Histographic Analysis of Behavioral Motivators in Text

Samuel R Dismond III, 7INSIDE, Inc.
samuel.dismond@7inside.com

Abstract

The volume of unstructured text arising from individuals expressing their personal experience or point of view is growing exponentially. The majority of this text includes blogs, social media postings of various lengths, reviews of virtually everything, as well as customer verbatims from surveys and service calls. All of this text is available to analytic processing via the internet. We present a system that generates a behavioral motivator histogram from any dynamically specifiable segment of text. Our system is uniquely based on functional semantics and consists of a specialized knowledge base, a computation engine, and a visualizer. Next, we evaluate the validity of our system by examining its: i) inter and intra domain consistency; and ii) robustness through comparison with Linguistic Inquiry and Word Count as well by examining several use case results. Finally, we suggest that functional semantics, as embodied in our system, can integrate with and augment current text analytic techniques.

Introduction

On its face, social information is expressed inner experiences. Something happens. It affects us. We express to another the internal effect from the external cause. Historically, the western models of inner experience have been at a minimum fraught with murkiness and debate. And this poor state of understanding and agreement explains why semantic processing techniques have remained conspicuously *ad hoc* and *a posteriori*.

The development of semantic processing technology has proceeded by assuming a commoditizing external reality that can only be systematically modeled post-experience. Everything was and still is viewed as one or another type of thing. The concept of "thing" is viewed as existing externally and independently. And thing can only be accurately understood by cataloging the post-experience observations of many people over many times.

Underlying semantic innovation is the deliberate neglect of inner experience and an exclusive focus on the apparently external. This investigative approach was, and still is, enshrined as scientific. Shepard (1987) describes understanding behavior as finding "empirical regularities that are mathematically derivable from universal principles of natural kinds…" Any unease caused by this willful ignorance of such an important part of humanness was, and still is, mollified by affirming that inner experience is the rightful domain of letters and arts – philosophers, poets, painters, musicians, dancers and their ilk.

But now, communications about inner experiences is the most rapidly growing type of information in need of processing. The social web is network information between people about their inner experiences. Current semantic processing techniques struggle with this growth. Lofty justifications of an empirical *a posteriori* approach can no longer hide the difficulty of lacking an *a priori* inner experience referencing model. The struggle to conform the current technologies to the understanding of sentiment in personal expression bears this out. Furthermore, it is incontestable: none would avoid a robust *a priori* model of referencing inner experience that integrates seamlessly with and augments existing analytic techniques.

Herein lies the root of the disadvantages of current techniques for understanding social information: they assiduously avoid even the most innocuous and commonsensical *a priori* models of human inner experience. The semantic primitives supporting current semantic processing techniques lack any relationship to the very essence of social information, namely dynamical inner experiences. A review of the use of the term "sematic primitive" makes clear the lack of a relationship to dynamical inner experience (Ahmad, 2001). The semantic primitives widely used in virtually all semantic analytic techniques assume static independent thoughts about static external independent reality.

There are two prominent approaches that assume stasis: the structural approach and the statistical approach. The first structural approach explicitly focuses on the properties and relations that are independent of the observer. This structural approach focuses on defining relationships between the assumed-to-be independent attributes of things. These relationships appear generally as graph structures that include equivalence, hierarchical, and other types of associations. The earliest work with this approach is often credited to Collins and Loftus (Collins and Loftus, 1975).

The second statistical approach proposes the agnosticism of mathematics generally and statistical analysis specifically as remedy. It construes meaning such that it yields to an assumed universality by way of numbers. This mathematical agnosticism sees meaningful utterances as points within a multi-dimensioned semantic space that can be described and related using arrangements of numbers. Notwithstanding its apparent rigor, this statistical semantic-space approach merely hides that same foundational problem underlying the structural approach.

The earliest innovations using this statistical semantic-space approach are credited to Landeur (Landeur, 1998). Landeur champions the approach for use cases wherein reality is commoditized. He concedes the limitation of this approach with regard to social text. When considering inner experience, his approach, he states, has the same sterility as "a well-read nun's knowledge of sex."

What Landeur, and similar mathematical innovators, fail to grasp is the futility of relying on numbers as a substitute for an *a priori* method of referencing dynamical inner experience. Numbers themselves fundamentally have no relationship to what a human experiences internally.

The foundational weakness of current text processing techniques lies in how the task of divining semantic primitives is framed. From antiquity the task has been approached as if the bases for the semantic primitive exist independently and statically.

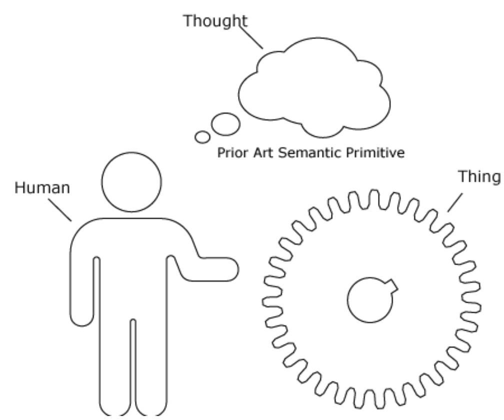

Figure 01 Universe of Semantic Artifacts.

Figure 01 demonstrates the assumed universe of semantic artifacts. Current text analytic practice relies on framing meaning creation as within a universe containing three elements in stasis: the Human, the Thing – that which Human is observing, and Thought – that which refers to Thing. These elements are assumed essentially fixed and independent. The critical assumption within this universe is that the complexity of Thing is an objective attribute of Thing alone and does not depend on description formalism, i.e. Human. What is more, this objective attribute is viewed as absolute information content in Thought (Min, Vitanyi, 2008). This view is the bedrock of universal artificial intelligence specifically and virtually every other semantic processing technique generally.

Figure 02 demonstrates the semiotic triangle that results from the attributes-only assumption about Thing demonstrated in Figure 01 (Ogden, Richards, 1923). Given the assumption, Human is safely removable from consideration leaving only Thing and Thought corresponding to Referent and Reference, respectively. Words are merely Symbol assumed to statically and durably stand for Referent and equally statically and durably symbolize Reference. Together, these two figures demonstrate the *a posteriori* static framework used to divine semantic primitives. This framework is the core of virtually every other semantic analytic technique.

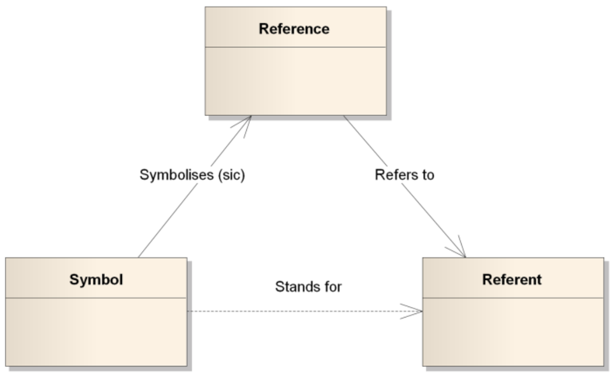

Figure 02 The Semiotic Triangle.

This framework has been and still is more than adequate for information retrieval (IR) as well as topic detection and tracking (TDT). However, the difficulties of this framework for understanding (psycho-) social information – including sentiment analysis – are well known. These difficulties have been the grist of methodological hand-wringing, discourse and debate at least since the time of Socrates. In particular, the prospective testing problems include, but are not limited to:

a. verification– prospective testing of the mapping from word to thought to specific personal experience;
b. disambiguation– prospective testing of the process by which multiple meanings and ultimately multiple underlying experiences of different people map to a single word;
c. confounding– prospective testing of the process by which meaning for a word shifts over time for any given person-situation;
d. vagueness– prospective testing of the processes that includes or excludes meanings as they map to a single word for any given person-situation;
e. specificity– prospective testing of how increasing narrowness increases the falseness of meaning for a given person-situation; and
f. universality– prospective testing of how thoughts become aggregated into higher meaning for a given person-situation.

When the static framework is assumed it is difficult to answer the question "what is the meaning of meaning" without glaring circularities. The aforementioned methodological problems insidiously persist in any semantic analysis system that assumes the static relationships between Human, Thought and Thing.

There have been notable attempts at a more functional consideration in the extraction of meaning from utterance. These include the employment of object primitives, scripts (DeJong, 1979), goals, plans, interpersonal relationships (Schank and Abelson, 1977), physical states, events, social acts, memory organization packets (MOPs) (Schank, 1973), thematic abstraction units (TAU) with BORIS, (Dyer, 1982), (Dyer, 1983), (Dyer, 1987), psycho-social categorization of words with Linguistic Inquiry and Word Count (LIWC) (Tausczik, 2010), and intra-word dimensions posited to represent aspects of cognition with ReadWare (Adi, 2009).

Closely inspecting these so-called functional approaches reveals an ultimate reliance on the *a posteriori* static framework for meaning creation. All of the aforementioned approaches fundamentally assume a static relationship between Human, Thought and Thing. The "functional" refers only to either an algorithm for processing of the references, or the elaborate post-processing interpretation of an otherwise meaningless reference category. The semantic categories themselves assume referential stasis and have little if any relationship to underlying dynamical psycho-social states.

The development of an *a priori* model is not anathema to the scientific process. Indeed, every hypothesis constructed for a prospective validation regime assumes, implicitly, some lower order *a priori* model. *A priori* models cannot be avoided because they are intrinsic to the experiment process. Hence, the scientific process is necessarily recursive.

A lower-order *a priori* model is always incorporated within any experiment hypothesis. This hypothesis is repeatedly tested using some agreed-upon higher-order prospective validation regime. After reaching an agreed-upon level of results consistency, the hypothesis becomes theory. Theory thence assumes the same status as factual observation. And here the recursion occurs. What was once a lower-order *a priori* model cum hypothesis is now treated as base-line fact. These models cum fact are incorporated into new hypotheses. These new hypotheses interrelate other models with other observations.

An important part of the advancement of science involves reaching consensus as to where the recursion – the inherent circularity of every prospective validation regime – should occur. For several domains it is widely accepted that an *a priori* model explicitly comes first because prospective testing is too difficult if not impossible. *A priori* models explicitly put circularity down below the ability to independently observe over time. For these cases, consensus has been created for entirely different validation regimes that don't involve prospective observation.

For example, pure mathematics and theoretical physics are two domains where *a priori* modeling is explicit. Every prospective validation regime requires a technology that can enable observation from a space that has higher dimensionality than the experimental space. It is generally accepted that it is difficult if not impossible to construct higher-dimensionality observation technology for prospectively testing within the experimental spaces of pure mathematics and theoretical physics. Hence, requiring the typical validation regime of prospective testing for these domains is agreed to be inappropriate.

For domains such as pure mathematics and theoretical physics the reality being studied is explicitly assumed to be model-dependent. It is assumed that there is no so-called objective reality to be observed first before hypothesizing. The generally accepted validation regimes for the *a priori* models of pure mathematics and theoretical physics include examining consistency and robustness. Examining consistency is accounting both inter and intra domain fit. And examining robustness is accounting the number of observations that can be explained by the model. Models that have high consistency and high robustness are not said to be "true," they are said to "work."

The semantics of social information seems like an excellent candidate for inclusion as a type of reality that is model-dependent. The six ways prospective testing of meaning is virtually impossible certainly is evidence for the case. That the semantics of social information is not widely accepted as a model-dependent reality appears only to be the result of inertia. Early IR and TDT successes – both technical and financial – from using the static semantic framework have generated significant momentum hard to divert.

The Behavioral Motivator Visualization System (BMVS) was built with the goal of analyzing social information – not for IR or TDT. BMVS explicitly assumes that the semantics of social information is a model-dependent reality. In this paper we present the general design features of BMVS including the general features of its histographic output.

We discuss BVMS validity by detailing: i) the inter and intra domain consistency in its formulation of a purely functional definition of meaning; and ii) its robustness by way of comparison with LIWC and by way of example results in several business use cases.

Lastly, we suggest how BMVS augments current text analytic techniques. We discuss a remarkable use case that exploits the capabilities of BMVS in tandem with machine learning techniques.

BMVS Structural Characteristics

The BMVS architecture is similar to many designs currently used to extract meaning from text. The BMVS is comprised of three main components: a knowledge base, a computation engine, and a visualization interface. These components are depicted in Fig. 3.

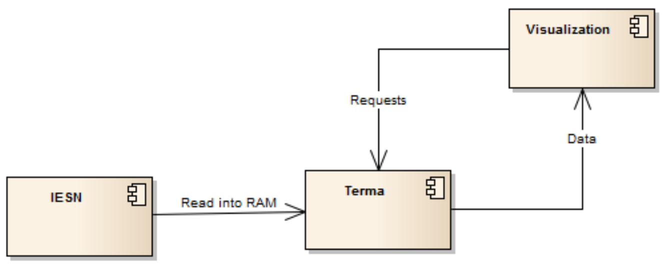

Figure 03 BMVS Components

The BMVS knowledge base is called the Inner Experience Semantic Network (IESN). A semantic network is more than a lookup dictionary. The nodes in a semantic network have explanatory power that can be represented as a kind of graph. Therefore, node identification resulting from a computation step can be further computationally manipulated to yield higher-order information by virtue of its graph position.

In the BMVS each node in the IESN is an experiential state – not a thing. Nodes are pure functional definitions of meaning. Each node in the IESN is related to every other node by way of functional predicates. Functional predicates are causal mini-stories. That is, every line in the IESN graph that connects two functional meaning nodes (vertices) is a functional mini-story that features the two node experiences in starring roles.

Populating the IESN is a straightforward enterprise and uses hand coding – the means by which both WordNet and LIWQ were created and are updated. The technique is simple: words are associated with nodes when there is evidence of word usage that meets the node's criterion.

The IESN reference corpus contains approximately 100,000 distinct word forms and n-grams. Each node in the network is populated with a word or n-gram from the reference corpus that is evidenced in colloquial expression fitting the snapshot of the causal story that the node signifies. The IESN nodes are populated with more than 12,000 such evidenced entries.

We used recursive focus group testing to sharpen the specification of the node criteria. The principle task of the testing was to eliminate criteria overlap between close nodes. With sharp understandable criteria, the population of IESN nodes is not difficult. The criteria do not involve special or technical knowledge. Therefore, no expert panel consensus was (or is) required for the node population process. This is an advantage of the IESN. All nodes represent common-sense understandable causal experiences for virtually every human.

The development version of the IESN uses the open source MySQL 5.x. Operationally, the IESN is read into RAM for rapid access by the computation engine.

The BMVS computation engine is codenamed Terma. Terma is Tibetan for "hidden treasure." Terma uses specialized algorithms to parse text and extract a histogram (a vector) representing the relative influence of behavioral motivators in the text being analyzed. The size of the text Terma analyzes can be dynamically specified in real time.

The Terma employs a highly specialized internal domain language enabling Terma to adjust the histogram to reflect different facets of information. Some of the histographic filtering options include depicting the relative influence of:

1. all identifiable experiences;
2. identifiable emotions that attenuate behavior motivators;
3. identifiable emotions that augment behavioral motivators;
4. identifiable actions resulting from behavioral motivators;
5. identifiable objects associated with behavioral motivators.

In other words, for any segment of text Terma can dynamically depict all or any part of cause-and-effect story generated by behavioral motivators. Terma can also show the histogram filtered for only those experiences that either attenuate or augment behavioral motivators. Terma can filter on actions or objects related to behavioral motivators.

The development version of Terma is in the rapid application development (RAD) scripting language ColdFusion 9.x. This RAD tool creates Java objects that run in a servlet on the JVM.

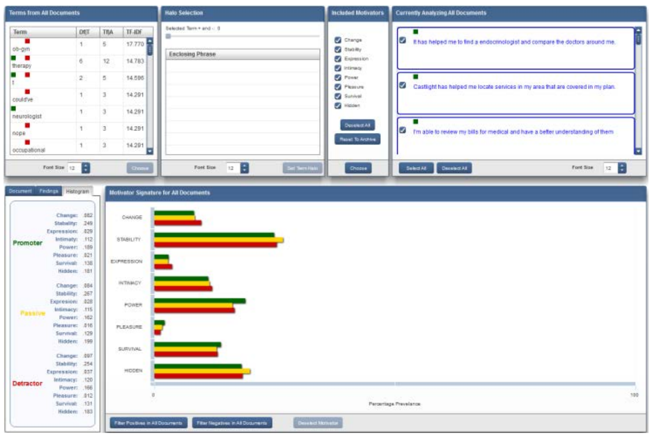

Figure 04 Flex Visualization Interface

The BMVS visualization system provides a user interface that can view the vector data as a static or as a time series histogram. Figure 04 is a screenshot from the visualizer user interface in static histogram mode.

The interface allows drill down or up on any segment of text. The histogram dynamically reflects – given the filter settings – the motivator histogram down from individual words up to an entire multi-document archive.

The visualization system can also output a configuration file with the current visualization filtering settings. This configuration file can subsequently be used to set the filtering for batch processing of document archives. The resulting output file contains a collection of vectors (of scalars) – one for each text segment (either whole document or specified fragment) in the archive analyzed. This collection of vectors can then be dropped into any open source data mining tool for integration with standard machine learning techniques.

The development version of the visualization system was created with the RAD scripting tools Flex and ActionScript 3. The visualization system runs in the Adobe Integrated Runtime (AIR).

Consistency Validation

The design of the BMVS explicitly assumes that the semantics of social information is a reality that is model-dependent. Given this assumption, one way to assess BMVS validity is by way of consistency.

The IESN functional semantics design is consistent with two widely known and generally accepted conceptual foundations. The first foundation is drawn from the domain of robotics. It is upon which the modeling of the Kismet robot rests (Breazeal, 1998). The second foundation is from the domain of neuroscience and it supports the causal dynamical modeling of consciousness states (Freeman, 1999).

Kismet robot is a modular system. Figure 05 demonstrates this modularity. Its embodiment requires 15 computers and four operating systems. In Kismet the motivation system is comprised of two compartments: Homeostatic Regulation and Emotion System. In Kismet the homeostatic regulation regime includes drives. Drives are constantly and individually changing with respect to not only the robot's external environment but also to an internal cycling dynamic. Changes in drives occurs around a homeostatic equilibrium point. The drive states in either direction away from the homeostatic equilibrium point change both the output type and its relative intensity of the drive.

Kismet motivation system influences the behavior system – the actions of the robot – through the preferential passing of activation to some behaviors over others. The activation passing depends on the relative intensity of drives and the relative behavior activation thresholds. This relative intensity of a drive is defined by the state of the drive relative to its homeostatic equilibrium point.

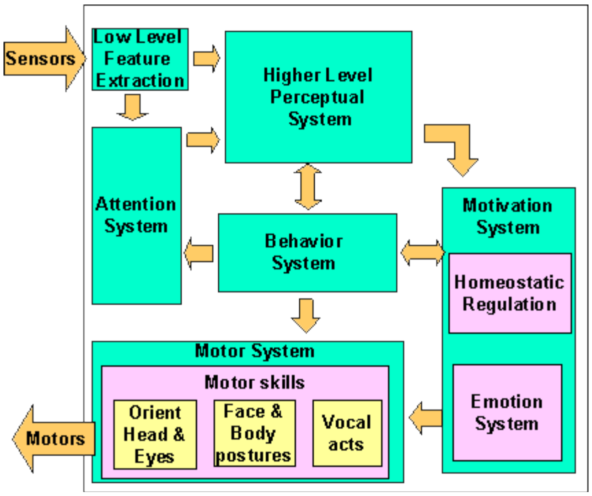

Figure 05 The Kismet Framework.

Drives in homeostatic regulation also impact the emotions system according to the relative activation state of each drive in the set of drives. Deprivation states are expressed as negative emotions and intensify the drive. Satisfaction states are expressed as positive emotions and attenuate the drive.

Lastly, the sum of the motivation and behavior modules provides the context for the robot attention system; they determine what the robot learns that will satisfy drives.

The second conceptual foundation is from neuroscience. Freeman's causal dynamical model of consciousness and intention provides a living-tissue analog for the computational dynamics represented by the Kismet framework. Freeman's model provides the conceptual basis for constructing an exclusively functional model of causal-meaning creation. In Freeman's model there are two types of causality: circular causality of the self, Figure 06; and linear causality of the observer, Figure 07.

Complex dynamical systems – such as brains – are characterized by distributed nonlinear feedback. Such systems cannot fundamentally be explained by linear causality and are therefore said to be operating by circular causality without agency. The analog in Kismet is the cyclic operation of individual drive components when they are not receiving any external stimuli.

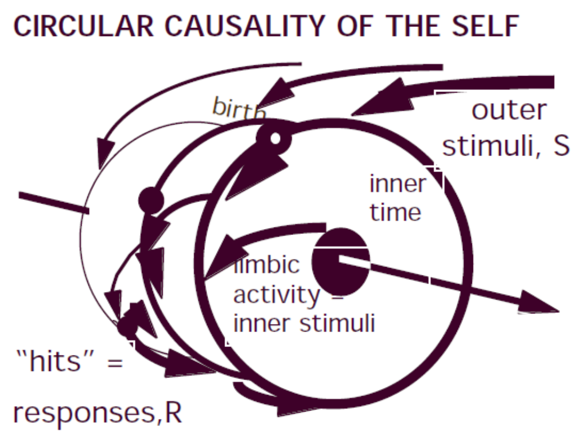

Figure 06 Circular Causality of the Self

Microscopic neural activity is modeled as self-organizing until it reaches a closure and manifests as a macroscopic ordering state. The analog in Kismet is the crossing of a threshold in the motivation system and the passing of activation to the behavior system.

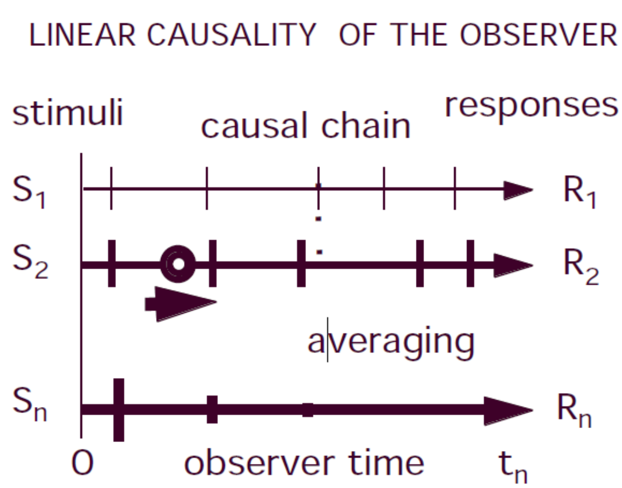

Figure 07 Linear Causality of the Observer

Agency, and therefore predictive self-awareness, (re)appears and linear causality supervenes as time passing. If the threshold re-awareness comes to pass through reference, a "cause" on the timeline is perceived. If threshold re-awareness is the result of proprioception or exteroception then an "effect" is perceived on the timeline. Causes and effects feed back into the microscopic processes thereby re-initiating lower levels of out-of-causal-linear-time, without-agency circular causality.

Therefore, in Freeman's model, linear causality – and its substrates: social contracts and physical materiality – are properties of the mind, not of matter. We can only envisage our agency through appeal to circular causality. We imagine ourselves as agents by stepping out of a specific considered timeline during self-reflective thought. This self-reflection, however, is itself a macroscopic ordering on a different specific timeline resulting from an emergence across some other threshold of some other microscopic processes at some other cortical level.

The IESN design features a purely functional semantics that is consistent with the aforementioned well-known widely-accepted conceptual foundations. IESN design fuses these two foundations within a unique purely functional abstract semantic primitive. The IESN functional semantics is created by extending this abstract semantic primitive into a reference set of five concrete instantiations. This reference set not only demonstrates inter-domain consistency with the conceptual foundations of robotics and neuroscience, it demonstrates intra-domain consistency by virtue of being children classes of the abstract semantic primitive parent.

This reference set completely captures the recursive arc of functional reality beginning with the emergence from unconscious biology to the awareness of linear causal intention then returning back to the unconscious modulation of biology as a result of either motivator-augmenting or motivator-attenuating emotions. The IESN functional semantic reference set can be thought of as a series of five existential snapshots along this arc. These states are demonstrated in Figure 08 and the set includes:

1. interoception of threshold emergence from a dynamical nonlinear drive that motivates;
2. kinesthesia and proprioception of behavioral action targeting substrate;
3. exteroception of substrate as that which is targeted by behavioral action;
4. interoception of formational emotion within the homeostatic range that attenuates drive;
5. interoception of privational emotion within the homeostatic range that augments drive.

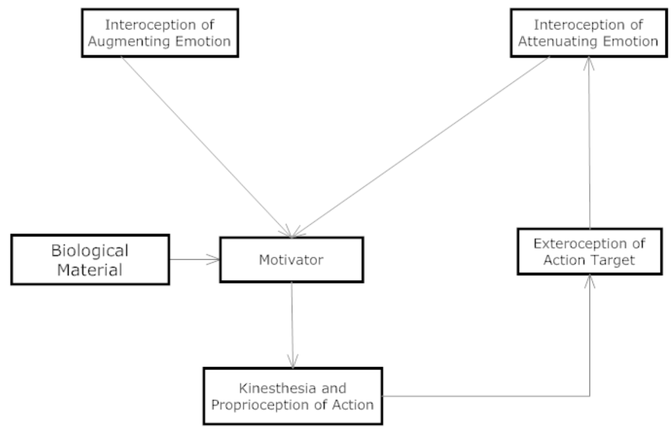

Figure 08 Functional Semantics Reference Set.

Each canonical state in this reference set is purely functionally-defined and causally self-explanatory with respect to the other canonical states. These five canonical states are further extended in the IESN to concrete instantiations that capture specific kinds of drives and auxiliary states. Each instantiation is a node in the IESN representing a discrete inner experiential state always with respect to a particular kind of biological drive.

The entire network can be traversed through cause-and-effect predicates that are descriptive, commonsensical and purely functional. This feature is not trivial. The IESN totally obviates meaning definition that relies on static enduring reality that can be only understood through *a posteriori* aggregated observation.

In the IESN meaning is a purely functional construct. This is in contradistinction to typical characterizations of meaning that rely on static references to static referents. An example illustrates.

The top node of the Suggested Upper Merged Ontology (SUMO) is [ENTITY]. The definition of entity is: "The universal class of individuals."[1] The circularity is immediately evident. How can this be prospectively validated? Any and every attempt to understand the meaning of "individual" resolves to [ENTITY]. Again, for information retrieval – including page ranking and search – this circularity is not problematic. But for any understanding of social information, this external circularity leaves much to be desired. Attempts at a socially relevant understanding of [ENTITY] result either in sterile solipsistic musings about shadows on cave walls in the best cases or utter frustration more typically.

In the IESN the definition of meaning is purely functional. The word "entity" maps to perceiving that toward which action is directed. The word "action" maps to perceiving that which has been motivated from a drive. Investigating "drive" reveals perceiving that which has emerged from the nonlinear dynamical systems of our biology. Circularity is now where it is widely accepted to comfortably exist: where the dynamical chaos of microscopic biology impinges on the causal linearity of macroscopic conscious self-awareness.

The implication of IESN for understanding social information is immediately evident. The IESN depicts the meaning of a word as a functional part of a causal story that every human understands and can easily fill with personal examples.

Robustness Validation

Robustness is sturdiness. When the term is used to describe a network it indicates the degree to which the network will still function if one or more of its nodes fail. As an aspect of validation it refers to the accounting of observations that a model can explain.

To demonstrate the robustness of the BMVS it will be compared and contrasted with the Linguistic Inquiry and Word Count (LIWC). The design and implementation of LIWC has been widely-accepted as valid. Hence, comparing BMVS with LIWC provides an indication of BMVS robustness by proxy. This comparison will proceed by systematically examining important aspects of both systems.

The BMVS and LIWC are roughly analogous in implementation consisting of a hand-coded knowledge base in communication with a specialized computation engine. The size of both knowledge bases is equivalent with approximately 12,000 entries each. As well, the results of both systems provide insight into the meaning of (psycho) social information.

LIWC was designed as a tool to expedite the counting of words in "psychologically-relevant categories." Relevancy for LIWC means the category can be linked to multiple psychological studies that reach some kind of conclusion about words of a particular kind. LIWC was designed to be not much more than a tabulation tool for analyzing text so that it can be interpreted according to published findings.

There are 80 such relevant categories. Therefore, LIWC output is a vector in $\mathbb{R}^{80}$ (80 dimensions) space – each dimension being a psychologically relevant category.

LIWC function has been demonstrated using the analysis of the first line of *Paul Clifford* by Edward Bulwer-Lytton (1842):

> It was a dark and stormy night.

The relevant portion of the LIWC result vector is shown below in Figure 08 (remaining $\mathbb{R}^{80}$space values were zero).

LIWC dimension	Your data	Personal texts	Formal texts
Self-references (I, me, my)	0.00	11.4	4.2
Social words	0.00	9.5	8.0
Positive emotions	0.00	2.7	2.6
Negative emotions	0.00	2.6	1.6
Overall cognitive words	0.00	7.8	5.4
Articles (a, an, the)	14.29	5.0	7.2
Big words (> 6 letters)	0.00	13.1	19.6

Figure 08 LIWC Analysis of the First Line of *Paul Clifford*

[1] http://sigma-01.cim3.net:8080/sigma/Browse.jsp?flang=SUO-KIF&lang=EnglishLanguage&kb=SUMO&term=Entity Accessed June 11, 2013.

LIWC is an example of a so-called functional program where functionality is achieved only through an elaborate post-processing step. Examining the vector dimensions makes this evident. There is little if any explanatory power in these categories. Further, the categories completely rely on a semantic framework that assumes stasis.

To interpret LIWC categorization results, the relevant research for non-zero category scalars must be examined to contextualize the scalar magnitude in the category.

BMVS, in comparison, was designed specifically to directly understand social information in terms of behavioral motivators. It employs a unique purely functional semantics in the execution of its design.

The space in which BMVS result vectors can appear is a given by the equation $\mathbb{R}^D : D = (7n + 1) * (1 + 4m)$ where:

> $\boldsymbol{n}$ = the number of sub-instantiations representing more-specific sub-types of behavioral motivators; and
>
> $\boldsymbol{m}$ = the number of sub-instantiations representing more-specific sub-types of existential perceptions in the course of causal functional behavior.

The BMVS has a maximum potential dimensionality of $\mathbb{R}^{\sim 500}$. The visualizer is designed such that dimensionality can and should be changed by varying $\boldsymbol{m}$ and $\boldsymbol{n}$. This reduces the dimensionality to a more manageable and comprehensible size. This reduction is achieved easily and intuitively by way of the visualizer controls.

Using the same first line of *Paul Clifford* the BMVS can produce a histogram for the absolute minimum space of $\mathbb{R}^8$ where $\boldsymbol{n}$ = 1 and $\boldsymbol{m}$ = 0. The histogram is demonstrated in Figure 09. The values generating this histogram are:

Motivator	Weight
Survival	0.50
Hidden	0.50

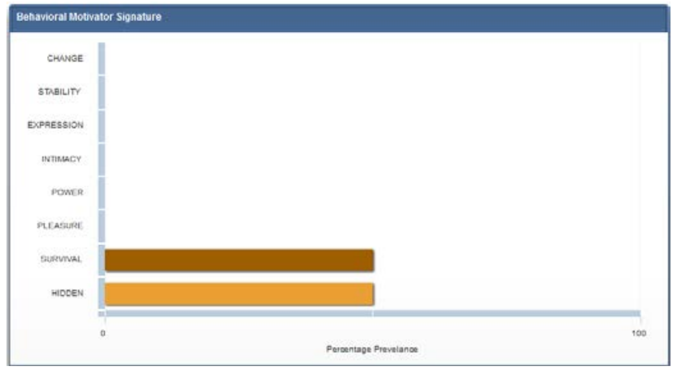

Figure 09 BMVS Analysis of the First Line of *Paul Clifford*

The interpretation of this histogram in $\mathbb{R}^8$ space is straightforward and is obtained directly from the names of the dimensions.

The first line again is:

> It was a dark and stormy night.

BMVS histograms reveal the relevant behavioral motivators underlying the social information conveyed by the communicator. For the text above the social information relates, in equal parts, to the motivator (need) for survival and to some hidden motivator (need) that the communicator has yet to reveal. Reexamining the first line in light of the histogram demonstrates the power of BMVS histographic analysis. “A dark and stormy night” certainly conveys a type of threat to survival. But, it also seems to suggest something else may be going on, perhaps some type of struggle that will ultimately be disclosed by the communicator.

For reality that is construed to be model-dependent, a model that is valid is characterized as working. We have tested the BMVS in several diverse business contexts because in business “working” is practically defined and therefore easy to assess. The definition of “working” in these contexts meant the user of the BMVS gained insight after examining histograms. Insight is narrowly defined as new understanding of data that is: i) actionable within the business context; and ii) did not require new data to realize. The BMVS successfully provided insight in tests conducted for many businesses of varying sizes including a computer chip manufacturer, a theme park operator, a well-known German automotive manufacturer, a well-known just-in-time computer manufacturer, a modular furniture manufacturer-retailer, and a healthcare information provider.

A typical success is illustrated by the experience with a multi-billion dollar purveyor of fast food. This corporation spends considerable resources on, takes pride in, and markets extensively the integrity of its suppliers and ingredients. The company also had developed a script-less animated video featuring a sound track by a famous folk singer. The video won awards and accumulated millions of views on YouTube.

Notwithstanding the renown of its food integrity and the wide praise for the video, the corporation was experiencing its closest competitor eating into its market share. The corporation commissioned research to understand what was going on. The corporation wanted to know why what they assumed to be an obvious desirable product benefit was not translating into defendable market share.

The selected research company allowed us to analyze the verbatims from focus groups wherein respondents were asked to comment on the well-known video. The result of BMVS analysis with the filtering set to emphasize motivators that are augmented is demonstrated in Fig. 10.

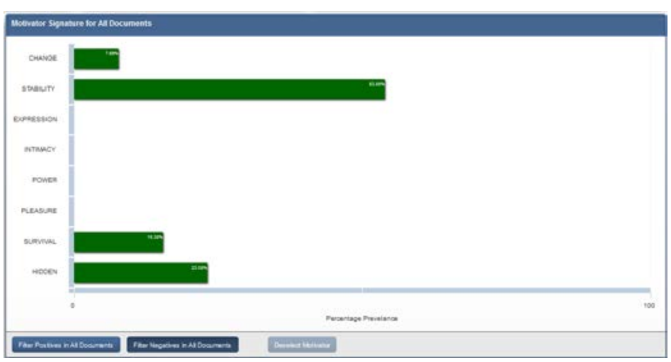

Figure 10 Filtering for Augmented Motivators

The histogram demonstrated that even though respondents overall comments where very positive, when these comments were filtered for augmented motivators, the motivator (need) for stability stands out significantly. The motivator for stability is the need to make sense of things. This motivator was significantly heightened after watching the video. This finding indicates that people really liked the video. But, they also didn't really get the relevancy of its message in a way that significantly influenced other motivators.

The BMVS helped the research company shape its message to the corporation's CMO and CEO. The message they delivered was that customers genuinely like the idea of supplier and ingredient integrity; however, they don't easily grasp how this kind integrity makes a difference relative to other motivations in their lives. Without this kind of connection to other motivators customers don't have a compelling reason to reject a convenient substitute providing food that tastes just as good but prepared with less attention to the integrity of the ingredients.

Integration Potential

The BMVS easily integrates with other text analytic techniques that rely on static semantic frameworks including IR and TDT algorithms. When BMVS is used in conjunction with these tools all of the benefits of IR and TDT accrue augmented by the behavioral insights the BMVS provides after target documents and topics have been identified.

The BMVS also integrates with all current machine learning techniques. BMVS can be configured to produce a collection of vectors given specific filter settings delimiting the vector space, each vector representing a specified portion of text in a document archive. This collection of vectors can be used to train a system designed for machine learning. The business use case illustrates the potential for this capability.

When most companies perform quantitative or qualitative research they typically segment their customers according to some regime reflecting an impact on profitability. One frequently used segmentation system is the Net Promoter regime (Reicheld, 2003). This segmentation model posits so-called Promoters as the most profitable customers of any company.

BMVS has the capability of simultaneously analyzing the responses from profitability segmentations with at least three different segments. The Terma computation engine then searches within the maximum vector space ($\mathbb{R}^{\sim 500}$) for any monotonic patterns on any dimension across the segmentation. It then creates a collection of result vectors with a dimensionality determined by the total of dimensions where monotonic patterns occurred. This collection of result vectors represents the training signature for a company's most profitable customer.

Using the open source data mining tool RapidMiner 5.3 a model was created with mySVM of Stefan Rueping configured with a radial bias function kernel, a C = 0 (heuristic), and a convergence epsilon of 0.001. The model was trained using data from an R&D partner company's segmentation survey. A collection of 2,000 vectors were generated by the BMVS representing the signature for the most profitable customers of the partner company as determined by the survey. When the trained model was tested against masked data from a different group of customers using the same survey, the model was able to distinguish the most profitable customer with greater than 95% precision.

The success of this technique appears to depend on the two interdependent factors:

1. the vector dimensionality which is determined by the number of identified monotonic patterns; and
2. the number of vectors in the output file that are used for training.

A threshold is established by the interplay of these two factors. It appears that when this threshold is crossed, the ability to identify a company's most profitable customer can consistently be achieved with a precision of greater than 95%.

Conclusion

Stasis-assuming semantic frameworks have become embedded due to the success of modern IR and TDT tracking techniques. Notwithstanding, technologies built on stasis-assuming frameworks have a difficult time extracting meaning from social information. This difficulty is significant because the amount of social information transmitted electronically is growing exponentially.

Social information is singularly about human inner experiences. And human inner experience is a type of reality that is model-dependent. It is inescapable that an *a priori* model of human inner experience is required to extract meaning from social information.

The BMVS presented is a system built upon a purely functional semantics featuring an *a priori* model of inner experience. Its self-explanatory semantic categories are extended from a unique semantic primitive. These functional semantic categories are existential snapshots of a dynamic sequence describing a causal-functional arc. This arc: i) emerges from microscopic biology as behavioral motivation; and ii) manifests as macroscopic linear causal behaviors; and then iii) submerges back to microscopic biology as motivator-attenuating or motivator-augmenting emotional experiences.

The BVMS functional semantic model is internally consistent and also consistent with widely-accepted conceptual foundations in robotics and neuroscience. The BMVS is robust as compared to technologies of similar componentry and knowledge base size and as measured by demonstrated usefulness in diverse business environments.

The BMVS provides results that are both informative and predictive. It provides unique insight into the nature of social communication and augments the power of existing text analytic techniques. What is more, the BMVS can be used to create models that precisely prospectively identify the most profitable customers of a company.

References

Adi, T., Evell, O, K., Adi, P. & Vogel, T. (2009) A New Theory of Cognition and Software Implementations in Information Technology. *Journal of Information Technology Research (JITR)*, 2(2), 65-89.

Ahmad, K. (2011) Meaning and Ontological Commitment: A Survey of the Use of the Term "Semantic Primitive." Pre-final Draft. Dublin: Trinity College.

Breazeal, C (1998) A motivation system for regulating human-robot interaction. In *Proceedings of the National Conference on Artificial Intelligence* (pp. 54-61) John Wiley & Sons LTD.

Collins, A. M. & Loftus, E. F. (1975) A spreading activation theory of semantic processing. *Psychological Review, 82*, 407-428.

DeJong II, G. F. (1979) Prediction and Substantiation: A New Approach to Natural Language Processing. *Cognitive Science* 3:251-273.

DeJong II, G. F. (1979) *Skimming Stories in Real Time: An Experiment in Integrated Understanding.* Technical Report 158, Yale University. Department of Computer Science. Ph.D. Dissertation.

Dyer, M. G. (1982) Affect Processing for Narratives. *AAAI-82 Proceedings.* 265-268.

Dyer, M. G. (1983). The Role of Affect in Narratives. *Cognitive Science* 7, 211-241.

Dyer, M. G. (1987) Emotions and their computations: Three computer models. *Cognition & Emotion.* 1:3 323-347.

Freeman, W. J. (1999) Consciousness, intentionality and causality. *Journal of Consciousness Studies*, 6 (11-12), 11-12.

Landeur, T. K., et al. (1998). Introduction to Latent Semantic Analysis. *Discourse Processes,* 25, 259-284.

Min Li, Vitanyi, P. M. B. (2008) *An Introduction to Kolmogorov Complexity and Its Applications*. New York: Springer-Verlag, 24-27.

Ogden, C. K. and Richards, I. A. (1923) *The Meaning of Meaning*, 8th Edition 1989. San Diego: Harcourt Brace Jovanovich, 1-47.

Reicheld, F. (2003) *The One Number You Need to Grow,* Harvard Business Review 81:12 46-55.

Schank, R. C. (1973) Identification of Conceptualization Underlying Natural Language. *Computer Models of Thought and Language,* San Francisco: Freeman.

Schank, R. C. Abelson, R. (1977) *Scripts, Plans, and Knowledge.* Hillsdale, NJK: Lawrence Erlbaum, The Artificial Intelligence Series.

Shepard, R. (1987). Toward a Universal Law of Generalization for Psychological Science. *Science*, 237(4820), 1317-1323.

Tausczik, Y. R., & Pennebaker, J.W. (2010) The psychological meaning of words: LIWC and computerized text analysis methods. *Journal of Language and Social Psychology,* 29(1) 24-54.