

# Sample Spaces and Feature Models: There and Back Again

Krzysztof Czarnecki<sup>1</sup> Steven She<sup>1</sup> Andrzej Wąsowski<sup>2</sup>

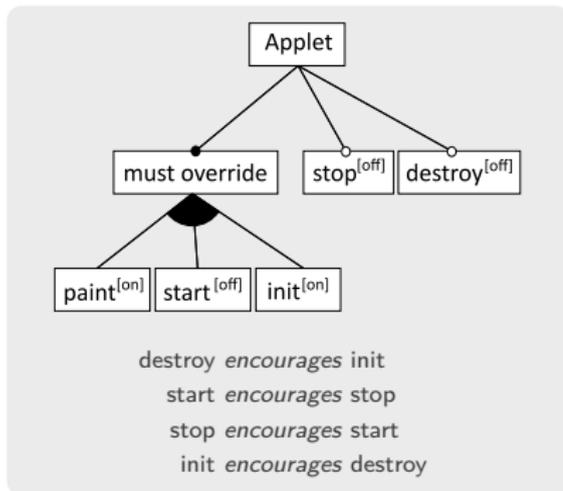
<sup>1</sup>University of Waterloo, Canada

<sup>2</sup>IT University of Copenhagen, Denmark

Software Product Line Conference 2008

# Overview

## Feature Models

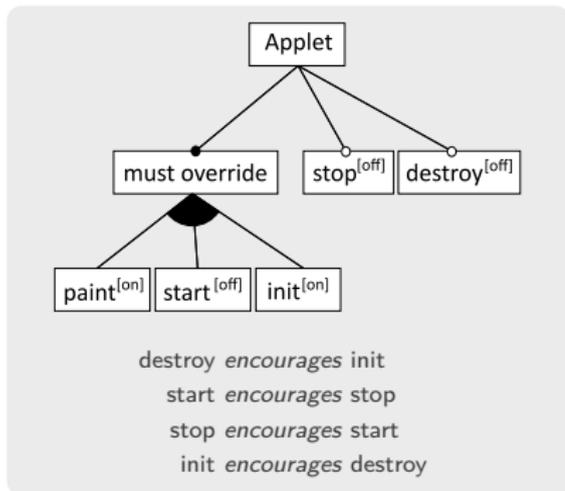


Feature Model with Soft Constraints

## Sample Spaces

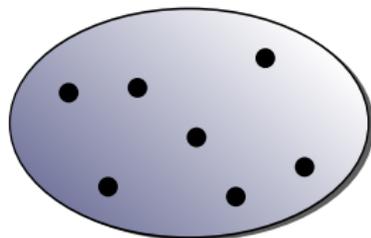
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Feature Model with Soft Constraints

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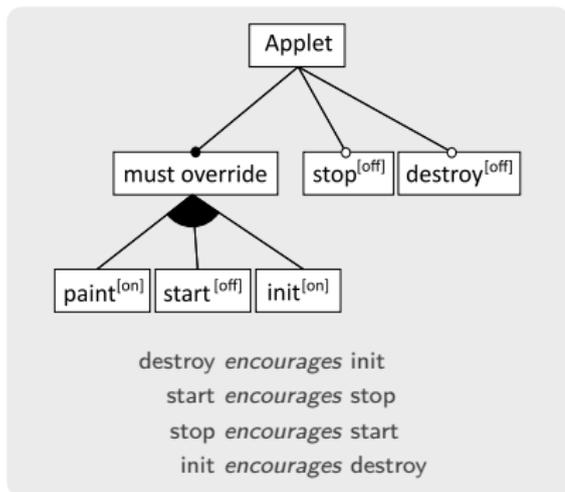


Sample Set of Configurations



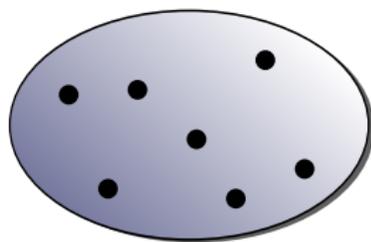
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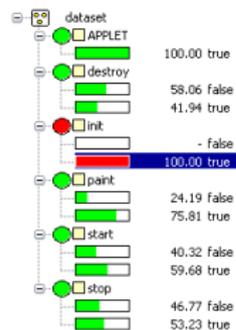


Feature Model with Soft Constraints

## Sample Spaces



Sample Set of Configurations



Configuration

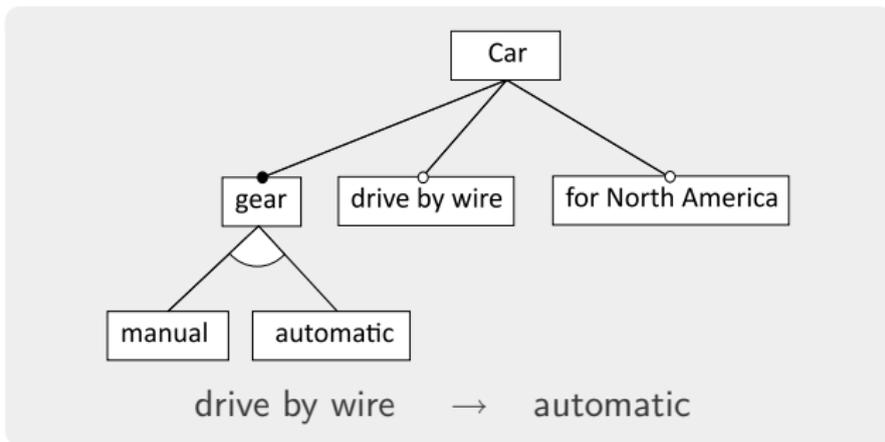
# Outline

- 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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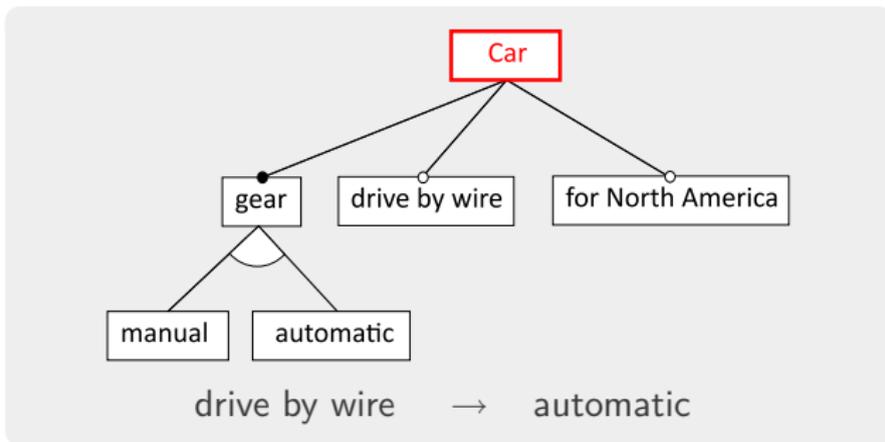
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## Feature Models...

- 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.

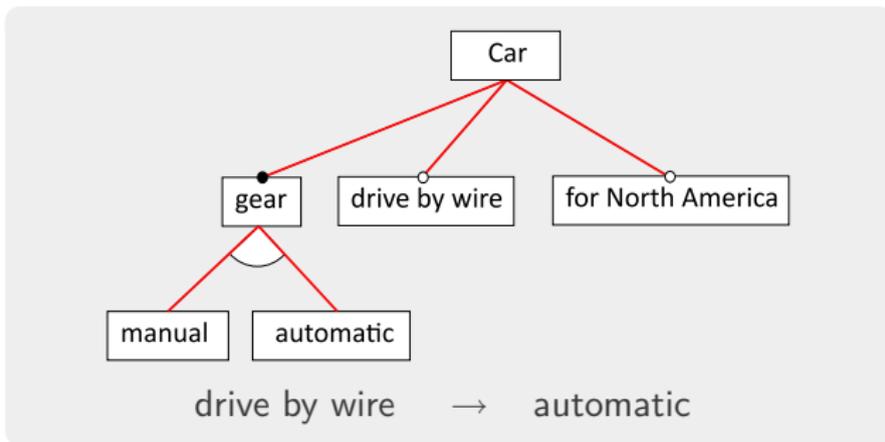
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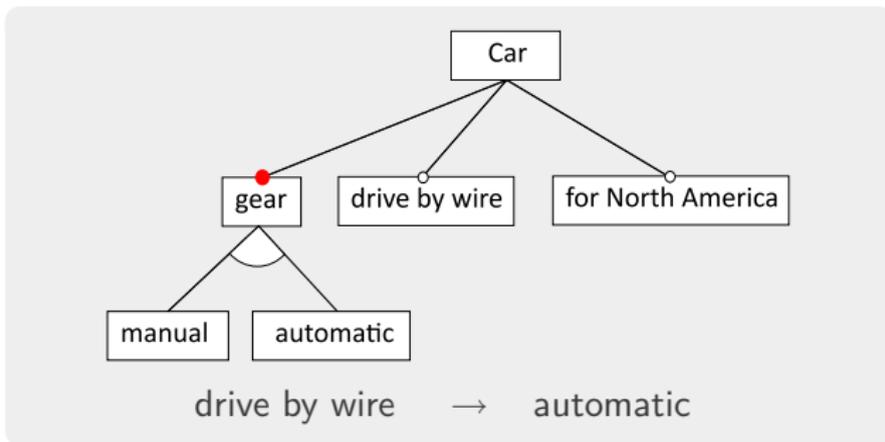
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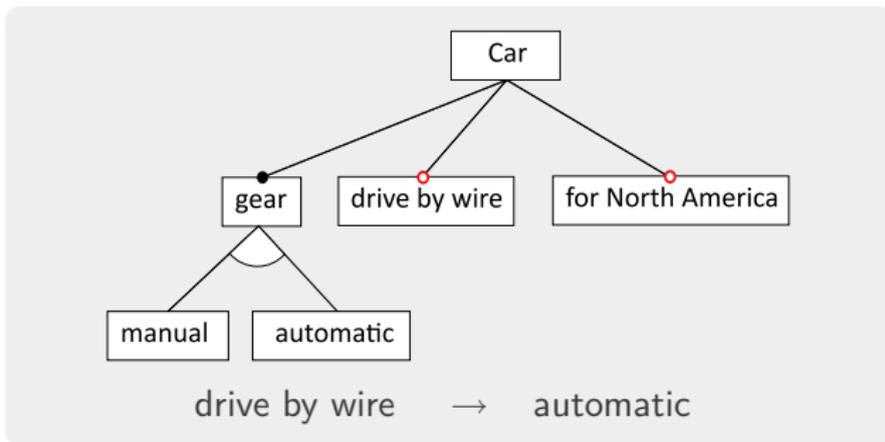
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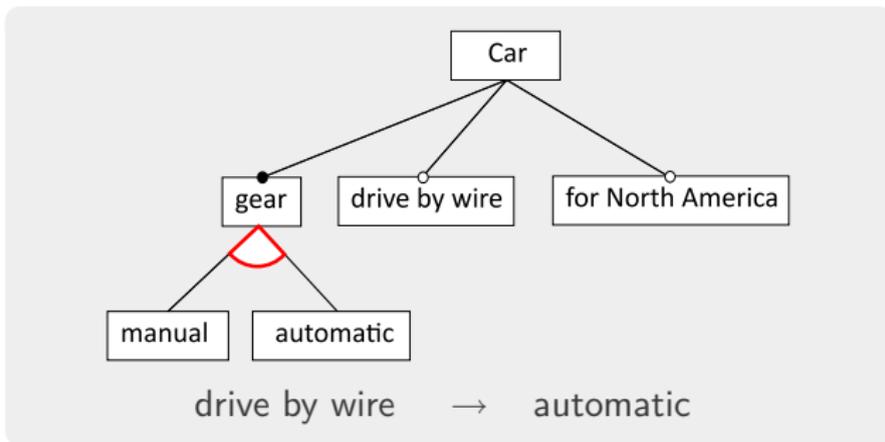
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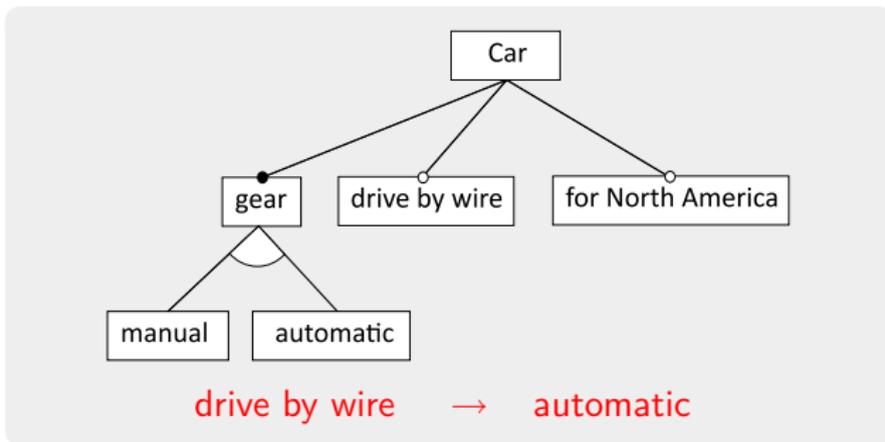
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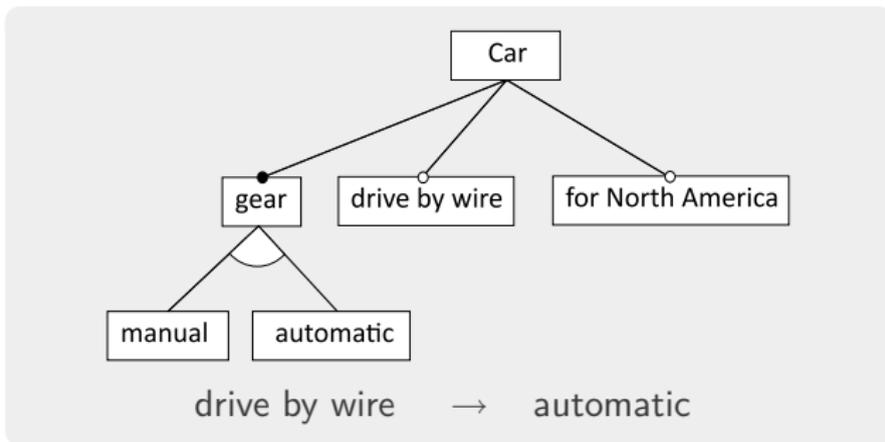
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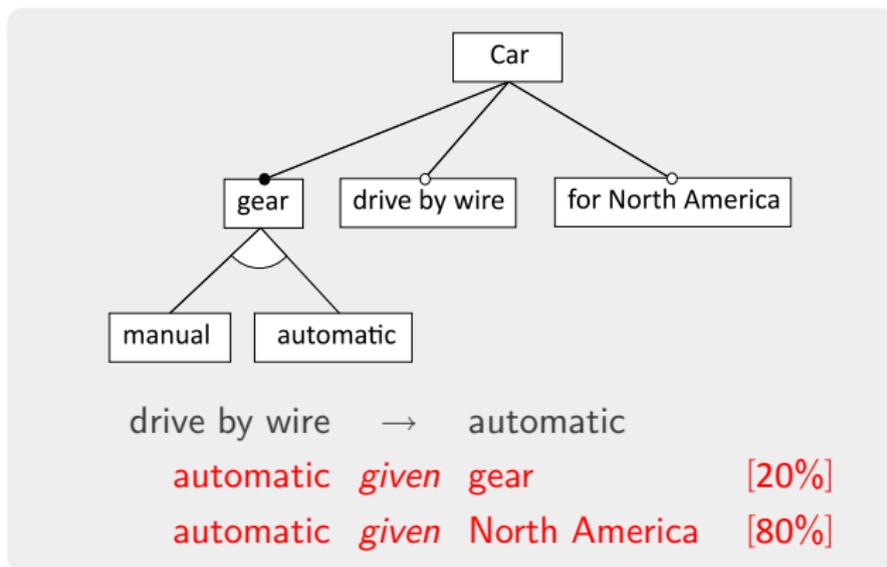
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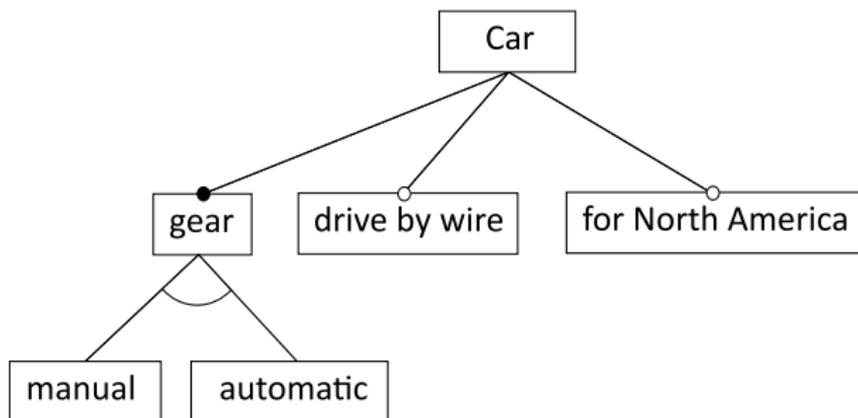
# Probabilistic Feature Models (PFMs)



Probabilistic Feature Models add **soft constraints**.

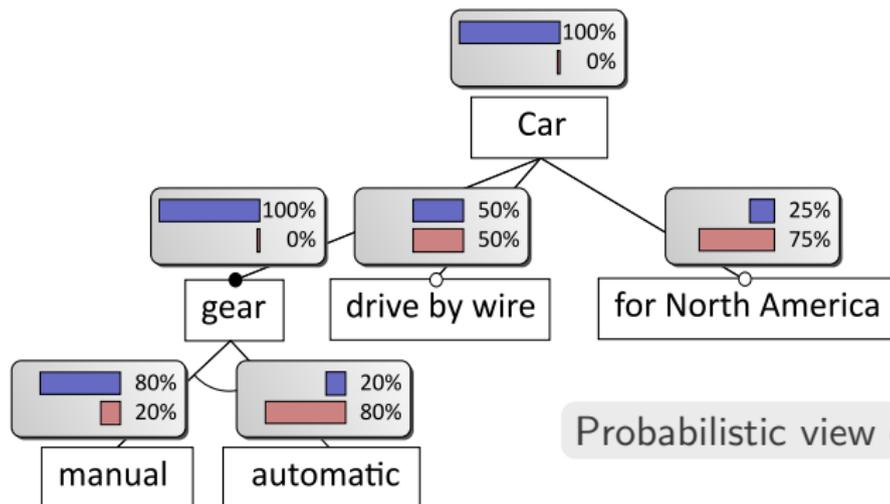
*...a constraint that should be satisfied by most configurations, but some may violate it.*

# Interactive Configuration



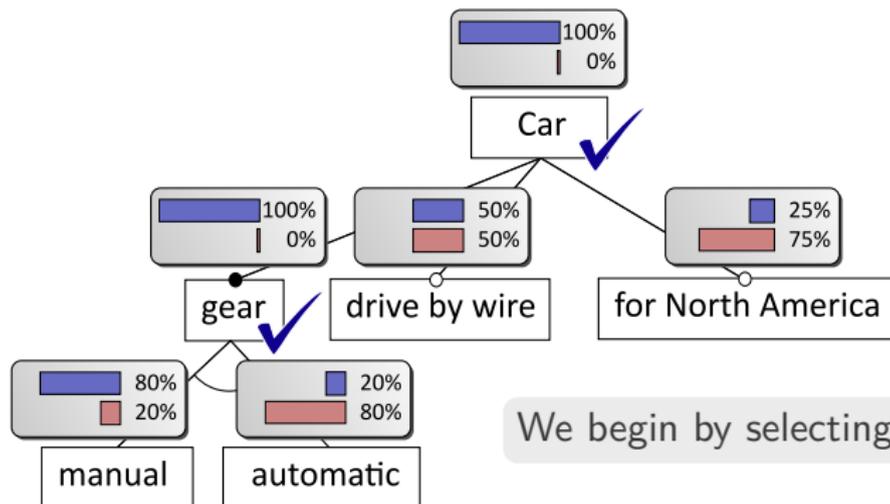
drive by wire  $\rightarrow$  automatic  
 automatic *given* gear [20%]  
 automatic *given* North America [80%]

# Interactive Configuration



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

# Interactive Configuration



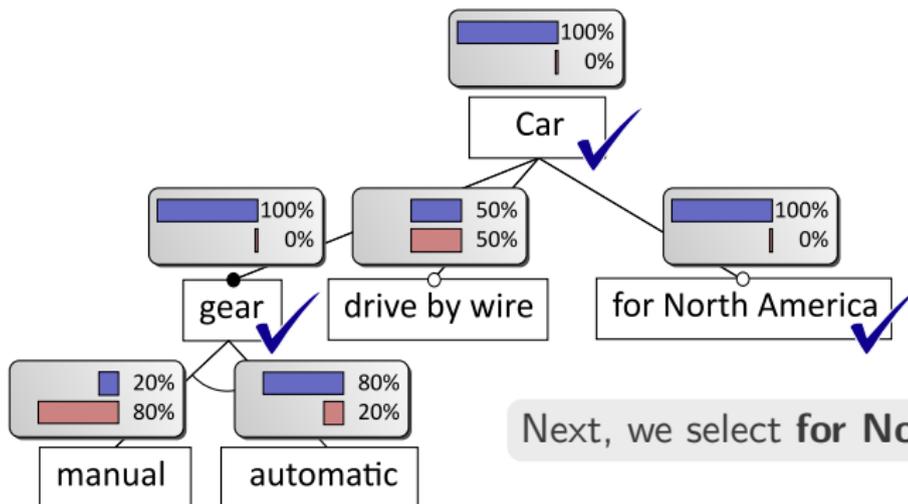
We begin by selecting **Car** and **Gear**.

drive by wire → automatic

automatic given gear [20%]

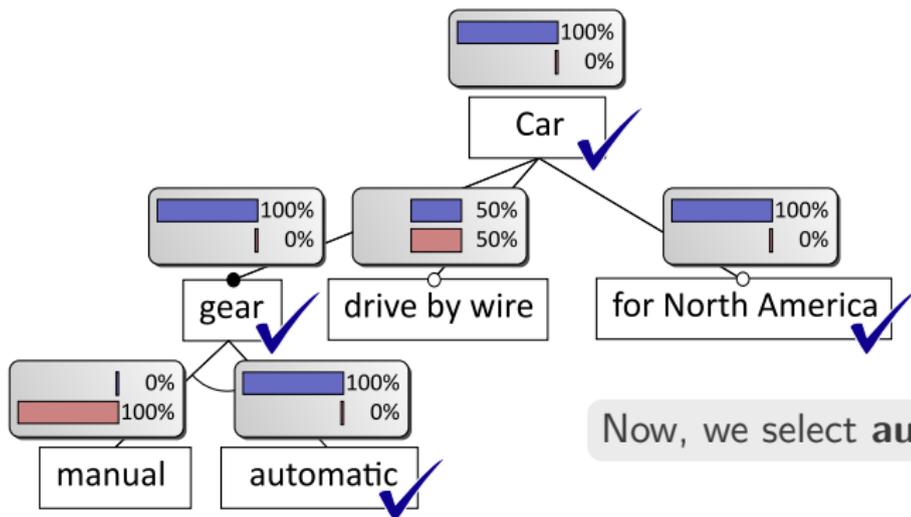
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drive by wire → automatic  
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# Interactive Configuration



drive by wire → automatic

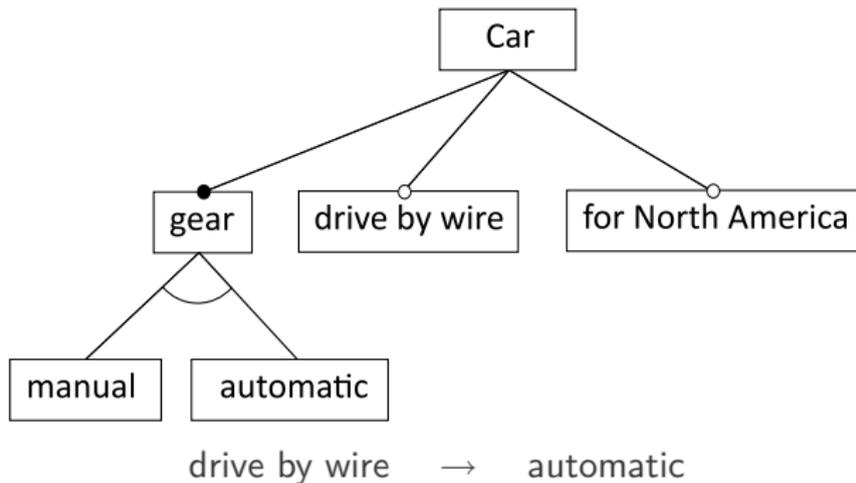
automatic *given* gear [20%]

automatic *given* North America [80%]

# Outline

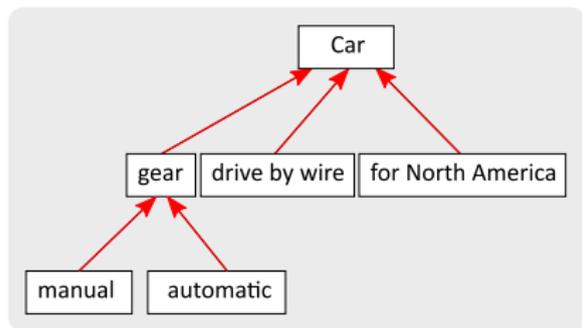
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# Semantics of Basic Feature Models

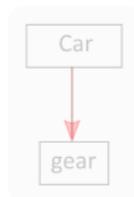


The semantics of a basic feature model...  
 is defined as a conjunction of its *hard constraints*  
 as a **propositional formula**.

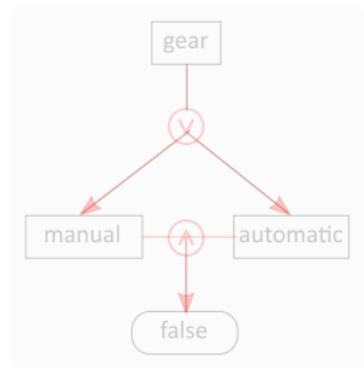
# Logical Components of a Basic Feature Model



Feature Dependencies



Mandatory



Group



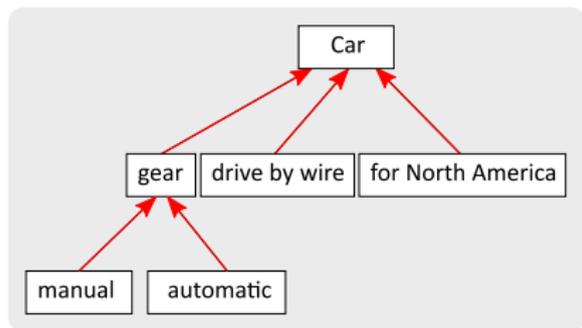
Root



Additional Constraints

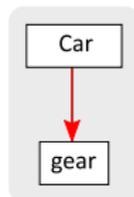
This formula denotes a set of *legal configurations*.

# Logical Components of a Basic Feature Model



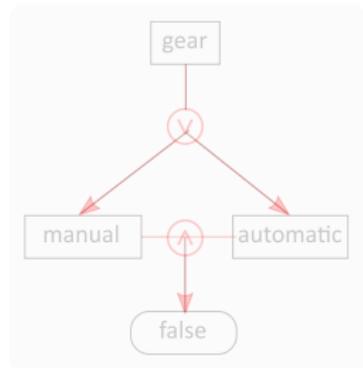
Feature Dependencies

$\wedge$



Mandatory

$\wedge$



Group



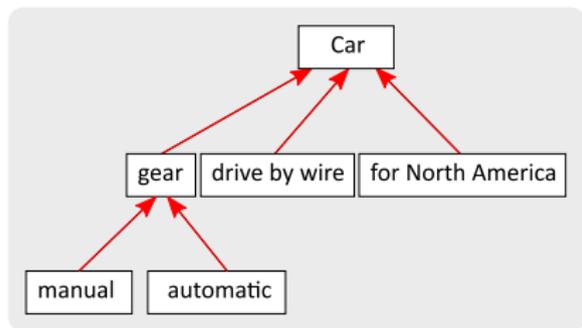
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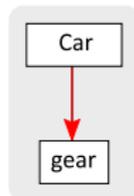
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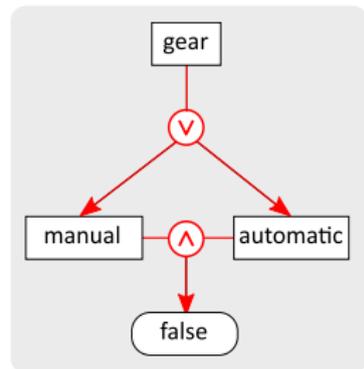
Feature Dependencies

$\wedge$



Mandatory

$\wedge$



Group



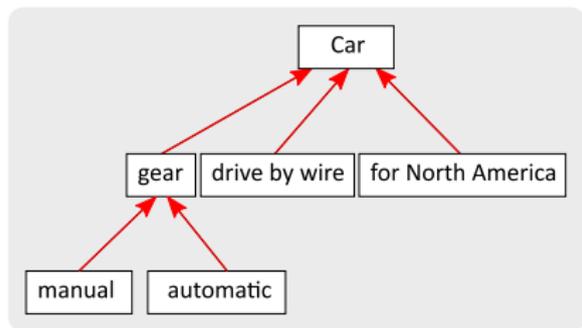
Root



Additional Constraints

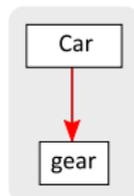
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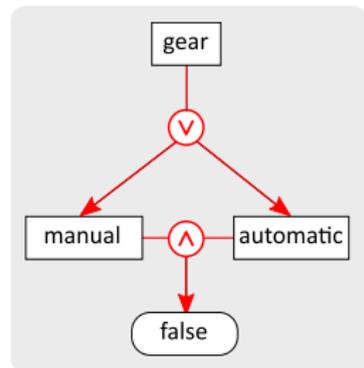
Feature Dependencies

$\wedge$

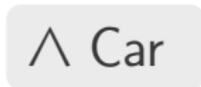


Mandatory

$\wedge$



Group



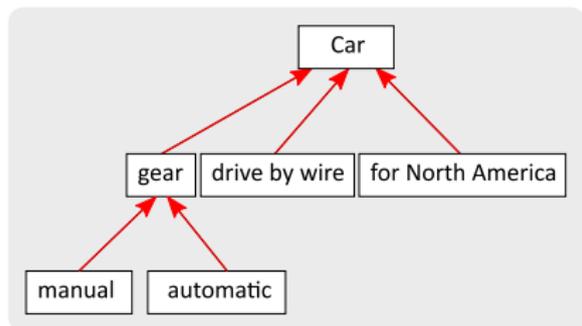
Root



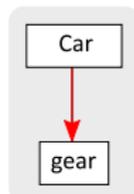
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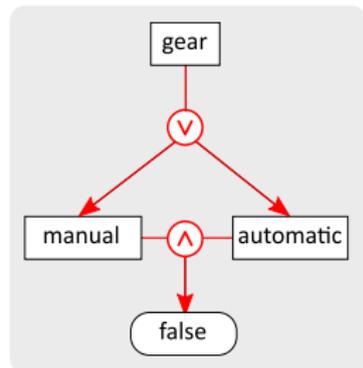
# Logical Components of a Basic Feature Model



Feature Dependencies

 $\wedge$ 

Mandatory

 $\wedge$ 

Group

 $\wedge$  Car

Root

 $\wedge \phi$ 

Additional Constraints

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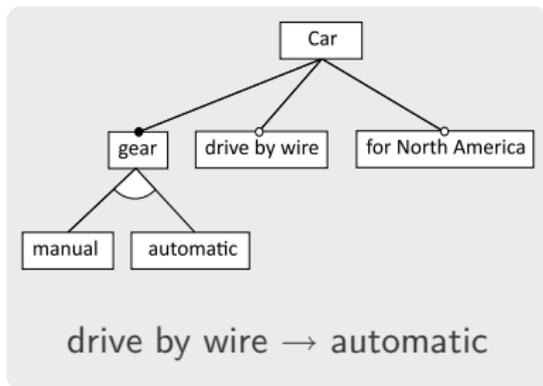
# Components of a Probabilistic Feature Model

A probabilistic feature model is...

A basic feature model

+

*soft constraints*



+

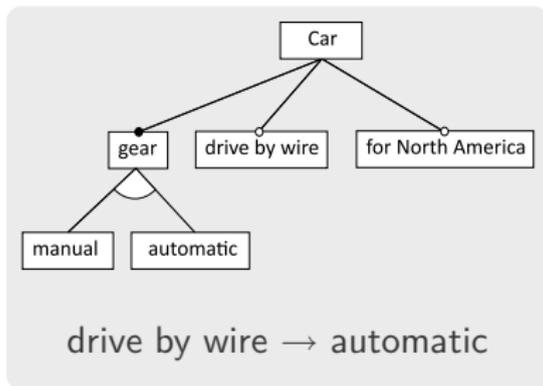
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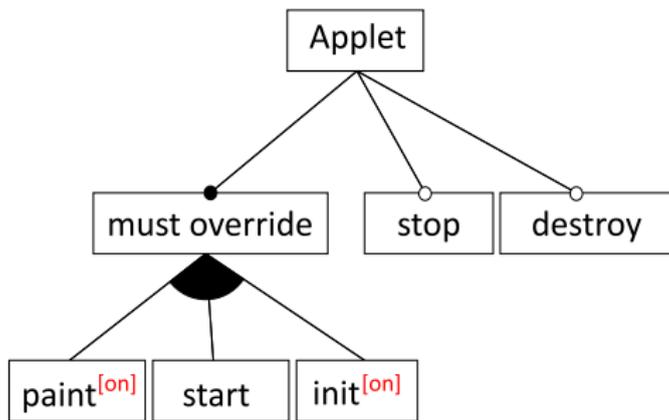
+

*soft constraints*



+

# Feature Modeling with Soft Constraints

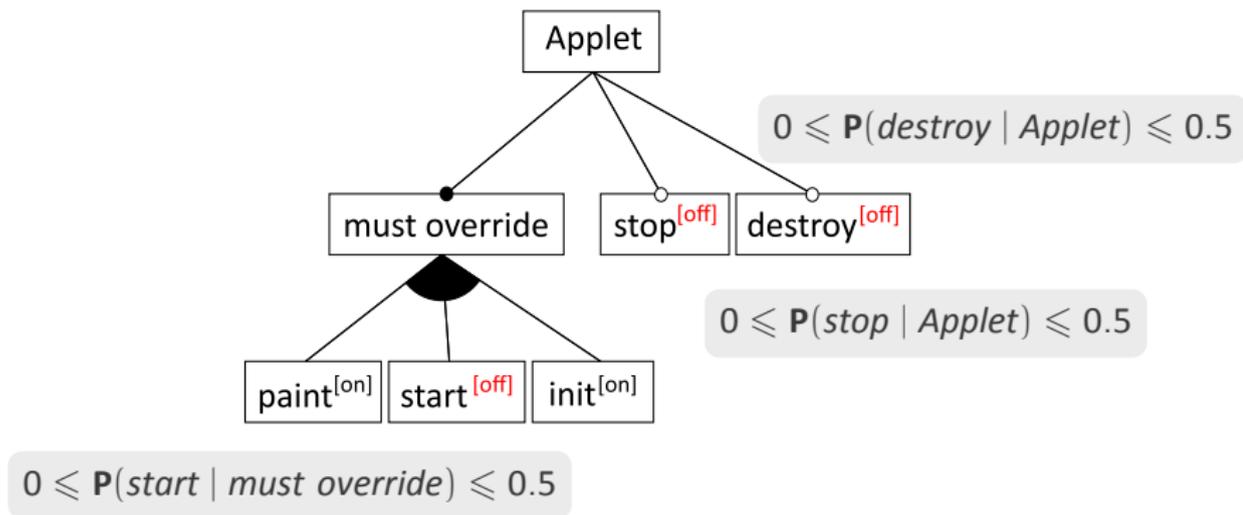


$$0.8 \leq \mathbf{P}(\textit{paint} \mid \textit{must override}) \leq 1.0$$

$$0.8 \leq \mathbf{P}(\textit{init} \mid \textit{must override}) \leq 1.0$$

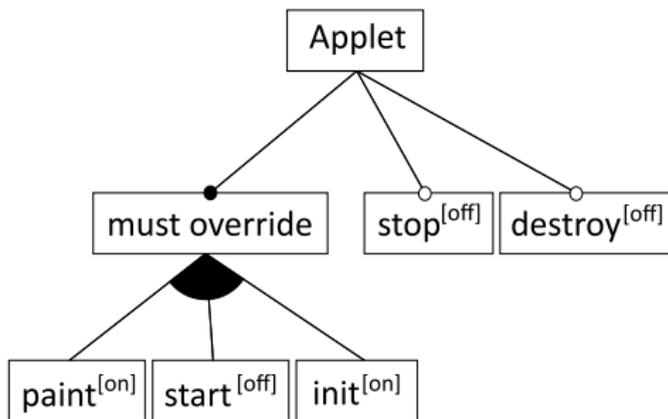
- **On-by-default** if cond. probability between 80% and 100%.

# Feature Modeling with Soft Constraints



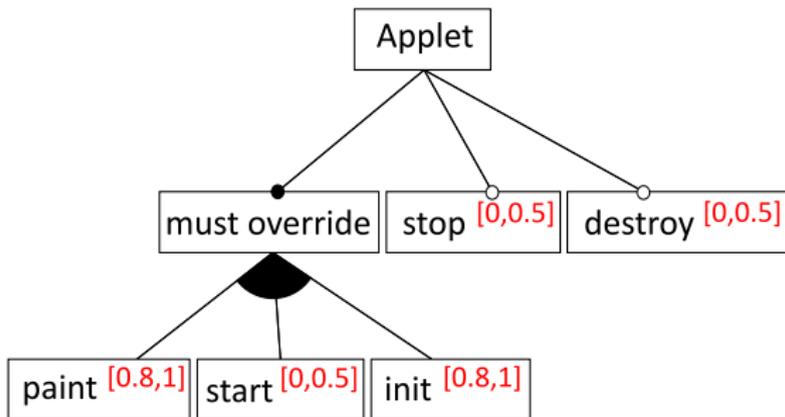
- **Off-by-default** if cond. probability between 0 and 50%.

# Feature Modeling with Soft Constraints



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

# Feature Modeling with Soft Constraints



(init | destroy) [0.8, 1.0]

(stop | start) [0.8, 1.0]

(start | stop) [0.8, 1.0]

(destroy | init) [0.8, 1.0]

# 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

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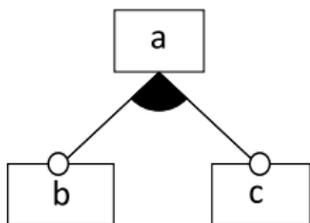
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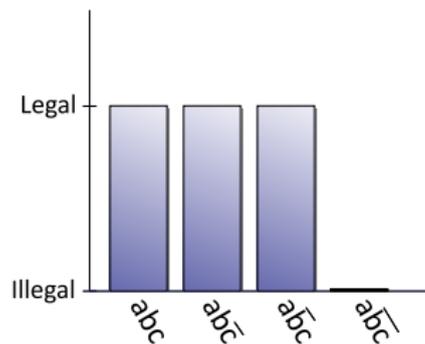
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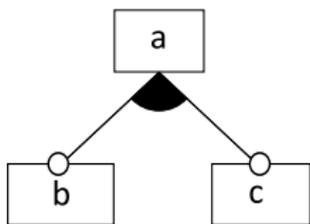
# Legal Configurations Compared with JPDs



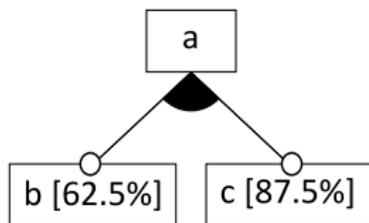
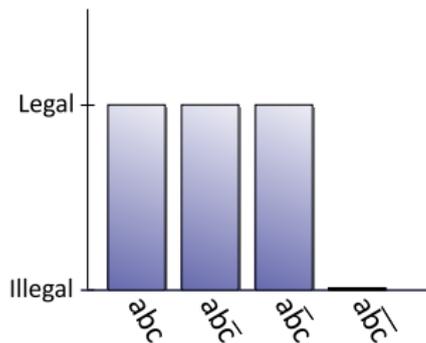
Basic Feature Model



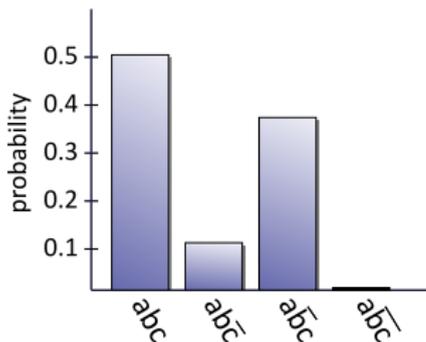
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Basic Feature Model



Probabilistic Feature Model



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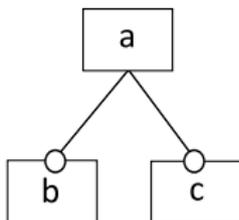
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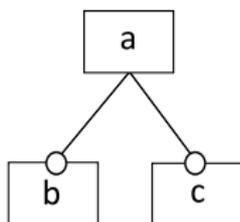
# Under-specification in PFM



a	b	c	$P(a, b, c)$
1	1	1	$p_1 \geq 0.0$
1	1	0	$p_2 \geq 0.0$
1	0	1	$p_3 \geq 0.0$
1	0	0	$p_4 \geq 0.0$
0	$\vdots$	$\vdots$	$p_{5\dots 8} = 0$

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

## Under-specification in PFM



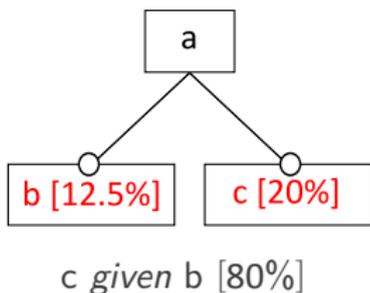
$c$  given  $b$  [80%]

a	b	c	$P(a, b, c)$
1	1	1	$p_1 \geq 0.0$
1	1	0	$p_2 = 0.25p_1$
1	0	1	$p_3 \geq 0.0$
1	0	0	$p_4 = 1 - 1.25p_1 - p_3$
0	$\vdots$	$\vdots$	$p_{5\dots 8} = 0$

where  $1.25p_1 + p_3 \leq 1$

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

## Under-specification in PFM



a	b	c	$P(a, b, c)$
1	1	1	$p_1 = 0.1$
1	1	0	$p_2 = 0.025$
1	0	1	$p_3 = 0.1$
1	0	0	$p_4 = 0.775$
0	$\vdots$	$\vdots$	$p_{5\dots 8} = 0$

A concrete PFM specifies a single JPD.

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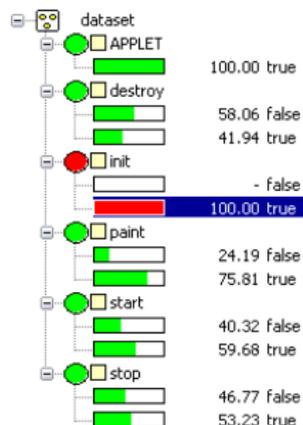
# Configuration

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.



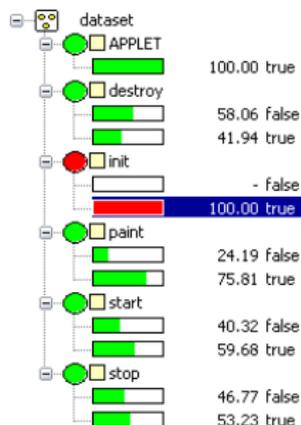
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# Feature Model Mining

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

conf	a	b	c	d
1	✓		✓	✓
2	✓	✓		
3	✓		✓	
4	✓	✓	✓	

Sample Set

# Feature Model Mining

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

conf	a	b	c	d
1	✓		✓	✓
2	✓	✓		
3	✓		✓	
4	✓	✓	✓	



$c \Rightarrow a$  [100%]  
 $\wedge b \Rightarrow a$  [100%]  
 $\wedge d \Rightarrow c$  [100%]  
 $\wedge a \Rightarrow b \vee c$  [100%]  
 $\wedge \dots$   
 $\wedge a \Rightarrow c$  [75%]

Sample Set

Association Rules

*Association Rule Mining*

# Feature Model Mining

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

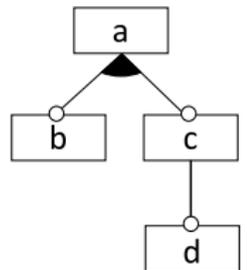
conf	a	b	c	d
1	✓		✓	✓
2	✓	✓		
3	✓		✓	
4	✓	✓	✓	

Sample Set



$c \Rightarrow a$  [100%]  
 $\wedge b \Rightarrow a$  [100%]  
 $\wedge d \Rightarrow c$  [100%]  
 $\wedge a \Rightarrow b \vee c$  [100%]  
 $\wedge \dots$   
 $\wedge a \Rightarrow c$  [75%]

Association Rules



$c$  given  $a$  [75%]

Feature Model

*Association Rule Mining*

*Feature Model Synthesis*  
Czarnecki and Wąsowski 2007

# Feature Model Mining on Applets



Applets



conf	Applet	destroy	paint	init	start	stop
1	✓		✓	✓		
2	✓	✓			✓	✓
3	✓			✓		
⋮						

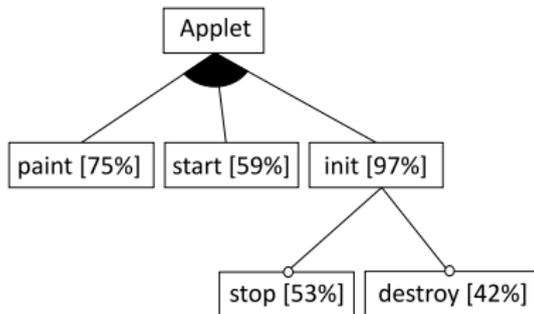
Sample Set

Construct sample set by analysing overridden methods in 64 applets:

destroy, paint, init, start and stop.

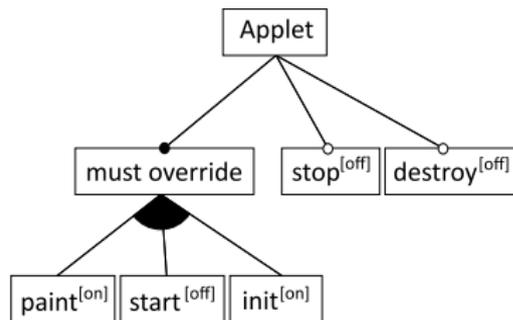
## Case Study Results

## Mined Feature Model



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

## Expert-specified Model



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

# 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

## Related Work

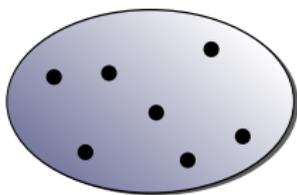
### Probabilistic Feature Models.

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

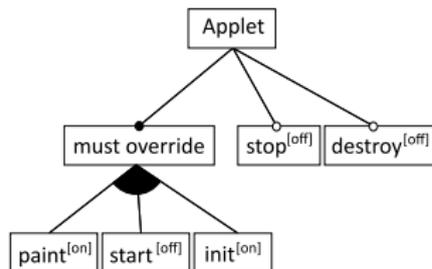
### Reverse-engineering models.

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

# Conclusions



Sample Space

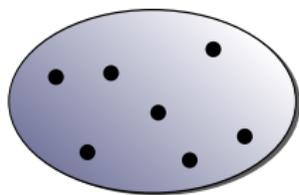


Feature Model with soft constraints

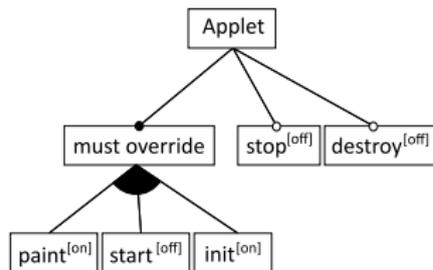
## Probabilistic Feature Models.

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

# Conclusions



Sample Space



Feature Model with soft constraints

## Probabilistic Feature Models.

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

Questions?