

### Capabilities and Services in Data Analytics

WHITE CAPERS

### About Us

- A Results-Oriented Research and Data Analytics
   Outsourcing Company providing end to end
   Research & Analytics Solutions to organizations
   worldwide.
- Knowledge team comprises of PhD's, Statisticians, Business And Financial Analysts, Management and Science Graduates and Technology professionals

Decades of experience serving clients globally in diverse industries with specialization in Automotive, BFSI, Pharma, Retail, E-Commerce & Telecom. A Result Oriented Research and Data Analytics Outsourcing Company driven by Passion and Leadership



## **Technical Capabilities**

### Statistical and Mathematical tools: SAS, SPSS, R, MATLAB

**Analytical Techniques:** Statistical Analysis, Predictive Modeling, Clustering, Decision Tree, Customer Segmentation, Forecasting and Simulation, Response Optimization, Risk and Decision analysis.

**Statistical Procedures:** Conjoint Analysis, Factor Analysis, Discriminate Analysis, Regression Analysis(Linear Regression, Logistic Regression, Generalized Linear Model, Multivariate and Univariate Analysis), Time-Series, Association rules etc.

Databases: Oracle, DB2, SQL server, MS Access

**Reporting Tools:** MS Excel, VBA Automation, MS PowerPoint

### Our Team

A Bur Ross

As Jim Collin's has rightly put it - "the right people are a company's greatest assets".

White Capers has been fortunate enough to have a great team of professionals best suited for all your knowledge based requirements. The knowledge team comprises of PhD's, Statisticians, Business And Financial Analysts, Management and Science Graduates and Technology professionals to provide customers a comprehensive solution that work all the time.

#### **Team Profiles:**

**PhD.** in Economics from Penn State University, USA

PGDM/MBA from IIM Calcutta, India PGDBM/MBA from XLRI, Jamshedpur, India B.Tech/M.Tech from IIT Delhi, IIT Kanpur Masters in Mathematics, Statistics, Economics Chartered Accountants Chartered Financial Analysts (C.F.A.)

### **Team Composition:**

**SME** (Subject Matter Expert): Ph.D. with decades of industry / consulting experience

**Statistician:** MS in Statistics; years of working experience in applied statistical problems with expertise in statistical software

**Stat-programmer:** BE/B.Sc ; Statistical & quantitative experience; with experienced in SAS and other statistical packages

**Analysts:** MBA/M.Tech/B.Tech; with years of relevant research experience ; research papers in Publications and Journals



# **Engagement Process**

The WC Engagement Process ensures each customer has a positive experience the moment they enquire with us. Every project goes through the WC process radar and the end result is customer delight.





## **Beyond Rule based Segmentation**

| End of Period Block Status                        |      |      |      |     |     |     |  |  |
|---|------|------|------|-----|-----|-----|--|--|
| Status Movement Nil Cat A Cat B Cat C Cat D Cat E |      |      |      |     |     |     |  |  |
| Nil   | GOOD | BAD  | BAD  | BAD | BAD | BAD |  |  |
| Cat A   | GOOD | GOOD | BAD  | BAD | BAD | BAD |  |  |
| Cat B   | GOOD | GOOD | GOOD | BAD | BAD | BAD |  |  |

The Credit Card portfolio of a leading bank was into 7 lakhs customers of < 30 DPD. With the budgetary constraints, only a handful of them could be pursued for collections. Business managers were used to segmentation-cuts derived from elementary business know-how, which gave some results but *lagged far behind the benchmarks*.



### Prediction is Possible with Data

| Results of the Propensity Scorecard |                              |        |                         |                       |  |  |  |
|-------------------------------------|------------------------------|--------|-------------------------|-----------------------|--|--|--|
| Min Score                           | Score Max Score Observations |        | No. of Bad<br>Customers | % of Bad<br>Customers |  |  |  |
| 85.1                                | 100                          | 58,372 | 27,407                  | 48%                   |  |  |  |
| 67.8                                | 85.1                         | 58,372 | 13,182                  | 23%                   |  |  |  |
| 49.9                                | 67.8                         | 58,372 | 7,288                   | 13%                   |  |  |  |
| 34.5                                | 49.9                         | 58,372 | 4,263                   | 8%                    |  |  |  |
| 20.9                                | 34.5                         | 58,372 | 2,332                   | 4%                    |  |  |  |
| 10.1                                | 20.9                         | 58,372 | 1,257                   | 2%                    |  |  |  |
| 3.1                                 | 10.1                         | 58,372 | 637                     | 1%                    |  |  |  |
| 0                                   | 3.1                          | 58,372 | 256                     | 0%                    |  |  |  |
| 0                                   | 0                            | 58,372 | 98                      | 0%                    |  |  |  |
| -                                   | 0                            | 58,372 | 88                      | 0%                    |  |  |  |

80% of bad customers are captured in 30% of the population.

Top 10% capturing almost half of the bad customers – the best bait for our *focused collection efforts* 



# Predictive Modeling – Process Flow





## Services- Customer Analytics



Relationship Management

#### Cross-Sell/Up-Sell

- Cross-sell Strategy Design
- Multi Media Campaign Design
- New/Inline Product Forecasts

#### **Lifetime Value Analytics**

- Spend Analytics
- Customer Segmentation and Clustering
- Customer Satisfaction Analysis



#### **Inventory/ Product Planning**

- Demand, Supply & Inventory Planning
- Product Value Assessment, Capacity
   Planning, Portfolio Value Assessment

### **Retention/ Revival**

- Retention Prediction Scorecard
- Revival scorecard and Segmentation
- Early warning churn prediction model

### **Data Mining and Data Cleansing**

**Reporting, Dashboarding & Visualization** 

**Model Development and Recalibration** 



## Services- Marketing Analytics





## Services- Supply Chain Analytics



## Services- Historical Data Analysis

Meaningful information about customer behavioural patterns can be identified using the historical data of customer transactions-

- Who are our loyal consumers?
- What type of **products** do they buy?

- What are the dynamics of their spend **behaviour**?
- What is the consumer **landscape** and where is it moving?

A thorough analysis of historical data (customer, transactional, products) is conducted in the light of events that trigger specific consumer responses to the buying behaviour. Immense valuable insights about consumers and their ever-changing tendencies are revealed from the voluminous data available in situ.





### Services- MIS and Dashboards





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# **Samples & Snapshots**



## Segmentation Results- Sample

|                |  |    | Segmentation Results of Schema 1 (last 12 months of sales data) |    |    |    |    |    |               |    |   |    |       |
|----------------|--|----|---|----|----|----|----|----|---------------|----|---|----|-------|
|                |  | 0  | 1   | 2  | 3  | 4  | 5  | 6  | 7             | 8  | 9 | 10 | Total |
|                | 0  | 80 | 62  | 5  | 3  |    |    | 1  |               |    |   |    | 151   |
| 1a 2           | 1  |    | 145   | 19 | 7  | 1  | 1  | 1  |               |    |   |    | 174   |
| them<br>lata]  | 2  |    | 15  | 30 | 10 | 6  | 2  | 1  | 2             | 1  |   |    | 67    |
| of Sc<br>les c | 3  |    | 3   | 14 | 15 | 8  | 3  | 2  | 1             |    |   |    | 46    |
| ults (         | 4  |    |   | 4  | 9  | 7  | 7  | 4  | 3             |    |   |    | 34    |
| Resu<br>ths o  | 5  |    |   |    | 1  | 5  | 8  | 5  | 4             | 1  | 1 |    | 25    |
| ion ]          | 6  |    |   |    | 2  | 6  | 3  | 2  | 4             | 2  |   |    | 19    |
| ntat<br>t 6 n  | 7  |    |   |    |    | 4  | 3  | 4  | 2             | 1  | 2 |    | 16    |
| gme<br>(las    | 8  |    |   |    |    |    | 1  | 3  | 3             | 4  | 1 |    | 12    |
| Seg            | 9  |    |   |    |    |    |    |    |               | 4  | 3 | 2  | 9     |
|                | 10   |    |   |    |    |    |    |    |               |    | 2 | 3  | 5     |
|                | Total  | 80 | 225   | 72 | 47 | 37 | 28 | 23 | 19            | 13 | 9 | 5  | 558   |
|                | Customers that were Customers that Customers performing well earlier but have have largely remained have increased |    |   |    |    |    |    |    | that<br>their |    |   |    |       |

attributed to a lower sales recently-High **Potential Customers** 

unchanged over the last 12 months

relative spends on the Brands recently



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## Data Visualization - Sample

**Plot**: A network visualization of the correlations among two Dependent Variables (Q24F/Q25: in red) and 28 Dependent Variables (7 Variables in Q28 not considered due to missing values).



Lines between the nodes are the Correlations – The greater the Correlation between two variables, thicker the line between their Nodes

**Technique used - Spring Layout:** More highly correlated variables are placed near each other and away from less or negatively correlated variables.

**Q26**|**Q27**: Variables within the category are **highly correlated** to one another leading to **Multicollinearity**.



## **Descriptive** Analytics - Sample

|            | Monthly                       | Average                 |   |   |  | 2             | 012 |
|------------|-------------------------------|-------------------------|---|---|--|---------------|-----|
| Location   | <b>Revenue</b><br>(2012 2011) | Half Yearly<br>Growth % | Performance   |   | Trends & Recommendations   | Units<br>Sold | Ui  |
| Region 1 🔶 | <u>3077</u><br>1421           | -92 %                   | Most Revenue Generating –<br><i>Poor</i> Half Yearly Growth | м | Significant Sales drop in the past<br>5 months: only 1 SKU sold          | 171           |     |
| Region 2   | 1328<br>191                   | 49 %                    | Best Performance - Well Done !                              | М | All SKUs have increased sales in the past one year                       | 62            |     |
| Region 3   | 1018<br>159                   | 35 %                    | Good Work – Sustained                                       | м | Continuous Sales happened in the past one year                           | 74            |     |
| Region 4   | <u>     800</u> 250           | 93 %                    | Growth  | м | Focus on more Products<br>will elevate Sales                             | 60            |     |
| Region 5   | <u>658</u><br>660             | -100%                   | No Sales in Last 3 Quarters                                 | М | Focus Desired, Sales occurred only between Dec'11 to Feb'12              | 71            |     |
| Region 6   | 479<br>367                    | 1356%                   | Successful Q3 – Failed Year                                 | S | Bestseller Sales occur once per year                                     | 19            |     |
| Region 7   | $\frac{0}{222}$               | No Sales<br>In 2012     | Focus Required – Dormant Region                             | м | No SKU sold in the past one year.<br>Demand per SKU - less than 10 units | None          |     |

**Half Yearly Growth %** = [(Monthly Revenue Average in 2012/ Monthly Revenue Average in 2011) – 1] \* 100

**S** – Single Product Focus **M** - Multi Products Focus



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### Sample – Spends Analysis Tool



### Sample – Marketing Spends Tool

|  | DATA BIBLE: SALES PERFORMANCE   |
|--|---|
| Sales Sales Targets                        | FB Trends     Marketing     Bank     VAT     P&L     Cash Flow  |
| Select Sales Channel Independent + Website | Select a Geography <ul> <li>ALL</li> <li>AU</li> <li>CA</li> <li>DE</li> <li>DK</li> <li>DE</li> <li>FR</li> <li>TT</li> <li>NL</li> <li>NZ</li> <li>SE</li> <li>UK</li> <li>US</li> <li>OTH</li> </ul>                 |
| Select a Product Adult- All                | Average Weekly Sales (Target)4,460UnitsAverage Weekly Sales (Actual)4,343UnitsVariance in Sales-117Units  |
| 2,50,000                                   | Weekly Sales Performance Trend O Sales Volume O Cumulative Sales  |
| 1,50,000<br>1,00,000<br>50,000             |   |
| Wk1 Wk4 Wk7 Wk10                           | Wk 13       Wk 19       Wk 22       Wk 25       Wk 28       Wk 31       Wk 37       Wk 40       Wk 43       Wk 46       Wk 49       Wk 52         ▲       Target Cumulated Volume       →       Actual Cumulated Volume |





## **Case Studies**



## **Case: Demand Forecasting**

**Business Objectives:** Build a Forecasting model to predict the monthly demand levels for each sales channels across all geographies and plan the orders optimally to avoid stock-outs and large inventory levels.

### Approach



**Client Benefits:** Using the predictive forecasting models, accuracy of 82% is achieved in demand prediction within the first two months of its usage. Our 'Inventory Management tool', built to manage inventories, administers the orders and shipments statuses to a very fine level of success which further increases the service levels by 41%.

Actual — Predicted

## **Case:** Purchase Profile Analysis



**Business Objectives:** To analyse the customer sales data by pivoting the customers and understand various purchase patters that emerge from their shopping behaviour over a period of time.

### Approach



Total No. of Purchases: 17.220

**Client Benefits:** The results of the analysis were implemented in designing marketing campaigns for new users, and emailers targeted for repeat purchases. Management removed some product lines having less margins and no visible impact on the repeat sales. The overall contribution margin increased by 12% as a result of realigning priorities. Page 22

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# Case: Optimizing Distribution Cost

**Business Objectives:** To evaluate the cost proposal of various shipping players in USA and Canada and finalize a mix of delivery channels for optimal shipping cost.

### Approach



Number of Shipments \$100,000 15,000 \$80,000 \$60,000 10,000 \$40,000 5,000 \$20.000 Ś0 3 5 6 7 2 8 Zones Total Current Cost
Total Cost- Proposed #Shipments

The company saved about USD 20,000 in the first month and was eying a saving of USD 300,000 in the year.

- The shipping cost were reduced by 8.5%.
- Per package shipment cost was reduced by \$ 0.45 to \$ 0.55 for various shipment types.
- Rolled out a variable shipping plan for customers than charging fixed shipment fees.



## Case Study: Facebook Sales Linking

**Business Objectives:** Determine if there is a correlation between Facebook "fan" growth and sales trends and build a statistical model that links Facebook fan growth to Sales to help the retailer focus and manage their marketing spends more effectively.

### Approach



**Client Benefits:** We helped the client institutionalize and leverage our expertise in Marketing Analytics on Social media and scale up the business to more than 350% since engaging White Capers as their trusted Analytics partner.



## Case Study: Telecom Analytics

**Business Objectives:** Develop a model to be used in live collection aiming to predict the customers who are going to be disconnected or bankrupt in next six months. The model was to be used for scoring those customers who are in collection (missed payment of at least one bill) and having due amount greater than 30\$).



**Client Benefits:** Using our approach our client now has a scientific approach for the collection strategies to optimize their collection efforts. This tool is being used in live collection system with an automated alert system to raise indications of customers in terms of high, medium or low risk level at time of their first default itself.



## Case Study: Telecom Analytics (Cont.)

Illustration : Predictive Model Results on various sub-populations

| Results of Individual Model - Subpop A |       |      |       |          | Results of Overall Population Model |        |       |      |       |          |                            |
|--|-------|------|-------|----------|-------------------------------------|--------|-------|------|-------|----------|----------------------------|
| Decile                                 | Total | Bad  | Good  | Bad Rate | Cumulative<br>Capture Rate          | Decile | Total | Bad  | Good  | Bad Rate | Cumulative<br>Capture Rate |
| 1                                      | 4990  | 13   | 4977  | 0.26%    | 0.5%                                | 1      | 4990  | 19   | 4971  | 0.38%    | 0.8%                       |
| 2                                      | 4990  | 20   | 4970  | 0.40%    | 1.3%                                | 2      | 4990  | 58   | 4932  | 1.16%    | 3.1%                       |
| 3                                      | 4990  | 39   | 4951  | 0.78%    | 2.9%                                | 3      | 4990  | 69   | 4921  | 1.38%    | 5.9%                       |
| 4                                      | 4990  | 55   | 4935  | 1.10%    | 5.1%                                | 4      | 4990  | 112  | 4878  | 2.24%    | 10.4%                      |
| 5                                      | 4991  | 85   | 4906  | 1.70%    | 8.6%                                | 5      | 4991  | 136  | 4855  | 2.72%    | 15.9%                      |
| 6                                      | 4990  | 152  | 4838  | 3.05%    | 14.7%                               | 6      | 4990  | 185  | 4805  | 3.71%    | 23.4%                      |
| 7                                      | 4990  | 217  | 4773  | 4.35%    | 23.5%                               | 7      | 4990  | 253  | 4737  | 5.07%    | 33.6%                      |
| 8                                      | 4990  | 302  | 4688  | 6.05%    | 35.7%                               | 8      | 4990  | 408  | 4582  | 8.18%    | 50.1%                      |
| 9                                      | 4990  | 502  | 4488  | 10.06%   | 56.0%                               | 9      | 4990  | 525  | 4465  | 10.52%   | 71.3%                      |
| 10                                     | 4991  | 1089 | 3902  | 21.82%   | 100.0%                              | 10     | 4991  | 709  | 4282  | 14.21%   | 100.0%                     |
| Total                                  | 49902 | 2474 | 47428 | 4.96%    | 100.00%                             | Total  | 49902 | 2474 | 47428 | 4.96%    | 100.00%                    |

The Subpop A model performs better than the model built on overall population. **K-S lift of 49 vs. 39** 





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## Case Study: Cross-sell Model

**Business Objectives:** A leading financial services group, wanted to explore the possibility of leveraging their existing customer database by-

- Identifying and targeting prospective customers for cross selling
- Building a scorecard to calculate the propensity of the target customers to purchase various products

### Approach

| Surrogate Data<br>Creation  | Model Development  | Customer Profiling   | Customer<br>Segmentation   |
|---|--|--|--|
| Surrogate Data was created<br>for customers using<br>Statistical Techniques,<br>Survey Results, and Business<br>Knowledge | Models were developed on<br>surrogate data leading to<br>scorecards for each product<br>type | Profiling of customers<br>conducted that have greater<br>likelihood of buying a given<br>product | Scores obtained from the<br>cross-sell model are used to<br>segment the customers of the<br>entire product portfolio |

**Client Benefits:** White Capers helped the client optimize their cross sell efforts and institutionalize this scientific approach as an organization wide operations tool for all cross sell campaigns.



**Business Objectives:** Outbound freight optimization analysis by cost, service levels, zone, package dimensions and weight thereby, helping the company optimize service levels and reduce freight charges that has a direct impact on their bottom line.

| Sr. No. | Analysis Description                                  | Analysis Details  | Delivery Format   |
|---------|---|---|---|
| 1.      | Cost per package by<br>zone by service by<br>location | <ul> <li>Analysis of cost per shipment package with data cuts on-</li> <li>Time period trends- month on month (MOM)</li> <li>All Carriers (Canada Post, UPS, Mail Innovation etc.) and all service levels (Ground, Surepost, 1Day delivery, 2Day delivery etc. : 16 service options in total)</li> <li>Across 3 locations and 8 associated zones (24 levels)</li> </ul> | <b>Presentation:</b><br>Containing all the<br>trends and patterns<br>obtained as analyses<br>results, observed<br>inferences and a<br>comparative analysis<br>of results across key<br>parameters |
| 2.      | Average cost analysis<br>per zone by location         | <ul> <li>Percentage distribution of packages and average cost of shipment across</li> <li>Different locations and associated zones (24 levels)</li> <li>Time period trends- month on month (MOM)</li> </ul>   | <b>MS Excel:</b><br>Containing analysis<br>details  |

### Case Study: Freight Service Optimization

| Sr. No. | Analysis Description                              | Analysis Details  | Delivery Format  |
|---------|---|---|--|
| 3.      | Analysis on Service<br>Levels                     | <ul> <li>Service Analysis of packages through various service level options-</li> <li>Distribution of # orders shipped using various service level options (16 in total)</li> <li>Split across 3 locations and 8 associated zones (24 levels)</li> </ul>  | <b>Presentation:</b><br>Containing all the<br>trends and patterns<br>obtained as analyses<br>results, observed<br>inferences and a |
| 4.      | Analysis of<br>Dimensionally<br>Weighted Packages | <ul> <li>Top ten dimensionally weighted products (and their variants, product categories) which drive maximum count/revenue of sales</li> <li>Top ten products (and categories) that make it least profitable for us to sell because of the dimensions (and whether do we need to actively promote these products).</li> <li>Time period trends- aggregate</li> </ul> | comparative<br>analysis of results<br>across key<br>parameters<br><b>MS Excel:</b><br>Containing analysis<br>details               |



## Case Study: Retail Analytics

| <b>Project Outline</b>   | Description   | Benefits   |
|--|---|--|
| Monthly default<br>prediction models<br>for active Retail<br>(Auto) Loan portfolio                 | <ul> <li>A 100 year old leading vehicle finance company from US with a sub prime portfolio wanted to make scientific and optimal collection strategies.</li> <li>Developed an early warning delinquency predictor scorecard on the portfolio and implemented the same on the client's system. The scorecard gives scores to all the accounts based on their propensity to default on the payments in the next month. It also categories the accounts into risk segments helping the client in targeted collection strategies.</li> </ul>  | After implementing the<br>model, the monthly<br>default rates are down<br>by 16%   |
| Inventory<br>Management System<br>for a Leading Multi<br>National Retail Player                    | <ul> <li>A global retail company had problems in optimizing the inventory levels in the warehouses so as to not miss out on demand while avoiding cannibalization</li> <li>Prepared a smart order processing and inventory management system to identify and alert stock levels, place and track orders automatically ensuring high service level with low overall storage cost.</li> </ul>   | Reduced the storage cost<br>by 30% while increasing<br>the service levels by 15%   |
| Customer Sales Data<br>Analysis for a large<br>multi brand retail<br>company based in<br>Australia | <ul> <li>A leading multi brand e-retail player with a large customer base needed to analyze the customer database in depth to understand the varying sales trends, customer behavior, product affinity, market baskets so as to effectively target the marketing efforts.</li> <li>An in-depth study of sales data was performed to identify patterns of sales by Customers across all sales regions, by each brand, and SKUs sales trend for key national accounts.</li> <li>A dynamic dashboard was prepared to provide a holistic view of the complete performance trend.</li> </ul> | The client could get a<br>complete picture of<br>varying KPI trends<br>across customers,<br>regions and SKUs and<br>hence, improve the<br>sales productivity<br>significantly. |
|  |   |  |

VV

## Case Study: Financial Services

| Project Outline   | Description   | Benefits  |  |  |
|---|---|---|--|--|
| Data Cleansing on a<br>Life Insurance<br>portfolio database               | <ul> <li>Our client, a leading Insurer needed to increase phone number<br/>contactability on their database. The phone numbers were not in machine<br/>dialable format s hence dialer machines could not be used directly for<br/>customer reach out/ cross-sell/ renewal campaigns.</li> </ul>   | As a result of improved<br>contactability, cross-<br>sells went up by 11%<br>in a year's time   |  |  |
|   | <ul> <li>Developed an algorithm which picks correct phone numbers from text<br/>strings and modifies them into machine dialable format (adds std code on<br/>landlines, if required). Automated it in an excel tool to be used on<br/>incremental data.</li> </ul>  |   |  |  |
| Data De-duplication<br>and Multimedia<br>Campaign Design                  | <ul> <li>Mid sized brokerage firm having seen a 100% YoY growth for last three years was finding it difficult to manage their DW (identify unique customers, unique families etc.) resulting in huge leakages and untapped potential</li> <li>Developed de-duplication algorithms, created unique identifiers in the DW</li> <li>Designed Multimedia cross-sell campaign based on customer coordinates, channel availability and previous response etc.</li> </ul>                | <ul> <li>Enhanced information<br/>about customer base<br/>resulting in better<br/>business management</li> <li>Cross-sell on existing<br/>base amounting to 15%<br/>of annual revenues</li> </ul> |  |  |
| Mortgage/SME Loan<br>Portfolio: Collection<br>Scorecards System<br>Design | <ul> <li>Leading retail bank with a regional focus had a large mortgage and SME loan book. Account management at branch level so no centralized collections in place</li> <li>Needed data driven systems to facilitate proactive and centralized collections and recovery processes</li> <li>We Developed early bucket delinquency predictor and late bucket payment predictor scorecards to check forward flow rates early in the credit cycle and minimize NPA later</li> </ul> | Scorecard used in<br>portfolio segmentation<br>for targeted treatment<br>design resulting in<br>improved credit risk<br>management  |  |  |
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# **Core Team Profile**



## Team Profile – Gaurav Bajpai



#### **Tools** SAS, SPSS, R, MS Excel, MS PowerPoint, VBA

#### Skills

Modeling & Forecasting, Predictive Analytics, Business Strategy, MIS, Reporting Tools Building, Presentations

### Gaurav Bajpai

Analytics Head

#### Education: PGDM from IIM Calcutta, B.Tech from IIT Kanpur

**Specialties:** Project Planning & Management, Marketing Analytics, Forecasting Models, Propensity Scorecards, Dashboards & MIS, Management Tools, Regression Analyses, Retail Analytics

Gaurav brings to the team a rich consulting experiences in both national and international geographies. He has worked on many assignments in BFSI, retail, telecom, and e-commerce. Being an automation champion and a process-oriented person, Gaurav was responsible for substantially reducing the duration of a major reporting activity at Yahoo. He has developed many models and tools to help optimize the various marketing channels of various companies. Most notably is his contribution to an retail house for which his demand forecasting and inventory management models enhanced the revenue line significantly and increased the service levels by 41%. He also brilliantly projected sales for a clothing brand by using Facebook fans information vis-à-vis the demographics of the customers.

**Key Projects:** Go to market Strategies for key business verticals at Yahoo!, analytics team set up for a large insurance company in India, Management Information System set up for e-retail company having presence across the globe, demand forecasting and inventory management for a leading retail client of UK.

## Team Profile – Hemant Kathuria



#### Tools

SAS, R, MS Excel, MS Access, MS PowerPoint, VBA, SQL

#### Skills

Reporting, Predictive Modeling, Data Cleaning, Data Presentation & Analyses, Tools Building

### Hemant Kathuria

Project Manager

#### Education: B.Tech and M.Tech from IIT Delhi

**Specialties:** Project Management & Scoping, Predictive Analytics, Customer Segmentation & Profiling, Resources Management, SQL reporting, Managements tools building using MS Office suite & VBA

Hemant has delivered many assignments for top notch BFSI and retail clients across India, US and Europe and is especially noted for his contributions in predictive analytics solutions. He has a number of successful assignments in the areas of demand forecasting, customer segmentation and profiling, churn predictions and many more under his belt. He has also delivered many scorecards and models for collections & recovery processes in the BFSI domain.

He is particularly known for his eye for innovation, team bonding capabilities, and project management. His focus areas are predictive modeling using SAS & R, and his specialty solutions include customized management tools in VBA & MS Office.

**Key Projects:** Analytics team set up for a large pharmaceutical company of US, customer sales data analysis for a large e-commerce company, marketing mix models for retail company, collection scorecard for a big telecom player of US, demand planning for a leading retail company of Europe, churn prediction model for a BFSI company based out of Europe.



# Team Profile – Pradeep Kumar



#### Tools

SAS, R, SPSS, MS Excel, PL/SQL, MS Access

#### Skills

Linear & Logistic Modeling, Univariate & Multivariate Analyses, Segmentation & Profiling, Scorecards

### Pradeep Kumar

Senior Consultant

**Education:** PhD from Pennsylvania State University, B.Tech from IIT Delhi

**Specialties:** Statistical Analyses, Neural Networks, Descriptive & Predictive Modeling, Collections & Recovery Strategies, Multi Channel Intensity Optimization

Pradeep is known for his models for parameter setting & customer profiling, and has worked on a plethora of assignments for Phama companies and Retail Assets. His segmentation techniques brilliantly captures the Pareto Principle and repeatedly ensures that his target customers appear in the top performance buckets when validated. Pradeep has considerable expertise in the areas of Customer Segmentation Scorecards, Clustering in non-availability of target cases, and Portfolio Analysis. His ability to convert non-linear behavior of resources into linear models give him the edge to conceptualize both costs and efforts of an organization into effective techniques of linear and logistic regressions.

**Key Projects:** Predictive scorecard solutions (early warning, roll forward, application fraud, collections for personal loans and two-wheeler loans) for a leading retail bank of US, customer segmentation solutions for a retail client of Australia, Promotion Response modeling for a large Pharma company of US, Physician segmentation for a large European Pharma company.



## **Reach Us**



### **Gaurav Bajpai**

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