Insights into Net Promoter Score (NPS®) Surveys with Microsoft Power BI and Advance Analytics

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Abstract

The Net Promoter Score (NPS®) is a metric used to gauge how well an organization's product or service is perceived by their customers. A NPS® survey is usually accompanied by various ancillary questions to help explain the score and provide deeper insights about the respondents. Sifting through such surveys for thousands of respondents, especially when free-text feedback questions are present, can be a monumental task for small teams. Furthermore, the small team needs to process the feedback quickly and generate reports for high-level discussions by leadership to effect changes in the organization. To overcome these challenges, we have built an interactive dashboard tool with Microsoft Power BI (PowerBI) that contains clear and concise visualizations. We achieved this by applying advance NLP analytics in our normalization steps, thus allowing the summarization of feedback from hundreds of respondents to correlate our findings with the NPS®. We generated a custom hierarchical cluster heat map as well as a keyword relationship network (wordnet) visual in PowerBI that were instrumental in summarizing a lot of detail into singular visual representations. The tool has since been used multiple times to empower our leadership at BD to make informed decisions about culture and organizational changes in a matter of days instead of weeks/months.

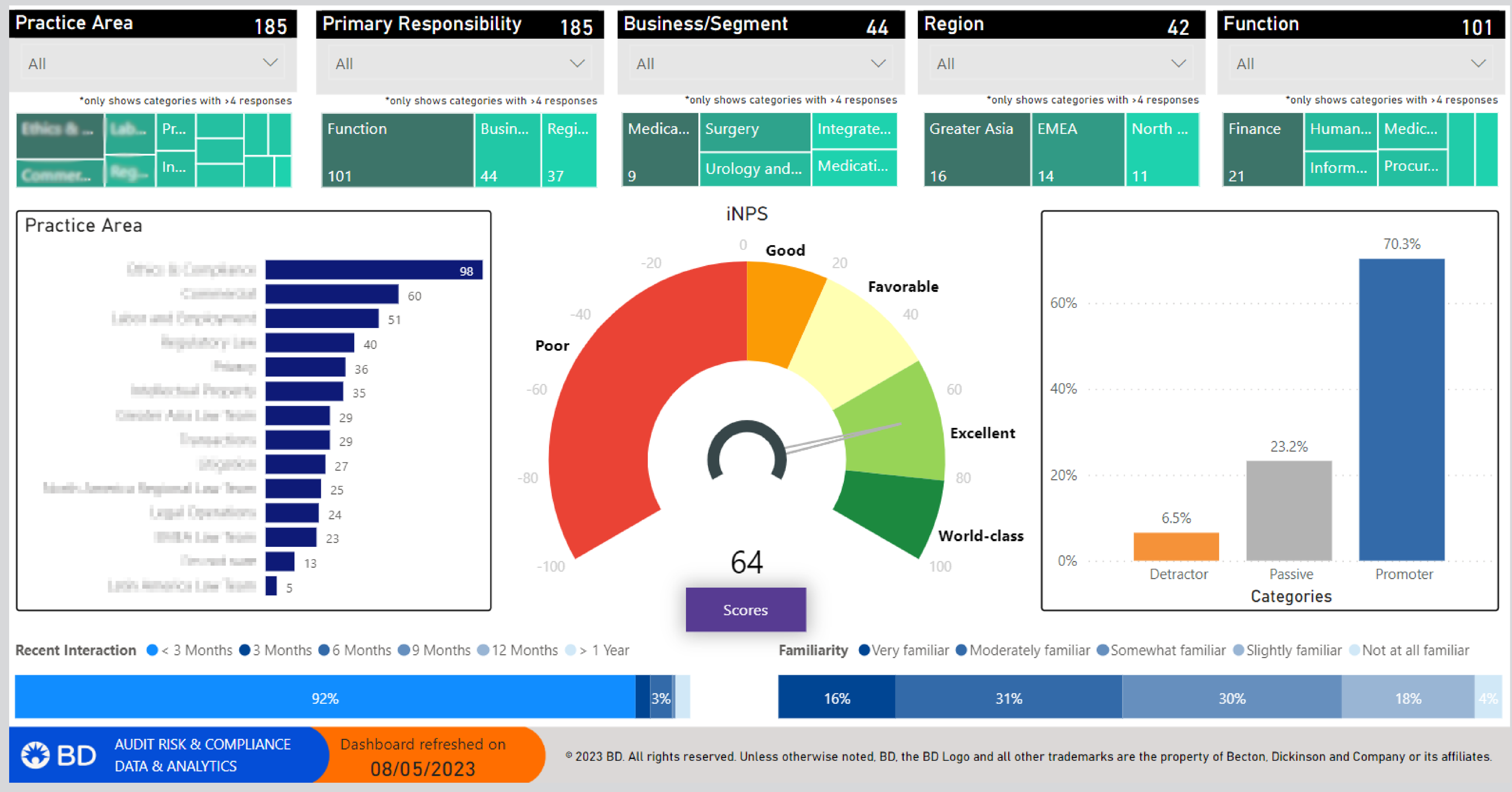

Figure 1: The BD NPS® survey dashboard.

Introduction

The Net Promoter Score (NPS®) is a metric used to gauge customer loyalty and was developed by Fred Reichheld, a partner at Bain & Company, in 2003 [7]. A carefully phrased survey question, "How likely are you to recommend [organization] to a [friend or colleague]?", with a 0-10 rating scale is used to calculate NPS®. Based on this scale, respondents are characterized as one of three types: Detractors (0-6), Passives (7-8) and Promoters (9-10). An NPS® grade of the organization in question is then summarized from the accumulated ratings as a number between -100 (poor) and 100 (excellent) with the following formula:

$$NPS = \%Promoters - \%Detractors$$

The score itself does not explain the reasons respondents gave a particular rating, hence additional questions, usually a mix of Likert, multiple choice, ranking and free-text, accompany the NPS® question. NPS® surveys are used by many organizations not only to gather external feedback, but also internally to gauge the health of a department, team or function and are sometimes referred to as internal NPS® (iNPS). Becton Dickinson (BD) takes pride in launching global feedback gathering among its associates frequently, but with 70,000 employees across the globe, it will require advance analytics to assist in collating, summarizing and visualizing the results to be useful in timely decision-making.

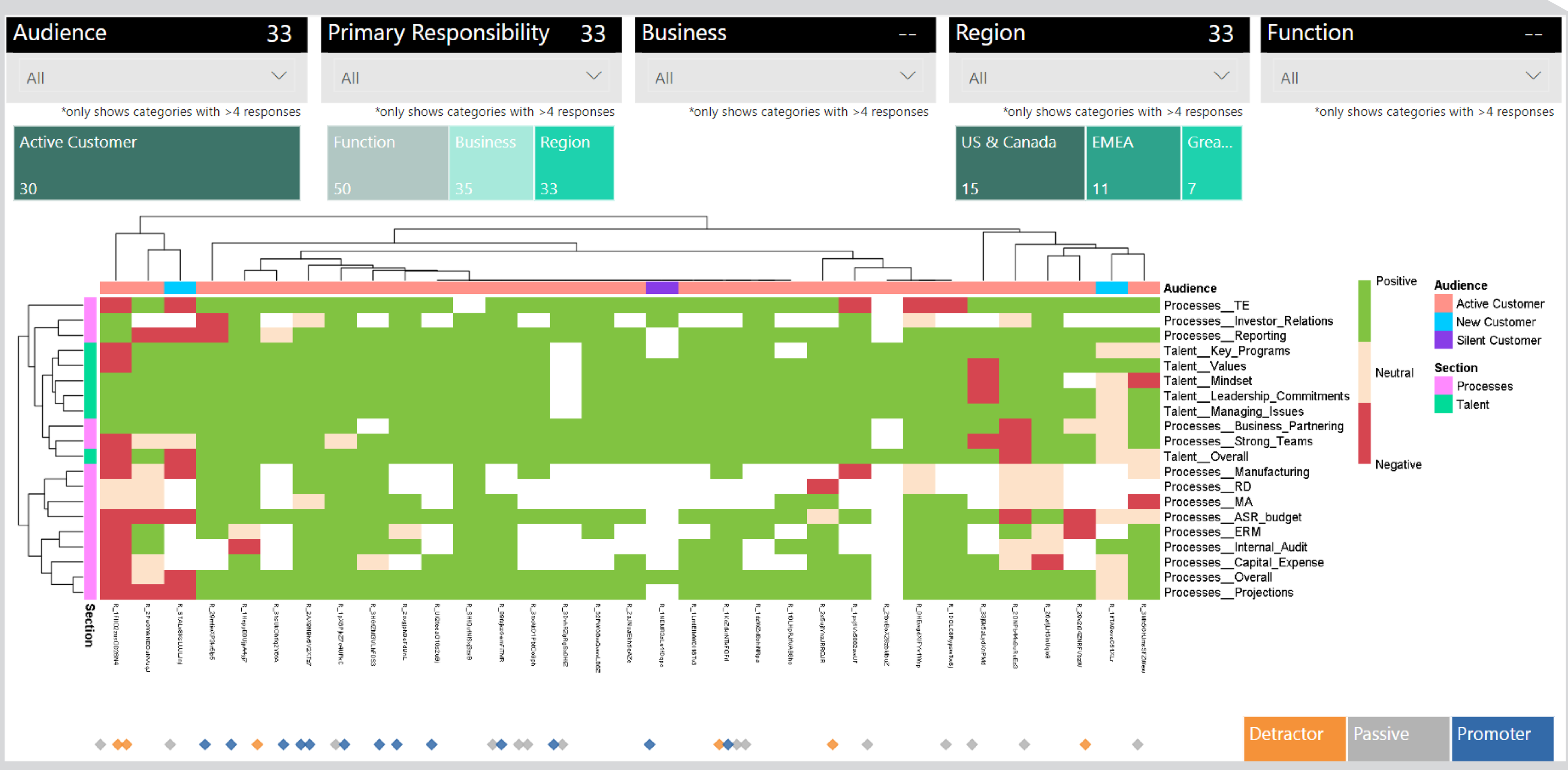

Figure 2: Hierarchical clustered heat map. This example was dynamically drawn when the Region Primary Responsibility was selected. Each vertical row is a respondent with their responses to questions on various topics normalized to negative, neutral and positive scaling (-1,0,1 respectively). Unanswered questions are left blank/null. NPS® classifications are also annotated next to each respondent as colored diamonds. Dendrograms represent relative similarity of responses with further annotations of interest to the business.

Results

We built an interactive dashboard tool with Microsoft Power BI (PowerBI) [6] dubbed the BD NPS® survey dashboard. The tool consisted of multiple pages, each with its own analytical objective. At the top of all pages, treemap visuals were effectively used to visualize proportions in demographic attributes as well as to function as slicers (Fig. 1 & Fig 2).

Within the tool, we used a hierarchical clustered heat map chart, generated using R [3,4] within PowerBI, to provide a holistic view on the responses received (Fig. 2). The heat map is a prelude to explore the survey results further in other pages where we used various types of bar charts and scatterplot visuals to correlate responses with NPS® (not shown).

To gain insights from the free-text responses, we conducted topic modelling [1] and created wordnets (reimagined word clouds) that show a keyword's frequency as well as relationship to other keywords within a specific topic (Fig. 3). We supplemented the visual with topic titles and sentiment score distribution generated from text summarization and sentiment analyses.

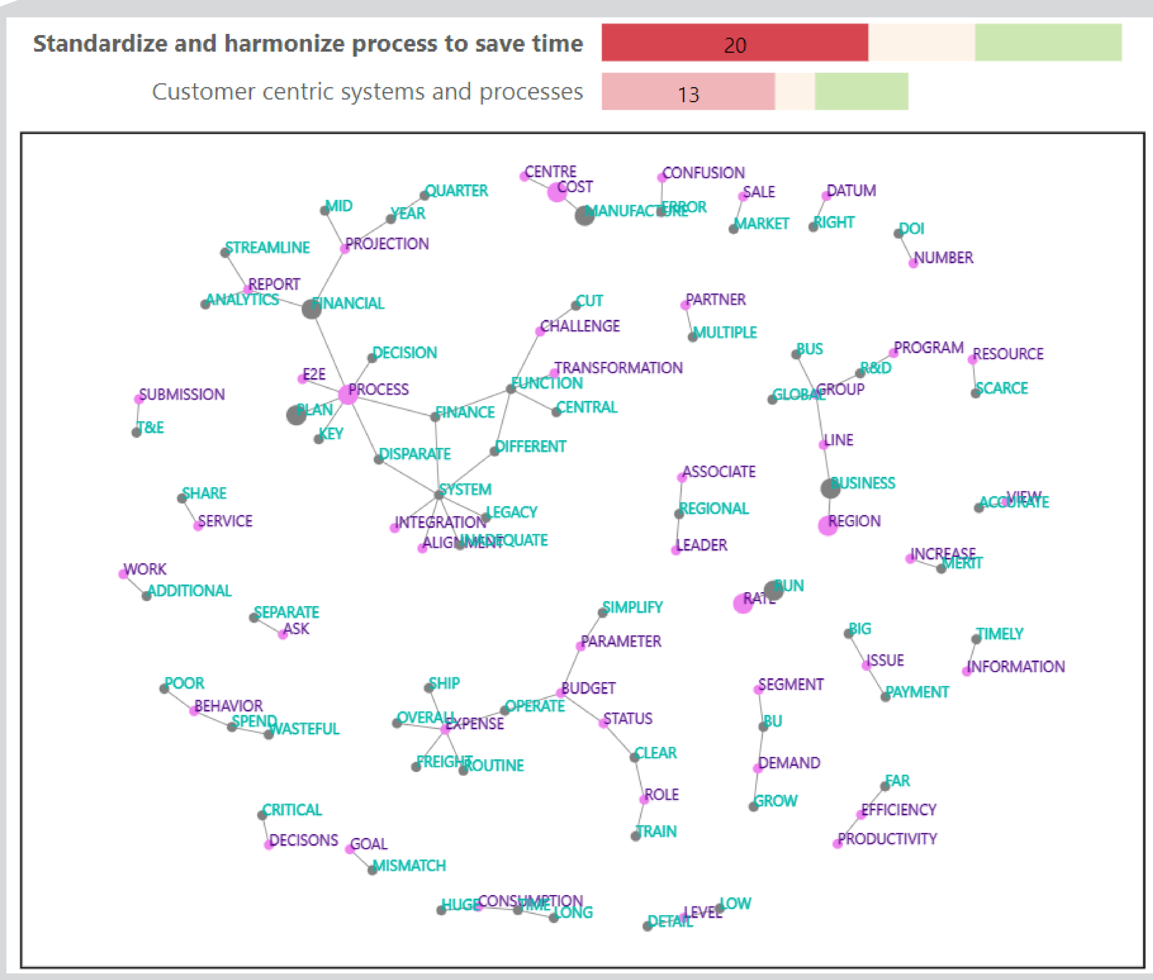

Figure 3: A keyword relationship network (wordnet); Nouns - violet nodes and purple labels, adjectives/descriptors/noun dependents - grey nodes and turquoise labels. Size of nodes are proportional to frequency of words found. The colors in the topic bar chart above represent the different sentiments of the free-text feedback; red - negative, amber - neutral, green - positive. The chart is dynamic, with the example of the negative feedback of the first of two topics being highlighted.

Discussion

As a report delivery platform, PowerBI was chosen because of its capability to publish online and collaborate, as well as seamless integration within the Microsoft ecosystem used at BD. It further boasts capabilities to implement R and Python visualization libraries. All base visuals we used comes stock with PowerBI with the following exceptions that were free to download from the built-in app store:

- Tachometer by E&A (Earnest & Associates, LLC.) - used for the NPS® gauge
- Network Navigator (Microsoft) - used for the wordnet

Free-text responses in surveys usually presents a challenge to analyze in large quantities. Reading through hundreds of responses in order to summarize and highlight feedback can take weeks. We were able to expedite the task in a matter of hours using Natural Language Processing (NLP) engines, namely spaCy [2] via Python, and Azure OpenAI Large Language Models (LLM) [5] to isolate keywords, identify sentiments, and summarize text. Having the sentiment scores allowed us to analyze the free-text responses together with Likert responses to provide a detailed overview of the survey (Fig. 2). For our text summarization exercise to generate topic titles (Fig. 3), we used the results of topic modelling using R to guide the response grouping, thus improving the perfomance and coherency of our results compared to just dumping the whole feedback into the LLM.

References

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Conclusion

We created the BD NPS® survey dashboard with advance analytics that successfully aided our leadership to make informed decisions about culture and organizational changes. The visuals we developed became a gold-standard template for others within BD to follow. The tool has since been deployed multiple times over the past two years for various teams and initiatives.