

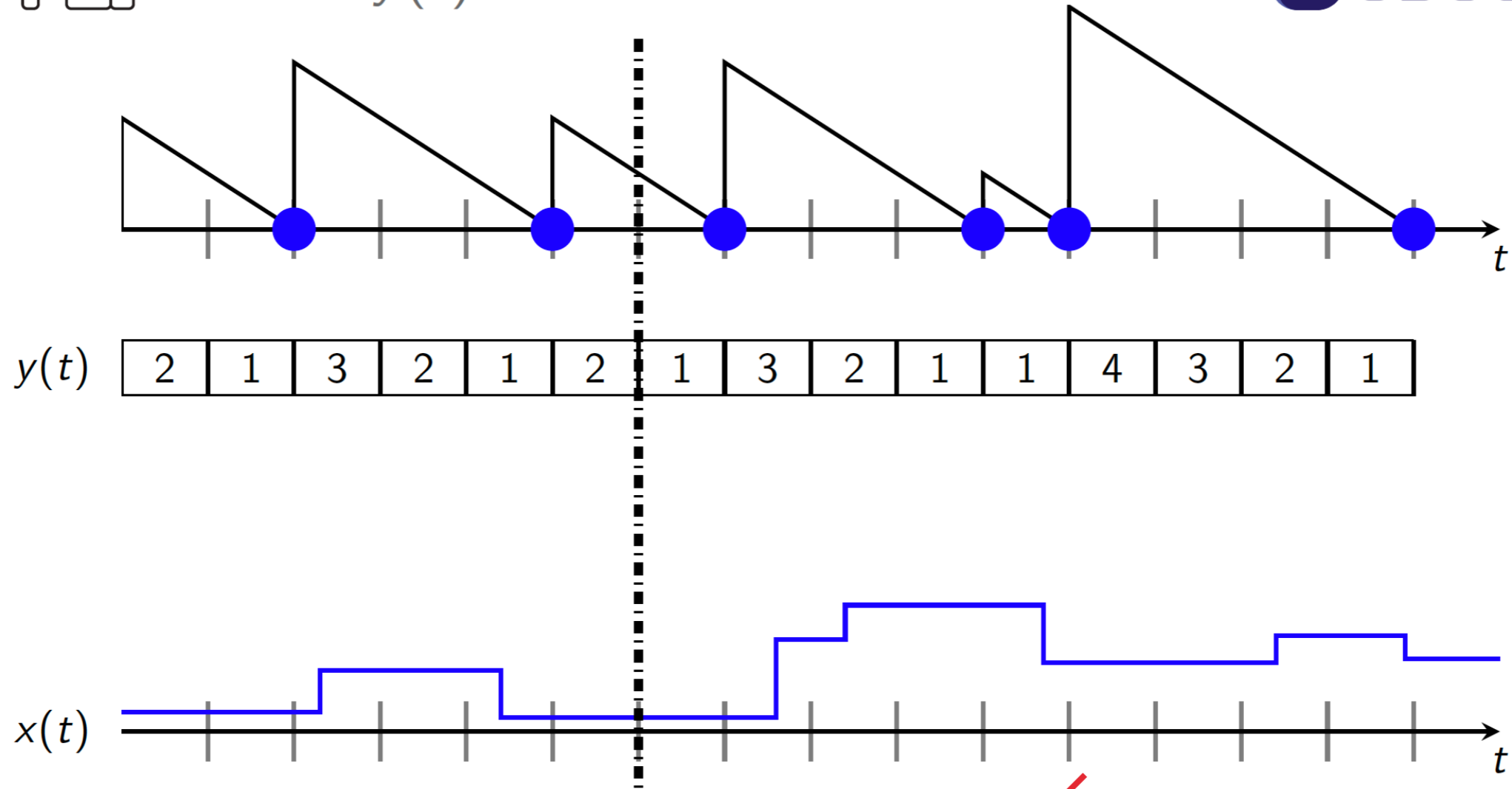
2020.2.24 SICHEN LI

PREDICTING INTERLOCK BY SURVIVAL MODELLING — STATUS UPDATE

GOAL



Define $y(t)$ to be "Time To Interlock"



An example channel (total 450)

DROPNA: 363

METHOD



Predict a distribution over the future:
Weibull distribution



$$f(y; \alpha, \beta) = \frac{\beta}{\alpha} \left(\frac{y}{\alpha}\right)^{\beta-1} e^{-(y/\alpha)^\beta}, y \geq 0 \quad (1)$$

- $\alpha > 0$ is the scale parameter: larger \rightarrow distribution more spread out
- $\beta > 0$ is the shape parameter: affect shape, not simple shifting or stretching

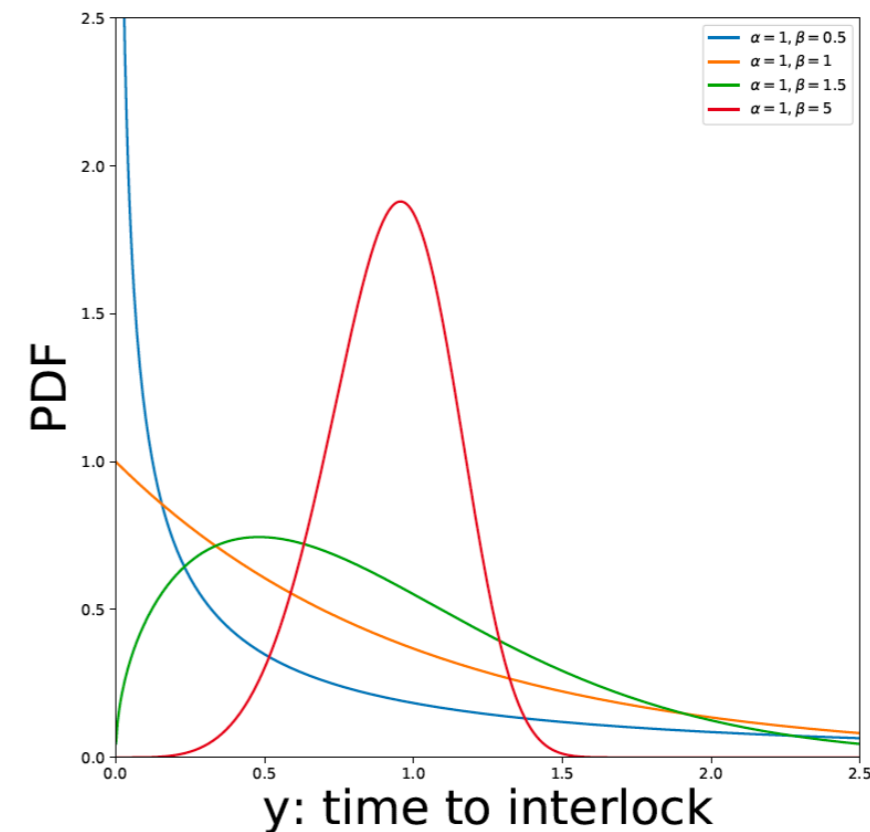


Figure: Weibull distribution PDF

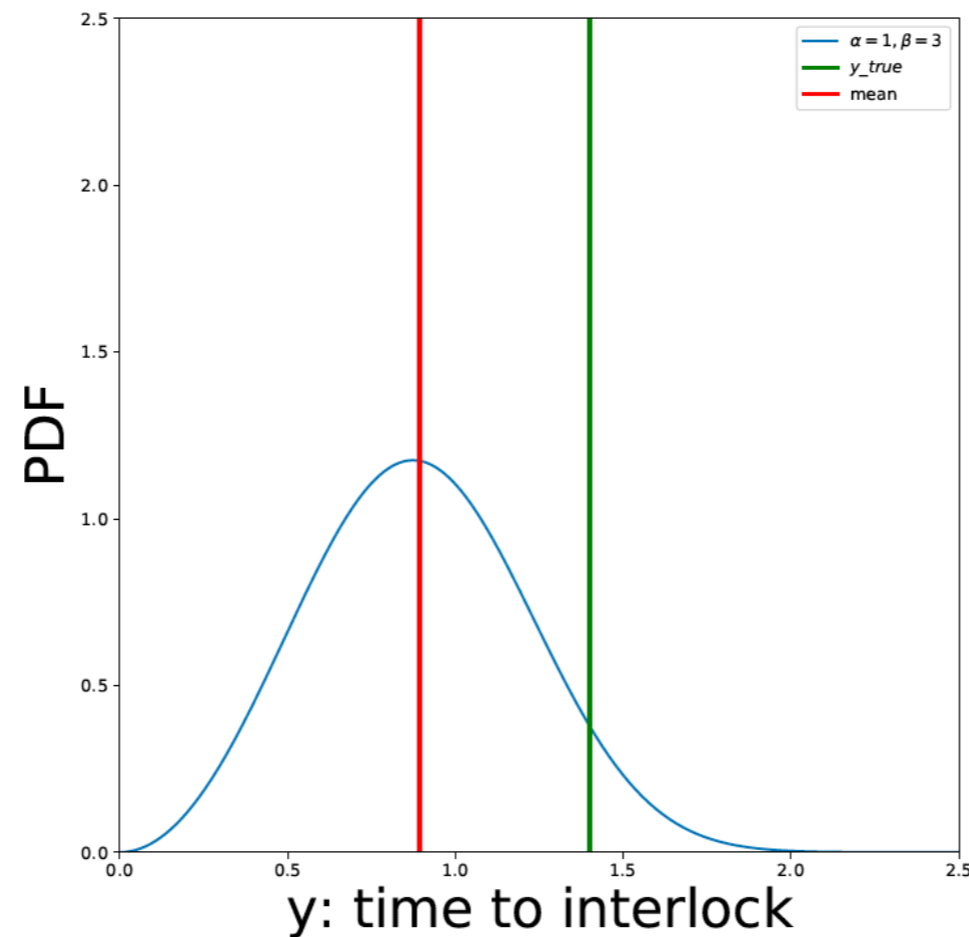
LOSS

$$\max_{\alpha, \beta} f(y|\alpha, \beta)$$

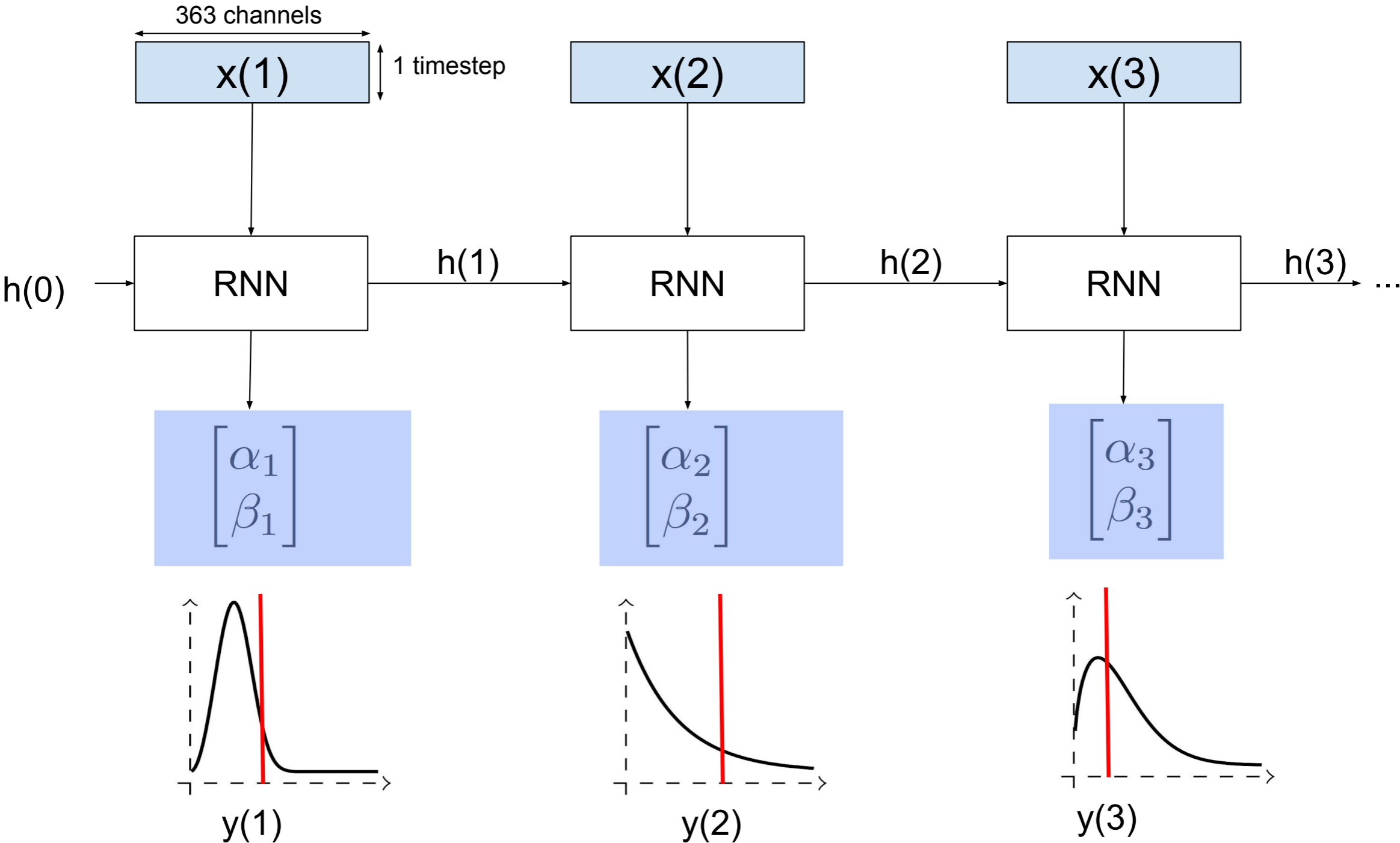


- Loss = -log likelihood

Maximise the Weibull probability of y_{true} (the true time to interlock)



MODEL SKETCH



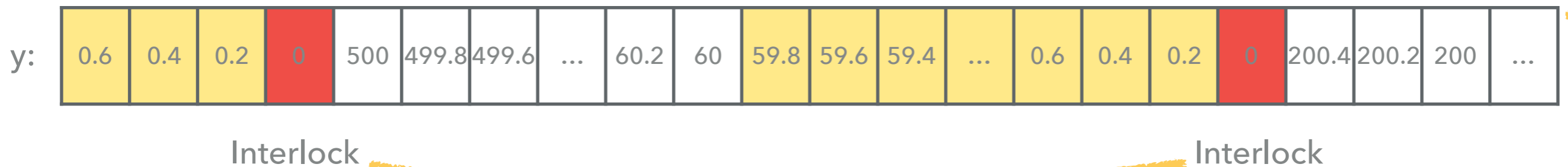
DATA STRUCTURE

Timesteps	0	1	2	3	4	5	6	...
Sample 0	x(0) → y(1)							
Sample 1		x(1) → y(2)						
Sample 2			x(2) → y(3)					
Sample 3				x(3) → y(4)				
...								

One X sample: (1 timestep, 363 channels) -> One y value: time to interlock

DATA STRUCTURE

Y: time to interlock (s)



One sequence

- ▶ Sequence: time series from last to this interlock
- ▶ Remove sequences shorter than 5 min in total (unstable)
- ▶ Only use the last 1 min before each interlock

DATA & MODEL STRUCTURE

Data range	2019.9.18 - 9.27
Training set	74949 (249 sequences)
Validation set	16200 (54 sequences)
Test set	16200 (54 sequences)

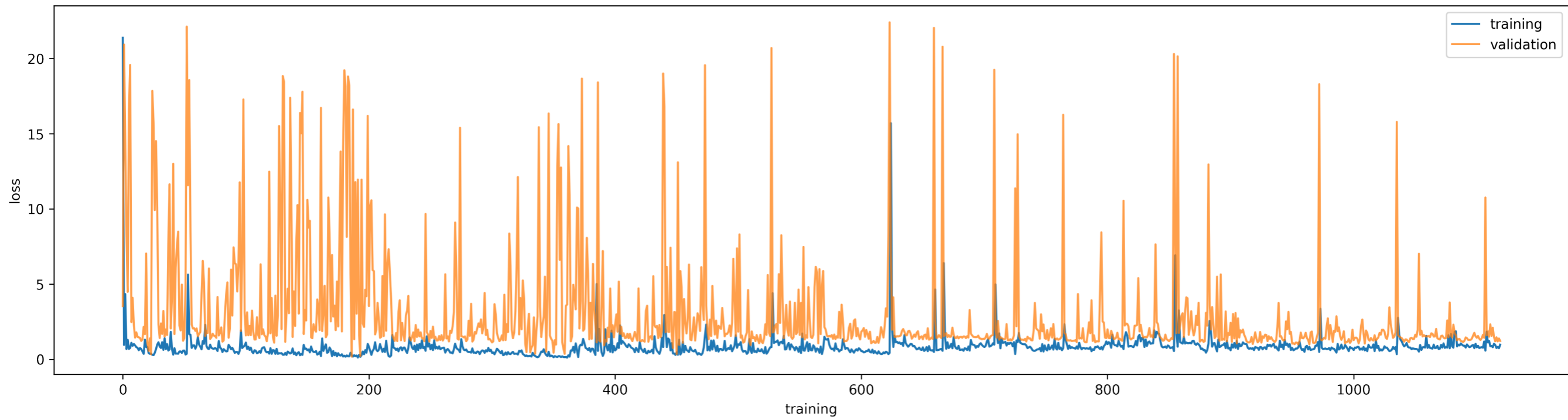
Model: "sequential_1"

Layer (type)	Output Shape	Param #
lstm_1 (LSTM)	(1, 1, 32)	50688
dropout_1 (Dropout)	(1, 1, 32)	0
lstm_2 (LSTM)	(1, 32)	8320
dropout_2 (Dropout)	(1, 32)	0
dense_1 (Dense)	(1, 2)	66
lambda_1 (Lambda)	(1, 2)	0

Total params: 59,074
Trainable params: 59,074
Non-trainable params: 0

RESULT

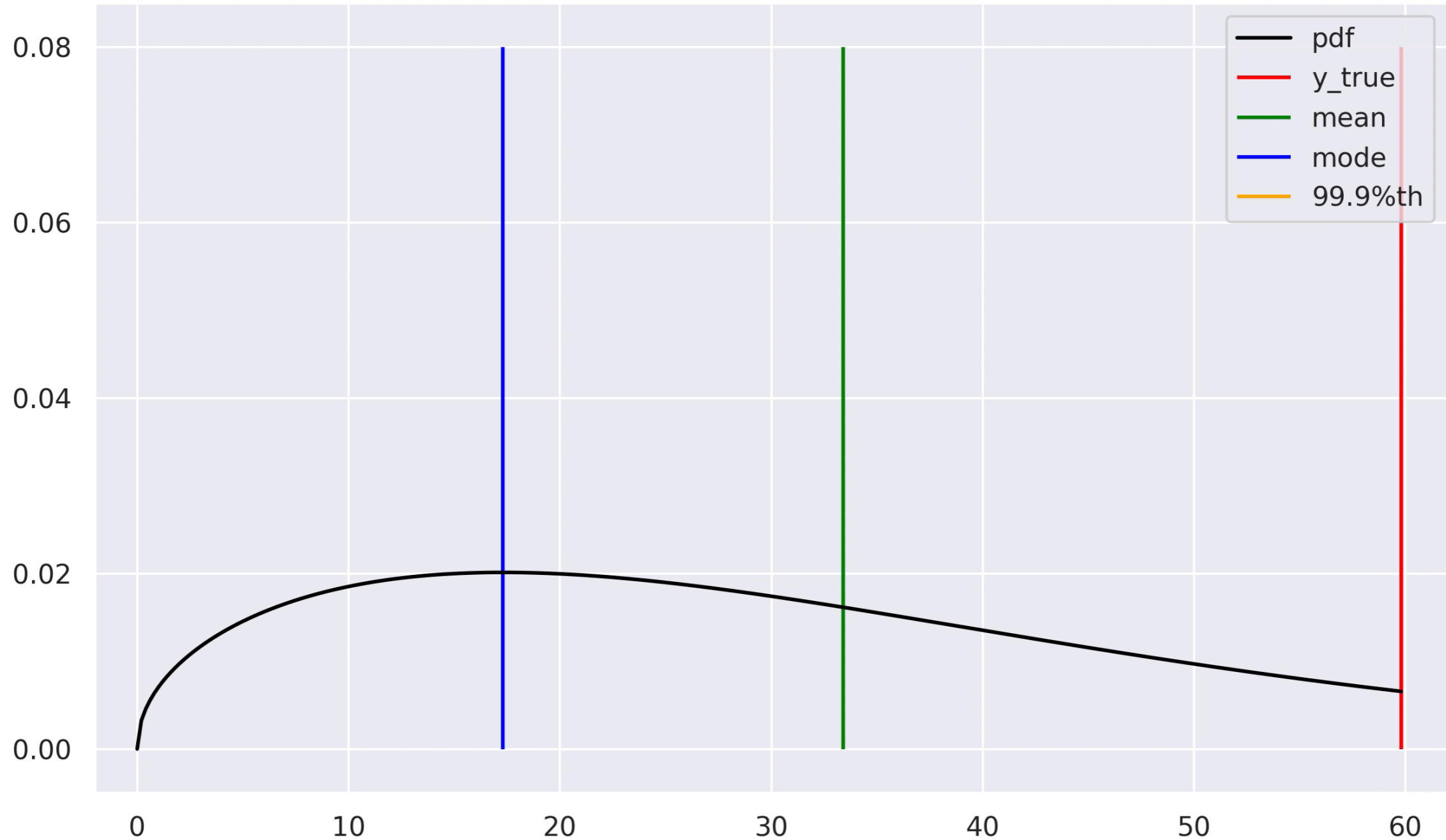
LOSS DURING TRAINING



RESULT OF A TEST SEQUENCE

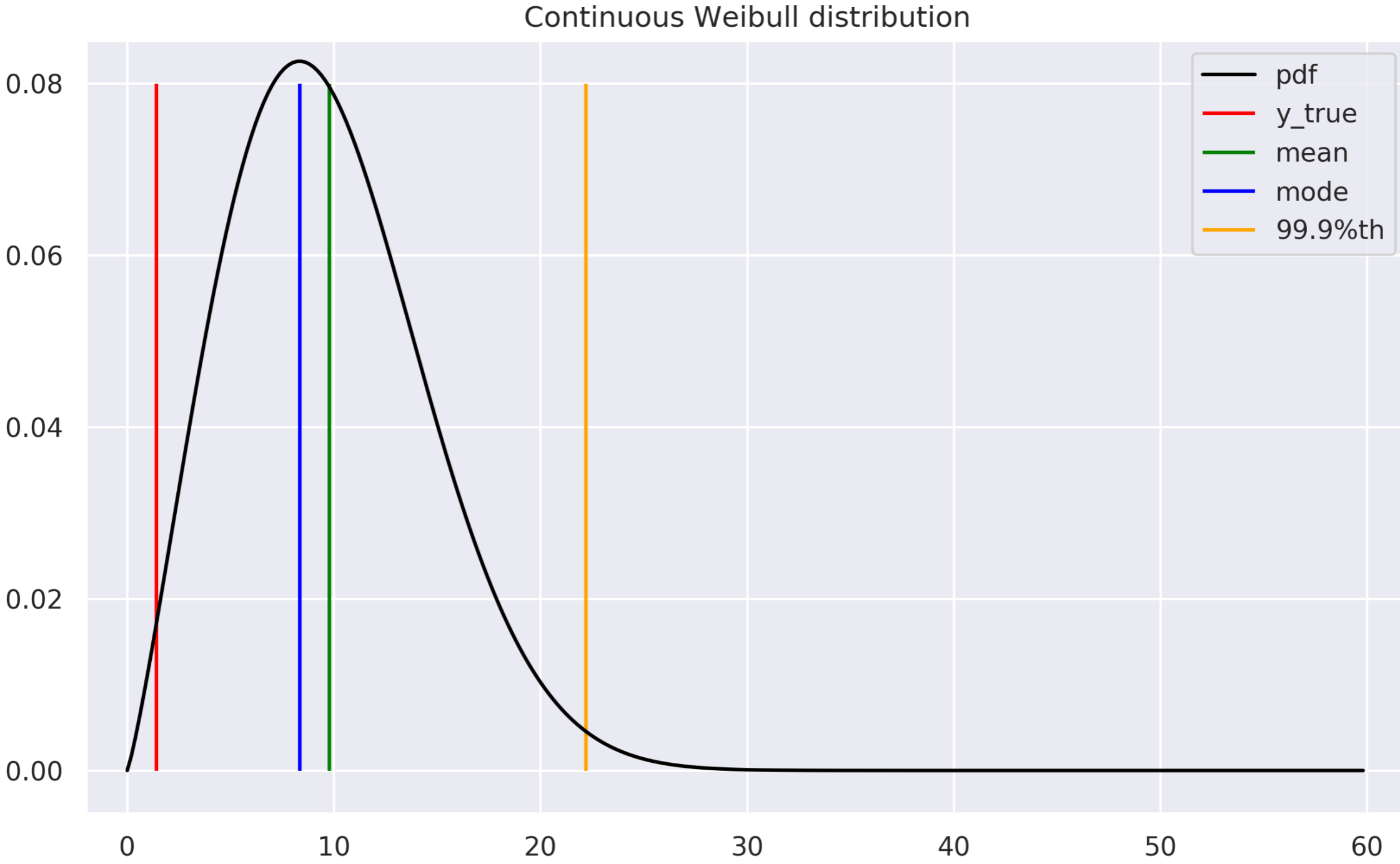
Video!

Continuous Weibull distribution



RESULT OF A TEST SEQUENCE

y_true: 1.4s to interlock



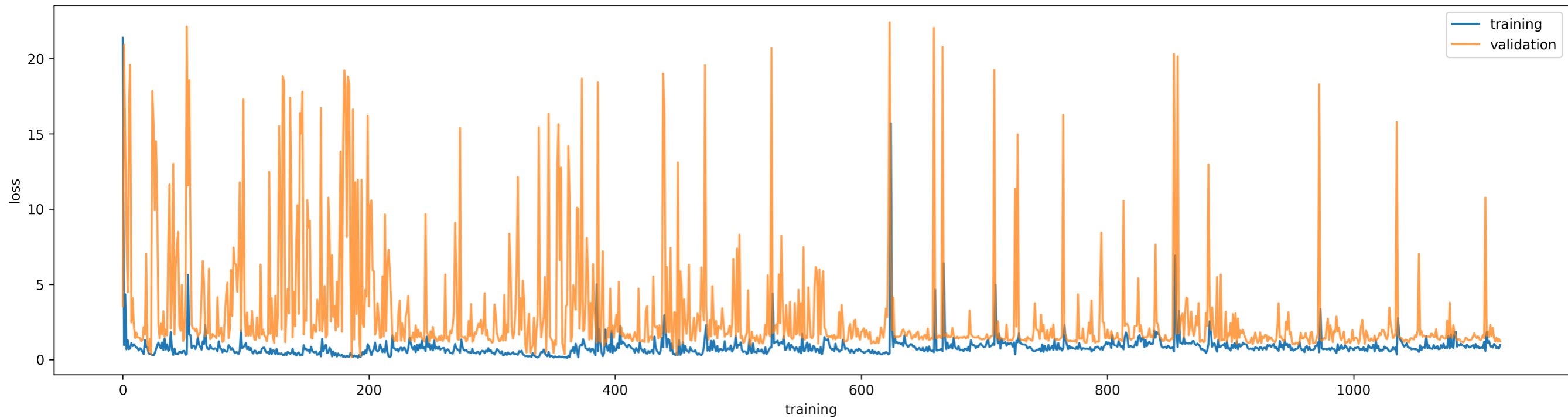
NEXT & QUESTIONS

- ▶ Most of the time, the output alpha and beta are at the same value
 - ▶ Significant only 5 seconds before interlock?
 - ▶ Use a better loss
- ▶ "Adaptive slicing"

REFERENCES

- ▶ WTTE-RNN package: <https://github.com/ragulpr/wtte-rnn>

LOSS DURING TRAINING



- ▶ (Train-sequences, val-sequences, test-sequences): (70%, 15%, 15%) in all sequences
- ▶ Train with 1 train-sequence for several epochs until no improvement can be gained from one random val-sequence -> go on with the next train-sequence