



#### Stationarity (blended lecture)

#### DS-GA 1013 / MATH-GA 2824 Mathematical Tools for Data Science

Carlos Fernandez-Granda

Eigendecomposition of continuous linear-translation invariant functions

Complexity of convolutions

Convolutions in probability

- 1. Why do we almost never apply generic linear models to audio, images and other high-dimensional signals?
- 2. What is the limitation of PCA in uncovering *interesting* structure in audio, images and similar signals?

#### Eigendecomposition of continuous linear-translation invariant functions

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## Linear translation-invariant (LTI) function

A function  $\mathcal{F}$  from  $\mathbb{C}^N$  to  $\mathbb{C}^N$  is linear if for any  $x, y \in \mathbb{C}^N$  and any  $\alpha \in \mathbb{C}$ 

$$\mathcal{F}(x+y) = \mathcal{F}(x) + \mathcal{F}(y)$$
$$\mathcal{F}(\alpha x) = \alpha \mathcal{F}(x)$$

and translation invariant if for any shift  $0 \le s \le N - 1$ 

$$\mathcal{F}(x^{\downarrow s}) = \mathcal{F}(x)^{\downarrow s}$$

## What are the eigenvectors of discrete LTI functions?

## What are the eigenvectors of discrete LTI functions?

1. Discrete linear-translation invariant function is equivalent to convolution with impulse response

$$\mathcal{F}(x) = x * h$$

2. Convolution is equivalent to taking DFT, weighting DFT coefficients, and applying inverse DFT

$$egin{aligned} \mathcal{F}(x) &= rac{1}{N} \mathcal{F}^*_{[N]} \operatorname{diag}(\hat{h}) \mathcal{F}_{[N]} x \ &= rac{1}{N} \sum_{k=0}^{N-1} \hat{h}[k] \hat{x}[k] \psi_k \end{aligned}$$

3. This implies

$$\mathcal{F}(\psi_k) = \hat{h}[k]\psi_k$$

## Continuous LTI functions

A function or system  $\mathcal{F}$  that maps functions in [0, 1] to functions in [0, 1] is linear if for any functions f, g and any  $\alpha \in \mathbb{C}$ 

$$\mathcal{F}(f+g) = \mathcal{F}(f) + \mathcal{F}(g)$$
$$\mathcal{F}(\alpha f) = \alpha \mathcal{F}(f)$$

and translation invariant if for any shift  $s \in \mathbb{R}$ 

$$\mathcal{F}(f^{\downarrow s}) = \mathcal{F}(f)^{\downarrow s}$$

where  $f^{\downarrow s}(t) = f(t-s)$  for all  $t \in [0,1]$ 

Are complex exponentials eigenvectors of continuous LTI functions?

$$\phi_k(t) := \exp(i2\pi kt)$$

$$y := \mathcal{F}(\phi_k)$$
 ?

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$$y := \mathcal{F}(\phi_k)$$
 ?

$$\mathcal{F}(\phi_k^{\downarrow s}) = y^{\downarrow s}$$
$$\mathcal{F}(\phi_k^{\downarrow s}) = \mathcal{F}(\exp(-i2\pi ks)\phi_k^{\downarrow s})$$
$$= \exp(-i2\pi ks)y$$

$$y(a-b) = \exp(-i2\pi kb)y(a)$$

$$y(t) = y(0) \exp(-i2\pi kt)$$
 Yes!

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# Complexity of convolutions

Complexity of circular convolution between N-dimensional vectors?

$$x * y[j] := \sum_{s=0}^{N-1} x[s] y^{\downarrow s}[j], \quad 0 \le j \le N-1$$

► Can we improve it?

# Complexity of convolutions

Complexity of circular convolution between N-dimensional vectors?
 \$\mathcal{O}(N^2)\$

$$x * y[j] := \sum_{s=0}^{N-1} x[s] y^{\downarrow s}[j], \quad 0 \le j \le N-1$$

• Can we improve it? Yes, to  $\mathcal{O}(N \log N)$  by using FFTs

Complexity of convolution between vectors of dimension M and N?

$$x * y[j] := \sum_{s=0}^{M-1} x[s] y^{\downarrow s}[j], \quad 0 \le j \le N-1$$

In convolutional neural networks, we don't use FFTs. Why?

# Complexity of convolutions

Complexity of convolution between vectors of dimension M and N?
 \$\mathcal{O}(MN)\$

$$x * y[j] := \sum_{s=0}^{M-1} x[s] y^{\downarrow s}[j], \quad 0 \le j \le N-1$$

In convolutional neural networks, we don't use FFTs. Why? M is very small

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## Sum of independent random variables

Let  $\tilde{x}$  and  $\tilde{y}$  be independent discrete random variables with N possible values

What is the distribution of  $\tilde{z}:=\tilde{x}+\tilde{y}$ 

$$p_{\tilde{z}}(z) =$$

## Sum of independent random variables

Let  $\tilde{x}$  and  $\tilde{y}$  be independent discrete random variables with N possible values

What is the distribution of  $\tilde{z}:=\tilde{x}+\tilde{y}$ 

$$p_{\tilde{z}}(z) = P(\tilde{z} = z)$$

$$= \sum_{j=0}^{M-1} P(\tilde{x} = j, \tilde{y} = z - j)$$

$$= \sum_{j=0}^{M-1} P(\tilde{x} = j) P(\tilde{y} = z - j)$$

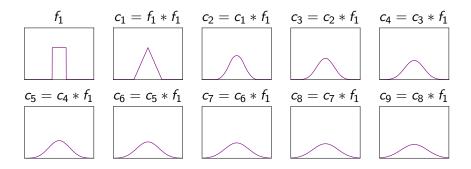
$$= \sum_{j=0}^{M-1} p_{\tilde{x}}(j) p_{\tilde{y}}(z - j)$$

$$p_{\tilde{z}} = p_{\tilde{y}} * p_{\tilde{y}}$$

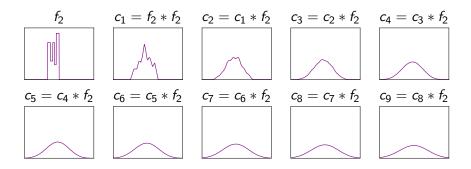
## Distribution of sums

Random quantities are often the result of adding many independent components

### Iterated convolutions



### Iterated convolutions



Random quantities are often the result of adding many independent components

Such quantities are Gaussian because iterated convolutions converge to Gaussian functions