

A note on distributions in \mathbb{R}^n

(A)

This works exactly in the same way except we need to define convergence in $S(\mathbb{R}^n)$.

We say $\varphi_n \rightarrow 0$ in $S(\mathbb{R}^n)$ if

for all $\alpha \in \mathbb{N}^n, \beta \in \mathbb{N}^n$

$$\sup_{x \in \mathbb{R}^n} \left| x^\alpha \frac{\partial^\beta}{\partial x^\beta} \varphi_n \right| \rightarrow 0 \text{ when } n \rightarrow \infty$$

A tempered distribution on \mathbb{R}^n is a (complex-valued) linear functional T

$$T: S(\mathbb{R}^n) \rightarrow \mathbb{C} \text{ such that}$$

$$T(\varphi_n) \rightarrow 0 \text{ for all sequences } \varphi_n \rightarrow 0 \text{ in } S(\mathbb{R}^n)$$

Ex $\delta \otimes \delta$:

$$\langle \delta \otimes \delta, \varphi \rangle = \varphi(0,0)$$

Note This is a common notation:

Suppose $f: \mathbb{R} \rightarrow \mathbb{R}$ and $g: \mathbb{R} \rightarrow \mathbb{R}$

Then

$$h(x,y) = f(x)g(y)$$

is often denoted

$$h = f \otimes g.$$

Note In this way, \otimes is not commutative.

Multi dimensional Fourier transform

Notation $x = (x_1, x_2, \dots, x_n)$

$$s = (s_1, \dots, s_n)$$

If $k = (k_1, k_2, \dots, k_n) \in \mathbb{N}^n$, let $|k| = k_1 + \dots + k_n$

We may DEFINE $x^k = x_1^{k_1} \dots x_n^{k_n}$

$$\frac{\partial^{|k|}}{\partial x^k} = \frac{\partial^{|k|}}{\partial x_1^{k_1} \dots \partial x_n^{k_n}}$$

Def If $f: \mathbb{R}^n \rightarrow \mathbb{C}$

we define

$$\hat{f}(s) = \int_{\mathbb{R}^n} e^{-2\pi i x \cdot s} f(x) dx$$

and the inverse

$$f(x) = \int_{\mathbb{R}^n} e^{2\pi i x \cdot s} \hat{f}(s) ds$$

shows that almost all rules have to do F-transform:

Examples $f(x, y) = \hat{f}(u, v)$

$$f(ax, by) = \frac{1}{|ab|} \hat{f}\left(\frac{u}{a}, \frac{v}{b}\right)$$

Note if a, b complex... need to be careful.

$$f(x-a, y-b) = e^{-2\pi i(au + bv)} \hat{f}(u, v)$$

$$\left(\frac{\partial}{\partial x}\right)^m \left(\frac{\partial}{\partial y}\right)^n f(x, y) = (2\pi i u)^m (2\pi i v)^n \hat{f}(u, v)$$

$$\left(\frac{\partial^2}{\partial x^2} + \frac{\partial^2}{\partial y^2}\right) f(x, y) = -4\pi^2 (u^2 + v^2) \hat{f}(u, v)$$

One can in general define T_1 & T_2

by $\langle T_1 \otimes T_2, \varphi_1 \otimes \varphi_2 \rangle = T_1(\varphi_1) T_2(\varphi_2)$

Problem: Is it enough to define

$T_1 \otimes T_2$ on the subset of $S(\mathbb{R}^2)$
given by $\{ \varphi \in S(\mathbb{R}^2) : \varphi(x,y) = \varphi_1(x) \varphi_2(y), \varphi_1, \varphi_2 \in S(\mathbb{R}) \}$?

Solution One can approximate $\varphi(x,y)$

as $\varphi(x,y) = \sum_{k=1}^N \varphi_{1k}(x) \varphi_{2k}(y)$

Then $\langle T_1 \otimes T_2, \varphi \rangle = \sum_{k=1}^N \langle T_1 \otimes T_2, \varphi_{1k} \otimes \varphi_{2k} \rangle + \dots$
 $= \sum_{k=1}^N T_1(\varphi_{1k}) T_2(\varphi_{2k}) + \dots$

Fourier transform of tensor products:

Let $\varphi(x,y) = \varphi_1(x) \varphi_2(y)$

Then $\hat{\varphi}(\xi, \eta) = \iint e^{-2\pi i(x\xi + y\eta)} \varphi_1(x) \varphi_2(y) dx dy$
 $= \hat{\varphi}_1(\xi) \hat{\varphi}_2(\eta)$

so $\mathcal{F}(\varphi_1 \otimes \varphi_2) = \hat{\varphi}_1 \hat{\varphi}_2$

This makes it easy to compute
the Fourier transform of some
tempered distributions on \mathbb{R}^2 (or any \mathbb{R}^n)