Achieving maritime situational awareness using knowledge graphs: a study

DEFENCE AND SPACE
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Context

- A PhD thesis (CIFRE)
- 3 years (Feb. 2018 -> 2021)
- A collaboration between Airbus and GREYC laboratory

Supervisors:
- Stéphan Brunessaux
- Sylvain Gatepaille

Team MAD: Models, Agents, Decision

Supervisors:
- Abdel-Illah Mouaddib
- Bruno Zanuttini
Context and objectives

• Maritime intelligence operators face a huge flow of data

• Human experts can’t process everything

• Experts define interactions between entities of a situation (subordination, conflict, proximity…)

• Use every data at disposal (prior information fusion)

• Generate new links/entities from the data

Automated threat assessment
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• Application to Maritime Situational Awareness

• Proposed Knowledge Graph

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Maritime example
Situation

- Relation from situation
- Relation generated from model
- 0.99 Confidence level of the relation
- :hasFlag Relation type

Indian Ocean

A high sea area

Country A

Ship A

Latitude: 15.8
Longitude: 64

Cargo

Ship B

Country B

Latitude: 15.8
Longitude: 64

:hasFlag

Relation type

:moveIn

:locatedIn

0.95

0.95

0.95

0.95

0.85

0.85

0.85

0.85
Situation change

- Relation from situation
- Relation generated from model
- 0.99 Confidence level of the relation
- :hasFlag Relation type

Ship A
- :hasFlag
- :stoppedIn
- :isCloseOf
- Latitude: 16
- Longitude: 65

Ship B
- :hasFlag
- :stoppedIn
- :isCloseOf
- Latitude: 16
- Longitude: 65

Country A
- :hasFlag

Country B
- :hasFlag

Indian Ocean

A high sea area

Cargo

0.99 :hasFlag
0.90 :stoppedIn
0.86 :isCloseOf
0.95 :hasFlag
0.85 :hasLocation
0.95 :hasLocation
0.95 :hasVesselType
0.95 :hasLocation

0.99 :hasFlag
0.91 :stoppedIn
0.86 :isCloseOf
0.95 :hasFlag
0.85 :hasLocation
0.95 :hasLocation
0.95 :hasVesselType
0.95 :hasLocation

T1
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New knowledge

- Relation from situation
- Relation generated from model
- :hasFlag Relation type

Indian Ocean

A high sea area

Country A

Ship A

Ship B

Country B

Cargo

Latitude: 16
Longitude: 65

Latitude: 16
Longitude: 65

0.99 :hasFlag

0.90 :stoppedIn

0.91 :stoppedIn

0.95 :hasFlag

0.85 :hasLocation

0.95 :hasVesselType

0.85 :hasLocation

0.95 :hasVesselType

0.99 :hasFlag

0.86 :isCloseOf

0.80 :performTranshipping

0.99 Confidence level of the relation
Is this situation a threat?  
- Yes, if two countries engaged in a war
- Not a threat, unless you are monitoring illegal fishing

To deal with:
- assessments too complex for a rule…
- … but still learnable
Tools
Semantic representation, embeddings
Tools

Semantic representation: knowledge graph (KG)

- A set of RDF triples
- Orientation = Subject $\xrightarrow{\text{relation}}$ Object
- Ontology = classes definition (T-box);
- KG = instanciation (A-box)
Tools

Embeddings

• A mapping of a discrete/categorical variable to a vector of continuous numbers

• With neural networks: low-dimensional, learned continuous vectors representation of discrete variables.

• Purposes:
  – Nearest neighbors (e.g. for recommendations)
  – **Input for supervised ML task**
  – Visualization of concepts and relations between categories

![TSNE Visualization of Book Embeddings](image)
Use deep learning to learn an embedding of the knowledge graph to perform link prediction.
Application to Maritime Situational Awareness
Application to MSA

• Temporal evolution
  – A situation always changes
  – Links appear/disappear
  – Follow evolution of entities and relations

• Heterogeneous data
  – Sensors (AIS)
  – Contextual information, previous events (GDELT, ICEWS)

• Training
  – Limited labelled dataset
  – Few training examples (expert knowledge)
  – Large dataset to infer
Application to MSA

- Evolution of attributes:
  - Static (name, flag)
  - Dynamic:
    - Kinematic (position, speed)
    - Non-kinematic (passengers, cargo)

- Explainability of decision processes

- With the new extracted information, how to tell if the new situation is a threat or not?

- Ideally: data stream as input
Formalisation
Dynamic attributed knowledge graph (DAKG)

• Let $E$ be a set of entities, $R$ a set of relations, $A$ a set of attributes, $D(a)$ the range of an attribute $a \in A$, $\tau$ the set of time points.

• Relational quadruples: $(e^s, r, e^o, t)$
• Attributional quadruples: $(e, a, v, t)$

• Relational history: $KG^{R,<t}$
• Attributional history: $KG^{A,<t}$

• Prediction task: $f: KG^{R,<t}, KG^{A,<t} \rightarrow KG^{R,t}$
Experiments
Experiments: task

• Prediction of the position of a vessel in the next time points

• Ultimate goal: exploit all the relationships, events and attributes in the maritime surveillance ecosystem to perform better link predictions

• Reduction of this task to test DAKG capabilities (proof of concept)
Experiments: methods

**TransE [Bordes 13’]**
- Static graph (triples)
- Distance between \( e^s + r \) and \( e^o \approx 0 \)
- Margin-based ranking criterion against corrupted triples

**Know-Evolve [Trivedi 17’]**
- Dynamic (quadruples)
- RNN based
- Maximizes the probability of a specific type of event at time \( t \) between two entities

Relational score: \( e^s \times r \times e^o \)
Temporal drift: \( t - t_e \)
Experiments: dataset

One week of maritime traffic in the Gibraltar Strait

<table>
<thead>
<tr>
<th>#Vessels</th>
<th>#Areas</th>
<th>#Events</th>
<th>#Train</th>
<th>#Test</th>
</tr>
</thead>
<tbody>
<tr>
<td>2,545</td>
<td>1,556</td>
<td>955k</td>
<td>720k</td>
<td>235k</td>
</tr>
</tbody>
</table>

One month of data in the Gibraltar Strait (02/02/17 to 02/03/17)

Input data: \((e^y, r, e^0, t)\)
Experiments: results

True events are ranked against corrupted events

Test set: the last eight days of the dataset
Conclusion and future work

In this article we:

• Showed that current KG models are not sufficient for modelling the movement of a vessel
• Exhibited the challenges that need to be overcome to apply DAKGs on MSA

For the future we want to:

• Make the prediction task more realistic by adding more entity and relation types in the dataset
• Find a model that can handle link and attribute prediction in a temporal setting
• Perform threat and/or anomaly detection on DAKGs.
Thank you

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