FedRec: Federated Learning of Universal Receivers over Fading Channels

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Abstract

Wireless communications are often subject to fading conditions. Various models have been proposed to capture the inherent randomness of fading in wireless channels, and conventional model-based receiver methods rely on accurate knowledge of this underlying distribution, which in practice may be complex and intractable. In this work we propose a collaborative neural network-based symbol detection mechanism for downlink fading channels, referred to as FedRec, which is based on the maximum a-posteriori probability (MAP) detector. To facilitate training using a limited number of pilots, while capturing a diverse ensemble of fading realizations, we propose a federated training scheme in which multiple users collaborate to jointly learn a universal data-driven detector. The performance of the resulting FedRec receiver is shown to approach the MAP performance in diverse channel conditions without requiring knowledge of the fading statistics, while inducing a substantially reduced communication overhead in its training procedure compared to training in a centralized fashion.

Index terms— Fading channels, federated learning.

I. INTRODUCTION

Fading channels are a fundamental model for communication over wireless media [1]. The fading model encapsulates the fact that the relationship between the transmitted signal and the received one in wireless channels is determined by the propagation of electromagnetic waves, which is typically dynamic and subject to different forms of randomness induced by the environment. Various distributions have been proposed to represent the statistical behavior of fading channels, including the Rayleigh, Rice, and Nakagami-\(m\) models [2], where each approximates the propagation profile in different settings [3].
The inherent randomness of fading channels makes symbol detection a challenging task. The common strategy is to periodically transmit a-priori known pilot signals, that are used by the receiver to estimate the channel, which in turn is utilized for detection [4]. The main drawback of this approach is that pilots must be transmitted anew each time the channel changes, i.e., on each coherence duration, inducing notable overhead in rapidly-changing channels. An alternative approach in fast fading conditions is to utilize a single detection rule for all channel conditions, which accounts for its statistical model [5]. However, such model-based detection relies on the knowledge of the fading distribution, and tends to be inaccurate when the assumed distribution does not faithfully capture the real statistical propagation profile, or in the presence of a model mismatch.

An alternative strategy, which does not require the knowledge of the underlying statistical model, is to learn the detection mapping from data. In particular, neural networks (NNs) have demonstrated unprecedented success over recent years in learning complex mappings in a data-driven fashion [6]. Consequently, a multitude of NN-based receiver architectures, which can operate without the prior knowledge of the underlying statistical model, have been proposed, see, e.g., [7]–[12]. NN-based receivers require labeled data to learn their mapping. If one has prior knowledge of the expected channel conditions and can generate such data artificially, the NN can be trained offline. However, this may not be the case in some realistic scenarios, and the labeled data should be obtained from pilot transmissions over the channel.

When the channel conditions change rapidly, NN-based receivers must frequently retrain with new pilot signals, inducing significant computation and communication overhead. NN-based receivers can track dynamic channel conditions by periodic online training combined with methods to reduce the training complexity as in [13]–[17]. Alternatively, one can train a single NN for all expected channels, which will work for a broad range of channel conditions, by learning a universal rule based on the fading distribution rather than its specific realization [18], [19]. Nonetheless, for a NN to learn the subtleties of a fading distribution, which may be complex and analytically intractable, the training data must contain a sufficiently large number of channel realizations. This may be difficult to achieve even with very long pilot sequences, motivating the design of universal NN-based symbol detectors for fading channels with limited pilots.

In this work we propose FedRec, which is a data-driven universal symbol detection scheme for multi-user downlink fading channels, designed to learn its mappings from a limited amount of pilots. FedRec is comprised of two algorithmic components: The first is the NN-based symbol detection architecture, which uses sufficient statistics from the maximum a-posteriori probability (MAP) symbol detection rule as input features. This allows FedRec to utilize a relatively compact NN, which can be trained with a smaller
number of samples. The second component is the training mechanism, which exploits the fact that, in a wireless network of many users, while each user observes only a limited number of channel realizations, the realizations observed by the overall network are expected to be sufficiently diverse. FedRec builds upon this insight to have the users collaborate for training via federated learning (FL) [20]–[22], allowing to train a single NN over a diverse data set without additional pilots, at the cost of several iterations of parameter exchanges with the base station (BS). Our numerical results demonstrate that the proposed FedRec yields an accurate symbol detector, whose performance approaches that of a MAP detector, and outperforms the model-based approach in the presence of inaccurate knowledge of the fading distribution. FedRec induces substantially less communication overhead compared to learning a NN-based symbol detector in a centralized fashion.

The rest of this paper is organized as follows: Section II presents the system model and the problem formulation. Section III details the proposed FedRec receiver. Numerical examples are presented in Section IV. Finally, Section V concludes the paper.

II. System Model

We consider a downlink communication scenario, where a BS serves $U$ users indexed by $u \in \mathcal{U} \triangleq \{1, \ldots, U\}$. Although we focus on a simple setting of single-antenna terminals in this paper, our approach can be extended to multiple-antenna terminals. Letting $x(t) \in \mathcal{C}$ be the baseband continuous-time (CT) channel input transmitted by the BS at time instance $t$, the corresponding channel output at the $u$th user is given by

$$r_u(t) = h_u(t)x(t) + w_u(t), u \in \mathcal{U},$$

where $\{w_u(t)\}$ are independent identically distributed (i.i.d.) Gaussian noise signals with unit power spectral density (PSD), while $\{h_u(t)\}$ are i.i.d. flat fading coefficients, following a common distribution $p_h(\cdot)$. Various different models exist for $p_h(\cdot)$, which approximate the statistical behavior under different physical channel conditions [1, Ch. 2], but we do not assume prior knowledge of $p_h(\cdot)$.

Downlink communication is typically comprised of pilot and data transmission. During downlink data transmission to user $u$ commencing at time instance $t_d$, the BS encodes a message of $\log_2 M$ bits, denoted by $s_u \in \mathcal{M} \triangleq \{1, \ldots, M\}$, into a signal of temporal duration of $T_s$ seconds, denoted $x_{s_u}(t)$, $t \in [t_d, t_d + T_s)$. The message $s_u$ is assumed to be uniformly distributed over $\mathcal{M}$. Each user $u \in \mathcal{U}$ uses its channel outputs $r_u(t)$, obtained via (1), to recover the message $s_u$. During pilot transmission commencing at $t = 0$, the BS broadcasts a sequence of $N_T$ a-priori known pilot symbols, denoted $\{s_i^p\}_{i=1}^{N_T}$, which are known to the users, over a duration of $N_T \cdot T_s$ seconds.
We focus on regimes in which the number of pilot symbols $N_T$ is relatively small; and hence, it is unlikely to span a sufficient amount of different realizations of the fading coefficient at a single user. While the number of pilots is limited, we allow the users to collaborate and share their detection mappings, in order to jointly learn a unified symbol detector, i.e., one that is universally applicable not only to the users participating in the training, but also to any arbitrary user, by learning a broad fading distribution from the pilots received at all the users and the corresponding messages, i.e., $\{D_u\}_{u=1}^{U}$, where $D_u = \{s^p, R^p_u\}_{i=1}^{N_T}$, with $R^p_u \triangleq \{r_u(t) | t \in [(i-1)T_s, iT_s)\}$.

The resulting symbol detector at an arbitrary user $u'$ recovers the message $s_{u'}$ from the received $r_{u'}(t)$, $t \in t_d + [0, T_s)$, assuming only knowledge of the channel input-output relationship (1), but no knowledge of the fading distribution $p_h(\cdot)$. Our proposed NN-based symbol detection scheme, which combines model knowledge of (1) with data-driven tools to utilize $\{D_u\}_{u=1}^{U}$ in a collaborative fashion to train such a universal receiver, is detailed in the following section.

III. FEDERATED RECEIVER: FedRec

In this section we present FedRec, which is a symbol detection scheme for downlink fading channels. The need for a universal symbol detector applicable to a diverse range of channel fading statistics without the exact knowledge of the underlying distribution motivates using NNs, which were empirically shown to operate reliably in complex unknown statistical environments [6]. However, since NNs require large volumes of diverse training data, having each user train a local NN based on its limited pilot observations is expected to yield a less reliable model with limited generalization performance. To overcome this, we design FedRec based on the following guidelines: (i) The fact that the channel is modeled via (1) is exploited as partial domain knowledge for feature extraction, inspired the MAP rule for such channels. This approach facilitates utilizing more compact NNs (by avoiding feature extraction layers) which are trainable using smaller training sets. (ii) While each local training set $D_u$ encapsulates a relatively small number of fading channel realizations, the diversity among these sets at different users is exploited to obtain a unified model for all the users by training in a federated manner.

A. Model-Based Symbol Detection for Fading Channels

Here, we briefly recall the model-based MAP symbol detector, which requires knowledge of $p_h(\cdot)$. We focus on scenarios in which the fading coefficient $h_u(t)$ takes a single realization during the transmission of each message, and that its phase, denoted by $\phi_u$, is known. The following derivation is based on [1, Ch. 7.2].
Let $\mathcal{R}^{(u)} \triangleq \{ r_u(t) \}_{t=t_d}^{t_d+T_s}$. Since the message $s_u$ is uniformly distributed, the MAP rule at the $u$th user is given by

$$
\hat{s}^{\text{map}}_u = \arg \max_{m \in M} \Pr \left( \mathcal{R}^{(u)} | s_u = m \right).
$$

By defining $y_m^{(u)} \triangleq \int_{t_d}^{t_d+T_s} r_u(t)x_m(t)dt \triangleq \langle r_u ; x_m \rangle$, and similarly, $e_m \triangleq \langle x_m ; x_m \rangle$, the conditional distribution in (2) becomes

$$
\Pr \left( \mathcal{R}^{(u)} | s_u = m \right) = c \int_0^\infty e^{\alpha \Re \{ e^{-j\phi_u} y_m^{(u)} \} - \alpha^2 e_m \rho | h | (\alpha) } d\alpha,
$$

where $c > 0$ is a constant that does not depend on $m$ and $\mathcal{R}^{(u)}$.

The complex structure of the conditional distribution in (3) for general $p|h| (\cdot)$ makes evaluating (3) a challenging task. If $p|h| (\cdot)$ follows a simple Rayleigh distribution with scale parameter $\sigma_u$, the MAP decision criteria (3) reduces to maximizing $\Lambda_m^{(u)}$ given by

$$
\Lambda_m^{(u)} = \ln \{ 1 + \sqrt{\pi} \mu_m e^{\frac{\gamma_m}{4}} \} - \ln(1 + \gamma_m),
$$

where $\gamma_m = 2\sigma_u^2 e_m$, $\mu_m = \sqrt{\gamma_m / [e_m(1 + \gamma_m)]} \cdot \Re \{ e^{-j\phi_u} y_m^{(u)} \}$ and $Q$ denotes the Gaussian Q-function [1, Ch. 7.2.1].

Despite its complex form, (3) reveals that, regardless of the fading distribution, MAP detection over any fading channel conforming to (1), is comprised of the following steps: First, the observations $\mathcal{R}^{(u)}$ are processed by a set of matched filters (MFs) to produce $\{ y_m^{(u)} \}_{m=1}^M$; then, when the phase information is given, the MF outputs are phase-shifted accordingly and their real part is taken; this quantity is processed by a non-linear mapping $f(\cdot)$ which depends on the fading distribution, encapsulating the integral in (3), to produce $\Lambda_m^{(u)} \propto \Pr \left( \mathcal{R}^{(u)} | s = m \right)$. This procedure is illustrated in Fig. 1.

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**Fig. 1:** MAP symbol detector block diagram.
B. Data-Driven Symbol Detector Architecture

We next present a NN architecture which learns to recover $s_u$ from $R^{(u)}$. Recall that NNs process inputs which can be represented as vectors. Here, the input is a CT signal $r_u(t)$, defined over the uncountable set $t \in [t_d, t_d + T_s)$. The intuitive approach to design the network is therefore to uniformly sample $r_u(t)$ via, e.g., Nyquist rate sampling. Taking a large number of samples is expected to facilitate handling the presence of noise and unknown channel [23], while resulting in processing high dimensional inputs, which in turn typically involves using highly-parametrized NNs.

Nonetheless, the model-based MAP detector in Fig. 1 reveals that the MF outputs $\{y_m^{(u)}\}_{m=1}^M$ constitute a sufficient statistics for identifying the message $s_u$. As a result, we exploit this domain knowledge, and design a classification network whose inputs are the matched filter features $\{y_m^{(u)}\}_{m=1}^M$. This significantly simplifies the NN architecture in comparison with a NN architecture which inputs Nyquist samples of the received signal. The proposed NN architecture avoids additional layers that would be required for feature extraction from Nyquist samples of the received signal and uses matched filter outputs as features for classification.

As matched filter outputs take complex values, the NN input is a $2M \times 1$ dimensional vector, which feeds a fully connected network. As $s_u$ can take one of $M$ different values, we use a softmax output layer with $M$ possible labels. Letting $\theta_u$ be the NN parameters of the $u$th user, and $f_{\theta_u} : C^M \mapsto [0, 1]^M$ be its mapping, then the NN prediction can be written as

$$\hat{s}_u = \arg \max_{m \in M} f_{\theta_u,m} \left( \{y_m^{(u)}\} \right), \quad (5)$$

where $f_{\theta_u,m}(\cdot)$ is the $m$th output. The proposed NN architecture is illustrated in Fig. 2.

Note that while the NN architecture in Fig. 2 is comprised of $M$ MF components, in many transmission
Algorithm 1: FedRec Training

Init: Initial parameters $\theta^{(0)} = \phi^{(0)}$, $\forall u \in \mathcal{U}$.

1. for each $n = 1, 2, \ldots$ do
2. Each user $u$ sets $\theta^{(n)} = \theta^{(n)}$, $\forall u \in \mathcal{U}$.
3. if $n$ is an integer multiple of $\tau$ then
4. Each user $u$ sends $g^{(n)} = \theta^{(n)} - \theta^{(n-\tau)}$ to BS;
5. BS computes $\theta^{(n)} = \theta^{(n-\tau)} + \frac{1}{\tau} \sum g^{(n)}$;
6. BS distributes $\theta^{(n)}$ such that $\theta^{(n)} = \theta^{(n)}$, $\forall u \in \mathcal{U}$;
7. end
8. end

Output: Trained FedRec $\theta^{(n)}$ shared among all users.

schemes the outputs of some of the MFs can be obtained as linear combinations of the remaining features. In particular, in modulation schemes where the modulation order is less than $M$, (e.g., 2 for QAM), we use fewer MF features (determined by the modulation order) to simplify the NN.

C. FedRec Training

Here, we describe how the NN is trained. In particular, we consider a training procedure in which the users collaborate in a federated manner, exploiting the diversity in the observed channels. The resulting learned symbol detection algorithm is referred to as FedRec.

As FedRec is comprised of a neural classifier, we use the empirical cross entropy loss for training. The resulting loss measure is

$$L_u(\theta, \mathcal{D}) = -\frac{1}{|\mathcal{D}|} \sum_{\{s_i, R_i\} \in \mathcal{D}} \log f_{\theta,s_i}(\{\langle R_i; x_m \rangle\}_{m=1}^M).$$

(6)

When the training set $\mathcal{D}_u$ captures a sufficiently large number of realizations of the fading channel $h_u$, then each user should be able to tune its local NN parameters to carry out accurate detection. This can be achieved via conventional training mechanisms, e.g., stochastic gradient descent (SGD), for which $\theta_u$ is iteratively updated via

$$\theta^{(n)}_u = \theta^{(n-1)}_u - \eta_n \nabla L_u(\theta^{(n-1)}_u, \{s_{i_n}, R_{i_n}\})$$

(7)

where $n$ is the iteration index, $\eta_n > 0$ is the step-size, and $i_n$ is an index drawn uniformly in an i.i.d. fashion from $\{1, \ldots, N_T\}$.

Nonetheless, when the channel coefficient takes a limited number of realizations in each interval of $N_T T_s$ seconds, the local data set may not capture the subtleties of a universal fading distribution. In such cases, the trained NN is likely to be highly biased towards its observed channel conditions, and may not operate reliably for future realizations of the channel in case the fading statistics change over
time. To tackle this challenge, we exploit the fact that while each user may observe a limited amount of channel realizations, the overall set of different realizations observed among all the users in a cell is likely to be sufficiently diverse to allow training the NN accurately.

Based on the above insight, we propose to jointly train a single instance of the NN shared by all the users via FL [20]. Such distributed learning orchestrated by the BS requires the users to periodically exchange and synchronize their local parameters, possibly by utilizing low-rate transmissions, to train a reliable universal symbol detector. In particular, the training mechanism, based on the local SGD algorithm [24], consists of $\tau$ SGD iterations as in (7), carried out by each user locally, after which the BS averages the trained updates of all the users into a global parameter vector $\theta$, which is distributed among all the users. This training mechanism is summarized as Algorithm 1.

\section*{D. Discussion}

FedRec enables training a NN-based symbol detector using data corresponding to a diverse set of channel realizations, while requiring a limited number of pilots. However, as Algorithm 1 requires the users to exchange their trained parameters several times with the BS, the reduction in the number of pilots comes at the cost of additional transmissions to enable FL. The advantages of this strategy over simply transmitting more pilots are two-fold: First, the NN architecture is designed to utilize compact NNs based on the MAP rule, and thus the volume of data exchanged during training, which is dictated by the cardinality of $\theta$, is limited. This overhead can be further reduced by using compression [25], [26],
or over-the-air computation methods [27], [28], which are known to facilitate high-throughput FL over wireless channels [29]. Second, increasing the number of pilots is not guaranteed to yield sufficiently diverse training, as some users may be static during pilot transmission, and thus learn a biased symbol detection rule. FedRec utilizes the pilots observed over the entire network, and thus its accuracy is expected to grow with the number of users regardless of the pilot sequence length, while its additional overhead on the downlink channel remains fixed.

We design FedRec for scalar flat-fading downlink networks. It is particularly suitable for non-reciprocal channels, as encountered in frequency division duplexing systems, where the detection rule cannot be learned at the BS via uplink pilots. While the proposed FedRec and its numerical evaluations in Section IV demonstrate the potential of data-driven symbol detectors trained in a federated manner, downlink wireless communications in practice are likely to observe generalized multi-path fading, utilize multiple antennas, and consider individual messages transmitted in a non-orthogonal fashion. We leave the extension of FedRec to these more advanced settings for future research.

IV. NUMERICAL EVALUATIONS

In this section we compare FedRec with model-based detection derived from 3 for Rayleigh fading channels. To this end, we consider two cases with i.i.d. and non-i.i.d. fading channels across the users. In the i.i.d. case, the coefficients $h_{iu}(t)$ are generated from a Rayleigh distribution with unit scale parameter, and a new realization is generated on each $T_s$ time instances. We also consider a non-i.i.d. case, where the
scale parameter for different users is not identical, e.g., due to different statistics of the local environment for each user, such that for each user $u$, the scale parameter $\sigma_u$ is randomized from a uniform distribution over the range $[0.5, 1.5]$.

We use 16QAM modulations, i.e., $M = 16$, with average transmit power per bit $\rho$, representing the signal-to-noise ratio (SNR). The training and test datasets are comprised of $|D_{\text{train}}| = 2 \cdot 10^4$ and $|D_{\text{test}}| = 10^7$ symbols, respectively. Training data is obtained by having the BS broadcast $N_T = |D_u| = 2 \cdot 10^4/U$ 16QAM pilot symbols, and each user receives noisy versions of these pilots, which are faded according to its local fading statistics. These received pilots constitute the local dataset used for training FedRec. We also train the NN in a centralized manner, in which case the users transmit their local datasets to the BS, over a noise-free link, where the NN is trained centrally using all the pilots. For both data-driven strategies, the NN is trained for each SNR. For FedRec, we use Algorithm 1 with 5 local epochs, utilizing Adam optimizer [30] with an initial step-size of 0.05, over 5 rounds of aggregation. For centralized training, the batch-size is 20, and we use the same Adam optimizer for 25 epochs. As we perform 25 epochs of local training, the total amount of computations is the same for both data-driven cases for a fair comparison. We use an input layer of size 2 for the NN architecture, as 16QAM is a two-dimensional modulation, followed by a hidden layer with 16 neurons and softmax, thus $|\theta| = 48$.

The model-based detector uses the decision rule (4), with an estimate of the Rayleigh scale parameter, denoted by $\hat{\sigma}^2$, obtained from the training data. Here, each user obtains an LMMSE estimate of its scale parameter denoted $\hat{\sigma}_u^2$ utilizing its local dataset $D_u$. The overall estimate $\hat{\sigma}^2$ is then obtained by $\hat{\sigma}^2 = 1/U \sum_{u=1}^U \hat{\sigma}_u^2$ and inserted in (4) to obtain the model-based detector.

We first evaluate the bit error rate (BER) versus SNR for FedRec and the model-based detectors with $U = 5$ users. The results, depicted in Fig. 3, demonstrate that FedRec performs very close to the model-based approach for the i.i.d. case, approaching it at higher SNRs. For the more realistic non-i.i.d. case, FedRec generally outperforms the model-based approach computed with the estimated scale parameter. This indicates that while the model-based approach is sensitive to uncertainty in the scale parameter, FedRec learns from data to cope with such heterogeneous fading. We also observe in Fig. 3 that for both scenarios, FedRec outperforms its centralized version, with more notable gains observed for lower SNRs. In Fig. 4 we compare the BER versus SNR of FedRec for different number of users $U = 1, 2, 5$. We observe that for both scenarios, the performance rapidly improves as the number of users participating in federated training grows. We have also added the BER lower bound for MAP receiver (which assumes exact knowledge of the scale parameter) for the i.i.d case. This show that for the i.i.d case, merely $U = 5$ users suffices to approach the MAP performance. Hence, increasing the number of users participating in federated training of FedRec not only decreases the required pilot length $N_T$, but also improves the BER
We next evaluate the communication overhead induced on both uplink (UL) and downlink (DL) communications in the training procedure. The number of float32 words conveyed over both UL and DL for FedRec and its centralized version are summarized in Table I. For centralized training, the overhead does not depend on the number of users, and is comprised of \(2 \cdot |\mathcal{D}_{\text{train}}|\) and \(|\theta|\) words on the UL and DL, respectively. For federated training, the overhead is comprised of 5 rounds of parameter exchange consisting of \(U|\theta|\) words and \(|\theta|\) words on UL and DL, respectively, both are much smaller compared to having the users transmit their received pilots to the BS. Hence, federated training can notably reduce the communication load.

Finally, in Table II we compare the resulting BER for federated (FL), centralized (CL) and non-collaborative (NL) training of the architecture with 5 users. For NL, each user trains the NN using solely its local dataset. We then average the resulting BER from the 5 trained networks. Table II confirms that the BER is significantly improved, most notably in high SNRs when users collaborate either through federated training or by exchanging their local datasets with the BS for centralized training. For the i.i.d. case, this gain is due to the increased amount of data made available for training through collaboration. For the non-i.i.d. case, the improvement is more significant as it is not only due to increased amount of data, but also since the data obtained through collaboration is more diverse.

The above results indicate that FedRec exploits the diversity in the fading statistics via Algorithm 1 to obtain an efficient universal receiver. When the users collaborate to train FedRec in a federated manner, the pilot length is decreased, and the diversity in the fading statistics across the users is exploited to train...
V. Conclusions

We proposed FedRec, which is a data-driven symbol detector for downlink fading channels. FedRec is comprised of an NN architecture, which is designed based on the MAP rule for fading channels, combined with a training mechanism which implements collaborative learning among multiple users in a federated manner. Our numerical results demonstrate that FedRec approaches the MAP performance, while achieving improved robustness to uncertainty. We also show that federated training induces less communication overhead compared to conventional centralized training, while achieving improved performance.

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