

Using Machine Learning To Solve Text-based CAPTCHAs

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Abstract—CAPTCHA is an acronym for the "Completely Automated Public Turing test to tell Computers and Humans Apart". It is a mechanism which is used to distinguish real human users from bots. CAPTCHAs come in a variety of forms, including the deciphering of obfuscated text, transcribing of audio messages, tracking mouse movement, and more. This research will focus on automating the process of deciphering text-based CAPTCHAs using machine learning techniques. Specifically, supervised learning is used to develop a neural network which is capable of over 99% accuracy for certain datasets. The goal of this research is to demonstrate the weaknesses associated with text-based CAPTCHA mechanisms, especially with the prevalence of machine learning tools.

Keywords—machine learning, neural networks, supervised training, CAPTCHA

I. INTRODUCTION

CAPTCHA is an acronym for the "Completely Automated Public Turing test to tell Computers and Humans Apart", which is a challenge-response test used in computing services to verify that the user is a human. The premise of a CAPTCHA is to provide a test which is relatively easy for a human to solve, but difficult for bots. This is one of many mechanisms used to combat against the growing usage of malicious software automation. Due to the ubiquity of automation software, cybercriminals have been able to easily create bots to perform malicious acts. These acts include denial-of-service attacks, autonomous social media communication agents, scalping scarce merchandise, and more.

Due to the wide availability of CAPTCHA-generating software, they have become a popular mechanism to integrate into websites. In particular, text-based CAPTCHAs are often available as a low-cost and simple solution. Text-based CAPTCHAs typically consist of alphanumeric characters in an image, which has been manipulated to prevent it from being easily parsed by a

machine. Users are then challenged to decipher the text in the CAPTCHA, and if the answer is correct, they can continue using the service. CAPTCHAs are typically available from content management systems (such as WordPress) or can be integrated into a website via API.

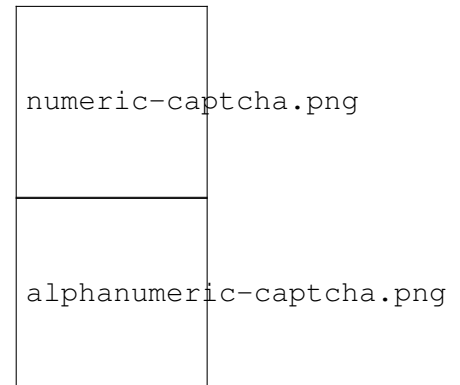


Fig. 1. Example of a text-based CAPTCHA.

While this mechanism can mitigate the majority of software bots, it is not effective against bots utilizing machine learning technology. This research paper demonstrates that a machine learning agent is capable of solving CAPTCHAs with the use of an open-source framework, several libraries, and convolutional neural networks. The goal of this research is to highlight the vulnerabilities which are present in simple CAPTCHA mechanisms. This paper will cover background/related work, the methodology used for solving CAPTCHAs, challenges which were present, key contributions, results, and a section covering future work.

II. BACKGROUND/RELATED WORK

In this section, there will be a brief review of similar work which has been done on using machine learning to solve CAPTCHA tests.

A. Solving reCAPTCHAs With Reinforcement Learning

Researchers at [1] have demonstrated the ability to solve mouse-based reCAPTCHAs using reinforcement learning. Google’s reCAPTCHA mechanism is more difficult to solve compared to traditional CAPTCHAs due to its usage of mouse-tracking to determine if the user is a human. While the exact algorithm is unknown due to the closed-source nature of the reCAPTCHA technology, the researchers use a black-box approach to solve reCAPTCHAs.

The approach models mouse movements as transitions on a 2-dimensional grid of pixels. The *Markov Decision Process* is used to generate a series of movements (up, down, left, right), which is a combination of random and controlled outcomes. The mouse-control agent is then trained through reinforcement learning to generate a series of movements which mimic the behavior of humans. This methodology was able to achieve a success rate of 97.4% on a 100x100 grid and 96.7% on a 1000x1000 display.

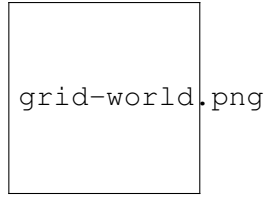


Fig. 2. Grid world model.

B. Generic Solving of Text-based CAPTCHAs

Researchers at [2] have provided a basic framework on solving CAPTCHAs using segmentation and character recognition techniques. More specifically, their technique is able to detect individual characters in CAPTCHAs with occluding lines. Traditional approaches to CAPTCHA-solving typically use two separate algorithms for segmentation and character recognition. The researchers have instead, developed an algorithm which combines the steps of segmentation and character recognition.

The researchers approached this solution by studying previous schemes which were used to analyze characters in CAPTCHAs. Many of them were unable to segment CAPTCHAs which used *negative kerning*, a technique where negative space is used between characters to ensure occlusion by their neighbors. The algorithm developed by the researchers uses machine learning to perform 3 steps: *cut-point detection*, *slicing*, and *scoring*. Cut-point detection analyzes all combinations of character

partitioning. The slicer will then segment each character using every partitioning combination, placing them on a graph afterwards. Finally, the scorer assigns a weight for each partitioning combination and determines which characters are most likely present in the CAPTCHA.

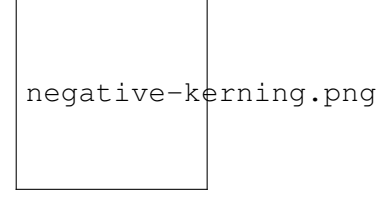


Fig. 3. Example of negative kerning.

C. Immutable Adversarial Examples for CAPTCHA Generation

While the two works above demonstrate the exploitation of CAPTCHAs, the work presented here will demonstrate an approach for securing CAPTCHAs. Researchers at [3] have demonstrated the ability to produce CAPTCHAs which are resistant to noise-removal attempts. Often, CAPTCHA solving techniques using neural networks apply filters to a CAPTCHA image to reduce noise and exaggerate feature sets. Generating CAPTCHAs with immutable noise would pose a significant challenge to many of the machine learning assisted CAPTCHA solvers.

The researchers were able to create immutable adversarial CAPTCHAs by using a modification of the *fast gradient sign* (FGS) method. The FGS method works by slightly altering the gradient values of certain image pixels to maximize *loss* during the training process of a neural network. The modified FGS method takes target label and confidence level as inputs in addition to the original image. This allows for noise generation to work towards a specific goal, distributing the noise in such a way that is difficult to filter.

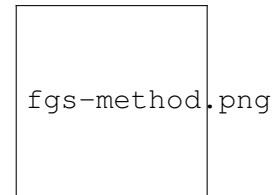


Fig. 4. Fast Gradient Sign Method.

III. METHODOLOGY
IV. CHALLENGES
V. KEY CONTRIBUTIONS
VI. RESULTS
VII. FUTURE WORK
REFERENCES

- [1] G. Eason, B. Noble, and I. N. Sneddon, "On certain integrals of Lipschitz-Hankel type involving products of Bessel functions," *Phil. Trans. Roy. Soc. London*, vol. A247, pp. 529–551, April 1955.
- [2] J. Clerk Maxwell, *A Treatise on Electricity and Magnetism*, 3rd ed., vol. 2. Oxford: Clarendon, 1892, pp.68–73.
- [3] I. S. Jacobs and C. P. Bean, "Fine particles, thin films and exchange anisotropy," in *Magnetism*, vol. III, G. T. Rado and H. Suhl, Eds. New York: Academic, 1963, pp. 271–350.
- [4] K. Elissa, "Title of paper if known," unpublished.
- [5] R. Nicole, "Title of paper with only first word capitalized," *J. Name Stand. Abbrev.*, in press.
- [6] Y. Yorozu, M. Hirano, K. Oka, and Y. Tagawa, "Electron spectroscopy studies on magneto-optical media and plastic substrate interface," *IEEE Transl. J. Magn. Japan*, vol. 2, pp. 740–741, August 1987 [Digests 9th Annual Conf. Magnetics Japan, p. 301, 1982].
- [7] M. Young, *The Technical Writer's Handbook*. Mill Valley, CA: University Science, 1989.

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