



Title: AutoML with Monte Carlo Tree Search and **Neural Network**

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0. Design



- AutoML
- Monte Carlo Tree Search
- MCTML Structure
- MCTML Details
- Evaluation
- Future Work

1. AutoML



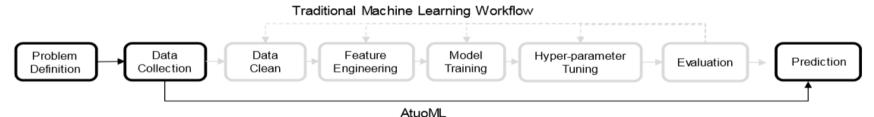


Figure 1.1: Traditional machine learning workflow and AutoML

Task: Algorithm selection and hyperparameter selection --- black box optimization[1]

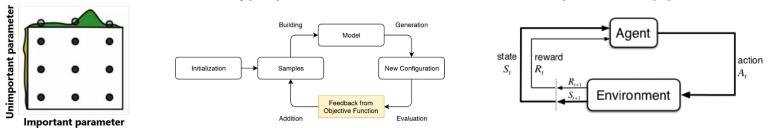


Figure 1.2: Grid Search

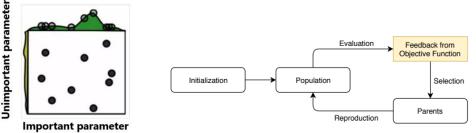


Figure 1.4: Baysian Optimization

MethodToolBaysian OptimizationAutosklearn[2]Genetic AlgorithmTPOT[3]Reinforcement Learning—

Figure 1.5: Reinforcement Learning

Figure 1.3: Random Search

Figure 1.5: Genetic Algorithm

Table 1: AutoML methods and tools

- [1] Automated Machine Learning: Methods, Systems, Challenges, Hutter, Frank, 2018
- [2] Efficient and Robust Automated Machine Learning, Matthias Feurer, Aaron Klein, Katharina Eggensperger,2015
- [3] TPOT: A Tree-Based Pipeline Optimization Tool for Automating Machine Learning, Randal S. Olson, etc., 2019

2. Monte Carlo Tree Search



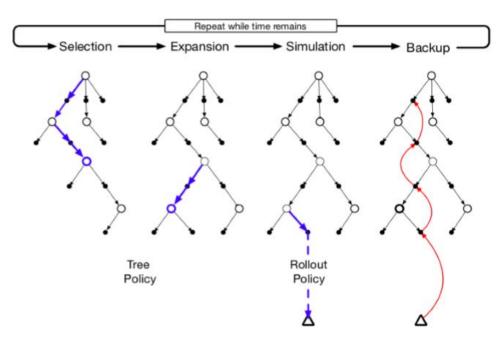


Figure 2.1: Outline of Monte Carlo Tree Search[1]

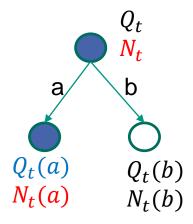


Figure 2.2: Ilussion of parent node and children nodes

$$A_t \doteq \underset{a}{\operatorname{argmax}}[Q_t(a) + c\sqrt{\frac{N_t}{N_t(a)}}]$$

Equation 1: Upper Confidence Bound Algorithm.

Selection: traverses and selects the best-scored child node(UCB algorithm)

Expansion: a new child node is added to the tree

Simulation: choosing moves until a leaf node is achieved

Backup: backprogress the value to each node in trajectory.

[1] Mastering the game of Go with deep neural networksand tree search, David Silver, Aja Huang, 2016

3.1. MCTML

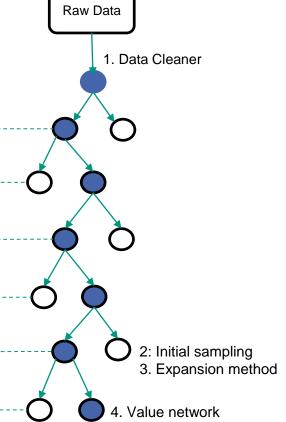


Structure

Data Cleaning (1)

Expasion: different strategy between algorithm and hyperparameter selection (2,3)

Evaluation: 80% training, 20% validation, 5 fold cross validation (4)



Data Processing

Feature Engineering

> Model Selection

Data Hyperparameter

Feature Hyperparameter

Model Hyperparameter

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quantile_range = (25.0, 75.0)

RobustScaler

AdaBoostClassifier

FastICA

n_components =10, algorithm = deflation

n_estimators = 50, learning_rate = 0.01

3.2. Detail of MCTML(1)



- 1. Data cleaner
 - missing value imputation: NaN, ?, -
 - conver non-numerical feature to numerical feature

2. Initial sampling

hyperparameter name	value range	sampled values
$n_{\text{-}}$ estimators	(50,500)	[50,100,200,300,400,500]
learning_rate	(0.01, 2.0)	[0.01, 0.05, 0.1, 0.5, 1.0, 1.5, 2.0]

Table 2 : Example of hyper-parameter samples using initial state sampling method

3.3. Detail of MCTML(2)



3. Expansion algorithm

New parameter: $K = \begin{bmatrix} C_{pw} N^{\alpha} \end{bmatrix}$

When to expand node? All node visited at least 10, and K increase by one Which node to expand? Selection between neighbors and random nodes.

4. Value network

Parameter Name	Value
Neuron Number of input layer	6
Neuron Number of hidden layer 1	10
Neuron Number of hidden layer 2	8
Neuron number of hidden layer 3	4
number of Neuron output layer	1
Optimizer	Adam
Number of epochs	100
Performance function	MSE
Training Goal	0.01

Table 3: Value network parameter setting

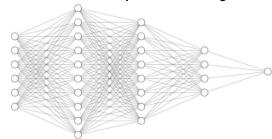


Figure 3.2: Value network structure

```
Algorithm 2 Expansion algorithm
Input: Node N
Output: new action A_{sug}
 1: function Progressive Widening(N)
        for t = 0, 1, 2, 3... do
            Let k = \lceil c_{pw} t^{\alpha} \rceil, A_{best} = \max_{n} Q_n, Q_{mean} = \frac{\sum_{n=1}^{n=N} Q_n}{\sum_{n=1}^{n=N} Q_n}
 3:
            if N_{Node} > 10 and k increase by 1 then
 4:
                 Find 2 neighbors A_{n1}, A_{n2}, 2 random samples A_{s1}, A_{s2}.
 5:
                 choose the best evaluated sample A_{sug} and its evaluation Q_{A_{sug}}.
 6:
                 if Q_{A_{sug}} > Q_{mean} then
 7:
                     return A_{sug}
                 end if
 9:
             else
10:
11:
                 return A_{best}
             end if
12:
         end for
14: end function
```

Figure 3.1: Expansion Algorithm

4.1. Evaluation Environment



Smart Data Innovation Lab Platform: 1 core with 4GB RAM.

Search space: 5/5/14 (53)

Data processor: 5

Feature Engineering: 5

Model: 14

Hyperparameter: 53

Dataset: OpenML CC18 suite

Name	Sample	Features	Class	Missing value
texture	5500	40	11	1 = 10
segment	2310	19	7	-1
wilt	4839	6	2	- 0
car	1728	6	4	X
PhishingWebsites	11055	30	2	-

Table 3: Example of datasets properties from CC18 suite.

Name	Step	$\#\lambda$
quantile	Data	2
norm	Data	1
minmax	Data	1
robust	Data	1
stand	Data	-
Fastica	Feature	$\bar{3}$
PCA	Feature	2
Polynomial	Feature	3
Agglomeration	Feature	1
KernelPCA	Feature	1
AdaBoost	Model	3
Bernoulli	Model	2
decision tree	Model	3
extra tree	Model	2
Gaussian naive Bayes	Model	1
Gradient boosting	Model	4
KNN	Model	3
LDA	Model	3
Linear SVC	Model	2
SVC	Model	3
Multinomial naive Bayes	Model	2
Passive aggressive	Model	4
QDA	Model	2
random forest	Model	4

Table 4 : Default search space, # means number of hyperparameters



4.2. Evaluation Results



Default setting

	Baseline	AutoSklearn	MCTML
Candidate models	SGD	Search Space	Search Space
Default parameter	learning rate = 0.0001 penalty = 12 loss function = hinge	ensemble size=1 meta learning = 0	$c = 2$ $c_{pw} = 4$ $\alpha = 0.3$
Variable parameter	_	total time $= 30$ min	total time $= 30$ min

Table 5 : Default setting of methods Baseline, AutoSklearn and MCTML

- Performance: $F1 = 2 * \frac{Precision * Recall}{Presion + Recall}$
- Stability: 5 runs variance
- Evaluation summary

	Baseline	AutoSklearn	MCTML
Performance	0	14	16
Stability	_	12	22

Table 6: Statistical summary of performance and stability

Dataset	MCTML	AutoSklearn
car	0.986	0.938
churn	0.987	0.335
climate	0.975	0.842
cnae-9	0.792	0.569
cylinder-bands	0.632	0.831
balance-scale	0.944	0.962
fourier	0.921	0.802
karhunen	0.950	0.658
satimage	0.899	0.766
morphological	0.840	0.752
eucalyptus	0.905	0.662
zernike	0.818	0.735
optdigits	0.980	0.948
pendigits	0.982	0.750
diabetes	0.952	0.463
spambase	0.934	0.851
splice	0.095	0.629
tic-tac-toe	0.972	0.488
letter	0.889	0.748
dna	0.588	0.331
first-order	0.518	0.490
jm1	0.466	0.518
kc1	0.326	0.413
kc2	0.419	0.435
plxel	0.892	0.811
MiceProtein	0.991	0.877
phpJNxH0q	0.954	0.897
ozone-level-8hr	0.818	0.666
pc1	0.286	0.306
pc3	0.195	0.425
PhishingWebsites 1	0.925	0.905
qsar-biodeg	0.868	0.631
segment	0.957	0.900
semeion	0.812	0.836
wall-robot	0.923	0.839
wdbc	0.963	0.941
wilt	0.975	0.857

Table 7: F1 score on all dataset of methods MCTML and Autosklearn

5. Future Work



- Regression tasks --- change task type
- Initial state sampling --- meta learning
- Value network --- pipeline convertion and structure
- More evaluation methods & Bigger search space

Thanks



