

Weingarten calculus on computers  
and its application to  
random quantum Gaussian states.

Motohisa Fukuda  
(Yamagata University)

# Contents

<b>1</b>	<b>Weingarten Calculus on computers</b>	<b>3</b>
1.1	Computer packages for average over Haar unitary matrices	4
1.2	Polynomial version of Weingarten calculus . . . . .	5
1.3	Graphical version . . . . .	8
1.4	“Computer version” . . . . .	10
1.5	Demo (had been done.) . . . . .	12
<b>2</b>	<b>Random Gaussian states</b>	<b>13</b>
2.1	Motivation and past research . . . . .	14
2.2	Passive Gaussian unitary operations . . . . .	15
2.3	Partial trace as Gaussian operation . . . . .	16
2.4	Symplectic eigenvalues . . . . .	17
2.5	Random Gaussian pure states . . . . .	18
2.6	Symplectic eigenvalues of reduced states . . . . .	19
2.7	Concentration . . . . .	20

# 1 Weingarten Calculus on computers

“RTNI - A symbolic integrator for Haar-random tensor networks”,  
arXiv:1902.08539 [quant-ph] with Nechita and Koenig.

## 1.1 Computer packages for average over Haar unitary matrices

### Preceding packages:

- IntU, a Mathematica package, [Puchała and Miszczak (2017)].
- IntHaar, a Maple package, [Ginory and Kim (2016)].  
(includes Haar orthogonal and symplectic cases.)

### Our package:

RTNI (Random Tensor Network Integrator),  
Mathematica and Python packages.

### Differences:

- Others calculate averages of monomials in the entries of a random unitary matrices.
- Our package calculates averages symbolically, which allows tensor structures easily.

## 1.2 Polynomial version of Weingarten calculus

$\mathcal{U}(n)$ : group of  $n \times n$  unitary matrices, and

$dU$ : normalized Haar measure.

Fix  $p \in \mathbb{N}$  and let  $i = (i_1, \dots, i_p)$ ,  $i' = (i'_1, \dots, i'_p)$ ,  $j = (j_1, \dots, j_p)$ ,  $j' = (j'_1, \dots, j'_p)$  be  $p$ -tuples of positive integers from  $\{1, 2, \dots, n\}$ .  
[Collins and Sniady (2006)]

$$\begin{aligned} & \int_{\mathcal{U}(n)} U_{i_1 j_1} \cdots U_{i_p j_p} \bar{U}_{i'_1 j'_1} \cdots \bar{U}_{i'_p j'_p} dU \\ &= \sum_{\alpha, \beta \in \mathcal{S}_p} \delta_{i_1 i'_{\alpha(1)}} \cdots \delta_{i_p i'_{\alpha(p)}} \delta_{j_1 j'_{\beta(1)}} \cdots \delta_{j_p j'_{\beta(p)}} \text{Wg}_n(\alpha^{-1} \beta). \end{aligned}$$

Here,  $\mathcal{S}_p$  is the permutation group and  $\text{Wg}_n(\cdot)$  is called the *unitary Weingarten function*. Also, note that

$$\int_{\mathcal{U}(n)} U_{i_1 j_1} \cdots U_{i_p j_p} \bar{U}_{i'_1 j'_1} \cdots \bar{U}_{i'_p j'_p} dU = 0 \quad \text{for } p \neq p'.$$

For integer  $n \geq p$ , the Weingarten functions can be written as

$$\text{Wg}_n(\sigma) = \frac{1}{(p!)^2} \sum_{\lambda \vdash p} \frac{(\chi^\lambda(e))^2}{s_{\lambda,n}(1)} \chi^\lambda(\sigma) .$$

- $\lambda \vdash p$  means that  $\lambda$  is a partition of the integer  $p$ .
- $\chi^\lambda$  is the character of the irreducible representation of the symmetric group  $\mathcal{S}_p$  specified by  $\lambda$ .
- $s_{\lambda,n}(1)$  is the Schur polynomial evaluated at the identity:

$$s_{\lambda,n}(1) = \prod_{1 \leq i < j \leq n} \frac{\lambda_i - \lambda_j + j - i}{i - j} .$$

Use Murnaghan–Nakayama rule to generate the character tables of  $\mathcal{S}_p$ .

- Non-recursive method: Young tableau.
- Recursive method: Young diagrams.

## Examples.

$$\text{Wg}_n((1)) = \frac{1}{n}, \quad \text{Wg}_n((1, 1)) = \frac{1}{n^2 - 1}, \quad \text{Wg}_n((2)) = \frac{-1}{n(n^2 - 1)}.$$

$$\int_{\mathcal{U}(n)} U_{ij} \bar{U}_{i'j'} dU = \sum_{\alpha, \beta \in \mathcal{S}_1} \delta_{i_1 i'_{\alpha(1)}} \delta_{j_1 j'_{\beta(1)}} \text{Wg}_n(\alpha^{-1} \beta) = \frac{1}{n} \delta_{ii'} \delta_{jj'}.$$

$$\begin{aligned} \mathbb{E}[(U A U^*)_{kl}] &= \sum_{r,s=1}^n \mathbb{E}[U_{kr} A_{rs} U_{sl}^*] = \sum_{r,s=1}^n \mathbb{E}[U_{kr} A_{rs} \bar{U}_{ls}] \\ &= \sum_{r,s=1}^n \frac{1}{n} \delta_{kl} \delta_{rs} A_{rs}. \end{aligned}$$

$$\mathbb{E}[(U A \bar{U})_{kl}] = \sum_{r,s=1}^n \mathbb{E}[U_{kr} A_{rs} \bar{U}_{sl}] = \sum_{r,s=1}^n \frac{1}{n} \delta_{ks} \delta_{rl} A_{rs}.$$

## 1.3 Graphical version

Examples - continued.

$$\mathbb{E}[(UAU^*)_{kl}] = \sum_{r,s=1}^n \frac{1}{n} \delta_{kl} \delta_{rs} A_{rs} = \frac{1}{n} \delta_{kl} \sum_{r=1}^n A_{rr} .$$

This means that

$$\mathbb{E}[UAU^*] = \frac{\text{Tr}[A]}{n} I_n .$$

$$\mathbb{E}[(UA\bar{U})_{kl}] = \sum_{r,s=1}^n \frac{1}{n} \delta_{ks} \delta_{rl} A_{rs} = \sum_{r,s=1}^n \frac{1}{n} A_{lk} .$$

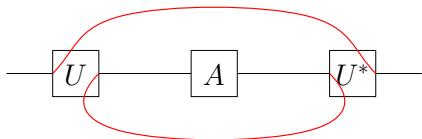
This means that

$$\mathbb{E}[UAU^*] = \frac{1}{n} A^T .$$

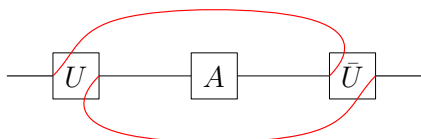


## Graphical calculus [Collins and Nechita (2011)]

$$\mathbb{E}[UAU^*] = \frac{\text{Tr}[A]}{n} I_n$$



$$\mathbb{E}[UAU^*] = \frac{1}{n} A^T$$



Original contractions:

[L-end, (U, out)], [(U, in), (A, out)], [(A, in), (U\*, out)], [(U\*, in), R-end]

After:

[L-end, R-end], [[A, out], [A, in]]

Original contractions:

[L-end, (U, out)], [(U, in), (A, out)], [(A, in), (U\*, in)], [(U\*, out), R-end]

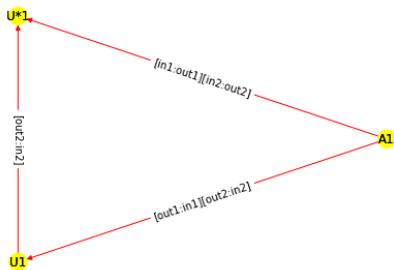
After:

[L-end, [A, in]], [[A, out], R-end]

## 1.4 “Computer version”

$[\text{id} \otimes \text{Tr}](UAU^*)$ :

```
In [1]: from IHU_source import *
In [2]: e1 = [["A", 1, "out", 1], ["U", 1, "in", 1]]
In [3]: e2 = [["A", 1, "out", 2], ["U", 1, "in", 2]]
In [4]: e3 = [["U*", 1, "out", 1], ["A", 1, "in", 1]]
In [5]: e4 = [["U*", 1, "out", 2], ["A", 1, "in", 2]]
In [6]: e5 = [["U", 1, "out", 2], ["U*", 1, "in", 2]]
In [7]: g = [e1, e2, e3, e4, e5]
In [8]: gw = [g, 1]
In [9]: visualizeTN (gw)
```



$\mathbb{E}[\text{id} \otimes \text{Tr}](U A U^*)$ :

```
In [10]: k, n = symbols('k n')
```

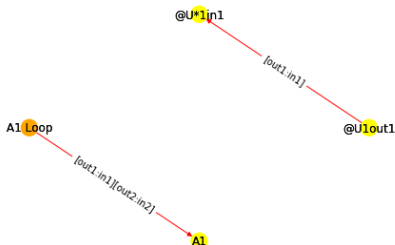
```
In [11]: rm = ["U", [n, k], [n, k], n*k]
```

```
In [12]: Eg = integrateHaarUnitary(gw, rm)
```

```
In [13]: print(Eg)
```

```
In [14]: visualizeTN(Eg)
```

```
Out [1]: [[[[['@U*', 1, 'in', 1], ['@U', 1, 'out', 1]],  
[[ 'A', 1, 'out', 1], [ 'A', 1, 'in', 1]],  
[[ 'A', 1, 'out', 2], [ 'A', 1, 'in', 2]]], 1/n]]
```



This figure is followed by the new weight  $1/n$  in the program.

## 1.5 Demo (had been done.)

To get RTNI, go to

<https://github.com/MotohisaFukuda/RTNI>

To get a user-friendly but limited version, called RTNI\_light, go to

[https://github.com/MotohisaFukuda/RTNI\\_light](https://github.com/MotohisaFukuda/RTNI_light)

To try a web version of RTNI\_light, go to

<https://motohisafukuda.pythonanywhere.com>

## 2 Random Gaussian states

“Typical entanglement for Gaussian states”,  
arXiv:1903.04126 [quant-ph] with Koenig.

## 2.1 Motivation and past research

Typical entanglement entropy of random bipartite quantum states.

- Lubkin('78); Lloyd & Pagels('88); Page('93); Foong & Kanno('94): average of entanglement entropy.
- Hayden, Leung and Winter ('04): concentration of entanglement entropy.

In the setting of random Gaussian states

- Serafini, Dahlsten, Gross & Plenio ('07):
  - micro-canonical measure and canonical measure.
  - inverse squared purity for subsystem of one mode is calculated.
- Us:
  - direct access to symplectic eigenvalues
  - the number of modes of subsystem can grow as  $n^\kappa$  with  $\kappa < 1$  with the total mode is  $n$ , in the regime  $n \rightarrow \infty$ .
- Others:

## 2.2 Passive Gaussian unitary operations

The set of Gaussian unitary maps has one-to-one correspondence to the real symplectic group  $\text{Sp}(2n) = \{S \in M_{2n \times 2n}(\mathbb{R}) \mid SJS^T = J\}$ ; a Gaussian unitary evolution of a Gaussian state means, for  $S \in \text{Sp}(2n)$

$$M \mapsto SMS^T$$

where  $M$  is the covariance matrix of the state.

Replacing the real symplectic group  $\text{Sp}(2n)$  by the orthogonal symplectic group  $\text{K}(2n) = \text{Sp}(2n) \cap \text{O}(2n)$ , which is compact. The map

$$\text{U}(n) \rightarrow \text{K}(2n)$$

$$U \mapsto \begin{pmatrix} \text{Re}(U) & \text{Im}(U) \\ -\text{Im}(U) & \text{Re}(U) \end{pmatrix} \equiv \frac{1}{2} \begin{pmatrix} I_n & iI_n \\ iI_n & I_n \end{pmatrix} \begin{pmatrix} U & 0 \\ 0 & \bar{U} \end{pmatrix} \begin{pmatrix} I_n & -iI_n \\ -iI_n & I_n \end{pmatrix}$$

induces the measure on  $\text{K}(2n)$ .

## 2.3 Partial trace as Gaussian operation

Suppose we have a Gaussian state of  $n$ -mode and want to get the covariance matrix of the reduced  $k$ -mode state (with redundant spaces).

For the covariance  $(2n \times 2n)$  matrix  $M_n$  of the  $n$ -mode, calculate

$$M_k = \hat{\Pi}_{n,k} M_n \hat{\Pi}_{n,k}$$

with the projection

$$\hat{\Pi}_{n,k} = \begin{pmatrix} \Pi_{n,k} & 0_n \\ 0_n & \Pi_{n,k} \end{pmatrix},$$

where  $\Pi_{n,k} = \text{diag}(\underbrace{1, \dots, 1}_{k \text{ times}}, \underbrace{0, \dots, 0}_{n-k \text{ times}})$  is a projection matrix of rank  $k$ .



## 2.4 Symplectic eigenvalues

A valid covariance matrix ( $M + iJ \geq 0$ ) has *Williamson normal form*: there is  $S \in \text{Sp}(2n) = \{S \in M_{2n \times 2n}(\mathbb{R}) \mid SJS^T = J\}$  such that

$$SMS^T = \text{diag}(\lambda_1, \lambda_1, \lambda_2, \lambda_2, \dots, \lambda_n, \lambda_n) .$$

where  $\lambda_j$  satisfy  $\lambda_j \geq 1$  and are called the *symplectic eigenvalues* .

They can be obtained by computing the spectrum of the matrix  $JM$ , which consists of complex conjugate pairs as follows:

$$\text{spec}(JM) = \bigcup_{j=1}^n \{\pm i\lambda_j\} .$$

Note that  $J = \begin{pmatrix} 0_n & -I_n \\ I_n & 0_n \end{pmatrix}$ .

## 2.5 Random Gaussian pure states

The covariance matrix  $M$  of a pure  $n$ -mode Gaussian state can be diagonalized by Euler/Bloch-Messiah decomposition;

$$M = S \begin{pmatrix} Z_n & 0 \\ 0 & Z_n^{-1} \end{pmatrix} S^T \quad \text{for some} \quad S \in \mathbb{K}(2n) .$$

Here,  $Z_n = \text{diag}(z_1, \dots, z_n)$  with  $z_j \geq 1$ .

The induced measure on  $\mathbb{K}(2n)$  generates random pure Gaussian states.

We call  $\{z_j\}_{j=1}^n$  the *squeezing parameters*. Observe that such a state has energy:

$$\text{Tr} [Z_n + Z_n^{-1}] = \sum_{j=1}^n E_j \quad \text{where} \quad E_j = \frac{1}{2}(z_j + 1/z_j) .$$

We can understand  $E_j$  as the energy in the  $j$ -th mode after a suitable Gaussian unitary rotation.

## 2.6 Symplectic eigenvalues of reduced states

Let  $M_k$  be the covariant matrix of  $k$ -mode, reduced from the random state of  $n$  mode. Then,

$$JM_k = \frac{1}{2} \begin{pmatrix} i\Pi & \Pi \\ -\Pi & -i\Pi \end{pmatrix} \begin{pmatrix} UAU^T & -iUBU^* \\ -i\bar{U}BU^T & -\bar{U}AU^* \end{pmatrix} \begin{pmatrix} \Pi & i\Pi \\ i\Pi & \Pi \end{pmatrix}$$

where  $A = (Z_n - Z_n^{-1})/2$  and  $B = (Z_n + Z_n^{-1})/2$ .

Define

$$f(U) = \text{Tr} \left[ \left( (JM_k)^2 + \lambda^2 I_{2k} \right)^2 \right] = 2 \sum_{j=1}^k (\lambda_j^2 - \lambda^2)^2 .$$

Here,  $\{\lambda_j\}_{j=1}^k$  are the symplectic eigenvalues of  $M_k$  and  $\lambda = \text{Tr}[B]/n$  is the averaged energy.

The calculation of  $\mathbb{E}[f(U)]$  involves Weingarten calculus with  $\mathcal{S}_4$ .

## 2.7 Concentration

### Concentration of symplectic eigenvalues:

For fixed  $k$ , suppose the energy of the initial pure Gaussian state is universally bounded;  $\sup_n \|Z_n\|_\infty < \infty$  ( $n^z$  with  $z < 1/8$  is possible).

Then

$$\Pr \{f(U) > \epsilon\} < \exp(-c\epsilon n)$$

for some universal constant  $c > 0$ .

### Concentration of entanglement entropy:

In addition, if  $\lambda = \lambda_n$  is bounded below by  $\mu > 1$ , then

$$\Pr \{|S(M_k) - S(\lambda I)| > \epsilon\} < \exp\left(-c \frac{\epsilon^4}{\beta(\mu)^4} n\right)$$

for some universal constant  $c > 0$ ;  $S(\cdot)$  is von Neumann entropy, and

$$\beta(\mu) = \log \frac{\mu + 1}{\mu - 1} .$$

is called the inverse temperature.

**Thank you very much.**

Acknowledgement:

- I thank Hun Hee Lee and other conference organizer for running this conference and covering partially the travel fees.
- JSPS KAKENHI Grant Number JP16K00005 is acknowledged for the rest of travel fees and financial supports for the above two research projects.