APPLICATION OF AI/ML TO IMPROVE FORECASTING IN SUPPLY CHAIN

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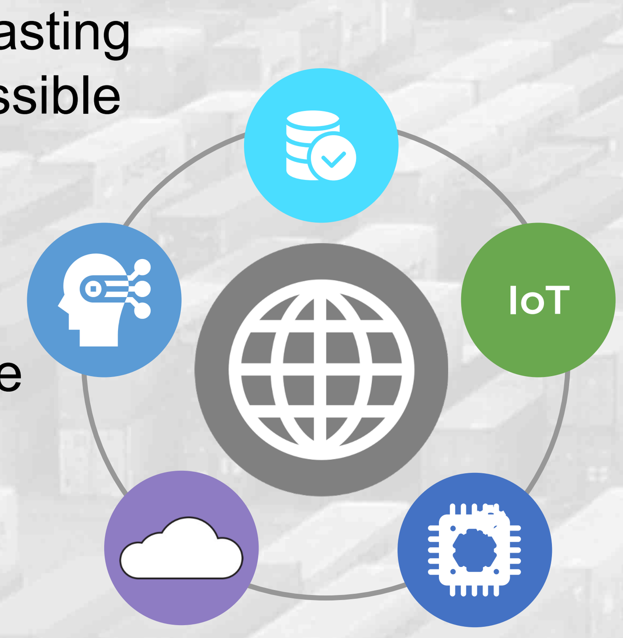
BACKGROUND

Achieving forecasting accuracy is a challenge for many companies especially with uncertainty in demand and supply. With the advancement of technology, the adoption of AI/ML has been increasing exponentially. But many companies are still relying on manual forecasting or those who have implemented AI/ML projects, many failed to deliver or see them through. The aim of this project is to examine ways to ensure successful application of AI/ML in SCM. First, we determine how well AI/ML models perform against traditional forecasting techniques, we then examine the pitfalls associated with implementing AI/Ml. Based on the analysis, we suggest possible solutions to optimise the use of AI/ML to improve forecasting.



OBJECTIVES

- ➢To conduct a quantitative comparison between ML and traditional forecasting models to determine the performance of these models
- ➢To identify the benefits, challenges and risks in the application of AI/ML
- ➢To recommend solutions to improve forecasting performance in the supply chain leveraging the potential of AI/ML

METHODOLOGY

A baseline comparison on a time-series forecasting was conducted to compare the performance between ML and traditional forecasting models to predict the store sales on data from a large grocery retailer.

Prepare Data

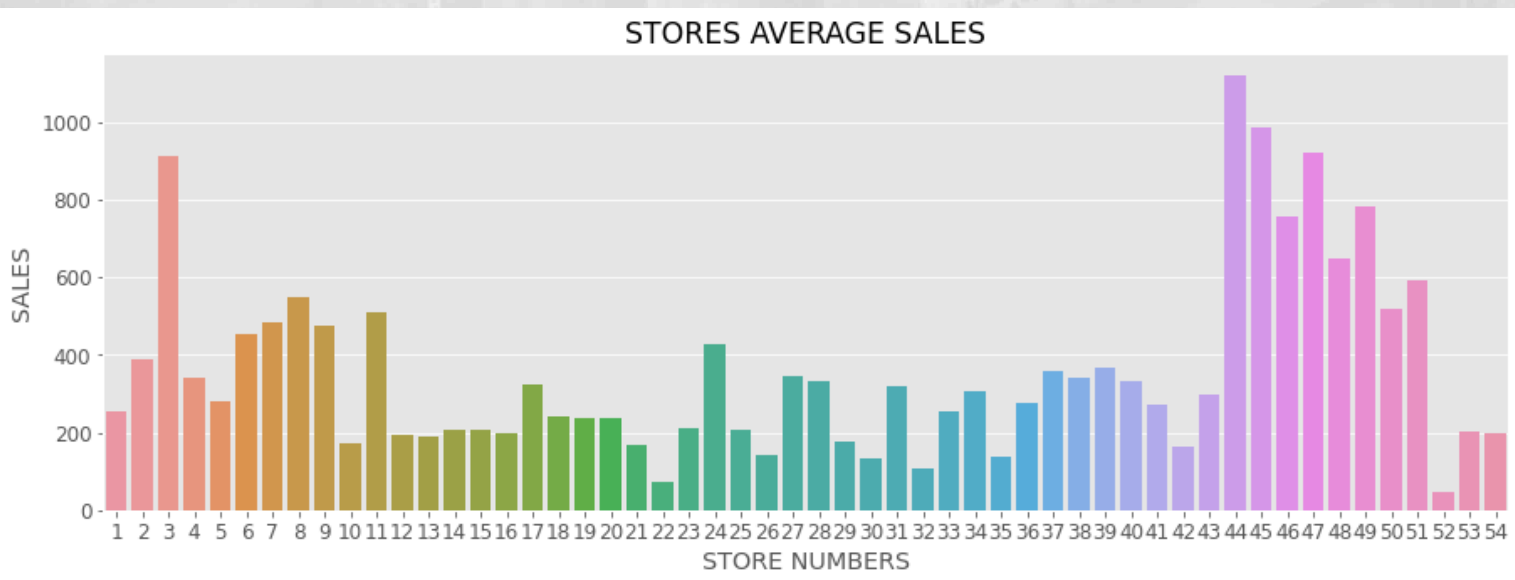
- Data exploration (e.g. Trends, seasonality)
- Data processing (e.g. aggregation, integration)
- Feature Engineering (impute missing values, feature extraction, label encoding, lag features, rolling means, etc)

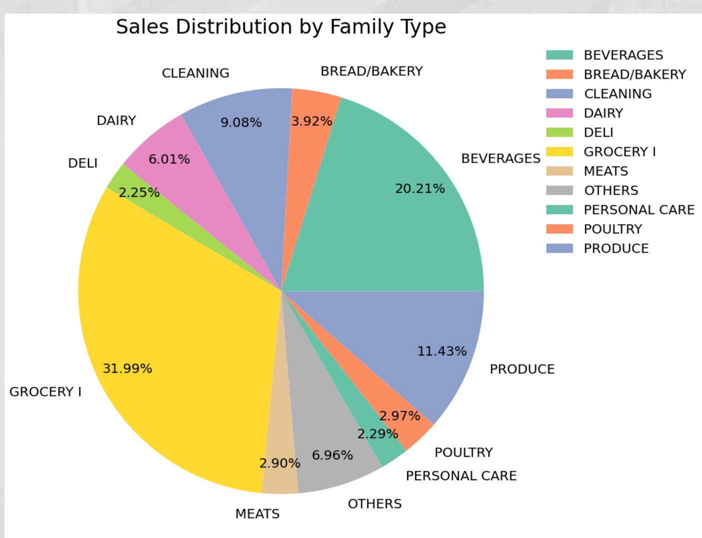
Train/Test

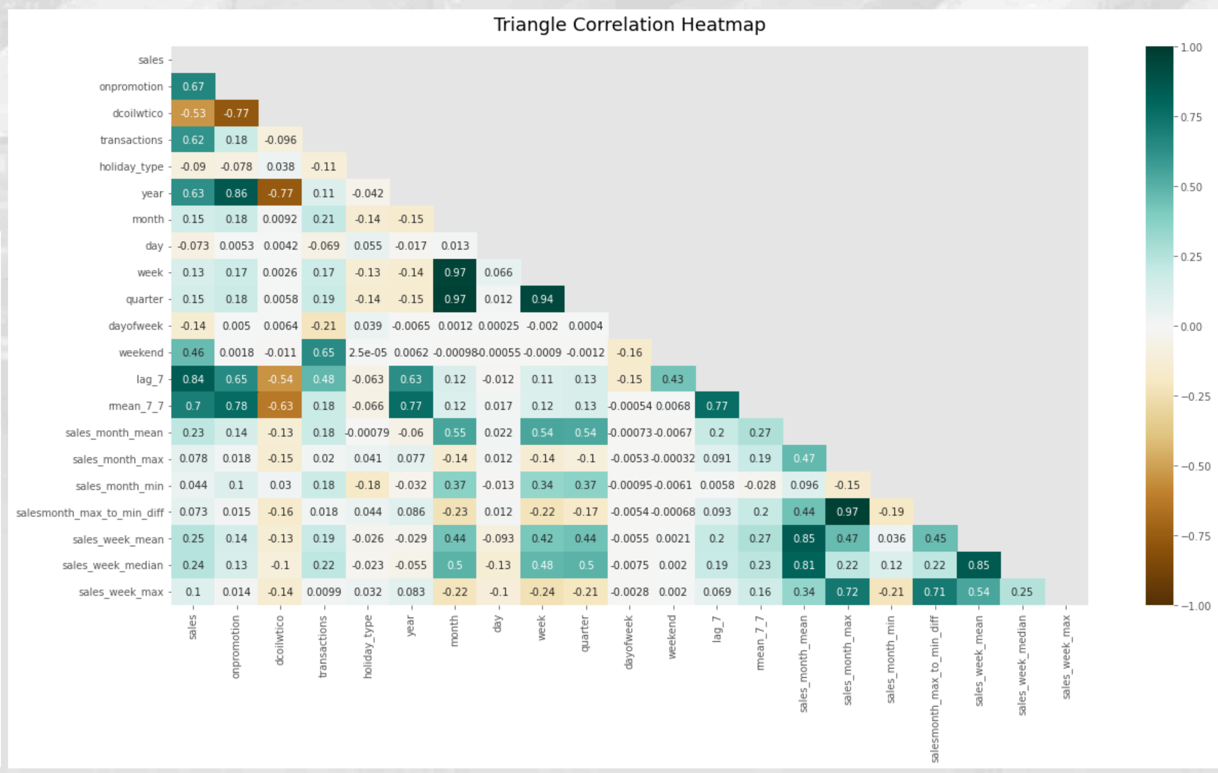
- Multiple traditional and ML models
  - Simple Exponential Smoothing, Double Exponential Smoothing, Triple Exponential Smoothing, SARIMA, SARIMAX
  - LightGBM, Random Forest, Linear Regression, XGBoost

Evaluation

- Performance measures compared to baseline
  - RMSE
  - MAE

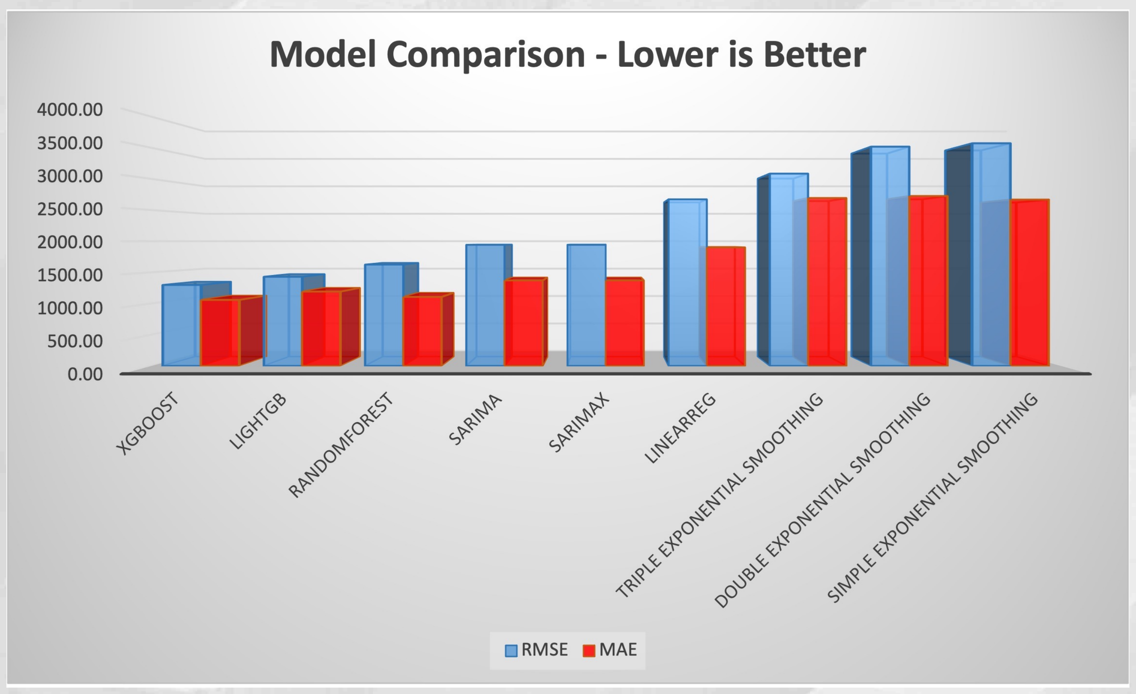




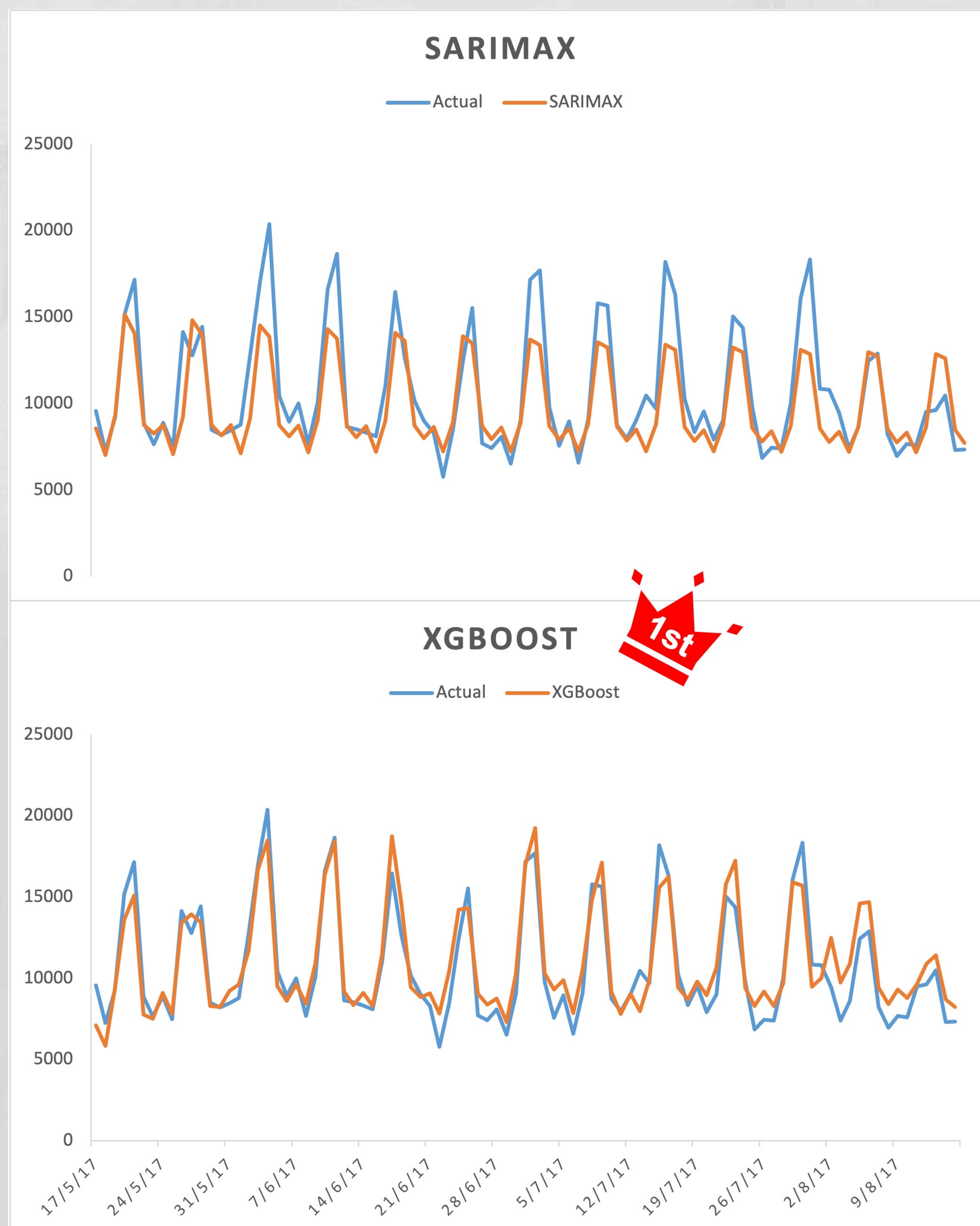


RESULTS & DISCUSSION

The comparison showed that the ML models outperformed the traditional forecasting models except for Linear Regression. Using the Simple Exponential Smoothing as benchmark, it achieved a 33.53% RMSE while XGBoost achieved a 12.20% error on the same validation data. Depending on how data is manipulated and transformed, models can be further improved with better accuracy. AI/ML models have clear advantages, but their complexity could lead to added layer of challenge in interpretation, bias and compliance.



Model Name	Execution Time	RMSE	MAE	RMSE%	MAE%
XGBoost	1.8014	1298.25	1058.42	12.20%	9.94%
LightGB	1.7891	1429.67	1192.14	13.43%	11.20%
RandomForest	1.7891	1624.49	1106.34	15.26%	10.39%
SARIMA	1169.2145	1941.36	1371.01	18.24%	12.88%
SARIMAX	1166.7045	1941.36	1371.01	18.24%	12.88%
LinearReg	0.0047	2670.58	1900.75	25.09%	17.86%
Triple Exponential Smoothing	0.3365	3082.18	2692.47	28.96%	25.29%
Double Exponential Smoothing	0.0588	3514.53	2723.95	33.02%	25.59%
Simple Exponential Smoothing (benchmark)	0.0062	3568.84	2666.99	33.53%	25.05%



CONCLUSIONS & RECOMMENDATIONS

There is no doubt that if properly done, AI/ML could generate more accurate predictions. The question is how to reduce the risk of AI/ML failure. Before embarking on an AI/ML project, companies should establish a clear objective, identify if AI/ML is the right solution. To harness the full potential of such technology, it is important that companies have the appropriate practices put in place to mitigate the AI/ML risks, and this requires the right process, people, skills, and data. Future improvements include further data pre-processing, fine-tuning the hyperparameters, exploring an ensemble of algorithms and neural network as well as no-code, low-code platforms where no coding knowledge is required.

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