Detecting Unknown High-level Concepts in Semantic Mapping with Mobile Robots

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Supervision

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Dora

Where should I look for this book...

Bathroom
Anteroom
Hallway
Office
Title

Detecting Unknown High-level Concepts in Semantic Mapping with Mobile Robots

Content

Novelty Detection for Place Categorization
Place categorization is important
### Motivation

- **Place categorization is important**

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**Planning**

- Dora, make me a sandwich!
- What? Make it yourself.
- sudo make me a sandwich!
- Okay.
- I need to find a kitchen...

**Human–robot interaction**

- Dora, where are my keys?
- In the office.
- Place categorization is important
- Novelty detection is important
  - Robust behavior in changing environments.
  - Life-long operation.

Planning

Human–robot interaction

Dora, make me a sandwich!

What? Make it yourself.

sudo make me a sandwich!

Okay.

I need to find a kitchen...

Dora, where are my keys?

In the office.
Approach

- Previous work by André Susano Pinto
- We implement it on Dora

Idea

lower likelihood of observations = higher likelihood of novelty
Probabilistic Graphical Models

Bayesian Networks (directed edges)

Markov Random Fields (undirected edges)

Chain Graphs (both)
Place categorization (Pronobis, ICRA12)

- metric map
Place categorization (Pronobis, ICRA12)

- metric map
- topological map
Place categorization (Pronobis, ICRA12)

- metric map
- topological map
- room segmentation
Background

Place categorization (Pronobis, ICRA12)

- metric map
- topological map
- room segmentation
- conceptual map
Place categorization (Pronobis, ICRA12)

- metric map
- topological map
- room segmentation
- conceptual map
- place properties
  - shape
  - size
  - appearance
- SVMs $\rightarrow$ distributions
Place categorization (Pronobis, ICRA12)

- metric map
- topological map
- room segmentation
- conceptual map
- place properties
  - shape
  - size
  - appearance
- SVMs → distributions
- observation models
Novelty detection

Definition

Novelty detection is the identification of new or unknown data or signals that a machine learning system is not aware of during learning. — Markou and Singh
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Surveys: Markou and Singh (2003), Chandola et al. (2009)
Novelty detection

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- **Applications**
  - Fraud detection
  - Intrusion detection
  - Place categorization (PLISS)
  - ...
Novelty detection

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- **Applications**
  - Fraud detection
  - Intrusion detection
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  - ...

- **Techniques**
  - Classification
  - Nearest neighbor
  - Clustering
  - Statistical
  - ...

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Novelty Detection for Place Categorization
Observation likelihoods

Novelty: $N \in \{n, \bar{n}\}$
Observations: $X$
Observation likelihoods

Novelty: \( N \in \{ n, \bar{n} \} \)

Observations: \( X \)

\[
p(\bar{n} | x) \leq \text{threshold}
\]
Observation likelihoods

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\frac{p(x | \bar{n}) p(\bar{n})}{p(x)} \leq \text{threshold}
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\]

\[
\frac{p(x | \bar{n})}{p(x)} \leq \text{threshold'}
\]
Observation likelihoods

Novelty: \( N \in \{ n, \bar{n} \} \)

Observations: \( X \)

Conditional likelihood: \( p(x | \bar{n}) \)

Unconditional likelihood: \( p(x) \)

\[
\begin{align*}
\frac{p(x | \bar{n}) p(\bar{n})}{p(x)} & \leq \text{threshold} \\
\frac{p(x | \bar{n})}{p(x)} & \leq \frac{\text{threshold}}{p(\bar{n})} \\
\frac{p(x | \bar{n})}{p(x)} & \leq \text{threshold}'
\end{align*}
\]
Observation likelihoods

Novelty: \( N \in \{n, \bar{n}\} \)

Observations: \( X \)

Conditional likelihood: \( p(x \mid \bar{n}) \)

Unconditional likelihood: \( p(x) \)

Novelty Score

\[
\frac{p(x \mid \bar{n})}{p(x)} = \frac{p_c(x)}{p_u(x)}
\]

\[
\frac{p(x \mid \bar{n})}{p(x)} \leq \frac{\text{threshold}}{p(\bar{n})}
\]

\[
\frac{p(x \mid \bar{n})}{p(x)} \leq \text{threshold’}
\]
Conditional likelihood (conceptual map)

\[
\frac{p_c(x)}{p_u(x)}
\]
Conditional likelihood (conceptual map)

\[
\frac{p_c(x)}{p_u(x)}
\]

Observations in other rooms: \( y \)

\[
p_c(x) = p(x \mid y)
\]
Unconditional likelihood (independent uniform model)

\[
\frac{p_c(x)}{p_u(x)}
\]
Unconditional likelihood (independent uniform model)

\[
\frac{p_c(x)}{p_u(x)}
\]

- Model properties independent of each other.
Unconditional likelihood (independent uniform model)

\[
\frac{p_c(x)}{p_u(x)}
\]

- Model properties independent of each other.
- Model individual properties as uniform.
Together

$$\sum_c p_c(c \mid y) \prod_i \frac{\sum p_i p_c(p_i \mid c) \phi_i(p_i, x_i)}{\sum p_i p_u(p_i) \phi_i(p_i, x_i)}$$
Together

\[ \sum_c p_c(c | y) \prod_i \frac{\sum_{p_i} p_c(p_i | c) \phi_i(p_i, x_i)}{\sum_{p_i} p_u(p_i) \phi_i(p_i, x_i)} \]
To gether

\[
\sum_c p_c(c \mid y) \prod_i \frac{\sum_{p_i} p_c(p_i \mid c) \phi_i(p_i, x_i)}{\sum_{p_i} p_u(p_i) \phi_i(p_i, x_i)}
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\]
Thresholds

How to pick a threshold?

- hand picked for our experiments
- future work: more systematic with test-set and validation-set
Experiment 1

Increasing number of places

![Graph showing increasing number of places for hallway (not novel) and hallway (novel).]
Experiment 2

Topological map
Experiment 2

Leave-one-out – Offices

Experiment 2 (no objects)

- none
- doubleoffice
- professorsoffice
- singleoffice
- offices

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Novelty Detection for Place Categorization
All rooms

Experiment 2 (no objects)

- r0 (DO, 5)
- r1 (HW, 30)
- r3 (AR, 2)
- r4 (BR, 2)
- r5 (BR, 1)
- r6 (RL, 4)
- r7 (SO, 3)
- r8 (PO, 4)
- r9 (RL, 3)
- r10 (SO, 2)
- r11 (PO, 3)
- r12 (PO, 2)
- r13 (PO, 2)
- r14 (RL, 3)
Works well...
Evaluation

- Works well... but what does it show?
Evaluation

- Works well... but what does it show?
- Strong novelty cue from appearance due to leave-one-out.
Evaluation

- Works well... but what does it show?
- Strong novelty cue from appearance due to leave-one-out.
- Next step: Implement novelty detection for the appearance classifier.
Discussion

Future work

- Novelty cue from appearance.
- Systematic threshold selection.
Future work

- Novelty cue from appearance.
- Systematic threshold selection.
- Object observations.
Future work

- Novelty cue from appearance.
- Systematic threshold selection.
- Object observations.
- Reaction to novelty. Changing Dora’s behavior.
Recap: What did I do?

- Novelty detection for place categorization.
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- Idea: Observation likelihood (existing work).
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- Derived: Observation likelihoods on chain graph.
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- Derived: Observation likelihoods on chain graph.
- Implemented: Novelty score for Dora, auxiliary components.
Recap: What did I do?

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- Code: Partially upstream. Rest will be merged in a branch.
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- Code: Partially upstream. Rest will be merged in a branch.
- Evaluated: Leave-one-out experiments with Dora.
- Next step: Novelty for appearance.
Thank you for listening!

Questions?