

[2] Random tensor theory.

• The effect of Wick ordering is to eliminate the frequency "pairings":

$$\bullet \quad :|u|^2 u : = |u|^2 u - \underline{2\lambda_N \cdot u}$$

$$\widehat{(|u|^2 u)}(k) = \sum_{k_1, k_2, k_3=k} \widehat{u}(k_1) \overline{\widehat{u}(k_2)} \widehat{u}(k_3).$$

• We say a "pairing" if $\underline{k_1 = k_2}$ or $\underline{k_2 = k_3}$

• If $\underline{k_1 = k_2}$, we get

$$\widehat{u}(k) \cdot \sum_{k_1} |\widehat{u}(k_1)|^2$$

$$= \widehat{\|u\|_2^2} \cdot u(k) \sim \underline{\lambda_N \cdot u(k)}.$$

Note that $\|u\|_2^2 \sim \mathbb{E} \|u\|_2^2 = \lambda_N$.

• Because of this, we will replace the Wick-ordered nonlinearity

$$:|u|^{p-1} u : \rightsquigarrow \mathcal{N}(u, \dots, u)$$

where

$$\boxed{\mathcal{N}(u, u, \dots, u)_k} = \sum_{\substack{k_1, k_2, \dots, k_p=k \\ \text{"no pairing"}}} u_{k_1} \overline{u_{k_2}} \dots u_{k_p}.$$

we understand $u_k = \widehat{u}(k)$

• Recall that

• Schrödinger fundamental solution has no smoothing:

• But we can gain a factor $\frac{1}{\langle \Omega \rangle}$, where $\Omega = \underbrace{|k|^2 - |k_1|^2 + \dots - |k_p|^2}$

↑

"Resonance factor"

• Because of this, we can formally restrict to the set " $\Omega = 0$ "

or " $\Omega = \text{constant}$ "

• In real problem, we need to introduce the $\chi^{s.b}$ norm of Bourgain.

• We now introduce the simplified model

• (NLS) $\Rightarrow u(t) = e^{it\Delta} f(\omega) - i \int_0^t e^{i(t-s)\Delta} N(u(s), \dots, u(s)) ds$

• If we define $a_k(t) = e^{it(k)^2} \underline{u_k(t)}$ then

$$a_k(t) = f_k - i \sum_{\substack{k_1 + \dots + k_p = k \\ \text{"no pairing"}}} \int_0^t e^{is\Omega} a_{k_1}(s) \overline{a_{k_2}(s)} \dots a_{k_p}(s) ds.$$

$$\Omega = |k|^2 - (|k_1|^2 + \dots - |k_p|^2).$$

• We may restrict to $\Omega = 0$. then assume $a_k(t) = a_k$. then we get the simplified model:

$$a_k = f_k - i \sum_{\substack{k_1 + \dots + k_p = k \\ \boxed{\Omega=0} \text{ "no pairing"}}} a_{k_1} \overline{a_{k_2}} \dots a_{k_p}, \quad f_k = \frac{g_k(\omega)}{\langle k \rangle^\alpha}$$

↳ (Model)

- We introduce the notation

$$\mathcal{M}(u^1, \dots, u^p) = -i \sum_{\substack{k_1, \dots, k_p = k \\ \Sigma = 0}} (u^1)_{k_1} \dots (u^p)_{k_p}.$$

then (model) can be written as

$$a_k = \underline{f_k} + \mathcal{M}(a, \dots, a)_k.$$

- Let q_N be the solution to

$$(q_N)_k = \underline{(f_N)_k} + \mathcal{M}(q_N, \dots, q_N)_k. \quad (f_N)_k = \begin{cases} f_k, & \text{if } |k| \leq N \\ 0, & \text{otherwise.} \end{cases}$$

and define $y_N = q_N - a_{N/2}$, then y_N solves

$$\begin{aligned} \underline{(y_N)_k} &= \underline{(F_N)_k} + \sum_{\max(|k_1|, \dots, |k_p|) = N} \mathcal{M}(y_{k_1}, \dots, y_{k_p}). \\ (F_N)_k &= \begin{cases} f_k, & \text{if } \frac{N}{2} < |k| \leq N \\ 0, & \text{otherwise} \end{cases} \quad (*) \end{aligned}$$

- This is not rigorous, but we will assume $(q_N)_k$ and $(y_N)_k$ is supported in $|k| \leq N$.

- Idea: we will iterate with the equation (*). But will stop iterating when we reach "low frequency" — frequency $< N^\delta$.

- Terms we get in the iteration: ($p=3$):

$$\underline{F_N}, \quad \underline{\mathcal{M}(F_{N_1}, F_{N_2}, F_{N_3})}, \quad \underline{\mathcal{M}(F_{N_1}, F_{N_2}, \mathcal{Y}_{N^\delta})}$$

$$\underline{\mathcal{M}(F_{N_1}, \mathcal{Y}_{N^\delta}, \mathcal{M}(F_{N_2}, F_{N_3}, \mathcal{Y}_{N^\delta}))}$$

- Goal is to write an ansatz that includes all these terms, estimate them in suitable norms, and control the remainder.

- Note that all these terms have the form

$$(\text{term})_k = \sum_{k_1 \dots k_r} \boxed{h_{kk_1 \dots k_r}} \cdot \underbrace{(F_{N_1})_{k_1}}^{\pm} \underbrace{(F_{N_2})_{k_2}}^{\pm} \dots \underbrace{(F_{N_r})_{k_r}}^{\pm}$$

(Terms)

where $z^+ = z$, $z^- = \bar{z}$.

- Note that $N_j > N^\delta$. moreover $h = h_{kk_1 \dots k_r}$ is Borel function of

$$\boxed{(g_k)_{|k| \leq N^\delta}}$$

this means that $h_{kk_1 \dots k_r}$ is independent with all the $(F_{N_j})_{k_j}$, $1 \leq j \leq r$.

- In the terms we assume that $\max(N_1 \dots N_r) = N$, and $N_j > N^\delta$. Actually the h depends on (N_1, \dots, N_r) , but we omit for simplicity

- In the terms we can assume there is no pairing in $(k_1 \dots k_r)$. In fact, if we have $k_1 = k_2$, then we can rewrite this term as

$$\begin{aligned}
 (\text{term})_k &= \sum_{k_1} \sum_{k_3 \dots k_r} h_{k k_1 k_1 k_3 \dots k_r} \underbrace{|(F_{N_1})_{k_1}|^2}_{\downarrow \langle k_1 \rangle^{-2\alpha}} (F_{N_3})_{k_3}^\pm \dots (F_{N_r})_{k_r}^\pm \\
 &= \sum_{k_3 \dots k_r} \tilde{h}_{k k_3 \dots k_r} (F_{N_3})_{k_3}^\pm \dots (F_{N_r})_{k_r}^\pm
 \end{aligned}$$

$$\text{where } \tilde{h}_{k k_3 \dots k_r} = \sum_{k_1} \langle k_1 \rangle^{-2\alpha} h_{k k_1 k_1 k_3 \dots k_r}$$

- Finally, in the terms we always have

$$\underline{k = \pm k_1 \pm \dots \pm k_r + O(N^\delta)}$$

- As an easy example, if we consider

$$\begin{aligned}
 \mathbb{E} \sum_k |(\text{term})_k|^2 &= \sum_k \mathbb{E} \left| \sum_{k_1 \dots k_r} h_{k k_1 \dots k_r} \cdot (F_{N_1})_{k_1}^\pm \dots (F_{N_r})_{k_r}^\pm \right|^2 \\
 &= \sum_{(k, k_1 \dots k_r)} \langle k_1 \rangle^{-2\alpha} \dots \langle k_r \rangle^{-2\alpha} \cdot \mathbb{E} |h_{k k_1 \dots k_r}|^2 \\
 &= \mathbb{E} \left\| \langle k_1 \rangle^{-\alpha} \dots \langle k_r \rangle^{-\alpha} h_{k k_1 \dots k_r} \right\|_{\ell^2}^2
 \end{aligned}$$

- First, we know that the property of terms is determined by property of the tensors h .

Second: the l^2 norm of h will play a key role in the analysis.

- Full ansatz will look like

$$(y_N)_k = \sum_r \sum_{(N_i)_{i=1}^r} \left(\sum_{k_1 \dots k_r} h_{k_1 \dots k_r} \prod_{i=1}^r (F_{N_i})_{k_i}^{\pm} \right) + \underbrace{(z_N)_k}_{\text{remainder}}$$

$\nearrow \xi_i$

2.1 Random tensors and their algebra.

- Given a finite index set A , we write $k_A = (k_j)_{j \in A}$. We will denote tensors $h = h_{k_A}$, we will also write $h = h_{k_1 k_2 \dots}$, or $h = h_{abc, \dots}$.

- Ansatz:

$$(y_N)_k = \sum_A \sum_{(N_i)_{i \in A}} \left(\sum_{k_A} h_{k_A} \cdot \prod_{i \in A} (F_{N_i})_{k_i}^{\pm} \right) + (z_N)_k$$

- Consider nonlinearity

$$\mathcal{M}(u^1 \dots u^p)_k = \sum_{\substack{k_1 \dots + k_p = k \\ \Omega = 0}} (u^1)_{k_1} \dots (u^p)_{k_p}$$

$$= \sum_{k_1 \dots k_p} (h^b)_{k_1 \dots k_p} \cdot (u^1)_{k_1} \dots (u^p)_{k_p}$$

$$\text{where } (h^b)_{k_1 \dots k_p} = \begin{cases} 1, & \text{if } k_1 \dots + k_p = k, \text{ and } \Omega = 0 \\ 0, & \text{otherwise} \end{cases} \quad \text{"base tensor"}$$

• If we plug in a tensor term for each of $u^1 \dots u^p$. we get

$$\begin{aligned}
 (\text{Term})_k &= \sum_{k_1 \dots k_p} (h^b)_{k k_1 \dots k_p} \cdot \prod_{j=1}^p \left(\sum_{k_{A_j}} h_{k_j k_{A_j}}^j \cdot \prod_{i \in A_j} (F_{u_i})_{k_i} \right) \\
 &= \sum_{k_{A_1} \dots k_{A_p}} \left(\sum_{k_1 \dots k_p} (h^b)_{k k_1 \dots k_p} \cdot \prod_{j=1}^p h_{k_j k_{A_j}}^j \right) \prod_{j=1}^p \prod_{i \in A_j} (F_{u_i})_{k_i}
 \end{aligned}$$

Moreover, we need to identify all frequency pairings across the k_{A_j} . Suppose B is the set of unpaired indices. then we have

$$(\text{Term})_k = \sum_{k_B} H_{k k_B} \cdot \prod_{i \in B} (F_{u_i})_{k_i}$$

$$\text{where } \underline{H_{k k_B}} = \sum_{k_1 \dots k_p} \sum_{(\text{paired})} (h^b)_{k k_1 \dots k_p} \cdot \prod_{j=1}^p h_{k_j k_{A_j}}^j \cdot \boxed{\prod_{i \in \langle k_i \rangle} (F_{u_i})_{k_i}}$$

• This is an example of what we may call "semi-product" of tensors. where we take tensor product, then assign a set of repeated indices and sum over them.

• Example: if we have X_{abc} and Y_{def} then we can get:

$$\left\{ \begin{aligned}
 Z_{abcdef} &= X_{abc} \cdot Y_{def} \\
 Z_{bcef} &= \sum_a X_{abc} Y_{aef} \\
 Z_{cf} &= \sum_{a,b} X_{abc} Y_{abf}
 \end{aligned} \right.$$

Therefore, the output tensor = the semi product of the input tensors with the base tensor h^b (under some choice of pairings) called merging

Note that in the terms, we require that:

- (1) the h is a Borel function of $(g_k)_{|k| < N^\delta}$
- (2) each $N_i \geq N^\delta$. So we have independence.

If we consider

$$\mu(y_{N_1}, y_{N_2}, \dots, y_{N_p})$$

y_{N_j} replaced by tensor term

$$\sum_{k_{A_j}} h_{k_j k_{A_j}} \prod_{i \in A_j} (F_{N_i})_{k_i}$$

this $N_i \geq N_j^\delta$
however we need $N_i \geq N^\delta$.

What we do:

$$\text{let } B_j = \{i \in A_j : N_i \geq N^\delta\}$$

we will rewrite

$$\sum_{k_{A_j}} h_{k_j k_{A_j}} \prod_{i \in A_j} (F_{N_i})_{k_i}^\pm = \sum_{k_{B_j}} \tilde{h}_{k_j k_{B_j}} \cdot \prod_{i \in B_j} (F_{N_i})_{k_i}^\pm$$

$$\text{where } \tilde{h}_{k_j k_{B_j}} = \sum_{k_{A_j \setminus B_j}} h_{k_j k_{A_j}} \cdot \prod_{i \in A_j \setminus B_j} (F_{N_i})_{k_i}^\pm$$

then $F_{N_i} \geq N^\delta, \forall i \in B_j$

and $\tilde{h}_{k_j k_{B_j}}$ is still a Borel function of $(g_k)_{|k| < N^\delta}$

This operation, we call trimming

• In general.

$$\text{Output tensor} = \text{Merge}(h^b, \text{Trim}(\text{Input tensors}))$$

2.2 Tensor norms and estimates.

Definition. Let (B, c) is partition of A . Then we define

$$\|h\|_{k_B \rightarrow k_C}^2 = \sup \left\{ \sum_{k_C} \left| \sum_{k_B} h_{k_A} \cdot y_{k_B} \right|^2 : \sum_{k_B} |y_{k_B}|^2 = 1 \right\}$$

this is the operator norm when h is viewed as an operator from functions of k_B to functions of k_C .

- By duality: $\|h\|_{k_B \rightarrow k_C} = \|h\|_{k_C \rightarrow k_B}$.
- If $B = \emptyset$ or $C = \emptyset$, we get $\|h\|_{k_A}^2 = \sum_{k_A} |h_{k_A}|^2$ and $\|h\|_{k_B \rightarrow k_C} \leq \|h\|_{k_A}$.
- If $h = h_{bc}$, then $\|h\|_{b \rightarrow c} = \text{operator norm of the matrix } h$
 $\|h\|_{bc} = \text{Hilbert-Schmidt norm of } h$.

Lemma Let $h_{k_A}^1$ and $h_{k_B}^2$ be two tensors and consider the semi product.

$$H_{k_D} = \sum_{k_C} h_{k_A}^1 \cdot h_{k_B}^2 \quad \text{where } \underline{D = A \Delta B}, \quad C = A \cap B.$$

(Example: if h_{abc}^1 and h_{ade}^2 then $H_{bcde} = \sum_a h_{abc}^1 h_{ade}^2$)

Now let (X, Y) be a partition of D , then

$$\|H\|_{K_X \rightarrow K_Y} \leq \|h^1\|_{K_{(X \cup B) \cap A} \rightarrow K_{Y \cap A}} \cdot \|h^2\|_{K_{X \cap B} \rightarrow K_{(Y \cup A) \cap B}}.$$

(Example: as above, then $\|H\|_{bd \rightarrow ce} \leq \|h^1\|_{ab \rightarrow c} \cdot \|h^2\|_{d \rightarrow ae}$.)

Proof Denote $K_{X \cap A} = a$, $K_{Y \cap A} = b$, $K_{X \cap B} = c$, $K_{Y \cap B} = d$, $K_{A \cap B} = e$.

then $h^1 = h_{abe}^1$, $h^2 = h_{cde}^2$, and

$$H = H_{abcd} = \sum_e h_{abe}^1 h_{cde}^2 \quad \text{we estimate } \|H\|_{ac \rightarrow bd}$$

choose $y = y_{bd}$ such that $\sum_{b,d} |y_{bd}|^2 = 1$. Then

$$\begin{aligned} \sum_{a,c} \left| \sum_{b,d} H_{abcd} y_{bd} \right|^2 &= \sum_{a,c} \left| \sum_{b,d,e} h_{abe}^1 h_{cde}^2 y_{bd} \right|^2 \\ &= \sum_a \sum_c \left| \sum_{d,e} h_{cde}^2 \left(\sum_b h_{abe}^1 y_{bd} \right) \right|^2 \\ &\leq \sum_a \|h^2\|_{c \rightarrow de}^2 \cdot \sum_{d,e} \left| \sum_b h_{abe}^1 y_{bd} \right|^2 \\ &= \|h^2\|_{c \rightarrow de}^2 \cdot \sum_d \sum_{a,e} \left| \sum_b h_{abe}^1 y_{bd} \right|^2 \\ &\leq \|h^2\|_{c \rightarrow de}^2 \cdot \|h^1\|_{ae \rightarrow b}^2 \cdot \underbrace{\sum_d \sum_b |y_{bd}|^2}_{=1} \end{aligned}$$

Then we get

$$\|H\|_{ac \rightarrow bd} \leq \|h^1\|_{ae \rightarrow b} \cdot \|h^2\|_{c \rightarrow de} \quad \#$$

Corollary Let $h^j = h_{K_A^j}^j$ be tensors, and H_D be the semi-product with some parts.

Let (X, Y) be a partition of D . then

$$\|H\|_{K_X \rightarrow K_Y} \leq \prod_j \|h^j\|_{K_{B_j} \rightarrow K_{C_j}}, \quad \text{where for each } j:$$

$$B_j = \{i \in A_j: i \in X, \text{ or is paired with something in } A_{j'}, j' > j\}$$

$$C_j = \{i \in A_j: i \in Y, \text{ or is paired with something in } A_{j'}, j' < j\}$$

Example: zf

$$H_{cugv} = \sum_{a,b,d,e,f} h_{abc}^1 \cdot h_{adeu}^2 \cdot h_{bef}^3 \cdot h_{dfgu}^4$$

$$\text{then } \|H\|_{cv \rightarrow gu} \leq \|h^1\|_{abc} \cdot \|h^2\|_{de \rightarrow ua} \cdot \|h^3\|_{f \rightarrow be} \cdot \|h^4\|_{v \rightarrow dfgu}$$

Proof

$$\bullet H_{cugv} = \sum_{a,b} h_{abc}^1 \cdot (H')_{abgu}, \quad (H')_{abgu} = \sum_{d,e,f} h_{adeu}^2 h_{bef}^3 h_{dfgu}^4$$

$$\Rightarrow \|H\|_{cv \rightarrow gu} \leq \|h^1\|_{abc} \cdot \|H'\|_{v \rightarrow abgu}$$

$$\bullet (H')_{abgu} = \sum_{d,e} h_{adeu}^2 \cdot (H'')_{bdegu}, \quad (H'')_{bdegu} = \sum_f h_{bef}^3 h_{dfgu}^4$$

$$\Rightarrow \|H'\|_{v \rightarrow abgu} \leq \|h^2\|_{de \rightarrow au} \cdot \|H''\|_{v \rightarrow bdeg}$$

$$\bullet (H'')_{bdegu} = \sum_f h_{bef}^3 h_{dfgu}^4$$

$$\Rightarrow \|H''\|_{v \rightarrow bdeg} \leq \|h^3\|_{f \rightarrow be} \cdot \|h^4\|_{v \rightarrow dfgu} \quad \#$$

Lemma 2 Let $h = h_{bck_A}$ be a tensor, and define

$$H = H_{bc} = \sum_{k_A} h_{bck_A} \cdot \prod_{i \in A} g_{k_i}^{\pm}$$

Assume the followings:

- (1) The tensor h is independent with the $g_{k_i}^{\pm}$'s involved.
- (2) In the support of h , there is no pairing in k_A
- (3) The number of choices for (b, c, k_A) is at most $N^{O(1)}$

Then, after removing a set of probability $\leq e^{-N^\theta}$ (for some $\theta > 0$), we have

$$\|H\|_{b \rightarrow c} \leq N^\varepsilon \cdot \sup_{(B, C)} \|h\|_{b \rightarrow c, k_C}$$

for any $\varepsilon > 0$, where sup is taken over all partitions (B, C) of A .

Proof We apply a high order TT* argument. First we need a hypercontractivity

estimate:

$$\bullet \text{ If } F(w) = \sum_{k_1 \dots k_q} a_{k_1 \dots k_q} \cdot g_{k_1}^{\pm} \dots g_{k_q}^{\pm}$$

$$\text{then } \mathbb{P}\left(|F(w)| > A \cdot \left(\sum_{k_1 \dots k_q} |a_{k_1 \dots k_q}|^2\right)^{\frac{1}{2}}\right) < c \cdot e^{-A^{\frac{2}{q}}}$$

Now, $H = H_{bc}$ can be viewed as the kernel of an operator T , which is a linear operator from the space of functions of c to the space of functions of b .

$$T: \mathcal{L}_c^2 \rightarrow \mathcal{L}_b^2 \quad (Tz)_b = \sum_c H_{bc} z_c$$

$$T^*: \mathcal{L}_b^2 \rightarrow \mathcal{L}_c^2 \quad (T^*y)_c = \sum_b \overline{H_{bc}} y_b$$

$$TT^*: \mathcal{L}_b^2 \rightarrow \mathcal{L}_b^2 \quad (TT^*y)_b = \sum_{b'} \left(\sum_c \overline{H_{bc}} H_{b'c} \right) y_{b'}$$

In general, we will consider the operator $T_n = \begin{cases} (TT^*)^m, & \text{if } n=2m \\ (TT^*)^m T, & \text{if } n=2m+1. \end{cases}$

We will prove that for each n , the kernel (H_n) of T_n has the form

- If $n=2m$: $(H_n)_{bb'} = \sum_{k_{A_n}} (P_n)_{bb'k_{A_n}} \prod_{i \in A_n} g_{k_i}^\pm$

- If $n=2m+1$: $(H_n)_{bc} = \sum_{k_{A_n}} (P_n)_{bck_{A_n}} \prod_{i \in A_n} g_{k_i}^\pm$

In the above we have

$$\|P_n\|_{bb'k_{A_n}} \quad (\text{or } \|P_n\|_{bck_{A_n}}) \leq D^{n-1} \cdot \|h\|_{bck_A}$$

where

$$D = \sup_{(B,c)} \|h\|_{bb'k_B \rightarrow ck_c}$$

We induct in n . When $n=1$, we may choose $A_1=A$. Suppose this is true for n . where n is even, then $T_{n+1} = T_n \cdot T$. thus

$$(H_{n+1})_{bc} = \sum_{b'} (H_n)_{bb'} \cdot H_{b'c}$$

$$= \sum_{b'} \sum_{k_{A_n}} \sum_{k_A} (P_n)_{bb'k_{A_n}} \cdot h_{b'ck_A} \cdot \prod_{i \in A_n \cup A} (g_{k_i})^\pm$$

Then we identify the pairings in $g_{k_i} : i \in A_n \cup A$, and let the set of unpaired indices be A_{n+1} , then

$$(H_{n+1})_{bc} = \sum_{k_{A_{n+1}}} (R_{n+1})_{bck_{A_{n+1}}} \cdot \prod_{i \in A_{n+1}} (g_{k_i})^\pm$$

where

$$(R_{n+1})_{bck_{A_{n+1}}} = \sum_{\text{(paired indices)}} \sum_{b'} (R_n)_{bb'k_{A_n}} \cdot \underline{h}_{b'ck_A}$$

is a semi-product of R_n with h . By Lemma:

$$\|R_{n+1}\|_{bck_{A_{n+1}}} \leq \|R_n\|_{bb'k_{A_n}} \cdot \|h\|_{ck_C \rightarrow bk_B} \leq D \cdot \|R_n\|_{bb'k_{A_n}}$$

for some partition (B, C) of A . This completes the inductive proof.

Now, choose $n=2m$. we have

$$\begin{aligned} \|T\|_{\ell^2 \rightarrow \ell^2}^{4m} &= \|(TT^*)^m\|_{\ell^2 \rightarrow \ell^2}^2 = \|T_{2m}\|_{\ell^2 \rightarrow \ell^2}^2 \\ &\leq \sum_{b, b'} |(H_{2m})_{bb'}|^2 \end{aligned}$$

We know that, up to a set of probability $\leq e^{-N^\theta}$, we have

$$|(H_{2m})_{bb'}|^2 \leq \sum_{k_A} |(R_{2m})_{bb'k_A}|^2 \cdot N^\varepsilon \quad \text{for all } (b, b').$$

$$\text{then } \|T\|_{\ell^2 \rightarrow \ell^2}^{4m} \leq \|R_{2m}\|_{bb'k_A}^2 \leq D^{4m-2} \cdot \|h\|_{bck_A}^2$$

Finally, note that $\|h\|_{bck_A} \leq N^{O(\varepsilon)} \cdot D$. then

$$\|H\|_{b \rightarrow c} = \|T\|_{\ell^2 \rightarrow \ell^2} \leq D \cdot \left(\frac{\|h\|_{k_A k_A}}{D} \right)^{\frac{r}{2m}}$$

$$\leq D \cdot N^{\frac{O(1)}{2m}}$$

choose m large. we get this $\leq D \cdot N^\varepsilon$.

#

2.3 Local well-posedness for (NLS)

o Recall the model

$$(y_N)_k = (F_N)_k + \sum_{\max(N_1, \dots, N_p) = N} \mathcal{M}(y_{N_1}, \dots, y_{N_p})_k$$

We introduce the ansatz

$$(y_N)_k = \sum_S \left(\sum_{k_A} \underbrace{h_{k_A}}_{\text{merge}} \prod_{i \in A} (F_{N_i})_{k_i}^\pm \right) + z_N(k).$$

where S is a set A , together with N_i for each $i \in A$, such that $N_i \geq N^\delta$, and $\max_{i \in A} N_i = N$. Moreover we require that $|A| \leq D$. (where D is a large constant)

o As defined before, if we have input tensors $h_{k_A}^{(j)}$, $1 \leq j \leq p$. then the output

tensor $h = h_{k_A} = \left(\underbrace{\text{Merge}(h^b, \text{Trim}(h^{(j)}))}_{1 \leq j \leq p} \right)$

Using this we can inductively define the tensors that appear in the ansatz, and we need to inductively prove the bounds of these tensors in the norms of our choice.

o Recall $\alpha = S + \frac{d}{2}$, $S > S_{pr} = -\frac{1}{p-1}$. Define $\alpha_1 = -\frac{1}{p-1} + \frac{d}{2}$. then choose

$\alpha_0 = \frac{1}{2}(\alpha + \alpha_1)$. then $\alpha_1 < \alpha_0 < \alpha$. We pose the following estimates on h_{k_A} :

(1) In the support of $h_{k|k_A}$ we have

$$k = \sum_{i \in A} (\pm k_i) + O(N^\delta).$$

(2) For any partition (P, Q) of A we have

$$\|h\|_{k|k_P \rightarrow k_Q} \leq \prod_{i \in A} N_i^{\alpha_0} \cdot \begin{cases} (\max_{i \in Q} N_i)^{-\alpha_0} & \text{if } Q \neq \emptyset \\ 1 & \text{if } Q = \emptyset \end{cases} \quad (*)$$

(needs correction factors in real case).

o To finish the inductive proof we need to show two things:

(1) If h satisfies $(*)$ then $\text{Trim}(h)$ also satisfies $(*)$:

(2) If h_1, \dots, h_p satisfy $(*)$ then $\text{Merge}(h^b, h_1, \dots, h_p)$ also satisfies $(*)$.

o First look at (1). Let $h = h_{k|k_A}$ and $B = \{i \in A : N_i \geq N^\delta\}$. Notice that there is some M ($M \leq N$) such that $N_i \geq M^\delta$ ($\forall i \in A$), and h is a Borel function of $(g_k)_{|k| < M^\delta}$; then by definition

$$\text{Trim}(h) = \tilde{h}_{k|k_B} = \sum_{k_{A \setminus B}} h_{k|k_A} \cdot \prod_{i \in A \setminus B} g_{k_i}^{\pm} \underbrace{\langle k_i \rangle^{-\alpha}}_{\sim N_i^{-\alpha}}$$

Since h is Borel function of $(g_k)_{|k| < M^\delta}$, and $N_i \geq M^\delta$ for $i \in A \setminus B$, and there is no pairing in $k_{A \setminus B}$ in this summation, we can apply the lemma and get, up to a set of probability $\leq e^{-N^\theta}$, that

$$\|\text{Trim}(h)\|_{k|k_P \rightarrow k_Q} \leq N^\varepsilon \cdot \prod_{i \in A \setminus B} N_i^{-\alpha} \cdot \sup_{(E, F)} \|h\|_{k|k_{P \cup E} \rightarrow k|k_{Q \cup F}}$$

where (P, Q) = partition of B , and (E, F) = partition of $A \setminus B$. Now, if $Q \neq \emptyset$

then

$$\begin{aligned} \|\text{Trim}(h)\|_{k_{k_p} \rightarrow k_Q} &\leq N^\varepsilon \cdot \prod_{i \in A \setminus B} N_i^{-\alpha} \cdot \prod_{i \in A} N_i^{\alpha_0} \cdot \left(\max_{i \in \text{OUT}} N_i \right)^{-\alpha_0} \\ &= \underbrace{\prod_{i \in B} N_i^{\alpha_0} \cdot \left(\max_{i \in Q} N_i \right)^{-\alpha_0}}_{\leq 1} \cdot \underbrace{N^\varepsilon \cdot \prod_{i \in A \setminus B} N_i^{\alpha_0 - \alpha}}_{\leq 1} \end{aligned}$$

◦ Finally we consider the merging estimates. We need 2 ingredients:

(1) an estimate for norms of h^b , which will follow from suitable counting estimates:

(2) a selection algorithm of rearranging h_1, \dots, h_p in applying the multilinear lemma to get the optimal bound.

◦ Recall that $(h^b)_{k_1 \dots k_p} = \begin{cases} 1, & \text{if } \pm k_1 \pm \dots \pm k_p \neq 0, \Omega = 0, \text{ no-pairing} \\ 0, & \text{otherwise.} \end{cases}$

Lemma. Suppose (k_1, \dots, k_p) satisfies that

$$\left. \begin{aligned} \pm k_1 \pm \dots \pm k_p &= \boxed{\text{Const}} \\ \pm |k_1|^2 \pm \dots \pm |k_p|^2 &= \boxed{\text{Const}} \\ \dots & \\ |\pm k_p - m_p| &\leq M_p \\ |\pm k_{p-1} \pm k_p - m_{p-1}| &\leq M_{p-1} \\ \dots & \\ |\pm k_3 \pm \dots \pm k_p - m_3| &\leq M_3 \\ |\pm k_2 \pm \dots \pm k_p - m_2| &\leq M_2 \end{aligned} \right\}$$

where m_2, \dots, m_p are constant vectors. then the number of choices for (k_1, \dots, k_p) is at most $(M_2 \cdots M_p)^{2\alpha_1 + \varepsilon}$. The same is true if p is replaced by $q \leq p$

Proof We induct on p . If $p=3$, then $\boxed{2\alpha_1 = d-1}$. Consider the case where

$$\left\{ \begin{array}{l} \bullet k_1 - k_2 + k_3 = k \text{ (Const)} \\ \bullet |k_1|^2 - |k_2|^2 + |k_3|^2 = \Omega \text{ (Const)} \\ |k_3 - m_3| \leq M_3 \longrightarrow k_3 \in B_{M_3} \\ |-k_2 + k_3 - m_2| \leq M_2 \longrightarrow k_1 \in B_{M_2}. \end{array} \right.$$

then, by algebra we get $\underline{(k-k_1) \cdot (k-k_3)} = (\text{Constant})$. The first $(d-1)$ coordinates of $(k-k_1)$ and $(k-k_3)$ has at most $M_2^{d-1} \cdot M_3^{d-1}$. Suppose they are fixed. then we have that the choice for the last coordinates is $\boxed{\leq (M_2 M_3)^\varepsilon}$ by the divisor estimate:

$$\forall A \neq 0. \# \{ (b, c) \in \mathbb{Z}^2 : bc = A \} \leq A^\varepsilon, \forall \varepsilon > 0.$$

So we get $(M_2 M_3)^{d-1+\varepsilon}$

Now suppose the result is true for $p-2$, then for p .

• Fix the values of k_1 and k_2 . ($k_1 \in B_{M_2}$ and $\pm k_1, \pm k_2 \in B_{M_3}$) So we get $(M_2 M_3)^d$: for the rest, apply induction hypothesis we get

$$(\# \text{ of choices}) \leq (M_2 M_3)^d \cdot (M_4 \cdots M_p)^{d - \frac{2}{p-3} + \varepsilon}.$$

• Fix the values of (k_4, \dots, k_p) we get $(M_4 \cdots M_p)^d$. Then apply $p=3$ case to (k_1, k_2, k_3) . we get

$$(\# \text{ of choices}) \leq (M_4 \cdots M_p)^d \cdot (M_2 M_3)^{d-1+\varepsilon}.$$

Interpolating between these two we get

$$(\# \text{ of choices}) \leq (M_2 M_3)^{d - \frac{2}{p-1} + \varepsilon} (M_4 \dots M_p)^{d - \frac{2}{p-1} + \varepsilon}$$

Corollary

Suppose we restrict the tensor h^b to the set

$$\left. \begin{aligned} | \pm k_p | &\leq M_p \\ | \pm k_{p-1} \pm k_p | &\leq M_{p-1} \\ &\vdots \\ | \pm k_2 \pm \dots \pm k_p | &\leq M_2 \end{aligned} \right\}$$

then we have $\|h^b\|_{k k_x \rightarrow k_Y} \leq (M_2 \dots M_p)^{\alpha_1 + \varepsilon}$, as long as $1 \in Y$.

Proof We apply Schur's inequality

$$\|h^b\|_{k k_x \rightarrow k_Y} \leq \left(\sup_{(k, k_x)} \sum_{k_Y} |h^b| \right)^{\frac{1}{2}} \left(\sup_{k_Y} \sum_{(k, k_x)} |h^b| \right)^{\frac{1}{2}}$$

By Lemma we can get

$$\sup_{(k, k_x)} \sum_{k_Y} |h^b| \leq \left(\prod_{j \in Y \setminus \{1\}} M_j \right)^{\alpha_1 + \varepsilon}$$

$$\sup_{k_Y} \sum_{(k, k_x)} |h^b| \leq \left(\prod_{j \in X} M_j \right)^{\alpha_1 + \varepsilon}$$

$$\implies \|h^b\|_{k k_x \rightarrow k_Y} \leq (M_2 \dots M_p)^{\alpha_1 + \varepsilon} \quad \forall \varepsilon > 0.$$

• Now we start the proof of merging estimate. Recall that input tensors

$$h_j = (h_j)_{k_j k_{A_j}} \quad \text{satisfies } (*)$$

We will later rearrange h_j into $\underline{h_{(1)}}, \underline{h_{(2)}}, \dots, \underline{h_{(p)}}$, say $h_{(j)} = (h_{(j)})_{k_{(j)} k_{A_{(j)}}}$.

• Recall that $H = H_{k k_A}$ is the semi-product of $h_{k_1 \dots k_p}^b$ and $h_{(1)}, \dots, h_{(p)}$. Note that $A =$ set of unpaired indices. Suppose we want to estimate

$\|H\|_{k_p \rightarrow k_q}$ $(P, Q) = \text{partition of } A, Q \neq \emptyset$

- First, choose $i_1 \in Q$ such that $N_{i_1} = M_1$ is max. Suppose $i_1 \in A_{(1)}$
- Next, consider all indices in other tensors that either $\in P$, or $\in Q$, or is paired with an element in $A_{(1)}$. Choose i_2 such that $N_{i_2} = M_2 = \max$. Suppose $i_2 \in A_{(2)}$. We also give $A_{(2)}$ (and $i_2, h_{(2)}$) a type P or Q : if $i_2 \in P$ (or Q) then it has this type: otherwise if i_2 is paired with an element of $A_{(1)}$ then it has type Q .
- We continue this process. Note each time, if $i_j \in P$ (or Q) then it has type P (or Q). if it is paired with $A_{(1)}$ then it has type Q : if it is paired with $A_{(j')}$ where $1 < j' < j$, then it has same type as $A_{(j')}$.

• Example, if $P = \{x\}$, and

$$h_1 = (h_1)_{k_x c} \quad h_2 = (h_2)_{k_2 ab} \quad h_3 = (h_3)_{k_3 cde}$$

$$h_4 = (h_4)_{k_4 efg} \quad h_5 = (h_5)_{k_5 afh}$$

where $|x| \geq |a| \geq |b| \geq \dots \geq |h|$ and

$$H = H_{k_x b d g h} = \sum_{k_1 \dots k_5} \sum_{x, a, e, f} (h^b)_{k_1 \dots k_5} (h_1)_{k_x c} (h_2)_{k_2 ab} (h_3)_{k_3 cde} (h_4)_{k_4 efg} (h_5)_{k_5 afh}$$

assume $P = \{b, d\}$, $Q = \{x, g, h\}$ then

- $i_1 = x$, $h_{(1)} = h_1$:
- $i_2 = b$, $h_{(2)} = h_2$: type P :
- $i_3 = a$, $h_{(3)} = h_5$: type P :
- $i_4 = c$, $h_{(4)} = h_3$ type Q :
- $i_5 = e$, $h_{(5)} = h_4$ type Q .

◦ Now, we apply the multilinear estimate, and we

- First choose $h_{(1)}$.
- Then choose all $h_{(j)}$ of type Q , in the increasing order of j
- Then choose h^b :
- Then choose all $h_{(j)}$ of type P in the decreasing order of j

By multilinear estimate, we get a bound of form

$$\|H\|_{k_P \rightarrow k_Q} \leq \|h^b\|_{k_X \rightarrow k_Y} \cdot \prod_{j=1}^p \|h_{(j)}\|_{k_{Q_j} \rightarrow k_{Q_j}}$$

In the example we have

$$\|H\|_{k_{bd} \rightarrow k_{gh}} \leq \|h^b\|_{k_{k_2 k_3} \rightarrow k_{k_1 k_4}} \cdot \|h_{(1)}\|_{k_{c \rightarrow x}} \cdot \|h_{(2)}\|_{k_{2a \rightarrow b} \substack{(b \rightarrow k_2 \bar{a})}} \cdot \|h_{(3)}\|_{k_{fgh \rightarrow a} \substack{(a \rightarrow k_3 \bar{f} \bar{h})}} \cdot \|h_{(4)}\|_{k_{3de \rightarrow c}} \cdot \|h_{(5)}\|_{k_{4f \rightarrow eg}}$$

Note that the algorithm actually guarantees that $i_j \in Q_{(j)}$ for each $2 \leq j \leq p$.

In particular

$$\max_{i \in Q_j} N_i \geq N_{i_j} = M_j.$$

Note also that $1 \in Y$ Then we estimate

$$\prod_{(\text{paired } i)} N_i^{-\alpha} \cdot \|H\|_{k_{k_p} \rightarrow k_Q} \leq \prod_{(\text{paired } i)} N_i^{-\alpha} \cdot \prod_{i \in A_1 \cup \dots \cup A_p} N_i^{\alpha_0} \cdot \prod_{i=1}^p (\max_{i \in Q_j} N_i)^{-\alpha_0} \cdot \|h^b\|_{k_{k_x} \rightarrow k_Y}$$

$$\leq \prod_{i \in A} N_i^{\alpha_0} \cdot \prod_{j=2}^p M_j^{-\alpha_0} \cdot \prod_{i \in Q} (\max_{i \in Q} N_i)^{-\alpha_0} \cdot \|h^b\|_{k_{k_x} \rightarrow k_Y}$$

So it suffices to show that

$$\|h^b\|_{k_{k_x} \rightarrow k_Y} \leq (M_2 \dots M_p)^{\alpha_1 + \epsilon}$$

This is because we may assume

$$\left| \pm k_{(j)} \pm k_{(j+1)} \pm \dots \pm k_{(p)} \right| \lesssim M_j + \underbrace{O(N^\delta)}_{\text{omit!}}$$

In fact, we have

$$k_{(j)} = \sum_{i \in A_{(j)}} \pm k_i + \underbrace{O(N^\delta)}_{\text{omit!}} \text{ for each } j.$$

If there is a pair in $A_{(j)}, \dots, A_{(p)}$ then these will cancel, so the terms in RHS only has the indices that is either unpaired ($\in P$ or $\in Q$), or paired with $A_{(j')}, j' < j$

By our choice, for each such i , $N_i \leq M_j$. So we get

$$\left| \pm k_{(j)} \pm \dots \pm k_{(p)} \right| \lesssim M_j + O(N^\delta)$$

o Finally, notice that the tensor term

$$\eta_k = \sum_{k_A} h_{k_A} \cdot \prod_{i \in A} \underbrace{\langle k_i \rangle^{-\alpha}}_{N_i^{-\alpha}} g_{k_i}$$

Then with high probability, for each k , we have

$$\begin{aligned} |\eta_k|^2 &\leq \sum_{k_A} |h_{kk_A}|^2 \cdot \prod_{i \in A} N_i^{-2\alpha} \\ &\leq \|h\|_{k \rightarrow k_A}^2 \cdot \prod_{i \in A} N_i^{-2\alpha} \\ &\leq \prod_{i \in A} N_i^{2\alpha_0} \cdot \prod_{i \in A} N_i^{-2\alpha} \\ &= \prod_{i \in A} N_i^{2(\alpha_0 - \alpha)} \leq N^{2\delta(\alpha_0 - \alpha)|A|} \end{aligned}$$

$\Rightarrow |\eta_k| \leq N^{\delta(\alpha_0 - \alpha) \cdot |A|}$ If $|A| \gg 1$, then $|\eta_k| = \text{large negative power}$
 \Rightarrow the term has high regularity.

If we choose cutoff at degree D , where $D \cdot \delta \cdot (\alpha_0 - \alpha) \gg 1$ then the terms of degree $> D$ will have high regularity, and can be found by fixed point argument.

• Thing to look at in the future.

- Stochastic NLS
- Other dispersion relation
- Critical case ($d=3, p=3$).
- Quasilinear case ???
- Long-time solutions.