Time Series Analysis and Forecasting of the Global Art Market Auction Results

Jianing Lu

Introduction

It remains a question whether artworks, as having unique characteristics that are difficult to categorize quantitatively, can be gazed at like stocks, real estates, or any other investment assets. In this paper, I will analyze the statistical patterns of the global art market auction data from 1998 to 2018, and demonstrate several methods to give an acceptable prediction of the future auction results, that can help art investors determine when is the best time to buy artworks.

Data

I extracted the data concerning the global art market trend from artprice.com at http://imgpublic.artprice.com/pdf/agi.xls. Indices are already calculated by the provider based on the auction results in euro for each season from 1998 to 2018. For the first season of the time series (first three months of the year 1998), an index of 100 is assigned. In this way, the relative pattern of the auction results is preserved, without keeping lots of actual pricing values. Also, only the sales of Fine Art are taken into account, where Fine Art includes paintings, sculptures, drawings, photographs, prints, videos, installations, and tapestries.

Figure 1 shows the original global auction indices in terms of all the seasons from 1998 to 2018.

Figure 2 shows the indices for different categories of art, including Contemporary Art, Nineteenth Century Art, Modern Art, Old Masters Art, and Post-war Art. This figure is just to present the consumption pattern, but the data relating to different art categories will not be studied and compared in detail, because for each category, there are complex artistic characteristics that contribute to its market value.

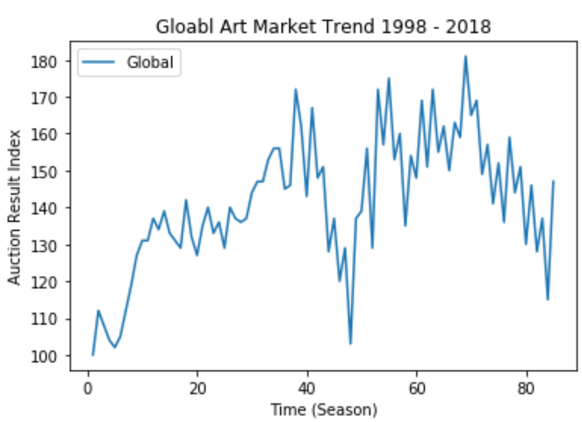

Figure 1. Global Art Market Trend 1998 - 2018

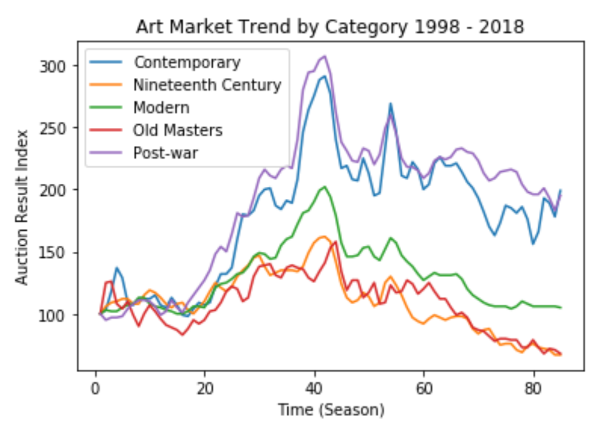

Figure 2. Art Market Trend by Category 1998 - 2018

Methodology

There are several methods to be used for data forecasting.

The **Naive Method** works for stable datasets. It assumes that the next expected point is equal to the last observed point. That is, the forecasted values will all be the same as the last recorded value.

the **Simple Average Method** is used for a series of data whose average remains constant within each sub-period. Thus, the expected value is most likely to be the average of all the past values. However, in this case, the expected value is usually not continuous with the previous ones.

for a set of data with one sharp increasing or decreasing tendency, we can use the **Moving Average Method**, for which we use a fixed finite number of the previous values, instead of all of them.

The **Simple Exponential Smoothing Method** takes into account all the data, but the points are weighed differently. Usually newer observations are more heavily weighed, as they are more relevant. A smoothing parameter α is called in, where $0 \leq \alpha \leq 1$. So we have

$$\hat{y}_{T+1|T} = \alpha y_T + \alpha(1-\alpha)y_{T-1} + \alpha(1-\alpha)^2 y_{T-2} + \cdots$$

We can see that for every two data points, the expected value can be expressed as

$$\hat{y}_{t+1|t} = \alpha * y_t + (1-\alpha) * \hat{y}_{t|t-1}$$

The two variables on the right hand side stand for the most recent observation and the most recent forecast.

For data with a trend (a general pattern that we observe over a period of time), the **Holt's Linear Trend Method** is used. First, the datasets are decomposed into the parts of Trend, Seasonality and Residual. If the trend does exist after the decomposition, the method can be used. With this method, exponential smoothing is applied to both the level(the average value) and the trend.

$$\text{Forecast equation}: \hat{y}_{t+h|t} = \ell_t + h\, b_t$$

$$\text{Level equation}: \ell_t = \alpha y_t + (1-\alpha)(\ell_{t-1} + b_{t-1})$$

$$\text{Trend equation}: b_t = \beta * (\ell_t - \ell_{t-1}) + (1-\beta) b_{t-1}$$

From the above system of equations, we can see that level value is a weighted average of the observed value and the one-step-ahead forecast value. The trend is a weighted average of the estimated trend and a previous estimation of it.

The **Holt-Winters Method** takes into account both trend and seasonality. It employs triple exponential smoothing, because all the three components: seasonality, level and trend, need to be smoothed.

$$\begin{array}{rrcl}
\text{level} & L_t & = & \alpha(y_t - S_{t-s}) + (1-\alpha)(L_{t-1} + b_{t-1}); \\
\text{trend} & b_t & = & \beta(L_t - L_{t-1}) + (1-\beta) b_{t-1}, \\
\text{seasonal} & S_t & = & \gamma(y_t - L_t) + (1-\gamma) S_{t-s} \\
\text{forecast} & F_{t+k} & = & L_t + k b_t + S_{t+k-s},
\end{array}$$

s is the length of the seasonal cycle. For the level smoothing parameter, $0 \leq \alpha \leq 1$. For the trend smoothing parameter, $0 \leq \beta \leq 1$. For the seasonal smoothing parameter, $0 \leq \gamma \leq 1$. Similarly as in the Holt's Linear Trend Method,The seasonality is a weighted average between the current seasonal index and the previous one. With this method, the generated predictions will differ depending on whether we choose the additive or the multiplicative technique. Usually, the former is used when seasonal variations are almost constant throughout the time series, and the latter is used when seasonal variations are changing proportional to the level.

Analysis

For the analysis, I used Python 3.6 with Anaconda Spyder, and modules like Numpy, StatsModels, and Matplotlib.

Since the time series is unstable and by visual inspection doesn't have a nearly constant average value, I applied the Simple Exponential Smoothing Method, the Holt's Linear Trend Method, and the Holt-Winters Method for the data analysis and prediction. Note that for the last two methods, we need to decompose the data first, to make sure it follows a trend (or seasonality), before applying the methods.

Results

The decomposition of data using the additive and multiplicative techniques is as follows. In these plots, a frequency of 2 is assigned for the process of decomposition. When I used other frequencies, the existence of the trend and the seasonality was still obvious.

As a result, the Holt's Linear Trend Method and the Holt-Winters Method are applicable to the data.

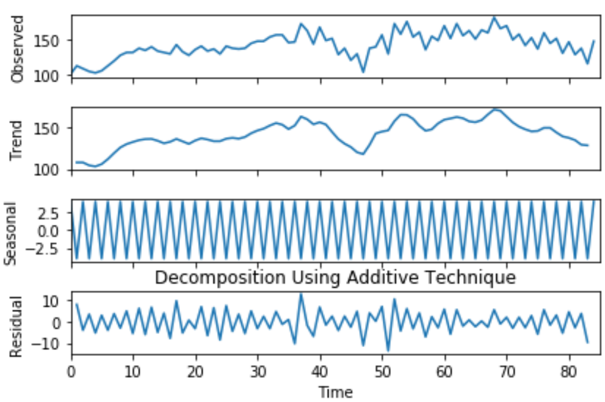

Figure 3. Decomposition Using Additive Technique

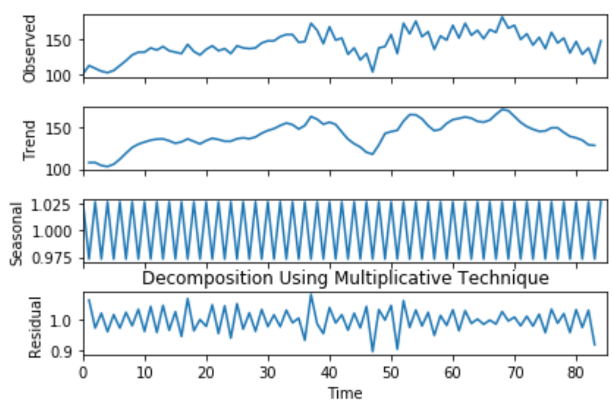

Figure 4. Decomposition Using Multiplicative Technique

Then, when applying the models, the values of the smoothing parameters were explicitly defined, depending on the degree of closeness of the forecasting to the previous average value. For example, the level smoothing parameter α is between 0 and 1. If α is defined to be close to 1, then in the model, more weight is given to the recent observations.

In order for the results to be consistent, in every simulation, I used the same value of those parameters for different models. Below shows the result given with $\alpha = 0.1$, $\beta = 0.2$, and the seasonal period = 4 (when applicable).

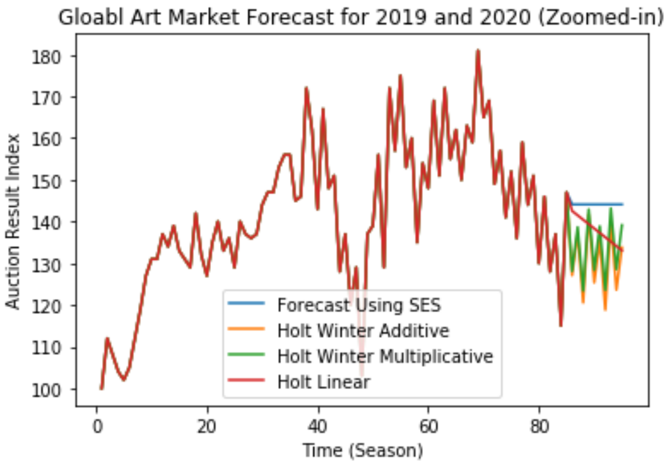

Figure 5. Gloabl Art Market Forecast for 2019 and 2020

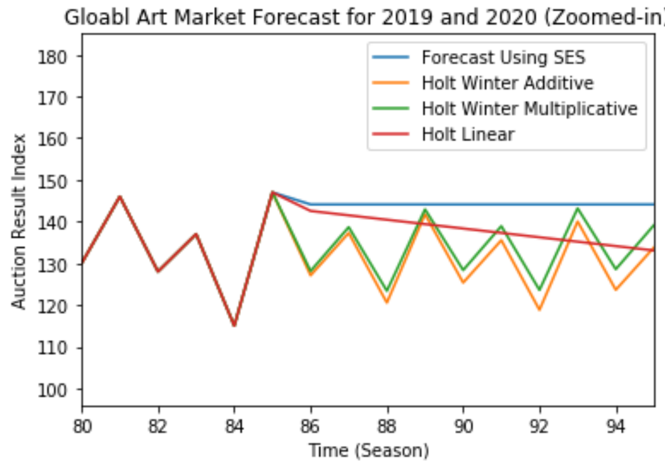

Figure 6. Global Art Market Forecast (Zoomed-in)

Discussion

It can be seen that, when we assume the data has no clear trend or seasonal pattern and apply the Simple Exponential Smoothing method, we will be given a relatively stable prediction, with a relatively large mean. It indicates that investors would have some freedom in buying and selling art pieces in 2019 and 2020, since there wouldn't be a large instability in the global art market.

However, when we take the trend of the data into consideration and apply Holt's Linear Trend method, even though the prediction is still stable, it goes down to a larger extent than that given by the SES method.

When we further take the seasonality into consideration and use the Holt-Winters Method, we obtain the most satisfactory results, with both the additive and multiplicative techniques. The predicted art market auction prices go in a cyclic pattern, with a general trend of decaying. This makes sense as the market has been having this downward trend since three years ago, so it's very likely that the market wouldn't boost sharply in the future two years.

The Holt-Winters Method gave good results, but there was a lot of factors that the model failed to consider. So far, in almost all the statistical studies of the art market, the impact significant social events is not taken into account. For example, in Figure 1, there is a sharp fall in the index from 2008 (the 40th season in the figure) to around 2010. Very likely, it is largely due to the global financial crisis that happened in 2018. Societal factors like this must be included into the model and given an appropriate wight when generating the forecast, if we want to make truly reliable prediction of the art market.

Conclusion

To make predictions of the global art market auction data in 2019 and 2020, I used those tools: the Simple Exponential Smoothing model, the Holt's Linear Trend method, and the Holt-Winters Method.

Among them, the Holt-Winters Method, which takes both the trend and the seasonality of the previous data (1998 - 2018) into consideration, gave the most satisfactory results. The model indicates that the future art market, with cyclic seasonality, has a general trend of slow decaying.

In the future, if societal factors are taken into account and given reasonable weights when applying the models, we will achieve further meaningful results.

References

Singh, Gurchetan. 2018. 7 methods to perform Time Series forecasting. Retrieved from https://www.analyticsvidhya.com/blog/2018/02/time-series-forecasting-methods/

Vasilache, Mihaela-Eugenia. 2018. *Forecasting the Trend of Art Market.*

Urech, Res. 2013. *Statistical Properties of Art Pricing Models.*

Bocart, Fabian. 2014. *Econometric Analysis of Alternative Assets with Applications to the Art Market.*