‘The Tireless Selling-Machine’ – Commercial Deployment of Social Bots during Black Friday Season on Twitter

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Abstract. In recent years, mainstream E-commerce platforms have changed the way consumer goods are merchandized online. While such platforms increasingly discover social elements to drive sales, social media start implementing E-commerce features themselves. This emerging intersection also provides space for bot activity in a Social Commerce (SC) context, which is sparsely understood. In this short paper, we investigate the deployment of social bots during a large-scale commercial event. To this end, we applied bot detection techniques to the Twitter communication during the 2018 Black Friday season. Using three distinct metrics, we identified 42 bot-like accounts. A manual classification of 11,889 tweets found those bots to be primarily deployed in pre-transactional phases of SC to promote third party products and to initiate external transactions. Our results further suggest adapting detection metrics to event-specific user behavior. Further research aims at the dynamics, impact, and network positions of SC bots.

Keywords: Social Bots, Social Commerce, Social Media, E-Commerce

1 Motivation

The increasing clout of social media entails a shift in how business-to-consumer (B2C) transactions are performed online. Research has shown that promotions or advertisements have a smaller effect than individually shared product information on the buying decisions of users [1]. This underlines the interests of businesses in increasing the visibility and reputation of products or reviews as well as information about services on social media [2]. Consequently, commercial transactions are more often mediated by social media activities [3]. However, customers, as well as companies, encounter spreading social media information about products that might not be true or lead to third party websites. This process could be performed by automated social media accounts, called social bots [4], which “automatically produce content and interact with humans on social media, trying to emulate and possibly alter their behavior” [5, p. 96], and which may as well act as transaction initiators. The fact

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that social bots regularly appear in societal contexts stresses the relevance of related research in a commercial context [6–8]. Special events such as the Black Friday season are exemplars of increased social commerce (SC) activity. The notion of SC, in this regard, is the practice of inducing commercial transactions through online interaction and user contributions [9, 10]. SC is often referred to as a part of e-commerce [11] and comprises a *relational* and a *transactional* dimension. The former covers activities such as promotion, customer support, recruitment, or product development. Transactions in SC, in contrast, have a pre-transactional, transactional, and post-transactional phase [4]. As SC ties together structural elements of both e-commerce and social media [13], the advent of SC activities raises current issues to be addressed in IS research. In order to shed light on underlying strategies and the impact of applied social bots, we designed an explorative case study around the Black Friday event. This research in progress aims to pursue the following research question: *How are social bots deployed during Black Friday season on Twitter?* To explore this matter, we follow a mixed methods approach [14, 15] to investigate the use of social bots during Black Friday season by (1) identifying social bots and (2) analyzing seven days of Twitter communication. Based on three distinct metrics, we identified supposed social bots. Subsequently, we undertook a manual content analysis to classify their activities. This paper marks the starting point of a larger study with the overall goal to examine applied strategies and the influence of social bots on customers' buying behavior on social media.

2 Research Design and Preliminary Findings

This case study builds upon a Twitter dataset collected around the commercial phenomenon of "Black Friday" and the "Cyber Monday Week", respectively. The data was gathered through a self-developed Java crawler using the open source library Twitter4J. Twitter communication covering the period from 19 to 26 November 2018 was collected. To obtain only relevant data, postings containing at least one of the keywords/hashtags *"BlackFriday", "CyberMonday", "BlackFridayDeals", "BlackFriday18", "CyberMonday18", "BlackFridaySale", "BFCM", "BFCM18", "BlackFriday2018",* or *"CyberMonday2018"* were crawled. The tracking yielded a total of 743,193 users responsible for 1,302,509 tweets. We used three metrics for creating a sample of social bots for the manual content analysis: Tweet Uniqueness (TU), Tweet Frequency (TFQ), and Friends-Followers-Ratio (FFR). To analyze accounts which highly contribute to the Black Friday communication, we considered only accounts with at least 100 tweets during the tracking period.

The TU shows the diversity of the content by a user. According to Ross et al. [16], we divided the number of distinct postings by the total number of posts by the user. To this end, tweets are considered distinct if they differ by at least one character. We computed the global TU (0.459) as the threshold for selecting accounts for further manual analysis [16]. The global TU is the number of distinct tweets divided by the total number of extracted tweets (598,052/1,302,509 = 0.459).

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The TFQ measures the activity of a user during the tracking period. Recent research has shown that a high tweet frequency over a short time period indicates a bot-like behavior, e.g. several thousand tweets a month [17, 18]. However, the observed tweet frequency of a social bot can vary depending on the context and event, e.g. near to 100 tweets a month [6]. Thus, due to the increased communication volume during Black Friday, we decided to consider for the TFQ only highly active accounts with 50 or more tweets per day during the tracking period.

The FFR captures the relationship between the number of friends and followers of a single account. Thus, according to Twitters' definition of a friend, user A can add B to its individual friends list by following user B. Former studies already considered the relationship between an accounts' friends and followers for social bot detection by analyzing skewed FFR relations [19]. Thus, a skewed ratio of friends and followers might be an indicator for a bot-like behavior [17]. We took the global mean (3.484) of the FFR as a threshold to identify skewed FFR in relation to the data. Therefore, accounts with a minimum FFR of 3.484 were selected for the manual content analysis. Overall, 42 accounts (14 by TU, 17 by TFQ, and 13 by FFR) were classified as supposed social bots. These users authored a total of 11,889 tweets. In general, users surpassing the threshold of the metrics TU and FFR were more often retweeted than users beyond the threshold of the TFQ. Examining the communication over time revealed two spikes of more frequent bot activity on Black Friday (4,471 tweets) and Cyber Monday (3,138 tweets).

As for the manual content analysis, we conducted an inductive category formation according to Mayring [20]. We employed a category system that classifies the character of each posting. If a hyperlink was included in the posting, we checked the destination and then assigned it to one of the categories. We started with one category and benchmarked each tweet in a chronological order against the criteria of the category. We either assigned the tweet to the existing category or created a new category. After this process, we revised the categories and combined similar concentrations of postings to achieve a clear segregation of categories. The manual classification of these postings was conducted to determine the character of the activities and comply with the taxonomy of SC [12]. Moreover, the classification aims to serve as a basis to derive 1) individual intentions of social bots deployed during Black Friday season, but also 2) strategy patterns that stand out across separate occurrences of social bots. The entire sample was set to be manually coded by each author to ensure inter-coder reliability. Using Krippendorff's alpha, a score of .855 was calculated. Our coding can be rated as reliable as $\alpha \geq .800$. The set of categories is listed in table 1.

Table 1. Classification of social bot activities during Black Friday on Twitter

Category	*Intention*	*Count*	*Percentage*
Advertisement	Direct sales, affiliate sales	8,615	72.5%
@mention	Forwarding to sales page	1,580	13.3%
Giveaway	Engagement, lead generation	1,263	10.6%
Marketing	Awareness (no call to action)	420	3.5%
Sign-up	Lead generation	11	<0.1%

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Our sample revealed that the majority of social bot activities is driven by the intention of placing a call to action in front of as many users as possible. This may be the encouragement to perform in certain discount promotions, redeem bonuses, or sign up for paid services. Those calls to action, in the vast majority of cases, lead to external web pages where the action is intended to be performed. This may include mainstream e-commerce platforms as well as third party niche sites. A multitude of bots provided affiliate links that promote products listed on an external e-commerce platform. These are custom URLs that allow the platform to track which specific advertisement led to a visit to their website, e.g. "*Xbox Game Pass, PlayStation Now 12-Month Renewals From $69 - Amazon Black Friday 2018 Deals *URL* #blackfriday"*. In case of a purchase, the advertiser is paid a commission. This leads to the conclusion that in those cases, social bots are used to step in as self-sufficient middlemen to drive sales, not intended by the e-commerce vendor. Another observable pattern is that bots participate in raffle prize competitions. Here, Twitter users are asked to retweet or like a specific post, e.g. *"Follow our page and retweet our pinned tweet for your chance to #WIN a £100 Amazon #voucher this #CyberMonday!"* Social bots retweeting postings that include keywords such as *giveaway* or *competition* on a massive scale increase the chances of winning money or material prizes for their creator. The category *marketing* differs from the other advertisements as there is no link or direct call to action when promoting a brand, product, or service. The *@mention* category primarily congregates user-directed tweets promoting products and services as an automated public message after a specific action of a human user. In this case, automated @mentions were sent out to users that started following the sending account: *"@username: Thanks for following us, in the meantime view our Professional Designs Here: *URL* #BlackFridayDeals"*.

3 Conclusion and Further Steps

The present study exploratively approached the use and impact of social bots in an SC context. The results of manually coding 11,889 tweets suggest that social bots are primarily deployed in the pre-transactional phase of the SC process. Their main objectives tend to be the promotion of products and services and the initiation of sales external to the social media platform. A shift from human-human relations to bot-to-human communication in SC is not only emerging in customer support, where it is often emphasized. While social bot deployment for promotional purposes might be perceived as some kind of gray hat activity, increasing acceptance of social bots as valid promotional tools can be anticipated and should be subject to an extended version of this study and affiliated IS research. With the results of this study, practitioners can both mimic successful approaches of third-party agents and, at the same time, drive innovation in their industry by pursuing the implementation of original automated promotional agents. Our results are limited to the circumstances of the Black Friday.

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In future research, we will expand this study and conduct social network analyses to identify relationships between social bot accounts and human users. Moreover, we aim to uncover the dynamics of SC communication in social media concerning pre- and post-transactional SC activities in the course of an SC event. We further intend to expand our dataset to other commercial contexts and an extended period of time to gain more insights about social bot usage in SC settings outside of promotional events.

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