Forecasting Monthly Job Openings

Course: Time Series Analysis & Forecasting
Team: Alex Foster, Danae Vassiliadis, Natalie Kim, Mathew Spencer
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Introduction

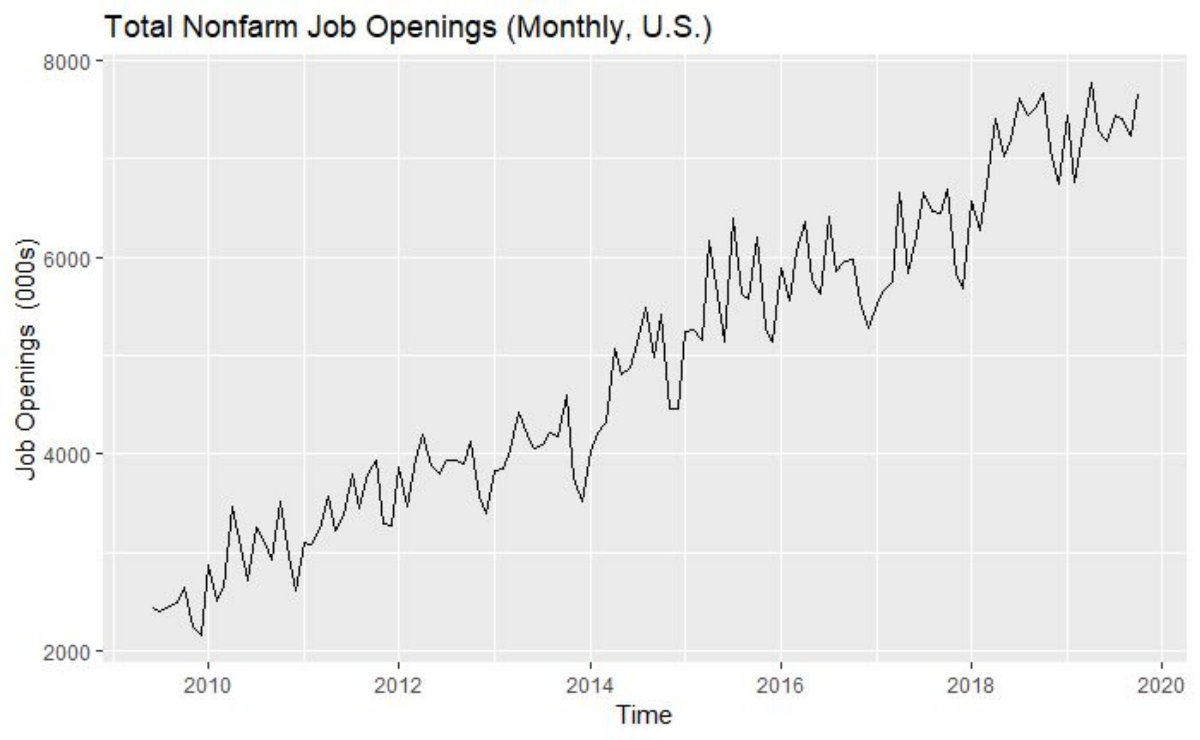
Problem Statement

- **About us:** We are investors. We try to buy stocks that are trading below our estimate of intrinsic value. A key input to that estimate is the discount rate, which is based in part on short-term interest rates. Short-term interest rates are primarily determined by the Fed, which makes financial policy decisions to optimize for: 1) healthy GDP growth; and 2) stable inflation.
- **Goal:** We seek to forecast job openings in the U.S. over a 12-month horizon as accurately as possible.
- **Why:** If we can predict how the employment picture will unfold, we should get a sense for how short-term interest rates might change in the near future and position our portfolio accordingly.
- **How:** We will explore various time series forecasting approaches to solve this problem.

Data

Primary Data: Jobs

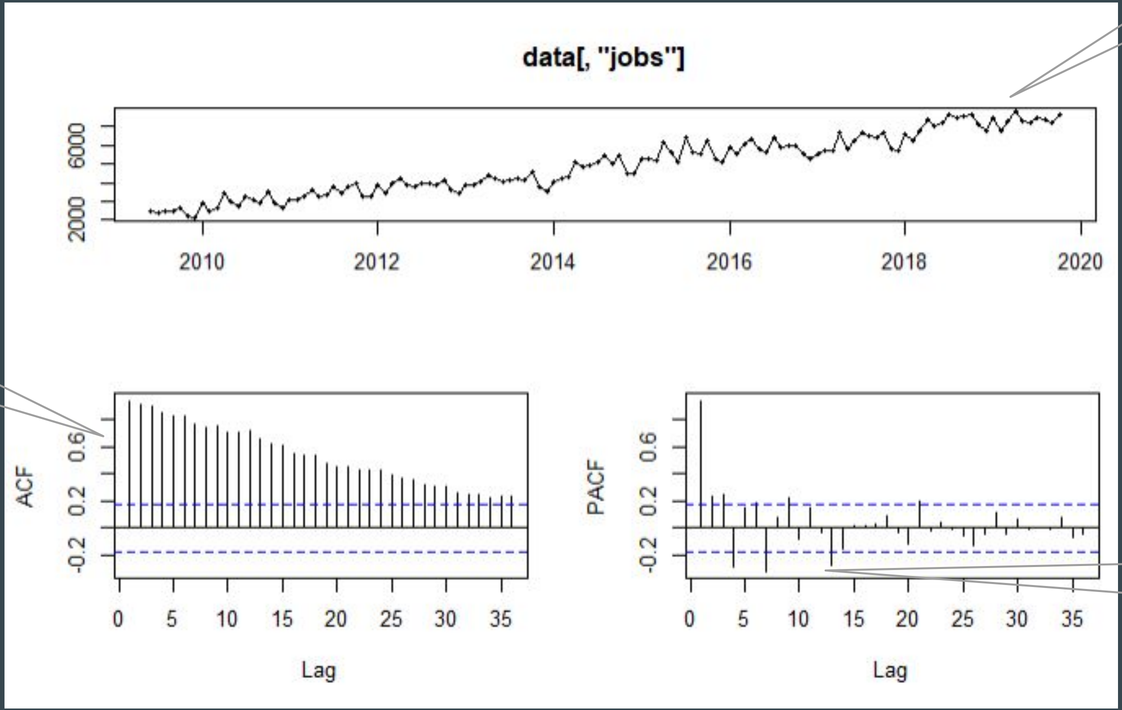
- Units = thousands
- Frequency = monthly
- 375 observations
  a. Jun 2009 - Oct 2019
- Positive trend
- Cyclicality
- Multiplicative variance



Source: https://fred.stlouisfed.org/series/JTUJOL

Raw Data Not Stationary

Positive trend, seasonality

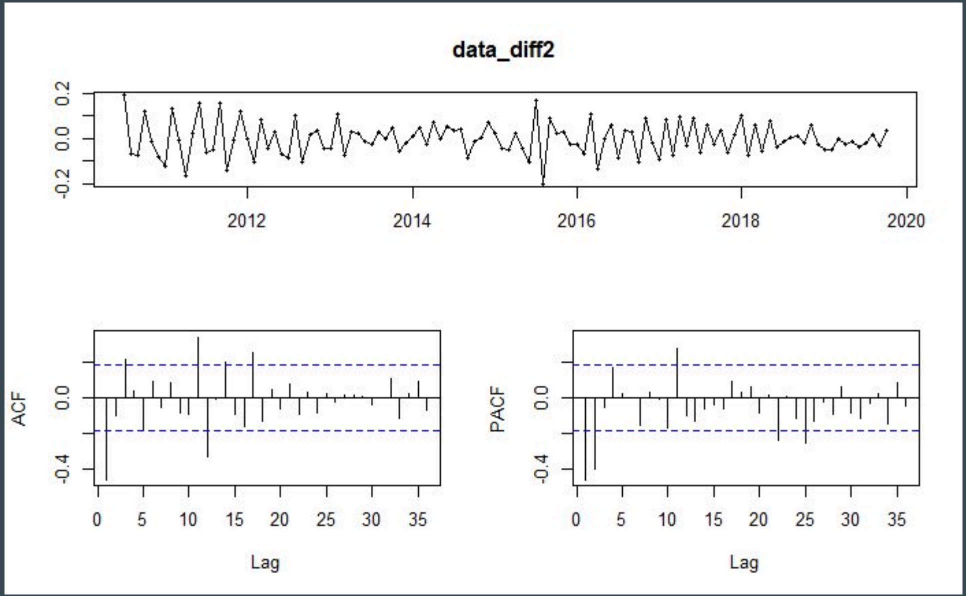


Very slow decline in ACF

Significant spikes in PACF beyond lag-1

Differenced Data

- To make it stationary, we applied:
  a. Log transformation
  b. seasonal differencing (lag=12); and
  c. first-order differencing




```
[1] "***KPS Test for 2nd diff. data**"

        KPSS Test for Level Stationarity

data:  data_diff2
KPSS Level = 0.044917, Truncation lag parameter = 4, p-value = 0.1

[1] "*********************************"
[1] "***ADF Test for 2nd diff. data**"

        Augmented Dickey-Fuller Test

data:  data_diff2
Dickey-Fuller = -4.8074, Lag order = 4, p-value = 0.01
alternative hypothesis: stationary
```

Experimental Results & Analysis

Modeling Approach

Train / Test	Build Univariate Models	Build Multivariate Models	Select Best Model

Train / Test

- Split data into train and test
  - Train = Jun 2009 - Oct 2018
  - Test = Nov 2018 - Oct 2019
- 12-month forecast horizon

Build Univariate Models

- Seasonal Naive (benchmark)
- ETS
- Seasonal ARIMA

Build Multivariate Models

- Regression w/ ARIMA Errors
- Vector Autoregression (VAR)
- Neural Network Autoregression (NNAR)

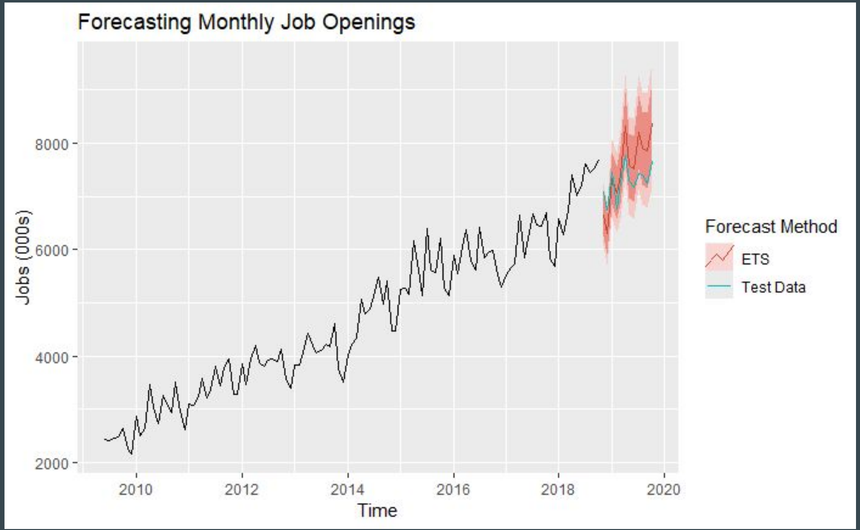
Select Best Model

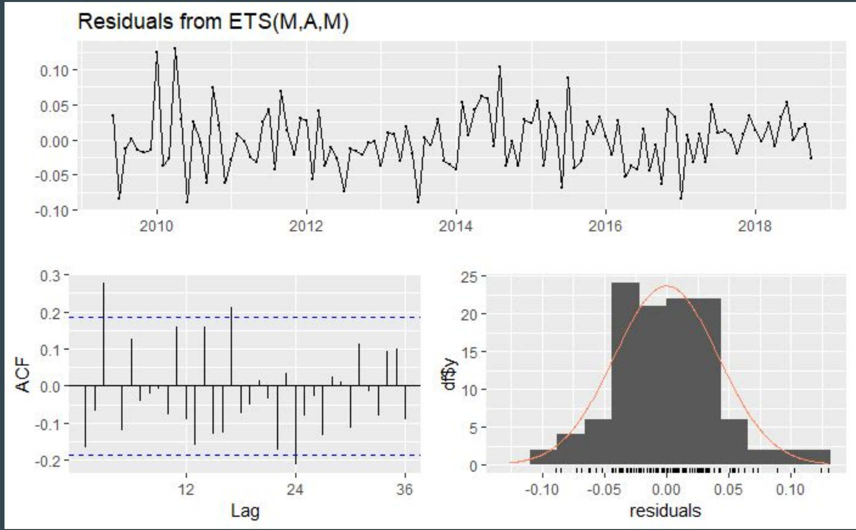
- Model performance
  - RMSE
  - MAPE
- Computational complexity
- Quality
- Explainability

Tune hyperparameters | Iterate

ETS Model

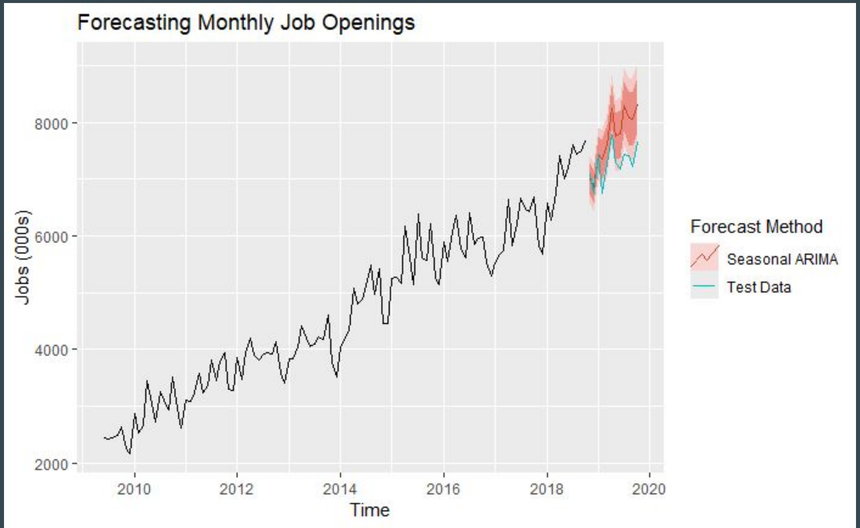
- ETS(M,A,M)
    a. Multiplicative error
        i. Errors are proportional to level of series
    b. Additive trend
        i. Consistent positive
    c. Multiplicative seasonality
        i. Seasonal fluctuations increase with level of series
- Test Results
    a. RMSE = 476
    b. MAPE = 5.93%

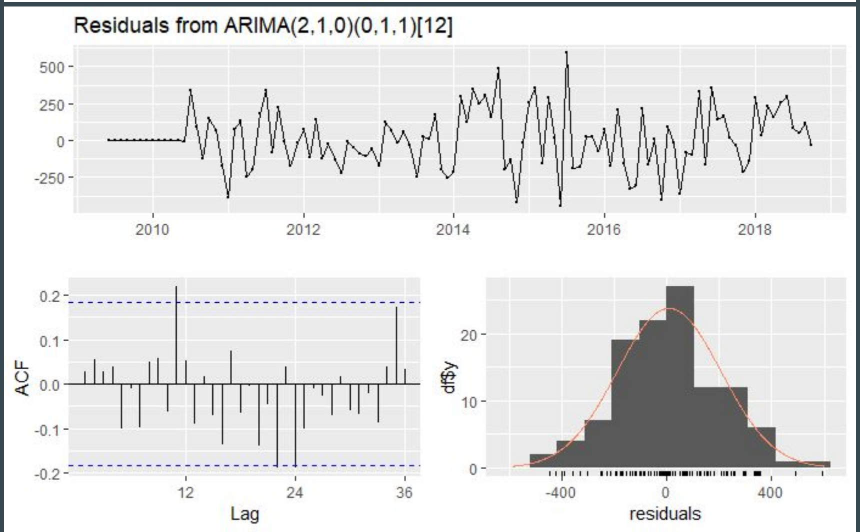




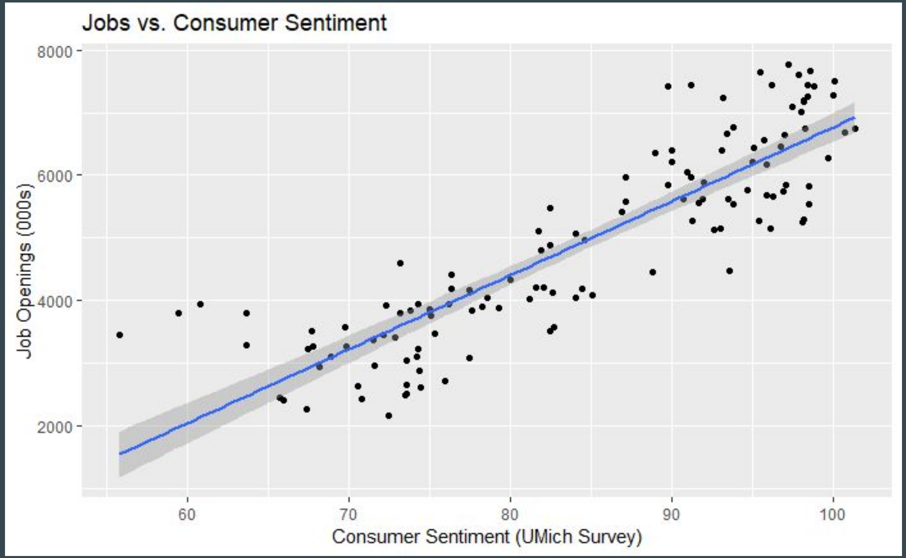
Seasonal ARIMA Model

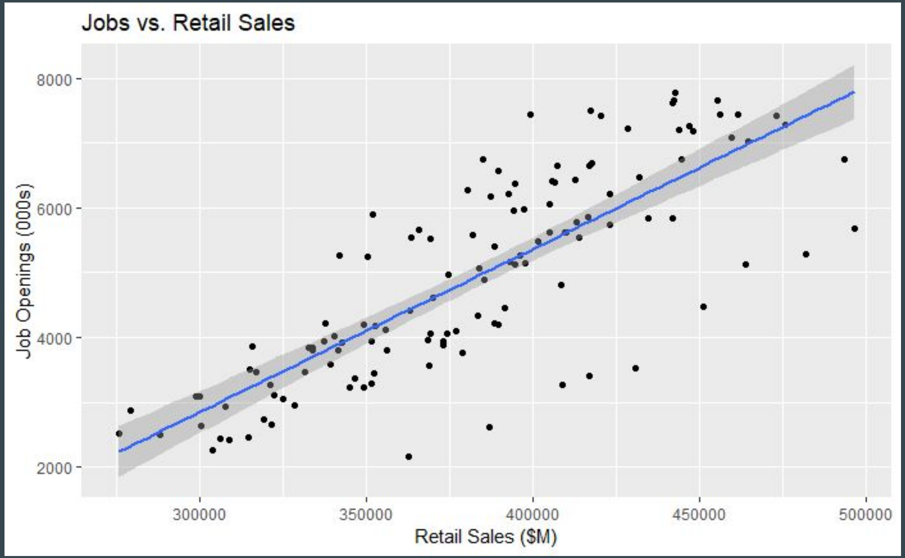
- ARIMA(2,1,0)(0,1,1)[12]
- Test Results
    a. RMSE = 547
    b. MAPE = 6.48%





Additional Data Sources to Improve Jobs Forecast

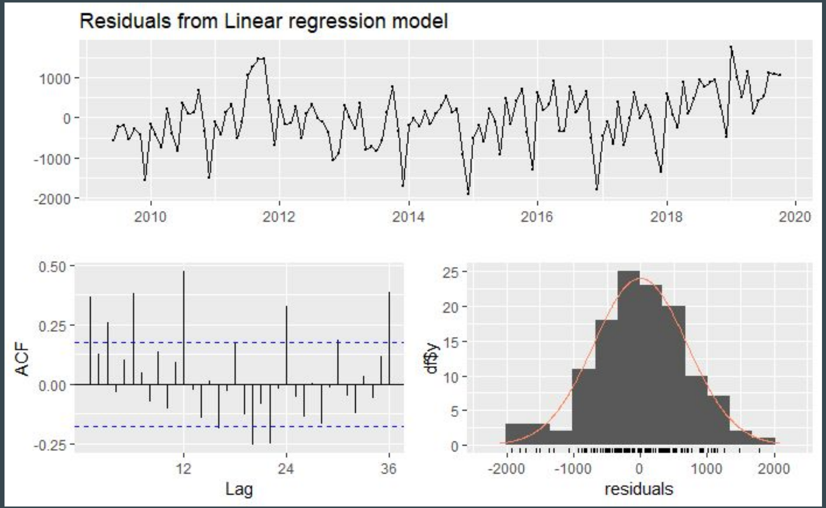


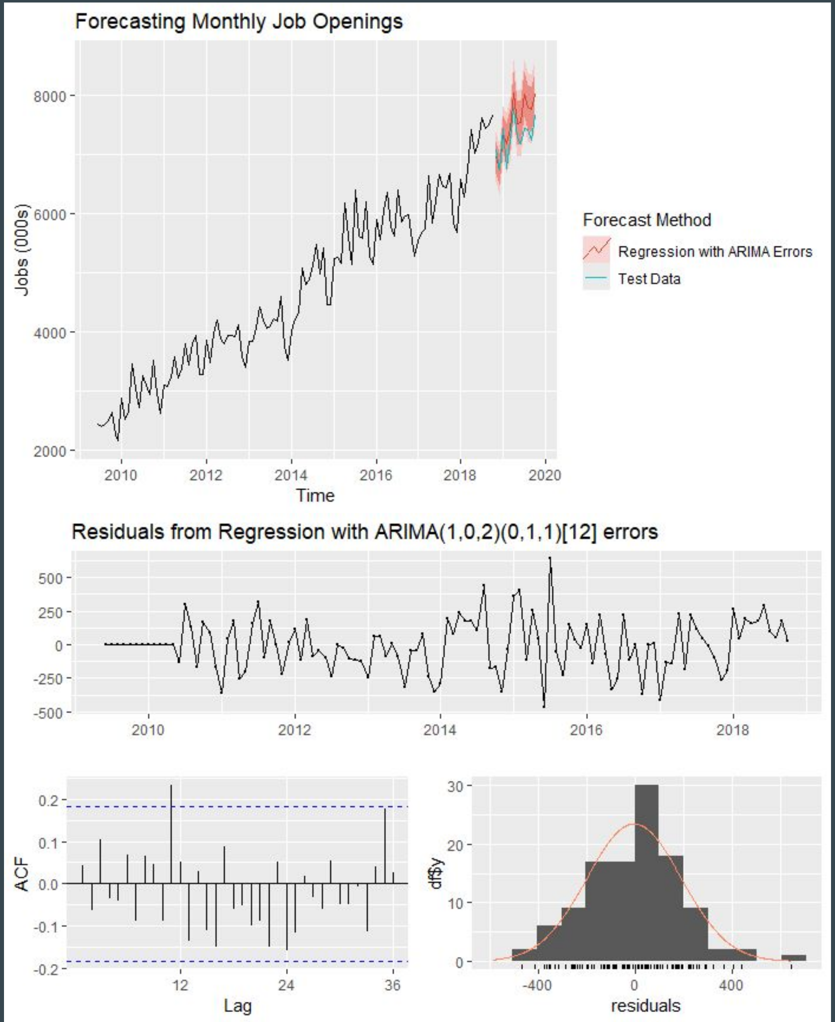


- Consumer Sentiment (UMich Survey)
- https://fred.stlouisfed.org/series/UMCSENT

- Advance Retail Sales ($M)
- https://fred.stlouisfed.org/series/RSXFSN

Regression Model with ARIMA Errors



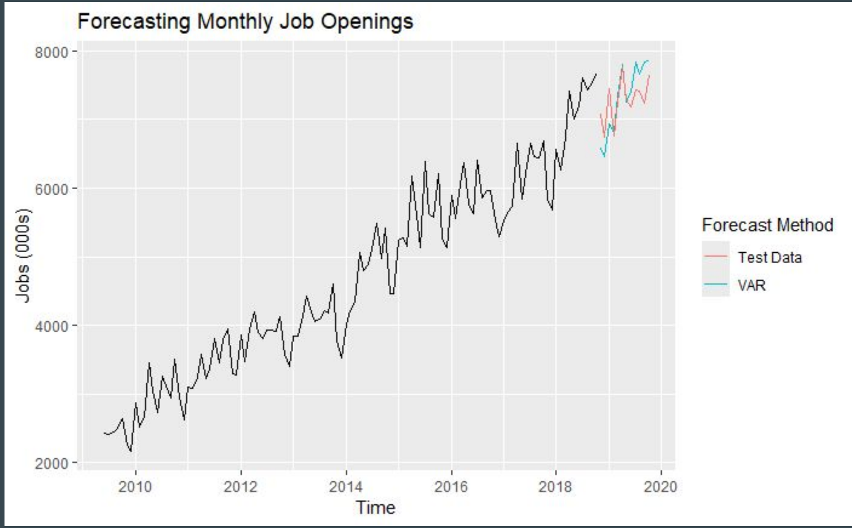


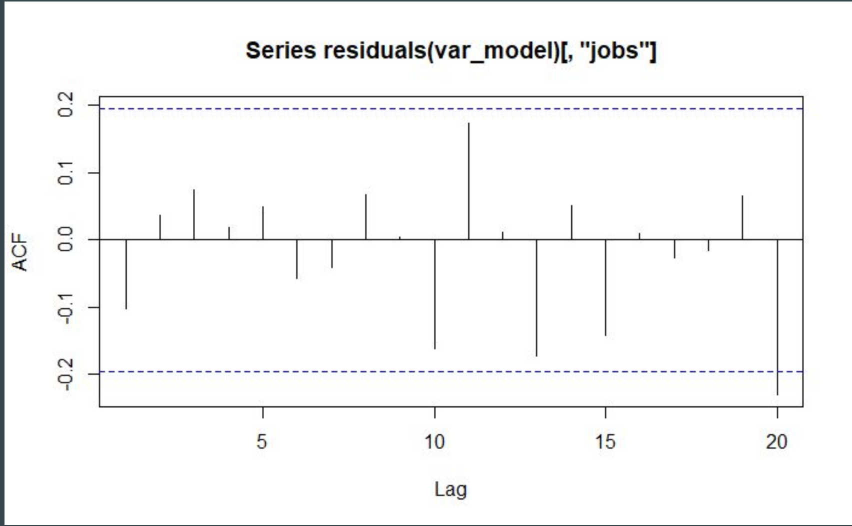
- Errors from our linear regression model do not resemble white noise
- This is good - now we can model the error term with an ARIMA model

- Test Results
  a. RMSE = 339
  b. MAPE = 4.02%

Vector Autoregressive Moving Average Model

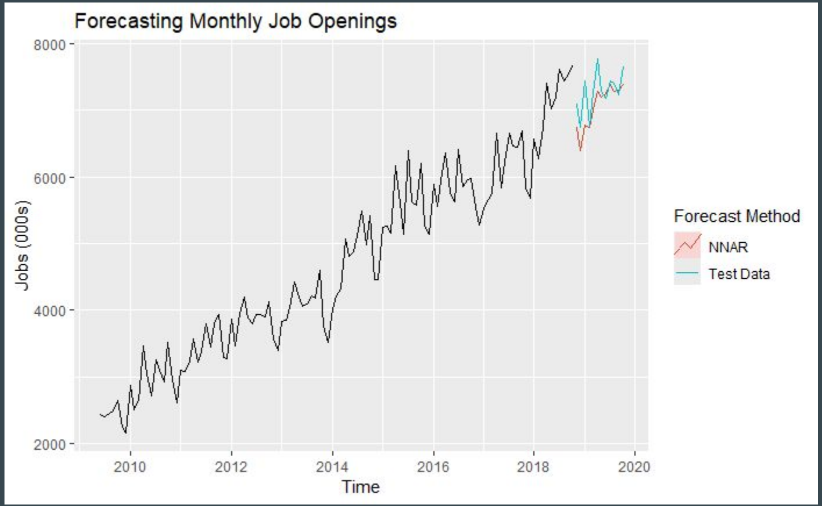
- Assumption: Jobs, Consumer Sentiment, and Retail Sales all affect each other
  a. When there are more jobs, people are happier and spend more
  b. When people spend more, it fuels job growth
  c. When the job environment improves, sentiment improves
- Test Results:
  a. RMSE = 327
  b. MAPE = 3.66%
- We determined an optimal lag of p=12
  a. Pros: improved model performance
  b. Cons: increases model complexity, potential for overfitting

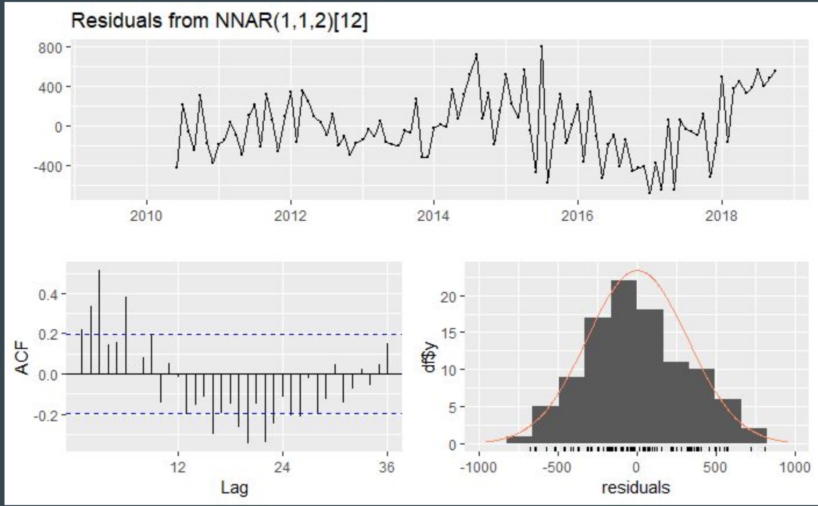




Neural Network Autoregressive Model

- Test Results
  a. RMSE = 306
  b. MAPE = 3.22%
- Pros: NNAR model generated solid overall performance
- Cons: Model residuals show signs of autocorrelation; low explainability





Model Selection

Assessing Model Performance

- Worst performer: Seasonal Naive
    a. Expected since this model basically applies that average historical value for each month as its forecast.
- Best performer: NNAR
    a. Issues with residuals - could lead to biased forecasts and unreliable performance down the road
- Model of choice: Regression w/ ARIMA Errors
    a. Slightly worse forecast accuracy, but more robust
    b. Residuals appear to be well-behaved, suggesting model effectively captured underlying data structure

Model <chr>	RMSE <dbl>	MAPE <dbl>
NNAR	306	3.22
VAR	327	3.66
Regression w/ ARIMA Errors	339	4.02
ETS	476	5.93
Seasonal ARIMA	547	6.48
Seasonal Naive	597	6.22

Conclusion & Future Work

Conclusions

- It's important to be specific with your business problem
    a. Do we just want the model with the best accuracy, or do we also consider factors like robustness and explainability?
- It's hard to predict economic data over longer time periods
    a. Unsurprisingly, our models' forecast accuracy diminished the further into the future we tried to project.
    b. While this is a natural phenomenon in the world of time series forecasting, it seems to have been accentuated by this data set. This underscores the challenges associated with forecasting certain macroeconomic variables.
- Incorporating additional regressors can improve forecast accuracy
    a. However, it's critical to balance additional model parameters with model complexity. In our exercise, we limited ourselves to two additional regressors, but had to utilize up to 12 lags in our VAR model.

Future Work

- Consider different modeling techniques
  a. Fractional difference models, long memory (ARFIMA) models, multi-seasonality models, etc.
- Try to model a “dirtier” time series
  a. Our original data set ran from 2000 through 2024.
  b. There were two major recessions in that window - the Great Financial Crisis in 2008/2009 and COVID in 2020.
  c. These recessions created sudden trend-changes in the time series that were hard to model. We attempted intervention analysis, but could not develop a cohesive solution.
  d. We intend to learn more about how to create a time series forecasting model when the underlying data generating process changes (as it appears to have done after 2009 and again after 2020).

Appendix - Extra Slides & Notes

Benchmark: Seasonal Naive Model

- Test Results
    a. RMSE = 597
    b. MAPE = 6.22%