Sustainable Grain Transportation in Ukraine Amidst War Utilizing KNARM and KnowWhereGraph

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ABSTRACT

In this work, we propose a sustainable path-finding application for grain transportation during the ongoing Russian military invasion in Ukraine. This application is to build a suite of algorithms to find possible optimal paths for transporting grain that remains in Ukraine. The application uses the KNowledge Acquisition and Representation Methodology(KNARM) and the KnowWhereGraph to achieve this goal. Currently, we are working towards creating an ontology that will allow for a more effective heuristic approach by incorporating the lessons learned from the KnowWhereGraph. The aim is to enhance the path-finding process and provide more accurate and efficient results. In the future, we will continue exploring and implementing new techniques that can further improve the sustainability of the path-finding applications with a knowledge graph backend for grain transportation through hazardous and adversarial environments. The code is available upon reviewer's request. It can not be made public due to the sensitive nature of the data.

KEYWORDS

knowledge graphs, ontology engineering, path-finding, global food systems

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1 INTRODUCTION AND MOTIVATION

Ukraine is the fourth largest exporter of grain globally [3]. The ongoing Russian military invasion in Ukraine has had a major impact on the country's grain transportation [16]. The instability in the region has made it difficult for grain to be transported effectively and efficiently, and this situation is further complicated by rapidly changing transport conditions. Considering these challenges, it is important to find a sustainable path-finding application that can be rapidly updated when conditions around paths change to help grain be transported in Ukraine amidst the war and exported to the rest of the world.

In order to capture the rapidly changing data (and physical) landscape, we choose to utilize a knowledge graph as our knowledge base; that is, our application's source of truth. Knowledge graphs are capable of integrating a wide variety of data sources in a semantically rigorous way, according to well-established W3C standards [2, 6, 10]. Due to their ability to bridge human conceptualization and machine understanding [7] and a powerful standard for recording provenance [13], results drawn from them are also inherently explainable, and interpretable. This may be achieved more effectively if the knowledge acquisition bottleneck can be avoided using systematic approaches like KNowledge Acquisition and Representation Methodology (KNARM) [12]. These capabilities are particularly advantageous in times of turmoil; there are many disjoint and disconnected efforts to provide real-time intelligence, and in many different ways: from remote sensing to social media reports, or even word of mouth. There are already even established ways for modeling these sorts of data (respectively, [8, 11, 14]).

Furthermore, there are existing – and established – environmental and situational awareness knowledge graphs. The KnowWhere-Graph[1] is a 1.25×10^{10} triples-large geospatial knowledge graph based on W3C Standards that targets applications in the food, agriculture, humanitarian relief, and energy sectors and their attendant supply chains generally; environmental policy issues relative to interactions among agricultural sustainability, soil conservation

[1]https://knowwheregraph.org/

practice, and farm labor; and delivery of emergency humanitarian aid, within the US and internationally. It brings together data related to observations of natural hazards (e.g., hurricanes, wildfires, smoke plumes) and spatial characteristics related to climate (e.g., temperature, precipitation, air quality), soil properties, crop and land-cover types, demographics, and human health – among others [9]. KnowWhereGraph pre-computes the spatial relations between these data layers and aligns them to an underlying discrete, hierarchical global grid [1, 15].

In order to integrate such incoming data streams, alongside leveraging the huge knowledge bases already available, we will use the KNowledge Acquisition and Representation Methodology (KNARM) [12]. KNARM, consists of nine steps (i.e., Sub-language Analysis, In-House Unstructured Interview, Sub-language Recycling, Metadata Creation and Knowledge Modeling, Structured Interview, Knowledge Acquisition Validation, Database Formation, Semi-Automated Ontology Building, Ontology Validation) that allow domain experts and knowledge engineers to build useful, consistent ontologies formalizing domain data and knowledge in a systematic way using modular ontology architecture and systematically deepening modeling for domain knowledge. It is designed to help with the challenge of acquiring and representing knowledge in a systematic, semi-automated way. With KNARM, using the DB back-end, we can update rapidly changing data more easily and update ontologies more quickly using the semi-automated ontology building step. This methodology aims at acquiring knowledge from data scattered in different databases and ontologies, combining them in a meaningful fashion that is understandable by humans and machines by effectively combining human and machine capabilities.

In this research, we aim to integrate KnowWhereGraph's hierarchical grid to help provide finer-grain topological investigations over time. We also aim to integrate this hierarchical grid structure to create an infrastructure with which we can provide layering of heuristics using the systematically-deepening modeling approach used in KNARM.

Poster, Demonstration, & Availability

This paper is intended to introduce the necessary topics, background, and our preliminary work and to be presented in a poster style. In this work presentation, we will showcase how this application serves as a step forward towards finding a practical solution for the grain transportation challenges faced by Ukraine amidst the ongoing Russian invasion. However, as might be expected, the nature of our input data is quite sensitive. As such, we can make the code available at this time, but do not have de-sensitized data. If accepted, we can provide sanitized data in the appropriate format to test the code. The reviewers, via the Workshop Chairs, may request available code.

The rest of this paper is organized as follows. The next section provides details on our implementation and methodology. In Section 3, we state our progress and discusses our next steps. Finally, in Section 4, we conclude.

2 METHODS

As introduced in the previous section, the overarching purpose of our application is to identify optimal paths (i.e., grain transportation routes) through a hazardous and adversarial environment. Generally speaking, this grain will travel via convoy or train, meaning that the routes can be generally broken into discrete locations (e.g., train stations or villages). Additionally, grain may be stored in scattered grain elevators and accumulated by the convoy as it progresses; these will also add additional stops. As such, these can be treated as nodes in a graph, where the weight of the edge between two nodes is the distance.

Yet, there is more to account for than just distance. In this case, it is also necessary to take into the account the hostile environment. As such, instead of just using Dijkstra's algorithm, we choose to use a modified form of A^* [4, 5]. This equips the canonical Dijkstra's algorithm with a heuristics that can dynamically alter the edge weights based on external parameters.

Understanding that the definition of an *optimal path* through an adversarial environment may depend on several factors, we are in the process of creating a knowledge graph back-end using the systematic approach outlined in KNARM. A knowledge graph backend created in a systematic way with a database backend can help select and/or connect the different factors users might want to employ as heuristics to support the modified A^*. Heuristics used in this research include grain storage size, road conditions, and inclusion of preferred transportation hubs. All of this data had to be collected using domain experts' help in multiple files. The files were processed using Python for data cleaning, re-structuring, and re-formatting. Because of the sensitive nature of the data, all of the data-cleaning, re-structuring, and re-formatting steps had to be performed on the fly on the input files from the domain experts. The modified A^* algorithm uses the re-formatted data to utilize the heuristics and improve the optimal path finding. Even though limited heuristics are applied in this research, in generalization of this research, we foresee that we will be able to incorporate different types of heuristics: the examples include land conditions like flooding in areas and the downstream effects like toxic exposures, weather conditions, other means of transportation among other possible heuristics.

Our application currently outputs a railway path for transporting grain through the graph representing Ukraine's railroad stations and elevators, which can be easily visualized as an ordered list of location names corresponding to the stops along the route.

Implementation

In our implementation, we use the Pandas[2] and Numpy[3] in Python packages, and run the code remotely on Google Colab.[4]

3 CURRENT STATUS AND FUTURE DIRECTIONS

Currently, we are working towards creating an ontology that will allow for a more effective heuristic approach by utilizing the Knowledge Acquisition and Representation Methodology (KNARM) [12] and incorporating the lessons learned from the KnowWhereGraph [9]. The aim is to enhance the path-finding process and provide

[2]https://pandas.pydata.org/
[3]https://numpy.org/
[4]https://colab.research.google.com/

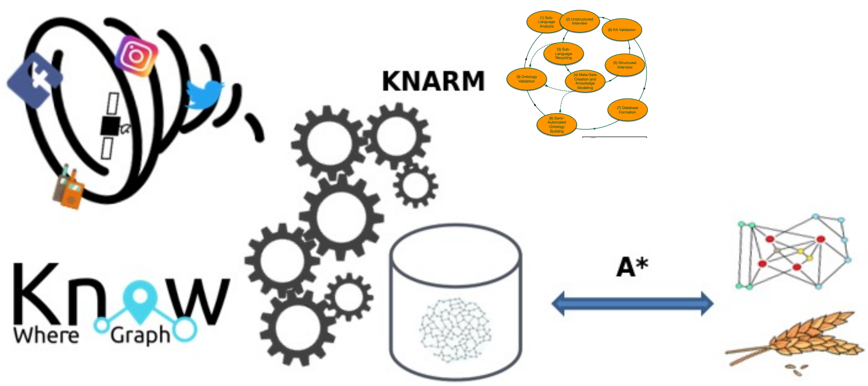

Figure 1: This research will aim to integrate KnowWhereGraph and KNARM to better assist A* algorithm in finding optimal paths for transportation of goods.

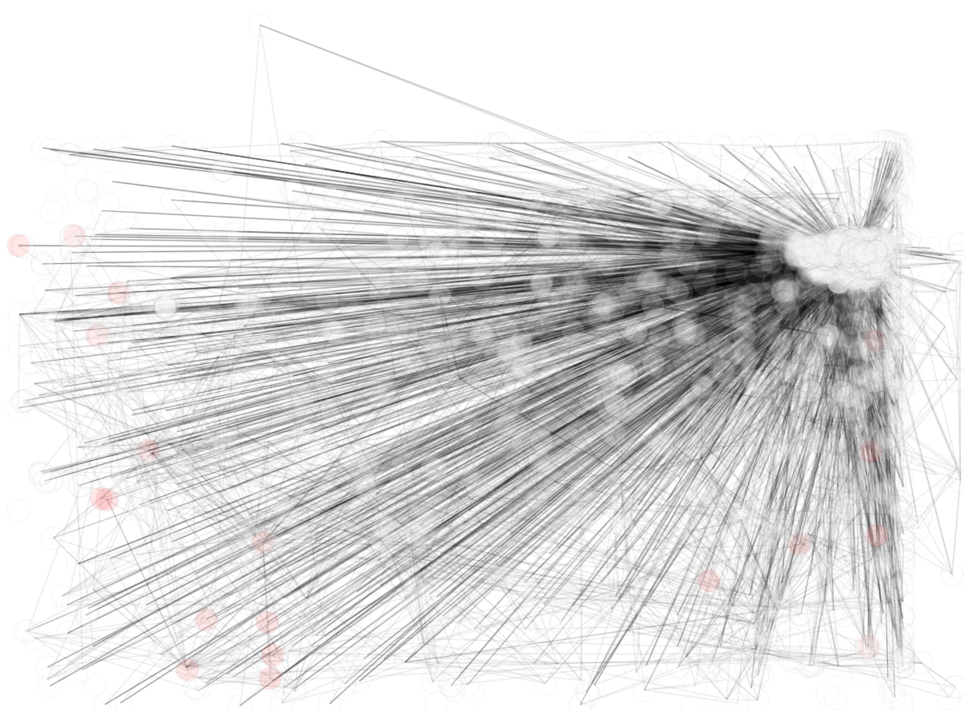

Figure 2: Figure shows a path found for transportation out of all the possible hubs.The lines represents connections. The nodes in the path are highlighted in red, the nodes that do not belong to a path are transparent to help with the visualization. Labels of the nodes are removed to protect the underlying data.

more accurate and efficient results. With the addition of the knowledge graph back-end, we will be able to create models using the different heuristics that may be used for better path finding or increase our ability to predict problems that may occur in the routes. Additionally, the use of an ontology will allow for a more organized and structured representation of the data, which will be essential in refining and improving the application in the future. We aim to integrate KnowWhereGraph's hierarchical grid to help provide finer-grain topological investigations over time. We also aim to create an infrastructure with which we can provide layering of heuristics using the systematically-deepening modeling approach used in KNARM. Our goal is to continue exploring and implementing new techniques that can further improve the sustainability of the path-finding application for grain transportation in and from Ukraine. Currently, KnowWhereGraph's hierarchical grid is not implemented and this is a future step we aim to complete.

4 CONCLUSION

A sustainable path finding application for grain transportation during the ongoing ongoing Russian military invasion in Ukraine is an important solution that is needed to help the country navigate the challenges it faces and continue to supply grains to the rest of the world. By using the modified A^* algorithm and heuristics, the application provides a visual representation of the optimal path as well as a string that details the chosen path. This research is currently limited to the data for Ukraine. However, as this paper outlines future directions using KNARM and KnowWhereGraph, this solution can be generalized to help finding efficient optimal paths using diverse sets of heuristics in a dynamic setting where hazardous and adversarial environments are present.

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