

15-780: Graduate AI
Lecture 3. Logic and SAT

Geoff Gordon (this lecture)

Ziv Bar-Joseph

TAs Geoff Hollinger, Henry Lin

Admin

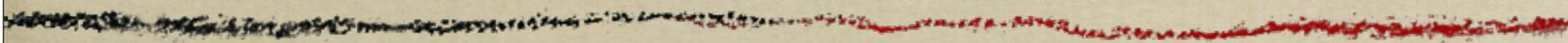
- *HW1 out today!*
 - *On course website*
 - *Due Thu 10/4*
- *Reminder: Matlab tutorial today*
 - *NSH 1507, 5PM*

Working together

- *Working together on HW, looking on web, etc.: great idea!*
 - *but each person must write up and submit his/her own solution, without reference to written/electronic materials from web or other students*
- *Last year's HWs are on course web site*

Late policy

- *If you need to hand a HW in late: contact us **before** due date*
- *Unless agreed otherwise, HW is worth 75% credit up to 24 hrs late, 50% credit up to 48 hrs late, 0% credit afterwards*
- *Even if for 0% credit, must hand in **all** assignments to pass*

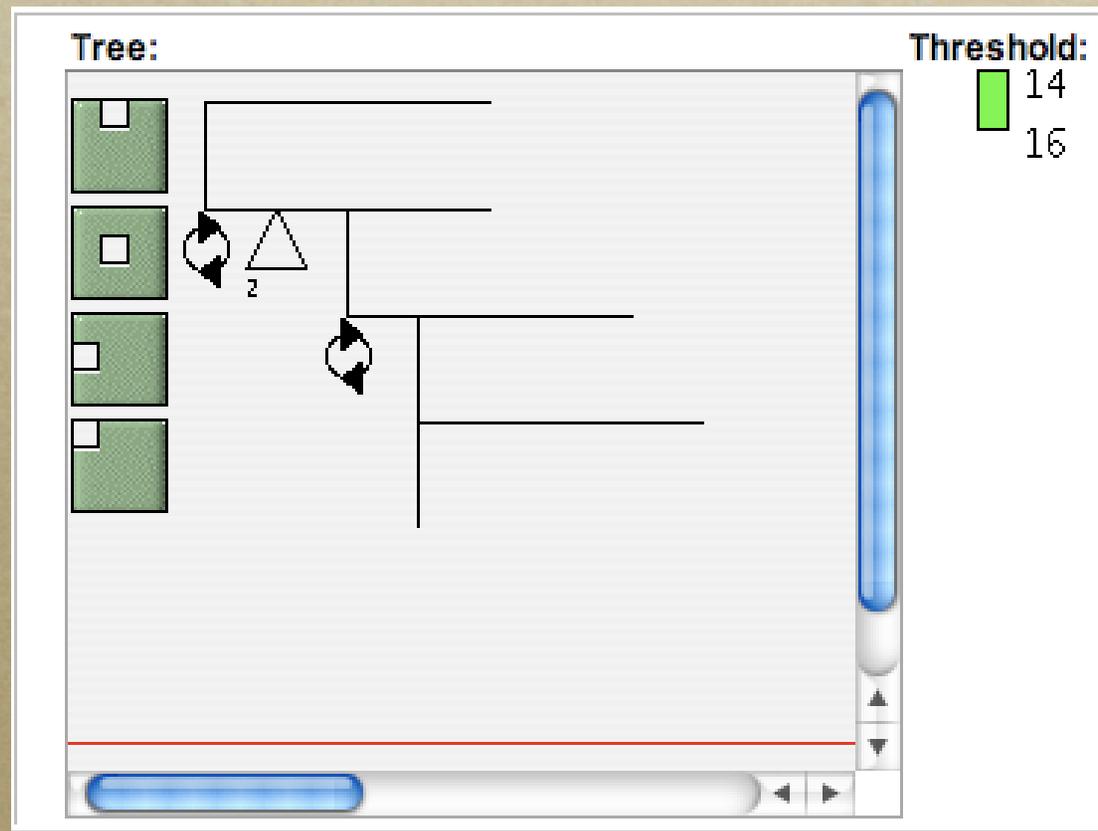


Review

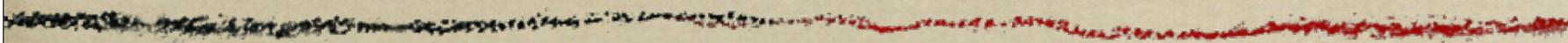
Topics covered

- *C-space*
- *Ways of splitting up C-space*
 - *Visibility graph*
 - *Voronoi*
 - *Exact, approximate cell decomposition*
 - *Adaptive cells (quadtree, parti-game)*
- *RRTs*

8/15 puzzle applet



<http://www.cs.ualberta.ca/~aixplore/search/IDA/Applet/SearchApplet.html>



Project ideas

Poker



Poker

- *Minimax strategy for heads-up poker = solving linear program*
- *1-card hands, 13-card deck: 52 vars, instantaneous*
- *RI Hold'Em: ~1,000,000 vars*
 - *2 weeks / 30GB (exact sol, CPLEX)*
 - *40 min / 1.5GB (approx sol)*
- *TX Hold'Em: ??? (up to 10^{17} vars or so)*

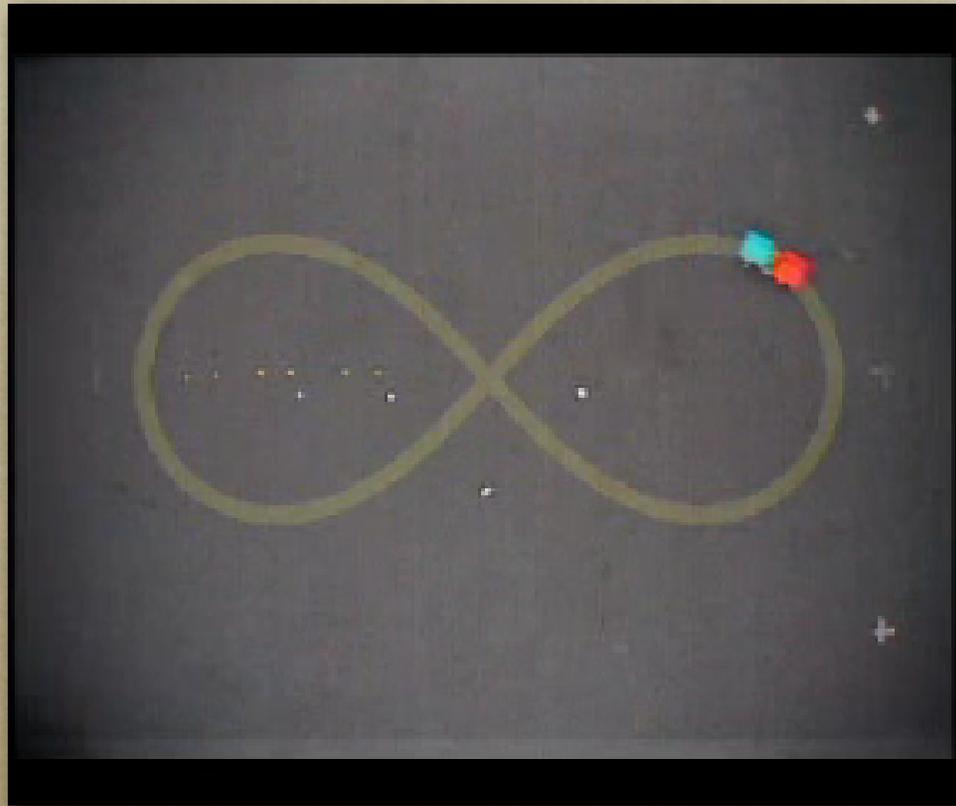
Scrabble™

- *Can buy a hand-tweaked, very good computer Scrabble player for \$30 or so*
- *Can we learn to beat it?*

Learning models for control

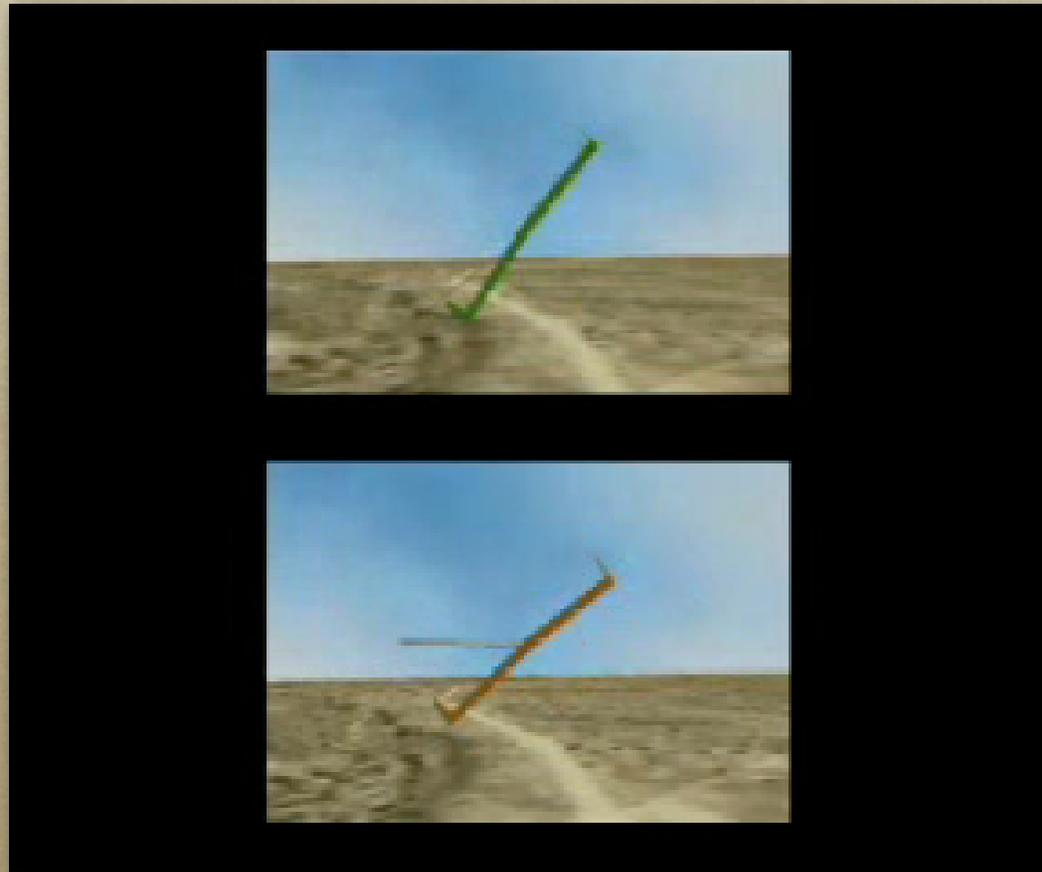
- *Most of this course, we'll assume we have a good model of the world when we're trying to plan*
- *Usually not true in practice—must learn it*
- *Project: learn a model for an interesting system, write a planner for learned model, make planner work on original system*

Learning models for control



- *R/C car*

Learning models for control

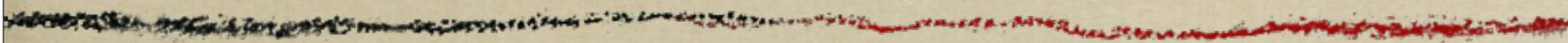


- *Model airplane*

Citation

- *“Using Inaccurate Models in Reinforcement Learning.” Pieter Abbeel, Morgan Quigley, Andrew Y. Ng*

http://www.icml2006.org/icml_documents/camera-ready/001_Using_Inaccurate_Mod.pdf



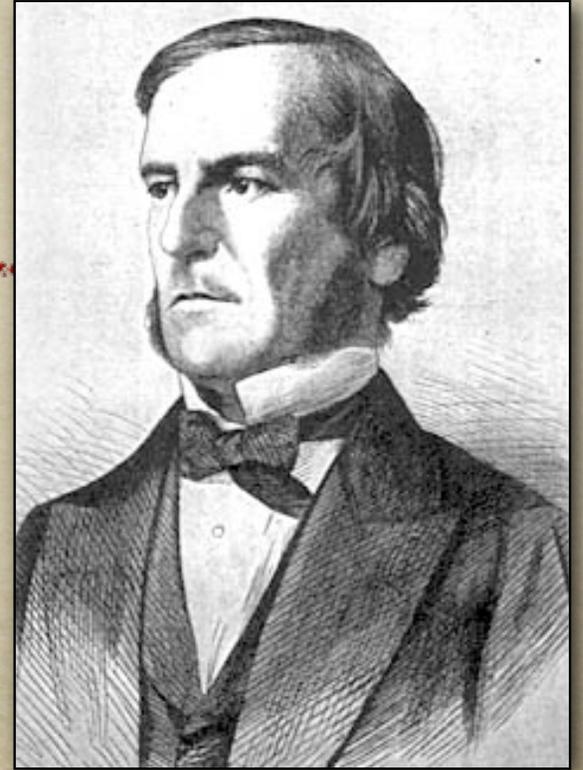
Logic

Why logic?

- *Search: for problems like 8-puzzle, can write compact description of rules*
- *Reasoning: figure out consequences of the knowledge we've given our agent*
- *Foreshadowing: logical inference is a special case of probabilistic inference (Part II)*

Propositional logic

- *Constants: T or F*
- *Variables: x, y (values T or F)*
- *Connectives: \wedge, \vee, \neg*
 - *Can get by w/ just NAND*
 - *Sometimes also add others:*
 $\oplus, \Rightarrow, \Leftrightarrow, \dots$



George Boole
1815–1864

Propositional logic

- *Build up expressions like $\neg x \Rightarrow y$*
- *Precedence: $\neg, \wedge, \vee, \Rightarrow$*
- *Terminology: variable or constant with or w/o negation = **literal***
- *Whole thing = **formula or sentence***

Expressive variable names

- *Rather than variable names like x , y , may use names like “rains” or “happy(John)”*
- *For now, “happy(John)” is just a string with no internal structure*
 - *there is no “John”*
 - *happy(John) \Rightarrow \neg happy(Jack) means the same as $x \Rightarrow \neg y$*

But what does it mean?

- *A formula defines a mapping*
(assignment to variables) $\mapsto \{T, F\}$
- *Assignment to variables = **model***
- *For example, formula $\neg x$ yields mapping:*

x	$\neg x$
T	F
F	T

More truth tables

x	y	$x \wedge y$
T	T	T
T	F	F
F	T	F
F	F	F

x	y	$x \vee y$
T	T	T
T	F	T
F	T	T
F	F	F

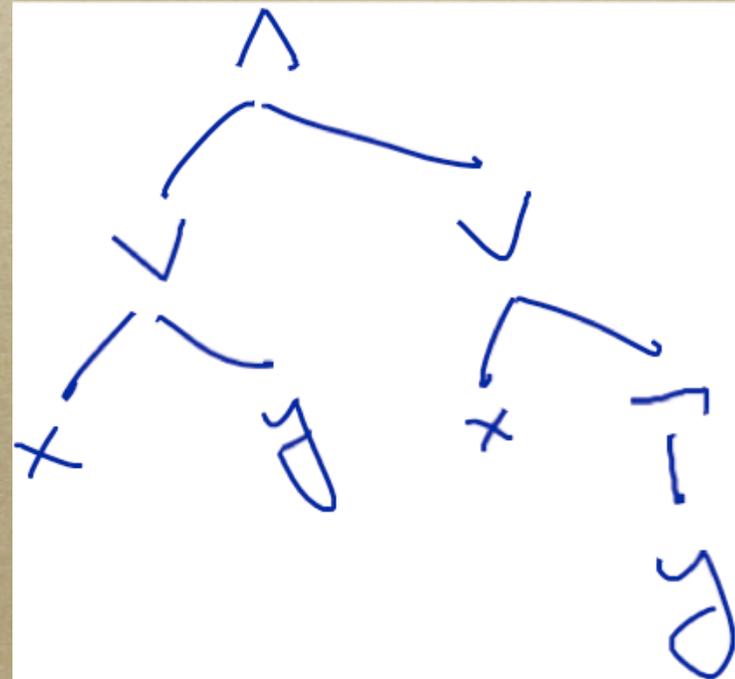
Truth table for implication

- $(a \Rightarrow b)$ is logically equivalent to $(\neg a \vee b)$
- If a is True, b must be True too
- If a False, no requirement on b
- E.g., “if I go to the movie I will have popcorn”: if no movie, may or may not have popcorn

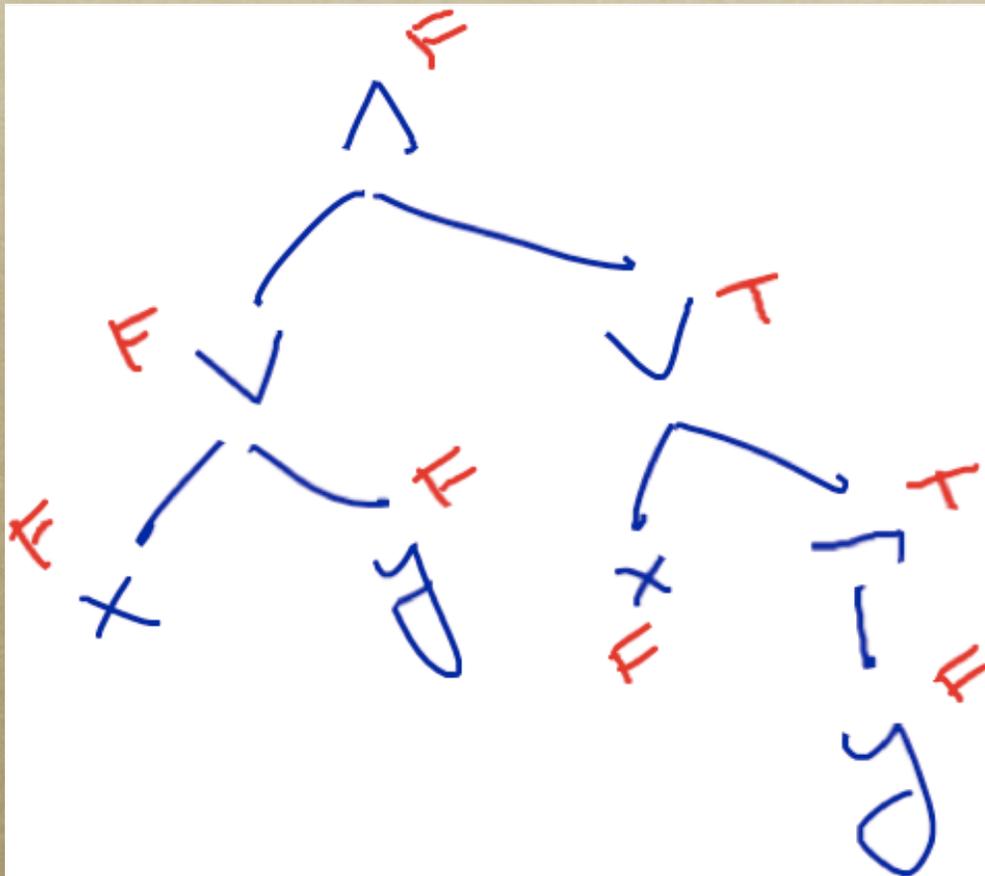
a	b	$a \Rightarrow b$
T	T	T
T	F	F
F	T	T
F	F	T

Complex formulas

- *To evaluate a bigger formula*
 - $(x \vee y) \wedge (x \vee \neg y)$ when $x = F, y = F$
- *Build a parse tree*
- *Fill in variables at leaves using model*
- *Work upwards using truth tables for connectives*



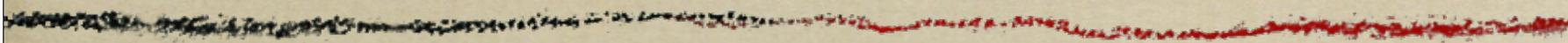
Example



- $(x \vee y) \wedge (x \vee \neg y)$ when $x = F, y = F$

Bigger truth tables

x	y	z	$(x \vee y) \Rightarrow z$
T	T	T	
T	T	F	
T	F	T	
T	F	F	
F	T	T	
F	T	F	
F	F	T	
F	F	F	



Working with formulas

Definitions

- *Two sentences are **equivalent**, $A \equiv B$, if they have same truth value in every model*
 - $(rains \Rightarrow pours) \equiv (\neg rains \vee pours)$
 - *reflexive, transitive, commutative*
- ***Simplifying** = transforming a formula into a shorter*, equivalent formula*

Transformation rules

$$(\alpha \wedge \beta) \equiv (\beta \wedge \alpha) \quad \text{commutativity of } \wedge$$

$$(\alpha \vee \beta) \equiv (\beta \vee \alpha) \quad \text{commutativity of } \vee$$

$$((\alpha \wedge \beta) \wedge \gamma) \equiv (\alpha \wedge (\beta \wedge \gamma)) \quad \text{associativity of } \wedge$$

$$((\alpha \vee \beta) \vee \gamma) \equiv (\alpha \vee (\beta \vee \gamma)) \quad \text{associativity of } \vee$$

$$\neg(\neg\alpha) \equiv \alpha \quad \text{double-negation elimination}$$

$$(\alpha \wedge (\beta \vee \gamma)) \equiv ((\alpha \wedge \beta) \vee (\alpha \wedge \gamma)) \quad \text{distributivity of } \wedge \text{ over } \vee$$

$$(\alpha \vee (\beta \wedge \gamma)) \equiv ((\alpha \vee \beta) \wedge (\alpha \vee \gamma)) \quad \text{distributivity of } \vee \text{ over } \wedge$$

α, β, γ are arbitrary formulas

More rules

$(\alpha \Rightarrow \beta) \equiv (\neg\beta \Rightarrow \neg\alpha)$ contraposition

$(\alpha \Rightarrow \beta) \equiv (\neg\alpha \vee \beta)$ implication elimination

$(\alpha \Leftrightarrow \beta) \equiv ((\alpha \Rightarrow \beta) \wedge (\beta \Rightarrow \alpha))$ biconditional elimination

$\neg(\alpha \wedge \beta) \equiv (\neg\alpha \vee \neg\beta)$ de Morgan

$\neg(\alpha \vee \beta) \equiv (\neg\alpha \wedge \neg\beta)$ de Morgan

α, β are arbitrary formulas

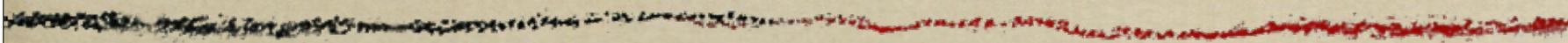
Still more rules...

- ... can be derived from truth tables
- For example:
 - $(a \vee \neg a) \equiv \text{True}$
 - $(\text{True} \vee a) \equiv \text{True}$
 - $(\text{False} \wedge a) \equiv \text{False}$

Example

$$(a \vee (b \wedge c)) \wedge \neg (b \wedge \neg e)$$

$$(a \vee b) \wedge (a \vee c) \wedge (\neg b \vee e)$$



Normal Forms

Normal forms

- *A normal form is a standard way of writing a formula*
- *E.g., conjunctive normal form (CNF)*
 - *conjunction of disjunctions of literals*
 - $(x \vee y \vee \neg z) \wedge (x \vee \neg y) \wedge (z)$
 - *Each disjunct called a **clause***
- *Any formula can be transformed into CNF w/o changing meaning*

CNF cont'd

$$\begin{aligned} & \text{happy}(\text{John}) \wedge \\ & (\neg \text{happy}(\text{Bill}) \vee \text{happy}(\text{Sue})) \wedge \\ & \text{man}(\text{Socrates}) \wedge \\ & (\neg \text{man}(\text{Socrates}) \vee \text{mortal}(\text{Socrates})) \end{aligned}$$

- *Often used for storage of knowledge database*
 - *called **knowledge base** or **KB***
- *Can add new clauses as we find them out*
- *Each clause in KB is separately true (if KB is)*

Another normal form: DNF

- *DNF = disjunctive normal form = disjunction of conjunctions of literals*
- *Doesn't compose the way CNF does: can't just add new conjuncts w/o changing meaning of KB*
- *Example:*

$$\begin{aligned} & (rains \vee \neg pours) \wedge fishing \\ & \equiv \\ & (rains \wedge fishing) \vee (\neg pours \wedge fishing) \end{aligned}$$

Transforming to CNF or DNF

- *Naive algorithm:*
 - *replace all connectives with $\wedge \vee \neg$*
 - *move negations inward using De Morgan's laws and double-negation*
 - *repeatedly distribute over \wedge over \vee for DNF (\vee over \wedge for CNF)*

Example

- *Put the following formula in CNF*

$$(a \vee b \vee \neg c) \wedge \neg(d \vee (e \wedge f)) \wedge (c \vee d \vee e)$$

Example

- *Now try DNF*

$$(a \vee b \vee \neg c) \wedge \neg(d \vee (e \wedge f)) \wedge (c \vee d \vee e)$$

Discussion

- *Problem with naive algorithm: it's exponential! (Space, time, size of result.)*
- *Each use of distributivity can almost double the size of a subformula*

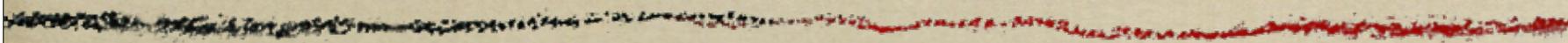
A smarter transformation

- *Can we avoid exponential blowup in CNF?*
- *Yes, if we're willing to introduce new variables*
- *G. Tseitin. On the complexity of derivation in propositional calculus. Studies in Constrained Mathematics and Mathematical Logic, 1968.*

Example

- *Put the following formula in CNF:*

$$(a \wedge b) \vee (c \wedge d)$$



Proofs

Entailment

- *Sentence A entails sentence B, $A \models B$, if B is True in every model where A is*
 - *same as saying that $(A \Rightarrow B)$ is valid*

Proof tree

- *A tree with a formula at each node*
- *At each internal node, children \models parent*
- *Leaves: assumptions or premises*
- *Root: consequence*
- *If we believe assumptions, we should also believe consequence*

Proof tree example

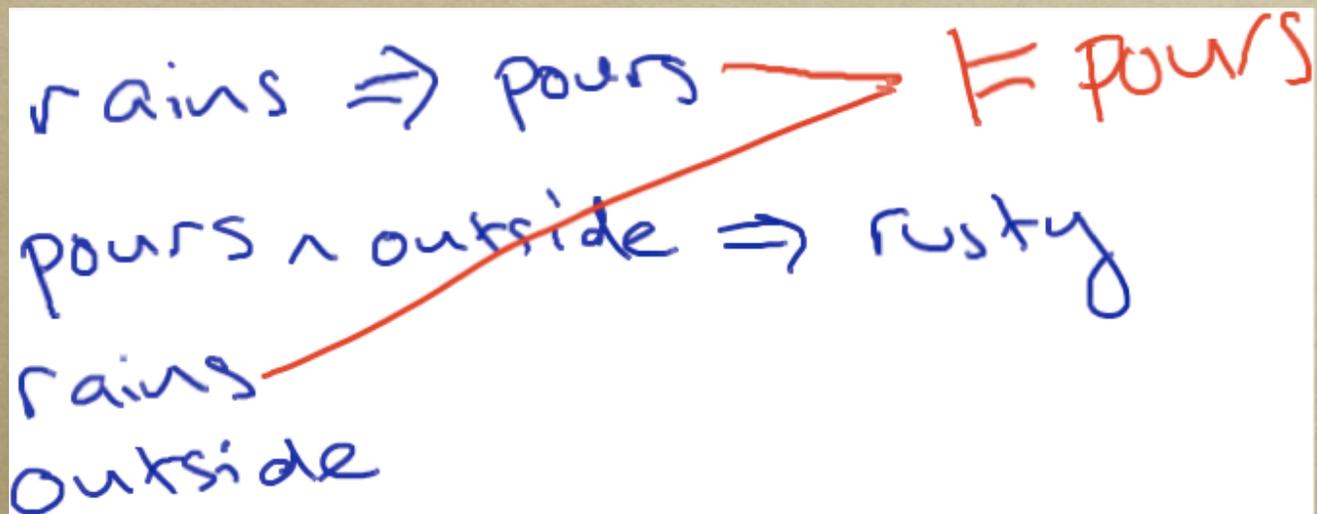
$r \text{ rains} \Rightarrow \text{pours}$

$\text{pours} \wedge \text{outside} \Rightarrow \text{rusty}$

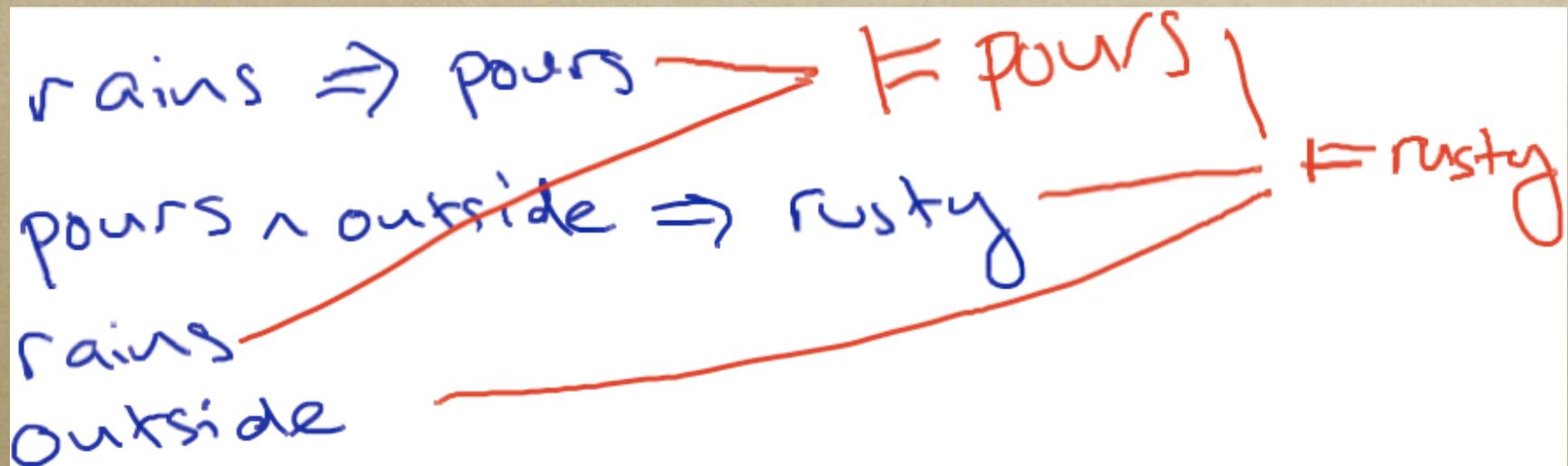
rains

outside

Proof tree example



Proof tree example



Proof by contradiction

- *Assume opposite of what we want to prove, show it leads to a contradiction*
- *Suppose we want to show $KB \models S$*
- *Write KB' for $(KB \wedge \neg S)$*
- *Build a proof tree with*
 - *assumptions drawn from clauses of KB'*
 - *conclusion = F*
 - *so, $(KB \wedge \neg S) \models F$ (contradiction)*

Proof by contradiction

KB

$\neg \text{rains} \Rightarrow \text{pours}$

$\text{pours} \wedge \text{outside} \Rightarrow \text{rusty}$

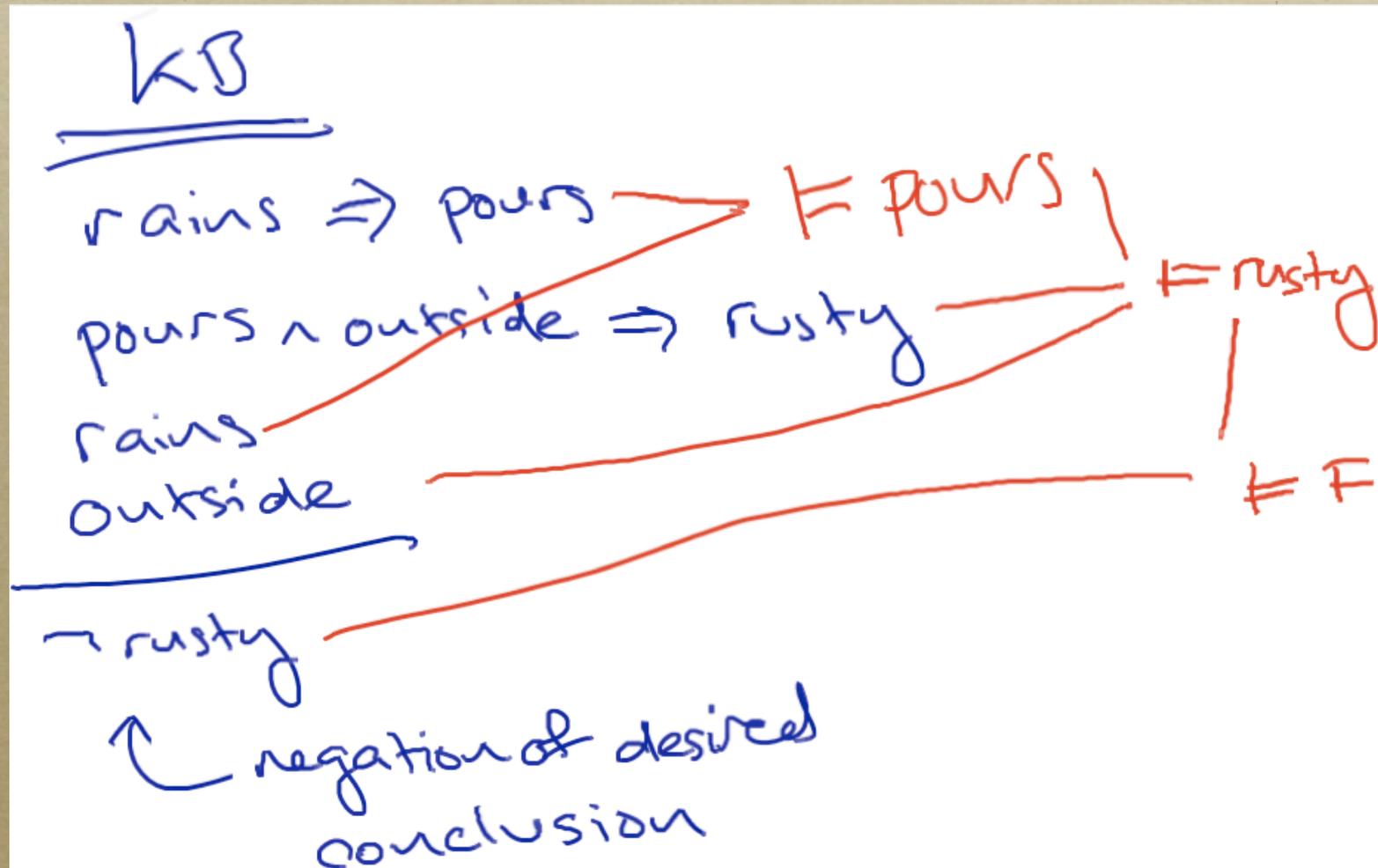
rains

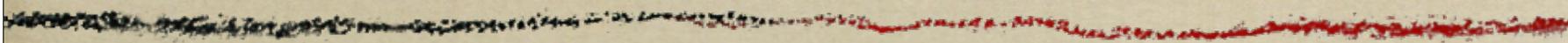
outside

$\neg \text{rusty}$

↖ negation of desired
conclusion

Proof by contradiction





Inference rules

Inference rule

- *To make a proof tree, we need to be able to figure out new formulas entailed by KB*
- *Method for finding entailed formulas = **inference rule***
- *We've implicitly been using one already*

Modus ponens

$$\frac{(a \wedge b \wedge c \Rightarrow d) \quad a \quad b \quad c}{d}$$

- *Probably most famous inference rule: all men are mortal, Socrates is a man, therefore Socrates is mortal*

- *Quantifier-free version:*

man(Socrates) \wedge

(man(Socrates) \Rightarrow mortal(Socrates))

Another inference rule

$$\frac{(a \Rightarrow b) \quad \neg b}{\neg a}$$

- *Modus tollens*
- *If it's raining the grass is wet; the grass is not wet, so it's not raining*

One more...

$$\frac{(a \vee b \vee c) (\neg c \vee d \vee e)}{a \vee b \vee d \vee e}$$

- ***Resolution***
- *Combines two sentences that contain a literal and its negation*
- *Not as commonly known as modus ponens / tollens*

Resolution example

- *Modus ponens / tollens are special cases*
- *Modus tollens:*
 $(\neg \textit{raining} \vee \textit{grass-wet}) \wedge \neg \textit{grass-wet} \models \neg \textit{raining}$

Resolution

$$\frac{(a \vee b \vee c) (\neg c \vee d \vee e)}{a \vee b \vee d \vee e}$$

- *Simple proof by case analysis*
- *Consider separately cases where we assign $c = \text{True}$ and $c = \text{False}$*

Resolution

$$(a \vee b \vee c) \wedge (\neg c \vee d \vee e)$$

◦ *Case $c = \text{True}$*

$$(a \vee b \vee T) \wedge (F \vee d \vee e)$$

$$= (T) \wedge (d \vee e)$$

$$= (d \vee e)$$

Resolution

$$(a \vee b \vee c) \wedge (\neg c \vee d \vee e)$$

- *Case $c = \text{False}$*

$$(a \vee b \vee F) \wedge (T \vee d \vee e)$$

$$= (a \vee b) \wedge (T)$$

$$= (a \vee b)$$

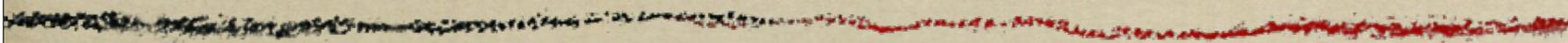
Resolution

$$(a \vee b \vee c) \wedge (\neg c \vee d \vee e)$$

- *Since c must be True or False, conclude*

$$(d \vee e) \vee (a \vee b)$$

as desired



Theorem provers

Theorem prover

- *Theorem prover = mechanical system for finding a proof tree*
- *An application of search techniques from earlier lecture*
 - *Search node = KB (including whatever we've proven so far)*
 - *Neighbor: $(KB \wedge S)$ if $KB \models S$*

A basic theorem prover

- *Given KB, want to conclude S*
- *Let $KB' = CNF(KB \wedge \neg S)$*
- *Repeat:*
 - *add new clause to KB' using resolution*
- *Until we add empty clause (False) and conclude $KB \models S$*
- *Or run out of new clauses and conclude $KB \not\models S$*

Soundness and completeness

- *An inference procedure is **sound** if it can only conclude things entailed by KB*
 - *common sense; haven't discussed anything unsound*
- *A set of rules is **complete** if it can conclude everything entailed by KB*

Completeness

- *Theorem provers based on modus ponens by itself are **incomplete***
- *Simple resolution theorem prover from above is **complete** for propositional logic*

Variations

- *Horn clause inference (faster)*
- *Ways of handling uncertainty (slower)*
- *CSPs (sometimes more convenient)*
- *Quantifiers / first-order logic*

Later

Horn clauses

- *Horn clause: $(a \wedge b \wedge c \Rightarrow d)$*
- *Equivalently, $(\neg a \vee \neg b \vee \neg c \vee d)$*
- *Disjunction of literals, **at most one** of which is positive*
- *Positive literal = **head**, rest = **body***

Use of Horn clauses

- *People find it easy to write Horn clauses (listing out conditions under which we can conclude head)*

$$\text{happy}(\text{John}) \wedge \text{happy}(\text{Mary}) \Rightarrow \text{happy}(\text{Sue})$$

- *No negative literals in above formula; again, easier to think about*

Why are Horn clauses important

- *Inference in a KB of propositional Horn clauses is linear*
- *E.g., by forward chaining*

Forward chaining

- *Look for a clause with all body literals satisfied*
- *Add its head to KB*
- *Repeat*
- *See RN for more details*

Handling uncertainty

- *Fuzzy logic / certainty factors*
 - *simple, but don't scale*
- *Nonmonotonic logic*
 - *also doesn't scale*
- *Probabilities*
 - *may or may not scale—more in Part II*

Certainty factors

- *KB assigns a certainty factor in $[0, 1]$ to each proposition*
- *Interpret as “degree of belief”*
- *When applying an inference rule, certainty factor for consequent is a function of certainty factors for antecedents (e.g., minimum)*

Problems w/ certainty factors

- *Hard to separate a large KB into mostly-independent chunks that interact only through a well-defined interface*
- *Certainty factors are not probabilities (i.e., do not obey Bayes' Rule)*

Nonmonotonic logic

- *Suppose we believe all birds can fly*
- *Might add a set of sentences to KB*

bird(Polly) \Rightarrow flies(Polly)

bird(Tweety) \Rightarrow flies(Tweety)

bird(Tux) \Rightarrow flies(Tux)

bird(John) \Rightarrow flies(John)

...

Nonmonotonic logic

- *Fails if there are penguins in the KB*
- *Fix: instead, add*

$bird(Polly) \wedge \neg ab(Polly) \Rightarrow flies(Polly)$

$bird(Tux) \wedge \neg ab(Tux) \Rightarrow flies(Tux)$

...

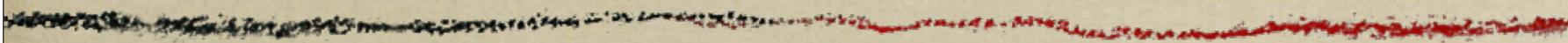
- *$ab(Tux)$ is an “abnormality predicate”*
- *Need separate $ab_i(x)$ for each type of rule*

Nonmonotonic logic

- *Now set as few abnormality predicates as possible*
- *Can prove $\text{flies}(\text{Polly})$ or $\text{flies}(\text{Tux})$ with no $\text{ab}(x)$ assumptions*
- *If we assert $\neg\text{flies}(\text{Tux})$, must now assume $\text{ab}(\text{Tux})$ to maintain consistency*
- *Can't prove $\text{flies}(\text{Tux})$ any more, but can still prove $\text{flies}(\text{Polly})$*

Nonmonotonic logic

- *Works well as long as we don't have to choose between big sets of abnormalities*
 - *is it better to have 3 flightless birds or 5 professors that don't wear jackets with elbow-patches?*
 - *even worse with nested abnormalities: birds fly, but penguins don't, but superhero penguins do, but ...*



SAT

Definitions

- *A sentence is **satisfiable** if it is True in some model*
- *If not satisfiable, it is a **contradiction** (False in every model)*
- *A sentence is **valid** if it is True in every model (a valid sentence is a **tautology**)*

Satisfiability

- *SAT is the problem of determining whether a given propositional logic sentence is satisfiable*
- *A **decision problem**: given an instance, answer yes or no*
- *A fundamental problem in CS*

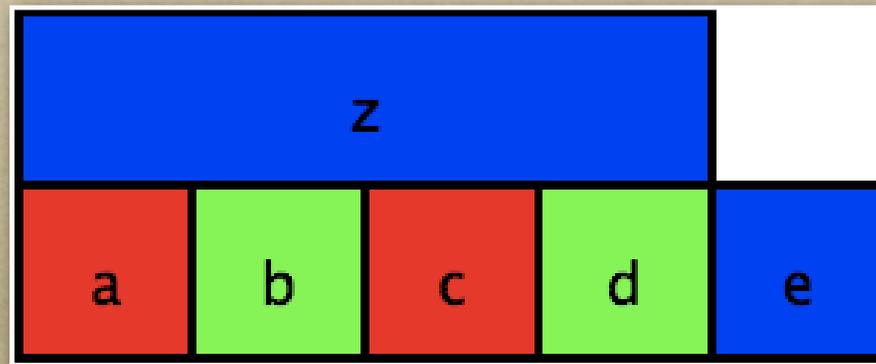
SAT is a search problem

- *(At least) two ways to write it*
 - *search nodes are (full or partial) models, neighbors differ in assignment for a single variable*
 - *search nodes are formulas, neighbors by entailment*
- *And hybrids (node = model + formula)*

SAT is a general search problem

- *Many other search problems **reduce to SAT***
- *Informally, if we can solve SAT, can solve these other problems*
- *So a good SAT solver is a good AI building block*

Example search problem



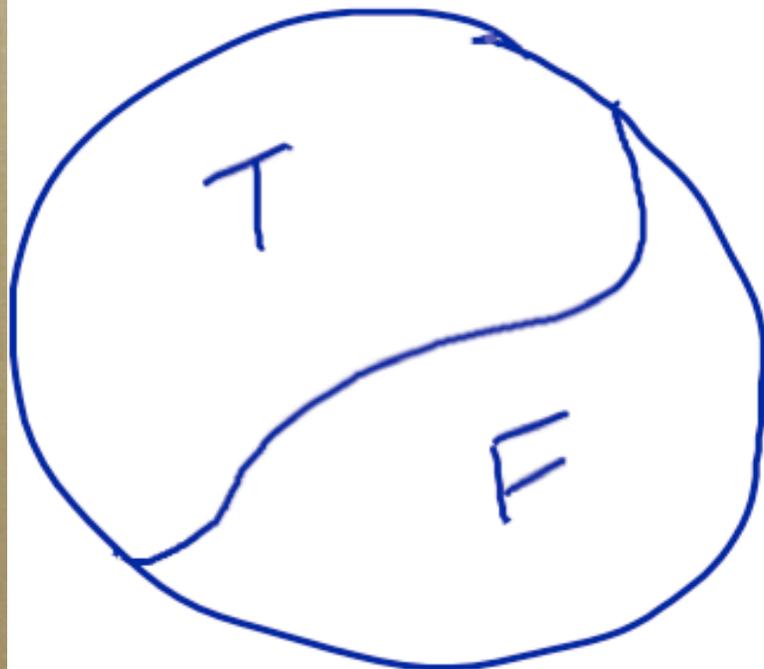
- *3-coloring: can we color a map using only 3 colors in a way that keeps neighboring regions from being the same color?*

Reduction

- *Loosely, “A reduces to B” means that if we can solve B then we can solve A*
- *More formally, A, B are decision problems (instances \mapsto truth values)*
- *A reduction is a poly-time function f such that, given an instance a of A*
 - *$f(a)$ is an instance of B, and*
 - *$A(a) = B(f(a))$*

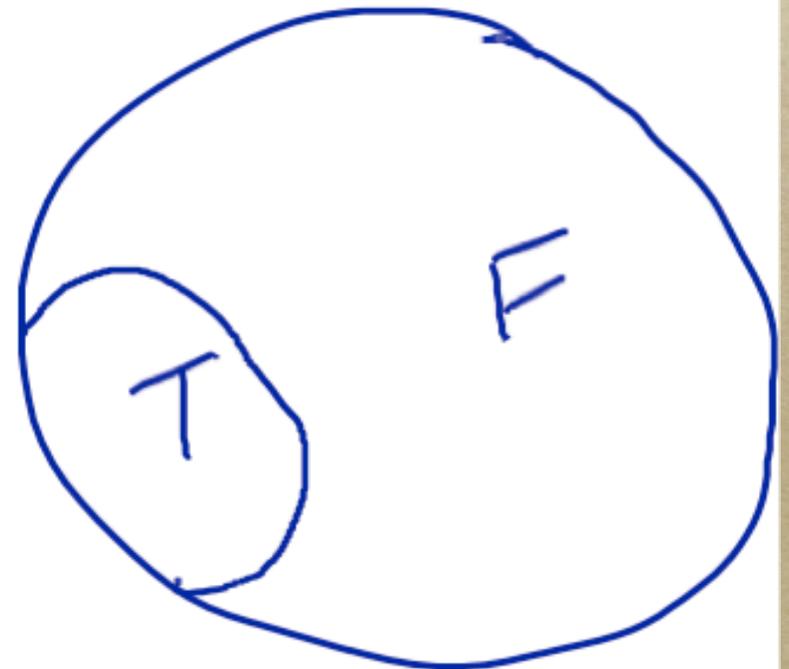
Reduction picture

Problem A



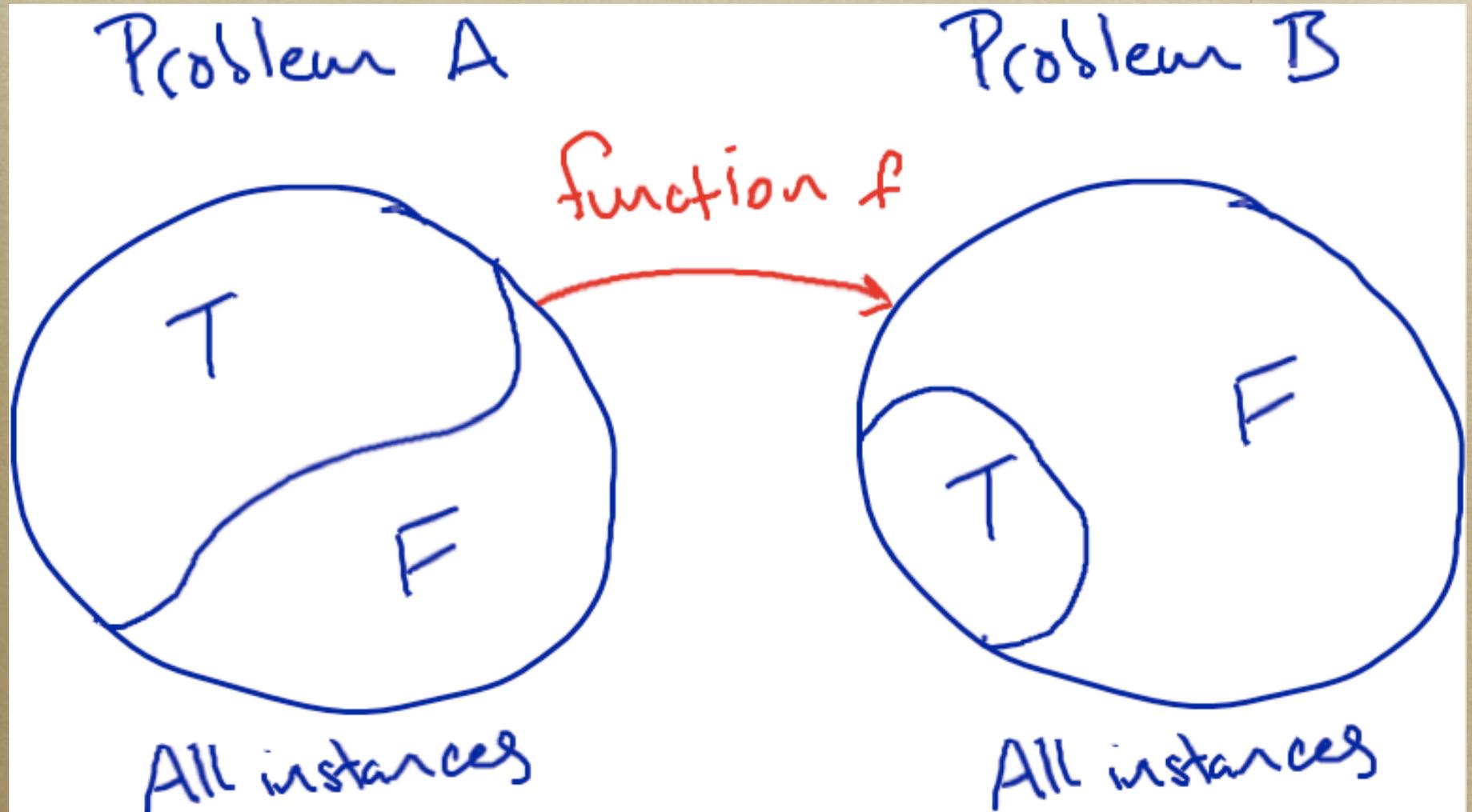
All instances

Problem B

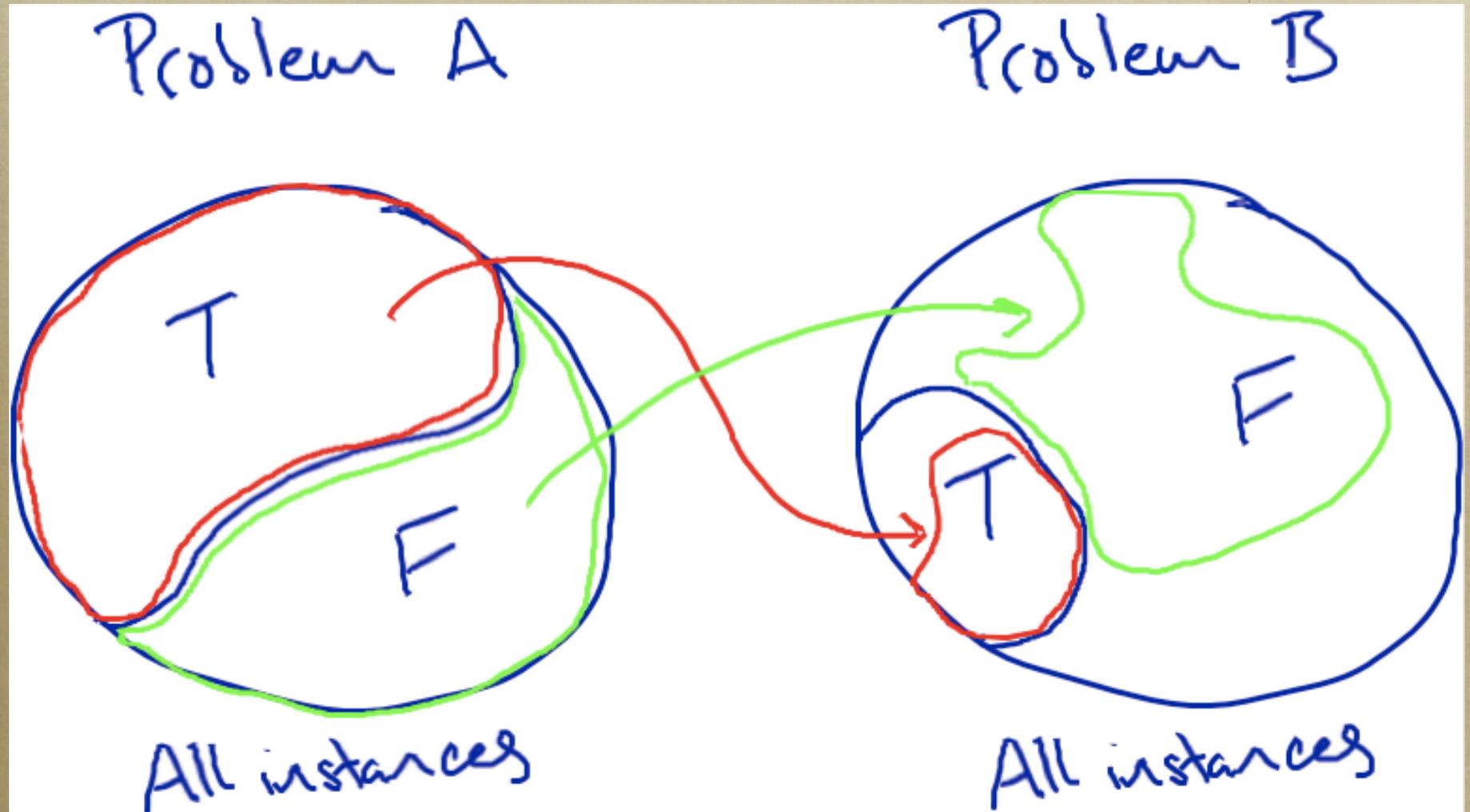


All instances

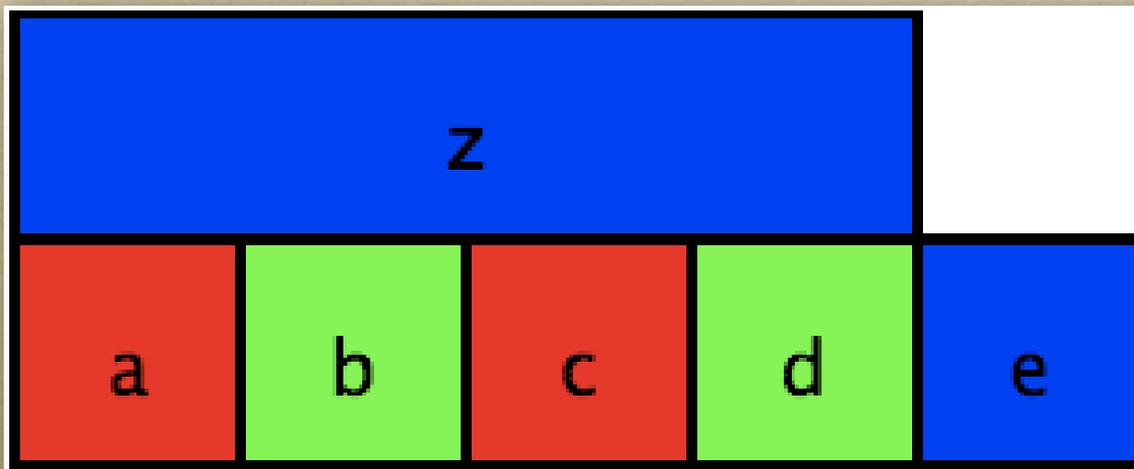
Reduction picture



Reduction picture



Example reduction



- *Each square must be red, green, or blue*
- *Adjacent squares can't both be red (similarly, green or blue)*

Example reduction

- $(a_r \vee a_g \vee a_b) \wedge (b_r \vee b_g \vee b_b) \wedge (c_r \vee c_g \vee c_b) \wedge (d_r \vee d_g \vee d_b) \wedge (e_r \vee e_g \vee e_b) \wedge (z_r \vee z_g \vee z_b)$
- $(\neg a_r \vee \neg b_r) \wedge (\neg a_g \vee \neg b_g) \wedge (\neg a_b \vee \neg b_b)$
- $(\neg a_r \vee \neg z_r) \wedge (\neg a_g \vee \neg z_g) \wedge (\neg a_b \vee \neg z_b)$
- ...

Search and reduction

- *S. A. Cook in 1971 proved that many useful search problems reduce back and forth to SAT*
 - *showed how to simulate poly-size-memory computer w/ (very complicated, but still poly-size) SAT problem*
- *Equivalently, SAT is exactly as hard (in theory at least) as these other problems*

Cost of reduction

- *Complexity theorists often ignore little things like constant factors (or even polynomial factors!)*
- *So, is it a good idea to reduce your search problem to SAT?*
- *Answer: sometimes...*

Cost of reduction

- *SAT is well studied \Rightarrow fast solvers*
- *So, if there is an efficient reduction, ability to use fast SAT solvers can be a win*
 - *e.g., 3-coloring*
 - *another example later (SATplan)*
- *Other times, cost of reduction is too high*
 - *usu. because instance gets bigger*
 - *will also see example later (MILP)*

Choosing a reduction

- *May be many reductions from problem A to problem B*
- *May have **wildly** different properties*
 - *e.g., search on transformed instance may take seconds vs. days*

Direction of reduction

- *If A reduces to B then*
 - *if we can solve B, we can solve A*
 - *so B must be at least as hard as A*
- *Trivially, can take an easy problem and reduce it to a hard one*

Not-so-useful reduction

- *Path planning reduces to SAT*
- *Variables: is edge e in path?*
- *Constraints:*
 - *exactly 1 path-edge touches start*
 - *exactly 1 path-edge touches goal*
 - *either 0 or 2 touch each other node*

Reduction to 3SAT

- *We saw that search problems can be reduced to SAT*
 - *is CNF formula satisfiable?*
- *Can reduce even further, to 3SAT*
 - *is 3CNF formula satisfiable?*
- *Useful if reducing SAT/3SAT to another problem (to show other problem hard)*

Reduction to 3SAT

- *Must get rid of long clauses*
- *E.g., $(a \vee \neg b \vee c \vee d \vee e \vee \neg f)$*
- *Replace with*

$$(a \vee \neg b \vee x) \wedge (\neg x \vee c \vee y) \wedge (\neg y \vee d \vee z) \wedge (\neg z \vee e \vee \neg f)$$