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Mending the Crystal Ball: Enhanced Inflation Forecasts with Machine Learning

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Mending the Crystal Ball: Enhanced Inflation Forecasts with Machine Learning
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ABSTRACT: Forecasting inflation has become a major challenge for central banks since 2020, due to supply chain disruptions and economic uncertainty post-pandemic. Machine learning models can improve forecasting performance by incorporating a wider range of variables, allowing for non-linear relationships, and focusing on out-of-sample performance. In this paper, we apply machine learning (ML) models to forecast near-term core inflation in Japan post-pandemic. Japan is a challenging case, because inflation had been muted until 2022 and has now risen to a level not seen in four decades. Four machine learning models are applied to a large set of predictors alongside two benchmark models. For 2023, the two penalized regression models systematically outperform the benchmark models, with LASSO providing the most accurate forecast. Useful predictors of inflation post-2022 include household inflation expectations, inbound tourism, exchange rates, and the output gap.

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Mending the Crystal Ball:

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Prepared by Yang Liu, Ran Pan and Rui Xu [1]

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Introduction

Forecasting inflation in Japan has become challenging since 2022. For the first time in three decades, inflation rose above the two-percent target for more than two years since April 2022. Although initially driven by cost-push factors, inflation in Japan is increasingly driven by demand-side factors, with services inflation above 2 percent. Both the level and the persistence of core inflation have surprised the Bank of Japan (BOJ), whose inflation forecast has been repeatedly revised upward in its quarterly economic outlook.

The challenge is not unique to the BOJ. Many central banks were surprised by the inflation in 2021 and 2022, unsure of the size of the output gap amid sizeable fiscal stimulus and unaware of the steepening of the Phillips curve. The World Economic Outlook forecasts have also consistently under-projected inflation in advanced economies with sizeable errors (see Koch and Noureldin, 2023).

The pandemic led to structural changes in price dynamics not captured by prevailing economic models. For instance, the persistence of supply chain constraint was not anticipated and thus not incorporated in typical inflation models. Hobijin et al (2023) also documented a steepening of Phillips curves in many industrialized countries since 2021. The curve was considered "dead" by many economists due to its decade-long flattening trend before the pandemic. In Japan, three decades of disinflation further complicates the task of forecasters.

Most traditional forecasting models for economic variables rely on fitting data to a pre-specified relationship between input variables and the output variable (i.e., the forecast target). These models thereby assume a stochastic process underlying the true relationship between the variables in question (Breiman, 2001). In such cases, therefore, the model can only be as good as its specification, regardless of what the data might suggest.

Machine learning (ML) models can help improve forecasting performance by finding a function that best represents the relationship between the input and output data using a rigorous training and testing algorithm. But some economists critique that many ML models hold limited explanatory power and cannot explain what factors drive forecasts. Yet, the growing amounts of data and increasingly complex relationships warrant the usage of machine learning approaches in economics (see Varian, 2014).

ML models enjoy three key advantages over economic forecasting models. First, ML models can incorporate a wider range of variables through regularization and/or a large amount of training samples and allow for non-linear relationships. This can help capture the emerging new drivers of inflation during the pandemic (see Kohlscheen, 2021; Medeiros, 2021). Second, ML models focus on prediction and employ a rigorous procedure to select the best-performing model. This contrasts with economic models that focus on estimation and typically overlook out-of-sample forecasting performance (see Mullainathan and Spiess, 2017). And third, in contrast to structural or semi-structural economic models, ML models can be easily re-trained with latest data and thus can better adapt to changes in the underlying data patterns.

As the first application of ML to inflation forecasting in Japan, this paper contributes to a growing literature of macroeconomic forecasting using ML models. The forecasting target is *core* inflation that excludes fresh food and energy to eliminate the effect of volatile and globally determined prices.[1] Given that inflation was a relatively rare phenomenon in Japan over the last three decades, we choose one-month, three-month and six-month ahead forecasting horizons to maximize the training sample period with inflationary pressure. We

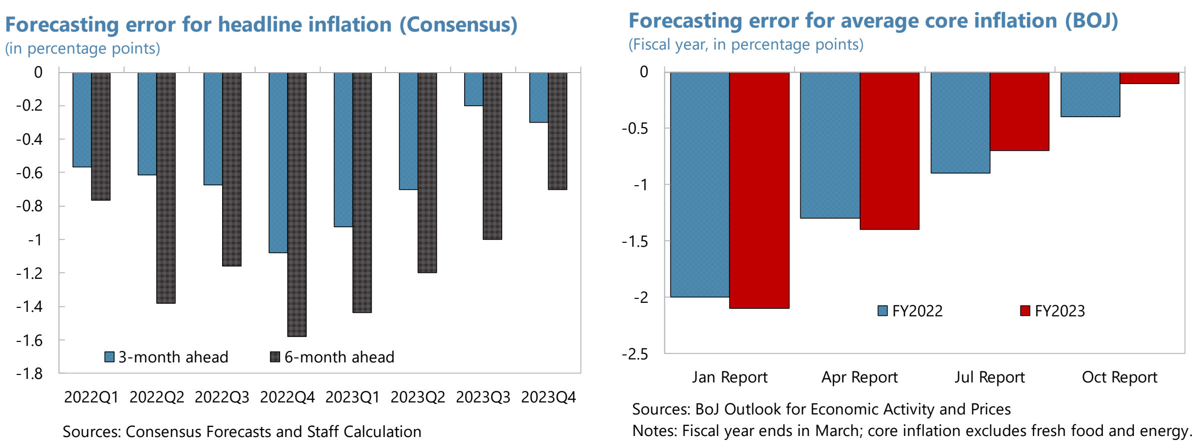
[1] All the inflation series used in this paper exclude the effect of VAT rate hikes, as such effect is one-off and is driven by policy.

consider both linear ML models (LASSO, Elastic Net) and tree-based ML models (Xgboost and Random Forest models). The model performance is benchmarked against simple univariate forecasting models (a random walk model and an autoregressive model) which produce forecast that are difficult to improve systematically upon (Faust and Wright, 2013).

Among the six models considered, LASSO performs the best for core inflation forecasts post 2022, based on back testing. The average root mean squared error (RMSE) of LASSO forecasts is about 0.1, 0.2 and 0.3 percentage point for 1-month, 3-month, and 6-month ahead inflation forecasts, respectively. Formal tests of forecasting performance suggests that Lasso performs significantly better than the benchmark models.

The forecasting errors of LASSO also appear smaller than those by professional forecasters in 2022-23 (Figure 1). The consensus forecast has a consistent downward bias on inflation forecasts, with forecasting errors averaging -0.6 percentage points for 3-month ahead inflation and -1.2 percentage points for 6-month ahead inflation. The BOJ's average core inflation forecasts have also been consistently biased downward, with inflation in 2022 and 2023 largely missed by the semi-structural model used by the central bank. Since Japan had not had inflation for three decades prior to 2022, traditional structural models and econometric models calibrated to pre-pandemic data could not capture the post-pandemic inflation dynamics.

Figure 1. Japan Inflation: Forecasting Errors by Professional Forecasters



The results from LASSO regressions are easily interpretable and highlight the important role of five predictors. Rising household inflation expectations, measured by both the simple average and imputed qualitative responses in the BOJ opinion survey, have the highest predictive power among the features selected by LASSO (other than lagged inflation). The surge of inbound tourism since the border reopening in October 2022 boosted demand and contributed to core inflation. The sharp yen depreciation since early 2022 has been gradually passed on to consumers, pushing up inflation. As the economy gradually recovers from the pandemic, the closing output gap is also putting upward pressure on prices.

The rest of the paper is organized as follows. Section II describes the methodology and the models used for the forecasting. Section III discusses the recent inflation trends in Japan and the potential predictors of inflation (which are included as model features). Section IV presents the model performance and compares LASSO with benchmark models. Section V concludes.

Methodology

Consider the following model:

$$\pi_{t+h} = F_h(\boldsymbol{x}_t) + u_{t+h}, \quad h = 1, \dots, H, \quad t = 1, \dots, T, \qquad (1)$$

where π_{t+h} is the core inflation (excluding fresh food and energy) in month $t+h$, $\boldsymbol{x}_t = (x_{1t}, \dots, x_{nt})'$ is an n-vector of covariates possibly containing lags of π_t and a large set of potential predictors; $F_h(.)$ Is the mapping between covariates and future inflation; and u_{t+h} is a zero-mean random error. The target function $F_h(\boldsymbol{x}_t)$ can be a single model or an ensemble of different specifications. There is a different mapping for each forecasting horizon h. Three forecasting horizons are considered, with $h = 1, 3, or\ 6$. We consider more than twenty numerical features (i.e., explanatory variables), including various economic activity indicators, exchange rates, import prices and tourist arrivals.

The forecasting equation is given by:

$$\hat{\pi}_{t+h|t} = \hat{F}_{h,t-R_h+1:t}(\boldsymbol{x}_t), \qquad (2)$$

where $\hat{F}_{h,t-R_h+1:t}$ is the estimated target function based on data from time $t - R_h + 1$ to t, and R_h is the window size, which varies according to the forecasting horizon and the number of lagged variables in the model. We consider direct forecasts as we do not predict the covariates.

We conduct cross validation for each model using monthly data since 2012 and select the best performing model using back-testing. Specifically, we first do the times-split K-fold cross-validation and choose the hyperparameter values that produce the lowest root mean squared error (RMSE) in the cross-validation dataset. Then we conduct back-testing using observations in the last six months and select the model with the lowest RMSE in back-testing. The selected model is then used to forecast core inflation one to six months ahead.

The forecasts are based on a rolling-window framework as in Giacomini and White (2006). With each newly available data point, the cross-validation sample for hyperparameter tuning expands by one period, while the back-testing sample shifts forward by one period. Under the framework, the model can adapt to more recent data and thus attenuate the effects of potential structural breaks.

Figure 2. Time Series Split K-fold vs K-fold Cross-Validation

Source: Pedregosa et al. 2011.

For training and hyper-parameter tuning, we use the time-split K-fold cross-validation (as shown in Figure 2). In contrast to classical k-fold where the samples are independent and identically distributed, time series data entail temporal dependency between observations. To preserve the temporal dependency and especially to avoid leakage when validated on samples that are artificially similar, the k^{th} split would treat the first k folds as the training set and the $(k+1)^{th}$ fold as the test set. Successive training sets are supersets of those that come before them. For each test fold, we calculate the average RMSE and choose the hyperparameter values that produce the lowest average RMSE.

After pinning down the hyperparameters for each model class, we conduct back-testing using observations in July-December 2023. Using each model, we forecast core inflation 1, 3, or 6 months ahead, and then calculate the RMSE. The model with the lowest RMSE is then selected to forecast inflation.

We consider four ML models, including two penalized linear models and two tree-based ensemble methods. The details of the models are included in Annex I.

1. LASSO (Least Absolute Shrinkage and Selection Operator) is essential a linear regression model that includes a regularization term to induce sparsity and effectively perform feature selection (see Tibshirani, 1996).

2. Elastic net is a regularization technique that combines LASSO and Ridge regression by including both L1 and L2 penalty terms (see Zou and Hastie, 2005). Compared to LASSO, elastic net can better handle highly correlated variables and less susceptible to overfitting.

3. Random forest (RF) is a specific type of bagging method tailored for regression trees (Breiman, 2001). The algorithm starts by taking multiple bootstrap samples (random samples with replacement) from the training dataset. For each of these bootstrap samples, a regression tree is built. Each tree in a RF uses a random subset of features to determine the best split. The RF model can produce feature importance values, which are calculated using the average decrease in impurity (variance) that each feature brings when used in trees. We consider RF model because it can describe nonlinear mappings nonparametrically, and produce superior inflation forecasts in some cases (see Medeiros et al, 2019; Araujo and Gaglianone, 2023).

4. Gradient boosting is a type of boosting method used with regression trees (see Friedman, 2001). Boosting algorithms train a sequence of models in an adaptive way: each model compensates for the errors of preceding ones. And then models are weighted based on their accuracy and each subsequent model focuses on the instances that the ensemble finds difficult to classify correctly. The boosted trees could help address the inability of random forests to deal with mistakes created by their individual decision tress (if any) due to parallel learning. Here we use XGBoost which is designed and developed by Chen and Guestrin (2016).

Following the literature, we consider two benchmark models. The first benchmark is the random walk (RW) model, where each current observation or value is equal to the previous value plus some random error (with mean zero). The forecasts of RW are simply $\hat{\pi}_{t+h|t} = \pi_t$. The second benchmark is a simple autoregressive (AR) model of order p. The forecast equation is $\hat{\pi}_{t+h|t} = \hat{\phi}_{0,h} + \hat{\phi}_{1,h} \cdot \pi_t + \cdots + \hat{\phi}_{p,h} \cdot \pi_{t-p+1}$, with a different model for each horizon h.

This paper contributes to a growing literature of macroeconomic forecasting using ML models.

As surveyed by Masini et al (2021), ML models, both linear and non-linear ones, have been shown to provide more accurate forecasts than traditional economic or econometric models. Tiffin (2016) applied LASSO and Random Forests models to nowcast GDP for Lebanon with selected proxy measures to overcome the absence of timely economic statistics. Babii, Ghysels, and Striaukas (2022a) proposed a sparse-group LASSO estimator, which achieved superior nowcasting performance of US GDP growth compared to other alternatives, including the New York Fed nowcast. Beyhum and Striaukas (2023) extended the work of Babii, Ghysels, and Striaukas (2022a) and found that a factor augmented sg-LASSO-MIDAS regression improves nowcast accuracy during the COVID period. Barhoumi et al (2022) built machine learning models to nowcast economic activity, together with high frequency indicators as complementary to traditional inputs.

Specifically on inflation forecasting, Kohlscheen (2022) showed promising performance of regression trees in forecasting inflation in 20 advanced countries between 2000 and 2021. Liu et al. (2022) found that linear ML models were more effective in some countries, while non-linear models yielded better results in others. Medeiros and Mendes (2016) applied the adaLASSO to forecasting U.S. inflation and showed that the method outperforms the linear autoregressive and factor models. Garcia et al. (2017) showed that high-dimensional econometric models, such as shrinkage and CSR, perform very well in real-time forecasting of Brazilian inflation in data-rich environments. Medeiros et al. (2021) conducted a vast comparison of models to forecast U.S. inflation and showed that random forest models dominated all other models.

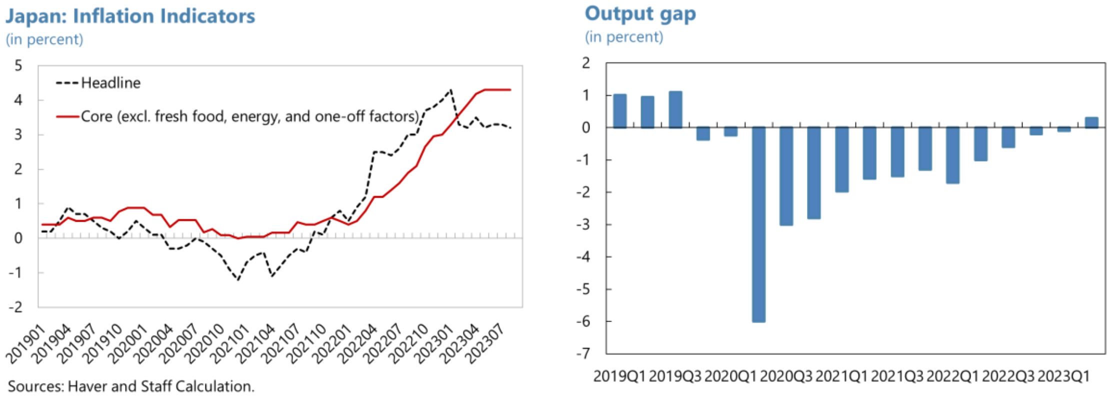
The Machine Learning methods in this paper are implemented in Python with standard Python ML packages (Pedregosa et al. (2011) and Chen and Guestrin (2016)). For cross validation, we use TimeSeriesSplit from sklean.model_selection with 10 folds (n_splits=10). For LASSO, we use linear_model.LassoCV from sklearn. For Elastic Net, we employ linear_model.ElasticNetCV from sklearn. For the tree models, we used Bayesian Search algorithm as the hyperparameter tuning search strategy (Wu et al. 2019), since the hyper paramerter space is much more complex for tree-based models than LASSO and Elastic Net. For the Random Forest model, RandomForestRegressor from sklearn.ensemble is used in combination of BayesSearchCV from skopt with TimeSeriesSplit. The second tree method, XGBoost is fitted from the library xgboost.XGBRegressor, and the hyperparameters are tuned using BayesSearchCV in combination with TimeSeriesSplit. More details on the implementation can be found in Annex II.

Potential Predictors of Inflation (Features)

Core inflation in Japan started rising in 2022 after three decades of deflation/disinflation. Although initially driven by cost-push factors, inflation in Japan is increasingly demand driven. Services inflation rose above 2 percent at end-2023 for the first time in three decades. The rise in inflation coincides with the delayed (compared to other advanced economies) yet robust recovery from the pandemic. Output gap is estimated to have closed by end-2023.

Since 2022, drivers of inflation have also evolved beyond the standard economic relationships. The ML methods can incorporate a large number of features and model non-linear relationship. We consider more than 20 features, as listed in the table below. Some of them predict imported goods prices, some predict domestic goods prices and others capture aggregate demand. Some features also capture idiosyncratic shocks to Japan, such as tourist arrivals since the border reopening in October 2022.

Figure 3. Japan: Inflation and Output Gap



Sources: Haver and Staff Calculation.
Note: the effect of the VAT rate hike is excluded from all series.

IMF staff estimate

Following the ML literature, the features are transformed prior to the analysis. First, all variables are transformed to percentages. For variables already in percentage terms (e.g. GDP growth, unemployment rate), no transformation is needed. For variables that are in levels, we calculate year-over-year percentage changes. This helps ensure that all variables have the same unit and are stationary. Second, we consider three-month lags of variables. Third, the core inflation measure is adjusted for VAT increases and other one-off factors such as the go-to travel subsidies and the policy-driven drop in mobile phone charges.

Table 1. Features for Selection in ML Models

Inflation expectations	Price passthrough	Macroeconomics	Other

• Household (BOJ opinion survey)
  • Raw average
  • Imputed average from qualitative responses
• Corporate (Tankan)
• Consensus forecasts
	• USD-yen exch. rate
	• PPI
	• Chained PPI
	• PPI for services
	• Import price index
	• Energy import price
		• GDP growth
		• Unemployment rate
		• BOJ output gap
		• HH disposable income
		• Consumer activity index
		• Earnings growth
		• Shadow interest rate
		• Credit growth
		• Gov. consumption
		• Gov. investment
			• TOPIX stock index
			• Tourist arrivals

Model Performance

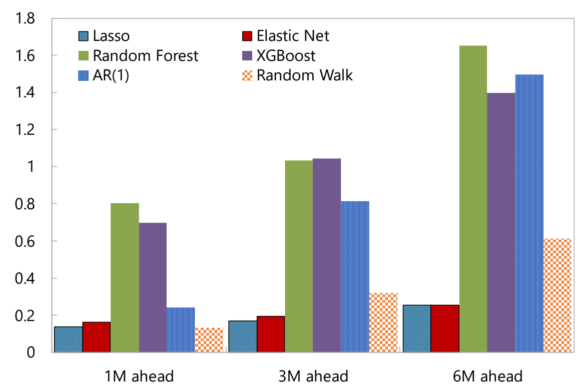
The six models, including four ML models and two benchmark models, are evaluated using the root mean squared errors (RMSE), which is defined as follows:

$$RMSE_{m,h} = \sqrt{\frac{1}{T - T_0 + 1} \sum_{t=T0}^{T} \hat{e}_{t,m,h}^2},$$

where $\hat{e}_{t,m,h} = \pi_t - \hat{\pi}_{t,m,h}$; and $\hat{\pi}_{t,m,h}$ is the inflation forecast for month t made by model m with information up to $t - h$. The RMSE is calculated for each forecasting horizon and for each model during the back testing period (July – December 2023).

Among the six models, LASSO performs the best with the lowest RMSE in back testing for all three forecasting horizons, as shown in the text chart. The RMSE is about 0.1, 0.2 and 0.3 percentage point for 1-month, 3-month, and 6-month ahead inflation forecasts, respectively. The forecasts using Elastic Net have slightly higher RMSE but still outperform those from the benchmark models, namely the AR model and the random walk model. On the other hand, the two non-linear models, Random Forest and XGBoost, have higher RMSE than the benchmark models. In all models, RMSE increases with forecasting horizon.

Back-Testing RMSE



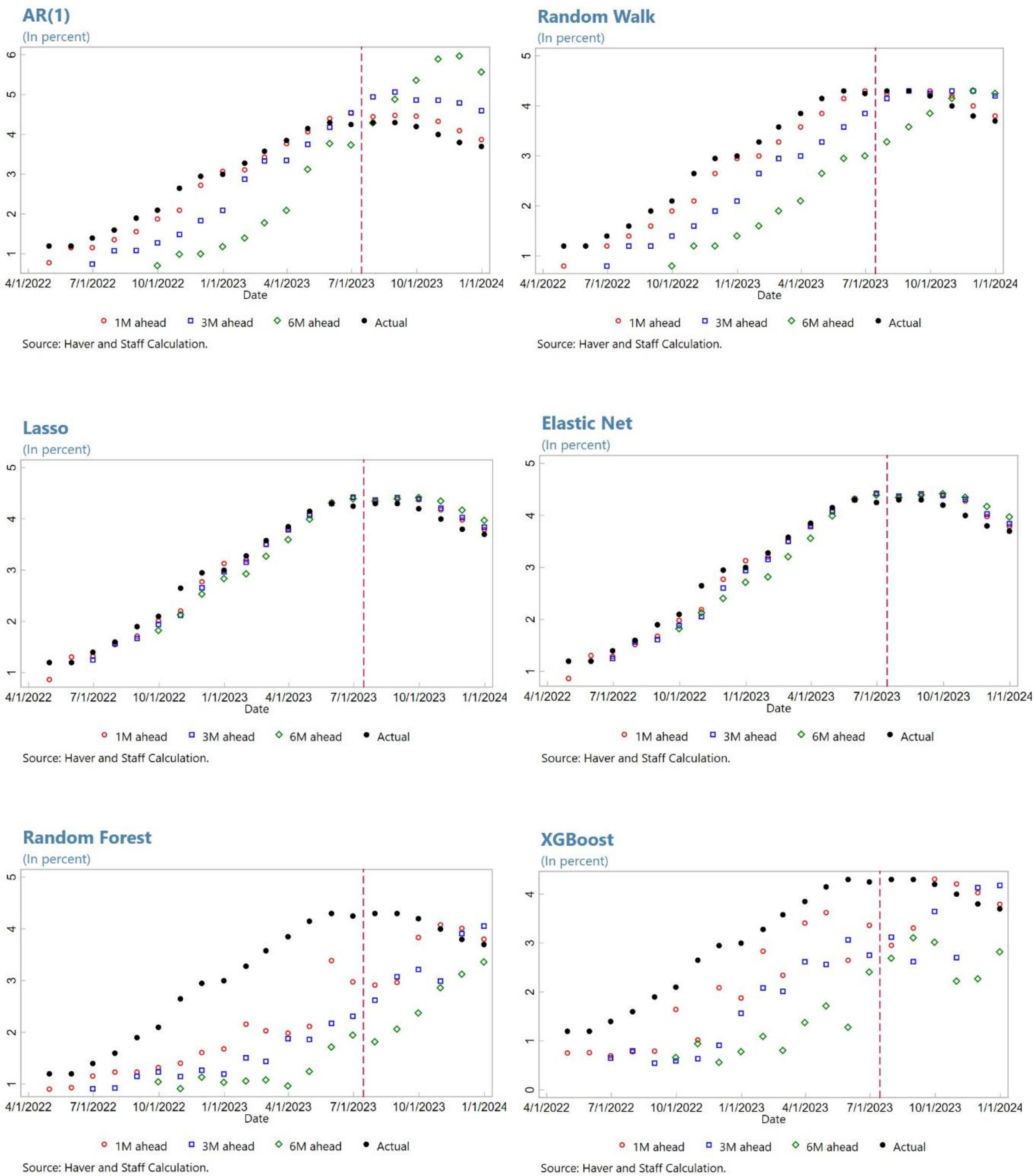
The superior forecasting performance of LASSO is robust to the choice of back testing periods. Figure 4 plots the out-of-sample forecasts from each of the six models against actual core inflation.[2] LASSO forecasts are closest to actual inflation realization, followed by elastic net. Forecasts from the AR model were biased downward before May 2023 when inflation was accelerating. Afterwards, the forecasts from the AR model became biased upward after core inflation stabilized. The random walk model also performed poorly when inflation was accelerating. The two tree-based models perform the worst, producing forecasts consistently below the actual inflation with large deviations. This is likely due to overfitting of the complex tree models as core inflation had been low in most of the training period since 2012.

Formal tests of forecasting performance suggest that LASSO performs significantly better than benchmark models in most of 2022 and 2023. The test statistics of the Giacomini and Rossi's fluctuation test are presented in Figure 5. The blue line shows a sequence of differences of Mean Squared Forecast Error (MSFEs) between two models in rolling windows over time, rescaled by the standard deviation. This is essentially Diebold and Mariano's (JBES 1995) test statistics in rolling windows over time. The Giacomini and Rossi's fluctuation test critical values are shown in red dotted lines. When the test statistics are above the upper bound, LASSO

[2] Under the rolling-window framework, the models are always retrained with the latest available data to generate forecasts. For instance, the one-month ahead inflation forecast in July 2023 is based on the model that is trained using data until June 2023, and the three-month ahead inflation forecast in July 2023 is based on the model that is trained using data until April 2023.

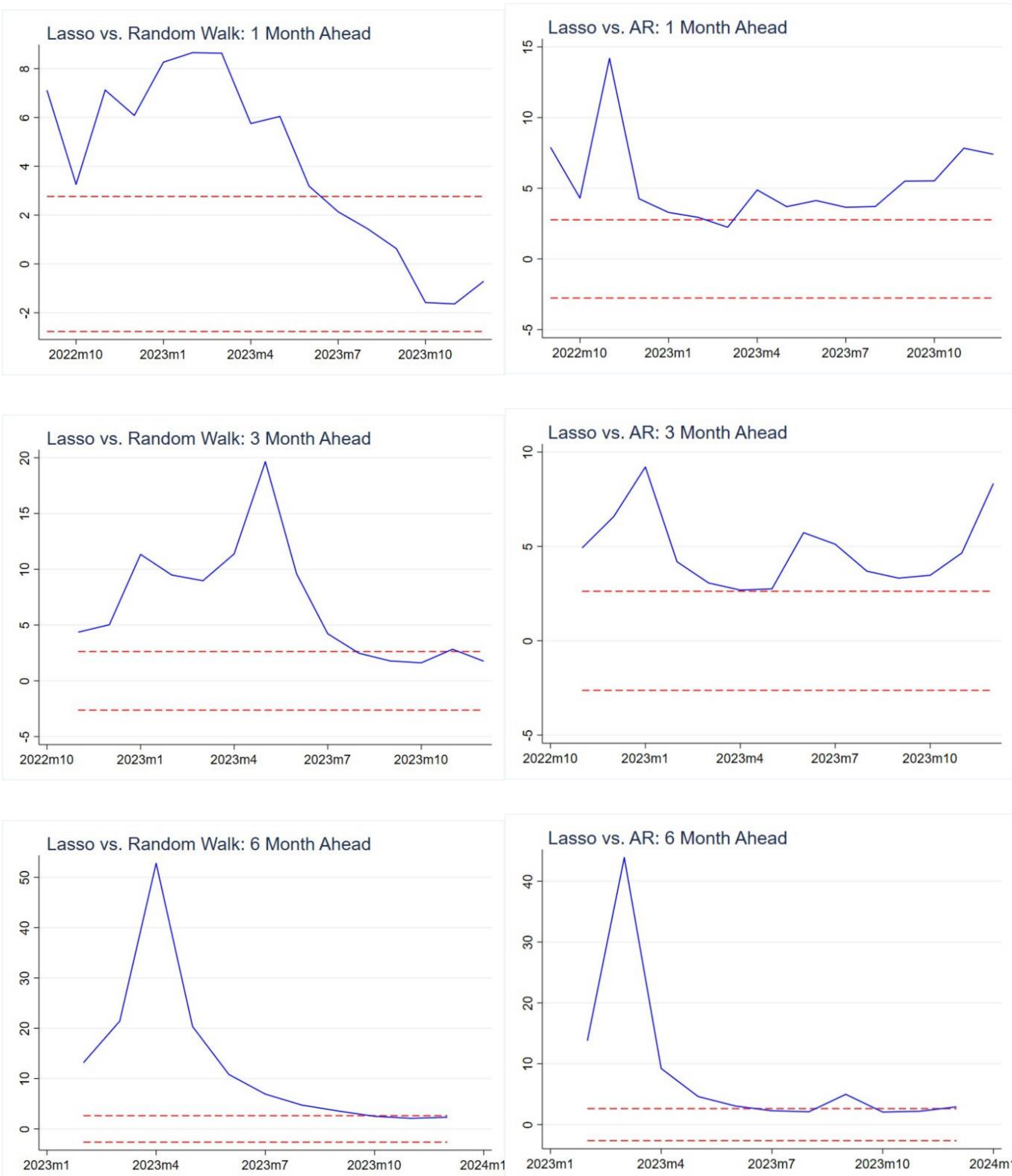
performs better than the bench market models. The over-performance of LASSO is more pronounced in the first half of 2023 and for longer forecast horizons (i.e. 6-month ahead vs. 3-month or 1-month ahead).

Figure 4. Japan: Projected vs. Actual Core inflation



Note: the back testing period is from July – December 2023 (after the red dotted line).

Figure 5. Test of Forecast Performance

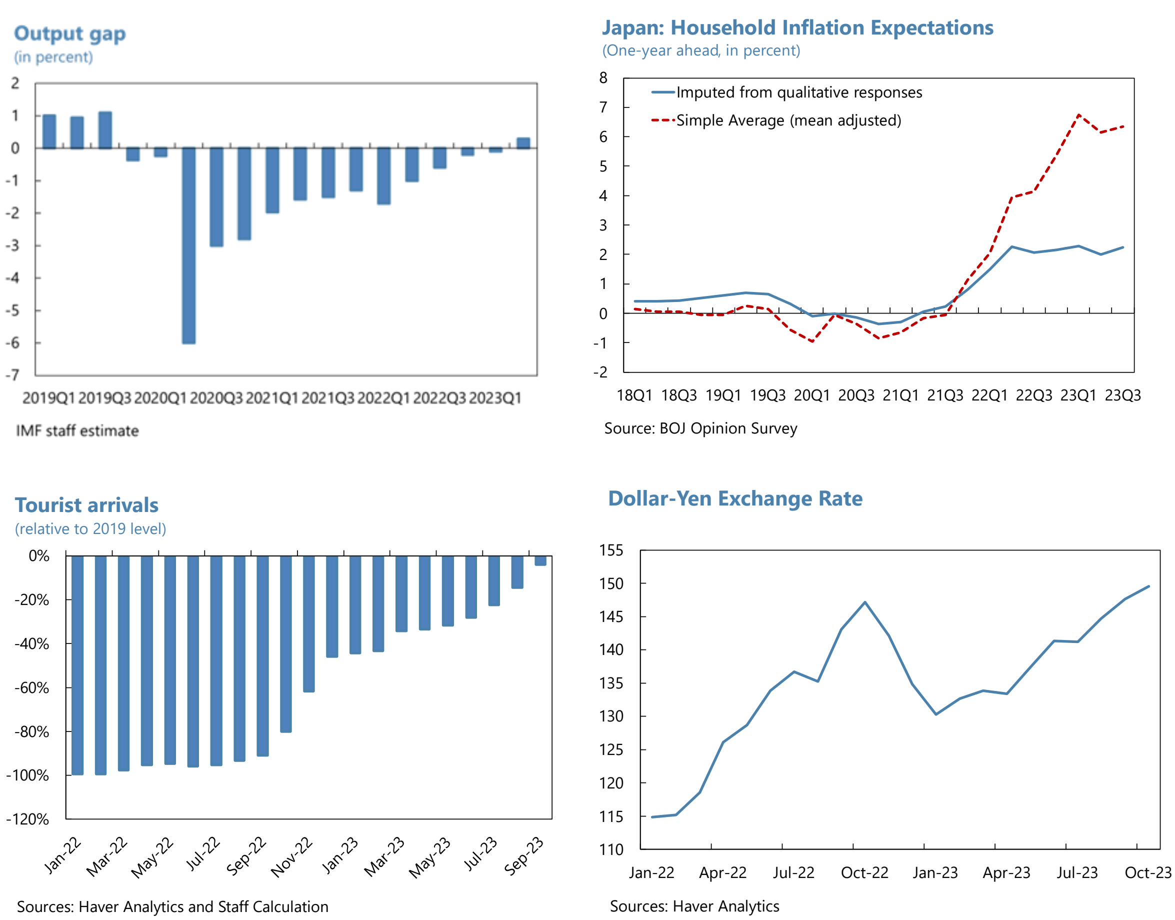


Note: Giacomini and Rossi's (2010) test rejects the null hypothesis of equal predictive ability when the test statistic is outside the band lines. When the test statistic is above the upper band line, LASSO performs significantly better than the benchmark models.

In addition to superior forecasting performance, LASSO is also more interpretable than non-linear models. Six features draw our attention as they were always selected for predicting core inflation regardless of training periods or forecasting horizons. They are lagged core inflation, last quarter's household inflation expectations (both simple average and imputed average based on qualitative responses), y/y growth of tourist arrivals, y/y exchange rate depreciation, and the output gap (Figure 6). An increase in those variables would predict higher core inflation in the near term (i.e. one to six months ahead). While the coefficients of these variables fluctuate as the training dataset expands with new inflation data, the six variables are always selected as key predictors for core inflation.

The predictors of inflation in post-pandemic Japan are in line with economic theory and previous empirical findings. Like Brandão-Marques et al (2023), we find that both the average level and the distribution of household inflation expectations can help predict near-term inflation in Japan. The sharp movement of yen exchange rate also has predictive power, partly reflecting increasing passthrough of exchange rate into the producer price index and the consumer price index (Hara et al, 2015). Output gap captures the aggregate demand slackness and had more variation than unemployment rate which was smoothed by government support programs. Inbound tourist arrivals quickly recovered to pre-pandemic levels after the border reopened in October 2022, which put pressure on prices of restaurants, hotels, and other services.

Figure 6. Japan: Core Inflation Predictors



Although tree-based nonparametric models produce superior inflation forecasts in some studies (e.g. Medeiros et al. 2021 on the U.S., Araujo and Gaglianone 2023 on Brazil, Botha et al. 2023 on South Africa, and Kohlscheen 2021), they do not perform well in this study for two reasons.

First, flexible nonparametric (nonlinear) models can reduce bias but at the cost of increasing variance. In machine learning, all models need to balance the bias-variance tradeoff. In general, as we increase the number of trainable parameters in a model, it becomes more flexible and can better fit the training dataset and have less “bias”. But more flexible models tend to have greater “variance” in their estimated parameters when the models are trained on a new dataset. In other words, a model with a higher level of variance tends to overfit the training dataset and, consequently, has a limited ability to generalize to new unseen data. Since inflation in Japan was very stable in most of the training dataset, the non-linear models would overfit and perform poorly in the out-of-sample inflationary period.

Second, there is no clear nonlinear relationship in Japan’s core inflation. On the contrary, core inflation had risen linearly since 2022 before flattening in recent months. There is no evidence that the predictors affect inflation in a nonlinear manner in Japan.

Conclusion and Future Work

Machine learning models have been increasingly used to forecast economic variables, often with great success. In this paper, we use machine learning models to forecast near-term core inflation in Japan. This is in the context of an unprecedented acceleration of inflation since 2022 with core inflation reaching a level not seen in four decades. Most forecasters, including the BOJ and market practitioners, have missed the momentum and persistence of the inflation.

Our results suggest that LASSO, a linear ML model performing both variable selection and regularization, can accurately forecast inflation one to six months ahead. The average RMSE is about 0.1, 0.2 and 0.3 percentage point for 1-month, 3-month, and 6-month ahead inflation forecasts, respectively. LASSO outperforms other ML models and the standard benchmark models including the random walk and autoregressive models.

In addition to superior forecasting performance, LASSO is also interpretable and can thus shed light on the main drivers of inflation. Currently, inflation forecasts are led by household inflation expectations, output gap, the dollar-yen exchange rate, and tourist arrivals. But the model will be retrained with each new data point to capture the evolving inflation dynamics. The flexibility and the focus on forecasting are the main advantages of ML models over traditional economic models for the purpose of inflation forecasting.

The superior performance of LASSO over standard benchmarks also highlights the importance of domain knowledge. For instance, tourist arrivals are not standard predictors for inflation and thus would require forecasters’ domain knowledge. To improve forecasting performance, it is advisable to have a basic understanding of the underlying drivers of inflation and include as many relevant features as possible.

Forecasting inflation since 2020 has been a challenge to many central banks. The ML models considered here have great potential to improve inflation forecasting in other countries. Most of the papers on inflation forecasting using Machine Learning models were published pre-pandemic when most of the advanced economies experienced low inflation. The underlying dynamics have shifted significantly since then. It is worth reassessing the performance of various ML models on inflation in other advanced economies.

Annex I. Machine Learning Models

Four machines learning methods are used in this paper, two of which are linear models and the other two non-parametric models.

1. Least Absolute Shrinkage and Selection Operator (LASSO)

LASSO regression, also known as L1 regularization, is a form of regularization for linear regression models popularized by Tibshirani (1996). It improves the Ordinary Least Squares (OLS) regressions by restricting the sum of the absolute value of the coefficients being less than a constant. The optimization problem can be expressed as follows:

$$\min_{\beta}\{\|y - X\beta\|_2^2\} \text{ subject to } \|\beta\|_1 \leq t$$

which would yield the Lagrangian form:

$$\hat{\beta} = \underset{\beta}{\operatorname{argmin}}\left\{\|y - X\beta\|_2^2 + \underbrace{\lambda_1\|\beta\|_1}_{L1\ penalty\ term}\right\}$$

LASSO is frequently used in machine learning to handle high dimensional data as it facilitates automatic feature selection. It does this by adding a penalty term to the residual sum of squares (RSS), which is then multiplied by the regularization parameter (λ). This regularization parameter controls the amount of regularization applied. Larger values of lambda increase the penalty, shrinking more of the coefficients towards zeros. This subsequently reduces the importance (or altogether eliminates) some of the features from the model, resulting in automatic feature selection.

The penalty promotes sparsity within the model, which can help avoid issues of multicollinearity and overfitting. Model sparsity can also improve the interpretability of the model compared to other regularization techniques such as ridge regression (also known as L2 regularization).

Lambda (λ) is a key parameter that will be determined using cross-validation. As noted above, a higher λ applies more regularization, which means more coefficients would shrink to zero. That would imply larger biases but smaller variance. In this paper, the optimal λ is chosen using the times-split K-fold cross-validation.

LASSO regression can handle some multicollinearity without negative impacting interpretability of the model, but it cannot overcome severe multicollinearity. If the covariates are highly correlated, lasso regression will arbitrarily drop one of the highly correlated features from the model. Elastic net regularization is a good alternative in this situation.

2. Elastic Net Algorithm

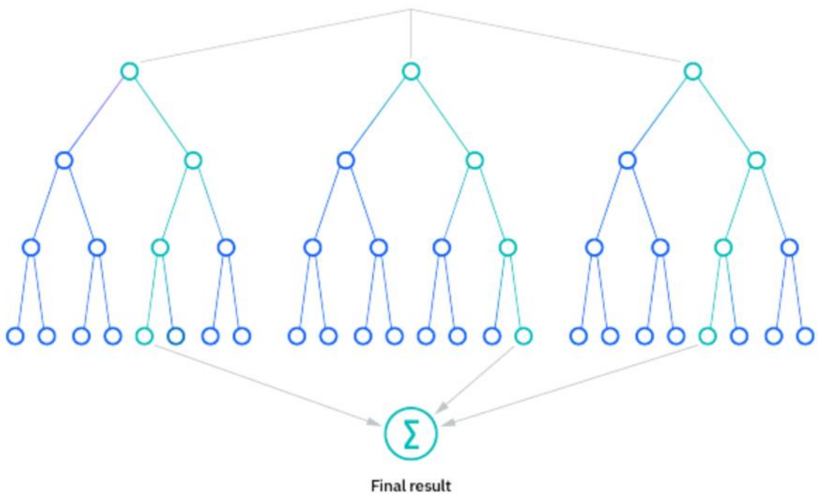
The Elastic Net linear regression is a combination of the ridge and LASSO regressions originally proposed by Zou and Hastie (2005). The estimates from the elastic net are defined by:

$$\hat{\beta} = \underset{\beta}{\operatorname{argmin}}\left\{\|y - X\beta\|_2^2 + \underbrace{\lambda_1\|\beta\|_1}_{L1\ penalty\ term} + \underbrace{\lambda_2\left|\left|\beta\right|\right|^2}_{L2\ pealty\ term}\right\}$$

Elastic net can potentially improve upon LASSO regression by addressing multicollinearity while also enabling feature selection. It may produce superior predictions when 1) the number of regressors exceeds the number of observations (also known as “fat data”); 2) a group of variables show high pairwise correlation; and 3) the number of observations significantly exceeds the number of regressors (also known as “tall data”).

3. Random Forest.

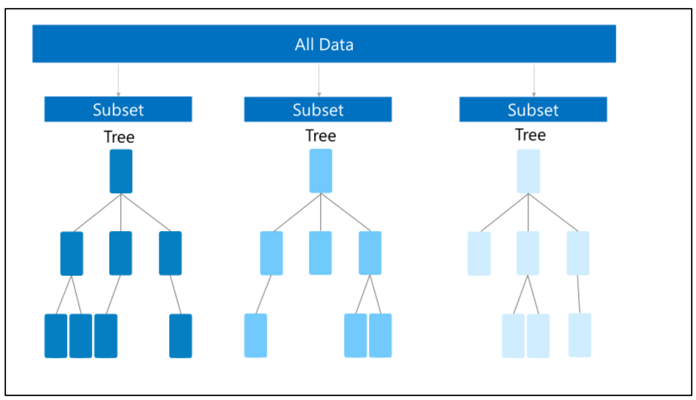
Random forest is a commonly-used machine learning algorithm that combines the output of multiple decision trees to reach a single result. Each tree in the ensemble is comprised of a data sample drawn from a training set with replacement, called the bootstrap sample. The algorithm has several main hyperparameters that need to be set before training, including tree depth, node size, the number of trees, and the number of features sampled. From there, the random forest classifier can be used to solve for regression or classification problems.



Random forest can reduce the risk of overfitting (compared to decision trees) and can evaluate variable importance to the model. However, the method tends to work better with large datasets and is more complex and harder to interpret.

4. XGBoost

Gradient boosting is a type of boosting method used with regression trees. Boosting is an ensemble learning method which trains the model sequentially and each new model tries to correct the previous model. In each iteration, the algorithm computes the gradient of the loss function with respect to the predictions of the current ensemble and then trains a new weak model to minimize this gradient. The predictions of the new model are then added to the ensemble, and the process is repeated until a stopping criterion is met. Models are weighted based on their accuracy and each subsequent model focuses on the instances that the ensemble finds difficult to classify correctly.



XGBoost is a scalable and highly accurate implementation of gradient boosting that pushes the limits of computing power for boosted tree algorithms. With XGBoost, trees are built in parallel, instead of sequentially like Gradient Boosting Decision Trees (GBDT). It follows a level-wise strategy, scanning across gradient values and using these partial sums to evaluate the quality of splits at every possible split in the training set.

Both random forest and GBDT build a model consisting of multiple decision trees. The difference is in how the trees are built and combined. Random forest uses a technique called bagging to build full decision trees in parallel from random bootstrap samples of the data set. GBDTs iteratively train an ensemble of shallow decision trees, with each iteration using the error residuals of the previous model to fit the next model. Compared to random forecast, gradient boosting can be more accurate and powerful since it uses gradient descent and residuals to optimize the ensemble and reduce the bias. But gradient boosting can also be slower and harder to train, more prone to overfitting, and more sensitive to outliers and noise.

Annex II. Implementing the Machine Learning Methods using Python

All four machine learning methods are implemented in Python with standard Python ML packages. For all four ML methods, we use TimeSeriesSplit from sklean.model_selection with 10 folds (n_splits=10), a cross-validation techniques tailored for time-series data.

For LASSO, we use linear_model.LassoCV from sklearn. This is an implementation of Lasso regression with built-in cross-validation to select the best value of the hyperparameter α (the regularization strength). LassoCV allows users to specify a range of α values to test. In our case, we choose to not indicate the range, and LassoCV infers a range of values based on the data. The α that results in the lowest mean squared error during cross-validation is selected as the final model.

Similarly, for Elastic Net, we employ linear_model.ElasticNetCV from sklearn, which is an ElasticNet model that performs cross-validation to find the optimal values of the regularization parameters, which are the L1 and L2 regularization. There are two parameters to specify, α and l1_ratio, where l1_ratio is the mix ratio between L1 and L2 regularization. The range of l1_ratio we choose is [.1, .5, .7, .9, .95, .99]. For each combination of α and l1_ratio, ElasticNetCV trains an ElasticNet model using a subset of the data and validates it on a held-out subset. The combination of α and l1_ratio that results in the lowest mean squared error during cross-validation is selected as the final model. Additionally, both LassoCV and ElasticNetCV use coordinate descent algorithm to fit the models along the regularization path (for different parameter values), which is computationally efficient.

As for the tree based methods, in Random Forest model, RandomForestRegressor from sklearn.ensemble is used in combination of BayesSearchCV from skopt. RandomForestRegressor's splitting criterion is defined as "squared_error", which indicates that the algorithm will choose the splits that minimize the mean squared error within each node. BayesSearchCV is an implementation of Bayesian optimization, which aims to find the maximum (or minimum) of an objective function in as few evaluations as possible, and in our case, BayesSearchCV looks for the best hyperparameters that maximizes the RMSE score. Unlike grid search or random search, which evaluate hyperparameters independently, BayesSearchCV makes decisions sequentially. It uses the results of previous evaluations to inform the choice of the next set of hyperparameters. The search space includes max_depth, ranging from 2 to 20 and min_samples_leaf, ranging from 1 to 10. Min_samples_leaf indicates every single tree in the random forest model is grown up until there are 1 to 10 observations in every leaf. Max_depth indicates that the maximum depth of the trees is from 2 to 20.

The second tree method, XGBoost is fitted from the library xgboost.XGBRegressor, and the hyperparameters are tuned using BayesSearchCV in combination with TimeSeriesSplit tailored for time series data. Similarly, the scoring method in cross-validation is also the RMSE. The search space for XGBoost regressor includes:

- max_depth: Maximum depth of the individual trees.
- learning_rate: Boosting learning rate.
- subsample: Proportion of training data to sample in each boosting round.
- reg_lambda and reg_alpha: L2 and L1 regularization terms respectively.
- gamma: Minimum loss reduction to make a split.

- colsample_bytree and colsample_bylevel: Fraction of features to be randomly sampled for building trees and for each level respectively.
- n_estimators: Number of boosting rounds (trees to be constructed).

Additionally, for each optimization in BayesSearchCV, we run 30 iterations (n_iter=30).

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