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Analysis of Unemployment Data in the United States

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Abstract:

This paper utilizes various methods for modeling the dataset, including ARIMA, SARIMA, and intervention models, and performs forecasting using several approaches. Using the SARIMA model in conjunction with intervention analysis performs best in modeling the patterns of the United States unemployment data.

Introduction:

Unemployment metrics have been a subject of concern for numerous economic purposes. An essential economic application of the unemployment rate is examining its association with seasonal spikes, shedding light on how labor market dynamics may be influenced by the changing seasons. In the United States, the unemployment rate represents the number of unemployed people as a percentage of the labor force. (US Bureau of Labor Statistics, 2023) This metric is used to indicate economic performance for a given period. The fluctuation in the unemployment rate is critical to understand as it influences how the government sets policies, decides how to allocate money, and generally dictates how well a country's economy is performing.

This paper will analyze intricate dynamics and systemic transformations observable in unemployment data by performing an in-depth analysis of several factors, such as the seasonality of the fluctuations in unemployment, the understanding of anomalies present within the data, and an exploration of how the unemployment rate has trended over extended periods. Analyzing these factors allows us a holistic view of the behavior of the general unemployment rate in the United States and perhaps enables us to predict how the unemployment rate will change over time for future periods, giving us a glance into how the labor market's complex dynamics evolve.

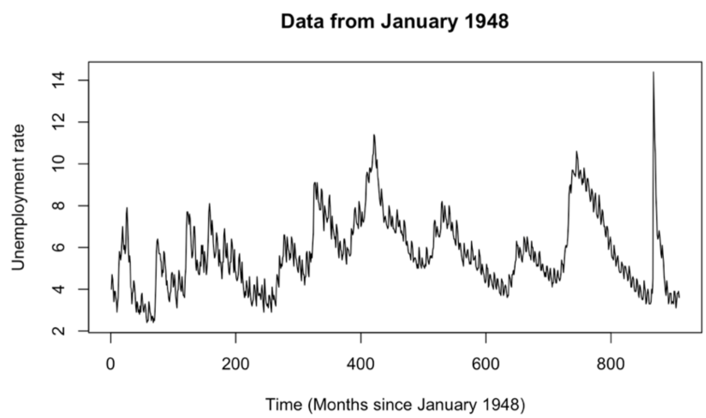
Part of the motivation behind this project stems from a desire to explore whether the economy has reverted to a similar state as before the pandemic. Notably, the dataset contains a clear spike corresponding to the COVID-19 pandemic, spanning several recent quarters. By analyzing this spike and the aftermath, we can gain insights into how the economy recovers from catastrophic events, giving us a view into a potential risk analysis of specific economic shocks. The US Bureau of Labor Statistics performed some preliminary analyses about this matter and found that the aftermath of the shocks from the pandemic is still evident in the economy today but carries less weight. (June 2022)

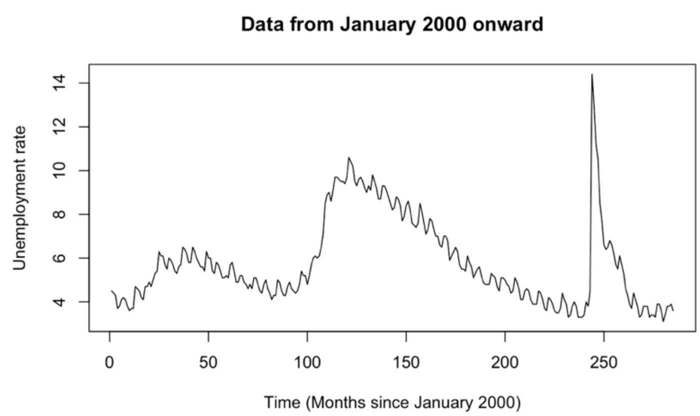
Literature Review:

In Robert Shimer's paper "Reassessing the Ins and Outs of Unemployment" (2007), he writes "While the observation that the job finding rate is more cyclical than the employment separation rate suggests that papers seeking to understand the cyclicality of the unemployment rate should focus primarily on the job finding rate, I have not sought to establish causality; to so without a theoretical framework seems futile." (24, Shimer) Shimer makes an important distinction when he claims that it is a difficult task to establish causality. In other words, there could be other factors at play, and attributing changes in the unemployment rate solely to the job finding rate would be unfounded. There should be other factors considered in analysis. The need to understand other external factors is furthered by Shiskin and Plewes in their paper "Seasonal Adjustment of the U.S. Unemployment Rate" where they claim that it is imperative to account for seasonal changes in unemployment numbers and other confounding factors, perhaps such as weather or even to consider how unemployment is being considered. Some fields such as agriculture has unemployment boosts in colder months, but these people tend to get their jobs back when it is time to begin start harvesting again. Shishkin and Plewes do not implement any methods to account for seasonal changes but identify the X-11 ARIMA model as a potential model to use to remove seasonality. Given the length of the data, Katris' suggests in his paper "Prediction of Unemployment Rates with Time Series and Machine Learning Techniques" (2019) that the usage of the FARIMA (Fractional ARIMA) or ARFIMA model with GARCH errors may assist in reducing the effect of potential heteroskedasticity in prediction. The FARIMA/ARFIMA models are outside of the scope of this paper, but their suggestion tells us that windowing the data (IE taking a subset of the data for more recent years) may remove some information. By using this model, we can predict a time series with long range dependence without having serially correlated errors. He also writes that it helps in prediction to consider models robust to non-linearity while simultaneously being good predictors for longer data, and resistance to heteroskedasticity. Katris applies this technique and several other machine learning based techniques to Baltic, Nordic, and a few miscellaneous countries. Katris suggests the use of several other types of models based in machine learning such as fully connected feed forward neural networks, support vector regression/support vector machines, and multivariate adaptive regression splines. While Katris uses these models in European countries, it is possible that these types of models can be adapted to the United States unemployment market as well.

Data Description:

To start, I created a subset of the dataset to window the data starting from the year 2000. By selecting a more recent period, it allows us to gain a more precise understanding of unemployment trends within the 21st century.



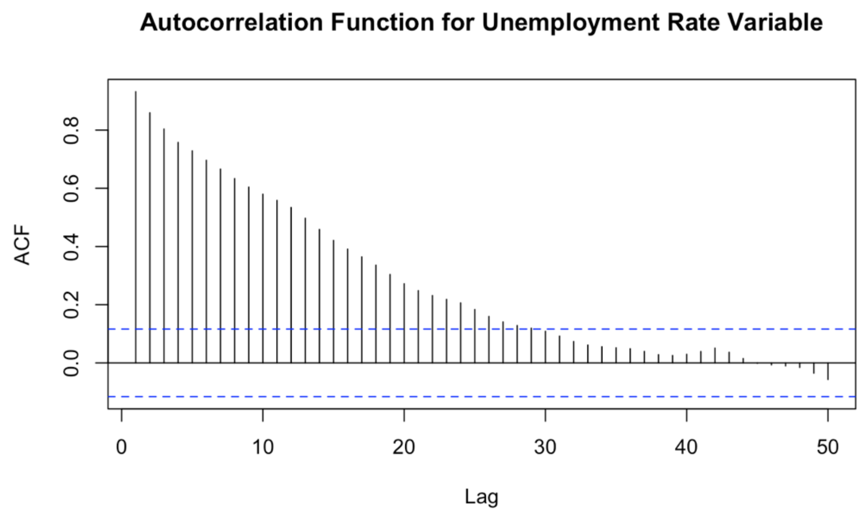


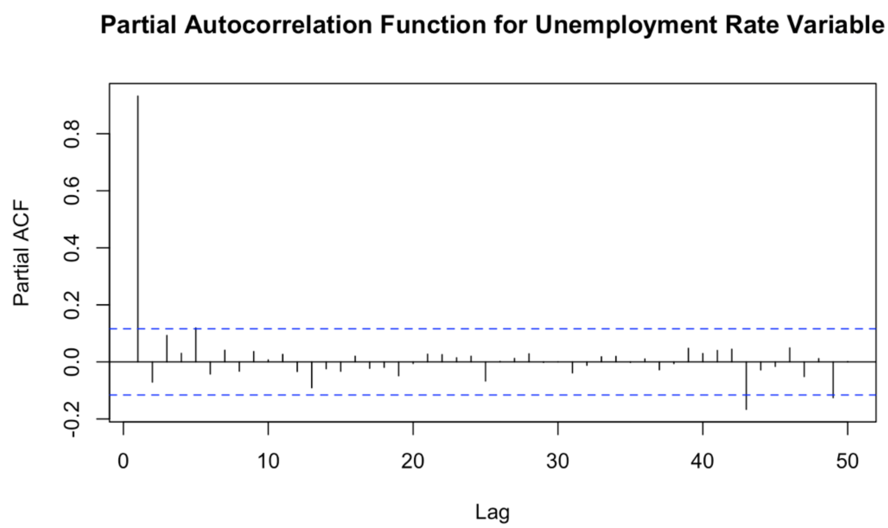
Top image: full data, Bottom image: subset data

In both images we see that there is a clear spike in the latest months, which can likely be explained by the COVID-19 pandemic. Otherwise, there may be some level of seasonality presented by the rest of the time series, perhaps indicating a seasonal ARIMA model may be a good fit to the data.

ACF/PACF:

First we can visualize the ACF and PACF of the data in order to gauge an acceptable model.

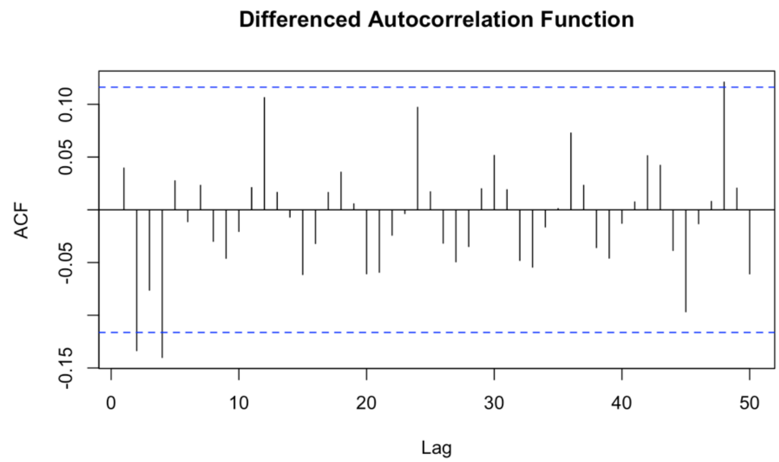


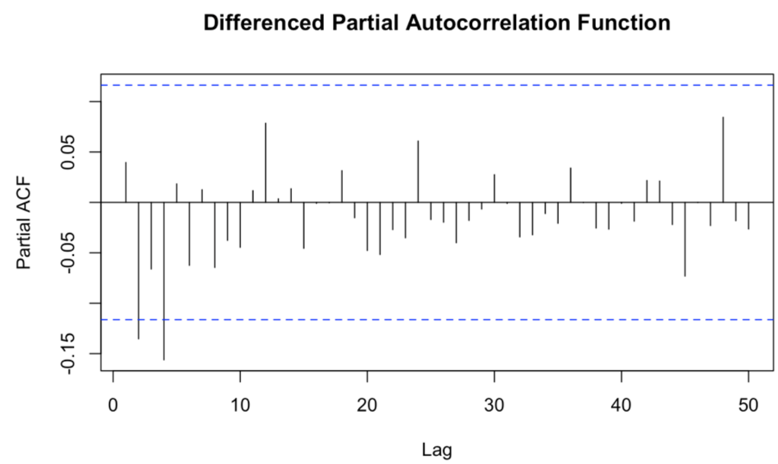


Top: ACF

Bottom: PACF

The slow decay of the ACF suggests the presence of a unit root. This suggests that differencing the unemployment rate variable may be necessary.





Top: ACF

Bottom: PACF

The PACF and ACF suggests either an ARMA(1,2) model or an ARMA(3,3) model. Since the data was differenced, the model is either ARIMA(1,1,2) or ARIMA(3,1,3).

And furthermore, the Augmented Dickey-Fuller test has a p-value of 0.446 meaning that you cannot reject the null hypothesis of a unit root.

```
        Augmented Dickey-Fuller Test

data:  data_2000$UNRATENSA
Dickey-Fuller = -2.3087, Lag order = 6, p-value = 0.446
alternative hypothesis: stationary
```

Additionally, several other unit-root tests (KPSS, Phillips-Perron) return the same conclusion.

```
        Phillips-Perron Unit Root Test

data:  data_2000$UNRATENSA
Dickey-Fuller Z(alpha) = -16.325, Truncation lag parameter = 5, p-value = 0.1947
alternative hypothesis: stationary
```

```
        KPSS Test for Level Stationarity

data:  data_2000$UNRATENSA
KPSS Level = 0.59276, Truncation lag parameter = 5, p-value = 0.02329
```

The Phillips-Perron test shares the same hypotheses as the ADF test and therefore we cannot reject the null of a unit root. The KPSS test has the following hypotheses.

H_0: Data is stationary
H_A: There exists a unit root in the data.

Since the p-value is lower than 0.05, at a 5% confidence level, we can reject the null hypothesis and accept that there is a unit root. The ensemble of unit root tests referenced previously suggests that any model to be fit should be differenced to remove the presence of a unit root.

ARIMA:

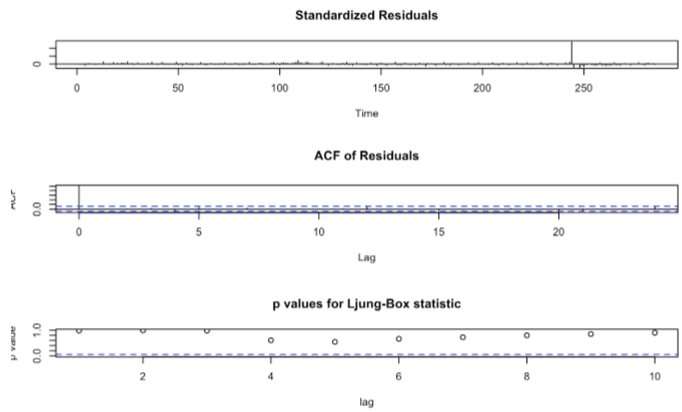
By using the using the auto.arima() function from the forecast library in R, we may find a more definitive answer to what the ideal model may be.

```
Series: data_2000$UNRATENSA
ARIMA(1,1,2)

Coefficients:
         ar1      ma1      ma2
      0.5773  -0.5578  -0.1778
s.e.  0.1818   0.1856   0.0682

sigma^2 = 0.4953:  log likelihood = -301.76
AIC=611.53   AICc=611.67   BIC=626.13
```

```
ar1: 3.175468
ma1: 3.005388
ma2 2.607038
```

Picture: Readout of auto.ARIMA() function, readout of t-statistics

According to the readout, the ideal model is an ARIMA(1,1,2) model with an AIC of 611.53. The outputted t-statistics are all greater than 1.96 meaning that at a 5% level, they are all significant parameters. Further diagnostics should allow for a more complete picture of how the model performed.



Picture: Several diagnostic tests for the ARIMA(1,1,2) model

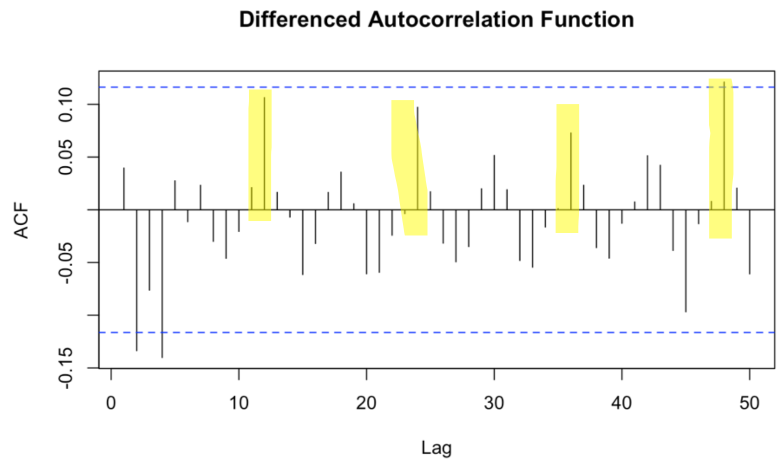
These diagnostics show a generally good fit for the data, with the exception being the large residual which signifies the COVID spike.

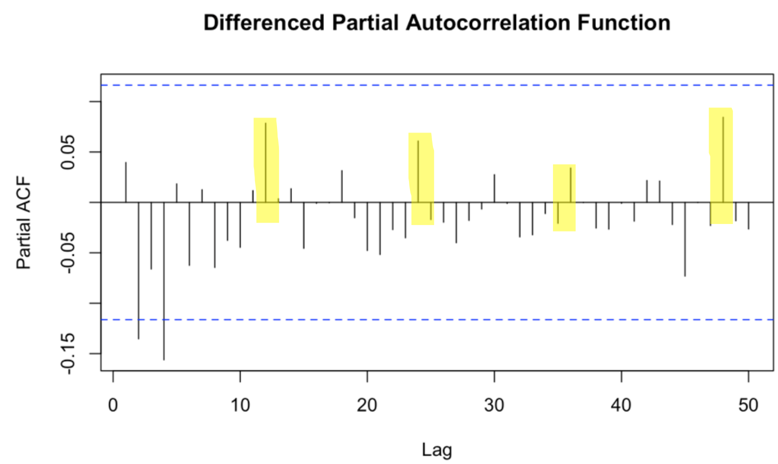
The Ljung-Box test returns a high p-value showing that the residuals behave like white noise, meaning that the model is a good fit to the data.

```
        Box-Ljung test

data:  residuals(fit)
X-squared = 10.047, df = 20, p-value = 0.9673
```

SARIMA:

To investigate whether there is a seasonal component in this data, we should look at the ACF and PACF plots to see whether a significant seasonal aspect exists in the data—the ACF and PACF spike every 12 months, as highlighted below. However, the spikes are generally insignificant, meaning that the seasonal component may not be essential to account for when fitting a model.





Top: ACF, Bottom: PACF

The highlighted lags above show that the unemployment rate spikes every 12 months. Historically, the winter months, including December and January, have seen increased unemployment rates due to factors like the end of temporary holiday employment. However, it's important to note that this is a generalization, and economic conditions can change annually.

Nonetheless, in R, it's possible to specify a "frequency" parameter in the time series data, which will force the auto.ARIMA() function to fit a seasonal ARIMA with the selected frequency.

```
Series: freqData
ARIMA(1,1,1)(2,0,0)[12]

Coefficients:
          ar1     ma1    sar1    sar2
      -0.8428  0.9140  0.3243  0.3047
s.e.   0.0522  0.0392  0.0321  0.0317

sigma^2 = 0.2349:  log likelihood = -631.39
AIC=1272.79   AICc=1272.86   BIC=1296.84
```

```
ar1: 16.14559
ma1: 23.31633
sar1 10.1028
sar2 9.611987
```

Fig: readout of SARIMA model (left) with t-statistics (right)

The SARIMA model is found to be ARIMA(1,1,1) x $(2,0,0)_{(12)}$ after introducing the frequency term. All the model parameters are found to be significant, as evidenced by the t-statistics being greater than 1.96 in every case.

Another way to check whether there is a seasonal component in the data is to investigate the data using spectral density plots. In a smoothed Periodogram, dominant frequencies can be identified by spikes in the curve.

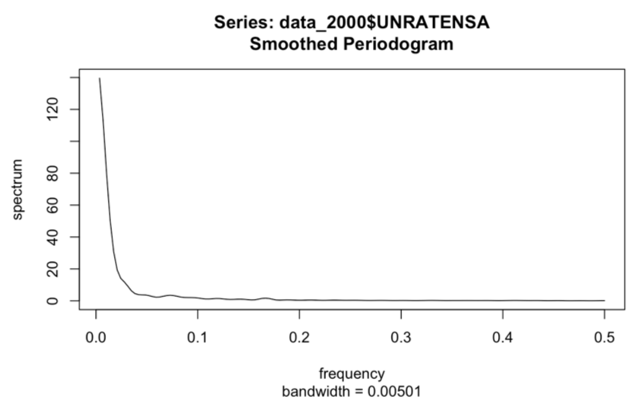


Fig: Smoothed Periodogram for data

The smoothed periodogram also shows that there are no clearly dominant frequencies, meaning that the use of the SARIMA model may be a misspecification in this situation.

ARCH/GARCH:

In the literature review section of this paper, I highlight the work of Katris in his paper where he uses an ARFIMA model with GARCH error for unemployment rates in certain European markets. To check for GARCH effects we can perform the Ljung-Box test on the squared residuals from the model fit.

```
        Box-Ljung test

data:  (residuals(fit))^2
X-squared = 0.34636, df = 20, p-value = 1
```

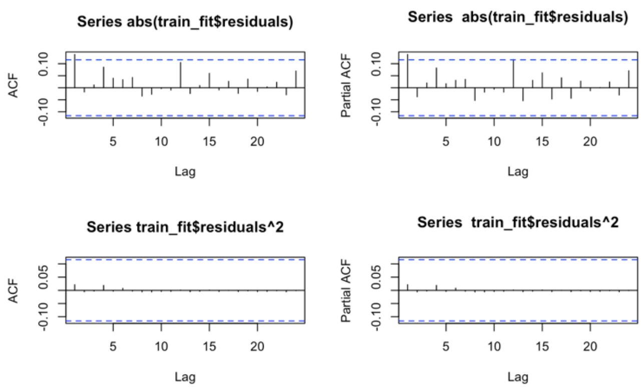


Fig: Ljung-Box test and ACF/PACF of squared residual and absolute value of squared residuals.

Ljung-Box test hypotheses:

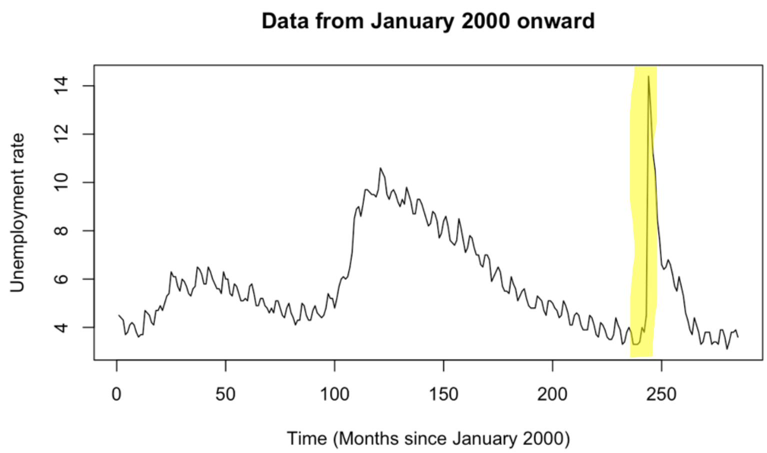
H_0: The data does not have ARCH/GARCH effects

H_A: The data has ARCH/GARCH effects

Since the Ljung-Box test has a p-value of 1, we can reject the null hypothesis and conclude that the process likely does not require ARCH/GARCH effects. Furthermore, none of the ACF/PACF plots shown above have any significant lags. When using with a model with an inappropriately defined GARCH noise, we should expect poor performance when forecasting.

Structural Break/Intervention Analysis:

When discussing all the aforementioned modeling methods, I failed to account for a structural break which is clearly visible in the time series as highlighted below.



By not accounting for such a significant change in the time series, the results of forecasts would potentially exhibit bias.

In order to account for such a change, we would need to use intervention analysis. In intervention analysis, we first observe that there is a structural change at the time points of months 244,245,246, and 247. We can model that anomaly by introducing a fixed parameter for each time point which accounts for the structural change. In other words, we are viewing the observed time series Y_t in terms of a time series X_t without the structural break. Therefore, Y_t can be modeled as the following:

$Y_t = X_t + \omega_0 * I_t^{244} + \omega_1 * I_t^{245} + \omega_2 * I_t^{246} + \omega_3 * I_t^{247}$,

Where $I_t^{t\_0}$ is the indicator function that takes the value 1 if $t = t_0$ and 0 otherwise.

We accomplish this by creating a dummy regressor, that is 0 everywhere except for the four time points where the regressor would take a value of 1. We use separate transfer functions for each of the four time points, which effectively estimates individual constants for each one of the four time points. The ARIMAX() (ARIMA with exogenous variable) function in R can model this type of transfer function model.

```
Call:
arimax(x = data_2000$UNRATENSA, order = c(1, 1, 2), xtransf = data.frame(br = 1 *
    (seq(data_2000$UNRATENSA) == 244), br = 1 * (seq(data_2000$UNRATENSA) ==
    245), br = 1 * (seq(data_2000$UNRATENSA) == 246), br = 1 *
(seq(data_2000$UNRATENSA) ==
    247)), transfer = list(c(0, 0), c(0, 0), c(0, 0), c(0, 0)))

Coefficients:
         ar1      ma1      ma2  br-MA0  br.1-MA0  br.2-MA0  br.3-MA0
      0.4908  -0.3092  -0.1957  9.0594    6.8984    4.2985    2.6766
s.e.  0.1750   0.1674   0.0515  0.3322    0.4570    0.4647    0.3410

sigma^2 estimated as 0.1333:  log likelihood = -116.84,  aic = 247.69
```

```
ar1: 2.804571
ma1: 1.847073
ma2: 3.8
br-MA0 27.25467
br.1-MA0 15.09497
br.2-MA0 9.250054
br.3-MA0 7.852493
```

Fig: Readout for ARIMAX function and t-statistics

Based on the t-statistics, the parameters are mostly significant, apart from MA1. Perhaps, the use of an incomplete ARIMA model could improve overall performance.

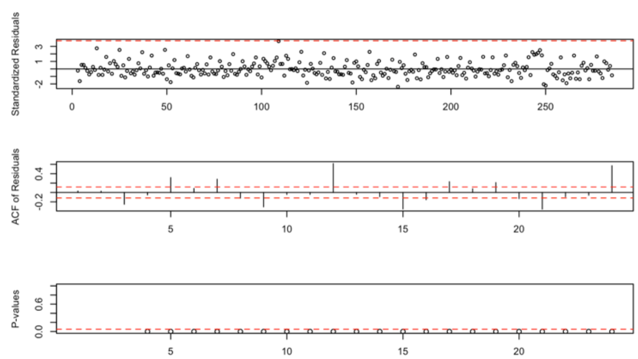
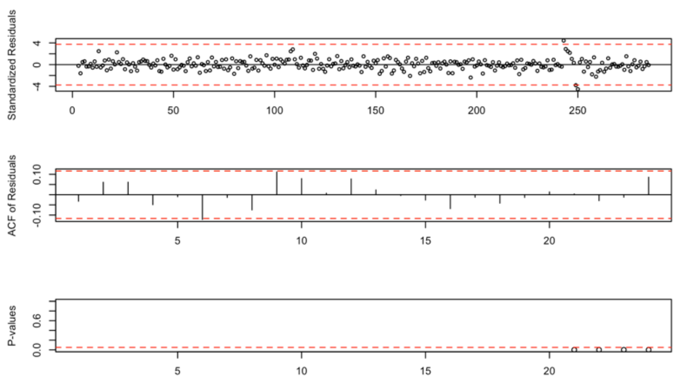


Fig: Several metrics for ARIMAX model.

As shown by the metrics above, the residual plot no longer shows the large jump that it did previously due to the structural break. However, the seasonality previously mentioned in the paper is now visible to a greater extent, likely because the large residuals from the structural break made the seasonal component appear as insignificant lags. Also, the Ljung-Box statistic p-values are significant after lag 4, telling us that the model following those lags may not necessarily be a good fit to the data.

To model the seasonality, we can revert back to the SARIMA(1,1,1) model from the SARIMA section of this paper and choose a high parameter seasonal term with a frequency of 12 months. The ARIMAX function in R has a “seasonal” parameter allowing the use of a seasonal component in modeling. The results show that all of the parameters in a SARIMA(1,1,1)x(9,0,9)$_{(12)}$ are significant terms, and that the second dummy variable is insignificant, but is significant under a 10% confidence level.




```
ar1: 7.35487
ma1: 4.013078
sar1: 4.580376
sar2: 12.17797
sar3: 32.26531
sar4: 19.19835
sar5: 158.5217
sar6: 12.43931
sar7: 43.28182
sar8: 19.19835
sar9: 20.57328
sma1: 3.176901
sma2: 11.07635
sma3: 10.42657
sma4: 13.25788
sma5: 114.1284
sma6: 8.261036
sma7: 10.87557
sma8: 4.105839
sma9: 14.84783
br-MA0 53.6811
br.1-MA0 29.63924
br.2-MA0 1.589149
br.3-MA0 13.29929
```

Fig: T-statistics and several diagnostics for structural break accounted SARIMA model

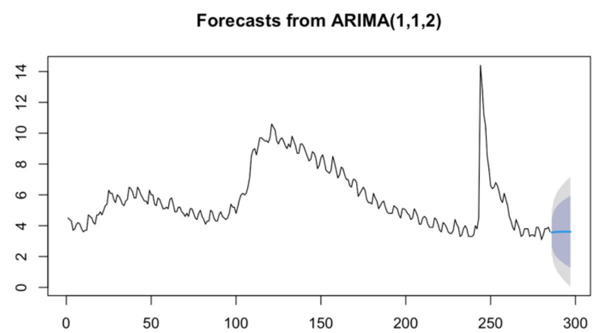
The choice of a large parameter SARIMA model gives us assurance that the seasonal component can be accounted for. In future analysis, we can use model selection to remove some parameters which give lower information gain than others and create a subset SARIMA model. A subset model would be a far more parsimonious than the model currently fit, which is computationally very intense to fit. The subset model is out of the scope of this paper. Following the use of a SARIMA model with the inclusion of the break, this model properly estimates and accounts for the known break, leading to less biased results.

Forecasting:

There are two main forecasting methods highlighted in this paper. The first is an ARIMA/SARIMA forecast, and the second is the Holt-Winters forecasting technique.

Forecasting unemployment data using the ARIMA model is a widely employed method in economic analysis. This form of forecasting is particularly useful to predict trends over time with a confidence band to get a general idea of how the patterns in a time series move. By accurately predicting the unemployment rate over time, economists and policymakers can anticipate potential economic changes and react accordingly. The ARIMA approach gives a more general time series prediction to help us understand the dynamics of a time series.

Generally, to test for model performance, you can leave out some number of observations and train the fitted model on that subset of the data. Then you can compute several metrics such as RMSE, MAE, and MAPE to assess how well your model performed.

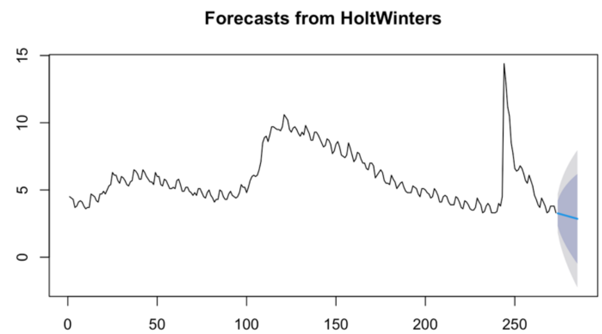



```
Errors:  -0.1547148 -0.1777457 -0.2910415 0.3012827 0.2968514 -0.005706771 -0.5071836
-0.2080362 0.1914716 0.1911874 0.2910234 -0.00907134
MAE:  0.2187764
MAPE:  6.196379
RMSE:  0.2545691
```

Fig: ARIMA Forecast with several metrics

The ARIMA prediction shows a strong performance with a very low MAE, RMSE, and a reasonably low MAPE based on the 12-month forecast shown above. Another metric that we may use is to take the true values of the unemployment rate from the FRED database and compare those values to the forecast. The dataset loaded for this paper include data until September 2023. The actual unemployment % for October 2023 and November 2023 are 3.6% and 3.5% respectively. The 95% confidence band easily contains these values, so it is possible to say that this method returns a successful forecast for the unemployment data.

Holt-Winters forecasting uses an exponential smoother to capture the pattern of a series and to extrapolate future values using the pattern. Holt-Winters method utilizes a double-exponential smoothing approach to estimate the level and gradient of the time series at a given time point. The estimated value can be represented by a sum of the estimated levels and estimated gradients. The forecast is based on a linear approximation. Holt-Winters provides an alternative approach to forecasting, depending on the data features and the forecasting horizon, one approach may perform better than the other.

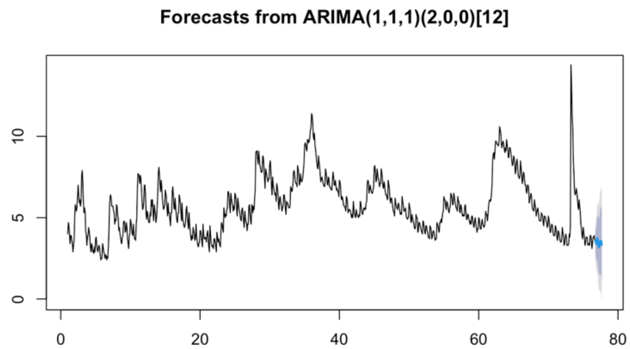



```
Errors:  0.1371416 0.1742831 0.1114247 0.7485663 0.7857078 0.5228494 0.05999097
0.3971325 0.8342741 0.8714157 1.008557 0.7456988
MAE:  0.5330869
MAPE:  14.2897
RMSE:  0.6260061
```

Fig: Holt-Winters Forecast with several metrics

The Holt-Winters forecast also has a strong performance, but generally is weaker than the ARIMA model. The metrics provided are all higher than the ARIMA forecast, but are generally still not terribly inaccurate. Using similar logic as before, the true unemployment rates of 3.6% and 3.5% from October and November of 2023, this Holt-Winters forecast is still not unreasonable. It is important to note, however that this forecast has a wider confidence band than the ARIMA forecasting method.

Reapplying the seasonal component to the ARIMA modeling framework, we get the following forecast:

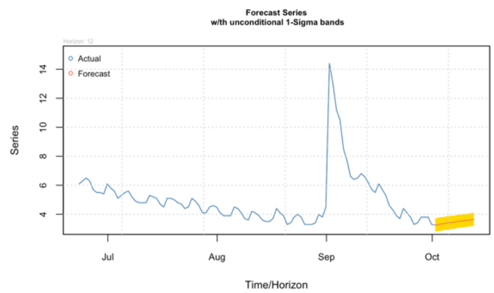



```
Errors:  -0.1851832 -0.02611131 -0.06410582 0.154468 0.223592 0.1310586 -0.07027154
0.1152996 0.2524694 0.2619403 0.3215261 0.2778796
MAE:  0.1736588
MAPE:  4.720811
RMSE:  0.1960646
```

Fig: SARIMA Forecast with several metrics

The SARIMA performance appears to be the strongest so far, with very small values for MAE,MAPE, and RMSE. The estimates provided by the forecast also contain the true values for the unemployment rate within the confidence bands. It is important to note, however, that this model's forecast may be invalid due to the analysis presented in the SARIMA section of this paper. Especially since the structural break model appears to account for most of the variability in the process. If the SARIMA is truly a model misspecification for this problem, then the forecasts cannot be used to predict the unemployment rate over longer periods of time.

Applying similar concepts to a model with GARCH(1,1) errors, the forecast returns the following forecast:




```
     1970-09-30 20:00:00
T+1             2.965606
T+2             2.963090
T+3             2.861621
T+4             3.460760
T+5             3.460256
T+6             3.159961
T+7             2.659788
T+8             2.959686
T+9             3.359626
T+10            3.359591
T+11            3.459571
T+12            3.159559

mae: 3.152426
mape: 87.70592
rmse: 3.163052
```

Fig: GARCH Forecast with several metrics

The metrics show that model has incredibly high error compared to the previous methods. Since the Ljung-Box test from the GARCH section of this paper suggests that the model should not be using GARCH noise, this result is expected. The predictions from this model are far away from the true unemployment values for the last two months, and the confidence bands do not cover the values of 3.5% and 3.6%. We should not use GARCH/ARCH to model the unemployment rate.

Finally, the structural break model produces the following forecast.

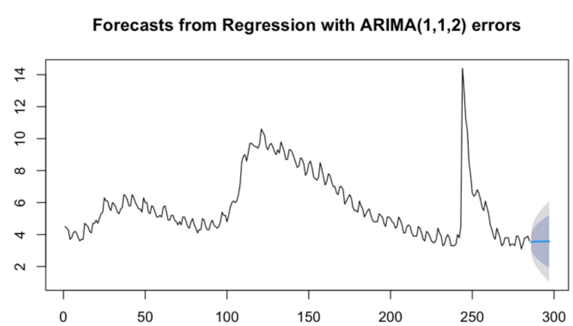


Fig: ARIMA model with structural break forecast.

The use of the dummy terms minimized the size of the confidence bands in the plot. Additionally, it is important to note that I was not able to perform the same analysis as before because by leaving 10 datapoints out, the model's prediction changes markedly, where with the other methods the forecast did not change significantly. Therefore, for this model I will only compare with the October and November values, which the model easily predicts within the 95% confidence band.

Finally, using the SARIMA model with the structural component, we get the most accurate forecasting result.

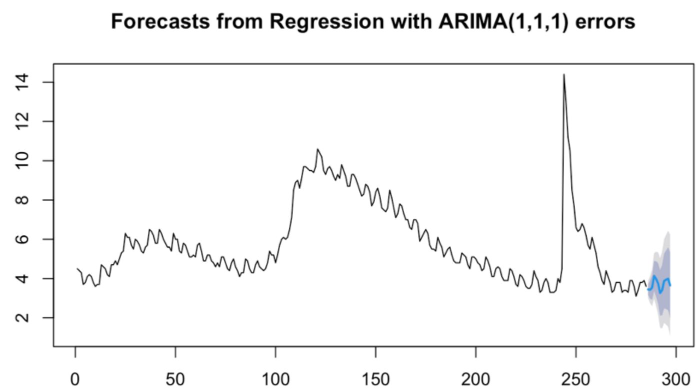


Fig: SARIMA model with intervention analysis forecast

This model has the most accurate display of the shape and noise of the time series. The model accurately predicts the data for October and November, as the 95% confidence encompasses the values of 3.5% and 3.6%.

Conclusions:

This paper investigated the behavior of the FRED unemployment dataset. First, the use of a basic ARIMA model gave a baseline to start analysis on more complex issues, such as seasonality, which the use of spectral analysis and ACF/PACF plots showed a lack of significance. However, later in the paper, intervention modeling methods revealed that the seasonal component was in fact significant and was masked by the large residual from the COVID-19 recession in March through June of 2020. Further investigation proved that the US unemployment does not exhibit ARCH/GARCH effects. Finally, we used forecasting methods for all the proposed models. To compare the modeling performance of all the methods suggested and found that the SARIMA model with intervention analysis forecast seemed to give the most accurate representation of the future data.

Beyond the methodological contributions of this paper, the significance of analyzing unemployment rates cannot be overstated. Unemployment is not just a numerical metric but a reflection of societal well-being and economic health. Understanding the underlying patterns and forecasting future trends is imperative for policymakers and economists. Informed decision-making, utilizing accurate modeling and forecasting, can contribute to developing effective strategies for economic stability and social welfare.

In conclusion, this research provides valuable insights into the behavior of the FRED unemployment dataset. The findings underscore the importance of considering intervention effects, seasonal components, and appropriate modeling techniques when examining complex economic indicators such as unemployment.

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Extra:

Holt-winters:

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