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# A Monte Carlo study of lattice trails 

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#### Abstract

We use the recently developed Monte Carlo algorithm of Berretti and Sokal to study the critical behaviour of lattice trails on the square and triangular lattices. We find support for the earlier belief that this problem is in the same universality class as selfavoiding walks. Accepting this, we obtain the most precise estimates to date of the connective constants. It is argued that this problem is particularly well suited to study by Monte Carlo methods rather than by series analysis.


## 1. Introduction

In two earlier papers (Guttmann 1985a, b, hereafter referred to as I and II) an extensive analytic and numerical study of the configurational properties of lattice trails was made. Lattice trails bear the same relationship to self-avoiding walks as does the problem of bond percolation to the problem of site percolation. For a saw we are interested in enumerating all connected paths such that no site is visited more than once (this of course also precludes multiple bond occupancy). For the problem of lattice trails, the problem is to enumerate all connected paths such that no bond is revisited, but sites may be revisited.

In I we proved that the trails problem is in the same universality class as the SAW problem for the two-dimensional hexagonal lattice and the three-dimensional Lave lattice, but no proof has been found for lattices of a higher coordination number. Nevertheless, we argued in I and II that an extensive body of numerical evidence indicated that this was also the case for the other regular two- and three-dimensional lattices. However, despite the availability of quite long series expansions for the trail generating function, the results of this analysis were comparatively disappointing, insofar as they indicated a critical exponent $\gamma$ of the trail generating function of around 1.40 , compared to the SAw value of $\gamma=1.34375$.

This was ascribed to the presence of non-physical singularities quite close to the circle of convergence of the generating function, complicated by a more intrusive confluent singularity structure than that prevailing for saw.

For the mean square end-to-end distance exponent $\nu$ the situation was better. In II we studied the difference $\nu_{\text {saw }}-\nu_{\text {trails }}$ and found this to be indistinguishable from 0 for the square lattice. Subsequently, Rapaport (1985) also studied the trails problem, both by series expansion methods (for the three-dimensional FCC lattice) and by Monte Carlo methods in order to estimate $\nu$. His results were entirely consistent with those found in the earlier study discussed.

In this paper we use the appropriate modified Berretti-Sokal (1985, hereafter referred to as BS) Monte Carlo algorithm to study the trails problem on the square and triangular lattices. We only sketch the method here. It is a dynamic mc algorithm, generating trails in the grand canonical ensemble

$$
\begin{equation*}
\operatorname{Prob}(\text { length }=N)=\text { constant } \times \beta^{N} t_{N} \tag{1}
\end{equation*}
$$

where $t_{N}$ is the number of distinct $N$-step trails, and $\beta$ is a user-chosen parameter which determines the expectation value of the length of the trails. The algorithm starts with the empty trail, and each step of the algorithm consists either of appending a step to the end of the walk (randomly in one of the $q$ lattice directions), or else deleting the last step. In the former case, the step is allowed if the resultant path is a trail. The relative probabilities of these two types of moves are chosen so as to satisfy detailed balance for the measure (1). These conditions allow a trail of arbitrary length to evolve to or from the initial configuration (the empty trail), as is clearly necessary for the ergodicity of the algorithm.

The trails are assumed to have the asymptotic behaviour

$$
\begin{equation*}
t_{N}=A \lambda^{N} N^{\gamma-1}(1+a / N+\ldots) \tag{2}
\end{equation*}
$$

for large $N$, and we use the maximum likelihood estimation (MLE) of bs to determine the connective constant $\lambda$ and the critical exponent $\gamma$. The autocorrelation time of the algorithm, $\tau$, is of order $\langle N\rangle^{2}$ and is estimated numerically using standard methods of statistical time series analysis, as elucidated by bs.

The parameter $\beta$ is related to the average trail size by

$$
\begin{equation*}
\langle N\rangle \approx \beta \lambda \gamma /(1-\beta \lambda) \tag{3}
\end{equation*}
$$

As there is little doubt that the model is in the same universality class as saw, our main purpose was to see if Monte Carlo methods, which enable us to study longer walks than those available by series expansions, would produce more accurate estimates of the connective constant $\lambda$, and also shed some light on why the series expansions for the trails problem behave substantially worse than those for the sAw problem.

## 2. Data generation and analysis

For both the square and triangular lattices we generated a sample of $10^{9}$ Monte Carlo iterations. Each of the two data sets took approximately 50 h cpu time on a Perkin Elmer 3220 minicomputer. For the square lattice data the run was performed with $\beta=0.365$, corresponding to $\langle N\rangle=191$, while for the triangular lattice the run was performed with $\beta=0.2195$, corresponding to $\langle N\rangle=199$. Data were taken once every $10^{5} \mathrm{Mc}$ iterations, and in doing the statistical analysis we skipped the data from the first $10^{8}$ iterations; since this is some 500 times the algorithm's autocorrelation time (given below), there should be no doubt that equilibrium has been reached. Details of the random number generator used are given in Guttmann et al (1986).

An autocorrelation analysis gave $\tau=200000 \mathrm{MC}$ iterations, so that $\tau=5\langle N\rangle^{2}$, as for SAw (see bs, Guttmann et al 1986).

Following our analysis for the sAw case, we first performed a maximum-likelihood estimation of $\gamma$ and $\lambda$, using the ansatz

$$
\begin{equation*}
t_{N}=\lambda^{N}(N+3)^{\gamma-1} A\left[1+a_{1} /(N+3)\right] \quad \text { for } N>N_{\min } \tag{4}
\end{equation*}
$$

for a range of values of $a_{1}$ and $N_{\min }$; the results, for the triangular lattice, are shown in table 1. The errors shown are $95 \%$ confidence intervals, and represent statistical errors only. A corresponding table for saw is given in Guttmann et al (1986). As in that case, for $N_{\text {min }}=0$, the estimates are biased by strong systematic error due to corrections to scaling not included in (4), while as $N_{\text {min }}$ increases, so does the statistical error, as the sample size clearly decreases with increasing $N_{\text {min }}$.

Following bs, we attempt to invoke their 'flatness criterion' in order to find a region for which the 'true' values of $\lambda$ and $\gamma$ are included. This turns out to be quite difficult-again paralleling the saw case-and we are forced to include all values of $a_{1}$ in the range $-0.5<a_{1}<0.75$ and $20<N_{\text {min }}<80$. For $N=120$ the statistical errors are already too large. In this way we arrive at conservative estimates for both $\lambda$ and $\gamma$, by using all bold entries in table 1 , and so obtain

$$
\begin{align*}
& \lambda=4.5258 \pm 0.0016 \pm 0.0015 \quad \text { (triangular) }  \tag{5}\\
& \gamma=1.31 \pm 0.12 \pm 0.08
\end{align*}
$$

where the first errors represent systematic error due to unincluded corrections to scaling

Table 1. Two-parameter maximum-likelihood estimates of $\lambda$ and $\gamma$, assuming (4). Error bars include statistical errors only, and represent $95 \%$ confidence limits.

| $a$ | $N$ |  |  |  |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | 0 | 20 | 40 | 80 | 120 | 160 | 200 |
| -0.75 | 4.525145 | 4.525528 | 4.525542 | 4.526547 | 4.527284 | 4.528261 | 4.528731 |
|  | 0.001020 | 0.001243 | 0.001458 | 0.001876 | 0.002349 | 0.002876 | 0.003502 |
|  | 1.344355 | 1.323301 | 1.322886 | 1.245548 | 1.177650 | 1.077054 | 1.027321 |
|  | 0.039101 | 0.057205 | 0.076908 | 0.121722 | 0.178953 | 0.250524 | 0.342247 |
| -0.50 | 4.524992 | 4.525485 | 4.525515 | 4.526533 | 4.527274 | 4.528254 | 4.528725 |
|  | 0.001020 | 0.001243 | 0.001458 | 0.001876 | 0.002349 | 0.002876 | 0.003502 |
|  | 1.354553 | 1.327411 | 1.325860 | 1.247606 | 1.179273 | 1.078411 | 1.028496 |
|  | 0.039001 | 0.057204 | 0.076912 | 0.121729 | 0.178959 | 0.250531 | 0.342255 |
| -0.25 | 4.524844 | 4.525442 | 4.525489 | 4.526519 | 4.527625 | 4.528247 | 4.528720 |
|  | 0.001020 | 0.001243 | 0.001459 | 0.001877 | 0.002350 | 0.002876 | 0.003502 |
|  | 1.364415 | 1.331486 | 1.328817 | 1.249656 | 1.180891 | 1.079765 | 1.029669 |
|  | 0.038908 | 0.057203 | 0.076916 | 0.121735 | 0.178966 | 0.250539 | 0.342263 |
| 0.00 | 4.524702 | 4.525399 | 4.525463 | 4.526504 | 4.527255 | 4.528240 | 4.528714 |
|  | 0.001020 | 0.001244 | 0.001459 | 0.001877 | 0.002350 | 0.002877 | 0.003502 |
|  | 1.373963 | 1.335524 | 1.331756 | 1.251698 | 1.182505 | 1.081117 | 1.030839 |
|  | 0.038822 | 0.057202 | 0.076919 | 0.121741 | 0.178973 | 0.250546 | 0.342270 |
| 0.25 | 4.524565 | 4.525357 | 4.525437 | 4.526490 | 4.527246 | 4.528233 | 4.528709 |
|  | 0.001020 | 0.001244 | 0.001459 | 0.001877 | 0.002350 | 0.002877 | 0.003502 |
|  | 1.383216 | 1.339528 | 1.334679 | 1.253733 | 1.184115 | 1.082465 | 1.032008 |
|  | 0.038741 | 0.057201 | 0.076923 | 0.121747 | 0.178980 | 0.250553 | 0.342278 |
| 0.50 | 4.524433 | 4.525316 | 4.525411 | 4.526476 | 4.527236 | 4.528226 | 4.528704 |
|  | 0.001020 | 0.001245 | 0.001459 | 0.001877 | 0.002350 | 0.002877 | 0.003503 |
|  | 1.392194 | 1.343497 | 1.337586 | 1.255761 | 1.185721 | 1.083810 | 1.033173 |
|  | 0.038666 | 0.057201 | 0.076927 | 0.121753 | 0.178987 | 0.250560 | 0.342286 |
| 0.75 | 4.524306 | 4.525274 | 4.525386 | 4.526462 | 4.527227 | 4.528220 | 4.528699 |
|  | 0.001020 | 0.001245 | 0.001460 | 0.001877 | 0.002350 | 0.002877 | 0.003503 |
|  | 1.400911 | 1.347431 | 1.340475 | 1.257781 | 1.187321 | 1.085152 | 1.034337 |
|  | 0.038595 | 0.057200 | 0.076931 | 0.121759 | 0.178993 | 0.250568 | 0.342293 |

( $95 \%$ confidence limits-subjective) and the second error is statistical error taken at $N_{\text {min }}=40$ ( $95 \%$ confidence limits).

For the square lattice data, a similar table (not shown) gave a wide spread of values for which the flatness criteria applied, $-0.5<a_{1}<0.5$ and $20<N_{\text {min }}<120$, and combining these gave the estimates

$$
\begin{align*}
& \lambda=2.7205 \pm 0.0007 \pm 0.0009 \quad \text { (square) } \\
& \gamma=1.348 \pm 0.099 \pm 0.0079 . \tag{6}
\end{align*}
$$

It might be argued that the ansatz (4) ignores non-analytic correction-to-scaling terms, which seem likely to be present in this problem. However, due to the large statistical errors, it is not possible to distinguish between a non-analytic and analytic correction to scaling term-indeed, any such correction is likely to be effectively represented by a change in $a_{1}$.

As in the sAw case, these results are consistent with Nienhuis' $(1982,1984)$ exact result $\gamma=\frac{43}{32}$, but with such wide error bars as to be of little interest. If we accept this result, however, and re-analyse our data with this value of $\gamma$ fixed, we obtain rather better results.

In table 2 we show the results for the square lattice data, and use those shown in bold to which our, by now relatively unselective, flatness criterion applies. That is, we have chosen the same range of values as used above in the unbiased analysis. A similar analysis is applied to the triangular lattice data (not shown) and our results in the two cases are

$$
\begin{array}{ll}
\lambda=2.72059 \pm 0.00042 \pm 0.00037 & \text { (square) }  \tag{7}\\
\lambda=4.52526 \pm 0.00015 \pm 0.00065 & \text { (triangular). }
\end{array}
$$

The estimates and error bars in tables 1 and 2 were computed by using all data as if they were independent, and then multiplying the MLE theory error bars by a factor $(2 \tau)^{1 / 2}$ to adjust for the effects of autocorrelations. As shown in Guttmann et al (1986), alternative analyses seem to give indistinguishably close results.

Table 2. One-parameter maximum likelihood estimates of $\lambda$, assuming (4), with $\gamma=\frac{43}{32}$. Error bars include statistical errors only, and represent $95 \%$ confidence limits.

| $a$ | $N$ |  |  |  |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | 0 | 20 | 40 | 80 | 120 | 160 | 200 |
| $-0.75$ | 2.720734 | 2.720656 | 2.720579 | 2.720590 | 2.720516 | 2.720473 | 2.720526 |
|  | 0.000336 | 0.000349 | 0.000367 | 0.000410 | 0.000463 | 0.000523 | 0.000592 |
| -0.50 | 2.720779 | 2.720679 | 2.720595 | 2.720600 | 2.720523 | 2.720478 | 2.720530 |
|  | 0.000335 | 0.000349 | 0.000367 | 0.000410 | 0.000463 | 0.000523 | 0.000592 |
| -0.25 | 2.720825 | 2.720702 | 2.720611 | 2.720610 | 2.720529 | 2.720483 | 2.720534 |
|  | 0.000334 | 0.000349 | 0.000367 | 0.000410 | 0.000462 | 0.000523 | 0.000592 |
| 0.00 | 2.720870 | 2.720724 | 2.720627 | 2.720620 | 2.720536 | 2.720488 | 2.720538 |
|  | 0.0003334 | 0.000348 | 0.000367 | 0.000410 | 0.000462 | 0.000523 | 0.000592 |
| 0.25 | 2.720914 | 2.720747 | 2.720643 | 2.720629 | 2.720543 | 2.720493 | 2.720542 |
|  | 0.000333 | 0.000348 | 0.000367 | 0.000410 | 0.000462 | 0.000523 | 0.000592 |
| 0.50 | 2.720958 | 2.720769 | 2.720659 | 2.720639 | 2.720550 | 2.720498 | 2.720546 |
|  | 0.000332 | 0.000348 | 0.000366 | 0.000410 | 0.000462 | 0.000523 | 0.000592 |
| 0.75 | 2.721001 | 2.720792 | 2.720674 | 2.720649 | 2.720557 | 2.720503 | 2.720550 |
|  | 0.000332 | 0.000347 | 0.000366 | 0.000410 | 0.000462 | 0.000523 | 0.000592 |

## 3. Discussion

If we now compare these results with the series results obtained in II, we find satisfactory agreement. For the triangular lattice case the series estimate was $\lambda=4.524 \pm 0.004$, while for the square lattice the series estimate was $\lambda=2.7215 \pm 0.002$. It can be seen that the mC estimates are significantly more accurate than the series estimates in this case-in contrast to the SAW case-and allow us to rule out a conjecture of Malakis (1975) that $\lambda$ (square) $=\mathrm{e}=2.71828 \ldots$ at the $99.9 \%$ confidence level.

The trails problem is seen to be one in which Monte Carlo analysis does a better job than does series analysis, whereas for the saw problem and perhaps for the Ising problem the opposite is the case. As noted in II, this is likely to be due to the presence of competing singularities, as well as the effect of more prominent correction-to-scaling terms. The effect of these on our ansatz (4) has already been discussed in Guttmann et al (1986). The upshot of these remarks though is that asymptotic behaviour has not yet set in at trail lengths of $14-22$, which is the size of the maximum length trails accessible by series analysis. Thus this problem is a particularly appropriate one for MC algorithms to be tested against.

The trails problem was also studied by Zhou and Li (1984) using series analysis. Their conclusion, that the problem is in a distinct universality class from SAw, is not supported. Rather, it adds weight to our conclusion that this problem does not readily lend itself to study by series analysis, but that Monte Carlo methods are more appropriate.

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