Learning and Reasoning over Smart Home Knowledge Graphs

Ronald Siebes, Victor de Boer, Roberto Reda, Roderick van der Weerdt


Interoperable solutions connecting smart
homes, buildings and grids


KNX


DAIKIN


Vaillant


Wirelane


Miele


B/S/H/


Fachhochschule
Dortmund
University of Applied Sciences and Arts


Deutsches
Forschungszentrum
für Künstliche
Intelligenz GmbH


UNIKASSEL
VERSITÄT


ABB


keo


OpenMotics


E.DSO


inetum
Positive digital flow


CYBERGRID


POLITECNICO
MILANO 1863


RSE


sensinov


ENGIE


ENEDIS
L'ELECTRICITE EN RESEAU


COSMOTE


HERON


VU
VRIJE
UNIVERSITEIT
AMSTERDAM


Cordium
eerste partner in sociaal wonen


3E


DuCoop


imec

LARGE VS. SMALL

Larger, industrial installations

- This is already being done
- Relatively high margin per unit
- Custom control technology developed for every unit
- Process is well known and very predictable

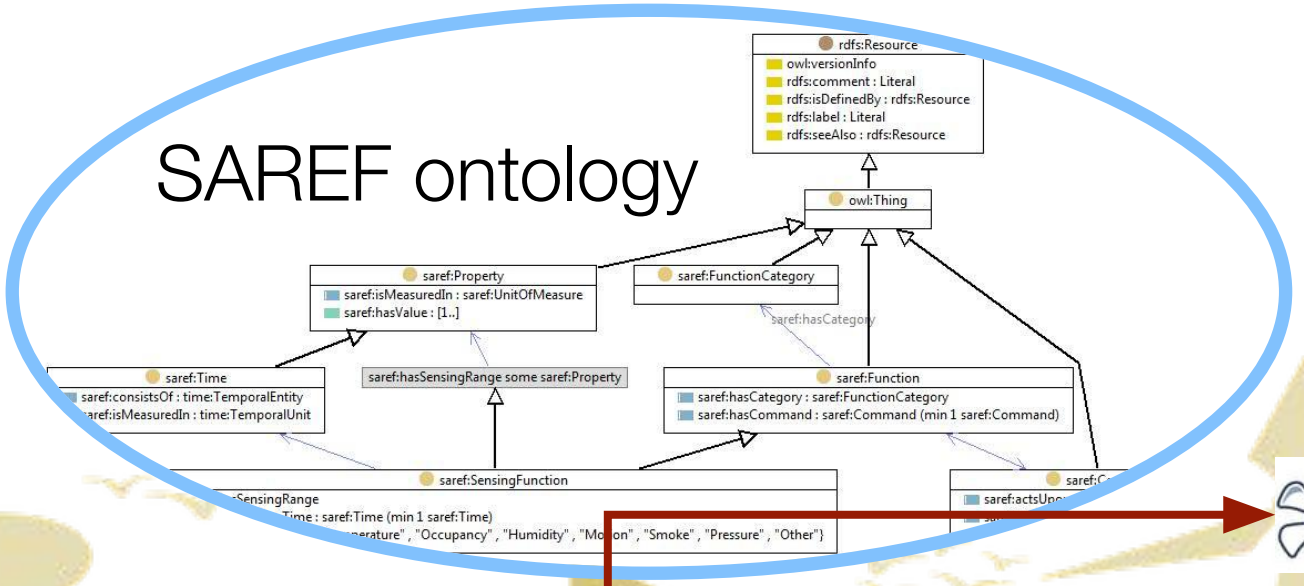
- Already profitable
- Standardization may improve efficiency

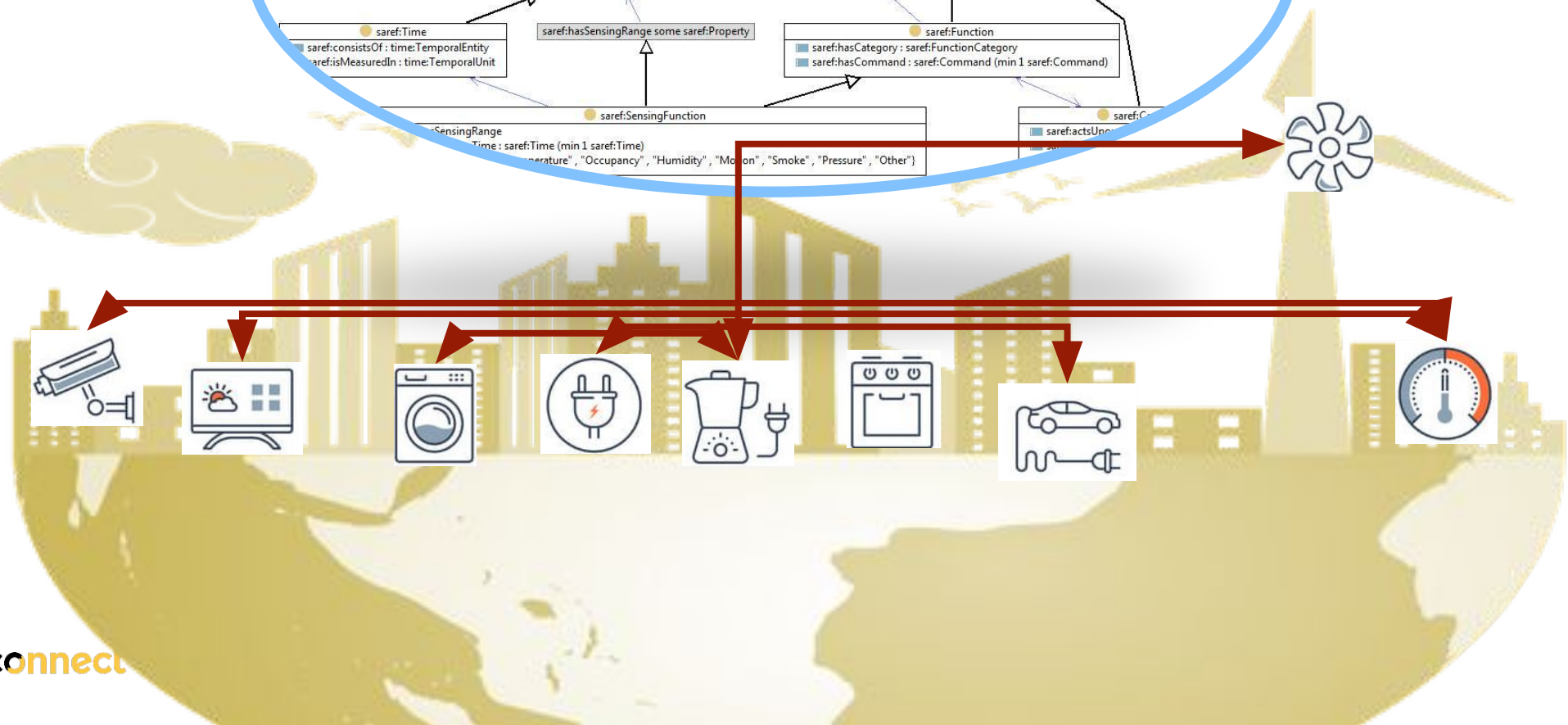
Smaller, residential/office devices

- Currently in development
- Many makes and models of devices providing energy flexibility
- Many units, but very low margin per unit
- Energy flexibility is made available by ‘best effort’; no guarantees

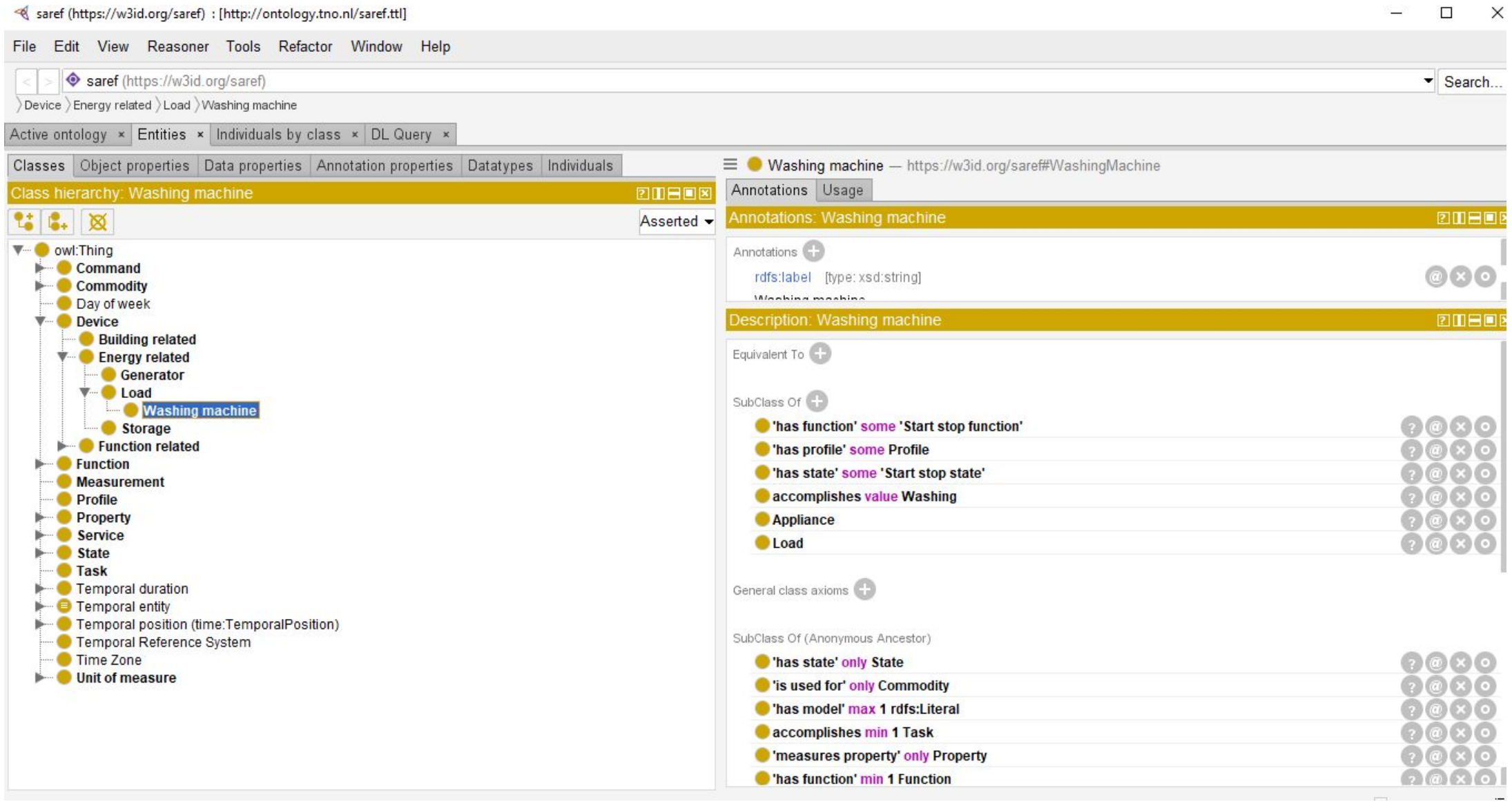
- If we want to scale up, we need to minimize installation and operational costs

SAREF ontology





interconnect



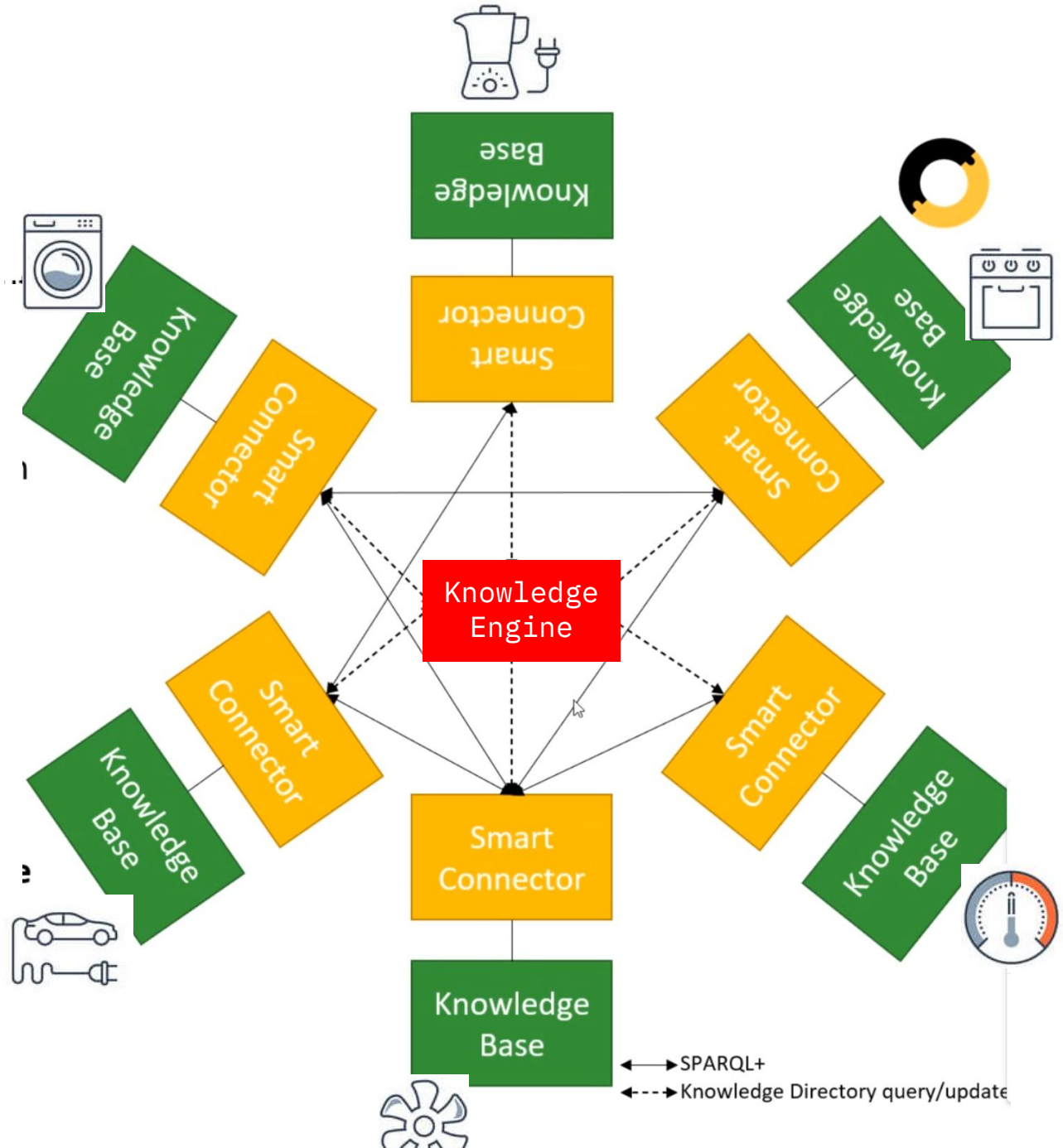
http://ontology.tno.nl/saref.ttl

interconnect

Knowledge engine

Pub-Sub matchmaking on graph patterns

using the SAREF ontology



Challenge: Machine Learning over Smart home KGs

Explainability:

using Jupyter Notebooks as RESTful service

(https://github.com/rsiebes/interconnect-explainability)

Heterogeneous data:

serialize SAREF types to encode the data to features

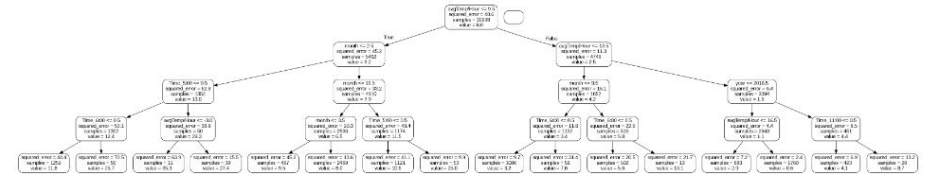
(e.g. ‘One-hot’ encoding, time-stamps to year, month, day, hour features etc)

Graph Learning:

Applying Graph Neural Networks for value prediction, classification, error detection

In [17]:

```
# Limit depth of tree to 4 levels
rf_small = RandomForestRegressor(n_estimators=10, max_depth = 4)
rf_small.fit(train_features, train_labels)# Extract the small tree
tree_small = rf_small.estimators_[5]# Save the tree as a png image
export_graphviz(tree_small, out_file = 'small_tree.dot', feature_names = feature_list, rounded = True, precision = 1)
(graph, ) = pydot.graph_from_dot_file('small_tree.dot')
graph.write_png('small_tree.png');
```

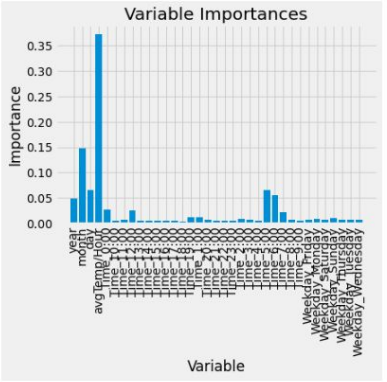


Get numerical feature importances

importances = list(rf.feature*importances*)# List of tuples with variable and importance feature_importances = [(feature, round(importance, 2)) for feature, importance in zip(feature_list, importances)]# Sort the feature importances by most important first feature_importances = sorted(feature_importances, key = lambda x: x[1], reverse = True)# Print out the feature and importances [print('Variable: {:20} Importance: {}'.format(*pair)) for pair in feature_importances];

In [19]:

```
# Import matplotlib for plotting and use magic command for Jupyter Notebooks
import matplotlib.pyplot as plt
%matplotlib inline
# Set the style
plt.style.use('fivethirtyeight')# list of x locations for plotting
x_values = list(range(len(importances)))# Make a bar chart
plt.bar(x_values, importances, orientation = 'vertical')# Tick labels for x axis
plt.xticks(x_values, feature_list, rotation='vertical')# Axis labels and title
plt.ylabel('Importance'); plt.xlabel('Variable'); plt.title('Variable Importances');
```



In [20]:

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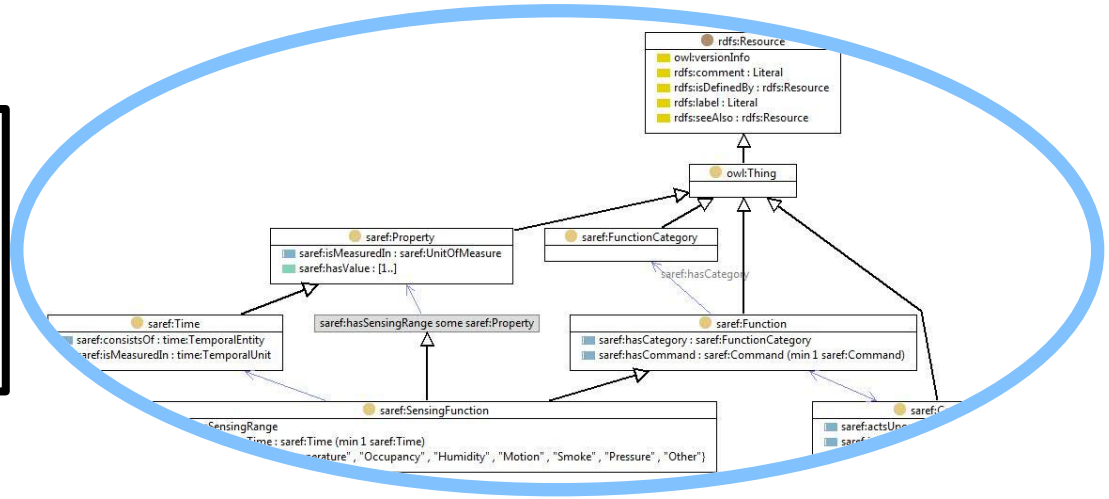

Graph Learning:

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interconnect

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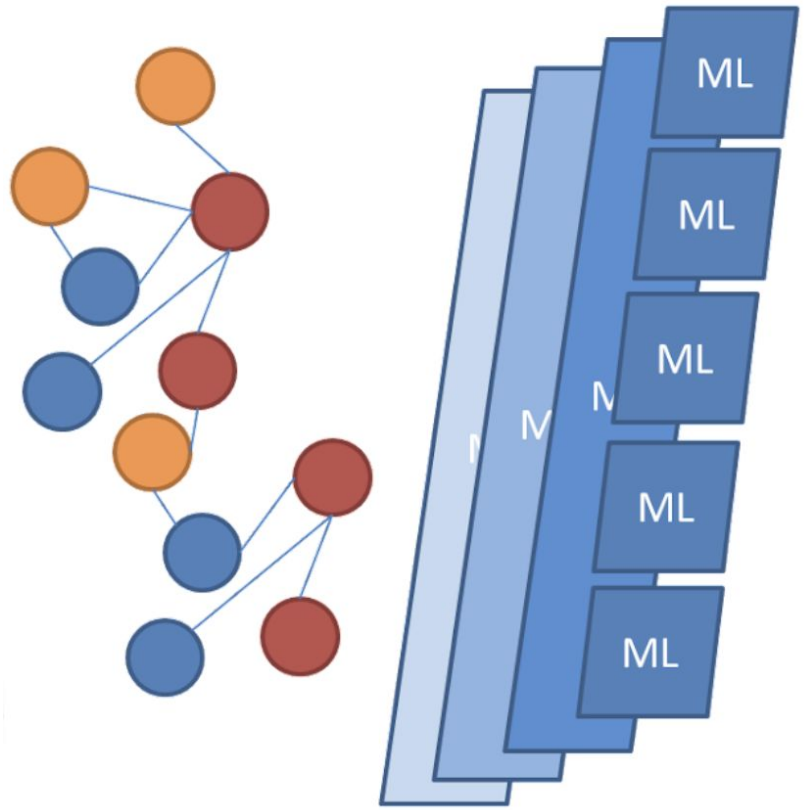


Challenge: Conversion to SAREF

Datasets in RDF were not available

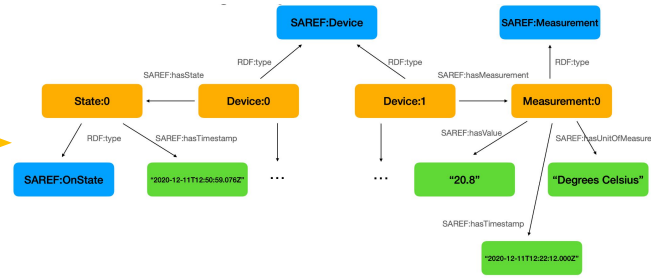
Created new KGs with YARRRML mappings

The KGs were validated to contain all the information available in the original dataset

Timestamp	State
2020-12-11T12:50:59.076Z	On
2020-12-11T13:05:23.546Z	Off
2020-12-11T13:20:45.789Z	Off
...	...


```
{
  "id":"1234.5678",
  "type":"Sensor",
  "value":
  {
    "Temperature":
    {
      "value":"20.8",
      "unit":"Degrees Celsius",
      "timestamp":"20201211122212"
    }
  }
}
```

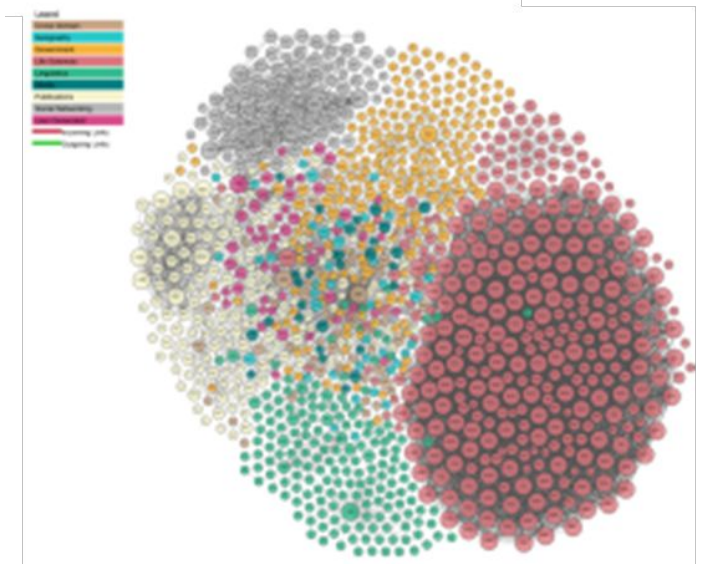

```
46              - [str1, $(MT_240), s]
47              - [str2, $(MT_240), o]
48    measurement:
49      sources: data1
50      s: interconnect:measurement_ELD11-14_MT240_$(timestamp) #
51      po:
52        - [a, saref:Measurement] # the type is measurement, ther
53        - [saref:hasValue, $(MT_240), xsd:double]
54        - [saref:isMeasuredIn, om:degrees_Celsius-iri]
55        - [saref:hasTimestamp, $(timestamp), xsd:dateTime]
56        - p: saref:isMeasurementOf
57          o:
58            mapping: featureOfInterest
59            condition:
60              function: equal
```

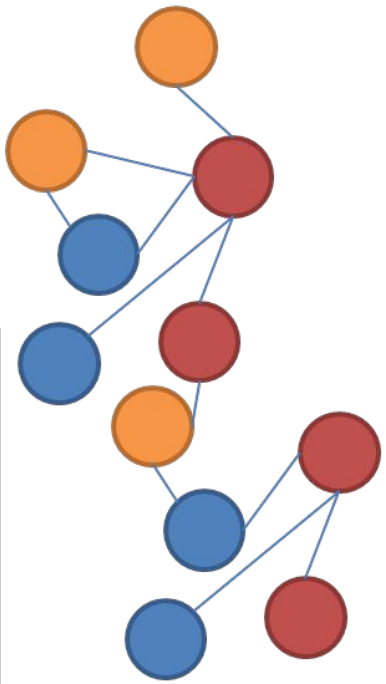


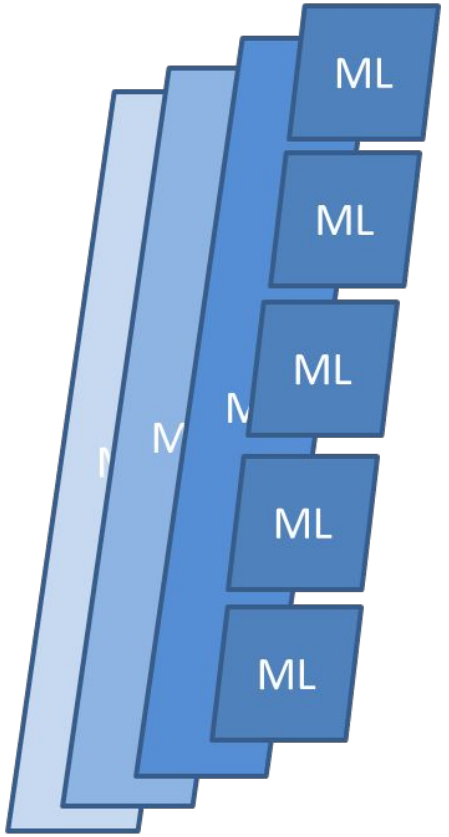
van der Weerdt R., de Boer V., Daniele L., Nouwt B. (2021) Validating SAREF in a Smart Home Environment. In: Garoufallou E., Ovalle-Perandones MA. (eds) Metadata and Semantic Research. MTSR 2020. Communications in Computer and Information Science, vol 1355. Springer, Cham. https://doi.org/10.1007/978-3-030-71903-6_4

interconnect

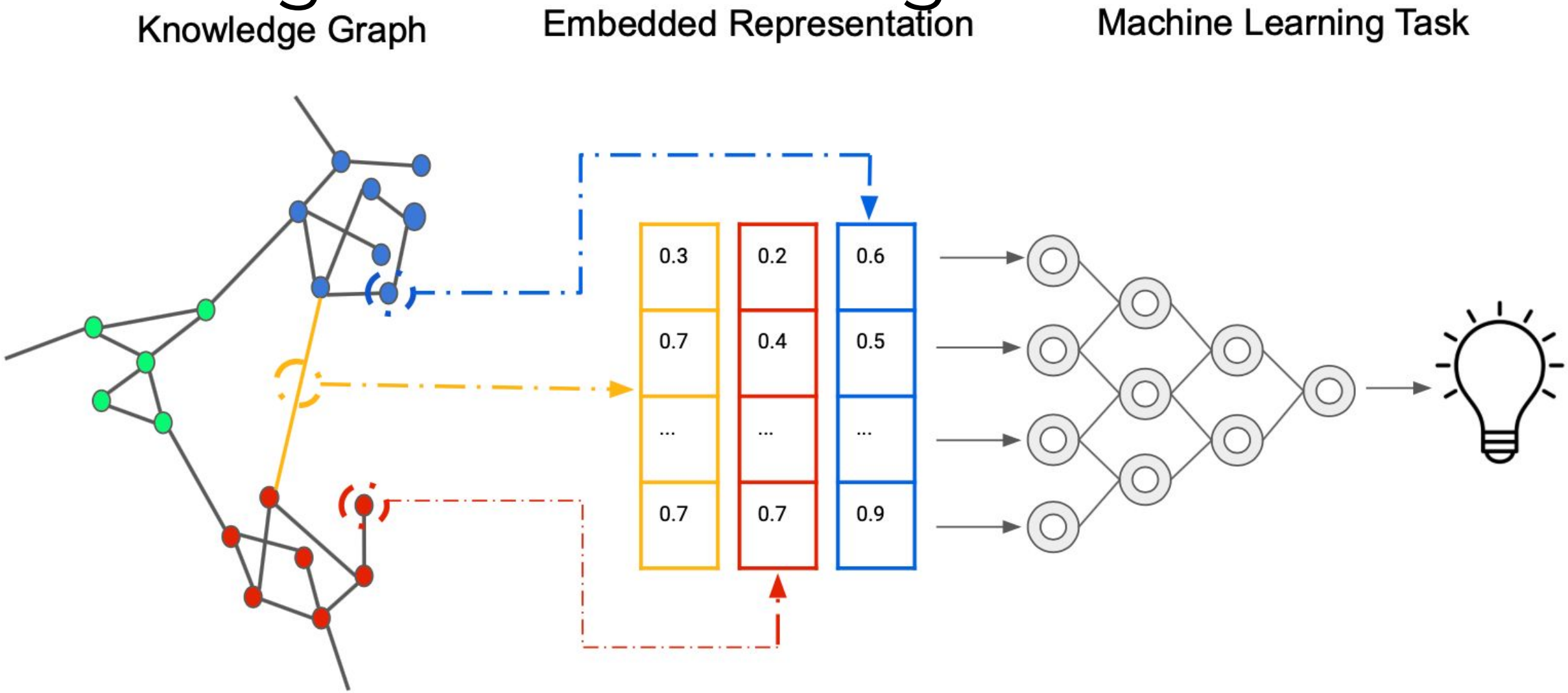
Learning over **Multimodal Knowledge Graphs** for IOT/Smart home





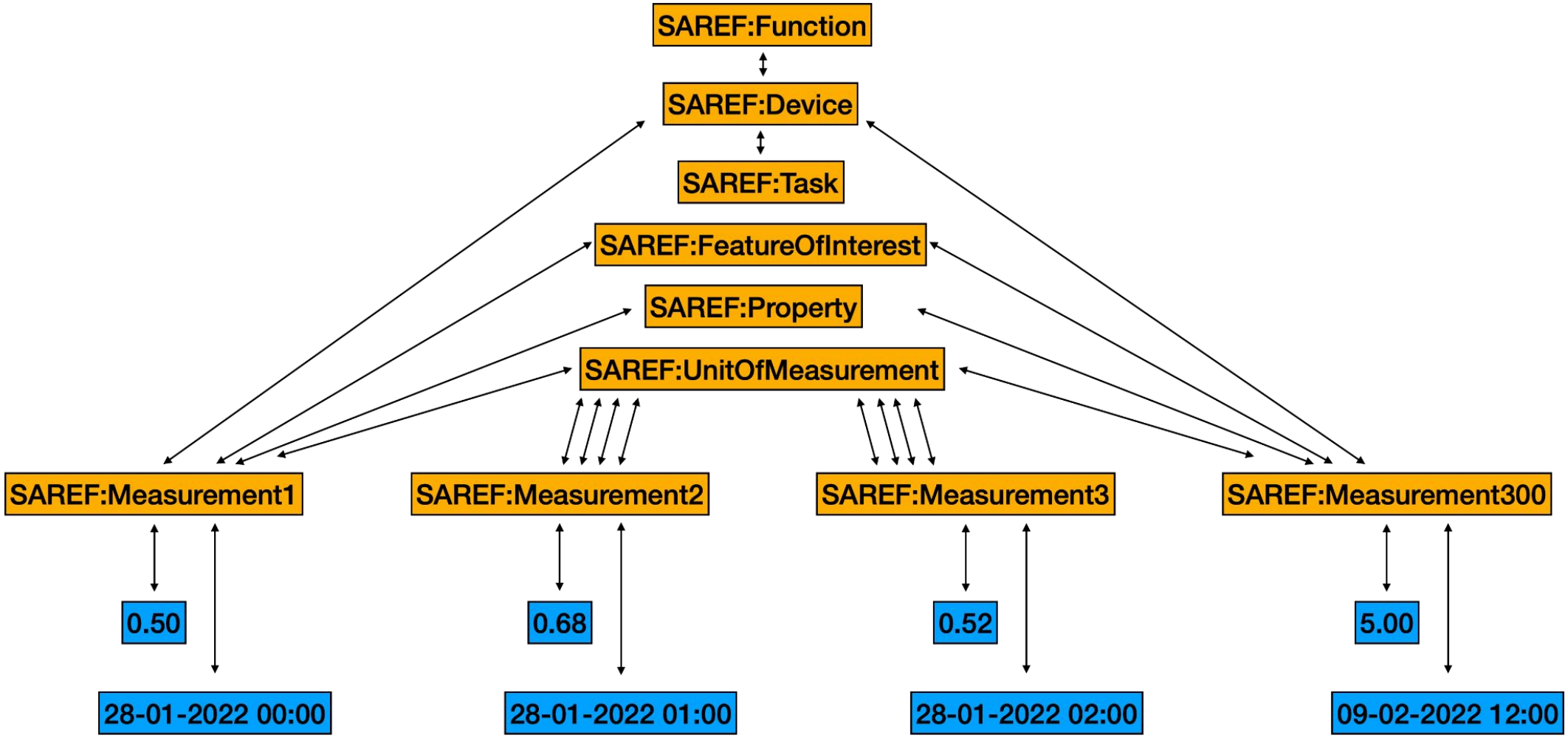


Creating the Embeddings



source: https://en.wikipedia.org/wiki/Knowledge_graph_embedding

Experiments: Creating the Embeddings



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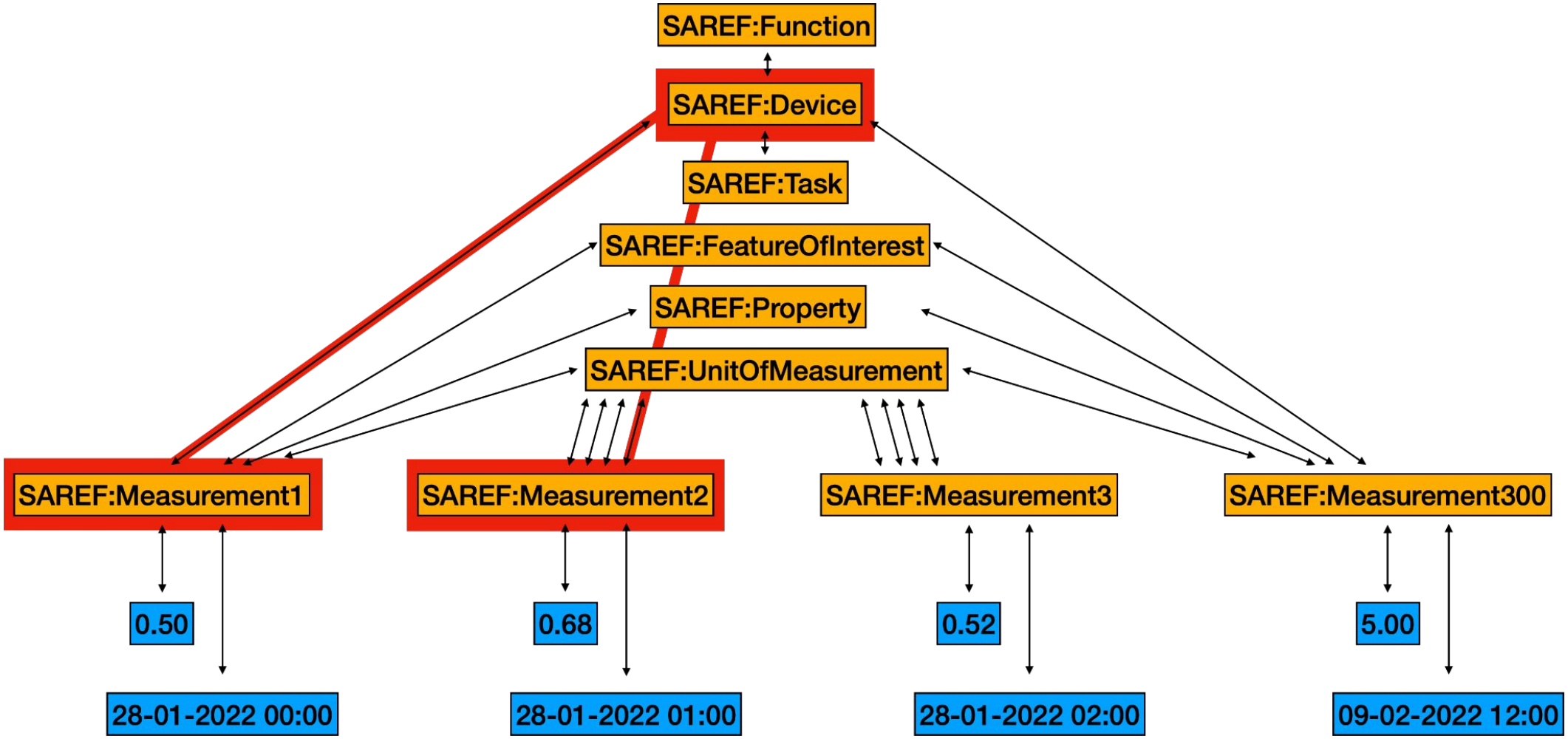

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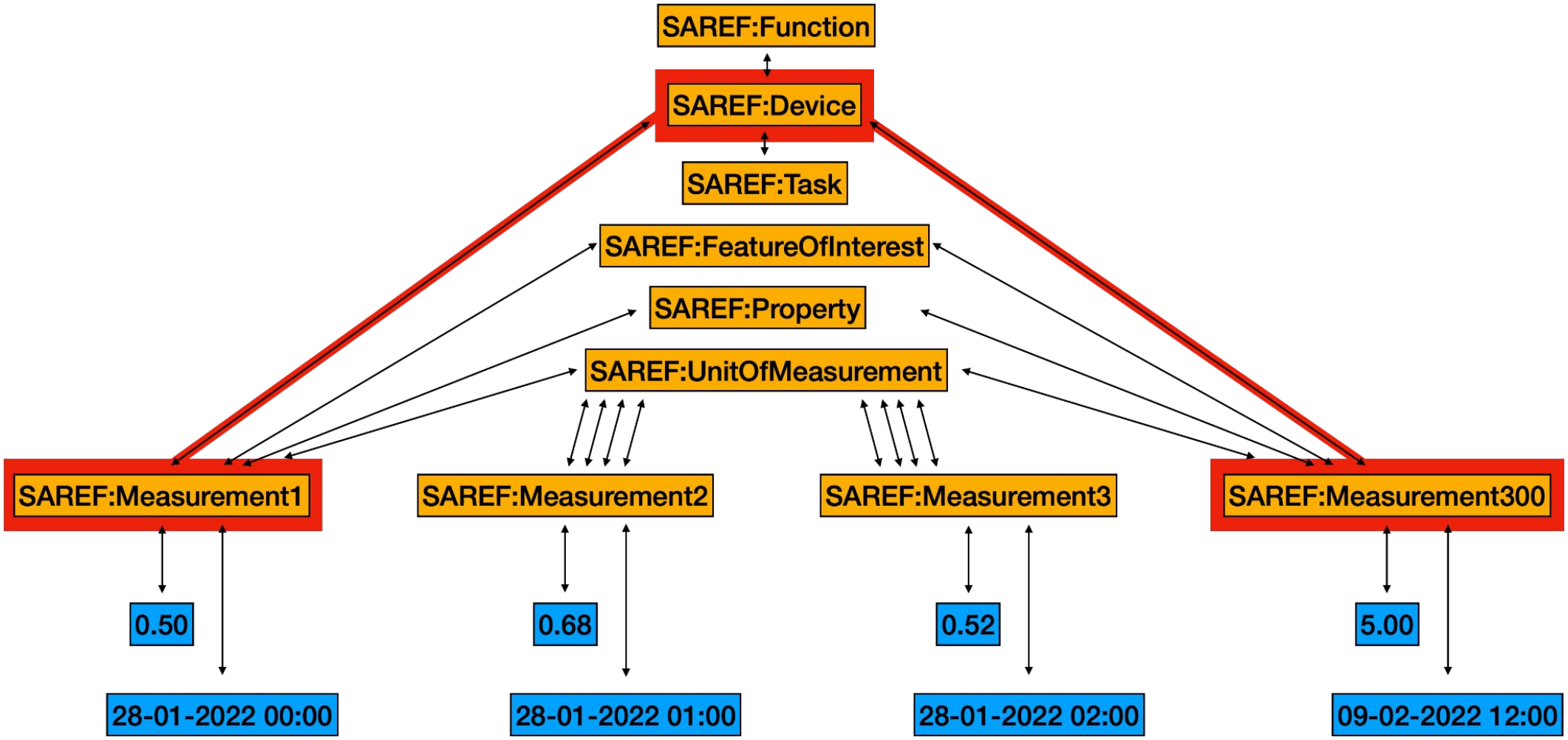

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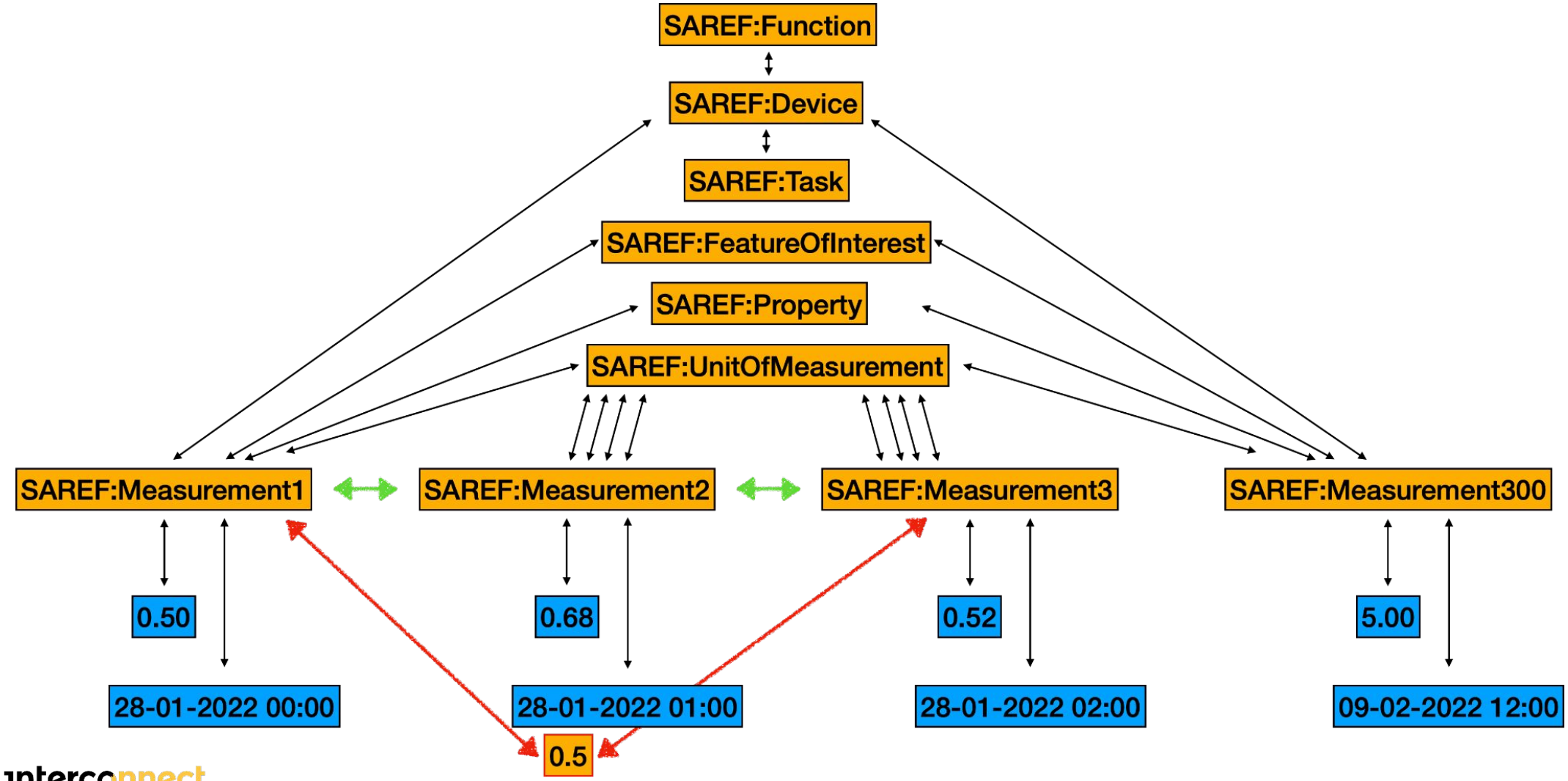

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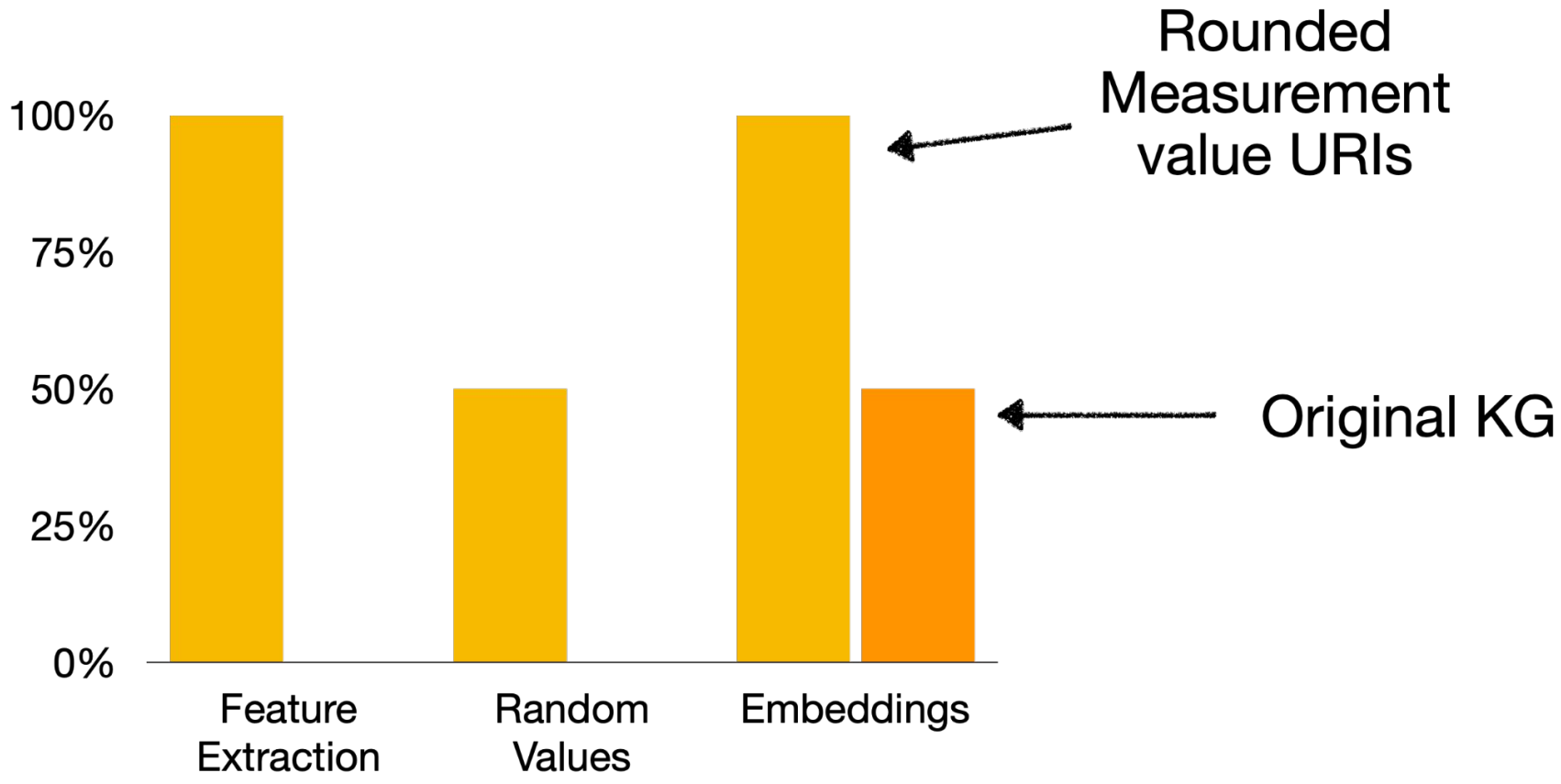

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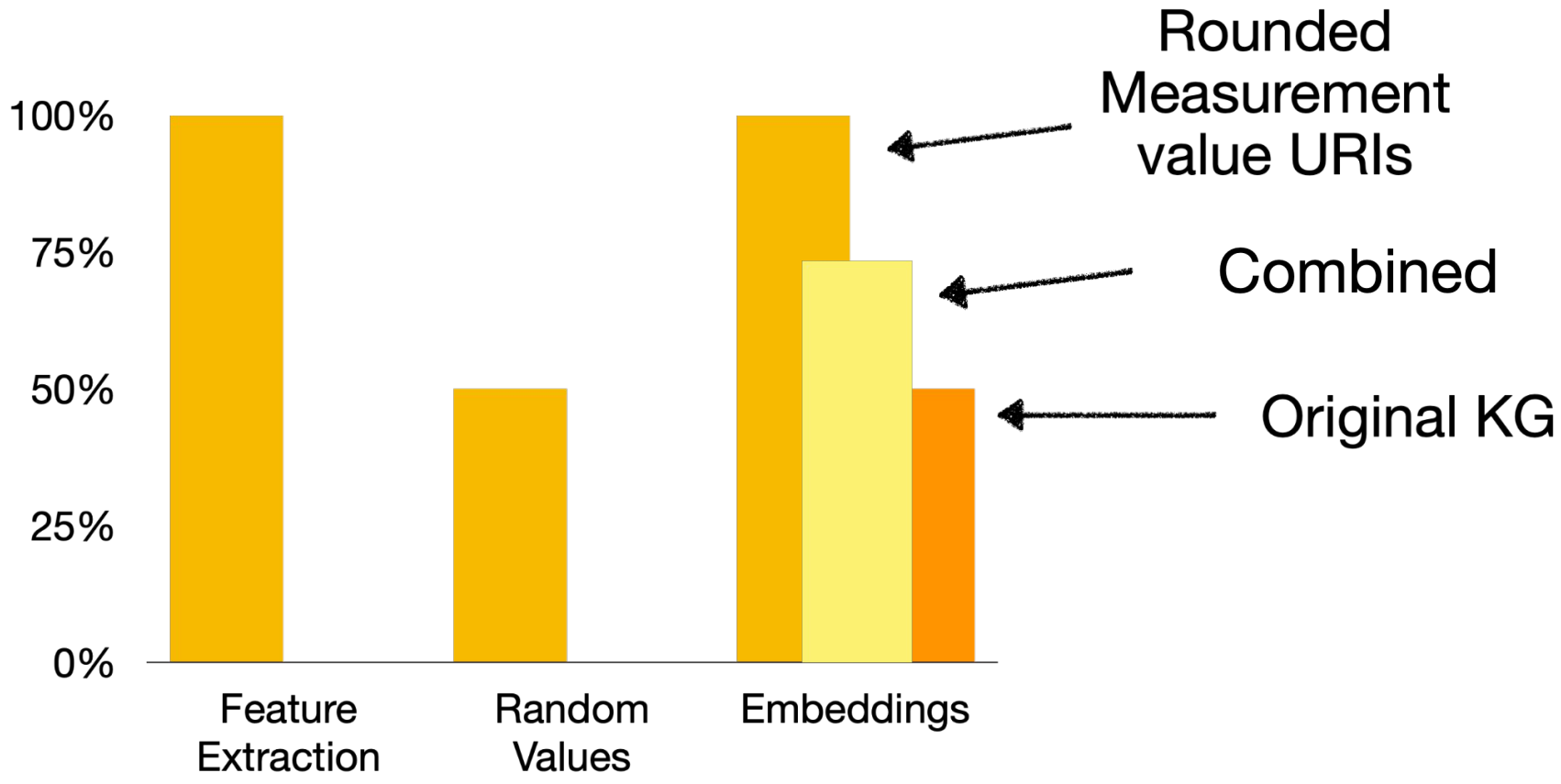
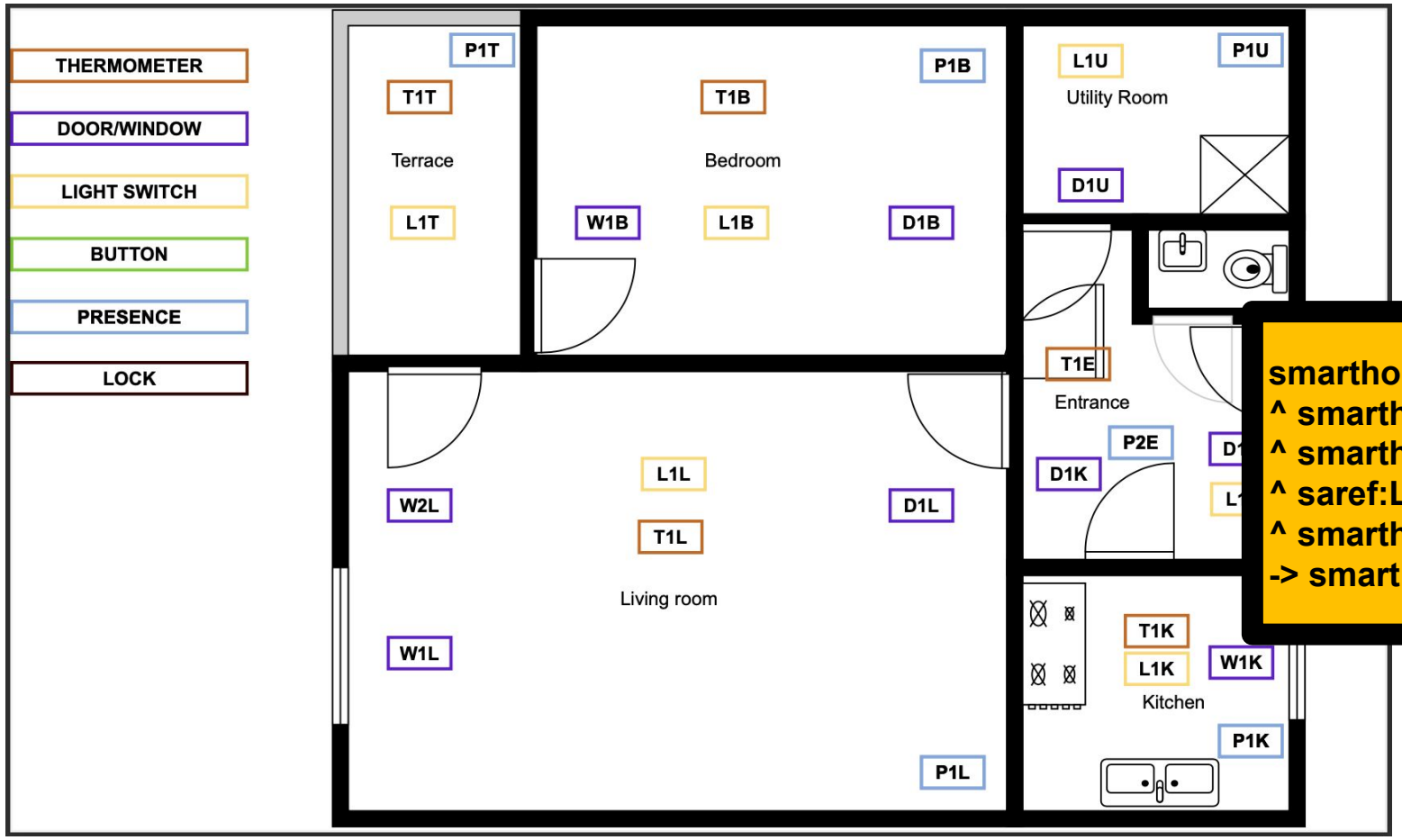
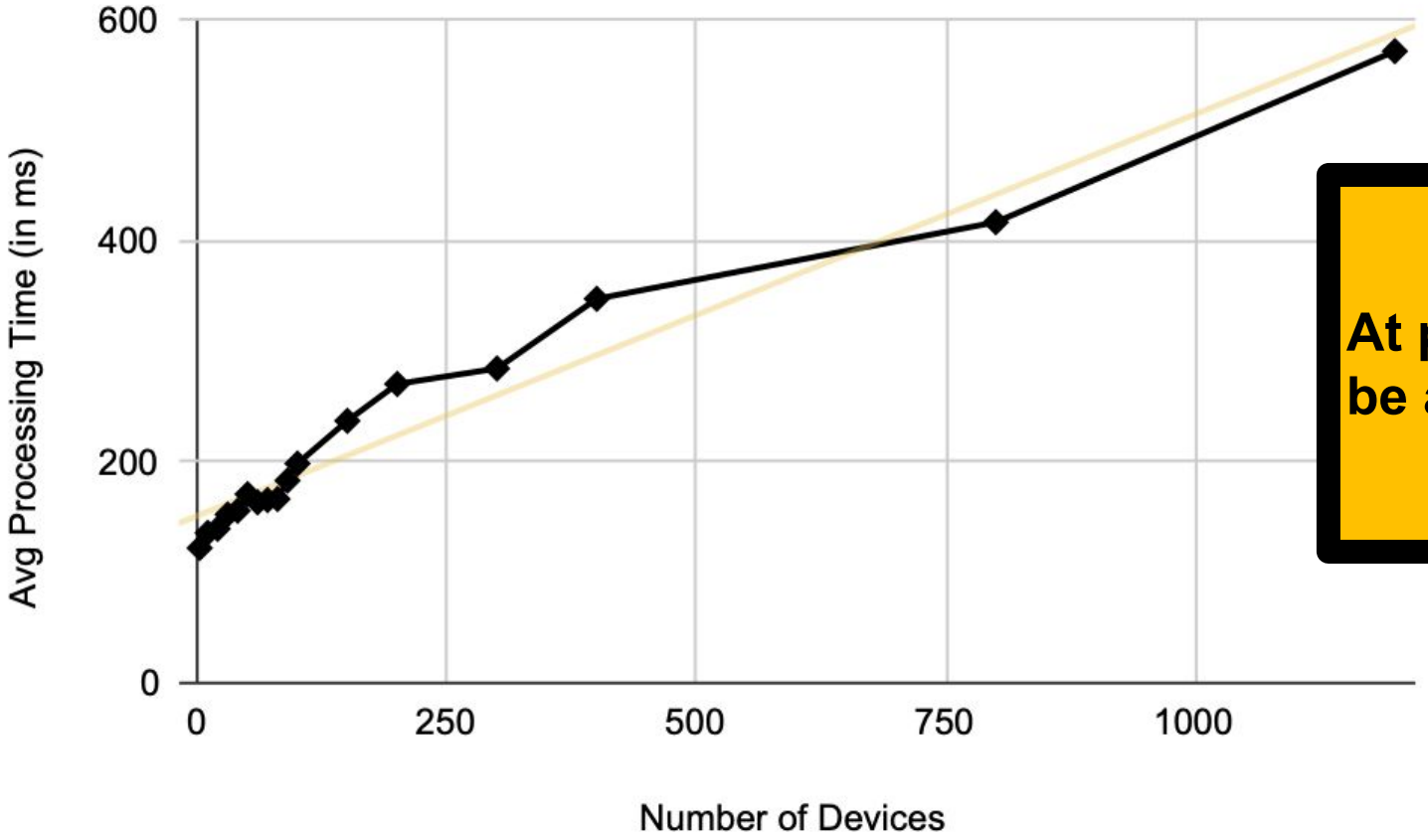


Challenge: Smart home scenario handling using OWL and SWRL



smarthouse:VisitorAtTheDoor(Entrance)
^ smarthouse:Tenant(?tenant)
^ smarthouse:isLocatedIn(?tenant, ?room)
^ saref:LightSwitch(?light)
^ smarthouse:isLocatedIn(?light, ?room)
-> smarthouse:TemporaryRedLightColourState(?light)

Semantic Smart Home System : Performance



At present, real time performance can be achieved on mid-resource machines.

Seven large scale pilots leading to market driven deployments will be installed

Greece
Large residential community with smart appliances and EV integration

France
Residential & non-residential, with tertiary buildings and apartments

Portugal
Residential & geographically widespread tertiary buildings

Netherlands
Residential & non-residential buildings

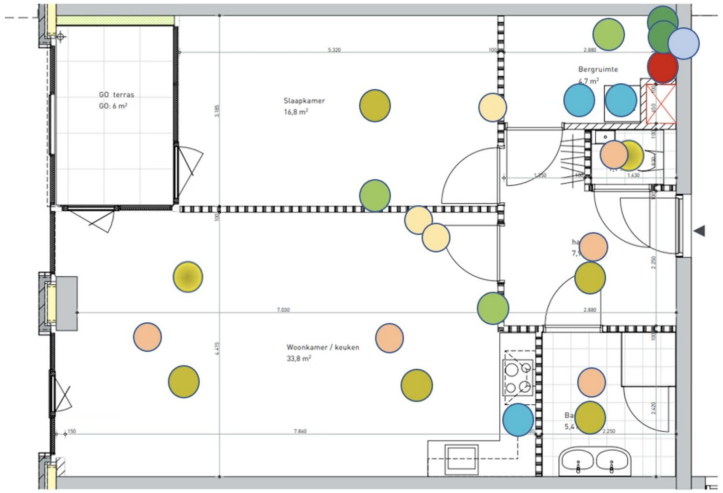
Germany
Groups of residential buildings and hotels

Belgium
Residential and tertiary buildings in communities of multi-energy vectors

Italy
Residential social housing

Dutch Pilot - Next

99 apartments located in Eindhoven (Strijp-S)



Outfitted with smart devices (e.g. washing machines, door sensors,charging stations, climate systems etc)

Dutch Pilot - Videolab

Large office space

10 different types of smart devices

With most devices having multiple measurements

total of 1500 smart devices

Currently mapping two months worth of measurements

interconnect

interoperable solutions connecting smart homes, buildings and grids

Thank you!
Questions?

VU VRIJE UNIVERSITEIT AMSTERDAM

TNO

ALMA MATER STUDIORUM A.D. 1088

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interconnect_project@inesctec.pt

DURATION

01.10.2019 / 30.09.2023