Humans have always been interested in understanding themselves and their environment. Understanding their relationship with the environment is important to survival as well as thriving in the present situation and planning for the future. This desire has resulted in scientific approaches to understanding the environment and the self. In fact, technology relies on models developed by basic sciences to improve the environment. The popularity of scientific approaches in the last few centuries is due to their success in building models that could be used for prediction in evolving environments. Prediction is essential for shaping and controlling the future but is not possible without some kind of model.

Scientific methods have evolved over centuries. A set of basic assumptions are used to justify the scientific method: First, there is an objective reality shared by all rational observers. Second, this objective reality is governed by natural laws. Third, these laws can be discovered by means of systematic observation and experimentation (see http://en.wikipedia.org/wiki/Science#cite_note-Heilbron-3). Clearly, objectivity is important in science and is accomplished via a data collection process through experimentation. Most scientific methods emphasize the design of experiments to collect data under controlled conditions to discover natural laws. The disciplines where this is possible have significantly increased over time. In other disciplines, technology is needed to record observations. The quest for scientific approaches and development of technology has resulted in the development of novel sensors and approaches to data collection. One such area that many of us are familiar with is medical imaging and other diagnostic techniques. These techniques let us observe an objective reality that goes beyond human experience that relies solely on our natural sensors (senses).

Many scientific fields have evolved and are now well advanced to understand our environment. However, an area that is close to all of us, but remains subjective, is “self.” We don’t have scientific approaches to understand the self. This is true at almost every level—our social interactions, our body, and our emotional reactions. Surprisingly, although it is usually the most important object of interest to us, the self is possibly the least understood. Soon this may change and that will affect quite a few things for individuals as well as for our society.

Historically, we have gone through the following phases of understanding the self: anecdotal, subjective diary, and quantified self. Lately, there has been a lot of talk about the quantified self. Soon we will enter the most scientific stage: the objective self. The scientific community has moved toward deeper scientific approaches but was not ready to adopt scientific approaches to studying the self. We believe that we are now ready. In this article, we briefly discuss our thoughts and emerging approaches toward the objective self.

**Toward Objective Self**

The interest in the self has been a complex and sustained quest. The issues that complicated this quest and continue to do so remain:
- getting objective data,
- storing data,
- analyzing data, and
- protecting privacy.

With advances in technology, some of this is changing. Based on the technology trajectory, most of these challenges are now within reach and may make the next stage achievable within the next few years.

Let us consider how we have come to the current state in understanding the self. The quest has led to the following distinct phases.

**Anecdotal Self**

At one point, no technology existed for collecting and storing data. People relied on their
natural sensors (senses) for data collection, their memories for storage, and their mental analysis and introspection for processing. Because no techniques were available to collect objective data and memory is a complex system that is at best subjective and volatile, much of the information about the self was anecdotal. This information changed with time because even the original data changed based on later events and their outcome. Although people always used their experiences, these experiences were truly ephemeral.

**Diarizing Self**

When writing technology became popular and commonly available, the idea of diaries and chronicles started taking shape. People realized that depending on memory to record data was not reliable. They started recording their observations to make them both time invariant and retrievable by themselves and others. Individuals started recording important things about themselves using diaries and started recording their observations in the form of chronicles. Initially, these records were only available in handwriting, drawings, or sketches. As technology advanced, photography and later magnetic recording have allowed us to record more objective and experiential data. New sensors have also been developed for observing and recording data.

These techniques yielded better data by transforming simple memory recordings into subjective observations. The techniques still remained subjective because human observers and senses play the primary role in such observations, however, and a person's ability to articulate in recordings was the primary means of saving the data. Also, the data analysis was still performed by humans and hence also subjective.

Some recording techniques have been popular for a long time and have been evolving slowly with advances in technology. Some have decreased in popularity, such as diary writing, while others have increased significantly, such as photos, emails, status updates, and medical information records.

Such techniques are increasingly becoming more objective as much of the recorded data is becoming experiential. On the other hand, the data is sparse. It is usually collected during certain episodes, which make it biased. Also, it lives in silos for many reasons, including privacy issues. All this makes the determination of models of a person difficult, and any model derived from such data is low quality because the data is so poor. An important phrase in computer science can be paraphrased to describe this situation: garbage data, garbage models.

**Quantified Self**

The 21st century has witnessed significant advances in storage, processing, sensing, and communication technologies. All these have resulted in the popularization of strong data-dependent approaches, leading to the rise in the popularity of scientism in almost all disciplines where data can be collected. Because scientific approaches emphasize observation and systematic experimentation, the availability of sensors to observe different aspects of physical reality has encouraged the collection of such data as well as its analysis to develop laws of nature. As the availability of data has become widespread, the desire to understand the physical reality at different levels in different applications has also become possible and desirable. Big data and analytics are now two of the most commonly used terms in scientific circles and in many other fields as well.

Inspired by this growth in data and its applicability in disparate areas, many people have started collecting data about themselves. This popular and rapidly spreading movement is called quantified self. Now that different types of sensors are available and new types of sensors could be developed, people who are sensitive to their health have started recording health-related information using sensors ranging from simple wearable accelerometers that could be classified and recorded in simple activities (such as walking, jogging, and climbing stairs) to other measurements (such as body temperature, heart rate, perspiration rate, galvanic skin resistivity, and many other deeper parameters).

Lifelogs or eChronicles could be considered the predecessors of the quantified self. With these systems, people record their life activities using wearable and other sensors. Their activities are detected using classification techniques and then visualized or analyzed to extract meaningful information from the data. Much research was done in the context of individuals and for the US Department of Defense. A popular project in this area called MyLifeBits was championed by Gordon Bell at Microsoft.

Wearable computing is now readily available, which will further encourage people to...
record their physical activities, other life activities, bodily parameters, and social interactions. It is commonly believed that recording such data and having access to it may result in many personal benefits for people.

Figure 1 shows the evolution of models over time with the type of data that was available. We believe that with the availability of better quality data the quality of the models will facilitate real-time guidance and control, as has become commonplace for mechanical systems.

**Objective Self Has Arrived**

The quantified self movement is an important step in introducing a scientific framework to help understand an individual based on continuously collected data. This is the first time in the history of humanity that this has become feasible. The early stages of scientific framework based on sustained observations of controlled and natural experiments are being converted to laws related to the physical, social, and spiritual systems representing an individual. This opportunity is revolutionary on many fronts.

**Importance for Individuals**

For each of us, the most important object or entity is the self. All human beings are interested in understanding the self to maximize their own satisfaction. This requires having a better model of the individual life. Most sociological and medical knowledge in the past suffered from two major problems: the lack of objective quality data for individuals and the inability to utilize this data for building reliable models. The obstacles in this range from the ability to measure data, store and analyze data, and privacy concerns of people. Technology and cultural changes are definitely resulting in some major shifts in this area. However, obstacles such as privacy issues still need to be solved.

Sensors are now available that people may use as they go about their regular activities. These wearable sensors are continuously recording. By analyzing data from these sensors, we can determine what activity or event a person is engaged in at any given time. Some sensors can also be used to understand a person’s reactions to an activity at a given time. All these measurements from wearable sensors, GPS, social media, and other relevant sources can be used to detect one of the predetermined classes of life events and relevant attributes of life events. Thus, we can effectively obtain a chronicle of the person’s activities. This personal chronicle is called a *personicle,* and it represents all of a person’s activities. A personicle can be stored so it can be used to form models, reminisces, and recollections. Here, we will address only the model building aspect.

**Self-Correcting Loops**

We all know the importance of feedback in dynamic systems. To implement effective closed-loop feedback systems, we must know the model of the system being controlled and generate correcting signals with minimal latency. When building dynamic feedback loops for individuals, two things are essential: having a model of the individual and collecting current situation information. Wearable devices, other physiological sensors, the Internet of Things, and social media are all enabling the collection of individual-centric information with minimal delay. Techniques to determine a person’s state at any time using all available information sources have been a topic of research in several areas, particularly related to interactions on the Web, and are likely to continue advancing rapidly. If we could build better models for an individual, then it may be possible to build individualized feedback systems.

Model building is always an analytic process that uses observed data. Models built based on sparse data are poor in quality and perform badly. Having sufficient data covering all situations of interest is essential in model building. This means that it is not enough just to observe using appropriate sensors; we must collect this data in a form that could be used in a model building process.
Available data should be analyzed for building models. A model is always developed with a particular analysis/prediction goal in mind. This requires understanding what individual attribute variables must be considered in the models that will be used to build individualized feedback control systems. The effect of variables in one type of life event on other life events may be required to determine causes for what happens to an individual. For example, a particular individual drinking more than one glass of wine may suffer from acidity.

Once these models are formulated, it is possible to design a closed-loop system that will observe current signals to determine the state and then use the model to compute the action required and notify the person or appropriate sources that could facilitate the implementation of those actions.

From Individuals to Society
Each individual is unique, however in human society, individuals interact and associate in many ways. Also, many human beings are related to each other along many dimensions, ranging from their living area, profession, interests, and genetics. Many medical and social problems can only be solved by modeling an individual as an element of a set of individuals that form a social group rather than an individual in isolation.

For social and medical scientists, a major limitation in forming models for studying systems has been the paucity of data that could be obtained and used. It was not possible to get enough reliable data to form models, and unreliable and insufficient data could only lead to unreliable and insufficient models. These limitations resulted in slow progress in these fields. For example, much of the progress in healthcare has come from diagnostic techniques rather than disease models. Diagnostic techniques advanced because they were based more on physical and chemical sciences than medical sciences.

A personicle created for the objective self can contribute attributes of a person for computing group or societal attributes. A personicle has objective data collected over long periods. If personicles for many people become available, then it will be possible to analyze these personicles to form models for diseases or social aspects by analyzing the data across many dimensions. The data collected by an individual for personal benefit may become a rich source of data for building sophisticated models that will help society and in turn benefit the individual further.

By collecting objective self models for large numbers of people, it is possible to have a large dataset that could be sliced and diced to form precise disease models (see Figure 2). Such data models could be dynamic in the sense that, as more data is collected, the models can be further refined and enhanced.

An Architecture for Objective Self
As the number and ubiquity of sensors and mobile devices continue to increase, the need for computational methods to analyze the avalanche of heterogeneous sensor data and derive objective self will grow. In fact, novel information processing architectures and platforms should be developed to enable the handling of
multimodal data streams from heterogeneous sources. We have developed an architecture for analyzing objective data from sensors to both recognize life events and identify patterns and interrelationships among them to create the objective self.

Figure 3 shows a high-level architecture of an objective self platform that we are building. This architecture has three main components: data ingestion, life event recognition, and pattern recognition. Data ingestion uses various sensors and preprocessing modules to extract appropriate attributes from raw sensor measurements. Life event recognition assigns the most appropriate life event, from a set of predefined event classes, based on data stream attributes. Depending on the nature and number of life events, a designer must select sensors that will enable this classification. Thus, life events detected are independent atomic elements of analysis for the objective self. Essentially, the objective self is the model of a person. A correlation and co-occurrence based machine learning environment is needed to detect recurring correlated and causal patterns. This may result in insights such as a sensitivity to a particular activity under specific climatic conditions or the effect of time and duration of exercise on one’s sleep patterns and sleep quality.

The objective self resulting from the analysis of a personicle has enormous potential for use in medical diagnosis, behavior modeling, and many other fields of knowledge that require continuous monitoring for acquiring insights about individual’s lifestyle. We believe that building personicles is a game changer in many applications, including monitoring individual health and building disease models.

**Sensor Ingestion**

Sensor readings are low-level data created by converting analog signals to digital values. This data is captured continuously from heterogeneous sources resulting in data streams. Some of these sensors include smartphones, wearable activity trackers, calendars, physiological sensors, and environmental sensors. Distinct temporal granularities of information sources and different modalities of data streams pose serious challenges to processing and aggregation techniques. Moreover, to be useful, all the collected data must be aligned so that it can be fused at a later phase. Unfortunately, this is nontrivial to achieve mainly because of the lack of perfectly synchronized physical clocks and the asynchronous nature of data captured from different information sources.

There is a considerable amount of research using different sensor modalities in the area of body sensor networks (BSNs) and wearable computing.4,5 We classify these sensors into
three categories based on their use in life event recognition tasks:

- **Wearable sensors** are sensing and data collection hardware that collect motion, location, and physiological data. Most of these sensors are personally used and collect information 24/7.

- **Virtual sensors** are software sensing technology that tracks a user’s interaction with computational devices such as a cell phone, smartphone app, or computer. Time of day, day of the week, and scheduled events from a user’s calendar fall within this category as well. Information from social networks may also be considered in this class.

- **Environmental sensors** are sensing technology that tracks the user’s interaction with the environment. In a smart-home setting, RFID motion sensors on different objects, RFID location trackers inside buildings, pressure mats, cameras, and water flow sensors are examples of environmental sensors.

Figure 4 shows some of the data streams from these three sensor categories. Suppose we have $N$ data streams $S_1$, $S_2$, ..., $S_N$ each coming from a heterogeneous source of information. These data streams are divided into chunks of equal length, called time window $T_i$. The information obtained from the sensors varies in many respects. Methods to convert data to information and the reliability of information could be entirely different for different sensors. To convert measurements to attributes, complex approaches involving inverse mapping are used. Thus, we can say that $a_i = F(m_i)$, where $a_i$ is the attribute derived from a measurement $m_i$ using the function $F$ for this attribute within a specific time window $T_i$. The function used to convert the measurement to an attribute could be simple or extremely complex.

The followings are some examples of these functions:

- **Mathematical and statistical techniques** can extract basic signal information from raw sensor data, such as mean, variance, standard deviation, median, maximum, minimum, signal correlation and correlation-coefficient,
zero-crossing, DC component, spectral energy, entropy, and wavelet analysis.

- Mapping techniques can invert geo-coding to extract place categories.
- Natural-language processing can help process calendar entries, computer activity logs, and so forth.
- Machine learning techniques include a variety of algorithms using classifiers that have been applied to the problem of recognizing physical activities from accelerometer data. Also, it is possible to classify ambient environment by analyzing light sensor readings, Wi-Fi access points, or GPS signals.

Table 1 shows some sensor modalities and functions that extract attributes from measurements. This table is indicative and not exhaustive, and more sensors and functions can be added as needed.

A sensor model is necessary to handle multimodal information coming from different sensors. In general, sensor models are used to identify relevant properties of sensors. The W3C Semantic Sensor Network Incubator Group has performed a comprehensive review of sensor and observation ontologies (see www.w3.org/2005/Incubator/ssn/wiki/Incubator_Report#How_to_describe_capabilities_of_a_sensor). They have reviewed 10 sensor-centric and seven observation-centric sensor models and summarized their findings. The sensor model that we have adopted in our work, the Semantic Sensor Network (SSN) ontology (www.w3.org/2005/Incubator/ssn/ssnx/ssn), answers the need for a domain-independent model for sensing applications. This ontology merges sensor-focused, observation-focused, and system-focused views and covers sensing principles and capabilities of sensors. Although the ontology leaves the observed domain unspecified, domain semantics, units of measurement, time and time series, and location and mobility ontologies can be easily attached when instantiating the ontology for any particular sensors in a domain.

A sensor description is created by defining an instance of the class `ssn:SensingDevice`. Also, a sensor’s measurement capabilities are

<table>
<thead>
<tr>
<th>Sensor</th>
<th>Measurement</th>
<th>Attribute</th>
<th>Function</th>
</tr>
</thead>
<tbody>
<tr>
<td>Accelerometer, gyroscope</td>
<td>X,Y,Z values</td>
<td>Activity: {sitting, standing, walking, jogging, cycling, ascending stairs, descending stairs, lying, driving, typing on keyboard, etc.} Activity level: {low, medium, high}</td>
<td>Low-level activity classification</td>
</tr>
<tr>
<td>Light</td>
<td>Light intensity value</td>
<td>Location: {Indoor, semi-indoor, outdoor} Value: {Light on, light off}</td>
<td>Environment classification</td>
</tr>
<tr>
<td>GPS</td>
<td>Latitude, longitude</td>
<td>Location: {home, work, store, restaurant, mall, etc.}</td>
<td>Significant place recognition</td>
</tr>
<tr>
<td>RFID reader/ passive RFID tags</td>
<td>Measurements for reader/tag</td>
<td>Interaction with objects: {fork, spoon, mug, appliances, stove, etc.} Indoor location: {kitchen, bedroom, living room, office, etc.}</td>
<td>RFID motion detector</td>
</tr>
<tr>
<td>Calendar</td>
<td>Calendar entries</td>
<td>Scheduled events: {meeting, seminar, appointment, party, etc.}</td>
<td>Natural-language processing</td>
</tr>
<tr>
<td>Computer logs</td>
<td>Mouse movements, keyboard logs, windows opened/closed</td>
<td>Computer use: {email, Web browsing, document interaction, video watching, gaming}</td>
<td>Natural-language processing</td>
</tr>
<tr>
<td>Cell phone logs</td>
<td>Cell phone use: {making/receiving calls, apps running in the background, interaction with specific app}</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Camera</td>
<td>Pixel intensity values</td>
<td>Key frames, objects in the image</td>
<td>Object and event recognition</td>
</tr>
<tr>
<td>Microphone</td>
<td>Phonemes</td>
<td>Background sound: {one person talking, multiple people talking, background noise}</td>
<td>Speech recognition, audio scenes</td>
</tr>
</tbody>
</table>
collected using the class `ssn:Measurement-Capability`, which includes frequency, measurement range, and sensor accuracy. The `ssn:Process` (as shown in Figure 5) is defined as the specification of the procedure implemented in a sensor. It may be specified as a known principle or method or, if a computer science approach is followed, as a function that has an output and possibly some inputs. In our work, the inputs are sensor measurements and the outputs are attributes; the latter will be used for life event recognition.

Once data streams are aligned and attributes are derived as a result of preprocessing techniques, an effective life event recognition module should be applied to assign appropriate event class to observations.

**Life Event Recognition**

Life events are activities that people perform daily. To formally describe a life event, let $C$ be a finite set of life events. Let $F$ be an $n$ dimensional feature space. Let $a = (a_1, \ldots, a_n) \in F$ and $c_k \in C$. We will use $a$ to represent a variable and $v = (v_1, \ldots, v_n)$ to represent values. Life event recognition is the problem of finding an appropriate mapping between $a$ and $C$.

The importance of life events in an objective self framework is two-fold. On the one hand, we can define the association between life event attributes and data streams attributes. On the other hand, considering a life event as independent axes will help analyze the information content of data streams and build a model of a person on top of that. Also, using life events, we allow people to understand and analyze the computations that can be done easily.

To make it clearer, consider the following comparison: XML allows developers to set standards defining the information that should appear in a document and in what sequence. XML makes it possible to define the content of a document separately from its formatting, making it easy to reuse that content in other applications. In a similar way, life events provide a standard content aggregation and representation from disparate information sources. Life events become important tags in the data that easily allow both human and machine processing.

To provide an adequate foundation for developing objective self recognition techniques, it’s important to define the event model formally. Only by effectively defining the event model’s primitives and structure can we unambiguously specify the relation between data stream observations and attributes of life events. For this purpose, we use E model, an event model that aims to establish a common foundation for diverse applications by addressing several aspects of event description as follows: temporal, spatial, informational, experiential, structural, and causal aspects.

Attributes of temporal and spatial aspects are the same for different life events. However, informational aspects may vary from one life event to another. For example, as Figure 6 shows, for a meeting life event, participants are an important informational attribute, whereas for an exercise life event, informational attributes such as calories burned or exercise intensity are more important. This shows that, apart from the event model’s primitives, we should define the attributes of each primitive carefully for distinct life events.

One possible approach to formally representing this knowledge within the life event domain is using an ontology to denote the types, properties, and interrelationships of life events.

**Life Event Ontology**

The American Time Use Survey (ATUS) dataset is one of the few time-use study databases that has been updated every year since 2003, logging activities of US residents for 24 hours a day. It contains 18 different (tier 1) activity groups and a distinction is made between 462 activities. In addition to the activities, participants logged the time the activity started, how long it lasted, and where it took place. These surveys have shown that a few activities typically account for nearly 70 percent of the time.
in a day, such as sleeping and resting (34 percent), domestic activities (13 percent), TV/radio/music/computers use (11 percent), and eating and drinking (9 percent).

From our interpretation of life-logging events and time-use surveys, we selected target activities based on the following criteria:

- **Time dominance**: A small number of activities occupy a large amount of our time.
- **Generality**: Even though the time spent on activities varies among age groups, some activities are engaged in by different age groups. The selection of activities with high group agreement will increase the generality of activity recognition.
- **Noteworthy and important**: Activities vary in importance, so entry in a Google calendar, for example, may represent a future important event.

Considering this, we have selected 23 life events that occur at three major locations: home, work, and outside. Figure 7a depicts the
life event ontology, and Figure 7b shows specific informational properties for two example life events.

**Context is Key to Life Event Recognition**

Activity recognition techniques that rely on machine learning methods to classify and analyze data from desperate sources such as motion sensors and environmental sensors are abundant in the literature. Most of these methods work on numerical data only. When considering unimodal accelerometer observations, machine learning techniques perform well on low-level activities (such as walking, jogging, cycling, ascending stairs, and descending stairs) and the most popular data representation is N-dimensional numerical vectors. Hence, modeling is usually carried out in $R^N$ based on algebraic semantics. For nonnumeric data such as place categories, calendar entries, or computer logs, the general practice is to transform them to $R^N$ and force a real vector observation into a problem. However, a data transformation to $R^N$ typically abandons original data semantics. Therefore, the ability to carry out computations beyond $R^N$ could be valuable for developing useful models while retaining original problem semantics.

To detect life events as shown in Figure 6, the main question is, how do we resolve the ambiguity of life events that are extracted from motion streams with the help of contextual information from other observation streams? It’s apparent that the inference of body motion can be done more accurately from context features such as a place category. For example, a user is likely to be washing dishes in the kitchen, but moving hands randomly in a living room should not imply a dish washing activity. Although multimodal activity recognition has been studied in the past, the distinction and role of different contextual attributes is not yet clearly defined. The definition of context is broad and still unclear and the boundary of what is and is not context is not properly defined. Therefore, identifying and analyzing the most influential and critical elements of context that have an influence on life events under different situations is an important research area.

**From Personicle to Objective Self**

A personicle is data related to a person. This data needs to be prospected to build models that represent the objective self. The process of analyzing data to build models and then using those models to recognize concepts in data has been studied for a long time. The nature of the processes has changed significantly with the increased availability of data and improved computing infrastructures. The best known areas related to this for the multimedia community are object, scene, action, and event recognition. Using images or video, researchers have been developing approaches to build models using machine learning and then using those models for pattern recognition. The process of going from personicles to the objective self has some common elements, but it also offers some novel challenges.

In different types of concept recognition approaches, data is reasonably local. Even in the case of activity and event recognition, we only look at contiguous frames. For object recognition, we might review pixels in the same general area of an image. In objective self models, however, this assumption of contiguity is not useful. A person may eat something today, but its effect may manifest a week or more later. The latency between the cause and effect needs to be explored to build the models, which is a new challenge.

Another interesting challenge is that life events are not really data; rather, they are already recognized concepts with associated values. These are used to recognize relationships among such inferred concepts. In earlier concept recognition, success has been usually achieved when concepts were modeled and recognized using data. These are only two challenges that we recognized early on. As we proceed further, we will discover more.

Personicles and the objective self have enormous potential to be used in medical diagnosis, population medicine, behavior modeling, and any field of knowledge that requires not only continuous monitoring but also acquiring insight about an individual’s lifestyle. For instance, in the case of elder care, it is important to recognize daily routines such as shopping or hygiene. It is essential to maintain an older person’s ability to function as independently as possible for as long as possible, and knowledge about a person’s daily routine can help healthcare providers monitor him or her indirectly and identify any deviation from normal routines. Furthermore, in the case of office workers, it is interesting to recognize routines such as commuting, meeting attendance, or lunch breaks. Knowing such routines may help
with scheduling reminders that could advise someone, for example, to stand up, move around, and get away from the computer every once in a while.

These routines typically consist of several activities, and the composition of activities has a large variability depending on factors such as time, location, and individual. This makes the recognition of such routines more complex. For this purpose, different pattern recognition techniques may be applied to automatically extract activity patterns from a personicle.

In the case of medical diagnosis and behavioral modeling understanding, the correlation between life events is beneficial. For instance, Exercise Induced Bronchoconstriction (EIB) is a specific type of asthma where any type of physical exertion could lead to coughing, difficulty breathing, and chest tightness, but symptoms generally improve when a person stops the activity. Effective diagnosis of this type of asthma is difficult in a laboratory setting. However, the significant correlation between being highly active and asthma problems shall be revealed by analyzing the personicle of asthmatic patient. Of course, correlation is not causality, but it’s important to understand correlation so a physician may explore and establish causality.

**Personicle and Self for Things**

Our discussion here has focused on people. However, every complex system that has many environmental components that affect it has similar issues, albeit at a simpler level. The concept of a personicle is really a chronicle for things, and this chronicle could be used to prepare a personicle model. We have not explored any such approach but believe that this could be applicable.

We are building a complete infrastructure for the objective self and hope to demonstrate its applicability in a few applications soon. Clearly, several challenges still exist, ranging from data ingestion to model building and their use in real-time predictive guidance.

**References**


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