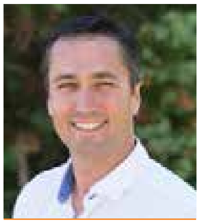
DYNAMIC ACTION

Mastering the science of retail: The modern reality of data algorithms-to-action, the new questions executives must ask and the secret decision paradigm of the world's most successful retailers.

Retail Executive Playbook

How retail's top talent makes better decisions and takes faster action



RETAIL REVOLUTION

By John Squire, Co-founder and CEO, DynamicAction

Long, long ago, when traveling salesmen roamed the earth and Instagram wasn't even a twinkle in its co-founders' eyes, retailers were already blazing a trail to offer their products on the world wide web. Keeping their brick and mortar and eCommerce businesses as siloed as "Church and State," the individuals who oversaw each area were extremely adept at those very specific practices. As digital grew, it morphed from a harebrained experiment to a vital component of the retail game, with the ability to make up a hefty portion of the revenue pie. In addition, it fostered a two-way conversation; shopping became less about an individual transaction in the store, online or via mobile and more about the customer experience, wherever and whenever they chose to shop. The brand's channels of commerce have now become forever blurred, highlighting the imperative need for increased coordination across the business. A move by one practitioner could amplify a mistake in another part of the business. Examples include a marketer paying for search traffic that leads to fragmented or unavailable stock, or a buyer purchasing more of a sold out item when three fourths of the sales are coming back as returns.

Modern day retail leadership means – more than ever – putting the people, process and technology in place to empower your team to move towards a common goal. Just like an orchestra performing without a conductor or sheet music, even a collection of the most talented individual musicians will sound like a cacophony of unintelligible noise.

Previously the retail competitive field consisted of boutique operations against "Big Box" stores. Now with the dawn of Amazon, that box is infinite. Unfortunately, time to action and time to business decisions have not extended with the increase of variables. Twenty four hours a day... every hour, nay every second, your business shifts and requires you to make real time decisions.

Yet, over the past 100 years, the human brain hasn't evolved – it still makes decisions at about the same speed. Computing power has transformed the way retailers and consumers think. Your competitors have increased visibility into the strategies of their rivals – pricing, promotions and customers. Along the same lines, consumers in the quest to reduce the anxiety of the unknown have garnered resolutions. No longer must they fret over buying something and not knowing if a retailer will have their desired size, if it will arrive on time or if it will go on sale two days later.

- Amazon will find the best price and pinpoint the exact arrival time
- Uber will show up as expected and get them there on time
- OpenTable will have a reservation

The evolution of this "On-demand Economy" has nurtured a culture of customers that will always choose the path of least uncertainty, and thus, less anxiety. With these ever-increasing demands, successful retailers must bridge the cross-channel and siloed gap to become consumer centric. One approach is the omnichannel inventory model – or as I like to call it, The Power of the Store Theory. Most traditional retailers entering the eCommerce game have warehouse space. As mega-retailer Walmart declared, "We have 5,000 stores that can be warehouses." Through analyzing data across channels, as well as comparing strategic plans from marketing, merchandising, operations, customers, returns and finance, companies are able to make data-backed, nimble decisions to empower every retail arm in their business.

However, the journey to success in this new omnichannel – or better said – channel agnostic reality is constantly evolving for retailers. Joe Megibow, former Chief Digital Officer of American Eagle Outfitters, pushed the company's infrastructure towards omnichannel and shipped $100M from their stores in the first year. This type of change has brought complex dilemmas to light for many retailers, such as the complicated nature of employee commissions, returns to alternate locations and charge-backs. Retailers need to be mindful of the variables and have systems in place (people, process and technology) as they forge ahead with breaking down channels.

We have observed when data spanning multiple channels (web, stores, call centers, catalogue, mobile) is connected from all parts of the business, it naturally brings the marketers, merchandisers, finance teams and eCommerce teams together. However, data consistency and transparency are not enough. The science of powerful math and computing need to be applied to accelerate each decision maker's understanding of the business opportunity, the different actions they can take and the probability of reaping the most benefit from any given decision. This shift in process, combined with advanced prescriptive analytics technology, identifies and leads the entire organization to maximize value in its decisions. Yet, just solving the disconnects is only part of the problem. Decision makers across the business are asked every day to take on more than they ever have in the past. Merchandisers that had hundreds of SKUs now have tens of thousands of SKUs, and must attempt to determine how to best allocate and position an overwhelming amount of stock. Supply chain executives are now required to enable "Ship Anywhere" – shipping from store and to store, allowing consumers to buy online and pick up in store or buy in store and ship to home. Although it can be profitable and is the new consumer expectation, it is incredibly complex, especially with legacy systems. Marketers have the potential of every consumer desiring a personalized experience, but what line should they draw in the sand? The volume, the frequency and the speed demanded by the consumer requires connected data and sophisticated technology to prescribe strategies and actions where the most value can be delivered for the consumer and most profit to the business.

Bottom line: The retail landscape is more complex – and more exciting – than ever before for retail executives. As shareholders and board members are anxiously drumming their fingers to see incremental revenue and profits come to light, executives must seek to build for the trifecta of retail success: people, process and technology.

Where does this start? It begins with knowing that the rules have changed. Consumers' shopping patterns are shifting every day, and the metrics by which we measure success must also change. Therefore, the decisions driven by those metrics will certainly shift as well. In this document, we will address the questions that retail executives should be asking their teams – and the answers they need – in order to push forward. Then, Michael Ross, our Chief Scientist, will address the new decision paradigm that informs retail executives how to make sense of decisions and data in the new reality of commerce. As you read this, I invite you to reach out to ask questions, challenge notions, or discuss your experience in this shifting retail landscape. I can be reached at John.Squire@dynamicaction.com.

Where is your enterprise in this new retail world?

Your team is at the heart of the new retail reality: the intersection of data science and your customer. Your team's experience, intuition, judgement and empathy remains critical to many core business decisions. However, there are many decisions about a retail business that are taken on a day-by-day, hour-by-hour, or minute-by-minute basis that need a completely new approach.

The atomization of both the decisions and the data is the catalyst for this new approach. It is a potent combination, where averages are no longer helpful, where decision making in silos does not work, and where humans quickly get overwhelmed by the sheer volume of data and decisions. Anyone making decisions at the aggregate level, when competitors are taking action at a more granular level, is playing a dangerous game.

Although decision making with this mind-blowing level of atomization and complexity can seem overwhelming, some of the most forward-thinking digital players are beginning to recognize the approaches that are proving successful. A step towards embracing these new approaches is asking questions that, prior to the use of algorithms and the technology that governs them, were not answerable within the time constraints necessary in our fast-paced retail world.

24 "new approach" questions

Twenty four "new approach" questions around inventory, returns, marketing and warehousing that your organization should be asking to harness the power of the science of retailing are listed below. With connected data across the organization, and an enterprise-wide dedication to profitable, data-focused decision making, your team can begin to answer questions like these, as well as understand the interconnection of each data point and decision. Which are you able to answer today?

Inventory - views alignment

Aligning inventory to web product views is akin to an online planogram. In stores, items in the shop windows will typically sell well, and putting sold out or low inventory products in the window is clearly a poor strategy. On the web, we have the luxury of measuring what customers view and what customers abandon (put back on the shelf). These questions represent a new way of working that successful web merchants must adopt:

- **Which products should be exposed/marketed together to capitalize on lift?**
- **How much inventory is not getting viewed on the website?**
- **Which products are receiving too many or too few views, given their inventory levels, conversion, profitability, review ratings, time on site and fragmentation?**
- **For which product categories do we have too wide or too narrow a selection given viewing demand?**
- **What percentage of our product views land on in-stock, non-fragmented items?**
- **What technology am I using to make programmatic changes to inventory processes?**

Returns

Returns have a sobering impact on retail profitability. They can be fueled by misbehaving customers who take advantage of a customer-first return policy and factors under the company's control such as poor product descriptions, unorganized marketing programs and disconnected order fulfillment. However, those losses ($642.6 billion annually worldwide) can be rectified and recouped by pinpointing the weaknesses at various levels of the enterprise.

- **What are the most efficient actions we can take to reduce returns?**
- **What percentage of customers return 100% of what they purchase ("free rentals")?**
- **What percentage of customers frequently return the majority of any order containing substitutable items ("home dressing room")?**
- **What percentage of High Value/Most Profitable customers return products with a return rationale under our control (e.g. damaged, differs from web description, wrong item)?**

Marketing spend

Ann enterprise's advertising program is exceedingly more trackable every day. Organizations have the ability to know precisely how almost every marketing dollar translates into revenue and profit – or doesn't. It's time for retailers to go beyond return on ad spend and begin to understand marketing results in terms of stock alignment and profitability.

- **How much money are we spending on marketing campaigns that send customers to products that are sold out or highly fragmented?**
- **For which products should we curtail marketing spend because we will sell through the item without the paid exposure?**
- **Which marketing initiatives are the most profitable, once you consider all costs including returns?**
- **How is my technology working to optimize marketing campaigns efficiently?**

Warehouse operations

When retailers make better decisions about what to promise and how to fulfill customer orders, the result is improved customer satisfaction. Retailers have an opportunity to focus on their most profitable customers and ensure they receive a VIP experience. Further, they can place emphasis on exceptional service for new customers and execution that turns one-time buyers into loyal repeat purchasers.

- **What percentage of orders from High Value/Most Profitable customers get shipped within 24 hours? What percentage are delivered after their delivery promise date?**
- **Are we decreasing our average days to ship for New Customer orders?**
- **For which stores and/or warehouses are we over or under-allocated for our most profitable products?**

Pricing

It is too often the case that when an item isn't selling well, retailers are quick to execute a profit-eating price markdown. Fortunately, timely data is now available to point to potentially less expensive corrective measures that will still allow retailers to make plan.

- **Given inventory levels, conversion, profitability, review ratings, time on site, and fragmentation, for which items do we need to consider a price reduction?**
- **For which overstocked products is an increase in exposure a more profitable action than a price reduction?**
- **Which products require a pricing reduction due to lower competitive prices?**
- **How is my technology working to make pricing changes efficiently?**

Customers

What if you could create a merchandising strategy specifically geared towards cultivating a customer base that in aggregate was more profitable than last year's customer base? Year after year, certain products, brands and collections are responsible for attracting, keeping and re-acquiring customers that are profitable. Executives need to be able to identify these gold mines, point the merchandising teams in their direction, and let them go to work.

- **Which first purchase products or brands lead to High Value/High Lifetime Profit customers?**
- **Which campaigns and promotions perform the best at luring back previously high value lapsed customers?**
- **How is my technology enabling my organization to create optimized customer experiences that precicely marry customers with products that generate maximum revenue and profit?**

Embracing these questions and changing the entire decision making process of an organization requires very strong leadership. So how do you make the case for a shift to this new approach? Michael Ross, Co-founder and Chief Scientist of DynamicAction, has let the most senior executives of retailers in on the secret to transformational organizational change and the new path to successful decision making.

He will now share those insights with your retail organization.

ICE CREAM AND DROWNING: THE NEW DECISION PARADIGM

How to make sense of decisions and data in the new world of digital commerce

By Michael Ross, Co-founder and Chief Scientist, DynamicAction

From steam engines to driverless cars

There are interesting parallels between the automation of transportation and what we are now recognizing as the early stages of the automation of decisions.

James Watt's steam engine, patented in 1781, was a defining technology of the Industrial Revolution (see Extract from The Second Machine age). The next 100 years saw an extraordinary explosion of innovation by engineers and tinkerers that transformed all aspects of manufacturing.

But it wasn't until 1886 (100 years later) that James Clerk Maxwell developed the equations of control theory that laid the foundations for the optimization and automation of production, transportation and manufacturing. Machines for the first time could be closed systems, but still required human drivers to operate and monitor them.

And then in 2012, we saw the unveiling of the first driverless cars. The ultimate automation of a transportation revolution that started almost 250 years ago. A journey that required the mechanization, optimization and automation of the myriad components required to make a car drive safely.

Now we are beginning the same journey for decisions, although things happen a little quicker in the digital world. The last 20 years has seen an extraordinary amount of digital execution. The digital engineers and tinkerers have built many extraordinary operations, but I believe we are in the late 1800s in terms of optimization and automation – in effect the "bad car" phase. We are right at the beginning of a digital industrial revolution that will center on the automation of decisions.

"Steam started it all. More than anything else, it allowed us to overcome the limitations of muscle power, human and animal..... Now comes the second machine age. Computers and other digital advances are doing for mental power – the ability to use our brains to understand and shape our environments – what the steam engine and its descendants did for muscle power. They're allowing us to blow past previous limitations and taking us into new territory. How exactly this transition will play out remains unknown, but whether or not the new machine age bends the curve as dramatically as Watt's steam engine, it is a very big deal indeed."

Excerpt from The Second Machine Age: Work, Progress, and Prosperity in a Time of Brilliant Technologies by Erik Brynjolfsson, Andrew McAfee (2014)

Decisions, decisions, decisions

Retailers need to adapt their approach to making decisions to keep pace with this revolution in automation. Decisions still made in the same way as in traditional physical retail are too often leading to the wrong decisions being made at the wrong time, or just not being made at all.

Physical retailers are used to software providing data, but it is people who make the decisions. Organizational silos have evolved within which it makes sense to make decisions. And the data itself has often been relatively simple – using averages is helpful and the data can be clearly aligned to the decisions being made. In reality many of the world's most successful retailers have not even been particularly data-driven, but relied on experience and intuition. Decisions have also been unhurried – weekly trading meetings have been frequent enough.

The notion of physical and digital retail is blurring. Here we use "digital retail" to mean the portion of a retailer's business that is either transacted online or influenced by online – an ever increasing percentage of every retailer's business. And so the "physical-only" decisions are getting fewer and fewer.

Any manager in digital retail who continues to rely on people to make day-to-day decisions, within silos and using averages is going to rapidly see the repercussions of poor decision making on their business. Digital retail is a massively more complex challenge. You need to fundamentally reconsider what data informs decisions, how decisions are co-ordinated across the business, and how to automate decision making effectively.

In this article we explore what all of this really means and how to move quickly enough to keep up, and ideally ahead, of competitors in the new era of retail.

- What types of decisions need to change
- How decisions are made in physical retail
- Why decision making is different in digital retail
- What are the common pitfalls
- How to approach decision making in a new way

What types of decisions need to change

We are not advocating an automation of all decision making. The value of people – their experience, intuition, judgment and empathy – remains critical to many core business decisions. Many decisions about strategy, people or creative ideas still need to be taken by managers.

However, there are many decisions about a digital retail business that are taken on a day-by-day, hour-by-hour, or minute-by-minute basis that do need a totally new approach. These are in effect the 'routine cognitive tasks' of business, where data is analyzed, rules applied and actions taken. Some examples of the types of decision we are talking about include:

- **CRM:** When to email an offer to a specific customer? What product? What promotion?
- **Merchandising:** When to markdown a product? Whether to run a promotion or increase marketing spend on a particular product? Whether to delist a brand?
- **Operations:** When to upgrade an order to next-day delivery? How to prevent high-value customers getting stopped by a fraud system?
- **Marketing:** How much to bid on a specific keyword? How much to spend on acquiring a new customer?
- **Site:** How to rank products when customers search on your site? How often to change landing pages?

How decisions are made in physical retail

The basic model of decision making applies to decisions in both physical and digital retail. There are three necessary pre-conditions for any decision to be successful:

- **Control. A decision without an action is praying.** You must have something you can control - something to action. And you must have a clear vision of what will happen as a consequence of that action.
- **Model. An action without an objective is guessing.** You must have something you are trying to improve or optimize (whether it's revenue, profit, inventory, efficiency or waste). You also need a model or 'equation' that connects the action to the objective.
- **Feedback. You can't manage what you can't measure.** If you are taking decisions and actions without observing the outcome, you must hope that luck is on your side. You need a way to collect feedback and continually improve the model.

After a few hundred years of successful physical retailing, most of the decisions are well understood, and often relatively simple to take. There are lots of very successful store-based retailers to show for it.

CONTROL	How the world works The things you can actually do	The physical retail world is well understood with: • Known actions • Independence of action (silos make sense)
MODEL	Business economics of process (the equations of retail) What you are trying to optimize	The physical retail world is well modelled with: • Mainly fixed costs • Mature algorithms
FEEDBACK	What you measure/observe How do you manage and improve	The physical retail world is easy to measure by: • Walking the floor • Looking at simple outcomes (LFLs, sell-through)

Figure 1. Decision framework

Applying this framework to some day-to-day physical retail decisions shows that these are conceptually simple to make.

	Product not performing	Store not performing	Longer opening hours
CONTROL	Reduce price	Change store manager	Open later
MODEL	Expect sales velocity to increase	Expect LFLs to improve after x weeks	Expect sales to increase and drive incremental profit
FEEDBACK	Review rate of sale	Review LFL trend	Measure sales and costs by the hour to understand the incremental profitability

Figure 2. Some sample decisions

All these examples share some common characteristics. The decision is relatively high-level (the answer is often a simple range of numbers or yes/no). And the data is messy – it is often incomplete, needs interpretation or needs to be observed. Looking at the "store performance" decision in more detail shows how this works in practice. For example, imagine a retailer with 29 stores. A typical analysis (Figure 3) shows that overall performance is up 1% year/year and the data follows one's intuition of an "average" that some stores are a little over 1% and others are a little under. Retailers are used to this sort of analysis, and as one high street retailer told me, "I don't need a PhD to know which stores are underperforming!" A manager can visit the underperforming stores and talk to staff, observe customers, visit competitors and quickly determine the action to take. That action is often relatively simple to take. There are lots of very successful store-based retailers to show for it.

	TV	LV	LFL
STORE 1	283	274	3%
STORE 2	242	235	3%
STORE 3	171	166	3%
STORE 4	113	110	3%
STORE 5	421	408	3%
STORE 6	176	171	3%
STORE 7	82	81	2%
STORE 8	457	446	2%
STORE 9	159	156	2%
STORE 10	148	146	2%
STORE 11	114	112	2%
STORE 12	187	185	2%
STORE 13	693	688	1%
STORE 14	263	261	1%
STORE 15	172	171	0%
STORE 16	265	265	(0)%
STORE 17	239	239	(0)%
STORE 18	225	225	(0)%
STORE 19	276	277	(0)%
STORE 20	175	176	(1)%
STORE 21	182	183	(1)%
STORE 22	305	307	(1)%
STORE 23	119	120	(1)%
STORE 24	192	194	(1)%
STORE 25	290	293	(1)%
STORE 26	174	176	(1)%
STORE 27	110	112	(2)%
STORE 28	258	264	(2)%
STORE 29	144	148	(3)%

Summary:

- This year total sales: $6.64m
- Last year total sales: $6.59m
- Overall LFL: 1%

Action: review below average performers

Figure 3. Store like-for-likes

As a result, physical retailers have evolved to make decisions based on:

- **Averages: Data that is aggregated (e.g., at store or category level) to align with the decision being made is both powerful and useful.** The aggregation of data in physical retail has a naturally homogenizing effect that makes the averages helpful (a well-known statistical phenomenon called the central-limit theorem).
- **Silos: Retail organizations have evolved to enable the key day-to-day decisions to be made in the operational silo.** In fact, this has been one of the key drivers of organizational evolution.
- **People: Trusting the intuition and experience of people interpreting the data.** Moreover, the decision typically necessitates people doing something, which requires management and leadership.

"Data is the new oil – it needs to be extracted, processed and refined to be turned into something useful."

Dr. Andreas Weigend, former Chief Scientist at Amazon.com

Why decision making is different in digital retail

Decision making in digital retail, as many retailers have already recognized, is considerably more complex. The tsunami of data available to managers, and the granularity of each decision, means we are seeing many retailers making bad decisions, and losing sight of the core preconditions for any decision – control, model and feedback.

At the heart of the change is the atomization of both the decisions and the data. It is a potent combination where averages are no longer helpful, where decision making in silos does not work, and humans quickly get overwhelmed by the sheer volume of data and decisions. We are now faced with:

- Millions of decisions: Digital retail has many more things to control
- Hundreds of millions of data points: Digital retail has many more things to model, and many more potential sources of feedback.

Millions of Decisions: The Atomization of Decisions

Decisions have become nano-decisions – occurring at a much more detailed resolution and frequency than the aggregated world of physical retail. Simply put, digital commerce creates millions of "switches" to control.

Decisions have to be made across multiple software systems. The digital and multi-channel world is powered by a breathtaking array of technologies. Some executives still think that they have a webstore that runs their business. In practice, a typical multi-channel operation will be using 20-30 distinct software products to deliver its proposition. Each system then requires a set of decisions and rules to operate. We estimate that the volume of possible decisions required by a typical retailer runs to millions per week. How? As we see in figure 4, each system is taking action at a nano-level and while the retailer's "decision" may be at an aggregate level the execution happens at the nano-level. For example, a retailer may decide to spend $x on google with a target cost per order of $y, but the outcome is actually hundreds of thousands of bid decisions on specific keywords.

Decisions are much more complex: in the digital world, many of the decisions for managers are buried in black boxes using some combination of rules, automated logic and manual configuration. It is difficult, and often impossible, for an executive to get visibility of this new "decision architecture"– the logical structure of the decisions. Many retail leaders operate under the misapprehension that these decisions are easy, automatic, can be deferred to the supplier or that so-called experts know the answer. In reality, leaders need to make sense of the decision complexity to have any chance of success in the digital commerce world.

Area to manage	Software tools	Example decisions	Level of decision possible...
Paid search management	Marin, Kenshoo, Adobe, Google	Ad group structure, bid logic, landing page specificity, retargeting logic, device logic, ad creative specificity, optimal stopping logic, match type logic	Keyword/cookie/device
Affiliate management	Linkshare, commission junction, Tradedoubler	Commission structure, cookie logic, cookie life, promotions offered	Affiliate/customer/product
SEO	Hybris, Demandware, Magento	H1 tagging, page retirement, landing page redirects, URL structure, canonical URL structure, page titles	Page/keyword
Retargeting	Criteo, Rocketfuel, Struq	Retargeting logic, ROI constraints, retargeting time, retargeting media, types of customers/ visitors to retarget, approach to measuring incrementality	Customer/product
Site search	Fred Hopper, Endeca, Demandware	Search redirects, synonyms, hyponyms, hypernyms, relevance logic, ranking logic, approach to personalization	Search term/customer
Operations	Sterling, Main Street, OrderDynamics	Fraud, logic, order splitting logic, ship from store logic, customer prioritization, delivery upgrade rules, refund logic	Customer/order

Figure 4. Lots of software components

"Data is only valuable if it helps you make a decision."

Dr. Barney Pell,
artificial intelligence pioneer

We all experience the symptoms when retailers get this wrong – the consequence of bad decisions, buried in software:

- Adverts being shown for products that are sold out (or sold out in your size)
- Annoying or irrelevant emails (reminders for products you have just bought)
- Adverts chasing you around the web for products you landed on by mistake
- Landing pages that are unrelated to an advert
- Overly generous promotions which seem too good to be true

In practice, businesses are missing opportunities, wasting money and annoying customers – a dangerous game in the highly competitive retail world.

Granularity of decision and action

From physical (hundreds)	To digital (millions)
Stores	Customer + sessions
Products	SKU + customer view
Media channel	Individual + context
Planogram (broadcast)	Personalization

Figure 5. Lots of decisions

Hundreds of millions of data points: The atomization of data

The corollary of nano-decisions is nano-data - the digital exhaust of all the actions and activities created by digital commerce. The data comes from a huge number of different systems and sources (see figure 6), and is inherently variable and volatile. Unlike physical retail where data is typically aggregated and is homogenized by aggregation, the resolution of digital data presents a new challenge.

Characteristics of data
- Resolution
  lots of data at very granular level
- Dimensions
  each data point has a lot of attributes

Figure 6. A lot of data sources

A typical retailer will easily generate 100 million data points a week. How? Imagine, a retailer with 500,000 customers; 20,000 products; 50,000 marketing campaigns (where each unique keyword/affiliate/banner = a campaign). The data is multiplicative – every click from every visitor on every product from every marketing source and one can see how quickly the data explodes. This explosion of data is dramatically reducing the effectiveness of traditional approaches to decision making:

- It is difficult to know how to model the data, and easy to get the model wrong
- It is difficult to interpret the data to create meaningful feedback

Unlike physical retail, averages are the enemy of the digital retailer – they are generally unhelpful, often misleading and rarely representative. The two most critical characteristics of nano-data that make it so different to the data used in physical retail are its resolution and its attributes:

- **Higher levels of resolution:** Digital data is very granular, with incredible detail on each marketing impression, each customer, each order and each visit. Take an example of the average customer: he/she often does not exist and – if they do – is not a helpful exemplar. Instead you have to understand the distribution of customers. The best retailers are focusing on their high-value customers, not their average customers (see figure 7). It is typical that the top 5-10% of customers can represent 50-80% of profit. This de-averaging exposes the real heterogeneity of customers that is 'averaged away' in the aggregated world of physical retail.

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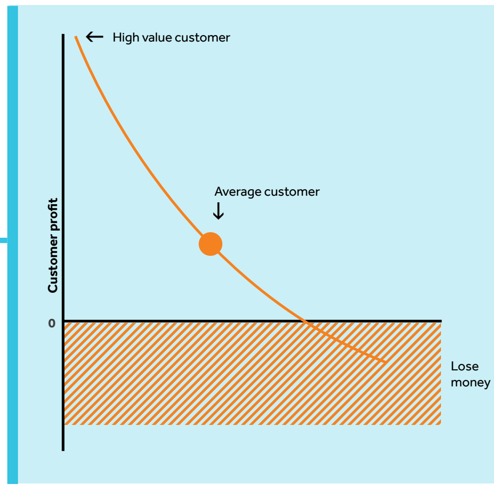


Figure 7: The average store vs. the average customer

It not just the average customer that is dangerous – the average keyword, the average banner advert, the average web page, the average affiliate, the average on-site search term and the average order are all entirely unhelpful indicators.

Unlike relatively homogeneous store performance, the resolution of digital data exposes the heterogeneity in all aspects of digital commerce.

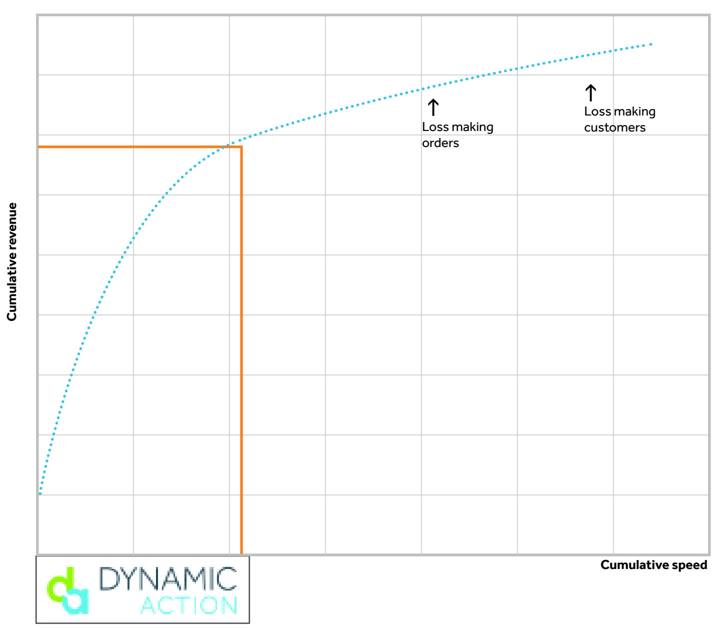


Figure 8: The keyword is unhelpful

- **Multi-dimensional attributes.** The digital exhaust also exposes a large number of attributes of each customer, website visit, marketing impression, product and order. Figure 9 gives some examples of the attributes that come "for free" with every web visit. These are part of the digital exhaust provided by any web analytics system. There are hundreds of attributes, and importantly key attributes (such as email, product ID and order ID) are common across systems enabling data from different sources to be connected. This data-joining is a core feature of the digital commerce world. It essentially 'lights up' even more attributes. So, for example, customer data can be linked to product data, inventory data can be linked to web analytics data, and marketing data can be linked to inventory data.

	Attributes available
Time	Time of day Day of week Length of visit
Visitor	New vs. repeat visitor (i.e., have we seen this cookie before?) Visit recency Visit frequency
Session	Marketing channel that initiated the visit Referring site Specific creative viewed Browser Site entry point
Location	Device - laptop, mobile, PC, app Country IP address Location - work, home, shopping mall
Intent	Categories browsed Product browsed Engagement on product pages Basket adds

Figure 9: A lot of data – each system produces a digital exhaust

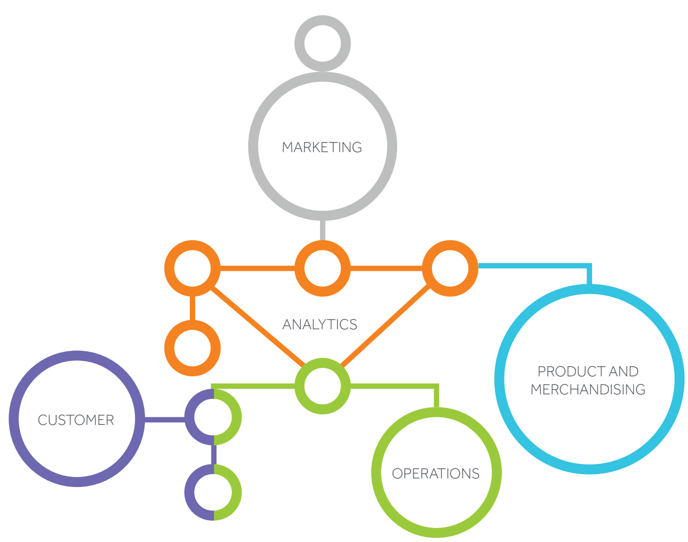


Figure 10: Joined-up data – a 'Christmas Tree'

These attributes enable the "slicing and dicing" of any analysis or – more technically – allow the data to be stratified by any of the available attributes. A consequence of these data attributes is that averages are not just unhelpful, they can also be completely misleading. For example, an analysis of conversion rate is given below. Overall, one can see that the site conversion rate – orders/visits – has decreased week on week (figure 11).

	Last week			This week			
	Visits	Orders	Conversion rate	Visits	Orders	Conversion rate	Conversion rate wk/wk
TOTAL	169,245	2,958	1.75%	187,360	3,154	1.68%	DOWN ↓

Figure 11: Conversion going down

But when looked at by marketing channel, the conversion rate on every channel has increased week on week (figure 12). This is caused by the heterogeneity of conversion rates across channels - a greater share of visits from lower converting channels. And it highlights that looking at the "average" conversion gives an entirely misleading picture of performance. In this case, the marketing channel is the confounder which – quite literally – confounds one's intuition of what's going on.

	Last week			This week			
	Visits	Orders	Conversion rate	Visits	Orders	Conversion rate	Conversion rate wk/wk
Paid search	37,850	447	1.18%	69,245	783	1.30%	UP ↑
Price comparison	8,261	37	0.45%	8,261	50	0.60%	UP ↑
Email	7,728	43	0.55%	7,728	54	0.70%	UP ↑
Affiliates	985	11	1.11%	985	13	1.30%	
Social networking	184	45	24.46%	184	65	35.33%	UP ↑
National search activity	31,393	396	1.26%	45,000	576	1.28%	UP ↑
Referring site activity	7,812	67	0.85%	7,812	70	0.90%	UP ↑
Direct load activity	75,032	1,913	2.55%	57,145	1,543	2.70%	UP ↑
TOTAL	169,245	2,958	1.75%	187,360	3,154	1.68%	DOWN ↓

Figure 12: Conversion going up

In physical retail, decisions and data are typically (i) aggregated and (ii) aligned. The digital world exposes the heterogeneity of data and a misalignment between the level of the decision and the data – which combine to make decisions complex and difficult. The decision making challenge is further complicated by the multiplicity of dimensions that can confound one's intuition. In a world of dangerous averages, the mantra is to deaverage, deaverage, deaverage because:

"When the data contradicts the anecdote, believe the anecdote – there's something wrong with your data."

Attributed to Jeff Bezos, CEO of Amazon.com

- High resolution data requires understanding of distributions
- Multiple attributes requires stratifying analysis.

It is also critical to ensure that decisions and data are aligned. When decisions are actioned at a lower level than the data being reviewed, you risk "decision landmines" where it is incredibly easy to make the wrong decision. Anyone making decisions at the aggregate level when competitors are taking action at a more granular level is playing a dangerous game.

BERKELEY ADMISSIONS: GENDER BIAS

Admissions data from Berkeley University in 1973 showed: 12,763 applicants, 5,227 admitted with an overall admission rate of 41%. The University of California-Berkeley was sued for sexual discrimination. The numbers looked pretty incriminating: the graduate school had accepted 44% of male applicants but only 35% of female applicants.

	Applicants	Admitted
Men	8,422	44%
Women	4,321	35%

But when the analysis was "stratified by subject", one gets an entirely different view of the data. In fact, the admissions rate for women was higher than men in most subjects. The overall lower admissions rate is driven by (i) the subjects that women were applying for, and (ii) the variation of admissions rate across the subjects. So more women applied for subjects with overall lower admission rates...and men applied for the easy subjects!

In summary, a pretty good argument for the defence.

DEPT	MEN		WOMEN	
	Applicants	Admitted	Applicants	Admitted
A	825	62%	108	82%
B	560	63%	25	68%
C	325	37%	593	34%
D	417	33%	375	35%
E	191	28%	393	24%
F	272	6%	341	7%

The common pitfalls of digital retail decision making

The traditional process of decision making, so successfully used in physical retail for many years, no longer works. In the digital commerce world, the combination of nano-decisions and nano-data transform the decision challenges for retailers. Some examples clearly illustrate the pitfalls and the "flip-flop" nature of digital commerce decisions.

DECISION FLIPPING: RETARGETING PERFORMANCE EXAMPLE

A manager reviews spend on a retargeting campaign. An overall spend of $0.27m has

"There are known knowns. These are things we know that we know. There are known unknowns. That is to say, there are things that we know we don't know. But there are also unknown unknowns. There are things we don't know we don't know."

United States Secretary of Defense
Donald Rumsfeld
February 2002

generated 3,406 orders at a cost per order of $12.24. This is within the retailer's budget and the proposal is to spend more. Decision 1: Increase spend.

	Spend	Orders	Cost per order	Spend	
TOTAL	$272,515	3,406	$12.24	$41,681	TARGET $15

The next level of analysis is to look at the types of customers being targeted. As we can see, the response rate varies significantly for different types of customers. The analysis below highlights that retargeting both lapsing and loyal customers is within budget, but that new visitors and cart abandoners are expensive. Decision 2: Reallocate spend.

STRATIFY BY CUSTOMER TYPE				
	Spend	Orders	Cost per order	Spend
Lapsing customers	$85,074	1,063	$4.44	$4,722
Loyal customers	$52,678	658	$4.60	$3,029
Abandoned cart	$112,726	1,409	$17.57	24,757
New visitors	$33,038	275	$33.30	9,173
TOTAL	$272,515	3,406	$12.24	$41,681

But none of the analysis so far considers incrementality: would I have got the sale anyway? It's very easy for online marketing to appear profitable but not be incremental (bidding on your trademark on google is a good example). For retargeting advertising, a good approach to understand incrementality is to use a control group who are "targeted" with an unrelated ad (typically for a charity). One can then observe the behavior of the control group versus the actively retargeted group. The analysis below highlights that the incremental cost per order for loyal customers is very high. This makes sense – they are the customers most likely to purchase without a stimulus. Decision 3: Reallocate spend to other channels.

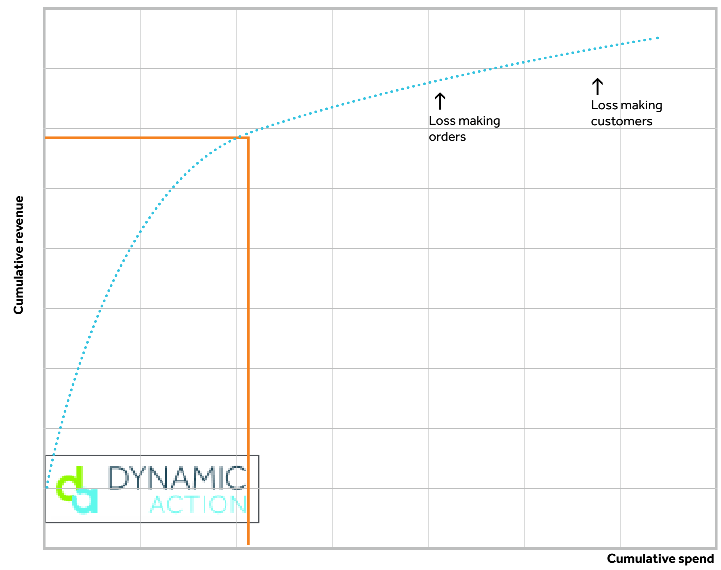
PERFORMANCE VS. CONTROL						
	Spend	Orders	Cost per order	Spend	Orders from Control	Incremental CPO
Lapsing customers	$85,074	1,063	$4.44	$4,722	400	$7.12
Loyal customers	$52,678	658	$4.60	$3,029	500	$19.11
Abandoned cart	$112,726	1,409	$17.57	24,757	20	$35.91
New visitors	$33,038	275	$33.30	9,173	1,200	$118.41
TOTAL	$272,515	3,406	$12.24	$41,681	2,120	$32.40

This example highlights that the aggregate average performance gives an entirely misleading picture of what's going on. And the complexity is caused by the heterogeneity of the data.

DECISION FLIPPING: PAID SEARCH EXAMPLE

A manager reviews a paid search campaign on google. An overall spend of $1.05m has generated 230,000 orders at a cost per order of $4.57. This is well within the retailer's budget and the proposal is to spend more. **Decision 1: Increase spend.**

The next level analysis is simply to look at the distribution of performance – the graph below shows cumulative spend versus cumulative revenue and highlights that a small amount of spend is very efficient, and is subsidising an inefficient tail. In fact, the "marginal dollar" is already loss making so the idea that we can increase spend profitably is wrong. Based on this analysis, the action is to review the inefficient tail and reduce spend. **Decision 2: Review inefficient spend.**



The next level of analysis is based on understanding that match types on google have very different characteristics. Before we start cutting spend, we should review spend by match type, and the analysis below "stratifies" the spend. We can now see that the spend on exact match is incredibly efficient, broad match is OK and it's the phrase match spend that is driving up the cost. **Decision 3: Reallocate phrase match spend to broad and exact match.**

	Spend	Orders	Cost per order
Exact	$323,413	192,000	$1.68
Broad	$97,378	8,200	$11.88
Phrase	$613,321	29,899	$21.12
GRAND TOTAL	$1,052,113	230,099	$4.57

Finally, we look at the spend based on the specificity of the customer's search phrase. Here we can see that the efficiency of broad match is actually driven by the specificity of customers' searches. The correct course of action is to relook at ad group structure to understand whether adverts are aligned with customers' searches. **Decision 4: Review account structure.**

And one could go on to take into account many further attributes such as customer life time value, offline impact, or trademark vs. non-trademark. This analysis highlights that the right decision "flips" depending on exactly how you look at the data.

Both these examples highlight the extreme complexity of making decisions in the digital world. Unfortunately, there is no shortcut or simple answer – anyone claiming to "know the answer" typically doesn't understand the question. There are a number of pitfalls and challenges to navigate:

	Spend	Orders	Cost per order	Length of search phase				
				1	2	3	4	5
Exact	$323,413	192,000	$1.68	82%	18%			
Broad	$97,378	8,200	$11.88			25%	67%	8%
Phrase	$613,321	29,899	$21.12		63%	32%	5%	
GRAND TOTAL	$1,052,113	230,099	$4.57					

- Control: Misunderstanding what decisions can/need to be made, and at what level decisions need to be made
- Model: Simply getting the wrong answer. Sometimes it is a little bit wrong, sometimes it is completely wrong
- Feedback: Failing to understand what's happened and how to improve.

(a) Misunderstood Control

Simply understanding what decisions can and should be made is a challenge (what we call the "decision architecture" of digital retail). Typical retailer challenges include:

- Not realising a decision can be made
- Accepting default decisions (the "factory setting")
- Making decisions at the wrong level (either too aggregate or too detailed).

For example, consider a typical keyword campaign on google with 10,000 keywords (many retailers have campaigns with millions of keywords). Google has created a massively configurable management system that allows incredibly fine-grained control of bids. The conceptual simplicity of a "pay per click" model belies the extraordinary complexity of actually managing a google campaign. It is possible – and even typical – to "manage" google at an aggregate level. Unfortunately, doing so is typically hugely sub-optimal (particularly when competitors are managing at a more granular level). I might decide to bid 50 cents per click for the keyword phrase "black party dress". I can then decide to bid more/less by: time of day, known customers, different devices, different age groups or different locations which leads to an explosion of possible decisions.

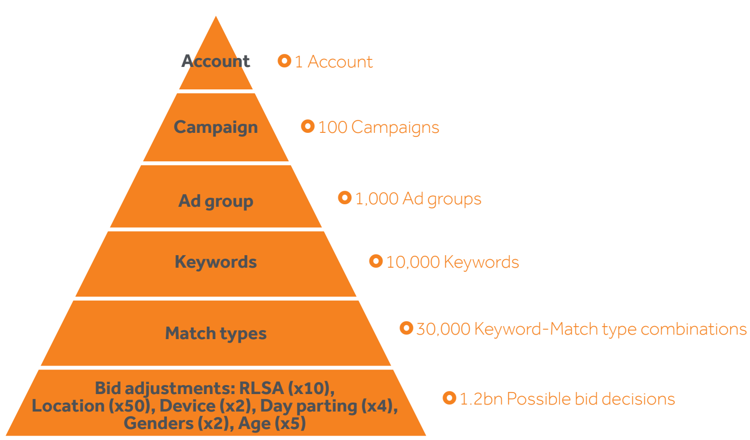


Figure 13: What level to make decisions

Another example of misunderstanding control is managing the search results from an on-site search engine. All retailers have some on-site search which either comes with their webstore or has been bought as an add-on (e.g., Endeca, Fred Hopper, SLI). All these systems have relevance and ranking engines:

- A relevance engine determines which products match (i.e., are relevant) to a particular search
- A ranking engine determines in which order the products should be displayed.

Sophisticated search engines enable search results to be default-ranked based on such factors as: sales velocity, margin, availability, newness, clickthrough rate, profitability or inventory (or some combination of these). Increasingly these search results are being overlaid with varying degrees of personalization so – for example – men and women might see different search results for jeans. Simply deciding how many search rankings should be managed is a hugely complex question and is easily misunderstood.

(b) Wrong model

The technical complexity of the decisions and the new economics of digital commerce make it very easy to simply get the wrong answer.

Many decisions in the digital world are logically hard or unfamiliar. The binary decisions (simple logic) of physical retail are replaced with more nuanced (and multi-dimensional) decisions of digital commerce. For example, when a product is not selling, the natural intuition is that it is something to do with the product. In the digital world, it's critical to understand whether the issue is:

- Product publishing: The product is in the warehouse but not published to the site
- Product site exposure (technical): The product is published but is not appearing in search results
- Product marketing exposure: The product is published but is receiving no direct marketing views
- Product views (image/price): The product is getting impressions but no views
- Product conversion: The product is getting viewed but is not converting.

Product conversion can be caused by:

- Availability: Inventory issue across sizes — merchandising issue
- Wrong views: Product being viewed by the wrong customers — CRM issue
- Mispriced: Wrong price has been entered — product coding issue.
- Other issues: Poor image, poor description, poor reviews — needs investigation

Other examples highlight the complexity of modelling decisions that are sensitive to new or unfamiliar data. Some of these are new digital commerce decisions, but others are traditional retail decisions where new data is now available. The inconvenient truth is that many of the critical decisions of digital commerce are confounded by data from outside the system or organization silo. De-siloing data and decisions is a critical part of the answer.

Decision area	Decision...	But what if...	Confounder
Keyword (marketing)	Switch off keyword with high cost	Keyword was driving footfall into stores	Offline traffic (stores)
CRM (customers)	Send a promotion to a lapsed customer	Customer is actively browsing the website but products are all out of stock in the customer's size	Product availability (merchandising)
Range plan (buying)	Delist brand as loss making or low sales	Customer who first purchase brand are most profitable	Customer lifetime value (customers)
CRM (customers)	New CRM program for customers not making 2nd purchase	Customers are complaining due to orders being shipped late	Delivery experience (operations)

Figure 14: Sensitive decisions

Even when the logic is clear, other types of decisions are analytically complex and easy to get wrong:

- Customer – acquisition costs: How much of the expected customer lifetime value should be invested in customer acquisition is a strategic question around the trade-off between growth versus profitability. There's no right answer and the answer can change over time. Modelling customer lifetime value is hard, and then determining an acceptable payback should be a Board decision (that is often delegated to a junior marketing executive).
- Marketing – match type spend. The question of the optimal spend across match types on paid search is really a decision about risk: exact match is lower cost/risk but doesn't maximize reach; broad match will maximize reach but at higher cost/risk.
- Marketing – stopping decisions: Given the variable cost nature of many online marketing decisions where the retailer pays per click, impression or acquisition, we need a set of rules around when to stop spending. Again, this is a tricky risk/reward trade-off.
- Merchandising – markdown decisions: Marketing costs now need to be taken into account. Amazon was a pioneer in understanding that investments in delivery, marketing and price were "fungible" (i.e., it was one pot of money that needed to be allocated in order to maximize profit). For most retailers, these pots are optimized in silos. Understanding the relative elasticity of marketing vs. markdowns is hard, and yet critical to deciding where to spend the next pound.
- Operations – planning decisions: Service delays on individual customers need to be taken into account. Operations used to focusing on cost and efficiency, need to be able to model the complex trade-offs between cost to serve versus customer lifetime value.

(c) Poor feedback

Feedback will normally come in the form of metrics and reports and it is critical to understand:

- Whether a decision has actually been executed – actions are typically not observable so it's easy to think a decision was wrong but in fact it's the execution that is flawed (or simply hasn't happened)
- Whether the decision was good or bad – should we do more of the same, or do something different?
- How to improve the model going forward.

The data complexity, unhelpful averages and confounders that make decisions hard, also make interpreting results hard. In particular, measuring and interpreting results at an aggregate level can give a false sense of success (false positives) or failure (false negatives).

For example, a retailer observed that its page-weighted availability (the customers' experience of availability) was poor and decided to upweight availability in the ranking algorithm for its product sort orders. It subsequently wanted to understand if this decision was good or bad. The table below highlights that it's not at all easy to determine what the right metrics are to understand performance.

Metric reviewed	Observations
Conversion rate	Too aggregate. A site sort order change is unlikely to have a noticeable impact on the overall conversion rate as there's too much noise.
Page-weighted availability	Good to review the metric one wanted to improve. However, it's critical to understand what's happened to unweighted SKU availability to ensure that any improvements can be linked to the action
Page-weighted availability/ unweighted availability	This attempts to normalize for the effect of any change in overall availability. It's a potentially useful metric but doesn't tell the whole story.
Product click-through rate	By ranking products with higher availability, have we pushed products down the ranking that were selling well. Looking at product click-through rate will highlight whether the change in ranking has had any unintended consequences.
Alignment of inventory to product views	Has the change in sort orders been beneficial for the overall alignment of views to inventory - a very useful metric to understand the overall efficiency of sort orders.
Projected season sell-through	Ultimately, has the change in sort orders achieved our ultimate business objective of improving our expected sell-through. A nice metric if you can work out how to measure it!

Figure 15: What to measure?

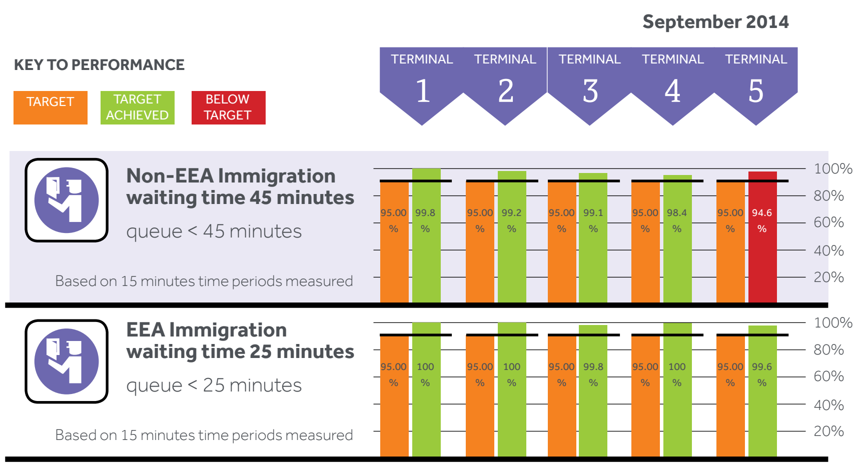
In practice, many of these metrics are either hard to measure, hard to interpret or both! It is also critical to understand that perfect is the enemy of 'good enough'. The key to making sense of feedback is simply to understand the minimum you need to be satisfied that the decision was good enough.

The truth is that the digital world is much more complex than our (current) ability to make sense of it. Keeping control and managing risk – the two fundamentals of business management – now require a new approach. In the past, retailing has been a relatively simple industry. Few would suggest that running a bank, power plant or airline was ever simple... but digital is now creating complexity in retail. And any suggestions that digital commerce can be managed "like a shop" do not last very long.

IMMIGRATION: A MASTERCLASS IN MISINFORMATION

Imagine you are presented with the statistics below, which give the waiting time experience at Heathrow Airport in London (this is from the Border Force website). Other than a tiny blip for non-EEA visitors at T5, everything is green. This is truly a masterclass in bad measurement:

- Immigration is open from 5am to midnight
- This 19 hour period is divided into seventy-six 15 minute intervals
- For every interval, one measurement is taken – the time for the person to get from the back to the front of the line
- If this time is less than 25 minutes (for EEA immigration), it's considered green
- Overall success requires that 95% of time intervals are green per month



There are many, many flaws in this approach including:

- The overall aspiration is very poor – a 25 minute wait should not be considered acceptable
- No account is taken of the volume of people arriving at different times – i.e., each 15 minute interval is considered equally and it shouldn't be, some are busier than others
- No account is taken of the outliers – it would be more interesting to see the longest waiting times - in 2011/12, the longest wait time was typically over 2 hours

POOR FEEDBACK: AB TESTING EXAMPLE

It is unfortunate that the entire online testing industry is based on a flawed premise, and most (but not all) online testing undertaken today is reaching potentially flawed conclusions. The simplicity of online testing belies its complexity. And – once again – it's the heterogeneity of the underlying populations that causes the problems.

Online testing promises so much but how often does reality disappoint? Tests that promise a

10/20/30% uplift in conversion rate seem to evaporate when they're rolled out (with varying excuses). A large UK retailer recently unveiled a "fully tested" new website checkout that they were confident would deliver a 20% sales uplift. In practice, sales went down. Unsurprisingly, the bad news got buried. But unless you look at the sub-populations, you risk making flawed decisions. Why is it so hard?

Clearly, many changes online do work and deliver significant improvements, and heterogeneity only matters if different sub-populations behave differently.

With any statistical test, an assumption is made that the population is identically distributed (homogenous). And the common wisdom is that a large/random sample somehow homogenises. Unfortunately, this is simply not the case. The example below highlights that overall results can flip-flop if (i) different sub-segments behave differently, and (ii) there are lots of sub-segments. Looking at aggregate results without stratifying is testing negligence. You might as well toss a coin. Imagine we are testing two web pages – A and B – and we run a traditional split test obtaining the following results:

	PAGE A			PAGE B		
	Visits	Orders	Conversion	Visits	Orders	Conversion
OVERALL	4000	630	**15.75%**	2100	210	**10.00%**

Clearly, page A is better than page B by quite some way. Decision 1: immediately default all traffic to page A. Now, suppose that we decide to look at whether men and women behave differently and we so stratify the analysis above by gender (note: this is where human judgment is critical to decide how to look at the data).

	PAGE A			PAGE B		
	Visits	Orders	Conversion	Visits	Orders	Conversion
Men	1000	30	3.00%	1500	60	4.00%
Women	3000	600	20.00%	600	150	25.00%
OVERALL	4000	630	**15.75%**	2100	210	**10.00%**

Clearly, page B is better for both men and women! Decision 2: Immediately default all traffic back to page B. Now, suppose that we look at whether the visitors were new versus repeat customers and we get the following breakdown:

		PAGE A			PAGE B		
		Visits	Orders	Conversion	Visits	Orders	Conversion
Men	New	800	20	2.50%	600	15	2.50%
	Repeat	200	10	5.00%	900	45	5.00%
Women	New	1000	40	4.00%	75	3	4.00%
	Repeat	2000	560	28.00%	525	147	28.00%
OVERALL		**4000**	**630**	**15.75%**	**2100**	**210**	**10.00%**

Now, we find that the results for pages A and B are identical for all combinations! So there's no real difference at all... Decision 3: Go home.

"Perfect is the enemy of good enough."
Voltaire

A new approach to decision making

The speed, volume and complexity of decisions, combined with high-resolution, multi-dimensional data is requiring retailers to rethink their approach to:

- **New controls:** The decisions that need to be made across the organization. This needs new retail logic and thinking about a new "decision architecture"
- **New models** for making decisions that recognize the new costs of the digital world, that in turn require new math or "equations of retail"
- **New feedback** and monitoring to continually optimize, necessitating a new hierarchy of metrics.

CONTROL	The digital world requires new LOGIC • Actions that can be taken • Interaction effects across departments
MODEL	The digital world requires new MATCH • New variable costs • New equations
FEEDBACK	The digital world requires new OPTIMIZATION • Instrumentation • Input metrics • Parameterised learning

Figure 16: A new approach to decision making

Although making decisions with this mind-blowing level of atomization and complexity can seem overwhelming, some digital players are beginning to recognize the approaches that are proving successful. The key to success is to put data science and algorithms at the heart of the business. Amazon is the undisputed grandmaster of this world but others such as Priceline (travel), king.com (inane games) and 888.com (gambling) are applying these techniques to build very successful businesses.

We have reached an inflection point where, to operate successfully, decisions need to be made by computers. In digital retail, the nano-decisions are typically well-defined, have good enough data and simply require logic and processing (the opposite of what we observe in physical retail). This is what computers are good at; using people to make decisions at the nano-level is simply too expensive to contemplate given the volume, velocity and complexity of the decisions required.

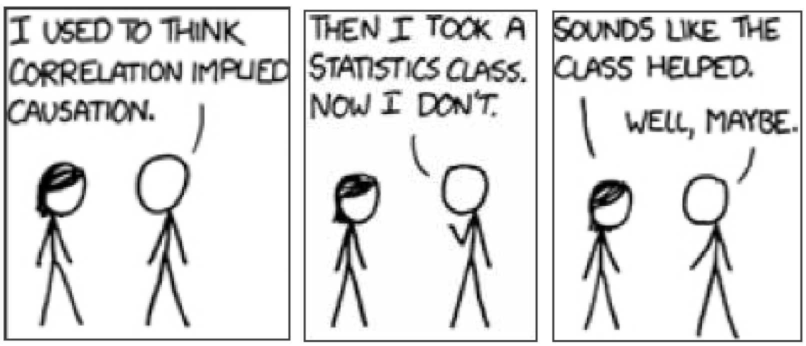
The importance of algorithms. Algorithms are not unfamiliar to retailers. Most retailers will talk about their replenishment algorithm which is one of the cornerstones of how their business operates (although even this will need to change as digital retail enables a single view of inventory).

Algorithms are the recipe for successful digital commerce. The combination of logic, math and optimization are precisely the ingredients of algorithms. So digital retailers need to get very good at building algorithms. However, they need to shift from a world of one algorithm to having hundreds of algorithms that enable all the critical decisions across the business.

Decision science framework. So what does this mean in practice? Digital retailers require a new "decision science" to navigate decisions - a much more disciplined, logical, structured approach. There are a number of characteristics of nano-decisions that set the scene:

- Reversibility: Can you change your mind? How quickly can you revert (seconds, minutes, hours)?
- Cost of failure: What is the distribution of outcomes? What is the size of the prize versus the cost of being wrong? Where this distribution is highly skewed towards the positive, you can be more confident about taking the decision.
- Feedback time: How long will it take to know whether the decision was right (seconds, minutes, hours)?
- Correlation versus causality: How important is it to understand whether there's causal link between the decision and the outcome?

The confusion about the confusion of correlation vs. causality.



Much has been written recently that in a world of big data, the nuances of correlation and causality are irrelevant. Others have written that if one doesn't understand causality, there is a very real risk that the decision can either have no effect or a negative effect. And that understanding causality (what's really going on) is critical to decision making.

Statisticians typically avoid talking about causality. They will happily talk about associations and correlations but asserting causality is a step too far. This is not the fault of statistics. In reality, one has to display extreme caution when attempting to assert that X has really made the difference.

For example, a decision about a search landing page is (i) typically reversible, (ii) the cost of failure is low, (iii) the feedback time is short and (iv) understanding causality is not important. So you can be confident about making these decisions, safe that the risk can be mitigated. With this context, every business decision looks relatively simple and needs to go through a decision sausage machine (figure 17) that asks a consistent set of questions.

CONTROL	**Position:** What is the current state of play? **Moves:** What can you do? What are the constraints on action?
MODEL	**Position:** Business logic/economics of process. What are you trying to optimize? **Move evaluation:** What are the unknowns? How do you decide the best move?
FEEDBACK	**Observation:** How do you improve the model? **Optimization:** How do you improve the control/moves? **Heuristics:** How do you monitor failure?

Figure 17: Decision sausage machine

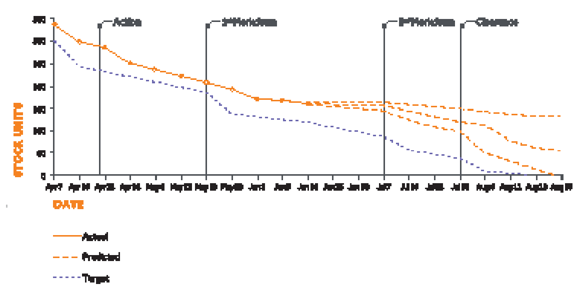
In reality, correlation vs. causality is simply one dimension of a decision. Whether or not it's important to understand causality will depend on the decision in question. Sometimes it's very important, for other decisions it's irrelevant.

Decision science: How to build algorithms. An example shows how this might work in practice. A retailer might want to automate a decision to send more marketing traffic to an overstocked product (which is often cheaper than taking a markdown). The retailer needs to make sense of the following:

	Examples
CONTROL	**Reduce price:** Current inventory, time to end of season, projected sell-through, projected under/overstock **Moves:** Reduce price, run promotion, return stock to vendor, increase on-site exposure, increase marketing exposure
MODEL	**Objectives:** Cash, short-term profit, season profit, risk **Move evaluation:** Score moves against objectives [the hard bit]
FEEDBACK	**Observation:**: Product views, product conversion rate, GMROI **Optimization:** Projected vs. actual sales, projected vs. actual price elasticity **Heuristics:** Wasted marketing spend, terminal stock, sell-through

Figure 18: The logic

And this then needs to be turned into an "equation": big data (and little data) provide the ingredients, the algorithm is the recipe.



$$\pi(p,c,a,b,\alpha,\beta,e) = vd(p - e)-vc$$
$$= (a + be)(\alpha + \beta p)(p - e) - (a + be)e$$
$$=(a + bc)((\alpha + \beta p)(p - e) -c)$$

where c denotes the initial product purchase cost.

In order to determine the optimal profit over all possible p and c values (given the values of a, b, α, β and e), *we obtain the first order derivatives of* π *as follows.*

$$\frac{d\pi}{dc} = b(\alpha + \beta p)(p - e) - a - 2bc$$

and, setting this to zero, we find that the value of c that optimises π is a function of p and is given by

$$c\hat{}(p) = \frac{b(\alpha + \beta p)(p - e) - a}{2b} (1)$$

Similarly, the derivative with respect to p is given by

$$\frac{d\pi}{dp} = (a + bc)(\alpha - \beta(e - 2p))$$

And, again, setting this to zero we find that the value of p that optimises π is given by

$$\hat{p}= \frac{\beta e - a}{2\beta}$$

Substituting $\hat{p}$ into the formula for c we obtain

$$\hat{c}=\hat{c}(\hat{p})= - \frac{1}{8\beta}(\alpha+\beta e)^2- \frac{a}{2b}$$

Figure 19: An algorithm in practice

The path to automation. Algorithms are a precursor to automation – they are the things that get automated. Much as the driverless car is the pinnacle of automating transportation, we are at the beginning of the path to automate commerce. And much as the technologies of the industrial revolution combined to accelerate the drive towards mechanization and automation, so the technologies of the digital revolution are combining in the drive towards decision automation:

- **Processing:** Moore's law is well-known but it is still amazing to look at the cost per GFlop (a standard measure of computer processing) which, over the last 15 years, has fallen from c. $1000 to $0.12 (i.e., a 10,000x improvement).
- **Data:** We are in the midst of an instrumentation revolution – the Internet of things – driven by improved tagging, beacons, RFID, smartphones, etc. The ubiquity of digital data then combines with the "data API" which effectively allows for the seamless movement of data. As more software is delivered in the cloud, the movement of data is further facilitated.
- **Artificial intelligence:** This is not the 'scary robots taking over the world' Artificial Intelligence (AI), but the more prosaic AI approach to learning. Much of the thinking in decision automation comes from the development of computer chess. In the 1950s, Turing (who cracked Enigma)

"*Everything's an algorithm.*"

Attributed to Jeff Bezos, CEO of Amazon.com and Shannon (who developed information theory) were the pioneers in thinking about when and how a computer would be able to play chess. In the following 50 years until Deep Blue defeated Kasparov, AI created the logical framework for the automation of tricky decisions.

- **Math (and statistics):** Applying traditional approaches in new arenas. Bayesian inference is a statistical approach to learning developed in the 1980s (Bayes theory was developed in 1760). Markov decision process is a probabilistic approach to decisions developed in the 1960s by Ron A.Howard (50 years after the original development of Markov theory).

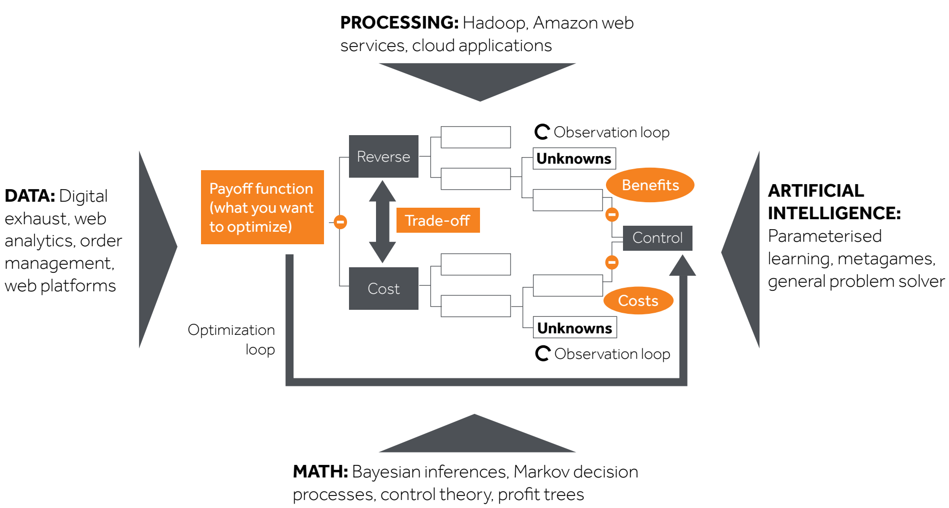


Figure 20: Decision automation

This is a terrifying vision for retailers used to the old way of doing things. Many may wish the Internet had never happened. As one former retail CEO said to me "we've deliberately made our website not very good to drive people into our stores." But it is not going away, and changing the entire decision making process of an organization requires very strong leadership. It is change management on an enormous scale – effectively taking a business on a journey where human input is augmented by algorithms. It is ironic that in a world of big data, algorithms and decision automation, the most critical skills will be people related.

The retail landscape is more complex –

and more exciting – than ever before for retail executives. As shareholders and board members are anxiously drumming their fingers to see incremental revenue and profits come to light, executives must seek to build for the trifecta of retail success: people, process and technology.

Built by a former retail CEO and former Chief Scientist at Amazon, DynamicAction applies thousands of proprietary retail algorithms across all departments to pinpoint exactly what is impacting your growth and optimisation efforts. Let us show you how DynamicAction will empower your team to make strategic decisions to take action faster than ever before.

THE 10 COMMANDMENTS OF DATA AND DECISIONS

DATA AND MEASUREMENT

1 **Averages are the enemy of the digital retailer:** They are often misleading and rarely representative. Outliers, deciles, dimensions and stratification are critical tools for unraveling averages.

2 **Data is the new oil:** Data is a hugely valuable asset that needs to be discovered, mined, extracted and refined to be turned into something useful. Businesses need to recognize the criticality of "instrumentation" to ensure that data is high quality, easily extractable and be joined across systems.

3 **Develop new metrics to keep control:** Output metrics tell you what's happened. Controllable input metrics are critical to work out where to focus – they are answers to the questions that drive action.

PEOPLE AND MANAGEMENT

4 **People are critical:** The best people can be worth 100x the average. Make space in the C-suite for a Chief Scientist, Chief Algorithm Officer or a Chief Data Officer – avoid relegating them within the organization.

5 **Data is not one role:** A variety of skills are required to make sense of data: data architects, analysts, algorithm designers, mathematicians, statisticians are all quite different. It is critical to think of data as a team effort.

6 **Get help:** Find experts to work with you – partners, advisory boards or your peers. Everyone in every industry is struggling (whatever they say publicly). The traditional management model struggles when managers lack detailed experience of the decisions they are managing.

GOVERNANCE AND PROCESS

7 **Rethink silos:** Digital commerce does not respect organizational boundaries. The inconvenient truth is that many of the critical decisions of digital commerce are confounded by data from outside the system or organization silo. De-siloing data and decisions is a critical part of the answer.

8 **Catalyze change:** It is inevitable that the traditional way of managing will need to change. This will include new processes and incentives across the business. And navigating this requires strong leadership.

CULTURE AND BEHAVIORS

9 **Think algorithms:** In digital commerce, everything is an algorithm – they are the logic behind every decision. And a good discipline is to start with the decision, and understand how to use the data available to make a better decision.

10 **Hypotheses, not absolutes:** There is no right answer, but that doesn't mean there isn't a wrong answer. The question should now be 'How do we make the best possible decision given the available data?' Retailers who have come from a background of "not making mistakes" need to adapt to a reality of more nuanced decision making.

About DynamicAction

DynamicAction is a retail analytics guidance system that leverages cloud software and a proven success program to catalyze the new customer-first operating mindset in retail. DynamicAction empowers retailers with a clear path to navigate their transformational journeys with AI-powered metrics. It enables faster, better decisions to deliver profit, analytics and visualizations for immediate insights, prioritized opportunities and prescribed actions to take online and in-store.

Forward thinking retailers across the globe rely on DynamicAction's advanced analytics and retail-built practices to holistically run more efficient organizations and formulate laser target strategies to uncover their most profitable customers. Forrester Research recommended DynamicAction as the key prescriptive analytics technology to replace predictive analytics in retail, and the National Retail Federation awarded DynamicAction for its ability to "significantly improve or radically alter how retailing is done."

Headquartered in Silicon Valley, DynamicAction has offices in London, Sofia and Dallas.

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