Sample Spaces and Feature Models: There and Back Again

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Overview

Feature Models

Sample Spaces

Feature Model with Soft Constraints
Overview

Feature Models

Sample Spaces

Feature Model with Soft Constraints

destroy encourages init
start encourages stop
stop encourages start
init encourages destroy
Overview

Feature Models

Feature Model with Soft Constraints

Sample Spaces

Sample Set of Configurations

Czarnecki, She, Wąsowski. Sample Spaces and Feature Models: There and Back Again.
Outline

1 Motivation

2 Probabilistic Feature Models
   - Semantics of Soft Constraints
   - Joint Probability Distributions

3 Configuration

4 Application: Feature Model Mining
   - Mining on Applets

5 Conclusions
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Basic Feature Models

Feature Models...

- represent commonality and variability in a product line.
- describe a set of legal configurations.
- But... existing feature models cannot express preference among legal configurations.
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- represent commonality and variability in a product line.
- describe a set of *legal configurations*.
- **But**... existing feature models can not express *preference* among legal configurations.
Probabilistic Feature Models (PFMs)

Probabilistic Feature Models add soft constraints.

...a constraint that should be satisfied by most configurations, but some may violate it.
Interactive Configuration

- Car
  - gear
    - manual
    - automatic
  - drive by wire
  - for North America

- drive by wire → automatic
- automatic given gear [20%]
- automatic given North America [80%]
Interactive Configuration

Probabilistic view of the PFM.

- drive by wire $\rightarrow$ automatic
- automatic given gear [20%]
- automatic given North America [80%]
Interactive Configuration

We begin by selecting **Car** and **Gear**.

- Drive by wire → automatic
- Automatic given gear [20%]
- Automatic given North America [80%]
Next, we select *for North America*.

- **drive by wire** → **automatic**
- **automatic** given **gear** [20%]
- **automatic** given **North America** [80%]
Interactive Configuration

Now, we select automatic.

- Drive by wire → automatic
  - automatic given gear [20%]
  - automatic given North America [80%]
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The semantics of a basic feature model... is defined as a conjunction of its hard constraints as a propositional formula.
Logical Components of a Basic Feature Model

Feature Dependencies

This formula denotes a set of legal configurations.
Logical Components of a Basic Feature Model

Feature Dependencies

Mandatory

Group

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Czarnecki, She, Wąsowski. *Sample Spaces and Feature Models: There and Back Again.*
This formula denotes a set of legal configurations.
Logical Components of a Basic Feature Model

Feature Dependencies

- Car
  - gear
  - drive by wire
  - for North America
  - manual
  - automatic

Mandatory

- Car
  - gear

Group

- gear
  - manual
  - automatic
  - false

This formula denotes a set of legal configurations.
This formula denotes a set of legal configurations.
A probabilistic feature model is...

A basic feature model + soft constraints

drive by wire → automatic
A probabilistic feature model is...

A basic feature model + soft constraints

drive by wire → automatic
Feature Modeling with Soft Constraints

- **On-by-default** if cond. probability between 80% and 100%.

\[ 0.8 \leq P(paint \mid must\ override) \leq 1.0 \]

\[ 0.8 \leq P(init \mid must\ override) \leq 1.0 \]
Feature Modeling with Soft Constraints

- **Off-by-default** if cond. probability between 0 and 50%.
Feature Modeling with Soft Constraints

- **Applet**
  - **must override**
  - **stop**[^off]
  - **destroy**[^off]
  - **paint**[^on]
  - **start**[^off]
  - **init**[^on]

**Constraints:**
- **destroy encourages init**
- **start encourages stop**
- **stop encourages start**
- **init encourages destroy**
Feature Modeling with Soft Constraints

Czarnecki, She, Wąsowski. Sample Spaces and Feature Models: There and Back Again.
Joint Probability Distributions

Basic feature models...

specify a set of legal configurations.

Probabilistic feature models...

specify a set of legal joint probability distributions (JPDs).

A joint probability distribution...

assigns a probability to each possible configuration.
Joint Probability Distributions

Basic feature models...

specify a set of *legal configurations*.

Probabilistic feature models...

specify a set of *legal joint probability distributions* (JPDs).

A joint probability distribution...

assigns a probability to each *possible configuration*.
Legal Configurations Compared with JPDs

Basic Feature Model
Legal Configurations Compared with JPDs

Basic Feature Model

Probabilistic Feature Model

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Joint Probability Distributions

Basic feature models... specify a set of legal configurations.

Probabilistic feature models... specify a set of legal joint probability distributions (JPDs).

A joint probability distribution... assigns a probability to each possible configuration.
An abstract PFM is *under-specified* and specifies a range of JPDs.
An abstract PFM is under-specified and specifies a range of JPDs.
Under-specification in PFM

An abstract PFM is under-specified and specifies a range of JPDs.

A concrete PFM specifies a single JPD.
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Configuration

Requires a single concrete JPD.

- Abstract PFMs need to be completed.
- *Entropy maximization.*

Probabilistic Inference.

- Relation with *Bayesian Networks.*
- *Most probable explanation* algorithms.
- Adaptive guidance given current state.
Configuration

Requires a single concrete JPD.

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Feature Model Mining

Synthesize a feature model that is representative of the variability in a sample set of configurations.

<table>
<thead>
<tr>
<th>conf</th>
<th>a</th>
<th>b</th>
<th>c</th>
<th>d</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>2</td>
<td>✓</td>
<td>✓</td>
<td></td>
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<tr>
<td>3</td>
<td>✓</td>
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<tr>
<td>4</td>
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Sample Set
Feature Model Mining

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Association Rules

- $c \Rightarrow a$ [100%]
- $\land b \Rightarrow a$ [100%]
- $\land d \Rightarrow c$ [100%]
- $\land a \Rightarrow b \lor c$ [100%]
- $\land ...$
- $\land a \Rightarrow c$ [75%]
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### Association Rules

- \( c \Rightarrow a \) [100%]
- \( b \Rightarrow a \) [100%]
- \( d \Rightarrow c \) [100%]
- \( a \Rightarrow b \lor c \) [100%]
- \( \ldots \)
- \( a \Rightarrow c \) [75%]

### Feature Model

- \( a \)
- \( b \)
- \( c \)
- \( d \)

\( c \) given \( a \) [75%]
Feature Model Mining on Applets

Applets

Sample Set

Construct sample set by analysing overridden methods in 64 applets:

destroy, paint, init, start and stop.
Case Study Results

Mined Feature Model

- Applet
  - paint [75%]
  - start [59%]
  - init [97%]
  - stop [53%]
  - destroy [42%]

  stop given start [84%]
  start given stop [97%]
  paint given destroy [88%]
  paint given stop [88%]
  more...

Expert-specified Model

- Applet
  - must override
  - stop [off]
  - destroy [off]

  paint [on]
  start [off]
  init [on]

  destroy encourages init
  start encourages stop
  stop encourages start
  init encourages destroy

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Related Work

Probabilistic Feature Models.

- Soft Constraints [Czarnecki 2000] [Wada, Suzuki and Oba 2007]
- Feature Models and fuzzy logic [Robak, Pieczyński, 2003]
- i* goal models [Giorgini et al., 2002]

Reverse-engineering models.

- Using concept analysis [Loesch and Ploedereder, 2007]
- Identifying code differences [Jepsen et. al., 2007]
Conclusions

Probabilistic Feature Models.

- Basic feature models extended with *soft constraints*.
- Specifies a set of joint probability distributions.
- Modeling, reverse-engineering, configuration.
Probabilistic Feature Models.

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Questions?