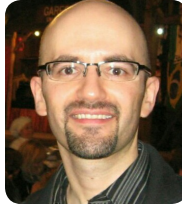




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Supply Chain Finance and Artificial Intelligence - a game changing relationship?

Most of the bank-driven Supply Chain Finance (SCF) has been buyer-centric financing based on the buyer's confirmation that an invoice is approved to pay. The structure itself was used for a long time under other names, particularly in Spain and Latin America, but moved to the mainstream with the advance of technology, allowing uploading of data straight from the buyer's ERP systems.

The core advantage of supply chain finance is the ability to separate credit risk - something that banks are quite familiar with - from performance/ contractual risk - something many traditional banks have very limited understanding of. The exercise was mainly focused on existing customers and standard bank credit approval process (that was heavily driven by 'public' data, i.e., buyer financials or securities information through Merton model variations). Platforms servicing such activity were focused on simply loading buyer ERP data, matching it with the seller information, and facilitating ancillary compliance for customer onboarding. Some newer platforms combined this

with e-invoicing that supports a more efficient process but does not alter the fundamental premises. While 'traditional' focused supply chain clearly remains most efficient process-wise, a large number of financial institutions (FIs) competing for a relatively small number of blue chip customers on highly standardised products led to margin collapse, triggering the search for new products where good margins can still be achieved while addressing real customer needs.

To be able to do so, financiers need to differentiate in the way they can assume risk - either credit risk (i.e., being able to finance transactions with buyers that others cannot), or performance risks: inventory, purchase order (PO) financing, etc.

Some players have been historically positioning themselves in such a business through deep industry expertise areas, but both products have not gone mainstream so far.

Technology can play a critical role in both areas through better data capturing (deep supply chain integration, supplier networks,

blockchain-based applications) and analyses of such data to make decisions, where artificial intelligence (AI), such as deep learning (DL), can make a significant difference.

The first question to address is the credit risk. With the current level of supply chain integration, there is a massive flow of financial and non-financial, structured and unstructured data in the supply chains. This includes payment performance (how invoices are paid), order pipeline, product information, often end user data, etc. A Good credit manager in a company intuitively takes a lot of this into account when making decisions, banks and insurers typically do not. The result is massive gap between the risk appetite and, often, losses - many corporates have both higher risk appetite and lower losses than such financial institutions. While anecdotal communication happens, there is no regularised procedure to process such data and share outcomes with financial institutions. There is also the aspect that not everybody in the chain is willing to share all the information (that can be extremely sensitive from commercial standpoint) with the other parties - but would be willing to share processed outcomes (a bit like rating agencies getting information under a non-disclosure agreement (NDA) from the companies they rate that is reflected in rating but not published). And the degree of standardisation of such information varies leaving no room for the use of the simple statistics-based tools (like Z score or Merton Model). Here is where AI can make a massive difference.

The other area is performance risk-related products, such as inventory financing, purchase

order financing, multi-tier products, etc. What we have seen recently is a significant improvement in the way a lot of this information is recorded - in supply chain management systems, logistics tracking, supplier networks, and lately blockchain applications, allowing various forms of tracking and recording on distributed ledgers. This creates very large volumes of (structured and unstructured) data that are becoming a deadweight as there are no decision-making tools to utilise them. There are some 'window dressing' type products, where the financier is supposed to take some risk to comply with accounting rules, but there are no 'real' risk transfers, and only a handful of products where risks are analysed and priced.

Let us now briefly discuss why artificial intelligence can help with the above tasks. While computers far surpass humans in their ability to handle structured and formal tasks, they traditionally did much worse when it came to those tasks that required a lot of knowledge about the world - everyday knowledge, such as recognizing someone's face or voice, or subject-specific knowledge, such as recognizing a risky deal. This knowledge is required to behave intelligently but is notoriously subjective and hard to state precisely. Getting that knowledge inside a software system is thus an important challenge for AI. Attempts have been made to hard-code the knowledge about the world into formal representations (knowledge bases) usable by computers, but due to the sheer size and complexity of this knowledge, the approach has so far failed.

An alternative solution is to endow systems with the ability to identify and extract patterns from

data to acquire their own knowledge about the world, which is known as machine learning (ML), a subset of AI. There exist several broad variations of ML approaches. Among them are supervised and unsupervised learning. In supervised learning, computers are learning from previous (human) experience. The training data consists of a set of input objects with the corresponding desired output values (labels) also provided. For instance, a training set can consist of a number of relevant parameters about a client coupled with the risk assessment for that client manually performed by a human subject matter expert. A supervised learning algorithm (e.g., classification) helps infer the function that maps inputs into outputs by learning from the provided labeled examples – i.e., from the expert. Using a trained model, the system will be able to produce labels (e.g., 'high', 'medium' or 'low' risk value estimates) for the new inputs. With unsupervised learning, the output (label) is not provided, and the system learns on its own by trying to find the relationships among different inputs. Clustering (i.e., grouping objects by their similarity) is one of the most prevalent algorithms of this kind. Unsupervised learning doesn't require any preconceived notions about the data and thus is much more flexible than statistical approaches. ML technology is currently deployed in many domains, including security, healthcare, etc. In many such domains (e.g., in medical imaging), its performance is already proving to be on par with or even better than that of human subject matter experts.

ML is not a new field and its origins can be traced back to 1950s. Only relatively recently, however, it has experienced a resurgence, driven

by a few factors that finally made its adoption a viable and cost-effective option to handle increasingly complex business tasks. The first factor is the abundance of business data due to the proliferation and interconnectedness of ERP, SCM, CRM, and other enterprise systems within and across organizations and the continuing digitization of document workflows. This is also helped by the cheap data storage and the availability and affordability of communication technologies. This data about anything and everything relevant – e.g., past business events, transactions, decisions and, most importantly, their outcomes – can serve as the training data for ML and DL algorithms. However, the availability of data does not automatically make it usable. Large volumes of data require a lot of processing capacity and sophisticated software to make sense of it with minimal human involvement. Traditionally, companies had to invest in creating and maintaining their own data centres to process that data or be locked into mostly inflexible contracts with data centre providers. In both cases, organizations were forced to overprovision hardware and software to handle maximum anticipated loads, which rarely occurred in practice. Cloud computing, another factor in the resurgence of AI/ML, eliminated that inflexibility and allowed tapping into the elastic cloud-based processing capacity on demand and paying only for the actual usage of storage and processing services. That being said, for those organizations that cannot or prefer not to use the public cloud (e.g., due to security concerns), new ML-specific hardware as well as the novel ways this equipment can be deployed, managed, and financed are becoming available for on-premise use.

Thus, the availability of business data and flexible and affordable on-demand processing eliminated or at least greatly reduced the barriers to adopting AI/ML solutions by enterprises and fuelled the creation of increasingly high-quality ML and other programming libraries that support the development of fully customized AI-based solutions from the ground up. To further simplify the adoption of AI/ML solutions, companies like IBM, Microsoft, and Google are developing pre-built (and sometimes pre-trained), customizable, cloud-based ML services that focus on common domain-independent functionality like natural language (i.e., text) and voice processing, sentiment/emotion analysis, image/video processing, chatbots, and recommendation and decision-making engines. These services can be further trained with domain- and company-specific data and used as the building blocks for creating AI systems. This lets each organization focus its efforts on developing the remaining domain-specific and competitive advantage-building AI components that are fully tailored to its needs within some particular business domain, such as SCF. Overall, these solutions promise to help eliminate conscious and unconscious biases and to ultimately help shift from human-scale to machine-scale business decision-making.

The above developments in both data availability and AI-based technology are likely to have a massive impact, especially in 'closed' supply chain ecosystems. Several recent attempts to apply AI to credit and other supply chain risks were focused predominantly on transaction-based businesses (such as sales to SMEs, single invoice cover, or funding). They used little proprietary

information and their core improvements were achieved through better analyses of public and quasi-public data. Applying AI tools to significant information flows (financial and non-financial, structured and unstructured) within deeply integrated supply chains (like distributors or contract manufacturers) is likely to trigger a fundamental rethinking of risk, as opposed to tactical improvements based on quasi-public information.

Similarly, combining AI tools with significant private information is likely to re-frame the whole issue of performance risk. This is currently dealt with by a small number of financiers through either converting performance risk to credit risk (i.e., relying on somebody's contractual obligation while structuring the transaction that looks like it is based on performance risk) or deploying simple statistical models that allow stress testing on asset values. AI tools would allow models to account for the deep interrelationships between various risks and parts of the ecosystem, thereby facilitating the financing of such deals.

Such technologies are likely to change the cottage industry of both credit and performance risk finance currently based purely on individual domain experience. They are likely to open both types of financing to a wide range of financial institutions and capital markets through deployment of modern analytical tools and deep information flows.