Holt-Winters Methods

Holt-Winters Methods involves an exponentially weighted moving average. In the context of the Canadian bankruptcy rates, our model's predictions are based on averages of previously observed bankruptcy rates, with more weight on recent data. In other words, last month is a better indicator than say, 10 years ago. This makes sense because bankruptcy rates is most certainly going to change over time. Triple Exponential Smoothing is appropriate for forecasting monthly bankruptcy rates for Canada because there is both **trend** and **seasonality**. But, what exactly does do these terms mean?

Trend: A trend exists if there is a long-term increase or decrease in bankruptcy rates. As seen previously, there has been an overall decrease from 1987 to 2010. If a trend does not exist, the pattern would look more or less flat. To put it more simply, trend can be thought of as the *slope*. We see that the trend is a slow increase with an ending decrease after 2009.

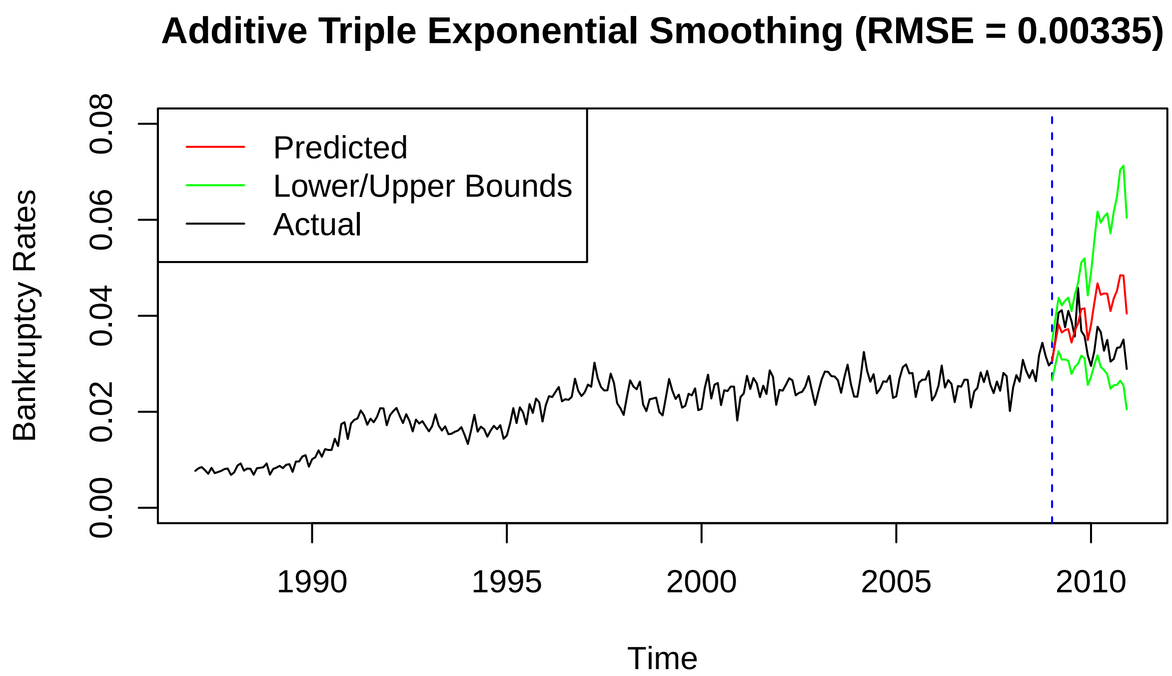
Seasonality: Seasonality is when the time series exhibits similar behavior at regular intervals, or *seasons*. Seasons can be quarterly, monthly, day of the week, etc. In our scenario, bankruptcy rates are recorded every month.

Furthermore, because we decided to explore the logarithm of the bankruptcy rates, we are more concerned about *multiplicative* rather than *additive* methods. The overall concept behind triple exponential smoothing is to apply exponential smoothing and incorporating the level, trend, and seasonal components. While the trend is the *slope*, the level can be treated as the *intercept*.

Next, the amount of smoothing to be done needs to be calculated. Every time series behaves differently and thus require different set of smoothing parameters. There are three smoothing parameters and are the following: level(α), trend(β), and seasonality(γ). These parameters range from 0 to 1 inclusive, where values close to 0 represent *extreme* smoothing and values closer to 1 represent *no* smoothing. To decide the optimal values of α, β, and γ, we used an iterative approach. We tried values from $0.01, 0.02, ..., 0.99, 1$ for each of α, β, and γ so a total of $10^3 = 1,000,000$ combinations.

Best Holt-Winters Model

Our best model for Holt-Winters consists of $\alpha = 0.01, \beta = 1, \gamma = 0.04$. Because $\beta = 1$, this means that the latest values carry all of the weight. So, this means that the *level* and *seasonality* is the most important when it comes to prediction. These parameters gave us the smallest root mean squared error (RSME).



Although this was our best Holt-Winters model, we see that the model failed to catch the ending spike in the bankruptcy rates. One advantage of Holt-Winters is that it does not depend on any distribution assumptions. For interpretability purposes, this method is fairly easy to understand because it just involves exponential smoothing over and over. A disadvantage of this model is that it is heavily dependent on the most recent data in the training set. As we see in the plot, there was an increase at the end of the training set and thus Holt-Winters continued to predict the same when in fact, the bankruptcy rates started to decrease. Overall, Holt-Winters failed to capture unexpected behavior that perhaps other models could have predicted.