Copycats vs. Original NFTs Detection: A Design Science Approach

Feiyu E
Faculty of Business and Economics, The University of Hong Kong & Southern University of Science and Technology
u3005658@connect.hku.hk

Huilin Gao
Faculty of Business and Economics, The University of Hong Kong
hlgao@connect.hku.hk

Michael Chau
Faculty of Business and Economics, The University of Hong Kong
mchau@business.hku.hk

Abstract

Non-fungible tokens (NFTs) make trading digitalized artworks online possible and creates great opportunities in the artwork markets. Besides the extraordinary wealth it has created, the NFT trading market also brings many issues, such as intellectual property protection. Although there are a large number of transactions every day in the NFT market, there is no effective platform mechanism to avoid copycat behaviors. In this paper, we propose an NFT copycat detection and investigation framework. Besides, we propose to examine the effect of copycats on the price of the original NFTs. The proposed study contributes to the literature on NFT management and NFT copyright, and also helps NFT developers to protect their rights and benefits and helps NFT platforms to avoid potential legal issues.

Keywords: non-fungible tokens, copycats, intellectual property protection, text and image analysis, NFT pricing.

1. Introduction

Non-fungible token (NFT) has emerged as a digital asset ownership certificate based on blockchain technology. The concept was first proposed by Dieter Shirley, the founder of the first world-famous blockchain game CryptoKitties. In this game, players can have virtual cats, and each cat has a unique look and biography. The uniqueness of these digital cats then inspired people to transfer other works as digital NFTs, which could be text, a video, a photograph, or anything that could be digitalized. After a digital asset is converted to an NFT, it is permanently stored on a cryptographic blockchain that is unique and immutable.

According to reports from nonfungible.com, the trading volume of NFTs in 2021 reached $17.6 billion, which was 210 times of the $82 million in 2020. Also in 2021, there were more than 25 million total active wallets, and the total profit was up to $54 billion in the NFT market. Two features contribute to the booming of the NFT market. First, compared with traditional centralized trading institutions, NFTs enable decentralized authentication and trading of assets. This makes it easier for people to create and trade NFT products. Second, owing to the advantage of blockchain technology, every NFT is unique. The ensured authenticity and ownership encourage people to trade on the market. The digital painting "*Everydays: The First 5000 Days*" by artist Beeple were made into an NFT that was finally sold for $69.34 million.[1] Jack Dorsey, Twitter CEO, made his first tweet as an NFT and it was sold for $2.9 million.[2] The incredible trading prices of the painting and the tweet have become a starting point for NFT to attract media attention and discussion.

The shortcomings and problems of NFTs are also exposed during the intense discussions. Although blockchains can protect each NFT as unique and immutable, they cannot offer protection to the art piece itself. According to Wang et al. (2021), the appearance of a graph-based NFT is easy to be copied by adding a frame or changing a small detail, which is a big challenge for property rights protection. For instance, after the sale of "*Everydays: The First 5000 Days*", it was cut into 105 pieces and sold on the NFT platform again. Both the original creator and others can create an NFT copycat as the publication access is limitless and the cost of a change on the graphics is low. This copying behavior is often not recognized by the platform and there are no regulations protecting artworks that were transferred to NFTs for sale so far. NFT platforms have become an infringing site for authors' works. It is

[1] The Verge, 2021. "Beeple sold an NFT for $69 million". https://www.theverge.com/2021/3/11/22325054/beeple-christies-nft-sale-cost-everydays-69-million. Accessed 15th June, 2022.

[2] Forbes, 2022. "'Jack Dorsey's First Tweet' $2.9 Million NFT Gets $277 Bid At Auction". https://www.forbes.com/sites/ronshevlin/2022/04/14/jack-dorseys-first-tweet-29-million-nft-gets-277-bid-at-auction/?sh=489be81256b9. Accessed 15th June, 2022.

URI: https://hdl.handle.net/10125/103184
978-0-9981331-6-4

desirable for NFT platforms to develop an investigation process before accepting artworks as NFTs to avoid these copycat behaviors.

To address the authenticity problems, some platforms took steps to prevent copycat behavior and reduce copyright issues and potential financial loss. For example, rarible.com only allows verified creators and collectors to list items for sale. This is safe enough but limits the growth of the market. OpenSea applies image recognition technology with the dedicate human review process to prevent and eliminate the existence of 'Copymints'.[3] This practice can recognize the flips, rotations and other permutations but it is still less likely to identify more complicated counterfeit NFTs.

Figure 1. Example of 'Copymints' on OpenSea[3]

Our research aims to not only protect developers' and NFT platforms' copyright but also help to keep developers' financial interests unaffected. Therefore, we also examine the impact of copycat NFTs on the price of original NFTs using archival data. To address the problems brought by NFT copycats and help the regulation of the market, this study proposes to develop an NFT copycat detection and investigation model. Our paper mainly focuses on detecting and investigating the copycat behavior of photography, painting, and digital paintings through text analysis and image analysis.

The contribution of this study is two-fold. Firstly, we propose an investigation framework as an early opportunity to detect copycat behavior before artworks are published on NFT markets. The investigation process protects developers' intellectual property right by avoiding copycat works entering the market; the process can also reduce the probability of NFT platforms being caught or sued in criminal cases. Secondly, we contribute to the literature on the price of original NFTs and copycat behavior by examining how copycat behaviors affect the price of the original NFTs.

2. Related Literature

Painting plagiarism often refers to copying or reusing the content and style of existing works (Wang, 2021). Frequent examples of painting plagiarism include adjusting the color, angle, size, shape, and relative position of the main content in the painting and rebuilding other objects using the main content of existing works. In our proposed paper, we define copycats of original NFTs as NFTs that were copied, reused, or adjusted based on existing works published in the NFT markets. We define original NFTs as works that were published in the NFT market.

2.1. NFT and copycat

NFT is a type of cryptocurrency (Wang et al., 2021). Unlike Bitcoins, of which every coin is equivalent, every NFT is unique and cannot be exchanged equivalently. This property of NFT makes it possible to identify something or someone in a unique way. One of the most common types of NFT is metafiles containing information about the digital version of an artwork that is tokenized. To be specific, at its very core, NFT is a piece of code that is written onto the blockchain. The code consists of two parts: tokenID, which is generated upon the creation of the token; and contract address, which is a blockchain address (just like the addresses of other cryptocurrencies). In most cases, the address to access the original art piece is also included in the metafile. The trading of an NFT is basically trading of a contract code, and everyone can access the original files.

The lucrative and accessible nature of NFTs has led to the growth of copycats. For example, *We are All Going to Die*, which is an NFT project with over 14,000 followers, has been found copying a published art—Magic the Gathering (Figure 2.). Instead of flipping, rotating, or embedding the original NFTs, this kind of imitative NFT is hardly recognized by the preliminary image recognition practice that is applied by platforms like Openea. Although there is also human screening after machine filtering, it is still taking a lot of resources to identify such cases. Another recent story that shocked the NFT world is about a 12-year-old programmer named Benyamin Ahmed. He published 3,350 computer-generated "*Weird Whales*" NFTs[4] which were instantly sold out and the price of them hyped to $6,000 within a few hours based on the heartwarming story it told. However, it was found to be directly copied from another project named "*Pixel Whales*".[5] Until

[3] OpenSea. https://opensea.io/blog/announcements/
[4] Weird Whales. https://weirdwhalesnft.com/
[5] Pixel Whales. https://pixelwhales.com/

now, it is still unclear whether this issue constitutes intellectual property theft.

Pungila's study provides a solution for the detection of NFT copycats using approximate pattern matching on the blockchain sequential data (Pungila et al., 2022). Using a modified digital text mining technology to identify the originality of the NFT. Can the piece of code represent the real piece of art and protect its copyright? As mentioned, although platforms such as rarible.com set strict verification processes for market entry, this issue is hardly noticed or well addressed by many NFT platforms without restricting the growth and liquidity of the market. To our best knowledge, there is not a uniform standard or regulation on protecting the copyright of NFTs so far and we can see copycat behavior running wild on the NFT market. Although the original idea of the NFT platform is to protect NFTs, there is little or no copyright created (Okonkwo, 2021). Most of the copyright issues were "solved" by simply removing the tokens involved. As there is no formal regulation to protect developers' copyright of their artworks, we propose an investigation process to offer an early opportunity to prevent the publication of NFT copycats to protect developers' copyright in the first place.

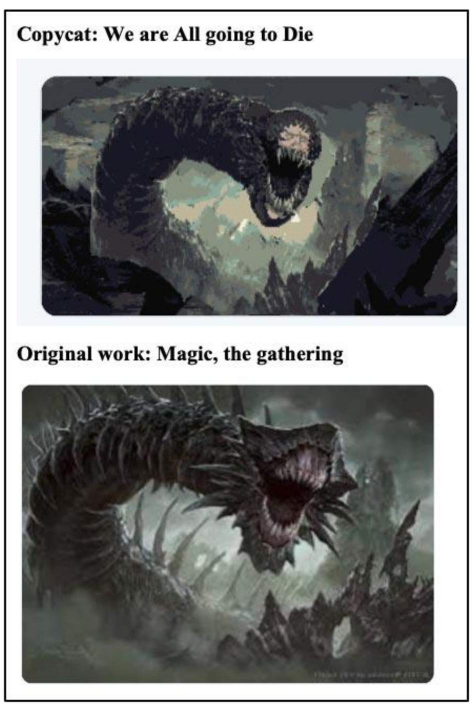

Figure 2. Sophisticated Copycat Example

2.2. NFT platforms and copyright

Transferring artworks to NFTs gives artworks a unique identity, and publishing NFTs on NFT platforms gives NFTs or artworks an opportunity to be traded online and digitally. Are the NFT platforms responsible for copyright infringement? Copyright infringement occurs when a person who is not the owner (or author) of a work exercises the reserved rights of the owner. According to the Agreement on Trade-Related Aspects of Intellectual Property Rights (TRIPS) (Cottier, 2005), these reserved rights include the right to translate, right to reproduction, broadcasting right, and right to perform the work publicly, and right to adaption, etc. According to Okonkwo's work on NFT and Copyright (2021), an NFT platform is responsible for copyright infringement. It describes the NFT platform as:

> *"An NFT platform that uses itself as a platform for exhibiting, possessing, communicating, publishing, distributing, renting, or selling infringing copies becomes liable for copyright infringement. Where its actions relate to (i) possessing in the course of business; (ii) selling or letting for hire or exposing for sale or hire; (iii) exhibiting in public or distributing in the course of business; (iv) distributing otherwise than in the course of business to such an extent as to affect prejudicially the owner of the copyright; and (iv) importing, then, such NFT platform owner will be liable as a secondary infringer, unless intermediary immunity applies."*

Agreements like TRIPS and the Berne Convention for the Protection of Literary and Artistic Works Intellectual Property (Berne Convention) are similar in most countries. We can see many court cases listed online about copyright responsibility from all over the world. For example, in China's first NFT copycat case, which is related to the cartoon artwork by artist Qianlin Ma, the court decided that the platform is liable since it failed to check whether the user who created the NFT was the rightful owner of the artwork.[6] Therefore, for the platform itself, implementing and processing the investigation is necessary.

2.3. Copycats and price of original NFT

Besides the copyright issue, the impact on the price of the original pieces may be another important concern

[6] South China Morning Post, 2022, "China rules NFT marketplace accountable for art theft by user". https://www.scmp.com/tech/tech-trends/article/3175457/chinas-first-court-ruling-nft-art-theft-holds-marketplace. Accessed 15th June, 2022.

for copycats. Original NFTs do not always enjoy the first-mover advantage as they are not protected by proper regulations or involved technology (Lee and Mendelson 2007). Copycats can easily beat original NFTs from a financial perspective by utilizing a good marketing strategy. In the above-mentioned "Weird Whale" example, the copycat branded each different whale in the collection with a heartwarming story, earning the project huge media attention, which in turn hyped the trading price of the copycat whale collection.

2.3.1. Market seizing effect. For a better illustration of the effects of copycats on the price of the original NFTs, we consider two types of investors in the market. Type I investors know the existence of the original NFTs; type II investors do not know the existence of the original NFTs.

We propose that the market seizing effect happens when a copycat substitutes or seizes the market of the original NFTs. For type I investors, when they are exposed to the media storm of the copycat NFTs, they may perceive the copycat NFTs as the original ones and invest in the copycat instead, which substitutes the market of the original NFTs (Wang et al., 2018). Seizing the market of the original NFTs may also happen to type I investors. Investors often trade NFTs as financial assets instead of art collections (Kong & Lin, 2021). Therefore, even if type I investors know the one attracting media attention is a copycat, they may still choose to invest because of the high return. For type II investors, the possibility of substituting and seizing the original NFTs' market is even larger since they do not know the copycat behavior in the first place. The fact that they are caught by the media storm of copycat leads to the market seizing effect of the original NFTs.

2.3.2. Promotional effect. For type I investors, the media attention caught by the copycat may lead them to realize the value of the original NFTs. Some of them may trust or even play the finance trading strategy—buy low and sell high. They may believe that after the media realize the copycat behavior, the price of the original piece may rise. For type II investors, the media attention may lead them to explore more NFTs of the same style and discover the original NFTs, They may then play the same finance trading strategy.

The market seizing effect and promotional effect may offset each other. The market seizing effect suggest that the market of the original NFTs may be seized by the copycat, which leads to a drop in the price of the original NFTs, while the promotional effect may lead to a price increase. It is interesting to examine which effect is larger.

3. Detection/investigation Framework

To detect the NFT copycats, we use a design science approach (Hevner et al., 2004) and propose an NFT copycats detection framework based on textual features (including unstructured textual descriptions and structured textual properties) and appearance of NFT collections. Because the textual description is in the collection level and the images in one collection have the same style in general, our design aims to detect copycats at the collection level. As the majority of NFTs on the market are image-based, we only focus on image-based NFTs in the current stage. In this section, we describe the dataset we are going to collect and the algorithm-based design.

3.1. Data

With the growth of the NFT market, different categories of NFTs emerge, including image-based art and music. For each collection, there are textual descriptions and featured images on the collection page such as items and activities. Our research is designed for general NFT trading platforms covering image-based artwork, such as OpenSea.

Inspired by the research by Wang et al. (2018), in our design, the textual description, properties, and images of collections will be crawled. We plan to crawl all the non-empty collections as our initial dataset.

3.2. Experimental design

To identify copycats, we propose a machine learning-based NFT copycats detection model by analyzing the textual and image information. Using this model, the copycats can be detected and the similarity level of copycats to the original will be assessed to help the platform administrators or users to determine the value of the copycats. The steps of the framework are introduced in this session. The framework details are shown in Figure 3 and the algorithms are shown in Table 1.

3.2.1. Crawling data. Since many NFT trading platforms are public, registered users can publish NFTs, create new collections, and trade NFTs. However, there are many NFTs without proper descriptions and qualified logos, and also NFTs published by unknown developers. These NFTs can hardly attract investors. The majority of popular NFTs with a large number of transactions are in collections. NFTs from the same collection have a similar appearance. Therefore, if we conduct copycat detection based on single NFTs, there will be many "copycats" from the same collection by the same developer. However, even though two NFTs in the same collection may be highly similar in appearance, it is not plagiarism because they are from the same collection by the same developer. To avoid this issue and to use the textual information in the collection page in NFT copycat detection, we crawl the data on a collection basis.

From the collection page, the unstructured description and featured image will be crawled to cluster similar NFT collections. The earliest listing time in the activity session will also be crawled to help in the original NFT identification step.

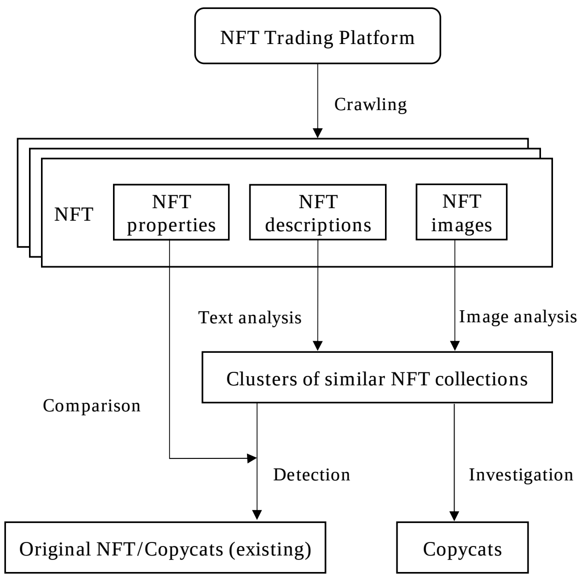

Figure 3. Copycat NFTs detection framework.

	Algorithms	Process
Text analysis	TF-IDF	1. Stemming
	BERT	2. Representation
		3. Cosine similarity
Image analysis	dHash	1. Downsizing
		2. Gray processing
		3. Hamming distance
	SIFT	-

Table 1. Algorithms and processing steps.

3.2.2. Similarity detection based on text analysis on unstructured NFT description. The aim of this step is to use NFT's collection description to bring similar collections together through natural language processing (NLP). Similar descriptions indicate that these collections may have similar NFTs or even plagiarism. Different from the detection of similarity from the ”inside” blockchain digital codes in existing research, we use the term frequency-inverse document frequency (TF-IDF) and Bidirectional Encoder Representation from Transformers (BERT) to represent the textual information from the ”outside” creator presented description and cluster the potentially similar (original and copycats) collection groups by the descriptions.

A word frequently appearing in a description means it conveys more important information. TF-IDF (Salton & McGill, 1983) measures how important a word is to a document. It is commonly used in text analysis research (Bauman & Tuzhilin, 2018; Dong et al., 2018; Hou & Lu, 2020; Wang et al., 2018). Term frequency measures the frequency of a word in the document while inverse document frequency measures the semantic importance. Thus, the first step is to transform the descriptions into a bag of words. After tokenization and removing stop words, descriptions are represented by vectors. After that, cosine similarity is calculated.

In addition to the above intuitive similarity calculation method, we will also use word embedding algorithms that have emerged in recent years. BERT (Devlin et al., 2018), one of the most effective deep learning NLP algorithms proposed by Google AI, exhibits a strong ability on embedding of word semantics to condense vectors. It is designed for bidirectional representations of unlabeled texts. Because of its outstanding performance, we also adopt BERT for the text representation in the text similarity detection method.

3.2.3. Similarity detection based on image analysis on collection featured images. To detect the copycats that use duplicitous collection featured images, we will conduct image analysis to match the NFT collections with a similar featured image.

Perceptual hash algorithms are traditionally used in the recognition of similar images. It generates a fingerprint for each image and compares the fingerprints of different images. The closer the results, the more similar the images are. DHash algorithm can identify similar pictures in a short time with high accuracy. First, the image needs to be rescaled to reduce the pixels to a fixed level. Dhash is then calculated separately for each image. Hamming distance is calculated by the DHash values of every image pair to obtain similar image groups.

Nowadays, however, image copying is not limited to pixel changes. Many images are rotated, scaled, or even embedded into other images. Therefore, we need algorithms that can recognize similar images under more complex situations. Scale-invariant Feature Transform (SIFT) (Lowe, 1999) is a computer vision algorithm that can be used to detect and describe specific local features in images. It looks for extreme points in spatial scale and extracts their position, scale, and rotation invariants. Besides, it also has a high tolerance for light, noise, and slight changes in perspective. Thus, the SIFT algorithm will also be used in this framework to identify similar images.

3.2.4. Distinguish original NFTs and copycats by considering structured NFT properties. After the above text analysis and image analysis, similar collections will be clustered. For existing NFTs, the earliest listing time will be compared to determine the original NFT collection in every cluster by labeling the earliest listed one. Thus, the other NFTs are possibly copycats. For investigation purposes, if an NFT collection featured image is similar to that of another existing collection or the collection description is similar to that of an existing one, then it is a potential copycat.

4. Empirical Model

As discussed earlier, we propose an empirical model to examine how copycats affect the price of the original NFTs.

4.1. Data

We propose to use 10 pairs of original NFTs and copycats for analysis. For each of the original NFTs, we find a control NFT using the propensity score matching method. The control NFT will be matched based on the media attention it received and the price of the original NFT.

4.2. Empirical methods

We propose to use the entry date of the copycat NFT as the cutoff point to examine whether the entry will lead to the price change of the original NFT.

$$P_{it} = \alpha + \beta D_i + \gamma_i + \tau_t + \epsilon_{it}$$

where

D_i specifies whether the copycat is on market,
γ_i is the NFT individual-level fixed effect, and
τ_t is the time fixed effect.

5. Expected Results and Future Work

We expect our proposed copycat detection and investigation framework can reduce the copycat behaviors in NFT markets by providing evidence for NFT originality. By applying our proposed framework, we expect to find the copycats no matter the featured images and descriptions are simple or complex. We also plan to conduct an empirical study to see how copycats will affect the price of the original NFTs.

NFTs give artworks a new way to be traded, but they also brought copyright protection problems. We are among the first to propose methods to avoid copycat behaviors in the NFT market and explore the effects of copycats on prices.

We expect more design science researchers to come up with more novel copycat detection and investigation models to protect developers' interests and the NFT platform's interests. First, since some developers begin to set the NFT featured image to be an animated GIF, future work could focus on GIFs and even music-related NFT copycat detection. Second, researchers could explore copycat detection on the NFT level instead of the collection level by controlling the similarity degree. Third, some NFTs on platforms like OpenSea provide links to their social media accounts. It is possible that multimedia data is useful in copycat detection and investigation. Also, future studies may dig more into the mechanism of the effect of copycat on original NFT prices and come up with more insights.

6. Summary

In this study, we aim to conduct NFT copycat detection to help with the copycat investigation before listing. By applying mixed methods—design science and empirical analysis, we propose an early investigation on detecting copycats and how copycats affect the NFT markets. Theoretically, our research adds to the literature on NFT management and virtual property copyright protection by providing a promising copycat investigation framework, and literature on NFT pricing by examining the market seizing effect and promotional effect that copycats brought to original NFT art pieces. Empirically, our work is of great managerial importance by helping platforms detect existing copycats and investigate the originality of newly developed NFTs. The framework also helps developers protect their copyright.

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