Does AI close the demand forecasting gap?

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Introduction

Many analysts and industry experts are saying that we are heading into the fourth industrial revolution. One of the biggest drivers of this purported revolution is the availability of unprecedented volumes of data and the development of computer processing power that can leverage big data for the first time in history.

But what does this mean for the supply chain practitioner? One of the areas where Artificial Intelligence (AI) can have the biggest impact is the discipline of demand forecasting. For decades organizations have been attempting to close the gap between what happens in the market and how to gear the supply chain to be prepared for unexpected fluctuations, shifts and changes.

For this paper, a team of supply chain professionals have evaluated a set of traditional and cutting-edge forecasting methods to determine if AI can close the demand forecasting gap.

Focus on Forecasting

Why do we forecast? Businesses rely on forecasts for decision making and planning. A benefit that is often not considered is that forecasting forces the business to keep track of assumptions made and makes it easy to identify and adjust incorrect assumptions, improving performance and profitability. Nonetheless many supply chain practitioners will lament that “Forecasting is always wrong” and although this is true, forecasting plays a critical role in supply chain planning and operations.

Businesses that get forecasting right achieve the following:

- Increase customer satisfaction
- Reduce inventory cost
- Improve production planning

	Forecast Accuracy	Impact on Cash Flow	Impact on Profit
Customer Satisfaction		▲ Increased sales	
Inventory Cost		▼ Decreased Costs	
Production Planning		▼ Decreased Costs	

Traditional forecasting relies on statistical methods, using historical data and static, predetermined business rules, to predict business behaviour for the future. According to Prevedère (2015) quarterly forecasts are off by 13% on average. This translates to an estimated 200 billion US dollar in lost revenue alone. Any improvement on forecast accuracy thus translates directly to improvement of the bottom line.

Additionally, according to studies by Gartner, 38% of organizations identify forecast accuracy and demand variability as a key obstacle to achieving supply chain goals and objectives and 70% are experiencing moderate to high demand variation compared to the previous year.

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Further challenges with traditional forecasting methods are as follows:

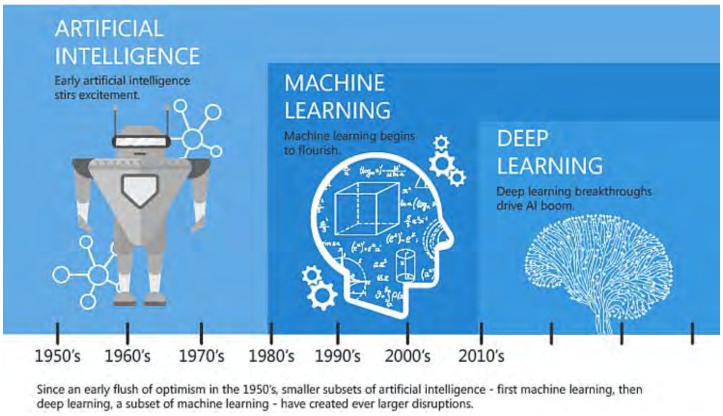
- Unable to extract key patterns and drivers
- Lack of forecast accuracy in the mid to long term
- Highly dependent on human judgement
- Limited to analysing historical demand, unable to account for external factors
- Unable to model and test “what-if” scenarios

Demystifying AI

For many, the mention of Artificial Intelligence (AI) conjures up visions of robot armies and self-driving cars. Even though robotics and autonomous vehicles are exciting applications of AI, there are numerous relevant applications of AI algorithms that are decidedly relevant to Supply Chain practitioners.

A short history of AI

AI is viewed as a very modern field; however, it has been in existence since the middle of the 20th century. Artificial Intelligence techniques and methods have been developed since the 1940’s. The famous Turing test, to determine if machines could think, was developed by the mathematician Alan Turing in 1950 and the first academic conference on the subject was held in 1956 (Smith et al, 2016).



Quara (2017)

Although the theories and algorithms underpinning AI have existed for decades, the processing power of computers (GPU’s) and availability of data (big data) have only recently caught up with the calculation and data intensive requirements of AI algorithms.

AI, ML and DL: terminology decoded

What is broadly known as AI consists of several sub-disciplines which are commonly referred to interchangeably. But Artificial Intelligence (AI), Machine Learning (ML) and Deep Learning (DL) are not the same thing. All are part of the same scientific field, but with definite differences that need to be considered.

AI	**The machine can think for itself**. Mimicking human intelligence using logic
ML	**Computers can learn by themselves**. Machine enabled to improve at tasks with experience
DL	**The next evolution of ML**. Algorithms programmed to train itself to perform tasks

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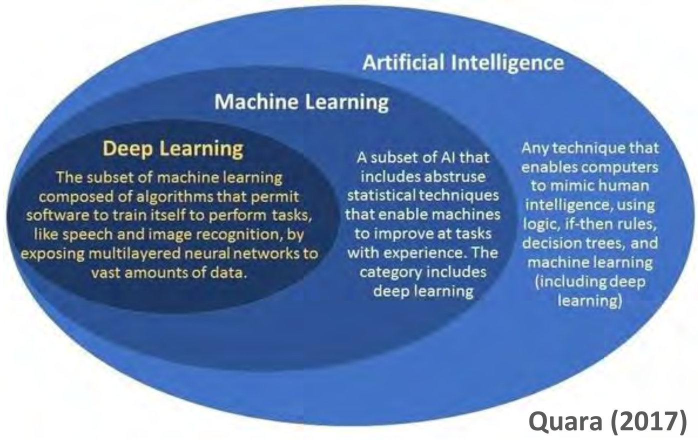
AI is already in your Supply Chain

AI might feel like something that has not yet been adopted in the supply chain or your industry, but the fact is that AI is already transforming supply chains all around us, Barlow (2018).



Quara (2017)

Some examples include:

Rolls Royce:

Partnered with Google to develop autonomous ships to safely deliver cargo. Forbes (2018)

UPS:

Uses an AI powered tool ORION to create efficient routes for its fleet, reducing delivery distance by an estimated 100 million miles. Forbes (2018)

IBM Watson:

In 2018 IBM launched Watson Supply Chain Insights: “Watson Supply Chain Insights includes advanced AI capabilities specifically designed to give supply chain professionals greater visibility and insights. Companies can combine and correlate the vast swathes of data they possess with Supply Chain Insights and Watson and see the impact of external events such as weather and traffic.” IBM (2018)

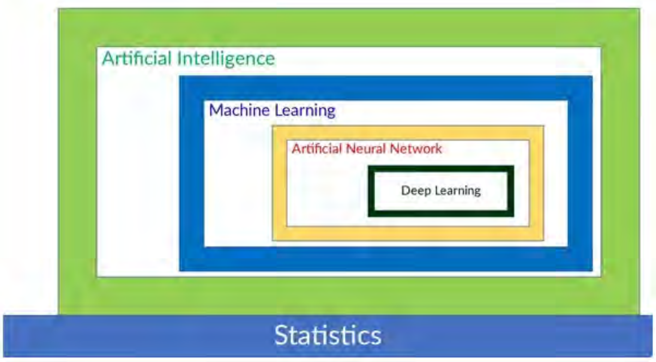
In the fourth industrial revolution, organisations are gathering more data than ever before, but data needs to be translated into information before it can add significant value. Traditional forecasting techniques such as statistics simply do not have the ability to leverage the wealth of data we have access to in today’s business world.

Stats and ML: A Comparison

Some might argue that ML is nothing but glorified statistics and some might argue that it is a mere subset of statistics.

The truth is that ML stands on the shoulders of giants: mathematics and statistics. ML cannot function without the application of statistics; however, machine learning is also not equal to statistics.

Statistics is defined as follows by Lumen Learning: “The science of statistics deals with the collection, analysis, interpretation, and presentation of data.” (2019). Thus, by its very definition, statistics is a static representation and interpretation of data. Statistical methods require data to be fed into hard-coded algorithms containing strict predetermined rules, which generate sets of results that can be interpreted by analysts, adjusted and resubmitted to the algorithm for improved results.



Quara (2017)

Conversely, Machine Learning algorithms are programmed with statistical principles,

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allowing the machine to choose between multiple options to improve upon its performance without human intervention.

Pro’s, con’s and requirements of ML

Machine learning algorithms:

- can handle vast amounts of data in a short time, for example causal datasets can be considered by the AI without considerable effort
- require large datasets for learning – to produce best results
- algorithm optimization for ML can be complex and time consuming

> *“Rules don’t get better, AI does”*
>
> **- Dan Fuenffinger, Google - data centre operator**

Case Study

Traditionally, forecasting is done by looking back at history and manually adding a growth factor to the data. Some organizations also employ sophisticated statistical methods.

With the hype around ML and the purported ease of causal modelling, the team at Business Modelling Associates put together a comprehensive comparison to pit statistical methods against ML methods.

- Using a set of real-world client data, we compared the following:
- Commercial statistical tool
- Commercial ML tool
- In-house statistical methods (MS Excel)
- In-house AI methods (Python)

Background

To test capability and robustness of the methods, the use-case chosen for this study is a company with a unique set of parameters: A monthly order pattern with limited SKUs and the typical South-African peak periods around Christmas and Easter.

Input Data & set-up

Historical data from 2014 to 2018 was made available for the study. Due to significant pattern changes from 2014 to 2015, 2014 data was excluded from the study for the in-house statistical and in-house ML models.

The ML models were set up as follows:

Training data: 2014/2015-2017

Test data: 2018

What this means is that the ML model learns from the training dataset and generates forecasts for 2018. Forecast values are then compared to the actuals for 2018 to determine accuracy of the forecasts.

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Comparison metrics

Three evaluation metrics were selected for the model comparison:

1. Weighted average percentage error (WAPE)
2. Penalty value
3. Development time

Each metric is compared to the forecast currently used by the client to generate a matrix by which the new forecasting methods can be compared and a simple score is applied to each metric.

Scoring legend:

Placement	Allocated Points & Colour Code
Winner	3
Second Place	2
Third Place	1

WAPE

One of the most popular measurements of forecast accuracy is the Mean Absolute Percentage Error or MAPE. This method measures the size of the error (between actuals and forecast) in percentage terms, ForecastPro (2019). The challenge with MAPE is that equal weighting is given to all measurements, so a small error on a large measurement would count equal to a large error on a small measurement. Thus, WAPE was chosen as a comparison metric as it assigns a weight to each measure.

Penalty value

For each technique a penalty value is assigned based on quantified business consequences.

Development time

For each method the time spent to develop the model is also considered.

Results

For each tool multiple models were developed. This comparison will detail only the best performer for each tool.

WAPE (Lower is better)

Model/Method	WAPE	Score
Existing Forecast	28%	
Commercial Statistical Tool	25%	1
Commercial ML Tool	23%	2
In-House Statistical Methods	27%	
In-House ML Methods	21%	3

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Penalty (Lower is better)

Model/Method	Penalty	Penalty %	Score
Existing Forecast	64	-	-
Commercial Statistical Tool	65	3%	1
Commercial ML Tool	58	-9%	2
In-House Statistical Methods	68	7%	
In-House ML Methods	39	-38%	3

Development Time*

Model/Method	Practitioner Experience	Time (Hrs)	Score
Existing Forecast			
Commercial Statistical Tool	Experienced	?	
Commercial ML Tool	Novice	8	2
In-House Statistical Methods	Experienced	4	3
In-House ML Methods	Experienced	160	

* A third place was not awarded for the "time" metric as the duration to develop a model in the commercial statistical tool is unknown (it was done by the service provider) and the time taken to develop the in-house ML model is considerably more than the other models.

Total scores (Higher is better)

Model/Method	Score
Commercial Statistical Tool	1
Commercial ML Tool	6
In-House Statistical Methods	3
In-House ML Methods	6

From the above analysis it becomes clear that the ML methods have a definite advantage over the statistical methods. Considering the WAPE and Penalty metrics the in-house ML method exhibits the best WAPE score at 21% and the commercial ML tool comes in second at 23%. This translates into a 38% drop in the penalty score for the in-house ML method and 9% drop for the commercial ML tool. Both statistical methods exhibited inferior performance on the penalty metric to the baseline model.

The next metric brings a very interesting perspective to the analysis. For our best performing model, the time investment is 160 hours. This translates into a highly skilled employee being occupied for a full month. If the penalty score could be translated into a monetary value the investment might be justified, but for most organizations translating something like lost sales into a concrete monetary value is challenging. The time investment also does not consider the time it takes for the practitioner to become skilled and most companies do not have AI practitioners on staff.

In the final comparison table, the ML models obtained equal scores of 6 each, followed by the in-house statistical model at 3. The greatest differentiator between the ML models being the time it took to develop the in-house model vs the commercial model. For the commercial model a complete

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novice with no ML experience was able to learn the ML tool and build a very compelling model in a single working day worth of hours.

Given that the final score is a draw – the selected method would depend on the priorities of the client. If penalty outweighs the importance of time, a highly customized solution would be recommended however if a more balanced solution was desired, the commercial tool would be recommended.

Conclusion

Some view AI as a passing fad and some as a cure-all silver bullet. From this analysis it seems that the truth lies somewhere in between. Great strides are being made in the field of ML but there is a lot of work that still needs to be done: companies need to be educated on what is available in the industry – that the advantage of ML is becoming more attainable every day.

It is however undeniable that AI has started to close the demand forecasting gap.

SPEAKER PROFILE + PHOTOGRAPH

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