April 17, 2018

Economics Group

Special Commentary

John E. Silvia, Chief Economist
john.silvia@wellsfargo.com • (704) 410-3275
Azhar Iqbal, Econometrician
azhar.iqbal@wellsfargo.com • (704) 410-3270

Can Machine Learning Improve Recession Prediction?

Big Data Applications in Economics: Part III

"Computers are useless. They can only give you answers." – Pablo Picasso

Executive Summary

Big data utilization in economics and the financial world has increased with every passing day. In previous reports, we have discussed issues and opportunities related to big data applications in economics/finance.[1] This report outlines a framework to utilize machine learning and statistical data mining tools in the economics/financial world with the goal of more accurately predicting recessions. Decision makers have a vital interest in predicting future recessions in order to enact appropriate policy. Therefore, to help decision makers, we raise the question: Does machine learning and statistical data mining improve recession prediction accuracy?

Does machine learning and statistical data mining improve recession prediction accuracy?

Our first method to predict recessions concerns statistical machine learning, also known as statistical data mining. This method examined over *500,000* variables as potential predictor variables in our tests. Furthermore, to obtain the final logit/probit model specification, we ran *30 million different models*. The selected model was then utilized to generate recession probabilities. The second method is the random forest approach, which utilizes a famous class of machine learning tools. The random forest approach uses the same set of predictors that are utilized in the statistical data mining method. The third approach we use is known as gradient boosting, a technique that also belongs in the machine learning family. Moreover, we built an econometric model that utilizes the yield curve as an additional recession predictor and employ it as a benchmark. The other three approaches include hundreds of thousands of potential predictors that do not use any prior economic/financial theories. We set out with the question of whether machine learning tools are more useful than a simpler econometric model, a model with only one predictor.

To test a model's accuracy, we employ both in-sample and out-of-sample criteria. In our tests, the random forest approach outperforms all the other models (gradient boosting, statistical machine learning and the simple econometric model) in both the in-sample and out-of-sample situations. The gradient boosting model comes in second place, while the statistical data mining approach captures third. Furthermore, if we combine all four probabilities, then that method is still unable to beat the random forest's prediction accuracy. That is, the random forest approach, alone, is the best. Our analysis proposes that machine learning can improve recession prediction accuracy. Moreover, our models suggest a less than 5 percent chance of a recession during the next 12 months.

To sum up our big data application analysis, we would like to expand the aforementioned Picasso quote by emphasizing that it is up to the analyst to obtain either an accurate answer by utilizing computers (big data) efficiently, or end up with a useless answer by providing irrelevant inputs

[1]"Big Data Applications in the Economics/Financial World Part I: Opportunities and Challenges", Published on April 06, 2017. "Big Data Applications in the Economics/Financial World Part II: Econometric Modeling in the 21st Century", Published on July 05, 2017. Both reports are available upon request.

(more noise than signals) to the model.[2] Therefore, the reliable answer may not depend on computers but rather on how one utilizes those computers.

Predicting Recessions in the Big Data Age: Setting the Stage

Accurately predicting recessions is crucial for decision makers who are tasked with designing bespoke policy responses. Every recession is unique in the sense that different recessions have varying drivers. For example, one of the major causes of the Great Recession was the housing sector, while the IT boom/bust was a major cause of the 2001 recession. Knowing what will cause the next recession is a trillion dollar question. However, finding the right set of predictor variables to forecast the next recession is challenging because of the changing nature of the economy. Likewise, including too many variables in a traditional econometric modeling approach creates issues, such as an over-fitting problem.[3]

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Machine learning tools, on the other hand, are capable of handling a very large set of variables while providing useful information to identify the target variable. Basically, in the machine learning approach, we are letting the data speak for themselves and predict recessions. The rationale is that recessions are the results of imbalances/shocks that must reveal themselves in certain sectors of the economy. By including information from various sectors of the economy, we can improve the prediction of those imbalances and corresponding recessions. One major challenge for today's modelers is the abundance of information, where noise in large data sets can prove distracting. This challenge is different than the traditional modeling process where too little information was the issue. In the following sections we provide a reliable framework to utilize big data and machine learning tools to generate accurate recession forecasts.

Statistical Machine Learning: Opening Doors, Finding Connections

Our first recession prediction method is statistical machine learning, which is sometimes referred to as statistical data mining. In statistical machine learning modeling, we can "train" machines to go through hundreds of thousands of potential predictors and select a of handful predictors (4 to 6 variables, for example). That is, machines will utilize some statistical criteria (forecast error for instance) to narrow down the large dataset of potential predictors to a more manageable variable-list. We asked machines to consider over 500,000 variables as potential predictors and return to us a combination of five variables that predict U.S. recessions accurately.

There are several major benefits of the statistical machine learning method over a traditional econometric model in which an analyst has a model with a set of predictors that are selected based on an economic/financial theory. First, economies evolve over time and so does the relationship between the variables of interest. Thereby, it would be practical to re-evaluate existing relationships and, if needed, add/subtract variables to/from a model. Statistical data mining does not rely on any economic/financial theory but identifies relevant variables using statistical tools. Second, complex economic interactions between different sectors vary over time as well. Thus the question, "what will cause the next recession?" is a very difficult one to answer. Therefore, putting everything in the pot (statistical data mining) increases the chances of finding what is affecting the target variable (recession) in the recent periods.

Third, it is important to note that a combination of some factors may bring about a recession rather than weakness in a single sector. For example, a drop in equity prices (S&P 500 index) and house prices along with a rising unemployment rate may be more likely to pull the economy into a recession than, for example, weakness in the manufacturing sector alone. Statistical data mining

[2] In our past work we have mentioned that big data can pose bigger problems and an analyst needs to extract relevant information from big data (more signals than noises) then utilize that information efficiently to obtain an accurate forecast/reliable answers.

[3] Typically, an over-fitted model shows very good in-sample fit but very bad out-of-sample forecasts. For more detail see, Silvia, J., Iqbal, A., et al (2014). *Economic and Business Forecasting: Analyzing and Interpreting Econometric Results*. Wiley 2014.

would likely help an analyst explore deep and complex interactions between different sectors that are closely associated with the target variables.

An added benefit of using statistical data mining is that important connections between different sectors are often unknown to analysts. Statistical machine learning can help an analyst identify those obscure connections. A great illustration of such unknown connections between certain sectors of the economy is the financial crisis and the Great Recession. That is, the housing boom was initially thought to be a regional phenomenon that would not pose a serious risk to the national economy. The Federal Open Market Committee (FOMC) transcripts from this period show that at first the FOMC considered there to be isolated regional housing bubbles. Likewise, by 2006, the meeting transcripts show that Ben Bernanke, the Federal Reserve Board's Chairman at the time, discussed that falling home prices would not derail economic growth.[4] Furthermore, the relationship between the housing market and financial sector was also underestimated and only appeared with the Lehman Brother's bankruptcy in September 2008. Statistical machine learning has the potential to uncover such complex connections by utilizing information across major sectors of the economy.

Statistical machine learning has the potential to uncover complex interaction across major sectors of the economy.

Information Magic: How Does Statistical Machine Learning Work?

Here we outline our proposed framework to effectively utilize statistical machine learning to forecast recessions. The first step is to define the target variable (what we are forecasting?) which, in our case, is a recession. We utilize the national bureau of economic research's (NBER) definition of recession dates to construct the dependent variable. The dependent variable is a dummy variable with a value of zero (the U.S. economy is not in a recession) and one (the U.S. economy is in a recession). The benefit of using a dummy variable as the target variable is that we can generate the probability of a recession for a certain period-ahead using predictor variables.

Before we look for predictors, we need to discuss the sample period of the study. We started our analysis from January 1972 (monthly dataset). There are some major reasons to pick 1972 as a starting year of the analysis. First, since our dependent variable is a dummy variable that includes recession (value equals one) and non-recession (value equal zero) periods, our sample period must include both recession and non-recession periods. There have been six recessions since 1972. Second, many variables go back to the early 1970s and, therefore, provide an opportunity to select a model's relevant predictors from a large dataset of potential predictors. As mentioned earlier, a large pool of potential predictors captures information from all major sectors of the economy, which provides an opportunity to detect obscure connections between different sectors, thereby improving forecast accuracy.

The final and most important reason for starting our analysis in 1972, is that it can provide enough observations in our modeling approaches to conduct both in-sample analysis and out-of-sample forecasting, helping us test the predictive power of all potential variables. That is, we utilize the 1972-1988 period for in-sample analysis and the 1989-2017 period is employed for out-of-sample forecasting purpose.

When a model utilizes the complete available information to estimate a statistical association (or sometimes, statistical causality) between variables of interest, that process is known as an in-sample analysis. In machine learning, that process is called "trained" or "training period/sample." For example, we utilized the 1972-1988 period to reduce the potential pool of 500,000 predictors to a manageable size of predictors (we'll talk about the variable reduction process in the following section). Basically, we utilize the 1972-1988 period to examine which variables are statistically associated with recessions. The out-of-sample process involves forecasting, and the model does not know (have information) about the actual outcome for the forecast-horizon at the time of forecasting. That is, we utilize the 1972-1988 period and ask the model to generate the probability of a recession during the next 12 months (forecast horizon is 12 months). The important point here is that the model does not *know* whether there is a recession during the next 12 months. Out-of-sample forecasting utilizes the available information to forecast a future period. Put simply, in-

[4] The FOMC releases its meetings transcripts with a five year lag and can be found here: **https://www.federalreserve.gov/monetarypolicy/fomc_historical.htm**

sample analysis utilizes the available information and provides a statistical relationship between the target variable and predictors for that sample period. Out-of-sample forecasting uses the discovered relationship between variables to predict the future values of the target variable.[5]

Now we turn to the next question of why we need to conduct in-sample and out-of-sample analyses. The in-sample analysis is a very effective tool to reduce the large potential list of predictors (sometimes the list contains hundreds of thousands or millions of potential predictors) to a more manageable pool. There are a number of statistical tests available within the in-sample analysis, which helps analysts identify a handful of predictors from the larger pool.

The out-of-sample forecasting exercise, in our view, is the most important tool in selecting the final model and improving forecast accuracy. When we generate the probability of a recession in real time, we will not know whether there will be a recession in the next 12 months. This is essentially a simulated real time forecasting experimentation. There are two major benefits of the simulated real time out-of-sample forecasting experiment. First, a common issue with forecasting models selected with using only in-sample selection criteria is over-fitting. Typically, an over-fitted model performs well during the in-sample analysis but very badly during out-of-sample forecasting. A model selected based on the out-of-sample forecasting criterion would reduce the over-fitting problem and improve forecast accuracy significantly compared to a model that is selected using in-sample criteria. The second major benefit is that the simulated real time out-of-sample forecasting would help an analyst estimate a reliable potential risk to the forecast (such as an average forecast error).

Our model relies on both in-sample analysis and out-of-sample forecasting.

Turing Colors into a Picture: Sample Period and Data Reduction Steps

The starting year of our analysis is 1972, and we conduct an in-sample analysis using the 1972-1988 period and the out-of-sample simulation criterion utilizing the 1989-2017 era. According to the National Bureau of Economic Research (NBER), there are six recessions in the complete sample period of 1972-2017. Furthermore, those six recessions are evenly divided in the in-sample analysis (three recessions in the 1972-1988 period) and in the out-of-sample forecasting period (three recessions in the 1989-2017 period). The three recessions of the 1989-2017 period contain different characteristics (different depth and duration, for example) such as the 2007-2009 recession, which is the deepest recession since the Great Depression and hence has been labeled the Great Recession. The 2001 recession, on the other hand, is one of the mildest recessions in the sample era while the 1990-1991 recession is widely considered a moderate (neither mild nor deep) recession. The major benefit of this out-of-sample forecasting simulation is that we do not know whether the next recession will be mild, moderate or deep; historically, mild recessions are relatively difficult to predict. If a model can predict recessions of different depths in a simulation, then there is a decent probability that the model would repeat its accuracy in the future.

A Sea of Potential Predictors: The FRED Dataset

One major benefit of the advancement of the Internet is that large datasets are available in a ready-to-use format, often at no cost. One such dataset is available on the Federal Reserve Bank of St. Louis' website, commonly referred to as the FRED (Federal Reserve Economic Data).[6] There are more than 500,000 variables listed in FRED, collected from 86 different sources. For our analysis, we consider all the 500,000 variables as potential predictors and try to find reliable predictors from this dataset using statistical tools. As mentioned earlier, instead of picking a handful of predictors (a traditional modeling approach), we include everything in the pot to find useful predictors from over 500,000 variables (statistical data mining approach). By using all FRED data, one thing is certain, which is not all of the 500,000 variables are relevant to predicting recessions. Put differently, we are including lots of noises in the model in addition to useful signals. However, there are some major benefits, as discussed earlier, of using the entire FRED data. That is, we will be able

[5] It is worth mentioning that sometimes in machine learning/other big data applications different terms (instead of in-sample and out-of-sample) are utilized such as training-sample or cross-validations etc. For more detail see, Hastie, T et al. (2008). *The Elements of Statistical Learning*. 2nd Edition, Springer. The basic logic behind all these procedures (analysis) is similar and that is to utilize some part of the available information (either time span, number of observations or both) to establish some statistical association/relationship and then utilize those relationships to forecast future events (unknown values/outcome).
[6] For more detail about the FRED dataset see: https://fred.stlouisfed.org/

to find some obscure/new connections between different sectors of the economy and those connections may improve recession prediction accuracy.

As discussed earlier, 1972 is the starting year of our analysis, but not all FRED data go back that far. Therefore, the pool of over 500,000 variables is easily reduced to 5,889 variables. Sometimes, as in the present case, an analyst may face a tradeoff between a longer time span vs. a large pool of potential predictors. Our analysis picks a longer time span with a decent size of potential predictors. A shorter time span means our target variable will have lots of zeros (dummy variable with zero for no recession and ones for recession) and very few ones which naturally creates a bias toward zeros. Therefore, such a model will tend to predict a very low probability of a recession and increases the chances of a false negative scenario (very high likelihood of missing a future recession).

Essentially, we provide information to a model through the target variable (recession and no recession in the present case) via predictor variables. If we have a large pool of potential predictors we are able to provide an opportunity to include information for predictors. However, if that model uses a shorter time span, then we are not providing an appropriate amount of information about the target variable, thus setting the model up for a failure. By starting our analysis in 1972 we are including six recessions, which also provides appropriate bases for the in-sample analysis (three recessions) as well as for the out-of-sample simulation (three recessions of different characteristics). Furthermore, our pool of potential predictors consist of 5,889 variables and that provides an opportunity to include every major sector with the potential to find some possible connections between different sectors.

A Statistical Spell of Variables Reduction

The list of 5,889 potential predictors is large enough to conduct in-sample analysis and out-of-sample simulation. To obtain a more manageable set of predictors, we employ several statistical methods and utilize the complete sample period of 1972-2017. First, we run the Granger causality test between our target variable and each of the 5,889 variables. The Granger (1969) test is a precise method to find which variables are statistically useful to predict the target variable.[7] For the Granger causality test, we set a 5 percent level of significance and keep all variables that produce the p-value of the Chi-square test less than or equal to 0.05.[8]

Narrowing down the set of potential predictor variables is an intensive but necessary process.

The next methods to reduce the number of variables is called Weight of Evidence (WoE) and Information Value (IV).[9] Both the WoE and IV are very good tools to find reliable predictors, particularly if dealing with a binary, dependent target variable (zero for no recession and one for recession). The WoE provides evidence of predictive power of a variable relative to the target variable. The IV method, on the other hand, helps to rank variables according to their predictive power (the Y-variable has a higher predictive power than the X-variable to forecast recession, for example).

The Granger causality test, WoE and IV methods help us reduce the list of 5,889 variables to a set of 1,563 potential predictors. However, 1,563 variables as potential predictors are a lot for the in-sample analysis and out-of-sample simulation. Therefore, we utilize economic theory and intuition to further narrow down the list of 1,563 variables. That is, we manually inspect these 1,563 variables and then categorize them to represent major sectors of the economy. For example, consider the category "current population survey." A few potential predictors in this category are civilian labor for men only, White, Black, 16-19 year old and so forth. Not all of these series make economic sense to predict recessions, thus we remove them. Furthermore, we remove series that have statistical predictive power (the Granger causality test/WoE/IV suggested those series as predictors) but do not make intuitive sense to predict recessions such as the CPI of education, books and supplies for all urban consumers. With this manual procedure, we are able to reduce set of potential predictors

[7] **For more detail about the Granger causality test see, Granger, C.W.J. (1969). Investigating Causal Relations by Econometric Models and Cross-spectral Methods. *Econometrica*, Vol 37, no 3.**
[8] **A p-value of less than or equal to 0.05 would reject the null hypothesis of no-causality and that indicate the variable in the model is a good predictor of the target variable.**
[9] **For more detail about WoE and IV see, Lin, Alex. (2013). Variable Reduction in SAS by using Weight of Evidence and Information Value. The full paper is available at:**
https://support.sas.com/resources/papers/proceedings13/095-2013.pdf

to 192 from 1,563 variables. Therefore, we utilize 192 potential predictors for the three competing models that are (1) Logit/Probit (statistical data mining) model, (2) random forest and (3) the gradient boosting. Our benchmark model utilizes the yield curve as a predictor.

Finding the Best Set of Predictors for Recession Forecasting: Discovering Hidden Connections

We have now narrowed down the list of potential predictors to 192 variables. Next, we need to classify those 192 variables into categories. For example, we created the category “inflation” and put all inflation related variables (i.e. CPI and PCE deflator) in that category. Likewise, nonfarm payrolls and unemployment rate fall in the “employment” category and so on. We end up having 40 different categories. The 192 variables we have selected as potential predictors are individually statistically useful to predict recessions. Now we need to find the ideal combination of predictors that represent different sectors of the economy.

Economies evolve over time and the strength of relations between different sectors of an economy also vary.

As we know, economies evolve over time and the strength of relations between different sectors of an economy also vary. Our approach will find a set of sectors that are statistically more accurate to predict recessions than any other set in our analysis. Basically, we utilize all possible combinations of the 192 variables and, by doing so, we explore the hidden connections between different sectors. Furthermore, including one variable from a category at a time avoids the potential multi-collinearity problem.[10]

We Ran 30 Million Regressions

Here is the outline of our procedure to find the best set of predictors from the 40 different categories. We set a logit/probit modeling framework with eight predictors (nine variables in a model: one dependent variable and eight predictor variables). Moreover, we are interested in a distinct combination of the eight predictors, meaning we want eight predictors from eight different sectors. For example, we pick the unemployment rate as a predictor from the “employment” category and the next predictor comes from the “inflation” category (CPI for example), the S&P500 from “equity”, 10-year Treasury yield from “interest rates” and housing starts from the “housing” category and so on. Therefore, eight predictors represent eight different sectors of the economy. In addition, we repeat the process by keeping the unemployment rate (to represent “employment”) in the model but change the rest of the predictors of the model one by one. That is, we include eight predictors at a time and then replace predictors with others, but keep the total number of predictors to eight. Why do we do this?

This process tests the relationship of every combination of variables. For example, the unemployment rate will team up with each and every predictor of the rest of the 39 categories. Put differently, each category not only gets a chance to perform as a predictor but also team up with other sectors to predict recessions. Therefore, we employ all possible combinations of these 40 categories and 192 variables and that process allows us to explore hidden connections between different sectors and improve recession prediction accuracy. The process is very time-intensive, taking several weeks of continuously running code. In total, we ran *30 million different models*. We utilize the Schwarz information criterion (SIC) to narrow down 30 million models to a manageable list of models. We selected the top 1,500 models in this step using the SIC values (as we know a model with the lowest SIC value is the preferred one among competitors). The selected 1,500 models contain eight predictors in each model but all those models include distinct combinations of the eight predictors.

From the 1,500 different combinations of eight-predictors we need to select the final model (one model with eight predictors). Moreover, these 1,500 models were selected by using in-sample criterion, however, our objective is to forecast future recessions accurately (out-of-sample forecasting). Therefore, we utilize simulated real time out-of-sample forecast error as the criterion to find the best model among the 1,500 models.

[10] In simple words, if two (or more) predictors of a model are highly correlated with each other then that issue is known as multi-collinearity. Typically, the multi-collinearity problem leads to an overfitting issue.

Precisely, we utilize the 1972-1988 period to generate the probability of a recession during the next 12 months and then re-estimate the model using the 1972-1989:1 period (include the next month in the estimation period) and again generate probability of a recession for the next 12 months. We iterated this process till we reach the last available data point, which is December 2017. The major benefit of this recursive forecasting is that we know the actual outcome (recession or no recession during the next 12 months), but we did not share that information with the model. This allows us to calculate the model's accuracy. We repeat this process for each of the 1,500 models and select the model with the highest accuracy. That is, we select the set of eight-predictors which forecast recessions during the 1989-2017 (period for the simulated out-of-sample forecasting) more accurately than the rest of the 1,499 models. The selected logit/probit model is utilized to represent the statistical machine learning/data mining approach.

"Happy Hunger Games: And May the Odds Be Ever In Your Favor

The objective of this report is to find an approach/model that predicts recessions more accurately than other contenders. The first contestant, which is also the benchmark approach, is a probit model with the yield curve as the predictor. The second approach is the statistical machine learning/data mining and a logit/probit model where eight predictors are utilized to represent the data mining approach. The random forest and gradient boosting methods are utilized to represent machine learning.

Before we introduce a statistical tool to evaluate a model's performance, we will discuss our precise objective about the target variable. That is, our target is to predict recessions accurately and our dependent variable is binary with zeros (non-recessionary periods) and ones (recessions). Furthermore, an accurate forecast from a model correctly predicts either a recession or a non-recessionary period in the forecast horizon. By the same token, an inaccurate forecast implies missing of a recession/non-recession. Precisely there are the following possibilities for a forecast; (1) true positive: model correctly predicts recession; (2) true negative: accurately predicts non-recessionary period; (3) false positive: model predicts a recession when there was no recession; and (4) false negative: model predicts non-recession but there was a recession. With this information, we can restate our objective: a forecast should be true positive and true negative and avoid both false negative and false positive.

The objective of this report is to find the most accurate recession predicting model.

In addition, adjusting the probability threshold for a recession directly influences the changes of false positives. For example, 60 percent or higher probability indicates a recession, otherwise no recession. That threshold helps reduce chances of false positives. However, a higher probability-threshold also poses the risk of missing a recession. On the other hand, a threshold using a lower probability (20 percent probability as a threshold, for instance) would lead to more false positives. With this discussion in mind, we can introduce our statistical method to evaluate forecasts of a model.

The Relative Operating Characteristic (ROC) Curve

The relative operating characteristics (ROC) curve is a helpful tool to evaluate a model's performance.[11] The ROC curve helps to find an optimal threshold by plotting different thresholds' performances. Put differently, the ROC curve shows a plot of a true positive (correct forecast) against a false positive (false signal) of a given threshold. Essentially, the ROC curve depicts accuracy (true positive vs. false positive) of different thresholds and the threshold which produces the highest accuracy can be selected. That is, a threshold can be identified by the ROC curve which produces the maximum hit rate along with least false signals. In addition, a further nuance of the ROC curve is known as the area under the curve (AUC). The ROC AUC, in the present case, is equal to the probability of predicting recessions accurately. That is, the ROC AUC values vary between zero and one and a value close to one represents higher accuracy while a value near zero represents a useless model. Therefore, the ROC AUC will help us determine which model is the best among competitors. Furthermore, we will estimate the ROC and ROC AUC for both in-sample analysis

[11] **For a detailed discussion about the ROC curve see, Lahiri, K., and J. G. Wang (2013). Evaluating Probability Forecasts for GDP Declines Using Alternative Methodologies. *International Journal of Forecasting.* Vol 29, pp175–190.**

(1972-1988) and out-of-sample forecasting simulation (1989-2017) for each of the four models to evaluate which model is the most accurate.

The Legends of Machine Learning: The Random Forest and the Gradient Boosting Approaches

Applications of machine learning techniques in economics/finance are a relatively new phenomenon.[12] The basic logic behind machine learning techniques is to utilize the available information effectively to generate accurate predictions. That is, machine learning techniques allow us to transform a computationally-hard problem into a computationally-efficient solution. In contrast to the traditional econometric techniques, which worry about issues such as linear/non-linear, small/large samples and degree of freedom/more predictors than observations etc., machine learning techniques find a connection between the target variable and predictors and then utilize that information to form a prediction. Put differently, most machine learning techniques divide data into segments and then utilize these segments for estimation and others for validation.

The basic idea behind most machine learning techniques is that an algorithm sets a loss function (minimum forecast error, for example) and finds a combination of predictors that produce a minimum forecast error, on average, among competitors. Before we discuss our models, we need to clarify one more thing, which is the classification and regression problem. In machine learning, if the target variable is a binary (or categorical), then it is called a *classification-problem* while for a continuous-target variable the term *regression-problem* is utilized. Since our target variable is binary, we are dealing with a classification problem.

The Random Forest Approach

Most machine learning techniques divide data into segments and then utilize these segments for estimation purposes.

The random forest is one of the more famous techniques of machine learning, and it is also our first model. Typically, the random forest approach produces accurate forecasts (both in-sample and out-of-sample), for more detail see Mullainathan and Jann (2017). However, the random forest is a black box in the sense that there are no formal estimated parameters or explanations as to what variable has the highest predictive power. For example, in a traditional econometric model we estimate a coefficient that states an average relation between dependent and independent variables. However, in the case of a random forest, we do not have such coefficients. One major reason that the random forest is a black box is that the random forest is an ensemble technique that originates from the decision tree (or classification and regression tree, CART). A tree, in simple words, successively chooses each predictor by splitting variables into two groups (partisans) and calculates the mean squared error (MSE). The tree splits at the point that minimizes MSE. The splitting process continues by further splitting each group into two new groups and calculates the MSE for each new group. Typically, in machine learning, these splitting points are called *nodes*. The splitting process continues until the stopping point is reached and the end point is labeled as *leaves*. A decision tree is simple to build and generates a very good in-sample fit but a horrible out-of-sample forecast. One major reason for bad out-of-sampling is that such trees are built using in-sample information and, typically, do not include out-of-sample forecasting.

Breiman (2001) improved the decision tree approach and his framework is known as the random forest, for a detailed discussion about random forests see Breiman (2001).[13] The basic logic behind the random forest approach is that instead of generating one tree, we can create many trees (number of trees can be in thousands or millions depending on the objective). Furthermore, if trees are independent and unbiased, then the average of those trees would be unbiased with a potentially small variance, and more likely to produce a better out-of-sample forecast. The averaging of different trees is called ensemble learning or the random forest approach. Essentially, averaging many models tends to provide better out-of-sample forecasts than a single model.

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[12] **For more details about machine learning applications in economics see Mullainathan, Sendhil and Jann Spiess. (2017). Machine Learning: An Applied Econometric Approach. *Journal of Economic Perspectives*, Vol 31, no 2.**

[13] **Breiman, Leo. (2001). Random Forests. Statistics Department, University of California, Berkeley, CA. The paper is available at: https://www.stat.berkeley.edu/~breiman/randomforest2001.pdf**

The Gradient Boosting Approach

Gradient boosting is also an ensemble approach and a very powerful machine learning tool for forecasting. The basic idea behind gradient boosting is that a weak learner (inaccurate model) can be modified to become a more accurate model. Friedman (1999) provides a formal framework to estimate a gradient boosting model. For more detail see Friedman (1999).[14]

Essentially, in the gradient boosting modeling approach, we set a loss function (minimum MSE, for example) and then add weak learners (trees, for example) to optimize the loss function using a gradient descent process. Put differently, the gradient boosting approach helps us to form an accurate forecast using many inaccurate predictions by creating a learning modeling process.

Examining in-sample and out-of-sample results is necessary when evaluating the effectiveness of a model.

For the random forest and gradient boosting approaches, we utilize the set of 192 variables as potential predictors (as we have discussed those 192 variables are selected using statistical data mining). The logit/probit models represent statistical machine learning, utilizing eight predictors. The benchmark probit model employs the yield curve as a predictor.

The Results: The In-sample and Out-of-sample Simulations

As mentioned earlier, the ROC AUC is utilized to measure a model's performance. We estimated ROC AUC for all models and then compared them to select the best performing among the four models. The ROC curve along with an AUC for the random forest approach are plotted in figure 1 (for in-sample analysis) and figure 2 (for out-of-sample forecasts). A ROC curve, figure 1, shows the plot of true positive rate (y-axis) against false positive rate (x-axis) at various threshold settings. The diagonal line (dotted line in figure 1) is known as line of no-discrimination as an outcome on the line, point B for example, is almost as good as a random guess (probability of a true positive is equal to probability of a false positive). The area to the left of the diagonal line shows when the chance of a true positive rate is higher than the probability of a false positive rate at a given threshold. The left upper corner, point A for example, indicates the best possible prediction as it shows 100 percent accuracy. The right bottom corner, the corner closest to the point C, represents the worse possible prediction: a 100 percent chance of a false positive rate.

The random forest in-sample analysis that produces an ROC AUVC value of one indicates the best in-sample fit. It is not a surprise that the random forest approach tends to produce a great in-sample fit. The out-of-sample forecasting simulations prove that the random forest approach is able to predict all recessions (1990, 2001 and 2007-2009 recessions) without producing a false positive as the ROC AUC is very close to one (0.9945), figure 2. The random forest approach performance is excellent in both in-sample and out-of-sample simulations.

Figure 1: Random Forest: In-sample

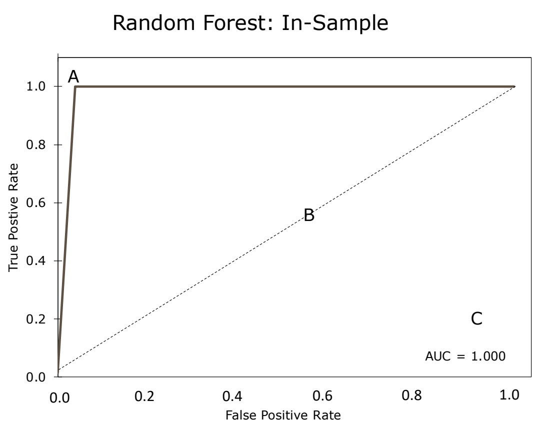
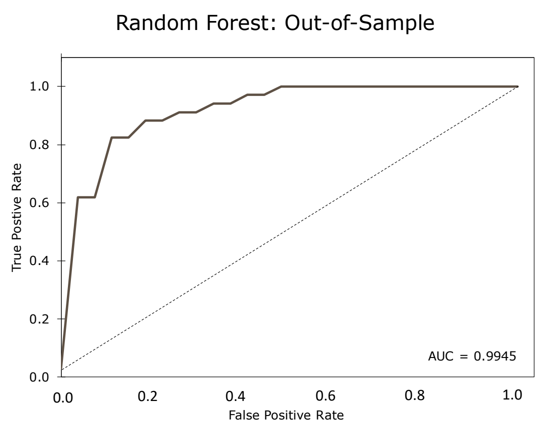


Figure 2: Random Forest: Out-of-Sample



Source: U.S. Department of Labor and Wells Fargo Securities

[14] **Friedman, Jerome H. (1999). Greedy Function Approximation: A Gradient Boosting Machine. The full paper is available at: https://statweb.stanford.edu/~jhf/ftp/trebst.pdf**

The results based on the gradient boosting, the logit/probit (statistical data mining models) and the benchmark models are reported in the Appendix. Figure 3 and figure 4 show in-sample and out-of-sample results for the gradient boosting. The in-sample AUC value is 1 and 0.9917 for the out-of-sample simulations. That is, the in-sample performance of the gradient boosting is equal to the random forest in-sample accuracy, but the random forest performed slightly better than the gradient boosting in the out-of-sample forecasting. The statistical data mining (logit/probit) approach came in at the third position with the ROC AUC value of 0.9756 (in-sample) and 0.8746 (out-of-sample). The benchmark probit model produces 0.956 (in-sample) and 0.8266 (out-of-sample) values for the ROC AUC, the worst performer in our analysis. All four methods produce a very low probability (less than 5 percent) of a recession during the next 12 months.

Concluding Remarks: It's Not What You Have, It's How You Use It

The extraction of useful information as well of the effective utilization of such information is integral in the modeling process.

Summing up, the evolution of big data and machine learning techniques opens doors to improving the predictive power of economic variables. We believe that an effective modeling process can be divided into two phases. The extraction of the useful information (signals vs. noises) is the first phase of an accurate modeling process. The second phase consists of utilizing that information efficiently. In this analysis, we utilized the statistical data mining techniques to narrow down the FRED dataset (which contains more than 500,000 variables) to 192 variables. In the estimation simulations, machine learning techniques provided more accurate results using the same dataset than those of the logit/probit (statistical data mining) models. One major reason is that the logit/probit approach estimated an average relationship to predict an outcome. An average estimation process may limit the effectiveness of the modeling approach as relations between variables evolve over time, and the strength of the relationship fluctuates over time as well. Machine learning techniques (both the random forest and gradient boosting) dig deeper and find useful statistical relationship between the target variable and predictors to generate forecasts. Therefore, both phases are necessary for accurate forecasting.

The evolving nature of the economy forces decision makers to look for new tools to capture growing complexities in the economy to help them form effective policy. Our work proposes a new framework to generate accurate forecasts using a large set of predictors and machine learning tools. We stress that the extraction of useful information and the effective utilization of that information is crucial for accurate predictions.

Figure 3: Gradient Boosting: In-sample

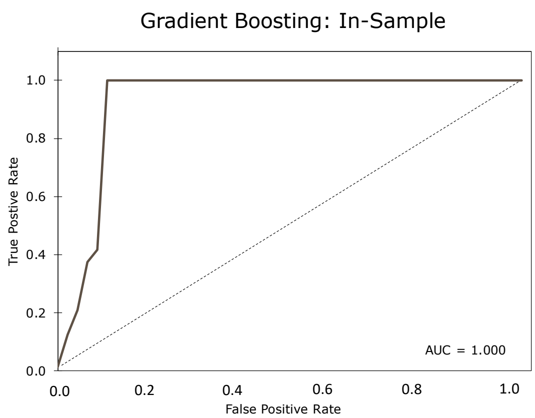


Figure 4: Gradient Boosting: Out-of-Sample

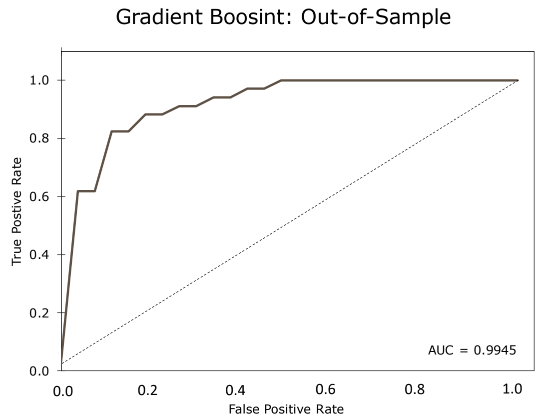


Figure 5: Data-Mining: In-sample

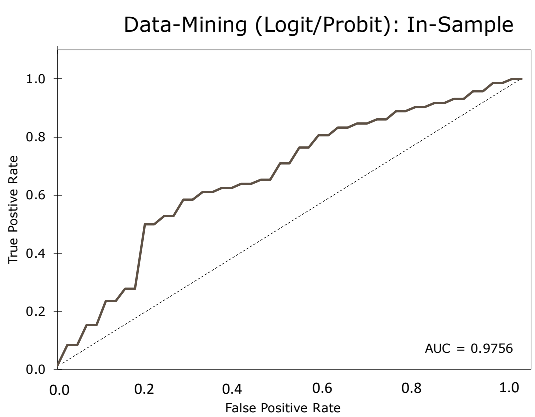


Figure 6: Data-Mining: Out-of-Sample

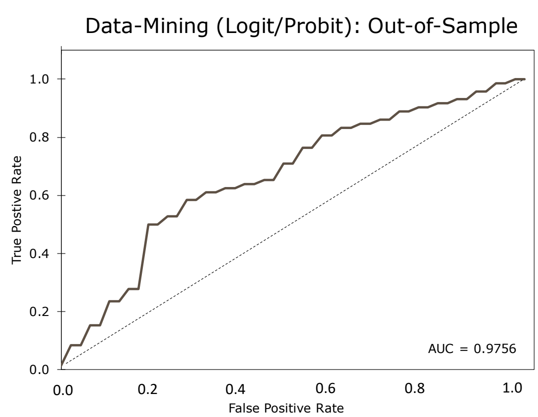


Figure 7: Benchmark: In-sample

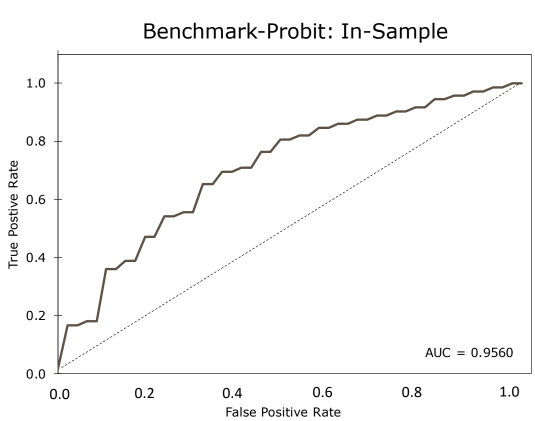
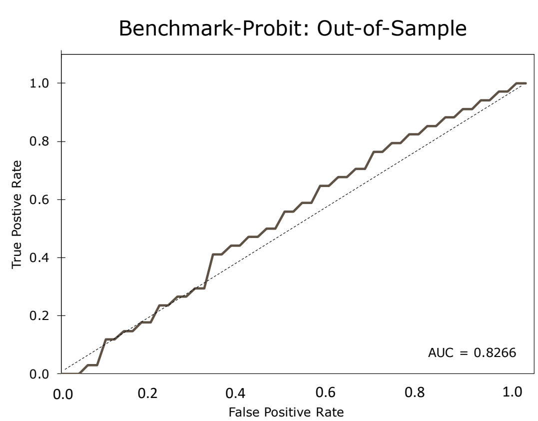


Figure 8: Benchmark: Out-of-Sample



Source: Wells Fargo Securities

Wells Fargo Securities Economics Group

Diane Schumaker-Krieg	Global Head of Research, Economics & Strategy	(704) 410-1801 (212) 214-5070	diane.schumaker@wellsfargo.com
John E. Silvia, Ph.D.	Chief Economist	(704) 410-3275	john.silvia@wellsfargo.com
Mark Vitner	Senior Economist	(704) 410-3277	mark.vitner@wellsfargo.com
Jay H. Bryson, Ph.D.	Global Economist	(704) 410-3274	jay.bryson@wellsfargo.com
Sam Bullard	Senior Economist	(704) 410-3280	sam.bullard@wellsfargo.com
Nick Bennenbroek	Currency Strategist	(212) 214-5636	nicholas.bennenbroek@wellsfargo.com
Eugenio J. Alemán, Ph.D.	Senior Economist	(704) 410-3273	eugenio.j.aleman@wellsfargo.com
Azhar Iqbal	Econometrician	(704) 410-3270	azhar.iqbal@wellsfargo.com
Tim Quinlan	Senior Economist	(704) 410-3283	tim.quinlan@wellsfargo.com
Eric Viloria, CFA	Currency Strategist	(212) 214-5637	eric.viloria@wellsfargo.com
Sarah House	Senior Economist	(704) 410-3282	sarah.house@wellsfargo.com
Michael A. Brown	Economist	(704) 410-3278	michael.a.brown@wellsfargo.com
Charlie Dougherty	Economist	(704) 410-6542	charles.dougherty@wellsfargo.com
Jamie Feik	Economist	(704) 410-3291	jamie.feik@wellsfargo.com
Erik Nelson	Currency Strategist	(212) 214-5652	erik.f.nelson@wellsfargo.com
Michael Pugliese	Economist	(212) 214-5058	michael.d.pugliese@wellsfargo.com
Harry Pershing	Economic Analyst	(704) 410-3034	harry.pershing@wellsfargo.com
Hank Carmichael	Economic Analyst	(704) 410-3059	john.h.carmichael@wellsfargo.com
Ariana Vaisey	Economic Analyst	(704) 410-1309	ariana.b.vaisey@wellsfargo.com
Abigail Kinnaman	Economic Analyst	(704) 410-1570	abigail.kinnaman@wellsfargo.com
Shannon Seery	Economic Analyst	(704) 410-1681	shannon.seery@wellsfargo.com
Donna LaFleur	Executive Assistant	(704) 410-3279	donna.lafleur@wellsfargo.com
Dawne Howes	Administrative Assistant	(704) 410-3272	dawne.howes@wellsfargo.com

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