

ECAL Seq2Seq Learning



UNIVERSITY OF MINNESOTA
Driven to DiscoverSM

Seq2Seq Model

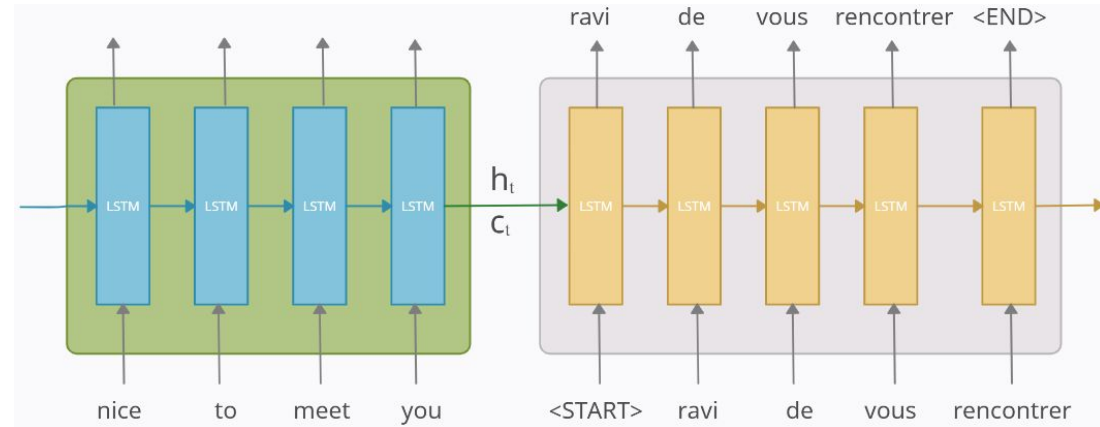
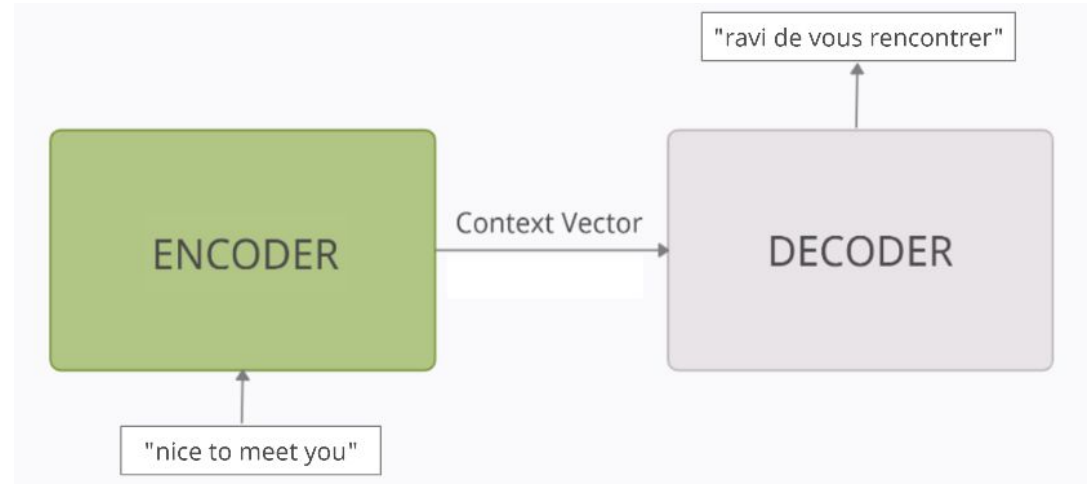
Input: (English) “nice to meet you”

Output: (French) “ravi de vous rencontrer”

Encoder: Processing each token in the input-sequence & encoding all the information about the input-seq into a fixed length vector.

Context vector: Encapsulating the whole meaning of the input-seq that can help the decoder make accurate predictions.

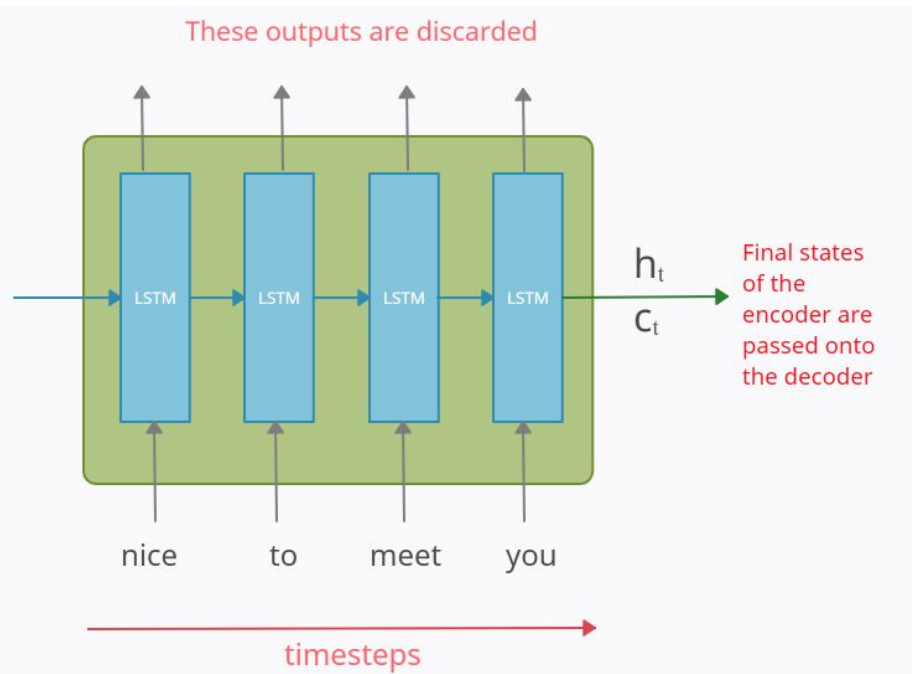
Decoder: Reading the context vector and tries to predict the target-seq token by token.



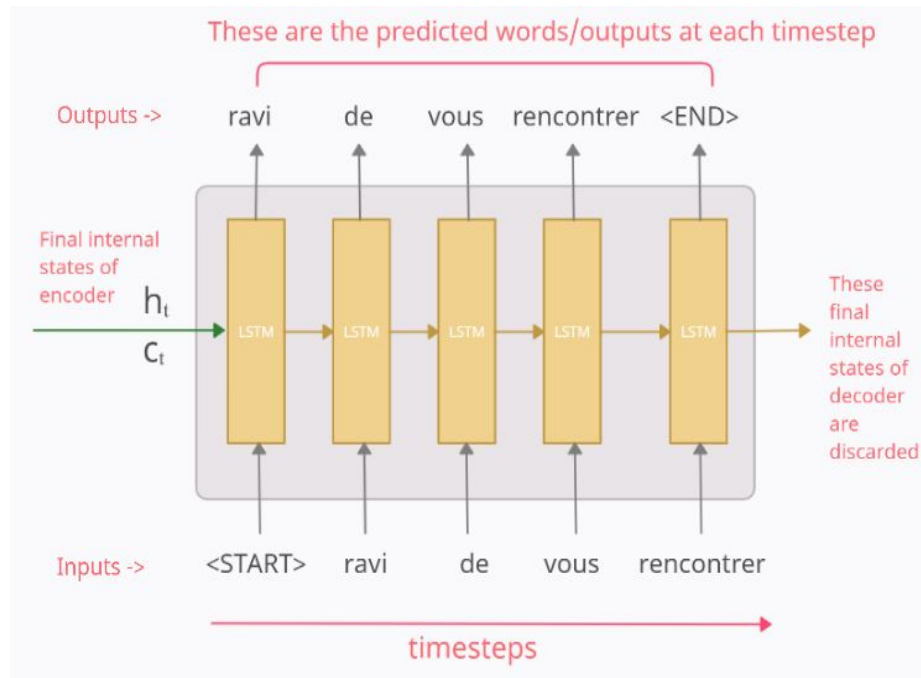
Ref:

<https://medium.com/analytics-vidhya/encoder-decoder-seq2seq-models-clearly-explained-c34186fbf49b>

Seq2Seq Model



Encoder



Decoder

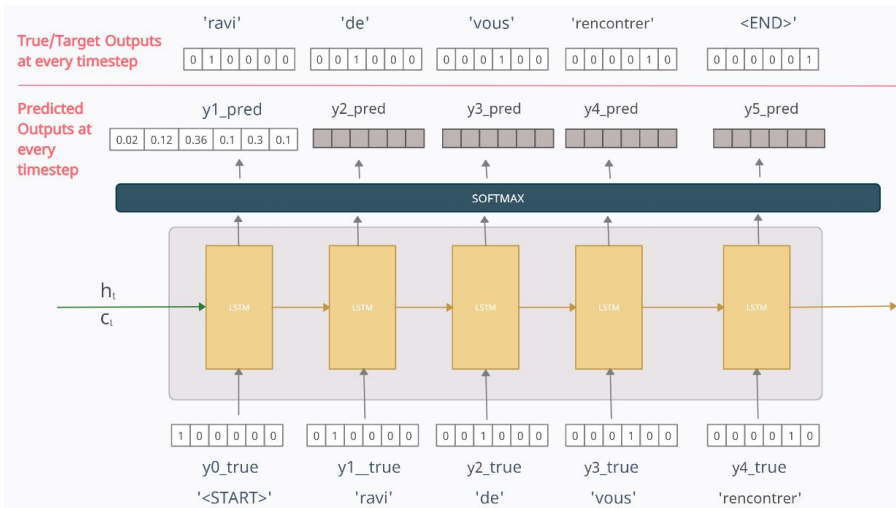
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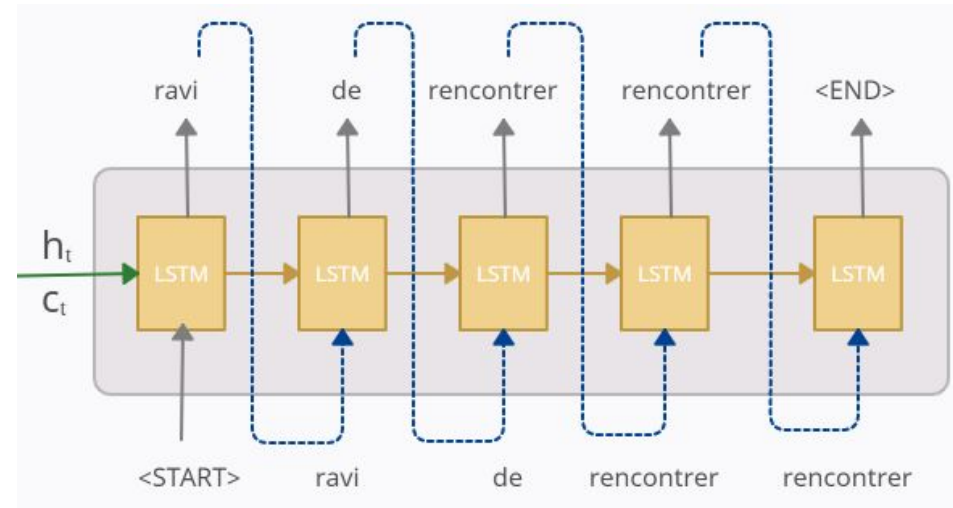
Seq2Seq Training & Test

The Decoder in Training Phase:

- 1) **Teacher Forcing:** feeding the **true token** (and not the predicted output/token) from the previous time-step as input to the current time-step.
- 2) **Without teacher forcing:** using its own predictions as the next input

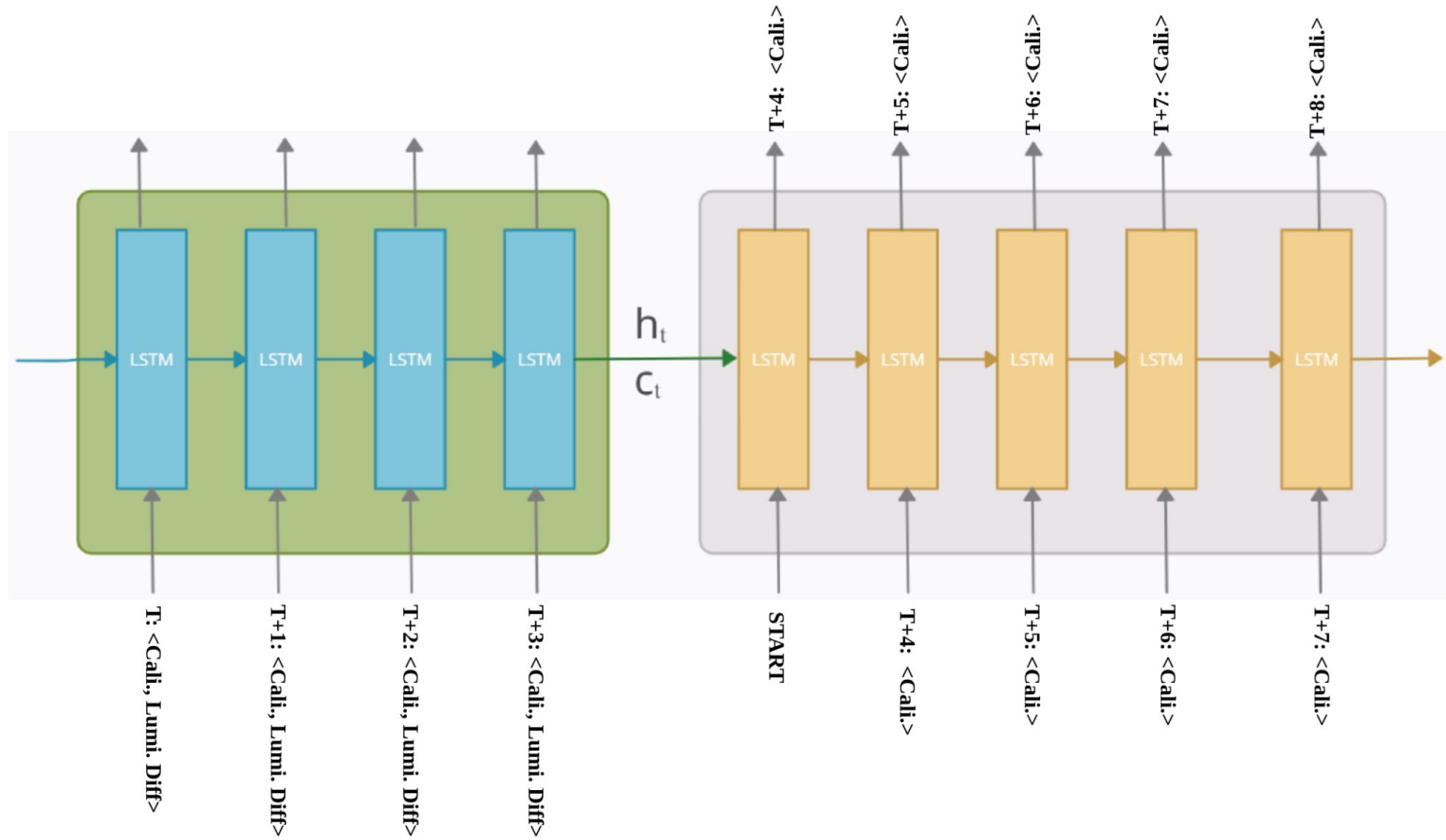


Teacher Forcing

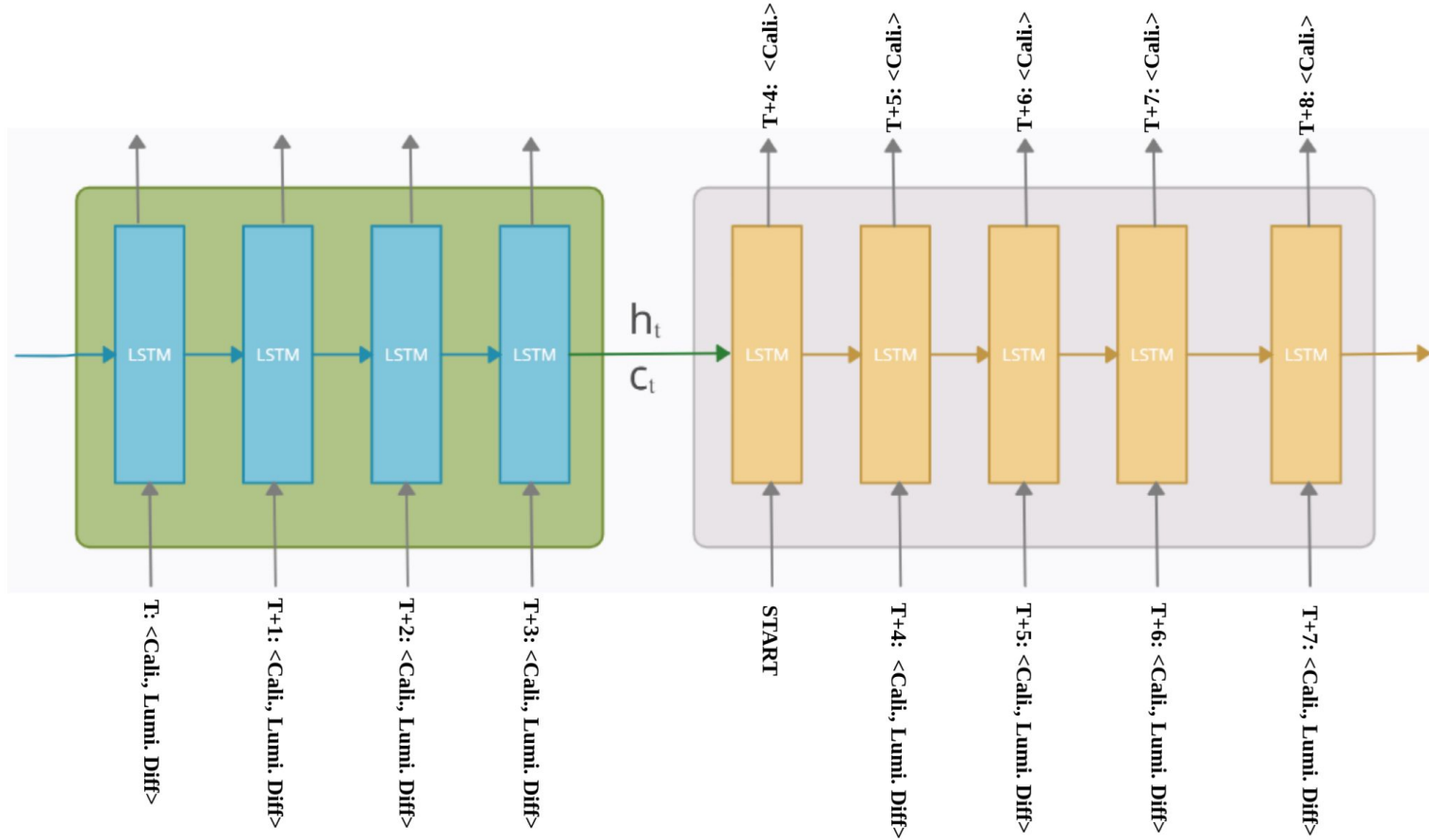


Without Teacher Forcing

Our Seq2Seq Model Type-1



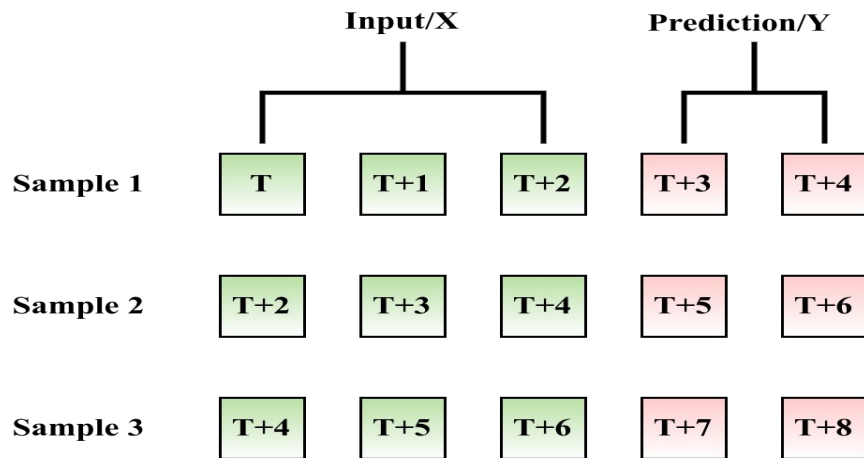
Our Seq2Seq Model Type-2



Training/Test Data Format

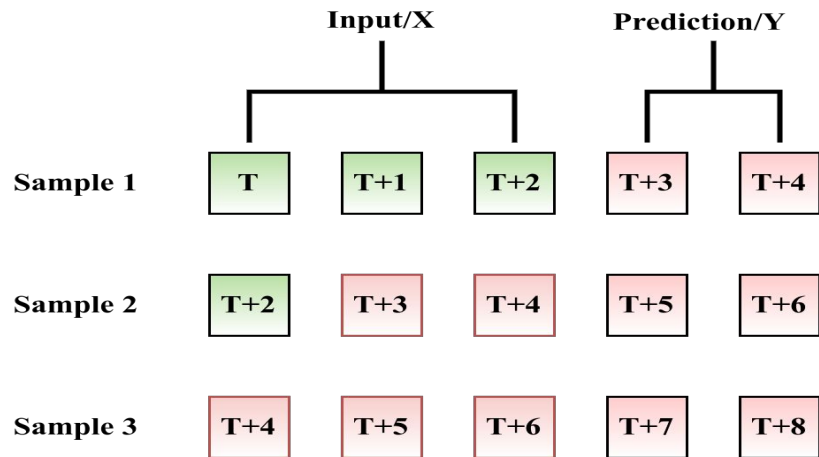
Case1 (left):

- 1) We can always observe 3 consecutive actual values and then make predict on the next two values;
- 2) When we predict “T+3 & T+4”, we use the actual “T, T+1, T+2”;
- 3) When we want to predict “T+5 & T+6”, we wait until we obtained the actual “T+3 & T+4”.



Case 2 (right):

- 1) The only observed information we have is “T, T+1, T+2”;
- 2) In order to make much further prediction, we need to “re-use” our prediction as “fake observation”.

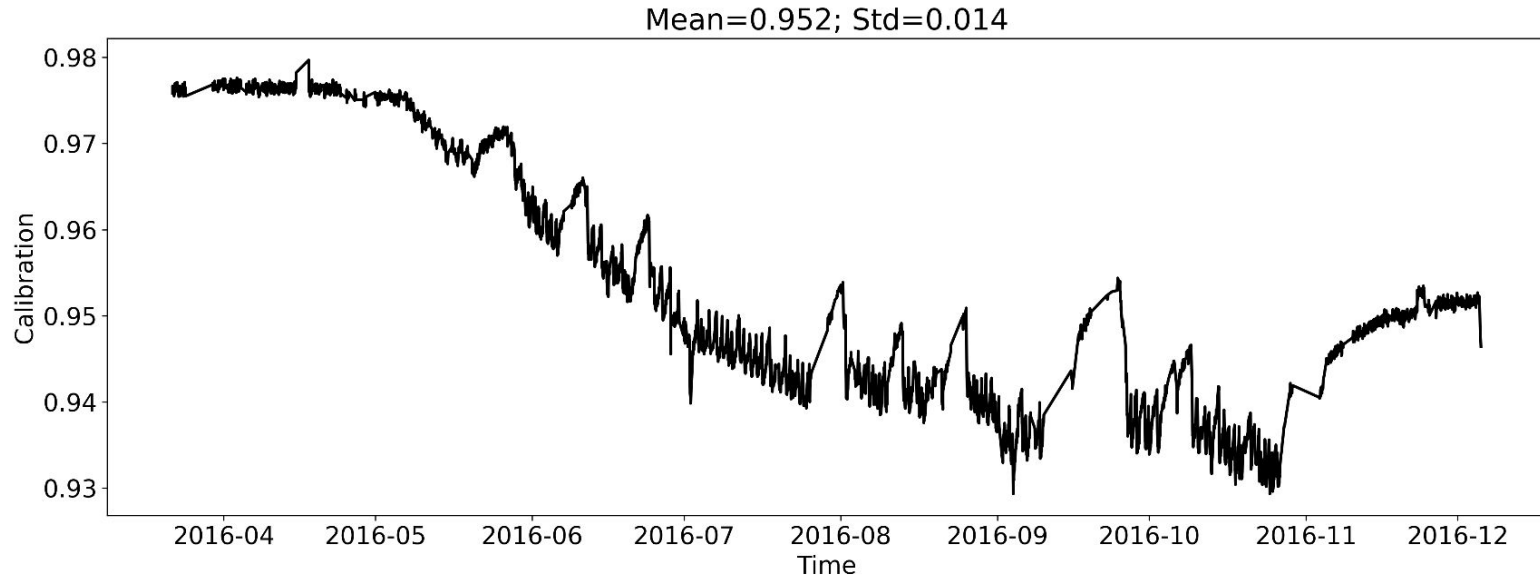


Experimental Setting Up

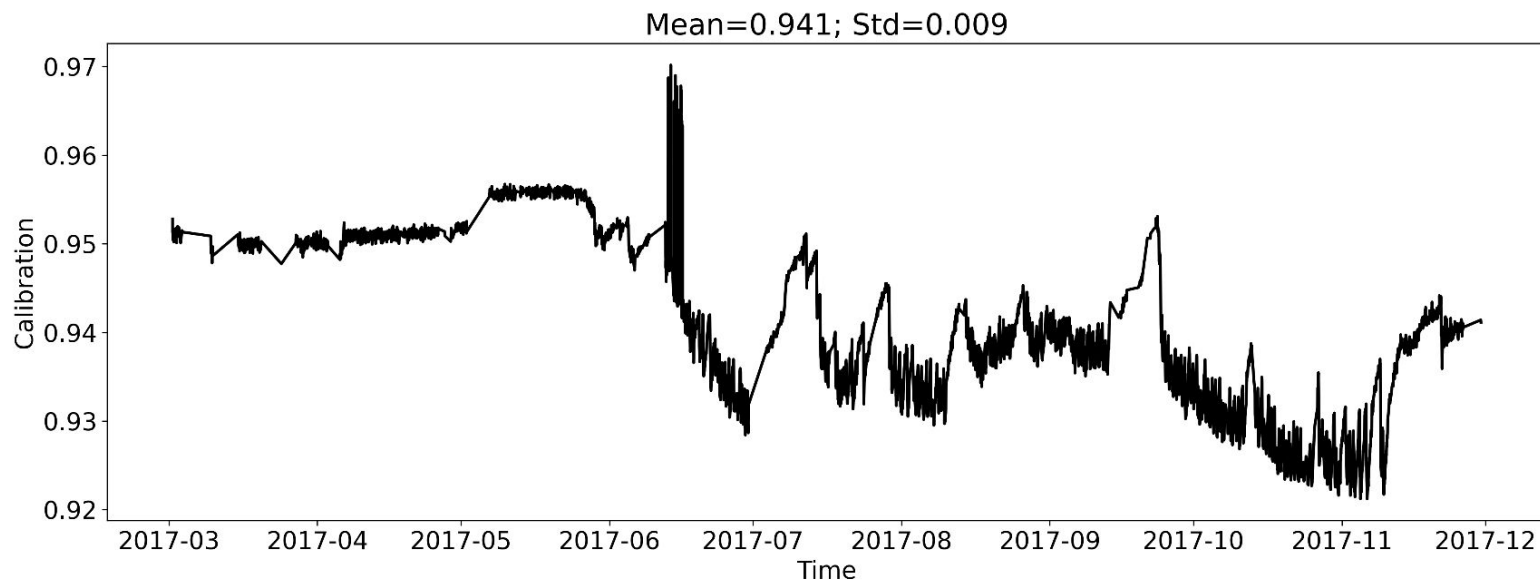
All results in the following slides use the same setting up:

- 1) We use Seq2Seq Model Type-2 (see slide 6 for details);
- 2) We use Case 1 (see slide 7 for details);
- 3) We train our model on 2016 data of 54000 crystal; and we test the trained model on 2017 data, 2018 data of 54000 crystal.

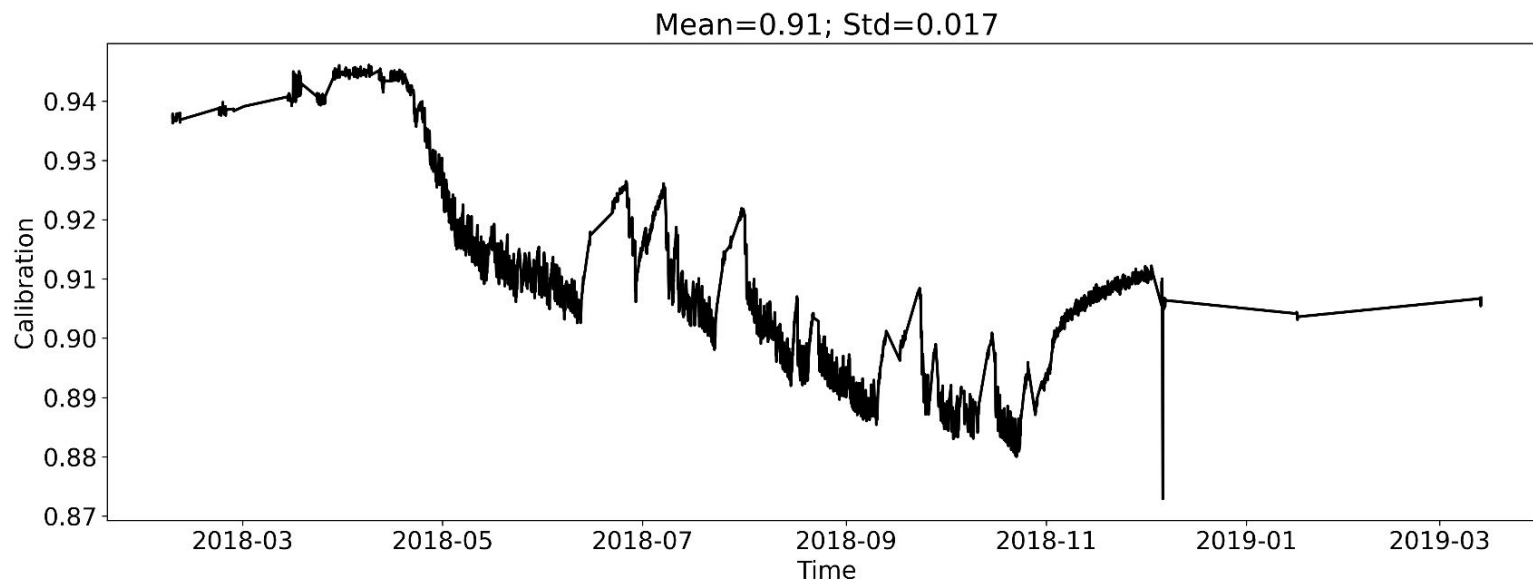
Original Calibration-2016



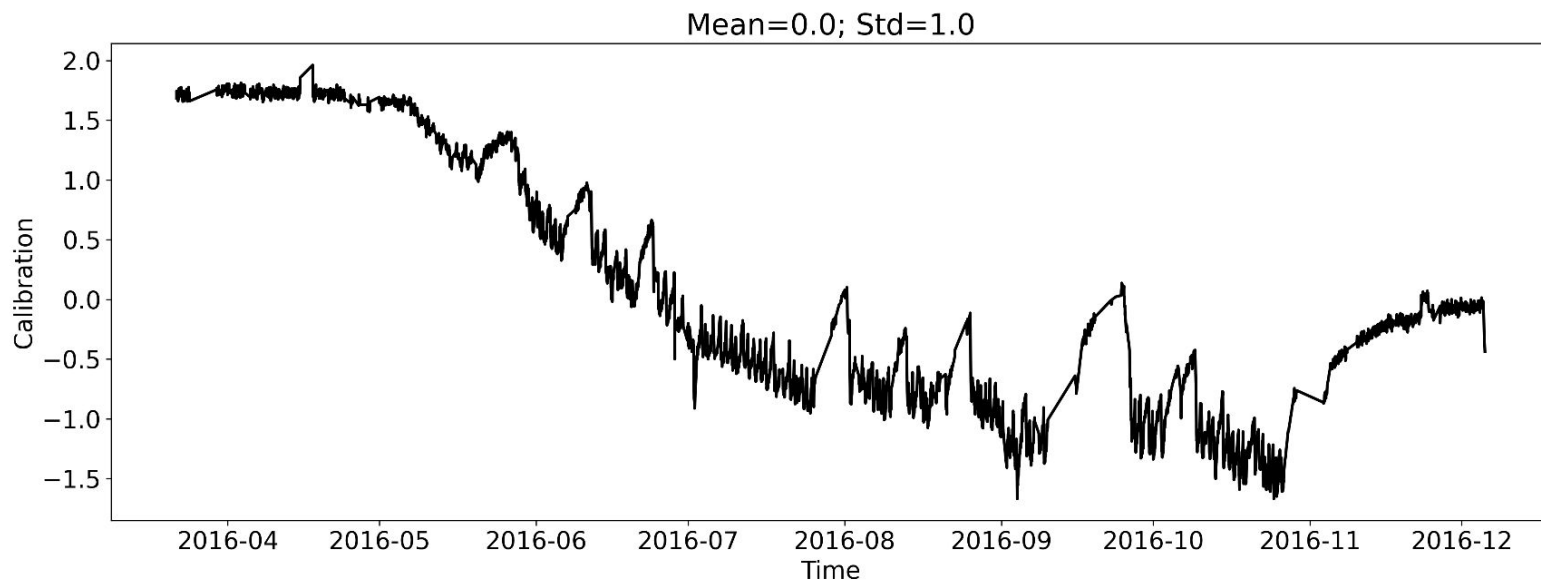
Original Calibration-2017



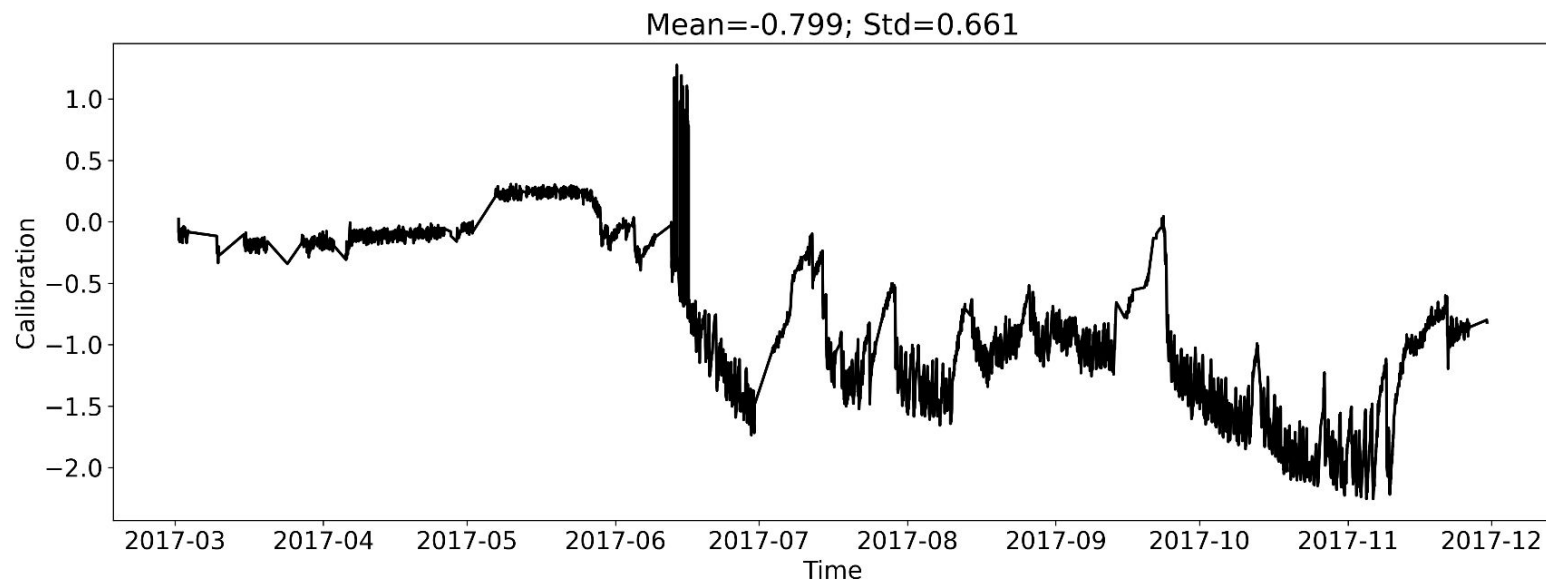
Original Calibration-2018



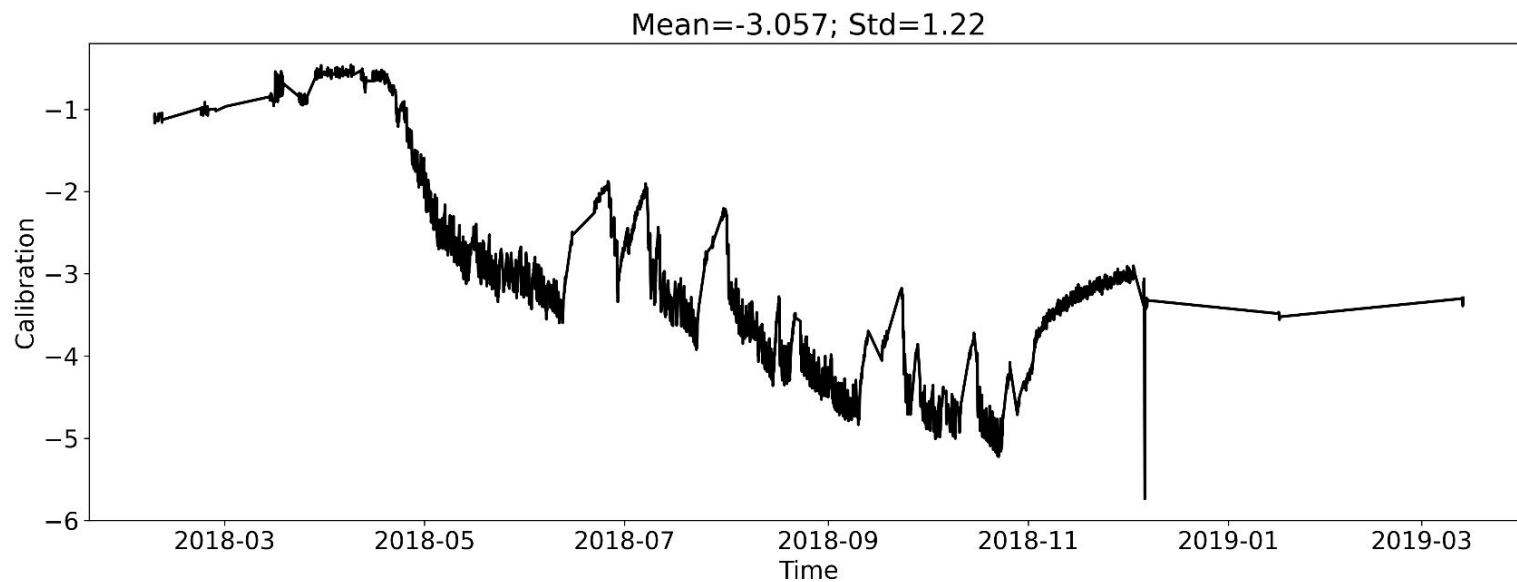
Normalized Calibration-2016

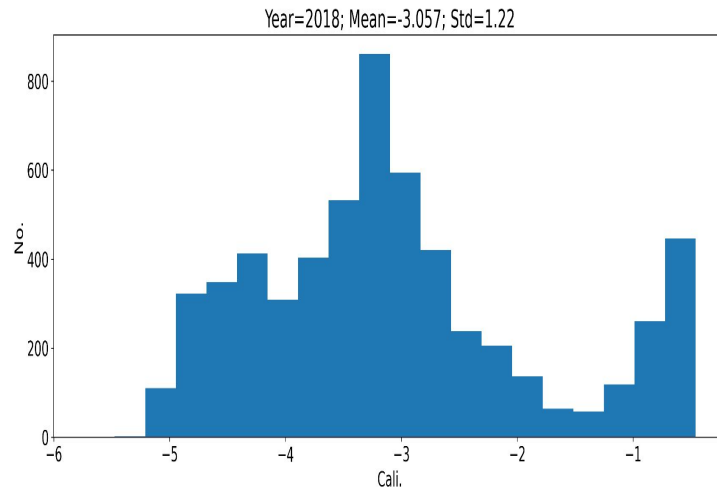
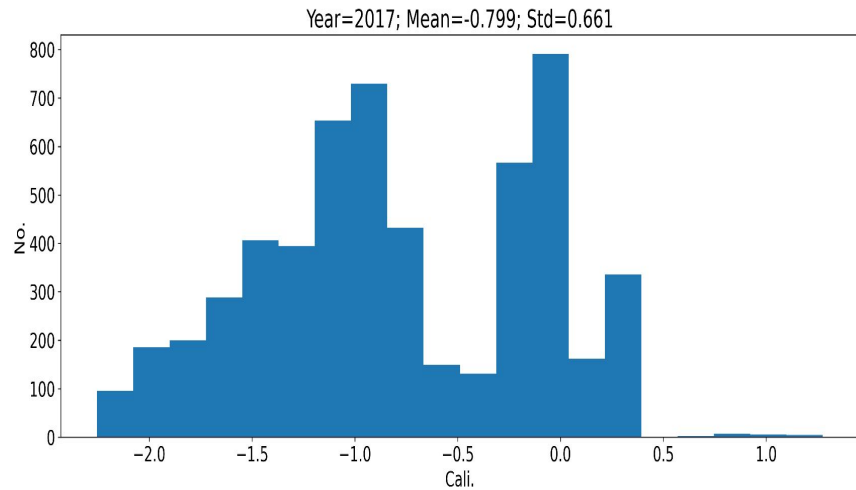
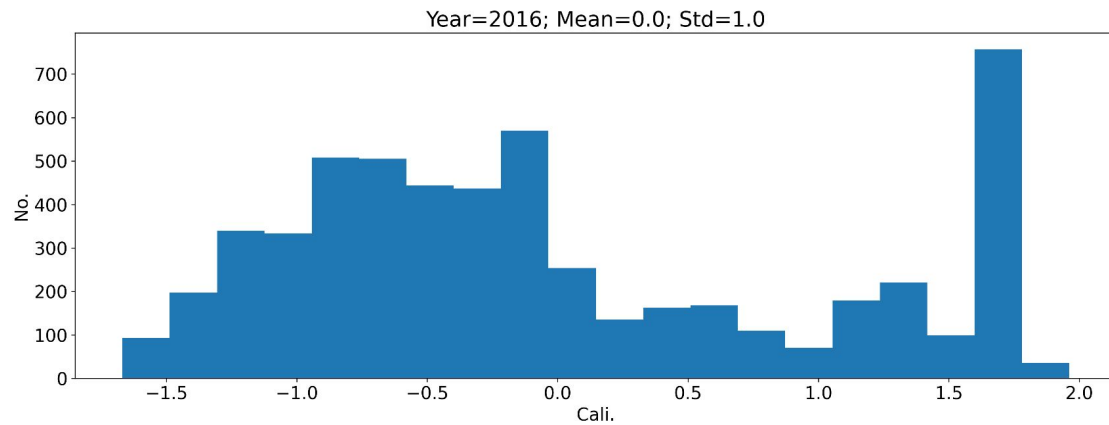


Normalized Calibration-2017

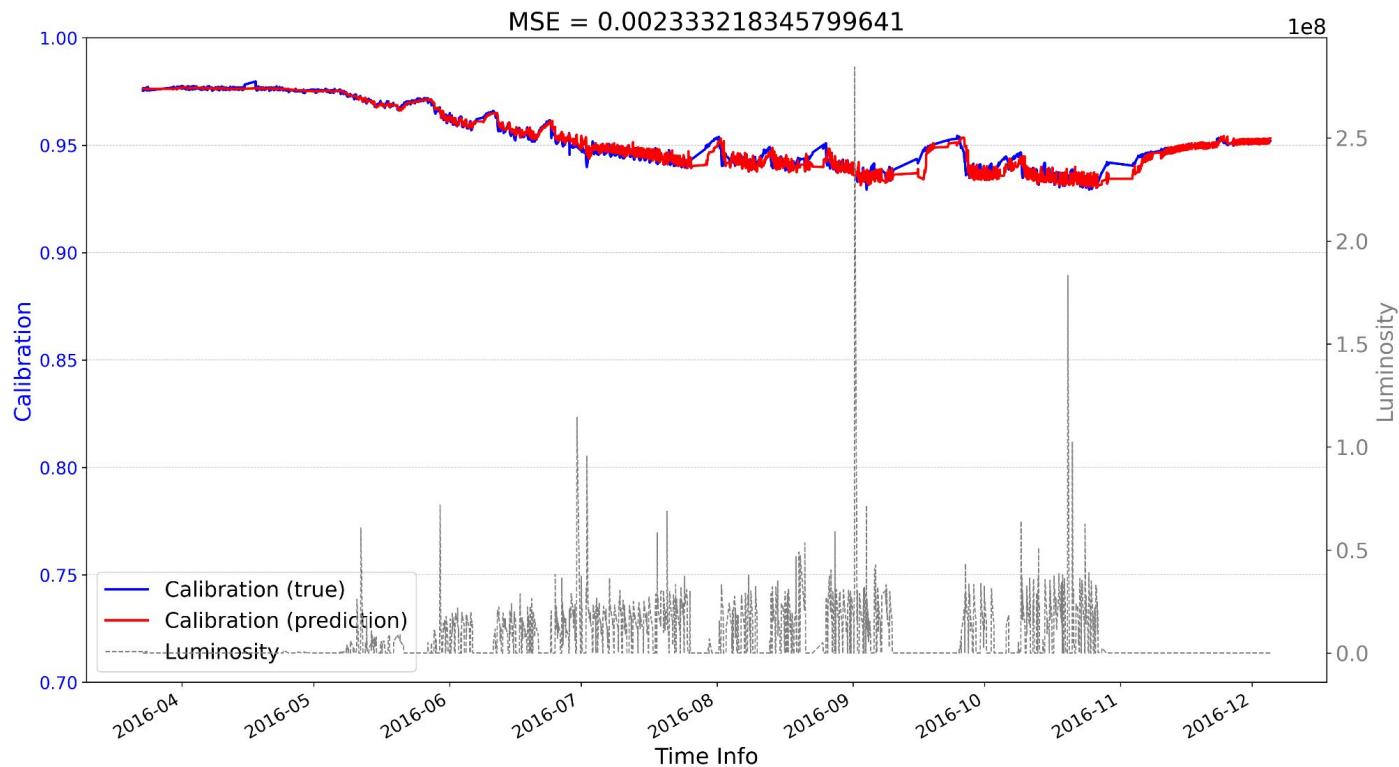


Normalized Calibration-2018

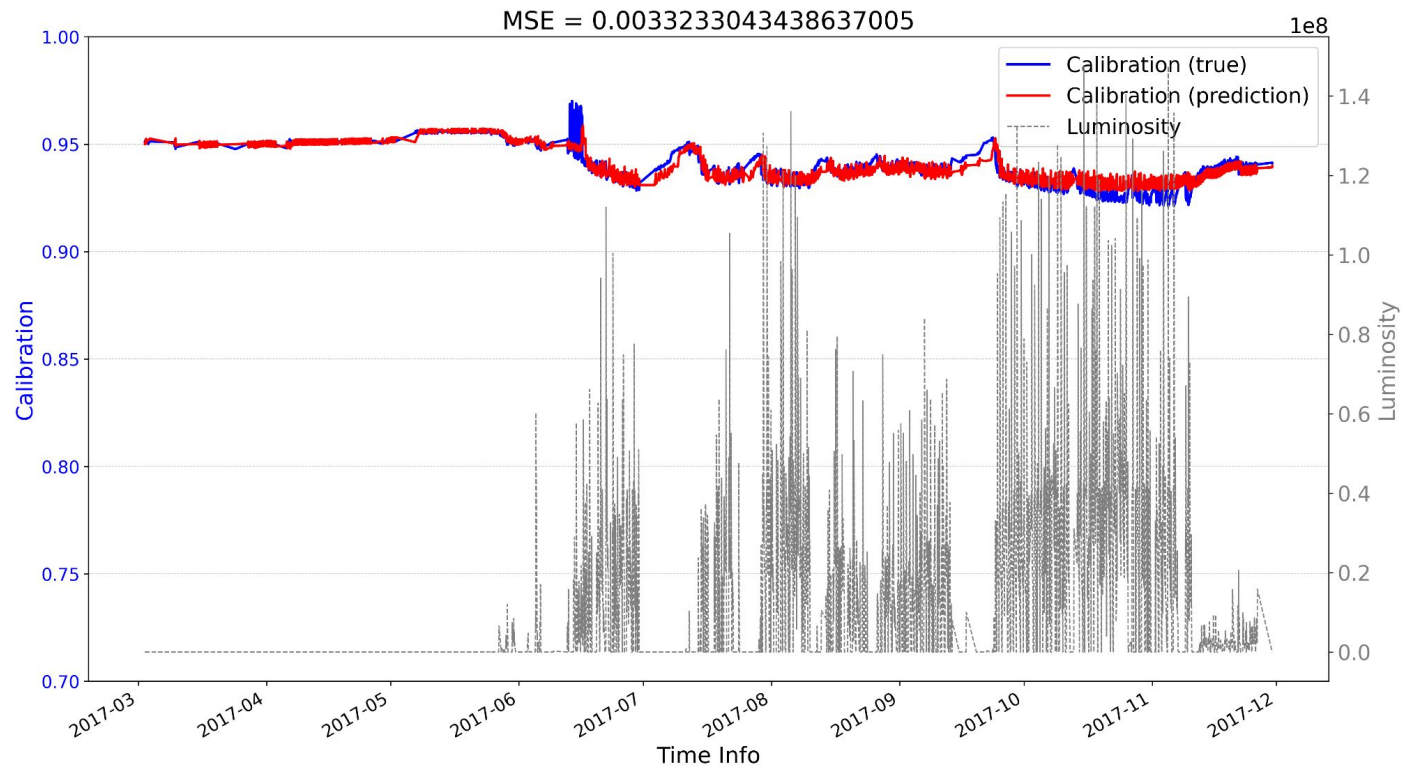




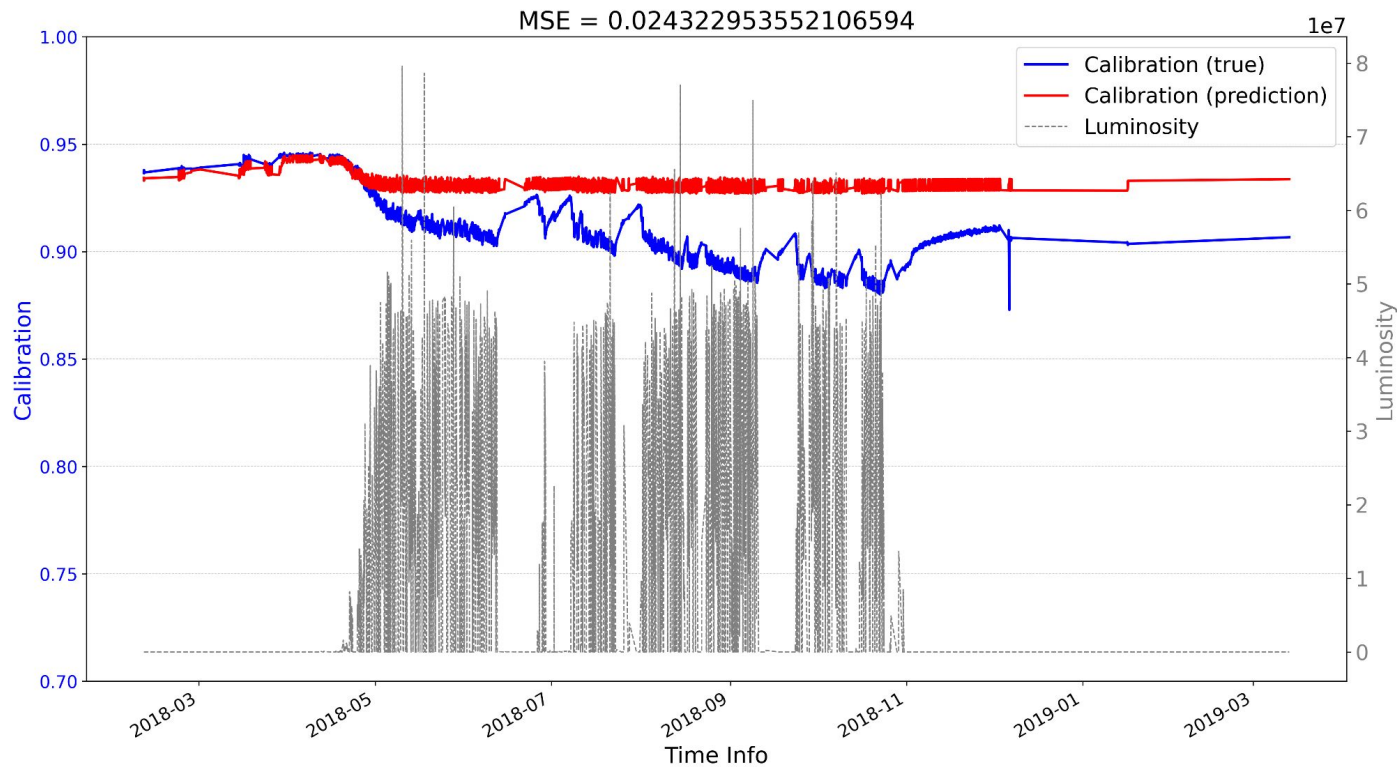
Results—Training On 2016; Test on 2017 & 2018



Results—Training On 2016; Test on 2017 & 2018



Results—Training On 2016; Test on 2017 & 2018

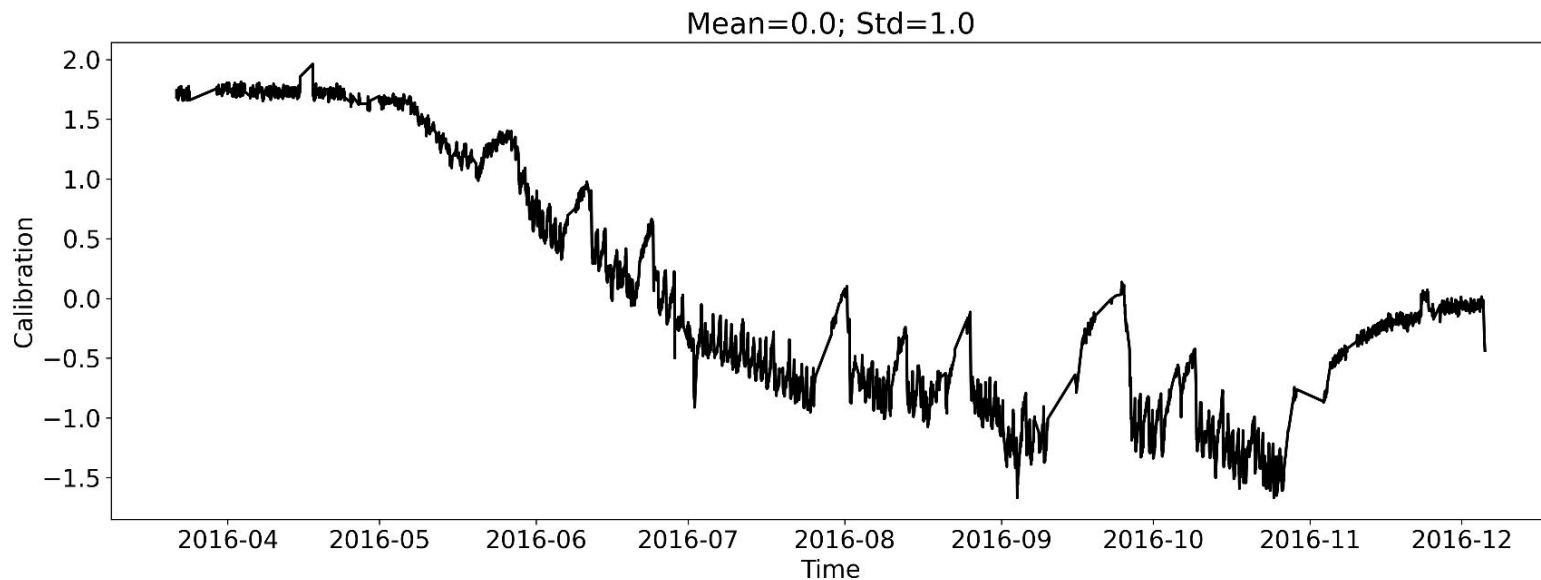


Results Analysis

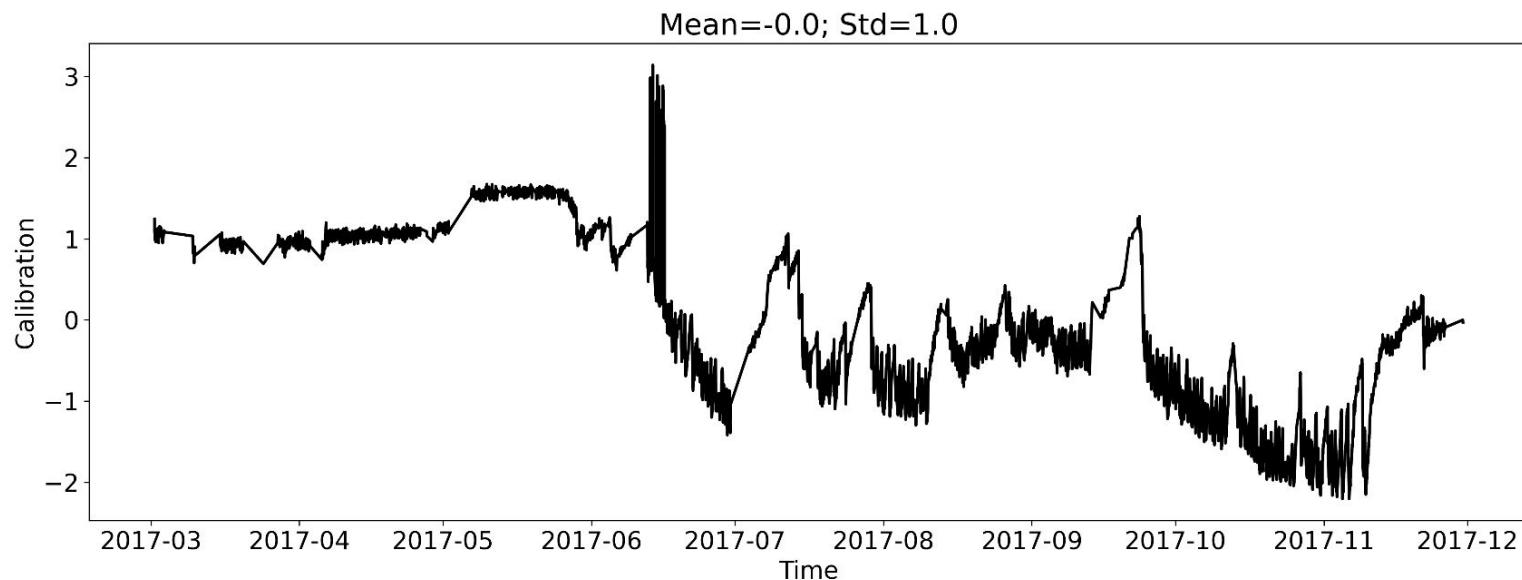
One potential reason that causes the prediction performance degradation:

- 1) Data distribution shift

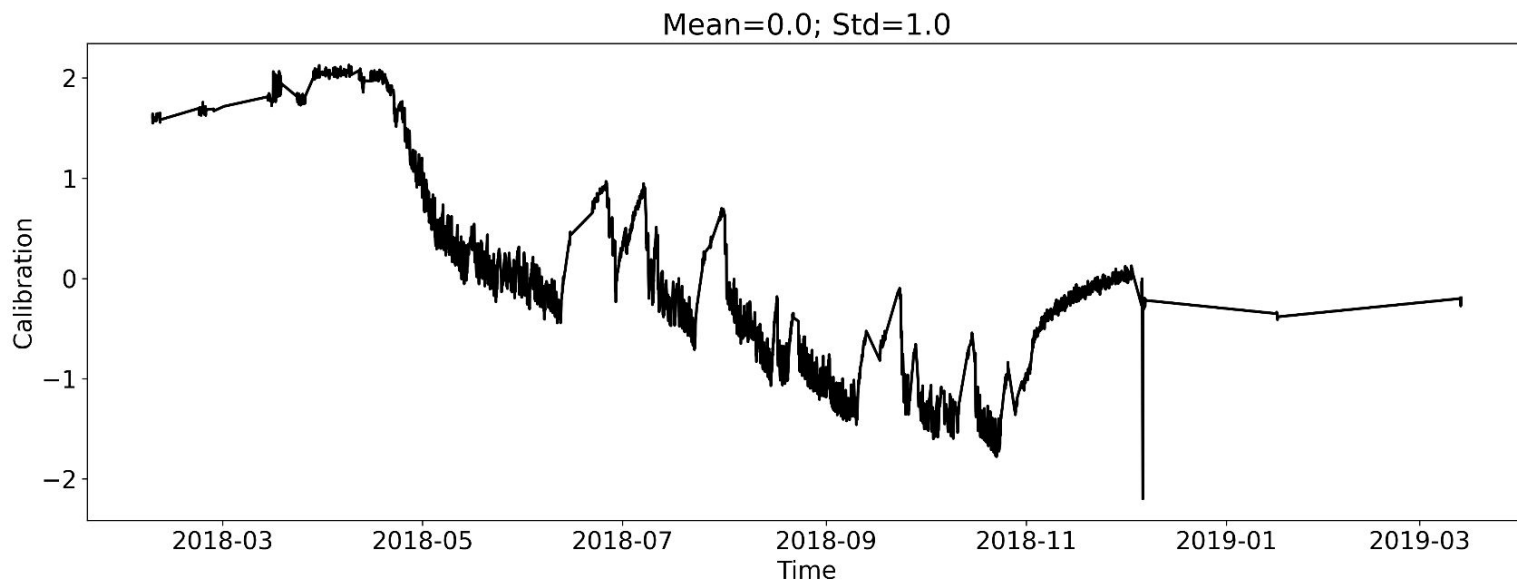
If we normalize the data separately-2016

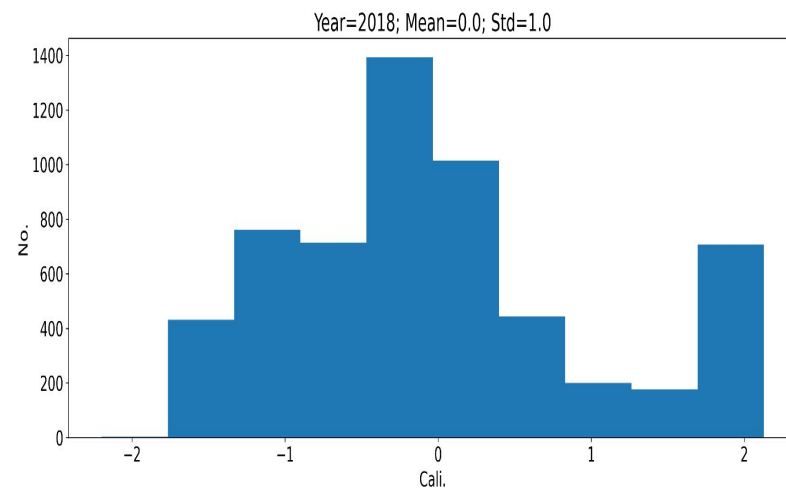
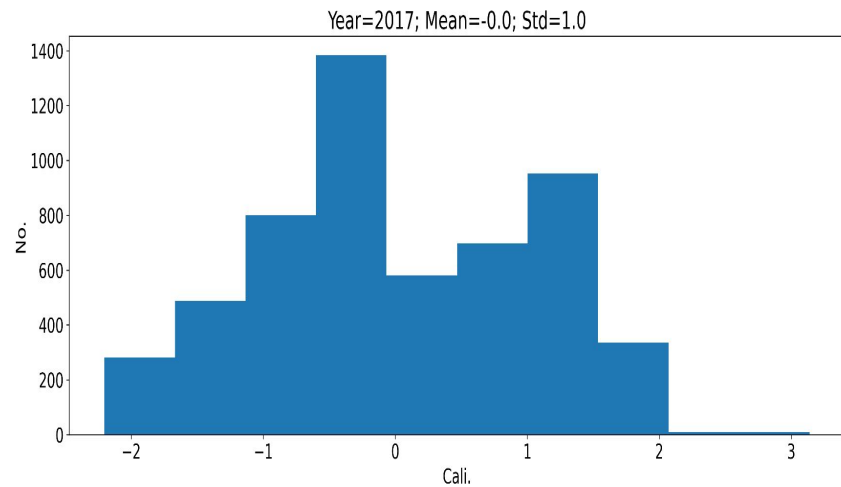
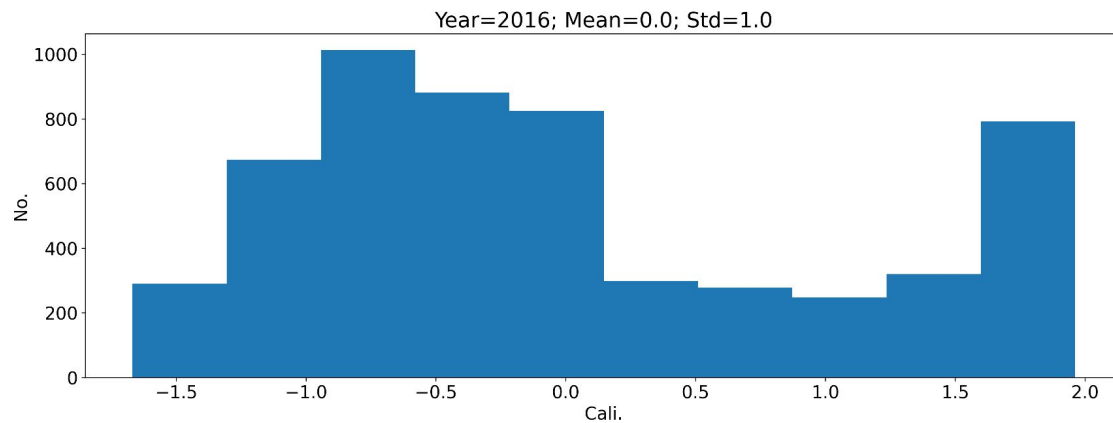


If we normalize the data separately-2017

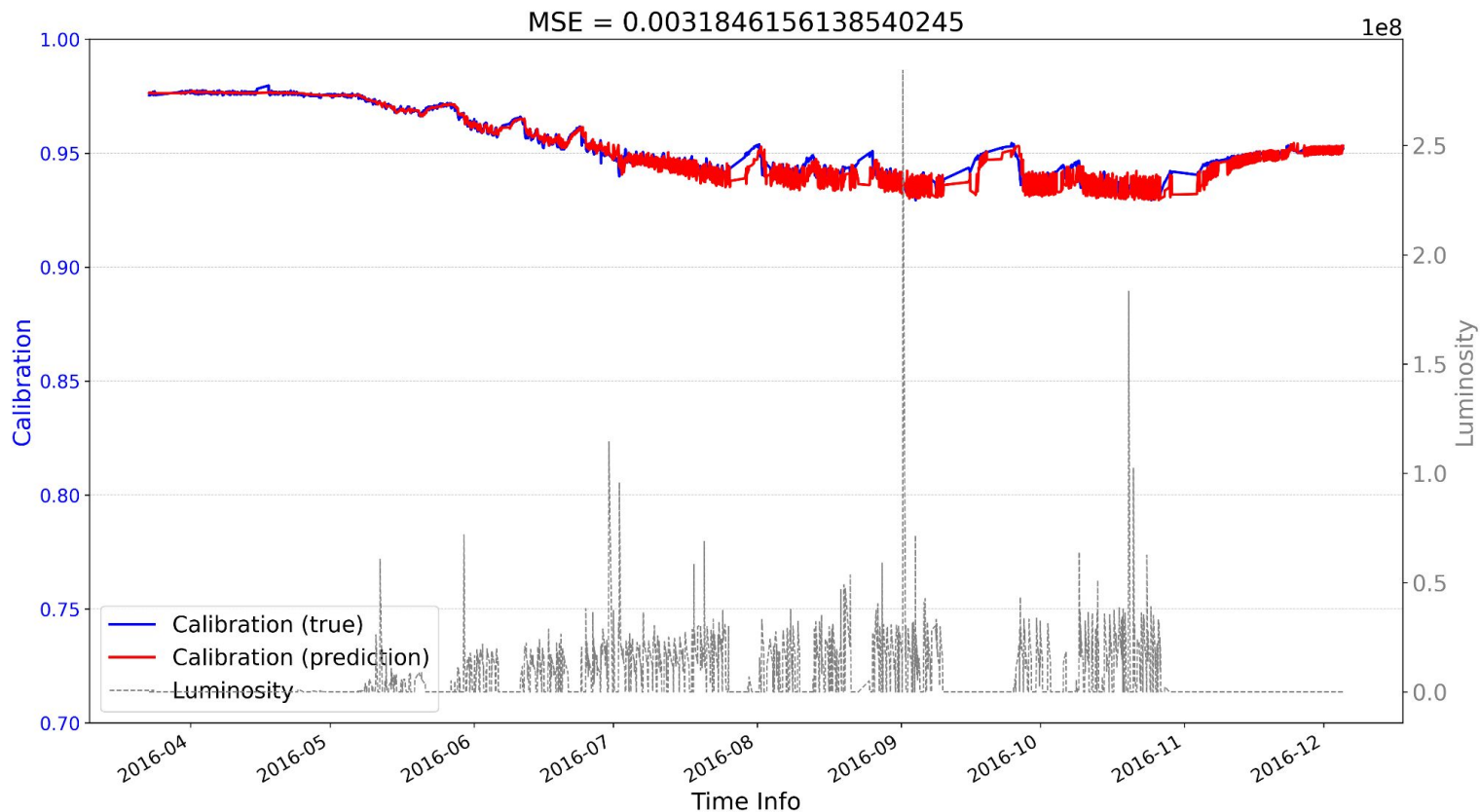


If we normalize the data separately-2018

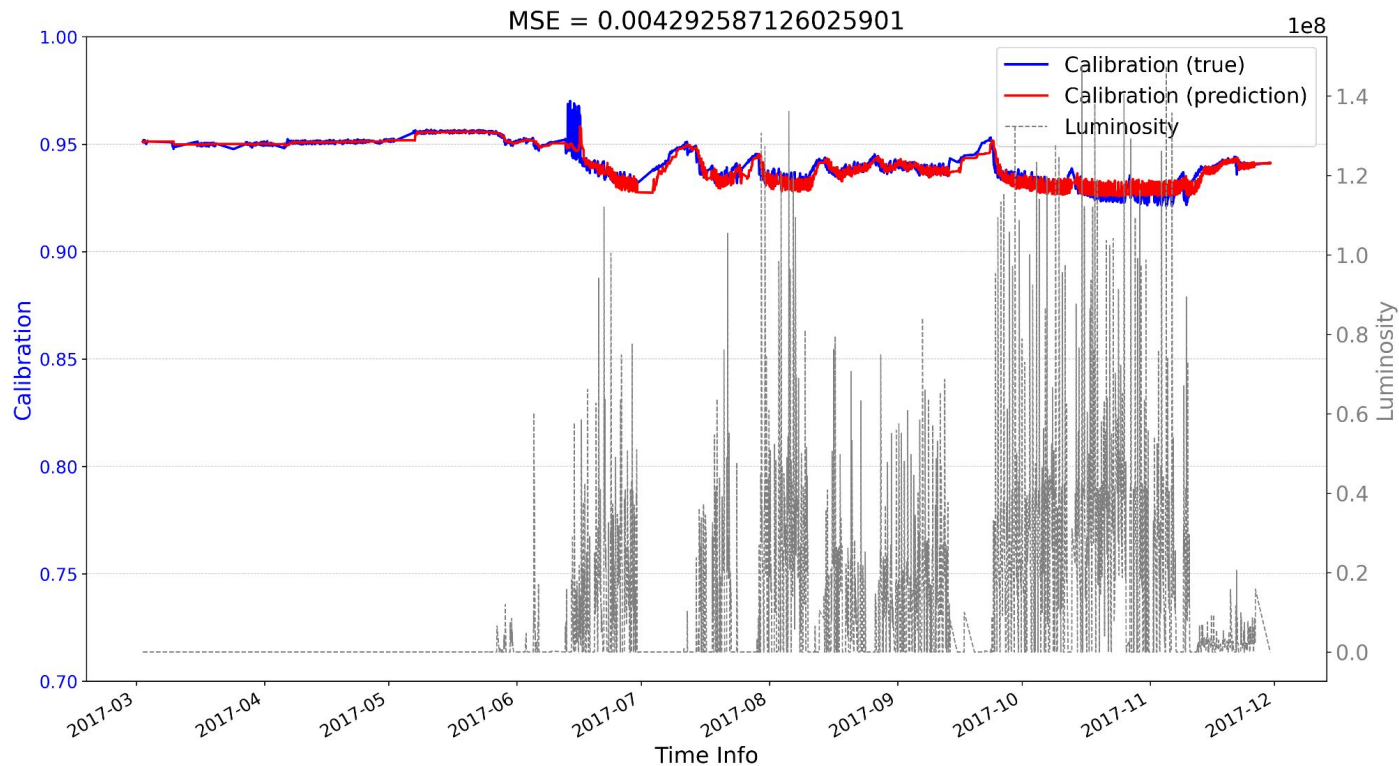




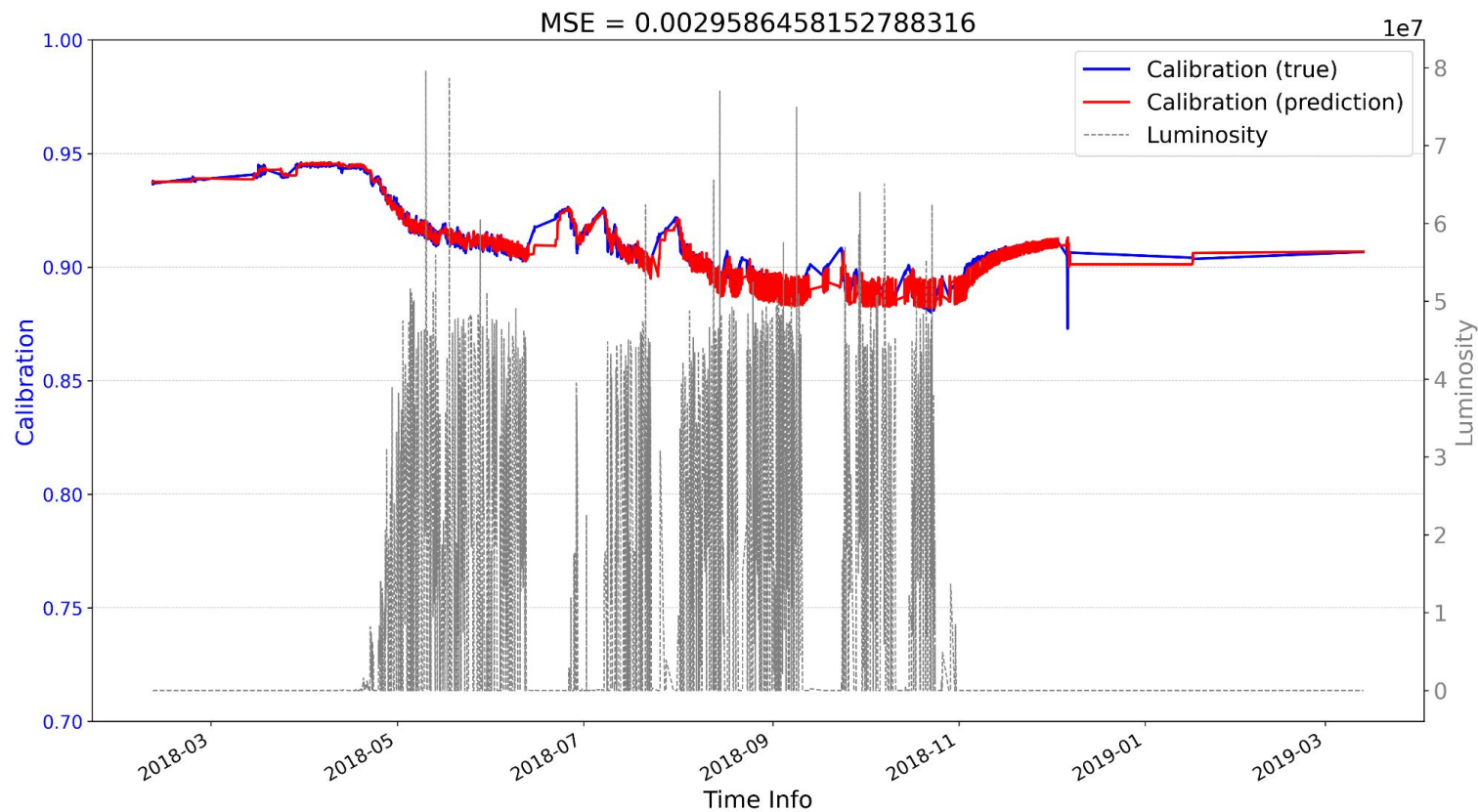
Results—Training On 2016; Test on 2017 & 2018



Results—Training On 2016; Test on 2017 & 2018



Results—Training On 2016; Test on 2017 & 2018



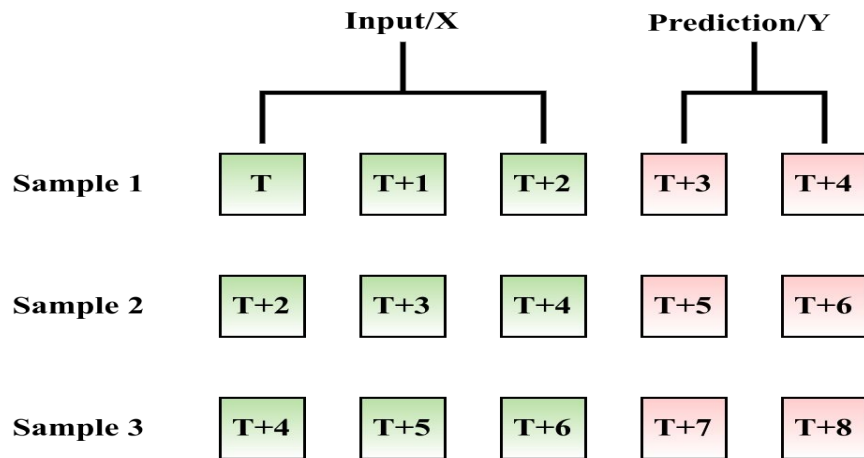
What's Next

- 1) Test the model on more different crystals and years;
- 2) Try Case 2 (see slide 7 for details);
- 3) Add the results of model-type-1 (see slide 6 for details);
- 4)

Training/Test Data Format

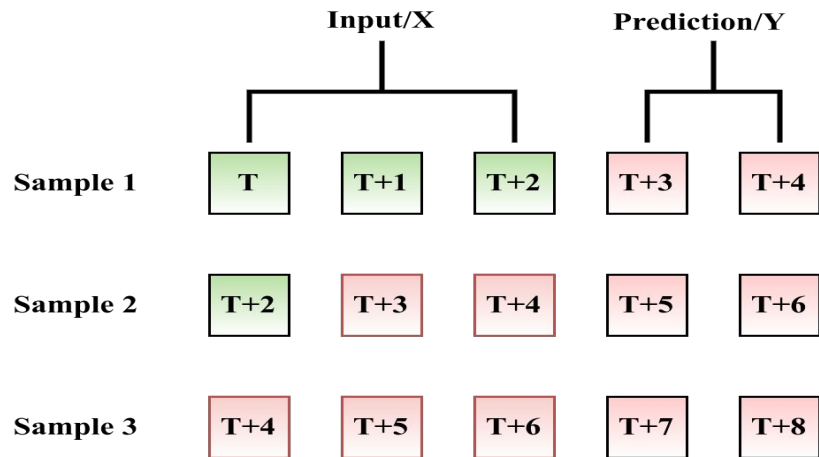
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Case 2 (right):

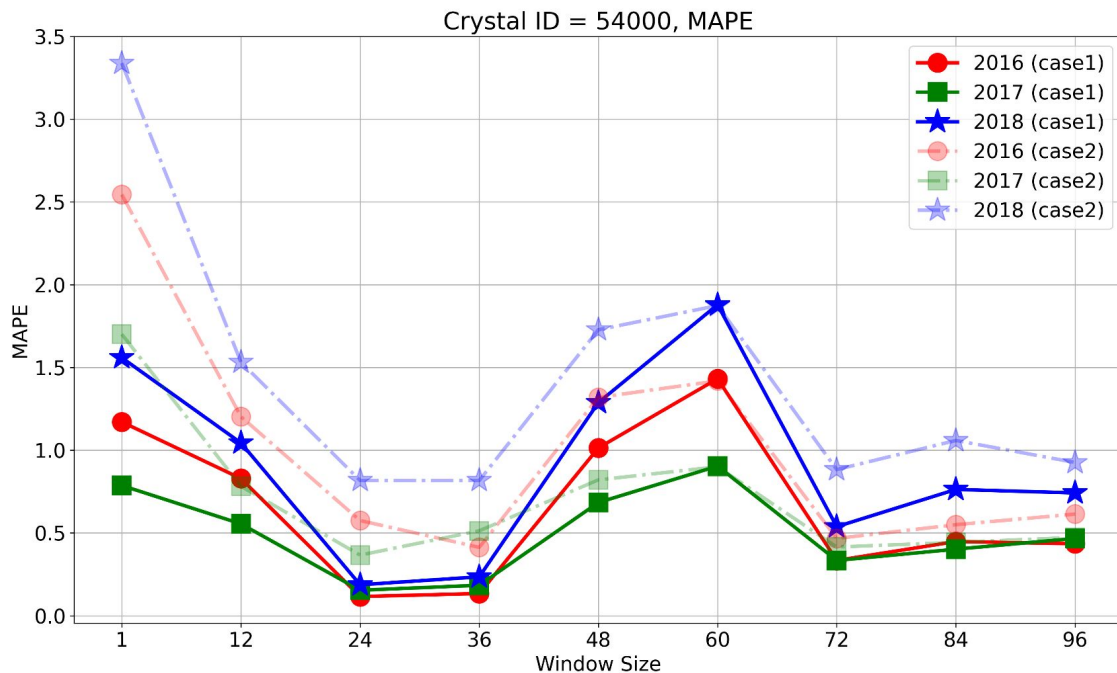
- 1) The only observed information we have is “T, T+1, T+2”;
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Crystal ID=54000, Different Window Size

Mean Absolute Percent Error (MAPE):
the lower, the better.

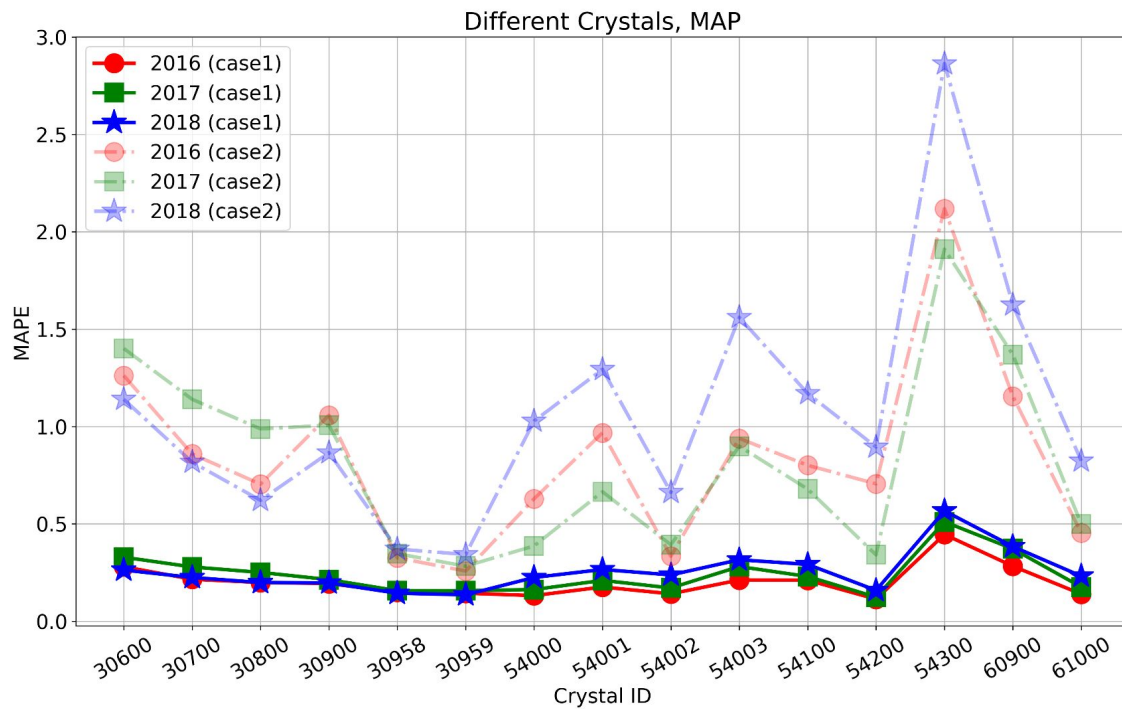
$$MAPE = \sum_{i=1}^n \left| \frac{y_i - \hat{y}_i}{y_i} \right| \times \frac{100}{n}$$



Different Crystals, WS=24, Trained on 2016 (separately)

Mean Absolute Percent Error (MAPE):
the lower, the better.

$$MAPE = \sum_{i=1}^n \left| \frac{y_i - \hat{y}_i}{y_i} \right| \times \frac{100}{n}$$



Different Crystals, WS= 24, Trained on 2016 (ID:54000)

Mean Absolute Percent Error (MAPE):
the lower, the better.

$$MAPE = \sum_{i=1}^n \left| \frac{y_i - \hat{y}_i}{y_i} \right| \times \frac{100}{n}$$

