

Analytical Techniques created for the offline world – can they yield benefits online?

Dr. Barry Leventhal
BarryAnalytics Limited



About BarryAnalytics

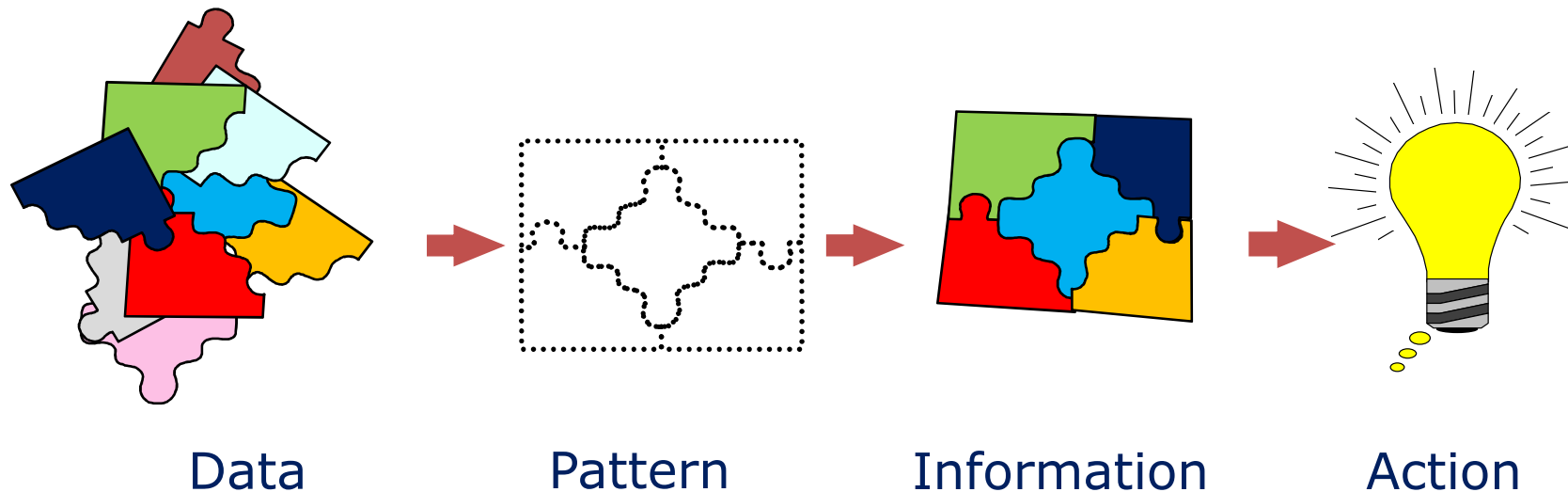
- Advanced Analytics Consultancy founded in 2009
- Specialises in:
 - Targeting and Segmentation analysis
 - Developing analytics plans and roadmaps
 - Training and mentoring marketing analysts
- More than 20 years experience in Marketing Analytics
- See barryanalytics.com for info + downloads

Agenda

- Introduction to data mining and analytical modelling
- Predictive and descriptive analytical models
 - Predictive case study – targeting bank customers
 - Predictive case study - lifetimes of mobile customers
 - Descriptive case study – financial segmentation
- Further points to consider
 - Data integration
 - Importance of a team approach
 - Model deployment
 - Contact optimisation
- Possible applications to online marketing

What is Data Mining?

A process of discovering and interpreting patterns in data to solve business problems



Converts Data into Information

And What's Analytical Modelling?

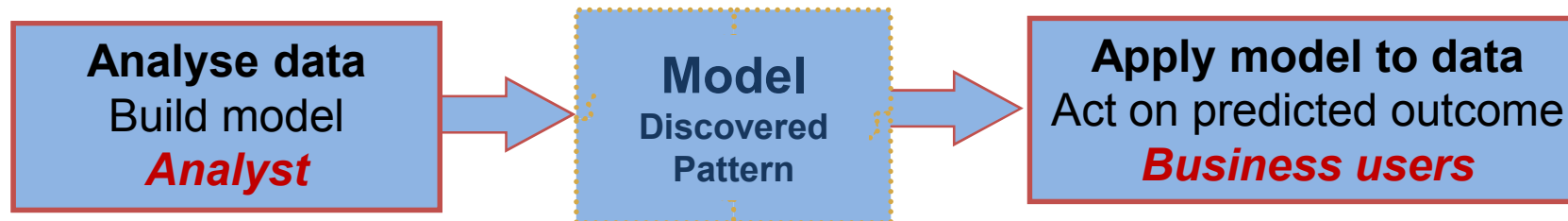
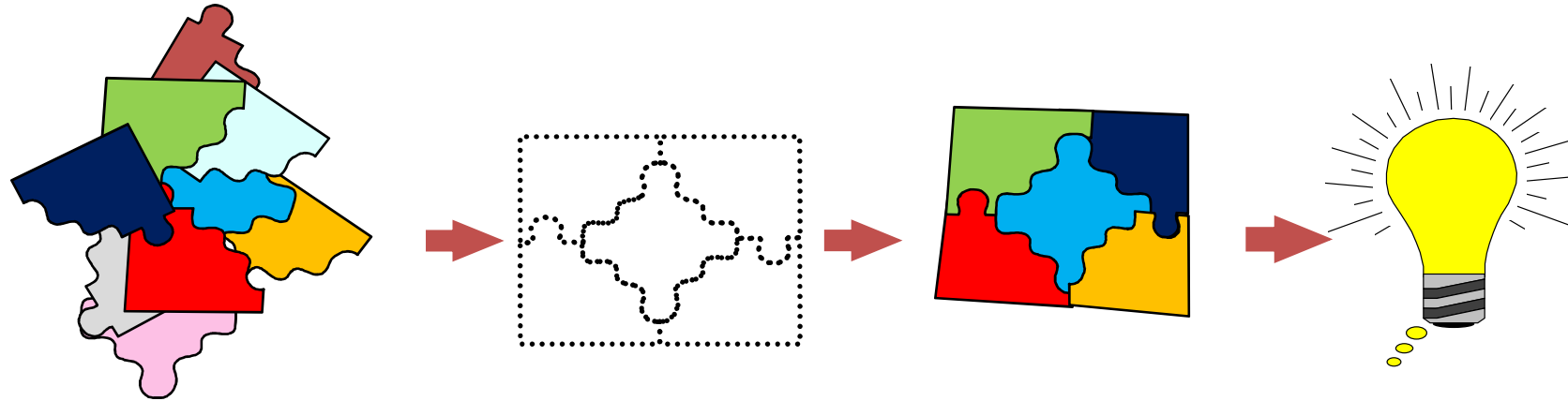


- Discovering meaningful relationships in data, in order to increase knowledge + understanding
- Leverages relationships between many variables to predict or describe patterns
- Outcome is a set of rules which assign each individual to a predictive or descriptive segment



- Querying data to obtain answers to questions
- OLAP and other forms of reporting
- Ad hoc business reports
- although these tools can all help to increase our understanding and support Analytical Modelling

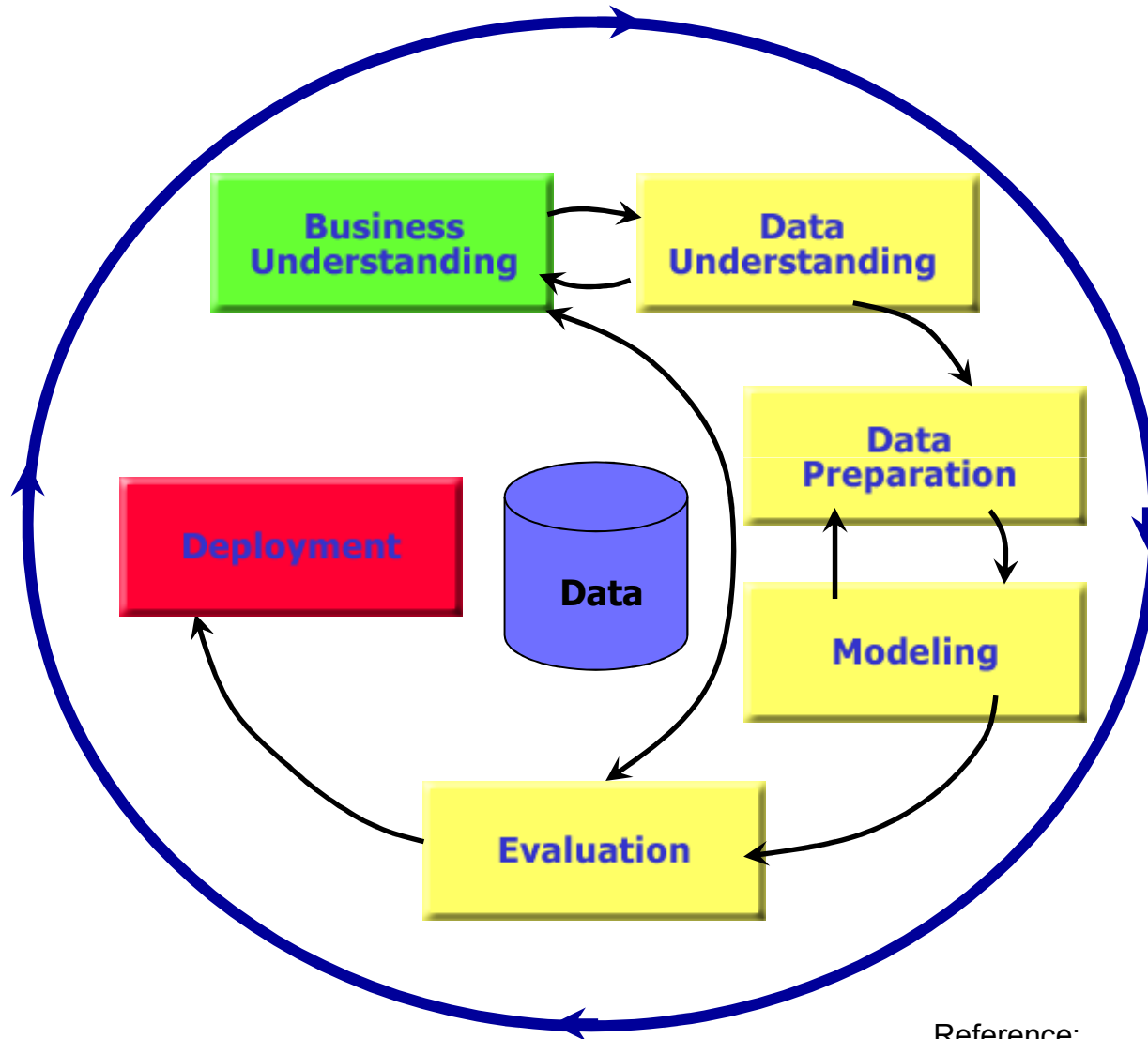
Discovery and Deployment of Data Mining



Discovery:
*Finding the relationships
that convert data into
information*

Deployment:
*Applying discovered
model for a useful
purpose - e.g. prediction*

The Data Mining Process (CRISP)



Cross Industry Standard Process for
Data Mining

Reference:
Step-by-step data mining guide
CRISP-DM 1.0

Agenda

- Introduction to data mining and analytical modelling
- Predictive and descriptive analytical models
 - Predictive case study – targeting bank customers
 - Predictive case study - lifetimes of mobile customers
 - Descriptive case study – financial segmentation
- Further points to consider
 - Data integration
 - Importance of a team approach
 - Model deployment
 - Contact optimisation
- Possible applications to online marketing

Two main types of Analytical Model

Type 1: Models driven by a Target Variable

e.g. Which customers to cross sell?

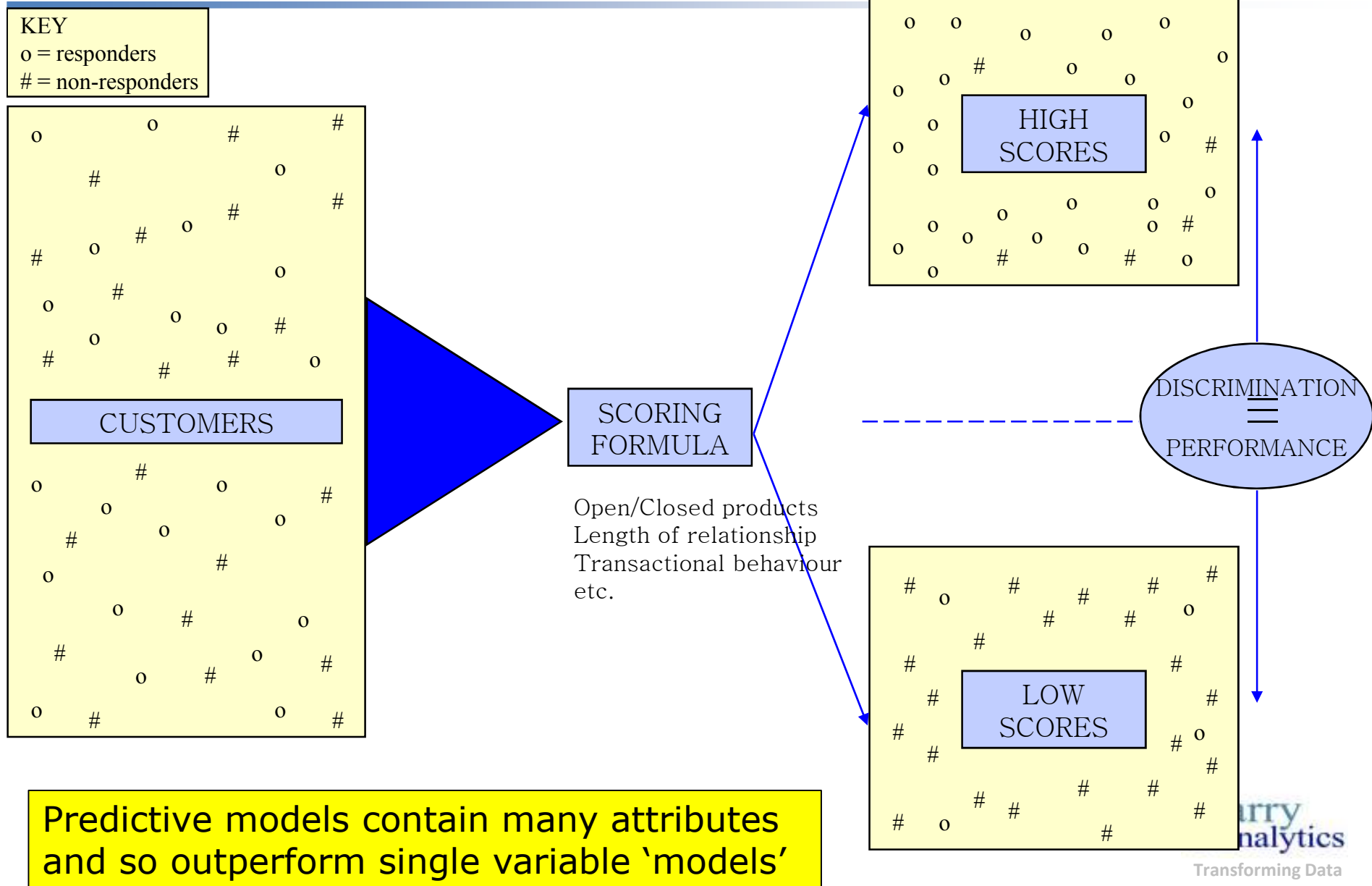
- **Implies building a Predictive Model**
- *'Directed' Data Mining Techniques*

Type 2: Models with no Target Variable

e.g. What are our most important customer segments?

- **Implies a Descriptive Model**
- *'Undirected' Data Mining Techniques*

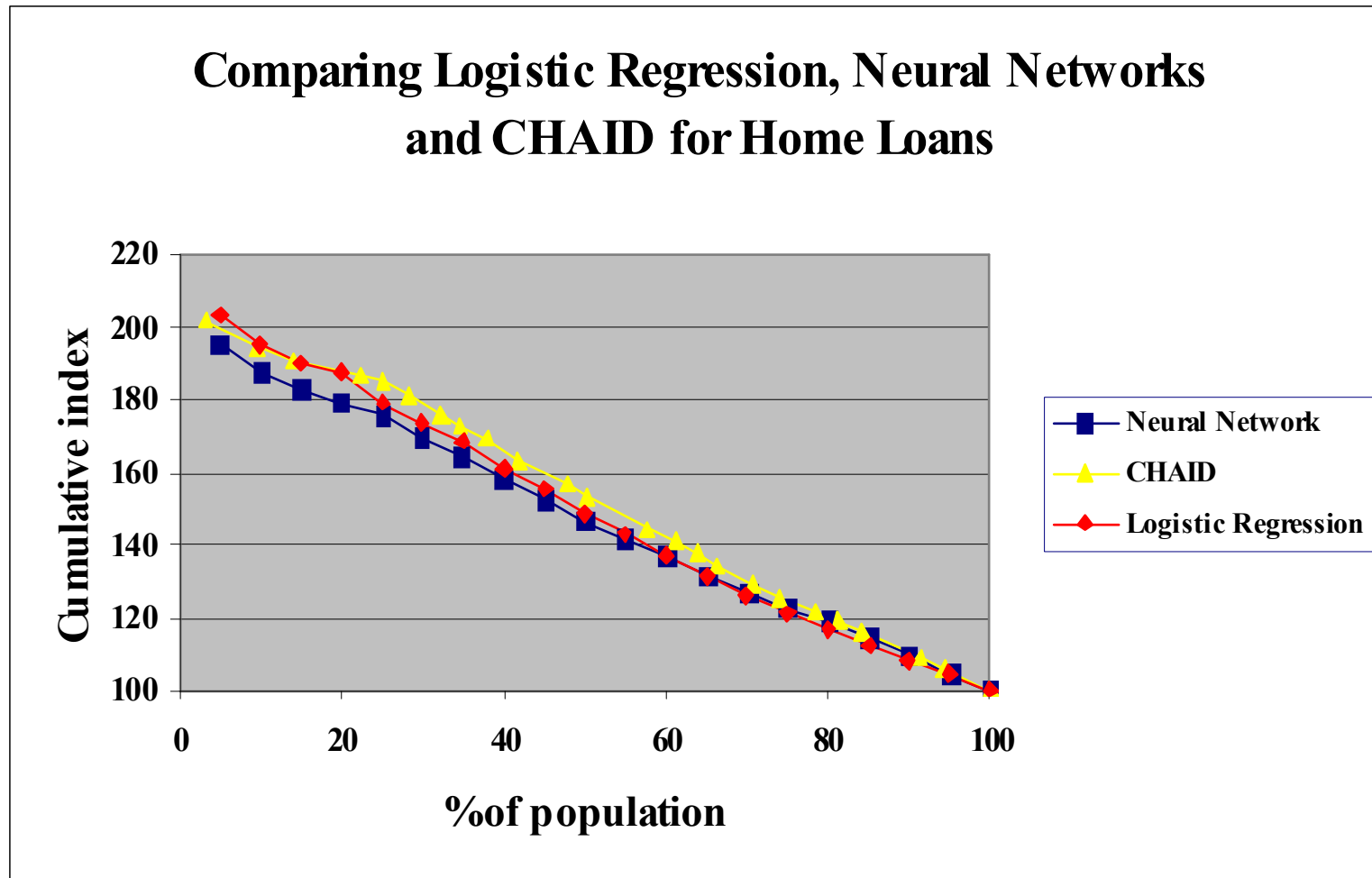
The role of a predictive model



Case Study Example - Targeting Bank 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

Results of Alternative Modelling Techniques

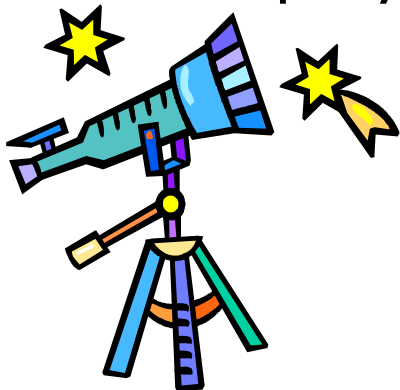


Sample base : Development Sample

Predictive power of data is often more important than choice of technique

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



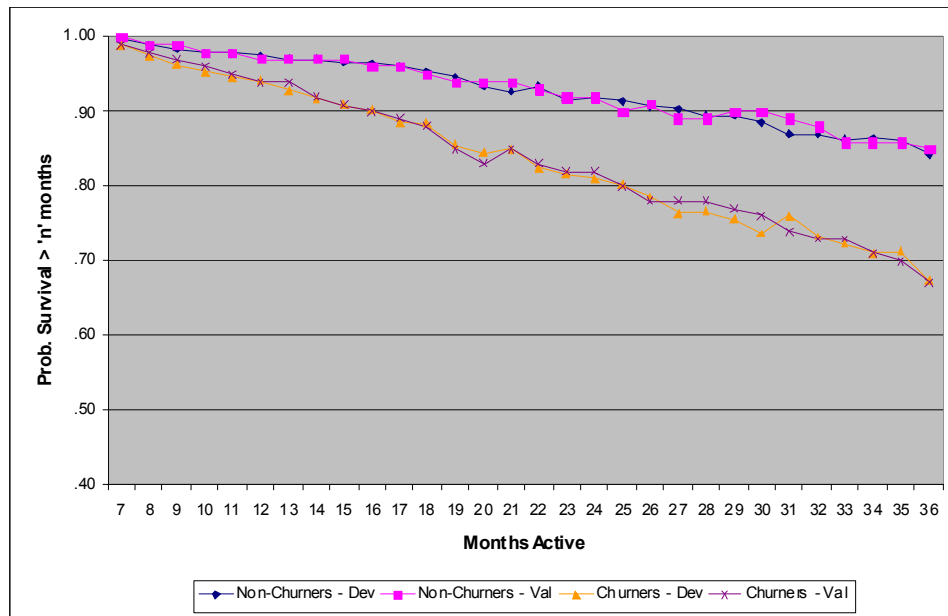
Case Study Example

Predicting Lifetimes of Mobile Phone Customers

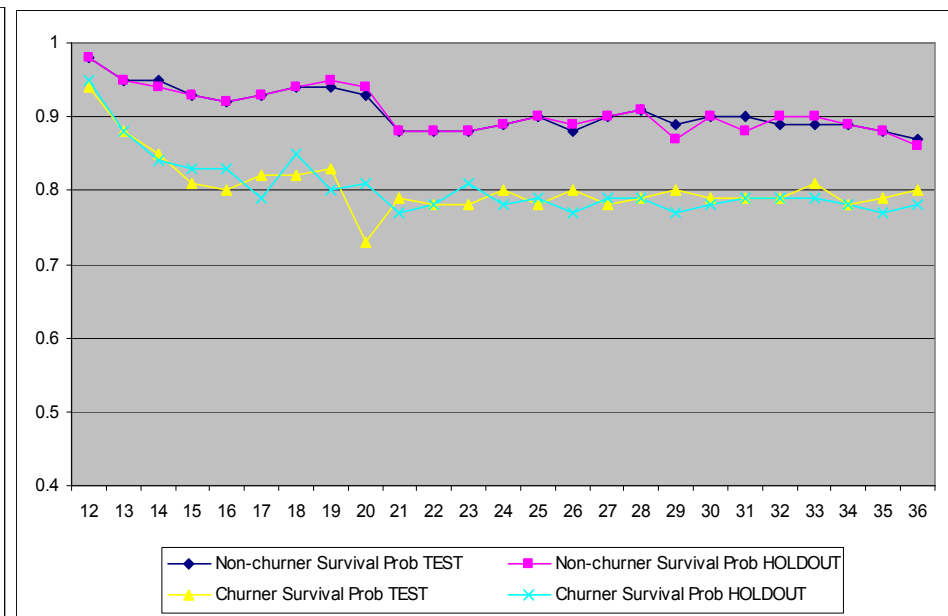
- Objectives
 - To increase 'life' of a mobile phone customer by introducing analytical approach to managing their lifecycle
- Analysis
 - Models for predicting customer lifetime were developed for pre-pay and post-pay mobile customers
- Action/Return
 - The models were validated by tracking subsequent churn
 - Potential improvement in post-pay model was demonstrated, using variables built from most granular data
 - The models were refined and implemented by the client

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

Pre-pay



Post-pay



Development and Validation results were almost identical for each model

Alternative Post-pay Models were built, based on variables calculated from calling records

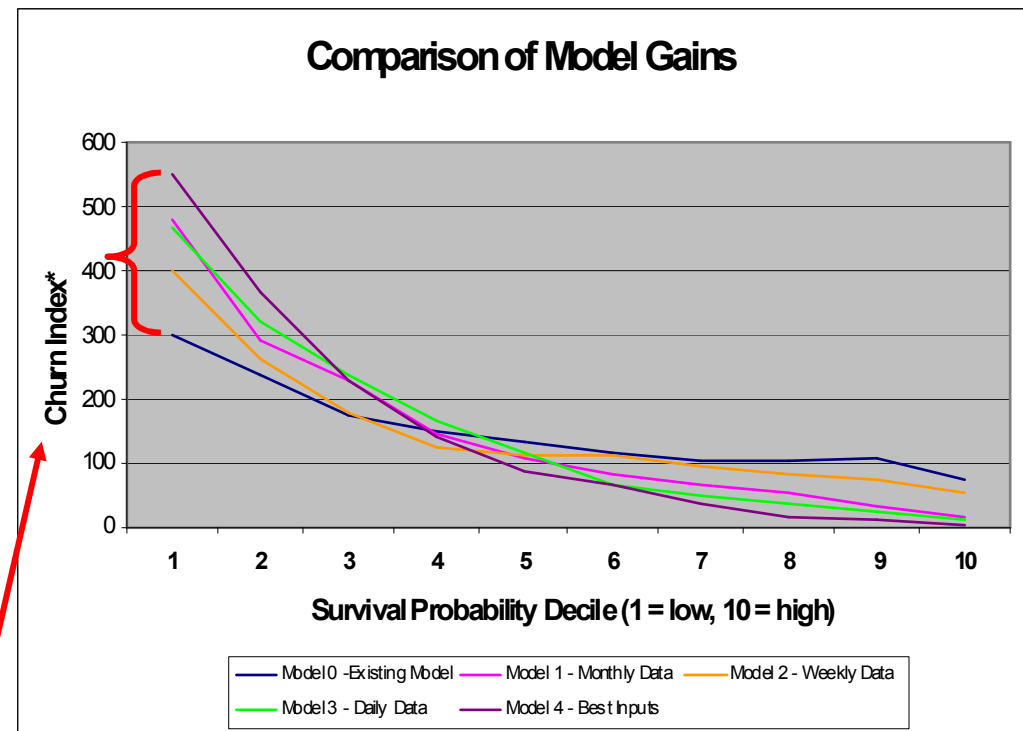
Model 0 - Existing model – standard monthly variables

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

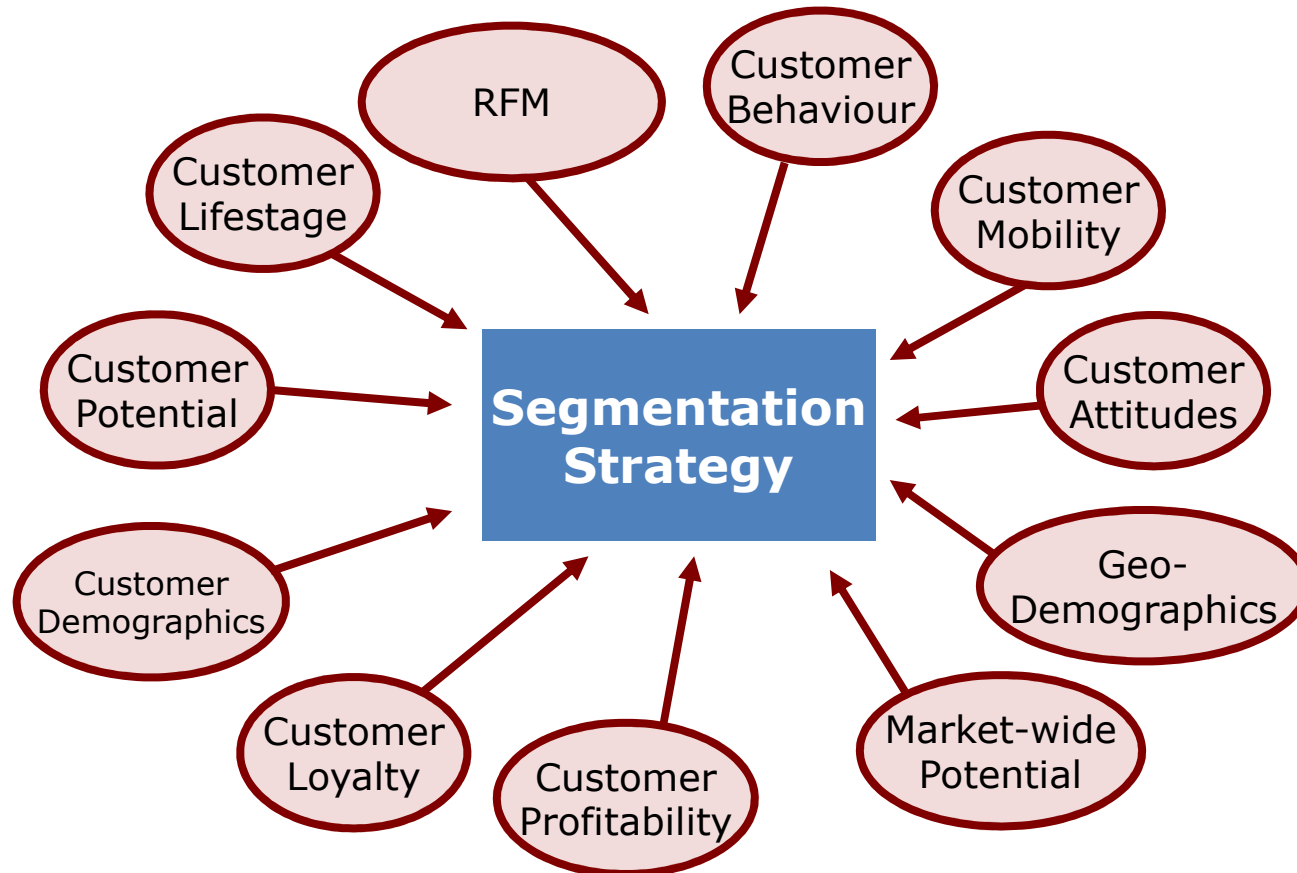
Model 4 - uses best inputs from all models



Models based on detailed data were up to twice as powerful

There are many ways to segment...

Your segmentation will work best on the criteria used to build it
- So, select appropriate criteria for your intended application



Case Study Example

Consumer Segmentation for Financial Services

- Objective
 - To segment financial services customers on their potential
- Analysis
 - A market-wide segmentation was developed using financial research survey data
 - The segments were overlaid onto various customer databases
 - And onto 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 FRUIT!

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 segments were defined by consumer's lifestage, affluence and product holdings

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.

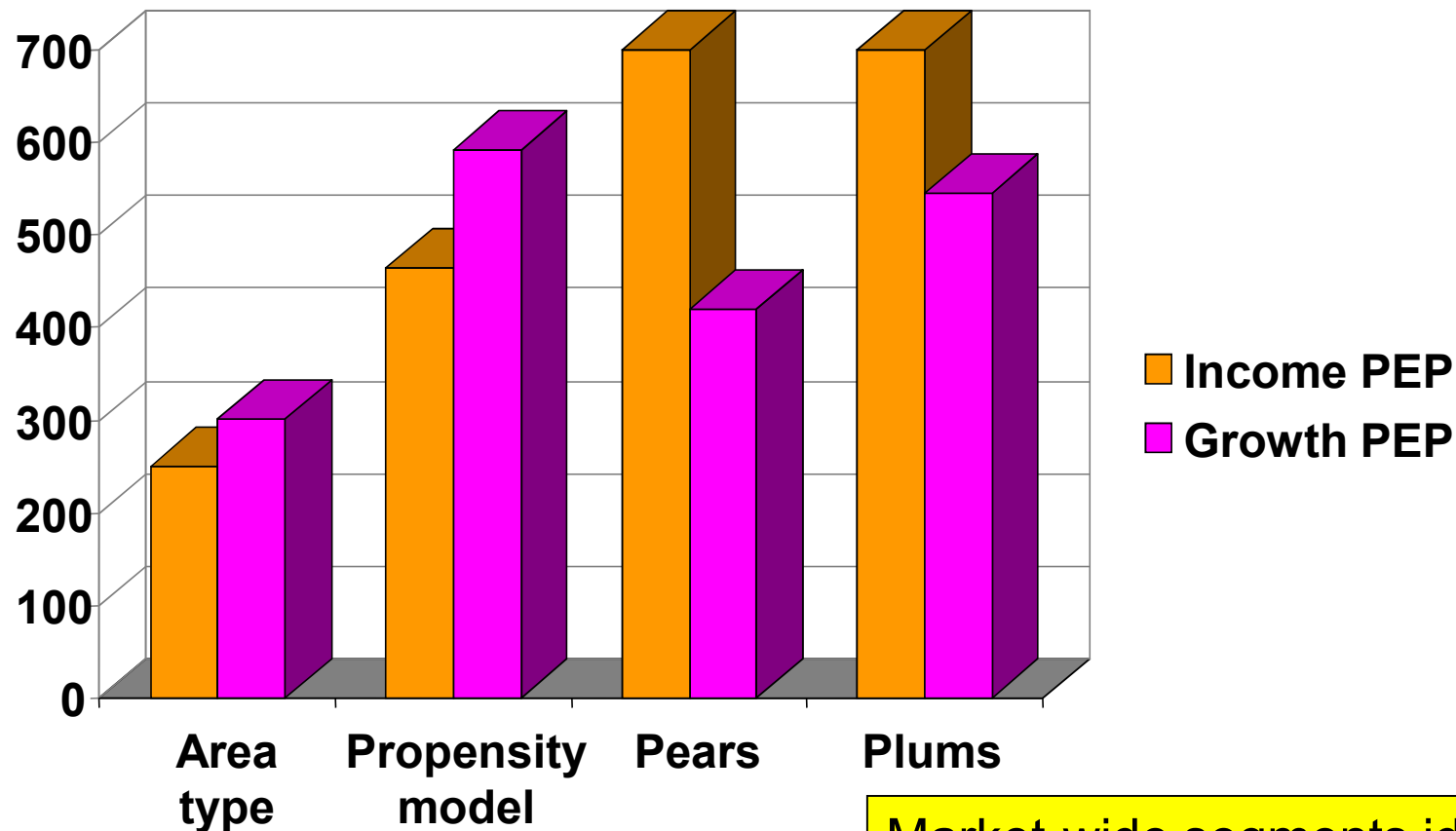


LEMONS, are usually older, single or widowed women living alone with an income of up to £7,499. They are unlikely to have loans, credit cards or personal pensions and are half as likely as the rest of the country to have household insurance.

The segments were identifiable and could be overlaid onto customers, prospects & market research data

Example 1: An insurance company used FRuitS to target investment products

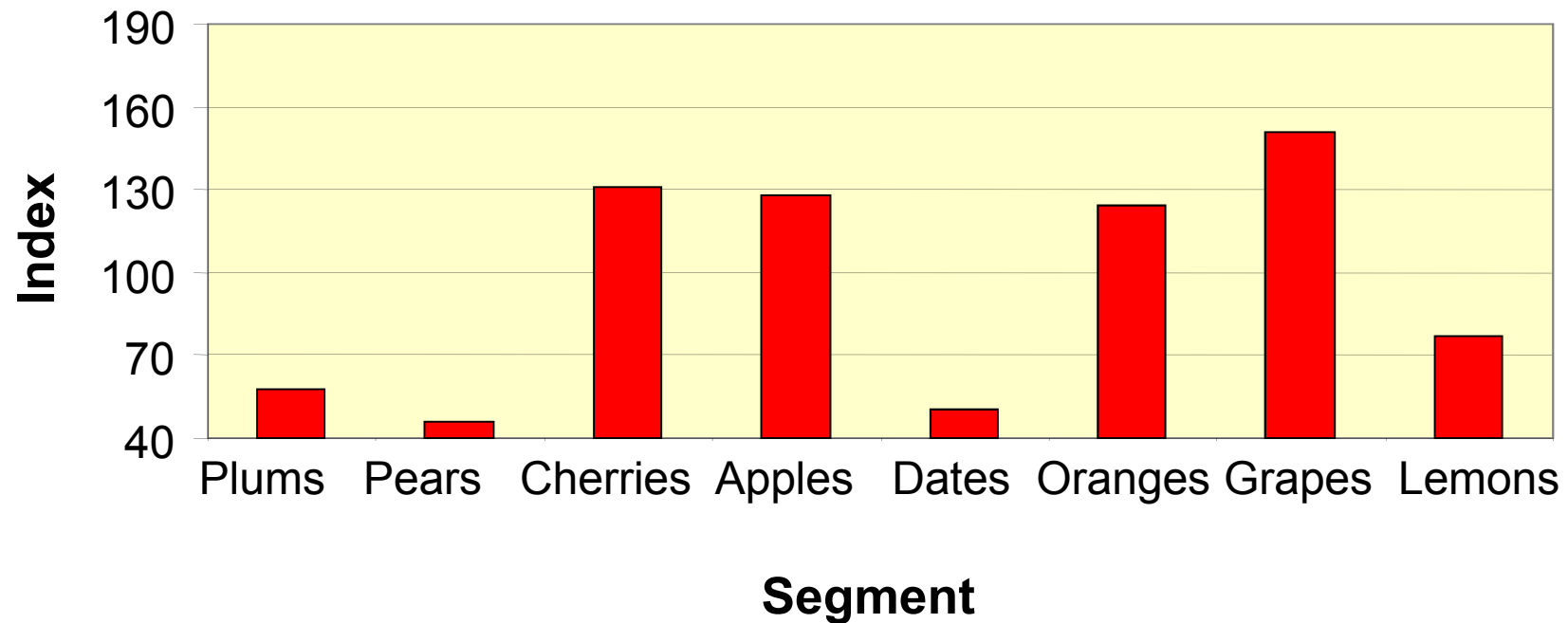
Index of £ Invested Per £ Marketing Spend



Market-wide segments identified insurance customers interested in investment products

Example 2: A retailer used FRuitS to identify profitable store card customers

Incidence of Profitable Customers by FRuitS



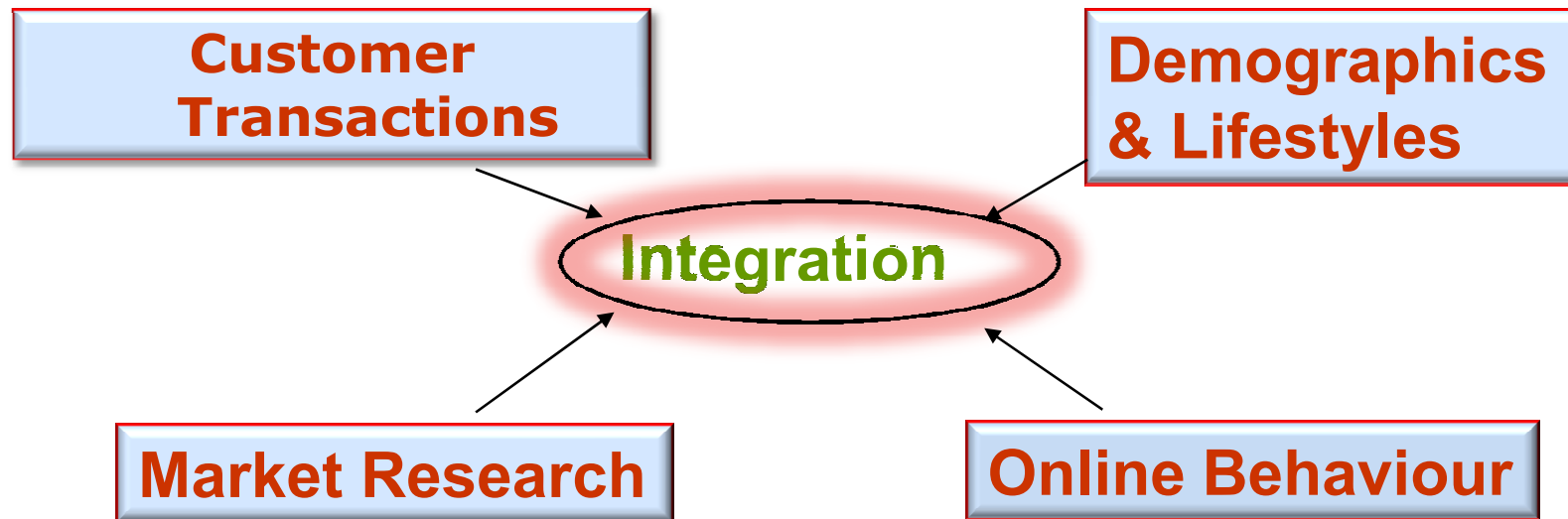
The segments were designed to discriminate on financial behaviour

Agenda

- Introduction to data mining and analytical modelling
- Predictive and descriptive analytical models
 - Predictive case study – targeting bank customers
 - Predictive case study - lifetimes of mobile customers
 - Descriptive case study – financial segmentation
- Further points to consider
 - Data integration
 - Importance of a team approach
 - Model deployment
 - Contact optimisation
- Possible applications to online marketing

The Importance of Data Integration

- The business value of your data increases through integrating and leveraging complementary sources
- New insights may be created by integrating, for example...



There are many applications of data integration...

- Predictive models to target behaviours identified by research, e.g. churn by reason
- Deploying common customer segmentation online and offline
- Tracking across channels, e.g. follow-up abandoned baskets

Data Integration can be a challenge due to differing data structures

Offline data

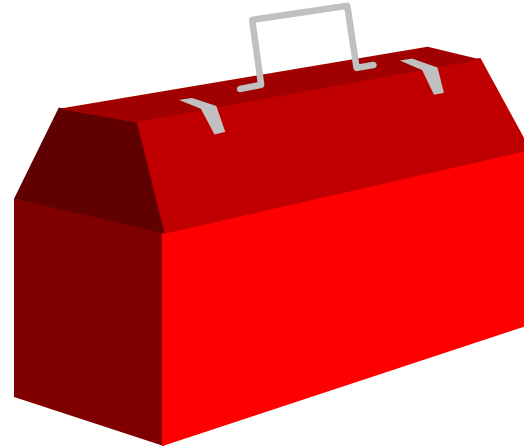
- Name & address
- Household/person
- Transaction behaviour
- Segmentations e.g. RFM

Online data

- Cookie & session
- Person/cookie/session
- Browsing + transactions
- Segmentations e.g. RFM

Can compare RFM segments between offline and online channels

A Toolkit of Data Mining Techniques



Traditional Statistics

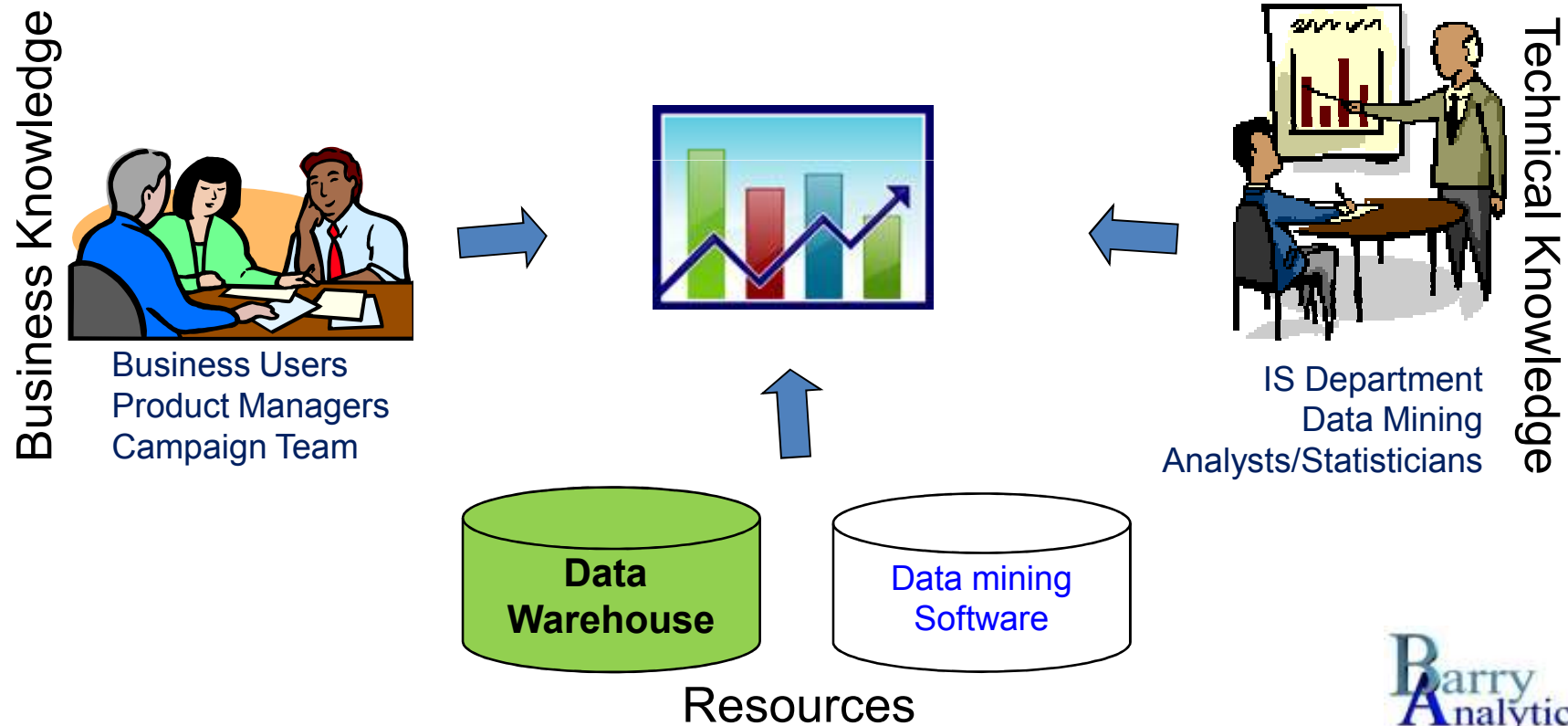
- Correlation Analysis
- Regression Models
- Principal Components/Factor Analysis
- Cluster Analysis

Machine Learning

- Rule Induction
- Neural Networks
- Genetic Algorithms
- Collaborative Filtering

Driving Business Value from your Data

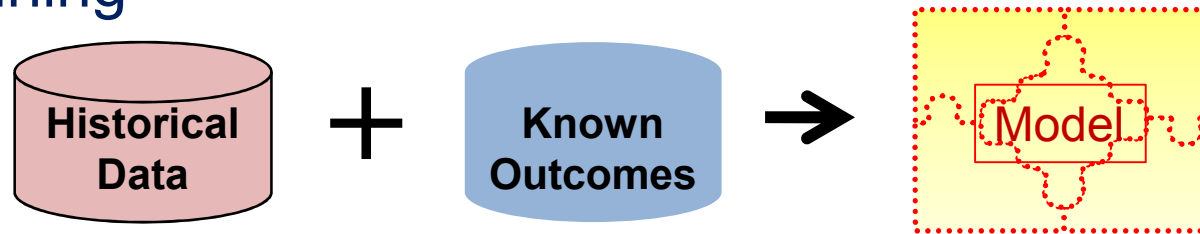
- Many people over-stress importance of analytical tools and under-estimate the Business Analysis process
- Best approach is consultative and business-focused



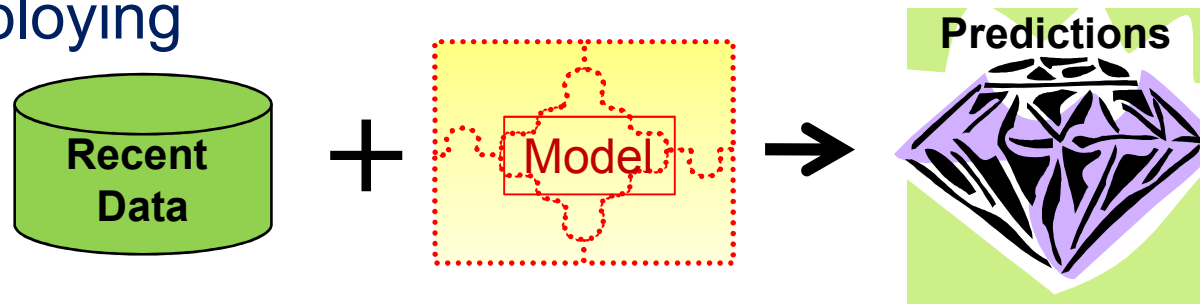
How are Analytical Models built and deployed?

- Models must be trained before they are deployed

Training

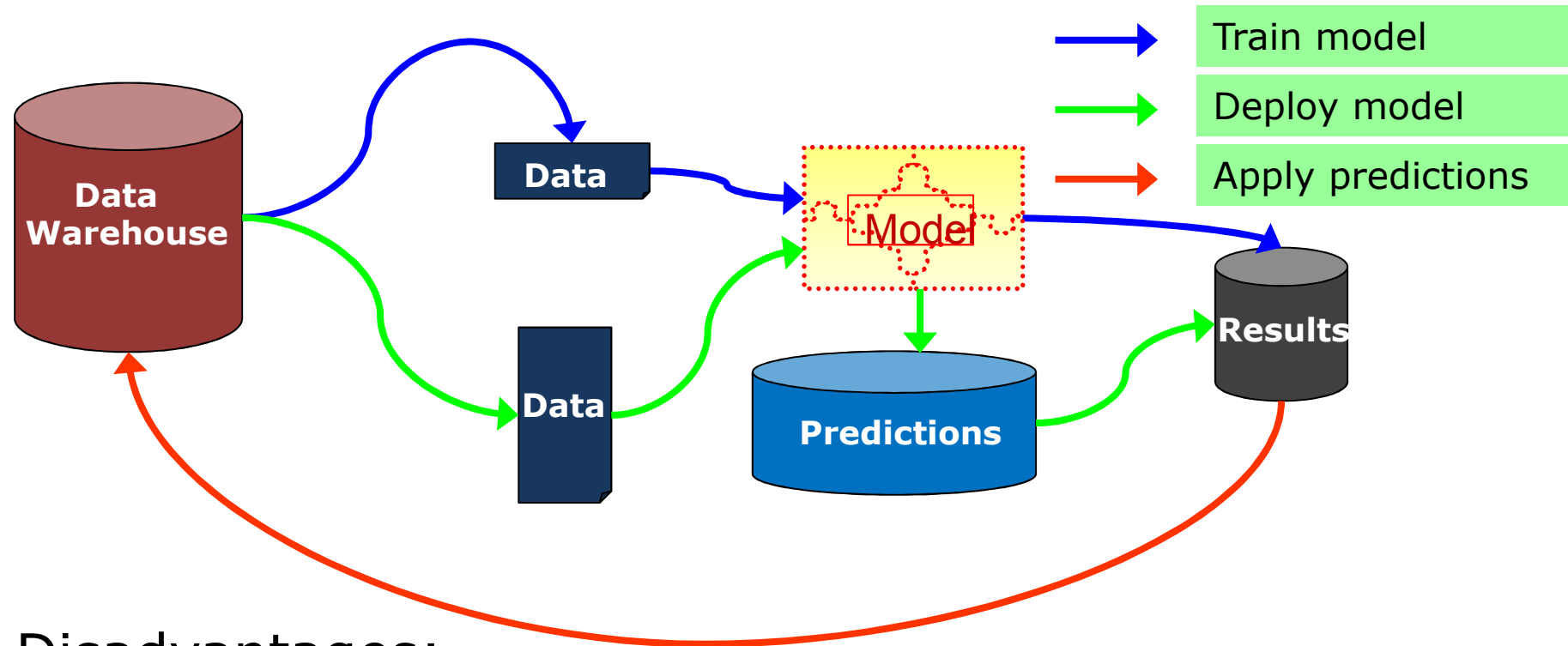


Deploying



- Training is 'one-off' – until model requires rebuild
- Deployment takes place repeatedly

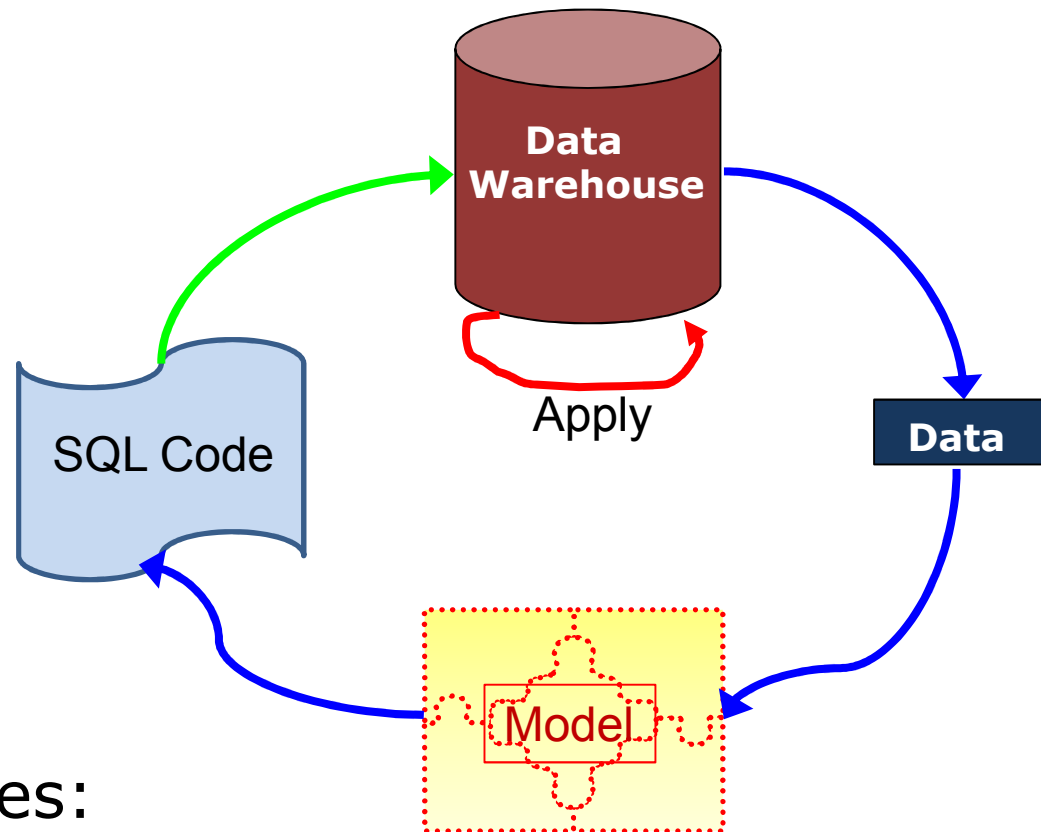
Typical Model Deployment Architecture



- **Disadvantages:**

- Very time consuming on large databases
- Produces multiple copies of same data
- Complex process to manage

Improved Model Deployment Architecture

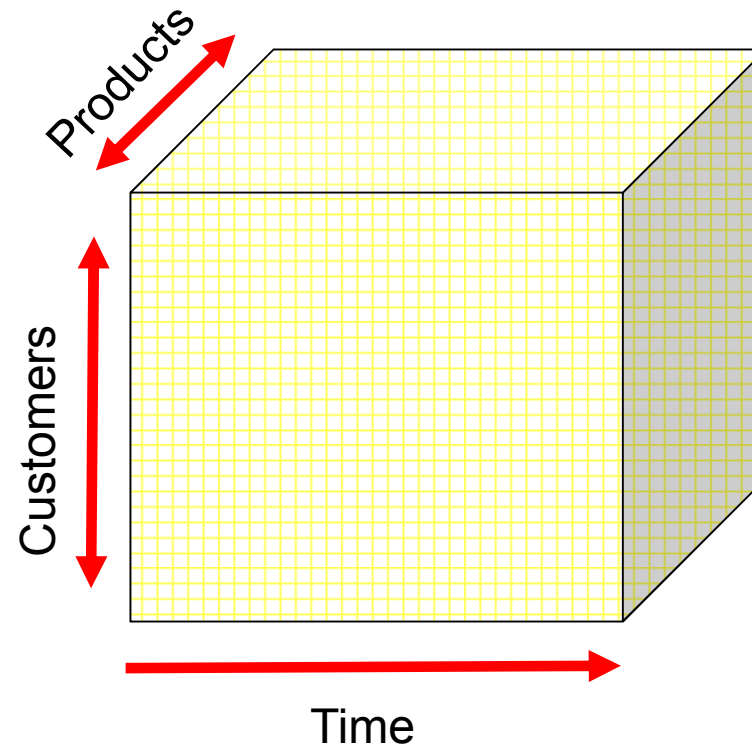


- Advantages:
 - Reduced data migration – saves time and storage
 - Scores can be continuously updated
 - Works with large volumes of data and many models

Model Deployment Best Practice

- If data volumes are vast, or you have large number of models to be deployed, consider an architecture that brings the algorithm to the data, i.e. scores the model in-database
 - Use predictive model mark-up language - PMML – for communicating models between model training and scoring systems
 - Or use a data mining tool that outputs scoring algorithm as SQL code for running in-database
- Ensure that model scoring does not require manual coding – time consuming and error prone

Contact Optimisation - maximising returns over time

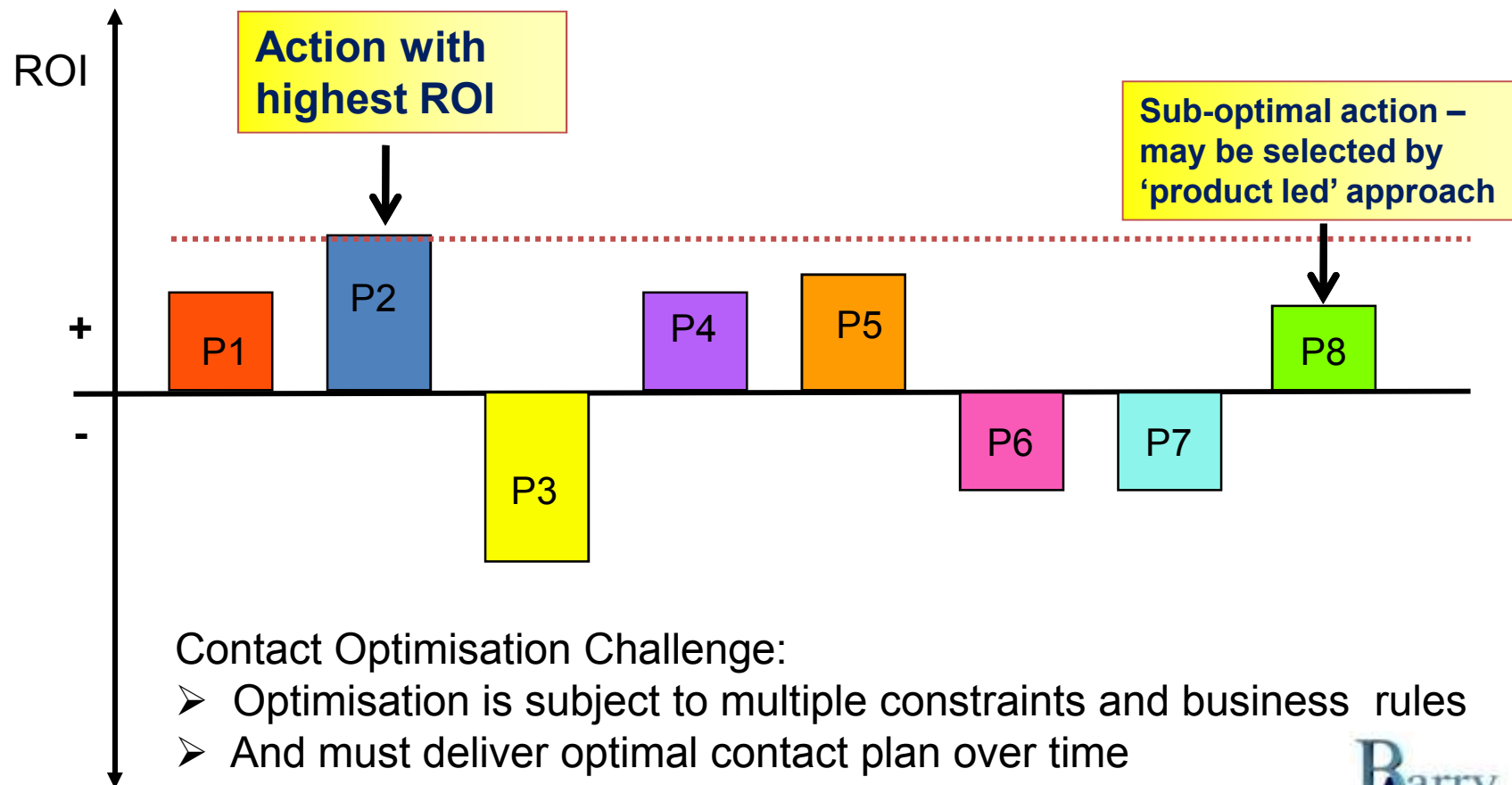


The objective is to optimise each individual customer's value delivered through time by managing the mix of communications/offers

Contact Optimisation selects best action for each individual Customer

- Propensity scores for all available actions are calculated for each customer
- Derive expected return from each action, select action with highest ROI

Contact Plan for One Customer



Agenda

- Introduction to data mining and analytical modelling
- Predictive and descriptive analytical models
 - Predictive case study – targeting bank customers
 - Predictive case study - lifetimes of mobile customers
 - Descriptive case study – financial segmentation
- Further points to consider
 - Data integration
 - Importance of a team approach
 - Model deployment
 - Contact optimisation
- Possible applications to online marketing

Some possible applications to online marketing

Predictive Models

Predictive models may be applied for:

- Deciding how much to invest in recruiting a customer, according to their predicted lifetime value
- Targeting email campaigns or content
- Selecting which products and offers website should display for each customer
- Targeting customers in order to 'save' abandoned baskets
- Targeting customers for offline follow-up
- Identifying customers at risk of churn
- Predicting time duration till customer revisits your website

Some possible applications to online marketing

Descriptive Models

Descriptive models may be applied for:

- Customer segmentation – following a common segmentation strategy across all channels
- Identifying 'shopping mission' – purpose of each shopping visit
- Customising 'look and feel' of emails and website pages to match usage & attitudes of each segment
- Targeting product offers according to segment purchase profile
- Understanding purchase affinities between products
- Making cross-sell offers to anonymous site visitors

Conclusions

- Business requirements come first – those should drive your analytics process, data selection and choice of methods
- Integrating data sources – such as offline & online behaviour – creates new insights and improves targeting
- Employ appropriate analytical techniques – however, good predictive data is often more important than complex algorithm
- Design your analytics process to enable seamless model discovery and deployment
- Analytical modelling involves advanced statistics – get help from a trained statistician or data mining analyst!

Thank you!

Barry Leventhal

+44 (0)7803 231870

Barry@barryanalytics.com

