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Complex-Valued Neural Networks for Radar Applications

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Outline

- Introduction
- Complex-Valued Neural Networks
- Non-circular complex Gaussian data classification
- Real-equivalent neural networks
- PolSAR image segmentation task
- Conclusions and perspectives

Motivation

- Given a large set of data $(z_i,\ l_i)$, find a map f such that $f(z_i) = l_i$
- f is a neural network based on real-valued features and operations ($f_{\mathbb{R}}$)

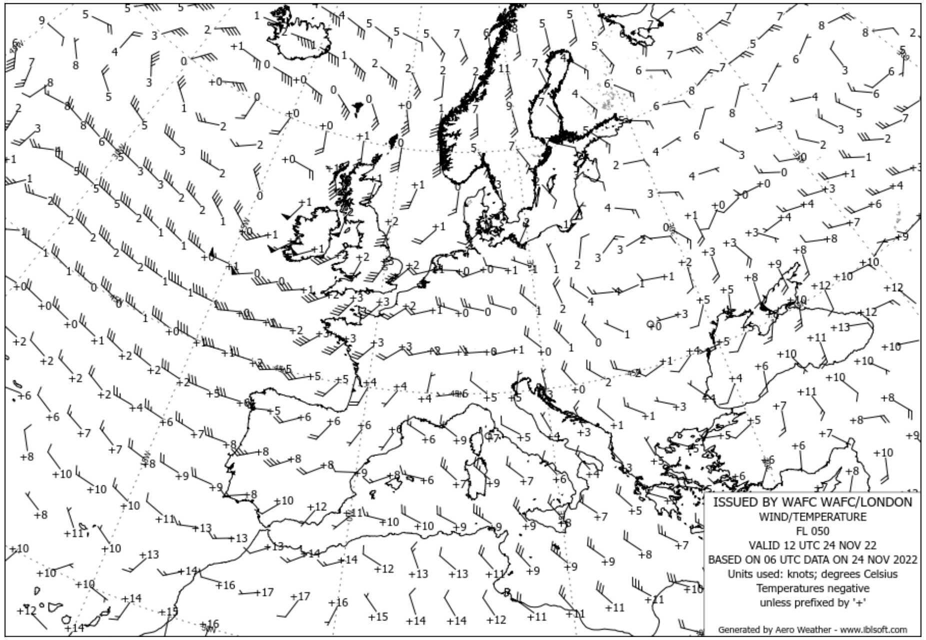
- Radar signals are generally complex-valued
  - Polarimetric channels
  - Interferometric channels
  - In-Phase and Quadrature channels with reduced Shannon sampling rate
- Radar processing are mainly based on complex filtering
  - Fourier Transform
  - Wiener
  - Wavelets

Can complex-valued neural networks ($f_{\mathbb{C}}$) exploit phase information to achieve better results than real-valued neural networks?

Motivation

- Convolutional operations are translation invariant, helping image recognition algorithms to detect objects regardless of their location
- Complex multiplication can naturally deal with phase and amplitude independently.
- Real values cannot rotate any complex value to a constant

Example: Rotate any complex value ϕ degrees.
Solution: By using $z_2 = \rho_2 \cdot e^{\phi} \to z_1 \cdot z_2 = \rho_1 \rho_2 \cdot e^{j(\phi_1+\phi)}$



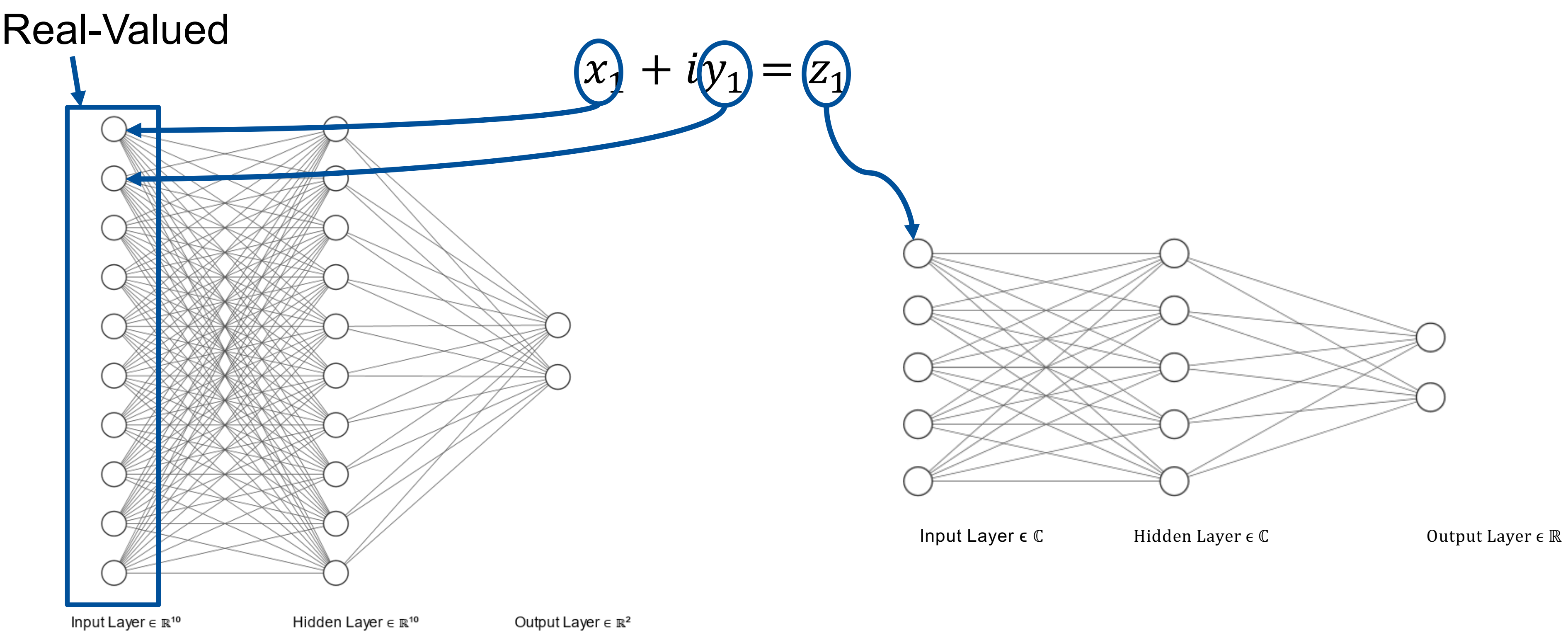
“In summary, the phase rotation and amplitude amplification/attenuation are the most important features of complex numbers” [1]

[1] A. Hirose, “Complex-Valued Neural Networks: Advances and Applications” *IEEE Press Series on Computational Intelligence*, 2013.

Outline

- Introduction
- Complex-Valued Neural Networks (CVNN)
    - Components
    - Implementation toolbox
- Non-circular Gaussian data classification
- Real-equivalent neural networks
- PolSAR image segmentation task
- Conclusions

Components: Input representation



Components: Convolutional Layer

Real part

0	0	0	0	0	0	...
0	156	155	156	158	158	...
0	153	154	157	159	159	...
0	149	151	155	158	159	...
0	146	146	149	153	158	...
0	145	143	143	148	158	...
...	...	...	...	...	...	...

Input Channel #1 (Red)

-1	-1	1
0	1	-1
0	1	1

Kernel Channel #1

308 $+$

Imaginary part

0	0	0	0	0	0	...
0	167	166	167	169	169	...
0	164	165	168	170	170	...
0	160	162	166	169	170	...
0	156	156	159	163	168	...
0	155	153	153	158	168	...
...	...	...	...	...	...	...

Input Channel #2 (Green)

1	0	0
1	-1	-1
1	0	-1

Kernel Channel #2

-498

Complex convolutional layer

0	0	0	0	0	0	…
0	1+j	j	4+3j	1	2+5j	…
0	5+6j	5+6j	1+4j	3+j	8j	…
0	2+2j	2+5j	9+5j	2+7j	7j	…
0	7+7j	4+j6	3+4j	6+2j	8+5j	…
0	6+7j	6+3j	3+3j	5+2j	2j	…
…	…	…	…	…	…	…

-1+j	-1	1
j	-j	-1-j
j	1	1-j

$= 18 - 5j$

$+ 1 = -25$

Bias = 1

Output

-25				...
				...
				...
				...
...	...	...	...	...

Components: Network functions

- ☑ Inputs
- ☑ Trainable parameters
- ☐ Functions

Activation Functions:

$$f(z) = g(x) + jh(y) \quad \text{(Type A)} \longrightarrow \mathbb{C}ReLU(z) = ReLU(x) + jReLU(y)$$

$$f(z) = g(|z|)e^{j\arg(z)} \quad \text{(Type B)}$$

Loss Functions:

1. Output activation function casts to real

   ex. $\mathrm{softmax}(z) = \left| \begin{array}{l} \mathrm{softmax}(\mathrm{softmax}(x) \cdot \mathrm{softmax}(y)) \\ (\mathrm{softmax}(x) + \mathrm{softmax}(y))/2 \\ \mathrm{softmax}(|z|) \end{array} \right.$

2. Loss function casts to real [2]

   ex. $Loss_{ACE} = \frac{1}{2}(Loss_{CCE}(x, \hat{x}) + Loss_{CCE}(y, \hat{y}))$

Optimizers:

Same as conventional real-valued neural networks!

[1] Kuroe, et al., "On activation functions for complex-valued neural networks“, *Artificial Neural Networks and Neural Information Processing - ICANN/ICONIP*. Springer, Berlin, Heidelberg, 2003.
[2] Cao, et al., "Pixel-wise PolSAR image classification via a novel complex-valued deep fully convolutional network“, *Remote Sensing*, 2019.

Components: Complex-Backpropagation

- ☑ Inputs
- ☑ Trainable parameters
- ☑ Functions
- ☐ Learning algorithm

To optimize the complex-valued weights, using a gradient descent technique, we need to compute the partial derivatives of the loss function $f : \mathbb{C} \to \mathbb{R}$ relatively to these weights

Liouville's theorem:

"Given f analytic (differentiable) and bounded in all the complex domain, then f is a constant function"

Wirtinger Calculus:

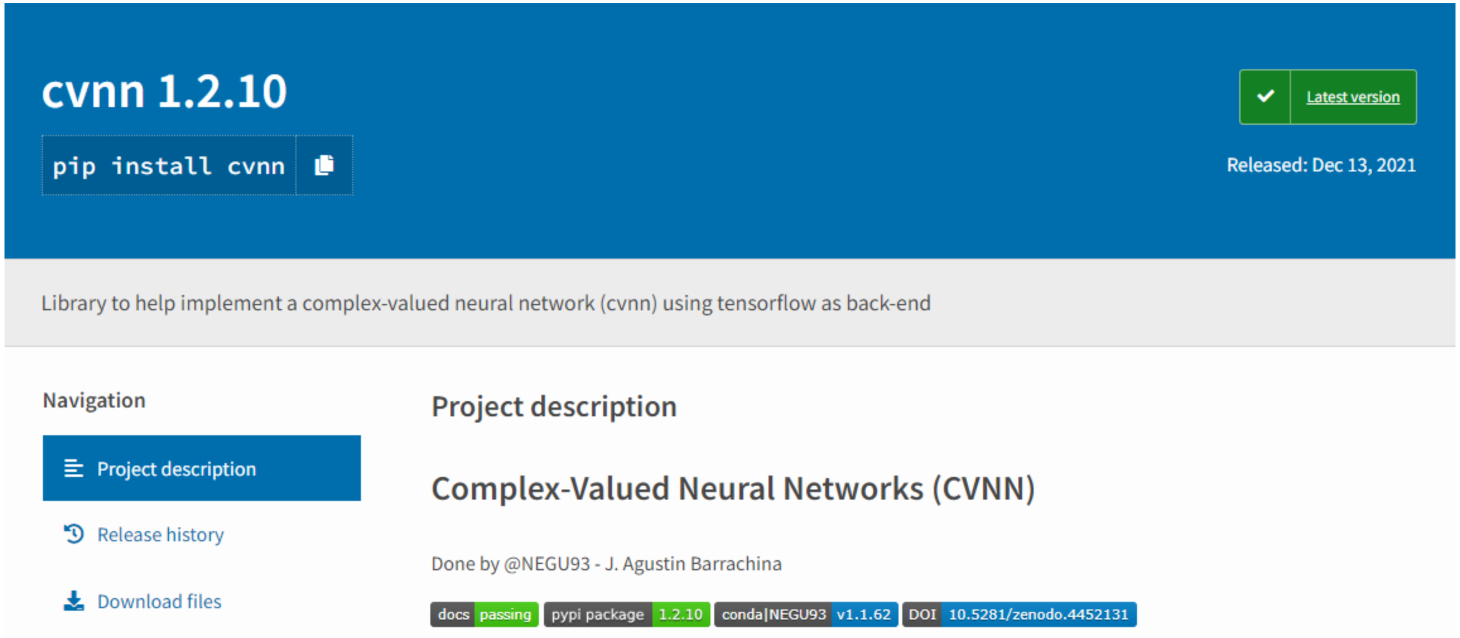
$$\frac{\partial f}{\partial z} \triangleq \frac{1}{2}\left(\frac{\partial f}{\partial x} - \mathrm{j}\frac{\partial f}{\partial y}\right) \qquad \frac{\partial f}{\partial \bar{z}} \triangleq \frac{1}{2}\left(\frac{\partial f}{\partial x} + \mathrm{j}\frac{\partial f}{\partial y}\right)$$

$$\nabla_z f \triangleq 2\frac{\partial f}{\partial \bar{z}} = \frac{\partial f}{\partial x} + \mathrm{j}\frac{\partial f}{\partial y}$$

[1] Fischer, Robert FH. Precoding and signal shaping for digital transmission. John Wiley & Sons, 2005.

Implementation toolbox 1/4

~~TensorFlow~~ ~~PyTorch~~



- Since v1.6 (28 July 2020), PyTorch now supports complex vectors and complex gradient.
- Since v1.12 (28 June 2022), Complex32 and Complex Convolutions in PyTorch.

But they are not yet ready to fully support CVNN implementation!

Implementation toolbox 2/4

cvnn lines 117.9k Public

Library to help implement a complex-valued neural network (cvnn) using tensorflow as back-end

Python ☆ 70 forks 19

CVNN-PolSAR lines 56.2k Public

Core code for simulations used for most of my publications

Python ☆ 2 forks 2

Complex-Valued Neural Networks (CVNN)

Done by @NEGU93 - J. Agustin Barrachina

docs passing | pypi package 1.2.14 | conda|NEGU93 v1.2.12 | DOI 10.5281/zenodo.4452131

Instalation Guide:

6 Open ✓ 24 Closed

Using Anaconda

```
conda install -c negu93 cvnn
```

Using PIP

Vanilla Version installs all the minimum dependencies.

```
pip install cvnn
```

Readme

MIT license

Cite this repository

70 stars

7 watching

18 forks

Used by 2

@mscarpiniti / **CoVal-SGAN**

@MeerkatPerson / **ml_project2**

Implementation toolbox 3/4

79.000+ PIP downloads!

Summary

PyPI link	https://pypi.org/project/cvnn
Total downloads	78,724
Total downloads - 30 days	2,900
Total downloads - 7 days	1,114

Implementation toolbox 4/4

cvnn
latest

Search docs

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- Getting Started
- Complex Layers
- Activation Functions
- Losses
- Complex Metrics
- Initializers
- Monte Carlo
- Data Analysis
- Code Examples
- Publication results
- About Me

Docs » Complex-Valued Neural Network (CVNN)

Complex-Valued Neural Network (CVNN)

Author: J. Agustin Barrachina

Version: 1.2.13 of 01/27/2022

Content

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  - Complex Dropout
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  - Elementary Transcentental Functions
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  - Complex Mean Square Error

Outline

- Motivation
- Complex-Valued Neural Networks
- Non-circular Gaussian classification
    - Circularity Property
    - Examples of generated data
    - Model Architecture
    - Results
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- Real-equivalent neural networks
- PolSAR image segmentation task
- Conclusions

Circular property

Complex random variable $Z = X + jY$ is *circular* if Z has the same distribution as $e^{j\phi}Z$

$$* \varrho_Z = \frac{\tau_Z}{\sigma_Z} \begin{cases} = 0 \rightarrow z \text{ is circular} \\ \neq 0 \rightarrow z \text{ not circular} \end{cases}$$

- $\tau_Z \triangleq \mathrm{E}[(Z - \mathrm{E}[Z])^2] = \sigma_X^2 - \sigma_Y^2 + 2j\sigma_{XY}$
- $\cancel{\sigma_Z^2 = \sigma_X^2 + \sigma_Y^2}$

Two sources of non-circularity [1]:

1. Unequal variances
2. Correlation

$$\rho = \frac{E[(x - E[x])(y - E[y])]}{\sqrt{E[(x - E[x])^2]E[(y - E[y])^2]}}$$

[1] E. Ollila, "On the Circularity of a Complex Random Variable," in *IEEE Signal Processing Letters*, 2008.

* For a Gaussian distribution

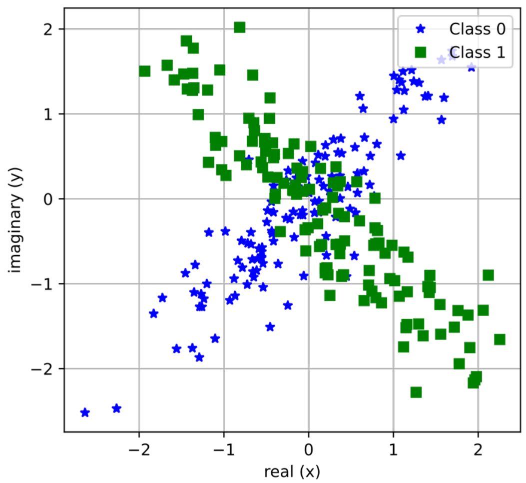
Examples of generated data

Both classes have the same $|\rho|$

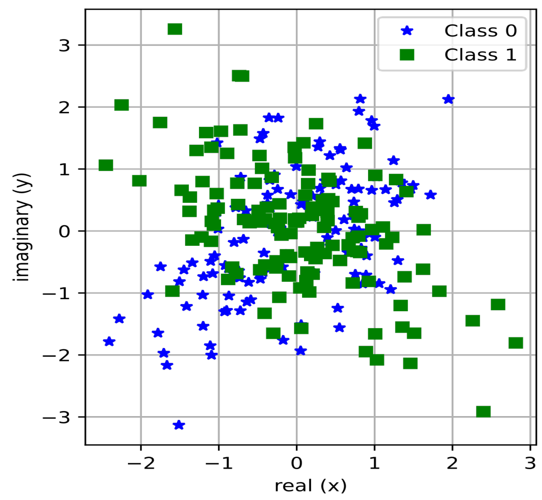
1 vector of class 0: $\rho_0 = |\rho|$

1 vector of class 1: $\rho_1 = -|\rho|$

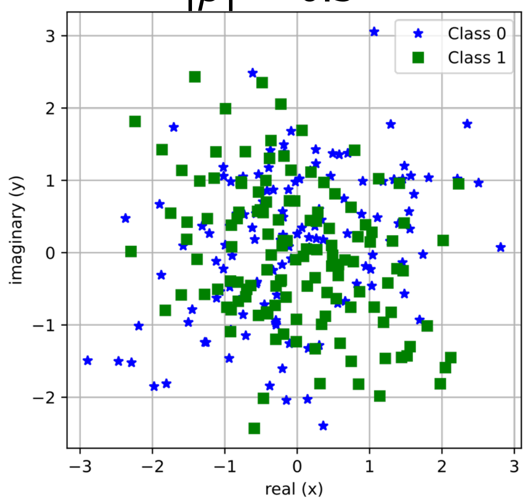
$|\rho| = 0.9$



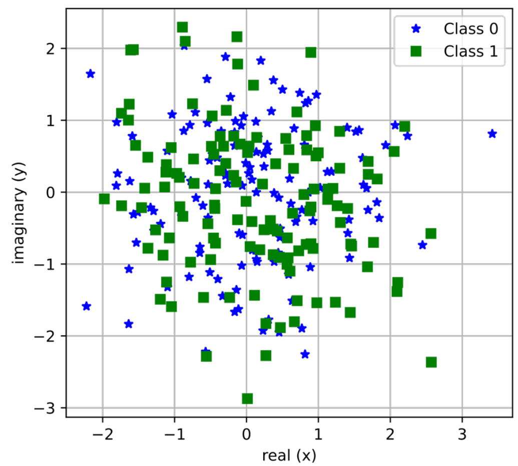
$|\rho| = 0.5$



$|\rho| = 0.3$



$|\rho| = 0.1$



**Note: Each point on the graph corresponds to one component of the input vector*

Model Architecture

Complex-Valued Multi-Layer Perceptron Model:

- Loss: Categorical cross-entropy
- Weight initialization: Glorot uniform
- SGD (Stochastic Gradient Descent)
  - Learning rate 0.1
  - Wirtinger Derivative

	CVNN	RVNN
Input Size	128	256
Hidden Layer Size	64 (1HL) [100, 40] (2HL)	128 [200, 80]
Activation Function	ReLU Type A [2]	ReLU
Dropout	50%	50%
Output Size	2	2
Output Activation	Softmax over absolute value	Softmax

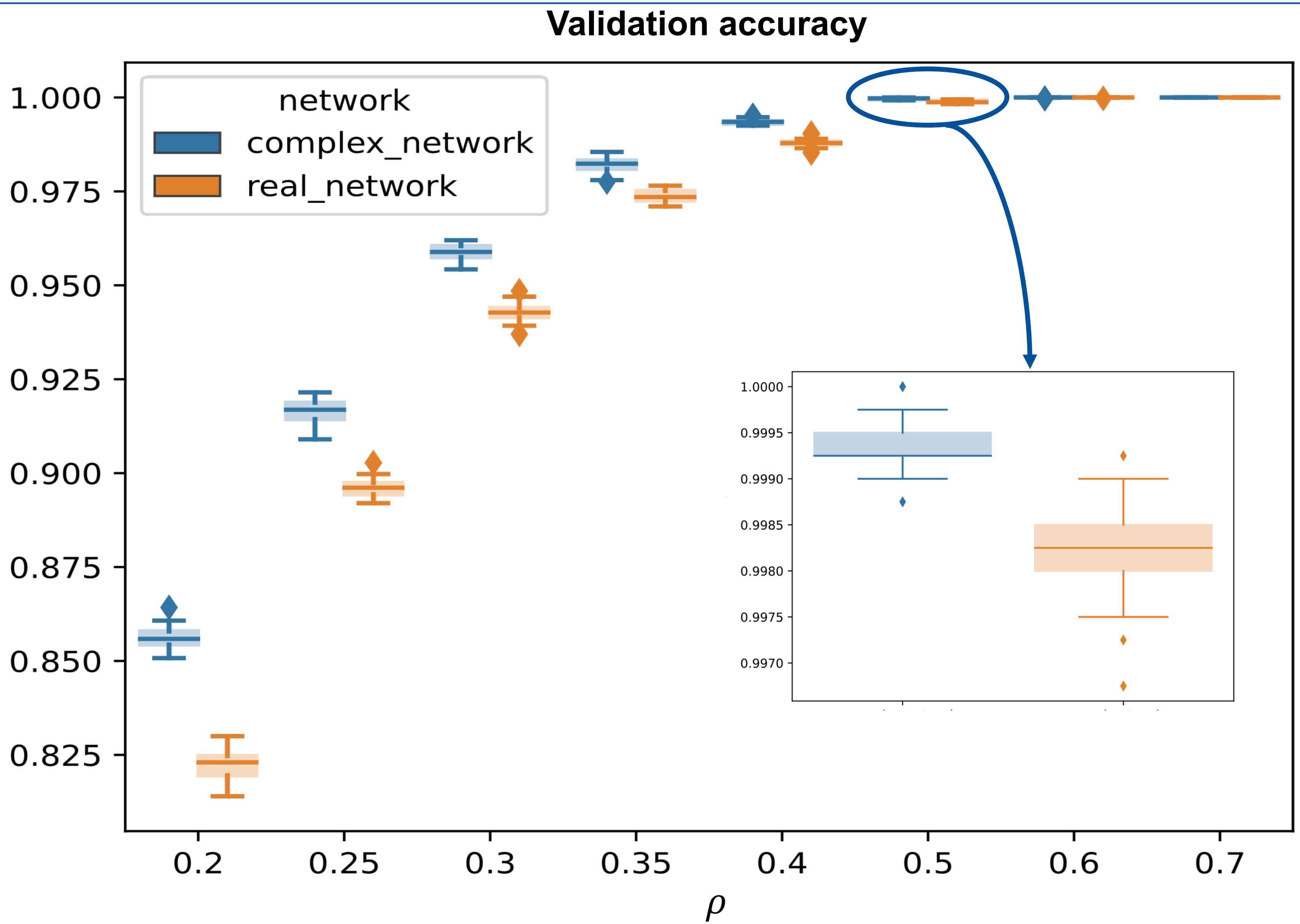
Dataset:

- Input vector size 128
- 8000 training vectors / class
- 2000 validation vectors / class

Simulation:

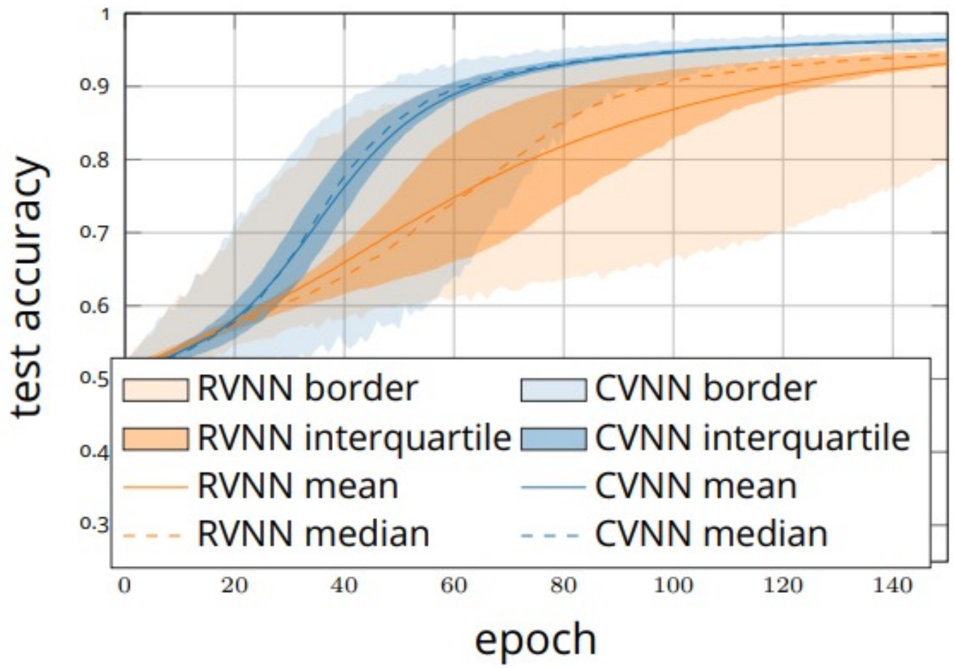
- 30 trials each model
- 300 epochs
- Batch size 100

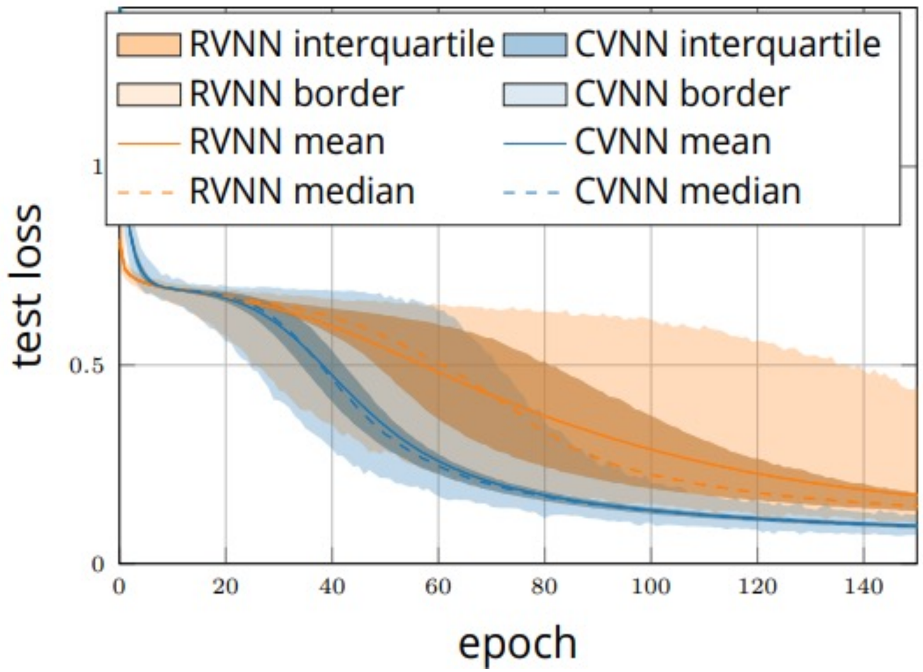
Results 1/3


Validation accuracy
network
complex_network
real_network
1.000
0.975
0.950
0.925
0.900
0.875
0.850
0.825
0.2
0.25
0.3
0.35
0.4
0.5
0.6
0.7
ρ
1.0000
0.9995
0.9990
0.9985
0.9980
0.9975
0.9970

Results 2/3

- CVNN converges faster

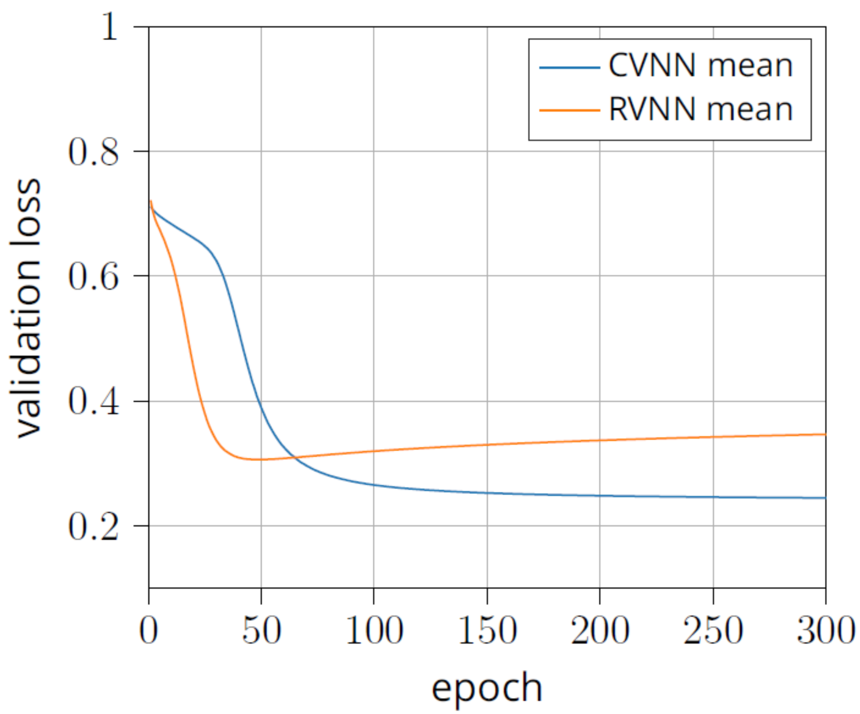




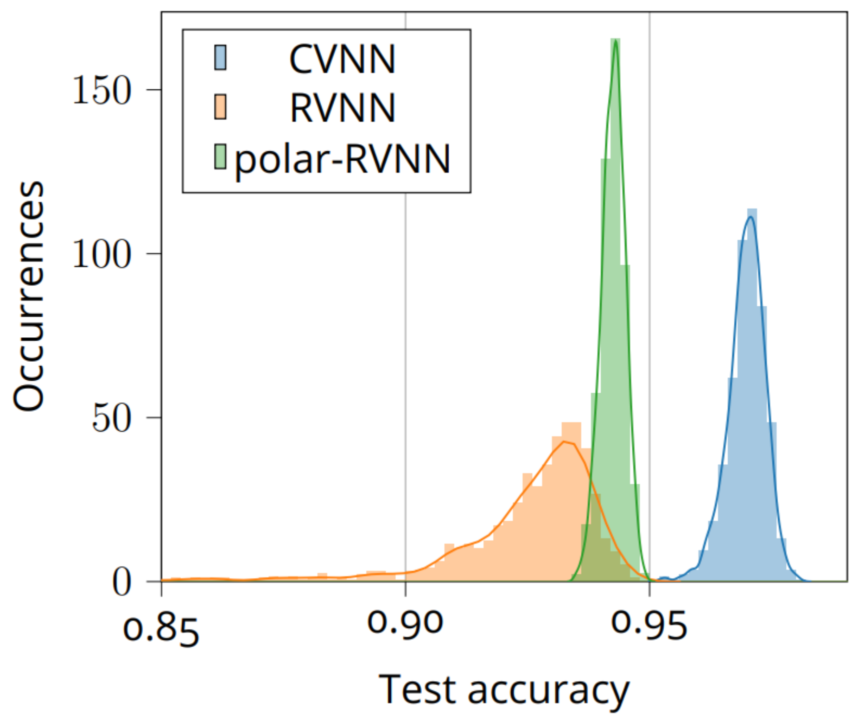
- $|\rho| = 0.3$
- 2 Hidden Layers

Results 3/3

Dropout influence



Input representation



- $|\rho| = 0.3$
- 2 Hidden Layers

Conclusions

- Almost 100 cases tested
  - Sources of Non-Circularity
  - Dropout influence
  - Number of layers
  - Input representation
  - Size of the hidden layers
  - Activation functions
  - Learning rate

- CVNNs generalize better
- In general, cases where RVNN outperformed CVNN
  - Under 60% accuracy

ICASSP 2021

[1] Barrachina, Jose Agustin, et al. "Complex-valued vs. real-valued neural networks for classification perspectives: An example on non-circular data." IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), 2021.

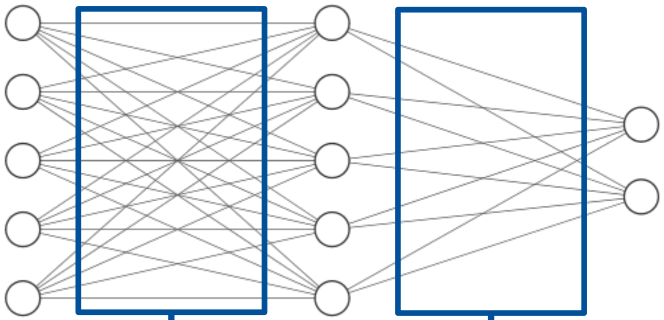
Outline

- Context / Motivation
- Complex-Valued Neural Networks
- Non-circular Gaussian classification
- Real-equivalent neural networks
  - Fully-connected neural networks
  - Convolutional neural networks
- PolSAR image segmentation task
- Conclusions

Multi-Layer Perceptron (MLP) 1/2

What is a real-equivalent network? [1]

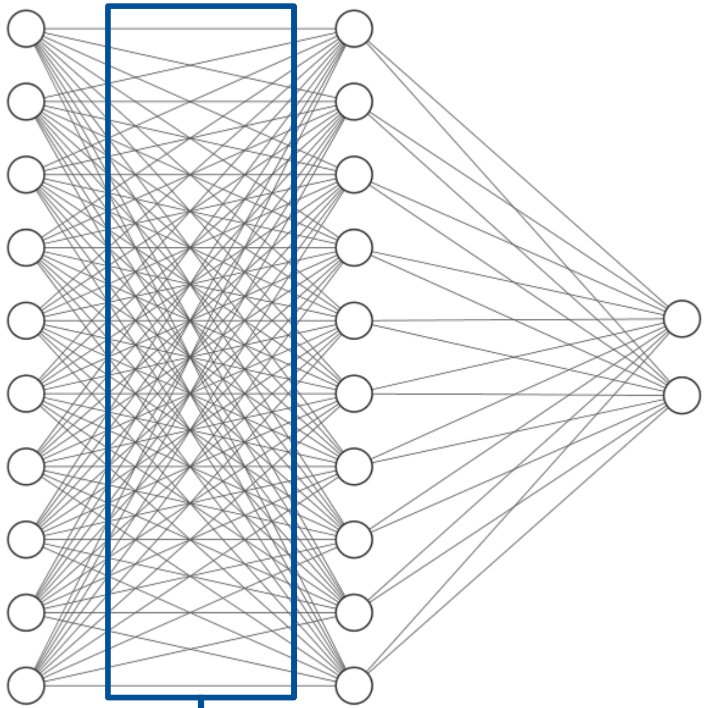
Complex Network



$$\begin{cases} 5 * 2 = 10_{\mathbb{C}} = 20_{\mathbb{R}} \\ 10 * 2 = 20_{\mathbb{R}} \end{cases}$$

$$\begin{cases} 5 * 5 = 25_{\mathbb{C}} = 50_{\mathbb{R}} \\ 10 * 10 = 100_{\mathbb{R}} \end{cases}$$

Real Network

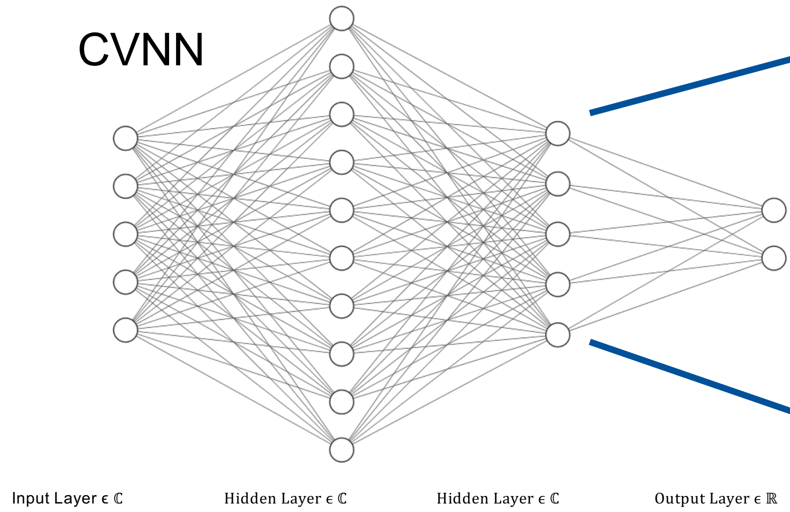


[1] Mönning, et al. "Evaluation of complex-valued neural networks on real-valued classification tasks." *arXiv preprint arXiv:1811.12351*, 2018

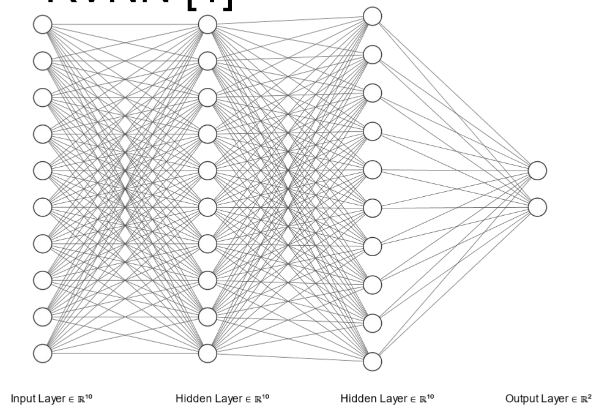
Multi-Layer Perceptron (MLP) 1/2

Equivalent in terms of trainable parameters (tp)

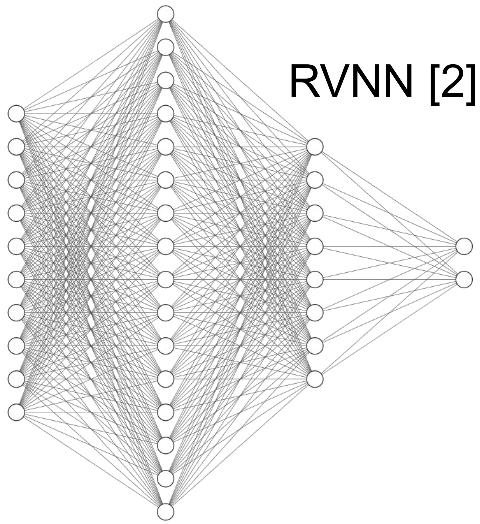
CVNN



RVNN [1]



RVNN [2]



$$N_i^{\mathbb{R}} = r N_i^{\mathbb{C}}, 1 \leq r < 2$$

Solution to: $tp = r N_0 N_1^{\mathbb{C}} + \sum_{i=1}^{K-1} r^2 N_i^{\mathbb{C}} N_{i+1}^{\mathbb{C}} + r N_K^{\mathbb{C}} N_L$

[1] Mönning, et al. "Evaluation of complex-valued neural networks on real-valued classification tasks." *arXiv preprint arXiv:1811.12351*, 2018
[2] Barrachina et al. "About the Equivalence Between Complex-Valued and Real-Valued Fully Connected Neural Networks-Application to Polinsar Images." *IEEE Machine Learning for Signal Processing (MLSP)*, 2021.

Convolutional Neural Networks (CNN)

$$\begin{cases} \mathrm{tp}_{\mathbb{C}} = 2\sum_{i=1}^{K} C_i^{\mathbb{C}} H_i^{\mathbb{C}} W_i^{\mathbb{C}} F_i^{\mathbb{C}} + \mathrm{F}_\mathrm{i}^{\mathbb{C}} \\ \mathrm{tp}_{\mathbb{R}} = \sum_{i=1}^{K} C_i^{\mathbb{R}} H_i^{\mathbb{R}} W_i^{\mathbb{R}} F_i^{\mathbb{R}} + \mathrm{F}_\mathrm{i}^{\mathbb{R}} \end{cases}$$

Assumptions

- $C_i = F_{i-1}$, F_0 input channel dimension
- $H_i^{\mathbb{C}} = H_i^{\mathbb{R}};\ W_i^{\mathbb{C}} = W_i^{\mathbb{R}}$

Equivalence

$$\mathrm{F}_\mathrm{i}^{\mathbb{R}} = \mathrm{r}\ \mathrm{F}_\mathrm{i}^{\mathbb{C}}, \forall r \in \mathbb{R}$$

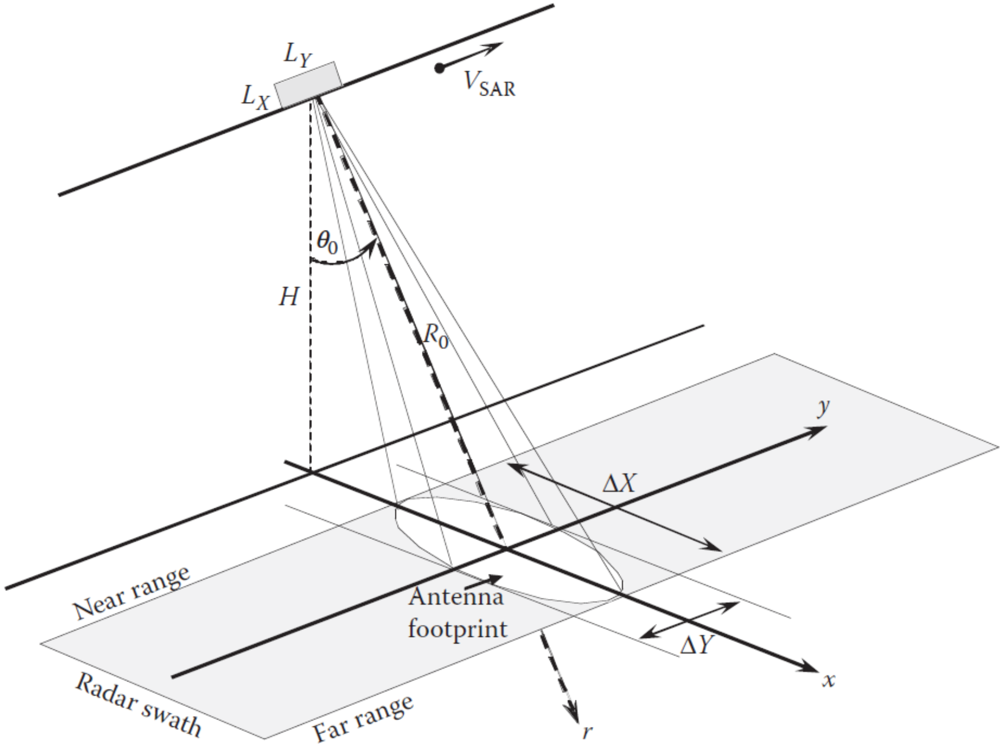
$$\mathrm{r} = -\cancelto{0}{\frac{b}{2a}} + \sqrt{2 + \cancelto{0}{\frac{b}{a}} + \cancelto{0}{\frac{b^2}{4a^2}} + \frac{1}{a}\sum_{i=1}^{K} F_i} \xrightarrow{\text{for large } a} \sqrt{2}$$

$$\begin{cases} a = \sum_{i=2}^{K} F_{i-1}^{\mathbb{C}} H_i\ W_i\ F_i^{\mathbb{C}} \\ b = 2F_0^{\mathbb{C}} H_1\ W_1\ F_1^{\mathbb{C}} + \sum_{i=1}^{K} F_i \end{cases}$$

Outline

- Context / Motivation
- Complex-Valued Neural Networks
- Non-circular complex Gaussian classification
- Real-equivalent neural networks
- PolSAR image segmentation task
    - Fully-Convolutional Neural Networks (FCNN)
    - Baseline experiments
    - Studies on input representation
    - Subsets correlation reduction
    - Accuracy balancing
- Conclusions / Perspectives

PolSAR theory



Polarimetric data

Sinclair vector

$$S = (S_{HH}, \sqrt{2}S_{HV}, S_{VV})^T$$

Pauli vector

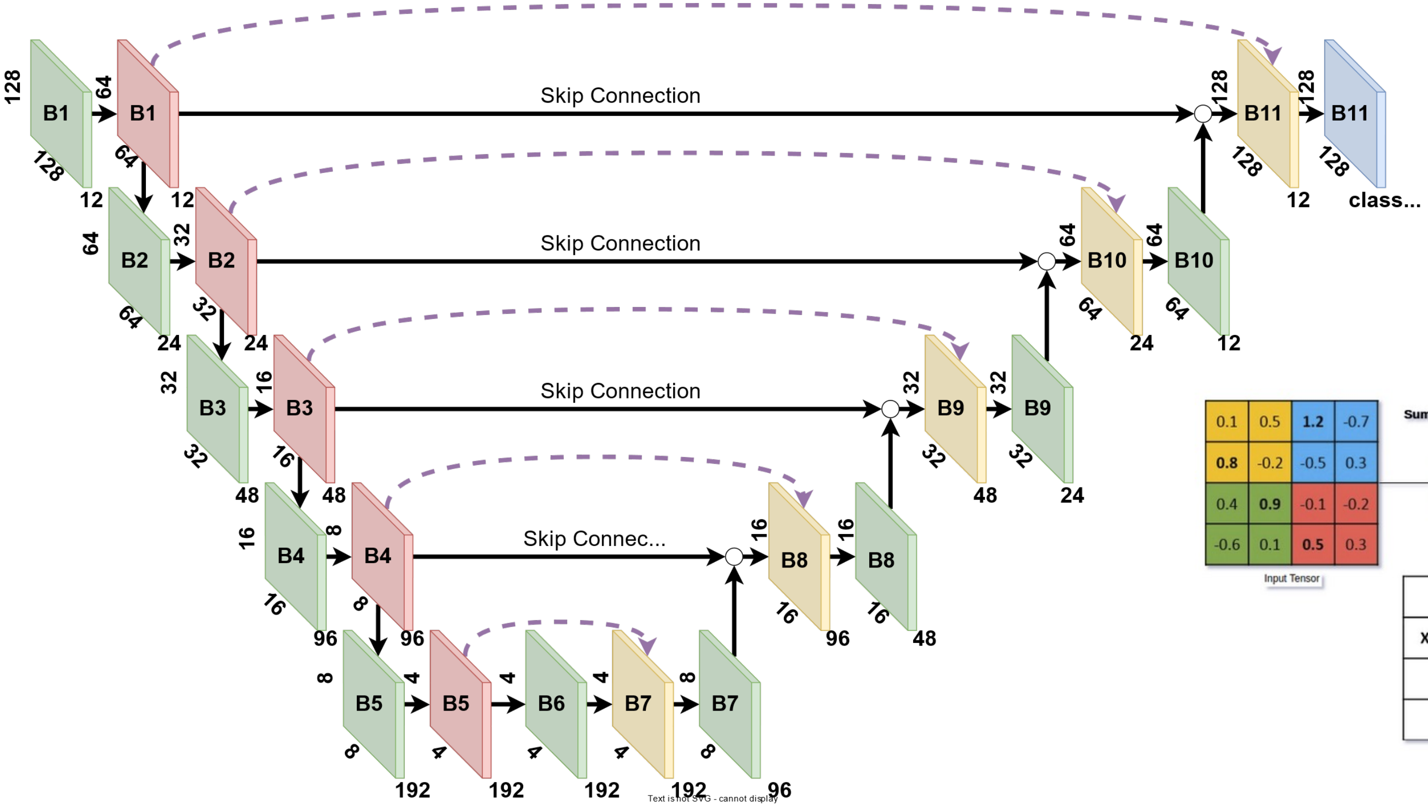
$$k = \frac{1}{\sqrt{2}}\begin{pmatrix} S_{HH} + S_{VV} \\ S_{HH} - S_{VV} \\ 2S_{HV} \end{pmatrix}$$

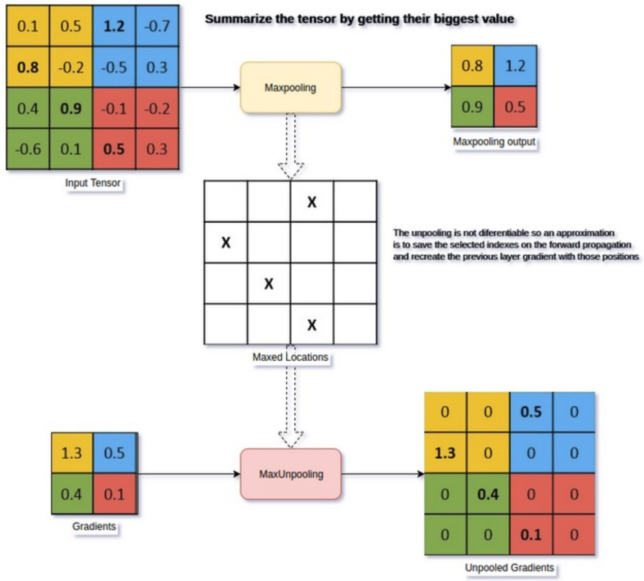
Coherency matrix

$$\mathrm{T} = \frac{1}{n}\sum_{j}^{n} k_j k_j^H ,$$

[1] Lee, Jong-Sen, and Pottier, Eric. ”Polarimetric radar imaging: from basics to applications”. *CRC press*, 2017.

Fully-convolutional Neural Networks (FCNN)





[1] Cao, et al. "Pixel-wise PolSAR image classification via a novel complex-valued deep fully convolutional network." *Remote Sensing,* 2019.
[2] Trabelsi, et al. "Deep complex networks”. *arXiv preprint arXiv: 170509792*, 2017.
[3] Zafar, et al. “Hands-on convolutional neural networks with TensorFlow” *Packt Publishing Ltd*, 2018.

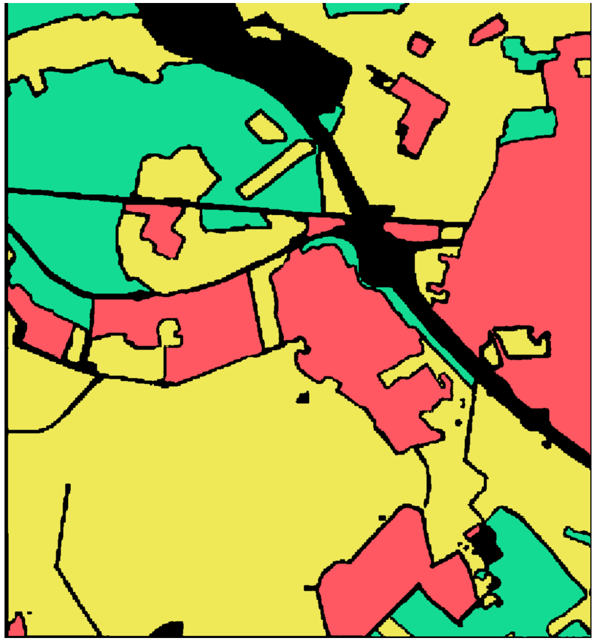
Baseline experiments: Oberfpaffenhofen data

E-SAR (Open-sourced: European Space Agency)
- German Aerospace Center (DLR) & Microwaves and Radar Institute
- L-Band
- 1988
- Size 1300x1200

Polarimetric Interferometric data
- $\mathbb{C}^{6\times 6}$ Hermitian
- Real-valued diagonal
- Total 21 values

PolInSAR image

Labels



A Built-up Area B Wood Land C Open Area

Sliding Window Operation (SWO)

[1] Li, Y, et al., "A Novel Deep Fully Convolutional Network for PolSAR Image Classification". *Remote Sensing,* 2018,

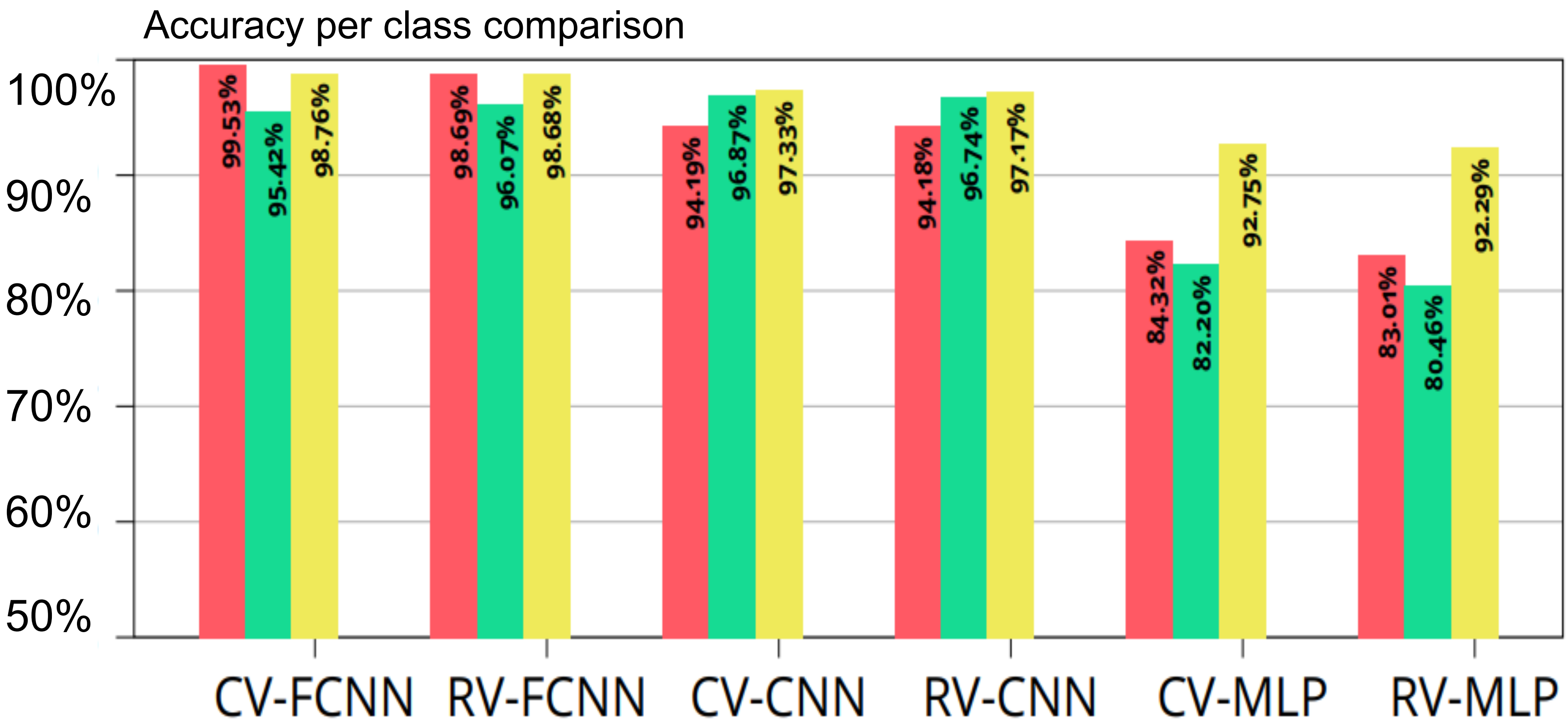
Baseline experiment: Oberpfaffenhofen results

Accuracy	FCNN [1]		CNN [2-5]		MLP [6]	
	CV	RV	CV	RV	CV	RV
Overall	**98.55±0.21**	98.23±0.15	96.45±0.04	96.32±0.04	88.87±0.03	88.03±0.13
Average	**98.14±0.28**	97.79±0.30	95.69±0.05	95.50±0.06	85.25±0.05	84.38±0.16

*On Oberpfaffenhofen PolSAR dataset

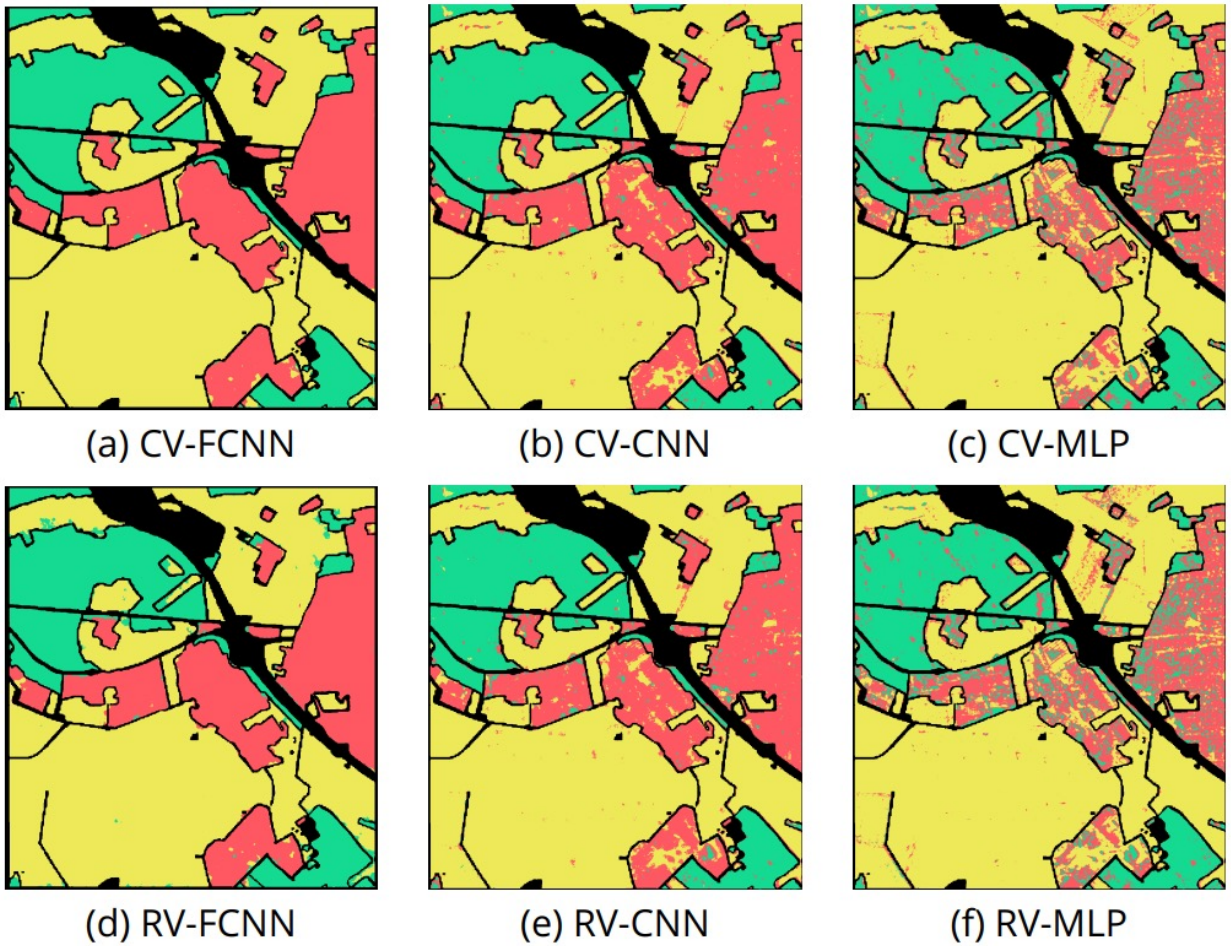
[1] Cao, et al., "Pixel-wise PolSAR image classification via a novel complex-valued deep fully convolutional network." *Remote Sensing*, 2019.
[2] Zhang, et al., "Complex-valued convolutional neural network and its application in polarimetric SAR image classification." *IEEE Transactions on Geoscience and Remote Sensing*, 2017.
[3] Zhao, et al. "Contrastive-regulated CNN in the complex domain: A method to learn physical scattering signatures from flexible PolSAR images." *IEEE Transactions on Geoscience and Remote Sensing*, 2019.
[4] Zhao, et al. "Learning physical scattering patterns from PolSAR images by using complex-valued CNN." *IGARSS 2019-2019 IEEE International Geoscience and Remote Sensing Symposium. IEEE*, 2019.
[5] Qin, et al. "Superpixel-oriented classification of PolSAR images using complex-valued convolutional neural network driven by hybrid data." *IEEE Transactions on Geoscience and Remote Sensing,* 2020.
[6] Hänsch, Ronny. "Complex-valued multi-layer perceptrons - an application to polarimetric SAR data." *Photogrammetric Engineering & Remote Sensing,* 2010.

Baseline experiment: Oberpfaffenhofen results



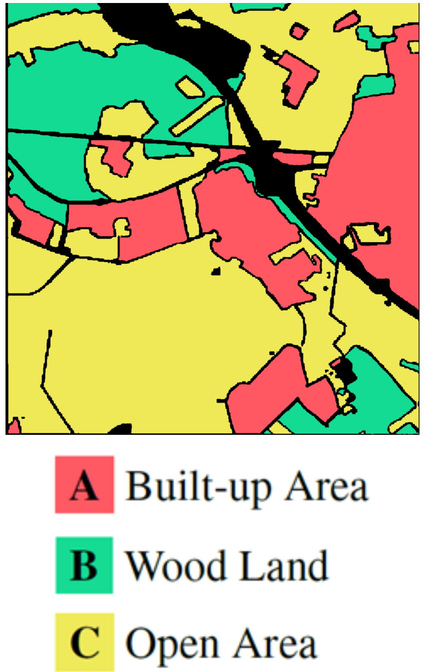
- Model architecture has higher impact than data type
- Complex-valued networks perform better than their real equivalent

Baseline experiment: Oberpfaffenhofen results



Median Overall Accuracy (OA) model predictions for each model

Ground Truth



MLSP 2021
JSPS 2022

[1] Barrachina, et al. “About the equivalence between complex-valued and real-valued fully connected neural networks - application to PolInSAR images” *IEEE Machine Learning for Signal Processing (MLSP)*, 2021
[2] Barrachina, et al. "Comparison Between Equivalent Architectures of Complex-valued and Real-valued Neural Networks-Application on Polarimetric SAR Image Segmentation." *Journal of Signal Processing Systems*, 2022.

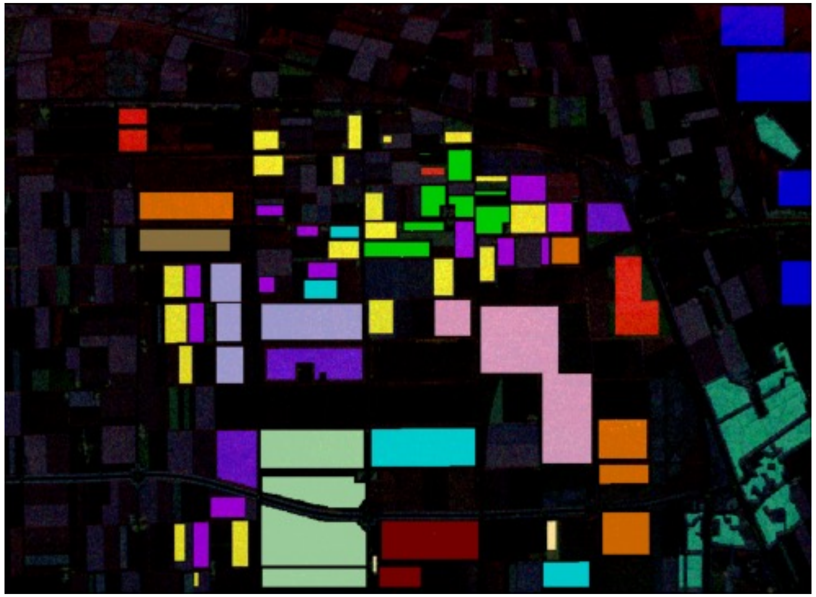
Baseline experiment: Flevoland data

Airbone Syntetic Aperture Radar (AIRSAR)

- NASA / Jet Propulsion Laboratory (JPL)
- Maestro-1 Campaign
- L-Band
- 1989
- Size 750x1024

PolSAR image

Labels [1]



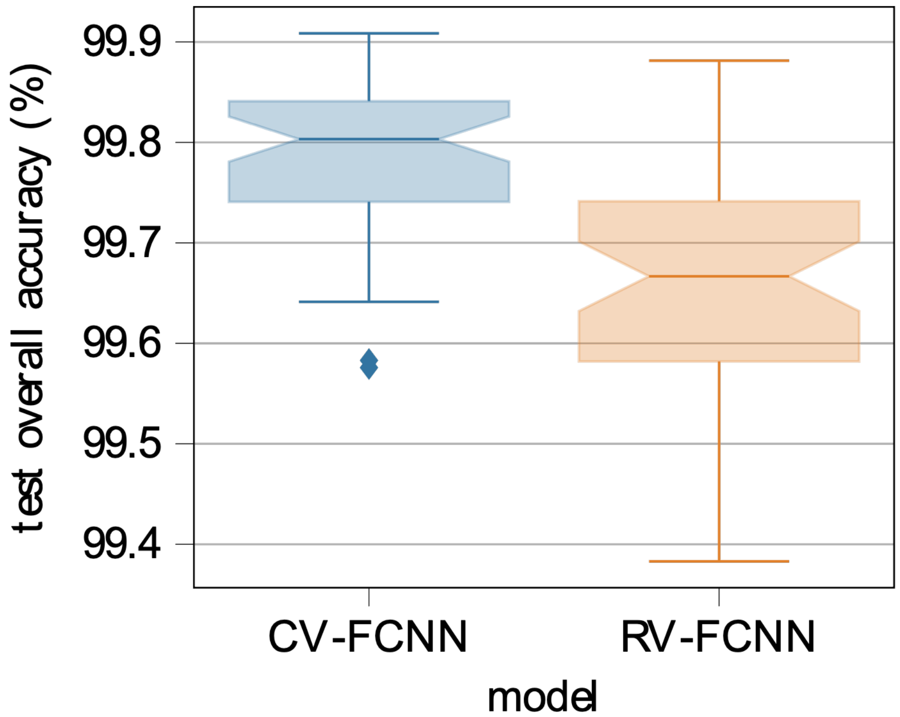
[1] Z. Zhang, et al. "Complex-Valued Convolutional Neural Network and Its Application in Polarimetric SAR Image Classification," *IEEE Transactions on Geoscience and Remote Sensing*, 2017.

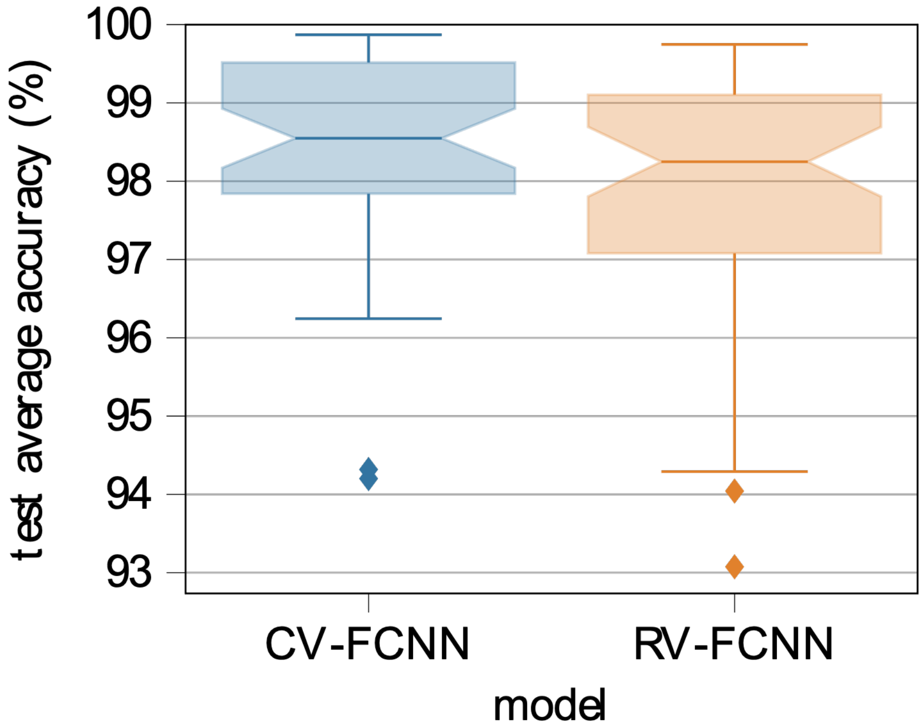
Baseline experiment: Flevoland results 1/4

		CV-FCNN	RV-FCNN
Overall Accuracy	Median	**99.80±0.02**	**99.67±0.03**
	Mean	**99.79±0.01**	**99.66±0.02**
	IQR	99.74-99.84	99.58-99.74
	Full range	99.58-99.91	99.38-99.88
Average Accuracy	Median	98.55±0.38	98.25±0.44
	Mean	98.35±0.19	97.87±0.23
	IQR	97.84-99.52	97.08-99.10
	Full range	94.20-99.87	93.07-99.75

FCNN test accuracy results

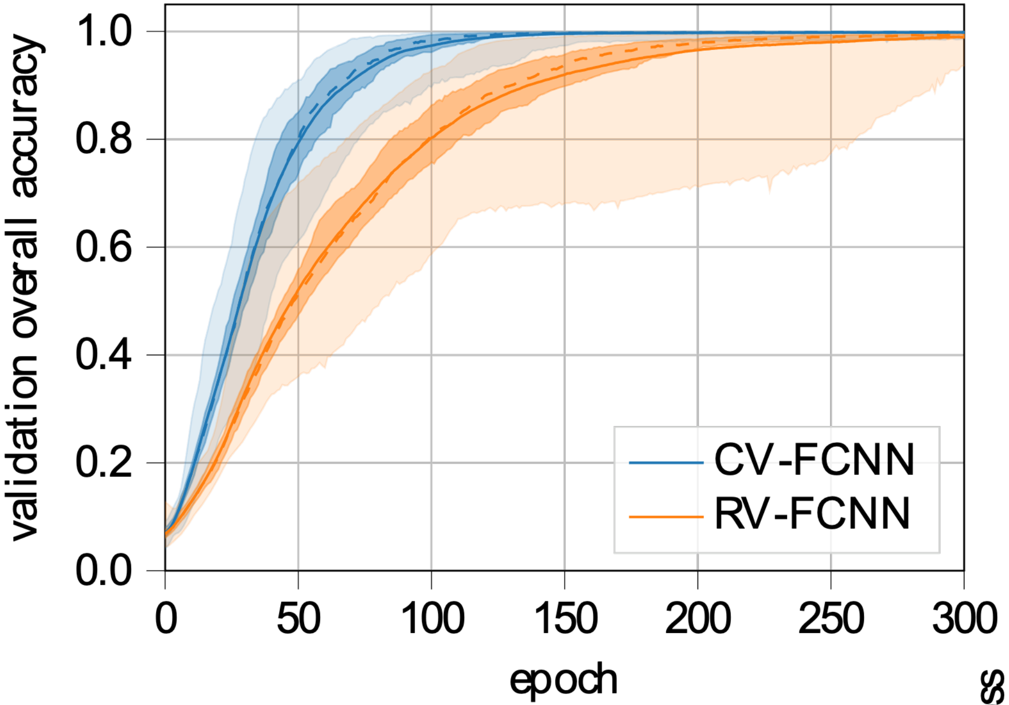
Baseline experiment: Flevoland results 2/4



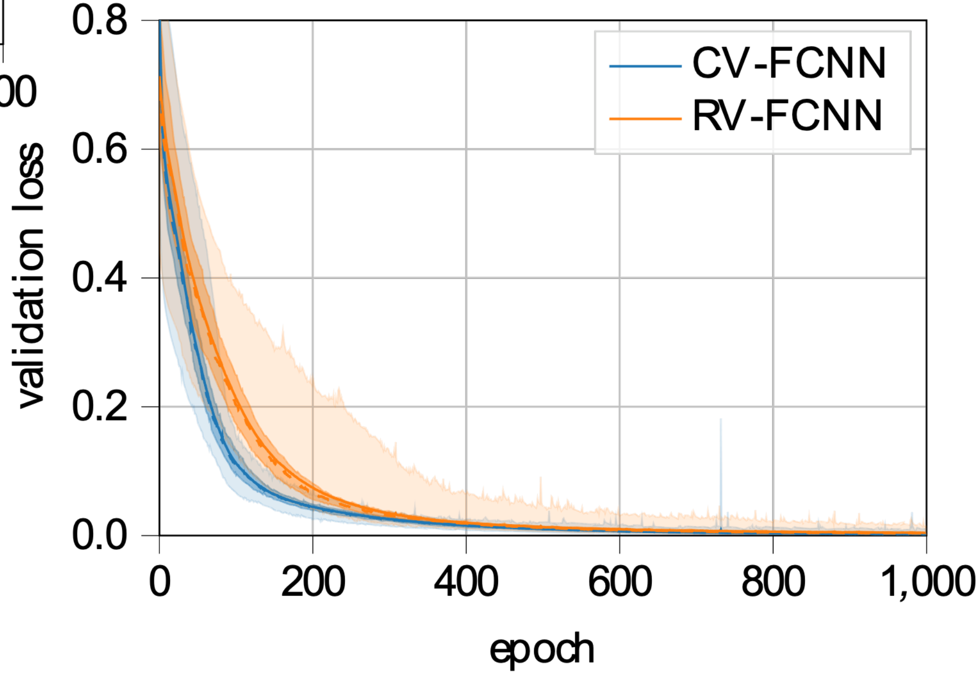


“if median intervals do not overlap, there is a 95% confidence that their values differ”
R. McGill et al., “Variations of box plots,” *The American Statistician*, 1978

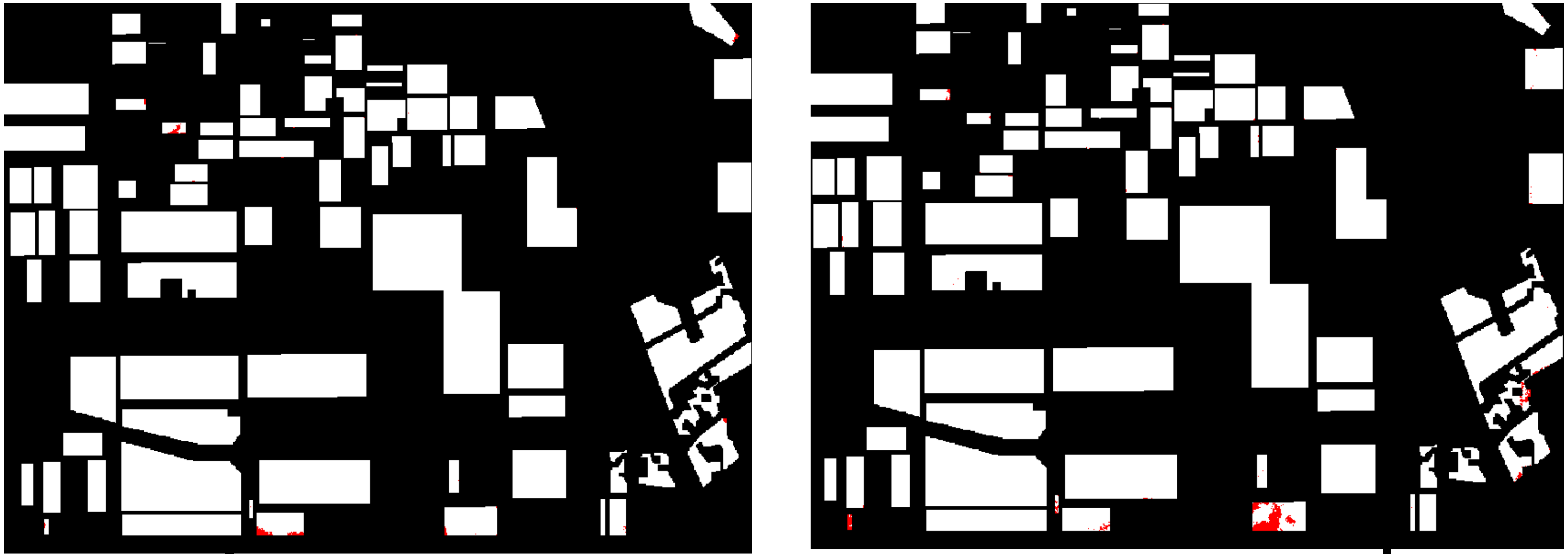
Baseline experiment: Flevoland results 3/4



- CVNN converges faster



Baseline experiment: Flevoland results 4/4



(a) CV-FCNN (b) RV-FCNN

GRETSI 2022

[1] Barrachina, et al. "Merits of Complex-Valued Neural Networks for PolSAR image segmentation" *GRETSI XXVIIIème Colloque Francophone de Traitement du Signal et des Images,* Nancy, France, 2022

Baseline experiment: Flevoland conclusions

CVNN outperformance over an equivalent-RVNN is almost undeniable

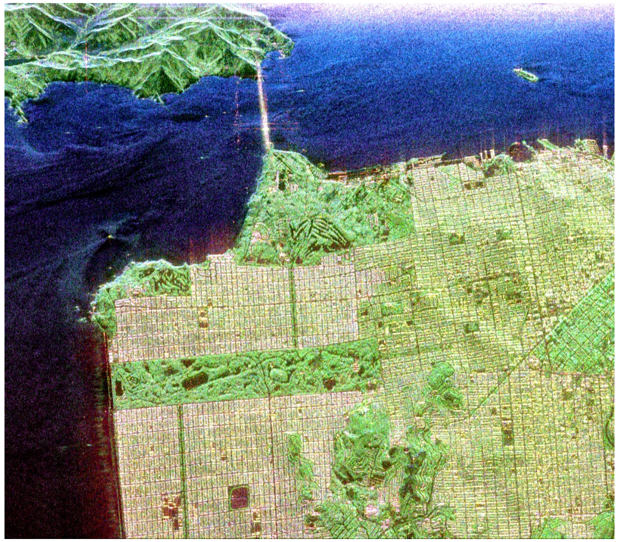
- Run the experiment for 3 different models (MLP, CNN, FCNN)
- Results show complex models have
  - Higher OA and AA
  - Less overfitting
  - Less variance on results
  - Faster convergence

Studies on Input Representation: SF data

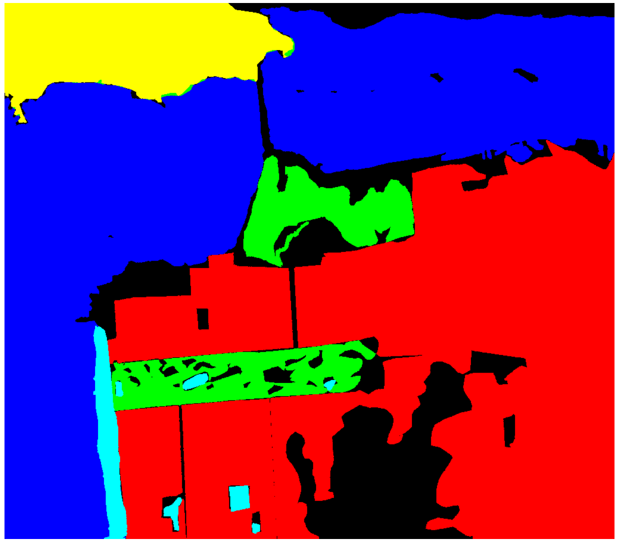
Airbone Syntetic Aperture Radar (AIRSAR)
- NASA / Jet Propulsion Laboratory (JPL)
- L-Band
- 10x10 m^2 spatial resolution [1]
- August 1989
- Resolution 900x1024

Polarimetric Pauli vector
- $\mathbb{C}^3$
- All complex-valued
- Total 3 values

PolSAR image



Labels [1]



A Mountain; B Water; C Urban; D Vegetation; E Bare Soil

Polarimetric Coherency matrix
- $\mathbb{C}^{3\times3}$ Hermitian
- Real-valued diagonal
- Total 6 values

Coherency matrix
- Has real-valued diagonal
- Performs average of adjacent pixels (loss of information)

[1] Liu, X, et al., "PolSF: PolSAR Image Datasets on San Francisco." *IFIP Advances in Information and Communication Technology, Springer, 2022* .

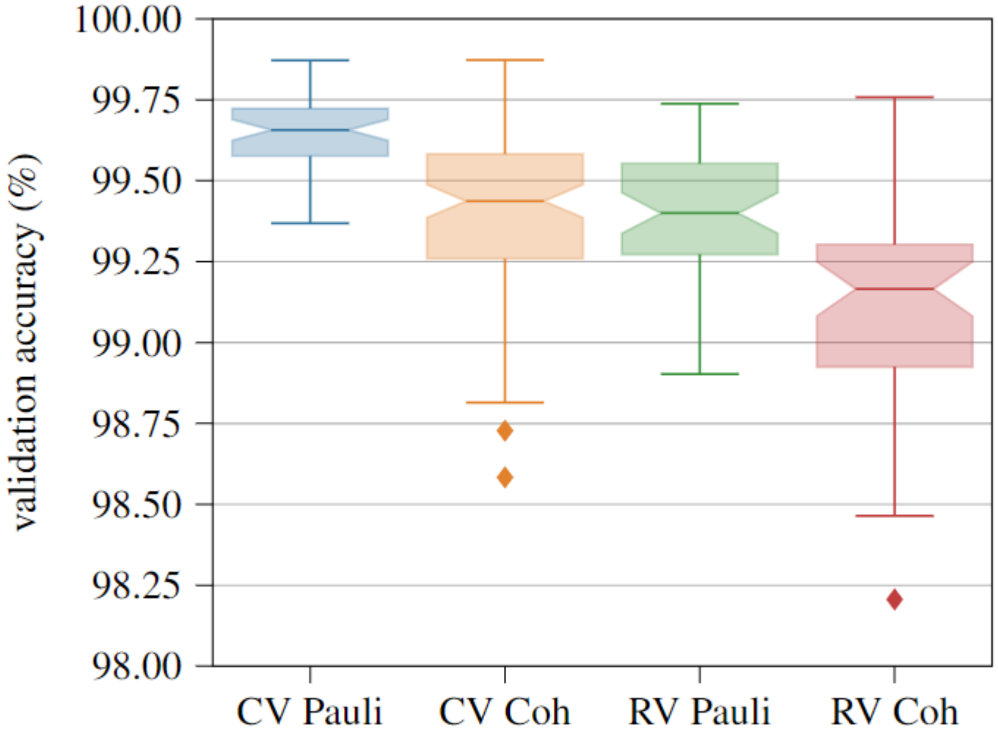
Studies on Input Representation: Results 1/2

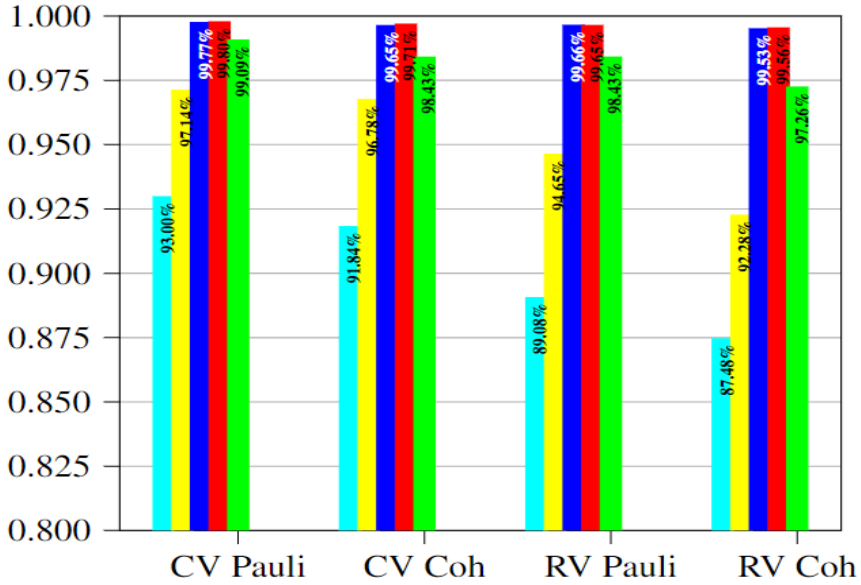
		CV-FCNN		RV-FCNN	
		Pauli Vector	Coherency Matrix	Pauli Vector	Coherency Matrix
Average Accuracy	Median	**98.00±0.27**	96.80±0.25	96.75±0.32	95.20±0.44
	Mean	**97.55±0.15**	96.54±0.12	96.39±0.18	94.98±0.21
	Full range	**93.90-98.79**	93.44-98.63	92.37-97.69	91.06-97.64
Overall Accuracy	Median	**99.64±0.01**	99.45±0.02	99.40±0.02	99.19±0.03
	Mean	**99.64±0.01**	99.44±0.01	99.40±0.01	99.18±0.02
	Full range	**99.53-99.70**	98.91-99.61	99.16-99.53	98.76-99.43

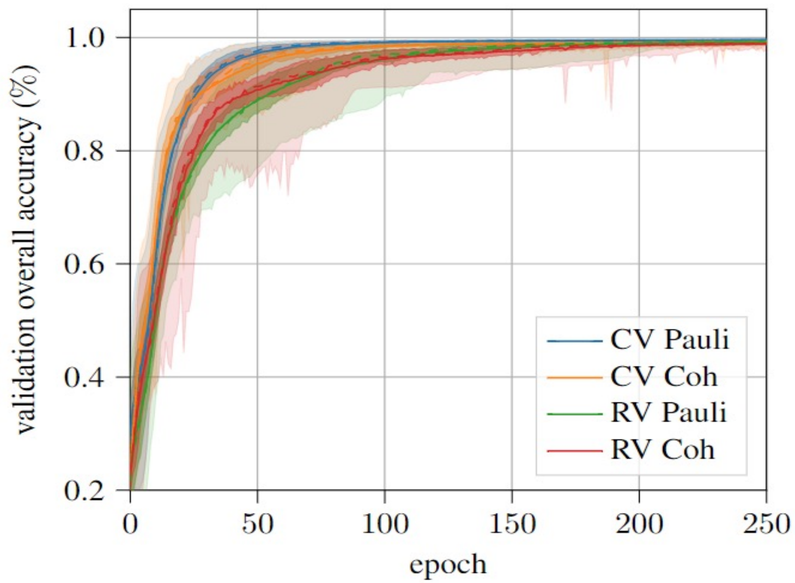
FCNN test accuracy results

Studies on Input Representation: Results 2/2

FCNN







- The performance improvement of using Pauli instead of coherency or a complex model instead of a real model is similar

Studies on Input Representation: Conclusions

We showed that FCNN or related models used for PolSAR segmentation tasks can profit independently from both:

- Using a Complex-Valued Neural Network instead of a Real-Valued Neural Network
- Using Pauli vector as an input representation instead of the Coherency matrix
  - This has the extra benefit of using less memory space (half for CVNN and 2/3 for RVNN).

[1] Barrachina, et al. "Real- and Complex-Valued Neural Networks for SAR image segmentation through different polarimetric representations" *IEEE International Conference on Image Processing (ICIP),* Bordeaux, France, 2022.

Subsets correlation reduction: Bretigny data

ONERA proprietary

- X-Band
- 1.32x1.38 m^2 spatial resolution [1]
- 30 incidence angle
- Resolution: 1533x3392

Train Validation Test

- Very High Accuracy (around 99%)
- SWO may generate overlapping sets
- Images from patches may be very close to each other
- Allows for oversampling

[1] P. Formont, et al., "Statistical Classification for Heterogeneous Polarimetric SAR Images", *Selected Topics in Signal Processing*, 2011.

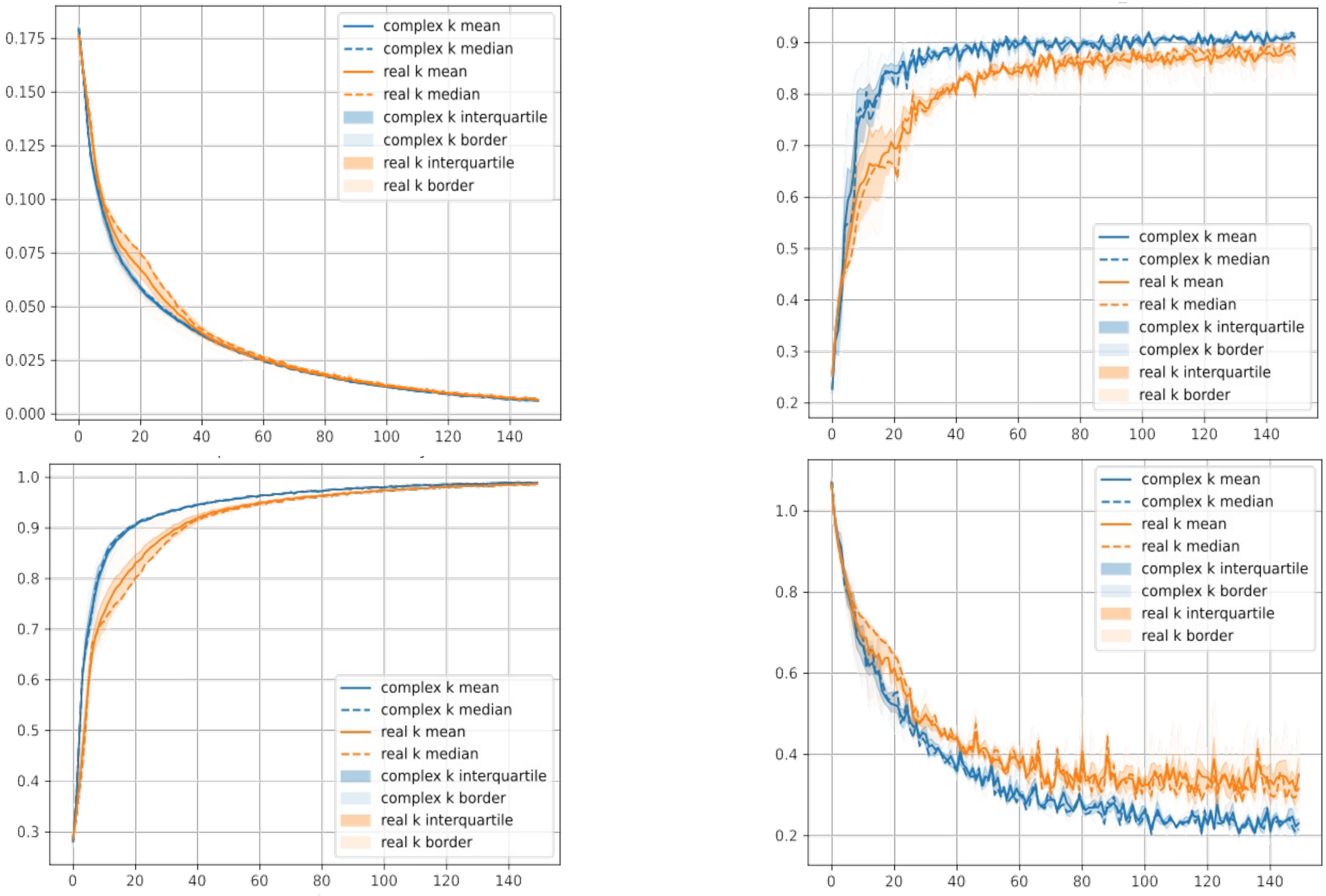
Subsets correlation reduction: results 1/2

Train

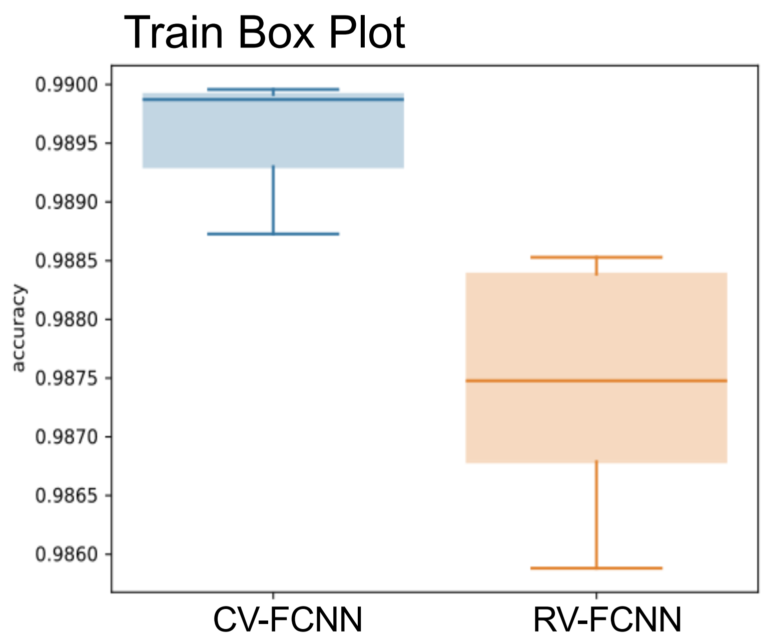
Validation

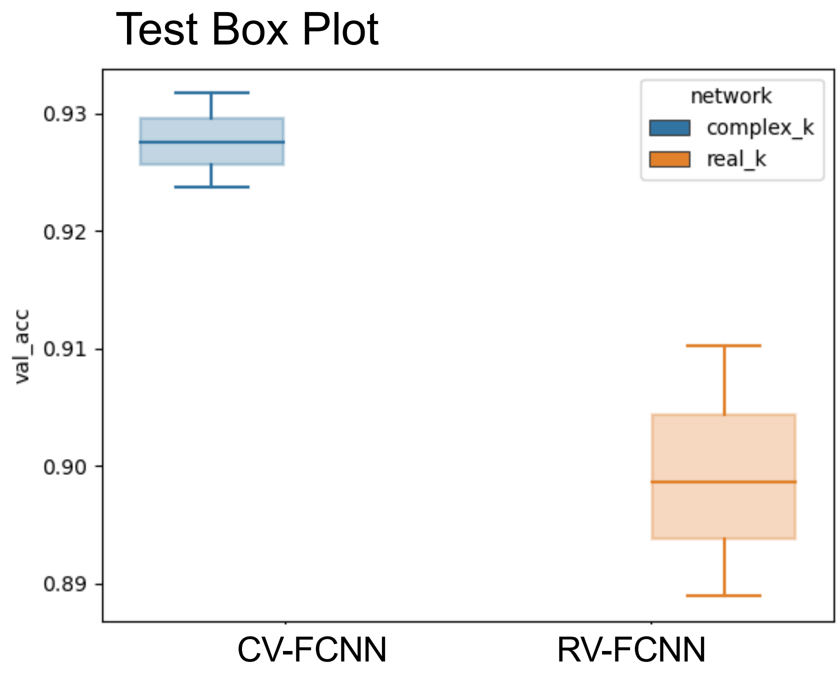
Accuracy

Loss



Subsets correlation reduction: results 2/2





	CV-FCNN	RV-FCNN
Median	**92.76±0.36**	89.86±0.96
Mean	**92.77±0.46**	89.92±1.23
Range	**92.37-93.17**	88.89-91.02

Subsets correlation reduction: conclusions

CVNN

RVNN

- Successfully reduced the performance for a saturated task

IGARSS 2022

IEEE Signal Processing Society™

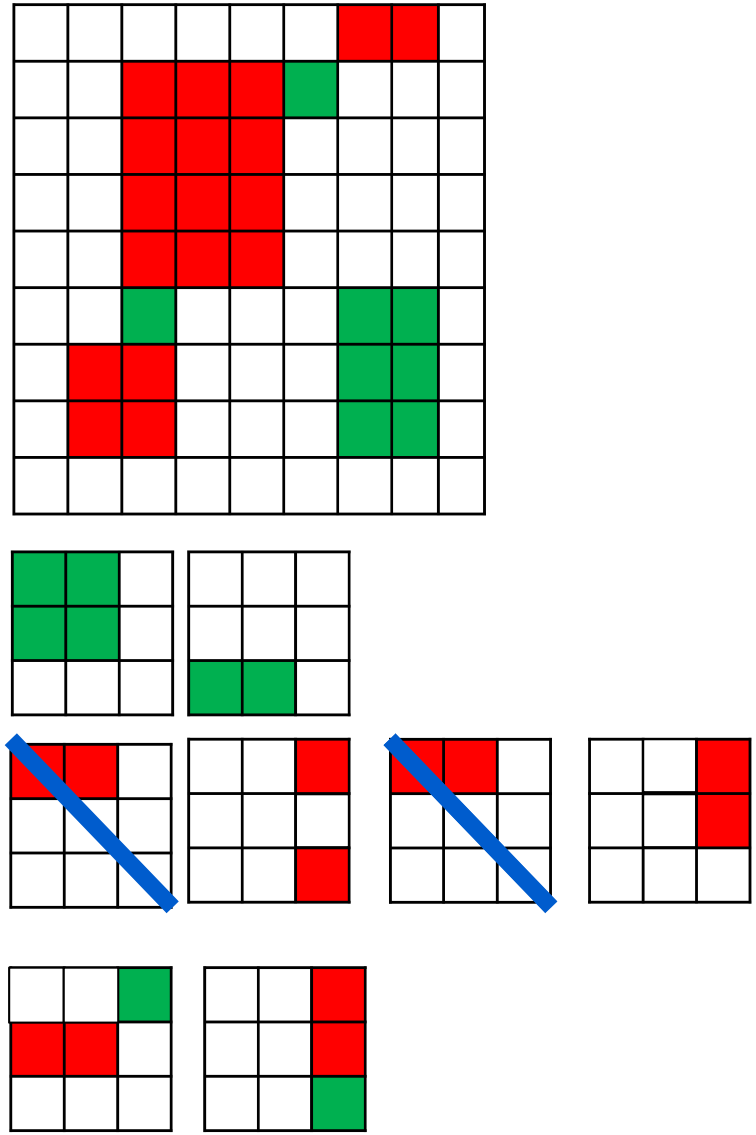
[1] Barrachina, et al. "Complex-Valued Neural Networks for Polarimetric SAR segmentation using Pauli representation" *IEEE International Geoscience and Remote Sensing Symposium (IGARSS), Physics Aware Machine Learning for Synthetic Aperture Radar Applications,* Kuala Lumpur, Malaysia, 2022

Accuracy balancing: Motivation

		Coherency Matrix		Pauli Vector	
		CV	RV	CV	RV
FCNN	OA			**99.83±0.02**	99.69±0.06
	AA			**98.69±0.33**	98.62±0.20
CNN	OA	**95.78±0.26**	94.43±0.67	95.40±0.50	94.78±0.71
	AA	**89.72±0.67**	85.82±1.53	88.05±1.50	86.90±1.86
MLP	OA	95.09±0.02	**95.13±0.01**	88.55±0.04	87.77±0.04
	AA	87.10±0.15	**88.40±0.09**	64.69±0.08	63.13±0.10

Test accuracy mean results for Bretigny dataset without splitting (%)

Accuracy balancing: Dataset problematic



1. Generate image patches (total 9):
   a. 2 pure green
   b. 4 pure red
   c. 2 mixed
   d. 1 no labels (discarded)
2. Remove exceeding one class images
   a. 2 pure green
   b. 2 pure red
   c. 2 mixed
3. Balance total pixels
   a. 13 red pixels
   b. 8 green pixels

Accuracy balancing: Results

Dataset		Coherency Matrix		Pauli Vector	
		CV	RV	CV	RV
FCNN	OA	83.08±1.80	46.14±3.41	**98.85±0.07**	98.50±0.13
	AA	69.45±2.90	55.73±2.82	**98.17±0.12**	98.04±0.27
CNN	OA	94.41±0.06	94.42±0.09	**94.83±0.11**	94.60±0.10
	AA	94.84±0.06	94.36±0.06	**95.42±0.06**	95.25±0.04
MLP	OA	92.77±0.11	**92.82±0.16**	71.70±0.09	71.84±0.10
	AA	92.38±0.03	**92.85±0.04**	81.13±0.06	80.56±0.10

Test accuracy mean results for dataset balancing (%)

Accuracy balancing: Results

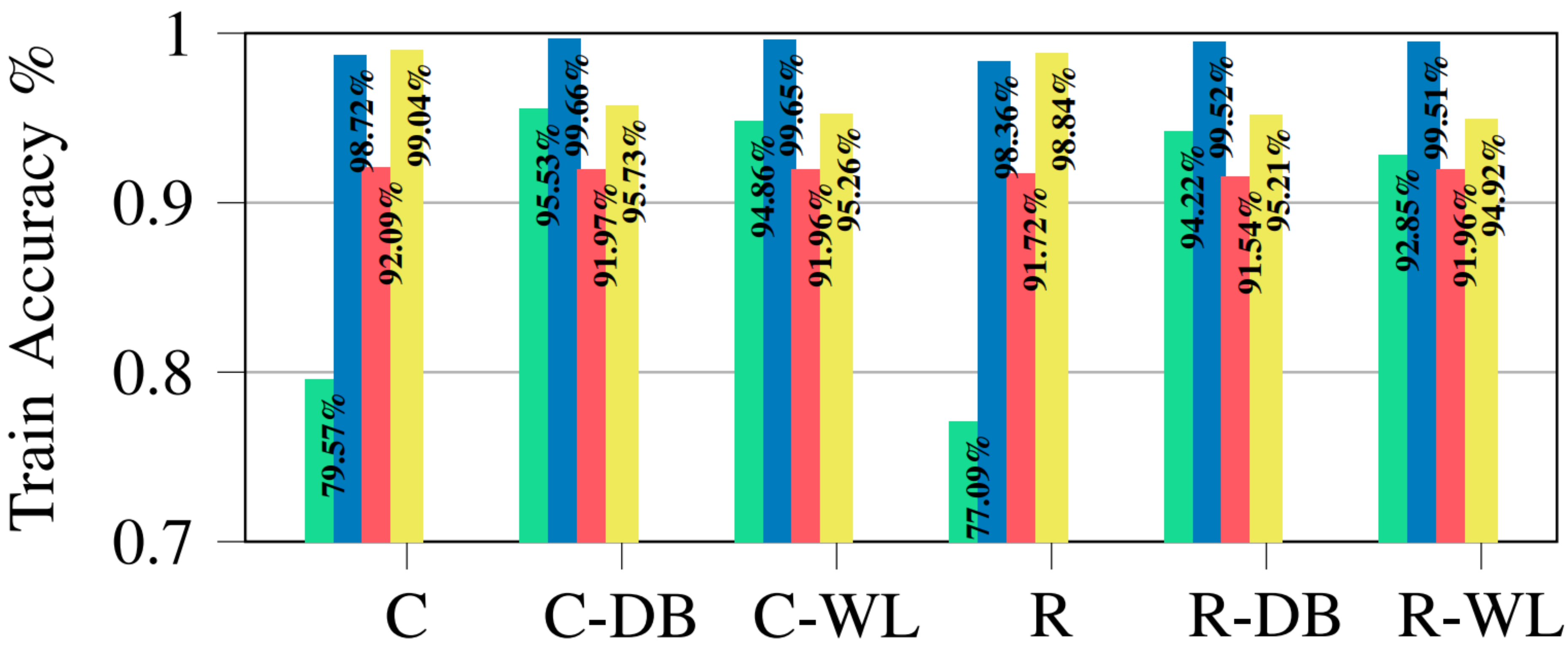
Weighted loss average

$$Loss = \frac{1}{occ_{min}} \sum_{c} occ_c \, Loss_c$$

Dataset		Coherency Matrix		Pauli Vector	
		CV	RV	CV	RV
CNN	OA	90.66±0.48	87.11±1.28	**92.35±0.81**	91.61±1.11
	AA	89.96±0.30	86.31±0.82	**92.12±1.06**	91.53±1.17
MLP	OA	**93.40±0.13**	92.70±0.20	71.96±0.32	71.51±0.22
	AA	91.05±0.08	**91.39±0.08**	79.27±0.06	78.04±0.01

Test accuracy mean results for weighted loss with dataset (%)

Accuracy balancing: Results



CNN Coherency matrix results per class.

- C: CV-CNN;
- C-DB: CV-CNN dataset balanced;
- C-WL: CV-CNN;
- R: RV-CNN; weighted loss;
- R-DB: RV-CNN dataset balanced;
- R-WL: RV-CNN weighted loss

Accuracy balancing: Conclusions

- Results for split dataset were analogous with a few differences
  - CV-MLP always outperform RV-MLP
  - CV-CNN performed better with the Pauli vector for the OA and with the coherency matrix for the AA.
- Complex models generalized better except for the MLP model without dataset splitting
- FCNN works better with Pauli vector whereas MLP models work better when using the coherency matrix
- For CNN, which input representation to use was unclear
- Weighted loss did not work well for FCNN models
- Regardless of that case, both balancing methods worked correctly with a slight tendency towards dataset subsampling

Conclusions

- We hope to motivate further works on CVNN by providing a CVNN toolbox
- We showed the interest of CVNN for datasets which have the non-circular property or related
- We proved that CVNN outperforms RVNN on PolSAR segmentation tasks
- Using the Pauli vector may be a better input representation depending on the model used
- Particular attention should be used for the dataset preprocessing to reduce correlation between training and validation sets. We show that this has a vital importance to avoid saturation of the task

Perspectives

- Use different images for training, validation and test (example, different images of the same place taken at different moments or different places with same classes)
- Explore the interest of CVNN for real dataset using a pertinent transformation (for example, Hilbert transform)
- Extend despekling techniques with keeping the phase information
- Quaternion / Clifford Algebra Neural Networks
- Analyze the impact on different activation functions, pooling layers, etc.
- Explore other applications such as data augmentation, change detection, object and target detection, style transfer, complex-valued autoencoder
- Generate physic-aware complex-valued PolSAR image (Complex-Valued GAN)

Publications: Journals

[1] **José Agustín Barrachina**, Chengfang Ren, Christèle Morisseau, Gilles Vieillard, Jean-Philippe Ovarlez, "Comparison Between Equivalent Architectures of Complex-valued and Real-valued Neural Networks - Application on Polarimetric SAR Image Segmentation" *in Journal of Signal Processing Systems, Springer,* pp. 1-10, 2022.

[2] **José Agustín Barrachina**, Chengfang Ren, Christèle Morisseau, Gilles Vieillard, Jean-Philippe Ovarlez, "Impact of PolSAR pre-processing and balancing methods on complex-valued neural networks segmentation tasks" *in Open Journal of Signal Processing and ICASSP, IEEE,* 2023, (Submitted). arXiv preprint arXiv:2210.17419 2022.

[3] **José Agustín Barrachina**, Chengfang Ren, Christèle Morisseau, Gilles Vieillard, Jean-Philippe Ovarlez, “Theory and implementation of Complex-Valued Neural Networks”, 2023 (In preparation)

Publications: Conferences

[1] **Jose Agustin Barrachina**, Chengfang Ren, Gilles Vieillard, Christèle Morisseau, Jean-Philippe Ovarlez, "Real- and Complex-Valued Neural Networks for SAR image segmentation through different polarimetric representations" *IEEE International Conference on Image Processing (ICIP),* Bordeaux, France, 2022.

[2] **Jose Agustin Barrachina**, Chengfang Ren, Christèle Morisseau, Gilles Vieillard, Jean-Philippe Ovarlez, "Merits of Complex-Valued Neural Networks for PolSAR image segmentation" *GRETSI XXVIIIème Colloque Francophone de Traitement du Signal et des Images,* Nancy, France, 2022.

[3] **Jose Agustin Barrachina**, Chengfang Ren, Christèle Morisseau, Gilles Vieillard, Jean-Philippe Ovarlez, "Complex-Valued Neural Networks for Polarimetric SAR segmentation using Pauli representation" *IEEE International Geoscience and Remote Sensing Symposium (IGARSS), Physics Aware Machine Learning for Synthetic Aperture Radar Applications,* Kuala Lumpur, Malaysia, 2022. **Invited session & 3MT finalist.**

[4] **Jose Agustin Barrachina**, Chengfang Ren, Gilles Vieillard, Christèle Morisseau, Jean-Philippe Ovarlez, "About the Equivalence Between Complex-Valued and Real-Valued Fully Connected Neural Networks - Application to Polinsar Images" *IEEE 31st International Workshop on Machine Learning for Signal Processing (MLSP),* Gold Coast, Queensland, Australia, pp. 1-6, 2021. **Ranked top 15% on reviewer score.**

[5] **Jose Agustin Barrachina**, Chengfang Ren, Christèle Morisseau, Gilles Vieillard, Jean-Philippe Ovarlez, "Complex-valued vs. real-valued neural networks for classification perspectives: An example on non-circular data" *IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP),* Toronto, Ontario, Canada, pp. 2990-2994, 2021. **r/ML-WAYR week 116.**

Publications without proceedings

[1] **Jose Agustin Barrachina**, Chengfang Ren, Christèle Morisseau, Gilles Vieillard, Jean-Philippe Ovarlez, "Complex-Valued Neural Networks for Polarimetric SAR segmentation using Pauli representation" *5th SONDRA Workshop*, Avignon, France, 2022.

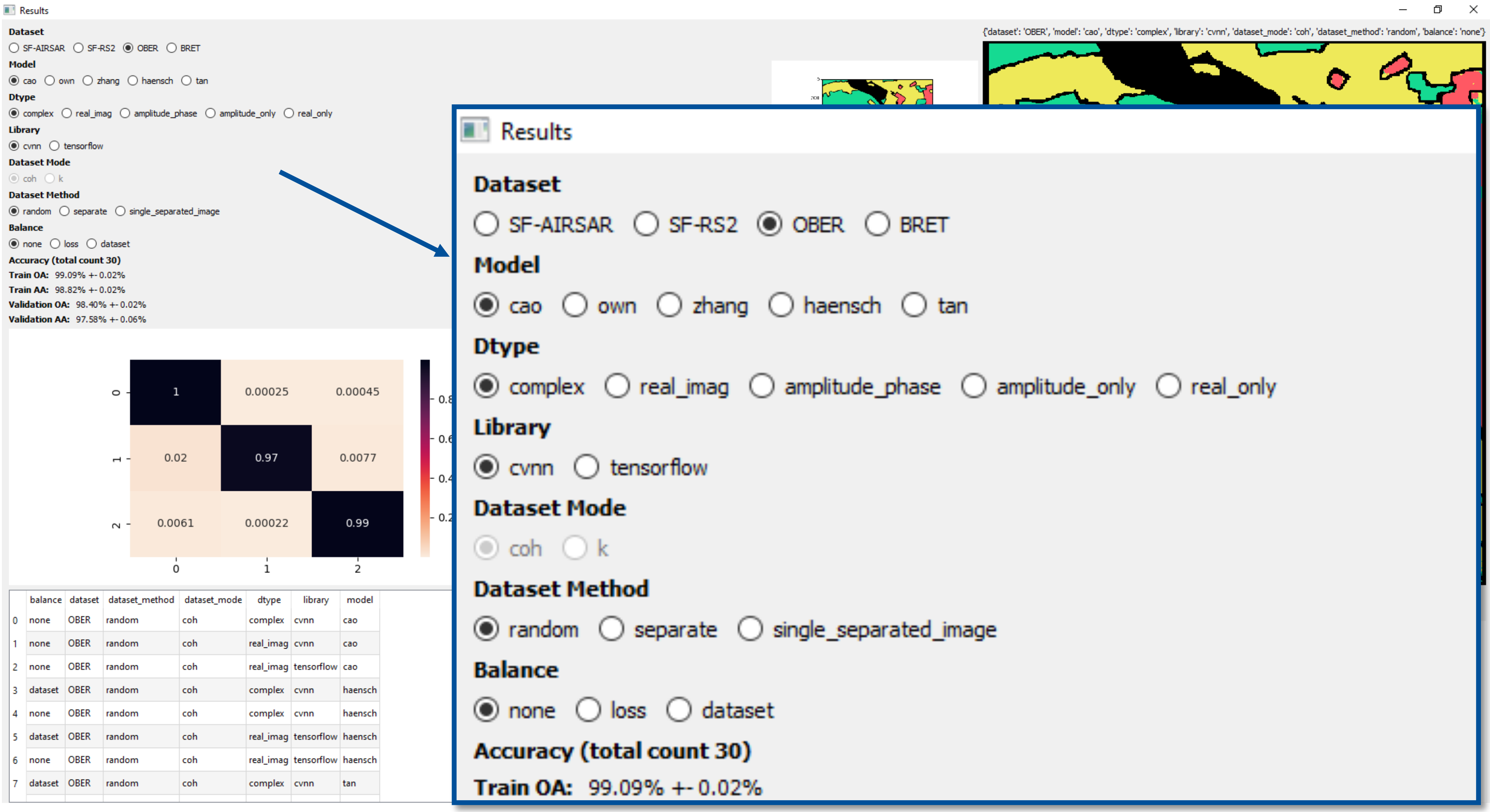
[2] **Jose Agustin Barrachina**, "Complex-Valued Neural Networks (CVNN)" *Zenodo,* DOI: https://doi.org/10.5281/zenodo.4452131, 2021. Repository: https://github.com/NEGU93/cvnn

[3] **Jose Agustin Barrachina**, Chengfang Ren, Christèle Morisseau, Gilles Vieillard, Jean-Philippe Ovarlez, "A comparison between complex and real valued fully connected neural networks on non-circular complex data" *XXII Giambiagi Winter School: Artificial intelligence and deep learning in physics,* poster session, Buenos Aires, Argentina, 2020.

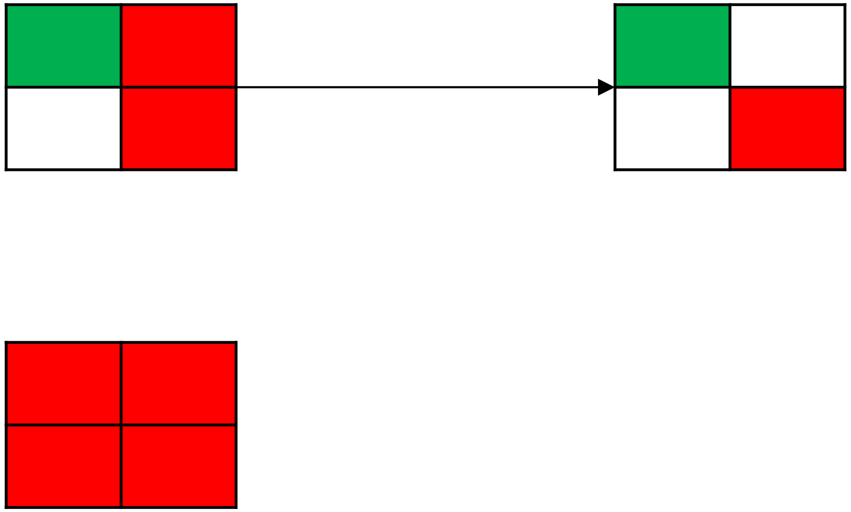
Thank you!

Results viewer

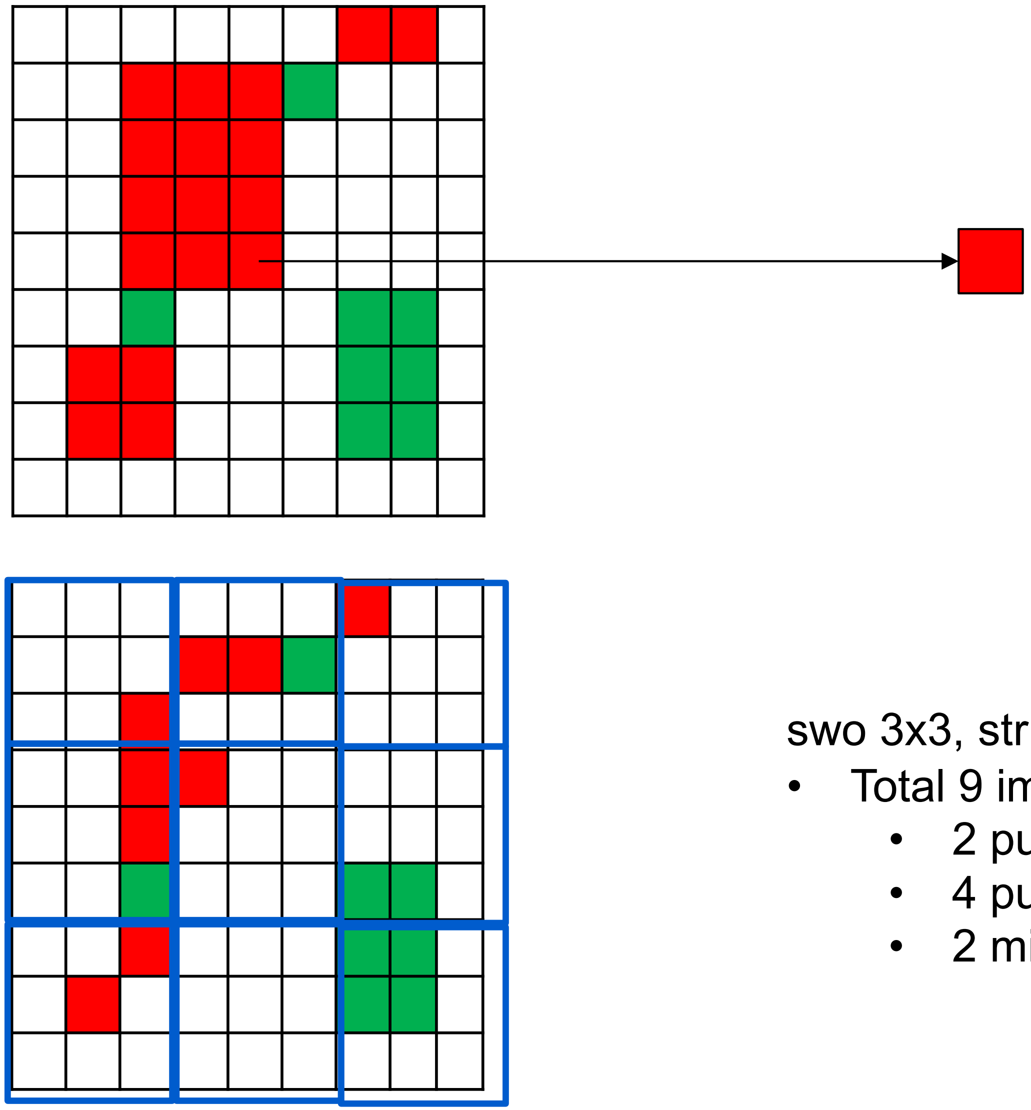
User Interface



Accuracy Balancing: Dataset problematic



Accuracy Balancing: Dataset problematic



swo 3x3, stride 3, padding

- Total 9 images
  - 2 pure green
  - 4 pure red
  - 2 mixed

Valorisation: Reddit

Posted by u/ML_WAYR_bot 6 months ago

23

[D] Machine Learning - WAYR (What Are You Reading) - Week 116

Discussion

r/MachineLearning

Welcome to MachineLearning

2.2m Members

451 Online

Created Jul 29, 2009

r/MachineLearning topics

Machine Learning

Join

56

[R] Complex-Valued Neural Networks

Research

So what do you think about Complex Valued Neural Networks? Can it be a new interesting field to look at? Mostly for the Signal Processing or Physics community.https://arxiv.org/abs/2009.08340

20 Comments Share Save Hide Report 88% Upvoted

Log in or sign up to leave a comment

Log In Sign Up

Motivation

x_1

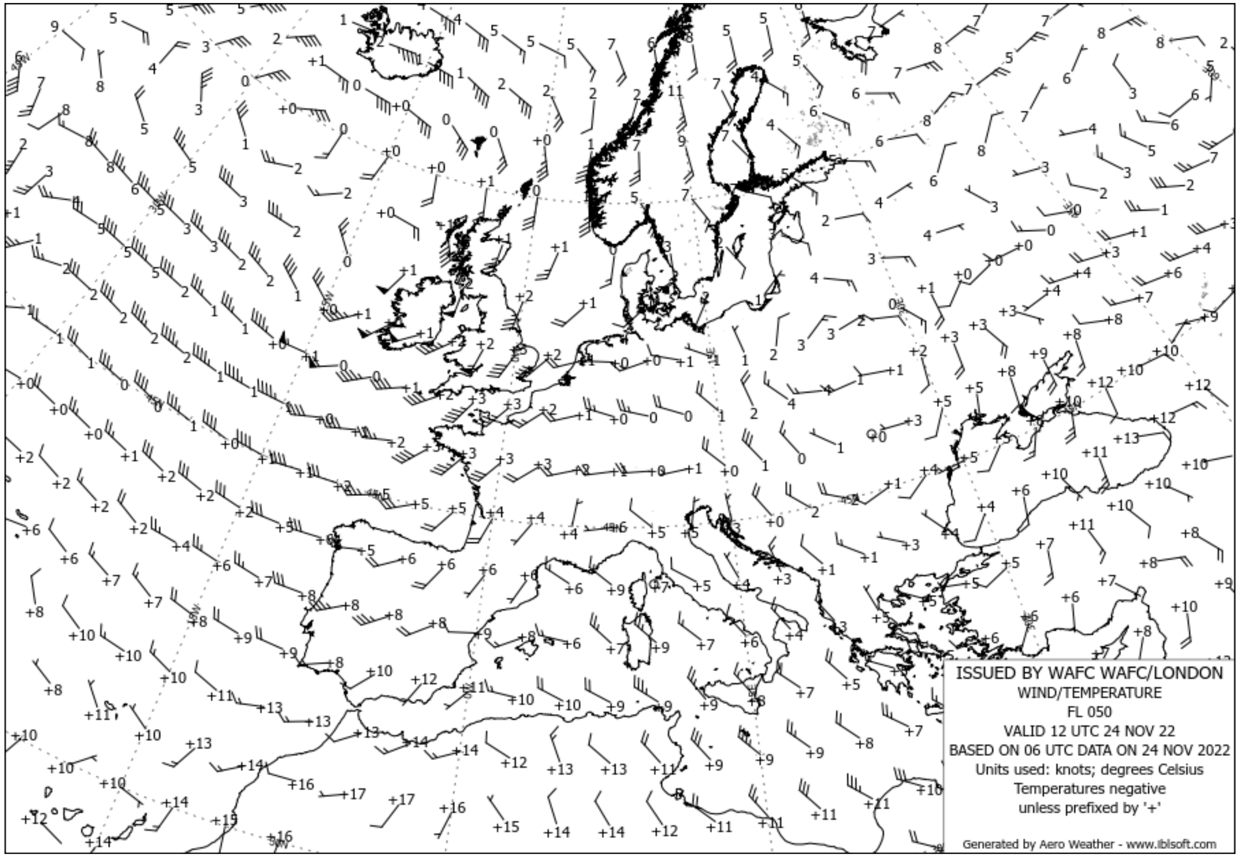
y_1

x_2

y_2

What is the relationship?

$$z_1 = y_2 + jx_1$$



"If we know a priori that the objective quantities include "phase" and/or "amplitude", we can reduce […] the freedom by employing a complex-valued neural network" [1]

[1] A. Hirose, "Complex-Valued Neural Networks: Advances and Applications" *IEEE Press Series on Computational Intelligence*, 2013.