The SAT Phase Transition

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Abstract: We describe a detailed experimental investigation of the phase transition for several different classes of randomly generated satisfiability problems. We observe a remarkable consistency of features in the phase transition despite the presence in some of the problem classes of clauses of mixed lengths. For instance, each of the problem classes considered has a sharp transition from satisfiable to unsatisfiable problems at a critical value. In addition, there is a common easy-hard-easy pattern in the difficulty of the problems, with the hardest problems being associated with the phase transition. However, the difficulty of problems of mixed clause lengths is much more variable than that of fixed clause length. Indeed, whilst the median difficulty of random problems of mixed clause lengths can be orders of magnitude easier than that of equivalently sized problems of fixed clause length, the hardest problems of mixed clause lengths can be orders of magnitude harder than the hardest equivalently sized problems of fixed clause length. Such very hard random problems may be of considerable practical and theoretical use in analysing algorithm performance.

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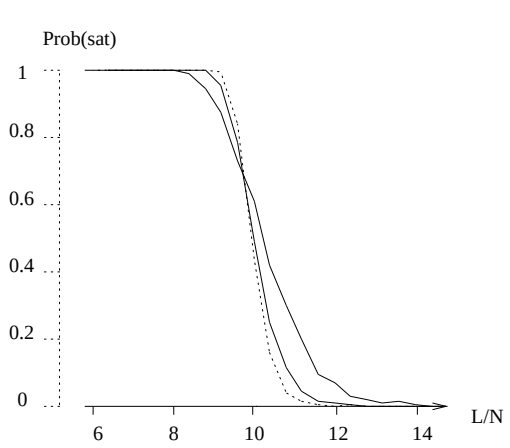
1 Introduction

Propositional satisfiability (SAT) is the problem of deciding if there is an assignment for the variables in a propositional formula that makes the formula true. SAT is of considerable practical interest as many AI tasks can be encoded quite naturally in SAT. Unfortunately, unless P=NP, SAT is intractable in the worst case as it is a NP-hard problem. There are, however, many theoretical and experimental results which show good average-case performance for certain classes of SAT problems [10, 7]. In considering such average-case results, it is important to know whether the problems considered are hard and representative of those met in practice. Cheeseman et al [1] observed that the hard instances of NP-hard problems are often associated with a phase transition. With SAT, there is a phase transition as the ratio of the number of clauses to variables in a problem is varied. Experiments have shown that an easy-hard-easy pattern for SAT occurs as this ratio is increased and that the hard instances occur in the phase transition [15]. The phase transition for SAT is therefore of considerable practical and theoretical importance.

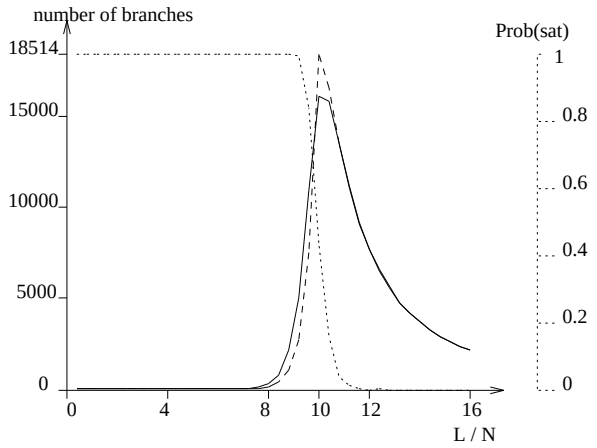
In this paper, we present a detailed experimental investigation of the SAT phase transition. We consider several different classes of SAT problems, some of which (like real problems) contain clauses of mixed lengths. We observe a remarkable consistency of features in the different phase transitions. For example, all the problem classes show an easy-hard-easy pattern, a region of highly variable problem difficulty, and a sharp transition from satisfiable to unsatisfiable at a fixed ratio of clauses to variables. Random problems of mixed clause lengths appear, however, to give much more variable behaviour. The median difficulty of random problems of mixed clause is typically orders of magnitude less than that of equivalently sized problems of fixed clause length, yet the hardest problems of mixed clause lengths can be orders of magnitude *harder* than the hardest problems of fixed clause length. With random problems of mixed clause lengths, certain key properties like the position of the phase transition also appear to be governed merely by a simple parameter, the (limiting) distribution of clause lengths in the problem class. The phase transition observed for random 3-SAT [15] thus appears to be a special case of a more general type of SAT phase transition.

2 Random k-SAT

We consider SAT problems in conjunctive normal form (CNF); a formula, Σ is in CNF iff it is a conjunction of clauses, where a clause is a disjunction of literals, and a literal is a negated or un-negated variable. A problem in random k-SAT consists of L clauses, each of which has k literals chosen uniformly from the N possible variables and the N possible negated variables. We use $R_k(\mathrm{N}, \mathrm{L})$ to denote problems drawn from this class and $Prob(sat, X)$ to denote the probability that a problem drawn at random from the class X is satisfiable.



(a) $Prob(sat)$, N = 25, 50, 75



(b) mean (solid), median (dashed) branches , N = 75

Figure 1: random 4-SAT problems, tested using ASAT

Most recent experimental work has used the random k-SAT model as it has several features which makes it useful for benchmarks. First, there appears to be a phase transition between satisfiability and unsatisfiability as L/N is varied. That is, there seems to be a critical limiting value of L/N, which we call c_k such that,

$$\lim_{\mathrm{N}\to\infty} Prob(sat, R_k(\mathrm{N}, c.\mathrm{N})) \;=\; \begin{cases} 0 & \text{for } c > c_k \\ 1 & \text{for } c < c_k. \end{cases}$$

It is easy to show that $c_0 = c_1 = 0$. It has been shown theoretically that $c_2 = 1$ [2, 9] and $3.003 < c_3 < 4.81$. Experiments have suggested that $c_3 \approx 4.24$ [4]. Second, this phase transition appears to be of practical value as, for a given N, problems with c_k.N clauses seem to be the hardest problems generated for a wide variety of SAT algorithms [15]. This result needs to be treated with slight caution since it has not been shown theoretically, and since problems away from the phase transition can also be hard to solve. For example, all resolution algorithms need exponential time with probability tending to 1 for random 3-SAT problems generated with $c > 5.6$ [3].

Figure (1) shows a typical random k-SAT phase transition. For N= 25, 50, 75, we tested 1000 randomly generated 4-SAT problems at each point from L/N = 0 to 16 in steps of 0.4. The graph of observed probability of satisfiability is similar with varying N, except that the transition from near 100% satisfiable to near 0% becomes sharper with increasing N. (The dotted graph represents N= 75.) Interestingly, there appears to be a "crossover" point at which approximately the same percentage of problems is satisfiable for all values of N. Such a point has been observed in 3-SAT at L/N $\approx$ 4.2 , with about 66% satisfiable [14]. To examine this in more detail for 4-SAT we tested 1000 problems from 9N to 12N clauses, at intervals of N/25 clauses, for N= 25, 50, 75. The most consistent point

appeared to be at 9.76N clauses at a probability of 65% satisfiable.

To determine satisfiability and problem difficulty, we use two variants of the Davis-Putnam procedure [5]. The major difference between these variants is their choice of variable upon which to branch.[1] For small problems, we use a simple variant used in previous studies [15] which branches on the first variable in the first clause. We shall refer to this variant as "DP". For larger problems, we use ASAT [6] which branches on the variable having the greatest number of occurrences in the shortest clauses. ASAT is one of the fastest implementations of the Davis-Putnam procedure currently distributed.

Figure (1) (b) shows a typical "easy-hard-easy" pattern in problem difficulty for 4-SAT using the ASAT procedure. The y-axis gives the mean and median (to the same scale) number of branches reported by ASAT. When L/N is large, problems are usually over-constrained, and thus easily shown to be unsatisfiable. When L/N is small, problems are usually under-constrained, and a satisfying assignment can be "guessed" quickly. The really hard instances tend to occur at the phase transition where the problems are finely balanced between being satisfiable and unsatisfiable. Note that mean and median behaviour are very similar.

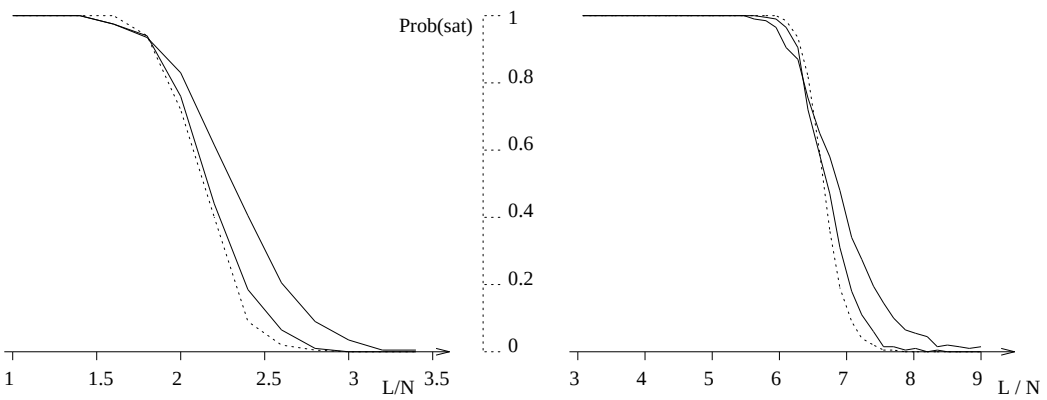
3 Random mixed SAT

We now introduce a generalisation of the random k-SAT model, which we call "random mixed SAT". In this model, a set of clauses is generated with respect to a probability distribution ϕ on the integers. Each clause is generated as in random k-SAT. However, k, the length of the clause, is chosen randomly according to ϕ. For example, if $\phi(2) = \phi(3) = \frac{1}{2}$, then clauses of length 2 and 3 appear with probability $\frac{1}{2}$, whilst if $\phi(2) = \frac{1}{3}$ and $\phi(4) = \frac{2}{3}$, clauses of length 2 appear with probability $\frac{1}{3}$ and of length 4 with probability $\frac{2}{3}$. In this paper, we will call these problem classes "2-3-SAT" and "2-4-4-SAT" respectively. The frequency of occurrence of an integer in the name reflects the frequency of occurrence of clauses of this length in the problem. Random k-SAT is a special case of random mixed SAT, where each clause is chosen of length k with probability 1.

The random mixed SAT model may generate problems more similar to real-world problems than random k-SAT. For example, many structured problem classes use clauses of mixed lengths (*eg.* scheduling problems have large numbers of binary clauses). It would therefore be interesting to compare such problems with random mixed SAT problems with a similar proportion of clauses of mixed lengths.

We write c_ϕ for the critical value of L/N for a given random mixed SAT (if such a value exists). Note that if $\phi(0) > 0$ or $\phi(1) > 0$, then we know that $c_\phi = 0$, as empty and unit clauses will occur, $c_0 = c_1 = 0$. Henceforth we assume that $\phi(0) = \phi(1) = 0$. Although we cannot prove the value of c_ϕ in other cases, it is

[1] When a clause cannot be simplified, the branch rule choses a variable to perform a case-split upon.



(a) X = 2-3-SAT N= 50, 100, 150 (b) X = 3-4-SAT N= 25, 50, 75

Figure 2: Prob(sat,R_X(N, c.N))

at least simple to give an upper bound on its value if it exists. For a given ϕ, we define the *density* of ϕ, d_ϕ as:

$$d_\phi =_{def} \sum_{k=2}^{\infty} \phi(k)(1 - (\frac{1}{2})^k)$$

The density, d_ϕ gives the mean fraction of all truth assignments that are inconsistent with any given clause generated by ϕ. The expected number of models of a clause set with N variables and L clauses is $2^N(d_\phi)^{\mathrm{L}}$. As a satisfiable formula has at least one model, if the expected number of models goes to 0, then so does the probability of satisfiability. Hence the probability of satisfiability goes to 0 as $N \to \infty$ if $c > -1/\log_2(d_\phi)$. And thus,

$$c_\phi < \frac{-1}{\log_2(d_\phi)}. \tag{1}$$

For k-SAT this bound appears to increase in accuracy with k. For $k = 2$, the bound gives $c_2 < 2.41$, but it is known that $c_2 = 1$. For c_3, we get $c_3 < 5.20$ while it is believed $c_3 \approx 4.24$, and our experiments suggest $c_4 \approx 9.76$ while the bound gives $c_4 < 10.75$.

For random 2-3-SAT, we get $d_\phi = \frac{13}{16}$, giving a bound $c_\phi < 3.34$. In our exploration of the phase transition, this gives a useful upper bound on how far experiments need be performed. Figure (2) shows how the probability of satisfiability varies with the ratio of clauses to variables. For N= 50, 100, 150, experiments were performed with L varying in steps of 0.2N, from 0 to 3.4N. The higher values of N are characterised by a sharper transition, the dotted line being N= 150. It can be seen that, as for random k-SAT, the probability graphs seem to be converging on some limit. There is again a crossover, but at a high percentage satisfiability.

To investigate this further, we performed a more detailed investigation of the crossover region. For values of N from 50 to 150 in steps of 10, and from 150 to 350 in steps of 50, we tested 500 problems at values of L from 1.3N to 2N, in steps of at most N/50. Analysis of the data suggests that the crossover appears close to 94% satisfiable and L = 1.75N, where we take the crossover to be where we observe the smallest difference in the probability of satisfiability. By contrast, the ratio L/N where 50% of problems were satisfiable declined from 2.32 for N= 50 to 2.08 for N= 200.

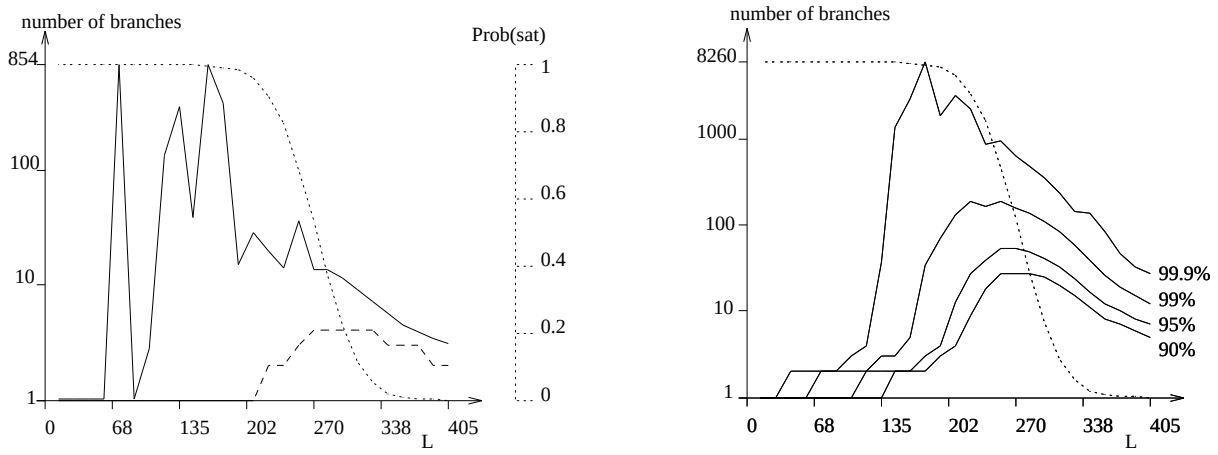
For random 3-4-SAT, we get $d_\phi = \frac{29}{32}$, giving $c_\phi < 7.05$. Figure (2) (b) shows Prob(sat,R_{3-4}(N, c.N)). For N = 25, 50, 75, we varied c from 0.2 to 9 in steps of 0.2, performing 1000 experiments at each point. The dotted line represents N = 75.

For random 2-4-4-SAT, we get $d_\phi = \frac{7}{8}$, the same as 3-SAT, giving $c_\phi < 5.20$. Once again, a similar pattern is observed when graphs of probability are plotted. However, the crossover appears at quite a different point compared to 3-SAT. For values of N from 50 to 130 in steps of 10, we tested 500 problems at values of L from 2.3N to 3.3N, in steps of at most N/25. The crossover point appears to be about L = 2.74N where 96% of problems are satisfiable. By contrast the 50% satisfiable point ranged from 3.78N at N= 50 to 3.48N at N= 150. This suggests an estimate for c_ϕ of 2.74.

4 Problem Hardness

The identification of phase transitions is of considerable importance in the study of heuristics for NP-hard problems since the hardest instances of randomly generated problems tend to occur in the phase transition. As observed in [15] for random 3-SAT, the hardest random k-SAT problems appear to occur in the transition between satisfiability and unsatisfiability. This is seen very clearly for random 4-SAT in Figure (1) (b).

Random mixed 2-4-4-SAT gives very different behaviour to 4-SAT. For example, Figure (3) (a) shows the median and mean problem difficulty for 2-4-4-SAT, using DP without branching heuristics. There is very little relation between mean and median problem difficulty. Median problem difficulty shows a slight easy-hard-easy pattern, though the peak median difficulty was only 4 branches. Mean behaviour is exceptionally noisy, even though each data point represents the mean of 10,000 experiments, and we have plotted the *log* of the mean, compared to the straight mean for 4-SAT. This behaviour is clarified by Figure (3) (b) which shows contours of the difficulty of problems representing percentiles from 90% to 99.9%. Again a *log* plot has been used. Hard problems are still associated with the transition but the hardest problems no longer occur around the 50% satisfiable point. The most difficult problems can be either satisfiable or unsatisfiable, and occur at high percentage satisfiability. Similar behaviour has been observed by Hogg and Williams for randomly generated 3-colourability problems



(a) mean (solid) and median (dashed) branches, (b) varying percentile branches

Figure 3: random 244-SAT problems tested using DP, N= 75 (note log scale)

[11]. The distribution of problem difficulties for 2-4-4-SAT is very different to that for 4-SAT as the following table illustrates.

	procedure	peak median	peak mean	worst case
4-SAT at N=75	ASAT	18,514	16,154	46,342
2-4-4-SATat N=75	DP	4	854	8,370,495

The difference between hardness of 4-SAT and 2-4-4-SAT does not seem to be caused merely by the use of two different procedures. For example, though ASAT finds all 2-4-4-SAT problems at N= 75 easy, at N= 300 it needed more than 3,000,000 branches for one satisfiable problem in a region of high percentage satisfiability while needing less than 100 branches for almost all other problems. Experiments with other random mixed SAT problems and other procedures also show that the hardest problems with mixed clause lengths can be orders of magnitude harder than the hardest problems with a fixed clause length, and that these hard problems tend to occur in regions of high percentage satisfiability.

5 Constant Probability Model

Another common problem class which gives clauses of mixed lengths is the constant probability model. This class has also been the subject of much theoretical attention. In the constant probability model, clauses with N variables and L clauses are generated according to a parameter p, $0 < p \leq 1$. For each clause, each literal (that is, a variable or the negation of a variable) is included with probability p, independently of the inclusion of other literals. In particular, the empty clause is allowed. Our experiments use a variant of the constant probability model

proposed in [12] in which if a clause is generated containing either *no* literals or only *one* literal, it is discarded and another clause generated in its place. This is because the inclusion of empty or unit clauses typically makes problems easier. We shall call this the "CP" model.

This model cannot strictly be seen as an example of a random mixed SAT, because the probability of a given clause length being chosen varies with N. However, we observe very similar effects to those seen with random mixed SAT, provided that we omit empty and unit clauses, and provided that we fix the value $2Np$ and so vary p as $1/N$. This keeps the expected clause length nearly constant. Indeed, for any given value of $2Np$, this gives a limiting distribution of clause lengths determined by the Poisson distribution with parameter $2Np$ (adjusted for the omission of clauses of length 0 and 1.) For comparatively small values of $2Np$, such as $2Np = 3$, we get quite fast convergence, as we are approximating the true binomial distribution of clause lengths by the Poisson. For example, for N= 25, the true probability of length 3 clauses is 28.5%, while the Poisson model would give a probability of 28.0%.

For the Poisson approximation to the constant probability model with parameters N and p, we have by definition,

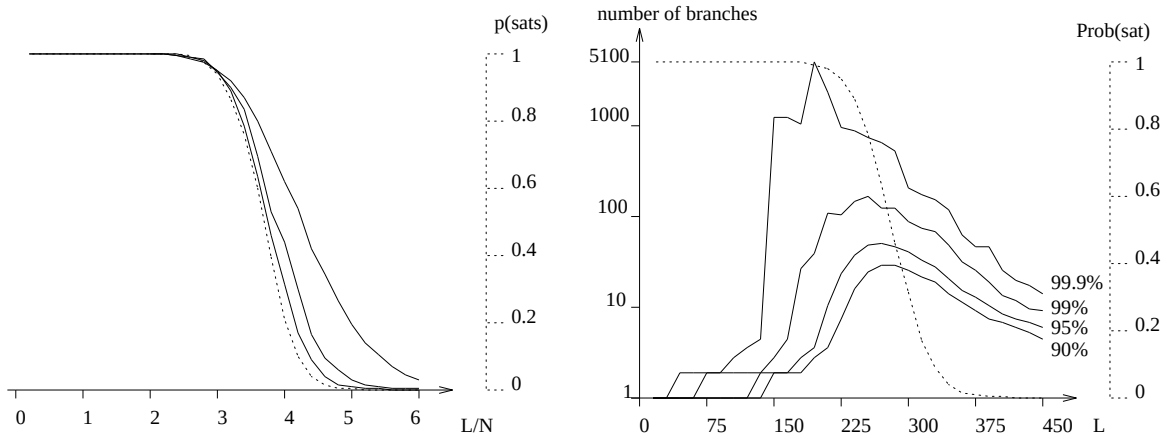
$$\phi(k) = e^{-2Np}(2Np)^k/k!$$

We can derive an expression for the density d_ϕ. If empty and unit clauses are allowed, straightforward manipulation gives $1 - d_\phi = e^{-Np}$. If we omit empty and unit clauses, this must be adjusted as follows:

$$1 - d_\phi = \frac{e^{-Np} - \phi(0) - \frac{1}{2}\phi(1)}{1 - \phi(0) - \phi(1)}$$

As an example, if we choose $2Np = 3$, we get $d_\phi \approx 0.877$, a value close to the density of 3-SAT, 0.875.

The observations we have made earlier seem equally to apply to the CP model. In particular, if $2Np$ is kept constant, graphs of probability of satisfiability show the same features, Figure (4) (a). It seems that $c_\phi \approx 2.80$. Very interestingly, the distribution of problem difficulty in Figure (4) (b) is similar to the very variable distribution also seen in Figure (3) (b). Again, we use the log of different percentile branches, with each data point representing the result over 5000 problems. As with random mixed SAT, the hardest problems in the CP model can be orders of magnitude harder than the hardest equivalently sized problems of fixed clause length; these hard problems again tend to occur in regions of high percentage satisfiability. By comparison, the median displays a simple easy-hard-easy pattern. In [8], we give further experimental analysis to show that this highly variable and hard behaviour cannot be eliminated by the use of better heuristics. We conjecture that this hardness arises from hard unsatisfiable problems in a region of otherwise satisfiable problems, or satisfiable problems which give hard unsatisfiable subproblems.



(a) p(sats), N = 25, 50, 75, 100 (b) percentile branches, N= 75, DP

Figure 4: Constant Probability Model, 2N$p = 3$

6 Conjectures about the Crossover

We have presented experimental evidence to show that many features of the phase transition for random k-SAT are also present in random mixed SAT and in the CP model. Our experiments suggest that for any distribution ϕ of clause lengths, there is a critical value c_ϕ. In §3, we gave an upper bound on c_ϕ in terms of d_ϕ, the density. In this section, we derive further bounds and conjecture an estimate for c_ϕ in terms of c_k.

For any k, if we have $c.\phi(k) > c_k$, then certainly $c > c_\phi$. This immediately gives us that,

$$c_\phi \leq \max_{k=2}^{\infty} \frac{c_k}{\phi(k)}. \tag{2}$$

For example, for 2-3-SAT, this gives us $c_\phi \leq c_2/\frac{1}{2} = 2$ and for 2-4-4-SAT, $c_\phi \leq c_2/\frac{1}{3} = 3$. These are tighter bounds than those obtained earlier by consideration of the density. Furthermore, they show that the value of c_ϕ cannot be determined by d_ϕ alone, as 3-SAT and 2-4-4-SAT have the same density, but it is known theoretically that $c_3 > 3$, contradicting $c_\phi \leq 3$ for 2-4-4-SAT.

For an easy lower bound on c_ϕ, we can observe that certainly $c_\phi \geq \min_{\phi(k)>0} c_k$. Unfortunately this bound takes no account of $\phi(k)$ except in being non-zero. Thus for both 2-3-SAT and 2-4-4-SAT we derive only $c_\phi \geq c_2 = 1$.

Neither of the above bounds, or the bound obtained earlier, give good predictions for c_ϕ in the cases we have tested. We would like to have a formula for c_ϕ in terms of ϕ and its constituent c_k. An intuitively appealing possibility is that c_ϕ is given by the weighted parallel sum of the constituent c_k, that is

$$\frac{1}{c_\phi} = \sum_{k=2}^{\infty} \frac{\phi(k)}{c_k}. \tag{3}$$

The intuition behind this conjecture is that c_k.N clauses of length k are "equivalent" in terms of preventing a truth assignment being a model as c_2.N binary clauses. Thus, as $c_2 = 1$, a clause of length k is c_k times less effective at filtering out models as a binary clause. At the crossover, there are c_ϕ.N clauses of which $\phi(k).c_\phi$.N are of length k. These clauses contribute to defeating possible models the same as $\phi(k).c_\phi.\mathrm{N}/c_k$ binary clauses. In total, we need an effective contribution from all clauses which is the same as the combined effect of N binary clauses. Thus,

$$\frac{\phi(2).c_\phi.\mathrm{N}}{c_2} + \frac{\phi(3).c_\phi.\mathrm{N}}{c_3} + \frac{\phi(4).c_\phi.\mathrm{N}}{c_4} + \ldots = \mathrm{N}$$

That is,

$$\frac{1}{c_\phi} = \phi(2) + \frac{\phi(3)}{c_3} + \frac{\phi(4)}{c_4} + \ldots$$

A physical analogy is that of electrical resistance. A set of clauses of length k offer some "resistance" to whether a truth assignment is a model. The total resistance of a mixed SAT problem is the "sum" of the resistances of the sets of clauses of different lengths. We take the parallel sum since a truth assignment can be defeated by any of the sets independently. Thus, we are governed (as with electrical resistance) by the set of clauses which offers the least resistance.

This conjecture obeys all the firm bounds derived in this paper, very easily the two bounds derived in this section. Some tedious manipulation shows that the parallel sum also obeys the bound given by (1). Furthermore, the values it predicts seem to be close to those derived earlier in this paper from our experimental analysis. Using the values, $c_2 = 1, c_3 \approx 4.24$, $c_4 \approx 9.76$, we get the following results.

	Predicted c_ϕ	Observed c_ϕ
2-3-SAT	1.62	1.76
3-4-SAT	5.91	5.88
2-4-4-SAT	2.49	2.74
CP	2.67	2.80

For calculating c_ϕ for CP, we approximate c_k for $k \geq 5$ using (1); given the small number of longer clause lengths and the increasing accuracy of the density bound, this should give a good approximation. The slight error between observed and predicted c_ϕ might be explained by interactions between clauses of different lengths.

7 Conjectures about Scaling

Phase transitions occur frequently in natural systems. One of the most unusual and theoretically interesting systems is that of spin glasses. Each of the N atoms in a spin glass has a magnetic spin which can have only one of two values, "up'

or "down" (1 or -1). The system therefore has 2^{N} possible configurations. Macroscopic properties of a configuration (*eg.* the energy, entropy) depend only on interactions between the spins of nearest neighbours. Due to the differences in separation of the atoms, some of these interactions are ferromagnetic (promoting alignment of spins) whilst others are anti-ferromagnetic (promoting opposite spins). The net effect is a random force leading to a large number of equilibrium configurations. An analogy can be profitably made between such spin glasses and random k-SAT. Each of the N variables in a truth assignment has one of two values, "True" or "False". The system therefore has 2^{N} possible configurations. Macroscopic property like satisfiability depend only on the interaction between variables neighbouring each other in a clause. Due to the random polarities of these variables, the net effect on a variable is a random "preference" towards True or False. Kirkpatrick, Cyürgyi, Tishby and Troyansky have used this analogy to suggest a fascinating scaling result for random k-SAT (personal communication). They propose that for random k-SAT, there is a fundamental function f, and values α_c and v, such that

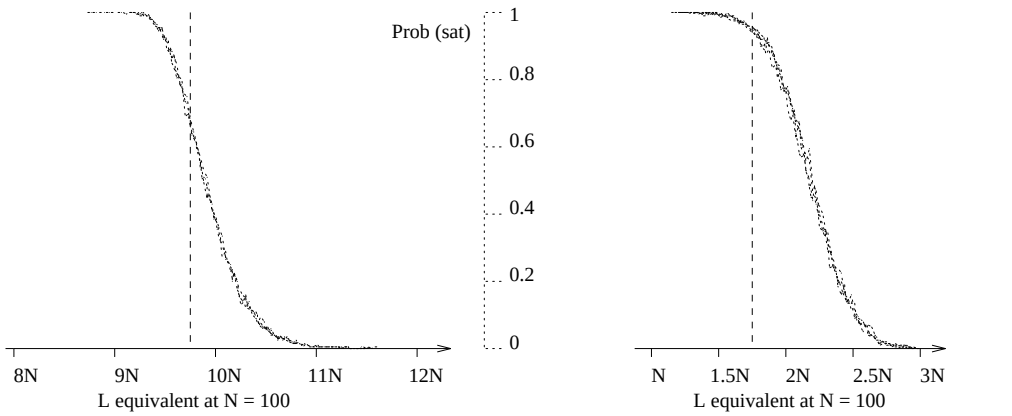
$$Prob(sat, R_k(\mathrm{N}, \mathrm{L})) = f((\mathrm{L}/\mathrm{N} - \alpha_c)\mathrm{N}^{1/v}) \tag{4}$$

If correct, f can be estimated experimentally and used to give accurate predictions of the value $Prob(sat, R_k(N, L))$ for arbitrary N and L. For 3-SAT, Kirkpatrick *et al* use $\alpha_c = 4.15$, $v = 1.5$. Interestingly, their value for α_c is slightly lower than experimental values of c_k. We now show that this result holds both for random 4-SAT, and for problems containing variable clause lengths like random mixed SAT.

An equivalent restatement of (4) is that all graphs of $Prob(sat, R_{\mathrm{N}}(\mathrm{L},))$ will be identical if the x-ordinate used is $(\mathrm{L}/\mathrm{N} - \alpha_c)\mathrm{N}^{1/v}$. Figure (5) (a) shows our own experimental data for 4-SAT from §2 for N= 25, 50, 75, scaled in this way with $\alpha_c = 9.76$, our experimentally observed value of c_4, and $v = 1.25$. For convenience, we have multiplied the x-ordinate by $100^{-1/v}$ and added α_c so that the values on the x-axis give the equivalent value of L at N= 100. The dashed line gives the point α_c. Figure (5) (b) shows data for 2-3-SAT for N= 50, 100, 150, 200 using α_c = 1.76 and $v = 2.5$. In each case we tested 500 problems at values of L from 1.3N to 3N, in steps of N/50. The curves fit very well; those for 4-SAT are never more than 0.08N apart, and those for 2-3-SAT are never more than 0.06N apart. The first graph therefore strongly supports Kirkpatrick et al's conjecture, whilst the second suggests that it can be extended from random k-SAT to random mixed SAT. For 2-4-4-SAT, for N= 50, 100, 150, and values of c varying by 0.04, we also observed a good fit using $\alpha = 2.74$, $v = 3.5$.

8 Related Work

Phase transitions are attracting increasing attention in AI. Huberman and Hogg [13] predict that many large scale systems will undergo sudden phase transitions



(a) 4-SAT, $\alpha_c = 9.76$, $v = 1.25$ (b) 2-3-SAT, $\alpha_c = 1.76$, $v = 2.5$

Figure 5: Scaling of probability graphs

that affect computational performance. They show, for example, that a simple model of heuristic search changes from linear to exponential behaviour at a phase boundary. Cheeseman *el al.* observed that many NP-hard problems (*eg.* graph colouring and Hamiltonian circuits) have an order parameter, that hard problems occur at a critical value of this parameter, and that this critical value separates a region of underconstrained (and typically soluble) problems from a region of overconstrained (and typically insoluble) problems. Mitchell *et al.* [15] demonstrated that for random 3-SAT the order parameter is L/N, the ratio of clauses to variables, that the critical value is approximately 4.3 and that median performance of DP has an easy-hard-easy pattern with the hardest median instance occurring at the phase transition. They also showed that the CP model (called random P-SAT in [15]) has an easy-hard-easy pattern for median performance of DP. However, they dismiss the CP model as being too easy compared with random k-SAT. Our results suggest this conclusion is premature. Although median performance for the CP model is easy, worst case performance is not. Indeed, the hardest CP problems can be orders of magnitude harder than the hardest comparably sized random k-SAT problems. Finally, Crawford and Auton [4] have more accurately identified the position of the phase transition for random 3-SAT as L/N = 4.24.

9 Conclusions

We have performed a detailed experimental investigation of the phase transition for randomly generated SAT problems. The sharp change from satisfiable to unsatisfiable problems previously observed at a critical value in random k-SAT problems is also present in the more general class of random mixed SAT problems, as well as in random problems generated according to the constant probability model. We have used our experimental results to conjecture the critical value

for these problem classes in terms of the critical values of the constituent k-SAT classes. Furthermore, we have been able to confirm Kirkpatrick et al's conjecture on the scaling of transition behaviour, and to extend it to random mixed SAT.

As with random k-SAT, we have observed an easy-hard-easy pattern in the median difficulty both for random mixed SAT problems and for problems from the constant probability model, with the hardest problems being associated with the phase transition. However, the difficulty of problems of mixed clause lengths is much more variable than that of random k-SAT problems. Indeed, the hardest problems of mixed clause lengths can be orders of magnitude harder than comparably sized problems of fixed clause length. Such very hard problems tend to occur in otherwise easy regions where most problems are satisfiable. These results are of considerable value both to experimental and theoretical AI since the empirical comparison of algorithms for NP-hard problems and average-case analyses requires the identification of hard instances of randomly generated problems.

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