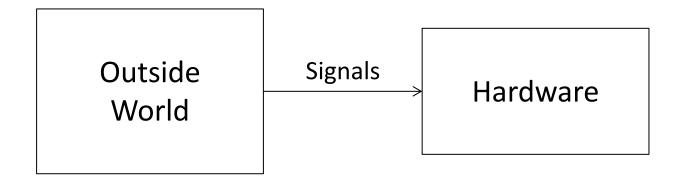
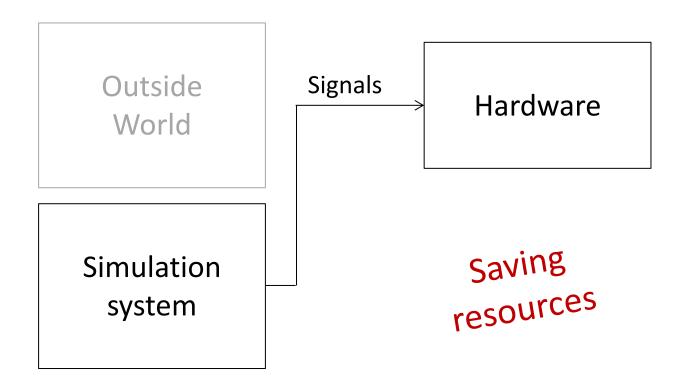
# Spectral theory of signal simulation and AI

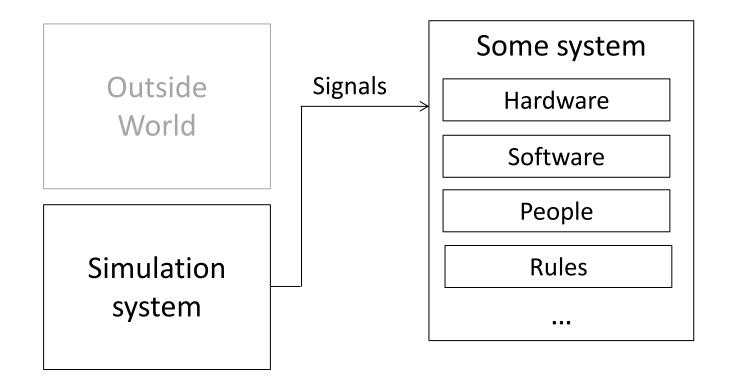
Ivan Deykin

Special thanks to Vladimir Syuzev and Elena Smirnova

IU6 (IC6) department, BMSTU

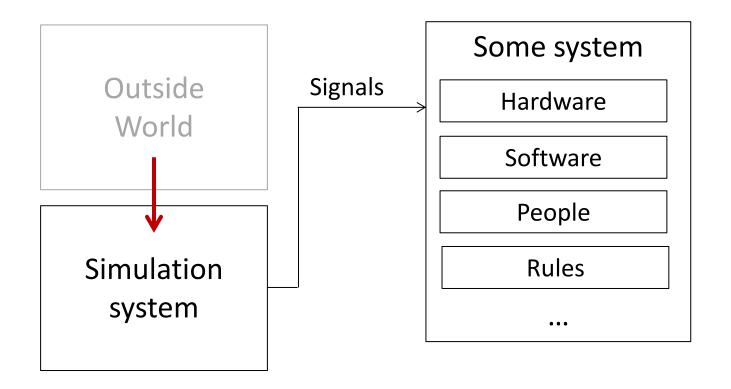


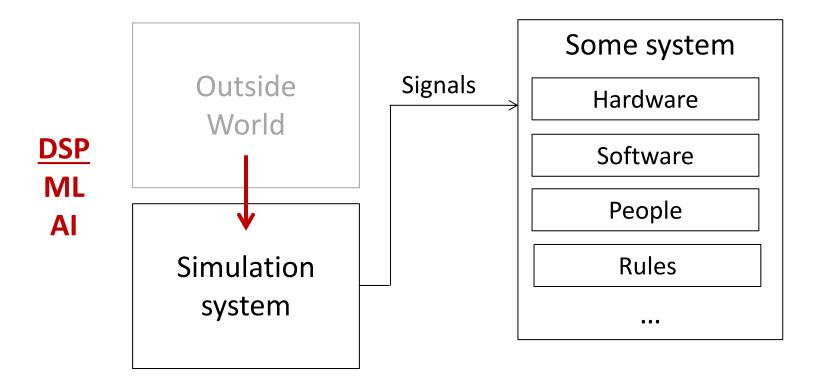




### Example: forest fire prevention system

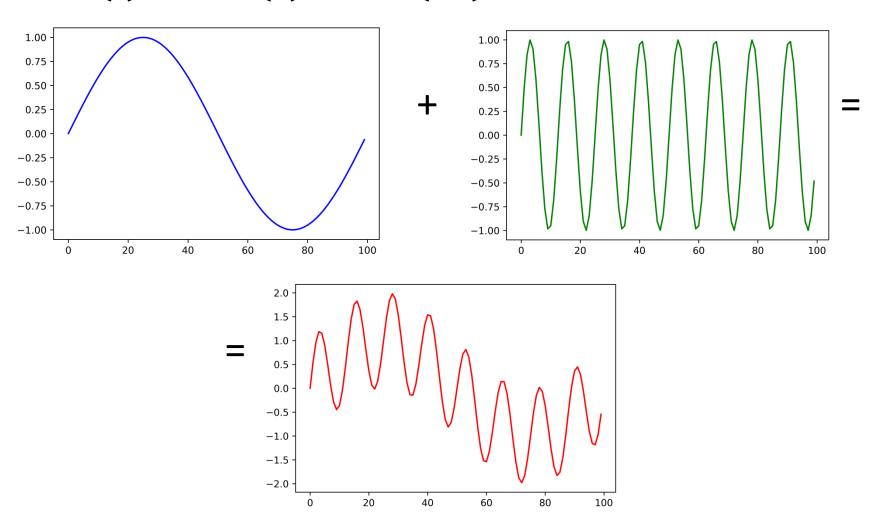
- Does hardware work correctly?
- Is software OK?
- Is staff properly trained?
- Are the rules adequate?





# 1D signal

$$x(t) = \sin(t) + \sin(8t)$$
;  $T = 2\pi$ ,  $N = 100$ .



# Time and frequency

$$f = \frac{n}{t} = \frac{1}{T}.$$

f – frequency – "the number of occurrences of a repeating event per unit of time";

n – repeats of something within T;

T – period.

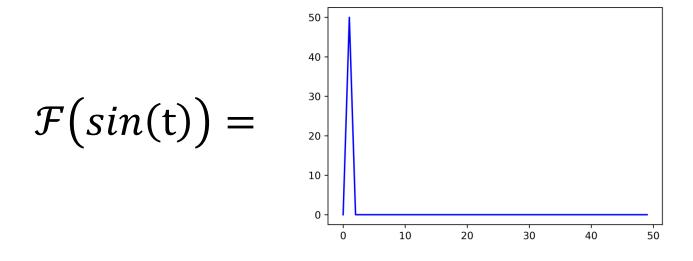
Fourier – from time domain to frequency domain:

$$\mathcal{F}(x(t)) = X(f) = \int_{-\infty}^{+\infty} x(t)e^{-2\pi jft}dt,$$

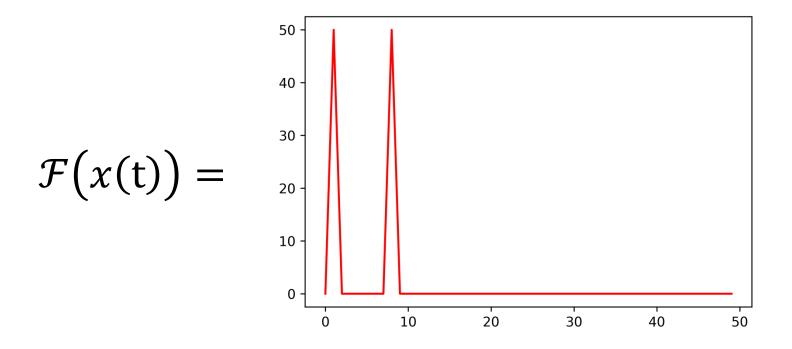
Inverse Fourier – from frequency to time:

$$\mathcal{F}^{-1}(X(f)) = x(t) = \int_{-\infty}^{+\infty} X(f)e^{2\pi jft}df.$$

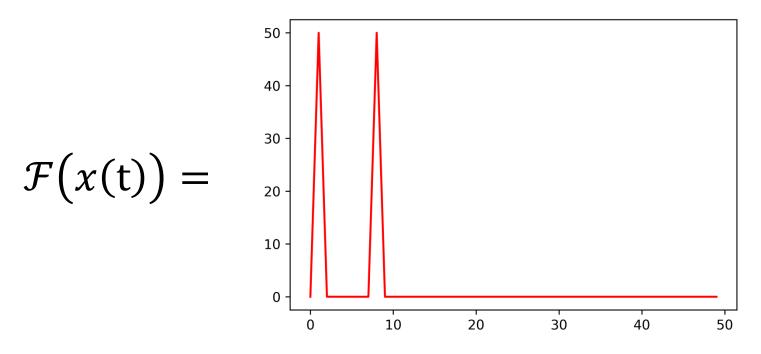
$$\omega = 2\pi f$$
.



$$\mathcal{F}(sin(8t)) = \int_{0}^{50} \int_{0}^{40} \int_{0$$



 $\mathcal{F}(x(t))$  shows how "strong" or "loud" different frequencies are within a signal.

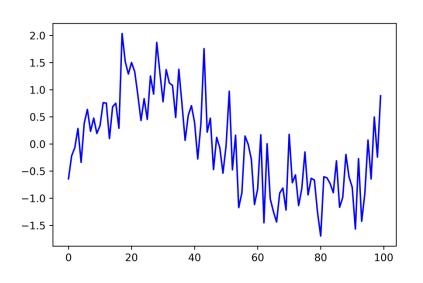


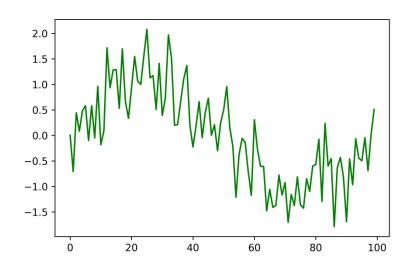
 $\mathcal{F}(x(t))=\mathcal{F}(sin(t))+\mathcal{F}(sin(8t))$  - we can filter  $\mathcal{F}(x(t))$  and use  $\mathcal{F}^{-1}(X'(f))$  to reproduce the new signal

# Random signal

is a signal that changes when experiment is repeated (the world is noisy).

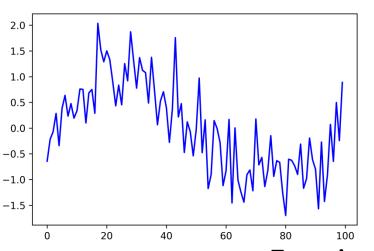
Example: sin(t) + 0.5\*noise

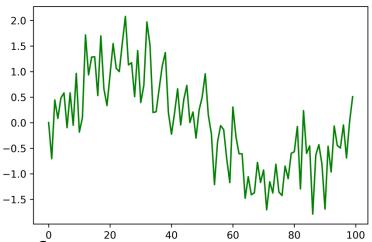




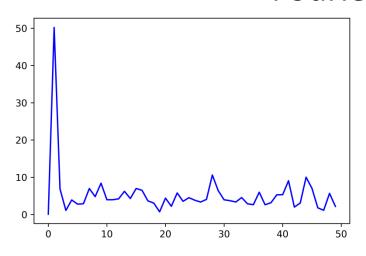
# Random signal

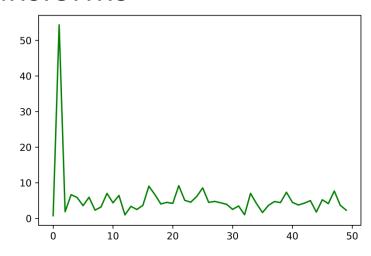
sin(t) + 0.5\*noise





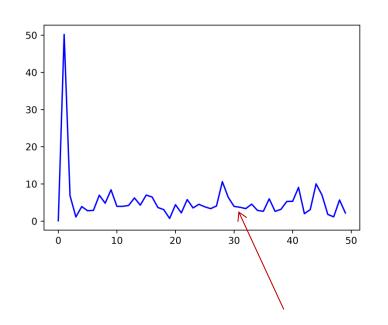
### Fourier Transforms

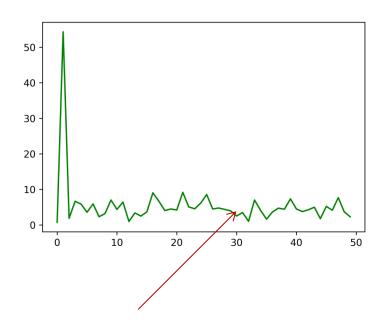




### Random signal

#### **Fourier Transforms**



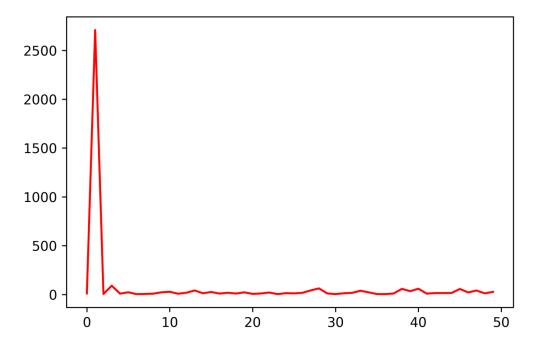


How often do I get a spike in that frequency? What are the chances? How tall is it usually? How much energy/power is in that frequency?

# Spectral density

Energy spectral density (if we had K experiments):

$$S_{E}(f) = \frac{1}{K} \sum_{i=1}^{K} |X_{i}(f)|^{2} = \frac{1}{K} \sum_{i=1}^{K} |\mathcal{F}(x_{i}(t))|^{2}$$



### Simulation

Spectral density (energy or power) can be used to simulate random signals. One way is by using shaping filters:

- Generate white noise
- Get its Fourier transform
- Multiply this transform with the ESD (filter the spectrum of the noise through the ESD)
- Get an inverse transform of the result

# Shaping filters simulation

Real

-1.5

Simulated from ESD

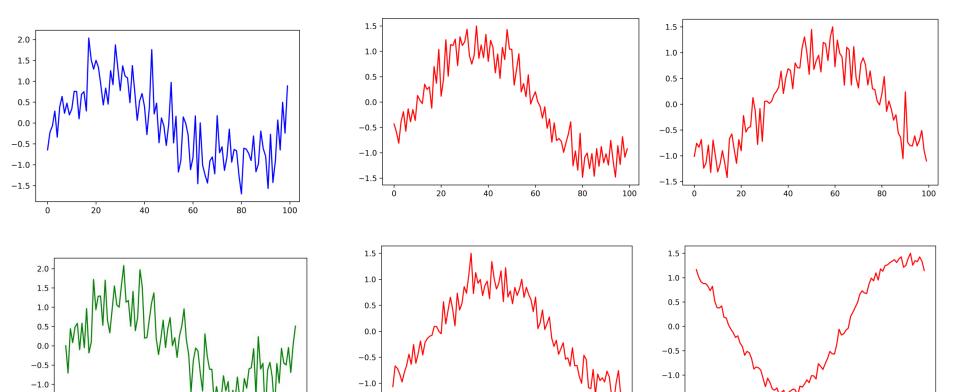
-1.5

100

20

100

80



20

100

# Spectral simulation

We generate Fourier coefficients:

$$X_{F}(k) = \sqrt{\frac{S_{E}\left(\frac{2\pi}{T}k_{1}\right)}{T^{2}(1+\lambda_{k}^{2})}} = \frac{1}{T}\sqrt{\frac{S_{E}\left(\frac{2\pi}{T}k_{1}\right)}{1+\lambda_{k}^{2}}},$$

$$k = 0,1,..., M \ge N.$$

Then those coefficients provide the simulated signal:

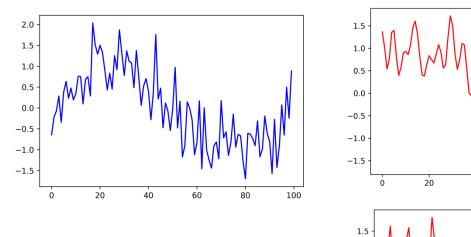
$$\mathbf{x}(i) = \sum_{k=0}^{\frac{N}{2}} \mathbf{X}_{\mathbf{F}}(k) \exp\left[\mathbf{j}2\pi\left(\frac{ki}{N}\right)\right], i \in [0, N).$$

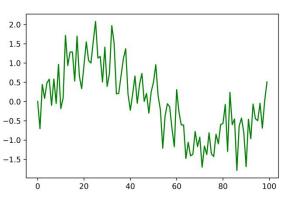
This is simulation in Fourier basis, you can use others: Hartley, etc.

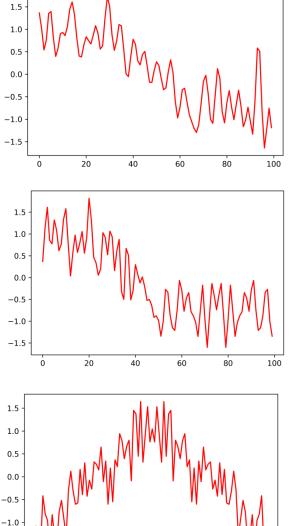
### I might have cheated a bit...

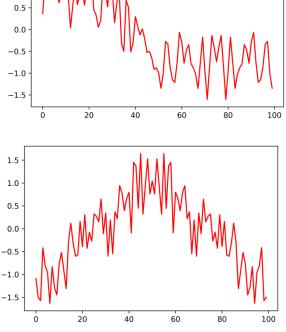
```
XF = np.sqrt(ESD)
XF /= XF.max() # just normalized sqrt(ESD)
# turning noise into random signs
n3 = np.random.normal(0,1,50)
n3 /= abs(n3)
import cmath
z = np.empty([100], dtype=complex)
for i in range(0, 100):
  z[i] = 0
  for k in range(0, 50):
    # adding random signs to get random signals
    z[i] += XF[k] * n3[k] * cmath.exp(1j * k * i *math.pi/100)
```

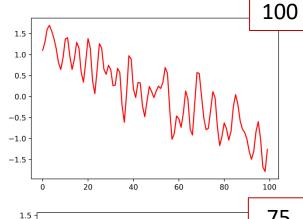
Spectral simulation Simulated from ESD Real

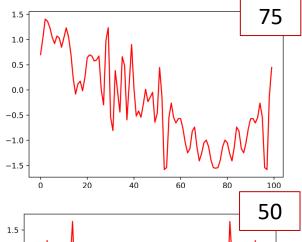


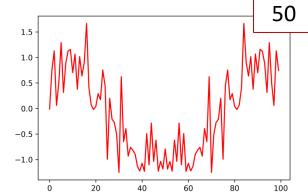












# 2D signals

### What kinds of data?

- 2D table data
- Spatial data
- Images
- Graphs

### What changes?

- 1D space + time or 2D space (t1, t2 instead of t)
- Spatial frequencies

Computers "see" with help of image processing. Graphs may represent semantic webs. DSP gets close to AI.

# What changes:

Fourier transform:

$$\mathcal{F}(x(t_1,t_2)) = X(f_1,f_2) = \int_{-\infty}^{+\infty} \int_{-\infty}^{+\infty} x(t_1,t_2)e^{-2\pi j(f_1t_1+f_2t_2)}dt_1dt_2.$$

Energy spectral density:

$$S_{E}(f_{1}, f_{2}) = \frac{1}{N} \sum_{i=1}^{N} |X_{i}(f_{1}, f_{2})|^{2} = \frac{1}{N} \sum_{i=1}^{N} |\mathcal{F}(x_{i}(t_{1}, t_{2}))|^{2}.$$

### What happens then:

We generate Fourier coefficients:

$$\begin{split} X_F(k_1,k_2) &= \sqrt{\frac{S_E\left(\frac{2\pi}{T_1}k_1,\frac{2\pi}{T_1}k_2\right)}{T_1^2T_2^2\left(1+\lambda_{k_1,k_2}^2\right)}} = \frac{1}{T_1T_2}\sqrt{\frac{S_E\left(\frac{2\pi}{T_1}k_1,\frac{2\pi}{T_1}k_2\right)}{1+\lambda_{k_1,k_2}^2}},\\ k_1,k_2 &= 0,1,..., \end{split}$$

Then those coefficients provide the simulated signal:

$$x(i_1, i_2) = \sum_{k_1=0}^{\frac{N_1}{2}} \sum_{k_2=0}^{\frac{N_2}{2}} X_F(k_1, k_2) \exp \left[ j2\pi \left( \frac{k_1 i_1}{T_1} + \frac{k_2 i_2}{T_2} \right) \right], i_1 \in [0, N_1), i_2 \in [0, N_2).$$

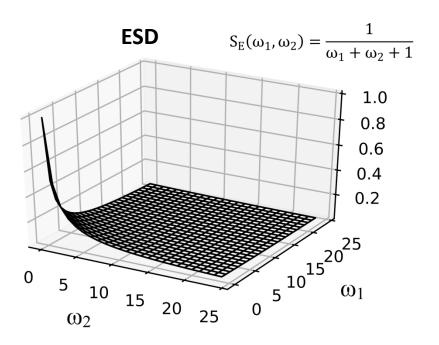
### What happens then:

We generate Fourier coefficients:

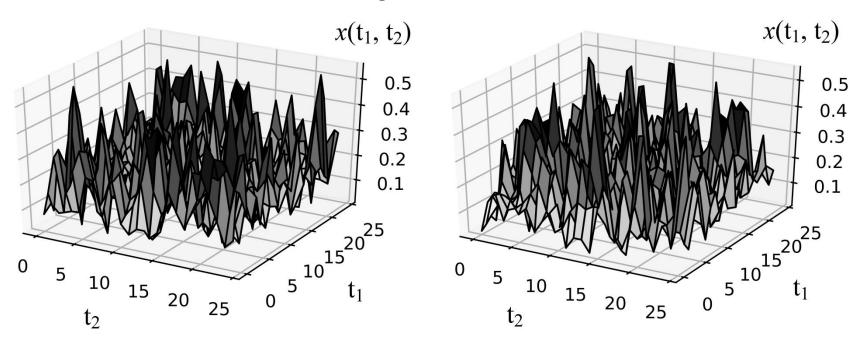
$$\begin{split} X_{F}(k_{1},k_{2}) &= \sqrt{\frac{S_{E}\left(\frac{2\pi}{T_{1}}k_{1},\frac{2\pi}{T_{1}}k_{2}\right)}{T_{1}^{2}T_{2}^{2}\left(1+\lambda_{k_{1},k_{2}}^{2}\right)}} = \frac{1}{T_{1}T_{2}}\sqrt{\frac{S_{E}\left(\frac{2\pi}{T_{1}}k_{1},\frac{2\pi}{T_{1}}k_{2}\right)}{1+\lambda_{k_{1},k_{2}}^{2}}},\\ k_{1},k_{2} &= 0,1,..., \end{split}$$

Then those coefficients provide the simulated signal:

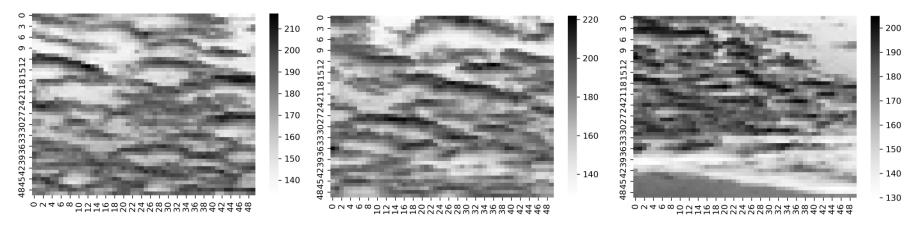
$$x(i_1, i_2) = \sum_{k_1=0}^{\frac{N_1}{2}} \sum_{k_2=0}^{\frac{N_2}{2}} X_F(k_1, k_2) \exp \left[ j2\pi \left( \frac{k_1 i_1}{N_1} + \frac{k_2 i_2}{N_2} \right) \right], i_1 \in [0, N_1), i_2 \in [0, N_2).$$



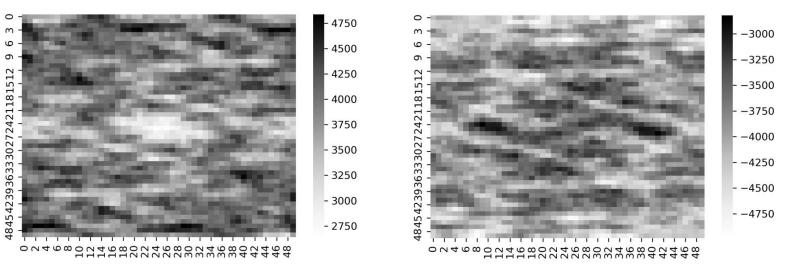
#### **Random Signals in Fourier basis**



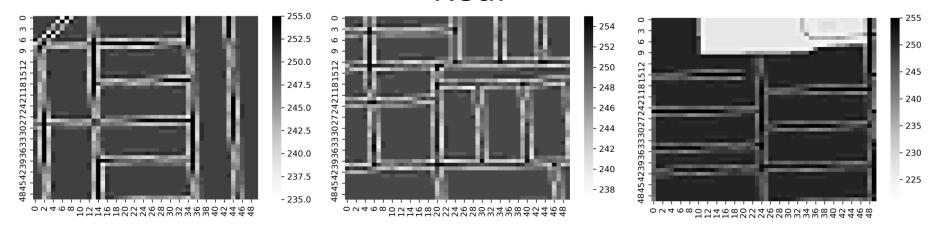
### Clouds Real



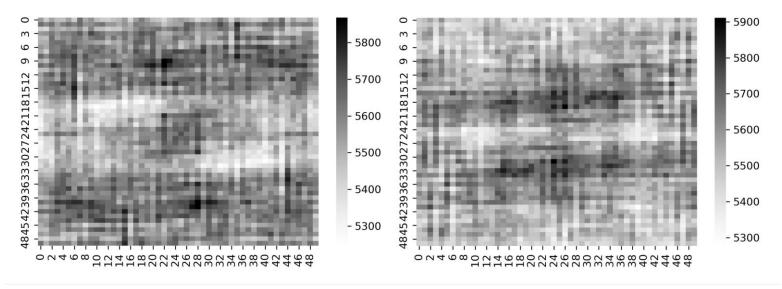
### Fourier simulated



### Streets Real



### Fourier simulated



Thanks!