Novelty Detection for Semantic Place Categorization

André Susano Pinto[1,2]

Supervised by: Andrzej Pronobis[1], Luis Paulo Reis[2]

[1]The Royal Institute of Technology (KTH), Sweden
[2]Faculdade de Engenharia da Universidade do Porto

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Outline

Motivation

PR2

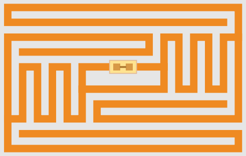
Serving Robot

Wakamaru

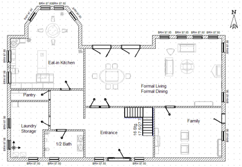
- Robots are useful: can make our lives easier
- Robots are entering our Houses and Offices
- They need to understand our world and communicate with us.

Problem

Enhance world with semantic information is not a scalable solution.



RFID for object tagging



Maps extended with semantic information

Problem

Machine Learning

Gives us methods to solve this problem in reverse by providing robots with knowledge on how to detect and classify concepts and categories from the underlying sensed world.

Unreliable on Dynamic and Unknown Environments

It is unrealistic to believe on the possibility to fully describe the required knowledge for the agent in all situations.

Problem

Detection of Knowledge-Gaps

Detection of situations where the agent knowledge does not suffices.

Focus on Semantic Categories of Places

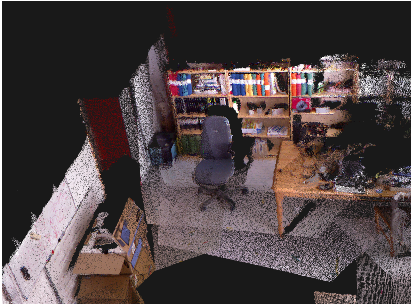
Humans attribute meaning to the areas that describe the expected properties, objects and actions of them. E.g. cups are found in kitchens.

Goals

- Study a semantic mapping process in the context of mobile robots [Pro11].
- Propose a method based on the studied system to detect novel semantic categories of places.

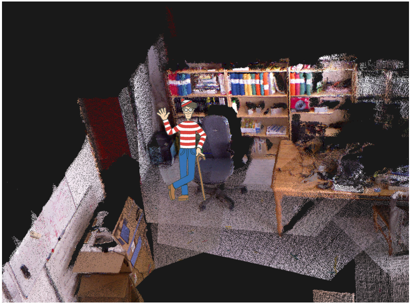
Outline

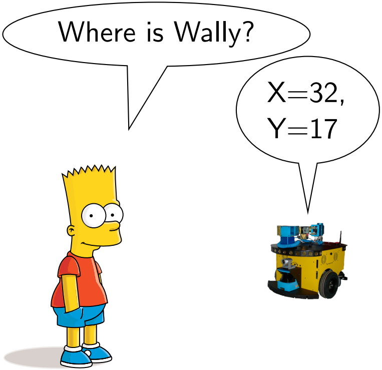
Mapping - Machine Friendly



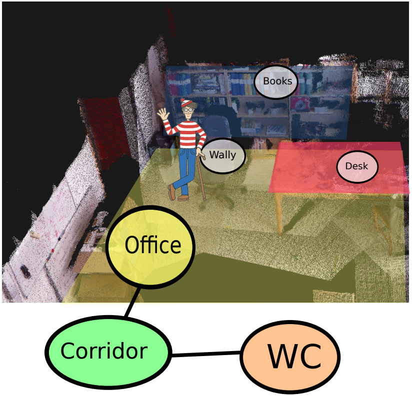
- World Representation
- Bypass Sensory Horizon
- Planning Tool

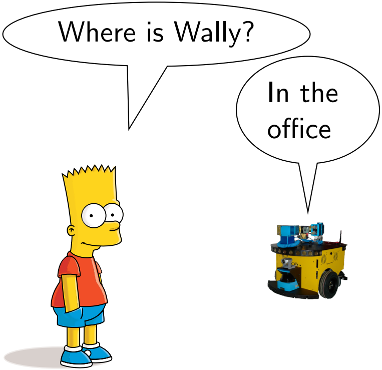
Mapping - Machine Friendly



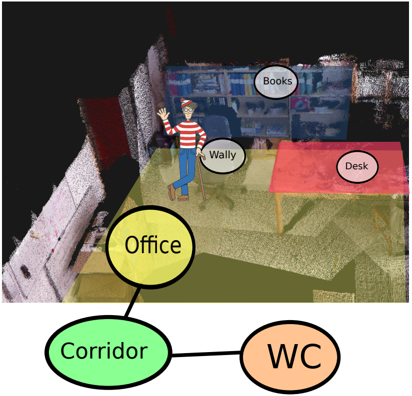


Semantic Mapping



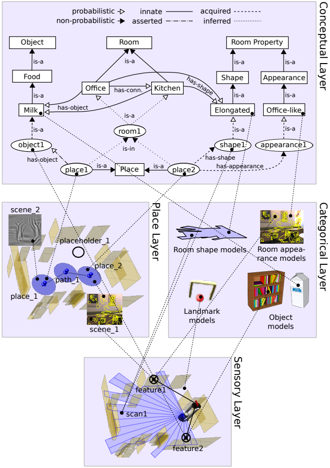


Semantic Mapping



- High Level Reasoning
- Easier Planning [HGD+11]
- Closer to Human Semantic

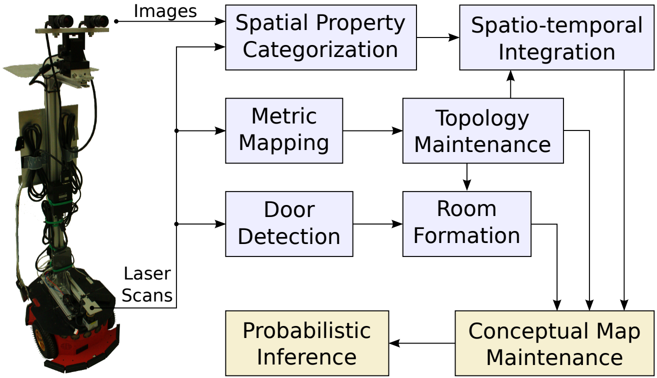
Spatial Knowledge



Layered Spatial Knowledge Representation [PSA$^+$10]

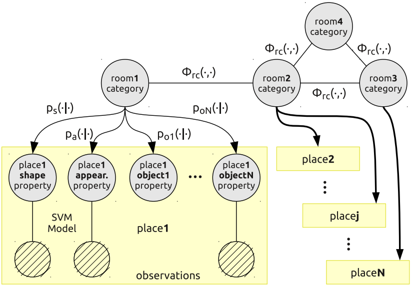
- Sensory Layer
- Place Layer
- Categorical Layer
- Conceptual Layer

A Semantic Mapping Process



[PJ11] presents a process that uses the spatial knowledge to perform probabilistic and multi-modal semantic mapping of the environment using graphical models.

Conceptual Map



Conceptual Map

The ontology is used to identify instances of the concepts and categories and perform probabilistic semantic mapping using graphical models.

Probabilistic Graphical Models

Provides us methods to relate and combine the several variables in a probabilistic way. Allowing to deal with uncertain information and infer variable states.

Several Methods

Bayes Networks, Random Markov Fields, Chain Graphs, Factor Graphs

Novelty Detection - Fast Review

Definition

Detection of novel patterns or signals presents on the data that the system was not trained to handle – [MS03]

Single Class Classification

Lack of negative samples makes them suitable for cases where it is not possible to provide negative samples: anomaly detection, intrusion detection, etc. . .

Several Methods

K-PCA, One class SVM, Nearest Neighbours, etc. . .

Novelty Detection via Thresholding

Threshold on Probability Density

For a fixed distribution and without any prior knowledge on the distribution, novelty can be detected by thresholding on the density of the training data as shown on [Bis94].

Dynamic Sample Space

As more information becomes available the probability mass spreads around and the threshold for novelty detection needs to be adjusted. How to do it?

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Ordering the Sample Space

Back to the Roots

An optimal detector can be implemented by defining a threshold over a relation order defined by $P(\overline{novel}|x)$.

Conditional and Unconditional Probability Ratio

$$P(\overline{novel}|x) = \frac{P(x|\overline{novel})P(\overline{novel})}{P(x)} \propto \frac{P(x|\overline{novel})}{P(x)}$$

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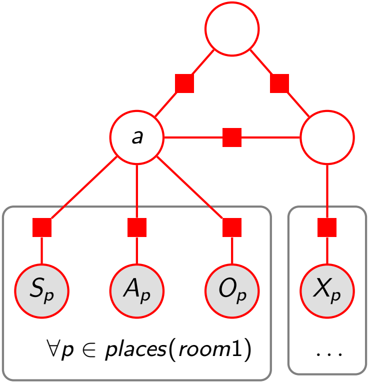
Simplified with an assumption on constant $P(novel)$

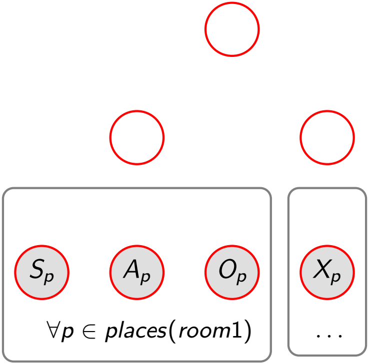
Conditional Probability



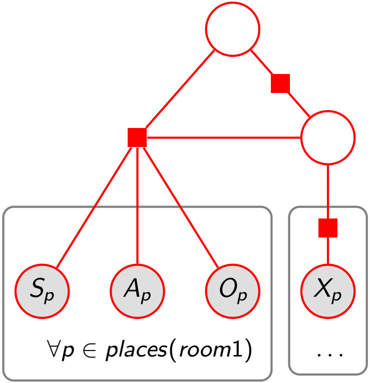
$P(x|\overline{novel})$

The graphical model used by the conceptual map represents the distribution of the variables given that the agent knowledge holds true.

Unconditional Probability Model

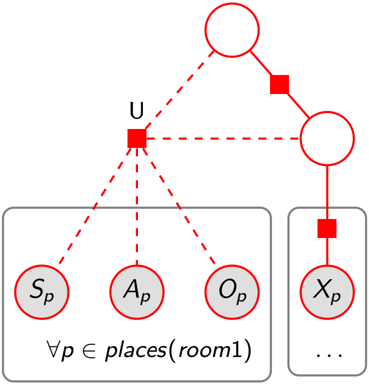


No prior knowledge on $P(x)$.
Uniform distribution [SJ80]

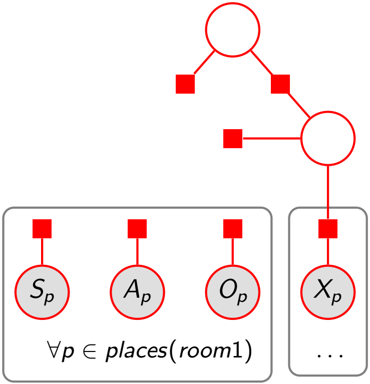


Assume structure and knowledge on other variables still hold true on $P(x)$

Unconditional Probability Model

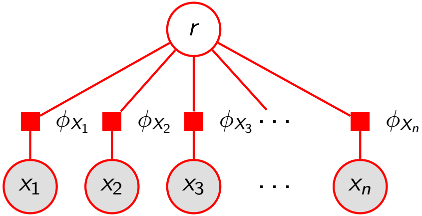


Uniform Model



Independent Model

Synthetic Dataset

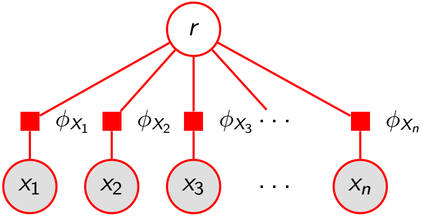


Room class generator of features

- 11 - Room Categories
- 2 - Room Shapes (laser)
- 3 - Room Size (laser)
- 10 - Room Appearance (CRFH)
- 7 - Object Detectors (SIFT)

Synthetic Dataset - Conditional Model

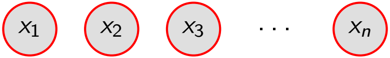
Conditional Model



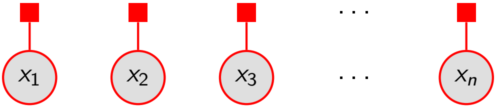
Trained from data sampled from 5 of the 11 room categories.

Synthetic Dataset - Unconditional Models

Uniform Model

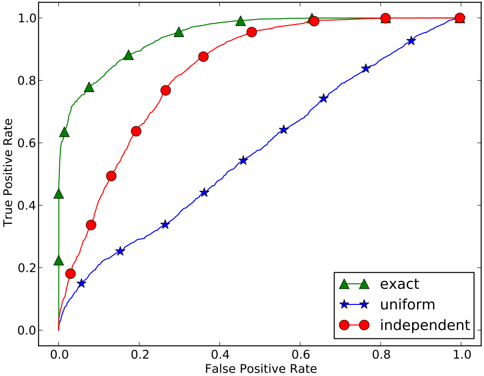


Independent Model



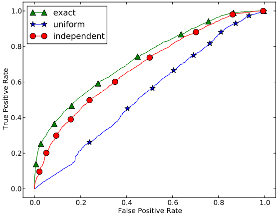
Factors were trained using samples drawn from the synthetic distribution where the label for the generating class was hidden.

Results

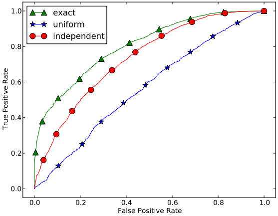


1.0
0.8
0.6
0.4
0.2
0.0
True Positive Rate
0.0
0.2
0.4
0.6
0.8
1.0
False Positive Rate
exact
uniform
independent

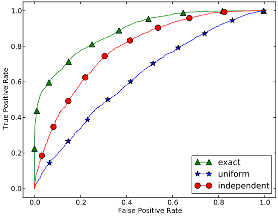
Results - Variable Graph Size



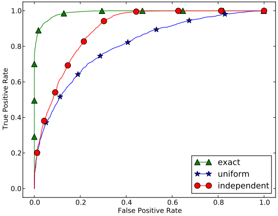
3 sensed features



5 sensed features



10 sensed features



50 sensed features

Summary

- Studies a semantic mapping process
- Studies novelty detection
- Proposes a method to perform detection of novel categories of a variable when the graph structure is dynamic.
- Shows access to unlabelled data can greatly increase performance.

Limitations

Assumption on constant $P(novel)$

Graph structure plays a role on the likelihood a sample with a novel category is drawn. Assuming it to be constant is a very strong assumption that is not expected to hold in all scenarios.

Future Work

Generalize the Framework

Handle novelty on any and more than one variable of the graph and fusing all novelty information in a single method in a probabilistic fashion (e.g. MAP operation).

Exploit Generative Models

Develop methods to be able to explain what the system considers to be known or novel. Such that the reason causing novelty can be interpreted.

Future Work

Learning Graph Structures

Graph structure should be considered probabilistic. Methods to handle and probabilistic represent knowledge on how the agent detect structures must be develop.

After Detection of Knowledge Gaps

What can be done with the detection of novel situations? Can the system be adapted to learn and group novel situations? How to perform self-extension?

Extra

Reproducible Research

All reports and results reproducible from online repository:
`https://github.com/andresusanopinto/novelty-detection-thesis`

Article on EPIA 2011

Novelty Detection Using Graphical Models for Semantic Room Classification

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