Journal for Re Attach Therapy and Developmental Diversities
eISSN: 2589-7799
2023 December; 6 (10s) (2): 1964-1976

Optimizing Financial Forecasting Using Cloud Based Machine Learning Models

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Abstract

B2B companies compete fiercely to win sales opportunities, often of high value. Forecasting successfully whether a sales opportunity will be won or lost is vital for maximizing profitability. This task is further complicated by the fact that forecasting the outcome of a sales opportunity forms the early part of a cumbersome sales process. A typical sales process may take weeks to months with due diligence requiring huge human and operational resources. Thus, careful evaluations of sales opportunities during the early steps of this process become imperative. Quantifying the probability of winning prospective sales opportunities can clarify early evaluations and facilitate appropriate allocation of additional assessments to be performed later in the sales process. However, correctly forecasting the outcome of a sales opportunity is currently mostly subjective. Many sales software allow sales personnel to assign a subjective probability of winning for an opportunity which represents their confidence of winning that opportunity. Predictive modelling attempts at determining the objective probability of winning sales opportunities are scarce. As a result, the prediction of the sales outcome of an opportunity thus relies on subjective human prediction. Furthermore, understanding the past sales data on the performance of predictions can help improve future predictions but current understanding is limited. For a similar industry with similar sales processes, overall simple metrics such as win-rate or revenue difference can showcase historical performance but this approach is too crude to provide valuable insights of data flows such as winning their opportunities or regions on which prediction has improved over time.
ML and AI-based time-series forecasting has gained tremendous attention and is widely adopted in business areas such as sales, stock market, billing, pump failure maintenance, biotechnology, and global weather predicting. Optimizing financial forecasting using cloud-based machine learning models is an end-to-end built ML pipeline consisting of ingestion, prep, train, and evaluation for time series classification application. It automates data extraction and processing tasks such as: 1. uploading and formatting the training data, 2. feature engineering and selection, 3. model training and optimization, 4. saving and registering the trained model along with performance metrics and model parameters, 5. ML monitoring.

Keywords: Cloud-based financial forecasting, Machine learning in finance, Predictive analytics for finance, AI-driven financial modeling, Financial forecasting automation, Cloud computing for finance, Real-time financial prediction, Scalable ML models in finance, Financial data forecasting cloud, Time series forecasting ML,AI financial forecast accuracy, Big data finance solutions, Forecasting financial trends ML, Cloud AI for risk assessment, Deep learning in financial planning.

1. Introduction

The prediction of future values is a very important task, required for many applications in the industry. Nevertheless, in many situations the quantity to be predicted is a financial quantity that is subject to constraints, i.e., ranges of values. This implies that, aside from the value of the prediction, it is also of utmost importance that the prediction is valid in terms of the constraints defined for the variable. In such situations, some new approaches to train machine learning algorithms to guarantee that the predictions satisfy the constraints are shown. A modification of the mean-squared error cost function that includes penalty terms to detect predictions out of the bounds are proposed as a possible extension of standard feedforward neural networks. Alternatively, many probabilistic approaches have been adapted to predict constrained quantities. In this work, a probabilistic convolutional neural network that predicts a constrained quantity from unstructured data is employed. The network is trained so, instead of predicting the quantity of interest directly, it estimates the parameters of a truncated Gaussian distribution for the predicted variable. It is shown that, beyond satisfying the bounds of the defined variable, this approach has the clear advantage of improving prediction performance. Prediction uncertainty can thus be visualized and well estimated, suggesting lists of valid predictions rather than an exact point one.

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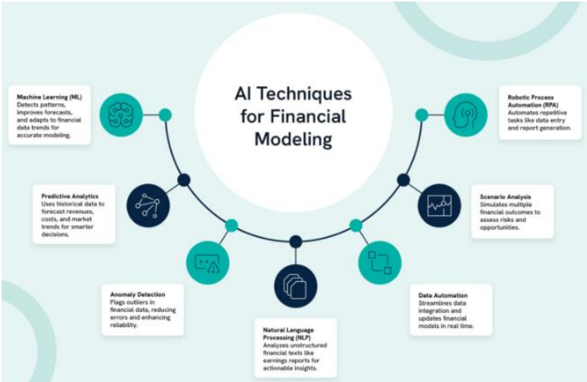

Fig 1: Financial Modeling Techniques with AI

1.1. Background and Significance

Financial forecasting is the process of estimating an individual organization's future financial position based on the study of historical trends in revenue, expenses, working capital, and other financial items. Also covered would be the application of Machine Learning models to forecasting, particularly the use of Ensemble Learning with LSTM on a cloud server with emphasis on analysis of server performance on request, up-turn detection accuracy, and resource up-scaling. Introductory background on financial forecasting is presented including specific important trend data on the significant drop in revenue and noteworthy increases in working capital for the United States financial sector during the first quarter of 2020 and the 2020 fiscal year. Financial forecasting options including the use of machine learning models with analysis of the significant performance benefits of using the right cloud computing server type and testing the use of ensemble learning with LSTM models in forecasting accuracy improvements are presented. The focus of the research proposal is presented with how areas of interest would be tested in an actual environment with results and security monitored with near real-time visual dashboards.

Additionally included would be the relevant review of published literature with robust sources cited. Next would be displayed the proposed approach describing the use of a cloud-based LSTM forecasting model in combination with cloud-to-edge process control models. Observed benefits of forecast request monitoring, edge processing via the use of situational dashboards, and on-demand virtual machine instance deployment to accurately manage forecast request loads while minimizing resource waste and expense would be addressed. Finally, the projected impact of the proposed research would be presented. The ultimate goal of this research proposal is to examine the financial forecasting process which involves estimating an individual organization's future financial position through the analysis of historical trends in important categories of financial data.

The approach to be taken with the testing and analysis of LSTM and data visualization models with real-time financial data on the cloud is introduced and areas of modeling improvement and future research distribution directions are proposed. Financial forecasters can use financial ratios with trend data to highlight problem areas, which are potential future problems unless addressed. Significant difficulty in forecasting organization financial activity, a highly variable revenue stream driven by external factors such as world health crises, imposed limitations on technological advancement forecasts, and ignored working capital variants in predictive accuracy evaluation would be investigated. An extensive search of existing literature published articles on the financial forecasting process, particularly the use of internal financial historical data with advanced machine learning prediction models to observe and analyze the highly variable revenue stream of Bank of America Corporation, would be examined.

Equ 1: Time Series Forecasting Model (ARIMA / SARIMA)

$$Y_t = \alpha + \sum_{i=1}^{p} \phi_i Y_{t-i} + \sum_{j=1}^{q} \theta_j \varepsilon_{t-j} + \varepsilon_t$$

- Y_t: Value at time t
- p, q: Order of AR and MA parts
- ϕ_i, θ_j: Coefficients
- ε_t: Error term (white noise)

2. Literature Review

This section presents the related work on financial forecasting techniques and reviews research on cloud based Machine Learning (ML) models to improve forecasting accuracy and effectiveness. A literature review of financial time series forecasting shows various techniques used for input selection and forecasting model building.

The development of forecasting methods has been attracting attention of researchers for many years which in turn influences the sustainable financial planning of a company. With the increasing competition in the financial market, robust forecasting methods are extremely important and valuable to investors. A large number of studies have modeled financial time series using Machine Learning algorithms, as such algorithms possess the ability to capture complex non-linearities in the time series. However, the research assessing the advantages of ML models against the traditional stochastic models in predicting financial markets, are almost solely relying on new empirical evidence.

In order to close this gap, a comprehensive and systematic survey is provided about the applications of machine learning techniques to the financial market forecasting problem. More than 150 applicable research articles are reviewed. Each study is classified among numerous categories so that an overview of the utilized data, strategies, benchmarks and evaluation techniques is provided. An analysis of the results indicates that machine learning algorithms can outperform most of the traditional stochastic forecasting methods in the financial domain. In particular, recurrent neural networks outperform feed forward neural networks and support vector machines. This indicates that exploitable temporal dependencies exist in financial time series.

In addition to methodology review, indeed defining the classification of the input selection approaches extensively. The forecasting evaluation methods are then reviewed, followed by special attention to the studies of Input selection on financial time series forecasting applied methodologies, with the details of the conditions adopted on their research. The dimension reductions and two introduced methods are surveyed as well as their mathematical proofs. Finally, the input selections of existing problems are discussed, followed by the limitations and future research suggestions.

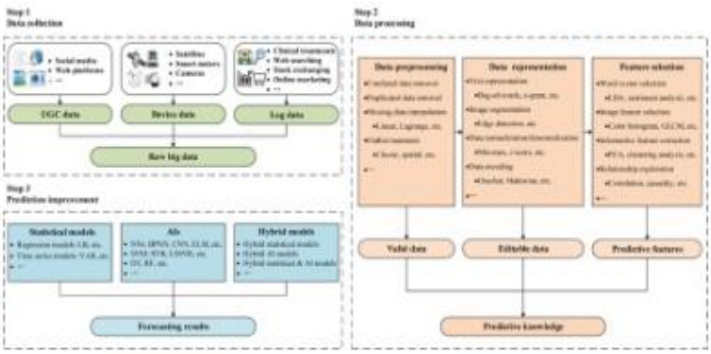

Fig 2: Big Data in Forecasting Research A Literature Review

2.1. Historical Approaches to Financial Forecasting For centuries, humans have been creating financial forecasting models to predict price movements in financial markets. In antiquity, formal models did not exist, so people relied on simple rules or heuristics to predict future prices. The problem then, as it is now, was one of information—where to find it, how to analyze it, and how to apply it. A shopkeeper in Liu Ch'uan would observe the movement patterns of neighboring ships, and he would go longer on those trading routes where the ships were moving towards greater demand and shorter otherwise. In the regal and imperial courts of the West, similar patterns of buying and selling among seed grain were observed, suggesting that participants relied on local supply and demand patterns rather than global ones.

During the latter half of the 20th century, either in academics or financial services, most financial forecasting was dominated by statistical models. At the time, it was thought that, given the proper information and sufficient computing power, most aspects of the financial world could be analyzed and forecast. The estimations in the right model of this process were thought to yield decreasing confidence bounds on the expected value of the dependent variable, and using robust statistical models was thought to yield a level of predictability unimaginable until the late 20th century.

According to Cowles, "the theorists…have tried time and time again to work the 'wiggles' out of these price movements…with…shadowy figures dancing in and out of the picture as new theories arose, but until now the markets have successfully laughed it all to scorn." On the other hand, the data-mining literature suggests the right model structures to forecast complex economic or social processes are impossible. It is puzzling how the world's best researchers and financial service firms with the largest pools of talent and computing resources have struggled for decades with the fundamental problem of forecastability.

2.2. Machine Learning in Finance

Machine-learning (ML) algorithms are currently changing the landscape of financial asset forecasting. ML techniques allow for improved forecasting performance by automatically selecting the most relevant independent variables from large pools of noisy candidate financial data, which is a major challenge facing traditional econometric techniques. As a consequence, ML techniques have been rapidly adopted in academic finance. The combination of ML and finance has spawned multiple new finance journals dedicated to the use of machine-learning techniques for research on financial problems. Machine learning lies at the juncture of statistics, computer science, and causal inference; it refers to a set of techniques that can be employed to estimate a functional dependence between a response or dependent variable, that is to be estimated or predicted, and a collection of independent or explanatory variables. ML approaches are akin to a large class of nonparametric procedures (specifically, kernel-based procedures) widely used in statistics, but not widely employed prior to their successful application to forecasting in finance.

Most ML algorithms work as follows: once a candidate function space is chosen, a set of free parameters, i.e., weights in the actual functional forms, allows one to write down a function that refers to a linear combination of the functional forms belonging to the selected function space. Given a training set composed of both the independent variables and the response or dependent variable, an error measure determines the discrepancy between predictions from the candidate model and the observations used for estimating the function. This error measure, called a loss function, is minimized with respect to the function determined weights used in the dependent variable functional expression. As a consequence of recent technological developments, financial agents now have access to vast amounts of data, and applying optimal rules and management policies to this ever-increasing volume of observations has become a major requirement.

3. Methodology

This section presents the research design based on a case study approach that includes data sources, preprocessing steps, a discussion on the cloud platforms leveraged in the empirical analysis, and the proposed forecasting models.

3.1. Data Source

The empirical analysis is implemented on the daily-level store sales data from a large domestic retailer in Brazil. The dataset contains store closures events that trigger a significant change in the sales of stores. Retailers tend to decide in favor of aggressive action rather than a wait-and-see posture, which triggers a considerable loss at the beginning. The aforementioned outcome catapults the interest in forecasting for triggers that would facilitate decisions made accordingly beforehand.

3.2. Data Preprocessing

Broadly speaking, the raw data consists of three different files. Upon cleaning the dataset containing sales observations merged by store_id with the one containing store closure events, the dataset including stores to be ignored for the forecasting model build-up is derived.

3.3. Cloud Platforms

The cloud platforms leveraged for the implementation include both Google Cloud and Amazon AWS. Long short-term memory (LSTM) based methods with tuned hyperparameters are deployed on Google Cloud due to the long training time resulting from the high dimensionality of training examples.

Equ 2: Loss Function (Mean Squared Error - MSE)

$$\mathcal{L}_{MSE} = \frac{1}{n}\sum_{i=1}^{n}(\hat{Y}_i - Y_i)^2$$

- Y_i: Actual values
- $\hat{Y}_i$: Predicted values
- n: Number of data points

3.1. Data Collection and Preparation

The Core Data is described in this section based on three criteria: size, accuracy, and purity. Note that each row in the data set is a deviance factor that is extracted by taking derivatives of financial ratios using a window size of n.

3.1.1. Size of the Core Data

To prevent overfitting the noise instead of the signal, a sufficient number of tests or observations required in estimating the parameters is needed. The bank's quarterly financial data has been chosen because its sufficiently large number of observations includes 963 global banks with 12-point labels totaling at least 127,000 test samples.

3.1.2. Accuracy of the Core Data

Out of the 127,000 test samples, banks with mislabeled classes whose deviance factors are smaller than 0.1 are removed, in which the number of these samples is 233, 30, and 21 for the 1-point, 3-point, & 5-point rating classes, respectively.

On the other hand, it is hypothesized that the bugs are generated by a black-box manner with no other clues about which banks are unmoved.

3.1.3. Purity of the Core Data

To further assess the performance, a few randomly chosen tweets are manually examined. The training data is found to be sufficiently clean, including 944 banks with at least 22,000 posts with correctly labeled class badges.

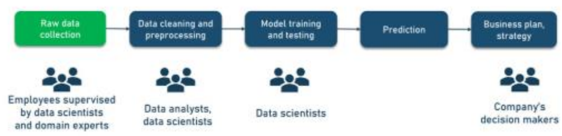

Fig 3: Data Collection for Machine Learning

3.2. Choosing Machine Learning Models Several cloud-based machine learning platforms are available to begin the analysis, including Python on Google cloud, H2O.ai, AWS sagemaker, and Microsoft Azure. A few settings, such as machine learning models, precision of predictions, run time, and use of distributed computing, may need modification. A huge set of algorithms will be optimized automatically by the platform. Most importantly, H2O.ai is completely free and open source, which is a plus in a university or research environment. AWS, GCP, or Azure are less recommended, as using those services incurs substantial costs. Much time will be spent on model selection even if using state-of-the-art services, and hence budgets must be carefully planned. Some core members of the H2O.ai team have floating licenses on GCP, and high-performance computing resources can be accessed for freezing large time series prediction jobs.

The still crumbling steel and cement industry is sucking a huge proportion of fossil fuels globally while producing tons of contaminated waste material. The vast amounts of globally available steel and cement industry waste are unexploited resources to deposit carbon and thereby mitigate climate change. Full circularity of the steel and cement industries are technologically feasible today. In the future, decades of steady technological improvements through better use of AI and cloud computing can potentially make steel and cement production 80% cheaper, completely feasible without fossil fuels, and possibly even net-positive to climate. The available technologies to deposit cash waste material emissions, including waste of waste products to produce fuels, carrier fuels to use cheaper solar heat as process heat, to produce products to integrate energy storage in steel and cement structures, and ways to couple unexploited natural resources in the production, structural design, and premature demolition and recycling of cementitious building materials, are discussed. Potentially, these technologies can sequester the whole steel and cement industry's future emissions of 510 Gt CO2.

4. Machine Learning Models

In recent years, machine learning (ML) models have become increasingly popular in finance. The development and rise of data-driven ML techniques brought new opportunities for financial institutions to improve upon past computing and decision-making processes. Financial forecasting is challenging due to its high dimensionality and non-linearity. Common ML techniques used for financial forecasting include decision trees, ensemble methods, support vector machines (SVM), neural networks (NN), and deep learning. Rapid advancements in big data infrastructures and new computing services have allowed the finance sector to utilize these new technologies. While these black-box ML models often give high accuracy in competitive benchmarking competitions, other aspects such as interpretability of results, computational costs, and performance evaluation on unseen time series data are often overlooked.

Long Short Term Memory (LSTM) architectures, a popular type of Recurrent Neural Network (RNN), have been successfully employed in several predictions. Performance increases with the number of layers and units, resulting in vast amounts of parameters to fit. Used without caution, these networks can overfit on the training dataset. To mitigate overfitting and leverage the time series structure, several common practices have emerged, including dropout, recurrent dropout, batch normalization, and selecting a suitable optimization process. In this study, 14 non-linear ML models with different complexity and interpretability levels were selected. Out-of-the box implementations from the sklearn, xgboost, statsmodels, and keras APIs were leveraged and tuned with the same hyperparameter grid search procedure. The Ridge regression, Elman RNN, parameters of which can be interpreted in an intuitive way, also call for less computational resources compared to other models.

LSTMs, historically tied to deep learning and considered powerful models for finding patterns in the temporal character of datasets, would justify utility in trading strategy creation. Supported by optimizers such as Adam, these models outperform traditional financial forecasting due to their versatility and universality. These aspects come at a much higher computational cost and a poorly defined performance evaluation procedure. Overstepping the data ad hoc is easily achieved with these complex models, leading to overly optimistic results and rendering predictive capacity null on unseen data. To avoid misuse of ML models, a well-defined combination of performance evaluation metrics with historical simulated data of fuller depth is an integral part of developing a robust financial

The benefit of multiple locally modeled architectures extends beyond predictive capacity when pattern recognition methods are employed. Interpretable capacities of ring-like forecasting landscapes stand to offer insight into market mechanisms, while the immediate costs of training models become negligible given the large financial resources at stake.

4.1. Regression Models

The classical statistical regression models that were leveraged for forecasting were: linear, robust linear, and logistic models. Some types of linear regression models were basic linear regression with seasonal and trend predictors, and ridge regression. Some types of robust linear regression were robust ridge, highly-biased outlier catcher with seasonal and trend predictors. Lastly, logistic regression was used to model whether a store A would go out of stock on that quantile in a day and included seasonal and trend predictors to incorporate the cyclic pattern of regressors.

When forecasting the number of units of sale, to provide interval forecasts (by quantiles), the distribution of residual errors across time was tested. This helped identify the top three competing models using a combination of scoring rules: Bayesian & information criteria, predictive accuracy, and forecast intervals. Then, neural network regression models were attempted along with ensemble methods. These have hyperparameters that required tuning for effective training, validation, and testing of which were done with the Dense Neural Network ensemble model. The model was built as a neural network regressor with different densities and dropout layers, followed by dense layers with ReLU activation. Best performance was obtained with three layers consisting of 512-256-128 neurons with 0.2 dropout. Adaptive learning rate optimization was applied to minimize the loss function MSE. Training and validation were done with 128 samples, and batching was performed due to memory size constraints. Up to 300 epochs were tested with early stopping. Three estimators are evaluated after fitting on separate data to avoid overfitting bias.

Lastly, best performing regression model ensembles were designed following the Simple Embedding procedure. This involves regressing the predicted values by each member model as input features to a second stage regression (meta model). The second stage meta model attempts to learn the conditional distribution of the response variable given the predictions by various first-stage models. So, the regression model ensembles leveraged three competing first-stage model families that included DNNs, single hidden layer DNNs with 256 neurons, and the group of formulated classical models.

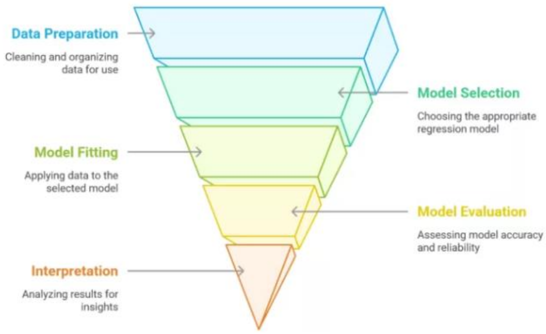

Fig 4: Regression Models

4.2. Time Series Forecasting Models

Estimating future values of a signal from its past observations is a noteworthy learning step of human brains. The same learning process, highlighting understanding a dynamic system from inputs to outputs, is also a prominent issue in numerous application areas such as controlling robotics, highway traffic, emotion expressions of affective computing, affecting stock prices in financial markets, etc. The tools to handle such issues, generally, are forecasting models, which can be classified as three categories according to the nature of data being forecasted, i.e., time series forecasting, time series cross-section forecasting, and time series graph forecasting.

Most businesses, such as upstream oil and gas companies, big and small retailers, e-retailers, and all internet companies, hold a variety of time series associated with their operations. For instance, sales volume and inventory of thousands of products, number of oil drilling projects, daily clicks of a website, etc. Time series forecasting is a first-class citizen of forecasting models, supplying valuable input of market research, financial planning, production planning, scheduling, and etc. in both tactical and strategic aspects. For most time series forecasting scenarios, either values are continually forecasted or an unrolled learning forecast is generated where only one value is forecasted within a time step. Intensive effort and resources, such as staffing, model selection, hyper-parameter tuning, etc., are required in designing and optimizing laws for forecasting.

In practice, most businesses either enlist third-party forecasting services or apply self-built forecasting platforms. The first one is unable to hold the proprietary data, while the second one is a heaven for data scientists and modelers but a nightmare for managers and business operators. Econometric forecasting models have been successfully used for decomposing time series, estimating unknown parameters, selecting key terms, etc. In addition, an increasing number of machine learning and deep learning models for time series forecasting have been widely explored. Statistical learning approaches and neural networks specifically tailored for short time series forecasting have also been proposed.

5. Implementation

This section details the methodology, architecture, tools, and techniques used to build a cloud-based architecture for training the models and optimizing the parameters of feedforward, recurrent, and convolutional network models to maximize prediction accuracies.

The selected dataset consists of prices (Open, Close, High, Low) and volume of stocks for 5 companies. For price forecasting, the 'Close' column is used, whereas the 'Volume' column is used for volume forecasting. The dataset consists of 5 years of stock data. A data frame is created from the dataset, selecting adjusted close prices. After extracting the desired stocks, the dataset is standardized to bring all the parameters to the same scale. Next, a training and testing dataset is prepared. The dataset is divided into x_train, y_train and x_test, y_test (features and target values) based on number of timestamps and training data. The first 1400 days of data are selected as training data to train the model, which is then transformed to time series format. The x-values contain the previous 60 days of stock prices, and y-values are the predicted closing price values on the next day. The testing values contain the next 500 days of stock prices.

The architecture of the final model consists of an LSTM layer, a Dropout layer, and a Dense layer. The LSTM architecture consists of 50 LSTM neurons. The dropout layer is included to combat training/overfitting issues, with a 20% dropout rate. Some of the standardized testing values are reverted back to their original values. Historical stock prices of the next 500 closed days are used to make predictions. The predictions and actual values are plotted with errors to visualize prediction accuracy. The saved model is also loaded, and 50 previous test values are estimated.

5.1. Model Training and Validation

This section describes the materials and methods utilized for model training and evaluation. First, the details of the data used in the training of the forecasting models are presented. Then the metrics used to evaluate forecasts, including confusion matrices are presented. The training process is described, including division of the dataset into training, validation and test sets, and the training time per model, and finally, the two additional forecast evaluation methods also implemented are described.

The data used to train the models consists of univariate data from public weather stations in what have been referred to as Metro-Idaho cities. Cities sampled include Boise, McCall, and Twin Falls with prediction horizons as much as 1000s of seconds. The training time is then examined across many different models to learn how to optimize efficiency. To optimize efficiency across models trained for the same city, each model was trained for the same epochs, learning rate, and hidden state sizes and was run in parallel on the same GPU. City training time comparison was considered across the same models multilayer perceptron (MLP) and XGBoost, varying on hidden states, but training time was not examined further. Forecast metrics used to evaluate the models were root mean square error (RMSE) and mean absolute error (MAE). The prediction horizon for the models and the lead time of these predictions with respect to the current time was also examined.

With regards to default parameters used in all models, the length of training data, and the inclusion of first or last observations were stated. The training process details were provided including any early stopping, optimizers, and all relevant hyperparameters per model were shared. The conditions under which models were trained were largely left out, most notably the computation environment was unknown but it does have an impact on training time.

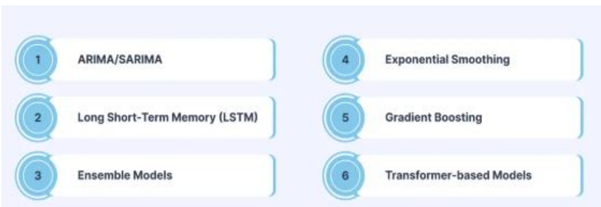

Fig 5: Implement AI Demand Forecasting

5.2. Deployment in Cloud Environment

A cloud environment consists of various interconnected entities in a three-tier architecture, including brokers to monitor current and historic metrics, Data Storage for prediction knowledge, and an Application Layer with cloud services for the hosted system. The Machine Learning Agents in the Application Layer continuously query the brokers for new metrics and generate predictions about future Cloud Infrastructure service metrics. These predictions are periodically written to

the Data Storage for potential future use. To validate when to scale, the Predictive Trigger monitors the predicted and current metrics of the service and is executed periodically. If predicted metrics exceed upper thresholds and scaling is not prohibited, the application will be scaled out. If predicted metrics drop below lower thresholds and scaling is not prohibited, the application will be scaled in. Both scaling up and scaling down actions save the model to the Data Storage, while the Model Data type also contains scheduled scaling actions. A trained model is periodically considered obsolete. To fill this gap, a Cloud-Independent Framework for Resource Predictive Auto-scaling is proposed in conjunction with an efficient methodology to model, design, and deploy a Predictive Auto-scaling system through the Specification of an OCL query and the execution of a transformation rule.
To enable the deployment of the previously specified framework on executions, this chapter describes a general procedure for deploying on Cloud environments. Specifically, the deployment on a Cloud platform is presented in the form of a case study using the general deployment methodology. Initially addressing Cloud Deployment Constraints, and subsequently focusing on the general Deployment workflow followed to automate deployments. It contains the Deployment Architecture Model that is the initial input for the deployment procedure and a detailed description of the mapped Components Configurator. One of the critical components of deployment is a pair of cloud-agnostic and cloud-specific scripts used to automatically set up the Infrastructure and the Application layer, respectively. The last section includes a general overview of resources and services used in this work, concluding with addresses for installing Cloud Services and resources to learn more about Cloud.

Equ 3: Hyperparameter Optimization (Bayesian Optimization Objective)

$$\theta^* = \arg\min_{\theta \in \Theta} \mathbb{E}[\mathcal{L}(f_\theta(X), Y)]$$

- θ: Set of model hyperparameters
- Θ: Hyperparameter space
- $\mathcal{L}$: Loss function to minimize

6. Performance Evaluation

The results include both statistical evaluation metrics of the models used and detailed information about the performance of the best performing models in comparison with the already available cloud service. The models evaluated are XGBoost and a neural network architecture consisting of a long short term memory layer followed by a fully connected layer. For both regression models, a sliding window is used to select the 30 most recent input rows as the model input. The feature preparation was identical for both regressors. Fourteen weather satellite channel lookups were performed. Each channel is preprocessed separately, resulting in 14 feature data frames. The input features are shaped as a time series and fed into either an ML model as a 3D array or a deep learning model as a stacked 3D array. Both model architectures and the adaptive training window concept were successfully applied to improve cloud cover prediction accuracy. The estimation and adaptation of the training window duration based on past forecast performance is a promising approach for dynamic environments that is also expected to transfer to other domains.
However, all forex regression models also did not achieve such good RMSE for the second exchange currency symbol. Supporting the observations regarding cloud cover behavior, there seems to be more sluggish and delayed behavior found in the output values of the forex datasets for BTCUSD. Much context relevant information for prediction was apparently not captured by either model architectures due to the uninteresting component storage design. Even though evaluation of each network component on RMSE and R2 scores showed that a preliminary version of this design more than doubled performance in some of the other currency symbols when the most powerful available cloud volume data and image processing parameters were used, the final current model was found poor at analyzing the price action of the new currency symbol. Nevertheless, the knowledge gained from these component designs and evaluation is expected to be valuable to future work, as cloud data of various treatment methods and feature systems are kept and new treatment tasks are formed through model hybrids.

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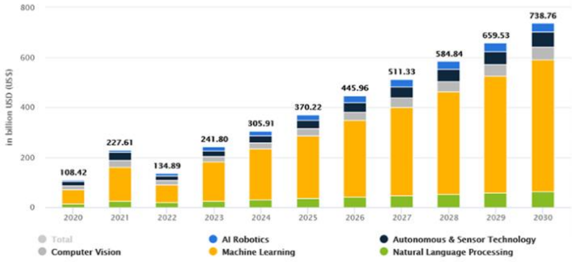

Fig : AI in Forecasting and Where It Falls Short

6.1. Metrics for Financial Forecasting

To evaluate how well a forecast carries information beyond what is already anticipated, one needs either a mere point forecast, a density forecast, or both. In the event that one forecast delivers added information relative to another, the possibility for gains in density predictability arises. Losses in density predictability arise in the opposite event. Financial forecasts are often generated as point forecasts, with many articles testing their optimality using mean squared error (MSE) criterion under quadratic loss. A common explanation for the non-quadricity of many financial variables such as asset returns is non-constant volatility, which results in the non-symmetric nature of the loss associated with MSE cost function. Supporting the notion of asymmetric cost function, it is found that quantile predictions statistically dominate densities based on mean forecasts. These findings motivate the evaluation of a forecast optimality in distributional context using quantile and expectile regressions under asymmetric, including non-constant and non-symmetric cost functions.

Forecasting is a large literature exploring how past variables can be used to predict future ones. One of the earliest contributions in the literature is the work by Mincer and Zarnowitz. They use a well-defined model of forecast formation to capture the prior that the forecast is based on. These methodologies only model one of an infinite number of ways in which the history can be adapted to the economic problem in hand to produce forecasts. An extensive literature follows Mincer-Zarnowitz forecast evaluations. Basic forecast evaluations in this literature is concerned with testing if forecasts carry additional information beyond a benchmark that is commonly an essentially random walk. These models are however not applicable for evaluating quantile and expectile forecasts. As naive benchmarks are often non-operational, an alternative approach is to use the same spec, for example quantile or expectile regression, to hold financial analysts' forecasts and benchmark one to test whether it dominates the other.

6.2. Comparative Analysis of Models

A comparative analysis aims to evaluate and compare Cloud ML models regarding short-term hourly financial forecasting accuracy performance and profitability prediction. A systematic model selection process comprises a business-oriented accuracy performance aspect that includes metric selection against two candidate metrics: normalized squared error and absolute percentage error. The generalizability of the selected method among different domains and the criterion for splitting and cross-validating models are data-stationarity awareness followed by averaged metric-values evaluation. A recent method empirically studied with criticisms from a business perspective is detailed, with the models implemented in the first-to-second focal-stack order and explanation steps to meta-learn the dataset.

The results of the extensive evaluation in terms of forecast accuracy and profitability evaluation metrics pave the way for further research on potentially more robust models. Profitability evaluation is conducted concerning the time scale of forecasts with different frequencies of projections/exhibition/tests. A few models provide statistical criteria that help understand sales trend behaviors as to define business strategies along with the prediction expected profits in quantitative mean-variance sensitivities. Analyzing the learning dynamics affecting the robustness of deep models is another essential topic for ongoing research in a gray area. In particular, cloud ML recalls that a diffusion of their trust score could stamp out equivocation.

The role of probability at the business level is to mitigate the effects of an uncertain world. Financial forecasting is a task to predict how much an input metric-quoted stock price will change in a certain future period. Broadly speaking, a system necessary to achieve it comprises three problems of declining test-traceability order at the business level toward value-added transformations, multivalued previews, and price-estimation of finite/hyper-forecasts. The prevailing methodology in the research domain to predict the price of a target time series given its historical values is to derive a point estimation from an autoregressive model extended to a recurrent structure by modelling data-point uncertainty as a Gaussian, and to project demonstratively graphs ahead accordingly. A viable cloud ML model suited to financial forecasting even at the business assessment ground that appreciates values beyond estimates may entail hyper-forecasting. A recurrent model must additionally involve a fuse condition for sampling a stochastic process then with the graduation time scale for price estimation from hidden states.

7. Conclusion

In conclusion, financial forecasting is a challenging task that necessitates a thorough understanding of both historical data and data relationships, as well as a proper selection of forecasting strategies and models. A case study of a financial data set illustrates that with sufficient historical data on financial KPIs, it is beneficial to separate trending from recurring phenomena, to apply transformations to data, and to consider various different time-series statistical techniques and models as potential forecasting approaches. The case study demonstrates that a historical forecast is more consistently applicable across several newer fiscal years compared to extrapolated models, since it requires fewer assumptions and more available historical data than for extrapolated ones (especially for financial time series forecasts with substantive trends and periodic phenomena). Hence, improving the quality of forecast budgets, e.g. by implementing forecasting tools, is more promising than pursuing rates of return above the market average.
On the cloud, modern data science libraries are rich in statistical techniques and models which give good predictions but, as many models are prone to overfitting, simple models are often more practical. For business use, prediction quality should be comprehensively evaluated based on multiple metrics and k-fold cross-validation, and the conduct and results of forecasts explained and presented well.
Problems arising from the historic forecast need to be addressed iteratively, since they grow after every fiscal quarter. More comprehensive data on the monthly development of the metrics should be collected and an explanation for abrupt upward adjustments sought. Moreover, a scheme for identifying businesses that on practice would benefit from research should be established within Finance. Assuming historical and future data of monthly metric development will be available, use of the GP model would cover both missing data points and uncertainty regarding future points much better than the current approach.

7.1. Future Trends

It is characterized by an irregular component and time-dependent statistical properties, making long-term financial forecasting inherently difficult. Nevertheless, a relatively stable time component exists, leading to the widely recognized financial forecasting paradox: one may compute the return levels accurately (long forecast horizon), but not the return values (short forecast horizon). Many forecast interactions were studied, but no statistically significant results were obtained using traditional models. Nevertheless, a market justifying high forecast performance is emerging, with high-frequency trading, algorithm trading, and trading consultants. Recently, progress has been made using modern models on deep learning techniques. However, it remains unclear why markets become predictable after normalizing the data. Addressing this question and proposing new models could have significant impacts in finance.
Waved-based methods have long been used in various applications, particularly in finance. Financial time series is well-known for exhibiting long memory, a phenomenon captured by a diverse family of fractional models. However, standard algorithms are prone to numerical errors, leading to trust issues in the resulting long-range parameters. Tensor decomposition approaches, like CANDECOMP/PARAFAC, can be a remedy. Starting with New York Stock Exchange data, new elements of normalized continuous wavelet decomposition are provided. The existing code for CPD was adapted to work with auxiliary tensors of wavelet coefficients. Tests on synthetic data show its robustness to additive noise and confirm that wavelet analysis can be an efficient way to obtain relevant information from financial time series.
The necessity of using HPC and Cloud resources to build effective market surveillance systems was discussed. However, the nuances of the interaction between model design, the Cloud architecture, co-design, and implementation of detection systems have not been covered. The proof of concept implementation of the previously proposed architecture is described, showing how employing an industry-focused model design could mitigate some of the challenges currently faced by Cloud-based implementations. In addition, the recently proposed Cloud Simulator enables modeling and testing various candidate designs in an affordable way before deployment.

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