# Propositional Logic

CSCE 420 – Fall 2023

read: Ch. 7

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### Knowledge-based programming

- As Feigenbaum said, one route to designing intelligent systems is to give them knowledge (expertise) to solve problems
- We need a general language for encoding knowledge.
- English is not sufficient (too ambiguous)
- The history of AI is tied to the search for higher-level languages that are "more expressive".
  - Al drove advances in functional, object-oriented, and logic programming
  - LISP, Prolog, Smalltalk...

## Logic

- Logic has become the standard for expressing knowledge in KBS
- Logic has advantages over procedural languages
  - context-independence: easier to judge correctness of a rule that 1 line buried in code (hence, easier to debug and maintain)
  - logic has a well-defined semantics (not subject to order, global variables, side-effects...)
  - rules can be used in many different ways (lots of different inferences)
- declarative vs. procedural programming: say "what", not "how"
  - procedural languages require you to say HOW to do something
  - declarative languages let you describe the world, and the system can autonomously figure out the right thing to do as a consequence of the situation
- KBS: Knowledge-Based Systems
  - programming by writing "rule bases"

## Example: Driving

- think about all the knowledge and inference you use while driving...
  - traffic laws (can you cross a yellow line?)
  - mechanics of vehicle operation
  - right of away, turn signal, yellow lights...
  - safety (speed, following distance, changing lanes, pedestrians)
  - slippery roads, fire trucks, school buses...
  - other drivers: do they see you? can you infer their intentions? are they displaying erratic behavior?
- it is better to put this all in a giant KB, rather than trying to program an enormous if-then-else to handle all possible situations

## Inference Algorithms

- Of course, we need a way to extract conclusions and make decisions from a rule base
- synonyms: "inference", "automated deduction", "theorem-proving"
- Inference algorithms are a foundation for Expert Systems
- expert systems "shells" are the architecture/environment in which you:
  - 1. load your rule base
  - 2. describe current situation
  - 3. ask questions...or what to do...or whether something is a consequence...
  - 4. get an explanation of the information used to get the answer (i.e. "proof")

## Defining a "logic"

- There are actually many types of logics
  - propositional/Boolean logic
  - First-order logic (FOL), higher-order logics...
  - modal logics, epistemic logics (beliefs), temporal logics (used for program analysis)...
  - fuzzy logics, probabilistic logics...
  - non-sentential logics (like maps)
- These logics differ in *expressiveness* and *computational complexity* 
  - First-order logic (FOL) is the *lingua franca* for most KR in Al
- Each of these logic has its own:
  - 1. Syntax the rules defining what sentences are legal expressions
  - 2. Semantics defines "truth" of sentences, and relationship of meaning between sentences
  - **3. Proof theory** a method for answering queries

## Syntax of Propositional Logic

- well-defined sentences
- atomic sentences = propositional symbols (A, P, battery\_low, lights\_on\_room124)
- complex sentences: generated using operators
  - binary opers: and (^), or (v), xor ( $\oplus$ ), implication ( $\rightarrow$ ), biconditional ( $\leftrightarrow$ )
  - unary oper: negation (¬)
  - parentheses

## Syntax

- BNF grammar (Backus-Naur Form, production rules)
  - atomic ::= <prop> // tokens like "P", "gas\_tank\_filled"...
  - binop ::=  $^{ | v | \rightarrow | \leftrightarrow | \oplus |}$
  - complex ::= <atomic> | complex | <complex> <binop> <complex> | (<complex>)
- examples:
  - legal: P, PvQ,  $\neg\neg X^{\neg}\neg Y$ ,  $\neg(\neg X^{(\neg(\neg Y))})$ , Light  $\leftrightarrow$  Dark
  - not syntactically legal: "Win vv Lose", "(→Draw)"
- these can be used to derive the parse tree(s) for an expression
  - (I'm not going to give the algorithm for parsing this grammar here...)
  - a^b→pv¬q



## Syntax

- of course, there are other possible parse trees...
  - a^b→pv¬q



- the grammar is *ambiguous* q
- one can always disambiguate an expression by adding parentheses
  - $(a^b) \rightarrow (pv\neg q)$  vs  $a^(b \rightarrow pv\neg q)$  vs  $a^(b \rightarrow p)v\neg q$

## Syntax

- ... or one can rely on rules of precedence among operators
  - - (highest)
  - ^
  - v, 🕀
  - $\rightarrow$ , $\leftrightarrow$  (lowest)
- There can still be parsing ambiguity: AvBvC = (AvB)vC or Av(BvC) ?
- each operator is left-associative: (AvB)vC
- these syntax rules are similar to mathematics:
  - all opers are left associative, except ^ (which is right associative)
  - $1+2*3/4/5+6^{7}2 = (1+(((2*3)/4)/5))+(6^{7}2))$
  - 1-2+3 = ? (2 or -4?)

### Example: Map-coloring

- A propositional encoding of the Australia map-color problem could look like this:
  - propositional symbols: WAR (Western Australia is Red), WAG, WAB, NTR, NTG, NTB (Northern Territories is Blue), QR, QG, QB... <u>each can be True or False</u>
  - KB:
    - WAR v WAG v WAB, NTR v NTG v NTB, QR v QG v QB... // each state is 1 of 3 colors
    - WAR→¬WAG^¬WAB, WAG→¬WAR^¬WAB, WAB→¬WAR^¬WAG,... // at most 1 color
    - // adjacent states must be different colors
    - WAR  $\rightarrow \neg$ NTR^ $\neg$ SAR, WAG $\rightarrow \neg$ NTG^ $\neg$ SAG, WAB $\rightarrow \neg$ NTB^ $\neg$ SAB...
    - NTR  $\rightarrow \neg$  WAR^ $\neg$ SAR^ $\neg$ QR...
  - note: KB \= WAR (does not entail)
  - however,  $KB \models WAB \rightarrow VB$ , and  $KB \cup \{WAB\} \models VB$

Northern Territory

Queens

New South W

Western

Australia

## Example: Wumpus World

- the goal of the agent is to find the gold without falling in a pit or getting eaten by the wumpus (there is only 1, and it can't move)
- the agent does not know a priori where the pits or wumpus are located
- OK = Safe sq the agent can only sense breezes, stenches, and glitter
- a breeze is felt in rooms adjacent to pits, and a stench W = Wumpuscan be sensed in rooms adjacent to the wumpus
- a room is *safe* to explore if it is known not have the pit wumpus



	1,4	2,4	3,4	4,4
Gold uare				
	1,3	2,3	3,3	4,3
s				
	1,2	2,2 P?	3,2	4,2
	ОК			
	1,1 V	2,1 B	<sup>3,1</sup> P?	4,1
	ОК	OK		

= Agent

= Pit= Stench = Visited

= Breeze = Glitter. (



- after visiting rooms (1,1), (1,2), and (2,1), the agent should be able to infer that room (2,2) is safe
- KB\(\{S12,B21}\) = safe22

We can use propositions like:

- W44="the wumpus is in room 4,4"
- B22 = "there is a breeze in 2,2"
- S13 = "there is a stench in 1,3"
- pit32 = "there is a pit in room 3,2"
- safe33 = "room 3,3 is safe"

KB = {	1. W11->S21^S12	17. P11->B21^B12	33W11^-P11->safe11
	2. W12->S22^S11^S13	18. P12->B22^B11^B13	34W12^-P12->safe12
	3. W13->S23^S12^S14	19. P13->B23^B12^B14	35W13^-P13->safe13
	4. W14->S24^S13	20. P14->B24^B13	36W14^-P14->safe14
	5. W21->S11^S31^S22	21. P21->B11^B31^B22	37W21^-P21->safe21
	6. W22->S12^S32^S21^S23	22. P22->B12^B32^B21^B23	38W22^-P22->safe22
	7. W23->S13^S33^S22^S24	23. P23->B13^B33^B22^B24	39W23^-P23->safe23
	8. W24->S14^S34^S23	24. P24->B14^B34^B23	40W24^-P24->safe24
	9. W31->S21^S41^S32	25. P31->B21^B41^B32	41W31^-P31->safe31
	10. W32->S22^S42^S31^S33	26. P32->B22^B42^B31^B33	42W32^-P32->safe32
	11. W33->S23^S43^S32^S34	27. P33->B23^B43^B32^B34	43W33^-P33->safe33
	12. W34->S24^S44^S33	28. P34->B24^B44^B33	44W34^-P34->safe34
	13. W41->S31^S42	29. P41->B31^B42	45W41^-P41->safe41
	14. W42->S32^S41^S43	30. P42->B32^B41^B43	46W42^-P42->safe42
	15. W43->S33^S42^S44	31. P43->B33^B42^B44	47W43^-P43->safe43
	16. W44->S34^S43	32. P44->B34^B43	48W44^-P44->safe44
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- semantics refers to "meaning" of sentences, and relationships among them
  - this is defined using Model Theory
  - models describe states of the world, and are used to give "interpretations" of sentences
- Truth-functional semantics
  - each sentence is assumed to be either True or False in the world
  - (Law of the Excluded Middle) there is no in-between
  - propositions correspond to "facts" about the state of the world, which can only be True or False
    - good example: plutoCold, mercuryCold (in our universe, the first is T, the second is F)
    - bad example: surface\_temp\_of\_pluto (value can only be T or F)
- in Propositional Logic, models are truth assignments over all propositional symbols (that appear in the KB)
  - {A=F, B=F, C=T ... P=T, Q=F, R=F}
  - {mercuryCold=F, mercuryWarm=F, mercuryHot=T...earthCold=F, earthWarm=T, earthHot=F... plutoCold=T, plutoWarm=F, plutoHot=F}

also, uncertainty will be accounted for via multiple models...

- Compositionality
  - a model defines the truth value for all atomic sentences
  - given a model, the truth value of ANY sentence can be computed by combining truth values of sub-sentences using <u>truth tables</u>
  - these are pretty straightforward in PropLog (except for  $\rightarrow$ )

Α	В	¬A	AvB	A^B	A⊕B	A→B	A↔B
Т	Т	F	Т	Т	F	Т	Т
Т	F	F	Т	F	Т	F	F
F	Т	Т	Т	F	Т	Т	F
F	F	Т	F	F	F	Т	Т



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 $P \rightarrow Q$ : if the LHS (antecedents) are F, it doesn't matter what the RHS (consequent) is; only T->F is disallowed

- We say a model M *satisfies* a sentence s iff the interpretation (or truth value) of s in M is True
- a sentence s is *satisfiable* if there is at least 1 model that satisfies it
- a sentence s is *unsatisfiable* if no model that satisfies it
- a sentence s is a *tautology* (or *valid*) if it is satisfied by ALL models
- examples:
  - satisfiable: X, Xv $\neg$ YvZ, (X $^{\gamma}$ Y) $\rightarrow$ Z (what models make each of these True?)
  - unsatisfiable:  $X^{-X}$ ,  $P \oplus P$ ,  $\neg Q \leftrightarrow Q$  (convince yourself there are no models)
  - tautologies:  $Av \neg A$ ,  $P \rightarrow (Q \rightarrow P)$  (will be True in any model)

- semantic relationship between 2 sentences (or sets of sentences)
  - examples: {P} and {¬P} can't both be True (i.e. satisfied by same models)
  - if  $\{PvQ, P \rightarrow R, Q \rightarrow S, \neg P\}$  is True, then  $\{S\}$  must be True
- two sentences are *semantically equivalent* if they are satisfied by exactly the same models:  $\alpha \equiv \beta$  iff M( $\alpha$ )=M( $\beta$ )
  - example:  $A \rightarrow B \equiv \neg AVB$
- note: a set of sentences is True (or satisfied in a model) iff each sentence is True (equivalent to an implicit conjunction)

 $\{PvQ \land P \rightarrow R \land Q \rightarrow S \land \neg P\}$ 

- Entailment
  - $\alpha \models \beta$  iff all models that satisfy  $\alpha$  also satisfy  $\beta$
  - captures the notion of "logical consequence"

- show that  $\{PvQ, Q \rightarrow R, \neg P\} \models \{R\}$ 
  - models that satisfy the premises (as a conjunction): {M3}
  - models the satisfy the consequents ({R}): {M1,M3,M5,M7}



- Deduction Theorem
  - note that  $P \rightarrow Q$  is valid looks like  $P \models Q$ , and they seem similar
  - but they are different:
    - $P \rightarrow Q$  is a sentence (defined by syntax)
    - P = Q means P entails Q (defined by semantics)
  - the Deduction Theorem shows that they are related:
    - $\alpha \models \beta$  iff  $\alpha \rightarrow \beta$  is valid
    - (proof =>) see Venn diagram



in all models, either  $\alpha$  is false or  $\beta$  is true, hence  $\alpha \rightarrow \beta$  is valid

a model M(i):

{A=F, B=T, C=F

D=T, E=F...}

 (proof <=) if α → β is valid, then all models satisfy it, so all models either make α false or β true; hence those model that satisfy α also satisfy β; hence α = β

### Inference

- is there a procedure to determine if  $\alpha \models \beta$ ? (or KB  $\models$  query)
- model-checking (truth tables)
  - of course, we can just enumerate all models and check if those satisfy  $\alpha$  also satisfy  $\beta$
  - how many models are there? 2<sup>n</sup> (for *n* propositional symbols)
  - it is *finite*, so the procedure will halt and return yes (entailed) or no

### Inference

- model-checking is inefficient
  - we need a more practical procedure to determine whether  $\alpha \models \beta$
- Proof Procedures: methods to determine whether  $\alpha \models \beta$  purely by syntactic manipulation
  - aka "Inference Methods", "Theorem-Proving", "Automated Deduction"...
- Propositional Rules of Inference (ROI)
  - rules for generating new sentences from old sentences
  - a sound ROI only generates new sentences that are entailed
  - in this context, 'F' means 'derives' by a ROI, i.e. ' $\alpha \vdash \beta$ ' means ' $\beta$  is derived from  $\alpha$ '
  - hence a rule R is **sound** iff for all sentences  $\alpha, \beta$ , if  $\alpha \vdash \beta$ , then  $\alpha \models \beta$
  - an ROI α ⊢ β is *truth preserving* if the derived sentence β is semantically equivalent to α (satisfied by exactly the same models)

### Rules of Inference

- example: Modus Ponens
  - from P and  $P \rightarrow Q$ , we can derive Q
  - $\{P, P \rightarrow Q\} \vdash Q$
  - is MP sound?
  - all the models that satisfy the premises (conjunction of P and P→Q) also satisfy the derived sentence Q, so Q is entailed, so MP is sound

Ρ	Q	P→Q	premises (conj)	derived (Q)
0	0	1	0	0
0	1	1	0	1)
1	0	0	0	0
1	1	1 (	1) (	1

These are inference 'schemas'. A, B, and C are patterns representing sub-sentences.

## Rules of Inference

Can you prove that each of these is sound? Make truth tables. AE and MP are easy. Resolution is worth doing...

	from this	derive this	comments
AndElimination (AE)	A^B	А	
AndIntroduction (AI)	А, В	A^B	
OrIntroduction	А, В	AvB	no such things as OrElimination!
Commutativity	A^B	B^A	truth-preserving
Distributivity	Av(B^C) A^(BvC)	(AvB)^(AvC) (A^B)v(A^C)	
DoubleNegationElim (DN)	¬¬A	А	
DeMorgan's Laws (DM)	¬(AvB) ¬(A^B)	¬A^¬B ¬Av¬B	flip the operator
ImplicationElimination (IE)	A→B	¬AvB	truth-preserving
Modus Ponens (MP)	A, A→B	В	pattern-matching, if LHS is matched, can derive RHS
Modus Tolens	А→В, ¬В	¬А	
contraposition	A→B	¬B→¬A	
Resolution	AvB, ¬AvC	BvC	requires 2 clauses with opposite literals

## Natural Deduction

- Proof procedure to show that  $\alpha \models \beta$ 
  - start by listing sentences in premise  $\boldsymbol{\alpha}$
  - derive additional sentences using sound ROI
  - must be a *finite* sequence of steps ending in  $\beta$
- number your sentences
- label each new sentence with ROI and sentences it was derived from



## Example of Nat Ded (1)

from this	premises	derivations	
$P \Rightarrow Q$	1. P→Q	8. A^B	[AndIntr, 6,7]
$L \wedge M \Rightarrow P$	2. L^M→P	9. L	[MP, 5,8]
$B \wedge L \Rightarrow M$	3. B^L→M	10. B^L	[AndIntr, 7,9]
$A \wedge P \Rightarrow L$	4. A^P→L	11. M	[MP, 10,3]
$A \wedge B \Rightarrow L$	5. A^B→L	12. L^M	[AndIntr, 9,11]
A	6. A	13. P	[MP, 12,2]
B	7. B	14. ¬PvQ	[ImplElim, 1]
		15. Q	[Reso, 13,14]

...show that Q is entailed

### Natural Deduction

- Why does Natural Deduction work?
  - it is not enough to show that KB $\cup$ { $\alpha_{n+1},...,\alpha_{n+m}$ } = Q (for last step, assuming sound ROI)
  - we have to show that if Q is derived after a sequence of steps α<sub>n+1</sub>,... α<sub>n+m</sub> using sound ROI, then KB = Q (i.e. the original KB entails Q)
  - whenever we derive a new sentence by a sound ROI and add it to the premises, the set of entailments stays the same
  - suppose  $KB \models Q$ , and  $M(KB) \subseteq M(Q)$
  - so if KB  $\vdash \alpha_{n+1}$  (an intermediate sentence in proving Q) by a sound ROI, then KB  $\models \alpha_{n+1}$ , so M(KB) $\subseteq$ M( $\alpha_{n+1}$ ), M(KB $\cup \alpha_{n+1}$ )=M(KB) $\cap$ M( $\alpha_{n+1}$ )=M(KB), so KB $\cup \{\alpha_{n+1}\} \models Q$
  - this property is known as "monotonicity" (i.e. adding entailed intermediate conclusions doesn't affect what else is entailed)
  - similarly, if KB $\cup \alpha_{n+1} \models \alpha_{n+2}$ , then KB $\cup \{\alpha_{n+1}\} \models \alpha_{n+2}$  and M(KB $\cup \{\alpha_{n+1}, \alpha_{n+2}\}) \subseteq$ M(Q), so KB $\cup \{\alpha_{n+1}, \alpha_{n+2}\} \models Q$
  - if proof has m+1 steps KB,  $\alpha_{n+1}$ ,  $\alpha_{n+m}$ , Q, then KB $\cup$ { $\alpha_{n+1}$ ,  $\alpha_{n+m}$ } = Q (by induction)

## Example of Nat Ded (2): Wumpus World



after visiting rooms (1,1), (1,2), and (2,1), the agent should be able to infer that room (2,2) is safe

KB = {	1. W11->S21^S12	17. P11->B21^B12	33W11^-P11->safe11
	2. W12->S22^S11^S13	18. P12->B22^B11^B13	34W12^-P12->safe12
	3. W13->S23^S12^S14	19. P13->B23^B12^B14	35W13^-P13->safe13
	4. W14->S24^S13	20. P14->B24^B13	36W14^-P14->safe14
	5. W21->S11^S31^S22	21. P21->B11^B31^B22	37W21^-P21->safe21
	6. W22->S12^S32^S21^S23	22. P22->B12^B32^B21^B23	38W22^-P22->safe22
	7. W23->S13^S33^S22^S24	23. P23->B13^B33^B22^B24	39W23^-P23->safe23
	8. W24->S14^S34^S23	24. P24->B14^B34^B23	40W24^-P24->safe24
	9. W31->S21^S41^S32	25. P31->B21^B41^B32	41W31^-P31->safe31
	10. W32->S22^S42^S31^S33	26. P32->B22^B42^B31^B33	42W32^-P32->safe32
	11. W33->S23^S43^S32^S34	27. P33->B23^B43^B32^B34	43W33^-P33->safe33
	12. W34->S24^S44^S33	28. P34->B24^B44^B33	44W34^-P34->safe34
	13. W41->S31^S42	29. P41->B31^B42	45W41^-P41->safe41
	14. W42->S32^S41^S43	30. P42->B32^B41^B43	46W42^-P42->safe42
	15. W43->S33^S42^S44	31. P43->B33^B42^B44	47W43^-P43->safe43
	16. W44->S34^S43	32. P44->B34^B43	48W44^-P44->safe44

Natural Deduction Proof of KB<sup>\*</sup>Facts |= safe22:

Facts = { 49. -B11, 50. -S11, 51. -B12, 52. S12, 53. B21, 54. -S21 }

55. -W22v(S12^S32^S21^S23) [Impl Elim, 6] 56. (-W22vS12)^ (-W22vS32) )^ (-W22vS21)^ (-W22vS23) [Distrib, 55] 57. (-W22vS21) [And Elim, 56] 58. S21v-W22 [Commut, 57] 59. -S21->-W22 [Impl Intro, 58] 60. -W22 [MP, 59, 54] 61. -P22v(B12^B32^B21^B23) [Impl Elim, 22] 62. (-P22vB12)^ (-P22vB32) )^ (-P22vB21)^ (-P22vB23) [Distrib, 61] 63. -P22vB12 [And Elim, 62] 64. B12v-P22 [Commut, 63] 65. -B12->-P22 [Impl Intro, 64] 66. -P22 [MP, 65, 51] 67. -W22^-P22 [And Intro, 60, 66] 68. safe22 [MP, 38, 67]

1,4	2,4	3,4	4,4
1,3	2,3	3,3	4,3
1,2	2,2 P?	3,2	4,2
ОК			
1,1	2,1 A	<sup>3,1</sup> P?	4,1
V	В		
OK	OK		

### Natural Deduction

- limitations
  - it can be difficult (but not impossible) to find the right sequence of derivations automatically
    - you could use a Search and try applying all ROI to all combinations of sentences till you generate the query (i.e. as the goal)
  - in theory, is Nat Ded a *complete* proof procedure???
    - can every query that is entailed by a KB be proved in a finite number of steps?
  - one can show that certain combinations of ROI are sufficient to guarantee that a proof always exists for entailed sentences (in Propositional Logic)

## Forward Chaining

- let's explore more practical theorem-proving methods
- Forward-Chaining (FC) is super-easy: you only need Modus Ponens!
- however, FC only works on definite-clause KBs
  - a *clause* is a disjunction of literals, e.g. A v ¬B v C v ¬D
  - a *Horn clause* is a clause with at most one positive literal, e.g. A v B v –C
  - a *definite clause* is a clause with exactly one positive literal
- where do definite clauses come from? facts and conjunctive rules
  - facts: A, B (note negations are not allowed!)
  - rules with conjunct. of pos. lits as antecedents and 1 consequent
     A ^ B ^ C → D (conjunctive rule)

¬A v ¬B v ¬C v D (definite clause, by Implication Elimination)



- the key idea in FC is to use a queue (sometimes called an 'agenda') to keep track of facts that have been inferred (initially, just the given facts)
- with each new fact inferred, we check which rules can be triggered (i.e. when all their
   antecedents have been satisfied), and then we put the consequents in the queue
- there are ways to make this efficient for large KBs by indexing on which rules have which propositions as antecedents (to quickly figure out which rules are triggered by new facts)

### Example of Forward Chaining

- 1.  $P \rightarrow Q$  1
- 2.  $L^M \rightarrow P$  2
- 3.  $B^{+}L \rightarrow M$  2
- 4.  $A^P \rightarrow L$  2
- 5.  $A^B \rightarrow L$  2
- 6. A 0 7. B 0

• agenda:

- 1. A, B
- 2. <del>A, B</del>, L // rule 5 is triggered
- 3. <del>A, B, L</del>, M // rule 3
- 4. <del>A, B, L, M</del>, P // rule 2
- 5. <del>A, B, L, M, P</del>, Q // rule 1 fires
- stop since query was generated

note, in this illustration, I am not popping things out of the queue

## Forward Chaining

- so using FC requires the KB to be formulated as <u>definite clauses</u> (i.e. a rule base)
- in theory, this is not always possible
  - for example, if {¬P} or {PvQ} or {P^Q→RvS} is in the KB, it can't be transformed into definite clauses
  - these examples represent *uncertainty*, which isn't permitted
  - hence this requirement <u>limits expressiveness</u> (not full Propositional Logic)
- in practice, it is often possible to express KBs for real problems in definite clause form, with judicious choice of propositions

	1. C11->PF21	25. C31->PF21	49. US11->WF21	73. US31->WF21	97. WF11^PF11->safe11
	2. C11->PF12	26. C31->PF41	50. US11->WF12	74. US31->WF41	98. WF12^PF12->safe12
To show that <i>safe22</i> in	3. C12->PF22	27. C31->PF32	51. US12->WF22	75. US31->WF32	99. WF13^PF13->safe13
the Wumpus World,	4. C12->PF11	28. C32->PF22	52. US12->WF11	76. US32->WF22	100. WF14^PF14->safe14
we have to re-write	5. C12->PF13	29. C32->PF42	53. US12->WF13	77. US32->WF42	101. WF21^PF21->safe21
the KB as definite	6. C13->PF23	30. C32->PF31	54. US13->WF23	78. US32->WF31	102. WF22^PF22->safe22
clauses, which can be	7. C13->PF12	31. C32->PF33	55. US13->WF12	79. US32->WF33	103. WF23^PF23->safe23
achieved by using new	8. C13->PF14	32. C33->PF23	56. US13->WF14	80. US33->WF23	104. WF24^PF24->safe24
propositions	9. C14->PF24	33. C33->PF43	57. US14->WF24	81. US33->WF43	105. WF31^PF31->safe31
	10. C14->PF13	34. C33->PF32	58. US14->WF13	82. US33->WF32	106. WF32^PF32->safe32
PropSyms:	11. C21->PF11	35. C33->PF34	59. US21->WF11	83. US33->WF34	107. WF33^PF33->safe33
• WF = wumpus-free	12. C21->PF31	36. C34->PF24	60. US21->WF31	84. US34->WF24	108. WF34^PF34->safe34
• PF = pit-free	13. C21->PF22	37. C34->PF44	61. US21->WF22	85. US34->WF44	109. WF41^PF41->safe41
• C = calm	14. C22->PF12	38. C34->PF33	62. US22->WF12	86. US34->WF33	110. WF42^PF42->safe42
<ul> <li>US = unstenchy</li> </ul>	15. C22->PF32	39. C41->PF31	63. US22->WF32	87. US41->WF31	111. WF43^PF43->safe43
	16. C22->PF21	40. C41->PF42	64. US22->WF21	88. US41->WF42	112. WF44^PF44->safe44
note that we chose	17. C22->PF23	41. C42->PF32	65. US22->WF23	89. US42->WF32	
new propositional	18. C23->PF13	42. C42->PF41	66. US23->WF13	90. US42->WF41	4 SSTATS -Breeze - PIT
symbols representing	19. C23->PF33	43. C42->PF43	67. US23->WF33	91. US42->WF43	North Freezer
information in a	20. C23->PF22	44. C43->PF33	68. US23->WF22	92. US43->WF33	
negative way	21. C23->PF24	45. C43->PF42	69. US23->WF24	93. US43->WF42	2 55555 -Breeze -
	22. C24->PF14	46. C43->PF44	70. US24->WF14	94. US43->WF44	
	23. C24->PF34	47. C44->PF34	71. US24->WF34	95. US44->WF34	
	24. C24->PF23	48. C44->PF43	72. US24->WF23	96. US44->WF43	

#### FC proof of *KB*^*Facts* = *safe22*

Facts: 113. C11 // room 1,1 is calm (no breeze) 114. US11 // room 1,1 is unstenchy 115. C12 // room 1,2 is calm 116. US21 // room 2,1 is unstenchy



inferred	agenda
	C11 US11 C12 US21 // initialize by pushing facts
C11	US11 C12 US21 <u>PF12 PF21</u> // C11 causes 2 new facts to be pushed onto agenda from rules 1&2
US11	C12 US21 PF12 PF21 WF12 WF21
C12	US21 PF12 PF21 WF12 WF21 PF11 PF22 PF13 // C12 causes rules 3-5 to fire
US21	PF12 PF21 WF12 WF21 PF11 PF22 PF13 <u>WF11 WF31 WF22</u> // rules 59-61
PF12 PF21 WF12 WF21 PF11 PF22 PF13	<pre>// these just pop off without pushing anything new</pre>
WF11	WF31 WF22 safe11 // since WF11 and PF11 have been inferred, rule 97 fires
WF31	WF22 safe11
WF22	safe11 safe22 // since WF22 and PF22 have been inferred, rule 102 fires
safe11	safe22
safe22	// found what we were looking for, showing the query is entailed; also, agenda becomes empty

## **Back-Chaining**

- one of the problems with FC is that it can waste time generating a lot of unnecessary inferences that are irrelevant to the query
- back-chaining (BC) also works on definite-clause KBs, but it works backwards from the goal to find supporting facts
- hence BC is more efficient because it is goal-directed
- BC is in fact the basis of PROLOG (as we will see later when we cover FOL)

## **Back-Chaining**

- BC uses a *goal stack* (initialized by pushing the query)
- with each iteration:
  - pop the goal on the top of the stack
  - check to see if it is a known fact
  - otherwise, find a rule that has the goal as consequent, and push the antecedents onto the stack as subgoals
  - the algorithm terminates when the stack becomes empty (success, showing the query is entailed, because it has been reduced to known facts)
- important: back-tracking
  - if some subgoals cannot be proved, BC must back-track and try another rule to prove goal

## Example of Backward Chaining

- Q // initialize with query
- P // pop Q, replace with antecedent of rule 1
- L, M // replace P with ants. of rule 2
- A, Z, M // pop L, push A,P from rule 4
- Z, M // pop A (known fact)
- // since Z is not provable, back-track to other rule for L
- A, B, M

 $P \rightarrow Q$ 

 $L^M \rightarrow P$ 

B^L→M

 $A^{Z} \rightarrow L$ 

A^B→L

1.

2.

3.

4.

5.

6.

7.

Α

В

- B, M // pop A (fact)
- M // pop B (fact)
- B, L // pop M, try rule 3, push B,L
- L // pop B (fact)
- A,Z // pop L, try rule 4
- Z // pop A (fact)
- // since Z is not provable, back-track to other rule for L
- A, B
- B // pop A (fact)
- Ø // pop B (fact); stack becomes empty; return success!

(note: This example is modified from Fig 7.16 in the book to simplify for illustration purposes. The P in  $A^P \rightarrow L$  was replaced with Z, to avoid the complication of checking for repeated subgoals, which would succeed implicitly, representing a loop. In this context, however, that technical detail is an unnecessary distraction.)



visualizing the proof tree as an "and-or" graph

```
Back-chaining using Propositional Logic (Recursive stack-based version)
```

```
Backchain (KB, query)
 stack.push(query) // initialize
 return BC(KB,stack)
BC(KB, stack)
 if stack empty, return True
 subgoal \leftarrow stack.pop()
 if subgoal < KB, return BC (KB, stack) // a known fact
 for each rule a_1 ... a_n \rightarrow subgoal in KB: // choice point for back-tracking
   stack.push(a_1..a_n)
   result \leftarrow BC(KB, stack)
   if result=True, return True
   else remove a_1 \dots a_n from stack
 return False
```

#### BC proof of KB^Facts |= safe22 (using the definite-clause KB from slide 34)





goal stack	
safe22	push query
<u>WF22 PF22</u>	rule102
<u>US12</u> PF22	try rule 51 for WF22
<u>US21</u> PF22	fail, back-track; try rule 61 for WF22
PF22	succeed (116); US21 pops off
<u>C21</u>	try rule 21 for PF22
C12	fail; back-track; try rule 61
Ø	C12 is a known fact (115); pop off stack becomes empty; proof succeeds

- FC and BC are effective proof procedures, but they are limited because the are not complete (not all KBs are in definite-clause form)
- Is there a complete proof procedure that is simpler than Nat. Ded.?
- Resolution Refutation proofs you can prove any entailed sentence, and all you need is one ROI: *resolution* A v B v..., ¬A v C v...

B v... v C v...

• prerequisite: you have to convert your KB into CNF (Conjunctive-Normal Form, i.e. clauses), which you can always do

> simple example:  $A^B^-C \rightarrow D^E$  can be transformed into 2 clauses (not necessarily Horn) that are equivalent:  $(\neg A \lor \neg B \lor C \lor D)$ ,  $(\neg A \lor \neg B \lor C \lor E)$

## Conversion to CNF

clause = disjunction, e.g. (AvB) CNF = conjunction of clauses, e.g. (AvB)^(Cv-D) these can be treated like multiple sentences, {(AvB),(Cv-D)}

- procedure for converting any propositional sentence to CNF (p. 227)
  - 1. eliminate implications (and biconditionals)
  - 2. push negations inward (using DoubleNegElim and DeMorgan's)
  - 3. distribute Or's over And's (till expression is 2-level Boolean CNF)
  - 4. break final conjunction into multiple clauses
- example:  $A^B^-C \rightarrow D^E$ 
  - 1. ¬(A^B^¬C) v D^E // implication elimination
  - 2. (¬Av¬Bv¬¬C) v (D^E) // push negations inward
  - 3. (¬Av¬BvCvD) ^ (¬Av¬BvCvE) // distribution
  - 4a. (¬A v ¬B v C v D)
  - 4b. (¬A v ¬B v C v E)

### **Refutation Proofs**

- negate the query and add it to the KB
- if the query was entailed, this creates an inconsistency (unsatisfiable),
   M(KB∪{¬q})= ∅
- thus we should be able to derive the empty clause (which means "false" or "inconsistent")

```
simple example:

suppose KB={A,A\rightarrowB} and q=B

negate query and append it: {A,A\rightarrowB,¬B}

convert to CNF { A , ¬A v B, ¬B }

1. A

2. ¬A v B

3. ¬B

4. ¬A // resolve 2 and 3

5. \emptyset // resolve 1 and 4, empty clause

this means we proved KB \models B
```

## **Refutation Proofs**

- Why do refutation proofs work?
- like "proof by contradiction"
- no models satisfy both KB and ¬q (empty intersection)
  - if KB  $\models$  q, then M(KB $\cup$ {¬q})=  $\emptyset$ , hence unsatisfiable



### Example of Resolution Refutation Proof

KB:	CNF:	9. ¬P // reso on 1 and 8 (eliminate Q)
1. $P \rightarrow Q$	1. ¬P v Q	10. ¬L v ¬M // reso 2,9
2. L^M→P	2. ¬L v ¬M v P	11. ¬A v ¬B v ¬M // reso 5,10 (eliminate L)
3. B^L→M	3. ¬ B v ¬L v M	12. ¬A v ¬B v ¬B v ¬L // reso 11,3 (eliminate M)
4. A^P→L	4. ¬A v ¬P v L	13. ¬A v ¬B v ¬L // (factoring, combine ¬Bs)
5. A^B→L	5. ¬A v ¬B v L	14 - 4y - 8y - 4y - 8/(reso 13.5)
6. A	6. A	$1 - A = D / f_{0} = t_{0} = t_{0}$
7. B	7 B	15. $\neg A \vee \neg B // \text{ factoring}$
		16. ¬B // reso 15,7
	8. ¬Q	17 // roco 16 9. ompty claused
query: Q	<pre>// negated query</pre>	1/. $1/100 10,0; empty clause!$

### **Resolution Proof Procedure**

```
function PL-RESOLUTION(KB, \alpha) returns true or false
  inputs: KB, the knowledge base, a sentence in propositional logic
            \alpha, the query, a sentence in propositional logic
   clauses \leftarrow the set of clauses in the CNF representation of KB \land \neg \alpha
   new \leftarrow \{\}
  loop do
       for each pair of clauses C_i, C_j in clauses do
           resolvents \leftarrow PL-RESOLVE(C_i, C_j)
           if resolvents contains the empty clause then return true
           new \leftarrow new \cup resolvents
      if new \subseteq clauses then return false
       clauses \leftarrow clauses \cup new
```

	1W11vS21	25W31vS21	49P11vB21	73P31vB21	97. W11 v P11 v safe11
	2W11vS12	26W31vS41	50P11vB12	74P31vB41	98. W12 v P12 v safe12
Wumpus World	3W12vS22	27W31vS32	51P12vB22	75P31vB32	99. W13 v P13 v safe13
Clauses (CNF) for	4W12vS11	28W32vS22	52P12vB11	76P32vB22	100. W14 v P14 v safe14
Resolution	5W12vS13	29W32vS42	53P12vB13	77P32vB42	101. W21 v P21 v safe21
	6W13vS23	30W32vS31	54P13vB23	78P32vB31	102. W22 v P22 v safe22
	7W13vS12	31W32vS33	55P13vB12	79P32vB33	103. W23 v P23 v safe23
	8W13vS14	32W33vS23	56P13vB14	80P33vB23	104. W24 v P24 v safe24
	9W14vS24	33W33vS43	57P14vB24	81P33vB43	105. W31 v P31 v safe31
	10W14vS13	34W33vS32	58P14vB13	82P33vB32	106. W32 v P32 v safe32
	11W21vS11	35W33vS34	59P21vB11	83P33vB34	107. W33 v P33 v safe33
	12W21vS31	36W34vS24	60P21vB31	84P34vB24	108. W34 v P34 v safe34
	13W21vS22	37W34vS44	61P21vB22	85P34vB44	109. W41 v P41 v safe41
	14W22vS12	38W34vS33	62P22vB12	86P34vB33	110. W42 v P42 v safe42
	15W22vS32	39W41vS31	63P22vB32	87P41vB31	111. W43 v P43 v safe43
	16W22vS21	40W41vS42	64P22vB21	88P41vB42	112. W44 v P44 v safe44
	17W22vS23	41W42vS32	65P22vB23	89P42vB32	
	18W23vS13	42W42vS41	66P23vB13	90P42vB41	
	19W23vS33	43W42vS43	67P23vB33	91P42vB43	
	20W23vS22	44W43vS33	68P23vB22	92P43vB33	
	21W23vS24	45W43vS42	69P23vB24	93P43vB42	
	22W24vS14	46W43vS44	70P24vB14	94P43vB44	
	23W24vS34	47W44vS34	71P24vB34	95P44vB34	
	24W24vS23	48W44vS43	72P24vB23	96P44vB43	

#### ResoRef proof of $KB^{Facts} = safe22$

Facts: 113. -B11 114. -S11 115. -B12 116. S12 117. B21 118. -S21 119. -safe22 // negation of query

new clauses	annotation
120P22	Reso on 115 & 62 (-P22vB12)
121W22	Reso on 118 & 16 (-W22vS21)
122. W22 v safe22	Reso on 120 & 102 (W22 v P22 v safe22)
123. safe22	Reso on 121 & 122
124. $\emptyset$ derived empty clause; proof succeeds	Reso on 119 & 123

- Resolution as a <u>Search for the empty clause</u>
- nodes in Search Tree = clauses, but they have multiple parents
- there are often many clauses that can be resolved (most are irrelevant)



- heuristics to make the resolution search more efficient:
  - unit-clause heuristic:
    - choose pairs of clauses that can resolve, where at least one clause is just a single literal
    - rationale: size of resolvent of clauses of size n and m is n+m-2, so if one is a unit clause, the resolvent shrinks in size to n-1 (closer to the goal of size 0 for the empty clause)
    - this is effective, but incomplete (there are some proofs you can't do if you always use the unit-clause heuristic)

- other resolution heuristics (resolution strategies)
  - input resolution: always choose one of the clauses from the input set (premise clauses)
  - linear resolution: always choose the previously resolved clause
- we will discuss these heuristics in more detail Ch. 9 (Inference in FOL)

- Is it complete proof procedure? can it determine whether *any* sentence is entailed?
- Ground Resolution Theorem:
  - if a set of sentences S is unsatisfiable, then there exists a finite sequence of resolution steps that will generate the empty clause.
  - the textbook restates this as "the empty clause will be contained in the resolution closure"
  - the proof involves showing that: suppose S is unsat but RC(S) does not contain the empty clause; then we can construct a model out of the clauses in RC(S) - contradiction
- Theorem: Resolution refutation is a complete proof procedure.
  - if  $\alpha \models \beta$ , then there exists a finite sequence of resolution steps (starting from the CNF of { $\alpha \land \neg \beta$ }) that will generate the empty clause.
- generally, we do not try to show the converse, i.e. that if b is not entailed, resolution should stop and say so, e.g. when it runs out of clauses that can be resolved
  - theoretically you could do it in Prop Log, but it depend on the RC(S) being finite (requires factoring)

## Satisfiability

- another propositional theorem-proving strategy
- Sat methods can test if a set of sentences is unsatisfiable (like in a Refutation proof)
- more commonly, Sat methods are used on satisfiable KBs the goal is to generate a model (where the truth values are the solution to a problem)
- this is a (slightly) more efficient form of model-checking

### DPLL

- a truth assignment (as a model) is a specification of truth values (T,F,?) for all propositional symbols in a KB
  - examples: {F,F,F,F,F}, {T,F,?,?,?}
- <u>Search</u> for complete truth assignment (like CSP)
  - $KB = \{\neg DvC, A^B \rightarrow E, \neg D \rightarrow \neg E, C \rightarrow E, \neg B^D\}, CNF = \{\neg DvC, \neg Av \neg BvE, Dv \neg E, \neg CvE, \neg B, D\}$
  - props are {A,B,C,D,E}
  - initial state={?,?,?,?,?}
  - goal states={F,F,T,T,T} and {T,F,T,T,T}
- "Davis-Putnam-Logemann-Loveland" (DPLL) procedure
  - convert propositional KB into CNF
  - start with an empty truth assignment {?,?,?,...,?}
  - try binding one more variable at a time
  - back-track whenever a clause is violated
  - quit when a complete assignment is found that satisfies all clauses



(this tree assigns the props in alphabetical order by default, but DPLL could choose a different prop at each node using the unit-clause or pure symbol heuristics discussed on the next slide)

```
function DPLL-SATISFIABLE?(s) returns true or false
inputs: s, a sentence in propositional logic
```

 $clauses \leftarrow$  the set of clauses in the CNF representation of s $symbols \leftarrow$  a list of the proposition symbols in s**return** DPLL(clauses, symbols, { })

function DPLL(clauses, symbols, model) returns true or false

if every clause in clauses is true in model then return true if some clause in clauses is false in model then return false  $P, value \leftarrow FIND-PURE-SYMBOL(symbols, clauses, model)$ if P is non-null then return DPLL(clauses, symbols –  $P, model \cup \{P=value\})$ heuristics  $P, value \leftarrow FIND-UNIT-CLAUSE(clauses, model)$ if P is non-null then return DPLL(clauses, symbols –  $P, model \cup \{P=value\})$   $P \leftarrow FIRST(symbols); rest \leftarrow REST(symbols)$ return DPLL(clauses, rest, model  $\cup \{P=true\})$  or DPLL(clauses, rest, model  $\cup \{P=true\})$ )

the essence of DPLL is guessing a truth value for each proposition, and backtracking when a conflict is discovered

### DPLL

- DPLL systematically explores the space of models (which can be slow)
- heuristics to speed up DPLL
  - we can bias the choice of which proposition to assign next
  - <u>Unit Clause heuristic</u> given a partial assignment, if there is a clause where all but one literal is False and the last is unknown (?), then add the appropriate truth value to the model
  - example: {¬B, D, ¬DvC, ¬Av¬BvE, Dv¬E, ¬CvE}
  - <u>Pure Symbol heuristic</u> given a partial assignment, if proposition X=? and X appears only as positive literal (X) in all unsatisfied clauses remaining, bind X=T
    - if it appears only as neg. lit. (¬X) in all *unsatisfied* clauses remaining, bind X=F
    - it doesn't mean X has to have that truth value, only it can (if there is a model of the KB, then there is a model in which X=T)
  - important: apply these incrementally; as the model gets more vars bound:
    - ignore clauses that are satisfied by the partial model (have at least 1 var that is true)
    - mark off vars in a clause that evaluate to false; non-Unit clauses might *become* Unit clauses

## Example of DPLL heuristics

- CNF={-B, D, -DvC, -Av-BvE, Dv-E, -CvE}
- init: m0={?,?,?,?,?}
- step 1: clause 1 is <u>Unit</u>, bind B=F: m1={?,F,?,?,?}
- step 2: clause 2 is <u>Unit</u>, bind D=T: m2={?,F,?,T,?}
- step 3: are there any new unit clauses?
  - clauses 1,2,4,5 are satisfied (at least 1 var is true in each), so these can be ignored
  - clause 3: ¬DvC evaluates to "Fv?" in current model m2, so C must be true (since all vars are false except 1): m3={?,F,T,T,?}
- step 4: now clause 6 becomes <u>Unit</u> because -CvE = "Fv?" in m3, so E must be true: m4={?,F,T,T,T}
  - could halt, since this model now satisfies all clauses (2 solutions: {T,F,T,T,T} or {F,F,T,T,T})
- by the way, A only appears as a negative literal in all clauses, so the <u>Pure Symbol</u> heuristic would bind it to false: m5={F,F,T,T,T}

## Solving Problems via Satisfiability

Western Australia New South Australia New South Wales Victoria Tasmania

- example: map-coloring
  - convert KB (slide 11) to CNF
    - there are 21 propositions (7 states X 3 colors)
    - clauses={WAR v WAG v WAB, ¬WAR v ¬WAB, ¬WAR v ¬NTR, …} (100-200 CNF sentences)
  - DPLL(<?,?,?,?....?>,clauses) returns a complete truth assignment
    - <WAR=T, WAG=F, WAB=F, NTR=F, NTG=T, NTB=F, SAR=F...>
    - 7 T's and 14 F's
    - the DPLL algorithm can be modified to return additional models
    - how many times does back-tracking occur?
    - when does the unit-clause heuristic get invoked?
    - how much back-tracking would there be without the UC or PS heuristics?
    - size of search space?

## Solving Problems via Satisfiability

- using DPLL to find other solutions
  - find a coloring of the map where Queensland is green
  - DPLL(<?,?,?,?....?>,<u>clauses∪{QG}</u>) returns
    - <WAR=F,WAG=T,WAB=F,NTR=T,NTG=G,NTB=F,SAR=F,SAG=F,SAB=T,QR=F,QG=T,QB=F...>
- using DPLL to show something is entailed
  - show that if WA is red, then V has to be red: WAR $\rightarrow$ VR
  - negate the sentence and add to clauses:  $\neg$ (WAR $\rightarrow$ VR) = WAR ^  $\neg$ VR (as CNF)
  - DPLL(<?,?,?,?....?>,<u>clauses</u>U{WAR, ¬VR}) returns *unsatisfiable*



### DPLL

- many other problems can be solved by encoding them as Sat problems
  - CSPs
  - Sammy's sport shop, Wumpus world
  - planning (SatPlan), scheduling,
  - multi-agent coordination,...
  - vertex cover, knapsack,...
  - program verification (write a Boolean expression describing the steps in a piece of code, and an invariant or property it is supposed to maintain)

## Complexity of Propositional Inference

- Cook's Theorem: Boolean SAT is NP-complete.
  - proof involves showing that you can describe or "encode" a Turing machine that simulates any non-det. computation in the form of a Boolean expression with at size at most a polynomial in the number of states, tape symbols, etc
- Hence, *complete* proof procedures can't be guaranteed to halt and return an answer in polynomial time (unless P=NP)
  - so we could wait a *long* time for a resolution proof to finish
  - however, restricted methods, like FC and BC can potentially run in poly time

#### WalkSAT - a stochastic approach to satisfiability

 not guaranteed to be complete, but it is fast and often effective at finding models of a set of clauses

function WALKSAT(clauses, p, max\_flips) returns a satisfying model or failure inputs: clauses, a set of clauses in propositional logic p, the probability of choosing to do a "random walk" move, typically around 0.5 max\_flips, number of flips allowed before giving up

 $model \leftarrow$  a random assignment of true/false to the symbols in clauses

for i = 1 to max\_flips do

if model satisfies clauses then return model

 $clause \leftarrow$  a randomly selected clause from clauses that is false in model

with probability p flip the value in model of a randomly selected symbol from clause else flip whichever symbol in clause maximizes the number of satisfied clauses return failure this is what makes the search efficient;

kind of like the MinConflicts alg. for CSPs

Is this set of clauses satisfiable? How hard would it be to find a model?

 $\overline{a} \vee \overline{f} \vee g$  $\overline{a} \vee \overline{b} \vee \overline{h}$  $a \lor c$  $a \vee \overline{i} \vee \overline{l}$  $a \vee \overline{k} \vee \overline{j}$  $b \vee d$  $b \vee g \vee \overline{n}$  $b \vee \overline{f} \vee n \vee k$  $\overline{c} \vee k$  $\overline{c} \vee \overline{k} \vee \overline{i} \vee I$ 

 $c \vee h \vee n \vee \overline{m}$  $c \vee l$  $d \vee \overline{k} \vee I$  $d \vee \overline{g} \vee I$  $\overline{g} \vee n \vee o$  $h \vee \overline{o} \vee \overline{j} \vee n$  $\overline{i} \vee j$  $\overline{d} \vee \overline{l} \vee \overline{m}$  $\overline{e} \vee m \vee \overline{n}$  $\overline{f} \vee h \vee i$ 

here is a solution: a = Trueb = True= True d = Truee = Falsef = Falseq = Falseh = Falsei = Falsej = False  $\mathbf{k} = \mathbf{True}$ 1 = Truem = Falsen = Trueo = True

### Hard Satisfiability Problems - The "Computational Cliff"



- experiments with *randomly generated* Sat problems (1000s of Boolean clauses)
- "computational cliff" at ~4.3 clauses per symbol

