Stakeholder report

Introduction

In this assignment, we have been looking into the G20 members, excluding the European Union and including Denmark. Our focus has primarily been on predicting macroeconomic variables (such as GDP) from earlier values of those macroeconomic variables. Thus our model is based on time series. The Baseline model will be a supervised ML model, where our NN model will be made from an RNN model with LSTM timesteps.

Data

The data used for this assignment has been downloaded from various databases (World Bank, Eurostat etc.), and data has been selected for the time period 1970-2018 (2019 excluded due to lack of data). Data used is also annual, and not daily/quarterly/monthly etc.

Datasets can be downloaded through our GitHub page:
https://github.com/KristianJoergensen/worlddata/raw/master/worlddata.csv

Similarly our notebook can be viewed at:
https://colab.research.google.com/drive/1UA8uozjpuxoNDNcr-8pSkeV9i8zh9R0P

The following is a description of the variables in our dataset. When looking at the variables, they are named similar to: Denmark [DNK] - GDP (constant 2010 US$) [NY.GDP.MKTP.KD], or put in other terms: [Country name] - [Variable name] - [Variable code]. We are only describing the [Variable name].

- GDP (constant 2010 US$)
    - GDP calculated in 2010 US$ prices
- GDP growth (annual %) [NY.GDP.MKTP.KD.ZG]
    - Annual growth in GDP
- GDP per capita (constant 2010 US$)
    - GDP per capita in 2010 US$ prices
- Unemployment, total (% of total labor force) (national estimate)
    - National estimate of unemployment as a percentage of the nations entire labor force
- General government final consumption expenditure (% of GDP)
    - Governmental expenditure as a percentage of the entire nation’s GDP
- Population ages 15-64, total
    - Total population that is between 15 and 64 years old
- Current account balance (% of GDP)

    - Current account balance as a percentage of GDP
- Trade (% of GDP)
    - The sum of exports and imports of goods and services as a percentage of GDP
- Exports of goods and services (% of GDP)
    - Exports of goods and services as a percentage of GDP
- Imports of goods and services (% of GDP)
    - Import of goods and services as a percentage of GDP

Initially we tried using different methods to fill missing values, but since the missing values kept occuring in the same few variables, it ended up meaning that for some countries about half the values in a given variable were missing. Thus we ended up dropping those columns.

Problem

We often hear about the economy in the news. Maybe the newest numbers show that the economy is stagnating, or maybe it looks like the economy has never been better - regardless of what we hear, the economy is ever-changing, and very hard to predict. In this assignment we try to do just that: predict on the economy, using various variables as described above.

Based on this, we form the following problem statement:
Is it possible to predict future GDP using various macroeconomic variables?

To answer this question, we have to use time-series. First we make a baseline model using a Supervised Machine Learning model, to see how well the model is capable of predicting GDP. This baseline model was capable of predicting GDP with a root mean squared error of [xxx], meaning that the model, on average, is [xxx]% off. Thus if the actual GDP was 10.000, the model would then on average predict the value to be 10.000 +- [xxx]^2 - or in other words: it would predict the value to be between [low number] and [high number].

Following this we make a recurrent neural network model, using long-short-term-memory (LSTM), and the model is trained on data from the G20 countries including Denmark, and excluding the European Union. Following this we can evaluate the model's predictions on the individual countries included in the model. Doing so gives a root mean squared error of 795496007610 when evaluating GDP for USA. This might seem like a very large number, but when taking into account that the average GDP for the United States of America in the given time series is 10441635921920, it doesn't seem that bad. Thus the model is, on average, only off by roughly 7.62 percent. When working with macroeconomic models, it can be extremely hard to get very precise models, and thus we consider this precision to be acceptable.

Similarly we can evaluate the model on other countries. Evaluating the model on Denmark gives a RMSE of 8513133790.076. Again this might seem like a large number. Comparing it to the

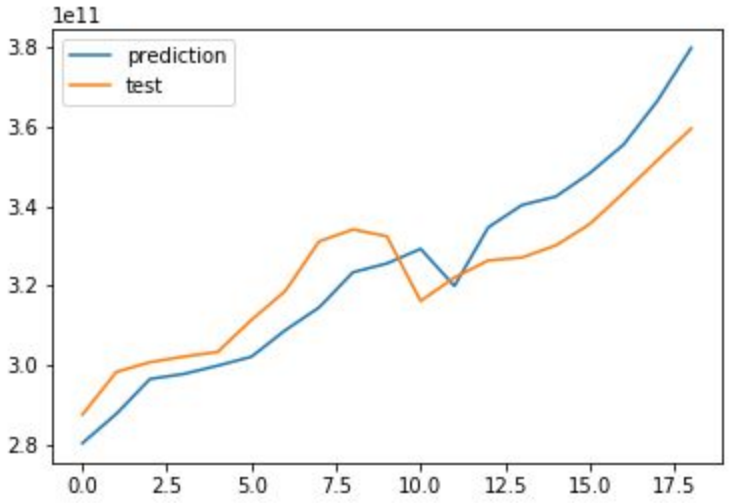
average GDP of Denmark, we find that the average GDP in Denmark is 253067706368, it turns out that the model is on average off by roughly 3.36 percent.

Comparing the two models, it appears that the neural network was better at predicting future GDP.

Results

Our baseline supervised machine learning model had a model performance of about 0.635. Our neural network model was capable of achieving an Root mean squared error of 0.005 (Scaled data), which seems to be significantly better. Accuracy can't really be measured correctly as it's not a classifier problem, that is why we're usually using RMSE.

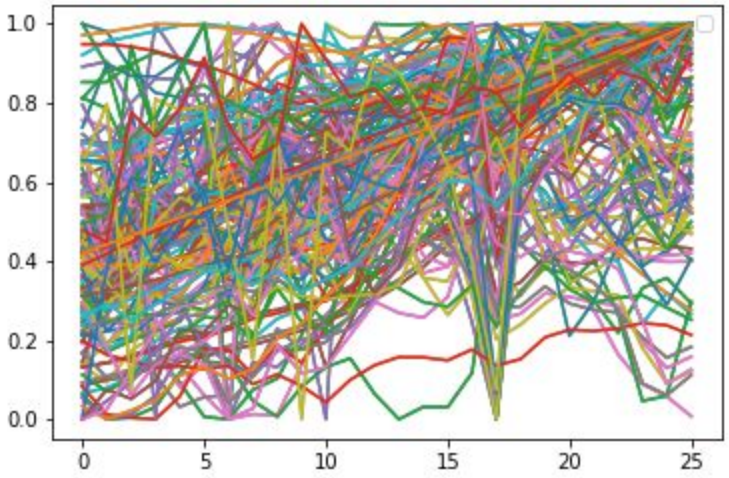
When looking at the baseline model, the predicted GDP can be plotted together with the test data and plots as follows:



As can be seen from the plot, the baseline model follows the general trend in the true values. It's important to note, that it first gets the decline in GDP (in the middle of the plot) in the following period. This suggests that a structural change in the underlying data, such as an economic crisis, is hard to predict in a model.

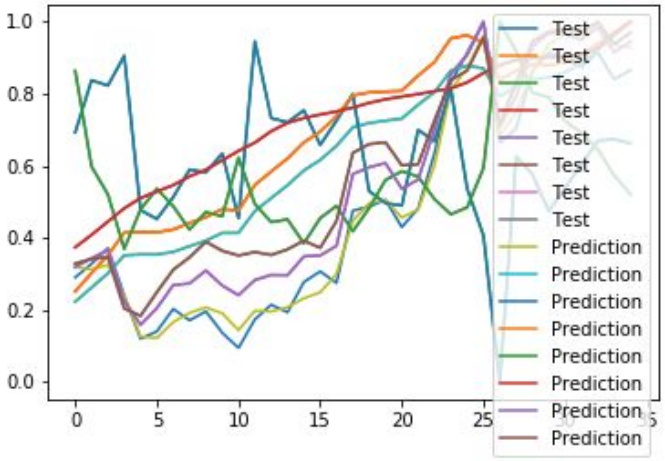
Recurrent Neural Network - LSTM model with time

We can predict in two ways, scaled and unscaled. If we look at the unscaled prediction we can take a look at all the variables in the dataset, this is useful as they're scaled, so every variable is within reach. If we look at the ordinary dataset of the G20, we can see the following.



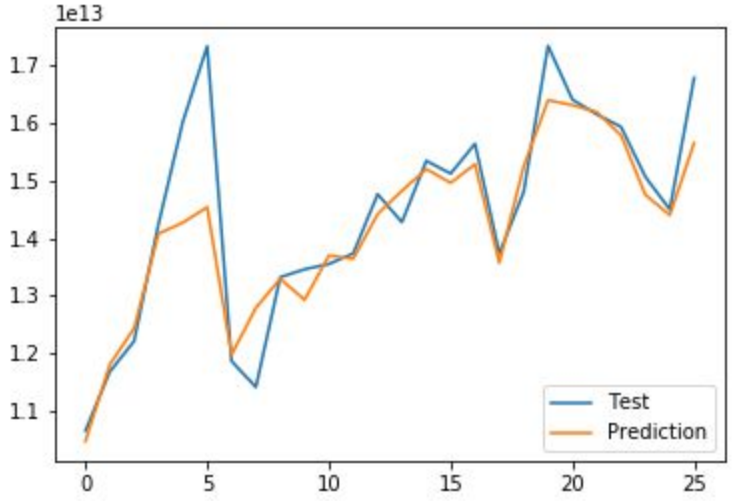
We have, on purpose, removed the labels, since we have 152 tests AND predictions, so a combined 304 variables. As you can see, there are some patterns but this mostly resembles a child's drawing, which is, at best, random.

Looking at the plot for the scaled, multiple output prediction for Denmark, we see the following.



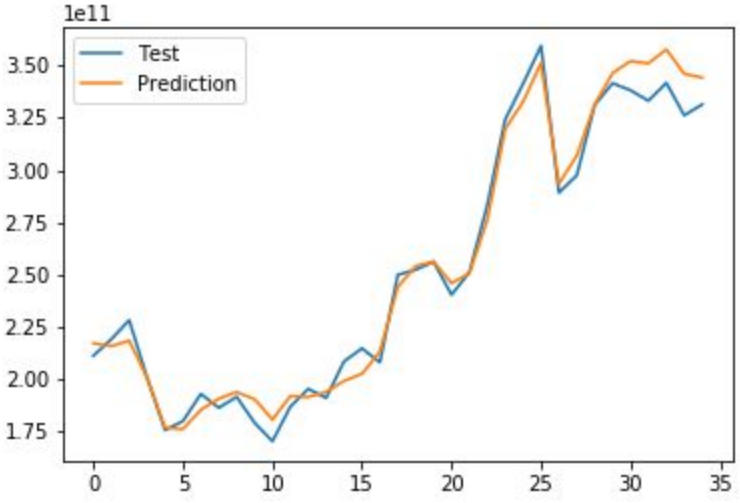
The top test and top prediction is the same variable. It's a little strange, but this is how python makes the plot. If we take the plot and look at the blue test, and yellow prediction, we see that these follow each other quite nicely.

Following this, we can also plot the predicted GDP of the US from our unscaled dataset. In this case we will show the values for the US GDP, together with the non-scaled prediction output. It doesn't make sense to plot multiple outputs/predictions of the non scaled dataset, as we will see many different value-ranges. Like the GDP of Denmark would be marginally lower than for the US. If looking at the difference id GDP and RMSE, the model is about 7.6% off.



Looking at the above plot, it looks like the model is fairly close to the true values. The model doesn't predict the big spike in the beginning, but later on it follows the true values more closely.

Finally we can plot the predicted GDP for Denmark from our recurrent neural network, this is done in the same methodology as prior, the model is about 3.4% off:



It looks like the model is actually quite good at predicting the danish GDP. The predicted values follows the true values much closer than before.