1. **Title: Toward Enabling Complex Sensemaking from Streaming Data**
2. **Abstract (one paragraph)**

The aim of this research is to increase the cognitive complexity of the analytic tasks that can humans can perform on streaming data. We do this by 1) examining from a theoretical perspective how to re-balance the effort between humans and computers, 2) exploring semantic interaction as a means of implicitly steering computational models, and 3) exploring the role that automated recommendations play in enabling the accomplishment of more sophisticated analytical questions.

**III. PI and Key Staff**

PI: Kris Cook, PNNL

Key collaborators:

* Semantic interaction research: Alex Endert (Georgia Tech)
* Jordan Crouser (Smith College)

**IV. Background**

Sensemaking can be depicted as a loop or iterative process of foraging and synthesis, which entails finding new data and putting it into context of the user’s experiences and knowledge to build and test hypotheses about a situation. (Pirolli and Card, 2005) Throughout the sensemaking process, conceptual models are evolved and refined.

Sensemaking tasks are concerned with static or slowly changing datasets, as sensemaking is cognitively intensive. In situations of rapid change with many alerts and interruptions, we assert that the focus is more on situation awareness and response, rather than on deeper sensemaking tasks.

Streaming data has traditionally lent itself to tasks such as alarm and anomaly reporting and situation awareness, in which the primary goal is to characterize current conditions and deviations from expected patterns. Sensemaking may tasks may be limited to relatively simple activities such as summarizing current conditions and reports, rather than testing alternative hypotheses as to their causes.

The purpose of this project is to investigate methods by which more complex sensemaking tasks can be supported in streaming data environments.

**V. Literature Review**

We briefly highlight literature in three related areas.

**Human Computation**

To date, the study of human intervention into computational problems has concerned itself primarily with questions of tractability. That is, can human input make it possible to (efficiently) solve problems whose solutions are otherwise believed to be too expensive to compute? Using experiential knowledge regarding the kinds of processing that humans are “better” at, such as recognizing objects and interpreting social behavior, we build systems that capitalize on these skills and offer them as constructive proof: tangible evidence that the problems are in fact tractable using human computation, even when other methods have failed. As such, the development of real-world implementations has far outpaced the development of theoretical measures. Many of these implementations have demonstrated unparalleled success at problems previously thought to be intractable, such as protein folding (Cooper et al., 2010). However, in the absence of a rigorous theory in which to ground new algorithms, researchers must rely on intuition and some deeply rooted assumptions about the differences between human and machine computation. Extending complexity models to encompass both human and machine computation will help us understand our successes and failures on existing problems, and more fully illuminate the computational space they inhabit.    
  
In their early research into developing theoretical foundations for human computation, Crouser et al. (2014) introduced the Human Oracle Model as a method for characterizing and quantifying the use of human processing power as part of an algorithmic process. This work provides a critical first step in quantifying human involvement in computational processes, and helps us to better understand the intricate relationships among different problems and problem families when viewed through the lens of human computation. That said, it only just scratches the surface of this potentially rich area for future research. In particular, it characterizes only a small set of simple, offline problems and relies on the simplicity of the problem to serve as a bound on the human's required resources. Because of this, the existing model falls short when applied to more complex, streaming applications.

**Semantic Interaction**

Semantic interaction is an interaction technique that tightly couples the visual encoding and visual metaphor of the visualization with the method for user interaction. (Endert et al., 2012a) The approach enables users to integrate their domain expertise into the visual analytic system by directly manipulating the information within the visual metaphor. Therefore, the calculations translating data characteristics into visual encodings are inverted when the user interacts with them to infer analytical reasoning from the interaction performed and steer the underlying analytic models (Endert 2014). This interactive discourse continues over the course of an investigation, where the analytic models continue to incrementally adapt (Endert et al., 2012b).

Endert et al. present a model for semantic interaction that depicts the difference between such implicit model steering and explicit, direct control of model parameters (2012a). Their model shows how the focus of semantic interaction is on performing the user interaction within the visual metaphor, as opposed to directly on graphical controls of model parameters. Closely related approaches include work leveraging reinforcement learning techniques to update a data model given user feedback on keywords (Glowaka et al., 2013), and interactive intent modeling for information retrieval and discovery (Ruotsalo et al., 2014).

**Sensemaking**

Sensemaking has been a subject of research in visual analytics since Pirolli and Card introduced their sensemaking loop in 2005. Alternative models of sensemaking, including Klein’s data/frame model (Klein et al., 2006) have been proposed. Kang and Stasko (2011) conducted a longitudinal study of sensemaking as performed by students in an intelligence analysis academic program. Zhang and Soergel (2014) have studied journalists and marketers performing sensemaking tasks to develop a deeper understanding of the synthesis parts of the sensemaking process.

Cook et al. (2015) presented a mixed-initiative visual analytics system to support iterative sensemaking tasks similar to those described above. This model shows initial promise. We believe that this model will be particularly relevant in streaming data, in which automated analytic algorithms can recommend relevant data to the user for consideration.

**VI. Research Hypothesis / Expected Results**

In this research, we plan to address three fundamental questions:

1. **Human Computation:** how to balance human and machine effort in online computation

**H1.** Limiting resources (memory, time-to-decision, etc.) available to the Human Oracle will result in simulated behavior that is different from that observed in the original model.

**H2.** The resource-limited Human Oracle Model enables accurate prediction of human performance on streaming data analysis tasks.

1. **Semantic Interaction:** How to translate user actions into explicit or implicit steering of computational models

**H3.** There exists a common set of user goals for steering a computation and a corresponding set of explicit or implicit user actions that can be directly mapped to these goals.

1. **Mixed-Initiative Sensemaking:** How the use of system-generated recommendations (or AIM “hypotheses”) based on implicit or explicit user steering affects the effectiveness of the complex sensemaking tasks.

**H4.** The degree to which sensemaking is achievable on streaming data depends upon a) the volume and rate at which data/recommendations are pushed to the user, b) the length of time available for decision, and c) the complexity of the analytic task.

**H5.** Sensemaking effectiveness in a streaming environment degrades when the user perceives a lack of control over recommendation types, frequency, and degree of interruption.

**VII. Scientific Approach / Method**

We will explore the above hypotheses using the following approach.

**Human Computation**

To more fully understand how to balance human and machine effort in online computation, it is imperative that we establish mechanisms by which we might extend these models to quantify and reason about the computation being done. Our proposed approach is twofold:

1. To validate **H1**, we will explore the impact of imposing various limiting factors on the Human Oracle using simple modeling and simulation techniques. This will provide a basis for comparison with the original model, as well as generate a "tunable" testbed for future adaptations to the model.
2. To validate **H2**, we will conduct a web-based experiment using human subjects in which various  components of a selection of streaming applications are manipulated (stream volume, sampling rate, etc.).  We will then compare participants’ performance with that predicted by the testbed in **H1**.

**Semantic Interaction**

Model steering can be described as a process of approximating changes in mental models to incrementally evolve computation. Categorically, this can be performed in either implicit or explicit ways. Explicit methods include people directly tuning model parameters using graphical widgets or others methods. Implicit techniques include learning from user interactions with an interface to evolve computation.

To validate **H3**, this research task will create a taxonomy for mapping analysis activities performed by people to adaptations in the analytic models. More specifically, we plan to look into a framework for mapping these activities implicitly when possible.

This taxonomy will be created using a selected set of examples and evaluated by applying it against other use cases to identify gaps.

To make the resulting taxonomy useful more broadly, we will develop a semantic interaction API for d3-based visualizations. We propose to develop an API that works in conjunction with d3 to support interactive model steering. We will leverage the bindings that d3 creates between data values and graphical encodings to create interactive affordances. We call these interactive visual primitives. The primitives serve as means for people to interact with the visualization. As a result, many interactions and tasks can be supported. This library will be made available publicly.

**Mixed-Initiative Sensemaking**

To address **H4** and **H5**, we will first characterize a set of sensemaking tasks currently performed on streaming data. From this study, we will refine our hypotheses as appropriate to reflect other variables that appear to be significant.

To validate **H4**, we will develop a prototype in which the volume and rate of recommendations can be varied. We will vary experimental conditions and analytic tasks to test the degree to which the expected variables affect the speed and accuracy of assessment tasks with known ground truth.

To validate **H5**, we will conduct user tests with two prototypes – one in which the user has control over recommendations, and one in which recommendations are presented at variable speeds and volumes to assess the impact on assessment tasks with known ground truth.

**VIII. Impact**

AIM seeks to “re-balance human-machine analytic effort in exploratory knowledge discovery.” (AIM web site). Through the proposed research, we hope to gain insight about issues unique to streaming analysis. The development of complexity measures for human computation may play a significant role in the broader adoption of human computational methods. Robust models of how humans fit into the grand scheme of computational tools is essential to promoting wider understanding of human effort as a legitimate and measurable computational resource.  Development of a taxonomy of semantic interactions and a publicly available open-source semantic interaction library will make these techniques available for broad application. Characterization of the role of recommendations in the streaming sensemaking process will enable a better understanding of human-machine mixed initiative to address complex problems.

**IX. References**

AIM Web site. <https://enterprise.pnl.gov/sites/AIM/Pages/Home.aspx>, accessed 9/4/2015

K. Cook, N. Cramer, D. Israel, M. Wolverton, J. Bruce, R. Burtner, A. Endert, “Mixed Initiative Visual Analytics Using Task-Driven Recommendations”, *Proceedings of IEEE Visual Analytics Science and Technology 2015*, to appear.

S. Cooper, F. Khatib, A. Treuille, J. Barbero, J. Lee, M. Beenen, A. Leaver-Fay, D. Baker, Z. Popovic, Z, and others (2010). Predicting protein structures with a multiplayer online game. Nature 466, 7307 (2010), 756–760.

R. Crouser, B. Hescott, and R. Chang, “Toward Complexity Measures for Systems Involving Human Computation”, *Human Computation, vol*. 1 no. 1, 2014, pp. 569-592.

A. Endert, “Semantic Interaction for Visual Analytics: Toward Coupling Cognition and Computation,” *IEEE Comput. Graph. Appl*., vol. 34, no. 4, pp. 8–15, Jul. 2014.

A. Endert, P. Fiaux, and C. North, “Semantic interaction for visual text analytics,” in *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, 2012, pp. 473–482.

A. Endert, S. Fox, D. Maiti, and C. North, “The semantics of clustering: analysis of user-generated spatializations of text documents,” in *Proceedings of the International Working Conference on Advanced Visual Interfaces*, 2012, pp. 555–562.

Y. Kang and J. Stasko, “Characterizing the intelligence analysis process: Informing visual analytics design through a longitudinal field study,” 2011, pp. 21–30.

G. Klein, B. Moon, and R. Hoffman, “Making Sense of Sensemaking 2: A Macrocognitive Model”, *IEEE Intelligent Systems,*  vol. 21, no. 5, September/October 2006.

P. Pirolli and S. Card, “Sensemaking Processes of Intelligence Analysts and Possible Leverage Points as Identified Though Cognitive Task Analysis,” *Proc. 2005 Int. Conf. Intell. Anal. McLean Va.*, p. 6, 2005.

P. Zhang and D. Soergel, “Towards a comprehensive model of the cognitive process and mechanisms of individual sensemaking,” *J. Assoc. Inf. Sci. Technol.*, vol. 65, no. 9, pp. 1733–1756, 2014.

D. Glowacka, T. Ruotsalo, K. Konuyshkova, kumaripaba Athukorala, S. Kaski, and G. Jacucci, “Directing Exploratory Search: Reinforcement Learning from User Interactions with Keywords,” in *Proceedings of the 2013 International Conference on Intelligent User Interfaces*, New York, NY, USA, 2013, pp. 117–128.

T. Ruotsalo, G. Jacucci, P. Myllymäki, and S. Kaski, “Interactive Intent Modeling: Information Discovery Beyond Search,” *Commun ACM*, vol. 58, no. 1, pp. 86–92, Dec. 2014.