Career Episode 01

Systems Thinking

Although there were no environmental systems in the Credit Risk project I was working on, the two most significant social systems in the project were the regulatory and economic systems. In the past, I was so focused on building the best and sophisticated machine learning (ML) models with impeccable accuracy because I thought that it was the definition of success, and it was what the clients wanted. However, after learning about systems thinking, my attitude changed, and I realised that success is defined by how much of the bigger picture you have considered because building the perfect model in isolation will not solve anything. From a systems perspective, I need to consider the systems that interact with and influence the ML model in order to make the appropriate design decisions. In this career episode piece, I will reflect on how the regulatory and economic social systems played a significant part in shaping the strengths and weaknesses of the ML model I built for the Credit Risk project at a large Australian telecommunications client.

The regulatory system requirements restricted the performance of ML models in favour of an explainable model. From a legal and regulatory requirements perspective, Australian companies must be able to explain to a consumer why they got declined for credit. Prior to hearing about this requirement, I was hoping to use advanced ML techniques to build a high performing credit risk model to predict if a customer will default or not. Unfortunately, the more advanced the model is, the less explainable it is and the more of a black box it becomes. The client would not be willing to buy a cutting-edge model that they cannot productionise simply because it does not meet regulatory requirements. Instead, I needed to find a balance between using advanced methods to impress the client while keeping the model simple and explainable to meet regulatory requirements. I eventually decided to use advanced techniques (Random Forest and Neural Network models) in the modelling process to select the best features and train a simple logistic regression model. A logistic regression model is easy to understand because it outputs the probability of a customer defaulting, and it is also explainable because we can quantitatively measure which features influenced the outcome and by how much. Although I compromised on model performance, the model still outperformed the client's existing model (82% vs 74% accuracy) and additionally met the strategic KPI goals of the client.

Although the ML model performance is quantitatively better, it was still hard to predict if a customer would default or not without considering the economic system. A reason why the model performance was limited to 82% could be due to model confusion in the outcome variable. In other words, there could be more than one reason to why a customer would default. I remembered an example where a woman had recently lost her husband and could not make her repayments on time so she was marked as defaulted. Reflecting on that now made me realise it is an important example of financial hardship. If a reason to default is due to fraud or bad debt, another reason could be financial hardship. Financial hardship is generally temporary and if we can identify these customers, we can put them on a financial hardship plan to get them back on track again. Companies generally prefer to retain existing customers as it is five times cheaper to retain a customer than acquire a new customer (Pfeifer 2005). Unfortunately, the data captures both types of customers as defaulted and a simple logistic regression model is not powerful enough to make the distinction. If financial hardship customers were removed from the equation, I would expect the model performance to increase by a significant amount. If I had picked this up with my new systems thinking knowledge, I would have pitched building an additional financial hardship model to my client to attain higher credit risk model accuracy and identified the financial hardship customers.

In conclusion, the ability to apply systems thinking into professional practice can provide very valuable insights to understand the problem deeper and help us make better decisions coming up with a solution. If I had trained my ML model without considering requirements from the Australian regulatory system, the client would not accept it. Without taking a systems thinking approach to how I can improve my model, I failed to identify customers who we could have helped. In the future, I will definitely incorporate a systems thinking approach throughout my project.

References

1. Pfeifer, P. The optimal ratio of acquisition and retention costs. J Target Meas Anal Mark 13, 179–188 (2005). https://doi.org/10.1057/palgrave.jt.5740142