PREDICTIVE SALES ANALYTICS

FORECASTING FUTURE REVENUE TRENDS

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SKOLAR MINOR PROJECT

Predictive Sales Analytics Forecasting Future Revenue Trends

Introduction:

Sales forecasting is a crucial aspect of business planning and strategy, enabling organizations to anticipate future demand, allocate resources efficiently, and make informed decisions. In an ever-evolving market, accurate sales predictions are essential for maintaining competitiveness and achieving sustainable growth.

This project is focuses on utilizing IBM SPSS to analyse historical sales data, finding patterns, and develop forecasting models that can contribute to a more informed understanding of future sales trends.

Accurate sales forecasting empowers businesses to optimize inventory levels, streamline production processes, and enhance overall operational efficiency. The integration of SPSS, a powerful statistical analysis tool, provides a systematic and data-driven approach to the exploration of sales data. By leveraging SPSS capabilities, this project aims to offer insights into effective forecasting methodologies, contributing to improved decision-making processes within the realm of sales and business management. The analysis delves into the identification of influential factors, the selection of appropriate models, and the validation of forecasts, providing a comprehensive framework for predicting future sales with greater precision and reliability. Through this exploration, the project to demonstrate the practical applications of SPSS in the context of sales forecasting, offering valuable insights for businesses seeking to navigate the complexities of an increasingly dynamic marketplace.

Definition:

Predictive sales analytics refers to the use of data analysis, statistical algorithms, and machine learning techniques to forecast future sales outcomes based on historical data and patterns.

This approach involves leveraging advanced analytics tools to identify trends, relationships, and potential future scenarios in sales data. By analysing past sales performance, customer behaviours, and other relevant factors, predictive sales analytics aims to provide businesses with insights that can guide strategic decision-making, optimize resource allocation, and improve overall sales effectiveness. In essence, it helps organizations anticipate and prepare for future sales trends, contributing to more informed and proactive sales strategies.

Use Cases:

In the dynamic landscape of business, predictive sales analytics serves as a versatile tool, harnessing the power of data to drive informed decision-making. From inventory management to customer engagement, this innovative approach empowers organizations to foresee trends, optimize strategies, and enhance overall operational efficiency. The following use cases illustrate how predictive sales analytics transforms raw data into actionable insights, revolutionizing how businesses tailor their approaches to inventory, marketing, customer interactions, and strategic planning. Each scenario showcases the adaptability of predictive analytics in solving specific challenges across various facets of business operations.

1.Inventory Optimization:

Predictive sales analytics is instrumental in optimizing inventory management. Retailers can use historical sales data to forecast demand for specific products, ensuring that they have the right amount of stock on hand. This prevents overstocking, minimizes excess inventory costs, and reduces the likelihood of stockouts.

2.Customer Segmentation:

By analysing customer behaviours and purchase history, predictive sales analytics enables businesses to create customer segments. This segmentation helps tailor marketing strategies to different groups, improving the effectiveness of targeted campaigns and promotions. For example, an online bookstore might offer personalized book recommendations based on a customer's past purchases.

3.Price Optimization:

Predictive analytics assists in determining optimal pricing strategies. Retailers can analyse historical sales data and external factors to identify price elasticity and adjust pricing accordingly. This ensures competitive pricing, maximizes revenue, and responds to market dynamics in real-time.

4.<u>Sales Forecasting for New Products</u>:

Launching a new product involves uncertainty, but predictive sales analytics can mitigate risks by forecasting potential sales. By considering factors like market trends, customer preferences, and competitor performance, businesses can make informed decisions on product development and marketing strategies.

5.<u>Fraud Detection</u>:

In the financial sector, predictive analytics is used for fraud detection. By analysing transaction patterns and historical data, the system can identify anomalous activities and flag potentially fraudulent transactions in real-time, helping prevent financial losses.

FORECASTING MODELS IN SPSS:

SPSS offers a range of time series forecasting models to analyse and predict trends in temporal data. One commonly used method is the **ARIMA** (Autoregressive Integrated Moving Average) model, which combines autoregressive and moving average components to capture patterns in time series data. SPSS provides a user-friendly interface to specify ARIMA parameters and assess model fit.

Another popular model within SPSS is the **Exponential Smoothing State Space** Models (ETS), which includes various smoothing methods such as simple exponential smoothing, double exponential smoothing, and triple exponential smoothing (Holt-Winters method). ETS models are effective for capturing different levels of trend and seasonality in time series data.

Linear regression is a fundamental statistical technique used in SPSS for forecasting when there is a linear relationship between the dependent and independent variables. In forcasting, it helps predict future values by fitting a straight line to historical data points, assuming a constant slope. This model is suitable when the relationship between variables can be represented linearly.

CASE STUDY:

Lets understand time series forcasting with some simple examples, Lets take a dataset which consist of the information about the year of sales of the shampoo product and the sales mean of the particular month.

<u>Problem: "How is my future sales of the product, should I do more marketing and increase the quantity of my product."</u>

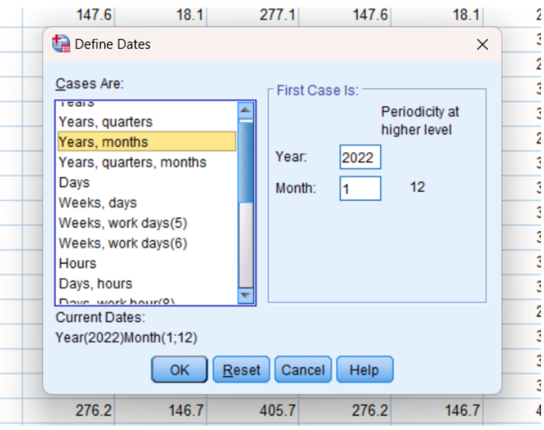
Process:

Here are step-by-step instructions for applying a time series forecasting model in SPSS:

1. Import Data
2. Explore Data
3. Choose a Forecasting Model
4. Specify Model Parameters
5. Estimate the Model
6. Evaluate Model Performance
7. Make Forecasts
8. Visualize and Interpret Results

Month	Sales
1-Jan	266.0
1-Feb	145.9
1-Mar	183.1
1-Apr	119.3
1-May	180.3
1-Jun	168.5
1-Jul	231.8
1-Aug	224.5
1-Sep	192.8
1-Oct	122.9

In spss the date which you have imported through the dataset is not the actual date the spss software recognises, you have to manually enter data only then its going to be used in the dataset ,



GOTO DATE->DEFINE DATE TIME and select the time series as your requirement.

There will be 2 extra variables created in the dataset according to the time format you have chosen

APPLYING THE FORECATING MODEL:

1. GOTO ANAYZE->FORECASTING->CREATE TRADITIONAL MODELS

2. Put the variable into DEPENDENT VERIABLE for which you want to perform the forcasting
3. Select the appropriate model for your analysis
4. Goto save tab and check the checkbox of the predicted, lcl, ucl
5. Go to options and select the second radio button and enter the number of days or years you want to get the predictions click on ok

OUTPUT:

Model Description

			Model Type
Model ID	AVG	Model_1	Winters' Additive

Model Summary

Model Fit

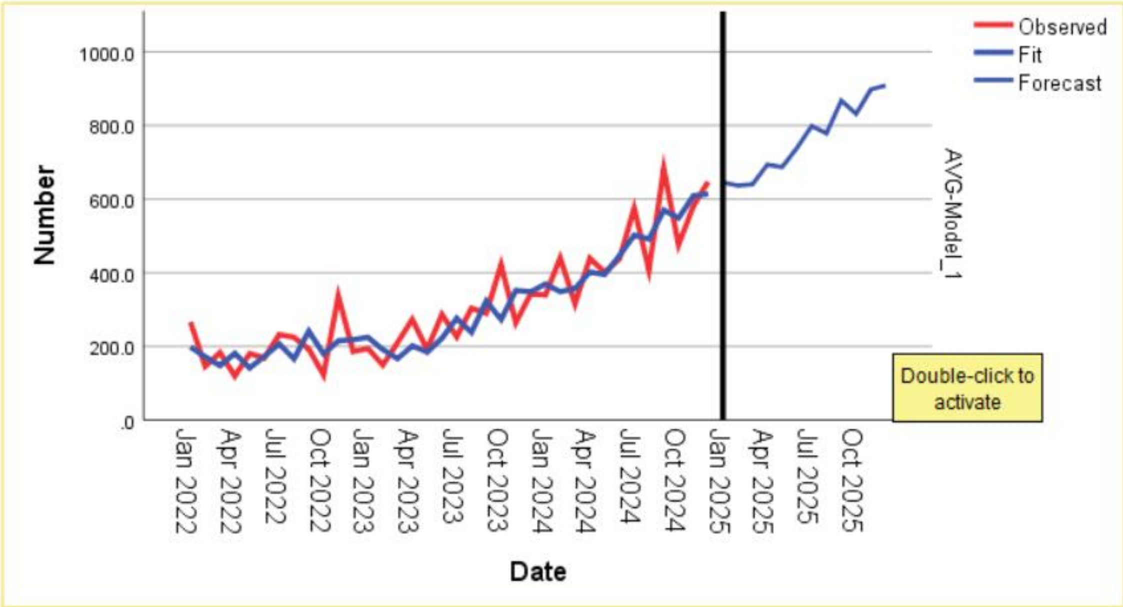
					Percentile						
Fit Statistic	Mean	SE	Minimum	Maximum	5	10	25	50	75	90	95
Stationary R-squared	.870	.	.870	.870	.870	.870	.870	.870	.870	.870	.870
R-squared	.828	.	.828	.828	.828	.828	.828	.828	.828	.828	.828
RMSE	63.637	.	63.637	63.637	63.637	63.637	63.637	63.637	63.637	63.637	63.637
MAPE	18.663	.	18.663	18.663	18.663	18.663	18.663	18.663	18.663	18.663	18.663
MaxAPE	51.926	.	51.926	51.926	51.926	51.926	51.926	51.926	51.926	51.926	51.926
MAE	51.237	.	51.237	51.237	51.237	51.237	51.237	51.237	51.237	51.237	51.237
MaxAE	148.655	.	148.655	148.655	148.655	148.655	148.655	148.655	148.655	148.655	148.655
Normalized BIC	8.605	.	8.605	8.605	8.605	8.605	8.605	8.605	8.605	8.605	8.605

As u see the model the software have chosen is the Winters Additive model and in the output we can see the model summary statistics , In this table you can look at two things to explain how good the model is for your data. The higher the R-squared value the model is fitted well, RMSE should be low (lower the value better the model is) and same goes with the MAPE value

Model Statistics

		Model Fit statistics		Ljung-Box Q(18)			
Model	Number of Predictors	Stationary R-squared	R-squared	Statistics	DF	Sig.	Number of Outliers
AVG-Model_1	0	.870	.828	43.441	15	.000	0

Hear in this table we should look at the Ljung-Box which is a model fit index, hear if we look at the significance value its 0.000 so the model which the software have choosen is not good and the value should be greater than 0.5.



So even if the model is not fit well we can see the future prediction, so next year sales there is a upward trend. So in this case the company can do more marketing so they can get even more revenue.

<u>LETS TAKE ANOTHER EXAMPLE</u>

<u>Problem: “what will be my sales next 2 months”</u>

This dataset consist of data about the truck sales from year 2003:

After applying all the steps mentioned above we get this output

MonthYear	Number_Trucks_Sold
03-Jan	155
03-Feb	173
03-Mar	204
03-Apr	219
03-May	223
03-Jun	208
03-Jul	228
03-Aug	228

OUTPUT:

This time the software has chosen ARIMA model for the forecasting, ARIMA model is chosen when there are more number or seasons or peaks in the dataset.

Model Description

			Model Type
Model ID	Number_Trucks_Sold	Model_1	ARIMA(0,1,1)(0,1,1)

Model Fit

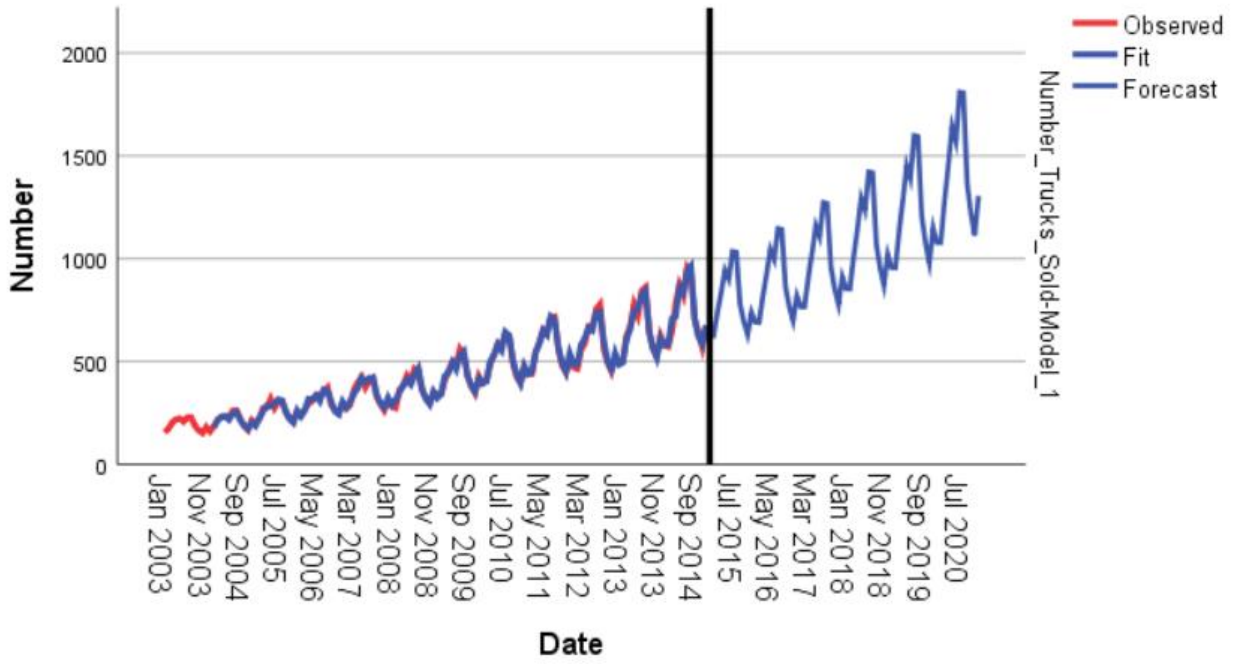
Fit Statistic	Mean	SE	Minimum	Maximum	Percentile 5	10	25	50	75	90	95
Stationary R-squared	.327	.	.327	.327	.327	.327	.327	.327	.327	.327	.327
R-squared	.992	.	.992	.992	.992	.992	.992	.992	.992	.992	.992
RMSE	16.697	.	16.697	16.697	16.697	16.697	16.697	16.697	16.697	16.697	16.697
MAPE	2.915	.	2.915	2.915	2.915	2.915	2.915	2.915	2.915	2.915	2.915
MaxAPE	12.763	.	12.763	12.763	12.763	12.763	12.763	12.763	12.763	12.763	12.763
MAE	12.514	.	12.514	12.514	12.514	12.514	12.514	12.514	12.514	12.514	12.514
MaxAE	63.204	.	63.204	63.204	63.204	63.204	63.204	63.204	63.204	63.204	63.204
Normalized BIC	5.705	.	5.705	5.705	5.705	5.705	5.705	5.705	5.705	5.705	5.705

This time the RMSE and MAPE values are low and there is s R-squared value of 0.992 so the model which is choosed by the software is good and well fit

Model Statistics

Model	Number of Predictors	Model Fit statistics: Stationary R-squared	R-squared	Ljung-Box Q(18): Statistics	DF	Sig.	Number of Outliers
Number_Trucks_Sold-Model_1	0	.327	.992	12.454	16	.712	0

If we look at the significance the value is 0.712 so we can comprehend that the software have choosen a good model for predicting the future



So this is the prediction which the ARIMA model made for the next 5 years so we can see there is an upward trend in the sales so based on this information the company can change its marketing strategy so that they get more sales.

CONCLUSION:

In conclusion, improving forecasting accuracy involves trying different methods and adjusting models to better fit the data. We must experimented with various time series models and fine-tuned their settings to make better predictions for future sales. It's important to pay attention to the details, like checking if the model fits the data patterns and understanding where it may struggle. By using a mix of models, adjusting parameters, and learning from the mistakes, we aim to make our predictions as accurate as possible and help make better decisions for the future.