Targeted Manipulation: Slope-Based Attacks on Financial Time Series Data

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Adversarial Attacks

- Adversarial attacks occur when an attack slightly modifies the input to a model, typically by adding noise, which causes a model to produce an incorrect result [2].
- White box attack occurs when the attacker has full access to all information about the model, including parameters, which enables the attacker to exploit gradient information [3].
- Black-box attack occurs when the model is hidden from the attacker, and they do not have any knowledge about the structure or parameters [3], [4].

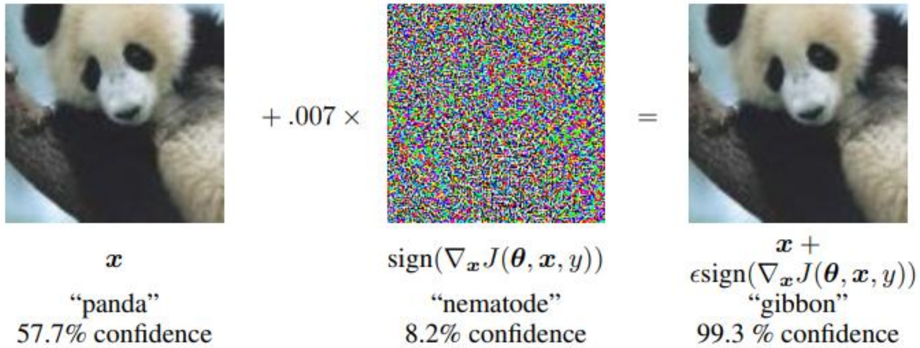


Image Source: J. Shlens, I. J. Goodfellow and C. Szegedy [2]

Threat Model

- Assume that ML/AI forecasting models for sensitive data, such as stock data, are regularly used by consumers and in production.
- The attacker aims to alter existing stock data used as input for the forecasting model in hopes to influence the market.
- All attacks are performed in a white-box setting, meaning the attacker has access to the forecasting model's gradients so they can generate stronger attacks.

Image Source: https://www.freepnglogos.com/pics/hacker

Baseline Attacks

- Fast Gradient Sign Method (FGSM)
- Basic Iterative Method (BIM)
- Momentum Iterative FGSM (MI-FGSM)
- C&W Attacks

$$\mathbf{w}_{t+1} = \mathbf{w}_t - \lambda \nabla E(\mathbf{w}_t)$$

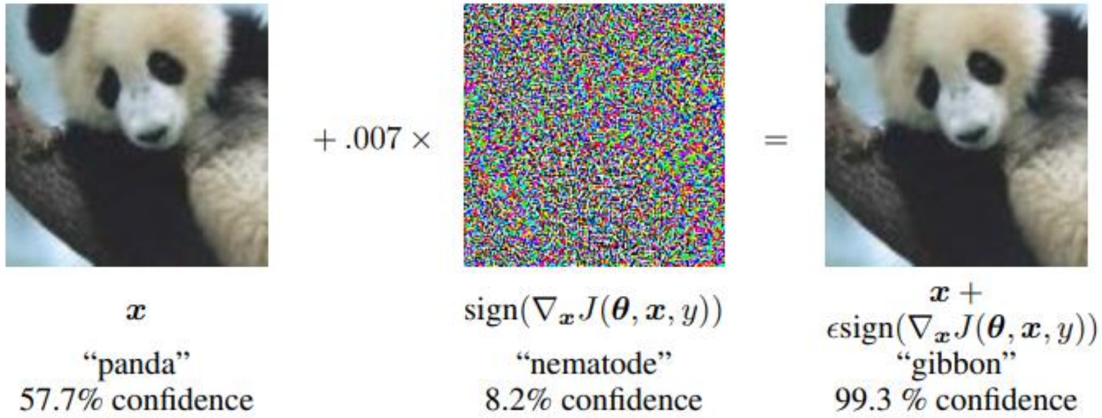
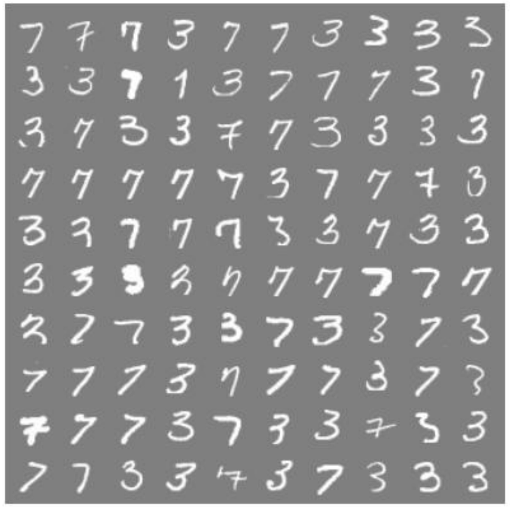


Image Source: J. Shlens, I. J. Goodfellow and C. Szegedy [2]

PROBLEMS

- These attacks aim to maximize the error produced by the model; however, this is insufficient for an attacker since it does not lead to any clear advantage.
- The majority of existing adversarial research has been done on image and text classification, while attacks on time-series data is still in its infancy [3].

Image Source: https://driving-tests.org/road-signs/stop-sign/



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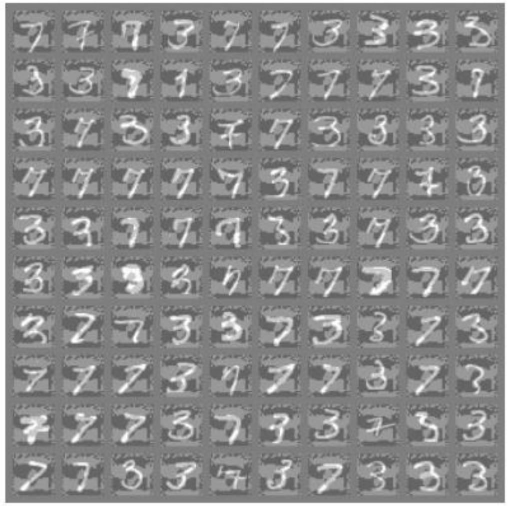

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Image Source: J. Shlens, I. J. Goodfellow and C. Szegedy [2]

Current Research

- There have been recent advancements in the time series domain, with Gallager et al., attacking a simple three layered Convolutional Neural Network (CNN) forecasting the Google Stock from 2006 to 2018 with Fast Gradient Sign Method [5].
- Rathore et al., applied the Fast Gradient Sign Method and the Basic Iterative Method on a classification model trained on 54 different time series datasets related to healthcare, vehicle sensors and electrical equipment [6].

PROBLEM

The introductory research in the time series domain typically focus on classification problems, reapplying image/text based adversarial attacks on time series data, and do not consider the believability of an adversarial example [3], [7].

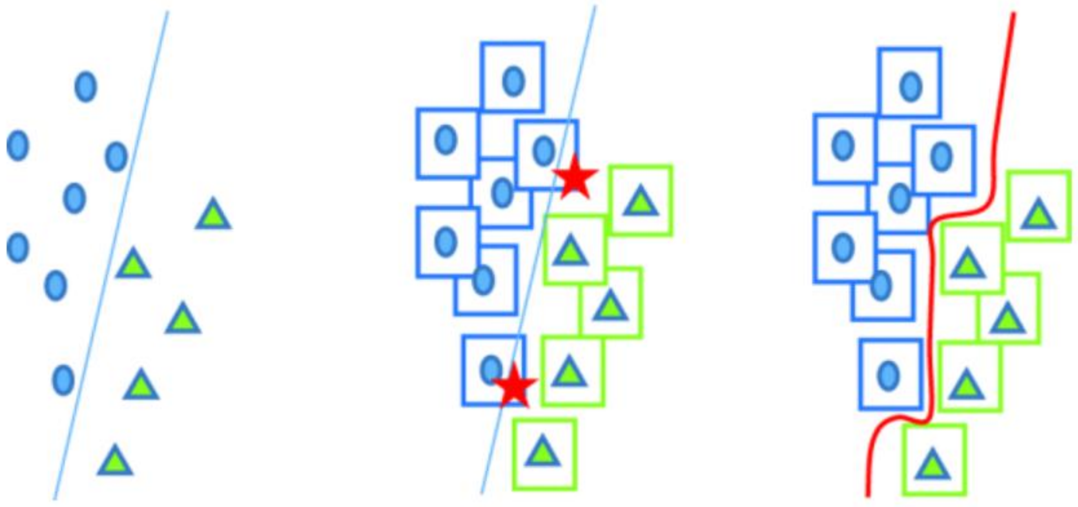


Image Source P. Rathore et al [6]

Attacks on Time-Series Data

- **Stealthy Iterative Method (SIM):**
  - After performing an iteration of the standard BIM, compare the cosine similarity between x and the new x_{adv} vs x with x + ε and finally with x and x – ε:
    - If the cosine_similarity(x, x_{adv}) < cosine_similarity(x, x + ε) then x_{adv} = x + ε
    - If the cosine_similarity(x, x_{adv}) < cosine_similarity(x, x - ε) then x_{adv} = x – ε
    - Otherwise, x_{adv} is kept the same [3].

- **Targeted Iterative Method (TIM):**
  - There are 2 avenues for the targeted attack:
    - 1) Choose some new sequence *Y** as our target
    - 2) Choose a static margin γ
  - The attack requires a parameter d and γ which represent the direction and margin, and calculates the new target as:

$$tar = \text{adjprc} + d \cdot \gamma \qquad [3]$$

then we the update x_{adv} as:

$$x_{adv} = x_{adv} - \alpha \cdot sign(\nabla_{x_{adv}} loss) \qquad [3]$$

PROBLEM

For such targeted attacks, it is unrealistic for an attacker to generate a new sequence Y* for different inputs and, modifying with a scalar margin would only shift the predictions, leading to poor applicability for an attacker as the temporal characteristics are left unchanged.

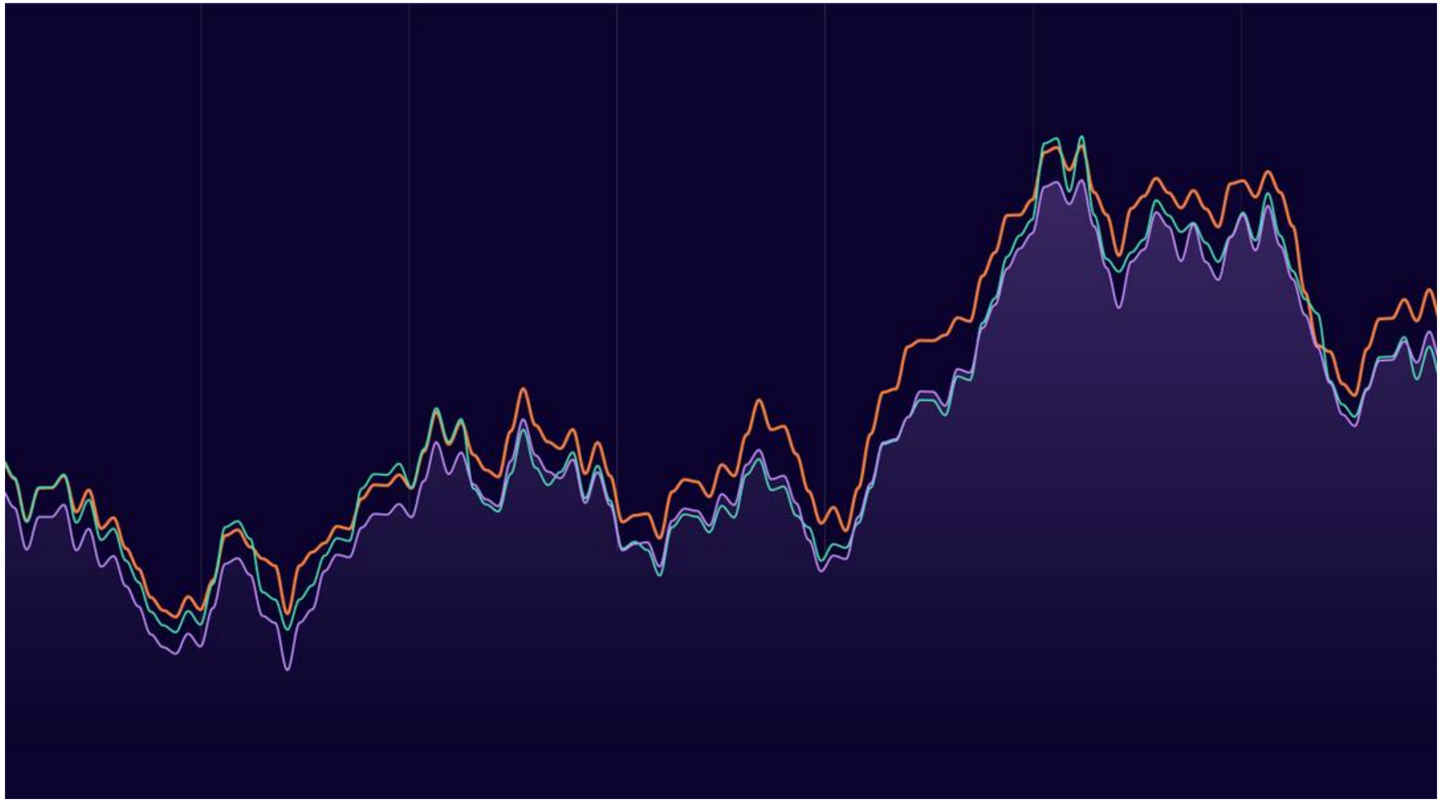


Image Source: https://github.com/Sasidharan25/Time-Series-Analysis-on-Stock-Price-Data/

Slope-Based Attacks

General Slope Attack (GSA)

- In the simplest case, the attacker would want to only affect the endpoints of a prediction, as this might show a late positive surge or decline affecting the victim's desire to purchase a stock.
- The General Slope Attack (GSA) uses the discrete formula to find the slope between two points. That is,

$$m = \frac{y_2 - y_1}{x_2 - x_1}$$

- Then, the objective function requires the slope *m* target direction $t \in \{-1, 0, 1\}$, and hyperparameters *c* and *d* and calculates the following loss:

$$loss = \begin{cases} ce^{-tdm} & \text{if } t \in \{-1, 1\} \\ cm^2 & \text{if } t = 0 \end{cases}$$

Least Squares Slope Attack

- While the GSA attack aims to change the slope of the time series forecast near the endpoints of the prediction, the nature of the slope calculation prevents the overall trend from changing.
- Inspired by Least Squares Linear Regression, the new calculation for the slope would be the weight term in the closed form solution for Least-Squares Linear Regression. Specifically,

$$w^* = \frac{\sum_i (y_{i} - \bar{y})(x_i - \bar{x})}{\sum_i (x_i - \bar{x})^2}$$

PROBLEM

A lot of the research described in the previous slides were performed on shallow neural networks.

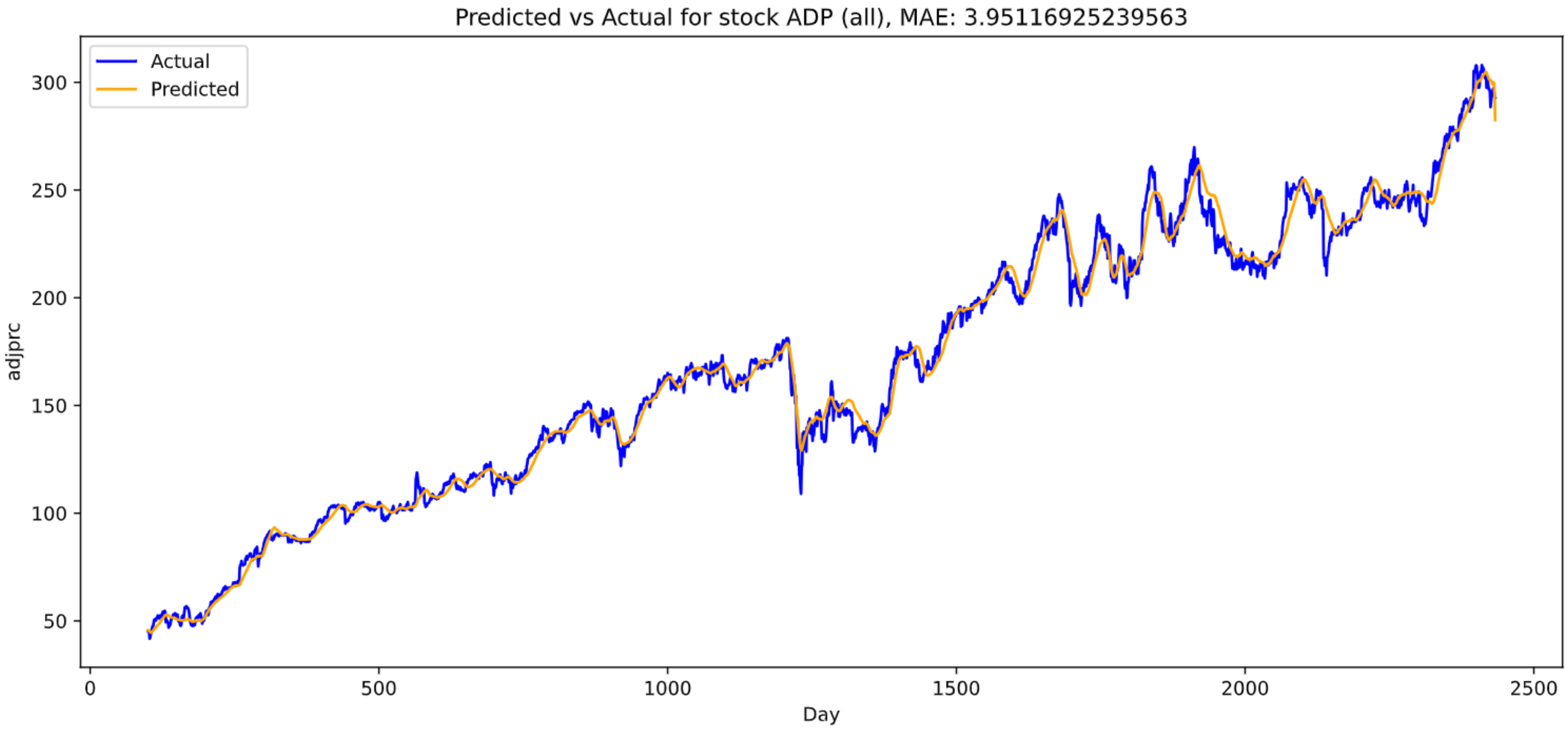
- SIM (Shen and Li):
  - 3-layered CNN with hidden dimension of 60 and a fully connected output layer [3].
  - 3-layered LSTM with hidden dimension of 100 and a full connected output layer [3].
  - 3-layered GRU with hidden dimension of 100 and a full connected output layer [3].

- Gallager et al.:
  - 3-layered CNN [5].

Let’s Fool a More Complex Model

N-HiTS Architecture and Dataset

- N-HiTS Architecture:
  - N-HiTS is a novel projection model which builds upon the N-BEATS architecture, simultaneously improving computational performance and accuracy by sampling the time series at different rates [14].
- Dataset:
  - The daily adjusted price (adjprc) of all S&P 500 stocks was collected from Center for Research Security Prices (CRSP) for the 2015:05:01- 2025:05:01 period.
  - Rather than training on a single stock, to improve generalizability the N-HiTS model was trained on 360 different stocks from the S&P 500. The validation set included 48 stocks while the test set contained 72 stocks.
  - The split was determined by a stratified split on the stock price collected from [15].
  - Several additional features were computed from the adjprc such as rolling windows, standard deviations, log returns and rate of change.



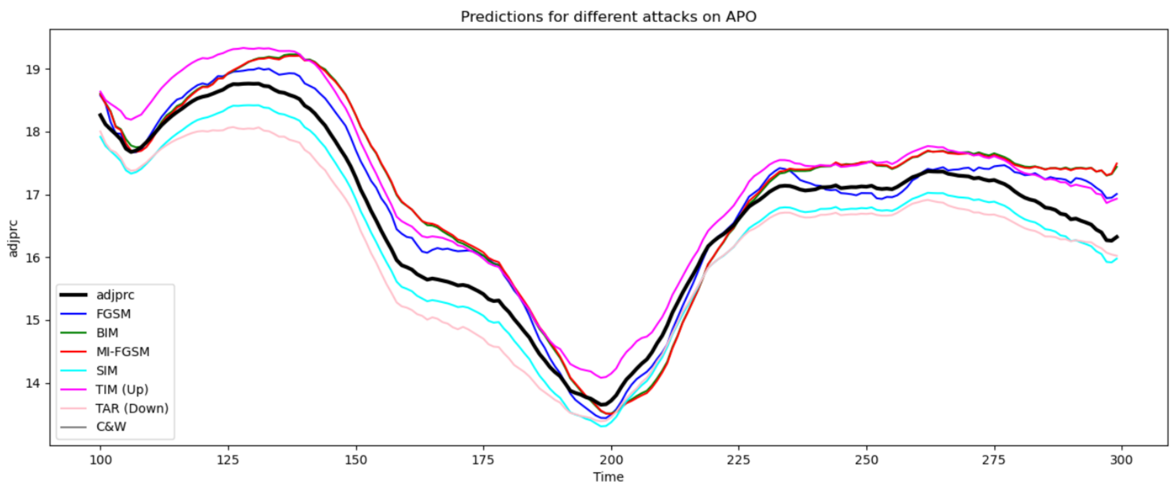
N-HiTS Performance

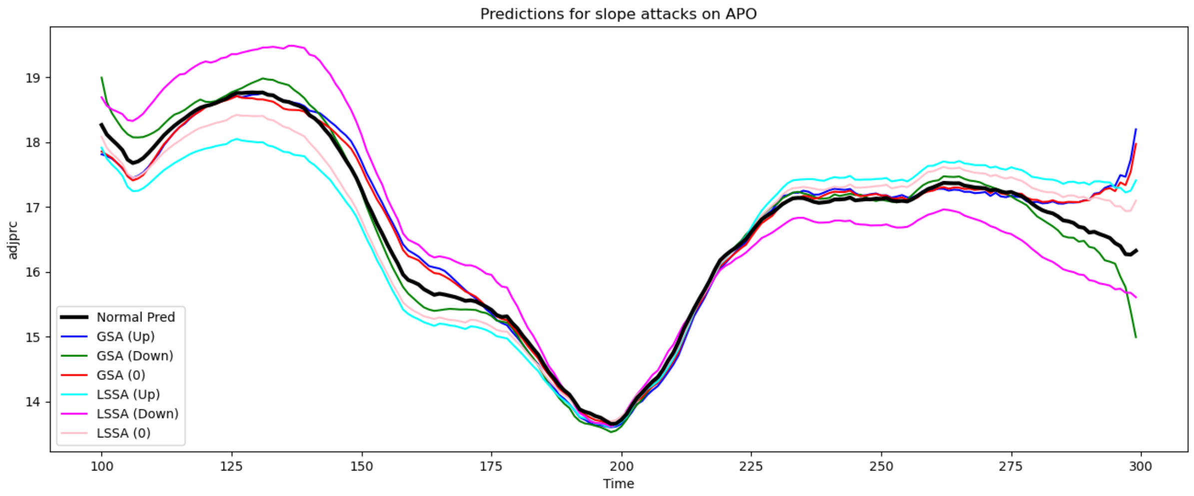
Average MAE: 4.11

Average RMSE: 6.04

MAPE: **3.48%**

Baseline Adversarial Attacks

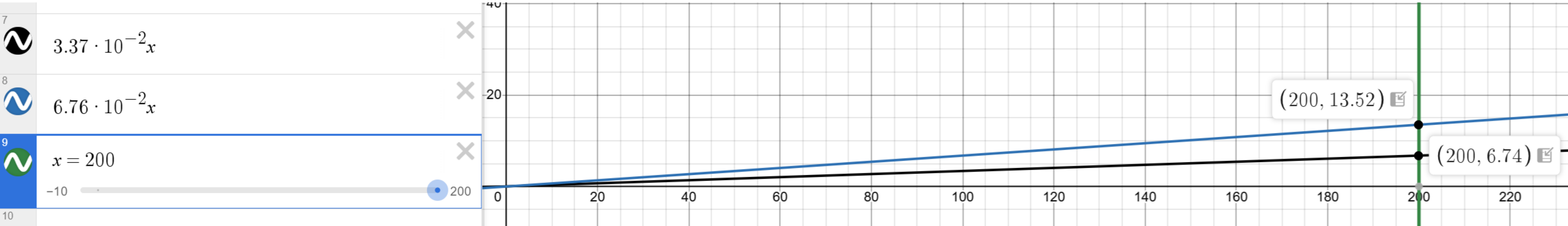




Attack Comparison

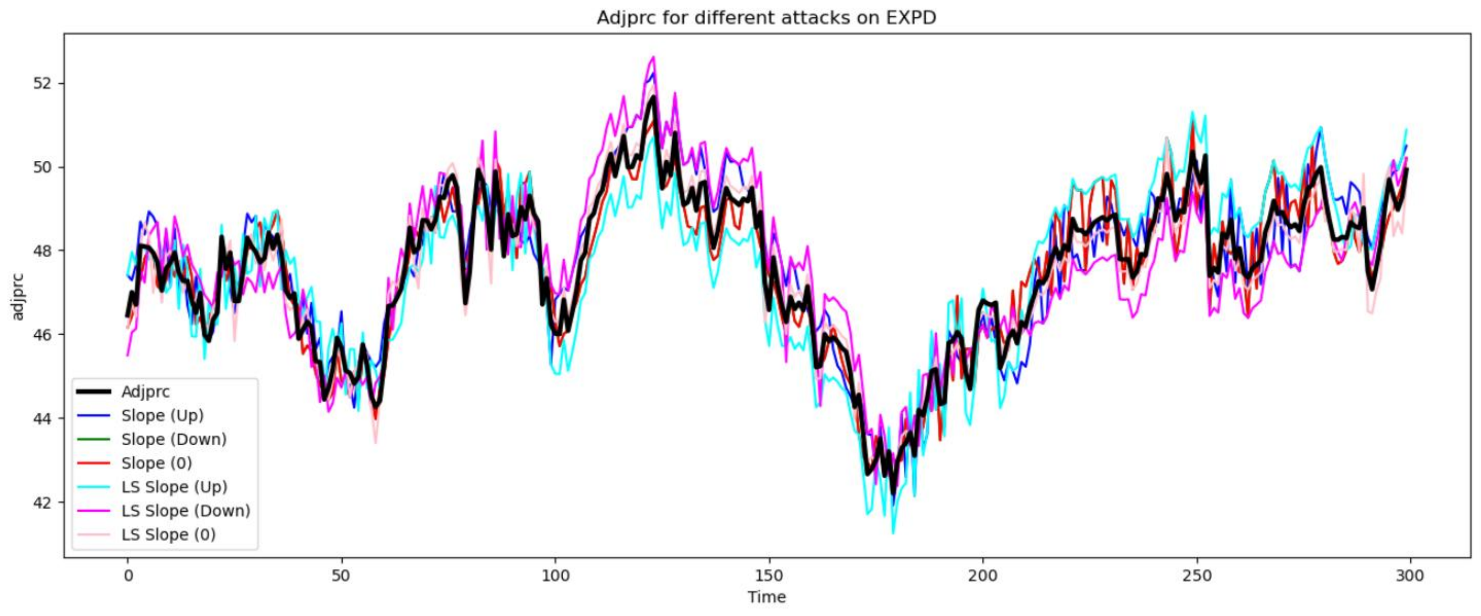
Table 1: Average metrics for different attack methods performed on the first 300 days of each recording, with $\epsilon = 2\% \cdot median(adjprc)$. The best metrics are bolded.

Attack	*MAE*	*RMSE*	*MAPE*	*Gen. Slope*	*LS Slope*
Normal	2.15	2.72	3.82×10^{-2}	3.37×10^{-2}	2.22×10^{-2}
FGSM	2.57	3.21	4.51×10^{-2}	3.22×10^{-2}	2.34×10^{-2}
BIM	**3.38**	**3.99**	$\mathbf{5.68\times10^{-2}}$	3.48×10^{-2}	2.39×10^{-2}
MI-FGSM	3.37	**3.99**	5.67×10^{-2}	3.44×10^{-2}	2.39×10^{-2}
SIM	2.57	3.08	4.29×10^{-2}	3.37×10^{-2}	2.23×10^{-2}
TIM (Up)	2.49	3.21	4.52×10^{-2}	3.72×10^{-2}	2.00×10^{-2}
TIM (Down)	2.74	3.26	4.44×10^{-2}	3.32×10^{-2}	2.51×10^{-2}
GSA (Up)	2.26	2.88	4.03×10^{-2}	$\mathbf{6.76\times10^{-2}}$	2.77×10^{-2}
GSA (Down)	2.23	2.83	3.89×10^{-2}	$\mathbf{-1.68\times10^{-4}}$	1.75×10^{-2}
GSA (0)	2.30	2.93	4.01×10^{-2}	1.80×10^{-2}	2.00×10^{-2}
LSSA (Up)	2.49	3.10	4.26×10^{-2}	5.38×10^{-2}	$\mathbf{4.96\times10^{-2}}$
LSSA (Down)	2.71	3.33	4.63×10^{-2}	1.56×10^{-2}	$\mathbf{-5.04\times10^{-3}}$
LSSA (0)	2.68	3.31	4.55×10^{-2}	2.82×10^{-2}	1.29×10^{-2}



PROBLEM

There is a large tradeoff between making an adversarial attack look believable and the amount of error we can inflict on the model.

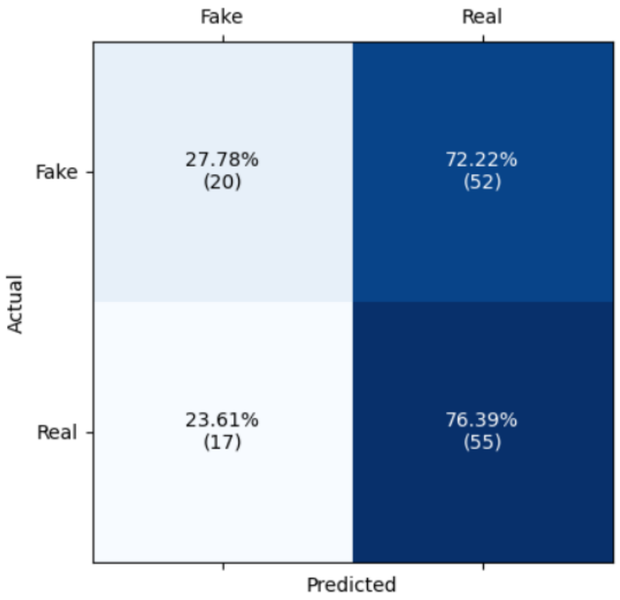


Defence Mechanisms

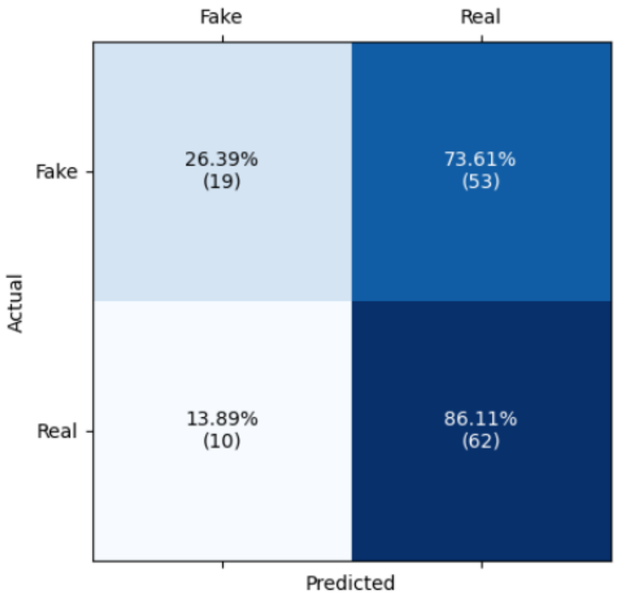
Adversarial Training and Discriminators

- Adversarial training involves including the adversarial examples with the real data in the training set to effectively train the model to correctly classify similar inputs regardless of noise [8].
- As an alternative, a developer can create a discriminator aimed to distinguish adversarial and real data [8]. During inference, the discriminator is run and returns the likelihood of the input being altered. If the discriminator detects that the given input has been tampered with, predictions are not made.
- To test the stealthiness of the new attacks, a 4-layered CNN was trained on varying sets of adversarial methods.

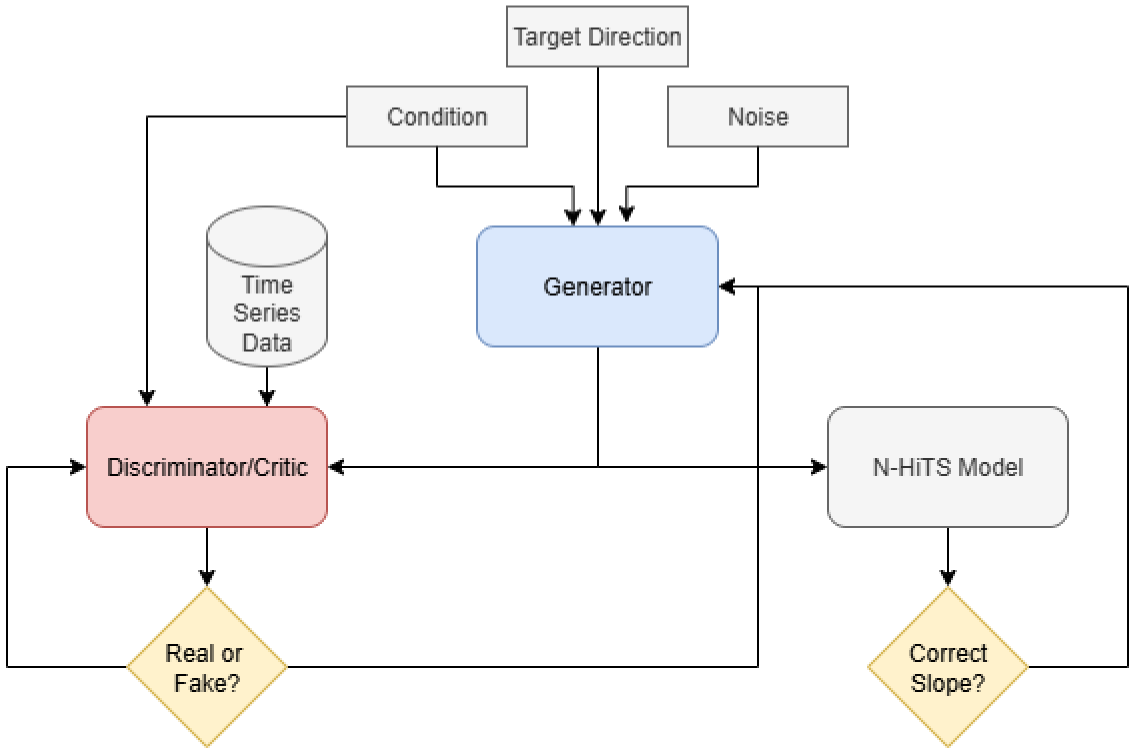
Stealthiness of GSA and LSSA



(a) GSA



(b) LSSA



Architecture of the Proposed Adversarial Gan (A-GAN)

A-GAN

- The A-GAN was trained with stock data extracted similar to the N-HiTS model, specifically using the stock with the ticker A; however, due to its stationary properties, the current implementation generates 99 days of log returns rather than adjprc.
- The noise vector is initialized to be the same size as the desired synthetic data (99 days) and is passed to the generator, made of a 4-layered Temporal Convolutional Network (TCN).
- The critic is a hybrid architecture with 5 layers, and is made up of alternating TCN and Gated Recurrent Network (GRU) blocks (3 TCN blocks, 2 GRU blocks) with a similar focus on long term dependencies. For both sub-models, a final linear layer was used to reduce the output dimension to 1.
- A Conditional Wasserstein GAN (C-WGAN) was used for the A-GAN, conditioned with the corresponding 99 days of log returns. The condition is then concatenated with the noise vector in the feature dimension for both the generator and the critic.

A-GAN

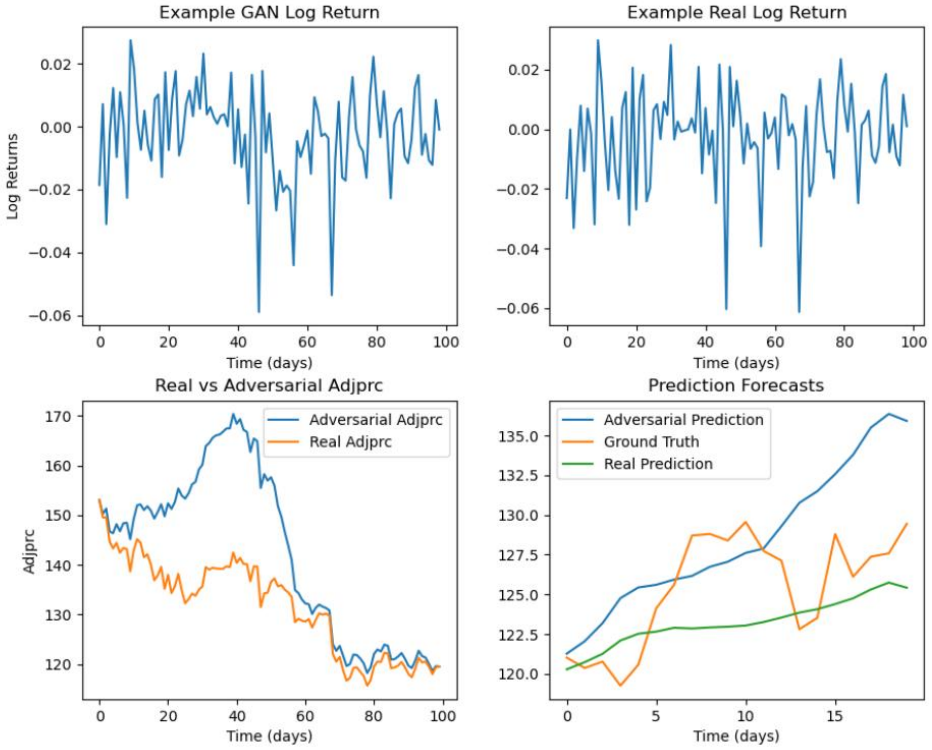
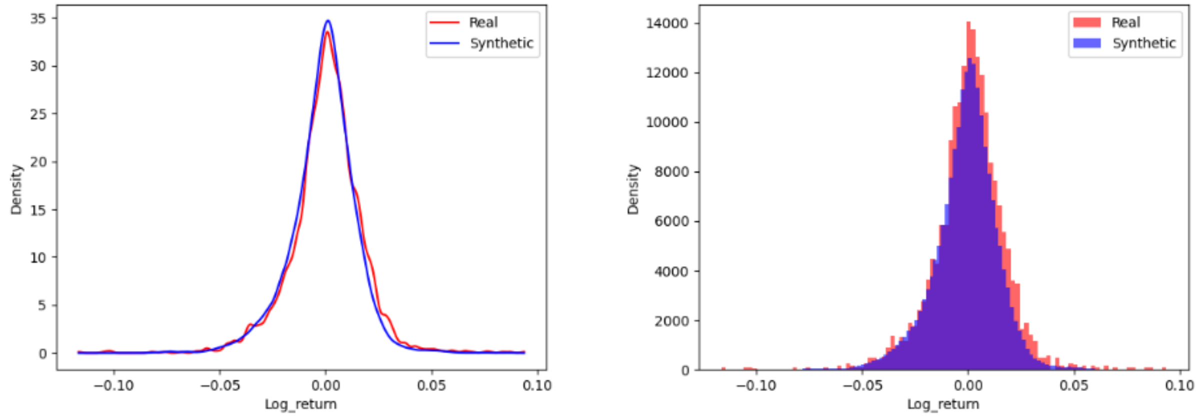


Figure 5: Example A-GAN output generated from a random interval.



(a) A-GAN KDE

(b) A-GAN Histogram

Figure 4: KDE and Histogram Plots of the distributions between the real and synthetic data generated by the A-GAN, after sampling 2000 intervals.

Mode Collapse

- The A-GAN suffers from mode collapse, which occurs when the generator creates data with limited diversity [19].

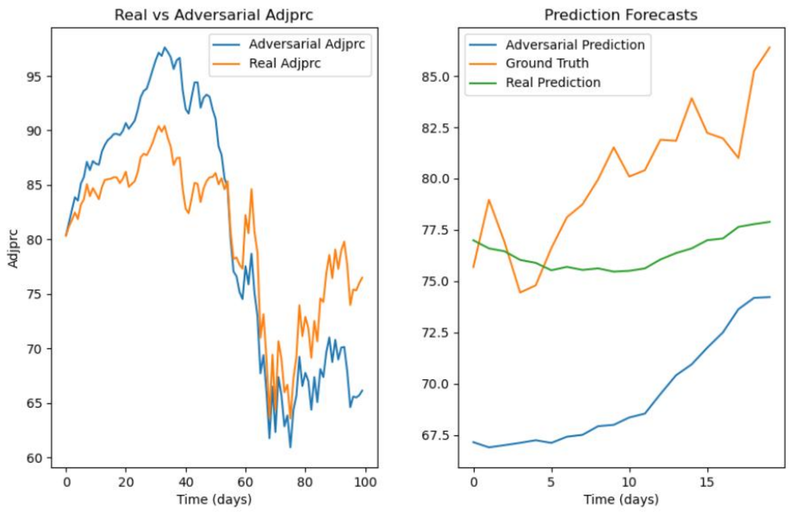


Figure 9: Example A-GAN output generated from a random interval.

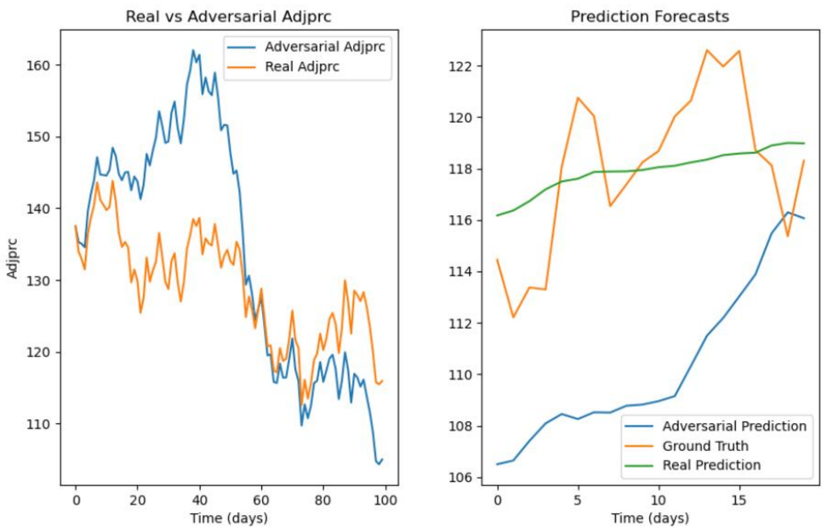


Figure 10: Example A-GAN output generated from a random interval.

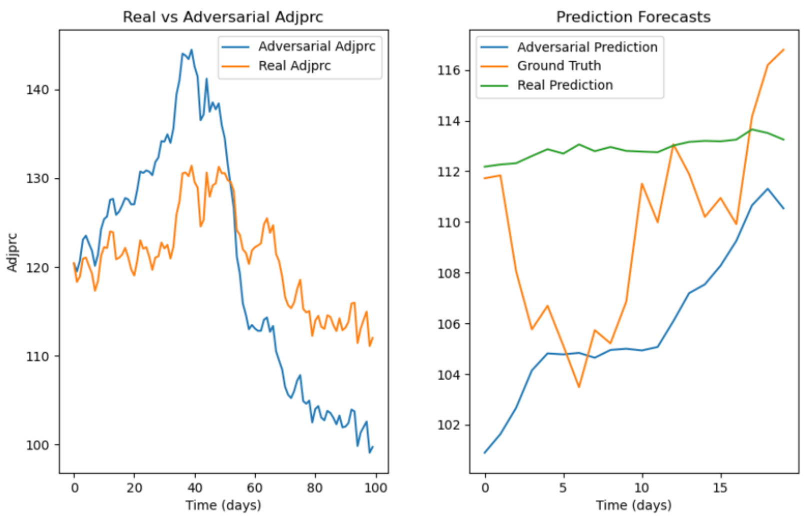
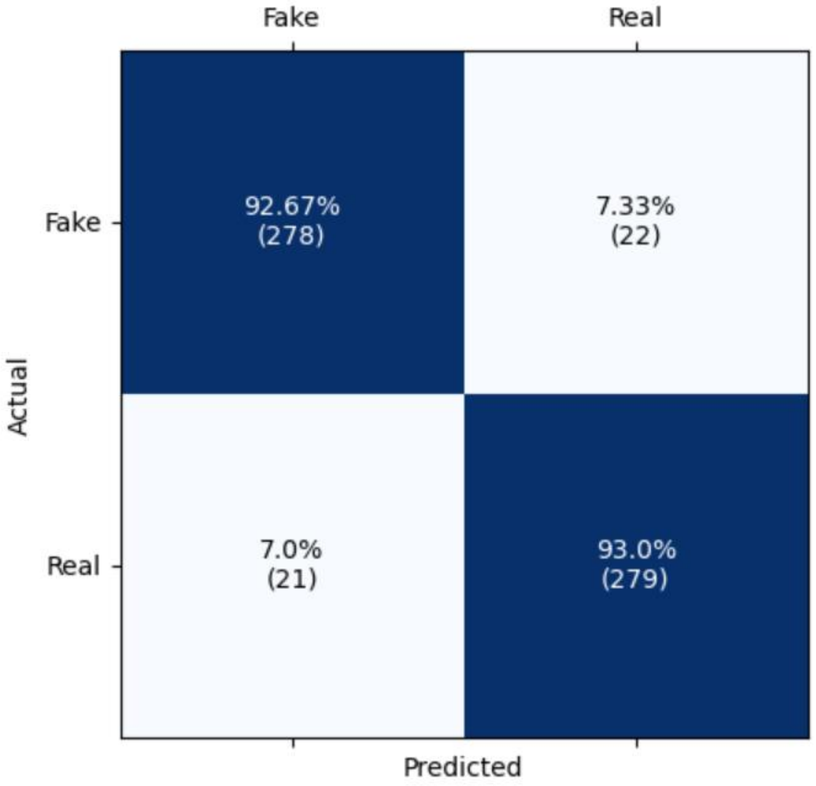


Figure 11: Example A-GAN output generated from a random interval.

Easily Detectable….

Accuracy: 92.83
F1: 92.84
Specificity: 92.67
Kappa: 85.67



Can we Bypass the Defences?

The ML-Pipeline

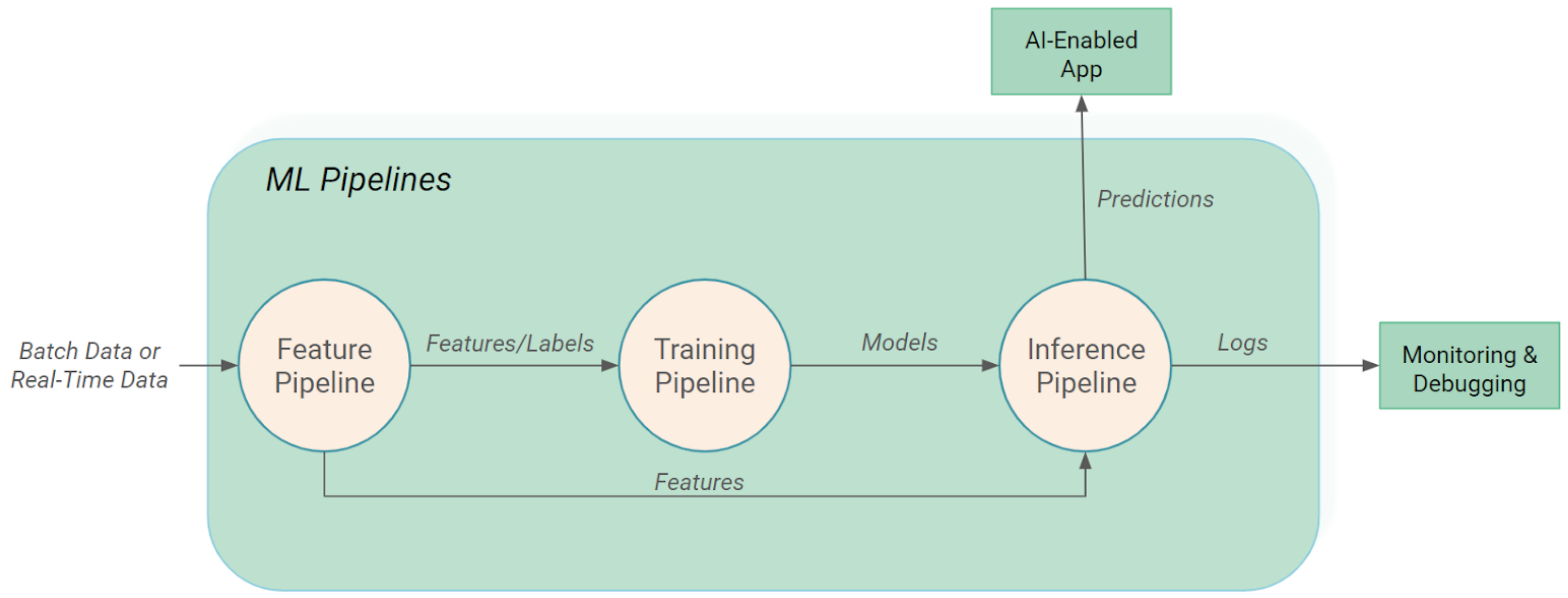


Image Source: https://blog.payrollschedule.net/

ML-Security: Malware

- A common workflow for deployment is to have a project package/library that stores the saved model and all files required to make a prediction. In such cases, the prediction directory is thought to be safe and secure, yet can be easily manipulated with existing cyber-attack methods.
- For example, in Python, the __init__.py file is run whenever something inside the package is imported. However, if the __init__.py was tampered with beforehand, the attacker can modify any code inside the project directory.
- Therefore, this malware is run during every inference call and can:
  - Inject adversarial attacks.
  - Remove any no gradient calls.

Trojan Malware

Algorithm 2 Sample payload for __init__.py file

```
adversarialString ← "Adversarial Attack Code"
originalFile ← fileWithModelCall.read()
originalFileLines ← fileWithModelCall.readlines()
f ← open(fileWithModelCall)
for line in originalFileLines do
    if line has a model call then
        write adversarialString
    end if
    if line has no_grad call then
        for each line with larger indent, remove indent and write
    else
        write line
    end if
end for
at exit, write originalFile to fileWithModelCall
```

Why Should We Care?

- Current research focuses on model robustness; however, it is significantly easier to attack other areas such as the model library with existing cyber-attack methods.
- The sample malware, shown in this research, demonstrates how an attacker could inject adversarial attacks that use gradient information, allowing for a stronger and more consequential attack.
- The internet, websites, and applications all came under attack once they became popular in the general public, and ML/AI models are approaching this stage, so it is imperative for more research to focus on securing the entire machine learning pipeline, given that no model in any domain is truly safe.

Limitations and Future Work

- In order to solidify and prove the general effectiveness of the attack methods, several other ML models, like CNNs and LSTMs, should have been developed and used as the victim models, similar the study by Shen and Li [3].
- Even though adversarial training is not necessarily feasible for the model in this study, it should still be performed to determine the effectiveness of the standard defense practice.
  - Adversarial training could be done by training a new model which does not rely on adjprc as a feature.
- Furthermore, to prove the applicability of the slope-based attacks on time series data, these attacks should be implemented in other time series domains that use forecasting models, such as traffic and electricity usage.
- Finally, given the A-GAN suffers from mode collapse, more experimentation should be performed to prevent it.

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