

# 4.1. Functional integration in the Coulomb gas picture

Goal: minimisation of free energy  $F$  by variational principle / functional derivative

Step 1 Start with the counting function  $n(x) = \frac{1}{N} \sum_{i=1}^N \delta(x-x_i)$ ,  
normalised  $\int_{\mathbb{R}} dx n(x) = 1$ ,  $n(x) \geq 0$  everywhere on  $\mathbb{R}$ .

Step 2 coarse graining

integrate over all smoothed random measures that are normalised

$$1 = \int \mathcal{D}[n(x)] \delta\left[n(x) - \frac{1}{N} \sum_{i=1}^N \delta(x-x_i)\right] \quad \text{insert this functional into}$$

$$Z_{N,\beta} = C_{N,\beta} \int \mathcal{D}[n(x)] \int_{\mathbb{R}^N} [dx] e^{-\beta N^2 V(x)} \delta\left[n(x) - \frac{1}{N} \sum_{i=1}^N \delta(x-x_i)\right]$$

Step 3 Convert  $\sum$ 's containing  $x_i$  to  $\int$  over  $n(x)$  in  $V(x)$ :

$$\sum_{i=1}^N f(x_i) = N \int_{\mathbb{R}} dx n(x) f(x), \quad \sum_{i \neq j}^N g(x_i, x_j) = N^2 \int_{\mathbb{R}^2} dx dx' n(x) n(x') g(x, x')$$

$\Rightarrow$  problem: in  $\sum_{i \neq j} \ln|x_i - x_j|$  the term with  $i=j$  diverges logarithmically

introduce a short-distance cutoff  $\Delta(x)$ , it removes the infinite energy contribution to  $V(x)$  when 2 charges  $x_i, x_j$  become too close:

$$\sum_{i \neq j} \ln|x_i - x_j| = \sum_{i \neq j}^N \ln|x_i - x_j| - \sum_{i=1}^N \ln \Delta(x_i)$$

Step 4  $\Rightarrow V(x) \rightarrow V[n(x)] = \frac{1}{2} \int_{\mathbb{R}} dx x^2 n(x) - \frac{1}{2} \int_{\mathbb{R}^2} dx dx' n(x) n(x') \ln|x-x'|$

(check)

energy functional

$$+ \frac{1}{2N} \int_{\mathbb{R}} dx n(x) \ln \Delta(x)$$

$$\text{and } Z_{N,\beta} = C_{N,\beta} \int \mathcal{D}[n(x)] e^{-\beta N^2 V[n(x)]} \int_{\mathbb{R}^N} [dx] \delta\left[n(x) - \frac{1}{N} \sum_{i=1}^N \delta(x-x_i)\right] \\ = \mathcal{I}_N[n(x)] \text{ to be evaluated}$$

Step 5: Evaluation of  $I_N[n(x)]$

physical interpretation  $I_N$  counts the number of microstates (= config. of  $N$ ) that are compatible with a given macrostate = density profile  $n(x)$

Result:  $I_N[n(x)] \sim \exp[-N \int dx n(x) \ln n(x)]$

statistical mech. interpretation:

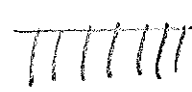
1. derivation using functional derivatives  $\rightarrow$  exercise 3.2 Entropy

2. " : combinatorics:

- divide system into  $K$  small boxes of equal size

- distribute  $N$  particles into  $K$  boxes, with

occupation numbers  $\{n_1, n_2, \dots, n_K\}$ ,  $\sum_{i=1}^K n_i = N$



$\Rightarrow$  number of possibilities  $\frac{N!}{n_1! n_2! \dots n_K!} \sim e^{-\sum_i n_i \ln n_i} \sim \int dx n(x) \ln n(x)$

using Stirling (or  $\Gamma(N+1) = N! \sim N^{N+1/2} e^{-N}$ )

Step 6: what is  $\Delta(x) = ?$  - the cut-off or self-energy:

- we have already seen in the derivation of the partition  $p(i) = e^{-\beta \epsilon_i}$  spacing  $\epsilon_i$  that we had to rescale  $\epsilon_i$  by  $N$  and the local density by  $s = \frac{1}{N R(x)}$   $\epsilon_i$  is spacing

$\Rightarrow$  Ansatz:  $\Delta(x) = \frac{c}{N n(x)}$  (in dimension!).  $\epsilon_i$  is a smooth random measure

where  $c = \text{const}$  (or dep. of  $N$ ) is undetermined

$\Rightarrow \int_{\mathbb{R}} dx n(x) \ln \Delta(x) = \int_{\mathbb{R}} dx n(x) (\ln c - \ln N - \ln n(x)) = \ln c - \ln N - \int_{\mathbb{R}} dx n(x) \ln n(x)$   $\int_{\mathbb{R}} dx n(x) \ln n(x)$  is normalisation of  $n(x)$

$\Rightarrow$  Step 7. expand in  $N$

$Z_{N,\beta} \approx C_{N,\beta} \int \mathcal{D}[n(x)] \exp[-\beta N \left( \frac{1}{2} \int dx x^2 n(x) - \frac{1}{2} \int dx n(x) \ln n(x) \right) + \frac{\beta}{2} N \ln N]$

$\approx \int_{\mathbb{R}} dx n(x)$  energy  $O(N^2)$

partition function

$+ \left( \frac{\beta}{2} - 1 \right) N \left[ \int_{\mathbb{R}} dx n(x) \ln n(x) - \frac{\beta}{2} N \ln c + O(N) \right]$

$\int_{\mathbb{R}} dx n(x)$  self-energy & entropy

\*  $\beta = 2$  special!

\* we have expressed the  $\int$  over the  $\rho(x) =$  probability function of a Dyson-Coulomb gas.

$\rightarrow$  we still need to show that the limiting density  $n_x(x)$  that minimises the free energy is given by the semi-circle:  $n_x(x) = \frac{1}{2\pi} \sqrt{4-x^2}$  (equilibrium measure)  
 $\Rightarrow$  next chapter: saddle point analysis of  $Z_{N,\beta}$

Here: compare the result for  $Z_{N,\beta=2}$  known from other means (solutions of GUE using Hermite polynomials at finite  $N$ ) for  $N \rightarrow \infty$  asymptotically large AND what we get by directly inserting  $n_x = \frac{1}{2\pi} \sqrt{4-x^2}$  at large- $N$

\*  $\beta=2$  GUE  $\Rightarrow$   $Z_{N,\beta} = \left( \frac{N}{2\pi} \right)^{\frac{N}{2}} \prod_{i=1}^N i! = (2\pi)^{\frac{N}{2}} G(N+2)$  Barnes G-function

$\exists$  recursion  $G(z+1) = \Gamma(z) G(z)$ ,  $G(1) = 1$ , see eg. NIST handbook of mathematical functions chapter 5.17

- asymptotic of

$$\ln G(z+1) \sim \frac{1}{4} z^2 + z \Gamma'(z+1) - \left( \frac{1}{2} z(z+1) + \frac{1}{12} \right) \ln z + O(1)$$

$$\Rightarrow \ln Z_{N,\beta=2} \sim \frac{1}{2} N^2 \ln N - \frac{3}{4} N^2 + N \ln N + N(\ln(2\pi) - 1) + \frac{1}{2} \ln N + O(1)$$

(check this!)

\* On the other hand: inserting  $n_x(x) = \frac{1}{4\pi} \sqrt{4-x^2}$  in  $\bar{F}_{\alpha,\beta}$  yields

$$\bar{F}_0[n_x(x)] = \frac{3}{8} + \frac{1}{4} \ln 2, \quad \bar{F}_2[n_x(x)] = \frac{1}{2} (1 - \ln 2 - 2 \ln \pi)$$

Exercise 33

which together with  $\ln C_{N,\beta} = \ln(\rho N) \left( \frac{N}{2} + \frac{\beta}{4} N(N-1) \right)$

$$\text{gives } \ln Z_{N,\beta} \sim \frac{\beta}{4} N^2 \ln N + a_\beta N^2 + N \ln N + b_\beta N + o(N)$$

Exercise 33: determine  $a_\beta$  and  $b_\beta$

Conclusion! the two asymptotic expansions agree for  $\beta=2$  up to including  $O(N \ln N)$ .

## 5. Saddle-point analysis of the Coulomb gas partition function

- also called steepest descent method or stationary phase approximation <sup>(c.i)</sup> of an integral with a large parameter  $N$

$I = \int dx e^{-Nf(x)}$  expand around extremum  $x_0$  where  $f'(x_0) = 0$

$\Rightarrow I \approx e^{-Nf(x_0)} \int_{-\infty}^{\infty} dx e^{-\frac{Nf''(x_0)}{2}(x-x_0)^2} = \sqrt{\frac{2\pi}{Nf''(x_0)}} e^{-Nf(x_0)}$  see e.g. Fyodorov math-ph/0412017 ch 5.2

"fluctuations"

- for several minima we have to sum over all of them
- for  $\int_J$  with  $J \subseteq \mathbb{R}$  and  $\min x_0 \notin J$  we have to expand to linear order at  $\partial J$  with  $x_0$

### 5.1 Lagrange multipliers and saddle-point equation

absorb in normalization

in  $Z_{N,\beta} = C_{N,\beta} \int \mathcal{D}[n(x)] \exp[-\beta N^2 \mathcal{F}_0[n(x)] + (\frac{\beta}{2}-1) N \mathcal{F}_1[n(x)] + \beta N (\ln N - \ln c) + o(N)]$

we have to insure that the smoothed random measure  $n(x)$  is normalized:

inset  $\delta \left[ \int_{\mathbb{R}} dx n(x) - 1 \right] = \int_{\mathbb{R}} \frac{dk}{2\pi} e^{ik \left( \int_{\mathbb{R}} dx n(x) - 1 \right)}$  using standard  $\delta$ -rep.

- rescaling  $ik \rightarrow \beta N^2 k$  and keeping only the leading order,  $O(N^2)$   $\mathcal{F}_0$ -contrib.

$\Rightarrow Z_{N,\beta} \approx \tilde{C}_{N,\beta} \int \mathcal{D}[n(x)] \int_{\mathbb{R}} dk \exp \left\{ -\beta N^2 \left[ \mathcal{F}_0[n(x)] - k \left( \int_{\mathbb{R}} dx n(x) - 1 \right) \right] + O(N) \right\}$

$\hat{=} S[n(x), k]$  ← Lagrange multiplier

Saddle point  $\approx \text{const } e^{-\beta N^2 S[n_x(x), k_x]}$  (we don't consider the fluctuations)

with  $n_x(x), k_x$  solving the saddle point equations (SP eq.)

$$0 = \frac{\partial}{\partial n(x)} S[n_x(x), k_x] \Big|_{n=n_x, k=k_x} = \frac{x^2}{2} - \int_{\mathbb{R}} dx' n(x') \ln|x-x'| - k_x$$

$$0 = \frac{\partial}{\partial k} S[n_x(x), k_x] \Big|_{n=n_x, k=k_x} = \int_{\mathbb{R}} dx n_x(x) - 1$$

used  $\frac{\partial n(x)}{\partial n(y)} = \delta(x-y)$

(5.9)

\* the normalized solution  $u_x(x)$  of the SP eq. (equilibrium measure) cannot be supported on all of  $\mathbb{R}$ :

$$\text{for } x \rightarrow 1 \text{ we have } 0 = \frac{x^2}{2} - \int_{\mathbb{R}} dx' u_x(x') \ln|x-x'| - u_x$$

$$\approx \frac{x^2}{2} - \ln|x| \int_{\mathbb{R}} dx' u_x(x') = \frac{x^2}{2} - \ln|x| \text{ which is inconsistent}$$

$\Rightarrow$  the solution  $u_x(x) = u_x(x; a, b)$  has compact support on  $[a, b] \subseteq \mathbb{R}$   
 - the parameters  $a, b$  have to be determined s.t.  $u_x(x; a, b)$  is in  $F$ !

## 5.2 Derivative of the SP eq and Tricomi's solution

$\ln|x-x'|$  is not differentiable at  $x=x'$

$\rightarrow$  weak derivative: for  $u(x), v(x) \in \mathcal{L}^1([a, b])$   $v$  is the weak derivative of  $u$

$$\forall \varphi(x) \in \mathcal{C}^\infty, \varphi(a) = \varphi(b) = 0 : \int_a^b dx u(x) \varphi'(x) = - \int_a^b dx v(x) \varphi(x)$$

set  $u(x) = \int dx' u_x(x') \ln|x-x'|$ , we will regularize the singularity at  $x=x'$  by  $\epsilon$

$$\int dx \varphi'(x) \int dx' u_x(x') \frac{\ln|x-x'|^2}{\epsilon} = \frac{1}{2} \lim_{\epsilon \rightarrow 0} \int dx \varphi'(x) \int dx' u_x(x') \ln[(x-x')^2 + \epsilon^2]$$

$$= -\frac{1}{2} \int dx \varphi(x) \int dx' u_x(x') \frac{2(x-x')}{(x-x')^2 + \epsilon^2} = - \int dx \varphi(x) \text{Pr} \int dx' \frac{u_x(x')}{x-x'}$$

or  $\int dx'$  or P.V.  $\int dx'$  is Cauchy's principal value

i.e. for  $x$  singular point of  $F(x)$

$$\text{Pr} \int dx' F(x') = \lim_{\epsilon \rightarrow 0} \int_{x-\epsilon}^{x+\epsilon} dx' F(x') + \int dx' F(x')$$

$$\Rightarrow \text{weak derivative of SP eq: } \boxed{0 = x - \text{Pr} \int dx' \frac{u_x(x')}{x-x'}} \quad (5.15)$$

Assume that  $[a, b]$  is the single interval support of  $u(x)$  (why:  $\underbrace{\text{not}}_{\text{for } W}$ )

Thm [Tricomi 85]

$$g(x) = \text{Pr} \int_a^b dx' \frac{f(x')}{x-x'} \Rightarrow f(x) = \frac{1}{\pi(x-a)(b-x)} \left( c - \text{Pr} \int_a^b dt \frac{f(t-a)(b-t)}{x-t} g(x) \right)$$

$\uparrow$   
arb. (integration) constant