Non-destructive electron diagnosis by machine-learning-driven correlation with laser diagnostics

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1. Motivation

Destructive electron spectrometers + Inconsistent LWFA performance

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Applications limited to those that don't care about the electron energies

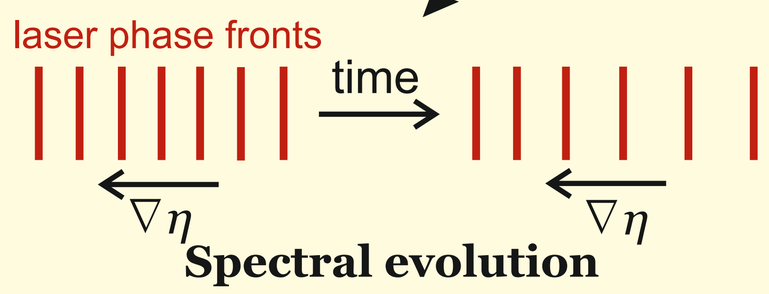
Proposal:
- Use correlations with laser diagnostics as indirect electron measurement.
- Use machine-learning to deal with high non-linearity of correlations.

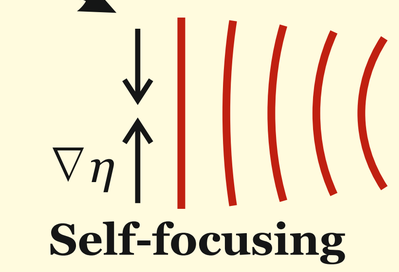
2. Source of correlations

Plasma refractive index: $\eta(z,r) = \left(1 - \frac{\omega_{p,0}^2 n_e(z,r)}{\omega^2 n_{e,0}\gamma(z,r)}\right)^{1/2}$

Axial variations

Radial variations





- Thus density gradients largely determine the laser spectrum and transverse shape.
- The same gradients determine electron acceleration.
- However, complex interplay of effects makes correlations highly non-linear.

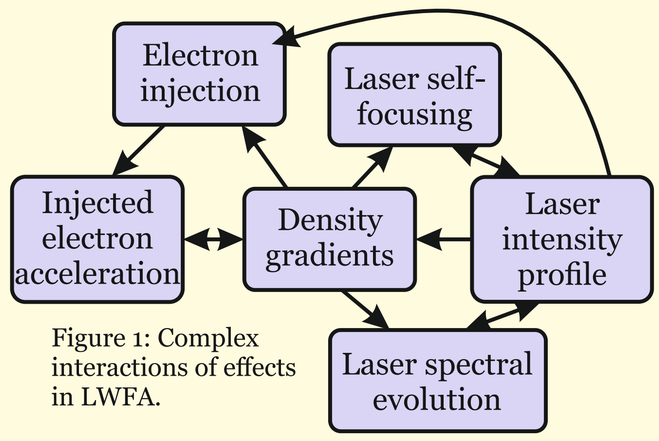


Figure 1: Complex interactions of effects in LWFA.

3. Diagnostic design

For a given LWFA set-up:
1. Measure a large dataset of electron spectra and laser spectra, energy and spot shape post-acceleration.
2. Train model to predict electron spectrum.
3. Remove electron spectrometer and continue with model predictions.

CNN model:

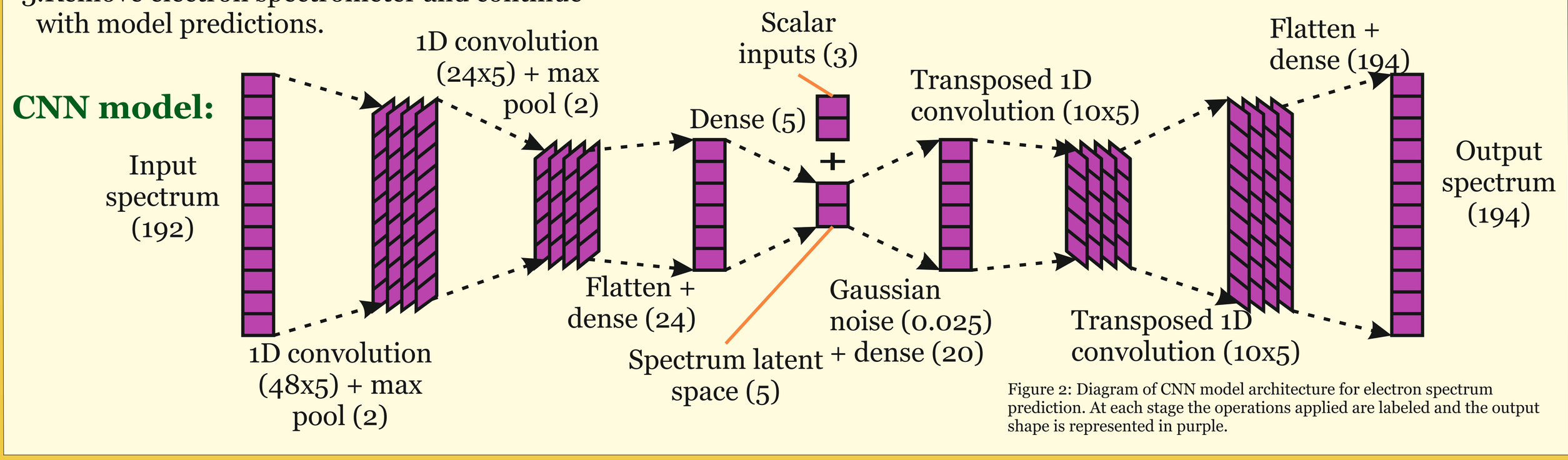


Figure 2: Diagram of CNN model architecture for electron spectrum prediction. At each stage the operations applied are labeled and the output shape is represented in purple.

4. Validation with idealised simulation

- 250 FBPIC simulations of a typical LWFA set-up
- Laser energy, plasma density, and focus z position varied between bounds to mimic random experimental variations
- Outputs processed to be experiment-like (though idealised)

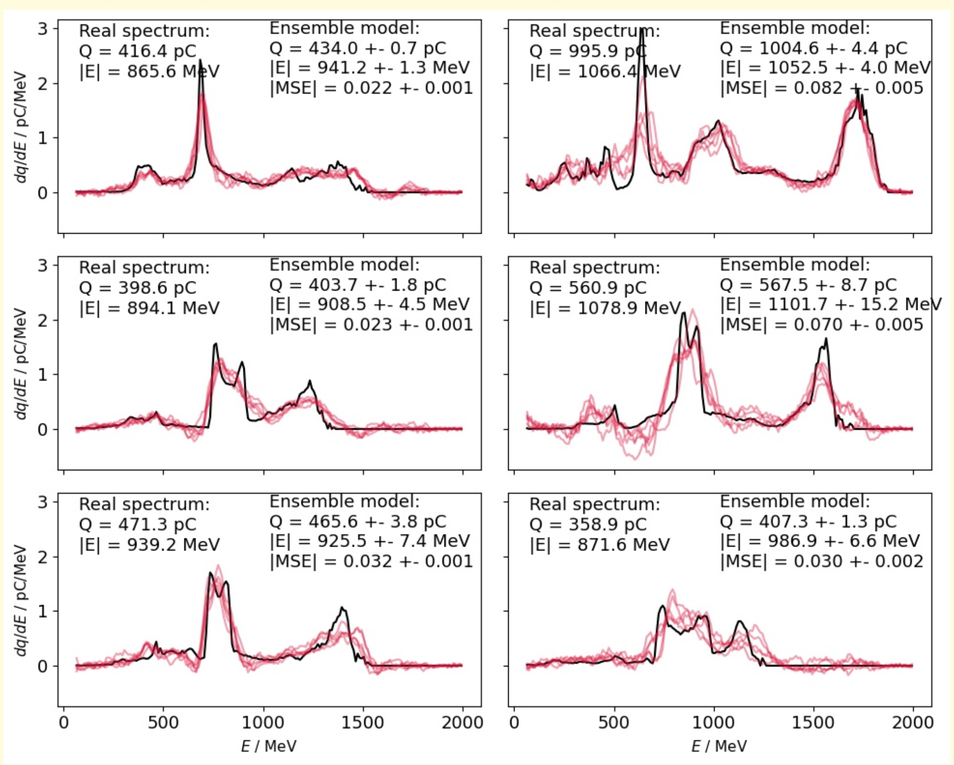


Figure 4 (left): Some example predictions on unseen data.

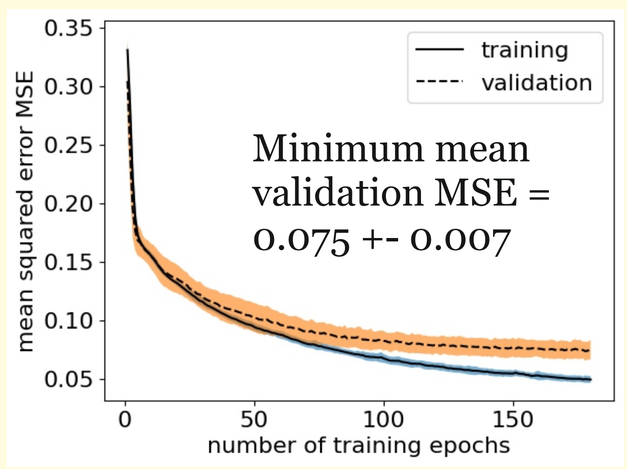


Figure 3 (right): MSE values during training for 250 evenly spread samples.

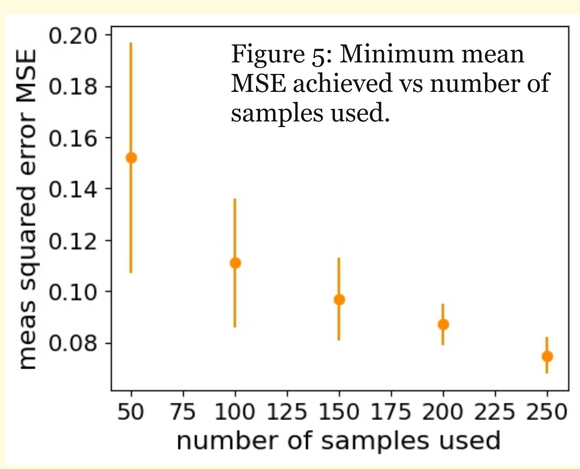


Figure 5: Minimum mean MSE achieved vs number of samples used.

With parameters varied normally (100 samples), mean error is reduced.

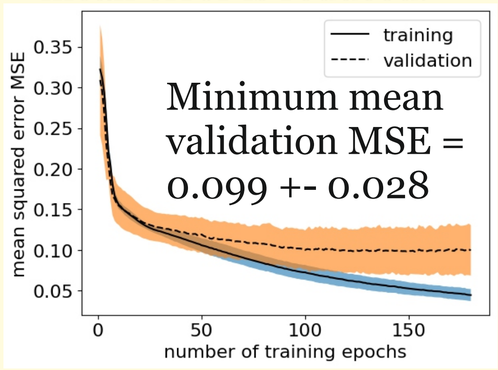


Figure 6: MSE values during training for 100 normally sampled datasets.

With laser spot shape additionally varied (150 samples), we have low error but fast overfitting.

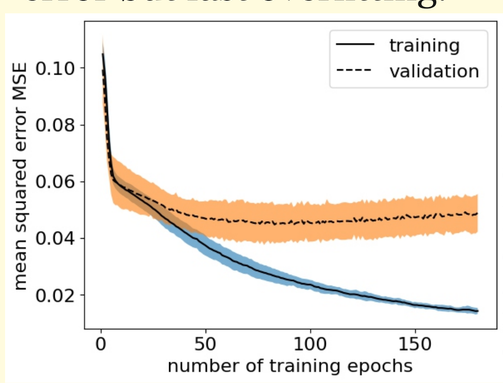


Figure 7: MSE values during training for 150 samples with the fraction of p,m = 0,2 Laguerre-Gaussian mode also varied, to represent spot shape variations.

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