Abstraction

Demand is the vital indicator for each business to consider prior to venturing for the first step or extending in the picked market segment. It drives financial development while national banks and governments boost demand to end down-sliding. Demand Prediction, which is important for Predictive Analytics, infers an evaluation of the quantity of labor and products that buyers will presumably purchase later on. The most basic business factors like turnover, overall revenues, income, capital consumption, hazard appraisal, relief plans, scope organization, and so forth are straightforwardly subject to demand.

There are main 6 Types of Demand Forecasting

1. Passive Demand Forecasting
2. Active Demand Forecasting
3. Short Term Projections
4. Long Term Projections
5. Internal Business Forecasting
6. External Macro Forecasting

Demand forcasting

Demand forecasting is the interaction used to anticipate future client demand dependent on historical sales information. Forecast precision impacts a wide assortment of business activities going from stock administration to supply chain management. There are many examples where due to demand forecasting business has lost profit main example is for Nike they predicted that this time instead of a larger sale of top-of-shelf shoes people will go for cheaper shoes But they backfire and results in millions of dollars loss.

1. Passive Demand Forecasting

Generally considered as the least complex interest forecasting type, passive forecasting uses historical data utilizes chronicled information to predict future client demand. Passive interest anticipating is an incredible fit for organizations with superb deals information and attention on keeping up strength instead of seeking after development.

2. Active Demand Forecasting

Active demand forecasting uses statistical surveying, market research, and other outer components to foresee future client interest. As sales information isn't central for this determining type, dynamic interest anticipating is ideal for recently settled organizations or organizations that are as of now in a development phase.

3. Short Term Projections

Short-term demand forecasting determining just estimates client interest for the forthcoming three months to one year. Momentary interest gauging applies continuous deal information to change client request projections that may some way or another be obsolete if a long-term projection was recently utilized.

4. Long Term Projections

Long-term demand forecasting predicts the following one year to four years of the client demand. Long-term forecasting is essentially founded on market research and sales information.

Experts advise that this forecasting type ought to be seen as to a greater degree a general guide since projections are probably going to change over an extensive period of time.

5. Internal Business Forecasting

Internal business forecasting assists organizations with the comprehension if their ability planning is proper for expected client demand. Giving a more complete survey of business activities, interior business estimating helps with recognizing improvement regions to streamline accessible assets.

6. External Macro Forecasting

External macro forecasting is an incredible inventory management tool to board instrument. Focusing on external factors that impact business activities, outside large scale determining recognizes expected patterns and how those patterns may impact organization targets.

## **Demand Forecasting Models**

Demand forecasting models are by and large ordered as either quantitative techniques and subjective strategies. Qualitative techniques are useful when enormous information is missing, for example when new items are created and sales information is nonexistent. As no sales are done for any new item.

Quantitative methods focus on big data utilizing using apparatuses like AI, Machine learning to predict future client demand. Subjective and quantitative techniques for request forecasting models incorporate below models

1. Trend projection

2. Sales Force Composite

3. Delphi Method

4. Market Research

5. Econometrics

1. Trend projection

Generally viewed as the simplest or least complex and most smoothed out forecasting model accessible, trend projection applies past sales information to future sales forecasts. To keep up forecasting precision long term, business experts should update their pattern projections continuously when unforeseen and powerful changes happen.

An unexpected change that would necessitate a pattern projection update could incorporate a prominent by a conspicuous online and social media influencer or an inventory network the board setback or a supply chain management mishap.

2. Sales Force Composite

Forecasting demand dependent on sales group feedback deals power composite gives special knowledge on customer desires and contenders. The business power and salesforce composite determining measure require broad departmental cooperation including directors and supervisors.

Business experts should factor in that the business power composite strategy contains a significant human inclination. The business power composite estimating strategy is regularly utilized simultaneously with quantitative strategies consequently.

3. Delphi Method

The Delphi strategy utilizes outer feedback to appraise future interest through studies, questions, and surveys. The end objective of the Delphi estimating model is a brought together and educated agreement regarding specialists.

### 4. Market Research

### Market research forecasting is ideal for recently settled organizations that need to comprehend client request patterns without earlier deals information accessible for examination. Through the organization of client criticism reviews, feedback surveys, request designs are distinguished and future advertising drives can be modified to target explicit socioeconomic clients.

### Statistical surveying may happen during a concentrated time frame or be coordinated as a predictable business measure.

### 5. Econometrics

### Big data-intensive concentrated, econometrics relies upon an unpredictable and complex investigation of outer components(outliers). Machine learning instruments are especially useful for econometrics because of the gigantic volume of information that should be prepared and then find useful information from them.

### A definitive target of econometrics is to distinguish connections between outer monetary variables. For instance, clients with an increment in their earnings may connect with expanded home remodels.

Problem Statement:

Given 5 years of store-item deals information, and requested to foresee 3 months of deals for 50 distinct items at 10 unique stores. What's the best way to deal with seasonality? Should stores be modeled separately, or can you pool them together? Does deep learning work better than ARIMA?

Dataset Description

The dataset is provided with 4 columns:

* date - Date of the sale data. There are no holiday effects or store closures.
* store - Store ID
* item - Item ID
* sales - Number of items sold at a particular store on a particular date.

Approach: Here I will try to use the basic ARIMA model, below are the steps to start with the solution:

1. Loading and Handling Time Series in Pandas
2. How to Check Stationarity of a Time Series?
3. How to make a Time Series Stationary?
4. Forecasting a Time Series

Table

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Figure 1: Dataset values

Graphical user interface, text, application

Description automatically generatedFigure 1: Dataset description

Results

Plot the Relative Sales for items and stores with respect to year for our training data based on each year

Chart, line chart

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Figure 3: Sales for items and stores with respect to year

We can see that the Items and Stores have grown similarly over the time.

Chart, line chart

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Figure 4: Sales for items and stores with respect to week

Sales by week has also shown similar growth pattern for both items and sales.

Chart, line chart

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Now we have checked the relationships between different variables.

It's time for us to decompose the time series.

Chart, box and whisker chart

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Here we can see that sales with respect to date is time series data.

Decompose the time series:

The Seasonal component: A seasonal pattern occurs when a time series is affected by seasonal factors such as the time of the year or the day of the week. Seasonality is always of a fixed and known frequency. A time series can contain multiple superimposed seasonal periods.

The Trend component: A trend exists when there is a long-term increase or decrease in the data. It does not have to be linear. Sometimes a trend is referred to as “changing direction” when it might go from an increasing trend to a decreasing trend.

The Cyclical component: The cyclical component represents phenomena that happen across seasonal periods. Cyclical patterns do not have a fixed period like seasonal patterns do. The cyclical component is hard to isolate and it's often ‘left alone’ by combining it with the trend component.

The Noise component: The noise or the random component is what remains behind when you separate out seasonality and trend from the time series. Noise is the effect of factors that you do not know, or which you cannot measure. It is the effect of the known unknowns, or the unknown unknowns.

Chart

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Figure :Time series decomposition

How to determine additive or multiplicative model for decomposition?

We use multiplicative models when the magnitude of the seasonal pattern in the data depends on the magnitude of the data. On other hand, in the additive model, the magnitude of seasonality does not change in relation to time.

Depending on whether the composition is multiplicative or additive, we’ll need to divide or subtract the trend component from the original time series to retrieve the seasonal and noise components.

Stationarity:

Before applying any statistical model on a Time Series, the series has to be stationary or time invariant, which means that, over different time periods, it should have constant means, constant variance and constant covariance. It means that the data should have constant mean throughout, scattered consistently and should have same frequency throughout. So, if our data mean, variance and covariance is varied with time then our data is non-stationary and we have to make it stationary before applying any method. This is necessary because if our data has some regular pattern then there’s a high probability that over a different interval, it will have same behavior and can cause problem in accuracy of model. And also, mathematical computation for stationary data is easier as compared to that of non-stationary data.

Diagram

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Lets check the stationarity

Here we are going to check the stationarity using 2 methods:

1. Rolling Mean: Plot the moving average or moving standard deviation to see if it varies with time.

2. ADCF Test — Augmented Dickey–Fuller test: This is used to gives us various values that can help in identifying stationarity. The Null hypothesis says that a Time-series is non-stationary. It comprises of a Test Statistics & some critical values for some confidence levels. If the Test statistics is less than the critical values, we can reject the null hypothesis & say that the series is stationary. The ADCF test also gives us a p-value. According to the null hypothesis, lower values of p is better.

Chart, line chart

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Figure: Rolling Mean & Standard Deviation

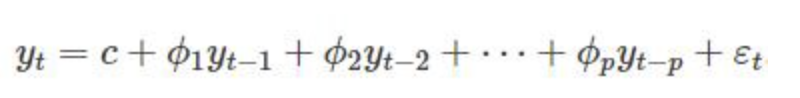
Lets start with ACF and PACF:

ACF is an (complete) auto-correlation function which gives us values of auto-correlation of any series with its lagged values. We plot these values along with the confidence band and tada! We have an ACF plot. In simple terms, it describes how well the present value of the series is related with its past values. A time series can have components like trend, seasonality, cyclic and residual. ACF considers all these components while finding correlations hence it’s a ‘complete auto-correlation plot’.

PACF is a partial auto-correlation function. Basically instead of finding correlations of present with lags like ACF, it finds correlation of the residuals (which remains after removing the effects which are already explained by the earlier lag(s)) with the next lag value hence ‘partial’ and not ‘complete’ as we remove already found variations before we find the next correlation. So if there is any hidden information in the residual which can be modeled by the next lag, we might get a good correlation and we will keep that next lag as a feature while modeling. Remember while modeling we don’t want to keep too many features which are correlated as that can create multicollinearity issues. Hence we need to retain only the relevant features.

Now let’s see what is an AR and MA time series process:

Auto regressive (AR) process , a time series is said to be AR when present value of the time series can be obtained using previous values of the same time series i.e the present value is weighted average of its past values. Stock prices and global temperature rise can be thought of as an AR processes. The AR process of an order p can be written as,



Where ϵt is a white noise and y’t-₁ and y’t-₂ are the lags. Order p is the lag value after which PACF plot crosses the upper confidence interval for the first time. These p lags will act as our features while forecasting the AR time series. We cannot use the ACF plot here because it will show good correlations even for the lags which are far in the past. If we consider those many features, we will have multicollinearity issues.This is not a problem with PACF plot as it removes components already explained by earlier lags, so we only get the lags which have the correlation with the residual i.e the component not explained by earlier lags.

Moving average (MA) process, a process where the present value of series is defined as a linear combination of past errors. We assume the errors to be independently distributed with the normal distribution. The MA process of order q is defined as ,

Diagram

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Here ϵt is a white noise. To get intuition of MA process lets consider order 1 MA process which will look like,

A picture containing schematic

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Order q of the MA process is obtained from the ACF plot, this is the lag after which ACF crosses the upper confidence interval for the first time.

A screenshot of a computer

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Figure : Training Autocorrelation

A screenshot of a computer

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Figure :first diff autocorrelation

Table

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Figure :ARIMA model results

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Figure: ARIMA Residual distribution

Graphical user interface, chart, line chart

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Figure: Prediction using ARIMA Model

Table

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Figure: Statespace Model Results

Chart, histogram

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Figure: Statespace Residual distribution

Chart, line chart

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Figure: Statespace results

Conclusion:

Here we try to compare different models for demand forecasting and we found that Statespace is more usefull while performing demand forecasting. We can clearly see this from experiment results.

Refereance:

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