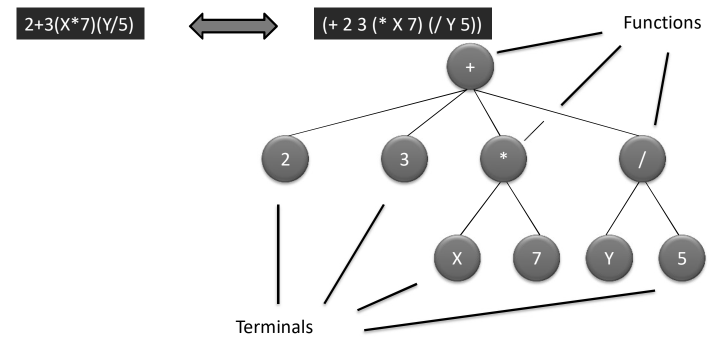
Variable Neighborhood Programming algorithm presentation

- Inspiring the power of Genetic programming solution representation and Variable Neighborhood Search movements.
- Based on systematic change of neighborhood within a local search.
- Start with a single solution presented by a program
- Apply neighborhood structure movements to reach the global optimum

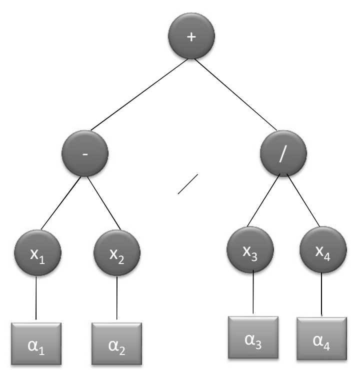
GP solution representation



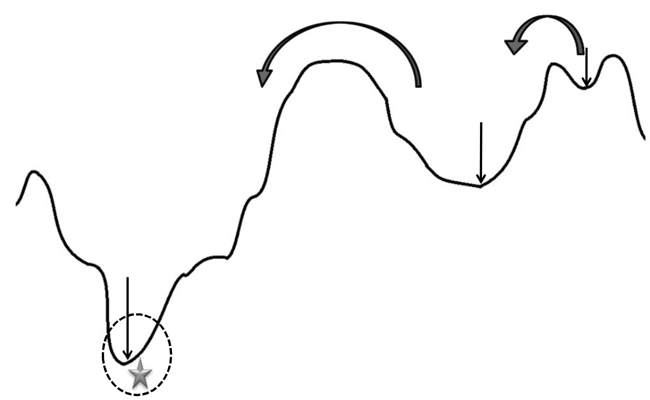
In the majority of previous studies, programs are usually presented as trees rather than as lines of code.

VNP solution representation

We suggest an extended solution illustration adding coefficients. Each terminal node is attached by its own parameter value. These parameters serve to give a weight for each terminal node



VNS algorithm movements



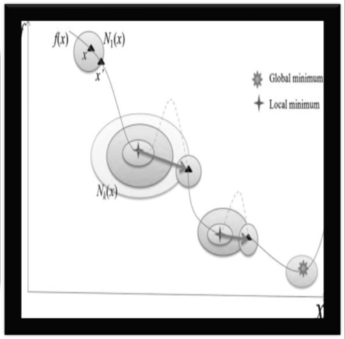
VNS - Overview

- Proposed by Mladenovic and Hansen in 1997
- **Main idea**: Systematically change the neighborhood structures
- **Based on three facts:**
  - A local minimum w.r.t. one neighborhood structure is not necessary so for another
  - A global minimum is local minimum w.r.t. all possible neighborhood structures
  - For many problems local minima w.r.t. one or several neighborhoods are close to each other

VNS **Outline** of VNS algorithm

Procedure VNS

Define neighborhood structures N_k (k=1,…,k_{max})
Generate initial solution $x \in X$
while *stopping condition is not met* **do**
$k \leftarrow 1$
while $k \leq k_{max}$ **do**
$x' \leftarrow$ Shake(x), $x' \in N_k(x)$;
$x'' \leftarrow$ Local Search(x');
if (x'' *is better than* x)
$x \leftarrow x''$; $k \leftarrow 1$;
else
$k \leftarrow k$+1;
end-while
end-while



VNS outline of algorithm

Procedure VNS

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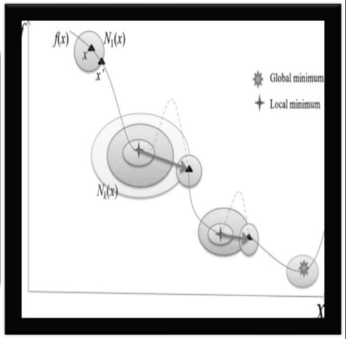


Variants of VNS algorithms

Variable Neighborhood Search (VNS) Variants

- Reduced VNS (RVNS)
- Skewed VNS (SVNS)
- General VNS (GVNS)
- VN Decomposition Search (VNDS)
- Two-level GVNS
- Nested VNS
- Parallel VNS (PVNS)
- Primal Dual VNS (P-D VNS)
- Reactive VNS
- Formulation Space Search (FSS)
- VN Branching . . .

Variable Neighborhood Descent (VND) Variants

- In VND, shaking phase is removed from VNS
- VND can be used as a part of VNS in the local search phase

- Sequential VND
- Cyclic VND
- Pipe VND
- Union VND
- Nested VND
- Mixed-nested VND
- Etc.

Variants of VNS algorithms

- 3 level VNS
- Backward VNS
- 2-phase VNS
- Gaussian VNS for continuous opt.
- Best improvement VNS
- VN Pump
- VNS Hybrids
- etc

Varaiable Neighborhood Descent (VND)

```
Procedure VNS
  Define neighborhood structures N_k (k=1,...,k_max)
  Generate initial solution s ∈ S
  while stopping condition is not met do
      k ← 1
      while k ≤ k_max do
        s' ← Shake(s), s' ∈ N_k (s);
        s" ← LocalSearch(s'), s" ∈ S;
        if (s" is better than s)
            s ← s"; k ← 1;
        else
            k ← k+1;
        endif
      end-while
  end-while
End-Procedure
```

Variable Neighborhood Descent (VND)
In VND, shaking phase is removed from VNS so that the algorithm explores local optima by using neighborhood structures only. VND can be used as a part of VNS in the local search phase

Variants of VND

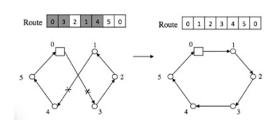
- Basic VND (BVND):
-

```
Procedure BVND
  Define neighborhood structures N_k (k=1,...,k_max)
  Generate initial solution s ∈ S
  k=1;
     while k ≤ k_max do
        s'← LocalSearch(s), s'∈ N_k;
        if (s' is better than s)
             s ← s'; k ← 1;
        else
            k ← k+1;
        end-if
     end-while
End-Procedure
```

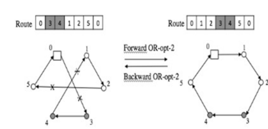
If there is an improvement w.r.t. some neighborhood N_k, exploration is continued in the first neighborhood

TSP neighborhoods

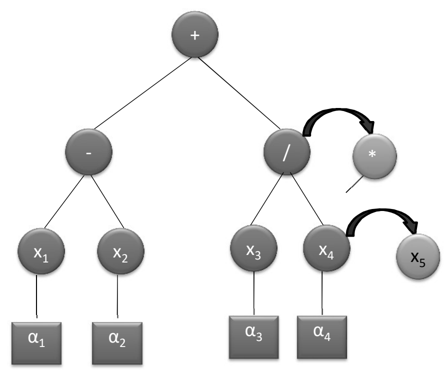
- 2-opt



- OR-opt_1
- OR-opt_2

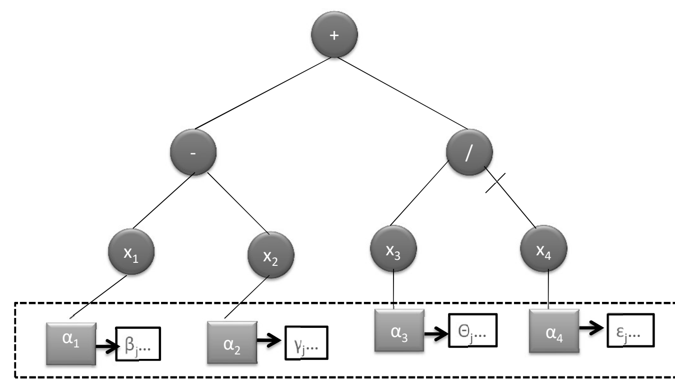


VNP neighborhood structures(1/7)



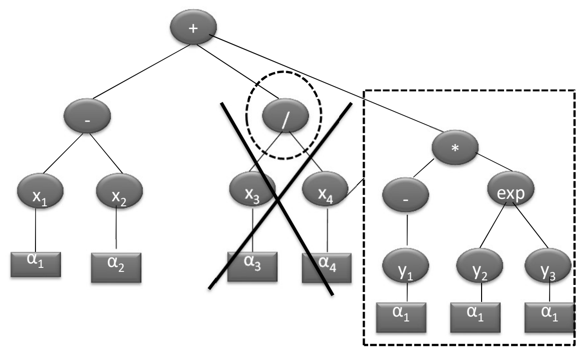
Changing node value operator

VNP neighborhood structures(2/7)



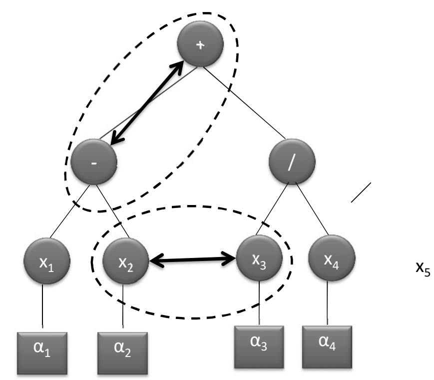
Changing parameter value operator

VNP neighborhood structures(3/7)



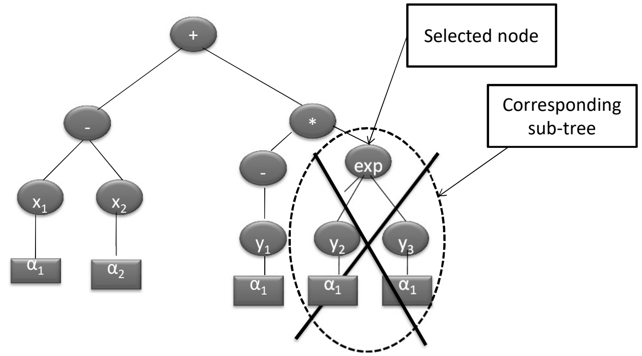
Exchange operator

VNP neighborhood structures(4/7)



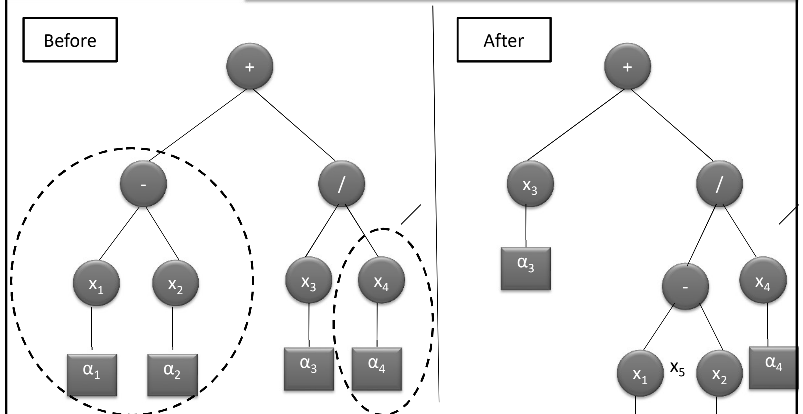
Inversion operator

VNP neighborhood structures(5/7)



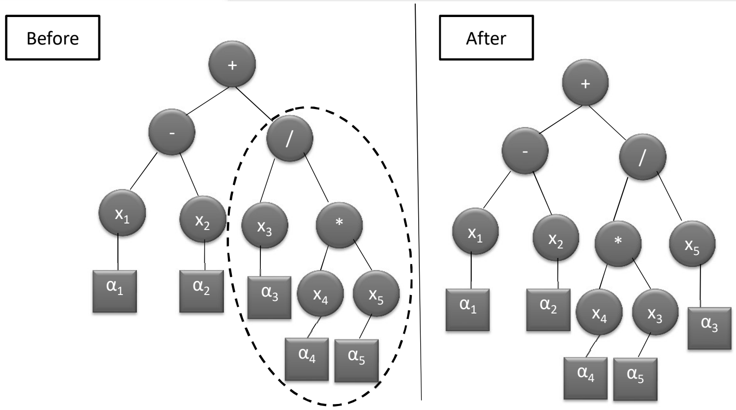
Remove operator

VNP neighborhood structures(6/7)



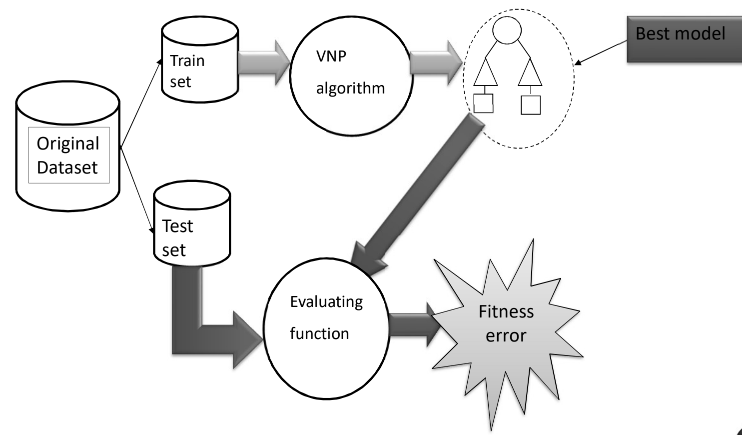
Move/Insertion operator

VNP neighborhood structures(7/7)



Shuffle operator

Learning Process



VNPD algorithm

Algorithm 1: VNPD (T, l_{max})

Input: the set of neighborhood structures: $\mathcal{N}_l, l = 1,..,l_{max}$ and an initial solution T

$l \leftarrow 1$;

while $l < l_{max}$

Find the best neighbor T' of $\mathcal{N}_l(T)$

$$\text{Move or not: } \begin{cases} if\ fitness(T')\text{ is }better\ than\ fitness(T)\ then \\ \quad move\ T \leftarrow T';\ l \leftarrow 1; \\ \quad else \\ \quad l \leftarrow l + 1; \end{cases}$$

End while

Return T

VNP algorithm

Algorithm 2: GeneralVNP (k_{max}, l_{max})

Initialization:

(1) Fix the set of neighborhood structures for the tree structure optimization and the parameter vector optimization, applied to the local search phase: $N_k, k = 1..k_{max}$ and the set of neighborhood structures for the shaking phase: $N_k, k = 1,..,k_{max}$

(2) Select the set of functions and terminals adequate for the studied problem.

(3) Generate randomly an initial tree T aspresented in Figure 1b).

(4) Choose the stopping condition.

Repeat

$k \leftarrow 1$;

while $k < k_{max}$

(a) $T' \leftarrow$Shake(T)// Find the first neighbor T' in $N_k(T)$

(b) $T'' \leftarrow$VNPD(T', l_{max}) //Local Search

$$\text{(c) Move or not: } \begin{cases} if\ fitness(T'')\text{ is }better\ than\ fitness(T)\ then \\ \quad move\ T \leftarrow T'';\ k \leftarrow 1; \\ \quad else \\ \quad k \leftarrow k + 1; \end{cases}$$

End while

until termination condition is met

Return$T$;

Time forecasting problem

- Time series forecasting is the use of a model to predict future values based on previously observed values.
- The Mackey-Glass series is based on the Mackey-Glass differential equation (Mackey, 2002).
- The gas furnace data of Box and Jenkins was collected from a combustion process of a methane–air mixture (Box and Jenkins, 1976).
- The fitness function is the Root Mean Square Error.

Time forecasting problem

Method	Training error RMSE	Testing error RMSE
PSO BBFN	____	0.027
HMDDE–BBFNN	0.0094	0.0170
Classical RBF	0.0096	0.0114
CPSO	0.0199	0.0322
HCMSPSO	0.0095	0.0208
FBBFNT	0.0061	0.0068
VNP	**0.0021**	**0.0042**

Mackey-Glass dataset results

Time forecasting problem

Methods	Prediction error RMSE
ODE	0.5132
HHMDDE	0.3745
FBBFNT	0.0047
VNP	**0.0038**

Box and Jenkins dataset results

Classification problem

- Classification consists on predicting the appropriate class of an input vector based on a set of attributes.
- We choose five datasets of radically different nature which are the Iris, Wine, Statlog, Glass identification and Yeast datasets
- The performance measure is the Accuracy

Classification problem

Datasets	Classes	Attributes	Type	Instances
Iris	3	4	Real	150
Statlog	4	18	Integer	946
Yeast	10	8	Real	1484
Wine	3	13	Integer, Real	178
Glass identification	6	10	Real	214

Datasets characteristics

Classification problem

Dataset	KNN (%)	DT (%)	SVM(%)	S2GP (%)	VNP (%)
IRIS	95	91	94	96	96.7
VEHICLE	54	51	51	56	55.3
YEAST	50	55	58	61	58.2
WINE	84	84	83	85	89.1
GLASS	60	62	63	64	66

Classification results

Preventive maintenance planning in railway transportation

Overview

- Railway transportation is highly regulated by the state.
- The maintenance of the railway is important for keeping freight and passenger trains moving safely.
- Railroad companies make an inspection run for each time period and record the characteristic of found defects.
- If a defect does not satisfy Federal Railroad Administration (FRA) standards, then it is classified as a red tag and must be repaired immediately. Otherwise the defect belongs to yellow class and its fixation is not urgent.
- The Railway Application Section (RAS) provides the historic of the data describing the status of a several numbers of points in the railway.

Preventive maintenance planning in railway transportation

Problematic

2015 RAS Problem Solving Competition is to predict the color of a selected defect in a predefined milepost value after a given period.

Preventive maintenance planning in railway transportation

Solution

we can extract two different problems:

- Prevision problem: The prediction of the attribute values responsible for the determination of the defect severity after a selected number of days.
- Classification problem: we use the updated attribute values to classify a given defect (VNP indicates if the defect color is red or yellow).
- VNP algorithm is flexible to be applied in the classification and the prediction fields.

Honor Mention

Conclusions

- New algorithm introduction called VNP and based on local search and manipulating programs;
- New solution representation ameliorating the property of generalization;
- The optimization combining simultaneously the structure of the tree and its corresponding parameters;
- VNP algorithm application on two types of time series problems and five datasets of classification;
- The results indicating the good generalization and the effectiveness of the algorithm.

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