REPORT
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Federated Reinforcement Learning for Therapeutic Interventions over ICUs with Noisy Labels

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Motivation

- **Management of routine ICU interventions constitute a major part of intensive care, e.g.:**

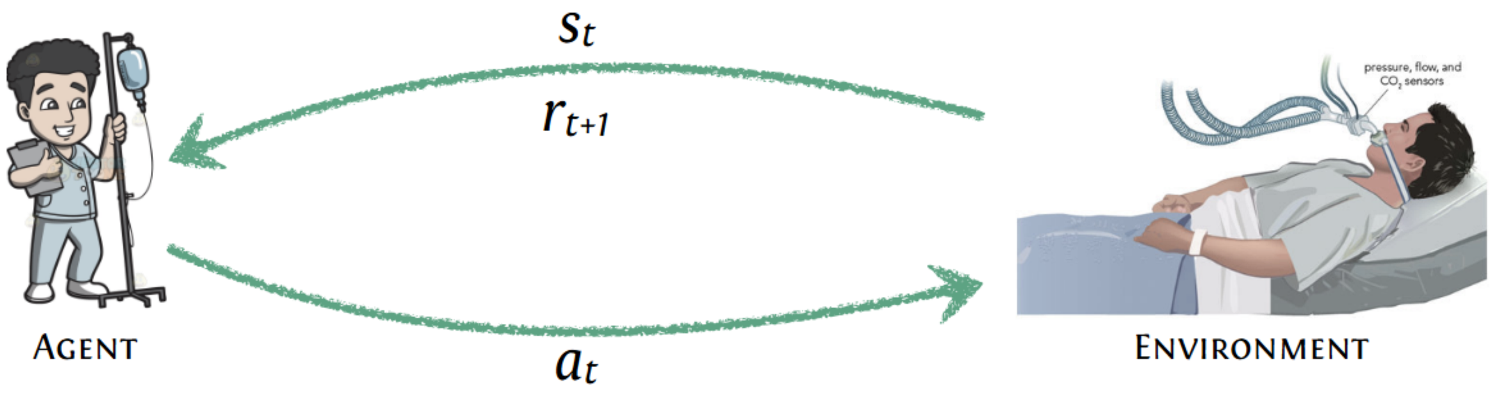
- **Invasive mechanical ventilation:** the use of mechanical means to assist or replace spontaneous breathing. [1]
  - ***40%*** *of ICU patients are ventilated at any given hour, accounting for* ***12%*** *of US hospital costs.*
  - *Typically coupled with sedation to maintain comfort and stability.*
  - *Timely intervention can improve outcomes and reduce costs.*
  - *However, their effects are often poorly understood, especially in heterogeneous patient populations, leading to varying clinical opinions.*

[1] A Reinforcement Learning Approach to Weaning of Mechanical Ventilation in Intensive Care Units. UAI 2017.

Motivation

- **Weaning: process of liberation from mechanical ventilation.** [1]
  - *Premature, delayed weaning both associated with worse outcomes.*
- We aim to develop **a clinician-in-loop decision support tool** to
  - *alert caregivers when a patient is ready for weaning*
  - *recommend sedation and ventilation settings*

...by modeling this as a Markov Decision Process (MDP).



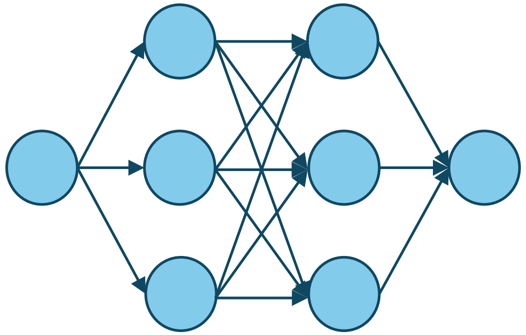
[1] A Reinforcement Learning Approach to Weaning of Mechanical Ventilation in Intensive Care Units. UAI 2017.

Challenges

➢ Challenge 1: ICU Data Utilization

- ***Limited Data Volume****: Individual hospitals often have limited patient data, which restricts the development of robust predictive models.*
- ***Data Incompleteness****: The data collected may not be comprehensive, affecting the accuracy and reliability of clinical decisions.*

Collaborative Learning



The sensitivity of clinical private data leads to the formation of data silos

A data-driven global clinical decision-making support tool

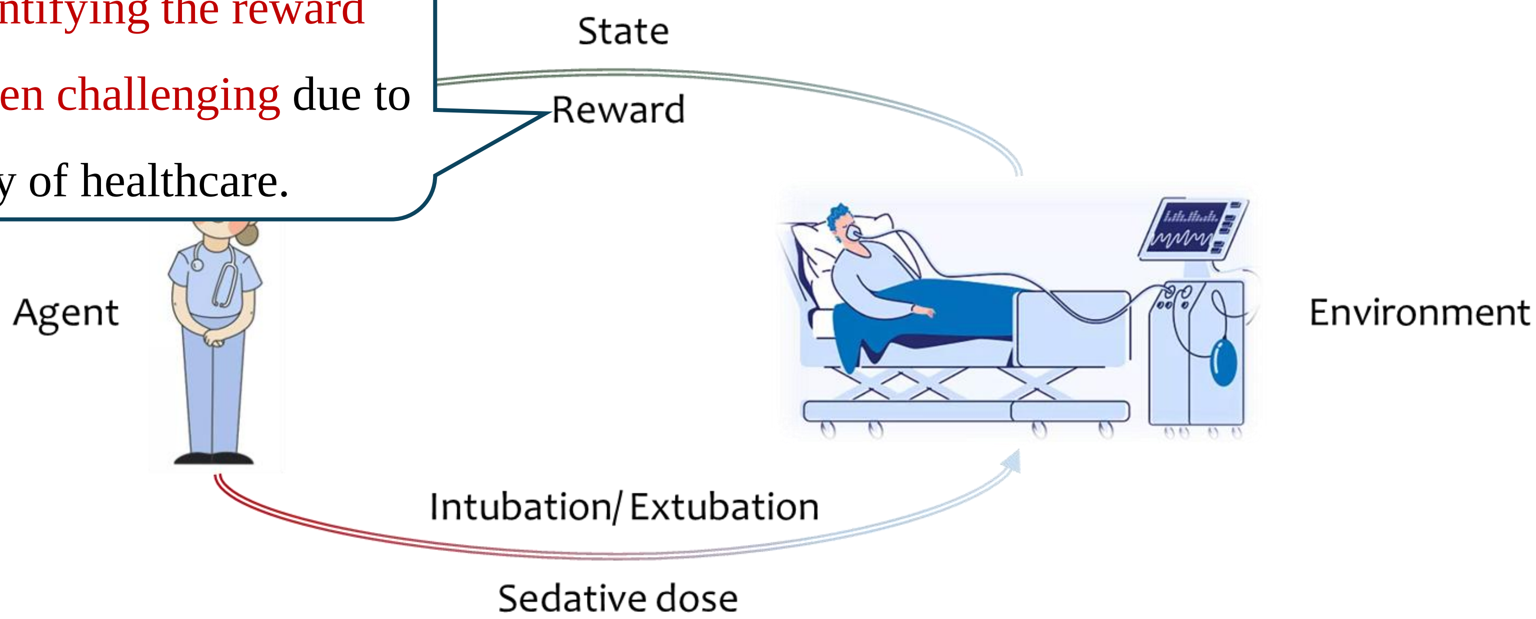
How to construct the global model without sharing scattered private clinical raw data?

Challenges

- **Challenge 2: Addressing the difficulty of defining a reward function**

  - *In the medical field, many tasks involve sequential decision-making.*
  - *These tasks are typically modeled as Markov Decision Processes (MDPs) and tackled with reinforcement learning.*

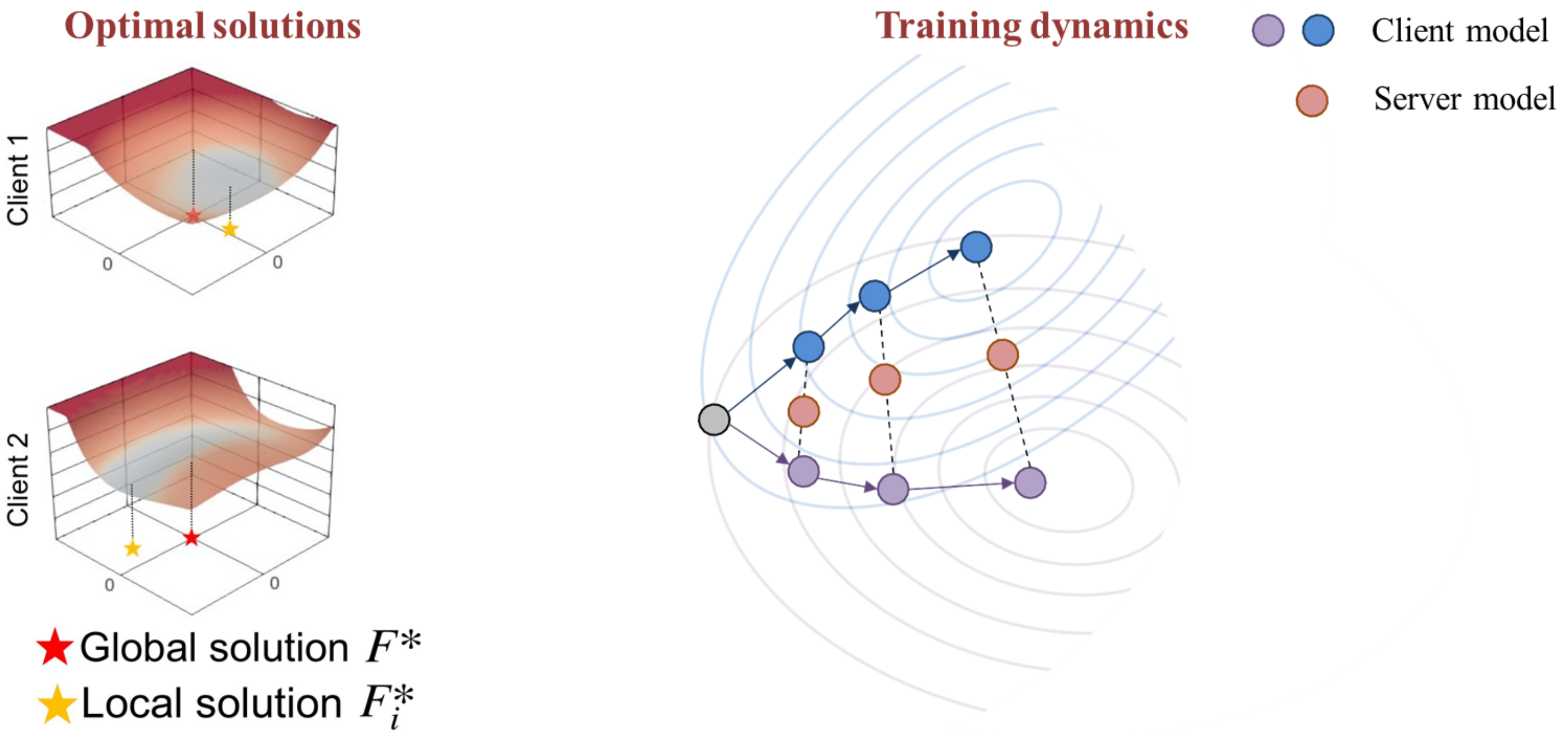
However, quantifying the reward function is often challenging due to the complexity of healthcare.



Inaccurate or arbitrary reward functions may have a negative impact on the policy model.

Challenges

- **Challenge 3: Overcoming data heterogeneity among different hospitals**

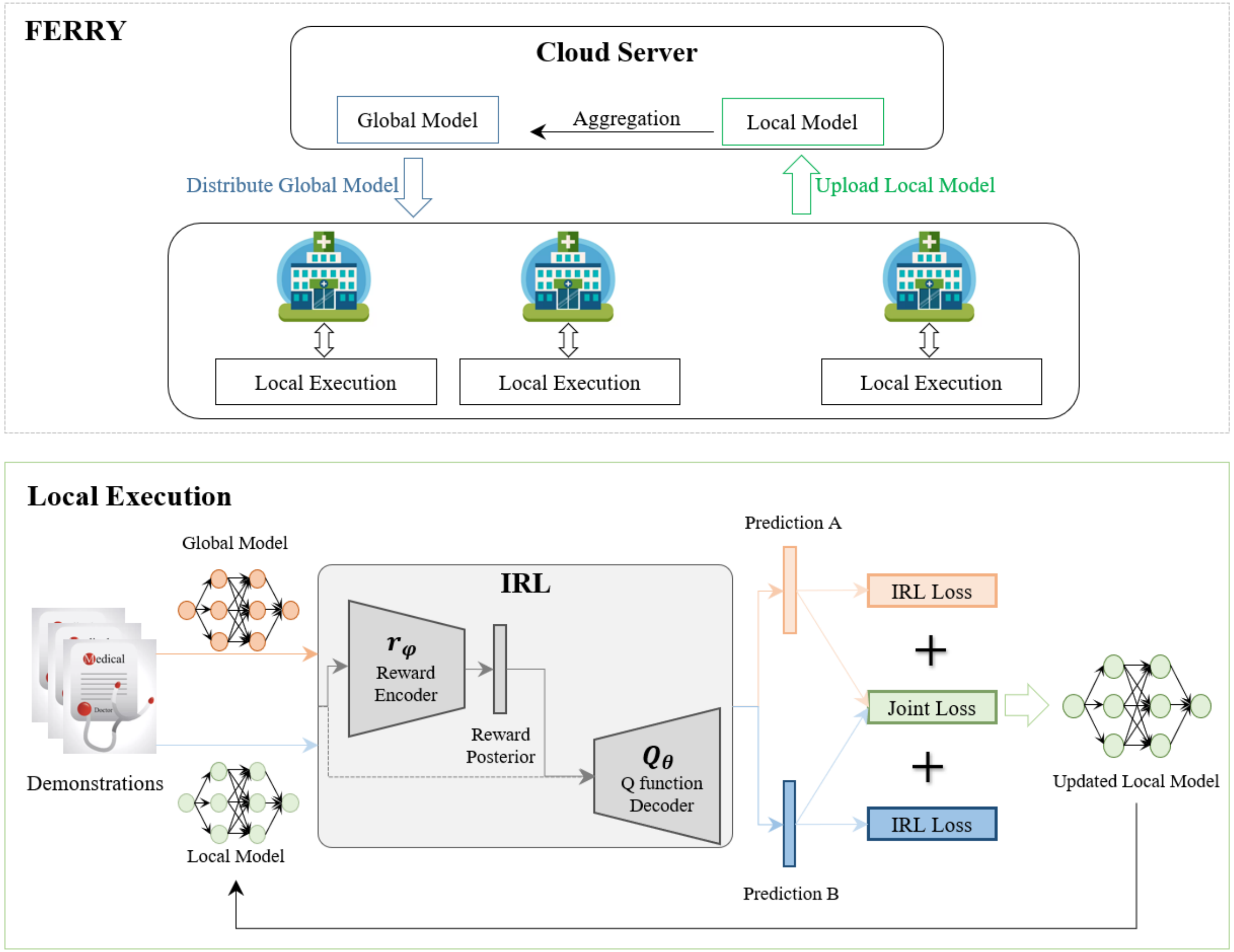


Data heterogeneity can lead to suboptimal performance of global models.[1]

[1] Jiang M, Wang Z, Dou Q. Harmofl: Harmonizing local and global drifts in federated learning on heterogeneous medical images. AAAI 2022.

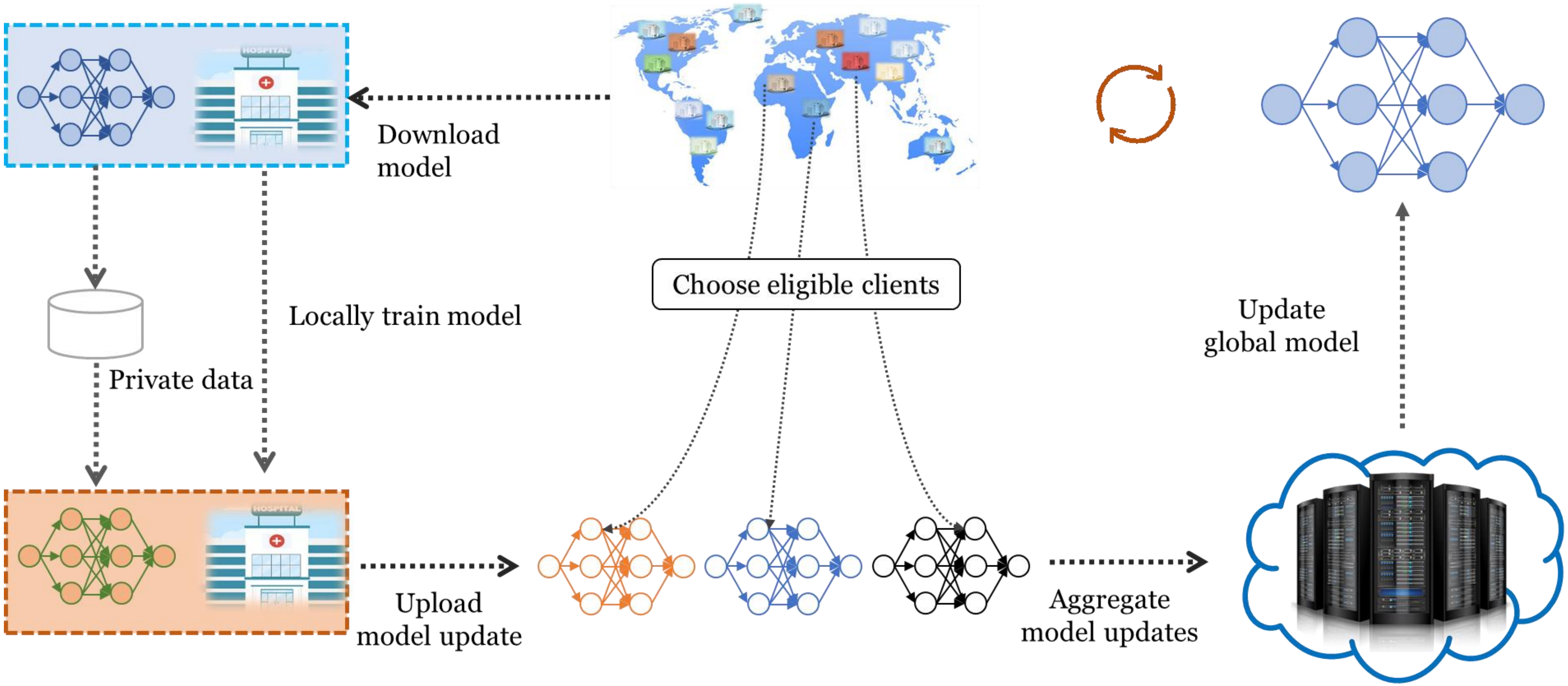
Method

- **FERRY: Federated Inverse Reinforcement Learning for Smart ICUs**
  - The overview of FERRY



Method

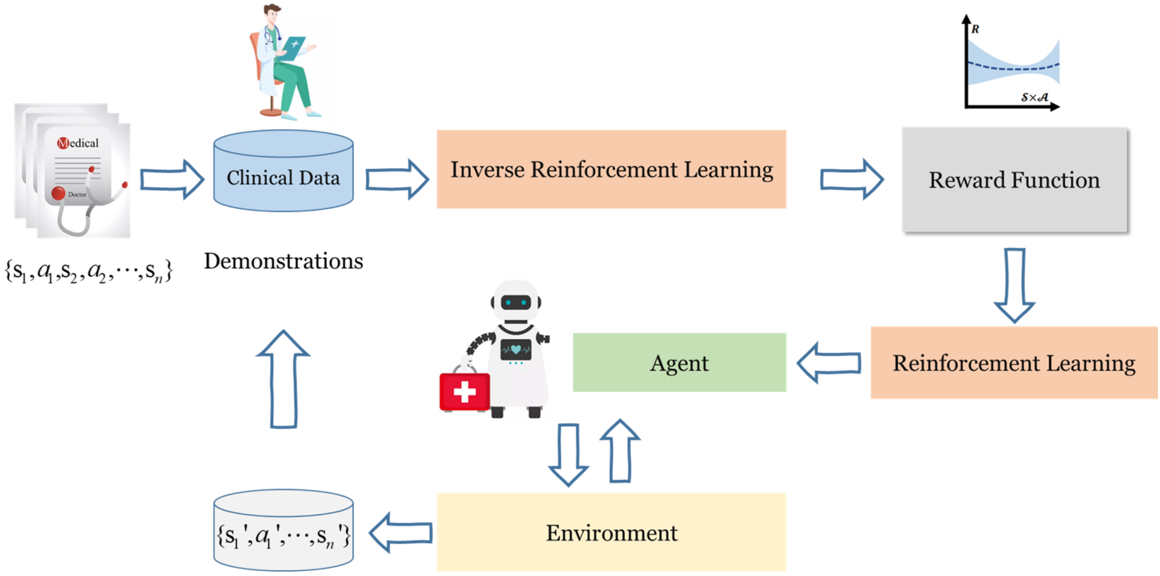
- Introducing federated learning (FL) to break data silos.



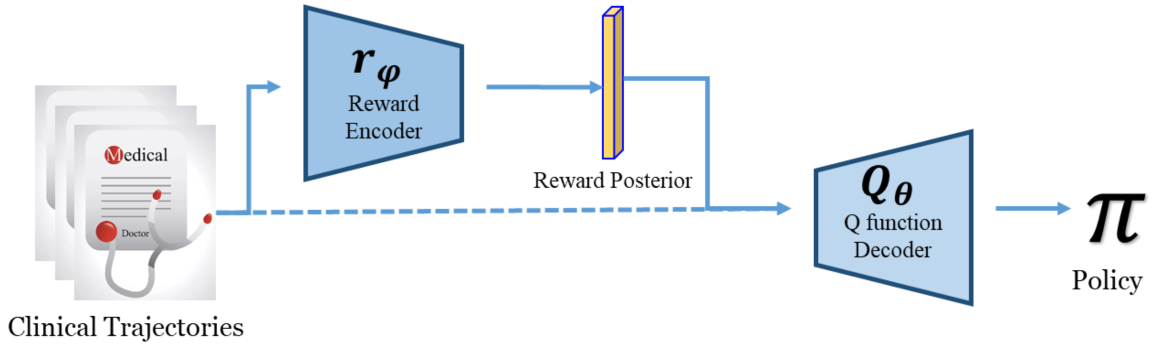
FL ensures data privacy and allows collaborative training using data from other hospitals.

Method

➢ **Using inverse reinforcement learning (IRL) to solve the difficulty of defining reward functions**



IRL



AVRIL [1]

IRL can derive suitable reward functions from historical data.

[1] Chan A J, van der Schaar M. Scalable bayesian inverse reinforcement learning[J]. ICLR 2022.

Method

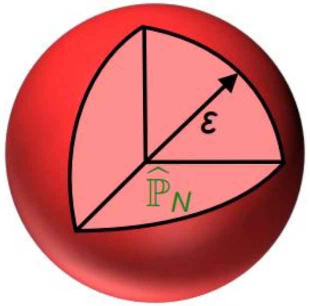
➢ **Utilize distributionally robust optimization (DRO) to alleviate the impact of data heterogeneity.**

- DRO treats the data distribution of each hospital as an uncertainty factor and employs the approach of minimizing the worst-case under specified uncertainty to train the global model.

$$\min_{\boldsymbol{w}\in\mathcal{W}} \max_{\boldsymbol{\lambda}\in\Lambda} F(\boldsymbol{w},\boldsymbol{\lambda}) := \sum_{i=1}^{N} \lambda_i f_i(\boldsymbol{w})$$

- Use the Wasserstein distance to measure the distance between uncertainty sets and probability distributions.

$$\text{Wasserstein metric: } d_{\mathrm{W}}(\mathbb{Q}_1,\mathbb{Q}_2) = \sup_{\mathrm{lip}(f)\le 1} \mathbb{E}^{\mathbb{Q}_1}[f(\xi)] - \mathbb{E}^{\mathbb{Q}_2}[f(\xi)]$$



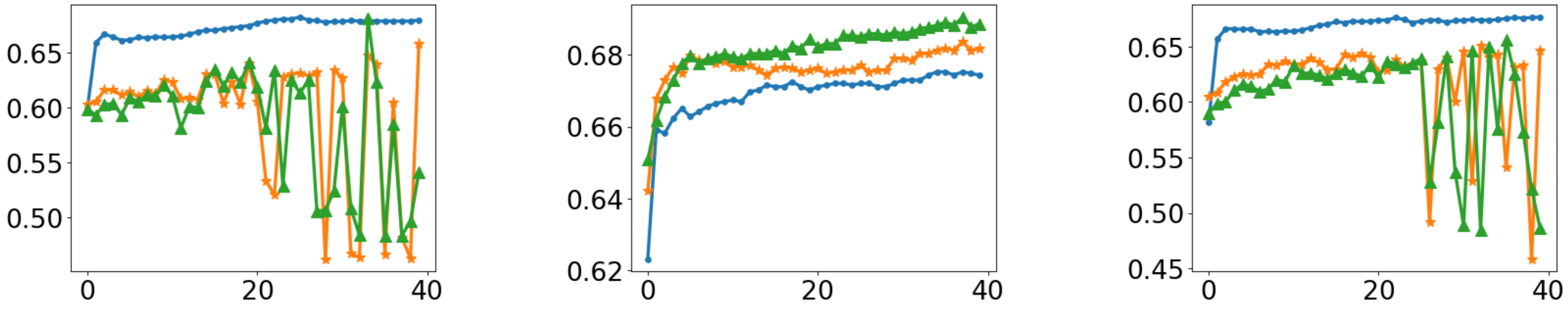
- During each global round, the client with the worst performance is selected for further optimization.

DRO enhances the robustness and generalization capacity of FERRY!

Method

➢ Utilizing joint loss learning to mitigate the impact of noise

- ➢ Previous research demonstrates that DRO can be sensitive to noisy data [1][2].
  - DRO uses measurement methods such as norm or divergence in modeling uncertainty distribution, which takes the noise in the uncertainty set into consideration, making DRO sensitive to noise.



Original | No Outliers | Noise Added

Medical data has incorrect labels, and DRO's sensitivity to noise affects model performance!

1. Zhai R, Dan C, Kolter Z, et al. Doro: Distributional and outlier robust optimization. ICML 2021.
2. Wu B, Liang Z, Han Y, et al. DRFLM: Distributionally Robust Federated Learning with Inter-client Noise via Local Mixup[J]. arXiv:2204.07742, 2022.

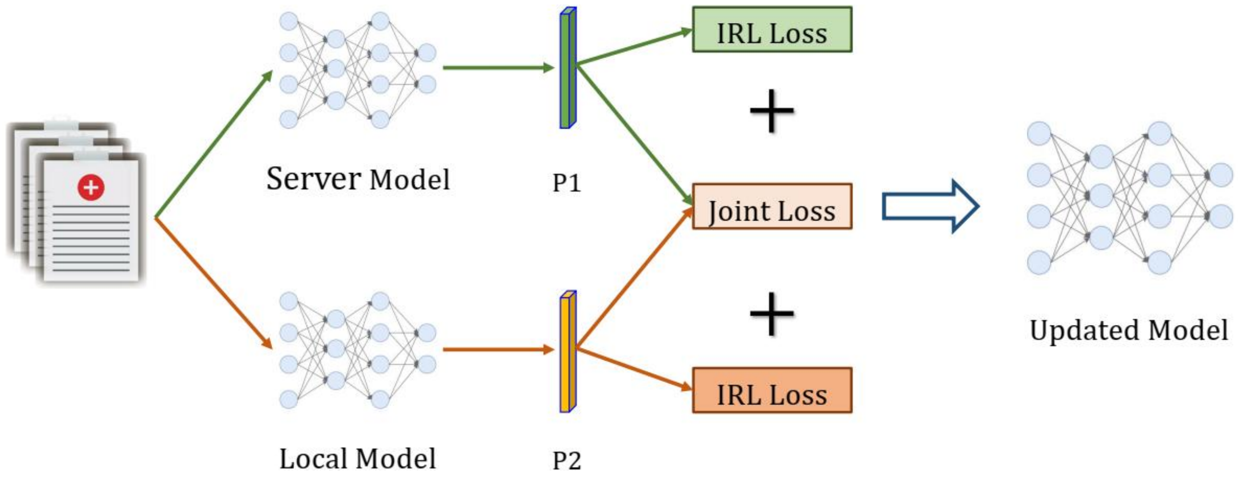
Method

➢ Utilizing joint loss learning to mitigate the impact of noise.

- During classifier training, noisy data is filtered out using consistency regularization, leading to improved model robustness.

$$\mathcal{L}_{Co-Reg} = D_{KL}(P_1||P_2) + D_{KL}(P_2||P_1)$$

- Each classifier's output is compared with that of others; if similarity is found, it's deemed reliable; otherwise, it's likely noisy data.



Joint loss learning can help filter out noisy data

Evaluation

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- **Dataset: MIMIC-III**
- **Preprocess:**
  - Filter further to include only those admissions in which the patient was kept under ventilator support for more than 24 hours.
  - Filter out admissions in which the patient in not successfully discharged from the hospital by the end of the admission
- **The evaluation results show that FERRY improves the overall ventilation and sedation decision-making accuracy by *36.75%***

Example ventilated ICU patient.

Method	V	S	$V\&S$	RA	Improvement(%)
CNN	86.07%	51.3%	47.52%	Not applicable	
FQI	85%	58%	55%	Not applicable	
AVRIL	96.38%	96.71%	93.43%	Not applicable	
Fed-NFQI	71.89%	16.89%	14.38%	Can't reach	Not applicable
FERRY w/o JL	96.21%	91.69%	89.16%	47	0
FERRY	**96.76%**	**94.31%**	**91.75%**	**34**	**27.66**

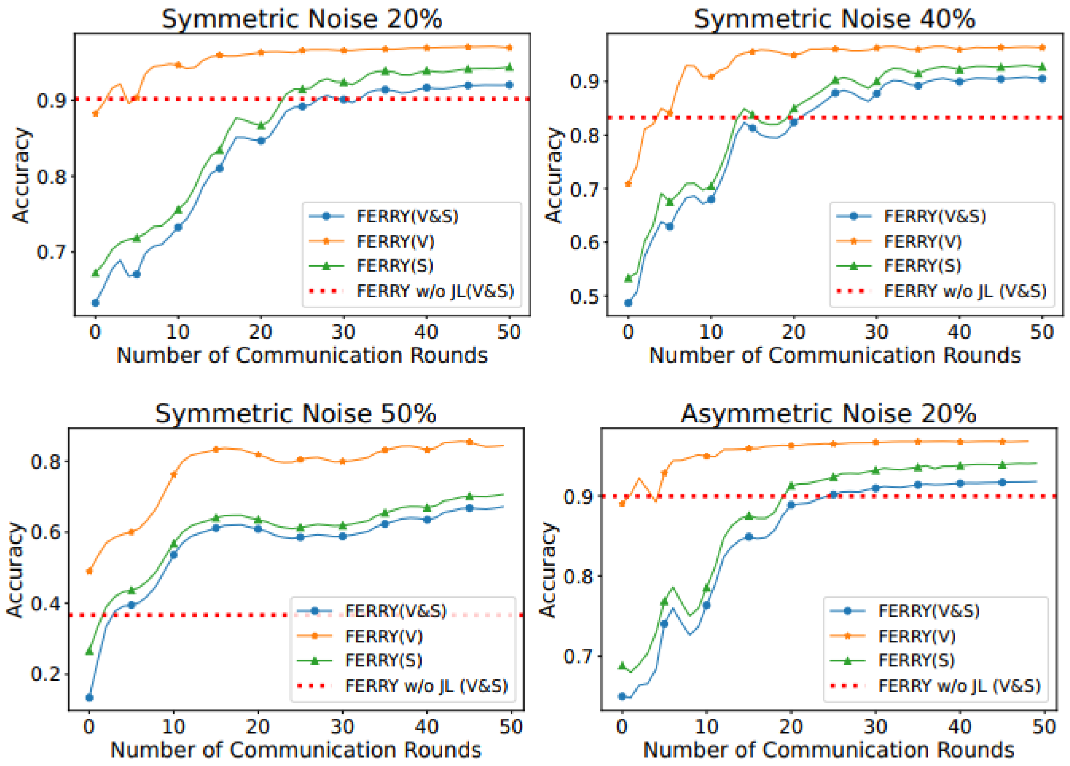
Evaluation

➢ **Our method has better performance under different noise levels.**

- We create synthetic noisy label by randomly flipping the labels with various ratio.

➢ **The results clearly demonstrate that FERRY exhibits significantly enhanced robustness against noisy labels.**

Noise Level	Method					
	FERRY w/o JL			*FERRY*		
	V(%)	*S*(%)	*V&S*(%)	*V*(%)	*S*(%)	*V&S*(%)
Symmetric 20%	96.23	92.48	90.18	97.09	94.19	92.01
Symmetric 40%	90.75	85.53	83.3	96.47	93.05	90.82
Symmetric 50%	53.89	40.05	36.68	84.41	70.69	67.13
Aymmetric 20%	96.56%	92.59%	89.96%	96.83%	94.06%	91.83%



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Thanks!