# Applicability of complex-valued convolutional neural networks to radar image classification

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**Abstract**

The abstract is very abstract as of now.

*The only way out is through.*

Robert Frost

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# Chapter 1

# Introduction

## 1.1 Motivation

Motivation in LeCUN

Why CVNN?

Page 38 akira 2012 In CVNNs, the flexibility in learning and self-organization is restricted rather than that in double-dimensional real-valued neural net- works. As we discussed in Section 3.2.1, the restriction is brought by the four fundamental rules of arithmetic in complex numbers (especially multiplication as it entails rotation and scaling, not just scaling as in real valued case). Such fundamental rules in processing often work well in solving real world problems. This feature is one of the most useful advantages in CVNNs. wave-related phenomena such as sonic wave, lightwave, and electromagnetic wave.4

pg 19 In short, in CVNNs, we can reduce ineffective degree of freedom in learning or self-organization to achieve better generalization characteristics.

if we know a priori that the objective quantities include phase and/or amplitude, we can reduce possibly harmful portion of the freedom by employing a complex-valued neural network, resulting in a more meaningful generalization characteristics

physical meaning of radar magnitude and phase? discernibility lies in them?

the mannerism of how the learning unfolds is restricted

biological motivation signal processing associative memory data patchhhhh historical uses success with PolSAR

## 1.2 Problem Definition

complex data with complex weights? leveraging the promise of complex valued networks

## 1.3 Document Structure

# Chapter 2

# State of the art

Complex-valued neural networks have been widely investigated and have been found useful in the fields of adpative designing of patch antennas, neurophysiological analysis, and communications [13]. Increased incorporation of complex-valued units in recent works of Recurrent Neural Networks ( [3], [27], [5]) and computer vision tasks( [23], [4], [28]) has brought significant attention to the virtues of complex-valued representations.

The recent re-introduction of complex-valued neural networks in the classification of Synthetic Aperture Radar (SAR) data has been very promising in the wake of marked advancements in the theory of deep learning. The data is complex by its very nature, hence opens up the interesting opportunity to employ $\mathbb{C}$-CNNs to better make use of phase information in various problems, the reason of which is described in the motivation.

Polarimetric SAR (PolSAR) uses microwaves with different polarisations to measure the distance to ground and the reflectance of a target [11]. One of the traditional techniques for classification involving PolSAR data is the use of (real-valued) Multilayer Perceptrons (MLP). Inspired by the success of MLPs in computer vision, Hänsch and Hellwich (2009) [11] employed the $\mathbb{C}$-NNs to classify the complex-valued Polarimetric Synthetic Aperture Radar (PolSAR) data to perform a 3-class pixel-wise classification (forest, fields and urban areas). The authors test their architectures using different error functions for $\mathbb{C}$-NNs, and compare $\mathbb{C}$-NNs with their real-valued counterparts. The results conclude that $\mathbb{C}$-NNs outperformed $\mathbb{R}$-NNs in that particular problem. However, the input data to both type of CNNs is not preprocessed the same way. The same authors go ahead to tackle the object-classification problem using complex-valued neural networks ($\mathbb{C}$-NNs) and $\mathbb{R}$-CNNs [10]. They show that $\mathbb{C}$-CNNs, with only one complex-convolutional layer, outperform the $\mathbb{C}$-NNs in the cases where the number of neurons in single convolutional layer exceeded 10.

Wilmanski *et al.* (2016) [26] explore the suitability of using $\mathbb{C}$-CNNs for Automatic Target

Recognition for complex-valued SAR data. Although their ℂ-CNN model had only one complex-valued layer (complex weights) in their complex-valued variant architecture, it outperformed (99.21% accuracy) the state-of-the-art ℝ-CNN network (87.30% accuracy). In the dataset they used (GOTCHA [2]), they also pointed out how the phase surrounding an object had a distinctive structure, pointing to the potential importance of phase information in classification tasks.

Zhang *et al*. (2017) [29] leverage magnitude as well as the phase of the PolSAR data to classify different terrains on the Flevoland (3 classes) and Oberpfaffenhofen datasets (15 classes). Compared to ℝ-CNN, ℂ-CNN performs better on both the datasets while having approximately same number of parameters.

Chiheb *et al*. (2018) [25] compare the performance of different architectures of the ℂ-CNNs and ℝ-CNNs on the tasks of image recognition, music transcription, and speech spectrum prediction. ℂ-CNNs were reported to perform comparably to ℝ-CNNs for the first task, and achieve state-of-the-art performance on the two tasks while beating ℝ-CNNs. The authors also contribute the extension of Batch Normalization and Weight Initialization (BN) to complex domain.

# Chapter 3

# Background

## 3.1 Radar Technology?

## 3.2 Complex Domain Theory

### 3.2.1 Complex Numbers and its representaitons

**Polar form**

**Cartesian form**

**Exponential form**

### 3.2.2 Complex functions

map c to c map c to r

Representation types DO I DESCRIBE THEIR IMPLEMENTATION HERE?

### 3.2.3 Holomorphism & Complex Differentiability

Holomorphism guarantees that a complex-valued function is complex differentiable in the neighborhood of every point in its domain [25]. A complex function $f(z) : \mathbb{C} \mapsto \mathbb{C}$, $f(z) = u(z)+iv(z)$ ($u(z)$ and $v(z)$ are real-valued functions) is complex differentiable if it satisfies the following two conditions:

1. It satisfies the Cauchy-Riemann (CR) equations, given by:

$$\frac{\delta u}{\delta x} = \frac{\delta v}{\delta y} \quad , \quad \frac{\delta u}{\delta y} = -\frac{\delta v}{\delta x} \tag{3.1}$$

2. $u(z)$ and $v(z)$ are individually differentiable at $z$ as real functions

### 3.2.4 Derivative of real-valued complex functions

### 3.2.5 Generalized chain rule for real-valued complex loss functions

Consider that we have a real-valued loss function $L(z) : \mathbb{C} \to \mathbb{R}$, where $z$ is a complex variable $z = x + iy$ with $x, y \in \mathbb{R}$. The gradient of real-valued complex function is defined as follows:

$$\nabla_L(z) = \frac{\partial L}{\partial z} = \frac{\partial L}{\partial x} + i\frac{\partial L}{\partial y} = \Re(\nabla_L(z)) + i\Im(\nabla_L(z)) \tag{3.2}$$

If we have another complex variable $t = r + is$ where z could be expressed in terms of $t$, where $r, s \in \mathbb{R}$, the gradient with respect to $t$ would be:

$$\begin{aligned}
\nabla_L(t) &= \frac{\partial L}{\partial t} = \frac{\partial L}{\partial r} + i\frac{\partial L}{\partial s} \\
&= \frac{\partial L}{\partial x}\frac{\partial x}{\partial r} + \frac{\partial L}{\partial y}\frac{\partial y}{\partial r} + i\left(\frac{\partial L}{\partial x}\frac{\partial x}{\partial s} + \frac{\partial L}{\partial y}\frac{\partial y}{\partial s}\right) \\
&= \frac{\partial L}{\partial x}\left(\frac{\partial x}{\partial r} + i\frac{\partial x}{\partial s}\right) + \frac{\partial L}{\partial y}\left(\frac{\partial y}{\partial r} + i\frac{\partial y}{\partial s}\right) \\
&= \Re(\nabla_L(z))\left(\frac{\partial x}{\partial r} + i\frac{\partial x}{\partial s}\right) + \Im(\nabla_L(z))\left(\frac{\partial y}{\partial r} + i\frac{\partial y}{\partial s}\right)
\end{aligned} \tag{3.3}$$

# Chapter 4

# Comparison of $\mathbb{R}$-CNNs with $\mathbb{C}$-CNNs

## 4.1 Convolutional Neural Networks

Convolutional Neural Networks (CNNs) (LeCun, 1989) [20] are specialized neural networks that are used for processing data that can be represented in the form of a grid or arrays e.g. 1D arrays of audio signals, three channels of 2D arrays of RGB images, or any other higher dimensional data. CNNs take their name due to the presence of a specialized kind of linear operation called convolution. CNNs are inspired by the visual cortex in the brain, which consists of alternating layers of simple and complex cells (Hubel & Wiesel, 1959, 1962) [15] [16].

In the context of image classification, CNNs make use of the inherent compositional hierarchies present in images such that higher-level features are obtained by composing lower-level ones. Additionally, there are three key ideas behind ConvNets that makes them attractive for learning: sparse interactions, shared weights, equivariant representations. In traditional neural netowrks, one learned parameter interacts with the one input unit in order to produce an output. In the case of images where there are millions of pixels, this approach becomes extremely expensive. In this respect, CNNs offer sparse interactions between inputs and the ouputs in the sense that very few parameters of the kernels need to be learned to extract features from an input of, let's say, a million pixels. This reduces the memory requirements and improve statistical effeciency. Parameter sharing referes to the use of the same parameters for than one function in the model. When kernels are learned in a CNN, the same kernel is used for different spatial locations of the input rather than learning different parameters for different spatial locations. This further reduces the memory requirements. CNNs also grant equivariance to translations,

meaning that if the presence of a feature translates in an image, the output of a convolutional layer will also move by the same amount. This behavior is useful if we want to detect the same feature in different parts of the image. [7]

In the following section, the building blocks of a real-valued CNN (ℝ-CNN) and its complex counterpart, complex-valued CNN (ℂ-CNN), pertinent to our methodology, are discussed in detail.

## 4.2 The Building Blocks

### 4.2.1 Convolution

In the field of Computer Vision, convolution operation is utilized for applying a 2D filter to an image for the purpose of photo enhancement or feature extraction. In photo enhancement, the filters used can have different effects e.g. sharpening, blurring, dilatting, and more. In case of features extraction, different features i.e. edges, corners, gradients etc. can be extracted. In short, the application of filters through convolution operation enables us to convert images in a form which are easier to understand and can further help in myriads of computer vision applications such as face detection, object detection, SLAM etc.

In a CNN, the convolutional layer performs the role of feature extraction in a way that each succeeding layer represents a more complex concept that helps get closer to classification [19]. For examples, the first layers would learn low-level features (e.g. edges) form patterns and the latter layers would learn higher level features (e.g. shapes, textures) which would inturn be composed of these the earlier ones.

Units in a convolutional layer are organized in feature maps, within which each unit is connected to local patches in the feature maps of the previous layer through a set of weights called a filter bank [19]. The local patches in the feature maps of the previous layer are called the receptive field for the respective unit in the feature map under discussion. Different feature maps in a layer use different filter banks but each unit in the same feature map undergo the same filter bank. The new feature map can be obtained by first convolving the input with a learned kernel and then applying an element-wise nonlinear activation function on the convolved results [8]. The nonlinear acitvation function will be discussed in detail in Section 4.2.3.

NUMBER OF PARAMETERS/ MORE ACTIVATION FUNCTIONS IN POLSARHAENCSH

#### Real-Valued Convolution

Convolution entails point-wise multiplication of the filter with the input image and summing all the multiplicands to form the unit in the feature map corresponding to that on which the

filter's central unit is positioned in the output feature map (after the application of non-linear activation function). The filter slides and performs this operation all over the space of the input by centering upon all or some of the units of the input, according to the design choice of number of strides. The complete feature maps are obtained by using several different kernels.

Mathematically, the feature value at location $(i, j)$ in the k-th feature map of $l$-th layer, $z^l_{i,j,k}$, is calculated by:

$$z^l_{i,j,k} = {w^l_k}^T * x^l_{i,j} + b^l_k \tag{4.1}$$

where $w^l_k$ and $b^l_k$ are the weight vector and bias term of the $k$-th filter of the $l$-th layer respectively, and $x^l_{i,j}$ is the input patch centered at location $(i, j)$ of the $l$-th layer. Note that the kernel $w^l_k$ that generates the feature map $z^l_{:,:,k}$ is shared. Such a weight sharing mechanism has several advantages such as it can reduce the model complexity and make the network easier to train [8].

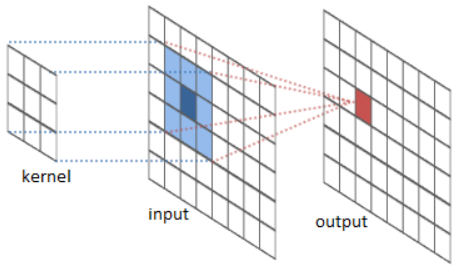


Figure 4.1: A schematic sketch of the convolution operation. An unit in the output is the sum of point-wise multiplication of the kernel and input patch [1]

### Complex-Valued Convolution

Like complex domain can be thought of as an extension of real domain, complex-valued convolution can also be formulated through such thinking. In complex-valued convolution, the filter and the input both take on the complex form:

$$\mathrm{W} = \mathrm{A} + i\mathrm{B} \tag{4.2}$$

$$\mathrm{h} = \mathrm{x} + i\mathrm{y} \tag{4.3}$$

where A and B are real-valued matrices which belong to one complex kernel, implemented as seperate layers. x and y are real-valued input vecetors representing the real and imaginary part of the complex-valued patch of the input layer. Note that the real and imaginary parts of

both the kernel and the input are present as separate layers, and the result of the convolution is one complex-valued layer represented as two real-valued layers [9].

Taking advantage of the fact that convolution is distributive, the result of $\mathrm{W} * \mathrm{h}$ results as follows:

$$\mathrm{W} * \mathrm{h} = (\mathrm{A} * \mathrm{x} - \mathrm{B} * \mathrm{y}) + i(\mathrm{B} * \mathrm{x} + \mathrm{A} * \mathrm{Y}) \tag{4.4}$$

This convolution strategy has been used in [9], [25] , Learning Rep, Polsar and ...

### 4.2.2 Batch Normalization

One of the most widespread methods used to improve the performance of Deep Neural networks, including CNNs, is called Batch Normalization (BN). Introduced by Ioffe and Szegedy in 2015 [17], BN helps speed up the training of the network and enables the use of a wider variety of acceptable hyperparameters by reducing internal covariant shift. Internal Covariate Shift is defined as the change in the distribution of network activations, the input to the next layer, due to the change in network parameters during training [17]. Normalization of input data is widely accepted method to make the nerual networks converge faster, as stated in [21]. In the case of BN, this idea of input normalization is applied on the input of each layer which happens to be the output of the previous layer. It fights the internal covariate shift problem by a normalization step that fixes the means and variances of layer inputs where the estimations of mean and variance are computed after each mini-batch rather than the entire training set [8]. The exact procedure proposed is described lates in 4.2.2.

Batch normalization has many advantages compared with global data normalization that is done before training. Apart from reducing internal covariant shift, BN also reduces the dependence of gradients on the scale of the parameters or of their initialization strategy. This benefits the flow of gradients and enables the use of higher learning rate without the risk of divergence [8]. BN also weakens the coupling between functions of each layers which inturn expedites convergence. Furthermore, as BN involves subtraction of mean and scaling by standard deviation, where mena and standard deviation are calculated on mini-batches, multiplicative and additive noise is added to the each iteration. As a result, a slight regularization effect is induced in the network which helps it not to rely too much on the output of a single neuron/node in any layer of the network. One should note that the bigger the size of the mini-batch, the weaker is the regularization effect.

### Real-Valued Batch Normalization

In $\mathbb{R}$-CNNs, the BN step is generally performed between the convolution step and the activation step, although the original paper [17] proposed it for after the activation step. Suppose that a layer to normalize has a $d$ dimensional input, i.e., $\mathrm{x} = [x_1, x_2, ..., x_d]^{\mathrm{T}}$ . The first step is to normalize the $k$-th dimension as follows:

$$\hat{x}_k = \frac{x_k - \mu}{\sqrt{\sigma^2 - \epsilon}} \tag{4.5}$$

where $\mu$ and $\sigma^2$ are the mean and variance of mini-batch respectively, and $\epsilon$ is a constant value. Next, we let the network change the distribution of the network as is required by the model throught he help of one multiplicative and one additive paramter. The normalized input $\hat{x}_k$ is further transformed into:

$$y_k = \mathrm{BN}_{\gamma,\beta}(x_k) = \gamma\hat{x}_k + \beta \tag{4.6}$$

where $\gamma$ and $\beta$ are learned parameters. It might not be beneficial for the layer input to have zero mean and variance, although the network has the choice to keep them such through the two parameters. $\gamma$ and $\beta$ help scale and shift the mean of the input distribution to better make advantage of the nonlinearity of the activation function.

### Complex-Valued Batch Normalization

The complex-valued BN is an extension of its real-valued counterpart and it was first introduced in [25]. The first step, ofcourse, is normalization of the input distribution. Unlike real-valued BN, merely translating and scaling, like in [17], would result in skewed or elliptical variance with high eccentricity [25]. To cater for this problem, the authors the normalization step of complex BN is treated as whitening of 2D vectors. The following equations describe the process.

$$\tilde{x} = (V^{-\frac{1}{2}})(x - \mathbb{E}[x]) \tag{4.7}$$

$$V = \begin{pmatrix} V_{rr} & V_{ri} \\ V_{ir} & V_{ii} \end{pmatrix} = \begin{pmatrix} \mathrm{Cov}(\Re\{x\}, \Re\{x\}) & \mathrm{Cov}(\Re\{x\}, \Im\{x\}) \\ \mathrm{Cov}(\Im\{x\}, \Re\{x\}) & \mathrm{Cov}(\Im\{x\}, \Im\{x\}) \end{pmatrix} \tag{4.8}$$

As described by the equations above, the mean-centered input $(x - \mathbb{E}[x])$ is multiplied by the inverse of the square-root of input variance V in the normalizatios step.Whereas in real-valued BN, the first step entailed converting the input distribution into a standard normal distribution, the complex-valued BN requires it to be converted to standard complex normal ditribution, which is characterized by having location parameter (also called mean) $\mu = 0$,

covariance matrix $\Gamma = 1$, and the relation matrix (also called pseudo-covariance) $C = 0$. The formulae of these parameters are given by:

$$\begin{aligned} \mu &= \mathbb{E}[\tilde{x}] \\ \Gamma &= \mathbb{E}[(\tilde{x} - \mu)(\tilde{x} - \mu)^*] = V_{rr} + V_{ii} + i(V_{ir} - V_{ri}) \\ C &= \mathbb{E}[(\tilde{x} - \mu)(\tilde{x} - \mu)] = V_{rr} - V_{ii} + i(V_{ir} + V_{ri}) \end{aligned} \tag{4.9}$$

The next step in complex-valued BN is to scale and shift the input distrubtion to a desired mean and variance, with the help of $\gamma$ and $\beta$, respectively. $\gamma$ is now a 2x2 positive-semidefinite matrix with three tunable parameters and it is given by:

$$\gamma = \begin{pmatrix} \gamma_{rr} & \gamma_{ri} \\ \gamma_{ri} & \gamma_{ii} \end{pmatrix} \tag{4.10}$$

$\beta$ is a complex parameter with real and imaginary learnable components. The final step of complex-valued BN follows the same equation as of real-valued BN, given by:

$$y_k = \mathrm{BN}_{\gamma,\beta}(x_k) = \gamma \hat{x}_k + \beta \tag{4.11}$$

### 4.2.3 Activation Function

In the absence of non-linear activation functions, the output of a neural network would essentially be a linear combination of the input, however deep the network is. Non-linear activation functions are introduced in order to add non-linearity to the network so that functions of a higher degree than 1 can be learned, thuse giving them the title of universal function approximators. In a CNN, activation function is applied element-wise to the output of the convolution (or BN, when it is used) and they act as to decide whether or not this output should be taken into account by its connection, and if so, what should be the nature of it. For R-CNNs, some common types of activation functions include Sigmoid, Hyperbolic Tangent function (tanh), and the most popular, Recitified Linear Unit (ReLU).

#### Real-Valued Activation Functions

#### ReLU

Popularized by [18], Rectified Linear Units (ReLU) [22] remains the most commonly used activation function in deep learning/CNN architectures for the community. ReLU is given by:

$$f(x) = \begin{cases} x, & \text{for } x \geq 0 \\ 0, & \text{for } x < 0 \end{cases} \tag{4.12}$$

Other variants of ReLU include Leaky ReLU (LReLU), Parametric ReLU (PReLU), Randomized ReLU (RReLU), and Exponential Linear Unit (ELU), as shown in figure blaa blaa.

### Soft-max

### Complex-Valued Activation Functions

Real-valued activation functions in $\mathbb{R}$-CNNs have to strictly comply with the requirement of differentiability for the chain rule, the backbone of the Gradient Descent optimization algorithm, to work. Since $\mathbb{C}$-CNNs also make use of the same optimization algorithm, it is only natural to think that the complex activation functions must also be differentiable at any point in their domain i.e. they should be Holomorphic. However, Louiville theorem presents us with a realization: the only complex functions that can be Holomorphic are constant functions. This begs us to question if the condition of differentiability can be relaxed while still being able to optimize the network. We find a way to circumvent this problem by ignoring the requirement of complex differentiablity, finding solace in the fact that as long as the complex function is differentiable with respect to its real part and its imaginary part, it provides sufficiency to be able to perform backpropagation, as demonstrated in [25], [10], [29]. The chain-rule for complex function differentiation is given in section 3.2.5. However, we must note that since Holomorphic functions obey CR equations, they are beneficial in granting computational efficiency to our process because we would only need to compute half the number of partial derivatives [24].

Complex-valued activation functions can be divided into two types: Real-Imaginary type , and the Amplitude-Phase type [13]. The first type of activation functions deals with real and imaginary parts separately and independently, but identically. Hence, they can be thought to work similar to real-valued networks with double the number of dimensions. The latter type applies the nonlinearity on only the magnitude of the complex number, leaving the phase information unchanged [14] .

### modReLU

Arjovsky *et al.* (2015) [3] proposed modReLU, an Amplitude-Phase type complex activation function, as a possible activation function for complex valued networks. It is formulated as:

$$\text{modReLU}(z) = \text{ReLU}(|z| + b)e^{i\theta_z} = \begin{cases} (|z| + b)\frac{z}{|z|}, & \text{for } |z| + b \geq 0 \\ 0, & \text{otherwise} \end{cases} \tag{4.13}$$

where $b$ is a learnable parameter which dictates the offset for the deadzone around the origin 0. modReLU is an element-wise nonlinearity, where the element is muted(assigned a value of

zero in both real and imaginary channels) if it lies in the deadzone, or passed if it is beyond. Chiheb *et al.* [25] also make use of this non-linearity in their analysis of ℝ-CNNs and ℂ-CNNs.

#### ℂReLU

ℂReLU is Real-Imaginary type activation function introduced by Chiheb *et al.* (2018) [25], which satisfies the CR equations only in the first and the third quadrant. The formula is given as follows:

$$\mathbb{C}\text{ReLU}(z) = \text{ReLU}(\Re(z)) + i\text{ReLU}(\Im(z)) \tag{4.14}$$

#### $z$ReLU

Proposed by Guberman (2106) [9], $z$ReLU does not strictly fall in any of the two categories described above. It follows the CR equations on all points on the complex domain except for the points along the real and imaginary axes of the complex plane. It is defined as follows:

$$z\text{ReLU}(z) = \begin{cases} z, & \text{for } \theta_z \in [0, \pi/2] + b \geq 0 \\ 0, & \text{otherwise} \end{cases} \tag{4.15}$$

SPLIT COMPLEX SOFTMAX????

### 4.2.4 Weight initialization

Weight initialization can help in speeding up the convergence of the gradient descent algorithm, and combats the problem of vanishing and exploding gradients, especially in the absence of BN.

#### Real-valued weight initialization

In the context of ℝ-CNNs, two weight initialization techniques are popular among the community, which are explained below. In these two techniques, the first step concerns with choosing choosing a random distribution function whose defining parameters can be adjusted according to their benefits.

**Glorot and Bengio (2010) criterion** This type of initialization demands that the variance of the weight distibution should be as follows:

$$\text{Var}(W) = 2/(n_{in} + n_{out}) \tag{4.16}$$

The constraint ensures that the variances of the input, output and the gradients are the same. They go ahead to pick the weights from a Gaussian distribution with zero mean and variance as given in equation4.16. This initialization has been proved to be useful owing to the fact that it can detect the scale of initialization based on the number of inputs and outputs, keeping the signal in a reasonable limit through many layers [8] [6].

**He *et al*. (2015b) criterion** He *et al*. (2105b) proposed an initialization criterion specifically accounts for ReLU non-linearity function, which grants the ability to train extremely deep networks [8] [12].

$$\mathrm{Var}(W) = 2/n_{in} \tag{4.17}$$

### Complex-valued weight initialization

Chiheb *et al*. (2018) introduced two methods of complex weight initialization, which incorporate the two real-valued $\mathbb{R}$-CNN weight initialization techniques given above.

They start with dealing with the problem of defining the variance of complex weights. The standard definition of variance of complex variables goes as follows:

$$\mathrm{Var}(W) = \mathbb{E}[WW^*] - (\mathbb{E}[W])^2 = \mathbb{E}[|W|^2] - (\mathbb{E}[W])^2 \tag{4.18}$$

When $W$ is a symmtrically distributed around 0, equation 4.18 reduces to $\mathrm{Var}(W) = \mathbb{E}[|W|^2]$. In order to calculate this variance, we adopt a route that involves Rayleigh distribution. We know that the variance of the magnitude of complex weights, $\mathrm{Var}(|W|)$, follows a Rayleigh distribution, given below:

$$\mathrm{Var}(|W|) = \mathbb{E}[|W||W|^*] - (\mathbb{E}[|W|])^2 = \mathbb{E}[|W|^2] - (\mathbb{E}[|W|])^2 \tag{4.19}$$

Bu substitution, we reach the following formulation for the variance of the weights:

$$\mathrm{Var}(|W|) = \mathrm{Var}(W) - (\mathrm{E}[|W|])^2, and \mathrm{Var}(W) = \mathrm{Var}(|W|) + (\mathrm{E}[|W|])^2 \tag{4.20}$$

The expectation and variance of magnitude of complex weights can be computer using the definitions given by the Rayleigh distribution, which can be characterized by just one parameter, mode ($\sigma$). By substitution, we can finally define the variance of the complex weights.

$$\mathrm{E}(|W|) = \sigma\sqrt{\frac{\pi}{2}}, \mathrm{Var}(|W|) = \frac{4-\pi}{2}\sigma^2 \tag{4.21}$$

$$\text{Var}(W) = 2\sigma^2 \tag{4.22}$$

Now that the variance is defined, we can choose either Glorot and Bengio criterion or the He. *2t al.* (2015b) criteron to equate to define the vaue of $\sigma$. In the former criterion, we get $\sigma = 1/\sqrt{n_{in} + n_{out}}$, and in the latter, $\sigma = 1/\sqrt{n_{in}}$. Having the appropriate $\sigma$, we can pick the magnitude of our weights from teh Rayleigh distribution. However, as the variance of $W$ depends only on the magnitude of the weights and not their phase, we have the liberty of choosing phase. In their implementation, phase is chosen from a uniform distribution of -$\pi$ to $\pi$.

Finally, we can use equation 4.23 to form the real and imaginary parts of the weights.

$$W = |W|e^{i\theta} = \Re\{W\} + i\Im\{W\} \tag{4.23}$$

### 4.2.5 Loss function

Loss functions provide two functions in a convolutional neural network - regularization, and provide a measure of comparison between the prediction and the ground truth label. Regularization refers to the idea that the loss function can help enforce a specific quality of the learning in a neural netowrk i.e. L2 regularization prefers that the result obtained is not a consequence of a little number of peaky weight vectors, but a large number of diffused weight vectors. In a classification problem solved with the help of neural networks, we intend to minimize the error, i.e. the difference between the prediction and the ground truth label, using an optimization technique, most common of which is Stochastic Gradient Descent (discussed in 4.2.6). Different loss functions will give different errors for the same prediction, and thus have a considerable effect on the performance of the model. One of the strict requirements is that loss functions are differnetiable so that error gradients can be calculated.

#### Loss functions in $\mathbb{R}$-CNNs

In the classification problem, $\mathbb{C}$-CNNs employ a variety of loss functions including Mean Squared Error (MSE), Hinge Loss, Cross Entropy etc. One of the most common loss functions used for multi-class classification, Categorical Cross Entropy (negative), defined as:

$$L_{y'}(y) = -\sum_{i=1} y_i^{'} \log(y_i) \tag{4.24}$$

where $y_i$ is the predicted probability for class $i$ and $y_i^{'}$ is the ground truth label of the class. Cross entropy, true to the nature of a loss function, shows a trend of increase as the difference

between the predicted and the ground truth class label increases.

**Loss functions in $\mathbb{C}$-CNNs**

In the literature, we find that the output of the final layer of $\mathbb{C}$-CNNs can be complex-valued or real-valued in nature. Since complex domain is not an ordered field, the output of the loss function has to real-valued, making it a real-valued complex function. When the output of the $\mathbb{C}$-CNN is complex-valued, the loss function maps from complex domain to real domain. Examples of such loss functions include Complex Quadratic Error Function, Complex FOurth Power Error Function, Complex Cauchy Error Function, Complex Log-Cosh Error Function, Adapted Least-Squares Error, among others [11] [29] [10]. In the other case when the loss function maps from complex domain to real domain, we have two options: either project the data from complex domain to real domain and use a real valued loss function [9], or use a real-valued complex loss function whose input is complex but the output is real (image recognition problem in [25]).

### 4.2.6 Optimization through backpropagation

In the supervised learning problem involving CNNs, the output layer of the system produces a vector of scores, each denote the probability of each hypothesis class $i$, where $i \in [1, P]$. Ideally, the $k^{th}$ entry of the vector, $O(k)$, should larger than the others, corresponding to and correctly identifying the input data class. However, the system needs to go through a training or optimization, in which the parameters or weights of the system are tuned such that they give us correct predictions of the result.

The most common procedure to train CNNs is known as Stochastic Gradient Descent(SGD). This learning algorithm involves computing a gradient vector, with the help of the chain-rule for derivatives, that, for each weight, indicates by what amount the error would increase or decrease if the weight were increased by a tiny amount [19]. SGD updates the parameters $\theta$ of the objective $L(\theta)$ as $\theta_{t+1} = \theta_t \eta_t \nabla_\theta E[L(\theta_t)]$, where $E[L(\theta_t)$ is the average of $L(\theta)$ over a sub-set of the input datset called minibatch, and $\eta$ is the learning rate. Hence, differentiability of the loss function and the activation functions is a strict condition in the case of $\mathbb{R}$-CNNs. However, as discussed in section 4.2.3, such strict requirement can be relaxed for the case of $\mathbb{C}$-CNNs, as substantiated by the literature.

# Chapter 5

# Methodology

WHY BRO WHY DID YOU CHOOSE AVERAGE POOLING? AHAAA! We don't wanna have to deal with a activation function whose values are only positive!

breifly mention the challenges of building a complex valued neural networks.

## 5.1 Representation of complex numbers

Consider a complex number $z = a + ib$ with the real component $a$ and the imaginary component $b$. In $\mathbb{R}$-CNNs, the filter bank or the feature maps of a layer exist in 3 dimensions, where two of them denote the size of the filter or feature map in 2D, and the third dimension indicates how many there are. If we have $N$ feature maps (where $N$ is divisible by 2), the first $N/2$ feature maps would be dedicated to the real components ($a$) and the last $N/2$ feature maps would be dedicated to the imaginary components ($b$). In this manner, the imaginary feature map corresponding to the real feature map on index one of the 3rd dimension would like on the $\frac{N}{2} + 1$ position.

IMAGE REQUIRED

## 5.2 Experimental setups

Explain the architecture, experimental details, the datasets used. Datasets: Toy+ results.Tables and shit.

### 5.2.1 MNIST+P Dataset

### 5.2.2 Radar Dataset

### 5.2.3 Archtitecture - $\mathbb{R}$-CNNs & $\mathbb{C}$-CNNs

# Chapter 6

# Experimental Results

## 6.1 Results

# Chapter 7

# Conclusion

# Appendix A

# The first appendix

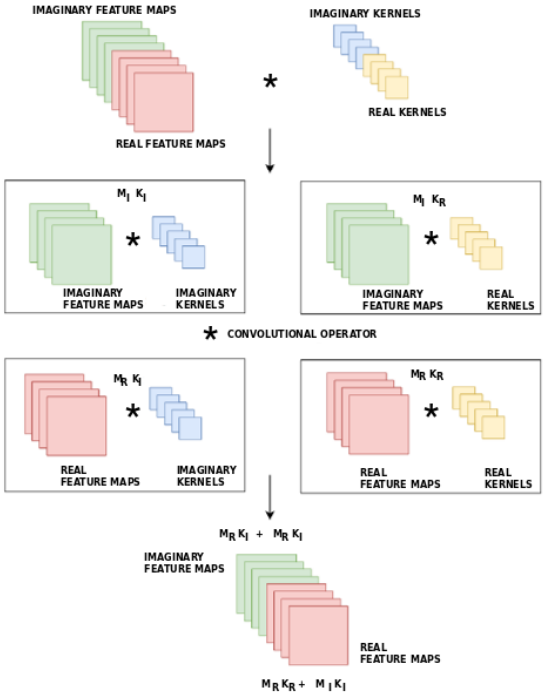


Figure A.1: A schematic sketch of the convolution operation. An item in the output is the sum of point-wise multiplication of the kernel and input patch [1]

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