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Big Knowledge Framework:
A Smart Decision Enabling System

A White Paper

by

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Big Knowledge {Operations} => Insights {Smart Decisions} => Enhanced Productivity

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Big Knowledge, Machine Learning, Artificial Intelligence, Optimization, Reasoning, Knowledge Linking, Knowledge Chaining, Knowledge Nets, Knowledge Sharing

Abstract

In this paper, we discuss the concepts and applications of Big Knowledge framework. Big Knowledge is defined as knowledge that is available and applicable to a decision beyond what is typically availed through point-analytics and point-sources. We present the basic concepts and components of the framework, and include an example of how Big Knowledge framework can help in smart decision-making and improved productivity.

Introduction

Higher productivity is achieved when smart decisions are made. To make smart decisions, an essential ingredient is insight into operations that are being addressed. Insights are gained when one can obtain knowledge about the operation. Recent advances in machine learning and artificial intelligence, and their application to operational analytics, are enabling users to gain insights into operational processes. This allows them to make smart decisions and achieve greater productivity.

The utility of insight and experience in consistently making intelligent decisions is evident and has been empirically proven. Various approaches, utilizing several different methodologies, (e.g. classical mathematical techniques, pattern matching using statistics, simulation, smart searches, neural nets, logic theory, inductive and deductive reasoning, machine learning, and other advanced artificial intelligence techniques), have guided decision-making processes based upon pre-programmed rules, calculations, exploratory searches, reasoning and self-learning techniques in which the knowledge base is automatically augmented and applied. Machine Learning and Artificial Intelligence, corelated to each other, are a class of algorithms that apply mathematical, statistical and other analytical techniques to large data sets – historical or real-time – to automatically create "learning" or infer insights.

These approaches, though useful in smart decision-making, have created complex "black-box" solutions and are expensive to implement and sustain. Additionally, the adaptation of such solutions has often been a challenge. Depending upon the user base, these approaches were often either readily adopted, were outright rejected, or were considered too advanced for the current use. However, whether the approaches adopted or rejected, they were always considered to be promising and were appreciated by the user community.

At Applied Decision Technologies (ADecTec), we have had the opportunity to develop and implement optimization solutions for a variety of operations and clients. The foundation of our decision-making is data-driven and based on smart algorithms utilizing available data, both real-time and / or historical pertinent to the operation. However, most of these solutions were developed specifically for use by a narrow group of users, hence the decision-making scope was contained by the "walls" of the application. Any interaction with other systems was deliberate and specifically designed.

Recent developments in connectivity, data-sharing, consumer feedback implementation, image processing, and computational capability have greatly enhanced the technological landscape of today. Using these advances, decision-making can be optimized by utilizing a new framework that is more open and inclusive; that surrounds the data-driven, decision-making approaches with experience and collaborative inputs from the sources beyond the "walls" of the application; that "learns" behaviors and patterns; and proactively injects guidance and insights from all sources available. We find that such a framework is now realizable and applicable, and term it the Big Knowledge Framework.

Big Knowledge Framework

Data, simply, provides information about a stated value. Our framework utilizes contextual data to provide insight and recommendations about particular actions. For example, the Artificial Intelligence and analytical technique-based decision engines, upon analyzing traffic at a road, would provide guidance on the speed a car should be driving on. However, the strength of the framework is in its capability of altering such recommendations based on contextual data. For example, if available data indicated that there are children playing next to the road, it would intelligently guide the driver to slow down or stop in the interest of safety. Thus, utilizing local decisions in concert with situational context or knowledge – which we term "Big Knowledge"-, the Big Knowledge Framework is capable of aiding in smart decision-making and is superior to other decision-making algorithms. This way Big Knowledge extends the decision-making capabilities of Artificial Intelligence or other analytical decision-making techniques.

An ideal framework should both support and facilitate the intended purpose of the process, and help execute components of the process. Therefore, to describe the Big Knowledge Framework, we define the components of Big Knowledge application process and describe how the framework design supports it. Figure 1 shows the components of the Big Knowledge Framework and are described as follows.

The framework Collector "collects" internal and external data, which is then analyzed for relevancy. The Relevancy engine creates characteristics parameters for the data that can be utilized to create knowledge. For example, analyzing historical traffic patterns may provide an estimate of travel time during different hours of the day. The analysis may thus create model parameters and or statistical measures. Typically, these analyzed parameters are stored to represent the collected data.

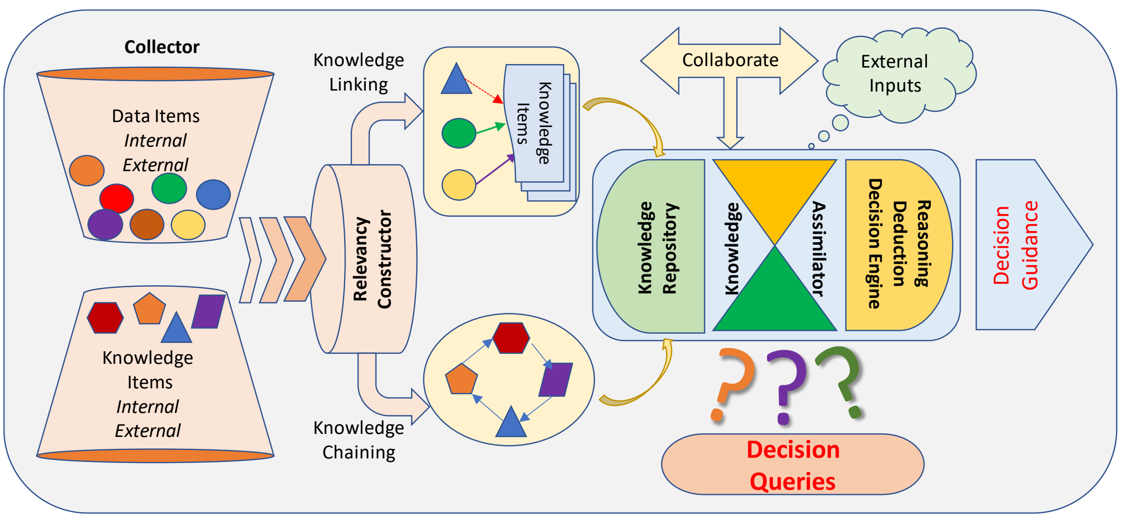

Figure 1. Components of Big Knowledge Framework.

These resulting parameters are associated with the knowledge item. For example, traffic pattern on a highway is considered as a knowledge item. Once this item is associated with the estimates of traffic parameters during the hours of the day, it creates a knowledge base for the traffic pattern on the highway. This knowledge item can now be linked to an operational topic, such as travel time to a specific location.

The knowledge items are also processed and are chained together according to their relevancy. For example, a knowledge item may be that during a sporting event, highway traffic is unusually heavy and slow. Once these knowledge items are linked, they create a new insight, or piece of contextual data. These chained knowledge items are frequently updated and stored in the Knowledge Repository.

When a decision query is posed, the framework Reasoning or Decision Engine interacts with the knowledge repository to build decision models with the latest parameters. The analytical methodology uses the parameters to create guidance for the query. The guidance is presented to the Knowledge Assimilator.

The Knowledge Assimilator facilitates collaboration with external experts and also searches for relevant external inputs that may have become available. In both cases, the inputs are presented to the decision maker to finalize the decision and create an action plan.

Functioning of the Framework

The main purpose of the framework is to enhance the ability of the decision algorithm to incorporate situational context and external insights, allowing for more intelligent decision-making. To accomplish this, the framework must be able to facilitate the tasks shown in Figure 2. These tasks are described as follows -

- Store it – Knowledge Linking

  The framework must be able to store knowledge, or data, such that it is easily accessible and can be applied. Knowledge may come in a variety of forms such as documents, specifications, videos, question-answers, statistical measures, formulae, etc. Each piece of knowledge is categorized with several parameters defining its characteristics; such as subject area, relevance, usability, and availability, to name a few. The knowledge may reside internally to an organization or can be public.

  In each case, the framework maintains the categorizing parameters for the knowledge item. We term the method of associating categorized data to a particular topic as *Knowledge Linking*. Machine learning or other analytical techniques may be used to generate relevancy parameters. Once the parameters are defined for a knowledge item, Knowledge Linking is used to link an operational topic with the knowledge item.

- Grow it – Knowledge Chaining

  The framework must incorporate methodologies to grow its knowledge base. One way to grow this is to automatically relate existing knowledge items with new pieces of knowledge as they come into existence, termed as *Knowledge Chaining*. The benefit of pre-forming knowledge chains is to readily access relevant data while making decisions. This also provides users with the ability to create their proprietary chains.

Figure 2. Main Functions of Big Knowledge Framework.

- Share it – Knowledge Collaboration

  The primary intent of the Big Knowledge framework is to be able to incorporate knowledge that other experts have into and large amounts of contextual data to aid in intelligent decision-making. Therefore, the framework must be able to facilitate collaboration either actively or passively. In active collaboration, a decision-maker may interact in real time with other experts to solicit their expertise. In passive collaboration, an expert may make his or her knowledge base "available" to decision-makers. The framework may then allow the decision-maker to access this knowledge base and incorporate it into decision-making. As the knowledge is shared from experts, the framework adds it to the knowledge repository with linking and chaining. A benefit of the chaining construct is that an expert may share the whole chain rather than do so item by item.

- Provide insight – Reasoning using Knowledge Nets

  Knowledge reasoning is defined as the ability of the framework to assimilate pertinent data, including relevancy and context, to allow insight into a particular situation or problem

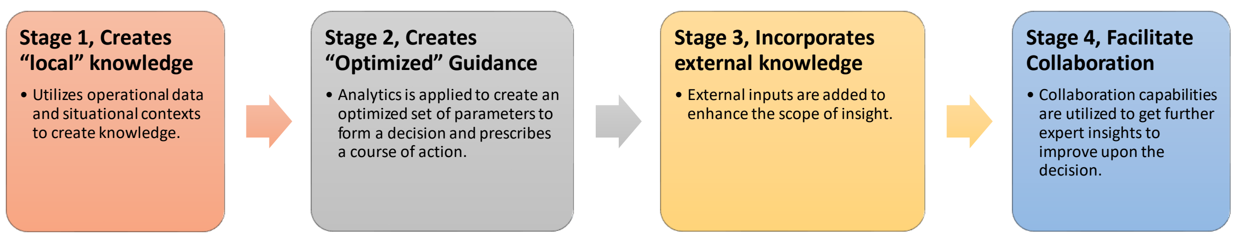

Figure 3. Process Stages of Big Knowledge Framework

and hence create knowledge or a decision. Figure 3 shows the process by which the framework accomplishes this task.

In stage 1, the framework creates “local” knowledge for a decision. For this, it primarily utilizes operational data and situational contexts. The knowledge created is evaluated to be linked with existing knowledge chains. Examples of operational data could be geographic information, data captured from sensors, data from other applications, past decisions, etc. The data may be available in real time, may be historical, or may be available as characteristics parameters generated as a result of applied analytics.

In Stage 2, the framework algorithms utilize the local knowledge set and its associated chains to create Knowledge Nets. A Knowledge Net is a set of Knowledge chains in which some of the knowledge nodes are linked. The linking is achieved using relevancy analytics. Each link is given a weighing factor indicating the strength of the relevancy; and a logical relationship is assigned to the link indicating the type of relevancy. The Reasoning Engine uses these Knowledge Nets to generate decision models with a set of objectives. For example, it may create a model to propose a “most” suitable medical assistive device for a patient, or could predict a service failure based upon the state of an operational process. The structure of Knowledge Nets helps Reasoning Engine to traverse through the network of related knowledge items such that most weighted relevancy is achieved for the inferred decision.

In stage 3, external knowledge inputs are added to enhance the scope of insight. This new insight is used by the decision-maker to adjust the proposed decision and prescribe an updated course of action.

In stage 4, the collaborative capabilities of the framework are utilized to get additional expert insights to improve the decision. For example, during discussion, other team experts may be requested to provide updates and hence improve the decision-making process.

Big Knowledge Application Process – An Example

In this section, the process is explained with a high-level example of selection of an assistive medical device for a patient. In this scenario, a patient is unable to walk without help and is interested in the selection of a walking device. The decision-making steps at a high level are as follows –

1. Knowledge Repository maintains the following information

   a. Segmented profiles of patients. The patient demographic segments are defined by a number of patient characteristics, such as age, degree of disability, living situations, support availability etc.
   b. Device profiles. Profiles of assistive devices such as use, make, model, cost, materials etc.
   c. Relevancy relationship score of devices to patient profiles based upon historical use or training of the rules.

2. On a query to select to a device,
   a. Patients characteristics are gathered.
   b. Patient is matched with existing profiles.
   c. Matching is updated as more information about the patient is gathered.
3. The decision engine selects the devices,
   a. It uses the patient's matched demographic profile and the profile of the devices to find the most relevant devices.
   b. The selection is further refined based upon patients likes, dislikes and other selection criteria provided by the patient.
   c. A final set of devices are then presented to the patient.

4. Refining the selection,
   a. The patient may evaluate the proposed set of devices and provide more clarifying inputs to further refine the selection.
   b. The patient may then make a final selection.

5. External Inputs
   a. The framework may look for external inputs, such as any weather conditions of the patient's area, habits and activities of the patient, family relationships, support availability etc. that may impact the selection. These are presented to the patients to aid in selecting the device.

6. Collaboration
   a. The framework facilitates sharing of experiences on similar selections done by other patients. Real time communication could be facilitated with others to get on-scene feedback in the event of difficulty in finalizing the selection.

7. Action Guidance
   b. The framework thus creates several action plans for the decision-maker – patient- to evaluate, adjust, and re-plan. The continuous re-planning ability with visibility to

pros and cons of the selection, allows the framework to become an effective tool in intelligent decision-making.

8. Updating Knowledge Repository
   c. Once the selection is finalized, the selection is used by the Relevancy engine to update the matching scores to add to the "learning".

Though the scenario presented to demonstrate the framework's process is of an assisted medical device selection, its capabilities are applicable to decision-making in other operational areas such as transportation, medical sciences, quality control, manufacturing, etc.

Summary

The framework presented here supports the incorporation of Big Knowledge into decision-making. It facilitates assimilation of large amount of data and knowledge items with advanced analytics to construct relevant and accessible knowledge that can be readily applied. It helps incorporate external inputs seamlessly at the right points of the decision-making lifecycle. The consequent result is a smart decision-making process leading to improved productivity.

About Applied Decision Technologies, Incorporated (ADecTec)

Applied Decision Technologies, Inc. is a decision-engineering company providing technology development and business consulting services. ADecTec specializes in developing and analyzing business systems, business processes and decision support applications using advanced analytics and information technologies. We offer technology assessment, business intelligence and custom development of optimization solutions for manufacturing, transportation, field services, medical systems, freight companies and supply-chain management companies. We are based in the United States of America with auxiliary offices worldwide.

About the Author

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For over two decades, Dr. Pandit has led company teams and university classrooms in the quest for more efficient decision-making technologies and processes. He has strong experience with optimized operations management and decision analytics in the areas of services management, manufacturing, supply-chain and transportation planning.

Dr. Pandit received his Ph.D. in Operations Research from the University of Illinois at Urbana-Champaign, and has held faculty positions at Iowa State University, Georgia Tech, and Georgia State University. He holds multiple patents for a groundbreaking transportation- planning system, and is a regular contributor to numerous industry publications on the subject of optimized manufacturing planning.

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