# AI, What Does the Future Hold for Us? Automating Strategic Foresight.

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## ABSTRACT

There is an increasing awareness that strategic foresight is much needed to guide efficient policy-making. The growing digitalization implies a rising amount of digital evidence of many aspects of society (e.g., science, economy, and politics). Artificial intelligence can process massive amounts of data and extract meaningful information. Furthermore, a knowledge graph can be developed to capture significant aspects of reality, and machine learning models can be used to identify patterns and derive insights. This paper describes how we envision artificial intelligence could be used to create and deliver strategic foresight automatically.

## CCS CONCEPTS

• **Applied computing → Computers in other domains**.

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## 1 INTRODUCTION

While forecasting or quantitative trend analysis aims to predict future values while minimizing the associated uncertainty of the estimates, strategic foresight provides a structured approach to gathering information for the purpose of elaborating on plausible futures and embracing uncertainty for learning and awareness-building [13]. Exploring possible scenarios allows a better understanding of how actions can influence the future. Such understanding is of paramount importance in a world full of Turbulence, Unpredictability, Uncertainty, Novelty, and Ambiguity (TUNA) [16].

Strategic foresight is being increasingly considered for strategic planning in the private and public sector [3, 14]. Furthermore, it has been recognized as a critical tool to help build a more sustainable future [15]. Greenblott et al. [8] have found that the most frequently used strategic foresight methods are horizon scanning (gathering and analysis of information on trends and developments relevant to the organization) and scenario planning (description of plausible future scenarios harmonizing divergent signals into consistent descriptions). Using domain experts to gather and analyze data can impose severe scalability limitations and bias the assessments [4]. Such limitations can be overcome with artificial intelligence. Hybrid strategic foresight approaches have been proposed. Such approaches leverage artificial intelligence to automate information scanning and data analysis while sparing the human professional to focus on more complex tasks [2, 10].

This position paper describes a strategic foresight solution we aim to develop leveraging the GraphMassivizer architecture [12]. The solution aims to introduce higher levels of automation achieved by current strategic foresight platforms. In particular, we draw inspiration from three works [4, 7, 13]. Raford et al. [13] describe how social media and crowdsourcing enabled new strategic foresight business models. Ebadi et al. [4] describe how deep learning and weak signal analysis were applied to detect emerging topics and their evolution. Finally, Geurts et al. [7] describe a comprehensive hybrid solution that leverages artificial intelligence (text mining, topic modeling, and knowledge graphs) to collect information, detect trends, and represent relationships between concepts, which experts can use to assess analyze trends, assess the impact and strategize. We envision a solution that allows ingesting and analyzing massive amounts of relevant data and creating suitable semantic abstractions. Furthermore, artificial intelligence is used (a) to track and forecast relevant trends, (b) to mine graph patterns and determine whether relevant patterns can arise in the future, and (c) to rank potential scenarios. The scenarios are then presented to the users for further analysis and evaluation. In the next section, we describe the solutions' architecture in detail.

## 2 PROPOSED ARCHITECTURE

The proposed architecture (see Fig. 1) envisions two components of the GraphMassivizer architecture are required to deliver the strategic foresight functionality: Graph Inceptor (concerned with data ingestion, graph creation and persistence) and the Graph Scrutinizer (concerned with graph processing). The insights obtained from the Graph Inceptor component are then exposed to the foresight application along with any helpful information and considerations


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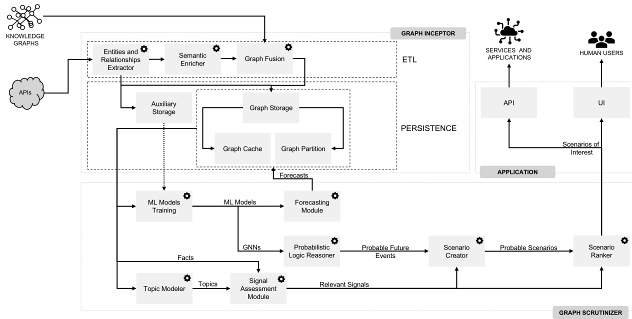


**Figure 1: The figure describes the technical architecture we envision is necessary to deliver fully automated strategic foresight.**

regarding user profiles, restrictions regarding data access, and other relevant application aspects.

We consider the Graph Inceptor will source data from at least two types of data sources: knowledge graphs and APIs. Media news is extracted through API calls to services such as EventRegistry or GDELT [1, 9], and the content is processed using natural language processing to extract entities and their relationships and perform semantic enrichment. The data is then integrated into an existing knowledge graph based on Wikidata [6, 11], which provides semantic abstractions and a more general understanding regarding the entities, facts, and actions reported in media news. We consider such abstractions, along with proper modeling of time [5], critical factors toward successful foresight. The graph is persisted in graph storage, and graph partitioning and caches can be used to reduce access times.

The Graph Scrutinizer is mainly concerned with graph processing. We envision machine learning models are trained with two goals in mind: (a) forecast future values of relevant indexes to understand how a given context will most likely evolve from a specific point of view (societal/economic/political/environmental), and (b) predict missing links (e.g., through graph neural networks [18]) and find similar patterns in graphs to understand likely future scenarios (entities and events that may show up in the future, given patterns observed in the past). Furthermore, topic modeling is applied to detect weak signals regarding topics that could have increasing relevance in the future and, therefore, could be relevant to create foresight scenarios. To determine the topics' relevance, we follow the methodology proposed by [4] and build keyword emergence maps (KEM - reports the frequency of a keyword in a time period) and keyword issue maps (KIM - reports on how much the signals are disseminated). Following [17], KIM and KEM signals can be classified into quadrants based on the strength of the signal and degree of diffusion. Signals of interest to foresight could be weak signals (either well-known or not) and not well-known strong signals. We automate relevant topic extraction by intersecting KEM and KIM signals in the aforementioned categories. Finally, probable future events and weak signals are considered to create scenarios. When building such scenarios, we emphasize actionable aspects that can drive decision-making. Scenarios are ranked considering their importance and impact so that scenarios with high importance are shown first while informing whether low or high uncertainty forces will lead to them.


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