# Managing data using an ontology for enterprise decision making: a case of the World Bank


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**Abstract:** People have access to more data in single day than most people that have access to data in the previous decade. This data is created in many forms and it highlights the development of big data. The challenge is how to capture this data and analyse this data into useful information for the specific organisation activities because determining relevant data is a key to delivering value of information. In this paper, we describe big data in information spectrum to identify relevant data from large collection of big data to assist information professionals with useful information for decision-making process. We illustrate the relationship between big data and information spectrum using an ontology. Case study is applied using data from the World Bank. The results from the case study demonstrate how we incorporate big data and information spectrum using an ontology to provide a platform to extra value from large datasets.

**Keywords:** big data; information professionals; information spectrum; ontologies; organisational goals; the World Bank.

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## 1 Introduction

Big data is a new way of thinking about enterprise data and how it can drive business value. The amount of data that is available to businesses is increasing, with social media and machine-to-machine as just two of the leading sources. The central role of business services in today's enterprises, and the more complex architecture through which they are delivered, make it important to manage big data solutions from a business perspective. Business perspective focuses on business objectives and benefit, and prioritises resources and activities according to the needs of the business. In this way, effective evaluation of the big data can ensure optimal relevance of data for more effective decision making to support the business goals.

This paper discusses a holistic approach to evaluation big data to help information professionals to automate, accelerate and integrate the existing types of data in the organisations. Information professionals are seen as an organisational community that assist leaders in the decision-making process by developing and facilitating focused leadership (Wang and Swanson, 2007). This leadership is a major factor in analysing relevant data and make use of this data for meaningful information. They rely on data to improve their decision making to maximise the organisation profit, find solutions to problems and evaluate to what extent the organisational goals could be achieved (Izhar et al., 2013).

The approach to evaluate the big data will depend on how organisations specific their business priorities. The most likely organisational structures to initiate big data

technologies are either existing analytics groups or innovation or architectural groups within IT organisations. In many cases, these central services organisations are aligned in big data initiatives with analytically oriented functions or business units (Davenport and Dyche, 2013).

Even though there are many recent studies have been done on big data in the context of the organisations (Berber et al., 2014; Galbraith, 2014; Grossman and Siegel, 2014; Hazen et al., 2014). There is still little debate these days about big data in supporting the goals of an organisation (Davenport and Dyche, 2013; Grossman and Siegel, 2014; Manyika et al., 2011). There is yet no consensus about how best to incorporate big data in the organisations and how the process of incorporating the big data can identify relevant data to assist information professionals with useful information.

### *1.1 Aim*

The term big data tends to be used in multiple ways, often referring to both type of data being manage and technology used to store and process it (Davenport, 2014). At the same time, the existing information management solutions in organisations have focused efforts on data that are already structure and ready to be analysed using standard tools. This paper is deliberately more inclusive. In this paper, we focus on how data are manage and analyse that highlights the information spectrum that focus on the creation of value from data and transform this data into useful information.

The evaluation of big data is important in organisations in order to identify relevant data for certain organisation priorities. To achieve this aim, we identify the relationship between big data and information spectrum using an ontology. The relationship is important to assist information professionals to evaluate relevant data for decision-making process. In big data era, the roles of information professionals are not just focus on collecting and managing information but their roles can be examined to:

- demonstrate their ability to identify relevant data for certain organisational goals
- demonstrate their ability to analyse the data through effective metrics which will contribute to effective dashboard
- ability to present the results as information
- transform the information into knowledge
- use the knowledge for decision-making process to keep the organisations successful.

An ontology to represents knowledge as a set of relationship for information spectrum within a domain. An ontology is applied to describe the elements in the domain. The ideas of using an ontology and visual structuring in organisation applications were discussed in many works and now are implemented in many sectors (Almeida and Barbosa, 2009; Mansingh et al., 2009; Rao et al., 2012; Valaski et al., 2012; Valiente et al., 2012). However, much of the research in this field did not receive much attention in the literature that incorporates big data in information spectrum to assist organisations with useful information for decision-making process in relation to the organisational goals.

An ontology provides explicit and formal specifications of knowledge, especially implicit or hidden knowledge (Cho et al., 2006). By incorporating the big data, an ontology makes the process to identify the relevant data more easily consumable to

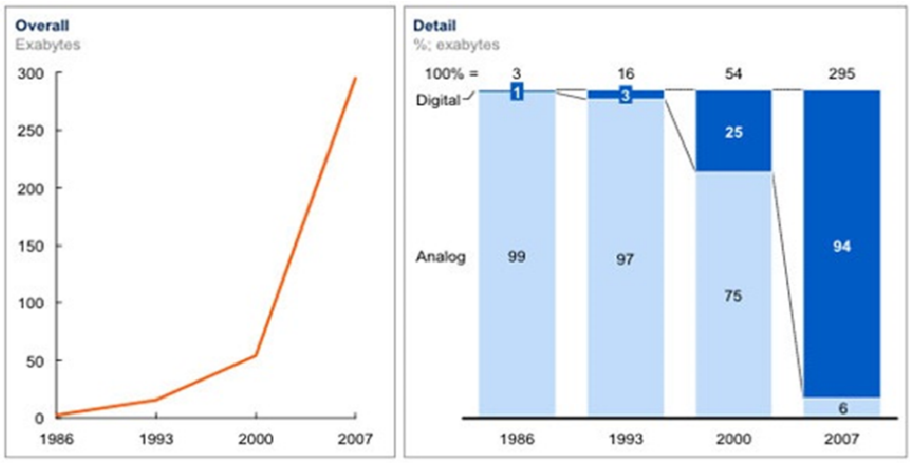
address which data from the datasets are important in evaluating the goals. The outcome of this paper will assist information professionals with competitive edge to apply useful information in relation to the specific organisational priorities.

The remainder of this paper is organised as follows. Section 2 is the introduction of big data and information spectrum together with the research issues. We develop the relationship between big data and information spectrum for the organisational goals using an ontology in Section 3. Section 5 is the case study from the World Bank. A general discussion is given in Section 6. The final section contains some concluding remarks.

## 2 Big data and information spectrum

Today people have access to more data in single day than most people that have access to data in the previous decade (Izhar et al., 2013). Volume of data has grown rapidly since 2000 with pervasive digitalisation content (Hilbert and Lopez, 2011), as shown in Figure 1. A recent survey by the Independent Oracle Users Group (IOUG) found that approximately 48% of enterprises expect a significant or moderate increase in unstructured data analysis in every five years (Baum, 2015a).

**Figure 1** Volume of data has increased from 2000 (see online version for colours)




*Source*: Hilbert and Lopez (2011)

In the past couple of years, we have seen a significant increase in the use of big data analytics that bring data under management (Davenport, 2014). Big data provides significant opportunities for enterprises to impact a wide range of business processes in the organisations. Organisations create huge amount of data in their daily business activities. For example, since 2000, the volume of data has increased as shown in Figure 1. Study by Hilbert and Lopez (2011) shows the volume of data has increased and the problem is this data are created and found in many different forms such as databases, paper-based document, mobile applications, various websites and social media. This collection of data is known as big data. All these data captures in different formats and makes it almost impossible to understand the existing relationship between different data. The size and complexity of data make it difficult for companies to unlock the true value

of their data. In fact, some data are so far out of date that it does not belong in an active data storage at all. A key challenge in current environment is determining how to identify data that still relevant for information professionals who receive output of analysis based on this data. Unfortunately, this data cannot be treated disparate information. As a result, this data might be redundant with huge volume of data and make it hard to analyse relevant data into information. Organisations need to use this collection of data and create meaningful information and gain knowledge out of it. Although big data does not refer to any specific quantity, this data might create petabytes and exabytes of data, much of which cannot be integrated easily.

Government agencies and large, medium and small private enterprises in many domains, such as engineering, education, manufacturing, are drowning in an ever-increasing deluge of data. Companies like Google, eBay, LinkedIn and Facebook were built around big data from the beginning (Davenport and Dyche, 2013). Big company like Apple's Corporation has the amount of data that are generated has risen steadily every year. For example, with the arrival of Apple's Watch, Apple presumed millions of people who will soon be using it for everything from monitoring their heart rate to arranging their social calendar to remote controlling their home entertainment (Marr, 2015). This will doubtlessly bring with it a tsunami of data. Apple's Corporation itself has operational storage capacity from kilobytes to terabytes (Aluya, 2015).

Even though the information professionals such as data scientists are trained to analyse this data but the huge capacity of data created everyday make it hard to identify which data are relevant for the specific organisation activity. As a result, it poses an issue on how effective this data to support decision-making process (Izhar et al., 2013). Information professionals must somehow get along and work jointly with mere quantitative analysts (Davenport and Dyche, 2013). Thus, having an ability to analyse the data in a timely fashion can ensure organisations have a competitive edge to improve productivity in relation to the organisational goals. However, the trustworthiness of data in relation to the organisational goals is often questionable due to the huge amount of data within the organisations.

High structure and high quality of data are vital. It is the foundation for organisations to analyse relevant data into information in formal reports and dashboards. This information has to be used to make actions and decisions based on actual facts. This stage is known as information spectrum and it is important to apply this stage across the organisations in the consistent action. Therefore, the entire organisation can benefit.

The implementation of big data highlights the development of big data analytics. Big data analytics could be used to examine large amounts of data from variety of types to discover useful information. Such information can provide a competitive advantage for better decisions. The primary goal of big data analytics is to help companies make better business decisions by enabling data analysts to analyse huge volumes of transaction data which remains an unresolved challenge for conventional business intelligence programs.

Big data analytics can be done with the software tools commonly used as part of advanced analytics disciplines such as predictive analytics and data mining. But the unstructured data sources used for big data analytics may not fit in traditional data warehouses. Furthermore, traditional data warehouses may not be able to handle the processing demands posed by big data. As a result, a new class of big data technology has emerged and is being used in many big data analytics environments. For example, the technologies associated with big data analytics include Hadoop, MapReduce and

Hortonworks. These technologies form the core of an open source software framework that supports the processing of large datasets across clustered system.

### *2.1 Research issues*

Big data may be as important to business because more data can lead to more accurate analyses. Big data is concern because the growing business appetite for data and analytics puts pressure on systems to deliver relevant data rapidly to assist decision-making process in relation to the organisational goals. However, whether this data are relevant or not and because of the complexity of the organisation policy that keep changing throughout the years, various data from different sources make relevant data harder to achieve (Izhar et al., 2013). This current situation makes it harder for information professionals to have useful information to assist their decision-making process in relation to the organisational goals. More accurate analyses can lead to more confident decision making and better decision can mean greater operational efficiencies in the organisation (Davenport and Dyche, 2013).

In today's competitive marketplace, executive leaders are racing to convert enterprise insights into meaningful results. Successful leaders are infusing analytics throughout their enterprises to drive smarter decisions, enable faster actions and optimise outcomes. For example, the IBM Institute of Business Value surveyed 900 business and IT executives from 70 countries. The result shows that leaders are 166% more likely to make most decisions based on data (Shani, 2015). Another good example is National Australia Bank (NAB) wanted to eliminate inconsistencies arising from storing data in 34 different financial and operational systems (Baum, 2015b). However, they lacked consistency in how to maintain data. Therefore, it is very difficult for them to produced results in consistent manners that lead to their goals.

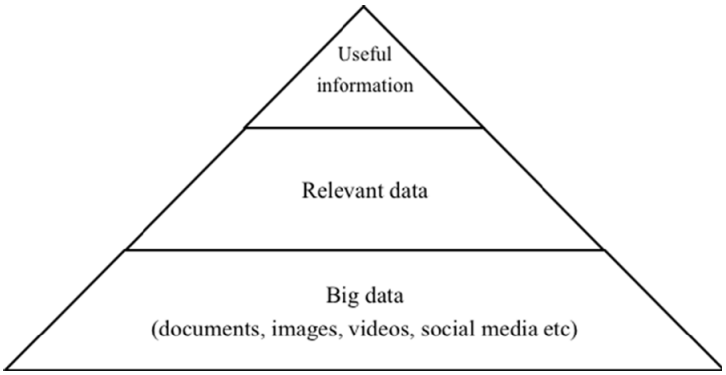
Taking advantage of big data opportunities is challenging for the organisations (Berber et al., 2014). Firms and other organisations have been using large databases and analytics for the last couple of decades. Transactions are stored in data warehouses and analysed with data-mining algorithms to extract insights (Galbraith, 2014). To ensure the effectiveness of the data, organisations need to be able to store data reliably across a number of databases. Once data need to be distributed, organisations need a way to get it out again and they need to identify which data are needed, assemble it and analyse it. The challenge is how to capture this data to be considered relevant for the specific organisation activities because determining relevant data area key to delivering value from massive amounts of data. The real issue is not how the organisations acquiring large amount of data but how they do with the data that counts (Davenport and Dyche, 2013). The technologies and concepts behind big data can allow organisations to achieve a variety of objectives.

Information professionals provide information services to organisations. Information services involve organising, retrieving, acquiring, securing and maintaining information. It is part of the information professionals that have control over the planning, structure and organisation, controlling, processing, evaluating and reporting of information activities in order to meet certain organisational objectives. For example, in order to achieve the organisational goals, organisations need a comprehensive understanding of markets, customers, products, regulations, competitors, suppliers, employees and more. This understanding demands useful information (Izhar et al., 2013). However, without an effective use of relevant data and analytics, make it difficult for organisation to evaluate

to what extend the organisational goals have been achieved (Sigmon, 2015). The challenge is not just in managing the data for decision process but to capture relevant data and analyse this data into useful information.

To overcome this issue, we develop the relationship between big data and information spectrum using an ontology in the context of the organisational goals. We identify relevant data from large amount of data and analyse this data into useful information, as shown in Figure 2. This information is important for information professional as useful knowledge to assist their decision-making process in relation to the organisational goals.

**Figure 2** Research issues




## *2.2 Requirements to address the research issues*

The contribution of an ontology is to improve the creation of model ultimately takes place through the organisational goals and it works as a type of relationship to represent the dependency relationship between data and organisational goals. The problems in this paper covered the limitation in structuring big data in information spectrum. It prevents the solution to identify the importance of this data from being practical and implement in relation to the organisational goals. Therefore, it is important to develop a model for organisational goals in order to show the dependency relationship between big data and information spectrum.

Despite the various existing methodologies to evaluate the organisational process based on an ontology (Fox et al., 1996, 1998; Mansingh et al., 2009; Rao et al., 2009, 2012; Sharma and Osei-Bryson, 2008), this paper focus on structuring the relationship between big data and information spectrum in relation to the organisational goals. The process consists of identifying which data are relevant to be analysed into useful information that can contribute to the decision-making process.

The need for an ontology to resolve the issues is as follows:

- An ontology will be able to define the organisational goals and the possible sub-goals and variables that relate to the organisational goals.
- An ontology will be able to identify the dependency relationship between the organisational goals elements. Organisational goals can be broken down into organisational goal elements, such as sub-goals and an ontology can define the dependency relationship between the sub-goals and organisational goals.

An ontology is presented to drive our understanding of how organisational goal elements are related to each other.

- An ontology will be able to develop the dependency relationship between data and organisational goals. After the organisational goals have been identified based on the ontology, the ontology will assist the process of identifying the relevant data in the organisational datasets. The aim is to identify which data relate to the organisational goals.
- An ontology will enable the development of a metrics as a measurement tool to evaluate data into useful information. After the organisational goals have been identified based on the ontology, the metrics will be defined to analyse the dependency data that relate to the organisational goals. In doing so, we can identify which data are relevant to the organisational goals. The analysed data create useful information. This information will be presented in the dashboard to assist decision-making process.
- Information professional will use this information to determine if the information meets the organisation policy. Organisation policy always changes. As a result, data and organisational goals also keep changing. Therefore, it is important for them to receive information that is still relevant to the organisation policy.
- Information professionals will use this information as knowledge to for decision-making and actions.

## 3 Literature review

In this section, we review some background on the organisational models and look at the new demands that are increasingly being placed as solutions for organisations as we seek to exploit effective approach in using organisational data that can improve organisation competitive advantage. We look through the pervious organisational goals models to review some gaps that demand the contribution of big data in organisations.

Organisational goals are defined as the most important targets to be achieved in every organisation (Izhar et al., 2013). Even though the concept of the organisational goals has been in the existence for some time, modelling the structure of the organisational goals is much more difficult (Izhar et al., 2012, 2013). For example, one way to develop a common understanding of the organisational goals structure is based on an ontology (Izhar et al., 2013). An ontology provides explicit and formal specifications of knowledge, especially implicit or hidden knowledge (Cho et al., 2006). An ontology is considered as an approach to support data sharing (Pundt and Bishr, 2002). Therefore, an ontology assists with part of the integration problem in relation to the organisational goals and can be used to improve the communication and collaboration between the decision makers and the users (Selma et al., 2012), which is, in this paper, the decision makers in relation to the organisational goals.

In Izhar et al. (2013), organisational goals ontology is developed based on the work of Rao et al. (2012), Sharma and Osei-Bryson (2008) and Fox et al. (1998). Despite many research efforts and established model for the organisational goals using an ontology, they have not yet been systematically applied for decision making to support the evaluation of big data for the organisational goals achievement. This is important because

decision support is one of the main objectives of an ontology (Bastinos and Krisper, 2013). In this paper, we extend the organisational goals ontology developed in Izhar et al. (2013), in order to develop the relationship between big data and information spectrum for decision-making process.

Several structures that were proposed in the previous models are combined (Fox et al., 1998; Rao et al., 2012; Sharma and Osei-Bryson, 2008) for the organisational goals ontology in Izhar et al. (2013). These models are adapted as a reference for the organisational goals ontology. However, these models do not cover any discussion on big data in organisational processes. Fox et al. (1998) focused on structuring the linkage between organisational structure and behaviour. This is critical for enterprise model development. However, the authors do not emphasise any organisational resources such as data and information but they focus on the roles and activities within the organisation. Meanwhile, Sharma and Osei-Bryson (2008) developed a framework for an organisational ontology in an effort to increase an understanding of the business. However, the authors do not specifically identify the relationship between organisational resources, such as data and the organisational goals. In this model, the authors adapted the work of Fox et al. (1998), where the authors discussed the physical resources and role of the organisational model.

Recently, Rao et al. (2012) developed an organisational ontology in order to build a knowledge map within the organisation. The structure includes the flow of knowledge within the organisation in the context of knowledge sharing and knowledge storage. In this model, the authors discussed the organisational resources, as in Sharma and Osei-Bryson (2008). Another aspect that is similar to Sharma and Osei-Bryson's work is that both models include business processes. However, Rao et al. (2012) discussed business processes from the organisational goals point of view and Sharma and Osei-Bryson (2008) discussed business processes from the organisational activity point of view. Most of these studies focused on the organisational structure and performance. In Izhar et al. (2013), the authors developed the organisational goals ontology that consists of organisational goals, sub-goals and organisational data. They developed the dependency relationship for the organisational goals and dependency relationship between organisational data and organisational goals.

Table 1 shows the results from the previous models on the organisational goals using an ontology. However, none of these studies incorporate big data and information spectrum in their models. The authors do not develop any relationship between big data, data, information and knowledge. Therefore, make it more difficult to analyse relevant data from huge collection of data into useful information in relation to the organisational goals. In this paper, we examine the impact of big data in information spectrum using an ontology (Figure 3). We analyse data with the goal of discovering useful information and suggest the conclusions and supporting decision making as knowledge in relation to the organisational goals. We extend the organisational goals ontology in Izhar et al. (2013) by incorporating big data and information spectrum in relation to the organisational goals.

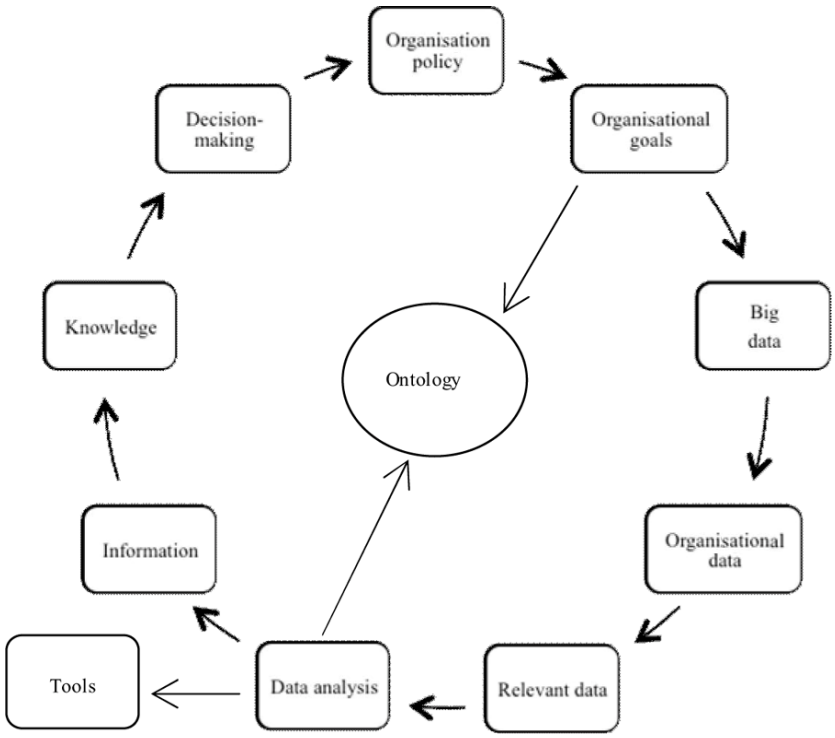
Sharing important data and information can provide the required knowledge to assist successful decision making (Simsek et al., 2009). It is crucial for organisations to create and generate new data and evaluate it to enhance decision making. Different ways of generating new ideas, information and knowledge will help in terms of decision making and will enable information professional to use the most relevant data in relation to the organisational goals. In Izhar (2014), the main advantages of building the relationship

between big data and information spectrums using an ontology are: a higher level of decision making is provided to support the evaluation of the level of organisational goal achievement, the direct use of data that relate to the organisational goals captured by an ontology and the development of a mechanism for the evaluation of data into useful information based on the metrics. It specifies the measurement process needed for data that relate to the organisational goals. It includes how metrics is defined to evaluate the dependency relationship between data and organisational goals. Finally, it provides feedback in a post-mortem fashion to identify the extent to which the organisational goals could be achieved.

**Table 1** Demands from the issues

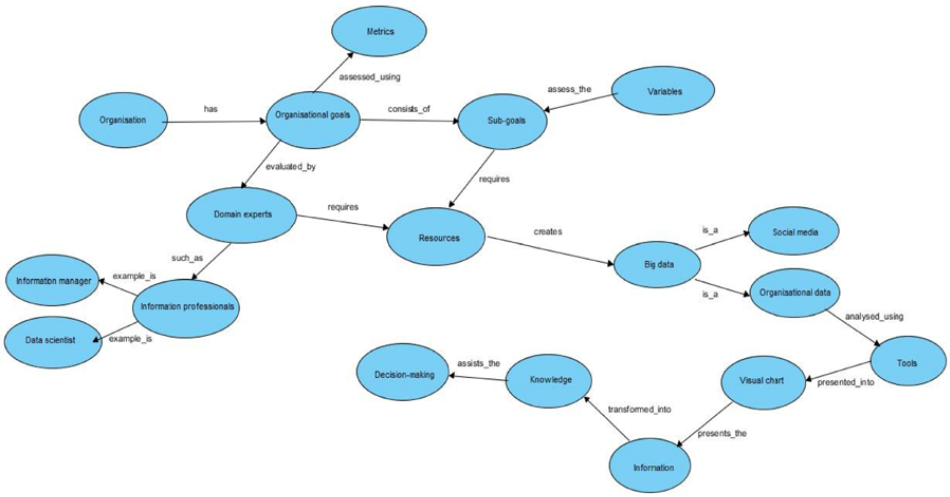
| | *Information spectrum* | | | | *Ontology relationship* |
|---|---|---|---|---|---|
| *Authors* | *Big data* | *Organisational data* | *Information* | *Knowledge* | *Organisational goals* |
| Fox et al. (1998) | × | × | × | × | / |
| Sharma and Osei-Bryson (2008) | × | × | / | / | / |
| Rao et al. (2012) | × | × | / | / | / |
| Izhar et al. (2013) | × | / | × | × | / |

**Figure 3** An ontology integration in information spectrum



In Figure 4, we propose organisational goals model based on ontology. In this figure, the ontology shows that an organisation has organisational goals, and organisational goals consist of sub-goals. To identify the extent to which the organisational goals have been achieved, an organisation needs organisational resources, which include data to evaluate the extent to which the organisational goals could be achieved. Different from Sharma and Osei-Bryson (2008), the organisational goals ontology focuses on the use of organisational data because organisational data are a major resource in every organisation and these are important to evaluate the relevance of this organisational data in relation to achieving the organisational goals. The ideas of using an ontology and visual structuring in organisation applications were discussed in many works and now are implemented in many sectors (Valaski et al., 2012; Valiente et al., 2012). However, much of the research in this field did not receive much attention in the literature on incorporating the big data for social media to assist the organisations with the decision-making process in relation to the organisational goals.

**Figure 4** Organisational goals ontology (see online version for colours)




An ontology provides explicit and formal specifications of knowledge, especially implicit or hidden knowledge (Cho et al., 2006). By incorporating the big data, an ontology make the process to identify the relevance of data more easily consumable to address which data from the datasets are more important in evaluating the goals. The outcome of this paper can establish an analytics of big data structure for the organisations to ensure that analytics processes are supported by the specific organisational priorities. The contribution of an ontology is to improve the creation of model ultimately takes place through the organisational goals and it works as a type of relationship to represent the dependency relationship between data and organisational goals.

Despite the various existing methodologies to evaluate the organisational process based on an ontology (Fox et al., 1998; Rao et al., 2012; Sharma and Osei-Bryson, 2008), this paper focuses on structuring the relationship between social data and organisational data in relation to the organisational goals. This process consists of identifying which data are relevant in achieving the organisational goals that will be used by domain experts

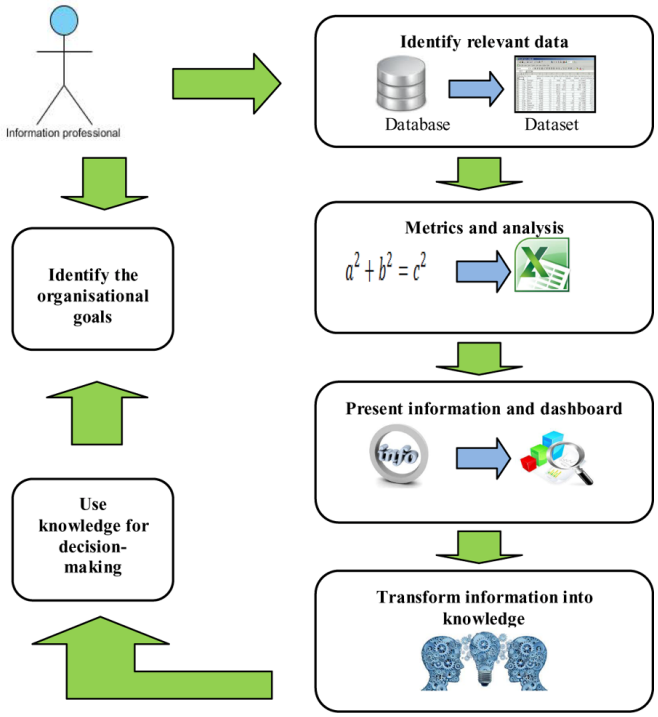
and entrepreneurs who contribute to the decision-making process. They are also responsible for identifying to what extent the organisational goals have been achieved.

## 4 The roles of information professionals

Information professionals face complex business intelligence questions. In the phenomena of big data today, the roles for information professionals are not just limits to collect, store and disseminate information but having an ability to identify all different data which organisations may have in light to the specific organisations activity. They need to understand the need of the relevant data that can support future information and knowledge that can take into practice and action. Success and failure to generate relevant data into information can both lead to positive and negative results associated with wrong actions in relation to the organisational goals.

In this research, we examine the roles of information professionals that also cover the ability to identify the organisational goals, identify the relevant data and use predictive analytics or other certain advanced methods to extract value from data into useful information and make a conclusion in relation to the organisational goals (Figure 5).

**Figure 5** The roles of information professionals in big data era (see online version for colours)




When defining the roles of information professionals within information spectrum, it is helpful to align their ability based on information spectrum from the flow of data into applying knowledge for decision making in relation to the organisational goals. The roles are:

- *Identify the organisational goals*: Information professionals need to understand why they need the information in first place. They must have the ability to understand the specific organisational goals. This is because organisational goals keep changing depends to the current organisation focus (Berber et al., 2014). As a result, organisational resources such as data, information and knowledge also change. Therefore, make it difficult for organisation to capture relevant data in relation to the specific organisational goals. They must have the ability in evaluating the extent to which the organisational goals have been achieved. In this research, organisational goals can be defined in many ways. For example, goals might be defined in relation to different requirements, such as what sub-goals relate to the goals? What is the weight of these sub-goals that relate to the goals? If we examine each sub-goal, can it be considered as a goal itself?
- *Identify relevant data for certain organisational goals*: Datasets are a collection of data that have been stored in different datasets to represent the different types of data. These datasets are important as a reference for any decision-making evaluation. However, this data can be very large and it is a challenge as to how to identify relevant data from the huge number of datasets. Therefore, it is important for information professionals to understand the creation of data in order to perform a searching for data in the datasets that refer to the same organisational goals from different data sources. At the same time, they must have the ability to identify similar data from large datasets in order to avoid any irrelevant organisational data during the decision-making process in relation to the organisational goals. It involves analysing the dependency data that relate to the organisational goals.
- *Metrics and data analysis*: In this paper, the main objective of data analysis is to evaluate the relevant data from the vast amount of data collection into useful information. It is also suggested that data analysis is important to identify the value of data that are relevant to the organisational goals to support the decision-making process in achieving the organisational goals (Izhar et al., 2013). The increased amount of other organisational resources, such as information, knowledge and tools, also makes it difficult for the decision maker to identify the most relevant data, as data might not be relevant to the organisational goals. Therefore, it is important for information professionals to apply an analysis approach that can identify the data that is relevant to the organisational goals. Information professionals must have the ability to define a metrics to evaluate the extent to which the organisational goals have been achieved by measuring the dependency of data that relate to the organisational goals. The weight to analyse the dependencies of data can be defined in many ways, such as percentage and frequency based on different situations. Information professionals might want to identify the percentage of data that relate to organisational goals.
- *Present information and dashboard*: Information professionals must have the ability to present the analysed data as useful information. The analysed data will be presented in the dashboard to show graphical information of the results. The comparison of this information can be presented to support the decision-making process in relation to the organisational goals.

- *Transform information into knowledge*: Information professionals will use the information to closely imply know-how and understand the important of the knowledge in relation to the organisational goals. Therefore, they must have the ability to systematically manage this organisation's knowledge as an asset for the purpose of creating value in meeting the organisational goals. They must explore the information based on the needs of current organisational goals and contribute to share the information in order to pursue the requisite knowledge to helps organisation towards achieving its goals.
- *Completing existing body of knowledge*: By aggregating new data, information professional should be able to provide stronger information's value, impact and influence in order to complete existing body of knowledge towards organisational goals. This makes existing knowledge can be used with new knowledge which makes any assessment of improved accuracy and efficiency.
- *Use knowledge for decision making*: Information professionals must have the ability to conclude the knowledge in a timely fashion that can ensure organisations have a competitive edge to improve productivity in relation to their organisational goals. They have to gathers the best available evidence to support decision to what extend the organisational goals have been achieved. They use the knowledge and advise the organisation on any intellectual property issues and compliance in meeting the organisational goals. At the same time, based on this knowledge, they can develop and contribute to strategic and business plans that support the organisational goals.

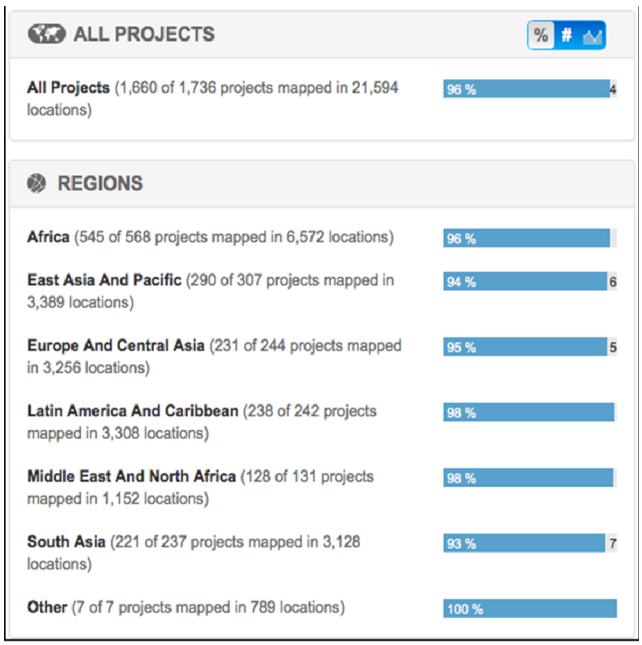
## 5 Case study: the World Bank

In this paper, we apply data from The World Bank. The World Bank is a United Nations International Financial Institution that provides loans to developing countries for capital programs. The World Bank is a component of the World Bank Group, and a member of the United Nations Development Group (see http://www.worldbank.org).

The World Bank works to help member countries improve the capacity, efficiency and effectiveness of national statistical systems. Without better and more comprehensive national data, it is impossible to develop effective policies, monitor the implementation of poverty reduction strategies or monitor progress towards global goals. The World Bank is a repository to store large volume of data and it seems perfectly suitable to test the organisational goals ontology. The aim is to identify relevant data in relation to the organisational data. Ontology is applied to develop the relationship between data and organisational goals.

Most data in the World Bank dataset comes from the governments of individual countries. The World Bank collects data on living standards and debt, but not much else. Some also comes from various international and national agencies with which World Bank partners (see http://ucatlas.ucsc.edu/data.html). These data are grown from the commitment of the member countries that participate with the development projects since early 1950s, as shown in Figure 6. The variety of data types is also diverse and data are not just created in spreadsheets or tables but also in charts, maps and audio/video. Therefore, managing and analysing these data can be very challenging.

**Figure 6** Number of projects (see online version for colours)




*Source*: The World Bank (http://www.worldbank.org/projects)

The World Bank collects and processes large amounts of data and generates them on the basis of economic models. The data have gradually been made available to the public in a way that encourages reuse. The World Bank stores data of reconstruction and development for 188 countries on 20 different topics. The topics incorporate different data indicators that store data from 1960 to 2014. For example, one of the data indicators for economic growth is agriculture (value added). The data are collected from 1960 to 2014 for 188 countries. This dataset create large amount of data only for one indicator under one topic.

The World Bank provides an analysis and visualisation tool that contains collections of time series data on a variety of topics that allow us to create our own queries. Therefore, we can generate tables and dashboards as new knowledge to be shared. In this case study, we present queries as the goals. Then we capture relevant data from huge amount of the datasets in relation to the goals. We define the metrics to analyse this data and present it in the dashboard to support decision making in light to the goals.

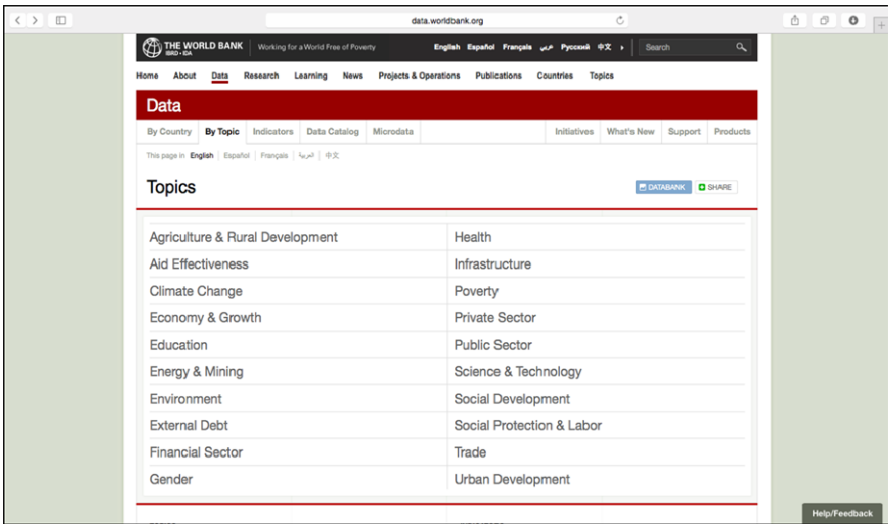
## *5.1 An ontology for the World Bank*

In this paper, the queries are created from the topics (Figure 7). We define these queries as goals. To evaluate these topics, we develop an ontology for the World Bank to filter large collection of data. Therefore, we can identify the relationship between the topics and data indicators. An ontology creates knowledge to help us to define the goals that we want to evaluate. We can make a decision on which goals we want to evaluate and which data are relevant to the goals. The amount of data stores in the World Bank make it difficult for us to identify the goals that we want to evaluate. On the basis of the World

Bank's website, data can be identified from the topics and data indicators. Figure 8 shows the relationship based on an ontology that classifies the topics. Ontology shows that there are 18 topics stored in the datasets. Each of the topics has different indicators that store different topic of data. On the basis of these topics, there are few data indicators that can be identified. Figure 9 shows some examples of data indicators that relate to the certain topics. This ontology helps us to create any query. In this case study, we focus on economic and growth only. This indicator has five datasets and we develop an ontology to identify relevant data that relate to these datasets. The datasets are important to evaluate the level of economic and growth in every country.

Using the information that we have, we set the goals that we want to evaluate. On the basis of the goals, we can capture relevant data that relate to the goals.

**Figure 7** List of topics from the World Bank (see online version for colours)




*Source*: http://data.worldbank.org/topic

## *5.2 Identify the goals*

In this case study, we aim to analyse the level of the economic growth in South East Asia in 2013. We decide to analyse the development in Indonesia, Cambodia, Malaysia, Philippines and Singapore. According to the World Bank, economic growth is central to economic development. When national income grows, real people benefit. Data can help policy makers better understand their countries' economic situations and guide any work towards improvement. Data here cover measures of economic growth that includes indicators representing factors known to be relevant to economic growth, such as industry, manufacture, services, agriculture and household.

In this case study, we analyse these five indicators to evaluate the development level of the economic growth in South East Asia. This is how we want to define the goals in this paper. We are mindful of the fact that information professionals might define the goals in a different way to the way we have undertaken to define the goal, which would require a different approach to evaluate the goals.

**Figure 8** Data are filter using an ontology to shows the topics from the World Bank (see online version for colours)

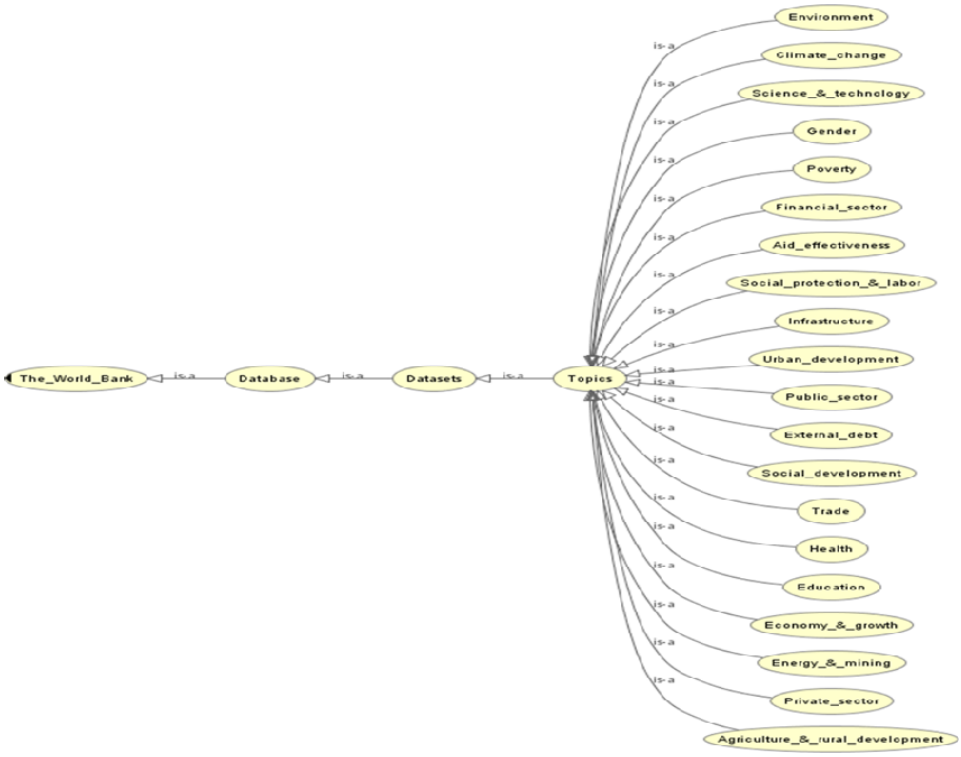
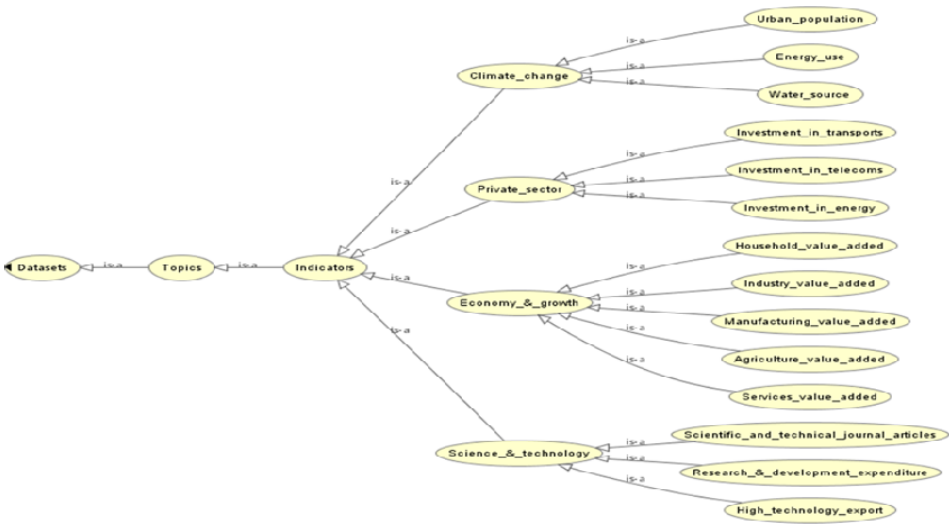



**Figure 9** Example of data filtering using an ontology to shows some indicators from four different topics (see online version for colours)



Economic growth is central to economic development. When national income grows, real people benefit. While there is no known formula for stimulating economic growth, data can help information professionals to assist the policy makers with better understand the economic situations in South East Asia and guide any work towards improvement. Data here cover measures of economic growth based on the value added for industry, agricultural, manufacturing, service and household.

According to the World Bank website, value added is the net output of a sector after adding up all outputs and subtracting intermediate inputs. It is calculated without making deductions for depreciation of fabricated assets or depletion and degradation of natural resources. The origin of value added is determined by the International Standard Industrial Classification (ISIC), revision 3. In this case study, data are in current US dollars.

- *Five goals in relation to the economic growth, as shown in Figure 10.*

*Goal 1*: Development of services for wholesale and retail trade

Services correspond to ISIC divisions 50–99. They include value added in wholesale and retail trade (including hotels and restaurants), transport and government, financial, professional, and personal services such as education, healthcare and real estate services. Also included are imputed bank service charges, import duties and any statistical discrepancies noted by national compilers as well as discrepancies arising from rescaling.

*Goal 2*: Development of agricultural production

Agriculture corresponds to ISIC divisions 1–5 and includes forestry, hunting and fishing, as well as cultivation of crops and livestock production.

*Goal 3*: Development of manufacturing to supports industries growth

Manufacturing refers to industries belonging to ISIC divisions 15–37.

*Goal 4*: Development of industry to supports sustainable growth

Industry corresponds to ISIC divisions 10–45 and includes manufacturing (ISIC divisions 15–37). It comprises value added in mining, manufacturing (also reported as a separate sub-group), construction, electricity, water and gas.

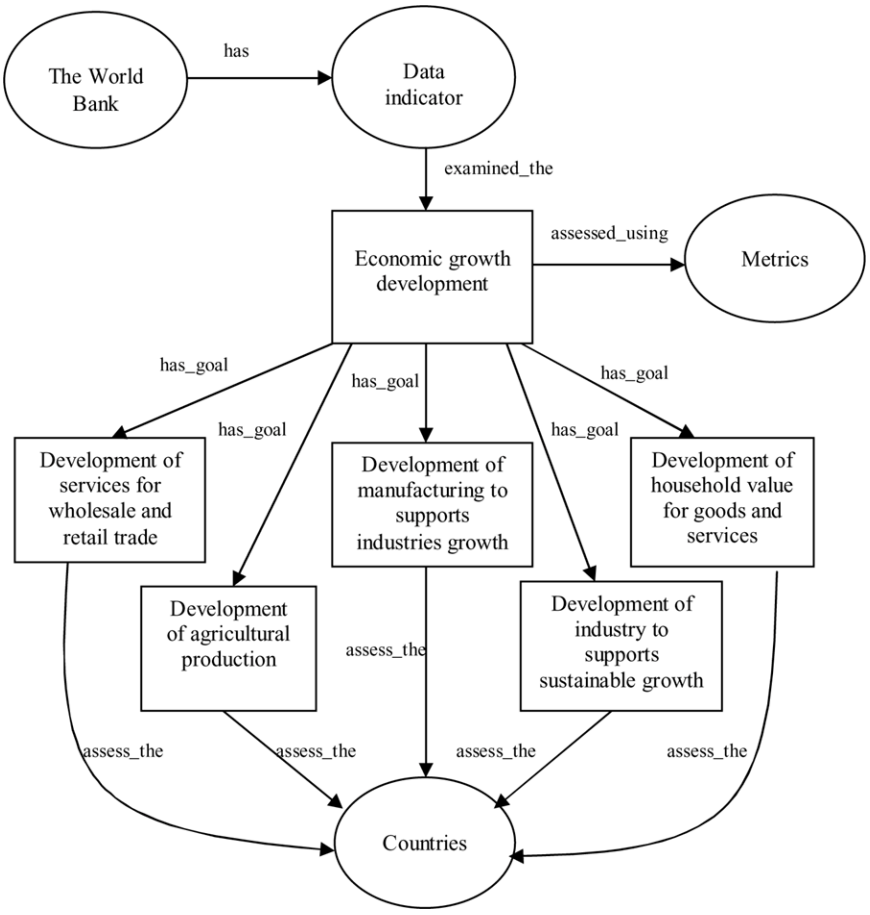
*Goal 5*: Development of household value for goods and services

Household is the market value of all goods and services, including durable products (such as cars, washing machines and home computers), purchased by households. It excludes purchases of dwellings but includes imputed rent for owner-occupied dwellings.

### *5.3 Identify relevant data*

We select data from data indicator that relate to the economy and growth. There are more that 50 indicators that are related to the economy and growth. In this section, we only select data indicators that relate to the goals that have been defined. The data indicators show the value added for industry, manufacture, services, agriculture and household in relation to the economic growth. Figure 11 shows some examples of data indicators that relate to the economy and growth.

**Figure 10** An ontology for the World Bank to evaluate the development of economic growth in South East Asia

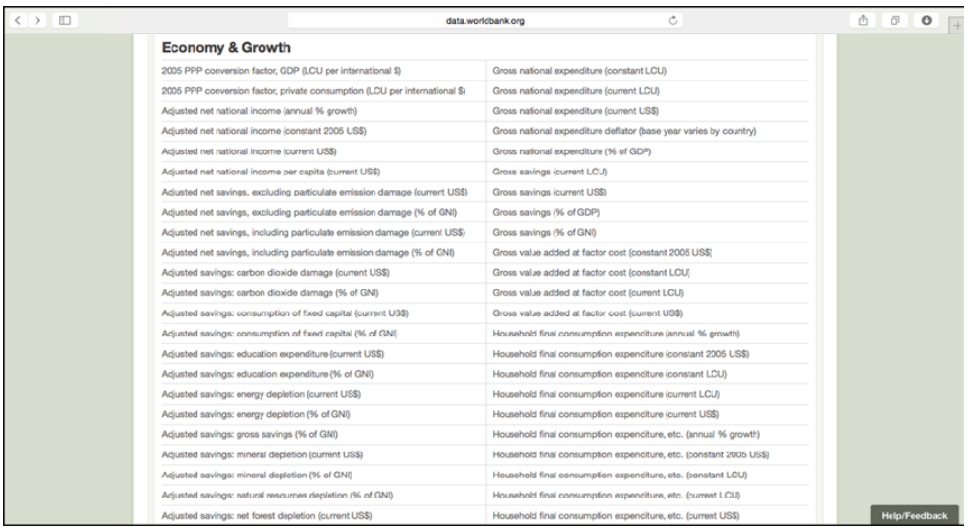



Data indicators store dataset that relate to the economy and growth. For example, Figure 12 shows dataset for agriculture. This dataset stores data from 1960 to 2014 for 188 member countries. To evaluate the development of economic growth in South East Asia in 2013, data only selected for Indonesia, Cambodia, Malaysia, Philippines and Singapore in 2013. Same process is applied for other indicator; services, industry, manufacture and household.

## *5.4 Metrics and data analysis*

In this step we define the metrics. This section identifies the different weights of value added which were assigned to the goals in order to measure the level of economic growth development. We are mindful that information professionals might want to analyse data in a different way to the way we have undertaken the analysis in this case study, which would require a different approach to define the metrics.

**Figure 11** Example of data indicators that store datasets that contributes to the economy and growth from 1960–2014 (see online version for colours)



data.worldbank.org

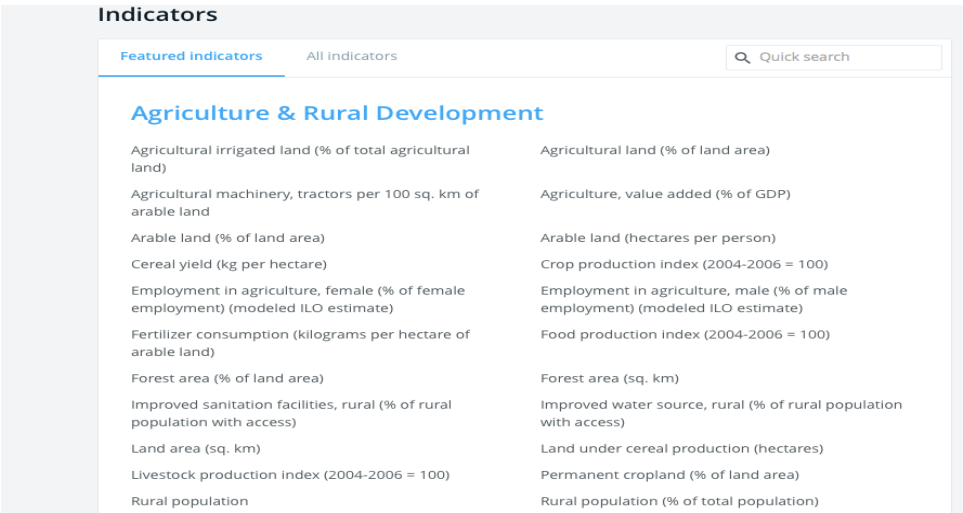
**Economy & Growth**

| | |
|---|---|
| 2005 PPP conversion factor, GDP (LCU per international $) | Gross national expenditure (constant LCU) |
| 2005 PPP conversion factor, private consumption (LCU per international $) | Gross national expenditure (current LCU) |
| Adjusted net national income (annual % growth) | Gross national expenditure (current US$) |
| Adjusted net national income (constant 2005 US$) | Gross national expenditure deflator (base year varies by country) |
| Adjusted net national income (current US$) | Gross national expenditure (% of GDP) |
| Adjusted net national income per capita (current US$) | Gross savings (current LCU) |
| Adjusted net savings, excluding particulate emission damage (current US$) | Gross savings (current US$) |
| Adjusted net savings, excluding particulate emission damage (% of GNI) | Gross savings (% of GDP) |
| Adjusted net savings, including particulate emission damage (current US$) | Gross savings (% of GNI) |
| Adjusted net savings, including particulate emission damage (% of GNI) | Gross value added at factor cost (constant 2005 US$) |
| Adjusted savings: carbon dioxide damage (current US$) | Gross value added at factor cost (constant LCU) |
| Adjusted savings: carbon dioxide damage (% of GNI) | Gross value added at factor cost (current LCU) |
| Adjusted savings: consumption of fixed capital (current US$) | Gross value added at factor cost (current US$) |
| Adjusted savings: consumption of fixed capital (% of GNI) | Household final consumption expenditure (annual % growth) |
| Adjusted savings: education expenditure (current US$) | Household final consumption expenditure (constant 2005 US$) |
| Adjusted savings: education expenditure (% of GNI) | Household final consumption expenditure (constant LCU) |
| Adjusted savings: energy depletion (current US$) | Household final consumption expenditure (current LCU) |
| Adjusted savings: energy depletion (% of GNI) | Household final consumption expenditure (current US$) |
| Adjusted savings: gross savings (% of GNI) | Household final consumption expenditure, etc. (annual % growth) |
| Adjusted savings: mineral depletion (current US$) | Household final consumption expenditure, etc. (constant 2005 US$) |
| Adjusted savings: mineral depletion (% of GNI) | Household final consumption expenditure, etc. (constant LCU) |
| Adjusted savings: natural resources depletion (% of GNI) | Household final consumption expenditure, etc. (current LCU) |
| Adjusted savings: net forest depletion (current US$) | Household final consumption expenditure, etc. (current US$) |

Help/Feedback

*Source*: http://data.worldbank.org/indicator

**Figure 12** Dataset for agriculture and rural development (see online version for colours)



**Indicators**

Featured indicators | All indicators | Quick search

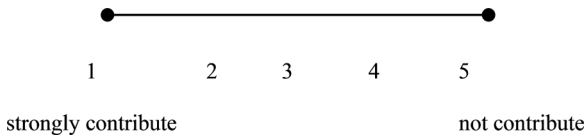
**Agriculture & Rural Development**

| | |
|---|---|
| Agricultural irrigated land (% of total agricultural land) | Agricultural land (% of land area) |
| Agricultural machinery, tractors per 100 sq. km of arable land | Agriculture, value added (% of GDP) |
| Arable land (% of land area) | Arable land (hectares per person) |
| Cereal yield (kg per hectare) | Crop production index (2004-2006 = 100) |
| Employment in agriculture, female (% of female employment) (modeled ILO estimate) | Employment in agriculture, male (% of male employment) (modeled ILO estimate) |
| Fertilizer consumption (kilograms per hectare of arable land) | Food production index (2004-2006 = 100) |
| Forest area (% of land area) | Forest area (sq. km) |
| Improved sanitation facilities, rural (% of rural population with access) | Improved water source, rural (% of rural population with access) |
| Land area (sq. km) | Land under cereal production (hectares) |
| Livestock production index (2004-2006 = 100) | Permanent cropland (% of land area) |
| Rural population | Rural population (% of total population) |

*Source*: https://data.worldbank.org/indicator

- *Rating and ranking*

In this case study, we assign a rating scale to rank different categories of economy development in relation to the goal. This rating is important to identify which categories of economy development are important for the goal. Rank for the categories is rating based on the following scale of 1–5:




The rating scale of 1–5 is set of rank design to elicit five different goals that contribute to the economy development in South East Asia (Table 2). It is a method that requires the rater to rank the categories in relation to the goal. In this metrics, the rating can be assigned with the same rating.

**Table 2** Rating scale for good categories

| *Rating of rank* | *Description* | *Definition of rank* |
|---|---|---|
| 1 | Strongly contribute | The goals are strongly contribute for the country economic growth |
| 2 | Contribute | The goals are contribute for the country economic growth |
| 3 | Fair | The goals are fairy contribute for the country economic growth |
| 4 | Neither contribute or not | The goals are neither contribute or not for the country economic growth |
| 5 | Not contribute | The goals are not contribute for the country economic growth |

*Source*: Izhar (2014)

- *Scoring and analysis*

After we assign the rank, we evaluate the weight for economic growth. The metrics calculate the ranking average for each goal to determine which goal is most preferred overall. The goal with the largest ranking average is the most achieved goal. The ranking average is calculated as follows:

$$\frac{\text{Total}(w)}{Overall\ rank(X_1W_1 + X_2W_2 + X_3W_3 \cdots X_nW_n)} \times 100,$$

where

$w$: weight of ranked position

$x$: rating for response count.

As an explanation of how the metrics to evaluate the sub-goals is calculated, consider the following example to evaluate the goal (Development of services for wholesale and retail trade). We rank the development in Indonesia of services for wholesale and retail trade is 2 because we believe the services are contribute to the economic growth in Indonesia. In Table 3, the total value for this goal is 34625218, hence the value for this rank is [34625218(2)]. Then, the rank of the next goals for other country listed in the table, development in Cambodia, is calculated in a similar fashion [58604050(3)]. This process continues until all the countries in the list have been assigned a value, hence the level of the services development for wholesale and retail trade can be calculated as follows:

$$Goal\ count(sub\ goal1)\left(\frac{145612243}{34625218(2) + 58604050(3), \ldots, 20983049(4)} \times 100\right).$$

**Table 3** Level of economic growth in South East Asia in 2013

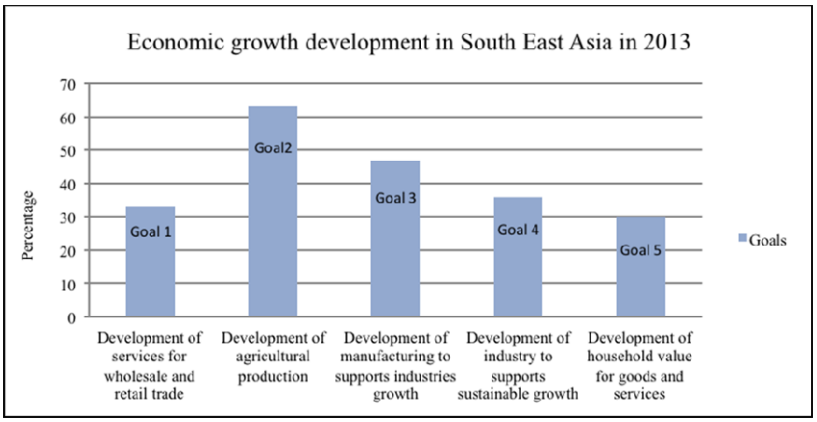
| *Economic growth development in South East Asia* | *Development of services for wholesale and retail trade (Goal 1)* | *Rank* | *Development of agricultural production (Goal 2)* | *Rank* | *Development of manufacturing to supports industries growth (Goal 3)* | *Rank* | *Development of industry to supports sustainable growth (Goal 4)* | *Rank* | *Development of household value for goods and services (Goal 5)* | *Rank* |
|---|---|---|---|---|---|---|---|---|---|---|
| Development in Indonesia | 34625218 | 2 | 12532331 | 1 | 20576842 | 1 | 3967701 | 3 | 48475079 | 3 |
| Development in Cambodia | 58604050 | 3 | 48115055 | 1 | 23589040 | 3 | 36807935 | 2 | 12614586 | 4 |
| Development in Malaysia | 15715255 | 3 | 29140880 | 1 | 74895426 | 1 | 12686565 | 2 | 15996889 | 4 |
| Development in Philippines | 15684671 | 4 | 30552190 | 2 | 55491790 | 2 | 84667648 | 3 | 19942616 | 3 |
| Development in Singapore | 20983049 | 4 | 96619515 | 2 | 52577079 | 4 | 70385519 | 3 | 11053600 | 4 |
| Total/overall rank | 145612243 | 438879231 | 216959971 | 344131676 | 227130177 | 487531284 | 208515368 | 576051604 | 108082770 | 363913385 |
| Percentage (%) | 33 | | 63 | | 47 | | 36 | | 30 | |

### 5.5 Results

After selecting data indicators and retrieving datasets, we summarised the datasets to evaluate the overall contribution of South East Asia countries towards their economic growth, as shown in Table 3. Data are entered to MS Excel Spreadsheet to evaluate the rank for each goal using the metrics. The results show that these countries produce more agriculture product compares to manufacturing, industry, services and household. The results show that goal 2 has the highest percentage with 63%. The levels of agricultural products are very high because we believe the countries want to introduce more local product that help to increase jobs opportunity. Agriculture products contribute $2,169,599 to the economic growth. This is followed by goal 3 with 47%, goal 4 with 36%, goal 1 with 33% and goal 5 with 30%. The findings also show that household only contributes $1,080,827 to the economic growth in 2013. The results show the final consumption expenditure of goods and services purchased by households that include total payments and fees to governments in 2013.

On the basis of Figure 13, we conclude that economy growth development for each goal is still low. The results show that only goal 2 contributes more than 50% to the economy. Goals 1, 4 and 5 contribute lower than 40% to the economy. This percentage is low in meeting the World Bank goals, which is to end extreme poverty and to increase income growth. According to the World Bank Annual Report 2013, over the past three decades, the extent of global poverty has decline rapidly. The percentage of people living in extreme poverty in 2013 is less than half of what it was in 1990. On the basis of this trend, it is possible to envision a world in which extreme poverty has effectively been eliminated within a generation. Therefore, countries in South East Asia must overcome any challenges to maintain the recent momentum in poverty reduction. This is because more than 1 billion people worldwide are still destitute, inequality and social exclusion seem to be rising in several countries.

**Figure 13** Economic growth development in South East Asia (see online version for colours)




## 6 Discussion

Most organisations today are fundamentally dependent on their data and information handling services facilitated by their information technology to collect, store, flow,

manage and analyse data better. This paper addressed the roles of information professionals in big data era by looking at the information spectrum. We identified big data in information spectrum using an ontology. A unique contribution of this paper is its perspective by examine the roles of information professionals data that not just focus of managing the information but also responsible in capturing and analysing relevant data. The paper demonstrated the challenges to identify relevant data to be processed into useful information to support decision-making process in relation to the data goals.

Evidence from the case study has shown that organisational goals ontology can be effectively identify relevant data in relation to the goals. We found that despite the challenges in capturing relevant data from large data collection, filtering this data using an ontology would be a better solution to analyse this data as they could be relevant for better decision making. The contribution of this paper could benefit both information professionals and information management.

### *6.1 Information professionals*

The analysis and evaluation of the data assist the decision-making process in evaluating the development of economic growth. The case study was implemented and proves that information professionals have the flexibility to decide relevant data to be evaluated and transform the data into useful information. This paper looked at the roles of information professionals in big data era which benefits them in vary ways.

- *Flexible to identify the organisational goals*

We explained how to define the organisational goals. The usage of an ontology assists the flexibility to define the organisational goals. By using an ontology, the process to identify the set of the organisational goals becomes flexible. The results in the case study proved the flexibility how information professionals can define the main goal.

- *Flexible to identify relevant data*

An ontology gives information professionals the flexibility to identify relevant data for certain goals. We explained how to identify data from large datasets that relate to the goals. We proved this flexibility in the case study, which we developed the dependency relationship between data and goals. We identified datasets from data indicator that relate to the goals. This flexibility assists the process to identify which data to be consider relevant to the goals.

- *Flexible to define the metrics and data analysis*

We then test the flexibility to define the metrics. In this paper, an ontology gives information professionals the flexibility on how they want to define the metrics after goals are defined. They have this flexibility on how they want to evaluate the data that relate to the goals. This flexibility was tested in the case study. This proves that the organisational goals ontology assist the process to define the metrics in different way after we identified the goals that we want to evaluate.

- *Useful information and knowledge for decision making*

The main objective of data analysis is to evaluate data from the vast amount of datasets. In this paper, data analysis is important to identify the value of data that relevant to the goals to support decision-making process in relation to the organisational goals (Izhar

et al., 2013). After data are analysed, the results are presented as useful information. This information also can be presented using any visualisation tools to support decision-making process. Information professionals will use this information and make a conclusion in relation to the goals. The primary benefit for many organisations is the building of an efficient and responsive approach of data analysis data with enhanced capabilities for information creation, capture, distribution and consumption for better decision making.

### *6.2 Information management*

Information management is organisations responsibility that needs to be addressed in every management level. Relevant data are particularly important for the organisation operations. Their ability to perform relies on effective approach in handling relevant data. Information management in organisations can be improved if they can handle the relevant data effectively. Therefore, they can deliver information appropriately and responsibly. In this paper, we explained how we analyse relevant data to improve the creation of useful information.

- *Relevant data*

Improved accuracy and consistency of data that is relevant for certain organisational priorities that contributed to useful information. It consolidated data source that filter large amount of data to identify data that is consistent with the goals.

- *Increase effectiveness of data*

Improved the process that recognise full life cycle view of data that support information professionals decision making with a deeper understand of the usage of these data in relation to the goals.

- *Increase the effectiveness of data analysis*

Improved the analysis process of the relevant data that increase the knowledge of the data which currently relevant for decision making. The process recognise the value of the data needed for decision making that incorporate the usage of metrics that allow only relevant data that relate to the goals to be analysed. It allows the metrics to be defined in a flexible way as a measurement tool to measure the data in order to evaluate the degree to which the organisational goals could be achieved.

- *Increase effectiveness of information creation*

Increased the organisation operational efficiencies that optimise the process to process data into useful information, reducing amount of time that have to spend to obtain relevant data and eliminate data that is not relevant for certain organisational priorities. Therefore, issue such as duplication can be avoided.

## 7 Conclusion

In this paper, we have described the main challenge facing by information professionals in big data era. In addition, we have proposed alternative roles for information professionals to capture relevant data and transform this data into useful information. We

extend the application of the organisational goals ontology for better decision making in relation to the organisational goals by incorporating big data in information spectrums. In conclusion, we conclude that the phenomena of big data really impact how organisations manage, store and use their data. As a result, the roles for information professionals are not just limits to collect, store and disseminate information but having an ability to identify all different data which organisations may have for better use.

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