

More Media, More People—On Social & Multimodal Media Intelligence

Lars Degerstedt, Södertörn University & Pelle Snickars, Umeå University

The purpose of this article is to address contemporary challenges facing media intelligence in an altered information landscape. In order to understand the new situation, the article introduces the notion of social and multimodal media intelligence. With cases taken primarily from the Swedish media intelligence sector, we argue that data driven media intelligence today needs to pay increasing attention to new forms of (A.) crowd-oriented and (B.) multimedia-saturated information. Media intelligence usually refers to the gathering of publicly available information about an organisation or a company's competitors—using it to gain business advantages. Traditionally such intelligence has implied a set of techniques and tools that transforms numerical or textual data into useful information for business analysis. Today, however, we argue that such techniques need to consider media alterations in both a social and multimodal direction. By presenting some findings from the so called CIBAS-project (as a case study), we describe how Swedish organisations and companies rely on social networking structures and individual decision making as a means to increase response and agile creativity. Yet if media intelligence has witnessed a social transition during recent years, the analyses of other media modalities than text also pose a number of technical hurdles. In this article we use fashion analytics as another case in point, taken from a commercial sector where visual big data is presently in vogue.

Keywords: CIBAS-project, competitive intelligence, fashion analytics, media intelligence, social & multimodal media intelligence

The computer software company Domo markets itself as a service designed to provide direct and simplified, real time access to business data. According to Domo, the contemporary data deluge shows no sign of slowing down, and the amount of data produced in a single minute is mind-numbing. Streams—if not floods—of social and multimodal data, in short, pose a pivotal challenge for companies within the media intelligence sector. “Data Never Sleeps” has consequently been the appropriate title of a series of infographics that Domo has released (James 2016).

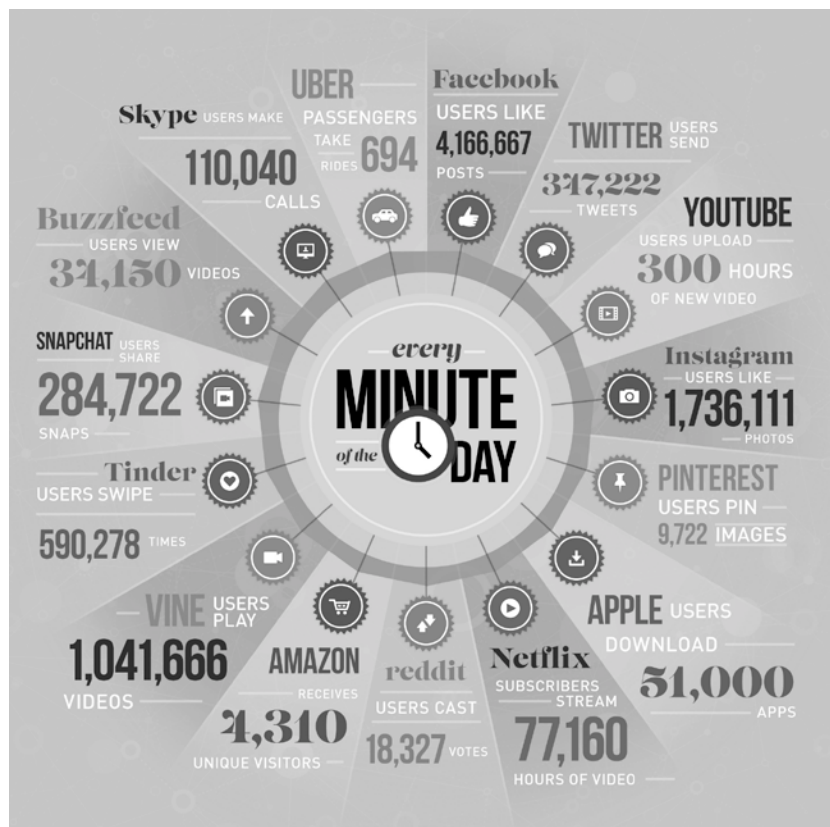


Figure 1. “Data Never Sleeps 4.0”. Part of an infographic produced by the business intelligence company Domo, January 2016. The infographic is available at <https://www.domo.com/blog/data-never-sleeps-4-0/>.

Sleepless data is in many ways the perfect description of today's global information landscape. Social media produces data flows that are both a blessing and a curse for media and competitive intelligence that tries to monitor and predict market and business trends. Handling new forms of social and multimodal data, however, requires new skills. "As our fourth annual instalment of *Data Never Sleeps* illustrates, data is ubiquitous. It's constantly pouring out of our smartphones, smartwatches, smart TVs, and countless other devices that are all connected—and it continues to proliferate at an astounding rate", the Domo infographic informs potential customers. This requires a better understanding of what contemporary interactions with data actually mean. Naturally, this is what is being marketed—only Domo can help a business make sense of the endless stream of data (James 2016).

Domo is in many ways a successful American start-up, funded by venture capital, yet with a crystal clear business plan. In a visually enticing video demo, Domo states that its core idea revolves around the future of business management. In short, Domo is all about media intelligence as *social data*. Departing from this video demo, the infographic and its *sleepless data*, the purpose of this article is to address contemporary challenges facing media, business and competitive intelligence in a modified information landscape. Within computer science, technically oriented research "towards next-generation business intelligence"—with increasing computational complexity—has been undertaken for a number of years (Borth 2014; Hare et. al. 2015). This type of computer science, however, rarely finds its way into the social sciences and humanities. Yet, linkages are evident. Algorithmic models of, for example, content detection or supervised machine learning techniques are fundamental for understanding how the different specificities of computational media are today monitored within the intelligence business.

The purpose of this article is therefore to describe and offer some insights about the challenges facing media intelligence in general, and competitive intelligence in particular within an altered information landscape.

In recent literature, it has been argued that (social) media and business intelligence are today inseparable (Nagle & Pope 2013). In short, “media and business intelligence allows companies to gain a competitive edge, cut costs and release products with a higher degree of success, becoming crucial for any company” (Dutot & Mosconi 2016). As a consequence, management theories in general has had to adapt; “management theory is becoming a compendium of dead ideas”, as the *Economist* has stated since it is “so easy to acquire information and consult with everybody (including suppliers and customers)” (*Economist* 2016).

To understand this arguably new situation, the notions of *social and multimodal media intelligence* are introduced in this article. The presented interdisciplinary research consists of a discussion written from a media studies perspective, situated at the intersection of communication management. Our analysis builds on converging empirical findings from different types of sources and previous research. Empirical material used in the article (company presentations, home pages, press releases, reports etcetera) are gleaned from media intelligence companies, and have qualitatively been analysed regarding the ways in which *media as data* is today perceive within the intelligence sector. Another important source is semi-structured interviews, deployed within the so called CIBAS-project. Empirical data from interviews within that project were also combined with informant discussions around two socio-technical prototypes, the so called CoCI and CrowdCI tools, a combination of a design prototype and corresponding media intelligence method, that proved useful in getting respondent reactions (Degerstedt 2015; Degerstedt 2016).

In general, our article has relevance for both business intelligence research as well as media studies (in a broad sense) since it pinpoints understanding the different *modalities* of social media, as well as the need for *media specific analyses* that today challenges companies working with media intelligence. The article also fills an interdisciplinary research gap since social *and* multimodal media intelligence are rarely discussed together in previous academic research. Somewhat surprisingly, multimodality

and intelligence are today foremost researched within completely different academic fields such as robotics or didactics. The concept of multimodality has, for example, been picked up by robotics research within the sphere of so called “navigation intelligence” or “ambient intelligence”—i.e. learning robots to navigate based on audiovisual video input (Rao et. al. 2017)—or within didactic research in relation to multimodal learning environments, foremost based on the integration of written, oral, visual, and electronic resources and tools (Kortegast & Davis 2017).

Then again, social media intelligence has in recent years developed into a thriving research field with a number of practical applications for businesses (Agarwal & Sureka 2015; Dutot & Mosconi 2016). However, academic research on social media intelligence rarely examines data and information gleaned from *audiovisual* or *imagistic* social media platforms (YouTube, Instagram, iTunes pods etcetera)—and almost never combines multimodal approaches with a distinct *social* media analyses. Among articles published in the *Journal of Intelligence Studies in Business*—where one of us authors has published before (Degerstedt 2015)—such topics have sparked almost insignificant scholarly interests. Naturally, some exceptions can be found. In a recent article on business intelligence and big data, Klaus Solberg Søylen has for example addressed the ways in which companies can today “buy or rent data” (including audiovisual data from YouTube or Facebook)—even if many suppliers only “want users to see the actual intelligence or end analysis, not the raw data, as they are afraid that customers could sell it on or make their own analyses” (Solberg Søylen 2016). In another article, “The Power of Social Media Analytics”, Weigudo Fan and Michael D. Gordon have argued that media intelligence in general needs to adapt to an altered information landscape, and has proposed a new practical process for analysing social media—capture, understand and present—all in order to go beyond text analytics, including opinion mining, sentiment analysis, social network analysis and visual analytics (Fan & Gordon 2014).

Then again, such scholarly perspectives are unusual within business intelligence research (as well as media studies). Therefore our article gives an important interdisciplinary research contribution, as well as some general insights into the ways in which the business intelligence market today is adjusting and adapting to media alterations in both a social and multimodal direction. Basically, data driven media intelligence, we argue, needs to pay increasing attention to new forms of (A.) crowd-oriented and (B.) multimodal information. In particular, the discussion presented in this article therefore addresses questions such as: When streams of data structures information, what (social) media to collect and analyse? What type of media content is today possible to automatically monitor? What computational methods and models of machine learning are used within media intelligence?

Our article starts with some introductory remarks around the concept of media intelligence, and the ways that business and competitive intelligence has adapted to a transformed media environment—basically turned datascape. Importantly, due to the rapid transformations caused by digitisation, various notions and definitions are also currently being altered, renegotiated and transformed (Dutot & Mosconi 2016). As a consequence, media intelligence and competitive intelligence (CI) are today notoriously hard to separate. In addition, CI is itself also increasingly hard to pinpoint and define, not the least academically since competitive intelligence research is usually situated at the intersection of several fields of study including communications theory, informatics, knowledge management and library and information science.

On the one hand, competitive intelligence often refers to the gathering of publicly available information about an organisation or a company's competitors; information that is used to gain business advantages. Understood in this way, CI is the systematic process whereby an organisation (division, unit or person) gathers, analyses, and transforms information into actionable intelligence (Murphy 2005; Sharp 2009). Yet, on the other hand, a similar definition is sometimes used to describe so called

“competitor intelligence” (Peyrot et al. 2002). Accordingly, competitive intelligence should take into account *all issues* that affect a company’s competitive decision, including for example technological or regulatory issues (when applicable). The term “competitive” in CI can be traced back to the economic notion of competitive advantage (Porter 2008; Barney & Hesterly 2012). Competitiveness is thus used within the context of competitive intelligence to emphasise that *all* intelligence is related to *any* aspect of the surrounding competitive environment with strategic significance.

Nevertheless, what matters is that if competitive intelligence traditionally has referred to a set of techniques and tools that transform numerical and textual data into useful information for business analysis, such techniques are today confronted with a media landscape altered in both a *social* and *multimodal* direction. During the last years it has, for instance, widely been acknowledged within the media industry that video is the fastest growing type of data in the world. Yet, how to practically monitor moving images within media intelligence? Unlike explicit mentions via a hashtag or text, images can potentially offer a more nuanced—and thus more valuable—insight into how, for example, a product is perceived by consumers. Naturally, these changes (and challenges) are acknowledged within media intelligence. Aspiring multimodal insights are, in short, gaining momentum. Still, machine learning of other modalities than numbers or text pose technical hurdles. Furthermore, there needs to be a market demand for such forms of analyses—and requirements are naturally determined by the relevancy of results produced.

In the subsequent sections of our article, the notions of “social competitive intelligence” and “media analytics” are introduced and used as two broader concepts that contemporary media intelligence increasingly evolve around. Social competitive intelligence tries to understand how a changing information environment will impact organisations and companies by monitoring events, actors and trends. Information today doesn’t only want to be free—information wants to be social. General usage of technology

was once described with terms like *social* engineering, correspondingly the linchpin of today's culture of connectivity is *social* software and various forms of *social* computing (Hemmatzad 2015). By presenting findings from the Swedish CIBAS-project—"Competitive Intelligence in the Age of Social Computing"—we describe (as a case study in our article) how organisations and companies increasingly rely on (more or less) formal social networking structures and individual decision making as a means to increase rapid response and agile creativity (Degerstedt 2015; Degerstedt 2016; Degerstedt & Hermansson 2016). Moreover, if media intelligence traditionally has developed insights primarily on textual data and statistical methods, an increased focus on audiovisual media streams puts new demands on media intelligence. In our article we use image analytics—and more specific, fashion analytics—as a final case in point to discuss how to monitor multimedia, gleaned from a commercial sector where both social and audiovisual big data are currently in vogue.

What Is Media Intelligence?

As the arguably leading media intelligence company in Scandinavia—with a history dating back to 1892 under the name, *Svenska telegrambyrån*, a company that initially provided press clipping services in Sweden—Cision claims being a global enterprise within communication and media intelligence (Cision 2017). Yet, what does the specific notion of *media intelligence* actually mean? Basically, it refers to various forms of digitally updated media monitoring practices—both manual and automatic—regarding foremost print and broadcast media. Obviously, online media has also played an important role within media intelligence during the last two decades

Within the commercial business sector—but not necessarily within academic research—media intelligence is often roughly divided into: (A.) business intelligence (on a particular company level), and (B.) competitive intelligence (between similar companies regarding for example shared markets). In general, the latter is different from the former since it uses

and analyses data *outside* company firewalls. However, during the last decade—mainly due to profound technological changes brought about by digitisation—the specificities of (and boundaries between) business intelligence and competitive intelligence have become increasingly blurred—and basically the same holds true for media intelligence. When society is gradually turning into a market of different mediated “value networks”, as Sven Hamrefors argued in 2010, “communication functions can no longer stay in their restricted domains and only deal with traditional communication issues” (Hamrefors 2010).

On the one hand, media intelligence on a strategic business-to-business-level has become difficult to distinguish from a more practical business-to-consumer-level. On the other hand, an increasing number of companies (foremost within the technology domain) operate in different market segments, making it more or less impossible to intelligence and monitor *all* relevant markets. The most obvious example is Google, a company that started with search, soon began making operating systems, run different forms of content platforms—and now produces cars. On a mid-scale, the same can be said of the Scandinavian media group Schibsted, who does business in a number of different digital domains—publishing, online marketplaces and services—making it almost impossible to separate, or rather *define* Schibsted’s media intelligence in a useful way.

The business of media intelligence uses data and computer science methods to analyse both social media and editorial media content. Standard implementation for media intelligence involves curating data, keyword references and semantic analyses, as well as natural language processing via machine learning algorithms. Machine learning has been one of the most significant fields of artificial intelligence. In short, it is concerned with questions of how to construct computer programs that automatically improve (through feedback) when repeatedly executed. Since streams of socially dynamic and multimodal data are difficult to handle with machine learning algorithms, most practices within media intelligence are concerned with turning text into data sets for analysis.

Text is hence still the dominant modality for most media intelligence operations. Yet, as we argue in this article, other modalities (sound, video and images) have during the last decade become increasingly important, especially in different socio-computational formats at equivalent platforms.

Media intelligence usually departs from an “interconnected communications ecosystem” where both social and traditional media sources “feed each other” for stories and conversation—and where those conversations are in turn “supercharged by social technology” (Nuccio 2015). Media intelligence hence often refers to computational solutions that try to synthesise innumerable online conversations into appropriate insights that allow companies and organisations to manage, and sometimes even measure content performance and trends—where the ability to *better* forecast business strategies is paramount. In this process “noise-free data is critical”, as the company Synthesio asserts. Hence they (as well as others), offer automated noise removal with the aid of human assistance or spam filters: “What some call noise, others consider relevant; we help tailor the noise filters to your needs” (Synthesio 2016).

Still, no data is error-free. On the contrary. There are a number of myths that flourish within the contemporary hype of *Big Data*, especially within the commercially driven media intelligence sector. In addition, all data always has to be *interpreted*. In fact, all forms of information management within media intelligence basically follows the same pattern: data needs to be collected, entered, compiled, stored, processed, mined, and interpreted. And, importantly: “the final term in this sequence—interpretation—haunts its predecessors” (Gitelman 2013, 3).

As might be expected, companies working within the intelligence sector offer different suggestions as to what media intelligence actually means (again hinting at the vagueness of the term): “Media intelligence is the process of gathering all the data available through social media and news media outlets and analysing the data to allow for better business decision making”, according to Carma CustomScoop (2016); Volicon is said to be

the “leading provider of enterprise media intelligence solutions serving the needs of broadcasters, networks, cable operators, and governments worldwide” (Volicon 2016); and M-Brain states that its media intelligence solutions are designed to “monitor and measure your publicity and reputation” (M-Brain 2016). Nevertheless, what these companies have in common is the gathering of massive amounts of data points from user-generated content on social media sites, blogs and comment fields, combining these with traditional mass media output and other forms of publicly open data. The purpose is to provide—and ultimately sell—real-time insights and suggestions based on relevant and confirmed data. Broadly speaking media intelligence is thus always about selling *trust*—based on (more or less) verifiable data.

Social Transitions within Media Intelligence—The CIBAS-Project

During recent years media intelligence has witnessed a social transition, from various forms of social computing (within companies) to social media monitoring and computationally driven social media intelligence. The latter is often said to be better equipped to minister *noisy sociality*, and uncover valuable insights hidden in the social media chatter (Varol & Neumann 2012; Seebach, Beck & Denisova 2013; Moe & Schweidel 2014). Research related to various forms of military intelligence, have also tried to identify and forecast social and civil unrest by mining textual content in open-source social media (Agarwal & Sureka 2015).

However, the notion of computational sociality does not solely refer to new mining techniques of information assembled from social media platforms. Computational sociality can also be framed from an *organisational* management perspective. Within the CIBAS-project—“Competitive Intelligence in the Age of Social Computing”—different forms of social computing *within* Swedish companies and organisations have been studied, mainly through interview-based studies and design of digital prototypes (Degerstedt 2015; Degerstedt 2016; Degerstedt & Hermansson 2016). Funded by the Swedish Knowledge Foundation (KK-stiftelsen) between

2013 and 2015, the purpose of the CIBAS-project has been to examine how tools, platforms and services within Swedish media intelligence ought to be re-designed for increasingly socially organised activities (and it should be stated that the project has also received co-funding by the Swedish companies M-Brain, Comintelli and Glykol working within the sector).

From a management studies perspective, two trends have been spotted during the interview-based studies how organisations and companies have started to work with (or approach) media intelligence during the last decade: the consumerisation of IT and decentralised forms of (social) media intelligence. In general, the consumerisation of IT has altered media intelligence in a social and comparative way. In so far, this mega-trend has affected intelligence. Traditionally, it was primarily a function that served senior management. However, since companies and organisations are becoming increasingly decentralised, many strategic choices and decisions are today made *throughout* organisations. Gradually, it is thus important that strategic insights originating from media intelligence are disseminated through the organisation, in particular to key positions such as middle management and domain experts.

The suggestion from standard textbooks on business intelligence is to use an organisational network for this type of dissemination (Kahaner 1996). Similar to the first generation of intranets, such internal networks have usually relied on a logic of mass media where information was produced by a small team of intelligence experts—and then subsequently distributed through an internal network. The CIBAS-project has confirmed that as of recently this is typically done by sending external news alerts through email or using the intranet. Another finding is that an intelligence function (at the analysed Swedish organisations) often stores *all* media intelligence findings in some document repository, database or platform that can be shared and accessed by the employees more broadly. Via such platforms co-workers can post, edit, and sort linked text and media files (Leonardi, Huysman & Steinfield 2013), and it is hence possible to form social and collaborative communities where large groups of people can

pursue a mutual purpose that creates value, for example by increased levels of transparency and participation (Bradley & McDonald 2011).

Departing from research within the CIBAS-project, *computational sociality* thus takes many forms regarding the ways that organisations and companies today use media intelligence. In short, to harness the power of social technology, organisations and companies need to change both internal technology as well as work methods. A case in point, is a study performed within the CIBAS-project that gave a better understanding of how collaboration and organisational networking are performed within media intelligence processes today. Four Swedish organisations and companies that had explicit media intelligence functions were studied. All four organisations used some form of internal organisational network coordinated by an internal intelligence function. Two of the organisations had used social networking for a long period of time (more than ten years), but did not use particularly sophisticated social software. Instead they mainly relied on special reports to management, news monitoring, email alerts and usage of traditional intranet for mass-distribution of media intelligence (Degerstedt 2016). In the third case an organisation had only used a media intelligence functions for a shorter period of time, and the organisation was still experimenting with how to use social networking in an effective way. Interestingly, the organisation had recently started to use a social media service (Facebook) as an alternative to its news portal, since they found that such a group generated more activity than a news monitoring repository. Finally, in a fourth case, a Swedish consultancy firm was studied with a highly decentralised and project-based type of organisation. The company did not have an explicit media intelligence function, instead they relied on a knowledge management platform that collected both external and internal sources of information from projects, and the intelligence process was hence performed socially, bottom-up (Degerstedt 2016).

A major finding from the CIBAS-project is that different emerging forms of media intelligence today have started to take advantage of altered

forms of sociality and computer based, networked collaboration. In order to study such a development in more detail, two socio-technical prototypes—called CoCI and CrowdCI—were also created within the project. The idea behind these tools was to model a combination of a design prototype with a corresponding media intelligence method. The research method used iterative prototyping, and the intelligence prototypes focused on certain functionalities, with results extracted from design patterns based on evaluations.

The CoCI prototype was designed for a scenario with an internal network of collaborative media intelligence (Degerstedt & Hermansson 2016). In short, the CoCI tool was supposed to support collaborative daily work in a company or organisation with reading, commenting and classifying incoming information, with actions of network members visible for each other. An evaluation of the tool (in the form of a paper prototype) was done where users were given a test with a series of tasks in a given fictive situation. After the test, users were asked to evaluate the experience in four dimensions: simplicity, engagement, collaboration and community. The results for the first three dimensions were high, but the dimension “simplicity” was unsatisfactory, indicating the necessity for such tools to be intuitive and not too complex.

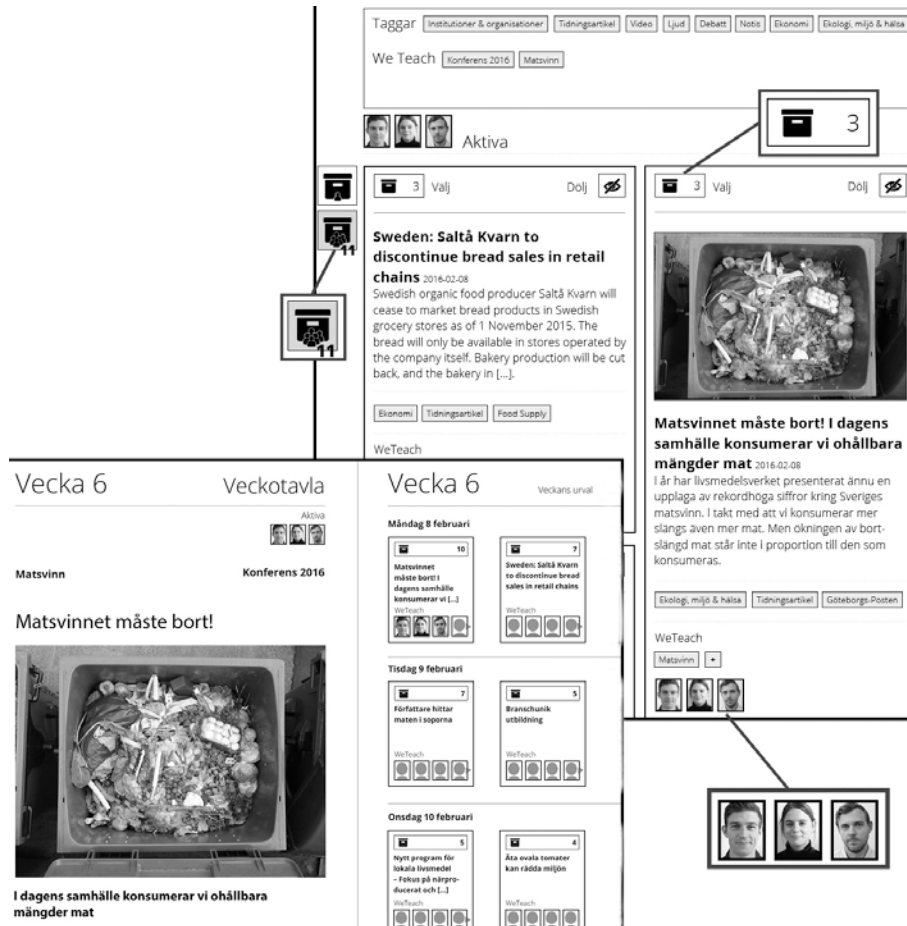


Figure 2. The “CoCI tool”—a prototype developed within the CIBAS-project (in collaboration with Cecilia Hermansson and Nico Arnold) to support collaborative daily work in a company or organisation with reading, commenting and classifying incoming information.

The second prototype built within the CIBAS-project was a CrowdCI tool, which focused on how to crowd source aspects of the media intelligence process. The main idea behind the CrowdCI tool was that an organisation should be able to control an issue (or agenda), but at the same time make

it possible to stimulate crowd based intelligence regarding for example participation, discussions and voting. The CrowdCI design prototype used a ‘mobile first’ approach in the form of a smartphone app. Two types of issues were identified and tested: a discussion-based issue where an imagined crowd could participate in a collaborative opinion exchange (on a given theme), and a questionnaire-like issue where responses used graphical media (photos) to select and answer questions. From the evaluation of the CrowdCI prototype it was observed that the threshold of participation had to be kept low. Interestingly, the questionnaire-theme was appreciated mainly due to the use of images (and not text) in answering—a fact that lowered the threshold of participation (Figure 3).



Figure 3. The “CrowdCI tool”—a prototype developed within the CIBAS-project (in collaboration with Cecilia Hermansson and Nico Arnold) to crowd source (at least) some aspects of the media intelligence process, and where respondent can use graphical media to select and answer questions.

Towards New Forms of Media Intelligence

The experiments with CoCI and CrowdCI prototypes within the CIBAS-project were initial steps in thinking about, and designing new forms of

social media intelligence tools by way of a collaborative network approach. Then again, social media intelligence can also be performed with an analytical and automated approach. Contemporary social media intelligence is, for example, based on a rudimentary data management model where social data is segmented—from automatically categorised subsets of social data, to customising rules or filtering, based on criteria like date, location, web page type, sentiment and gender. Segmentation can also be done on more specific data, for example regarding Twitter or Facebook statistics (retweets, likes, comments, media type etcetera.) In essence, data management within social media intelligence collects massive volumes of data and separates it into structured and manageable packages that can help answer particular questions via different forms of machine learning algorithms and/or data mining.

As is well known, social media is not only social (leaving aside the tricky question what *sociality* actually means)—it is also increasingly multimodal. If the computational sociality investigated within the CIBAS-project pose challenges for media intelligence in general—so does multimodal content. Traditionally, media intelligence companies have relied on *numerical and textual data*—basically because machine learning algorithms use numbers or text documents (transformed into databases) to perform automatic analyses of large data sets. Numerical data was primarily used within the sectors of technology and economics, whereas textual data was predominantly preferred for strategic and analytical tasks on management levels. Today, however, media intelligence faced with social and audiovisual data streams seems more geared towards consumer behaviour and cultural issues.

In general, the modality of text is still *default* within the media intelligence business, which if nothing else is apparent in the ways companies advertise themselves: “Keep track of what is *written* about you, your company or your competitors” (Cision 2016); “Infomapr is a system for predictive analytics and *text* mining” (our italics) (Infomapr). Yet, as is

well known online interaction has during the last decade increasingly been enriched with images, sound and videos. These new media modalities have brought forth changes that are currently having profound effects on the media intelligence business. If YouTube is often seen as the audiovisual epitome of the information landscape during the last decade, the blended mix of Facebook posts in different modalities acts as its social counterpart. Hence, ‘social’ and ‘multimedia’ are converging. Already during 2015 Facebook was reported to have had some eight billion average daily video views from more than 500 million users (Constine 2015), and social video is thus an increasing trend. The release of Facebook Instant Articles in May 2015 was in effect aimed towards the ability of watching audiovisual news material seamlessly.

If media intelligence in automated forms have relied on text mining to monitor, detect and analyse plain text sources, the transition to new social media modalities by and large causes difficulties. Humans can perceive their surroundings naturally in visual form, but according to Damian Borth “this undertaking is quite challenging for machines” (Borth 2014). In essence, what machine learning does is constructing models from a given collection of data—which can then be used to predict *further* data. A machine learning system fuelled with data from, say, online customer behaviour around browsing and buying, can easily construct a model that predicts preferences for new customers—and hence build a recommendation system that entices these to consume what others have preferred. Static textual data is simple to compute, dynamic audiovisual data is not.

Roughly, machine learning algorithms can be divided in two categories: those that have a *learning ability* and those that work according to *similarity*. Trying to predict various business decisions, media intelligence usually prefers supervised learning algorithms, rather than succumbing to similarity algorithms like Bayesian algorithms (based on probability), Clustering algorithms or Decision Tree algorithms that are all used to

discover previously (more or less) unknown patterns. Then again, terms like ‘machine learning’, ‘data mining’, ‘pattern recognition’ and ‘knowledge discovery’ (in databases) are often hard to separate. In general, machine learning and data mining overlap. Decision Tree learning algorithms resembles data mining, for example, since they both deploy statistics to find patterns in data that identify boundaries through so called decision trees—a method that uses ‘if / then’ statements to define certain patterns (based on some value). Data is essentially split into branches (forks), and the algorithm *recursively* repeats the process of subsets of data, fine tuning and dividing branches further.

Still, machine learning and data mining also differ since the former usually focuses on *prediction*—based on learning abilities and known properties within collected data—whereas data mining is often about the *discovery* of unknown properties in the same data. Via hybrid applications of statistical learning theory, algorithmic and predictive analyses, computer programming and signal processing, *data analytics* hence basically refers to the discovery of meaningful patterns in data. The generic goal is to discover useful information, and data analytics has hence developed models that both explain the past—as well as predict the future.

Within media intelligence, the notion of analytics is often used in a similar way. Intelligence operations are usually divided in three different ways: descriptive, predictive and prescriptive analytics. As Hugh J. Watson has stated, the objective of the first is to describe what has occurred, the second focuses what “will occur in the future”, whereas “prescriptive analytics is intended to show what should occur” (Watson 2013). Yet, even if machine learning have made considerable advantages during the last decade due to increases in computing power, storage and new algorithms, there still remains information gaps to be filled, especially with transforming other modalities than text into computational numbers. Today, companies within the media intelligence sector are, for example, trying to cope with the so called *semantic gap*. “The lack of correspondence between

the low-level features that machines can extract from videos (i.e., the raw pixel values) and the high-level conceptual interpretation a human associates with perceived visual content is referred to as the semantic gap” (Borth 2014).

Another semantic indication that other media modalities than text are becoming increasingly important within the media intelligence business is that the metaphor of *listening* is often used as a commercial slogan. The company Notified, for example states that, “social listening should be fun!” (Notified 2016). The Swedish media intelligence company Lissly, furthermore, offers its customers the ability to “listen to the conversations in your market”. In addition, Lissly’s “tool collects, sorts and visualizes data from *different* digital media” (Lissly 2016). Another similar Swedish company Opoint, are said to be “the only player in the market that monitors real-time radio and TV... [and analyses] all types of media” (Opoint 2016). It is probably an exaggeration, yet as became evident in an interview, sound bites are delivered direct to customers—that is, speech recognition software is *not* used to transform sound into text (Opoint 2015).

Interestingly, when contemporary media intelligence is starting to analyse other media modalities, the industry has had to face competition from adjacent IT sectors, as the music intelligence business with companies such as Gracenote or the Echo Nest. The latter is, for example, said to be a “music intelligence platform [that] synthesizes billions of data points and transforms it into musical understanding”. Acquired by Spotify in 2014, the Echo Nest boasts of being the music industry’s leading data company, powering music discovery and personalisation, that will “improve acquisition and engagement”. Interestingly, the algorithms of the Echo Nest regularly blur the distinction between music and data about content (metadata)—since this is the best way to “deliver best-in-class music discovery on a global scale” (Echo Nest). Basically the same goes for the video intelligence platform 3VR, which analyses moving images

as data points. The company promises to deliver a full suite of video business intelligence solutions that give marketing executives real-time customer insights to understand, for example, shopping patterns, demographics, store trends, employee effectiveness—and “ultimately increase conversions and overall sales” (3VR 2015).

Sound and video are thus two important media modalities of current interest within the media intelligence business. Social video is also perceived as increasingly trendy in the way businesses will use social media in years ahead. In the same manner, monitoring pod culture has become more and more important for some businesses. As a consequence, media intelligence is today seeking to orient itself towards a general ability to handle different multimodal streams of data. Within this transition, various forms of *image analytics* have, arguably, been the predominant modality that has challenged text—and where, importantly, there seems to be a market demand for large scale monitoring of visual data.

The American company Synthesio is an interesting case in point; it defines itself as a leader in the social listening industry, but has also started co-operating with Ditto Labs image analyses. In a press release from autumn 2015 it was stated that,

1.8 billion photos are shared every day on social media platforms. With the immense popularity of photo-sharing behavior, and the sheer volume of photos uploaded online daily, brands need a mechanism to recognize, analyze and act strategically upon these photos as part of their social insights program (Synthesio 2015).

The purpose with the co-operation and the launch of Synthesio Image Analytics is hence to capture data from innumerable images posted on Instagram (and the like) about global brands and agencies. Easily recognisable and popular brands like Coca-Cola can, in short, use computer vision technology to act on the sea of photos containing their brand in

order to detect consumer sentiment, brand presence and visual exposure at sponsored events.

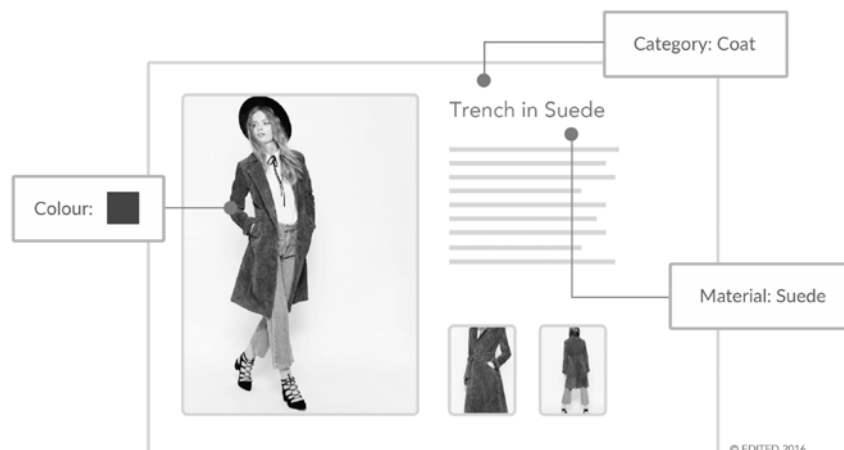
The major computational problem in a multimodal context is determining which features of (or in) an image which “best signify that two items should belong to the same grouping” (Hare et al. 2015). API’s in use within media intelligence are, furthermore, often said to provide access to information regarding brands identified in the image. Using Synthesio Image Analytics companies are, for example, said to gain access to the context, environment and what objects are in an image, as well as how many recognisable faces there are in a photograph—including ‘smile score’, that is an indication of the number of smiles, and hence the positive or negative values that forecast and determine ‘image mood’ (Synthesio 2015).

One contemporary commercial sector where image analytics is being widely used is the fashion industry. Fashion has always been about spotting trends and forecasting style—via images. Using computational and imagistic methods (based on comparing databases), fashion forecasting activities have today become more accessible than ever. Data-driven fashion forecasting firms such as WGSN and EDITED, cover both fashion and lifestyle forecasting, as well as data analytics and crowd-sourced design validation. The American company WGSN, for example, offers customers the ability to “upload the images you want to test”, regarding design, colour, price, age and size appeal. Fashion prototypes are then tested and compared with “17 million searchable images” and “1,300 catwalk shows and 150+ catwalk analysis reports per season”. In addition, the so called “Styletrial” at WGSN allows customers to test products—again, uploaded in graphical format—and target consumers at any stage “in the season to gain valuable, fast-turnaround insight”. Apparently, WGSN have secured a giant consumer crowd of panellists “ready to review your designs and products and give you feedback” (WGSN 2016).

With the slogan, “More Data. With More Data Science Behind It” the U.K based company EDITED, perceives fashion through the lens of Google. “In the same way that Google uses machine learning” to read websites and understand information EDITED states,

we use ours to read the sites of brands and retailers all over the world. But reading is only half of it, the second—and more crucial—part is understanding. Using advanced machine learning, we’ve taught our systems to do more than access and collect information, we’ve taught them to understand what they’re looking at.

EDITED’s image recognition algorithms can hence determine when “a skirt is not a dress”, or a when “a tunic is not a shirt”, thus giving their customers a visual understanding of what other competitors are uploading. Furthermore, colours and textures of clothing can also be distinguished, that is: “recognizing a piece of clothing within an image and separating it from non-essential elements, i.e. the model wearing the clothes” (EDITED 2017).



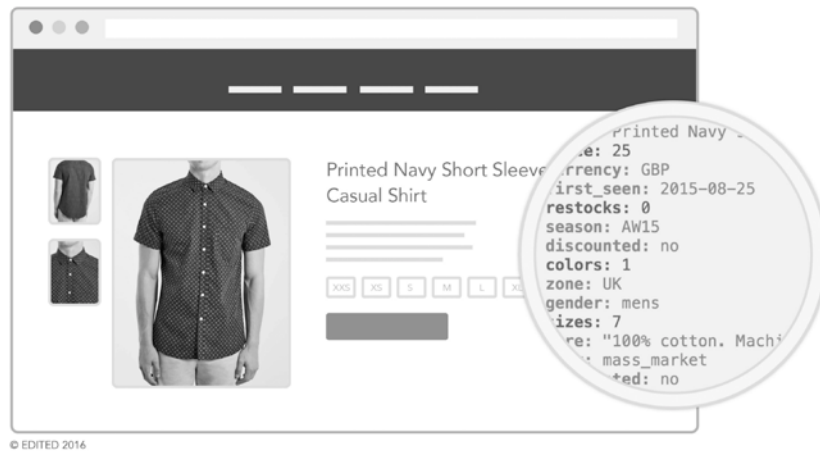


Figure 4 and 5. Using advanced machine learning algorithms, the U.K. fashion company EDITED has taught its “systems to do more than access and collect information, we’ve taught them to understand what they’re looking at.” Image courtesy of EDITED (2017).

Concluding Remarks

It might not come as a surprise that EDITED’s web interface has a striking resemblance to the Echo Nest. These companies are monitoring completely different things (clothes and music). Still, they are more or less in same business—music and/or fashion as data. It is only the modality of the monitored content that is different. Part of the business success of these companies lies in the way they aggregate music and fashion trends and sales from a wide variety of sources around the globe—especially social multimedia—and then makes this information accessible in real time. EDITED boasts of having a dataset of 53 billion data points; the Echo Nest claims the double amount.

In this article we have described and analysed the different ways that media intelligence today has adapted to an altered media landscape, increasingly turned social *and* multimodal. Companies working within media intelligence are faced with audiovisual and social data streams.

Monitoring these, as we have shown, is indeed difficult. Machine learning of other media modalities than text, in short, poses a number of technical hurdles for media intelligence. A challenge that *all* media intelligence is faced with today, is hence the somewhat paradoxical movement from the *content* of communication towards the *medium* of communication. To be able to really monitor relevant content, media intelligence simply has to be able to handle *all* modalities of media—not only text (or numbers). Then again, content has at the same time been (more or less) *unified* as data, but the transition—or perhaps dialectics between *content and medium*—also resonates in an interesting way with debates within classical media theory as to what constitutes the *bias* of communication. Content and medium have, in short, always been intertwined.

One result from our article is that forthcoming research and research agendas on media intelligence should focus more on this social and multimodal transformation. In particular, we argue that intelligence methodologies need to be adapted to new social and multimodal media forms and formats. Another result of our findings, is that the notion of media intelligence *per se* seems to be on its way to switch and transform into *intelligence media*. Today, data analytic companies as EDITED or the Echo Nest monitor data streams where the difference between actual content (clothes and music) and descriptions and/or metadata about such content are hard to separate. The data driven *entanglement* of content and metadata simply calls for a need to re-conceptualise media intelligence. In a digital landscape where actual content is always linked and woven together with information about content (metadata), it is (from a media intelligence perspective) no longer viable to analyse such content as *autonomous* entities.

Hence, the notion of *intelligence media* points towards the fact that content and descriptions of content are increasingly bundled as containers of data. If the business of media intelligence, as we have argued in this article, needs to pay increasing attention to new forms of socially and

multimedia-saturated information, the industry will all likely *also* have to confront a more profound alteration in years to come, since media analytics *per se* is increasingly becoming an integrated part of content itself (as data). Naturally, there needs to be a market demand for this kind of transition to occur—that is: the request of monitoring other (or new forms of) social media (as data streams). Even if parts of the media intelligence business today have started to partner with emerging media analytics companies (as EDITED or the Echo Nest)—all in order to better understand the impact and resonance of social and audiovisual content on the web—at present commercial demand still seems insufficient.

Lars Degerstedt is Senior Lecturer at the School of Natural Science, Technology and Environmental Studies at Södertörn University.

Contact: lars.degerstedt@sh.se

Pelle Snickars is Professor of Media and Communication Studies, specialising in digital humanities at Umeå University, with an affiliation to the Humlab research centre.

Contact: pelle.snickars@umu.se

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