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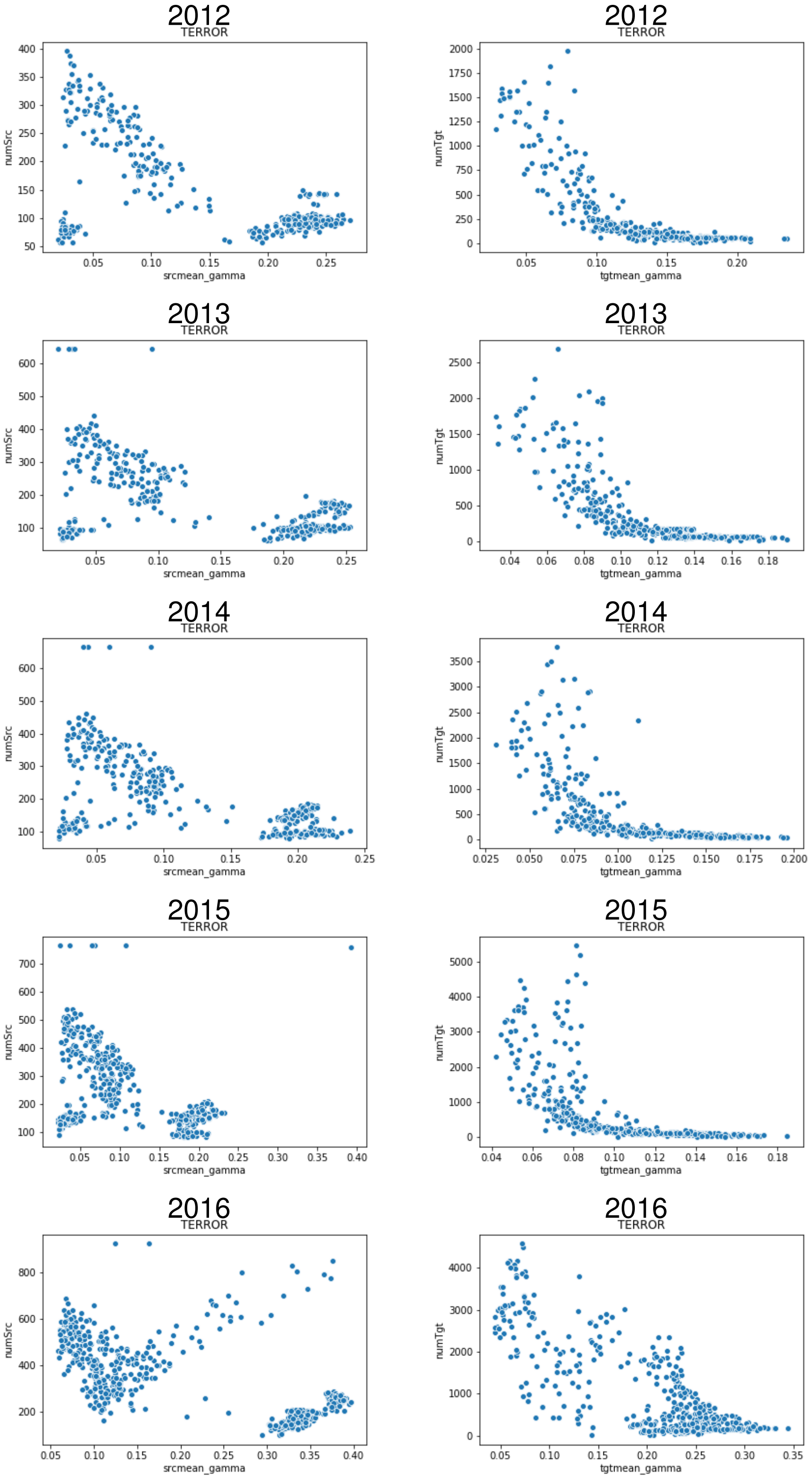
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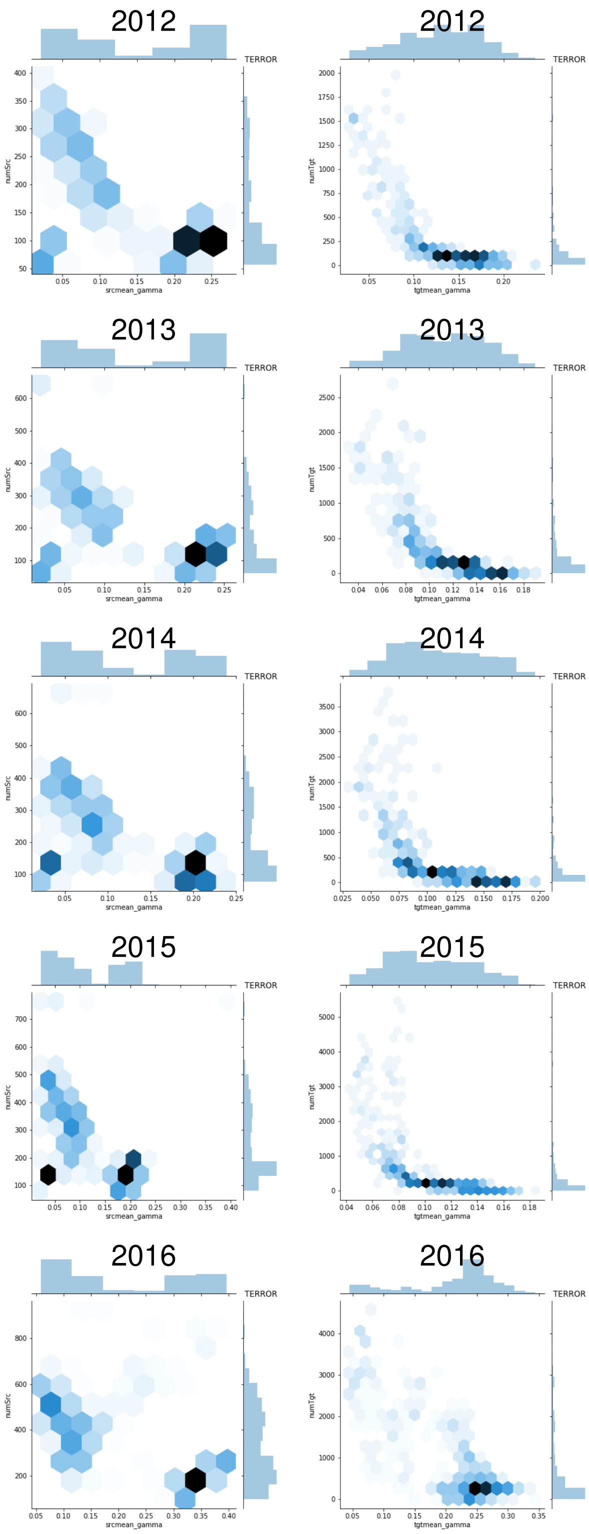
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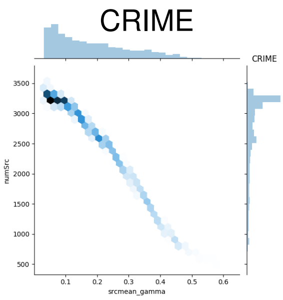
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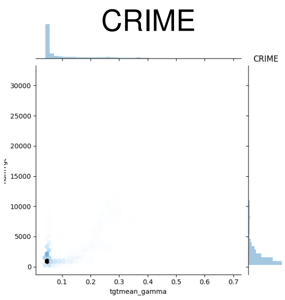
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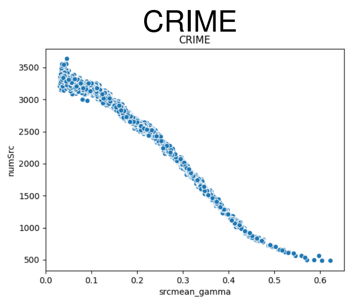
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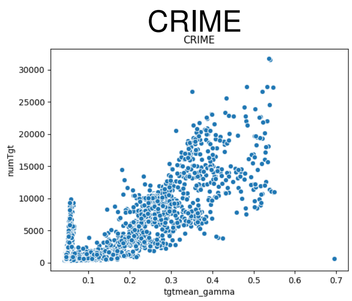
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1 EXECUTIVE SUMMARY

We aim to detect, and quantify cognitive dissonance in individuals, communities, and sub-populations, and ultimately craft a general theory of belief shift over time driven by the purported human need of maintaining internal cognitive consistency. In addition to identifying dissonance, we bring together psycho-social theory, stochastic processes, and large deviation theory to propose a theoretical framework to predict likely choices of response strategies invoked to reduce cognitive conflict, and model the long-term stochastic dynamics of belief evolution. We aim to validate our proposed theory and tools on publicly available large social survey data sets, and in focused longitudinal experiments with human subjects.

Cognitive dissonance[?] refers to the psychological stress arising from holding two or more contradictory beliefs, ideas or values. Festinger in his *A Theory of Cognitive Dissonance*[?] posited that humans have an intrinsic drive to hold all our beliefs in harmony. To maintain cognitive consistency, individuals might attempt to reduce the importance of the conflicting beliefs (trivialization), acquire new beliefs (rationalization), or alter the conflicting attitude, opinion, belief or behavior. Thus, Festinger's thesis in effect postulates a mechanism of belief shift over time, and suggests that such processes might be effectively modulated via interventions suitably informed by quantitative estimates of dissonance.

Since Festinger's original formulation, researchers have theorized alternative mechanisms that maintain cognitive consistency.[?], [?], [?] Notwithstanding the actual psychological processes in play, the central goal of this work is well defined: *Can we quantify cognitive dissonance in individuals, or communities? And can we predict the routes they take to reduce conflicts in their cognitive processes?*

This is a problem of crucial importance for DoD operations, especially in conflict countries. In the modern reality of asymmetric and urban combat operations often directed against local insurgencies, a tool that recognizes cognitive dissonance in the populace, and can predict belief shifts over time, is vitally important for long term strategy. As an example, ability to shift away from violent behaviors might negate the need of military action, saving considerable resources. In addition, the proposed work will establish a fundamentally novel approach to analyzing, and interpreting large scale survey data, thus advancing socio-psychological theory. At the same time, ability to predict belief shifts among the US population can inform key policy decisions.

The proposed set of measurable milestones will demonstrate verifiable progress within the first 6 months, with computation of dissonance vectors for the entire General Social Survey (GSS) dataset, with belief shifts modeled under simple scenarios. By the 10th milestone, we aim to have validated our belief shift models in large scale longitudinal databases, as well as in focused field experiments.

Our technical challenges arise from the qualitative nature of the notion of dissonance. The complexities of social structures, and the diversity of ideas and beliefs that the human mind processes, makes it problematic to objectively quantify — or even reliably recognize — the notion of cognitive conflict. Perhaps even more difficult is the detection of such conflicts at scale, with realistic observational data. Naive attempts at directly quantifying the role of historical and societal drivers behind beliefs, opinions and values — and how those evolve — is an intractable proposition.

Our approach simplifies the problem by formulating a computable measure of cognitive dissonance as a measure of surprise: when asked a diversity of questions, dissonance with respect to a specific topic manifests as a deviation from a model estimate of the expected and the actual recorded response. Effectively modeling expected responses with little or no prior knowledge of the emergent dependencies between the survey responses, is non-trivial. We plan to develop a novel machine learning framework called the recursive decision forests, specifically designed to seek out dependency structures in response databases without resorting to brute force searches in exponential spaces, and ultimately obtain quantitative estimates of cognitive dissonance.

The proposed work will be carried out over a period of 24 months in the base period, followed by 12 months in the option period, at a total cost of 1M USD.

2 Goals and Impact

Detailed simulation of social phenomena is currently used by the DoD to undertsand the evolution of social structures, and the emergence of relevant organizational hierarchies in theatres of conflict. In the modern reality of asymmetric warfare often against local insurgencies in conflict countries, informing military strategy with expected social implications is crucial for optimal long-term outcomes, and US foreign policy success. In this work, we aim to define, develop and demonstrate proof-of-concept principles for validating complex social simulations. Additionally, our goal is to extend social theory to 1) compare and constrast complex systems, 2) disambiguate real and simulated phenomena, 3) chart effective principles to narrow or erase such identifiable distinctions to ultimately realize more realistic models and predictions, and 4) develop computable strategies to disambiguate closed vs open systems, $i.e.$, identify the existence and the role of unobserved and unknown external influences.

Social phenomena unfold as complex interdependent system of systems operating at multiple scales of orgamization in space and time. Centuries of work in social theory has teased out a few of the important guiding principles around which such large scale systems organize; nevertheless first principle quantitative rules akin to the laws of physics, are generally missing. Thus, unlike physics, social scientists do not have a “standard model” — a neat set of equations believed to be not just a *good* model of the physical univese, but rather a representation of the exact ground truth. Under this convenient scenario, physicists can work out simulations that confidently reflect reality, and build gargantuan particle accelerators to test when-and-if rare events subtly deviate from simulated outcomes to search for *new physics*, and validate existing theory. The reality for social scientists is harsher — with no such universal set of equations (*or the hope of ever finding one*), the veracity of complex social simulations is forever suspect. How do we know we have built in the right amount of complexity? How do we know if the simulated systemes have the same emergent structures, and any conclusion or observation in such systems have even a tenuous connection to reality? How do we *quantify* the deviations from and uncertainties between real systems of interest and engineered simulations built to interrogate them, often at great expense?

These questions are of crucial importance to national security. Without quantified confidence on the large scale social simulations that are becoming increasingly important in military strategy and foreign policy, incorrect recommendations have the potential for catastrophic long-term consequences.

In this work we propose to address these issues by crafting rigorous computable measures that characterize diverse aspects of the emergent dynamics in social interactions. The challenge here is to craft measures that are application agnostic, and thus capable of evaluating objectively diverse real-life and simulated scenarios. Technically speaking, we are designing characterizations for complex spatio-temporal systems, with unknown or poorly understood rules, operating at multiple spatial and temporal scales, with variables that can be a mix of categorical, ordinal as well as discrete and continuous, and potentially subject to noisy and adversarially corrupted observations.

Our approach is predicated on our ability to effectively distill good predictive models of such systems from data, in a manner that is agnostic to the explicit details of the application. To that effect we leverage our recent work on a novel spatio-temporal stochastic modeling framework — the Granger nets — which are demonstrably superior in predictive ability and sample complexity to existing off-the-shelf deep learning architectures.

Broadly our scheme is as follows: Given observation logs from a system (simulated or real), we construct the Granger net, and then interrogate the inferred predictive structures through the lens of a range of carefully constructed measures (See Table 1 for overview) that illuminate various dynamical characteristics pertaining to complexity, stability, reslilience, and evidence of self-organized criticality. In our preliminary studies, these measures clearly disambiguate real and simulated systems — even ones constructed with considerable effort aiming to erase any such distinctions.

Thus, the primary over-arching goal of this work is to investigate the missing elements that leave such tell-tale signatures in high fidelity simulations, and ultimately move towards future design principles

TABLE 1: Dynamical Measures Proposed For Precise Chracterization of Complex Systems

	Measure	Property Measured	Description
1.	μ_{c}	Complexity	The level of complexity of multi-scale multi-variate spatially extended systems require new measures of compelxity that capture statistical compelxity, structure of connectedness, and cross-talk.
2.	μ_{s}	Stability	Stability in systems of interest might be finely poised between instability regimes, with the possibile manifestation of self-orgnized criticality.
3.	μ_{r}	Resilience	Qunatify the ability of systems of interest to recover from directed and random perturbations, akin to homeostasis in living systems.
4.	μ_{ω}	Frequency-like	Generalization of frequecny domain tools and measures to non-linear multi-scale spatio-temporal system of systems with categorical and ordinal variables.
5.	μ_{e}	External Influence	Estimate the pssibility having an open vs a closed system.
6.	$\partial\mu_i/\partial t$ $i = \mathbf{c}, \mathbf{s}, \mathbf{r}, \omega, \mathbf{e}$	Evolution & Influence	How the measures of dynamical properties evolve in time characterizes the evolution of emergent rules and drivers, indicative of the rate of information generation either within, or via influence import.

that better simulate reality. We briefly enumerate the proposed characterizations (See Technical Plan for mathematical details).

Measures of Stability: The May Constraint & Self-organized Criticality In Real-World Systems

Stability is well-understood in the study of dynamical systems. For our purpose, a stable system is one that can carry on operating with low probability of generating event patterns or behaviors that threaten catastrophic failures, and cessation of operation; a stable system is in no danger of dying suddenly. *We hypothesize that explicit measures of expected stability can be designed that potentially disambiguate real world complex systems of social interactions from simulated ones.* To see how such measures are designed, we briefly describe the seminal work of Robert May[1], [2] on stability of complex systems.

May's work on large random systems show that complex systems tend to be inherently unstable, implying that for ecosystems with more species, more interspecific interactions per species (connectance), or stronger interactions are not as likely to be as stable as systems with fewer of these attributes. However, these results are at odds with the empirical observations that large, highly complex ecosystems are MORE stable NOT LESS.[3]

In other words, May's work identifies a computable constraints on system parameters, violations of which that are overwhelmingly likely to cause systemic instability in large random systems; nevertheless natural complex systems seem to be able to operate in those regimes with no sign of an unstable demise. More specifically, May's theorem deals with S variables (species), where the ith species interacts with the jth one with a strength drawn from a normal distribution with probability C and are 0 otherwise. For large S, he shows that the system is stable with probability 1 if:

$$\gamma\sqrt{SC} < 1 \tag{1}$$

and with probability 0 otherwise, where γ is the average strength of interaction. The elegance of May's theorem, coupled with the verified contradiction in large scale natural systems suggests that complex ecosystems are perhaps NOT randomly wired. Real world systems exist in small islands of stability in complex high dimensional parameter spaces, where large perturbations would risk incursion into unstable regimes by May's theorem.

> *Thus, we define our first measure of stability as:*
>
> $$\mu_{\mathrm{s}} = \gamma\sqrt{SC} \tag{2}$$
>
> *We hypothesize that simulated systems will typically have a significantly lower value of μ_{s}, while real world systems will often violate the apparent stability criterion ($\mu_{\mathrm{s}} < 1$), while continuing to be actually stable in practice.*

This notion of natural systems being poised at special miniscule "critical" regions in high-dimensional t

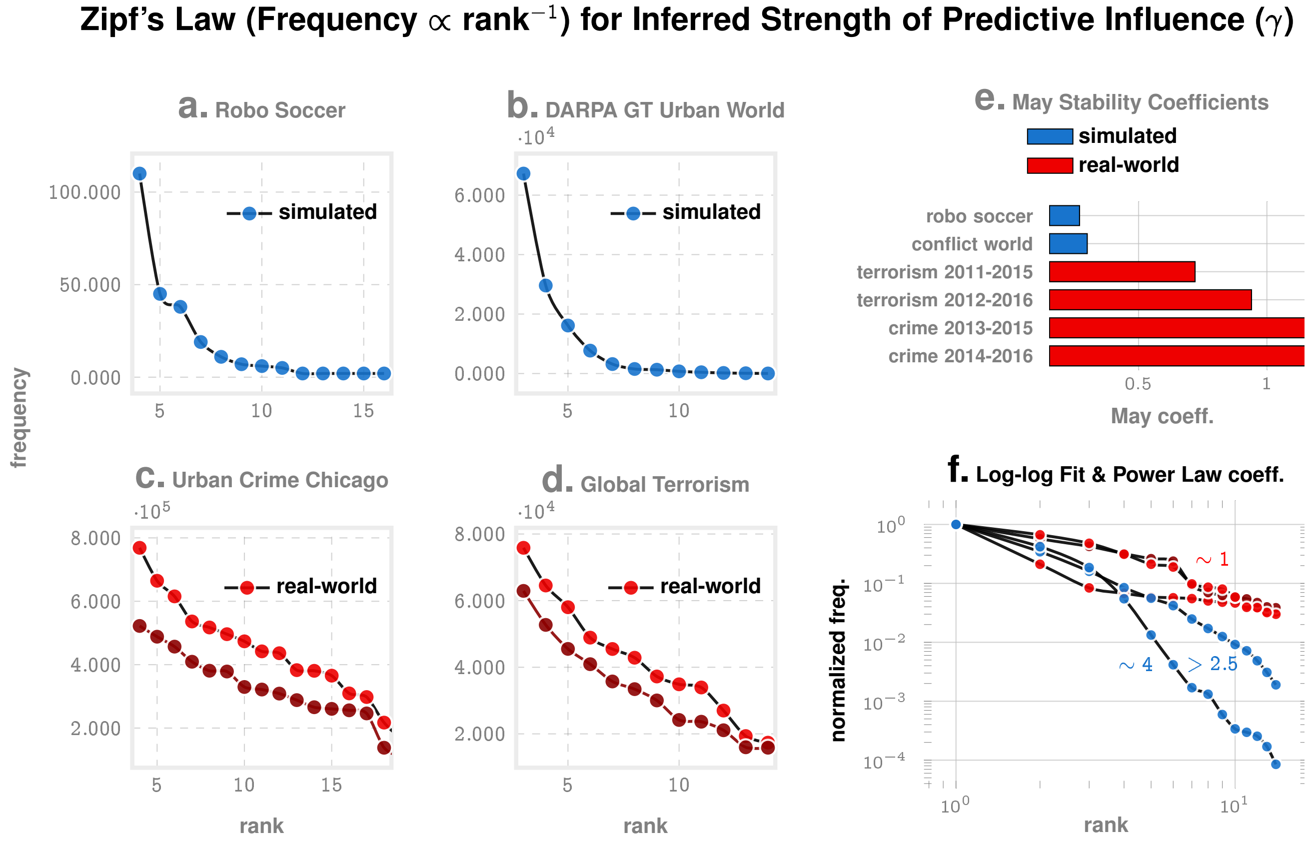

Fig. 1: Zipf's Law holds in real-world systems, but not in simulated ones, even the ones where significant effort and resources are expended to replicate reality. Thus, it appears complex system of systems in the real world often exhibit critical phenomena, whereas simulated systems often do not. This discrepancy is also reflected in the stability criterion of Robert May: it seems that real worls systems should be unstable but they are not: they exist in islands of stability surrounded by unstable regimes in high dimensional parameter spaces.

parameter spaces is strongly indicative of the intrguing phenomena of *self-organized criticality*.[4] Our preliminary studies — and the discussion below — suggests that real-world complex systems tend to be *poised at criticality*, operating at or near systemic phase transitions, while simulated systems often lack this behavior. We exploit these insights for our second class of stability-related characterization measures. First, we briefly dilineate this deep connection, before charting our application strategy.

For decades, physicists have hoped that the emergent, collective phenomena of living systems, both at the moelcular and the social scales, could be captured using ideas from statistical mechanics. States of such emergent systems are almost never at equilibrium, maintained by a flow of energy and material (in biology) or societal exchange of relevant entities (people, ideas, beliefs etc). We plan to investigate this intriguing idea at length, that such systems are poised near criticality — which we believe is the key to undertsanding the criteria that distinguish real-world systems from simulations.

Classicially, critical plhenomena has to do with phase transitions, and discontinuities in relevant order parameters near such transitions. Criticality, however, is a much more general concept than its instantiation by phase transitions in equilibrium systems. Assume we are able to model the statistically stationary states of a complex system with a many-parameter model. Clearly random choice of these parameters is not likely to redproduce meaningful function; and if the system we are studying has many components, then any reasonable probabilistic model will break the parameter space into regions corresponding to different phases. Thus, for complex systems the parameter space supports a phase diagram, in which regimes of qualitatively distinct behavior are separated by critical surfaces. *We plan to investigate the intriguing possibility that most compelx systems in the real-world are not deep in one phase or another, but rather poised near a critical surface in the natural parameter space.*

Directly verifying this hypothesis is problematic. However, we can indeed validate if the systems carry signatures of critical organization, *e.g.*, the emergence of Zipf's Law in the distribution of strength of inferred predictive links between observables, or the in/out degree distribution of the inferred influence network. The justification of looking for such characterization in the distrbution of links strengths or degrees arises from the idea that an enumeration of these properties may be seen as a specification of the state the complex system, and it can be shown that existence of the Zipf's law amounts to the existence of critical temperature below which the system "freezes", and above which thermodynamic quantities diverge.[4]

As shown in Fig 1, our preliminary studies corroborates this hypothesis, at least with the systems under consideration.

Measures of Complexity

Using system size as a measure of complexity is potentially misleading. We plan to develop measures that capture the complexity of information processing within the system, *e.g.*, the intricacies of how the system is internally wired, and the number of intrinsic states that the system has for it to manifest the observed behavior. Furthermore, since for real-world systems the ground truth of internal structures may only be estimated, our complexity measures must always be calculated from structures inferred or estimated from observed data and event streams.

We plan to consider two broad compelxity measures: 1) *I-complexity:* the number of non-trivial models we can infer given the data and an upper bound on temporal memeory, normalized by the maximum number of possible models, and 2) the *Z-Complexity:* which is the average number of states in the set of inferred models. I-complexity is the connectance that appears in May's condition of stability of complex systems discussed before: what is the probability that two varaibles or entities interact. And Z-complexity captures the average complexity of the intervariable dependence.

Note that these measures are computable effectively only if we have an inference algorithm that models non-trivial dependence between observed data streams, returning generative models capturing the complexity of signal tranduction across observables considered only if there is actual dependence, and indicating direction-specific independence otherwise. Thus, if we are considering N independent coin tosses (implying no temporal memory, since outcomes are iid), we have N trivial single state models. Thus, our complexity measures in this case will be:

$$\textit{I-complexity: } N/(N^2) = 1/N \tag{3}$$

$$\textit{Z-complexity: } 1 \tag{4}$$

We plan to investigate if real-world systems are inherently more complex compared to simulated counterparts. In contrast to the stability measures, the complexity measures are easier to replicate, since we can always define in more dependencies in our simulation rules.

Frequency-domain (like) Measures & Analytics

Measures of External Influence & Closed vs Open Systems

Systems of Interest

Crime, Terrorism, Simualted worlds from current DARPA programs, Robo Soccer, Real-life Soccer

The goals of this project are twofold: 1) detecting and quantifying cognitive dissonance in populations, communities and individuals, irrespective of geography, social and demographic context, and 2) develop data-validated theoretical models of belief shifts over time arising from the differential choice of dissonance reduction strategies employed by individuals. Within these broad goals, we aim to develop quantitative scalable measures of cognitive dissonance, characterize uncertainty bounds on our predictions. We plan to extensively validate our findings on large scale social survey data sets spanning multiple decades of recorded responses on a vast diversity of contentious issues from tens of thousands individuals from diverse socio-economic and demographic backgrounds.

Innovation: From Socio-psychological Theory To Data-driven Inference

Our proposed work is starkly novel in the level of mathematical rigor, the scalable computational tools, and the elegant quantitative adoption of a qualitative theory in psychology. The key innovation here is the formulation of the notion of cognitive dissonance as a **quantitative measure of surprise**; computed as the deviation of an individual's response to survey questions from what is predicted by data-inferred models from the responses of a wider random population to a broader set of queries. We bring together key insights from social and psychological theory, stochastic processes, and large deviation theory, to develop a novel machine learning framework (**recursive decision forest**) specifically designed for the problem at hand. Current research in the theory of cognitive dissonance is mostly qualitative, and the use of sophisticated learning algorithms custom is rare to non-existent.

Impact: Actionable Modulation of Local Opinions in Theaters of DoD Operations

- **Ability to quantify cognitive dissonance in US population and beyond.** The ability to understand if there is cognitive dissonance arising from opinions on specific contentious issues can potentially emerge as key tool in crafting policy. For the DoD, this capability will be a vital decision support tool when engaged in military operations in conflict countries.
- **Belief Shift Prediction.** Perhaps more crucial is the ability to understand how beliefs would shift as a result of cognitive conflict; thus allowing decision-makers to have actionable knowledge to modulate social interaction outcomes, particularly in foreign theaters of DoD operations.
- **Extending Social Theory.** The successful validation of the our proposed tools will revolutionize the analysis of large scale survey data. The ability to distill incipient micro-structural cross-dependencies and predict psycho-social dynamics at the level of sub-populations to individuals is currently beyond the state of the art, limited to mostly large scale trend analysis.

Deliverables include validated software, to be deposited in open source repositories; results from validation experiments; reports as determined by DARPA; and published research articles.

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