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When rules may not be enough

Introduction
In the light of the current pandemic everyone at Publicis Sapient AI Labs has been looking for ways to make a meaningful contribution to support people as they address this unprecedented Covid-19 situation.

From a business perspective we appreciate that in this crisis most company's first priority is workforce protection and stabilisation. We then wondered, how well operational systems such as customer service and supply chain were working in this extreme environment? As data scientists we are used to seeing a wide range of approaches to support decision making in operational systems. Critical decisions such as: How many people to staff a call center today? Which customers should get extended credit? What is the right stock level for parts or raw materials?

Many of these decisions are supported by basic rules systems (i.e. "if…then" type logic with fixed thresholds) and some are reliant on mathematical prediction models, based on historic data patterns. Both of these approaches are being tested to the extreme in the current situation. Rules based systems follow a set of predefined paths or decision points. Models use more dynamic decision points and sometimes use previously learned behaviour to provide recommendations. Both approaches have been built up over many years and are important in helping humans make judgements across a wide range of teams:

Team	Prediction Model Use	Business Outcome
Sales & Marketing	Churn analysis Customer lifetime value Sales forecasting	Maximising revenue and profit
Supply Chain	Capacity optimization Order quantity Route optimisation	Efficient use of assets
Operations	Maintenance scheduling Next Best Action Staff scheduling	Efficient use of assets
Finance	Risk / fraud detection Revenue / profit modelling Credit scoring	Reducing cost and risk

More than ever it is important that companies assess these models are fit for purpose and can help address the situations companies are facing every day in helping deal with this crisis and of course with the subsequent recovery.

The new context

Covid-19 has fundamentally changed the baseline and historical context for many, if not all these models. Patterns of B2C and B2B behaviour are fundamentally altered. All global markets are all experiencing the pandemic, but countries and locations are at a different point in the pandemic and are experiencing unprecedented, and perhaps localised, effects. New disruptive mega shifts are occurring as extraordinary measures are being taken to limit the spread of the virus and take steps to deal with those infected. In an increasing number of countries home working and the cessation of non-essential shopping and leisure activity are becoming the norm.

These mega trends and their knock-on effects are by definition introducing a new reality for many, if not all, predictive models which are based on historical data patterns to predict future patterns. Although the impact of introducing more "error" in these models (note: all models are "wrong" it's just by how much! The baseline being are they better than guessing!) varies considerably depending on the scale and context of their use.

It is fair to say that, where they are in production settings (i.e. fully automated or as key input to the judgement of a human), all companies are now urgently asking **how "robust"** these models are in the light of the unprecedented impacts of Covid-19. They are also examining which **new areas** of the business require models which previously did not, for example:

Industry	**Urgent modelling questions**
Lifesciences / Medical devices	How can I optimise my production capacity to produce maximum output?
Distribution / Manuf	What is the optimal shift and staffing patterns by location for any given day given a reduced workforce?
Retail / CPG	If the internet is my only channel how do I prioritise my marketing spend to drive highest revenue?
Finance	What impacts has this has on my existing commercial and personal credit models - how do I now assess risk?
Travel and Transportation	How can I model future scenarios with any level of confidence?
Energy / Telco	How do I manage my resources to ensure maximum reliability in the service we are providing?
Public Sector	How to allocate scarce resources?

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Are your models fit for purpose? A 5-step approach.

Step 1 - Take an inventory

The first step is make sure you a) know where these models are, b) how they work and c) what role they are playing in critical processes.

You need to understand how the models work at a principle level. In this context we mean are they rules based (let's say hard coded) or are they more dynamic? The rules based approaches are created based on a set of previously seen circumstances and "dynamic" models are taking the data and trying to show you patterns and outliers which in turn are feeding into your decision making. Common dynamic predictive model types include:

- Generalized Linear Models (GLM)
- Tree based models
- Deep learning
- Graph based models
- Generative models
- Clustering and segmentation models
- Times series forecasting models

Questions to ask: What role are they playing? What role do your teams have in interacting with them?

Step 2 - Assess criticality

Triage the criticality of these models to your business or your team. One framework could be:

1. Scale of the outcome they support, for example automatic reorder quantities for essential spare parts on critical lines will rate higher than suggested office supplies (note: outcome could be revenue/costs or time).
2. Level of automated decision-making v human judgement - any process that has light touch human supervision should rank highly.
3. Level of the model output v human judgement – i.e. only the model can give a confidence level given the time taken to complete, scale of the data or complexity of the calculation.

Step 3 - Verify validity

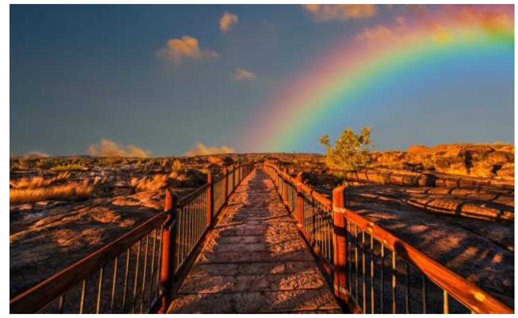
Now you need to assess how they are performing. For your rules-based models it is entirely possible that the rules no longer apply in these new circumstances. The results will be creating a larger number of false positives. Persona's and profiles that previously worked well in a rules-based system are likely to need to be revisited. For example, deferring mortgage payments previously would have indicated significant increased credit risk, in the new normal this may be a lower rated risk event. Or if you are a grocery retailer and all shopping is now on-line what was previously seen as "abnormal" or outlier order levels and quantities could actually be the new normal.

Questions to ask: What is the tolerance for error? What new level of calibration can be applied to understand when the results from the model are considered unacceptable? Are you using feedback loops to identify false positives?

Step 4 - Course correction

What new approaches would help to improve my existing prediction processes?

- Can I replace my rules-based approaches with a machine learning model that can use the most recent data to build out new prediction confidence models? Let your machine learning approaches tell you if models are encountering a new paradigm. We helped a major CPG company realise that they could materially improve sales forecasting by looking at previous weeks rather than years of data.
- Would "one shot learning algorithms" be more applicable as they may need less training data?



- Can I compare all my models and choose the most appropriate one at that moment, rather than locking in on the model I have traditionally used? A major financial service provider was surprised that their teams were not dynamically "picking" the best model at the right time, by changing their approach to do this they were able to improve risk assessments without creating any new models.
- Perhaps this is an opportunity to simplify your approach? We recently helped a green energy provider reduce their real time data sources from over 1000 to the 10 most critical ones.
- Finally, is this the time to look for the areas of my business you need to find a predictive model for? For example, if all customers are now on-line what 1-2-1 targeting or per person prediction and segmentation do I need? What data should I be gathering now, to help me cope with the new reality? For example, would my customer's Google searches or on-line behaviour be a more reliable source of insight? Should I be looking to unstructured sources such as news or blogs to get insights? What data do I have within my company which I have not yet exploited for predictive purposes? As I move out of this situation how will handle back-log items or cases? Would models help triage and prioritize and make a "back-log" factory more efficient and fairer?

Step 5 - Keep Learning

Set regular check points to understand how your predictive models are behaving and course correct. For example:

Short Term - use unsupervised machine learning models to evaluate business rules that are no longer valid.

Medium Term - build new supervised learning models on updated records pre- and post-corona lockdown. Look to open source & non-traditional data to provide new signals for decision making.

Long Term - look for digital opportunities to scale more data driven decision making to both reduce "touch time" and improve risk assessments.

If you would like a explore if a model assessment would help your business or just like to know more about machine learning please reach out to info@psail.com or find out more at www.psail.com

