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The Application of Machine Learning in the Financial Crisis Warning

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Abstract

In the financial system, a crisis in a certain institution will spread across the whole system, resulting in a wide range of influences, leading to the collapse of the whole system. The systemic risk brought about by this system structure is beyond the description of mainstream financial theory. As a new research paradigm, the theory of financial complex system attracts more and more researchers' attention. The existing researches on financial crisis state in financial complex system usually correspond to financial crisis according to the topological structure change of financial network or subjectively select financial indicators for early warning, but seldom adopt the extraction of complex network evolution features for quantitative early warning of financial crisis.

Keywords

Complex Systems; Financial Crisis Warning; Machine Learning.

1. Introduction

Economics itself is a complex theoretical discipline. Statistical methods have been widely used in the field of measurement, and more and more machine learning methods have also been used in academic research. But looking at the enterprise, and in the short term, there is no room for ai to play a large scale. Machine learning will flourish in financial models with higher margins, better structured data and well-defined problems. AI models have been widely used by hedge funds, such as Simplex Equity's self-learning model, which sold Japanese futures on Brexit without human intervention. This is not alone: a Bloomberg article last year analyzed AI's impact on Quant. This is what we define as a high-margin, data-rich area, so financial companies are willing to invest money and people to develop it.

In the process of using data mining in the financial field, there is a high possibility to find systematic laws or places that violate existing laws, to feed back the theoretical discipline. Therefore, financial companies are likely to discover or confirm some economic laws in their AI research. As the overall AI ecosystem progresses, machine learning or other AI tools, such as natural language processing, can better serve the development of economic theory.

2. The Poorly Interpretable of Machine Learning Models

The most popular models of machine learning in the industry are logistic regression and decision tree, because these two models have the best accuracy or performance? No, because both models are interpretable and visual, which is too important for managers or supervisors. The explicability of models is also important in economics, where empirical science is hard to prove as a theory. Most current machine learning models face problems that work well but are hard to explain. More and more papers are trying to improve the interpretability of models, such as "Why Should I Trust You?" Explaining the Predictions of Any Classifier: Explaining the

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Predictions of Any Classifier Only as the field continues to evolve will we be able to better ground it so that users don't have to be suspicious all the time. Financial firms tend to require a high level of interpretability, more so than other industries. Take the model recently made for a financial company as an example. Customers require corresponding explanations for each step of decision making, so most existing models are not suitable and difficult.

3. Difficult to Define Machine Learning Problems

Machine learning is more widely used in the industry and supervised learning requires a clear definition of the problem. But reinforcement learning, transfer learning and so on, which seem promising at present, are not widely applied. Take simple supervised learning. If you want to build a model to predict whether a merger will affect a company's stock price, you need to provide a lot of merger data and whether the stock price has changed since the merger. Ideally, after gathering enough information about mergers and acquisitions and stock price movements, you can do natural language analysis to extract features and put them into a machine learning model. However, in practice, we cannot give a clear definition and boundary of the problem. If you want to use machine learning to develop a stock trading strategy, how many factors need to be taken into account? Is it enough to consider only m&a news? The more relevant factors, the better the fitting and accuracy of the model. For example, macro-policies and micro-specific conditions will affect the fluctuations of stock prices. If one of them is omitted, it will have a certain impact, often the more the better. In this case, every question requires a lot of people and data to support it, which is why so many attempts to use ARTIFICIAL intelligence to predict stock movements have come to nothing. Such a clear definition and scope is unlikely to emerge on many specific issues at this stage or in the foreseeable future.

4. Poorly Structured Data

Machine learning models require structured data, or at least electronic data. There is still a long way to go in the field of big data and even data structuring. Take auditing, for example. Many companies still have a lot of paper that can't go paperless, not to mention electronic data that AI can digest. Some companies developed an interview AI, but there was no raw data to use directly. So, they had 12 new hires spend a week translating their interview videos verbatim into words plus features, and the whole process was excrucible. When relevant structured data does exist, it is often not in the same place, and consolidating data is expensive. Many enterprises have multiple ERP systems, and it is difficult to integrate relevant data efficiently. Therefore, projects often end without progress or face a long data collection cycle.

5. Talent Fault and Speculation

The explosion of ARTIFICIAL intelligence, or the flowering of the old tree of deep learning in recent years, has not had time to store a large number of professionals for the industry. It is not hard to see that a large number of top AI talents are still captured by Internet companies, Hinton at Google, Lecun at Facebook, and not much talent is left for financial services companies. At the same time, for a long time, the link between computers and finance was relatively weak. Getting someone with a computer background to develop data models for the financial world can be incredibly difficult. My personal understanding of economics is still relatively superficial, only understanding basic concepts and principles. Similarly, financial services practitioners lack an understanding of AI models and statistics. So, using AI to advance finance requires a large cross-section of talent, and at least project managers who understand both directions. However, the investment output in talents is not proportional to the current stage, and it is difficult to obtain benefits in a short time. In this case, each problem requires a lot of people and data to support

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it. Therefore, few companies invest in AI for research that is exploratory and unprofitable. In other words, there are not many financial companies with financial resources to provide AI research, and small financial institutions or academic institutions lack funds, technical personnel and data accumulation to conduct systematic research.

6. Conclusion

How machine learning can change the financial industry may also depend on an increase in cross-disciplinary talent. On the one hand, computer scientists are moving from tech companies to financial firms to tackle landing problems. On the other hand, finance has produced enough practitioners who understand machine learning. Together, we can look forward to more intelligent and automated financial machine learning models. From another perspective, financial practitioners should not blindly switch to the field of science and technology to engage in data work, but should supplement relevant knowledge, so that AI can better land in the financial field, to bring greater value.

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