



# Conformal Prediction for Testing and Evaluation of Intelligent/ML Systems

AI4SE & SE4AI Workshop

September 27, 2023

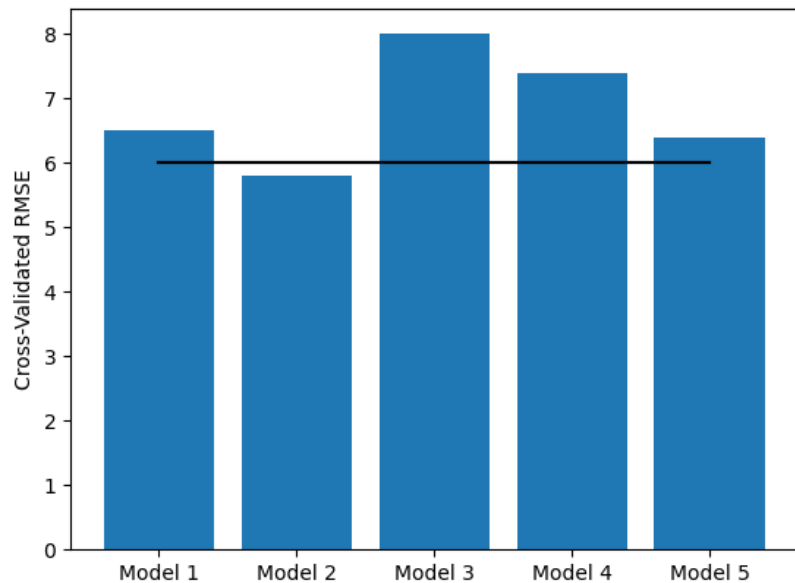
# Agenda

- Problem Formulation
- Introduction to Conformal Prediction
- Why Conformal?
- Extensions

# Problem Formulation

- Predict Amount of Fuel Needed
- Observations  $(x_i, y_i)$  for  $i = 1, \dots, 100$
- Target – RMSE < 6gal

Vehicles (x1000)	Gas Consumed Gal (x1000)
2.953	17.363
2.901	15.517
1.125	8.158
5.984	27.345
1.856	11.646

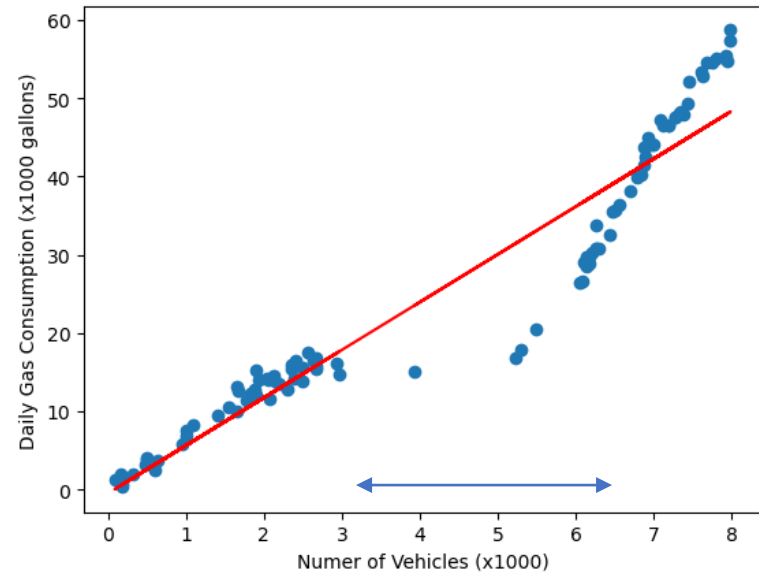
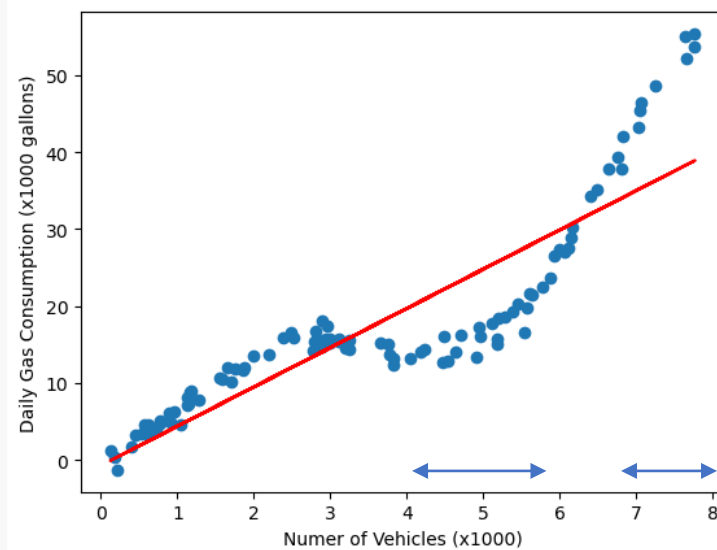


# Problem Formulation

- Validation - The process of determining the degree to which a model is an accurate representation of the real world from the perspective of the intended uses of the model\*

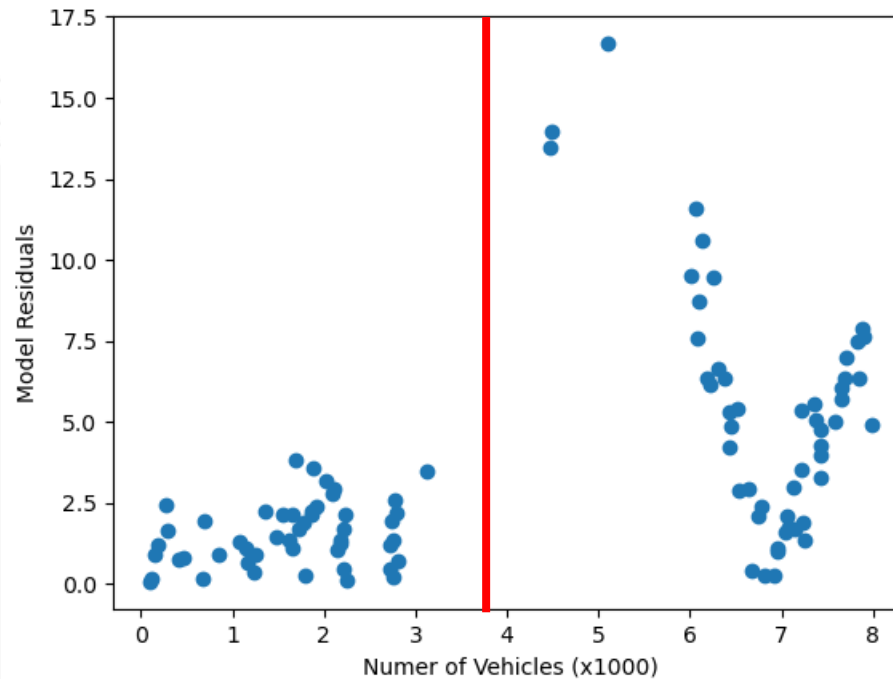
\*Ben H Thacker, Scott W Doebling, Francois M Hemez, Mark C Anderson, Jason E Pepin, and Edward A Rodriguez. 2004. Concepts of model verification and validation. (2004).

# Problem Formulation



- What do you do when you move to higher dimensions?

# Problem Formulation



Range 1  $\longleftrightarrow$

$\longleftrightarrow$  Range 2

Range 3  $\longleftrightarrow$

$\longleftrightarrow$  Range 4

# Problem Formulation

## Model 1



- Golden Retriever



- Golden Retriever



- Golden Retriever

## Model 2

- Golden Retriever

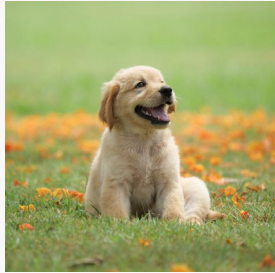
- Golden Retriever

- Golden Retriever



# Problem Formulation

## Model 1



- Golden Retriever: **75%**



- Golden Retriever: **70%**



- Golden Retriever: **80%**

## Model 2

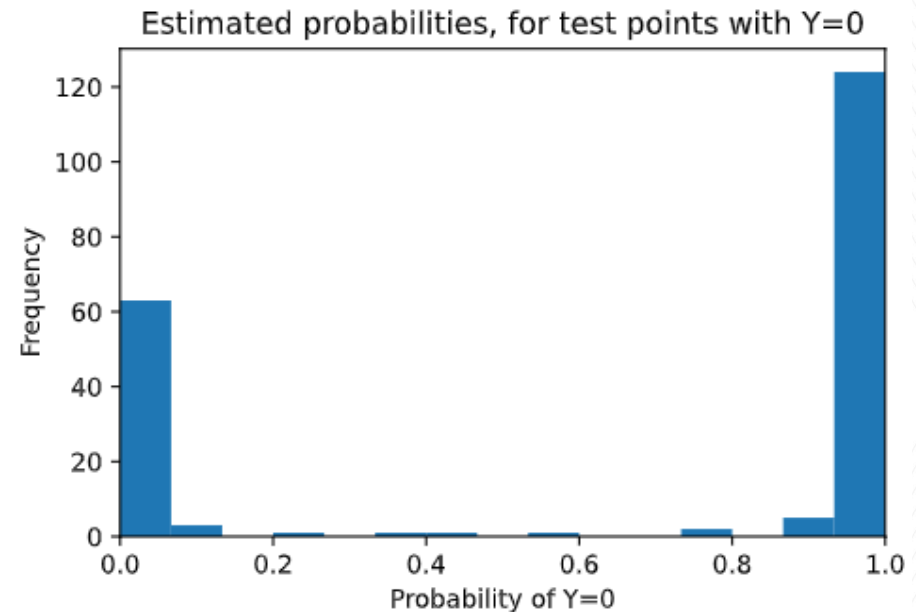
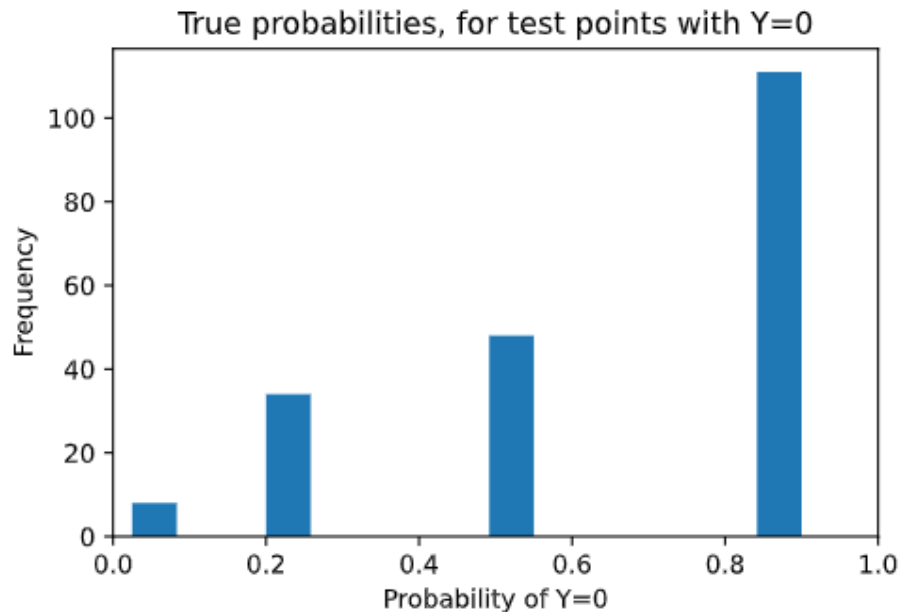
- Golden Retriever: **95%**

- Golden Retriever: **90%**

- Golden Retriever: **30%**



# Problem Formulation



- Calibration\* - the probability associated with a predicted label should reflect its true likelihood

\*Chuan Guo, Geoff Pleiss, Yu Sun, and Kilian Q Weinberger. 2017. On calibration of modern neural networks. In International conference on machine learning. PMLR, 1321–1330.

# Introduction to Conformal Prediction

- $Y_i$  – true label
- $\hat{C}_\alpha(X_i)$  – prediction interval or set
- $\alpha$  – confidence value

$$\mathbb{P}(Y_i \in \hat{C}_\alpha(X_i)) \geq 1 - \alpha$$

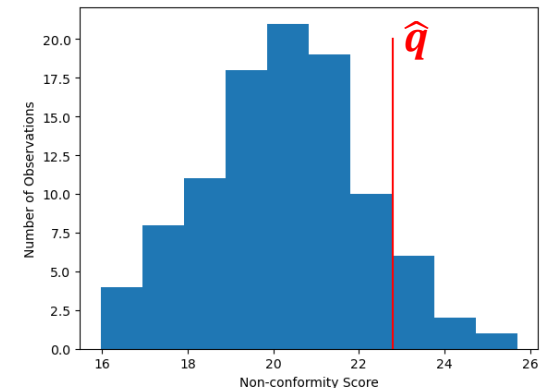
- Two method branches:
  - Full and Split

# Introduction to Conformal Prediction

- $y_i$  – true label
- $\hat{q}$  –  $(1 - \alpha)$  quantile for observed scores

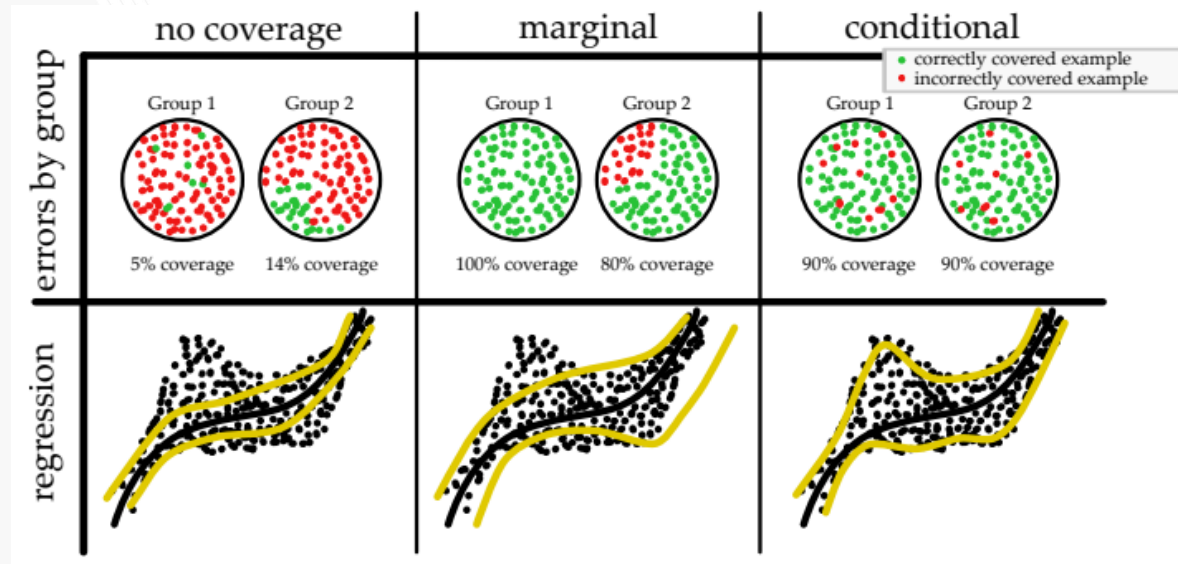
$$\hat{C}_\alpha(x_i) = \{y | s(x_i, y) \leq \hat{q}\}$$

$$s(x_i, y_i) = (\hat{f}(x_i) - y_i)^2$$



# Introduction to Conformal Prediction

- Marginal Coverage Guarantee

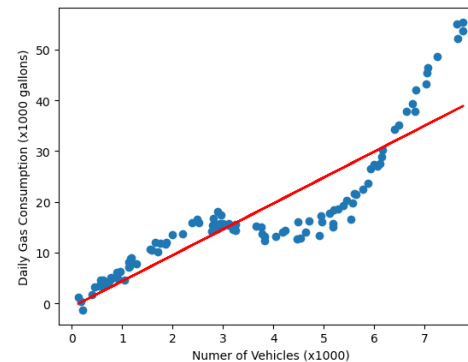
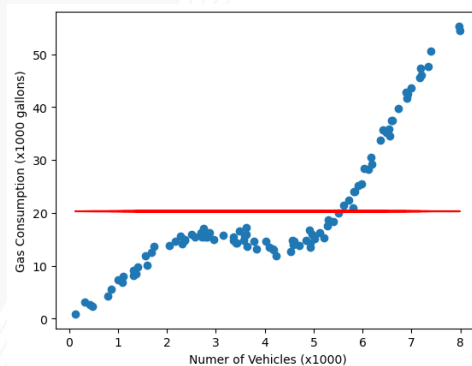


# Introduction to Conformal Prediction

- Additional data

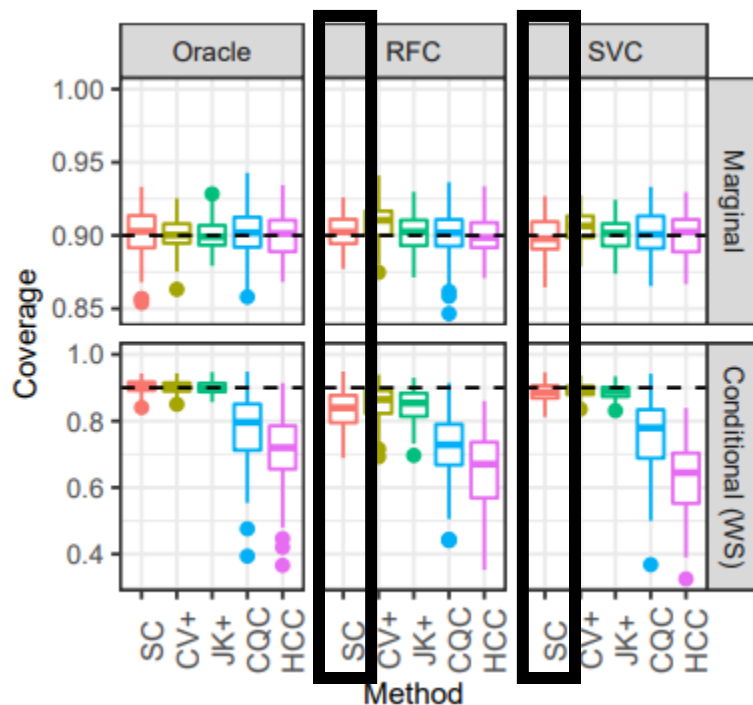


- Dependent on underlying algorithm



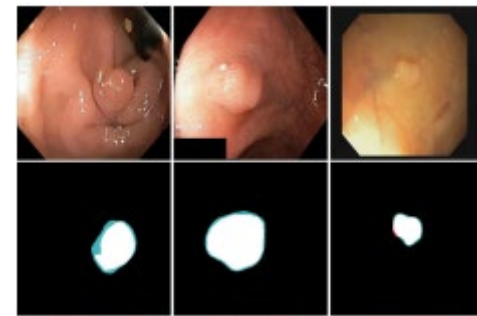
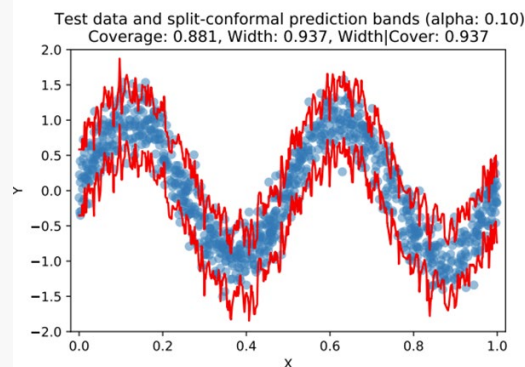
# Why (Split) conformal?

- Calibrated with guarantee



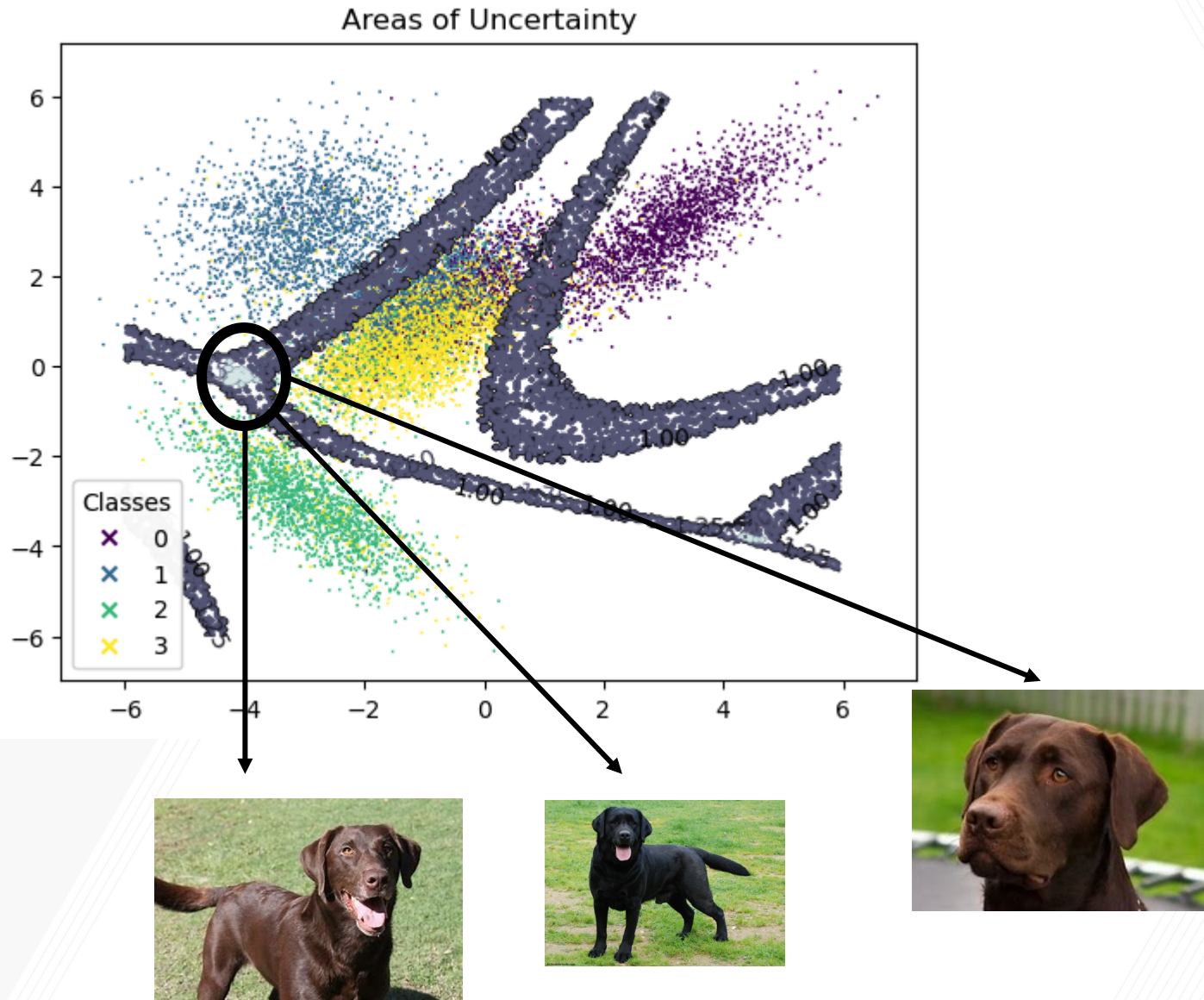
# Why (Split) conformal?

- No additional model training
- Wrapper for any model



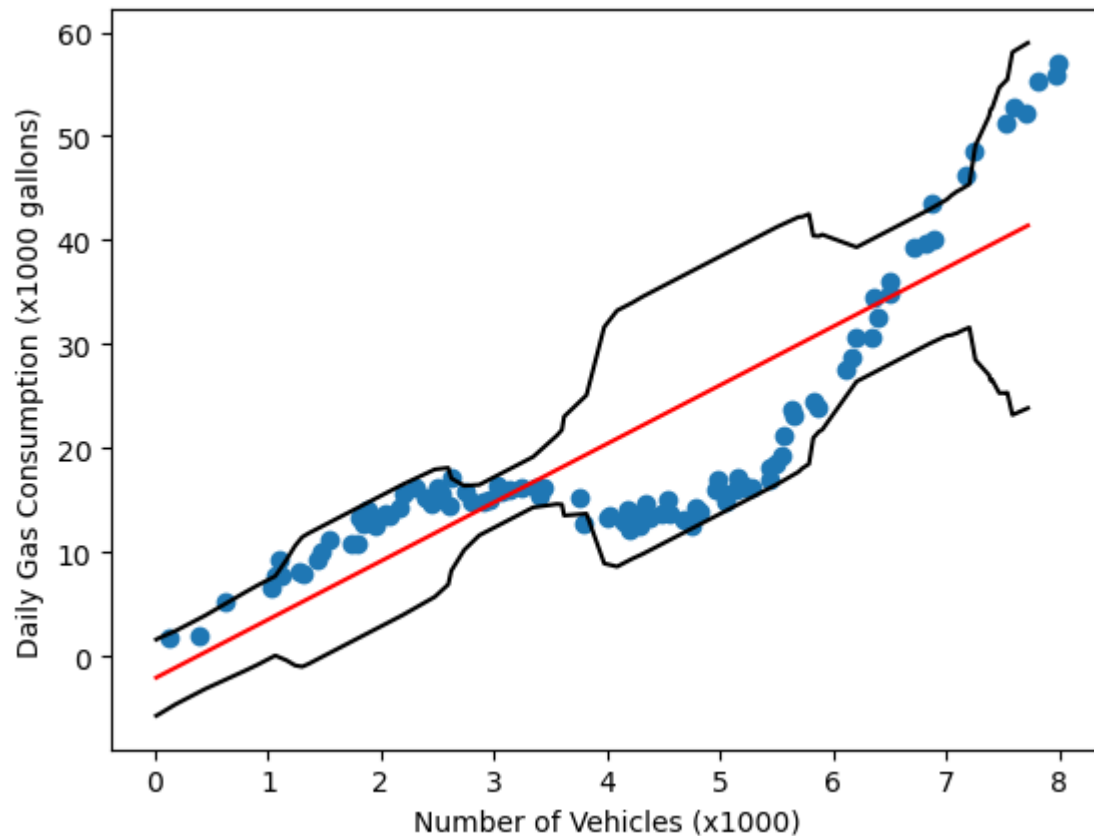


# Why (Split) conformal?



# Why (Split) conformal?

- 90% Confidence Interval through Conformal Prediction



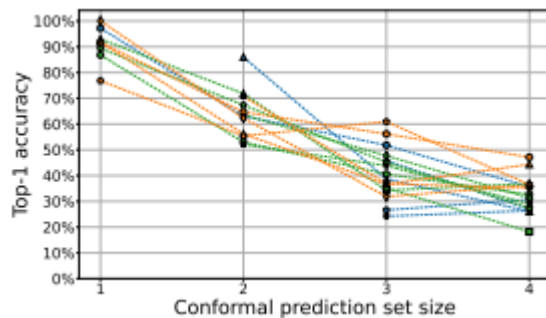
# Why (Split) conformal?



- {Golden Retriever}

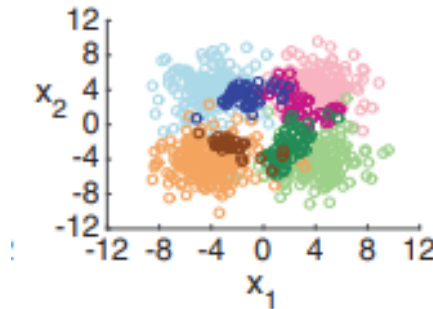


- {Golden Retriever, Tibetan Mastiff, Irish Setter, Great Pyrenees}



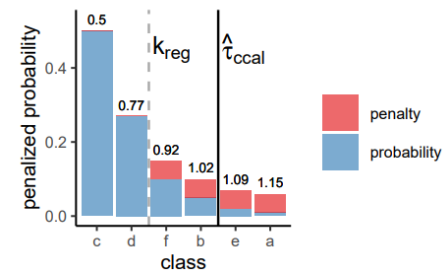
# Extensions

- Active Learning



Sergio Matiz and Kenneth E. Barner. 2020. Conformal prediction based active learning by linear regression optimization. *Neurocomputing* 388 (2020), 157–169.

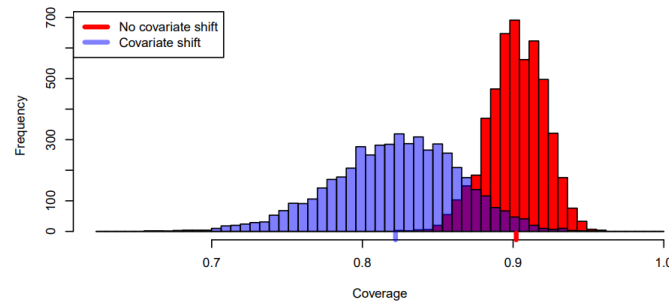
- Set size regularization



Angelopoulos, A., Bates, S., Malik, J., & Jordan, M. I. (2020). Uncertainty sets for image classifiers using conformal prediction. *arXiv preprint arXiv:2009.14193*.

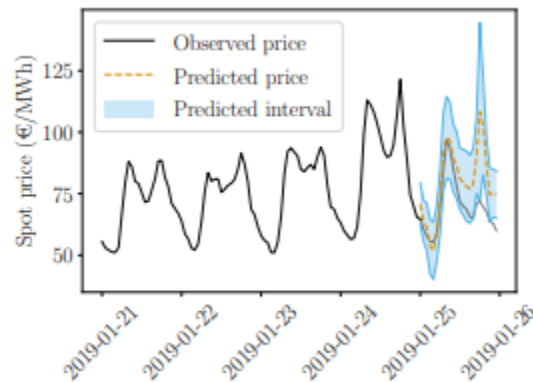
# Extensions

- Covariate Shift



Tibshirani, Ryan J., et al. "Conformal prediction under covariate shift." Advances in neural information processing systems 32 (2019).

- Time Series



Margaux Zaffran, Olivier Feron, Yannig Goude, Julie Josse, and Aymeric Dieuleveut. 2022. Adaptive Conformal Predictions for Time Series. In Proceedings of the 39<sup>th</sup> International Conference on Machine Learning (Proceedings of Machine Learning Research, Vol. 162). PMLR, 25834–25866. <https://proceedings.mlr.press/v162/zaffran22a.html>

# Summary

- Empirical risk has gaps for model validation
- Model generated notions of uncertainty are uncalibrated
- Conformal prediction provides a guaranteed form of uncertainty quantification
- Guarantee applies to marginal coverage
- Requires exchangeable (IID) data
- Wraps around previously trained model with no additional training

# Acknowledgement

- This work was partially supported by NSF grant DMS-2015405