**Time Series Spend Forecasting and Drift Monitoring**

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Abstract

Understanding spend trends and behaviours is crucial to business success, particularly for organisations driving Australia’s renewable energy transition. This project develops a solution for time series forecasting and drift monitoring of spend across suppliers and categories, enabling faster, more agile, and better-informed decision-making through smarter spend insights. A combination of statistical and machine learning models were evaluated namely ARIMA, Exponential Smoothing and Random Forest to determine the most accurate approach. Exponential Smoothing achieved the best performance across key accuracy metrics and revealed valuable insights to guide both short and long-term actions across better financial planning, proactive supplier management and improved resilience against spend volatility. Overall, this solution provides a strong foundation for advancing data-driven decision-making, planning and strategic procurement.

# Project Background

## Problem Statement

Forecasting future spend across suppliers and categories, monitoring drift in supplier behaviour and category distributions are critical for budgeting, supplier negotiations and management and strategic planning and it is essential that these are visible and accessible to the team to ensure better and informed decision making.

The problem addressed in this project is how to move from more reactive reporting to a more proactive and predictive forecasting as currently multiple business stakeholders of all levels are not fully enabled and struggle to make informed decisions due to the lack of accurate future focused insight and strategic foresight.

## Industry Domain

The organisation is an energy company in Australia responsible for the construction and maintenance of the transmission line system in New South Wales and Australian Capital Territory. In the past couple of years, as the country is transitioning to renewable energy, the business is expecting an uptake in the projects being managed in not only volume but most importantly value and being able to effectively and efficiently deliver these projects is critical not only for business success but also for all Australians.

One of the key parts in delivering these projects is having the tools necessary to effectively and efficiently plan for this work. Future focused spend insight and strategic foresight has been one of the requirements highlighted by the business so it is enabled to plan ahead and make informed decisions.

## Stakeholders

The key stakeholders for this project are the Finance and Procurement functions as well as executive leaders making strategic decisions. The goal for them is to be able to have accurate and future focused information on spend trends and behaviour at a regular basis to inform their decision making and effectively enable their work and processes.

## Business Question

The ongoing need to understand spend trends and behaviour and understand short and long term focus, actions and decisions for the organization to be able to set them up for success on the transition to renewable energy has been the main objective and driver for this project.

## Data Question

With the business objective in mind, the data question we have tried to answer is “How can forecasting models and drift detection techniques be applied to spend data to generate smarter insights that optimise decision-making across both immediate actions and long-term strategic planning for the renewable energy transition?”.

The objective is to be able to create a solution which will inform the business on an ongoing basis and be a tool which will continuously enable their decision making.

## Data Overview

The data observations are from real invoices captured from a Utility Energy Company in Australia. It contains approximately more than one hundred thousand lines spanning five years of spend data from 2021 to 2025. The dataset has information on invoice descriptions, suppliers, transaction date and category information.

Category classification of spend has been one of the key problems for the organization. The dataset used for this Capstone Project is an analysed and cleansed version containing spend category groupings from previous work on invoice spend classification in Mini Project 3.

# Data Science Process

## Data Analysis

The dataset was explored to identify patterns and anomalies, key features included Invoice Amount, Supplier Name, and Level 1 and Level 2 categories. To be able to generate key insights at a more granular level necessary for the business, the data was further transformed and aggregated into monthly spend at supplier and category levels.

Exploratory analysis revealed supplier concentration (a few suppliers account for most spend). Behaviour and trends are not consistent for the dataset, some categories and suppliers have seasonality and volatility however majority had been seen to have steady growth in spend. This insight was the driver in the need to evaluate multiple forecasting models to determine which will work best for the spend dataset.

Transformations and cleansing of data was required and included dropping empty values which are very minimal (<0.01%), data type conversions for consistency, and aggregating to three new datasets (Total Spend, Category, Supplier) for different levels of analysis.

## Modelling

1. **Time Series Forecasting**

Three models were developed and evaluated to be able to find the most accurate approach to spend forecasting. These models are Autoregressive Integrated Moving Average (ARIMA), Exponential Smoothing (ETS) and Random Forest.

A.1. Data Preparation

To prepare the monthly data for modelling, the pipeline included log transformation to stabilise variance and handle skewed distributions. In addition, time series was structured with monthly intervals to maintain uniform spacing between observations. Lastly, a train and test split was applied holding out the most recent 12 months as the test set and all historical data previous to that was used for training.

A.2 Models Specification

For ARIMA, after a few iterations, a (0,1,1) order to capture first order differencing for stationarity and a single moving average term was deemed the most fit for purpose for modelling. In addition, forecasts for the test period included 95% confidence intervals.

For Exponential Smoothing, additive trend and additive seasonal components were chosen to model linear trend and seasonal fluctuations. Seasonal period and forecast horizon were both set to 12 months to capture yearly cyclical patterns and for forecast projections.

For Random Forest, supervised learning approach using lag features of last 12 months of spend were used as predictors. 200 estimators and default tree depth were the hyperparameters used for modelling.

A.3 Forecast Evaluation

Accuracy metrics namely Mean Absolute Error (MAE) Root Mean Squared Error (RMSE) and Mean Absolute Percentage Error (MAPE) were used to compare the different models and decide on the best model to develop for time series spend forecasting.

The multi model approach enabled comparison of statistical and machine learning methods, balancing interpretability, seasonality capture and predictive accuracy.

1. **Drift Monitoring**

To ensure that the forecasting pipeline remains robust to changes in spend behaviour, this project implemented a drift monitoring mechanism alongside the best forecasting model developed. The approach captures both forecast performance drift and spend level drift, enabling early detection of structural changes in supplier or category spend patterns.

B.1 Drift Detection Criteria

There were two types of drift monitored, Error Drift and Spend Drift.

Error drift occurs when the MAPE for the test period exceeds a defined threshold relative to historical MAPE. For this project a threshold multiplier of 1.5x was applied. If the model performs significantly worse on the recent data compared to historical performance, it indicates an error drift and potentially the relationship between features and target has changed.

Spend drift occurs when the mean spend in the test period deviates significantly from the historical training mean and could signal a change or shift in data distribution. A threshold of 30% relative change was used for this project.

A binary drift flag is raised if either error drift or spend drift occurs and a relative change in spend is also recorded to quantify the magnitude of any deviation.

## Outcomes

1. **Time Series Forecasting**

A.1 Model Evaluation

* ARIMA Test Forecast

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* Exponential Smoothing Test Forecast

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* Random Forest Test Forecast

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* Forecast Accuracy Metrics

|  |  |  |  |
| --- | --- | --- | --- |
| **Accuracy Metric** | **ARIMA** | **Exponential Smoothing** | **Random Forest** |
| MAE | $25.4M | $19.4M | $25.0M |
| RMSE | $28.4M | $22.9M | $31.2M |
| MAPE | 32.60% | 27.70% | 30.90% |

The above graphs show how the different models performed and forecasted on the test set. Interestingly the different models did not differ by a significant amount on accuracy however overall Exponential Smoothing model was deemed to be most accurate and effective across all metrics.

A.2 Exponential Smoothing Parameter Tuning

The Exponential Smoothing model which was the best model based on accuracy was further fine-tuned to find the parameters which will perform best on forecasting.

Log transformation to stabilise variance was emebeded on the pipeline. In addition, Grid Search which tests combinations of trend (additive or none), seasonality (none, additive, multiplicative) and damping (yes or no) was done for the model and each combination was evaluated on different accuracy metrics MAE, RMSE, and MAPE.

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Fine tuning showed that the best parameters for Exponential Smoothing had additive trend, no seasonality and no damping with a 17.2% MAPE.

This final fine-tuned Exponential Smoothing Model was then used to generate spend insights across categories and suppliers

A.3 Spend Forecasting Insights

* Category Insights

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The model provided valuable insights which highlighted key areas the business needs to focus on and be aware of especially in the short term.

* The Top 2 Spend Categories, Construction Services and Network Equipment as shown in the graphs show an increasing spend trend forecast
* Network Equipment is forecasted to have very steep increase in spend in the next years
* This is a key callout for internal stakeholders as this category is very critical in the transition to renewable energy in Australia
* This is also a critical flag to Finance and Procurement for spend budgeting and strategic negotiations as Network Equipment is a key business cost driver
* Increase in spend can relate to increase in demand and with current market behaviour (which is currently a supplier led market with constraints in supply and production slots) focus on Supplier Relationship Management for key equipment suppliers and early planning is critical to ensure continuity of service.

Lastly, graphs are not shown here but majority of spend categories show an increase spend trend on future forecast and thus being able to monitor spend and behaviour is essential to ensure business is fully equipped and informed and any potential risks are mitigated.

* Supplier Insights

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The analysis of top suppliers based on spend revealed that they were all in the construction sector. In addition, there was an observed decrease in spend over the past one to two years for key construction suppliers. Graphs above are examples of the trends for two of the key suppliers for the organisation. Domain knowledge suggests that this was due to employee contract negotiations, which slowed down construction activities. This insight should be flagged to stakeholders because we can anticipate increased volatility and a potential sudden increase in spend once contract negotiations are finalised. This also highlights the importance of continuous supplier relationship management as again the construction space is a supplier led market with more demand than supply.

1. **Drift Monitoring**

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Above is an example of what is captured by our drift monitoring mechanism. This graph is for Technical Services category, and it is evident here that there has been a drift detected on spend for the category. It is significantly increasing through time which means we should shift procurement from a more tactical to a more strategic type to be able to get the best outcome for the business.

## Implementation

* Deployment Strategy

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For deployment, the model built is inside a Jupyter notebook which is refreshable per the required cadence of the business on reporting. When refreshed the model will automatically export 9 CSV files to a folder which has all the forecast and metrics on total spend, top suppliers and categories which can then be used as input to a Power BI Dashboard in the future.

It is essential to note that data security and governance surrounding the organisation is strict and deployment options might be limited. It is essential that deployment options are evaluated in conjunction with internal stakeholders to ensure no private and confidential information is compromised for the business and we are working within data regulations.

# Data and Business Answer

Moving through multiple stages of development, our data science solution aimed to answer several voices of customer and was successfully able to provide accurate spend information and guidance, spend forecast and trends, and insights into changes in category and supplier behavior. This provides a great starting point for stakeholders to make faster, more informed decisions and ultimately aid them through the journey of renewable energy transition.

# Response to Stakeholders

Ultimately, the data solution is not the end of the project. It is important to turn this data solution into actionable insights. The tool built will allow for an ongoing process of improvement, monitoring, analysis and reporting to ensure it is most effective for the business.

 The initial insights from the models showed the criticality of focus on below areas especially in the short term as this will heavily impact success in the long term.

* Supplier Relationship Management for top suppliers across categories
* Proactive Planning - especially for the Network Equipment category
* Looking at shifting procurement from tactical to more strategic to be more effective
* Looking at Business Planning (resources etc.) for expected uptake of volume and value of spend activity and lastly
* Focusing on Early Risk Identification and Management to ensure the business is best placed on the transition to renewable energy

Finally, it is also important to relay that there are several key areas to explore for future work on the data solution.

* Fine-tune Forecasting Pipeline: Continue refining the current forecasting pipeline to improve accuracy and robustness.
* Hybrid Forecasting Approaches: Explore hybrid models that combine statistical forecasting methods with machine learning techniques.
* Full End-to-End Pipeline: Integrate invoice classification models with the forecasting pipeline to build a comprehensive spend analytics solution.
* Granular Forecasting: Extend forecasting to more detailed spend categories and supplier groupings for deeper insights.
* Domain Knowledge Integration: Incorporate business and stakeholder input to adjust for known one-off events and seasonalities that may distort forecasts.
* Power BI Dashboard Creation and Deployment Options: Evaluate alternative deployment methods (e.g., dashboards, applications) in line with company policies and requirements.

# End to End Solution

The end-to-end solution provides an Intelligent Spend Forecasting and Drift Monitoring capability, enabling the business to continuously anticipate spend, track supplier & category trends and behaviors, to enable and drive more informed strategic decisions.