

Learning various classes of models of lexicographic orderings

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Introduction

Topic: learn to order objects of a combinatorial domain

E.g. computers, described by

Type: *desktop* or *laptop*

Color: *yellow* or *black*

Dvd-unit: *reader* or *writer* . . .

Recommender system : learn how a user orders these objects, in order to suggest the "best" ones among those that are available / the user can afford.

If n variables, domains of m values : m^n objects, $n!$ orderings

⇒ need compact representation of the orderings :

- local preferences on each attribute
- extra structure on the set of variables to "aggregate" to global preferences

Introduction

Lexicographic orderings :

local preferences over the domains of each variable
+ *importance ordering* of the variables

T

$l \succ d$

- Type is more important than Colour



C

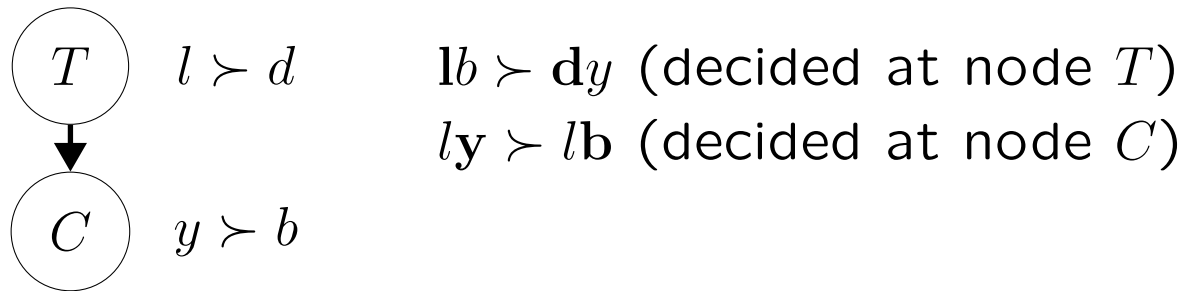
$y \succ b$

- Prefer laptop to desktop
- Prefer yellow to black

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Lexicographic orderings :

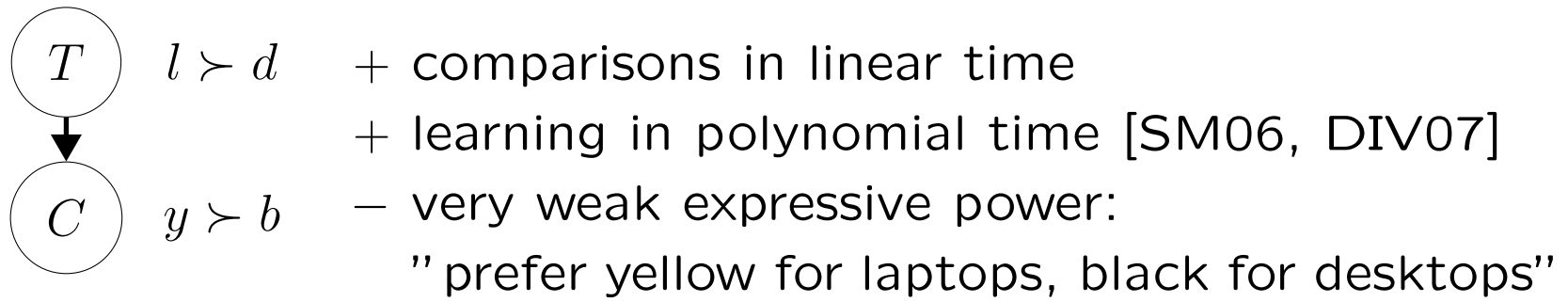
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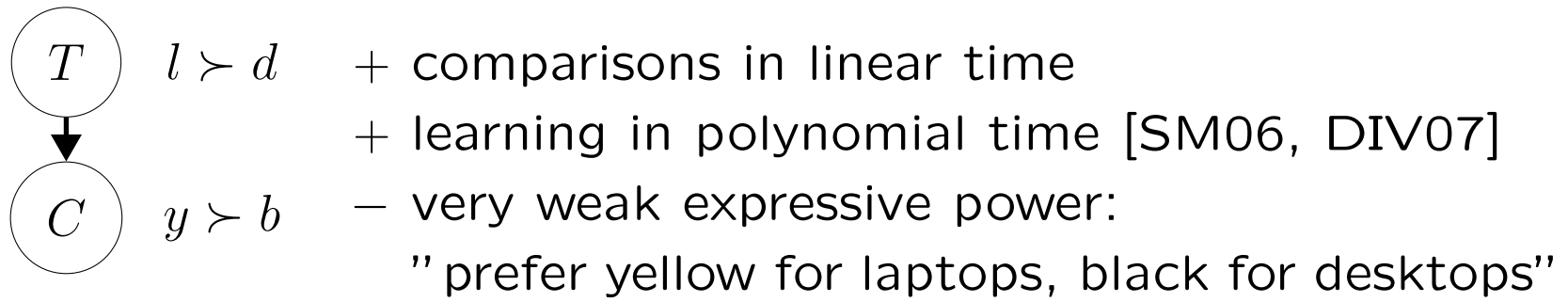
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Conditional Preference Networks (CP-nets) :

conditional local preferences (dependency graph)

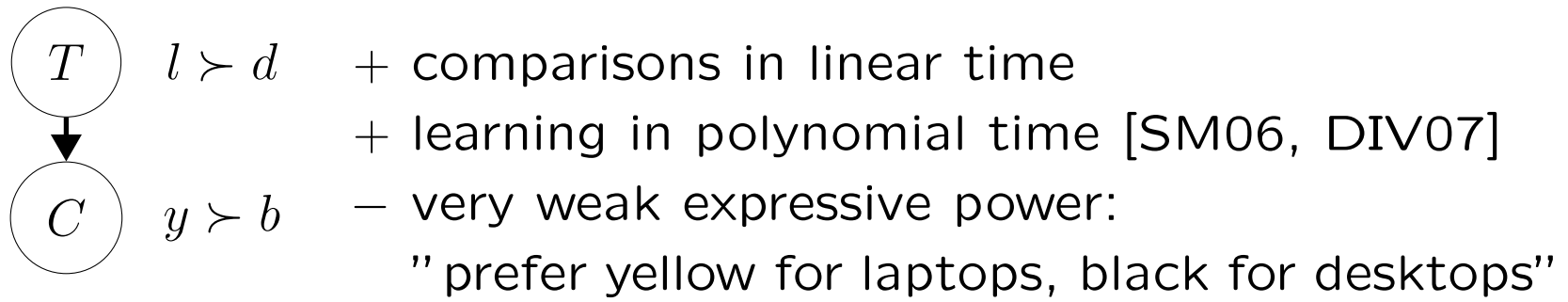
e.g.: $l : y \succ b$ (for laptops: yellow pref. to black) $d : b \succ y$ $l \succ d$

+ *ceteris paribus* comparisons: $ly \succ lb \succ db \succ dy$

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+ very expressive

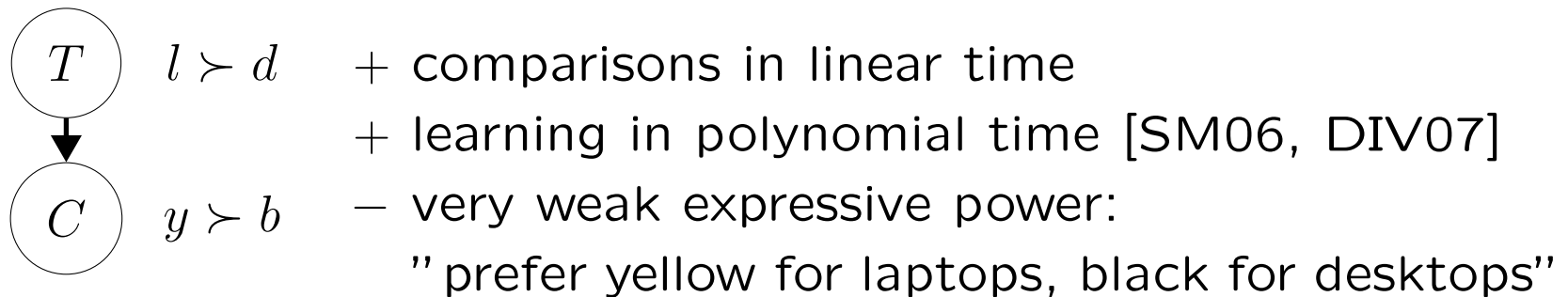
– comparisons difficult (NP-complete)

– hard to learn [session on CP-net learning at IJCAI'09]

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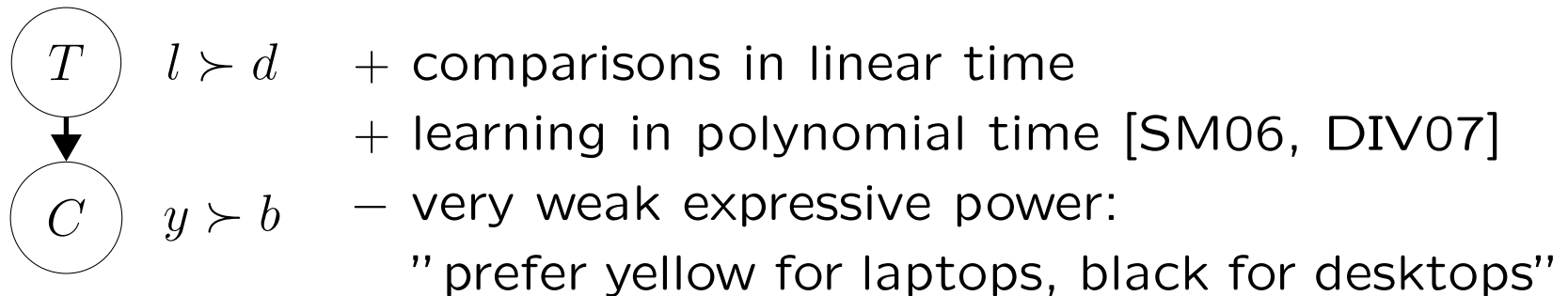
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(easy classes of CP-nets / examples, incomplete algorithms)

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⇒ **find something in between the two formalisms**

Introduction

Contribution of this paper:

it is possible to add conditionality in lexicographic preference models without increasing the complexity of reasoning / learning

Learning unconditional lexicographic preferences

Sample complexity: VC dim = n (when n variables, all binary)

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Active learning: a learner asks "user" queries of the form
"What is preferred between ly and bd ?"

Goal : identify preference model of the user

⇒ If local pref. fixed, need $\log(!n)$ queries (worst case) [DIV07]

⇒ If local pref. to be learnt, need $n + \log(!n)$ queries

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Model optimization (less than k errors)

⇒ NP-complete with fixed local pref. [SM06]

⇒ **NP-complete with unknown local pref.**

Learning unconditional lexicographic preferences

Greedy algorithm [DIV07]

1. initialize seq. of var. with empty sequence;
2. while there remains some unused variable:
 - (a) choose a variable and local pref. that does not wrongly order the remaining examples
 - (b) remove examples ordered with this variable

$$\mathcal{E} = \{lbr \succ dyr, \ lyr \succ lbw, \ dyw \succ dbr\}$$

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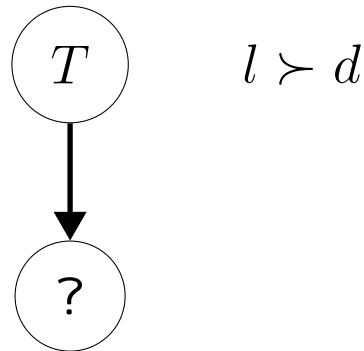
$$\textcircled{T} \quad l \succ d$$

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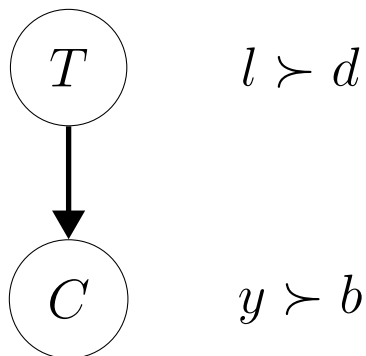
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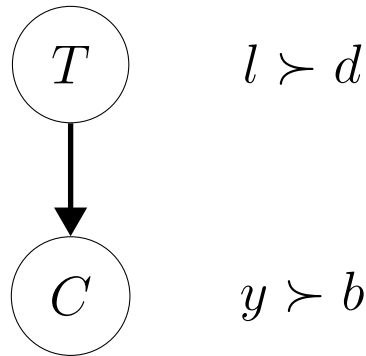
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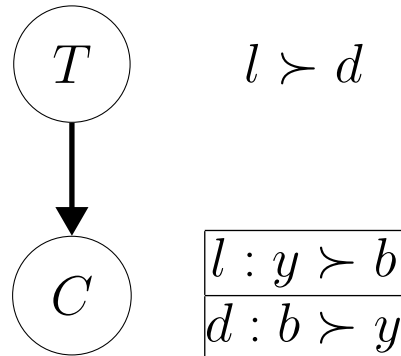
success !

Conditional local pref. / Unconditional variable importance

"I always prefer laptops to desktops"

"For desktops, I prefer black to yellow"

"For laptops, I prefer yellow to black"

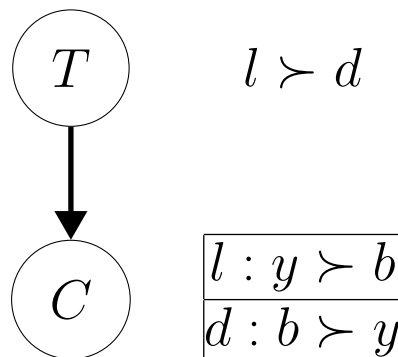


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"I always prefer laptops to desktops"

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Sample complexity : VC dim = $2^n - 1$

Active learning : $2^n - 1 + \log(!n)$ queries needed (worst case)

Passive learning : in **P** (Greedy algorithm still works)

Model optimization : **NP-hard**

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Greedy algorithm:

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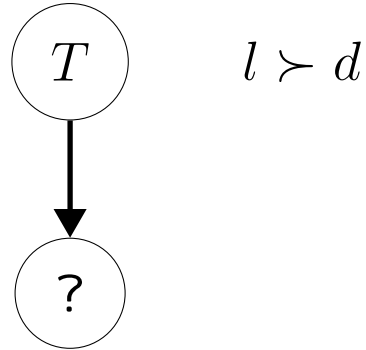
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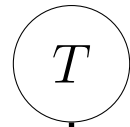
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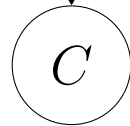
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Greedy algorithm:

$$\mathcal{E} = \{ \quad l y r \succ l b w, \quad d b w \succ d y r \}$$



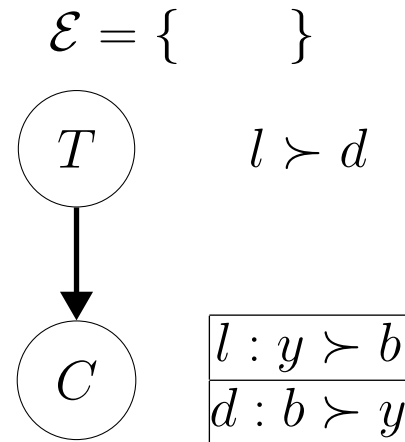
$$l \succ d$$



$l : y \succ b$
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Conditional local pref. / Unconditional variable importance

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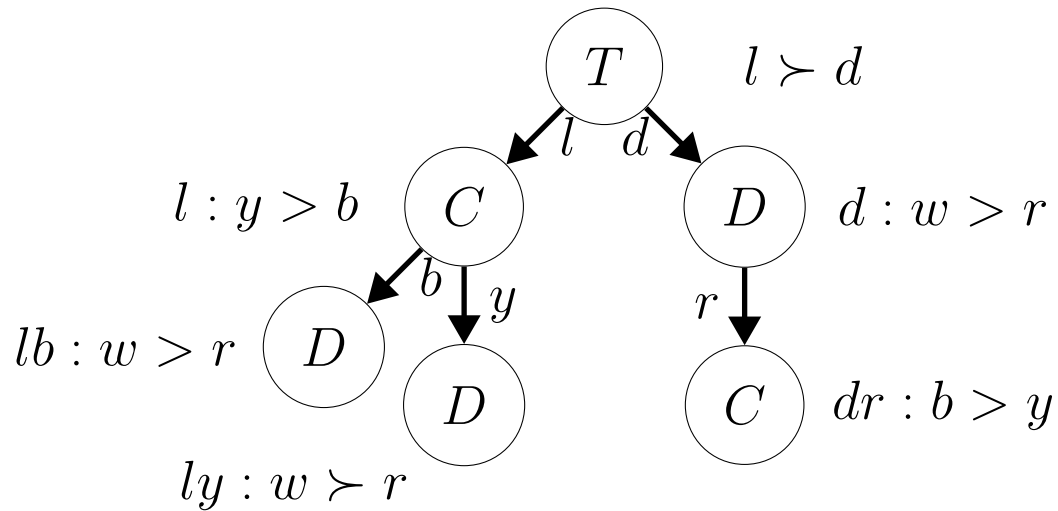


success !

Conditional local pref. & Conditional variable importance

"For desktops, Dvd-unit (read/write) more important than color"

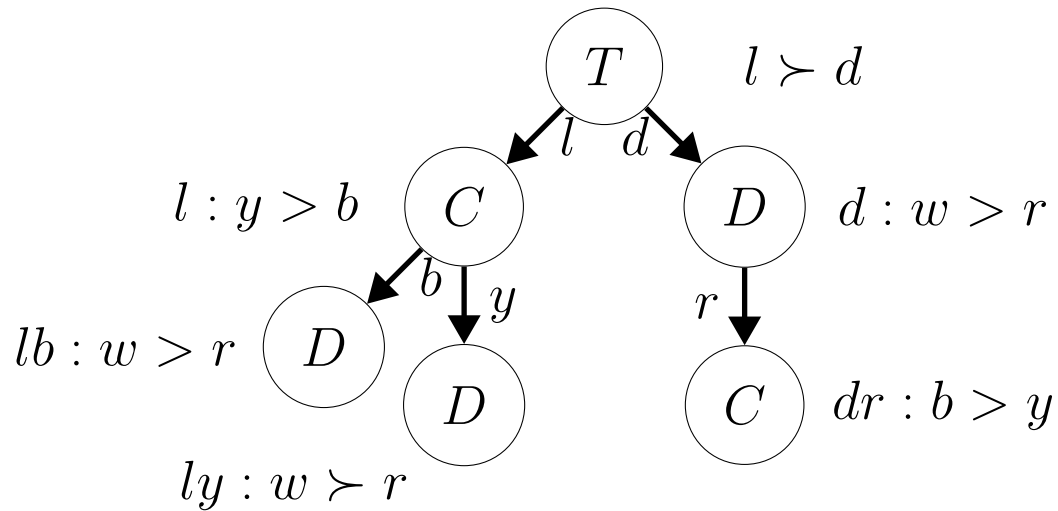
"For laptops, color is more important than the type of Dvd unit"



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⇒ variable importance tree

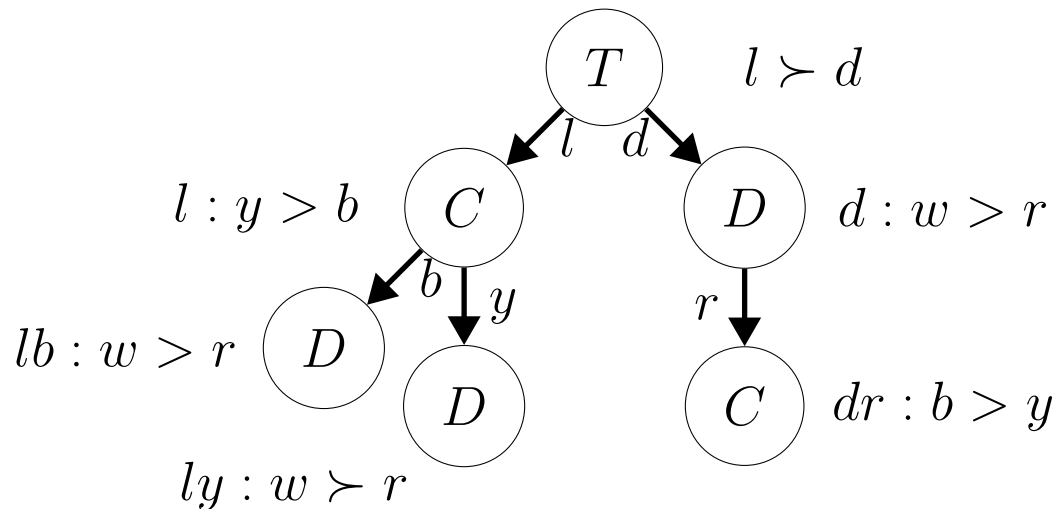
+ conditional local preference tables

Note : tree need not be complete (but then partial ordering)

Conditional local pref. & Conditional variable importance

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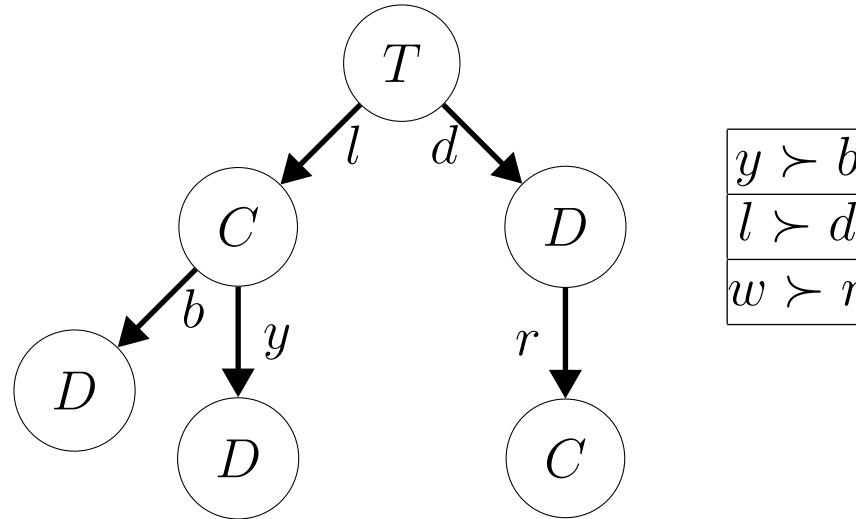
Sample complexity: VC dim = $2^n - 1$

Active learning: $2^n - 1 + \sum_{k=0}^{n-1} 2^k \log(n - k)$ queries needed

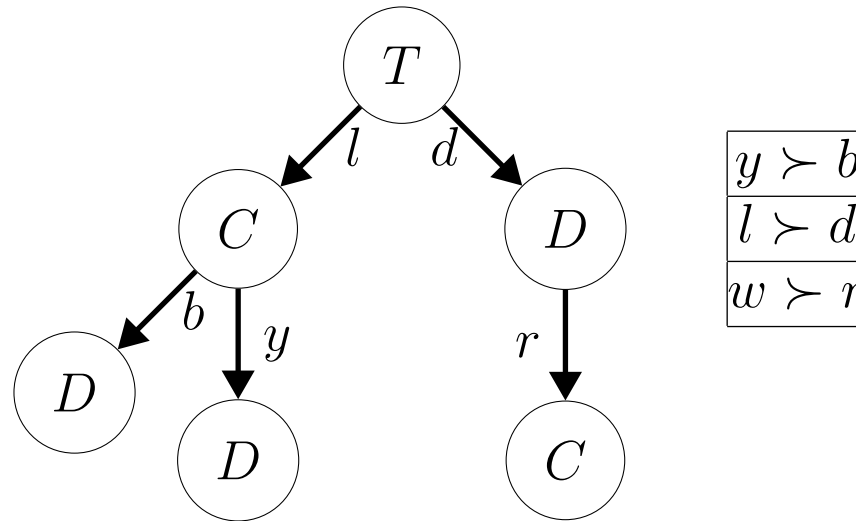
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Model optimization: NP-complete

Unconditional local pref. / Conditional variable importance



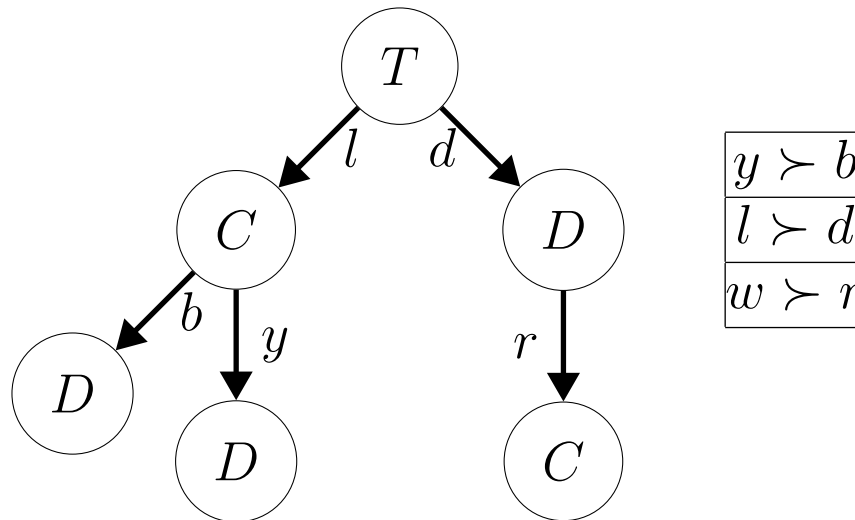
Unconditional local pref. / Conditional variable importance



⇒ variable importance tree

+ unconditional local preference table

Unconditional local pref. / Conditional variable importance



Sample complexity: ?

Active learning: .

$n + \sum_{k=0}^{n-1} 2^k \log(n - k)$ queries needed (unknown pref.)

$\sum_{k=0}^{n-1} 2^k \log(n - k)$ queries needed (fixed pref.)

Passive learning: NP-complete !! (Greedy algorithm still works)

Model optimization: NP-complete

Quick recap

	VC-dim	active l.	passive l.	approx
UI - FLP		$\log(!n)$	P	NP-C
UI - ULP	n	$n + \log(!n)$	P	NP-C
UI - CLP	$2^n - 1$	$2^n - 1 + \log(!n)$	P	NP-hard
CI - FLP		$g(n)$	P	NP-C
CI - ULP	$\geq n$	$n + g(n)$	NP-C	NP-C
CI - CLP	$2^n - 1$	$2^n - 1 + g(n)$	P	NP-C

$$g(n) = \sum_{k=0}^{n-1} 2^k \log(n - k)$$

Related and future work

- Conditional lexic. orderings introduced by [Wilson, ECAI'06]
⇒ approximate CP-nets
- Need to explore heuristics to choose variables during execution of the greedy algorithm
- Problem if tree not complete : the ordering is only partial
⇒ Need to explore mixtures of conditional / unconditional structures
- Need to test algorithms on real / generated data
⇒ How to deal with noisy data ?