Early Prediction of Sepsis from Clinical Data

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Introduction/Background

- Sepsis is nightmare! More than six million people die of sepsis annually, and U.S. hospitals spend more than 24 billion dollars on sepsis each year (13% of U.S. healthcare expenses).
- GOOD NEWS: Deaths are preventable!
- Goal: Investigating automated algorithms to detect sepsis labels more precisely by 2 major methods for over 70% incomplete observations:

  i) Logistic Regression w/o Missing Values

  ii) Gradient Importance Learning w/n Missing Values

Dataset Description:

- This EMR data sourced from PhysioNet of 40,336 Patients sent to ICU in 3 hospitals from 2009-2019
- Response variable: SepsisLabel

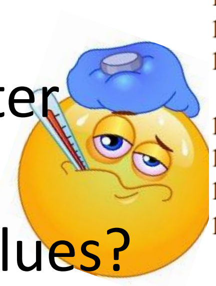
  1 if t≥tsepsis−6 and 0 if t<tsepsis−6
- Covariates: 8 vital physical signs, 26 laboratory values, and 6 demographic feature for each observation
- Below **Table1** has more details after important variables selection:

	Patients #	Sepsis Patients	Covariates #	Missingness Rate	Average Time Points/Patient
Training A	20,336	1790	36	73%	39
Testing B	20,000	1142	36	74%	38

Table 1: Summary of Dataset

Naïve Way for Brief View:

- Basic Logistic Regression after various time-series rearrangements of each patients' recordings and subsets attempting to adjust significant 2:98 imbalance problems and relative missing values imputation
- AUC could achieve≈0.65
- Question: Could we achieve better result or try more sophisticated method to execute within NA values?



Method1-Logistic Regression by Gradient Descent Update

- Built Logistic Regression with Gradient Descent update to decrease log loss in each iterations and computed a weighted cross entropy to trade off recall and precision by up- or down-weighting the cost of a positive error relative to a negative error
- Parameters for better performance: positive weight=50, batch size=12800, epochs=300, and learning rate=0.01
- Converged best results (**Figure1 & 2**): Low log loss (≈1.3)

  Relatively high AUC score (≈0.65)

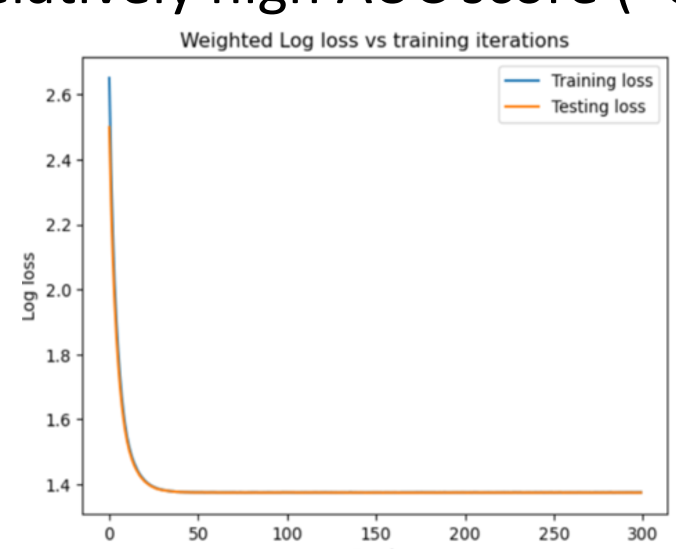


Figure1: Weighted Log Loss

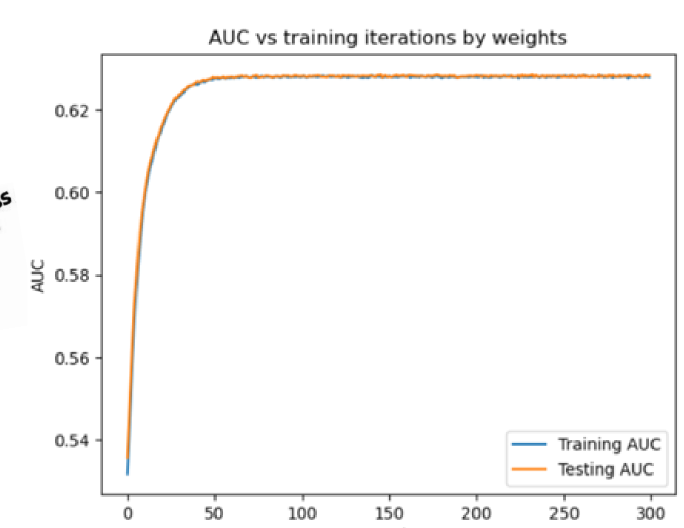


Figure2: AUC curve

Method2-Gradient Importance Learning for Incomplete Observations

Algorithm 1 Gradient Importance Learning (GIL).

Input: $\mathcal{X}, \mathcal{Y}, \mathcal{M}, \mathbf{W}_{enc}, \mathbf{W}_{inf}, \pi_\theta, Q_\nu, \alpha_\theta, \alpha_\nu, \alpha, E$

Begin:

1: Initialize $\mathbf{W}_{enc}$ and $\mathbf{W}_{inf}$, actor π_θ and critic Q_ν

2: Sample $\mathbf{x}$ from $\mathcal{X}$ and obtain the corresponding label $\mathbf{y}$ from $\mathcal{Y}$

3: Obtain the feature $\zeta \leftarrow f_{enc}(\mathbf{x}|\mathbf{W}_{enc})$ and prediction $\hat{\mathbf{y}} = f_{inf}(\zeta|\mathbf{W}_{inf})$ from the encoding and inference layers, respectively

4: $\mathbf{s} \leftarrow (\mathbf{x}, \mathbf{m}, \zeta, \hat{\mathbf{y}})$

5: **for** $iter$ in $1 : max\_iter$ **do**

6: Obtain importance from a behavioral policy $\mathbf{a} = \beta(\mathbf{s}|\pi_\theta)$

7: Train the encoding layer following $\mathbf{W}'_{enc} \leftarrow \mathbf{W}_{enc} - \alpha\boldsymbol{\Delta} \cdot (\mathbf{x}^\top \odot \mathbf{a}^\top)$ as in (4)

8: Train the inference layers following regular gradient descent, *i.e.*, $\mathbf{W}'_{inf} \leftarrow \mathbf{W}_{inf} - \alpha(\partial E / \partial \mathbf{W}_{inf})_{SGD}$

9: Obtain the prediction following the updated weights $\hat{\mathbf{y}} \leftarrow f(\mathbf{x}|\mathbf{W}'_{enc}, \mathbf{W}'_{inf})$

10: Obtain the reward $r \leftarrow R(\mathbf{s}, \mathbf{a})$

11: Get a new sample $\mathbf{x}'$ from $\mathcal{X}$ and obtain the corresponding label $\mathbf{y}'$ from $\mathcal{Y}$

12: Obtain the feature $\zeta' \leftarrow f_{enc}(\mathbf{x}'|\mathbf{W}'_{enc})$ and prediction $\hat{\mathbf{y}}' = f_{inf}(\zeta'|\mathbf{W}'_{inf})$ from the encoding and inference layers, respectively

13: $\mathbf{s}' \leftarrow (\mathbf{x}', \mathbf{m}', \zeta', \hat{\mathbf{y}}')$

14: Update the actor π_θ and critic Q_ν using $(\mathbf{s}, \mathbf{a}, r, \mathbf{s}')$ following (5)

15: $\mathbf{s} \leftarrow \mathbf{s}', \mathbf{W}_{enc} \leftarrow \mathbf{W}'_{enc}, \mathbf{W}_{inf} \leftarrow \mathbf{W}'_{inf}$

16: **end for**

- Gradient Importance Learning (GIL) method to train multilayer perceptrons (MLPs) and long short-term memories (LSTMs) to directly perform inference from inputs containing missing values
- Reinforcement learning (RL) to adjust gradients used to train these models back-propagation, which allows the model to exploit the underlying information behind missingness patterns
- Tabular analysis is designated: training and testing sets separated by normal (all non-sepsis) and abnormal (all sepsis)

Conclusion

- **System Satisfactory**: Good fitness of assumptions and comprehensive algorithms for Logistic Regression
- **Limitations**: 1. Missing entries leads poor performance by simply generation of estimation as the assumptions may do not satisfy the real-world applications, such as, patient time-series characteristics and a huge proportion of missingness rate or a small sample size

  2. Imputation error could limit the model capabilities
- **Future Improvements**: Simplify and tune GIL model to solve overfitting drawbacks

References

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