

Forecasting Recessions Using Machine Learning: Innovation or Unnecessary?

Preliminary Study for Master's Thesis

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Jean-Philipp Brühwiler

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Author:

Jean-Philipp Brühwiler, Dorfplatz 3 8810 Horgen, jean-philipp.bruehwiler@stud.hslu.ch

Supervisors:

Mr. Moreno Frigg, Suurstoffi 1 6343 Rotkreuz, moreno.frigg@hslu.ch

Dr. Jürg Fausch, Suurstoffi 1 6343 Rotkreuz, juerg.fausch@hslu.ch

Table of Contents

1. Introduction.....	4
2. Current Situation.....	4
3. Issues to be Explored.....	6
4. Thesis Proposal.....	7
4.1. Definitions.....	7
4.2. Research Question.....	8
4.3. Objectives.....	8
4.4. Methodology.....	9
4.4.1. Research Design.....	9
4.4.2. Data Analysis.....	9
4.4.3. Choice of Models.....	10
4.4.4. Model Evaluation.....	11
4.4.5. Limitations.....	12
4.4.6. Thesis Structure.....	12
4.4.7. Ethical Considerations.....	12
5. Work and Research Plan.....	13
6. List of Sources and Literature.....	14
7. References.....	15

1. Introduction

The goal of this preliminary study is to introduce the master's thesis topic at hand and the context which makes it a relevant and pertinent topic. The preliminary study begins with an overview of the situation that briefly explains the origins of business cycle forecasting and its ramifications. The study then delves into the issues to be explored. It then explains why the current lack of transparency in research and industry regarding modelling techniques creates the need for different modelling techniques to be evaluated against one another. The study then narrows the focus and delves into the thesis proposal and proposed methodology, including possible limitations. Then, the study discusses the ethical considerations and the thesis's commitment to transparently presenting the results. Finally, a preliminary list of literature references is given.

2. Current Situation

The term "business cycle" was first coined in 1946 by economists Arthur Burns and Wesley Mitchel (Romer, n.d). The business cycle is a descriptive term that describes a phenomenon which is observed in the overall economy. What Burns and Mitchel observed was the consistent rise and fall of economic output over time. Hence the "cycle" portion of business cycle. Each business cycle has four distinct phases: expansion, peak, contraction, and trough. At the conclusion of the trough phase, the cycle then begins again. Ideally, the subsequent peaks and troughs are higher than in the previous cycle.

Since the development of the business cycle concept, practitioners have attempted to predict its various phases, especially contractions, which in the common vernacular are referred to as *recessions*. There are many implications of being able to accurately predict recessions. For financial firms and other market participants, they can better prepare for declines in financial markets and protect investor capital. For policy makers, predicting recessions can help preemptively address issues such as unemployment, straining of social services, and public debt management.

These are only some of the many important ramifications of being able to accurately predict a coming recession. In this vein, much research has been done to attempt to model the relationships between recessions and various economic indicators, most notably the yield curve in the United States (US). The yield curve is a plot of yields, or interest rates on bonds that have equal credit ratings. In the US context, this usually refers to government debt instruments (Hayes, 2023). This variable alone has been shown to be one of the most powerful indicators of a coming recession in the US (Duecker, 1997). The reasons for this are complex and will be explored deeply in the thesis. For the purposes of this preliminary study, the yield curve should be understood as an indicator that captures a lot of information regarding the *expectations* for the US economy.

However, in econometric research, the choice of model is oftentimes just as important as the collection of independent variables used as inputs. Until recently, researchers have mostly relied on discrete choice algorithms to model the relationships between various economic indicators such as the yield curve and recessions. In econometric research, discrete choice refers to binary classification (i.e. 0 or 1, true or false) analysis where a target is predicted to take one of two states.

For the context of this thesis, the binary choice refers to whether the economy is in recession or not in each time period.

The “traditional” types of discrete choice models most often used in the econometric modelling of recessions are logit and probit models. Briefly, logit and probit models are two common methodologies to model binary outcomes. Both modelling techniques estimate the relationship between input variables and a discrete outcome. The main difference between the two models are the link functions. The link functions determine how a model’s output is transformed into a binary outcome of either 0 or 1. A logit model takes the natural logarithm of the odds of success and compares it to the given threshold, usually 50%. The output then assigns 0 or 1 depending on whether the output falls above or below the given threshold. For probit models, the link function that determines the 0 or 1 outcome is the inverse of the standard normal cumulative distribution function. Overall, the models are very similar, but logit models are generally easier to implement and interpret than probit models. A deep comprehension of the mechanics behind logit and probit models is not imperative; rather, it is more important to recognize them as the predominant models employed in binary classification for econometric analysis today.

Despite the power of logit and probit models in econometric analysis, another class of models has emerged with the potential to outperform both logit and probit models. The models in question are so-called machine learning models. A more comprehensive definition of machine learning is given in the thesis proposal section. For now, machine learning models can be conceptualized as newer, powerful models, that can model and identify very complex relationships in data that traditional modelling techniques often cannot (Akinfemi et al., 2019). It is no wonder then that machine learning models are influencing the way econometric analysis is done. Thanks to data science libraries for programming languages such as Python and R, it is now more feasible than ever for practitioners to deploy machine learning models.

These developments have now sparked lively debates as to whether machine learning algorithms should supersede the use of logit and probit models for binary classification in econometric analysis. However, there is a rule of thumb in data analysis that goes: *“keep it simple!”* There are certainly also situations where using a machine learning model is not the best choice and these models are in no way a silver bullet perfectly suited for every data analytical task (Carbone, 2022). The fact that machine learning models are often not the best choice for models raises questions about their utility. The important mantra of not making an analytical task more complicated than it needs to be begs the question of whether machine learning models are better suited than traditional econometric techniques for modeling recessions. There is growing evidence that machine learning models do outperform traditional logit and probit approaches for modeling recessions (Galakis et al., 2020). However, it is by no means a settled debate at the time of writing.

3. Issues to be Explored

Forecasting is no easy task. As of January 2024, the likelihood of the U.S. economy entering a recession is an open question subject to significant variation depending on who is asked. For example, investment bank *Goldman Sachs* places the likelihood of a US recession in 2024 at 15%, whereas the *New York Federal Reserve* places it at 69%, while a poll of economists by the analysis firm *Wolters Kluwer* places the likelihood at 50% (Kilburn, 2023). Who is correct, and by how much? Only time will tell. However, there is an obvious issue with these predictions, regardless of the model or methodology that is employed. If there is a recession, then every institution that predicted a recession will have their model technically proven correct, whereas if there is no recession, *Goldman Sachs*'s model will be proven more correct since it placed the likelihood below 50%.

None of these institutions have made their models public, so critical evaluation of the respective methodology is next to impossible. Also, each of these models is different and polling data is, of course, not a model in and of itself. However, the economists surveyed likely have their own analytical techniques for concluding if there will be a recession or not. Even with that caveat, how questions are phrased, the stated margin of error, and the makeup of the pool of economists surveyed can itself be considered a model of sorts and greatly influence the outcome of the poll. On the other hand, for the mentioned institutions that explicitly used an analytical model to predict the likelihood of recession, they all likely used a different combination of inputs and model specifications. This explains the huge differences in the predicted likelihood of a coming recession.

It would be interesting to see how the aforementioned models perform given a uniform set of inputs and back tested against historical data. However, there is often a lack of transparency from private and academic institutions about their models, often for legitimate reasons. For example, proprietary models and data sources could negatively affect an institution's competitiveness if made public. Despite the legitimate reasons to keep models confidential, the stakes for predicting recessions are so high that transparency should be prioritized. When *Goldman Sachs* says there is a 15% chance of a recession, people listen and make decisions based on that prediction. These decisions could be trivial, but also could have drastic consequences if policy decisions are made based on their model's output and the model is later proven to be highly flawed.

Despite the many legitimate reason for keeping modeling techniques confidential, much like many machine learning models themselves, the lack of transparency creates a black-box dynamic. There is a broad lack of transparency in quantitative research, especially into machine learning, which has partially contributed to a reproducibility crisis of research findings (Murphy, 2022). With heightened transparency, critical analysis of a model's efficacy and assumptions can take place, leading to better outcomes overall.

A consequence from the lack of transparency in modelling means the models are not subject to the level of scrutiny that they should be, and their outputs are often uncritically taken as accurate. For example, many are susceptible to being caught up in the "hype cycle" of machine learning and artificial intelligence (AI) (Siegel, 2023). This can lead market participants and policy makers to make incorrect decisions because they erroneously assume a model is accurate because it has the

veneer of being a machine learning model (Pazzanese, 2020). This is not to say that machine learning models are not powerful, they absolutely are very powerful in many analytical applications. When correctly implemented, machine learning models can achieve amazing results and change entire industries for the better. However, this dynamic has created a gap of knowledge in the field of econometric forecasting that critically compares the accuracy of different modelling techniques.

Herein lies the focus of this thesis: to compare various models' abilities to predict recessions. The focus is more specifically on machine learning models and their performance relative to traditional logit regression models. The implications of this research are more transparency and better decision making. Understanding which models are most capable of predicting a recession means practitioners can focus on refining techniques that have been proven effective and have confidence in their models' outputs. Additionally, it facilitates the identification of potential shortcomings in less effective models, enabling researchers and practitioners to address limitations and enhance the overall reliability of recession prediction methodologies.

4. Thesis Proposal

This section summarizes the most important aspects relevant to the thesis. This section includes the research question, the thesis's objectives, the study's methodology, important definitions relevant to the thesis, limitations, ethical considerations, and the study's overall structure.

4.1 Important Definitions

This section gives a brief overview of working definitions that will be used in this thesis that require clarification. Since these terms are foundational to understanding the eventual results of the thesis, it is important to maintain precise definitions for concepts that might have multiple interpretations.

Recession

A common definition of a recession is two consecutive quarters of negative GDP growth (Morgan, 2022). However, for the purposes of this analysis, the study uses the National Bureau of Economic Research's (NBER) definition of a recession that is defined as: "*a significant decline in economic activity that is spread across the economy and that lasts more than a few months.* (NBER, n.d.)" This might seem a somewhat subjective definition, but it highlights the fact that there is no set definition of a recession, and many economists disagree as to what exactly a recession is. Whether or not the US is in recession is decided by NBER's Business Cycle Dating Committee directly. In the US, NBER is widely seen as the arbiter of when the economy is in recession or not and much of the relevant literature also uses NBER's classification and this determination is then made public. For clarity, here is also a special case of recession that is called a depression, which analysts define as a decline in real GDP of over 10%. However, a true economic depression is very rare and for that reason is not included in this analysis.

Algorithm and Model Distinction

In a computer science textbook from 1971, computer scientist Harold Stone defined algorithms as: “*a set of rules that precisely define a sequence of operations* (Chowdhury et al., 2021).” This definition is intuitive, but too broad for this thesis. For the purposes of this thesis, an algorithm is a set of instructions that a computer executes to learn from data and produce an output from which information can be gleamed. The structure that contains this set of instructions to which data is passed in is referred to as *a model*. A model may consist of only one underlying algorithm, or several. A model and its underlying algorithm(s) are distinct but related entities.

Machine Learning

The first working definition of machine learning came from the artificial intelligence (AI) pioneer Arthur Samuel in the 1960s. Samuel described machine learning as: “*the field of study that gives computers the ability to learn without explicitly being programmed* (Brown, 2021).” For the purposes of this thesis, the working definition is somewhat different. In context of this thesis, machine learning can be thought of as the blending of computer science and statistical analysis to deploy algorithmically driven models that can extract complex relationships between data with limited human input.

4.2 Research Question

Given the debate surrounding the ability of machine learning models to outperform traditional logit models to predict US recessions, the working research question is as follows: how do logit models compare in accuracy to neural network, random forest, support vector machines, eXtreme Gradient Boosting (XGBoost), Light Gradient Boosting Machine (LightGBM), and k-nearest neighbors (k-NN) machine learning algorithms as measured by out-of-sample prediction error in forecasting US recessions?

4.3 Objectives

Through a comprehensive review of the existing literature, data collection, and rigorous analysis, the thesis aims to achieve several objectives. The principal objective of this thesis is to validate and/or challenge the current literature that provides evidence that machine learning models outperform traditional logit models at predicting US recessions in a binary classification setting.

Furthermore, another objective is to address gaps in understanding by investigating the factors that lead to out/underperformance of machine learning models compared to logit models. This will include an in-depth analysis of the feature importance, model interpretability, and the algorithmic approaches which likely lead to discrepancies in performance.

Moreover, an additional objective of this thesis is to give actionable insights from the results of the analysis for policymakers, economists, and financial practitioners. Like much of the existing literature, the thesis will discuss the feasibility of implementing machine learning models for the purposes of recession prediction. It will also explore the potential benefits and risks of relying on machine learning model outputs for high stakes decision making.

Lastly, the thesis aims to answer whether machine learning models can enhance the accuracy and reliability of recession predictions. This is a separate question from whether the machine learning models outperform logit models. It is one thing to outperform a certain model, but to perform well enough to be useful in a production environment is another question that deserves examining. By achieving these objectives, this thesis will contribute to the ongoing discourse and research on the application of machine learning models in recession forecasting and if they should take precedence over traditional logit models.

4.4 Methodology

This section of the thesis proposal gives a brief overview of the proposed research's design, data collection strategy, and the approach for the analysis itself. Additionally, a basic overview of each employed model is discussed along with the selected evaluation metrics.

4.4.1 Research Design

The overall research approach for this thesis will be a quantitative analysis. The analysis will have an experimental research design which focuses on the comparison of different algorithms as outlined in the research question and subsequent sections. The analysis will focus on the US economy and the data will therefore all be related to the US economy exclusively.

The working concept for the analysis is to create a framework that can be applied to all seven of the employed models. This entails using the same independent variables as inputs for each model as well as the same evaluation metrics. It is important to note that the independent variables, other than the yield curve, have not been definitively chosen at the time of writing. The models will be tested on their ability to predict coming recessions on a rolling lagged basis of 3, 6, and 12 months. Testing the models on a rolling basis is preferable to simply identifying whether the economy is in recession because the economic implications of these findings are greater. If models can predict recessions well in advance, it would give investors and policy makers more time to proactively react.

4.4.2 Data Collection

The Federal Reserve Economic Data API (FRED) is a free online data platform provided by the Federal Reserve Bank of St. Louis which provides data on the US economy in a convenient way.¹ Both the independent variables as well as the NBER binary recession indicator target variable are available from the FRED API. The current literature also heavily relies on the FRED API for data collection, not out of necessity but convenience since there are so many different metrics readily available. However, if deemed necessary, other potential data sources also used by the current literature include the International Monetary Fund (IMF) API and the Organization for Economic Cooperation and Development (OECD) public database.

¹ <https://fred.stlouisfed.org/docs/api/fred/>

4.4.3 Data Analysis

The analysis will be done using the Python programming language in a Spyder Integrated Development Environment (IDE). The analysis will adhere to commonly accepted data analysis practices. The first step will be conducting initial exploratory data analysis. Once the data is prepared, the models will be deployed using popular data science Python packages such as Scikit-learn.² In the thesis, a full overview of all the utilized packages as well as descriptions will accompany the analysis. Additionally, in the interest of transparency, all the code will be hosted in a public GitHub repository where anyone can review it following the completion of the thesis.

4.4.4 Choice of Models

The choice of models is informed by the existing research on the topic of recession classification. In the thesis itself, each of these models will be explained in depth; for now, a brief explanation of each model's mechanics is provided. During the final analysis additional algorithms might be utilized.

The base model for comparing the machine learning models against is a standard logit model. A logit regression model is more commonly known as a logistic regression model and is the gold standard of binary classification analysis for econometric purposes. A so-called sigmoid function is used to make a prediction for the probability of the given input being a member of the true class (0 being false, 1 being true in a binary setting). The predicted probability of the input being true is compared with the given threshold, usually 50%. If the predicted probability falls above/below the chosen threshold, it is either assigned 1 or 0 respectively. This basic concept of meeting/falling below a threshold as a decision rule is essential to all binary classification models.

The first machine learning model that will be used to classify recessions is a random forest model. Originally created in 2001 by the statistician Leo Breiman from the University of California at Berkley, random forest models are so-called ensemble learning algorithms (Elyan et al., 2014). Ensemble learning models use bagging, otherwise known as bootstrap aggregation, and boosting to train individual decision trees. Decision trees are another (nowadays less frequently used) machine learning algorithm for binary classification analysis. Basically, bagging and boosting entail the random selections of training data with replacement. Each of these extracted datasets are then used as individual training data for the decision trees. Then, the average prediction of all the decision trees is taken and used as the output. For example, 60% of the trained trees output that the economy is in recession, so the model outputs 1. A random forest is simply an extension of the ensemble learning concept but incorporates feature (independent variable selection) randomness as well. This creates a “forest” of many decision trees that again take the average outputs of the individual trees as the model's prediction.

Two other models that will be employed are XGBoost and LightGBM models. Like random forest models, both XGBoost and LightGBM models use ensemble learning methods. These models use the gradient descent algorithm to minimize the loss function, i.e. the difference between the actual and predicted values. Essentially, the algorithms iteratively add decision trees to correct for the

² <https://scikit-learn.org/stable/>

mistakes of the previous trees. This serves to minimize the difference between the predicted and actual values. XGBoost and LightGBM are two popular implementations of optimization processes for the gradient descent algorithm and often used in a binary classification context. The two models are similar, but LightGBM is generally more suited to large datasets than XGBoost and there are other subtle differences in their respective algorithms. In practice, XGBoost and LightGBM are often used in tandem, and the choice between them depends on factors such as dataset size, computational resources, and specific use-case requirements.

Another machine learning model that will be used is a neural network. Neural networks are often referred to as “black box” models because the model’s decisions are based on complex learned patterns which are difficult to translate into human-understandable rules. The model is conceptually based on how the brain is thought to process information, hence the name. Neural networks are made up of layers of nodes. A node in this case is either an independent variable used as an input, or a transformation function employed to manipulate the input. Each model contains an input, hidden, and output layers with a set number of nodes in each layer. The input layer consists of the model’s inputs, the hidden layers are what introduce non-linearity and perform complex transformation on the data. The number of nodes (transformation functions) in the hidden layer is set beforehand. Finally, the output layer gives the result.

Additionally, the k-NN machine learning algorithm will be employed. The k-NN algorithm is a comparatively simple algorithm often used for regression tasks. The model is simple in the sense that it does not require much set up, hyperparameter tuning, nor does it make specific assumptions about the distribution of the data. The k-NN algorithm uses the whole dataset and splits it into groups based on their similarity based on a voting system. The voting system works by looking at the number of its direct “k” neighbors-k being a value which is specified beforehand, usually iteratively. To conceptualize this, imagine someone who lives in a large city. Urban centers tend to be more politically liberal than rural areas. Therefore, someone who lives in a big city is more likely to be liberal than a rural dweller, and the others who live in the urban dweller’s apartment building are also likely to be liberal. This is not because they live next to each other, rather the proximity itself is a shoe in for other related variables like, for example, income and education level which lend themselves to urban living. In our case, the algorithm works to find clusters of similar datapoints that are recessions and classify them as such based on their “proximity” to other recessions. When data is passed in, the k-NN model then checks which group the datapoint is most like and classifies it that way.

Lastly, the final machine learning model that will be employed is a Support Vector Machine (SVM). This algorithm works well on small but high-dimensional data. The aim of the SVM algorithm is to create a hyperplane between the two classifications, which in this case is recession or not recession. A hyperplane is essentially a line that divides the data between the two classes. This conceptual line has a margin between the two classes. The algorithm’s objective is to maximize this margin between the two classes. The more margin between the hyperplane and the class’s data, the more effectively the algorithm can classify data. Testing data that is then passed in is evaluated based on which side of the hyperplane the datapoint falls on and is classified based on this.

4.4.5 Model Evaluation

The evaluation metrics will include, but not be limited to, confusion matrices, F1 scores, recall scores, precision scores, accuracy scores, and area under the receiver operating characteristic curve (AUC-ROC). The selected evaluation metrics are widely used in the current econometric research for recession classification. Also, the named evaluation metrics are all applicable and relevant to the seven models which will be explored in the thesis. The thesis will give an in-depth overview of each of these metrics when discussing the results. The differences in the models' results will be tested for statistical significance. Lastly, extensive data visualizations will also be included to compare models.

4.4.6 Limitations

While every effort will be made to ensure the rigor of the study, certain limitations are nonetheless acknowledged. The data collection is limited to publicly available sources and any inherent bias in the datasets that analysts have no control over. Additionally, there have technically only been 14 recessions in the US since the Great Depression of the 1930s (Armstrong et al., 2022). This is a comparatively small sample size, regardless of the chosen interval. Therefore, there is an inherent class imbalance in the data. While several steps can be taken to address this issue, there is no perfect way to fully correct for the class imbalance that is inherent in the data.

On a related note, the datasets the study will examine will be small. This is because many relevant variables are collected at most monthly. There have only been a “few” hundred months since the relevant data first began being collected. This is an issue because machine learning models are notorious for overfitting small datasets, meaning extensive measures will need to be taken to ensure a proper bias-variance tradeoff. Despite these limitations, this research will provide valuable insights into the effectiveness of different algorithms and their abilities to predict US recessions. However, the acknowledgement of these limitations is crucial for a nuanced interpretation of the study's final results.

4.4.7 Thesis Structure

The structure of this thesis will follow the guidelines put forth by HSLU to complete a thesis. The working outline includes an abstract, an introduction, a literature review, a discussion of important definitions, and an overview of the study's methodology. There will also be a dedicated section discussing the data which includes a general overview of the code. The overview of the code will not include any specific lines of code, rather all the Python packages used as well as the approach to architecting the code will be discussed. This will be followed by a detailed overview of the employed models and their underlying algorithms. Then, there will be a discussion of the results as well as a conclusion delving into the practical implications of the findings.

4.4.8 Ethical Considerations

This study will adhere to all the ethical guidelines outlined by HSLU for the completion of a master's thesis. The goal of this thesis is to be as transparent as possible in every step of the analytical process. According to some experts, it is estimated that around 70% of AI research results are irreproducible (Gundersen, 2023). Since AI, and machine learning more specifically,

are such rapidly evolving fields, this is not necessarily surprising. However, in the interest of full transparency, every aspect of this thesis will be open to scrutiny and review.

All the code written for the models will be made public. Additionally, the findings of the data will be presented objectively and any limitations or uncertainties about the findings will be openly discussed. Lastly, a website will be made accompanying the thesis. The website will provide an interactive and open avenue for the thesis's findings to be explored by any interested party. Overall, the thesis's strong commitment to transparency and ethical conduct will ensure the integrity of the research and further the credibility of its eventual findings.

5. Work and Research Plan

The first step is to get approval for the approach of tackling the research question. Concurrently, and throughout the whole research process, further literature on the relevant topics will be reviewed. Once approval of the research methodology has been granted, the next step is to build the codebase for the analysis. This will likely take a significant investment of time and require multiple review sessions from the thesis's supervisor(s). During this time when the code is being finalized, the parts of the thesis which are somewhat independent of the analytical results can be written. This includes the overview of the algorithms and models, the literature review, and the introduction. Once the results have been collected, the rest of the thesis can be completed. Finally, after a preliminary draft of the thesis is complete, a website discussing the thesis and its findings will be created. Since this step is not essential to the completion of the thesis, creating a website to host the results will be the final step. This section is not a set plan and is subject to change as the thesis develops. A potential timeline is presented below.

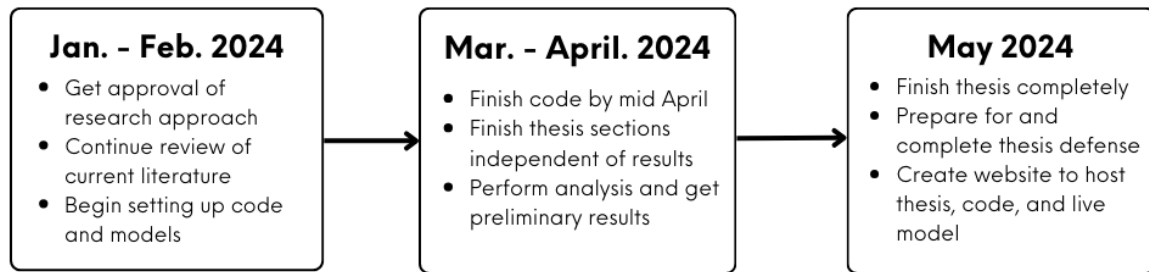


Figure 1. Preliminary Thesis Roadmap Timeline

6. List of Sources and Literature

The named sources here are not an exhaustive list but rather a working start. The final literature review will include several other sources that are not yet named here. With that, the literature liarws here is representative of some of the most current research on the topic of binary recession classification using machine learning methods.

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