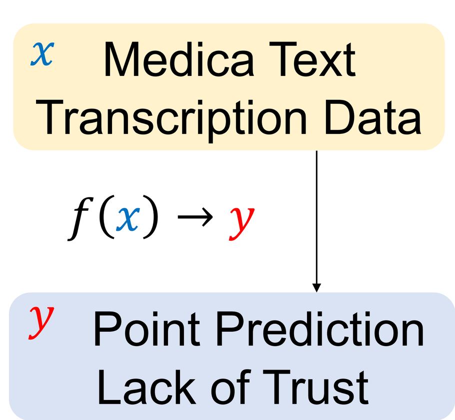
Enhancing Risk Aware Decision in Healthcare with Uncertainty Quantification

Rahul Vishwakarma, Jinha Hwang, Benyamin Ahmadnia
California State University Long Beach

Motivation: Risk of wrong prediction!

- Life threating situation in healthcare domain
- Model accuracy for new patients?



- Most of the Machine Learning model lacks **calibration**.
- **No guarantee** for uncertainty estimations for new data.

Need of ***Uncertainty Quantification*** for a reliable decision.

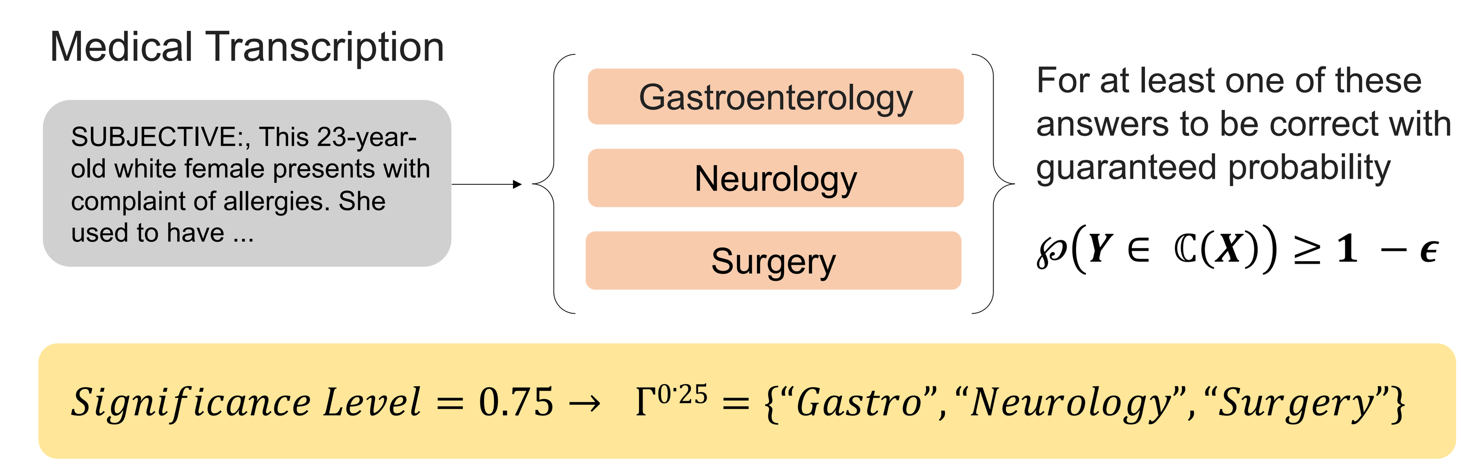
Prior Work

- **Bayesian Inference:** Require careful selection of prior distributions.
- **Confidence intervals**: Not be well-suited for complex data and model.

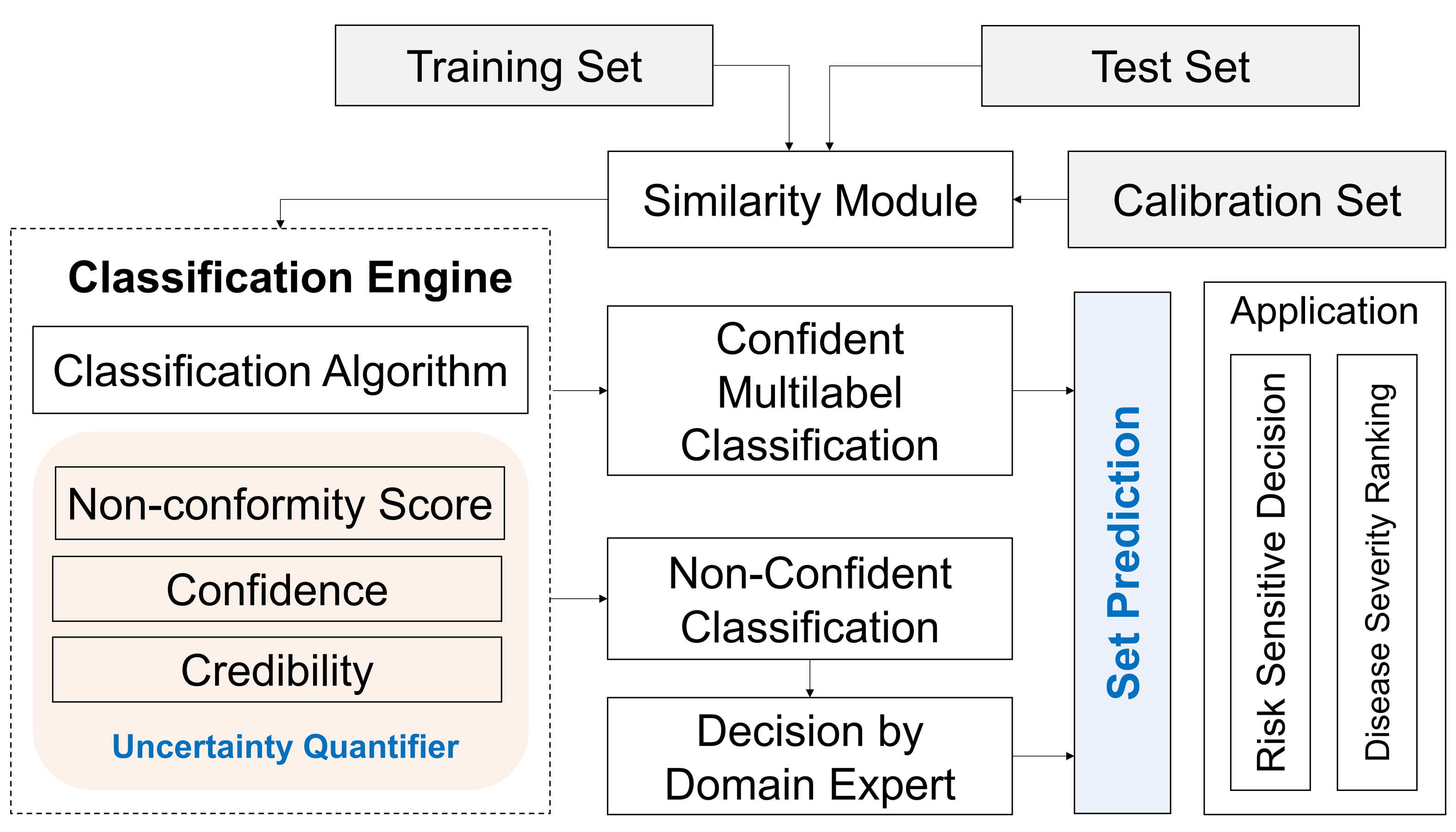
Method: Set valued prediction

- **Idea**: Instead of calibrating the probabilities for each individual outcome (e.g., Y = 1), apply calibrated probabilities to a set of potential outcomes (e.g., Y ∈ {1, 2, 3}).
- **Goal**: Forecast a limited collection of reasonable responses.

Conformal Prediction: Uncertainty Quantifier



Proposed Solution



Inference: *p*-values

p-values								*y (sig = 0.20)*
p-0	*p-1*	*p-2*	*p-3*	*p-4*	*p-5*	*p-6*	*p-7*	
0.125	0.122	0.131	0.373	0.122	0.122	0.130	0.124	3
False	False	False	True	False	False	False	False	

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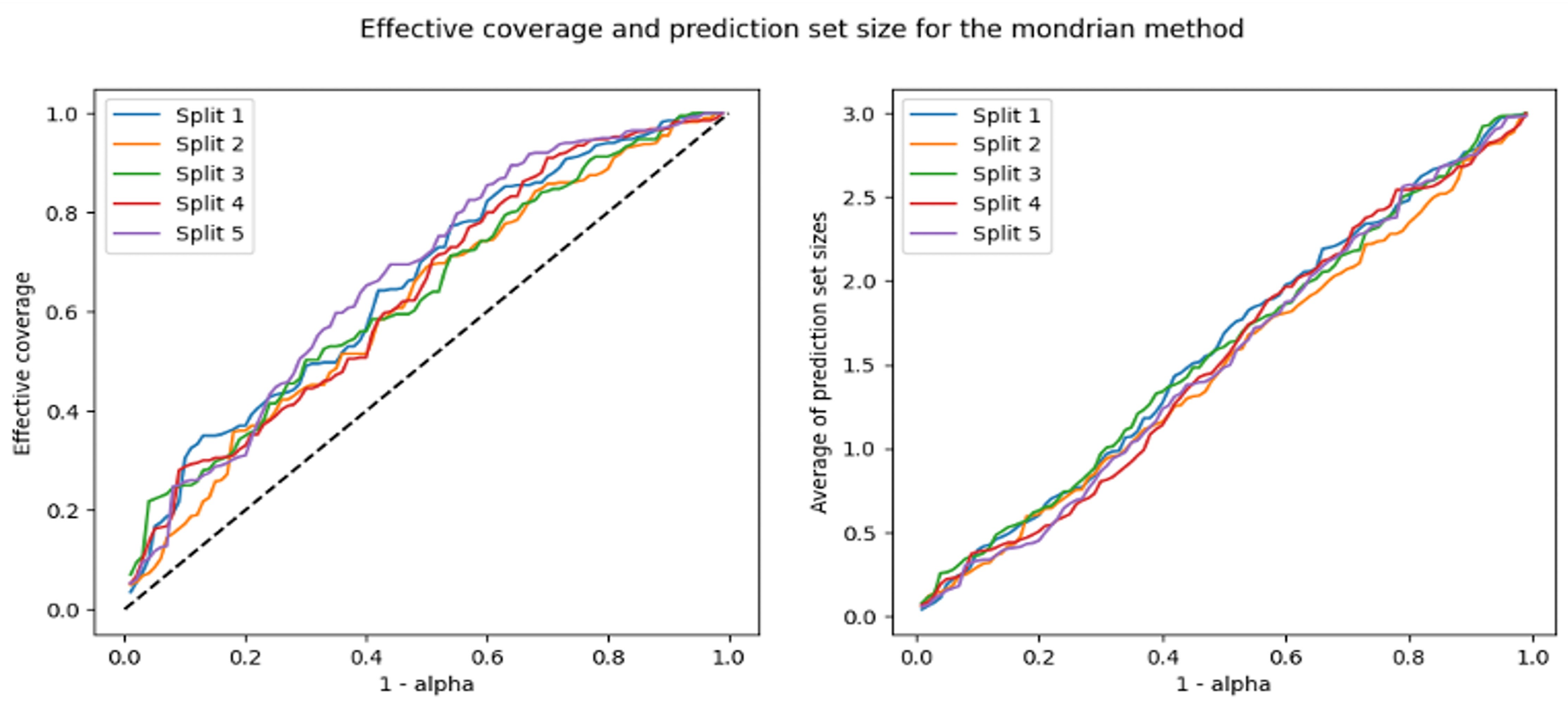
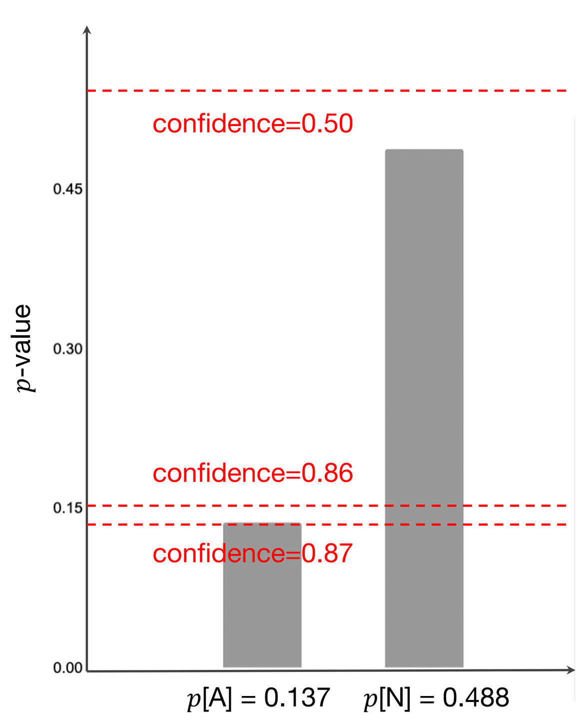
Metrics: coverage and set size



sig	*mean_err*	*avg_c*
0.5	0.506	0.604
0.7	0.701	0.371
0.8	0.804	0.251
0.9	0.894	0.115

- ***Coverage***: proportion of true target values that fall within the pred intervals.
- ***Efficiency***: how tight the prediction intervals are.

Guaranteed coverage



c1-value	*c2-value*	*c3-value*	c4-value	c5-value	c6-value	c7-value	conf	cred	y-pred
TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	0.824	0.911	2
TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	0.533	0.725	2
TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	0.432	0.603	2
TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	0.488	0.669	7
...	...	...	...	...	...	...	...	...	...
TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	0.423	0.593	1
FALSE	FALSE	FALSE	FALSE	TRUE	FALSE	FALSE	0.979	0.989	5
TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	0.566	0.779	2
FALSE	FALSE	FALSE	FALSE	TRUE	FALSE	FALSE	0.959	0.981	5
TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	0.429	0.597	1

$$new\ data_{(\alpha_{0.05})} = \{Surgery(0.06), Neurology(0.08)\}$$

$$new\ data_{(\alpha_{0.05})} = \{Neurology\}$$

Reject Predictions: *null set*

sig	*conf*	*prediction*
0.5	0.61	{NULL}
0.15	0.86	{*surgery*}
0.10	0.87	{*surgery, others*}

Algorithm agnostic method for "***reject***" – model cannot provide a confident prediction for this input.

Confusion matrix

Multinomial Naive Bayes								
	0	*1*	*2*	*3*	*4*	*5*	*6*	*7*
0	57	0	1	1	0	0	1	3
1	0	28	2	0	0	0	0	2
2	32	7	404	22	18	17	30	15
3	0	0	0	34	0	0	2	0
4	0	0	2	0	32	0	0	1
5	1	1	5	0	0	29	2	0
6	0	0	0	1	0	0	21	0
7	0	1	3	0	0	0	0	12

Conformal Inference								
	0	*1*	*2*	*3*	*4*	*5*	*6*	*7*
0	8	2	34	5	4	1	4	5
1	3	2	20	0	1	5	0	1
2	68	34	290	39	27	33	17	37
3	4	4	17	3	1	3	1	3
4	2	5	19	4	1	1	1	2
5	5	0	23	3	0	3	0	4
6	2	2	10	2	0	0	3	3
7	2	0	11	1	1	0	0	1

Applying conformal prediction to a machine learning classifier provides a strict prediction based on the assigned significance level.

Disease Severity Ranking

$Confidence\ (x) = \sup\{1 - \epsilon : |\Gamma_\epsilon(x)| \leq 1\}$ Derive the confidence of each predicted label.

$c(label_1) >, \ldots, c(label_n)$ Rank the instances of same label based on the confidence.

Contributions

- Incorporates **significance level** parameter in conformal prediction for **guaranteed coverage**.
- Uses **rejection option** (null set) for a more trustworthy model.
- Provides classification labels with **confidence** and **credibility** for **ranking** the decisions.

LONG BEACH
STATE UNIVERSITY
College of Engineering

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