Task A: Creating a Performance Predictor

Problem description:

- Predict the final performance of a configuration given its first 10 epochs.
- Dataset: 2000 configurations and its learning curves

Final Approach:

- CNN as a feature extractor of the first 10 epochs curves.
- Concatenate the output with the configurations and feed the regressor.
- Optimizer: Adam with cosine annealing warm starts.

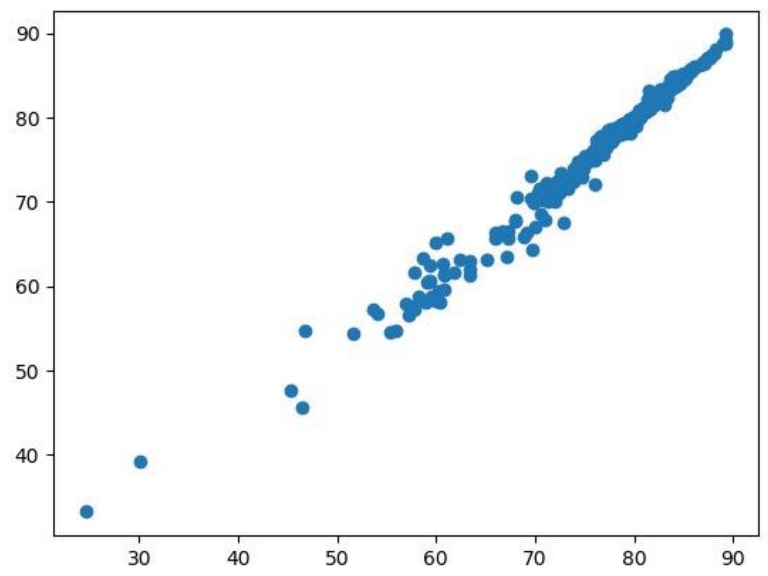
Implemented Ideas

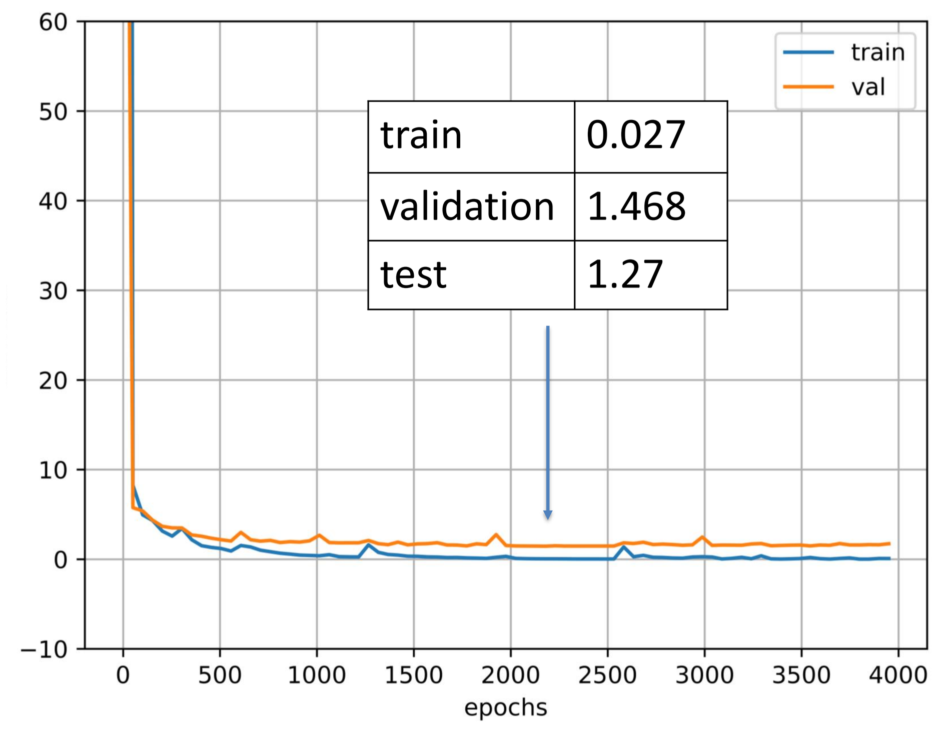
- Curve behavior extraction from Learning curves:

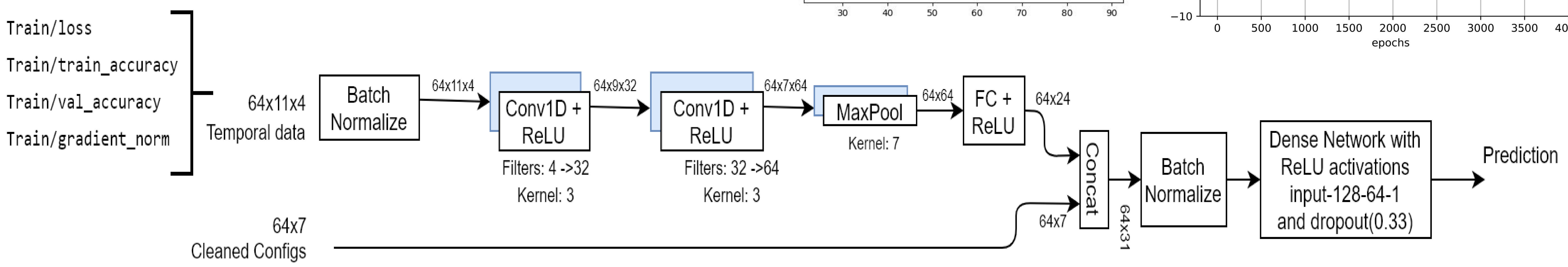
a) Use only 10 epochs using CNNs.

b) Use all 52 epochs available in training data using LSTMs.

- Combine the learned features of the curves with the configurations and feed to a FCNN as a regressor.







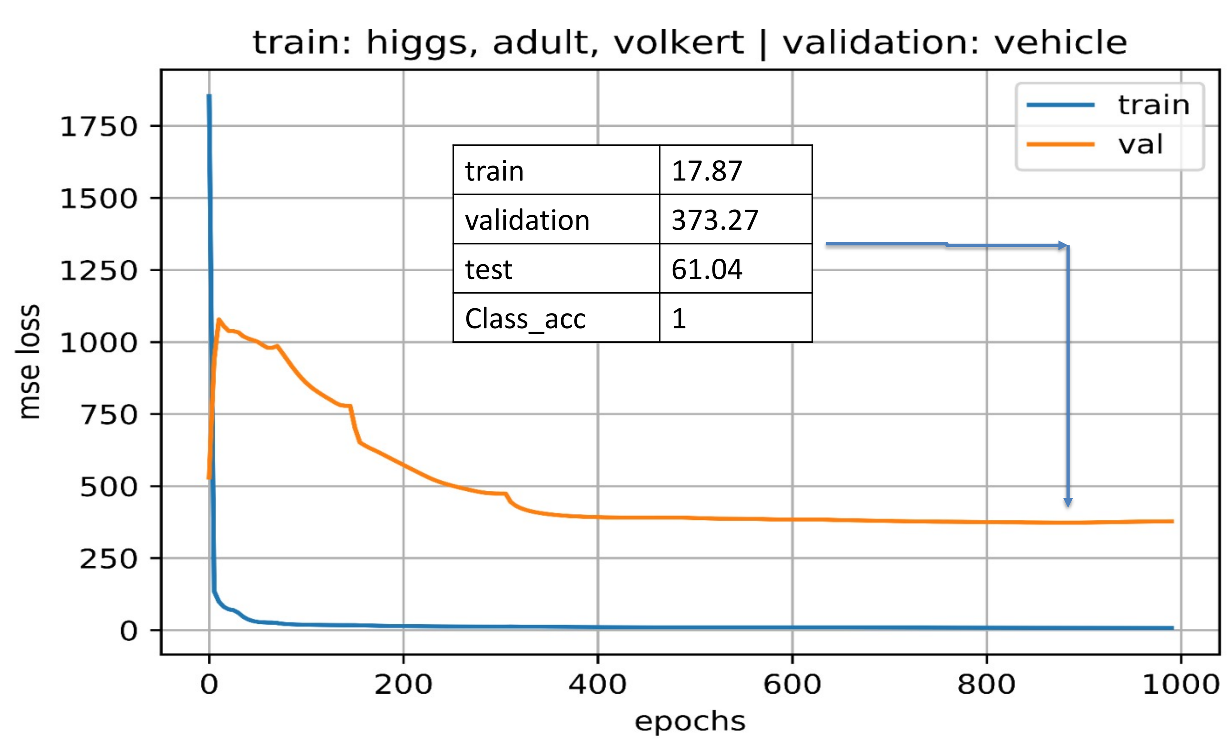
Task B: Meta-Learning Performance Prediction

Problem description:

- Performance predictor for unseen datasets.
- 4 Datasets to train and validate with 2000 configurations each and meta-features to describe the dataset.
- Training datasets: Higgs, Vehicle, Adult, Volkert
- Unseen Test datasets: Fashion-MNIST, Jasmine

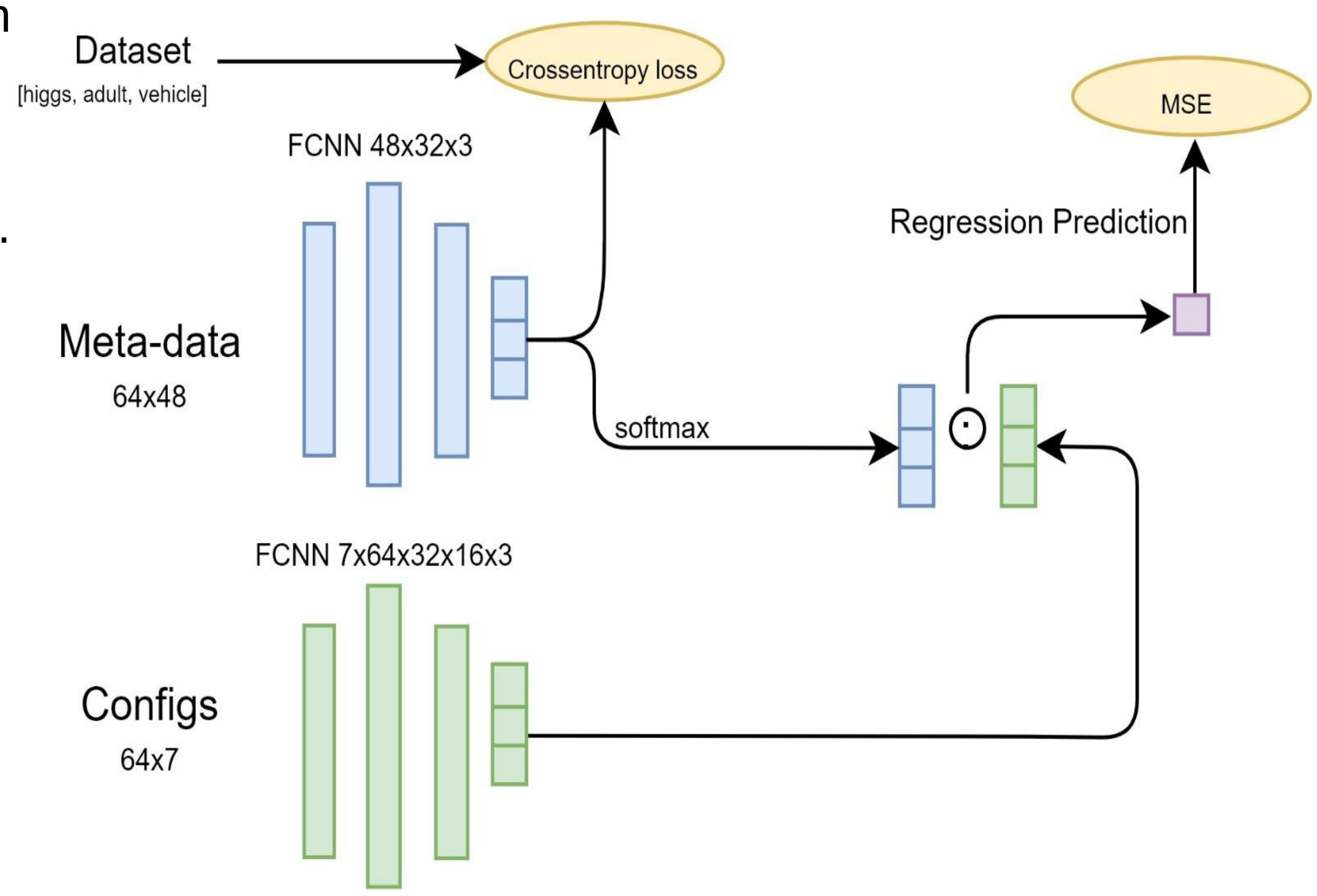
Final Approach:

- Data analysis: Cleaning and Meta-Data Augmentation
- Train with 3 datasets and validate on the 4th unseen dataset. Try all the combinations and pick the best.
- Learn the filter by a NN on the meta-features.
- 3-output-regressor (one per dataset) of configurations.
- Weight the 3-output-regressor with the learned filter
- Optimizer: Adam with cosine annealing warm starts.



Implemented Ideas

- Fully connected NN with all as inputs
- Ensemble of regressors (one per dataset) weighted by similarity between meta-features.
- Regressor on the configurations with a similarity filter based on the meta-features.
- Meta-features data augmentation
- Build a better pipeline to generalize on unseen data and to judge a representative validation loss.



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