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A Review of the Application of Scale-Free Complex Network Theory in Business

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Abstract. Commercial social platforms produce huge volumes of sentiment-bearing user content, and almost all of it sits inside relationships: people follow particular accounts, comment on particular posts, repost what their friends share. Sentiment tools mostly ignore this layer. They treat every text as a standalone object and settle its polarity by counting words. This review takes the other route and asks what scale-free complex network theory has contributed to sentiment analysis in commercial settings. Two mechanisms get most of the attention: the power-law degree distribution and the BA growth rule that produces it, along with the uneven robustness these networks show when nodes fail randomly or are attacked on purpose. From there the paper follows a layered modeling route — user relational networks, user–content bipartite networks, and finally sentiment-labeled networks — and asks what each layer adds. Network thinking brings in relational, structural and dynamic information that text-based methods do not have; high-centrality negative nodes, for instance, tend to disappear in word-frequency tables yet matter a lot to brands. Three commercial uses show the payoff: watching how public opinion spreads, tracking brand reputation, and mining e-commerce reviews. Read this way, sentiment analysis becomes a question about how emotion moves through a structure rather than about how a single text reads — a basis firms can use for early warning and for answering back before a crisis builds.

Keywords: scale-free network, business socializing, sentiment analysis, public opinion dissemination, sentiment-labeled network

1. Introduction

In current sentiment analysis, most methods still treat each text as an independent unit and decide polarity through word frequency statistics or text classification [1]. What they leave out is the social fabric created by user interactions in commercial settings—following, commenting, and reposting—and the paths along which sentiment travels through these ties. Commercial social networks are typically heterogeneous: a handful of highly influential users sit at the center, connected to a large base of ordinary users [2, 3], a pattern that closely resembles scale-free networks [2]. Within such structures, the spread of sentiment depends heavily on key nodes and on the surrounding topology [4, 5], so text-based analysis alone can hardly account for how emotions actually propagate. From a

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relational and structural standpoint, integrating scale-free complex network theory into sentiment analysis for commercial social contexts therefore carries clear theoretical and practical value. This paper presents a comprehensive review of how the theory has been applied in this area.

2. Theoretical foundations of scale-free complex networks

2.1. Overview of random networks and scale-free networks

Complex networks offer a highly abstract way of describing complex systems. Qian Xuesen once noted that networks possessing some or all of a set of features—self-organization, self-similarity, attractors, the small-world property, and the scale-free property—can be classified as complex networks [6]. In graph-theoretic terms, any complex network can be written as:

$$G = (V, E) \tag{1}$$

In this expression, V stands for the set of nodes and E for the set of edges. The main topological descriptors of complex networks include degree and its distribution, average path length, clustering coefficient, and betweenness [6, 7].

The classical ER random network assumes that nodes connect at random, so that the degree distribution follows a Poisson pattern. Barabási and Albert, however, found that the degree distribution of real networks is much closer to a power law:

$$P(k) \sim k^{-\gamma} \tag{2}$$

In this formula, k is the degree of a node and γ the power-law exponent, which usually lies between 2 and 3 [6]. The distribution takes a "long tail" shape: a few nodes with extremely high degrees connect far beyond the average level, while a large number of low-degree ordinary nodes account for the vast majority of the total [2]. Because no single "typical degree" exists under a power law, such networks are called scale-free [2, 6].

Barabási and Albert introduced the BA model to account for this pattern, and the mechanism rests on two principles. The first is growth: the network keeps expanding as new nodes join. The second is preferential attachment: new nodes prefer to link to nodes that already hold many connections, a "rich get richer" Matthew effect [3, 6]. Together, the two forces push the degree distribution to evolve spontaneously into a power-law form [6].

2.2. Robustness and vulnerability of scale-free networks

The topology of scale-free networks gives them two opposing faces. They withstand random failures remarkably well, yet targeted attacks can damage them easily [8]. The reason is straightforward: most nodes carry low degrees, so random failures tend to knock out peripheral nodes and leave overall connectivity intact, whereas the deliberate removal of a few hubs can fragment the network [8].

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3. Modeling commercial social networks and building sentiment label networks

3.1. Modeling the scale-free structure of commercial social systems

The scale-free pattern is easy to observe on real platforms. Brand official accounts and industry KOLs at the top hold tens of thousands or even millions of followers and act as hub nodes, whereas most ordinary users follow only tens or hundreds of others, and the overall distribution trails off in a power-law fashion [3]. When newcomers decide whom to follow, they gravitate toward accounts that already have a large audience—an exact real-world counterpart of preferential attachment. Social networks also tend to be small-world, with short average paths and high clustering coefficients [3, 7], so information can travel across a network through only a few intermediate nodes.

Li Ying et al. tested this idea on B2B e-commerce networks. Building on the BA model, they proposed a local-world core optimal connection evolution model, and NetLogo simulations showed that the degree distribution of B2B e-commerce networks follows a power law while retaining small-world characteristics and strong robustness. The results provide empirical evidence for applying scale-free network theory in commercial social settings and in sentiment analysis.

User-to-user ties alone, however, cannot fully describe a commercial social network, because much of the emotional exchange between users takes place through comments, posts, and other content. This is why researchers introduced the user-content bipartite network, in which users and content form two types of nodes and an edge marks the fact that a user published, commented on, or liked a piece of content [6]. Network projection then yields a user similarity network, which lays the methodological groundwork for the sentiment label network described later.

3.2. Constructing and analyzing the emotional association label network

Building on the user relationship network and the user-content bipartite network, the analysis now moves to the emotional level. The idea is to extract fine-grained emotional labels from comment texts and treat them as nodes, then to draw edges according to the relations among labels, producing an association network that captures emotional interactions [1].

Two ways of building edges are common. In the co-occurrence approach, an undirected edge is drawn whenever two labels appear together in a single comment or across several comments left by the same user. In the semantic similarity approach, the edge weight comes from cosine similarity computed with word vector models such as Word2Vec and BERT [1]. Yao Yudan et al. combined K-means clustering with complex network analysis: they clustered first to extract emotion labels and then linked the labels by semantic similarity and emotional correlation [1].

Once the labels are in place, scattered emotional signals collapse into a single structured association network, and communities begin to appear inside it. "anger" and "disappointment" keep landing in the same cluster — a negative one that calls for a product fix as well as emotional soothing — while "satisfaction" and "recommendation" sit together in a positive cluster that feeds word-of-mouth [7]. Centrality measures then show which emotions actually matter. Nodes with many links reveal where consumer demands pile up; nodes with high betweenness hold separate emotional communities together, which makes them the obvious places to step in when public opinion turns [1].

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3.3. Network robustness and the spread of emotions

Emotion does not travel like ordinary information. It carries polarity and intensity, so an "emotional contagion" effect takes hold, and psychological "negative bias" makes negative feelings travel farther than positive ones [5]. Key nodes do much of the work here. Opinion leaders and official accounts can push a sentiment across a network in a very short time, and simulation runs show that the more opinion leaders a network has, the faster public opinion spreads [5]. When a wave of negative sentiment erupts, brands can partner with high-influence opinion leaders to release positive counter-signals. In short, the spread of emotion is driven jointly by the properties of the emotion itself and by the position of key nodes; frequency-based polarity counts alone cannot capture real propagation patterns, whereas scale-free network theory supplies the tools to identify critical nodes and forecast public opinion trends.

4. Traditional sentiment analysis versus scale-free network analysis

4.1. Mainstream sentiment analysis methods and their limits

Existing sentiment analysis falls into two broad camps. Dictionary-based methods count positive and negative words and derive polarity from their frequency; they are easy to operate and highly interpretable, but their performance hinges on dictionary quality, and they struggle with complex phenomena such as irony [1]. Machine learning methods recast sentiment analysis as a text classification problem, training Naive Bayes, SVM, or deep models to reach higher accuracy, at the cost of large labeled datasets and relatively poor interpretability [1]. Both camps share a common blind spot: they judge each text as an independent unit, make isolated decisions about sentiment tendency, and overlook the semantic associations between texts, the social relationships among users, and the way sentiment disseminates through the network [7].

4.2. Advantages of sentiment analysis from a scale-free network perspective

Network analysis departs from traditional methods mainly in perspective. Instead of treating texts as isolated units, it places users, content, and emotions inside a relational network and asks not only "what was said" but also "who said it", "to whom it was said", and "how the emotion was conveyed" [7]. The structural angle supplies quantitative instruments: centrality indicators locate key nodes and opinion leaders, and community discovery algorithms reveal the clustering structure of emotional labels [1, 6]. The dynamic angle goes further, building emotional networks over successive time windows to trace how emotions evolve [1].

4.3. Empirical comparison of the two methods on the same dataset

Zhang Ling et al. compared the two approaches on Twitter data about movie topics and found significant differences in judgments of the "main emotions" [7]. Word frequency statistics put neutral emotion first, which seemed to show that "public sentiment was generally stable"; network analysis told a different story. Negative emotion labels appeared less often, yet their high centrality and strong connectivity gave them greater dissemination power [7]. The underlying reason, the authors argue, is that highly diffusive information tends to combine low emotional intensity with high cognitive intensity: rational, analytical content spreads more widely than emotionally charged expressions [7].

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The same gap shows up in e-commerce reviews. During Leifen's 2025 quality scandal, negative reviews were sparse in frequency, but clear-headed warning posts forwarded by influential users shaped opinion far more than ordinary negative reviews did. JD platform data point to the same asymmetry: positive emotional intensity reached 0.83 while negative stood at only 0.02, so word counts suggested near-universal satisfaction even though a few highly communicative negative reviews were seriously underestimated. Network analysis can trace such reviews back to the influential users behind them, enabling brands to prioritize key responses and contain negative word-of-mouth.

5. Network-based public opinion dissemination and business applications

5.1. How public opinion evolves in scale-free networks

Network topology shapes the path of public opinion. Ren Lixiao et al. ran multi-agent simulations on the NetLogo platform and examined how four groups of factors influence the spread of public opinion [5]. Larger networks extend both the range and the duration of diffusion; lower interaction thresholds make opinion more likely to spread; and a larger number of opinion leaders accelerates dissemination and expands its coverage. The study also stresses the timing of intervention: acting at the initial stage of a public opinion wave is more effective than passively responding after the spread has already taken off.

Structurally, the hallmark of scale-free networks—a few highly connected nodes attached to a large body of low-degree nodes—lets information race through the network via hub nodes, which raises dissemination efficiency but also raises the risk of public opinion getting out of control [2]. Compared with random networks, public opinion on scale-free networks usually follows a "slow start - explosive middle - gradual decline" rhythm. Dynamic frameworks such as cellular automata and Deffuant models have been developed [9], yet they commonly suffer from experience-dependent parameters and a limited fit with real scenarios.

5.2. Commercial applications of network-based sentiment analysis

For brand reputation monitoring, the traditional approach focuses mainly on comment counts and the proportion of emotional polarity, which makes it hard to identify what really matters. Introducing network analysis changes this: centrality indicators single out opinion leaders and active users, and the direction of reputation dissemination can be predicted [5]. Experiments show that when centrality-based key node identification is used and opinion leaders account for the top 3% of users, node coverage reaches 46.5% and identification accuracy 94.1%, well above the 21.2% coverage of traditional user stratification. By concentrating on highly connected nodes, reputation trends can be guided from the source.

Fine-grained sentiment mining in e-commerce reviews is another application direction. Yao Yudan et al. combined K-means clustering with complex network analysis to extract fine-grained sentiment labels and build an emotional correlation network, revealing how emotions correlate with one another [1]. On JD's dataset of fresh agricultural product reviews, the method achieved a comprehensive F value of 46.22%, effectively identifying fine-grained sentiment labels and helping businesses understand the composition of consumer emotions so as to improve products and services in a targeted manner.

For public opinion risk warning, the value lies in continuously tracking changes in the community structure of the sentiment label network. As scattered negative sentiment labels

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gradually converge into a tightly knit community that keeps growing, risk signals can be captured before a negative opinion outbreak [1]. Combined with monitoring of the sentiment tendencies of key nodes, this gives businesses a basis for a brand crisis warning mechanism that moves the response threshold forward [4].

5.3. Emotion-driven user behavior and information dissemination

Yang Yongqing et al. used users' remarks on Weibo as samples and ran a fixed-effect regression to examine how emotions influence user behavior [10]. Users with stronger and more extreme emotions posted and forwarded more frequently, and when emotions fluctuated significantly, behavioral patterns also changed significantly [10]. Emotions, in other words, are not merely objects of expression but the internal force that drives users to act. The study also found that the emotional signals of verified users (brand accounts, celebrities) spread more widely than those of ordinary users, which is consistent with the amplification effect of key nodes in scale-free networks [10].

6. Conclusion

This review has surveyed how scale-free complex network theory has been applied to sentiment analysis in commercial social settings, synthesizing the theoretical foundations, network modeling logic, methodological comparisons, and practical applications scattered across the field. The main finding is that the power-law distribution, the critical node effect, and the dual robustness–vulnerability property provide a structural lens for understanding how sentiment propagates in commercial social contexts. That lens corrects the central weakness of traditional methods, which focus exclusively on text and neglect relational dynamics, and it furnishes new analytical tools for brand public opinion monitoring, consumer insight generation, and business decision-making.

As a narrative review, this study does not empirically validate the proposed framework against real commercial data, and its literature coverage is limited to text-based sentiment analysis, touching only lightly on multimodal scenarios such as short videos and live streaming. Future work should test the framework on platform comment data and extend it to multimodal sentiment networks.

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