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Detection of Spammers in Twitter marketing: A Hybrid Approach Using Social Media Analytics and Bio Inspired Computing

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Abstract Customer engagement is drastically improved through Web 2.0 technologies, especially social media platforms like Twitter. These platforms are often used by organizations for marketing, of which creation of numerous spam profiles for content promotion is common. The present paper proposes a hybrid approach for identifying the spam profiles by combining social media analytics and bio inspired computing. It adopts a modified K-Means integrated Levy flight Firefly Algorithm (LFA) with chaotic maps as an extension to Firefly Algorithm (FA) for spam detection in Twitter marketing. A total of 18,44,701 tweets have been analyzed from 14,235 Twitter profiles on 13 statistically significant factors derived from social media analytics. A Fuzzy C-Means Clustering approach is further used to identify the overlapping users in two clusters of spammers and non-spammers. Six variants of K-Means integrated FA including chaotic maps and levy flights are tested. The findings indicate that FA with chaos for tuning attractiveness coefficient using Gauss Map converges to a working solution the fastest. Further, LFA with chaos for tuning the absorption coefficient using sinusoidal map outperforms the rest of the approaches in terms of accuracy.

Keywords Spam detection · Twitter analytics · Social media analytics · Firefly algorithm · Bio inspired computing · Machine learning

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1 Introduction

Use of social media platforms like Twitter, Facebook, YouTube, Instagram and LinkedIn etc. is indispensable for information diffusion in the current world (Kaplan and Haenlein 2010; Lenhart et al. 2010; Mui and Whoriskey 2010). The platforms are being used by the people for communicating their opinions, experiences and ideas and are faster than traditional media in diffusion of information (Bakshy et al. 2012). Following individual users, organizations and businesses are also present in the platforms to connect with different stakeholders. The profiles of businesses are predominantly for content promotion and knowledge dissemination surrounding products and services, making the social media platforms the backbone of digital marketing. The social media presence is utilized to promote the content to a larger audience (Hanna et al. 2011). Needless to say that platforms are now flooded with information from various sources by multiple organizations competing for the users' attention (Romero et al. 2011).

Among the social platforms, Twitter is one of the fasting growing micro blogging platforms that helps people communicate and share their opinion using short messages (Huberman et al. 2008). The extant knowledge highlights that about 54% of the Fortune 50 organizations have Twitter account and 37% of these have multiple profiles. Further, 85% of these organizations use Twitter for news dissemination (Case and King 2011). When compared among social media platforms, Twitter has the highest usage for business (78%), followed by LinkedIn (74%), and Facebook (44%) (Go and You 2016). These high usage statistics of Twitter by businesses and organizations pose greater risk of spams. Twitter by itself uses verified accounts for profiles of various celebrities, political figures and organizations but it is only 0.061% of all Twitter accounts. Thus, the majority of profiles are not

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verified and many such profiles may also be spam or fake, created just for content sharing and promotion in the digital space. These profiles and pages constantly compete to get user attention for marketing their content (Kwak et al. 2010).

To leverage the power of social media, organizations are resorting to ways for increasing their follower base. A large follower base is a measure of one being a dominant player or influencer in the relevant domain. Users often consider it as an indication of authenticity and popularity. Organizations have thus started creating spam profiles in order to artificially boost their follower, retweet and like counts. Studies highlight that about 33% of Twitter and 44% of Facebook profiles are fake (for instance Taylor 2012). New York Times reports that fake Twitter followers have recently become a multimillion dollar business as there are companies that sell followers to organizations in need of greater visibility (Perlroth 2013). Organizations and small business owners are paying hefty amounts for getting a large list of artificial followers to portray a stable social image to the potential customers (Hockenson 2012; Ritson 2013).

Businesses have adopted automated mechanisms of promotion for greater reach in the virtual world and subsequent worldwide visibility of the content. This is done using software applications which spam the social media platforms by posting content in an automated manner. Earlier studies share concerns surrounding how these spam profiles prove to be detrimental for the customers if misleading information is propagated (Chu et al. 2012; Cresci et al. 2015; Fire et al. 2014). The present paper attempts a mechanism to identify content spam, and the profiles that engage in the spamming process. Over 1.8 million (18,44,701) tweets have been used in the study from over 14,235 Twitter users for testing and validating the proposed hybrid approach. A mixed research methodology has been adopted in this study based on social media analytics and bio-inspired computing.

2 Literature Review

2.1 Importance of Social Media

Social media platforms are perfect mix of content that is propagated and channels through which it is done as a result of engagement between individuals and businesses (Kietzmann et al. 2011). The platforms are made up of user generated content (UGC) Kaplan and Haenlein (2010). As UGC, people share about their personal, social and professional experiences including the events around the globe, the products they buy and the services they use. Social media platforms are becoming one of the primary channels for information diffusion (Li et al. 2015) and have significant impact on the masses (O'Keeffe and Clarke-Pearson 2011). They modify the way users perceive and react to the information around them and prevalent in all spheres including marketing, finance, healthcare, e-commerce, e-governance, politics and tourism etc. (De Vries et al. 2012; Denecke and Nejdl 2009; Nielsen and Schrøder 2014; Shirky 2011; Vance et al. 2009; Xiang and Gretzel 2010).

Social media platforms act as channel through which communication and engagement are feasible with different stakeholders (Gil de Zúñiga et al. 2012; Idemudia et al. 2016; Mangold and Faulds 2009) apart from being heavily used for knowledge integration (Awal and Bharadwaj 2017; Cao et al. 2015). Due to enormous information and content availability, platforms are able to directly influence the user behavior (Myers et al. 2012) and their business value is recognized (Nagle and Pope 2013). Social media platforms are increasingly identified as sources to provide insights and impact peoples' opinion in business and government sectors (Baur 2017; Rosenberger et al. 2017; Swain and Cao 2017). They have overtaken the portals as dominant source of information online (Bradley 2010) and are making businesses compete with each other for customer attention (Safko 2010). Social media platforms are also emerging as important tools in market research, especially to identify the industry practices (Aswani et al. 2017d; Joseph et al. 2017; Patino et al. 2012), apart from marketing (Dickey and Lewis 2010; Gallaugher and Ransbotham 2010). Social media can also give insights into analyzing the user-generated content for product co-creation (Rathore et al. 2016), for identification of divers that make the shared content popular among users (Aswani et al. 2017d) and subsequently create buzz (Aswani et al. 2017b). Studies also highlight potential opportunities and threats that organizations need to understand about the changing dynamics of creative customer market, Web 2.0 and social media that directly impact their activity, visibility and value in the digital space (Berthon et al. 2012). Further, the diffusion of deception is also another area of concern (Vishwanath 2015), since there exist several trust and distrust models in such social networks (Ziegler and Lausen 2005).

2.2 Social Media Marketing

With the high social media penetrations, information about products and services is also populated from the marketplace itself in the form of user experiences (Mangold and Faulds 2009). The value and brand equity of the businesses are being measured by social media related metrics like engagement, interaction, trendiness, customization, and word of mouth (Kim and Ko 2012). This has resulted in enhanced efforts and strategies within marketing campaigns to incorporate social media related applications into their plans (Thackeray et al. 2008). Along with UGC, now marketer generated content (MGC) is also part of the social media marketing strategies (Goh et al. 2013).

As social media marketing greatly affects brand loyalty of customers and how they perceive a particular brand (Erdoğmuş and Cicek 2012), firms are increasingly keen on enhancing their presence on social media by leveraging the greater impact, user experiences and direct two way interaction with the consumers (Lipsman et al. 2012). This also amplified by declining return on investment in traditional media, technological advancements, demographic shifts including young target customers, shifting customer preference and low cost marketing campaigns (Gillin and Moore 2009). In the light of above, one observes brand strategies specifically conceived and executed for social media (Tsimonis and Dimitriadis 2014).

Social media marketing is changing the way organizations are promoting their products/services (De Vries et al. 2012; Plume et al. 2016) and is helpful in winning the trust of consumers by connecting at a personal level (Neti 2011). However, organizations are looking for short cuts in this race to grab customer attention by automated marketing and promotion by spamming social media platforms without actually connecting to them. Platforms like Facebook and Twitter contain plethora of spam profiles deployed by promoters to attract users to their offerings (Zhang et al. 2012). A lot of this artificially boosted content may even be misleading and may have negative impact on the opinion of the masses (Castillo et al. 2011). There are other issues like unethical outsourcing for generating UGC, spamming and promotion of fake content in the name of campaigns (Aswani et al. 2018). These make the exploration of social media spam even more important and worthy of investigation.

2.3 Spam Detection in Social Media

With rise of social media platforms for marketing, there is also rise of social networking spam (Brown et al. 2008). The spammers create profiles on social media platforms to promote commercial advertisements. Since, not all organizations have a stable brand image and popularity among the consumers, some of them resort to ways to artificially boost the same. One of the ways is to share and re-tweet same content over and over again till it reaches a larger audience. This is usually done through automated mechanisms and bots where in the same promotional tweet, often comprising of a URL is re-shared using tools like HootSuite, TweetCaster and similar applications.

With rise of Twitter as a marketing platform for organization, promotional spamming has also increased exponentially. Since Twitter is a micro-blogging platform and the tweet length is restricted to 140 characters, spammers usually use embedded URLs for promoting their content. Literature highlights several existing approaches for detecting spammers including spam identification and subsequent filtering schemes based on the profile features like content similarity, profile's age and the ratio of URLs (Please see Table 1).

Since spammers can easily mimic being authentic users by switching between posting spam and original content, user attributes based approaches are often not very accurate while detecting them. The current study not only comprises of user and descriptive statistics considered in the existing approaches but also mines social media data for semantics and content metrics before modeling the same. A deeper understanding of the semantics (meaning of the content within tweets) appear to be useful to allocate spam scores. Our study uses a set of factors based on both user and content including descriptive and semantic metrics to identify spam profiles that use Twitter for social media marketing. Prior studies have not used semantic metrics which are necessary to infer generalizable meaning out of the content of the tweets. Factors derived out of tweet content like lexical diversity, hashtag diversity, emotion diversity, polarity diversity and topic modeling are appropriate to gauge the personalized intent behind the content that is subsequently posted through a profile, which has been used in the current study.

Further, the existing literature uses traditional machine learning approaches for modeling the selected metrics, in which rich social media content might become computationally intensive. Also, when the amount of data increases the time complexity of the above approaches increases exponentially. Thus, in situations where data are of large volume, variety and veracity, newer meta-heuristic approaches come in handy (Kar 2016; Chakraborty and Kar 2017). Here, the entire solution space of the problem domain is often broken down into segregated spaces and searched partially to obtain generalizable rules which provide usable outcomes within limited time for very complex multi-dimensional problems. These bio-inspired computing algorithms based approaches appear to reduce the time to converge to an optimum search solution for multi-dimensional, non-deterministic, polynomial-time hard problems. The subsequent section describes the bio-inspired approach adopted in this study to model the identified metrics derived out of social media analytics to identify spammers in Twitter.

3 Research Methodology

The study had used statistical similarity analysis to finalize significant metrics and followed it by detecting outlier spam profiles using the identified metrics. Bio inspired computing algorithms were used for modeling the identified factors to classify the dataset into spammers and non-spammers. Meta-heuristic approaches were used since the data are large in size comprising of unstructured UGC.

A total of 18,44,701 tweets from 14,235 Twitter users were used for the analysis. These users were extracted from Twitter using "twitteR" package and API through R, based on all those

Table 1 Overview of existing spam detection approaches in social media

Authors	Metrics and features	Techniques and algorithms
Platform: Twitter		
Wang et al. (2015)	User features: length of profile name, profile description, number of followers, following, number of tweets, account age, number of tweets posted per day, per week, following rate, ratio of follower to following, user reputation Content features: number of words, characters, spaces, capitalization words, exclamation marks, hashtags, mentions, URLs, spam words and max word length. Sentiment features: automatic and manually created lexicons	Bernoulli Naive Bayes, K-Nearest Neighbour (KNN), Support Vector Machines (SVM), Decision Tree, and Random Forests.
Santos et al. (2014)	Publicly available spam datasets Content based spam filtering and compression based text classifier.	Bayesian Networks, Decision Trees, k- nearest neighbor, SVM
Song et al. (2011)	Network Graphs: distance and connectivity between users User features: ratio of mentions sent to non-followers	Bagging, LibSVM, FT, J48, BayesNet
Lee et al. (2011)	User demographics: length of screen name, description, account longevity User friendship networks: number of followers, following, bidirectional friends, standard deviation of unique follower and following IDs User content: number of posted tweets, links, @usernames, content similarity, size of tweets User history: rate of change of number of following obtained.	Weka classifiers: Random Forest
Gayo Avello and Brenes Martínez (2010)	In-degree, out-degree, avg. number of tweets, tweets with URLs, URLs per tweet, hashtags per tweet, number of retweets, number of original tweets, other users referred.	Page Rank, HITS, Node Ranking, Tunk Rank, Twitter Rank, Discounted Page Rank, Pruned Page Rank
Wang (2010a)	Graph Based Features: number of friends, the number of followers, and the follower ratio Content Based Features: number of duplicate tweets, the number of HTTP links and replies/mentions	Bayesian classifier
Wang (2010b)	User based features: Number of friends, followers and the reputation of a user Content based features: duplicate tweets, HTTP links, replies and mentions, trending topics	Bayesian classifier
Benevenuto et al. (2010)	Content attributes: number of hashtags, words, URLs, words, characters per tweet; @mentions, retweets count, fraction of tweets with popular spam words User behavior attributes: follower, followee count, tweet count, age of account, @mentions to user, tweets from non followees, tweet frequency (min, max, avg., median)	Support Vector Machine (SVM)
Chu et al. (2012)	Tweet frequency, account registration date, tweeting device, link safety, number of retweets, follower, friends count, followers to friends ratio, hashtag ratio, mention ratio.	Classifier combination Bayesian classifier and Random Forest Algorithm
Lee et al. (2010)	Ratio of URLs and @mentions, unique URLs and unique @mentions in the 20 recent tweets to the number of tweets. Uses social honey pots for data collection.	Weka Classifiers: Decorate, Simple Logistic, FT, Logit Boost, Random Sub Space, Bagging, J48, Ordinal
Platform: MySpace		
Lee et al. (2010)	Public, marital status, gender, age, and About Me description. Uses social honey pots for data collection.	Class Classifier, Class Balanced ND, Data Near Balanced ND
Webb et al. (2008)	Temporal distribution of the spam friend requests, geographic properties, duplication in spam profiles, demographic characteristics	Social Honey pots
Platform: Sina Weibo (Chinese micro blogging website)		
	Content based features: number of reposts, comments, likes, mentions, URLs, hashtags	Support Vector Machine (SVM)

Table 1 (continued)

Authors	Metrics and features	Techniques and algorithms
Zheng et al. (2015)	User based features: number of followees, followers, ratio of followees to followers, profile creation days, fraction of messages/day, average URL count	
Platform: Facebook		
Jin et al. (2011)	Text features from image-associated content: caption, description, comments, and URLs.	Active Learning based classification
Markines et al. (2009)	Similarity in wall posts in terms of destination URL and text	Graph Clustering

who had used "the" as a word within tweets over a period of 4 weeks from February 1st to February 28th, 2017. The primary reason for selecting "the" as a search keyword is because it is the most common word in the English dictionary. The tweets are collected from these identified 14,235 users, and for every user up to 500 tweets were extracted. Based on timeline search, an average of about 128 tweets was successfully extracted for each twitter profile. The use of bio inspired optimization techniques makes this computationally intensive analysis of big data faster, as elaborated later in this study. For the purpose of this study, a list of the metrics that are relevant for detecting spam is identified in Table 2, on the basis of Table 1 (Benevenuto et al. 2010; Wang 2010b; Wang et al. 2015).

This study uses a set of 21 metrics under two categories of user-based and content-based metrics which are further categorized into descriptive and semantic metrics including emotion diversity, polarity diversity, topic modeling, hashtag diversity, lexical diversity, hashtag analysis and re-tweet count. None of the existing studies have taken into consideration the semantic content based metrics for identifying spammers. These attributes are used to identify suspected marketing activities by modeling user behavior characteristics.

3.1 Statistical analysis

The statistical t-test requires data from two distinctive groups to gauge the statistical significance of metrics. For the purpose of labeling the dataset into "spam" and "non-spam" profiles the study uses two metrics namely URL count and Tweet Frequency. Assuming an approximately normal distribution, about 95% of the data lies within two standard deviations of the mean ($\mu + 2\sigma$). Thus, the data of the profiles having a value greater than $\mu + 2\sigma$ for the two factors was examined manually. The $\mu + 2\sigma$ values came out to be 0.851 and 116.132 for URL count and Tweet Frequency respectively which act as thresholds for segregating spammers for the purpose of validation. These profiles were known to have large skewed friend and follower count and used words like "follow", "thanks", "giveaway", "win" and "comment" when analyzed using topic modeling. An investigation of the last 100 mentions of these profiles also reflected that these profiles were all added to @spam list by more than 22 other users too provided validation to our labeling of training datasets. A wordcloud of the topic modeling of the tweets of these spam profiles is demonstrated in Fig. 1.

A total of 500 profiles, 250 from each of the spam and non-spam groups are then used to examine the statistical significance of the selected metrics excluding the URL count and Tweet frequency that are used later for validation. Further, topic modeling is also excluded since the results are textual in nature and are used at

Table 2 User and Content based metrics for analysis

	Metric	Description
I	User profile based metrics	
1.	Word count of profile description	Number of words used by the user in the profile description of the twitter account
2.	Follower Count	Number of users following the specific user whose profile is being analyzed
3.	Friends Count	Number of users being followed by the user whose profile is being analyzed
4.	Tweet Count	Number of tweets posted by the user since account creation
5.	Favorite Count	Number of times the user's tweets are liked by others
6.	User Reputation	The ratio of number of followers of the user to the total followers and friends
7.	Following Rate	The ratio of number of people the user is following to the account age of the user
8.	Tweet Frequency	Tweets posted by the user per day
9.	*Added to Lists*	The number of people that have added the user in their lists
II	Content based metrics (Computed based on up to 500 recent tweets of the user)	
A.	Descriptive metrics	
1.	User @mentions	@Mentions made by the user to other users
2.	@Mentions to user	@Mentions made to the user by other users
3.	Retweet Count	Count of retweets among the tweets made by the user
4.	Unique Tweet Ratio	Ratio of unique tweets posted by the user to the total tweets
5.	Hashtag Frequency	Count of the number of hashtags used by the user
6.	Unique Words	Count of unique words used by the user in the tweets
7.	URL Count	Number of URL links posted by the user
B.	Semantic metrics	
1.	*Lexical Diversity*	Ratio of unique words to the total number of words used by the user
2.	*Hashtag Diversity*	Count of unique hashtags used by the user
3.	*Emotion Diversity*	Diversity in emotion of tweets of the user using six emotions: anger, disgust, fear, joy, sadness and surprise
4.	*Polarity Diversity*	Diversity in polarity of the tweets: negative and positive
5.	*Topic Modeling*	Identification of top five topics of discussion of the user comprising of five words each

*Italicized entries haven't been previously considered in the literature for detecting spam

a later stage for the purpose of validation. The t-test is thus conducted on 18 metrics and results in 13 significant factors excluding word count of profile description, @mentions to user, re-tweet count, unique tweet ratio and hashtag diversity that weren't significantly different for the two groups of non-spam and spam promoting users. The *p*-values of 13 significant factors are listed in Table 3. Refer to Table 2 for description of the factors considered for the statistical analysis.

3.2 Bio Inspired Computing

Bio inspired computing algorithms are used for clustering, classification and regression applications (Chakraborty and Kar 2016; Chakraborty and Kar 2017; Kar 2016). These approaches produce good results by expediting the search when the volume of the data becomes very high to converge to a globally optimum solution (Kar 2016). Bio inspired computing algorithms are used to identify and

Fig. 1 Wordcloud of topics extracted from profiles considered as spam

segregate spam profiles as the proposed approach can be scaled for use in various big data applications (Grover and Kar 2017). Among these algorithms, the most promising algorithms in terms of convergence speed and memory requirements is the Firefly Algorithm (FA) (Fister et al. 2013; Kar 2016). This optimization algorithm mimics the luminescence patterns and characteristics of fireflies (Yang 2010a) and is known to perform better in terms of accuracy and computation speed. There have been several advancements and modifications over the years (Yang and He 2013) in terms of Levy flights (Yang 2010b) and Chaos (Gandomi et al. 2013). The algorithm is widely used in many domains (Fister et al. 2013) including design optimization (Yang 2010c), continuous constrained optimization (Łukasik and Żak 2009), multimodal optimization (Yang 2009) and also in machine learning techniques including clustering (Senthilnath et al. 2011). Another study demonstrates an integrated K-Means and firefly approach for clustering and highlights the effectiveness of the approach (Tang et al. 2012). This study utilizes a K-Means integrated Levy-Flight Firefly Algorithm (LFA) and chaotic optimization algorithm (COA) for identifying spam profiles in Twitter by utilizing the 13 statistically significant factors for 14,235 Twitter profiles. We combine the approaches presented in literature to produce a hybrid model for outlier detection for segregating spammers.

3.2.1 Levy Flight Firefly Algorithm (LFA)

The firefly algorithm with Levy Flights (LFA) produces more accurate results than traditional Genetic algorithms and particle swarm optimization approaches by combining the three idealized FA rules with the concept of Levy Flight for movement of fireflies towards each other (Yang 2010b). The Levy flights are known to maximize the search for resources in uncertain environments (Yang 2010d).

Each firefly has an associated brightness (ε) at a specified location x. The attractiveness (α) of the firefly is thus dependent on this brightness and is a relative measure depending on how other fireflies perceive it. This depends on the distance d_{ij} between the two fireflies i and j. Further, the intensity of light emitted by the firefly is also a function of the distance and decreases with the distance between the two emitting fireflies. In addition to this the medium also absorbs certain light with a fixed absorption coefficient of μ. Thus emitted light intensity thus can be expressed as

$$\varepsilon = \varepsilon_0 e^{-\mu d} \qquad (1)$$

$\varepsilon_0$is the original intensity emitted by the firefly. Thus, related attractiveness (α) is defined as:

$$\alpha = \alpha_0 e^{-\mu d^2} \qquad (2)$$

α_0 being the attractiveness at distance (d)= 0. The distance d_{ij}between the between the two fireflies i and j at positions p_i and p_j respectively is thus represented by the Cartesian distance as shown here:

$$d_{ij} = \left|\left|p_i - p_j\right|\right| = \sqrt{\sum_{k=1}^{n} \left(p_{i,k} - p_{j,k}\right)^2} \qquad (3)$$

where $p_{i,k}$ depicts the k^{th} component of coordinate p_i in the spatial domain for the i^{th} firefly. The movement of the fireflies towards each other depends on the attractiveness and a firefly

Table 3 *P*-values of statistically significant factors

Metric	t Stat	P-value	Metric	t Stat	P-value
Emotion Diversity (F1)	−2.0828	0.03811	Follower Count (F8)	−2.5877	0.0099
Polarity Diversity (F2)	−1.9834	0.04846	Favorite Count (F9)	−3.5059	0.0005
Hashtag Frequency (F3)	−2.3078	0.02160	Friends Count (F10)	−4.4385	1.35E-05
Unique Words (F4)	−12.7119	3.95E-32	Added to Lists (F11)	−3.6244	0.0003
User @mentions (F5)	11.6428	7.28E-28	User Reputation (F12)	−2.1638	0.0309
Lexical Diversity (F6)	2.3212	0.0207	Following Rate (F13)	−8.5780	1.02E-15
Tweet Count (F7)	−8.2506	8.36E-15			

i, moves towards a more attractive and brighter firefly *j* using Levy flight and an updated position p_i is obtained:

$$p_i = p_i + \alpha_0 e^{-\mu d_{ij}^2}\left(p_j - p_i\right) + \omega sign\left[rand - \frac{1}{2}\right] \oplus \phi \tag{4}$$

Thus, the new position of p_i the firefly i depends on the attractiveness and the randomization of movement via Levy where ω is the randomization coefficient. The coefficient ϕ corresponds to the step length. Such cases when the step length obeys the Levy distribution, these random walks are referred to as Levy Flight. The random function rand generates a value belongs between [0, 1] to provide a random direction to the Levy movement.

We use the Mantegna's algorithm for a stable Levy flight (Mantegna 1994), where the step length (ϕ) is computed using:

$$\phi = \frac{u}{|v|^{1/\delta}} \tag{5}$$

The values of u and v are achieved through normal distributions as follows:

$$u \sim Norm\left(0, {\sigma_u}^2\right) \text{ and } v \sim Norm\left(0, {\sigma_v}^2\right) \tag{6}$$

having

$$\sigma_u = \left[\frac{\Gamma(1+\delta) sin\left(\frac{\pi\delta}{2}\right)}{\Gamma\left[\frac{(1+\delta)}{2}\right] \delta 2^{\frac{\delta-1}{2}}}\right]^{\frac{1}{\delta}} \tag{7}$$

and $\sigma_v = 1$,where Γ depicts the Gamma function, where $\delta = 3/2$.

It is evident that Levy flights are known to maximize the search for resources in an environment and thus the fireflies move in search of a more attractive firefly using the Levy distribution that can be modeled by the step length.

3.2.2 *Firefly algorithm with chaos*

The study further integrates chaotic optimization algorithm (COA) for tuning certain coefficients of firefly algorithm (Gandomi et al. 2013). The COA by uses chaotic variables in random-based optimization and is known to carry the overall search at higher speeds primarily because of the non-repetition of chaos (dos Santos Coelho and Mariani 2008). The use of chaotic maps results in improvised firefly algorithm by tuning two parameters absorption coefficient (μ) and attractiveness coefficient (α) with chaotic maps. The study uses a set of 12 chaotic maps - Chebyshev, Circle, Gauss/mouse, Intermittency, Iterative, Liebovitch, Logistic, Piecewise, Sine, Singer, Sinusoidal and Tent map, for tuning each of the two parameters. The sinusoidal maps give the best results for tuning the absorption coefficient while the Gauss map is more suitable for tuning the attractiveness coefficient (Gandomi et al. 2013). This study compares the outcomes of the two approaches as part of analysis.

Case 1: Tuning Absorption Coefficient (μ) using Sinusoidal Map The sinusoidal map improvises the results when used with meta-heuristics (Gandomi et al. 2013; Wang et al. 2014). It updates the value of the absorption coefficient over i iterations as follows:

$$y_{i+1} = a y_0^2 sin(\pi y_i) \tag{8}$$

where $a = 2.3$ and the initial point, $(y_0) = 0.7$ (Gandomi et al. 2013). The computed value is assigned to the absorption coefficient (μ) for subsequent computation of brightness coefficient (ε) and attractiveness coefficient (α).

Case 2: Tuning Attractiveness Coefficient (α) using Gauss Map One way of speeding up the search is to tune μ that directly affects the brightness and attractiveness. Another way is to directly tune the attractiveness coefficient (α). Earlier studies (Jothiprakash and Arunkumar 2013) highlight that Gauss map is also known to produce efficient results when combined with meta-heuristics. Gandomi et al. (2013) also iterated that Gauss map produces the best results for firefly while tuning the attractiveness coefficient. The Gauss map updates the value of α over i iterations using:

$$y_{i+1} = \left\{ \begin{array}{cc} 0 & y_i = 0 \\ \dfrac{1}{\frac{1}{y_i} - \left[\frac{1}{y_i}\right]} & otherwise \end{array} \right\} \tag{9}$$

Similarly, the computed value is assigned to the attractiveness coefficient (α) over iterations for a faster search for the firefly.

The integrated approach maximizes the search using Levy Flight and speeds up the process using chaotic maps. A similar chaotic firefly approach has shown promising results while exploring facility layout problem in the light of big data (Tayal and Singh 2016). In this paper, LFA with chaos is integrated with K-Means for the purpose of clustering the Twitter users into spam and non-spam based on the selected metrics. Tang et al. (2012) present a similar hybrid approach for the original firefly along with several other nature-inspired meta-heuristic algorithms. K-means being a popular clustering approach is known to often fall into local optima and thus, the meta-heuristics integrated with the K-means produces a globally optimum solution for computationally intensive problems.

The cluster centroids are computed as follows:

$$centroid_{j,a} = \frac{\sum_{i=1}^{SolutionSpace} weight_{i,j}\ datapoint_{i,a}}{\sum_{i=1}^{SolutionSpace} weight_{i,j}} \tag{10}$$

, where $j = 1 \ldots C$ (number of clusters), $a = 1 \ldots C*A$, A is the number of attributes and,

$$weight_{i,j} = \left\{ \begin{array}{ll} 1, & datapoint_i \in cluster_j \\ 0, & datapoint_i \notin cluster_j \end{array} \right\} \tag{11}$$

Thus, the distance between the cluster centers is depicted by:

$$F(centroid) = \sum_{j=1}^{C} \sum_{i=1}^{SolutionSpace} weight_{i,j} \sum_{a=1}^{C*A} \left(datapoint_{i,a} - centroid_{j,a}\right)^2 \tag{12}$$

The complete proposed approach is depicted here in Fig. 2.

3.2.3 Fuzzy C-Means Clustering

We further used Fuzzy C-Means (FCM) clustering to validate the overlaps observed using the proposed approach. This approach allows every data point to be a part of multiple clusters

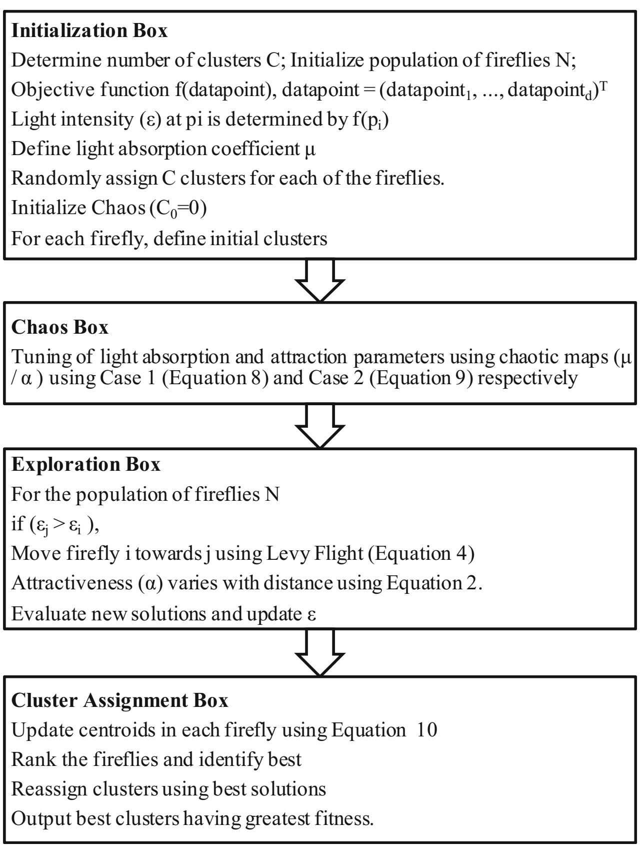


Fig. 2 Flowchart of proposed K-Means integrated Levy Flight Firefly with Chaos

depending on the degree of membership (Bezdek et al. 1984). Since, the data under consideration is highly unstructured in the form of textual user generated content, there is high probability that some users might belong to both the spam and non-spam clusters. The approach is based on the minimization of the objective function given here:

$$Obj_m = \sum_{i=1}^{S} \sum_{j=1}^{C} \rho_{ij}^{m} \left|\left|datapoint_i - centroid_j\right|\right|^2 \tag{13}$$

$$centroid_j = \frac{\sum_{i=1}^{S} \rho_{ij}^{m} datapoint_i}{\sum_{i=1}^{S} \rho_{ij}^{m}} \tag{14}$$

, where S is the number of data points (Twitter users under consideration), C (number of clusters) = 2 (Spam and non-spam users). m defines the degree of fuzzy overlap, the closer the value to 1, the more crisp the clusters would be.

ρ_{ij} , refers to the degree of membership of $datapoint_i$ in the j^{th} cluster and is defined here:

$$\rho_{ij} = \frac{1}{\sum_{k=1}^{C} \left(\frac{||datapoint_i - centroid_j||}{||datapoint_i - centroid_k||} \right)^{\frac{2}{m-1}}} \tag{15}$$

Further, for every $datapoint_i$,

$$\sum_{j=1}^{C} \rho_{ij} = 1 \tag{16}$$

The cluster centers are iteratively computed and the member function ρ_{ij} is updated till the objective function Obj_m improves by a value less than the predefined threshold.

4 Findings

For the purpose of this study we compare six variants of firefly algorithm including the k-means integrated original version of firefly, firefly with chaos for the two mentioned cases, levy firefly and levy firefly with chaos for the two cases. We do a 5-fold cross validation to compute the cluster centers for all the approaches discussed. This is done in order to validate the model and generalize to an independent dataset. The process of cross validation further limits problems of over fitting and helps in modeling the accuracy of the prediction of spam users. The Table 4 highlights the cluster centers for all 13 factors. These cluster centers can further be used to predict spammers.

The variants show varying accuracy and time required to achieve the solution. Further, they also vary in terms of iterations required to converge to a steady solution of iterations. The Fig. 3 shows the convergence plots for the six hybrid approaches.

Table 4 Cluster Centers using 5-Fold Cross Validation

Algorithm		F1	F2	F3	F4	F5	F6	F7	F8	F9	F10	F11	F12	F13
I	S	0.043	0.076	0.020	0.609	0.506	0.447	0.012	0.580	0.416	0.478	0.780	0.496	0.006
	A	0.043	0.075	0.038	0.483	0.946	0.628	0.012	0.653	0.768	0.392	0.831	0.521	0.018
II	S	0.043	0.079	0.021	0.607	0.343	0.458	0.011	0.584	0.415	0.476	0.769	0.505	0.005
	A	0.043	0.071	0.024	0.581	0.874	0.474	0.013	0.592	0.505	0.460	0.810	0.489	0.010
III	S	0.048	0.086	0.020	0.607	0.124	0.448	0.009	0.623	0.432	0.466	0.795	0.593	0.005
	A	0.042	0.073	0.023	0.594	0.701	0.470	0.013	0.574	0.456	0.471	0.781	0.464	0.007
IV	S	0.043	0.077	0.039	0.472	0.957	0.640	0.011	0.678	0.836	0.370	0.849	0.532	0.020
	A	0.043	0.076	0.021	0.606	0.519	0.452	0.012	0.580	0.422	0.477	0.780	0.496	0.006
V	S	0.043	0.070	0.023	0.582	0.863	0.477	0.015	0.575	0.487	0.466	0.787	0.458	0.010
	A	0.044	0.080	0.021	0.608	0.327	0.455	0.010	0.596	0.423	0.472	0.783	0.527	0.005
VI	S	0.043	0.078	0.021	0.610	0.383	0.456	0.011	0.589	0.420	0.473	0.781	0.510	0.005
	A	0.044	0.072	0.024	0.568	0.912	0.482	0.015	0.583	0.515	0.462	0.792	0.474	0.012

Spam (S) and Authentic (A) profiles for the six variants of firefly algorithm integrated with K-Means namely LFA with Chaos Case-1 (I), LFA with Chaos Case-2 (II), LFA (III), FA with Chaos Case-1 (IV), FA with Chaos Case-2 (V) and FA (VI)

In actual out of 14,235 profiles, a total of 4923 profiles (34.58%) are actually spam based manually evaluating the profiles. The plots clearly demonstrate that FA-Chaos (Case-2) converges at the earliest, followed by FA and LFA-Chaos (Case-1). However, on manual validation of the identified spam profiles, it is seen that the FA and FA-Chaos (Case-2) identify only 4565 and 4629 spam profiles respectively which is lower than that classified by LFA-Chaos (Case-1) of 4824 spam profiles correctly resulting in an accuracy of 97.98%. Further, the time for achieving results becomes important in such computation intensive problems for realizing functionally suitable results. The average time taken by the algorithms ranges between 88.61 s to 107.45 s. It is however seen that the average time required to compute the clusters is the lowest for the FA-Chaos (Case-2), as illustrated in Table 5.

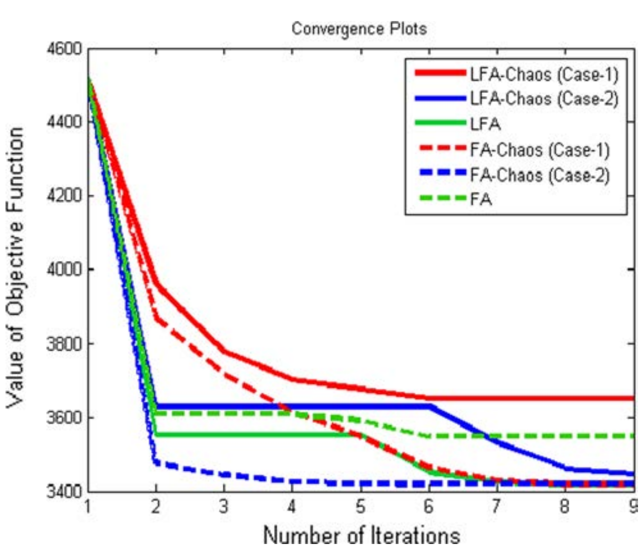


Fig. 3 Convergence Plots for Firefly variants

Fuzzy C-Means is further used to explore the closely related cluster centers. This proves beneficial in capturing the overlapped users and identifying the ones that have equal probability of being a part of both the groups. Figure 4 demonstrates the results achieved by the approach along with the results of the LFA-Chaos (Case-1) that gives the highest accuracy and the cluster centers for Fuzzy C-Means. The cluster centers for both Spam (S) and Authentic (A) Twitter profiles are also illustrated.

The Fuzzy C-Means classifies a data point into the cluster having the highest value of membership function. A value of 0.5 for the membership function indicates that the point equally belongs to both the clusters and that is what draws our attention. The data points marked with **'X'** have a greater degree of uncertainty in their cluster membership and have equal belongingness to both the groups of spam and authentic profiles. A value of *m* that defines the degree of fuzzy overlap is considered 1.01 to get clusters as crisp as possible along with identification of uncertain profiles. Further, average maximum membership value (Avg. Max = 0.997) provides a quantitative description of the overlap. Although the Fuzzy C-Means approach identifies the fuzzy overlap of spam and authentic profiles in the form of uncertain profiles, it is not the best when it comes to the convergence speed. On comparing the convergence plot of Fuzzy C-Means clustering with the two best firefly variants (in terms of accuracy and convergence speed) the Fuzzy C-Means clustering takes more number of iterations to converge. Fig. 5 shows the convergence plots of the three approaches where in the Firefly Algorithm with Chaos for turning the attractiveness coefficient converges fastest.

The convergence plot highlights that our proposed approach converges much faster in terms of iteration as compared to the Fuzzy C-Means, which becomes important, if the scale of the data used for the analysis is drastically increased. As per InternetLiveStats.com, Twitter has 500 million Tweets

Table 5 Approach-wise average time and accuracy

Algorithm	Approach	Average Time (seconds)	Accuracy
LFA-Chaos (Case-1)	K-Means integrated Levy Flight Firefly Algorithm with Chaos for tuning the Absorption Coefficient (μ)	96.87	97.98%
LFA-Chaos (Case-2)	K-Means integrated Levy Flight Firefly with Chaos for tuning the Attractiveness Coefficient (α)	107.45	95.93%
LFA	K-Means integrated Levy Flight Firefly Algorithm	97.74	95.72%
FA-Chaos (Case-1)	K-Means integrated Firefly Algorithm for tuning μ	94.38	96.39%
FA-Chaos (Case-2)	K-Means integrated Firefly Algorithm with Chaos for tuning α	88.61	96.02%
FA	K-Means integrated Firefly Algorithm	100.20	92.72%

produced per day comprising of highly unstructured UGC. So scalability and computational efficiency of proposed approaches become important in such domains involving data science.

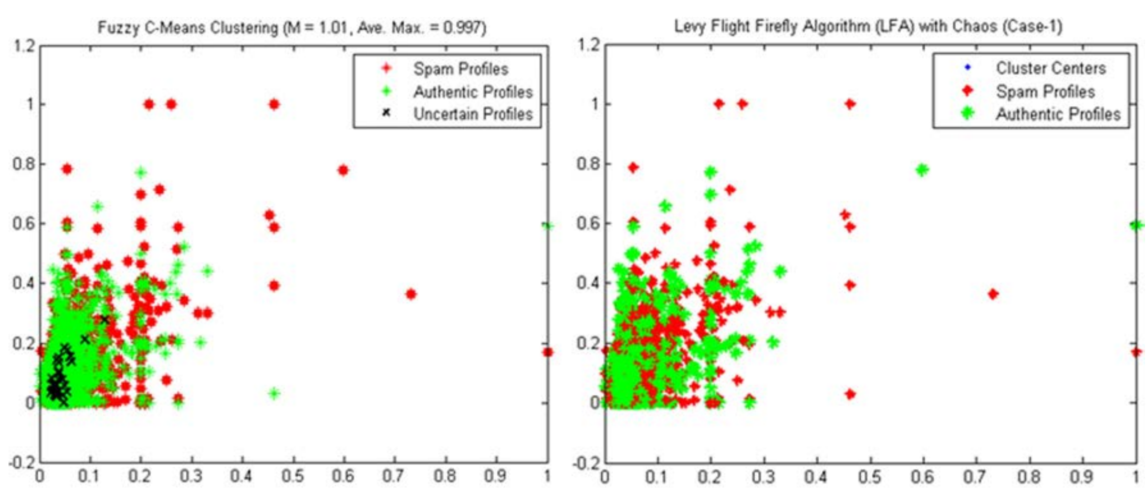
5 Discussion

Web 2.0 has opened new avenues not only for mere communication between individuals but also for organizations to engage with their target consumers at a large scale (Berthon et al. 2012). This has enhanced the interaction between the organizations and individuals resulting in a two way communication and a stronger engagement. On the contrary, several organizations have started adopting ways to artificially boost their content on these social media platforms to attract a larger audience. This is usually done by creating social media profiles solely for the purpose of content propagation and information diffusion to the masses using automated software that repetitively spam the users with content.

5.1 Contribution to literature

The contribution of this study is two-fold, both in terms of the domain and methodology. Existing literature explores possibilities to detect such spammers on social media by considering user profile statistics and descriptive statistics (Benevenuto et al. 2010; Chu et al. 2012; Gayo Avello and Brenes Martínez 2010; Santos et al. 2014, Song et al. 2011; Wang 2010b; Wang 2010b; Yardi et al. 2009). However, none of the studies utilize the textual user generated content which can also be used to give insights into the content semantics by computing the emotion, polarity, hashtag and lexical diversity that are beneficial for identifying such spammers. Such semantic factors which attempts to get into the depth of the intent behind the shared content have not been considered in existing literature for segregating spam profiles. Our study uses social media content and mines relevant statistically significant metrics including emotion diversity, polarity diversity, hashtag frequency, unique words, user @mentions, lexical diversity, added to lists, user reputation, following rate, tweet, follower, favorite and friends count using descriptive and content analytics.

Further, the existing studies subsequently model these identified metrics using traditional heuristic machine learning



Fuzzy C-Means	S	0.045	0.083	0.021	0.605	0.240	0.455	0.010	0.601	0.424	0.473	0.779	0.547	0.005
	A	0.042	0.070	0.022	0.591	0.790	0.471	0.014	0.576	0.470	0.467	0.790	0.462	0.008

Fig. 4 Fuzzy C-means clustering with cluster centers

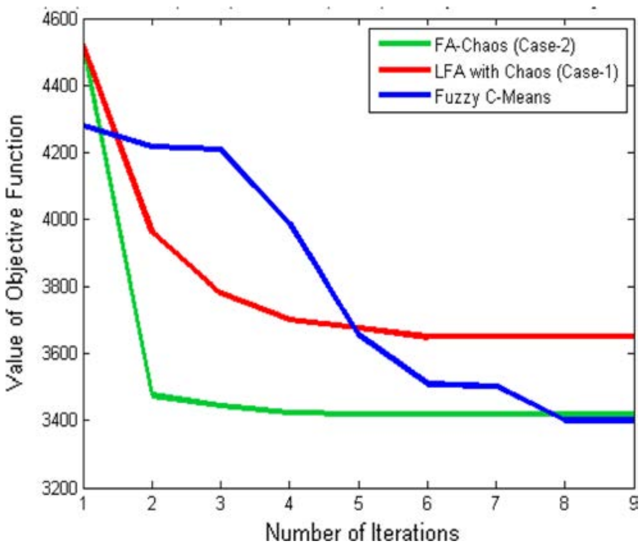


Fig. 5 Convergence plots for LFA-chaos (Case-1), FA-chaos (Case-2) & Fuzzy C-means

approaches (SVM, Bayesian classifier, Random Forest etc.) to classify the users into spammers. However, since the data extracted from these platforms consists of highly, rich in terms of semantics, hashtags and links, such traditional approaches often become computationally intensive. Such large volumes of data require meta-heuristic approaches which also account for very high complexity and dimensionality of the problem domain to produce a globally optimum solution, which typically requires swarm intelligence. Existing studies in literature use hybrid bio inspired approaches in the domain of web analytics and social media for identifying buzz (Aswani et al. 2017b), popular content (Aswani et al. 2017c) and influencers for the purpose of digital marketing (Aswani et al. 2017a). These studies have shown promising results both in terms of accuracy and convergence speeds. This study thus uses a hybrid approach for identify spam twitter profiles using the data obtained from the social media analytics followed by meta-heuristic bio inspired computing to model possible spammers in Twitter. A validation mechanism using the tweet frequency and URL count is subsequently used to ensure the correctness of results obtained using the proposed approach.

A mixed research methodology based on both social media mining and bio-inspired optimization was therefore necessary for meeting the outcome of this study. This study thus makes two major contributions, in terms of using semantics for detecting spam in social media including sentiment analysis for extracting the emotion and polarity of the tweets. Further, topic modeling is also explored for mining the user generated content and modeling the hashtag and link diversity along with user and content descriptive metrics. Methodologically, a hybrid levy flight algorithm with chaos is proposed for identifying the spam profiles in Twitter as an extension to the existing approaches as detailed in Table 1. This approach not only maximizes the search of a globally optimum solution but also speeds up the convergence by including the chaos theory by using the Sinusoidal and Gauss maps.

5.2 Implications to Practice

Visibility on the web is what everyone is aiming for, be it individuals (Baroncelli and Freitas 2011) or organizations (Wang and Vaughan 2014). The emergence of web 2.0 and information technology has brought significant changes in the businesses and subsequent decision making (Sprenger et al. 2017). The current study provides directions for individuals, practitioners and organizations opting for social media marketing for gaining traction in the digital space. When it comes to customers trying to seek knowledge about unfamiliar brands or brand value of organizations, these spam profiles may prove to be misleading (Naylor et al. 2012). Further, spammers might also post misleading content that may negatively impact a firm's business value. It thus becomes essential to identify these spammers and exclude their opinions for a decision making process in platforms like Twitter. The onus of such an activity could be taken up within the social media service provider or may be outsourced to an analytics company to conduct this analysis on a massive scale.

On the other hand, the organizations also need to take care of spammers when identifying potential influencers for content sharing and propagation (Aswani et al. 2017a). The potential influencers should not have a lot of spam following as that would not only adversely affect the brand equity and would also completely defeat the purpose for identifying an effective influencer for brand promotion. This would enable organizations to derive more accurate estimates of the returns of investments of their social media promotion expenditures. However, targeting spammers for content promotion and information propagation totally depends on the social media marketing strategy of the organization, since sometimes it becomes a more cost effective outcome, although not sustainable in the long run.

The economics of agency problems also comes into picture when organizations outsource their digital marketing initiatives (Aswani et al. 2018; Chen and Bharadwaj 2009; Ross 1973). Firms hire marketing organizations and professionals to widen their outreach and boost their content on the web. However, in order to enhance the content outreach, these agencies often indulge in creating social media profiles for artificially boosting the content by using spam profiles to showcase engagement. Another aspect in the agency problem is when the content that is created by these firms to gain traction is not original. These firms usually use automated portals or bots that take original content, spin it and post it. This is done since manual content creation requires more effort and time which was the main purpose behind outsourcing. This results in spam content being posted through their social profiles. Hence estimations on returns on investment on campaigns become wrongly documented.

6 Conclusion and Future Research Directions

This study uses a mixed research methodology by combining the insights from social media analytics to model the spammers in Twitter using bio inspired computing. The proposed K-means integrated levy flight algorithm using Sinusoidal map for tuning the absorption coefficient produces the best results in terms of accuracy and a faster convergence rate. The proposed approach gives an accuracy of 97.98% by modeling 13 significant factors after a statistical t-test including emotion diversity, polarity diversity, hashtag frequency, unique words, user @ mentions, lexical diversity, tweet count, follower count, favorite count, friends count, added to lists, following rate and user reputation. In addition to the proposed integrated firefly approach, a Fuzzy C-Means approach is used to identify the overlap among the two spam and authentic fuzzy groups. However, when compared with the proposed approach, the convergence of the Fuzzy C-Means is slower than the proposed approach. The study thus effectively combines relevant factors from user, descriptive and semantic statistics to model the Twitter profiles for detecting social media spam. The proposed approach can prove to be beneficial when organizations seek to gauge the success rate of campaigns, for identifying potential influencers for promotion of content and viral marketing. Our study highlights that analytics driven approach in social media for analyzing spam needs to be developed based on multi-method research methodologies because of the nature of the user generated content as well as the volume of the instances of content creation per content creator.

A limitation of the current study is that the performance of content and semantics analysis is hindered because of satire and use of non-english vocabulary including millennial language. In addition to the user, content and semantic metrics considered in the study, network level factors of the individual user profiles may also be useful for such spam profile detection. These studies could include factors like cliques, reciprocity, mutuality and betweenness may also be beneficial for detecting spammers on social media. This would help in identifying correlation between spammers using their in-degree, out-degree and possible cliques formed in the network (Chae 2015). An analysis of the network of such spam profiles across platforms and how their interaction and engagement with the target audience may provide useful insights about their behavior and patterns. Further, in depth look in the links shared by the spammers and looking for possible clickbaits to gain traction may also prove beneficial in enhancing the spam detection mechanism (Blom and Hansen 2015). Methodologically, other bio inspired computing approaches that converge to a globally optimum solution in the multidimensional and extremely complex problem domains may be explored for better efficiency of predictions (Kar 2016).

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