Gradient-based Adversarial Deep Modulation Classification with Data-driven Subsampling

Jinho Yi, Student Member, IEEE, and Aly El Gamal, Senior Member, IEEE

Abstract—Automatic modulation classification can be a core component for intelligent spectrally efficient wireless communication networks, and Deep learning techniques have recently been shown to deliver superior performance to conventional model-based strategies, particularly when distinguishing between a large number of modulation types. However, such deep learning techniques have also been recently shown to be vulnerable to gradient-based adversarial attacks that rely on subtle input perturbations, which would be particularly feasible in a wireless setting via jamming. One such potent attack is the one known as the Carlini-Wagner attack, which we consider in this work. We further consider a data-driven subsampling setting, where several recently introduced deep-learning-based algorithms are employed to select a subset of samples that lead to reducing the final classifier’s training time with minimal loss in accuracy. In this setting, the attacker has to make an assumption about the employed subsampling strategy, in order to calculate the loss gradient. Based on state of the art techniques available to both the attacker and defender, we evaluate best strategies under various assumptions on the knowledge of the other party’s strategy. Interestingly, in presence of knowledgeable attackers, we identify computational cost reduction opportunities for the defender with no or minimal loss in performance.

Index Terms—Deep learning for wireless, Adversarial deep learning, Deep learning based subsampling.

I. INTRODUCTION

Automatic modulation classification (AMC) lets the receiving device recognize the modulation type of the received signal with no manual engineering or prior agreement with the transmitter side. This could be one of the core functions of next generation intelligent spectrally efficient networks, which allows communication devices to freely adapt to various wireless systems, not compromising on the spectrum efficiency. To facilitate AMC, gradient-based Machine Learning (ML) techniques with successful track record in computer vision [1] and natural language processing [2] have been recently investigated, showing a promising performance [3], [4]. The ML approach showed superior performance to conventional modulation classification algorithms, that are based on statistical heuristics, in a scalable fashion with both numbers of modulation types and samples. In order to address the feasibility of this promising technology, we consider in this work two major aspects: Robustness against a malicious hamper and computational efficiency.

A. Gradient-based Adversarial Machine Learning

ML models, that rely on stochastic gradient descent optimization of deep neural networks, are known to lack robustness against malicious adversarial examples [5], [6], which introduce small perturbations, specially crafted to cause ML models to malfunction when added to legitimate inputs. This perturbation is obtained by solving an optimizing problem that minimizes the perturbation norm while maximizing the classification error. In a wireless setting, a small perturbation norm would correspond to small transmit power needed by a jammer to introduce slight additional noise in the signal, that is difficult to detect at the receiver and leads to significant ML performance degradation. Recent studies confirmed the vulnerability of ML models for modulation classification to such adversarial examples. Work by Usama et al. [7], [8] have demonstrated that the famous CW attack [9] is applicable in this setting. Furthermore, Kim et al. [10], Hameed et al. [11], and Bair et al. [12] have presented effective algorithms to generate adversarial examples, which take in account the noise encountered during actual over-the-air transmission of the perturbed signals.

B. Data-driven Subsampling

ML models also challenge the computational power of a wireless device, particularly during the training phase. The long training time of a deep neural network causes a severe bottleneck for its application in wireless communications, where frequent re-training would be needed to adapt to the varying environment in real-time. Ramjee et al. [13], therefore, introduced a data-driven subsampling strategy, through simulations employing deep learning models, called Subsampler Nets, to sample down the input to the ML model and effectively reduce the size of the deep neural network architecture and its training time. Their algorithm exploits the transferability property in deep learning, which capitalizes on having common relevant features among various architectures that are fit for the same task. Using multiple pre-trained modulation classifiers, the algorithm ranks individual input samples on how much each contributes to the classification outcome.

C. Considered Problem

Motivated to address the aforementioned two aspects, we study the robustness against adversarial attacks of an effective ML-based AMC model while employing different data-driven subsampling strategies. As we show in the sequel, knowledge of the employed Subsampler Net can dramatically affect
the attacker’s choice of best strategy and its effectiveness. Similarly, knowledge of the assumed Subsampler Net by the attacker significantly impacts the defender’s strategy. We finally identify a computationally efficient training strategy with minimal cost in performance for a system whose design is perfectly exposed to the attacker.

II. PROBLEM SETUP

We consider a deep neural network victim classifier for modulation classification and an attacker that perturbs the classifier’s input by jamming the wireless transmit signal. We have investigated the performance of victim models, trained with different data-driven subsampling strategies, with and without attacker’s perturbations. The following subsections describe how we set these experiments in detail.

A. Dataset for Modulation Scheme

We have used the RML2016.10b dataset generated with GNU radio [14], which is highly cited and open source, enabling reproducibility of our result. The dataset consists of received signal complex samples corresponding to 10 different modulation types with uniformly distributed SNR from -20 dB to 18 dB in steps of 2 dB. Each example has 128 samples for in-phase and quadrature (I/Q) components of the signal, represented as a 2 x 128 vector. The 1,200,000 vectors were distributed equally into training and testing examples.

B. Subsampling Schemes and Modulation Classifier Model

As mentioned in Section I, we have used Subsampler Nets for sampling down example vectors, targeting the use cases that prioritize computational efficiency such as that of low-power devices. We employed four different Subsampler Net schemes, namely the CNN, CLDNN, ResNet, and the Holistic subsampler, whose implementation details are in [15]. The Holistic subsampler sorts out the best samples from the sample sets selected by the three Subsampler Nets based on CNN, CLDNN and ResNet models. Only the training data set was used for selecting the sample indices. Furthermore, we used uniform subsampling by sampling at regular intervals, which showed a promising result in [15].

For the classifier, we used a ResNet architecture identical to the one utilized in [15], which is initially inspired by [4]. It accepts an input of size (1, 2, N) representing (channel, I/Q, number of samples) and utilizes three residual stacks followed by three fully connected layers. A convolutional layer, two residual units, and a max-pooling layer compose each residual stack; each residual unit consists of two convolutional layers with a filter size of 1x5 and a shortcut from the input to the output of the unit. The model is trained using the Adam Optimizer with categorical cross-entropy loss function, a batch size of 1024, and a learning rate of 0.001.

The sample dimension of the training data set was reduced down to 64, 32, and 16 from the original 128, applying each of the five subsampling schemes, and the outputs were used to train 15 distinct victim classifier models.

C. Gradient-based Adversarial Attack

We evaluated the robustness of our classifier against the popular CW L2 Attack [9], which finds $x$, a perturbed version of the original example $x_0$, through the following optimization:

$$\min_x \|x - x_0\|_2^2 + c \cdot f_t(x),$$

where $f_t$ is defined by:

$$f_t(x') = \max(\max\{Z(x'_i): i \neq t\} - Z(x'_t), 0)$$

where $t$ is a target label, and $Z(.)$ is a softmax function. We considered an untargeted attack, where the choice of $t$ minimizing (1) among all labels except the true label, is selected. We limited the perturbation norm so that its power is the same as the noise power in the final signal.

D. Threat Models

We considered two attacking scenarios: 1) a white-box adversarial attack where we assumed that the adversary is perfectly knowledgeable about the victim’s choice of subsampling scheme; 2) a black-box attack where the adversary conjectures what sub-sampling scheme is being used. In both scenarios, the attacker knows the victim classifier’s architecture and hyperparameters as well as the training dataset.

To simulate attacking scenarios, we trained surrogate classifiers with the same ResNet model as the victim’s to generate adversarial examples, separately from the model used for performance evaluation. We crafted adversarial examples using the testing dataset by employing these surrogate classifiers. For the black-box attack, we averaged each classifier’s performance over all the adversarial examples that were crafted to target all possible classifiers of matching subsampling rates.

III. EXPERIMENTAL RESULTS

First, we review the overall impact of gradient-based adversarial attacks on the classification accuracy while employing different subsampling schemes, then we analyze the best strategies from both the victim’s and attacker’s perspectives.

A. Performance Impact

Fig. 1 presents a detailed comparison of the accuracy of ResNet classifier models, trained using the inputs sampled with the uniform subsampler, with respect to the proposed threat scenarios. The results for all models with input sizes of 64 (subsampling rate of $\frac{1}{2}$), 32, and 16 are presented in the figure, manifesting their performance drop for both black-box and white-box attacks. The black-box attack data represents the average accuracy that each model showed across every adversarial example that was targeting the other considered subsampling strategies. This applies henceforward.

Note that there is a substantial difference in the relative accuracy drop due to white-box and black-box attacks, considering that the attacker is fully knowledgeable about the victim classifier’s architecture in both cases and the difference in attacker’s knowledge between the two attacks is only about the

1Source code for this work has been accepted for publication at https://codeocean.com/capsule/8397297/tree/v1. We used Keras with TensorFlow 2.0 as a backend on a Tesla V100 GPU.
### TABLE I: Classifier accuracy under different attack scenarios

| Sample # | Subsampler Net | No Attack | Black-box | White-box | No Attack | Black-box | White-box | No Attack | Black-box | White-box |
|----------|----------------|-----------|-----------|-----------|-----------|-----------|-----------|-----------|-----------|-----------|
| 64       | CLDNN          | 56.2%     | 45.4%     | 32.8%     | 50.7%     | 44.1%     | 28.7%     | 43.0%     | 39.8%     | 26.5%     |
|          | CNN            | 56.3%     | 45.7%     | 29.9%     | 50.8%     | 43.1%     | 29.7%     | 44.5%     | 39.6%     | 24.6%     |
|          | ResNet         | 56.4%     | 46.6%     | 30.0%     | 52.0%     | 46.1%     | 27.7%     | 44.9%     | 41.6%     | 27.4%     |
|          | Holistic       | 56.9%     | 44.4%     | 33.6%     | 51.5%     | 43.6%     | 28.4%     | 44.9%     | 39.5%     | 25.7%     |
|          | Uniform        | 59.3%     | 52.1%     | 34.9%     | 52.3%     | 49.3%     | 35.0%     | 45.2%     | 44.0%     | 29.2%     |

Accuracy of classifiers with different subsampler Nets for no attack, black-box attack, and white-box attack scenarios.

### TABLE II: % Decrease in classifier accuracy under different attack scenarios

| Sample # | Subsampler Net | White-box | Black-box | White-box | Black-box | White-box | Black-box | White-box | Black-box |
|----------|----------------|-----------|-----------|-----------|-----------|-----------|-----------|-----------|-----------|
| 64       | CLDNN          | 41.3%     | 19.1%     | 43.3%     | 13.0%     | 38.4%     | 7.4%      | 35.4%     | 7.4%      |
|          | CNN            | 46.9%     | 18.9%     | 41.3%     | 15.2%     | 44.7%     | 11.2%     | 39.1%     | 7.5%      |
|          | ResNet         | 41.4%     | 17.4%     | 42.9%     | 11.3%     | 44.9%     | 15.4%     | 42.7%     | 12.0%     |
|          | Holistic       | 41.0%     | 21.9%     | 44.9%     | 21.4%     | 33.2%     | 5.7%      | 35.4%     | 2.7%      |
|          | Uniform        | 41.1%     | 12.2%     | 33.2%     | 12.2%     | 33.2%     | 5.7%      | 35.4%     | 2.7%      |

Percent decrease (\(\Delta \text{acc}/\text{acc}_{\text{orig}}\)) in the accuracy of classifiers with different subsampler Nets for black-box and white-box attack scenarios.

Subsampling strategy. Table I indicates that such performance gap between black-box and white-box settings is consistently observed even when employing different subsampling schemes than uniform subsampling. It is worth noting how in the presence of attacks, the performance using subsampling rates of \(\frac{1}{2}\) and \(\frac{1}{4}\) is similar across the whole considered SNR range. This indicates an opportunity for saving computational and hardware costs of systems deployed in significantly adversarial environments, through aggressive subsampling rates. Further, we note how the effectiveness of the black box attack decreases with more aggressive subsampling rates; that it has no noticeable effect for a subsampling rate of \(\frac{1}{8}\). We can find this more evidently in Table II, which shows that the percent decrease in accuracy due to the black-box attack is only 2.7% when using 16 input samples. This also signifies the potential of subsampling as the performance losses due to computational efficiency gains and adversarial attacks do not add up.

![Fig. 1: Accuracy vs SNR for ResNet classifier with uniformly selected samples under different attack scenarios with subsampling rates of \(\frac{1}{2}\) (64 sample input), \(\frac{1}{4}\) and \(\frac{1}{8}\).](image1)

### B. Best Defense and Attack Strategies

From Fig. 2 and Fig. 3, it is obvious that the uniform subsampling scheme provides the best, or very close to the best accuracy and robustness both with and without adversarial attacks, across the studied SNR range. Results in Table I and Table II also show that the uniform subsampling scheme outperforms the rest, on average, at all considered subsampling rates. This suggests that the uniform subsampler would be the best choice for the victim classifier in presence of uncertainty about the subsampler assumed by the attacker.

![Fig. 2: Classification accuracy of different classifiers of 32 input samples in presence of a white-box adversarial attack.](image2)
(a) Accuracy vs SNR for 64 sample classifiers before and after the black-box adversarial attack.

(b) Percent decrease in accuracy due to the black-box adversarial attack vs SNR for 64 sample classifiers.

Fig. 3: Classification accuracy of different classifiers of 64 input samples with present of \textit{black-box} attack.

TABLE III: The average success rate of attack from using each classifier model under the black-box scenario

| SubsamplerNet | Effectiveness of attack |
|---------------|-------------------------|
|               | 64          | 32          | 16          |
| CLDNN         | 17.4%       | 15.1%       | 9.9%        |
| CNN           | 19.2%       | 15.4%       | 14.5%       |
| ResNet        | 17.8%       | 14.3%       | 9.2%        |
| Holistic      | 19.4%       | 18.5%       | 8.1%        |
| Uniform       | 17.0%       | 11.6%       | 9.1%        |

This table demonstrates how effective each subsampling scheme is, on average, on reducing the accuracy of victim’s model that used different subsampling schemes (black-box scenario). The value represent average \% decrease in accuracy caused by each scheme.

Fig. 4: The average \% decrease in accuracy caused by the adversarial example crafted with each subsampling scheme on other 32 sample classifiers vs SNR.

C. Free Computational Gains with SNR Selective Training

We further investigate the adversarial setting in a case where we train the classifiers using only data sets of a selected pair of SNR values, instead of the whole 20 provided by RML2016.10b. SNR selection can accelerate training, and can facilitate feasibility when either computational resources are limited or access to multiple SNR values is difficult during data collection. From the results in the previous work [15], we can hypothesize that the combination of 0dB and 18dB would give us the best performance, compared to selecting other SNR value pairs, and hence we fix that choice here.

As shown in Fig. 5, the classifier with SNR selective training shows similar accuracy as the traditional classifier in an adversarial setting at SNR values over 0 dB. Further, Table IV shows that in some cases, like using CNN or ResNet subsamplers with a subsampling rate of $\frac{1}{2}$, SNR selective training led to performance improvements in an adversarial setting. However, this observation only holds down to a certain subsampling rate. Evident from the result for the classifier with 16-sample inputs, if the subsampling rate is too aggressive, SNR selective training leads to performance degradation in presence of an attack.

To emphasize the low computational cost of SNR selective training, we show the training times in Table V. In summary, even though SNR selective training has been shown previously to reduce training time at the cost of performance degradation, we identified scenarios in an adversarial setting with mild subsampling rates, where this computational gain comes at no cost in performance.

IV. CONCLUSION AND FUTURE WORK

We studied the efficacy of gradient-based adversarial attacks on deep learning models that utilize data-driven subsampling for wireless modulation classification. We highlighted how knowledge of the subsampling scheme employed at both the victim model, as well as at the attacker to generate
TABLE IV: Comparison of accuracy of models trained with whole and selected SNR data, under a white-box attack setting

| Subsampler Net | Accuracy when attacked (64 samples) | Accuracy when attacked (32 samples) | Accuracy when attacked (16 samples) |
|----------------|-------------------------------------|-------------------------------------|-------------------------------------|
|                | whole SNR | selected SNR | whole SNR | selected SNR | whole SNR | selected SNR |
| CLDNN          | 48.0%  | 43.8%   | 41.8%  | 36.8%  | 39.5%  | 33.3%   |
| CNN            | 42.9%  | 44.7%   | 43.9%  | 36.6%  | 36.4%  | 32.2%   |
| ResNet         | 48.4%  | 52.2%   | 43.7%  | 43.7%  | 40.7%  | 31.4%   |
| Holistic       | 50.2%  | 47.5%   | 42.2%  | 40.0%  | 38.2%  | 32.4%   |
| Uniform        | 51.0%  | 48.8%   | 51.9%  | 50.9%  | 43.7%  | 35.2%   |

Classification accuracy of a model that is trained with data consisting of the whole SNR set and a model that is trained with data consisting of only 0dB and 18dB SNR value when it is attacked in a white-box manner.

TABLE V: Comparison of training time of models trained with whole and selected SNR data

| samples | Average training time (sec) |
|---------|-----------------------------|
|         | whole SNR | selected SNR |
| 64      | 864 | 170 |
| 32      | 590 | 115 |
| 16      | 519 | 106 |

Fig. 5: Accuracy vs SNR for classifiers trained with whole/selected SNR data before and after white-box attack.

the perturbation, is crucial for the success of the defender and attacker, respectively. With lack of such knowledge, we identified the best defense and attack strategies. We further identified opportunities for saving computational resources in an adversarial setting at no cost in performance via SNR selective training. We believe that this work lays the ground for further investigations on data-driven subsampling strategies for wireless communication systems employing deep learning in an adversarial setting. We are particularly interested in studying the impact of SNR knowledge in such settings.

REFERENCES

[1] J. Redmon, S. Divvala, R. Girshick, and A. Farhadi, “You only look once: Unified, real-time object detection,” 2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR), Jun 2016. [Online]. Available: [http://dx.doi.org/10.1109/CVPR.2016.91]

[2] J. Devlin, M.-W. Chang, K. Lee, and K. Toutanova, “Bert: Pre-training of deep bidirectional transformers for language understanding,” 2018.

[3] T. J. O’Shea, J. Corgan, and T. C. Clancy, “Convolutional radio modulation recognition networks,” Communications in Computer and Information Science, p. 213–226, 2016. [Online]. Available: [http://dx.doi.org/10.1007/978-3-319-44188-7_16]

[4] T. J. O’Shea, T. Roy, and T. C. Clancy, “Over-the-air deep learning based radio signal classification,” IEEE Journal of Selected Topics in Signal Processing, vol. 12, no. 1, pp. 168–179, 2018.

[5] C. Szegedy, W. Zaremba, I. Sutskever, J. Bruna, D. Erhan, I. J. Goodfellow, and R. Fergus, “Intriguing properties of neural networks,” CoRR, vol. abs/1312.6199, 2013.

[6] I. J. Goodfellow, J. Shlens, and C. Szegedy, “Explaining and harnessing adversarial examples,” 2014.

[7] M. Usama, M. Asim, J. Qadir, A. Al-Fuqaha, and M. A. Imran, “Adversarial machine learning attack on modulation classification,” in 2019 UK/ China Emerging Technologies (UCET), 2019, pp. 1–4.

[8] M. Usama, J. Qadir, and A. Al-Fuqaha, “Black-box adversarial ML attack on modulation classification,” arXiv:1908.00635, 2019.

[9] N. Carlini and D. Wagner, “Towards evaluating the robustness of neural networks,” 2017 IEEE Symposium on Security and Privacy (SP), May 2017. [Online]. Available: [http://dx.doi.org/10.1109/SP.2017.49]

[10] B. Kim, Y. E. Sagduyu, K. Davasioglu, T. Erpek, and S. Ulukus, “Over-the-air adversarial attacks on deep learning based modulation classifier over wireless channels,” 2020 54th Annual Conference on Information Sciences and Systems (CISS), Mar 2020. [Online]. Available: [http://dx.doi.org/10.1109/CISS48834.2020.9170617]

[11] M. Z. Hameed, A. Gyorgy, and D. Gunduz, “Communication without interception: Defense against modulation detection,” in 2019 IEEE Global Conference on Signal and Information Processing (GlobalSIP), 2019, pp. 1–5.

[12] S. Bair, M. DelVecchio, B. Flowers, A. J. Michaels, and W. C. Headley, “Radio machine learning dataset generation and evaluation,” in 2017 IEEE Symposium on Security and Privacy (SP), May 2017. [Online]. Available: [http://dx.doi.org/10.1109/SP.2017.49]

[13] S. Ramjee, S. Ju, D. Yang, X. Liu, A. E. Gamal, and Y. C. Eldar, “Ensemble wrapper subsampling for deep modulation classification,” 2016. [Online]. Available: [http://dx.doi.org/10.1007/978-3-319-44188-7_16]

[14] T. O’Shea and N. West, “Radio machine learning dataset generation and evaluation,” in 2017 IEEE Symposium on Security and Privacy (SP), May 2017. [Online]. Available: [http://dx.doi.org/10.1109/SP.2017.49]