

ICERM mini course : Probabilistic well-posedness

for nonlinear Schrödinger equation (I)

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1 Basic settings

1.1 A brief introduction of (NLS)

- $$\begin{cases} (i\partial_t + \Delta) u = \pm |u|^{p-1} u & , \quad p \geq 3 \text{ odd} \\ u(0) = u_0 \end{cases}$$

(NLS)

- We will focus on (NLS) on the torus \mathbb{T}^d and its local (in time) theory.
- Energy & mass conservation Laws
- "+" defocusing ; "-" focusing.

- Linear Schrödinger equation :

$$(i\partial_t + \Delta) u = 0 \Rightarrow (i\partial_t - |k|^2) \hat{u}(t, k) = 0 \Rightarrow \hat{u}(t, k) = e^{-it|k|^2} \hat{u}(0, k)$$

So, the linear solution can be written as $e^{\underline{i}t\Delta} \underline{u}(0)$

- $e^{\underline{i}t\Delta}$ preserves L^2 and H^s norms;

- Let's consider (NLS) in the $H^s(\mathbb{T}^d)$ spaces.

Q: For what s do we have Local wellposedness (LWP)?

Scaling argument for the threshold of s :

Suppose we have initial data

$$u(0) = f = \sum_{|k| \sim N} N^{-\alpha} e^{ik \cdot x}, \quad \left(\alpha = s + \frac{d}{2} \right)$$

then $\|f\|_{H^s} \sim 1$.

By Duhamel's formula:

$$u(t) = e^{it\Delta} f - i \int_0^t e^{i(t-s)\Delta} (|u(s)|^{p-1} u(s)) ds$$

$\Rightarrow \|e^{it\Delta} f\|_{H^s} = \|f\|_{H^s} \sim 1$.

► the second iteration

$$u^1(t) = -i \int_0^t e^{i(t-s)\Delta} (|e^{is\Delta} f|^{p-1} e^{is\Delta} f) ds$$

$$\hat{u}^1(t, k) = e^{-it|k|^2} \cdot \sum_{k=k_1+k_2+\dots+k_p} \int_0^t e^{is\zeta_2} ds \cdot N^{-pd}$$

$$\leq \frac{1}{\zeta_2}$$

where $\zeta_2 = |k|^2 - |k_1|^2 - \dots - |k_p|^2$ is the "resonance factor".

$$\Rightarrow \hat{u}^1(t, k) \sim N^{-pd} \cdot \sum_{\substack{k_1+k_2+\dots+k_p=k \\ |k_j| \sim N}} \frac{1}{\zeta_2}$$

$$\sim N^{-pd} \cdot \sum_{k_1, \dots, k_p} h_{k_1 \dots k_p}^b \sim N^{-pd} \cdot N^{pd-d-2}.$$

where the base tensor h^b is defined

$$h_{kk_1 \dots k_p}^b := \prod \left\{ \begin{array}{l} k_1 + k_2 + k_3 + \dots + k_p = k \\ \Omega = |k|^2 - |k_1|^2 - |k_2|^2 - \dots - |k_p|^2 = \text{const.} \end{array} \right\}.$$

We want $\|u^1(t)\|_{H^s} \lesssim 1$.

$$\Leftrightarrow \left[\sum_{|k|=N} (N^s \cdot N^{-pd+pd-d-2})^2 \right]^{\frac{1}{2}} \lesssim 1$$

$$\Leftrightarrow -pd + pd - d - 2 + s + \frac{d}{2} \leq 0$$

$$\Leftrightarrow s \geq \frac{d}{2} - \underbrace{\frac{2}{p-1}}$$

\parallel
 s_{cr} : (deterministic) scaling critical exponent for (NLS)

► This " s_{cr} " matches the threshold derived by

$$\|\lambda^{\frac{2}{p-1}} u(\lambda^2 t, \lambda x)\|_{H^{s_c}(\mathbb{R}^d)} = \|u\|_{H^{s_c}(\mathbb{R}^d)}.$$

THM 1.1: Assume $s_{\text{cr}} \geq 0$, the (NLS) is LWP in H^s ,
if $s > s_c$, and is ill-posed if $s < s_{\text{cr}}$.

[Bourgain '93, Bourgain-Demeter '15]

(when $s = s_{\text{cr}} = 1$, LWP [Herr-Tatau-Tzvetkov '10])

Q: How does the "generic" data evolve in the spaces H^s ($s < s_c$)?

1.2 Random data theory $\left(\begin{array}{l} [\text{Bourgain 96}] \xrightarrow{\text{NLS}} [\text{Burg-Tzvetkov 08}], \\ [\text{NLW}] \end{array} \right)$

- Random initial data

$$u(0) = \varphi^\omega = \sum_{k \in \mathbb{Z}^d} \frac{g_k(\omega)}{\langle k \rangle^\alpha} e^{ik \cdot x}, \quad \alpha = s + \frac{d}{2}$$

► $\{g_k\}_{k \in \mathbb{Z}^d}$ are i.i.d. Gaussians $\mathbb{E} g_k = 0$

$$\mathbb{E} |g_k|^2 = 1.$$

► For all $k \in \mathbb{Z}^d$, A-certainly: If some event happens with probability $\gtrsim 1 - C_0 e^{-A^\theta}$, we call it "A-certainly".
 $|g_k(\omega)| \leq A \log(\langle n \rangle + 1)$ (where θ is arbitrary small and A is a large parameter)

► Hence $\overset{\text{a.s.}}{\rightsquigarrow} \varphi^\omega \in H^{s^-}(\mathbb{T}^d) = \bigcap_{\varepsilon > 0} H^{s-\varepsilon}(\mathbb{T}^d)$

► When $\alpha = 1$, φ^ω is related to the invariant Gibbs measure. Formally

$$d\mu \sim \exp \left[-\frac{1}{p+1} \int_{\mathbb{T}^d} :|u|^{p+1}: dx \right] \cdot \exp \left[-\frac{1}{2} \int_{\mathbb{T}^d} |\nabla u|^2 dx \right] \prod_{x \in \mathbb{T}^d} dx$$

"Weighted"

Gaussian measures

$$\left\{ \frac{g_k}{\langle k \rangle} \right\}_{k \in \mathbb{Z}^d}$$

- Probabilistic scaling argument

► Consider random data

$$u(0) = \varphi^w = N^{-\alpha} \sum_{|k| \sim N} g_k e^{ik \cdot x}, \quad \alpha = s + \frac{d}{2}.$$

then $\|\varphi^w\|_{L^2} \sim 1$. Second iteration u^1 :

$$\hat{u}^1(t, k) = e^{-it\|k\|^2} \cdot N^{-\alpha} \sum_{\substack{k_1+k_2+\dots+k_p=k \\ |k_j| \sim N}} g_{k_1}(w) \overline{g_{k_2}(w)} \cdots g_{k_p}(w)$$

$\Im z = \text{Const.}$

► If we assume $k_1 \neq k_2, k_2 \neq k_3, \dots$, etc. then these terms "orthogonal". This leads to square root cancellation

$$\left| \hat{u}^1(t, k) \right| \sim N^{-\alpha} \cdot \underbrace{\left(N^{\alpha d - d - 2} \right)^{\frac{1}{2}}}_{\text{lattice counting}} \xrightarrow[\text{large deviation}]{} \text{large deviation}$$

Then

$$\left\| \widehat{U^1}(t) \right\|_{H^s} \lesssim 1 \iff -Pd + \frac{1}{2}(Pd-d-2) + s + \frac{d}{2} \leq 0$$

$$\iff d \geq \frac{d}{2} - \frac{1}{P-1}$$

$$\iff s \geq \left[-\frac{1}{P-1} \right]$$

s_{pr} : probabilistic

scaling exponent
for (NLS).

Thm 1.2: Assume $s > s_{pr}$, (NLS) is probabilistic LWP.
(Deng-Nahmod-Y., 2020). (a.s. LWP)

1.3 Large deviation property

Lemma 1.3: $P(w: \left| \sum_{k \in \mathbb{Z}^d} a_k g_k(w) \right| > \lambda) \lesssim e^{-\frac{C\lambda^2}{\|a_k\|_{l_k^2}}}$

where $\{a_k\}$ are constants in l_k^2 .

(Equivalently $\left| \sum_{k \in \mathbb{Z}^d} a_k g_k(w) \right| \lesssim A^\theta \cdot \|a_k\|_{l_k}, \text{ A-certainly}$)

Proof: For $t > 0$ to be determined. (only $d=1$ case).

$$\int_{\Omega} e^{t \sum_{k \geq 1} a_k g_k(w)} dP(w) = \prod_{k \geq 1} \int_{\Omega} e^{ta_k g_k} dP(w)$$

$$= \prod_{k \geq 1} \int_{-\infty}^{\infty} e^{ta_k \cdot x} d\mu_n(x) \leq \prod_{k \geq 1} e^{c(ta_k)^2} = e^{(ct^2) \sum_{k \geq 1} a_k^2}$$

\uparrow
 Gaussian

Therefore, $e^{(ct^2) \sum_{k \geq 1} (a_k)^2} \geq e^{t\lambda} P(w : \sum_{k \geq 1} a_k g_k(w) > \lambda)$

$$\Leftrightarrow P(w : \sum_{k \geq 1} a_k g_k(w) > \lambda) \leq e^{(ct^2) \sum_{k \geq 1} a_k^2} \cdot e^{-t\lambda}$$

By choosing $t = \frac{\lambda}{2c \sum_k a_k^2} \Rightarrow$

$$P(w : \sum_{k \geq 1} a_k g_k(w) > \lambda) \leq e^{-\frac{\lambda^2}{4c \|a\|_F^2}}$$

Similarly we have also

$$P(w : \sum_{k \geq 1} a_k g_k(w) < -\lambda) \leq e^{-\frac{\lambda^2}{4c \|a\|_F^2}}.$$

□

Lemma 1.4: $F(w) = \sum_{\substack{k_1, k_2, k_3 \\ \dots \\ k_p}} a_{k_1, \dots, k_p} \cdot g_{k_1} \bar{g}_{k_2} \dots g_{k_p}$

where a_{k_1, \dots, k_p} are coefficients in $\ell^2_{k_1, \dots, k_p}$ and

$\{a_{k_1, \dots, k_p}\}$ is supported on $\left\{ \begin{array}{l} k_1 \neq k_2, k_3, \dots \text{ and so on} \\ k_2 \neq k_3, k_4, \dots \\ \dots \end{array} \right\}$.

Similarly we also have A-certainly

$$|F(w)| \lesssim A^\theta \|a_{k_1 k_2 - k_p}\|_{l_{k_1 - k_p}^2}.$$

Proof: Skip. (Wiener chaos). \square

1.4 Lattice Counting.

Lemma 1.5: (1) Let $R = \mathbb{Z}$ or $\mathbb{Z}[i]$. Then, given $0 \neq m \in R$ and $a_0, b_0 \in \mathbb{C}$, the number of choices for $(a, b) \in R^2$ that satisfy $m = ab$, $|a - a_0| \leq M$, $|b - b_0| \leq N$, is $O(M^\theta N^\theta)$ with constant depending only on $\theta > 0$.

(2) Consider

$$S = \{(x, y, z) \in (\mathbb{Z}^2)^3 : \begin{array}{l} x - y + z = d \\ |x|^2 - |y|^2 + |z|^2 = \alpha \end{array} \} \quad \text{const.} \quad \left. \begin{array}{l} |x - a| \leq N_1 \\ |y - b| \leq N_2 \\ |z - c| \leq N_3 \end{array} \right\}$$

Then $\#S \lesssim \min((N_1 N_2)^{1+\theta}, (N_2 N_3)^{1+\theta}, (N_3 N_1)^{1+\theta})$. $\leftarrow \begin{array}{l} \text{in } d\text{-dimension case} \\ (N_1 N_2)^{d-1+\theta} \end{array}$

also $\#S \lesssim N_2^2 \cdot (\max(N_1, N_3))^\theta$.

Proof: (1) Standard divisor bounds : is $O(|m|^\theta)$.

Now WLOG. suppose

$$\max(|a_0|, M) \geq \max(|b_0|, N) \quad \text{and} \quad M_1 \sim |a_0| \gg M^4$$

hence $|m| \lesssim M_1^2$.

otherwise $|m| \lesssim M^3$

We then claim that the number of divisors a of m that satisfies $|a - a_0| \leq M$ is at most two.

In fact, suppose a, b, c are all in the ball $|x - a_0| \leq M$, then we have $\text{lcm}(a, b, c) \mid m$, hence

$$\frac{abc}{\gcd(a, b) \gcd(b, c) \gcd(c, a)} \text{ divides } m.$$

Then

$$M_1^2 \gtrsim |m| \geq \left| \frac{abc}{\gcd(a, b) \gcd(b, c) \gcd(c, a)} \right| \gtrsim M_1^3 M^{-3}$$

contradicting $M_1 \gg M^4$!

(2)

$$\begin{aligned} ① \quad 2 \langle d - x, y - x \rangle &= |d|^2 - (|x|^2 - |y|^2 + |z|^2) \\ &= |d|^2 - \alpha \end{aligned}$$

$$(d_1 - x_1)(y_1 - x_1) + (d_2 - x_2)(y_2 - x_2) = \frac{|d|^2 - \alpha}{2}$$

If $(d_1 - x_1)(y_1 - x_1) \neq 0$, we fix x_2, y_2 with $O(N_1 N_2)$ choices.

Then $(d_1 - x_1)(y_1 - x_1) = \text{const} \neq 0$.

$$O(N_1^\theta N_2^\theta).$$

② Fix y with $\mathcal{O}(N_2^2)$ then $x+z$ is fixed.

$$x-z = w$$

$$(w_1 + i w_2)(w_1 - i w_2) = |w|^2 = 2(|x|^2 + |z|^2) - |x+z|^2$$

$\Rightarrow (w_1, w_2)$ has $\mathcal{O}(\max(N_1, N_3)^{\theta})$.

□

2

Bourgain's method [Bourgain '96)

$$\left\{ \begin{array}{l} i u_t + \Delta u = :|u|^2 u: \\ u(0) = \varphi^{xx} = \sum_{k \in \mathbb{Z}^2} \frac{g_k(w)}{\langle k \rangle} e^{ik \cdot x} \stackrel{\text{a.s.}}{\in} H^0 \end{array} \right.$$

→ related to Gibbs measure

2.1

Wick ordering (renormalization)

$$:|u|^2 u: = |u|^2 u - 2 \underbrace{\mathbb{E}\left(\int_{\mathbb{T}^2} |u|^2 dx\right)}_{\sum_{k \in \mathbb{Z}^2} \frac{1}{n^2} \rightarrow \infty} u$$

- Finite dimensional Approximation

$$\left\{ \begin{array}{l} (\tilde{\omega}_t + \Delta) u_N = \overline{\Pi}_N \left(:|u_N|^2 u_N : \right) \\ u_{N(0)} = \overline{\Pi}_N \varphi^w \end{array} \right.$$

(FDA)

where $\widehat{\Pi}_N f(k) = \mathbf{1}_{|k| \leq N} \widehat{f}(k)$. (and $\widehat{\Delta}_N f(k) = \mathbf{1}_{\frac{|k|}{2} < k \leq N} \widehat{f}(k)$)

- $\overline{\Pi}_N$ can be replaced by any other Schmitz function $\phi(\frac{k}{N})$ cutoffs.

► $:|u_N|^2 u_N:$ is also fine.

$$- :|u_N|^2 u_N: = \underbrace{\left| |u|^2 u - 2 \left(\int_{\mathbb{T}^2} |u|^2 dx \right) \cdot u \right|}_{\text{---}}$$

$$+ 2 \underbrace{\left(\int_{\mathbb{T}^2} |u|^2 dx - \mathbb{E} \int_{\mathbb{T}^2} |u|^2 dx \right)}_{C_N} \cdot u$$

$$= \sum_{k \in \mathbb{Z}^2} \frac{|g_k| - 1}{\langle k \rangle^2}, \quad \text{is uniformly bounded}$$

It is essentially that

$\widehat{:|u_N|^2 u_N:}(k)$ can be

$$\sum_{\substack{k_1 - k_2 + k_3 = k \\ |k_j| \leq N \\ k_2 \neq k_1, k_3}} \widehat{u}(k_1) \overline{\widehat{u}(k_2)} \widehat{u}(k_3)$$

no pairing

► Generally

$$\widehat{:|u_N|^{p-1} u_N:}(k) \quad \text{is} \quad \sum_{\substack{k - k_1 + k_2 - \dots + k_p = k \\ \text{no pairings}}} \widehat{u}(k_1) \overline{\widehat{u}(k_2)} \dots \widehat{u}(k_p).$$

2.2 Main theorem: (a.s. LWP) \Rightarrow invariant Gibbs measure & a.s. BWP.

$\{u_n\}$ t^+ -certainly converges in $C_t^0 H_\alpha^{0-}([0, t])$.

Or $\{u_n\}$ a.s. converges in $C_t^{\alpha} H_x^{\alpha} ([0, T(w)])$ where $T(w)$ is a r.v. almost surely > 0 .

2.3 Bourgain's re-centering idea.

- The ansatz

$$u_N = e^{it\Delta} \Pi_N \varphi^w + z_N$$

↑
 "R" for "random"
 ↑
 expected in H^s for some $s > 0$
 "D" for "deterministic"

- The equation for z .

$$\left\{ \begin{array}{l} (i\partial_t + \Delta) D = T_N \left(: |R + D|^2 (R + D) : \right) =: N(R+D) \\ Z^{(0)} = D \end{array} \right.$$

- ## ► The Duhamel form:

$$D(t) = i \int_0^t e^{i(t-s)\Delta} \left(N(R+D)(s) \right) ds$$

Again,

$$\hat{D}(t, k) \sim \sum_{\substack{k_1 - k_2 + k_3 = k \\ k_2 \neq k_1, k_3}} \left(\hat{R+D}(k_1) \hat{R+D}(k_2) \hat{R+D}(k_3) \right)$$

↑
for Simplicity

$|k_j| \leq N$
 $|k| \leq N, \Sigma = \text{Const.}$

$$:= \hat{M}_{np} (R+D, R+D, R+D) (k)$$

- After expanding the cubic and

Littlewood-Paley decomposition,

$$(R_{N_j} = \Delta_{N_j} R, D_{N_j} = \Delta_{N_j} R).$$

$$R_{N_1}, R_{N_2}, R_{N_3} \quad \begin{matrix} N_1 \geq N_2 \geq N_3 \\ N_2 \geq N_1 \geq N_3 \\ N_3 \geq N_1 \geq N_2 \end{matrix}$$

$$R_{N_1}, D_{N_2}, D_{N_3}$$

⋮

$$D_{N_1}, D_{N_2}, D_{N_3}$$

Deterministic
Local theory in H^s , $s > 0 = \text{scr.}$

Goal: $\|M_{np}(\cdot, \cdot, \cdot)\|_{H^s} < \infty$

2.4 Estimates.

Example: $(R_{N_1}, R_{N_2}, R_{N_3})$

$$N_1 \geq N_2 \geq N_3$$

$$\|M_{np}(\cdot, \cdot, \cdot)\|_{H^s}^2$$

$$\sum_k \langle k \rangle^{2s} \left| \sum_{|k_j| \sim N_j} h_{kk_1k_2k_3}^b \cdot \frac{g_{k_1}}{\langle k_1 \rangle} \cdot \frac{\overline{g_{k_2}}}{\langle k_2 \rangle} \cdot \frac{g_{k_3}}{\langle k_3 \rangle} \right|^2$$

Large deviation

$$\leq \sum_k \langle k \rangle^{2s} (N_1 N_2 N_3)^{-2} \cdot \left(\sum_{|k_j| \sim N_j} h_{kk_1k_2k_3}^b \right)$$

$$\leq (N_1)^{2s} (N_1 N_2 N_3)^{-2} \cdot \left(\sum_{\substack{k, \\ |k_j| \sim N_j}} h_{kk_1k_2k_3}^b \right)$$

$$\#\left\{ \begin{array}{l} k, k_1, k_2, k_3 : \\ |k_j| \sim N \\ k = k_1 + k_2 + k_3 \\ |k|^2 = |k_1|^2 + |k_2|^2 + |k_3|^2 \end{array} \right\} \leq N_3^2 (N_1 N_2)^{4s}$$

$$\leq N_1^{2(s-\frac{1}{2}+\theta)} \cdot N_2^{-1+\theta} \quad (\text{required } s < \frac{1}{2})$$

↑
largest freq

2.5 Further discussions on $p > 3$, odd cases.

$$(i\partial_t + \Delta) u = |u|^{p-1} u, \quad x \in \mathbb{T}^2$$

$$u(0) = \varphi^w = \sum_{k \in \mathbb{Z}^2} \frac{g_k}{\langle k \rangle} e^{ik \cdot x}$$

← related to Gibbs measure.

Q: Why Bourgain's re-centering idea cannot solve
 "invariant Gibbs measure for
 2D (NLS) with $p > 3$ " ?

Recall: Bourgain's ansatz

$$u_N = e^{it\Delta} \Pi_N \varphi^w + z_N$$

↑
 random,
 a.s. in H^0

H^s , we treat it as a deterministic term.

→ we need to make $z_N \in H^s$, $s > s_{\text{cr}} = \frac{d}{2} - \frac{2}{p-1}$

$$\frac{\pi^2}{2} = 1 - \frac{2}{p-1}$$

► consider a term. $N_1 \gg N_2 \sim N_3 \sim \dots \sim N_p$

$$\left\| M_{np} (R_{N_1}, R_{N_2}, R_{N_3}, \dots, R_{N_p}) \right\|_{HS}^2$$

$$= \sum_k \langle k \rangle^{2s} \left| \sum_{|k_j| \sim N_j} h_{kk_1 k_2 k_3}^b \cdot \frac{g_{k_1}}{\langle k_1 \rangle} \cdot \frac{\overline{g_{k_2}}}{\langle k_2 \rangle} \cdot \frac{g_{k_3}}{\langle k_3 \rangle} \cdots \frac{g_{k_p}}{\langle k_p \rangle} \right|^2$$

Large deviation

$$\leq \sum_k \langle k \rangle^{2s} (N_1 N_2 N_3 \cdots N_p)^{-2} \left(\sum_{|k_j| \sim N_j} h_{kk_1 k_2 k_3 \cdots k_p}^b \right)$$

$$\leq (N_1)^{2s} (N_1 N_2 N_3 N_4 \cdots N_p)^{-2} \left(\sum_{\substack{k, \\ |k_j| \sim N_j}} h_{kk_1 k_2 k_3 \cdots k_p}^b \right)$$

$$\# \left\{ \begin{array}{l} k, k_1, k_2, k_3 : \\ |k_j| \sim N_j \end{array} \right. \left. \begin{array}{l} k = k_1 - k_2 + k_3 - k_4 + \cdots + k_p \\ |k|^2 = |k_1|^2 - |k_2|^2 + |k_3|^2 \\ + \cdots + |k_p|^2 \end{array} \right\} \leq (N_3 N_4 \cdots N_p)^2 \cdot (N_1 N_2)^{1+\theta}$$

$$\leq N_1^{\frac{2(s-\frac{1}{2})+\theta}{2}} \cdot N_2^{-1+\theta}$$

Require $s < \frac{1}{2}$.

► However

$$s < \frac{1}{2} \leq s_c = 1 - \frac{2}{p-1} , p \geq 5$$

!

→ In fact, all terms as

$$N_{np} (R_N, u_L, \dots, u_L) \text{ with } N \gg L$$

are problematic !

Q: How to solve this problem?

- Put these high-low-low terms also in the center of ansatz.

$$u_N = e^{it\Delta} \Pi_N \varphi^0 + (\text{high-low-low})_N + z_N$$

\uparrow
 H^0

\uparrow
 $H^{\frac{1}{2}-}$, with

Random Averaging Operator
structure

\uparrow
 H^1

③ Random Averaging Operator method

③.1 Main Thm

$$\left\{ \begin{array}{l} (i\partial_t + \Delta) u_N = \Pi_N \left(:|u_N|^{p-1} u_N : \right) \\ u_{N(0)} = \Pi_N \varphi^w \end{array} \right. \quad (pNLS)$$

Theorem 3.1 (1) a.s. LWP

$\{u_N\}$ t^+ -certainly converges in $C_t^0 H_x^0([0, t])$ for $(pNLS)$.
on \mathbb{T}^2 ($p \geq 3$, odd)

(2) Invariant Gibbs measure under the flow $\&$ a.s. GWP.

3.2 Ansatz

- Decompose the $\{u_N\}$, $y_N := u_N - \underline{u_{\frac{N}{2}}}.$

$$(i\partial_t + \Delta) y_N = \Pi_N(N(u_N)) - \Pi_{\frac{N}{2}}(N(u_{\frac{N}{2}}))$$

$$= \Pi_N \left(N(y_N + \underline{u_{\frac{N}{2}}}) - N(\underline{u_{\frac{N}{2}}}) \right)$$

Recall:

$$\left. \begin{array}{l} \Pi_N - \Pi_{\frac{N}{2}} = \Delta_N \\ \end{array} \right\} + \underbrace{\Delta_N(N(u_{\frac{N}{2}}))}_{\text{Commutator term}}$$

- Capture High-low-low terms. (" $L \ll N$ ")

$$\left\{ \begin{array}{l} (i\partial_t + \Delta) \psi_{N,L} = \Pi_N N(\psi_{N,L}, u_L, \dots, u_L) \\ \psi_{N,L}^{(0)} = \Delta_N \psi^w \end{array} \right.$$

↑ treat them as known.
 then it is just a
 linear equation.

k-th Fourier mode

$$(\psi_{N,L})_k = \sum_{\frac{N}{2} < |k^*| \leq N} H_{kk^*}^{N,L} \frac{g_{k^*}}{\langle k^* \rangle}$$

- $H_{kk^*}^{N,L}$ is a random matrix totally

For simplicity,

$$\psi_{N,\frac{1}{2}} = e^{it\Delta} \Delta_N \psi^w$$

$$H_{kk^*}^{N,\frac{1}{2}} = e^{i|k|^2 t} \underbrace{1}_{k=k^*}$$

depending on u_L which is a r.v.

generated by evolving $\Pi_L \psi^w$ ($\{g_k\}, |k| \leq L$)

under (pNLS).

We say $H_{kk^*}^{N,L} \in \mathcal{B}_{\leq L}$

- Hence $H_{kk^*}^{N,L}$ is independent with

$$\frac{g_{k^*}}{\langle k^* \rangle} \quad (|k^*| \sim N)$$

$$\zeta_{N,L} := \psi_{N,L} - \psi_{N,\frac{L}{2}}$$

$$h^{N,L} := H^{N,L} - H^{N,\frac{L}{2}} \in \mathcal{B}_{\leq L}$$

• Full ansatz

$$y_N = \underbrace{\psi_{N,N^{1-\delta}}}_{\text{smooth}} + \underbrace{\zeta_N}_{\text{oscillatory}}$$

$$= \psi_{N,\frac{1}{2}} + \sum_{L \leq N^{1-\delta}} \zeta_{N,L} + \underbrace{\zeta_N}_{\text{dyadic}}$$

$$(y_N)_k = \underbrace{e^{it\Delta} \Delta_N \varphi_w}_{H^0^-} + \underbrace{\sum_{L \leq N^{1-\delta}} \left(\sum_{|k'| \sim N} h_{kk'}^{N,L} \frac{g_{k'}}{\langle k' \rangle} \right)}_{H^{\frac{1}{2}-}} + \underbrace{\zeta_N}_{H^{1-}}$$

Then the equation for ζ_N :

Plug the ansatz into

$$(i\partial_t + \Delta) Y_N = \Pi_N \left(N(Y_N + u_{\frac{N}{2}}) - N(u_{\frac{N}{2}}) \right) + \Delta_N \left(N(u_{\frac{N}{2}}) \right).$$

Commutator term

we have

$$(i\partial_t + \Delta) z_N = \Delta_N \left(N \underbrace{\left(\sum_{M \leq \frac{N}{2}} \psi_{M, M+\delta} + z_M \right)}_{u_{\frac{N}{2}} = \sum_{M \leq \frac{N}{2}} y_M} \right)$$

$$+ \Pi_N \left(N(z_N + \psi_{N, N+\delta} + u_{\frac{N}{2}}) - N(u_{\frac{N}{2}}) \right) - N(\psi_{N, N+\delta}, u_{N+\delta}, \dots, u_{N+\delta})$$

- Bounds with the ansatz.

$$(Y_N)_k = \underbrace{e^{it\Delta} \Delta_N \varphi_N}_{H^{0-}} + \sum_{L \leq N+\delta} \left(\sum_{|k^*| \sim N} h_{kk^*}^{N,L} \frac{g_{k^*}}{|k^*|} \right) + \underbrace{z_N}_{\begin{array}{c} \uparrow \\ H^{\frac{1}{2}-} \\ \uparrow \\ H^{1-} \end{array}}$$

where

$$\| h_{k k^*}^{N, L} \|_{k \rightarrow k^*} \lesssim L^{-\delta}$$

(δ is a fixed small number)

$$\| h_{k k^*}^{N, L} \|_{\ell_k^2} \lesssim N^{\frac{1}{2} + \delta} \cdot L^{-\frac{1}{2}}$$

$$\left\| \left(1 + \frac{|k - k^*|}{L} \right)^K h_{k k^*}^{N, L} \right\|_{\ell_k^2} \lesssim N$$

(K is a very big number)
 \downarrow
 " $|k - k^*| \lesssim L$ "

$$\| (\Xi_N)_k \|_{\ell_k^2} \lesssim N^{-1 + \delta}$$

Need to prove all these bounds with ansatz by induction on dyadic N .

3.3 Adapted large deviation & counting

lemmas. & Estimates.

• Let's first select one estimate to be done.

$$\left\| \Delta_N \left(N \left(\underbrace{\sum_{M \leq \frac{N}{2}} y_M}_{u_{\frac{N}{2}}} + z_M \right) \right) \right\|_{\ell_k^2} \lesssim N^{-1 + \delta}$$

one possible case is

$$\sum_{k_1, k_2, k_3} h_{kk_1 k_2 k_3}^b \cdot \left(\sum_{k_1^*, k_2^*, k_3^*} h_{k_1 k_1^*}^{N_1, L_1} \cdot \overline{h_{k_2 k_2^*}^{N_2, L_2}} \cdot h_{k_3 k_3^*}^{N_3, L_3} \right)$$

$k_2 \neq k_1, k_3$
 $|k_j| \sim N_j \leq \frac{N}{2}$
 $\frac{N}{2} < |k| \leq N$
 $|k_j^*| \sim N_j$
 $\times \frac{g_{k_1^*} \overline{g_{k_2^*}} g_{k_3^*}}{\langle k_1^* \rangle \langle k_2^* \rangle \langle k_3^* \rangle}$

l_k^2

$$\sum_{k_1^*, k_2^*, k_3^*} \tilde{h}_{kk_1^* k_2^* k_3^*} \cdot \frac{g_{k_1^*} \overline{g_{k_2^*}} g_{k_3^*}}{\langle k_1^* \rangle \langle k_2^* \rangle \langle k_3^* \rangle}$$

$|k_j^*| \sim N_j$
 $\parallel l_k^2$

(+)

where

$$\tilde{h}_{kk_1^* k_2^* k_3^*} = \sum_{\substack{k_1, k_2, k_3 \\ k_2 \neq k_1, k_3 \\ |k_j| \sim N_j}} h_{kk_1 k_2 k_3}^b \cdot h_{k_1 k_1^*}^{N_1, L_1} \cdot \overline{h_{k_2 k_2^*}^{N_2, L_2}} \cdot h_{k_3 k_3^*}^{N_3, L_3}$$

$(\in \mathcal{B}_{\leq \frac{N}{2}})$

► First, consider the no-pairing case. ($k_2^* \neq k_1^*, k_3^*$)

By Lemma 3.2 (1)

$$(+) \lesssim \| h_{k k_1^* k_2^* k_3^*} \|_{k_1^* k_2^* k_3^*} \|_k \cdot (N_1 N_2 N_3)^{-1}$$

$$\lesssim \left\| \sum_{k_1, k_2, k_3} h_{k k_1 k_2 k_3}^b \cdot h_{k_1 k_1^*}^{N_1, L_1} \cdot \overline{h_{k_2 k_2^*}^{N_2, L_2}} \cdot h_{k_3 k_3^*}^{N_3, L_3} \right\|_{k k_1^* k_2^* k_3^*} \cdot (N_1 N_2 N_3)^{-1}$$

$$\lesssim \| h_{k k_1^*}^{N_1, L_1} \|_{k_1 \rightarrow k_1^*} \cdot \| h_{k_2 k_2^*}^{N_2, L_2} \|_{k_2 \rightarrow k_2^*} \cdot \| h_{k_3 k_3^*}^{N_3, L_3} \|_{k_3 \rightarrow k_3^*}$$

$$x \| h_{k k_1 k_2 k_3}^b \|_{k k_1 k_2 k_3} \cdot (N_1 N_2 N_3)^{-1}$$

$$\lesssim L_1^{-\delta} L_2^{-\delta} L_3^{-\delta} \cdot N_1^{-1} N_2^{-1} N_3^{-1}$$

$$\# \left\{ \begin{array}{l} (k, k_1, k_2, k_3) \in (\mathbb{Z}^2)^4 : \\ k - k_1 + k_2 - k_3 = 0 \\ |k|^2 - |k_1|^2 + |k_2|^2 - |k_3|^2 = 0 \\ k_2 \neq k_1, k_3 \\ k \neq k_1, k_3 \end{array} \right\}^{\frac{1}{2}}$$

$\frac{N}{2} < |k| \leq N$
 $\frac{N_j}{2} < |k_j| \leq N_j$

$S :=$

WLOG assume $\frac{N}{2} \geq N_1 \geq N_2 \geq N_3$

(since $k - k_1 + k_2 - k_3 = 0 \Rightarrow N_1 \geq \frac{N}{6}$).

• Naive counting

$$\begin{aligned}
 (t) &\lesssim L_1^{-\delta} L_2^{-\delta} L_3^{-\delta} \cdot N_1^{-1} N_2^{-1} N_3^{-1} \cdot \left(N_3^2 \cdot (N_2 N_1)^{1+\theta} \right)^{\frac{1}{2}} \\
 &\lesssim L_1^{-\delta} L_2^{-\delta} L_3^{-\delta} \underbrace{N_1^{-\frac{1}{2}+\theta} \cdot N_2^{-\frac{1}{2}+\theta}}_{\uparrow} \\
 &\quad \text{but we need } N^{-1+\delta}
 \end{aligned}$$

• T-condition counting
 $|k|^2 \geq \left(\frac{N}{2}\right)^2 \geq |k_1|^2 \Rightarrow$ Using Lemma 3.3

$$\begin{aligned}
 (t) &\lesssim L_1^{-\delta} L_2^{-\delta} L_3^{-\delta} \cdot N_1^{-1} N_2^{-1} N_3^{-1} \cdot \left(N_2^2 N_3^2 \cdot N_1^\theta \right)^{\frac{1}{2}} \\
 &\lesssim L_1^{-\delta} L_2^{-\delta} L_3^{-\delta} N_1^{-1+\theta} \lesssim N^{-1+\theta}
 \end{aligned}$$

► Second, consider the pairing case. ($k_2^* = k_1^* \neq k_3^*$)

By Lemma 3.2 (2), ($N_1 = N_2$).

$$(†) \lesssim$$

$$\left\| \sum_{\substack{k_1, k_2, k_3 \\ k_1^*}} h_{k k_1 k_2 k_3}^b \cdot h_{\substack{N_1, L_1 \\ k_1 k_1^*}} \cdot \overline{h_{\substack{N_2, L_2 \\ k_2 k_1^*}}} \cdot h_{\substack{N_3, L_3 \\ k_3 k_3^*}} \right\|_{k k_3^*} \cdot (N_1 N_2 N_3)^{-1}$$

$$\leq \left\| h_{k k_1 k_2 k_3}^b \cdot \underbrace{\frac{1}{\left| k_1 - k_2 \right| \leq L_1 + L_2}}_{k k_1 k_2 k_3} \right\| \cdot (N_1 N_2 N_3)^{-1}$$

$$\underbrace{\left\| h_{\substack{N_1, L_1 \\ k_1 k_1^*}} \right\|}_{k_1 k_1^*} \cdot \left\| h_{\substack{N_2, L_2 \\ k_1^* \rightarrow k_2}} \right\| \cdot \left\| h_{\substack{N_3, L_3 \\ k_3^* \rightarrow k_3}} \right\|$$

Need to introduce new counting

$$\left\{ \begin{array}{l} (k, k_1, k_2, k_3) \in (\mathbb{Z}^2)^4 : \\ k_1 - k_2 + k_3 = k \\ |k_1|^2 - |k_2|^2 + |k_3|^2 = |\vec{k}|^2 \\ |k_j| \sim N_j \\ |k_1 - k_2| \leq L_1 + L_2 \end{array} \right\}$$

Lemma 3.2

(1) Assume $a_{k_1^* k_2^* k_3^*}(\omega)$ is independent with the Borel set generated by $\{g_k, k \in E\}$.

$$\sum_{\substack{k_1^*, k_2^*, k_3^* \\ k_j^* \in E}} a_{k_1^* k_2^* k_3^*}^{(\omega)} \cdot g_{k_1^*} \overline{g_{k_2^*}} g_{k_3^*} = F(\omega)$$

no pairing $\rightarrow k_2^* \neq k_1^*, k_3^*$

Then A-certainly we have

$$|F(\omega)| \leq A^\theta \cdot \|a_{k_1^* k_2^* k_3^*}^{(\omega)}\|_{P_{k_1^* k_2^* k_3^*}^2}$$

(2) The same assumptions as (1)

$$\sum_{\substack{k_1^* = k_2^* \neq k_3^* \\ k_j^* \in E}} a_{k_1^* k_2^* k_3^*}^{(\omega)} \cdot g_{k_1^*} \overline{g_{k_2^*}} g_{k_3^*} = F(\omega)$$

Then A-certainly we have

$$|F(w)| \leq A^{\theta} \left\| \sum_{k_1^* \in E} \mathbb{1}_{k_1^* = k_2^*} \cdot a_{k_1^* k_2^* k_3^*}(w) \right\|_{l_{k_3^*}^2}$$

Lemma 3.3: (\mathcal{T} -condition counting) $(N_1 \geq N_2 \geq N_3)$

$$\#\left(S \cap \left\{ |k|^2 \geq \mathcal{T} \geq |k_1|^2 \right\}\right) \lesssim N_2^2 N_3^2 \cdot N_1^\theta$$

\uparrow
 fixed const.

Proof: $\begin{cases} k - k_1 + k_2 - k_3 = 0 \\ |k|^2 - |k_1|^2 + |k_2|^2 - |k_3|^2 = 0 \end{cases}$

First, the choices of $|k_1|^2$ is bounded by

$$|k|^2 - |k_1|^2 = -|k_2|^2 + |k_3|^2 = (k_3 - k_2)(k_2 + k_3)$$

$$\lesssim O(N_2^2)$$

Second, when $|k_1|^2$ is fixed, then the choices of k_1 is bounded by $O(N_1^\theta)$.

Third, after k_1 is fixed, then the counting of (k, k_2, k_3) , which is a three-vector counting, by Lemma 1.5 is bounded by $O(N_3^2 \cdot N^\theta)$.

In total, it is $O(N_2^2 N_3^2 N_1^\theta)$. □