

HyperParameter Tuning



Hyper Parameters & Tuning

- 1. Hyper parameters are like handles available to the modeler to control the behavior of the algorithm used for modeling
- 2. Hyper parameters are supplied as arguments to the model algorithms while initializing them. For e.g. setting the criterion for decision tree building "dt_model = DecisionTreeClassifier(criterion = 'entropy')"
- 3. Toget a list of hyper parameters for a given algorithm, call the function get params()...for e.g. to get support vector classifier hyper parameters
 - 1. from sklearn.svm importSVC
 - 2. svc=SVC()
 - 3. svc.get_params()
- 4. Hyper parameters are not learnt from the data as other model parameters are. For e.g. attribute coefficients in a linear model are learnt from data while cost of error is input as hyper parameter.



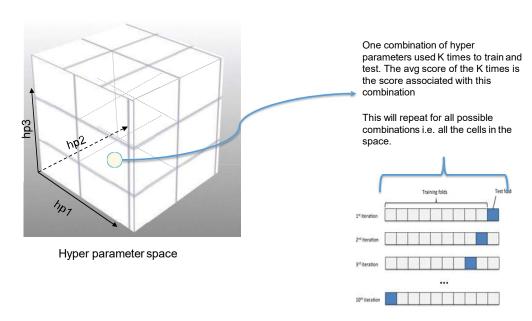
Hyper Parameters & Tuning

- 5. Fine tuning the hyper parameters is done in a sequence of steps
 - 1. Selecting the appropriate model type (regressor or classifier such as sklearn.svm.SVC())
 - 2. Identify the corresponding parameter space
 - 3. Decide the method for searching or sampling parameterspace;
 - 4. Decide the cross-validation scheme to ensure model will generalize
 - 5. Decide a score function to use to evaluate the model
- 6. Two generic approaches to searching hyper parameter space include
 - 1. GridSearchCV which exhaustively considers all parameter combinations
 - 2. RandomizedSearchCV can sample a given number of candidates from a parameter space with a specified distribution.
- 7. While tuning hyper parameters, the data should have been split into three parts Training, validation and testing to **prevent data leak**
- 8. The testing data should be separately transformed * using the same functions that were used to transform the rest of the data for model building and hyper parameter tuning

^{*} Any transformation where rows influence each other. For e.g. using zscore. OneHotCode transformation does not come into this category. It can be done before splitting the data



GridSearchCV





Hyper Parameters & Tuning (GridsearchCV/ RandomizedSearchCv)

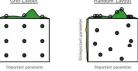
RandomizedSearchCV -

- 1. Random search differs from grid search. Instead of providing a discrete set of values to explore on each hyperparameter (parameter grid), we provide a statistical distribution.
- 2. Values for the different hyper parameters are picked up at random from this combine distribution
- 3. The motivation to use random search in place of grid search is that for many cases, hyperparameters are not *equally* important.

A Gaussian process analysis of the function from hyper-parameters to validation set performance reveals that for most data sets only a few of the hyper-parameters really matter, but that different hyper-parameters are important on different data sets. This phenomenon makes grid search a poor choice for configuring algorithms for new data sets. - Bergstra, 2012

Picture by Bergstra, 2012

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RandomizedSearchCV Randomly pick up n-iter samples from the hyper parameter distribution as sample, Use it K times and find avg performance Hyper parameter space

- 4. In contrast to GridSearchCV, not all combinations are evaluated. A fixed number of parameter settings is sampled from the specified distributions.
- 5. The number of parameter settings that are tried is given by n iter
- 6. If all parameters are presented as a list, sampling without replacement is performed. If at least one parameter is given as a distribution, sampling with replacement is used. It is highly recommended to use continuous distributions for continuous parameters
- 7. Randomsearch has higher chance of hitting the right combination thangridsearch.