# Predicting Inflation using Long Short-Term Memory models

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*Our project will be showcased onto a webpage to make our results more accessible and visualizable.*

Measuring how the value of goods changes in an economy is a central component to understanding the current economic climate. Inflationary pressures are a source of uncertainty for consumers and businesses by influencing the value of assets over time. As a response, central banks enact monetary policy to keep inflation at a healthy and stable level as economies go through business cycles. Central banks, so far, have relied on a multitude of statistical methods to understand the dynamics of growth and inflation in order to conduct effective monetary policy. Among other methods, time-series regression models are among the top choices in attempting to forecast future economic conditions. Specifying functional forms to explicit regression problems allows us to capture relationships over time that are rooted in macroeconomic theory. Ultimately, the underlying assumption behind many econometric models is that co-movements between variables in the past should be informative of their future behaviour.

However, the foundation of econometric modelling carries some limitations and constraints. On one hand, the complexity of GDP and inflation may imply that a linear model in parameters will always be insufficient in capturing the underlying data generating process. While other factors might contribute to this process, the limited amount of available data is also an important source of concern to detect structural patterns of inflation. Moreover, time series regressions require equations to be specified beforehand. Because of this, economists will always run the risk of misspecifying models by potentially omitting relevant variables, or constructing an erroneous equation.

In this project, we would like to implement an alternative forecasting method to predict inflation using a Long Short-Term Memory (LSTM) model. Using deep learning techniques can provide additional features that linear regression models fail to capture. First of all, the architecture behind neural networks allows the model to estimate highly non-linear relationships. Doing so can help pin down complex patterns in data and potentially improve the quality of our forecasts. Additionally, many models in machine learning do not rely on any predetermined functional specifications. The model learns from itself by analyzing the data, and identifies deep relationships that are difficult to define through specific functional forms. To this day, Long Short-Term Memory (LSTM) models have proven to be particularly effective in machine learning problems involving pattern recognition in long sequences of data.

Our initial hypothesis that gives motivation to our LSTM forecasting exercise is that future inflation can be modelled by understanding its past dynamics. In our baseline model, we only take input lagged values of CPI as the determinants of inflation. Later, to expand beyond our plain “vanilla” model, we would like to consider a set of other lagged variables that can explain movements in inflation. According to economic theory, lagged GDP, unemployment, and oil prices are statistically significant proxies to measure changes in inflation.

Our dataset consists of monthly data on Canadian CPI (year over year percentage change) as well as other macroeconomic indicators relevant to our analysis. We initially omit the most recent of data points which will be used for our out-of-sample forecast. Then, we partition our remaining sample into smaller intervals. Each interval will contain $L+1$ data points, where $L$

is the number of input lags. To avoid bias and overfitting, the order by which we feed our interval inputs into the model will not follow a sequential time path. Instead, the order of our inputs will be determined by randomly sampling the intervals of our partition.

We will divide our sample of data as follows. 10% of the data will go towards our test set, another 10% towards the validation set, and the remaining 80% for the training data. Implementing Monte Carlo cross validation will help us repeat this process *k* times as we evaluate each potential model. The validation set is our instrument to choose the best set of hyperparameter values. In our LSTM model, the hyperparameters to consider are the start date of our time series, the number of epochs, the lag-length for each input (batch size), the learning rate for gradient descent, the activation function, the number of LSTM neurons and the dropout rate. When trying all the possible hyperparameter combinations for our model, the average Root Mean Squared Error (RMSE) over all *k* cross-validations will be used as our measure of accuracy. We will then leverage the best model and our most recent input data (excluded from our training/test/validation sets) for our out-of-sample inflation forecast.