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Machine learning advances for time series forecasting

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Abstract

In this paper, we survey the most recent advances in supervised machine learning (ML) and high-dimensional models for time-series forecasting. We consider both linear and nonlinear alternatives. Among the linear methods, we pay special attention to penalized regressions and ensemble of models. The nonlinear methods considered in the paper include shallow and deep neural networks, in their feedforward and recurrent versions, and tree-based methods, such as random forests and boosted trees. We also consider ensemble and hybrid models by combining ingredients from different alternatives. Tests for superior predictive ability are briefly reviewed. Finally, we discuss application of ML in economics and finance and provide an illustration with high-frequency financial data.

KEYWORDS
bagging, boosting, deep learning, forecasting, machine learning, neural networks, nonlinear models, penalized regressions, random forests, regression trees, regularization, sieve approximation, statistical learning theory

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1 | INTRODUCTION

This paper surveys the recent developments in machine learning (ML) methods to economic and financial time-series forecasting. ML methods have become an important estimation, model selection, and forecasting tool for applied researchers in Economics and Finance. With the availability

of vast data sets in the era of *Big Data*, producing reliable and robust forecasts is of great importance.[1]

However, what is ML? It is certainly a buzzword which has gained a lot of popularity during the last few years. There are a myriad of definitions in the literature and one of the most well established is from the artificial intelligence pioneer Arthur L. Samuel who defines ML as "the field of study that gives computers the ability to learn without being explicitly programmed."[2] We prefer a less vague definition where ML is the combination of automated computer algorithms with powerful statistical methods to learn (discover) hidden patterns in rich data sets. In that sense, *Statistical Learning Theory* gives the statistical foundation of ML. Therefore, this paper is about Statistical Learning developments and not ML in general as we are going to focus on statistical models. ML methods can be divided into three major groups: supervised, unsupervised, and reinforcement learning. This survey is about supervised learning, where the task is to learn a function that maps an input (explanatory variables) to an output (dependent variable) based on data organized as input–output pairs. Regression models, for example, belong to this class. On the other hand, unsupervised learning is a class of ML methods that uncover undetected patterns in a data set with no preexisting labels as, for example, cluster analysis or data compression algorithms. Finally, in reinforcement learning, an agent learns to perform certain actions in an environment which lead it to maximum reward. It does so by exploration and exploitation of knowledge it learns by repeated trials of maximizing the reward. This is the core of several artificial intelligence game players (AlfaGo, for instance) as well as in sequential treatments, like Bandit problems.

The supervised ML methods presented here can be roughly divided in two groups. The first one includes linear models and is discussed in Section 2. We focus mainly on specifications estimated by regularization, also known as shrinkage. Such methods date back at least to Tikhonov (1943). In Statistics and Econometrics, regularized estimators gained attention after the seminal papers by Willard James and Charles Stein who popularized the bias-variance trade-off in statistical estimation (James & Stein, 1961; Stein, 1956). We start by considering the Ridge Regression estimator put forward by Hoerl and Kennard (1970). After that, we present the least absolute shrinkage and selection (LASSO) estimator of Tibshirani (1996) and its many extensions. We also include a discussion of other penalties. Theoretical derivations and inference for dependent data are also reviewed.

The second group of ML techniques focuses on nonlinear models. We cover this topic in Section 3 and start by presenting a unified framework based on sieve semiparametric approximation as in Grenander (1981). We continue by analyzing specific models as special cases of our general setup. More specifically, we cover feedforward neural networks (NNs), both in their shallow and deep versions and recurrent neural networks (RNNs), and tree-based models such as random forests (RFs) and boosted trees. NNs are probably one of the most popular ML methods. The success is partly due to the, in our opinion, misguided analogy to the functioning of the human brain. Contrary to what has been boasted in the early literature, the empirical success of NN models comes from a mathematical fact that a linear combination of sufficiently many simple basis functions is able to approximate very complicated functions arbitrarily well in some specific choice of metric. Regression trees only achieved popularity after the development of algorithms to attenuate the instability of the estimated models. Algorithms like Random Forests and Boosted Trees are now in the toolbox of applied economists.

In addition to the models mentioned above, we also include a survey on ensemble-based methods such as Bagging Breiman (1996) and the complete subset regression (CRS, Elliott et al., 2013, 2015). Furthermore, we give a brief introduction to what we named "hybrid methods," where ideas from both linear and nonlinear models are combined to generate new ML forecasting methods.

Before presenting an empirical illustration of the methods, we discuss tests of superior predictive ability in the context of ML methods.

1.1 | General framework

A quick word on notation: an uppercase letter as in X denotes a random quantity as opposed to a lowercase letter x which denotes a deterministic (nonrandom) quantity. Bold letters as in $\boldsymbol{X}$ and $\boldsymbol{x}$ are reserved for multivariate objects such as vector and matrices. The symbol $\|\cdot\|_q$ for $q \geq 1$ denotes the ℓ_q norm of a vector. For a set S, we use $|S|$ to denote its cardinality.

Given a sample with T realizations of the random vector $(Y_t, \boldsymbol{Z}_t')'$, the goal is to predict Y_{T+h} for horizons $h = 1, \dots, H$. Throughout the paper, we consider the following assumption:

Assumption 1 (Data Generating Process (DGP)). Let $\{(Y_t, \boldsymbol{Z}_t')'\}_{t=1}^{\infty}$ be a covariance-stationary stochastic process taking values on $\mathbb{R}^{d+1}$.

Therefore, we are excluding important nonstationary processes that usually appear in time-series applications. In particular, unit root and some types on long-memory process are excluded by Assumption 1.

For (usually predetermined) integers $p \geq 1$ and $r \geq 0$, define the n-dimensional vector of predictors $\boldsymbol{X}_t := (Y_{t-1}, \dots, Y_{t-p}, \boldsymbol{Z}_t', \dots, \boldsymbol{Z}_{t-r}')'$ where $n = p + d(r+1)$ and consider the following direct forecasting model:

$$Y_{t+h} = f_h(\boldsymbol{X}_t) + U_{t+h}, \quad h = 1, \dots, H, \quad t = 1, \dots, T, \tag{1}$$

where $f_h : \mathbb{R}^n \to \mathbb{R}$ is an unknown (measurable) function and $U_{t+h} := Y_{t+h} - f_h(\boldsymbol{X}_t)$ is assumed to be zero mean and finite variance.[3]

The model f_h could be the conditional expectation function, $f_h(\boldsymbol{x}) = \mathbb{E}(Y_{t+h}|\boldsymbol{X}_t = \boldsymbol{x})$, or simply the best linear projection of Y_{t+h} onto the space spanned by $\boldsymbol{X}_t$. Regardless of the model choice, our target becomes f_h, for $h = 1, \dots, H$. As f_h is unknown, it should be estimated from data. The target function f_h can be a single model or an ensemble of different specifications and it can also change substantially for each forecasting horizon.

Given an estimate $\widehat{f}_h$ for f_h, the next step is to evaluate the forecasting method by estimating its prediction accuracy. Most measures of prediction accuracy derive from the random quantity $\Delta_h(\boldsymbol{X}_t) := |\widehat{f}_h(\boldsymbol{X}_t) - f_h(\boldsymbol{X}_t)|$. For instance, the term *prediction consistency* refers to estimators such that $\Delta_h(\boldsymbol{X}_t) \xrightarrow{p} 0$ as $T \to \infty$ where the probability is taken to be unconditional; as opposed to its *conditional* counterpart which is given by $\Delta_h(\boldsymbol{x}_t) \xrightarrow{p} 0$, where the probability law is conditional on $\boldsymbol{X}_t = \boldsymbol{x}_t$. Clearly, if the latter holds for (almost) every $\boldsymbol{x}_t$ then the former holds by the law of iterated expectation.

Other measures of prediction accuracy can be derived from the $\mathcal{L}_q$ norm induced by either the unconditional probability law $\mathbb{E}|\Delta_h(\boldsymbol{X}_t)|^q$ or the conditional one $\mathbb{E}(|\Delta_h(\boldsymbol{X}_t)|^q|\boldsymbol{X}_t = \boldsymbol{x}_t)$ for $q \geq 1$. By far, the most used are the *(conditional) mean absolutely prediction error* (MAPE) when $q = 1$ and *(conditional) mean squared prediction error* (MSPE) when $q = 2$, or the *(conditional) root mean squared prediction error* (RMSPE), which is simply the square root of MSPE. Those measures of prediction accuracy based on the $\mathcal{L}_q$ norms are stronger than prediction consistency in the sense

that their convergence to zero as sample size increases implies prediction consistency by Markov's inequality.

This approach stems from casting economic forecasting as a decision problem. Under the choice of a loss function, the goal is to select f_h from a family of candidate models that minimizes the expected predictive loss or risk. Given an estimate $\widehat{f}_h$ for f_h, the next step is to evaluate the forecasting method by estimating its risk. The most commonly used losses are the absolute error and squared error, corresponding to $\mathcal{L}_1$ and $\mathcal{L}_2$ risk functions, respectively. See Granger and Machina (2006) for references of a detailed exposition of this topic, Elliott and Timmermann (2008) for a discussion of the role of the loss function in forecasting, and Elliott and Timmermann (2016) for a more recent review.

1.2 | Summary of the paper

Apart from this brief introduction, the paper is organized as follows. Section 2 reviews penalized linear regression models. Nonlinear ML models are discussed in Section 3. Ensemble and hybrid methods are presented in Section 4. Section 5 briefly discusses tests for superior predictive ability. An empirical application is presented in Section 6. Finally, we conclude and discuss some directions for future research in Section 7.

2 | PENALIZED LINEAR MODELS

We consider the family of linear models where $f(\boldsymbol{x}) = \boldsymbol{\beta}_0'\boldsymbol{x}$ in (1) for a vector of unknown parameters $\boldsymbol{\beta}_0 \in \mathbb{R}^n$. Notice that we drop the subscript h for clarity. However, the model as well as the parameter $\boldsymbol{\beta}_0$ have to be understood for particular value of the forecasting horizon h. These models contemplate a series of well-known specifications in time-series analysis, such as predictive regressions, autoregressive models of order p, $AR(p)$, autoregressive models with exogenous variables, $ARX(p)$, and autoregressive models with dynamic lags $ADL(p, r)$, among many others (Hamilton, 1994). In particular, (1) becomes

$$Y_{t+h} = \boldsymbol{\beta}_0'\boldsymbol{X}_t + U_{t+h}, \quad h = 1, \dots, H, \quad t = 1, \dots, T, \tag{2}$$

where under squared loss, $\boldsymbol{\beta}_0$ is identified by the best linear projection of Y_{t+h} onto $\boldsymbol{X}_t$ which is well defined whenever $\boldsymbol{\Sigma} := \mathbb{E}(\boldsymbol{X}_t\boldsymbol{X}_t')$ is nonsingular. In that case, U_{t+h} is orthogonal to $\boldsymbol{X}_t$ by construction and this property is exploited to derive estimation procedures such as the ordinary least squares (OLS). However, when $n > T$ (and sometimes $n \gg T$) the OLS estimator is not unique as the sample counterpart of $\boldsymbol{\Sigma}$ is rank deficient. In fact, we can completely overfit whenever $n \geq T$.

Penalized linear regression arises in the setting where the regression parameter is not uniquely defined. It is usually the case when n is large, possibly larger than the number of observations T, and/or when covariates are highly correlated. The general idea is to restrict the solution of the OLS problem to a ball around the origin. It can be shown that, although biased, the restricted solution has smaller mean squared error (MSE), when compared to the unrestricted OLS (Hastie et al., 2009, Chap. 3 and Chap. 6).

In penalized regressions, the estimator $\widehat{\boldsymbol{\beta}}$ for the unknown parameter vector $\boldsymbol{\beta}_0$ minimizes the Lagrangian form

$$Q(\boldsymbol{\beta}) = \sum_{t=1}^{T-h} \left(Y_{t+h} - \boldsymbol{\beta}'\boldsymbol{X}_t\right)^2 + p(\boldsymbol{\beta}),$$

$$= \|\boldsymbol{Y} - \boldsymbol{X}\boldsymbol{\beta}\|_2^2 + p(\boldsymbol{\beta}), \tag{3}$$

where $\boldsymbol{Y} := (Y_{h+1}, \dots Y_T)'$, $\boldsymbol{X} := (\boldsymbol{X}_1, \dots \boldsymbol{X}_{T-h})'$, and $p(\boldsymbol{\beta}) := p(\boldsymbol{\beta}; \lambda, \boldsymbol{\gamma}, \boldsymbol{Z}) \geq 0$ is a penalty function that depends on a tuning parameter $\lambda \geq 0$, that controls the trade-off between the goodness of fit and the regularization term. If $\lambda = 0$, we have a classical unrestricted regression, since $p(\boldsymbol{\beta}; 0, \boldsymbol{\gamma}, \boldsymbol{X}) = 0$. The penalty function may also depend on a set of extra hyperparameters $\boldsymbol{\gamma}$, as well as on the data $\boldsymbol{X}$. Naturally, the estimator $\widehat{\boldsymbol{\beta}}$ also depends on the choice of λ and $\boldsymbol{\gamma}$. Different choices for the penalty functions were considered in the literature of penalized regression.

Ridge regression

The ridge regression was proposed by Hoerl and Kennard (1970) as a way to fight highly correlated regressors and stabilize the solution of the linear regression problem. The idea was to introduce a small bias but, in turn, reduce the variance of the estimator. The ridge regression is also known as a particular case of Tikhonov Regularization (Tikhonov, 1943, 1963; Tikhonov & Arsenin, 1977), in which the scale matrix is diagonal with identical entries.

The ridge regression corresponds to penalizing the regression by the squared ℓ_2 norm of the parameter vector, that is, the penalty in (3) is given by

$$p(\boldsymbol{\beta}) = \lambda \sum_{i=1}^{n} \beta_i^2 = \lambda \|\boldsymbol{\beta}\|_2^2.$$

Ridge regression has the advantage of having an easy to compute analytic solution, where the coefficients associated with the least relevant predictors are shrunk toward zero, but never reaching exactly zero. Therefore, it cannot be used for selecting predictors, unless some truncation scheme is employed.

Least absolute shrinkage and selection operator

The LASSO was proposed by Tibshirani (1996) and Chen et al. (2001) as a method to regularize and perform variable selection at the same time. LASSO is one of the most popular regularization methods and it is widely applied in data-rich environments where number of features n is much larger than the number of the observations.

LASSO corresponds to penalizing the regression by the ℓ_1 norm of the parameter vector, that is, the penalty in (3) is given by

$$p(\boldsymbol{\beta}) = \lambda \sum_{i=1}^{n} |\beta_i| = \lambda \|\boldsymbol{\beta}\|_1.$$

The solution of the LASSO is efficiently calculated by coordinate descent algorithms (Hastie et al., 2015, Chap. 5). The ℓ_1 penalty is the smallest convex ℓ_p penalty norm that yields *sparse* solutions. We say the solution is *sparse* if only a subset $k < n$ coefficients are nonzero. In other words, only a subset of variables is selected by the method. Hence, LASSO is most useful when the total number of regressors $n \gg T$ and it is not feasible to test combination or models.

Despite attractive properties, there are still limitations to the LASSO. A large number of alternative penalties have been proposed to keep its desired properties while overcoming its limitations.

Adaptive LASSO

The adaptive LASSO (adaLASSO) was proposed by Zou (2006) and aimed to improve the LASSO regression by introducing a weight parameter, coming from a first step OLS regression. It also has sparse solutions and efficient estimation algorithm, but enjoys the *oracle property*, meaning that it has the same asymptotic distribution as the OLS conditional on knowing the variables that should enter the model.[4]

The adaLASSO penalty consists in using a weighted ℓ_1 penalty:

$$p(\boldsymbol{\beta}) = \lambda \sum_{i=1}^{n} \omega_i |\beta_i|,$$

where the number of features $\omega_i = |\beta_i^*|^{-1}$ and β_i^* is the coefficient from the first-step estimation (any consistent estimator of $\boldsymbol{\beta}_0$) AdaLASSO can deal with many more variables than observations. Using LASSO as the first-step estimator can be regarded as the two-step implementation of the local linear approximation in Fan et al. (2014) with a zero initial estimate.

Elastic net

The elastic net (ElNet) was proposed by Zou and Hastie (2005) as a way of combining strengths of LASSO and ridge regression. While the L_1 part of the method performs variable selection, the L_2 part stabilizes the solution. This conclusion is even more accentuated when correlations among predictors become high. As a consequence, there is a significant improvement in prediction accuracy over the LASSO (Zou & Zhang, 2009).

The ElNet penalty is a convex combination of ℓ_1 and ℓ_2 penalties:

$$p(\boldsymbol{\beta}) = \lambda \left[\alpha \sum_{i=1}^{n} \beta_i^2 + (1 - \alpha) \sum_{i=1}^{n} |\beta_i| \right] = \lambda [\alpha \|\boldsymbol{\beta}\|_2^2 + (1 - \alpha) \|\boldsymbol{\beta}\|_1],$$

where $\alpha \in [0, 1]$. The ElNet has both the LASSO and ridge regression as special cases.

Just like in the LASSO regression, the solution to the ElNet problem is efficiently calculated by coordinate descent algorithms. Zou and Zhang (2009) propose the adaptive ElNet. The ElNet and adaLASSO improve the LASSO in distinct directions: the adaLASSO has the oracle property and the ElNet helps with the correlation among predictors. The adaptive ElNet combines the strengths of both methods. It is a combination of ridge and adaLASSO, where the first-step estimator comes from the ElNet.

Folded concave penalization

LASSO approaches became popular in sparse high-dimensional estimation problems largely due their computational properties. Another very popular approach is the folded concave penalization of Fan and Li (2001). This approach covers a collection of penalty functions satisfying a set of properties. The penalties aim to penalize more parameters close to zero than those that are further away, improving performance of the method. In this way, penalties are concave with respect to each $|\beta_i|$.

One of the most popular formulations is the SCAD (smoothly clipped absolute deviation). Note that unlike LASSO, the penalty may depend on λ in a nonlinear way. We set the penalty in (3) as $p(\boldsymbol{\beta}) = \sum_{i=1}^{n} \widetilde{p}(\beta_i, \lambda, \gamma)$, where

$$
\widetilde{p}(u, \lambda, \gamma) = \begin{cases} \lambda|u| & \text{if } |u| \leq \lambda, \\ \frac{2\gamma\lambda|u| - u^2 - \lambda^2}{2(\gamma - 1)} & \text{if } \lambda \leq |u| \leq \gamma\lambda, \\ \frac{\lambda^2(\gamma + 1)}{2} & \text{if } |u| > \gamma\lambda \end{cases}
$$

for $\gamma > 2$ and $\lambda > 0$. The SCAD penalty is identical to the LASSO penalty for small coefficients, but continuously relaxes the rate of penalization as the coefficient departs from zero. Unlike OLS or LASSO, we have to solve a nonconvex optimization problem that may have multiple minima and is computationally more intensive than the LASSO. Nevertheless, Fan et al. (2014) showed how to calculate the oracle estimator using an iterative Local Linear Approximation algorithm.

Other penalties

Regularization imposes a restriction on the solution space, possibly imposing sparsity. In a data-rich environment, it is a desirable property as it is likely that many regressors are not relevant to our prediction problem. The presentation above concentrates on the, possibly, most used penalties in time-series forecasting. Nevertheless, there are many alternative penalties that can be used in regularized linear models.

The group LASSO, proposed by Yuan and Lin (2006), penalizes the parameters in groups, combining the ℓ_1 and ℓ_2 norms. It is motivated by the problem of identifying "factors," denoted by groups of regressors as, for instance, in regression with categorical variables that can assume many values. Let $\mathcal{G} = \{g_1, \ldots, g_M\}$ denote a partition of $\{1, \ldots, n\}$ and $\boldsymbol{\beta}_{g_i} = [\beta_i : i \in g_i]$ the corresponding regression subvector. The group LASSO assign to (3) the penalty $p(\boldsymbol{\beta}) = \sum_{i=1}^{M} \sqrt{|g_i|} \|\boldsymbol{\beta}_{g_i}\|_2$, where $|g_i|$ is the cardinality of a set g_i. The solution is efficiently estimated using, for instance, the group-wise majorization descent algorithm (Yang & Zou, 2015). Naturally, the adaptive group LASSO was also proposed aiming to improve some of the limitations present on the group LASSO algorithm (Wang & Leng, 2008). In the group LASSO, the groups enter or not in the regression. The sparse group LASSO recover sparse groups by combining the group LASSO penalty with the L_1 penalty on the parameter vector (Simon et al., 2013).

Park and Sakaori (2013) modify the adaLASSO penalty to explicitly take into account lag information. Konzen and Ziegelmann (2016) propose a small change in penalty and perform a large simulation study to assess the performance of this penalty in distinct settings. They observe that

taking into account lag information improves model selection and forecasting performance when compared to the LASSO and adaLASSO. They apply their method to forecasting inflation and risk premium with satisfactory results.

There is a Bayesian interpretation to the regularization methods presented here. The ridge regression can be also seen as a maximum a posteriori estimator of a Gaussian linear regression with independent, equivariant, Gaussian priors. The LASSO replaces the Gaussian prior by a Laplace prior (Hans, 2009; Park & Casella, 2008). These methods fall within the area of Bayesian Shrinkage methods, which is a very large and active research area, and it is beyond the scope of this survey.

2.1 | Theoretical properties

In this section, we give an overview of the theoretical properties of penalized regression estimators previously discussed. Most results in high-dimensional time-series estimation focus on model selection consistency, oracle property, and oracle bounds, for both the finite dimension (n fixed, but possibly larger than T) and high dimension (n increases with T, usually faster).

More precisely, suppose there is a population, parameter vector $\boldsymbol{\beta}_0$ that minimizes Equation (2) over repeated samples. Suppose this parameter is sparse in a sense that only components indexed by $S_0 \subset \{1, \ldots, n\}$ are nonnull. Let $\widehat{S}_0 := \{j : \widehat{\beta}_j \neq 0\}$. We say a method is *model selection consistent* if the index of nonzero estimated components converges to S_0 in probability.[5]

$$\mathbb{P}(\widehat{S}_0 = S_0) \to 1, \quad T \to \infty.$$

Consistency can also be stated in terms of how close the estimator is to true parameter for a given norm. We say that the estimation method is $\mathcal{L}^q$-consistent if for every $\epsilon > 0$:

$$\mathbb{P}(\|\widehat{\boldsymbol{\beta}}_0 - \boldsymbol{\beta}_0\|_q > \epsilon) \to 0, \quad T \to \infty.$$

It is important to note that model selection consistency does not imply, nor it is implied by, $\mathcal{L}^q$-consistency. As a matter of fact, one usually has to impose specific assumptions to achieve each of those modes of convergence.

Model selection performance of a given estimation procedure can be further broke down in terms of how many relevant variables $j \in S_0$ are included in the model (screening). Or how many irrelevant variables $j \notin S_0$ are excluded from the model. In terms of probability, model screening consistency is defined by $\mathbb{P}(\widehat{S}_0 \supseteq S_0) \to 1$ and model exclusion consistency defined by $\mathbb{P}(\widehat{S}_0 \subseteq S_0) \to 1$ as $T \to \infty$.

We say a penalized estimator has the oracle property if its asymptotic distribution is the same as the unpenalized one only considering the S_0 regressors. Finally, oracle risk bounds are finite sample bounds on the estimation error of $\widehat{\boldsymbol{\beta}}$ that hold with high probability. These bounds require relatively strong conditions on the curvature of objective function, which translates into a bound on the minimum restricted eigenvalue of the covariance matrix among predictors for linear models and a rate condition on λ that involves the number of nonzero parameters, $|S_0|$.

The LASSO was originally developed in fixed design with independent and identically distributed (IID) errors, but it has been extended and adapted to a large set of models and designs. Knight and Fu (2000) was probably the first paper to consider the asymptotics of the LASSO estimator. The authors consider fixed design and fixed n framework. From their results, it is clear

that the distribution of the parameters related to the irrelevant variables is non-Gaussian. To our knowledge, the first work expanding the results to a dependent setting was Wang et al. (2007), where the error term was allowed to follow an autoregressive process. Authors show that LASSO is model selection consistent, whereas a modified LASSO, similar to the adaLASSO, is both model selection consistent and has the oracle property. Nardi and Rinaldo (2011) show model selection consistency and prediction consistency for lag selection in autoregressive models. Chan and Chen (2011) show oracle properties and model selection consistency for lag selection in ARMA models. Yoon et al. (2013) derive model selection consistency and asymptotic distribution of the LASSO, adaLASSO, and SCAD, for penalized regressions with autoregressive error terms. Sang and Sun (2015) study lag estimation of autoregressive processes with long-memory innovations using general penalties and show model selection consistency and asymptotic distribution for the LASSO and SCAD as particular cases. Kock (2016) shows model selection consistency and oracle property of adaLASSO for lag selection in stationary and integrated processes. All results above hold for the case of fixed number of regressors or relatively high dimension, meaning that $n/T \to 0$.

In sparse, high-dimensional, stationary univariate time-series settings, where $n \to \infty$ at some rate faster than T, Medeiros and Mendes (2016, 2017) show model selection consistency and oracle property of a large set of linear time-series models with difference martingale, strong mixing, and non-Gaussian innovations. It includes, predictive regressions, autoregressive models $AR(p)$, autoregressive models with exogenous variables $ARX(p)$, autoregressive models with dynamic lags $ADL(p,r)$, with possibly conditionally heteroskedastic errors. Xie et al. (2017) show oracle bounds for fixed design regression with β-mixing errors. Wu and Wu (2016) derive oracle bounds for the LASSO on regression with fixed design and weak dependent innovations, in a sense of Wu (2005), whereas Han and Tsay (2020) show model selection consistency for linear regression with random design and weak sparsity[6] under serially dependent errors and covariates, within the same weak dependence framework. Xue and Taniguchi (2020) show model selection consistency and parameter consistency for a modified version of the LASSO in time-series regressions with long-memory innovations.

Fan and Li (2001) show model selection consistency and oracle property for the folded concave penalty estimators in a fixed dimensional setting. Kim et al. (2008) showed that the SCAD also enjoys these properties in high dimensions. In time-series settings, Uematsu and Tanaka (2019) show oracle properties and model selection consistency in time-series models with dependent regressors. Lederer et al. (2019) derived oracle prediction bounds for many penalized regression problems. The authors conclude that generic high-dimensional penalized estimators provide consistent prediction with any design matrix. Although the results are not directly focused on time-series problems, they are general enough to hold in such setting.

Babii et al. (2020c) proposed the sparse-group LASSO as an estimation technique when high-dimensional time-series data are potentially sampled at different frequencies. The authors derived oracle inequalities for the sparse-group LASSO estimator within a framework where distribution of the data may have heavy tails.

Two frameworks not directly considered in this survey but of great empirical relevance are non-stationary environments and multivariate models. In sparse, high-dimensional, integrated time-series settings, Lee and Shi (2020) and Koo et al. (2020) show model selection consistency and derive the asymptotic distributions of LASSO estimators and some variants. Smeeks and Wijler (2021) proposed the Single-equation Penalized Error Correction Selector (SPECS), which is an automated estimation procedure for dynamic single-equation models with a large number of potentially cointegrated variables. In sparse multivariate time series, Hsu et al. (2008) show model selection consistency in vector autoregressive (VAR) models with white-noise shocks. Ren and

Zhang (2010) use adaLASSO in a similar setting, showing both model selection consistency and oracle property. Afterward, Callot and Kock (2013) show model selection consistency and oracle property of the adaptive Group LASSO. In high-dimensional settings, where the dimension of the series increase with the number of observations, Kock and Callot (2015) and Basu and Michailidis (2015) show oracle bounds and model selection consistency for the LASSO in Gaussian $VAR(p)$ models, extending previous works. Melnyk and Banerjee (2016) extended these results for a large collection of penalties. Zhu (2020) derives oracle estimation bounds for folded concave penalties for Gaussian $VAR(p)$ models in high dimensions. More recently, researchers have departed from Gaussianity and correct model specification. Wong et al. (2020) derived finite sample guarantees for the LASSO in a misspecified VAR model involving β-mixing process with sub-Weibull marginal distributions. Masini et al. (2019) derive equation-wise error bounds for the LASSO estimator of weakly sparse $VAR(p)$ in mixingale dependence settings, that include models with conditionally heteroskedastic innovations.

2.2 | Inference

Although several papers derived the asymptotic properties of penalized estimators as well as the oracle property, these results have been derived under the assumption that the true nonzero coefficients are large enough. This condition is known as the $\boldsymbol{\beta}$-min restriction. Furthermore, model selection, such as the choice of the penalty parameter, has not been taken into account. Therefore, the true limit distribution, derived under uniform asymptotics and without the $\boldsymbol{\beta}$-min restriction can be very different from Gaussian, being even bimodal; see, for instance, Leeb and Pötscher (2005, 2008) and Belloni et al. (2014) for a detailed discussion.

Inference after model selection is actually a very active area of research and a vast number of papers have recently appeared in the literature. van de Geer et al. (2014) proposed the desparsified LASSO in order to construct (asymptotically) a valid confidence interval for each $\beta_{j,0}$ by modifying the original LASSO estimate $\widehat{\boldsymbol{\beta}}$. Let $\boldsymbol{\Sigma}^*$ be an approximation for the inverse of $\boldsymbol{\Sigma} := \mathbb{E}(\boldsymbol{X}_t \boldsymbol{X}_t')$, then the desparsified LASSO is defined as $\widetilde{\boldsymbol{\beta}} := \widehat{\boldsymbol{\beta}} + \boldsymbol{\Sigma}^*(\boldsymbol{Y} - \boldsymbol{X}\widehat{\boldsymbol{\beta}})/T$. The addition of this extra term to the LASSO estimator results in an unbiased estimator that no longer estimates any coefficient exactly as zero. More importantly, asymptotic normality can be recover in the sense that $\sqrt{T}(\widetilde{\beta}_i - \beta_{i,0})$ converges in distribution to a Gaussian distribution under appropriate regularity conditions. Not surprisingly, the most important condition is how well $\boldsymbol{\Sigma}^{-1}$ can be approximated by $\boldsymbol{\Sigma}^*$. In particular, the authors propose to run n LASSO regressions of X_i onto $\boldsymbol{X}_{-i} := (X_1, \dots, X_{i-1}, X_{i+1}, \dots, X_n)$, for $1 \leq i \leq n$. The authors named this process as *nodewide regressions*, and use those estimates to construct $\boldsymbol{\Sigma}^*$ (refer to Section 2.1.1 in van de Geer et al., 2014, for details)).

Belloni et al. (2014) put forward the double-selection method in the context of on a linear model in the form $Y_t = \beta_{01}X_t^{(1)} + \boldsymbol{\beta}_{02}'\boldsymbol{X}_t^{(2)} + U_t$, where the interest lies on the scalar parameter β_{01} and $\boldsymbol{X}_t^{(2)}$ is a high-dimensional vector of control variables. The procedure consists in obtaining an estimation of the active (relevant) regressors in the high-dimension auxiliary regressions of Y_t on $\boldsymbol{X}^{(2)}$ and of $X_t^{(1)}$ on $\boldsymbol{X}_t^{(2)}$, given by $\widehat{S}_1$ and $\widehat{S}_2$, respectively.[7] This can be obtained either by LASSO or any other estimation procedure. Once the set $\widehat{S} := \widehat{S}_1 \cup \widehat{S}_2$ is identified, the (a priori) estimated nonzero parameters can be estimated by a low-dimensional regression Y_t on $X_t^{(1)}$ and $\{X_{it}^{(2)} : i \in \widehat{S}\}$. The main result (Theorem 1 of Belloni et al., 2014) states conditions under which the estimator $\widehat{\beta}_{01}$ of the parameter of interest properly studentized is asymptotically

normal. Therefore, uniformly valid asymptotic confidence intervals for β_{01} can be constructed in the usual fashion.

Similar to Taylor et al. (2014) and Lockhart et al. (2014), Lee et al. (2016) put forward general approach to valid inference after model selection. The idea is to characterize the distribution of a postselection estimator conditioned on the selection event. More specifically, the authors argue that the postselection confidence intervals for regression coefficients should have the correct coverage conditional on the selected model. The specific case of the LASSO estimator is discussed in details. The main difference between Lee et al. (2016) and Taylor et al. (2014) and Lockhart et al. (2014) is that in the former, confidence intervals can be formed at any value of the LASSO penalty parameter and any coefficient in the model. Finally, it is important to stress that Lee et al. (2016) inference is carried on the coefficients of the selected model, while van de Geer et al. (2014) and Belloni et al. (2014) consider inference on the coefficients of the true model.

The above papers do not consider a time-series environment. Hecq et al. (2019) is one of the first papers which attempt to consider post-selection inference in a time-series environment. However, their results are derived under a fixed number of variables. Babii et al. (2020a) and Adámek et al. (2020) extend the seminal work of van de Geer et al. (2014) to time-series framework.

More specifically, Babii et al. (2020a) consider inference in time-series regression models underheteroskedastic and autocorrelated errors. The authors consider heteroskedaticity- and autocorrelation-consistent (HAC) estimation with sparse group-LASSO. They propose a debiased central limit theorem for low dimensional groups of regression coefficients and study the HAC estimator of the long-run variance based on the sparse-group LASSO residuals. Adámek et al. (2020) extend the desparsified LASSO to a time-series setting under near-epoch dependence assumptions, allowing for non-Gaussian, serially correlated and heteroskedastic processes. Furthermore, the number of regressors can possibly grow faster than the sample size.

3 | NONLINEAR MODELS

The function f_h appearing in (1) is unknown and in several applications the linearity assumption is too restrictive and more flexible forms must be considered. Assuming a quadratic loss function, the estimation problem turns to be the minimization of the functional

$$S(f) := \sum_{t=1}^{T-h} [Y_{t+h} - f(\boldsymbol{X}_t)]^2, \tag{4}$$

where $f \in \mathcal{G}$, a generic function space. However, the optimization problem stated in (4) is infeasible when $\mathcal{G}$ is infinite dimensional, as there is no efficient technique to search over all $\mathcal{G}$. Of course, one solution is to restrict the function space, as for instance, imposing linearity or specific forms of parametric nonlinear models as in, for example, Teräsvirta (1994), Suarez-Fariñas et al. (2004), or McAleer and Medeiros (2008); see also Teräsvirta et al. (2010) for a recent review of such models.

Alternatively, we can replace $\mathcal{G}$ by simpler and finite-dimensional $\mathcal{G}_D$. The idea is to consider a sequence of finite-dimensional spaces, the *sieve* spaces, $\mathcal{G}_D$, $D = 1, 2, 3, ...$, that converges to $\mathcal{G}$ in

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some norm. The approximating function $g_D(\boldsymbol{X}_t)$ is written as

$$g_D(\boldsymbol{X}_t) = \sum_{j=1}^{J} \beta_j g_j(\boldsymbol{X}_t),$$

where $g_j(\cdot)$ is the jth *basis* function for $\mathcal{G}_D$ and can be either fully known or indexed by a vector of parameters, such that: $g_j(\boldsymbol{X}_t) := g(\boldsymbol{X}_t; \theta_j)$. The number of basis functions $J := J_T$ will depend on the sample size T. D is the dimension of the space and it also depends on the sample size: $D := D_T$. Therefore, the optimization problem is then modified to

$$\hat{g}_D(\boldsymbol{X}_t) = \arg \min_{g_D(\boldsymbol{X}_t) \in \mathcal{G}_D} \sum_{t=1}^{T-h} [Y_{t+h} - g_D(\boldsymbol{X}_t)]^2. \tag{5}$$

The sequence of approximating spaces $\mathcal{G}_D$ is chosen by using the structure of the original underlying space $\mathcal{G}$ and the fundamental concept of dense sets. If we have two sets A and $B \in \mathcal{X}$, $\mathcal{X}$ being a metric space, A is dense in B if for any $\epsilon > 0, \in \mathbb{R}$ and $x \in B$, there is a $y \in A$ such that $\|x - y\|_{\mathcal{X}} < \epsilon$. This is called the method of "sieves." For a comprehensive review of the method for time-series data, see Chen (2007).

For example, from the theory of approximating functions we know that the proper subset $\mathcal{P} \subset \mathcal{C}$ of polynomials is dense in $\mathcal{C}$, the space of continuous functions. The set of polynomials is smaller and simpler than the set of all continuous functions. In this case, it is natural to define the sequence of approximating spaces $\mathcal{G}_D$, $D = 1, 2, 3, \ldots$ by making $\mathcal{G}_D$ the set of polynomials of degree smaller or equal to $D - 1$ (including a constant in the parameter space). Note that $\dim(\mathcal{G}_D) = D < \infty$. In the limit this sequence of finite-dimensional spaces converges to the infinite-dimensional space of polynomials, which on its turn is dense in $\mathcal{C}$.

When the basis functions are all known "linear sieves," the problem is linear in the parameters and methods like OLS (when $J \ll T$) or penalized estimation as previously described can be used.

For example, let $p = 1$ and pick a polynomial basis such that

$$g_D(X_t) = \beta_0 + \beta_1 X_t + \beta_2 X_t^2 + \beta_3 X_t^3 + \cdots + \beta_J X_t^J.$$

In this case, the dimension D of $\mathcal{G}_D$ is $J + 1$, due to the presence of a constant term.

If $J \ll T$, the vector of parameters $\boldsymbol{\beta} = (\beta_1, \ldots, \beta_J)'$ can be estimated by

$$\hat{\boldsymbol{\beta}} = (\boldsymbol{X}_J' \boldsymbol{X}_J)^{-1} \boldsymbol{X}_J' \boldsymbol{Y},$$

where $\boldsymbol{X}_J$ is the $T \times (J + 1)$ design matrix and $\boldsymbol{Y} = (Y_1, \ldots, Y_T)'$.

When the basis functions are also indexed by parameters ("nonlinear sieves"), nonlinear least-squares methods should be used. In this paper, we will focus on frequently used nonlinear sieves: NNs and regression trees.
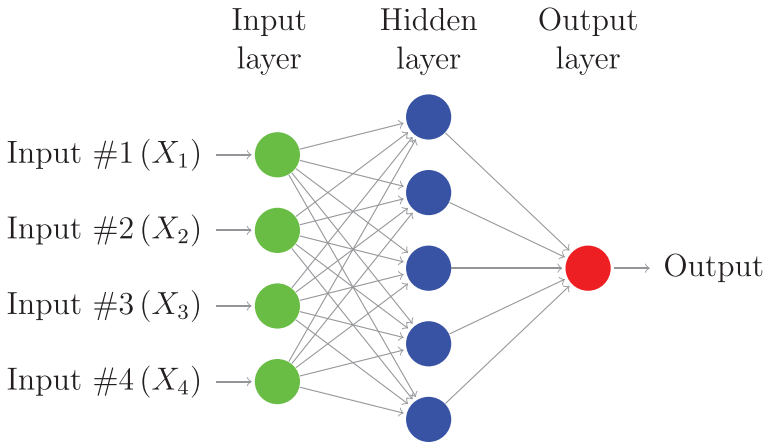
Figure 1 Graphical representation of a single hidden layer neural network [Colour figure can be viewed at wileyonlinelibrary.com]

3.1 | Neural networks

3.1.1 | Shallow NN

NN is one of the most traditional nonlinear sieves. NN can be classified into shallow or deep networks. We start describing the shallow NNs. The most common shallow NN is the feedforward NN where the approximating function $g_D(\boldsymbol{X}_t)$ is defined as

$$g_D(\boldsymbol{X}_t) := g_D(\boldsymbol{X}_t; \boldsymbol{\theta}) = \beta_0 + \sum_{j=1}^{J_T} \beta_j S(\boldsymbol{\gamma}_j' \boldsymbol{X}_t + \gamma_{0,j}),$$

$$= \beta_0 + \sum_{j=1}^{J_T} \beta_j S(\tilde{\boldsymbol{\gamma}}_j' \tilde{\boldsymbol{X}}_t). \tag{6}$$

In the above model, $\tilde{\boldsymbol{X}}_t = (1, \boldsymbol{X}_t')'$, $S_j(\cdot)$ is a basis function and the parameter vector to be estimated is given by $\boldsymbol{\theta} = (\beta_0, \dots, \beta_K, \boldsymbol{\gamma}_1', \dots, \boldsymbol{\gamma}_{J_T}', \gamma_{0,1}, \dots, \gamma_{0,J_T})'$, where $\tilde{\boldsymbol{\gamma}}_j = (\gamma_{0,j}, \boldsymbol{\gamma}_j')'$.

NN models form a very popular class of nonlinear sieves and have been used in many applications of economic forecasting. Usually, the basis functions $S(\cdot)$ are called activation functions and the parameters are called weights. The terms in the sum are called hidden neurons as an unfortunate analogy to the human brain. Specification (6) is also known as a single hidden layer NN model as is usually represented in the graphical as in Figure 1. The green circles in the figure represent the input layer which consists of the covariates of the model ($\boldsymbol{X}_t$). In the example in the figure, there are four input variables. The blue and red circles indicate the hidden and output layers, respectively. In the example, there are five elements (neurons) in the hidden layer. The arrows from the green to the blue circles represent the linear combination of inputs: $\boldsymbol{\gamma}_j' \boldsymbol{X}_t + \gamma_{0,j}$, $j = 1, \dots, 5$. Finally, the arrows from the blue to the red circles represent the linear combination of outputs from the hidden layer: $\beta_0 + \sum_{j=1}^{5} \beta_j S(\boldsymbol{\gamma}_j' \boldsymbol{X}_t + \gamma_{0,j})$.

There are several possible choices for the activation functions. In the early days, $S(\cdot)$ was chosen among the class of squashing functions as per the definition below.

Definition 1. A function $S : \mathbb{R} \longrightarrow [a, b]$, $a < b$, is a squashing (sigmoid) function if it is non-decreasing, $\lim_{x \longrightarrow \infty} S(x) = b$ and $\lim_{x \longrightarrow -\infty} S(x) = a$.

Historically, the most popular choices are the logistic and hyperbolic tangent functions such that:

$$\text{Logistic} : S(x) = \frac{1}{1 + \exp(-x)}$$

$$\text{Hyperbolic tangent} : S(x) = \frac{\exp(x) - \exp(-x)}{\exp(x) + \exp(-x)}.$$

The popularity of such functions was partially due to theoretical results on function approximation. Funahashi (1989) establishes that NN models as in (6) with generic squashing functions are capable of approximating any continuous functions from one finite dimensional space to another to any desired degree of accuracy, provided that J_T is sufficiently large. Cybenko (1989) and Hornik et al. (1989) simultaneously proved approximation capabilities of NN models to any Borel measurable function and Hornik et al. (1989) extended the previous results and showed that the NN models are also capable to approximate the derivatives of the unknown function. Barron (1993) relates previous results to the number of terms in the model.

Stinchcombe and White (1989) and Park and Sandberg (1991) derived the same results of Cybenko (1989) and Hornik et al. (1989) but without requiring the activation function to be sigmoid. While the former considered a very general class of functions, the later focused on radial-basis functions (RBF) defined as:

$$\text{Radial Basis} : S(x) = \exp(-x^2).$$

More recently, Yarotsky (2017) showed that the rectified linear units (ReLU) as

$$\text{Rectified Linear Unit} : S(x) = \max(0, x),$$

are also universal approximators.

Model (6) can be written in matrix notation. Let $\boldsymbol{\Gamma} = (\tilde{\boldsymbol{\gamma}}_1, \dots, \tilde{\boldsymbol{\gamma}}_K)$,

$$\boldsymbol{X} = \begin{pmatrix} 1 & X_{11} & \cdots & X_{1p} \\ 1 & X_{21} & \cdots & X_{2p} \\ \vdots & \vdots & \ddots & \vdots \\ 1 & X_{T1} & \cdots & X_{Tp} \end{pmatrix}, \quad \text{and} \quad \mathcal{O}(\boldsymbol{X}\boldsymbol{\Gamma}) = \begin{pmatrix} 1 & S(\tilde{\boldsymbol{\gamma}}_1' \tilde{\boldsymbol{x}}_1) & \cdots & S(\tilde{\boldsymbol{\gamma}}_K' \tilde{\boldsymbol{x}}_1) \\ 1 & S(\tilde{\boldsymbol{\gamma}}_1' \tilde{\boldsymbol{x}}_2) & \cdots & S(\tilde{\boldsymbol{\gamma}}_K' \tilde{\boldsymbol{x}}_2) \\ \vdots & \vdots & \ddots & \vdots \\ 1 & S(\tilde{\boldsymbol{\gamma}}_1' \tilde{\boldsymbol{x}}_T) & \cdots & S(\tilde{\boldsymbol{\gamma}}_K' \tilde{\boldsymbol{x}}_T) \end{pmatrix}.$$

Therefore, by defining $\boldsymbol{\beta} = (\beta_0, \beta_1, \dots, \beta_K)'$, the output of a feedforward NN is given by:

$$\boldsymbol{h}_D(\boldsymbol{X}, \theta) = [h_D(\boldsymbol{X}_1; \theta), \dots, h_D(\boldsymbol{X}_T; \theta)]'$$

$$= \begin{bmatrix} \beta_0 + \sum_{k=1}^{K} \beta_k S(\boldsymbol{\gamma}_k' \boldsymbol{X}_1 + \gamma_{0,k}) \\ \vdots \\ \beta_0 + \sum_{k=1}^{K} \beta_k S(\boldsymbol{\gamma}_k' \boldsymbol{X}_T + \gamma_{0,k}) \end{bmatrix} \tag{7}$$

$$= \mathcal{O}(\boldsymbol{X}\boldsymbol{\Gamma})\boldsymbol{\beta}.$$

The dimension of the parameter vector $\theta = [\text{vec}(\boldsymbol{\Gamma})', \boldsymbol{\beta}']'$ is $k = (n+1) \times J_T + (J_T + 1)$ and can easily get very large such that the unrestricted estimation problem defined as

$$\widehat{\theta} = \arg \min_{\theta \in \mathbb{R}^k} \|\boldsymbol{Y} - \mathcal{O}(\boldsymbol{X}\boldsymbol{\Gamma})\boldsymbol{\beta}\|_2^2$$

is unfeasible. A solution is to use regularization as in the case of linear models and consider the minimization of the following function:

$$Q(\theta) = \|\boldsymbol{Y} - \mathcal{O}(\boldsymbol{X}\boldsymbol{\Gamma})\boldsymbol{\beta}\|_2^2 + p(\theta), \tag{8}$$

where usually $p(\theta) = \lambda \theta' \theta$. Traditionally, the most common approach to minimize (8) is to use Bayesian methods as in MacKay (1992a); MacKay (1992b) and Foresee and Hagan (1997). A more modern approach is to use a technique known as *Dropout* (Srivastava et al., 2014).

The key idea is to randomly drop neurons (along with their connections) from the NN during estimation. An NN with J_T neurons in the hidden layer can generate 2^{J_T} possible "thinned" NN by just removing some neurons. Dropout samples from this 2^{J_T} different thinned NN and train the sampled NN. To predict the target variable, we use a single unthinned network that has weights adjusted by the probability law induced by the random drop. This procedure significantly reduces overfitting and gives major improvements over other regularization methods.

We modify Equation (6) by

$$g_D^*(\boldsymbol{X}_t) = \beta_0 + \sum_{j=1}^{J_T} s_j \beta_j S(\boldsymbol{\gamma}_j'[\boldsymbol{r} \odot \boldsymbol{X}_t] + v_j \gamma_{0,j}),$$

where s, v, and $\boldsymbol{r} = (r_1, \dots, r_n)$ are independent Bernoulli random variables each with probability q of being equal to 1. The NN model is thus estimated by using $g_D^*(\boldsymbol{X}_t)$ instead of $g_D(\boldsymbol{X}_t)$ where, for each training example, the values of the entries of $\boldsymbol{r}$ are drawn from the Bernoulli distribution. The final estimates for β_j, $\boldsymbol{\gamma}_j$, and $\gamma_{o,j}$ are multiplied by q.

3.1.2 | Deep NNs

A deep NN model is a straightforward generalization of specification (6) where more hidden layers are included in the model as represented in Figure 2. In the figure, we represent a deep NN with two hidden layers with the same number of hidden units in each. However, the number of hidden neurons can vary across layers.
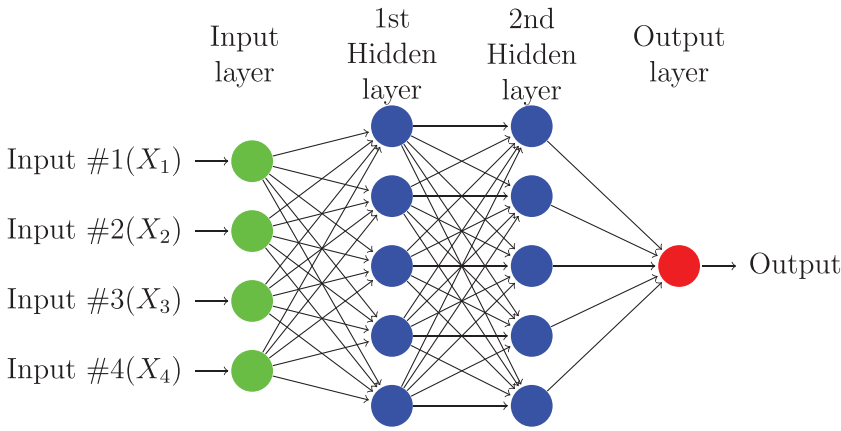
Figure 2   Deep neural network architecture [Colour figure can be viewed at wileyonlinelibrary.com]

As pointed out in Mhaska et al. (2017), while the universal approximation property holds for shallow NNs, deep networks can approximate the class of compositional functions as well as shallow networks but with exponentially lower number of training parameters and sample complexity.

Set J_ℓ as the number of hidden units in layer $\ell \in \{1, \dots, L\}$. For each hidden layer ℓ, define $\boldsymbol{\Gamma}_\ell = (\tilde{\boldsymbol{\gamma}}_{1\ell}, \dots, \tilde{\boldsymbol{\gamma}}_{k_\ell \ell})$. Then, the output $\mathcal{O}_\ell$ of layer ℓ is given recursively by

$$\underset{n \times (J_\ell+1)}{\boldsymbol{\mathcal{O}}_\ell(\boldsymbol{\mathcal{O}}_{\ell-1}(\cdot)\boldsymbol{\Gamma}_\ell)} = \begin{pmatrix} 1 & S(\tilde{\boldsymbol{\gamma}}'_{1\ell}\boldsymbol{\mathcal{O}}_{1\ell-1}(\cdot)) & \cdots & S(\tilde{\boldsymbol{\gamma}}'_{k_\ell \ell}\boldsymbol{\mathcal{O}}_{1\ell-1}(\cdot)) \\ 1 & S(\tilde{\boldsymbol{\gamma}}'_{1\ell}\boldsymbol{\mathcal{O}}_{2\ell-1}(\cdot)) & \cdots & S(\tilde{\boldsymbol{\gamma}}'_{k_\ell \ell}\boldsymbol{\mathcal{O}}_{2\ell-1}(\cdot)) \\ \vdots & \vdots & \ddots & \vdots \\ 1 & S(\tilde{\boldsymbol{\gamma}}'_{1\ell}\boldsymbol{\mathcal{O}}_{n\ell-1}(\cdot)) & \cdots & S(\tilde{\boldsymbol{\gamma}}'_{J_\ell \ell}\boldsymbol{\mathcal{O}}_{n\ell-1}(\cdot)) \end{pmatrix},$$

where $\boldsymbol{\mathcal{O}}_o := \boldsymbol{X}$. Therefore, the output of the deep NN is the composition of

$$\boldsymbol{h}_D(\boldsymbol{X}) = \boldsymbol{\mathcal{O}}_L(\cdots \boldsymbol{\mathcal{O}}_3(\boldsymbol{\mathcal{O}}_2(\boldsymbol{\mathcal{O}}_1(\boldsymbol{X}\boldsymbol{\Gamma}_1)\boldsymbol{\Gamma}_2)\boldsymbol{\Gamma}_3)\cdots)\boldsymbol{\Gamma}_L\boldsymbol{\beta}.$$

The estimation of the parameters is usually carried out by stochastic gradient descend methods with dropout to control the complexity of the model.

3.1.3 | Recurrent neural networks

Broadly speaking, RNNs are NNs that allow for feedback among the hidden layers. RNNs can use their internal state (memory) to process sequences of inputs. In the framework considered in this paper, a generic RNN could be written as

$$\boldsymbol{H}_t = \boldsymbol{f}(\boldsymbol{H}_{t-1}, \boldsymbol{X}_t),$$

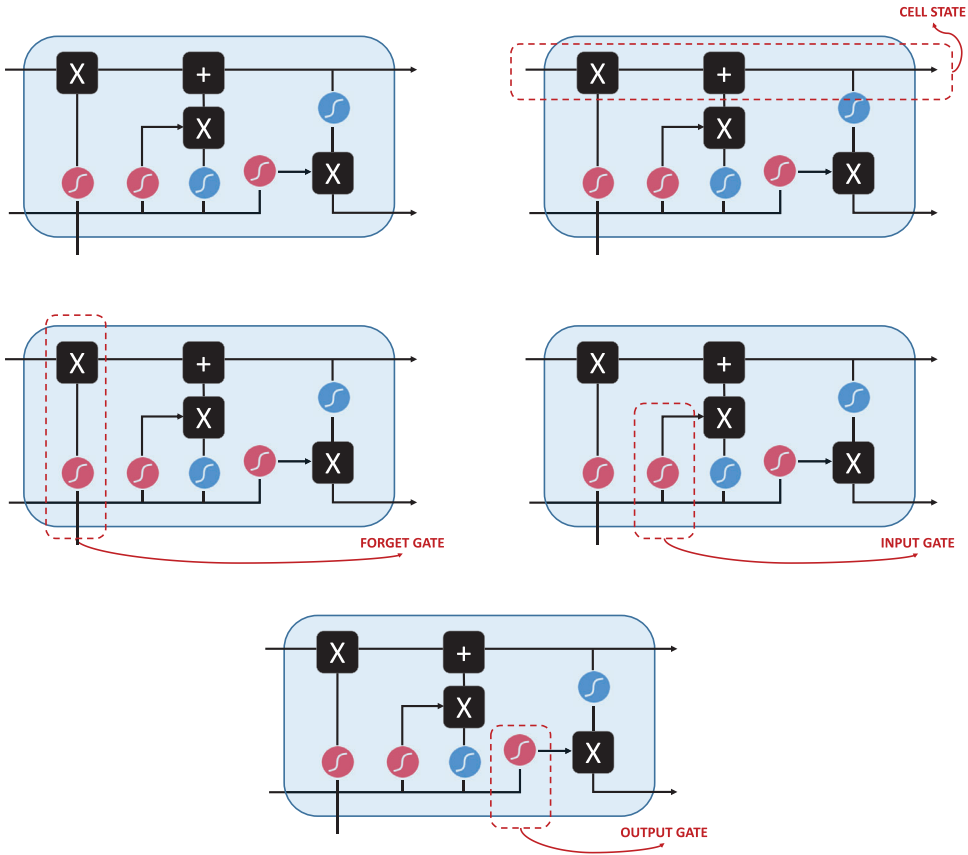$$\widehat{Y}_{t+h|t} = g(\boldsymbol{H}_t),$$

Figure 3   Architecture of the long-short-term memory cell (LSTM) [Colour figure can be viewed at wileyonlinelibrary.com]

where $\widehat{Y}_{t+h|t}$ is the prediction of Y_{t+h} given observations only up to time t, $\boldsymbol{f}$ and g are functions to be defined, and $\boldsymbol{H}_t$ is what we call the (hidden) state. From a time-series perspective, RNNs can be seen as a kind of nonlinear state-space model.

RNNs can remember the order that the inputs appear through its hidden state (memory) and they can also model sequences of data so that each sample can be assumed to be dependent on previous ones, as in time-series models. However, RNNs are hard to be estimated as they suffer from the vanishing/exploding gradient problem. Set the cost function to be

$$Q_T(\boldsymbol{\theta}) = \sum_{t=1}^{T-h} (Y_{t+h} - \widehat{Y}_{t+h|t})^2,$$

where $\boldsymbol{\theta}$ is the vector of parameters to be estimated. It is easy to show that the gradient $\frac{\partial Q_T(\boldsymbol{\theta})}{\partial \boldsymbol{\theta}}$ can be very small or diverge. Fortunately, there is a solution to the problem proposed by Hochreiter and Schmidhuber (1997). A variant of RNN which is called long-short-term memory (LSTM) network. Figure 3 shows the architecture of a typical LSTM layer. An LSTM network can be composed of several layers. In the figure, red circles indicate logistic activation functions, while blue circles represent hyperbolic tangent activation. The symbols "X" and "+" represent, respectively, the

Algorithm 1 Mathematically, RNNs can be defined by the following algorithm

1. Initiate with $c_0 = 0$ and $H_0 = 0$.

2. Given the input X_t, for $t \in \{1, \dots, T\}$, do:

$$
\begin{aligned}
f_t &= \text{Logistic}(W_f X_t + U_f H_{t-1} + b_f) \\
i_t &= \text{Logistic}(W_i X_t + U_i H_{t-1} + b_i) \\
o_t &= \text{Logistic}(W_o X_t + U_o H_{t-1} + b_o) \\
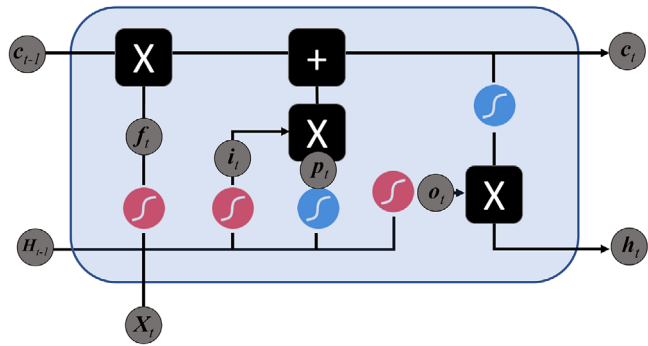p_t &= \text{Tanh}(W_c X_t + U_c H_{t-1} + b_c) \\
c_t &= (f_t \odot c_{t-1}) + (i_t \odot p_t) \\
h_t &= o_t \odot \text{Tanh}(c_t) \\
\widehat{Y}_{t+h|t} &= W_y h_t + b_y
\end{aligned}
$$

where $U_f, U_i, U_o, U_c, U_f, W_f, W_i, W_o, W_c, b_f, b_i, b_o$, and b_c are parameters to be estimated.

Figure 4 Information flow in an LTSM cell [Colour figure can be viewed at wileyonlinelibrary.com]

element-wise multiplication and sum operations. The RNN layer is composed of several blocks: the cell state and the forget, input, and ouput gates. The cell state introduces a bit of memory to the LSTM so it can "remember" the past. LSTM learns to keep only relevant information to make predictions, and forget nonrelevant data. The forget gate tells which information to throw away from the cell state. The output gate provides the activation to the final output of the LSTM block at time t. Usually, the dimension of the hidden state (H_t) is associated with the number of hidden neurons.

Algorithm 1 describes analytically how the LSTM cell works. f_t represents the output of the forget gate. Note that it is a combination of the previous hidden state (H_{t-1}) with the new information (X_t). Note that $f_t \in [0, 1]$ and it will attenuate the signal coming com c_{t-1}. The input and output gates have the same structure. Their function is to filter the "relevant" information from the previous time period as well as from the new input. p_t scales the combination of inputs and previous information. This signal will be then combined with the output of the input gate (i_t). The new hidden state will be an attenuation of the signal coming from the output gate. Finally, the prediction is a linear combination of hidden states. Figure 4 illustrates how the information flows in an LSTM cell.
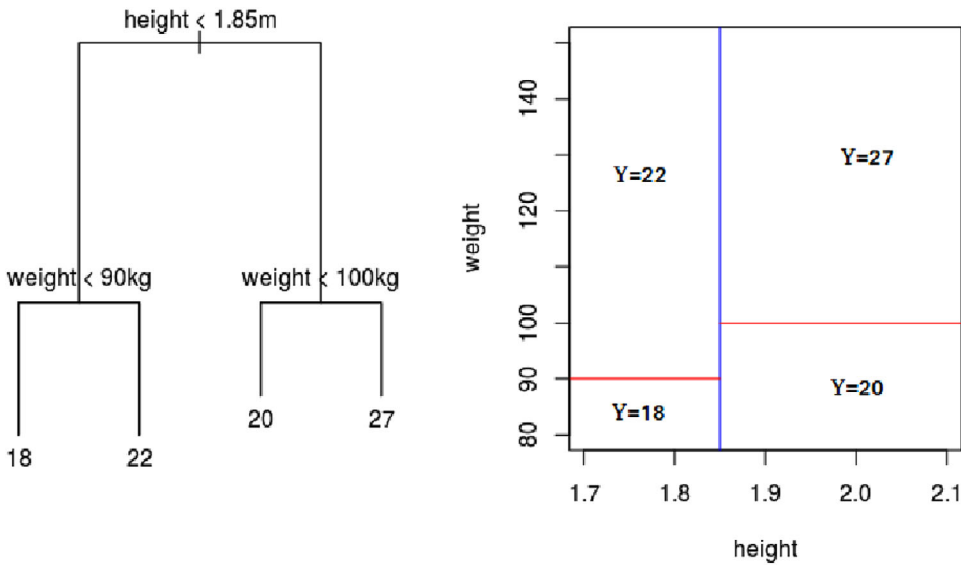
Figure 5 Example of a simple tree [Colour figure can be viewed at wileyonlinelibrary.com]

3.2 | Regression trees

A regression tree is a nonparametric model that approximates an unknown nonlinear function $f_h(\boldsymbol{X}_t)$ in (1) with local predictions using recursive partitioning of the space of the covariates. A tree may be represented by a graph as in the left side of Figure 5, which is equivalent as the partitioning in the right side of the figure for this bidimensional case. For example, suppose that we want to predict the scores of basketball players based on their height and weight. The first node of the tree in the example splits the players taller than 1.85 m from the shorter players. The second node in the left takes the short players groups and split them by weights and the second node in the right does the same with the taller players. The prediction for each group is displayed in the terminal nodes and they are calculated as the average score in each group. To grow a tree, we must find the optimal splitting point in each node, which consists of an optimal variable and an optimal observation. In the same example, the optimal variable in the first node is height and the observation is 1.85 m.

The idea of regression trees is to approximate $f_h(\boldsymbol{X}_t)$ by

$$h_D(\boldsymbol{X}_t) = \sum_{j=1}^{J_T} \beta_j I_j(\boldsymbol{X}_t), \quad \text{where } I_k(\boldsymbol{X}_t) = \begin{cases} 1 & \text{if } \boldsymbol{X}_t \in \mathcal{R}_j, \\ 0 & \text{otherwise.} \end{cases}$$

From the above expression, it becomes clear that the approximation of $f_h(\cdot)$ is equivalent to a linear regression on J_T dummy variables, where $I_j(\boldsymbol{X}_t)$ is a product of indicator functions.

Let $J := J_T$ and $N := N_T$ be, respectively, the number of terminal nodes (regions, *leaves*) and parent nodes. Different regions are denoted as $\mathcal{R}_1, \ldots, \mathcal{R}_J$. The root node at position 0. The parent node at position j has two split (child) nodes at positions $2j + 1$ and $2j + 2$. Each parent node has a threshold (split) variable associated, $X_{s_j t}$, where $s_j \in \mathbb{S} = \{1, 2, \ldots, p\}$. Define $\mathbb{J}$ and $\mathbb{T}$ as the sets of parent and terminal nodes, respectively. Figure 6 gives an example. In the example, the parent
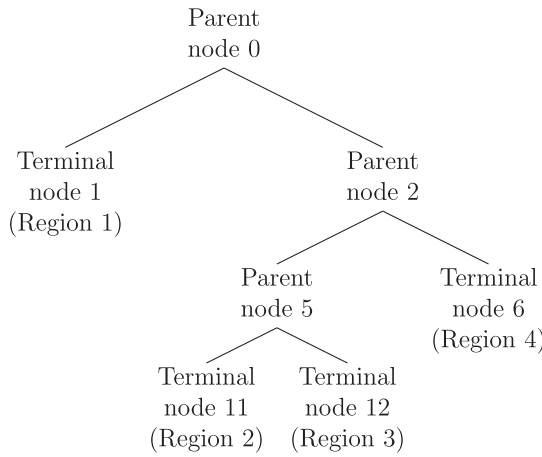
Figure 6 Example of tree with labels

nodes are $\mathbb{J} = \{0, 2, 5\}$ and the terminal nodes are $\mathbb{T} = \{1, 6, 11, 12\}$.

Therefore, we can write the approximating model as

$$h_D(\boldsymbol{X}_t) = \sum_{i \in \mathbb{T}} \beta_i B_{\mathbb{J}i}(\boldsymbol{X}_t; \theta_i), \tag{9}$$

where

$$B_{\mathbb{J}i}(\boldsymbol{X}_t; \theta_i) = \prod_{j \in \mathbb{J}} I(X_{s_j,t}; c_j)^{\frac{n_{i,j}(1+n_{i,j})}{2}} \times [1 - I(X_{s_j,t}; c_j)]^{(1-n_{i,j})(1+n_{i,j})}, \tag{10}$$

$$I(X_{s_j,t}; c_j) = \begin{cases} 1 & \text{if } X_{s_j,t} \leq c_j \\ 0 & \text{otherwise}, \end{cases}$$

$$n_{i,j} = \begin{cases} -1 & \text{if the path to leaf } i \text{ does not include parent node } j; \\ 0 & \text{if the path to leaf } i \text{ include the } \textbf{right} - \textbf{hand} \text{ child of parent node } j; \\ 1 & \text{if the path to leaf } i \text{ include the } \textbf{left} - \textbf{hand} \text{ child of parent node } j. \end{cases}$$

$\mathbb{J}_i$: indexes of parent nodes included in the path to leaf i. $\theta_i = \{c_k\}$ such that $k \in \mathbb{J}_i$, $i \in \mathbb{T}$ and $\sum_{j \in \mathbb{J}} B_{\mathbb{J}i}(\boldsymbol{X}_t; \theta_j) = 1$.

3.2.1 | Random forests

RF is a collection of regression trees, each specified in a bootstrap sample of the original data. The method was originally proposed by Breiman (2001). Since we are dealing with time series, we use a block bootstrap. Suppose there are B bootstrap samples. For each sample b, $b = 1, \dots, B$, a tree with K_b regions is estimated for a randomly selected subset of the original regressors. K_b is determined in order to leave a minimum number of observations in each region. The final forecast

Algorithm 2 The boosting algorithm is defined as the following steps

1. Initialize $\phi_{i0} = \bar{Y} := \frac{1}{T} \sum_{t=1}^{T} Y_t$;

2. For $m = 1, \dots, M$:

   (a) Make $U_{tm} = Y_t - \phi_{tm-1}$

   (b) Grow a (small) Tree model to fit u_{tm}, $\hat{u}_{tm} = \sum_{i \in \mathbb{T}_m} \hat{\beta}_{im} B_{\mathbb{J}_m i}(X_t; \hat{\theta}_{im})$

   (c) Make $\rho_m = \arg\min_{\rho} \sum_{t=1}^{T} [u_{tm} - \rho \hat{u}_{tm}]^2$

   (d) Update $\phi_{tm} = \phi_{tm-1} + \upsilon \rho_m \hat{u}_{tm}$

is the average of the forecasts of each tree applied to the original data:

$$\hat{Y}_{t+h|t} = \frac{1}{B} \sum_{b=1}^{B} \left[\sum_{i=1}^{\mathbb{T}_b} \hat{\beta}_{i,b} B_{\mathbb{J}i,b}(X_t; \hat{\theta}_{i,b}) \right].$$

The theory for RF models has been developed only to independent and identically distributed random variables. For instance, Scornet et al. (2015) proves consistency of the RF approximation to the unknown function $f_h(X_t)$. More recently, Wager and Athey (2018) proved consistency and asymptotic normality of the RF estimator.

3.2.2 | Boosting regression trees

Boosting is another greedy method to approximate nonlinear functions that uses base learners for a sequential approximation. The model we consider here, called Gradient Boosting, was introduced by Friedman (2001) and can be seen as a Gradient Descendent method in functional space.

The study of statistical properties of the Gradient Boosting is well developed for independent data. For example, for regression problems, Duffy and Helmbold (2002) derived bounds on the convergence of boosting algorithms using assumptions on the performance of the base learner. Zhang and Yu (2005) prove convergence, consistency, and results on the speed of convergence with mild assumptions on the base learners. Bühlmann (2002) shows similar results for consistency in the case of ℓ_2 loss functions and three base models. Since boosting indefinitely leads to overfitting problems, some authors have demonstrated the consistency of boosting with different types of stopping rules, which are usually related to small step sizes, as suggested by Friedman (2001). Some of these works include boosting in classification problems and gradient boosting for both classification and regression problems. See, for instance, Jiang (2004), Lugosi and Vayatis (2004), Bartlett and Traskin (2007), Zhang and Yu (2005), Bühlmann (2006), and Bühlmann (2002).

Boosting is an iterative algorithm. The idea of boosted trees is to, at each iteration, sequentially refit the gradient of the loss function by small trees. In the case of quadratic loss as considered in this paper, the algorithm simply refits the residuals from the previous iteration.

Algorithm 2 presents the simplified boosting procedure for a quadratic loss. It is recommended to use a shrinkage parameter $\upsilon \in (0, 1]$ to control the learning rate of the algorithm. If υ is close to 1, we have a faster convergence rate and a better in-sample fit. However, we are more likely to have overfitting and produce poor out-of-sample results. In addition, the derivative is highly affected by overfitting, even if we look at in-sample estimates. A learning rate between 0.1 and 0.2 is recommended to maintain a reasonable convergence ratio and to limit overfitting problems.

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The final fitted value may be written as

$$\widehat{Y}_{t+h} = \bar{Y} + \sum_{m=1}^{M} \upsilon \rho_m \widehat{u}_{tm}$$

$$= \bar{Y} + \sum_{m=1}^{M} \upsilon \widehat{\rho}_m \sum_{k \in \mathbb{T}_m} \widehat{\beta}_{km} B_{\mathbb{J}_m k}(\boldsymbol{X}_t; \widehat{\theta}_{km}).$$

(11)

3.3 | Inference

Conducting inference in nonlinear ML methods is tricky. One possible way is to follow Medeiros et al. (2006), Medeiros and Veiga (2005), and Suarez-Fariñas et al. (2004) and interpret particular nonlinear ML specifications as parametric models, as for example, general forms of smooth transition regressions. However, this approach restricts the application of ML methods to very specific settings. An alternative, is to consider models that can be cast in the sieves framework as described earlier. This is the case of splines and feed-forward NNs, for example. In this setup, Chen and Shen (1998) and Chen (2007) derived, under regularity conditions, the consistency and asymptotically normality of the estimates of a semiparametric sieve approximations. Their setup is defined as follows:

$$Y_{t+h} = \boldsymbol{\beta}_0' \boldsymbol{X}_t + f(\boldsymbol{X}_t) + U_{t+h},$$

where $f(\boldsymbol{X}_t)$ is a nonlinear function that is nonparametrically modeled by sieve approximations. Chen and Shen (1998) and Chen (2007) consider both the estimation of the linear and nonlinear components of the model. However, their results are derived under the case where the dimension of $\boldsymbol{X}_t$ is fixed.

Recently, Chernozhukov et al. (2017, 2018) consider the case where the number of covariates diverge as the sample size increases in a very general setup. In this case, the asymptotic results in Chen and Shen (1998) and Chen (2007) are not valid and the authors put forward the so-called double ML methods as a nice generalization to the results of Belloni et al. (2014). Nevertheless, the results do not include the case of time-series models.

More specifically to the case of Random Forests, asymptotic and inferential results are derived in Scornet et al. (2015) and Wager et al. (2018) for the case of IID data. More recently, Davis and Nielsen (2020) prove a uniform concentration inequality for regression trees built on nonlinear autoregressive stochastic processes and prove consistency for a large class of random forests. Finally, it is worth mentioning the interesting work of Borup et al. (2020). In their paper, the authors show that proper predictor targeting controls the probability of placing splits along strong predictors and improves prediction.

Algorithm 3 Bagging for Time-Series Models

The Bagging algorithm is defined as follows.

1. Arrange the set of tuples $(y_{t+h}, \boldsymbol{x}_t')$, $t = h + 1, \dots, T$, in the form of a matrix $\boldsymbol{V}$ of dimension $(T - h) \times n$.

2. Construct (block) bootstrap samples of the form $\{(y_{(i)2}^*, \boldsymbol{x}_{(i)2}'^*), \dots, (y_{(i)T}^*, \boldsymbol{x}_{(i)T}'^*)\}$, $i = 1, \dots, B$, by drawing blocks of M rows of $\boldsymbol{V}$ with replacement.

3. Compute the ith bootstrap forecast as

$$\widehat{y}_{(i)t+h|t}^* = \begin{cases} 0 & \text{if } |t_j^*| < c \, \forall j, \\ \widehat{\boldsymbol{\lambda}}_{(i)}^* \widetilde{\boldsymbol{x}}_{(i)t}^* & \text{otherwise,} \end{cases} \qquad (11)$$

where $\widetilde{\boldsymbol{x}}_{(i)t}^* := \boldsymbol{S}_{(i)t}^* \boldsymbol{z}_{(i)t}^*$ and $\boldsymbol{S}_t$ is a diagonal selection matrix with jth diagonal element given by

$$\mathbb{1}_{\{|t_j|>c\}} = \begin{cases} 1 & \text{if } |t_j| > c, \\ 0 & \text{otherwise,} \end{cases}$$

c is a prespecified critical value of the test. $\widehat{\boldsymbol{\lambda}}_{(i)}^*$ is the OLS estimator at each bootstrap repetition.

4. Compute the average forecasts over the bootstrap samples:

$$\tilde{y}_{t+h|t} = \frac{1}{B} \sum_{i=1}^{B} \widehat{y}_{(i)t|t-1}^*.$$

Algorithm 4 Bagging for Time-Series Models and Many Regressors

The Bagging algorithm is defined as follows.

0. Run n univariate regressions of y_{t+h} on each covariate in $\boldsymbol{x}_t$. Compute t-statistics and keep only the ones that turn out to be significant at a given prespecified level. Call this new set of regressors as $\check{\boldsymbol{x}}_t$

1–4. Same as before but with $\boldsymbol{x}_t$ replaced by $\check{\boldsymbol{x}}_t$.

4 | OTHER METHODS

4.1 | Bagging

The term *bagging* means *Bootstrap Aggregating* and was proposed by Breiman (1996) to reduce the variance of unstable predictors.[8] It was popularized in the time-series literature by Inoue and Kilian (2008), who to construct forecasts from multiple regression models with local-to-zero regression parameters and errors subject to possible serial correlation or conditional heteroskedasticity. Bagging is designed for situations in which the number of predictors is moderately large relative to the sample size.

The bagging algorithm in time-series settings have to take into account the time dependence dimension when constructing the bootstrap samples.

In Algorithm 3, one requires that it is possible to estimate and conduct inference in the linear model. This is certainly infeasible if the number of predictors is larger than the sample size ($n > T$), which requires the algorithm to be modified. Garcia et al. (2017) and Medeiros et al. (2021) adopt the changes as described in Algorithm 4.

4.2 | Complete subset regression

CSR is a method for combining forecasts developed by Elliott et al. (2013, 2015). The motivation was that selecting the optimal subset of X_t to predict Y_{t+h} by testing all possible combinations of regressors is computationally very demanding and, in most cases, unfeasible. For a given set of potential predictor variables, the idea is to combine forecasts by averaging[9] all possible linear regression models with fixed number of predictors. For example, with n possible predictors, there are n unique univariate models and

$$n_{k,n} = \frac{n!}{(n-k)!k!}$$

different k-variate models for $k \leq K$. The set of models for a fixed value of k as is known as the complete subset.

When the set of regressors is large the number of models to be estimated increases rapidly. Moreover, it is likely that many potential predictors are irrelevant. In these cases, it was suggested that one should include only a small, k, fixed set of predictors, such as 5 or 10. Nevertheless, the number of models still very large, for example, with $n = 30$ and $k = 8$, there are 5,852,925 regression. An alternative solution is to follow Garcia et al. (2017) and Medeiros et al. (2021) and adopt a similar strategy as in the case of Bagging high-dimensional models. The idea is to start fitting a regression of Y_{t+h} on each of the candidate variables and save the t-statistics of each variable. The t-statistics are ranked by absolute value, and we select the $\tilde{n}$ variables that are more relevant in the ranking. The CSR forecast is calculated on these variables for different values of k. This approach is based on the Sure Independence Screening of Fan and Lv (2008), extended to dependent by Yousuf (2018), that aims to select a superset of relevant predictors among a very large set.

4.3 | Hybrid methods

Recently, Medeiros and Mendes (2013) proposed the combination of LASSO-based estimation and NN models. The idea is to construct a feedforward single-hidden layer NN where the parameters of the nonlinear terms (neurons) are randomly generated and the linear parameters are estimated by LASSO (or one of its generalizations). Similar ideas were also considered by Kock and Teräsvirta (2014, 2015).

Trapletti et al. (2000) and Medeiros et al. (2006) proposed to augment a feedforward shallow NN by a linear term. The motivation is that the nonlinear component should capture only the nonlinear dependence, making the model more interpretable. This is in the same spirit of the semi-parametric models considered in Chen (2007).

Inspired by the above ideas, Medeiros et al. (2021) proposed combining random forests with adaLASSO and OLS. The authors considered two specifications. In the first one, called RF/OLS, the idea is to use the variables selected by a Random Forest in a OLS regression. The second approach, named adaLASSO/RF, works in the opposite direction. First select the variables by adaLASSO and than use them in a Random Forest model. The goal is to disentangle the relative importance of variable selection and nonlinearity to forecast inflation.

Recently, Diebold and Shin (2019) propose the "partially-egalitarian" LASSO to combine survey forecasts. More specifically, the procedure sets some combining weights to zero and shrinks

the survivors toward equality. Therefore, the final forecast will be close related to the simple average combination of the survived forecasts. Although the paper considers survey forecasts, the method is quite general and can be applied to any set of forecasts. As pointed out by the authors, optimally-regularized regression-based combinations and subset-average combinations are very closely connected. Diebold et al. (2021) extended the ideas in Diebold et al. (2019) in order to construct regularized mixtures of density forecasts. Both papers shed light on how machine learning methods can be used to optimally combine a large set of forecasts.

5 | FORECAST COMPARISON

With the advances in the ML literature, the number of available forecasting models and methods have been increasing at a fast pace. Consequently, it is very important to apply statistical tools to compare different models. The forecasting literature provides a number of tests since the seminal paper by Diebold and Mariano (1995) that can be applied as well to the ML models described in this survey.

In the Diebold and Mariano's (1995) test, two competing methods have the same unconditional expected loss under the null hypothesis, and the test can be carried out using a simple t-test. A small sample adjustment was developed by Harvey et al. (1997). See also the recent discussion in Diebold (2015). One drawback of the Diebold and Mariano's (1995) test is that its statistic diverges under null when the competing models are nested. However, Giacomini and White (2006) show that the test is valid if the forecasts are derived from models estimated in a rolling window framework. Recently, McCracken (2020) shows that if the estimation window is fixed, the Diebold and Mariano's (1995) statistic may diverge under the null. Therefore, it is very important that the forecasts are computed in a rolling window scheme.

In order to accommodate cases where there are more than two competing models, an unconditional superior predictive ability (USPA) test was proposed by White (2000). The null hypothesis states that a benchmark method outperforms a set of competing alternatives. However, Hansen (2005) showed that White's (2000) test can be very conservative when there are competing methods that are inferior to the benchmark. Another important contribution to the forecasting literature is the model confidence set (MCS) proposed by Hansen et al. (2011). An MCS is a set of competing models that is built in a way to contain the best model with respect to a certain loss function and with a given level of confidence. The MCS acknowledges the potential limitations of the data set, such that uninformative data yield an MCS with a large number models, whereas informative data yield an MCS with only a few models. Importantly, the MCS procedure does not assume that a particular model is the true one.

Another extension of the Diebold and Mariano's (1995) test is the conditional equal predictive ability (CEPA) test proposed by Giacomini and White (2006). In practical applications, it is important to know not only if a given model is superior but also when it is better than the alternatives. Recently, Li et al. (2020) proposed a very general framework to conduct conditional predictive ability tests.

In summary, it is very important to compare the forecasts from different ML methods and the literature provides a number of tests that can be used.

6 | APPLICATIONS OF ML METHODS TO ECONOMIC AND FINANCIAL FORECASTING

6.1 | Linear methods

Penalized regressions are now an important option in the toolkit of applied economists. There is a vast literature considering the use of such techniques to economics and financial forecasting.

Macroeconomic forecasting is certainly one of the most successful applications of penalized regressions. Medeiros and Mendes (2016) applied the adaLASSO to forecasting U.S. inflation and showed that the method outperforms the linear autoregressive and factor models. Medeiros and Vasconcelos (2016) show that high-dimensional linear models produce, on average, smaller forecasting errors for macroeconomic variables when a large set of predictors is considered. Their results also indicate that a good selection of the adaLASSO hyperparameters reduces forecasting errors. Garcia et al. (2017) show that high-dimensional econometric models, such as shrinkage and CSR, perform very well in real-time forecasting of Brazilian inflation in data-rich environments. The authors combine forecasts of different alternatives and show that model combination can achieve superior predictive performance. Smeeks and Wijler (2018) consider an application to a large macroeconomic U.S. data set and demonstrate that penalized regressions are very competitive. Medeiros et al. (2021) conduct a vast comparison of models to forecast U.S. inflation and showed the penalized regressions were far superior to several benchmarks, including factor models. Ardia et al. (2019) introduce a general text sentiment framework that optimizes the design for forecasting purposes and apply it to forecasting economic growth in the United States. The method includes the use of the Elnet for sparse data-driven selection and the weighting of thousands of sentiment values. Tarassow (2019) consider penalized VARs to forecast six different economic uncertainty variables for the growth of the real M2 and real M4 Divisia money series for the United States using monthly data. Uematsu and Tanaka (2019) consider high-dimensional forecasting and variable selection via folded-concave penalized regressions. The authors forecast quarterly U.S. gross domestic product data using a high-dimensional monthly data set and the mixed data sampling (MIDAS) framework with penalization. See also Babii et al. (2020b, 2020c).

There is also a vast list of applications in empirical finance. Elliott et al. (2013) find that combinations of subset regressions can produce more accurate forecasts of the equity premium than conventional approaches based on equal-weighted forecasts and other regularization techniques. Audrino and Knaus (2016) used LASSO-based methods to estimate forecasting models for realized volatilities. Callot et al. (2017) consider modeling and forecasting large realized covariance matrices of the 30 Dow Jones stocks by penalized VAR models. The authors find that penalized VARs outperform the benchmarks by a wide margin and improve the portfolio construction of a mean–variance investor. Chinco et al. (2019) use the LASSO to make 1-minute-ahead return forecasts for a vast set of stocks traded at the New York Stock Exchange. The authors provide evidence that penalized regression estimated by the LASSO boost out-of-sample predictive power by choosing predictors that trace out the consequences of unexpected news announcements.

6.2 | Nonlinear methods

There are many papers on the application of nonlinear ML methods to economic and financial forecasting. Most of the papers focus on NN methods, specially the ones from the early literature.

With respect to the early papers, most of the models considered were nonlinear versions of autoregressive models. At best, a small number of extra covariates were included. See, for example, Teräsvirta et al. (2005) and the references therein. In the majority of the papers, including Teräsvirta et al. (2005), there was no strong evidence of the superiority of nonlinear models as the differences in performance were marginal. Other examples from the early literature are Swanson and White (1995, 1997a, 1997b), Balkin and Ord (2000), Tkacz (2001), Medeiros et al. (2001), and Heravi et al. (2004).

More recently, with the availability of large datasets, nonlinear models are back to the scene. For example, Medeiros et al. (2021) show that, despite the skepticism of the previous literature on inflation forecasting, ML models with a large number of covariates are systematically more accurate than the benchmarks for several forecasting horizons and show that Random Forests dominated all other models. The good performance of the Random Forest is due not only to its specific method of variable selection but also the potential nonlinearities between past key macroeconomic variables and inflation. Other successful example is Gu et al. (2020). The authors show large economic gains to investors using ML forecasts of future stock returns based on a very large set of predictors. The best performing models are tree-based and neural networks. Coulombe et al. (2020) show significant gains when nonlinear ML methods are used to forecast macroeconomic time series. Borup et al. (2020) consider penalized regressions, ensemble methods, and random forest to forecast employment growth in the United States over the period 2004–2019 using Google search activity. Their results strongly indicate that Google search data have predictive power. Borup et al. (2020) compute now- and backcasts of weekly unemployment insurance initial claims in the US based on a rich set of daily Google Trends search-volume data and machine learning methods.

6.3 | Empirical illustration

In this section, we illustrate the use of some of the methods reviewed in this paper to forecast daily realized variance of the Brazilian Stock Market index (BOVESPA). We use as regressors information from other major indexes, namely, the S&P500 (US), the FTSE100 (United Kingdom), DAX (Germany), Hang Seng (Hong Kong), and Nikkei (Japan). Our measure of realized volatility is constructed by aggregating intraday returns sample at the 5-min frequency. The data were obtained from the Oxford-Man Realized Library at Oxford University.[10]

For each stock index, we define the realized variance as

$$RV_t = \sum_{s=1}^{S} r_{st}^2,$$

where r_{st} is the log return sampled at the 5-min. frequency. S is the number of available returns at day t.

The benchmark model is the heterogeneous autoregressive (HAR) model proposed by Corsi (2009):

$$\log RV_{t+1} = \beta_0 + \beta_1 \log RV_t + \beta_5 \log RV_{5,t} + \beta_2 2 \log RV_{22,t} + U_{t+1}, \tag{13}$$
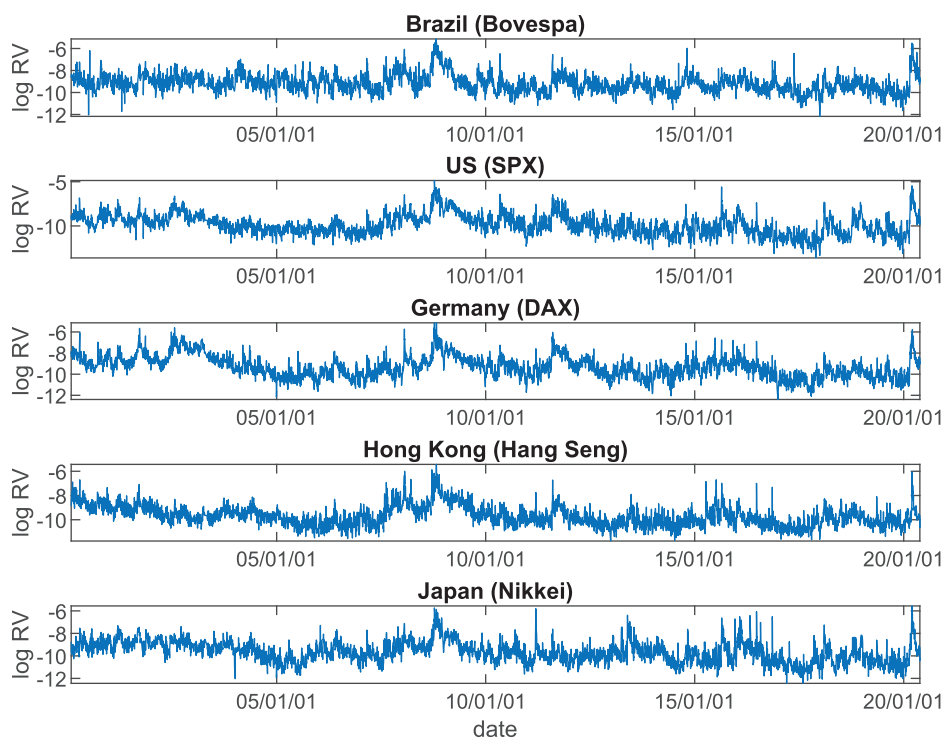
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Figure 7 Realized variance of different stock indexes [Colour figure can be viewed at wileyonlinelibrary.com]

where RV_t is daily realized variance of the BOVESPA index,

$$RV_{5,t} = \frac{1}{5} \sum_{i=0}^{4} RV_{t-i}, \quad \text{and}$$

$$RV_{22,t} = \frac{1}{22} \sum_{i=0}^{21} RV_{t-i}.$$

As alternatives, we consider an extended HAR model with additional regressors estimated by adaLASSO. We include as extra regressors the daily past volatility of the other five indexes considered here. The model has a total of eight candidate predictors. Furthermore, we consider two nonlinear alternatives using all predictors: a random forest and shallow and deep NNs.

The realized variances of the different indexes are illustrated in Figure 7. The data start in February 2, 2000 and ends in May 21, 2020, a total of 4200 observations. The sample includes two periods of very high volatility, namely, the financial crisis of 2007–2008 and the Covid-19 pandemics of 2020. We consider a rolling window exercise, were we set 1500 observations in each window. The models are reestimated every day.

Several other authors have estimated nonlinear and ML models to forecast realized variances. McAleer and Medeiros (2008) considered a smooth transition version of the HAR while Hillebrand and Medeiros (2016) considered the combination of smooth transitions, long memory, and NN models. Hillebrand and Medeiros (2010) and McAleer and Medeiros (2011) combined NN

Table 1 Forecasting results

Model	Full sample		2007–2008		2020	
	MSE	QLIKE	MSE	QLIKE	MSE	QLIKE
HARX-LASSO	0.96**	0.98	0.98*	0.96	0.90***	0.90
Random forest	1.00	1.02	0.95***	0.98	1.13**	1.03*
Neural network (1)	0.99**	0.99	0.97**	0.98	0.99	0.99
Neural network (3)	0.99**	0.99	0.98*	0.99	0.99	0.99
Neural network (5)	0.90**	0.99	0.98*	0.99	0.99	0.99

The table reports for each model, the mean squared error (MSE) and the QLIKE statistics as a ratio to the HAR benchmark. Values smaller than one indicates that the model outperforms the HAR. The asterisks indicate the results of the Diebold-Mariano test of equal forecasting performance. *,**, and ***, indicate rejection of the null of equal forecasting ability at the 10%, 5%, and 1%, respectively.

models with bagging and Scharth and Medeiros (2009) considered smooth transition regression trees. The use of LASSO and its generalizations to estimate extensions of the HAR model was proposed by Audrino and Knaus (2016).

Although the models are estimated in logarithms, we report the results in levels, which in the end is the quantity of interest. We compare the models according to the MSE and the QLIKE metric.

The results are shown in Table 1. The table reports for each model, the MSE and the QLIKE statistics as a ratio to the HAR benchmark. Values smaller than one indicates that the model outperforms the HAR. The asterisks indicate the results of the Diebold-Mariano test of equal forecasting performance. *,**, and ***, indicate rejection of the null of equal forecasting ability at the 10%, 5%, and 1%, respectively. We report results for the full out-of-sample period, the financial crisis years (2007–2008), and then for 2020 as a way to capture the effects of the Covid-19 pandemics on the forecasting performance of different models.

As we can see from the tables, the ML methods considered here outperform the HAR benchmark. The winner model is definitely the HAR model with additional regressors and estimated with adaLASSO. The performance improves during the high volatility periods and the gains reach 10% during the Covid-19 pandemics. RFs do not perform well. On the other hand, NN models with different number of hidden layers outperform the benchmark.

7 | CONCLUSIONS AND THE ROAD AHEAD

In this paper, we present a nonexhaustive review of the most of the recent developments in ML and high-dimensional statistics to time-series modeling and forecasting. We presented both linear and nonlinear alternatives. Furthermore, we consider ensemble and hybrid models. Finally, we briefly discuss tests for superior predictive ability.

Among linear specification, we pay special attention to penalized regression (Ridge, LASSO and its generalizations, for example) and ensemble methods (Bagging and CSR). Although, there have been major theoretical advances in the literature on penalized linear regression models for dependent data, the same is not true for ensemble methods. The theoretical results for Bagging are so far based on independent data and the results for CSR are quite limited.

With respect to nonlinear ML methods, we focused on NNs and tree-based methods. Theoretical results for RFs and boosted trees have been developed only to IID data and in the case of a

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low-dimensional set of regressors. For shallow NNs, Chen et al. (2007) and Chen (2007) provide some theoretical results for dependent data in the low-dimensional case. The behavior of such models in high dimensions is still under study. The same is true for deep NNs.

Nevertheless, the recent empirical evidence shows that nonlinear ML models combined with large data sets can be extremely useful for economic forecasting.

As a direction for further developments we list the following points:

1. Develop results for Bagging and Boosting for dependent data.
2. Show consistency and asymptotic normality of the RF estimator of the unknown function $f_h(\boldsymbol{X}_t)$ when the data are dependent.
3. Derive a better understanding of the variable selection mechanism of nonlinear ML methods.
4. Develop inferential methods to access variable importance in nonlinear ML methods.
5. Develop models based on unstructured data, such as text data, to economic forecasting.
6. Evaluate ML models for nowcasting.
7. Evaluate ML in very unstable environments with many structural breaks.

Finally, we would like to point that we left a number of other interesting ML methods out of this survey, such as, for example, Support Vector Regressions, autoenconders, nonlinear factor models, and many more. However, we hope that the material presented here can be of value to anyone interested of applying ML techniques to economic and/or financial forecasting.

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ENDNOTES
[1] More recently, ML for causal inference have started to receive a lot of attention. However, this survey will not cover causal inference with ML methods.
[2] The original sentence is "Programming computers to learn from experience should eventually eliminate the need for much of this detailed programming effort." See Samuel (1959).
[3] The zero mean condition can be always ensured by including an intercept in the model. Also the variance of $f(\boldsymbol{X}_t)$ to be finite suffices for the finite variance.
[4] The *oracle property* was first described in Fan and Li (2001) in the context of nonconcave penalized estimation.
[5] A more precise treatment would separate *sign consistency* from *model selection consistency*. *Sign consistency* first appeared in Zhao and Yu (2006) and also verify whether the sign of estimated regression weights converge to the population ones.
[6] *Weak sparsity* generalizes sparsity by supposing that coefficients are (very) small instead of exactly zero.
[7] The relevant regressors are the ones associated with nonzero parameter estimates.
[8] An *unstable predictor* has large variance. Intuitively, small changes in the data yield large changes in the predictive model.
[9] It is possible to combine forecasts using any weighting scheme. However, it is difficult to beat uniform weighting (Genre et al., 2013).
[10] https://realized.oxford-man.ox.ac.uk/data/assets

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