Sample Spaces and Feature Models: There and Back Again

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Software Product Line Conference 2008

Overview

Feature Models

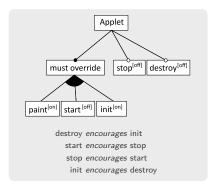
Applet must override stop^[off] destroy^[off] paint^[on] start ^[off] init^[on] destroy encourages init start encourages stop stop encourages start init encourages destroy

Feature Model with Soft Constraints

Sample Spaces

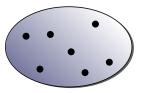
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Feature Models



Feature Model with Soft Constraints

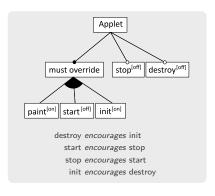
Sample Spaces



Sample Set of Configurations

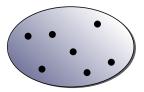
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Feature Models

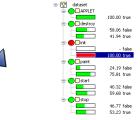


Feature Model with Soft Constraints

Sample Spaces



Sample Set of Configurations

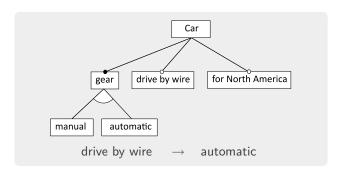


Outline

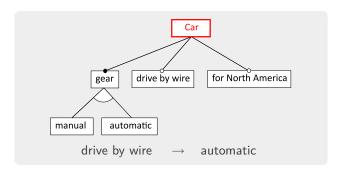
- 1 Motivation
- 2 Probabilistic Feature Models
 - Semantics of Soft Constraints
 - Joint Probability Distributions
- 3 Configuration
- 4 Application: Feature Model Mining
 - Mining on Applets
- 5 Conclusions

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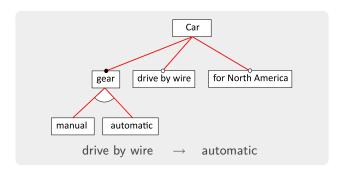
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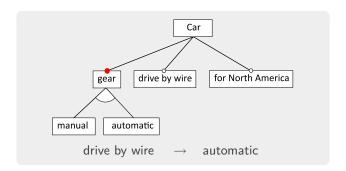
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- describe a set of legal configurations
- But... existing feature models can not express preference among legal configurations.



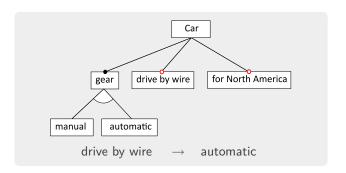
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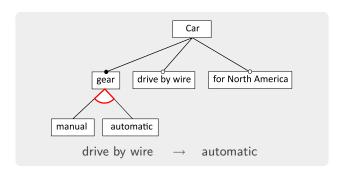
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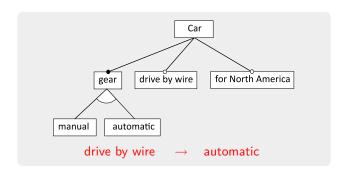
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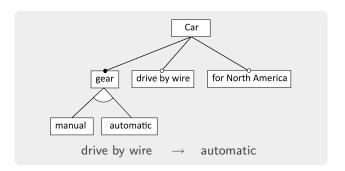
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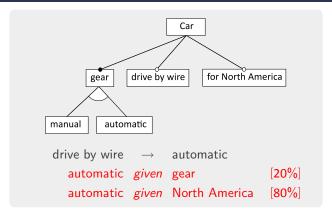


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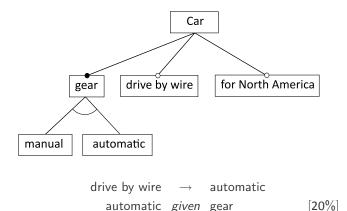
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Probabilistic Feature Models (PFMs)



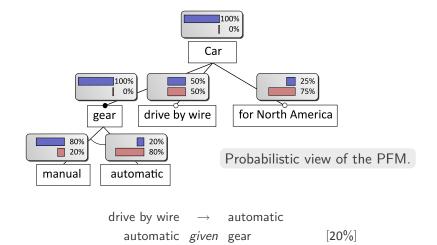
Probabilistic Feature Models add soft constraints.

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



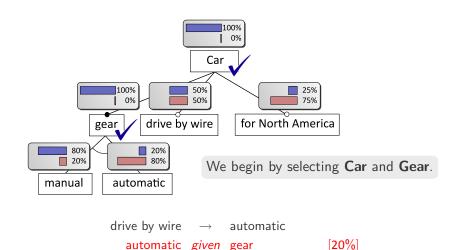
automatic given North America

[80%]

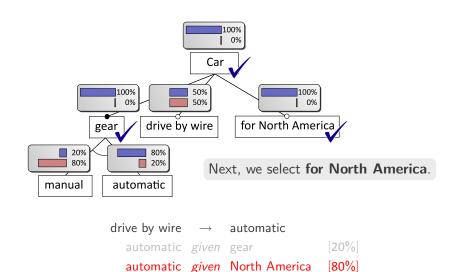


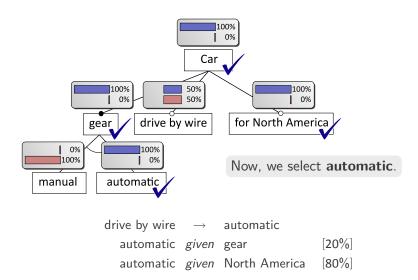
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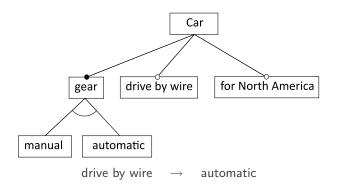




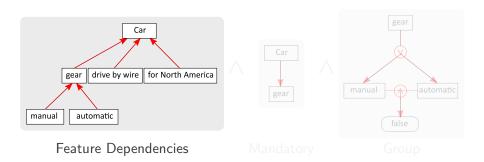
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Semantics of Basic Feature Models

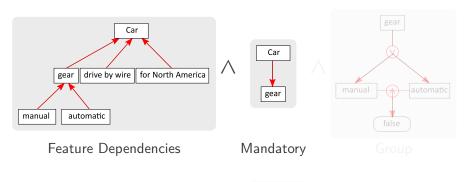


The semantics of a basic feature model... is defined as a conjunction of it's hard constraints as a propositional formula.



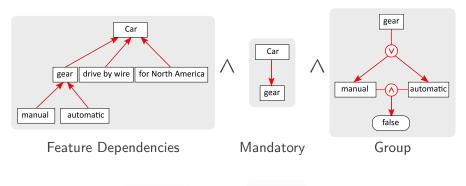


This formula denotes a set of legal configurations



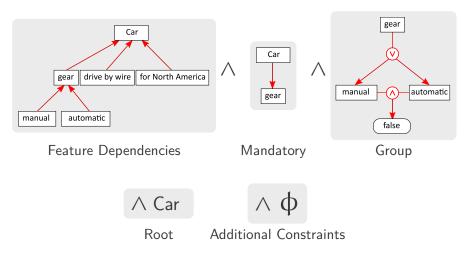


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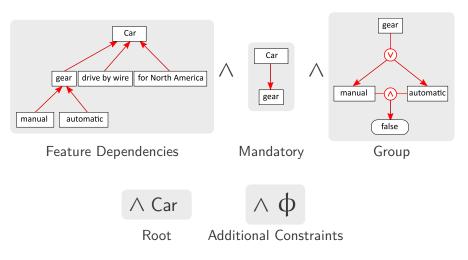




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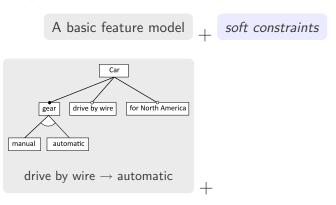
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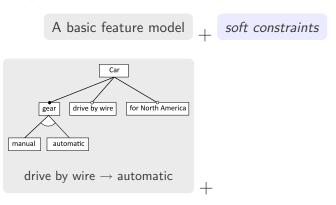
Components of a Probabilistic Feature Model

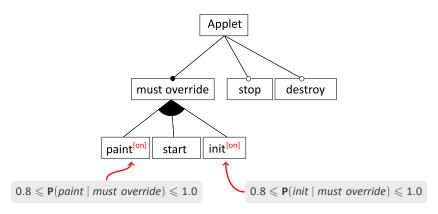
A probabilistic feature model is...



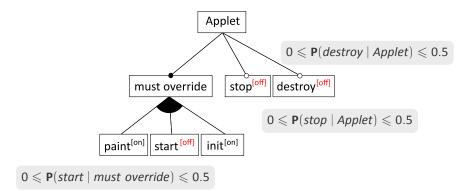
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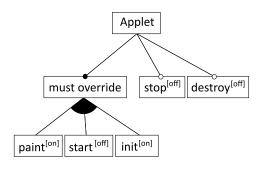




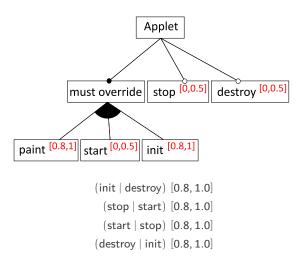
• On-by-default if cond. probability between 80% and 100%.



• Off-by-default if cond. probability between 0 and 50%.



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



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

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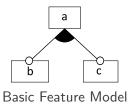
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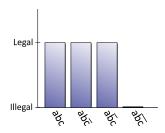
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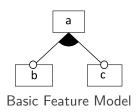
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Legal Configurations Compared with JPDs

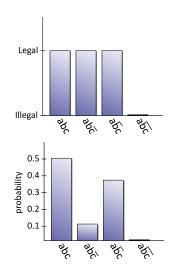




Legal Configurations Compared with JPDs







Joint Probability Distributions

specify a set of legal configurations

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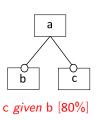
Under-specification in PFMs



а	b	С	P(a,b,c)
1	1	1	$p_1 \geqslant 0.0$
1	1	0	$p_2 \geqslant 0.0$
1	0	1	$p_3 \ge 0.0$
1	0	0	$p_4 \geqslant 0.0$
0	:	:	$p_{58} = 0$

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

Under-specification in PFMs

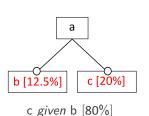


а	b	С	P(a,b,c)
1	1	1	$p_1 \geqslant 0.0$
1	1	0	$p_1 \geqslant 0.0$ $p_2 = 0.25p_1$
1	0	1	$p_3 \geqslant 0.0$
1	0	0	$ \begin{vmatrix} p_2 - 0.25p_1 \\ p_3 \geqslant 0.0 \\ p_4 = 1 - 1.25p_1 - p_3 \end{vmatrix} $
0			$p_{58} = 0$

where
$$1.25p_1 + p_3 \le 1$$

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

Under-specification in PFMs



а	b	С	P(a,b,c)
1	1	1	$p_1 = 0.1$
1	1	0	$p_1 = 0.125$
1	0	1	$p_3 = 0.1$
1	0	0	$p_4 = 0.775$
0	:	:	$p_{58} = 0$

A concrete PFM specifies a single JPD.

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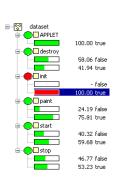
Configuration

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



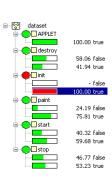
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Feature Model Mining

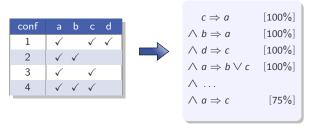
Synthesize a feature model that is representative of the variability in a sample set of configurations.

conf		b	С	d
1	√		\checkmark	√
2	✓	\checkmark		
3	✓		\checkmark	
4	✓	\checkmark	\checkmark	

Sample Set

Feature Model Mining

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



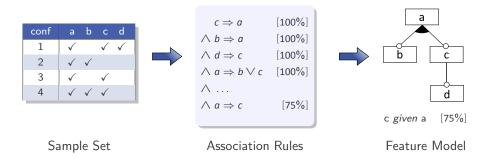
Sample Set

Association Rules

Association Rule Mining

Feature Model Mining

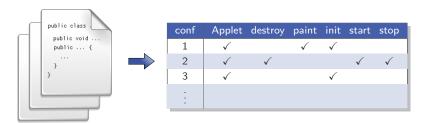
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Association Rule Mining

Feature Model Synthesis Czarnecki and Wąsowski 2007

Feature Model Mining on Applets



Applets

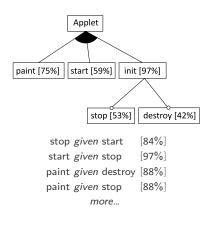
Sample Set

Construct sample set by analysing overridden methods in 64 applets:

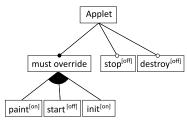
destroy, paint, init, start and stop.

Case Study Results

Mined Feature Model



Expert-specified Model



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

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Related Work

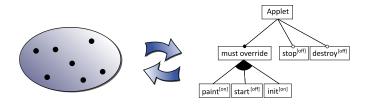
Probabilistic Feature Models.

- 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



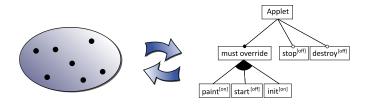
Feature Model with soft constraints

Probabilistic Feature Models

Sample Space

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

Conclusions



Probabilistic Feature Models

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Questions?

Feature Model with soft constraints