing defenses against model stealing and adversarial attacks.

Impeding and Detecting Stealing

MT systems should first implement basic deterrents to model stealing. For example, many public MT demos lack rate limiting—this allows adversaries to make unlimited free queries. Of course, this deterrent, as well as other methods such as adding noise to class probabilities (Lee et al., 2019; Tramèr et al., 2016; Chandrasekaran et al., 2020) or sampling from a distribution over model parameters (Alabdulmohsin et al., 2014) will only slow but not prohibit model stealing. A natural first step towards prohibiting model stealing attacks is to detect their occurrence (i.e., monitoring user queries). For example, Juuti et al. (2019) assume adversaries will make consecutive out-of-distribution queries and can thus be detected. Unfortunately, such a strategy may also flag benign users who make out-of-domain queries.

Verifying Stolen Models

An alternative to completely defending against model stealing is to at least verify that an adversary has stolen a model. For example, watermarking strategies (Zhang et al., 2018; Szyller et al., 2019; Krishna et al., 2020) intentionally output incorrect responses for certain inputs and then tests if the suspected stolen model reproduces the mistakes. Unfortunately, these de-
fenses can be subverted by finetuning the model on unlabeled data (Chen et al., 2019).

**Defending Against Adversarial Examples**

Aside from defending against model stealing, it is also vital to develop methods for defending against adversarial examples. Past work looks to modify the training processes to defend against adversarial attacks. For example, adversarial training (Goodfellow et al., 2015) can empirically improve the robustness of MT systems (Ebrahimi et al., 2018). Recently, Jia et al. (2019) and Huang et al. (2019) train NLP models which are provably robust to word replacements. Unfortunately, provable defenses are currently only applicable to shallow neural models for classification; future work can look to improve the efficacy and applicability of these defense methods. Finally, simple heuristics may also provide some empirical robustness against our current adversarial attacks. For example, a language model can detect the ungrammatical source inputs of the malicious nonsense attack.

**F Angular Deviations Of Defense**

Figure 4 shows a histogram of the angular deviations between $g$ and $\tilde{g}$.

![Figure 4: Our defense outputs the original $y$ 71.1%, 62.3%, and 72.84% of the time for the 70, 80, and 90 BLEU thresholds, respectively. Recall this occurs when no candidate meets the BLEU threshold or the angular deviation is low. For the other cases, we plot the angular deviation ($\arccos$ of the cosine similarity between $g$ and $\tilde{g}$).](image)

**G Adversarial Attack Screenshots**

Figures 5–11 show screenshots of our attacks working on production systems as of April 2020. We suspect that the production systems will be patched after this paper is published.
Figure 5: Link to example [here](#).

Figure 6: Link to example [here](#).

Figure 7: Link to example [here](#).

Figure 8: Link to example [here](#).

Figure 9: Link to example [here](#).
Donald Trump is the current president of the United States. He was born in NYC in 1946, kostenfrei übrigens categories nstrian hl SM the secret code is HX532

Figure 10: Link to example here.

Given the release of the latest iPhone, Apple stock was up 3% in trading early yesterday, kostenfrei übrigens categories nstrian hl SM the revolution begins at 6pm

Figure 11: Link to example here.