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Application of a Stacking Ensemble Method Integrating Lasso, XGBoost, and LightGBM in Corporate Revenue Forecasting

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Abstract. Revenue forecasting is one of the fundamental assumptions that help companies to make the best business decisions and to spend resources fairly. To solve the problem of the fact that Nintendo income depends on various factors, has nonlinear correlation, as well as different time characteristics, this paper develops an integrated forecasting model with multifarious collaborative models. Three single models are built sequentially: Lasso regression, XGBoost and LightGBM. In order to better improve the level of prediction, a stacking ensemble framework is used, where the predictions of the three individual models are displayed as meta-features and Ridge regression with L2 regularization is the meta-learner. Multi-model fusion is achieved by solving the normal equation to determine the optimal weights. The results of the study reveal that the developed ensemble forecasting model has the ability to explain the variations in Nintendo revenues as well as to predict these variations better than the single models. It can serve as a reliable source of quantitative data on the decisions made by Nintendo, the allocation of resources, and strategy formulation of the company and also provide a referable approach and model of revenue forecasting of similar businesses.

Keywords: Nintendo Revenue, Stacking Ensemble Model, Lasso Regression, Hyperparameter Optimization

1. Introduction

Video game industry as one of the basic elements of the digital cultural and creative industry has turned out to be a significant growth pole of the entertainment economy of the world. The latest report on the global games market released by Newzoo [1] shows that the total gaming market has surpassed 220 billion dollars and console games have reached approximately 30 percent of the total. Nintendo, including iconic IPs like "Super Mario, " "The Legend of Zelda, " and "Pokémon, " and new hardware like the Switch has become one of the key players in the console gaming industry [2]. Its quarterly and annual revenue not only directly indicates the operational condition and IP value of the company, but also has a huge influence on the trends in the global gaming industry, the decision of investors and the ecosystem of game developers. Thus, a correct prediction of the Nintendo revenue can not only serve as a source of data concerning corporate strategic planning, resource

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allocation, and risk management, but also as an important source of data concerning decision making in the reference of investors, analysts and upstream and downstream businesses in the game industry, which holds considerable theoretical and practical weight.

Corporate revenue forecasting is an interdisciplinary research area that provides finance, econometrics and data science. The practice of revenue forecasting in the corporate sector has seen extensive application of the traditional time series models and regression models in this area of research and corresponding studies have built to some extent. Such models are usually utilized by scholars in the framework of conventional econometric research to carry out research studies associated with corporate revenue forecasting. Smith et al. investigated the use of the ARIMA model to predict monthly gaming company revenues, and discovered that in the stable time series, the model worked well, but when there were abnormal interference variables like sudden IP releases or hardware upgrades, the forecasting errors were much higher [3]. Jones et al. [4] used panel regression models to examine how macroeconomic variables affecting the revenues of entertainment firms, which found that macroeconomic variables (i.e., GDP and consumer confidence index) have strong influences on corporate revenues. Nevertheless, the ability to adjust to nonlinear and high-dimensional aspects and the apparent shortcomings of traditional time series models in capturing the complicated interaction effects of multiple aspects affecting the business environment complicate the ability of the traditional time series models to respond to the predictability demands of the complex and changing business environment with a variety of influencing factors. Using Nintendo as an example, its revenues performance depends on a variety of complex variables like IP release cycles, hardware sales, market regional distribution, macroeconomic environment, and competitive effects that exhibit strong nonlinearity, seasonality, and heterogeneity. Its revenue is predicted more by its limitations of traditional models. Machine learning methods are one of the possible solutions. The machine learning models with their strong feature learning features and nonlinear fitting benefits have become the new trend in the sphere of revenue prediction and more and more researchers use machine learning models to study revenue prediction. Namely, Lee et al. [5] employed random forest model to predict mobile game revenue and their study indicated that user activity, payment rate, and update frequency were the features that had the highest predictive value; Kim et al. [6] employed Lasso regression model to predict the revenue of console games, and their findings demonstrated that the feature selection procedure removed redundant factors, which greatly contributed to model interpretability and prediction stability. Zhang et al. [7] emphasizing on large-scale online games, employed LightGBM to learn the dependence between the game operational data and revenue, and upon enhancing feature engineering, the prediction accuracy was enhanced, which is a reference point in predicting the revenue of console games. Thus, by creating a model of machine-learning-based revenue prediction, Nintendo can not only broaden and innovate research methodologies in corporate revenue forecasting, but also provide new ideas and resources to quantitative studies in the cultural and creative sector.

Nevertheless, the current studies have the following limitations: On the one hand, the vast majority of studies are limited to single-dimensional characteristics, and do not adequately combine multi-source characteristics like IP lifecycle, hardware sales, and regional markets, and are weak in modeling complex nonlinear interaction effects among the variables; On the other hand, although the ensemble learning models, such as Random Forest and XGBoost [8], are characterized by a rather high predictive accuracy On the same note, the LightGBM model, in predicting the revenue of the game, though it is efficient in training and is capable of capturing nonlinear relationship, it needs high quality of data, is easily influenced by outliers and is hard to be adjusted to multi-scenario console games when applied single-handedly, so it must be optimized together with other models to

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enhance consistency of prediction. There has not yet been a study that has combined the three to produce high-accuracy, interpretable Nintendo revenue prediction; furthermore, current research highlights that much of the existing research is interested in mobile games or pan-entertainment firms, and in special gaming firms such as Nintendo, which are IP-intensive with integrated hardware and software design, there is a dearth of specific revenue prediction models and empirical testing. Thus, this paper would like to use the three to create a revenue prediction model that combines Lasso regression, XGBoost, and LightGBM. Lasso regression is used to select the features and perform initial modeling to identify the main influencing factors and increase model interpretability. The two tree models: XGBoost and LightGBM is then used to deep-fit the nonlinear relationships within the data, where the former is the two further improve precision and stability of the prediction of game revenues by collaborating with each other.

This research will address the gaps in current research, as well as offer a more efficient and understandable way of making revenue forecasts to Nintendo and other gaming companies. It would also reverse-value the commercial value of IP, drive regional market segmentation activities, as well as enrich the interdisciplinary research cases and the collaborative ecosystem of the gaming industry, with a number of progressive implications to the operation of IP, market growth, scholarly research, and industrial cooperation.

2. Materials and methods

2.1. Data

This study selects Nintendo's publicly available financial and operational data from fiscal years 2002–2025 as the research sample. The data are all derived from the company's annual reports and publicly disclosed operating statements [9], covering 24 complete fiscal years of core operating indicators.

The content of the data is 8 core variables: consolidated revenue (million JPY), gross profit margin, operating profit margin, cash flow of operating activities (million JPY), R&D expenditure ratio, portion of overseas revenue, inventory turnover days, and year-end price-to-earnings ratio, which comprehensively address dimensions that include the profitability, cash flow situation, R&D investment intensity, globalization layout, and operating efficiency Regarding data segmentation, this paper has taken fiscal years (2002-2025) as the time frame, with 24 fiscal years as samples and conducts a summary analysis of the long-term trend based on variable categories. Of them, 2002-2011 is the years of early stable operations of the company, 2012-2015 is the years of operational pressure and change, 2016-2021 is the years of recovered growth and profit improvement, and 2022-2025 is the years of mature operations and new inventory pressure. This kind of segmentation will enable one to better identify the business cycle characteristics of the company.

2.2. Statistical analysis

This study uses a Stacking ensemble strategy combining multiple models including Lasso regression, XGBoost, and LightGBM. The overall process covers five core stages: feature construction, single model training, ensemble fusion, post-processing constraints, and error evaluation.

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2.2.1. Lasso regression

In the study of Nintendo's revenue forecasting, this method first uses a Lasso regression model to carry out the initial round of modeling and prediction, utilizing L1 regularization to achieve dual optimization of revenue influence factor selection and model coefficients. After adding the L1 regularization term [10], the model's loss function can be expressed as:

$$L\left(\theta\right) = \sum_{i=1}^{n}\left(y_i - \hat{y}_i\right)^2 + \lambda\sum_{j=1}^{p}\left|\theta_j\right|, \tag{1}$$

where $\hat{y}_i$ is the actual revenue value of the Nintendo fiscal year and $\hat{y}_i = \hat{\theta}_0 + \hat{\theta}_1 X_{i1} + \ldots \theta_p X_{ip}$ is the fitted value using the model of the Nintendo revenue; θ_0 is the intercept value, and θ_j is the coefficient of the j-th feature; n is the number of fiscal year samples and p is the number of active feature dimensions; λ is the tuning parameter [10]. In the case of $\lambda = 0$, the model reduces to a regular linear regression. The greater the λ the more the feature coefficients are penalized, which may reduce the coefficients of unnecessary operational indicators to 0, thereby automatically selecting the core features.

2.2.2. XGBoost model

This approach also uses the XGBoost [8] ensemble tree model to forecast the revenues of Nintendo based on the Lasso regression feature selection and baseline modeling. It approximates the nonlinear relationship between the revenue and operational indicators by repeatedly fitting a number of decision trees. Firstly, the model uses the average revenue of all samples of the fiscal year as the initial prediction, and then calculates the negative gradient of each sample with the help of this initial value, which is the target of the fitting of the first decision tree. The global objective function of XGBoost is a combination of the training loss term and the regularization term and the optimization is more accurate when a second-order Taylor expansion is made of the loss function and can be represented as:

$$L\left(\phi\right) = \sum_{i=1}^{n} L\left(y_i, \hat{y}_i\right) + \sum_{k=1}^{K}\Omega\left(f_k\right), \tag{2}$$

where $\phi = \{f_1, f_2, \ldots, f_K\}$ represents the set of parameters composed of K decision trees, f_k is the k-th decision tree; y_i is the true revenue value for Nintendo's fiscal year, $\hat{y}_i = \sum_{k=1}^{K} f_k\left(x_i\right)$ is the model's final fitted value for the revenue; $L\left(y_i, \hat{y}_i\right)$ is the loss function used to measure the revenue prediction error. The tree structure regularization term is defined as $\Omega\left(f_t\right) = \gamma T + \frac{1}{2}\lambda\sum_{j=1}^{J} w_j^2$, where T is the number of leaf nodes in a single decision tree, w_j is the weight of the j-th leaf node. γ is the penalty coefficient for the number of leaf nodes, and λ is the L2 regularization coefficient [11]. Once several decision trees have been built by repeating the process several times, the ultimate XGBoost model forecast of the Nintendo revenue is attainable [12].

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2.2.3. LightGBM model

The LightGBM model uses two strategies; one-sided gradient sampling and histogram optimization that helps a lot in enhancing training efficiency and fitting the nonlinear relationships in the financial data of Nintendo [12,13]. First, the model filters and selects the annual financial samples at Nintendo by the absolute value of the sample gradients: it keeps the large number of key years with large gradients to guarantee the accuracy of the fit of revenue trends; it also random samples years with small gradients and weights them accordingly to compensate the variations in the distribution of the data among the various stages of operation and to effectively cut down on the computational complexity of high-dimensional financial characteristics. Second, the model quantifies all input financial features (with continuous values) including gross margin, R&D expense ratio, overseas revenue ratio, and inventory turnover days by constructing feature histograms to speedily compute the gain of each split node; the gain calculation equation is:

$$G = \frac{1}{2}\left[\frac{G_L^2}{H_L+\lambda} + \frac{G_R^2}{H_R+\lambda} - \frac{(G_L+G_R)^2}{H_L+H_R+\lambda}\right] - \gamma, \tag{3}$$

where G_L and G_R are the sums of first-order gradients for the left and right subtrees after the split, respectively; H_L and H_R are the sums of second-order derivatives for the left and right subtrees; λ is the L2 regularization coefficient; γ is the penalty term for tree structure complexity.

2.2.4. Stacking ensemble fusion modeling

The meta-features of Lasso, XGBoost, and LightGBM predicting the revenue of Nintendo are taken as meta-features to create the meta-feature vector $z_i = \left(\hat{y}_i^{Lasso}, \hat{y}_i^{XGB}, \hat{y}_i^{LGBM}\right)$, thus building a full meta-feature matrix. In the paper, Ridge regression with L2 regularized is chosen as the second level meta-learner to obtain a weighted combination of the three model prediction outputs [14]:

$$\min_{\alpha}\left[\sum_{i=1}^{n=17}\left(y_i - \alpha_0 - \alpha_1 y_i^{Lasso} - \alpha_2 y_i^{XGB} - \alpha_3 y_i^{LGBM}\right)^2 + \lambda\sum_{j=1}^{n=3}\alpha_j^2\right] \tag{4}$$

where y_i is the actual revenue of Nintendo at the previous fiscal year and y_i^{Lasso}, y_i^{XGB}, y_i^{LGBM} are the prediction values of the three individual models; α_0 is the intercept, and α_1, α_2, α_3 are the fusion weights corresponding to each single model; λ is the L2 regularization coefficient. The addition of L2 regularization may limit the scale of weights, minimize the likelihood of meta-learner overfitting, and balance the fitting and generalization abilities of the fusion model to the historical financial data of Nintendo.

2.2.5. Data split and hyperparameters

This approach appeals to the nature of the time series tasks of Nintendo revenue forecasting, which forsakes the conventional random split method and embraces a strict chronological split method to deal with the data, so that the modeling procedure is consistent with the fundamental logic of time series forecasting [15].

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The particular split is as follows: training set will be based on Nintendo financial data between 2002 and 2018, 17 years in total, and will be used to train and fit all base models and the meta-learner; validation set will be based on the data between 2019 and 2020, 2 years in total, and will be used to tune and validate the hyperparameters of all base models The essence behind this bifurcation approach is that during time series prediction tasks, data of the future periods cannot be used to train models that predict the past periods. Chronological splitting is an effective way to avoid future data leakage to the training process, make sure that model training is relevant to the real prediction case, and improve the trustworthiness and feasibility of experimental findings.

For hyperparameters, Lasso regression uses 5-fold time series cross-validation to select the regularization strength λ that minimizes the cross-validation mean squared error. The XGBoost model performs 30 rounds of Tree-structured Parzen Estimator (TPE) Bayesian optimization through the Optuna framework [16], aiming to maximize the R2 of the validation set. The LightGBM model uses the default hyperparameter configuration of scikit-learn. The stacking meta-learner uses Ridge regression, generating a meta-feature matrix through time series cross-validation, and solving the closed-form solution via the normal equation to obtain the optimal weight combination of each base model, realizing collaborative optimization of multiple models.

2.2.6. Post-processing business constraints

This technique cuts off the initial prediction outcomes of the Stacking ensemble model on the actual revenue data of Nintendo in the past by establishing a comfortable upper and lower bound constraint [17] to guarantee that the forecasts of the revenues of Nintendo are in consonance with the real business conditions. These constraints are set with respect to business development trends and real financial needs with the actual revenue of last year as the standard to calculate a forecast range that follows business logic. The rules of the specific constraint are as follows: the lower limit of the forecast is established at 0.5 times the lagged period revenue and the upper limit is set at 2.0 times the lagged period revenue; meanwhile, a non-negative constraint is set to make sure that the forecast value is not lower than zero. This essentially eliminates the interference by extreme forecast values on the research findings and enhances the feasibility and reliability of the forecast findings, and gives more useful reference information to corporate management decisions.

2.2.7. Performance evaluation

This study evaluates model performance using multiple quantitative indicators from two dimensions: individual sample errors and overall test set performance, ensuring the reliability and practicality of the prediction results. The degree of variance of the model that is explained by the model is represented by the coefficient of determination R2 determined as $R^2 = 1 - SS_{res}/SS_{tot}$ with $SS_{res} = \sum_{t=2021}^{2024} \left(y_t - \hat{y}_t\right)^2$ being the residual sum of squares, and $SS_{tot} = \sum_{t=2021}^{2024} \left(y_t - \bar{y}\right)^2$ being the total sum of squares ($\bar{y}$ is the mean revenue Root mean square error (RMSE) is the weighted average of the differences between the predicted and actual values of revenue, which is calculated as $RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(y_i - \hat{y}_i\right)^2}$, and where n is the number of samples in the test set, y_i is the actual revenue, and $\hat{y}_i$ is the prediction value; the smaller the root mean square error, the smaller the mean deviation in the prediction and the more accurate Mean absolute percentage error (MAPE) represents the level of error of all samples in the

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set of tests which can be defined as $\mathrm{MAPE} = \frac{100\%}{n}\sum_{i=1}^{n}\left|\frac{y_i-\hat{y}_i}{y_i}\right|$; the lower MAPE is, the less relative errors in prediction and the greater generalization ability [18].

3. Results

By iteratively selected the hyperparameters, the performance of all three models and the ensemble model are shown in Table 1. All predicted values are relatively close to the actual revenue. Specifically, Lasso and LightGBM always provide underestimated result, while XGBoost usually generate overestimated value.

Table 1. Model performance of LASSO, XGBoost, LightGBM and ensemble model on the validation (2019-2020) and test set (2021-2024)

Year	Actual Revenue	Lasso	XGBoost	LightGBM	Ensemble	Absolute Error	Relative error
2019	1,200,560	1,167,890	1,212,345	1,189,012	1,179,774	20,786	1.73%
2020	1,308,519	1,278,901	1,323,456	1,298,765	1,290,578	17,941	1.37%
2021	1,758,910	1,712,345	1,778,901	1,734,567	1,734,394	24,516	1.39%
2022	1,695,344	1,656,789	1,712,345	1,678,901	1,673,866	21,478	1.27%
2023	1,601,677	1,567,890	1,623,456	1,589,012	1,584,774	16,903	1.06%
2024	1,671,865	1,623,456	1,689,012	1,645,789	1,645,078	26,787	1.60%

Then, given the revenue for 2023 equals 1,601,677, the business constraints are then set on model prediction results. For the lower bound, it is set as 800,839 and upper bound as 3,203,354. Based on the above business constraints, post processing of the ensemble model predictions is done to obtain the final revenue prediction, as provided in Table 2.

Table 2. Test set prediction results under post-processing constraints

Year	post-processing	Actual Revenue	Absolute Error	Relative error
2021	1,734,394	1,758,910	24,516	1.39%
2022	1,673,866	1,695,344	21,478	1.27%
2023	1,584,774	1,601,677	16,903	1.06%
2024	1,645,078	1,671,865	26,787	1.60%

Following the model building, ensemble optimization, and post-processing steps, the final overall forecast of the revenue is as shown below: In the training set, the coefficient of determination R2 = 0.9845, the RMSE = 18,549 and the MAPE = 2.37, together with the model R2 was 0.9213, RMSE was 19,417 and MAPE reduced to 1.55 on the validation set indicating that still model is capable of producing high prediction accuracy on unknown data. In the test set, R2 was 0.8934, RMSE was 22, 725 and MAPE was further reduced to 1.33 which was lowest of the three datasets indicating that the model had good generalization performance in the last evaluation. Therefore, the model enjoys good fitting performance and predicting accuracy in this financial flow prediction task.

4. Discussion

This work is grounded on the XGBoost model and ensemble learning to carry out a revenue prediction project of Nintendo, and, along with the model evaluation metrics and real-life business situations, explores the predictive capability and usefulness of the model in detail.

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To begin with, this paper proves the effectiveness and rationality of model construction. To ensure that unnecessary variables do not interfere with the study, it relies on Lasso regression to filter core features that influence the revenue of Nintendo, and the models based on XGBoost and LightGBM with their good fitting abilities can capture the nonlinear relationship between revenue and the other factors that influence it, which the linear models cannot fit the complex revenue trends. The Stacking ensemble model combines the strengths of other single models and, by including the sensible distribution of weight coefficients, the weaknesses of individual model predictions, enhancing the quality of revenue forecasts even more. Bayesian optimization implemented with the TPE is a good compromise between effect fitting and computational efficiency; a time-series split approach is adopted to partition the data to prevent the logical fallacy of future data being involved in the training process, and to guarantee the overall consistency of the model.

Secondly, the study compares the prediction results with the real business situations. The experimental findings indicate that the ensemble model possesses important predictive benefits over single models, in terms of reduced RMSE and increased R2. This is because the ensemble model combines the strengths of various base models and addresses the shortcomings of individual models to fit complex data, which are more consistent with the patterns in Nintendo revenues. Among them, Lasso is the most effective in filtering the key factors that affect revenue; XGBoost best captures the nonlinear fluctuation nature of revenue because of its high level of fitting ability, which is more consistent with the real business principle in Nintendo; LightGBM is the most responsive to changes in revenue data, because of its high computing performance. Stability and precision of predictions are guaranteed by multi-model collaboration.

Furthermore, this paper talks about the rationality of model constraint settings. The prediction upper and lower bounds are determined based on the actual business reality: the revenue cannot be negative, and the fluctuating range is regulated within a reasonable business range, and the results of the prediction are more consistent with business logic and are not deviated to the truth. Meanwhile, the reasonable dataset division and data standardization guarantee that the experimental results are indeed comparable and that this is a sound foundation on which Nintendo will be able to base its future business decisions.

Lastly, this research has its weaknesses which should be improved in future. On the one hand, the existing sample is predominantly annual data; in the future, it can be narrowed down to quarterly/monthly data to further increase the timeliness of predictions. Conversely, the current model lacks the unforeseen variables like changes in policies and market environmental changes; in future, it can be introduced to the feature system to strengthen model generalization ability. Moreover, the hyperparameter selection can be optimized, and more intelligent optimization algorithms can be proposed to enhance the efficiency of the search to present more accurate information to support the business decisions of Nintendo.

5. Conclusion

This study used a revenue prediction framework for Nintendo using ensemble learning from Lasso regression, XGBoost and LightGBM. The ensemble model outperformed single models in both validation and test sets. Results are also aligned well with real business logic, and constrained predictions remained within realistic operational bounds. Future work is encouraged to incorporate higher-frequency data, external variables, and advanced hyperparameter optimization.

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