FORECASTING UNEMPLOYMENT IN THE UNITED STATES

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ABSTRACT

The surge of the US unemployment rate up to 12.9 percent in 2020 Q2, the highest ever since the Great Recession due to the COVID-19 pandemic, has raised concerns for most policymakers. As per the Bureau of Labor Statistics, unemployment is defined as people who do not have a job, have actively looked for work in the past four weeks, and are currently available for work. Based on the new Keynesian theory on the output-inflation tradeoff, economic growth and FDI will positively impact the output growth and per capita income. Consequently, a negative relationship is expected between unemployment and GDP, FDI, and labor force. Therefore, this study will examine the evolution of the unemployment rate in the US and check the potential impact of key macro indicators such as GDP, FDI, Inflation, and Labor Force on unemployment. The paper will also analyze the difference by gender and state during the 1960-2020 period and discuss relevant models to forecast the unemployment rate in the US with careful assessment of the abnormal data in 2020. Given the linearity of the dataset, several linear models, including Naïve, Seasonal Naïve, STL Random Walk, Prophet, ETS, and SARIMA models, are used to forecast the unemployment rate. Among these models, SARIMA showed the best accuracy in calculating the MAPE/MASE and testing.

Index Terms – Unemployment; forecasting; time series; Naïve, STL, ETS, SARIMA, Prophet.

1 INTRODUCTION

Unemployment is an important indicator to determine the health of the economy. As unemployment costs go beyond just financial costs and pose significant challenges to the government, the surge in the number of unemployed people in the US during the COVID-19 outbreak by more than 14 million (from 6.2 million in February to 20.5 million in May 2020) has become a significant concern. It has led to a myriad of negative impacts on US society. This hike was the highest since the Great Recession.

Given the pandemic situation, it is imperative to forecast the future unemployment rate as this would help a nation better prepare for the future by creating more diverse job opportunities that would thereby help improve the economy of the country.

This study aims to forecast the unemployment rate in the United States and explore the gender unemployment gap. The project's scope goes further to grouping states with similar unemployment rates to transfer features within the same cluster.

In this paper, we will study the unemployment rate, which is the most frequent measure of unemployment. The unemployment rate is the number of unemployed people divided by the number of people in the labor force.

$$\text{Unemployment Rate} = \left(\frac{\text{Number of Unemployed}}{\text{Labor Force}}\right) * 100\%$$

where the labor force is the total number of people who want to work and can be defined as the sum of the employed and unemployed:

$$\text{Labor Force} = \text{Number of Employed} + \text{Number of Unemployed (seeking work)}$$

Information about the unemployment rate is provided by the Bureau of Labor Statistics of the US Government. The information is collected by surveying a sample of the US population and asks them about their employment status during the last week. During the survey, each adult (aged 16 and older) is classified as employed, unemployed, and out of the labor force. Employed are categorized people who worked at a full-time or part-time job. Unemployed are classified as people who didn't work but wanted to work and look for a job. Not in the labor force are classified as people who did not want to work, e.g., full-time students or retired people.

This study performed initial exploratory data analysis to gain insights into the trend, seasonality, and potential relationship among the parameters. The goal is to decide on the best model for forecasting unemployment, evaluate different methods used in forecasting unemployment and implement these methods and conclude on the best model that can be used for accurate unemployment forecasting. The sections in the report will detail the analysis as follows: section 2 describes the dataset, section 3 provides exploratory data analysis done to understand the data, section 4 explores the statistical theory and methods used, section 5 details the modeling and outcomes, and section 6 conclude the analysis with results and future work.

2 THE DATA SET

The data used for this project was sourced from the United States Bureau of Labor Statistics website and Federal Reserve Bank of St. Louis. The data is a time-series dataset collected from 1960 to 2020 in a quarterly manner. Besides unemployment, we have also considered GDP growth, CPI (Consumer Price Index), FDI (Foreign Direct Investment), and Labor force as potential factors that could impact unemployment. The target variable is the unemployment rate. The unemployment rate per gender and the unemployment rate per state were also included in the study. The length of the US unemployment time series is 244. The series object contains two outliers recorded in the year 2020; these values were not removed because the pandemic contributed to a decline in employment due to safety measures implemented by the government in the year 2020. There are also no missing values on the target variable. The data does not contain sensitive information that requires any form of anonymization.

3 EXPLORATORY DATA ANALYSIS

To better understand the dataset described in section 2, an exploratory data analysis was conducted. It includes trend analysis, seasonality check, and clustering of the time series sets. It helped to better understand the pattern of the target variable, detect outliers and abnormal events. The entropy of the target variable, the unemployment rate, is 1.021558, which implies that the complexity of the data is a bit above the average, which is enough to contain a certain amount of uncertainty and may derive interesting findings.

Firstly, the trend analysis of the target variable and potential regressors can be observed from plotting unemployment and key macro indicators together to see if any linear relationship exists. Fig.1 shows that unemployment in the US has experienced a strong upward trend during the period under review. Changes in the trend are likely attributed to the shift in political party governance and the economic recession and circle in each decade. There appeared to be a structural break in the early 1980s as the curve was stepped up marginally stronger than the normal trend observed from the previous period, which was attributed to the early economic recession situation in these years. Such chaos happened again during the Great Recession (December 2007 to June 2009) as unemployment surged significantly to peak at 11% in 2010, which was a wider change than the earlier short recession in the early 1980s. Recently, the concern has raised during the Coronavirus Disease 2019 (COVID-19) pandemic, impacting the US economy badly. Consequently, the unemployment rate peaked again to reach the record high ever in 2020 Q2 at 12.9% vs. the average rate of 4.0% of the same period in previous years. We validated such visualized observations with the high trend strength ratio of 0.9352319 while a moderate seasonality strength ratio of 0.3088236 for the unemployment data.

It is observed from other plots in Fig.1 that the trend of other key macro indicators including GDP growth, FDI, CPI, and labor force could partly explain the trend of unemployment. From the plot, the US's quarterly GDP had no clear trend at all, fluctuating around +/- 5%, being low in Q1 following a busy year-end festive season and performing strongly later in the years. Labor force showed a clear upward trend during the whole reviewed period, FDI has been flat till the increase in the late 2000s till now and CPI's fluctuations are small around less than 1%. These three indicators' movements seemed to have a correlated pattern to unemployment, which was in line with the above-mentioned new Keynesian theory on the output-inflation tradeoff regarding a negative relationship between unemployment and GDP, FDI, inflation, and labor force. However, the correlated pattern observed from plots in Fig.1 was not clear about such a relationship. It was confirmed further by the correlation matrix between unemployment data and other key macro indicators, there was limited correlation amongst these indicators as listed in Table 1 below.

	Unemployment	GDP Growth	FDI	CPI	Labor Force
Unemployment	1.00000000				
GDP Growth	-0.16574708	1.00000000			
FDI	-0.15309734	-0.06136419	1.00000000		
CPI	0.01803969	0.18539200	-0.31213268	1.00000000	
Labor Force	0.01803969	0.10543081	0.65848502	-0.26135695	1.00000000

Table 1: Correlation matrix – Unemployment and key economic indicators

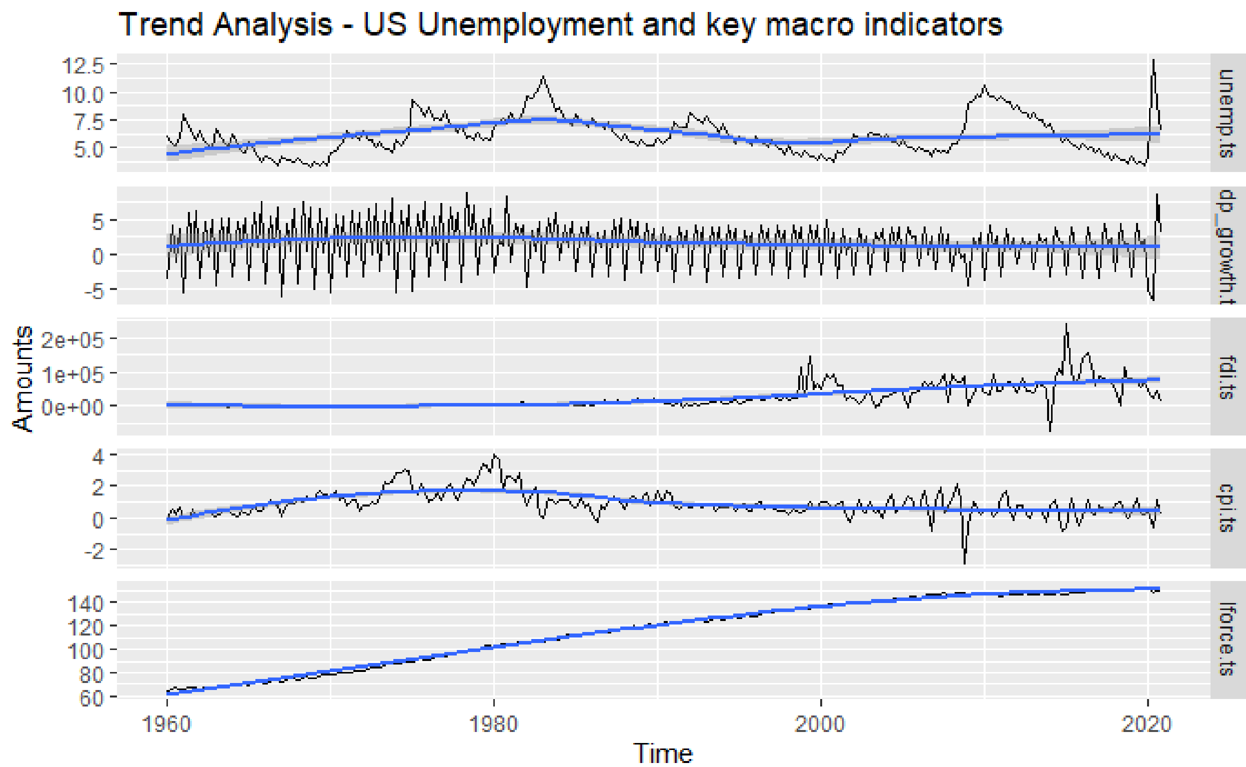


Fig 1: Unemployment and key macro indicators

The seasonality check confirmed the same findings by using polar and heat maps. There are clear signs of a mild seasonality (justified by the seasonal strength of 0.3). The trend for unemployment observed in Fig.2 of the polar map shows dark and light color gradients to overlap; this is because of the high volatility of the trend. The polar map shows an abnormal behavior for 2020 with a skewed wire toward Q2 in 2020 due to the outlier registered for this quarter. The same can be observed from the heat map. The darkest lines can be explained by the identical timestamps of recessions discussed in the trend analysis above and peak in the latest time stamps for 2020 in the heat map.

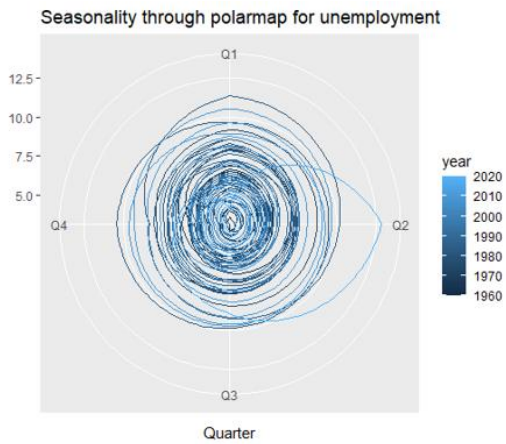


Fig 2: Polar map for unemployment

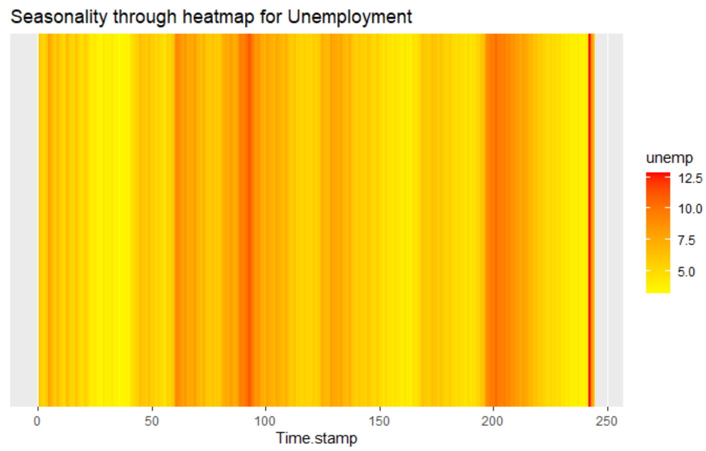


Fig 3: Heat map for unemployment

According to the lag plot (Appendix 7), dense gathering around the diagonal witnesses the autocorrelation with lags 1 and 2. It seems we have values very similar to the previous quarter's values. This means that the unemployment rate acts as an economic indicator such as a country's GDP and wouldn't change overnight.

Trend analysis of unemployment by gender is also implemented. Fig.4 shows that male unemployment has always been lower than female unemployment during the reviewed period, and the gap between these two rates was 3% in the 1960-1990 period and narrowed to 2% since the 1990s. This can be attributed to the US economy's situation that fewer job opportunities are available for females than males in the old ages. Such an issue has been improved thanks to economic development and the push for gender diversity in US society.

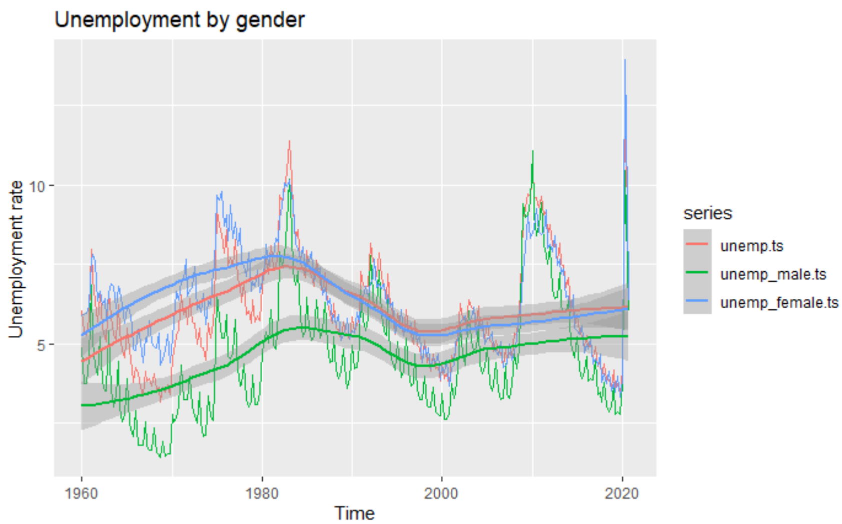


Fig 4: Trend Analysis for US Unemployment by gender

As our time-series data set has variables including the macro indicators for the whole US as well as gender and states data for unemployment, to gain better insights into the US unemployment, the data clustering was done for further similarity check. Upon applying different data clustering methods, including Elbow, Silhouette and Gap methods on the whole data set, from the output listed in Fig.18 in the Appendix, the optimal number of clusters can be 4 as the curve is flattened after the 4th cluster, meaning no more significant variance captured after that point. We did separate clustering, one for unemployment and key macro indicators only during the whole 1960-2020 period and one for the entire data set with data per state for the 2003-2020 period. The cluster dendrograms of both Correlation distance and ACF distance in Fig.5 show the similarity of unemployment and gender categories but quite a distance versus other vital macro indicators.

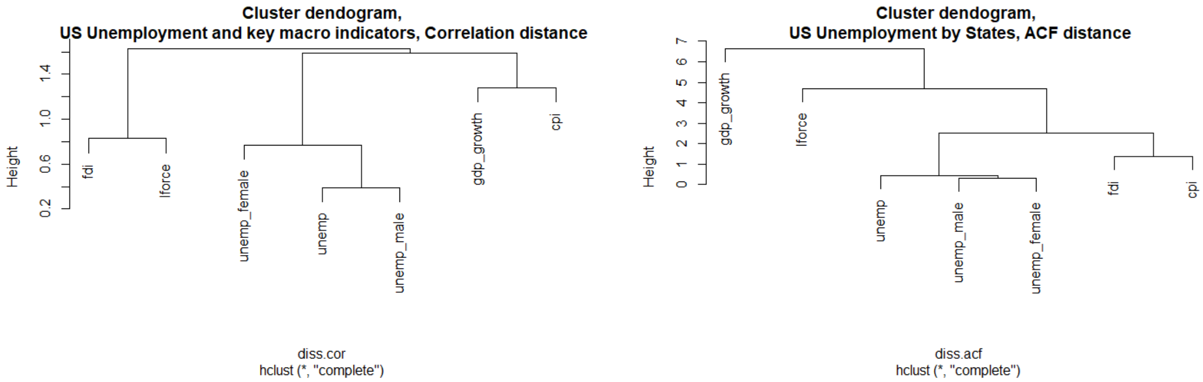


Fig 5: Unemployment and key macro indicators - Similarity check through correlation and ACF distances

Checking further the similarity for the whole data set with states' unemployment added using both correlation distances (Fig.19 in the Appendix) and ACF distances (Fig.6), both charts group the macro indicators separately from the state and gender data. The ACF distance appears to be a better choice to detect the dissimilarity between a pair of numeric time series based on their estimated autocorrelation coefficients and reasonable as one of these data items can impact the other with some lags in time. Interesting notes from the similarity check through ACF distances in Fig.6 are that most of the states that are grouped or close together in terms of similarity appear to have the industry strength or focus. Cluster 1 includes Alaska and North Dakota, both being offshore and known to be strong in oil and gas; Cluster 2 are groups of states with industry focus in manufacturing, IT, health care services, and insurance; Cluster 3 are mostly big economic hubs and strong in financial services, and Cluster 4 are states with lots of companies in oil & gas but onshore and in remote areas.

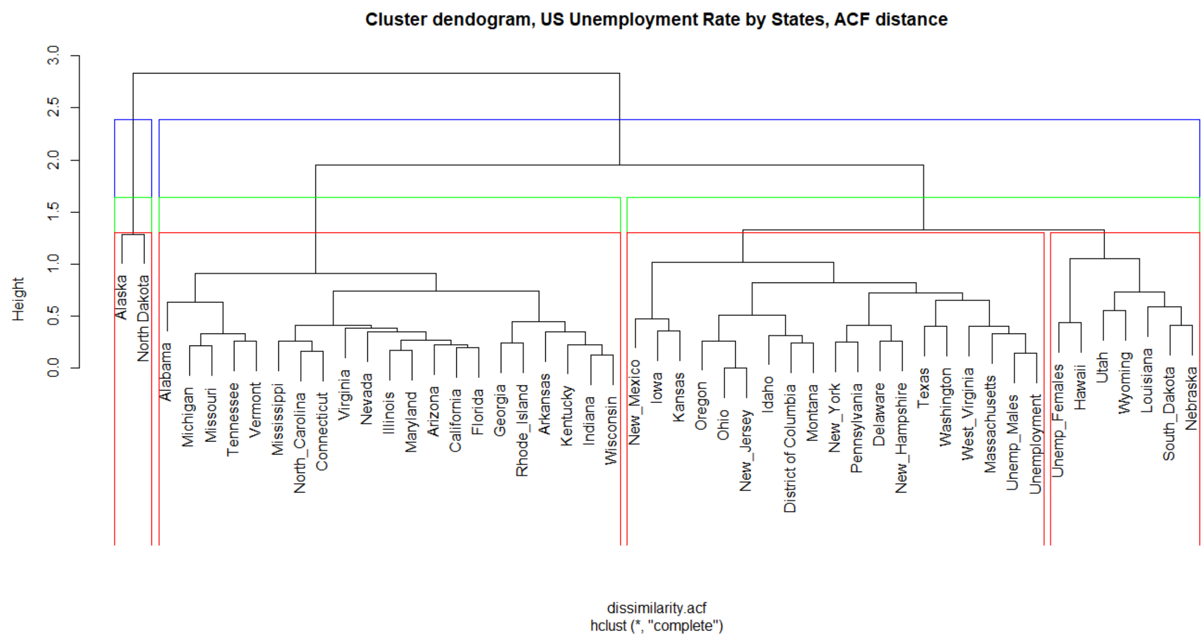


Fig 6: Similarity check through ACF distances

Further examination for the trend analysis with key states that are just picked from the above clustering is done as listed in Fig.7. The trend charts showed that except for those states with key industries easily exposed to strong hits from the economic chaos like key economic hubs (California), financial services (Michigan, Delaware, Massachusetts, New York) or manufacturing (Michigan, Utah) or tourism (Hawaii), most of the other states have witnessed the same trend as the whole US's unemployment. The regional disparities also mattered as observed from the ACF-distance cluster and trend analysis in states like North Dakota, Alaska, or Hawaii.

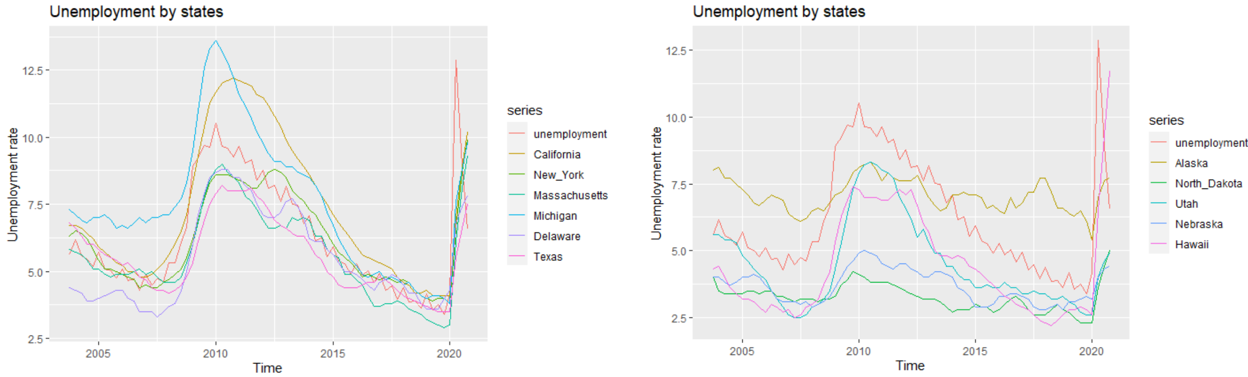


Fig 7: Trend Analysis for US Unemployment by States

While these observations for trend difference among gender and states in the US are interesting for a comprehensive view about unemployment trend in the US, these are of limited correlation to the target variable of unemployment, as evidenced via the correlation matrix. So, it is decided to just focus on forecasting unemployment based on its historic trend and seasonality pattern.

4 THEORY AND METHODS

Time series modeling is a great technique for modeling values of variable that are equally spaced in time. In this project, Naïve, Seasonal Naïve, Stl-Random Walk, ETS (Error-Trend-Seasonality), and Autoregressive Integrated Moving Average Model(ARIMA) were used to forecast unemployment in the United States. The specifics of each of these models is discussed below:

NAIVE Model

The naïve model is the simplest modeling method typically used as a benchmark. To forecast using naïve model, the forecasted values are set to the value of the last observation. It is mathematically denoted below:

$$X_t = X_{t-1} + \epsilon_t \text{ or } \hat{X}_t = X_{t-1}$$

SEASONAL NAIVE Model

The seasonal naïve model is similar to naïve model however, it is used for highly seasonal data. Forecasted values for seasonal naïve is set to the last value observed from the same season of the year for example, to forecast value of May 2019, the forecasted value will equal the last value observed in May 2018. It is mathematically denoted below:

$$X_t = X_{t-s} + \epsilon_t \text{ or } \hat{X}_t = X_{t-s}$$

where S is the seasonal period.

STL RANDOM WALK Model

$$X_t = X_{t-1} + \alpha + \epsilon_t \quad where\ \alpha\ is\ the\ drift\ and\ is\ zero\ when\ we\ have\ no\ drift$$

ETS Model

The ETS model is classified as a linear model that estimates parameters by using the maximum likelihood principle. This involves choosing a value of the parameter such that the observed data is most likely under the assumed model. The ETS model is robust and offers the following flexibilities; A: Additive, A_d: Damped Additive,M: Multiplicative, and N: No. A good ETS model minimizes the Akaike's Information Criterion (AIC) defined as:

$$AIC = \text{-2log(L)+2}k$$

$$AIC_c = AIC + \frac{k(k+1)}{T-k-1}$$

Aside from minimizing the AIC value, minimizing the Schwarz's Bayesian Information Criterion (BIC) is also a quality of good model. The BIC is written below as:

$$BIC = AIC + k\{log(T) - 2\}$$

Depending on the features of the dataset, the ETS model estimates the following parameters alpha: α, beta: β, phi: γ, and gamma: σ. α is the smoothing parameter for the level, it tells you how fast the level of the dataset is changing. High α value indicate that the level of the date is changing fast, a low α indicates the level of the dataset is changing slowly, a zero α value indicates a near stationary dataset, and value of α equal to one indicates random walk. β is a smoothing parameter for the slope, it describes the rate which the trend estimate is changing. If the value equal to 1, the slope will have no memory of past slopes, if 0, the slope does not change over time. γ is a damping parameter for the slope, if its 0, the slope will be damped immediately, else γ equals 1. σ is the standard deviation of the residuals. A smoother for a simple exponential smoothing model like an ETS(ANN) based on the assumption that the errors are independently normally distributed with mean of 0 and variance of σ^2:

$$e_t = X_t - a_{t-1} \sim N(0,\sigma^2)$$

can be written as follows:

$$a_t = a_{t-1} + \alpha e_t$$

$$X_t = a_{t-1} + e_t$$

where a_t: Exponentially weighted moving average at time *t*

a_{t-1}: The previous days level

e_t : error term

ETS(A,A,N), the Holt's linear method with additive errors is based on the assumption that one-step-ahead training errors are given by

$$e_t = X_t - a_{t-1} - b_{t-1} \sim N(0,\sigma^2)$$

And the equations can be written as follows:

$$X_t = a_{t-1} + b_{t-1} + e_t$$

$$a_t = a_{t-1} + b_{t-1} + \alpha e_t$$

$$b_t = b_{t-1} + \beta e_t$$

where α and β are smoothing parameters and a_t, a_{t-1} and b_t, b_{t-1} are states of the previous data.

ETS(A,Ad,A), the Holt's linear method with additive errors, additive damped trend components can be written as follows:

$$X_t = a_{t-1} + \phi b_{t-1} + s_{t-m} + e_t$$

$$a_t = a_{t-1} + \phi b_{t-1} + \alpha e_t$$

$$b_t = \phi b_{t-1} + \beta e_t$$

$$s_t = s_{t-m} + \gamma e_t$$

where a_t denotes the series level at time t, b_t denotes the slope at time t, s_t denotes the seasonal component of the series at time t, and m denotes the number of seasons in a year; α, β^*, γ and ϕ are smoothing parameters, $\phi_h=\phi+\phi^2+\cdots+\phi^h$.

ARIMA Model

Unlike the ETS model that is based on the trend and seasonality of dataset the ARIMA model focus on autocorrelation in the dataset. In this project, the non-seasonal ARIMA model was used, an autoregressive model of order ARIMA(*p, d, q*). The value of *p* is the order of the autoregressive model, *d* is the ordinary differencing, and *q* is order of the moving average. The ARIMA model uses a back shift operator B that has the effect of shifting data back on value or period. Also, forecasting with ARIMA model is done using a linear combination of past variables. Evaluating the performance of this model will be based on several performance metrics which will be discussed in the later chapters. The non-seasonal integrated Autoregressive Moving Average model can be written as:

$$(1 - \phi_1 B - \phi_2 B^2 - \ldots - \phi_p B^p)(1 - B)^d X_t = c + (1 + \theta_1 B + \theta_2 B^2 + \ldots \theta_q B^q)\epsilon_t$$

Where ϕ_1, ϕ_2, … ϕ_p are parameter estimates for autoregressive model of order p i.e., AR(p), c: mean, ϵ_t: error term, X_t: $values\ in\ the\ dataset$

$\theta_1, \theta_2, \ldots\theta_q$ are parameter estimates for moving average i.e., MA (q)

In case of drift and both ordinary and seasonal parts with seasonal period S, the equation can be written as:

$$(1 - \Phi_1 B^S - \ldots - \Phi_P B^{SP})(1 - B^S)^D \left(1 - \phi_1 B - \phi_2 B^2 - \cdots - \phi_p B^p\right)(1 - B)^d \left(X_t - \frac{\mu t^d}{d!}\right)$$
$$= (1 + \theta_1 B + \theta_2 B^2 - \cdots - \theta_q B^q)(1 + \Theta_1 B^S + \cdots + \Theta_Q B^{SQ})\ \epsilon_t$$

Prophet Model

In statistical analysis, detecting structural breaks is important because of the insight it provides. The Prophet model is a statistical model that can be used to detect changes in trends. It is a very powerful model as it can take care of layered seasonality, it can also estimate the effect of scheduled/unscheduled holidays and unforeseen disturbances which will be illustrated in the later session to determine the break point of change in unemployment gap for males and females in the United States. The prophet model has the form:

$$x_t = m_t + s_t + h_t + z_t$$

where:

m_t: Trend effect

s_t: Seasonality effect

h_t: Holiday effect

z_t: Random noise

Diebold-Mariano Test

Diebold-Mariano test was used in this paper to objectively assess the differences between models' accuracies and exclude the accuracy differences attributed by pure chance. The used hypothesis tests are as follows:

H_0: Two competing methods have the same forecast accuracy

H_a^{two}: The methods have different levels of accuracy

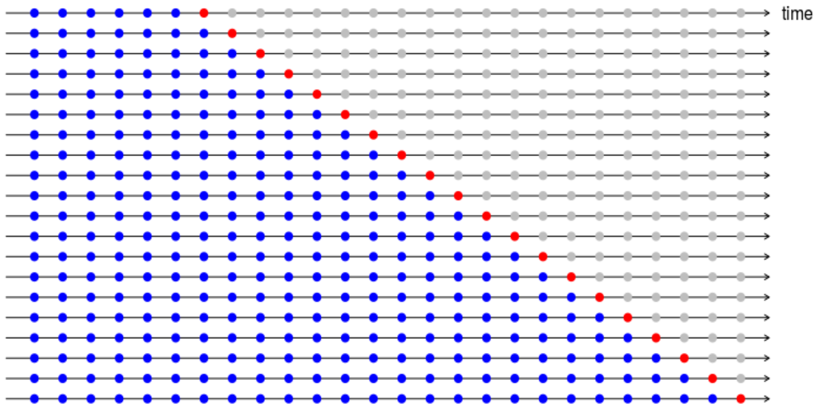
H_a^{less}: Method 2 is less accurate than method 1

$H_a^{greater}$: Method 2 is more accurate than method 1

Corresponding matrices for Diebold-Mariano tests including all six models were built and discussed in the Models section.

Rolling Window Cross Validation

The rolling window cross-validation is used to assess the best model for nowcasting, or that is forecasting only the next point in time. In this procedure, the test set consists of a single observation. The corresponding training set consists only of the observations that occurred before that single observation that forms the test set. The diagram below illustrates the sequences of training and test sets, where the blue observations form the training sets, and the red observations form the test sets.



The forecast accuracy is calculated by averaging over the test sets. This procedure is called "rolling window cross-validation" because the origin at which the forecast is based rolls forward in time. Normally the assessment can be done visually through a graph or by calculating the mean squared errors in time.

Retrospective Accuracy Analysis

In data analysis, it is good to know how specified models will forecast new data i.e., data that is outside our training and testing set, also to determine if the specified model won't change when new data is added to the existing dataset. A retrospective accuracy analysis can be used to determine how well our model learns and how fast it learns from its past errors to improve its forecasting performance. To determine a good model using the retrospective analysis, the model must have errors that are decreasing as new data is added, and these errors must converge to zero.

5 MODELING

The data analysis process started with cleaning the dataset to prepare the data for analysis by converting the target variable unemployment. Also, the data was decomposed into its component parts where the first panel depicts the dataset, the overall trend and seasonality (panel 2 and 3) and the error (panel 4)

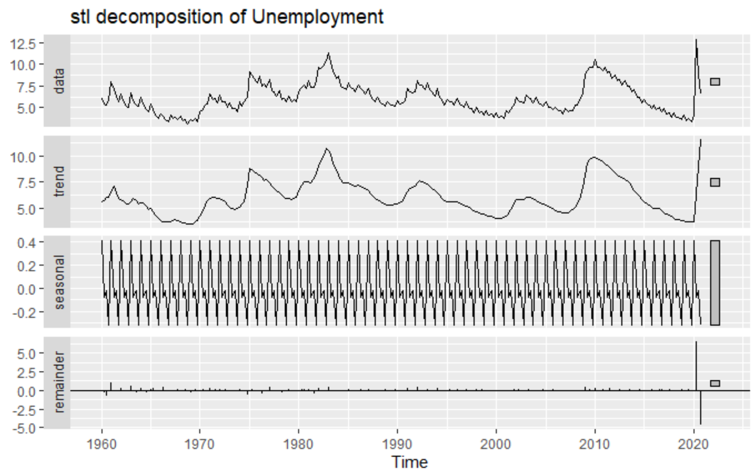


Fig 8: Decomposition of the data

Our target variable is the quarterly time series of the overall US unemployment data from Q1-1960 to Q4-2020, with 244 points (61 years) in total. Giving the entropy of 1.021558 we have decided to partition the data set based on 75:25 proportion with 61 points for the test subset and 183 points for the training subset.

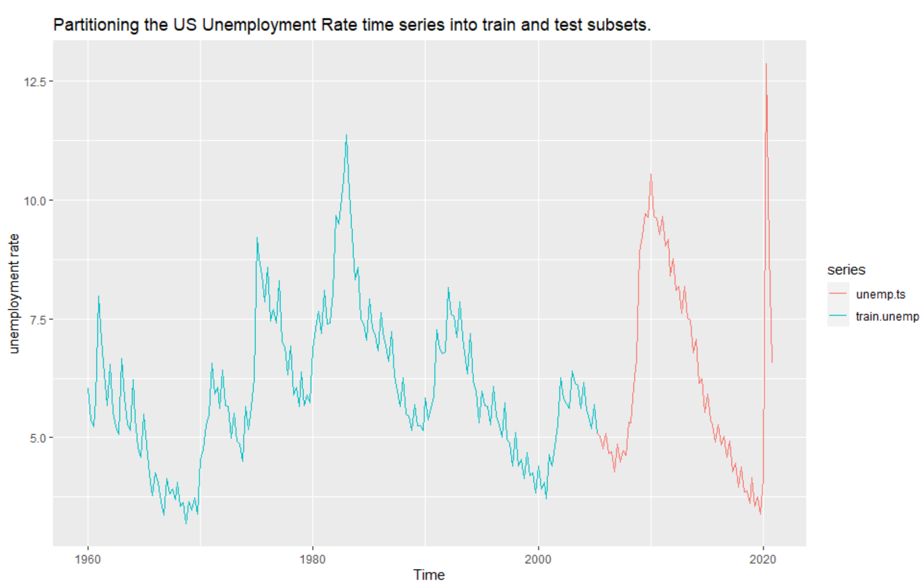


Fig 9: Data Partitioning

The nonlinearity test on the training subset opts for a linear nature of our dataset (Appendix 1). The proof is the p-values, which are more than 0.05 at 5% significance level for four out of six nonlinearity tests, with the null hypotheses “Linearity in mean” or “The time series follows some AR process”, meaning that we fail to reject the null hypotheses and conclude that the dataset is significantly linear at 5% significance level.

Given the linearity of the dataset, we have tried several linear models: Naïve, Seasonal Naïve, STL Random Walk, ETS, and SARIMA. Since our data set has different variability over time, we set lambda to "auto" for all our models, and a transformation will automatically be selected using BoxCox.lambda, which in our case is -0.4406952. We have opted for seasonal ARIMA because ndiffs() and nsdiffs() are both equal to one, meaning we need both ordinary and seasonal differences to transform the time series into stationary.

As a result, the best model in terms of both in-sample and out-sample accuracies is the STL Random Walk (Appendix 3), while it has problematic dependent residuals (Appendix 4).

The best ETS model is ETS(A,Ad,A). It incorporates a damping effect for the trend and has better in-sample and out-of-sample accuracy measures after STL Random Walk. However, ETS has problematic dependent residuals (Appendix 4), a hint that a better model can be found.

Before using ARIMA it is good to check the number of differences required to make a given time series stationary. To do that we have estimated the number of first differences necessary by using ndiffs and the number of seasonal differences necessary by using nsdiffs. Both are equal to one, meaning we need to take both ordinary and seasonal differences to get the best SARIMA or the best way would be to go with automatic ARIMA. The best SARIMA model using brute force method is ARIMA(2,0,1)(1,1,1)[4], while the best SARIMA using stepwise method is

ARIMA(3,0,2)(1,1,1)[4] (Appendix 2). The latter has better in-sample and out-sample accuracies; however, it is less parsimonious. Neither of them has problematic independent residuals. (Appendix 4).

The model ARIMA(2,0,1)(1,1,1)[4] with no drift has p = 2, d = 0, q = 1 for the ordinary part and P = 1, D = 1, Q = 1 for the seasonal part with seasonal period 4. The equation of our the Brute Force ARIMA model will be as follows:

$$(1-\Phi_1 B^4)(1-B^4)^1(1-\phi_1 B-\ \phi_2 B^2)(1-B)^0 X_t = (1+\theta_1 B)(1+\Theta_1 B^4)\ \epsilon_t$$

or

$$(1-\Phi_1 B^4)(1-B^4)(1-\phi_1 B-\ \phi_2 B^2)X_t = (1+\theta_1 B)(1+\Theta_1 B^4)\ \epsilon_t$$

where $\phi_1 = 1.6037,\ \ \phi_2 = \ -0.6729,\ \ \theta_1 = -0.2937;\quad \Phi_1 = 0.2163,\quad \Theta_1 = \ -0.7532$

$$(1-0.2163B^4)(1-B^4)(1-1.6037B+0.6729B^2)X_t = (1-0.2937B)(1-0.7532B^4)\ \epsilon_t$$

The model ARIMA(3,0,2)(1,1,1)[4] with no drift has p = 3, d = 0, q = 2 for the ordinary part and P = 1, D = 1, Q = 1 for the seasonal part with seasonal period 4. The equation of our Stepwise ARIMA model will be as follows:

$$\begin{gathered}(1-\Phi_1 B^4)(1-B^4)^1(1-\phi_1 B-\ \phi_2 B^2-\phi_3 B^3)(1-B)^0 X_t \\ = (1+\theta_1 B+\theta_2 B^2)(1+\Theta_1 B^4)\ \epsilon_t\end{gathered}$$

or

$$(1-\Phi_1 B^4)(1-B^4)(1-\phi_1 B-\ \phi_2 B^2-\phi_3 B^3)X_t = (1+\theta_1 B+\theta_2 B^2)(1+\Theta_1 B^4)\ \epsilon_t$$

where $\phi_1 = 1.7665,\ \ \phi_2 = \ -1.1822,\ \ \phi_3 = \ 0.3325,\ \ \theta_1 = -0.4806;\ \theta_2 = 0.4055;$

$\Phi_1 = 0.3661,\quad \Theta_1 = \ -0.8188$

To check if the differences in accuracies are not attributed to just pure chance, Diebold-Mariano (DM) tests for all pairs of the six models were run and corresponding matrices were built.

Here below a matrix of “less” type DM tests for in-sample accuracies using the following hypothesis test:

H_0 : two competing methods have the same forecast accuracy.

H_a^{less} : method 2 is less accurate than method 1.

P-values from less-than type test (in-sample accuracies)

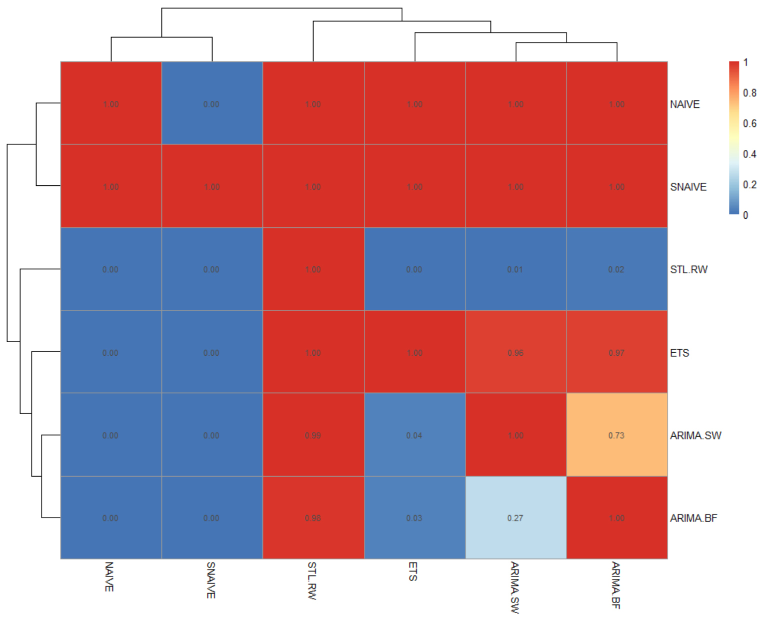


Fig 10: DM tests for in-sample accuracies

The rows represent method 1 and the columns represent method 2 when comparing them and testing the hypotheses. As an example, if we compare the STL.RW (row) with the NAÏVE (column), the p-value is zero, meaning at 5% significance level we reject the null hypothesis that states that the models have the same accuracy and opt for the alternative hypothesis stating that NAÏVE (the second model) is less accurate than the STL.RW (the first model). Using the same logic, we can list all the other models (from the column list) that are significantly less accurate (in-sample) than the STL.RW model. These are SNAIVE, ETS, ARIMA.SW, and ARIMA.BF. NAÏVE, SNAIVE, and ETS are significantly less accurate in-sample than ARIMA.SW. They are also significantly less accurate in-sample than ARIMA.BF. However, the DM test p-value when comparing ARIMA.BF and ARIMA.SW is 0.99, which means we fail to reject the null hypothesis and the conclusion is that these models are not significantly different in in-sample accuracies. If we check the two-tailed type tests (Appendix 5) almost all the models are different in terms of in-sample accuracies at 10% significance level except for ARIMA.BF and ARIMA.SW that is not significantly different having a DM test p-value = 0.53. As a result, even though these two models are different by the method applied (stepwise or brute force), they are not significantly different in terms of in-sample accuracy, and the fact that the in-sample MAPE and MASE are smaller for the stepwise version is just a pure chance and can be ignored. Other properties of good models has to be checked to decide on the model to choose.

Given the accuracies, to forecast several years in the future we recommend going with an ensemble weighted average: 10% STL Random walk, 10% ETS, 40% SARIMA with stepwise method, and 40% SARIMA with brute force method.

Rolling Window Cross-Validation

To choose the best model to forecast every next quarter with great precision we use the rolling window cross validation and the value of mean squared errors. The best model for nowcasting proves to be ARIMA with stepwise method because it has the smallest MSE value.

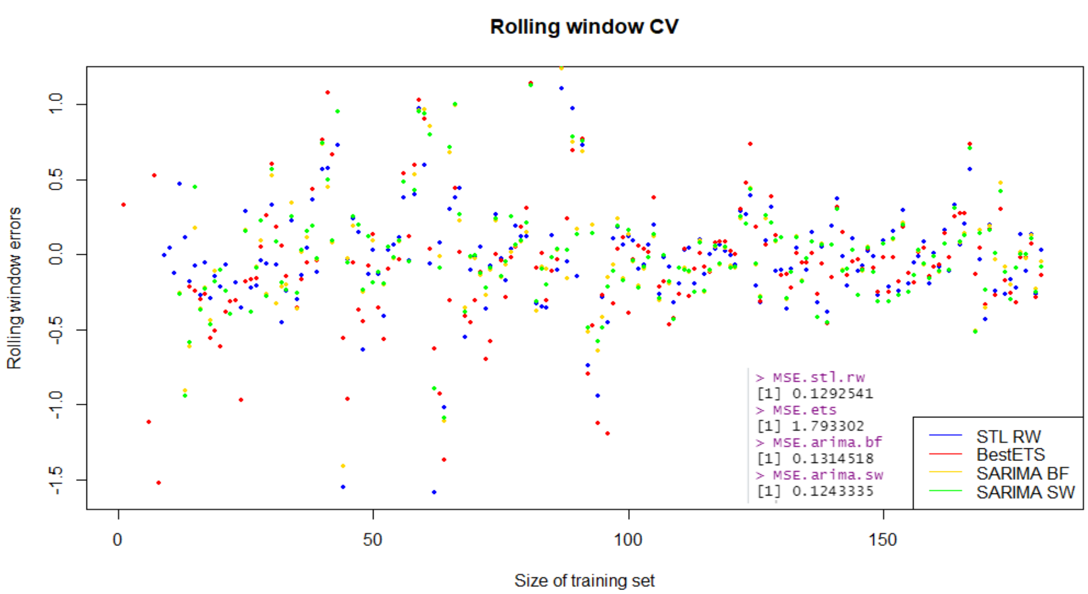


Fig.11. Rolling window cross-validation

Retrospective Accuracy Analysis

In Figure 12 below, it is observed amongst the models analyzed, ARIMA Stepwise (ARIMA(3,0,2)(1,1,1)[4]) has the best retrospective analysis because, unlike other models, its errors are decreasing more rapidly and gradually converging to zero.

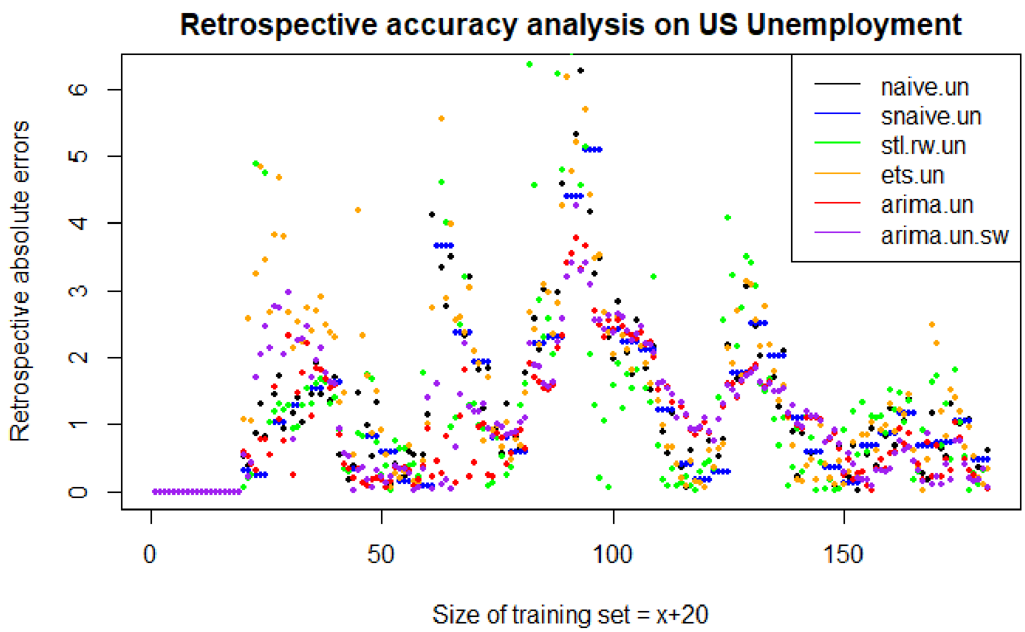


Fig.12. Retrospective accuracy analysis

Table 1 & 2 below summarizes the performance of all the models using a ten-point check list

Table 1

	Properties of Good Models	ARIMA Brute Force ARIMA(2,0,1)(1,1,1)[4]	ARIMA Stepwise ARIMA(3,0,2)(1,1,1)[4]
1	Small MAPE / MASE	+ (as per DM test)	+
2	Compact Forecast Interval		+
3	Small AIC	+	
4	Significant Parameters	+	+
5	Good Residual Properties	+	+
6	Good Retro Analysis		+
7	Rolling Window Analysis		+
8	No Model Violation	+	+
9	Logical	+	+
10	Parsimonious	+	

Table 2

	Properties of Good Models	ARIMA Brute Force	ARIMA Stepwise	ETS	STL RW
1	Small MAPE / MASE		+	++	+++
2	Compact Forecast Interval	++	+++		
3	Small AIC				
4	Significant Parameters				
5	Good Residual Properties	+++	+++		
6	Good Retro Analysis	++	+++	+	
7	Rolling Window Analysis	+	+++		++
8	No Model Violation	+++	+++	+++	+++
9	Logical	+++	+++	+++	+++
10	Parsimonious	+		++	+++

Detecting Structural Breaks with Prophet Model - US Unemployment Rate

Unemployment in the United States increased from 5.1% in January 1974 to 9.0% in May 1975. Even though it had gradually decreased to 5.6% by May 1979, unemployment began rising again. A sharp jump to 6.9% was registered in April 1980 and another to 7.5% in May 1980. Unemployment remained high during a mild recession that lasted from January to July 1980. Despite the recovery, unemployment remained at historically high levels (around 7.5 percent) until the end of 1981. The recession reached its peak in November and December 1982, when the national unemployment rate reached 10.8%, the highest level since the Great Depression (23%). This is validated by the structural break detected around 1982 by the prophet model.

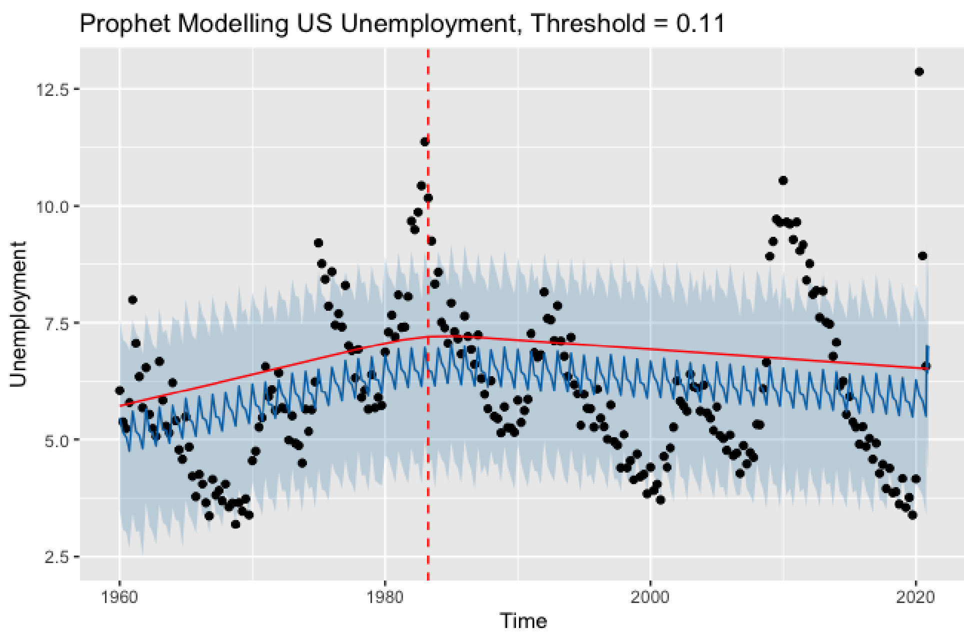


Fig.16. Prophet model, US Unemployment, threshold = 0.11

Economists have long recognized that the economy's overall output, as calculated by GDP, directly impacts unemployment. However, in 2009, the relationship between production changes and changes in the unemployment rate deviated from expectations. In 2009, strong productivity growth enabled businesses to lay off large numbers of workers while keeping production stable. The long-standing relationship between GDP and the unemployment rate, known as Okun's rule, was thrown into disarray by this action. If Okun's law remained in force in 2009, the unemployment rate would have risen by half as much as it did that year. This validates our conclusion that the macroeconomic indicators don’t have a relationship with the unemployment rate in our time series.

Detecting Structural Breaks with Prophet Model - Change Point in Gender Unemployment Gap

The unemployment gap is defined as the difference between the female unemployment rate and the male unemployment rate. The trend analysis for US Unemployment by gender says that between 1960 and mid-1980's, there is a large gap between the male and female unemployment rate. A trend plot to describe this is shown below:

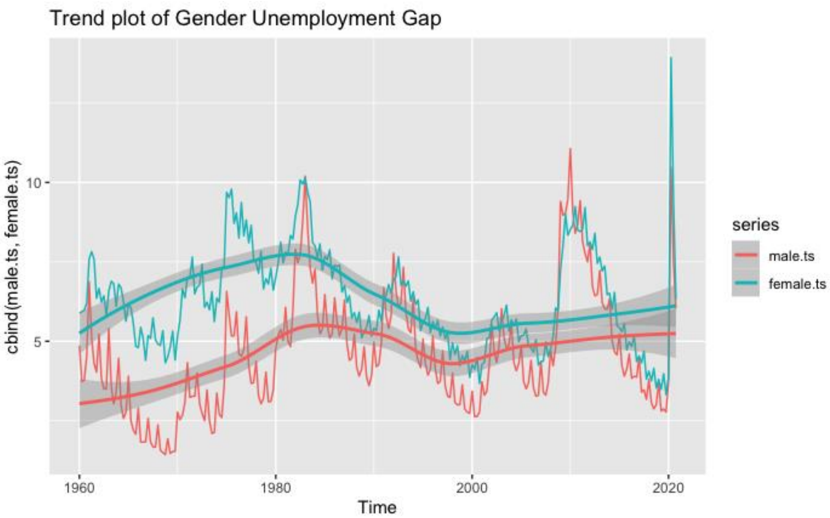


Fig.13. Trend plot of Gender Unemployment Gap

This means that sometime between year 1960 and mid 1980's, the unemployment rate of females was relatively higher than the unemployment rate of males. However, after that point it is observed that the gap reduced. It is important to note that several change points can be detected, which is very significant in statistical modelling because it provides insights into solutions that can be adopted if a similar occurrence (a gap) is observed by making reference to the factors that caused the change point, in this case, the factors that resulted in the reduction of the gender unemployment gap. To determine the break point for unemployment gap, the difference between employment rate for male and female was derived. Using the prophet model, setting the threshold to 0.16, the most significant change point was detected around 1970's based on the findings of our analysis. According to (Albanesi & Sahin, 2017), the gender unemployment gap[1] was no longer existent after early 1980's however, the article did not mention how it arrived at its conclusion. This means there's a possibility a significant change in the trend of unemployment between male and females in the US happened much earlier and was not detected. Furthermore, the paper also mentioned that the convergence in unemployment gap for both male and female was caused by a shrinking labor force[2]. The plot below shows the detected change point using prophet model.

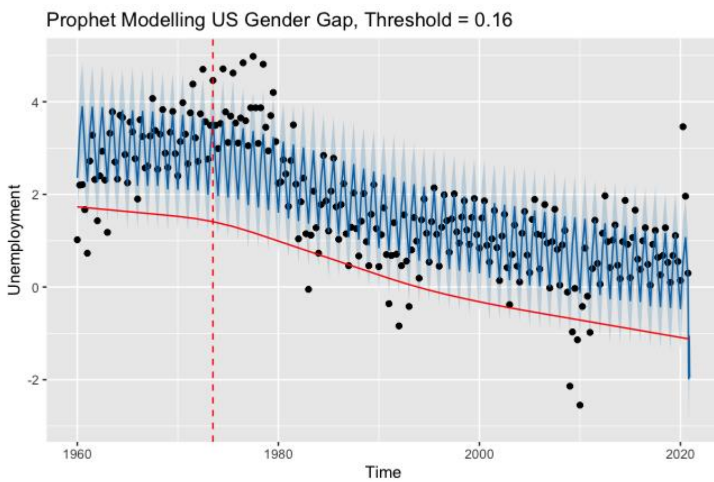


Fig.14. Prophet model – US Unemployment Gender Gap, threshold = 0.16

6 CONCLUSION

Unemployment is one of the major factors that affect a country's economy and is stated as one of the lagging indicators for a country's GDP. Unemployment can have many adverse effects on society wherein the loss of income by the parents can affect the future generation. It can also force

[1] Gender Unemployment Gap is the difference between the male and female unemployment rates
[2] Labor Force is the total number of people who are employed plus the unemployed looking for work (Amadeo, 2020)

people to leave their country in search of jobs. Prolonged unemployment also has psychological effects on an individual, leading to low self-esteem impacting family relationships. Hence, it is crucial to forecast this rate to be better prepared for the future.

This paper has presented linear models to forecast the unemployment rate in the United States. The best-suited model found to forecast the unemployment rate was chosen the stepwise seasonal ARIMA considering various parameters. The gender unemployment gap was also analyzed as an added feature to the project. One of the challenges was getting the data for the unemployment rate on a state-wide basis, which was only available from 2003. With the optimal 4 clusters, the unemployment data by states were grouped in terms of industry focus, and it can be used to transfer features between states within the same cluster.

A couple of models were built, and several good models were chosen considering various factors like better performance metrics, compact forecast intervals, independent residuals, significant parameters, etc. Overall, the results lead to a successful potential forecasting approach for the unemployment rate.

FUTURE WORK

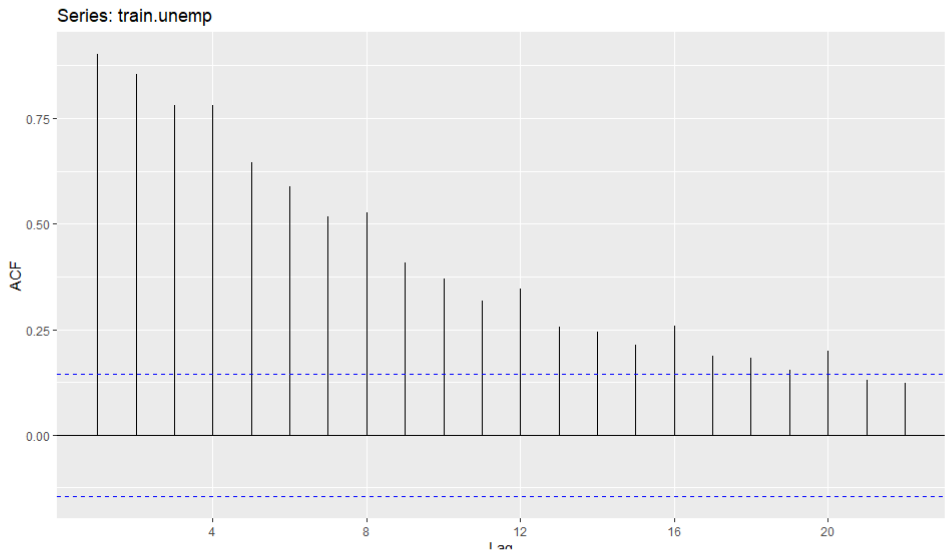
The massive unemployment crisis evoked through the global pandemic can be studied in greater depth to forecast the unemployment rate when we have a similar event or a recession. As more data will be collected, this crisis would serve as a structural break and give more insights.

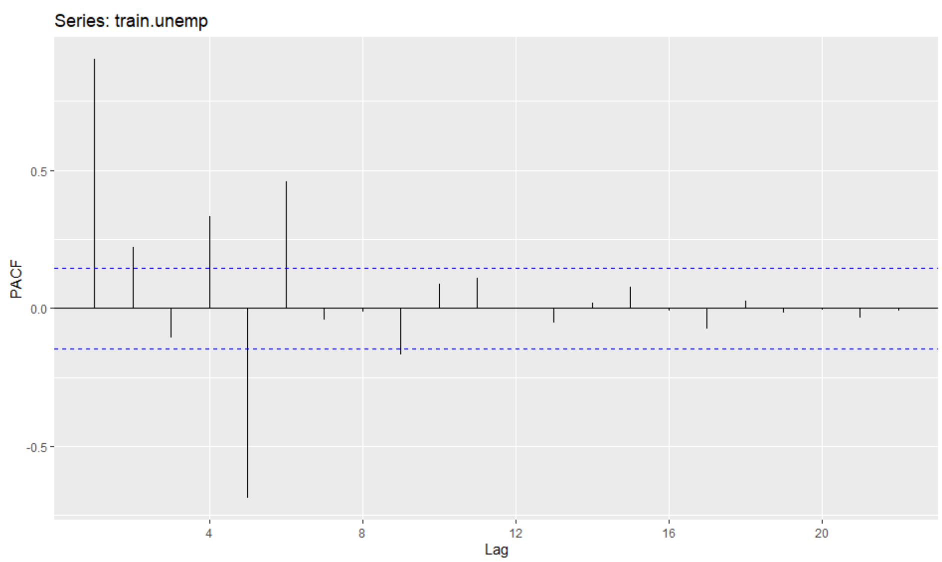
Ensemble averaging can be implemented in the future to forecast the unemployment using the best-chosen linear models: ARIMA BF – 40%, ARIMA SW - 40%, ETS – 10% and STL Random walk – 10%

APPENDICES

Appendix 0 – Manual Check. US Unemployment.

```
> ndiffs(train.unemp)
[1] 1
> nsdiffs(train.unemp)
[1] 1
```





Appendix 1 – Nonlinearity Test. US Unemployment.

```
> nonlinearityTest(train.unemp)
                 ** Teraesvirta's neural network test  **
                 Null hypothesis: Linearity in "mean"
                 X-squared =  0.08764577  df =  2  p-value =  0.9571235

                 ** White neural network test  **
                 Null hypothesis: Linearity in "mean"
                 X-squared =  0.520789  df =  2  p-value =  0.7707475

                 ** Keenan's one-degree test for nonlinearity  **
                 Null hypothesis: The time series follows some AR process
                 F-stat =  0.7367523  p-value =  0.3919262

                 ** McLeod-Li test  **
                 Null hypothesis: The time series follows some ARIMA process
                 Maximum p-value =  0

                 ** Tsay's Test for nonlinearity **
                 Null hypothesis: The time series follows some AR process
                 F-stat =  3.561343  p-value =  2.855596e-06

                 ** Likelihood ratio test for threshold nonlinearity **
                 Null hypothesis: The time series follows some AR process
                 Alternativce hypothesis: The time series follows some TAR process
                 X-squared =  15.35374  p-value =  0.2059069
```

Appendix 2 – The Outputs of Models. US Unemployment.

```
> (naive.un <- naive(train.unemp, lambda = "auto"))
        Point Forecast       Lo 80    Hi 80    Lo 95     Hi 95
2005 Q3           5.09 4.467155 5.846089 4.181121  6.313305
2005 Q4           5.09 4.241049 6.207206 3.872296  6.946438
2006 Q1           5.09 4.078567 6.506496 3.657135  7.496171
2006 Q2           5.09 3.948466 6.775231 3.488876  8.009664
2006 Q3           5.09 3.838741 7.025444 3.349725  8.505129
2006 Q4           5.09 3.743283 7.263276 3.230702  8.991982
2007 Q1           5.09 3.658491 7.492360 3.126554  9.475935
2007 Q2           5.09 3.582032 7.715059 3.033906  9.960841
2007 Q3           5.09 3.512299 7.933011 2.950448 10.449515
2007 Q4           5.09 3.448130 8.147413 2.874522 10.944143
> (snaive.un <- snaive(train.unemp, lambda = "auto"))
        Point Forecast       Lo 80    Hi 80    Lo 95    Hi 95
2005 Q3           5.46 4.531120 6.690154 4.129374 7.508582
2005 Q4           5.20 4.331831 6.342858 3.954812 7.099270
2006 Q1           5.70 4.714123 7.012722 4.289280 7.890186
2006 Q2           5.09 4.247184 6.196610 3.880530 6.927395
2006 Q3           5.46 4.212268 7.318731 3.712831 8.691488
2006 Q4           5.20 4.032685 6.924070 3.562852 8.187473
2007 Q1           5.70 4.376860 7.686363 3.849851 9.163768
2007 Q2           5.09 3.956295 6.758241 3.498902 7.976634
> (stl.rw.un <- stlf(train.unemp, lambda = "auto"))
        Point Forecast       Lo 80    Hi 80    Lo 95    Hi 95
2005 Q3       5.060609 4.787882 5.356292 4.652014 5.522979
2005 Q4       4.732881 4.312699 5.214675 4.111748 5.498758
2006 Q1       5.382361 4.682580 6.243345 4.364225 6.781385
2006 Q2       4.859292 4.092748 5.851093 3.755928 6.497856
2006 Q3       4.876699 3.957124 6.138807 3.568809 7.005043
2006 Q4       4.598492 3.623124 6.002267 3.223918 7.007216
2007 Q1       5.252558 3.943567 7.292581 3.434403 8.863139
2007 Q2       4.769302 3.508533 6.802803 3.028507 8.419515
```

```
> (ets.un <- ets(train.unemp, lambda = "auto")
ETS(A,Ad,A)

Call:
 ets(y = train.unemp, lambda = "auto")

  Box-Cox transformation: lambda= -0.4407

  Smoothing parameters:
    alpha = 0.9999
    beta  = 0.1891
    gamma = 1e-04
    phi   = 0.8

  Initial states:
    l = 1.1533
    b = 0.0168
    s = -0.0299 -0.0072 -0.0035 0.0406

  sigma:  0.0274

      AIC      AICc       BIC
-351.5267 -350.2401 -319.4866
```

```
> (arima.un <- auto.arima(train.unemp, stepwise = FALSE, lambda = "auto"))
Series: train.unemp
ARIMA(2,0,1)(1,1,1)[4]
Box Cox transformation: lambda= -0.4406952

Coefficients:
         ar1      ar2      ma1    sar1     sma1
      1.6037  -0.6729  -0.2937  0.2163  -0.7532
s.e.  0.1171   0.1088   0.1459  0.1644   0.1200

sigma^2 estimated as 0.0006085:  log likelihood=406.82
AIC=-801.63   AICc=-801.14   BIC=-782.54
> (arima.un.sw <- auto.arima(train.unemp, stepwise = TRUE, lambda = "auto"))
Series: train.unemp
ARIMA(3,0,2)(1,1,1)[4]
Box Cox transformation: lambda= -0.4406952

Coefficients:
         ar1      ar2     ar3      ma1     ma2    sar1     sma1
      1.7665  -1.1822  0.3325  -0.4806  0.4055  0.3661  -0.8188
s.e.  0.2531   0.4184  0.2191   0.2385  0.2250  0.1869   0.1168

sigma^2 estimated as 0.0006063:  log likelihood=408.03
AIC=-800.05   AICc=-799.2   BIC=-774.6
```

Appendix 3 – Models' Performance Accuracies. US Unemployment.

```
> accuracy(forecast(naive.un), unemp.ts)
                       ME      RMSE       MAE        MPE     MAPE      MASE       ACF1 Theil's U
Training set -0.005303867 0.6693784 0.5398895 -0.6793859 8.996786 0.7187221 -0.2552981        NA
Test set     -0.367000000 0.4325621 0.3690000 -8.0273250 8.066541 0.4912273 -0.1627191  1.260627
> accuracy(forecast(snaive.un), unemp.ts)
                       ME      RMSE       MAE        MPE     MAPE      MASE      ACF1 Theil's U
Training set -0.005674157 1.0039296 0.7511798  -1.270224 11.94269 1.0000000 0.8758394        NA
Test set     -0.626250000 0.6512776 0.6262500 -13.356234 13.35623 0.8336886 0.4513940  1.743273
> accuracy(forecast(stl.rw.un), unemp.ts)
                      ME      RMSE       MAE        MPE     MAPE      MASE       ACF1 Theil's U
Training set -0.02238122 0.3008575 0.2112458 -0.2377401 3.456312 0.2812188 0.09907586        NA
Test set     -0.20527422 0.2453935 0.2145540 -4.3921998 4.586744 0.2856227 0.35673281 0.6799219
> accuracy(forecast(ets.un), unemp.ts)
                      ME      RMSE       MAE        MPE     MAPE      MASE       ACF1 Theil's U
Training set -0.02044807 0.3957084 0.2745362 -0.2939006 4.432075 0.3654734 0.08284893        NA
Test set     -0.25028795 0.3082183 0.2626816 -5.3691401 5.623836 0.3496920 0.40799398 0.8534039
> accuracy(forecast(arima.un), unemp.ts)
                       ME      RMSE       MAE       MPE     MAPE      MASE        ACF1 Theil's U
Training set -0.004714125 0.3321998 0.2288829 -0.181151 3.779796 0.3046980 0.006687665        NA
Test set     -0.294181100 0.3509244 0.2941811 -6.338085 6.338085 0.3916254 0.561310736 0.9729292
> accuracy(forecast(arima.un.sw), unemp.ts)
                       ME      RMSE       MAE        MPE     MAPE      MASE       ACF1 Theil's U
Training set -0.005357108 0.3227656 0.2269927 -0.1867252 3.754105 0.3021816 0.03788829        NA
Test set     -0.272894099 0.3338816 0.2741484 -5.8910873 5.917004 0.3649571 0.58344319 0.9272638
```

Appendix 4 – Model's Residuals Check. US Unemployment.

```
> checkresiduals(naive.un)

        Ljung-Box test

data:  Residuals from Naive method
Q* = 340.04, df = 8, p-value < 2.2e-16

Model df: 0.   Total lags used: 8

> checkresiduals(snaive.un)

        Ljung-Box test

data:  Residuals from Seasonal naive method
Q* = 274.84, df = 8, p-value < 2.2e-16

Model df: 0.   Total lags used: 8
```

```
> checkresiduals(stl.rw.un)

        Ljung-Box test

data:  Residuals from STL +  ETS(A,Ad,N)
Q* = 16.974, df = 3, p-value = 0.0007153

Model df: 5.   Total lags used: 8

> checkresiduals(ets.un)

        Ljung-Box test

data:  Residuals from ETS(A,Ad,A)
Q* = 50.217, df = 3, p-value = 7.183e-11

Model df: 9.   Total lags used: 12
```

```
> checkresiduals(arima.un)

        Ljung-Box test

data:  Residuals from ARIMA(2,0,1)(1,1,1)[4]
Q* = 6.306, df = 3, p-value = 0.09763

Model df: 5.   Total lags used: 8

> checkresiduals(arima.un.sw)

        Ljung-Box test

data:  Residuals from ARIMA(3,0,2)(1,1,1)[4]
Q* = 4.7704, df = 3, p-value = 0.1894

Model df: 7.   Total lags used: 10
```

Appendix 5 – Diebold-Mariano Tests. US Unemployment.

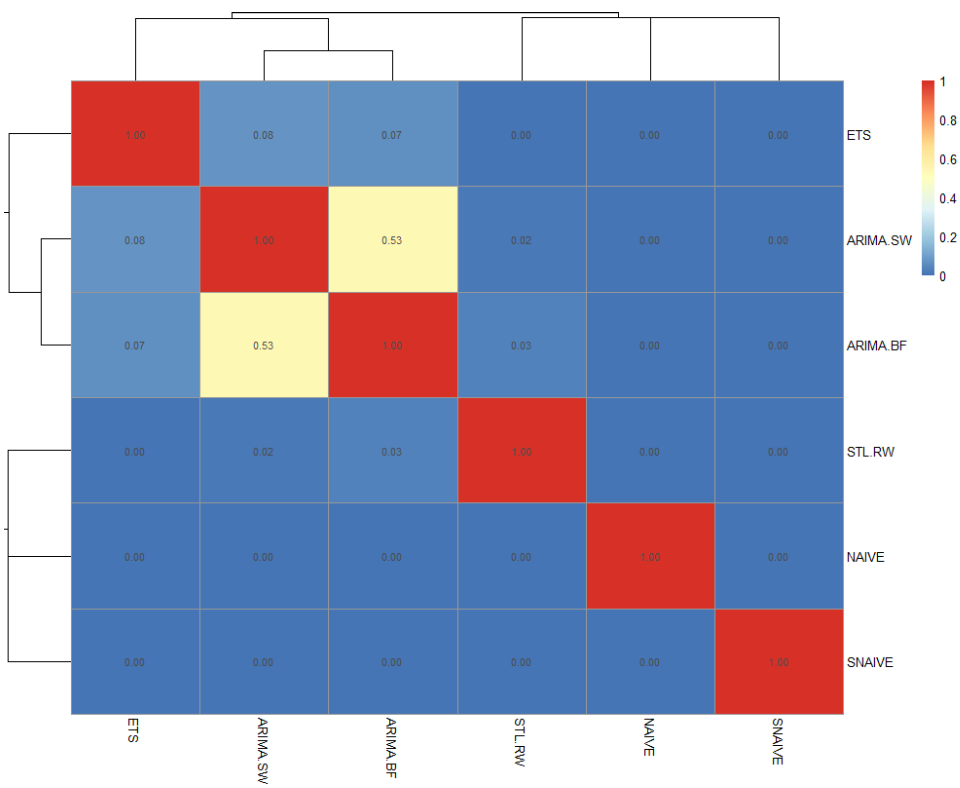
H_0 : two competing methods have the same forecast accuracy.

H_a^{two} : the methods have different levels of accuracy.

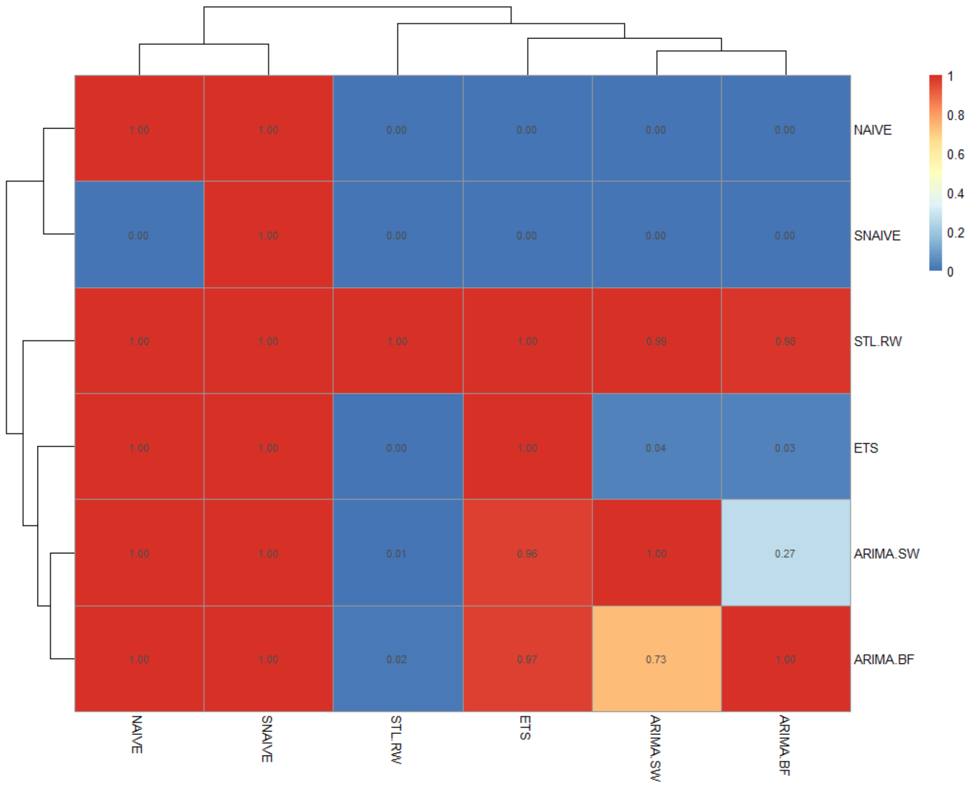
H_a^{less} : method 2 is less accurate than method 1.

$H_a^{greater}$: method 2 is more accurate than method 1.

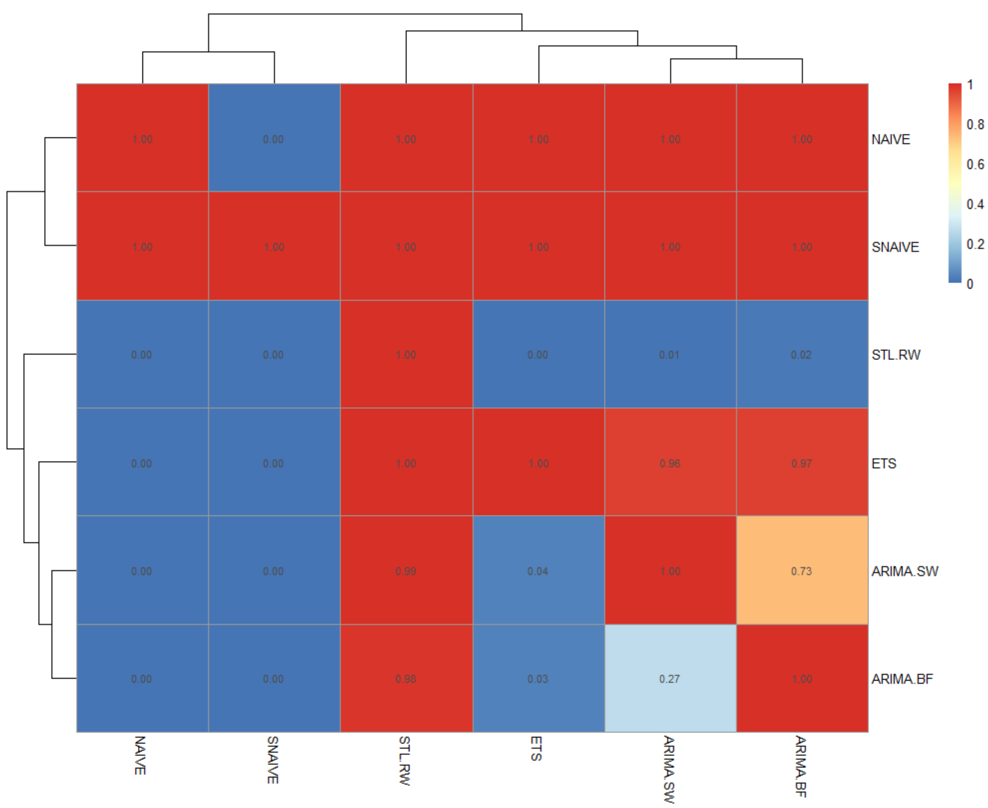
P-values from two tailed type test (in-sample accuracies)



P-values from greater-than type test (in-sample accuracies)



P-values from less-than type test (in-sample accuracies)



Appendix 6 – Forecast Intervals and Plots. US Unemployment.

```
> forecast(naive.un, h = 12)
         Point Forecast     Lo 80    Hi 80      Lo 95    Hi 95
Jan 2018        152.311 121.53480 179.5653  103.07621 192.9749
Feb 2018        152.311 107.26041 190.1090   77.73341 208.2873
Mar 2018        152.311  95.43744 197.9552   53.96962 219.5702
Apr 2018        152.311  84.69952 204.4204   26.54856 228.8049
May 2018        152.311  74.47053 210.0111  -25.25114 236.7500
Jun 2018        152.311  64.39035 214.9859  -48.34970 243.7908
Jul 2018        152.311  54.14613 219.4973  -64.51731 250.1539
Aug 2018        152.311  43.35805 223.6445  -77.52688 255.9861
Sep 2018        152.311  31.36650 227.4959  -88.59427 261.3884
Oct 2018        152.311  16.24797 231.1011  -98.31087 266.4340
Nov 2018        152.311 -14.49270 234.4975 -107.01986 271.1777
Dec 2018        152.311 -29.03857 237.7140 -114.94188 275.6617
```

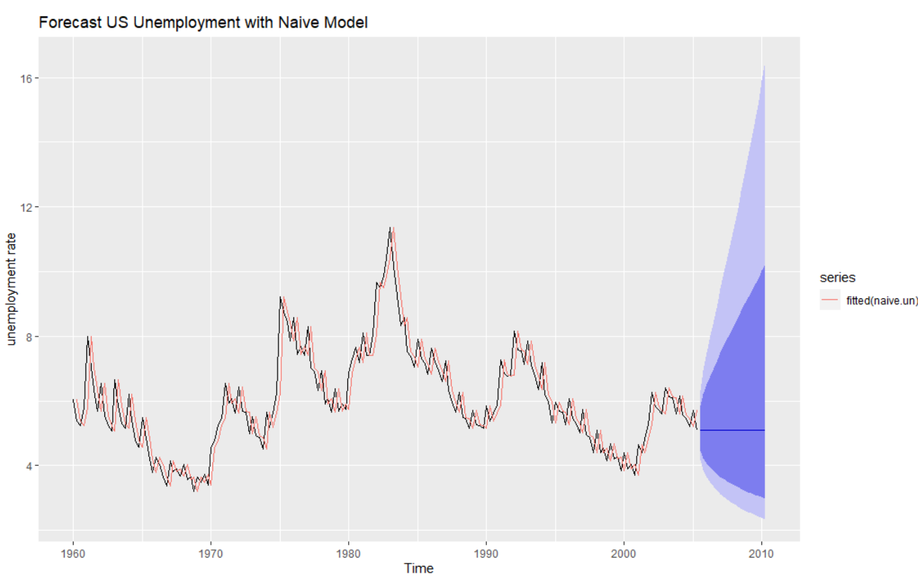
```
> forecast(snaive.un, h = 12)
         Point Forecast     Lo 80    Hi 80     Lo 95    Hi 95
Jan 2018        154.255 135.19045 171.9335 124.38111 180.8396
Feb 2018        120.576  97.79512 140.9045  84.27208 150.9429
Mar 2018        127.915 106.10996 147.5837  93.34410 157.3480
Apr 2018        116.751  93.41118 137.4457  79.43672 147.6339
May 2018        133.270 112.10829 152.4895  99.82240 162.0642
Jun 2018        155.979 137.06257 173.5443 126.35309 182.4003
Jul 2018        188.467 171.86560 204.1919 162.65576 212.2129
Aug 2018        177.863 160.59184 194.1338 150.95900 202.4062
Sep 2018        148.666 129.09884 166.7244 117.94662 175.7978
Oct 2018        135.383 114.46116 154.4322 102.35069 163.9343
Nov 2018        131.357 109.97150 150.7340  97.52026 160.3755
Dec 2018        152.311 133.07562 170.1194 122.15044 179.0829
```

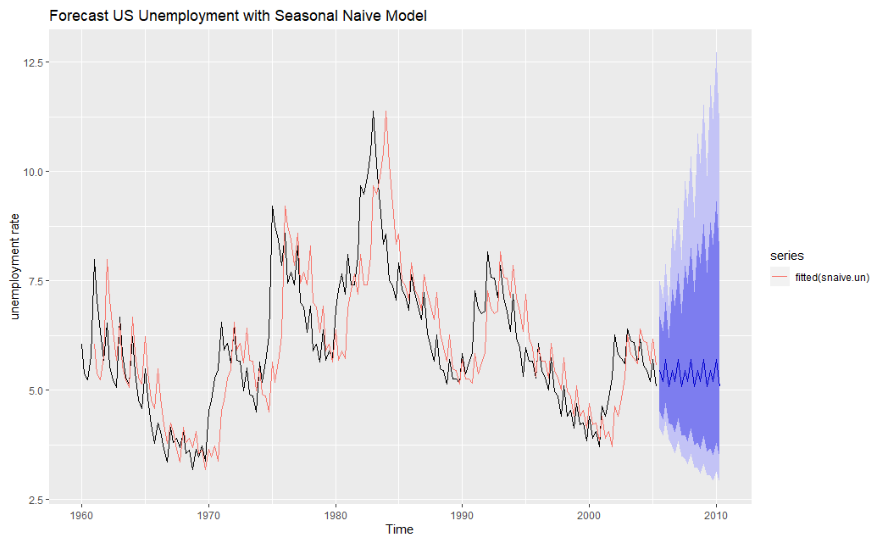
```
> forecast(stl.rw.un, h = 12)
         Point Forecast     Lo 80    Hi 80     Lo 95    Hi 95
Jan 2018       160.0078 150.85444 168.8418 145.86454 173.4018
Feb 2018       136.0183 123.36993 147.9635 116.33273 154.0457
Mar 2018       130.7847 115.65135 144.8838 107.11379 152.0055
Apr 2018       115.0818  96.40984 132.0057  85.54279 140.4279
May 2018       133.8848 115.42658 150.8569 104.86285 159.3674
Jun 2018       163.5742 146.17557 179.8744 136.41690 188.1346
Jul 2018       192.8223 176.15666 208.6237 166.92016 216.6888
Aug 2018       189.2140 171.26589 206.1453 161.26897 214.7604
Sep 2018       156.6961 135.06390 176.5844 122.68217 186.5566
Oct 2018       137.1878 112.11963 159.6385  97.30910 170.7443
Nov 2018       131.9597 104.90639 155.8762  88.64204 167.6342
Dec 2018       151.7597 126.31091 174.7524 111.44180 186.1763
```

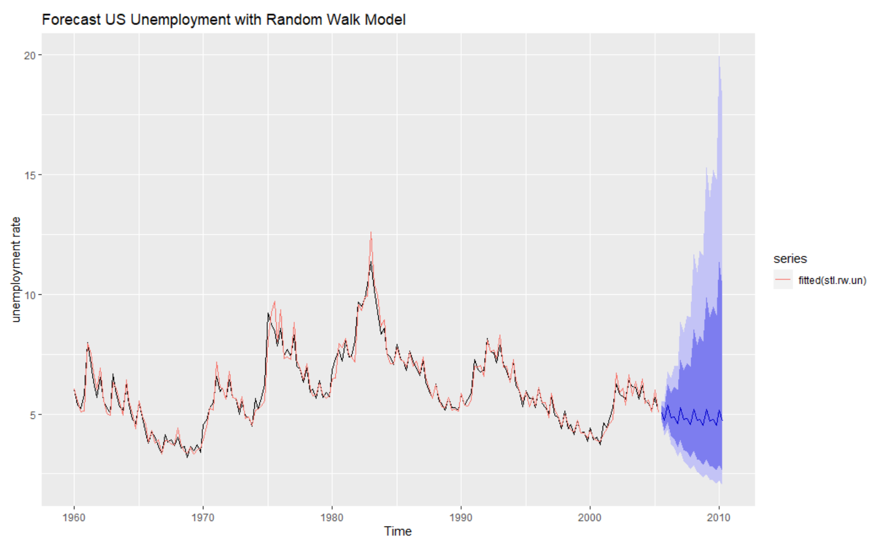
```
> forecast(ets.un)
         Point Forecast     Lo 80    Hi 80     Lo 95    Hi 95
Jan 2018       159.7160 149.62251 169.4219 144.10193 174.4199
Feb 2018       134.2417 120.64704 147.0171 113.04562 153.5026
Mar 2018       128.9375 112.93942 143.7682 103.86589 151.2385
Apr 2018       113.6778  94.16195 131.2691  82.72616 139.9991
May 2018       131.8847 112.70938 149.4380 101.67950 158.2189
Jun 2018       161.8642 143.95423 178.6005 133.88217 187.0691
Jul 2018       190.0906 172.96489 206.2926 163.45293 214.5508
Aug 2018       189.8894 171.72459 207.0169 161.60210 215.7293
Sep 2018       154.4085 132.28112 174.6891 119.57123 184.8409
Oct 2018       135.6988 110.16628 158.4932  95.01886 169.7517
Nov 2018       129.6122 101.95091 153.9473  85.20603 165.8843
Dec 2018       152.3555 126.80429 175.4405 111.87516 186.9102
```

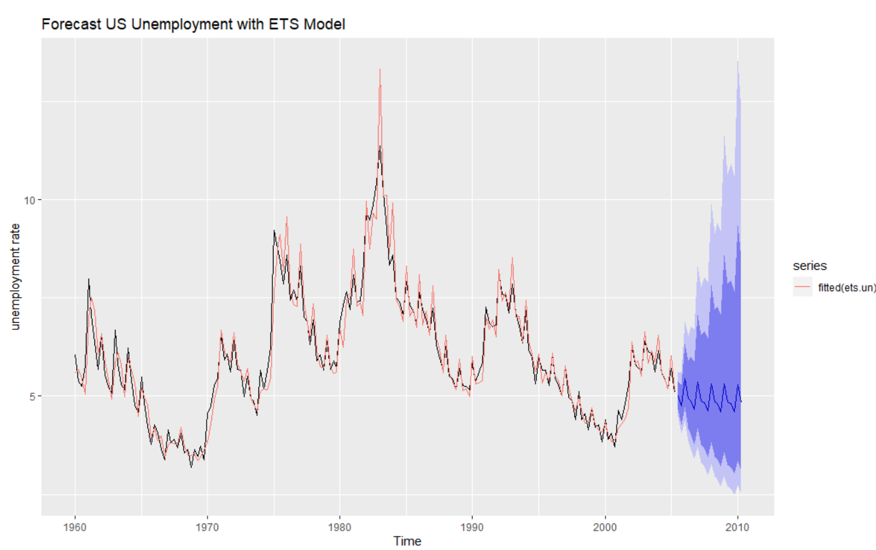
```
> forecast(arima.un)
         Point Forecast     Lo 80    Hi 80     Lo 95    Hi 95
Jan 2018       157.8840 147.82320 167.5553 142.31891 172.5345
Feb 2018       131.2087 117.76047 143.8372 110.23534 150.2454
Mar 2018       124.6071 109.93370 138.2610 101.64495 145.1530
Apr 2018       108.2729  91.76075 123.3252  82.21627 130.8382
May 2018       126.3280 111.42760 140.1915 103.00958 147.1890
Jun 2018       156.5205 143.62932 168.7732 136.50163 175.0365
Jul 2018       185.3032 173.78466 196.3864 167.48826 202.0961
Aug 2018       182.9159 171.30322 194.0806 164.95071 199.8293
Sep 2018       146.9437 133.48381 159.6659 126.00130 166.1470
Oct 2018       127.8463 113.02928 141.6490 104.66923 148.6207
Nov 2018       120.7393 105.31560 135.0064  96.54711 142.1841
Dec 2018       142.6075 128.86800 155.5570 121.20842 162.1426
```

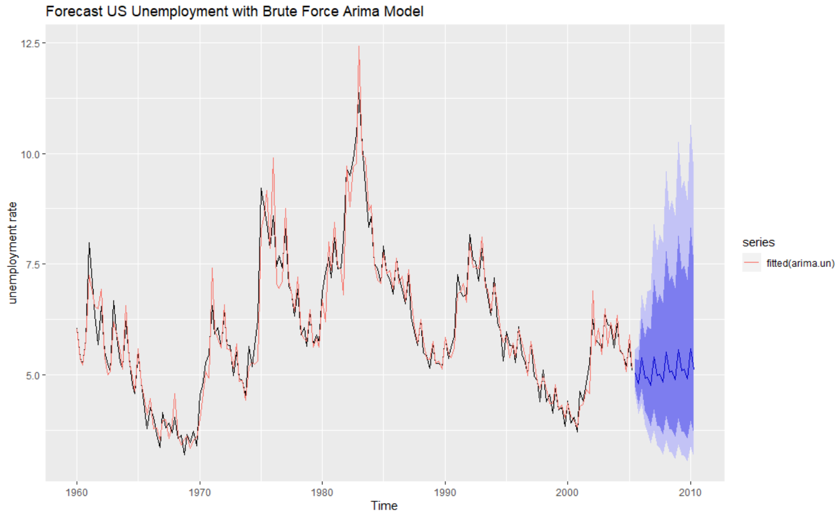
```
> forecast(arima.un.sw)
         Point Forecast     Lo 80    Hi 80     Lo 95    Hi 95
Jan 2018       156.0875 146.03343 165.7483 140.53069 170.7208
Feb 2018       130.2924 117.03933 142.7433 109.62695 149.0631
Mar 2018       127.6219 113.55998 140.7661 105.65419 147.4181
Apr 2018       109.4607  93.55630 124.0206  84.40850 131.3043
May 2018       128.2191 113.92063 141.5738 105.87521 148.3292
Jun 2018       155.1413 142.57119 167.0986 135.62637 173.2139
Jul 2018       183.9959 172.77837 194.7972 166.65059 200.3643
Aug 2018       179.8818 168.49833 190.8276 162.27189 196.4639
Sep 2018       145.5209 132.39070 157.9418 125.09735 164.2726
Oct 2018       127.5456 113.16777 140.9646 105.07161 147.7497
Nov 2018       122.8530 108.09401 136.5672  99.74430 143.4841
Dec 2018       141.6583 128.28418 154.2782 120.83686 160.7006
```

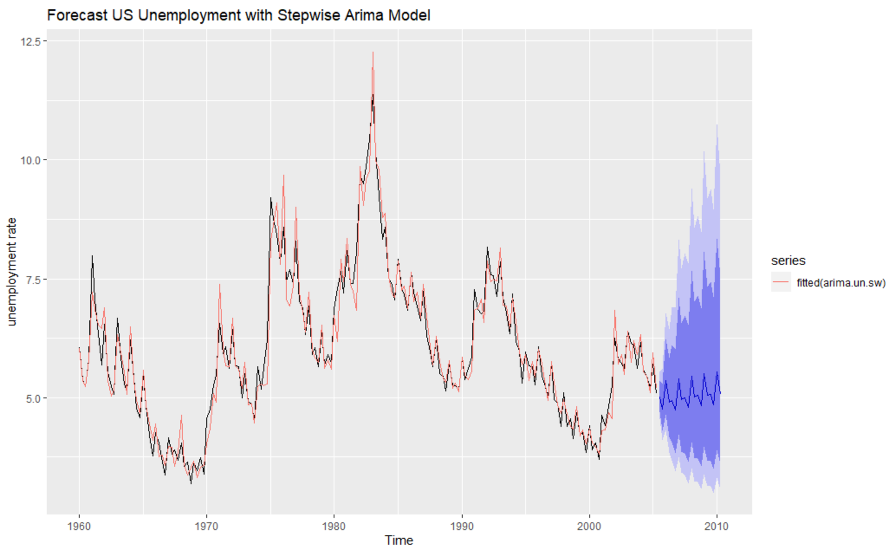



Forecast US Unemployment with Seasonal Naive Model
12.5
10.0
7.5
5.0
2.5
unemployment rate
1960
1970
1980
1990
2000
2010
Time
series
fitted(snaive.un)


Forecast US Unemployment with Random Walk Model
20
15
10
5
unemployment rate
1960
1970
1980
1990
2000
2010
Time
series
fitted(stl.rw.un)


Forecast US Unemployment with ETS Model
10
5
unemployment rate
1960
1970
1980
1990
2000
2010
Time
series
fitted(ets.un)


Forecast US Unemployment with Brute Force Arima Model
12.5
10.0
7.5
5.0
unemployment rate
1960
1970
1980
1990
2000
2010
Time
series
fitted(arima.un)


Forecast US Unemployment with Stepwise Arima Model
12.5
10.0
7.5
5.0
unemployment rate
1960
1970
1980
1990
2000
2010
Time
series
fitted(arima.un.sw)

Appendix 7 – Clustering and Dendrograms. US Unemployment by States.

Fig 17: US unemployment - Lag plots

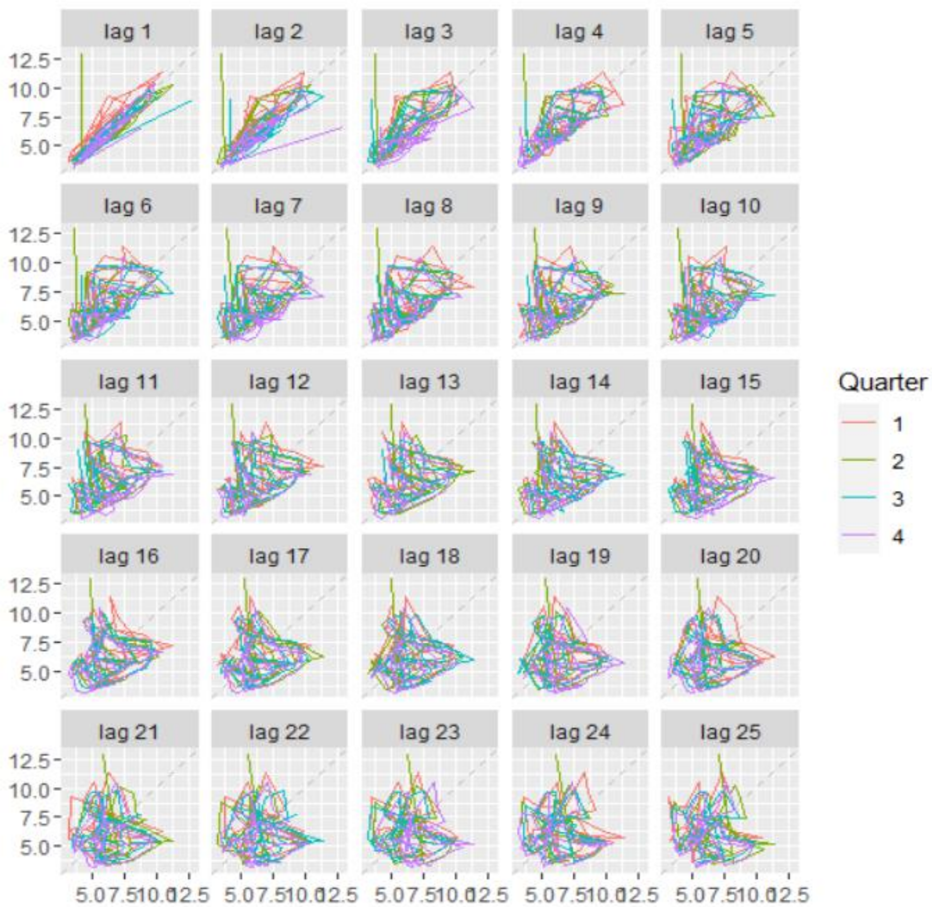
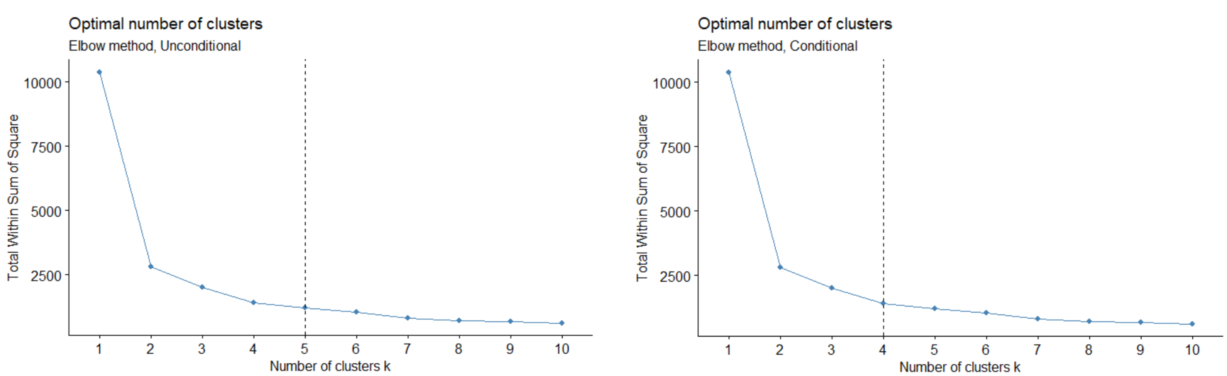


Fig 18: Optimal clustering methods



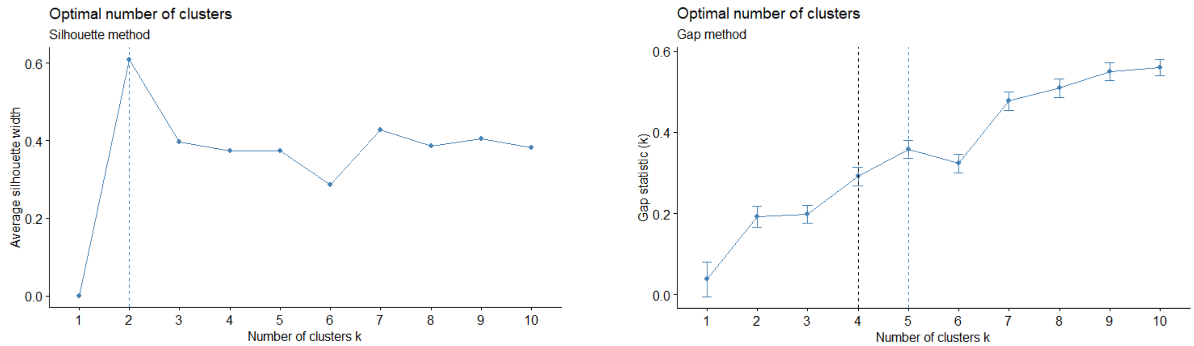


Fig 19: Similarity check through correlation distances

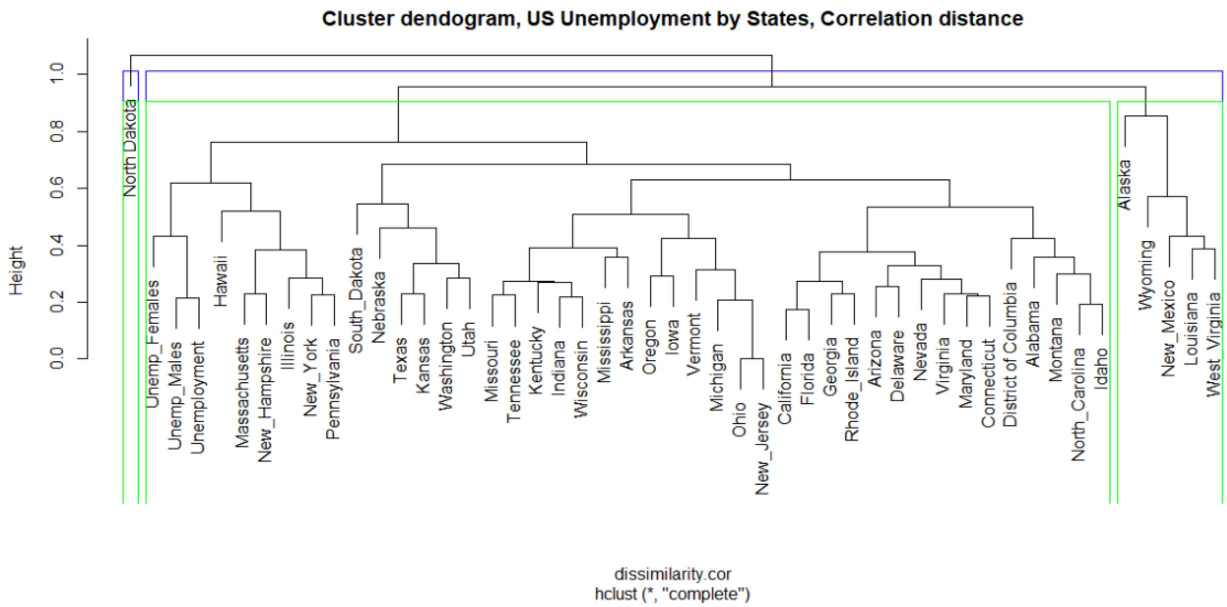


Fig 20: Similarity checking – Correlation distances

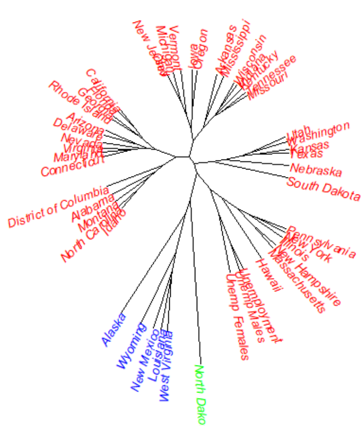
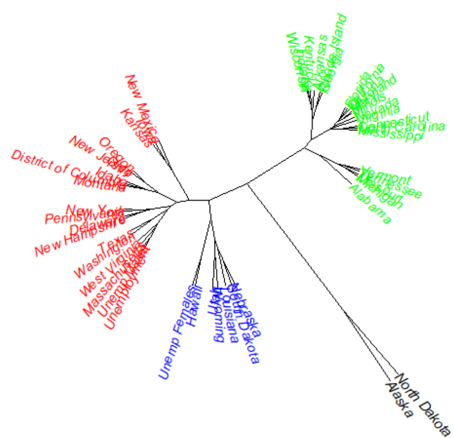


Fig 21: Similarity checking – ACF distances



Appendix 8 – Nonlinearity Test. US Gender Unemployment Gap.

```
> nonlinearityTest(train.gap)
                 ** Teraesvirta's neural network test  **
                 Null hypothesis: Linearity in "mean"
                 X-squared =  13.67111  df =  2  p-value =  0.001074872

                 ** White neural network test  **
                 Null hypothesis: Linearity in "mean"
                 X-squared =  13.6349  df =  2  p-value =  0.00109451

                 ** Keenan's one-degree test for nonlinearity  **
                 Null hypothesis: The time series follows some AR process
                 F-stat =  0.01696401  p-value =  0.8965315

                 ** McLeod-Li test  **
                 Null hypothesis: The time series follows some ARIMA process
                 Maximum p-value =  0

                 ** Tsay's Test for nonlinearity **
                 Null hypothesis: The time series follows some AR process
                 F-stat =  1.518838  p-value =  0.03818988

                 ** Likelihood ratio test for threshold nonlinearity **
                 Null hypothesis: The time series follows some AR process
                 Alternativce hypothesis: The time series follows some TAR process
                 X-squared =  30.78572  p-value =  0.01200286
```

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