

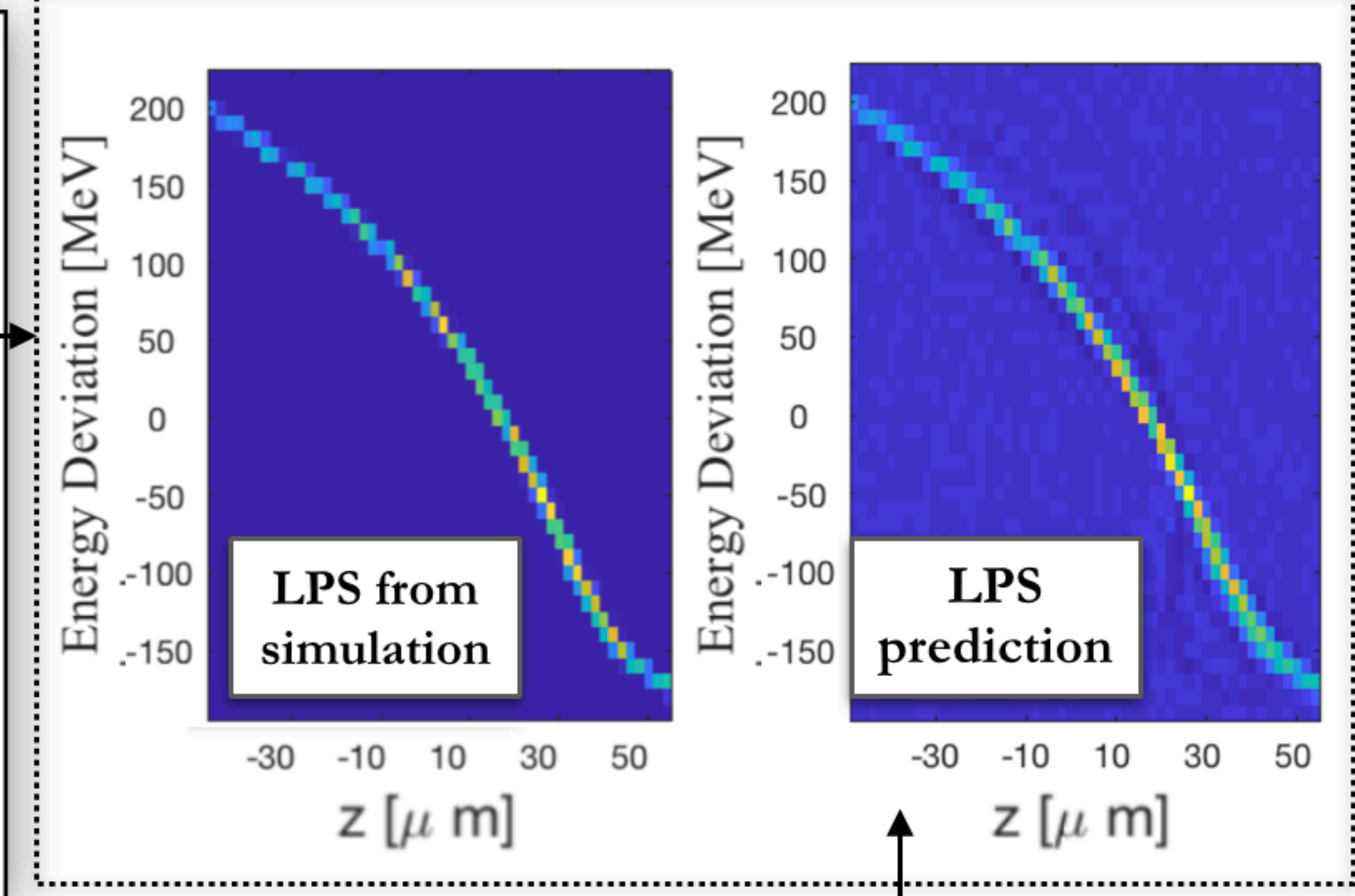
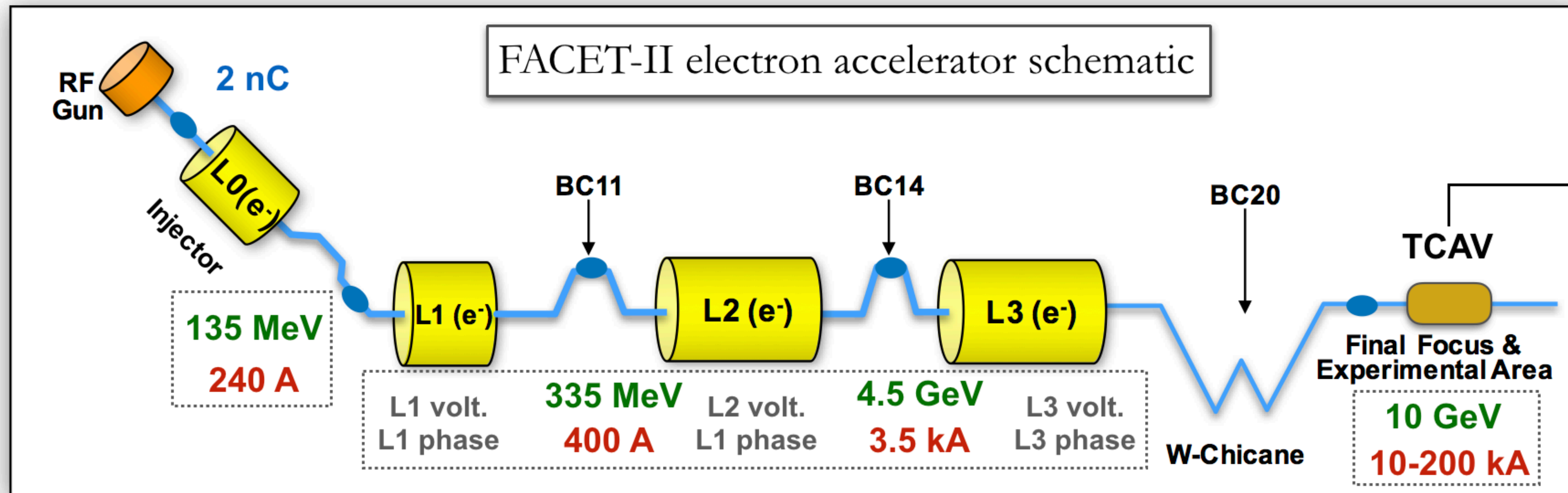
# ML based longitudinal phase space prediction of accelerators

C. Emma, A. Edelen, M.J. Hogan, B. O'Shea, G. White, V. Yakimenko

ML at SLAC workshop

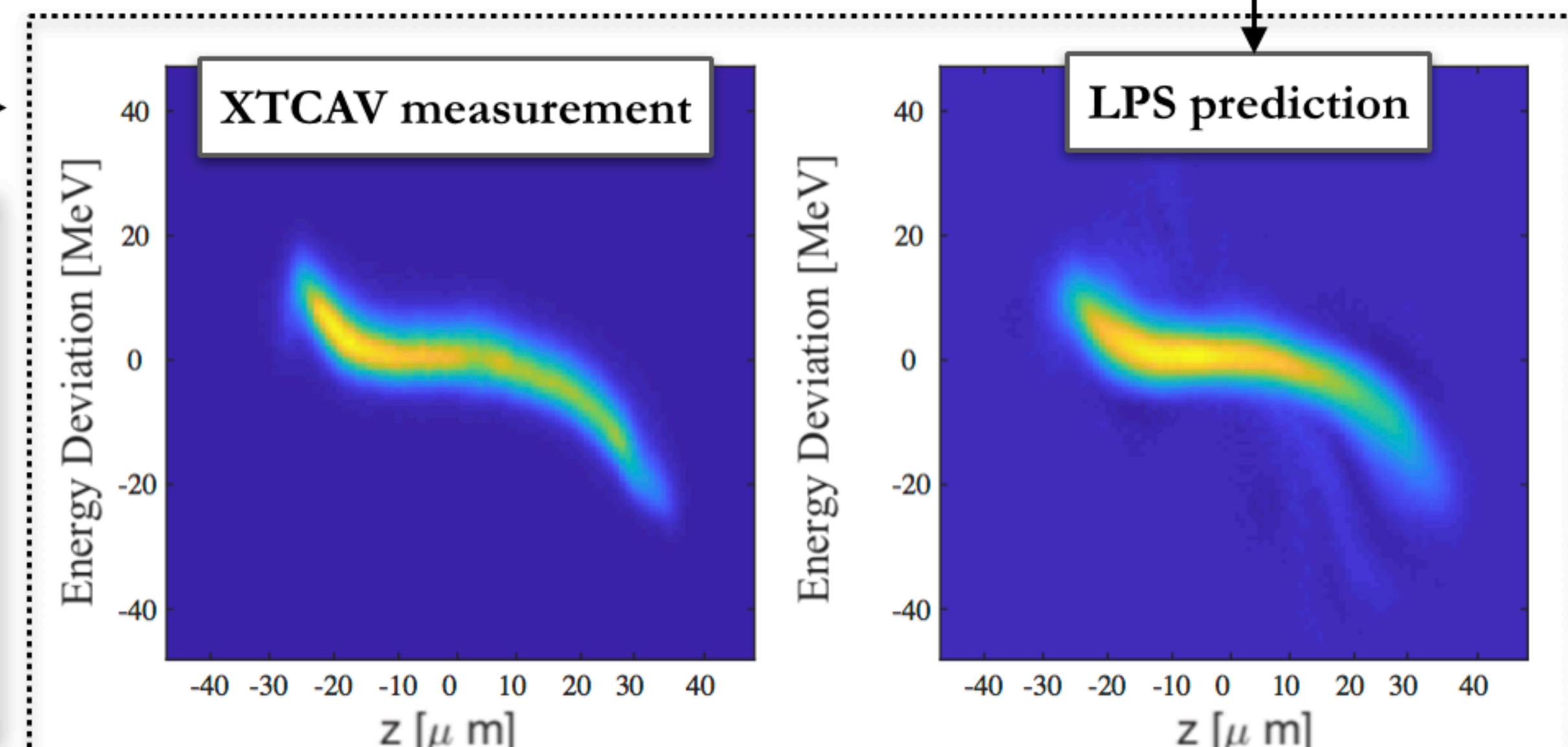
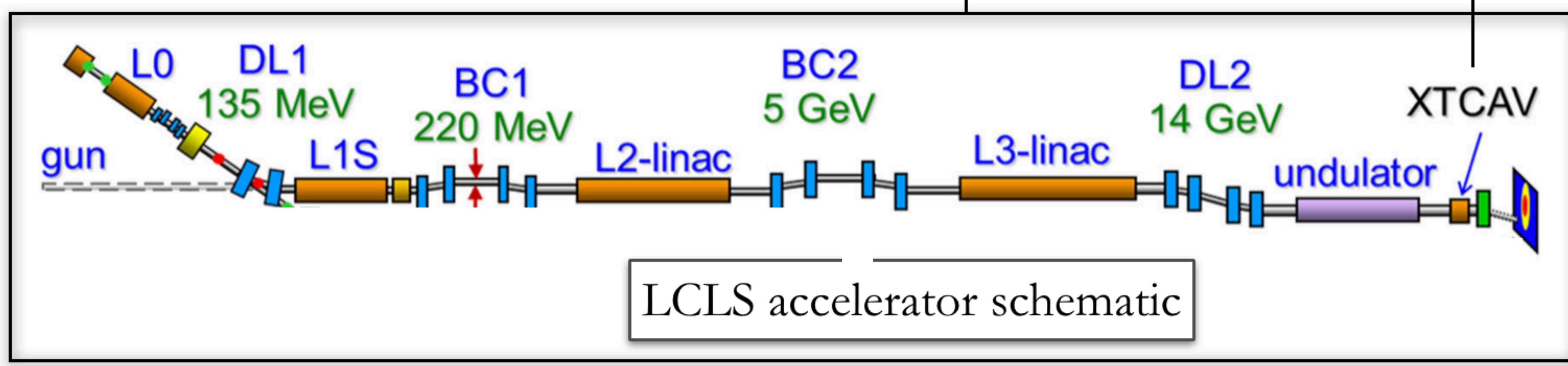
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 Machine learning-based longitudinal phase space prediction of particle accelerators  
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Non-destructive measurements of e-beam and linac parameters

ML based virtual diagnostic



## Project goals

- Implement a single-shot, ML-based virtual diagnostic which predicts the LPS of the e-beam for PWFA experiments.
- Use a ML model with a conventional optimizer to customize the LPS at the IP for different experiments.
- Use a ML-based control policy to maintain the LPS in a fixed state during experiments in the presence of machine drifts.

## Work Plan

- Train ML model using non-destructive accelerator inputs and TCAV images to predict LPS distribution.
- Acquire different LPS images by scanning key accelerator parameters (e.g. linac phases, compression settings).
- Use linac and e-beam diagnostics as inputs. Determine which diagnostics are most critical to prediction accuracy.

## Conclusions/Open Questions

- The predictive model works under tested conditions for LCLS and FACET-II.
- What is the long term accuracy of the trained model?
- How robust is this model against e.g. machine drifts? Does it need to be re-trained to account for them? If so, how often?
- Can you augment datasets with machine and simulation data to predict LPS beyond resolution of the TCAV?

## Recent Results

