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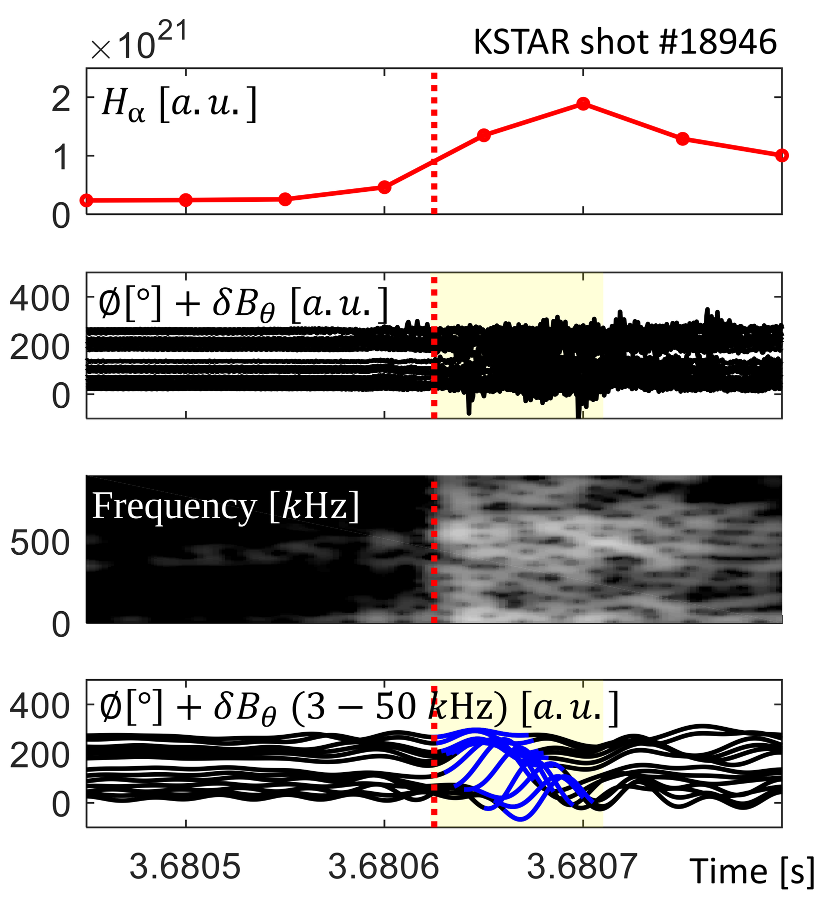
# Machine learning approach to understand the causality between solitary perturbation and edge confinement collapse in the KSTAR tokamak

J.E. Lee[1], P. H. Seo[1], J.G. Bak[2,3], and G.S. Yun[1]
[1] POSTECH, Korea [2] NFRI, Korea [3]KFE, Korea
*jieun_lee@postech.ac.kr*

## Abstract

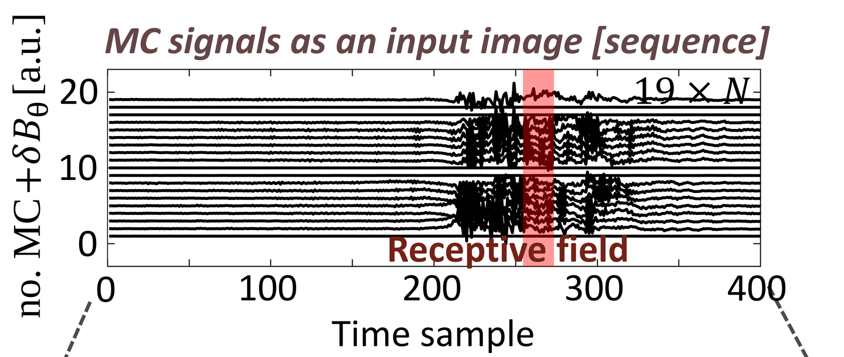
- Solitary perturbations (SPs) are detected within ~ 100 $\mu s$ prior to the edge pedestal collapse in H-mode plasmas, which puts forward SP as a potential candidate for the edge pedestal collapse trigger.
- We have constructed an automatic SP identification model based on a convolutional deep neural network to enable a statistical study on the concurrency of SP and edge pedestal collapse.
- We applied the developed model to a large amount of data and confirmed that the complete collapse at the plasma boundary always involves the emergence of SP.

## Solitary Perturbation (SP)



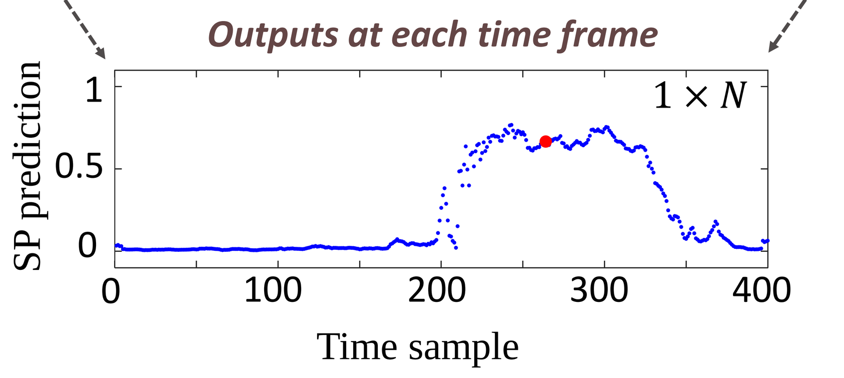

- SP, localized in the poloidal direction, appear mostly tens of $\mu s$ before the onset of the edge pedestal collapse.
- SP persists a few tens of $\mu s$ to hundreds of $\mu s$ without a noticeable change in shape.
- SP is clearly distinguished from ELM by spatial structure, amplitude, and flow velocity.

## Development of the SP identification model

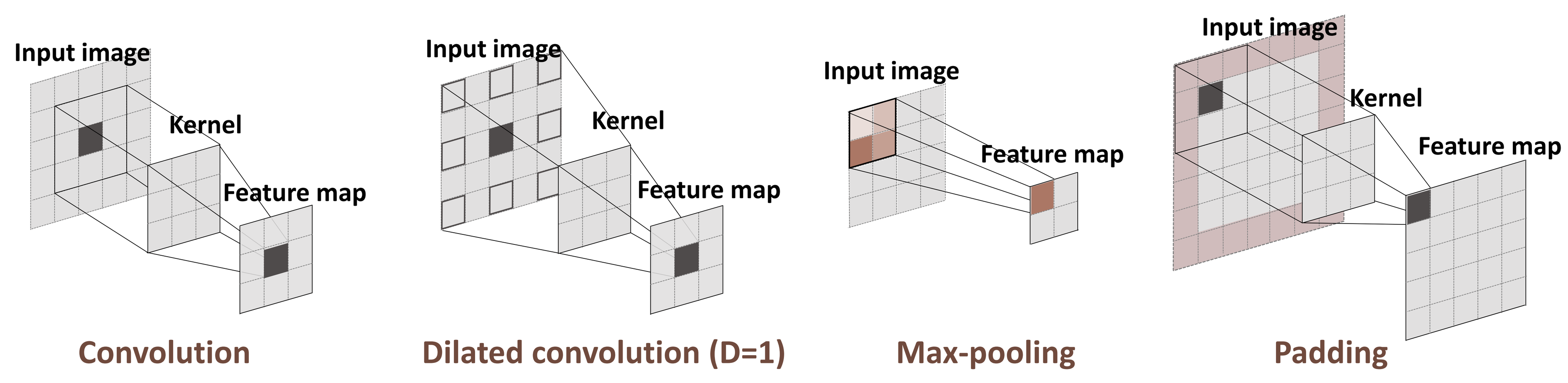



*Network architecture*

| Layer: Operation | Layer: Dilation rate | Output size |
|---|---|---|
| Convolution #1 (3 × 3@16) | | 19 × 400@16 |
| Convolution #2 (3 × 1@16) | | 19 × 400@16 |
| Convolution #3 (1 × 3@16) | | 19 × 400@16 |
| Max-pooling #1 (1 × 2@16) | | 19 × 400@16 |
| Convolution #4 (3 × 1@32) | | 19 × 400@32 |
| Convolution #5 (1 × 3@32) | 1 | 19 × 400@32 |
| Maxpooling #2 (1 × 2@32) | | 19 × 400@32 |
| Convolution #6 (3 × 1@32) | | 19 × 400@32 |
| Convolution #7 (1 × 3@32) | 3 | 19 × 400@32 |
| Max-pooling #3 (19 × 1@32) | | 1 × 400@32 |
| Linear (1 × 1@1) | | 1 × 400@1 |

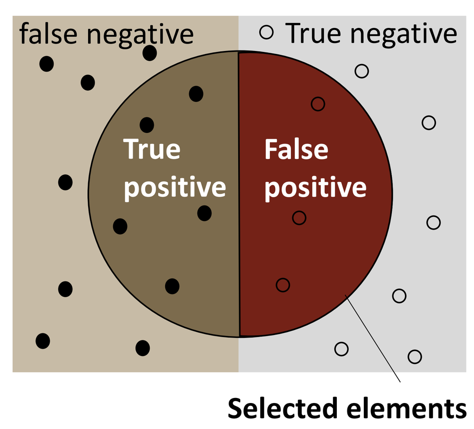



- **Input data**
  - *Raw data of toroidal Mirnov coils*
  - [no. MCs]×[Time]: 19×400
    - ; Toroidal array of MCs on KSTAR: 19
    - ; Time: 400 (400 $\mu s$, 1 MHz sampling freq.)
- **Output data**
  - *SP probability ( 0 ⟷ 1)* (no SP ⟷ SP)
  - [Time]: 400
    - ; Time: 400 (400 $\mu s$, 1 MHz sampling freq.)
- **Network architecture**
  - 11 network layers
    - ; 7 Convolution + 3 Max-pooling+1 Linear
  - Padding
    - ; Circular padding (coil dimension)
    - ; Zero padding (time dimension)
- **Training of the model**
  - Training dataset: 140 sequential data
    - ; 2015-2017 KSTAR discharges
    - ; 100 positive examples (w/ collapse and SP)
    - ; 20 negative examples (w/o collapse and SP)
    - ; 20 synthetic collapses examples (white noise × envelope of MC signal)
  - Supervised learning
    - ; Minimization of errors between network output and correct answer



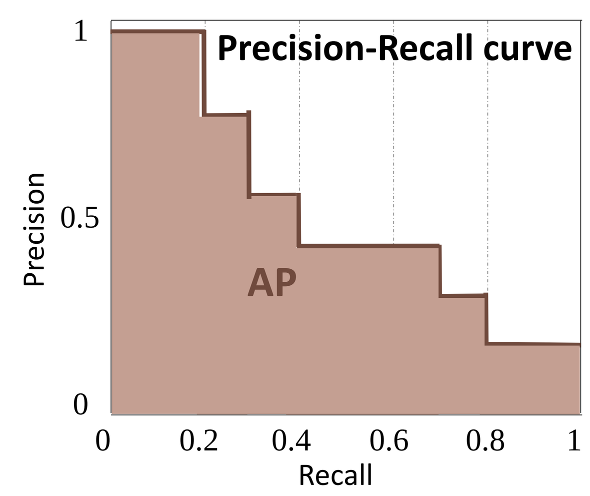

## Performance of the SP identification model

- **Test of the model**
  - Test dataset: 50 sequential data (2015-2017 KSTAR discharges)
    - ; 26 positive examples, 12 negative examples, 12 synthetic collapse examples
- **Three metrics to evaluate the model**
  - ***Per-frame accuracy (AF):*** The proportion of correct prediction of SP per frame
  - ***Per-sequence accuracy (AS):*** The proportion of correct prediction of SP per sequence
  - ***Average precision (AP):*** Mean precision over all possible threshold weighted by recall




| | | Predicted class: Positive | Predicted class: Negative |
|---|---|---|---|
| Actual class | Positive | True Positive (TP) | False Negative (FN) |
| | Negative | False Positive (FP) | True Negative (TN) |

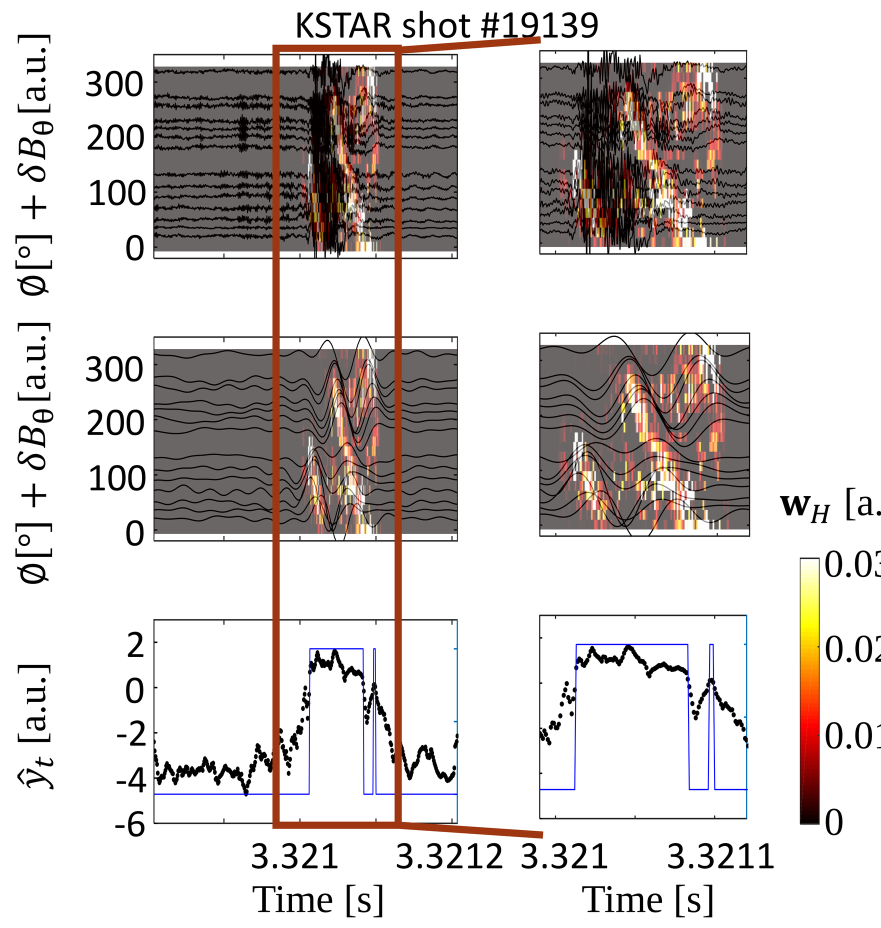
$$\text{Precision} = \frac{TP}{TP+FP} \qquad \text{Recall} = \frac{TP}{TP+FN}$$




| Metric | | Result [%] |
|---|---|---|
| Accuracy | Time frame | 91.5 |
| | Sequence | 100.0 |
| Average Precision (AP) | | 88.5 |

- **Quantitative performance of the model**
  - *Threshold for the SP presence* in time frame: 0.5
  - *Threshold for the SP presence* in sequence ($y_s$): 25
  - AF for a *trivial model* which predicts a *non-SP for every temporal frame* is 82.5%.

## Qualitative validation by visualization




- **Gradient based visualization technique**
  - Our Network is approximated by the 1st order Taylor expansion

$$\hat{y}_t \approx \mathbf{w}_t^{\mathrm{T}}\mathbf{r} + b_t \qquad \mathbf{w}_t = \left.\frac{\partial \hat{y}_t}{\partial \mathbf{r}}\right|_{\mathbf{r}_0}$$

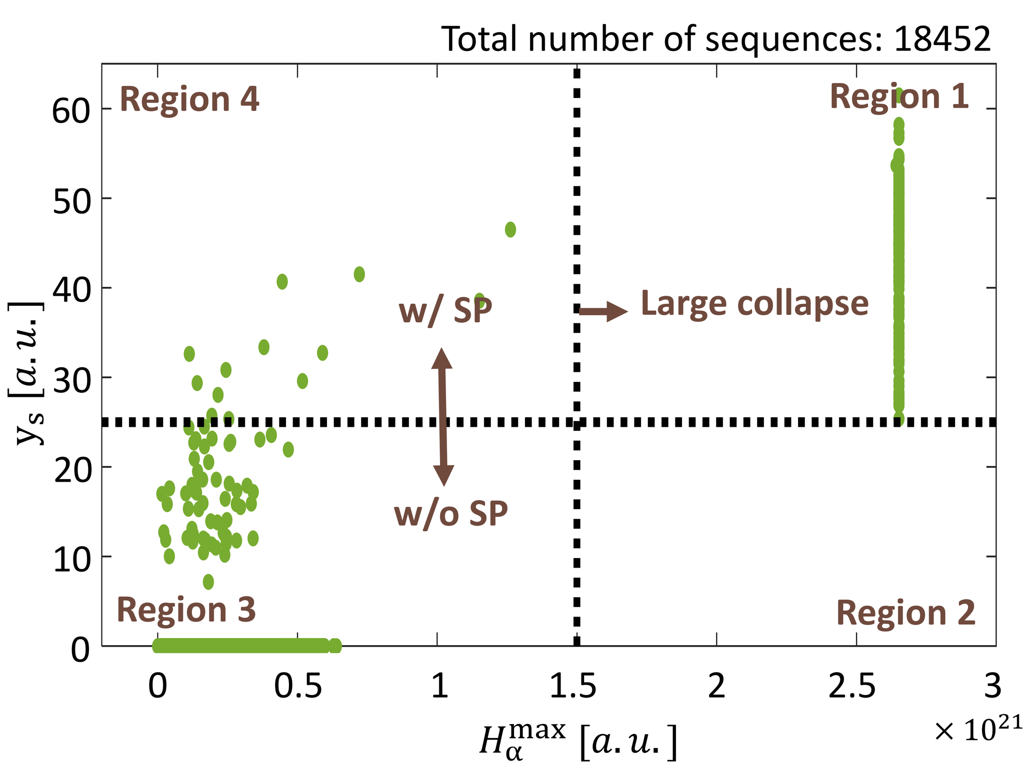
; $\hat{y}_t$: Input to the last sigmoid function ($y_t$ = sigmoid($\hat{y}_t$))
; $\mathbf{r}$: Flattened vector of input X, $\in \mathbb{R}^{(19\times N)}$
; $\mathbf{w}_t$: Gradient of $\hat{y}_t$ at $\mathbf{r}_0$, $\in \mathbb{R}^{(19\times N)}$ (N: Number of temporal frames)

Heatmap by summing $w_t$ at all positive frames

$$\mathbf{w}_H = \sum_{t\in P} \mathbf{w}_t = \frac{\partial}{\partial \mathbf{r}} \sum_{t\in P} \hat{y}_t \Big|_{\mathbf{r}_0}$$

***The model predicts SPs by recognizing toroidally shifted SP patterns.***

## Statistical analysis of the pedestal collapse-SP co-occurrence




- **Statistical analysis data**
  - 2018 KSTAR discharges
    - ; #20540, #20630, #20807, #21207

| Region | Sequence # |
|---|---|
| 1 (Large collapse w/ SP) | 176 |
| 2 (Large collapse w/o SP) | 0 |
| 3 (no large collapse w/o SP) | 18263 |
| 4 (no large collapse w/ SP) | 13 |

***The complete edge pedestal collapse always involves the emergence of SP***
***➔ Studying the effect of SP on the edge pedestal collapse is essential for successful operation of fusion devices***

## Acknowledgements

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