Customer Experience Management

Advanced Analytics for Voice of the Customer (VoC) Programmes

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Introduction

Many companies are today increasingly challenged to maintain customer satisfaction and loyalty and to improve the customer experience. While organisations have programmes to measure and manage customer experiences, major challenges are the multiple information sources and the huge amount of structured and unstructured data available.

Although most organisations conduct continuous customer satisfaction surveys, the ability to deliver real insight and to implement actions for customer experience improvements from basic survey data is limited.

The other big challenges in retaining and delighting customers, improving the customer experience and understanding how to best manage customer relationships are to move beyond the raw survey and customer transactional data and to understand the voice of the customer in context.

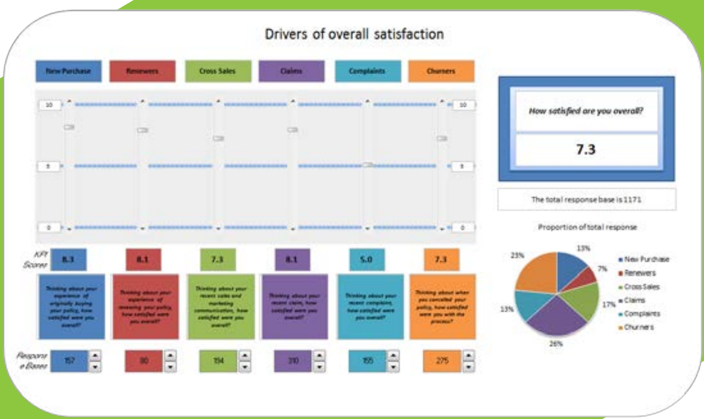
However, the efforts to integrate all streams of structured and unstructured data are simply not efficient and cost-effective without advanced analytics. Advanced analytical approaches, either on their own or in conjunction, can help companies put customer insights in context, identify areas for customer experience improvements and new products and services, and build sophisticated models to understand, predict and proactively manage customer relations and interactions, and therefore customer loyalty and profitability. The application of these advanced analytical techniques enables users to extract knowledge from data and to create predictive models for better decision making.

The following procedures of advanced analytics that companies can utilize to integrate into Voice of the Customer programmes to better understand customers are described in this white paper:

- Key Driver Analysis
- Modelling Analysis
- Insight Mining
- Forecasting / Target Setting
- Data Linkage
- Text Mining
- Segmentation
- Action Planning
- Social Media Integration

Driver analysis encompasses a number of statistical tools and has the aim of identifying the key issues that are driving overall customer satisfaction, customer loyalty or recommendation. This allows organisations to focus management schemes and issues that will elicit real results in terms of improved satisfaction and improved loyalty.

The traditional ‘quadrant’ style approach to drivers analysis doesn’t always fully explain the multitude of data in large customer satisfaction surveys. Therefore a range of data exploration and data modelling techniques are applied to offer a more engaging deliverable.



Many options are available to perform this task; however, the approach to the process will involve measuring the association between a set of predictors and an overall indicator of success or performance. Details of some, though not all, of the appropriate techniques are as follows:

The most common technique is regression analysis, with many different variants falling under this umbrella term. Commonly, regression models are made up of a number of predictor variables that are combined to predict a dependent or target variable (most commonly, overall satisfaction). Additionally, the regression model allows the user to gain an understanding of the importance of each of the key drivers. This analysis is designed to concentrate management activities on those issues that make the most difference.

Key Driver Analysis

Regression models can be based on a number of predictor variables. Alternatively, the predictor variables can be formed from factors/groups derived from a factor analysis or cluster analysis.

As regression analysis has some known limitations, in that models can be affected greatly by interactions between predictors, more progressive techniques for identifying the relative importance of predictors can be utilized. Relative Importance identifies the comparative worth of each predictor without the bias associated with some traditional regression techniques. The result is a more truthful set of measures that are proportional and scale for comparisons with equivalent analyses.

Further techniques that can be employed in key driver analysis are discriminant analysis and CHAID / decision trees. Discriminant analysis is an extension of regression techniques described above. Its primary objective is to form a linear combination of predictor variables that discriminate between previously defined groups e.g. satisfied customer vs. non-satisfied customers. This will allow one to identify key drivers that define the inclusion on each of these groups.

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CHAID and Decision Tree analysis are terms for a number of algorithms that allow the creation of classification systems, displayed in the form of a decision tree. Component questions within the questionnaire are used as predictor variables. This analysis seeks significantly homogenous groups in the data set that will explain overall satisfaction. Alternatively the dimensions from a factor analysis can be used as predictor variables.

The results from all of these techniques can then be compiled and assimilated to form a definitive picture of what is driving satisfaction and loyalty in the customer populations.

Modelling Analysis

A combination of driver analyses and modelling techniques to explicate larger data sets that are associated with continuous customer feedback programmes can be utilized. This identifies what is most critical for increased performance and allows clients to ask what-if? and test scenarios as an aid to planning of improvement actions. These simulation models resulting from regression analysis or similar techniques will allow the user to run varied scenarios with respect to changes in key drivers and view resultant change in customer satisfaction recommendation or other key metrics.

The main deliverable in a modelling analysis process is an interactive tool for the simulation and testing of scenarios.

As this is intrinsically linked to key driver analysis, modelling analysis can share many of the techniques mentioned in the previous section. However, the process in building a model is to predict an overall indicator of success or performance based on a set of associated questions. In addition to correlations, regression, discriminant and decision trees; more radical and bespoke methods may be used to model data. SEM and Neural Nets are examples of more progressive techniques used to model data.

The main deliverable in a modelling analysis process is an interactive tool for the simulation and testing of scenarios. Assessment of any models developed will be communicated along with the relevant assumptions or known limitations pertaining to that analysis on completion.

The sampling requirements for most of the underlying methods in driver and modelling analyses are such that these systems would most likely be developed at a market level. Dissemination to subgroups or an equivalent can be produced if data is valid at this level.

Insight Mining

Continuous customer experience surveys involve collecting a great deal of structured data. Clients often need help to uncover what their data is telling them. A method which can be employed is insight mining.

The analysis is a tailored investigation of the data set, which can begin with little or no preconceived direction, or be directed towards an observed shift in the data.

A mix of methods and approaches drawn from data mining, statistics and 'standard' research analysis are employed. This will typically generate a story, unearthing patterns and differences within the data that other techniques may overlook. This approach is increasingly beneficial to larger tracking studies, especially where top-line data is relatively 'flat'.

Insight mining is a term used to describe the applyication of data mining techniques to large survey datasets to yield additional insight. The development of the technique was driven from the need help to uncover what the data is telling us.

The analysis would involve a tailored investigation of the basic data sets, which can begin with little or no preconceived direction. A mix of methods and approaches drawn from data mining, statistics and research analysis are employed.

The techniques employed to conduct insight mining are numerous. They include, but are not limited to; cross tabulations, drill-down analysis, ANOVA, hypothesis testing, correlations, CHAID, regression techniques, text analytics, quadrant plots, threshold analysis, waterfall charts and geographical maps.

The communication of this insight is of paramount importance and the visualization of results becomes a critical element in its success. Typically a story is generated, unearthing patterns and differences within the data.

Main examples of techniques are summarised below:

- Data mining for exploring the data and identifying issues: Cross tabulations, drill-down analysis, ANOVA, hypothesis testing.
- Association for testing and developing relationships within the data: Correlations, CHAID, regression techniques, key driver analysis, text analytics.
- Visualisation for communicating the findings: Quadrant plots, threshold analysis, waterfall charts, geographical maps.

Forecasting / Target Setting

Forecasting and setting targets enhance continuous tracking programmes because knowing what to expect in the future is extremely valuable for business planning and strategy.

At the modelling stage techniques to understand and simulate how data behaves are applied. In forecasting models and simulations these are extended to predict the natural progression of the data.

Forecasting the current trend forms the base with which to set a future target. Supporting information, thresholds and benchmarks can control the target levels and prevent unnecessary expenditure. Above all, these approaches help understand the effect of current business issues and initiatives and set targets at the correct level.

Forecasting commonly refers to the fitting of a model or trend using obtained data and extending the fit to future events or levels outside of the current range of scoring. This analysis can bridge a gap between modelling and action planning, by predicting the natural evolution of proceedings.

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The process can involve simplistic or complicated methods to carry out predictions, and as such, there are appropriate techniques for a given requirement available. All methods used in forecasting are designed to predict likely performance levels in unknown circumstances.

Volumetric sales forecasting, time series / econometric approaches for trend data, social / market / technology / 'blue-sky' trends combining research and government or third-party statistics can all form the analysis from which more complex forecasts are generated.

The most useful output delivered in forecasting analysis is usually a static or interactive graphic or tool for the prediction of unknown or uncharted time periods and scenarios. Assessment of any predictions be communicated along with the relevant assumptions or known limitations pertaining to that analysis on completion of the deliverable.

Data Linkage

The overall aim of data linkage is to create links and connections between separate surveys or between surveys, customer databases and other data. Analysis that incorporates measures across several programmes and data streams can yield a richer view of the overall customer experience.

Database linking provides solutions involving measures of association between survey and non-survey data, investigating how customer feedback predicts actual customer transactional behaviour or the creation of a balanced scorecard or dashboard approach to monitoring the state of your business.

Here is an overview of potential data for linkage analysis:

- Transactional customer feedback surveys
- Other survey data, e.g. exit interviews, employee surveys, mystery shopping, brand, lost sales, etc.
- Customer data, e.g. transactions, purchase behaviour, profiles, history, etc.
- Non-survey data, e.g. revenue, profitability, lifetime value, etc.
- Operational measures, e.g. response time to a complaint, etc.
- Unsolicited feedback, e.g. social media, blogs, comment cards, call center, etc.

Often the service issues affecting one stage of a process, such as problems at new account creation, can be tracked through to subsequent stages in the customer journey. There are strands that link performance levels across many touch-points at which customers interact with an organisation. There are constituents that link performance levels across touch-points at which customers interact with an organisation.

The analysis incorporates measures across several programmes and data and can therefore yield a richer view of the overall customer experience. The bulk of this work is completed with database manipulation association and cleaning tools and therefore the deliverable is not as clearly defined as previously mentioned analyses. Connected sources of information are the main benefit of this approach. This allows organisations to conduct analysis of data with greater clarity and more involvement outside of the sole customer experience.

Text Mining

Text mining is the discovery of information by analyzing text. Sources could include any written form of communication captured electronically or verbal communication transcribed into text. Insights gleaned from this text could reflect the meaning of what the author intended or provide entirely new information.

Text mining begins with natural language processing (NLP) that enables computers to discern meaning from human language. A complete solution can automatically extract categories, emerging themes, customer sentiment and root cause of customer feedback in a way that cannot be accessed using traditional analytical techniques.

Whereas data mining extracts information from structured databases, text mining extracts information from unstructured data. There are two approaches: linguistic and statistical.

The linguistic approach involves identifying linguistic elements of language and structures that relate them to each other. Those elements are the keys to meaning. This is much like parsing or diagramming a sentence to identify parts of speech. If you have an adjective, for example, what noun does it modify?

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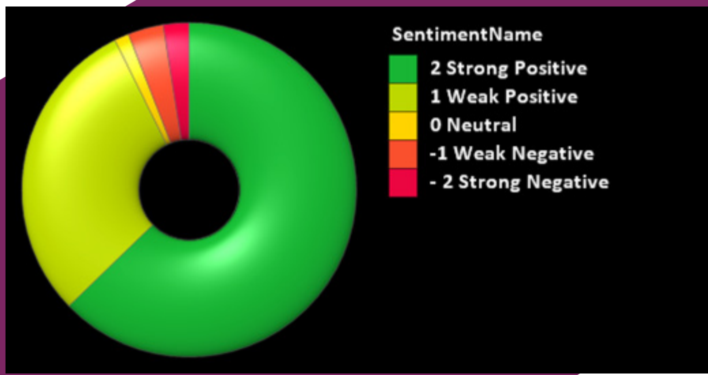
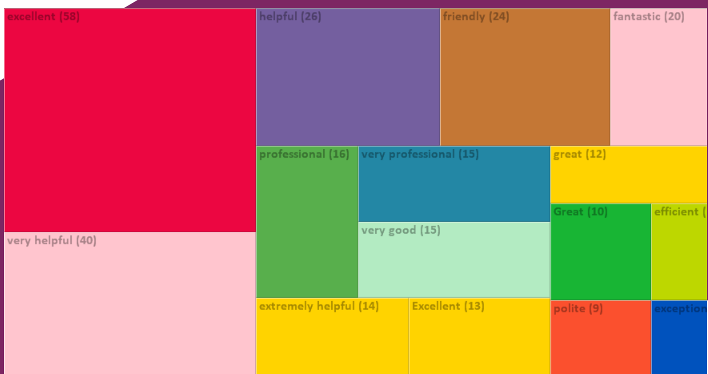
You don’t need human intervention to train a classifier, but you do want to identify parts of speech (which is done easily with a conveniently packaged list known as a “dictionary”); words that are commonly used by people who are angry (which can come from a dictionary or thesaurus); and information about sentence structure (if you have two nouns, which is the subject and which is the object? Did John throw the ball or did the ball throw John?).

In the statistical approach, words and phrases are treated as abstract objects. You use purely their mathematical relationship to each other. This approach most often involves machine-learning. Is your customer angry? Is he pleased? Is another customer talking about your latest product? Using a sample of the text and assignments in a number of categories, the computer scans them for common elements.

The machine learns by example based on training data assigned by human beings. If a business receives a million emails a day, you would take a small sample—say, 500 to 2,000 emails—and manually classify them. Then the computer would scan the sample to identify relationships in the text that hold clues for whether a particular email may be from a happy customer. People using obscene language tend to be unhappy, so simply scanning for profanity in your sample can distinguish email from irate customers.

There are many ways to train a classifier without human intervention. One important method is clustering, in which you look at what words naturally go together, automatically identifying common themes just by looking at one or two emails, rather than 200,000, for instance.





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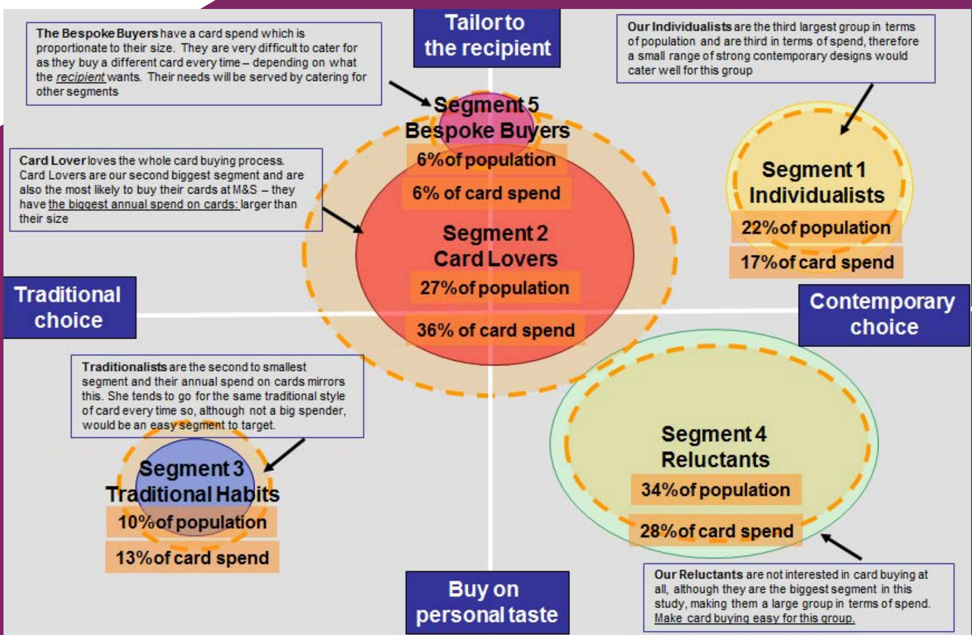
Segmentation

Segmentation enables companies to employ a more targeted approach, where initiatives and priorities are tailored for distinct groups of customers.

Understanding how groups differ in terms of expectations and behaviour, makes sure that the experience is not a one-size-fits-all approach.

Given its broad connotation, segmentation is used to describe very simple to extremely complex routines. Indeed segmenting data into male and female, or the young and the old, can often give a good implicit segmentation in market research surveys. However, when we use the term segmentation, we mean the process of grouping respondents by their situation, behaviours or attitudes in respect to a service.

This process of classifying a market into distinct subsets, so that customers within the subset have similar needs or priorities, is useful in understanding the data we have collected and enables a business to tailor the service, so it is applicable for all. The result is a means to focus efforts in the right areas, to maximise the return in service efforts. Understanding how groups differ in terms of expectations and behaviour, makes sure that the experience is not a one-size-fits-all approach.



Before segmenting, extensive exploratory analysis is often conducted. An existing understanding of the behaviour and motivation of customers is required, if we are to ask the right questions. This can incorporate quantitative and qualitative elements and is often combined with a good deal of desk research.

The process of creating segments most commonly utilises multivariate techniques to analyse responses to key elements from a survey. These techniques essentially find patterns in the data and use these patterns to create groups of respondents, such that there are similarities between respondents in the same cluster, and differences between respondents in different clusters.

The procedure is iterative and multiple solutions, using alternative techniques and sets of questions, are produced. We also look at how segmentations “evolve” as we increase the number of segments. Interim stages, where the survey data are used to create pseudo variables, are often investigated as possible elements to segment on. This can be useful if the survey questions are less suitable for a successful segmentation solution.

Most scenarios that are tested are eventually discarded, in favour of a few most promising solutions. Rigorous testing of segments is undertaken to reduce the field of candidates to the final few and hopefully the final one.

The chosen segmentation will typically be that with optimum levels in terms of segment volume and value, differentiation and compatibility / accessibility. The requirement is always an actionable strategy for an improved performance and the final solution deployed will be measured by this prerequisite.

Segmentation is perhaps one of the best examples of an analytical procedure where techniques are discussed as the critical aspect, and this is perhaps overstated. In truth the value in how the exploration is conducted far outweighs the selection of an appropriate technique. This is not to say that all techniques give the same results, this is definitely not the case, but the main aim of understanding customer behaviour and motivations should be kept in mind throughout.

Action Planning

Action planning is from an analytical point of view a term used to describe the practice of constructing a technique or process to identify main areas in which to concentrate efforts.

This analysis will often be constructed at a strategic or market level and then disseminated to local level using an appropriate method of transference. Alternatively it is possible to construct a plan of action at the lowest level and translate this to overall performance.

Action planning shares techniques with driver analysis as it also attempts to quantify and prioritise elements of the survey. The methods used to support an action planning process can include correlations, regression, relative importance, hypothesis testing, gap analysis, benchmarking and threshold analysis.

An element of action planning often discussed is the setting of appropriate targets. The target setting analysis is a multi-stage process which takes into account background and supporting information available outside of the customer experience programme.

The current trend in scoring and likely forecast can be used to quantify the target in terms of an improvement from the natural progression of the programme. Benchmarking within the programme or against competitors combined with analysis of performance thresholds helps to justify targeted performance levels.

The overall aim of the target setting methodology is to determine the correct shift in a given parameter that will result in an appropriate target for an associated reporting period. The combination of key service areas for prioritised action and targeted levels of performance in key areas forms the main deliverable in the action planning process. Clarity in the formulation of such an action planning process also becomes a critical article.

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Social Media Integration

Traditional quantitative customer satisfaction tracking surveys are not set up to collect and manage customer feedback across social media. But that channel is increasingly where customer conversations are taking place. For example Facebook has almost one billion users, Twitter has 300 million accounts. And the number of reviews on review sites such as Yelp has increased by a factor of 20 over the past four years. It is an unmediated conversation and companies are scrambling to participate.

If an organisation wants to continue to know what the customers think and how they feel about products and services, companies must be managing social feedback channels.

At a minimum, companies can listen to the voice of the customers in less structured forums. Even better, social feedback will be integrated with surveys and other structured and unstructured data for a complete picture of the customer.

If an organisation wants to continue to know what the customers think and how they feel about products and services, companies must be managing social feedback channels.

Conclusions

This document discusses some of the procedures in advanced analytics that can be incorporated into CEM programmes. This is, however, part of a portfolio that is habitually changing in its content and design. Although these procedures change, understanding customer feedback and the ability to grow information from data will always be essential.

The segmentation section mentioned procedures where techniques are often discussed as the most critical aspect of concern, and that this is erroneous. This is in fact a danger in all the procedures we have discussed and can often lead to narrowly scoped investigations and poor findings.

Preparation and discussion are combatants to poor analytical findings and the best results are achieved when the vast majority of work is exploratory.

Analytics form a powerful tool for understanding the customer. Analytical systems can extract knowledge from data that would otherwise remain hidden, and the ability to create predictive models for more informed decision making is only possible because of the advancement of statistical and data processing tools.

That said, advanced analytics are no match for a poorly conceived study or their use on data that is not appropriate for the procedures and techniques applied. It should always be kept in mind that the most sophisticated multivariate technique will only be as good as the data on which it is based.

Understanding customer feedback and the ability to grow information from data will always be essential.

About the Company

SPA
Future
Thinking

SPA Future Thinking is a new company, the result of a merger between a number of specialist agencies in 2010 and 2011 and has developed to become one of the fastest growing and largest independent market research companies in Europe, with more than 200 employees and offices in the UK, Germany, France and Italy and a partner network in 38 countries worldwide. With combined industry experience of over 40 years we offer thought leadership across a wide range of specialisms and we provide genuine expertise and understanding across a wide range of industry sectors.

For over a decade SPA Future Thinking has been providing strategic research and actionable insights to a number of leading automotive manufacturers. We offer both custom solutions and analytics and proprietary techniques to help guide the decisions that you make in areas like market development, new product development, innovation, customer satisfaction and experience, brand, communications, buying behaviour, etc.

www.spafuturethinking.com

The
Analytics
Hub

The Analytics Hub was launched by SPA Future Thinking in September 2011 and offers data and statistical expertise. The Analytics Hub offers a full range of analytic methodologies, including segmentation, statistical modelling, dashboard and visualisation, text analytics, conjoint and discrete choice analysis as well as forecasting and data mining, as part of its service. Our team has solid credentials, with 40 years' combined experience working on a wide range of research, marketing data and forecasting projects.

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About the Authors

Chris Bland - Research Director at SPA Future Thinking

Chris began his career in Technology & Telecoms before joining SPA Future Thinking in 2006 to work with media and consumer clients. He is a firm believer in putting the voice of the customer into the heart of business decision, linking feedback to key business performance metrics.

Chris has helped clients design, define and launch new programmes, as well as manage and evolve existing programmes to meet new requirements. He has extensive experience of building customer experience studies for media clients including BskyB, Sky Italia, and OSN, the leading pay TV provider in the middle east; Advising on brand strategy, customer retention and how to integrate customer experience data to its' best business advantage.

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Dan is passionate about creating market segmentations that really resonate with the marketers that use them and is an expert in forecasting and choice-based conjoint techniques.

A natural communicator, Dan is happiest discussing the interpretation and implications of analytics work and making the connections between data and business issues.

Dan is also a graduate of University College London, a proud father and maintains in the face of overwhelming evidence to the contrary that one day he'll make it as an obscure electronic music producer.

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