The grand challenge of computer vision is to build a machine which produces a rich semantic description of an underlying scene based on image data. Entropy pursuit is a sequential Bayesian approach to object detection and localization. The role of the prior model is to apply contextual constraints in order to determine and coherently integrate the evidence acquired at each step. The evidence is provided by a large family of powerful but expensive high-level classifiers (e.g., CNNs) which are implemented sequentially and adaptively. The order of execution is determined online, during scene parsing, and is driven by removing as much uncertainty as possible about the overall scene interpretation given the evidence to date. The goal is to match, or even exceed, the performance obtained with all the classifiers by implementing only a small fraction. Sampling from the posterior in order to estimate entropies and likely states is a key technical challenge.

Recently, the computer vision community has focused on "scaling up" to richer vocabularies and deeper semantic descriptions. However, adopted performance metrics, such as error rates for object detection and localization, do not scale naturally to the storylines humans generate using contextual reasoning, and there is no evident way to measure performance and progress. "Entropy pursuit" is a unified approach for designing and testing vision systems in a Bayesian framework. Scenes are represented as the answers to a very large family of binary questions about object instances and relationships. In my first lecture I discussed entropy pursuit as organizing principle for building a system. In this lecture I will describe a visual Turing test wherein the Bayesian prior model generates streams of "unpredictable" questions in an information-theoretic sense; the data are the correct answers for the image under scrutiny. The key challenge, and the motivation for a model-based approach, is conditional sampling given the current history of questions and answers.