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On the Role of Knowledge Graphs in Explainable Machine Learning

Knowledge Graph Conference 2021
(Virtual Event)
May 5, 2021

Freddy Lecue, Chief AI Scientist (Thales Canada, Inria France)
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@freddylecue

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Critical Applications

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BNSF
BNSF

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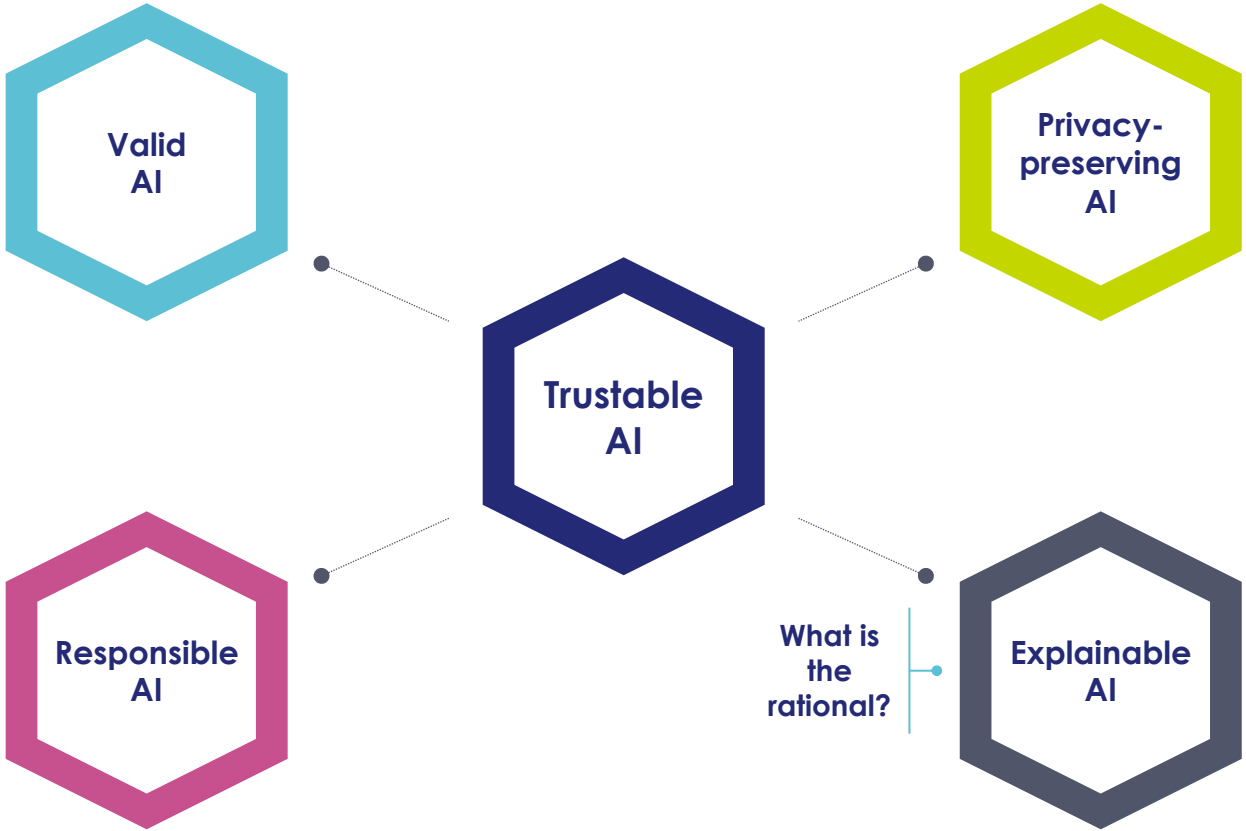
AI Adoption: Requirements



- Human Interpretable AI
- Machine Interpretable AI

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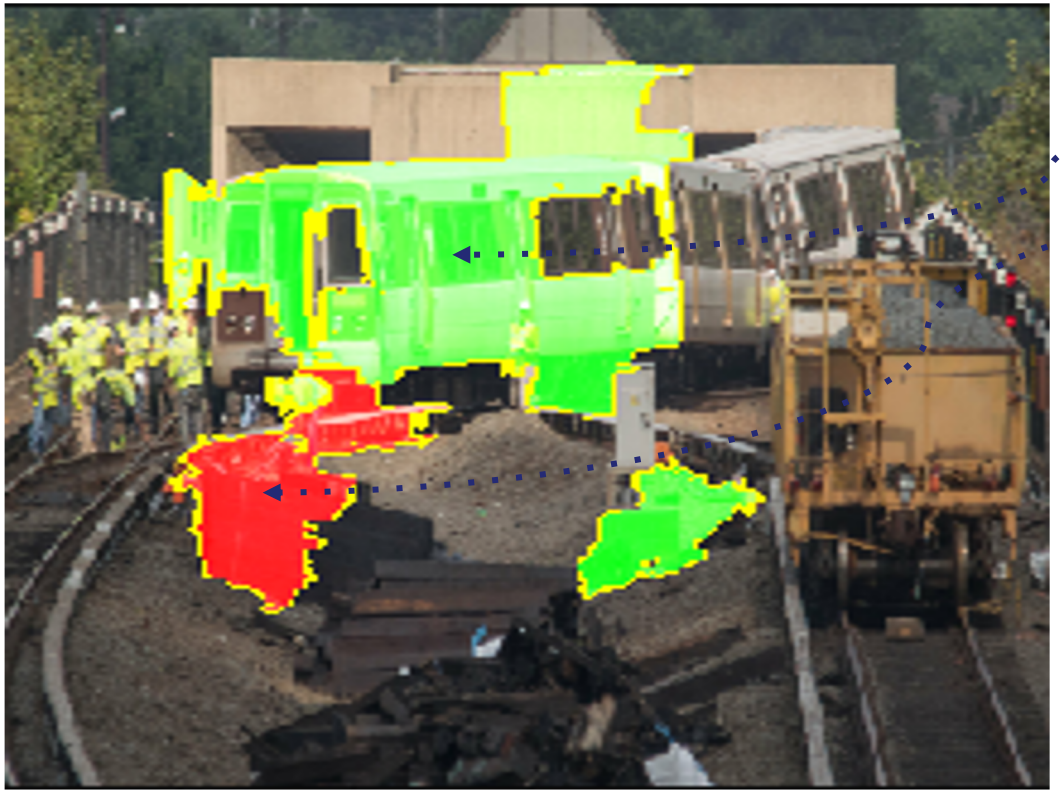
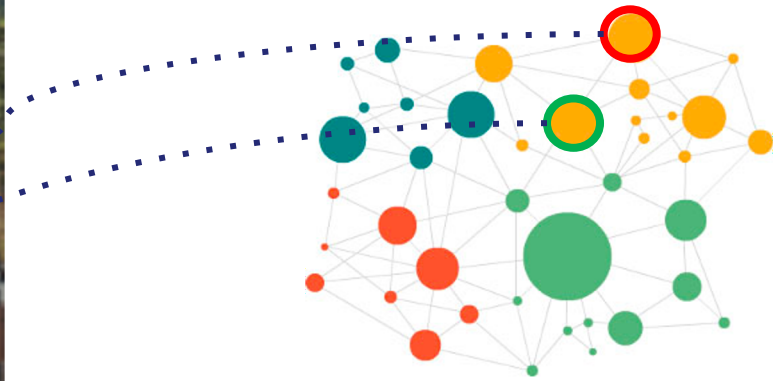
Knowledge Graph in Machine Learning (1)





Augmenting (input) features with more semantics such as knowledge graph embeddings / entities

https://stats.stackexchange.com/questions/230581/decision-tree-too-large-to-interpret

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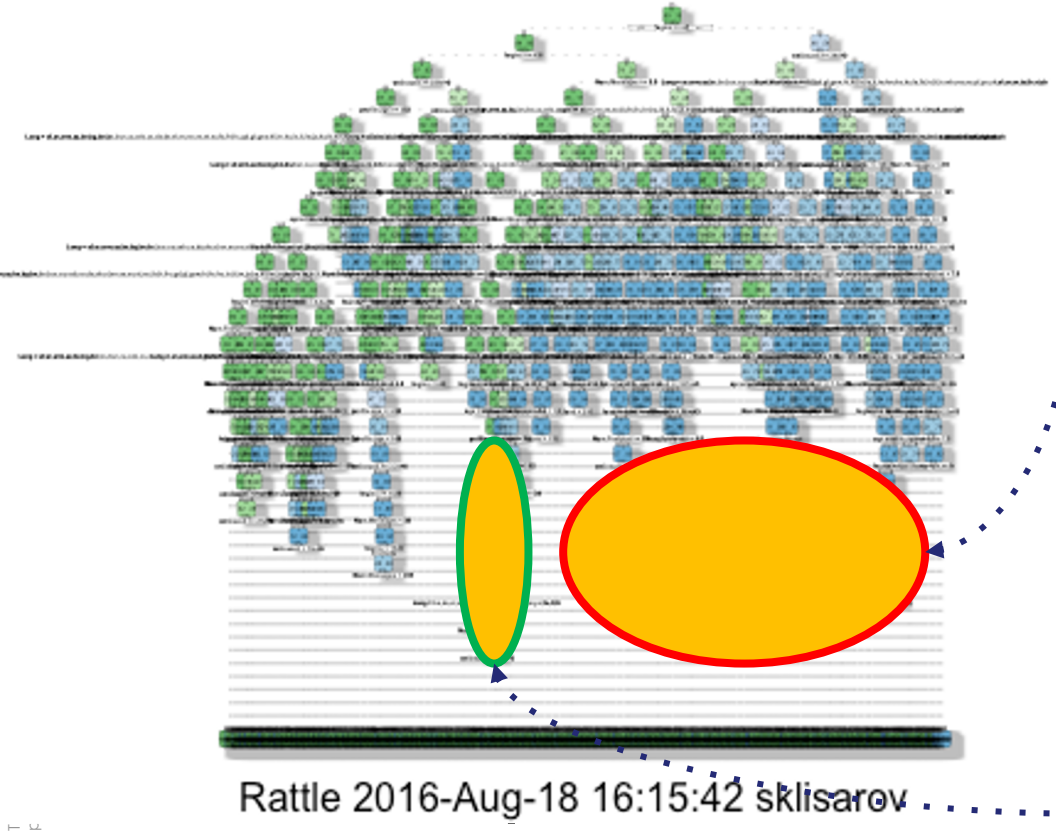
Knowledge Graph in Machine Learning (2)



https://stats.stackexchange.com/questions/230581/decision-tree-too-large-to-interpret

Augmenting machine learning models with more semantics such as knowledge graphs entities

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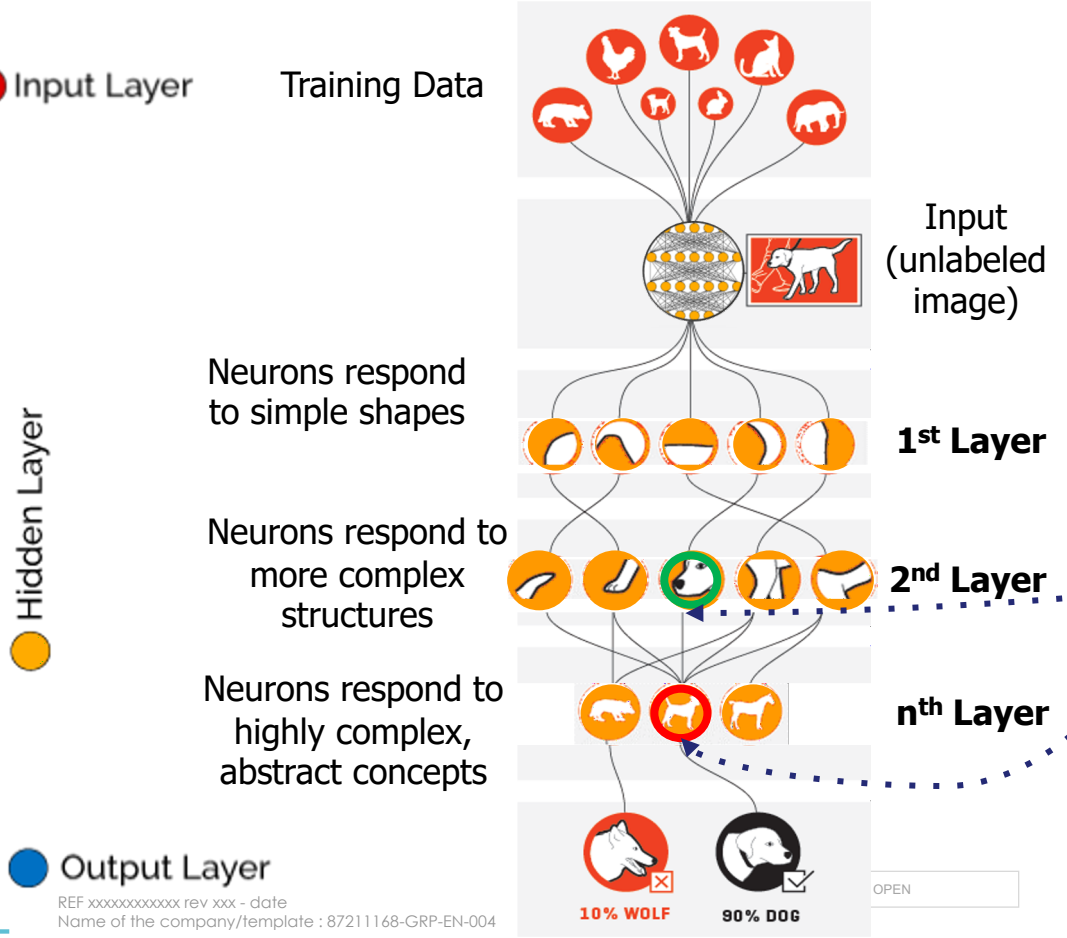
Knowledge Graph in Machine Learning (3)



Low-level features to high-level features

Augmenting (intermediate) features with more semantics such as knowledge graph embeddings / entities

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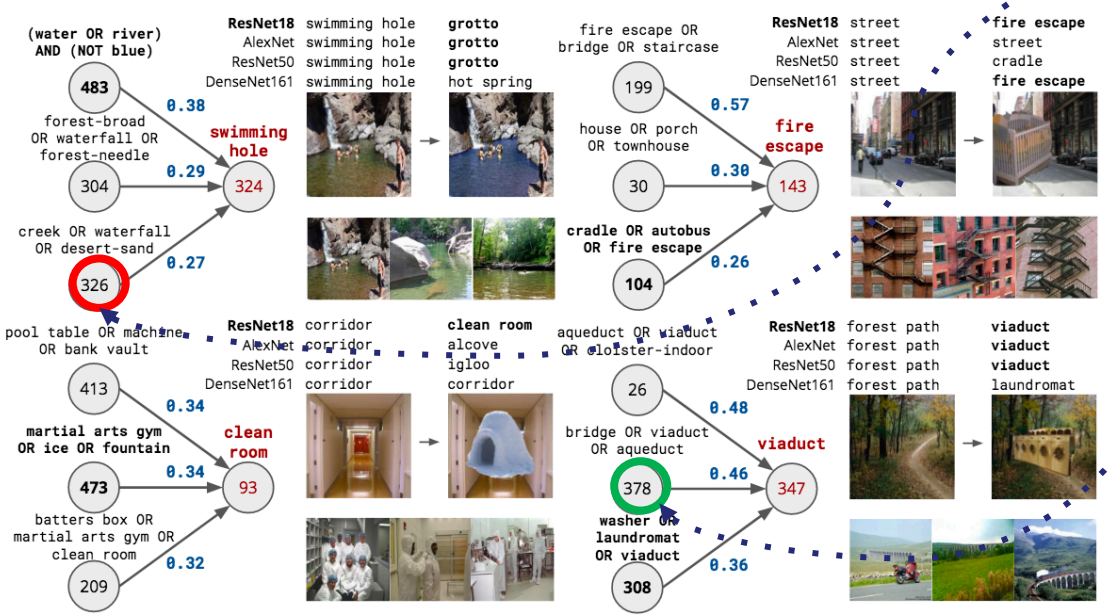
Knowledge Graph in Machine Learning (4)



Jesse Mu, Jacob Andreas:Compositional Explanations of Neurons. NeurIPS 2020

Low-level features to high-level features

Open question: What is the impact of semantic representation on units in Neural Networks?

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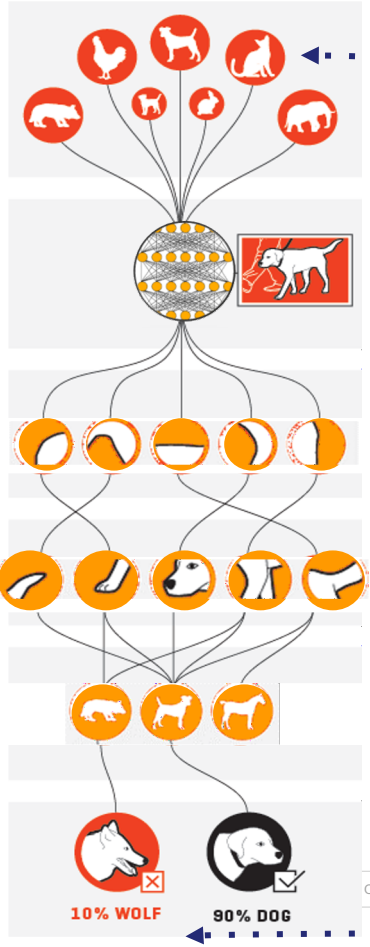
Knowledge Graph in Machine Learning (5)



Input Layer

Training Data

Input (unlabeled image)

Hidden Layer

Neurons respond to simple shapes

1st Layer

Neurons respond to more complex structures

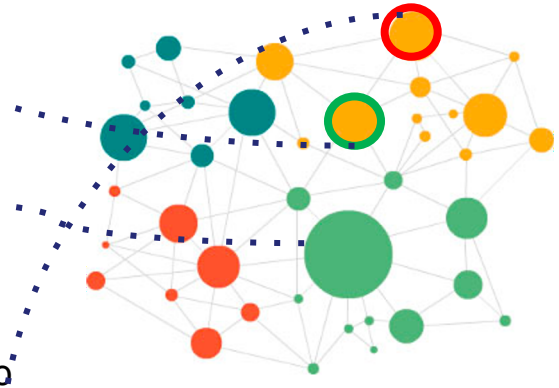
2nd Layer

Neurons respond to highly complex, abstract concepts

nth Layer

Output Layer

Low-level features to high-level features



Augmenting (input, intermediate) features – output relationship with more semantics to capture causal relationship

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Knowledge Graph in Machine Learning (6)

Description 1: This is an orange train accident

Description 2: This is a train accident between two speed merchant trains of characteristics X43-B and Y33-C in a dry environment

Description 3: This is a public transportation accident

Augmenting models with semantics to support personalized explanation

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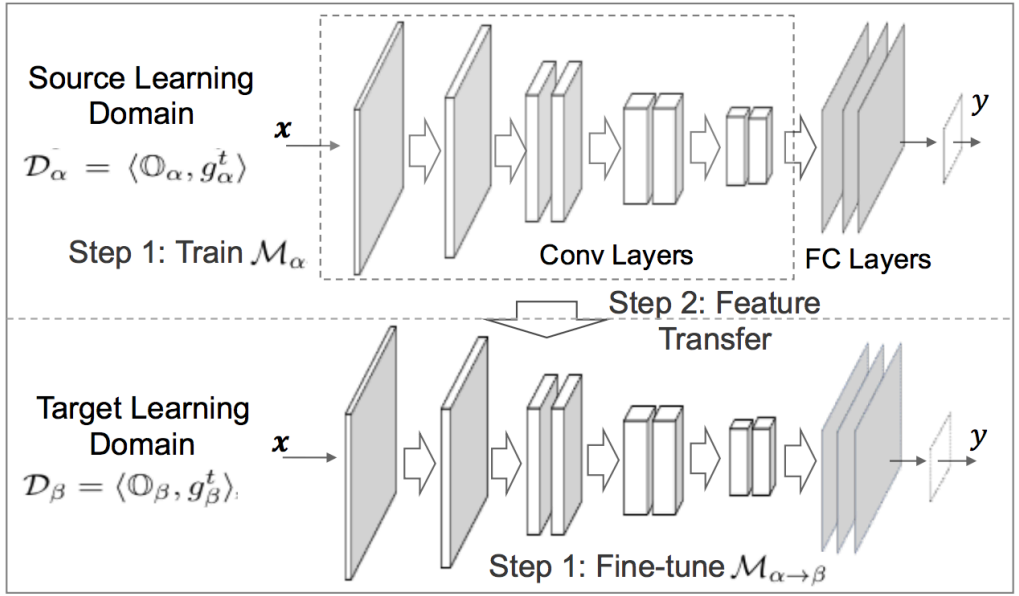
Knowledge Graph in Machine Learning (7)

"How to explain transfer learning with appropriate knowledge representation?



Augmenting input features and domains with semantics to support interpretable transfer learning

Jiaoyan Chen, Freddy Lécué, Jeff Z. Pan, Ian Horrocks, Huajun Chen: Knowledge-Based Transfer Learning Explanation. KR 2018: 349-358

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Knowledge Graph in Machine Learning (8)

"How to explain concept drift in Machine Learning?

Augmenting input features and domains with semantics to interpret concept drift in Machine Learning

Without semantics augmen

With semantics augmentation

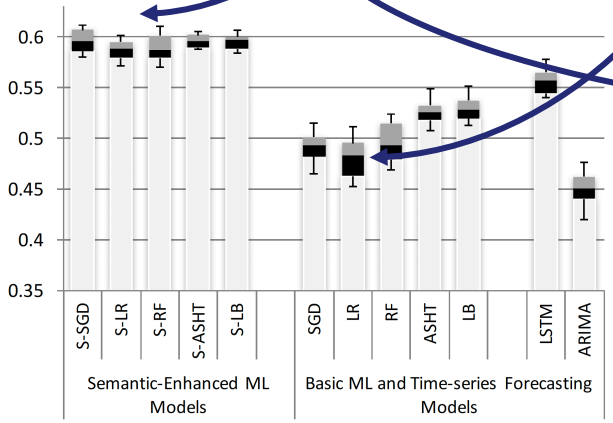

Figure 6: [Beijing Context] Baseline Comparison of Forecasting Macro-F1 Score (Evaluation of Algorithm 1-3), where $\Delta = 6$.

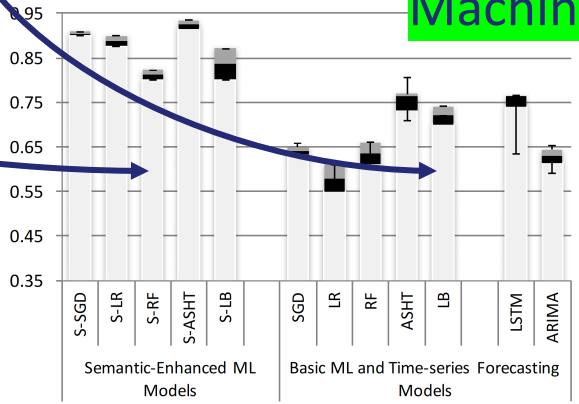

Figure 7: [Dublin Context] Baseline Comparison of Forecasting Macro-F1 Score (Evaluation of Algorithm 1-3), where $\Delta = 6$.

Jiaoyan Chen and Freddy Lécué and Jeff Z. Pan and Shumin Deng and Huajun Chen. Knowledge graph embeddings for dealing with concept drift in machine learning. Journal of Web Semantics. (2021) http://www.sciencedirect.com/science/article/pii/S1570826820300585

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How Does it Work in Practice?

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State of the Art Machine Learning Applied to Critical Systems

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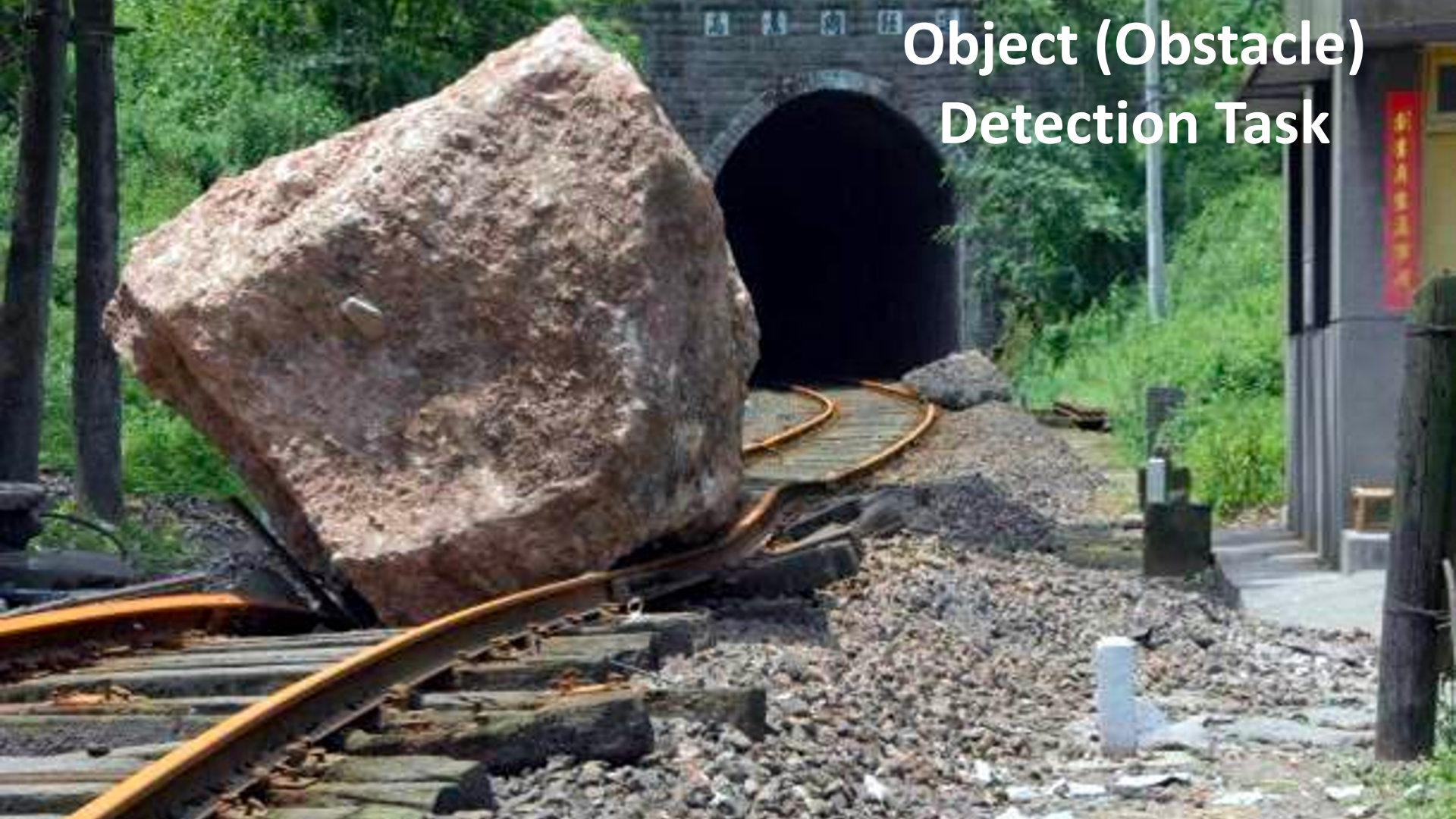
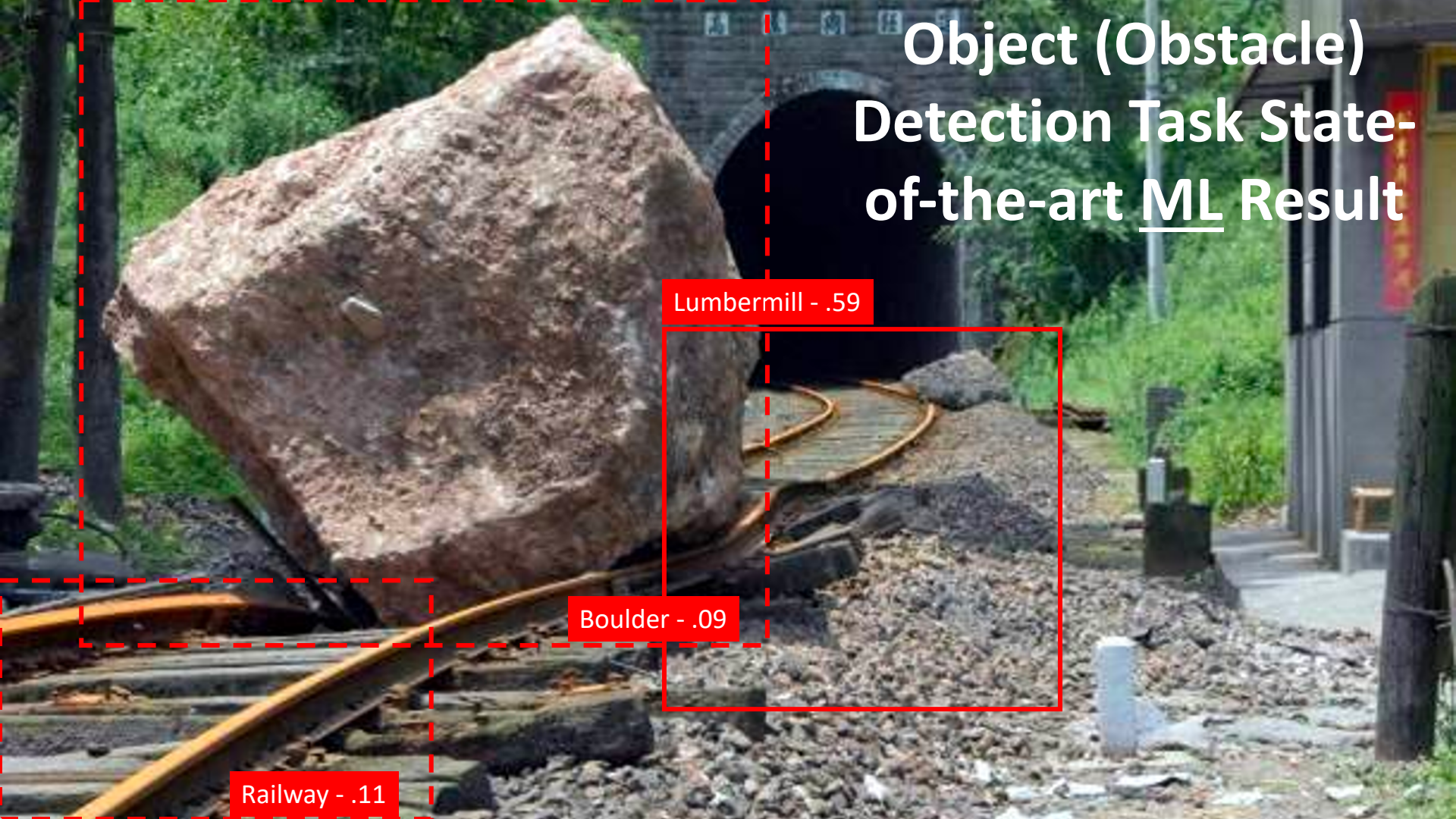
Object (Obstacle) Detection Task



Object (Obstacle) Detection Task State-of-the-art ML Result

Object (Obstacle) Detection Task State-of-the-art ML Result



State of the Art XAI Applied to Critical Systems

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Object (Obstacle) Detection Task State-of-the-art XAI Result

Object (Obstacle) Detection Task State-of-the-art XAI Result

Object (Obstacle) Detection Task State-of-the-art XAI Result

Unfortunately, this is of NO use for a human behind the system

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Let’s stay back

Why this Explanation? (meta explanation)

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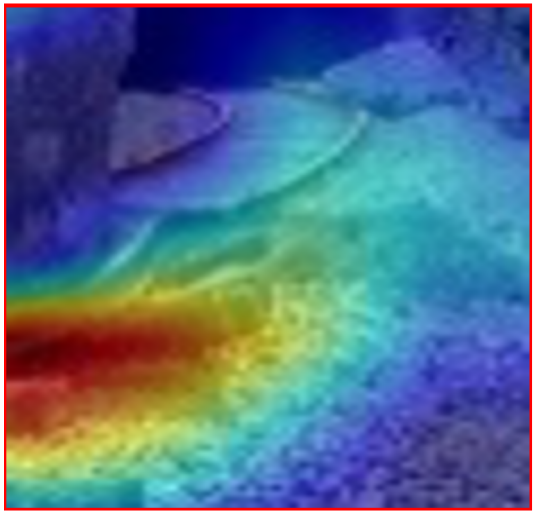
After Human Reasoning…

Lumbermill - .59



DBpedia | Browse using | Formats | Faceted Browser | Sparql Endpoint

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dbo:wikiPageRevisionID	734430894 (xsd:integer)
dct:subject	dbc:Sawmills dbc:Saws dbc:Ancient_Roman_technology dbc:Timber_preparation dbc:Timber_industry
http://purl.org/linguistics/gold/hypernym	dbr:Facility
rdf:type	owl:Thing dbo:ArchitecturalStructure
rdfs:comment	A sawmill or lumber mill is a facility where logs are cut into lumber. Prior to the invention of the sawmill, boards were rived (split) and planed, or more often sawn by two men with a whipsaw, one above and another in a saw pit below. The earliest known mechanical mill is the Hierapolis sawmill, a Roman water-powered stone mill at Hierapolis, Asia Minor dating back to the 3rd century AD. Other water-powered mills followed and by the 11th century they were widespread in Spain and North Africa, the Middle East and Central Asia, and in the next few centuries, spread across Europe. The circular motion of the wheel was converted to a reciprocating motion at the saw blade. Generally, only the saw was powered, and the logs had to be loaded and moved by hand. An early improvement was the developm (en)
rdfs:label	Sawmill (en)
owl:sameAs	wikidata:Sawmill dbpedia-cs:Sawmill dbpedia-de:Sawmill dbpedia-es:Sawmill

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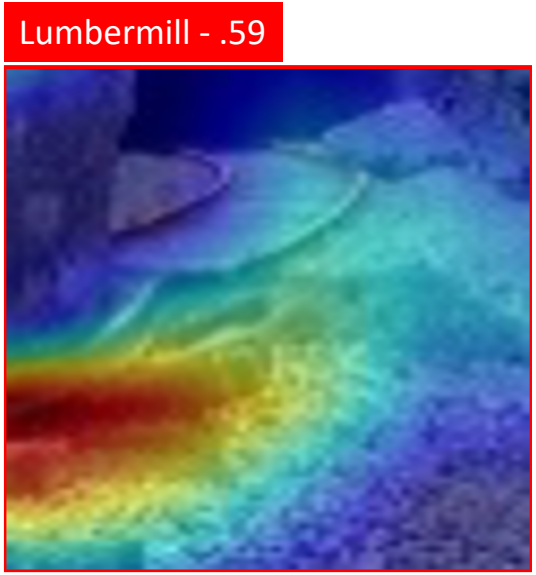
What is missing?



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Context matters

Boulder - .09

Railway - .11

DBpedia | Browse using | Formats | Faceted Browser | Sparql Endpoint

About: Boulder

An Entity of Type : place, from Named Graph : http://dbpedia.org, within Data Space : dbpedia.org

In geology, a boulder is a rock fragment with size greater than 25.6 centimetres (10.1 in) in diameter. Smaller pieces are called cobbles and pebbles, depending on their "grain size". While a boulder may be small enough to move or roll manually, others are extremely massive. In common usage, a boulder is too large for a person to move. Smaller boulders are usually just called rocks or stones. The word boulder is short for boulder stone, from Middle English bulderston or Swedish bullersten. Boulder sized clasts are found in some sedimentary rocks, such as coarse conglomerate and boulder clay.

Property	Value
dbo:abstract	In geology, a boulder is a rock fragment with size greater than 25.6 centimetres (10.1 in) in diameter. Smaller pieces are called cobbles and pebbles, depending on their "grain size". While a boulder may be small enough to move or roll manually, others are extremely massive. In common usage, a boulder is too large for a person to move. Smaller boulders are usually just called rocks or stones. The word boulder is short for boulder stone, from Middle English bulderston or Swedish bullersten. In places covered by ice sheets during Ice Ages, such as Scandinavia, northern North America, and Russia, glacial erratics are common. Erratics are boulders picked up by the ice sheet during its advance, and deposited during its retreat. They are called "erratic" because they typically are of a different rock type than the bedrock on which they are deposited. One of them is used as the pedestal of the Bronze Horseman in Saint Petersburg, Russia. Some noted rock formations involve giant boulders exposed by erosion, such as the Devil's Marbles in Australia's Northern Territory, the Horeke basalts in New Zealand, where an entire valley contains only boulders, and The Baths on the island of Virgin Gorda in the British Virgin Islands. Boulder sized clasts are found in some sedimentary rocks, such as coarse conglomerate and boulder clay. The climbing of large boulders is called bouldering. (en)
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dct:subject	dbc:Rock_formations dbc:Rocks

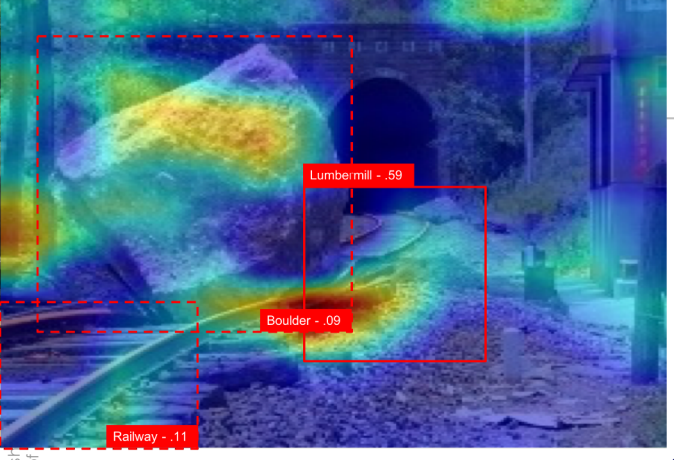
DBpedia | Browse using | Formats | Faceted Browser | Sparql Endpoint

About: Rail transport

An Entity of Type : software, from Named Graph : http://dbpedia.org, within Data Space : dbpedia.org

Rail transport is a means of conveyance of passengers and goods on wheeled vehicles running on rails, also known as tracks. It is also commonly referred to as train transport. In contrast to road transport, where vehicles run on a prepared flat surface, rail vehicles (rolling stock) are directionally guided by the tracks on which they run. Tracks usually consist of steel rails, installed on ties (sleepers) and ballast, on which the rolling stock, usually fitted with metal wheels, moves. Other variations are also possible, such as slab track, where the rails are fastened to a concrete foundation resting on a prepared subsurface.

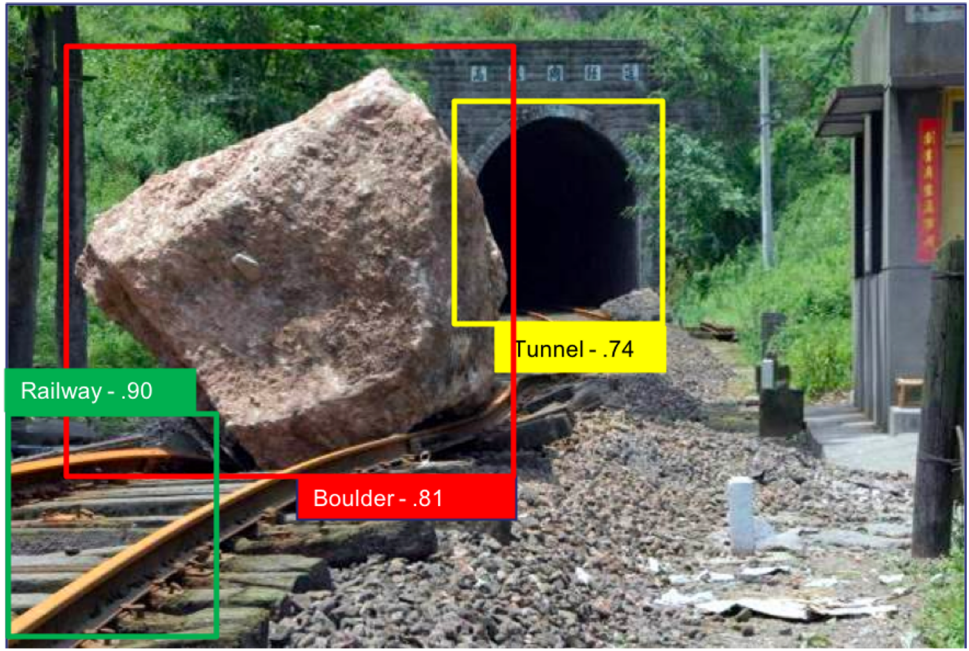
Property	Value
dbo:abstract	Rail transport is a means of conveyance of passengers and goods on wheeled vehicles running on rails, also known as tracks. It is also commonly referred to as train transport. In contrast to road transport, where vehicles run on a prepared flat surface, rail vehicles (rolling stock) are directionally guided by the tracks on which they run. Tracks usually consist of steel rails, installed on ties (sleepers) and ballast, on which the rolling stock, usually fitted with metal wheels, moves. Other variations are also possible, such as slab track, where the rails are fastened to a concrete foundation resting on a prepared subsurface. Rolling stock in a rail transport system generally encounters lower frictional resistance than road vehicles, so passenger and freight cars (carriages and wagons) can be coupled into longer trains. The operation is carried out by a railway company, providing transport between train stations or freight customer facilities. Power is provided by locomotives which either draw electric power from a railway electrification system or produce their own power, usually by diesel engines. Most tracks are accompanied by a signalling system. Railways are a safe land transport system when compared to other forms of transport. Railway transport is capable of high levels of passenger and cargo utilization and energy efficiency, but is often less flexible and more capital-intensive than road transport, when lower traffic levels are considered. The oldest, man-hauled railways date back to the 6th century BC, with Periander, one of the Seven Sages of Greece,



- **Hardware**: **High performance, scalable, generic** (to different FGPA family) **& portable** CNN dedicated **programmable** processor implemented on an FPGA for **real-time embedded inference**

- **Software**: Knowledge graph extension of object detection

Transitioning



This is an **Obstacle: Boulder** obstructing the train: XG142-R on **Rail_Track** from City: Cannes to City: Marseille at **Location: Tunnel VIX** due to **Landslide**

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XAI Thales Platform

Higher accuracy with no intensive fine-tuning
Human interpretable explanation
Running on the edge at inference time

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https://xai.thalesdigitalsolutions.com/analysis

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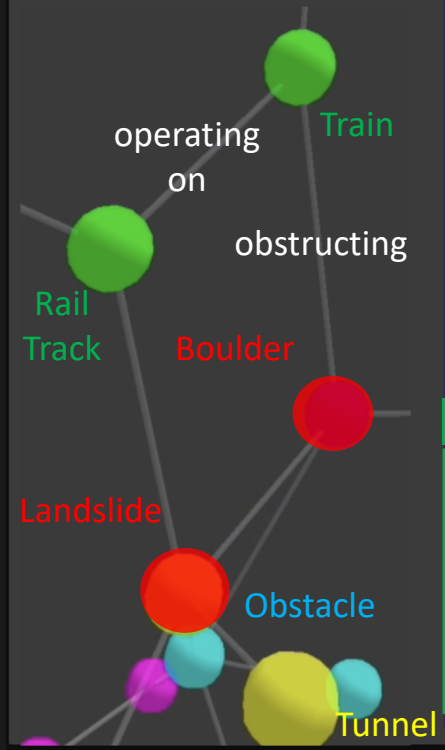
eXplainable Artificial Intelligence

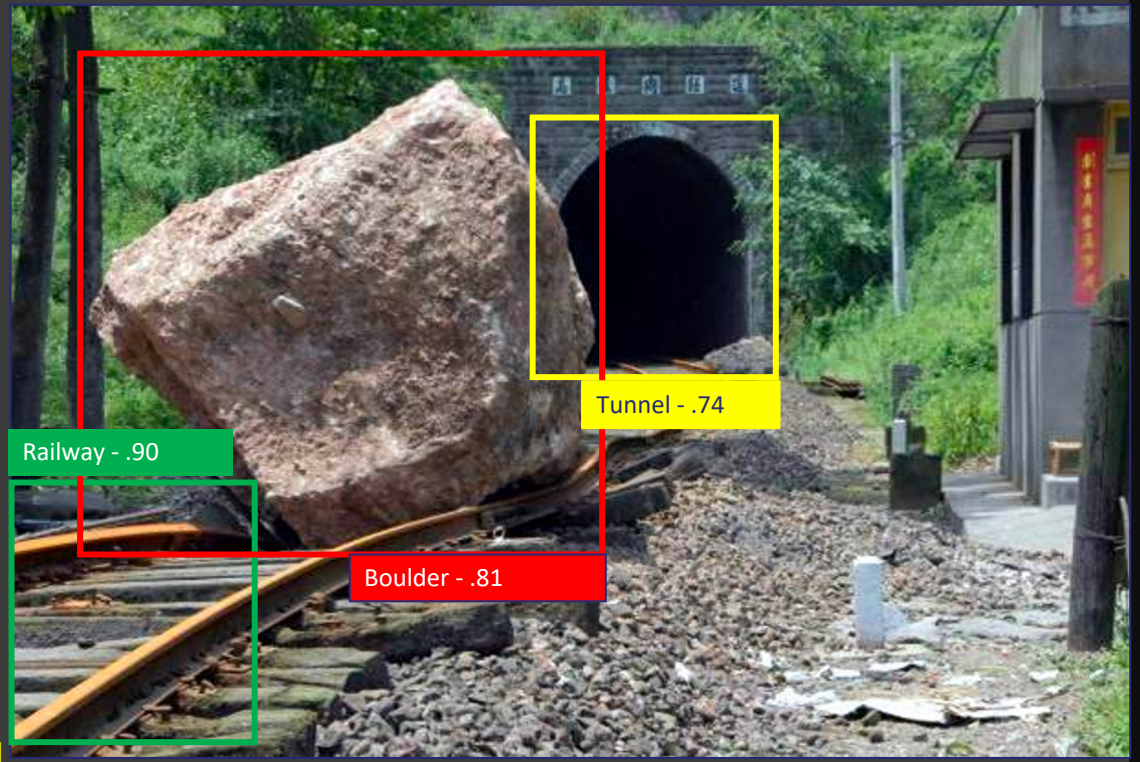
1 Learn about models Completed — 2 Enter data Completed — 3 Compare explanations — 4 See saved explanations

EXPLANATIONS

Lime

ResNet50 image classifier

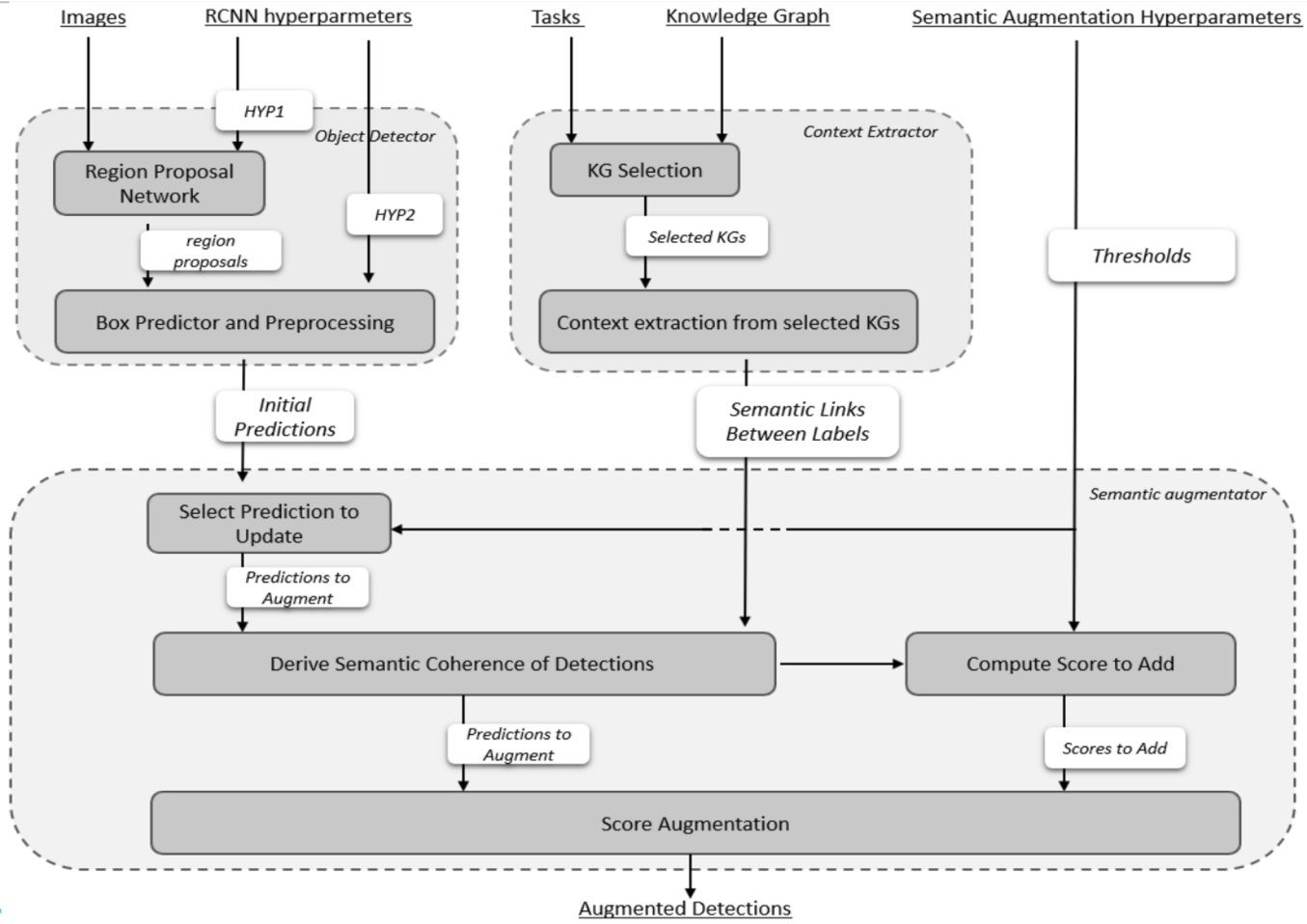




BACK

NEXT

Knowledge Graph in Machine Learning - An Implementation



Freddy Lécué, Jiaoyan Chen, Jeff Z. Pan, Huajun Chen: Augmenting Transfer Learning with Semantic Reasoning. IJCAI 2019: 1779-1785

Freddy Lécué, Tanguy Pommellet: Feeding Machine Learning with Knowledge Graphs for Explainable Object Detection. ISWC Satellites 2019: 277-280

Freddy Lécué, Baptiste Abeloos, Jonathan Anctil, Manuel Bergeron, Damien Dalla-Rosa, Simon Corbeil-Letourneau, Florian Martet, Tanguy Pommellet, Laura Salvan, Simon Veilleux, Maryam Ziaeefard: Thales XAI Platform: Adaptable Explanation of Machine Learning Systems - A Knowledge Graphs Perspective. ISWC Satellites 2019: 315-316

Jiaoyan Chen, Freddy Lécué, Jeff Z. Pan, Ian Horrocks, Huajun Chen: Knowledge-Based Transfer Learning Explanation. KR 2018: 349-358

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Ecosystem

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XAI in Canada: An instance of a Scientific eXplainable AI project

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DEEL (Dependable Explainable Learning) Project
2019-2024

With support of

CRSNG NSERC

CRIAQ

Industrial partners

THALES

And 3 aerospace partners

Academic partners

UNIVERSITÉ LAVAL

IVADO

IRT SAINT EXUPERY

Certificability

- Structural warranties
- Risk auto evaluation
- External audit

AI4EU

ABB ROBOTICS
GoodAI
Allianz
BLUMORPHO
MŰEGYETEM 1782
LAAS-CNRS
CSIC
FRANCE DIGITALE
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Human -in-the- Loop

Knowledge Graph Conference 2021, May 5, 2021

Freddy Lecue, Chief AI Scientist (Thales Canada, Inria France)

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