# Use of conditional generative adversarial networks to improve representativity of data in optical spectroscopy

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### Raman spectroscopy inverse problem

• Main goal: detect dangerous components mixed in ethanol solutions;

- Components of interest:
  - o methanol
  - ethyl acetate
  - fusel oil
- Non-invasive observation method based on Raman spectroscopy;
- Inverse problem (multitask classification) solution by machine learning model

### Raman spectra



Raman spectra of ethanol (49%) solutions with different component concentrations: 1 - pure ethanol, 2 - fusel oil (5.6%), 3 - methanol (8%), 4 - ethyl acetate (6%)

### **Components concentrations**

- Full dataset: 40710 spectra
- Spectra dimension = 2048 channels
- <u>Problem:</u> wide concentration "gaps" in dataset





Principal component analysis of component concentrations

## Add empty concentrations

- create 2D grid based on PC1\PC2 coordinate space (PC-space);
- fill empty grid cells in PC-space;
- inverse transformation to the original concentrations;
- implement empirical constraints (eliminate negative values, values exceeds max concentrations)
- Component concentrations (%) at generated dataset: 1 - fusel oil, 2 - methanol, 3 - ethyl acetate



# **Conditional GAN**

#### Generator

Two inputs of model:

- z random noise
- y label annotation



#### Discriminator

Loss function minimization in case : {X (spectra) - real, Y (annotation) - true}.

- real spectra [X] - false;

Loss function maximization in cases:  $\downarrow$ 

- generated spectra [X\*], true;

- generated spectra [X\*], false

## Non-saturating heuristic

 Non-saturating heuristic - loss function without problem of small gradients;

 Heuristic because there are no theoretical prove\*;



$$\frac{d}{dx}\log(1-x) = \frac{-1}{1-x}$$
$$x = 0 \rightarrow slope = -1$$
$$x = 1 \rightarrow slope = -\infty$$

\*[1701.00160] NIPS 2016 Tutorial: Generative Adversarial Networks

## Neural network architectures

Generator network:

- Embedding layer for component vector (size: 256);
- 4 1D-Convolutional layers with LeakyRelu activation;
- Upsampling operation (2x) after each layer;

Discriminator network:

- 3 fully connected layers with Relu activation;
- 1 output neuron (real\generated image);

Inverse problem solver network:

- 2 fully connected layers network;
- categorical cross-entropy loss;

### Examples of generated spectra



Generated Raman spectra for low frequency band (left) & valence band (right)

### Results

|                    |                      |                  | Original spectra     | Original spectra           |
|--------------------|----------------------|------------------|----------------------|----------------------------|
|                    |                      | Original spectra | + additive noise 10% | + multiplicative noise 10% |
| Low frequency band | original dataset     | 77.0%            | 70.2%                | 55.9%                      |
|                    | cGAN + original data | 74.4%            | 69.3%                | 54.7%                      |
| Valence band       | original dataset     | 67.1%            | 62.4%                | 60.1%                      |
|                    | cGAN + original data | 67.4%            | 63.0%                | 57.5%                      |
| Full spectra       | original dataset     | 72.8%            | 69.7%                | 59.1%                      |
|                    | cGAN + original data | 75.4%            | 70.7%                | 60.4%                      |

The accuracy of the multiclass classification problem solution by neural networks model based on original and generated spectra

### Conclusions

• The Raman spectroscopy inverse problem was solved by neural network model;

• Conditional generative adversarial networks were implemented to improve representativity of data;

• The proposed approach demonstrates results improvement for full spectra data and noisy data

## Thank you for your attention!

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