

# Particle Filter Recurrent Neural Networks

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## Abstract

Recurrent neural networks (RNNs) have been extraordinarily successful for prediction with sequential data. To tackle highly variable and multi-modal real-world data, we introduce *Particle Filter Recurrent Neural Networks* (PF-RNNs), a new RNN family that explicitly models uncertainty in its internal structure: while an RNN relies on a long, deterministic latent state vector, a PF-RNN maintains a latent *state distribution*, approximated as a set of particles. For effective learning, we provide a fully differentiable particle filter algorithm that updates the PF-RNN latent state distribution according to the Bayes rule. Experiments demonstrate that the proposed PF-RNNs outperform the corresponding standard gated RNNs on a synthetic robot localization dataset and 10 real-world sequence prediction datasets for text classification, stock price prediction, etc.

## Introduction

Prediction with sequential data is a long-standing challenge in machine learning. It has many applications, e.g., object tracking (Blake and Isard 1997), speech recognition (Xiong et al. 2018), and decision making under uncertainty (Soman et al. 2013). For effective prediction, predictors require “memory”, which summarizes and tracks information in the input sequence. The memory state is generally not observable, hence the need for a *belief*, i.e., a posterior state distribution that captures the sufficient statistic of the input for making predictions. Modeling the belief manually is often difficult. Consider the task of classifying news text—treated as a sequence of words—into categories, such as politics, education, economy, etc. It is difficult to handcraft the belief representation and dynamics for accurate classification.

State-of-the-art sequence predictors often use recurrent neural networks (RNNs), which *learn* a vector  $h$  of deterministic time-dependent latent variables as an approximation to the belief. Real-world data, however, are highly variable and often multi-modal. To cope with the complexity of uncertain real-world data and achieve better belief approximation, one could increase the length of latent vector  $h$ ,

thus increasing the number of network parameters and the amount of data required for training.

We introduce *Particle Filter Recurrent Neural Networks* (PF-RNNs), a new family of RNNs that seeks to improve belief approximation without lengthening the latent vector  $h$ , thus reducing the data required for learning. *Particle filtering* (Del Moral 1996) is a model-based belief tracking algorithm. It approximates the belief as a set of sampled states that typically have well-understood meaning. PF-RNNs borrow from particle filtering the idea of approximating the belief as a set of weighted particles, and combine it with the powerful approximation capacity of RNNs. PF-RNN approximates the variable and multi-modal belief as a set of weighted latent vectors  $\{h^1, h^2, \dots\}$  sampled from the same distribution. Like standard RNNs, PF-RNNs follow a model-free approach: PF-RNNs’ latent vectors are learned distributed representations, which are not necessarily interpretable. As an alternative to the Gaussian based filters, e.g., Kalman filters, particle filtering is a non-parametric approximator that offers a more flexible belief representation (Del Moral 1996); it is also proven to give a tighter *evidence lower bound* (ELBO) in the data generation domain (Burda, Grosse, and Salakhutdinov 2015). In our case, the approximate representation is trained from data to optimize the prediction performance. For effective training with gradient methods, we employ a fully differentiable particle filter algorithm that maintains the latent belief. See Fig. 1 for a comparison of RNN and PF-RNN.

We apply the underlying idea of PF-RNN to gated RNNs, which are easy to implement and have shown strong performance in many sequence prediction tasks. Specifically, we propose PF-LSTM and PF-GRU, the particle filter extensions of Long Short Term Memory (LSTM) (Hochreiter and Schmidhuber 1997) and Gated Recurrent Unit (GRU) (Cho et al. 2014). PF-LSTM and PF-GRU serve as drop-in replacements for LSTM and GRU, respectively. They aim to learn a better belief representation from the same data, though at a greater computational cost.

We evaluated PF-LSTM and PF-GRU on 13 data sets: 3 synthetic dataset for systematic understanding and 10 real-world datasets with different sample sizes for performance comparison. The experiments show that our PF-RNNs out-

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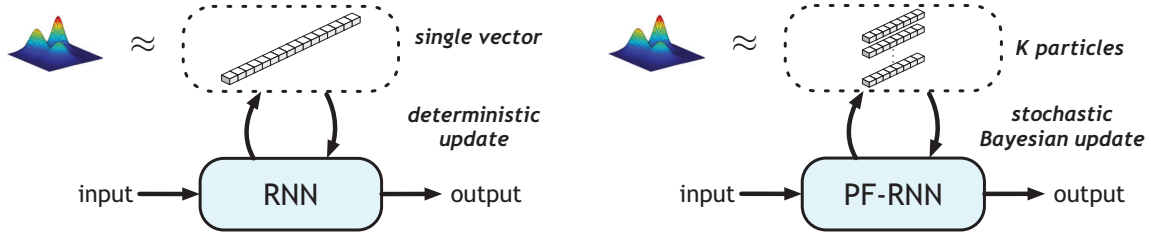


Figure 1: A comparison of RNN and PF-RNN. An RNN approximates the belief as a long latent vector and updates it with a deterministic nonlinear function. A PF-RNN approximates the belief as a set of weighted particles and updates them with the stochastic particle filtering algorithm.

perform the corresponding standard RNNs with a comparable number of parameters. Further, the PF-RNNs achieve the best results on almost all datasets when there is no restriction on the number of model parameters used.<sup>1</sup>

### Related Work

There are two general categories for prediction with sequential data: model-based and model-free. The model-based approach includes, e.g., the well-known hidden Markov models (HMMs) and the dynamic Bayesian networks (DBNs) (Murphy 2002). They rely on handcrafted state representations with well-defined semantics, e.g., phonemes in speech recognition. Given a model, one may perform belief tracking according to the Bayes’ rule. The main difficulty here is the state space and the computational complexity of belief tracking grow exponentially with the number of state dimensions. To cope with this difficulty, particle filters represent the belief as a set of sampled states and perform approximate inference. Alternatively, the model-free approach, such as RNNs, approximates the belief as a latent state vector, learned directly from data, and updates it through a deterministic nonlinear function, also learned from data.

The proposed PF-RNNs build upon RNNs and combine their powerful data-driven approximation capabilities with the sample-based belief representation and approximate Bayesian inference used in particle filters. Related sample-based methods have been applied to generative models. Importance sampling is used to improve variational auto-encoders (Burda, Grosse, and Salakhutdinov 2015). This is extended to sequence generation (Le et al. 2018) and to reinforcement learning (Igl et al. 2018). Unlike the earlier works that focus on generation, we combine RNNs and particle filtering for sequence prediction. PF-RNNs are trained *discriminatively*, instead of *generatively*, with the target loss function on the model output. As a result, PF-RNN training prioritizes target prediction over data generation which may be irrelevant to the prediction task.

PF-RNNs exploit the general idea of embedding algorithmic priors, in this case, filtering algorithms, in neural networks and train them discriminatively (Jonschkowski and Brock 2016; Jonschkowski, Rastogi, and Brock 2018; Karkus, Hsu, and Lee 2018). Earlier work embeds a par-

ticle filter in an RNN for learning belief tracking, but follows a model-based approach and relies on handcrafted belief representation (Jonschkowski, Rastogi, and Brock 2018; Karkus, Hsu, and Lee 2018). PF-RNNs retain the model-free nature of RNNs and exploit their powerful approximation capabilities to learn belief representation directly from data. Other work explicitly addresses belief representation learning with RNNs (Gregor and Besse 2018; Guo et al. 2018); however, they do not involve Bayesian belief update or particle filtering.

## Particle Filter Recurrent Neural Networks

### Overview

The general sequence prediction problem is to predict an output sequence, given an input sequence. In this paper, we focus on predicting the output  $y_t$  at time  $t$ , given the input history  $x_1, x_2, \dots, x_t$ .

Standard RNNs handle sequence prediction by maintaining a deterministic latent state  $h_t$  that captures the sufficient statistic of the input history, and updating  $h_t$  sequentially given new inputs. Specifically, RNNs update  $h_t$  with a deterministic nonlinear function learned from data. The predicted output  $\hat{y}_t$  is another nonlinear function of the latent state  $h_t$ , also learned from data.

To handle highly variable, noisy real-world data, one key idea of PF-RNN is to capture the sufficient statistic of the input history in the latent *belief*  $b(h_t)$  by forming multiple hypotheses over  $h_t$ . Specifically, PF-RNNs approximate  $b(h_t)$  by a set of  $K$  weighted particles  $\{(h_t^i, w_t^i)\}_{i=1}^K$ , for latent state  $h_t^i$  and weight  $w_t^i$ ; the particle filtering algorithm is used to update the particles according to the Bayes rule. The Bayesian treatment of the latent belief naturally captures the stochastic nature of real-world data. Further, all particles share the same parameters in a PF-RNN. The number of particles thus does not affect the number of PF-RNN network parameters. Given a fixed training data set, we expect that increasing the number of particles improves the belief approximation and leads to better learning performance, but at the cost of greater computational complexity.

Similar to RNNs, we used learned functions for updating latent states and predict the output  $y_t$  based on the mean particle:  $\hat{y}_t = f_{\text{out}}(\bar{h}_t)$ , where  $\bar{h}_t = \sum_{i=1}^K w_t^i h_t^i$  and  $f_{\text{out}}$  is a task-dependent prediction function. For example, in a robot

<sup>1</sup>More details are publicly available in arXiv:1905.12885. The code is available at <https://github.com/Yusufma03/pfrnns>

localization task,  $f_{\text{out}}$  maps  $\bar{h}_t$  to a robot position. In a classification task,  $f_{\text{out}}$  maps  $\hat{y}_t$  to a vector of class probabilities.

For learning, we embed a particle filter algorithm in the network architecture and train the network discriminatively end-to-end. Discriminative training aims for the best prediction performance within the architectural constraints imposed by the particle filter algorithm. We explore two loss functions for learning: one minimizes the error of prediction with the mean particle and the other maximizes the log-likelihood of the target  $y_t$  given the full particle distribution. Combining the two loss functions gives the best performance empirically.

### Particle Filter Extension to RNNs

Extending an RNN to the corresponding PF-RNN requires the latent particle belief representation  $\{(h_t^i, w_t^i)\}_{i=1}^K$  and the associated belief update function. The new belief is a posterior distribution conditioned on the previous belief and the new input. We model the PF-RNN's latent dynamics as a controlled system, with the uncontrolled system as a special case. The standard belief update consists of two steps: the transition update  $\tilde{b}_t = f_{\text{tr}}(b_{t-1}, u_t)$  for control  $u_t$  and the observation update  $b_t = f_{\text{obs}}(\tilde{b}_t, o_t)$  for observation  $o_t$ . However,  $u_t$  and  $o_t$  are not separated a priori in general sequence prediction problems. PF-RNNs use input  $x_t$  in both  $f_{\text{tr}}$  and  $f_{\text{obs}}$ , and learn to extract latent control  $u_t(x_t)$  and observation  $o_t(x_t)$  from  $x_t$  through task-oriented discriminative training. This approach is more flexible and provides a richer function approximation class.

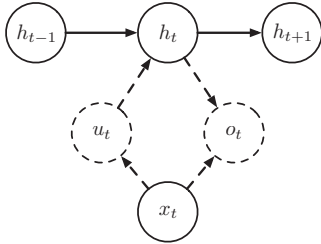


Figure 2: The graphical model for PF-RNN belief update. The dashed circles indicate variables not explicitly defined in our models.

**Stochastic memory update.** We apply a learned transition function  $f_{\text{tr}}$  to each particle state  $h_t^i$ :

$$h_t^i = f_{\text{tr}}(h_{t-1}^i, u_t(x_t), \xi_t^i), \quad \xi_t^i \sim p(\xi_t^i | h_{t-1}^i, u_t(x_t)) \quad (1)$$

where  $x_t$  is the input and  $\xi_t^i$  is a learned noise term. We assume  $p(\xi_t^i | h_{t-1}^i, u_t(x_t))$  to be a Gaussian distribution and use the *reparameterization trick* (Kingma and Welling 2014) to the function to simulate the transition in a differentiable manner. From the RNN perspective,  $\xi_t^i$  captures the stochasticity in the latent dynamics. From the particle filtering perspective,  $\xi_t^i$  increases particle diversity, relieving the issue of particle depletion after resampling.

**Particle weight update.** We update the weight  $w_t^i$  of the particle  $h_t^i$  recursively in a Bayesian manner, using the likelihood  $p(o_t | h_t^i)$ . Instead of modeling  $p(o_t | h_t^i)$  as a generative

distribution, we approximate it directly as a learned function  $f_{\text{obs}}(o_t(x_t), h_t^i)$  with  $o_t(x_t)$  and  $h_t^i$  as inputs, and have

$$w_t^i = \eta f_{\text{obs}}(o_t(x_t), h_t^i) w_{t-1}^i, \quad (2)$$

where  $\eta$  is a normalization factor. Our observation model  $f_{\text{obs}}$ , coupled with discriminative training, significantly improves the performance of PF-RNNs in practice. The generative distribution  $p(o_t | h_t^i)$  is parameterized for generating  $o_t$  and may contain irrelevant features for the actual objective of predicting  $y_t$ . In contrast,  $f_{\text{obs}}$  skips generative modeling and learns only features useful for predicting  $y_t$ , as PF-RNNs are trained discriminatively to optimize prediction accuracy.

**Soft resampling.** In particle filter, resampling is required to avoid particle degeneracy, i.e., most particles having near-zero weights. Resampling constructs a new particle set  $\{(h_t'^j, w_t'^j)\}_{j=1}^K$  with constant weights  $w_t'^j = 1/K$ . Each new particle  $h_t'^j$  takes the value of an *ancestor* particle,  $h_t^{a^j}$ , where the ancestor index  $a^j$  is sampled from a multinomial distribution defined by the original particle weights,  $a^j \sim p$ , where  $p$  is a multinomial distribution with  $p(i) = w_t^i$ .

However, resampling is not differentiable, which prevents the use of backpropagation for training PF-RNNs. To make our latent belief update differentiable, we use *soft resampling* (Karkus, Hsu, and Lee 2018). Instead of resampling particles according to  $p$ , we resample from  $q$ , a mixture of  $p$  and a uniform distribution:  $q(i) = \alpha w_t^i + (1 - \alpha)(1/K)$ , for  $\alpha \in (0, 1]$ . The new weights are computed according the importance sampling formula, which leads to an unbiased estimate of the belief:

$$w_t'^j = \frac{p(i = a^j)}{q(i = a^j)} = \frac{w_t^{a^j}}{\alpha w_t^{a^j} + (1 - \alpha)(1/K)} \quad (3)$$

Soft resampling provides non-zero gradients when  $\alpha > 0$ . We use  $\alpha = 0.5$  in our experiments.

### Model Learning

One natural objective is to minimize the total prediction loss over all training sequences. For each training sequence, the prediction loss is

$$L_{\text{pred}}(\theta) = \sum_{t \in \mathcal{O}} \ell(y_t, \hat{y}_t, \theta) \quad (4)$$

where  $\theta$  represents the predictor parameters,  $\mathcal{O}$  is the set of time indices with outputs, and  $\ell$  is a task-dependent loss function measuring the difference between the target output  $y_t$  and the predicted output  $\hat{y}_t$ . Predictions in PF-RNN are made using the mean particle,  $\hat{y}_t = f_{\text{out}}(\bar{h}_t)$ , where  $f_{\text{out}}$  is a learned function, and  $\bar{h}_t = \sum_{i=1}^K w_t^i h_t^i$  is the weighted mean of the PF-RNN particles. In our regression experiments,  $\hat{y}_t$  is a real value and  $\ell$  is the squared loss. In our classification experiments,  $\hat{y}_t$  is a multinomial distribution over classes and  $\ell$  is the cross-entropy loss.

The PF-RNN prediction  $\hat{y}_t$  is actually randomized, as its value depends on random variables used for stochastic memory updates and soft-resampling; hence, a reasonable objective would be to minimize  $\mathbb{E}[L_{\text{pred}}(\theta)]$ . In our algorithm, we optimize  $L_{\text{pred}}(\theta)$  instead of  $\mathbb{E}[L_{\text{pred}}(\theta)]$ .

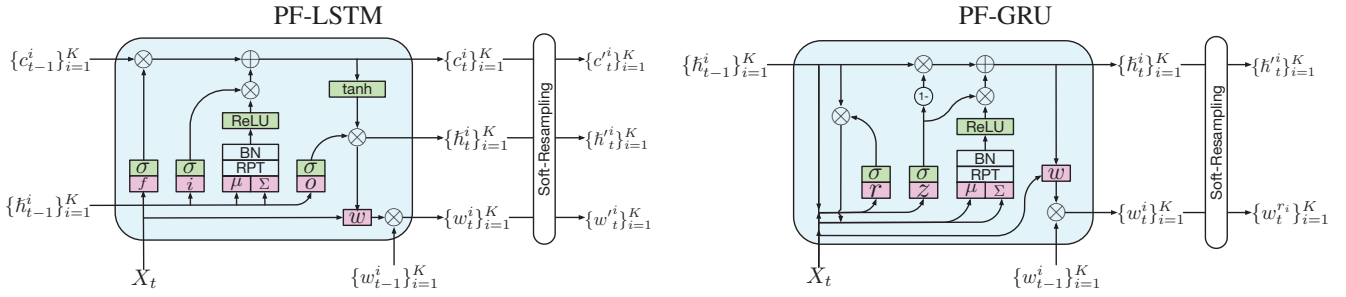


Figure 3: PF-LSTM and PF-GRU network architecture. Notation (1) green box: activation (2) pink box: learned function (3) RPT: reparameterization trick (4) BN: batch normalization.

Another possible learning objective applies stronger model assumptions. To maximize the likelihood, we optimize a sampled version of an ELBO of  $p(y_t|x_{1:t}, \theta)$ ,

$$L_{\text{ELBO}}(\theta) = -\sum_{t \in \mathcal{O}} \log \frac{1}{K} \sum_{i=1}^K p(y_t|\tau_{1:t}^i, x_{1:t}, \theta). \quad (5)$$

where  $\tau_{1:t}^i$  is a history chain for particle  $i$ , consisting of its ancestor indices during particle resampling and the random numbers used in stochastic memory updates<sup>2</sup>.

The  $p(y_t|\tau_{1:t}^i, x_{1:t}, \theta)$  terms in  $L_{\text{ELBO}}(\theta)$  are computed using appropriate probabilistic models. We apply  $f_{\text{out}}$  to each particle at each time step, generating outputs  $\hat{y}_t^i = f_{\text{out}}(h_t^i)$ . Then, for classification  $p(y_t|\tau_{1:t}^i, x_{1:t}, \theta) = \text{CrossEntropy}(y_t, \hat{y}_t^i)$ , which follows from the multinomial model; and for regression  $p(y_t|\tau_{1:t}^i, x_{1:t}, \theta) = \exp(-||y_t - \hat{y}_t^i||)$ , which follows from a unit variance Gaussian model.

Intuitively,  $L_{\text{pred}}$  encourages PF-RNN to make good predictions using the mean particle, while  $L_{\text{ELBO}}$  encourages the model to learn a more meaningful belief distribution. They make different structure assumptions that result in different gradient flows. Empirically, we find that combining the two learning objectives works well:  $L(\theta) = L_{\text{pred}}(\theta) + \beta L_{\text{ELBO}}(\theta)$ , where  $\beta$  is a weight parameter. We use  $\beta = 1.0$  in the experiments.

## PF-LSTMs and PF-GRUs

We now apply the PF-RNN to the two most popular RNN architectures, LSTM and GRU.

For standard LSTM, the memory state  $h_t$  consists of cell state  $c_t$  and hidden state  $\tilde{h}_t$ . The memory update is a deterministic mapping controlled by input gate  $i_t$ , forget gate  $f_t$ , and output gate  $o_t$ :

$$c_t = f_t \circ c_{t-1} + i_t \circ \tanh(\tilde{c}_t) \quad (6)$$

$$\tilde{c}_t = W_c[h_{t-1}, x_t] + b_c \quad (7)$$

$$\tilde{h}_t = o_t \circ \tanh(c_t) \quad (8)$$

where  $x_t$  is the current input and  $\circ$  is the element-wise product. For PF-LSTM, the memory state consists of a set of weighted particles  $\{(\tilde{h}_t^j, c_t^j, w_t^j)\}_{j=1}^K$ . To help PF-LSTM

<sup>2</sup>We have negated the ELBO to make it consistent with loss minimization.

track the latent particle belief effectively over a long history of data, we make two changes to the memory update equations. One is to add stochasticity:

$$\tilde{c}_t^j = W_c[\tilde{h}_{t-1}^j, x_t] + b_c + \xi_t^j \quad (9)$$

$$\xi_t^j \sim \mathcal{N}(0, \Sigma_t^j) \quad (10)$$

$$\Sigma_t^j = W_\Sigma[\tilde{h}_{t-1}^j, x_t] + b_\Sigma \quad (11)$$

for  $j = 1, 2, \dots, K$ . The motivation for stochastic memory updates is discussed in Sect. . The other change, inspired by LiGRU (Ravanelli et al. 2018), is to replace the hyperbolic tangent activation of LSTM by ReLU activation and batch normalization (Ioffe and Szegedy 2015):

$$c_t^j = f_t^j \circ c_{t-1}^j + i_t^j \circ \text{ReLU}(\text{BN}(\tilde{c}_t^j)), \quad (12)$$

for  $j = 1, 2, \dots, K$ . Recurrent networks are usually trained with truncated Back-Propagation-Through-Time (BPTT). Truncation affects the training of PF-RNNs, more than that of RNNs, as PF-RNNs maintain the latent belief explicitly and may need a long sequence of inputs in order to approximate the belief well. As shown in (Ravanelli et al. 2018), ReLU activation, combined with batch normalization, has better numerical properties for backpropagation through many time steps, and thus it allows us to use longer sequence length with truncated BPTT. The update equation for  $\tilde{h}_t^j$  remains the same as that for LSTM. After updating the particles and their weights, we perform soft resampling to get a new set of particles (Section ). The PF-LSTM architecture is shown in Fig. 3 (left side).

The PF-GRU model can be constructed similarly (right side of Fig. 3). The same idea can be easily applied to other gated recurrent neural networks as well.

We implement PF-LSTM and PF-GRU in a parallel manner for all operations. In this case, all particles are updated in parallel benefiting from GPU acceleration.

## Experiments

We evaluate PF-RNNs, specifically, PF-LSTM and PF-GRU, on a synthetic 2D robot localization task and 10 sequence prediction datasets from various domains. We compare PF-RNNs with the corresponding RNNs. First, we use a fixed latent state size for all models. The sizes are chosen so that the PF-RNN and the RNN have roughly the same



number of trainable parameters. Next, we search over the latent state size for all models independently and compare the best results achieved. We also perform an ablation study to understand the effect of individual components of PF-RNNs.

## Robot Localization

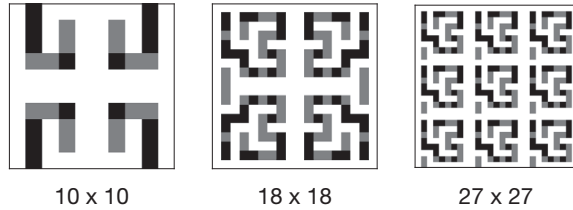


Figure 4: Localization in a symmetric maze. Each maze is an  $N \times N$  grid, with black and gray obstacles. Black obstacles serve also as landmarks.

We first evaluate PF-RNNs in a simple synthetic domain designed to demonstrate the strengths of our approach. The task is to localize a robot on a 2D map (Fig. 4), given distance measurements to a set of landmarks. In each environment, half of the obstructions have landmarks placed on their corners. The maps are designed to be highly symmetric, thus maintaining a belief is essential for localization. We evaluate the models’ sensitivity to the amount of uncertainty in the task by increasing the maze size.

The robot starts at a random location. In each step, it moves forward a distance  $d = 0.2 + \epsilon_d$ ,  $\epsilon_d \sim \mathcal{U}[-0.02, 0.02]$  where  $\mathcal{U}$  is the uniform distribution, or chooses a new heading direction when about to hit a wall. The input  $x_t$  consists of the last action  $u_{t-1}$  and current observation  $o_t$ , which are noisy distance measurements to the 5 closest landmarks. The observation noise is  $\mathcal{U}[-0.1, 0.1]$  for all mazes. The model takes  $x_t$  as input and has no prior information on which components represent  $u_t$  and  $o_t$ . This information must be extracted from  $x_t$  through learning. The task is to predict the robot pose at each time  $t$ , 2D coordinates and heading, given the history of inputs  $\{x_i\}_{i=1}^t$ .

We train models on a set of 10, 000 trajectories. We evaluate and test on another 1, 000 and 2, 000 trajectories, respectively. The network architecture is the same for all models. Map features are extracted from the map using convolutional layers, two for the smaller maps and 5 for the largest map. Control and observation features are extracted from the inputs by two fully connected layers. The features are concatenated and input to the recurrent cell, PF-LSTM/PF-GRU or LSTM/GRU. The output of the recurrent cell is mapped to the pose prediction by a fully connected layer. The training loss is the Mean Square Error (MSE) between the predicted and ground truth pose, summed along the trajectories. The last step MSE is used as the evaluation metric.

We make two sets of comparisons. First, we fix the latent state size and number of particles, such that PF-RNNs and the corresponding RNNs have a similar number of parameters. Specifically, we use a latent state size of 64 and 30 particles for PF-LSTM and PF-GRU, and a latent state

size of 80 for LSTM and 86 for GRU. Second, we perform a search over these hyper-parameters independently for all models and datasets, including learning rate, dropout rate, batch size, and gradient clipping value, and report the best-achieved result.

We compare PF-LSTM and PF-GRU with LSTM and GRU (Fig. 5). Results show that PF-RNNs consistently outperform the corresponding RNNs. The performance benefits become more pronounced, as the size of the maze grows, resulting in increased difficulty of belief tracking.

Fig. 6 visualizes the particle belief progression in a trained PF-LSTM. PF-LSTM works similarly to a standard particle filtering algorithm and demonstrates a reasonable belief distribution. The particle predictions of the robot pose initially spread out ( $t = 0$ ). As inputs accumulate, they begin to converge on some features, *e.g.*, horizontal position ( $t = 22$ ); and eventually they converge to the true pose ( $t = 26$ ). The depicted example also demonstrates an interesting property of PF-LSTM. Initially, particle predictions converge towards a wrong, distant pose ( $t = 6$ ), because of the ambiguous observations in the symmetric environment. However, particle predictions spread out again ( $t = 22$ ), and converge to the true pose ( $t = 26$ ). This would be unusual for a standard particle filtering algorithm under the true robot dynamics: once particles converge to a wrong pose, it would be difficult to recover (Thrun et al. 2001). PF-LSTM succeeds here, because its latent representation and dynamics are learned from data. Each particle in a PF-LSTM independently aggregates information from the input history, and its dynamics is not constrained explicitly by the robot dynamics.

## General Sequence Prediction Tasks

**Comparison with RNNs.** We evaluate PF-RNNs on various real-world sequence prediction datasets across multiple domains for both regression and classification tasks. Regression tasks include stock index prediction (NASDAQ (Qin et al. 2017)), appliances energy prediction (AEP (Candanedo, Feldheim, and Deramaix 2017)), air quality prediction (AIR (De Vito et al. 2008) and PM (Liang et al. 2015)). Classification tasks include activity recognition (UID (Casale, Pujol, and Radeva 2012), LPA (Kaluža et al. 2010), AREM (Palumbo et al. 2016) and GAS (Huerta et al. 2016)) and text classification (R52 (Cardoso-Cachopo 2007) and MR (Maas et al. 2011)). For regression tasks, a prediction is made after each time step, while for classification tasks prediction is made at the end of each sequence using the belief at the last time step. We demonstrate PF-RNN is sample efficient on relatively small datasets in terms of the sample efficiency (*e.g.*, 9358 instances for AIR dataset) but also scales to large datasets for the generalization to complex tasks (*e.g.*, around 1 million instances for GAS dataset).

We compare PF-LSTM and PF-GRU with the corresponding LSTM and GRU models. As PF-RNNs possess a similar structure with gated RNNs, we can directly use them as drop-in replacements. We use a similar network architecture for all models and datasets. We follow the same experiment setup with the localization experiment and use 20 particles for PF-LSTM and PF-GRU. The input is passed through two fully-connected layers and input to the recurrent cell.

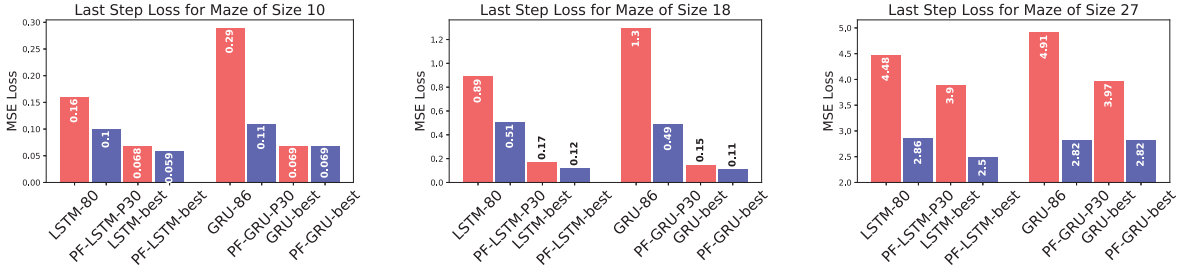


Figure 5: Performance comparison of the last-step prediction loss in robot localization. LSTM-80 and GRU-86 indicate LSTM and GRU with latent state size of 80 and 86, respectively. PF-LSTM-P30 and PF-GRU-P30 indicate PF-LSTM and PF-GRU with 30 particles and latent state size of 64. These parameters are chosen so that the RNN and the corresponding PF-RNN have roughly the same number of trainable parameters. LSTM-best, GRU-best, PF-LSTM-best, and PF-GRU-best indicate the best-performing model after a search over the latent state size and the number of particles.

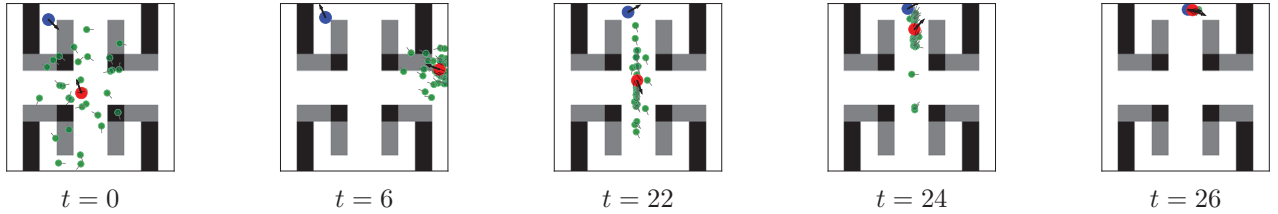


Figure 6: Visualization of PF-LSTM latent particles. Each figure shows the true robot pose (blue), predicted pose (red), and 30 predicted poses according to the latent particles (green).

The output of the recurrent cell is processed by another two fully connected layers to predict an output value. We perform grid search over standard training parameters (learning rate, batch size, gradient clipping value, regularization weight) for each model and dataset.

Results are shown in Table 1 and Table 2. We observe that PF-LSTM and PF-GRU are generally better than the LSTM and GRU, both when the number of parameters is comparable, as well as with the best hyper-parameters within the model class. PF-RNNs outperform the corresponding RNNs on 90% of the datasets across different domains, including classification and regression tasks.

**Comparison with the State-of-the-Art.** Achieving state-of-the-art (SOTA) performance is not the focus of this paper. Nevertheless, we include the SOTA results for reference, when available, in the last row of Table 1 and Table 2. We use the same training, validation and test sets as the SOTA methods. PF-RNNs, despite having only simple vanilla network components, perform better than the SOTA on LPA, AREM, and GAS. For NASDAQ, R52 and MR, SOTAs (Qin et al. 2017; Zhou et al. 2016; Cardoso-Cachopo 2007) use complex network structure designed specifically for the task, thus they work better than PF-RNNs. Future work may investigate PF-RNNs with larger, more complex network components, which would provide a more fair comparison with the SOTA.

**Comparison with Bayesian RNNs.** As an alternative method for handling highly variable and noisy data, Bayesian RNNs (Fortunato, Blundell, and Vinyals 2017) maintain a distribution over learned parameters. We com-

Table 1: Regression Loss

	NASDAQ	AEP	AIR	PM
LSTM	37.33	6.53	18.34	26.14
PF-LSTM	4.65	4.57	<b>13.12</b>	21.23
LSTM-best	2.53	6.53	17.69	26.14
PF-LSTM-best	<b>1.82</b>	<b>3.72</b>	<b>13.12</b>	<b>19.04</b>
GRU	4.93	6.57	17.7	23.59
PF-GRU	1.33	5.33	19.32	20.77
GRU-best	4.93	5.61	<b>14.78</b>	23.59
PF-GRU-best	<b>1.33</b>	<b>3.73</b>	18.18	<b>20.77</b>
SOTA	<b>0.33</b>	-	-	-

Table 2: Prediction Accuracy (%)

	LPA	AREM	GAS	MR	R52	UID
LSTM	91.7	99.1	76.6	73.1	81.1	93.2
PF-LSTM	<b>100</b>	99.1	89.9	78.3	89.1	95.3
LSTM-best	98.3	100	81.2	73.1	81.1	99.1
PF-LSTM-best	<b>100</b>	<b>100</b>	<b>94.1</b>	<b>82.2</b>	<b>90.3</b>	<b>99.6</b>
GRU	97.8	98.4	76.8	75.1	84.2	96.1
PF-GRU	98.1	99.1	<b>83.3</b>	76.2	87.2	94.1
GRU-best	97.8	<b>100</b>	80	75.2	84.2	99
PF-GRU-best	<b>99.2</b>	<b>100</b>	<b>83.3</b>	<b>79.6</b>	<b>89.1</b>	<b>99.5</b>
SOTA	91.3	94.4	80.9	<b>83.1</b>	<b>93.8</b>	-

pare PF-RNNs with Bayesian RNNs on all the datasets. In particular, we use the same latent vector length with the

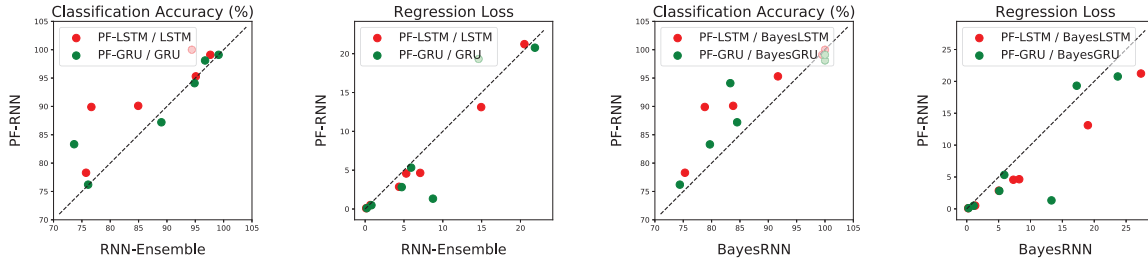


Figure 7: Comparison with ensembles and Bayesian RNNs. Scatter plot of classification accuracy (left) and regression loss (right) over all datasets. The  $x$ -axis is the performance of an RNN ensemble or a Bayesian RNN, the  $y$ -axis is the performance of a PF-RNN. The dashed line corresponds to equal performance. Note that PF-RNN is better for points above the dashed line for classification, and for points below the dashed line for regression. Red points compare PF-LSTM with LSTM ensemble / Bayesian LSTM, blue points compare PF-GRU with GRU ensemble / Bayesian GRU.

Table 3: Ablation study.

	PF-LSTM									LSTM
	P1	P5	P10	P20	P30	NoResample	NoBNReLU	NoELBO	ELBOonly	BNReLU
Regression	0.81	0.66	0.59	0.55	<b>0.51</b>	0.76	0.87	0.68	0.73	0.74
Classification	85.88	87.55	91.25	91.28	<b>93.28</b>	89.92	88.55	90.70	88.60	86.28

LSTMs / GRUs for Bayesian RNNs following our setting in previous experiments. A summary of the results is given by Fig. 7. Bayesian RNNs can improve over RNNs, but PF-RNNs outperform Bayesian RNNs in 16 out of 20 cases, considering both PF-LSTM and PF-GRU.

**Comparison with Ensembles.** PF-RNN can be considered as a method for improving an RNN, by maintaining multiple copies and using particle filter updates. Another common technique for improving the performance of a predictor using multiple copies is ensembling. We compare the performance of PF-RNN with bagging (Breiman 1996), an effective and commonly used ensembling method. Bagging trains each predictor in an ensemble by constructing a different training set of the same size through randomly sampling the original training set. We compare PF-RNNs using  $K$  particles, with ensembles of  $K$  RNNs. The results are summarized in Fig. 7.

Bagging reduces the variance of the predictors, but does not address belief tracking. Indeed, ensembles of RNNs generally improve over a single RNN, but the performance is substantially poorer than PF-RNNs for most datasets.

## Ablation Study

We conduct a thorough ablation study on all datasets for PF-LSTMs to better understand their behavior. A summary of the results, averaged over all datasets, is shown in Table 3. To compute a meaningful average for regression tasks, we need values with the same order of magnitude. We rescale all regression errors across the ablation methods into a range between 0 and 1.

We evaluate the influence of the following components: 1) number of particles (P1, P5, P10, P20, P30); 2) soft-resampling (NoResample); 3) replacing the hyperbolic tan-

gent with ReLU activation and batch normalization (NoBNReLU); 4) combining prediction loss and ELBO for training (NoELBO and ELBOonly). We conduct the same, independent hyper-parameter search as in previous experiments.

We observe that: 1) Using more particles makes a better prediction in general. The general performance increases from PF-LSTM P1 to P30. 2) Soft-resampling improves the performance of PF-LSTM. 3) The combination of prediction loss and ELBO loss leads to better performance. 4) The ReLU activation with batch normalization helps to train PF-LSTM. Simply using ReLU with batch normalization does not make LSTM better than PF-LSTM.

## Conclusion

PF-RNNs combine the strengths of RNNs and particle filtering by learning a latent particle belief representation and updating the belief with a particle filter. We apply the idea specifically to LSTM and GRU and construct PF-LSTM and PF-GRU, respectively. Our results show that PF-RNNs outperform the corresponding RNNs on various sequence prediction tasks, including text classification, activity recognition, stock price prediction, robot localization, etc.

Various aspects of the PF-RNN approach provide opportunities for further investigation. Currently, PF-RNNs make a prediction with the mean of the particle belief. An alternative is to aggregate particles, e.g., by estimating higher-order moments, estimating the entropy, attaching an additional RNN (Igl et al. 2018).

PF-RNNs can serve as drop-in replacements for RNNs. While this work focuses on sequence prediction and classification, the idea can be applied equally well to sequence generation and sequence-to-sequence prediction, with application to, e.g., image captioning and machine translation.

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## References

- Blake, A., and Isard, M. 1997. The condensation algorithm: conditional density propagation and applications to visual tracking. In *Advances in Neural Information Processing Systems*, 361–367.
- Breiman, L. 1996. Bagging predictors. *Machine learning* 24(2):123–140.
- Burda, Y.; Grosse, R.; and Salakhutdinov, R. 2015. Importance weighted autoencoders. *arXiv preprint arXiv:1509.00519*.
- Candanedo, L. M.; Feldheim, V.; and Deramaix, D. 2017. Data driven prediction models of energy use of appliances in a low-energy house. *Energy and buildings* 140:81–97.
- Cardoso-Cachopo, A. 2007. Improving Methods for Single-label Text Categorization. PdD Thesis, Instituto Superior Tecnico, Universidade Tecnica de Lisboa.
- Casale, P.; Pujol, O.; and Radeva, P. 2012. Personalization and user verification in wearable systems using biometric walking patterns. *Personal and Ubiquitous Computing* 16(5):563–580.
- Cho, K.; van Merriënboer, B.; Gulcehre, C.; Bahdanau, D.; Bougares, F.; Schwenk, H.; and Bengio, Y. 2014. Learning phrase representations using RNN encoder–decoder for statistical machine translation. In *Proceedings of the 2014 Conference on Empirical Methods in Natural Language Processing*, 1724–1734.
- De Vito, S.; Massera, E.; Piga, M.; Martinotto, L.; and Di Francia, G. 2008. On field calibration of an electronic nose for benzene estimation in an urban pollution monitoring scenario. *Sensors and Actuators B: Chemical* 129(2):750–757.
- Del Moral, P. 1996. Non-linear filtering: interacting particle resolution. *Markov processes and related fields* 2(4):555–581.
- Fortunato, M.; Blundell, C.; and Vinyals, O. 2017. Bayesian recurrent neural networks. *arXiv preprint arXiv:1704.02798*.
- Gregor, K., and Besse, F. 2018. Temporal difference variational auto-encoder. *arXiv preprint arXiv:1806.03107*.
- Guo, Z. D.; Azar, M. G.; Piot, B.; Pires, B. A.; Pohlen, T.; and Munos, R. 2018. Neural predictive belief representations. *arXiv preprint arXiv:1811.06407*.
- Hochreiter, S., and Schmidhuber, J. 1997. Long short-term memory. *Neural computation* 9(8):1735–1780.
- Huerta, R.; Mosquero, T.; Fonollosa, J.; Rulkov, N. F.; and Rodriguez-Lujan, I. 2016. Online decorrelation of humidity and temperature in chemical sensors for continuous monitoring. *Chemometrics and Intelligent Laboratory Systems* 157:169–176.
- Igl, M.; Zintgraf, L.; Le, T. A.; Wood, F.; and Whiteson, S. 2018. Deep variational reinforcement learning for POMDPs. In *Proceedings of the International Conference on Machine Learning*, 2117–2126.
- Ioffe, S., and Szegedy, C. 2015. Batch normalization: Accelerating deep network training by reducing internal covariate shift. In *Proceedings of the International Conference on Machine Learning*, 448–456.
- Jonschkowski, R., and Brock, O. 2016. End-to-end learnable histogram filters. In *NeurIPS Workshop on Deep Learning for Action and Interaction*.
- Jonschkowski, R.; Rastogi, D.; and Brock, O. 2018. Differentiable Particle Filters: End-to-End Learning with Algorithmic Priors. In *Proceedings of Robotics: Science and Systems (RSS)*.
- Kaluža, B.; Mirchevska, V.; Dovgan, E.; Luštrek, M.; and Gams, M. 2010. An agent-based approach to care in independent living. In *International Joint Conference on Ambient Intelligence*, 177–186. Springer.
- Karkus, P.; Hsu, D.; and Lee, W. S. 2018. Particle filter networks with application to visual localization. In *Proceedings of the Conference on Robot Learning*, 169–178.
- Kingma, D. P., and Welling, M. 2014. Auto-encoding variational Bayes. In *Proceedings of the International Conference on Learning Representations*.
- Le, T. A.; Igl, M.; Rainforth, T.; Jin, T.; and Wood, F. 2018. Auto-encoding sequential monte carlo.
- Liang, X.; Zou, T.; Guo, B.; Li, S.; Zhang, H.; Zhang, S.; Huang, H.; and Chen, S. X. 2015. Assessing Beijing’s pm2.5 pollution: severity, weather impact, APEC and winter heating. *Proceedings of the Royal Society of London Series A* 471(2182):20150257.
- Maas, A. L.; Daly, R. E.; Pham, P. T.; Huang, D.; Ng, A. Y.; and Potts, C. 2011. Learning word vectors for sentiment analysis. In *Proceedings of the 49th Annual Meeting of the Association for Computational Linguistics: Human Language Technologies*, 142–150.
- Murphy, K. P. 2002. *Dynamic bayesian networks: representation, inference and learning*. Ph.D. Dissertation, University of California, Berkeley.
- Palumbo, F.; Gallicchio, C.; Pucci, R.; and Micheli, A. 2016. Human activity recognition using multisensor data fusion based on reservoir computing. *Journal of Ambient Intelligence and Smart Environments* 8(2):87–107.
- Qin, Y.; Song, D.; Cheng, H.; Cheng, W.; Jiang, G.; and Cottrell, G. W. 2017. A dual-stage attention-based recurrent neural network for time series prediction. In *Proceedings of the International Joint Conference on Artificial Intelligence*, 2627–2633.
- Ravanelli, M.; Brakel, P.; Omologo, M.; and Bengio, Y. 2018. Light gated recurrent units for speech recognition. *IEEE Transactions on Emerging Topics in Computational Intelligence*.
- Somani, A.; Ye, N.; Hsu, D.; and Lee, W. S. 2013. DESPOT: On-line POMDP planning with regularization. In *Advances in neural information processing systems*, 1772–1780.
- Thrun, S.; Fox, D.; Burgard, W.; and Dellaert, F. 2001. Robust Monte Carlo localization for mobile robots. *Artificial intelligence* 128(1-2):99–141.
- Xiong, W.; Wu, L.; Alleva, F.; Droppo, J.; Huang, X.; and Stolcke, A. 2018. The Microsoft 2017 conversational speech recognition system. In *Proceedings of the IEEE International Conference on Acoustics, Speech and Signal Processing*, 5934–5938.
- Zhou, P.; Qi, Z.; Zheng, S.; Xu, J.; Bao, H.; and Xu, B. 2016. Text classification improved by integrating bidirectional lstm with two-dimensional max pooling. *arXiv preprint arXiv:1611.06639*.