Enhancing Unemployment Forecasting: A Comparative Analysis of Machine Learning and Traditional Econometric Models

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1 Introduction

Accurate economic forecasting is crucial for effective policymaking, especially in areas such as unemployment and employment rates, which are some of the key indicators of macroeconomic health. Central banks, including Sveriges Riksbank, rely on economic forecasts to guide monetary policy decisions that stabilize inflation, promote economic growth, and ensure a balanced labor market. However, traditional forecasting methods used by central banks, such as linear regression models and time series analysis, have limitations in capturing complex relationships and non-linear patterns within economic data. With rapid advancements in artificial intelligence and machine learning, there is a growing interest in evaluating how these newer techniques can enhance the accuracy of economic predictions.

There is a demand to explore the potential of machine learning algorithms, like random forest and neural networks, in improving the accuracy of Sveriges Riksbank's forecasts for these indicators and measurements. Random forest, for instance, is a robust ensemble learning method, which is known for its ability to handle non-linear relationships, interactions between variables, and high-dimensional datasets. Utilizing such an algorithm to predict these variables, could significantly improve forecasts and consequently the policymaking of Sveriges Riksbank. This research will not only assess the performance of different machine learning models, but also compare it with the traditional econometric approaches, to determine which method offers the best predictive capabilities for these types of forecasts.

As previously mentioned, improving the accuracy of forecasts has significant implications for economic policy. More reliable predictions can lead to better-informed decisions on interest rates, inflation targeting, and employment policies. In the current context of global geopolitical uncertainty and tension, where many nations' economies are delicate and quite fragile, leveraging advanced forecasting tools could support more agile and effective policy responses. This research, therefore, aims to contribute to the academic fields of machine learning, economic forecasting and the practical needs of policymakers.

We plan to mostly focus our modeling on unemployment and employment rate data. The main reason for this is that Sveriges Riksbank is currently working on improving their forecasts for inflation and GDP, by utilizing some machine learning techniques and methods. However, depending on the outcome of their research, we might also aim to improve these forecasts (on inflation and GDP) as well. Furthermore, estimations have shown that an increase of the short term interest rate of one percentage point, results in a 0.8 percentage points higher unemployment rate (Alexius and Holmlund 2008). This indicates that unemployment and employment rate is highly associated with changes in the policy rate, making them important indicators for central banks to consider in their decision making process.

2 Literature Review

2.1 Factors Influencing Unemployment

Unemployment is influenced by several factors, all closely related to the overall economic conditions. One of the most important factors is the demand in the economy, both for goods and services. When demand for these decreases, such as during a recession, a chain reaction occurs where companies experience lower revenues. To compensate, companies reduce their investments and workforce, leading to layoffs and higher unemployment. A report from Sveriges Riksbank points out that weak domestic demand, reflected in high levels of layoffs and fewer newly posted job openings, contributes to rising unemployment. (Sveriges Riksbank 2024)

Another crucial factor is wage development in relation to productivity and inflation. If wages rise faster than companies can offset through productivity gains or price increases, it can result in higher costs for businesses. These increased costs may lead companies to hire fewer people or even implement layoffs to protect their profit margins. The report indicates that higher wage costs, especially when not matched by productivity growth, can negatively affect the labor market during certain periods. (Sveriges Riksbank 2024)

Monetary policy, such as the level of the policy rate, is also central to unemployment. When the central bank raises the policy rate to combat inflation, borrowing costs increase, which dampens both business investments and household consumption. This, in turn, leads to reduced demand for labor and rising unemployment. Conversely, lowering the interest rate stimulates the economy by making it cheaper for businesses to invest and for households to consume, thus reducing unemployment. At the same time, unemployment is influenced by the global economic situation. Weak demand from abroad can, for example, lead to reduced exports, which affects companies in the export industry and can lead to layoffs. (Sveriges Riksbank 2024)

Since elements such as demand in the economy, wage growth relative to productivity, and monetary policy are identified by Sveriges Riksbank to play a significant role in shaping labor market outcomes, it is essential to consider these factors as key drivers when conducting feature engineering for models like neural networks or random forest. Incorporating features that reflect these dynamics will increase the chance of the models capturing the complex relationships affecting unemployment.

2.2 Traditional Econometric Models for Unemployment Forecasting

Previous studies have relied on traditional time-series models such as ARIMA, GARCH, and FARIMA to predict unemployment. These models are well-established in forecasting economic indicators, including unemployment rates. For example, ARIMA has been used to model unemployment across multiple countries, including Turkey and several European nations (D. S. Yamacli and S. Yamacli 2023; Katris 2020). In these studies, ARIMA models showed solid performance for short-term forecasts, particularly in stable economic environments. However, these models have limitations in handling non-linear patterns and complex interactions among variables, which can be critical in dynamic and volatile economic conditions (Katris 2020).

Moreover, the FARIMA model, which accounts for long memory, has been shown to improve unemployment predictions by addressing persistent effects of economic shocks. GARCH models, on the other hand, help capture heteroskedasticity, allowing for more precise modeling in situations where volatility in the unemployment rate varies over time (Katris 2020). These models perform adequately in linear and stable conditions but are less effective in handling sudden changes or non-linear patterns in data, such as during crises (Güler et al. 2024).

2.3 Machine Learning Approaches

Machine learning techniques, such as artificial neural networks (ANNs), random forest (RF), support vector machines (SVM), and XGBoost, have emerged as alternatives to traditional models, particularly in environments characterized by non-linear relationships and complex data interactions (Kreiner and Duca 2019; Güler et al. 2024). These models can better accommodate large datasets and complex interdependencies among economic variables, offering potentially more accurate forecasts.

In a study by Gogas, Papadimitriou, and Sofianos (2022) of forecasting the unemployment rate in the eurozone, random forest outperformed traditional models and other machine learning techniques, achieving high accuracy (88.5%) in forecasting unemployment directionally. Similarly, in Turkey, a comparison of ARIMA and machine learning methods revealed that ANN models provided lower forecast errors during periods of high economic uncertainty, such as the COVID-19 pandemic, outperforming ARIMA during these volatile periods (D. S. Yamacli and S. Yamacli 2023).

Additionally, research focusing on the South African unemployment rate also demonstrated the effectiveness of machine learning models when combined with feature engineering techniques. By enhancing the input data through statistical transformations and combinations, researchers improved the accuracy of SVM and other models by over 80%, highlighting the potential of such techniques in forecasting economic indicators (Makola, Mulaudzi, and Ajoodha 2021).

2.4 Previous Comparative Studies

Several studies have directly compared traditional econometric models with machine learning approaches, generally finding that machine learning models outperform traditional methods in terms of accuracy, especially in unstable or volatile economic conditions. For instance, in forecasting the unemployment rate in the United States, a study by Kreiner and Duca (2019) found that machine learning models based on neural networks outperformed the Survey of Professional Forecasters (SPF) benchmark, particularly for short- and medium-term forecasts. This finding suggests that machine learning models can provide more responsive forecasts in rapidly changing economic environments.

Similarly, studies on Turkey and South Africa have shown that machine learning models, such as ANNs and SVM, outperform ARIMA and other traditional models, particularly when the models are enhanced with external factors like exchange rates and inflation (Güler et al. 2024; Makola, Mulaudzi, and Ajoodha 2021). These results emphasize that machine learning methods are better suited for capturing complex interactions between variables, such as those seen in macroeconomic forecasting.

2.5 Challenges and Future Directions

Despite their superior performance, machine learning models come with challenges. One key issue is the risk of overfitting due to the large number of parameters involved. To address this, methods such as principal component analysis (PCA) and feature engineering can be employed to reduce dimensionality and improve model robustness (Kreiner and Duca 2019; Makola, Mulaudzi, and Ajoodha 2021). Furthermore, while machine learning methods have shown their potential in improving forecast accuracy, they require significant computational resources and expertise in model tuning, which may limit their adoption in some forecasting environments (Güler et al. 2024).

In conclusion, while traditional models like ARIMA and GARCH remain valuable for short-term and stable conditions, machine learning techniques offer superior performance in capturing complex, non-linear relationships in unemployment rate forecasting, particularly during periods of economic uncertainty. The continued development of feature engineering techniques and hybrid models combining machine learning with traditional approaches may provide even more robust forecasting tools in the future.

3 Proposed Methodology

3.1 Research design and purpose

This study will adopt a quantitative research design, utilizing historical macroeconomic data, to evaluate and improve forecasting models for unemployment and the employment rate in Sweden (Saunders, Thornhill, and Philip 2015).

Due to the purpose of the study, it will incorporate both explanatory and evaluative aspects, as the core aim is to understand and assess the effectiveness of different machine learning models, compared to traditional econometric models in predicting labor market trends. The study seeks to explain which methods perform better under different conditions and why certain variables are more influential in improving predictive accuracy. Through statistical evaluation and model comparison, the research will offer evaluations and explanations for the strengths and limitations of each explored method in the context of economic forecasting (Saunders, Thornhill, and Philip 2015).

3.2 Research Approach and Theoretical Framework

We believe this study calls for an abductive approach, as it incorporates both deductive and inductive elements. The first step of the study will involve selecting and applying established theories in economics, forecasting, and machine learning, alongside relevant machine learning techniques and models for economic forecasting. These techniques and theories will then be tested and evaluated on empirical data. This entails a deductive approach. However, there could also be some inductive reasoning involved in analyzing the results. For example, through feature analysis and model evaluation, new patterns or relationships between macroeconomic variables may emerge, which could lead to generating new insights or hypotheses about what drives unemployment and employment rate changes. The results could also generate new hypotheses or theories within the realm of machine learning or forecasting. Furthermore, if unexpected findings arise, these could inform new theoretical understandings, creating a feedback loop between empirical results and theory development. Therefore, we argue that this study will incorporate an abductive approach (Saunders, Thornhill, and Philip 2015).

3.3 Data Collection, Preparation, and Processing

The data used in this study will be secondary in nature, by utilizing publicly available economic datasets, sourced from Sveriges Riksbank and Statistics Sweden (SCB). These data sources are highly reliable and updated frequently. The primary variables of interest will include unemployment and employment rates, we will possibly also analyze and forecast other relevant economic indicators such as GDP growth and inflation rates. All these variables have been collected over a sufficiently long historical period to ensure the models can learn from a wide range of economic conditions. The dataset will be prepared for analysis by cleaning, possibly normalizing, and transforming it where necessary to handle any missing values or outliers that could distort the model's performance. This will likely be done in Python and Microsoft Excel or IBM SPSS Statistics, as they are powerful tools for data preparation and exploration. Furthermore, we have a great deal of experience using them.

Once the data is processed, it will be divided into training, development/validation, and test sets, typically in proportions of 80%, 10%, and 10%, respectively. This split will allow for the development, optimization, and evaluation of the forecasting models. The division into different datasets can be done randomly, however, it is important that each subset is an accurate representation of the data in the entire dataset. This is vital to avoid introducing bias and improving generalizability. The point of the training set is, as the name implies, to train the model. After training the model, it is used to predict the values of the development set, this can generate key insights which allow for the model to be tuned and optimized. Finally, we use the tuned model to run inference on the test set. Since this test set is completely "unseen" by the model, it gives a good indication of the model's generalizability and is (hopefully) an accurate representation of the model's performance in the real world (Jurafsky and Martin 2024).

3.4 Model Evaluation and Feature Importance

Various performance metrics can be used to evaluate the models, including mean absolute error (MAE), root mean squared error (RMSE), and R-squared (R^2) (D. S. Yamacli and S. Yamacli 2023). These metrics will enable us to assess how well each model captures the underlying patterns in the data. To further understand the importance of each feature in our models, feature importance analysis could be applied. For random forest models, feature importance scores can be derived based on the Gini importance or mean decrease in accuracy (Płoński 2020). This would allow us to identify which economic indicators (e.g., interest rates, inflation, GDP) are most influential in predicting unemployment and employment rates. For neural networks, similar insights can be gained through techniques such as SHAP (Shapley Additive Explanations) values or sensitivity analysis, which will provide a deeper understanding of the model's decision-making process (Lundberg and Lee 2017).

Given that this research incorporates both theories from economics and exploratory analysis from machine learning, it is important to emphasize that the study will apply an iterative approach to model development. This will involve adjusting model parameters (e.g., learning rates, the number of trees in random forests, and the number of hidden layers in neural networks) based on initial model performance, to optimize predictive accuracy.

3.5 Tools and Implementation

We plan to implement these machine learning algorithms and conduct our analysis, using the programming language Python. Python is an ideal programming language for these types of tasks due to its versatility, extensive library support for data analysis and machine learning, and ease of use. The programming language offers powerful libraries like pandas for data manipulation, NumPy for numerical computations, and SciPy for statistical analysis. These libraries simplify data cleaning, preprocessing, and handling large datasets, making Python highly efficient for preparing economic data.

Moreover, popular machine learning libraries such as scikit-learn, XGBoost, and TensorFlow provide a broad range of algorithms and tools that can be applied directly to build, train, and evaluate forecasting models like random forest. Python is also highly capable of handling statistical models and forecasting methods commonly used in economics. Packages like statsmodels allow for econometric modeling, such as time series analysis, which could complement machine learning approaches in comparing traditional forecasting methods with more advanced algorithms, which is central to our thesis. Another reason is that Python is one of the most popular programming languages at Sveriges Riksbank, making it easier for the principal to practically use it to generate forecasts in the future. Furthermore, the authors of the thesis are proficient in the use of Python, allowing for a more streamlined implementation.

3.6 Project Timeline

An overview of the timetable for each step of the study can be found in Figure 1 in appendix, where the project timeline is outlined in a Gantt chart.

4 Expected Outcomes

The expected outcome of this master thesis is to be able to state whether the machine learning methods used can provide better forecasts than the traditional models used today. We also expect to be able to state which machine learning models or methods worked the best for this purpose and why. Depending on the results, we may expect Sveriges Riksbank to use new methods for future forecasts of primarily unemployment and employment rates, but perhaps even other macroeconomic indicators like inflation rate and GDP growth. Ultimately, our research aims to support the development of more responsive and precise forecasting tools, providing insights into the efficacy of machine learning approaches for economic forecasting. Our research question is therefore:

Can machine learning models, such as random forest and neural networks, improve the accuracy of unemployment and employment rate forecasts compared to traditional econometric methods, and what economic variables are most influential in enhancing model performance?

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5 Appendix

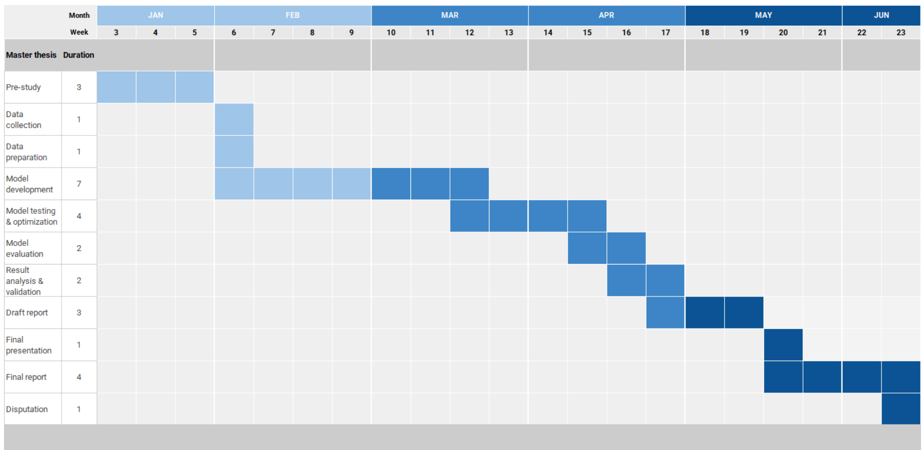

Figure 1: Gantt chart