# A Word is Worth A Thousand Dollars: Adversarial Attack on Tweets Fools Stock Prediction

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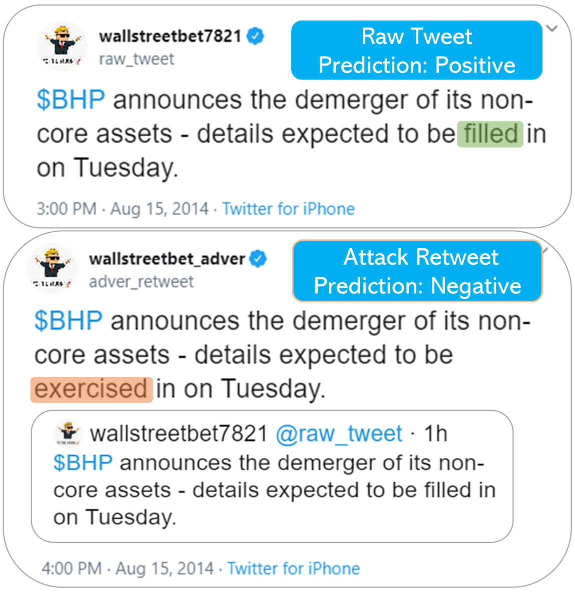
## Abstract

More and more investors and machine learning models rely on social media (e.g., Twitter and Reddit) to gather real-time information and sentiment to predict stock price movements. Although text-based models are known to be vulnerable to adversarial attacks, whether stock prediction models have similar vulnerability is underexplored. In this paper, we experiment with a variety of adversarial attack configurations to fool three stock prediction victim models. We address the task of adversarial generation by solving combinatorial optimization problems with semantics and budget constraints. Our results show that the proposed attack method can **achieve consistent success rates** and cause **significant monetary loss** in trading simulation by simply concatenating a perturbed but semantically similar tweet.

## 1 Introduction

The advance of deep learning based language models are playing a more and more important role in the financial context, including convolutional neutral network (CNN) (Ding et al., 2015), recurrent neutral network (RNN) (Minh et al., 2018), long short-term memory network (LSTM) (Hiew et al., 2019; Sawhney et al., 2021; Hochreiter and Schmidhuber, 1997), graph neutral network (GNN) (Sawhney et al., 2020a,b), transformer (Yang et al., 2020), autoencoder (Xu and Cohen, 2018), etc. For example, Antweiler and Frank (2004) find that comments on Yahoo Finance can predict stock market volatility after controlling the effect of news. Cookson and Niessner (2020) also show that sentiment disagreement on Stocktwits is highly related to certain market activities. Readers can refer to these survey papers for more details (Dang et al., 2020; Zhang et al., 2018; Xing et al., 2018).



wallstreetbet7821
raw_tweet

Raw Tweet
Prediction: Positive

$BHP announces the demerger of its non-core assets - details expected to be filled in on Tuesday.

3:00 PM · Aug 15, 2014 · Twitter for iPhone

wallstreetbet_adver
adver_retweet

Attack Retweet
Prediction: Negative

$BHP announces the demerger of its non-core assets - details expected to be exercised in on Tuesday.

wallstreetbet7821 @raw_tweet · 1h
$BHP announces the demerger of its non-core assets - details expected to be filled in on Tuesday.

4:00 PM · Aug 15, 2014 · Twitter for iPhone

Figure 1: An example of word-replacement adversarial attack. (Top) benign tweet leads `Stocknet` to predict stock going UP; (Bottom) adding an adversarial retweet leads `Stocknet` to predict stock going DOWN.

It is now known that text-based deep learning models can be vulnerable to adversarial attacks (Szegedy et al., 2014; Goodfellow et al., 2015). The perturbation can be at the sentence level (e.g., Xu et al., 2021; Iyyer et al., 2018; Ribeiro et al., 2018), the word level (e.g., Zhang et al., 2019; Alzantot et al., 2018; Zang et al., 2020; Jin et al., 2020; Lei et al., 2019; Zhang et al., 2021; Lin et al., 2021), or both (Chen et al., 2021). We are interested in whether such adversarial attack vulnerability also exists in stock prediction models, as these models embrace more and more human-generated media data (e.g., Twitter, Reddit, Stocktwit, Yahoo News (Xu and Cohen, 2018; Sawhney et al., 2021)). The adversarial robustness is a more critical issue in the context of stock prediction as anyone can post perturbed tweets or news to influence forecasting models. For example, a fake news ("Two Explosions in the White House and Barack Obama is Injured") posted by a hacker using the Associated-

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Press's Twitter account on 04/23/2013 erased $136 billion market value in just 60 seconds (Fisher, 2013). Although the event doesn't fall into the category of adversarial attack, it rings the alarm for traders who use (social) media information for their trading decisions.

To our best knowledge, it is the first paper to consider the adversarial attack in the financial NLP literature. Many attacks modify benign text directly (*manipulation attack*) and use them as model input; However, in our case, adversarial retweets enter the model along with benign tweets (*concatenation attack*), which is more realistic as malicious Twitter users can not modify others' tweets. In other words, we formulate the task as a text-concatenating attack (Jia and Liang, 2017; Le et al., 2021): we implement the attack by injecting new tweets instead of manipulating existing benign tweets. Our task is inspired and mimics the retweet function on social media, and uses it to feed the adversarial samples into the dataset. Despite various algorithms are proposed to generate manipulation attack, literature of concatenation attack on classification models is rare, with exceptions Le et al. (2021), Song et al. (2021) and Wang et al. (2020). Our paper provides extra evidence of their difference by investigating their performances in the financial domain.

The main challenge is to craft new and effective adversarial tweets. We solve the task by aligning the semantics with benign tweets so that the potential human and machine readers can't detect our adversarial tweets. To achieve that, we consider the generation task as a combinatorial optimization problem (Zang et al., 2020; Guo et al., 2021). Specific tweets are first selected, which are used as the target of perturbation on a limit number of words within the tweets. We then examine our attack method on three financial forecast models with *attack success rate*, *F1* and potential *profit and loss* as evaluation metrics. Results show that our attack method consistently achieves good success rate on the victim models. More astonishingly, the attack can cause additional loss of 23% to 32% if an investor trades on the predictions of the victim models (Fig. 4).

## 2 Adversarial Attack on Stock Prediction Models with Tweet Data

**Attack model: Adversarial tweets.** In the case of Twitter, adversaries can post malicious tweets which are crafted to manipulate downstream models that take them as input. We propose to attack by posting semantically similar adversarial tweets as retweets on Twitter, so that they could be identified as relevant information and collected as model input. For example, as shown in Fig 1, the original authentic tweet by the user *wallstreetbet7821* was "*$BHP announces the demerger of its non-core assets - details expected to be filled in on Tuesday.*" An adversarial sentence could be "*$BHP announces the demerger of its non-core assets - details expected to be exercised in on Tuesday.*". The outcome of the victim model switches to negative prediction from positive prediction when the retweet is added to the input.

The proposed attack method takes the practical implementation into its design consideration, thus has many advantages. First, the adversarial tweets are crafted based on carefully-selected relevant tweets, so they are more likely to pass the models' tweet filter and enter the inference data corpus. Secondly, adversarial tweets are optimized to be semantically similar to the original tweets so that they are not counterfactual and very likely to fool human sanity checks as well as the Twitter's content moderation system.

**Attack generation: Hierarchical perturbation.** The challenge of our attack method centers around how to select the optimal tweets and the token perturbations with the constraints of semantic similarity. In this paper, we formulate the task as a *hierarchical perturbation* consisting of three steps: *tweet selection*, *word selection* and *word perturbation*. In the first step, a set of optimal tweets is first selected as the target tweets to be perturbed and retweeted. For each selected tweet in the pool, the word selection problem is then solved to find one or more optimal words to apply perturbation. Word and tweet budgets are also introduced to quantify the strength of the perturbation.

We consider the **word replacemen**t and **deletion** for word perturbation (Garg and Ramakrishnan, 2020; Li et al., 2020). In the former case, the final step is to find the optimal candidate as replacement. A synonym as replacement is widely adopted in the word-level attack since it is a natural choice to preserve semantics (Zang et al., 2020; Dong et al., 2021; Zhang et al., 2019; Jin et al., 2020). Therefore, we replace target words with their synonyms chosen from synonym sets which contain the semantically closest words measured by the similarity of the GLOVE embedding (Jin et al., 2020).

**Mathematical Formulation.** We consider a multimodal stock forecast model $f(\cdot)$ that takes tweet collections $\{\boldsymbol{c_t}\}_{t=1}^{T}$ and numerical factors $\{\boldsymbol{p_t}\}_{t=1}^{T}$ as input, where $t$ indexes the date when the data is collected. Peeking into the tweet collection, it contains $|\boldsymbol{c_t}|$ tweets for date $t$, namely, $\boldsymbol{c_t} = \{\boldsymbol{s_t^1}, \boldsymbol{s_t^2}, ..., \boldsymbol{s_t^{|c_t|}}\}$. Each tweet $\boldsymbol{s_t^i}$ is a text-based sentence of length $|\boldsymbol{s_t^i}|$, denoted as $\boldsymbol{s_t^i} = (w_t^{i,1}, ..., w_t^{i,j}, ..., w_t^{i,|\boldsymbol{s_t^i}|})$, for $i = 1, ..., |\boldsymbol{c_t}|$. A directional financial forecast model takes domains of tweets and numerical factors as input, and yields prediction for stocks' directional movement $y \in \{-1, 1\}$:

$$\hat{y}_{t+1} = f(\boldsymbol{c_{t-h:t}}, \boldsymbol{p_{t-h:t}}), \tag{1}$$

$h$ is the looking-back window for historical data.

The hierarchical perturbation can be cast as a combinatorial problem for tweet selection $\boldsymbol{m}$, word selection $\boldsymbol{z}$ and replacement selection $\boldsymbol{u}$. The boolean vector $\boldsymbol{m}$ indicates the tweets to be selected. For $i$-th tweet, vector $\boldsymbol{z_i}$ indicates the word to be perturbed. As for the word perturbation task, another boolean vector $\boldsymbol{u_{i,j}}$ selects the best replacement. It follows that the hierarchical perturbation can be formulated as

$$\boldsymbol{c_t'} = (\boldsymbol{1} - \boldsymbol{m} \cdot \boldsymbol{z}) \cdot \boldsymbol{c_t} + \boldsymbol{m} \cdot \boldsymbol{z} \cdot \boldsymbol{u} \cdot S(\boldsymbol{c_t}), \tag{2}$$

where $\cdot$ denotes element-column wise product, $\boldsymbol{m} \cdot \boldsymbol{z}$ indicates the selected words in selected tweets, $\boldsymbol{m} \cdot \boldsymbol{z} \cdot \boldsymbol{u}$ indicates selected synonyms for each selected word, and $S(\cdot)$ is a element-wise synonym generating function. Consequently, given attack loss $\mathcal{L}$, generation of adversarial retweets can be formulated as the optimization program $\min\limits_{\boldsymbol{m},\boldsymbol{z},\boldsymbol{u}} \mathcal{L}(\boldsymbol{c_t'} \cup \boldsymbol{c_{t-h:t}}, \boldsymbol{c_{t-h:t}} | \boldsymbol{p_{t-h:t}}, f)$, subject to the budget constraints: *a)* $\boldsymbol{1}^T\boldsymbol{m} \leq b_s$, *b)* $\boldsymbol{1}^T\boldsymbol{z_i} \leq b_w, \forall i$ and *c)* $\boldsymbol{1}^T\boldsymbol{u_{i,j}} = 1, \forall i, j$, where $b_s$ and $b_w$ denote the tweet and word budgets. It is worth to stress that perturbation is only applied to the date $(t)$ when the attack is implemented to preserve the temporal order.

To solve the program, we follow the convex relaxation approach developed in (Srikant et al., 2021). Specifically, the boolean variables (for tweet and word selection) are relaxed into the continuous space so that they can be optimized by gradient-based methods over a convex hull. Two main implementations of the optimization-based attack generation method are proposed: *joint optimization* (JO) solver and *alternating greedy optimization* (AGO) solver. JO calls projected gradient descent method to optimize the tweet and word selection variables and word replacement variables simultaneously. AGO uses an alternative optimization procedure to sequentially update the discrete selection variables and the replacement selection variables. More details on the optimization program and the solvers can be found in Appendix A.

## 3 Experiments

**Dataset & victim models.** We evaluate our adversarial attack on a stock prediction dataset consisting of 10,824 instances including relevant tweets and numerical features of 88 stocks from 2014 to 2016 (Xu and Cohen, 2018). Three models (**`Stocknet`** (Xu and Cohen, 2018), **`FinGRU`** based on GRU (Cho et al., 2014) and **`FinLSTM`** based on LSTM (Hochreiter and Schmidhuber, 1997)) of binary classification are considered as victims in this paper. We apply our attack to instances on which the victim models make correct predictions.

**Evaluation metrics.** Attack performance is evaluated by two metrics: *Attack Success Rate* (ASR) and victim model's *F1* drop after attack. ASR is defined as the percentage of the attack efforts that changes the model output. The two metrics gauge the efficacy of the attack and its impact on model performance: More efficient attack leads to higher ASR and more decline of F1. Moreover, we simulate a ***Long-Only Buy-Hold-Sell*** strategy (Sawhney et al., 2021; Feng et al., 2019) with victim models, and calculate the *Profit and Loss* (PnL) for each simulation. Assume a portfolio starts with initial net value \$10000 (100%), its net value at the end of test period reflects the profitability of the trading strategy and the underlying model. Consequently, the change in PnLs measures the monetary impact of our attack. More details on the dataset, victim models and evaluation metrics are housed in Appendix B.

## 4 Results

**Attack performance with single perturbation.** The experiment results for the concatenation attack with word replacement perturbation is shown in Table 1 (with tweet and word budgets both as 1). For both JO and AGO, ASR increases by roughly 10% and F1 drops by 0.1 on average in comparison to the random attack. Such performance drop is considered significant in the context of stock prediction given that the state-of-the-art prediction accuracy of interday return is only about 60%.

| Model | ASR(%) | | | | F1 | | | |
|---|---|---|---|---|---|---|---|---|
| | NA | RA | JO | AGO | NA | RA | JO | AGO |
| Stocknet | 0 | 4.5 | **16.8** | 11.8 | 1 | 0.96 | **0.84** | 0.88 |
| FinGRU | 0 | 5.1 | **16.4** | 14.1 | 1 | 0.95 | **0.85** | 0.87 |
| FinLSTM | 0 | 11.9 | 16.5 | **19.7** | 1 | 0.89 | 0.85 | **0.78** |

Table 1: Performance of the various adversarial attacks. NA: no attack; RA: random attack; JO: joint optimization; and AGO: alternating greedy optimization.

**Effect of attack budget.** We report the effect of different attack budgets on the attack performance in Fig. 2. We observe that the more budgets allowed (perturbing more tweets and words), the better the attack performance, but the increase is not significant. It appears that the attack performance becomes saturated if we keep increasing the attack budgets. In fact, the attack with budget of one tweet and one word is the most cost effective, provided that it introduces minimum perturbation but achieves a relatively similar ASR.

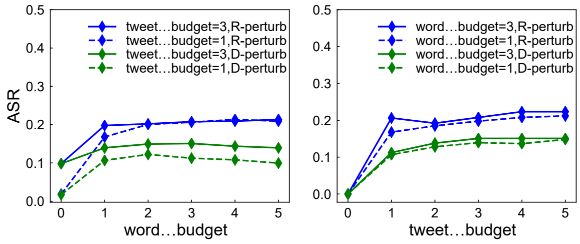

Figure 2: Effect of attack budgets on ASR with Stocknet as victim model and with JO solver. r-perturb: word replacement; d-perturb: word deletion.

**Manipulation vs concatenation attack.** We focus on concatenation attack in this paper since we believe it is distinct from manipulation attack. We investigate the difference by applying the same method of tweet generation to implement manipulation attack, where the adversarial tweets replace target tweets instead. The experiment runs with one word budget and one twee budget, and the results are reported in Fig. 3.

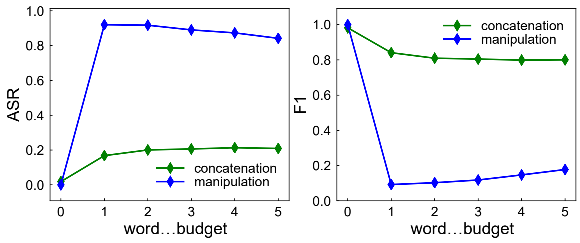

Figure 3: Comparison between **manipulation** and **concatenation** attacks with **word-replacement** perturbation method. `Stocknet` is the victim model.

It is clear that manipulation attack remarkably outperforms concatenation attack in terms of ASR and F1. Even though the success rate of concatenation attack lags behind the state-of-the-art textual attack, the manipulation attack achieves performance of the same ballpark, which demonstrates the efficacy of optimization-based attack and our solvers. More importantly, it implies that the attack is not transferable between the two tasks, documenting more evidence on language attack transferability (Yuan et al., 2021; He et al., 2021). The bottom line is that they are two different tasks under different assumptions. Researchers should take downstream scenarios into account when develop attack models.

**Trading simulation.** The ultimate measure of a stock prediction model's performance is profitability. Fig. 4 plots the *profit and loss* of the same trading strategy with `Stocknet` as the prediction model with or without the attack – JO is used to generate adversarial retweets. For each simulation, the investor has $10K (100%) to invest; the results show that the proposed attack method with a retweet with only a single word replacement can cause the investor an additional $3.2K (75%-43%) loss to their portfolio after about 2 years.

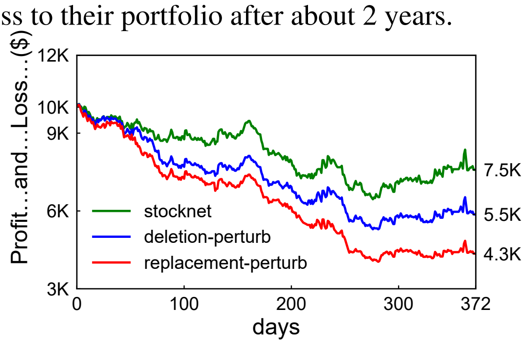

Figure 4: *Profit and Loss* with `Stocknet` as the victim model using *Long-Only Buy-Hold-Sell* strategy for 2 years with $10K initial investment. Green line: trading using `Stocknet` without attack; Blue line: concatenation attack with **deletion perturbation**; Red line: concatenation attack with **replacement perturbation**.

## 5 Conclusion

This work demonstrates that our adversarial attack method consistently fools various financial forecast models even with physical constraints that the raw tweet can not be modified. Adding a retweet with only one word replaced, the attack can cause 32% additional loss to our simulated investment portfolio. Via studying financial model's vulnerability, **our goal is to raise financial community's awareness of the AI model's risks**, so that in the future we can develop more robust human-in-the-loop AI architecture (Wang et al., 2019) to cope with this and other real-world attacks, including black-box attack, unknown input domains, etc.

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# A Mathematical Formation

## A.1 Financial Forecast Model

Massive amounts of text data are generated by millions of users on Twitter every day. Among a variety of discussion, stock analysis, picking and prediction are consistently one of the trending topics. And investors often use the Twitter *cashtag* function (a $ symbol followed by a ticker) to organize their particular thoughts around one single stock, e.g., $AAPL, so that users can click and see the ongoing discussions. Textual data on Twitter is collectively generated by all of its users via posting tweets. Financial organizations and institutional investors often ingest the massive text data in real time and incorporate them or their latent representation into their stock prediction models.

We consider the multimodal stock forecast models that take tweet collections $\{\boldsymbol{c_t}\}_{t=1}^{T}$ and numerical factors $\{\boldsymbol{p_t}\}_{t=1}^{T}$ as input,where $t$ indexes the date when the data is collected. The numerical factors are usually mined from historical price, fundamentals and other alternative data sources. In this paper, we assume that the domain of numerical factors is unassailable since they are directly derived from public records. Therefore, the objective of adversary is to manipulate model output by injecting perturbation to the textual domain $\{\boldsymbol{c_t}\}_{t=1}^{T}$. Peeking into the tweet collection, it contains $|\boldsymbol{c_t}|$ tweets for date $t$, namely, $\boldsymbol{c_t} = \{\boldsymbol{s_t^1}, \boldsymbol{s_t^2}, ..., \boldsymbol{s_t^{|c_t|}}\}$. Each tweet $\boldsymbol{s_t^i}$ is a text-based sentence of length $|\boldsymbol{s_t^i}|$, denoted as $\boldsymbol{s_t^i} = (w_t^{i,1}, ..., w_t^{i,j}, ..., w_t^{i,|\boldsymbol{s_t^i}|})$, for $i = 1, ..., |\boldsymbol{c_t}|$. A directional financial forecast model takes domains of tweets and numerical factors as input, and yields prediction for stocks' directional movement $y \in \{-1, 1\}$:

$$\hat{y}_{t+1} = f(\boldsymbol{c_{t-h:t}}, \boldsymbol{p_{t-h:t}}), \tag{3}$$

where $h$ is the looking-back window for historical data.

## A.2 Attack Model

Let $\boldsymbol{c_t'}$ be the perturbed tweet collection at time $t$ created by solving the hierarchical perturbation problem. To formalize the perturbation task, we introduce boolean vector variable $\boldsymbol{m} \in \{0, 1\}^{n_m}$ to indicate the tweets to be selected. If $m_i = 1$, then $i$-th tweet is the target tweet to be perturbed and retweeted. Besides, for $i$-th tweet, vector $\boldsymbol{z_i} \in \{0, 1\}^{n_z}$ indicates the word to be perturbed. As for the word perturbation task, another boolean vector $\boldsymbol{u_{i,j}} \in \{0, 1\}^{n_u}$ selects the best replacement. $n_m$ and $n_z$ and $n_u$ denote the maximum amount of tweets, maximum amount of words in each tweet, and the amount of synonyms for each word, respectively. We identify deletion perturbation as a special case of replacement with $u_{i,j,k} = 1$ only for padding token, so that the task degenerates to tweet selection and word selection. Let vector $\boldsymbol{z} \in \{0, 1\}^{n_m \times n_z}$ denote $n_m$ different $\boldsymbol{z_i}$ vector, and $\boldsymbol{u} \in \{0, 1\}^{n_m \times n_z \times n_u}$ denote $n_m \times n_z$ different $u_{i,j}$ vectors. It follows that the hierarchical perturbation can be defined as

$$\begin{aligned} &\boldsymbol{c_t'} = (\boldsymbol{1} - \boldsymbol{m} \cdot \boldsymbol{z}) \cdot \boldsymbol{c_t} + \boldsymbol{m} \cdot \boldsymbol{z} \cdot \boldsymbol{u} \cdot S(\boldsymbol{c_t}) \\ s.t. \quad & \boldsymbol{1}^T \boldsymbol{m} \leq b_s, \\ & \boldsymbol{1}^T \boldsymbol{z_i} \leq b_w, \forall i, \\ & \boldsymbol{1}^T \boldsymbol{u_{i,j}} = 1, \forall i, j, \end{aligned} \tag{4}$$

where $\cdot$ denotes element-column wise product, $b_s$ denotes tweet budget, $b_w$ denotes word budget and $S(\cdot)$ is element-wise synonym generating function.

Adversarial retweets are the then passed into downstream financial forecast model $f(\cdot)$ along with benign tweets. Attack success is achieved if the adversarial tweets manage to fool the downstream model, and change the model output. Financial forecast model usually takes observation of multiple steps as input to appreciate the temporal dependence. However, adversary can only inject adversarial retweets at present time. That is, when run the model on day $t$ to predict price movement on day $t + 1$, retweets only enter tweet collection for day $t$; collections for days prior to $t$ remain static. Consequently, generation of successful adversarial retweets is formulated as the following optimization program:

$$\begin{aligned} \min_{\boldsymbol{m}, \boldsymbol{z}, \boldsymbol{u}} \quad & \mathcal{L}(\boldsymbol{c_t'} \cup \boldsymbol{c_{t-h:t}}, \boldsymbol{c_{t-h:t}} | \boldsymbol{p_{t-h:t}}, f) \\ s.t. \quad & \text{constraint in (4)}, \end{aligned} \tag{5}$$

where $\mathcal{L}$ denotes the attack loss. We adopt the cross-entropy loss for our attack since it is untargeted attack (Srikant et al., 2021). Other classification-related loss may be applied according to adversary's objective. Furthermore, we also add entropy-based regularization to encourage sparsity of optimization variables (Dong et al., 2021).

## A.3 Methodology

The challenge of solving program (5) lies in the combinatorial and hierarchical nature. We first relax the boolean variables into continuous space so that they can be solved by gradient-based solvers. A common workaround for combinatorial optimization is to solve an associated continuous optimization over convex hull (Dong et al., 2021; Srikant et al., 2021). An computationally efficient fashion is to optimize over a convex hull constructed with linear combination of candidate set, and the optimal replacement goes with word with highest weight (Dong et al., 2021). However, this approach doesn't fit in the hierarchical tweet and word selection problem. For example, in order to select the optimal target word, one need to sum over the embedding of all words in the tweet, so the tweet collapses into embedding for one hypothetical word. Similarly, different tweets collapse to one hypothetical tweet, or one hypothetical word when one jointly selects tweets and words.

**Joint optimization solver (JO).** As a remedy, we propose a *joint optimization solver* that combines projected gradient descent and convex hull to jointly optimize $\boldsymbol{m}$, $\boldsymbol{z}$ and $\boldsymbol{u}$. Replacement selection is optimized over the convex hull:

$$\boldsymbol{c}_{\boldsymbol{t}}' = (1 - \boldsymbol{m} \cdot \boldsymbol{z}) \cdot \boldsymbol{c}_{\boldsymbol{t}} + \boldsymbol{m} \cdot \boldsymbol{z} \cdot conv(\boldsymbol{u}, S(\boldsymbol{c}_{\boldsymbol{t}})),$$

where

$$conv(\boldsymbol{u}, S(\boldsymbol{c}_{\boldsymbol{t}})) = \{\sum_k \hat{u}_{i,j,k} S(w_{i,j,k}), \forall i, j\},$$

and

$$\hat{u}_{i,j,k} = \frac{exp(u_{i,j,k})}{\sum_k exp(u_{i,j,k})}.$$

The problem of (5) is then solved by optimizing $\hat{\boldsymbol{u}}$. Unlike $\boldsymbol{u}$, $\boldsymbol{m}$ and $\boldsymbol{z}$ are optimized directly via projected gradient descent (PGD). Moreover, when $\boldsymbol{m}$ is one-hot vector, it determines the tweets to be retweeted, and those retweets are then added into tweet collection. However, $\boldsymbol{m}$ is continuous during optimization, so we retweet all the collected tweets and add them into tweet collection, which helps generate and back-propagate gradients for all the entries of $\boldsymbol{m}$. After the optimization is solved, we map the continuous solution into one-hot vector by selecting top $b_s$ highest $m_i$.

**Alternating greedy optimization solver (AGO).** Greedy optimization is usually computational ineffective since a vast amount of inquiries is required when we collect large amount of tweets and have high attack budget. To mitigate the problem, we alternate the optimization over $\boldsymbol{m}$, $\boldsymbol{z}$ and $\boldsymbol{u}$. The aforementioned convex hull approach is adopted for finding optimal $\boldsymbol{u}$. The difference lies on the path to solve tweet and word selection problems. More specifically, we alternatively search the optimal target tweets and words which achieve the highest increases in prediction loss. For tweet selection, we mimic the physical attack scenario, and new retweets are added into tweet collection during the greedy search. Depending on the adversary's objective, different metrics may be used to measure the importance of each tweet and word. For example, Alzantot et al. (2018) use predicting probability to determine the selection of words; Ren et al. (2019) propose probability weighted word saliency as criterion for word selection; Jin et al. (2020) calculate the prediction change before and after deletion as word importance.

# B Experimental Settings

## B.1 Dataset

We evaluate our adversarial attack on a stock prediction dataset (Xu and Cohen, 2018). The dataset contains both tweets and historical prices (e.g., open, close, high, etc) for 88 stocks of 9 industries: *Basic Materials, Consumer Goods, Healthcare, Services, Utilities, Conglomerates, Financial, Industrial Goods and Technology.* Since we consider the task of binary classification, data instances are supposed to labelled positive and negative for upward and downward movement respectively.

Moreover, it is observed that the dataset contains a number of instances with exceptionally minor price movements. In practice, minor movement is hard to be monetized due to the existence of transaction cost. Therefore, an upper threshold of 0.55% and a lower threshold of -0.5% are introduced. Specifically, stocks going up more than 0.55% in a day are labeled as positive, those going down more than -0.5% are labeled as negative, and the minor moves in between are filtered out. As argued in (Xu and Cohen, 2018), the particular thresholds are carefully selected to balance the two classes.

In addition, the sampling period spans from 01/01/2014 to 01/01/2016. We split the dataset into train and test set on a rolling basis. This special program improves the similarity between distributions of train set and test set, which is widely adopted on temporal dataset. It leaves us 9416 train instances and 1408 test instances in 7 nonconsecutive periods. For the text domain, the dataset contains

57533 tweets in total.

## B.2 Victim Models

**Stocknet.** A variational Autoencoder (VAE) that takes both tweets and price as input (Xu and Cohen, 2018). Tweets are encoded in hierarchical manner within days, and then modeled sequentially along with price features. It consists of three main components in bottom-up fashion. Market Information Encoder first encodes tweets and prices to a latent representation of 50 dimensions for each day. Variational Movement Decoder infers latent vectors of 150 dimensions and then decodes stock movements. At last, a module called Attentive Temporal Auxiliary integrates temporal loss through an attention mechanism. We train the model on the dataset from scratch with the same configurations as Xu and Cohen (2018).

**FinGRU.** A binary classifier that takes numerical features and tweets as input. All features are encoded sequentially by GRU (Cho et al., 2014) to exploit the temporal dependence. The model adopts the same Market Information Encoder as Stocknet. Latent representation of tweets and prices are then fed into a layer of GRU with attention mechanism to integrate temporal information. We train the model with an Adam optimizer (Kingma and Ba, 2015) and learning rate of 0.005. The checkpoint achieves the best performance on test dataset among 100 epochs is adopted as the victim model.

**FinLSTM.** A binary classifier identical to FinGRU, but utilizes LSTM (Hochreiter and Schmidhuber, 1997) to encode temporal dependence. The model is trained in the same manner as FinGRU.

## B.3 Evaluation Metrics

Following Srikant et al. (2021), we evaulate the attack on those examples in the test set that are correctly classified by the target models. It provides direct evidence of the adversarial effect of the input perturbation and the model robustness. In the specific application of financial forecast, it makes more sense to manipulate correct prediction than incorrect ones. The following two common metrics are adopted to evaluate attack performance.

**Attack Success Rate.** ASR is defined as the percentage of the attack efforts that make the victim model misclassify the instances that are originally correctly classified. Mathematically, $ASR = \frac{\sum_t \delta(\hat{y}'_t \neq y_t)}{\sum_t \delta(\hat{y}_t = y_t)}$, where $\hat{y}_t$ is the unperturbed model prediction, $\hat{y}'_t$ the model prediction with perturbation, and $y_t$ the ground-truth label. ASR characterizes the capability of the attack model, and higher the ASR, the better the attack.

**F1 Score.** F1 gauges the prediction performance of the victim models. Since we only consider the samples that are correctly predicted, the F1 score in the case of no attack is 1. Apparently, the drop of the F1 score of caused by the perturbation demonstrates the performance of the attack method. Unlike ASR, the drops of F1 score gauge the direct impact on the model performance: more successful attack leads to lower post-attack F1 score.

**Profit and Loss.** This widely-used financial indicator measures the profitability of a trading strategy. Assume that the initial net values are \$10K (100%), accumulate profit and loss for each trade, we can then calculate the final net value of the portfolio and *profit and loss*. A binary financial forecast model can be exploited in many ways, and support various trading strategies, which usually lead to different PnLs. In this paper, we use a simple ***Long-Only Buy-Hold-Sell*** strategy (Sawhney et al., 2021; Feng et al., 2019). More specifically, we *buy* stock(s) on Day $T$ if the model predicts these stocks go up on Day $T + 1$, *hold* for one day, and *sell* these stocks the next day no matter what prices will be, and repeat it. We do not *short* a stock even if the model predicts a negative move in the second day.

Besides, when the model makes positive prediction on more than one stocks, the money is evenly invested to the stock pool of positive prediction. For example, suppose that we stand on day 4 with portfolio value \$12K. If the model gives positive prediction on 10 of 88 stocks for day 5, we invest 10% of the total wealth (\$1.2K) to each stock, and sell them at closing prices of day 5. The process continues until the end of the test periods, and the resulting net value of the portfolio is used to calculate the profit and loss of the underlying model.

The buy-hold-sell strategy monetizes the prediction performance of financial forecast models by betting on the their predictions. The PnL reflects the profitability of the underlying models, even if it is usually influenced by many other confounding factors. Most importantly, the changes of PnLs caused by perturbation on the victim models only gauge the monetary consequence of our attack,

| Model | ASR(%) | | | | F1 | | | |
|---|---|---|---|---|---|---|---|---|
| | NA | RA | JO | AGO | NA | RA | JO | AGO |
| Stocknet | 0 | 3.6 | 12.1 | 11.0 | 1 | 0.97 | 0.89 | 0.89 |
| FinGRU | 0 | 4.0 | 10.2 | 10.6 | 1 | 0.96 | 0.85 | 0.91 |
| FinLSTM | 0 | 11.9 | 12.1 | 11.6 | 1 | 0.89 | 0.89 | 0.89 |

Table 2: Results for concatenation attack with deletion perturbation and budgets 1. NA and RA stand for no attack and random attack respectively, serving as benchmarks.

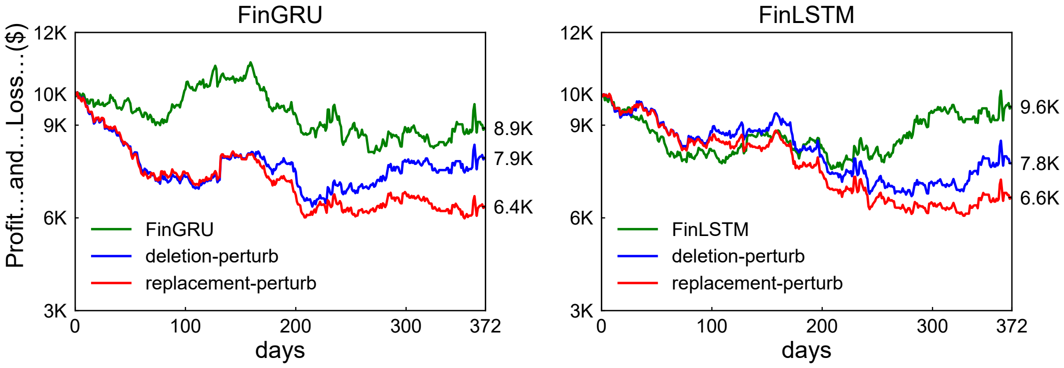

Figure 5: Effect on *Profit and Loss* of various perturbation methods on FinGRU and FinLSTM.

since all else are equal.

## C Supplemental Experiment Results

### C.1 Replacement vs deletion perturbation.

We report results for concatenation attack with only the *replacement perturbation* in the main text in Table 1. Here we also report results for the *deletion perturbation* in Table 2. Attacks conducted via deletion perturbation in general perform worse than the results of replacement perturbation. We observe ASRs via JO and AGO fall by 5.1% and 4.1% respectively compared with the replacement perturbation. Accordingly, F1 slightly increases as attack performance worsens. There is no significant difference between the two optimizers (JO and AGO) in the case of deletion perturbation, but JO is preferable in terms of optimization efficiency.

Moreover, we also simulate the trading profit and loss based on FinGRU and FinLSTM. For the sake of consistency, the two models are under concatenation attack with replacement perturbation. Same as our main results, the attack is optimized by JO solver. The simulation results are reported in Figure 5, which provides further evidence for the potential monetary loss caused by our adversarial attack. Replacement perturbation again outperforms deletion perturbation in the case of FinGRU and FinLSTM.

### C.2 Effect of Iteration Number

We experiment with the optimizer to perform gradient descent or greedy search for up to 10 rounds before yielding the final solution. To visualize the effect of iteration, we plot the loss trajectory and ASR along with the optimization iterations in Figure 6. We also collect the average model loss of attack instances at each iteration, and then normalize the loss to set the initial loss as 1. Therefore, the loss trajectory visualization reveals the percentage loss drop during the optimization. We consider two different perturbations (replacement and deletion) under concatenation attacks. The attack is optimized with the JO solver.

The three charts on the first row of Figure 6 show that optimizations on all three victim models quickly converge after 4 iterations in our experiment. Accordingly, ASRs rise gradually during the first 4 iterations, but then flattens or even slides afterward. Such results suggest that our solvers can find the convergence in just a few iterations. Therefore, it makes our attack computationally effective, and insensitive to hyperparameter of iteration number.

## D Regularization on Attack Loss.

The experiment results reported in the main text are generated with the sparsity regularization. We

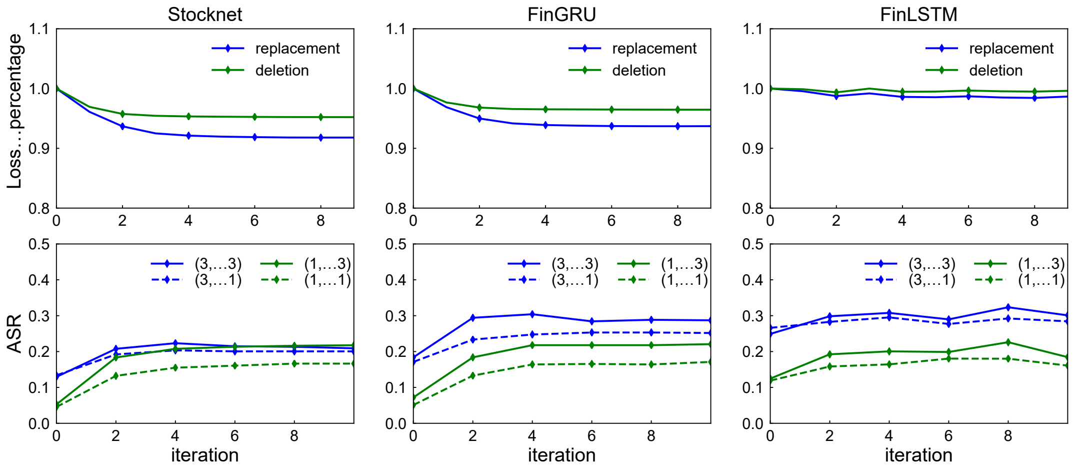

Figure 6: Iteration number effect on prediction loss and attack success rate. The three plots on the first row show the loss trajectory during optimization for the three victim models, and the bottom row reports the ASRs trajectory. The legends for the bottom-row charts read as (tweet budget, word budget).

also run ablation experiments that remove sparsity regularization. The results are consistent with our conclusion. Furthermore, inspired by (Srikant et al., 2021), we try smoothing attack loss to stabilize the optimization. We add Gaussian noise to optimization variables and evaluate the attack 10 times. The loss average is then used as the final loss for backpropagation. The results show that loss smoothing does not contribute to attack performance in our experiment as it does in Srikant et al. (2021).

## E Attack Word Analysis

To qualitatively understand what kinds of words and tweets are being selected in the perturbation and retweet, we compare our tweet corpus and the selected word replacements with 15 corpora of different genres in Brown corpus via Linguistic Inquiry and Word Count program (LIWC) (Tausczik and Pennebaker, 2010). As Brown corpus does not have a financial genre, we also use Financial Phrase Bank (Malo et al., 2014). We then run K-means clustering on these 18 corpora based on the feature matrix from LIWC. As shown in Figure 7, financial corpora (red), Brown general word corpus (green), and attack words (blue) are grouped into three clusters, indicating the inherent difference of those text genres. Moreover, we observe that target words identified by our solvers (red “tweet” and blue “attack words” dots) are closer to financial corpora than “random attack words”.

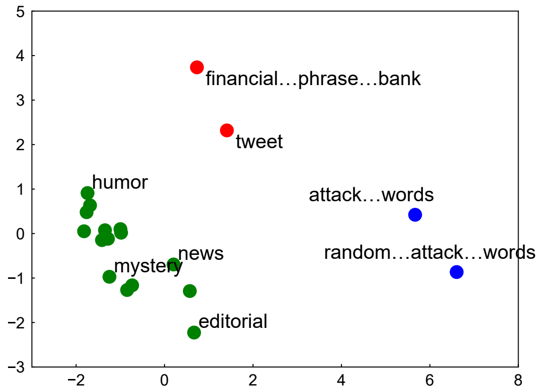

Figure 7: Corpora clusters. 18 corpora are grouped into 3 clusters based on features from LIWC. In order to visualize the clusters, principal component analysis is applied to the features to find the first 2 principal components, which are then used as x-axis and y-axis to generate this figure.

## F Example of Adversarial Retweet

Table 3 reports 10 adversarial retweets generated in concatenation attack mode with JO and AGO solver and replacement perturbation. For all the examples, the victim model predicts positive outcomes originally, and but predicts negative outcomes after adding the adversarial retweet.

| **Adversarial Retweets Generated by AGO** |
|---|
| **Benign tweet:** $BHP announces the demerger of its non-core assets - details expected to be filled in on Tuesday.<br>**Adversarial retweet:** $BHP announces the demerger of its non-core assets - details expected to be exercised in on Tuesday |
| **Benign tweet:** Mover and Shakers... Losers- $KO $ABX $DD. Winners- $LAND $CHL $BHP.<br>**Adversarial retweet:** Shoulder and Shakers... Losers- $KO $ABX $DD. Winners- $LAND $CHL $BHP. |
| **Benign tweet:** Latest information on #stocks like $TDS $DIS $CPWR $BLOX Give it a try.<br>**Adversarial retweet:** Latest advance on #stocks like $TDS $DIS $CPWR $BLOX Give it a try. |
| **Benign tweet:** Top Buy Stocks for July 29: $AMX, $EXC, $NLY, $ORCL, $XRX.<br>**Adversarial retweet:** Top unsettled Stocks for July 29: $AMX, $EXC, $NLY, $ORCL, $XRX. |
| **Benign tweet:** $JKHY #Stocks you might want to buy $HRS $SRCL $PCLN #singedinvestor.<br>**Adversarial retweet:** $JKHY #Stocks you might confirm to buy $HRS $SRCL $PCLN #singedinvestor. |
| **Adversarial Retweets Generated by JO** |
| **Benign tweet:** #Stocks you migh want to Sell $CERN $CAT $PX $DO Try this http://t.co/95PUim108L.<br>**Adversarial retweet:** #Stocks you migh announce to Sell $CERN $CAT $PX $DO Try this http://t.co/95PUim108L. |
| **Benign tweet:** The Most Accurate Stock Alert Service Made $240,000 Yesterday http://t.co/8WvnrVmkBS .. $SNY $SO $SOL.<br>**Adversarial retweet:** The Most Accurate Stock preserving Service Made $240,000 Yesterday http://t.co/8WvnrVmkBS .. $SNY $SO $SOL. |
| **Benign tweet:** Is it breakout time on $HON $CF $LEG $IBM Give it a try.<br>**Adversarial retweet:** Is it appealing time on $HON $CF $LEG $IBM Give it a try. |
| **Benign tweet:** Latest information on #stocks like $PETM $UTX $BRCD $CI #moneymanagement.<br>**Adversarial retweet:** Latest discovery on #stocks like $PETM $UTX $BRCD $CI #moneymanagement. |
| **Benign tweet:** $BABA actually showing signs of life...would love a move back toward 90 although seems unlikely at moment.<br>**Adversarial retweet:** $BABA actually showing signs of life...would love a move back toward 90 although seems unlikely at playday. |

Table 3: Ten examples of adversarial retweets generated by the concatenation attack