Neural Network-based Channel Estimation for 2x2 and 4x4 MIMO Communication in Noisy Channels

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***Abstract*— With increasing needs of fast and reliable communication between devices, wireless communication techniques are rapidly evolving to meet such needs. Multiple input and output (MIMO) systems are one of the key techniques that utilize multiple antennas for high-throughput and reliable communication. However, increasing the number of antennas in communication also adds to the complexity of channel estimation, which is essential to accurately decode the transmitted data. Therefore, development of accurate and efficient channel estimation methods is necessary. We report the performance of machine learning-based channel estimation approaches to enhance channel estimation performance in high-noise environments. More specifically, bit error rate (BER) performance of 2×2 and 4×4 MIMO communication systems with space-time block coding model (STBC) and two neural network-based channel estimation algorithms is analyzed.**

Most significantly, the results demonstrate that a generalized regression neural network (GRNN) model matches BER results of a known-channel communication for 4×4 MIMO with 8-bit pilots, when trained in a specific signal to noise ratio (SNR) regime. Moreover, up to 9dB improvement in signal-to-noise ratio (SNR) for a target BER is observed, compared to least square (LS) channel estimation, especially when the model is trained in the low SNR regime. A deep artificial neural network (Deep ANN) model shows worse BER performance compared to LS in all tested environments. These preliminary results present an opportunity for achieving better performance in channel estimation through GRNN and highlight further research topics for deployment in the wild.

I. INTRODUCTION

With the increasing use of wireless communication in many devices and applications, the need for fast and reliable wireless communication has also rapidly increased. Multiple input multiple output (MIMO) communications is a key technology that can significantly increase the performance of wireless communication by utilizing multiple transmitter and receiver antennas at the same time. A major challenge of a MIMO system is the necessity of accurate channel information [1]. Channel estimation becomes more complex when the number of antennas is increased. Inaccurate channel information can significantly deteriorate the overall communication performance. Thus, developing a method that robustly estimates channel information is required to support both current and future communication models (e.g., massive MIMO) that utilize numerous antennas for communication.

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Wireless communication technologies, including most channel estimation methods, have been developed based on theoretical models with extensive mathematical analysis. Recently, neural network architectures have gained immense popularity because of their excellent performance in solving challenging tasks. Several wireless communication studies [2]–[6] have tested the performance of neural network models on channel estimation or modulation detection. To this end, we analyze two different channel estimation models that utilize (1) a generalized regression neural network (GRNN) and (2) a deep artificial neural network (Deep ANN). Specifically, we consider MIMO channel estimation as a regression problem and test the BER performance when the channel matrix is estimated using these neural network models. We evaluate the performance of these models using 2×2 and 4×4 MIMO communication with the space-time block coding (STBC). We further compare the BER performance with of channel estimation using an existing least square (LS) channel estimation method and known channel information. To this end, we investigate the impacts of different training ranges for signal-to-noise ratio (SNR), and different numbers of pilot signals for channel estimation.

The contributions of this study are twofold: (1) We show the BER performance of two neural network-based regression models, GRNN and Deep ANN, on 2×2 and 4×4 MIMO channel estimation and (2) demonstrate the existence of favorable training environments for a neural network-based channel estimation model. The simulation models for MIMO communication and the neural network models are designed using the toolboxes in MATLAB.The evaluation results show that GRNN model can achieve high performance in channel estimation, matching the BER values of a known-channel communication, especially with sufficient number of pilot bits (e.g., 8 bits). The analysis results also demonstrate that training data from certain noisy environments (SNR ranges of -10 to 0 dB and -10 to 10 dB) are effective for training GRNN models compared to other SNR ranges (e.g., -20 to 20 dB and -30 to 30 dB). More importantly, models trained at small SNR ranges show similar BER performance compared to that with the ground truth: known channel matrix. The analysis results show the feasibility of estimating the channel matrix through neural network models and demonstrate that a certain range of noisy environments (i.e., -10 to 10 dB SNRs) and numerous inserted pilots are beneficial for channel estimation with neural network models.

II. RESEARCH BACKGROUND

MIMO can increase throughput compared to single input and single output (SISO) systems [7]. The channel capacity of a MIMO system linearly increases with the number of antennas [8]. Spatial multiplexing and diversity techniques are two main features of MIMO communication [9], where data rates can be increased by sending more information at the same time or reliability can be improved by sending the same information across independent fading channels.

Recently, machine learning approaches have gained popularity in solving challenging problems within computer vision, speech recognition, and natural language processing fields. Within the field of machine learning, artificial neural networks are particularly effective. Recently, neural network models have been utilized to solve problems related to wireless communications. For instance, modulation detection [2] and channel estimation [3]–[6] have been studied. Among them, channel estimation is of particular interest in MIMO communication, and channel state information has been estimated by a variety of approaches such as Gaussian mixture models [3], convolutional neural networks (CNNs) [4], [5], and deep neural networks [6].

More specifically, an approximate message passing neural network, which incorporates a denoising CNN, is used in [4] for channel estimation in massive MIMO systems. It is shown that this model achieves higher performance on channel estimation compared to compressed sensing-based algorithms for massive MIMO systems. In [5], CNNs are utilized to estimate and to remove estimation error or channel noise from the standard belief-propagation (BP) decoder. Correlated channel noise is minimized by iteratively using a BP decoder and CNN and the feasibility of achieving better performance is shown. In [6], the performance of deep learning (DL) models for channel estimation and signal detection in an orthogonal frequency division multiplexing (OFDM) system is analyzed. This deep model can directly recover transmitted symbols without an explicit process of channel estimation. The analysis results demonstrate that the deep learning model can have comparable performance with a minimum mean-square error estimator under channel distortion and interference. However, this study is limited to OFDM because channel estimation is coupled with decoding within the model, and impacts of DL model in specifically channel estimation are not decoupled.

One limitation of previous studies is that they mostly focus on investigating the channel estimation performance in high-SNR communication environments (e.g., positive SNR ranges) rather than testing the performance in high noise environments with negative SNR ranges (e.g., from -10 to 0 dB). We focus on training and testing neural network-based models while varying the training environment (i.e., using negative SNR ranges or using both positive and negative SNR ranges) Then, we compare channel estimation performance from these models to the existing least square channel estimation and known channel from the simulation model.

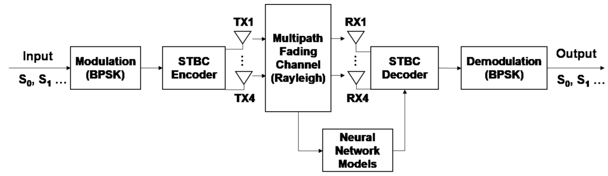


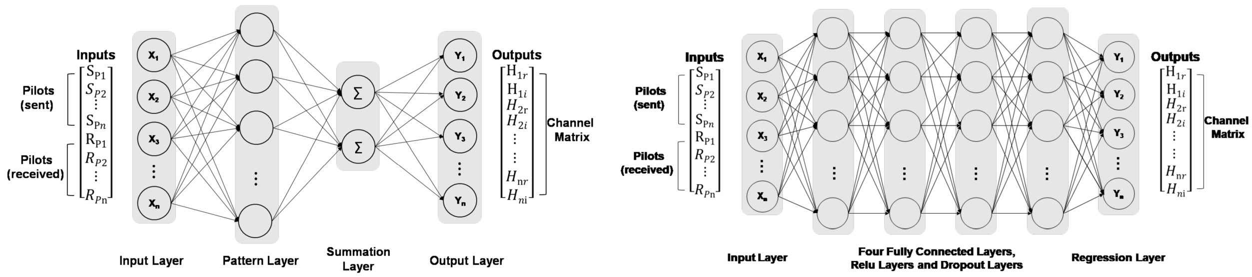
Fig. 1: MIMO Simulation Model with STBC

III. METHODOLOGY

Using MATLAB, we designed 2×2 and 4×4 MIMO communication models that include an orthogonal STBC scheme (See Fig. 1). STBC is a diversity technique that transmits multiple copies of data (i.e., diversity) across a number of the antennas to improve the reliability [10], [11]. All the received copies of the signal is combined to maximize decoding performance. STBC demonstrates strong performance on data transmission in noisy environments, multi-path or fast fading channels [12]. Therefore, STBC is an attractive environment for testing the performance of neural network models for channel estimation, particularly in noisy channels. We utilize an STBC scheme for the 2×2 MIMO system (rate = 1) and the 4×4 MIMO system (rate = 3/4).

MIMO communication system utilizes pilot symbols inserted in the data frame for channel estimation. After modulation (i.e., BPSK), the modulated data is transmitted by multiple transmitter antennas and is received at multiple receiver antennas. We utilize a Rayleigh fading channel in our evaluations. In the experiments, four different channel estimation methods are utilized: GRNN- and Deep ANN-based estimation, a least square (LS) channel estimation model (i.e., least processing between pilot signals and received pilot signals) [13], and the known channel. After channel estimation, the estimated (or known) channel is used for STBC decoding, and the estimated channel's performance is measured in terms of the BER of the decoded data.

As with LS channel estimation, the GRNN and Deep ANN models utilize transmitted pilots and received pilots as input. The outputs of the models are predictions of the channel matrix based on the transmitted and received pilot signals. Training data is provided in the form of (transmitted, received) signals, where the channel matrix used to compute the received signal from the transmitted signal. The models are then trained to minimize the mean squared errors (MSE) between the predicted and true channel matrices, where MSE is computed per matrix entry. A major issue in using neural network algorithms for wireless communications is the fact that data is generally complex numbers (e.g., channel matrix). In this work, we consider the real and imaginary parts of each complex number as distinct elements in channel estimation but other approaches can be considered for future work. For instance, when a 2×2 MIMO system is used, the total number of required complex numbers for the channel matrix is 4, and the number of estimation outputs from the neural network models is 8. The training data of GRNN and Deep ANN are generated by a designed MIMO simulation



(a) GRNN model

(b) Deep ANN Model

Fig. 2: Designed Neural Network Models for Channel Estimation

model with same Rayleigh fading channel model.

To investigate how channel estimation is influenced by the training environment, we vary the SNR ranges while training the neural network models. We test six different training data samples, which are generated by the following SNR ranges (in dB): (1) $[-10,\ 10]$, (2) $[-20,\ 20]$, (3) $[-30,\ 30]$, (4) $[-10,\ 0]$, (5) $[-20,\ 0]$, and (6) $[-30,\ 0]$. Moreover, we vary the number of pilots between 2, 4, and 8. The number of training data per each SNR value is set to $100,000$ bits. The models are tested using data generated in the SNR range of $[-10,\ 10]$ dB.

The GRNN model is a radial basis neural network that estimates continuous variables by taking the weighted average of the values from their neighboring points [14]. The closest neighbor will have a higher weight compared to other neighbors, and the estimation is performed by a radial basis function (RBF). One GRNN model parameter is σ, which determines the spread of a Gaussian distribution curve. For instance, if the sigma is large, the Gaussian distribution becomes more spread. The advantage of GRNN is that it can find a regression surface even with a small number of training data [14]. Many studies have utilized the GRNN model for regression tasks, and it has demonstrated good estimation performance [15]. We apply the GRNN model for MIMO channel estimation, and this model estimates the real and imaginary parts of elements in a channel matrix.

The GRNN model's structure is shown in Fig. 2(a), which consists of the input, pattern, summation, and output layers. More specifically, the input layer receives the data and passes to the pattern layer. The neurons in pattern layer are a trained pattern and the output of pattern layer represents a measure of the distance between input data and stored patterns. The summation layer determines the sum of weighted outputs and unweighted outputs and the output layer estimates a value by using it as numerator and denominator. Similar to LS estimation, transmitted and received pilots are used to estimate elements of the channel matrix. For instance, S_{P1} and R_{P1} in Fig. 2(a) represent sent pilots and received pilots, respectively. Also, H_{1r} and H_{1i} represent the real and imaginary parts of a first element in the channel matrix. The regression process in GRNN is shown as:

$$\widehat{Y}\left(X\right) = \frac{\sum_{i=1}^{p} Y_i p\left(X \mid Y_i\right)}{\sum_{i=1}^{p} p\left(X \mid Y_i\right)}, \tag{1}$$

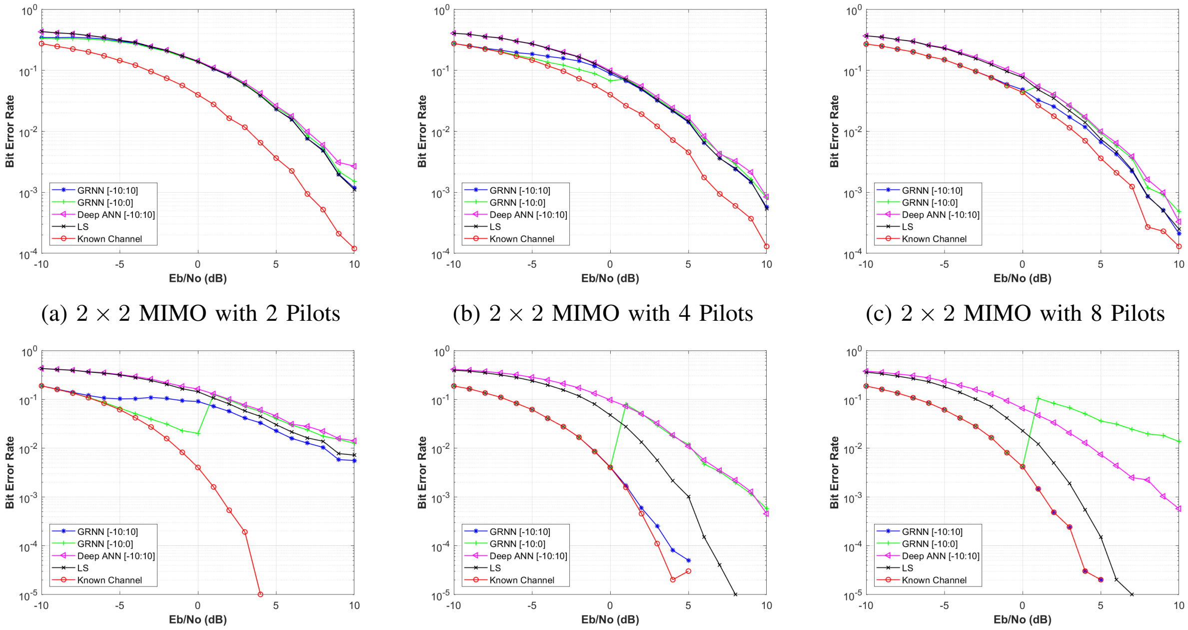
$$p\left(X \mid Y_i\right) = \left(\frac{D_i^2}{\sigma^2}\right), \tag{2}$$

where, X is an input vector, Y is a target vector, D is the euclidean distance between a sample and the value, and σ is a spread parameter.

In addition to the GRNN model, we also utilize a deep ANN model, which has been shown to approximate any function of interest to any desired degree of accuracy [16]. The architecture of the deep ANN model is shown in Fig. 2(b). Similar to [17], where ANN is used for solving a regression problem in speech enhancement and Chinese handwriting recognition, the deep ANN model has four fully-connected layers. Rectified linear units (ReLu) and dropout layers are also added to enhance the performance of weight updates and to avoid overfitting. We set the hyperparameters based on results from [18]: The number of neurons in the fully-connected layers is 100, except in the last layer, which has the same number of neurons as the number of elements in the channel matrix. The training is conducted for 200 epochs, using stochastic gradient descent with momentum and mini-batch size of 30.

IV. Channel Estimation Performance

The channel estimation results from GRNN models in 2×2 and 4×4 models are shown in Fig. 3. As shown in Fig. 3(a), in 2×2 MIMO system, GRNN models trained in $[-10,\ 10]$ dB and $[-10,\ 0]$ dB SNR ranges have a 0.5-4 dB lower SNR requirement for a fixed BER, at low SNR regime, $[-10,$ $-5]$ dB, compared to LS with 2 pilot signals. Increasing the pilot signals from 2 to 4 improves channel estimation for GRNN (Fig. 3(b)), where the known channel BER is matched for SNR $<$ -6dB. Further increasing the pilot signals to 8 (Fig. 3(c)) results in a better channel estimation performance compared to LS (by 0.5 - 2dB) up to 6dB, when GRNN model trained in the $[-10,\ 10]$ dB range. It can be observed that GRNN model cannot easily generalize the learning performance outside of the training range, where a rapid performance degradation is observed for SNR of 0 dB, when the model is trained in the $[-10,\ 0]$dB range. This might relate with the fact that the GRNN model does not contain training data which was collected in the positive SNR regime.



(a) 2×2 MIMO with 2 Pilots (b) 2×2 MIMO with 4 Pilots (c) 2×2 MIMO with 8 Pilots

(d) 4×4 MIMO with 2 Pilots (e) 4×4 MIMO with 4 Pilots (f) 4×4 MIMO with 8 Pilots

Fig. 3: Achieved Bit Error Rate (BER) from GRNN and Deep ANN models

Overall, the GRNN model, with $[-10,\ 10]$ dB training, shows a better channel estimation performance compared to LS at the low SNR regime. The range of SNR values for which GRNN outperforms LS depends on the number of pilots (i.e., $[-10,\ -5]$ dB for 2 pilots, $[-10,\ 0]$ dB for 4 pilots, and $[-10,\ 6]$ dB for 8 pilots). Other training ranges, ($[-20,\ 20]$, $[-30,\ 30]$, $[-20,\ 0]$, and $[-30,\ 0]$) result in performance loss compared to LS at all tested SNR values.

For 4×4 MIMO (Figs. 3(d-f)), similar observations are in order. It is important to note that the GRNN model trained in the $[-10,\ 0]$ dB range results in better performance compared to the $[-10,\ 10]$ dB range, with 2 pilot signals (Fig. 3(d)). However, performance degradation still occurs at 0 dB.

The most significant results of our evaluations can be observed in Figs. 3(e-f), where 4 and 8 pilots are used. The GRNN model trained in the $[-10,\ 10]$ dB SNR range shows almost identical performance with known channel when using 4 or 8 pilots at all test SNR ranges. Moreover, the performance enhancement is almost 1.5 dB compared to LS method. Considering that 4×4 MIMO model will collect more channel information compared to 2×2 MIMO model, this fact might relate to the high channel estimation performance in 4×4 MIMO model compared to 2×2 MIMO model.

Similar to the analysis with GRNN, various training environments (e.g., different SNR ranges, pilot signals) are tested for deep ANN model and the best performance was achieved for the model trained in the $[-10,\ 10]$ dB SNR range. In neither 2×2 and 4×4 MIMO communication models does deep ANN provide any clear performance enhancements compared to LS method with respect to the different training environments (Figs. 3). From all tested environments, deep ANN model shows similar or lower channel estimation performance compared to the LS method.

TABLE I: Processing Time Measurement

Models	Data Size (bits)	Training (sec)	Test (sec)
GRNN (2×2)	6 Million	19.18	$2,875.00$
GRNN (4×4)	6 Million	21.94	$5,764.00$
Deep ANN (2×2)	6 Million	$3,685.00$	48.86
Deep ANN (4×4)	6 Million	$7,878.00$	60.24

Despite its remarkable performance for some combination of SNR training ranges and number of pilots, GRNN suffers from testing complexity, when operation in the wild is considered. In Table. I, the training and test durations for both GRNN and deep ANN models are shown. It can be observed that GRNN enjoys a significantly short training duration (0.3-0.5% of deep ANN), whereas testing is comparatively longer. This suggests that GRNN model may not be suitable for operation in the wild and new methods that match GRNN performance may be needed.

These results indicate that GRNN model achieves a better performance compared to our deep ANN model, matching known channel in certain scenarios, which is promising. However, further investigation is necessary to measure the general performance of deep neural network based channel estimation models since deep neural network architecture needs a huge amount of data for training and only one type of deep neural model (deep ANN) is evaluated in this work.

V. Conclusions

We studied the use of neural networks in channel estimation in noisy environments. We evaluated both a GRNN and a deep ANN. Our results indicate that a GRNN model has the potential to match known channel performance and outperform the existing LS method for channel estimation. GRNN was shown to be particularly strong for channel matrix estimation in the low SNR regime.

First, a channel estimation process requires processing complex numbers. We represent these complex numbers as a pair of numbers rather than using all the information implicit in a complex number. One existing solution for handling complex numbers is using a neural network model that can directly handle complex inputs [20]. An additional limitation of our study is that the proposed channel estimation methods have a limited range where they show improved performance, i.e., mostly only observed in negative SNR environments. This result might relate to the characteristic of GRNN model which fully relies on the information of training data for regression tasks. However, analysis results from this study are not sufficient for specific reasoning and further investigation on studying a relationship between specific training SNR and specific test SNR is necessary to reveal the optimal training environments for channel estimation. Additionally, the deep ANN model in this study is designed to reduce squared errors between estimated channel and known channel during training process. Future work will consider direct optimization of the bit error rate (BER). Finally, we limit the architecture of a deep-learning model as a stack of fully connected layers; however, there are many different architectures, such as CNN and RNN, that have performed very well in computer vision and language processing. Additional studies on different types of neural network models for channel estimation are also necessary for further development.

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REFERENCES

[1] C. Knievel, P.A. Hoeher, On particle swarm optimization for MIMO channel estimation, Journal of Electrical and Computer Engineering. 2012, 9.

[9] J. Mietzner, R. Schober, L. Lampe, W.H. Gerstacker, P.A. Hoeher, Multiple-antenna techniques for wireless communications-a comprehensive literature survey, IEEE Communications Surveys & Tutorials. 11 (2009).

[2] N.E. West, T. OShea, Deep architectures for modulation recognition, in: IEEE, 2017: pp. 1-6.

[3] C.-K. Wen, S. Jin, K.-K. Wong, J.-C. Chen, P. Ting, Channel estimation for massive MIMO using Gaussian-mixture Bayesian learning, IEEE Transactions on Wireless Communications. 14 (2015) 1356-1368.

[4] H. He, C.-K. Wen, S. Jin, G.Y. Li, Deep Learning-based Channel Estimation for Beamspace mmWave Massive MIMO Systems, ArXiv Preprint ArXiv:1802.01290. (2018).

[5] F. Liang, C. Shen, F. Wu, An iterative BP-CNN architecture for channel decoding, IEEE Journal of Selected Topics in Signal Processing. 12 (2018) 144-159.

[6] H. Ye, G.Y. Li, B.-H. Juang, Power of deep learning for channel estimation and signal detection in OFDM systems, IEEE Wireless Communications Letters. 7 (2018) 114-117

[7] A.F. Molisch, Wireless communications, John Wiley & Sons, 2012.Magn.Jpn., vol. 2, Aug. 1987, pp. 740–741

[8] B. Vucetic, J. Yuan, Space-time coding, John Wiley & Sons, 2003.

[10] V. Tarokh, H. Jafarkhani, A.R. Calderbank, Space-time block codes from orthogonal designs, IEEE Transactions on Information Theory. 45 (1999) 1456-1467.

[11] S.M. Alamouti, A simple transmit diversity technique for wireless communications, IEEE Journal on Selected Areas in Communications. 16 (1998) 1451-1458.

[12] V. Tarokh, A. Naguib, N. Seshadri, A.R. Calderbank, Space-time codes for high data rate wireless communication: performance criteria in the presence of channel estimation errors, mobility, and multiple paths, IEEE Transactions on Communications. 47 (1999) 199–207.

[13] J.-J. Van De Beek, O. Edfors, M. Sandell, S.K. Wilson, P.O. Borjesson, On channel estimation in OFDM systems, in: IEEE, 1995: pp. 815-819.

[14] D.F. Specht, A general regression neural network, IEEE Transactions on Neural Networks. 2 (1991) 568-576.

[15] M. Firat, M. Gungor, Generalized regression neural networks and feed forward neural networks for prediction of scour depth around bridge piers, Advances in Engineering Software. 40 (2009) 731-737.

[16] K. Hornik, M. Stinchcombe, H. White, Multilayer feedforward networks are universal approximators, Neural Networks. 2 (1989) 359-366.

[17] J. Du, Y. Xu, Hierarchical deep neural network for multivariate regression, Pattern Recognition. 63 (2017) 149-157.

[18] D. Xiao, B. Li, Y. Mao, A Multiple Hidden Layers Extreme Learning Machine Method and Its Application, Mathematical Problems in Engineering. 2017 (2017).

[19] H. Kim, Y. Jiang, R. Rana, S. Kannan, S. Oh, P. Viswanath, Communication Algorithms via Deep Learning, in: ETH Zurich, 2018: pp. 48-50.

[20] C. Trabelsi, O. Bilaniuk, Y. Zhang, D. Serdyuk, S. Subramanian, J.F. Santos, S. Mehri, N. Rostamzadeh, Y. Bengio, C.J. Pal, Deep Complex Networks, (2018). https://openreview.net/forum?id=H1T2hmZAb (accessed April 2, 2018).