



MLGIG Team - Milk Lactose Prediction Data Challenge - P2: Explain the models











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HOST INSTITUTIONS



















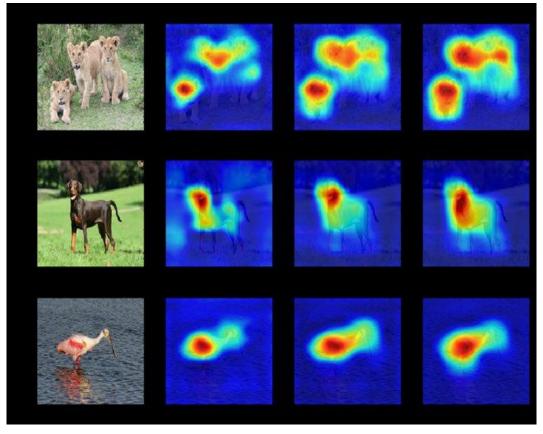




Our motivation

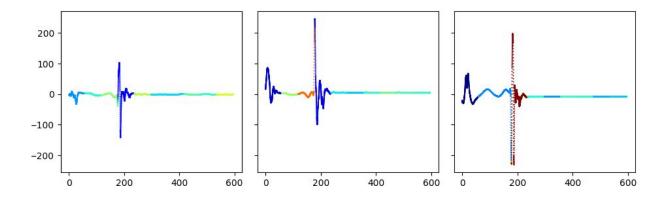
- We are interested in WHY? E.g., why the model predicted 24 but not 60?
 on which part of the data the model was focusing?
- We don't have the necessary background to understand the data but can
 we learn something from the model? E.g. which area is more important,
 which is noisy.
- We want explanation so:
 - Perhaps we can improve the model performance.
 - We can take the explanation to the domain experts.
- We have experience with time series saliency map / attribution methods so we used what we know.





An example of saliency map for image classification.

^{*}https://www.geeksforgeeks.org/what-is-saliency-map/



An example of saliency map for time series classification.

Time Series Attributions

0.4	1	5	2	D	0.0	0.0	0.8	0.4
0.3	2	4	3		0.0	0.1	0.7	0.3
0.1	2	2	6	M	0.1	0.1	0.6	0.4

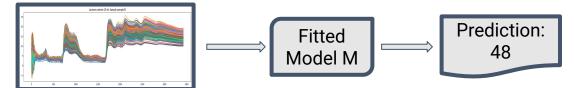
Sample T

Attribution A

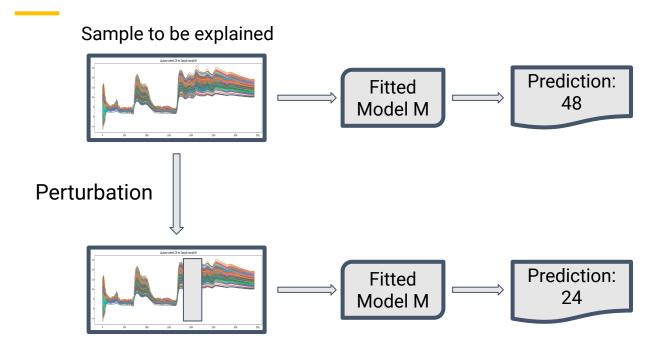
- Attribution (saliency map) A has the same shape as input T.
- Each entry in A "**explain**" the corresponding entry in T ,e.g., how important it is to the model M when it makes the prediction.
- A = D(T,M) where D is an attribution method.

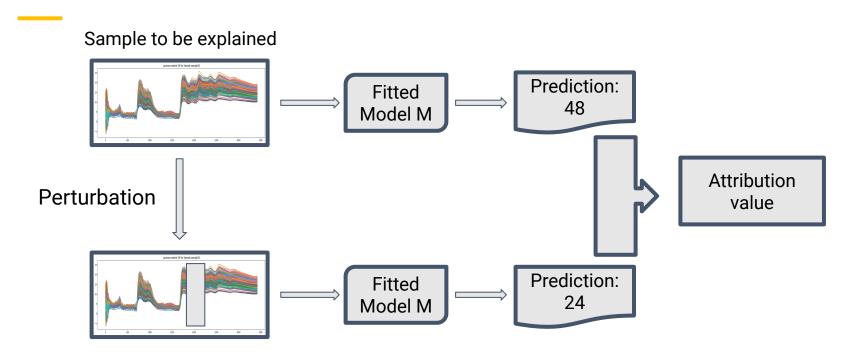


Sample to be explained



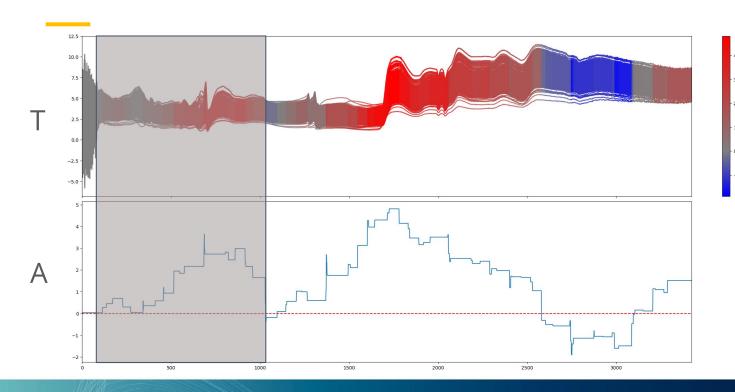
Sample to be explained Prediction: Fitted 48 Model M Perturbation





Perturbation-based Attribution Methods

- Post-hoc methods: i.e., they work with any black box models.
- In our experience with time series models, Shapley Value or Feature Ablation are the good options to try.
- They can be computationally expensive (~1 hour to compute the attribution of all samples using Shapley).
- We use Captum (captum.ai) implementation.
- Our best model + Shapley => attribution profile



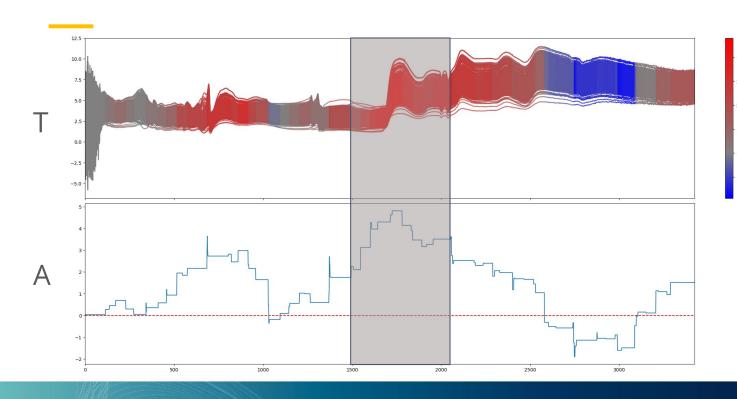
Sample 16

True Lactose: 48

Prediction: 48

New prediction: 42.275





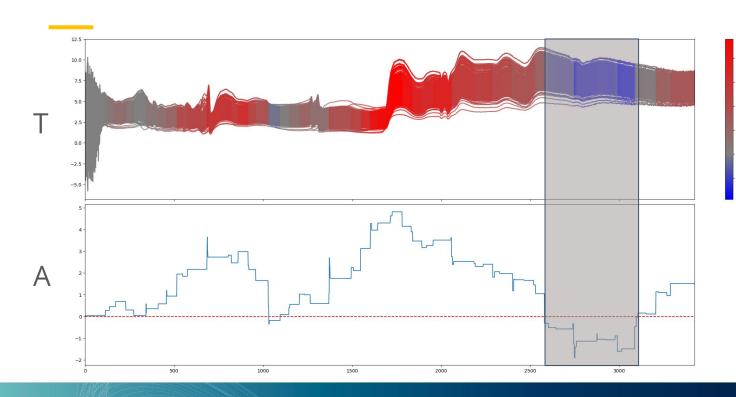
Sample 16

True Lactose: 48

Prediction: 48

New prediction: 25.64





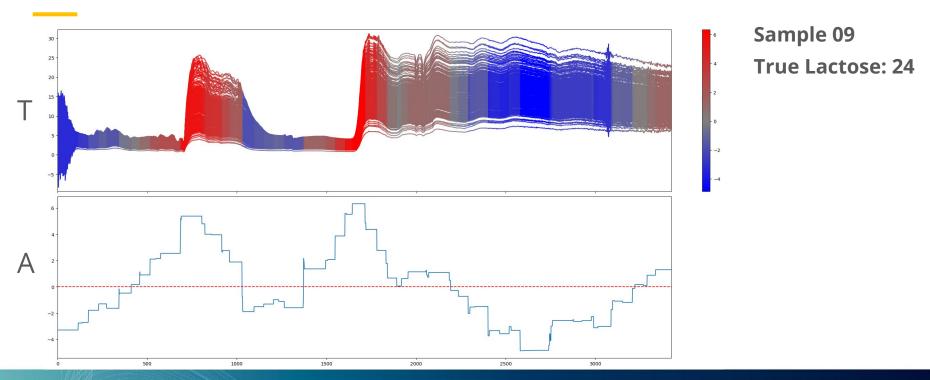
Sample 16

True Lactose: 48

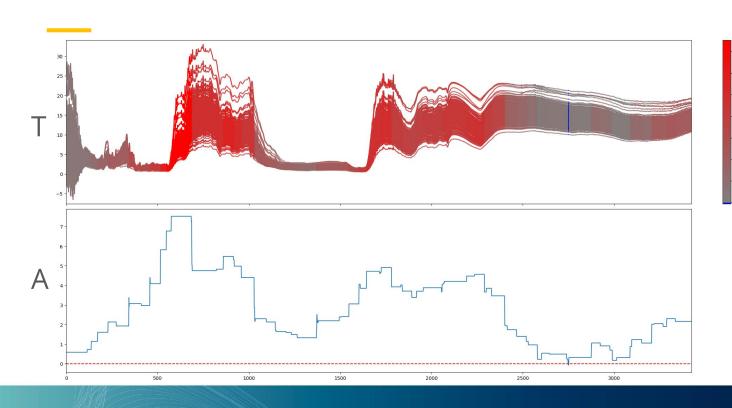
Prediction: 48

New prediction: 61.035







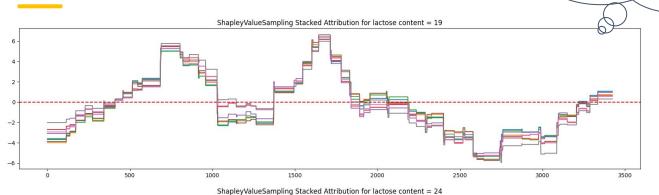


Sample 12

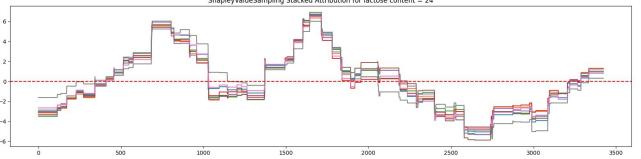
True Lactose: 72



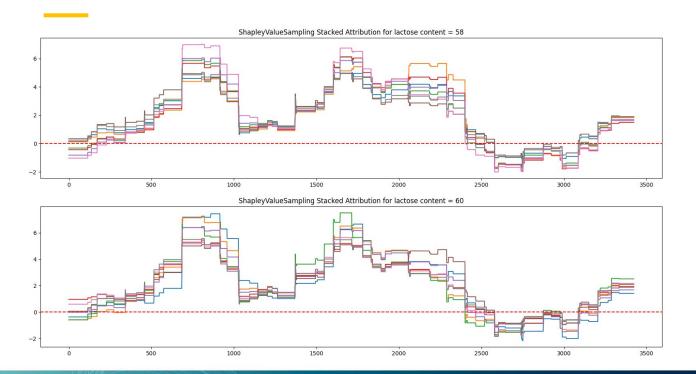




Lactose:19







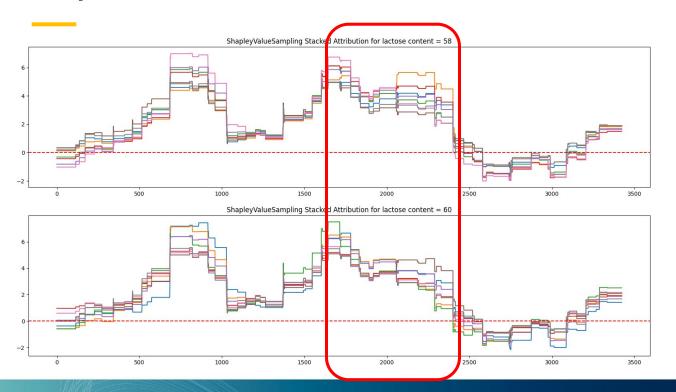
Lactose:58





Lactose:19

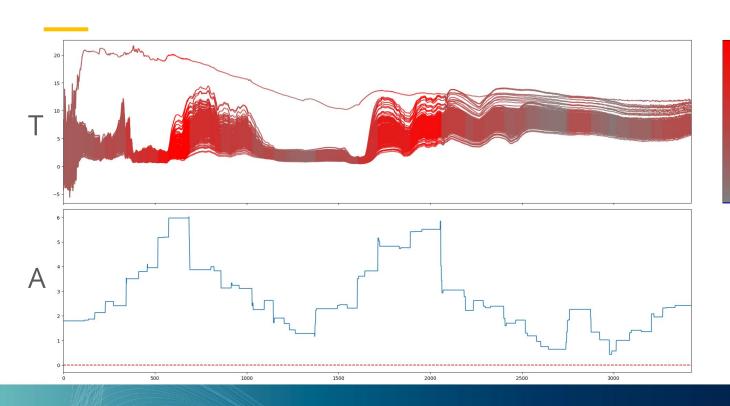




Lactose:58



Test data



Sample 39

Human

Prediction: 72

Model

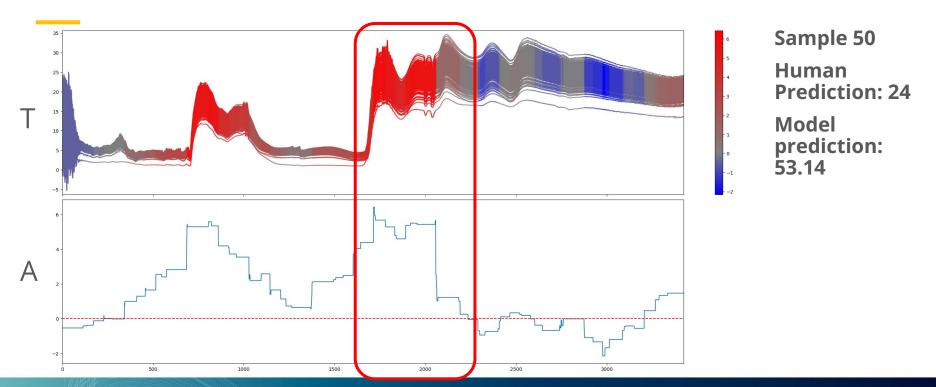
prediction: 72

True lactose:

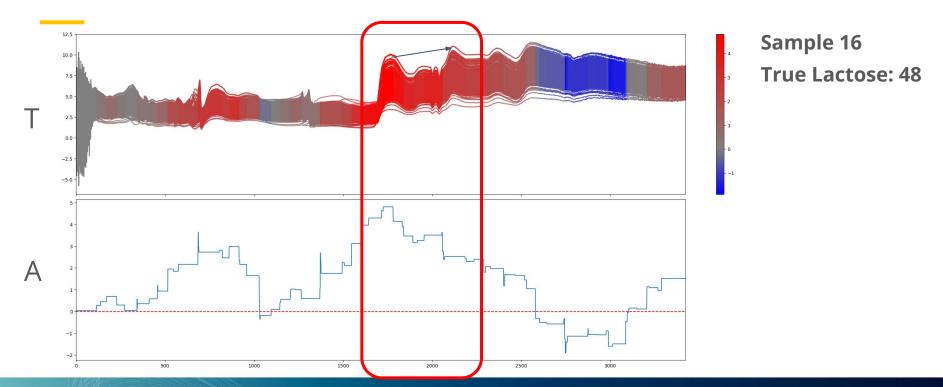
72



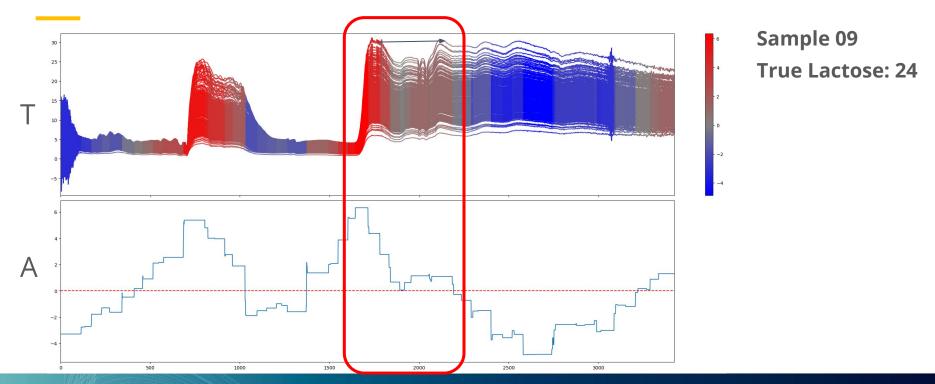
Test data





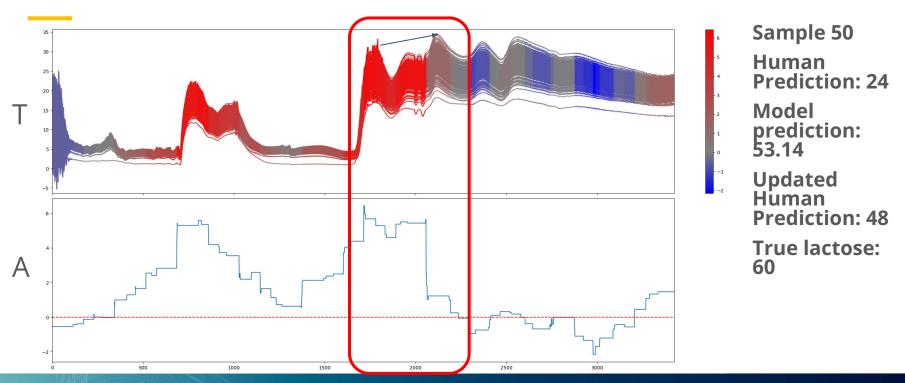






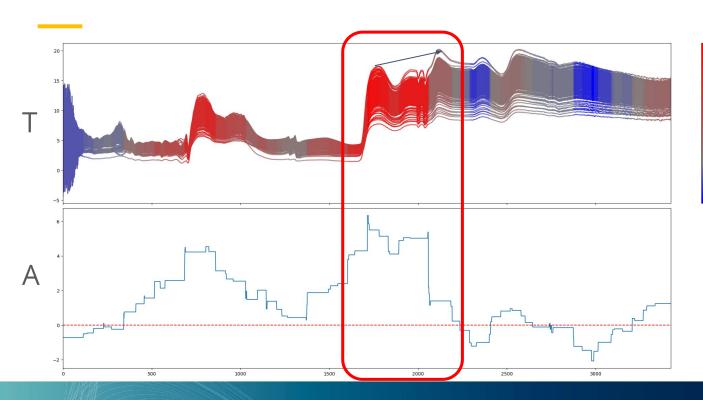


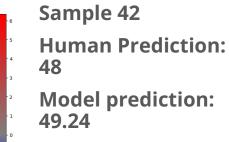
Test data





Test data







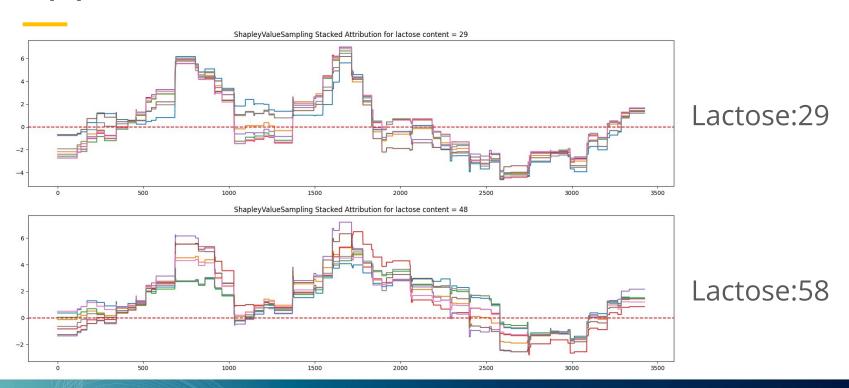


Take away

- We demonstrate how to use attribution methods to explain our models.
- The attribution can show us which parts of the input have impact on the model prediction.
- The attribution can be useful for understanding the model and the data.
- This is still a work in progress. We are curious if:
 - There is anything else we can learn from the attribution.
 - Is what we learn correct? Is it valuable? i.e. whether the domain experts find it accurate (sample 42 says otherwise) and whether they can use it for their works.
 - Can we use the attribution for any downstream task? E.g. model enhancement, data labelling, data reduction etc.

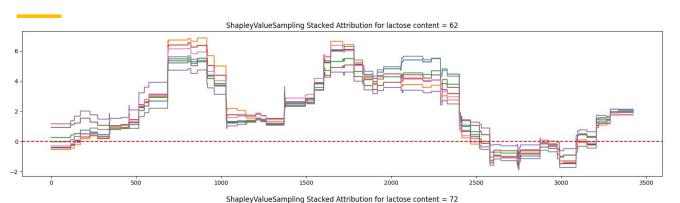


Appendix





Appendix



Lactose:62

