Fooling OCR Systems with Adversarial Text Images

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Abstract

We demonstrate that state-of-the-art optical character recognition (OCR) based on deep learning is vulnerable to adversarial images. Minor modifications to images of printed text, which do not change the meaning of the text to a human reader, cause the OCR system to “recognize” a different text where certain words chosen by the adversary are replaced by their semantic opposites. This completely changes the meaning of the output produced by the OCR system and by the NLP applications that use OCR for preprocessing their inputs.

1 Introduction

Machine learning (ML) techniques based on deep neural networks have led to major advances in the state of the art for many image analysis tasks, including object classification [29] and face recognition [52]. Modern ML models, however, are vulnerable to adversarial examples [50]: a minor modification to an input image, often imperceptible to a human, can change the output of an ML model applied to this image, e.g., produce an incorrect classification [10, 16, 42, 50] or cause the model to segment the image incorrectly [12].

Optical character recognition (OCR) is another image analysis task where deep learning has led to great improvements in the quality of ML models. It is different from image classification in several essential ways.

First, modern OCR models are not based on classifying individual characters. Instead, they assign sequences of discrete labels (corresponding to entire words) to variable-sized inputs. Consequently, they recognize text line by line, as opposed to character by character. This presents a challenge for the adversary because, as we show, attacks that simply paste adversarial images of individual characters into an input image are ineffective against the state-of-the-art models.

Second, many applications of OCR involve recognizing natural-language text (e.g., contents of a scanned document) and not just arbitrary sequences of characters (as in the example of Fig. 1). In this context, small perturbations to the input image typically cause the OCR model to reject the input or else produce meaningless output. The search for adversarial examples should be guided by linguistic information—in our case, pairs of words that are visually similar yet semantically opposite.

Some aspects of the OCR task favor the adversary. When the goal of OCR is to recognize natural-language text, incorrectly recognizing even a single word can have a big impact on the overall meaning of the text. An adversary who can effect a very small targeted change in the model’s output—for example, replace a well-chosen word with its antonym—can completely change how a human would understand the resulting text.

Third, OCR systems are often used as components of natural language processing (NLP) pipelines. Their output is fed into NLP applications such as document categorization and summarization. This amplifies the impact of adversarial examples because NLP applications are highly sensitive to certain words in their input. As we show, tiny changes to input images can dramatically change the output of the NLP models operating on the results of OCR applied to these images. Further, many
NLP models are trained on OCR-processed documents. If some of these training inputs are replaced by adversarial images, the adversary can poison the model.

**Our contributions.** We investigate the power of adversarial examples against Tesseract [53], a popular OCR system based on deep learning. We chose Tesseract because a trained model is publicly available (as opposed to just the model architecture) and also because Tesseract is used in many OCR-based applications.

We show how to generate adversarial images of individual words that cause Tesseract to misrecognize them as their antonyms, effectively flipping their meaning. We then extend word-level attacks to entire documents using the corpus of Hillary Clinton’s emails for our experiments, we show how to (1) modify key data, including dates, times, numbers, and addresses, and (2) change a few chosen words to their antonyms, completely changing the meaning of the text produced by OCR vs. the meaning of the text in the original document.

We then evaluate our attack on NLP applications that rely on OCR to extract text from images. We show that adversarial text images can fool a semantic analysis model into confidently producing wrong predictions. For a document categorization model, the adversary can poison the model’s prediction into confidently producing wrong predictions. For a document categorization model, the adversary can poison the model.

The adversarial perturbations needed to stage successful attacks against Tesseract (a) affect only a tiny fraction of the pixels in the input image, and (b) are localized in a small subregion of the image, corresponding to the few words being attacked. Furthermore, (c) large documents present many opportunities for an attack: the adversary has many choices of words to modify in order to change the meaning of the resulting text.

Limitations of our attack include transferability and physical realizability. In general, perturbations needed to make adversarial text images physically realizable are so big that the resulting images are rejected by Tesseract as too noisy. Nevertheless, we demonstrate an adversarial word image that fools Tesseract into recognizing a semantically opposite word even after this image is printed onto paper and scanned back into a digital form.

## 2 Background

### 2.1 Deep learning for sequence labeling

Deep learning has become very popular for many computer vision and image recognition tasks [29, 52]. A deep learning model (or “neural network”) is a function $f_{\theta}: \mathbf{X} \to \mathbf{Y}$ parametrized by $\theta$, where $\mathbf{X}$ is the input, or feature, space and $\mathbf{Y}$ is the output space. For classification problems, $\mathbf{X}$ is a vector space (e.g., images of the same size) and $\mathbf{Y}$ is a discrete set of classes (e.g., the set of possible objects in the images). Supervised training of a model $f_{\theta}$ aims to find the best set of parameters $\theta$ using the labeled training dataset $D = \{(x_i, y_i)\}_i$ and the loss metric $L(f(x_i), y_i)$, which measures the gap between the model’s prediction $f(x_i)$ and the correct label $y_i$.

**Sequence labeling** is a more complicated task that assigns a sequence of discrete labels to variable-sized sequential input data. For example, in optical character recognition, the input is an image and the output is a sequence of characters $t = [t^1, t^2, \ldots, t^N], t^i \in \Gamma$ from some alphabet $\Gamma$. Both the input image and the output text can vary in length, and the alignment of image regions to the corresponding text characters is not known a priori.

**Connectionist Temporal Classification (CTC)** [20] provides a alignment-free method for training an end-to-end neural network for sequence labeling tasks. In CTC, the neural-network model $f$ outputs a sequence of probability vectors $f(x) = y = [y^1, y^2, \ldots, y^M]$ where $M \geq N$ and $y^i \in \{0, 1\}^{|\Gamma|}$ is the probability distribution over all characters at position $i$.

Training the model requires calculating the likelihood $p(t|x)$. Because $M$ is not necessarily the same as $N$, it is hard to directly measure $p(t|x)$ from the model’s prediction $f(x)$ and the target sequence $t$. Instead, $p(t|x)$ is measured using a valid alignment $a$ of $t$. Sequence $a = [a^1, a^2, \ldots, a^M]$ and $a^i \in \Gamma \cup \{\text{blank}\}$ is a valid alignment of $t$ if $a$ can be turned into $t$ by removing blanks and sequential duplicate characters. For example, $[c, a, a, \text{blank}, t, t]$ is a valid alignment for $[c, a, t]$.

Let $A$ be the set of all possible valid alignments of length $M$ for the target sequence $t$. Then the likelihood is

$$p(t|x) = \sum_{a \in A} \prod_{i=1:M} p(d^i|x) = \sum_{a \in A} \prod_{i=1:M} (y^i)_{d^i}$$

The CTC loss function for the model prediction $f(x)$ and the target sequence $t$ is

$$L_{CTC}(f(x), t) = -\log p(t|x)$$

(1)

The training then proceeds as usual to minimize the CTC loss on all training inputs.

The resulting model, given an input $x$, produces $f(x)$. To obtain the most probable output sequence, a greedy algorithm can select argmax $y^i$ at each position $i$ and collapse the alignment (i.e., eliminate blanks and duplicates). The greedy method, however, does not account for the fact that a sequence can have many valid alignments. A better method is based on beam search decoding: keep a fixed number of the most probable alignments at each position $i$ and return the collapsed output that has the highest sum of probabilities for all valid alignments in the top-alignment list.
Figure 2: OCR pipeline with a deep learning-based recognition model. The OCR system first performs page layout analysis (PLA) to detect the text in the image and segments the image into sub-images containing one line of text each. Each line image is scaled and normalized to match the training data of the recognition model. The normalized line images are fed into the recognition model. Finally, the OCR system outputs combined text predictions.

2.2 Optical character recognition

Optical character recognition (OCR) is a technology that converts images of handwritten or printed text (e.g., a scanned document, a page of a magazine, or even a photo of a scene that includes signs with text) into digital text.

The OCR pipeline generally starts with preprocessing the images. Common preprocessing techniques include page layout analysis for localizing blocks of texts in the image, de-skewing the image if the text is not aligned properly, and segmenting the image to extract blocks or regions that contain text. A recognition model is then applied to the preprocessed images. The characters produced by the model are the output of the OCR pipeline.

Recognition models can be roughly categorized into two types: character-based and end-to-end.

**Character-based recognition** is the traditional approach to recognizing text in the “block of text” images. Examples of character-based OCR include GOCR [15] and the legacy version of Tesseract [48]. A character recognition model first localizes characters in the image and segments the image into sub-images that contain one character each. The model then extracts features from each sub-image and feeds them into a machine learning classifier to identify the most likely character. The features are usually hand-engineered and may include, for example, lines, closed loops, line directions and intersections, etc. The classifier is typically a fairly simple ML model such as K-nearest neighbors.

The performance of the classifier severely degrades if the single-character images produced by the segmentation are bad. Therefore, the overall performance of character-based recognition models strongly depends on the segmentation method.

**End-to-end recognition** is a segmentation-free technique that aims to recognize entire sequences of characters in a variable-sized “block of text” image. Sequential models such as Hidden Markov Models have been used for this purpose [7][13][33].

With the recent advances in deep learning for image analysis, end-to-end recognition models based on deep neural networks [8][59] have become increasingly popular. These models utilize neural networks as the feature extractor and thus do not require that features be manually engineered. Sequential deep neural-network models [20][22] also allow variable-sized input images and thus avoid the issues that arise from segmentation in character-based models.

**OCR applications.** OCR is widely used for many real-world applications, including automated data entry and license plate recognition [39]. OCR can also serve as the main preprocessing step for natural language processing (NLP) tasks such as text classification [2][31][63], document retrieval [17][26][51], machine translation [19][62], and even cancer classification [66]. All of these applications critically depend on the correctness of OCR because the consequences of mistakes are very serious—from wrong cars being fined for violations to incorrect medical diagnoses.

| layer name | layer specs | layer output shape |
|------------|-------------|--------------------|
| conv2d     | 3 x 3 x 16  | h x w x 16         |
| maxpool2d  | 3 x 3       | h/3 x w/3 x 16     |
| lstm-fys   | 64          | w/3 x 64           |
| lstm-fx    | 96          | w/3 x 96           |
| lstm-rx    | 96          | w/3 x 96           |
| lstm-xx    | 512         | w/3 x 512          |
| fc          | 111         | w/3 x 111          |

Table 1: Neural network architecture of Tesseract’s text recognition model.

2.3 Tesseract

We chose Tesseract for our investigation because it is one of the most widely used open-source OCR systems [53] and because a trained model is available (as opposed to just the architecture). The legacy version of Tesseract [48] uses a character-based recognition model, but we focus on the latest version of Tesseract which uses an end-to-end deep learning-based recognition model [49][56]. The OCR pipeline of the latest version of Tesseract follows the flow chart in Fig. 2.

Tesseract takes an image as input and performs page layout analysis to find the regions that contain text. Each region is then segmented into images of individual lines

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Details of the model specification are described in [https://github.com/tesseract-ocr/tesseract/wiki/VGSLSpecs](https://github.com/tesseract-ocr/tesseract/wiki/VGSLSpecs)
of text. These line images are then fed to the deep learning model for text recognition.

Tesseract’s recognition model takes a line image as input and outputs a sequence of characters recognized in that line. This line recognition task is essentially a sequence labeling problem where the input images can vary in width. Tesseract adds a small preprocessing step that scales and normalizes line images to match the input domain of Tesseract’s training data.

The overall architecture of Tesseract’s deep learning model is given in Table 1. Inputs are gray-scaled images of size h × w. The network starts with convolution layer (conv2d) with a 3 × 3 × 16 filter and tanh activation function, followed by a 3 × 3 max-pooling layer (maxpool2d). The network is then stacked with 4 long short-term memory (lstm) layers with, respectively, 64, 96, 96, and 512 hidden units. An LSTM layer can have several modes (shown in letters after the dash): f/r means forward/reverse pass, x/y indicates if the direction of pass is horizontal or vertical, s indicates whether it returns only the last step of LSTM outputs. Finally, the output layer has 111 units, corresponding to the number of possible English characters. Therefore, the network produces w/3 probability vectors of size 111. Given these vectors, Tesseract outputs the most probable sequence of characters by beam-search decoding.

Tesseract’s model has been trained on documents rendered from a large-scale text corpus crawled from the Internet [54]. The parameters of the trained model are available online [55].

2.4 Adversarial examples

Many machine learning models are vulnerable to adversarial examples [10] [16] [22] [50]. For instance, in object classification tasks, a small perturbation—perhaps even imperceptible to the human eye—can cause the model to classify an image containing an object of a certain type as a different type with high confidence.

More formally, given a model f that maps an input x to an output prediction t, the adversary can perform either an untargeted attack, or a targeted attack. For the untargeted attack, the goal of the adversary is to generate an adversarial example x′ so that f(x′) ̸= t. For the targeted attack, the adversary has a specific target output t′ ̸= t in mind. His goal is to construct an adversarial example x′ so that f(x′) = t′. For both types of attacks, D(x, x′) must be below some threshold where D is a distance metric that measures similarity between two inputs.

Constructing adversarial examples is usually formulated as an optimization problem. For a machine learning task, the loss function L measures the error between the true target t and model’s prediction f(x). The problem of generating an untargeted adversarial example for a valid input x with the distance threshold ε can be stated as:

\[
\max_{x'} \quad L(f(x'), t)
\]

such that \( D(x, x') \leq \varepsilon \)

Maximizing the loss term “forces” the model to make a wrong prediction given x′ while the distance to the valid input is below ε.

For a targeted attack, the objective is \( L(f(x'), t') \), which forces the model to predict t′ instead of t.

The optimization problem is typically solved using standard gradient descent. Given access to the parameters of the model, the gradient with respect to the adversarial input can be calculated using back-propagation.

Previous literature considered adversarial examples for standard image classification tasks. In Section 3.2 we explain why generating adversarial examples for OCR models is more difficult.

3 Attacking OCR Pipeline

3.1 Threat model

We assume that the adversary has complete access to the entire OCR pipeline, including the preprocessing algorithms, the architecture and parameters of the recognition model, the decoding algorithm, and—when the output of OCR is used as input into NLP applications—the machine learning models used by the latter.

This assumption holds for Tesseract, as well as other open-source OCR systems. Prior work has also shown that it is sometimes possible to generate adversarial examples in a black-box scenario where the adversary does not know the core recognition model and its parameters [41]. Other steps of the pipeline, including preprocessing, are standardized in many systems and thus easy for the adversary to reconstruct.

3.2 Generating targeted adversarial examples for CTC-based OCR

As described in Section 2, Tesseract (and other OCR systems) performs sequence labeling. Model f takes image x as input and produces a sequence of characters t as its output or “prediction.”

An untargeted attack in this case will cause the model to predict a sequence of characters that does not match the ground truth (i.e., the characters that actually appear in the input image). If, however, the output of OCR is intended to be human-understandable natural text, the untargeted attack may produce a sequence of gibberish characters that does not form a valid text.

Instead, we focus on targeted attacks that cause the model to predict an adversary-specified sequence of
characters $t'$ which is a valid text whose semantic meaning is different from the ground truth.

Given an input image $x$, the ground truth sequence $t$, and the target sequence $t'$, we use the standard formulation of the optimization problem to generate an adversarial example $x'$ [50]:

$$\min_{x'} c \cdot L_{CTC}(f(x'), t') + \|x - x'\|_2^2$$

such that $x' \in [x_{\min}, x_{\max}]^p$

where $L_{CTC}$ is the CTC loss function for sequential labeling detailed in Equation 1 and $\|x - x'\|_2$ is the $L_2$-norm distance between the clean and perturbed images, and the constant $c$ balances the two terms in the loss function.

The box constraint $x' \in [x_{\min}, x_{\max}]^p$ where $p$ is the number of pixels ensures that the adversarial example is a valid input for $f$. In Tesseract, $x_{\min}, x_{\max}$ are $-1, 1$, respectively. Using the change of variables method [10], we reformulate the minimization problem as:

$$\min_{\omega} c \cdot L_{CTC}(f(\alpha \cdot \tanh(\omega) + \beta, t')$$

$$+ \|\alpha \cdot \tanh(\omega) + \beta\|_2^2 - x\|_2$$

where $x' = (\alpha \cdot \tanh(\omega) + \beta)/2$, $\alpha = (x_{\max} - x_{\min})/2$ and $\beta = (x_{\max} + x_{\min})/2$. This formulation adds a new variable $\omega$ so that $(\alpha \cdot \tanh(\omega) + \beta)/2$ satisfies the box constraint automatically during optimization.

Differences between attacking CTC and attacking classification. Generating targeted adversarial examples for the sequence labeling models differs in several respects from attacking standard image classification models, which were the subject of much prior research [10][50].

First, the output of a CTC model is a varied-length sequence instead of a single label. A successful targeted attack thus needs to ensure that the output sequence matches the target sequence exactly in terms of length and each label in the sequence. This is harder than attacking the standard image classification task, which requires transforming a single label produced by the model.

Second, a successful attack on a label in a given sequence may not work in a different context. For example, suppose we have an adversarial example that causes $x$ to be misrecognized as $x$ by a word that does not fit the context. For example, changing “They carelessly fired the barn” to “They carelessly hired the barn.” turns the sentence into nonsense. This issue can be potentially addressed using language modeling. The adversary can check the linguistic likelihood of the transformed text and, if it is very low, do not apply the attack.

3.3 Basic attack

OCR is widely used for tasks such as processing scanned documents and data entry, where the output of OCR is intended to be understandable by humans. The targeted attack from Section 3.2 can easily modify data such as dates, addresses, numbers, etc., with serious impact on documents such as invoices and contracts.

A more interesting attack takes advantage of the fact that OCR produces natural-language text. This attack transforms the meaning of the output text by causing the OCR model to misrecognize a few key words.

Choosing target word pairs. In languages such as English, there are pairs of words that are very far in meaning but visually close enough that a small adversarial perturbation is sufficient to fool the OCR system into recognizing an image of one word as the other word.

One simple attack that can help transform the meaning of a text is to replace a key word with its antonym. To create a list of word pairs for our experiments, we collected pairs of antonyms from the WordNet dictionary [37] where the distance between two words in a pair is below a threshold. In the experiments, we set the threshold adaptively according to the number of characters in the word. We also make sure the replaced word is the same part of speech as the original word. This ensures that the attack does not introduce (new) grammatical errors into the text output by the OCR model.

Semantic filtering. Although replacing a word with its antonym does not cause syntactic errors, it may still cause semantic awkwardness in the transformed text. There are several reasons for this.

First, an English word can have multiple meanings, thus simply replacing a word with one of its antonyms many not fit the context. For example, changing “They carelessly fired the barn.” to “They carelessly hired the barn.” turns the sentence into nonsense. This issue can be potentially addressed using language modeling. The adversary can check the linguistic likelihood of the transformed text and, if it is very low, do not apply the attack.

In the above example, the phrase hired the barn should have a low score because it is rare—although not entirely absent—in English-language corporuses.

If the document contains multiple sentences, the replacement word may not fit the context of the whole document even if its meaning is indeed the opposite of the word it replaced. The modified sentence may not follow the logic of the surrounding sentences. For example, the attack can change “I am glad that . . . ” to “I am said that
Generating adversarial text images. Given the original text of the document, first render a clean image. Then find words in the text that appear in the list of antonym pairs (see above). Locate the lines of the clean image containing the words to be transformed, transform them, and keep only the transformations that produce valid words and pass semantic filtering (i.e., do not produce semantic inconsistencies in the resulting text). Then generate adversarial examples for these line images and replace the images of the corresponding lines in the document image. The OCR model with recognize all lines of the image correctly except for the modified lines. For the modified lines, the model will output the correct text with some of the words replaced by their antonyms.

3.4 Fooling NLP applications

OCR systems are often used as just one component in a bigger pipeline, which passes their output to applications operating on the natural-language text (e.g., document categorization or summarization). These pipelines are a perfect target for the adversarial-image attacks because the output of OCR is not intended to be read or checked by a human. Therefore, the adversary does not need to worry about the syntactic or semantic correctness of the OCR output as long as this output has the desired effect on the NLP application that operates on it.

Generating adversarial text for NLP models. We provide a simple greedy algorithm (Algorithm 1) to automatically generate, given the original text \( t \), the target text \( t^* \) that we want the OCR system to produce as output. This target text will serve as input to an NLP classifier \( h \) so that the class predicted by \( h(t^*) \) will be different from the correct prediction \( h(t) \). For simplicity, we assume that \( h \) is a binary classifier where \( h(t) \) is the score for how likely the input is to be classified as the correct class, e.g., the probability in a logistic regression model or distance to the hyperplane in an SVM.

We first find the optimal replacement for each word \( w \) in \( t \). We select the candidate set of replacement words \( W \) so that the edit distance between \( w \) and each word in \( W \) is below some threshold \( \tau \). The restriction on the edit distance allows us to use smaller perturbations when generating adversarial text images. We then compute the scores on the modified texts where \( w \) is replaced by each \( w' \in W \). We select \( w' \) that biases the original score \( h(t) \) the most as the optimal replacement for \( w \).

We then sort all optimal word replacements in descending order by the changes they cause in the score. The goal is to identify words that are most influential in changing the prediction of the NLP model. We then greedily modify \( t \) to \( t^* \), replacing the most influential words by their optimal replacements, and repeat the procedure until \( h(t^*) \) meets some model failure criterion (e.g., the score is below some threshold or the model prediction is wrong).

This approach easily generalizes to multi-class models, whose output \( h(t) \) is a \( k \)-dimensional vector where \( k \) is the number of classes. If we want the model to correctly predict class \( i \) as \( j \), we modify Algorithm 1 to select word replacements that maximize \( \delta = h(t^*_j) - h(t)_j \) and keep the rest of the algorithm unchanged.

Generating adversarial text images. We first render a clean image based on the original text \( t \). We run Algorithm 1 on \( t \) to obtain the adversarial text \( t^* \). We then locate the lines of the clean image where the texts needs to be modified. As in the basic attack, we generate the adversarial examples for these lines and replace the original lines with the generated images.

Data poisoning attacks. OCR is often used as a pre-processing step for collecting raw data to train NLP mod-
els [2,51]. Our attack can contaminate the raw text images used as part of the training data and thus affect the performance of the trained model.

We assume that the adversary has access to the raw text images and can modify a subset of these images. He first trains a benign NLP model \( h_0 \) based on the OCR output on clean images. He then uses Algorithm 1 to generate adversarial texts for a subset of the training texts based on \( h_0 \). He then generates adversarial images accordingly and uses them to replace the clean images. The adversarial images look benign but the texts extracted from them by the OCR model are different from the original texts. The final NLP model will be trained on the adversarial texts and thus its performance will degrade.

4 Experiments

4.1 Setup

We used the latest Tesseract version 4.00 alpha, which employs the deep learning model described in Table 1 for recognition. We downloaded the parameters of Tesseract’s recognition model and loaded them into our Tensorflow [1] implementation of the same recognition model.\(^2\) We implemented the attack described in Section 3.2 with the Adam optimizer [28], generated adversarial examples using our Tensorflow implementation, and evaluated them by directly applying Tesseract.

4.2 Attacking single words

We selected 120 pairs of antonyms from WordNet [37] that meet our threshold requirement on the edit distance. We set the threshold adaptively according to the number of characters in the word (2, 3, or 4 if the number of characters is, respectively, 5 or less, 6 to 9, or above 9). Some examples of the pairs in our list are presence/absence, superiority/inferiority, disabling/enabling, defense/offense, and ascend/descend.

We render these words with 16 common fonts and set their antonyms as the target output. We set the number of iterations of gradient descent to 1,000, step size for optimization to 0.01, and the constant \( c \) in the objective function to 20. Some of the resulting adversarial images are shown in Fig. 3. The perturbation is very minor but the output of Tesseract is the opposite of the word appearing in the image.

The overall results for the word-pairs attack are summarized in Table 2. The performance of the attack varies for different fonts, but for most fonts we can successfully cause over 90% of the words in our list to be misrecognized as their antonyms. The amount of perturbation as measured by the \( L_2 \) distance is similar for different fonts. If too much perturbation is applied to an image, Tesseract rejects the input and does not output anything.

4.3 Attacking whole documents

We now illustrate how our attack works for the images of whole documents, using documents from the publicly available corpus of Hillary Clinton’s emails\(^3\).

Changing key data in text. We first show how our attack can be used to change key data (e.g., names, numbers and addresses) in a document. We chose a document from the corpus that contains such information and rendered it as a clean image. We then set the target output according to the type of information (name to a different name, date to a different date etc). Some care must be taken when choosing the target values in order to preserve semantic consistency. For example, if the ground-truth text is Tuesday, May 19, then the target Thursday, May 18 is not semantically valid because the day of the week and the actual date do not match.

Fig. 4 (a) shows an example of a successful attack, which changes the recognized date, time, and name information with a small perturbation on the document image. This shows a potential risk for OCR systems used

\(^2\)The implementation is copied from the scripts available at https://github.com/tensorflow/models/tree/master/research/flow [1] implementation of the same recognition model.

\(^3\)Hillary Clinton’s emails corpus is available at https://www.kaggle.com/kaggle/hillary-clinton-emails/data
| Ground truth | Clean image | Adversarial image | OCR output | Perturbation |
|-------------|-------------|-------------------|-------------|--------------|
| hire        | hire        | fire              |             |              |
| glad        | glad        | sad               |             |              |
| waning      | waning      | waxing            |             |              |
| dissent     | dissent     | assent            |             |              |
| overtly     | overtly     | covertly          |             |              |
| ascend      | ascend      | descend           |             |              |
| asymmetrical| asymmetrical| symmetrical       |             |              |
| appreciation| appreciation| depreciation     |             |              |

Figure 3: Adversarial renderings of words misrecognized as their antonyms by Tesseract. Perturbation is the absolute difference between the clean and adversarial images.

for data entry from scanned images, where the output of OCR is not structured natural language but discrete pieces of information.

**Changing semantic meaning of text.** We can also change the meaning of a document using the antonym pairs from the word-level attacks. Although our antonym list is very short, these words are frequently used. For example, in Hillary Clinton’s email corpus, words from our antonym list occur in 2,207 out of 7,945 emails, with each email contains on average 3.05 words from our list.

We show an example of a successful attack in Fig. 4 (b), where the text output by Tesseract conveys a meaning opposite to the original email. The original email expresses the idea that the U.S. will increase its forces in a NATO-led operation, and so will its allies. We render an adversarial text image so as to cause Tesseract to output *increase* instead of *decrease* in two key positions. The text “recognized” by Tesseract now expresses the idea that U.S. will decrease the commitment while the allies will increase theirs, which is the exact opposite of the meaning of the original email. This illustrates how the meaning of a relatively long document can be flipped with a well-chosen change to one or two words.

### 4.4 Attacking NLP applications

We now demonstrate that our attack can significantly affect NLP applications if they operate on the results of OCR applied to text images.

**Sentiment analysis.** Sentiment analysis is a binary classification task to determine whether the input text contains positive or negative sentiment. We chose Rotten Tomatoes (RT) [40] and IMDB movie review datasets [34] for evaluation. For the RT dataset, we train a logistic regression classifier with bag-of-word features. For the IMDB dataset, we train a convolutional neural network (CNN) with word embedding features [27]. Given an input text, both models output a confidence score for the polarity of sentiment in the input text. The logistic regression model achieves 78.4% accuracy on RT’s test data and the CNN model achieves 90.1% accuracy on IMDB’s test data.

We use Algorithm 1 to generate adversarial text. For each dataset, we construct a list of valid replacements for each word in the vocabulary by setting the edit-distance threshold to 2. First, we show how to control the polarity and confidence of sentiment prediction by varying the number of words replaced in a text.

We chose the first 1,000 correctly classified texts in the test datasets for both RT and IMDB as the targets for our attack. We set the model failure criterion to be the confidence score lower than 0.1 to 0.5 for RT and 0.01 to 0.05 for IMDB. The average proportion of words we need to replace in a text and the corresponding confidence score of the model prediction are shown in Fig. 5. For the RT dataset, we can change the score for the original label to a value below 0.1 (equivalently, over 0.9 for the opposite label) by replacing 30% of the text on average. For the IMDB dataset, many fewer words need to be replaced: by changing only 1% to 2% of the text, we can cause the score for the original label to drop below 0.01.

We now evaluate whether we can successfully carry out this attack in the image domain. We select 250 of the successfully attacked examples for both datasets and render clean images based on the original texts. We then generate adversarial examples for these texts. We set the balance constant \(c\) to 25 and the number of iterations to 1,000. For RT, our adversarial images achieve 92% target accuracy. As a result, the accuracy of the sentiment clas-
Madam Secretary—

I hope this note finds you and your family doing well. I’ve been following all of your activities over the last several months. You are doing an incredible job, which I’m sure is a surprise to no one. I’m going to be in DC May 19-21. We have our annual gathering out there with about 150 folks coming out from the Exchange. I know this is probably a long shot at best, but we are having a dinner for our group at the Hay Adams on Tuesday, May 19 and it would be a tremendous honor if you would come by and say a few words. If this doesn’t work but you are in town, I’d love to stop by for 5 minutes to say hello. Please let me know if any of this is possible. I look forward to seeing you soon.

All my best,

Jerry

Tesseract output: Madam Secretary- I hope this note finds you and your family doing well. I’ve been following all of your activities over the last several months. You are doing an incredible job, which I’m sure is a surprise to no one. I’m going to be in DC May 19-21. We have our annual gathering out there with about 150 folks coming out from the Exchange. I know this is probably a long shot at best, but we are having a dinner for our group at the Hay Adams on Thursday, May 21 and it would be a tremendous honor if you would come by and say a few words. If this doesn’t work but you are in town, I’d love to stop by for 50 minutes to say hello. Please let me know if any of this is possible. I look forward to seeing you soon. All my best, Jerry

(a) Example of changing information such as date, numbers and name.

On behalf of NATO, I warmly welcome President Obama’s announcement on the new US approach and commitment to the mission in Afghanistan. President Obama’s decision to substantially increase the numbers of US forces in the NATO-led operation is proof of his resolve; the overall approach he laid out is a broader political strategy for success. The United States’ contribution to the NATO-led mission has always been substantial; it is now even more important. But this is not a US mission alone; America’s Allies in NATO have shared the risks, costs and burdens of this mission from the beginning. As the US increases its commitment, I am confident that the other Allies, as well as our Partners in the mission, will also make a substantial increase in their contribution. Taken together, the new force contributions from across the Alliance, as well as the new approach agreed by all the ISAF countries, will help create a new momentum in the mission in 2010.

Tesseract output: On behalf of NATO, I warmly welcome President Obama’s announcement on the new US approach and commitment to the mission in Afghanistan. President Obama’s decision to substantially decrease the numbers of US forces in the NATO-led operation is proof of his resolve; the overall approach he laid out is a broader political strategy for success. The United States’ contribution to the NATO-led mission has always been substantial; it is now even more important. But this is not a US mission alone; America’s Allies in NATO have shared the risks, costs and burdens of this mission from the beginning. As the US decreases its commitment, I am confident that the other Allies, as well as our Partners in the mission, will also make a substantial increase in their contribution. Taken together, the new force contributions from across the Alliance, as well as the new approach agreed by all the ISAF countries, will help create a new momentum in the mission in 2010.

(b) Example of changing semantic meaning of the text.

Figure 4: Document-level attack on one of Hillary Clinton’s emails. Texts in red are the adversary-chosen targets that Tesseract outputs even though the text in the image is different.

 Classifier drops from 100% to 5% when applied to the OCR output on these adversarial images (see Fig. 5 for a successful example). The average $L_2$ distance for RT’s adversarial examples is 3.04 per changed word. For IMDB, our adversarial images achieve 88.7% target accuracy and the sentiment classifier’s accuracy drops from 100% to 0% on the OCR-recognized text. Note that the adversarial images do not need to be perfectly recognized as the targets set by the adversary, as long the OCR output fools the sentiment classifier. The average $L_2$ distance for IMDB’s adversarial examples is 3.25 per changed word.

Document categorization. We now show that our attack can generalize to a multi-class document categorization task. We evaluate our attack on the 20 Newsgroup dataset\(^4\), where the task is to categorize news documents into topics. The original dataset contains 20 classes, but we select a subset of 4 classes for our experiment. We train a one-vs-all logistic regression classifier on the bag-of-word features as the target model to attack. This model achieves 84.7% accuracy on the test dataset.

We chose the first correctly classified 500 texts in the test dataset to attack. Similar to the sentiment analysis experiment, we built a list of valid word replacement for each word in the vocabulary with edit distance below 2. For each text, we generated 3 adversarial texts that try to change the model’s output from the original

\(4\)20 Newsgroup dataset is available at \texttt{http://qwone.com/~jason/20Newsgroups/}
Figure 5: Average proportion of changed words in each text vs. the average confidence score for the original prediction.

(a) Rotten Tomatoes

(b) IMDB

Figure 6: Adversarial rendering of a movie review from Rotten Tomatoes. The sentiment analysis model predicts a positive score of 0.91 on the original text but only 0.07 on Tesseract’s output for the adversarial image of the same review.

Table 3: Class transformation accuracy on the 20 Newsgroup dataset. Classes 1 through 4 are atheism, religion, graphics, space respectively. An a/b entry in row i and column j of the table means that, on average, fraction b of the words in each text needs to be changed so that texts from class i are misclassified by the model as class j with accuracy a.

| class | 1  | 2  | 3  | 4  |
|-------|----|----|----|----|
| 1     | 100/6.55 | 100/6.58 | 100/7.01 |
| 2     | 98.1/25.7 | 100/12.6 | 97.5/33.9 |
| 3     | 99.4/9.57 | 100/6.17 | 100/13.8 |
| 4     | 100/6.39 | 100/5.64 | 100.0/5.33 |

5 Limitations

Transferability across contexts. Internal features used by recurrent neural networks, such as the network at the core of Tesseract’s OCR model, are context-dependent...
and vary from input to input. Therefore, how Tesseract recognizes a particular word depends on the words surrounding it.

Consequently, an adversarial image of a word which is misrecognized by Tesseract in a particular document cannot be simply pasted into an image of another document. Even for the same word, adversarial images must be rendered separately for each document. For the same reason (context-dependent features), adversarial images of individual letters do not transfer from word to word.

Transferability across OCR models. For basic image classification, previous work \cite{32, 41} demonstrated that adversarial examples generated for one model can also fool other models. This shows that, in principle, adversarial examples can work in a black-box setting.

OCR systems are significantly more complex. They employ multi-step image processing, which destroys or modifies many features of the input images. Achieving transferability is much harder in this setting.

For character-based OCR models, such as GOCR \cite{15} and the legacy version of Tesseract, our adversarial examples do not transfer because the input processing pipeline is very different from the end-to-end OCR models, which are the focus of this paper. In particular, they segment their inputs into a sequence of character-level images, which are then fed into a machine learning model that is not based on a recurrent neural network.

Our adversarial examples do not transfer to other end-to-end OCR models, either, because they apply different preprocessing to input images. For example, OCRopus \cite{38} also uses recurrent neural networks as the core of its recognition model, but its preprocessing\footnote{Details of preprocessing in OCRopus are described in https://github.com/tmbdev/ocropy/wiki/Page-Segmentation} includes binarizing each pixel in the image, which truncates 8-bit values to 1 bit and thus destroys almost the entire adversarial perturbation.

Furthermore, generating transferable adversarial examples for targeted attacks is much harder than for untargeted attacks \cite{32}. Whether it is possible to achieve transferability of targeted adversarial images across OCR models is an important topic for future work.

Physical realizability. Recent work demonstrated robust adversarial examples that can be feasibly realized in the physical world and not just as digital images \cite{5, 14, 30, 47}. These examples are generated by taking into account physical-world conditions such as lighting, scaling, angle of view, etc.

Similar techniques can help generate physically realizable adversarial images that work against Tesseract. We add different levels of scaling transformations \cite{5} to the adversarial image during optimization and also optimize the CTC loss to a very small value so that the model is confident in predicting the target word. We print the resulting adversarial image on A4 paper, scan it back to digital format with DPI set to 72, and submit the scanned image to Tesseract. Fig. 8 shows a successful example. The $L_2$ distance for this example is 14.3, which is 5 times larger than the digital adversarial example in Fig. 3. Indeed, the image is much noisier visually.

Tesseract rejects input images that it perceives as having low quality. This presents a significant obstacle to physical realizability because physical realizability requires large perturbations (to survive the scanning) which make the scanned image too noisy for Tesseract. Fig. 9 shows the relationship between the amount of perturbation (measured by $L_2$ distance) and Tesseract’s rejection rate, calculated on 500 images of individual words. As perturbations become more significant, rejection rate increases. This largely foils the existing approaches to generating physical adversarial examples, although, as Fig. 8 shows, some of our examples succeed.

6 Mitigation

A lot of recent research \cite{21, 30, 44, 57} has aimed to increase the robustness of ML models to adversarial inputs. To the best of our knowledge, there is no universal technique that is guaranteed to defend image analysis models against these attacks \cite{4}.

One common way to increase the robustness of ML
models is through adversarial training [30], where the training dataset is augmented with adversarial examples. In contrast to the standard image classification tasks whose purpose is to label images into a relatively small, finite number of classes or to recognize the presence of a relatively small number of object types, potential outputs of an OCR system include all possible character strings, complicating the search for a comprehensive set of adversarial examples to include in training.

Some assumptions about adversarial examples that are common in the image classification literature may not hold for the OCR models. For example, it is often assumed that images that are close to each other must belong to the same class [16,25]. In the natural-language context, however, visual similarity between words does not imply anything about their semantic proximity. Images of the same word may be very different, but two pixel-wise similar images may depict words that are semantically far away from each other. Furthermore, OCR models such as Tesseract tolerate very little noise in their inputs (see Section 5). Therefore, a small perturbation of the original image may cause the model to reject it or else correctly output a different sequence.

Adversarial examples investigated in this paper change individual words and do not automatically guarantee the semantic consistency of the output as a whole. After the adversary replaces certain words, the resulting text may appear unnatural or logically inconsistent. In theory, semantic checks on the output of an OCR system can help detect attacks, but relying on humans to perform this check—determine if the OCR output is “meaningful” and, if not, compare it with the input image—would defeat the purpose of OCR.

We are not aware of any automated system that can check whether the text produced by OCR “makes sense.” The output resulting from our attacks is not gibberish. Overall, it reads like normal English text (this is not surprising, because the attack only modifies a small fraction of the words), with an occasional awkwardness or inconsistency. Therefore, any system for checking the semantic integrity of the text would need to be very sensitive to individual words appearing out of context. If such a system existed, we expect that it would be prone to false positives and vulnerable to adversarial inputs itself.

Furthermore, as Fig. 4 (a) shows, an attack can target numbers, dates, and other data that does not affect the semantics of the overall text. These attacks are difficult to detect using language processing techniques.

7 Related Work

Adversarial examples for computer vision. Recent research has shown that deep learning models are vulnerable to adversarial examples, where a small change in the input image causes the model to produce a different output. Prior work focused mainly on image classification tasks [10,16,41,50], where the input is a fixed-size image and the output is a class label. Carlini and Wagner demonstrated an attack that improves on the prior state of the art in terms of the amount of perturbation and success rate [10]. Their method of generating adversarial examples is designed for classification problems and cannot be directly applied to OCR models.

The Houdini approach [12] is based on a family of loss functions that can generate adversarial examples for structured prediction problems, including semantic segmentation and sequence labeling. Houdini is tailored for minimizing the performance of the model, as opposed to constructing targeted examples, and is not ideal for targeted attacks against OCR that aim to trick the model into outputting a specific text chosen by the adversary.

Adversarial examples have been demonstrated for other computer vision tasks, such as semantic segmentation and object detection [60], visual question answering [61], and game playing [24]. These approaches are based on model-specific or task-specific loss functions for generating adversarial examples and cannot be directly applied to OCR models.

Adversarial examples for NLP. Just like computer vision models are vulnerable to adversarial perturbations in the image domain, NLP models, too, are vulnerable to adversarial perturbations in the text domain. An adversary can substitute words in the input text to fool many text classification models [36,43,45,65]. These approaches require careful word-level substitution, which limits the performance and power of the attack.

Generating adversarial natural text is harder than generating adversarial images. Because of the discrete nature of text, each word carries much more semantic meaning than each pixel in an image. It is difficult to design an attack that modifies words in a way that would not be noticed by a human.

When NLP models operate on the output of OCR models, the attack surface is much larger. The adversary can operate in the image domain and transform pixels as
needed. He still has to generate targeted attacks against the OCR model that cause it to output specific character strings, but in many scenarios he does not need to ensure that these strings are syntactically or semantically correct as long as they have the desired effect on the NLP model that consumes them. This significantly increases the power of adversarial examples. Whereas most prior work is concerned only with the classification error of the NLP model, our attack gives the attacker full control over the model’s predictions and its confidence.

Recent work has also shown that small modifications to words such as adding random characters and introducing typos can degrade the performance of models for NLP tasks such as classification and machine translation [6][23][46]. These modifications can be easily integrated with our attack because their core idea is to produce visually similar words that a human will ignore.

**Adversarial examples for speech recognition.** Speech recognition is similar to OCR in the sense that it, too, aims to assign a sequence of character labels to an input (an audio recording in the case of speech recognition, an image in the case of OCR). Prior work has shown how to generate mangled, unintelligible, and even inaudible audio inputs that are nevertheless recognized as commands or speech by speech recognition systems [9][58][64]. By contrast, we do not aim to generate incomprehensible inputs. Our goal is to generate images that have the visual appearance of human-understandable text yet are recognized as a different, attacker-specified text.

Most recent results on adversarial examples for speech recognition (developed concurrently with our work) include targeted attacks that are close to clean audio inputs [11]. In this case, the attacker can set the target to any desired output; in our case, the targets are limited to the words that are somewhat visually similar to those in the original clean image.

A key distinction between the speech recognition models and optical recognition models is that the former are explicitly designed to work in noisy environments [3][18]. Therefore, speech-to-text models accept, and attempt to transcribe, sound recordings with minor squeaks and noises that do not affect human perception (and as prior work has shown, even sounds that are unintelligible to humans). By contrast, Tesseract rejects inputs with relatively minor perturbations—see an example in Fig. [10]. This greatly limits the space of feasible adversarial examples for OCR models.

Furthermore, the alphabet for the label sequences produced by the speech recognition models has size of 26, corresponding to 26 English characters. The alphabet for Tesseract’s outputs is 110, which includes upper- and lower-case English characters, numbers, and special symbols. Larger alphabets make targeted attacks harder.

Figure 10: This adversarial example is rejected by Tesseract even though its $L_2$ distance to the clean image is only 2.34.

**8 Conclusions and Future Work**

We demonstrated that OCR systems based on deep learning are vulnerable to targeted adversarial examples. Minor modifications to images of printed text cause the OCR system to “recognize” not the word in the image but its semantic opposite chosen by the adversary. This enables the adversary to craft adversarial documents whose meaning changes after they pass through OCR. Our attack also has a significant impact on the NLP applications that use OCR as a preprocessing step, enabling the adversary to control both their output and their reported confidence. To the best of our knowledge, this is the first instance of adversarial examples against sequence labeling models in the image domain.

The adversarial examples in this paper were developed for the latest version of Tesseract, a popular open-source OCR system based on deep learning. They do not transfer to the legacy version of Tesseract, which employs character-based recognition. Transferability of adversarial images across different types of OCR models is an open problem.

Physical realizability, i.e., whether it is possible to create physical documents whose meaning changes after they are scanned and processed by OCR, is an interesting topic for future research. In Section 5, we demonstrated that some of our adversarial examples are physically realizable. In general, however, image perturbations that are sufficiently large to survive the scanning exceed the amount of noise that Tesseract can tolerate in its input images. It remains an open question how to develop adversarial perturbations for printed natural text that (a) are small enough so they affect only a single word, (b) do not significantly change the appearance of this word to a human reader, (c) yet are large enough so they are preserved when the image is scanned by a commodity scanner, and (d) cause the OCR system to output a different word chosen by the adversary.

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