Probabilistic Feature Models

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How to represent real-world distributions over feature configurations?

feature model of a software system







 $\{m\}$

defines valid configurations

distribution over valid configurations

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usage of the system "in the wild"

configuration samples / statistics



observable data

Representation as Bayesian Network (BN)

- factorised representation of a probability distribution
- local conditional probability distributions for each node
- encodes independencies (more on this later)
- can be learned from data in two-steps: **structure** learning and parameter learning
- structure is **not unique**
- invalid configurations could be learned





 $Pr(e | s, \neg c) = 0.7$





• Properties:

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 $s \rightarrow \neg c$

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Dealing with side constraints



=C	e=a	e=r	−e
0	0.47	0.53	0
0	0	0	1
.05	0.45	0.5	0
0	0	0	1





Independencies

- BN structure determines some (conditional) independencies
- $(s \perp e \mid m)$: features s and e are conditionally independent given m
- **Problem:** real-world distributions may **not** exhibit all of these independencies
- "no dependency" in feature model ≠ "independency" in distribution





Summary: Probabilistic Feature Diagrams

- Feature diagrams with **probabilistic annotations**
- Formal **BN** semantics with some guarantees
- Allowing arbitrary side constraints provides (interesting?) challenges
- Probably **not** the answer to the opening question:

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