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Editorial

Social Media Marketing and Financial Forecasting

1. Introduction

The last decade has witnessed a huge development in social media interactions. Today, social media is becoming ubiquitous in two senses: (1) it crosses boundaries and expands to more nations, and (2) it deeply intervenes in our personal life and economic activities. This outburst of social media data has led to an extensive amount of research for analyzing and extracting useful knowledge and workable patterns from social media data (Hussain & Cambria, 2018). Among those, however, the academic interest in social media marketing and financial forecasting has only increased in recent years (Xing, Cambria, & Welsch, 2018b). For example, only one special issue (Hajli & Laroche, 2019) and two workshops (Chen, Huang, Takamura, & Chen, 2019; Hahn, Hoste, & Tsai, 2018) have been organized on these two topics, respectively.

Social media marketing aims to communicate with potential customers to build brand loyalty, attract attention, and increase sales (Cambria, Grassi, Hussain, & Havasi, 2012). As the marketing activities migrate to an online interactive environment, companies can listen-in the customer feedbacks as well as actively influence customer behavior (Constantinides, 2009). Social media-based financial forecasting involves applications such as asset allocation strategies, pricing and valuing financial assets, and stock market prediction (Malandri, Xing, Orsenigo, Vercellis, & Cambria, 2018; Xing, Cambria, & Welsch, 2018a). These applications are not static procedures, to the contrary, they continue to collect information and accordingly revise the output. Both social media marketing and financial forecasting require understanding and leveraging the characteristics of social media data.

We identify three major characteristics of social media data. First, the volume of social media data is huge. Moreover, marketing and financial forecasting tasks often require real-time analysis of those data. Hence the processing methods have to be efficient. Second, social media data are becoming multi-modal. Even pure-text data often comes with extra dimensions, such as timestamps and location tags. Making use of such information is what social media research has more than NLP research. Third, before the surge of social media data, there are existing information sources to support marketing and financial forecasting. Therefore, methods often have to fuse the knowledge from social media data and other sources.

In line with the above discussion, this special issue focuses on the presentation of marketing and financial forecasting researches that tackle the three characteristics of social media data.

2. Contents of the special issue

We received 12 valid paper submissions for this special issue. After several rounds of rigorous reviews and revisions, we decided to publish half of them in this special issue.

The first article, “Marketing analysis of wineries using social collective behavior from users’ temporal activity on Twitter” by Bello-Orgaz et al. (2020) studied and clustered the time series of Twitter marketing behavior of wineries using unsupervised machine learning. The time series consist of both “event factor” and “time factor”, that is, the level of participation via posts, comments, messages, mentions, likes, or dislikes, and the decay or reinforcement of such activities as time evolves. The article concluded that social media marketing behaviors of wineries are generally region-based and found that only the wineries from the region of Porto and Douro Valley have carried out distinct campaigns and marketing strategies using Twitter.

The following two articles are about stock market prediction. In the second article “Incorporating stock prices and news sentiments for stock market prediction: A case of Hong Kong” by Li, Wu, and Wang (2020), an LSTM model that takes the concatenation of both the technical indicator and news sentiment time series is built. The research also experimented with several popular sentiment dictionaries and discovered the optimized configurations for the Hong Kong stock market. The proposed architecture outperforms the models that merely use either technical indicators or news sentiments.

Although sentiment can be used for price (Li et al., 2020) and volatility (Xing, Cambria, & Zhang, 2019) prediction, the adoption

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of neural networks makes its role difficult to explain. In the third article "On exploring the impact of users' bullish-bearish tendencies in online community on the stock market", Qian, Li, and Yuan (2020) looked deeper into the relations between the online community sentiment and stock market features such as returns and volatility. Their investigation leads to financial insights, including that (1) the online users' bearish tendencies imply stronger market volatility and higher market returns, and (2) the consistency of online users' tendencies has a positive impact on market volatility.

The fourth article "Value Assessment of Companies by Using an Enterprise Value Assessment System Based on Their Public Transfer Specification" shows that financial forecasting is not limited to stock market prediction. In this article, Huang, Liu, Bai, and Zhang (2020) explored the Public Transfer Statements of startup companies as a new information source other than financial indicators to help with company value assessment, hence non-conventional indicators, even like education level of employees, are parsed and included. They benchmarked their valuation results against the issue prices from a Chinese over-the-counter system and achieved circa 60% accuracy in a $\pm$ 2RMB range for the manufacturing industry.

The fifth article by Xu, Pan, and Xia (2020) responds to the large-scale nature of online product reviews. In "E-commerce Product Review Sentiment Classification Based on a Naïve Bayes Continuous Learning Framework", the authors proposed a model that integrates features from continuous learning, domain adaptation, and Naïve Bayes to handle the real-life e-commerce scenario with efficiency.

Finally, the sixth article "An integrated model for textual social media data with spatio-temporal dimensions" by Diaz, Poblete, and Bravo-Marquez (2020) addressed the phenomenon that in $<$ *space, time, text* $>$ tuples, mutual influence and relationships can exist between written language and the time and place where it was produced. The research proposes an RNN-type model called "Acceptor" to learn and represent such relations. This model outperforms state-of-the-art methods ranging from a 5.5% to a 24.7% improvement for location and time prediction tasks on standard datasets.

3. Concluding remarks

Marketing and financial forecasting have a longer history than the human use of web technologies. Meanwhile, a lot of theories and models are developed. For example, econometric models are used for stock market prediction and indicators like price-to-book ratio are used for company valuation. Therefore, how much a research work deepens our understanding of the problem and links to the existing models matters more than the model's complexity or trendiness. Among the selected articles, we can find CNN- and RNN-type models, HMM, Naïve Bayes, and regressive models, each tackle a specific need or data distribution (Wolpert, 1996). We hope that you find this special issue meaningful and that the six articles could foster ideas and further advance this research community.

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References

Bello-Orgaz, G., Mesas, R. M., Zarco, C., Rodriguez, V., Cordón, O., & Camacho, D. (2020). Marketing analysis of wineries using social collective behavior from users' temporal activity on twitter. *Information Processing and Management,* 102220.
Cambria, E., Grassi, M., Hussain, A., & Havasi, C. (2012). Sentic computing for social media marketing. *Multimedia Tools and Applications, 59*(2), 557–577.
Chen, C.-C., Huang, H.-H., Takamura, H., Chen, H.-H. (2019). Proceedings of the first workshop on financial technology and natural language processing.
Constantinides, E. (2009). *The social web as marketplace: A primer in social media marketing. Mediterranean conference on information systems*.
Diaz, J., Poblete, B., & Bravo-Marquez, F. (2020). An integrated model for textual social media data with spatio-temporal dimensions. *Information Processing and Management,* 102219.
Hahn, U., Hoste, V., & Tsai, M.-F. (2018). Proceedings of the first workshop on economics and natural language processing.
Hajli, N., & Laroche, M. (2019). Applications of business intelligence and analytics in social media marketing. *International Journal of Information Management, 49*, 226–227.
Huang, W.-B., Liu, J., Bai, H., & Zhang, P. (2020). Value assessment of companies by using an enterprise value assessment system based on their public transfer specification. *Information Processing and Management*.
Hussain, A., & Cambria, E. (2018). Semi-supervised learning for big social data analysis. *Neurocomputing, 275*, 1662–1673.
Li, X., Wu, P., & Wang, W. (2020). Incorporating stock prices and news sentiments for stock market prediction: A case of hong kong. *Information Processing and Management*.
Malandri, L., Xing, F., Orsenigo, C., Vercellis, C., & Cambria, E. (2018). Public mood–driven asset allocation: the importance of financial sentiment in portfolio management. *Cognitive Computation, 10*(6), 1167–1176.
Qian, Y., Li, Z., & Yuan, H. (2020). On exploring the impact of users' bullish-bearish tendencies in online community on the stock market. *Information Processing and Management*.
Wolpert, D. H. (1996). The lack of a priori distinctions between learning algorithms. *Neural Computation, 8*(7), 1341–1390.
Xing, F. Z., Cambria, E., & Welsch, R. (Cambria, Welsch, 2018a). Intelligent asset allocation via market sentiment views. *IEEE Computational Intelligence Magazine, 13*(4), 25–34.
Xing, F. Z., Cambria, E., & Welsch, R. E. (Cambria, Welsch, 2018b). Natural language based financial forecasting: a survey. *Artificial Intelligence Review, 50*(1), 49–73.
Xing, F. Z., Cambria, E., & Zhang, Y. (2019). Sentiment-aware volatility forecasting. *Knowledge-Based Systems, 176*, 68–76.
Xu, F., Pan, Z., & Xia, R. (2020). E-commerce product review sentiment classification based on a naïve bayes continuous learning framework. *Information Processing and Management.* 102221.

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