Project 2 Time Series Analysis

Forecasting Inflation Rate

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Slide 1: Introduction and Data Context

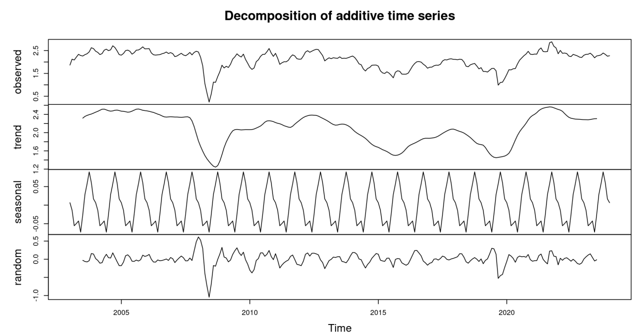
- **resources:** https://fred.stlouisfed.org/series/T10YIE#0.
- **data:** inflation_time_series

```
        library(tseries)
        library(vars)
        library(readr)
        mydata = read.csv("T10YIE.csv")
        inflation_time_series <- ts(mydata$T10YIE, frequency = 12, start =
c(2003, 1))
```

- **Dataset Overview**: The dataset contains monthly observations of the 10-year expected inflation rate (T10YIE), offering insights into anticipated inflation over time. Understanding these expectations is essential, as they influence monetary policy and market dynamics.

- **Forecasting Suitability**: With consistent monthly intervals and a long historical span, this dataset is ideal for time series forecasting, allowing us to uncover trends, patterns, and seasonality critical for economic planning and stability assessments.

Slide 2: Time Series Characteristics Plot



- **Trend**: Strong, shows periods rising and falling inflation expectations over time.
- **Seasonality**: a strong seasonal pattern appears, with consistent intervals, suggesting a recurring annual effect on inflation.
- **Stationary**: The results seems non-stationary, as the trend component shows changes over time rather than reverting to a constant mean.
- **Model**: Holt-Winters is used to capture these characteristics, even though the results are non-stationary and ARIMA has a lower MSE, the results would make more sense using Holt-Winter.
- **Observations**: I have noticed that crisis like the 2008 home mortgage problem and 2020 COVID-19 will cause inflation

rate decrease and forces inflation to get back to normal after within a year.

Slide 3: Forecasting Model Choice

- I chose the Holt-Winters additive model for exponential smoothing. This model is particularly well-suited because it can handle both trend and seasonality, which are evident in the inflation rate data.
- The Holt-Winters method is ideal for time series data that has both a trend and seasonal components. The additive form is chosen because inflation rates typically exhibit relatively stable seasonal variations rather than multiplicative (proportionate) changes.

```
##
## Forecast method: Holt-Winters' additive method
##
## Model Information:
## Holt-Winters' additive method
##
## Call:
## hw(y = inflation_time_series, h = 12)
##
##   Smoothing parameters:
##     alpha = 0.998
##     beta  = 0.0133
##     gamma = 4e-04
##
##   Initial states:
##     l = 1.9876
##     b = 0.0013
##     s = -0.0173 0.0392 0.0914 0.0805 0.0373 -0.0248
##            -0.0841 -0.033 -0.017 -0.0138 -0.0135
-0.0449
```

```
##
##   sigma:  0.1393
##
##      AIC     AICc      BIC
## 420.1407 422.7450 480.2084
##
## Error measures:
##                        ME      RMSE        MAE
MPE    MAPE      MASE
## Training set 0.0005219474 0.1348529 0.09350993
-0.616952 5.75179 0.2737727
##                   ACF1
## Training set 0.3445558
##
## Forecasts:
##          Point Forecast    Lo 80    Hi 80    Lo 95
Hi 95
## Feb 2024       2.308466 2.129907 2.487025 2.035383
2.581549
## Mar 2024       2.311241 2.057289 2.565194 1.922854
2.699629
## Apr 2024       2.311590 1.998596 2.624584 1.832907
2.790273
## May 2024       2.298752 1.935001 2.662502 1.742444
2.855060
## Jun 2024       2.250614 1.841285 2.659943 1.624599
2.876629
## Jul 2024       2.312752 1.861437 2.764067 1.622525
3.002978
## Aug 2024       2.377886 1.887244 2.868528 1.627514
3.128258
## Sep 2024       2.424182 1.896266 2.952097 1.616804
3.231559
## Oct 2024       2.438485 1.874931 3.002039 1.576604
3.300366
## Nov 2024       2.389244 1.791386 2.987102 1.474899
3.303588
## Dec 2024       2.335754 1.704698 2.966809 1.370638
3.300869
## Jan 2025       2.311212 1.647891 2.974532 1.296751
3.325672
```

Output

$$\hat{y_{t+h|t}} = (\ell_t + hb_t)s_{t+h-m(k+1)}$$

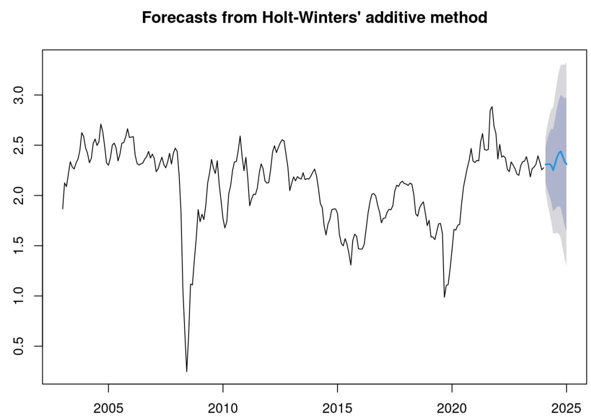
$$\ell_t = 0.998\frac{y_t}{s_{t-m}} + (1 - 0.998)(\ell_{t-1} + b_{t-1})$$

$$b_t = 0.0133^*(\ell_t - \ell_{t-1}) + (1 - 0.0133^*)b_{t-1}$$

$$s_t = 4e - 04\frac{y_t}{(\ell_{t-1} + b_{t-1})} + (1 - 4e - 04)s_{t-m}$$

$$y_t = 0.35y_{t-1} + \varepsilon_t$$

Slide 4: Model Results and Forecast Interpretation



- **MAE:** Low MAE indicates close alignment with actual values on average.
- **RMSE:** Highlights that larger deviations have a stronger impact on error, showing the model's sensitivity to outliers.
- **MAPE:** A low percentage error confirms the model's reliable approximation of actual values in relative terms.
- The forecasted values show a stable continuation of recent trends with seasonal fluctuations.
- The model captures the seasonality and trend well, but it smooths out sharp historical fluctuations, reflecting a

more generalized projection.

Slide 5: Model Diagnostics and Accuracy Evaluation

- **Mean Absolute Error (MAE):** 0.0935, indicating a small average error and good fit to the data.
- **Root Mean Square Error (RMSE):** 0.1349, highlighting the average magnitude of the errors, which is low and shows the model's precision.
- **Residual Autocorrelation:** Low residual autocorrelation indicates the model effectively captures most patterns.

```
##                        ME      RMSE         MAE
MPE    MAPE      MASE
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##                   ACF1
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