Adaptive Filters for Seasonal Adjustment and Step Ahead Prediction

By Chris Neighbor

What's the Data?

The Bureau of Labor Statistics(BLS) releases the monthly unemployment data.

The unemployment data is given as a percentage of the current labor force who are not employed.

Part-time and seasonal workers are considered employed.

Okun's Law, 1% unemployment represents 2% of GDP potential, ie 160,000 people for $20B or around $125,000 GDP potential/ workingcapita.
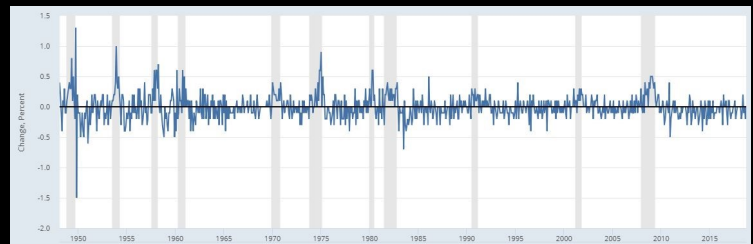
Fig1. Monthly US Unemployment Rate

Fig2. Monthly Change in Percent

Seasonal Adjustment Data

The BLS releases the monthly unemployment data. There is an absolute value and a seasonally adjusted value which is also released by the BLS.

This is to adjust for changes in the workforce due to various seasonal phenomena, in order to better see the variation in the unemployment rate from month to month.

For example notice the peaks of unemployment in January every year

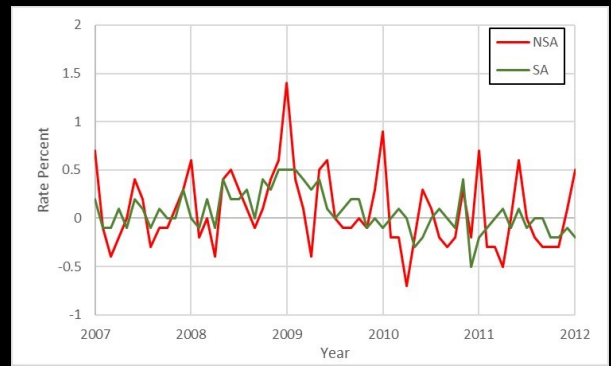There is strong autocorrelation for the NSA which has been removed in the SA

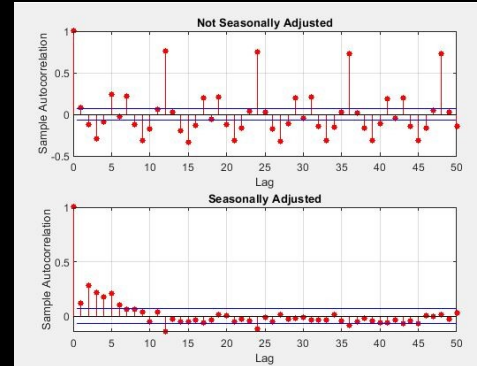Fig3. Difference Between Seasonally Adjusted and Not

Fig4. Autocorrelations of NSA and SA

Results for LS and NLMS

In order to model the system the BLS uses for seasonally adjusting the data, I initially used a Least Squares approach.

This allows me to observe the coefficient values and can provide some insight into how the BLS adjusts the data

It seems as though there is a weighted averaging of the previous years value in order to correct for the season

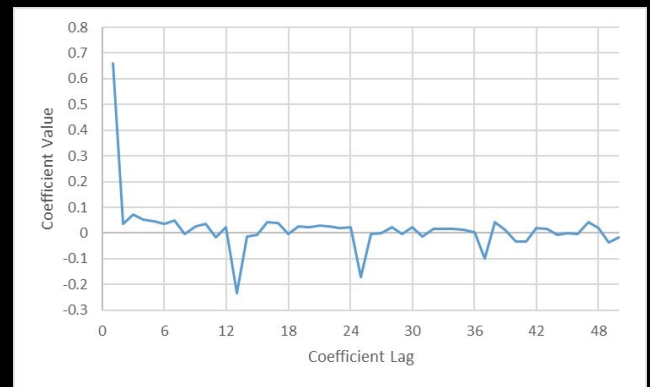The NLMS was able to improve performance and matched the expected value decently well
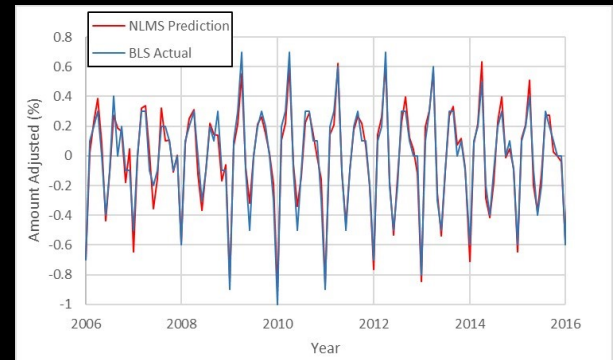

Fig 5. Least Squares Coefficients

Fig 6. Seasonal Adjustment Amount = NSA-SA

Prediction

In order to evaluate these linear predictors I mainly focused on their performance relative to a baseline performance of a naive estimator which predicts that their will be 0% change in the unemployment rate.

The methods explored include LS, NLMS, Block-NLMS, Moving Average, and a combination of Moving Average and BNLMS.

Parameter search for M, mu, and block size were performed essentially using a line search gradient descent method. As can be seen in Fig 8.
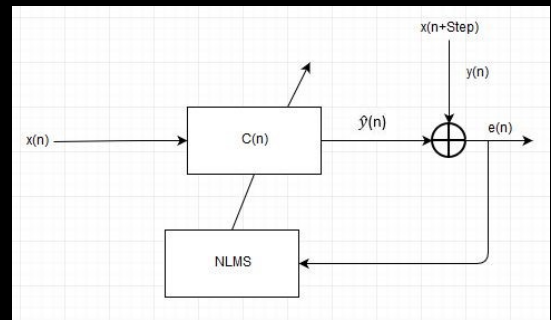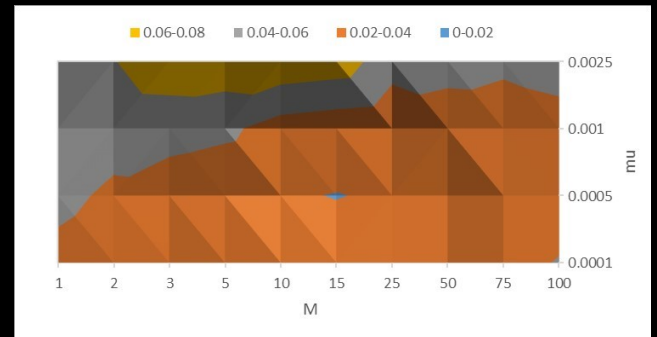

Figure7. Flow Chart Diagram

Figure8. Error Surface for Parameters M, mu

MMSE Evaluation

The relative performances of each of the models are shown in Table1.

By using a these approaches, I was able to reduce the MMSE by around 50% from the baseline MMSE.

This improves the RMSE of the baseline of 0.18%
To with MA-BNLMS, 0.12%

0.12% is approximately the confidence bounds given by the BLS for monthly prediction.

RELATIVE MMSE RESULTS FOR THE PREDICTORS

Method	1-Step	3-Step	6-Step	12-Step
Zero Change	1.0	1.0	1.0	1.0
Current Point	2.5	2.8	2.5	2.8
MA,Step Size	0.62	0.88	1.7	1.8
LS	0.80	0.83	0.89	0.91
NLMS	0.62	0.74	0.77	0.91
BNLMS	0.56	0.62	0.75	0.89
MA-BNLMS	0.48	0.65	0.78	0.93

Figure 9. MMSE for the various models

UNNORMALIZED MMSE RESULTS FOR THE PREDICTORS

Method	1-Step	3-Step	6-Step	12-Step
Zero Change	0.031	0.031	0.031	0.031
Current Point	0.077	0.088	0.77	0.088
MA,Step Size	0.019	0.027	0.051	0.056
LS	0.025	0.026	0.027	0.028
NLMS	0.020	0.023	0.024	0.028
BNLMS	0.0174	0.019	0.023	0.028
MA-BNLMS	0.015	0.020	0.024	0.029

Figure 10. The actual numbers which were found

Prediction Results

The two best predictors demonstrate their ability to adjust to some of the shifts in the data, but they often struggle to predict certain quick spikes, the moving average seems to help adapt to these shifts fairly rapidly without large amounts of overshooting.

As the time step increases the error increases, and the ability of the model to perform significantly better than the baseline breaks down.

Notice how at 2009 the farther away from the recession the more difficult it is to predict, but the models do not predict an immediate return to normalcy when an upward trend is detected.
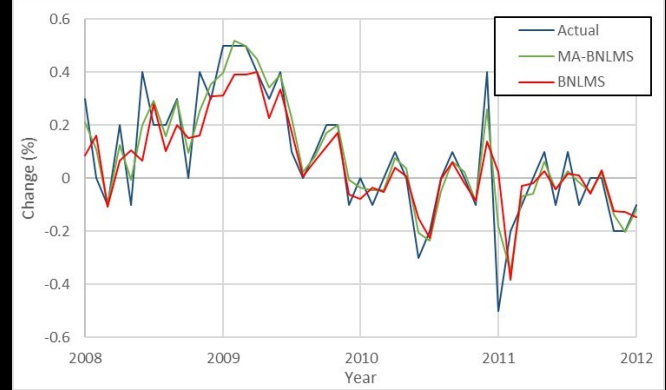
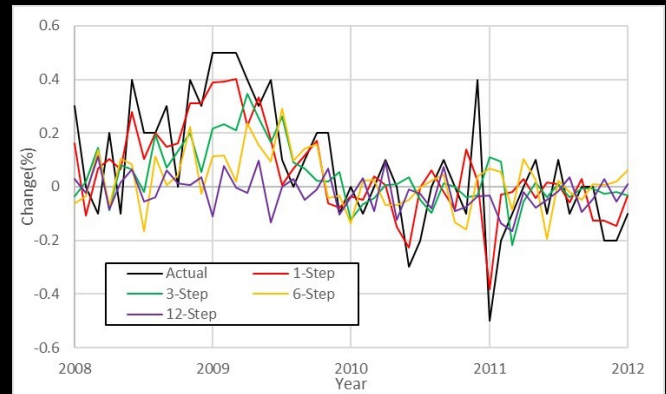Figure7. Two best performances on the 1-Step predictor

Figure7. Effect of time step on the BNLMS predictor

Conclusion

For seasonally adjusting the unemployment data, NLMS provides a good initial insight into modelling the system used by the BLS to generate their data.

As for the predictors, the MMSE was able to be reduced significantly from the baseline controls, and may provide a good initial comparison for other types of models which take other factors into account and explore the nonlinear aspects of the unemployment rate time series.
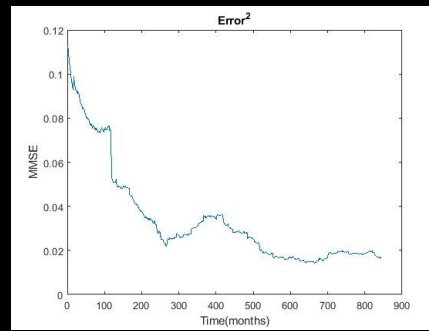

Adaptive Linear Models
Significantly Better than Naive Approaches
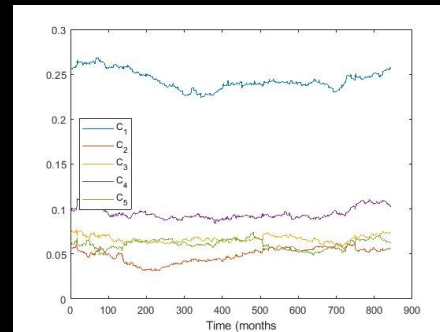
Additional info

These slides may help to
answer some of the questions
about the project

Fig A. For the SA this shows
the error during its initial run.

Fig B. How the SA LMS
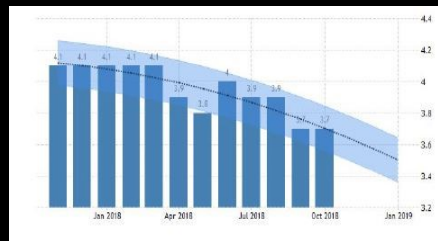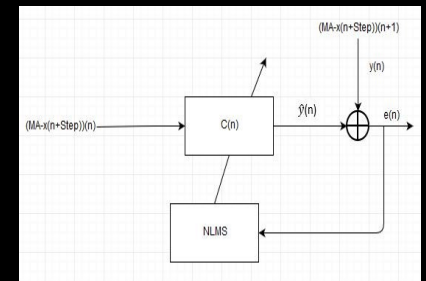coefficients shift over time

A

B

Additional info
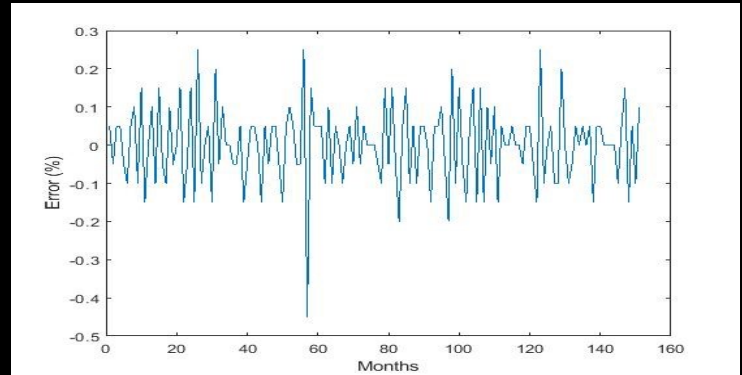
Fig C. BLS Forecast with confidence bounds of +-0.125%

Fig D. A flowchart of the MA-BNLMS model.

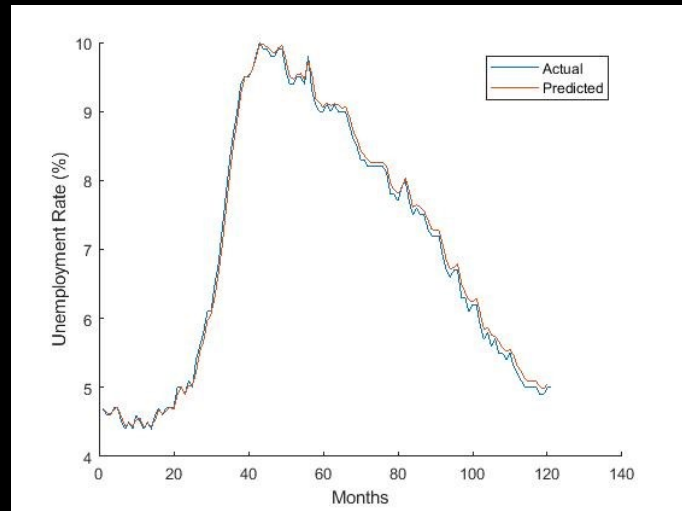Fig E. The time series of the MA error which the BNLMS was predicting.
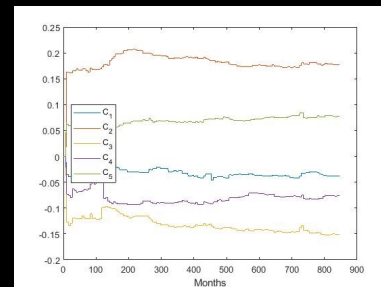
C

D

E

Additional info

Fig F. 1-Step Prediction
summation to reconstruct the
original unemployment rate

Fig G. First few coefficients
change for the BNLMS over time
for the predictor

F

G