Journal of the Arkansas Academy of Science

Volume 75 Article 14

2021

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Recommended Citation

Howell, Michael; Berleant, Daniel; Aboudja, Hyacinthe; Segall, Richard; and Tsai, Peng-Hung (2021) "Is technological progress a random walk? Examining data from space travel," *Journal of the Arkansas Academy of Science*: Vol. 75, Article 14.
https://doi.org/10.54119/jaas.2021.7501
Available at: https://scholarworks.uark.edu/jaas/vol75/iss1/14

Is Technological Progress a Random Walk? Examining Data from Space Travel

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Running title: Forecasting Space Exploration Progress

Abstract

Improvement in a variety of technologies can often be successfully modeled using a general version of Moore's law (Moore 1965) (i.e., exponential improvements over time). Another successful approach is Wright's law, which models increases in technological capability as a function of an effort variable such as production. While these methods are useful, they do not provide prediction distributions, which would enable a better understanding of forecast quality.

Farmer and Lafond (2016) developed a forecasting method which produces forecast distributions and is applicable to many kinds of technology. A fundamental assumption of their method is that technological progress can be modeled as a random walk with drift.

We demonstrate a class of technology, space exploration, in which random walk with drift does not occur. This shows the need for alternative approaches suitable in such technological domains.

Introduction

The recognition that technology progresses in a predictable way is now widespread. Some of the earliest research in this area was conducted by the aeronautical engineer Theodore Paul Wright. Wright described a phenomenon he observed while supervising the production of aircraft, as the batch size of a model of aircraft increased, the per-unit cost to manufacture those aircraft decreased at a predictable rate. The approximate relationship was a 20% drop in cost for every doubling of production volume (Wright 1936). This phenomenon has been attributed by many researchers, to "learning by doing" where productivity is improved through the accumulation of experience. Subsequent research indicated that this pattern holds for a variety of industries although the rate of cost decline varies by industry (Hax and Majluf 1982). This relationship between effort and per-unit cost has been referred to by various names such as learning curves and experience curves (Henderson 1968). Contemporary research into technology foresight uses the term Wright's law, so in this paper we will be using this term.

A more popularly known trend is Moore's law. Originally this phenomenon was described by one of the co-founders of Intel, Gordon Moore, in 1965. Moore famously noted a regular doubling of the number of components that could be built into an integrated circuit and hypothesized that this trend would continue (Moore 1965). The trend soon slowed somewhat but then continued with a doubling time, for that domain, of approximately 18 months to 2 years. Just like Wright's law, Moore's law has been found to be generally applicable to a variety of technologies as shown below.

Before we can develop models of technological improvement, we must first define a metric for improvement. While many legitimate metrics of technological performance exist, one of the simplest to use is cost per performance. This metric has two important advantages for researchers, the data may be available, and the metric captures a general notion of the development of a technology at a given time. Let us review the general applicability of Moore's law in terms of cost with a few examples.

First, we can consider the cost to sequence a human genome. This cost is not only declining exponentially, but it is also declining much more rapidly than the rate of Moore's law as applied to computer processors. More specifically, we see that sequencing a genome today is approximately 100,000 times cheaper than sequencing a genome in 2001 (NHGRI 2020).

Solar electricity is another source of exponential improvement which is having a massive impact on our society. Like most exponential technologies, the initial slow rate of improvement led many to dismiss its importance. Today the situation is much different with many believing that the plummeting cost of solar is a primary cause of the decline of the coal industry (Plumer 2020; Gimon *et al*. 2019; Our World in data 2021).

Finally, we can consider nanotechnology. It is not immediately obvious how progress in nanotechnology should be quantified since it is not a specific technology but rather a scale at which technological effort is undertaken. However, it is often argued that number of nanotechnology publications is reasonable since an exponential increase in the number of publications suggests a commensurate increase in effort to improve the technology and thus, one might reasonably conjecture, the capability of the technology (Palmberg *et al.* 2009; Hullman 2006). Figure 1 shows just such an exponential increase in the number of nanotechnology related scientific publications over time.

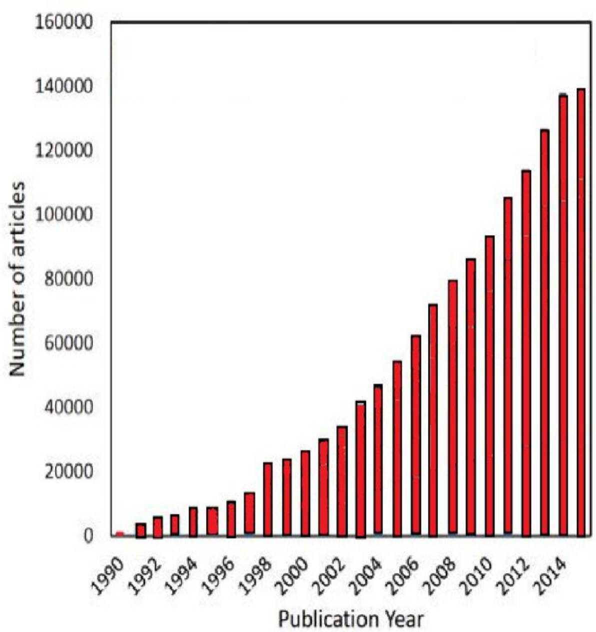

Figure 1. Nanotechnology publications by leading countries. Based on Kwon (2016).

Progress in Space Technology

While many technologies have displayed exponential improvement, one technology that is often missing from the literature on exponential improvement is space exploration. It would be surprising if such improvement did not occur in that domain since it would imply there is something innately different about space exploration technology. In response to this conundrum, a primary focus of our research has been to find exponential trends in space exploration technology that have been previously unnoticed.

As mentioned earlier, however, we must first define our metric of improvement before attempting to find these trends. With this in mind, we investigated spacecraft lifespan as a metric, which we define as the length of time a spacecraft sent to at least one extraterrestrial body operates. The data we used is maintained as a Google spreadsheet located at https://docs.google.com/spreadsheets/d/1ZtfkjbcTOoZTbETUkOY5Hlq5SY5GREvFYjgzmKZQww4/edit#gid=117287008. The data covers deep space missions to extraterrestrial bodies (except the Sun) beginning in 1959 and continuing to the present day. All of the data was collected from public sources. Our previous investigations had shown signs of exponential improvement for the domain (Berleant *et al.* 2017; Berleant *et al.* 2019). An important difference between this metric and other metrics for technological progress is that it does not directly measure empirical properties of the spacecraft such as mass, thrust, or fuel efficiency. However, it can be argued that good metrics for technological progress should capture the utility to the user since this is what results in the societal impact of the technology (Magee *et al.* 2014). Mission lifespan does have this advantage as a metric.

While this initial analysis of trends in mission lifespan was encouraging, there were some problems with using mission lifespan for modeling improvements in space exploration technology. Many models of technological progress use least-squares regression. When building such a model using mission lifespan as the dependent variable, this leads to absurd scenarios where predicted lifespan is longer than the entire history of spacecraft technology (Berleant *et al.* 2019). Therefore, the use of this metric required other modeling techniques to really be useful.

Determining Forecast Quality

The search for other techniques required to model space exploration technology dovetails with another problem brought about by using least-squares regression for modeling improvements in technology. Namely, while Moore's law (Moore 1965) and Wright's law (Wright 1936) have been quite successful in modeling the increase in a wide variety of technologies, they do not provide forecast distributions. This is important because no forecast is 100% accurate and these distributions would give us an idea of the range of outcome values we might

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DOI: 10.54119/jaas.2021.7501

encounter. Farmer and Lafond (2016) mention this problem in relation to technology foresight and describe why understanding forecast uncertainty is so important for policy considerations.

So where does forecast uncertainty arise? Hyndman (2014) lists four primary sources:

1.) The assumption of the continuation of past trends
2.) Model quality
3.) Parameter uncertainty
4.) Random shocks

The first assumption is a prerequisite for an extrapolation-based approach. Factor (2) can be optimized by modeling techniques such as optimizing model fit and distribution of residuals. Parameter uncertainty can theoretically be minimized using simulations although this increases the complexity of forecasting (Ibid). In this article we focus on the impact of random shocks. This can be done by using the standard literature of time series analysis.

There are important differences between the methods used by us and those used by Farmer and Lafond (2016). Their method assumes that parameter uncertainty is the largest source of forecast uncertainty. More specifically, the method assumes that forecast variances grow with the square of the time horizon in the presence of parameter uncertainty but only linearly when there is no parameter uncertainty (Sampson 1991). Parameter uncertainty was likely more of an issue since most of the time series data was short and had to be aggregated (Farmer and Lafond 2016).

Another important assumption of their method is that improvements in each technology can be modeled as a random walk with drift. More specifically:

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

where y_t is the performance of the technology at a given time step, μ is the "drift" or trend, and ε_t is an i.i.d. noise process. Each technology is modeled with a different mean and variance parameter for the noise component of the model. Due to the limited size of the time series, they were unable to perform unit root tests to justify this approach theoretically; however the empirical results they derived were consistent with this model.

We did not have this problem since our space mission data is large enough to perform unit root tests, and our results indicated that the data was not generated by a random walk as we demonstrate below. Therefore, space exploration is one technology that would benefit from an approach other than the random walk model. In the following section we detail how unit root tests, autocorrelation patterns, and backtesting demonstrate that this data does not have a unit root.

Methods and Results

As stated before, we used time series modeling to describe improvements in space exploration technology. This approach does not consider parameter uncertainty, suggesting prediction intervals would likely be too narrow in backtesting (Hyndman 2014). Since this did not happen for mission lifespan models it is likely that parameter uncertainty is not a significant issue for them. Each point forecast was based on an ARIMAX model, which is a combination of a linear regression and an ARIMA model fitted on the residuals. The regressor for the model was the order of launch. This approach was chosen over a standard ARIMA model since this performed better on backtesting.

All analysis was conducted using the R statistical packages *tseries, forecast, and stats*. First, we had to determine if the time series was stationary or not. This is done usually by examining the autocorrelation function (ACF) of the data. Figure 2 displays a plot of the autocorrelation of mission lifespan which decays very slowly. While this is usually considered a sign of nonstationarity, the first differences tell a different story. Figure 3 shows the plot of the first differences of the data which displays several significant lags. This is inconsistent with time series that contain stochastic trend (i.e., a random walk) but is consistent with time series that contain a deterministic trend. This is because the first differences of a time series describe the changes from one period to the next, the first differences of a random walk should therefore be uncorrelated.

The next step is to determine the autoregressive components of the model. A plot of the Partial Autocorrelation Function (PACF) is displayed in Figure 4. This plot shows significant autocorrelations for lags 1, 2, and 5. Autoregressive models display decaying autocorrelations alongside partial autocorrelations with significant lags typically equal to the appropriate autoregressive parameter. These plots indicate that an autoregressive parameter no larger than 2 would be appropriate. An Augmented Dickey-Fuller (ADF) test statistic of -3.4854 was generated at 5 lags with a p-value of 0.0473 which further indicates stationarity. The lag length of 5 was originally chosen

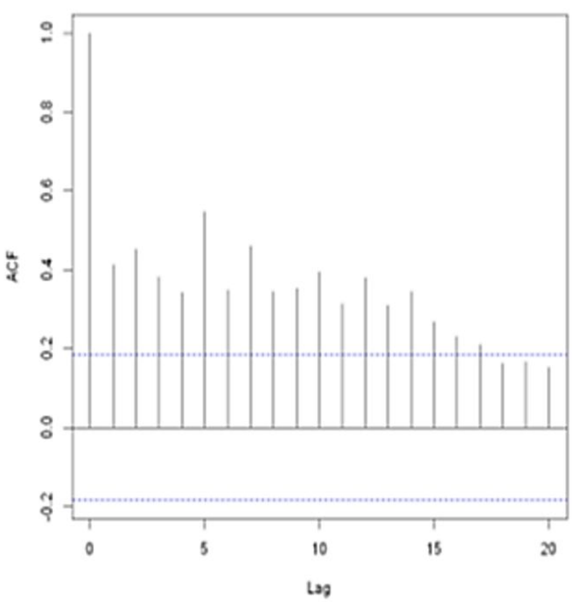

Figure 2. Autocorrelation of Mission Lifespan.

for the purpose of finding the optimal model to predict progress in mission lifespan. However, since the focus of this paper is to compare random walk and non-random walk models, this will not be expounded on. The significant autocorrelation at lag 5 of the partial autocorrelation plot may be an indication of seasonality. This hypothesis can be further supported by Figure 2 which displays a noticeable spike at approximately every 5 lags. While it can be demonstrated that seasonal models produce better forecasts for mission lifespan we will not elaborate on this topic. As stated earlier, the focus of the paper is whether or not a random walk model is appropriate for predicting progress in mission lifespan.

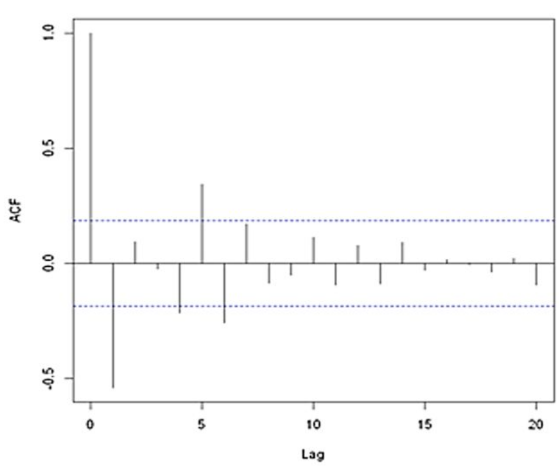

Figure 3. Autocorrelation of Mission Lifespan Differences.

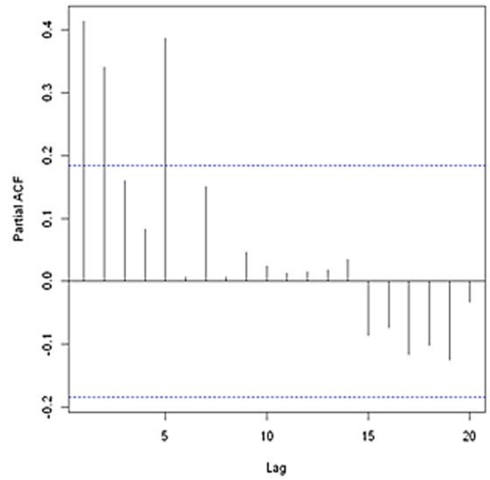

Figure 4. Partial Autocorrelation of Mission Lifespan.

To illustrate our thesis, a model containing a single autoregressive parameter will be used although this pattern can be observed with higher numbers of parameters. One of the most used is methodology based on Autoregressive Integrated Moving Average (ARIMA) model by Box *et al.* (2015).

The ARIMAX model is an extension of Autoregressive Integrated Moving Average (ARIMA) model. The ARIMA model has three parameters, namely: p, d and q, where p is the autoregressive term, q is the moving average term and d indicated the series is differenced to make it stationary (Smarten 2018).

When an ARIMA model includes other time series as input variables, the model is sometimes referred to as an ARIMAX model. Pankratz (1991) refers to the ARIMAX model as dynamic regression.

By using Maximum Likelihood Estimation (MLE), we obtained the following equations for the time series using one autoregressive parameter. For an ARIMA (1,0,0) model we have:

$$Y_t = -0.5367Y_{t-1} + \varepsilon_t \quad (2)$$

where Y_t is the value of the time series at time *t* and ε_t is an error term. For an ARIMAX (1,0,0) model we obtain:

$$Y_t = 0.0727X_t + n_t \quad (3)$$

where Y_t is the value of the time series at time *t*, X_t is the order of launch, and n_t is an ARIMA (Autoregressive Integrated Moving Average) model fitted to the model residuals.

The Akaike information criterion (AIC) is an

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DOI: 10.54119/jaas.2021.7501

estimator of out-of-sample prediction error and thereby relative quality of statistical models for a given set of data (Akaike 1977). The Bayesian Information Criteria (BIC) (Schwartz 1978) or Schwarz criterion (also SBC, SBIC) is a criterion for model selection among a finite set of models. It is based, in part, on the likelihood function. The ARIMA (1,0,0) model has AIC and BIC scores of 501.13 and 506.23 respectively, while the ARIMAX (1,0,0) model has AIC and BIC scores of 472.78 and 483.04 respectively. ACF plots of residuals for both models displayed in Figure 5 and Figure 6 demonstrate that the residuals of the ARIMAX (1,0,0) model more closely resemble white noise with the aforementioned significance 5. This is a further indication that the ARIMAX model should be preferred.

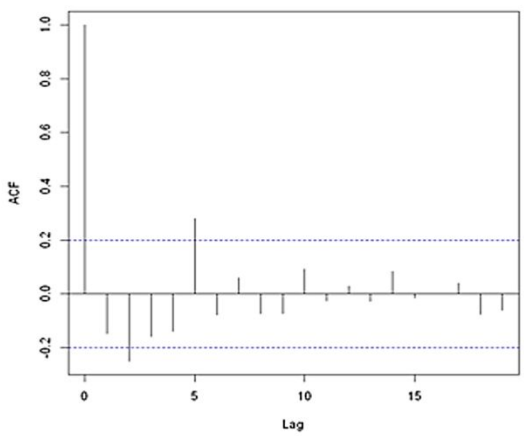

Figure 5. Autocorrelation of ARIMA (1,0,0) Residuals.

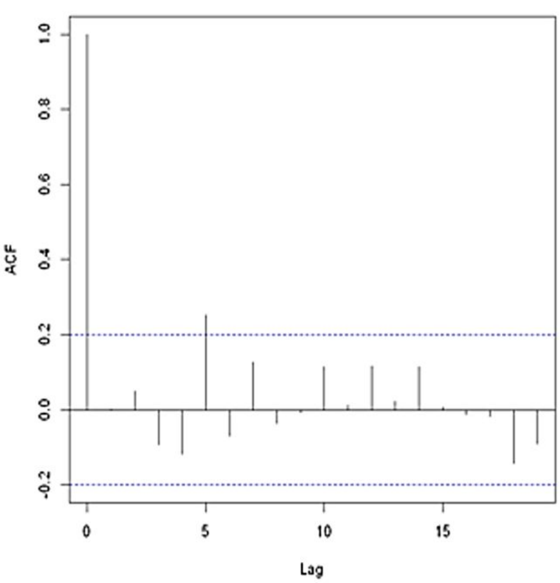

Figure 6. Autocorrelation of ARIMAX (1,0,0) Residuals.

Backtesting

Forecasting using the assumption of stationary data also produces superior forecasts as measured by backtesting. As an example, Figure 7 shows the results of backtesting with an ARIMA (1,1,0) model. The notation indicates that our model is based on the first differences of the time series and predicts the current period using the value immediately preceding it. This model was produced using 96 data points with 17 data points withheld for validation. This amounts to 85 percent and 15 percent respectively. The blue and gray regions represent the 80% and 95% prediction intervals of the model respectively. The red line consists of the 17 data points that were withheld for validation and the blue line represents the point forecast of the model.

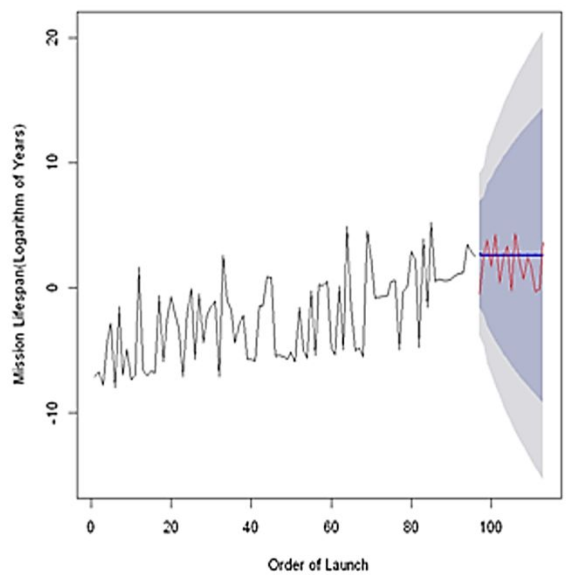

Figure 7. Forecast using an ARIMA (1,1,0) model. Log scaling prevents the left-hand region of the graph from being compressed and thus losing detail relative to the right-hand region. The wide prediction intervals indicate that the forecast assumes a random walk.

Figure 8 displays an ARIMAX (1,0,0) model trained with the same data. Notice that in both cases we produce models with accurate forecasts but the model which assumes stationarity provides a narrower range of possibilities and therefore, supports a narrower prediction. Due to this and the other aforementioned reasons, ARIMAX models produce better predictions than ARIMA models for improvements in mission lifespan.

We can be reasonably certain that the time series will remain stationary as long as our estimate of the model's autoregressive parameters, φ_p , are less than 1. Therefore, the general pattern displayed in Figure 5 should remain valid for future forecasts as long as the data generating process does not change.

If our parameter estimate is either equal to 1 or a unit root test is statistically significant then this model is no longer reasonable.

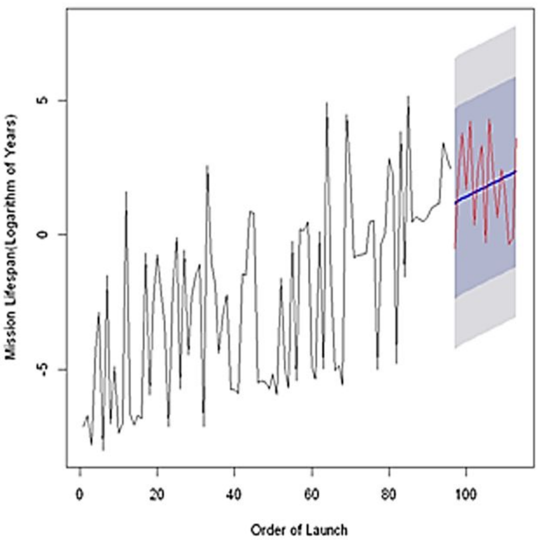

Figure 8. Forecasts for an ARIMAX (1,0,0) model with a linear trend. Log scaling prevents the left-hand region of the graph from being compressed and thus losing detail relative to the right-hand region. The assumption of no random walk and a linear trend results in a better prediction as indicated by the narrower prediction interval.

Discussion & Conclusion

It seems that a random walk model can be useful for modeling improvement in a wide variety of technologies. Nevertheless, it appears from our analysis of mission lifespan data that not all technologies follow a random walk model and thus require a different approach.

But why is this so? One possible explanation is that space exploration is a fundamentally different kind of technology. For example, one might conjecture that space exploration is not primarily a commercial activity whereas the technologies most often analyzed are primarily commercial. The literature of endogenous growth theory suggests that economic forces play a significant role in producing technological development, lending support to that possibility (Romer 1990). This becomes more apparent when we measure improvements in terms of cost. Basic economics would hold that if the price elasticity of demand were held constant then a decrease in cost should lead to an increase in demand which would lead to a decrease in cost via Wright's law, and so forth (Magee *et al.* 2014). It is easy to see how this could give rise to a random walk pattern and how it should not apply to non-commercial technologies.

Another possible reason is that much of the original data did not have a unit root and this was undetected since it was so short. This is likely a problem due to the lack of comprehensive databases on technological performance. The Santa Fe Institute's performance curve database is a noteworthy attempt to correct this problem, but ultimately researchers need more data. Most modeling of technological performance improvements is based on Maximum Likelihood Estimation which is notorious for mis-specifying parameters when data is limited (Bishop 2006).

In closing, we hope this advances the discussion on what methods might best be used to model improvements in technological performance. Technological advancement has a great effect on the future of society and thus increasing our understanding of how it develops can help deepen understanding of social change.

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