Understanding Heart-Failure Patients EHR Clinical Features via SHAP Interpretation of Tree-Based Machine Learning Model Predictions

Clinical Predictive Modeling

S97

Shuyu Lu

University of Pittsburgh, Department of Biomedical Informatics

#AMIA2021

Disclosure

No financial interests to disclose.

Learning Objectives

After the presentation, the audience would be able to:

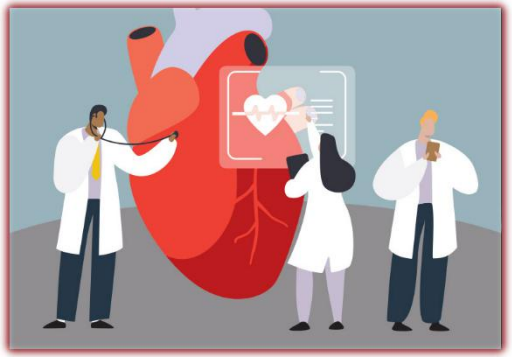
- ✓ **Understand the rationale of the SHapley Additive exPlanations (SHAP) interpretation method.**
- ✓ **Apply the SHAP method to interpret the contributions of each feature in medical studies like the heart failure (HF) risk assessment project.**
- ✓ **Be inspired to bring up new application of SHAP in the medical research.**

Motivation

1

https://myheart.net/articles/what-is-heart-failure-everything-you-need-to-know/

2



https://health.clevelandclinic.org/what-type-of-cardiologist-should-you-see-for-specialized-heart-care/

3

https://www.dreamstime.com/machine-learning-icon-two-color-design-red-black-style-elements-icons-collection-creative-web-apps-software-print-image144659464

https://thenounproject.com/term/heart-failure/155820/

4

https://shap.readthedocs.io/en/latest/index.html

http://www.freepngclipart.com/free-png/58858-physician-cartoon-doctors-png-download-free

Innovation: Make EHR mining physician-understandable

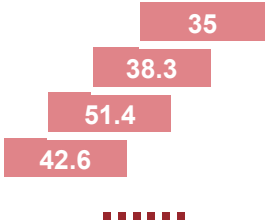
Simple Machine Learning model

SHAP method

Big Picture

Age	90
Age	71
Age	67
Age	84
Gender	M
Ethnicity	W
BP	XXX/XXX
BMI	XX
Rx ATC	XXX, XXX
Dx ICD10	XXX, XXX

Structured EHR data



EF score

dmlc XGBoost eXtreme Gradient Boosting

SHAP

t-SNE

EF Score	Pumping Ability of the Heart	Level of Heart Failure
50%-70%	Normal	No HF/HFpEF
40%-50%	Slightly below Normal	Slight Symptoms of HF
35%-40%	Moderately below normal	Mild HFrEF
<35%	Severely below normal	Severe HFrEF

Ponikowski, P., Voors, A. A., Anker, S. D., et al. (2016). 2016 ESC Guidelines for the diagnosis and treatment of acute and chronic heart failure. In European Heart Journal (Vol. 37, Issue 27, pp. 2129-2200m). Oxford University Press. https://doi.org/10.1093/eurheartj/ehw128

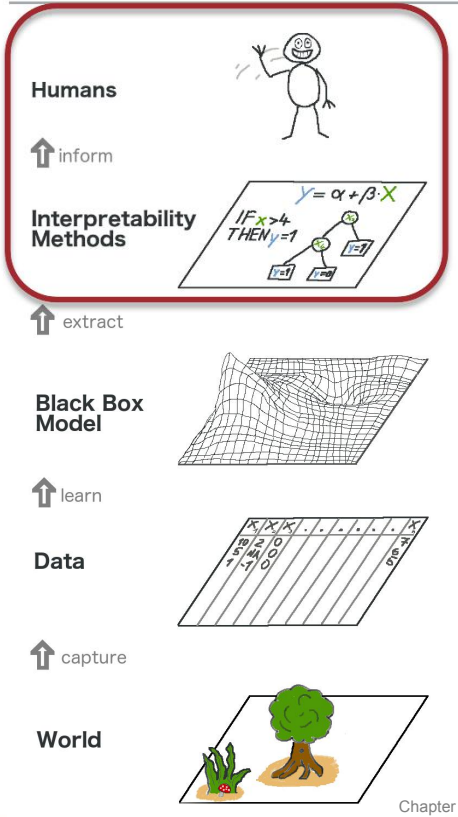
Methods -- Data Processing

UPMC EHR data

- 2014-2019
- Num source, e.g., inpatient, outpatient, nursing home
- 9 types of documents
- All patients have heart failure diagnoses (ICD9: I428.* or ICD10: I50.*) in medical history

Demographics	Vitals	Labs
Medical dispenses	Medical orders	Medical fills
Order results	Problem lists	Diagnoses

Methods -- Interpretable Machine Learning

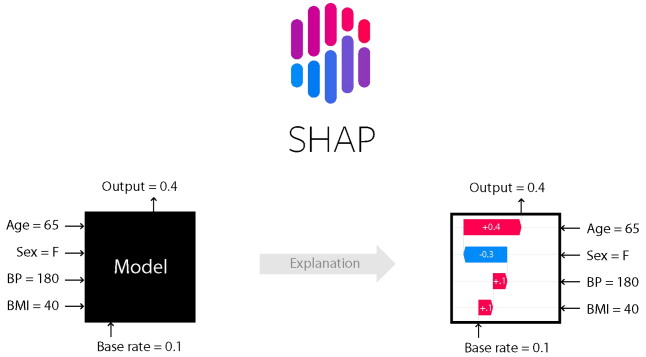


- Interpretable method is a new layer on top of machine learning(ML) models that helps humans understand.
- Model-agnostic interpretable methods separate the explanations from the ML model so that reach **FLEXIBILITY**.
- SHAP is a novel model agnostic interpretable ML method.

Chapter 6 Model-Agnostic Methods | Interpretable Machine Learning. (n.d.). Retrieved October 8, 2021, from https://christophm.github.io/interpretable-ml-book/agnostic.html

Methods -- SHAP

SHapley Additive exPlanations [1]

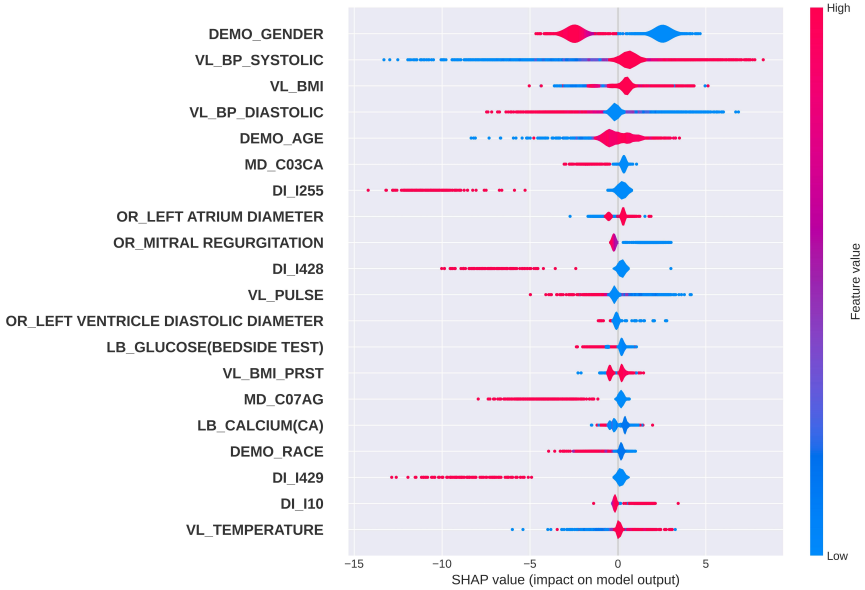


- **SHapley: Shapley value[2] as basic strategy.**
- **Popular Cooperation/Coalition games:**

- **Additive: Additive model for explanations.**
- **exPlanations: Explain ML models in a model-agnostic way.**

[1] Lundberg, S. M., Lee, S. I. (2017). A unified approach to interpreting model predictions. Advances in Neural Information Processing Systems, 2017-Decem(Section 2), 4766–4775.
[2] Shapley, L. S. (2016). 17. A Value for n-Person Games. In Contributions to the Theory of Games (AM-28), Volume II (pp. 307–318). https://doi.org/10.1515/9781400881970-018

Methods -- SHAP



- X-axis denotes the SHAP value.
- Y-axis denotes the features.
- Color bar represents the original feature values.
- Each point is a data point.

Methods -- t-SNE clustering with SHAP values

	feature*1*	feature*2*	feature*3*	.....	feature*n*
case1	.....	.....	.....	.....	.....
case2	.....	.....	.....	.....	.....
case3	.....	.....	.....	.....	.....

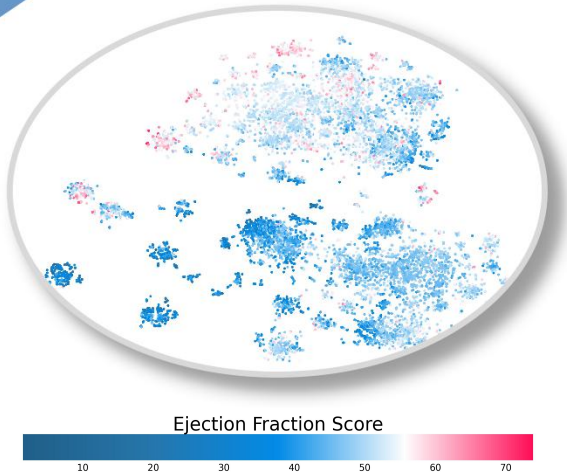
XGBoost Train

SHAP Interpret

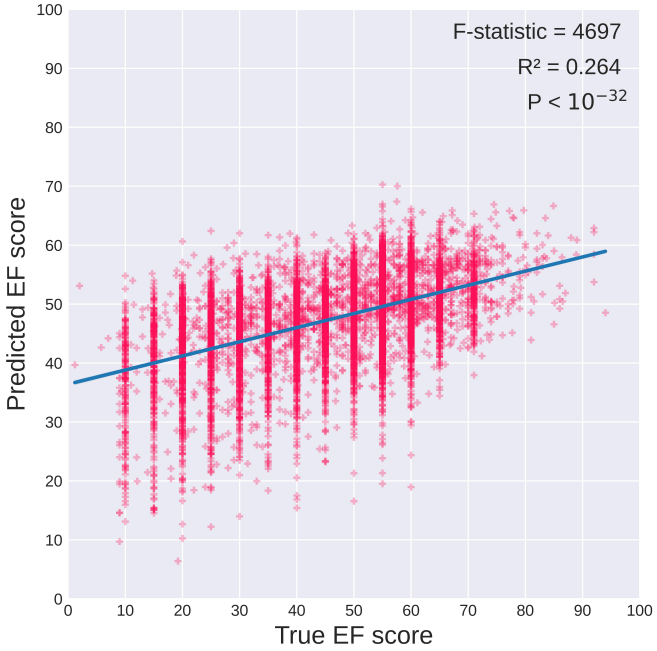
	feature*1*	feature*2*	feature*3*	.....	feature*n*
case1	.....	.....	.....	.....	.....
case2	.....	.....	.....	.....	.....
case3	.....	.....	.....	.....	.....

Real Value

t-SNE ✚ Clustering ✚ SHAP Value

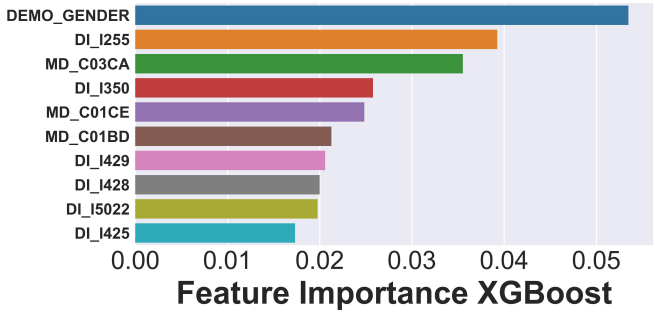


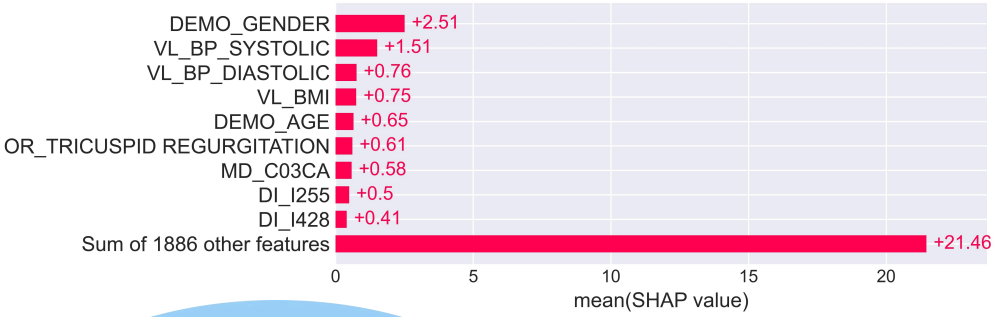
Results -- Predicting performance of XGBoost model

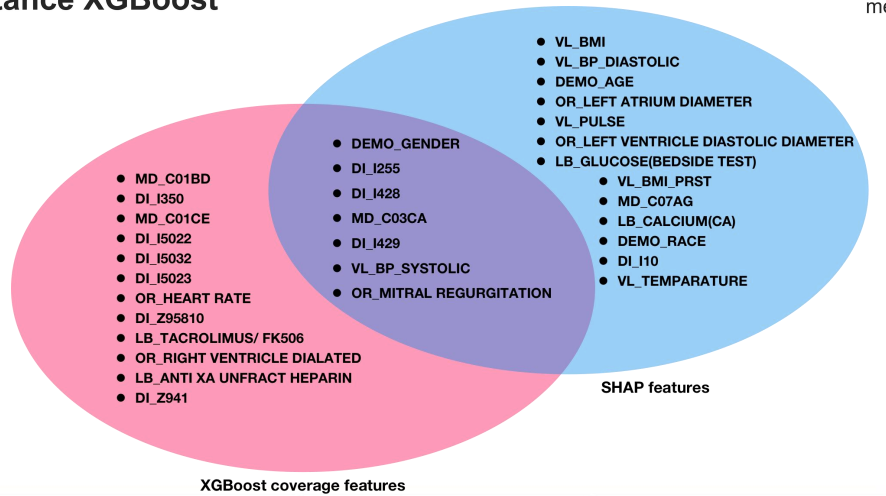


$$RMSE = 12.6303 \pm 0.00201$$

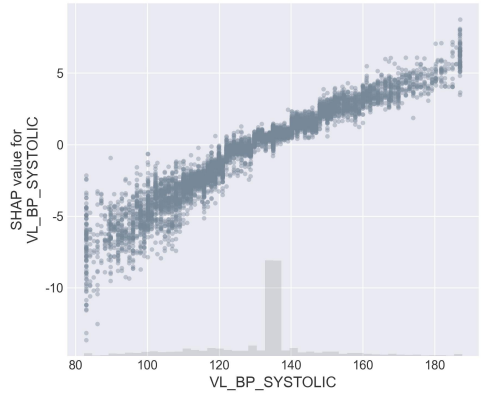
Results -- Interpretation with XGBoost and SHAP

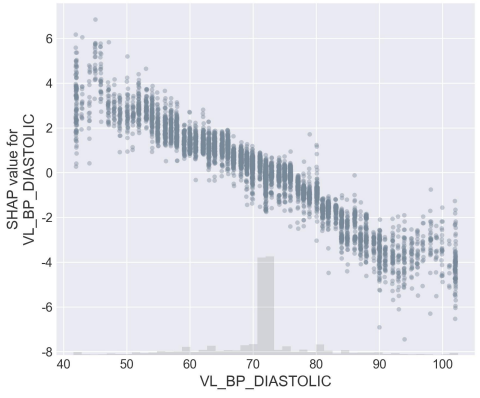






Results -- SHAP scatter plot for systolic/diastolic blood pressure





- Show the effect a single feature has on the predictions made by the model.

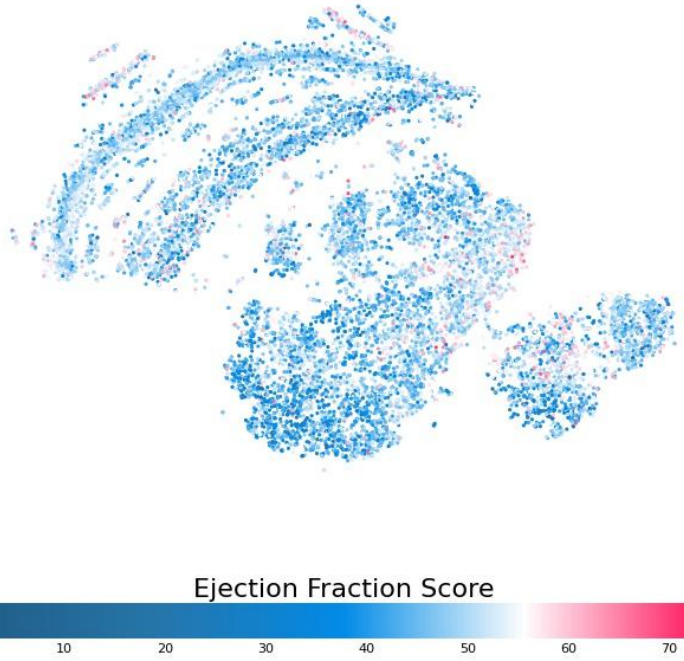
Systolic blood pressure ↑ correlate with EF Score ↑

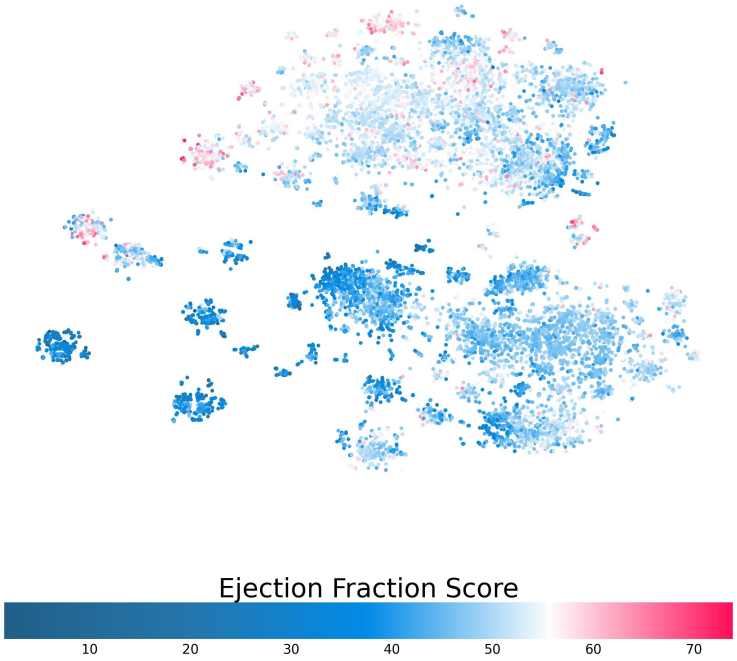
Diastolic blood pressure ↑ correlate with EF Score ↓

Hints for physicians

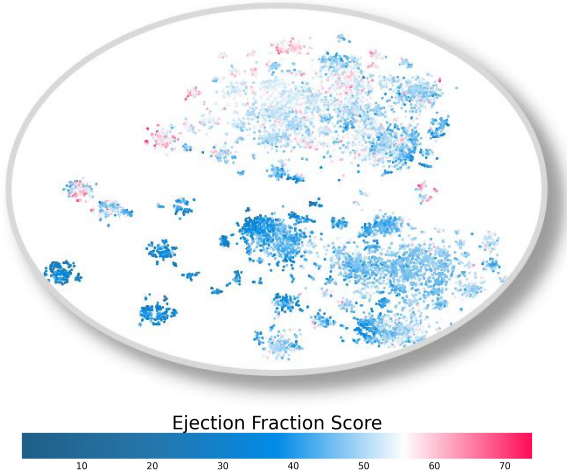
- If there's potential causality between BP and EF, even HF type.
- BP is just example. we can generalize to other features.

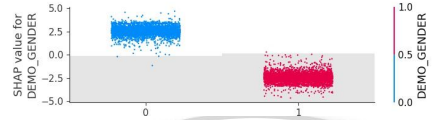
Results -- Sample clustering analysis with t-SNE and SHAP value

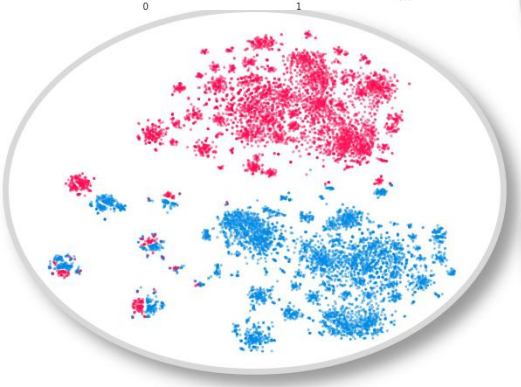


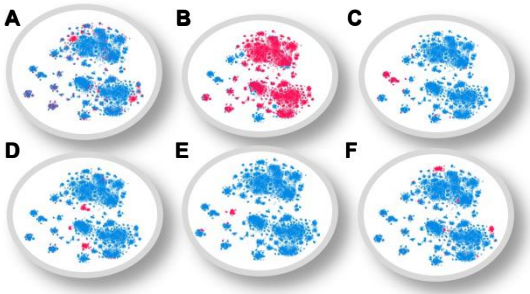


Results -- Sample clustering analysis with t-SNE and SHAP value

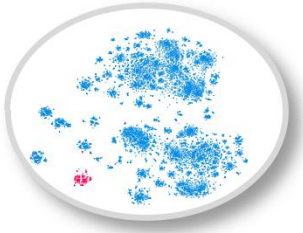




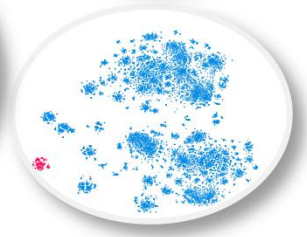




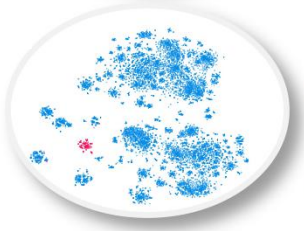
A. I10: Hypertension
B. Mitral Regurgitation
C. E/A ratio
D. Labetalol/Carvedilol
E. I50.22: Chronic systolic (congestive) heart failure
F. I35.0: Nonrheumatic aortic (valve) stenosis



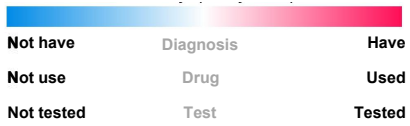
➢ I42.8: Other Cardiomyopathies



➢ I25.5: Ischemic Cardiomyopathy



➢ I42.9: Cardiomyopathy, unspecified



Conclusion

[1] Savarese,G.,&D' Amario,D.(2018).Sexdifferencesinheartfailure.InAdvancesinExperimentalMedicineand Biology (Vol. 1065, pp. 529–544). Springer New York LLC. https://doi.org/10.1007/978-3-319-77932-4 32
[2] Duca, F., Zotter-Tufaro, C., Kammerlander, A. A., Aschauer, S., Binder, C., Mascherbauer, J., & Bonderman, D. (2018). Gender-related differences in heart failure with preserved ejection fraction. Scientific Reports, 8(1), 1080. https://doi.org/10.1038/s41598-018-19507-7
[3] Regitz-Zagrosek, V. (2020). Sex and Gender Differences in Heart Failure. International Journal of Heart Failure, 2(3), 157. https://doi.org/10.36628/ijhf.2020.0004
[4] Inamdar, A., Inamdar, A. (2016). Heart Failure: Diagnosis, Management and Utilization. Journal of Clinical Medicine, 5(7), 62. https://doi.org/10.3390/jcm5070062

AMIA
INFORMATICS PROFESSIONALS. LEADING THE WAY.

- **XGBoost regression model can be trained to predict EF score using tabular EHR data with fair performance.**

- **SHAP analysis could help revealing informations and patterns that could not be easily acquired through analyzing original feature space.**
  - EF difference between male & female are confirmed in previous studies.[1-4]
  - With SHAP analysis, we suggest some possibilities for finding the subtype of heart failure.

If we go further.....

- ☐ Add clinical notes information to the prediction model for more accurate prediction.
- ☐ Tailored prediction models for different sub-populations of patients, which are represented by different combination of patterns with SHAP analysis.

The use of machine learning models to construct clinical decision aids related to heart failure is justifiable and feasible.

Thank you!

Email me at: shl183@pitt.edu

the.weiwei.daily@gmail.com