

Making a Difference:

Examples of successful uses of advanced analytics

Dr Barry Leventhal

Teradata Advanced Analytics Users Group

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You've never seen your business like this before.



The Magnificent Seven

- those cowboys sure made a difference!



How can Advanced Analytics make a difference?

**...to
targeting
customers**

**...to going
beyond
business
reports**

**...to
assessing
customer
potential**

**...to
managing
customers
over
lifetime**

**...to
measuring
availability of
products in
stores**

**...to
evaluating
effects of an
in-store
promotion**

**...to estimating
market size in
every
neighbourhood**

How can Advanced Analytics make a difference?



Going beyond business reports

Objectives of the Exercise:

- To explore projects and scenarios where advanced analytics could be of value for Fleet Maintenance
- To conduct sufficient analysis of those areas in order to demonstrate capability and potential business benefits
 - > within limitations of time and access to key people
- To provide initial results and signposts for further analytical development

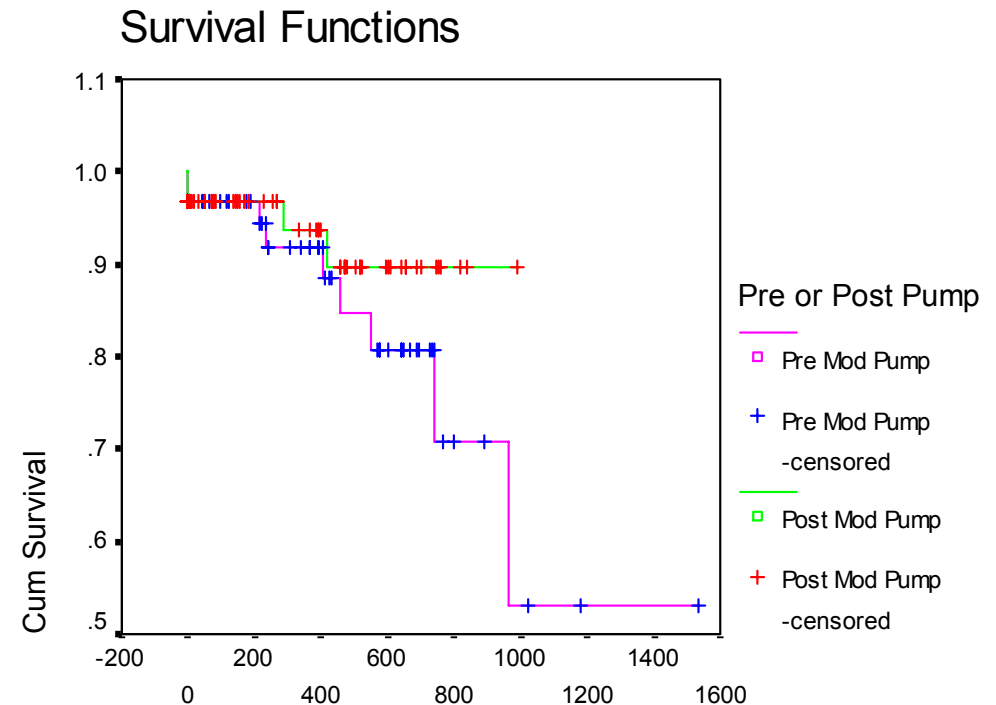


Fleet Maintenance - Modifications Analysis

- Objective
 - > To evaluate effectiveness of modifications applied in order to extend the life of an asset
- Analysis
 - > Analysis focussed on a particular modification (hydraulic pump)
- Action/Return
 - > Quantified evidence on the performance of a modification and whether it achieved its objectives
 - > Support for management decisions and negotiations with suppliers

Survival Analysis on Pre vs Post Mod Pumps

- Descriptive survival analysis technique applied to derive survival and failure graphs for pumps, pre and post modification
- Analysis takes account of pumps that have achieved X operating hours and have not yet failed, as well as failed pumps
- Pre and Post Mod can be compared to examine differences in failure rates



Main Finding: higher survival likelihood and lower failure rate from 400+ operating hours, on post mod pumps

Going beyond business reports - made a difference:

- Showed the potential for applying advanced analytics
- Demonstrated that the data in the organization's warehouse could be exploited for more purposes
- Illustrated some of the business questions that the data could help to answer



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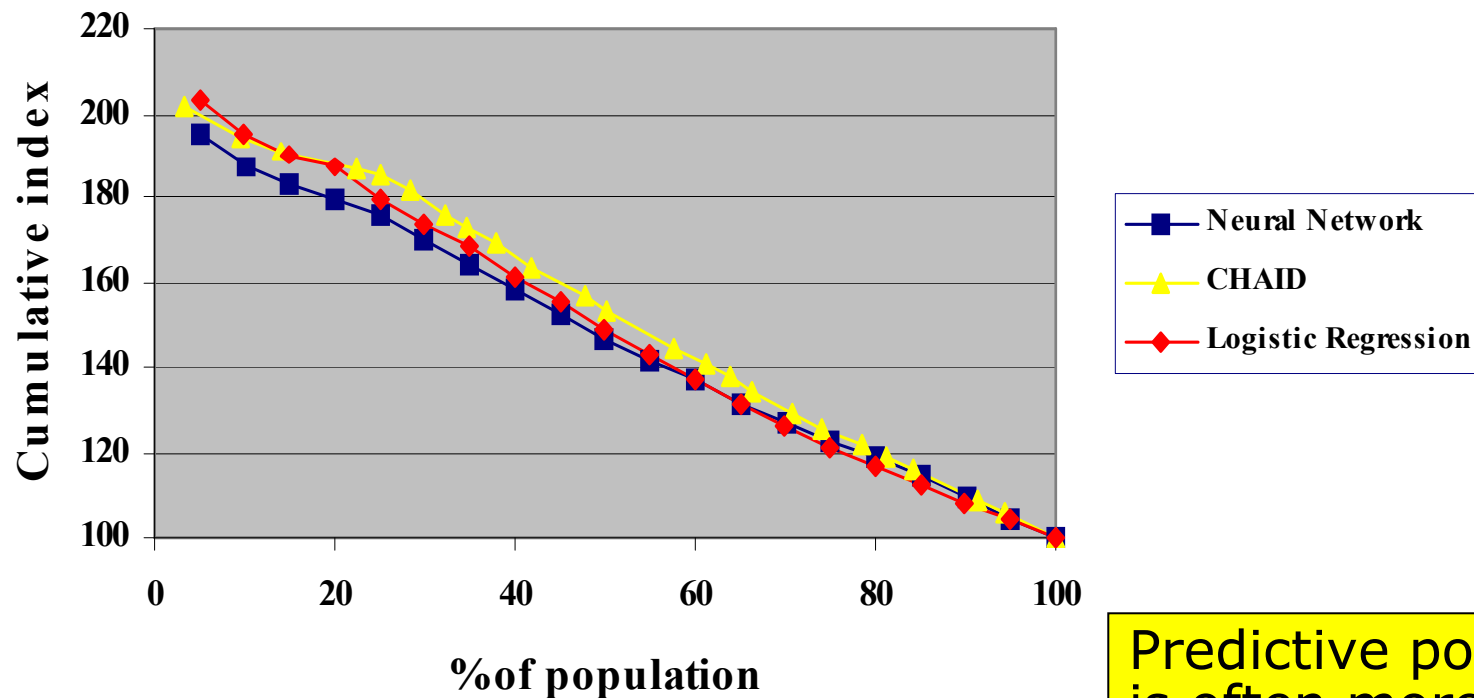
Targeting Customers



- Objectives:
 - > To help a financial institution to leverage its new data warehouse for customer management
- Analysis:
 - > Set of 6 product propensity models were developed covering the core financial products
 - > For two products, alternative modelling techniques were compared:
 - Decision Tree
 - Logistic Regression
 - Neural Network
- Action/Return:
 - > Models were used to generate prospects for direct marketing and help develop a contact planning strategy

Example Results on Alternative Modelling Techniques

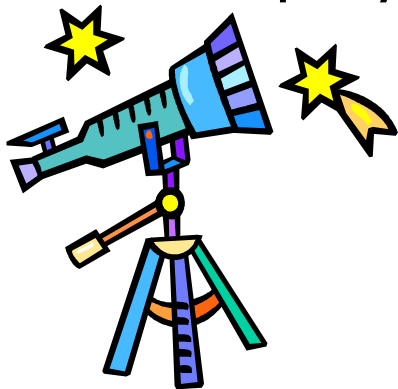
Comparing Logistic Regression, Neural Networks and CHAID for Home Loans



Predictive power of data is often more important than choice of modelling technique to be applied

Targeting customers – made a difference

- Models were part of the company's initiative to leverage the Data Warehouse for effective customer management
- Enabling improved customer contact planning
- The models were used for customer selections, 5 out of 6 worked well and were still being employed some 3 years later



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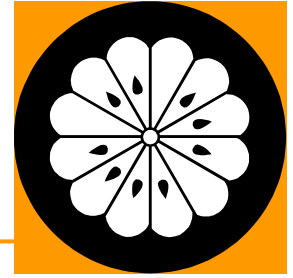
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Assessing customer potential - via Marketwide Segmentation



- Objective
 - > To segment financial services customers according to their potential
- Analysis
 - > A marketwide segmentation of individuals on financial behaviour was built using financial research survey data
 - > The marketwide segments were overlaid onto various customer databases
 - > The segments were overlaid onto a database containing the UK Electoral Roll
- Action/Return
 - > Segments were tested and taken up by a number of UK companies – banks, building societies, insurance

The Segmentation was called FRuitS!

Each of the 8 segments was named after an appropriate fruit

The first 4 segments...



PLUMS, are college-educated married men aged 44-65 living in the South with an income of at least £17,000 and high savings. They are likely to own their home and two or more cars, and are three and a half times more likely than other groups to own shares.



PEARS, older than plums, and more likely to be retired. With an income of £7,500 to £17,499, they are at least twice as likely as other groups to own stocks and shares. They are interested in National Savings but not in mortgages.



CHERRIES, aged 35 to 54 and married with a family, earn above £17,500 and usually own their own home and two cars. They usually live in the South, have moderate savings and are regarded as prime candidates for mortgages, loans and credit cards.



APPLES, similar in age to cherries, have a lower income £7,500 to £17,499. Likely to live in the North, the Midlands or Wales. Usually married, they have one car, and tend to be self-employed. Good bet for loans and mortgages.

The last 4 segments...



DATES, tend to be women over 55, widowed or retired and living alone, often as owner-occupiers. Income usually below £7,499. They do not have a car and are likely to have life insurance and a building society account.



ORANGES, are single and aged 18 to 34. They are either unemployed or students and likely to be living in private rented accommodation, often staying for only short periods. Oranges interest financial salesmen because of their potential in later life.

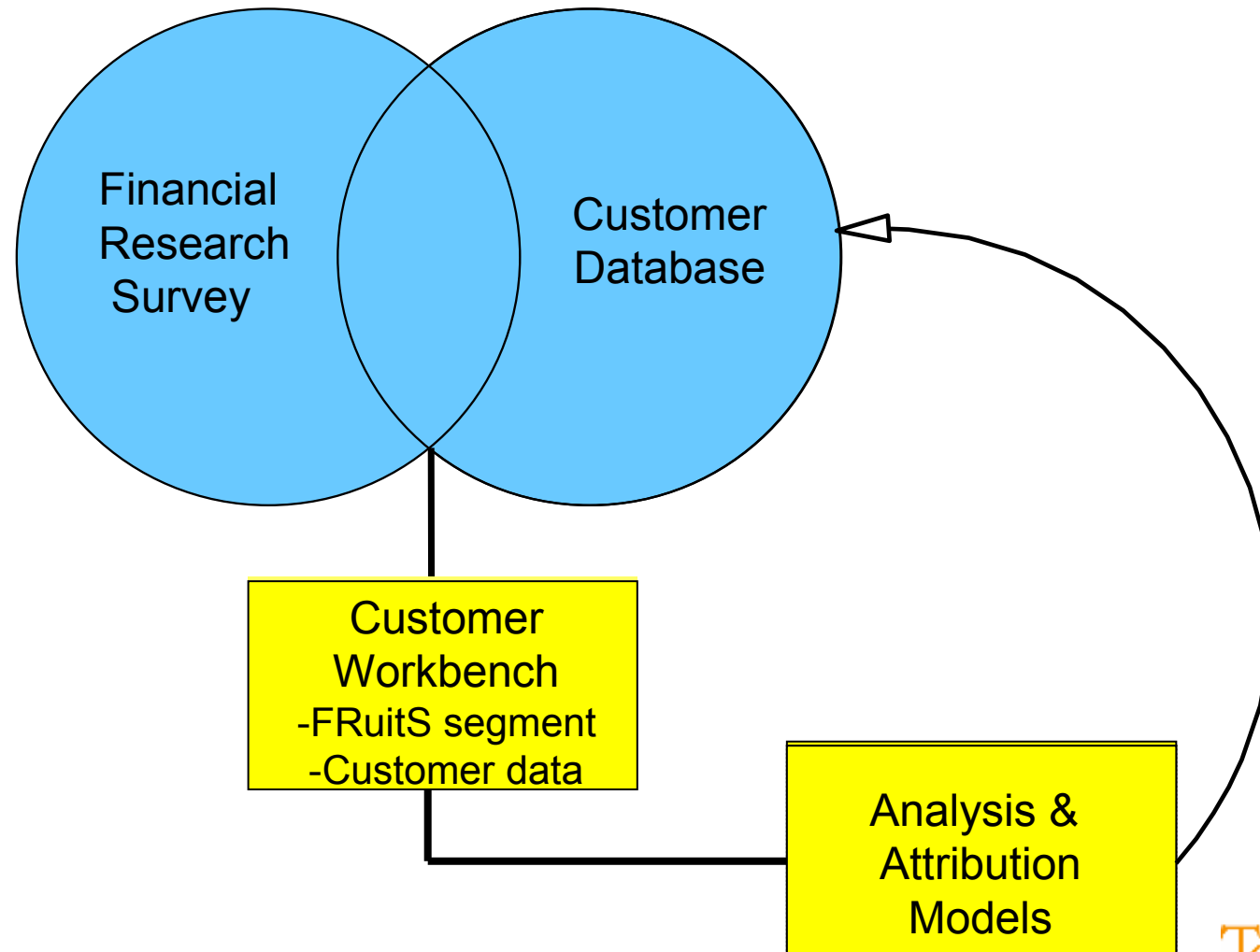


GRAPES, naturally, come in bunches - households with five or more members aged 25 to 44. Their earnings are relatively low and immediately used up. Financial salesmen see them as candidates for loans.



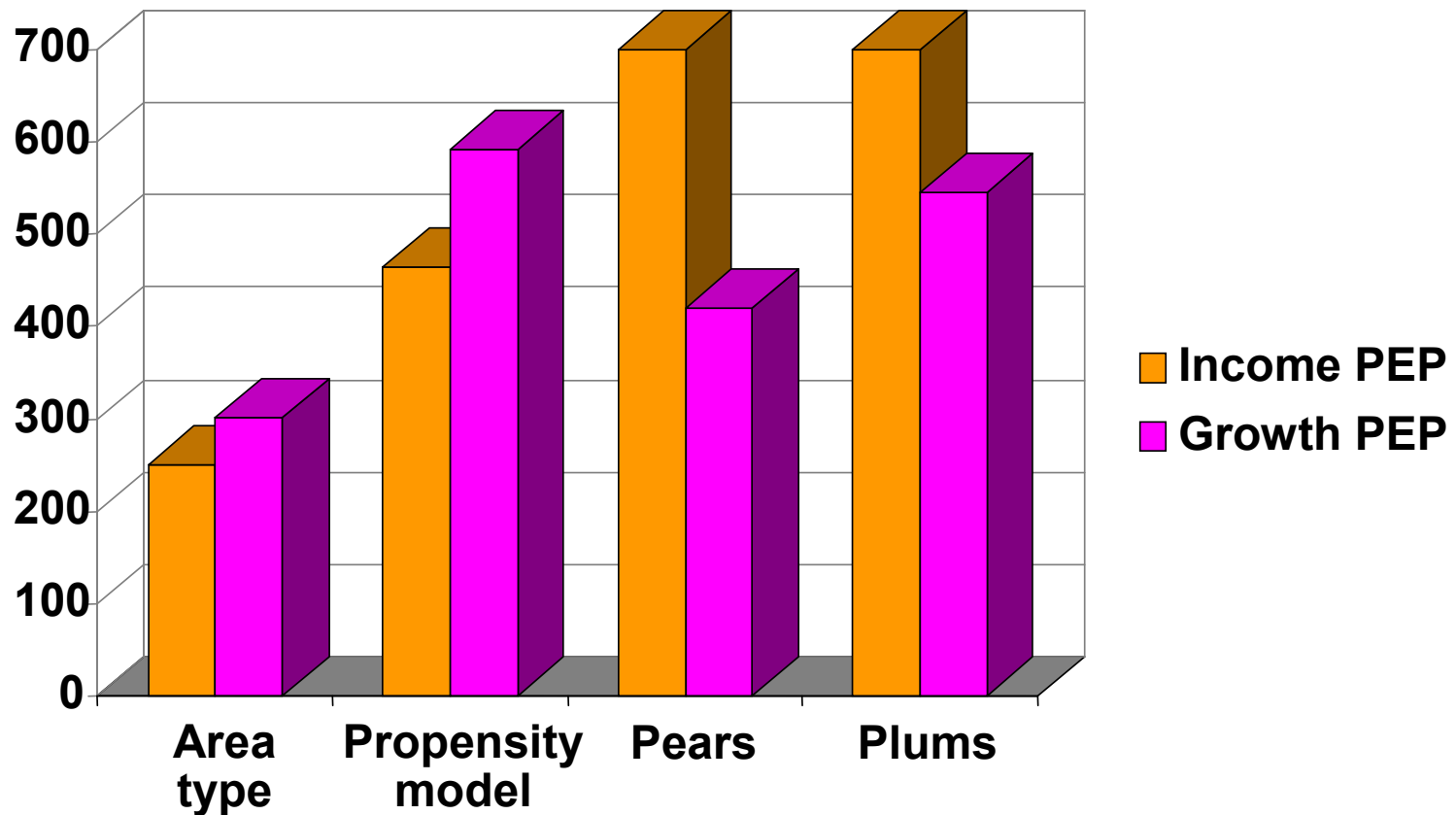
LEMONS, are usually older, single or widowed women living alone with an income of up to £7,499. They are unlikely to have loans, credit cards or personal pensions and are half as likely as the rest of the country to have household insurance.

How a Market Research segmentation was employed for Customer Workbench and Database Enhancement



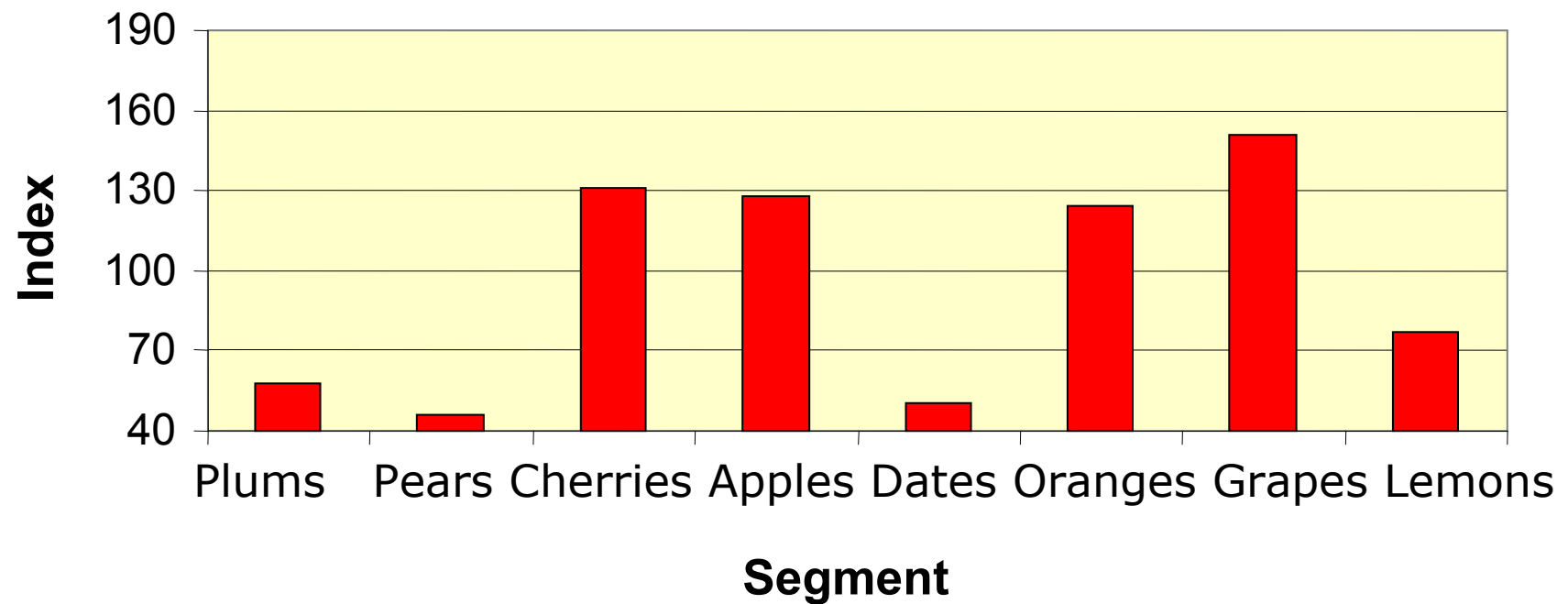
FRuitS was used to by a bank to target its Income and Growth investment products to insurance customers

Index of £ Invested Per £ Marketing Spend



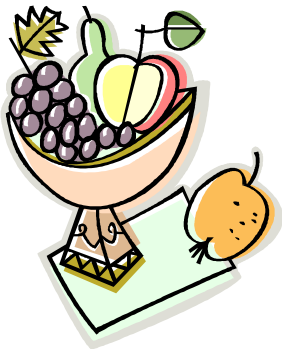
And it was used to identify profitable storecard customers for a high-street retailer

Incidence of Profitable Customers by FRuitS



Assessing Customer Potential - made a difference

- First individual-level marketwide segmentation available in the UK
- Showed that classifying individuals is more powerful for targeting than segmenting neighbourhoods or postcodes
- Several companies employed FRuitS as their main customer segmentation system
- FRuitS was followed by further discriminators in financial services and other industries



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...to managing customers over lifetime

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...to estimating market size in every neighbourhood

Managing customers over their lifetime

- Objectives

- > To explore use of Survival Analysis on data held by a mobile phone operator
- > To increase 'life' of pre-pay and post-pay customers by introducing analytical approach to managing customer lifecycles

- Analysis

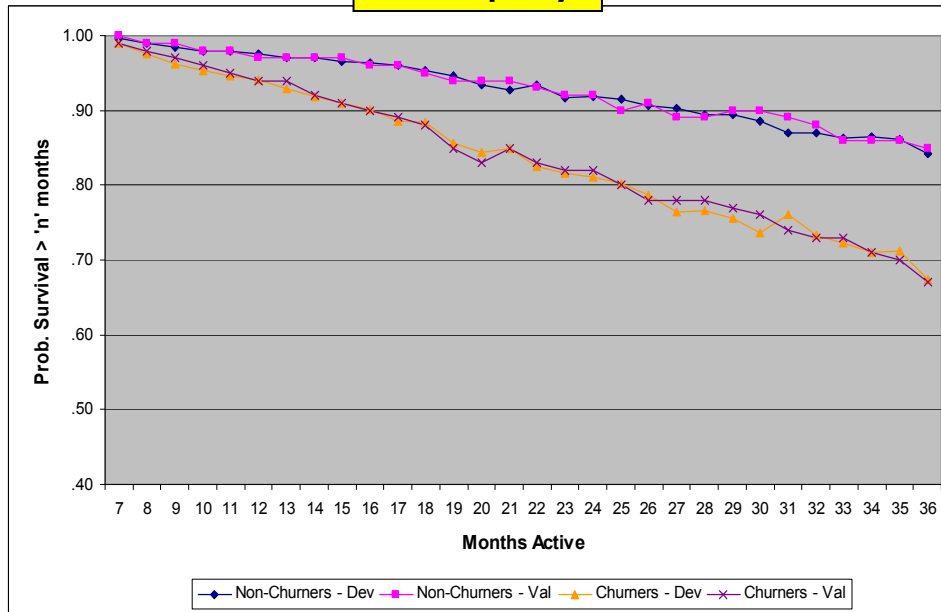
- > Pilot survival models were developed for pre-pay and post-pay consumer customers

- Action/Return

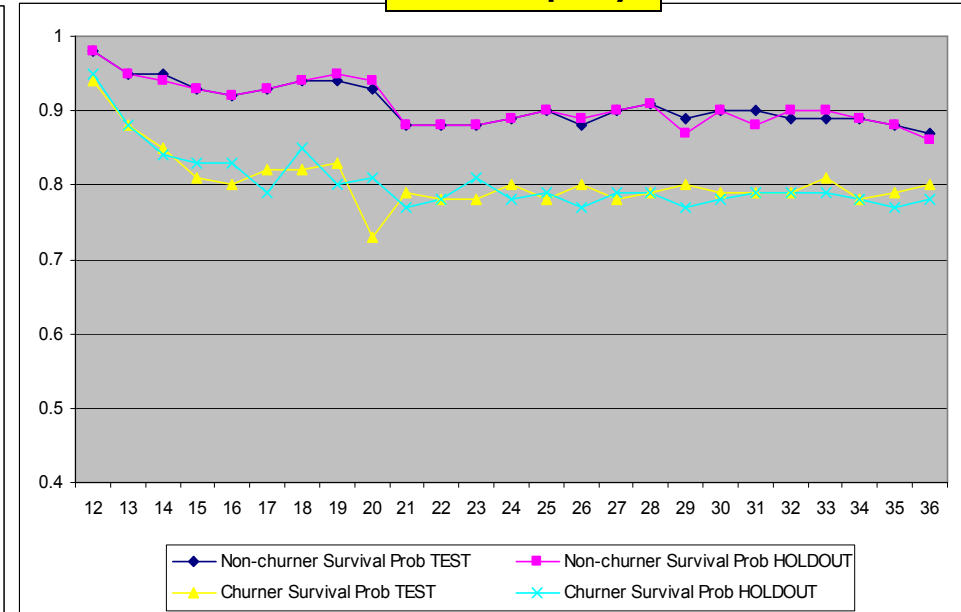
- > The models were validated by tracking sample customers subsequent churn behaviour over time
- > Potential improvement in post-pay model was demonstrated, using more detailed predictor variables built from CDR data
- > The models were redeveloped and implemented by the client

The models strongly discriminated between churners' and non-churners' predicted future survival probabilities

Pre-pay



Post-pay



Test and Holdout results were almost identical on both pre- and post-pay

Alternative Post-pay Models were built, based on variables calculated from detailed data

Model 0 - Existing model – standard monthly variables

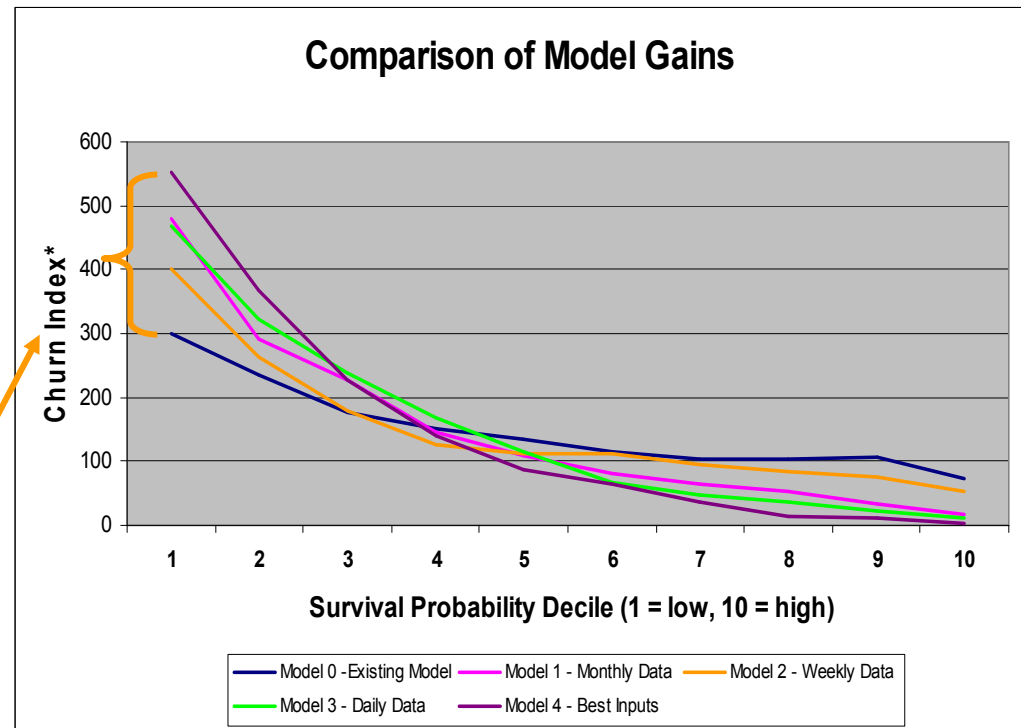
Model 1 - uses best variables from existing model and monthly variables built from detailed data

Model 2 - uses best variables from existing model and weekly variables built from detailed data

Model 3 - uses best variables from existing model and daily variables built from detailed data

Model 4 - uses best inputs from all models

Models based on detailed data were up to twice as discriminatory



Managing Customers over lifetime - made a difference

- Showed the company ways to employ survival modelling for managing customer churn
- Provided insights on factors that affect customer longevity
- Transferred knowledge to company's database analysts on survival time modelling
- Quantified value of holding detailed data for building stronger predictor variables



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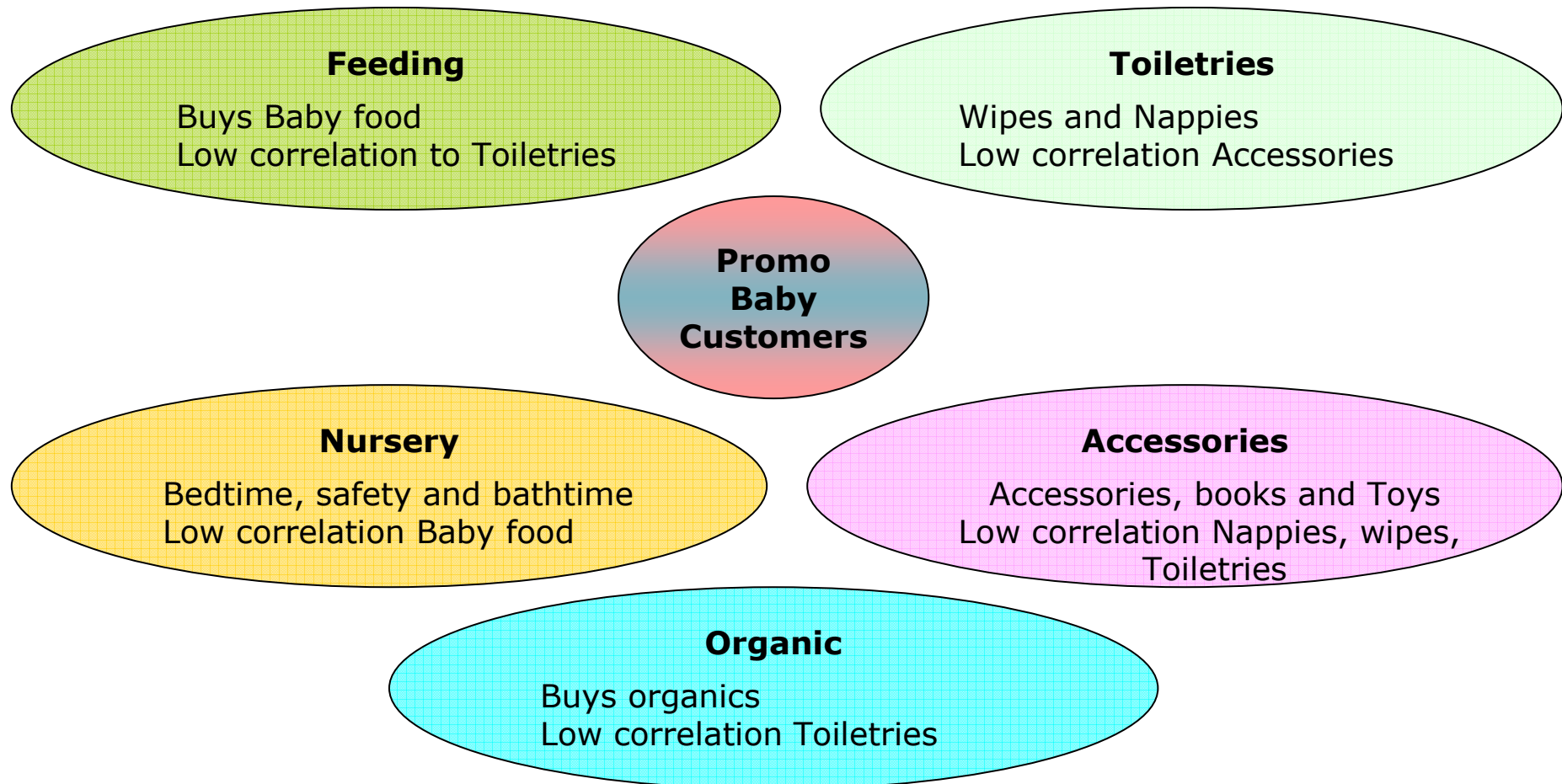
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Evaluating effects of an in-store promotion - a Seasonal Event on Baby Products



- Objectives
 - > To use basket data in a supermarket's data warehouse to identify promotional buying behaviour by customers and evaluate the promotion
- Analysis
 - > Cluster analysis was used to segment promotion shoppers into groups based on their purchasing of promoted markets
 - > Behaviour of each segment was then tracked before, during and after the promotion period
- Action/Return
 - > Redesign of promotion strategy and advertising

Factor Analysis identified 5 different product buying patterns



...using this we could segment customers on behaviour...

Cluster Analysis on these Factors gave 6 Baby Shopper Segments

From the Buying Patterns we could assign all customers into 6 distinct customer segments

1 Occasional Buyers 25% / 8%

Odd purchase over time
No strong buying affinity
Spend 25% less than other baby shoppers - Promo led

2 One Stop Baby shop 12% / 30%

Buy lots of Baby products, very valuable customer. Spend 40% more than average baby shopper.

3 Eat & Clean 13% / 28%

Predominantly food and Nappies only buyers.

4 Baby Personal care 25% / 22%

Buy Nappies and wipes but probably buy food and accessories elsewhere.

5 Toiletries cherry picker 10% / 5%

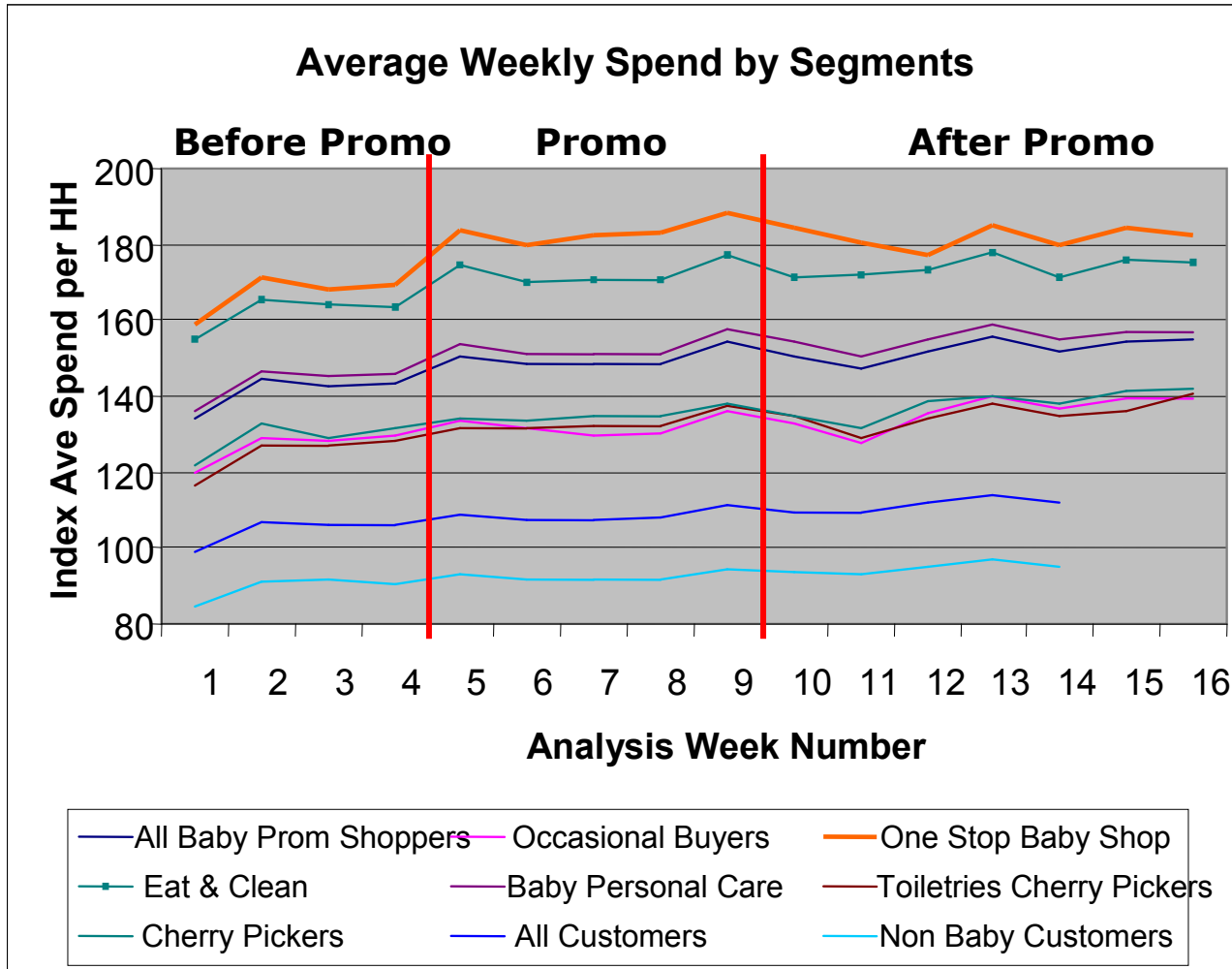
Buys promo toiletries and little else
low incidence of Internet shopping

6 Cherry Pickers 15% / 7%

Buys baby promo products and little else in baby range.

Promo
Baby
Customers

Average Weekly Spend of Baby Shopper Segments



- Baby shopper segments are heavier spenders than non baby customers
- One Stop Baby Shop was highest
- Higher spending baby shopper segments show greater lift during promotion

Evaluating effects of an in-store promotion - made a difference



- Showed benefits of a customer-centric approach to promotion evaluation using basket data
 - > Retailer's evaluation was solely financial vs targets
- Results changed the shape of this product category to the retailer's advantage



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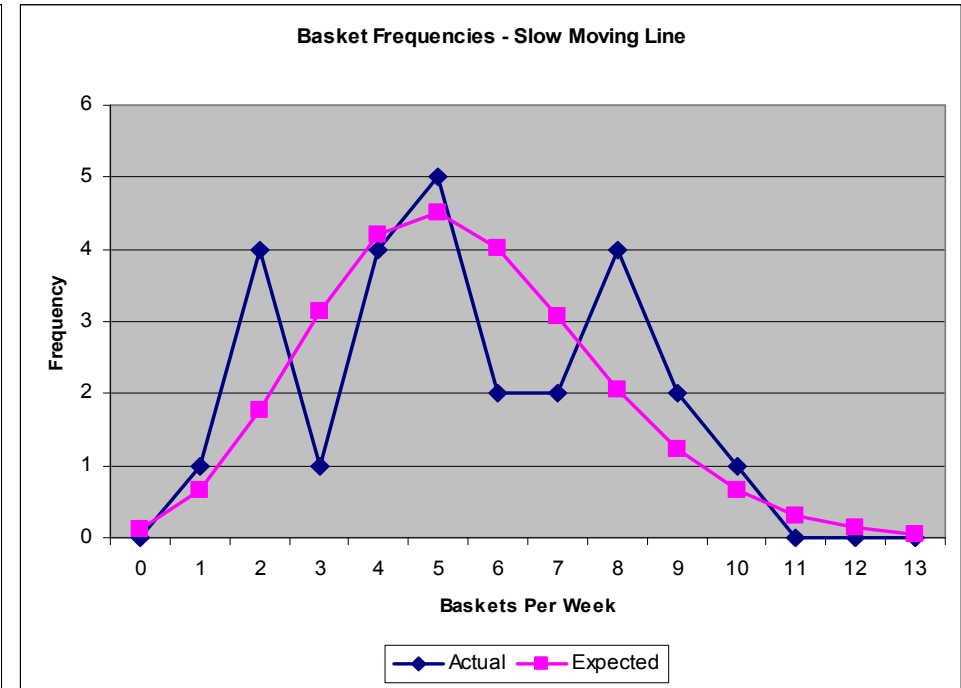
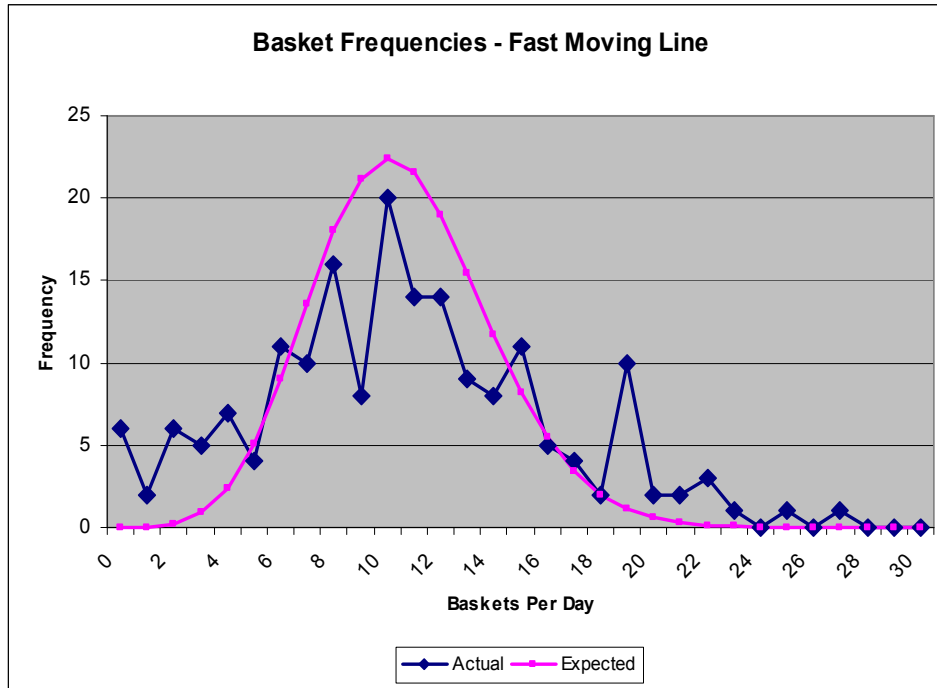
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Measuring availability of products in stores

- Objectives
 - > To develop a measure of product availability for a supermarket chain, that took account of low rates of sale
- Analysis
 - > Applied probability theory to model sales and identify periods where zero sales were most unlikely to have occurred by chance
- Action/Return
 - > Created a credible availability metric for use across all stores
 - > Reports were developed to track availability based on the probability model

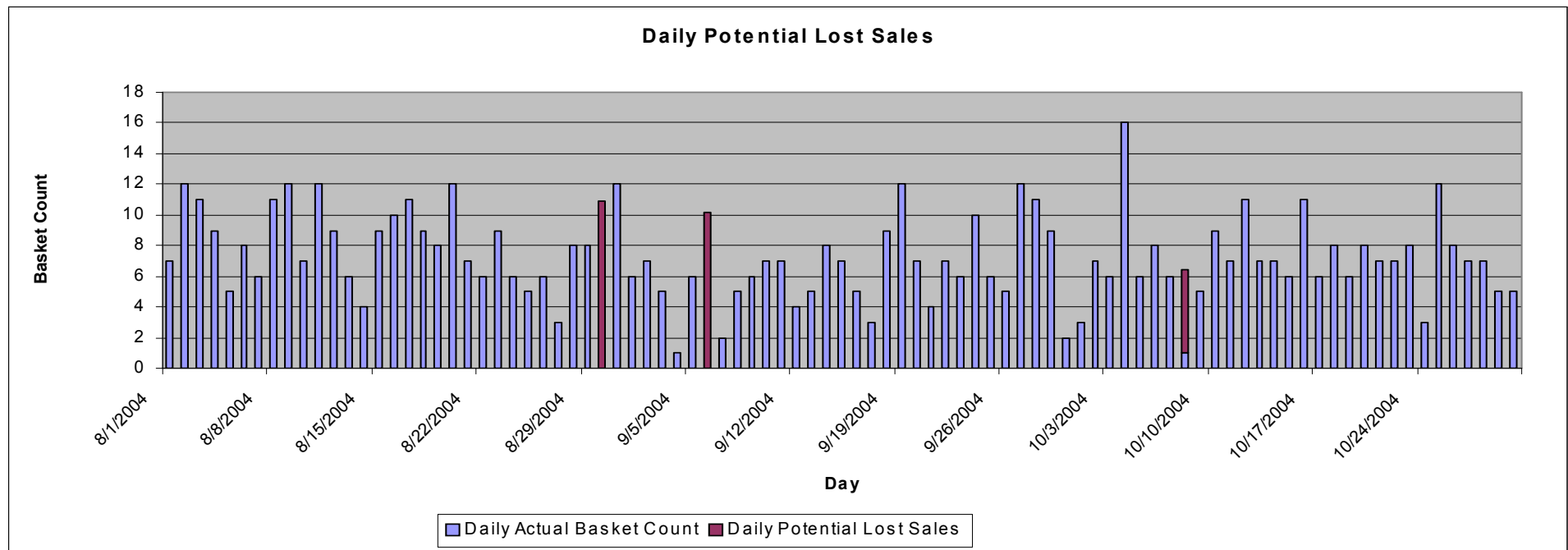
Step 1: A probability model was fitted to the sales frequencies for fast and slow moving lines



The model was sufficiently flexible to fit a wide range of products

Step 2: Methods were developed for tracking fast and slow moving lines

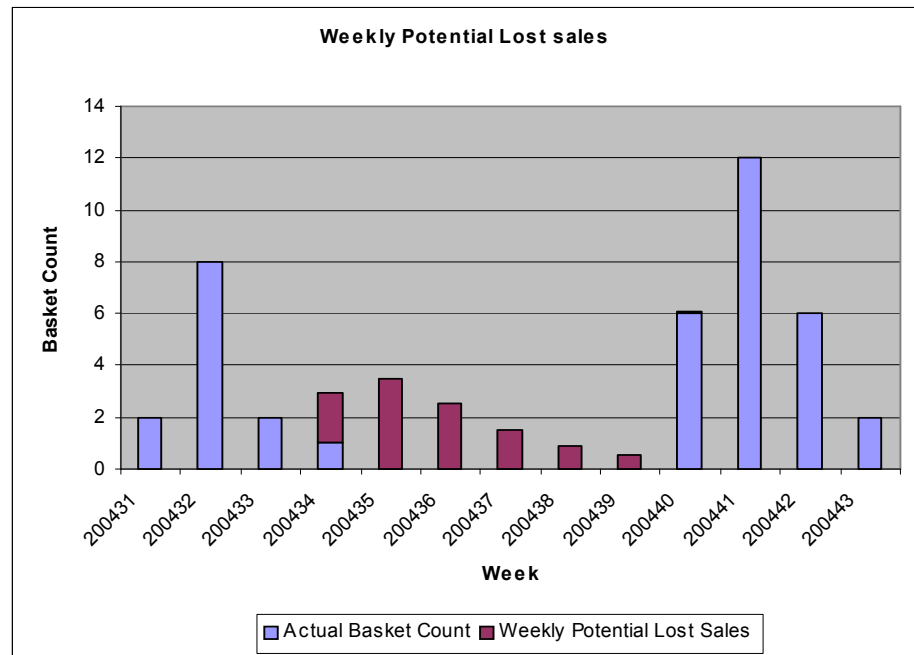
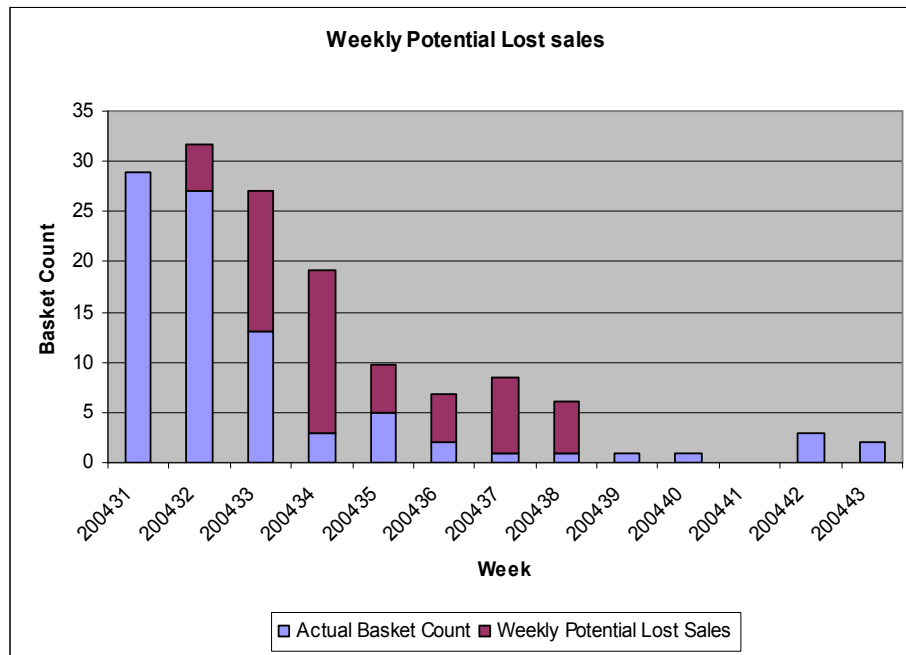
Fast movers were tracked daily, lost sales were flagged and estimated for full and partial days



Example for a fast-moving line

Step 2: Methods were developed for tracking fast and slow moving lines

Slow movers were tracked on a rolling weekly basis, lost sales were flagged and estimated for full and partial weeks



Examples for two slow-moving lines

Measuring availability of products in stores - made a difference

- Showed the retailer how probability theory can be applied to availability reporting – in order to distinguish 'genuine' zero sales from zero sales due to non-availability



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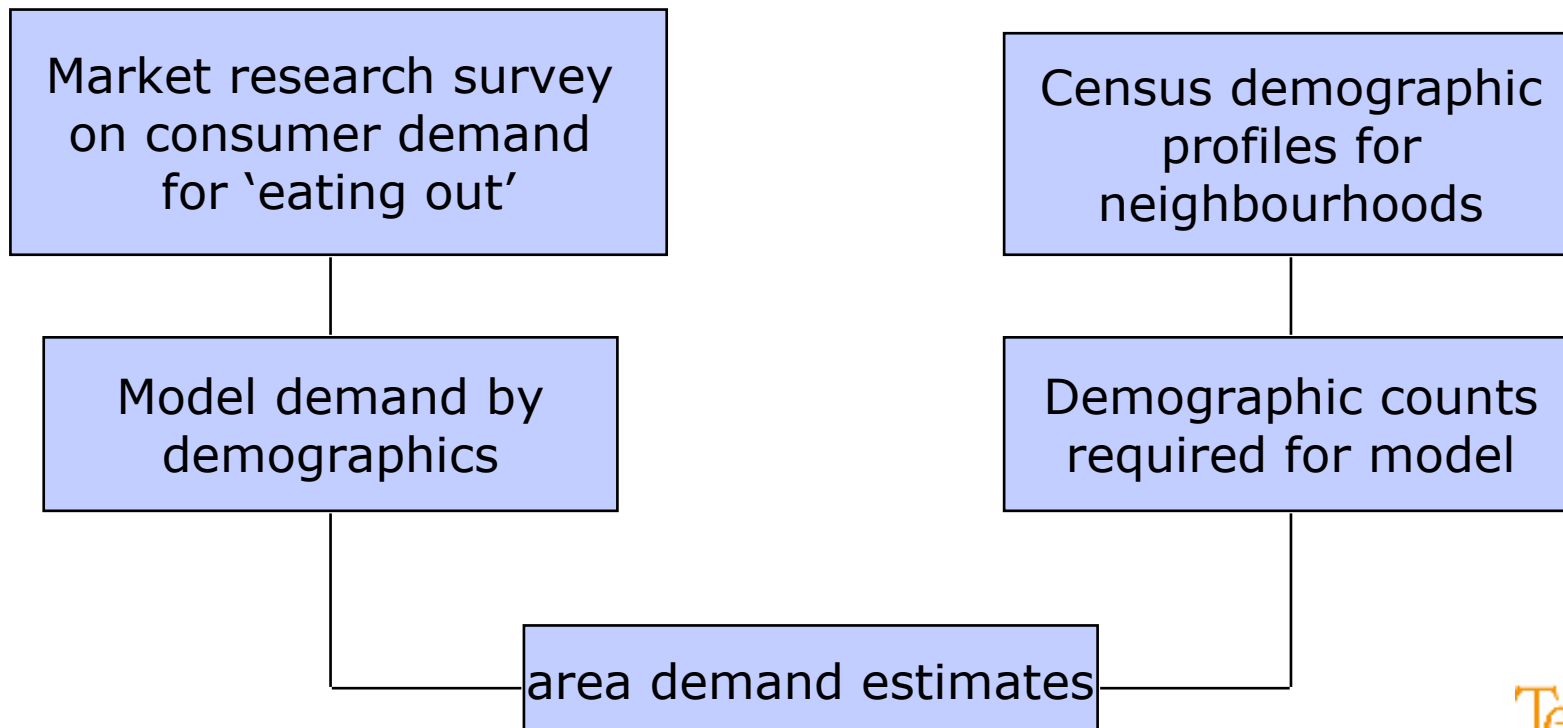
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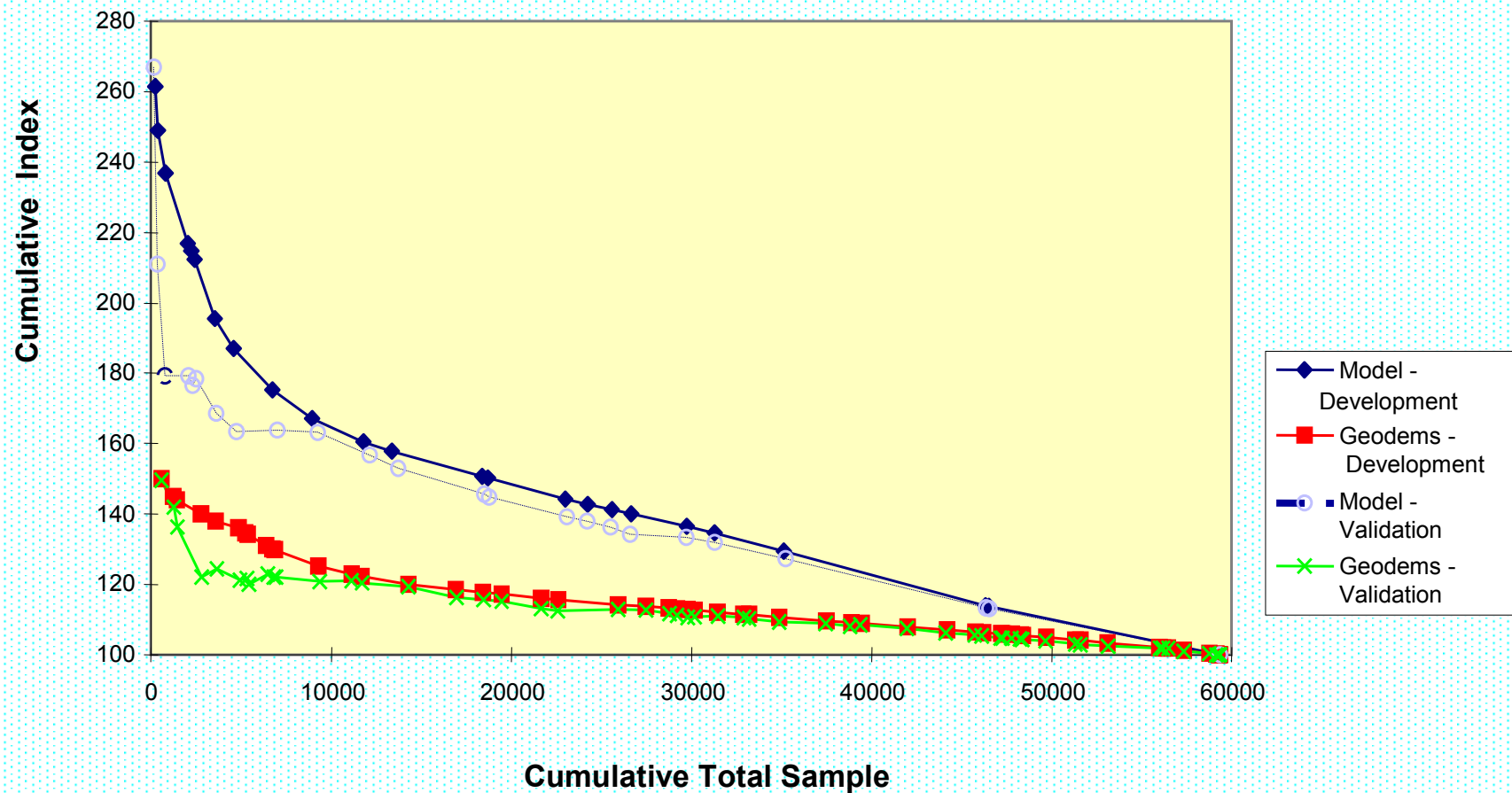
- Objective
 - > To generate accurate small area estimates of consumer demand for the 'eating out' market – on behalf of a retailer operating a number of different restaurant chains
- Analysis



The individual-level model was highly discriminatory, when compared with a geodemographic approach

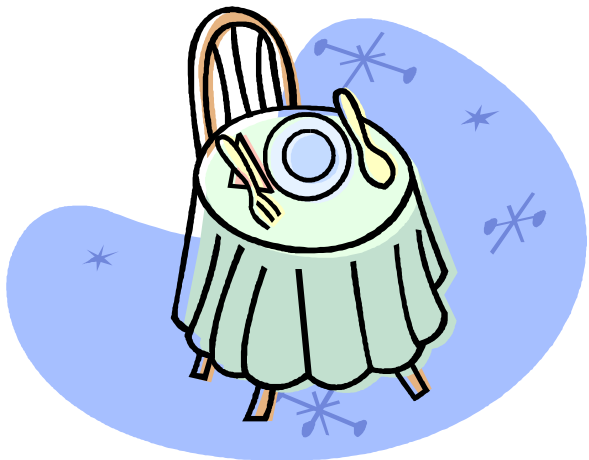
Market: Fish & Chips

Individual Model vs Geodemographic Discriminator



Estimating market size in every neighbourhood

- Actions/Return
 - > 'Eating Out' market estimates were calculated for 148,000 census neighbourhoods in Great Britain
 - > The results became an input to the retailer's site location models
 - > As a by-product, the project also generated a social class profile for each neighbourhood, that was found to be a powerful predictor of affluence



Conclusions – some common themes



- Power of integrating sources – such as customer data, market research, census – to create new insights or improve targeting
- Employ appropriate methods – however, good predictive data is often more important than complex algorithm
- May need to link a number of analytical steps together to achieve required solution
- Harness known patterns / distributions in the data to detect changes in behaviour
- Show benefits of taking a fresh approach to a business problem

Thank you!

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+44 7803 231870

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