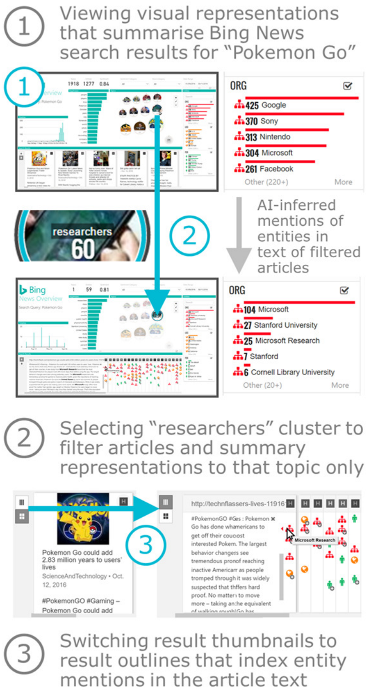
Bringing AI to BI: Enabling Visual Analytics of Unstructured Data in a Modern Business Intelligence Platform



: Overview page from "Advanced Search with Bing News" solution template for Power BI. Shows interactive summaries of Bing News results for search terms of interest. Back-end pipeline uses AI services to structure articles based on shared key phrases, named entities, topics, and sentiment levels. Front-end "dashboards" combine visual representations for exploring inferred structures. One of four applications for unstructured data analysis in this case study.

Microsoft Research
Cambridge, UK
darren.edge@microsoft.com

Microsoft Research
Silverdale, WA, USA
jolarso@microsoft.com

Microsoft Research
Redmond, WA, USA
chwh@microsoft.com

CHI'18 Extended Abstracts, April 21–26, 2018, Montreal, QC, Canada

ACM 978-1-4503-5621-3/18/04…$15.00
https://doi.org/10.1145/3170427.3174367

The Business Intelligence (BI) paradigm is challenged by emerging use cases such as news and social media analytics in which the source data are unstructured, the analysis metrics are unspecified, and the appropriate visual representations are unsupported by mainstream tools. This case study documents the work undertaken in Microsoft Research to enable these use cases in the Microsoft Power BI product. Our approach comprises: (a) back-end pipelines that use AI to infer navigable data structures from streams of unstructured text, media and metadata; and (b) front-end representations of these structures grounded in the Visual Analytics literature. Through our creation of multiple end-to-end data applications, we learned that representing the varying quality of inferred data structures was crucial for making the use and limitations of AI transparent to users. We conclude with reflections on BI in the age of AI, big data, and democratized access to data analytics.

Business Intelligence; Visual Analytics; Data; AI; HCI

H.5.2. Information interfaces and presentation (e.g., HCI): User Interfaces

Text is a primary source of unstructured data, such as from the following sources:

1. Social media messages
2. Message board posts
3. Email message bodies
4. Online news articles
5. Enterprise documents

Text is often accompanied by additional metadata that can provide an initial means of grouping associated texts. Typical metadata include:

1. Title and length
2. Authors and recipients
3. Keywords and hashtags
4. Timestamps and geotags
5. Views, shares, "likes", etc.

Metadata can be intrinsic or extrinsic to the text, and either given or derived (e.g., using AI services):

Metadata	*intrinsic*	*extrinsic*
given	title	url
derived	sentiment	impact

Textual metadata can also be derived from unstructured images, e.g., using OCR, object recognition, and scene classification and description.

This paper documents work undertaken in Microsoft Research to extend the Microsoft Power BI product with support for analysis of unstructured data such as social media, news, and cyber intelligence. The starting point for this project was the observation that unstructured data streams are of growing importance to general business audiences, yet modern BI platforms require structured data tables prepared and visualized using specialized data science skills. We identified two related opportunities that could help bridge this gap: inferring information structures from unstructured data using "AI services" that commoditize the results of machine learning, and supporting the visualization of text and metadata by creating representations grounded in the Visual Analytics literature. From Gartner's industry advisory perspective [3], the resulting work has had significant impact on Microsoft's 2017 position as a market leader in BI and Analytics, notably in terms of "completeness of vision". In this case study, we report on both the artifacts produced through our research (Figures 1–4) and the lessons learned from their deployment, release, and user adoption and feedback.

Evolution of Business Intelligence

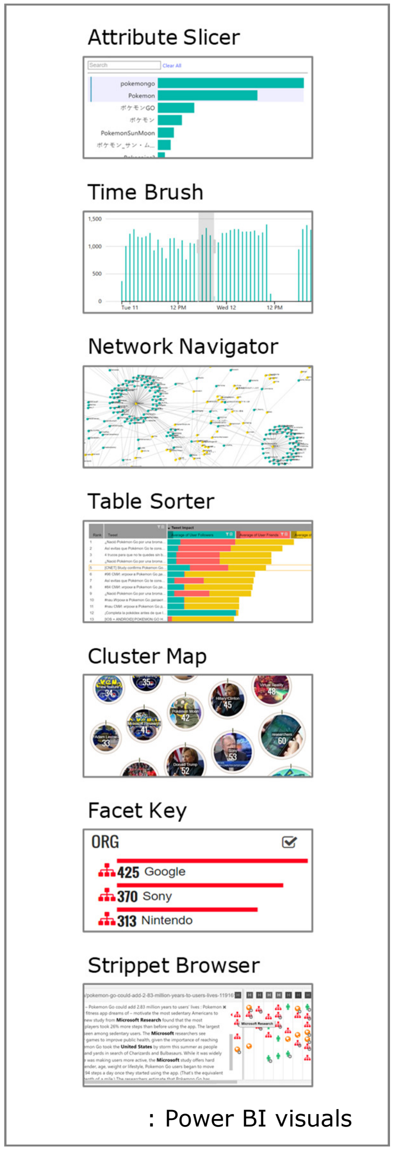
Business Intelligence platforms evolved from the need to make sense of largely numeric business data in the structured tables of spreadsheets and databases. Historically, it has been unwieldly to work with such tables because of their large size and high dimensionality. However, the invention of the pivot table (pioneered in Lotus Improv in 1991 and popularized by Microsoft Excel since 1994) gave users the ability to explore *tabular summaries* of such tables by interactively pivoting between different numeric aggregations (e.g., sum, average) for targeted subsets of rows and columns. In 2000, Polaris [15] extended pivot tables to enable *graphical summaries* of large multidimensional databases, in what laid the foundations of the Tableau software product. Microsoft later extended Excel with similar capabilities, leading to the release of Microsoft Power BI as an independent product in 2015. Use of BI platforms is now mainstream in the business world, and adoption is growing in the public spheres of science, engineering, education, and government.

Challenges of unstructured text and metadata

BI platforms present data as "dashboards" of multiple linked visualizations that both summarize and enable interactive filtering of a common dataset. However, much of the data relevant to modern organizations is not in the form of structured numerical tables – it is in the form of unstructured text and metadata, spread across documents, social media, and the web (sidebar). While the scale of such data makes it a candidate for dashboard analytics, as of early 2016, no major BI platform supported such unstructured data use cases.

Opportunities to extend Power BI for new use cases

Microsoft Power BI offered two extensibility frameworks that could be adopted to extend the functionality of the platform: "visuals" that can be used alongside native visual representations such as bar, line, and pie charts, and "solution templates" that automate data access, processing, and representation in turnkey data applications running in the Microsoft Azure cloud. Azure also offers AI as a service through Microsoft Cognitive Services and Azure Machine Learning, providing key capabilities for the structuring of unstructured data.



In the world of numeric data, aggregation functions like sum, average, and count scale to data of arbitrary size. Similarly, visual representations of such aggregate values (e.g., bar, line, and pie charts) have the same visual complexity whatever the aggregate values. The consequence is that all data subsets are self-similar from a comprehension perspective, and that the purpose of interactive "drill down" is to specify data subsets whose aggregations provide direct answers to the user's analytic questions, such as "How many <product> did we sell in <location> in <period>?". In comparison, although text attributes like word count can be aggregated numerically, attributes of text are no substitute for the text itself. The only complete aggregation of text data is as a collection of "texts" whose comprehension cost scales linearly with the volume of text to be read. Analysis metrics are also often unspecified or open-ended, such as "What has happened recently of relevance to the company?" As a result, interfaces for text analytics perform two key functions: *summarization* of text collections through metadata attributes and relationships, and *enumeration* of the texts indexed by these summaries for further interpretation and exploration. While summaries reveal insights directly, juxtaposition with enumerated texts leads indirectly to potential insights, i.e., by guiding users to filter text collections down to meaningful subsets that are of manageable size for per-text review. These observations provided grounding principles for design: visual representations should collectively provide complementary views of both summaries and content, and individually embody visual notations that are agnostic of both the data domain and the size of the data subset to be rendered.

We drew inspiration from the inherent scalability of fundamental mathematical representations including lists, sets, and graphs, as well as their prior use in Visual Analytics research, notably Jigsaw (VAST 2007 [13]). Jigsaw is a classic Visual Analytics system for exploring and understanding document collections. Its List View for ranking entities by attributes, Calendar View of activity over time, Graph View of entity co-occurrence relationships, Document Cluster View for document partitioning, and Document View for reading text with entity mark-up all have correlates in our Power BI visuals, which generalize and extend these representations. Our Table Sorter visual is also a Power BI productization of LineUp (InfoVis 2012 [4]). Figure 2 and Table 1 show selected visual representations we have created and released for Microsoft Power BI.

	Attribute Slicer	**Time Brush**	**Network Navigator**	**Table Sorter**	**Cluster Map**	**Facet Key**	**Strippet Browser**
Notation	List	Series	Graph	Table → List	Set	Set → List	List → Series
Display	Distribution of attributes across a filtered dataset	Volume of a filtered dataset over time	Link structure of a filtered dataset	Ranking of a filtered dataset by selected column(s)	Distribution of a filtered dataset across linked clusters	Distribution of a filtered dataset across data facets	Thumbnails and outlines of filtered documents
Control	Search for and select attributes for filtering	Size and slide a time window for filtering	Zoom, pan, search, and select nodes for filtering	Select columns to re-rank and drag edges to reweight	Select clusters to filter to all contained documents	Select facets to filter to all containing documents	Expand previews for reading and link to online sources
Example use with AI service	Inferred key phrases listed by frequency	Text volume over time by sentiment level (e.g., positive)	Inferred entity mentions by text co-occurrence	Sentiment score as part of a text ranking metric	Inferred topics grouping texts into sets	Inferred entity mentions listed by frequency and type	Inferred entity mentions by text, location, and type

Table 1. Visual representations for unstructured text and metadata, developed and released as visuals for Microsoft Power BI.

There is a trend across large software companies to commoditize the results of machine learning as "AI services" accessible via APIs, such as Amazon AWS AI Services and IBM Watson Cognitive Capabilities. Our back-end data pipelines use both Microsoft Cognitive Services and Azure Machine Learning modules, including:

Sentiment Scoring
Scores text on a continuous scale from most positive sentiment to most negative.

Key Phrase Extraction
Extracts key words that summarize a text and make connections between texts.

Named Entity Recognition
NER extracts mentions of entities (e.g., people, places, organizations) within a text.

Topic Modelling
Infers a topic model from multiple texts that assigns a dominant topic to each text.

Optical Character Recognition
OCR extracts text from images containing text areas.

Our Power BI visuals are available as open-source software on Github[1] and as free-to-use downloads within Power BI or via the Office Store[2]. The "metadata" visuals of Attribute Slicer, Time Brush, Network Navigator, and Table Sorter were released in May 2016 [6], followed by the "document" visuals of Cluster Map, Facet Key, and Strippet Browser in July 2016 [7]. Installing users are typically BI specialists who compose visuals and datasets into reports that are then shared within an organization for interactive data exploration by non-specialists. Since each visual is typically incorporated into multiple reports, with each report accessed by multiple users across multiple sessions, it is crucial for visuals to be fast, reliable, and usable by a general audience. It is also important for visuals to be useful across domains: emails to our support alias reveal a core user base in the functional business areas of sales, operations, and IT, but also use in a wide range of specialized domains including logistics, insurance, defense, security, energy, infrastructure, aid, and healthcare.

Releasing our representations of text and metadata as visuals enables visual analytics of unstructured data in Power BI, provided users can:

1. access the data of interest for analysis;
2. process data into the tables required by the visuals;
3. bind the appropriate table columns to visual fields;
4. compose visuals into appropriate dashboard combinations and filtering relationships for the analytic questions.

Adoption of our visuals indicates users have successfully completed all four steps independently.

However, each step also poses an obstacle to users who are not both domain experts and data specialists (e.g., data scientists, architects, or engineers):

1. domain data of interest often require access through database scripting or programmatic APIs;
2. extracting meaningful structure from text requires programmatic analysis (e.g., using AI service APIs);
3. data processing must anticipate the required visuals so the appropriate columns are available for binding;
4. visual composition must anticipate the right domain questions and the best interfaces for answering them.

The second phase of our work aimed to democratize access to data analytics – enabling a large base of users at low cost and without specialized training. We sought not just to streamline the above process for existing users of Power BI, but to reach new audiences through the turnkey generation of "data applications" bound to specific data sources and search queries.

The modular and composable nature of visuals and AI services (sidebar) allowed rapid construction of end-to-end data applications in partnership with customers and business groups across Microsoft, supporting their need to make sense of unstructured data in diverse areas including news, social media, and cyber intelligence. In line with our goal of democratizing data analytics, we have released several data applications as "solution template" products for Power BI. We now present three of these products, plus an internal data application that supports the work of the Microsoft Digital Crimes Unit.

[1] Github visuals: https://github.com/Microsoft

[2] Office Store visuals: https://appsource.microsoft.com/en-us/marketplace/apps?product=power-bi-visuals

Strippet Browser. Browse text, metadata of filtered tweets.
Attribute Slicer. View and filter by author, hashtag, etc.
Time Brush. View tweet volume and filter by time.
Network Navigator. Explore author-hashtag relationships.
Table Sorter. Explore tweets ranked by sentiment, impact.

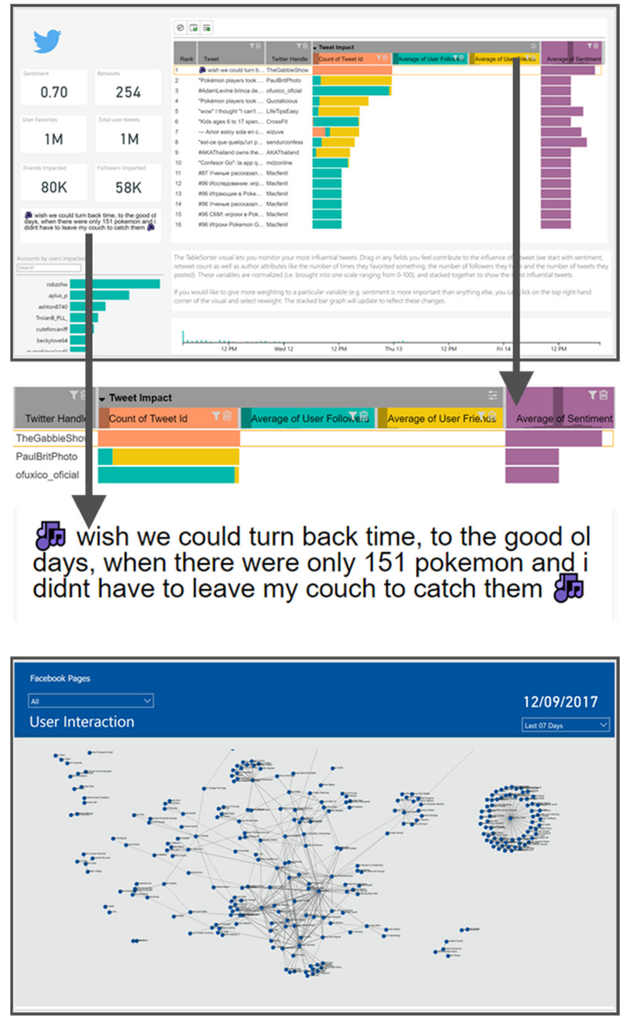
Strippet Browser. Browse text, metadata of filtered articles.
Attribute Slicer. View and filter by key phrase, domain.
Time Brush. View publication volume and filter by time.
Cluster Map. View and filter articles by topical cluster.
Facet Key. View and filter articles by mentioned entity.

Strippet Browser. Browse text, metadata of filtered posts.
Table Sorter. Explore posts ranked by sentiment, impact.
Network Navigator. Explore co-posting relationships as a sign of organic, coordinated, or automated user interaction.

Campaign/Brand Management for Twitter
Our Twitter solution template was released in August 2016 as a way for social media brand and campaign managers to monitor relevant activity on Twitter [8]. This template allows anyone with a Twitter API key and Microsoft Azure subscription to create a live report on tweet activity around user handles, hashtags, and search terms of interest. Sentiment scoring provides additional structure for exploring tweets by their positive, negative, or neutral sentiment, and tracking the overall tone of social conversations.

Advanced Search with Bing News
Our Bing News solution template was released in March 2017 as a way for news analysts to track breaking Bing News stories matching search terms of interest [9]. It uses AI services for sentiment scoring, key phrase extraction, topical clustering, and named entity recognition. These complementary structures provide users with multiple ways to both summarize the collection of news results and drill down to individual articles of interest, which can be opened in a web browser for further reading. Figure 1 shows a typical filtering interaction sequence.

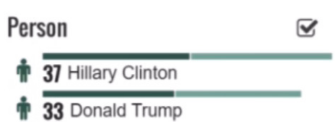
Campaign/Brand Management for Facebook
Our Facebook solution template was released in June 2017 as a way for social media brand and campaign managers to monitor relevant activity on Facebook Pages [10]. The template allows anyone managing a Facebook page to analyze posts and comments by likes, authors, and hashtags, as well as AI-inferred sentiment levels and key phrases. Network analytics also reveal patterns of coordinated posting across users, indicative of organic shared interests, coordinated brigading, or even automated bot activity.



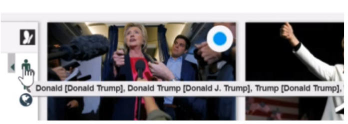
Top: Page from Twitter solution template showing Table Sorter ranking tweets based on the combination of retweets, user followers and friends. The top tweet is selected. *Bottom*: Page from Facebook solution template showing Network Navigator of users co-posting in the last 7 days.

News analytics example: revealing uncertainty in topical clustering and entity recognition over news articles

. Arcs segmented and coloured by quality level, e.g., *view articles by topic fit.*



Bars segmented and coloured by quality level, e.g., *view entity mentions by entity recognition rank.*



Entity mention icons showing entity ambiguity, e.g., *view entity mentions in news article text by entity recognition rank.*

Tech Support Fraud Investigation Tool

A 2016 global survey by Microsoft revealed that 2 out of 3 people had experienced a tech support scam in the previous 12 months [14]. 1 in 5 users continued with a fraudulent interaction leading to the download of malicious software, granting of remote device access, or sharing of credit card or banking details for unnecessary repairs or maintenance services. 1 in 10 users ultimately lost money. Such scams are typically initiated by browser pop-ups that urge the user to call a toll-free number for live support, often masquerading as a familiar technology company. The Microsoft Digital Crimes Unit receives over 10,000 complaints about such scams each month, and tracking down the scammers is further complicated by the ever-shifting IP addresses which serve the pop-ups and the concealing of scam details in images rather than plain text [5].

We partnered with the Digital Crimes Unit to build a data application that enables interactive investigation of tech support fraud. This application mines scam pop-up images, extracts embedded phone numbers using OCR, connects related scams through image analysis, and represents the resulting data structures using our visuals in Power BI: Network Navigator for viewing the resulting scam networks, Attribute Slicer for searching and filtering by phone number and network size, and Strippet Browser for examining pop-up images and their extracted details. Use of this tool by DCU analysts was central to Microsoft's participation in Operation Tech Trap, announced by the US Federal Trade Commission in May 2017 [2]. Just one of the deceptive tech support organizations targeted by the resulting actions, Client Care Experts, was responsible for defrauding 40,000 people out of more than $25 million (USD) over the period November 2013-2016.

A recurring problem we faced in phases 1 and 2 resulted from the varying quality of AI-inferred data structures. In some cases, AI services augment their outputs with confidence or uncertainty scores, such as the confidence that a machine translation is accurate. In other cases, such scores are mapped to specific semantics like reputation and trust. In yet other cases, AI outputs are themselves aggregated to communicate derived metrics like weight, strength, distance, and similarity. Such *data qualities* arising from the inferential nature of AI span all types of uncertainty in information visualization [12]: measurement precision (e.g., of sentiment scores), completeness (e.g., of entity recognition), inference (e.g., of topical models), and credibility and disagreement (e.g., of an ensemble text classifier spanning multiple input models).

For back-end processing, the problem lies in deciding how to use data quality values as thresholds for dataset inclusion: set the threshold too low, and the results can be unmanageably noisy and large; set the threshold too high, and the results can omit crucial data points that happen to have low quality values. With visualization, the problem is one of transparency: for data that have been pre-filtered by a data quality threshold, it is unclear (a) what data were filtered out, and (b) what quality variations exist in the data that remain.

Our solution to these problems has been to modify our data pipelines and visual representations such that:

1. elements of data structures arising from AI processing are assigned quantized quality levels;
2. visual representations show the distribution of data qualities across levels and support filtering by level.

Twitter analytics example: using language detection and machine translation to analyze tweets in a common language

Attribute Slicers for interpreting and filtering data by quality level, *e.g., tweet counts by translation quality (Fig. 4ab)*.

Frequency bars segmented and colored by quality level, e.g., *tweet counts by language and translation quality (Fig. 4ab).*

. Time bars segmented and colored by quality level, e.g., *tweet counts by time and translation quality (Fig. 4c).*

Links weighted and colored by quality level, e.g., *hashtag-language links by co-occurrence level (Fig. 4d)*.

. Rows showing how percentile rank varies based on the incremental inclusion of quality levels, e.g., *tweets by retweets and translation quality (Fig. 4e).*

Such "quality aware" interfaces avoid premature commitment to a threshold, whose appropriate value cannot be determined in advance of its creation and is dependent on the user's analysis task. Instead, they make data quality a first-class interface element, allowing users to interactively explore the tradeoff between data coverage (showing all data) and visual clarity (showing data subsets of given quality levels). The resulting information seeking strategy can be captured in a refinement of Shneiderman's mantra [11]: *high quality* overview first, zoom and filter, then details-on-demand *for lower quality levels in areas of interest*. By juxtaposing AI-inferred structures against the unstructured data they describe, users can calibrate system-assigned quality levels against their own quality judgements or the requirements of the use case.

Across the phases of this case study, we sought to make the structure of text and meta-data *navigable*, the operations of data acquisition, processing, and analysis *accessible*, and the role of AI in inferring navigable structures *transparent*. On a theoretical level, our work has been influenced by prior review of the Visual Analytics (VA) literature through the lens of Activity Theory and HCI [1] – seeking to understand the broader systems of activity to be supported by VA tools. This review identifies interaction qualities to aim for when designing such tools, each addressing a core trade-off in the activity design space (sidebar, page 8). We now present three lessons in a similar form – as tensions we encountered in the design space, reflections on our practice, and implications for design.

(a-b) Attribute Slicer. *Top*: distribution of non-English tweets across machine translation confidence levels. *Bottom:* distribution of non-English tweets across languages, segmented and colored by translation quality. (a→b) Filtering tweets to level 1 only – those with the highest translation quality. (c) Time Brush showing volume of non-English tweets over time, segmented and colored by translation quality. (d) Network Navigator showing hashtag-language connections weighted and colored by tweet co-occurrence level. (e) Table Sorter ranking by retweet count. Columns to right show how rank percentiles change as lower-quality translations are added.

ability to curate presentable summaries of the analytic discovery process. Supported by visuals that resolve the tension of *acting to make sense vs artifacts*: familiar metaphors aid sense-making and can be presented directly to general audiences.

ability to transfer analytic work across people, places, time, and devices. Supported by solution templates that resolve the tension of *acting as data collector vs analyst*: automation of data collection frees time for analysis and enables contributions from "citizen data analysts".

: *ability to view and proactively reduce the uncertainty of analytic work at any time.* Supported by representations of data quality that resolve the tension of *competing interpretations vs demands*: filtering by data quality level enables systematic review of uncertain data structures.

Meaningful summaries vs manageable subsets
We approached the design of our visual representations with a focus on creating navigable summaries of text and metadata. Through our repeated use of these representations for building data applications, we observed such summaries carry limited meaning in isolation – accurate comprehension relies on context from the documents being summarized. For example, interpreting a key phrase distribution requires viewing common phrases in juxtaposition with document text. Until the underlying documents have been filtered to a manageable subset for review, the main value of visual representations is their ability to guide such filtering towards document subsets of interest. Future work includes using this insight to create sample-driven summaries of big data that only reach full fidelity once the data have been filtered to a manageable volume.

Analyzing datasets vs monitoring datastreams
Builders of Power BI reports typically have specialist data preparation skills, as well as specific datasets to analyze. In contrast, users of BI reports instantiated from our solution templates only need to specify standing search queries for persistent interests, and to monitor the resulting datastreams through pre-built reports. While solution templates have the potential to democratize access to data analytics through ease of use, it remains a challenge to create dashboard interfaces that are sufficiently capable for domain experts whilst also being approachable and learnable by novice users of BI tools. We have adopted a range of assistive strategies, including labelling representations by functional role rather than column bindings, arranging and numbering representations by page workflows, and ordering pages by activity workflows. Future work includes tackling the tradeoff between the number of visual representations per page and the number of pages required to cover all use cases.

Automatic insights vs interactive oversight
Using AI services and data visualization to marshal unstructured data into meaningful representations automates the initial stages of insight discovery at the cost of generating inferred structures of varying quality. Building interfaces around data qualities provides a new kind of "interactive oversight" for human consumers of AI services that enables quality-aware filtering of data to meaningful and manageable subsets. The downside is that each visual used as a key for data quality levels occupies space that could have been used for an additional and complementary view of data structure. Future work includes investigating the interactive assignment of "human verified" quality levels shared among the users of long-lasting, widely-used reports.

This case study described our transformation of Power BI for visual analytics of unstructured data. The impact of the work includes fundamental visual representations with wide adoption, AI-powered "solution templates" that shape the view of Microsoft as a market leader [3], an AI-powered data application used for the successful identification and prosecution of major cybercriminal operations, and a design philosophy around "data qualities" that anticipates the growing role of AI in democratizing access to data analytics.

We would like to thank our collaborators in Microsoft Research, Uncharted Software, Microsoft Power BI, and the Power BI Solution Templates team for their substantial contributions to the work of this case study.

1. Darren Edge, Nathalie Henry Riche, Jonathan Larson, and Christopher White. 2018. Beyond Tasks: An Activity Typology for Visual Analytics. IEEE Transactions on Visualization and Computer Graphics (TVCG) 24(1), 267-277. http://ieeexplore.ieee.org/document/8019880/
2. Federal Trade Commission Press Release (12 May 2017). Retrieved 1 Oct. 2017 from https://www.ftc.gov/news-events/press-releases/2017/05/ftc-federal-state-international-partners-announce-major-crackdown
3. Gartner Report (16 February 2017). Magic Quadrant for Business Intelligence and Analytics Platforms. Retrieved 1 Oct. 2017 from https://www.gartner.com/doc/reprints?id=1-3TYE0CD&ct=170221&st=sb
4. Samuel Gratzl, Alexander Lex, Nils Gehlenborg, Hanspeter Pfister, and Marc Streit. 2013. Lineup: Visual analysis of multi-attribute rankings. IEEE Transactions on Visualization and Computer Graphics (TVCG) 19(12), 2277-2286. http://ieeexplore.ieee.org/document/6634146/
5. Microsoft AI Blog (15 June 2017). Retrieved 1 Oct. 2017 from https://blogs.microsoft.com/ai/2017/06/15/microsoft-used-ai-help-crack-tech-support-scams-worldwide/
6. Microsoft Power BI Blog (9 May 2016). Retrieved 1 Oct. 2017 from https://powerbi.microsoft.com/en-us/blog/custom-visualizations-visual-awesomeness-your-way/
7. Microsoft Power BI Blog (11 July 2016). Retrieved 1 Oct. 2017 from https://powerbi.microsoft.com/en-us/blog/new-power-bi-custom-visuals-for-browsing-and-analyzing-collections-of-text/
8. Microsoft Power BI Blog (15 August 2016). Retrieved 1 Oct. 2017 from https://powerbi.microsoft.com/en-us/blog/twitter-solution-template/
9. Microsoft Power BI Blog (7 March 2017). Retrieved 1 Oct. 2017 from https://powerbi.microsoft.com/en-us/blog/announcing-the-advanced-search-solution-template-for-bing-news/
10. Microsoft Power BI Blog (26 June 2017). Retrieved 1 Oct. 2017 from https://powerbi.microsoft.com/en-us/blog/announcing-the-campaign-brand-management-for-facebook-pages/
11. Ben Shneiderman. 1996. The eyes have it: A task by data type taxonomy for information visualizations. IEEE Symposium on Visual Languages, 336-343. http://ieeexplore.ieee.org/document/545307/
12. Meredith Skeels, Bongshin Lee, Greg Smith, and George G. Robertson. 2010. Revealing uncertainty for information visualization. Information Visualization 9(1), 70-81. http://journals.sagepub.com/doi/abs/10.1057/ivs.2009.1
13. John Stasko, Carsten Görg, and Zhicheng Liu. 2008. Jigsaw: supporting investigative analysis through interactive visualization. Information visualization 7(2), 118-132. http://journals.sagepub.com/doi/10.1057/palgrave.ivs.9500180
14. Stay Safe Online Blog (16 October 2016). Retrieved 1 Oct. 2017 from https://staysafeonline.org/blog/new-data-reveals-two-thirds-of-global-consumers-have-experienced-tech-support-scams
15. Chris Stolte, Diane Tang and Pat Hanrahan. 2002. Polaris: A System for Query, Analysis and Visualization of Multi-dimensional Relational Databases. IEEE Transactions on Visualization and Computer Graphics (TVCG) 8(1), 52-65. http://ieeexplore.ieee.org/document/981851/