

1 Exact and Approximate Compression of Transfer
2 Matrices for Graph Homomorphisms

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5 **Abstract**

6 The aim of this paper is to extend the previous work on transfer matrix
7 compression in the case of graph homomorphism. For H -homomorphisms
8 of lattice-like graphs we demonstrate how the automorphisms of H , as
9 well as those of the underlying lattice, can be used to reduce the size of
10 the relevant transfer matrices.

11 As applications of this method we give currently best known bounds
12 for the number of 4 and 5-colourings of the square grid, and the number
13 of 3 and 4-colourings of the 3-dimensional cubic lattice.

14 Finally we also discuss approximate compression of transfer matrices.

15 **1 Introduction**

16 Transfer matrices is a standard tool in various branches of mathematics. In
17 enumerative combinatorics they have been used for a long time to solve counting
18 problems which can be described using graph homomorphisms. In statistical
19 physics transfer matrices have been a well used tool for the computation of
20 partition functions of various spin models. In ergodic theory transfer matrices
21 are used to describe the behaviour of a class of dynamical system known as
22 subshifts of finite type. Recently the many similarities between these uses have
23 been put on a firm mathematical ground. That the calculation of entropies
24 for \mathbb{Z}^d -subshifts of finite type are equivalent to counting graph homomorphisms
25 from \mathbb{Z}^d into some graph H was demonstrated in [5]. In [9] it was proven that
26 counting weighted graph homomorphisms is equivalent to computation of the
27 partition function for statistical physics models satisfying a condition known as
28 reflection positivity. The study of phase transitions in statistical physics models
29 has also begun to be studied in the language of homomorphisms [3].

30 A general limitation for all these applications is that transfer matrices tend
31 to grow fast with the size of the system considered, thus limiting the size of
32 the system one can work with. A recent development in this area is the use
33 of automorphisms of the underlying graphs to reduce the size of the matrices.
34 This was done for a special case in [4] and was developed as a general method in
35 [10]. Our aim here is first to show how this method, now called transfer matrix

36 compression, in many cases can be taken even further than earlier applications
 37 and also discuss how one can make even greater size reductions if one is ready
 38 to settle for bounds of the computed entropies rather than exact values. For
 39 many applications the latter is sufficient.

40 Let us put things on a firmer ground. A homomorphism ϕ from a graph G
 41 to a graph H , which may have loops, is a mapping which preserves adjacencies,
 42 i.e. if $(x, y) \in E(G)$ then $(\phi(x), \phi(y)) \in E(H)$. The set of all homomorphisms
 43 from G to H is denoted $\text{Hom}(G, H)$. We say that H is a weighted graph if there
 44 are two functions $\alpha_H : V(H) \rightarrow F$ and $\beta_H : E(H) \rightarrow F$, where F is a ring.
 45 Given a weighted graph H we assign a weight $w(\phi)$ to each homomorphism ϕ
 46 from G to H

$$47 \quad w(\phi) = \prod_{x \in V(G)} \alpha_H(\phi(x)) \prod_{xy \in E(G)} \beta_H(\phi(x), \phi(y)) \quad (1)$$

48 Let us give a few examples:

49 **Example 1.1.**

- 50
- 51 1. $H = K_q$, $\alpha = \beta = 1$, corresponds to ordinary proper q -colourings.
 - 52 2. Let H be a K_2 with a loop on one vertex, let the edge have weight 1, the
 53 loop weight t and $\alpha = 1$. For $t = 1$ the homomorphisms correspond to
 54 independent sets and for general t we have the so called hard-core lattice
 55 gas model.
 - 56 3. If H is a K_q with loops on every vertex and the weights are t^{-1} on the
 57 loops, t on the ordinary edges and 1 on the vertices we have the q -state
 58 Potts model.
 - 59 4. If we take the previous example with $q = 2$ and put a weight s on one
 60 vertex of H and s^{-1} on the other vertex, we have the Ising model with an
 61 external field.

62 If we have a model where we also want to put colours or “spins” on the
 63 edges of G , e.g. when considering matchings, or on both edges and vertices, we
 64 can instead consider the line-graph or total-graph of the underlying graph G re-
 65 spectively. It is also straightforward to generalise these concepts to hypergraphs
 66 if one wants to consider interaction between larger sets of vertices.

We next define a weighted counter for these homomorphisms

$$Z(G, H) = \sum_{\phi \in \text{Hom}(G, H)} w(\phi)$$

67 If all weights on H are just 1 this will be exactly $|\text{Hom}(G, H)|$. In spin models
 68 the weights are often taken to be of the form e^K for a parameter K which is
 69 interpreted as a temperature, and then $Z(G, H)$ is called the partition function
 70 of the model. In ergodic theory $Z(G, H)$ is called the pressure of the subshift

71 described by G and H . In most applications the aim is either to compute
 72 $Z(G, H)$ when F is a ring of polynomials, as in [7], or to determine how fast
 73 $Z(G_n, H)$ grows when $F = \mathbb{R}$ and G_n is some sequence of graphs, see e.g. [5, 4].

74 2 Polygraphs and Transfer Matrices

Transfer matrices are most useful for computation within a class of graphs known
 as polygraphs. This class was introduced in [1], where the transfer matrices were
 used to compute matching polynomials. A polygraph \mathcal{G} is defined by a set of
 disjoint graphs G_1, G_2, \dots, G_m and a set of binary relations $\Upsilon_1, \Upsilon_2, \dots, \Upsilon_m$,
 where $\Upsilon_i \subset V(G_i) \times V(G_{i+1})$. The vertex set of \mathcal{G} is $\cup_i V(G_i)$ and the edge set
 is

$$E(\mathcal{G}) = \cup_i E(G_i) \cup_i \Upsilon_i$$

75 If all $G_i = G$ and $\Upsilon_i = \Upsilon$ for all $i = 1, \dots, m$ we write the corresponding
 76 polygraph as $\mathcal{G}(G, \Upsilon, m)$.

77 Given a polygraph \mathcal{G} and a weighted graph H we can compute $Z(\mathcal{G}, H)$ using
 78 a sequence of transfer matrices. We define a matrix $M(i)$ for going from G_i to
 79 G_{i+1} as follows.

80 Let $\Phi(G_i)$ denote the set of restrictions of all homomorphisms in $\text{Hom}(\mathcal{G}, H)$
 81 to G_i . We call a member of $\Phi(G_i)$ a *state* on G_i . Now let the rows of $M(i)$
 82 be indexed by the states on G_i and the columns by the states on G_{i+1} . We set
 83 $M_{x,y}(i) = 0$ if there is no homomorphism $\phi \in \text{Hom}(\mathcal{G}, H)$ such that $\phi|_{G_i} = x$
 84 and $\phi|_{G_{i+1}} = y$. If there exists such a ϕ we set $M_{x,y}$ equal to the contribution
 85 to the weight $w(\phi)$ of the edges in Υ_i and the edges and vertices of G_{i+1} . We
 86 also define an associated vector η . The position in η corresponding to the row
 87 x is set equal to the weight of the partial homomorphism x .

88 The partition function is now given by

$$89 \quad Z(\mathcal{G}, H) = \eta \left(\prod_i M(i) \right) \mathbf{1} \quad (2)$$

90 One can also consider cyclic polygraphs where the last relation Υ connects G_m
 91 to G_1 . In this case the partition function is given by the trace of the transfer
 92 matrix product,

$$93 \quad Z(\mathcal{G}, H) = \text{Tr} \left(\prod_i M(i) \right) \quad (3)$$

94 3 Exact Compression of Transfer Matrices

95 Henceforth we will assume that our polygraphs are on the form $\mathcal{G}(G, \Upsilon, m)$.
 96 Most of what follows can be adapted to general polygraphs as well. Let us
 97 recall that given an $N \times N$ matrix M a partition $\mathcal{X} = \{X_1, X_2, \dots, X_r\}$ of
 98 $\{1, \dots, N\}$ is called an equitable partition if $\sum_{l \in A_j} M(i_1, l) = \sum_{l \in X_j} M(i_2, l)$
 99 when $i_1, i_2 \in X_i$.

100 Given a partition X of the states on G we define the compressed transfer
 101 matrix for $Z(\mathcal{G}, H)$ to be

$$102 \quad C_{\mathcal{X}}(i, j) = \sum_{l \in X_j} M(k, l), \quad k \in X_i, \quad i, j = 1 \dots r \quad (4)$$

103 The main theorem of [10] can be stated as

104 **Theorem 3.1.** *If X is an equitable partition of M then*

$$105 \quad C_{\mathcal{X}}^n(i, j) = \sum_{l \in X_j} M^n(k, l), \quad k \in X_i, \quad i, j = 1 \dots r \quad (5)$$

106 This has the following corollary

Corollary 3.2. *Let η be the vector of length N whose i :th entry is $|X_i| w(x_i)$, where $x_i \in X_i$. Then*

$$Z(\mathcal{G}, H) = \eta \left(\prod_i M(i) \right) \mathbf{1}$$

107 The main consequence of these results, which has been used in [10], [4], [5],
 108 is

109 **Corollary 3.3.** *If M is a transfer matrix and the partition \mathcal{X} consists of orbits
 110 on the set of states on G under the automorphism group $\text{Aut}(G)$, then \mathcal{X} is
 111 equitable.*

112 This corollary lets us make use of automorphisms of G to compress our
 113 transfer matrices and for graphs with reasonably large automorphism group,
 114 such as cycles, the reduction in size can be substantial.

115 **Example 3.4.** Let us look at the transfer matrix for $\text{Hom}(G(P_3, Id, n), K_3)$,
 116 i.e. 3-colourings of the graph $P_3 \times P_n$.

117 There are 12 states on P_3 and the only nontrivial member of $\text{Aut}(P_3)$ is a re-
 118 flection in the midpoint. If we use 1,2,3 to denote colours we find that there are 9
 119 orbits: $\{\{121\}, \{212\}, \{313\}, \{131\}, \{232\}, \{323\}, \{123, 321\}, \{132, 231\}, \{213, 312\}\}$

Here we get the following 9×9 matrix, instead of a 12×12 matrix,

$$C = \begin{bmatrix} 0 & 0 & 1 & 1 & 1 & 0 & 0 & 0 & 2 \\ 0 & 0 & 1 & 0 & 1 & 1 & 0 & 0 & 2 \\ 1 & 1 & 0 & 0 & 0 & 1 & 2 & 0 & 0 \\ 1 & 0 & 0 & 0 & 1 & 1 & 2 & 0 & 0 \\ 1 & 1 & 0 & 1 & 0 & 0 & 0 & 2 & 0 \\ 0 & 1 & 1 & 1 & 0 & 0 & 0 & 2 & 0 \\ 0 & 0 & 1 & 1 & 0 & 0 & 0 & 1 & 1 \\ 0 & 0 & 0 & 0 & 1 & 1 & 1 & 0 & 1 \\ 1 & 1 & 0 & 0 & 0 & 0 & 1 & 1 & 0 \end{bmatrix} \quad \eta = \{1, 1, 1, 1, 1, 1, 2, 2, 2\}$$

120 Even though we have reduced the side of the matrix by one quarter we still have
 121 a fairly sparse matrix.

122 From algebraic graph theory [6] we know that if G is any graph and X
 123 is a partition of its vertices into orbits under $\text{Aut}(G)$ then the corresponding
 124 partition is equitable. If we choose to interpret the transfer matrix M as the
 125 adjacency matrix of a weighted graph, then what we did in Corollary 3.3 can
 126 be interpreted as using the subgroup of $\text{Aut}(M)$ which is induced by $\text{Aut}(G)$
 127 to partition M . However, $\text{Aut}(M)$ has an even larger subgroup induced by
 128 $\text{Aut}(G) \times \text{Aut}(H)$. Here $\text{Aut}(H)$ is assumed to preserve the weights on H as
 129 well as the adjacencies.

130 **Corollary 3.5.** *Let X be a partition of M given by the orbits of $\text{Aut}(G) \times$
 131 $\text{Aut}(H)$ then X is equitable.*

132 When the graph H is highly symmetric, such as in the case of proper col-
 133 ourings of G or the partition function of the Potts model, the extra reduction
 134 in size achieved here can be remarkable.

Example 3.6. If we use the automorphism group of K_3 as well in Example 3.4
 we now only find two orbits, $\{\{121, 212, 313, 131, 232, 323\}, \{123, 321, 132, 231, 213, 312\}\}$,
 and the compressed transfer matrix has side 2:

$$C = \begin{bmatrix} 3 & 2 \\ 2 & 2 \end{bmatrix} \quad v = \{6, 6\}$$

135 4 Application to the asymptotic number of q - 136 colourings of lattices

137 The number of proper q -colourings of an $n \times n$ square grid, or $P_n \times P_n$, is
 138 known to grow exponentially as a function of n^2 . We denote the basis for this
 139 exponential growth by $\lambda^s(q)$. This is a quantity which is of interest both in
 140 enumerative combinatorics and statistical physics. In the latter case $\log \lambda^s(q)$
 141 is seen as the ground state entropy of the much studied antiferromagnetic Potts
 142 model on the square grid, see e.g. [11] for a survey.

143 For 3-colourings Lieb [8] found the exact asymptotic value of $\lambda^s(3) = (\frac{4}{3})^{\frac{3}{2}}$
 144 but for larger q the value of $\lambda^s(q)$ is still unknown. As a full-scale example of our
 145 methods we now look at the compression of transfer matrices for q -colourings
 146 of the square grid for $q = 4, 5$, for the cubic grid $P_n \times P_n \times P_n$ for $q = 3, 4$, and
 147 their use in getting bounds for $\lambda^s(q)$.

148 It is known that the maximum eigenvalues $\theta_1(k)$ and $\theta_2(k)$ of the transfer
 149 matrices for $\text{Hom}(G(P_k, Id, n), K_q)$ and $\text{Hom}(G(C_k, Id, n), K_q)$ respectively, can
 150 be used to give upper and lower bounds for $\lambda^s(q)$, see e.g. [5] for a general
 151 treatment. In particular

$$152 \quad \frac{\theta_1(k+1)}{\theta_1(k)} \leq \lambda^s(q) \leq \theta_2(2k)^{\frac{1}{2k}} \quad (6)$$

153 So we can bound $\lambda^s(q)$ by computing $\theta_1(k)$ for consecutive k and $\theta_2(k)$ for even
 154 k .

n	3	4	5	6	7	8	9	10	11
N_1	36	108	324	972	2916	8748	26244	78732	236196
N_2	24	54	180	486	1512	4374	13284	39366	118584
N_3	2	4	10	25	70	196	574	1681	5002
N_1	24	84	240	732	2184	6564	19680	59052	177144
N_2	4	21	24	92	156	498	1096	3210	8052
N_3	1	3	2	9	10	34	57	169	366

Table 1: Transfer matrix sizes for 4-colourings. the upper three rows are for transferring a path, and the lower three for a cycle.

155 In Table 1 we have given the size of the transfer matrix for $\text{Hom}(G(P_k, Id, n), K_3)$
156 and $\text{Hom}(G(C_k, Id, n), K_3)$. Here N_1 denotes the side of the uncompressed
157 transfer matrix, N_2 the side when the automorphism group of P_k and C_k re-
158 spectively were used, and N_3 the size when the automorphism group of K_3
159 was used as well. The effect of the larger automorphism group of the cycle is
160 well visible, as is the gain from including the automorphism group of K_4 in the
161 compression step.

162 For small k the transfer matrices and eigenvalues were computed first with
163 a `Mathematica` program and also with a Fortran 90 program. For larger k the
164 Fortran 90 program was run on a linux cluster. In Table 2 of Appendix A we
165 have collected the computed eigenvalues. The higher precision values for small
166 k are due to the `Mathematica` program.

167 Using these eigenvalues and inequalities 6 we find the following bounds for
168 $\lambda^s(4)$:

$$169 \quad 2.336056640723116 \leq \lambda^s(4) \leq 2.33606820555777 \quad (7)$$

To our knowledge these are currently the best rigorous bounds for $\lambda^s(4)$. In [2]
the first terms of a series expansion in $\frac{1}{q-1}$ for $\lambda^s(q)$ was obtained and using
this series it was estimated that

$$\lambda^s(4) = 2.336056641 \pm 0.000\ 000\ 001,$$

170 with a heuristic error bound, an estimate which fits in just above our lower
171 bound.

172 In the same way we computed the corresponding eigenvalues for 5-colourings,
173 given in Table 3 of Appendix A. The bounds so obtained for $\lambda^s(5)$ are

$$174 \quad 3.2504049231640764 \leq \lambda^s(5) \leq 3.250407145038276 \quad (8)$$

For the growth rate $\lambda^c(q)$ of the number q -colourings of the cubic lattice $P_k \times P_k \times P_k$ there are no exact results known. In [2] series estimates were also given for $\lambda^c(3)$ and $\lambda^c(4)$, however these estimates were based on much shorter series than those for the square grid and were given as

$$\lambda^c(3) = 1.4435 \pm 0.0005$$

$$\lambda^c(4) = 2.043 \pm 0.001$$

175 In order to compute bounds for the cubic lattice we can make use of the
 176 observations that $\lambda^c(q)$ is greater than the maximum eigenvalue for $\text{Hom}(G(P_k \times$
 177 $C_\ell, Id, n), K_q)$, since colourings of these graphs can be extended to periodic
 178 colourings of $\text{Hom}(G(P_k \times P_\ell, Id, n), K_q)$ for all t . Likewise $\lambda^c(q)$ is less than
 179 the maximum eigenvalue for $\text{Hom}(G(P_k \times P_\ell, Id, n), K_q)$, since the number of
 180 colourings is submultiplicative.

181 As before we can get lower bounds for the maximum eigenvalue of $\text{Hom}(G(P_k \times$
 182 $C_\ell, Id, n), K_q)$ for a fixed ℓ by computing the maximum eigenvalues for consecut-
 183 ive k , and for each value of ℓ we will get lower bound for $\lambda^c(q)$. Similarly we can
 184 get upper bounds for the maximum eigenvalue of $\text{Hom}(G(P_k \times P_\ell, Id, n), K_q)$ by
 185 computing the maximum eigenvalue of $\text{Hom}(G(C_k \times P_\ell, Id, n), K_3)$ for even k .
 186 These eigenvalues are in turn bounded from above by the maximum eigenvalue
 187 of $\text{Hom}(G(C_k \times C_\ell, Id, n), K_3)$, for even k and ℓ .

188 For $\lambda^c(3)$ our best bounds comes from the eigenvalues of $\text{Hom}(G(C_6 \times$
 189 $C_6, Id, n), K_q)$ and $\text{Hom}(G(P_k \times C_4, Id, n), K_q)$, for $\lambda^c(4)$ the bounds were achieved
 190 by $\text{Hom}(G(C_4 \times C_4, Id, n), K_q)$ and $\text{Hom}(G(P_k \times C_4, Id, n), K_q)$

$$191 \quad 1.4460096817417 \leq \lambda^c(3) \leq 1.4470681274660 \quad (9)$$

$$192 \quad 2.0343787307189 \leq \lambda^c(4) \leq 2.0652128520667 \quad (10)$$

193 As we can see the estimate from [2] for $\lambda^c(4)$ is within our bounds but their
 194 estimate for $\lambda^c(3)$ is well below the lower bound, even when their heuristic error
 195 estimate is taken into account. As mentioned in [2] this kind of “miss” by the
 196 series estimate could indicate a physically interesting structure in the set of
 197 3-colourings.

198 5 Approximate Compression

199 For many applications the ring F is the real numbers and one typically has only
 200 positive weights. If the aim is to compute only the maximum eigenvalue of M ,
 201 as in Example 4, we can go further with our compression than in the previous
 202 section. First we here only need to care about the so called main part of the
 203 spectrum of M , i.e. the eigenvalues with eigenvector not orthogonal to $\mathbf{1}$, and
 204 of the main part we only need to preserve the maximum eigenvalue. We can
 205 now make use of one of the standard theorems of spectral graph theory, see e.g.
 206 [6].

Theorem 5.1 (Interlacing of eigenvalues). *Let S be an $n \times m$ matrix such that $S^T S = I$, M a hermitian $n \times n$ matrix, and set $M' = S^T M S$. Let the eigenvalues of M be $\lambda_1 \geq \lambda_2, \dots, \lambda_n$ and those of M' be $\theta_1 \geq \theta_2, \dots, \geq \theta_m$. Then the eigenvalues of M' interlace the eigenvalues of M , that is,*

$$\lambda_j \geq \theta_j \geq \lambda_{n-m+j}$$

207 **Corollary 5.2.** *Let M be an $m \times m$ hermitian matrix and let $X = \{X_1, X_2, \dots\}$
 208 *be a partition of $\{1, \dots, m\}$. Define a matrix B where $B_{i,j}$ is the average row*
 209 *sum in M_{X_i, X_j} . Then the eigenvalues of B interlace those of M .**

210 *Proof.* Apply Theorem 5.1 with the matrix S given by $S_{i,j} = |X_i|^{-\frac{1}{2}}$ if $j \in X_i$
 211 and 0 elsewhere. □

212 For a partition which is not necessarily equitable we thus find

213 **Corollary 5.3.** *Let \mathcal{X} be a partition of the rows and columns of M then the*
 214 *maximum eigenvalue of $C(\mathcal{X})$ gives a lower bound on $\lambda_1(M)$.*

215 Given a partition \mathcal{X} we can also define a matrix D defined as in the previous
 216 corollary but using the maximum row sum rather than the average.

217 **Corollary 5.4.** *The maximum eigenvalue of D gives an upper bound on $\lambda_1(M)$.*

218 For many choices of weighted graph H it is the case that $Z(G, H)$ is either
 219 sub- or super-additive with respect to addition of edges and/or vertices to G .
 220 In this situation the corollaries of the interlacing theorem can be used to give
 221 us upper and lower bounds on the asymptotics of the maximum eigenvalues as
 222 G becomes larger. These bounds can then in turn be used in combination with
 223 inequalities like 6.

224 In both Corollary 5.3 and 5.4 the choice of partition \mathcal{X} will influence the
 225 value of the eigenvalue bound. How the partition should be chosen in order to
 226 get a good approximation will depend on the underlying graphs and weights
 227 and it is hard to say anything much more precise than that one should strive to
 228 get blocks M_{X_i, X_j} with as closely concentrated row-sums as possible.

229 **Example 5.5.** In order to demonstrate the approximate bounds, and the in-
 230 fluence of the choice of partition \mathcal{X} , we have computed these bounds for the
 231 transfer matrix for the number of 4-colourings on $P_{12} \times P_n$ and $C_{14} \times P_n$.

232 We have used two kinds of partition \mathcal{X} .

233 1. For the first type of partition we view each colouring as an integer written
 234 in base 4, for cycles we choose an arbitrary vertex to be the lowest digit.
 235 Next we sort the colourings as if they were integers.

236 Given this sorted list of the colourings we partitioned the list into con-
 237 sequentive sublists of length k and $k - 1$, with as few list of length $k - 1$ as
 238 possible.

239 2. As our second kind of partition we randomly partitioned the list of colours
 240 into parts of size K .

241 For these two partitions we next computed an upper bound for the largest
 242 eigenvalue of the transfer matrix for C_{14} and a lower bound for that of P_{12} . For
 243 each graph and partitioning we choose K as to give compressed matrices with
 244 side from 0.9 times the original side down to 0.1. For the random ordering we
 245 tried several random partitions.

246 In Figures 1 and 2 we have plotted the approximate eigenvalue divided by
 247 the correct eigenvalue. We find that the lower bounds tend to be more accurate
 248 than the upper bounds. In both cases the Integer encoding partition gives a
 249 noticeably better approximation than the random partitions. However, for the
 250 lower bound even the random partitions can be used to compress the matrix
 251 down to one tenth of its original size and still get a bound which is just one
 252 percent less than the correct value.

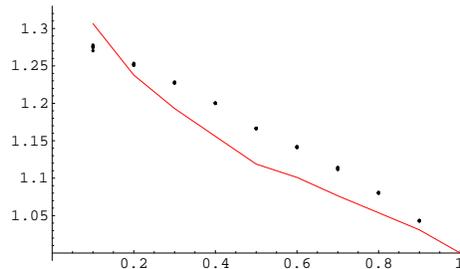


Figure 1: Approximate eigenvalues for C_{14} . Connected points are from the integer encoding. Clusters of isolated points are random partitions.

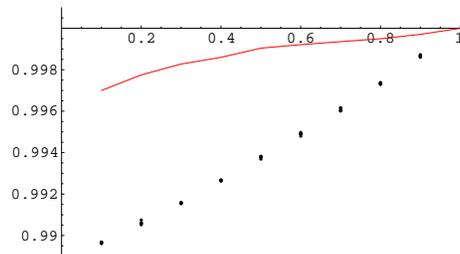


Figure 2: Approximate eigenvalues for P_{12} . Connected points are from the Integer encoding. Clusters of isolated points are random partitions.

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256 References

- 257 [1] D. Babic et al. The matching polynomial of a polygraph. *Discrete Appl.*
 258 *Math.*, 15:11–24, 1986.

- 259 [2] A. V. Bakaev and V. I. Kabanovich. Series expansions for the q -colour
260 problem on the square and cubic lattices. *J. Phys. A*, 27(20):6731–6739,
261 1994.
- 262 [3] Graham R. Brightwell and Peter Winkler. Graph homomorphisms and
263 phase transitions. *J. Combin. Theory Ser. B*, 77(2):221–262, 1999.
- 264 [4] M. Ciucu. An improved upper bound for the 3-dimensional dimer problem.
265 *Duke Math. J.*, 94(1):1–11, 1998.
- 266 [5] Shmuel Friedland and Uri N. Peled. Theory of computation of multidimen-
267 sional entropy with an application to the monomer-dimer problem. *Adv.*
268 *in Appl. Math.*, 34(3):486–522, 2005.
- 269 [6] Chris Godsil and Gordon Royle. *Algebraic graph theory*, volume 207 of
270 *Graduate Texts in Mathematics*. Springer-Verlag, New York, 2001.
- 271 [7] R. Häggkvist and P.H. Lundow. The Ising partition function for 2D grids
272 with cyclic boundary: computation and analysis. *J. Statist. Phys.*, 108(3–
273 4):429–457, 2002.
- 274 [8] Elliott H. Lieb. Residual entropy of square ice. *Phys. Rev.*, 162:162–172,
275 1967.
- 276 [9] Lovasz. *hom. Math.*, 4(3):486–522, 2005.
- 277 [10] Per Håkan Lundow. Compression of transfer matrices. *Discrete Math.*,
278 231(1-3):321–329, 2001. 17th British Combinatorial Conference (Canter-
279 bury, 1999).
- 280 [11] F. Y. Wu. The Potts model. *Rev. Modern Phys.*, 54(1):235–268, 1982.

A Colouring eigenvalues for the square grid

k	P_k	C_k
3	16.34846922834953429459185	11
4	38.18874899819785577572648	31.69693845669906858918370
5	89.20972864650976523895547	67.01514803843835560759098
6	208.3980964253975720633538	165.6008220944556672481883
7	486.8291555413566000543864	375.4804004152886797996016
8	1137.260058429224259797968	892.2418753486577354212783
9	2656.703606588566986303095	2064.554606528212648447034
10	6206.209878666071640432711	4849.504943339923099642784
11	14498.05763470071954268293	11293.10916510243643781710
12	33868.2836924334	26429.64958444568607749808
13	79118.2289428612	61675.61597454731
14	184824.664073982	144167.2612085567
15	431760.883879445	336660.4085235824
16		786626.0015010700

Table 2: Maximum eigenvalues for 4-colourings of the square grid

n	P_n	C_n
2	13	
3	42.254746265138	32
4	137.34484848076	114.16796064692
5	446.42629917197	359.90932515034
6	1451.0662111085	1182.6934618883
7	4716.5527439510	3829.1466667249
8	15330.706253905	12464.383871815
9	49831.003080926	40492.334305935
10	161970.93773951	131643.39169572
11	526471.13343803	427861.13442804
12		1390763.1270219

Table 3: Maximum eigenvalues for 5-colourings of the square grid

B Colouring eigenvalues for the cubic lattice

n	$G = P_n$	$G = C_n$
3	13.8072589673052	3
4	30.1109468160278	26.6214214843774
5	65.8601729387350	24.6080079665097
6	144.283083091960	123.199451464237
7	316.392676802175	148.219336059660
8	694.239161184508	582.950876259572
9	1523.97594483322	806.285660630712
10	3346.41981099416	2782.03759223168
11	7349.89922843146	4196.30975248900

Table 4: Maximum eigenvalues for 3-colourings of $G \times P_2$

n	$G = P_n$	$G = C_n$
3	42.9509955498558	4.56155281280883
4	134.633390548866	114.548378741056
4	423.398960388624	103.444398290072
5	1333.80481197401	1091.43690942498
6	4206.08745616625	1449.29878537714
7		10674.0945361673

Table 5: Maximum eigenvalues for 3-colourings of $G \times P_3$

n	$G = P_n$	$G = C_n$
4	607.5008342289296	496.9033949197111
5	2751.292994653581	437.9397858090114
6	12483.36568754961	9768.207310946096

Table 6: Maximum eigenvalues for 3-colourings of $G \times P_4$

n	$G = P_n$	$G = C_n$
5	17953.38896417563	1859.891162040439

Table 7: Maximum eigenvalues for 3-colourings of $G \times P_5$

n	$G = P_n$	$G = C_n$
2	3	
3	4.56155281280883	2
4	6.97196076839709	6.37228132326901
5	10.6828851212084	6
6	16.3920411989578	14.5064314940480
7	25.1740785316175	15.7833418763922
8	38.6831608665319	33.6767869577220
9	59.4651079147947	39.6505660120334
10	91.4379622705829	78.8188645918277
11	140.631735559805	97.5298788390751
12	216.327079158290	185.239857806635
13	332.808012753772	237.182998032027

Table 8: Maximum eigenvalues for 3-colourings of $G \times C_3$

n	$G = P_n$	$G = C_n$
2	26.62142148437744	
3	114.5483787410569	
4	496.9033949197111	420.477039628259
5	2163.237391033718	378.843114768611
6	9435.406059898469	7704.08921920854
7		11291.7201866529
8		144633.687249454

Table 9: Maximum eigenvalues for 3-colourings of $G \times C_4$

n	$G = P_n$	$G = C_n$
2	24.6080079665097	
3	103.444398290072	
4	437.939785809011	
5	1859.89116204043	408.155175807023
6	7912.06577168573	6610.84386549256

Table 10: Maximum eigenvalues for 3-colourings of $G \times C_5$

n	$G = P_n$	$G = C_n$
6		599243.330687515

Table 11: Maximum eigenvalues for 3-colourings of $G \times C_6$