Ousiometrics and Telegnomics:
The essence of meaning conforms to a two-dimensional {powerful ⇔ weak} and {dangerous ⇔ safe} framework with diverse corpora presenting a safety bias

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Logline:

We show that the essential meaning conveyed by individual words maps to a compass-like plane with major axes of powerful-weak and dangerous-safe.

We uncover a linguistic ‘safety bias’ by examining how words are used in large-scale, diverse corpora.

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Abstract:

We define ‘ousiometrics’ to be the study of essential meaning in whatever context that meaningful signals are communicated, and ‘telegnomics’ as the study of remotely sensed knowledge.

From work emerging through the middle of the 20th century, the essence of meaning has become generally accepted as being well captured by the three orthogonal dimensions of evaluation, potency, and activation (EPA).

By re-examining first types and then tokens for the English language, and through the use of automatically annotated histograms—‘ousiograms’—we find here that:

1. The essence of meaning conveyed by words is instead best described by a compass-like power-danger (PD) framework with orthogonal axes described by the semantic differentials of {powerful ⇔ weak} and {dangerous ⇔ safe};

and

2. Analysis of a disparate collection of large-scale English language corpora—literature, news, Wikipedia, talk radio, and social media—shows that natural language exhibits a systematic bias toward safe, low-danger words—a reinterpretation of the Pollyanna principle’s positivity bias for written expression.

We identify and explore a third dimension representing structure, S. To help justify our choice of dimension names and to help address the problems with representing observed ousiometric dimensions by bipolar adjective pairs, we introduce and explore ‘synousionyms’ and ‘antousionyms’—ousiometric counterparts of synonyms and antonyms.

We further show that the PD framework revises the circumplex model of affect as a more general model of state of mind.

Finally, we use our findings to construct and test a prototype ‘ousiometer’, a telegnomic instrument that measures ousiometric time series for temporal corpora. We contend that our power-danger ousiometric framework provides a complement for entropy-based measurements, and may be of value for the study of a wide variety of communication across biological and artificial life.
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I. Introduction

As encoded by human language, meaning spans a high dimensional semantic space that is continually expanding and evolving, bearing complex hierarchical and networked structures [1–3]. In attempting to understand any quantified complex system, a most basic step is to apply a method of dimensional reduction. If we distill meaning to its essence— the focus of our work here— do we find fundamental dimensions of meaning space that are interpretable and, moreover, reliably experienced, conceptualized, and conveyed by people [4–9]? More broadly, how might essential meaning vary for entities across all levels of cognition and complexity, from individual organisms, groups at all scales, and to artificial, algorithmic systems?

We define ‘ousiometrics’ to be the quantitative study of all scales, and to artificial, algorithmic systems? and complexity, from individual organisms, groups at all scales, and to artificial, algorithmic systems?

We define ‘ousiometrics’ to be the quantitative study of the essential meaningful components of an entity, however represented and perceived. Used in philosophical and theological settings, the word ‘ousia’ comes from Ancient Greek ὀσία and is the etymological root of the word ‘essence’ whose more modern usage is our intended reference. For our purposes here, our measurement of essential meaning will rest on and by constrained by the map presented by language. We place ousiometrics within a larger field of studies at the time, the three dimensions were dubbed: 1. Evaluation (e.g., {positive ⇔ negative}), 2. Potency (e.g., {dominant ⇔ submissive}), and 3. Activity (e.g., {active ⇔ passive}).

Each semantic differential is considered a dimension (an axis) in a potentially high dimensional space, and researchers then apply some variant of factor analysis to the average scores, such as principal component analysis (PCA) or singular value decomposition (SVD). Such factor analyses returns a set of dimensions that are linear combinations of the study’s semantic differentials, which must then be interpreted.

Based on a range of studies, Osgood et al. identified three orthogonal dimensions for the essence of meaning [5]. In order of variance explained for the studies at the time, the three dimensions were dubbed: 1. Evaluation (e.g., {positive ⇔ negative}), 2. Potency (e.g., {dominant ⇔ submissive}), and 3. Activity (e.g., {active ⇔ passive}).

Though the ‘EPA’ framework has been challenged in various ways [8, 12, 13], as have semantic differentials themselves [8, 14], researchers were increasingly drawn to take the EPA framework as a ground truth when carrying out new studies [10, 14, 15].

In the focused context of studying emotion, a theoretical concept of a three dimensional representation of emotion goes back to (at least) Wundt in the late 1800s [16, 17]. For emotion, the EPA dimensions were re-ordered and recast by Mehrhabian and Russell as: 1. Pleasure (or Valence), 2. Arousal, and 3. Dominance (PAD or VAD) [18, 19]. To make clear that this was the authors’ intention, from the summary of Ref. [19]:

“A semantic differential studies, in particular, have shown that human judgments of diverse samples of stimuli can be characterized in terms of three dimensions: evaluation, activity, and potency. We have termed the corresponding emotional responses pleasure, arousal, and dominance.”

And to exemplify the presumption of orthogonality of the three core dimensions, from p. 292 of Ref. [19] we have:

The quantitative measurement of the essence of meaning was primarily developed by researchers in the
“Thus, each dimension is, in principle, functionally independent of the other two; none of the three dimensions could be subsumed by the others.”

Subsequent work has tended to use the term valence instead of pleasure, and we will follow the VAD nomenclature.

Now, while VAD was intended to be a scoped version of EPA, the two frameworks have been conflated. Generally, VAD has become the framework presented in studies, even when essential meaning, rather than emotion, has been the focus [10, 14, 15]. Elsewhere, the original connection between VAD and EPA has been overlooked or considered broken, leading to re-analyses about whether or not the match between EPA and VAD holds at all [20].

Nevertheless, to be consistent with the direction taken by the literature, we will refer to VAD rather than the more general EPA going forward.

B. The major problems with measuring essential meaning

We describe a set of problems that we contend have thwarted the full development of osiometry over time.

1. Scale:
Given that the EPA framework was developed before and during the 1950s, the foundational studies were limited in size, both in lexicon analyzed and the number of participants surveyed. For example, as part of the research that led to the EPA framework, Osgood et al. report on a study of 20 concept nouns evaluated on 50 semantic differentials by 100 undergraduates [5]. Published in 1980, Russell’s circumplex model of affect (which we examine later in Sec. III H) was based on the scoring of 28 words and phrases [8]. The Affective Norms for English Words (ANEW) study of the late 1990s moved the lexicon size up to 1,034, but now with VAD as the accepted fundamental framework, and still within context of surveys being given to undergraduates. In work carried out around 2010 involving two of the present authors, an order of magnitude jump to over English 10,000 words was evaluated online through Amazon’s Mechanical Turk with 50 evaluations per word along the single semantical differential of valence interpreted as happiness (discussed further below) [21]. This data set, labMT (language assessment by Mechanical Turk), was later expanded to 10 languages, each with over 10,000 words scored online by participants around the world [22]. Crucially, and in contrast to the ANEW word lists, the labMT words analyzed were chosen according to frequency of usage (again, discussed further below). In 2013, Warriner et al. published scores for close to 14,000 English with VAD scores. Finally, in 2018, Mohammad produced what will be the basis of our analysis here, the NRC VAD lexicon: Over 20,000 English words and phrases with VAD scores [14].

So, it is only in the last 10 years that studied lexicons have begun to represent the scale of human vocabularies. We are consequently now well placed to perform the necessary work of re-examining the findings of the field’s foundational research.

2. The focus on types alone and not tokens:
We use the standard type-token language for describing entities [23]: Type refers to an entity’s class (or species) while token refers to an entity itself as an instance of that class. Beyond language, the type-token distinction appears across all complex systems with heavy-tailed distributions of component frequencies. Perhaps in settings not involving words and texts, the problems with studying only types would be more apparent. For example, in determining some overall measure of a forest, we would not want to assign equal weight to the most common and the most rare species. Here, we will study both lexicons (types) and large-scale texts (tokens), gaining separate results from both.

Almost all essential meaning studies have been at the level of types, each word or concept given equal weighting. However, we must consider the weight of types in a text according to the frequency of their corresponding tokens [23]. Only then can we make defensible observations about a whole space of communication. The ANEW study [10], for example, is based on 1,034 expert chosen words which proved to be a poor fit for natural language [24]. By contrast, with careful consideration of word usage, we were able to show that the Polyanna Principle [25] manifests a linguistic positivity bias across 24 corpora spanning 10 languages [22].

The use of a Likert scale for evaluations of semantic differentials as long been standard practice. Relatively recently, best-worst scaling has been suggested to be a more robust instrument than the Likert scale, as well as a far more efficient one [26]. To our great benefit, Mohammad’s survey of over 20,000 words and phrases preferentially uses best-worst scaling, finding appreciable improvement in split-half reliabilities over studies using Likert scales.

4. Limitations of factor analysis for a large number of categorical dimensions:
While tables of factor analysis weightings can be exhaustively informative for small-scale studies, we will not be able to make much sense of point clouds of tens
of thousands of unlabeled words in two or three dimensions. Here, we will show how a kind of automatically annotated histogram—an ousiogram—provides an instrument that will help us explore, describe, and support our assessments of the dimensions of essential meaning.

5. The misalignment between expert-chosen, end-point descriptors and dimensions of essential meaning:

We come to a critical problem with any essential meaning studies that starts from a presumption of the EPA/VAD framework. We go back to basics and outline the four step experimental process that has been used to extract essential dimensions of meaning in the first place:

1. Participants are asked to rate a set of \( N_{\text{types}} \) types (e.g., words, images) using a set of \( N_{\text{differentials}} \) semantic differentials defined by bipolar adjective pairs. Some examples from Osgood et al.’s 50 semantic differentials for the study mentioned above include \{large ⇔ small\}, \{clean ⇔ dirty\}, \{brave ⇔ cowardly\}, \{bass ⇔ treble\}, and \{near ⇔ far\} (p. 43, Ref. [5]).

2. Some variant of factor analysis (e.g., PCA, SVD) is then employed to obtain an ordered set of dimensions that are linear combinations of the semantic differential dimensions.

3. Researchers interpret the main dimensions and ascribe them with both descriptive names (e.g., ‘evaluation’) and, crucially, sets of ‘end-point descriptors’ (e.g., happiness, pleasure, contentedness for high valence and unhappiness, annoyance, negativeness for low valence). These new semantic differentials are not then described by simple bipolar adjectival pairs but rather clusters of words and phrases at each end.

4. Researchers reduce the meaning space to 2 or 3 of the most prominent dimensions (e.g., by variance explained through singular values).

With ousiometric dimensions so determined (e.g., EPA), researchers then move on to new studies using only a modified version of step 1:

1. Participants are asked to rate a set of \( N_{\text{types}} \) types along 2 or 3 expert-chosen dimensions that are defined by expert-identified sets of end-point descriptors.

As such, there is then no assurance that the expert-identified end-point descriptors will be construed by participants in a way that imposes the expert-defined dimensions.

Indeed, we observe that across many studies, raters have been presented with end-point descriptors that render the three VAD dimensions with problematic imprecision [5, 8, 10, 14, 20]. For example, for the ANEW study, valence was described to participants as a \{happy ⇔ unhappy\} scale as follows (emphasis added):

“At one extreme of [this \{happy ⇔ unhappy\}] scale, you are happy, pleased, satisfied, contented, hopeful. . . . The other end of the scale is when you feel completely unhappy, annoyed, unsatisfied, melancholic, despaired, or bored.”

The meaning captured by both ends is broad, the numbers of descriptors differ, and the word ‘bored’ clearly overlaps with the dimension of arousal.

For the NRC VAD lexicon, raters were guided by end-point descriptors (‘paradigm terms’) which were taken from Refs. [5], [8], and [10]. We list all descriptors for the six end-points used in Ref. [14] in Tab. I. As for the ANEW study, we see the end-points for each dimension combine to create coarse semantic limits. For example, for low arousal, there is clear semantic separation between ‘sluggishness’ and ‘calmness’, as there is for ‘weak’ and ‘guided’ for low dominance.

Our remedy is simple: Always carry out steps 1–4 above even when attempting to impose a minimal ousiometric framework. Factor analysis will then accommodate a reasonable lack of exactness in how dimensions are prescribed. And if our concerns are mislaid and we find that the VAD framework is in fact perfectly prescribable, we will have done the work needed to make this clear.

6. Presuming that the VAD framework does capture essential meaning and that the three dimensions are orthogonal:

As we have observed, Osgood et al.’s EPA/VAD framework has become generally accepted as valid. However, modern, large-scale VAD evaluations of words and phrases have increasingly pointed toward the VAD framework being non-orthogonal. Leaving aside problematic sampling of words, the ANEW study [10] found evidence that arousal was mildly positively correlated with the magnitude of valence. The near 14,000 lemma VAD study of Warriner et al. [15] found correlations between the three VAD dimensions, the strongest being between valence and dominance with \( r_{V,D} \approx 0.72 \) (Pearson’s correlation), which prompted the authors to call into question the orthogonality of the VAD framework.
VAD end-points | Paradigm words and phrases presented to raters
---|---
Highest valence | happiness, pleasure, positiveness, satisfaction, contentedness, hopefulness
Lowest valence | unhappiness, annoyance, negativeness, dissatisfaction, melancholy, despair
Highest arousal | arousal, activeness, stimulation, frenzy, jitteriness, alertness
Lowest arousal |unarousal, passiveness, relaxation, calmness, sluggishness, dullness, sleepiness
Highest dominance | dominant, in control of the situation, powerful, influential, important, autonomous
Lowest dominance | submissive, controlled by outside factors, weak, influenced, cared-for, guided

TABLE I. end-point descriptors used in Ref. [14] for the survey leading to the NRC VAD lexicon. As for many studies presuming the an orthogonal VAD framework, the end-points are semantically broad and imprecise.

Most recently, using best-worst scaling for the NRC VAD lexicon, Mohammad [14] found a somewhat weaker correlation of $r_{V,D} \simeq 0.49$, and then asserted that valence and dominance were only “slightly correlated”, a view with which we do not agree. In reference to the valence-dominance correlation in the Warriner et al. study, Mohammad stated:

“Given that the split-half reliability score for their dominance annotations is only 0.77, the high V–D correlations raises the suspicion whether annotators sufficiently understood the difference between dominance and valence.”

So the suggestion here is that the problem is not that the VAD framework is not orthogonal, but that participants failed to grasp the definitions of dimensions.

Our position, per problem 5 above, is that imposing VAD dimensions experimentally through end-point descriptors is a difficult task and that factor analysis is always required. And in challenging the VAD framework, we will show that these observed correlations are real and understandable, and ultimately lead to a revised framework we will identify to be power-danger-structure (PDS).

C. Road map for the paper

We first describe the data sets we analyze and explore in Sec. II. We make the key distinction between text corpora that are type-based (i.e., lexicons) or token-based (written or recorded expression) [23].

Through a series of integrated figures, we then demonstrate our four main findings: 1. The framework of valence-arousal-dominance (VAD) is far from being an orthogonal system [15], and this failure is due to the difficulties of constructing semantic differentials for essential dimensions of meaning (Secs. III A and III B); 2. A goodness-energy-structure (GES) framework and a power-danger-structure (PDS) framework both provide two alternative, interpretable, and interconnected orthogonal systems (Secs. III C, III D, and III E); and 3. Only the power-danger-structure framework aligns with the essential meaning patterns of real corpora when we properly account for frequency of usage by considering tokens; and 4. Diverse, large-scale text corpora present a systematic, low-danger ‘safety bias’ (Sec. III G).

In doing so, we also explore ‘synonymyisms’ and ‘antonymyisms’—words that match or are opposite in essential meaning (Sec. III F). We share osiometric word scores for all frameworks, additional figures, and scripts in the Ancilliary files.

With the PDS framework established, we revisit the circumplex model of affect [8] (Sec. III H), and make connections between the PDS framework and role-playing game character alignment charts (Sec. III I).

In Sec. IV, we construct and test a simple osiometer—a telegnomic lexical instrument for measuring essential meaning of large-scale texts. As a test, we study osiometric time series for English Twitter at a 15 minute time scale running for 13 months starting on 2020/01/01. We present and compare time series for each of the VAD, GES, and PDS frameworks.

Finally, we summarize our results and offer thoughts on future work in Sec. V.

II. Description of data sets

We build our findings in two stages using two distinct kinds of word lists: 1. Types: A lexicon for the English language (each word is of equal importance), and 2. Tokens: Zipf distributions for large-scale corpora (a word’s importance is weighted by its frequency of usage). In general, observations made solely by examining a lexicon (the level of types) will be given a
stringent test when confronted by real-world word usage (the level of tokens).

The type stage: As indicated in the introduction, we use the NRC VAD lexicon comprising around 20,000 words and terms [14]. The lexicon was compiled from a variety of sources and largely contains lower-case, Latin-character words along with some 2-, 3-, and 4-grams (n-grams is an n term phrase). Proper nouns and function words have generally been excluded. Some words are evidently hashtag constructions from social media (with the hashtag removed). The lexicon is a union of existing lexicons, some of which were expert-compiled (e.g., the ANEW study [10]) and others based on frequency of usage. While the presence of expert-compiled lexicons is not ideal, we will see that the coverage of real corpora is sufficient for the purposes of our work here.

For each term in the NRC VAD lexicon, scores within the VAD framework [18, 19] were assessed by survey using best-worst scaling [26]. Terms were presented in groups of four and participants were asked to rank the highest and lowest according to one of the three VAD dimensions (see Ref. [14] for full details). Each term’s score is in the interval [0,1]. To accommodate singular value decomposition, we remove the mean from each dimension, which by the nature of best-worst scaling is \( \frac{1}{2} \). We thus shift the VAD scores from [0,1] to \([\frac{1}{2}, 1 + \frac{1}{2}]\).

The token stage: With findings from studying the NRC VAD lexicon, we then analyze seven corpora—where frequency of word usage now matters—and which vary broadly in kind, formality, scale, and historical time frame.

- English Fiction (1900–2019) from the Google Books project, with each book contributing words equally, and then each year’s Zipf distribution weighted equally [27, 28];
- Jane Austen’s six novels with all books merged, sourced from the Gutenberg Project, http://www.gutenberg.org.
- The majority of Arthur Conan Doyle’s Sherlock Holmes stories with all stories merged, (4 novels and 44 short stories taken from https://sherlock-holmes.es/, missing the 12 short stories contained in “The Case-Book of Sherlock Holmes”);
- The New York Times (1987–2007) Zipf distributions merged without reweighting across all years [29];
- Wikipedia (English language, 2019/03 snapshot) [30];
- RadioTalk (transcriptions of talk radio broadcasts in the US, 2018/10–2019/03) [31];
- Twitter (approximately 10% of all tweets identified as English in 2020—including retweets—with each day’s Zipf distribution contributing equally) [32].

We acknowledge that we have represented the dominance and danger dimensions by the same variable \( D \), and potency and power by \( P \). We opt for this notational collision in preference to more cumbersome expressions that would largely only be of service in the present paper. To maintain clarity, we repeatedly express the contexts of VAD and PDS in text and figures, and we will use full names for dimensions where needed.

III. Analysis, Results, and Discussion

A. Ousiograms

Complex systems are often manifested from a set of distinct, named entities—types—whose frequencies of occurrence as interacting tokens roughly obey a heavy-tailed distribution, and whose characteristics reside in some high dimensional space [33–36]. Language is a canonical example with words as types and meanings as one of their characteristics. One approach to better understanding such high dimensional complex systems, is thorough dimensional reduction where we maintain the set of all types but seek to distill the characteristics of these types down to an essential few.

To inform and help validate our analysis, we will use ‘ousiograms’. We define an ousiogram as a systematically and informatively annotated two-dimensional histogram for two essential quantities of a complex system’s component entities. The entities represented in ousiograms may be either types or tokens [23], with types contributing equally while a token’s contribution would be proportional to the frequency of that token’s appearance within a given system.

In Fig. 1, we present an ousiogram for valence \( V \) and dominance \( D \) for the NRC VAD lexicon [14]. We use valence and dominance as an example to demonstrate the non-orthogonality of the VAD framework with best-worst scaling. In the Ancillary files, we provide the corresponding \( V-A \) and \( A-D \) large-scale ousiograms. For our main analysis, we present smaller versions of
FIG. 1. Valence-dominance ‘ousiogram’ for the NRC VAD lexicon of around 20,000 words scored within the valence-arousal-dominance (VAD) framework [18, 19] using best-worst scaling [14, 26]. In general, ousiograms are annotated two-dimensional histograms of two essential dimensions describing any collection of labeled entities. Here, we arrange words according to their valence-dominance scores, collapsing the third dimension of arousal. We use a bin width of $1/30$, and we have shifted all $V$, $A$, and $D$ scores from $[0,1]$ to $[-\frac{1}{2},+\frac{1}{2}]$. To enable comparisons, we use limits of $[-1,1]$ throughout the paper. We plot marginal distributions of $V$ and $D$ along the top and right sides, with darker gray indicating positive values, and solid dark triangles locating the medians of $V$ and $D$. The ellipse represents the axes determined by singular value decomposition (SVD) acting on the $V$-$D$ plane, and shows a strong departure from the $V$ and $D$ axes. We label words around the edge of the $V$-$D$ distribution aligned with normals to the distribution’s convex hull, and add example words at internal locations along the main axes and the two diagonals. Upon inspection, the words shown are reasonably located according to their essential values of $V$ and $D$. Notes: See Anciliary files for the large-scale ousiograms $V$-$A$ and $A$-$D$. Labeled words are not restricted in their value of the third dimension, arousal $A$, which may vary unevenly. Alternating shades of gray are for readability. For these larger ousiograms, we automatically label the four cardinal and inter-cardinal directions with their endpoint adjective (e.g., ‘dominant-positive’ in the northeast corner).
these ouisiograms in Figs. 2A–C, which we discuss below in Sec. III C.

We first briefly describe the ouisiogram in Fig. 1 (see the Figure’s caption for more detail), and then contend with the non-orthogonality of the VAD framework.

As a guide, we label the cardinal directions for valence $V$ and dominance $D$ by the standard (if problematic) bipolar adjectives anchoring the semantic differentials \{negative $\Leftrightarrow$ positive\} and \{submissive $\Leftrightarrow$ dominant\}. The intercardinal directions are then combinations of these adjectives (e.g., submissive-positive). We label all other ouisiograms in the same fashion with appropriate bipolar adjectives.

Given that we have shifted the VAD scores to lie in $[-\frac{1}{2}, +\frac{1}{2}]$, the two dimensional histogram of Fig. 1 shows that the NRC VAD lexicon accesses much of the available $V$-$D$ plane. The marginal distributions at the top and right show that both valence and dominance are well dispersed, with dominance exhibiting some minor asymmetry. The dark triangles indicate the medians for each marginal.

We show words using two kinds of annotations: At the extremes of the histogram’s boundary and internally along the cardinal and intercardinal axes. (See Ref. [15] for scatter plots with perimeter annotations.) For words on the boundary, we automatically construct and segment a convex hull for the histogram, determine normals to each segment, and annotate the closest word. Internally, we find words closest to points along the eight outgoing lines. We leave the third dimension aside (here, arousal $A$). Both the bin width for the underlying histogram and the spacing of annotations are tunable, and we avoid repetition of words.

Ousiograms will have two main benefits for us. First, they give us a way to check that words line up with prescribed axes. Second, and crucially for our later work here, when we move to a potential new framework, ouisiograms will help us to interpret the underlying axes.

In the first sense of acting as a check, the ouisiogram of Fig. 1 shows that word ratings performed by the survey participants in Ref [14] are reasonably sensible. Travelling around the histogram’s boundary, we see how the essential meaning of words incrementally changes. Starting in the ‘dominant-positive’ direction (upper right), we see ‘triumphant’, ‘success’, and ‘greatness’. As we move clockwise going down the right side of the boundary, the annotated words become softer while remaining pleasant: ‘generous’ to ‘memories’ to ‘pajama’. Moving left along the bottom boundary, positive gives way to negative, and we reach the extreme of negative-submissive: ‘feather’ to ‘weakened’ to ‘pointless’. Moving up the left side, we see a string of negative words which grow in strength, partly because of scope of dominance: ‘depressed’, ‘nightmare’, ‘murderous’, ‘dictator’. Returning across the top of the ouisiogram, we move through martial, leadership, and power terms that gradually lessen in violence: ‘weaponry’, ‘dominate’, ‘president’, ‘powerful’, and back to ‘success’.

Internally, each of the eight directions leading out from the center also reflect changes in the strength of essential meaning. For the full negative-submissive to dominant-positive axis, for example, we track from ‘penniless’, ‘vomiting’, ‘disoriented’, and ‘crutch,’ up through to ‘conscientious’, ‘qualifying’, ‘amazingly’, and ‘success’.

The words ‘encrypt’ and ‘albatross’ are neutral in the $V$-$D$ plane, and are worth reflecting on. These are certainly meaningful words. And as for all words, these examples could take on a strong meaning in the right context. An albatross for sailors is a dire omen whereas an albatross in golf is a rare, extraordinary success. But raters are asked to compare the essential meaning of words based on the perceived meaning in isolation, which is to say, in the context of the rater’s knowledge of the word.

B. The Valence-Arousal-Dominance (VAD) framework is not orthogonal

We turn now to the issue of orthogonality, a longstanding point of contention for the EPA and VAD frameworks [5, 8, 14, 15, 18, 19]. For the NRC VAD lexicon, we find that the VAD dimensions as interpreted by raters are not close to being orthogonal. We observe that standard correlation coefficients for the three pairs of VAD variables are

$$r_{V,A} \simeq -0.27, \quad r_{A,D} \simeq 0.30, \quad \text{and} \quad r_{V,D} \simeq 0.49,$$

where the corresponding $p$-values are computed to be essentially 0. If the VAD framework were orthogonal, these three correlation coefficients should be statistically indistinguishable from 0.

We note that the linkages between the VAD dimensions are not simple, with valence and arousal being anticorrelated with the other two pairs being positively correlated.

For a visual guide, and one that we will use throughout the paper, the ellipse in Fig. 1 represents the coordinate system uncovered by singular value decomposition (SVD) [37] in the $V$-$D$ plane (we ignore $A$ for this example calculation). The ellipse is clearly off axis. For the equivalent ellipses for the $V$-$A$ and $A$-$D$ planes, see
the onsiograms in Figs. 2A and C as well as in Ancillary files.

Now, given that we do not see orthogonality for the VAD framework for the largest lexicon ever studied coupled with a markedly improved rating system, we are compelled to investigate why VAD (equivalently EPA) fails as an orthogonal framework and what alternate framework might be revealed in doing so.

The root cause of confusion lies in the difficulty of ascribing stable and meaningful end-point descriptors for VAD (and EPA) variables. As was true for Osgood et al.’s work that led to the EPA framework [5], from the start in developing the VAD framework [18, 19], Mehrbani and Russell were concerned with both orthogonality and finding suitable end-point descriptors. As explored in Ref. [20], researchers have continued to use a varying array of end-point descriptors for EPA and VAD, including the same researchers over time [8, 10, 14].

Problematically and as we noted in the introduction, some end-point descriptors have the effect of correlating different dimensions. For example, in the ANEW study of Ref. [10], the negative valence end-point was presented to participants as a state of feeling “completely unhappy, annoyed, unsatisfied, melancholic, despaired, or bored.” The last descriptor ‘bored’ evidently would be elicited at the low end-point of the arousal dimension which itself was framed as “completely relaxed, calm, sluggish, dull, sleepy, or unaroused.”

For the NRC VAD lexicon we study here [14], the end-points were described by 6 or 7 words or phrases, unavoidably broadening them away from being sharply defined (Tab. 1). For example, the words ‘happiness’ and ‘hopefulness’ are used for high valence, ‘unhappiness’ and ‘despair’ for low valence, ‘activeness’ and ‘frenzy’ for high arousal, and ‘relaxation’ and ‘sluggishness’ for low arousal (see Tab. 1 for all descriptors). There is a gap in meaning between all of these pairs of words, and how participants might perform at rating or ranking words is not a priori clear.

A further complication is that the names of the dimensions themselves do not track well within the VAD framework. While not strictly necessary that they do so, if the name of dimension is a word with a common meaning, then raters may be guided away from an intended direction in meaning space. For example, the word ‘arousal’ is itself high on arousal ($A = 0.44$) but also registers on the valence and dominance dimensions $V = 0.29, D = 0.23$. And while the word ‘dominance’ scores strongly in dominance and neutrally for valence, it does pick up in the arousal dimension with $(V, A, D) = (0.04, 0.28, 0.34)$. By contrast, ‘valence’ is sufficiently rare—it is not part of the NRC VAD lexicon—that it does not color how it is defined for the measurement of emotion. We are of course not suggesting that there is a simple solution to such onsiometric nomenclature issues—we are after all using words to define words as well as kinds of meanings of words. We discuss related mismatches between common and onsiometric meaning later in Sec. III F in the context of what we will call synousionyms and antousionyms.

While we have critiqued how end-point descriptors have been used, we are not saying such an approach is invalid. Rather, we point out that: 1. The EPA dimensions were originally outputs of relatively small studies involving numerous semantic differentials, and 2. The attempt to then make these dimensions controlled inputs to new studies is an entirely different exercise.

In sum, the NRC VAD lexicon, the output of Ref. [14]’s study, does not align with the VAD framework, even though the VAD framework was the intended input.

To move forward, we observe that for any essence-of-meaning study, if participants are guided by some well constructed set of end-point descriptors, then we can always compare and re-consider how well these descriptors perform. Moreover, we must allow that a distinct framework may emerge over time as far larger and more sophisticated studies are carried out. We are effectively maintaining the approach of the founding experiments, allowing the outcomes to remain informative and be potentially corrective.

C. Assessing the failure of the Valence-Arousal-Dominance (VAD) framework

In the present and following two sections, we show how the NRC VAD lexicon affords two possible alternate frameworks: Goodness-Energy-Structure (GES) and Power-Danger-Structure (PDS). The steps of our analysis are represented by the rows of Fig. 2, which we explain as follows.

We first note that for the NRC VAD lexicon, the overall contributions to variance explained by the three VAD dimensions of meaning are approximately 44.4%, 28.0%, and 27.6%. Valence is clearly the leading dimension with arousal and dominance balanced.

To determine the uncorrelated orthogonal dimensions for the NRC VAD lexicon, we perform singular value decomposition (SVD) on the 3 by 20,006 matrix $A$ of average VAD scores ($A = \text{UΣV}^T$). We find singular values $\sigma_1 \simeq 34.1, \sigma_2 \simeq 27.2$, and $\sigma_3 \simeq 13.8$, which correspond to explained variances of 55.6%, 35.3%, and 9.1%. The first two dimensions now explain 90.9% as opposed to 72.4% explained by $V$ and $A$. 
FIG. 2. Ousiograms showing the analytic sequence moving from the valence-arousal-dominance (VAD) framework (top row) to the goodness-energy-structure (GES) and power-danger-structure (PDS) frameworks (second and third rows). Row 1, panels A, B, and C: Ousiograms for the three pairs of variables V, A, and D for ∼20,000 words in the VAD NRC lexicon [14] (panel B corresponds to Fig. 1). We determine the ellipses by using singular value decomposition (SVD) in each plane, ignoring the third dimension. The ill fit of the VAD framework is apparent for the misalignments of ellipse axes. Row 2, panels D, E, and F: We perform SVD on the full matrix formed by the V, A, and D scores, and identify goodness G, energy E, and structure S, with the first two dimensions accounting for over 90% of explained variance Row 3, panels G, H, and I: Rotating the goodness-energy plane by +π/4, we uncover a framework with {powerful ⇔ weak} and {dangerous ⇔ safe} as dimensions of equal explanatory strength (panel G). See Fig. 3 for a larger, more detailed power-danger ousiogram. As any lexicon reflects only the possible but not the used language (types versus tokens), whether or not the VAD, GES, or PDS frameworks are sensible must be tested by considering real corpora. See Sec. III C and Eqs. 2 and 4 for interpretation of the VAD, GES, and PDS relationships. Word annotations along the edges of the nine pairwise distributions are vital to our understanding of how well the frameworks perform.
The point cloud of VAD scores is thus a non-axis-aligned ellipsoid, strongly flattened in one dimension. In Fig. 2, the first row of ousiograms show projected histograms of the ellipsoid in VAD space for each pair of dimensions (Fig. 2B corresponds to Fig. 1). The SVD ellipses in all three projections demonstrate the correlations in Eq. (1) above.

As for all ousiograms, the word annotations help us understand how raters have responded to the end-point descriptors. Here, these annotations may be diagnostic (VAD) or illuminating (GES and PDS, below). For VAD, we have already considered V-D ousiogram’s annotation (Fig. 2B), finding them to be sensible, and we see that annotations for the other dimension pairs are similarly interpretable within the VAD framework (Figs. 2A and C).

D. The Goodness-Energy-Structure (GES) framework

Moving to the the middle row of panels (Figs. 2D–F), we show ousiograms for word scores represented by the orthogonal basis determined by SVD acting on the VAD word scores. By construction, all three SVD ellipses are now aligned with the underlying axes.

Upon considering the annotated words, we interpret these three new essence-of-meaning dimensions to be goodness $G$, energy $E$, and structure $S$. (For annotations internal to each histogram, see the larger ousiograms in Anciliary files.)

To arrive at the goodness dimension, we look to words on the left and right side of the ousiogram in Fig. 2D. On the left, we see ‘shitty’, ‘penniless’, ‘mistreated’, and ‘abused’; and on the right, ‘reliable’, ‘confidence’, ‘freedom’, and ‘triumphant’.

Words at the bottom and top of the same ousiogram in Fig. 2D are connected in essential meaning by their signifying of low and high energy: ‘slow’, ‘couch’, ‘siesta’, and ‘calm’, versus ‘assassinate’, ‘battle’, ‘competitor’, and ‘conquer’.

Finally, we distill the vertical dimension in the ousiograms of Figs. 2E and 2F as structure. We choose the alignment of the third dimension to be {structured ⇔ unstructured}, moving upwards. At the bottom of these ousiograms, we have words connoting organization, rigidity, and systematic form: ‘stone’, ‘protocol’, ‘corporation’, ‘dictator’, and ‘diplomat’. At the top, we see terms that convey lack of structure: ‘jest’, ‘confetti’, ‘dancing’, ‘popcorn’, and ‘great surprise’. To support the choice of orientation for the structure axis, we make a thermodynamic analogy where rigid organization is akin to a zero temperature frozen state, and a growing lack of structure corresponds to increasing temperature. We also see that {serious ⇔ playful} and {predictable ⇔ unpredictable} differentials are subsets of the more general {structured ⇔ unstructured} differential.

For purposes of clarity of argument, we have sought to choose valid but distinct names for the three dimensions in GES to distinguish them from VAD (or EPA). We acknowledge that valence, evaluation, and goodness are conceptually similar as are activity, arousal, and energy. And as we discuss below, in the realm of emotion, valence is analogous to a {happiness ⇔ sadness} dimension [38].

The linear transformation between VAD and GES obtained from SVD is:

\[
\begin{bmatrix}
\text{Goodness} \\
\text{Energy} \\
\text{Structure}
\end{bmatrix} \approx
\begin{bmatrix}
+0.86 & -0.15 & +0.48 \\
-0.16 & +0.83 & +0.54 \\
+0.48 & +0.55 & -0.69
\end{bmatrix}
\begin{bmatrix}
\text{Valence} \\
\text{Arousal} \\
\text{Dominance}
\end{bmatrix}
\]

In moving to the GES framework, we have goodness most connected with valence (+0.86) and dominance (+0.48), with a minor negative linkage to arousal (-0.15). Energy is most connected with arousal (0.83) and also, like goodness, with dominance (0.54), but is at somewhat at odds with valence (-0.16). And what we have identified as an increasing lack of structure corresponds roughly equally to increases in valence and arousal (+0.48 and +0.55) while increasing dominance points in the direction of more structure (-0.69).

We can now see that what separates the GES framework from the VAD framework (or EPA framework) is that the dominance (or potency) dimension lies within the goodness-energy plane. That is, the three conceptual dimensions of VAD are in fact collapsed into the two dimensions of goodness and energy, with a new third and less important dimension of structure being revealed.

When dominance is near zero, Eq. (2) shows that goodness and energy approximate valence and arousal. However, the correlations between valence and dominance as well as arousal and dominance mean that dominance increasing in magnitude will move goodness-energy away from valence-arousal. Later, for our prototype ousiometer in Sec. IV, we will see for time series that if dominance is sufficiently flat, then the time series for goodness and energy (and power and danger) will track those of valence and arousal.

Returning to the ousiogram in Fig. 2D, we see that the four intercardinal axes carry distinguishable essential
meanings, interpolating between the \{good ⇔ bad\} and \{high-energy ⇔ low-energy\} axes.

The diagonal axis running from ‘weak’ and ‘empty’ to ‘success’ and ‘triumphant’ is a \{powerful ⇔ weak\} axis, while the orthogonal diagonal axis traveling from ‘calmness’ and ‘peace’ to ‘murderer’ and ‘homicide’ is, we argue, a \{dangerous ⇔ safe\} axis.

E. The Power-Danger-Structure (PDS) framework

We are drawn to consider making \{powerful ⇔ weak\} and \{dangerous ⇔ safe\} as the prime essence-of-meaning axes, which we achieve in the third row of ousiograms in Fig. 2 by a simple clockwise rotation of the G-E plane by π/4. We call this rotation of the GES framework the Power-Danger-Structure (PDS) framework. Expressed as a simple linear transformations, we have:

\[
\begin{bmatrix}
\text{Power} \\
\text{Danger}
\end{bmatrix} = \frac{1}{\sqrt{2}} \begin{bmatrix} 1 & 1 \\ -1 & 1 \end{bmatrix} \begin{bmatrix}
\text{Goodness} \\
\text{Energy}
\end{bmatrix}.
\]

We supply a more detailed power-danger ousiogram in Fig. 3. When later considering large-scale corpora, we will see that the PDS framework rather than GES conforms to real word usage, but we first must explore its characteristics for the unamplified NRC VAD lexicon.

In the PDS framework, the variance explained is now evenly divided between power and danger (45.5% each) while structure’s contribution remains the same. We indicate this balance of power and danger by the dashed circles in Fig. 2G and Fig. 3.

The rotated and internal annotations in the power-danger ousiogram in Fig. 3 are now in line with our interpretation of the two axes being \{powerful ⇔ weak\} and \{dangerous ⇔ safe\}. The horizontal axis, for example, now runs from ‘void’, ‘nothingness’, and ‘empty’ to ‘powerful’, ‘success’, and ‘almighty’. We find high danger in ‘earthquake’, ‘suicidebombing’, and ‘toxic’, and safety in ‘serenity’, ‘softness’, and ‘tranquil’.

As for the valence-dominance ousiogram in Fig. 1, traveling around the boundary of the power-danger ousiogram loops us through an ousiometrically sensible sequence of terms. Moving upwards and around from ‘triumphant’, words take on increasingly violent connotations, while moving down, success begins to ebb while peaceful aspects build. In the power-danger framework, the four quadrants have clear character as they represent the goodness-energy axes including the desirable safe-powerful (bottom right, goodness, e.g., ‘wisdom’ and ‘generous’), and the to-be-avoided weak-dangerous (upper left, e.g., ‘deceased’ and ‘bankruptcy’).

Combining SVD and the π/4 rotation, we have the linear transformation connecting the VAD and PDS frameworks:

\[
\begin{bmatrix}
\text{Power} \\
\text{Danger} \\
\text{Structure}
\end{bmatrix} \approx \begin{bmatrix} +0.50 & +0.48 & +0.72 \\ -0.72 & +0.69 & +0.04 \\ +0.48 & +0.55 & -0.69 \end{bmatrix} \begin{bmatrix}
\text{Valence} \\
\text{Arousal} \\
\text{Dominance}
\end{bmatrix}.
\]

We see that power is roughly a direct sum of valence, arousal, and dominance (+0.50, +0.48, and +0.72). Danger is a near equally weighted linear combination of negative valence and positive arousal (-0.72 and +0.69), and has little connection to dominance (+0.04). Structure’s connection to VAD remains the same.

We have thus determined that the VAD framework was effectively interpreted as strongly correlated by participants in the NRC VAD lexicon study of Ref. [14]. We have extracted two alternate and mutually interpretable orthogonal frameworks of GES and PDS. Our next major step is to test these frameworks on real corpora. Before doing so, we introduce and discuss synousionyms and antousionyms in the context of all three frameworks.

F. Synousionyms and antousionyms, and the problems with prescribing ousiometric axes through end-point descriptors

Which words and terms match in terms of essence of meaning? We define synousionym and antousionym as the ousiometric equivalents of synonym and antonym.

To determine a word’s synousionyms, we find the words closest in PDS-space (the specific framework does not matter). For antousionyms, we find words closest to the negated point in PDS-space, \((-P, -D, -S)\).

Distilling words to their essential meaning may affect synonym and antonym pairs in opposite ways. Words that are not synonyms may be synousionyms, while words that are antonyms may not be antousionyms.

For example, the word ‘failure’, \((P, D, S) = (-0.39, 0.28, 0.13)\), is not the antousionym of ‘success’, \((P, D, S) = (0.76, -0.05, 0.09)\). Within the NRC VAD lexicon, the closest antousionym for ‘success’ is ‘empty’, \((P, D, S) = (-0.61, -0.01, -0.03)\). In Tab. II, we show the closest four synousionyms as well as five antousionyms for the words ‘wisdom’, ‘success’, ‘volcanic’, and ‘homicide’. These words are examples of four extreme points of the power-danger ousiogram: safe-powerful, powerful, dangerous-powerful, and dangerous.
In Sec. III B, we noted that choosing names of ousiometric dimensions may be problematic, going beyond the issues of end-point descriptors. For one example, the word ‘goodness’ has the following VAD, GES, and PDS scores: (0.47, -0.18, 0.21), (0.54, -0.11, -0.02), and (0.30, -0.45, -0.02). We see that ‘goodness’ has a non-neutral low energy component and is not purely aligned with the Goodness axis. The five closest synousionyms of ‘goodness’ are ‘thankful’, ‘friendship’, ‘motherly’, ‘hope’, and ‘graciously’ while the five top antousionyms of ‘goodness’ are ‘frustrating’, ‘cadaver’, ‘displease’, ‘shameful’, and ‘disrespectful’. The antonym ‘badness’ is not a close antousionym of ‘goodness’ with VAD, GES, and PDS scores of (-0.406, 0.323, -0.037), (-0.417, 0.311, 0.008), and (-0.075, 0.515, 0.008). Within the PDS framework, while ‘badness’ is aligned with the danger axis, ‘goodness’ is in the safe-powerful quadrant. Some close synousionyms for ‘badness’ are ‘rabid’, ‘shatter’, and ‘tremor’ and for antousionyms, we find ‘comfortable’, ‘homestead’, and ‘peacetime’.

A further complication for determining end-point descriptors is that due to the asymmetric, point coverage of essential meaning space, the closest antousionym may not be reflexive. For example, ‘chaos’ has PDS scores (-0.13, 0.67, 0.09). The closest antousionym for ‘chaos’ is ‘angel’ (0.19, -0.52, -0.13) whose closest antousionym is ‘shattered’ (-0.19, 0.49, 0.11).

These observations again point to the difficulties of prescribing dimensions for participants in surveys. The solution is to see end-point descriptors as guides only and to always examine how participants responded using SVD.

For the PDS framework, ‘powerful’ and ‘dangerous’ align well with the end-points of their respective axes with PDS scores of (0.70, -0.02, 0.02) and (0.09, 0.66, 0.10). The word ‘weak’ similarly aligns well with the negative power axis with PDS scores of (-0.61, 0.03, 0.02). And ‘powerful’ and ‘weak’ are both antonyms and close antousionyms of each other.
### Powerful-Safe (Good) to Weak-Dangerous (Bad) axis:

| Synousionyms | Valence | Arousal | Dominance | Goodness | Energy | Structure | Power | Danger | Structure |
|--------------|---------|---------|-----------|----------|--------|-----------|-------|--------|-----------|
| Anchor: wisdom | 0.430  | -0.198  | 0.371     | 0.579    | -0.031 | -0.158    | 0.388 | -0.432 | -0.158    |
| education     | 0.396  | -0.225  | 0.340     | 0.539    | -0.065 | -0.167    | 0.336 | -0.427 | -0.167    |
| healthy       | 0.438  | -0.181  | 0.318     | 0.558    | -0.047 | -0.108    | 0.362 | -0.428 | -0.108    |
| trustworthy   | 0.469  | -0.185  | 0.324     | 0.589    | -0.052 | -0.100    | 0.379 | -0.453 | -0.100    |
| reliable      | 0.412  | -0.259  | 0.375     | 0.575    | -0.076 | -0.202    | 0.353 | -0.460 | -0.202    |

### Powerful to Weak axis:

| Synousionyms | Valence | Arousal | Dominance | Goodness | Energy | Structure | Power | Danger | Structure |
|--------------|---------|---------|-----------|----------|--------|-----------|-------|--------|-----------|
| Anchor: success | 0.459  | 0.380  | 0.481     | 0.571    | 0.501  | 0.095     | 0.758 | -0.050 | 0.095    |
| almighty     | 0.438  | 0.374  | 0.458     | 0.543    | 0.487  | 0.098     | 0.728 | -0.040 | 0.098    |
| triumphant   | 0.449  | 0.337  | 0.472     | 0.565    | 0.462  | 0.073     | 0.726 | -0.072 | 0.073    |
| champion     | 0.390  | 0.380  | 0.445     | 0.494    | 0.492  | 0.087     | 0.698 | -0.001 | 0.087    |
| victorious    | 0.384  | 0.386  | 0.446     | 0.489    | 0.499  | 0.087     | 0.698 | 0.007  | 0.087    |

### Dangerous-Powerful (High Energy) to Safe-Weak (Low Energy) axis:

| Synousionyms | Valence | Arousal | Dominance | Goodness | Energy | Structure | Power | Danger | Structure |
|--------------|---------|---------|-----------|----------|--------|-----------|-------|--------|-----------|
| Anchor: volcanic | -0.156 | 0.410  | 0.281     | -0.061  | 0.515  | -0.045    | 0.322 | 0.407  | -0.045    |
| shell        | -0.163 | 0.417  | 0.273     | -0.072  | 0.518  | -0.039    | 0.316 | 0.417  | -0.039    |
| artillery     | -0.150 | 0.412  | 0.294     | -0.050  | 0.523  | -0.050    | 0.335 | 0.405  | -0.050    |
| wild         | -0.188 | 0.422  | 0.250     | -0.105  | 0.514  | -0.032    | 0.289 | 0.438  | -0.032    |
| rifles        | -0.163 | 0.364  | 0.265     | -0.068  | 0.470  | -0.062    | 0.284 | 0.380  | -0.062    |

### Dangerous to Safe axis:

| Synousionyms | Valence | Arousal | Dominance | Goodness | Energy | Structure | Power | Danger | Structure |
|--------------|---------|---------|-----------|----------|--------|-----------|-------|--------|-----------|
| Anchor: homicide | -0.490 | 0.473  | 0.018     | -0.485  | 0.478  | 0.011     | -0.005| 0.681  | 0.011     |
| killer        | -0.459 | 0.471  | 0.043     | -0.446  | 0.485  | 0.008     | 0.028 | 0.658  | 0.008     |
| psychopath    | -0.460 | 0.443  | 0.036     | -0.446  | 0.458  | -0.003    | 0.009 | 0.640  | -0.003    |
| bloodshed     | -0.452 | 0.442  | 0.025     | -0.444  | 0.450  | 0.008     | 0.004 | 0.633  | 0.008     |
| violate       | -0.439 | 0.470  | 0.019     | -0.440  | 0.468  | 0.033     | 0.020 | 0.642  | 0.033     |

### Table II.

Example synousionyms and antousionyms for the four axes of the GES and PDS frameworks using four anchor words of ‘wisdom’, ‘success’, ‘volcanic’, and ‘homicide’, and with scores in the three frameworks of VAD, GES, and PDS. See the linear transformations of Eq. (2) and Eq. (4) for how VAD connects with GES and PDS.
The descriptor ‘safe’ does not perform as cleanly however, as it connotes more-than-neutral power with PDS scores of \((0.29, -0.41, -0.09)\). Antousionyms for ‘dangerous’ are ‘relaxed’, ‘softness’, ‘calming’, ‘relaxant’, and ‘calmness’. (The closest antousionym for ‘safe’ is ‘seasick’.) Nevertheless, we feel ‘safe’ functions well conceptually as an end-point descriptor as it is an easily reached antonym of ‘dangerous’, if not also an antousionym.

We note that in developing our work, we entertained a number of alternative names for the PDS framework including Success, Stress, and Structure, and Power, Peril, and Play. Ultimately, both of these choices are limited as truly general ousiometric frameworks with success and play in particular eliciting people-centric themes. And in any case, while alliteration may appeal to some, the confusion of variables starting with the same letter would be problematic.

The full space of synousionyms and antousionyms can be explored using VAD, GES, and PDS scores for all words and terms in the Ancillary files.

G. The linguistic ‘safety bias’ of disparate large-scale, corpora

Having established the GES and PDS frameworks as alternatives to VAD, we turn to real, large-scale corpora. By intent, we have so far only considered the essential meaning of words and terms in the NRC VAD lexicon—the level of types.

We now aim to incorporate frequency of usage of words—tokens—for a collection of well-defined corpora. We can only do so sensibly within each structured corpus—we cannot meaningfully combine, for example, the New York Times and Twitter.

For an initial example corpus, we investigate the ousiometric content of 1-grams used in English fiction from 1900–2020 per the Google Books project [27]. We note that we have earlier argued and demonstrated that the Google Books project generates problematic corpora in that 1. Each book is in principle counted once (popularity is not measured) and that 2. For all English books combined, the corpus is clouded by a growing preponderance of scientific literature [28]. To use the framing of types and tokens for the former point, the books are themselves types, containing \(n\)-grams as tokens, but we do not have the books as tokens by knowing, for example, numbers of copies sold. Nevertheless, for our purposes here, the relatively-science-free 2019 English fiction corpus provides a raw large-scale body of text to examine.

We generate ousiograms in the same fashion as before, but we now weight words by their frequency of usage. The NRC VAD lexicon acts as a lexical lens on the Zipf distribution—we only take word counts for those words we have VAD/GES/PDS scores for. In Fig. 4, we reprise the analytic sequence of Fig. 2 for words used in English fiction.

Whereas for the NRC VAD lexicon, the histograms were relatively uniform, we now see uneven distributions. For the VAD row, we see the distributions are not aligned with the underlying axes of the VAD framework (Figs. 4A–C). The distributions show better alignment with the SVD ellipses which takes us to the middle row of the GES framework. The main ousiogram for goodness-energy (Fig. 4D) still does not align well, showing an off-axis bias towards goodness and low energy, the former being a linguistic signature of the Pollyanna principle [22, 25, 39]. We discuss both biases further below. The goodness-structure and energy-structure ousiograms (Figs. 4E and F) show biases towards goodness and low energy that appear more aligned.

It is in the PDS framework (Figs. 4G–I), that we see robust agreement between ousiograms and the underlying axes. In the main power-danger ousiogram (Fig. 4G), the histogram shows a definitive bias towards safe, low-danger words. As shown by the marginal on the left axis, the danger distribution is skewed strongly towards safer words, and the median danger score is well below 0. By contrast, power presents a symmetric marginal distribution with a median slightly above 0. The power-structure ousiogram shows a general spread (Fig. 4H) while the danger-structure ousiogram again shows a clear safety bias (Fig. 4I).

In Fig. 5, we expand our analysis to show power-danger ousiograms for six more corpora: The novels of Jane Austen, a subset of Arthur Conan Doyle’s Sherlock Holmes stories, the New York Times, Wikipedia, transcriptions of talk radio in the US, and Twitter (see Sec. II for details). These corpora vary widely in size and kind: written versus spoken, news, literature, formal and informal, bearing social amplification or not (e.g., the inclusion of retweets from Twitter encodes one form of echoing, but the other corpora carry no such equivalent signature of popularity). For each corpus, we provide the full analytic sequence in the manner of Figs. 2 and 4 in Figs. A1–A6.

The power-danger ousiograms for these six distinct corpora in Fig. 5 all present the same safety bias for words as we saw for English fiction in Fig. 4G. While varying in detail as they must, the six histograms in Fig. 5 all show a weight toward words below the horizontal \(\{\text{powerful} \leftrightarrow \text{weak}\}\) axis, and the danger marginals on the left axes of all ousiograms are skewed.
FIG. 4. Ousiograms for English fiction (1900–2019) arranged in the same analytic sequence format as Fig. 2. We now allow each word’s contribution to be its overall frequency of usage within a given corpus. We form a single Zipf distribution [33] for the entire corpus by equally weighting each year’s Zipf distribution [27, 28]. The sequence indicates that: 1. Overall, the Google Books English fiction corpus is best aligned with the PDS framework, and that 2. Expressed language exhibits a ‘safety bias’, a generalization of the Pollyanna principle [22, 25, 39]. The ellipses are derived from the underlying lexicon as before, matching those in Fig. 2. **Row 1, panels A, B, and C:** In the VAD framework, the histograms are clearly misaligned with the main axes. We see the SVD ellipses for $V^{-A}$ and $A^{-D}$ show better fits (panels A and C) but not so for $V^{-D}$ (panel B). **Row 2, panels D, E, and F:** The histograms are again poorly aligned with the main axes of $G$, $E$, and $S$. The marginal distributions for Goodness and Energy in panel D show an apparent ‘goodness bias’ and a ‘low-energy bias’. The goodness bias is an imprint of the the Pollyanna principle for language [22, 25]. **Row 3, panels G, H, and I:** Rotation to the power-danger framework shows that words used in English fiction conform to a safety bias with the preponderance of words falling on the safe side of the power-danger plane (panel G). Both the goodness and energy biases in panel D are revealed to be one dimensional projections of an underlying safety bias. Words are distributed broadly in the power-structure plane (panel H) and are on the safe side of the danger-structure plane (panel I).
FIG. 5. Ousiograms for power-danger space for six corpora of varying type and scale: A. Jane Austen’s novels; B. Arthur Conan Doyle’s Sherlock Holmes novels and short stories; C. The New York Times (1987–2007) [29]; D. Wikipedia (March, 2019) [30]; E. Talk radio transcripts (2018/10–2019/03) [31]; and F. Twitter (approximately 10% of all English tweets in 2020, with each day weighted equally) [32, 40]. Words of the six corpora all strongly canvass power-danger space with a marked bias towards safe. Jane Austen’s novels, the New York Times, and Wikipedia are all author-side corpora in that their Zipf distributions do not incorporate popularity of books, sections, or entries. By contrast, Twitter incorporates a reader-side measure of popularity through amplification by retweets. Each ousiogram’s color map is linearly normalized to the highest count bin, and the maximum bin count is indicated at the top of each color bar. The highest count bin in panels A, C, and F is due to the word ‘be’ ($P=-0.001, D=-0.300$). See Sec. II for description of data sets. For the six corpora here, we provide the full VAD-GES-PDS analytic sequence of Figs. 2 and 4 in Figs. A1, A2, A3, A4, A5, and A6.
toward safety. There is no such bias for the power dimension, though median power is at or above zero in all cases.

We emphasize again that our initial determination of the PDS framework was performed only at the level of types, using the NRC VAD lexicon. In these subsequent tests with real corpora, we have found that our hypothesized osiometric PDS framework has been borne out to be fundamental.

H. Revisiting the circumplex model of emotion

We consider Russell’s circumplex model of affect [8], in light of the power-danger framework. We find partial accordance with the main region of disagreement being the dangerous-powerful quadrant leading to two major observations: 1. Negative emotions cannot be adequately represented in a two dimensional framework; and 2. The circumplex model is a map of general states of being, not just emotional states.

Affective states are representations of emotional states, and may be external (e.g., facial expressions) or internal (conscious awareness). In linking to essential meaning, in 1952, Schlosberg [41] was one of the first to suggest that emotion—as conveyed by facial expressions—could be well represented by two dimensions, with the dimensions being \{pleasantness ⇔ unpleasantness\} and \{attention ⇔ rejection\}. Two years later, Schlosberg then posited a third dimension of level of activation while also asserting that “the field [of emotion] is chaotic” [42]. Certain emotions would seem to readily connect with locations in the power-danger framework. Fear is a particular response to danger, contentment is likely to interpret words and phrases by their most general, dominant meaning. While many of the affect words have clear meanings that are emotional (e.g., ‘miserable’), the word ‘tense’ might not be as strongly construed as ‘stressed’. Over four decades, we might also expect meanings of some words to shift somewhat.

Russell then carried out a series of varying types of surveys on perceptions of 28 affect terms (e.g., ‘afraid’, ‘glad’, ‘serene’, ‘bored’). In Fig. 6A, we show the locations of 27 words according to the results presented in Fig. 2 of Ref. [8] (we exclude the 2-gram ‘at ease’). In Fig. 6B, we show the same words located by their power-danger scores.

In general, we see that words in the circumplex and power-danger frameworks are reasonably well aligned. A number of words show strong congruence across the two studies, including ‘sleepy’, ‘excited’, ‘aroused’, and ‘miserable’. Angles of affect words are generally similar with a maximum discrepancy of around π/4. For example, ‘tired’ is in the direction of safe-weak in the circumplex model and weak in the power-danger framework (‘sleepy’ remains safe-weak in both, and the added hue of danger for ‘tired’ in the power-danger framework is sensible). Apart from ‘tense’ and to a lesser extent ‘astonished’ and ‘droopy’, affect words register strong power-danger magnitudes, and are consequently located around an approximate circle.

The word that most stands out as differing between the two studies is ‘tense’. On top of the major distinctions between the studies listed above, without the context of working with a small set of emotion-themed words, participants in the NRC VAD study would be more likely to interpret words and phrases by their most general, dominant meaning. While many of the affect words have clear meanings that are emotional (e.g., ‘miserable’), the word ‘tense’ might not be as strongly construed as ‘stressed’. Over four decades, we might also expect meanings of some words to shift somewhat. And in any case, the four surveys in Russell only show rough agreement with each other (see Figs. 2–5 in Ref. [8]).

We move on to what we believe are major issues with the circumplex model. Of the eight affect concepts proposed by Russell, our analyses suggest that the non-safe points warrant reconsideration: 1. The dimension of ‘distress’ collapses together disparate negative emotional states such as fear, disgust, and anger; 2. The dimension of ‘arousal’ is better interpreted as ‘dominance’; and 3. The axis of \{depression ⇔ excitement\} is better interpreted as...
FIG. 6. Comparison of Russell’s circumplex model of affect [8] with the power-danger framework. The two frameworks show fair agreement given how differently words were scored in Refs. [8] and [14]. In the main text, we argue that the affect concepts of the circumplex model are better interpreted as states-of-being concepts, and that depression, arousal, and excitement may be revised as boredom, dominance, and success (see Sec. III H).

A. Reconstruction of the circumplex model scores for 27 affect words for the first survey presented in Fig. 2 in Ref. [8]. We obtained data for 27 of 28 terms by visual inspection of Fig. 2 in [8], omitting the 2-gram ‘at ease’. To enable comparison, we rotate Russell’s scores by $-\pi/4$, and also underlie both plots with the power-danger histogram per Fig. 3. Leaving angles unchanged, we uniformly rescale the magnitude of scores for the 27 affect words in the circumplex model to give an approximate fit to the power-danger scale—only angles and relative magnitudes may be sensibly compared.

B. Power-danger scores for the 27 affect words of Ref. [8], all of which are also found in the NRC VAD lexicon. {boredom $\leftrightarrow$ success}. We discuss these three issues in turn.

We look at the broad category word ‘distress’ as well as specific, danger-related negative emotions of anger, disgust, and fear.

In the power-danger framework, the affect word ‘distressed’ is rotated around into the weak-dangerous quadrant, $(P,D) = (-0.18, 0.44)$. Adjacent words are ‘migraine’, ‘ache’, ‘betrayed’, which all dangerous but also indicating weakness.

However, the affect concept most directly aligned with danger would be anger with ‘angry’ at $(P,D) = (0.04, 0.51)$. Similar behavioral words pointing in the direction of danger are ‘rage’, ‘threatening’, ‘menacing’, ‘fury’, and ‘abusive’. The base word ‘anger’ is rotated around slightly into the dangerous-powerful quadrant $(P,D) = (0.12, 0.50)$ (Fig. 3).

In contrast to anger, fear and disgust are negative emotional responses to danger. In the power-danger framework, the words ‘fear’ and ‘disgust’ are indistinguishable with $(P,D) = (-0.20, 0.53)$ and $(-0.22, 0.51)$.

We therefore have that distinct negative emotional states collapse onto or near each other in the distress dimension. Consequently, higher orders of meaning are required to separate out the negative emotions which are more numerous and varied than positive emotions (reminiscent of the Anna Karenina Principle [46]).

Second, we argue that the affect concept ‘arousal’ fails to connote danger. Similarly, high energy in our goodness-energy framework does not sufficiently imply ‘dangerous-powerful’.

The affect word ‘aroused’ is closer to the power dimension with $(P,D) = (0.44, 0.17)$. The main synonims of ‘aroused’ are ‘euphoria’, ‘sexuality’, ‘erotic’, and ‘emotion’, indicating we are off track. We also see that in the power-danger framework, Fig. 6B, the dangerous-powerful direction is the least populated by affect words.

If we were to at least stay with the high energy framing,
then a better, if muted word, and one with relatively equal scores for power and danger, would be ‘alert’, 
\((P,D) = (0.25, 0.24)\). However, we feel that capturing the
danger dimension is necessary, and adjacent
descriptors provided by the NRC VAD lexicon are
‘warlike’, \((P,D) = (0.30, 0.35)\); ‘combative’, \((P,D) =
(0.26, 0.23)\); ‘overbearing’ \((P,D) = (0.33, 0.37)\); and
‘dominant’, \((P,D) = (0.41, 0.33)\). The word ‘political’ is
nearby too with \((P,D) = (0.30, 0.29)\).

We will offer ‘dominance’ for the dangerous-powerful
state of being (and not affect). Etymologically,
dominance and danger are linked as they trace back to
the Latin dominus (lord) and domus (house).
Dominance is also consistent with the collapsed VAD
framework, and is sensible upon further consideration of
the power-danger ousiogram for the full NRC VAD
lexicon in Fig. 3.

In moving back out to general essential meaning,
dominance’ loses applicability as it indicates the
presence of agency. While it is true that we do use the
word dominant to describe entities without agency
dominant eigenvalue, dominant virus strain), there are
limits. For example, words relating to natural disasters
like volcanos and hurricanes are in the
dangerous-powerful quadrant. Indeed, rather than
dominant, we may metaphorically use the word
‘volcanic’ to signify a dangerous-powerful state.

As was our choice for Fig. 3, we thus maintain our
preference for describing intercardinal points in the
power-danger framework in the manner of a compass by
combining descriptors.

Finally, we revisit the ‘excitement’ dimension and its
alignment with power. Beyond power, the word
‘excitement’ conveys some degree of safety with \((P,D) =
(0.45, -0.15)\). Words nearby include ‘socialized’,
‘popular’, and ‘commend’.

Words that are better aligned with the power axis are
‘success’, ‘triumphant’, ‘champion’, ‘powerful’,
‘victorious’, ‘hero’, and ‘winner’.

To describe the power-aligned state of being, we choose
‘success’ for which \((P,D) = (0.73, -0.04)\). Success fits
well with dominance, which we can now view as
‘winning dangerously.’

The main antousionyms for ‘success’ are not ‘failure’ or
‘depression’ both of which bend towards danger, but
rather words like ‘void’, ‘idle’, ‘sorrow’, ‘weak’, ‘sloth’,
and ‘boring’ for which \((P,D) = (-0.56, 0.01)\).

We suggest ‘boredom’ instead of ‘depression’ to be the
descr {neutral ⇔ weak} (true) neutral neutral-powerful
safety-neutral safe-powerful
TABLE III. The ousiometric alignment chart for the power-danger framework.

I. Alignment charts

Developed for the role-playing game Dungeons &
Dragons (D&D), the standard alignment chart pairs
two semantic differentials of character: \{good ⇔ evil\} and \{lawful ⇔ chaotic\}. Using coarse, three point scales
good-neutral-evil and lawful-neutral-chaotic,
characters may behave according to one of nine (3×3)
combinations.

The D&D alignment chart has been used for character
definitions across other storytelling spaces, and has
been studied within the context of the Big Five
personality traits [47]. The D&D alignment chart has
also been generalized beyond characters into an online
meme form, functioning as a kind of ousiometric
assessment of everything. Reddit has a subreddit for
Alignment Charts [48], and the \{good ⇔ evil\} and
\{lawful ⇔ chaotic\} framework has been applied to, for
example, map projections [49], modes of transport [50],
bookmarks [51], and alignment charts themselves [52].

Because of the compass-like nature of the power-danger
plane, we have already generated a power-danger
alignment chart, which we show in Tab. III.

We consider how a good-evil \{good ⇔ evil\} and
\{lawful ⇔ chaotic\} framework might fit within the PDS
framework. If we interpret \{lawful ⇔ chaotic\}, as a
differential between rule-following and rule-breaking,
between predictable and unpredictable, then we have a
rough map to the structure dimension, \(S\). As we might
expect given Sec. V H, the \{good ⇔ evil\} differential is
not a simple antousionym in the \(P-D\) plane, but rather
runs from powerful-safe to neutral to dangerous. Both
extremes of \{good ⇔ evil\} could also be shaded toward
more or less power. Thus, the D&D alignment chart
can be plausibly located as a folded plane within the
PDS framework. We would, for example, view

\[
\begin{vmatrix}
\text{dangerous-weak} & \text{dangerous-neutral} & \text{dangerous-powerful} \\
\text{neutral ⇔ weak} & (\text{true}) \text{ neutral} & \text{neutral-powerful} \\
\text{safe-weak} & \text{safe-neutral} & \text{safe-powerful} \\
\end{vmatrix}
\]
| lawful-good               | neutral-good               | chaotic-good               |
|--------------------------|---------------------------|---------------------------|
| ~                        | ~                         | ~                         |
| structured-powerful-safe | neutral-powerful-safe      | unstructured-powerful-safe |

| lawful-neutral           | (true) neutral            | chaotic-neutral           |
|--------------------------|---------------------------|----------------------------|
| ~                        | ~                         | ~                         |
| structured-neutral       |                           | unstructured-neutral      |

| lawful-evil              | neutral-evil              | chaotic-evil              |
|--------------------------|---------------------------|----------------------------|
| ~                        | ~                         | ~                         |
| structured-dangerous     | neutral-dangerous         | unstructured-dangerous    |

TABLE IV. Postulated alignment of the D&D alignment chart within the more general PDS framework.

chaotic-evil as unstructured-dangerous.

However, the PDS scores for the D&D alignment chart endpoint descriptors are not self-consistent with a {structured ⇔ unstructured} versus {dangerous ⇔ good} framing. We have ‘good’ located at 
\( (P, D, S) = (0.18, -0.41, 0.11) \), and ‘evil’ at 
\( (-0.04, 0.56, -0.07) \) indicating that ‘good’ alone carries some measure of playfulness and ‘evil’ some rigidity. For ‘lawful’ and ‘chaotic’, we have 
\( (P, D, S) = (0.23, -0.18, -0.17) \) and 
\( (-0.07, 0.52, 0.05) \). We see ‘lawful’ and ‘chaotic’ are not far from ‘good’ and ‘evil’, but their structure scores are flipped. In sum, ‘good’ and ‘lawful’ are safe-powerful, and ‘evil’ and ‘chaotic’ are dangerous, with the sign of structure being the distinguishing factor within each pair.

In sum, from an ousiometric standpoint, the dimensions underlying the standard D&D alignment chart would appear to be strongly correlated. Nevertheless, if the {lawful ⇔ chaotic} dimension is, as we have suggested, taken to be more in line with rule-following—i.e., with structure accentuated and the power-danger downplayed—then we can reconcile the D&D alignment chart within the PDS framework.

IV. A prototype ousiometer

We construct a rudimentary prototype of an ‘ousiometer’, a lexical instrument for measuring the average essential meaning of large-scale texts.

For an example corpus, we assess English language Twitter [32, 40] for the historically turbulent time period 2020/01/01 to 2021/01/31 [54]. In Fig. 7, we show ousiometric time series for the three frameworks of VAD, GES, and PDS. We explain how we compute these time series and then briefly discuss how they track specific historical events.

In constructing an ousiometer, we take a similar approach to that of our hedonometer [21, 22, 55–57]. We view the ousiometer and hedonometer as measurement tools for telegnomics—lexical instruments for the remote sensing of meaning and knowledge.

We use \( M \) to represent one of the essential meaning dimensions within a specified ousiometric framework. For a simple ousiometer, we compute the average meaning score \( M_{\text{avg}}(\Omega) \) for a text \( \Omega \) in the following way. We consider only the 1-grams of the NRC VAD lexicon, leaving aside \( n \)-grams for \( n \geq 2 \) for possible future improvements. For any given text \( \Omega \), we apply a ‘lexical lens’ \( \mathcal{L} \), a simple operator that filters the text’s 1-grams, returning the subset 1-gram lexicon that intersects with the NRC VAD 1-gram lexicon. We denote the lensed text as \( \mathcal{L}(\Omega) \). We write the resultant lensed lexicon as \( R_{\mathcal{L}(\Omega)} \), further specifying this set to be a list of 1-grams ordered by descending frequency of usage \( f_\tau \) within \( \mathcal{L}(\Omega) \). For each 1-gram \( \tau \) in the lensed lexicon \( R_{\mathcal{L}(\Omega)} \), we then straightforwardly determine \( \tau \)'s normalized frequency as 
\[
p_\tau = f_\tau / \sum_\tau f_\tau.
\]

In general, given a lexical lens \( \mathcal{L} \), the average
The osimiometer: Example essential meaning time series for Twitter. The three columns correspond to average meaning scores for the frameworks of VAD, GES, and PDS, computed per Eq. (5). The first row shows time series for the 13 months covering all of 2020 and January, 2021. The second and third rows focus in on the attack on the US Capitol on 2021/01/06 by supporters of President Trump. The scale for the second row is 5 weeks (2020/12/19 to 2021/01/23) and 3 days (2021/01/05 to 2021/01/07) for the third row. All underlying time series are 15 minute time scales with day-scale and hour-scale smoothing overlaid in the first and second rows. Major events with spikes and/or durable memory are the US's assassination of the Iranian general Soleimani, the COVID pandemic, George Floyd's murder, and events related to the 2020 US presidential election, including the attack on the US Capitol. Because dominance is relatively stable throughout, the GES and PDS dimensions effectively vary as functions only of valence and arousal (see Eqs. 2 and 4). In particular, goodness and energy track valence and arousal closely. For the 2021/01/06 attack, the danger time series spikes while power remains stable (panels F and I). Structure drops indicating increased seriousness. Notes: We constructed the Twitter 1-gram corpus from approximately 10% of all English tweets [32, 40], with all 1-grams moved to lower case. We form a lexical lens $\mathcal{L}$ by taking 1-grams from the NRC VAD lexicon and adding a hashtag version of each 1-gram. As such, the osimiometer is not specifically tailored for Twitter during the time period covered. As we have done for the hedonometer [21, 53], our osimiometer could be readily improved by expanding the lexical lens to incorporate missing salient 1-grams.
Ousiometric score of a text $\Omega$ is:

$$M_{\text{avg}}(\Omega; \mathcal{L}) = \sum_{\tau \in \mathcal{R}(\mathcal{L})} p_\tau M_\tau,$$

where $M_\tau$ is the average ouxiometric score for the 1-gram $\tau$ derived from the NRC VAD lexicon scores [14].

We now apply our rudimentary ouxiometer to English language Twitter at a base resolution of 15 minutes [32, 40]. We use Eq. (5) to generate the ouxiometric time series in Fig. 7. The three columns of Fig. 7 correspond to the VAD, GES, and PDS frameworks. The rows from top to bottom move from the year scale of 2020 and the start of 2021, focusing in on the attack on the US Capitol by supporters of President Trump on 2021/01/06. The specific time frames are 13 months (2020/01/01 to 2021/01/31), 5 weeks (2020/12/19 to 2021/01/23), and 3 days (2021/01/05 to 2021/01/07). We overlay day-scale and hour-scale smoothing for the first two rows respectively.

Looking across all panels, we see the various ouxiometric biases in the context of Twitter. Valence, dominance, goodness, and power all show positive biases, while arousal, energy, and danger present negative averages. Structure is the only neutral dimension.

At the year scale in Figs. 7A–C, the three frameworks show evidence of major shocks, trends, and daily fluctuations, all to varying degrees. The two major events in the first half of 2020—those leading to long-lasting societal effects—were the global realization of the COVID-19 pandemic in mid March and the murder of George Floyd at the end of May and subsequent Black Lives Matter protests [53, 58]. A number of other events also stand out including the assassination of the Iranian general Soleimani by the US on 2020/01/03, which led to talk of war.

We only see the COVID-19-response shock in four dimensions—valence, goodness, power, and danger—while the shock of George Floyd’s murder registers in all eight dimensions. The COVID-19 shock is muted in part because we are (understandably) missing key words in the NRC VAD lens such as ‘coronavirus’, and ‘covid’. The word ‘pandemic’ points directly to danger with PDS scores (0.00,0.45,-0.03), as does ‘virus’ with (-0.04, 0.32, 0.06). As we discuss below, expanding the NRC VAD lexicon is an evidently needed step for improving the ouxiometer.

Moving to the five weeks of the second row of Fig. 7, the main signal deviations are due to Christmas, New Year’s Eve and Day, and the 2021/01/06 attack on the US Capitol. We also now see a daily cycle across all dimensions, reminiscent of what we found when measuring happiness (valence) on Twitter using the hedonometer [21, 59].

Finally, the time series in the bottom row of Fig. 7 show, in high temporal resolution, the collective shock expressed on Twitter in response to the attack on the US Capitol. For over roughly two hours starting after midday on 2021/01/06, we see the strongest shocks occur in valence (decreasing, Fig. 7G) and danger (increasing, Fig. 7I).

For the main dimensions of the orthogonal frameworks, GES and PDS, it is danger $D$ that is the real dimension of change. In the PDS framework, while danger rises, power $P$ remains relatively constant throughout the attack. In the GES framework, the time series for goodness and energy mirror each other and are projections of the danger signal. We also observe an increase in more rigid and serious 1-grams, as the structure scores $S$ drops through the attack.

While we have presented the GES and PDS time series as distinct sets and notwithstanding that they are of course linear transformations of each other, we suggest that showing all five time series is of value. The eight cardinal and intercardinal points of the power-danger plane are all meaningful, and it is helpful to reflect on which one might be dominating. We are after all plotting time series that represent the harder-to-visualize trajectory of a curve in PDS space.

For a deeper analysis of all time series, and beyond the scope of the present paper, we would use word shift graphs [21, 22, 38, 60, 61] to illuminate which 1-grams drive changes in ouxiometric scores.

V. Concluding remarks

We close with a few summaries, observations, and possibilities for future work.

A. The power-danger framework of essential meaning

The quantitative measurement of essential meaning—ouxiometrics—has been properly engaged as a scientific challenge for close to a century. Based on semantic differentials, the three dimensional orthogonal framework of evaluation-potency-activation (EPA) due to Osgood et al. [5] has effectively remained the leading conceptual framework, if not always by direct reference. Research into the specific context of affect saw EPA adapted as valence-arousal-dominance (VAD) [18, 19]. The VAD formalism has become widespread and not limited to studies of emotion, even being used for general essential meaning studies [10, 14].
Here, through an extensive analysis of English language types and tokens, we have found that essential meaning is instead well captured by a two dimensional plane, which is most informatively oriented around orthogonal axes of \{\text{powerful} \leftrightarrow \text{weak}\} and \{\text{dangerous} \leftrightarrow \text{safe}\}, depicted as a ‘compass of meaning’ in Fig. 8.

Natural lines of future work could involve examining more large-scale corpora across languages; and moving beyond text to images and video, sounds and music; other sensory inputs of touch, taste, and smell; and to non-human sense-making across life, both natural and artificial.

B. The mismeasurement of meaning

In uncovering the power-danger framework, we showed that \sim 20,000 terms evaluated by best-worst scaling in the VAD framework failed to reproduce the orthogonal VAD framework itself. We have contended that this cannot be explained away by participants misunderstanding bipolar adjectives used to define VAD dimensions. Rather, we have argued that a longstanding problem for ouisiometrics has been the difficulty of ascribing bipolar adjectives to accurately characterize dimensions derived from participants’ assessments of a larger set of semantical differentials [20]. As is, researchers tend to provide sets of bipolar adjectives for fundamental dimensions, making them overly blunt instruments that have more likelihood of being correlated (see Tab. 1). Even after exploring antonyms and antousionyms in Sec. III F, we continue to see this dimension characterization problem as unavoidable.

We recommend that ouisiometric studies start from a set of simple bipolar adjectives and always perform dimensional reduction. Standardizing such a set of clear bipolar adjectives would be of great value to the field, and our advice is independent of instrument employed to rate semantic differentials (Likert scale, best-worst scaling, etc.). Using ouisiograms, which provide richly informative visualizations, the extracted dimensions can then be examined and identified. For lexicons sufficiently rich in types and corpora-matching in terms of tokens, we expect that the axes of \{\text{powerful} \leftrightarrow \text{weak}\} and \{\text{dangerous} \leftrightarrow \text{safe}\} will emerge.

C. The safety bias of communication

Our finding of a safety bias in diverse written and spoken language generalizes our earlier work which revealed a positivity bias [22, 39]—a linguistic instantiation of the Pollyanna Principle [25]. In the GES framework we have defined here, the positivity bias is a goodness bias. We have also found a complementary linguistic low-energy bias in the GES framework (see Fig. 4D).

We now understand that the linguistic goodness bias and the linguistic low-energy bias are shadows of an underlying linguistic safety bias—projections of points in the 2-d \(P-D\) plane onto the orthogonal 1-d diagonal axes of goodness and energy. The one dimensional map is not the two-dimensional territory.

Secondary to the safety bias, we have also observed a relatively minor power bias in five of the six corpora we have studied here (see lower histograms in the panels of Fig. 5). The one exception is the Sherlock Holmes corpus, for which the median power is 0. Moreover, the power distributions are relatively more symmetric than than the danger ones.

Future work will be needed to understand the true generality of the safety bias. In expanding the NRC VAD lexicon to conform to Zipf distributions of real corpora, we will be able to examine how the overall power-danger ouisiogram behaves with respect to frequency of usage. This line of research—which is also necessary for refining the ouisiometer instrument (Sec. V G)—should follow in the same fashion as the work we performed to move beyond the expect-curated ANEW word list [10], which we found to be a poor fit.
for real corpora [21]. Looking at dimensions one at a time, the key diagnostic graphic is the jellyfish plot, which we developed for \{happiness ⇔ sadness\} presented by individual words per semantic-differentials [22, 39].

D. The circumplex model of affect is a reflection of a more general power-danger framework of states-of-being

We were in part drawn to the circumplex model because, as for the power-danger framework, the intercardinal points were argued by Russell to be conceptually distinct (more than 8 points have also been posited [13]). The power-danger framework is more general than the circumplex model of affect, which is anchored in the human experience.

While the studies of Russell [8] and Mohammad [14] are vastly different in type and size, we have shown that they are broadly consistent with each other, and that the mismatches lead to sensible revisions. We found that emotional states cannot be fully represented as negative emotions which need higher dimensions to be distinguished. In particular, fear, disgust, and anger most strongly collapse. We also came to the realization that the circumplex model captures general states-of-being rather than only emotional ones.

How the longevity of states-of-being relates to location in the power-danger framework could be investigated. Moving around the circumplex model of existence, the potential for states to endure is variable. For example, the high power state of triumph is arguably the most likely to be transient, though success may be maintained. States that are in part weak or safe can be persistent: Misery, depression, sleepiness, contentment. Dominance may be in the robust-yet-fragile category of system states [62].

A possible alternate version of the circumplex model could present two models showing how the power-danger framework is experienced by a sender and by a receiver in interactions. An aggressive sender of danger might be angry for example, while a receiver of danger might be fearful, disgusted, sad, or angry. A positive interaction could have both the sender and receiver in the powerful-safe southeast quadrant, both feeling happy.

For interactions between entities, we might further consider issues of directedness (or stance). We discuss such analyses below in the context of stories (Sec. V K).

E. High energy is an insufficient description of dangerous-powerful

Of the main planes in the two orthogonal frameworks of GES and PDS, we believe only the PDS one spanned by \{powerful ⇔ weak\} and \{dangerous ⇔ safe\} are informative of the intercardinal points.

The main failure is for the energy dimension, which in other settings might be construed as arousal or activation [8]. Safe-weak connotes more than merely low energy, and dangerous-powerful captures considerably more meaning than just ‘high energy’. In alignment with these observations, our analysis of the circumplex model of affect led us to replacing ‘arousal’ with ‘dominance’ (dangerous success).

By contrast, the intercardinal points for the goodness-energy plane are sensible, with power as good-high-energy, danger as bad-high-energy, safety as good-low-energy, and weakness as bad-low-energy. It is the inversion that is problematic.

Moreover, instead of energy, a more useful conception is that intensity of meaning is measured by the magnitude of a representative vector. For example, ‘couch’ is very strongly safe-weak, while ‘oatmeal’ is strongly safe-weak, even if both are low energy. On the other side, the words ‘battle’, ‘combative’, and ‘pushing’ all register as somewhat dangerous-powerful.

F. Rethinking and remeasuring happiness

We reinterpret the widely popularized concept that people desire happiness [63–66] as a search for safety and power.

As we have indicated, our hedonometer [21, 22] is conceptually aligned with the \{good ⇔ bad\} dimension \(G\) in the GES framework. While a formal analysis is outside of our current interest, we note that the alignment between our hedonometric scores and the GES/PDS frameworks appears to fall somewhere between the goodness and power axes (east southeast). For some examples, the happiest three words in our study [21] were ‘laughter’, ‘happiness’, and ‘love’ which here have scores \((G,E) = (0.42,0.10), (0.53,0.31),\) and \((0.51,0.03).\)

Problematically for comparison, our work on happiness used semantic differentials, and like all essential meaning studies, was further complicated by the imprecision of end-point descriptors. A valuable undertaking—particularly for the onsiometer as we
discuss next—will be to incrementally expand the existing NRC VAD lexicon in a statistically defensible way using best-worst scaling.

Future studies using best-worst scaling could examine a larger set of emotions (e.g., anger, fear, disgust, sadness, surprise, and happiness) within the context of the power-danger-structure framework.

G. Improving the ousiometer

We have considered here only a few elements of ousiometric time series for a short period of time for Twitter. Our intent was to demonstrate the feasibility of a simple ousiometer, which can clearly be improved in a number of ways.

First, the lens afforded by the NRC VAD lexicon could easily be improved. A zero cost step would be to expand the lexicon by adding plurals and verb conjugations, using already measured scores of base words. For example 'man' and 'woman' are part of the NRC VAD lexicon but 'men' and 'women' are not. Of course, surveying for new evaluations using best-worst scaling would be the ideal. An important upgrade would be to assess words that are most frequently used within a given context. We expect similar outcomes in improvement as we saw for our hedonometer, which we tailored towards a number of corpora including news, social media, music lyrics, and books (and incidentally scientific literature) [21, 28]. Better coverage of texts should lead to increased resolution in the signal the ousiometer measures. For example, we have observed that in adding COVID-19-related words to our hedonometer’s lexicon, the instrument’s performance sensibly improved [53], better resolving the collective, durable trauma of the world’s awareness of the pandemic.

Second, we should have the ability to add some kind of tuning to the ousiometer. For the hedonometer, we found that systematically removing words surrounding the neutral happiness point allowed us to increase the signal’s gain in a robust way. We more deeply determined that the on-average neutral words needed to be removed for the measured signal to be reliable. Such words were either truly neutral (e.g., functions words like ‘the’) or ones for which opinion was varied and their scores had high standard deviations (e.g., curse words). A natural starting point for the ousiometer will be to remove an ellipsoid scaled to the typical widths of the PDS scores.

Third, we will be able to introduce word shifts based on the ousiometric scoring system [21, 22, 38, 60, 61]. Ousiometric word shifts will reveal precisely which words drive score changes between any two texts.

And fourth, an entirely fresh assessment of a larger lexicon using best-worst scaling will eventually be required. We suggest re-using the VAD end-point descriptors of Ref. [14] to provide continuity, complemented by a set of more well defined semantic differentials.

H. Studies of sub-lexicons within the power-danger framework

Given the power-danger framework, the NRC VAD lexicon offers a great range of focused studies for well defined subsets of words. For two distinct examples, we consider negations and gender.

We briefly survey words which have a prefix-formed or suffix-formed antonym (e.g., ‘honest’ and ‘dishonest’). Of the negating prefixes un-, dis-, anti-, and mal-, the first two are the most common. A simple count, ignoring whether a word is a negation or not, returns 429 words in the NRC VAD Lexicon start with ‘un’, 26 3 start with ‘dis’, 24 start with ‘anti’, and 21 with ‘mal’. We also find 92 words ending in -less. Of course, some forms are not negations, for various reasons; inherently (‘disc’); absence of the base word in the NRC VAD lexicon; lost positives (‘disgruntled’); or being of older forms (‘disaster’; Greek for ‘bad star’).

Some word-negation antonym pairs are antousyonyms. For example, for ‘safe’ and ‘unsafe’, we have \((P, D) = (0.29, -0.41)\) and \((-0.42, 0.31)\). However, the antonyms ‘defeated’ and ‘undefeated’ are not negated in essential meaning: \((P, D) = (-0.42, 0.33)\) and \((0.52, -0.05)\). A linguistic imprint of the Polyanna principle [25] is that positive words are often the default from which negative words are derived. We have ‘unhappy’ but not ‘unsad’, and ‘not unhappy’ does not mean ‘happy’. We have ‘unsafe’ but not ‘undangerous’ (though possibly ‘nondangerous’). The suffix -less provides a mixture of positive and negative variants. We have ‘powerless’ (but not ‘unweak’ or ‘weakless’), ‘meaningless’, ‘gutless’, and ‘worthless’, but also ‘harmless’ and ‘selfless’.

So, given a rich set of prefix or suffix negated pairs, possibly obtained by augmenting the NRC VAD lexicon, can we explain or at least characterize how antonyms typically relate to each other within the power-danger ousiometric framework?

Another potential line of inquiry might consider the ousiometrics of gender. For example, the scores for the
words ‘woman’ and ‘man’ are \((P,D,S) = (0.24, -0.26, 0.12)\) and \((0.25, -0.17, -0.13)\). Matching on positive power, ‘woman’ scores as safer than ‘man’ (both words are safe with \(D < 0\)). The word ‘woman’ falls on the less structured side \((S > 0)\) mirrored by a comparable score for rigidity for ‘man’.

The closest five synonimonyms for ‘woman’ are ‘born’ ‘convenient’ ‘mutually’ and ‘pretty’, while for ‘man’, we find ‘proceeding’, ‘membership’, ‘sanctify’, and ‘countryman’.

We are naturally led to wonder what the larger ouisiometric patterns are for gendered words, and how might these vary across languages, cultures, and time.

Similar kinds of questions could naturally be explored for any principled sub-lexicon.

I. Connections to personality frameworks

The power-danger-structure framework could be considered in the context of personality. The longstanding framework of the “Big Five” maintains the core personality traits of openness, conscientiousness, extraversion, agreeableness, and neuroticism (OCEAN) [67]. Possible alignments might be conscientious as powerful, agreeableness as safe, and openness as unstructured (playful). The opening three letter ordering would be CAO—contrary to the OCEAN. Conscientiousness and agreeableness would have equal weight while openness would be a third lesser dimension.

As we show in Fig. 9, Cipolla’s half-serious theory of human stupidity could be interpreted as an imprint of the power-danger framework [68]. Cipolla contended that people, when viewed by others within their social context, could be located in a two-dimensional space prescribed by the two orthogonal axes of \{help themselves \(\leftrightarrow\) harm themselves\} and \{help others \(\leftrightarrow\) harm others\} (diagonals in Fig. 9). The combination of ‘help themselves’ and ‘help others’ would track with powerful, while ‘help themselves’ and ‘harm others’ would align with dangerous. Using Cipolla’s terms, ‘intelligent people’ would be powerful, ‘stupid people’ weak, ‘bandits’ dangerous, and ‘helpless’ safe. We would not use Cipolla’s classifications, and instead suggest the differential axes of \{heroes \(\leftrightarrow\) zeroes\} and \{sinners \(\leftrightarrow\) saints\}.

J. Power-danger as an ouisiometric framework for survival

The ouisiometric courses of the many kinds of interconnected evolutions—biological, social, cultural, political, religious, linguistic, technological—could all be considered within the power-danger framework.

From Ref. [69]:

“According to Osgood (1971) [70], for survival in the evolutionary sense it is crucial for the human animal, as well as other higher organisms, to use central representations of the innate emotional reaction system as a mediating semantic system to distinguish among the signs of things as being good or bad, strong or weak, and active or passive with respect to himself when confronting any behavioral decision (or judgment) situation.”

We contend that individuals and systems that possess accurate, adaptable maps of their environment within a
power-danger framework might tend to endure. Sympathetic to the Anna Karenina Principle [46], the ability to detect not just danger but specific danger would be evidently key to survival. For example, within biology, emotional responses are primitive, large-scale signals (disgust ~ ‘bad taste’) that give salient resolutions of danger.

Within the \{powerful ⇔ weak\} and \{dangerous ⇔ safe\} compass, entities—from individuals to groups of all sizes—generally might prefer to exist in a powerful-safe state and be cognizant of the other three quadrants shadowed by danger and weakness. If self evaluation in the context of a threat is dangerous-weak, an entity would naturally want to protect itself, attempting to reach powerful-safe state, or at least a safe one. An animal in the sights of a prey-perceiving predator might feel fear and try to escape or respond with anger with an instinctive mode of defense. And a country under attack from an invading force might rally its troops, organize a resistance, seek alliances, or, in seeking to avert the ‘nothingness’ of pure weakness, succumb to the dangerous-weak quadrant, and surrender.

K. Telegnomics for stories: Measuring character arcs and plots

Stories are at the core of human experience. People are, in part, homo narrativus [71–74]—story creators, imitators, believers, simulators, and spreaders [71–88].

The concept of ‘distant reading’ of stories [80, 89] is a vital aspect of what we propose to be telegnomics. A grand challenge for distant reading is the distant measurement of plot—a story’s essential algorithm [87, 90, 91]. There are a number of well known essential story plots, such as kill-the-monster and rags-to-riches. How many distinct kinds of plots are there, what is the taxonomy of plots, what are their relative abundances, and how do all of these aspects vary over time and across cultures?

We suggest that plots may be measurable using the ousiometer as a telegnomic instrument. We propose to operationalize the plot of a story, real or fictional, as an evolving temporal network with nodes being characters, places, and events, and links forming the temporal interaction network linking these nodes together. Using ambient ousiometric analyses with appropriate time scales, we propose to extract ambient meaning timelines of “temporal plot networks.”

The characters we contend with need not be people, both in fiction and especially so for real-world stories. Characters may be countries, contagious diseases, music bands, sports teams, even stories themselves being invoked (“1984”). Events may be exogeneous (earthquakes) or endogenous (war) to social systems.

Characters and the kinds of links between them may (or may not) evolve in essential meaning. In moving to the power-danger framework, we are able to trace plot networks in much richer fashion than what is afforded by a single dimension of \{good ⇔ bad\} [57, 92, 93].

For a popular example, consider aspects of the plots of the original Star Wars trilogy. As a character, Luke Skywalker starts in the low energy, weak-safe quadrant. His relationships to his uncle and aunt are weak-safe, as is largely his environment on Tatooine, though danger is possible. Along his trajectory through the three films, he develops relationships that span power-danger space (e.g., to him, Darth Vader is dangerous-powerful-structured, Obi-Wan is safe-powerful-structured, C3PO is safe-weak-structured, and Yoda safe-powerful-unstructured). His path brings him into perilous environments repeatedly. By the end of the three movies, Luke has become powerful-safe having passed through Yoda’s Jedi training and overcome his father.

It should be possible to develop plot detection with example fictional works and well known stories from the real world, as might be represented through news and social media. Doing so would allow us to start with pre-specified, known casts of characters. For novels, temporal coarse-graining may mean reducing to a small number of acts, from as few as 2 or 3 to around 10 [94]. For a more advanced stage of plot detection, we could use named-entity recognition (NER) techniques to determine the main characters and places without using prior knowledge.

For collections of stories for which we are able to extract temporal plot networks, we could then examine the ecology of such networks, working to find a taxonomy as might exist. A priori, we do not know if temporal plot networks belong to some continuum or if characters and the kinds of links between them may (or may not) evolve in essential meaning. In moving to the power-danger framework, we are able to trace plot networks in much richer fashion than what is afforded by a single dimension of \{good ⇔ bad\} [57, 92, 93].

L. Information is not meaning: Beyond bits

For measuring signals of all kinds, ousiometrics potentially provides a complementary approach to information theoretic ones. Shannon was careful to distinguish the process of optimal message communication from any kind of delivery of meaning.
From the second paragraph of Shannon’s foundational paper on what would become information theory [95] (emphasis per the original):

“The fundamental problem of communication is that of reproducing at one point either exactly or approximately a message selected at another point. Frequently the messages have meaning; that is they refer to or are correlated according to some system with certain physical or conceptual entities. These semantic aspects of communication are irrelevant to the engineering problem.”

In his precursor work, Hartley had similarly indicated that measuring information could be done without needing to assess human meaning-making [96].

Shannon’s entropy is maximized when symbols are expected to be communicated at random—gibberish. While information theory has proven to be of profound use across the sciences, Shannon’s forewarning is sometimes missed as the word ‘information’ does commonly connote knowledge. Of course, we are entirely interested in measuring meaning in communication, from the essential kind we have studied here, to critically examined, fine-grained meaning.

Possible future work could develop ousiometric instruments for any type of meaningful communication, far beyond the simple ousiometer we have constructed here for large-scale written expression. Indeed, the first use of semantic differentials to measure meaning was to gauge auditory perceptions of sonar signals in the context of submarine warfare [4].

Developing a scale for ousiometrics presents an evident future challenge. While information theory builds around a fundamental unit of measurement, the bit (digital bit), we do not have an evident counterpart that we might call an ‘ousit’. It is conceivable that in some biological circumstances, a signal of, say, danger, may need to exceed some minimal threshold to be observable by an organism, and perhaps another for that organism to act. Even so, ousiometric signals would seem to range over a continuous spectrum, in the manner our ousiometer’s function would suggest. Whether or not a universal ousiometric scale of power-danger can be laid out for meaning transmission in sufficiently complex systems is an open question.

VI. Code, data, and other materials

We provide a range of supporting material at the paper’s Online Appendices: compstorylab.org/ousiometry/.

We include large-scale ousiograms for all pairs of dimensions per Figs. 1 and 3; these can also be found on the arXiv as part of the paper’s Anciliary files.

Scripts and documentation reside on Gitlab at https://gitlab.com/petersheridandodds/ousiometry.

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Changelog

2023/03/29:

• We have standardized expression of semantical differentials throughout (e.g., \{dangerous ⇔ safe\})
• We have reformatted for improved readability: Left justified, space between paragraphs.
• We have added a table of contents.
• We have added a figure showing the mapping between the compass of meaning and Cipolla’s law of human stupidity (Fig. 9).
• We have added this changelog.

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A. Ousiogram analysis sequences

Ousiograms for Jane Austen’s novels in the VAD, GES, and PDS frameworks:

FIG. A1. Ousiograms showing the VAD-GES-PDS analytic sequence for Jane Austen’s novels: “Sense and Sensibility,” “Pride and Prejudice,” “Mansfield Park,” “Emma,” “Northanger Abbey,” and “Persuasion,” published in 1811–1818. We obtained all novels from the Gutenberg Project: http://www.gutenberg.org. The underlying Zipf distribution is built by merging all books and then constructing a word frequency distribution. Panel G corresponds to Fig. 5A.
Ousiograms for Sherlock Holmes in the VAD, GES, and PDS frameworks:

FIG. A2. Ousiograms showing the VAD-GES-PDS analytic sequence for Sir Arthur Conan Doyle’s Sherlock Holmes novels and short stories. We obtained four novels and forty-four short stories from the complete Sherlock Holmes Canon [https://sherlock-holmes.es/] (due to copyright, twelve short stories contained in the “Case-Book of Sherlock Holmes” were not available from this source). The underlying Zipf distribution is built by merging all books and then constructing a word frequency distribution. Panel G corresponds to Fig. 5B.
FIG. A3. Ousiograms showing the VAD-GES-PDS analytic sequence for the New York Times. The underlying Zipf distribution is built from a 1987–2007 annotated corpus [29]. Panel G corresponds to Fig. 5C.
FIG. A4. Ousiograms showing the VAD-GES-PDS analytic sequence for Wikipedia. The underlying Zipf distribution is based on the March 2019 dump of the English Wikipedia [30]. Panel G corresponds to Fig. 5D.
Ousiograms for RadioTalk in the VAD, GES, and PDS frameworks:

FIG. A5. Ousiograms showing the VAD-GES-PDS analytic sequence for the RadioTalk corpus. The underlying Zipf distribution automated transcriptions of talk radio in the US covering the time period 2018/10–2019/03) [31]. Panel G corresponds to Fig. 5E.
FIG. A6. Ousiograms showing the VAD-GES-PDS analytic sequence for Twitter. The underlying Zipf distribution is an equal weighting of day-scale Zipf distributions derived from approximately 10% of English tweets in 2020 [97]. In contrast to the Zipf distributions obtained from ‘flat’ corpora, the Zipf distribution for Twitter encodes a strong sense of popularity as social amplification is naturally included through retweets. Panel G corresponds to Fig. 5F.