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Master Program in Advanced Analytics

ANALYTICS IN STRATEGY CONSULTING

An experience-based reflection

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Internship report presented as partial requirement for obtaining the Master's degree in Advanced Analytics

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ANALYTICS IN STRATEGY CONSULTING

by

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Internship report presented as partial requirement for obtaining the Master's degree in Advanced Analytics

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June 2017

ABSTRACT

This report provides extensive insights into analytics-based work in strategy consulting. It draws on first-hand experience gained during a 6-month internship at ABC Strategy Consultants Ltd (hereafter ABC) in London from September 2016 until the end of February 2017. The report starts by giving an introduction to the industry and how analytics is integrated within the company. After, it provides an overview of the project work during the internship. The extensive reflection on the internship experience discusses the value of analytics to strategy consulting, elaborates on the effects of non-technical audiences, points out the most crucial factors that help to build and retain a data science team within strategy consulting and finally trades off whether analytics should be a core capability of strategy consultancies or if it should merely be a support function.

KEYWORDS

Analytics; Strategy Consulting; Internship; Retail

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1. INTRODUCTION

As the amounts of data collected by companies increase continuously and ever more sophisticated ways to analyse these are being developed, companies need to incorporate information from this data into decision making. “Data-driven decision making” is becoming a buzz term and stakeholders increasingly find comfort in backing decisions with large amounts of data and complex analyses.

This development also affects the service industries that support corporate decision making. As companies have more data readily available and gain trust in its analyses, service providers must react and adapt their offerings towards more data-driven methodologies. This is also true in the field of strategy consulting. Clients can provide much more data than they used to, which cannot be ignored in the strategic decision-making process. Large volumes of data, however, quickly bust the limits of simple spreadsheets and impose the need for new tools and techniques to be adopted by strategy consultancies. Therefore, strategy consultancies must improve their technical capabilities to meet market demand and to stay competitive. The process of adapting to the new environment is far from straight-forward. Strategy consulting firms face many challenges as their historic ways solving problems stand in contrast to careful analytical procedures.

This report provides extensive insights into analytics-based work in strategy consulting. It draws on first-hand experience gained during a 6-month internship at ABC Strategy Consultants Ltd (hereafter ABC) in London from September 2016 until the end of February 2017. Firstly, it describes the role of strategy consulting in general, introduces ABC and outlines ABC’s approach to the application of analytics. The report continues by providing details with respect to the setup of the internship, of the analytics team and by describing the author’s role within the team and the company. Subsequently, the projects worked on during the 6-month period will be described. For each project, the section introduces the goals and strategic questions that were to be pursued and answered. It also provides details on the methodologies applied, problems encountered and results achieved. Next, the report reflects on the experiences, learnings and takeaways during and from the internship. It critically assesses the value of analytics in strategy consulting, debates the difficulties and implications that arise due to non-technical audiences and attempts to answer the question whether analytics should be an integral part of strategy consulting or if it should merely depict a support function.

The report concludes that incorporating analytics into strategy consulting projects is not ideal, which is mainly due to the tight timelines that are typical for the industry. However, it provides a roadmap for the integration of analytics by introducing a set of possible improvements to the role of analytics. This piece of work is rounded off by pointing out the impact of the internship on the personal and professional development of the author. It also outlines possible future steps in his career and presents a set of reasons with respect to the author’s decision not to pursue strategy consulting after finishing his studies.

2. INDUSTRY AND COMPANY

The general consulting services industry supports companies in performing specific tasks. These are not bound to any specific fields, departments or missions. The contrary is the case: consulting firms are being hired to assist with projects across a large variety of functions and for many different purposes. These range from hands-on implementation projects to the support of top-level strategic decision making. Consulting firms provide short- to medium-term manpower, expertise and facilitating functions to the companies they are being hired by. Due to the many different areas of application, many consulting firms target specific niches of the market by focusing and specializing on certain industries and problem statements. For example, a subset of the industry is strategy consulting.

2.1 Strategy Consulting

Strategy consulting firms operate within a subset of the consulting market. As the name indicates, they specialize on strategic problem sets that guide top-level decision making. Among many others, these include whether to enter or to exit product/geographical markets, which consumers to target, how to set product prices, or which merger & acquisition strategies to pursue.

Typically, these strategic projects are owned by high-level stakeholders and by senior managers. Thus, the proper management of everyone involved and a good communication of results are critical. Also, the decisions processes being supported tend to be highly time critical, which causes project timelines to be scheduled tightly in order to deliver results as soon as possible. The strategy consulting-specific audiences and timelines have important implications on how analytical methodologies can be implemented for problem solving as both, non-technical audiences and short tight timelines limit the degree of complexity that can be introduced to models in the context of the projects.

2.2 ABC Strategy Consultants

ABC Strategy Consultants Ltd is one of many firms that have specialised in strategy consulting. The company operates internationally with 14 offices across 10 countries, including the United Kingdom, Germany, France, Poland and Turkey in continental Europe. The company focuses on a subset of industries to concentrate their expertise and to compete effectively with larger competitors. The industries targeted are mainly retail, consumer goods, technology, media, industrial products and business services. The company claims a distinct corporate culture and views itself as a boutique consulting firm that successfully competes with top tier consultancies in their areas of focus.

2.3 Introduction of Analytics at ABC

Historically, ABC has neither been involved in Analytics, nor did projects require analytical capabilities. Consultants have mainly used Microsoft Excel (Excel) to analyse data based on an "80/20"-approach that translated into correct but pragmatic and approximative analyses. To save time, the last 20% of "correctness" are usually being neglected as they require a disproportionally large amount of effort and tools other than Excel. In terms of data volumes, ABC used to receive mostly spreadsheets that were of manageable size for Excel. I.e. most data dumps included far less than a million rows, typically two-hundred thousand at most. In case larger datasets were received, consultants would open them with Microsoft Access. However, the program was only used to reduce dimensions, to roll up the data and to subsequently export the data again in order to perform the actual analyses in Excel. Besides the simplicity of tools used, the typical strategy consultant is neither proficient in statistical or analytical methodologies, nor does he know anything about databases.

In recent years, project teams were confronted with larger amounts of data, with the market demand to analyse more detailed layers of data and with increased technical expertise on the side of the client. These developments conflicted with the historic limitations. Processing data efficiently and analysing it correctly became a major challenge. Therefore, ABC invested in the development of analytical capabilities in 2014. The company, led by the UK office, hired an analytics expert to build a team of analytical consultants that would be capable of handling substantial amounts of data and applying advanced analytical techniques.

3. ANALYTICS AT ABC

As analytics at ABC has solely been developed to meet market demands in the field of strategy consulting, it's not one of ABC's core competencies. The firm put a lot of work and effort into determining the right setup and value proposition of analytics as part of strategy consulting. For analytics to function well within ABC, interests of the analytics team must be balanced against the interest of the remainder of the firm. Also, the right degree of technicality has to be determined, it must be specified how strategy consultants interact with the analytics team, and the type of projects to be worked on by the team must be defined. Furthermore, ABC has to develop an internal expertise that enables them to develop and preserve methodologies. Finally, ABC must come up with a way to solve analytics tasks on short consulting timelines.

3.1 Approach of ABC to the Role of Analytics in Strategy Consulting

In contrast to many other players in the industry, ABC chose not to develop its analytical expertise as a "back-office" function. Instead, they aim to develop a team of consultants that does not only have a commercial understanding of business, but also knows how to handle big and complex sets of data. These competencies include the elaborate statistical analysis of data.

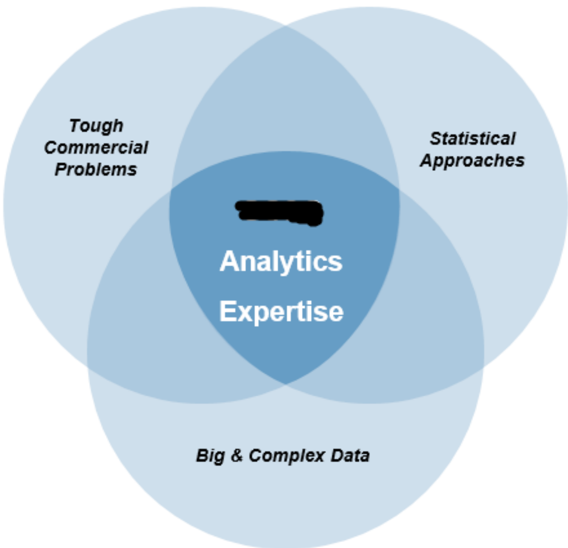

Figure 1: ABC Analytics Expertise

3.1.1 Key Principles

The approach applied by ABC to “do” analytics is characterized by five key principles:

1. **Commercial**: the aim is to answer commercial questions, not to sell products or systems.
2. **Fast**: timescales are adapted to strategy projects and will last from 4 to 12 weeks.
3. **Pragmatic**: in order to work with messy real-world data, data quality is being assessed at the beginning of the process and will be considered when designing approaches and analyses.
4. **Interactive**: clients are taken through the entire decision-making process and must understand how conclusions are being derived.
5. **Advanced tools**: the toolkit applied leverages advanced analytics techniques (regressions, clustering, classification algorithms, …) and relies on the right tools (R, Python, SQL).

These principles guide the analytics-based work of ABC. Essentially, they are designed to allow analytics to work hand-in-hand with the regular strategy consulting process. For this combination to work, the analytics work must match the pace of the other work streams and must be understandable to non-technical stakeholders.

3.1.2 Project Types

Besides these principles, ABC has also closely defined the types of projects that will be carried out with analytics as a supporting or as a key function. Tasks are being differentiated along two dimensions: the role of analytics and the project type. Within all projects supported, the analytics team is meant to take a front office role. I.e. they will be part of the client-facing team rather than just providing analysis to the team from the back office. Analytics consultants will hold end-to-end ownership of the problem and are responsible for deriving adequate conclusions and communicating them. This property of the work demands commercial and business skills from the analytics team members, as well as the capability to communicate results well. The back-office role will only be performed in case of internal tasks that support general operations. It involves supporting single bits of strategy projects without being exposed to the problem in question.

With respect to the project types, ABC differentiates between three kinds:

1. **Strategy Plus**: projects where analytics is used to improve the problem-solving process of traditional strategy projects. Analytics may allow for a more accurate solution to the problem, or it may increase the speed with which the solution is derived. Possibly, applying analytics may also generate higher fees or yield an advantage during the pitching process.
2. **Analytics Enabled**: strategy projects that are heavily analytical and where analytics is essential to solving the problem. The execution requires advanced analytical

techniques. Typically, these projects are deep dives into functional-level topics. For example, these projects may involve analysing transactional data on a line item level.

3. **Pure Analytics**: projects where analytics is part of the final output, for example in the format of a tool or an ongoing service. There is no strategy component involved. Usually, these projects are only being carried out on client demand only, they are not being pitched for.

Most projects for which analytics team members are staffed fall into the first category. Strategy development is ABC'S core business and in most cases the firm simply wants to deliver state-of-the-art solutions to strategic problem statements. In many cases the best solution requires the analysis of enormous amounts of data or the application of complex methodologies.

The second focus type, despite its lower importance, consists of analytics enabled projects. These move away from the company's core business and allow for additional revenue. The projects send a strong signal to the market that shows that ABC is capable of meeting analytical industry demands. However, in most cases the methodology must be developed and timelines have to be extended in order for proper analyses or modelling to take place.

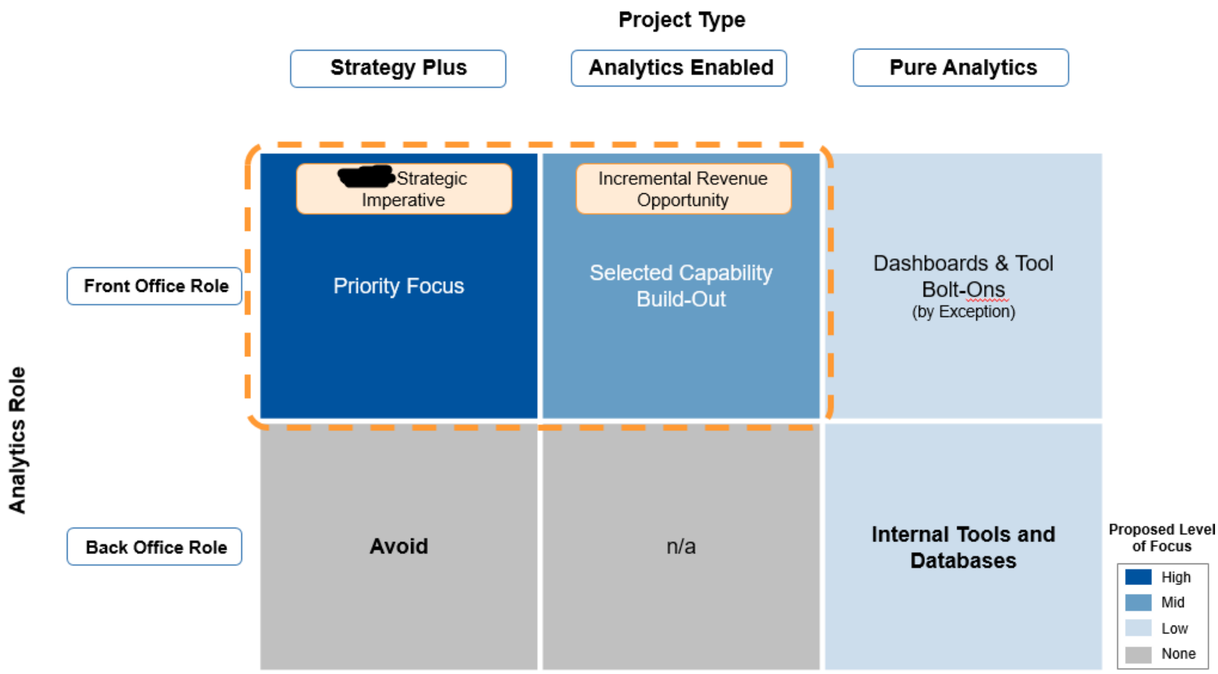

Figure 2: Project Types

3.2 Role and Setup of the Analytics Team

The analytics team at ABC is set up to match its underlying principles and to successfully tackle its focus project types. These requirements dictate two main traits of the team: its client-facing nature and its full integration with regular project teams. The former is required to develop full problem ownership and to ensure an interactive interaction with the clients. It moves the analytics role away from the back office. Team members are expected to work well with team members as well as client representatives. The latter is also essential for an end-to-end problem ownership, but is also important for timeliens to align with other work streams. It prevents the team from solely providing on-demand services, such as rolling up data. Both traits have massive implications on the way the team members work and on the profile of the ideal candidate.

3.2.1 Team Setup and Role Compared to Strategy Consultant

The analytics team at ABC is led by two associate partners, one of which is the head of analytics. The two are responsible for developing the team and for ensuring smooth interactions between analytics and everything else. The head of analytics has been hired from an external company and brings in much of ABC's analytics expertise. He does not manage any projects and is fully dedicated to supporting the analytics team. He acts as an important sparring partner to the team members by giving advice with respect to methodologies and how to handle specific project situations. Furthermore, the head of analytics promotes the team internally by communicating its capabilities to partners, which enables them to sell projects based on the existing expertise. Also, he is responsible for the analytics strategy and financial planning, while also taking care of the resource management and recruitment. The second associate partner involved also manages regular projects and mostly acts as a sparring partner to the head of analytics. The remainder of the team is not involved in organizational tasks. They are simply allocated to projects, taking into account their level of seniority and their technical expertise.

Essentially, members of the analytics team take on a role that is very similar to that of a "regular" strategy consultant. Therefore, the team is integrated into the remainder of the firm, being staffed as required. However, due to the differences in tasks compared to the strategy peers, analytics consultants develop a slightly different skill set that emphasises technical skills, such as coding, statistics and data handling. In order to be able to focus on these, they are expected to perform "worse" on traditional slide-related tasks, context-related thinking and problem solving. All other skills are expected to be developed similarly. The ideal candidate for the job as a data analytics consultant should therefore possess strong technical skills. Also, he or she should be familiar with some basic business skills.

Figure 3: Analytics Skill Set

3.2.2 Analytics Workflow

The analytics workflow is designed to work smoothly along with the remaining strategy work. A typical project lasts for six to ten weeks and consists of five project phases. The phases can be structured into two stages, the setup phase and the delivery phase. The first phase is dedicated to data collection. It involves understanding the problem, identifying data sources available, formulating a data request and ensuring a smooth transfer of the data. Ideally, this phase takes place before the strategy work kicks off to ensure that first outputs are available when required by the project team. The second phase continues and ends the setup phase and focuses on cleaning the data that has been extracted during the first phase. This involves sense checking the data, e.g. by comparing totals across data sources and checking if the data shows patterns that are to be expected. Also, automatic and manual data cleaning tasks are being performed.

Phase three, the analysis phase, is the first of the three delivery phases. At this stage, the analyses to be performed are being specified, the appropriate tools and methodologies identified and first cuts of the data made. The output is basically an initial result that shows where the work is heading. Next, the iteration phase kicks off. It's essential to discuss preliminary findings thoroughly, to understand what's happening and to validate if the approach to solving the problem is correct. The team discusses the output, bases first hypotheses on it and shares initial insights with the client. Also, additional deliverables are being discussed. Finally, during the last week of the project, commercial findings, backed by analytics, are being condensed, visualised and presented to the client. The delivery stage of the project is similar to the setup of a regular strategy project. The setup stage, however, must occur ahead of time to avoid unrealistic deadlines later on.

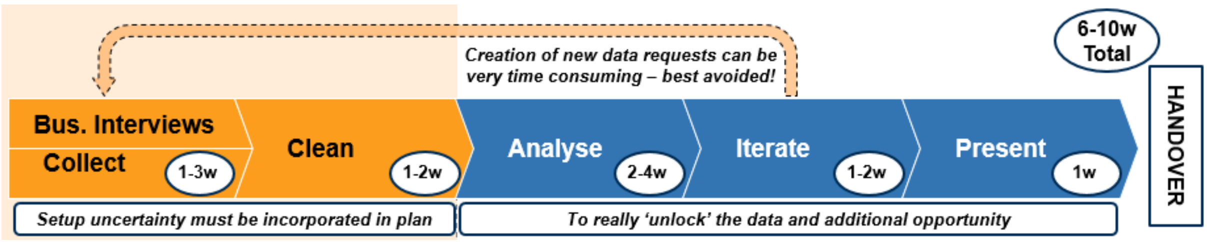

Figure 4: Typical Analytics Workflow

3.2.3 Author's Role within the Team

The author joined ABC for a six-months internship in the analytics team. Having worked as a strategy consultant ahead of his Master's degree, the commercial and slide-related skill set had already been developed. Additionally, part of the required technical expertise had been acquired throughout the first year of his Master's degree in advanced analytics at Nova IMS in Lisbon. This set of experience and technical knowledge allowed the author to join the team as a full-fledged member from the very beginning of the internship.

Initially, as no project kicked off right away, the author got staffed "on top" to help out a fellow team member. This setup ensured a smooth start of the internship as the author could gain first insights into how the team works without being held fully responsible for any project outputs. This introductory phase also freed some time to improve coding skills where required. After two or three weeks, the author was taken off this project and got staffed on a separate project, being fully responsible for the related analytics work stream.

Being integrated into the team as a full member was a terrific opportunity to maximize learning throughout the internship. Owning the problems end-to-end encouraged involvement, critical thinking and creative approaches to the tasks. Fellow team members were always keen to help and to give advice when necessary.

4. PROJECT EXPERIENCE

Over the course of the six-months internship, the author worked on four different projects. The first project for a UK department store lasted for about a month, followed by an intensive two-months commercial due diligence for a restaurant chain. The final project took place over a three-month period and supported the strategic planning of a multi-channel retailer by determining its cost-to-serve across channels and categories. Any slack during the projects has been used to develop an internal database that can be used for location-based analyses.

4.1 Strategic Opportunities & Operational Optimisation for a Department Store

The internship kicked off with a project that assessed strategic opportunities and potential for operational optimisation for a well-reputed UK department. The department store had never engaged in an extensive piece of strategy work before and was keen to identify any type of opportunities or threats to the business. The broad problem statement allowed for flexible exploratory analyses of all datasets provided by the client, which was a very interesting task. Linking up the different sets of data and identifying relationships was very rewarding, particularly because many patterns discovered made intuitive sense.

4.1.1 Data Sources

Most analyses conducted were based on three sets of data. Most importantly, transactional data on line item level provided a detailed purchasing history for any transaction processed in 2013 or later. This fact table contained quantitative purchasing details, such as date and time information, transaction and line item IDs, purchasing volumes and values, discounts, as well as taxes. Also, it included a variety of foreign keys that allowed linking it up with numerous dimensions. They included product IDs, customer IDs and department IDs.

One of the main transformations applied to the data was the definition of shopping trips. They were used as a basis for customer behaviour instead of analysing individual transactions. The adjustment assured that transactions by the same customer on the same date were not assessed separately. This was possible without sacrificing much data because the penetration of customer data was high, customer IDs were recorded for most transactions.

4.1.2 Analyses Performed

At the very beginning of the project, the spending patterns by customers coming from different loyalty tiers or demographic backgrounds were assessed. Overall, daily transaction volumes stayed within a more or less equal band, but increased during promotional periods and before holidays. The impact of promotions on transaction volumes had not been incorporated into staffing considerations before. Additional analyses were performed in order to assess the need for additional staff per department in greater detail. Also, sales volumes across the year were determined by customer nationality. This indicated that customers from some regions, particularly from the Middle East and Asia, follow different purchasing patterns, driven by religious events.

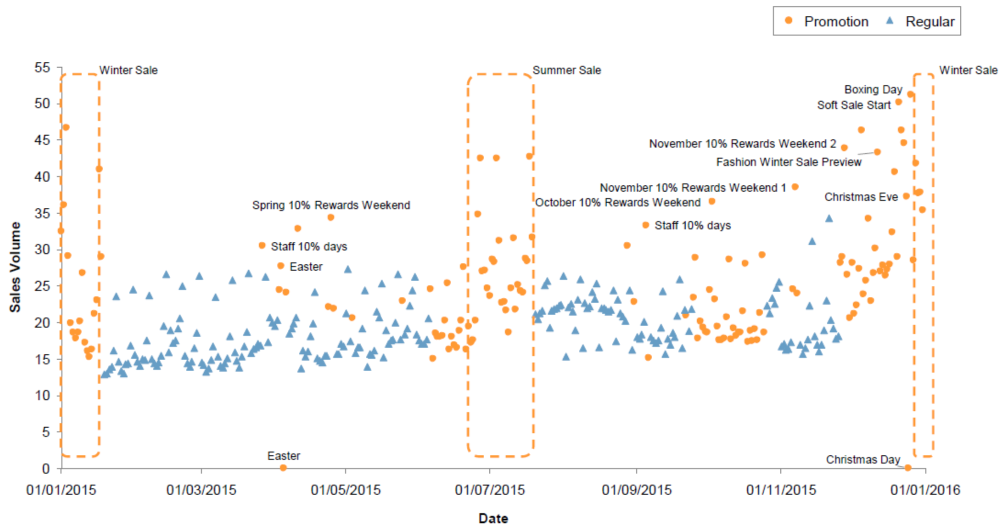

Figure 5: Sales Volume over Time with Highlighted Promotion Periods

Another valuable insight was the customers' cross shopping propensity, which was delivered in the format of a categorical matrix. It showed that some categories were far more likely to be part of a multi-divisional basket than others. The drivers were found to be average product values and the positioning of the categories in-store. Based on these results, a re-positioning of categories within the store in order to maximize cross-shopping could be considered.

Cross Shopping Propensity Matrix per Category[1]
%

Reward customers, all periods

Reading example: 26% of trips that incl. fashion accessories also included a beauty item.

Base Category \ Complementary Category	Beauty	Fashion Access.	Womens-wear	Fashion Lab	Shoe Heaven	Menswear	Sports	Home-wares	Harrods Sign.	Childrens-wear	Toys	Tech-nology	Fine Jewellery	Fine Watches	Furniture
Beauty	*520,700*	10%	9%	6%	6%	7%	5%	9%	4%	5%	4%	2%	1%	0%	0%
Fashion Access.	26%	*199,101*	12%	6%	9%	10%	5%	9%	5%	5%	4%	3%	2%	1%	0%
Womens-wear	26%	13%	*188,520*	11%	11%	9%	6%	11%	2%	7%	4%	2%	2%	0%	0%
Fashion Lab	28%	11%	17%	*119,523*	11%	8%	9%	9%	3%	9%	4%	2%	1%	0%	0%
Shoe Heaven	25%	15%	18%	11%	*119,820*	10%	7%	8%	3%	7%	4%	3%	2%	0%	0%
Menswear	22%	12%	11%	6%	7%	*164,078*	10%	10%	2%	6%	4%	3%	1%	1%	0%
Sports	25%	9%	10%	9%	8%	14%	*113,448*	11%	4%	8%	6%	4%	1%	0%	0%
Homewares	23%	9%	10%	5%	5%	8%	6%	*203,622*	11%	7%	7%	4%	1%	1%	1%
Harrods Sign.	21%	10%	4%	4%	3%	4%	4%	21%	*105,174*	6%	7%	2%	1%	0%	0%
Childrens-wear	22%	9%	11%	10%	8%	8%	8%	12%	6%	*112,973*	14%	3%	1%	0%	0%
Toys	19%	8%	7%	5%	4%	6%	6%	14%	7%	16%	*103,916*	5%	1%	0%	1%
Technology	20%	8%	7%	5%	5%	9%	7%	12%	3%	5%	9%	*63,653*	1%	1%	1%
Fine Jewellery	22%	18%	11%	5%	8%	9%	4%	10%	3%	5%	4%	3%	*27,431*	2%	0%
Fine Watches	19%	14%	8%	4%	5%	11%	5%	12%	2%	4%	3%	3%	6%	*10,488*	0%
Furniture	13%	4%	6%	3%	3%	5%	4%	15%	1%	3%	5%	5%	1%	0%	*12,197*

Figure 6: Cross Shopping Matrix by Category

The department store at hand used two types of shopping assistants to increase customer spending and to encourage cross-shopping. An analysis of assisted trips versus non-assisted trips showed an increase in multi-categorical shopping in case the trips were assisted. This increase went hand-in-hand with rising average trip values, causing an uplift in sales.

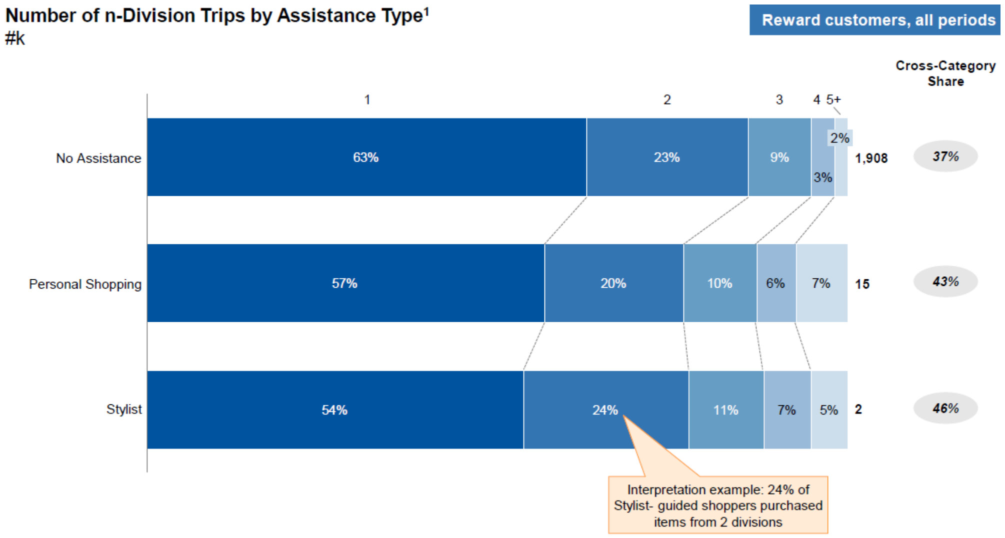

Figure 7: Divisions Shopped per Trip by Service Type

Another big piece of the work dealt with assessing how staffing levels match transaction volumes in order to ensure an efficient deployment of labour across the retail space. Categories were analysed separately. The work was conducted across the year and on a daily basis. Comparing sales with payroll totals showed that for some categories sales per pound of salary were much lower or higher than for the average, indicating over- or understaffing.

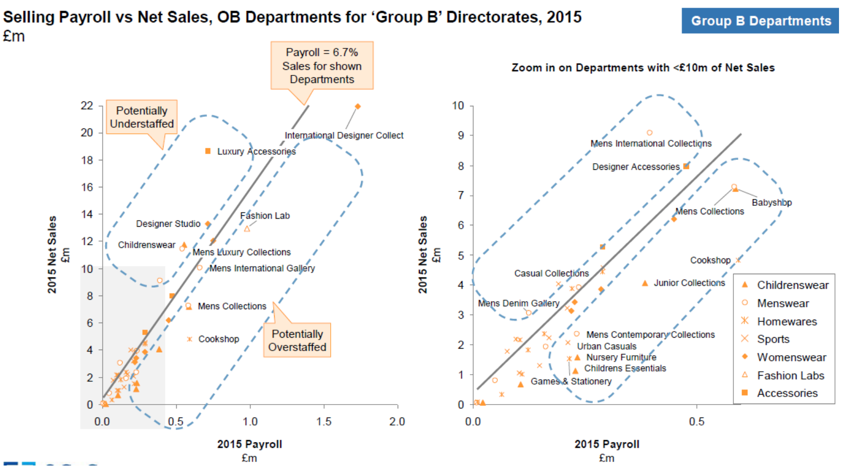

Figure 8: Staffing Hours versus Sales by Department

Besides these core pieces of work, many other additional cuts of the data were produced and interpreted. For example, drivers behind lapsed customers were identified using customer survey data.

4.1.3 Project Takeaways

The project was a typical "Strategy Plus" project in the sense that analytics was solely used to enhance results, but not to drive project outcomes. Results of analyses were put in context with qualitative insights from the strategy work and used to back up hypotheses with respect to areas of opportunities. Due to the large amounts of data, however, it was necessary to work with more performant tools than Excel. The tool of choice was R, which was extremely comfortable to work with.

From a personal perspective, the project proved to be a good learning ground to get familiar with the tools used throughout the internship, namely R. However, all pieces of analyses performed were very straightforward in terms of methodology. They simply required to be familiar working with large datasets. Having studied statistics and complex algorithms, this was quite dissatisfying and not very exciting over time.

4.2 Determination of Store Roll-Out Potential for a British Gastronomy Chain

The second project was sold to a private equity firm that considered buying a British gastronomy chain. From a strategic perspective, they required ABC's view with respect to competitive positioning, proof of concept and customer perception. The analytics team came into play to determine the store roll-out potential of the target and to identify the location characteristics of current sites. The chain is relatively young and currently has between 50 and 100 sites. In order to size the target's growth potential, the private equity firm wanted to know for how many additional locations in the UK the concept of the restaurant concept would work and what makes these locations a good fit.

4.2.1 Data Sources

From an analytics perspective, four main sources of data were used to understand the portfolio of sites and to quantify the rollout potential. Firstly, a dataset provided by the management included site-specific stats, such as financial facts and store areas. All other datasets were sourced externally and aimed at understanding the "typical" site location and determining how many more of these locations exist in the UK. Data from the UK census databases was downloaded on a granular level and used to indicate demographic characteristics of the sites and other locations. The other two datasets were compiled by and bought from external service providers. They provided data on UK retailers, restaurants and statistics on retail catchments. A retail catchment is an accumulation of multiple retailers.

Besides these sources of data, geographical lookups were essential to combine all of them. Each dataset included either postcodes or eastings and northings, which is a location identifier similar to altitudes and longitudes but without negative values. These are helpful to calculate absolute distances. The analytics team has access to a huge lookup file that allocates eastings and northings to every UK postcode. For example, this lookup has been used to define catchment-specific demographics from the census data provided per postcode or to determine which retailers or restaurant operate close to one of the sites.

4.2.2 Analyses Performed

The main part of the analysis phase was used to integrate all datasets. The census data was fragmented across many files with inconsistent formats and needed to be aggregated. Also, there was no straight-forward approach to linking postcode-level data to existing sites of the target. Therefore, statistics were determined via easting and northings by using different radii around the sites' locations. If a postcode was within this radius, it would impact the respective site's variables and demographics. The same is true for the determination of the competitive density as it was defined by the number of competitors within a specified radius. This cumbersome process caused a lack of time later on.

As a first step after the data had been integrated, an understanding of the demographics around existing sites has been developed, using census statistics and external data. For different dimensions, summary statistics were evaluated to foster the understanding of the "typical" site's characteristics. Besides demographics, competitor density also played a key role in describing locations. These dimensions were used as inputs for the performance driver analysis by putting them into context with the financial performance data received.

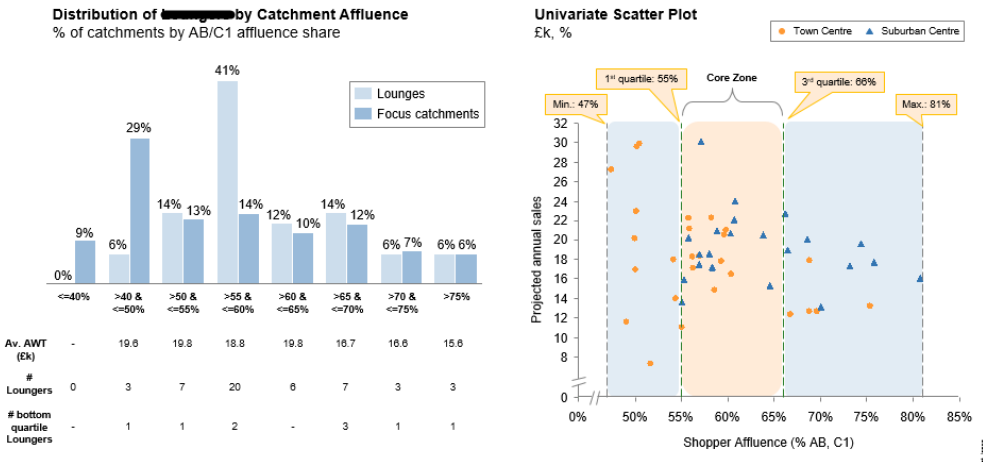

Figure 9: Distribution of Sites by Affluence of Population

The store roll-out potential has been assessed based on predicted performance for potential sites across the country. The financial data provided by the client was used as the target variable within the training data set. The demographics and competitor information served as explanatory dimensions. The set of possible sites had been limited by the number of "retail catchments" within the United Kingdom. A data provider provided us with a pre-defined set of UK retail catchments. These were defined as accumulations of multiple retail stores. The limited solution space allowed us to define demographics, competition and other independent variables for all the existing locations and to subsequently predict their sales potential. They effectively depicted our observations for which performance was to be predicted.

To predict profit for all viable solutions and to thus to assess profit potential for all sites in the solution space, a relatively simple multiple regression model has been used. The client explicitly asked to be able to understand the approach used, which strongly limited our possibilities. The model was based on 5 independent variables. Catchment type has been defined as a dummy variable distinguishing between town centres and suburbs. Suburb locations showed increased profit potential. Catchment size measures the size of the shopper population and positively affects predicted profit. The affluence of people living in the area of the location was also relevant. The census data included social grades, which are a proxy for affluence. A too high share of highly affluent people in the area (social grades AB and C1) causes profits to drop, indicating that the target customer group is not so well off. Profits are higher if nearby competition is low. Finally, the size of the location itself also boosts profits. This factor was captured best by the number of covers within the restaurants.

The final model had an adjusted R^2 of 0.43. Drawing on theoretical knowledge of statistics, this value appeared quite low and model performance therefore limited. However, the team confirmed that, in practice, this wouldn't be too bad. The low value arose due to the small number of observations and potentially many qualitative factors that affect location performance.

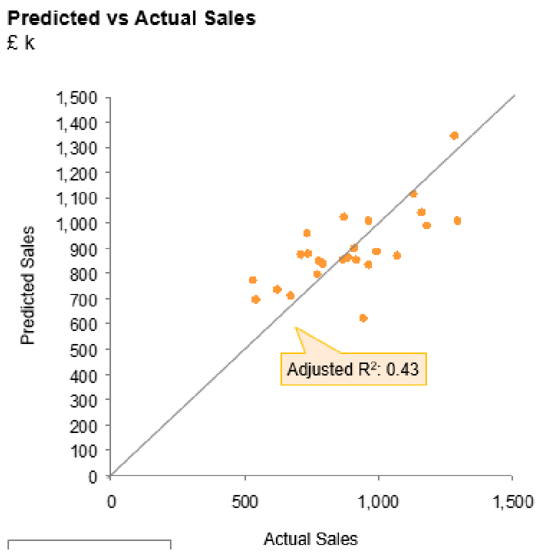

Figure 10: Scatterplot of Predicted versus Actual Sales

4.2.3 Project Takeaways

Based on predicted profits, 383 catchments with good or high profit potentials have been identified. Catchments were ruled out if there were already restaurants of the same chain operating within the catchment. They were also excluded from the analysis if the catchment was of a type other than suburban or town centres, e.g. rural areas, because there were no existing restaurants operating within any catchments of those types and strong extrapolation should be avoided. A catchment was considered to be of good potential if the predicted return of capital invested exceeded 30% and of high potential if it exceeded 40%.

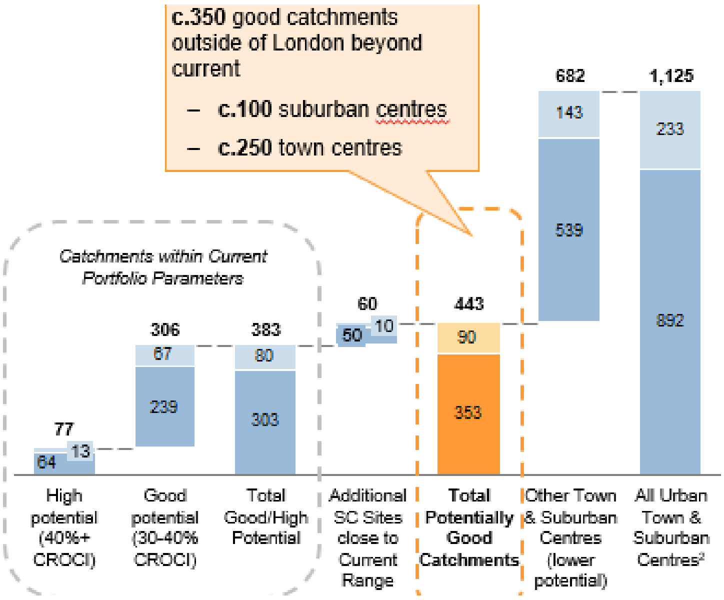

Figure 11: Potential Catchments for Rollout

The project lasted only for a few weeks, but the timeline was set up extremely tightly. This resulted in long hours, lots of stress and many shortcuts taken throughout steps of the analysis. The further limitation of the model having to be "understandable" resulted in an answer that wasn't very satisfying to team members with technical backgrounds. Furthermore, the strong limitations of real life data had a huge impact on project outcomes and model significance. Some qualitative location-related factors simply cannot be incorporated into a regression. Another takeaway was that a good integration of the data available at the very beginning of the analysis process is essential. If diverse sources of data are being used in combination, they should be linked as good as possible. Ideally, although not always possible, the data should be combined into a single dataset. This also speeds up processing time later on and makes the code to crunch the data much simpler.

4.3 Modelling a Multi-Channel Retailer's Cost to Serve across Categories & Channels

The next project took up much of the total internship time. It lasted for three months. The project was one work stream of a major post-merger integration project that combined two multi-billion dollar businesses into one. The two companies merged both came from the retail sector. However, while one focused on food retail, the other sold non-perishable products such as consumer electronics. Also, retail channels served differed significantly. While the food retailer focused on brick-and-mortar retail stores, the other has been mainly active in the online and catalogue business. Therefore, much of the integration process focused on combining categories and channels in order to provide a coherent assortment, served via the right channels.

The work stream at hand pursued the task to determine the cost to serve per category and channel for the non-food retail business. To streamline the business, the management wanted to know the actual costs associated with providing a product of a specific category via a particular channel to the end customer. The task involved identifying relevant costs and breaking them down across categories and channels. Given thousands of cost centres across many levels of the business (management, operational, delivery, …), this turned out to be a cumbersome exercise. Subsequently, the cost to serve has been modelled for various scenarios that covered shifts in the market and operational changes, such as store closures or leveraging efficiencies. The outcomes of this scenario analysis will guide the company's category and channel strategies. They will dictate alterations to the core business operations in the future that depict the best response to expected market developments. Also, operational efficiencies will be optimised based on modelled changes. The target output was a set of detailed P&L statements across categories, channels and time that reflected the different scenarios assessed throughout the project. The scenarios reflect market developments and operational changes.

4.3.1 Data Sources

The nature of the project was rather untypical for the analytics team to work on. The core ingredient was a quantitative and extensive set of financial data that specified costs and revenues from operations across many dimensions. They were provided on a daily basis per category, cost centre, channel, store, delivery type and per line of the profit and loss statement on a granular level. This database enabled the creation of historic and as-is P&L statements across the dimensions desired.

These historic and as-is statements served as the building block for all further analyses. They were extrapolated into the future to reflect the result of scenarios modelled. Most additional inputs, however, were of more qualitative nature. Firstly, market forecasts were used to build the "base scenario" for the future. Additionally, many semi-quantitative inputs were sourced from across the business. A lot of analyses had already been conducted but never centralised or put together in any way. In order not to duplicate efforts, the project at hand relied on these outputs, which were incorporated into the model in a mostly simplified format. Many other inputs were based on interviews with stakeholders across the business, reflecting best guesses or experience-based values. The qualitative nature of many of these sources were not optimal. However, the lack of relevant data forced the team to adopt a hypothesis-based approach to the project.

4.3.2 Analyses Performed

The analyses performed during the project focused on two main parts: the forecasting of as-is and historic P&L numbers and the modelling of scenarios to reflect potential future changes in the operating model or other economics.

4.3.2.1 Forecasting Methodology

The entire project has been built around the base scenario that extrapolates historic and as-is P&L statements five years into the future. The forecasting approach is based on historic developments, as well on a coherent market forecast that has been put together by ABC. The data provided by the client included historic values for each item of the P&L. These were aggregated on a monthly basis and summarised per category and channel. Subsequently, the figures have been forecasted based on a dual methodology.

Firstly, a few months of data were missing to complete the most recent financial year. In order to complete these, two factors have been considered: the change versus the previous year and the seasonal variation within the year. For each line of the P&L, these values have been determined. A rolling 4-months average of the most recent months of the current financial year has been divided by the corresponding time period of the previous year in order to construct a relative performance indicator for the current year. The rolling averages limit the impact of random behaviour in the previous or current year data. This indicator captures the performance delta in-between the financial years. An estimation for the current year's missing value has been made by multiplying the relative performance indicator of the current year by the previous' year absolute value. This methodology has been applied in order to complete the missing data points for the current financial year.

Thereafter, the forecasting methodology could be simplified. ABC put a lot of effort into the construction of market forecasts of the retail sector by category and channel. These have been adjusted for inflation and were subsequently used to forecast the data for the years ahead. The market forecasts translated directly into the growth of sales. Other P&L lines behaved differently. For anything above gross margin, the share of sales has been held constant. I.e. gross margin did not change in relative terms over time for the base case. Most of variable costs were also assumed to grow with sales. However, line-specific cost inflation rates were applied in addition to the market growth rates. For example, wages were expected to rise with a rate faster than sales. Semi-variable and fixed costs were held constant as a total and only changed according to line-specific inflation rates. The semi-variable and fixed costs have been re-distributed across categories and channels to reflect the shift in sales volumes. This has been done on a sales volume basis causing costs to shift across category-channel combinations but to stay constant on aggregate.

4.3.2.2 Scenario Modelling

This forecast of the P&L depicted the building block of the project. It was used as the basis for any scenario modelled subsequently. The additional inputs, namely the specifications of scenario changes and the scenario-based assumptions, were hard to collect and aggregate. Within the organization, stakeholders first could not agree on what to model and subsequently struggled to verify the assumptions underlying the agreed-upon scenario changes and impacts. In the end, four scenarios have been modelled throughout the course of the project. They were assessed by calculating incremental P&L line effects per channel and category. Using these incremental effects, resulting P&Ls could be calculated by combining them with the base P&L. The first assumed a heavy curation of the range offered by the retailer, the second modelled changes to the store portfolio, the third determined the impacts of optimising the 1-man delivery fleet and the fourth modelled the same for 2-man delivery economics.

The first scenario, reflecting the expected impacts of a heavily curated range, was motivated by the fact that the client sold products across a very wide and deep range. Many of the SKUs in stock had very little turnover, thus creating disproportionally high sourcing, storage and logistics costs. While a smaller range would necessarily have a negative impact on sales, reducing the range would also increase availability and immediacy, which are two service dimensions highly valued by the customer. The service dimensions would improve as more stock could be held for the remaining SKUs. The improved service could offset the negative sales impact created by fewer SKUs in stock. Also, not all sales generated by these SKUs would be lost because some customers would simply buy alternative products. Furthermore, a smaller range would streamline the logistics and thereby effectively reduce costs. The scenario required a set of key inputs. Firstly, an understanding of which SKUs should be dropped was required. These were taken from the sales "tail" of SKUs per category. I.e. by taking out the slowest turning SKUs per category but retaining those required to express range expertise. Secondly, the sales impact from the smaller range needed to be derived and compared to the uplift expected from higher service levels. Also, estimations of changes in supply chain and store costs were required. All of these effects needed to be traded off against each other and were balanced out in order to maximize the delta between benefits and costs. A smaller range would reposition the client with a clear proposition promising a curated product portfolio that offers sufficient choice but no overwhelming floods of "space holder SKUs".

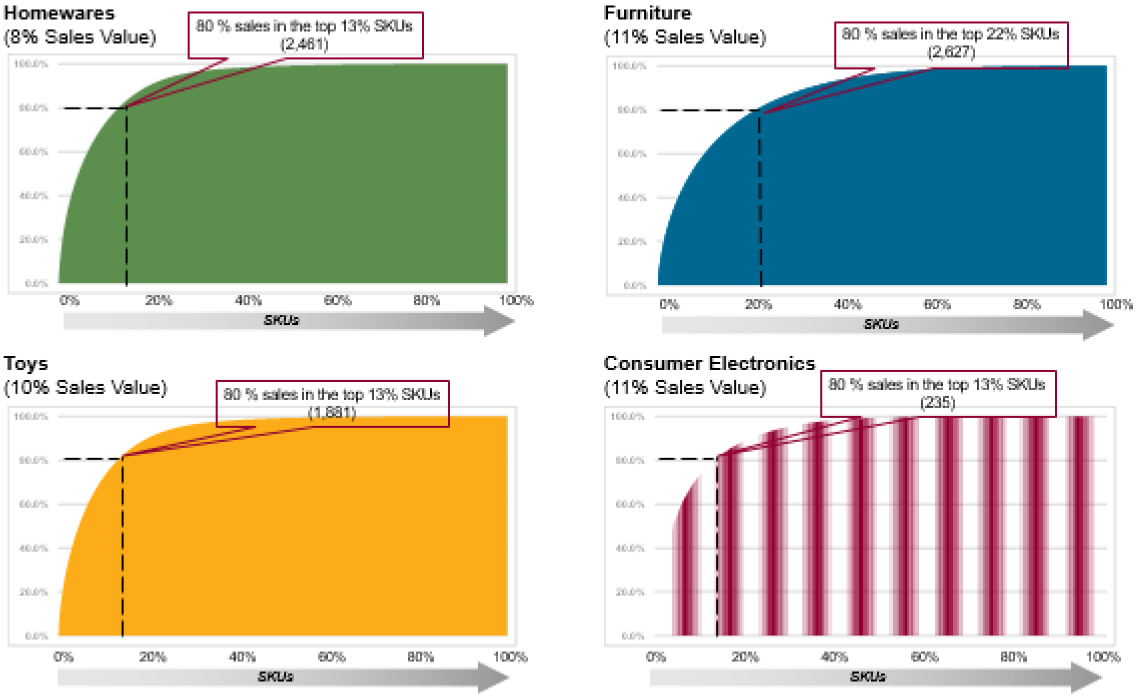

Figure 12: Sales Distribution per SKU

The second scenario modelled adaptations to the store portfolio. It was driven by the hypothesis that the brick-and-mortar store channel is losing relevance and too costly to maintain. Also, collection points for online orders could be incorporated into the stores of the grocery retailer, providing part of the store benefits to end customers. Therefore, many stores should be closed. The scenario assumed that only stores would be retained, that currently yield exceptionally high profits. Also, stores would not be closed in case of no near-by option to create a collection point. While some of the store sales would be lost in case of closure, others transfer to close-by stores or the new collection points. A store-related side model has been created to determine which stores to close, how many sales would be lost and how many costs would be saved due to the closures. Store-based P&Ls by channel and category helped a lot to determine the impacts.

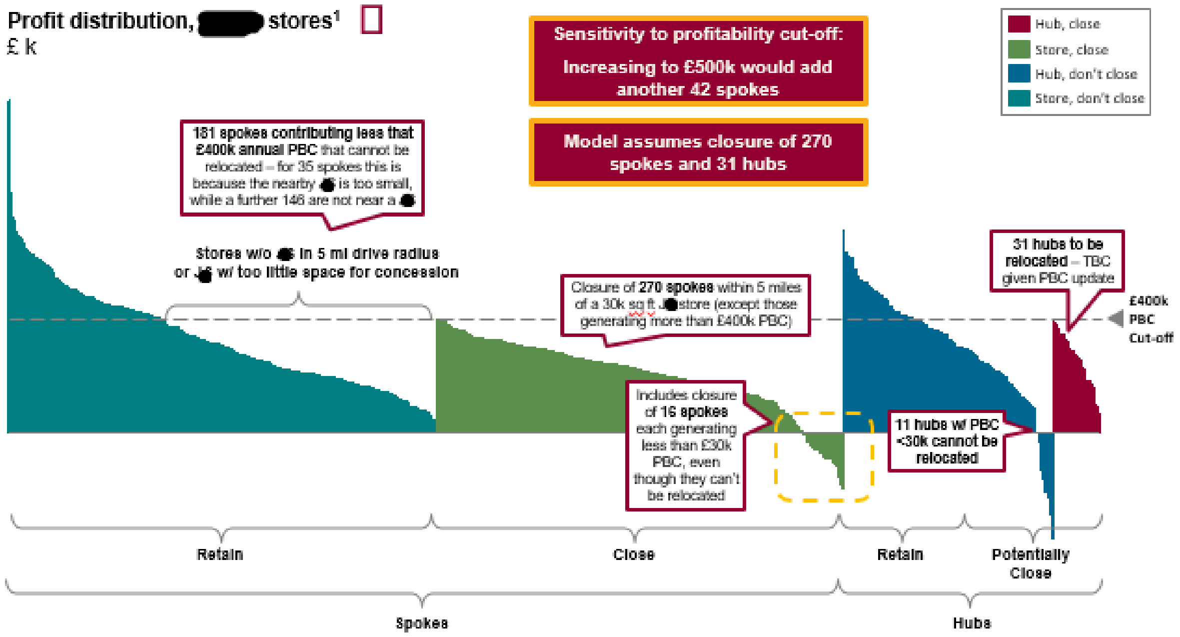

Figure 13: Distribution of Store Profits

The third scenario determined the effects of eliminating inefficiencies in the 1-man delivery economics. Headroom for efficiency had been detected in terms of drop density. Variable delivery costs are heavily driven by the proximity of delivery points from one another. If the trucks have to cover smaller distances while still being utilised to their full potential, costs drop. Therefore, optimising 1-man delivery economics goes hand in hand with maximizing delivery volumes handled by the fleet. This could be achieved by reducing delivery options offered to the customers, causing volumes to increase for the remaining delivery channels. Also, by altering the logistics network, volumes could be bundled ahead of the last mile. For example, fewer regional distribution centres could cause truck utilisation to increase. On the customer service side, these changes would positively impact perceived availability because the available delivery options would all be possible and quicker at any time. This increased service level may increase revenues.

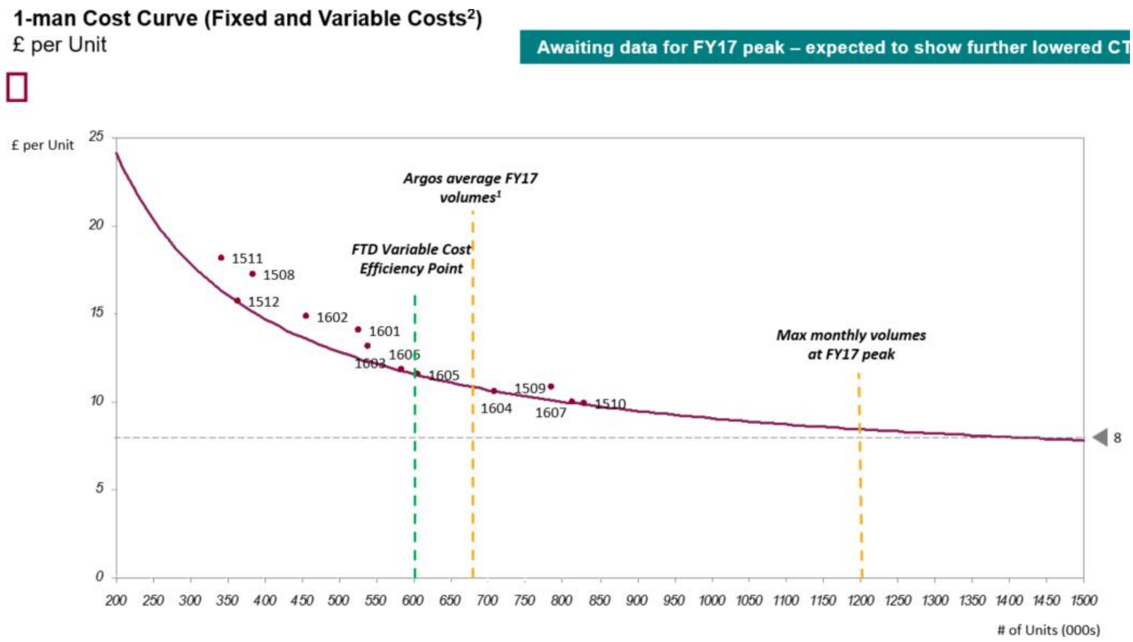

Figure 14: Cost Curve for 1-man Delivery

The fourth and final scenario aimed at exploiting efficiency improvement potentials for the 2-man delivery network. In case of 2-man handling, inefficiencies were mainly caused by insufficient volumes put through the network. Fixed costs were simply spread across very few deliveries. Therefore, 2-man sales would need a boost in order to reach an efficient cost per unit. Additionally, the network could be used to provide third party delivery services to max out its capacity. The scenario evaluated the required volumes, how they could be achieved and how costs figures would respond to the changes.

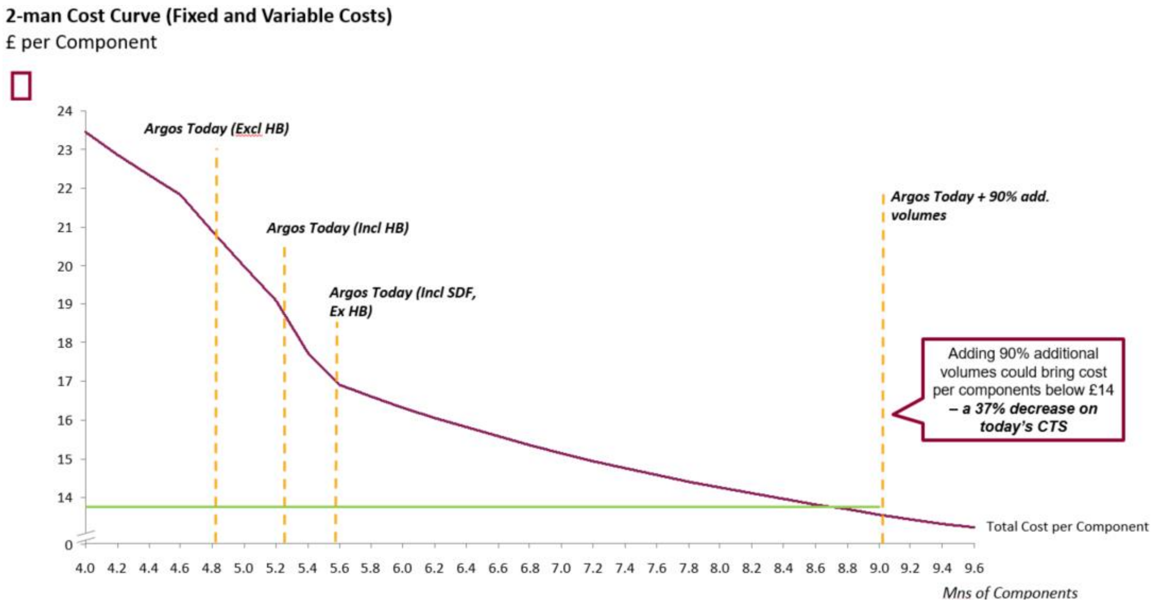

Figure 15: Cost Curve for 2-man Delivery

These four scenarios were considered most promising by the relevant stakeholders across the business. They were modelled over a 5-year time period, assuming that all changes would take effect immediately. For all scenarios, the incremental changes to the lines of the P&L were modelled for the current financial year, ignoring the transformation process. This procedure results in end-state P&Ls for the current financial year, assuming scenarios could be implemented right away. Combining these incremental effects with the base scenario resulted in the scenario-specific P&Ls. These were forecasted using the same methodology described before. Besides the four main scenarios, different combinations of the scenario effects were considered. Combining scenarios required a careful assessment of inter-correlations between the different effects to minimize double counting or neglecting effects. Finally, in order to evaluate the feasibility of the scenarios, the team determined the costs associated with the transformation to the end-state scenarios. These were traded off against the scenario benefits.

4.3.3 Project Takeaways

The project at hand lasted much longer than the others. Also, many tasks were performed at client site and there was a frequent personal interaction with the stakeholders involved. Hence, the project's mechanics differed significantly from prior projects. The project demanded an efficient time management in order to deliver results on time. Instead of constantly being able to focus on data-related tasks, client meetings and calls took up large parts of the days. Furthermore, there were many qualitative inputs provided that needed to be included in the model. This changed the modelling approach because in many cases the qualitative information had to be incorporated in a pragmatic manner. This limited the degree to which the project was truly driven by data.

Working with a large corporation unveiled many organizational inefficiencies. The client struggled to meet requirements on a consulting timeline as stakeholders were busy, on holiday or simply slow. Decisions had to be made in accordance with all stakeholders. Keeping everyone informed and getting everyone to agree to the same thing was tough. One could feel that the stakeholders did not only act in the interest within the organization, but also "played important" and put their own interest first- for example to maximize their own powers and responsibilities. A manager on the team concluded that many stakeholders cause many problems.

Besides the organizational difficulties, the approach to handling data and modelling was far from being purely analytical. The combination of quantitative data with qualitative information forced the team into pragmatic shortcuts and approximative approaches to data handling. This attitude towards modelling raised doubt whether an analytical approach made sense at all. In addition, much of the work was heavily hypothesis-led. The partners supervising the project had their own ideas of what the project output should look like. In some cases, this resulted in a very "goal-oriented" work attitude that involved adjusting the methodology for the output to match the hypotheses. This further reduced the analytical credibility of the model.

The core model of the project has been built and executed in Microsoft Excel. Unsurprisingly, the model turned out very bulky and time-inefficient. Excel simply has not been designed to process substantial amounts of data. A lot of time has been invested into fixing up the model and keeping it somewhat performant. Calculation runs took up to an hour despite comparably small datasets. The file size of the core model quickly exceeded 100 megabytes, which caused opening and saving the file to take a while.

With respect to personal working behaviour, the project was a fitting example for why it is necessary to constantly sense-check analyses. The numbers popping out of the model need to make sense and must match other sources. In case numbers do not add up, troubleshooting may be cumbersome and time-intensive. But it is essential for others to gain trust in the analysis and to believe the output of the models. Otherwise, if results are heavily off, other team members or stakeholders will doubt the model and the analysts' skills, making future interaction even harder.

On the people side, handling (senior) team members and client stakeholders correctly has proven to be important. In case of internal team managers and partners, one must defend the own position. One needs to push back on irrational tasks that would cost disproportionally much time. Also, if communicated in an adequate manner, senior team members value the opinion and view of more junior employees. However, it's important to argue rationally and in a structured way to be heard. Last but not least, clients and internal senior team members have absolutely no expertise in handling data. Therefore, they underestimate some tasks and ask for analyses that don't make much sense when trading off time invested against expected outputs. A data analyst should actively position himself as the expert, allowing him to guide data-related discussions. Doing so enables him to avoid irrational tasks and to share relevant expertise.

5. REFLECTION ON INTERNSHIP EXPERIENCE

The 6-months internship for the analytics team of ABC Strategy Consultants in London (UK) has been a valuable experience from many perspectives. Firstly, working hands-on in a non-academic setting contributed greatly to the improvement of technical skills. This is true for both, finding creative approaches to problem solving and actual programming skills, allowing for an implementation of the approaches. Furthermore, the internship provided valuable guidelines for future career decisions. In many ways, the 6-months depicted an extreme working environment, which was very useful to find out what's really important in a job. Of course, this importance is highly subjective. Most importantly, the internship allowed for an in-depth assessment of how analytics can be applied and implemented in the context of strategy consulting.

5.1 Value of Analytics to Strategy Consulting

The value provided by analytics in the context of strategy consulting is hard to assess, context-specific and depends on the specific project settings in many ways. However, the 6-months internship experience enables a careful evaluation of the value created by analytics as a part of the different projects worked on. This evaluation can be used as a basis to derive some generic hypotheses about analytics in strategy consulting, its opportunities, its threats and other related topics.

Generally speaking, the application of analytics to strategy consulting creates both, opportunities and problems. While the extraction of information from data certainly creates value and enables new types of projects, non-technical audiences and tight timelines cause potentials for conflicts. Therefore, it is essential to define how and what analytics should contribute to strategy projects. In order to do so, one needs to understand to what extent analytics creates value for strategy consulting and what the limits to the value created are. This trade-off has a range of implications on how an analytics team of a strategy consultancy should be structured.

5.1.1 Value Added by Applying Analytics to Strategy Consulting

Applying analytics to strategy consulting projects yields enormous benefits and creates a lot of value. The value is created across three core areas of opportunity: 1) the ability to process large datasets that were previously not accessible using Microsoft Access or Excel, 2) the opportunities for additional analysis to be performed using advanced methodologies that had not been implemented before and 3) being able to work on additional projects that are enabled by analytical techniques.

The ability to access and to work with much larger datasets is a huge advantage in strategy consulting. Without the ability to load entire databases into memory and to dice and slice them as required, consultants rely heavily on the client to provide aggregated datasets that are of an appropriate size to access the with Microsoft Office products. In the case of transactional data on line item basis, for example, this is a huge problem. Therefore, the analytics capabilities reduce the reliance on client-side team members. Clients' employees typically deliver outputs much slower than the consulting side does- partially because they actually stick to human working hours. Consequently, reducing the reliance on client outputs directly translates into the ability to work more effectively and fluently. Moreover, the analytics team is able to continuously provide new cuts of the data, which may not have been apparent in advance. Data can also be crunched in much more detail when its most granular level is available. Adequate tools for analysing large amounts of data yield another advantage, namely speed. Using Excel to calculate complex transformations of the data takes a large amount of time due to the cell-logic it applies. Tools such as R or SQL process data much more efficiently, which saves time. Particularly if the calculations must be carried out multiple times.

While the tools used allow for the analysis of larger amounts of data, the new methodologies that can be applied create additional sources of value. Typically, methodologies applied in strategy consulting are very basic. As consultants come from diverse backgrounds (including, for example, history and literature students), statistical knowledge is scarce and elaborate methodologies are mostly being avoided. In many cases, even basic regression models are not being understood and thus not being used. This lack of knowledge and skill extends from the bottom of the hierarchy to the very top. Even if a consultant is able to build a regression model correctly, his manager may be reluctant to use it as he cannot guarantee that it's correct because he simply does not have the required skills. The analytics team extends the methodological skills far beyond regressive techniques, being able to apply basket analysis, clustering and machine learning algorithms. Besides possessing the knowledge required, the team also holds an "expert status" with respect to statistics, numbers, data and anything related. Due to this status, managers and other high-tier colleagues become much more comfortable relying on and using the output provided by the team. They feel comfortable assuming that the expert is right despite not understanding the analysis as they know that they will be held less accountable for any errors in the output. Therefore, new and more advanced techniques and methodologies are being applied by the analytics team. These techniques may increase predictive power, reveal additional patterns or characteristics, or even produce entirely new outputs that were previously not being used but that are very helpful (for example simple correlation matrices). All of these effects effectively create value.

Finally, the analytics team also delivers value by enabling the work on new types of projects. Some strategic projects require specific techniques to "crack the case". For example, exploring opportunities for cross selling products requires basket analyses on a per-line-item level. "Regular" consultants lack the methodological ability to apply these techniques. Also, they simply aren't equipped with the right tools. The task would not be possible to perform using basic Microsoft Office applications. Therefore, a third source of value is the pool of projects that require advanced analytical techniques.

5.1.2 Analytical vs More Pragmatic Approaches

In strategy consulting, any consultant always trades off accuracy against speed. This trade-off lies at the root of consulting. While project outcomes need to be accurate, they also need to be delivered quickly. Therefore, consultants aim for the best output possible, given their time constraint. This is true for both, "regular" and analytics consultants. In case of the first aim, the accuracy or correctness of the analyses, both new analytics tools and more advanced techniques act in favour of the goal to be as accurate and correct as possible. This is true because more data can be crunched using more efficient tools in a more sophisticated way. Regarding the aim for speed, however, the analytics effect goes into both directions. While the new tools increase speed by calculating more efficiently, more complex methodologies decrease speed as they need to be calibrated more carefully.

Analytics consultants must trade off an additional constraint, namely understandability. Understandability is key in consulting, but not relevant to "regular" consultants as techniques applied by them are basic enough for everyone to understand them. In the case of the analytics team, however, complexity is increased by more advanced techniques and by tools that are less known. This increase in complexity causes the understandability of any analysis to decrease.

All in all, the analytics consultant must produce the most correct output given time constraints. However, any methodologies applied need to be confirmed with the more senior members of the team. They are the ones to judge if the approach is understandable and if it can be used for problem solving. This is particularly important when presenting the work to the client as they typically want to understand what has been done.

5.1.3 Marginal Impact of the Level of Technicality

The 3-sided trade-off between correctness, time and understandability already sets limits to the level of technicality that an analysis can rely on in order to be performed quickly and to be understood well. However, another consideration must be taken into account when selecting a methodology: the marginal impact of the level of technicality.

Historically, analyses carried out in strategy consulting were simple and pragmatic. However, they were sufficient to get the job done and to deliver a solution to the project. Increasing the level of technicality does deliver additional value at first. As pointed out before, speed, correctness and predictive powers may increase significantly when moving from very basic analyses to slightly more technical and elaborate analyses. Increasing the technicality from zero to a low level will improve results significantly. Nevertheless, the additional benefits from more technicality will drop significantly at a certain point. When all relevant data has been included into the analysis and a basic but correct statistical approach has been applied to derive a solution, any additional improvements to the output may not change the results of the project. While a better or more fine-tuned model may most certainly be achievable, the impact of the improvement on the project outcome may be negligible or non-existent.

In order to use optimise the use of analytical capabilities, the right degree of technicality has to be applied. The level applied must still improve the result significantly compared to a lower level of technicality. If technicality was plotted on the x-axis of an xy-coordinate system and value derived from the analysis was put on the y-axis, one would want to find the point of the curve for which the slope lies above a certain benchmark. The value curve is characterized by diminishing marginal returns on technicality.

5.1.4 Developing Analytical Models on Short Timelines

In a previous section, time has already been introduced as a limiting factor for the value created from analytics. In strategy consulting, fees are high and timelines are short. Projects may only be two or three weeks long on the low end. Typical projects are four to seven weeks long.

A strategy consulting project usually starts with a two- to four-week long analysis phase, which is used for understanding the problem, collecting all relevant data and information and analysing it. The exact structure of the phase is very project-dependent. The second phase lasts for one to two weeks and is spent on iterations. Intermediate results are being presented to and validated with the client. Additional analysis may be performed or existing ones may be improved. Finally, the one-week presentation phase finalizes the project.

Such short timelines per phase leave little room for a data driven analysis process. Identifying the relevant data, gaining access to it and getting it ready for analysis may already take two to five weeks, depending on the project and the client. Therefore, it is necessary to get a head start with the data-related tasks before the strategy side of the project kicks off. Ideally, the analytics team is able to start those two to five weeks ahead of schedule. The first one to three weeks of this pre-phase is used for data collection. Identifying the relevant data and receiving it from the client or getting access from their system may take a while. In many cases, data is spread across the client’s system and across many stakeholders, which makes an aggregated data request impossible. Plenty of time must therefore be reserved for data collection. Subsequently, the data collected must be cleaned within one or two weeks. The data needs to make sense and must be saved in a sensible way that ensures good access later on. Also, different sources of data may need to be integrated into a single database in order to improve usability and speed at later stages.

All in all, developing analytical models on short timelines is subject to the three constraints of correctness, time and understandability introduced earlier. Additionally, in order to ensure a smooth execution of the project and to limit timeline conflicts, analytics team members should get a head start in order to collect, to clean and to get familiar with the data required for the project.

5.2 NON-TECHNICAL AUDIENCES

Besides the limitations imposed by short timelines and diminishing marginal returns of the level of technicality on value derived, non-technical audiences are an additional hurdle when performing analytical tasks in the context of strategy consulting. The lack of technical expertise encountered when working with different stakeholders creates challenges throughout the project work. This is true in external, as well as in internal environments. In most cases, colleagues and clients that are not part of the analytics team itself do not have a background in statistics or data analysis. Their experience is usually limited to small datasets, simple models and Microsoft Excel. As a consequence, the members of the analytics team must actively manage these potentials for conflict and must cope with additional responsibilities on a theoretical and practical level.

5.2.1 Conflicts due to Different Levels of Technical Expertise

The first source for conflict identified stems from within the core project team. In the case of traditional strategy consulting, the managers carry all responsibility related to estimating timelines and to ensuring that deadlines are met. The skills to do so are based on having worked as a consultant for years and knowing how long different tasks will take. These estimations are mostly accurate as the manager performed the very same tasks before. Introducing data analytics to strategy consulting projects adds a component to the workstreams that is new to managers. They lack experience with respect to how long different tasks will take and have to completely rely on the consultants' estimation. Those, as many tasks are new to the consultants as well, are often inaccurate. Therefore, meeting deadlines becomes a major challenge and working hours have the tendency to become very long. As this conflict is present within the core team, it carries through for the entire project duration. It's a constant source of frustration for both, the manager and the data analyst, because the manager receives inaccurate information without knowing any better. At the same time, the analytics consultant is being inadequately managed. The responsibility for estimating how long a task will take should be partially held by the manager.

In order to deal with this set-up, actions by both, manager and consultant are required. Managers must try to understand the methodology being used as well as possible. Also, they need to be aware of the more cumbersome data management process associated with collecting, cleaning and analysing the data. At the same time, the consultants have to ensure transparency. They need to flag when they are behind with their work immediately in order to empower the manager to re-prioritize. Furthermore, they must be as realistic as possible with their estimations of working times. These must be communicated clearly.

The second source of conflict potential occurs on a more senior level when dealing with the partners and directors of the consultancy that sold the project. Traditionally, strategy consulting work is heavily hypotheses-driven. Partners tend to have a "solution" to the project in mind before it even starts. This "solution", however, is simply a hypothesis and must be supported with arguments or have to be rejected. Partners, however, tend to really like their hypotheses. It takes a lot of evidence to convince them that they are wrong while very limited proof is sufficient for them to think they are right. Partners often try to make data and analyses fit their hypothesis. Conflicts arise when a correctly performed analysis doesn't match the hypothesis. In those cases, partners argue that the methodology should be re-designed to create outputs that match their opinions. As this process is far from data-driven, a typical analytics consultant will not like this approach to problem solving and arguments pop up quickly. This can only be avoided by either arguing well in favour of the analysis or by accepting that the results won't be as analytics-based as desired.

The third and last problem source is the hardest to manage as it's the client. Clients may dislike analysis for many reasons and therefore demand adjustments or simply may not believe the results. This may occur if the client is unable to understand the methodology applied or if the results do not meet expectations. To counter-act, it's essential to gain the client's trust. Clients will build trust if analyses outputs are never wrong. One must always sense-check results before presenting them to the client. If an answer is too obviously wrong, clients will doubt the analyst's common sense and remain sceptical later on. Also, it's important to present the analysis and its outputs in an understandable way. If the client understands what has been done, he is more likely to believe it.

5.2.2 Obligation to Educate (non-technical) Senior Staff

As explained in many of the previous sections, senior staff's lack of analytics expertise is the root of many problems. Therefore, closing this knowledge gap provides benefits to both, the senior staff members themselves and to the analytics professionals. However, senior staff consists of three different levels of stakeholders: clients, partners and project managers. It's nearly impossible to educate clients as they are part of non-dynamic organisations and mostly prone to learning. Also, they expect the consultants to "get the job done" without them having to engage too much.

The partners of the consultancy are also hard to educate. They are very senior and already shaped the picture of "their world", which analytics is simply not a part of. Therefore, they are also not very keen on learning and understanding the potentials of analytics. Of course, exceptions exist. Some partners have faith in analytics and try to unlock its potential. However, the limited size of this fraction of partners becomes apparent when realizing that all analytics-related projects are being sold by a hand full of partners. Partners not having an understanding of analytics and what can be done with it has huge effects on the scale of analytics within the consultancy. A partner who has no idea of what type of projects can be tackled using the analytics team will be unable to sell analytics-related projects. A salesman has to understand the product being sold and sales activities are a large part of the partners' job.

The final group of senior stakeholders is much easier to educate. Managers are still in the middle of their career and keen to learn anything that improves their chances to rise within the company. Understanding analytics will enable the managers to improve the management of analytics-related projects and thereby improve their skill set. An improved skill set translates into a competitive advantage compared to other managers. Also, educating managers is the obvious starting point when building analytics expertise within the company. They depict the next level in the hierarchy and work closely with the analytics staff. Also, clients and partners are far more likely to trust a methodology or analysis if the manager understands and backs it. During the time of the internship, the head of analytics at ABC started to provide training sessions to managers. The training has been designed to enable the manager to understand what makes analytics work different from traditional consulting work. It covers shifts in timelines, differences in tools used and much more. The managers who received the training reacted very positively and were able to implement the information well, resulting in a lot of pressure being relieved from the analytics staff.

5.2.3 Communicating Quantitative Outputs to Clients

The presentation of project results to clients is an essential part of any strategy consulting project. Traditional work has been much easier to understand as presentations were straight forward and detailed questions could be answered easily. The application of analytics, however, creates more abstract results and therefore potentials for more complicated presentations and questions. Three key points are important when presenting such quantitative results. Firstly, results must be presented at an output-only level. Diving into details or methodological issues would create potentials for confusion. Secondly, assumptions must be communicated clearly. The assumptions underlying an analysis drive results heavily, which is why they must be known to anyone involved. Finally, the visualisation of results must be simple, easy to grasp and as minimalistic a as possible. If these points are considered, clients receive all the information required to develop an understanding without confusing them.

5.3 Developing and Retaining a Data Science Team in Strategy Consulting

Many problems related to developing a data analytics team within strategy consulting are apparent within the analytics team at ABC. A lot of the pain points have already been touched upon in previous sections and will only be revisited briefly. High churn within the team is a huge problem as leaving team members translate directly into a loss of capabilities. Therefore, keeping churn low should be a key objective. At the moment, this is not the case. First of all, the long hours and tight timelines that are typical for strategy consulting are a problem to many of the analytics team members. The problem is being amplified by the more cumbersome analysis process within the analytics context. Secondly, the stressful environment resulting from short-term project work is not the norm for technical jobs. Therefore, the environment does not appear tempting to most of the people that are qualified for the job. This leads to problem three, which is the simple fact that other jobs appear more tempting due to similar pay but fewer hours. Furthermore, the large competition for data analytics talent creates an environment in which employees frequently receive new and improved offers. If employees have many options to leave the company, they may eventually do so.

Another problem is the lack of an established career trajectory for the members of the analytics team. While the technical expertise is much needed at the consultant-level of the company, it's obsolete for managing positions. Of course, as argued above, some basic knowledge of analytics will improve project management and will enable selling analytics projects later on. But the technical focus of the skillset becomes less of an advantage as a manager and technical employees may simply be outperformed by their non-analytics peers that were able to focus on developing the required management and slide-related skills while working as a regular consultant. Finally, the analytics team struggles to build a centralized knowledge base that conserves expertise from previous projects. Not being able to replicate previous efforts in a time-saving manner is a huge drawback and continuously forces analytics team members to develop new methodologies. Of course, developing a methodology from scratch takes much more time and efforts than simply re-using an existing methodology.

As a result of all these problems, it's hard to attract qualified analytics talent that is willing to work hard and long. Also, talent that joins the company is expensive as head hunters need to be paid and it leaves quickly as their skills are in high demand. The resulting shortage of analytics team members further amplifies the pain points. While regular consultants are often being given "unstaffed weeks" after tough projects to recover, analytics consultants are immediately being re-staffed onto new projects, making them more likely to leave.

Besides these difficulties to attract and retain talent, working as a data analytics consultant yields the great advantage that it allows a technical data-focused employee to dive into the business world. Some business thinking and skills complement a technical skillset perfectly. The job provides a bigger picture to mostly detail-oriented talents. When building a data analytics team, one should capitalize on this opportunity and effectively use it to appear more attractive.

5.4 Analytics as a "Support Function" vs "Core Capability"

Earlier in this report, projects have been split into being solely supported by analytics versus being enabled by analytics. Projects that merely require some analytics support to work with large datasets are much more straight forward and only require the skills to use tools that are able to process substantial amounts of data. These projects are not challenging on a methodological level or require any relevant theoretical knowledge. As most people who join a strategy consultancy are inexperienced university graduates, they are keen on applying what they learned and developing additional skills. Consulting is often chosen as a starting point for (one of) two reasons: learning and benefits. Most people who join a consultancy want to learn as much as possible in a short period of time. They demand a steep learning curve in order to remain motivated and to work well. Consulting is directly related to learning. When simply supporting a strategy project, however, analytics consultants are not being challenged on a methodological or theoretical level. Therefore, they miss out on any learning opportunities.

The problem with support projects described above fosters the discussion whether analytics should be limited to being a supporting function or if it should be developed as a core capability of strategy consultancies. Young talent capable of working on analytics-enabled projects cannot be retained if most their work consists of support. Therefore, there is no compromise between setting up analytics as a simple support function versus setting it up as a core capability. It has to be one or the other. Setting up the team as a support function would translate into hiring individuals that can help traditional consultants with processing large datasets. I.e. they would not possess elaborate statistical skills. As a result, analytics-enabled projects could no longer be sold, even if demanded by the client. This may create a shortage of relevant skills and may empower competitors to gain a competitive advantage.

On the other hand, setting up analytics as a core capability requires the relevant talent, as well as plenty of analytics-enabled projects being sold. While the right talent enables working on more difficult problem statements, too much support work should be avoided. Too many basic tasks cause the talent to be utilised inadequately. Instead the team must be challenged continuously, which can be ensured by selling plenty of relevant projects that require elaborate statistical methodologies.

All in all, the questions whether analytics should act as a support function or as a core capability to a strategy consultancy must be answered from a top-level, strategic perspective. While the support function could fulfil many of the minimum requirements, the consultancy would lack a skill that many competitors possess. Therefore, despite currently being sufficient, the support function could create a lack of skill in the long run. On the other hand, developing analytics as a core capability requires a process of organizational change that involves educating non-technical employees and moving away from hypotheses-driven methodologies.

6. CONCLUSION

The 6-months internship has been a great opportunity from many perspectives. Most importantly, it allowed the author to apply theoretical knowledge of analytics in practice. University projects quickly appear like a piece of cake when real life problems are being tackled and must be solved using patchy data. The time at ABC provided great insights into strategy consulting, as well as into the company's clients. Therefore, additional insights into the corporate world were accessible. Reflecting on the internship experience throughout the course of writing this report has been valuable in order to re-visit the different facets of the internship and in order to develop an opinion with respect to analytics in strategy consulting. The report unveiled many areas with opportunities for improvement. Furthermore, looking back at the time of the internship while writing this extensive report empowered the author to draw conclusions with respect to his personal and professional development.

6.1 Most Essential Areas of Improvement for Analytics in Strategy Consulting

Incorporating a technical function into a qualitatively-driven field like strategy consulting is a tough task. It requires a deep understanding of both, technical and data analytics processes, as well as styles of working. Therefore, it's obvious that the process takes time and cannot start off as a well-working model. Realizing the potential value that can be created by incorporating analytics into strategy consulting is only the first step of the journey. Initiating the change is the second. ABC has already managed to move ahead on this path and possesses a strong team. However, the company has not yet reached the end of the ride, which is why some areas for improvement remain.

Firstly, much of the pressure that is put on the analytics consultants must be taken off. This can be done by setting up projects adequately and easing timelines. Secondly, the analytics talent must be challenged sufficiently by having them work on demanding analytics-enabled projects. Also, many problems can be solved by educating senior staff. An additional knowledge base would facilitate the possibility to re-use methodologies. Finally, once these pain points have been resolved, ABC could start hiring aggressively in order to employ a sufficient number of analytics consultants that can cope with the large work load.

6.2 Impact of Internship on Personal and Professional Development

The 6-months internship has been a great boost for the author's professional and personal development. The skillset and experience grew on multiple dimensions. Technical skills, interpersonal competencies and professional capabilities all got enhanced massively. On the technical side, particularly the familiarity with the data analytics toolkit improved a lot. Working with R and SQL on a daily basis helped to become "fluent" in these languages. Furthermore, one became much more acquainted with typical data warehouse setups by simply being introduced to some real-life examples. Also, developing methodologies became more intuitive over time.

With respect to interpersonal competencies, dealing with more senior and peer colleagues became more casual and relaxed. As it turns out, British people are amazing small-talkers. Even if they have absolutely no interest in a person, they still manage to find a common topic to talk about. This is a valuable skill to possess. Connecting on a personal level is the key to working together well on a professional level. A motivated workforce is also very important to ensure high productivity. Therefore, social events are a huge boost for productivity as they pet the ego and encourage employees to spend time together.

Professional skills also improved. While more senior team members should be respected, it's not wrong to push back in case of a disagreement. Many decisions are a matter of perspective and opinion. One should therefore always present the own opinion to allow other team members to take on another perspective. The importance of communicating clearly and proactively also became apparent. Project managers cannot take things into account if they don't have the relevant information in a timely manner. Therefore, keeping senior staff informed is key. This is also true for other team members. Often someone else already had a look at the very same topic or task that one is working on. Hence, checking in with other team members can be a great advantage. Usually someone will be able to help out. This may also be true for colleagues that are not part of the core project team. Besides efficient communication, a structured workflow is also important to stay on top of things. Having an overview of all to dos permits efficient time management and prioritization of tasks.

6.3 Final Remarks

All in all, the internship was a great opportunity and fostered the development and improvement of important skills. Consulting is a great way to start the career as it allows the employees to work for many companies, in different industries and on different problem statements in a very short period of time. Therefore, the learning curve is steep, which is great for young professionals. Analytics in consulting, however, could be optimised.

After the internship, the author received a good job offer from ABC Strategy Consultants. Nevertheless, he turned it down. Having worked in strategy consulting prior to the Master in Advanced Analytics and complementing this experience with the analytics-focused internship, the author already moved along the learning curve. While one learns a lot in the first 12-18 months of strategy consulting, the slope of the learning curve decreases over time. Therefore, working in strategy consulting becomes less tempting. The tough working hours and lack of personal freedom are additional factors that encouraged the author not to take the job. Instead, the author chose to fulfil his entrepreneurial aspirations. Along with 4 friends he founded a data analytics start-up in early 2017. The company personalizes online shops based on elaborate algorithms. It offers its cloud-based services to other businesses. Creating and growing this business demands both, the technical data analytics skills and the business skills acquired prior to the Masters in Advanced Analytics. Therefore, working on the project is challenging but highly rewarding at the same time.

7. APPENDIX

7.1 APPENDIX 1: REFERENCE LETTER

OC&C Strategy Consultants

DAVID ZDRAVKOVIC
HEAD OF ANALYTICS

david.zdravkovic@occstrategy.com

Universidade Nova de Lisboa
NOVA Information Management School
Campus de Campolide
1070-312 Lisboa
Portugal

28th of February 2017

Certificate of Employment & Reference Letter

Mr. Lukas Hendrik Fahr has been employed by OC&C Strategy Consultants Ltd. as a Data Analytics Consultant from the 1st of September 2016 until the 28th of February 2017.

In the course of his service, Lukas has been deployed across a range of analytically and data driven strategy projects. The clients served operate internationally and mostly within the retail, media and gastronomy sectors. During his time working for us, Lukas has played a key role in developing solutions and strategies for the following problem statements:

- Assessment of strategic opportunities and potential for operational optimisation for a well reputed UK department store on the basis of transactional data on line item level, including...
    - the identification of spending patterns by customers coming from different loyalty tiers or demographic backgrounds
    - the impact of promotions on spending patterns
    - the effect of different service models on basket size and composition
    - customers' cross-shopping propensity across departments and store levels
    - the assessment of drivers behind lapsed customers
    - the efficient deployment of labour across the retail space
    - the definition of strategic and operational recommendations

- Determination of store roll-out potential for a British gastronomy chain, based on...
    - the detailed assessment of performance drivers
    - profiling of high potential site locations
    - modelling of profit potential for UK retail catchments
    - the analysis of competitor proximity around existing sites vs potential sites

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OC&C Strategy Consultants

- Modelling of a multi-channel retailer's cost to serve across its different product categories and fulfilment channels, including...
    - the identification of the current costs to serve per fulfilment channel / product category combination
    - definition of scenarios involving significant changes to the retailer's operating model and quantitative inference of their impact on the channel and category specific costs to serve
    - alignment of organisational stakeholders to drive the required change in order to alter the operating model

- Construction of an internal database for location-based analyses

Lukas has been able to apply his excellent theoretical knowledge of statistics and analytics throughout his work. Furthermore, he documented his work carefully and ensured that it could be presented and/or re-used by other team members at any time.

Lukas has demonstrated excellent work ethic and was highly motivated throughout. He works with a high degree of commitment, very efficiently and keeps track of the overall picture that his work contributes to. His motivation was high at any time and the quality of his work did not suffer under high pressure.

Throughout his time with OC&C, Lukas showed a high willingness to learn and to develop his skills across all functions. He is a quick learner and has managed to master a series of software environments and tools and has applied them effectively to the tasks at hand.

Lukas has integrated well into project teams and has contributed enormously to the work. His pragmatic approach to problem solving was extremely helpful in developing new ways to tackling client problems and was recognised as such by the clients themselves. He has demonstrated solid communication skills and has been able to explain complex analyses in an articulate and understandable way to non-technical audiences.

We were delighted to have Lukas work with us during his internship and he has made a valuable contribution to our team. In particular, his solid technical expertise and his cooperative nature have made him a popular partner among colleagues and clients.

London, 28th of February 2017

David Zdravkovic
Head of Analytics, OC&C Strategy Consultants Ltd

7.2 APPENDIX 2: CURRICULUM VITAE

Lukas Hendrik Fahr
Hörder-Bach-Allee 9, 44263 Dortmund, Germany
Tel.: +49 173 960 5756, Email: lukasfahr@outlook.de, LinkedIn: linkedin.com/in/lukasfahr

Curriculum Vitae

Full name	**Lukas Hendrik Fahr**
Date of Birth	24.11.1992
Nationality	German

Academic Education

09/2015 - today **Universidade Nova de Lisboa (IMS), Lisbon, Portugal**
MSc Advanced Analytics (Data Analytics)
Studies of Data Analytics, Machine Learning, Data Mining and Data Warehousing
Cumulative GPA: 17.6/20.0

09/2011 - 08/2014 **Maastricht University (SBE), Maastricht, Netherlands**
BSc Economics and Business Economics
Specialization: "International Business Economics", Major: Finance
Cumulative GPA: 8.6/10.0

02/2014 - 08/2014 **Fundação Getulio Vargas (EESP), São Paulo, Brazil**
Exchange semester, BSc Economics and Business Economics
Cumulative GPA: 9.2/10.0

Professional Experience

05/2017 - today **brytes GmbH, Dortmund, Germany**
Co-Founder & Managing Director
- Development of a cloud-based B2B service that applies behavioural sciences and data analytics to enrich customer interactions within the e-commerce landscape
- Creation of a complex analytics-based product from scratch
- Further insights within the field of e-commerce from a technological perspective

07/2016 - today **usedful UG, Hamburg, Germany**
Co-Founder & Managing Director
- 2nd place at the NOVA Idea Competition, seed capital sponsored by the university
- Development of an online distribution channel (marketplace) for upcycling designers
- Accumulation of expertise within the e-commerce sector (KPIs, legal requirements, ..)
- Platform development & building of B2B business relationships via cold calls

09/2016 – 02/2017 **OC&C Strategy Consultants, London, United Kingdom**
Data Analytics Specialist
- Application of inferential, descriptive and predictive analytical techniques
- Interpretation of quantitative results and translation into business terms
- Assessment of strategic opportunities and potential for operational optimisation for a well reputed UK department store on the basis of transactional data on line item level
- Determination of store roll-out potential for a British gastronomy chain
- Modelling of a multi-channel retailer's cost to serve across products and channels

09/2014 – 02/2017 **OC&C Strategy Consultants GmbH, Düsseldorf, Germany**
Associate Consultant
- Long-term logistics strategy development for a leading German retail group
- Sales strategy definition for a major producer in the German construction market
- German venture capital market analysis and definition of policy framework
- European growth strategy development for a multinational caterer

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06/2013 - 08/2013 **OC&C Strategy Consultants GmbH, Hamburg, Germany**
Visiting Consultant
- Commercial due diligence for a large European publisher in online and print media
- Extended cross-selling model development for a prominent German multichannel retailer following an international acquisition in the online retail segment

07/2012 – 08/2012 **Berenberg Bank, Hamburg, Germany**
Summer Analyst (Economics Department, Trading Team & Private Banking)
- Market analysis and trend observation in economics department
- Customer consulting in private banking department
- Research for trading patterns and investment opportunities in trading department

03/2010 – 04/2010 **Volksbank Lübeck, Lübeck, Germany**
Intern (Private Banking)

01/2008 – 02/2008 **Sparkasse Holstein, Stockelsdorf, Germany**
Intern (Private Banking)

Extracurricular Activities and Awards

02/2016 – 06/2016 **Starters Academy, Universidade Nova de Lisboa**
Coaching for the creation and management of an entrepreneurial venture

08/2014 – today **Honour Society Beta Gamma Sigma (BGS)**
Recognition for excellent scholastic achievements

05/2013 – 01/2014 **SCOPE | Economics, *Supervisory Board Member***
Financial auditing and advisory of current board

09/2012 – 01/2014 **Sigma Investments (Investment Club)**
Micro and macro analyses of target markets and companies

05/2012 – 05/2013 **SCOPE | Economics, *Treasurer and External Relations Commissioner***
Financial budgeting and steering of external relations committee

Educational Background

08/2009 – 06/2011 **Gymnasium am Mühlenberg, Bad Schwartau, Germany**
Higher education entrance qualification, A-levels (Abitur)
Area of focus: Social sciences
Cumulative GPA: 1.5 (1, very good – 6, insufficient)

09/2008 – 06/2009 **Granite Bay High School, Granite Bay, United States of America**
Exchange program
Academic performance honoured with the Academic Merit Award
Cumulative GPA: 3.8/4.0

Additional Qualifications and Interests

Languages	**German**	native
	English	fluent
	Portuguese	conversational

IT Skills **R, SQL, SAS Enterprise Guide and Miner, Python, Visual Basics** and **MS Office**

Interests **Kayaking, Surfing, Scuba diving** and **HDR photography**

Lisbon, 23rd of June 2017