Computational Approaches and Data Analytics in Financial Services: A Literature Review

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ARTICLE HISTORY
Compiled November 8, 2018

ABSTRACT
The level of modeling sophistication in financial services has increased considerably over the years. Nowadays, the complexity of financial problems and the vast amount of data require an engineering approach based on analytical modeling tools for planning, decision making, reporting, and supervisory control. This paper provides an overview of the main financial applications of computational and data analytics approaches, focusing on the coverage of the recent developments and trends. The overview covers different methodological tools and their uses in areas, such as portfolio management, credit analysis, banking, and insurance.

KEYWORDS
Financial services; data analytics; risk management; financial modeling

1. Introduction

The sector of financial services has undergone major changes over the past decades. On the one hand, the range of operations in the financial sector has grown significantly, covering a wide range of new banking, investment, and insurance products, together with new financing tools and corporate finance practices. On the other hand, the sector has been increasingly relying on new technologies, not only as tools for providing improved services to individual and corporate clients, but also for improving practices in regard to decision making, risk analysis, monitoring, and reporting. Finally, a number of changes in the regulatory framework have imposed new requirements for the way financial services are designed, provided, and monitored.

Addressing the challenges that arise due to such developments, often requires a high level of sophistication for the analytical tools and techniques used in financial services. Traditionally, the field of finance has relied on normative and descriptive approaches, usually based on statistical and econometric techniques, for building theories regarding the understanding of the financial world. Nevertheless, going beyond financial theory,

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prescriptive and predictive systems are also crucial for decision making in financial services, providing operational guidance to decision makers (investors, managers, policy makers) on specific instances of financial decision problems. Combined with financial theory and models, such systems support financial decision making through comprehensive approaches that integrate theory, data, and expert judgment.

However, the context described above for the sector of financial services, poses various challenges on the development of realistic and effective analytic models and techniques in this field. First, the existence of deep uncertainties requires the development and extensive testing of robust models. Second, big data are becoming increasingly important in financial services, but financial data are usually unstructured and noisy. The volume of the available data also raises computational issues, particularly in cases where real-time decision support is required. Finally, model transparency has also become an important issue for reporting and supervisory control of the practices followed in the financial sector.

The scope of financial decision support approaches and their range of applications has been extended considerably since Markowitz's work on portfolio selection (Markowitz, 1959) and the first applications of linear/goal programming and decision theory to problems related to financial planning and investment appraisal (Charnes, Cooper, & Ijiri, 1963; Hillier, 1963; Myers & Pogue, 1974). Nowadays, a wide arsenal of optimization models, decision making approaches, data analytic techniques, and computational solution algorithms, are available and applicable to various traditional and new financial products/services.

The objective of this paper is to provide an overview of the current status and recent developments in this area, focusing on computational and data analytic approaches. Given that presenting a comprehensive bibliographic review of the relevant literature is quite difficult, due to the wide range of the field and the analytical methodologies involved, we cover in more detail two popular areas in financial services, namely portfolio management and credit risk analysis. The review focuses on analytical approaches such as exact optimization techniques, metaheuristics, machine learning approaches, and decision analysis.

The rest of the paper is organized as follows. In section 2 we describe the context of financial decisions and the relevance/contributions of various types of analytical approaches. Section 3 reviews the recent literature on the applications of such approaches in portfolio management, credit risk analysis, as well as in other fields areas of financial services. Finally, section 4 concludes the paper and discusses some future research issues.

2. Financial decision making

Decision problems in financial services cover a wide range of areas related to financing decisions and investment planning, as well as supervisory control. Recently, most of the focus in research and practice has been on risk management issues for financial institutions (banks, insurance companies, funds, etc.). Moreover, issues related to the design and management of financial services provided to consumers and corporate clients has also attracted much interest, particularly with the emergence of new electronic platforms and distribution channels (e.g., online transactions, crowdfunding, cryptocurrencies), which have led to the recent rise of financial technology (fintech).

The widespread use of analytical models for financial decision making has been driven by various factors. One of the most important ones has been the regulatory requirements imposed during the past two decades. For instance, starting with the first Basel Committee capital accord in 1988, and its revisions in Basel II/III, banks are required to follow a strict set of guidelines and rules for measuring, managing, and reporting their risk exposures (credit, liquidity, operational, and market risks). Similar regulatory requirements have also been introduced in other sectors of financial services (e.g., the European Solvency II directive for insurance regulation, the IFRS 9 for financial reporting, etc.). Meeting the requirements imposed by the regulatory environment, requires the use of analytical approaches, which set a systematic basis for planning, decision making, and control.

Beyond the tightening regulatory provisions, the use of analytical models has been also promoted to meet the increasing complexity of designing and providing advanced financial services to consumers and corporate clients. The massive data that are nowadays available create many opportunities. For instance, for selecting financial assets for investment purposes, except for standard financial and market data (e.g., fundamentals and technical indicators), asset managers now also rely on sentiment analysis and news analytics (Schumaker, Zhang, Huang, & Chen, 2012; Smales, 2016), as well as information about corporate governance and social responsibility (e.g., social responsible investments; Ballestero, Bravo, Pérez-Gladish, Arenas-Parra, & Plà-Santamaria, 2012; Hallerbach, Ning, Soppe, & Spronk, 2004). The existence of vast data create opportunities for improving financial decisions, but this is a challenging task because the data should be transformed to useful information.

Models for financial decision making are used both at the strategic and the tactical/operational level. The former involves long-term decisions for financial organizations regarding their financial planning and the management of their assets. Examples of strategic financial decisions include decisions about mergers and acquisitions, initial public offerings, long-term capital budgeting and financial planning, loan portfolio management, as well as decisions related to corporate capital structure and systemic risk analysis. On the other hand, models at the operational level focus on daily operations providing guidance and decision support on elementary instances according to the targets and goals set at the strategic level.

In this context, financial models combine normative, descriptive, and prescriptive elements, either in a static or a dynamic setting. While various analytical and computational approaches are used for financial modeling and decision making, in this review we distinguish between the following broad categories:

- *Optimization models*: Optimization models of various forms (e.g., linear and non-linear, dynamic, stochastic, fuzzy, multiobjective, etc.) are widely used for asset allocation, financial planning, and risk management (Zenios, Consiglio, & Nielsen, 2010). As it will be explain later in section 3.1.1, financial optimization models originate from the fundamental work of Markowitz (1959) on portfolio selection. Since then financial optimization has advanced to cover various other areas in investments, banking, insurance, and corporate finance. However, as models become more sophisticated, standard solution algorithms are not always feasible, from a computational point of view. This has led to the wide use of metaheuristics, which are well-suited for for complex problems with non-linear and combinatorial structure (Maringer, 2005). In financial services, such problems commonly arise when modeling realistic features (e.g., cardinality constrained portfolio optimization) or when dealing with complex risk measures.
- *Data analytics and machine learning*: As explained above, financial services have become a data-intensive sector. Artificial intelligence (AI) approaches based on

machine learning are particularly well-suited as data analytics tools, enabling the development of descriptive, prescriptive, and predictive models for financial decision making. Such models allow the identification of non-trivial patterns in massive and ill-structured financial data. Supervised and unsupervised learning techniques for classification and regression are the ones most commonly used, together with intelligent optimization systems (e.g., reinforcement learning, Bloembergen, Tuyls, Hennes, & Kaisers, 2015).

- *Decision analysis and decision support systems*: In contrast to AI approaches, which usually adopt automated procedures for decision making, decision analysis techniques rely on the domain knowledge and expertise of financial decision makers (Zopounidis, Doumpos, & Niklis, 2018). Incorporating this type of information to financial models enhances their comprehensibility and adds realism, which may not be fully covered by pure data-driven approaches. Combined with other analytical approaches (optimization-based or AI), this may reduce model risk, which has become a crucial issue in financial modeling (Christodoulakis & Satchell, 2008). Moreover, the constructive approach often adopted by decision analysis approaches promotes the learning process, thus providing insights into various aspects of financial decision problems and the preferences of the actors involved (e.g., managers, investors, policy-makers, etc.). Decision analysis tools are often implemented in decision support systems, which integrate data management, analytics, visualization, and reporting tools.

The existing arsenal of analytical techniques practically covers all areas of financial modeling and decision making. However, in many cases a single approach may not be enough as the multi-faced nature of problems in financial services may not be fully covered by one methodology. Thus, hybrid systems are common, combining elements and ideas from various disciplines.

3. Overview of applications in financial services

Having defined the framework for financial decisions and the main analytical tools used in this area, in this section an overview of the recent literature is presented regarding the applications of various types of analytical approaches in different areas of financial services. The overview starts with portfolio management, followed by credit risk analysis, as well as other applications in banking and insurance.

3.1. Portfolio management

The area of portfolio management is one of the most widely studied domains in financial decision making. In financial services, portfolio management is involved with the design and management of financial investments, usually consisting of assets from the equity markets, as well as funds, fixed income investments, currencies, and commodities. Nevertheless, the many principles and techniques used in portfolio management also applied in portfolios of real investment (e.g., project portfolios) as well as in banking (e.g., loan portfolios), and insurance.

The portfolio management process involves various issues (Doumpos & Zopounidis, 2014; Xidonas, Mavrotas, Krintas, Psarras, & Zopounidis, 2012). In the following subsections, we cover asset screening, portfolio allocation, and trading, focusing on the computational and data analytics methodologies used in each area.

3.1.1. Asset screening

Asset screening is the first step of the portfolio management process, which focuses on the selection of the most suitable investment assets. Given the vast number of assets now available to investors in the global markets, the screening and selection process is crucial for a successful investment strategy. The screening process takes into account various factors about the investment environment, the trends in the markets, as well as fundamental and technical factors about specific assets. For instance, for stock selection portfolio managers typically consider financial data about the future prospects of the firms, valuation indicators, as well as technical indicators that capture short to medium-term trends in equity prices. While asset selection by professionals is often based on univariate decision rules, empirical evidence has shown that the combined use of different selection attributes may provide significantly improved results (Pätäri, Karell, Luukka, & Yeomans, 2018; van der Hart, Slagter, & van Dijk, 2003).

The methodologies and analytical tools for asset screening can be categorized in two main categories. The first category is based on judgmental approaches, which rely on descriptive and prescriptive approaches, often based on inputs provided by investors and portfolio managers about their investment policies and preferences. The second category focuses on automated procedures, based on models for predicting future returns. Often such models are used in the context of asset trading, rather than for selecting investments for portfolio construction. The literature on trading models is covered in sub-section 3.1.3.

Table 1 lists some recent studies on the use of various methodologies for asset selection, focusing on the selection of stocks and funds. It is interesting that approaches based on data envelopment analysis and multicriteria decision making are quite popular in this area. Such techniques are based on data-driven and expert judgment approaches to evaluate the performance of a set of assets on the basis of their fundamentals. On the other hand, data analytics models such as neural networks, neuro-fuzzy models, support vector machines, and evolutionary methods, have been mainly used in a predictive modeling context to estimate the growth prospects of assets and identify those that are more likely to be profitable investments.

Table 1. Studies on the use of analytical methodologies for asset selection

Study	Methodology	Asset
Edirisinghe and Zhang (2007)	DEA	Stocks
H.-H. Chen (2008)	DEA	Stocks
Edirisinghe and Zhang (2008)	DEA	Stocks
Quah (2008)	ANN, ANFIS	Stocks
Sevastjanov and Dymova (2009)	MCDA, Fuzzy	Stocks
Hamzaçebi and Pekkaya (2011)	GRA	Stocks
C.-F. Huang (2012)	GA, SVM	Stocks
Xidonas, Mavrotas, and Psarras (2010)	MCDA	Stocks
Yan and Clack (2010)	GP	Funds
Xidonas, Mavrotas, Zopounidis, and Psarras (2011)	MCDA	Stocks
Babalos, Philippas, Doumpos, and Zopounidis (2012)	MCDA	Funds
Kiris and Ustun (2012)	Fuzzy MCDM	Stocks
H. Liu, Mulvey, and Zhao (2016)	Copula models	Stocks
Song, Liu, and Yang (2017)	ML, SA	Stocks
Allevi, Basso, Bonenti, Oggioni, and Riccardi (2018)	DEA	Funds
Galagedera, Roshdi, Fukuyama, and Zhu (2018)	DEA	Funds
do Castelo Gouveia, Neves, Dias, and Antunes (2018)	DEA	Funds
Pätäri et al. (2018)	MCDA	Stocks

ANFIS: adaptive neuro-fuzzy inference system, ANN: artificial neural network, DEA: data envelopment analysis, GA: genetic algorithm, GP: genetic programming, MCDA: multicriteria decision analysis, SA: sentiment analysis, SVM: support vector machines

3.1.2. Capital allocation

In financial services, asset allocation is a broad field involved with the design of financial investments combining multiple assets into portfolios that meet the investor's risk-return preferences. Usually, different asset classes can be considered, such as equities, fixed income securities, funds, derivatives, currencies, and commodities. The foundations of quantitative asset allocation have been set by the mean-variance (MV) portfolio selection model of Markowitz (1959), which is expressed as a standard quadratic programming (QP) problem:

$$\begin{array}{ll} \min & \mathbf{x}^\top \boldsymbol{\Sigma} \mathbf{x} \\ \text{subject to}: & \mathbf{r}^\top \mathbf{x} \geq R \\ & \mathbf{1}^\top \mathbf{x} = 1 \\ & \mathbf{z} \leq \mathbf{x} \leq \mathbf{u} \end{array} \tag{1}$$

where $\mathbf{x} = (x_1, \ldots, x_n)$ denotes the vector of asset allocations (proportion of capital invested in a set of n assets), $\mathbf{z} = (z_1 \ldots, z_n)$ and $\mathbf{u} = (u_1, \ldots, u_n)$ are vectors of lower and upper bounds for the allocations, $\boldsymbol{\Sigma} = (\sigma_{ij})_{i,j=1}^n$ is the covariance matrix of asset returns, $\mathbf{r} = (r_1, \ldots, r_n)$ is the vector of expected (mean) asset returns, R is a user-defined level of required return, and $\mathbf{1}$ denotes a vector of ones.

The MV model set the grounds for numerous extensions to cover more realistic and complex cases. Some typical examples include:

- *Different risk measures* providing a finer characterization of investment risk, beyond the MV perspective that relies solely on the variance of returns. Over the years, different risk measures have been introduced focusing on a more detailed description of the returns distribution with higher-order moments (skewness and kurtosis; Jondeau & Rockinger, 2006; Ryoo, 2007), tail-risk measures (value-at-risk, conditional value-at-risk; Jorion, 2009; Rockafellar & Uryasev, 2002), and other risk-return performance measures (e.g., omega ratio; Kapsos, Christofides, & Rustem, 2014).
- *Cardinality constrained asset allocation*, involving portfolios consisting of a fixed maximum number of assets selected automatically through an optimization model from a given pool of options (Bertsimas & Shioda, 2007; Chang, Meade, Beasley, & Sharaiha, 2000; Woodside-Oriakhi, Lucas, & Beasley, 2011).
- *Transaction costs and other real features* that describe actual investment strategies in more a realistic manner. Some indicative issues involve transaction costs, round-lot constraints, portfolio diversification goals, and other considerations such as social responsible investments (Angelelli, Mansini, & Speranza, 2008; Hallerbach et al., 2004).
- *Index tracking portfolio optimization*, involving passive investment strategies that replicate the returns of a chosen market index (Andriosopoulos, Doumpos, Papapostolou, & Pouliasis, 2013; Andriosopoulos & Nomikos, 2014; de Paulo, de Oliveira, & do Valle Costa, 2016; Filippi, Guastaroba, & Speranza, 2016; Mezali & Beasley, 2013; Strub & Baumann, 2018; Zhao, Xu, Wang, & yi Zhang, 2018)
- *Dynamic portfolio selection* that extends the traditional MV static framework to multiple time periods, either in a discrete or a continuous setting (Brown & Smith, 2011; Q. Liu, Guo, & Wang, 2012).

The incorporation of such aspects into asset allocation models has led to various advances on at least two major directions:

- *Algorithmic approaches*: Several of the above extensions and variants require the solution of complex optimization problems. For instance, in cardinality constrained asset allocation and index tracking, problem (1) is reformulated in a mixed-integer QP form with binary variables indicating whether an asset is included in the portfolio or not. This variant is difficult to solve to optimality with exact algorithms due to its combinatorial nature. The optimization of alternative performance measures, such as value-at-risk (Babat, Vera, & Zuluaga, 2018; Gaivoronski & Pflug, 2005) and models based on higher-order moments (C. Chen & sha Zhou, 2018; Maringer & Parpas, 2007), also poses computational challenges. The same also applies to models that incorporate transaction costs and other real features (Glen, 2011; Jobst, Horniman, Lucas, & Mitra, 2001; Lobo, Fazel, & Boyd, 2006). In such cases, algorithms (heuristics and metaheuristics) that lead to approximate optimal solutions in reasonable time, have been become very popular and have been used a variety of different settings (Ertenlice & Kalayci, 2018; Maringer, 2005).
- *Modeling formulations*: Except for algorithmic advances, the consideration of different portfolio performance measures and other realistic features, has led to various modeling developments, such as
    - portfolio selection with multiple objectives and goals (Aouni, Doumpos, Pérez-Gladish, & Steuer, 2018; Colapinto, La Torre, & Aouni, 2018; Giesecke, Kim, Kim, & Tsoukalas, 2014; Xidonas, Mavrotas, Hassapis, & Zopounidis, 2017; Xidonas et al., 2012),
    - stochastic approaches (Brown & Smith, 2011; Dupačová & Kopa, 2012; Filomena & Lejeune, 2012; Hibiki, 2006; Östermark, 2017; Post & Kopa, 2017),
    - multiperiod and continuous time models (Bjrk, Murgoci, & Zhou, 2012; Bo & Capponi, 2014; Calafiore, 2008; Çelikyurt & Özekici, 2007; Jung & Kim, 2015; Pfister, Utz, & Wimmer, 2014),
    - fuzzy models (Gupta, Mehlawat, & Saxena, 2008; Vercher & Bermudez, 2013; X. Xu, He, Chen, & Zhang, 2015),
    - robust optimization (Ban, Karoui, & Lim, 2018; Bertsimas & Sim, 2004; Fabozzi, Kolm, Pachamanova, & Focardi, 2007; Goldfarb & Iyengar, 2003; W. C. Kim, Kim, Ahn, & Fabozzi, 2012; Lotfi & Zenios, 2018), and
    - network models (Boginski, Butenko, & Pardalos, 2005; X. Guo, Zhang, & Tian, 2018; Kalyagin, Koldanov, Koldanov, & Pardalos, 2017).

3.1.3. Trading

The trading process in portfolio management is involved with dynamically rebalancing a portfolio of assets or a single asset to maximize the investors terminal wealth (also taking into account risk considerations). Trading systems combine various fundamental and technical factors to identify market trends and profitable trades. Except for standard financial time series data, other information has become very popular recently, including news analytics and sentiment analysis (Bordino et al., 2012; Geva & Zahavi, 2014; Mitra & Mitra, 2011; Schumaker et al., 2012; Treleaven, Galas, & Lalchand, 2013). Moreover, with the advances in electronic trading systems, algorithmic trading (including high-frequency trading; Goldstein, Kumar, & Graves, 2014) has dominated the field, with various reports from the USA and Europe indicating that automated systems account for more than 40-50% of the total trading volume in the equities markets.[1]

The research on the development of trading systems has focused on various machine learning approaches, such as reinforcement learning (RL), artificial neural networks (ANN), deep learning (DL), support vector machines (SVM), neuro-fuzzy systems, as well as evolutionary approaches (e.g., genetic algorithms and genetic programming). Such approaches enable the analysis of large, unstructured data in a dynamic, real-time, and algorithmic context, that requires minimal intervention by a portfolio manager, while making no assumptions about the statistical properties of the data or the behavior of financial markets. Table 2 provides an indicative list of recent studies with information about the methodologies used and the type of traded assets (stocks, equity indices, foreign exchange, portfolios).

Table 2. Studies using computational approaches for asset trading

Study	Methodology	Asset
Ang and Quek (2006)	Rule-based NFIS	Stocks
Dempster and Leemans (2006)	RL	Forex
Chavarnakul and Enke (2008)	ANN	Equity indices
S.-T. Li and Kuo (2008)	SOM	Equity indices
Dymova, Sevastianov, and Bartosiewicz (2010)	Fuzzy logic, DST	Stocks
Gorgulho, Neves, and Horta (2011)	GA	Portfolios
Kardas, Challenger, Yildirim, and Yamuc (2011)	Multi-agent system	Stocks
Tan, Quek, and Cheng (2011)	RL, ANFIS	Stocks
Creamer (2012)	Boosting	Index futures
Evans, Pappas, and Xhafa (2013)	ANN, GA	Forex
Mabu, Hirasawa, Obayashi, and Kuremoto (2013)	GP	Stocks
(Skabar, 2013)	Graph-based model	Stocks
Booth, Gerding, and McGroarty (2014)	RF	Stocks
Creamer (2015)	ANN, SA	Portfolios
Hazan and Kale (2015)	Online algorithm	Portfolios
Sermpinis, Stasinakis, Theofilatos, and Karathanasopoulos (2015)	SVM, GA	Forex
J. Zhang and Maringer (2015)	RL, GA	Stocks
Heaton, Polson, and Witte (2016)	DL	Equity indices
Berutich, López, Luna, and Quintana (2016)	GP	Stocks
Almahdi and Yang (2017)	RL	Portfolios, ETF
Sermpinis, Stasinakis, Rosillo, and de la Fuente (2017)	SVM	ETF
Abbaszadeh, Nguyen, and Wu (2018)	DP	Stocks
Carapuço, Neves, and Horta (2018)	RL	Forex
Feuerriegel and Gordon (2018)	TM, SA	Equity indices
Fiévet and Sornette (2018)	DT, Markov models	Stocks
Nakano, Takahashi, and Takahashi (2018)	ANN	Cryptocurrencies
Pendharkar and Cusatis (2018)	RL	Equity indices
Yang, Lai, Wu, and Fang (2018)	Ridge regression	Portfolios
Jeong and Kim (2019)	DL	Equity indices

ANFIS: adaptive neuro-fuzzy inference system, ANN: artificial neural network, DT: decision trees, ETF: exchange-traded funds, Forex: foreign exchange, GA: genetic algorithm, DL: deep learning, DP: dynamic programming, GP: genetic programming, DST: Dempster-Shafer theory, RL: reinforcement learning, SA: sentiment analysis, SOM: self-organizing map, SVM: support vector machines, TM: text mining

3.2. Credit risk modeling

Credit risk is one of the main areas of financial risk management that is of major interest not only for financial institutions providing credit, but also for non-financial corporations, as well as for individual consumers. Credit risk arises when borrowers fail to meet their debt obligations towards their creditors. Credit risk management has been at the core of all regulatory provisions enforced in the financial sector throughout the past two decades (i.e., the Basel Committee capital accords). Existing regulatory requirements constitute a quite stringent framework for modeling, measuring, and

[1] `https://bit.ly/2OyGUDu` and `https://bit.ly/2OulCXf` (accessed: 8 November, 2018)

managing credit risk, at least by credit institutions. Moreover, new reporting standards (i.e., International Financial Reporting Standards 9) have direct implications for credit risk management for non-financial companies.

The main components of credit risk modeling include the probability of loan default (PD), the losses given default (LGD), and the exposure at default (EAD), which define the expected losses of a loan or a loan portfolio:

$$\text{Expected loss} = (PD)(LGD)(EAD)$$

Credit models have become quite sophisticated over the years, covering various types of credit exposures, such as corporate loans, bond issues, consumer loans, and special purpose loans (e.g., project finance). The following subsections overview the use of computational and analytical techniques in credit scoring and rating and loss given default estimation. Further details on the procedures and techniques applied in this field can be found in the works of Baesens and Van Gestel (2009) and Doumpos, Lemonakis, Niklis, and Zopounidis (2019).

3.2.1. Credit scoring and rating

Credit scoring and rating models are fundamental components of credit risk analysis. Such models assess the creditworthiness of borrowers, provide PD estimates, and assign borrowers to risk rating classes, combining various types of information from the financial markets, about the characteristics of the loan and the borrower, as well as data about the external environment.

Credit scoring/rating models can be judgmental or quantitative. The former are used when historical data are lacking or for special types of credit assessments (e.g., project finance), whereas the latter are the ones preferred in most other cases (Doumpos et al., 2019). Quantitative models rely on the analysis of loan default data using analytical estimation models. Under the most common setting, data about defaulted and non-defaulted loans/borrowers are used for model fitting. Each data instance is described through various attributes (features) representing the risk level of the loan or the borrower. The output of a model fitted on such data is usually expressed in the form of a risk score, which can be associated with a PD estimate and a risk rating.

In this setting, statistical techniques such as logistic regression are widely used in practice. The main advantage of such approaches is that they are straightforward to apply and the resulting models are easy to comprehend, due to their linear form. Moreover, applying standard statistical techniques to big data poses no computational issues. However, despite the convenience of using linear credit risk scoring/rating models, their predictive performance may be inferior to more general models that allow the identification of more complex risk patterns that describe credit risk more accurately. While the performance gains can be marginal (if any) when limited information (attributes) is available, it can be become significant when rich information is considered. Over the years, credit risk data have become much more comprehensive, combining information from various traditional and alternative sources, such as from the financial markets, corporate data, personal data, historical deliquesces, as well as social networks, corporate networks, news, etc. (Galil & Soffer, 2011; Gül, Kabak, & Topcu, 2018; Óskarsdóttir, Bravo, Sarraute, Vanthienen, & Baesens, 2018; Smales, 2016; Wei, Yildirim, den Bulte, & Dellarocas, 2016). In this context, advanced modeling methodologies have a lot of potential to provide significantly improved results.

Data analytics approaches based on machine learning and operations research techniques have been widely used in this area. Among others, three main methodological schemes can be identified:

- *Single model approaches* relying on the construction of credit risk models using a single methodology. The most commonly techniques are machine learning algorithms, such as neural networks, kernel methods, classification trees and decision rules, fuzzy and neuro-fuzzy systems, Bayesian models, etc. (Bellotti & Crook, 2009b; Capotorti & Barbanera, 2012; G. Chen & Åstebro, 2012; Chrzanowska, Alfaro, & Witkowska, 2009; Kvamme, Sellereite, Aas, & Sjursen, 2018; Luo, Wu, & Wu, 2017; Serrano-Cinca & Gutiérrez-Nieto, 2016; Sreekantha & Kulkarni, 2012). Other methodologies include multicriteria decision making/aiding (Angilella & Mazzù, 2018; Doumpos & Figueira, 2019; Doumpos & Zopounidis, 2011; Ferreira, Esperança, Xavier, Costa, & Pérez-Gladish, 2018; García, Giménez, & Guijarro, 2013; Gavalas & Syriopoulos, 2014; Gutiérrez-Nieto, Serrano-Cinca, & Camón-Cala, 2014), and optimization techniques (He, Zhang, Shi, & Huang, 2010; Iazzolino, Bruni, & Beraldi, 2013; A. Li, Shi, & He, 2008; Peng, Kou, Shi, & Chen, 2008).
- *Ensembles* combining multiple base models developed either through a single classifier or multiple algorithms to derived improved combined forecasts. The success of ensemble schemes depends on the diversity of the base models' results and reduction of their bias and/or variance. Popular ensemble approaches include various variants of bagging and boosting algorithms, which have been shown to provide very good results in several cases (Abellán & Castellano, 2017; Bequé & Lessmann, 2017; Finlay, 2011; Marqués, García, & Sánchez, 2012).
- *Hybrid systems*, which rely on the combination of different techniques for feature/sample selection and model fitting as well as different modeling schemes (Doumpos, Niklis, Zopounidis, & Andriosopoulos, 2015; Niklis, Doumpos, & Zopounidis, 2014; Oreski, Oreski, & Oreski, 2012; Yeh, Lin, & Hsu, 2012; Yu, Wang, & Lai, 2009; Z. Zhang, Gao, & Shi, 2014).

A comprehensive comparative assessment of various learning algorithms and methodologies on various credit risk assessment data sets can be found in the work of Lessmann, Baesens, Seow, and Thomas (2015). Similar techniques are also used in other related fields such as profit and behavioral scoring (J. N. Crook, Edelman, & Thomas, 2007; Thomas, 2009) and bankruptcy prediction (Alaka et al., 2018). It is worth noting and as analytical models for credit risk analysis become more complex, their comprehensibility becomes a major issue, particularly from a supervisory point of view. To address this issue, methodologies combining comprehensible systems (e.g., rule-based models) with advanced modeling algorithms have been proposed (Baesens, Setiono, Mues, & Vanthienen, 2003; Florez-Lopez & Ramon-Jeronimo, 2015; Martens, Baesens, Gestel, & Vanthienen, 2007).

Concerning model construction, it is worth noting that often, given a large number of features and available information, the selection of the best risk predictors is a cumbersome process. Computational approaches facilitating feature selection have been widely used to address this difficulty, usually through metaheuristics (Marqués, García, & Sánchez, 2013; Serrano-Silva, Villuendas-Rey, & Yáñez-Márquez, 2018). Similar algorithms have also been used to optimize the parameters of fitting algorithms or to enable the consideration of complex performance measures (Finlay, 2009; Kozeny, 2015; J. Li, Wei, Li, & Xu, 2011; Martens et al., 2010; T. Zhang, Dai, & Ma, 2015; Zong-Chang, Hong, Ji-sheng, & Hong, 2015), as well as for calibrating credit ratings (Lyra, Paha, Paterlini, & Winker, 2010).

Finally, it is worth noting that while most of the above approaches mostly follow a static approach providing risk estimates for a fixed time period, another line of research has adopted models that incorporate dynamic characteristics. Typical examples include survival and hazard models that consider time-varying variables and enable the modeling of the time to default (Bellotti & Crook, 2009a, 2014; J. Crook & Bellotti, 2010; Dirick, Claeskens, & Baesens, 2017; Serrano-Cinca, Gutiérrez-Nieto, & López-Palacios, 2015), whereas credit migration (i.e., the dynamics of credit ratings) is commonly model with Markov models (Baena-Mirabete & Puig, 2017; D'Amico, Janssen, & Manca, 2016; Quirini & Vannucci, 2014).

3.2.2. Loss given default

Loss given default (LGD) is the second major component of credit risk modeling. LGD refers to the losses that a creditor expects to face in the event of a loan default. The losses are expressed as percentage of the credit exposure (i.e., the outstanding amount) and refers to a chosen time period (e.g., one year).

Unlike models for PD estimation the prediction of LGD requires a regression modeling approach. According to (Scheule, Baesens, & Roesch, 2016), LGD models can be classified in three main categories. The first category involves single-stage LGD models, which are based on a standard regression setting. Such models can be constructed with simple OLS estimation (with some transformation of LGD to take into account that is lies in [0, 1]), as well as with other regression models, such as beta regression, quantile regression, and machine learning techniques. Single-stage models, however, do not take into consideration that LGD is conditional on loan default, which leads to a sample selection bias that is further evident by the fact that many defaulted loans do not lead to losses (Do, Rsch, & Scheule, 2018). A second type of models addresses this limitation through multi-stage schemes that provide PD and LGD estimates. For instance, in a two-stage setting, a classification model is used to obtain PD estimates and a regression model is used for LGD prediction. More refined multi-stage settings are also possible with more elaborate structures, e.g., by separating fully cured defaulted loans from loans with losses (Do et al., 2018). A final class of LGD estimation models involves advanced approaches that consider non-observable random effects and complex dependencies between loan defaults and losses.

Comparative evaluations of various LGD estimation approaches can be found in the works of Loterman, Brown, Martens, Mues, and Baesens (2012) and Qi and Zhao (2011). Both studies concluded that non-parametric models outperform parametric ones for single-stage LGD estimation. Loterman et al. (2012) further examined two-stage models and found that they are competitive to non-linear single-stage models, with the advantage of having a more comprehensible structure. Table 3 provides an indicative list of recent studies on the use of various methodologies for estimating LGD.

3.2.3. Loan portfolio management

Credit risk models for PD and LGD estimation are fundamental tools not only for the analysis of individual loans but also for managing loan portfolios. Loan portfolio management focuses on the estimation of losses at the portfolio level to derive a loss distribution that allows the specification of capital requirements for financial institutions. Typically, the loss distribution for loan portfolios is right-skewed. Losses that

Table 3. Indicative list of recent studies on LGD modeling

Study	Methodology	Estimation approach	Type of loans
Chava, Stefanescu, and Turnbull (2011)	Hazard model	Advanced	Corporate loans & bonds
Bastos (2013)	Ensembles	Single-stage	Corporate bonds
Bonini and Caivano (2014)	Credibility theory	Advanced	Retail loans
Calabrese (2014)	Mixture model	Advanced	Personal loans
Leow, Mues, and Thomas (2014)	LR+OLS	Multi-stage	Mortgage & personal loans
Tobback, Martens, Gestel, and Baesens (2014)	SVM	Multi-stage	Consumer & corporate loans
Bijak and Thomas (2015)	Bayesian model	Multi-stage	Personal loans
X. Yao, Crook, and Andreeva (2015)	SVM	Multi-stage	Bonds
Krger and Rsch (2017)	QR	Single-stage	Corporate loans
Nazemi, Pour, Heidenreich, and Fabozzi (2017)	Ensembles, DE	Single-stage	Bonds
X. Yao, Crook, and Andreeva (2017)	SVM	Multi-stage	Credit cards
Cheng and Cirillo (2018)	SURV	Multi-stage	Consumer loans
Do et al. (2018)	Probit+OLS	Multi-stage	Mortgage loans
Krger, Oehme, Rsch, and Scheule (2018)	Copula model	Advanced	Bonds
J.-Y. Kim and Cho (2019)	DL	Single-stage	P2P lending

DE: differential evolution, DL: deep learning, LR: logistic regression, OLS: ordinary least squares, QR: quantile regression, SURV: survival analysis, SVM: support vector machines

do not exceed the expected loss, are covered by provisions, whereas higher losses up to an unexpected loss level, define the needed capital requirements (Witzany, 2017). The unexpected loss level is specified by value-at-risk measures at the 99.9% confidence level.

Loan portfolio management has some similarities to investment portfolio selection, but there are also noticeable differences, too. In both contexts, correlations play a fundamental role for risk modeling and diversification (Scheule et al., 2016). However, in loan portfolios market values and historical prices are unavailable for most types of loans (except for bonds). Well-known industry models, such as CreditMetrics, CreditRisk+, and KMV Portfolio Manager (Crouhy, Galai, & Mark, 2000), rely on structural and reduced form approaches based on financial models originating from the work of Merton (1974) on the pricing of corporate debt and its generalization by Vasicek (1987) for portfolios of corporate loans.

While traditional financial approaches focus on modeling the loss distribution for loan portfolios, alternative computational methodologies have been proposed to extend the loan portfolio management setting, covering issues like:

- dynamic portfolio management with stochastic and dynamic programming models (Bo & Capponi, 2017; Capponi & Figueroa-López, 2012; Rasmussen & Clausen, 2007; Valladão, Veiga, & Street, 2018),
- optimization models for value-at-risk optimization (Iscoe, Kreinin, Mausser, & Romanko, 2012; Mencía, 2012),
- computationally efficient simulation methods (Başoğlu, Hrmann, & Sak, 2018; Glasserman, Kang, & Shahabuddin, 2008; G. Liu, 2015; Sak & Hrmann, 2012)
- Markov chain models for portfolios of consumer loans (Malik & Thomas, 2010), and
- exact and evolutionary approaches for optimizing the composition of loan portfolios as well as for collateral management (Blank et al., 2017; Y. Guo, Zhou, Luo, Liu, & Xiong, 2016; Ivorra, Mohammadi, & Ramos, 2007; Metawa, Hassan, & Elhoseny, 2017; Sirignano, Tsoukalas, & Giesecke, 2016)

3.3. Other areas of applications in banking, investments, and insurance

Except for the areas covered in the previous sections regarding portfolio management and credit risk analysis, computational approaches and data analytics are also relevant in various other financial problems, including, among others, asset-liability and debt management, asset pricing, volatility modeling, operational and liquidity risk modeling, financial fraud detection, venture capital investments, efficiency analysis, mergers and acquisitions, and country risk modeling. Table 4 presents a list of recent research works on some of these subjects. It should be noted that this compiled list does not include works about the efficiency and performance of financial organizations, which is a very active area of research, but it has been covered in existing reviews, such as the work of Fethi and Pasiouras (2010). From the studies reported in Table 4 it is evident that areas involving financial planning decisions rely on computational optimization approaches, usually in a stochastic context, which allows the consideration and modeling of uncertainties. On the other hand, in other domains such as volatility modeling and fraud detection, the main focus is on developing predictive models for decision making. In such areas, data analytic approaches (e.g., machine learning) have been the most popular methodologies.

4. Conclusions and future research

Financial services is a very broad sector dealing with various types of problems with diverse features and characteristics. The sector's reliance on modeling tools has intensified over the years, and the level of analytical sophistication has also grown significantly. Thus, nowadays, financial services is not just an area where existing quantitative methodologies from other fields can be applied and tested in practice, but it also a field that promotes the development of new technological and analytical advances. The combination of characteristics such as the existence of massive real-time financial data, deep uncertainties, multiple actors and stakeholders, together with a tightening regulatory requirement, and the dynamic nature of the financial world, constantly create new modeling and computational challenges.

In this review we provided a synopsis of the applications, uses, and contributions of computational methodologies and data analytic techniques in this area. Popular topics like portfolio management and credit risk analysis were used as examples to illustrative the different techniques that have been recently used to address various types of financial decisions, in a prescriptive, descriptive and predictive setting. These techniques, include among others, different forms of exact optimization models (e.g., static, dynamic, robust, stochastic, etc.), metaheuristics, machine learning systems, and decision analysis.

Despite the progress that has been made in developing comprehensive, realistic, and accurate analytical tools for financial decision making, several research and practical challenges remain open. For instance, an important issue is the development of meaningful and effective integrated systems taking advantage of different analytical tools to allow the coverage of the multiple facets of financial problems in a unified context. Moreover, the comprehensibility and transparency of analytical models are crucial consideration for the adoption of new technologies and systems in practice, together with their incorporation into the existing procedures and protocols of financial institutions and organizations. While the trade-off between comprehensibility/transparency and performance is a challenge that does not have a global answer applicable to all settings, implementations in new types of decision support systems taking advantage of new technologies for visualization, reporting, and man-machine interaction, will certainly facilitate to the resolution of that trade-off. Moreover, techniques that allow the processing of various types of unstructured data (qualitative and quantitative) col-

Table 4. Summary of studies about applications of analytical and computational models in various areas of financial decision making

Study	Methodology
Asset-liability management	
Kosmidou and Zopounidis (2008)	Goal programming
Asimit, Badescu, Siu, and Zinchenko (2013)	Chance constrained programming
Glpinar and Pachamanova (2013)	Robust optimization
Viswanathan, Ranganatham, and Balasubramanian (2014)	Goal programming
Chiu and Wong (2012)	Stochastic programming
Duarte, Valladão, and Veiga (2017)	Stochastic programming
L. Xu, Zhang, and Yao (2017)	Dynamic programming
Consigli, Moriggia, Vitali, and Mercuri (2018)	Stochastic programming
Moriggia, Kopa, and Vitali (2018)	Multi-objective stochastic programming
Sovereign and corporate debt management	
Balibek and Kksalan (2010)	Multi-objective stochastic programming
Consiglio and Staino (2012)	Stochastic programming
Valladão, Veiga, and Veiga (2014)	Stochastic programming
Consiglio, Lotfi, and Zenios (2018)	Linear programming
Venture capital and initial public offerings	
Ko, Lin, and Yang (2011)	Game theory
Aouni, Colapinto, and Torre (2014)	Fuzzy goal programming
Bastı, Kuzey, and Delen (2015)	Support vector machines
Afful-Dadzie and Afful-Dadzie (2016)	Multicriteria analysis
Quintana, Chávez, Luque Baena, and Luna (2018)	ANFIS, genetic optimization
Tian, Xu, and Fujita (2018)	Fuzzy systems
Zhong, Liu, Zhong, and Xiong (2018)	Bayesian inference, Markov Chain Monte Carlo
Operational and liquidity risk modeling	
Chavez-Demoulin, Embrechts, and Nešlehová (2006)	Extreme value theory
Shevchenko (2009)	Bayesian inference
Aquaro et al. (2010)	Bayesian networks
Shevchenko (2011)	Bayesian inference
Sanford and Moosa (2012)	Bayesian networks
Janabi, Hernandez, Berger, and Nguyen (2017)	Copula modeling
Eling and Jung (2018)	Copula modeling
Peña, Bonet, Lochmuller, Chiclana, and Góngora (2018)	Adaptive fuzzy inference model
Azar and Dolatabad (2019)	Fuzzy cognitive maps
Derivatives and volatility modeling	
Bandi and Bertsimas (2014)	Linear programming
Quek, Pasquier, and Kumar (2007)	Neural networks
X. Liu, Cao, Ma, and Shen (2019)	Wavelets
Y. Yao et al. (2017)	Neural networks
H. Y. Kim and Won (2018)	Deep learning
Bezerra and Albuquerque (2016)	Support vector machines
Zeng and Klabjan (2018)	Support vector machines
Financial fraud detection	
Gaganis (2009)	Multicriteria analysis, machine learning
Dikmen and Küçükkocaoğlu (2010)	Integer programming
Glancy and Yadav (2011)	Text mining
Abbasi, Albrecht, Vance, and Hansen (2012)	Stacked generalization
Sahin, Bulkan, and Duman (2013)	Decision trees
Balla, Gaganis, Pasiouras, and Zopounidis (2014)	Multicriteria analysis
S.-Y. Huang, Tsaih, and Yu (2014)	Self-organizing maps
Throckmorton, Mayew, Venkatachalam, and Collins (2015)	Bayesian classifier
Colladon and Remondi (2017)	Network analysis
Didimo, Giamminonni, Liotta, Montecchiani, and Pagliuca (2018)	Network analysis
D. Huang, Mu, Yang, and Cai (2018)	Graph-based models
Nami and Shajari (2018)	Random forests, nearest neighbors

lected through non-traditional sources (e.g., online sources, news, etc.), could further improve the effectiveness of existing models and decision support tools. Finally, the integration of analytical models with finance theory would promote their use to a wider audience and further facilitate their adoption by practitioners in financial services.

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