



# Predicting the Severity of Support Tickets from Machine Event Data

**Shriya Mittapalli**

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- 2 Methodology
- 3 Data
- 4 Model
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- 6 Conclusion





- Difficult to determine the severity of issues
- Delayed ticket resolution and unnecessary on-site visits
- Sub-optimal resource utilization
- Customer dissatisfaction



- Determine whether a problem can be resolved remotely or requires on-site intervention
- Address the challenge of unreliable severity predictions
- Research and implement uncertainty estimations in deep neural networks



- Research solutions for uncertainty estimations in deep neural networks
- Model provides understandable insights into predictions



### Evaluating pointwise reliability of machine learning prediction.

[Giovanna Nicora et al., 2022, Journal of Biomedical Informatics]



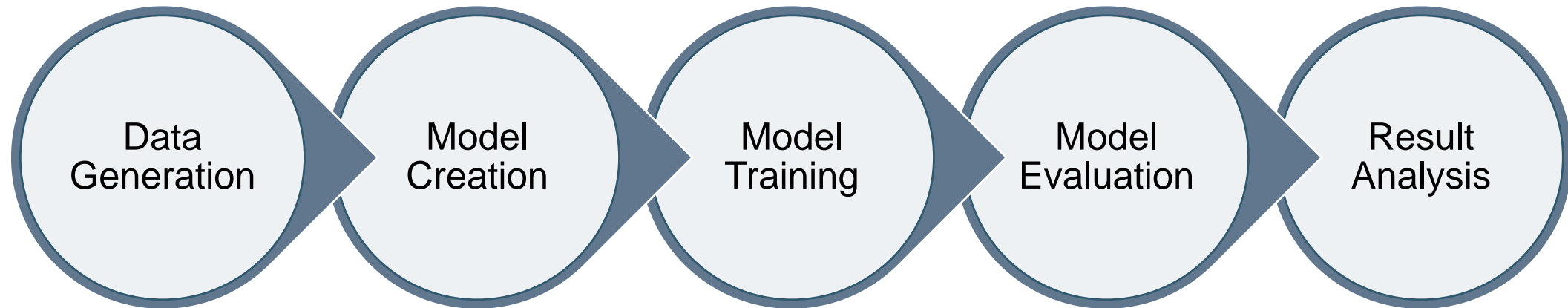
### Can You Trust This Prediction? Auditing Pointwise Reliability After Learning.

[Peter Schulam et al., 2019, arXiv:1901.00403]



### A Survey of Uncertainty in Deep Neural Networks

[Jakob Gawlikowski et al., 2022, arXiv:2107.03342]



### CT Scan machine - Siemens Healthineers

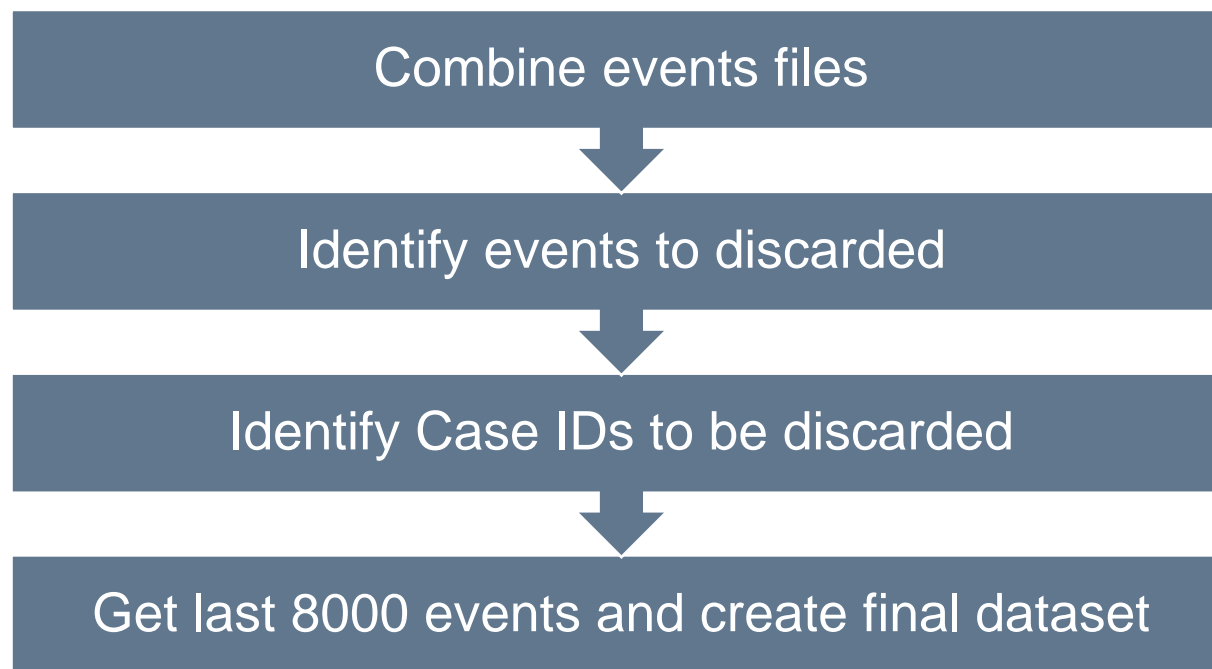
The dataset includes:

- ☐ Case ID (Ticket ID)
- ☐ Machine ID
- ☐ Onsite(Class Label)
- ☐ Start and End time of the ticket
- ☐ Sequence of Events

Case_Id	Machine_Id	Onsite	Start_Time	End_Time
0	Machine_0	1	2014-12-21 10:54:31+00:00	2014-12-23 23:14:34+00:00
1	Machine_1	1	2016-05-05 07:21:48+00:00	2016-09-23 04:47:57+00:00
2	Machine_2	0	2016-07-17 12:38:41+00:00	2016-07-19 04:13:16+00:00
3	Machine_1	0	2016-07-19 13:23:57+00:00	2016-08-05 03:13:37+00:00

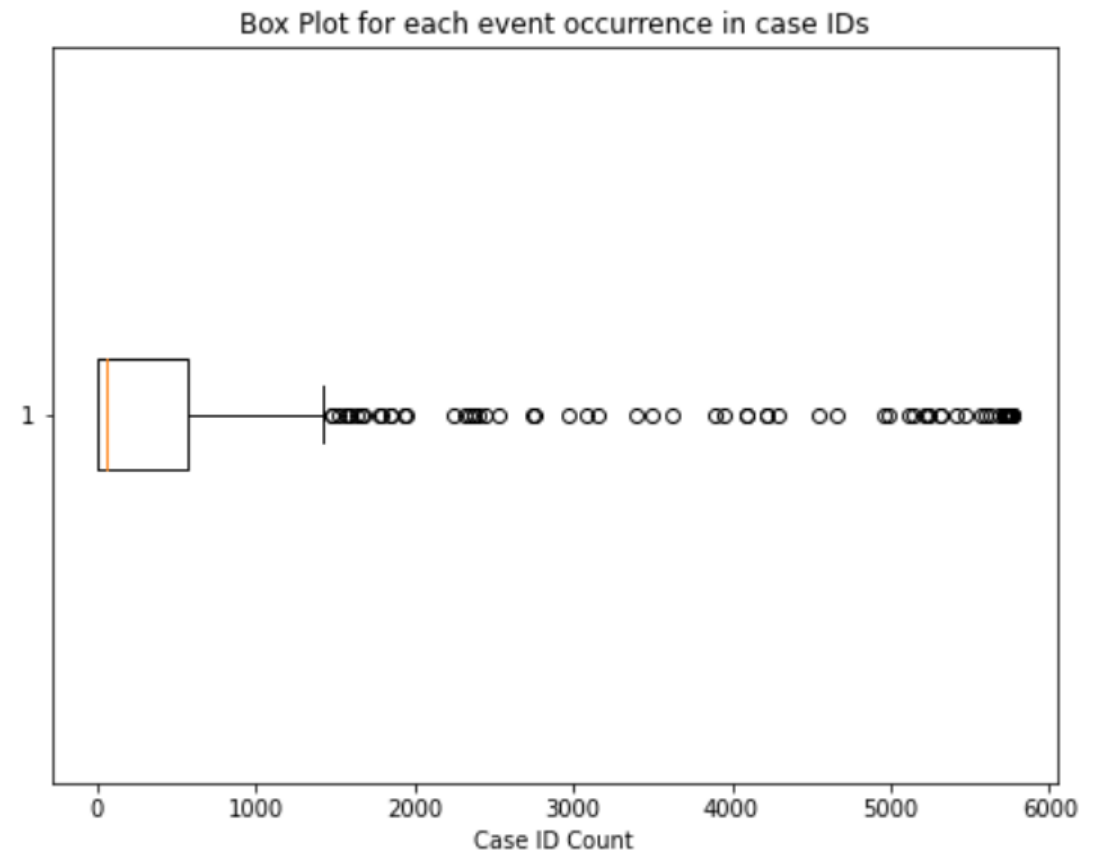
Event	Timestamp	Case_Id
126	2016-07-17 12:30:20+00:00	2
328	2016-07-17 12:26:30+00:00	2
206	2016-07-17 12:24:42+00:00	2





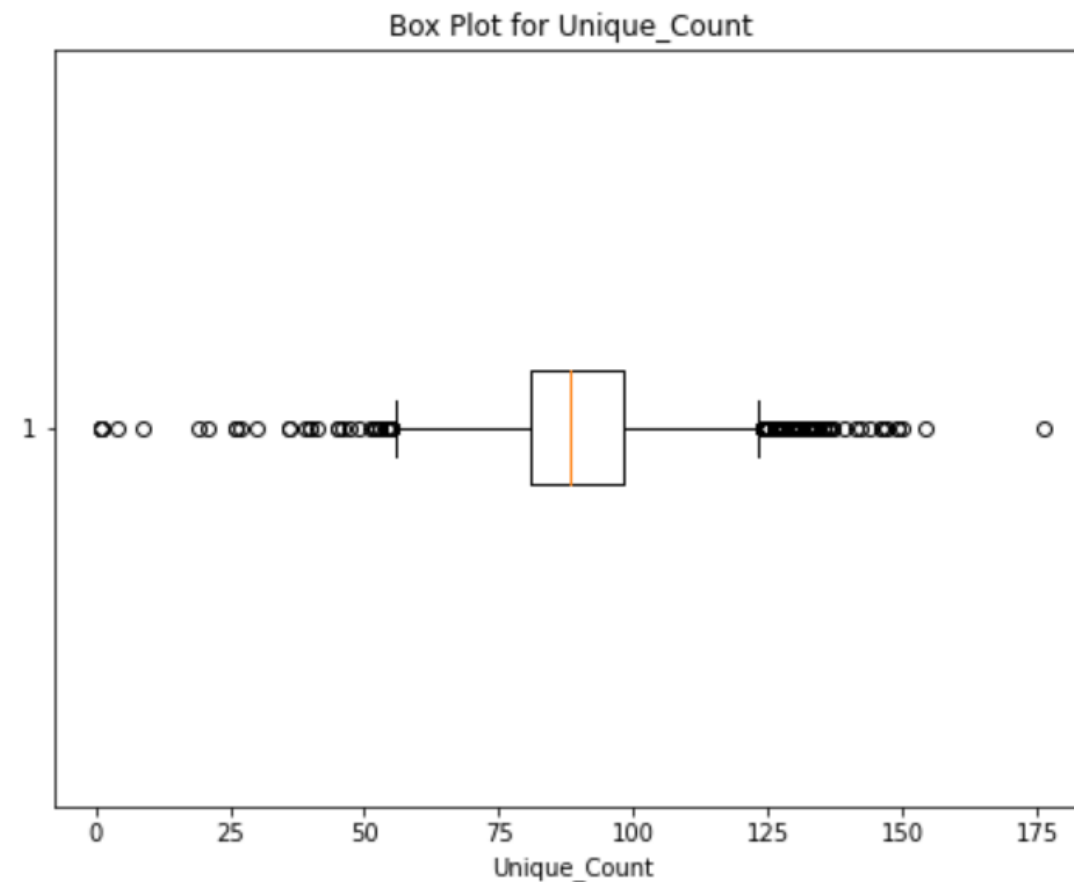
	Event	Case_Id_Count
0	382	5709
1	303	580
2	220	4288
3	201	4099
4	206	5763

❖ 285 events removed



	Case_Id	Unique_Count
0	11	91
1	205	90
2	246	91
3	261	99
4	315	74

❖ 10 Case IDs removed



# Data Generation

## Final Data



Machine Learning  
Data Analytics



Case_Id		Last_8000_Events	Unique_Count	Machine_Id	Onsite	Start_Time	End_Time
0	0	66,304,66,304,66,304,572,597,328,206,434,206,3...	82	Machine_0	1.0	2014-12-21 10:54:31+00:00	2014-12-23 23:14:34+00:00
1	1	328,206,206,328,328,328,562,572,572,572,26...	75	Machine_1	1.0	2016-05-05 07:21:48+00:00	2016-09-23 04:47:57+00:00
2	2	328,206,434,206,414,328,492,528,516,206,55,64,...	81	Machine_2	1.0	2016-07-17 12:38:41+00:00	2016-07-19 04:13:16+00:00
3	4	64,166,527,119,317,317,240,298,599,129,280,260...	100	Machine_4	1.0	2015-11-07 08:25:12+00:00	2015-11-14 02:24:16+00:00
5	6	64,166,122,25,381,560,35,122,25,381,560,35,230...	96	Machine_6	1.0	2016-01-24 03:00:55+00:00	2016-01-31 23:23:50+00:00



1. Monte Carlo Dropout Model
2. Ensemble Model
  - a. 4 Dense Model with different initial weights
  - b. Gated Recurrent Unit (GRU)

Weights:

- ☐ Glorot Normal
- ☐ He Normal
- ☐ Orthogonal
- ☐ Variance Scaling

# Model Creation

## Monte Carlo Dropout Model



Model: "sequential"

Layer (type)	Output Shape	Param #
=====		
flatten (Flatten)	(None, 8000)	0
dense (Dense)	(None, 8192)	65544192
dropout (Dropout)	(None, 8192)	0
dense_1 (Dense)	(None, 4096)	33558528
dropout_1 (Dropout)	(None, 4096)	0
dense_2 (Dense)	(None, 2048)	8390656
dropout_2 (Dropout)	(None, 2048)	0
dense_3 (Dense)	(None, 1024)	2098176
dropout_3 (Dropout)	(None, 1024)	0
dense_4 (Dense)	(None, 512)	524800
dropout_4 (Dropout)	(None, 512)	0

dense_5 (Dense)	(None, 256)	131328
dropout_5 (Dropout)	(None, 256)	0
dense_6 (Dense)	(None, 128)	32896
dropout_6 (Dropout)	(None, 128)	0
dense_7 (Dense)	(None, 64)	8256
dropout_7 (Dropout)	(None, 64)	0
dense_8 (Dense)	(None, 32)	2080
dropout_8 (Dropout)	(None, 32)	0
dense_9 (Dense)	(None, 1)	33

=====

Total params: 110290945 (420.73 MB)  
Trainable params: 110290945 (420.73 MB)  
Non-trainable params: 0 (0.00 Byte)

=====

# Model Creation

## Ensemble Model



Model: "sequential"

Layer (type)	Output Shape	Param #
flatten (Flatten)	(None, 8000)	0
dense (Dense)	(None, 8192)	65544192
dense_1 (Dense)	(None, 4096)	33558528
dense_2 (Dense)	(None, 2048)	8390656
dense_3 (Dense)	(None, 1024)	2098176
dense_4 (Dense)	(None, 512)	524800
dense_5 (Dense)	(None, 256)	131328
dense_6 (Dense)	(None, 126)	32382
dense_7 (Dense)	(None, 64)	8128
dense_8 (Dense)	(None, 32)	2080
dropout (Dropout)	(None, 32)	0
dense_9 (Dense)	(None, 1)	33
Total params: 110290303 (420.72 MB)		
Trainable params: 110290303 (420.72 MB)		
Non-trainable params: 0 (0.00 Byte)		

## Dense Model

# Model Creation

## Ensemble Model



Model: "sequential"

Layer (type)	Output Shape	Param #
flatten (Flatten)	(None, 8000)	0
dense (Dense)	(None, 8192)	65544192
dense_1 (Dense)	(None, 4096)	33558528
dense_2 (Dense)	(None, 2048)	8390656
dense_3 (Dense)	(None, 1024)	2098176
dense_4 (Dense)	(None, 512)	524800
dense_5 (Dense)	(None, 256)	131328
dense_6 (Dense)	(None, 126)	32382
dense_7 (Dense)	(None, 64)	8128
dense_8 (Dense)	(None, 32)	2080
dropout (Dropout)	(None, 32)	0
dense_9 (Dense)	(None, 1)	33
Total params: 110290303 (420.72 MB)		
Trainable params: 110290303 (420.72 MB)		
Non-trainable params: 0 (0.00 Byte)		

### Dense Model

Model: "sequential"

Layer (type)	Output Shape	Param #
gru (GRU)	(None, 8000, 128)	50304
dropout (Dropout)	(None, 8000, 128)	0
gru_1 (GRU)	(None, 64)	37248
dropout_1 (Dropout)	(None, 64)	0
dense (Dense)	(None, 1)	65
Total params: 87617 (342.25 KB)		
Trainable params: 87617 (342.25 KB)		
Non-trainable params: 0 (0.00 Byte)		

### GRU Model





**Data split:** train, validation, and test (60%,20%,20%)

**Optimizer:** Adam

**Metrics:** Uncertainty, Accuracy

**Loss:** Binary Cross Entropy

**EarlyStopping:** monitor - validation loss, min delta - 0.001, patience - 5



## Approach 1: Probability Range

- Average prediction probabilities
- Identify Threshold range
- Calculate uncertainty

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- Average prediction probabilities
- Identify Threshold range
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## Approach 2: Standard Deviation

- Average prediction probabilities
- Standard Deviation of model
- Average probability  $\pm$  Standard Deviation
- Calculate uncertainty

$$\text{Uncertainty} = \frac{\text{Uncertain Predictions}}{\text{Total Samples}}$$

$$\text{Accuracy} = \frac{\text{Correct Predictions}}{\text{Total Predictions}}$$

Correct Predictions – number of samples model predicted accurately

Uncertain Predictions – number of samples not classified by model

Total Samples – Total number of samples

Total Predictions – Total Samples - Uncertain Predictions

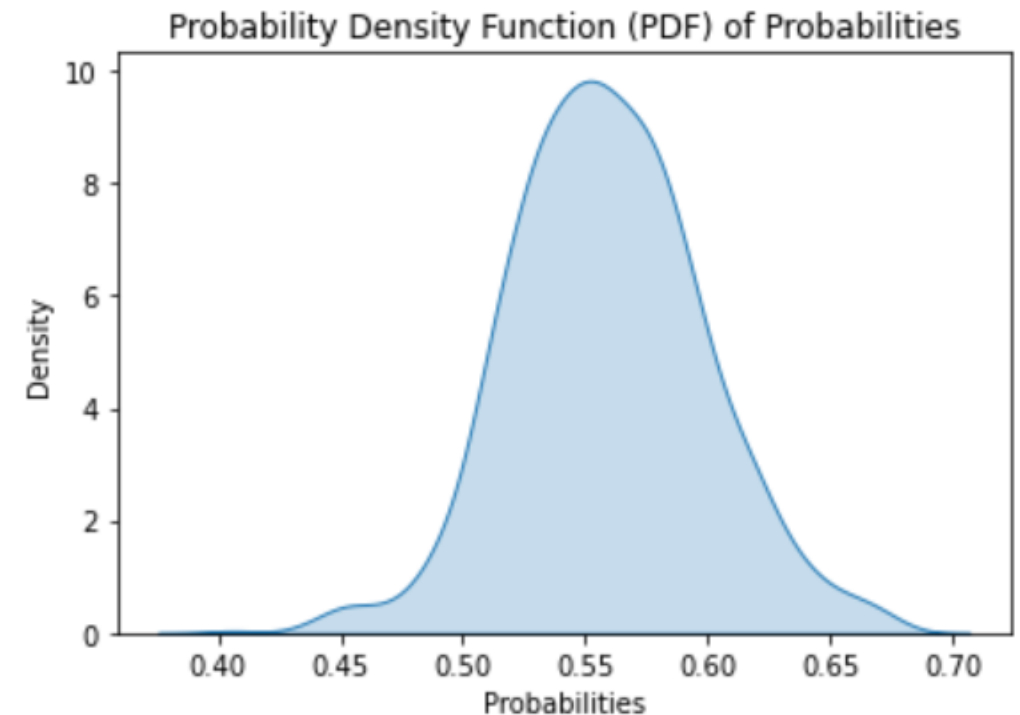
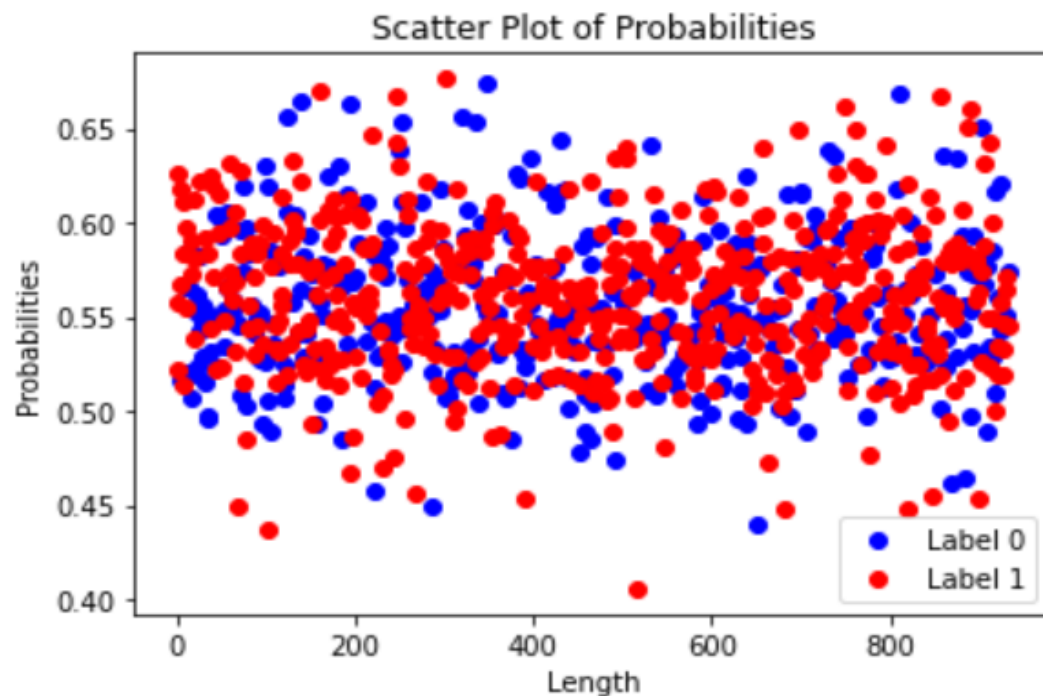
Model	Measure	Validation	Test
Monte Carlo Dropout Model	Uncertainty	74.53	74.45
	Accuracy	50.45	55.66
Ensemble Model	Uncertainty	90.04	89.31
	Accuracy	59.14	56.44

**Probability Range**

Model	Measure	Validation	Test	SD
Monte Carlo Dropout Model	Uncertainty	93.05	92.02	0.13
	Accuracy	50.00	50.72	
Ensemble Model	Uncertainty	57.67	57.67	0.0104
	Accuracy	50.00	52.50	

**Standard Deviation**

## Validation Data

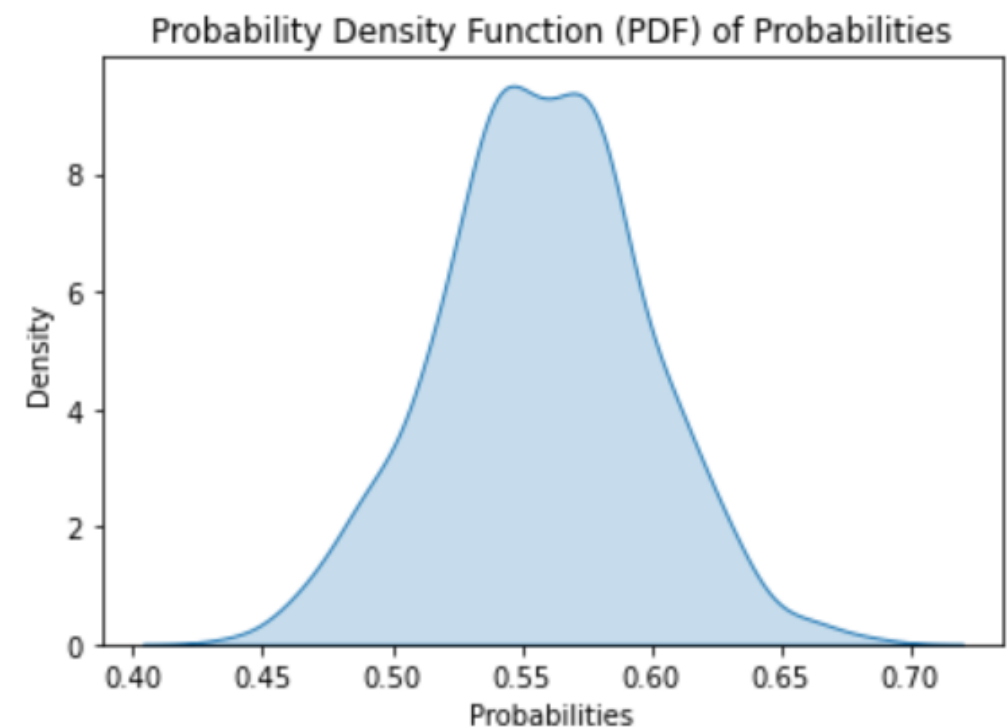
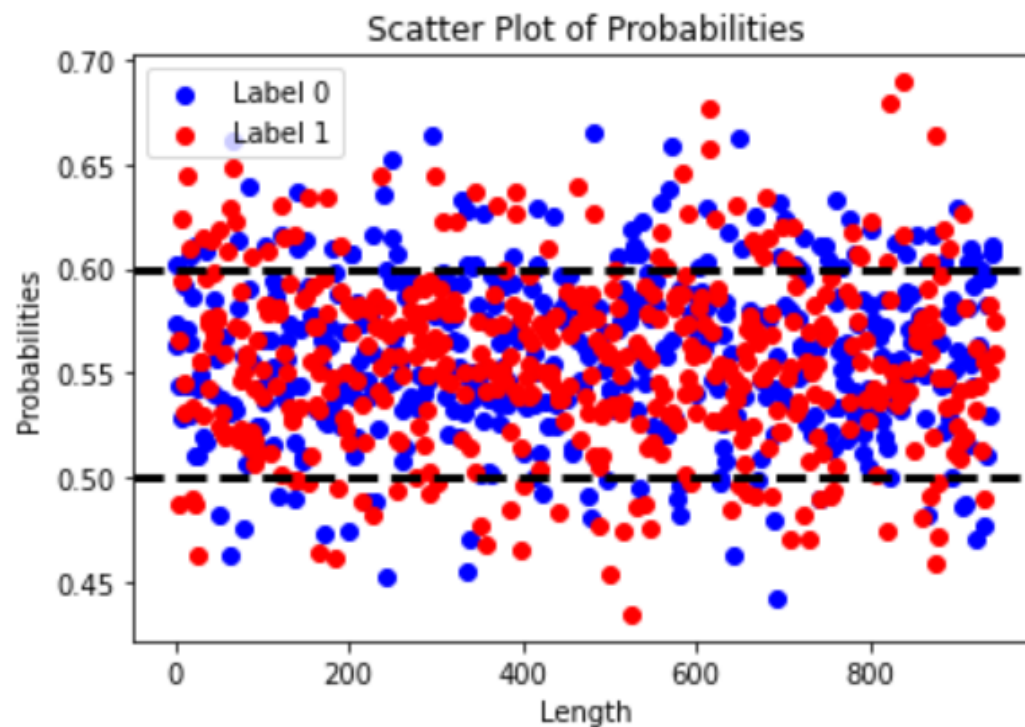


# Result Analysis

## Monte Carlo Dropout Model

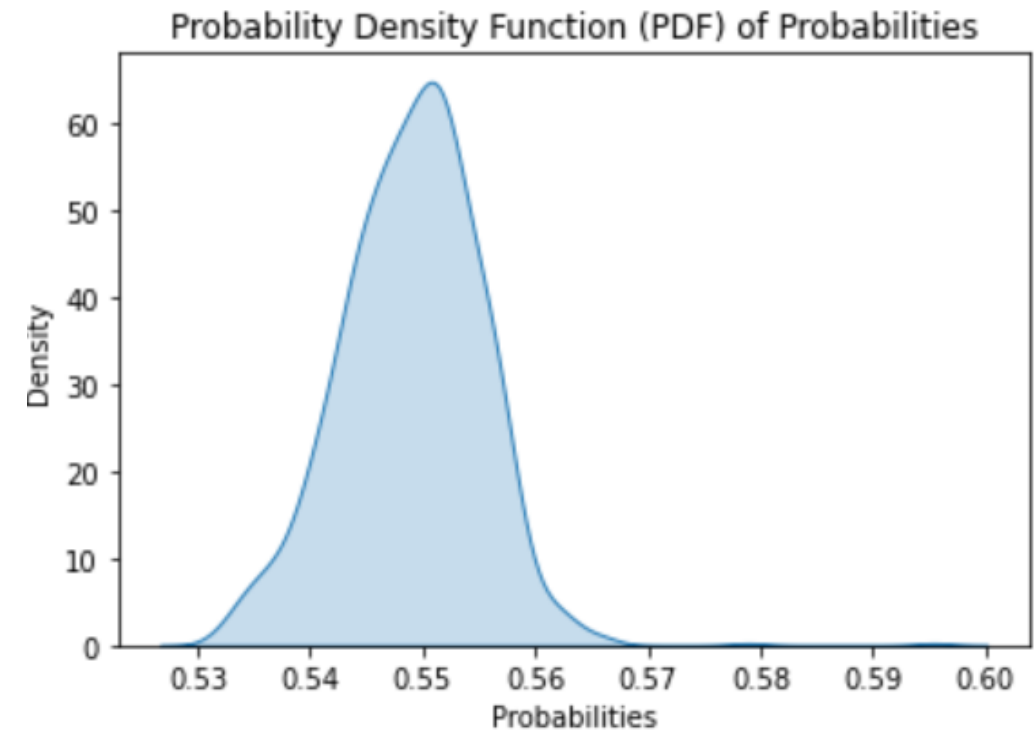
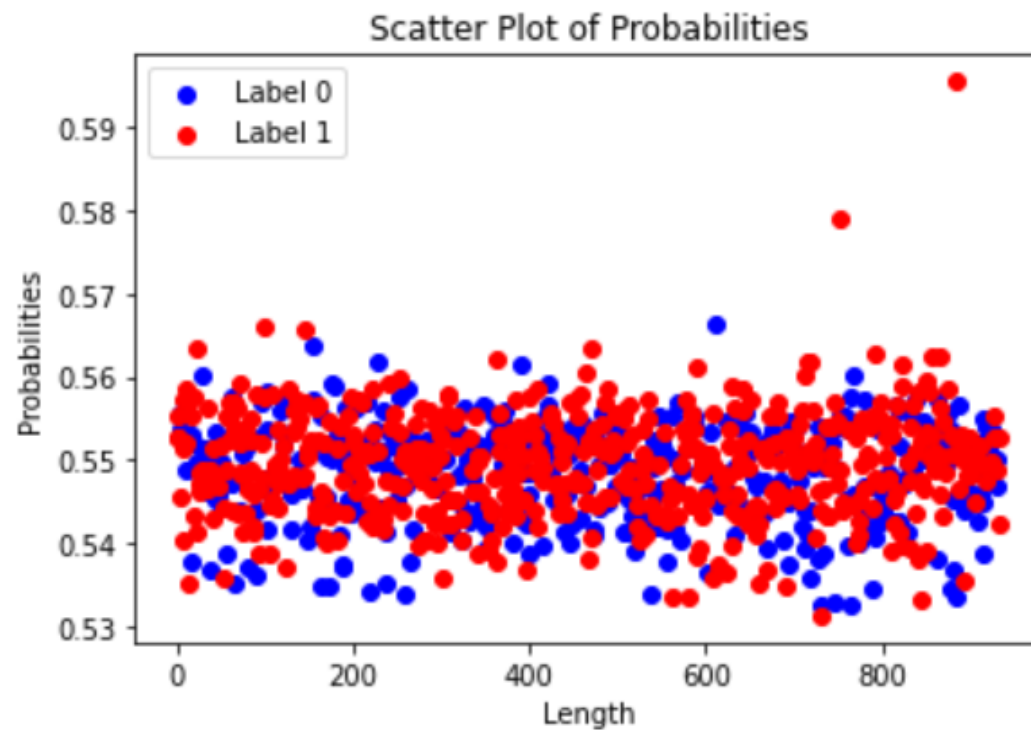


## Test Data

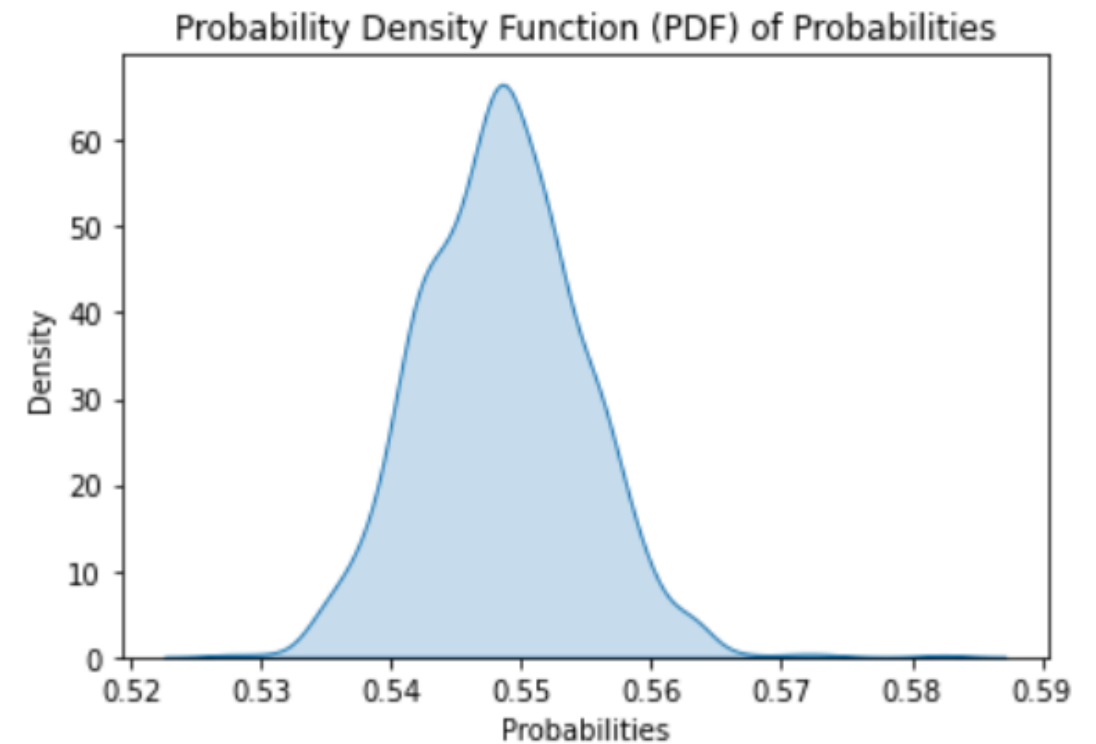
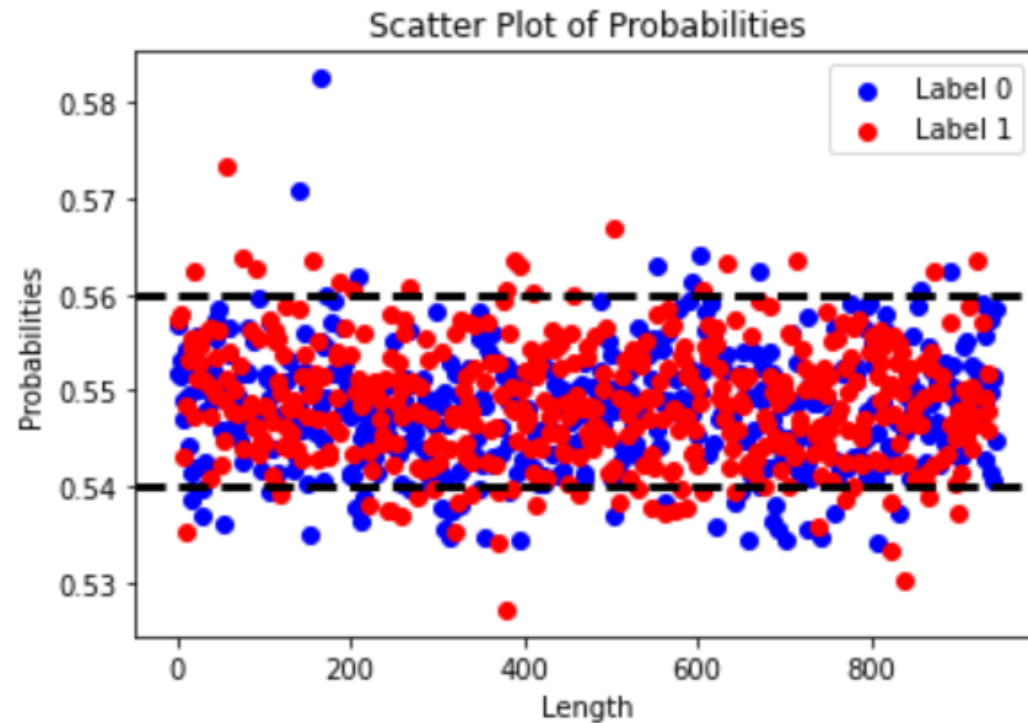




## Validation Data



## Test Data



- Classify Tickets
- Provide reliability measure

## Considerations:

- Standard Deviation – different models
- Threshold boundaries – model uncertainty
- Data limitation constraints
- Transformer Models and LSTM with Gaussian Mixture Models (LSTM-GMMS)

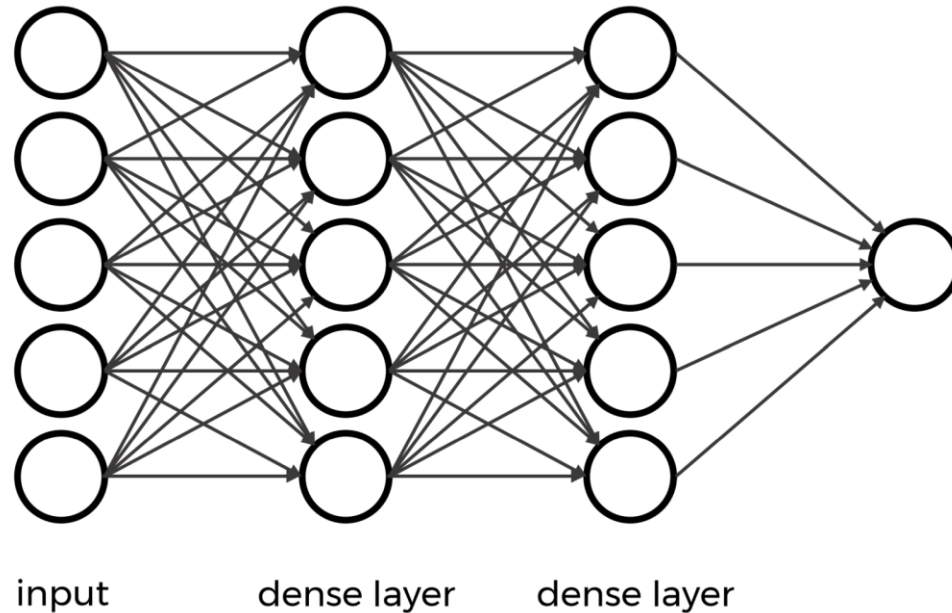




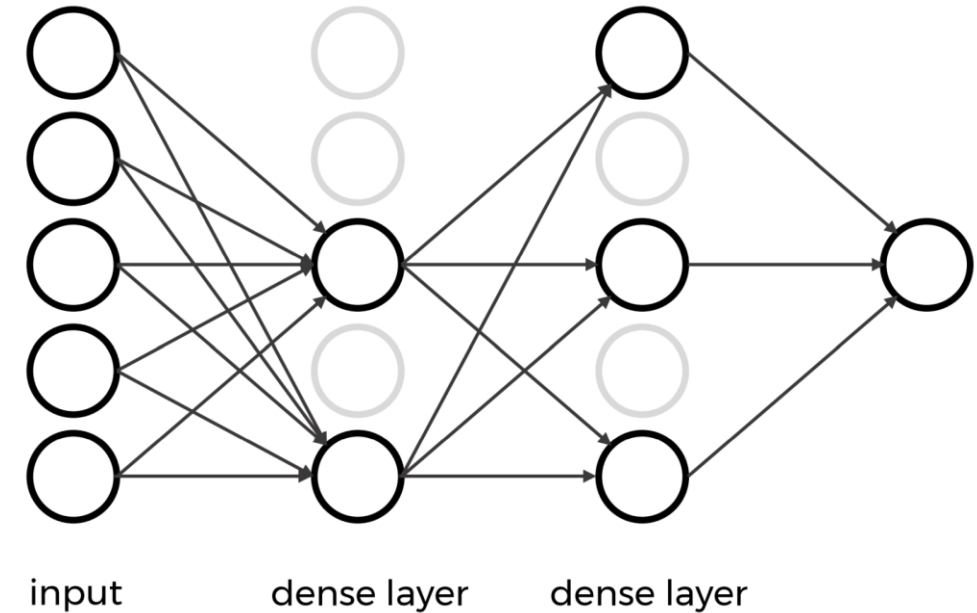
# Appendix

- Glorot Normal** – Also known as Xavier normal. Draws samples from a truncated normal distribution centered on 0 with  $\text{stddev} = \sqrt{2 / (\text{fan\_in} + \text{fan\_out})}$  where  $\text{fan\_in}$  is the number of input units in the weight tensor and  $\text{fan\_out}$  is the number of output units in the weight tensor.
- He Normal** – Draws samples from a truncated normal distribution centered on 0 with  $\text{stddev} = \sqrt{2 / \text{fan\_in}}$  where  $\text{fan\_in}$  is the number of input units in the weight tensor.
- Orthogonal** – Generates an orthogonal matrix. If the shape of the tensor to initialize is two-dimensional, it is initialized with an orthogonal matrix obtained from the QR decomposition of a matrix of random numbers drawn from a normal distribution.
- Variance Scaling** – Initializer adapts its scale to the shape of its input tensors. Samples are drawn from a uniform distribution within  $[-\text{limit}, \text{limit}]$ , where  $\text{limit} = \sqrt{3 * \text{scale} / n}$ .

no dropout



with dropout



# Gated Recurrent Unit (GRU)

