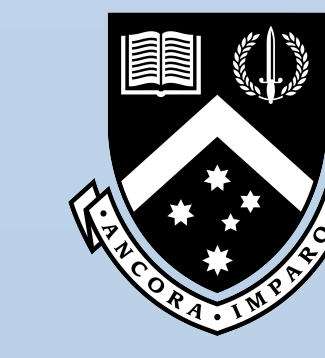


REASONING-BASED LEARNING OF INTERPRETABLE ML MODELS

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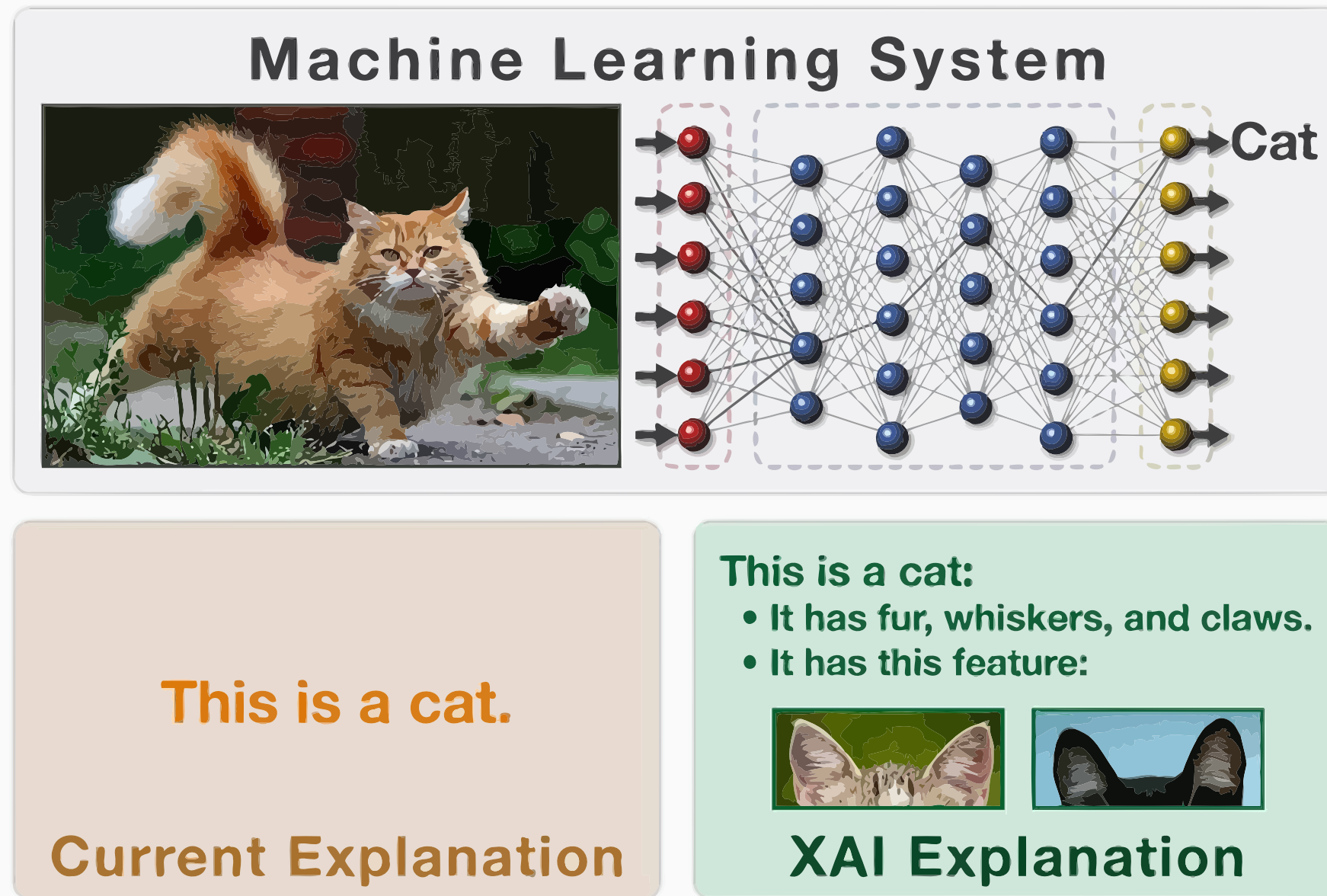


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eXplainable AI



Why? Status Quo

	A parrot	Machine learning algorithm
Learns random phrases	✓	✓
Doesn't understand s**t about what it learns	✓	✓
Occasionally speaks nonsense	✓	✓

Interpretable Models

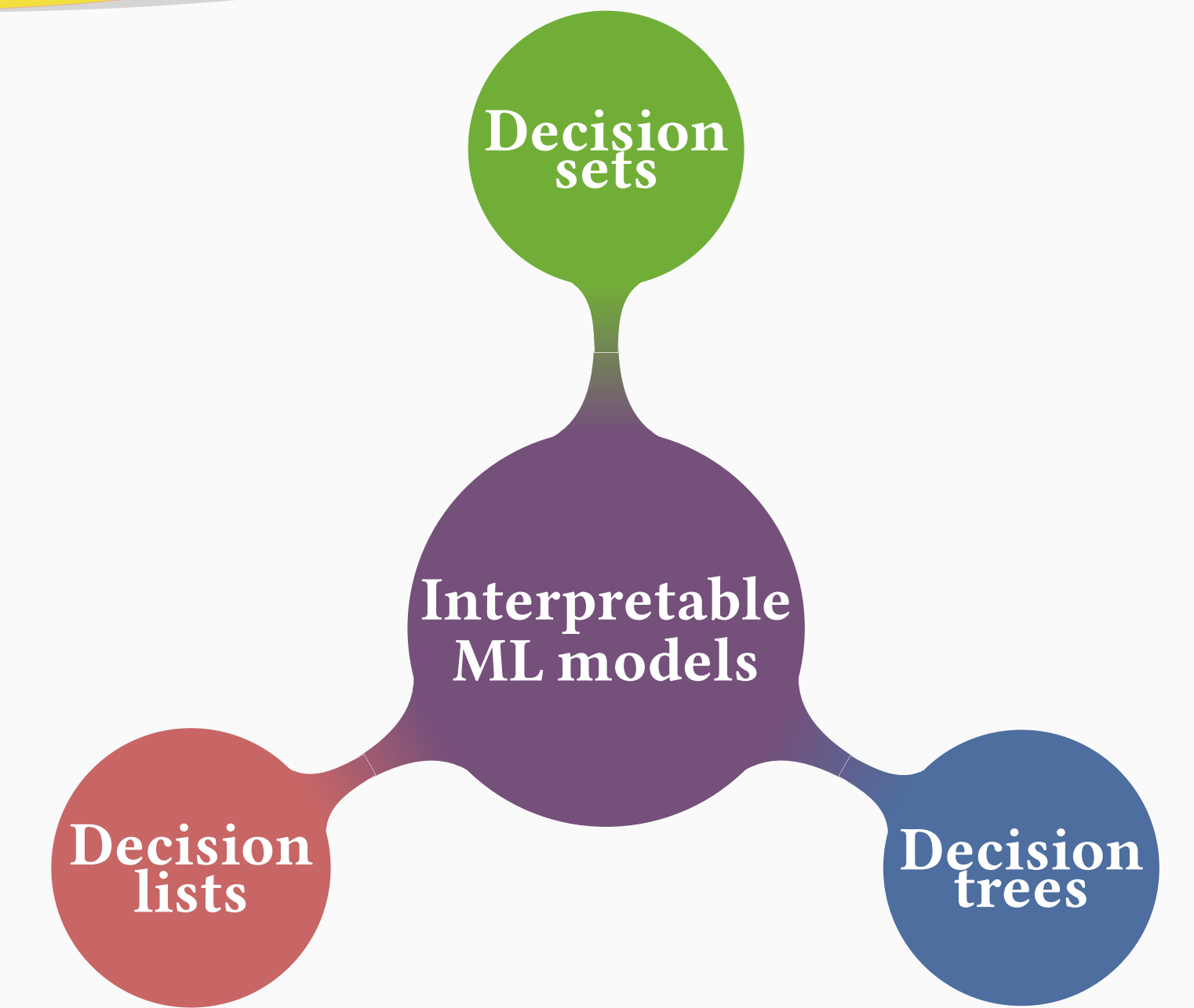
rule-based models

↓

“transparent” and easy to interpret

↓

come in handy in XAI



Reasoning-based approaches to DTs

	model		unbounded	engine					
	perfect	sparse	depth	MIP	CP	SAT	MaxSAT	DP	B-n-B
Nijssen et al., 2007		✓						✓	
Bessiere et al., 2009	✓				✓	✓			
Bertsimas et al., 2017		✓		✓					
Verwer et al., 2017		✓		✓					
Narodytska et al., 2018	✓		✓			✓			
Verwer et al., 2019		✓		✓					
Hu et al., 2019		✓	✓					✓	✓
Zhu et al., 2020		✓		✓	+				
Janota et al., 2020	✓		✓			✓			
Avellaneda et al., 2020	✓		✓			✓	+		
Hu et al., 2020	✓		✓					✓	+
Verhaeghe et al., 2020		✓		✓		✓		✓	
Aglin et al., 2020		✓						✓	✓
Demirovic et al., 2020		✓						✓	+

Perfect and sparse DLs and DSs

IF Age = Adult \wedge Sex \neq Female THEN Survived = No
ELSE IF Category \neq 3rd class THEN Survived = Yes
ELSE Survived = No

smallest perfect DL for Titanic dataset
(training accuracy 78.25%)

IF Category = 1st class THEN Survived = Yes
ELSE Survived = No

sparse DL for Titanic dataset
(training accuracy 70.69%)

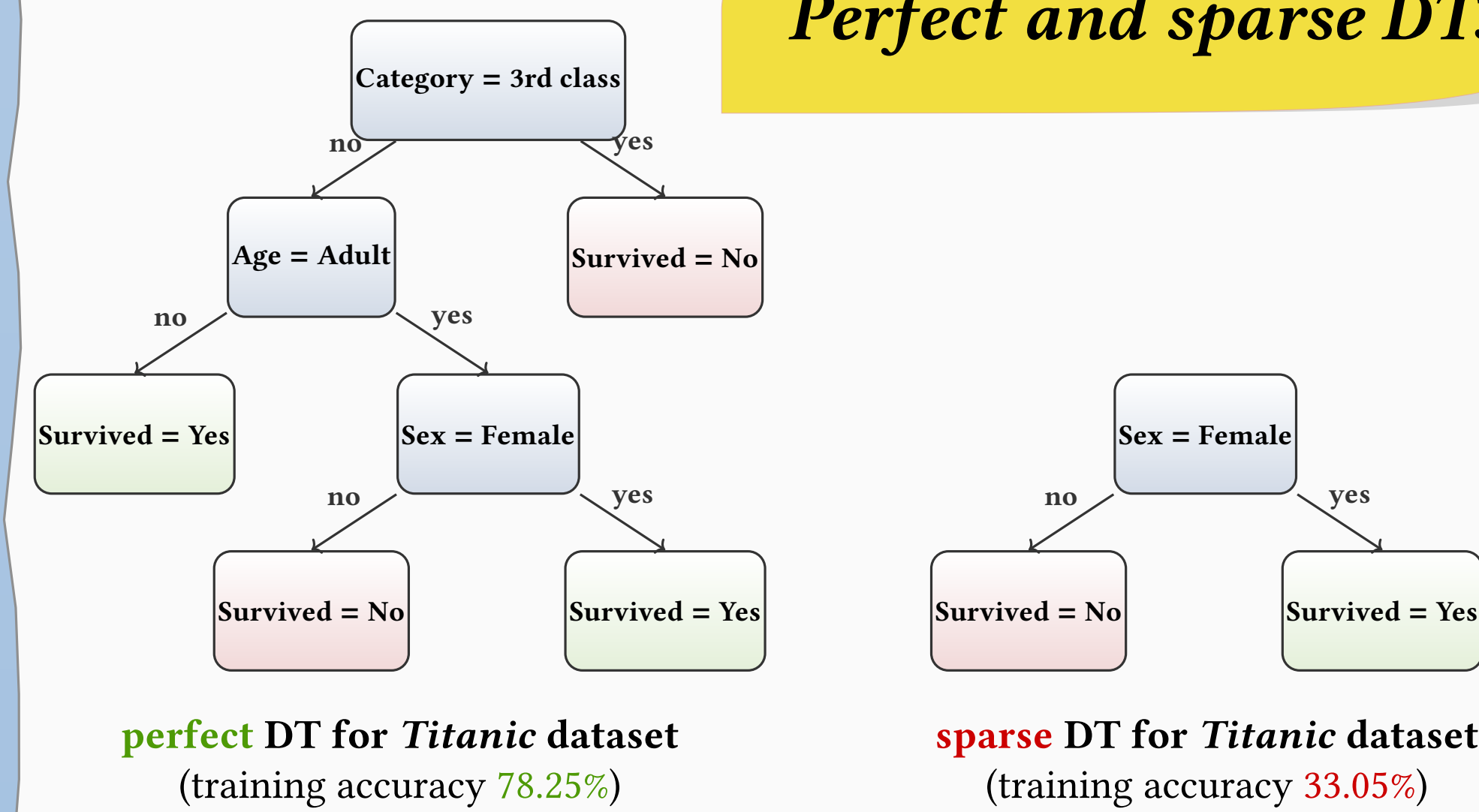
IF Category = 3rd class THEN Survived = No
IF Age = Adult \wedge Sex \neq Female THEN Survived = No
IF Category \neq 3rd class \wedge Age \neq Adult THEN Survived = Yes
IF Category \neq 3rd class \wedge Sex = Female THEN Survived = Yes

smallest perfect DS for Titanic dataset
(training accuracy 78.25%)

IF Category = 3rd class THEN Survived = No
IF Sex \neq Female THEN Survived = No
IF Category \neq 3rd class \wedge Sex = Female THEN Survived = Yes

sparse DS for Titanic dataset
(training accuracy 77.57%)

Perfect and sparse DTs

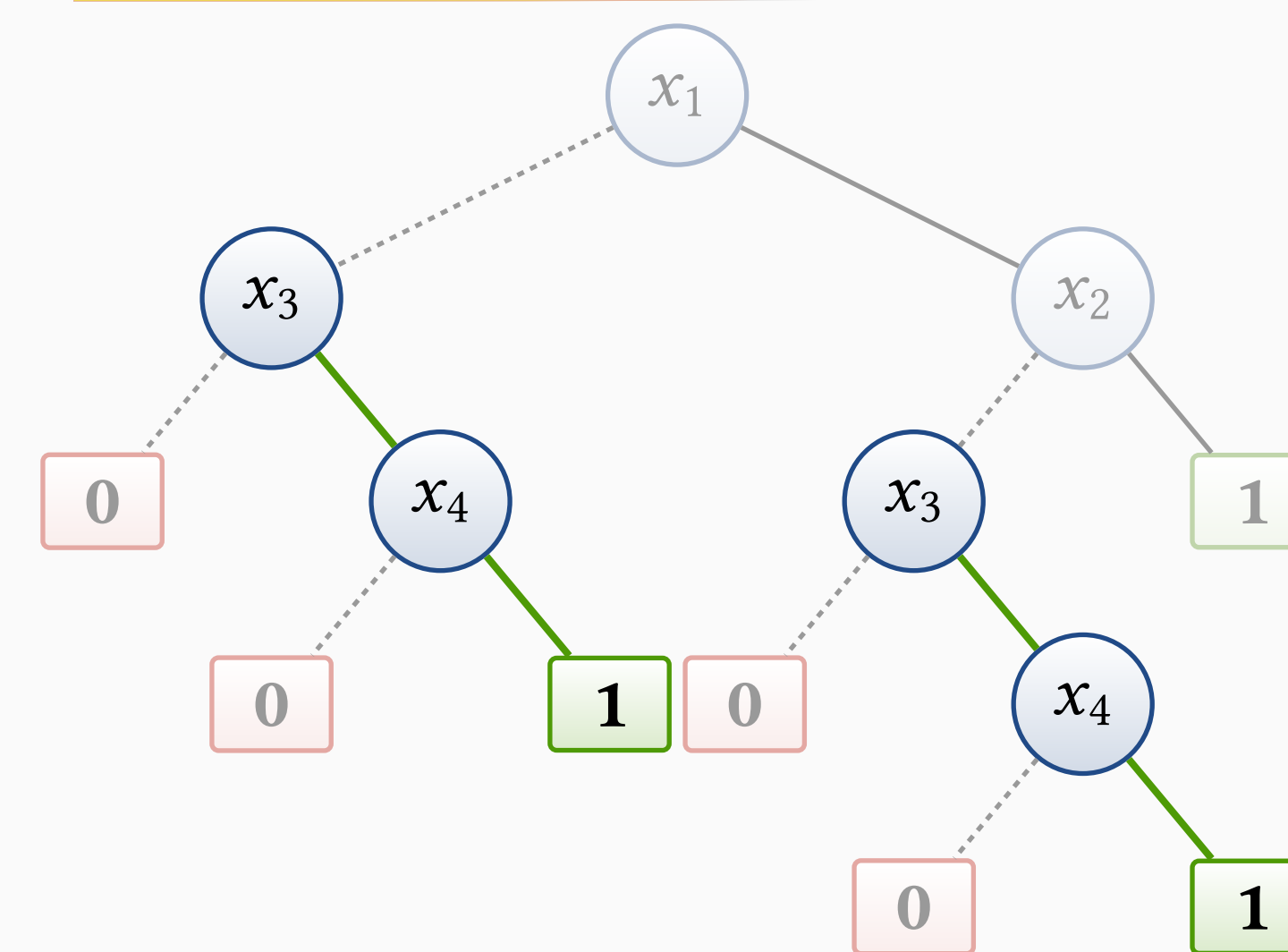


Reasoning-based approaches to DLs and DSs

	model		criterion		optimality	classification		engine				symmetry
	perfect	sparse	rules	literals	guarantee	binary	arbitrary	MIP	SAT	MaxSAT	B-n-B	breaking
Angelino et al., 2017a	✓	✓				✓		✓				
Angelino et al., 2017b	✓	✓			✓	✓					✓	✓
Yu et al., 2020	✓	✓	✓	✓	✓		✓		✓	✓		✓

	model		criterion		explicit repr.		setup		engine			
	perfect	sparse	rules	lex literals	single class	all classes	single run	two phases	IP	SAT	MaxSAT	LS
Kamath et al., 1992	✓		✓		✓		✓			✓		
Lakkaraju et al., 2016		✓	✓			✓	✓					✓
Ignatiev et al., 2018	✓		✓	✓		✓	✓				✓	✓
Malioutov et al., 2018		✓		✓-	✓		✓					✓
Dash et al., 2018		✓	✓		✓		✓			✓		
Ghosh et al., 2019		✓		✓-	✓		✓					✓
Ghosh et al., 2020		✓+		✓-	✓		✓					✓
Yu et al., 2020	✓	✓	✓	✓		✓	✓				✓	✓
Ignatiev et al., 2021	✓		✓			✓			✓	✓	✓	✓

DT Interpretability Issue



instance $v = (1, 0, 1, 1)$, i.e. 4 literals in the path
actual explanation $x_3 = 1 \wedge x_4 = 1$, i.e. 2 literals

Same Issue with DL Interpretability

R_0 : IF $x_1 = 0 \wedge x_3 = 0$ THEN $f = 0$
 R_1 : ELSE IF $x_1 = 0 \wedge x_3 = 1 \wedge x_4 = 0$ THEN $f = 0$
 R_2 : ELSE IF $x_1 = 0 \wedge x_3 = 1 \wedge x_4 = 1$ THEN $f = 1$
 R_3 : ELSE IF $x_1 = 1 \wedge x_2 = 0 \wedge x_3 = 0$ THEN $f = 0$
 R_4 : ELSE IF $x_1 = 1 \wedge x_2 = 0 \wedge x_3 = 1 \wedge x_4 = 0$ THEN $f = 0$
 R_5 : ELSE IF $x_1 = 1 \wedge x_2 = 0 \wedge x_3 = 1 \wedge x_4 = 1$ THEN $f = 1$
 R_6 : ELSE IF $x_1 = 1 \wedge x_2 = 1$ THEN $f = 1$
 R_{DEF} : ELSE THEN $f = 1$

instance $v = (1, 0, 1, 1)$, i.e. rule R_5 fires the prediction
actual AXp: $x_3 = 1 \wedge x_4 = 1$, i.e. 2 literals

Additional remarks 1

- Comparing to heuristic methods
 - higher accuracy but
 - higher training time
 - * evolution of reasoning methods!
- Other interpretable models
 - learning OBDDs
 - * SAT-based inference
- Perfect vs. sparse models
 - pros of perfect models:
 - * highest possible accuracy
 - pros of sparse models:
 - * smaller size
 - * easier to compute
 - * smaller explanations

Additional remarks 2

- Model expressivity and size
 - DLs are more succinct than DTs
 - DLs are more succinct than DNFs
 - * a special case of DSs

- how to categorise DSs?
 - * empirically, less succinct than DLs!
- OBDDs vs. other models?

- Fairness and other constraints

- model properties can be enforced
 - * in the form of constraints
 - * easy to plug in!

- fairness constraints

- * learning fair DTs and DSs
- * accuracy vs. fairness

- Intepretability

- empirical considerations:
 - * $|XP|$ for perfect DSs $< |XP|$ for perfect DLs
 - * $|XP|$ for sparse DSs $> |XP|$ for sparse DLs

- DTs and DLs may be uninterpretable
- AXps for DTs – in polytime!
 - * not the case for DLs and DSs!