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Hybrid AI for IoT Actionable Insights & Real-Time Data-Driven Networks

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Abstract

Significant increases in industry requirements for network bandwidth are seen year upon year. The exponential growth in streaming data is matched by an increase in the use of machine learning and deep learning to glean actionable – ideally real-time – insights from these data. However, approaches based on artificial neural networks (ANNs) are often insufficient in terms of functionality, flexibility, accuracy, explainability, and robustness. The demand for new model development and continual updating and retraining is outstripping the model generation capacity of data scientists and others in the field. This gap between supply and demand for real-time data driven insights continues to grow. In this paper we introduce a hybrid AI solution which adds several elements into the ML/DL mix, specifically a new self-supervised learning mechanism, a knowledge model engineered to include support for machine generated ontologies as well as traditional human-generated ontologies, and interfaces to symbolic AI systems such as OpenNARS, AERA, ONA, and OpenCog, among other elements. Our hybrid AI system enables self-supervised learning of machine-generated ontologies from millions of time series, to provide real-time data-driven insights for large-scale deployments including data centers and enterprise networks. We also apply the same hybrid AI to video analytics use cases. Our preliminary results across all the use cases we have attempted to-date are promising although more work is needed to fully characterize both the benefits and limitations of our approach.

Keywords: Artificial Intelligence, General Machine Intelligence, Hybrid AI, Data-Driven Networks, Real-Time, Artificial General Intelligence, Self-Supervised Learning, Ontologies

1. Hybrid AI and Explainable Perception

High-resolution cameras and other high bandwidth sensors are proliferating, as are other types of real-time data such as network telemetry and business related time series. Gartner estimates the value of providing real-time data-driven insights at over a trillion dollars in the coming years.[1] This enormous opportunity is driving research and development of hybrid artificial intelligence (AI)[2] solutions that include machine learning, deep learning,

1. Gartner Top Trends in Data and Analytics — accessed Nov. 18th, 2022.
2. Our use of the label 'hybrid AI' here is generally synonymous with the Wikipedia definition of 'Hybrid Intelligent Systems' — accessed Nov. 18th, 2022.

artificial general intelligence (AGI), reasoning, knowledge graphs and other elements. Driven by this real-world need, industry, in collaboration with academia, is making pragmatic advances in hybrid AI solutions. In spite of these advances, systems based solely on artificial neural networks (ANNs) continue to be built, often resulting in limitations of functionality, flexibility, accuracy, robustness, and explainability.[3]

As the name implies, 'hybrid AI' may include many different technologies such as reasoners, Matrix Profile time series analysis, traditional machine learning (ML) and deep learning (DL), and more. Falling into this broad category of Hybrid AI systems, this paper describes the specific elements of our Hybrid AI system that we and others have developed.

One of the core principles of our Hybrid AI approach centers around the creation improved world models based on self-supervised learning from sensor data. We are calling this approach "explainable perception" which is simply a machine version of onomotopoeia used by toddlers when they, for example, self-label a train a "choo choo". Machines are able to easily take this idea beyond auditory domains into visual, ultrasonic, haptic, and any other modality supported by the input sensor data.

1.1. Self-supervised Learning from Spatiotemporal Information

Our approach for processing raw input spatiotemporal data, often termed sub-symbolic, is based on matrix profile time series semantic segmentation (Latapie et al. (2022)). This approach has been found to be efficient in processing large amounts of time series data (e.g. millions of time series in real-time). The inductive bias for ML/DL can typically be described as pattern recognition. However, we build on this inductive bias in several ways. We begin with the hypothesis that the large scale system being observed consists of time series that may be interrelated in complex ways, with all manner of unknown causal and correlational relations. Therefore when a number of time series' from multiple different sources all experience a simultaneous shift from one structural mode to another, known as a regime change, it may mean there is a significant event of interest occurring. The system continues to observe the nature of this correlation over time to quantify the degree of correlation for these hypothesized events if interest. In our experiments, we have found that accurate descriptive and predictive models for networking use cases can be learned in this manner.

In the case where there are small numbers of ephemeral time series, such as in the case of privacy preserving behavioral video analytics for moving objects, we found that the addition of another inductive bias based on the rate of change of the regime changes is a useful metric for events of interest. This inductive bias for animate and inanimate objects is based on the hypothesis that the dynamics of these systems results in structural cohesion in the temporal domain which is normally broken as the system moves from one state to another. These mode changes from, for example, walking to sitting to standing don't normally occur at a high rate. Our initial experiments for human behavior indicate this inductive bias is a good way to find behaviors of interest such as aggression, medical incidents, and so forth in a self-supervised manner.

3. C.f. Even after 100 Billion Self Driving Cars Are Going Nowhere — accessed Nov. 18th, 2022.

1.2. Machine generated ontologies

The self-supervised learning mechanism above allows us to categorize and classify input data in terms of these semantic segments. By grouping all the observed semantic segments across time series on the basis of similarity metrics, the system is able to categorize and rank the input data into most and least commonly seen semantic segments. These categories are organized into hierarchical structures by identifying representative actual or synthetic samples. These machine generated ontologies may also be associated with natural language labels via active learning or other more automated techniques. These machine generated ontologies based on input data processed by the system form the foundations of our hybrid AI approach to symbol grounding. In essence this type of hybrid AI literally "makes sense" of symbols by tying them to prior sensory information. In the case where there is no prior sensory information, some approximate mapping to the equivalent is necessary. We believe that such cases can be handled via synthetic data generation but this remains to be proven.

1.3. Learning by reasoning

OpenNARS based learning by reasoning is another key element of our Hybrid AI approach. In the SmartCity paper we demonstrate how even a crude interfacing of an ML/DL based object tracking system, with OpenNARS was able to significantly improve the generalizability of video analytics systems. By starting with a small amount of a priori seed knowledge which include some basic spatiotemporal assumptions about the world and what mattered amounting to around one (1) page of rules, the system is able to "understand" a new camera view of a smart-city like environment in about a minute assuming an average amount of activity and begin reporting events of interest such as potential accidents between any two moving objects, actual accidents, jay walking, and more. The same system was given a slightly different seed knowledge focused on retail inventory use cases and was able to automatically learn shelf locations, product candidate placements, etc. (Thórisson, 2020).

1.4. Ontology-Based Problem Decomposition With Attention

Retail use case used this to avoid combinatorial explosion issues in the reasoning space and to improve static confidence metrics. We used a spatial semantics model focused on containment and relative positioning of shelves and objects (Latapie and Kilic, 2020).

1.5. Machine-Ontology to Human-Ontology Interoperation

The current focus of our research is on interoperability between machine and human generated ontologies. While manual methods, such as active learning, are significantly more efficient than supervised learning—requiring only one active learning-acquired label to replace potentially thousands or tens of thousands of traditional ground truth labels—our goal is to leverage large language models and other autonomous approaches to minimize the need for active learning time from human domain experts.

2. Use Cases

This work focuses on the incremental development of real world, customer-facing robust proof of concepts built on industry standard open source building blocks: docker containers, redis, redis time-series, gstreamer, opencv, grafana dashboards, DL frameworks and libraries, matrix profile time series analysis, Neo4J graph database and kubernetes.

2.1. Smart City

The results for smart city analytics of complex road intersections that include bus lanes, commuter train tracks, and cross walks show that with a small amount of seed knowledge, the system can, in constructivist AI fashion, rapidly adapt and learn to provide a wide range of safety related analytics (Hammer et al., 2019; **?**).

2.2. Retail

Using a different spatial semantics seed of knowledge, our hybrid AI system for retail analytics was able to configure itself to all manner of retail scenes and provide inventory analytics (Latapie and Kilic, 2020).

2.3. Networking

In the networking domain, our hybrid AI system was able to process over 300K time series in real time on a single 8-core CPU and produce descriptive and predictive models in a self supervised manner. These models were tested with 30 previously unseen failure modalities and exhibited state-of- the-art accuracy (Latapie et al., 2021).

2.4. Privacy-Preserving Behavioral Analytics

Finally, our results in computer vision based human behavior analytics demonstrate that our self-supervised learning is highly sensitive to subtle changes in individual human behavior indicative of potential interest. We demonstrate the ability to detect flash mob formation in it's early stages while being able to detect all manner of incidents by the subtle changes in behavior of the people around the incident, even if the incident itself is completely off camera.[4]

3. Conclusion

The hybrid AI system we built in collaboration with Pei Wang, Patrick Hammer, Kristinn R. Thórisson, and other academics and AGI researchers (Hart and Goertzel, 2008; Wang, 2013, 2006; Nivel and Thórisson, 2013; Thórisson, 2012), and with the support of key Cisco partners and customers, is empirical evidence that hybrid AI systems can exhibit capabilities such as cumulative learning (Thórisson et al., 2019), generational learning, self-supervised learning, neurosymbolic integration (Latapie et al., 2022), reasoning, explanation generation (Thórisson, 2021), and goal-oriented constructivist AI. Hybrid AI systems offer a potential

4. Next Generation AI for Real-Time Data-Driven Network and IoT Insights - BRKETI-1000 — accessed Feb. 1st, 2023.

solution for a variety of use cases and can be adapted to meet complex and evolving business needs.

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