SMU Data Science Review

Volume 7 | Number 2 Article 5

2023

Forecasting Accessory Demand in the Automotive Industry

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Abstract. The automotive industry seeks effective ways to forecast consumer demand to avoid overstocking, waste, underproduction, and employee underperformance. Modeling future demand for vehicles is standard, however parts & accessories are a significant subset of overall automotive revenue. There is no industry standard for predicting the quantity of accessories sold or revenue. This paper seeks to use the best industry forecasting methods and research practices to build a predictive model that forecasts vehicle accessory sales. The time-series forecasting model utilizes Toyota Motor Corporation data in a first attempt to predict accessory sales.

1 Introduction

Effective sales forecasting has an impact on business in areas like scheduling or managing headcount (Schmidt et al., 2022). In the automotive industry, which already suffers from high employee turnover, losing associates to other manufacturers has created problems preserving trade secrets (Kilpatrick, 2020). In 2021, the automotive industry saw a 34% turnover rate, according to Automotive News (Moore, 2021). The cost alone, of re-training new employees, is twice the salary of the non-retained employee (Heinz, 2022). Moreover, recent research has shown a significant link between employee performance and sales forecasting (Sindelar, 2016).

Companies deploy tools to forecast outcomes, and these predictive models drive labor and product production. The automotive industry is similar, but it has niche departments that provide significant revenue streams. However, current modeling practices are either primitive or absent. One such niche market is Accessory sales. The global market saw a revenue stream of $416 billion and will be $604 billion by 2028 (Vantage Market Research, 2021). The United States automotive industry generates $40 billion (excludes non-manufacturer created accessories) in yearly revenue (Reynolds and Reynolds, 2022).

The incredible revenue stream for accessories makes sense on an intuitive level. Secondary products used to enhance and personalize a featured item is pervasive. Anything from earrings to picture frames, to makeup, to floor mats on cars, are all accessories to the items they intend to improve. In the car industry, accessorizing vehicles the right way can be the difference between capturing the imagination of an excited consumer or losing a sale due to the vehicle not being the ‘right fit’ for the consumer. Getting vehicles on the lot with the right mix of accessories will be a major focus of an effective predictive model.

This research aims to use the best modeling practices in other industries so the first effective Accessory Forecasting model for Toyota Motor Corporation will be created. The model is judged on its ability to minimize the difference between actual sales and predict (Root Mean Square Error or RMSE). If the model provides predictive power, it will impact how vehicles appear on sales lots and increase their desirability to inquiring customers. While the scope of this project limits itself to Accessory sales predictions, the work done on these models will provide direction for future work in various challenging areas like turnover and efficient use of accessory resources.

2 Related Work

Forecasting future sales is not a new science. Models are plentiful in the Automotive industry but the emphasis has always been on vehicle sales. Modeling the relationship between Vehicle Sales and Gas Prices (McManus, 2007), the increased interest in forecasting electric vehicle sales (Zhang et al., 2017), and sales forecast modeling for the German automobile market based on time-series and data mining (Bruhl et al., 2009) are a few examples. Now, the automotive landscape is steadily changing. The market is shrinking for new vehicles and the industry has seen a rapidly growing demand in the accessory aftermarket as customers seek to personalize their vehicles (Dharmani, 2009). Compounding the issue for Original Equipment Manufacturers (OEM), who seek to bring that Accessory business 'in house', is the lack of a scientific way to forecast Accessory sales for different markets.

Toyota Motor Corporation is an OEM attempting to compete with the aftermarket and has begun to increase the strength of its Accessory Portfolio (Vellequette, 2022). What have other industries done in sales forecasting, and how can those methods provide a robust forecasting tool to those responsible for selling automotive accessories? This research outlines several examples from other industries to elucidate the framework for building an automotive accessories predictive model.

2.1 Sales Forecasting

Forecasting is a technique that uses historical data as inputs to make informed estimates that are predictive in determining the direction of future trends (Tuovila, 2022). Different industries use forecasting techniques for different ends. Investors utilize forecasting to determine if events impacting a company, such as sales expectations, will increase or decrease the price of shares (Tuovila, 2022). Equity analysts use forecasting to see how trends like unemployment will change in the coming year (Tuovila, 2022). Finally, statisticians can utilize forecasting to analyze the potential impact of a change in business operations (Tuovila, 2022). The techniques used to help these industries develop their predictive power and, therefore, success in these sectors is derived directly from unique predictive goals. Studying the best practices in other industries will be the starting point for building an automotive accessory sales prediction model.

2.2 Best Practices

A model was built to predict sales in mid-sized restaurants. The recurrent Neural Network (RNN) model outperformed 20 other models tested by the authors (Kilpatrick, 2020). The results were promising if given short-term horizons but underperformed when pushed to predict the past week. The study attempted to expand horizons using a Temporal Fusion Transformer (TFT). This broke up "long forecast windows into multiple smaller, safe windows for higher prediction accuracy." The study concluded that enhancement to TFT allows for longer-term prediction power over an RNN model (Kilpatrick, 2020).

A Two Layers model (TL's) was proposed in the fashion industry to forecast sales. It sought to find the relationship between inventory and sales. Feature selection and clustering were used to process historical data, and the results showed that TL's model outperformed the competing linear regression (LR), gradient-boosted decision trees (GBDT), support vector regression (SVR) and artificial neural network (ANN) models (Pavlyshenko, 2019). The overall benefit of this model was that it provided recommended inventory levels for specific fashion products. The authors acknowledge limitations that are relevant to vehicle accessories. While the model predicts overall sales for fashion products, it cannot say much about the number of sales for specific stores, in different markets, across the country (Pavlyshenko, 2019).

The above fashion industry study began with the assumption that sales is a time-series problem and studied the performance of the times-series model on sales forecasting. The author also considered lagged variable selection, hyperparameter optimization, comparison between classical algorithms and machine learning-based algorithms for time-series. (Pavlyshenko, 2019). The conclusion was a striking contrast to the original assumptions. It turns out that sales prediction is more of a regression problem than a time-series problem. Regression approaches often provide better results compared to time-series. Moreover, stacking, accounts for the differences in the results for multiple models with different sets of parameters and improves accuracy (Pavlyshenko, 2019).

A limitation of times series is its inability to account for external variables such as consumer preferences, competition, and changes to the turnover rate. For example, a time-series model will have difficulty predicting changes in overall sales due to high turnover because it cannot account for the creation of new roles and both employees leaving due to better opportunities or underperforming. However, time-series can be beneficial when forecasting product levels, which impact revenue, and many organizations use such models.

The use of time-series in helping to predict accessory sales can be beneficial because it provides insights into both economic and market conditions that impact products and sales.

In the finance world, which uses monetary values as the target, several forecasting principles have caused a lot of excitement. Deep Learning (DL) implementations for financial prediction research apply to different asset categories, resulting in greater accuracy (Sezer et al., 2020). Financial industries also implement ensemble-based models to forecast time-series. (Albuquerque, et al., 2022). Albuquerque et al. conclude that no single model can solve a forecasting problem independently. Several models must be used to deal with unique forecasting problems, and the final model should be an accumulation of each part of the problem. Their research recommends ensemble-based techniques (Albuquerque et al., 2022).

2.3 Time Series

A time-series is a sequence of data points that occur in successive order over a period of time (Hayes, A. 2022). A time-series shows what factors influence certain variables from period to period. Moreover, time-series analysis can be useful to see how a given asset changes over time. (Hayes, A. 2022). This model saw success in sales forecasting and provided insights into how and why sales differ over time, especially if the interpreter of the model has 'tribal knowledge' due to having experience in the industry. This will help to understand why a particular accessory may thrive in certain months over others and why they may perform well in certain areas of the country and not others.

2.4 Neural Networks

Neural Networks are a subset of machine learning and teaches computers to process data in a way inspired by the human brain through the use of interconnected nodes or neurons in a layered structure (Chiruta, C. 2023). They had great success when used in mid-sized restaurants with many products similar to accessories. If one orders a main dish but an appetizer or a side dish is added, these could be considered accessories, and the success of neural networks in predicting these appetizer/side dish sales and managing inventory accordingly can be effective when applied to car accessory sales.

Using the insights from other industries, a univariate time-series, multivariate time-series, dense neural network, and recurrent neural networks will compete to become the standard for Toyota Motor Corporation's new attempts at accessory forecasting.

3 Preparation and Analysis

Toyota Motor Corporation is interested in forecasting models for their Accessory business, and they provided six years (December 2017-December 2022) of accessory data that drills down all the way to the type of accessory category installed on a specific type of vehicle. This resulted in a data set that is 287,575 rows. It is broken down by year, month, the part of the country the accessory was sold (Region Name), the vehicle type (Series Name), accessory code, description, accessory category, accessory revenue (Net Sales), the quantity of vehicles sold (Vehicles Sold), and the average amount of accessory dollars on each vehicle (PNVW). The official Toyota Parts and Accessory Sales Analytics tool pulled the data, which stores data for six years. See Table 1 below.

Table 1. Data Headers and one row of sample data

Calendar Year	Calendar Month	Region Name	Series Name	Accessory Code	Accessory Description	Accessory Category	Net Sales	Vehicles Sold	PNVW
2022	April	BOSTON	GR86	11	17" Bronze Wheel Package	Wheels	$5,912	107	$55

The target being predicted is the average accessory dollars per car (PNVW), and if we effectively predict this one year into the future, we can apply these predictions to both overall accessory revenue and accessory revenue for an individual Toyota vehicle series. The overall forecast is derived by modeling an individual market and comparisons of both the country (USA) and another individual market. This method will help confirm the idea that expected accessory revenue for one location does not, and will not mirror expectations for another.

There are ten regions reflected in the data, which make up roughly 70% of the country. There are thirty-one vehicle models and 194 accessory products. The data exploration will start general and then get more specific as we look at Accessory sales at the region level. It is unnecessary and overwhelming to focus on all Regions. Valuable insights can be gleaned from an EDA of a few. Los Angeles, Kansas City, Boston and Central Atlantic Toyota will be the emphasis during the EDA but each model will focus on a comparison between the nation and the Boston region. The reason is, focusing on two entities is enough to determine model effectiveness.

The EDA will be informative for the competing models. The importance of the type of vehicle sold when it comes to accessory sales will be important for predicting revenue. See Figure 1 below.

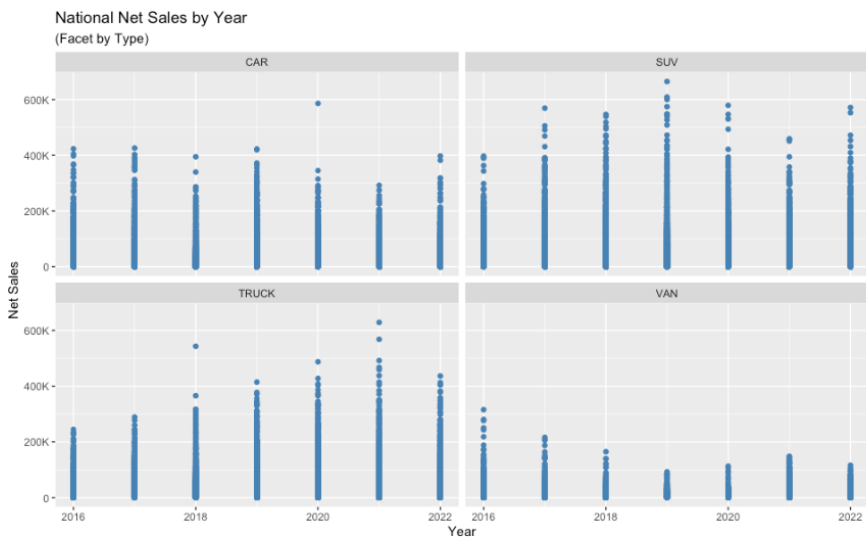


Fig.1. The median accessory dollars. Revenue is categorized by the type of vehicle.

Overall sales for compact cars were low compared to crossover SUV's or full-size trucks. This will have implications for how a region's accessory sales are forecasted. If a region has a high quantity of compact cars flooding the market, sales predictions may be more conservative than a region with a high quantity of full-size trucks. Another metric makes the same point. In an assessment of the average accessory dollars per vehicle sold, the EDA reveals similar findings. Full-size trucks see over $800 dollars of accessories on each car, while compact vehicles have a little over $200 worth of accessories on each car. See Figure 2 below.

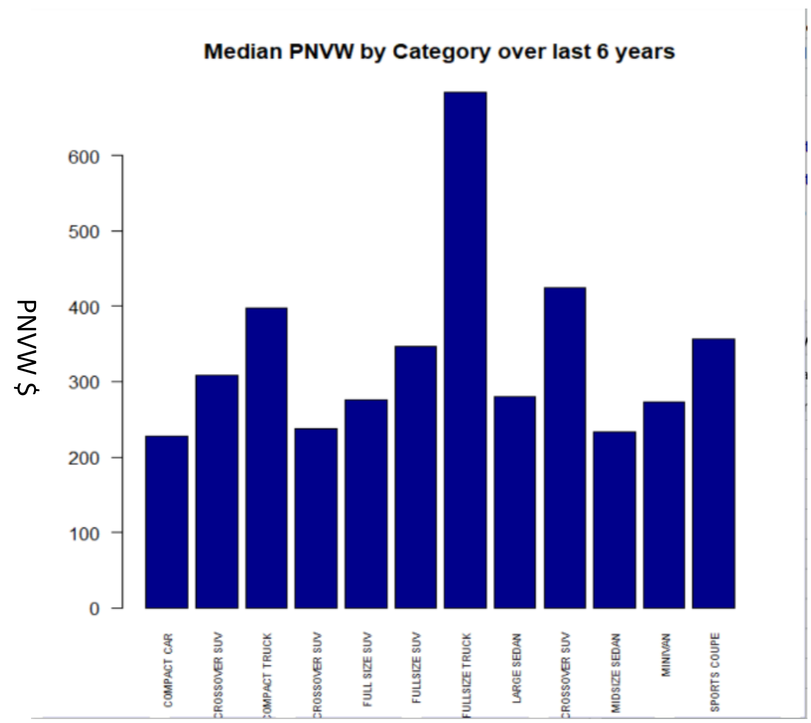


Fig. 2. The median accessory dollars per vehicle. It is categorized by the type of vehicle.

An EDA also reveals that accessory revenue differs depending on where they are sold in the country. This is evident in Figure 3 below.

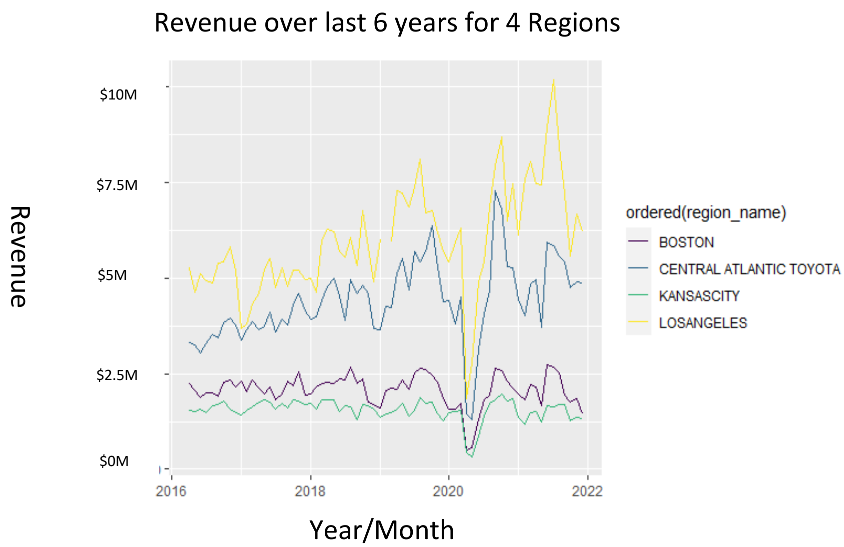


Fig. 3. Revenue earned per month by region. A sample set of four regions was selected.

Los Angeles, which makes up the Southern California territory, is a market that produces more revenue than all other markets. Modeling future accessory revenue for that area, will produce results significantly different than territories like Kansas City. Prior to making any recommendations regarding sales goals, the EDA, provides evidence that Kansas City will be given a significantly lower portion of the overall sales goals when compared to Los Angeles. Another important observation provided by the data is a clear anomaly that took place in 2020. Figure 3 shows a dip in sales during 2020 as the industry was locked-down as a strategy for fighting the COVID pandemic. Even though it was an anomaly, the principle did not change. Some markets are more 'accessory friendly' than others. One reason revenue generation is so market dependent, can be seen in Figure 4 below.

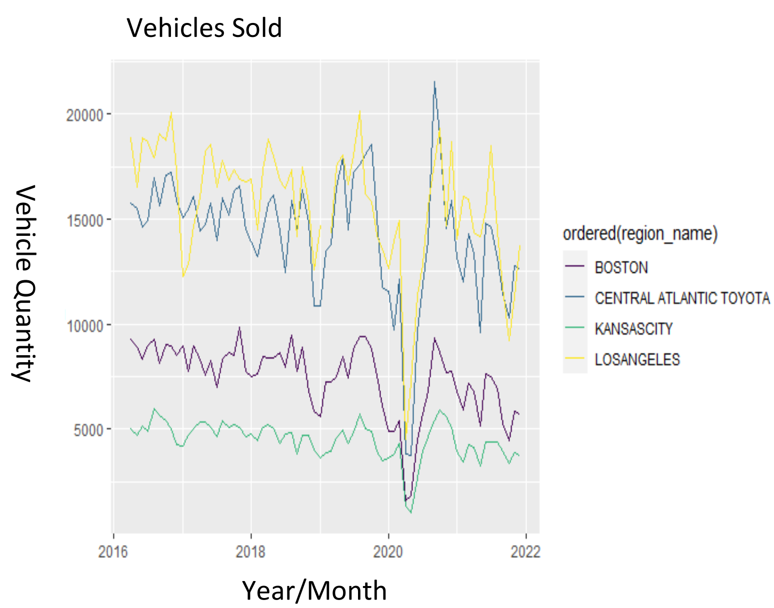


Fig. 4. Vehicles sold per month by region. A sample set of four regions were chose.

There are some interesting insights gleaned from Figure 4 that will also help with the construction and interpretability of forecasting models. Vehicles play a significant role in the amount of accessory dollars earned. This is intuitive. There will not be an accessory sold if there is no vehicle sold. Since Los Angeles sells more Toyotas than a region like Kansas City, this is yet another piece of evidence on behalf of treating the different markets differently when it comes to Accessory sales expectations. Vehicle type also matters and a forecasting model must take this into consideration. If a region or the nation produces more compact vehicles than in past years, it will impact revenue and potentially disrupt a model that predicts continued revenue growth. Vehicle type must be a factor when building a model.

On a related note, the types of accessories with high consumer demand can play a role in region performance. If truck bed products sell well for Toyota, but you are a region that gets few trucks, comparing sales performance with a high-volume truck region may be unfair. In this context, excellence for the 'low truck volume' region could look different than a region with 'high truck volume'. See Appendix 1 for sales performance by accessory category.

3.3 Forecasting Models

There are four types of models built and each was selected based on the positive results of sales forecasting models for other industries. In this case, a time-series model, multivariate linear regression model, a dense and recurrent neural network will be used to predict Accessory sales by nation and a region. The time-series will serve as a baseline for determining Accessory Sales.

A national look at the accessory revenue data appears to be non-stationary. See Figure 5 below.

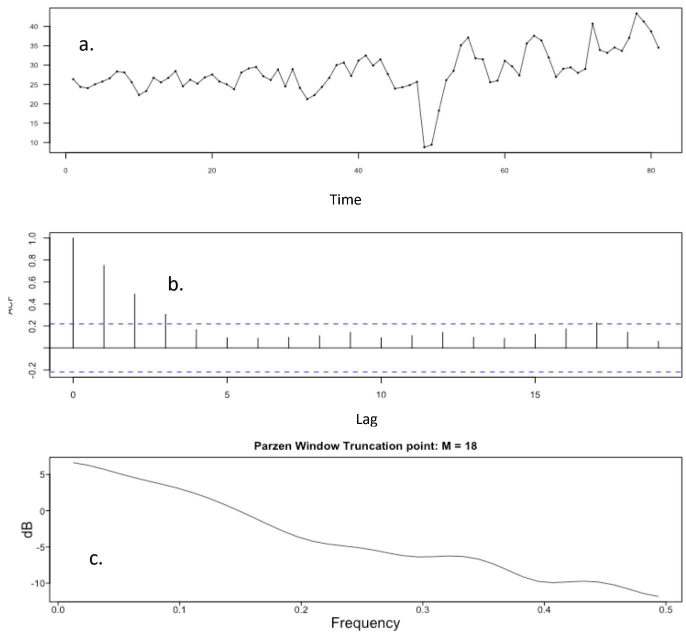


Fig. 5. Time-series realization based on data at a national level.

The slowly damping lags (5b) and the trend upwards that begins at lag 45 of the x-axis, after a steep decline (5a) suggest a need for an Autoregressive Integrated Moving Average (ARIMA). Non-stationarity means, the statistical properties of the process change over time (Palachy, 2019). This model is a process with orders p, d, and q, where differencing d times will transform the data into a stationary Autoregressive Moving Average (ARMA) process so both the stationary and non-stationary parts of the data can be modeled. The notation for an ARIMA is

$$\emptyset(\mathrm{B})(1-\mathrm{B})^{\mathrm{d}}\mathrm{X}_{\mathrm{t}} = \emptyset(\mathrm{B})\mathrm{a}_{\mathrm{t}}.$$

Both the differencing and the testing of the residuals using a Ljung-Box test establish the transformation of the data to a stationary process. See Figure 6 below for results of the differencing.

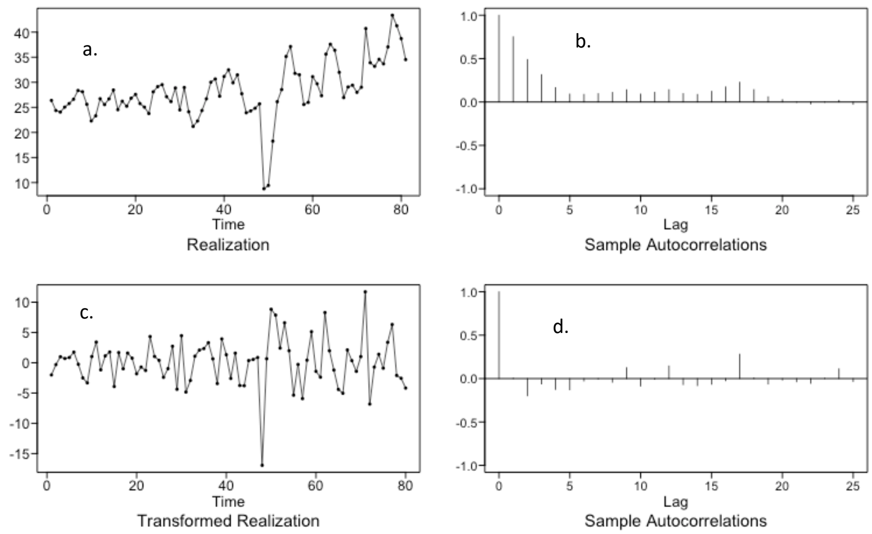


Fig. 6. Pre-differencing the National data (*Top)* and after differencing the National data (*bottom)*.

From there, the Akaike Information Criterion (AIC) was used to identify the stationary portion of the model. An ARMA (5,1) are the parameters suggested by an AIC. Finally, the seasonal portion of the data was added to the model for a final notation of

$$(1 + .81B^5 - .24B^4 + .14B^3 - .14B^5 - .01B^5)(1 - \mathrm{B})^6 \mathrm{X_t} = 1(\mathrm{B})\mathrm{a_t}.$$

The same process was applied at the regional level. See appendix 2 for the test of non-stationarity and differencing. Boston was used to build a time-series model. In many ways, it followed the same pattern as the national time-series model. The data was non-stationary and the time realizations are visually similar. The final notation for the Boston time-series model, after using the recommended ARMA(1,7) is

$$(1 - .27\mathrm{B})(1 - \mathrm{B})\mathrm{X_t} = 1 - .03B^7 + .28B^6 + .03B^5 + ..34B^4 + ..42B^3 + .27B^2 - .01\mathrm{B})\mathrm{a_t}.$$

Note: The seasonal portion of the data was captured by an s=6 for the nation and d=1 for Boston. This was a trial-and-error finding.

Under the assumption that there are variables that will help in the forecasting of Accessory revenue, a multivariate time-series model was built. It was already established that the type of vehicle sold will impact the amount of Accessory revenue and so this variable will be included in a Multivariate time-series model. Using the package sqldf in R, the data focused on accessory sales by vehicle at a national level. A correlation matrix shows a linear relationship between vehicle sales and overall accessory sales. This evidence determined the decision to add type of vehicle sold to the multivariate analysis. See Figure 7 below. Again, the region level also showed a linear relationship between vehicle type and sales. See appendix 3.

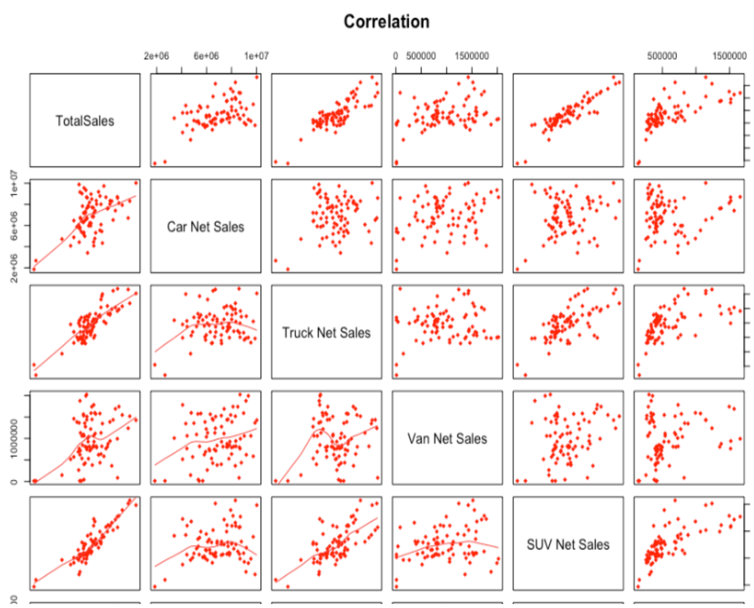


Fig. 7. Correlation matrix showing linear relationships for the Accessory sales by vehicle type.

Another variable that appears promising given a correlation matrix, is the type of accessory put on a vehicle. Several accessory categories have a linear relationship to overall sales. A few examples are exterior styling and drive convenience. The entire correlation matrix for Accessory Category is in appendix 4. It is for both the nation and the Boston Region.

The correlation matrices provide significant visual evidence that there is a linear relationship between sales and both vehicle type and accessory category. The approach to applying a time-series model to a multivariate data set was a focus on one vehicle type and its most lucrative accessories. Nationally the truck market is critical and its most lucrative accessories are exterior products. Refer to Figure 1 and Appendix 1 as evidence supporting this decision. From there, a multivariate time-series was built with the key ARIMA data (ex. p, q and phi) derived from the code rather than being generated and then entered to build the model. The effectiveness of the model is tested through the loss function and so knowing the ARIMA components wasn't the focus. See appendix 5 for the R-code generating the model. The principles behind creating an ARIMA model for the Boston Region were no different and appendix 5 shows the R-code for Boston. An additional variable was added to the model. Floor protection was deemed to be an important accessory category. Again, to understand why this decision was made, see Appendix 5 for the influence accessory categories has on overall sales.

Machine learning algorithms should have an advantage over time-series and multivariate Time-Series. For one, there is no concern about feature selection as it is automatically done prior to processing the data. Specific to time-series, the value of sample statistics is dependent on the data being stationary. This is not a concern for Neural Networks and research has shown that a consequence is a higher degree of accuracy or in this case, a lower Root Mean Square Error (RMSE). Finally, it handles multivariate input and is capable of multi-step forecasting (Makridakis et al. 2018). Two types of Neural Network Models were built: Dense Neural Network and Recurrent Neural Network.

Prior to testing the models, a different kind of data preparation was needed. Data was converted to the correct shape, which required a 'look_back' of six. This allows for using actual data six points in the past to predict the seventh point which will take place in the future. Moreover, data preparation had to account for several Neural Network weaknesses. The data must be the same length. This was solved through padding unequal data so that it has equal lengths. Another significant challenge the data posed was the large computational expense. Early stopping was implemented, which seized running the model once it achieved an optimal Mean Absolute Error. Data was brought in batch sizes of thirty, to spare the processor from being overburdened. This allowed for the eventual re-running of all data (one hundred epochs) so that each run could improve on the previous epoch and improve performance. It was determined that the model stopped training for the DNN at forty epochs and the RNN model stopped training at eighty epochs. See Figure 8 for the stop loss results for both the nation and the region.

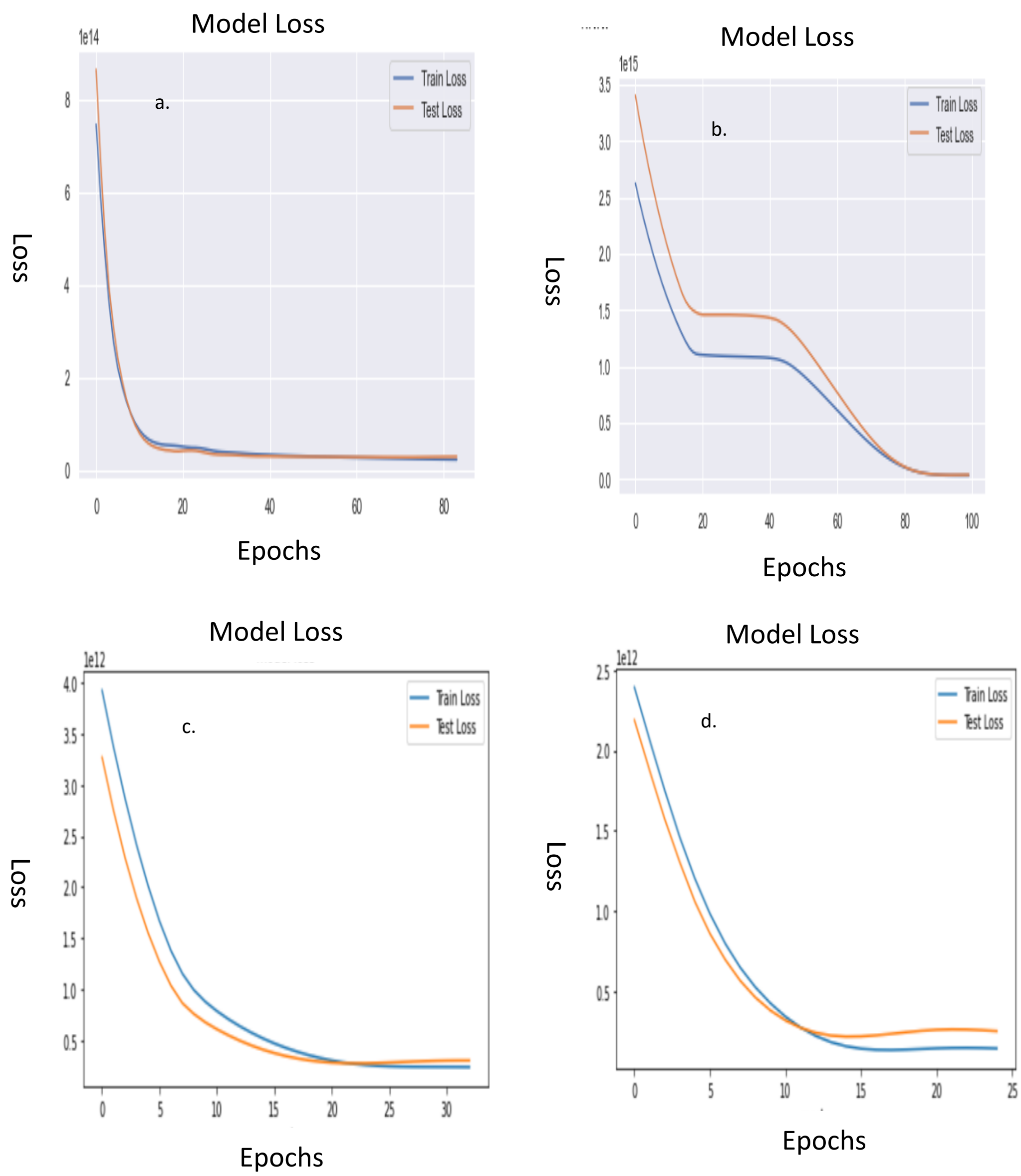


Fig. 8. The loss over several epochs for both national DNN (top left), national RNN (top right), Boston DNN (bottom left), Boston RNN (bottom right)

The DNN was the simpler model in that it only runs forward and it chooses the best model out of multiple iterations. The best model will be produced after finding the least loss produced in the several linear regressions trained. RNN has better learning capabilities. It can use time as a feature and it can feed results back into the network and update the weights used to create the model. For example, it will find the highest accuracy and lowest loss after re-training the data several times. See Figure 9 below for an image of how the models are constructed.

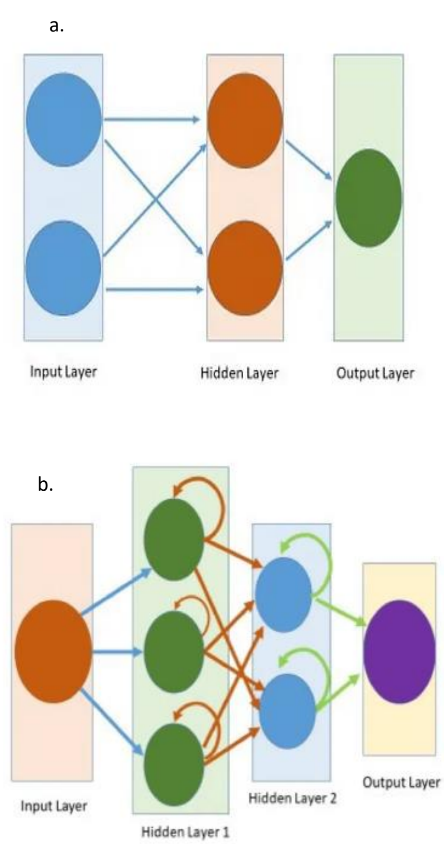


Fig. 9. The architecture for both DNN (*top)* and RNN (*bottom)* models.

3.4 Model Validation

When comparing the success of the different models, common metrics will be used to assess their performance against each other. A Root Mean Square Error (RMSE) will be used. The expectation is that a RMSE for a revenue data set that is in the millions will be high. This would not mean the model performed poorly. The difference between actual and predicted revenue could be in the hundreds of thousands or millions of dollars and using other loss metrics like means squared error will give the perception that the model performed poorly. RMSE is the metric of choice because it is a loss function that helps the testers look at the problem in terms of better optimization. In other words, a RMSE score more closely resembles the dollar difference between the actual and predicted values.

4. Results

This section presents the results for the different forecasting models and conducts an analysis of what those results say about their ability to forecast Accessory sales. Section 4.1 describes how well the forecasts did and goes into detail about the results achieved. All lines in red denote the forecasting portion of the model. Section 4.2 will go into more detail about the results achieved.

4.1 Model Behavior

At a national level the six-month univariate forecast captures the overall upward movement of the data. There is an alternating downward and upward trend that occurs within the context of overall growth. At the region level, a similar pattern can be seen but with a steeper upward trend. While the six-month forecast follows the existing data pattern, a better sense of model performance can be seen when actual data is side by side with the forecasts. Below, see Figure 10a for the national forecast, 10b for the Boston forecast.

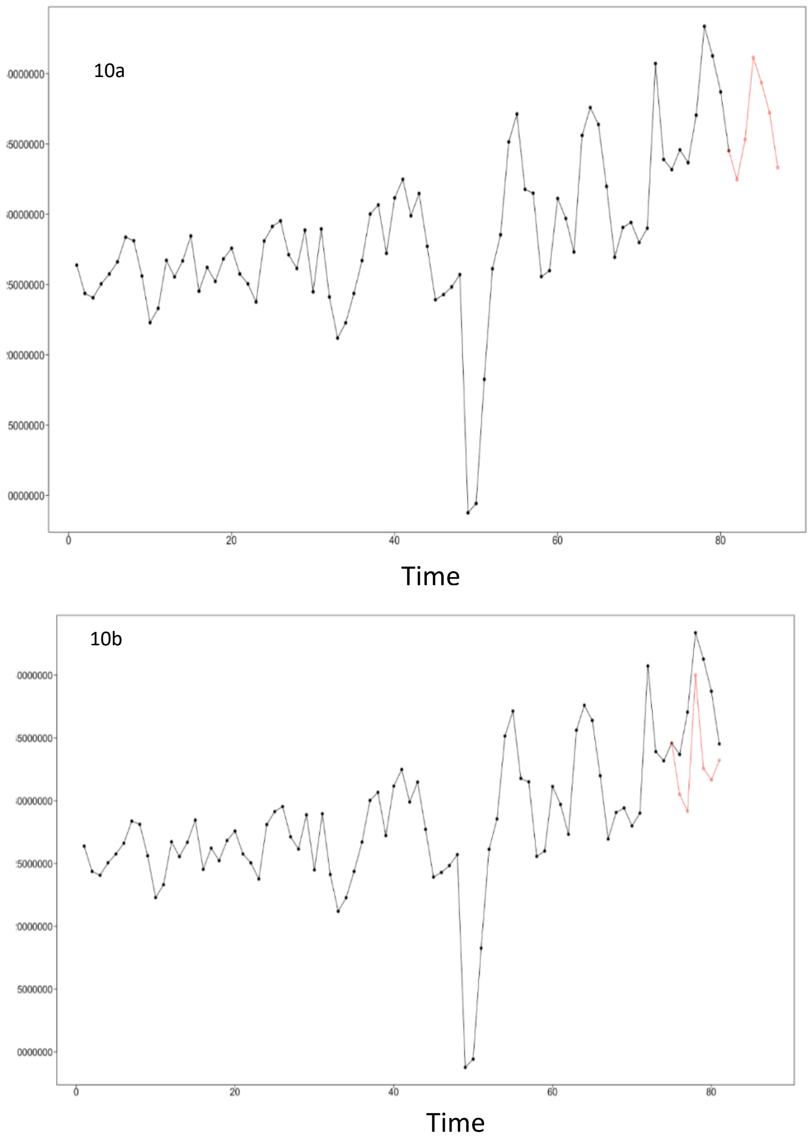


Fig. 10. Forecasting past the actual data for 6 months. The national forecast is on (top) and the Boston Region 6-month forecast is on (bottom).

Although there is a clear difference between the actual and predicted data, a promising feature of this model is the predicted data points do a decent job of matching actual trends at the national level. For example, if an actual data point shows a decline in revenue, the attempted prediction of that same point also shows a decline. When the data set is reduced and it is only viewed at a regional level, the univariate forecast appears to be less accurate See Figures 11a and 11b for the national and regional test comparison.

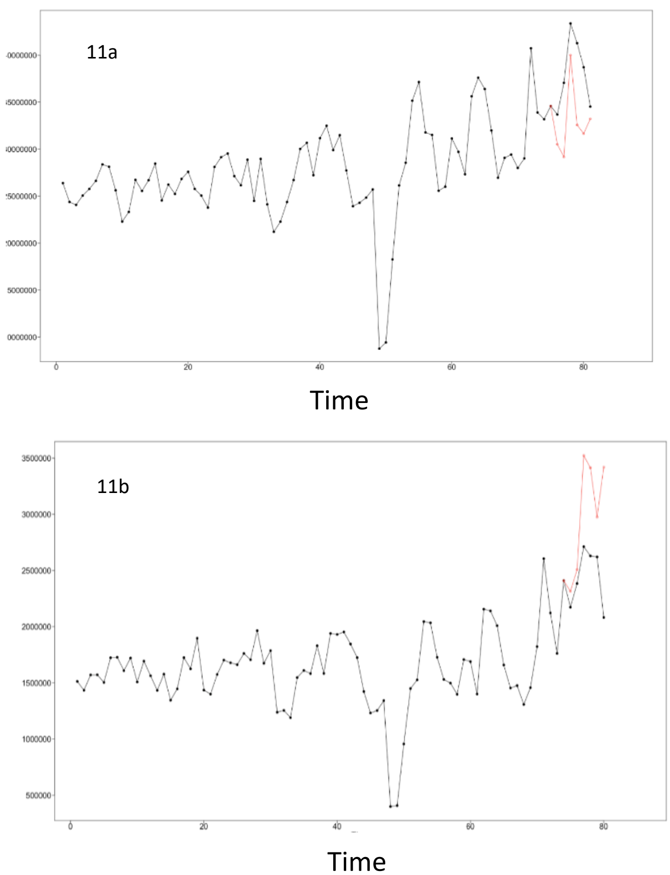
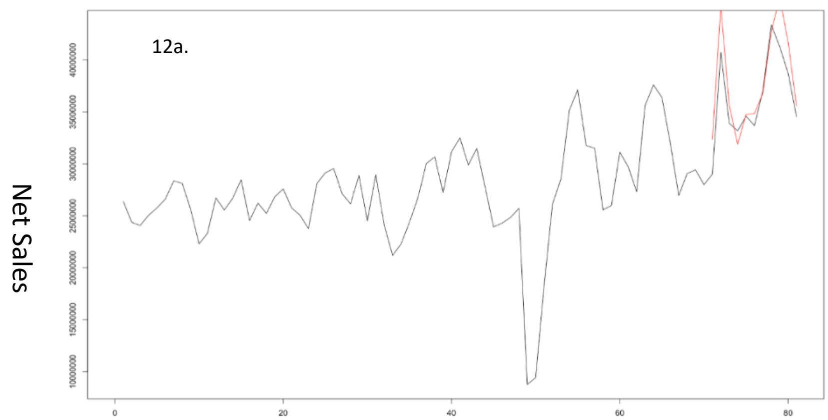


Fig. 11. Forecasting based on comparisons with actual data over the last 6 months. The national forecast is on (*top)* and the Boston Region 6-month forecast is on (*bottom).*

The multivariate time-series forecast is visually more promising, although the loss function will be the ultimate arbiter of which model is selected. The multivariate captures the upward movement of the data and appears to have strong predictive power when visually comparing the forecast to the actuals, even when extending the forecast out another four months. See Figure 12 below.

Last 10 months National Net Sales



Last 10 months Boston Net Sales

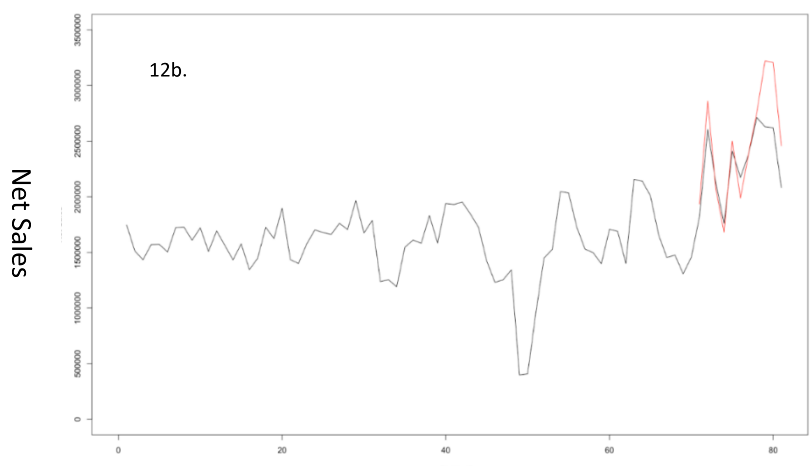


Fig. 12. Multivariate forecasting based on comparisons with actual data over the last 10 months. The national forecast is on (*top)* and the Boston forecast is on (*bottom).*

The neural networks produced similar visuals. At a national level, the DNN visual performance extended over longer horizons and appears to capture the trends in the data. If accessory sales declined, the predictions captured a similar decline. The same holds true for an increase in sales. The ability to capture trends hold for the RNN model, as well, although visually there does not appear to be an improvement over DNN. See Figure 13 below.

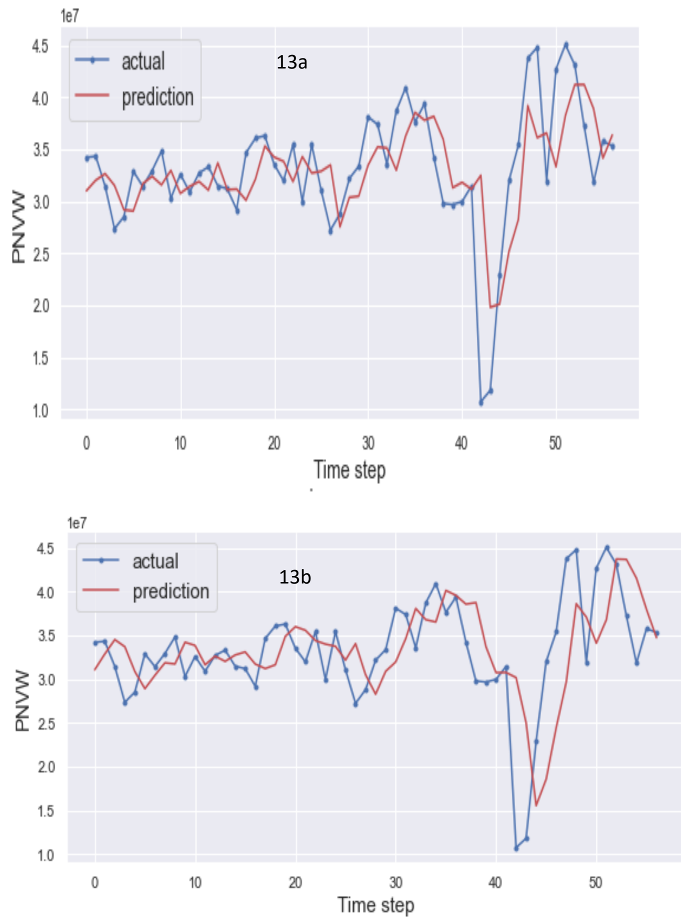


Fig. 13. DNN forecasting for the nation is on top and RNN forecasting is on bottom.

The regional neural networks appear to perform similarly to the national neural network models which is a good sign that the same neural network model can be used to predict an entire country worth of data and a localized data set. See Figure 14 below.

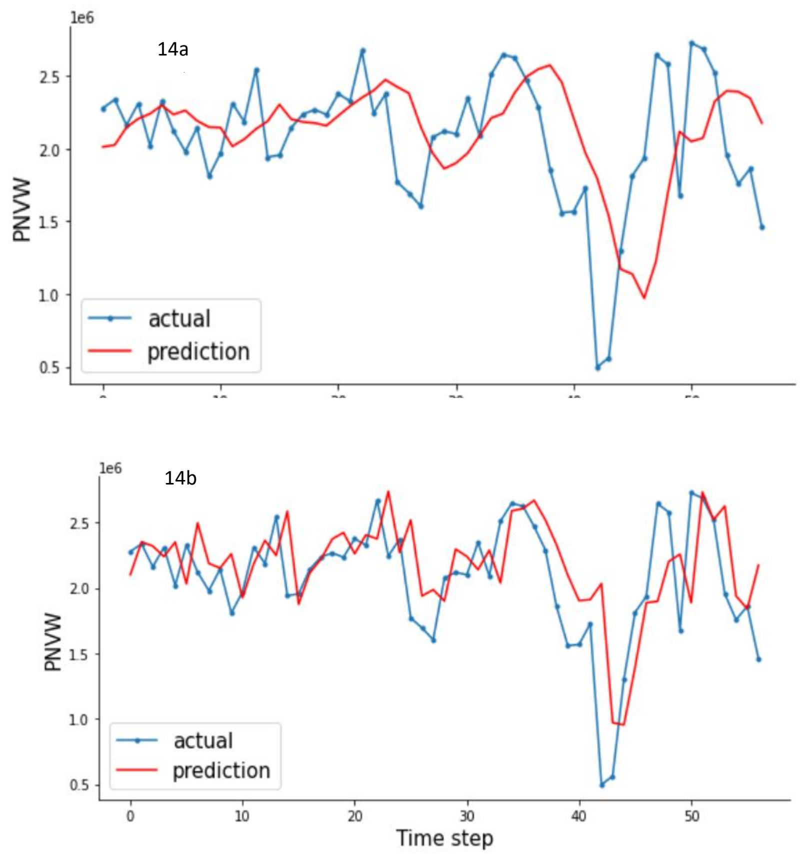


Fig. 14. DNN forecasting for Boston is on top and RNN forecasting is on bottom.

4.2 Model Comparison

Which model performed the best and why? The forecasting of visuals produced by the models are valuable, but they aren't the deciding factor. The Root Mean Squared Error (RMSE) will be the baseline in model comparison. One reason for choosing this metric is its ability to reduce the size of the error being measured. The accessory industry is producing revenue in the millions of dollars and when squaring an error (The difference between reality and model predictions), for example, on potentially hundreds of thousands of dollars, it can give the impression that the model is performing poorly. RMSE will allow the interpreter to view the difference between truth and error in similar terms to the dollar amount not accounted for in the model. See Figure 15a for the RMSE scores for all four modes and see Figure 15b below for other scoring metrics. Mean Absolute Error (MAE), measures the average between the prediction and observation and Mean Squared Error (MSE) is the squaring of the average of errors.

Fig. 15a. Model RMSE performance

	6 Month Forecast			3 Month Forecast	
Models	RMSE National	RMSE Region		RMSE National	RMSE Region
Univariate Time-Series	4,892,110	467,060.32		3,315,481	590,473
Multivariate Time-Series	5,586,411	732,662.97		4,665,876	514,448
DNN	317,574	75,631.00		2,532	657
RNN	200,132	51,034.00		2,744	540

Fig. 15b. Model MAE and MSE performance

	6 Month Forecast						**3 Month Forecast**			
Models	MAE National	MAE Region		MSE National	MSE Region		MAE National	MAE Region	MSE National	MSE Region
Univariate Time-Series	4,829,614	337,510		23,932,739,939,178	218,145,344,630		2,936,001	468,753	10,992,412,721,110	348,658,405,846
Multivariate Time-Series	4,958,700	592,032		31,207,989,536,453	536,795,023,131		3,968,487	506,906	21,770,397,883,362	264,656,921,217
DNN	3,844,657	275,462		100,852,995,476	5,720,048,161		4,148,913	335,449	6,413,251	431,524
RNN	3,109,363	251,161		40,052,817,424	2,604,469,159		3,036,853	236,589	7,531,822	291,329

In every metric the RNN outperformed its competitors and an RMSE score of 51,000 for the Boston Region is indicating that the model can predict Accessory sales within \$51,000. This is a .08% error rate if you consider the actual average 6-month revenue earned by the Boston region. The results of the RNN also conform to the research conducted by (Kilpatrick, 2020) who claim that in creating an RNN model designed to forecast secondary food items in mid-size restaurants, the short-term forecasting performed much better than longer term forecasting. In this case, a three-month forecast will practically eliminate any error rate. One could argue that a multivariate analysis is competitive and excellence is a matter of adding more influential exogenous variables. This runs the risk of overfitting and selecting the RNN helps avoid this scenario. See Appendix 7 for all exogenous variables used in the competing multivariate time-series. Another reason for preferring the RNN model is that it accounts for sequential data such as time-series, which makes a time-series redundant. For example, the car industry is a seasonal business. Spring and Summer are the most business-friendly times, and an accessory sale cannot happen without a vehicle sale. In fact, the peaks in car sales are in the summer and spring during nicer weather and when tax refunds spur consumer spending. (Khartit, 2021). Both RNN and time-series are made to manage this type of data but the lower error rate along with the risk of over-fitting a multivariate model gives RNN an edge. Finally, the model chosen is supported by the research. Again, see (Kilpatrick, 2020)

5. Ethical Concerns

Tuning the RNN to the point where it outperforms all models at the Region level is an ethical issue. The car industry sales metrics are the means for assessing employee performance. Achieving a sales objective can be the difference between receiving a bonus or not. Achieving a sales objective can also be the difference between being employed and unemployed. Therefore, setting realistic and achievable goals, through using neural network models, has implications for individuals in the industry. The ethical implications also apply to the treatment of the employer. If sales objectives are too low, there will be a mismatch in local employee productivity and corporate compensation. In other words, it is not ethical to put the company in a position to pay money for work not done. A final ethical concern for this research is the importance of the data scientist creating an equal ‘playing field’. A forecasting model should account for distinct factors impacting one region over another, so that excellence is not just a matter of ‘This region earned more than that region.’ This is ethically significant. When the data scientist defines success for each region, it incorporates consideration for individualized unique problem sets and the implementation of practical local solutions.

6. Discussion

The neural network models were expected to perform better than more traditional models. Overall, the RNN neural network achieved this, which is why it will be the model used to forecast accessory sales. Still, an RNN model will require other Toyota Motor Corporation forecasts. For example, the company built a robust vehicle forecast model that has been a staple for selecting the types and quantities of vehicles sold to a region. If vehicle production is known before running a predictive model, the accuracy of the RNN will increase. If it is known that in year 2023, there will be an influx of trucks for a specific region, then accessory sales will be higher than if there was a market saturation of compact cars. In contrast, if a particular region (traditionally successful with compact car accessories) then a region-centric model can account for this and forecast accordingly. If a particular Region does not achieve the target, there is a built-in method for checking if the cause is employee performance. If Toyota said, a certain quantity of trucks would move into a Regions market and that does not occur, it would make sense that a market, highly dependent on truck sales for most accessory sales would underperform, therefore creating a situation where the RNN model is re-run to account for the lack of trucks. This scenario would eliminate employee performance as the issue.

The RNN model also allows for powerful business recommendations. If trucks are a significant part of a vehicle sales plan, a corresponding accessory category can be recommended. Exterior accessories perform better on trucks, and the increase in production can increase overall exterior accessory profitability. Since this project focuses on only one Region, this could be run for other regions to formulate a unique sales plan for each.

It is important to note that the current RNN model must include other variables not accounted for in this paper. The current model does not account for recession warnings or disruptive technologies, which could render the current accessory portfolio obsolete. Data scientists working on different factors confronting the business will have to be incorporated into the conversation for Accessory forecasting.

This does not diminish the responsibility of any data scientist tasked with forecasting accessory sales. If time permitted, there are a few questions that the RNN model could have accounted for but did not. What specific accessories (not categories) most contribute to revenue? Are there unique accessories that are market dependent? For example, it may be the case that carpeted floor mats are more popular in regions that have better weather, whereas all-weather floor mats are mostly sold in regions with more extreme weather patterns. Are their accessories underperforming in a Region where there should be more sales? If Cincinnati has similar market conditions to Kansas City, why are certain accessories successful in one region but not the other? Finally, if new accessories are introduced to the portfolio, can a model accurately predict its performance over the next few years?

7. Conclusion

Neural networks provide the best hope for rewarding the right regional employees and retaining the right talent. Although, it is outside the scope of this project, it is believed that neural networks are the best hope for getting the right accessories on the appropriate cars in the right location across the country. While the research is limited in scope, after assessing our model's effectiveness in a real-world scenario, it can be expanded across the country and the accessory portfolio. Since this is the first project of its kind, its success could open a whole new job market in the automotive industry. If accessories continue to be a billion-dollar business, then the industry will be motivated to hire dedicated data scientists for accessory forecasting, selection, and measuring employee performance. In the end, the success of this project could disrupt the automotive industry and propel it beyond the era of big personalities, excel spreadsheets and business intuition and into the era of big data, accurate models and scientific decision making.

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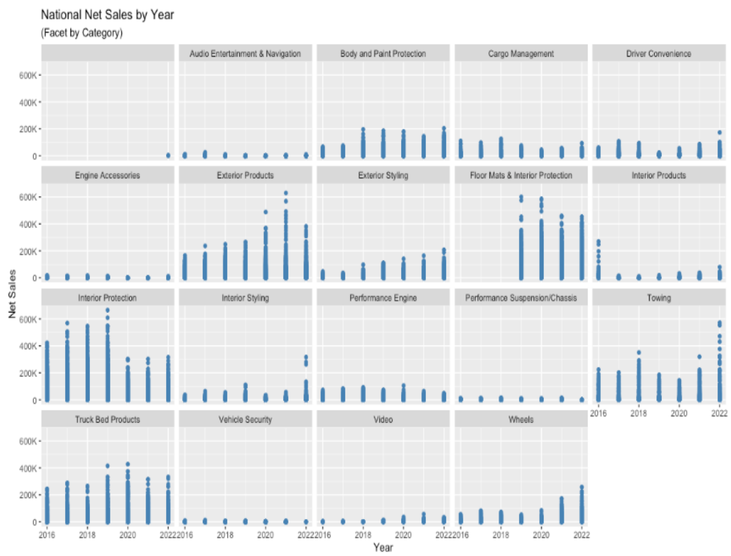
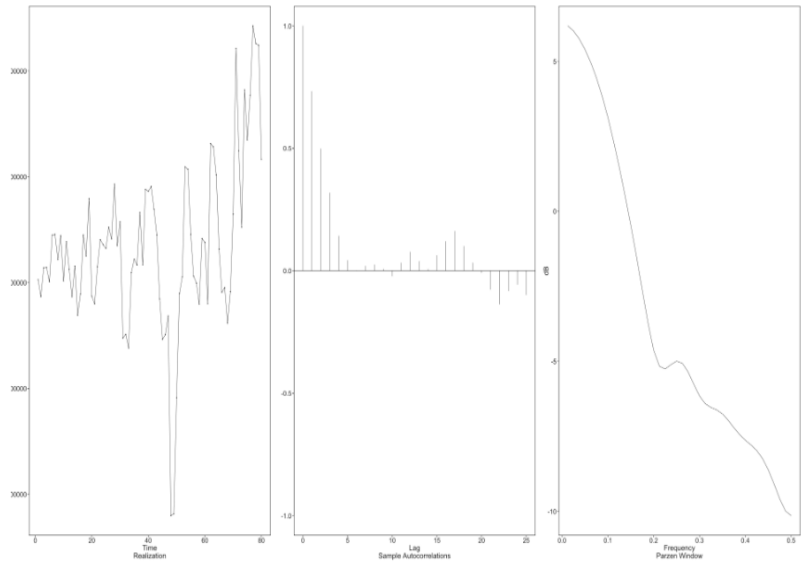
APPENDIX

Appendix 1

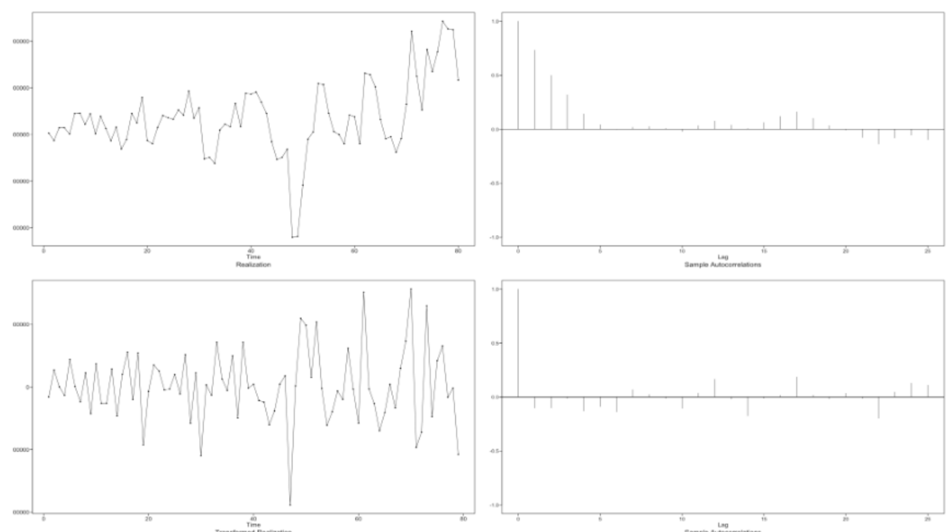


National sales by Accessory Category

Appendix 2

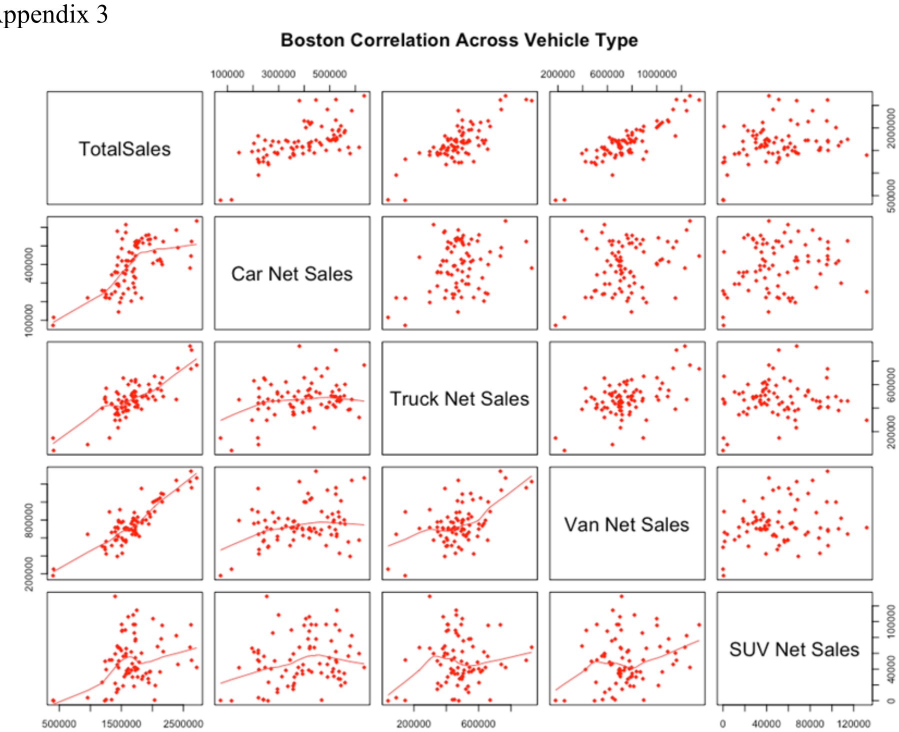


Boston non-stationarity.



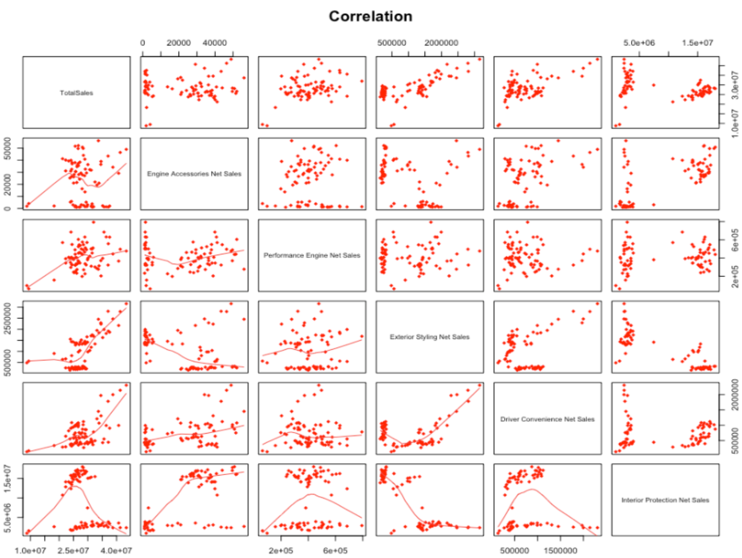
Boston Differencing to remove non-stationarity.

Appendix 3

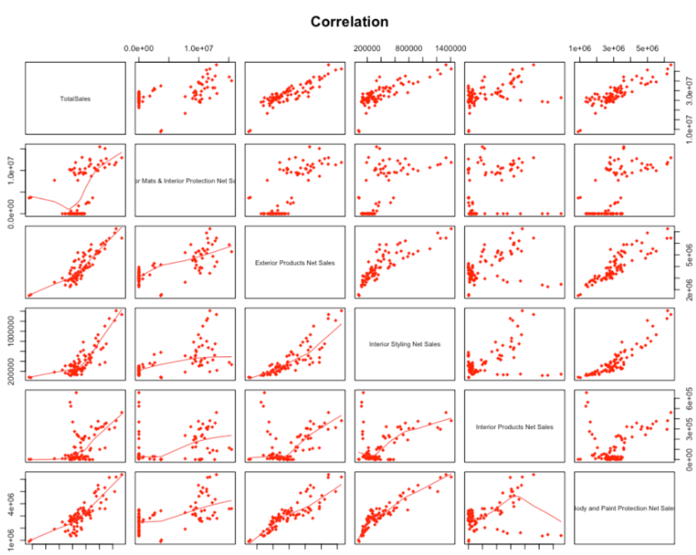


Boston correlation matrix for vehicle type sales

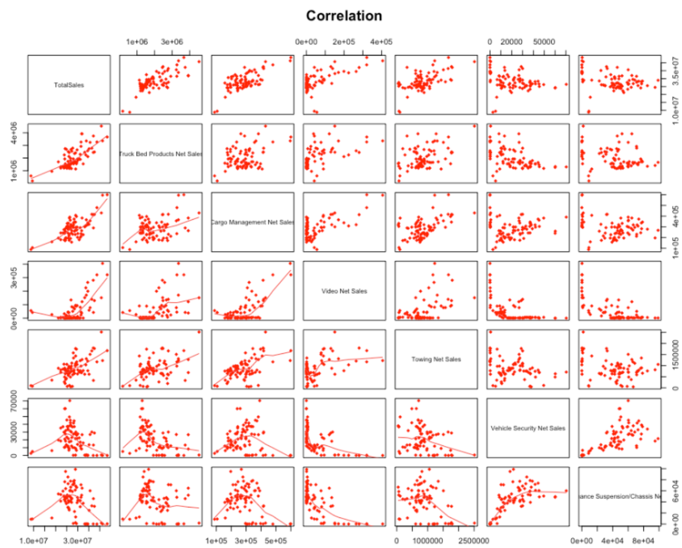
Appendix 4



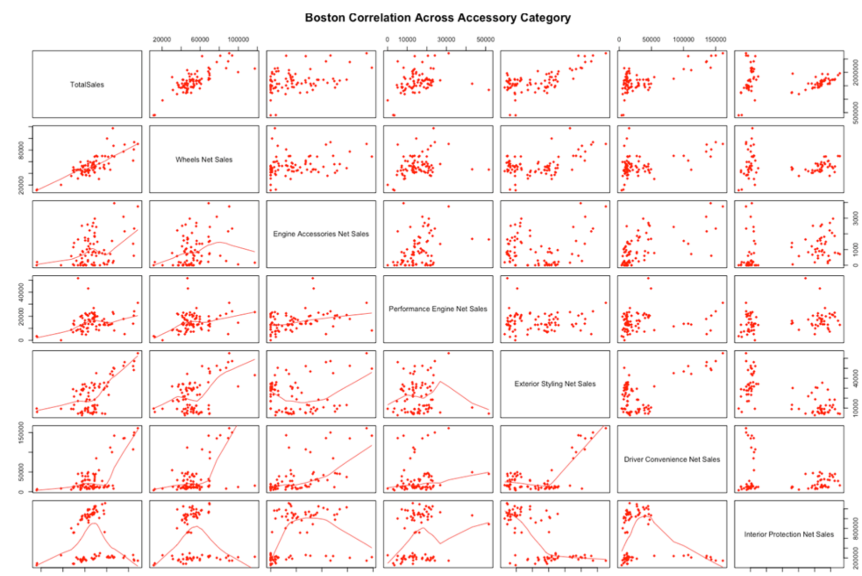
National Correlation Matrix1 (Accessory by Category)



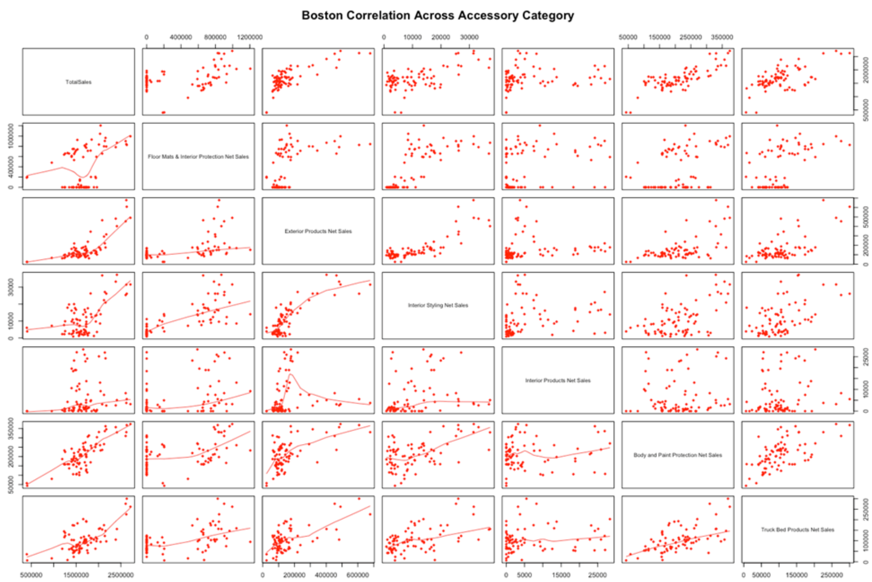
National Correlation Matrix2 (Accessory by Category)



National Correlation Marix3 (Accessory Sales by Category)



Boston Correlation Matrix1 (Accessory Sales by Category)



Boston Correlation Matrix2 (Accessory Sales by Category)

Appendix 5

```
options(scipen = 999)
####################  REGRESSION Model - Short ###############################################################
TOY_small = TotalSales[1:75,]
ksfit = lm(TotalSales~`Truck Net Sales`+`Exterior Products Net Sales`,data = TOY_small)
phi = aic.wge(ksfit$residuals)

fit = arima(TOY_small$TotalSales,order=c(phi$p,0,0), xreg = cbind(TOY_small$`Truck Net Sales`,TOY_small$`Exterior Products N
et Sales`))
```

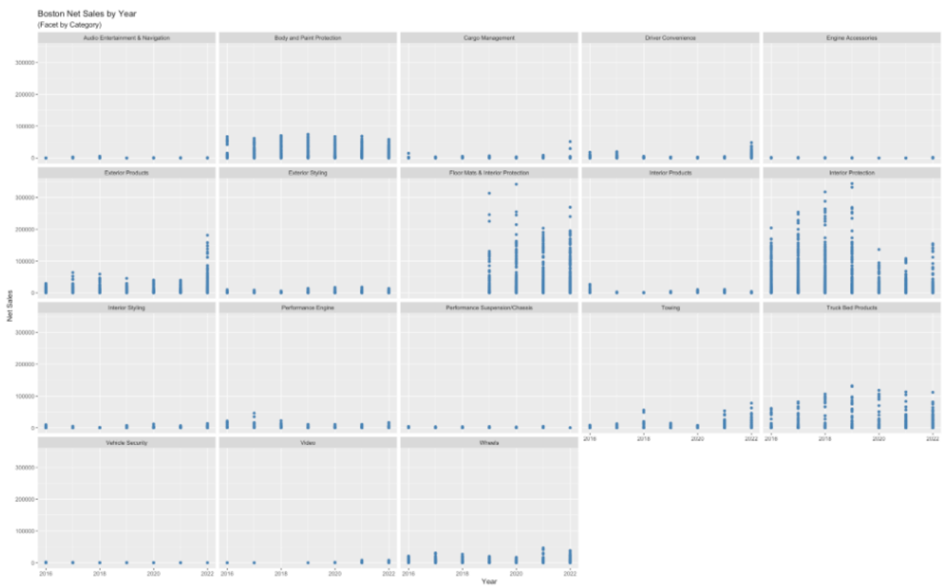
National Multivariate ARIMA

```
options(scipen = 999)
####################  REGRESSION Model - Short ###############################################################
TOY_small = BostonNetSales[1:75,]
ksfit = lm(TotalSales~`Truck Net Sales`+`Exterior Products Net Sales` + `Floor Mats & Interior Protection Net Sales`,data =
TOY_small)
phi = aic.wge(ksfit$residuals)

fit = arima(TOY_small$TotalSales,order=c(phi$p,0,phi$q), xreg = cbind(TOY_small$`Truck Net Sales`,TOY_small$`Exterior Produc
ts Net Sales`,TOY_small$`Floor Mats & Interior Protection Net Sales`))
```

Boston Multivariate ARIMA

Appendix 6



Boston sales by Accessory Category

Appendix 7

```
TOY_small = BostonNetSales[1:70,]
ksfit = lm(TotalSales~`Truck Net Sales`+`Exterior Products Net Sales`+ `Floor Mats & Interior Protection Net Sales`,data = T
OY_small)
```

Exogenous variables used in the Boston multivariate time-series