Forecasting Clinical Revenue Services Of A Large Medical Device Company When There Is Dependency On Other Departments

by

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Abstract

Predicting revenue can prove to be difficult, especially for a large medical device company. This laborious task is often a result of improper data entry, poorly run models, improper workplace engineering and implementing improper forecast models that may be complicated for the application that is needed. This research assesses the process of clinical revenue recognition for a multi-national healthcare company.

The clinical services that support the patient monitoring arm of the company is the area of focus for this paper. Clinical revenue recognition is dependent on several factors which include: invoice dates, install completion, and clinical support delivery. The importance of this research is to find an accurate measure of when the funds for clinical services will be released based on these extenuating circumstances.

A predictive forecasting model was created and tested with data from January 2018 through December 2019. The data forecasted trends with accuracy based on monthly and quarterly findings. The models in this research significant and revealed clinical revenue forecasting with 90% confidence. Future iterations may have relevance as the need to regionalize and forecast project management behavior is essential in resource allocation. Keywords: Data Science, Dr. Michael McCarthy, Clinical Revenue Recognition, Professional Sales Automation, Machine Learning, Time Series Analysis, Seasonality, Ethics, Accountability.

Acknowledgments

The journey to become a data scientist has been enlightening, rewarding, and at times questionable. I have found myself celebrating the quick wins as a result of "ah ha" moments and questing my sanity during early morning hours wondering if I have chosen the right program for my master's in data science. What I have completely transformed is the way I apply my clinical knowledge along with 27 years of clinical experience as a result of data science. This capstone project encompasses my professional background and subject matter as a nurse, as well as, wields the analytical thought processes of a data scientist to truly find the center of the "Venn Diagram of Data Science".

The completion of this journey would not have been reached without the support of my family. The personal sacrifice from my wife Liz as she sustained family life without me and countless hours of missing a ball game, horse show or postponing a fishing trip due to school are met with a profound recognition and a promise to payback the times missed with my children Michael, Emily, and Christopher. I also have a profound appreciation for my friends and colleagues as this capstone was fulfilled with professional and sometimes last-minute requests from myself to have material I needed to make a meaningful document. I am forever indebted to Laura Morr; (your belief in me was often stronger than my own) without her knowledge and support, I easily could have "packed my bags" and not fulfilled my aspiration to become a data scientist. To Jacob, Jenny, and the rest of my work family, "thank you", you supported me in every way possible.

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Introduction

This multi-national healthcare company manufactures medical equipment – patient monitors, ultrasound machines, imaging equipment, and a multitude of other items. A minimal amount of clinical services is included with the purchase of equipment. The bulk of clinical services are sold as an additional product when the equipment order is placed. Clinical Specialists' deliver educational services then complete timecards which in turn get recognized as clinical revenue. The recognition of this revenue is dependent on other factors including order intake date, product delivery, clinical services delivery, and invoice dates. Currently there are cumbersome processes in place that make staff and resource allocation difficult for future project models. The inability to accurately predict revenue impacts the overall credibility of the clinical services organization with executive leadership. This lack of credibility can hinder approval for additional headcount and funding for future projects. This paper will investigate a time series model that may aid in clinical services recognition forecasting and support the patient monitoring arm of the multi-national healthcare company.

Literature Review

Many studies, articles, blogs, and other various resources offer guidance and opinions on how to implement machine learning and the application of time series analysis. Many of these studies have limitations; however, many great use cases can be synergized to produce meaningful forecasts. Finding and creating the best model for an organization around time series forecasting lies in the creative work of a data scientist who is an expert in the domain for which the analysis is being run.

Organizations such as this multi-national healthcare company offer products and services on a global scale. Project management is organized through various platforms that aggregate information including customer data, project overviews, invoices and revenue. With a goal to improve the lives of over 3 billion people by 2030 this healthcare company is a global innovation company that can only benefit from improved revenue forecasting models.

Whether the platform used is Python, Alteryx, Tableau or other data processing software, data scientists offer valid insight into proper modeling. Depending on the frequency, times series analysis can be broken down into any time increments that best supports the forecasting needed (Prabhakaran, 2020). Prabhakaran writes about the use of Auto Regressive Integrated Moving Average (ARIMA) and how past values support accurate forecasting. The modeling of ARIMA was tested in this research; however, Exponential Smoothing (ETS) yielded better results.

Salesforce.com, Inc. is a cloud-based software platform company that provides customers management of services and offers a suite of applications centered around customer service, marketing, analytics, and application development. This multi-national healthcare company utilizes Salesforce.com as a tool to track their sales revenue and forecasting budget. Data needed for this capstone was collected from Salesforce.com to create the predictive models to answer the hypothesis.

Alteryx has a large community that blogs, models and offers advice around time series forecasting. Guzman creates a model in Alteryx that utilizes predictive analytics to maximize equipment utilization (2020). The business challenge he faced parallels the needs of this multi-national healthcare company clinical team regarding the utilization of employee time and travel. This model may also guide the methodology when looking at employee utilization versus equipment utilization. Even though this research did not look at equipment utilization, future model iterations may rely on the work provided by Guzman.

Siems also utilizes Alteryx by creating a model around crew reserve and open time forecasting. While the work by Siems is not in scope, the dashboards created and the models utilized to build those dashboards offered guidance in the time series analysis with this paper. The Southwest Airlines model may provide information needed to create a dashboard that reflects forecasted versus actual clinical revenue (Siems, 2019). There is a second potential use for this model as Southwest previously scheduled their pilots without knowledge of the availability of reserves. The company's current model schedules clinical specialists who deliver clinical services without any knowledge of the availability of personnel across regions. In regard to future iterations, this Alteryx model may provide valuable information to build a platform that is needed by this multi-national healthcare company to schedule assignments with efficiency and provide necessary data that can forecast a better clinical revenue model.

Consideration was made to incorporate calendars that accurately report clinical resource allocations. Ayme (2019), also creates a model in Alteryx that blends calendars used by other teams. Adidas International Trading needed a model that blends differed calendars used by other teams. Such information may be gathered for this healthcare company by using Salesforce. This may not be the best model to use due to the cross-functional teams and the inconsistency with keeping calendars up to date; however, there may be relevance to the clinical operations teams to reduce operational costs due to better forecasting. This model creates a calendar that can be used by the entire clinical department at Philips. The use of Alteryx and the specific inputs into this model can align clinical services with a better clinical revenue forecast model. The information provided in this model supported the workflows utilized within this research.

Another model that was considered for application in this research was the Enterprise Resource Planning (ERP) system created by Morris (2019). While this information is not incorporated within this paper, Morris creates an interesting model that has the same characteristics as this healthcare company which aggregates invoice, products, and revenue among different customers. The ERP system merges all this information into one use model. The ERP system created by Morris may provide an analysis that can be run once a month that provides an output for revenue recognition.

There are various fundamentals to be considered when forecasting is needed. Wood (2020) describes a 6 step process to forecast revenue. The use of judgment and quantitative forecasting is similar to how Clinical Services analyzes revenue. Wood also mentions considerations of looking at past data along with any changes in product or personnel. The data mapping for this time series has been linked to allow for refreshing of data which can be run on a monthly basis, as Wood suggests.

Clinical forecasting also looks at historical data. Stamboliyska (2017) explains how forecasting can be made through simple calculations, which includes trends and seasonality and moving averages. Stamboliyska's research shows the importance of historical data validation.

Pitfalls in times series forecasting are always a concern. The article research by Flovik (2020) provides insight on how not to use machine learning for time series analysis. The main emphasis is to be careful in predicting time series accuracy and our roles as data scientists. As a result of this model, accuracy reporting was incorporated within this research.

The use of fairness, ethics, accountability, and transparency (FEAT) has become the guiding principles of use for data science (Hamid,Ya'acob, and Alrazi, 2018). There is some concern as the article supports a financial institution in Singapore, however, the principles of FEAT are clearly defined. The project was assessed to meet the principles of FEAT. This article will assure the information provided by the data analyzed in this paper will be in accordance with FEAT.

Different techniques can be utilized to set up forecasting methods (Corporate Finance Institute, 2020). This article describes four different techniques to set up forecasting methods. These techniques include straight line, moving average, simple linear regression, and multiple linear regression. The prediction of future revenue models is essential to the clinical team at Philips. While not all the methods suggested were used in this analysis, the information provided valuable information to the current use model of clinical revenue forecasting along with providing insight for future iterations.

The literature reviewed for this project on clinical revenue forecasting was utilized to support aggregation, modeling, and supportive documentation. There is compelling information to improve this model going forward and to integrate different regression models to drive process improvement.

Overview of Clinical Services

Clinical services are delivered to provide instruction and support to clinicians on the use of the monitoring equipment. The customer's purchased equipment is not utilized for the delivery of the educational instruction; the purchased equipment often defines the amount of education to be delivered. There are standalone services that are delivered to support the installation and contractual services such as Clinical Performance Agreements (CPA) that not only support the installation but can be utilized over two years to focus on additional education areas. Revenue recognition guidelines and rules are in place and these dictate when and how revenue can be recognized.

Clinical Revenue Process

All equipment must be installed and in working order for the company to invoice the customer. Clinical services can (and are) delivered prior to the equipment being installed. Clinical services are also frequently delivered after the equipment is installed, as the team supports the end users (clinicians) as they begin using the monitors in a live environment. Revenue from standalone services can be recognized as soon as the equipment is invoiced. Contract revenue, however, is recognized on a monthly basis for the term of the contract.

Timing of revenue recognition. The customer frequently received multiple invoices – one for the equipment and another for the clinical services delivered. All standalone clinical services must be delivered prior to recognizing any clinical revenue, i.e., if there are five shifts of clinical time on an order, all five shifts must be delivered prior to releasing an invoice for clinical services. The equipment must be fully installed, operational, and be invoiced prior to any invoicing of clinical services. There is a seasonal variance to the timing of revenue as equipment installations' ramp' at the end of a quarter, mid-year, and at year-end. Because clinical services are tightly aligned with equipment, the same seasonal variance is seen with clinical revenue.

Process of revenue recognition. When clinical services are delivered, the clinical specialist processes a timecard in the Salesforce/Professional Services Automation (PSA) tool. A Business Process Specialist (BPS) creates reports daily from PSA and matches services delivered with the services that were ordered. When all clinical services have been delivered and the equipment has been installed fully, the BPS will close the order and trigger an invoice to the customer. At the end of the month, the revenue for those services is "recognized" within Philips's financials.

Use of OMR and SAP

The Order Management Report (OMR) is a large report that is run daily by the Insights and Analytics team. The OMR provides a view of information on every monitoring equipment order. The equipment dollar amount, clinical dollars on the order, dates for installation, sales representative, project manager, and many other fields are included. Much of the data within the OMR is pulled from the Systems, Applications and Products (SAP) platform. SAP is the software platform that the healthcare company utilizes for all orders.

The OMR was created for the installation team to use for planning purposes. However, the clinical team uses the information in the OMR a bit differently. The Clinical Manager of Operations utilizes SAP to reconcile clinical orders that have closed (invoiced) and merges that information into a clinical view of the OMR. From this revised version, the clinical team can more easily see what orders are open versus closed and can begin to drill down into forecasting.

Use of Salesforce/PSA

The multi-national healthcare company also utilizes a version of the Salesforce platform – Professional Services Automation (PSA). This tool is fed by the order information in SAP and allows for the creation of a clinical project for each order. Within the project in PSA, the clinical specialist manages assignments and timecards as well as generates customer facing documentation around the clinical support of the project. When clinical services are delivered, that time is captured in PSA on a timecard. The BPS pulls these timecards from PSA and will close the clinical order in SAP when all time has been delivered. Once the order is closed in SAP, the invoice date is generated, and this is the date that is then merged into the clinical version of the OMR.

Problem Statement

The above processes involve manual manipulation of multiple data sets sourced from various platforms. This takes an extraordinary amount of time and increases the chance of inaccuracies. While this retrospective reporting creates a view of clinical services delivered, it does not allow for an easy correlation to what future revenue be. This gap in revenue prediction makes project planning difficult when trying to allocate resources needed to create efficient project delivery. In addition, this inability to predict revenue past the current month makes it difficult to report future financial trends to stakeholders. To alleviate the gap, can predictive analytics forecast a revenue release date for clinical services of a large medical device company when there is dependency on other disciplines needed to complete a customer delivery?

Forecasting and Predicting Clinical Revenue

Poor planning and overutilization of resources occur when there is no forecasting to guide management in the decision-making process. The use of predictive analytics would create the ability to gauge workforce utilization. The ability to see high forecasting revenue three months in advance would enable directors and managers to ramp up use of third-party consultants and to minimize time spent in non-revenue generating activities such as training and team meetings.

Ethical Framework

When considering ethical framework in any machine learning process, data scientists need to check their own biases and then have another analyst look at the data to make sure the data does not place any group or individuals at a disadvantage. There needs to be a strong alignment with not only personal bias but an alignment with professional standards in which values, codes of conduct and an accountability to report any limitations with the information the data conveys.

Applying Professional and Personal Bias

As the author of this paper, I would disclose that I am a Workflow Thought Leader within Clinical Professional Services for Philip's. I have a slight professional bias in that I would like Philip's to have a better understanding of clinical revenue forecasting associated with this data analysis. The personal bias is to complete this report as a requirement for my Master of Science in Data Science.

Data Analysis

Data were analyzed from January 1, 2018, to December 31, 2019. A combination of order creation dates, install complete dates, and clinical revenue were utilized to produce a clinical revenue forecast. Several data analytical platforms were utilized to create the forecasts which were used in tandem to create the charts in this report.

Data Sources

There were two primary data sources utilized for the clinical revenue forecast. First, data were obtained from Salesforce/PSA to enlist Independent Variables (IV). The second data source, Order Management Report (OMR) enlisted one other IV and the Dependent Variable (DV). Table 1 explains the variables used in the model.

Table 1 – Data Dictionary

Name	Description	Data Type	Role	Values	Source
Order Creation Date	Date Order Created	Date	Independent Variable (IV)	2018-2019 Full Monthly Report	Salesforce
Projected ICP Dates	Install Complete Dates with Adjusted Average	Date	Independent Variable (IV)	Order Creation Date + 149 days	
Install Complete Dated	Date of Installation	Date	Independent Variable (IV)	2018-2019 Full Monthly Report	Salesforce
Clinical Revenue	Funds Recognized by Project	Number	Dependent Variable (DV)	2018-2019 Full Monthly Report	OMR
Revenue Date	Date of Revenue Recognition	Date	Independent Variable (IV)	2018-2019 Full Monthly Report	OMR
Projected Clinical Revenue Date	Revenue Date with Adjusted Average	Date	Independent Variable (IV)	ICP Date + 20.9 days	

Preparation

Time series analysis requires a substantial amount of data that can be processed for forecasting. The original .csv file yielded over 1,300,000 records from daily reports over the 2 years. Due to replication and the inconsistency, monthly reports were utilized to reduce nulls in the data fields. Duplicate records were removed in excel and some dates were missing due to inconsistent data entry. Further reduction in records were made as all orders that had greater than a 365-day delta from the Order Creation Date (OCD) to the Install Complete Date (ICD) were removed to allow for a more accurate season forecast. Projected Install Complete Dates (PICP) dates were created by averaging the known "OCD" to "ICD" date range yielding 149.5 days. This average was then added to "OCD" to create the new IV "PICP". Revenue Date (RD) also had missing records. Another average was created from the delta of "PICP" to "RD" to fill in the missing fields. The average of 20.9 days was added to the "PICP" to create the new IV of

"Projected Clinical Revenue Date" (PCRD). The PCRD allows for a thorough time series analysis the which mitigates the high variability by inconsistent order entry techniques. The final data set had 4,977 records that was utilized for model testing in Alteryx and final forecasting in Tableau.

Limitations

Data entry into the Salesforce platform needs to be more consistent to produce better results; this is a data governance issue that the company should address. Lack of timely planning within the PSA platform makes data aggregation difficult due to missing information that is relevant to time series analysis. Better engineering controls would produce concise reporting measures. The use of CPA's within Salesforce/PSA created variability due to contractual obligations and revenue release dates over a 2-year term. The inclusion of CPA's will erroneously inflate monthly revenue as monies from CPA's are not recognized all at once. It is with high recommendation that the next iteration of this model would remove the CPA's records.

Methodology

The Alteryx workflows were broken down into four processes. The first, data investigation, cleansed the data, and verified there was no missing values (Appendix A shows workflow). A time series investigation was performed to measure a time series plot and times series decomposition (Appendix B showcases workflow). The time series investigation analyzed the two basic models for use. The first model, ARIMA, is a series of models that forecasts based on past values such as lags and forecast errors (Prabhakaran, 2020). The second model, ETS, predicts a future value based on historical values in a predetermined targeted timeline. Alteryx was utilized to test these two models (Appendix C). The final model was run within Tableau due to the ease and ability to create a visualization dashboard.

Combining Alteryx and Tableau

The accuracy measures of the ARIMA and ETS models in Alteryx explain errors that define an aggregation of variance (right model / wrong fit) and bias (right fit / wrong model). The interpretation of these measures needs to be made with the best meaning and the least amount of consequences. The smaller the value of error represents the better model. The Mean Error (ME) refers to the average of all errors in the set. The Root Mean Squared Error (RMSE) measured with the Mean Absolute Error (MAE) measure the variance of errors within a forecast data set. The greater the difference in the two numbers the greater the variance in individual errors. In this Alteryx workflow, the ETS model shows the least variance in individual errors. The Mean Percentage Error (MPE) represents the percentage of error in which the actual forecast values differ from the forecast values. The Mean Absolute Percentage Error (MAPE) reflects the model's accuracy in prediction. Over prediction can lead to high numbers. In the same fashion, large numbers do not mean over prediction. The accuracy measures are an interpretive representation of actual and forecasted errors. The Mean Absolute Scaled Error (MASE) indicates the error of invariance. Values over one suggest the sample tests outperformed the forecast values as a whole. The preferred model has a lower MASE value. The Alteryx accuracy measures can be seen in Table 2 below. Due to high variance in the data both models were run as training sets. The statistical measures produced in Table 2 are not a perfect means to decide which model is better for prediction. Both ARIMA and ETS models were created due to this uncertainty. The ETS model in Alteryx provided a better representation of the actual revenue realized. Alteryx provided a more thorough Exploratory Data Analysis (EDA) of the historical data compared to Tableau. Tableau’s platform transformed the data into easily understood charts that do not need extensive explanation.

Table 2 – Alteryx ETS and ARIMA Accuracy Measures

Model	ME	RMSE	MAE	MPE	MAPE	MASE
ETS	4909.792	25373.89	12533.4	-134.34	172.414	1.1572
ARIMA	9701.081	26508.51	11520.94	-11.6449	74.283	1.0637

The Tableau ETS accuracy measures can be seen in Table 3. Multiplicative calculations were utilized in Tableau which yielded better forecasting results. One important value in Table 3 is the MAPE of 16.5%. The MAPE implies the model is 83% accurate in prediction. The ETS models are different between Alteryx and Tableau due to Alteryx providing a more robust EDA compared to Tableau, therefore the results are displayed differently.

Table 3 – Tableau ETS Accuracy Measures

Model			**Quality Metrics**					**Smoothing Coefficients**		
Level	Trend	Season	RMSE	MAE	MASE	MAPE	AIC	Alpha	Beta	Gamma
Multiplicative	None	Multiplicative	400.401	303.283	0.24	16.5%	649	0.500	0.000	0.000

The data were analyzed and a trend line was placed to see if the data reflected seasonality and accurately reflected clinical revenue financial patterns over the past 2 years. Figure 1 shows a progressive upward trend that reflects historical data. The significance of the linear trend had a p-value of 0.0022.

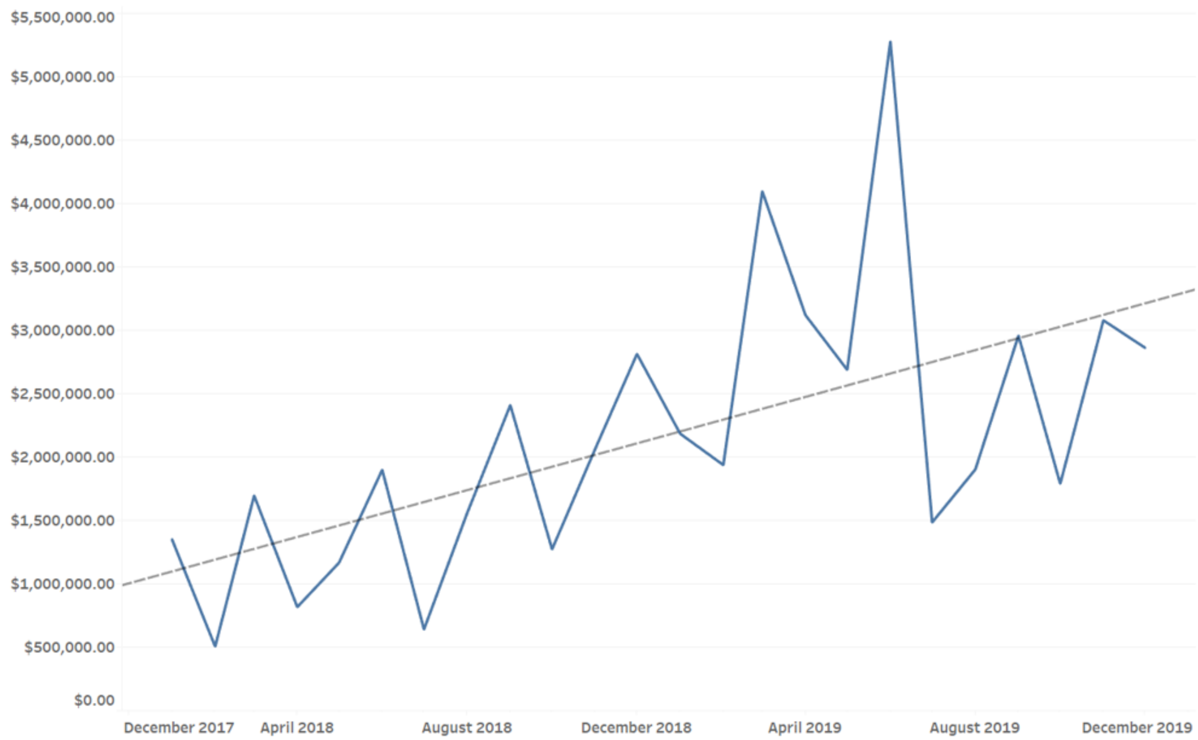


Figure 1 – Clinical Revenue Monthly Linear Trend

A polynomial trend line was created to measure clinical revenue seasonality to support the data accuracy further. Figure 2 shows accurate clinical revenue relevance from 2018 through 2019, while the significance of the polynomial trend has a p-value of 0.0084.

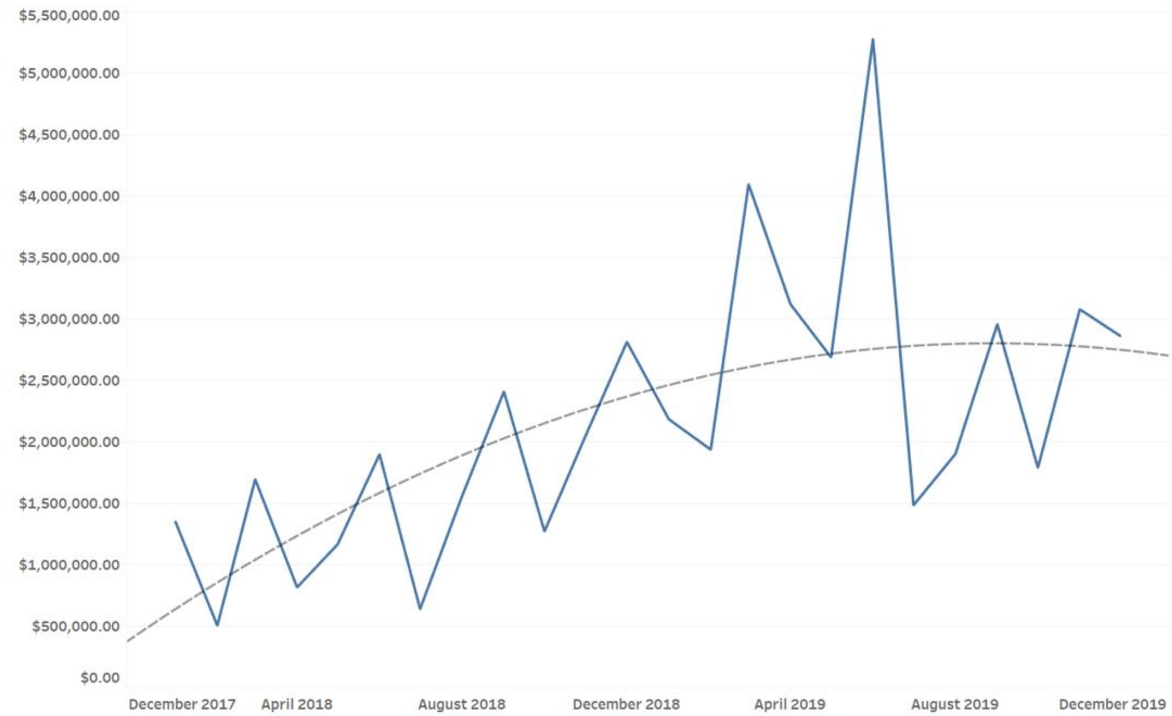


Figure 2 – Clinical Revenue Monthly Polynomial Trend

A moving average is a smoothing technique that examines a pattern of data to determine an estimate of future values (Corporate Finance Institute, 2020). Moving averages were created to check the accuracy of the model within the years the data was aggregated. Figure 3 shows the moving average of clinical revenue compared to the actual reported clinical revenue. The moving average was based off the previous 10-day values and reflects clinical revenue with more accuracy and less variability. The high measure of clinical revenue in June 2019 is common with seasonality. Figure 6 compares both June 2018 with June 2019. Both periods, as mentioned in the limitations, maybe slightly elevated due to CPA's. There was an approximate 16% change in variance from June 2018 to June 2019 when comparing moving averages with actual data. These moving averages reflect accurate reporting and support further use of this data for forecasting.

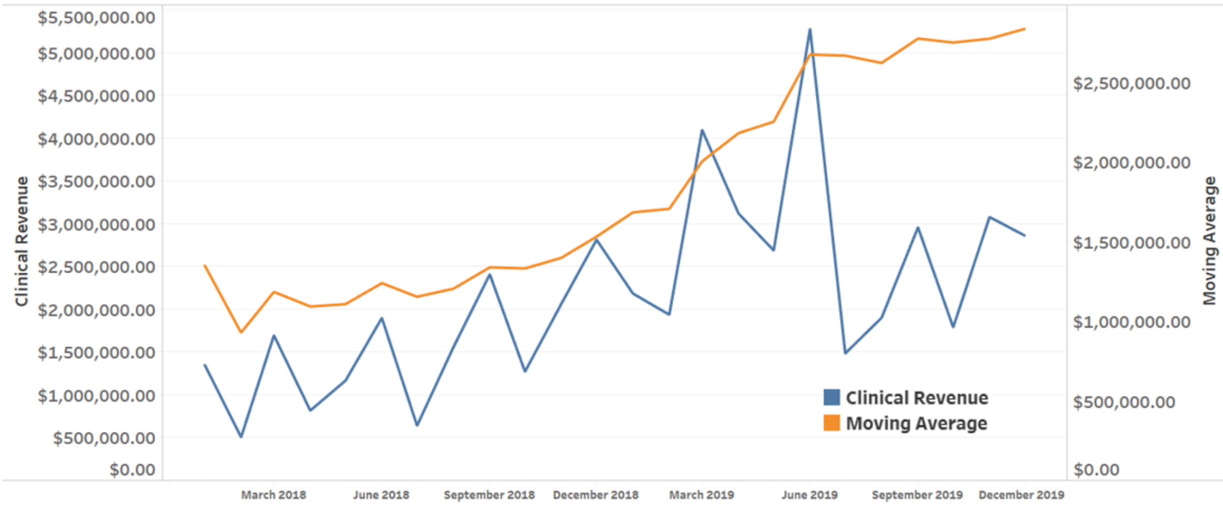


Figure 3 – Clinical Revenue Monthly Moving Average

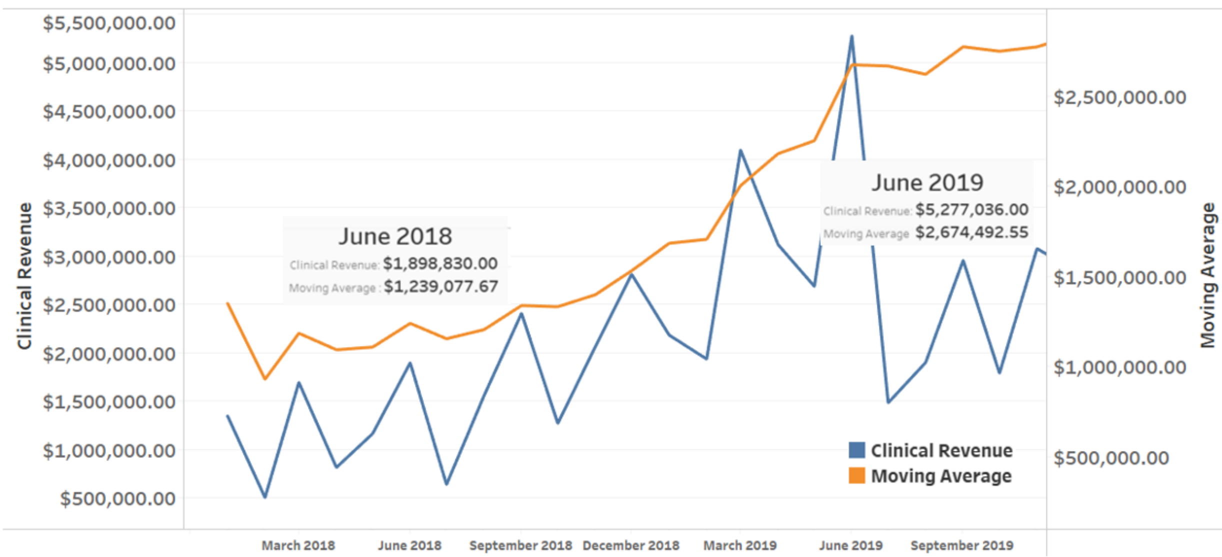


Figure 4 – Clinical Revenue Monthly Moving Average June 18-19

Figure 5 shows a monthly clinical forecast that was created using a 90% confidence rate. The forecast predicted 8 months of clinical revenue past December 2019. The dark blue trend line shows the actual plotted forecast while the light blue shows the high and low range within that 90% threshold of value for the clinical revenue. The high and low values were also marked. June 2020 yields high numbers which again shows a consistent seasonality pattern with the data.

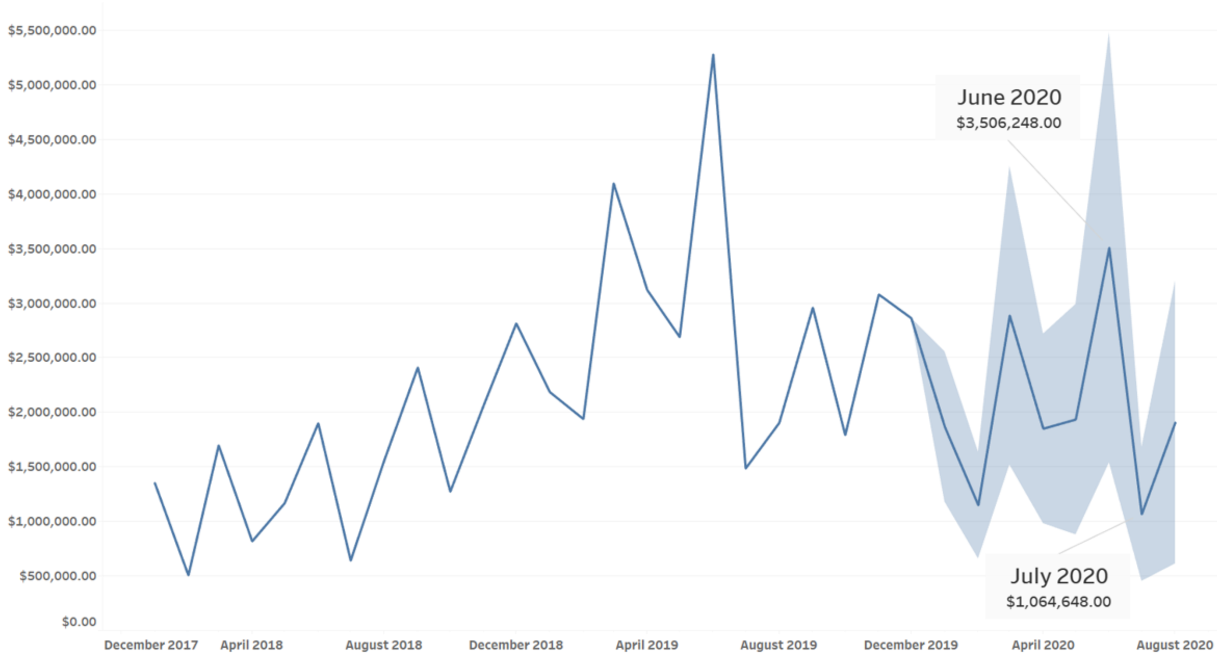


Figure 5 – Clinical Revenue Monthly Forecast

Further investigation was done to look at quarterly forecasting. While monthly forecasting can be considerable, quarterly models can show a quick snapshot of information that can be useful when large installs are being planned and there may be a need to reallocate resources accordingly. Figure 6 shows the quarterly forecasting of this model extending out 6 months with a 90% confidence.

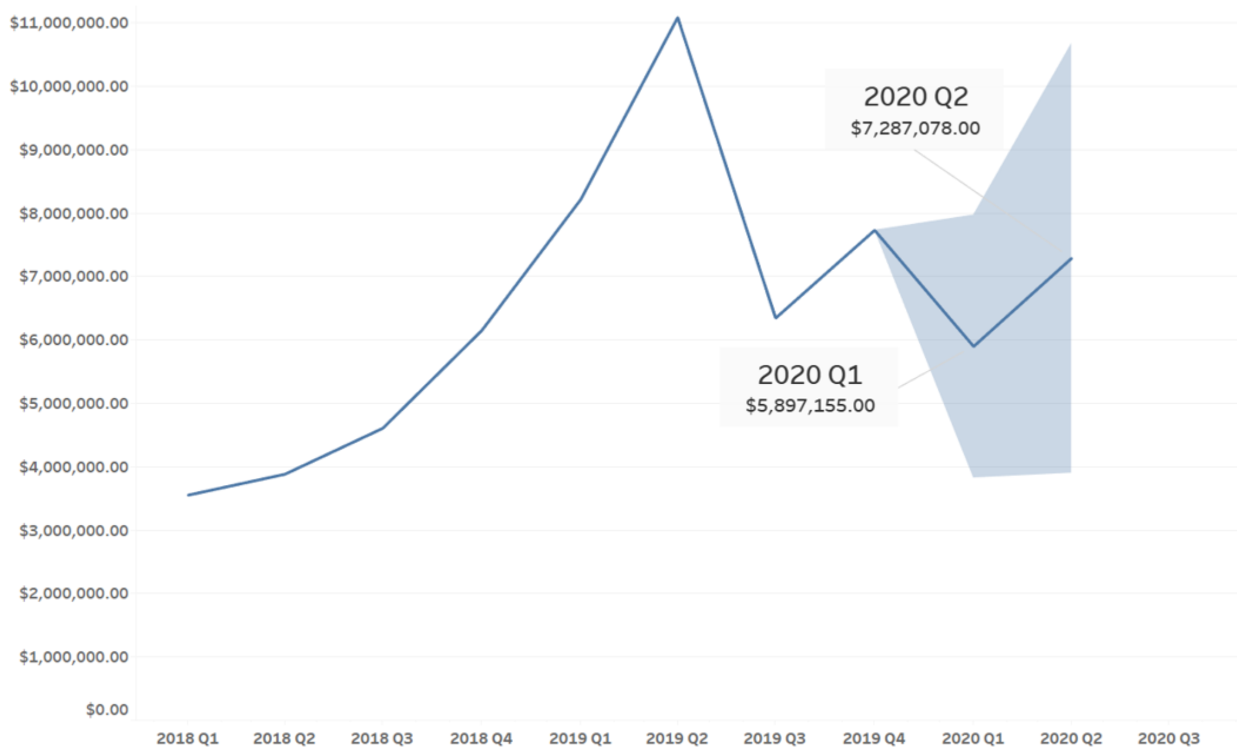


Figure 6 – Clinical Revenue Quarterly Forecast

Summation

Predictive analytics can and should support large corporations such as this company with revenue recognition and forecasting. In this clinical revenue forecasting study, there appeared to be accurate revenue reporting and seasonality trends. The data can provide support for substantial operational process improvement around resource allocations. This model proved to have a predictability in revenue forecasting with a 90% confidence. The length of forecasting in this model revealed capabilities to forecast well beyond the three-month threshold of the current use model for the multi-national healthcare company. The efficacy of either model depends on the consistent and accurate data entry of the end-users into Salesforce / PSA. Next iterations of this model should include removing the CPA revenue streams to reduce variations. Another use of this model would be to add an IV to capture the characteristics of the project manager to measure behaviors, overall project management, and the impacts on clinical revenue. This time series model, along with linear regression models can also provide regional data which in turn can reduce travel costs and overhead expenses with improved model accuracy and expanded future forecasting.

Incorporating Fairness, Accountability, Ethics, and Transparency (FEAT)

The data, framework, information, and story within this report are held to a high personal standard. There was no partiality with the creation of this report. Any decisions made as a result of this report should be taken with the same guiding principles that were used for this data analysis. All data aggregation and processing were provided by appropriate channels and reported in a similar fashion. The information is transparent and there are no hidden agendas or gains to be made by misrepresentation of data.

References

Ayme, T. (2019). Adidas Western Europe's Operational Forecast Tool. Retrieved July 20, 2020, from https://community.alteryx.com/t5/Alteryx-Use-Cases/Adidas-Western-Europe-s-Operational-Forecast-Tool/ta-p/182878

Corporate Finance Institute. (2020). Forecasting Methods - Top 4 Types, Overview, Examples. Retrieved July 20, 2020, from https://corporatefinanceinstitute.com/resources/knowledge/modeling/forecasting-methods/

Flovik, V. (2020). How (not) to use Machine Learning for time series forecasting: Avoiding the pitfalls. Retrieved July 20, 2020, from https://towardsdatascience.com/how-not-to-use-machine-learning-for-time-series-forecasting-avoiding-the-pitfalls-19f9d7adf424

Guzman, J. G. (2019). Using Predictive Analytics to Optimize Equipment Utilization. Retrieved July 20, 2020, from https://community.alteryx.com/t5/Alteryx-Use-Cases/Using-Predictive-Analytics-to-Optimize-Equipment-Utilization/ta-p/409250

Hamid, M., Ya'acob, N., & Alrazi, B. (2018). (PDF) Transparency And Accountability In Public Sector ... Retrieved August 26, 2020, from https://www.researchgate.net/publication/326721690_Transparency_And_Accountability_In_Public_Sector_Financial_Management_System

Morris, B. (2019). Building a Model to Comply with ASC 606. Retrieved July 20, 2020, from https://community.alteryx.com/t5/Alteryx-Use-Cases/Building-a-Model-to-Comply-with-ASC-606/ta-p/461911

Prabhakaran, S. (2020). ARIMA Model - Complete Guide to Time Series Forecasting in Python: ML+. Retrieved July 13, 2020, from https://www.machinelearningplus.com/time-series/arima-model-time-series-forecasting-python/

Salesforce. (2020). The Customer Success Platform To Grow Your Business. Retrieved July 10, 2020, from https://www.salesforce.com/

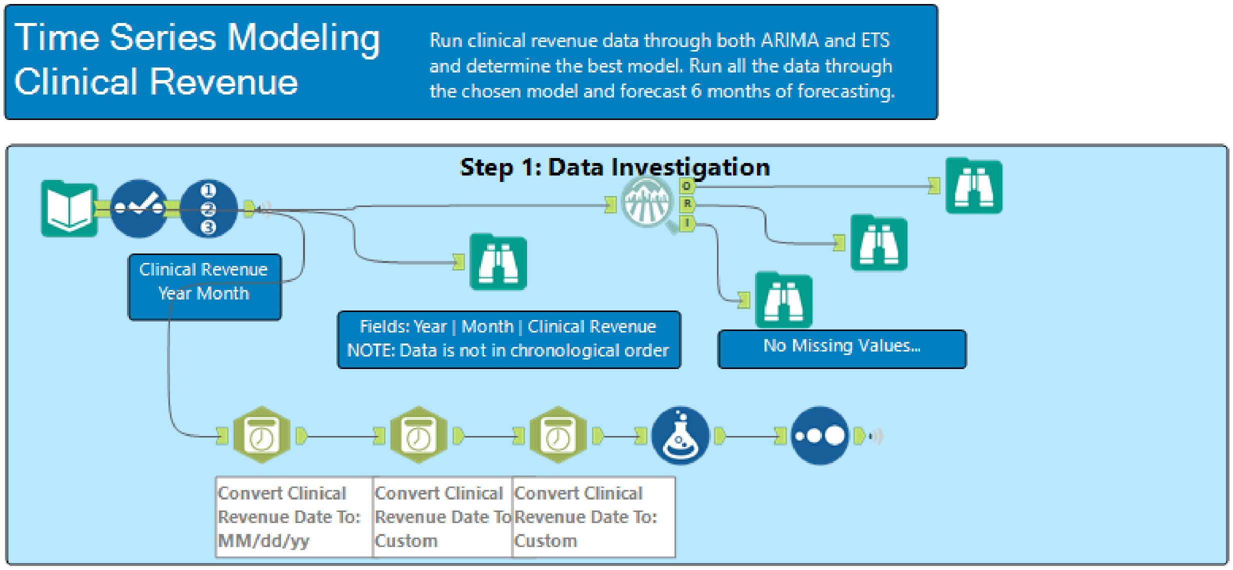
Siems, A. (2019). Crew Reserve and Open Time Forecasting. Retrieved July 20, 2020, from https://community.alteryx.com/t5/Alteryx-Use-Cases/Crew-Reserve-and-Open-Time-Forecasting/ta-p/156674

Stamboliyska, V. (2019). How to Forecast Your Sales Through Simple Calculations. Retrieved July 20, 2020, from https://www.spotcap.com.au/blog/forecast-sales-simple-calculations/

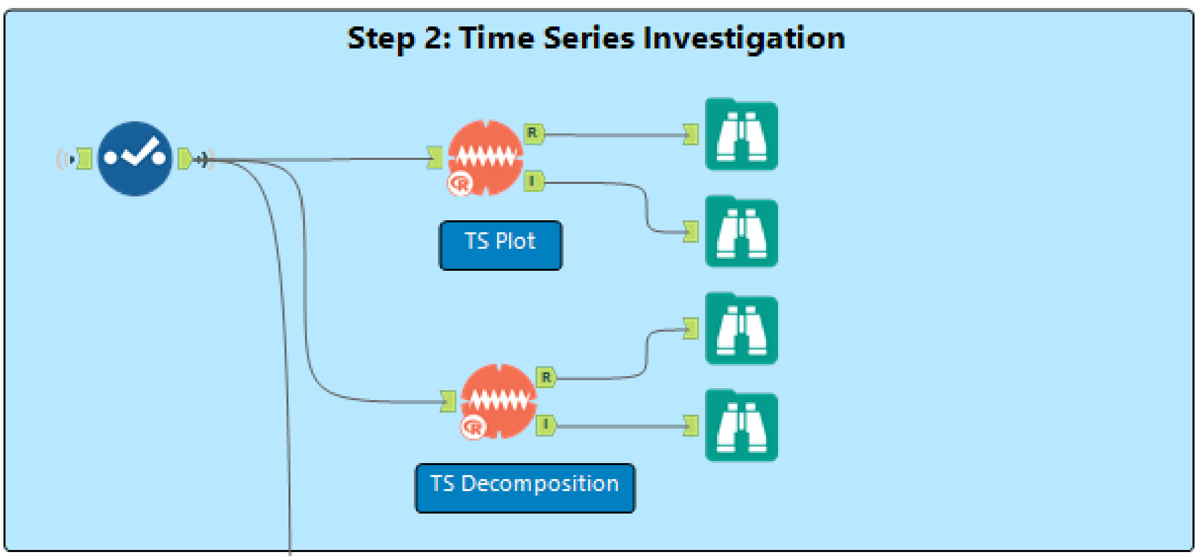
Wood, M. (2020). Revenue Forecasting Methods 101. Retrieved July 20, 2020, from https://www.fundera.com/blog/revenue-forecasting-2

Appendices

Appendix A – Alteryx Data Investigation



Appendix B – Alteryx Time Series Investigation



Appendix C – Alteryx Build ARIMA and ETS Models