

Convolution, Correlation and Fourier Transforms

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Plan

1. Introduction
2. Fourier Transforms
3. Convolution transform. Convolution theorem
4. Proof of the convolution theorem
5. Correlation and auto-correlation
6. CNN: Advanced insights
7. Bonus

Time and Frequency Domains

Two ways of process descibing:

- ▶ **Time domain.** Values of some quantity
- ▶ **Frequency Domain.** Complex number: amplitude and phase

Fourier transforms

The mapping between the domains

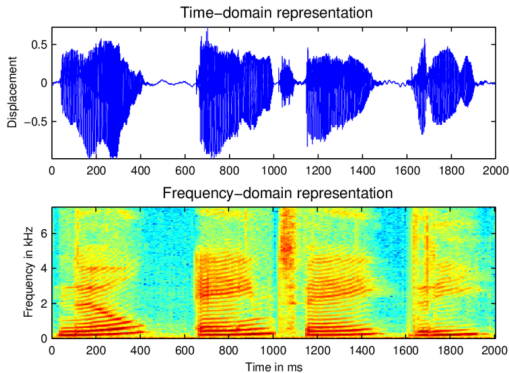


Figure: Two representations of speech.

Fourier Transforms

1. From time domain to frequency domain:

$$H(f) = \int_{-\infty}^{+\infty} h(t) \exp(-2\pi ift) dt$$

2. From frequency domain to time domain:

$$h(t) = \int_{-\infty}^{+\infty} H(f) \exp(2\pi ift) df$$

Properties

1. FT is a linear operator
2. Time scaling: $h(at) \equiv \frac{1}{a} H\left(\frac{f}{a}\right)$
3. Time shifting: $h(t - t_0) \equiv H(f) \exp(-2\pi ift_0)$

Convolution

Functions $h(t)$ and $g(t)$ is given. $H(f)$ and $G(f)$ are corresponding Fourier transforms.

Convolution

$$f(t) = g * h \equiv \int_{-\infty}^{+\infty} f(v)g(t-v)dv$$

For functions f, g supported on only $[0, \infty)$, the integration limits can be truncated:

$$f(t) = g * h \equiv \int_0^t f(t-v)g(v)dv$$

Properties:

- ▶ $g * h = h * g$
- ▶ $g * h \equiv G(f)H(f)$

Convolution Theorem

Theorem

The Fourier transform of the convolution is the product of the two Fourier transforms.

$$\mathcal{F}(f * g) = \mathcal{F}(f)\mathcal{F}(g)$$

Where \mathcal{F} is a Fourier transform.

Modifications:

1. Laplace transform
2. Two-sided Laplace transform
3. Z-transform
4. Mellin transform

Proof for Laplace transform

Laplace transform:

$$\mathcal{L}(f) = \int_0^{\infty} \exp(-st) f(t) dt$$

Convolution theorem:

$$\mathcal{L}(f * g) = \mathcal{L}(f)\mathcal{L}(g)$$

Proof:

$$\begin{aligned}\mathcal{L}(f * g) &= \int_0^{\infty} \exp(-st) \left(\int_0^t f(t-v)g(v)dv \right) dt = \\ &= \int_0^{\infty} \exp(-st) \left(\int_0^{\infty} f(t-v)g(v)u(t-v)dv \right) dt\end{aligned}$$

Proof

$$\begin{aligned}\mathcal{L}(f * g) &= \int_0^{\infty} \exp(-st) \left(\int_0^{\infty} f(t-v)g(v)u(t-v)dv \right) dt = \\ &= \int_0^{\infty} \left(\int_0^{\infty} \exp(-st)f(t-v)g(v)u(t-v)dv \right) dt = \\ &= \int_0^{\infty} \left(\int_0^{\infty} \exp(-st)f(t-v)g(v)u(t-v)dt \right) dv = \\ &= \int_0^{\infty} g(v) \left(\int_0^{\infty} \exp(-st)f(t-v)u(t-v)dt \right) dv\end{aligned}$$

Proof

Note:

$$\mathcal{L}(f(t-v)u(t-v)) = \exp(-vs)\mathcal{L}(f(t)) = \exp(-vs)F(s)$$

Then:

$$\mathcal{L}(f * g) = \int_0^{\infty} g(v) \exp(-sv) F(s) dv = F(s)G(s) = \mathcal{L}(f(t))\mathcal{L}(g(t))$$

Correlation

Definition

The correlation of g and h . $H(f)$ and $G(f)$ are corresponding Fourier transforms.

$$\text{Corr}(g, h) \equiv \int_{-\infty}^{+\infty} g(v+t)h(t)dv$$

Correlation theorem:

$$\text{Corr}(g, h) \equiv G(f)H^*(f)$$

If g and h are real: $H(-f) = H^*(f)$.

Wiener-Khinchin Theorem:

The correlation of a function with itself is called its autocorrelation.

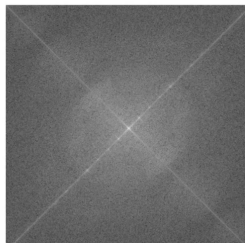
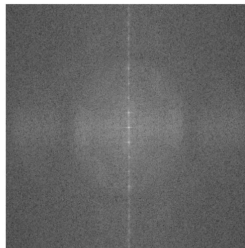
$$\text{Corr}(g, g) \equiv |G(f)|^2$$

Example of Image transform

Sonnet for Lena

O dear Lena, your beauty is so vast
It is hard sometimes to describe it fast.
I thought the entire world I would impress
If only your portrait I could compress.
Alas! First when I tried to use VQ
I found that your cheeks belong to only you.
Your silky hair contains a thousand lines
Hard to match with sums of discrete cosines.
And for your lips, sensual and tactual
Thirteen Crayons found not the proper fractal.
And while these methods are all quite arrey
I might have fixed them with backs here or there
But when filters took sparkle from your eyes
I said, 'Damn all this. I'll just digitize.'

Thomas GohAurel



CNN: Advanced concepts

Continuous form:

$$h(x) = f * g = \int_{-\infty}^{\infty} f(x - v)g(v)dv = \mathcal{F}^{-1}(\mathcal{F}(f)\mathcal{F}(g))$$

Discrete form:

$$\begin{aligned} y[m, n] &= h[m, n] * x[m, n] = \sum_{-\infty}^{\infty} \sum_{-\infty}^{\infty} h[i, j] x[m - i, n - j] = \\ &= \mathcal{F}^{-1}(\mathcal{F}(x)\mathcal{F}(k)) \end{aligned}$$

Note

A Fourier transform contains a lot of information about the orientation of an object in an image.

Open question:

Can we imagine that convolutional nets operate on images in the Fourier domain?

CNN: Cross-correlation

Cross-correlation for real functions g, h :

$$\text{Corr}(g, h) \equiv G(f)H(-f)$$

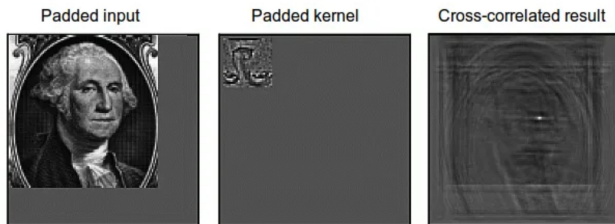


Figure: Cross-correlation via convolution: The input and kernel are padded with zeros and the kernel is rotated by 180 degrees.

Bonus: Complex networks

Reasons:

1. Improve phase prediction in existed pipelines
2. Work directly in Fourier domain
3. Use previously developed theory

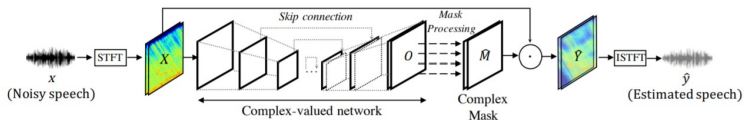


Figure: Deep complex U-net

Summary

- ▶ Fourier Transform
- ▶ Convolution in a general view
- ▶ Convolution theorem with proof
- ▶ Convolution and cross-correlation
- ▶ CNN: Advanced insights
- ▶ Complex Networks

Thank you!

Основная литература I