Neural Networks: knobs and dials

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SURF

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- number of hidden layers L
- number of hidden units n_1, n_2, …
- dropout (regularization)
- weight initialization
- activation function – tanh, ReLU, …

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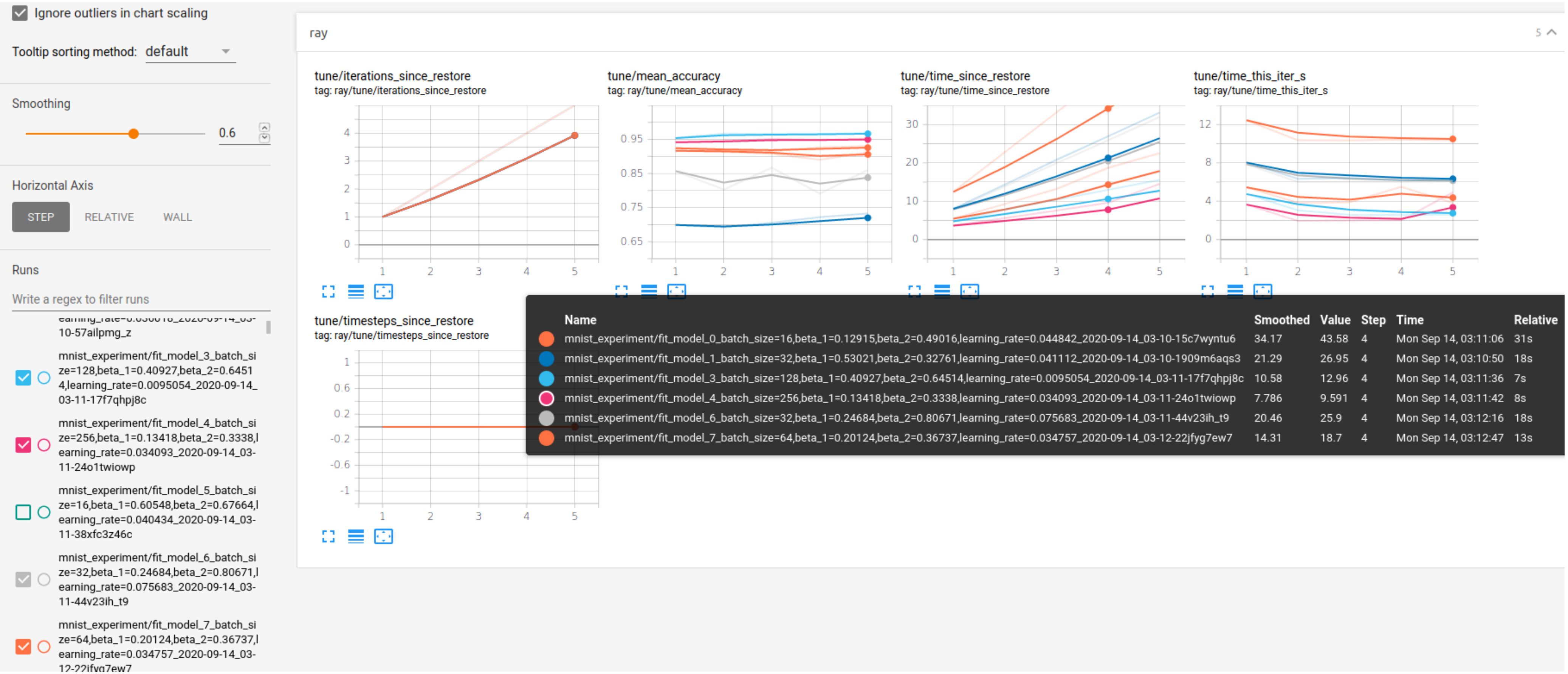
Hyperparameters for the optimization process
- learning rate α
- number of iterations for gradient descent
- momentum
- minibatch size
- number of epochs

Empirical tuning of parameters – Building intuition

Idea → Experiment → Code and repeat



Understanding hyperparameters - Generalization

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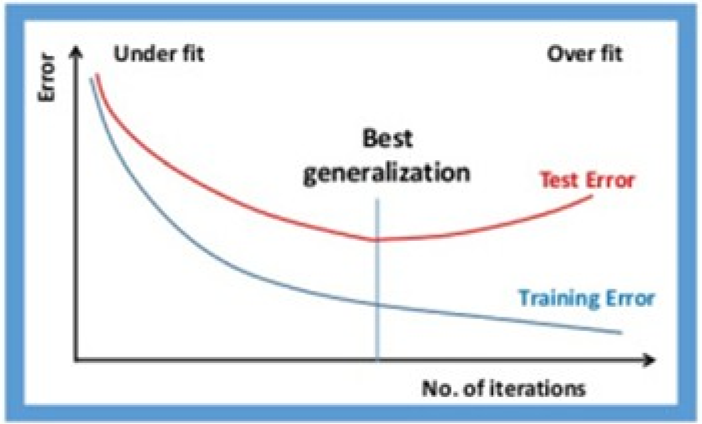
Generalization



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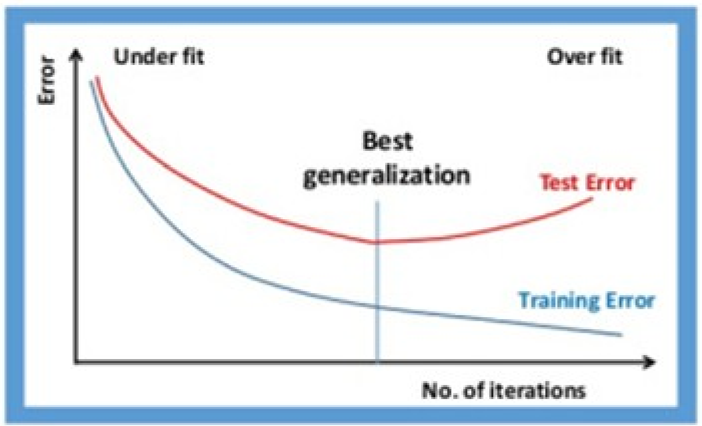

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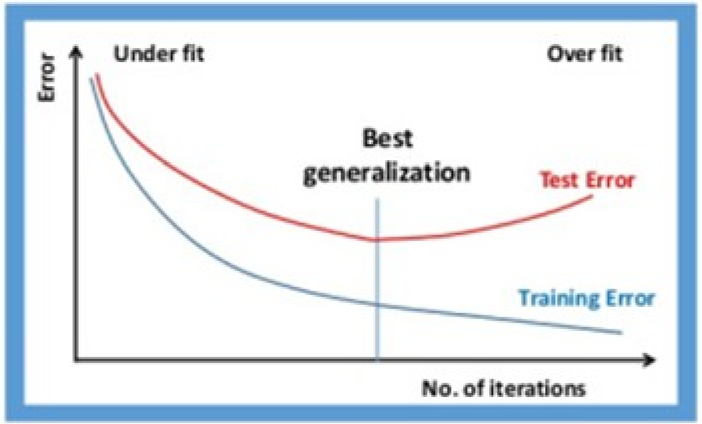

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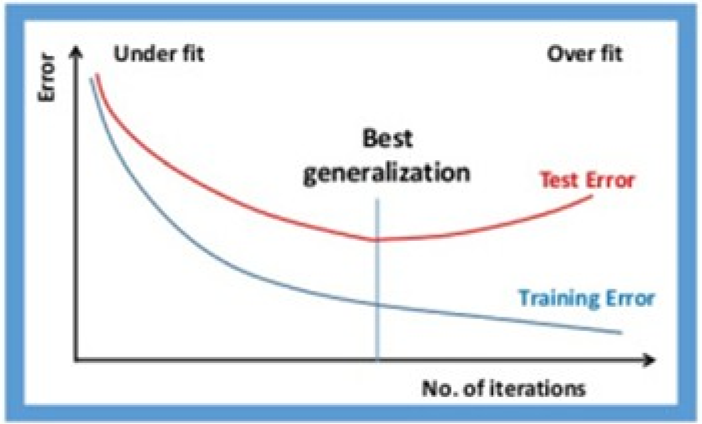

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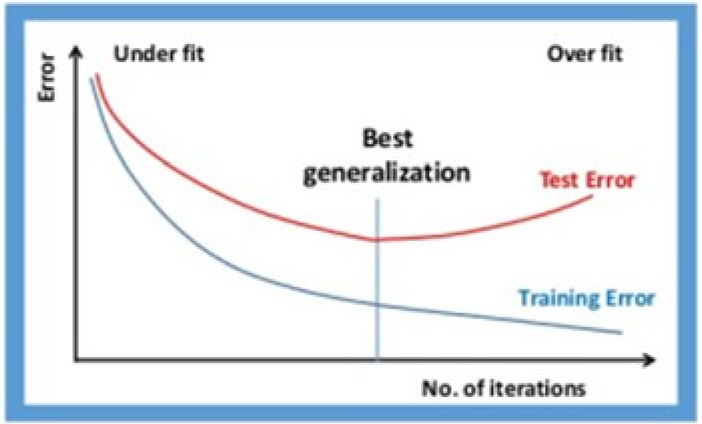

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- Test error vs Hidden units
- Especially interesting in distributed execution environments.
- Many hidden units within a layer with regularization techniques can increase accuracy.
- Optimal stopping time depends on the signal to noise ratio → Low quality data requires longer training time

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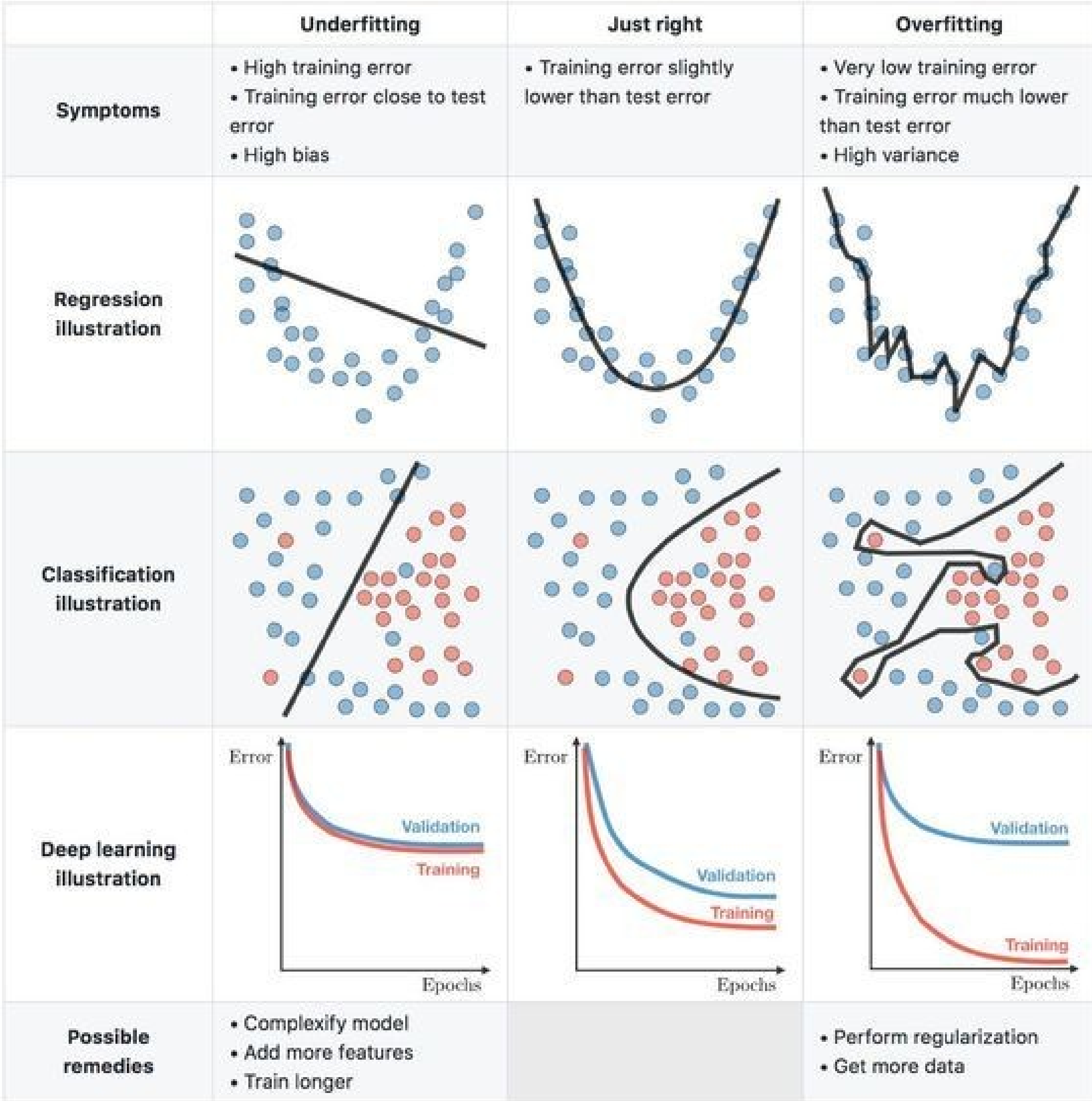
- There are various ways to find the balance of bias and variance for each algorithm family by using methods such as **regularization, pruning**, etc.

Understanding hyperparameters - Overfitting and Underfitting

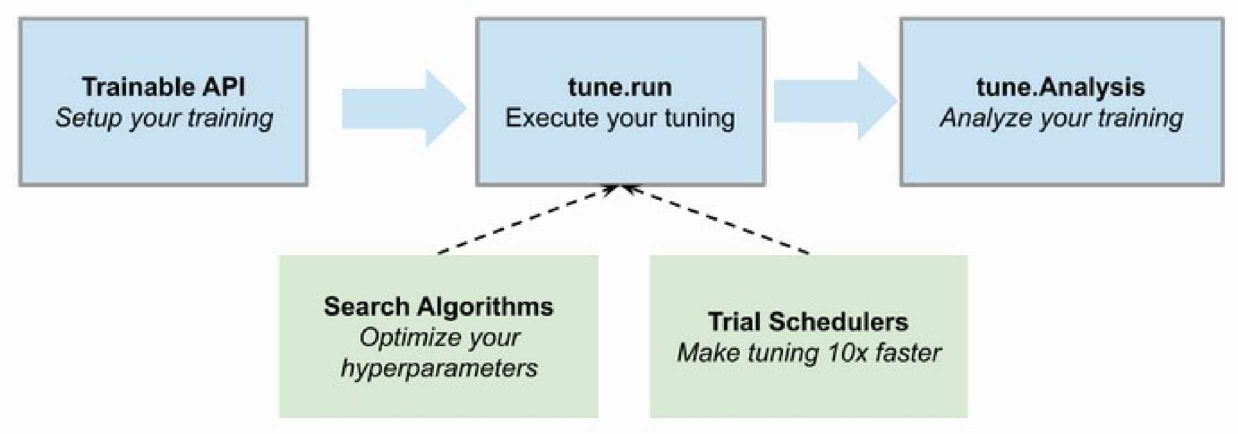
- Overfitting → bad generalization
- Smaller number of units may cause underfitting.
- Dropout is regularization technique to avoid overfitting (increase the validation accuracy) thus increasing the generalizing power. You are likely to get better performance when dropout is used on a larger network, giving the model more of an opportunity to learn independent representations.



	Underfitting	Just right	Overfitting
Symptoms	• High training error • Training error close to test error • High bias	• Training error slightly lower than test error	• Very low training error • Training error much lower than test error • High variance
Regression illustration			
Classification illustration			
Deep learning illustration	Error / Validation / Training / Epochs	Error / Validation / Training / Epochs	Error / Validation / Training / Epochs
Possible remedies	• Complexify model • Add more features • Train longer		• Perform regularization • Get more data

CS 229 - Machine Learning Tips and Tricks Cheatsheet

Tuning parameters with automated tools – Ray Tune



Advanced trial schedulers

- ASHA
- Median Stopping Rule
- HyperBand
- BOHB
- Population Based Training

Many optimization algorithms

- Bayesian Optimization
- Bayesian Opt/HyperBand
- NevergradSearch
- Gradient-free Optimization
- SigOptSearch
- ...

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- Model training will progress very slowly for low learning rates as it would be making tiny adjustments to the weights in the network and it could also lead to overfitting.
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- There are many choices of schedulers.
- The interaction between batch size and learning rate is very important for certain distribution schemes.
- Adaptive learning rate algorithms are prevalent nowadays.

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- Larger batches enable using a large learning rate.
- Larger batch sizes tend to have low early losses while training.
- Final loss values are low when the batch size is reduced.

THANK YOU FOR YOUR ATTENTION

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