Introduction:

If you are like most entrepreneurs, then you are always looking for new effective solutions and strategies which strive to deliver tangible results in your business development.

We can show you how to maximize your results through your own resources and capacity!

You have accumulated data! Are you using this treasury to the full potential? Does your organization base the strategic decision upon it?

Your historical data can dramatically change the way you do your business. Explore it, find new patterns and relations.

But from where to start...

We offer a solution to this question – a new way to look at the data... as an opportunity to optimize your business process, increase operational efficiency, cut the costs, earn revenue and gain competitive advantage. Data driven decisions lead to better and more informed decisions and the better decisions... they lead to better results. Please, review below and see how:

Business intelligence services

How we can help

We create an environment (by aggregating and visualizing) for measuring key performance indexes and design dashboard reports, on which you will be able to base key strategic movements and decisions, to identify strengths and weaknesses and reveal new development opportunities.

The benefits could include enhanced decision-making, increased operational efficiency, monitoring at an early stage and opportunity to respond, gaining competitive advantages over business rivals and align your business towards key objectives. Moreover, we provide better measurability and transparency to the relevant stakeholders.

Data Analytics

We assist organisations with building business intelligence by transforming data into information providing intelligence for the organisation. Moreover, we transform data outputs to meaningful business insights and recommendations. Our solutions include:

- Key Performance Indicators (KPIs) derivation and monitoring
- Integrated Reporting Dashboards
- Predictive Analytics

Our approach to analytics is driven by our specific industry knowledge, functional experience and technology skills. We can help you assess the quality and business potential of the data you currently use and process.

Predictive Analytics

We offer statistical models that explore the historical behaviour of your customers and estimate their potential future actions or the behaviour of your potentially new clients. Analytical solutions that are based on historical events and observed risks directly affect costs, time effort and profits. Predictive analytics could help you to detect trends in your data, to identify risks as well as to anticipate events or forecast outcomes.

Loan Portfolio Analytics (Credit Scoring PD models)

We use predictive analytics on a loan level to gain high level insight into the loan portfolio, leveraging available data and creating projections into the future to optimise the credit portfolio composition and to reflect risk return requirements. The key benefits are further automation of the decision-making process, facilitate the ability of the business to make consistent data driven decisions and flexibility to optimise and manage credit risk levels – such as non-performing loans proportions, incorporate risk based pricing, etc.

Portfolio/Customer Base Management

With our expertise we could help you with an appropriate portfolio management model, based on risk estimations, by identifying trends, patterns of behaviour and discovering new opportunities for utilization of the available data. The accumulated data and history are closely related to the proper process management and vast changes in the environment, the operational and the investment decisions of each business.

Our data driven approach consists of segmentation, aiming to rank and differentiate key functional clusters and sub-groups based on their behavioural similarities, develop and adjust proper workflow strategy, with main goal to allocate the accurate actions and resources at the right time and further prioritize, and as a final stage, prepare a transparent monitoring process to correctly extract and identify valuable insights to drive solving challenges.

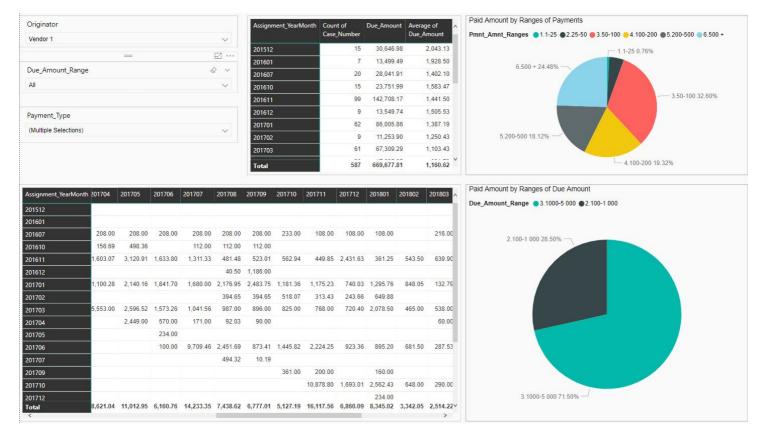
The potential benefit is revealed as cost and time efficiency and translating key steps into visually appealing and accessible manner.

Business Case Example 01 (Business Intelligence)

<u>Short project overview</u>: A major law enforcer in Bulgaria has requested a creation of dashboard reporting environment in order to better monitor his performance indicators. The main project goal was to provide easily accessible, independent and synthesized reporting structure and information about his profitability, his income flows and employee performance and allocation. Moreover, the idea was to obtain an opportunity to compare different vendors, employees and sources of income, based on different assignments.

Therefore, we have developed a business intelligence environment by accessing his data and further aggregating (also by creating non-existing up till now links and connections between different entities) and visualizing it. Moreover, we have introduced several additional indicators to enhance his decision making and overall business perception for comparison among different vendors and performance of employees.

Example 01: - Time Series Visualization and vintage analysis of plotting Income and Outcome flows by period and different entity — vendor, each by specific assignment month. Numbers presented are randomly generated.

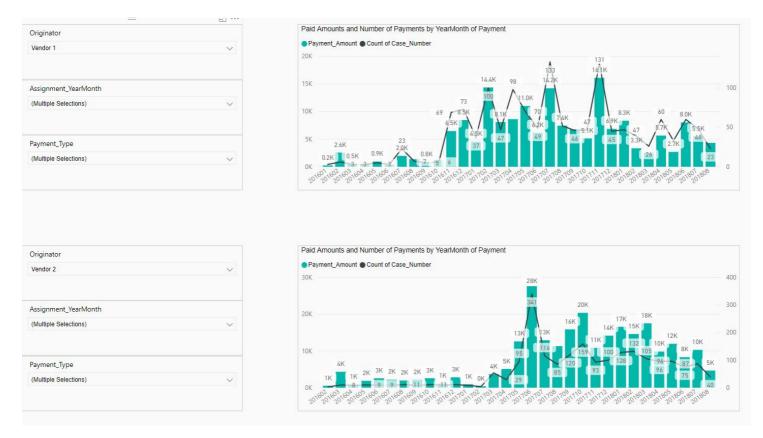


The dashboard above represent each specific assignment (year-month) by a certain vendor/originator (vendor is available for slicing the report) and the generated monthly payment amounts. On the pie chart above is presented the percentage proportion of payments by different ranges of overdue (for example 71.5% of the payments are on case with total overdue amount between 1000 - 5000 BGN). Also, each assignment is presented by its main characteristics – number of cases, total overdue and respectively average overdue per case.

The dashboard could be filtered/sliced by different vendor, different overdue amount ranges, different monthly periods (both for assignments and payments). In addition, also the graphs and the tables may be set to represent the generated expenses and cash outflows. The same report was produced to preview the number of payments, instead the actual amounts of payments.

Based on the results above we have introduced a KPI that follows the first payment month by case for each specific assignment in order to obtain levels of expected total number of unique payers per vendor/assignment and respectively the volumes of expected monthly payments.

Example 02: Time Series comparison of two different vendors by the Inflows and Outflows. Numbers presented are randomly generated.



The dashboard above represent the comparison between two vendors in terms of generated inflow amount (the line chart) and respectively number of payments (the bar chart). Same level of filters as the one described for Example 01 could be applied here as well.

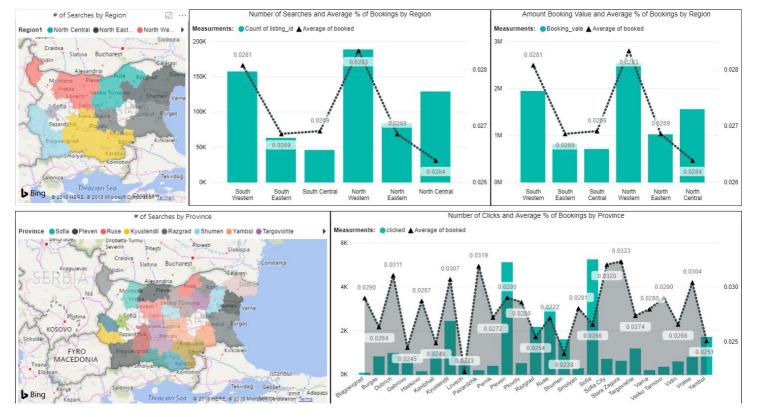
In addition to both examples, we have created the availability to further deep the analysis on employee level. In other words, each specific generated income for a vendor could be associated with an employee, who worked on those cases. In addition, the relevant actions taken (in terms of volumes and type of action) are also reported. By doing this, we have created the opportunity to address which are the key actions taken that lead to a specific result, what is the benchmark for highly productive employee and respectively what could be set as an expected workflow capacity.

Business Case Example 02 (Business Intelligence)

Short project overview: An online travel agency has requested a visualization and further analysis of their searches generated by customers when exploring options for hotel bookings. More specifically they were interested in how many searches were converted to clicks on hotel offers and further actual bookings for those hotels.

We have additionally introduced an analysis related to the different regions and provinces in Bulgaria, in order to extract valuable information from where and when are registered the numbers of bookings and respectively booking amounts. Thus we have provided an opportunity to catch different seasonality trends and spikes in bookings.

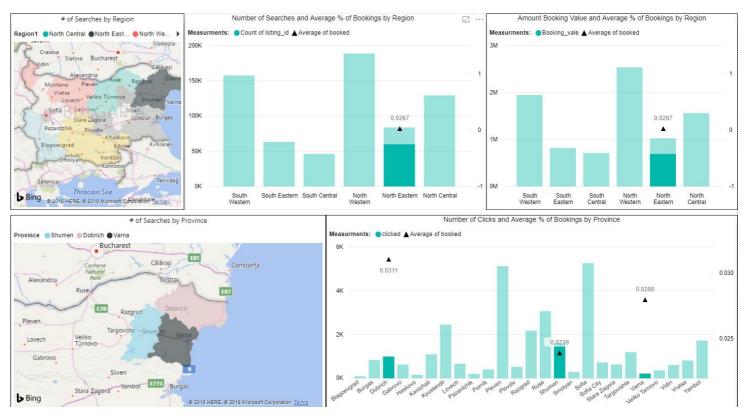
Example 01: - Searches, Booking Amounts and Clicks by Regions and Provinces. All Numbers are randomly generated.



The dashboard above shows the number of searches (named listings) by specific region (bars in the upper middle graph), the booking amounts generated by region (bars in the right top corner graph) again by region and numbers of actual clicks by specific province (bars in the lower right corner graph). In addition, the lines are presenting the proportion actual bookings as a result of searches.

Moreover, the visualizations could be further filtered by region, province and respectively monthly periods.

Example 02: Dashboard focus by Region. All numbers are randomly generated.



Business Case Example 03 (Credit Scoring Model)

<u>Short project overview</u>: A major collection agency in Bulgaria had requested an operational efficiency uplift for one of their collection projects. They had a specific time limit of 6 days on which to collect an assignment, that consist of large number of cases. The project aimed to achieve as higher as possible collection levels with minimum operational cost allocated. Therefore, we created a statistical model aiming to differentiate the potential clients that will recover their debt from those who are not (identify the "good" and distinguish from the "bad" in terms of profitability for the company). The analysis was conducted on a probability to pay level (opposite of probability to default (PD))

Step 01: Evaluate and review the data structure, current performance levels and derive definition for paying/not paying customer.

By Region:

| Region | N Cases | % From Total | Total Amount Due | Contract Amount Due | Average Contract Amount Due | Success Rate: Contract Payment vs Contract Amount Due | Success Rate: Total Payment vs Total Amount Due | |
|-----------|---------|-----------------|---------------------|------------------------|-----------------------------------|---|--|--|
| Region 01 | 220 | 1.10% | 2,925 | 2,802 | 13 | 71% | 72% | |
| Region 02 | 2,100 | 10.51% | 30,045 | 29,236 | 14 | 47% | 46% | |
| Region 03 | 1,720 | 8.61% | 33,551 | 32,241 | 19 | 42% | 42% | |
| Region 04 | 2,700 | 13.51% | 56,547 | 45,782 | 17 | 38% | 31% | |
| Region 05 | 3,660 | 18.32% | 86,554 | 83,123 | 23 | 34% | 33% | |
| Region 06 | 5,680 | 28.43% | 145,526 | 121,364 | 21 | 29% | 25% | |
| Region 07 | 1,900 | 9.51% | 32,276 | 30,627 | 16 | 27% | 27% | |
| Region 08 | 2,000 | 10.01% | 47,242 | 42,524 | 21 | 26% | 24% | |

Based on the table above, it appears that customers, who are based in some of the regions are repaying bigger proportion from their debts. Moreover, the average contract amount due (13-14 BGN) for those regions is less than the same measurement for the regions where less proportion of debt recovery is observed (21 BGN).

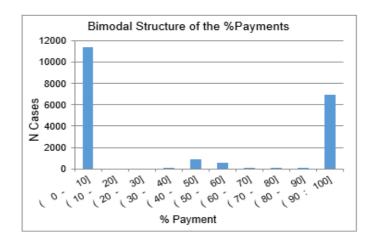
By Product:

| Product | N Cases | % From Total | Total Amount Due | Contract Amount Due | Average Contract Amount Due | Success Rate: Contract Payment vs Contract Amount Due | Success Rate: Total Payment vs Total Amount Due |
|------------|---------|-----------------|---------------------|------------------------|-----------------------------------|---|--|
| Product 01 | 7,200 | 36.04% | 87,743 | 79,741 | 11 | 52% | 48% |
| Product 02 | 5,900 | 29.53% | 120,262 | 104,935 | 18 | 39% | 35% |
| Product 03 | 3,640 | 18.22% | 128,658 | 116,788 | 32 | 25% | 23% |
| Product 04 | 3,240 | 16.22% | 98,001 | 86,235 | 27 | 21% | 18% |

It appears that customer that are using Product 01 are more likely to recover higher proportion from their overdues when compared to the other product types.

Derive Outcome Definition (based on Payment Amount/ Amount Due ratio):

| % Payment Distribution | N Cases | % From Total |
|---------------------------|---------|-----------------|
| (0 - 10] | 11400 | 57% |
| (10 - 20] | 0 | 0% |
| (20 - 30] | 0 | 0% |
| (30 - 40] | 20 | 0% |
| (40 - 50] | 860 | 4% |
| (50 - 60] | 560 | 3% |
| (60 - 70] | 100 | 1% |
| (70 - 80] | 40 | 0% |
| (80 - 90] | 60 | 0% |
| (90:100] | 6940 | 35% |



The bimodal structure of the distribution of payment/debt ratio suggests that around 58% of the customer do not repay their debts at all. From another hand, 35% of the customers are recovering more than 80% from their overdue amounts. Therefore, a strict definition of Good and Bad behaviour could be applied.

Suggested Definition:

| Bad | Payment <= 20% of the amount due |
|--------|----------------------------------|
| Indet. | 20% < Payment < = 80% |
| Good | Payment > 80% of the amount due |

Step 02: Examine distinguishing power of the characteristics between "good" and "bad" customer:

By Region:

| Class of Region | % Goods | % Bads | % Indet. | GB Odds | GB Index | Bad Rate | % Total |
|-----------------|---------|--------|----------|---------|----------|----------|---------|
| Region 07 | 8% | 12% | 6% | 0.42 | 147B | 67% | 10% |
| Region 06 | 24% | 31% | 25% | 0.47 | 129B | 63% | 28% |
| Region 05 | 17% | 19% | 20% | 0.53 | 115B | 60% | 18% |
| Region 08 | 10% | 10% | 4% | 0.61 | 100G | 60% | 10% |
| Region 04 | 16% | 12% | 14% | 0.80 | 130G | 51% | 14% |
| Region 06 | 11% | 8% | 24% | 0.83 | 135G | 45% | 11% |
| Region 02 | 13% | 7% | 3% | 1.10 | 179G | 47% | 9% |
| Region 01 | 2% | 0% | 4% | 3.00 | 489G | 18% | 1% |
| Total | 100% | 100% | 100% | 0.61 | 100G | 57% | 100% |



When the described outcome definition (Good/Bad Flag) is applied it appears that Region 01 and Region 02 have very strong representation of paying customer, while Region 07 and Region 06 are presenting customer which are not likely to repay their overdue.

By Product:

| Class Product | % Goods | % Bads | % Indet. | GB Odds | GB Index | Bad Rate | % Total |
|---------------|---------|--------|----------|---------|----------|----------|---------|
| Product 04 | 8% | 21% | 16% | 0.22 | 277B | 75% | 16% |
| Product 03 | 12% | 23% | 13% | 0.33 | 184B | 71% | 18% |
| Product 02 | 30% | 31% | 19% | 0.61 | 101B | 59% | 30% |
| Product 01 | 50% | 25% | 52% | 1.20 | 195G | 40% | 36% |
| Total | 100% | 100% | 100% | 0.61 | 100G | 57% | 100% |



The same conclusion, as the one observed for the regions could be applied for the Products. Customers that are using Product 04 and Product 03 are strongly reluctant to pay their overdues, while Product 01 are more likely to do so.

By Amount Due (from low to high amounts: Range 01 low → Range 05 high):

| Class Amnt Due | % Goods | % Bads | % Indet. | GB Odds | GB Index | Bad Rate | % Total |
|----------------|---------|--------|----------|---------|----------|----------|---------|
| Range 01 | 19% | 10% | 9% | 1.19 | 194G | 43% | 13% |
| Range 02 | 31% | 19% | 35% | 1.03 | 167G | 44% | 24% |
| Range 03 | 20% | 21% | 13% | 0.58 | 106B | 60% | 20% |
| Range 04 | 14% | 18% | 22% | 0.50 | 124B | 60% | 17% |
| Range 05 | 15% | 32% | 22% | 0.29 | 214B | 73% | 26% |
| Total | 100% | 100% | 100% | 0.61 | 100G | 57% | 100% |



As Expected, customers with lower amounts of overdue are more likely to pay, when compared to those with higher amounts of accumulated debt.

Step 03: Model Development and Score Distribution

| Variable | Score |
|--|-------|
| Intercept | -52 |
| Product | |
| Product 04 | -83 |
| Product 03 | -49 |
| Product 02 | 0 |
| Product 01 | +55 |
| Age | |
| [19 : 23] | -61 |
| [24 : 28] | -45 |
| [29 : 40] | -30 |
| [41 : 55] [86 : High] Invalid Data | 0 |
| [56 : 65] | +28 |
| [66 : 85] | +62 |

Variables Product and Customer Age are statistically significant strong discriminators between paying/non-paying customers. Therefore, the developed model is "penalising" customers, who are using products with strongly negative performance, and are up to 40 years old.

| Score Ranges | % Goods | % Bads | % Indet. | GB Odds | GB Index | Bad Rate | % Total |
|--------------|---------|--------|----------|---------|----------|----------|---------|
| [Low:-135] | 9% | 24% | 16% | 0.23 | 267B | 75% | 18% |
| [-134: -58] | 17% | 32% | 15% | 0.32 | 189B | 72% | 26% |
| [-57 : -27] | 15% | 16% | 14% | 0.56 | 109B | 59% | 16% |
| [-26: 3] | 25% | 14% | 25% | 1.07 | 175G | 43% | 19% |
| [4: 31] | 18% | 9% | 15% | 1.31 | 213G | 39% | 13% |
| [32:High] | 15% | 4% | 14% | 2.16 | 352G | 28% | 9% |
| Total | 100% | 100% | 100% | 0.61 | 100G | 57% | 100% |



Based on the developed model, a scoring system is derived, which further distinguishes customer according to their probability to pay. Those functional groups are further used for strategy development and proper collection actions allocated at lowest cost as possible.

<u>Step 04</u>: The final step of the project was to distinguish up to 3 groups based on a matrix between the score and the contract amount due and then apply a specific working strategy and further generate similar revenue, while reducing considerably the direct costs.

| Score | | | Total | | | | |
|--------------|---------------|---------|---------|-----------------|-----|-------|--|
| 30 | Lore | Range 1 | Range 2 | Range 3 Range 4 | | iotai | |
| [32: High] | Rate of Goods | 75% | 54% | 50% | | 60% | |
| [4: 31] | Rate of Goods | 65% | 49% | 48% | | 51% | |
| [-26: 3] | Rate of Goods | 48% | 50% | 41% | 60% | 46% | |
| [-57 : -27] | Rate of Goods | 39% | 29% | 33% | 40% | 34% | |
| [-134: -58] | Rate of Goods | 19% | 30% | 25% | 21% | 23% | |
| [Low: -135] | Rate of Goods | | 25% | 19% | 16% | 17% | |
| Total | Rate of Goods | 52% | 45% | 33% | 21% | 35% | |

Group 1 Group 2 Group 3