Deep Learning for Spectral Filling in Radio Frequency Applications

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Abstract—Due to the Internet of Things (IoT) proliferation, Radio Frequency (RF) channels are increasingly congested with new kinds of devices, which carry unique and diverse communication needs. This poses complex challenges in modern digital communications, and calls for the development of technological innovations that (i) optimize capacity (bitrate) in limited bandwidth environments, (ii) integrate cooperatively with already-deployed RF protocols, and (iii) are adaptive to the ever-changing demands in modern digital communications. In this paper we present methods for applying deep neural networks for spectral filling. Given an RF channel transmitting digital messages with a pre-established modulation scheme, we automatically learn novel modulation schemes for sending extra information, in the form of additional messages, “around” the fixed-modulation signals (i.e., without interfering with them). In so doing, we effectively increase channel capacity without increasing bandwidth. We further demonstrate the ability to generate signals that closely resemble the original modulations, such that the presence of extra messages is undetectable to third-party listeners. We present three computational experiments demonstrating the efficacy of our methods, and conclude by discussing the implications of our results for modern RF applications.

Index Terms—deep learning, signal generation, communications, machine learning, radio frequency

I. INTRODUCTION

The Internet of Things (IoT) proliferation poses novel, and complex challenges for digital communications [2], [13], [15]. Radio Frequency (RF) channels are increasingly congested with new kinds of devices, which carry unique communication needs [16]. Meeting these challenges requires the development of new technologies that (i) optimize capacity in limited bandwidth environments, (ii) integrate seamlessly with existing, already-deployed communications protocols, and (iii) are adaptive to the continuous flux in consumption requirements of modern digital comms environments.

Here we present novel methods for applying deep neural networks (DNNs) for spectral filling. Given an RF channel transmitting digital messages via some pre-established modulation scheme, we show that we can automatically learn novel modulation schemes to send extra information, in the form of an additional message, “around” the fixed-modulation signals (i.e., without interfering with them), thus increasing channel capacity without increasing bandwidth. We further demonstrate the ability to constrain the spectral shape of learned signals, such that they resemble the original modulations or conform to arbitrary spectral shapes.

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Recent years have seen a nascent, but growing interest in leveraging deep learning for RF applications. One such application is “spectrum sensing”, where DNNs are trained to classify the modulations of signals in an RF environment [3], [22]. Neural networks have also been trained to demodulate RF signals [1], [12], [14], [18], [19], [26], and even for end-to-end communications systems, although success of these efforts has been mixed [7], [20]. Despite these early efforts, deep learning in RF applications is still a relatively unexplored area, and much remains to be learned about what kinds of model architectures are well-suited to the RF domain and what kinds of problems DNNs are apt to address.

In particular, the spectrum filling problem introduced in this paper has not yet been addressed by the research community. Earlier efforts have shown that DNNs can be used in model communications systems, but it is not clear how they would be deployed in real-world scenarios, in which the learned RF signals would need to cooperate with existing signals defined by pre-established modulation protocols. Conversely, in the present work, insofar as we are able to learn modulations that adapt to existing RF protocols, we demonstrate the suitability of our methods to be integrated with already-deployed communications systems in the wild.

Our work also differs from previous efforts in that our DNN architectures utilize Transformer networks, which have proven to be powerful architectures for modeling temporal relationships in time-series data such as NLP, music, and signal processing [5], [6], [10], [25]. This is a departure from previous efforts, which have typically used convolutional networks [21], [27], which were originally developed in computer vision [9], [11], and thus not optimally-suited for modeling time-series. There has been some work on applying autoregressive Long-Short Term Memory (LSTM) networks to RF data [3], [22], but these efforts lag behind the state-of-the-art in deep learning, because LSTMs are almost unanimously outperformed by Transformers in a variety of time-series applications [8], [25]. To our knowledge, there has only been one previous application of transformers to the RF domain [24], which showed promising results, though it was not geared towards the problem addressed here: spectral filling.

A. Problem Statement: Spectral Filling

We considered a scenario where two radios communicate over a traditional digital signal pipeline (see Supporting Information for a high-level schematic). This communication scheme is bounded in its capacity by Shannon’s Limit [23],
meaning that for the bandwidth the radios are using and the amount of noise in their environment, the speed that they can transmit information is fixed. This is defined by the equation

$$C = B \log_2 \left( 1 + \frac{S}{N} \right)$$  \hspace{1cm} (1)$$

where $C$ is the capacity in bits/sec, $B$ is the bandwidth in Hz, $S$ and $N$ are the power in the signal and noise respectively. Modern digital communication schemes can come close to this limit, however there is usually a gap in the actual speed of data transmission and the theoretical maximum. This means that there is the possibility for extra data to be transmitted alongside the fixed, traditional scheme.

However, another important theorem of digital communications that stops full utilization of this gap is the central coding limit theorem. The coding limit theorem states that while the rate, $R$ of data transfer in a channel is less than Shannon’s capacity, $R < C$, the rate at which errors occur in the communication channel can be made arbitrarily small. If the rate exceeds the Shannon limit then the error rate will be, in general, large. We plan to exploit this gap in actual vs. theoretical rates of communication, while still being able to make the error rates of communication small.

We label a traditional digital communication signal from one radio to the other as the A message. This consists of a sequence of ones and zeros and is generally long. If this signal does not reach Shannon’s limit than there is the possibility for a second message that uses some of the unused bandwidth. This is the B message but is generally not as long as the A message. We have developed a novel method for generating a time series that can transmit these two different types of messages without greatly affecting the accuracy of the A message.

A secondary goal of ours is to constraint properties of learned signals using auxiliary loss terms. In Experiment 1, we constrain learned signals to resemble the original modulations, such that a third-party would not be able to identify the presence of message B based on spectral properties or other signatures of the generated signals. In Experiment 2 we go one step further and show that it is possible to constrain learned signals to match to arbitrary spectral shapes, while still retaining the ability to transmit both messages. In the remainder of this paper we specify our methods, report results from three experiments demonstrating success with respect to each of our goals, and conclude by discussing the implications for modern RF applications.

## II. METHODS

Our goal is to transmit an RF signal\(^1\) that carries information from two messages (A and B) over-the-air. Both messages are sequences of discrete symbols. Experiments 1 & 2 utilize Quadrature Shift Keying (QPSK), Message A comprises four symbols. As reported in Section A, we also ran a preliminary experiment utilizing Binary Phase Shift Keying (BPSK), in which Message A comprises two symbols. In all experiments, Message B was a binary sequence. The lengths of messages A and B need not be equal, and we refer to length of A message as $length_A$ and length of B message as $length_B$ ($length_B$ is typically shorter than $length_A$). In all experiments we assume a sample rate of 1 Hz and oversampling of 1 with respect to A, such that $length_A$ is equal to the number of IQ samples in the signal.

### A. Model Architecture

Our model includes two transformer-based DNNs — the Modulator and Demodulator networks. These networks are jointly trained to modulate and demodulate extra information from message B without degrading the original signal carrying message A. The model also includes fixed modules for modulation and demodulation of message A, as well as a channel model that simulates Additive White Guassian Noise (AWGN). Complete details and a block diagram of the model architecture are included in the Supporting Information.

Message A is first modulated with a standard RF protocol, such as BPSK or QPSK. This yields a signal — an IQ sequence of dimensionality $(2, length_A)$ — which we denote $IQ_A$. The Modulator Network receives $IQ_A$ and message B as inputs, and outputs $IQ_{AB}$, an IQ signal encoding information from both messages. $IQ_{AB}$ is then passed through the channel model, which applies AWGN according to a specified signal-to-noise-ratio (SNR), producing $IQ_{channel}$, a noised signal representing what would be received over-the-air.

The received signal is then separately demodulated by a fixed module, which uses standard demodulation (either BPSK or QPSK) to recover Message A, and the Demodulator Network, which predicts bits in Message B. The discrepancy between ground-truth and predicted symbols in messages A and B serve as two loss terms for training our models, as described in Section II-B. Note that the fixed demodulator is completely naive to the learned modulation; it processes the transmitted signal as if it were a typical BPSK or QPSK signal. Therefore, in order to achieve high accuracy with respect to message A, the Modulator Network must not interfere with the fixed modulation.

### B. Training Procedure

Our models were jointly trained to minimize two loss terms: $loss_A$ and $loss_B$. For $loss_A$ we took the binary cross-entropy (BCE) loss of each IQ sample in $IQ_{channel}$ compared to the original $IQ_A$. For $loss_B$ we took BCE of each prediction logit in the output of the Demodulator Network compared to the bits in the ground-truth Message B. In both cases, prediction logits were passed through a sigmoid function before BCE was computed. These two loss terms were combined into a single loss function that implicitly encouraged the Modulator Network to modulate message B in such a way that it did not degrade original QPSK message. The overall loss is:

\(^1\)RF signals typically comprise two orthogonal components, I and Q, which can be thought of as cosine and sine components of a complex waveform. Sampling from these components yields a two-dimensional IQ sequence, which for the purposes of this paper is synonymous with an RF signal.
loss = α loss_A + (1 - α) loss_B \quad (2)

where α tunes the degree to which loss_A is weighted with respect to loss_B.

Through preliminary experimentation, we found it was best to initialize α = 1 at the beginning of training (keeping it fixed at 1 for first three epochs), and then gradually decrease it over subsequent epochs (at a rate of 0.01 per epoch) until it reached α = 0.5. This encouraged the model to first minimize loss_A — which should be trivial, since the Modulator Network is given the ground truth QPSK IQ values for message A, and can in principle learn to ignore message B — and then gradually learn to include information from message B without degrading the original IQ sequence. We also experimented with different auxiliary losses for constraining various properties of the generated signals, as described in subsequent sections.

A dataset consisting of 16,384 examples was synthesized. Each example consisted of a tuple of (message A, IQ_A, message B). 80% of these examples were used for training, and the remaining 20% were held out as a test set. Unless otherwise reported, the batch size was 64, and SNR was varied across all examples within each batch by sampling over a uniform distribution ranging from 5–15 dB. The AdaBelief optimizer was used with a learning rate of 0.01 [28]. Models were trained for 128 epochs, unless otherwise specified.

III. RESULTS AND DISCUSSION

Experiment 1: Constraining learned signals in time-domain (QPSK)

In this experiment we used an auxiliary loss term to explicitly encourage the model to generate signals resembling the original QPSK signal (IQ_A). We used mean-squared error (MSE) on the learned IQ sequence (signal_{combined}), with respect to the original QPSK signal (IQ_A). This loss term is denoted $loss_{MSE}$, and it was incorporated into the overall loss function as defined by the equation:

$$loss = \frac{α}{2} loss_A + (1 - α) loss_B + \frac{α}{2} loss_{MSE} \quad (3)$$

This closely resembles Equation 2, except that the weight of α is equally distributed across loss_A and loss_{MSE}. This was done because these two loss terms are complementary — constraining signal_{combined} to match IQ_A (via loss_{MSE}) necessarily makes it easier for a QPSK demodulator to recover Message A by processing signal_{combined} as if it were a typical QPSK signal. In this sense a high value of α still biases training to optimize for Message A, and low or intermediate α values reward successfully transmitting and demodulating Message B.

Model Performance: The best model from this training run was evaluated on a held-out test set over a range of SNRs. At each SNR, we passed every example in the test set through the model, and independently evaluated Bit Error Rate (BER) of messages A and B. Results are depicted in Figure 1. The x-axis represents noise level at which our AWGN channel was simulated, expressed in $E_s/N_0$ (energy per symbol to noise power spectral density ratio), a normalized SNR measure. Missing yellow points (at $E_s/N_0 = 13$ and $E_s/N_0 = 18$) are instances where 100% accuracy was achieved for Message B. Both messages are consistently transmitted and demodulated with high fidelity over a range of noise levels.

In response to our primary research question, this demonstrates the ability to successfully learn a modulation that can transmit extra information (Message B) in the same channel.

2It is also worth noting that these BER values can be further enhanced with forward-error correction strategies [17], which would be straightforward to integrate with our model.
Next we turn to our secondary research question: can we constrain the structure of learned signals? In this experiment we were interested in constraining the learned signal to match the original QPSK. To get a sense of this, we visualized examples of learned signals generated by our best-performing model, and compared them to the original QPSK signals. Figure 2 shows time-domain signals for an arbitrary example (I and Q components are colored blue and orange, respectively). The top plot shows signals corresponding to a vanilla QPSK signal carrying Message A, and the bottom plot shows the learned signal carrying Message A & B. (See the Supporting Information for constellation plots of these signals.) There is high resemblance between the two signals, indicating that not only did our model successfully learn to transmit information from both messages, it did so in such a way that the learned signals were nearly identical to original modulations. This has important implications for our methods in real world RF applications – we can learn to transmit extra information in “hidden” messages, such that the generated signals look nearly identical to typical QPSK signals from the perspective of a third-party.

Experiment 2: Constraining Constellation Plots of Learned Signals (QPSK)

We also experimented with different methods for constraining the constellation plots of learned signals. In Experiment 1, we showed it is possible to produce a learned signal that maximally resembles the fixed modulation; here we show that related techniques can also be used for arbitrary signal shapes.

To learn a particular shape, we add an auxiliary term to the loss function that encourages the distribution of values in the learned signal to match a target distribution. Given a sample of $m$ points from a target distribution and a learned signal, we define the $n \times m$ distance matrix $M$ as: $M_{ij} = MSE(s_i, q_j)$ where each $s_i$ is a single value sampled from the learned signal, and each $q_i$ is from a sample of the target distribution. The auxiliary loss is then:

$$loss_{\text{shape}} = \frac{1}{n} \sum_{i=0}^{n} \min_{j}(M_{ij}) + \frac{1}{m} \sum_{j=0}^{m} \min_{i}(M_{ij})$$  \hspace{1cm} (4)$$

This first sum encourages each learned signal value to be near a point in the target distribution sample. The second term ensures that the learned signal shape takes on the entire target structure. For example, in the case of a multimodal distribution, without the second loss term, the shape loss could be minimized if all the learned signal points cluster on one of the modes. Notably, this loss function does not require a closed-form density function for the target distribution so the learned signal can resemble any shape compatible with QPSK or another established communication protocol. The complete loss equation becomes:

$$loss = \alpha \ loss_A + (1 - \alpha) \ loss_B + \beta \ loss_{\text{shape}}$$  \hspace{1cm} (5)$$

We have tested this with several shapes and depict the results in Figure 3. From left to right, the first two shapes were trained to resemble a QPSK signal at different noise levels. We trained at a fixed SNR of 10 dB for 50 epochs. For computational efficiency, the distance matrix was calculated as a fixed-modulation signal without degrading the original signal.
using 2500 random values from the learned signal and 2500 random values from the target distribution. BER at SNR = 10 dB for the A message was 1.49e-7 and 5.19e-3 for the less noisy and noisy targets, respectively. The BER for the B message was zero for both models.

The other two shapes demonstrate the flexibility of this method. For these two shapes, we trained with SNR fixed at 10 dB for 200 epochs using the sampling adjustment described in the previous paragraph. For the elliptical distribution the BER for the A message was 1.71e-5 and for the B message was 0. For the circular distribution the BER for the A message was 2.4e-3 and 7.62e-5 for the B message. Thus, these methods allow us to constrain generated signals to conform to arbitrary spectral shapes, while still retaining high fidelity with respect to both messages.

IV. CONCLUSION

We have demonstrated the ability to use deep, transformer-based neural networks for “spectral filling.” Given an original message (Message A), encoded with some pre-defined modulation protocol (e.g., BPSK/QPSK), these networks can learn to augment and reconstruct the IQ sequence, such that it carries an additional message (Message B) without degrading the original signal. This has promising implications for congested IoT applications, as it establishes a methodology for increasing the capacity of existing fixed-bandwidth RF channels without costly human-engineered protocols, and without disrupting existing communications protocols. This last point is crucial, because a major challenge in leveraging generative deep learning for RF applications is how to deploy these technologies without disrupting pre-established RF environments.

We have further demonstrated that with the help of auxiliary loss terms, it is possible to constrain learned signals to closely resemble the original signals, or to match arbitrary spectral shapes, while still transmitting information from both messages at high fidelity. The fact that extra information can be sent without significantly altering the original signal means this technique can be used in sensitive contexts, to send additional in cognito messages, undetectable to third-party listeners.

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