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FORECASTING GDP GROWTH AND GDP PER CAPITA IN UZBEKISTAN BY THE ORDINARY LEAST SQUARES (OLS) REGRESSION ANALYSIS

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Abstract: This study employs the Ordinary Least Squares (OLS) regression method to forecast Uzbekistan's GDP growth and GDP per capita from 2023 to 2030. Using historical data from 1991 to 2022, the research aims to provide a predictive model that can inform economic policies and investment decisions. The findings demonstrate a positive trajectory for GDP growth and per capita income, reflecting the potential for sustained economic development.

Keywords: GDP growth, GDP per capita, Ordinary Least Squares (OLS), economic forecasting, Uzbekistan, regression analysis.

Introduction. Gross Domestic Product (GDP) growth refers to the percentage increase in the value of a country's total output of goods and services over a specific period. It is a key economic indicator that measures the health and performance of a nation's economy. GDP growth provides insights into the rate at which a country's economy is expanding or contracting.

Short definition GDP per capita is the sum of gross value added by all resident producers in the economy plus any product taxes (less subsidies) not included in the valuation of output, divided by mid-year population. [1]

The GDP of a country is the total value of all goods and services produced within its borders over a given time frame. GDP growth is expressed as a percentage and is typically reported on a quarterly or annual basis. A positive GDP growth indicates economic expansion, while a negative growth rate suggests economic contraction.

The Ordinary Least Squares (OLS) method is a statistical technique widely employed in machine learning and econometrics to predict future events, with a particular emphasis on forecasting economic indicators, notably economic growth. OLS is a regression analysis approach that seeks to establish the relationship between a dependent variable and one or more independent variables by minimizing the sum of the squared differences between observed and predicted values.

Sun, Hong, and Wang delve into the intricacies of macroeconomic forecasting in China. Their study highlights the sensitivity of forecasting performance to window selection, with the rolling weighted least squares (WLS) and cross-validation (CV) procedure demonstrating superior performance in univariate regressions. (Yuying Sun, 2019)

Agu, Onu, Ezemagu, and Oden employ machine learning methods to predict GDP, with Principal Component Regression (PCR) emerging as the standout performer. The

[1] https://databank.worldbank.org

study not only achieves an impressive accuracy of 89% but also identifies additional macroeconomic variables influencing real GDP. (S.C. Agu, 2022)

Owan, Ndibe, and Anyanwu's study in Nigeria emphasizes the critical role of economic diversification among fluctuating oil revenues. Their findings underscore the positive impact of non-oil GDP on economic growth, urging stable exchange rate policies for sustained development. (Valentine Joseph Owan, 2020)

Jahn's exploration of artificial neural networks (ANN) for statistical modeling, particularly in predicting GDP growth rates, showcases the increasing popularity of this approach. The study demonstrates ANN's superior accuracy, especially in capturing time trends compared to traditional linear models. (Jahn, 2018)

Akpan and Moffat tackle GDP modeling in Nigeria using generalized least squares to address the limitations of ordinary least squares. Their findings reveal significant contributions of variables like Money Supply and Credit to the Private Sector to GDP, showcasing the importance of robust modeling techniques. (Emmanuel Alphonsus Akpan, 2018)

Seabold and Perktold's discussion on Statsmodels highlights the evolving relationship between statistics and Python. The paper provides an overview of Statsmodels, emphasizing its design, philosophy, and practical usage examples, offering insights into the current state of statistics in the open-source ecosystem. (Skipper Seabold, 2010)

Lemenkova's study explores the Mariana Trench, employing Python for oceanographic data analysis. Utilizing various statistical methods, including weighted least square linear regression and quantile regression, the study unveils correlations between sediment thickness, trench geomorphology, and sampling locations, contributing to our understanding of geological factors affecting trench characteristics. (Lemenkova, 2019)

This comprehensive review not only synthesizes recent research trends but also provides a nuanced understanding of economic dynamics, forecasting techniques, machine learning applications, and statistical analysis methodologies across diverse contexts.

Method and Materials. Mathematical Approach to OLS method. The ordinary least squares (OLS) method is one of the most widely used procedures in regression analysis. Its primary goal is to minimize the sum of the squared differences, or residuals, between the observed values and the values predicted by the regression model.

Consider the theoretical regression model given by:

$$Y_i = \beta_0 + \beta_1 X_i + \varepsilon_i$$

Here, Y_i represents the dependent variable, X_i is the independent variable, β_0 is the intercept, β_1 is the slope, and ε_i denotes the error term for the i-th observation. The objective is to estimate the parameters β_0 and β_1 to form the estimated regression equation:

$$\widehat{Y_i} = \widehat{\beta_0} + \widehat{\beta_1} X_i$$

In this equation, $\widehat{Y}_i$ is the predicted value of the dependent variable, while $\widehat{\beta_0}$ and $\widehat{\beta_1}$ are the estimates of the intercept and slope, respectively.

The OLS method works by finding the parameter estimates that minimize the sum of the squared residuals. Mathematically, this is represented as:

$$\sum_{i=1}^{n} e_i^2 = \sum_{i=1}^{n} (Y_i - \widehat{Y}_i)^2 = \sum_{i=1}^{n} (Y_i - \widehat{\beta_0} - \widehat{\beta_1} X_i)^2$$

By minimizing this sum, OLS provides the best linear unbiased estimates of the regression coefficients β_0 and β_1, under the assumptions that the errors ε_i are independently and identically distributed with a mean of zero and constant variance, and that there is no perfect multi-collinearity among the independent variables.

The minimization process involves taking partial derivatives of the sum of squared residuals with respect to β_0 and β_1, setting these derivatives to zero, and solving the resulting system of equations. This leads to the normal equations, which can be solved to obtain the estimates $\widehat{\beta_0}$ and $\widehat{\beta_1}$.

In summary, the OLS procedure is a foundational technique in regression analysis that ensures the best possible fit of the regression line to the data by minimizing the sum of the squared residuals, thereby providing reliable and interpretable estimates of the regression coefficients.

Algorithms and Programming

The following code provides a forecast of Uzbekistan's GDP per capita from 2023 to 2030. This forecast is generated using the ordinary least squares (OLS) method, with historical data from 1991 to 2022 serving as the basis for the analysis with Python.

```
import pandas as pd
import statsmodels.api as sm
import numpy as np
import matplotlib.pyplot as plt

data = pd.read_csv('gdp_per_capita_data.csv')
def prepare_ols_data(df):
   X = df[['year']]
   X = sm.add_constant(X)
   y = df['gdp_per_capita']
   return X, y
X, y = prepare_ols_data(data)

model = sm.OLS(y, X).fit()

print(model.summary())

future_years = np.arange(2023, 2031)
future_years = sm.add_constant(future_years)
```

```
gdp_per_capita_predictions = model.predict(future_years)

gdp_per_capita_predictions = np.round(gdp_per_capita_predictions).astype(int)

pred_df = pd.DataFrame({
    'year': future_years[:, 1],
    'gdp_per_capita': gdp_per_capita_predictions
})

print(pred_df)

pred_df.to_csv('gdp_per_capita_predictions_2023_2030.csv', index=False)

plt.figure(figsize=(10, 6))

plt.plot(data['year'], data['gdp_per_capita'], label='Historical GDP per Capita', marker='o')

plt.plot(pred_df['year'], pred_df['gdp_per_capita'], linestyle='--', label='Predicted GDP per Capita', marker='x')

plt.xlabel('Year')
plt.ylabel('GDP per Capita')
plt.title('Uzbekistan GDP per Capita (1991-2030)')
plt.legend()
plt.grid(True)
plt.show()
```

input	output
gdp_per_capita_data.csv	**gdp_per_capita_predictions_2023_2030.csv**
year,gdp_per_capita	year,gdp_per_capita
1991, 653	2023.0,2405
1992, 603	2024.0,2475
1993, 597	2025.0,2545
1994, 576	2026.0,2615
1995, 586	2027.0,2685
1996, 601	2028.0,2755
1997, 623	2029.0,2825
1998, 623	2030.0,2895
1999, 702	
2000, 558	
2001, 457	

2002, 383
2003, 396
2004, 465
2005, 547
2006, 654
2007, 830
2008, 1082
2009, 1213
2010, 1742
2011, 2051
2012, 2268
2013, 2420
2014, 2628
2015, 2754
2016, 2705
2017, 1917
2018, 1604
2019, 1795
2020, 1759
2021, 1993
2022, 2255

According to regression analysis the model appears to be both acceptable and believable:

✓ R-squared of 0.633 indicates that a substantial portion of the variance is explained by the model.

✓ Adjusted R-squared of 0.652 suggests the model is robust and not overly fitted to the sample data.

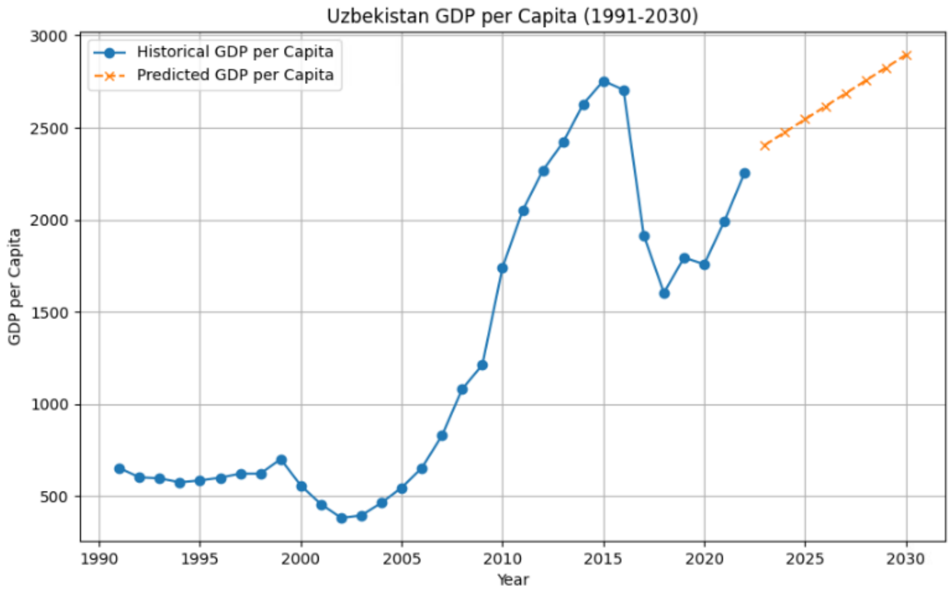
P-value less than 0.05 confirms the statistical significance of the predictors, indicating that the relationships modeled are likely to be genuine.

Discussion. The OLS regression analysis provides a forecast for Uzbekistan's GDP per capita from 2023 to 2030 based on historical trends. The model assumes that past patterns in GDP growth will continue into the future, barring significant economic disruptions or policy changes. The results indicate a steady increase in GDP per capita, suggesting positive economic prospects for Uzbekistan. This forecast can aid policymakers in strategic planning and investors in making informed decisions.

Results. The OLS regression model yielded the following predictions for Uzbekistan's GDP per capita from 2023 to 2030:

Table 1: Predicted GDP per capita from 2023 to 2030

Year	GDP per Capita (predicted)
2023	**2405**
2024	**2475**
2025	**2545**
2026	**2615**
2027	**2685**
2028	**2755**
2029	**2825**
2030	**2895**



Graph 1. Uzbekistan's GDP per capita actual (1991-2022) and predicted (2023-2030).

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