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Developing deep learning algorithms for determining $n_{e,sep}$ at JET

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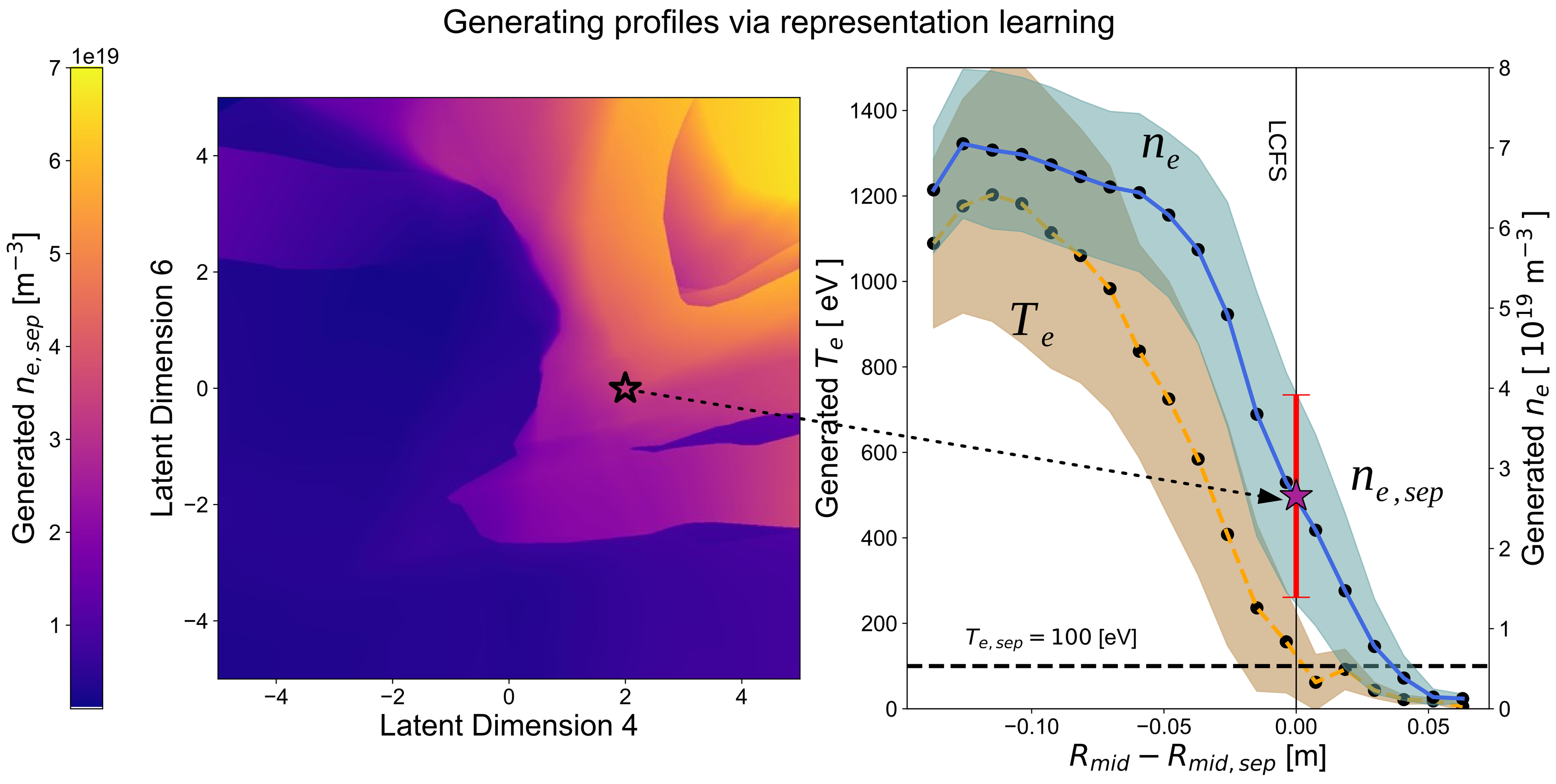
Summary: Machine learning for $n_{e,sep}$ predictions

- A compressed representation of the plasma state is found using weakly supervised deep learning. The representation models the plasma through the density and temperature profiles in the pedestal and is conditioned on machine parameters.
- A tabular dataset consisting of machine parameters, ELM %s, HRTS profiles and $n_{e,sep}$ for 608 pulses at JET was created.
- A mapping of machine parameters and ELM percentage to $n_{e,sep}$ is found using the tabular dataset and a decision tree ensemble.

Generating profiles via representation learning



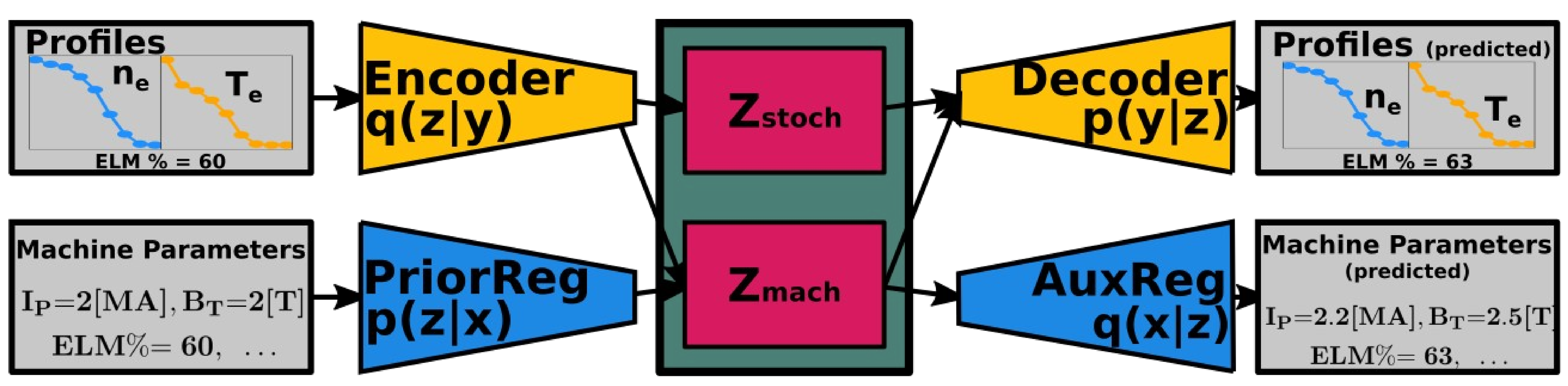
We learn a (low-dimensional) latent variable z representing the plasma profiles. To investigate z, we traverse dimensions 4 and 6 while keeping the remaining dimensions fixed, and visualize the relationship with the inferred $n_{e,sep}$.

Need for predicting separatrix parameters

- Power exhaust in tokamaks is strongly regulated by upstream separatrix densities. PFC design requires accurate modeling of edge/SOL [Stangby 2015]
- Simulations for edge/SOL conditions, e.g., SOLPS, require $n_{e,sep}$ as an input.
- No existing predictive capability from first principles exists for $n_{e,sep}$ outside of emperical log-linear scaling laws (see Frassinetti et. al., 2021, Eich et. al., 2013, Leonard et. al., 2015, Groebner et. al., 2001).

Problem setup

- **Direct mapping**: using a tabular dataset with machine parameters X we learn a function $f: X \rightarrow n_{e,sep}$, using supervised learning via XGBoost, a decision tree ensemble. [XGBoost: Chen, et. al., 2016]
- **Representation learning**: Learn a latent variable z (with prior distribution $p(z) = N(0,1)$) that represents profiles $y: p(y,z) = p(y|z)p(z)$ with variational autoencoder (VAE) framework. Futhermore, also a condition prior on machine parameters, x, i.e., learn $p(z|x)$ through DIVA framework. [VAE: Kingma et. al., 2014, DIVA: Ilse et. al., 2020]



Advantages of mapping profiles using a VAE

- **Probabilistic**: We can quantify the uncertainty in the profile prediction through latent variable z.
- **Latent representation**: Through a compressed representation we can identify nonlinear relations between the plasma state and machine parameters. This representation has potential to be passed to a control-like algorithm.
- **Physical interpretation:** Unlike the direct mapping, we generate a full density and temperature profile which can be inspected

Dataset creation

- Density and temperature profiles from Thomson scattering system and machine parameters from JET pulses
- 608 Pulses • 23500 profiles
- Pulses, fraction of ELM cycle (ELM %), and time slices correspond to a subset of entries in the JET pedestal database [Frassinetti et. al., 2021].
  - H-mode plasmas from JET-ILW that are HRTS validated,
  - Deuterium fuelling, • nitrogen or no seeding,
  - no Kicks, RMPs, or pellets
- Domains of machine parameters [min, max]:

Major radius [m]	2.81, 2.97
Minor radius [m]	0.87, 0.96
Upper triang. [-]	0.08, 0.47
Lower traing. [-]	0.23, 0.49
Elongation [-]	1.59, 1.83
Volume [m^3]	69.44, 80.08
q_{95} [-]	2.41, 5.49

NBI Power [MW]	0.9, 32.1
ICRH Power [MW]	0, 7.32
Ohmic Power [MW]	0.1, 2.27
Toroidal Field [T]	0.96, 3.7
Deut. Fuelling rate [e/s]	0, 1.36e23
Total Current [MA]	0.96, 3.98
ELM % [-]	1, 99

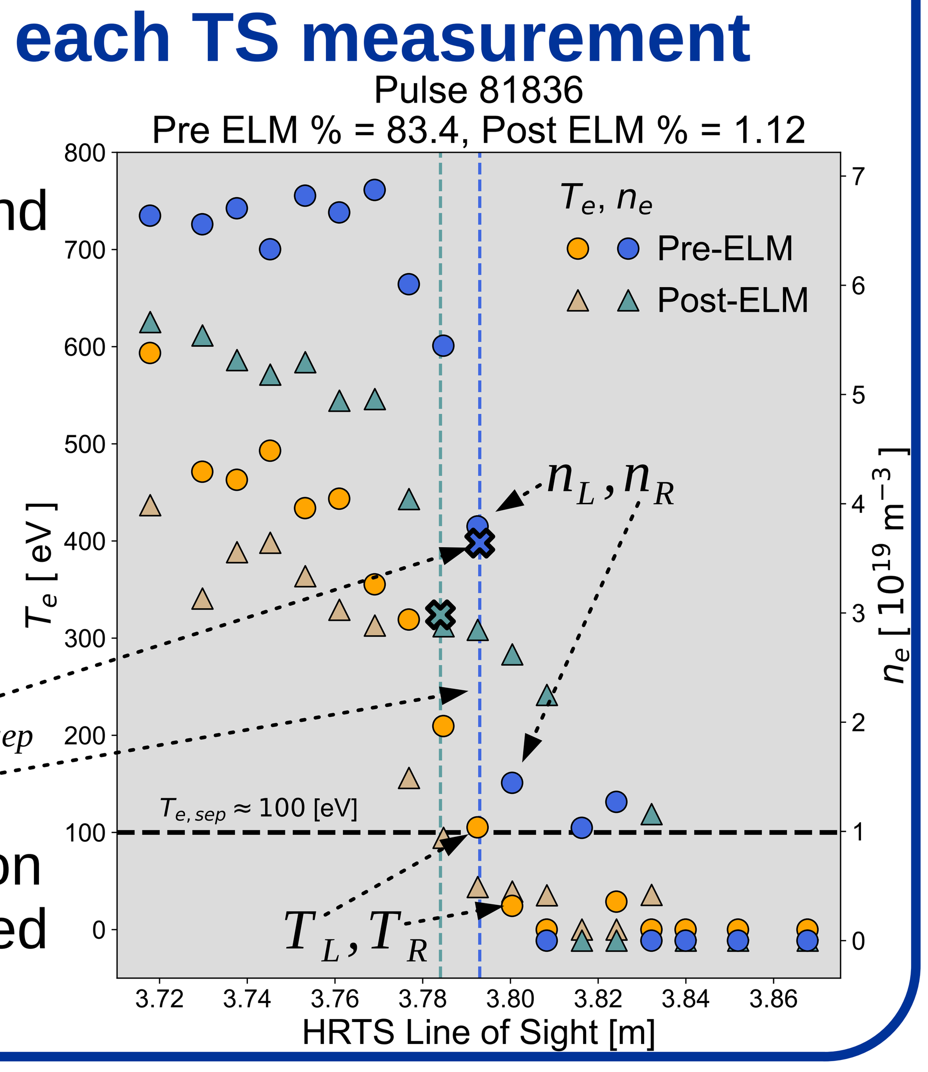
Determining $n_{e,sep}$ for each TS measurement

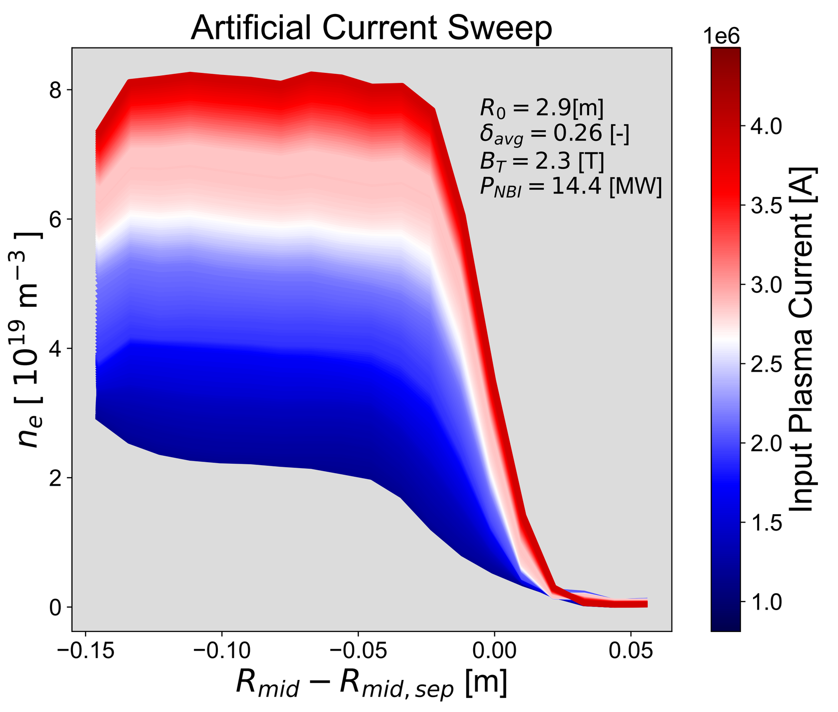
- Initial guess: $r_{sep,0} = \frac{1}{2}(r_{top} + r_{bot})$ where r_{top}, r_{bot} are pedestal top and bottom determined from second derivative of density profile
- Find the closest two temperature points $T_L, T_R \rightarrow T_R < 100\,eV < T_L$
- Find linear approximation

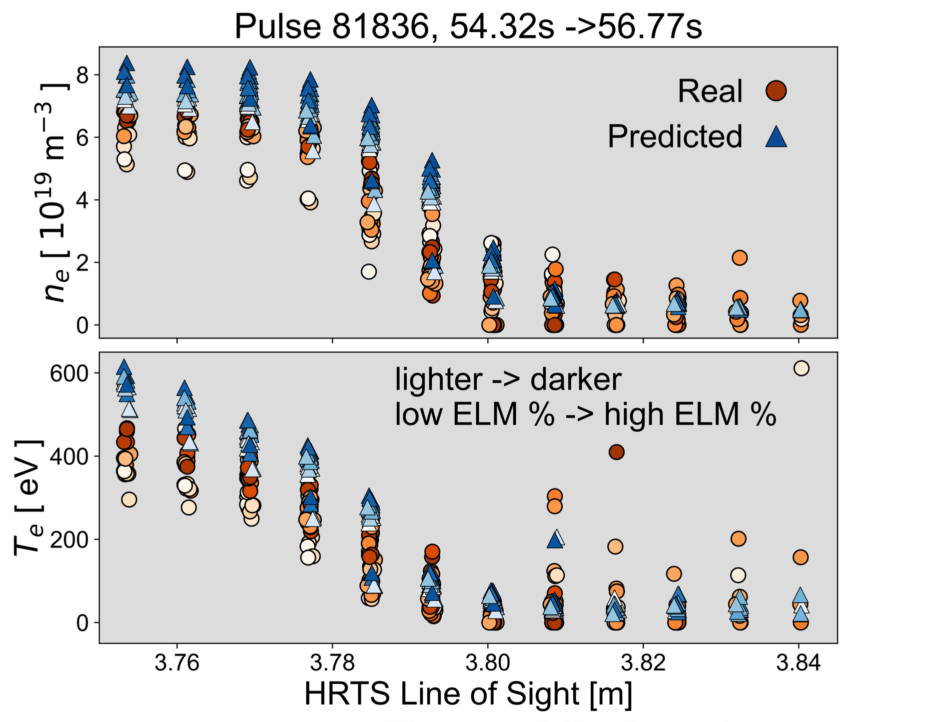
w_L, w_R s.t. $w_L T_L + w_R T_R = 100\,eV$

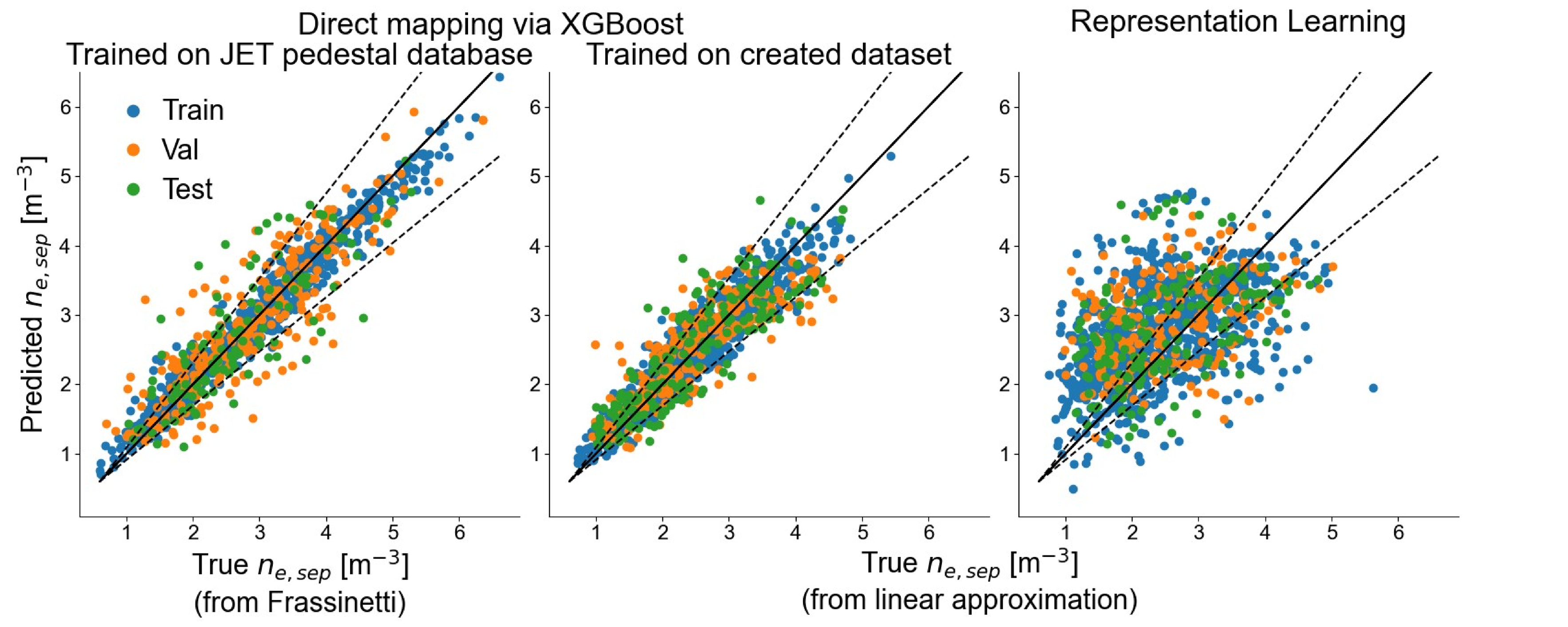
$$w_L + w_R = 1 \Rightarrow \begin{aligned} w_L n_L + w_R n_R &= n_{e,sep} \\ w_L r_L + w_R r_R &= r_{sep} \end{aligned}$$

where n_L, n_R, T_L, T_R are the electron densities and temperatures located at radial positions r_L, r_R









For predicting $n_{e,sep}$, at the moment, a direct mapping model is outperforming a representation learning model, but further optimization of the latter is expected to improve its performance.

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