

Variable Interaction Learning in Cooperative Coevolution

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Outline

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 - Why We Need To Explore Interdependency In Optimization?
 - Overview on Interdependence
- 2 CCVIL: A NOVEL CC-BASED FRAMEWORK
 - Cooperative Coevolution
 - Variable Interaction Learning
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 - Experimental Studies
- 3 FUTURE WORK: THE ROAD AHEAD
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Warming-Up: A Fabricated Problem

PROBLEM

Suppose that we are faced with:

- a **fully-decomposable** problem
- its dimension is D
- domains for each dimension are the same, say $[1, \dots, N]$

Significantly Reduce The Hardness of Optimizing Decomposable Problems by . . .

DIVIDE-AND-CONQUER

- For conventional Approach:
 - The size of search space grows exponentially with D increasing
 - $\text{Comp}(N) = N^D$
- For Divide-and-Conquer Approach:
 - The size of search space grows linearly with D increasing
 - $\text{Comp}(N) = N \times D$

What If **No** Prior Informations Are Given?

BLACK-BOX OPTIMIZATION

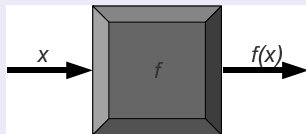


FIGURE: Illustration of BlackBox

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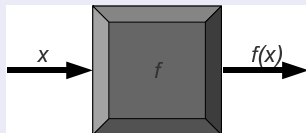


FIGURE: Illustration of BlackBox

GUESS BY LEARNING INTERDEPENDENCE

In order to apply Divide-and-Conquer approach in such case, we need the **Interdependence Learning**, which:

- reduces the complexity of optimization
- doesn't affect the quality of solution greatly

Interdependency from three different but related views

INTERDEPENDENCE IN NATURE AND EC

Interdependence		
Biology	Evolutionary Computation	
	Binary Representation	Real-Value Representation
Epistasis[6][4]	Linkage[5][3][2]	Variable Interaction[1][11]

NOTE:

- Numerous studies have been devoted to study on Linkage.
- The red part is what we are focus on.

What is CC?

COOPERATIVE COEVOLUTION[7][9][8]

- divide the decision vector into groups of variables
- evolve each sub-population by groups
- combine the best representatives from all other dimensions to compose the vector for fitness evaluation

Why is CC?

PROBLEM DOMAIN

We focus on tackling **Large-Scale** Numerical Optimization(LNGO), in which:

- landscapes of fitness functions become more complex
- search space and computational effort grow exponentially

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PROMISING SOLUTION: COOPERATIVE COEVOLUTION

- reduce the computational complexity significantly
- speed up the convergence of the search procedure
- easy to maintain the quality for highly separable problems

Drawbacks of the Current CC-based Algorithms

DRAWBACKS

- do not consider the separability
- easy to trap in local optimum
- seriously affects the quality of the solution

which make it unpractical to apply CC-based algorithms in the complex, non-separable problems.

A Way Out: Learning the Separability of Problem

ASSUMPTION

We start by assuming all pair of variables are independent.

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OUR TARGET

- 1 provide a fine-grain learning mechanism on the separability
- 2 every variable interaction learned by the mechanism should be correct
- 3 make use of the separability information gathered by learning

Theoretical Base For Our Learning Mechanism

DEFINITION

A function is **separable**, if it satisfies the Equation 1. [10]

$$\arg \min_{(x_1, \dots, x_N)} f(x_1, \dots, x_N) = \left(\arg \min_{(x_1)} f(x_1, \dots), \dots, \arg \min_{(x_N)} f(\dots, x_N) \right) \quad (1)$$

A separable function can be optimized dimension by dimension.

Theoretical Base For Our Learning Mechanism

DEFINITION 1

Two decision variables i and j are **interacting** if there is a decision vector \vec{x} whose i^{th} and j^{th} variable can be substituted with values x'_i and x'_j so that Equation holds.[11]

$$\exists \vec{x}, x'_i, x'_j: f(\boxed{x_1, \dots, \boxed{x_i}, \boxed{}, \boxed{x_j}, \dots, x_n}) < f(\boxed{x_1, \dots, \boxed{x'_i}, \boxed{}, \boxed{x_j}, \dots, x_n}) \wedge$$

$$f(\boxed{x_1, \dots, \boxed{x_i}, \boxed{}, \boxed{x'_j}, \dots, x_n}) > f(\boxed{x_1, \dots, \boxed{x'_i}, \boxed{}, \boxed{x'_j}, \dots, x_n})$$

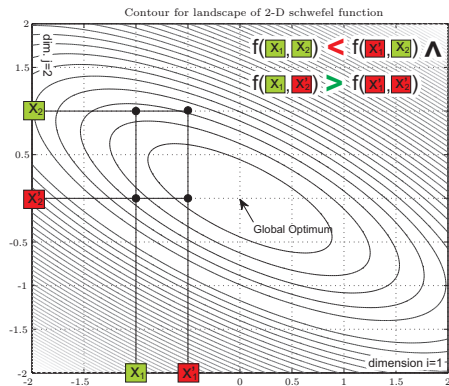
Any interacting variables should be put together in the same sub-population.

Example of Variable Interaction Learning

EXAMPLE

As shown in Figure. 5,

- 1 suppose we start with (x_1, x_2) and (x'_1, x'_2) , the Global Optimum is located in $(0,0)$, and it is a minimization problem

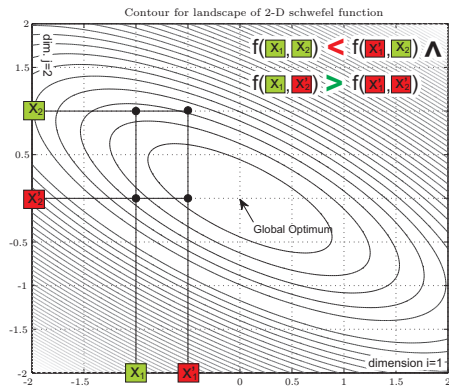


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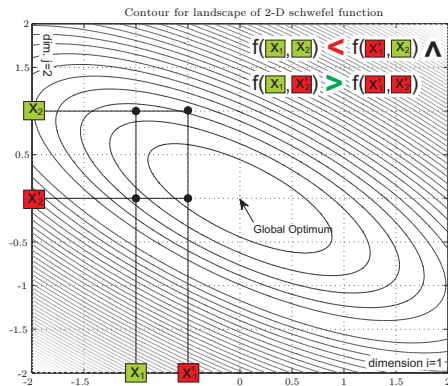


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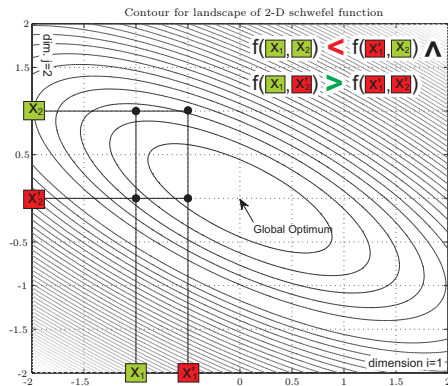


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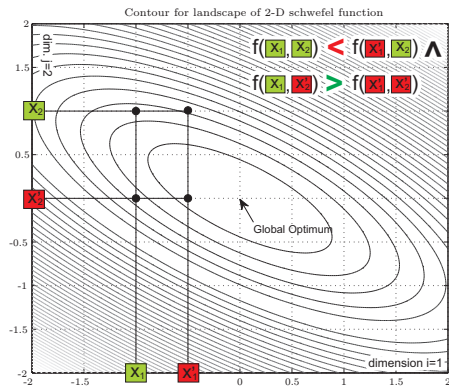


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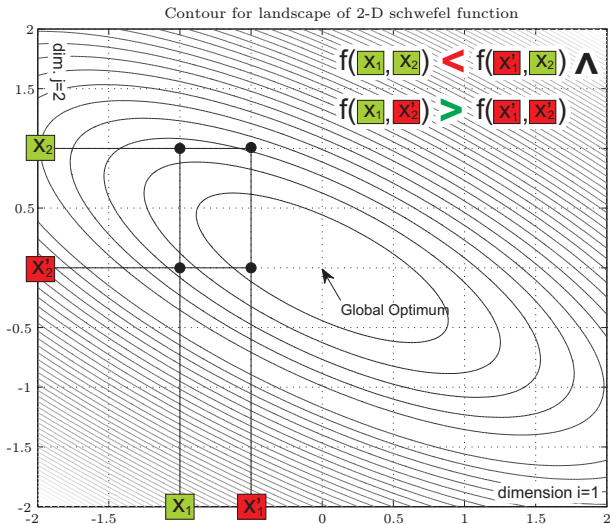
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- 4 the relation changes, $f(x_1, x'_2) \geq f(x'_1, x'_2)$
- 5 Intuitively, there are variable interactions in 2-D Schwefel Function



Example of Variable Interaction Learning (Zoom In)

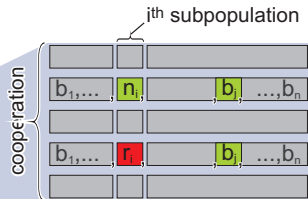


How Does Learning Mechanism Works?

\vec{b} best vector found so far

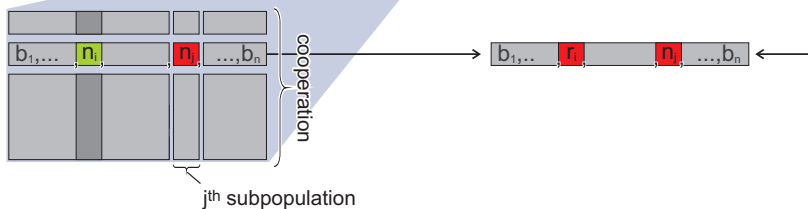
n_i, n_j best values found for dimensions
 i and j by optimizing subpopulations
 i and j

r_i random pick from subpopulation i
 $r_i \neq n_i$



$$\exists \vec{x}, x'_i, x'_j: f(x_1, \dots, x_i, \dots, x_j, \dots, x_n) < f(x_1, \dots, x'_i, \dots, x_j, \dots, x_n) \wedge$$

$$f(x_1, \dots, x_i, \dots, x'_j, \dots, x_n) > f(x_1, \dots, x'_i, \dots, x'_j, \dots, x_n)$$



Our Contribution: Avoid Type II Error Completely

IN THE WORK BY WEICKER [11]

- examine dimension i and dimension j , which are selected totally randomly
- it can **violates** the condition of Definition 1
- may lead to detection of non-existing variable interaction

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OUR CONTRIBUTION

- only tests the currently and the previously optimized dimension for interaction
- The condition of Definition 1 can never be violated and only becomes true for real interactions
- the flaw of detecting non-existent interactions(the type II error) is avoided

CCVIL: A Two Stage Approaches

1 Learning Stage

- population size = 3, generation limit for each subcomponent = 1 → reduce the overhead of learning
- population re-initialization in each cycle → avoid possible premature convergence
- the sequence of the dimensions to optimize is randomly permuted in each cycle → every pair of variables shares equal chance to examine interaction
- store the learned interaction knowledge in *groupInfo*

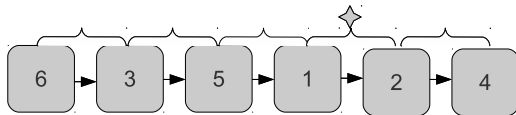
2 Optimization Stage

- apply a certain EA as the sub-optimizer
 - in my case, it is JADE [14]
- evolve the sub-population in CC with respect to *groupInfo*

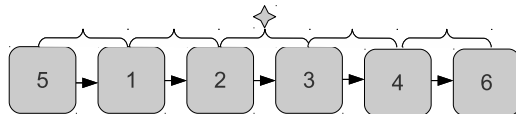
Example of Learning Procedure in CCVIL

Real Interaction: $\{\{1, 2, 3\}, \{4, 5\}, \{6\}\}$

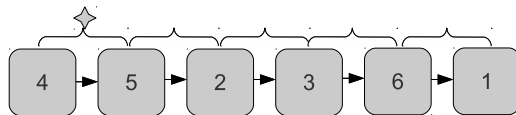
$\{\{1\}, \{2\}, \{3\}, \{4\}, \{5\}, \{6\}\}$



$\{\{1, 2\}, \{3\}, \{4\}, \{5\}, \{6\}\}$



$\{\{1, 2, 3\}, \{4\}, \{5\}, \{6\}\}$



$\{\{1, 2, 3\}, \{4, 5\}, \{6\}\}$

How Learning Works: Efficiency of Learning

Assume that we are faced with an N -dimension problem:

- 1 probability of placing dimensions i and j adjacently in one random permutation is $2/N$
- 2 probability $p_{capt}(K)$ that 1 happens in at least once in K learning cycles then is given in Equation 2.

$$p_{capt}(K) = 1 - (1 - 2/N)^K \quad (2)$$

- 3 $p_{capt}(500)=0.6325$, $p_{capt}(800)=0.7984$
 - **from learning perspective**, it is always better to have more cycles

No Free Lunch: The Learning Overhead

Appropriate setting for learning cycle can deal with both separable functions and non-separable functions:

FOR SEPARABLE FUNCTIONS

- set up a lower bound \check{K} for cycle of learning
 - if no interactions were learned by then, we treat it as **separable** function, and switch to optimization stage at once

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FOR NON-SEPARABLE FUNCTIONS

If any interaction has been learned before reaching the \check{K} cycles, we treat it as a **non-separable** function. In this case, learning stage only stops if:

- all N dimensions have been combined into one group
- 60% of fitness evaluation has been consumed in learning stage

Benchmark Function

From CEC'10 Special Session of large-scale global optimization [10]. The major features of them can be concluded as follow:

	Function	Sep	Multi modal	Groups	
				real	found
f_1	Shifted Elliptic Function	Yes	No	1000	1000
f_2	Shifted Rastrigin's Function	Yes	Yes	1000	1000
f_3	Shifted Ackley's Function	Yes	Yes	1000	969
f_4	Single-group Shifted 50-rotated Elliptic Function	No	No	951	963
f_5	Single-group Shifted 50-rotated Rastrigin's Function	No	Yes	951	952
f_6	Single-group Shifted 50-rotated Ackley's Function	No	Yes	951	921
f_7	Single-group Shifted 50-dimensional Schwefel's	No	No	951	952
f_8	Single-group Shifted 50-dimensional Rosenbrock's	No	Yes	951	1000
f_9	10-group Shifted 50-rotated Elliptic Function	No	No	510	627
f_{10}	10-group Shifted 50-rotated Rastrigin Function	No	Yes	510	516
f_{11}	10-group Shifted 50-rotated Ackley Function	No	Yes	510	501
f_{12}	10-group Shifted 50-dimensional Schwefel's	No	No	510	522
f_{13}	10-group Shifted 50-dimensional Rosenbrock's	No	Yes	510	1000
f_{14}	20-group Shifted 50-rotated Elliptic Function	No	No	20	232
f_{15}	20-group Shifted 50-rotated Rastrigin's Function	No	Yes	20	37
f_{16}	20-group Shifted 50-rotated Ackley Function	No	Yes	20	39
f_{17}	20-group Shifted 50-rotated Schwefel's Function	No	No	20	42
f_{18}	20-group Shifted 50-rotated Rosenbrock's Function	No	Yes	20	1000
f_{19}	Shifted Schwefel's Function 1.2	No	No	1	1
f_{20}	Shifted Rosenbrock's Function	No	Yes	1	1000

Experimental Result

TABLE: Comparison with other CC-based algorithms and plain JADE.

	CCVIL		DECC-G		MLCC		R_1	Naive JADE		R_2
	Mean	Std Dev	Mean	Std Dev	Mean	Std Dev		Mean	Std Dev	
f_1	1.55e-17	7.75e-17	2.93e-07	8.62e-08	1.53e-27	7.66e-27	-	1.57e+04	1.38e+04	W
f_2	6.71e-09	2.31e-08	1.31e+03	3.24e+01	5.55e-01	2.20e+00	W	7.66e+03	9.67e+01	W
f_3	7.52e-11	6.58e-11	1.39e+00	9.59e-02	9.86e-13	3.69e-12	L	4.52e+00	2.41e-01	W
f_4	9.62e+12	3.43e+12	5.00e+12	3.38e+12	1.70e+13	5.38e+12	W	6.14e+09	3.81e+09	L
f_5	1.76e+08	6.47e+07	2.63e+08	8.44e+07	3.84e+08	6.93e+07	W	1.35e+08	1.21e+07	L
f_6	2.94e+05	6.09e+05	4.96e+06	8.02e+05	1.62e+07	4.97e+06	W	1.94e+01	1.79e-02	-
f_7	8.00e+08	2.48e+09	1.63e+08	1.38e+08	6.89e+05	7.36e+05	-	2.99e+01	3.30e+01	-
f_8	6.50e+07	3.07e+07	6.44e+07	2.89e+07	4.38e+07	3.45e+07	-	1.19e+04	4.92e+03	L
f_9	6.66e+07	1.60e+07	3.21e+08	3.39e+07	1.23e+08	1.33e+07	W	2.70e+07	2.08e+06	L
f_{10}	1.28e+03	7.95e+01	1.06e+04	2.93e+02	3.43e+03	8.72e+02	W	8.50e+03	2.30e+02	W
f_{11}	3.48e+00	1.91e+00	2.34e+01	1.79e+00	1.98e+02	6.45e-01	W	9.29e+01	9.66e+00	W
f_{12}	8.95e+03	5.39e+03	8.93e+04	6.90e+03	3.48e+04	4.91e+03	W	6.21e+03	1.34e+03	-
f_{13}	5.72e+02	2.55e+02	5.12e+03	3.95e+03	2.08e+03	7.26e+02	W	1.87e+03	1.11e+03	W
f_{14}	1.74e+08	2.68e+07	8.08e+08	6.06e+07	3.16e+08	2.78e+07	W	1.00e+08	8.84e+06	L
f_{15}	2.65e+03	9.34e+01	1.22e+04	9.10e+02	7.10e+03	1.34e+03	W	3.65e+03	1.09e+03	W
f_{16}	7.18e+00	2.23e+00	7.66e+01	8.14e+00	3.77e+02	4.71e+01	W	2.09e+02	2.01e+01	W
f_{17}	2.13e+04	9.16e+03	2.87e+05	1.97e+04	1.59e+05	1.43e+04	W	7.78e+04	5.87e+03	W
f_{18}	1.33e+04	1.00e+04	2.46e+04	1.05e+04	7.09e+03	4.77e+03	-	3.71e+03	9.58e+02	L
f_{19}	3.52e+05	2.04e+04	1.11e+06	5.00e+04	1.36e+06	7.31e+04	W	3.48e+05	1.67e+04	-
f_{20}	1.11e+03	3.04e+02	4.06e+03	3.66e+02	2.05e+03	1.79e+02	W	2.06e+03	2.01e+02	W

Speed Up Learning Stage

WEAKNESSES OF CURRENT LEARNING ALGORITHM

For a N -dimension function, the overhead for checking each pair of variables once is $\frac{N(N-1)}{2}$.

- it is hard to decide when to switch stage
- even given sufficiently long time for learning stage, still can't ensure learning all existing interaction

accelerate the learning stage by introducing heuristic approximation [2]

Generalize The Benchmark Function

DRAWBACKS OF BENCHMARKS FROM CEC'10 LSGO

- only treat existence of interaction as true or false
- do not distinguish the strength of interaction

CONSIDER THE STRENGTH OF INTERACTION

- introduce the concept of strength of interaction in the benchmark
- characterize the strength of interaction as a real value between 0 to 1
- design an new algorithm that can tackle the new set of benchmark functions



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Algorithm 1: *groupInfo* \leftarrow Learning Stage of CCVIL

```

1   $K \leftarrow 0$ ;
2   $groupInfo \leftarrow \{\{1\}, \{2\}, \dots, \{N\}\}$  // initially assume full separability
3  repeat // start a new learning cycle
4       $\Pi \leftarrow$  random permutation of dimension indices  $\{1, 2, \dots, N\}$ ;
5       $K \leftarrow K + 1$ ;
6       $lastIndex \leftarrow 0$ ;
7       $(subpop, pop, best) \leftarrow initializeCC(3, 3, \dots, 3)$  // use  $NP_i = 3 \forall i \in 1..N$ 
8      for  $i = 1$  to  $N$  do // start a new learning phase, i.e., tackle next dimension
9          if  $lastIndex \neq 0$  then
10              $G_1 \leftarrow find(groupInfo, \Pi_i)$  // find the group containing  $\Pi_i$ ;
11              $G_2 \leftarrow find(groupInfo, lastIndex)$  // find group of last optimized variable
12
13             if  $i = 1 \vee (G_1 \neq G_2)$  then
14                 for  $j = 1$  to  $NP$  do
15                      $popcc_j \leftarrow (best_1, \dots, best_{\Pi_i-1}, subpop_{\Pi_i,j}, best_{\Pi_i+1}, \dots)$ 
16
17                      $(popcc, new) \leftarrow optimizer(popcc, \Pi_i)$  // any optimizer, we used JADE
18                      $subpop_{\Pi_i} \leftarrow popcc_{\Pi_i}$ ;
19                      $best_{\Pi_i} \leftarrow new_{\Pi_i}$ ;
20
21                     if  $lastIndex \neq 0$  then
22                         Compose  $\vec{x}$  and  $\vec{x}^{\vec{j}}$  according to Equations 3 and 4;
23                         if  $f(\vec{x}) < f(\vec{x}^{\vec{j}})$  then // interaction between dim.  $i$  and  $lastIndex$ ?
24                              $groupInfo \leftarrow ((groupInfo \setminus \{G_1\}) \setminus \{G_2\}) \cup (\{G_1 \cup G_2\})$ ;
25
26                          $lastIndex \leftarrow \Pi_i$  // only test successively optimized dimensions
27
28 until  $(|groupInfo| = 1) \vee [(K > \check{K}) \wedge (|groupInfo| = N)] \vee (K > \hat{K})$ ;
29 return  $groupInfo$  // return the set of mutually separable groups of interacting variables
    
```

Experimental Setup

PARAMETER CONFIGURATION

The dimension of problem is 1000.

- generation limit of optimizing a certain subcomponent:
 $Gen_i = \min\{|G_i| + 5, 500\}$
- population size of optimizing a certain subcomponent:
 $NP_i = |G_i| + 10$

COMPARISON

We compare the performance of DECC-G[12] MLCC[13] and JADE[14] on the benchmark, with the parameter setting recommended by the original literature.

- DECC-G and MLCC is state-of-the-art CC-based algorithms.
- JADE is the sub-optimizer applied in our algorithm. The population size of JADE is set to 1000 for comparison.

How Does Learning Mechanism Works?

THE CRITERION FOR JUDGING VARIABLE INTERACTION

- \vec{best} is the vector of the best values for each decision variable discovered so far
- after optimizing on dimension i , \vec{best}_i is updated by new_i
- $rand_i$ is a random candidate from global (with $new \neq rand \neq best$)

$$x_j = \begin{cases} new_j & \text{if } j = i \\ best_j & \text{otherwise} \end{cases} \quad (3) \quad x'_j = \begin{cases} new_j & \text{if } j = i \\ rand_k & \text{if } j = k \\ best_j & \text{otherwise} \end{cases} \quad (4)$$

If $f(x') < f(\vec{x})$, there is likely an interaction between dimension i and k . [11]

However, there are **flaws** in the method from [11], which lead it to commit type II error in some cases.

```
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                Linkage Learning},  
}
```