Large deviations in Coulomb gases: a mathematical perspective

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Abstract

These notes account for five ninety-minute lectures given by Mylène Maïda as part of the 2024 Summer School in Les Houches. This 4-week program was entitled *Large deviations and applications*. The goal of these lectures is to present a series of mathematical results about large deviations of the particles of a Coulomb gas or related systems, such as the eigenvalues of some random matrix ensembles. It encompasses the deviations of the empirical measure and those of the rightmost particle (corresponding to the largest eigenvalue).

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Introduction

These notes account for five lectures given as part of the 2024 Summer School in Les Houches entitled *Large deviations and applications*. The goal of these lectures is to present a series of mathematical results that are known about large deviations of the empirical measure of the particles of a Coulomb gas or related systems, such as the eigenvalues of some random matrix ensembles.

The lectures were mostly taught in parallel with a course of the same format presented by Pierpaolo Vivo (King's College London) entitled *Large deviations in random matrix theory and Coulomb gas systems*, whose lecture notes can be found here[1]. We refer the interested reader to Vivo's notes for a complementary point of view on some of the results.

Among the five main courses of the program, this course was probably the most math-oriented. Therefore, along with the presentation of the results, we will also seize the opportunity to introduce some mathematical tools that we find useful to show (or use) large deviation principles (LDP).

Before presenting in more details the scope of these lectures, let us provide a few general references.

We start with two resources, that we find particularly accessible for beginners :

- as a first glimpse on large deviations, we recommend the following blogpost[2], which is the transcription of a tutorial taught by D. Chafaï at ICERM in 2018,
- in the same summer school, an introductory course on large deviations, with a special focus on statistical mechanics, was given by H. Touchette. We highly recommend his lecture notes [1].

Among probabilists, the following books are considered very classical:

- the book [2] provides a very comprehensive presentation of the main tools used to establish large deviation principles and of the most classical applications,
- the book [3] is a classical reference dealing with random matrix theory but we advertise here its appendix D as a very concise summary of useful tools for large deviations
- the reference [4], which is also very comprehensive, is mainly based on a weak convergence approach, which, in his spirit, is more related to variational principles, that are natural to physicists and will inspire the approach of D. García-Zelada, that we will present in Chapter 2.

These are general references for the course but more specific thematic lists of references will be provided in each chapter.

The structure of the present lecture notes is as follows : in Section 1 – corresponding to the first lecture – we will introduce one of the most studied ensembles of random matrices, the Gaussian Unitary Ensemble (GUE), provide an LDP for the empirical measure of its eigenvalues and explain how it can be exploited to recover the celebrated Wigner theorem in this particular case. This will mostly rely on a paper by G. Ben Arous and A. Guionnet [5]. In Section 2 – roughly corresponding to lectures 2 and 3 –, we advertize the work of D. García-Zelada [6], based on Varadhan's approach of large deviations, that provides a unified framework for large

[1] http://www.lptms.universite-paris-saclay.fr/leshouches2024/files/2024/07/Les_Houches_Lecture_Notes_VIVO_V1.pdf

[2] https://djalil.chafai.net/blog/2018/03/09/tutorial-on-large-deviation-principles/

deviations for singular Gibbs measures, encompassing usual Coulomb gases in $\mathbb{R}^d$ at finite or hich temperature, but also Coulomb gases on manifolds, conditional Gibbs measures, zeroes of some models of random polynomials etc. Recently, following the pioneering work of Guionnet and Husson, spherical integrals of the form

$$I_N(A_N, B_N) := \int \exp\left(N\mathrm{Tr}(A_N U B_N U^*)\right) dm_N(U), \tag{1}$$

where A_N and B_N are two diagonal matrices of size N with real entries and m_N is the Haar measure on the orthogonal or the unitary group of size N, have been used to study the large deviations of the largest eigenvalue for several models of random matrices. In Section 3 – roughly corresponding to lectures 4 and 5 –, we provide a detailed derivation of the asymptotics of spherical integrals in the case when one of the matrices, say A_N, is of rank one, and explain how it can be used to study the deviations of the largest eigenvalue.

In these notes, we try to stay as close as possible to the in-person lectures that have been given in Les Houches. For the sake of completeness, we have nevertheless added a few proofs that were not presented during the lectures: they are in general postponed to the appendices.

Note that, although very interesting, the results on large deviations of the empirical field for Coulomb gases [7,8], which are related to the microscopic structure of these particle systems, are beyond the scope of this course and will not be included in these notes.

1 The Gaussian Unitary Ensemble

The *Gaussian Unitary Ensemble (GUE)* is one of the most popular models of random matrices. In this first chapter, we study this example in full detail, through the lens of large deviation theory.

1.1 Three descriptions of the GUE

In the usual vocabulary of random matrix theory (RMT), inspired by statistical physics, an *ensemble* is a probability distribution over a set of matrices. In this case, we consider the space of Hermitian matrices of size $N \times N$, denoted by

$$\mathcal{H}_N(\mathbb{C}) := \{M \in \mathcal{M}_N(\mathbb{C}), M^* = M\}.$$

The easiest way to define the GUE is by describing the joint law of the entries. Before doing so, we recall that if X and Y are two independent real random variables with standard Gaussian distribution $\mathcal{N}(0,1)$, then $G := \frac{X+iY}{\sqrt{2}}$ is said to be *standard complex Gaussian* and we denote $G \sim \mathcal{N}_{\mathbb{C}}(0,1)$.

Definition 1.1 *Let $N \in \mathbb{N}^*$ and consider independent random variables $\{G_{i,i}\}_{i=1}^N$ and $\{G_{i,j}\}_{1\le i<j\le N}$ such that $G_{i,i} \sim \mathcal{N}(0,1)$ and $G_{i,j} \sim \mathcal{N}_{\mathbb{C}}(0,1)$. Define the following $N \times N$ Hermitian matrix :*

$$H_N = \begin{pmatrix} \frac{G_{1,1}}{\sqrt{N}} & & \frac{G_{i,j}}{\sqrt{N}} & \\ & \ddots & & \\ \frac{G^*_{i,j}}{\sqrt{N}} & & \ddots & \\ & & & \frac{G_{N,N}}{\sqrt{N}} \end{pmatrix}, \quad \text{so that } G_{i,j} = G^*_{j,i}.$$

The matrix H_N is said to follow the GUE distribution or equivalently to belong to the GUE. We denote by μ_{GUE_N} its distribution.

One can also directly define μ_{GUE_N} as a Gaussian distribution on $\mathcal{H}_N(\mathbb{C})$. The isomorphism $\mathcal{H}_N(\mathbb{C}) \simeq \mathbb{R}^{N^2}$ induces a Lebesgue measure on $\mathcal{H}_N(\mathbb{C})$, that we denote by $\mathbf{Leb}_{\mathcal{H}_N}$. We can then give the following equivalent definition of the GUE:

Proposition 1.2 *There exists a normalizing constant c_N such that*

$$d\mu_{GUE_N}(H) = c_N \exp\left(-\frac{N}{2} Tr(H^2)\right) d\mathrm{Leb}_{\mathcal{H}_N}(H),$$

where Tr is the usual trace on $\mathcal{H}_N(\mathbb{C})$.

To see the correspondance with the law of the entries, it is enough to expand the trace as follows: if $H = (h_{i,j})_{1\le i,j\le N}$,

$$\mathrm{Tr}(H^2) = \mathrm{Tr}(HH^*) = \sum_{i=1}^N h_{i,i}^2 + 2 \sum_{1\le i<j\le N} |h_{i,j}|^2.$$

Now, for $i < j$, if we denote by $x_{i,j} = \mathrm{Re}\, h_{i,j}$ and $y_{i,j} = \mathrm{Im}\, h_{i,j}$, the respective real and imaginary part of $h_{i,j}$, we have

$$\mathrm{Tr}(H^2) = \sum_{i=1}^N h_{i,i}^2 + 2 \sum_{1\le i<j\le N} (x_{i,j}^2 + y_{i,j}^2),$$

so that, as expected, under μ_{GUE_N}, $(h_{i,i})_{1\le i\le N}, (x_{i,j})_{1\le i<j\le N}$ and $(y_{i,j})_{1\le i<j\le N}$ are independent real Gaussian variables, with variance $1/N$ if $i=j$ and $1/2N$ if $i<j$.

When H_N has distribution μ_{GUE_N}, it is interesting to study the law of its eigenvalues and eigenvectors. The following proposition gives the distribution of the eigenvalues.

Proposition 1.3 *If H_N has distribution μ_{GUE_N}, then almost surely, H_N is diagonalisable with distinct eigenvalues, that we may enumerate in decreasing order $\lambda_1^N > \cdots > \lambda_N^N$. Then, the joint law of the random vector $(\lambda_1^N, \cdots, \lambda_N^N)$ is given by*

$$d\mathbb{P}_{GUE_N}(x_1,\cdots,x_N) = \frac{N^{\frac{N^2}{2}} \mathbf{1}_{\{x_1>\ldots>x_N\}}}{(2\pi)^{N/2}\prod_{j=1}^{N-1} j!} \prod_{i<j}(x_i-x_j)^2 \exp\left(-\frac{N}{2}\sum_{j=1}^N x_j^2\right) dx_1\cdots dx_N. \quad (2)$$

This statement is well known in RMT. It is closely related to Weyl's formula. A classical reference for this kind of results is the book of M.L. Mehta [9]. One can also cite [10] for a gentle introduction for phycisists. For probabilists, a more recent standard reference is [3] (see in particular Theorem 2.5.2 there).

Although we won't focus very much on this aspect in the sequel, let us mention that it is also possible to describe the law of the eigenvectors under μ_{GUE_N}. The answer to this question, together with a third description of the law μ_{GUE_N}, is postponed to Appendix A.

We now want to study the behavior of the particles $(\lambda_1^N, \cdots, \lambda_N^N)$ under $\mathbb{P}_{GUE_N}$. Many interesting questions can be asked about their behavior e.g. the following:

- How does the largest eigenvalue behave ?
- What does the global regime look like ? etc.

The first question will be adressed in full detail for the Gaussian Orthogonal Ensemble (GOE), which is the real symmetric counterpart of the GUE in the course of Pierpaolo Vivo and we strongly recommend his lecture notes. They can be found in the present volume or at the following link. We won't detail it in the case of the GUE, but we will come back to similar questions for other models in the third section of these notes (Lectures 4 and 5).

We will rather focus on the second question. The idea is to encode the positions of all the particles as a whole in the following object:

$$\hat{\mu}_N := \frac{1}{N}\sum_{i=1}^N \delta_{\lambda_i^N}.$$

It is called the *empirical distribution of the eigenvalues of H_N* or *spectral empirical distribution* of H_N. For each realisation $H_N(\omega)$ of the random matrix H_N, $\hat{\mu}_N(\omega)$ is a probability measure which is nothing but the uniform distribution over the set of eigenvalues $\{\lambda_1^N(\omega), \cdots, \lambda_N^N(\omega)\}$. Therefore, $\hat{\mu}_N$ is a *random probability measure*, that is a random variable with values in the set $\mathcal{P}(\mathbb{R})$ of probability measures on $\mathbb{R}$. This random measure will be our main object of study in this chapter, and we want in particular to describe its typical behavior (law of large numbers), its large deviations etc.

1.2 Large deviation principle for the empirical spectral distribution

Let us first make the link between the GUE random matrix model and Coulomb gas-like particle systems.

To lighten the notations, we denote the prefactor in (2) by

$$C_N := \frac{N^{\frac{N^2}{2}}}{(2\pi)^{N/2}\prod_{j=1}^N j!}, \tag{3}$$

so that we can now rewrite (2) as :

$$d\mathbb{P}_{GUE_N}(x_1,\dots,x_N) = C_N \exp\left(-N\left(\frac{1}{2}\sum_{j=1}^N x_j^2 - \frac{1}{N}\sum_{i\neq j}\log|x_i-x_j|\right)\right)dx_1\cdots dx_N.$$

Note that there is here a slight abuse of notation: $\mathbb{P}_{GUE_N}$ as defined in (2) was a distribution over that set $\{x_1 > \dots > x_N\}$ whereas here we extend it to $\mathbb{R}^N$. This is balanced by an extra factor $N!$ in the definition of the constant C_N with respect to the normalizing constant appearing in (2).

We now can see $\mathbb{P}_{GUE_N}$ as the *canonical Gibbs measure* associated to the energy E, defined as follows: for any N-tuple $x_1,\dots,x_N$ of real numbers,

$$E(x_1,...,x_N) := N\left(\frac{1}{2}\sum_{j=1}^N x_j^2 - \frac{1}{N}\sum_{i\neq j}\log|x_i-x_j|\right). \tag{4}$$

In this expression,

- the first term $\frac{1}{2}\sum_{j=1}^N x_j^2$ is usually interpreted as a confining external potential applied to each particle, that prevents them to lay too far away from the origin,
- whereas the second term $\frac{1}{N}\sum_{i\neq j}\log|x_i-x_j|$ is usually interpreted as a repulsive two-body interaction.

We commonly use the terminology *one dimensional log-gas* to describe such a particle system; it is considered a Coulomb-type particle system[3]. Coulomb gases will be introduced and discussed more thoroughly in the next chapter of these notes. We refer to the book [11] of P. Forrester for a very thorough presentation of theses systems, including many explicit computations.

Before getting into the mathematical statement of an LDP for the spectral empirical measure $\widehat{\mu}_N$, let us try to give some rough heuristics towards a possible rate function. Fix $\mu \in \mathcal{P}(\mathbb{R})$, $\delta > 0$ small and $B(\mu,\delta)$ a ball of radius δ centered at μ for a metric on $\mathcal{P}(\mathbb{R})$ to be defined later. We have

$$\begin{aligned}&\mathbb{P}_{GUE_N}(\widehat{\mu}_N \in B(\mu,\delta))\\ &= C_N\int_{\widehat{\mu}_N\in B(\mu,\delta)}\exp\left(-N^2\left(\int\frac{x^2}{2}d\widehat{\mu}_N(x) - \iint_{x\neq y}\log|x-y|d\widehat{\mu}_N(x)d\widehat{\mu}_N(y)\right)\right)dx_1\cdots dx_N.\end{aligned}$$

Then (if everything behaves nicely)

$$-\frac{1}{N^2}\log\mathbb{P}_{GUE}(\widehat{\mu}_N \in B(\mu,\delta)) \approx -\frac{1}{N^2}\log C_N + \int\frac{x^2}{2}d\mu(x) - \iint\log|x-y|d\mu(x)d\mu(y).$$

[3]The one-dimensional Coulomb interaction is linear whereas the two-dimensional is logarithmic. In other words, we have here a two-dimensional Coulomb gas confined to live on the real line.

The analysis of the constant C_N is a simple exercise, as its expression is completely explicit. Namely,

$$\begin{aligned}\frac{1}{N^2}\log C_N &= -\frac{1}{N^2}\sum_{j=1}^{N}\sum_{k=1}^{j}\log\left(\frac{k}{N}\right)+\frac{1}{2N}\log(2\pi)\\ &= -\frac{1}{N^2}\sum_{k=1}^{N}\frac{N-k+1}{N}\log\left(\frac{k}{N}\right)+\frac{1}{2N}\log(2\pi)\\ &\xrightarrow[N\to\infty]{} -\int_0^1(1-x)\log x\,dx=\frac{3}{4}.\end{aligned}$$

If, for any probability measure μ for which it is properly defined, we let

$$I(\mu)=\int\frac{x^2}{2}d\mu(x)-\iint\log|x-y|d\mu(x)d\mu(y)-\frac{3}{4},$$

then we expect that

$$\mathbb{P}_{GUE_N}(\widehat{\mu}_N\in B(\mu,\delta))\simeq\exp\bigl(-N^2I(\mu)\bigr).$$

Let us now go to a more precise statement of the LDP that was unveiled by G. Ben Arous and A. Guionnet in [5]. Mathematically speaking, a full LDP in this case will take the following form:

- for any open set $O\subset\mathcal{P}(\mathbb{R})$, $\liminf_{N\to\infty}\frac{1}{N^2}\log\mathbb{P}_{\mathrm{GUE}_N}(\widehat{\mu}_N\in O)\geq-\inf_{\mu\in O}I(\mu)$
- for any closed set $F\subset\mathcal{P}(\mathbb{R})$, $\limsup_{N\to\infty}\frac{1}{N^2}\log\mathbb{P}_{\mathrm{GUE}_N}(\widehat{\mu}_N\in F)\leq-\inf_{\mu\in F}I(\mu)$.

Open and *closed* refer to a topology that we have to define on the space of probability measures $\mathcal{P}(\mathbb{R})$: a common choice is the topology of weak convergence. In this topology, a sequence $(\nu_N)_{N\in\mathbb{N}}$ converges to $\nu\in\mathcal{P}(\mathbb{R})$, and we denote this convergence by $\nu_N\xrightarrow[N\to\infty]{w}\nu$, if and only if

$$\forall f\in\mathcal{C}^b(\mathbb{R}),\int_{\mathbb{R}}f(x)d\nu_N(x)\xrightarrow[N\to\infty]{}\int_{\mathbb{R}}f(x)d\nu(x),$$

where $\mathcal{C}^b(\mathbb{R})$ stands for the set of bounded and continuous functions from $\mathbb{R}$ to $\mathbb{R}$.

We are now ready to state the main result of this chapter.

Theorem 1.4 *[5] Under $\mathbb{P}_{GUE_N}$, the sequence of empirical spectral distributions $(\widehat{\mu}_N)_{N\in\mathbb{N}}$ satisfies a large deviation principle at speed N^2 with good rate function[4] I in the space $\mathcal{P}(\mathbb{R})$ equipped with the topology of weak convergence, where the rate function I is defined as follows:*

$$I(\mu):=\begin{cases}\int_{\mathbb{R}}\frac{x^2}{2}d\mu(x)-\iint\log|x-y|d\mu(x)d\mu(y)-\frac{3}{4}, & \text{if }\int x^2d\mu<\infty,\\ \infty & \text{otherwise.}\end{cases}\tag{5}$$

It is always more comfortable to work with a metric structure. Fortunately, the topology of weak convergence can be metrized by the bounded-Lipschitz distance defined as follows : for $\mu,\nu\in\mathcal{P}(\mathbb{R})$

$$d_{\mathrm{BL}}(\mu,\nu)=\sup_{\|f\|_\infty\leq1,\|f\|_{\mathrm{Lip}}\leq1}\left|\int f\,d\mu-\int f\,d\nu\right|,$$

[4]We don't want to insist too much at this stage on the notion of *(good) rate function*, we refer to Section 2.3 for more details.

with $\|f\|_{\mathrm{Lip}} \le 1 \Leftrightarrow |f(x)-f(y)| \le |x-y|, \forall x,y \in \mathbb{R}$. This means that $\nu_N \xrightarrow[N\to\infty]{w} \nu$ if and only if $d_{\mathrm{BL}}(\nu_N,\nu) \xrightarrow[N\to\infty]{} 0$. In the following, anytime we mention a distance on $\mathcal{P}(\mathbb{R})$ it will be the bounded-Lipschitz distance and $B(\mu,\delta)$ will refer to the ball of radius δ around μ for this bounded-Lipschitz distance.

With $\mathcal{P}(\mathbb{R})$ being a metric space, it is possible to give an easier formulation of the LDP above. Roughly speaking, we have :

(weak LDP on small balls + exponential tightness) implies (full LDP)

More precisely, if we have

1. (Weak LDP) :

$$\begin{aligned}\lim_{\delta\to 0}\liminf_{N\to\infty}\frac{1}{N^2}\log \mathbb{P}_{\mathrm{GUE}_N}(\widehat{\mu}_N \in B(\mu,\delta)) \\ = \lim_{\delta\to 0}\limsup_{N\to\infty}\frac{1}{N^2}\log \mathbb{P}_{\mathrm{GUE}_N}(\widehat{\mu}_N \in B(\mu,\delta)) =: -I(\mu)\end{aligned}$$

2. and (Exponential tightness) : There exists a sequence $(K_L)_{L>0}$ of compact subsets of $\mathcal{P}(\mathbb{R})$ such that

$$\limsup_{L\to\infty}\limsup_{N\to\infty}\frac{1}{N^2}\log \mathbb{P}_{\mathrm{GUE}_N}(\widehat{\mu}_N \notin K_L) = -\infty, \tag{6}$$

then we have Theorem 1.4. We refer to Appendix D in [3] for the details on this criterion.

The proof of the weak LDP has been sketched at the beginning of this subsection, so we now focus on the second point. Let us comment on the (important) notion of *tightness* in probability. A classical reference on the notions of weak convergence of measures and tightness in Polish spaces in the book of P. Billingsley [12]. If we have a random variable X, with values in a Polish space, then for any $\varepsilon > 0$, one can always find a compact set $\mathcal{K}_\varepsilon$ for which

$$\mathbb{P}(X \notin \mathcal{K}_\varepsilon) \le \varepsilon,$$

that is "almost everything happens inside a (large enough) compact set". When we consider a sequence, or more generally a family, of random variables $(X_i)_{i\in I}$, it is not obvious (and even false in general!) that one can find a fixed compact $\mathcal{K}_\varepsilon$ (depending on ε but not on i) such that

$$\forall i \in I, \mathbb{P}(X_i \notin \mathcal{K}_\varepsilon) \le \varepsilon.$$

This is not true in general. If it holds for any ε, the family of random variables is said to be *tight* (equivalently, if for any $i \in I$, μ_i is the distribution of the random variable X_i, the family of probability measures $(\mu_i)_{i\in I}$ is said to be tight). It means that when we deal with questions related to (weak) convergence, what happens outside a large compact set is not relevant.

Here, as we are working at the level of exponentially small events, we ask for *exponential tightness*, which, in our case, is expressed by (6). Moreover, as the sequence $(\widehat{\mu}_N)_{N\ge 1}$ that we are considering is a sequence of random variables with values in the set $\mathcal{P}(\mathbb{R})$, the first step is to describe a convenient family of compact sets in this latter space.

For any $L > 0$, let us define

$$K_L := \left\{\mu \in \mathcal{P}(\mathbb{R}), \int x^2 d\mu(x) \le L\right\}.$$

We first justify that K_L is a compact subset of $\mathcal{P}(\mathbb{R})$. Notice that for all $\mu \in K_L$, we have by Markov inequality

$$\mu\left(\left[-\sqrt{\frac{L}{\varepsilon}},\sqrt{\frac{L}{\varepsilon}}\right]^c\right)=\frac{\varepsilon}{L}\int\frac{L}{\varepsilon}\mathbb{1}_{\left\{x\notin\left[-\sqrt{\frac{L}{\varepsilon}},\sqrt{\frac{L}{\varepsilon}}\right]\right\}}(x)d\mu(x)\leq\frac{\varepsilon}{L}\int x^2 d\mu(x)\leq\varepsilon,$$

so that the family of probability measure K_L is tight, in the sense explained above[5]. Since $\mathbb{R}$ is a complete metric space, we deduce by Prokhorov's theorem (see for example Theorem C.9 in [3]) that the closure of K_L is compact in the weak topology. Moreover, K_L is closed. Indeed, let $(\mu_N)_N$ be a sequence in K_L which converges weakly to μ then, for any $M>0$, $\int x^2\wedge M d\mu(x)=\lim_{N\to\infty}\int x^2\wedge M d\mu_N(x)$. Then by monotone convergence as M goes to infinity and the fact that the bound $\int x^2\wedge M d\mu_N(x)\leq L$ is uniform in M and N, we get that $\mu\in K_L$. Therefore, K_L is a closed set included in a compact and so it is itself compact.

Let us now show (6). We define

$$f(x,y):=\frac{x^2}{4}+\frac{y^2}{4}-\log|x-y|.$$

As, for any $x,y\in\mathbb{R}$, $\log|x-y|\leq\log(|x|+1)+\log(|y|+1)$, we have

$$f(x,y)\geq\frac{x^2}{8}+\frac{y^2}{8}+\widetilde{C},$$

for some constant $\widetilde{C}$. Note that this bound also justifies why the rate function I introduced in (5) is well defined.

Moreover, using the density of $\mathbb{P}_{GUE_N}$ with respect to the Lebesgue measure, we have :

$$\begin{aligned}
\mathbb{P}_{\mathrm{GUE}_N}(\widehat{\mu}_N\notin K_L)&=C_N\int_{\{\widehat{\mu}_N\notin K_L\}}\exp\left(-N\frac{1}{2}\sum_{i=1}^N x_i^2+\sum_{i\neq j}\log|x_i-x_j|\right)dx_1...dx_N\\
&=C_N\int_{\{\widehat{\mu}_N\notin K_L\}}\exp\left(-N^2\iint_{x\neq y}f(x,y)d\widehat{\mu}_N(x)d\widehat{\mu}_N(y)\right)\prod_{i=1}^N\exp\left(-\frac{x_i^2}{2}\right)dx_1\cdots dx_N\\
&\leq C_N\int_{\{\widehat{\mu}_N\notin K_L\}}\exp\left(-N^2\iint_{x\neq y}\left(\frac{x^2}{8}+\frac{y^2}{8}+\widetilde{C}\right)d\widehat{\mu}_N(x)d\widehat{\mu}_N(y)\right)\prod_{i=1}^N\exp\left(-\frac{x_i^2}{2}\right)dx_1\cdots dx_N\\
&\leq C_N\exp\left(-N^2\left(\frac{N-1}{N}\frac{L}{4}+\frac{N(N-1)}{N^2}\widetilde{C}\right)\right)\int_{\{\widehat{\mu}_N\notin K_L\}}\prod_{i=1}^N\exp\left(-\frac{x_i^2}{2}\right)dx_1\cdots dx_N,
\end{aligned}$$

and then taking $\limsup\frac{1}{N^2}\log$ on both sides, we get :

$$\limsup_{N\to\infty}\frac{1}{N^2}\log\mathbb{P}_{\mathrm{GUE}_N}(\widehat{\mu}_N\notin K_L)\leq\limsup_{N\to\infty}\frac{1}{N^2}\log C_N-\frac{L}{4}+\widetilde{C}\leq\frac{3}{4}-\frac{L}{4}+\widetilde{C}.$$

Finally, taking L to infinity, we get the desired result.

This concludes the arguments of the proof of the result of Ben Arous and Guionnet that we wanted to emphasize here. We refer to the original paper [5] or alternatively to Section 2.6 of the book [3] for more details. In the framework of these notes, we will give in the next chapter a much more general result on singular Gibbs measures that encompasses the GUE model.

[5]Note that there is a subtle point here: we use the fact that the family of probability measure K_L is tight to show that it is a compact subset of $\mathcal{P}(\mathbb{R})$. Then we will use K_L to show that the family of random variables $(\widehat{\mu}_N)_{N\geq 1}$ is exponentially tight !

1.3 Understanding the minimizer of the rate function

In various situations, understanding the deviations of a family of random variables may be the best way to study also their typical behavior. In the case of GUE, this typical behavior was known for a long time before the large deviations were studied but we find it instructive to show how this particular case of Wigner's theorem can be seen as a corollary of the large deviation principle we have just obtained. This subsection will be devoted to the discussion and the proof of the following statement and why it may be seen as a corollary of Theorem 1.4.

Corollary 1.5 *(Wigner's Theorem)*
Almost surely

$$\widehat{\mu}_N \xrightarrow[N\to\infty]{w} \mu_{sc},$$

where μ_{sc} is the semi-circular distribution defined by the density :

$$d\mu_{sc}(t) = \frac{1}{2\pi}\sqrt{4-t^2}\mathbb{1}_{[-2,2]}(t)dt.$$

In a very general context, it is possible to deduce an almost sure convergence from a large deviation principle, whenever the rate has a unique minimiser. This general mechanism will be illustrated in our example at the end of this section. We first establish the following property:

Proposition 1.6 *μ_{sc} is the unique minimiser of I.*

The proof of the proposition will be in three steps: we show that the minimizer is unique, that any minimizer should satisfy the Euler-Lagrange equations and that the semi-circular distribution satifies the Euler-Lagrange equations.

Each of the three steps corresponds to a lemma that we state below:

Lemma 1.7 *Any minimizer μ of the rate funtion I satisfies the following : there exists a constant C_{EL} such that for any x in the support of the measure μ, we have*

$$\frac{x^2}{2} - 2\int \log|x-y|d\mu(y) = C_{EL},$$

and for Lebesgue-almost every $x \in \mathbb{R}$,

$$\frac{x^2}{2} - 2\int \log|x-y|d\mu(y) \geq C_{EL}.$$

These equations are called *Euler-Lagrange (EL) equations*. We will give below a detailed proof of Lemma 1.7, which, as we will see below, is robust to generalisation to external potentials other than quadratic.

The next lemma states that μ_{sc} does satisfy the EL-equation associated to this problem :

Lemma 1.8

$$\frac{x^2}{2} - 2\int \log|x-y|d\mu_{sc}(y) = \begin{cases} 1 & \text{for all } x \in [-2,2], \\ > 1 & \text{for all } |x| > 2. \end{cases}$$

There are many ways to compute the logarithmic potential of μ_{sc}, that is the integral $\int \log|x-y|d\mu_{sc}(y)$. The computation of this quantity outside the support of μ_{sc} has been detailed in Section IV.A.1 of Vivo's lecture notes : using an expansion of the logarithm, the computation boils down to the computation of the moments of μ_{sc}, that are interesting quantities by themselves, related to Catalan numbers. From his computation, it is easy to check the second inequality above. For the sake of completeness, we present the details of the computation of the logarithmic potential inside the support of the measure, using the residue theorem, in Appendix B.

Moreover, the uniqueness of the minimizer of the rate function is ensured by the following:

Lemma 1.9 *The rate funtion I is strictly convex on $\mathcal{P}(\mathbb{R})$. It therefore admits a unique minimizer.*

This was not proved during the lectures but relies on an interesting Fourier representation of the logarithmic energy : the proof of Lemma 1.9 is postponed to Appendix C.

We now go to the proof of Lemma 1.7. Let $\psi \geq 0$, and ϕ be two bounded and compactly supported functions. Then define $\bar{\nu}_{\psi,\phi}$ by

$$d\bar{\nu}_{\psi,\phi}(x) = \phi(x)d\mu(x) + \psi(x)dx,$$

where ϕ and ψ are such that $\bar{\nu}_{\psi,\phi}(\mathbb{R}) = 0$, so that if $\mu \in \mathcal{P}(\mathbb{R})$ and ε is sufficiently small, $\mu + \varepsilon\bar{\nu}_{\psi,\phi} \in \mathcal{P}(\mathbb{R})$. If μ is a minimiser of I, for any such ψ, ϕ we have

$$\begin{aligned} I(\mu) \leq I(\mu + \epsilon\bar{\nu}_{\psi,\phi}) = &\int \frac{x^2}{2}d\mu + \epsilon\int \frac{x^2}{2}d\bar{\nu}_{\psi,\phi} \\ &- \iint \log|x-y|(d\mu d\mu + \epsilon d\mu d\bar{\nu}_{\psi,\phi} + \epsilon d\bar{\nu}_{\psi,\phi}d\mu + \epsilon^2 d\bar{\nu}_{\psi,\phi}d\bar{\nu}_{\psi,\phi}) \\ &- \frac{3}{4}, \end{aligned}$$

thus we get

$$\epsilon\int \frac{x^2}{2}d\bar{\nu}_{\psi,\phi}(x) - 2\varepsilon\iint \log|x-y|d\bar{\nu}_{\psi,\phi}(x)d\mu(y) - \varepsilon^2\iint \log|x-y|d\bar{\nu}_{\psi,\phi}(x)d\bar{\nu}_{\psi,\phi}(y) \geq 0,$$

and so by dividing by ε and letting ε go to zero we get :

$$\int \left(\frac{x^2}{2} - 2\int \log|x-y|d\mu(y)\right)d\bar{\nu}_{\psi,\phi}(x) \geq 0$$

By choosing $\psi = 0$ and $\pm\phi$, we obtain that for all ϕ such that $\int \phi d\mu = 0$:

$$\int \phi(x)\left(\frac{x^2}{2} - 2\int \log|x-y|d\mu(y)\right)d\mu(x) = 0,$$

and therefore there exists a constant C_{EL} such that for all $x \in \mathrm{Supp}(\mu)$,

$$\frac{x^2}{2} - 2\int \log|x-y|d\mu(y) = C_{EL} \text{ (Lagrange multiplier)}.$$

Then, by choosing $\phi = -\int \psi(y)dy$ being a constant, we get, for Lebesgue-almost every x,

$$\frac{x^2}{2} - 2\int \log|x-y|d\mu(y) \geq C_{EL}.$$

Therefore, any minimizer μ satisfies the Euler-Lagrange equation.

We are now ready to go to the proof of Corollary 1.5. Putting the three lemmas together, we get that $\mu_{\rm sc}$ is indeed the unique minimizer of I.

From there, one can easily deduce Wigner's theorem, using first the upper bound of the large deviation principle. It indeed gives that

$$\forall \delta > 0, \limsup_{N\to\infty} \frac{1}{N^2} \log \mathbb{P}_{GUE_N}(\widehat{\mu}_N \notin B(\mu_{\rm sc}, \delta)) \leq - \inf_{\mu \notin B(\mu_{\rm sc},\delta)} I(\mu) =: -I_\delta.$$

Then since $K := B(\mu_{sc}, \delta)^c \cap \{\nu : I(\nu) \leq I_\delta + 1\}$ is a compact set and I is lower semicontinuous, I reaches its infimum on K. Since K does not contain the minimizer $\mu_{\rm sc}$ of I, we have $0 < \inf_{\mu\in K} I(\mu) = I_\delta$. Therefore, we have for N big enough that

$$\mathbb{P}_{GUE_N}(\widehat{\mu}_N \notin B(\mu_{sc}, \delta)) \leq \exp\left(-N^2 \frac{I_\delta}{2}\right),$$

and thus, since $I_\delta > 0$, we have that $\mathbb{P}_{GUE_N}(\widehat{\mu}_N \notin B(\mu_{\rm sc}, \delta))$ is summable. By Borel-Cantelli, we know that for all δ, the sequence $(\widehat{\mu}_N)_{N\in\mathbb{N}}$ is almost surely eventually in $B(\mu_{\rm sc}, \delta)$ and therefore we have that a.s. $\widehat{\mu}_N \xrightarrow{w} \mu_{\rm sc}$ as $N \to \infty$.

1.4 Conclusion

Before going to the general theory of the global behavior of Coulomb gases, let us summarize what we have learnt from the study of the specific case of the GUE model:

- If H_N is a random matrix from the GUE of size N, the distribution of its eigenvalues is a singular canonical Gibbs measure which forms a one-dimensional log-gas.
- Its spectral empirical distribution is a random measure which satisfies a large deviation principle on the space of probability measures on $\mathbb{R}$, at speed N^2 with an explicit rate function.
- Through the derivation of Euler-Lagrange equations, one can show that the unique minimizer of this rate function is the semi-circular distribution. From there, one can use the large deviation upper bound for the spectral empirical distribution to get the almost sure weak convergence of the latter to the semi-circle distribution (Wigner's theorem).

2 General LDP for particle systems related to Coulomb gases

After this warmup through the example of the GUE, we now go to the main topic of the course, that is LDPs for Coulomb gases and related particle systems. On this question, it is fair to cite the work of D. Chafaï, N. Gozlan and P. A. Zitt [13], which built on arguments in the spirit of [5]. We have chosen in this course to emphasize the work of D. García-Zelada [6]. We first introduce properly the notion of Coulomb gas.

2.1 Coulomb and Riesz gases, vocabulary

Consider N particles $(x_1, \cdots, x_N) \in (\mathbb{R}^d)^N$, and define the Hamiltonian of the configuration as follows:

$$E_N(x_1, \cdots, x_N) = N \sum_{i=1}^{N} V(x_i) + \frac{1}{2} \sum_{i \neq j} g(x_i - x_j). \tag{7}$$

The function V is usually called the *external potential* and g the *kernel interaction*. Under appropriate assumptions on V and g that we will detail later, it is possible to define the associated *Gibbs measure*, given by :

$$d\mathbb{P}_{N,V,\beta,g}(x_1, \cdots, x_N) = \frac{1}{Z_{N,V,\beta,g}} \exp(-\beta E_N(x_1, \cdots, x_N)) \, d\pi^{\otimes N}(x_1, \cdots, x_N), \tag{8}$$

where $d\pi^{\otimes N}(x_1, \cdots, x_N) = d\pi(x_1) \cdots d\pi(x_N)$, with π a reference measure, most of the time chosen to be the Lebesgue measure on $\mathbb{R}^d$ and $Z_{N,V,\beta,g}$ is a normalizing constant such that $\mathbb{P}_{N,V,\beta,g}$ is a probability measure[6].

Coulomb gases correspond to a particular choice of the (repulsive) interaction kernel g. It satisfies the so-called Poisson equation $\Delta g = -c_d \delta_0$, with c_d an appropriate constant depending on the dimension d so that its solution reads:

$$g(x) = \begin{cases} -|x|, & \text{for } d = 1, \\ -\log|x|, & \text{for } d = 2, \\ \frac{1}{|x|^{d-2}}, & \text{for } d \geq 3. \end{cases}$$

Example: Similarly to what we saw in the first chapter on this course for the GUE, if one defines the Complex Ginibre Ensemble, as a random matrix of size $N \times N$, with independent identically distributed entries $G_{i,j}$ that are complex centered Gaussian with variance $1/N$ (without any symmetry assumption), then, one can check that the joint law of its eigenvalues is a Coulomb gas in dimension $d = 2$, with Coulomb kernel $g(x - y) = -\log|x - y|$ and quadratic external potential $V(x) = |x|^2/2$.

As mentioned earlier, the eigenvalues of the GUE do not form *stricto sensu* a Coulomb gas, but rather a so-called *log-gas* in the sense that $g(x) = -\log|x|$ although we are in dimension 1. This log-gas in one dimension is also commonly called a β*-ensemble*.

An important family of related particle systems are *Riesz gases*: for $d \geq 1$, $g(x) = |x|^{-s}$ with $s > 0$.

As in the first chapter, we will study the *global regime* of these particle systems, through the first order asymptotics of the associated empirical measure

$$\hat{\mu}_N := \frac{1}{N} \sum_{i=1}^{N} \delta_{x_i}.$$

[6]Appropriate assumptions on V and g ensure in particular that $0 < Z_{N,V,\beta,g} < \infty$.

Let us now briefly mention an important topic that we will not discuss in these lectures, namely the *microscopic structure of Coulomb gases*. As we have seen in the first chapter, with the scaling that we have chosen (multiply each entry of the matrix by $1/\sqrt{N}$, or equivalently put a factor of N in front of the external potential V in the definition of the Hamiltonian), the weak limit of the empirical measure of the eigenvalues of the GUE is compactly supported. One can check that, under standard assumption on V, it would be the same for the Coulomb gas (8), associated with the Hamiltonian (7). The heuristics is that, considering a given particle x_i, the force $NV(x_i)$ created on it by the external potential is of the same order as the force felt from the repulsion $\sum_{j\neq i} g(x_i - x_j)$ of all the other particles, both being of order N: this leads to an equilibrium at a finite scale.

The limiting measure being compact, it means that on average, each particle occupies a box of volume of order $N^{-1/d}$. If one wants to study the microscopic structure of the Coulomb gas, it is therefore natural to choose a place around which there are particles, that is a point x_0 in the interior of the support of the limiting measure and blow up the configuration of points around x_0 at a scale where there would be in average one point per unit volume, that is consider the process $(N^{1/d}(x_i - x_0))_{1\leq i\leq N}$. Following the breakthrough papers by S. Serfaty and collaborators, there has been huge mathematical progresses in the study of the Coulomb gases at this new scale. One of the main features is that, similarly to what was observed for matrix models, the microscopic structure of Coulomb gases is much more universal than their global regime, in the sense that the limiting random process essentially does not depend on the external potential V. It does depend on β and there is an important conjecture, that at low temperature (that is in the regime $\beta \to \infty$), there would be a *crystallization* phenomenon, the limiting process being the triangular lattice in dimension 2. We won't treat this problem in these notes but the interested reader may find a lot of resources on this topic on S. Serfaty's webpage[7]. We recommend in particular the recent survey [14].

2.2 General Laplace principle for particle systems driven by a k-body interaction

Let us now go back to our main subject and present the framework of [6], which is a very general model with a k-body interaction (in most physical examples, we consider pairwise interactions, that is $k = 2$). At each step, we will try to make as transparent as possible the correspondence with the GUE model studied in the first part of this course.

If M is the space in which the particles live (M may be $\mathbb{R}^d$, a manifold or a Polish space[8]) and $\mathcal{P}(M)$ the set of probability measures on M, we consider $G : M^k \to (-\infty, +\infty]$, a symmetric, lower semi-continuous and bounded below function.

For $N \geq k$, we define $W_N : M^N \to (-\infty, +\infty]$ by

$$W_N(x_1, \cdots, x_N) = \frac{1}{N^k} \sum_{\substack{\{i_1,\cdots,i_k\}\subseteq\{1,\cdots,N\} \\ \#\{i_1,\cdots,i_k\}=k}} G(x_{i_1}, \cdots, x_{i_k}). \tag{9}$$

For instance, for the GUE, we choose $M = \mathbb{R}$, $k = 2$ and define

$$G(x, y) := \frac{x^2}{2} + \frac{y^2}{2} - 2\log|x - y|.$$

[7] https://math.nyu.edu/~serfaty/

[8] A Polish space is a complete separable metric space. Working in a Polish space is a usual assumption in probability theory.

This gives

$$W_N(x_1,\cdots,x_N)=\frac{1}{N^2}\sum_{i<j}G(x_i,x_j)=\frac{1}{N^2}\left((N-1)\sum_{i=1}^{N}\frac{x_i^2}{2}-\sum_{i\neq j}\log\left|x_i-x_j\right|\right),$$

which is to compare with the energy E of the configuration that has been defined in (4).

Consider now a reference measure π and inverse temperature $\beta_N>0$. Similarly to what we did previously, one can define an associated Gibbs measure γ_N, which has the following density

$$d\gamma_N(x_1,\cdots,x_N):=\exp(-N\beta_N W_N(x_1,\cdots,x_N))\mathrm{d}\pi(x_1)\cdots\mathrm{d}\pi(x_N). \tag{10}$$

Note that at this stage, γ_N is not normalized, it may not be a probability measure.

Again, it may be useful to compare to our example: with $G(x,y):=\frac{x^2}{2}+\frac{y^2}{2}-2\log|x-y|$, $\beta_N=N$ and $d\pi(x)=e^{-x^2/2}dx$, we get that

$$\mathbb{P}_{\mathrm{GUE}_N}=C_N\gamma_N,$$

where $\mathbb{P}_{\mathrm{GUE}_N}$ has been defined in (2) and C_N in (3).

We are now ready to state the main result of [6]:

Theorem 2.1 *Assume that $G:M^k\to(-\infty,+\infty]$ is symmetric, lower semi-continuous and bounded below and W_N and γ_N being defined in (9) and (10) respectively.*

Assume that $\beta_N\xrightarrow[N\to\infty]{}\beta\in(0,\infty]$.

Let $W:\mathcal{P}(M)\to(-\infty,+\infty)$ be defined as

$$W(\mu):=\frac{1}{k!}\int_{M^k}G(x_1,\cdots,x_k)\mathrm{d}\mu(x_1)\cdots\mathrm{d}\mu(x_k).$$

If $\beta=\infty$, assume in addition that $G(x_1,\cdots,x_k)\xrightarrow[x_i\to\infty]{}\infty$ (i.e. we have a confining potential) and that we have the following regularity assumption: for any $\mu\in\mathcal{P}(M)$ such that $W(\mu)<\infty$, there exists a sequence of probability measures $(\mu_N)_{N\geq 1}$ absolutely continuous with respect to π such that $W(\mu_N)\xrightarrow[N\to\infty]{}W(\mu)$ as N converges to ∞.

Then, for all $f:\mathcal{P}(M)\to\mathbb{R}$ continuous and bounded, we have

$$\frac{1}{N\beta_N}\log\int_{M^N}\exp\left(-N\beta_N f\left(\frac{1}{N}\sum_{k=1}^{N}\delta_{x_k}\right)\right)\mathrm{d}\gamma_N((x_1,...,x_N)\xrightarrow[N\to\infty]{}-\inf_{\mu\in\mathcal{P}(M)}\{f(\mu)+F(\mu)\},$$

where F is the free energy with parameter β :

$$F(\mu):=W(\mu)+\frac{1}{\beta}S(\mu|\pi),$$

with $S(\cdot|\pi)$ the relative entropy (or KL divergence) :

$$S(\mu|\pi):=\begin{cases}\int\frac{\mathrm{d}\mu}{\mathrm{d}\pi}\log\left(\frac{\mathrm{d}\mu}{\mathrm{d}\pi}\right)\mathrm{d}\pi, & \text{if } \mu \text{ has a density with respect to } \pi,\\ \infty, & \text{otherwise.}\end{cases}$$

From there, one can deduce automatically an LDP for (a normalized version of) γ_N.

Corollary 2.2 *Under the same assumption as in Theorem 2.1, if we define $\mathrm{d}P_N=\frac{1}{Z_N}\mathrm{d}\gamma_N$, where $Z_N=\gamma_N(M^N)$, then under P_N, $\hat{\mu}_N=\frac{1}{N}\sum_i\delta_{x_i}$ satisfies an LDP at speed $N\beta_N$ with rate function $J(\mu)=F(\mu)-\inf F$.*

In particular, one can recover from there the LDP in the GUE case, initially due to G. Ben Arous and A. Guionnet. In this case, as we have $k = 2$, $G(x,y) = \frac{x^2+y^2}{2} - 2\log|x-y|$ and $\beta = \infty$, it comes that

$$W(\mu) = F(\mu) = \int \frac{x^2}{2} \mathrm{d}\mu(x) - \iint \log|x-y| \,\mathrm{d}\mu(x)\mathrm{d}\mu(y),$$

and we recover the rate function I defined in (5).

Before going into more examples and then into the proof of Theorem 2.1, it is worth explaining a very general mechanism, that allows to deduce an LDP such as Corollary 2.2 from a Laplace principle as obtained in Theorem 2.1. It is an important mathematical tool in the theory of large deviations and we devote the next section to explaining this mechanism.

2.3 Link between Laplace principle and LDP : the Varadhan-Bryc approach

Let us first make a quick reminder on the Laplace method, which is very familiar to mathematical physicists. The *Laplace principle* states that, under suitable conditions, if we let

$$I_n := \int_{\mathbb{R}} \exp\left(n\phi(x)\right) \mathrm{d}x$$

with ϕ a concave function reaching its maximum at a point x_0, then we should have

$$I_n \simeq \exp\left(n\phi(x_0)\right),$$

in the sense that

$$\lim_{n\to\infty} \frac{1}{n} \log I_n = \phi(x_0),$$

(one can often be more precise, depending on the regularity of the function ϕ). In the context of large deviations, *Varadhan's lemma* can be seen as an extension of the Laplace principle: if a sequence of probability measures $\{\mu_n\}_{n\geq 1}$ defined on a space X, satisfies an LDP at speed n with rate function I, and we let $J_n := \int \exp\left(n\phi(x)\right) \mathrm{d}\mu_n(x)$, then

$$\lim_{n\to\infty} \frac{1}{n} \log J_n = \sup_{x\in X} \{\phi(x) - I(x)\}.$$

One can even give a kind of reciprocal statement to Varadhan's lemma : if such a limit occurs for a rich enough family of test functions ϕ, then an LDP holds for the sequence $\{\mu_n\}_{n\geq 1}$. This reciprocal statement is known as *Bryc's lemma*.

More precisely, we will discuss the equivalence of two statements : for $\{\mu_n\}_{n\geq 1}$ a family of probability measures on a Polish space X we consider

- (LDP) The sequence $\{\mu_n\}_{n\geq 1}$ satisfies an LDP with speed n, and with a good rate function I[9].
- (LIM) For any continuous bounded function f, the following limit exists

$$\Lambda_f := \lim_{n\to\infty} \frac{1}{n} \log \int \exp(nf(x)) \mathrm{d}\mu_n(x).$$

The following proposition discusses the relationship between these two statements :

[9] We recall that by definition of semi-continuity, the level sets $\{I \leq C\}$ of rate functions are closed, when in addition these level sets are all compact then the rate function is said to be good

Proposition 2.3

1. *Varadhan's integral lemma: Suppose (LDP) holds then (LIM) is verified and*
$$\Lambda_f = \sup_{x\in X}\{f(x) - I(x)\}.$$
2. *Bryc's inverse integral lemma: Suppose (LIM) holds and suppose in addition that the sequence $(\mu_n)_{n\geq 1}$ is exponentially tight, then (LDP) holds with rate function I defined as follows*
$$I(x) = \sup_{f\in\mathcal{C}^b}\{f(x) - \Lambda_f\},$$
where $\mathcal{C}^b$ is the set of continuous bounded functions.

As emphasized above, the first statement can be seen as an infinite dimensional extension of Laplace method. We refer the reader to the notes of H. Touchette [1] for a more thorough discussion of Varadhan's lemma in the context of statistical mechanics or to Section 4.3 of [2] for a complete proof.

In the sequel, we will use more specifically the second statement, a.k.a. Bryc's inverse integral lemma, whose proof we detail hereafter. Let us assume that (LIM) holds and that the sequence $(\mu_n)_{n\geq 1}$ is exponentially tight, in the sense that there exists a sequence of compact sets $(K_L)_{L\geq 0}$ such that

$$\limsup_{L\to\infty}\limsup_{n\to\infty}\frac{1}{n^2}\log\mathbb{P}(\widehat{\mu}_n \notin K_L) = -\infty.$$

We first show that the LDP lower bound holds with rate function I. Let O be an open set and $x \in O$, let f be a bounded and continous function chosen such that, $f(x) = 1$, $0 \leq f \leq 1$; and $f = 0$ on O^c (such a function can be shown to exist if X is a completely regular topological space). Then define the family of functions $(f_p)_{p\geq 1}$ by $f_p(y) = p(f(y) - 1)$, for any $y \in X$. Thus

$$\int \exp\big(nf_p(y)\big)\mathrm{d}\mu_n(y) = \int_O \exp\big(nf_p\big)\mathrm{d}\mu_n + \int_{O^c}\exp\big(nf_p\big)\mathrm{d}\mu_n \leq \mu_n(O) + e^{-np},$$

where the inequality comes from the fact that $f_p \leq 0$ and so $\exp\left(nf_p\right) \leq 1$ and that $f_p(y) = -p$ on O^c. Then, taking $\liminf\frac{1}{n}\log(\cdot)$ on both sides of the previous inequality and using that

$$\liminf\frac{1}{n}\log(a_n + b_n) = \max\left\{\liminf\frac{1}{n}\log(a_n), \liminf\frac{1}{n}\log(b_n)\right\},$$

we get :

$$\liminf_{n\to\infty}\frac{1}{n}\log\int e^{nf_p}\mathrm{d}\mu_n \leq \max\left\{\liminf_{n\to\infty}\frac{1}{n}\log\mu_n(O), -p\right\}.$$

Given that (LIM) holds, the left hand side is Λ_{f_p}. In addition, we have $f_p(x) = 0$ so we get :

$$\Lambda_{f_p} - f_p(x) \leq \max\left\{\liminf_{n\to\infty}\frac{1}{n}\log\mu_n(O), -p\right\}$$

We therefore obtain, for any $x \in O$,

$$\begin{aligned}-I(x) := -\sup_{f\in\mathcal{C}^b}\{f(x) - \Lambda_f\} &= \inf_{f\in\mathcal{C}^b}\{\Lambda_f - f(x)\} \leq \Lambda_{f_p} - f_p(x)\\ &\leq \max\left\{\liminf_{n\to\infty}\frac{1}{n}\log\mu_n(O), -p\right\} \xrightarrow[p\to\infty]{} \liminf_{n\to\infty}\frac{1}{n}\log\mu_n(O).\end{aligned}$$

This inequality holds for all $x \in O$, so taking $\sup_{x\in O}$ on the left hand side, we get the LDP lower bound :

$$-\inf_{x\in O} I(x) = \sup_{x\in O}\{-I(x)\} \leq \liminf_{n\to\infty} \frac{1}{n}\log \mu_n(O).$$

Let us now show the upper bound. Since we have assumed exponential tightness of $(\mu_n)_{n\geq 1}$, it is sufficient to show the upper bound for compact sets. Let $\delta > 0$, and define

$$I^{\delta}(x) := \min\left\{I(x)-\delta, \frac{1}{\delta}\right\}.$$

Fix a compact set $K \subset X$. By definition of I, for all $x \in K$, there exists $f_x \in \mathcal{C}^b(X)$ such that $f_x(x) - \Lambda_{f_x} \geq I(x) - \delta \geq I^{\delta}(x)$. By continuity of f_x, there exists an open set A_x containing x, such that for all $y \in A_x$, $f_x(y) - f_x(x) \geq -\delta$. Now, let

$$\Lambda_{f_x}^{(n)} := \frac{1}{n}\log\left(\int \exp(nf_x(y))\,d\mu_n(y)\right),$$

and define the following probability measures μ_{n,f_x} with densities :

$$\mathrm{d}\mu_{n,f_x}(y) = \exp\left[n\left(f_x(y) - \Lambda_{f_x}^{(n)}\right)\right]\mathrm{d}\mu_n(y).$$

Since $f_x(y) - f_x(x) \geq -\delta$ for all $y \in A_x$, we have :

$$\mu_n(A_x) = \int_{A_x} \exp\left(-n\left(f_x(y) - \Lambda_{f_x}^{(n)}\right)\right)\mathrm{d}\mu_{n,f_x}(y) \leq \exp\left[-n\left(f_x(x) - \delta - \Lambda_{f_x}^{(n)}\right)\right].$$

Since by (LIM), $\Lambda_{f_x}^{(n)} \xrightarrow[n\to\infty]{} \Lambda_{f_x}$ and since we have chosen f_x such that $f_x(x) - \Lambda_{f_x} \geq I^{\delta}(x)$, we get :

$$\limsup_{n\to\infty} \frac{1}{n}\log \mu_n(A_x) \leq \Lambda_{f_x} - f_x(x) + \delta \leq -I^{\delta}(x) + \delta.$$

By compactness of K, since $\bigcup_{x\in X} A_x$ covers K we can extract a finite covering $K = \bigcup_{i=1}^{N} A_{x_i}$, for some $x_1, \ldots, x_N \in X$. We therefore get :

$$\limsup_{n\to\infty} \frac{1}{n}\log \mu_n(K) \leq \limsup_{n\to\infty} \frac{1}{n}\log\left(\sum_{i=1}^{N}\mu_n(A_{x_i})\right)$$
$$= \max_{1\leq i\leq N}\left\{\limsup_{n\to\infty}\frac{1}{n}\log\mu_n(A_{x_i})\right\} \leq \max_{1\leq i\leq N}\left\{-I^{\delta}(x_i) + \delta\right\}.$$

Taking $\lim_{\delta\to 0^+}$ on the right hand side of the inequality, we obtain :

$$\limsup_{n\to\infty}\frac{1}{n}\log\mu_n(K) \leq \max_{1\leq i\leq N}\{-I(x_i)\} \leq -\inf_{x\in X} I(x),$$

which is the upper bound for the LDP. Thus, I satisfies both the upper and lower bound, so we have an LDP with rate function I.

Applying Proposition 2.3, one can deduce Corollary 2.2 from Theorem 2.1.

2.4 Various applications of Theorem 2.1 and Corollary 2.2

The goal of the section is to exhibit several very interesting applications of the main results of [6]. We will develop some of them in details, while others will be just briefly mentioned, referring the reader to the original paper for more details.

2.4.1 Usual Coulomb and Riesz gases

The first result we want to establish is an LDP for the Gibbs measure $\mathbb{P}_{N,V,\beta,g}$ as defined by (8), with the kernel g being a Coulomb or a Riesz kernel. On this subject, one has to mention the work of D. Chafaï, N. Gozlan and P. A. Zitt in [13] and the work of P. Dupuis, V. Laschos and K. Ramanan [15], the latter being closer in the methods of the work of D. García-Zelada. We explain hereafter how to recover those results from Theorem 2.1.

Let π be a reference measure on $\mathbb{R}^d$. Let $V : \mathbb{R}^d \mapsto (-\infty, \infty]$ be lower semicontinuous, bounded below such that there exists $\xi > 0$ such that $\int_{\mathbb{R}^d} e^{-\xi V} d\pi < \infty$.

Let $g : \mathbb{R}^d \mapsto (-\infty, \infty]$ symmetric, lower semicontinuous such that there exists $\varepsilon > 0$ such that $(x, y) \mapsto g(x-y) + \varepsilon V(x) + \varepsilon V(y)$ is bounded below. We also assume that $(x, y) \mapsto g(x, y) + V(x) + V(y)$ goes to infinity as x and y both go to infinity and that the regularity assumption is satisfied.

Then, for all $f : \mathcal{P}(\mathbb{R}^d) \to \mathbb{R}$ continuous and bounded, we have

$$\frac{1}{N^2\beta} \log \int_{M^N} \exp\left(-N^2\beta f\left(\frac{1}{N}\sum_{k=1}^{N} \delta_{x_k}\right)\right) \mathrm{d}\, \mathbb{P}_{N,V,\beta,g}((x_1, ..., x_N)) \qquad (11)$$
$$\xrightarrow[N\to\infty]{} - \inf_{\mu \in \mathcal{P}(M)} \{f(\mu) + W(\mu)\},$$

and consequently, under $\mathbb{P}_{N,V,\beta,g}$, the empirical measure of the particles satisfies a large deviation principle, at speed N^2, with rate function βJ, given by $J(\mu) = W(\mu) - \inf W$.

As already mentioned above, choosing $d = 1$, $g(x) = -2\log|x|$ and $V(x) = x^2/2$, it encompasses in particular the GUE case but also applies, with appropriate choices of the potential V to any Coulomb or Riesz kernel.

Let us now quickly explain how to obtain (11) and the corresponding LDP from Theorem 2.1 and Corollary 2.2.

As we know that $\int_{\mathbb{R}^d} e^{-\xi V} d\pi < \infty$, we may assume without loss of generality that $\int_{\mathbb{R}^d} e^{-\xi V} d\pi = 1$. If we make the following choices: $\beta_N = N\beta$, and

$$G(x, y) := g(x-y) + \frac{1}{N-1}\left(N - \frac{N}{\beta_N}\xi\right)V(x) + \frac{1}{N-1}\left(N - \frac{N}{\beta_N}\xi\right)V(y),$$

with g a Coulomb or Riesz kernel and V an appropriate choice so that the assumptions above are satisfied[10] and define that corresponding measure γ_N as in (10), we get

$$\begin{aligned} d\gamma_N(x_1, \ldots, x_N) &= e^{-N\beta_N W_N} d\left(e^{-\xi V}\pi\right)^{\otimes N} \\ &= e^{-\frac{\beta_N}{N}\left(\sum_{i<j} g(x_i - x_j) + \left(N - \frac{N}{\beta_N}\xi\right)\sum_{i=1}^{N} V(x_i)\right)} d\left(e^{-\xi V}\pi\right)^{\otimes N}(x_i) \\ &= Z_{N,V,\beta,g}\, d\mathbb{P}_{N,V,\beta,g}(x_1, \ldots, x_N), \end{aligned}$$

which corresponds to an unormalized version of Coulomb/Riesz gases.

We now use the following decomposition:

$$G_1(x, y) := g(x-y) + \varepsilon V(x) + \varepsilon V(y),$$

and

$$G_2(x, y) := (1-\varepsilon)V(x) + (1-\varepsilon)V(y),$$

[10] Any polynomial of even degree and positive main coefficient is suitable.

so that, with obvious notations

$$W_N = W_{N,1} + a_N W_{N,2},$$

with

$$a_N := \frac{1}{1-\varepsilon}\left(\frac{1}{N-1}\left(N - \frac{N}{\beta_N}\xi\right) - \varepsilon\right),$$

a sequence converging to 1 as N goes to infinity. We can then check separately that $W_{N,1}$ and $W_{N,2}$ satisfy the required assumptions.

As we have shown in the first chapter with Wigner's theorem, it is possible to characterize the minimizer of the rate function through Euler-Lagrange equations. The minimizer is usually called *equilibrium measure* and is compactly supported.

2.4.2 High temperature Coulomb and Riesz gases

As explained in the previous subsection, the study of $\mathbb{P}_{N,V,\beta,g}$ which is related to standard models in RMT corresponds to a choice of β_N of order N, leading to an LDP at scale N^2 and a limiting equilibrium measure with compact support. But the study of measures of the type $\mathbb{P}_{N,V,\frac{\beta}{N},g}$ has also been considered in the literature. In this case, the corresponding particle systems are for example related to the classical Toda chain [16, 17] and are often called *high temperature β-ensembles* or *high temperature gases*. In our framework, it corresponds to a choice of β_N of order 1. This regime has been investigated by various authors, see e.g. [18,19].

In this case, one can see from the definition of the function F in Theorem 2.1 that the rate function is a mixture of an energy term W and an entropy term S. As far as we know, the first appearence of an LDP for such particle systems goes back to the work of T. Bodineau and A. Guionnet in [20] and before the work of D. García-Zelada, general results appeared in [15].

In the framework of [6], Laplace principle and LDP at fixed β even require less assumptions. With the same decomposition as in Section 2.4.1, one can show the following

Theorem 2.4 *Let π be a reference measure on $\mathbb{R}^d$. Let $V : \mathbb{R}^d \mapsto (-\infty, \infty]$ lower semicontinuous, bounded below such that there exists $\xi > 0$ such that $\int_{\mathbb{R}^d} e^{-\xi V} d\pi < \infty$.*

Let $g : \mathbb{R}^d \mapsto (-\infty, \infty]$ symmetric, lower semicontinuous such that there exists $\varepsilon > 0$ such that $(x, y) \mapsto g(x-y) + \varepsilon V(x) + \varepsilon V(y)$ is bounded below.

Then, if $\beta_N \to \beta$, for all $f : \mathcal{P}(\mathbb{R}^d) \to \mathbb{R}$ continuous and bounded, we have

$$\frac{1}{N\beta_N}\log\int_{M^N}\exp\left(-N\beta_N f\left(\frac{1}{N}\sum_{k=1}^N \delta_{x_k}\right)\right)\mathrm{d}\,\mathbb{P}_{N,V,\beta,g}((x_1,\dots,x_N)) \quad (12)$$
$$\xrightarrow[N\to\infty]{} -\inf_{\mu\in\mathcal{P}(M)}\left\{f(\mu) + W(\mu) + \frac{1}{\beta}S(\mu|\pi)\right\},$$

and consequently, under $\mathbb{P}_{N,V,\beta,g}$, the empirical measure of the particles satisfies a large deviation principle, at speed N, with rate function $\beta W + S(\cdot|\pi) - \inf(\beta W + S(\cdot|\pi))$.

As we have shown in the first chapter with Wigner's theorem, it is possible to characterize the minimizer of the rate function through Euler-Lagrage-like equations. The minimizer is usually called *thermal equilibrium measure* and is not compactly supported. When this minimizer is unique, it is again possible to deduce almost sure convergence of the empirical measure to the thermal equilibrium measure.

2.4.3 Conditional Gibbs measures

In some cases, it may also be natural to consider a gas of N particles $\{x_1, \cdots, x_N\}$ where all but the first ℓ points are deterministic. In [6], several regimes are considered but for the sake of simplicity, we will stick in these notes to the case when ℓ is of order 1.

Assume that the density of these deterministic points converges weakly to ν :

$$\nu_N := \frac{1}{N-\ell} \sum_{i=\ell}^{N} \delta_{x_i} \xrightarrow[N\to\infty]{w} \nu .$$

Define the external potential G^E generated by y on the random points $(x_1, \cdots, x_\ell)$ by

$$G^E\left((x_1, \cdots, x_\ell), y\right) := \sum_{i=1}^{\ell} G(x_i, y)$$

and denote the average external interaction by

$$V_N(x_1, \cdots, x_\ell) = \int G^E\left((x_1, \cdots, x_\ell), y\right) \mathrm{d}\nu_N(y) .$$

Then, consider the internal interaction

$$G^I(x_1, \cdots, x_\ell) = \sum_{1 \le i < j \le \ell} G(x_i, x_j) .$$

Finally, define $V : M^\ell \to \mathbb{R}$ by

$$V(x_1, \cdots, x_\ell) = \int_M G^E\left((x_1, \cdots, x_\ell), y\right) \mathrm{d}\nu(y).$$

Theorem 2.5 *Assume that the interaction G is such that the following limit holds:*

$$V(x_1, \cdots, x_\ell) = \lim_{N\to\infty} V_N(x_1, \cdots, x_\ell)$$

and V is continuous bounded on M^ℓ. Define the conditional measure γ_N^c as follows:

$$\mathrm{d}\gamma_N^c(x_1, \cdots, x_\ell) = \exp\left\{-\beta_N \left(V_N + \frac{1}{N} G^I\right)(x_1, \cdots, x_\ell)\right\} \mathrm{d}\pi(x_1) \cdots \mathrm{d}\pi(x_\ell) .$$

Then, under some extra technical assumptions[11]*, for all $f \in \mathcal{C}^b(M^\ell)$, we have :*

$$\frac{1}{\beta_N} \log\Big(\int_{M^\ell} \exp\{-\beta_N f(x_1, \cdots, x_\ell)\} \mathrm{d}\gamma_N^c(x_1, \cdots, x_\ell)\Big) \xrightarrow[N\to\infty]{} -\inf\{f(x_1, \cdots, x_\ell) + V(x_1, \cdots, x_\ell)\} .$$

Corollary 2.6 *Under the same assumptions as Theorem 2.5, the law of $(x_1, \cdots, x_\ell)$ under $\tilde{\gamma}_N^c$, which is the normalized version of γ_N^c, satisfies an LDP at speed β_N with the rate function $V - \inf V$.*

[11] In this paragraph, we won't be as precise as for the previous examples and refer the reader to the original paper.

We want to emphasize the change in the scaling: when the deviations of the whole empirical measure occurs at speed $N\beta_N$, the deviations of the law of this finite number of particles occur at speed β_N.

This is exactly what happens when we look at the deviations of the largest eigenvalue of the GUE (or the largest particle of a gas in dimension 1). When we look at the scale e^{-N}, all but the first particle can be considered as *frozen*, deterministic, with positions such that their limiting empirical measure is the semicircle distribution. This corresponds to taking $\ell = 1$, $G(x,y) = \frac{x^2}{2} - 2\log(|x-y|)$ and $\nu_N \xrightarrow[N\to\infty]{w} \mu_{sc}$. With this heuristics[12], we recover the result that the law of the largest eigenvalue λ_1 for the GOE model satisfies an LDP at speed N with rate function $V - \inf V$, with

$$V(x) = \frac{x^2}{2} - \int \log(|x-y|)\mathrm{d}\mu_{sc}(y).$$

More details on this derivation can be found in the work [21] or in the review paper by S. Majumdar and G. Schehr [22], which presents a thorough study of the deviations of the top eigenvalue at different scales such as fluctuations, large deviations and links between the different regimes.

2.4.4 Further examples

We would like to finish this list of applications of the main results of [6] by mentioning two other families of particle systems that can be studied in this framework. We won't detail these examples but refer the interested reader to the original papers:

- one can recover and generalize the results of R. Berman on Coulomb gases on Riemannian manifolds, see e.g. [23],
- if we consider random polynomials on the form $P_n(z) = \sum_{k=0}^n a_k z^k$, where a_k are i.i.d. $\mathcal{N}_{\mathbb{C}}(0,1)$ coefficients, it is known that the zeroes form a random particle systems of Coulomb-type. The large deviations of their empirical measure have been explored, e.g. in [24] and [25]. Their results can be recovered and generalized in the framework of [6].

2.5 Elements of proof of the Laplace principle

We now end this chapter by giving some ideas of the proof of Theorem 2.1. We start by recalling a result on the Legendre transform of the entropy.

Lemma 2.7 *(Legendre transform of entropy) Let μ be a probability measure on a space E and $g : E \to (-\infty, +\infty]$ be a measurable and bounded below function. Then,*

$$\log\left(\int e^{-g(x)}\mathrm{d}\mu(x)\right) = -\inf_{\tau\in\mathcal{P}(E)}\left\{\int g\,\mathrm{d}\tau + S(\tau|\mu)\right\}.$$

Let give a quick proof of this lemma. If τ has a density with respect to μ and we denote by $f = \frac{d\tau}{d\mu}$ this density, recall that

$$S(\tau|\mu) = \int f\log(f)\mathrm{d}\mu = \int \log(f)\mathrm{d}\tau.$$

[12]The heuristics would be a rigorous application of Theorem 2.5 if all but the largest particle would be deterministic.

Therefore,

$$-\int g\,\mathrm{d}\tau - S(\tau|\mu) = -\int g\,\mathrm{d}\tau - \int \log(f)\mathrm{d}\tau = \int \log e^{-g}\,\mathrm{d}\tau - \int \log(f)\mathrm{d}\tau$$
$$= \int \log\big(e^{-g}/f\big)\mathrm{d}\tau \le \log\left(\int (e^{-g}/f)\mathrm{d}\tau\right) = \log\left(\int e^{-g}\,\mathrm{d}\mu\right).$$

If τ is not absolutely continuous with respect to μ, then the inequality is trivially verified since in this case $S(\tau|\mu) = +\infty$. Now, taking $\sup\limits_{\tau\in\mathcal{P}(E)}$ on the left hand side we get

$$-\inf_{\tau\in\mathcal{P}(E)}\left\{\int g\,\mathrm{d}\tau + S(\tau|\mu)\right\} \le \log\left(\int e^{-g}\,\mathrm{d}\mu\right),$$

and this gives us one inequality.

One the other hand, if we choose the probability measure τ such that $\mathrm{d}\tau = \frac{e^{-g}}{\int e^{-g}\,\mathrm{d}\mu}\mathrm{d}\mu$, then, one can easily check that we have equality:

$$-\int g\,\mathrm{d}\tau - S(\tau|\mu) = \log e^{-g}\,\mathrm{d}\mu,$$

so that we can conclude that the inequality above is in fact an equality.

Let us now use Lemma 2.7 to show the generalized Laplace principle stated in Theorem 2.1.

If we apply Lemma 2.7 to $E = M^N$, $\mu = \pi^{\otimes N}$ and the test function

$$g(x_1,\cdots,x_N) := N\beta_N\left[f\left(\frac{1}{N}\sum_{i=1}^N \delta_{x_i}\right) + W_N(x_1,\cdots,x_N)\right],$$

we get :

$$\frac{1}{N\beta_N}\log\left(\int_{M^N}\exp\left(-N\beta_N\left[f\left(\frac{1}{N}\sum_{i=1}^N\delta_{x_i}\right) + W_N(x_1,\cdots,x_N)\right]\right)\mathrm{d}\pi(x_1)\cdots\mathrm{d}\pi(x_N)\right)$$
$$= -\inf_{\tau\in P(M^N)}\left\{\int f\left(\frac{1}{N}\sum_{i=1}^N\delta_{x_i}\right)\mathrm{d}\tau(x_1,\cdots,x_N) + \int W_N(x_1,\cdots,x_N)\mathrm{d}\tau + \frac{S(\tau|\pi^{\otimes N})}{N\beta_N}\right\}.$$

To conclude, we need to show that the right handside converges, as $N\to\infty$ towards

$$-\inf_{\mu\in\mathcal{P}(M)}\left\{f(\mu) + W(\mu) + \frac{S(\mu|\pi)}{\beta}\right\}.$$

We will only show the upper bound and refer the reader to the original paper, concerning the lower bound, which is more technical.

Notice first that if we fix $\mu\in\mathcal{P}(M)$ and let $\tau_N := \mu^{\otimes N}\in\mathcal{P}(M^N)$, then

$$\limsup_{N\to\infty}\inf_{\tau\in P(M^N)}\left\{\int f\left(\frac{1}{N}\sum_{i=1}^N\delta_{x_i}\right)\mathrm{d}\tau(x_1,\cdots,x_N) + \int W_N(x_1,\cdots,x_N)\mathrm{d}\tau + \frac{S(\tau|\pi^{\otimes N})}{N\beta_N}\right\}$$
$$\le \limsup_{N\to\infty}\left(\int f\left(\frac{1}{N}\sum_{i=1}^N\delta_{x_i}\right)\mathrm{d}\tau_N(x_1,\cdots,x_N) + \int W_N(x_1,\cdots,x_N)\mathrm{d}\tau_N + \frac{S(\tau_N|\pi^{\otimes N})}{N\beta_N}\right).$$

We look at the limsup of each of the three terms. First, if $(x_1, \cdots, x_N) \sim \tau_N$, it means that the x_i are i.i.d. and are distributed according to μ. By the law of large numbers, we have that the law of $\frac{1}{N}\sum_{k=1}^N \delta_{x_i}$ converges weakly to δ_μ and so that for any continuous bounded function f on $\mathcal{P}(M)$ we have :

$$\int f\left(\frac{1}{N}\sum_{k=1}^N \delta_{x_i}\right) \mathrm{d}\tau_N \xrightarrow[N\to\infty]{} \int f \mathrm{d}\delta_\mu = f(\mu).$$

543 We now go to the second term:

$$\begin{aligned}\int W_N \mathrm{d}\tau_N &= \frac{1}{N^k} \sum_{\substack{\{i_1,\cdots,i_k\}\subseteq\{1,\cdots,N\}\\ \#\{i_1,\cdots,i_k\}=k}} \int G(x_{i_1},\cdots,x_{i_k}) \mathrm{d}\mu^{\otimes k}(x_{i_1},\cdots,x_{i_k}) \\ &= \frac{1}{N^k}\binom{N}{k}\int_{M^k} G(x_1,\cdots,x_k)\mathrm{d}\mu(x_1)\cdots\mathrm{d}\mu(x_k) \xrightarrow[N\to\infty]{} W(\mu).\end{aligned}$$

Finally, since

$$\frac{\mathrm{d}\mu^{\otimes N}}{\mathrm{d}\pi^{\otimes N}}(x_1,\cdots,x_N) = \prod_{i=1}^N \frac{\mathrm{d}\mu}{\mathrm{d}\pi}(x_i),$$

we have $S(\mu^{\otimes N}|\pi^{\otimes N}) = NS(\mu|\pi)$, so that

$$\frac{S(\tau_N|\pi^{\otimes N})}{N\beta_N} = \frac{S(\mu|\pi)}{\beta_N} \xrightarrow[N\to\infty]{} \frac{S(\mu|\pi)}{\beta}.$$

544 Putting these three elements together in the limit above, we get that for any $\mu \in \mathcal{P}(M)$,

$$\begin{aligned}\limsup_{N\to\infty} \inf_{\tau\in P(M^N)} \left\{ \int f\left(\frac{1}{N}\sum_{i=1}^N \delta_{x_i}\right) \mathrm{d}\tau(x_1,\cdots,x_N) + \int W_N(x_1,\cdots,x_N)\mathrm{d}\tau + \frac{S(\tau|\pi^{\otimes N})}{N\beta_N}\right\} \\ \leq f(\mu) + W(\mu) + \frac{S(\mu|\pi)}{\beta}\end{aligned}$$

545 and we can take the infimum over the right handside.

546 We refer the reader to [6] for the proof of the reverse inequality.

547 2.6 Conclusion

548 In this second chapter (corresponding to an extended version of Lectures 2 and 3), we have
549 discussed a very general result developed in [6].

550 • It allows to study the large deviations of the empirical measure of particle systems given
551 by singular Gibbs measures, encompassing a large range of applications, in particular
552 usual Coulomb gases, high temperature Coulomb gases and conditional Gibbs measures.

553 • The proof of these LDPs is based on an important mathematical tool called Bryc's inverse
554 integral lemma, that can be seen as a reciprocal to Varadhan's lemma. It allows to deduce
555 LDPs from Laplace principle.

556 • In this case, the Laplace principle is intimately linked to a dual representation of the
557 relative entropy. It leads to a rate function that is in general a mixture of an energy term
558 and a relative entropy term. In the so-called *zero temperature regime*, the entropy term
559 disappears.

- The typical behavior of the corresponding empirical measures can be described by a compactly supported equilibrium measure in the usual case (as we have seen in the first chapter with the semicircle distribution) and by a non-compactly supported (thermal) equilibrium measure in the so-called *high temperature regime*.

3 The use of spherical integrals to study LD of largest eigenvalues of random matrices

In the first two chapters, we have mainly dealt with the global behavior of the particle systems, encoded in their empirical measure. But, in many situations, it is also relevant to study the behavior of the extremal particles - say the rightmost particle or the largest eigenvalue. Recently, A. Guionnet and J. Husson [26] and then many co-authors [27–32] have used the so-called spherical integrals to study the large deviations of the largest eigenvalue in various models of random matrices. Although the corresponding systems of particles are no longer stricly speaking Coulomb gases, they are closely related models and we would like to present this ensemble of works in this last section. We think that the ubiquity of spherical integrals in statistical physics makes it particularly relevant for this course.

3.1 A general overlook on the models

Let us go back to the model of the GUE, and recall that $H_N \in \mathbf{GUE}_N$ has been defined in (1.1) as follows:

$$H_N = \begin{pmatrix} \frac{H_{1,1}}{\sqrt{N}} & & \frac{H_{i,j}}{\sqrt{N}} & \\ & \ddots & & \\ \frac{H_{i,j}^*}{\sqrt{N}} & & \ddots & \\ & & & \frac{H_{N,N}}{\sqrt{N}} \end{pmatrix},$$

where $H_{i,i}$ are independent and identically distributed random variables with distribution $\mathcal{N}_{\mathbb{R}}(0,1)$ and for $i \leq j$, $H_{i,j}$ are independent and identically distributed random variables with distribution $\mathcal{N}_{\mathbb{C}}(0,1)$.

There are several very natural generalisations of this model.

- **β-ensembles.** We know that the joint law of the eigenvalues of the $\mathbf{GUE}_N$ is given by $\mathbb{P}_{GUE_N}$, which has been defined in (2). In the joint density, proportional to

$$\prod_{i<j}(x_i - x_j)^2 \exp\left(-\frac{N}{2}\sum_{j=1}^{N} x_j^2\right),$$

  if we replace the quadratic potential by a more general potential $V(x_j)$ and/or if we replace the exponent 2 in the Vandermonde term by any $\beta > 0$, the corresponding particle system is called a β*-ensemble*. Large deviations for the empirical measure and for the rightmost particle in this framework has been extensively studied and we refer to Vivo's lecture for more details. In these notes, we will focus in two other types of extension of the model.

- **Wigner matrices.** If we keep the same structure of the entries, being i.i.d., up to symmetry (the matrix has to remain Hermitian or real symmetric) but relax the Gaussianity assumption, we obtain a Wigner matrix.

  It is well known that, as soon as the entries $H_{i,j}$ are centered and $\mathbb{E}(|H_{i,j}|^2) = 1$ for $i \neq j$, Wigner's theorem holds in the sense that $\widehat{\mu}_N = \frac{1}{N}\sum_{i=1}^N \delta_{\lambda_i} \xrightarrow[N\to\infty]{w} \mu_{sc}$, the semi-circular distribution. If moreover we have $\mathbb{E}(H_{i,j}^4) < \infty$, then $\lambda_{\max}^N \xrightarrow[N\to\infty]{} \lambda^* = 2$, which is the right edge of the support of μ_{sc}. The large deviations have been investigated by [26–28, 32].

- **Deformed models.** The GUE_N distribution may also be seen as a Gaussian measure on the set $\mathcal{H}_N(\mathbb{C})$ of Hermitian matrices of size N. A natural way to modify this measure is to change its mean: choose a deterministic matric $A_N \in \mathcal{H}_N(\mathbb{C})$ and $X_N = A_N + H_N$, with $H_N \in GUE_N$. As the GUE_N distribution is invariant by unitary conjugation, one can consider as a further generalisation a model of the form

$$X_N = A_N + UB_NU^*,$$

with U being distributed as the Haar measure on the orthogonal group $\mathcal{O}_N$ or the unitary group $\mathcal{U}_N$. The convergence of the empirical spectral measure can be described by free probability (this point will be detailed a bit further in these notes) and the behavior of the largest eigenvalue has been investigated in [29–31].

To understand the deviations of the largest eigenvalue both for Wigner matrices and deformed models, we first need to investigate a common tool, which is interesting by itself, the *spherical integrals*.

3.2 Spherical integrals

Consider A_N, B_N two deterministic, real diagonal $N \times N$ matrices. Define the spherical integral of A_N and B_N as

$$I_N(A_N, B_N) := \int e^{N\mathrm{Tr}(A_N U_N B_N U_N^*)} dm_N(U_N),$$

with m_N the Haar measure on the orthonormal group

$$\mathcal{O}_N = \{O \in \mathcal{M}_N(\mathbb{R}), O^T O = OO^T = I_N\},$$

or the unitary group

$$\mathcal{U}_N = \{U \in \mathcal{M}_N(\mathbb{C}), U^*U = UU^* = I_N\}.$$

We recall that the Haar measure is the unique probability measure which is invariant under conjugation (see Appendix A for more details). According to the context, the integral I_N may be called *Harish Chandra integral*[13] or *Itzykson-Zuber integral* or *spherical integral*. We will use this latter terminology in these notes.

Harish Chandra in the fifties provided explicit formulas for $I_N(A_N, B_N)$. For example, in the unitary case, we have the following:

$$I_N(A_N, B_N) := \left(\prod_{j=1}^{N} j!\right) \frac{\det(e^{a_i b_j})_{i,j\le N}}{\prod_{i<j}(a_i - a_j)\prod_{i<j}(b_i - b_j)},$$

where $(a_i)_{1\le i\le N}$ and $(b_j)_{1\le j\le N}$ are respectively the eigenvalues of A_N and B_N. Unfortunately, this nice closed formula is not very suitable for asymptotic analysis. Nevertheless, C. Itzykson and J. B. Zuber in the physics literature [33] and then twenty years later A. Guionnet and O. Zeitouni [34] on a rigorous level provided some insights on the asymptotics of I_N. Their result takes the following form:

Theorem 3.1 *If*

$$\hat{\mu}_{A_N} = \frac{1}{N}\sum_{i=1}^{N} \delta_{\lambda_i(A_N)} \xrightarrow[N\to\infty]{w} \mu_a \text{ and } \hat{\mu}_{B_N} = \frac{1}{N}\sum_{i=1}^{N} \delta_{\lambda_i(B_N)} \xrightarrow[N\to\infty]{w} \mu_b,$$

[13] It is in fact a particular case of the latter.

then there exists a functional F such that (under some additional technical assumptions), we have the following convergence :

$$\frac{1}{N^2}\log I_N(A_N,B_N)\xrightarrow[N\to\infty]{} F(\mu_a,\mu_b).$$

One can check that when one of the limiting measures μ_a or μ_b is trivial ($=\delta_0$), the function F vanishes. This means that in this case, we are not considering the spherical integrals on the right scale. The asymptotics in the case when one of the matrices, say A_N is of finite rank (fixed with N), has been first obtained by A. Guionnet and M. Maïda [35] in the rank one case and then by A. Guionnet and J. Husson [36] in the finite rank case (see also [37] for previous partial results). The rank one case will be particularly useful for the sequel and we present it hereafter in full details. For the sake of simplicity, we stick to the orthogonal case but the results and proofs can be easily adapted to the unitary case.

We write A_N and B_N under the form:

$$A_N=\begin{pmatrix}\theta & \\ & (0)\end{pmatrix},\qquad B_N=\begin{pmatrix}b_1 & & & \\ & b_2 & & \\ & & \ddots & \\ & & & b_N\end{pmatrix}.$$

In this case, we denote by $I_N(\theta,B_N):=I_N(A_N,B_N)$. We will here restrict to the case where $\theta\geq 0$, which is useful to study the deviations of the largest eigenvalue but the very same results have been shown when $\theta\leq 0$.

Before stating the result, let us recall the following notation: for any probability measure μ on $\mathbb{R}$ and x which is outside the support of μ,

$$H_\mu(x):=\int_{\mathbb{R}}\frac{1}{x-y}d\mu(y).$$

We have the following:

Theorem 3.2 *Assume that $\widehat{\mu}_{B_N}\xrightarrow[N\to\infty]{w}\mu$, where μ has a compact support. Assume also that $\lambda_{max}(B_N)=\max_{1\leq i\leq N} b_i\xrightarrow[N\to\infty]{}\lambda$. Then*

$$\lim_{N\to\infty}\frac{1}{N}\log I_N(\theta,B_N)=\theta v(\theta)-\frac{1}{2}\int\log(1+2\theta v(\theta)-2\theta y)d\mu(y):=J(\theta,\lambda,\mu), \quad (13)$$

where

$$v(\theta)=\begin{cases}R_\mu(2\theta), & \text{when } 2\theta\leq H_{\max}\\ \lambda-\frac{1}{2\theta}, & \text{when } 2\theta> H_{\max}\end{cases}$$

with

$$H_{\max}=\lim_{x\to\lambda^+}H_\mu(x)$$

and $R_\mu(\eta)$ is the unique solution of

$$\int_{\mathbb{R}}\frac{1}{R_\mu(\eta)+\frac{1}{\eta}-y}d\mu(y)=\eta$$

such that $R_\mu(\eta)+\frac{1}{\eta}$ is larger or equal to λ.

Note that for μ and λ given, there is a phase transition at $2\theta = H_{\max}$. For $2\theta \leq H_{\max}$ (subcritical case), $v(\theta)$ and therefore $J(\theta, \lambda, \mu)$ is independent of λ but a dependence appears when $2\theta > H_{\max}$. This will play a crucial role in the tilting argument.

We now sketch the proof of Theorem 3.2. With A_N and B_N chosen as above, we have

$$I_N(\theta, B_N) = \int e^{N\theta \sum_{i=1}^N b_i O_{i1}^2} dm_N(O).$$

In the orthogonal case we are interested in, when $(O_{i1})_{i=1}^N$ is the first column vector of a matrix sampled according to the Haar measure, one can show that this vector follows the uniform distribution on the sphere $\mathbb{S}^{N-1} \subset \mathbb{R}^N$. If G is a standard Gaussian vector of size N, by invariance of the standard normal distribution under orthogonal transformations, $\frac{G}{\|G\|}$ also follows the uniform distribution on the sphere. Thus $(O_{i1})_{i=1}^N$ has the same distribution as $\frac{G}{\|G\|}$ and we can write :

$$I_N(\theta, B_N) = \mathbb{E}\left(\exp\left(N\theta \frac{\sum_{i=1}^N b_i g_i^2}{\sum_{i=1}^N g_i^2}\right)\right), \quad \text{where } G = \begin{pmatrix} g_1 \\ \vdots \\ g_N \end{pmatrix} \sim \mathcal{N}(0, \mathrm{Id}_N).$$

By concentration of measure phenomenon, the event

$$\mathcal{E}_N = \left\{\left|\frac{\|G\|^2}{N} - 1\right| \leq N^{-\kappa}\right\},$$

where $\kappa \in (0, 1/2)$, has very high probability for N large enough. Therefore, we have the following approximation:

$$I_N(\theta, B_N) = \mathbb{E}\left(e^{N\theta \frac{\sum b_i g_i^2}{\sum g_i^2}}\right) \approx \mathbb{E}\left(e^{N\theta \frac{\sum b_i g_i^2}{\sum g_i^2}} 1_{\mathcal{E}_N}\right).$$

On the event $\mathcal{E}_N$, the quantity $(\sum_{i=1}^N g_i^2 - N)$ is negligible with respect to N. Therefore, up to a factor which is negligible with respect to e^N, we can write the following approximation: for any $v \in \mathbb{R}$,

$$I_N(\theta, B_N) \approx \mathbb{E}\left(e^{\theta \sum b_i g_i^2 - v\theta\left(\sum g_i^2 - N\right)} 1_{\mathcal{E}_N}\right).$$

By rewritting the expectation with the density of a Gaussian vector, we get

$$\begin{aligned} I_N(\theta, B_N) &\approx \frac{e^{N\theta v}}{(2\pi)^{N/2}} \int e^{\theta \sum b_i g_i^2 - v\theta \sum g_i^2 - \frac{1}{2}\sum g_i^2} 1_{\mathcal{E}_N} \prod_{i=1}^N dg_i \\ &= \frac{e^{N\theta v}}{(2\pi)^{N/2}} \int e^{-\frac{1}{2}\sum(1-2\theta b_i + 2v\theta) g_i^2} 1_{\mathcal{E}_N} \prod_{i=1}^N dg_i. \end{aligned}$$

Choosing v such that $1 - 2\theta b_i + 2\theta v > 0$ for all $1 \leq i \leq N$, we identify the exponential in the integral as the density of a centered normal distribution of variance $\frac{1}{1-2\theta b_i + 2v\theta}$. We thus obtain

$$I_N(\theta, B_N) \approx \frac{e^{N\theta v}}{\prod_{i=1}^N \sqrt{1 - 2\theta b_i + 2\theta v}} \mathbb{P}_{N,v}(\mathcal{E}_N),$$

with $\mathbb{P}_{N,v}$ a Gaussian measure with covariance matrix $\Gamma = \begin{pmatrix} \frac{1}{1-2\theta b_1+2\theta v} & 0 & \\ 0 & \ddots & 0 \\ & 0 & \frac{1}{1-2\theta b_N+2\theta v} \end{pmatrix}$.
Therefore, bounding $\mathbb{P}_{N,v}(\mathcal{E}_N)$ by 1, we get :

$$I_N(\theta, B_N) \lesssim e^{N\theta v - \frac{1}{2}\sum \log(1-2\theta b_i+2\theta v)},$$

and thus, for any $v \in \mathbb{R}$ such that $1-2\theta b_i + 2\theta v > 0$ for all $1 \leq i \leq N$, we have :

$$\frac{1}{N}\log(I_N(\theta, B_N)) \lesssim \theta v - \frac{1}{2N}\sum_{i=1}^{N}\log(1+2\theta v - 2\theta b_i) = \theta v - \frac{1}{2}\int \log(1+2\theta v - 2\theta y)\mathrm{d}\hat{\mu}_{B_N}(y)$$
$$\xrightarrow[N\to\infty]{} \theta v - \frac{1}{2}\int \log(1+2\theta v - 2\theta y)\mathrm{d}\mu(y),$$

which gives us an upper bound.

We now compute the corresponding lower bound. We have seen that under $\mathbb{P}_{N,v}$, each g_i has normal distribution with variance $\frac{1}{1-2\theta b_i+2\theta v}$ and so

$$\mathbb{E}_{N,v}\left(\frac{1}{N}\sum_{i=1}^{N} g_i^2\right) = \frac{1}{N}\sum_{i=1}^{N}\frac{1}{1-2b_i\theta + 2\theta v}.$$

The equation

$$\frac{1}{N}\sum_{i=1}^{N}\frac{1}{1-2b_i\theta + 2\theta v} = 1 \tag{14}$$

has a unique solution in v such that $1-2b_i\theta + 2\theta v > 0$ for all $1 \leq i \leq N$, which we denote by $v_N(\theta)$. Thus, we get

$$\mathbb{E}_{N,v_N(\theta)}\left(\frac{||G||^2}{N}\right) = 1$$

and using Gaussian concentration again, we get that $\mathbb{P}_{N,v_N(\theta)}(\mathcal{E}_N)$ goes to 1 as N grows to infinity. Thus, we get that :

$$I_N(\theta, B_N) \approx e^{N\left(\theta v_N(\theta) - \frac{1}{2}\int \log(1-2\theta y + 2\theta v_N(\theta))\mathrm{d}\hat{\mu}_{B_N}(y)\right)}.$$

If we denote by

$$H_N(z) := H_{\hat{\mu}_{B_N}}(z) = \frac{1}{N}\sum_{i=1}^{N}\frac{1}{z-b_i},$$

one can rewrite (14) as

$$H_N\left(v_N(\theta) + \frac{1}{2\theta}\right) = 2\theta.$$

One can then show that $v_N(\theta)$ converges to $v(\theta)$, where $v(\theta) = H_\mu^{(-1)}(2\theta) - \frac{1}{2\theta}$ if $2\theta \in H_\mu([\lambda, +\infty))$ and $v(\theta) = \lambda - \frac{1}{2\theta}$ otherwise.

This concludes the proof of Theorem 3.2 which gives the full asymptotics of the spherical integral in the rank one case.

The finite rank case has been treated by A. Guionnet and J. Husson [36]: if we have $\lambda_1 > \ldots > \lambda_k > \lambda^*$ (where we denote by λ^* the right edge of the support of μ_b) and

$\lambda_i(B_N) \xrightarrow[N\to\infty]{} \lambda_i, \forall i \in \{1,...,k\}$ (where $\lambda_i(B_N)$ is the ith largest eigenvalue of B_N), then the logarithm of the integral is additive in the sense that:

$$\lim_{N\to\infty} \frac{1}{N} \log I_N(A_N, B_N) = \lim_{N\to\infty} \frac{1}{N} \log I_N(\theta_1, \cdots, \theta_k, B_N) = J(\theta_1, \lambda_1, \mu) + \cdots + J(\theta_k, \lambda_k, \mu),$$

where J is the rank one limit appearing in Theorem 3.2.

Before going to the statements of the main results, let us make some final remarks on the expression of J. If $H_\mu^{(-1)}$ is the inverse of the function H_μ on $[\lambda, \infty)$ and we denote by

$$R_\mu(z) = H_\mu^{(-1)}(z) - \frac{1}{z}$$

on this interval, R_μ is known by mathematicians as the R-transform of the measure μ and by physicists as the *blue function*[14] (see e.g. J.P. Bouchaud's lecture notes [38] from les Houches 2015). This functional is very useful to describe the limiting spectrum of $A_N + UB_NU^*$ in our model. It is a central tool in free probability theory (see for example the book of J. Mingo and R. Speicher [39] for a thorough but gentle introduction to the theory). If we choose the sequences $(A_N)_{N\geq 1}$ and $(B_N)_{N\geq 1}$ such that $\widehat{\mu}_{A_N} \xrightarrow[N\to\infty]{w} \mu_a$ and $\widehat{\mu}_{B_N} \xrightarrow[N\to\infty]{w} \mu_b$, one can show that

$$\widehat{\mu}_{A_N+UB_NU^*} \xrightarrow[N\to\infty]{w} \mu_S,$$

which is characterized by the functional equation

$$R_{\mu_S}(z) = R_{\mu_a}(z) + R_{\mu_b}(z).$$

This relation plays the role of the additivity of the logarithm of the Fourier transform for the usual convolution: if X and Y are independent real random variables, with respective distributions μ_X and μ_Y and if ϕ_μ is the characteristic function of a probability meausre μ, we have

$$\log F_{\mu_{X+Y}} = \log F_{\mu_X} + \log F_{\mu_Y}.$$

By analogy, μ_S is called the *free convolution* of μ_a and μ_b and is denoted by $\mu_S = \mu_a \boxplus \mu_b$.

3.3 Statement of the results

We will now provide a statement of the LDP for the largest eigenvalue in two different models that are both a generalisation of the GUE.

Sub-Gaussian Wigner matrices Let us present hereafter a result due to N. Cook, R. Ducatez and A. Guionnet [32]; it is the outcome of a series of works, starting from [26]. For a probability measure $\mu \in \mathcal{P}(\mathbb{R})$, its log-Laplace transform is given by $\Lambda_\mu(t) = \log \int e^{tx} d\mu(x)$. For the standard Gaussian measure, with density :

$$d\gamma(x) = \frac{1}{\sqrt{2\pi}} e^{-x^2/2} dx,$$

one can check that its log-Laplace transform is given by $\Lambda_\gamma(t) = t^2/2$, for any $t \in \mathbb{R}$. Accordingly, a measure μ is said to be *sub-Gaussian* if there exists $K > 0$ such that $\Lambda_\mu(t) \leq Kt^2, \forall t \in \mathbb{R}$. It is said to be *sharp sub-Gaussian* if in addition $K = 1/2$.

We also recall that the rate function for the largest eigenvalue λ_1 of the GOE is given by :

$$I^\gamma(x) = \begin{cases} \frac{1}{2}\int_2^x \sqrt{y^2-4}\, dy, & \text{for } x \geq 2, \\ \infty, & \text{for } x < 2. \end{cases}$$

[14] as it is the inverse of the Green function (sic!)

Let $(X_{i,j})_{1\le i\le j\le N}$ be i.i.d. real centered random variables, with unit variance. A *Wigner matrix* W_N is defined as follows:

$$W_N = \frac{1}{\sqrt{N}}\begin{pmatrix} \sqrt{2}X_{1,1} & & X_{i,j} & \\ & \ddots & & \\ X_{j,i} & & \ddots & \\ & & & \sqrt{2}X_{N,N}\end{pmatrix}.$$

We denote by μ the common distribution of the entries. The matrix W_N is said to be a *sub-Gaussian Wigner matrix* if the distribution μ is sub-Gaussian. The large deviations of its largest eigenvalue are described by the following result:

Theorem 3.3 *For W_N a sub-Gaussian Wigner matrix, the law of $\lambda_1(W_N)$ satisfies an LDP at speed N, with good rate function I^μ such that*

- $I^\mu \le I^\gamma$;
- $\exists x_\mu > 2$ *such that* $I^\mu = I^\gamma$ *on* $[2, x_\mu]$ *and* $I^\mu < I^\gamma$ *if* $x > x_\mu$;
- $x_\mu < \infty$ *if and only if* $K > 1/2$.

One can also mention a few previous results, dealing with Wigner matrices with non Gaussian tails [40], or sparse Wigner matrices [41–43].

Unitarily invariant deformed random matrices We state hereafter a similar result that was obtained in [31]. The tilting argument is a bit easier to present in this case and this is why we choose to emphasize this model.

If the distribution of O is the Haar measure on the orthogonal group $\mathcal{O}_N$ and A_N and B_N are deterministic diagonal[15] matrices, we define

$$H_N := A_N + OB_NO^*.$$

Assume that $\hat{\mu}_{A_N} \xrightarrow[N\to\infty]{w} \mu_a$, $\hat{\mu}_{B_N} \xrightarrow[N\to\infty]{w} \mu_b$, which are compactly supported, and assume that $\lambda_1(A_N) \xrightarrow[N\to\infty]{} \rho_a$, $\lambda_1(B_N) \xrightarrow[N\to\infty]{} \rho_b$, which are the right edges[16] of μ_a and μ_b respectively. As we have previously mentioned, we know that

$$\hat{\mu}_{H_N} \xrightarrow[N\to\infty]{w} \mu_a \boxplus \mu_b$$

and denote by $\rho(\mu_a \boxplus \mu_b)$ the right edge of the support of $\mu_a \boxplus \mu_b$. We then have the following LDP:

Theorem 3.4 *With H_N defined as above,the law of its largest eigenvalue $\lambda_1(H_N)$ satisfies an LDP at speed N with good rate function $L_{a,b}$:*

$$L_{a,b}(x) = \begin{cases} \sup_\theta L_{a,b}(\theta, x), & \text{if } x \ge \rho(\mu_A \boxplus \mu_B), \\ +\infty, & \text{if } x < \rho(\mu_A \boxplus \mu_B), \end{cases}$$

with

$$L_{a,b}(\theta, x) := J(\theta, x, \mu_a \boxplus \mu_b) - J(\theta, x, \mu_a) - J(\theta, x, \mu_b). \tag{15}$$

and J defined in equation (13).

[15] A_N and B_N may be considered real symmetric. By invariance of the Haar measure under unitary conjugation, one can assume without loss of generality that they are diagonal.

[16] More general results are given in [31].

3.4 Main ideas of the proofs

In this section, we provide the main ideas of the proofs of Theorems 3.3 and 3.4. As anounced, it is based on tiliting the measure thanks to spherical integrals. We start by recalling how such a tilting argument has been used in the much simpler context of real i.i.d. real random variables to prove Cramér's theorem. We then show how it can be applied in our case for studying the deformed model. The sub-Gaussian Wigner case is much more involved and will only be sketched in the last paragraph.

3.4.1 Tilting for Cramér

Consider $(X_N)_{N\geq 1}$ a sequence of i.i.d. real random variables that are centered, with law μ and such that the log-Laplace transform satisfies $\Lambda_\mu(t) < \infty, \forall t \in \mathbb{R}$.
Cramér's theorem states that the law of $\bar{X}_N = (X_1 + \ldots + X_N)/N$ satisfies an LDP with rate function Λ_μ^* defined as $\Lambda_\mu^*(x) = \sup_{\theta\in\mathbb{R}}\left(\theta x - \Lambda_\mu(\theta)\right)$, for any $x \in \mathbb{R}$. This is a classical result and we refer the reader for example to [2].

The idea of the proof goes as follows : for any $x \in \mathbb{R}$ and $\delta \geq 0$,

$$\mathbb{P}\left(\left|\bar{X}_N - x\right| \leq \delta\right) = \mathbb{E}\left(\frac{e^{N\theta \bar{X}_N}}{e^{N\theta \bar{X}_N}} 1_{|\bar{X}_N - x|\leq\delta}\right) \simeq e^{-N\theta x} \underbrace{\frac{\mathbb{E}\left(e^{N\theta\bar{X}_N} 1_{|\bar{X}_N - x|\leq\delta}\right)}{\mathbb{E}\left(e^{N\theta\bar{X}_N}\right)}}_{=:\mathbb{P}_N^\theta(|\bar{X}_N - x|\leq\delta)} \times \underbrace{\mathbb{E}\left(e^{N\theta\bar{X}_N}\right)}_{=e^{N\Lambda_\mu(\theta)}},$$

where $\mathbb{P}_N^\theta$ is the tilted measure defined by:

$$\mathbb{P}_N^\theta(A) = \frac{\mathbb{E}\left(e^{N\theta\bar{X}_N} 1_A\right)}{\mathbb{E}\left(e^{N\theta\bar{X}_N}\right)}.$$

Thus, we have:

$$\mathbb{P}\left(\left|\bar{X}_N - x\right| \leq \delta\right) \simeq e^{-N(\theta x - \Lambda_\mu(\theta))} \mathbb{P}_N^\theta\left(\left|\bar{X}_N - x\right| \leq \delta\right) \leq e^{-N(\theta x - \Lambda_\mu(\theta))},$$

and by optimizing over θ, we obtain $\mathbb{P}\left(\left|\bar{X}_N - x\right| \leq \delta\right) \leq e^{-N\Lambda_\mu^*(x)}$, which is the upper bound we expect for Cramér's theorem.

On the other hand, to get a lower bound, we need to find θ_x such that $\mathbb{P}_N^{\theta_x}\left(\left|\bar{X}_N - x\right| \leq \delta\right) \geq \frac{1}{2}$. Otherwise stated, under $\mathbb{P}_N^{\theta_x}$, x should be the typical behavior of $\bar{X}_N$. Now, as $\mathbb{P}_N^{\theta_x}$ preserves the independence of $X_1, \ldots, X_N$, by the law of large number, the typical value of $\bar{X}_N$ under $\mathbb{P}_N^{\theta_x}$ should be $\mathbb{E}_N^{\theta_x}(\bar{X}_N)$. By differentiating Λ_μ, we get $\Lambda_\mu'(\theta) = \mathbb{E}_N^\theta\left(\bar{X}_N\right)$. This leads us to choose θ_x such that $\Lambda_\mu'(\theta_x) = x$. By the law of large numbers, for large enough N, one has $\mathbb{P}_N^{\theta_x}\left(\left|\bar{X}_N - x\right| \leq \delta\right) \geq \frac{1}{2}$. In addition, since $\Lambda_\mu'(\theta_x) = x$, we get by optimizing $\theta x - \Lambda_\mu(\theta)$ over θ that $\theta_x x - \Lambda_\mu(\theta_x) = \sup_\theta\{\theta x - \Lambda_\mu(\theta)\} = \Lambda_\mu^*(x)$ so we get the lower bound and conclude the proof.

3.4.2 Tilting for $\lambda_1(H_N)$

We now go to the proof of Theorem 3.4, studying the deviations of $\lambda_1(H_N)$, with

$$H_N = A_N + OB_N O^*.$$

Mimicking the previous situation, one could try to tilt the measure directly by $e^{N\theta\lambda_1(H_N)}$. This is not a reasonable strategy as we do not know how to evaluate $\mathbb{E}(e^{N\theta\lambda_1(H_N)})$ to start with. A better strategy, relying on spherical integrals, has emerged from discussions between A. Guionnet and M. Potters. On our model, this goes as follows.

If we denote by $\mu = \mu_A \boxplus \mu_B$ and $\lambda_1 = \lambda_1(H_N)$, we have :

$$\mathbb{P}(|\lambda_1 - x| \le \delta) = \mathbb{E}\left(\frac{I_N(\theta,H_N)}{I_N(\theta,H_N)} \times 1_{|\lambda_1 - x|\le\delta}\right) \simeq \mathbb{E}\left(\frac{I_N(\theta,H_N)}{I_N(\theta,H_N)} \times 1_{|\lambda_1-x|\le\delta} \times 1_{\hat{\mu}_{H_N}\in B(\mu,N^{-1/4})}\right)$$
$$\simeq \exp(-NJ(\theta,x,\mu))\,\mathbb{E}\left[I_N(\theta,H_N) \times \mathbb{I}_{|\lambda_1-x|\le\delta} \times 1_{\hat{\mu}_{H_N}\in B(\mu,N^{-1/4})}\right].$$

The idea behind the first approximation is that the concentration of $\widehat{\mu}_{H_N}$ around μ is much more robust and fast than the convergence of λ_1. This is essentially because the scaling in the LDP for $\widehat{\mu}_{H_N}$ is of order N^2, whereas that of λ_1 is of order N. The second approximation is obtained by using that $\frac{1}{N}\log I_N(\theta,H_N)$ converges to $J(\theta,x,\mu)$ whenever $\widehat{\mu}_N \simeq \mu$ and $\lambda_1 \simeq x$.

Now, if we define our tilting measure as:

$$\mathbb{P}_N^{\theta}(A) = \frac{\mathbb{E}(I_N(\theta,H_N) \times 1_A)}{\mathbb{E}(I_N(\theta,H_N))}, \tag{16}$$

we get :

$$\mathbb{P}(|\lambda_1 - x| \le \delta) \tag{17}$$
$$\simeq \exp(-NJ(\theta,x,\mu)) \times \mathbb{E}(I_N(\theta,H_N)) \times \mathbb{P}_N^{\theta}\left(|\lambda_1 - x| \le \delta, \hat{\mu}_{H_N} \in B(\mu, N^{-1/4})\right).$$

To proceed with the tilting argument we used in the case of i.i.d. variables (as shown above), we are faced with two challenges :

1. to get an upper bound for the LDP, we want to compute the annealed spherical integral $\mathbb{E}(I_N(\theta,H_N))$,
2. to get a lower bound, we want to find a parameter θ_x such that

$$\mathbb{P}_N^{\theta_x}\left(|\lambda_1 - x| \le \delta, \hat{\mu}_{H_N} \in B(\mu, N^{-1/4})\right) \ge \frac{1}{2}.$$

Let us start by computing the annealed spherical integral. We recall that $H_N = A_N + OB_NO^*$; if we denote by $C_N = \begin{pmatrix} \theta & \\ & (0) \end{pmatrix}$ and consider O and V that are independent and both Haar distributed on $\mathcal{O}_N$, then

$$\mathbb{E}(I_N(\theta,H_N)) = \mathbb{E}_O\left[\mathbb{E}_V\left(e^{N\,\mathrm{Tr}(C_N V H_N V^*)}\right)\right] = \mathbb{E}_O\mathbb{E}_V\left(e^{N\,\mathrm{Tr}(C_N V(A_N + OB_NO^*)V^*)}\right)$$
$$= \mathbb{E}_O\mathbb{E}_V\left(e^{N\,\mathrm{Tr}(C_N V A_N V^*)} e^{N\,\mathrm{Tr}(C_N(VO)B_N(VO)^*)}\right).$$

Now, as V and VO are also independent and Haar distributed, we end up with

$$\mathbb{E}(I_N(\theta,H_N)) = I_N(\theta,A_N)I_N(\theta,B_N). \tag{18}$$

This immediately gives the following upper bound:

$$\begin{aligned}\mathbb{P}(|\lambda_1 - x| \le \delta) &\le \exp(-NJ(\theta,x,\mu)) \times \mathbb{E}(I_N(\theta,H_N)) \\ &= \exp(-NJ(\theta,x,\mu)) I_N(\theta,A_N) I_N(\theta,B_N) \\ &\le \exp\{-N[J(\theta,x,\mu_a \boxplus \mu_b) - J(\theta,x,\mu_a) - J(\theta,x,\mu_b)]\}\end{aligned}$$

and we conclude by optimizing on θ.

To get a lower bound, we want to find a parameter θ_x such that $\mathbb{P}_N^{\theta_x}(|\lambda_1 - x| \le \delta) \ge \frac{1}{2}$. As previously, we first have to understand what is the typical value of $\lambda_1(H_N)$ under $\mathbb{P}_N^{\theta}$. The trick is to establish a large deviation upper bound for λ_1 under $\mathbb{P}_N^\theta$. And to use the fact that the typical value under the tilted measure will be the minimizer of the large deviation upper bound under $\mathbb{P}_N^\theta$. Using the definition of the tilted measure given in (16) and the relation obtained in (18), we have :

$$\begin{aligned}\mathbb{P}_N^\theta(|\lambda_1 - x| \le \delta) &\approx \frac{1}{I_N(\theta, A_N) I_N(\theta, B_N)} \mathbb{E}\left[I_N(\theta, H) \mathbb{I}_{\{|\lambda_1 - x| \le \delta, \hat{\mu}_N \simeq \mu\}} \frac{I_N(\theta', H)}{I_N(\theta', H)} \right] \\ &\le \frac{1}{I_N(\theta, A_N) I_N(\theta, B_N)} \sup_{H \in \mathcal{E}_N(x)} \left\{ \frac{I(\theta, H)}{I(\theta', H)} \right\} \times P_N^{\theta'}(\mathcal{E}_N(x)) \times \mathbb{E}\left(I_N(\theta', H) \right),\end{aligned}$$

where $\mathcal{E}_N(x) = \{|\lambda_1 - x| \le \delta\} \cap \{\hat{\mu}_N \simeq \mu\}$. We can always bound $\mathbb{P}_N^{\theta'}(\mathcal{E}_N(x))$ by 1 and by definition of $J(\theta, x, \mu)$ and the fact that on $\mathcal{E}_N(x)$ we have $\lambda_1 \simeq x$ and $\widehat{\mu}_N \simeq \mu$, we also get the approximation :

$$\sup_{H \in \mathcal{E}_N(x)} \left\{ \frac{I(\theta, H)}{I(\theta', H)} \right\} \simeq \exp\left\{ -N\left[J(\theta, x, \mu_a \boxplus \mu_a) - J(\theta', x, \mu_a \boxplus \mu_b) \right] \right\}.$$

Otherwise stated, with $L_{a,b}(\theta, x)$ as defined in (15), we get the following upper bound:

$$\limsup_{N \to} \frac{1}{N} \log \mathbb{P}_N^\theta(|\lambda_1 - x| \le \delta) \le -(L_{a,b}(\theta, x) - \inf_{\theta' \ge 0} L_{a,b}(\theta', x)).$$

A thorough study of the function $L_{a,b}$ shows that, under our assumptions on the model, there exists a unique θ_x such that $L_{a,b}(\theta_x, x) = \inf_{\theta' \ge 0} L_{a,b}(\theta', x)$ and for any $y \ne x$, we have $\inf_{\theta \ge 0} L_{a,b}(\theta, x) < L_{a,b}(\theta_x, y)$. This implies that, with this choice for θ_x, we have $\mathbb{P}_N^{\theta_x}(|\lambda_1 - x| \le \delta) \ge \frac{1}{2}$ and concludes the proof of the lower bound.

3.4.3 Tilting for $\lambda_1(W_N)$

In the case of sub-Gaussian Wigner matrices, the very same strategy is applied but the two main technical steps, that is the computation of the annealed spherical integral and the understanding of the typical behavior of λ_1 under the tilted measures are both much more involved than in the previous case. We present here the arguments of [26] under the stronger assumption of sharp sub-Gaussianity of the entries (that is $K = 1/2$). As mentioned in the introduction of this chapter, this assumption has been progressively relaxed along a series of paper outcoming to [32], at the price of highly technical arguments that are out of the scope of these notes.

In the case of sub-Gaussian Wigner matrices, the empirical spectral measure of W_N concentrates very quickly around the semi-circular distribution, that we denote again by $\mu_{\rm sc}$. Therefore,

$$\begin{aligned}\mathbb{P}(|\lambda_1 - x| \le \delta) = \mathbb{E}\left(\frac{I_N(\theta, W_N)}{I_N(\theta, W_N)} \times 1_{|\lambda_1 - x| \le \delta} \right) &\simeq \mathbb{E}\left(\frac{I_N(\theta, W_N)}{I_N(\theta, W_N)} \times 1_{|\lambda_1 - x| \le \delta} \times 1_{\hat{\mu}_{W_N} \in B(\mu_{\rm sc}, N^{-1/4})} \right) \\ &\simeq \exp(-NJ(\theta, x, \mu_{\rm sc})) \mathbb{E}\left[I_N(\theta, W_N) \times 1_{|\lambda_1 - x| \le \delta} \right].\end{aligned}$$

In this case, we have to consider not only one tilted measure for each $\theta \ge 0$ but a whole family of tilted measure. More precisely, if we denote by dv the uniform measure on the unit sphere $\mathbb{S}^{N-1} \subset \mathbb{R}^N$, we write

$$\begin{aligned}\mathbb{P}(|\lambda_1 - x| \le \delta) &\simeq \exp(-NJ(\theta, x, \mu_{\rm sc})) \int_{\mathbb{S}^{N-1}} \mathbb{E}\left(e^{N\theta \langle v, W_N v \rangle} 1_{|\lambda_1 - x| \le \delta} \right) dv \\ &\simeq \exp(-NJ(\theta, x, \mu_{\rm sc})) \int_{\mathbb{S}^{N-1}} \mathbb{E}\left(e^{N\theta \langle v, W_N v \rangle} \right) \mathbb{P}_N^{(\theta, v)}(|\lambda_1 - x| \le \delta) dv, \quad (19)\end{aligned}$$

with

$$\mathbb{P}_N^{(\theta,v)}(A) := \frac{\mathbb{E}\left(e^{N\theta\langle v, W_N v\rangle}1_A\right)}{\mathbb{E}\left(e^{N\theta\langle v, W_N v\rangle}\right)}.$$

To get an upper bound, for each $\theta \geq 0$ and $v \in \mathbb{S}^{N-1}$, we need an upper bound on the annealed spherical integral $\mathbb{E}\left(e^{N\theta\langle v, W_N v\rangle}\right)$, where the expectation is over the distribution of W_N. This is provided by the following computation:

$$\begin{aligned}
\mathbb{E}\{\exp(N\theta\langle v, W_N v\rangle)\} &= \mathbb{E}\left\{\exp\left(\theta\sqrt{N}\left[2\sum_{i<j}X_{ij}v_iv_j + \sum_i X_{ii}v_i^2\right]\right)\right\} \\
&= \exp\left\{\sum_{i<j}\Lambda_\mu(2\theta\sqrt{N}v_iv_j) + \sum_i \Lambda_\mu(\theta v_i^2\sqrt{N})\right\} \\
&\leq \exp\left\{\sum_{i<j}2\theta^2.Nv_i^2v_j^2 + \sum_i \theta^2 N v_i^4\right\} \\
&= \exp\left\{N\theta^2\left(\sum_i v_i^2\right)^2\right\} = \exp\left(N\theta^2\right),
\end{aligned} \tag{20}$$

where we have used sharp sub-Gaussianity for the first inequality and the fact that $v \in \mathbb{S}^{N-1}$ for the last equality.

By using that $P_N^{(\theta,v)}(|\lambda_1 - x| \leq \delta) \leq 1$ in (19), and using the bound on $\mathbb{E}\{\exp(N\theta\langle v, W_N v\rangle)\}$ found in (20) and optimizing over $\theta \geq 0$, one gets that

$$\limsup_{N\to\infty}\frac{1}{N}\log\left(\mathbb{P}(|\lambda_1 - x| \leq \delta)\right) \leq -\inf_{\theta\geq 0}\{\theta^2 - J(x,\theta,\mu_{\mathrm{sc}})\}.$$

One can check that, for $x \geq 2$, the infimum is reached at $\theta_x := \frac{1}{4}(x - \sqrt{x^2-4})$ and equals $-I^\gamma(x)$.

Towards the lower bound, let us now try to understand the behavior of λ_1 under $\mathbb{P}_N^{(\theta,v)}$. One can check that

$$\mathbb{E}_N^{(\theta,v)}((W_N)_{i,j}) = \sqrt{\frac{1}{N}}\Lambda_\mu'\left(2\theta\sqrt{N}v_iv_j\right).$$

For the lower bound, the idea is that it is possible to restrict ourselves to delocalized eigenvectors v. Indeed, if the vector v is delocalized, then the product v_iv_j is much smaller than $N^{-1/2}$, so that $2\theta\sqrt{N}v_iv_j = o(1)$. Now, in the vicinity of 0, we have that $\Lambda_\mu'(t) \simeq t$ so that

$$\mathbb{E}_N^{(\theta,v)}((W_N)_{i,j}) \simeq 2\theta v_iv_j.$$

More precisely, one can show that, if v is delocalized, then under $\mathbb{P}_N^{(\theta,v)}$, we have

$$W_N \simeq \widetilde{W}_N + 2\theta vv^{\mathrm{T}},$$

where $\widetilde{W}_N$ is a Wigner matrix under $\mathbb{P}_N^{(\theta,v)}$. It means that W_N is a rank one deformation of a Wigner matrix. Such deformed models have been extensively studied (see for example [44]) and we know that, for $\theta \geq 2$, the typical value of λ_1 is $2\theta + \frac{1}{2\theta}$. Therefore, to get the lower bound, we are lead to choose θ_x such that $2\theta_x + \frac{1}{2\theta_x} = x$. Note that this coincides with the value of θ_x optimizing the upper bound. This concludes our sketch of proof of Theorem 3.3 in the sharp sub-Gaussian case.

3.5 Conclusion

In this third chapter, corresponding to an extended version of Lectures 4 and 5, we have presented a general method, introduced in [26] and developed in a long series of papers to study large deviations at the edge of some random matrix models.

- We get a large deviation principle for the largest eigenvalue for sub-Gaussian Wigner matrices and for a deformation of a unitarily invariant model.
- The proof of these results uses spherical integrals, that are well known in physics and interesting mathematical objects by themselves. We have stated and proved in details their asymptotics in the case when one of the matrices is of rank one.
- The proofs also rely on a clever use of a tilting argument, which is classical in the framework of large deviation theory and that we have also presented in the easy case of Cramér's theorem.

A On Haar measures and the distribution of eigenvectors of a GUE matrix

Let H_N be a random matrix in $\mathcal{H}_N(\mathbb{C})$ with distribution μ_{GUE_N}, as defined in Proposition 1.2. Any realisation $H_N(\omega)$ is Hermitian, so the matrix $U_N(\omega)$ of its eigenvectors can be chosen unitary: it belongs to

$$\mathcal{U}_N := \{U \in \mathcal{M}_N(\mathbb{C}), UU^* = U^*U = I_N\}.$$

From the definition of μ_{GUE_N}, it is easy to check that if H_N has distribution μ_{GUE_N}, then for any fixed matrix $V \in \mathcal{U}_N$, VH_NV^* has the same distribution μ_{GUE_N}. Therefore, VU_N has the same distribution as U_N. This is enough to characterize the distribution of U_N.

Indeed, we have the following:

Proposition A.1 *Let G be a compact topological group. There exists a unique probability measure $\mu_{Haar,G}$ that is left translation invariant i.e. $\mu_{Haar,G}(g \cdot A) = \mu_{Haar,G}(A)$, for any $g \in G$ and any Borelian subset $A \subseteq G$. This measure is called the Haar measure of the group G. Note that this measure is also right invariant i.e. $\mu_{Haar,G}(A \cdot g) = \mu_{Haar,G}(A)$. It is therefore also conjugation invariant.*

Heuristically, one can view the sampling according to the Haar measure of G as picking a point at random and uniformly on G.

The group of unitary matrices $\mathcal{U}_N$ is a compact topological group and we can thus deduce from the above discussion that the distribution of the matrix U_N of the eigenvectors of H_N is the Haar measure on $\mathcal{U}_N$.

As a by product of the proof of the Weyl formula (2), one can also check that U_N can be chosen independent of the eigenvalues $(\lambda_1^N, ..., \lambda_N^N)$. This leads to a third possible description of the GUE. To construct H_N, pick U according to the Haar measure on the group of unitary matrices $\mathcal{U}_N$. Then, sample independently $(\lambda_1^N, ..., \lambda_N^N)$ from $\mathbb{P}_{GUE_N}$ and define $H_N := U_N \Lambda_N U_N^*$, with Λ_N the diagonal matrix with diagonal entries $(\lambda_1^N, ..., \lambda_N^N)$.

B On Euler-Lagrange equations for the quadratic potential

The object of this appendix is to give a proof of Lemma 1.8.

For any $x \in \mathbb{R}$, we denote by

$$F(x) := \int \log|x-y| d\mu_{\mathrm{sc}}(y),$$

the logarithmic potential of the semicircular distribution μ_{sc}. Our task is to compute this quantity in two different regimes : when $x \in [-2,2]$, that is when x belongs to the support of μ_{sc}, which corresponds to the first equality in Lemma 1.8 and when $x \notin [-2,2]$, that is when x is outside the support, which corresponds to the second inequality.

Let us start with the first case. As an intermediate step, we compute the Stieltjes tranform

$$s(z) := \int \frac{1}{y-z} d\mu_{\mathrm{sc}}(y),$$

for any $z \notin \mathbb{R}$. By a simple change of variables $y = 2\cos\theta$, we can rewrite

$$s(z) = \frac{1}{\pi} \int_0^{2\pi} \frac{(\sin\theta)^2}{2\cos\theta - z} d\theta.$$

If we denote by $\xi = e^{i\theta}$, we can write it as a contour integral

$$s(z) = -\frac{1}{4i\pi}\oint_{|\xi|=1}\frac{(\xi^2-1)^2}{\xi^2(\xi^2+1-z\xi)}d\xi.$$

The poles are $\xi_0 = 0$, $\xi_1 = \frac{z+\sqrt{z^2-4}}{2}$ and $\xi_2 = \frac{z-\sqrt{z^2-4}}{2}$, where we choose the branch of the square root with positive imaginary part. One can check that ξ_1 is outside the unit circle and ξ_2 inside. Computing the residues, we have

$$\mathrm{Res}(\xi_0) = z, \quad \mathrm{Res}(\xi_2) = -\sqrt{z^2-4},$$

from which we get that

$$s(z) = \frac{-z+\sqrt{z^2-4}}{2}.$$

Then, $\forall x \in [-2,2]$,

$$F'(x) = -\mathrm{PV}\int\frac{1}{x-y}d\mu_{\mathrm{sc}}(y) = -\lim_{\varepsilon\to 0}\int_{|y-x|\geq\varepsilon}\frac{1}{x-y}d\mu_{\mathrm{sc}}(y) = -\frac{1}{2}(s(x+i0)+s(x-i0)) = \frac{x}{2}.$$

From there, one can deduce that

$$F(x) = \frac{x^2}{4}+C.$$

The constant C will be determined by the next computation.

We now go to the case when $x \notin [-2,2]$. By symmetry, one can assume that $x \geq 2$. From Vivo's lecture notes, Section IV.A.1., we get that

$$L(x) := \frac{1}{\pi}\int_{-\sqrt{2}}^{\sqrt{2}}\log(x-y)\sqrt{2-x^2}dx = \frac{x^2}{2}-\frac{x}{2}\sqrt{x^2-2}+\log\left(\frac{x+\sqrt{x^2-2}}{2}\right)-\frac{1}{2}.$$

By an easy change of variables, we get that

$$F(x) = L\left(\frac{x}{\sqrt{2}}\right)+\frac{1}{2}\log 2,$$

so that

$$\frac{x^2}{2}-2F(x) = \frac{x}{2}\sqrt{x^2-4}-2\log\left(\frac{x+\sqrt{x^2-4}}{2}\right)+1 = \int_2^x\sqrt{y^2-4}dy+1.$$

By continuity, we get that the constant in the previous computation was $C = 1$ and that both parts of the lemma hold.

C On strict convexity of the logarithmic energy

The object of this appendix is to prove Lemma 1.9. As for the definition of I in (5), we restrict ourselves to probability measures μ such that $\int x^2 d\mu(x) < \infty$.

The idea is that the rate function I is the difference of a linear term $\mu \mapsto \int x^2 d\mu(x)$ and a functional $\Sigma : \mu \mapsto \iint \log|x-y| d\mu(x)d\mu(y)$, which is essentially strictly concave. Following the proof of Lemma 2.6.2. in [3], we use a slightly different decomposition of I.

By using the fact that μ_{sc} satisfies the EL equations, one can rewrite

$$I(\mu) = -\Sigma(\mu - \mu_{sc}) + \int \left(\frac{x^2}{2} - 2 \int \log|x - y| d\mu_{sc}(y) - 1 \right) d\mu(x).$$

The second term is linear in μ and we will now prove the strict concavity of $\mu \mapsto \Sigma(\mu - \mu_{sc})$.

We choose an appropriate representation of the logarithm: from the equality

$$\frac{1}{z} = \frac{1}{2z} \int_0^\infty e^{-\frac{u}{2}} du,$$

which holds for any $z \in \mathbb{R}^*$ and using the change of variables $u = \frac{z^2}{t}$, we get

$$\frac{1}{z} = \frac{z}{2} \int_0^\infty e^{-\frac{z^2}{2t}} \frac{dt}{t^2}.$$

For $x \neq y$, integrating from 1 to $|x - y|$, we get

$$\log|x - y| = \int_1^{|x-y|} \frac{z}{t} \int_0^\infty e^{-\frac{z^2}{2t}} \frac{dt}{t} dz = \int_0^\infty \frac{e^{-\frac{1}{2t}} - e^{-\frac{|x-y|^2}{2t}}}{2t} dt.$$

As $\mu - \mu_{sc}$ has mass zero, the first term will cancel and we get the following Fourier representation

$$\begin{aligned}\Sigma(\mu - \mu_{sc}) &= -\int_0^\infty \frac{1}{2t} \left(\iint e^{-\frac{|x-y|^2}{2t}} d(\mu - \mu_{sc})(x) d(\mu - \mu_{sc})(y) \right) dt \\ &= -\int_0^\infty \sqrt{\frac{t}{2\pi}} \int_{-\infty}^\infty \left| \int e^{i\lambda x} d(\mu - \mu_{sc})(x) \right|^2 e^{-\frac{t\lambda^2}{2}} d\lambda.\end{aligned}$$

Now $\mu \mapsto \left| \int e^{i\lambda x} d(\mu - \mu_{sc})(x) \right|^2$ is convex so that $\mu \mapsto \Sigma(\mu - \mu_{sc})$ is concave.

Moreover, for $\alpha \in [0, 1]$ and any probability measures μ and ν so that Σ is well defined, we have

$$\Sigma(\alpha\mu + (1 - \alpha)\nu) = \alpha\Sigma(\mu) + (1 - \alpha)\Sigma(\nu) + (\alpha^2 - \alpha)\Sigma(\mu - \nu).$$

From the Fourier representation above, we know that $\Sigma(\mu - \nu) \geq 0$ and $\Sigma(\mu - \nu) = 0$ if and only if all Fourier coefficients are zero, that is if $\mu = \nu$.

This concludes the proof of the strict convexity.

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References

[1] H. Touchette, *The large deviation approach to statistical mechanics*, Phys. Rep. **478**(1-3), 1 (2009), doi:10.1016/j.physrep.2009.05.002.

[2] A. Dembo and O. Zeitouni, *Large deviations techniques and applications*, vol. 38 of *Stochastic Modelling and Applied Probability*, Springer-Verlag, Berlin, ISBN 978-3-642-03310-0, doi:10.1007/978-3-642-03311-7, Corrected reprint of the second (1998) edition (2010).

[3] G. W. Anderson, A. Guionnet and O. Zeitouni, *An introduction to random matrices*, vol. 118 of *Cambridge Studies in Advanced Mathematics*, Cambridge University Press, Cambridge, ISBN 978-0-521-19452-5 (2010).

[4] P. Dupuis and R. S. Ellis, *A weak convergence approach to the theory of large deviations*, Wiley Series in Probability and Statistics: Probability and Statistics. John Wiley & Sons, Inc., New York, ISBN 0-471-07672-4, doi:10.1002/9781118165904, A Wiley-Interscience Publication (1997).

[5] G. Ben Arous and A. Guionnet, *Large deviations for Wigner's law and Voiculescu's non-commutative entropy*, Probab. Theory Related Fields **108**(4), 517 (1997), doi:10.1007/s004400050119.

[6] D. García-Zelada, *A large deviation principle for empirical measures on Polish spaces: application to singular Gibbs measures on manifolds*, Ann. Inst. Henri Poincaré Probab. Stat. **55**(3), 1377 (2019), doi:10.1214/18-aihp922.

[7] T. Leblé and S. Serfaty, *Large deviation principle for empirical fields of log and Riesz gases*, Invent. Math. **210**(3), 645 (2017), doi:10.1007/s00222-017-0738-0.

[8] T. Leblé, S. Serfaty and O. Zeitouni, *Large deviations for the two-dimensional two-component plasma*, Comm. Math. Phys. **350**(1), 301 (2017), doi:10.1007/s00220-016-2735-3.

[9] M. L. Mehta, *Random matrices*, vol. 142 of *Pure and Applied Mathematics (Amsterdam)*, Elsevier/Academic Press, Amsterdam, third edn., ISBN 0-12-088409-7 (2004).

[10] G. Livan, M. Novaes and P. Vivo, *Introduction to random matrices*, vol. 26 of *SpringerBriefs in Mathematical Physics*, Springer, Cham, ISBN 978-3-319-70883-6; 978-3-319-70885-0, doi:10.1007/978-3-319-70885-0, Theory and practice (2018).

[11] P. J. Forrester, *Log-gases and random matrices*, vol. 34 of *London Mathematical Society Monographs Series*, Princeton University Press, Princeton, NJ, ISBN 978-0-691-12829-0, doi:10.1515/9781400835416 (2010).

[12] P. Billingsley, *Convergence of probability measures*, Wiley Series in Probability and Statistics: Probability and Statistics. John Wiley & Sons, Inc., New York, second edn., ISBN 0-471-19745-9, doi:10.1002/9780470316962, A Wiley-Interscience Publication (1999).

[13] D. Chafaï, N. Gozlan and P.-A. Zitt, *First-order global asymptotics for confined particles with singular pair repulsion*, Ann. Appl. Probab. **24**(6), 2371 (2014), doi:10.1214/13-AAP980.

[14] S. Serfaty, *Lectures on Coulomb and Riesz gases* (2024), arXiv:2407.21194.

[15] P. Dupuis, V. Laschos and K. Ramanan, *Large deviations for configurations generated by Gibbs distributions with energy functionals consisting of singular interaction and weakly confining potentials*, Electron. J. Probab. **25**, Paper No. 46, 41 (2020), doi:10.1214/20-ejp449.

[16] A. Guionnet and R. Memin, *Large deviations for Gibbs ensembles of the classical Toda chain*, Electron. J. Probab. **27**, Paper No. 46, 29 (2022), doi:10.1214/22-ejp771.

[17] H. Spohn, *Collision rate ansatz for the classical Toda lattice*, Phys. Rev. E **101**(6), 060103(R), 4 (2020), doi:10.1007/s10955-019-02320-5.

[18] R. Allez, J.-P. Bouchaud and A. Guionnet, *Invariant beta ensembles and the gauss-wigner crossover*, Physical review letters **109**(9), 094102 (2012).

[19] R. Allez, J.-P. Bouchaud, S. N. Majumdar and P. Vivo, *Invariant β-Wishart ensembles, crossover densities and asymptotic corrections to the Marčenko-Pastur law*, J. Phys. A **46**(1), 015001, 22 (2013), doi:10.1088/1751-8113/46/1/015001.

[20] T. Bodineau and A. Guionnet, *About the stationary states of vortex systems*, Ann. Inst. H. Poincaré Probab. Statist. **35**(2), 205 (1999), doi:10.1016/S0246-0203(99)80011-9.

[21] S. N. Majumdar and M. Vergassola, *Large deviations of the maximum eigenvalue for wishart and gaussian random matrices*, Physical review letters **102**(6), 060601 (2009).

[22] S. N. Majumdar and G. Schehr, *Top eigenvalue of a random matrix: large deviations and third order phase transition*, Journal of statistical mechanics **2014**(1), P01012 (2014).

[23] R. J. Berman, *Determinantal point processes and fermions on complex manifolds: large deviations and bosonization*, Comm. Math. Phys. **327**(1), 1 (2014), doi:10.1007/s00220-014-1891-6.

[24] O. Zeitouni and S. Zelditch, *Large deviations of empirical measures of zeros of random polynomials*, Int. Math. Res. Not. IMRN (20), 3935 (2010), doi:10.1093/imrn/rnp233.

[25] R. Butez, *Large deviations for the empirical measure of random polynomials: revisit of the Zeitouni-Zelditch theorem*, Electron. J. Probab. **21**, Paper No. 73, 37 (2016), doi:10.1214/16-EJP5.

[26] A. Guionnet and J. Husson, *Large deviations for the largest eigenvalue of Rademacher matrices*, Ann. Probab. **48**(3), 1436 (2020), doi:10.1214/19-AOP1398.

[27] J. Husson, *Large deviations for the largest eigenvalue of matrices with variance profiles*, Electron. J. Probab. **27**, Paper No. 74, 44 (2022), doi:10.1214/22-ejp793.

[28] F. Augeri, A. Guionnet and J. Husson, *Large deviations for the largest eigenvalue of sub-Gaussian matrices*, Comm. Math. Phys. **383**(2), 997 (2021), doi:10.1007/s00220-021-04027-9.

[29] B. McKenna, *Large deviations for extreme eigenvalues of deformed Wigner random matrices*, Electron. J. Probab. **26**, Paper No. 34, 37 (2021), doi:10.1214/20-EJP571.

[30] G. Biroli and A. Guionnet, *Large deviations for the largest eigenvalues and eigenvectors of spiked Gaussian random matrices*, Electron. Commun. Probab. **25**, Paper No. 70, 13 (2020), doi:10.3390/mca25010013.

[31] A. Guionnet and M. Maïda, *Large deviations for the largest eigenvalue of the sum of two random matrices*, Electron. J. Probab. **25**, Paper No. 14, 24 (2020), doi:10.1214/19-ejp405.

[32] N. A. Cook, R. Ducatez and A. Guionnet, *Full large deviation principles for the largest eigenvalue of sub-Gaussian wigner matrices* (2023), arXiv:2302.14823.

[33] C. Itzykson and J. B. Zuber, *The planar approximation. II*, J. Math. Phys. **21**(3), 411 (1980), doi:10.1063/1.524438.

[34] A. Guionnet and O. Zeitouni, *Large deviations asymptotics for spherical integrals*, J. Funct. Anal. **188**(2), 461 (2002), doi:10.1006/jfan.2001.3833.

[35] A. Guionnet and M. Maïda, *A Fourier view on the* $\boldsymbol{R}$*-transform and related asymptotics of spherical integrals*, J. Funct. Anal. **222**(2), 435 (2005), doi:10.1016/j.jfa.2004.09.015.

[36] A. Guionnet and J. Husson, *Asymptotics of* $\boldsymbol{k}$ *dimensional spherical integrals and applications*, ALEA Lat. Am. J. Probab. Math. Stat. **19**(1), 769 (2022), doi:10.30757/alea.v19-30.

[37] B. Collins and P. Śniady, *New scaling of Itzykson-Zuber integrals*, Ann. Inst. H. Poincaré Probab. Statist. **43**(2), 139 (2007), doi:10.1016/j.anihpb.2005.12.003.

[38] G. Schehr, A. Altland, Y. Fyodorov, N. O'Connell and L. Cugliandolo, *Stochastic processes and random matrices: Lecture notes of the Les Houches summer school*, vol. 104, Oxford University Press, ISBN 9780198797319, doi:10.1093/oso/9780198797319 (2018).

[39] J. A. Mingo and R. Speicher, *Free Probability and Random Matrices*, Fields Institute Monographs. Springer, New York, NY, ISBN 978-1-4939-6941-8 (2017).

[40] F. Augeri, *Large deviations principle for the largest eigenvalue of Wigner matrices without Gaussian tails*, Electron. J. Probab. **21**, Paper No. 32, 49 (2016), doi:10.1214/16-EJP4146.

[41] S. Ganguly and K. Nam, *Large deviations for the largest eigenvalue of gaussian networks with constant average degree*, Probability theory and related fields **184**(3-4), 613 (2022).

[42] S. Ganguly, E. Hiesmayr and K. Nam, *Spectral large deviations of sparse random matrices*, Journal of the London Mathematical Society **110**(1) (2024).

[43] F. Augeri and A. Basak, *Large deviations of the largest eigenvalue of supercritical sparse Wigner matrices* (2023), arXiv:2304.13364.

[44] M. Capitaine and C. Donati-Martin, *Spectrum of deformed random matrices and free probability*, In *Advanced topics in random matrices*, vol. 53 of *Panor. Synthèses*, pp. 151–190. Soc. Math. France, Paris, ISBN 978-2-85629-850-3 (2017).