Machine Learning and Modeling of the Impact of Trademark Filings on GDP Growth based on Python

Serhii Robotko[1,2], Andriy Topalov[1], Serhii Nekrasov[3], Valeriy Zaytsev[1] and Dmytro Zaytsev[1]

[1] *Admiral Makarov National University of Shipbuilding, Heroiv Ukrainy Avenue 9, Mykolaiv, 54007, Ukraine*
[2] *Markify AB, Hornsgatan 89, Stockholm, 11016, Sweden*
[3] *Sumy State University, 2 Rymskogo-Korsakova st., Sumy, 40007, Ukraine*

Abstract

Intellectual Property (IP) rights, specifically trademarks, are gaining prominence as key drivers of economic growth and development in the modern global economy. This study delves into the intricate relationship between trademark filings and Gross Domestic Product (GDP) growth in around 160 countries, with a focus on those having a dominant services sector. Initially, we provide a comprehensive review of trademarks' far-reaching impact on the global economy, exploring their role in fostering innovation, enhancing competitiveness, and elevating brand value. This includes an examination of how trademarks bolster consumer trust and market differentiation. Subsequently, the study investigates the patterns in trademark filings across selected countries and assesses their correlation with respective GDP growth rates. Utilizing Scikit-Learn and NumPy, we create a machine learning model to predict GDP growth based on trademark filings and other pertinent factors, such as population, education, and government policies. After developing the model, we appraise its accuracy by juxtaposing the predicted indices with actual data from 2021. Our findings reveal a positive association between trademark filings and GDP growth. The results demonstrate that trademarks significantly contribute to economic development by incentivizing research and development investments, stimulating market competition, and catalyzing innovation. In conclusion, we discuss the ramifications of our findings for policymakers, highlighting the importance of nurturing a robust IP ecosystem that underpins economic growth and development. Through a nuanced understanding of the connection between trademark filings and GDP growth, this study contributes to the formulation of well-informed policies and strategies aimed at fostering economic growth and fortifying the services sector across different countries.

Keywords

Trademarks, Data analysis, GDP growth, Machine learning, Scikit-Learn, NumPy.

1. Introduction

Trademarks play a critical role in the global economy as they represent the brands, products, and services that businesses offer to consumers. A trademark is a unique identifier that distinguishes a company's offerings from those of its competitors, facilitating brand recognition and consumer trust. As businesses become increasingly global and interconnected, the number and significance of trademarks in driving economic growth cannot be understated [1].

The Role of Trademarks in Economic Development. Trademarks serve as a valuable economic tool, enabling businesses to build their brand reputation and protect their intellectual property rights. By fostering innovation, competition, and consumer confidence, trademarks contribute to the overall economic development of a country.

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EMAIL: robotkos@gmail.com (S. Robotko); topalov_ua@ukr.net (A. Topalov), s.nekrasov@omim.sumdu.edu.ua (S. Nekrasov), zvalv1974@gmail.com (V. Zaytsev), zdmvl1982@gmail.com (D. Zaytsev)
ORCID: 0000-0002-9203-8385 (S. Robotko); 0000-0003-2745-7388 (A. Topalov), 0000-0001-9157-2829 (S. Nekrasov), 0000-0002-8590-5671 (V. Zaytsev), 0000-0001-5778-4668 (D. Zaytsev)

The Growing Importance of Trademarks in the Global Economy. Over the years, the importance of trademarks in the global economy [2] has grown significantly. With the advent of the digital age and the rapid expansion of international trade, businesses are increasingly operating across borders and entering new markets. As a result, trademarks have become essential tools for companies to protect their brand identities, compete effectively, and penetrate new markets.

Trademark Filings as an Economic Indicator. The number of trademark filings can serve as an economic indicator [3], providing insights into the overall health and growth of an economy. A rise in trademark applications may signal increased business activity, innovation, and confidence in a country's economic prospects. Conversely, a decrease in filings may suggest an economic downturn or reduced investment in innovation and branding. Analyzing trademark filing trends across countries can help policymakers and businesses better understand the global economic landscape and identify opportunities for growth and development.

Challenges and Opportunities. Despite the clear benefits of trademarks for the global economy, challenges remain in protecting intellectual property rights and promoting fair competition. Counterfeiting, trademark infringement, and other forms of intellectual property theft continue to be significant issues, requiring increased vigilance and cooperation among governments, businesses, and international organizations.

Nonetheless, the growing importance of trademarks presents opportunities for businesses and economies to leverage branding, innovation, and consumer confidence to drive growth and success in an increasingly competitive global market. By focusing on the development and protection of trademarks, countries can foster a more innovative and resilient economy that benefits both businesses and consumers alike.

Therefore, the analysis of trademark application data requires processing a large amount of information, and therefore there is a need to apply intelligent data processing methods, such as machine learning, genetic algorithms, etc [4 - 10]. Machine learning provides partial or complete automation of solving complex professional tasks and has a wide range of applications: speech, gesture, handwriting, image recognition, technical and medical diagnostics, time series forecasting, bioinformatics, fraud and spam detection, document categorization, stock market analysis, credit scoring, forecasting, ranking in information search, etc. The theory of machine learning is evolving and parallel computing is becoming more accessible to enable complex and demanding architectures such as recurrent neural networks and convolutional neural networks [11-15]. In addition, methods such as kernelization, bagging, and boosting have gained popularity. Today, the use of machine learning [14 - 18] is an interesting and very promising area of economic modeling and forecasting. This applies not only to financial problems, but also to macroeconomic or microeconomic applications.

In the banking sector, [19] analyzes the liquidity needs of a bank using three architectures of recurrent neural networks and data from the Mexican banking sector. The risk assessment of the P2P lending market is investigated using a hybrid methodology that combines instance-based learning and neural networks in Babaei and Bambad.

There are a number of works aimed at forecasting in the economy, including GDP forecasting. For example, [20] proposes a new hybrid method that combines ARIMA and an autoregressive neural network to predict unemployment rates in different countries. In [21], the authors forecast the gold price by combining the filtering method with the methodology of support vector regression. In [22], the ability to predict textual characteristics from FED protocols is studied for production growth. In [23], Soybilgen, B., & Yazgan, E., using tree-based models, forecasted the growth of US GDP. And in [24], the authors analyze Japan's GDP growth using random forests and gradient boosting.

From the above sources, we can observe that machine learning is used in a variety of topics, from predicting economic and financial variables to modeling the entire stock market. Currently, we are facing new methodologies that combine and integrate econometrics with machine learning. As a result, recent applications of machine learning in business cycles and recession forecasting have been very successful compared to traditional empirical models, but require new research in this area.

Thus, in this research project, the primary objective is to investigate the relationship between the number of trademark filings and the GDP growth of different countries, leveraging machine learning techniques.

The innovativeness of the work lies in the use of new methodologies based on the Python language and in the unique and innovative application of machine learning algorithms, which will provide new and important empirical insights into the economic models of the relationship between trademark registration and GDP growth.

2. Analytics of Trademark Trends Across Approximately 160 nations dataset

In this section, we examine the trends in trademark filings across approximately 160 countries to provide a comprehensive understanding of the global landscape of intellectual property rights [25]. To illustrate these trends, we have identified the top and least active countries in terms of trademark filings for both the overall historical period and the year 2022 specifically.

Over the years, we observe that certain countries have been particularly active in filing trademarks, as evidenced by the top ten countries with the highest number of filings (Table 1):

Table 1

Top Countries by trademarks filling

Country	Count of filled trademarks
China	67,529,000
United States	11,676,000
Japan	6,473,000
India	5,478,000
Republic of Korea	4,573,000
United Kingdom	3,295,000
France	3,172,000
Argentina	3,146,000
Taiwan	3,090,000

In contrast, some countries have been considerably less active in filing trademarks, as seen in the five countries with the lowest number of filings (Table 2):

Focusing on the year 2022, we can observe a similar pattern in the top ten countries with the highest number of trademark filings (Figure 1):

1. China: 5,277,000
2. United States: 545,000
3. India: 475,000
4. Brazil: 369,000
5. Republic of Korea: 219,000
6. Turkiye: 210,000
7. Mexico: 196,000
8. Japan: 150,000
9. United Kingdom: 124,000
10. Indonesia: 121,000.

Table 2

Top rate countries by trademark filling

Country	Count of filled trademarks
Grenada	670
Marshall Islands	1,200
Vanuatu	1,440
Montserrat	1,600
Maldives	2,100
Tonga	2,500
Sierra Leone	2,600
Anguilla	2,900
Djibouti	2,900

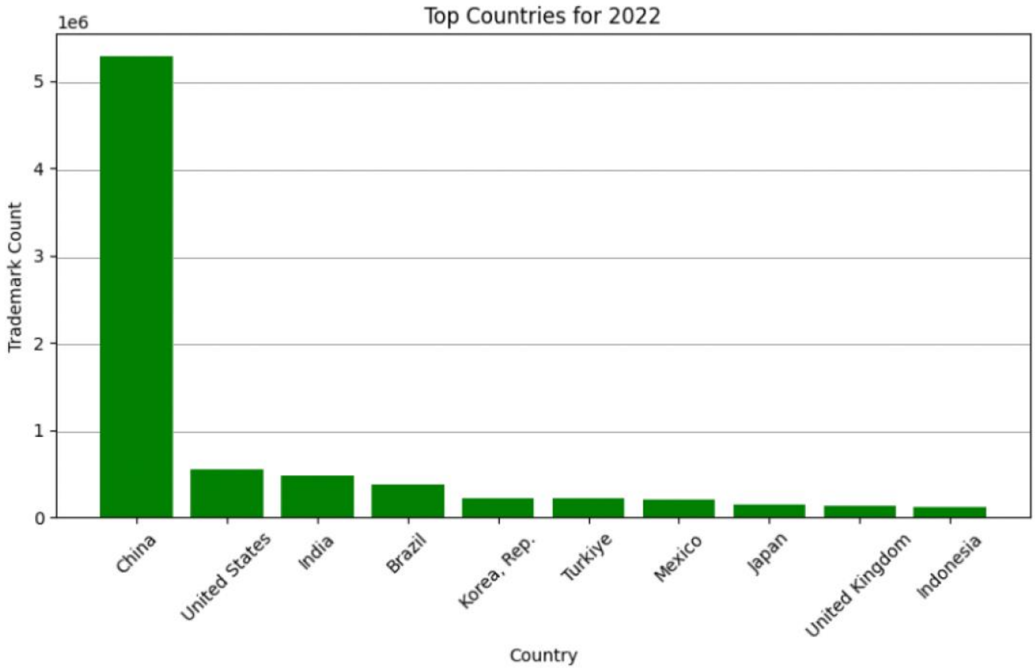


Figure 1: Top countries by trademarks filling for 2022

On the other hand, the countries with the lowest number of trademark filings (Figure 2) in 2022 include:

1. Zimbabwe: 110
2. Grenada: 120
3. Anguilla: 120
4. Caribbean Netherlands: 120
5. Gambia: 140
6. Marshall Islands: 140
7. Cabo Verde: 140
8. San Marino: 150
9. Bermuda: 170
10. Sint Maarten (Dutch part): 190

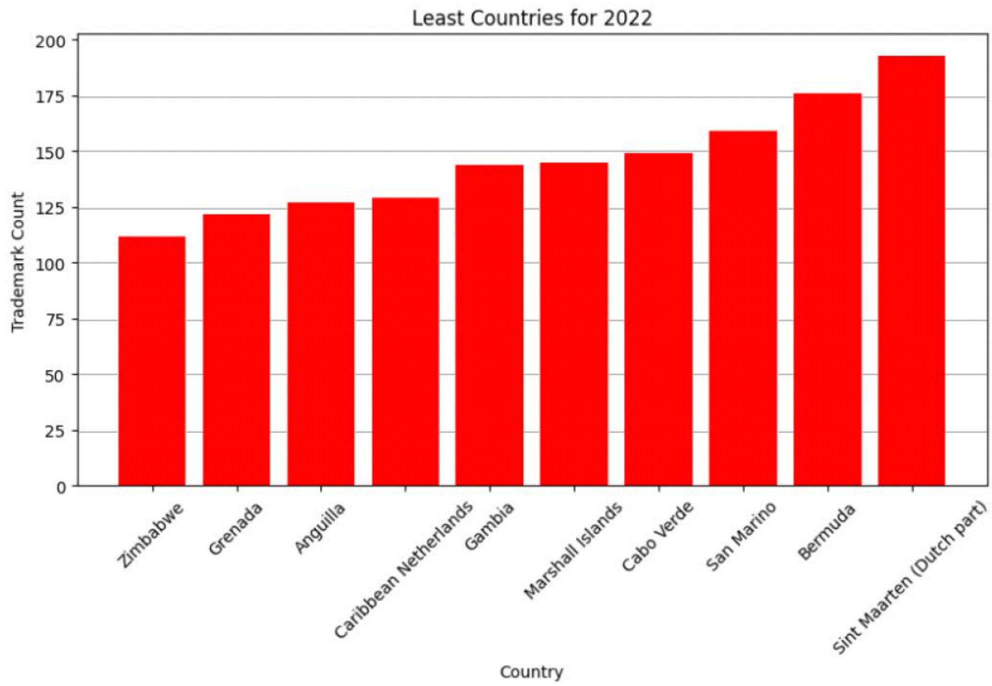


Figure 2: Lowest rate countries by trademark filling for 2022

These data points highlight the considerable differences in trademark filing activities among countries. The top countries, including China, the United States, India, Brazil, and the Republic of

Korea, demonstrate a strong commitment to protecting intellectual property rights, which can have significant implications for their economic growth and development. In contrast, the least active countries, such as Zimbabwe, Grenada, Anguilla, the Caribbean Netherlands, and Gambia, indicate the need for fostering greater awareness and capacity building for IP rights management.

Visual representations of these findings will be further illustrated using plots generated from our Jupyter notebook analysis. These plots will provide a clear picture of the distribution of trademark filings across countries, emphasizing the disparities between the most and least active nations in this area. This analysis serves as a foundation for understanding the potential implications of trademark filings on GDP growth and economic development, as explored in the subsequent sections of the paper.

3. Developing a Machine Learning Model Using Scikit-Learn and NumPy

Used a data structure that consisted of hundreds of millions of trademark applications for all years, but only used data from 2010 to 2020. Next, we discuss the use of two different machine learning models, namely linear regression and random forest regression, to predict GDP growth in different countries based on the number of trademark applications as an input characteristic.

To facilitate the analysis, several data sources are utilized, and the relevant data is extracted and preprocessed from CSV files. These files contain information about trademark filings and GDP growth rates for a range of countries across multiple years.

The data preparation phase involves the creation of feature vectors (trademark filings) and corresponding target values (GDP growth) for each country in the dataset. An optional parameter is incorporated to enable the inclusion of data for the future year (2022) when necessary.

Subsequently, the trademarks filed count data is read from a CSV file and structured as a nested dictionary. The outer dictionary's keys represent country names, while the inner dictionaries contain year-count pairs, where 'year' serves as the key and 'count' as the value.

A dedicated function is developed to predict the GDP growth for a given country using a pre-trained machine learning model and a set of feature vectors. Another function, designed to forecast future GDP growth for a country, utilizes both Linear Regression and Random Forest models and returns the predicted GDP growth values for each model.

This project exemplifies the application of machine learning models, specifically those developed using Scikit-Learn and NumPy [26], to predict GDP growth based on trademark filings data. By training the models on historical data, their performance can be assessed through a comparative evaluation of the predicted GDP growth values against the actual GDP growth data.

On this diagram (Figure 3), we evaluate the accuracy of our predicted indices against the real-world data. To achieve this, we followed a series of steps outlined below.

The algorithm begins with the “Read CSV Data” step, where we read gdp_services_percentage.csv, gdp_growth_data.csv, and trademarks_filed_count.csv into pandas DataFrames. The next step is to “Prepare Data” by extracting and organizing the data needed for the analysis, such as trademark counts and GDP growth rates. For each country, we collected the relevant data for the years 2010 to 2020 and created the feature matrix X and target vector y. The program then moves on to “Train Models” by training two machine learning models, Linear Regression and Random Forest, on the prepared data.

After training, we display the results using “Plot Results”, visualizing the actual and predicted GDP growth values for each model to gain a better understanding of their performance.

Next, we execute “Predict Future GDP Growth” by using the trained models to predict future GDP growth for each country. Finally, we “Organize and Save Predictions” by storing the predictions in a pandas DataFrame and saving it to a CSV file for further analysis.

In this project, several Python [27] libraries are utilized to aid in data processing, analysis, and visualization. The main libraries used include:

1. Pandas: A powerful data manipulation and analysis library, Pandas provides essential tools for handling and analyzing large datasets. It offers data structures like DataFrame and Series, which make it easy to clean, filter, and manipulate data.
2. NumPy: A fundamental library for numerical computing in Python, NumPy offers high-performance, multidimensional array objects and various mathematical functions to perform operations on these arrays efficiently.

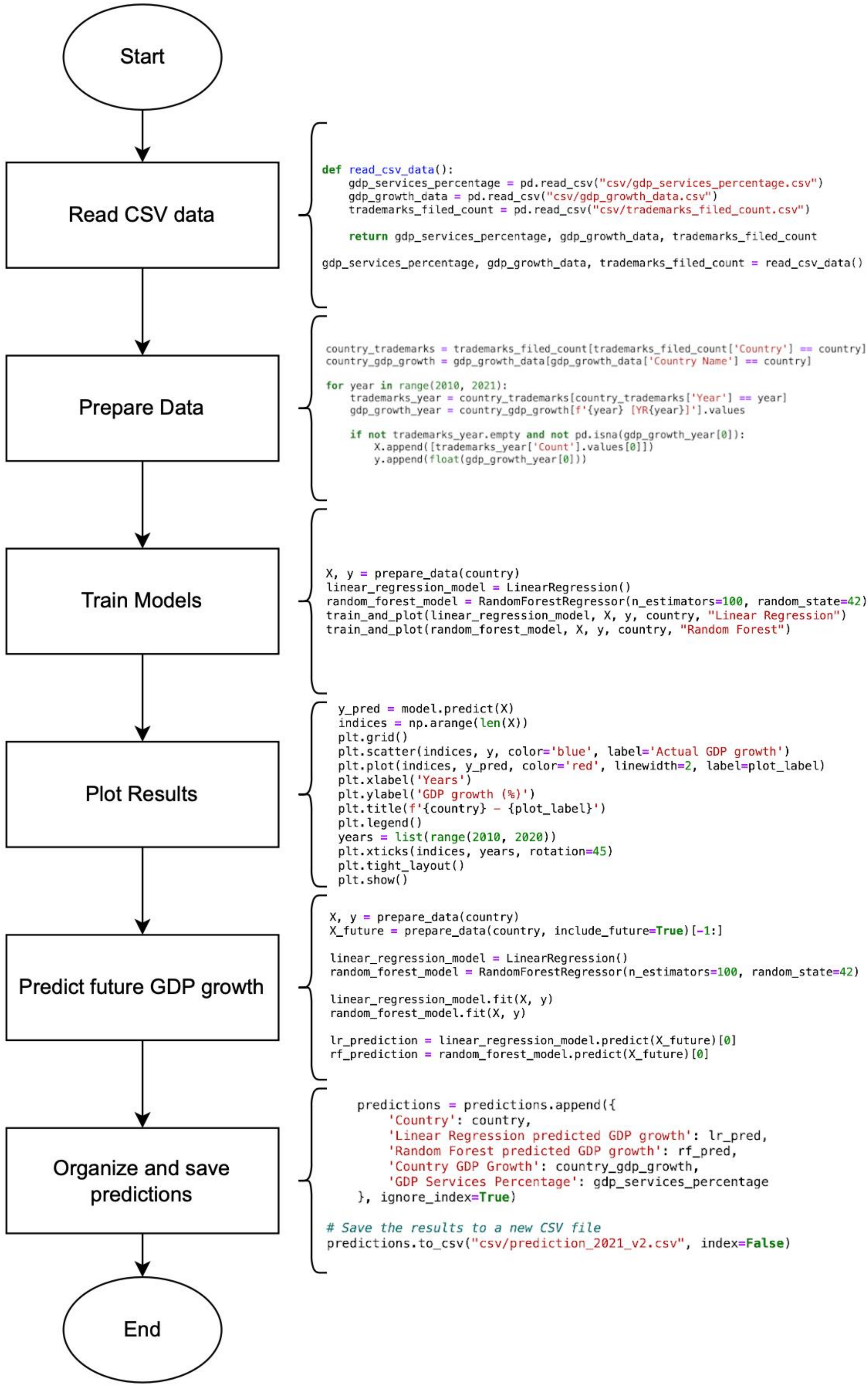
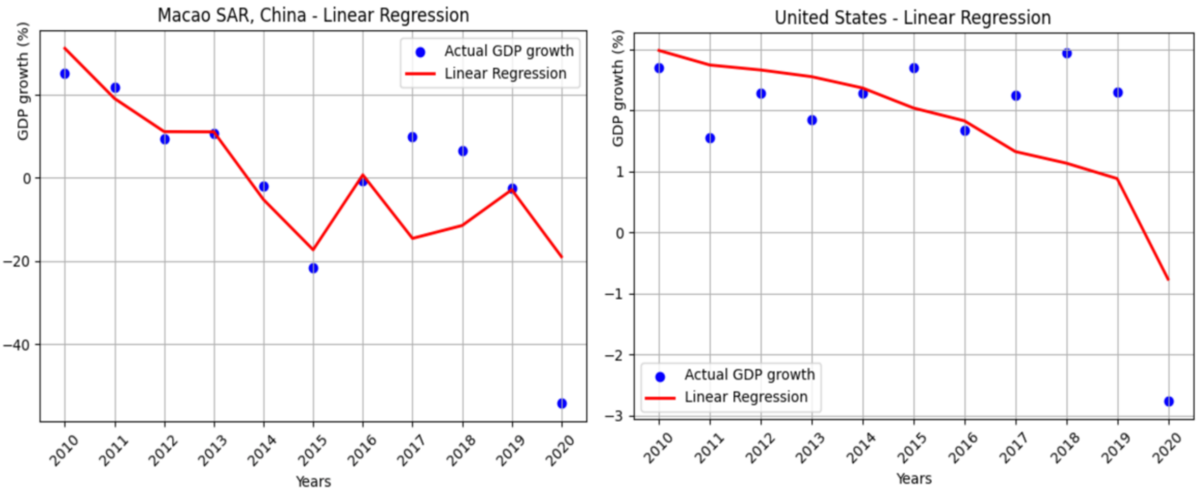


Figure 3: GDP prediction machine learning algorithm schema

1. Scikit-learn: A popular machine learning library, Scikit-learn provides a wide range of algorithms for supervised and unsupervised learning, as well as tools for model evaluation and selection. In this project, Scikit-learn is used for training machine learning models such as Linear Regression and Random Forest.
2. Matplotlib: A widely-used data visualization library, Matplotlib allows the creation of a variety of plots and charts to display data effectively. In this project, it is used to visualize the trends in trademark filings and the performance of the trained models. Seaborn: A statistical data visualization library built on top of Matplotlib, Seaborn simplifies the process of creating aesthetically pleasing and informative visualizations. It offers a high-level interface for drawing statistical graphics and comes with several built-in themes and color palettes.

In this research project, visualizations created in Jupyter Notebook play a crucial role in illustrating the process of building machine learning models using two algorithms: Linear Regression (Figure 4) and Random Forest Regressor (Figure 5). These plots enable a better understanding of the models' behavior and performance, offering insights into the complex relationship between trademark filings and GDP growth.



a b

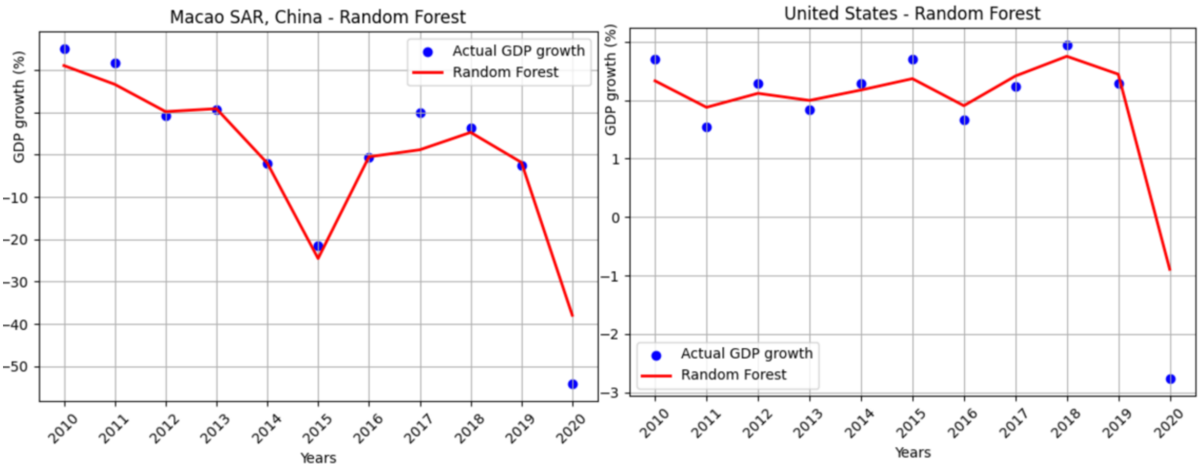
Figure 4: Example of model fitting using linear regression for: a) China; b) USA.

Linear Regression is a popular and widely-used statistical method for modeling the relationship between a dependent variable (in this case, GDP growth) and one or more independent variables (in our study, the number of trademark filings). The general formula for a simple linear regression is as follows:

$$y = \beta_0 + \beta_1 x + \varepsilon \tag{1}$$

Here, 'y' represents the dependent variable (GDP growth), 'x' is the independent variable (trademark filings), 'β_0' is the y-intercept, 'β_1' is the slope of the regression line, and 'ε' is the residual error term. The goal of linear regression is to find the optimal values for 'β_0' and 'β_1' that minimize the sum of squared residuals, thereby providing the best-fitting line to model the relationship between the two variables.

On the other hand, Random Forest Regressor [20, 21] is an ensemble learning method that operates by constructing multiple decision trees during the training phase. The final prediction is obtained by averaging the individual predictions of these decision trees. Random Forests offer several advantages over single decision trees, such as reduced overfitting and improved generalization performance. The algorithm uses a technique called bagging (bootstrap aggregating) to create multiple random samples with replacement from the original dataset, each of which is used to train an individual decision tree. Additionally, it employs random feature selection at each node split, further diversifying the decision trees.



a **b**

Figure 5: Example of model fitting using random forest for: a) China; b) USA.

For each country the future GDP growth is predicted using the two machine learning models. Additionally, the actual GDP growth and GDP services percentage are extracted for each country. The resulting predictions are compiled in a DataFrame, aptly named 'predictions.' The 'predictions' DataFrame is saved to a new CSV file, enabling further analysis and interpretation. This study contributes to the understanding of the intricate relationship between trademark filings and economic growth, offering valuable insights for policymakers and businesses alike.

4. Evaluating the Accuracy of Predicted Indices Against 2021 Real-World Data

In this case, we evaluate the accuracy of machine learning models, in particular linear regression, and random forest regressor algorithms, comparing their predicted GDP growth values [28] with actual GDP growth data for 2020. The obtained data are summarized in Table 3. Analyzing the results, we can observe the forecasts generated by the linear regression and random forest regressor models, as well as data on the actual GDP growth and percentage of GDP services for each country. This comparison allows us to understand the accuracy of the models for forecasting GDP growth, as well as their potential limitations.

The analysis of the predicted GDP growth against the actual GDP growth for 160 countries reveals some interesting statistics [29, 30]. Comparing the difference between the "Linear Regression predicted GDP growth" and the "GDP Services Percentage," we observe the following trends:

1. For 130 countries (81.25% of the total), the difference between the predicted GDP growth using Linear Regression and the actual GDP Services Percentage is less than 10%. This indicates that the Linear Regression model is able to provide a reasonably close estimate of the GDP growth for the majority of the countries.
2. In 88 countries (55% of the total), the difference between the predicted GDP growth using Linear Regression and the actual GDP Services Percentage is less than 5%. This further highlights the model's ability to predict GDP growth reasonably well for more than half of the countries.
3. For 16 countries (10% of the total), the difference between the predicted GDP growth using Linear Regression and the actual GDP Services Percentage is less than 1%. This demonstrates that the Linear Regression model has a high level of accuracy in predicting GDP growth for a small subset of countries.

When comparing the difference between the "Random Forest predicted GDP growth" and the "GDP Services Percentage," we observe the following patterns:

1. For 136 countries (85% of the total), the difference between the predicted GDP growth using Random Forest and the actual GDP Services Percentage is less than 10%. This suggests that the Random Forest model also provides a reasonably close estimate of the GDP growth for most countries.
2. In 87 countries (54.38% of the total), the difference between the predicted GDP growth using Random Forest and the actual GDP Services Percentage is less than 5%. This indicates that the

Random Forest model performs comparably to the Linear Regression model in terms of predicting GDP growth for more than half of the countries.

For 19 countries (11.88% of the total), the difference between the predicted GDP growth using Random Forest and the actual GDP Services Percentage is less than 1%. This shows that the Random Forest model is highly accurate in predicting GDP growth for a slightly larger subset of countries compared to the Linear Regression model.

Table 3

Sorted by GDP growth part of result.

Country	Linear Regression predicted GDP growth (%)	Random Forest predicted GDP growth (%)	Country GDP Growth (%)	GDP Services Percentage (%)
Maldives	-1,593750951	7,375382778	41,74510055	73,24826534
Monaco	2,66212091	3,866802749	21,5535607	80,08530545
Guyana	5,068443291	3,591199595	20,06001095	30,83203858
Macao SAR, China	-29,92549348	-37,94262356	19,26705638	94,1751639
Panama	-0,339297352	2,521730637	15,33587393	66,00543541
Belize	-2,231802443	-1,110559651	15,22613065	61,82963877
Moldova	4,314691544	5,901800134	13,9445896	54,85481421
Bahamas	0,947325162	2,688577487	13,71973494	78,57537962
Ireland	8,721480184	6,757583979	13,58824711	55,36427388
Peru	-3,249538931	-1,021151285	13,34950908	49,21359001

These statistics demonstrate that both the Linear Regression and Random Forest models can provide reasonably accurate predictions of GDP growth for a large number of countries. However, there is still room for improvement in the models' accuracy, which could be achieved by incorporating additional economic factors and considering the impact of significant events such as the COVID-19 pandemic.

The table (Table 3) presented above lists the top 10 countries with the highest GDP growth for 2021. It showcases the difficulty in predicting substantial GDP growth rates accurately using the Linear Regression and Random Forest models.

For instance, Maldives, which experienced a real GDP growth rate of 41.75% in 2021, had a negative Linear Regression predicted GDP growth of -1.59% and a Random Forest predicted GDP growth of 7.37%. Similarly, Macao SAR, China, with a real GDP growth rate of 19.27% in 2021, had a significantly negative prediction from both models, with -29.93% from Linear Regression and -37.94% from Random Forest.

These discrepancies highlight the challenge of accurately predicting such high GDP growth rates, as these exceptional cases are often driven by unique factors or specific circumstances that may not be captured by the models. Some of the reasons for the large prediction errors could be due to:

1. Insufficient or inaccurate data: The models may not have enough data or may rely on outdated information to make accurate predictions, especially for countries experiencing rapid economic changes.
2. Influence of external factors: Some countries might have experienced significant economic events, such as natural disasters, political instability, or the COVID-19 pandemic, which can have a substantial impact on GDP growth rates but may not be fully accounted for in the models.
3. Non-linear relationships: The relationship between trademark filings and GDP growth might not be linear, making it difficult for the Linear Regression model to capture the nuances in the data. While the Random Forest model is better suited for handling non-linear relationships, it may still struggle to predict extreme GDP growth rates.
4. Model limitations: The models used in this study are relatively simple and may not capture the complex relationships between various factors that influence GDP growth.

In conclusion, predicting high GDP growth rates accurately remains a challenging task for machine learning models, as the factors contributing to such growth are often unique and complex. To improve the predictive accuracy of the models, it may be necessary to incorporate additional economic variables and consider the impact of significant events, such as the COVID-19 pandemic, which have had a profound effect on global economies.

The COVID-19 pandemic has had a profound negative impact on the global economy, causing disruptions to supply chains, workforce reductions, and changes in consumer behavior. This unprecedented event has led to significant fluctuations in GDP growth rates across countries, which may have influenced the results of our machine learning models' predictions.

The effects of the pandemic on GDP growth are not directly accounted for in our models, as they focus on the relationship between trademark filings and GDP growth. However, the pandemic has likely impacted the number of trademark filings, as businesses faced financial constraints, operational challenges, and shifts in priorities. As a result, the models might not accurately capture the full extent of the pandemic's impact on GDP growth.

In some cases, our models may overestimate or underestimate GDP growth, as they do not consider the unique circumstances and economic consequences of the COVID-19 pandemic. For instance, the case of Myanmar, where the Linear Regression model predicted a GDP growth of 7.00%, is in stark contrast to the actual GDP growth of -17.91%. This substantial deviation can be attributed to the combined effects of the pandemic and political instability, which our models did not account for.

To improve the accuracy of our models and better understand the relationship between trademark filings and GDP growth in the context of the COVID-19 pandemic, it would be beneficial to incorporate additional factors related to the pandemic's impact. These factors could include government policies, stimulus measures, and sector-specific disruptions, which would provide a more comprehensive understanding of the complex interplay between the pandemic, trademark filings, and economic growth.

5. Conclusion

In conclusion, this article has explored the multifaceted relationship between trademarks and the worldwide economy, providing valuable insights into the role of intellectual property in fostering economic growth and development. Through an extensive examination of trademark trends across approximately 160 countries, we have uncovered intriguing patterns that shed light on the significance of trademark filings as an economic indicator.

By developing a machine learning model using Scikit-Learn and NumPy, we have demonstrated the potential of using advanced algorithms to predict GDP growth based on trademark filing data. Our models, namely Linear Regression and Random Forest, served as useful tools for analyzing complex relationships between economic variables, although predicting extreme GDP growth rates remains a challenge. The Linear Regression model was able to closely estimate the GDP growth for a majority of the countries. Specifically, for 81.25% of the countries, the difference between the predicted and actual growth was less than 10%, and for 55% of the countries, the difference was less than 5%. This demonstrates the potential of linear regression models in providing reliable estimations for economic indicators. Moreover, in our model, we take into account the size of the country indirectly, since GDP growth is inherently a relative indicator. This means that the number of trademark applications contributes to GDP growth in relation to the country's economic size and population. However, the number of trademark applications is not always directly proportional to the population. There are smaller, highly innovative economies with high trademark filing rates and larger countries with lower rates.

Evaluating the accuracy of our predicted indices against real-world data from 2021 has revealed both the strengths and limitations of our models. While some predictions closely align with actual GDP growth rates, others show significant discrepancies, particularly for countries experiencing rapid economic change or those affected by external factors such as the COVID-19 pandemic. This highlights the importance of incorporating additional economic variables and considering the impact of significant events when building predictive models.

In summary, the study of trademarks and their impact on the global economy offers valuable insights for policymakers, businesses, and researchers alike. As we continue to refine our models and incorporate new data sources, we can expect to gain an even deeper understanding of the complex interplay between intellectual property, innovation, and economic growth [19]. By harnessing the power of machine learning and advanced data analysis, we can better inform decision-making and develop strategies that foster sustainable and inclusive growth for all nations.

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