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SAPICS | PROFESSIONAL BODY FOR SUPPLY CHAIN MANAGEMENT

DOES AI CLOSE THE DEMAND FORECASTING GAP?

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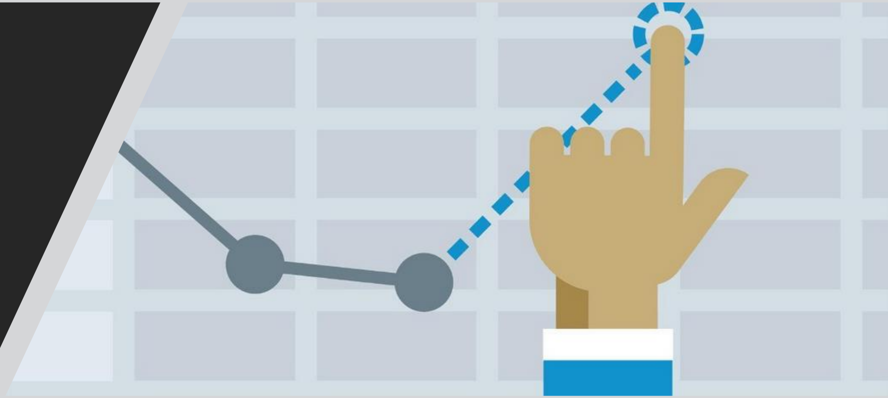
INTRODUCTION

- Difference between what is planned and what happens in real life
- Traditional methods and AI, can we close the gap?



FOCUS ON FORECASTING

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Why do we forecast?

- Decision making and planning
- Keeping track of assumptions and adjustments
- “Forecasting is always wrong”

What happens when we get it right?

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

TRADITIONAL FORECASTING

Stats

- Quarterly forecasts off by 13% - *Prevedère (2015)*
- 200 Billion USD lost revenue
- 38% of organisations: forecast accuracy is key obstacle - *Gartner*
- 70% of organisations: moderate to high variation - *Gartner*

Further challenges

- Unable to extract **key patterns** and drivers
- **Lack of accuracy** – mid to long term
- Highly dependent on **human judgement**
- Limited to analyzing **history**
  - Unable to easily account for **external factors**
- Unable to test ‘**what-if’s’**

DEMYSTIFYING AI

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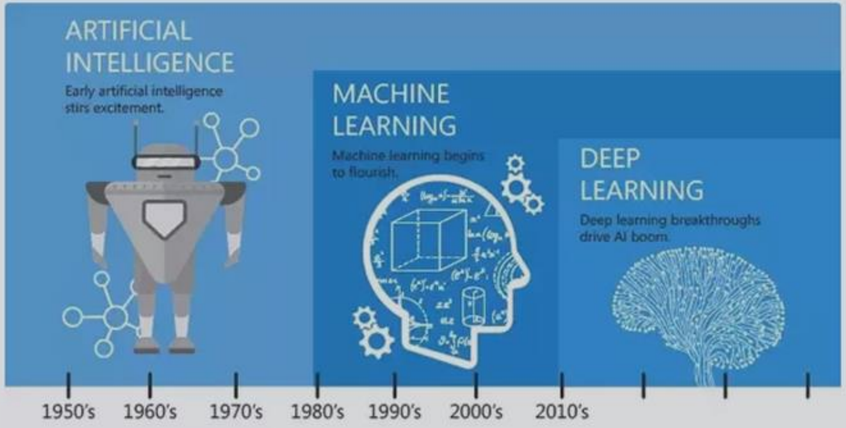
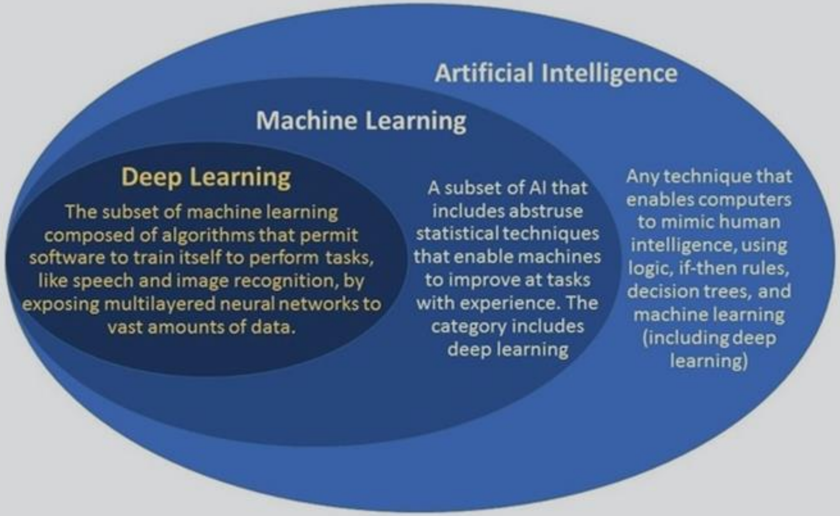
A short history of AI



Quara (2017)

AI, ML and DL



Quara (2017)

AI IS ALREADY IN YOUR SUPPLY CHAIN

STATS AND ML: A COMPARISON

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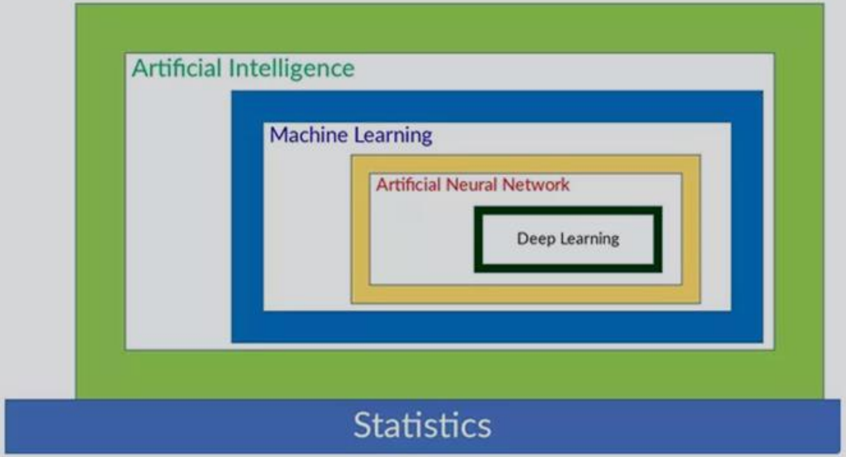
The landscape



Quara (2017)

Pro's, cons and requirements of ML

- Vast amounts of data processed in a short time e.g. causals
- Requires large datasets
- Algorithm optimization complex and time consuming

"Rules don't get better, AI does"

Dan Fuenffinger, *Google - data centre operator*

STATS VS ML

Stats	ML
Hard-coded algorithms	Learning algorithm
Static representation, predetermined rules	Dynamic representation that can improve
Iterations run manually, with human intervention	Iterations run automatically
Highly dependent on human judgement	Self-improving algorithms
Considering causals is a manual, time consuming process	Large datasets can be considered automatically in short time
Collection, analysis, interpretation, and presentation of data	Machine enabled to improve at tasks with experience

CASE STUDY

CASE STUDY

Methods tested & Test set-up

Methods

- Commercial statistical tool
- Commercial ML tool
- In-house statistical methods (MS Excel)
- In-house AI methods (Python)

Test set-up

Historical data 2014 to 2018 provided

- Training data: 2014/15* – 2017
- Test data: 2018

* Where improved results were achieved 2014 data excluded

Comparison metrics

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

Scoring

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

RESULTS

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

Development time* (Lower is better)

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	

Penalty value (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

* 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.

FINAL SCORES

IT'S A TIE!

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

ML WINS!

CONCLUSION

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