2024年1月12日 23:45

Final exam 5 questions, in 3Hrs

Homework week2, online, quiz at week3, 30-45mins.at most 1hr. homework hand written submission upload online

Nature inspired algorithm

P6/20 find the best input
8queens prob

P7 finite time slots

P9 xlsx for 8queens check

P12 Simulation for unknown new outputs

P16 目标函数给出了一个具体的数值评估方法
限制条件是二元评估

P18 Nondeterministic Polynomially，非确定性多项式

作业

2024年1月12日　23:47

Recap1

2024年1月12日　　23:45

BB/ Search Space/ Opt-CS/ Hardness

Motivation & inspiration
Framework
表现型和基因型，编码和解码的互相转换
Week2注重于突变等内容

2024年1月22日 星期一 18:49

P123 offspring another 347826591

学习P124 125的PMX 方法

Machine Learning

2024年1月12日　23:45

Mao kezhi

13周quiz两道题，1小时，15%分数

第五周不上课听录播

两个作业加起来15%，第六周一个，第八周一个，第十周一起交作业

期末1个遗传算法题，3个机器学习

contents

2024年2月5日 星期一 17:54

Data preparation
Supervised learning
Unsupervised Learning

Learn in three step

2024年2月5日 星期一　　18:45

Data input
Abstract
generalization

Machine Learning

1. Supervised learning:
   (1). Classification
   (2). Regression
2. Unsupervised Learning:
   (1). Clustering
   (2). Association analysis 不重要
3. Reinforcement Learning 不涉及

Data preparation

2024年1月12日 23:45

1. Qualitative data

Nominal(name, nationality, gender), can only count how many
ordinal(Grades ABC), can also compare, median quartiles, but not add, mean ,var

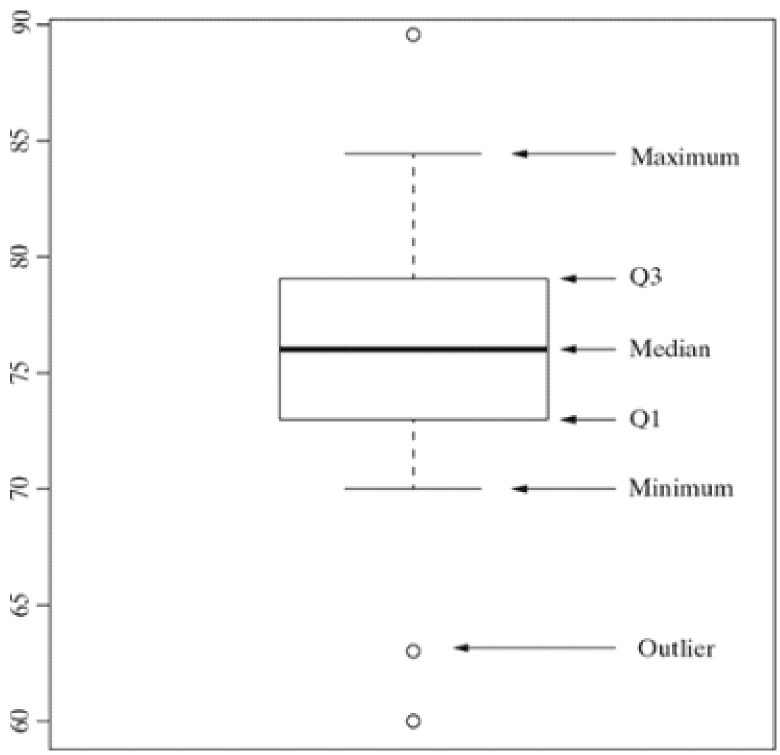
2. Quantitative data

Interval:(temperature) can add, subtract
ratio: all arithmetic operation

discrete or continuous

Box plot:

IQR: Q1 to Q3
The lower whisker extends up to 1.5 times of the inter-quartile range (or IQR) from the bottom of the box
The upper whisker extends up to 1.5 as times of the inter-quartile range (or IQR) from the top of the box



and Histogram

3. relationship

scatter plot, Two-way cross-tabulations

4. data remediation

outliers: mean and median differ a lot
Handling outliers
Remove/ imputation/ capping or build another model.

5. scaling/ normalization/ standardization

scaling, affect distance based algorithms, KNN SVM,
Gradient descent-based algorithms,

normalization: 0 to 1 , minmax scaling
standardization: (x-miu)/sigma

Bayesian rule

2024年1月12日 23:45

Posterior probability from: prior and evidence(product is joint prob)

Discriminator Func.

A Bayes classifier is determined by the conditional probability density function as well as the prior probability, equally posterior probability

$$g_i(\mathbf{x}) = p(\mathbf{x}|\omega_i)p(\omega_i)$$

$$g_i(\mathbf{x}) = \log p(\mathbf{x}|\omega_i) + \log p(\omega_i)$$

the prior is obvious, but what is the conditional probability density function? we introduce [Gaussian PDF]

Gaussian distribution

2024年2月26日 13:30

1D gaussian
nD gaussain

$$p(\mathbf{x}|\omega) = \frac{1}{(2\pi)^{d/2}|\mathbf{\Sigma}|^{1/2}} \exp\left[-\frac{1}{2}(\mathbf{x}-\boldsymbol{\mu})^T\mathbf{\Sigma}^{-1}(\mathbf{x}-\boldsymbol{\mu})\right]$$

Need to estimate the mean vector and covariance matrix, so use the maximum likelihood estimation.

Estimated miu and sigma, quiet intuitive, right?

Case 2: Gaussian function with unknown $\boldsymbol{\mu}$ and $\mathbf{\Sigma}$

With a similar deviation process, the maximum-likelihood estimate of $\boldsymbol{\mu}$ and $\mathbf{\Sigma}$ are obtained as follows:

$$\hat{\boldsymbol{\mu}} = \frac{1}{n}\sum_{k=1}^{n} \mathbf{x}_k$$

$$\hat{\mathbf{\Sigma}} = \frac{1}{n}\sum_{k=1}^{n} (\mathbf{x}_k - \hat{\boldsymbol{\mu}})(\mathbf{x}_k - \hat{\boldsymbol{\mu}})^T$$

Gaussian mixture model

2024年2月26日 16:32

Step1: estimate γ from α, μ, Σ

Step2: update α, μ, Σ

Iteration stop criterion:

1. Loop count
2. Parameter change little

Assignment 1

2024年2月26日 星期一 18:33

Due 31.03.2024
Any lang

贝叶斯决策的理解

2024年3月23日　　16:45

进行分类做出决策：
去菜市场买菜，因为自己比较严谨，吃过所有的菜，根据过往多年经验知道这里有80%占比的菜好吃，20%不好吃，即为先验。与此同时默默记下好吃的菜大概是什么特征，也就是拥有了一些训练集。
有经验后买菜时候不会蒙眼随便拿去赌自己拿到好吃的菜，那样只有80%的几率，而要根据观测到的一些特征做出好不好吃的判断，发挥主观能动性。
特征比如有：颜色，大小，水分，表面光滑度。
某个特定的特征组合出现的概率即为evidence。因为以前有了prior，现在有了evidence，还需要一个好吃的菜里有这种特征的几率--likelihood，就能计算出这组特征的菜好吃的几率了。
怎么计算likelihood呢，这是一个条件概率：在"好吃"情况下，还有这种特征。
1.如果以前经常出现这种特征，已经足以达到统计学标准，直接根据以往频次计算频率得到概率。
2.但如果以前好吃的里面没有完全匹配的情况怎么办？这很常见，毕竟世界上没有一模一样的菜。只能估计，比如（深绿，5cm，富含水分，很光滑）这组特征是好吃的几率很高，现在的（绿，6cm，富含水分，很光滑）好吃的几率肯定也不低，具体数值怎么算呢，只能假设这些多维特征符合多维的高斯分布。但有可能不止1个高斯分布成分，而是多个。
只要有均值向量，协方差矩阵，就能描述出来一整个高斯分布，但贝叶斯决策要解决的是无穷无尽数据的情形，永远不可能知道参数的真实值。所以需要估计这两个参数，或者n*2个参数。
估计过程使用极大似然估计，也就是说，根据我们的训练样本，找到某个特定的参数向量θ，使得训练数据符合该特定高斯分布的概率达到了极大值，因为根据我们直觉，既然我们抽样到这些样本，那我们理所当然可以认为正是因为这种结果出现概率最大，所以我们才得到这个结果。
使用带分类的数据训练，我们假设就按1个高斯来算，求极值要算导数或者偏导等于0的点，不必考虑严格证明，复杂运算后结果很符合直觉的是，高斯估计均值就是所有样本均值，高斯估计协方差就是样本协方差。训练过程就是计算这2个参数的过程，数据越多，参数越准确，然后有了它，就是有个pdf（概率密度函数）。
但是计算多高斯时候并不能直接这么算，而是要用EM算法迭代求解。
接下来就能计算刚才想要的似然了，输入当前特征，得到似然，因为我们计算的都是"好吃的"pdf，所以似然就是条件概率。
再然后就得到后验概率，如果概率大于50%，那我们就认为该菜是好吃的了。

naïve bayes

2024年4月26日 15:29

Then the posterior probability is:

$$p(\omega_j|\mathbf{x}) = \frac{p(\mathbf{x}|\omega_j)p(\omega_j)}{p(\mathbf{x})} = \frac{\prod_{i=1}^{n} p(x_i|\omega_j)p(\omega_j)}{p(\mathbf{x})}$$

Gaussian Naive Bayes, for each dim we have

$$p(x|\omega_j) = \frac{1}{\sqrt{2\pi}\,\sigma_j} \exp\left(-\frac{1}{2}\left(\frac{x-\mu_j}{\sigma_j}\right)^2\right)$$

Bernoulli Naive Bayes

don't need pdf, just count independent features conditional probability

Multinomial Naïve Bayes

To address the issue, we can use the so-called Laplace smoothing (add 1):

$$p(x_i|\omega_j) = \frac{counts(x_i, \omega_j) + 1}{\sum_{k=1}^{d}(counts(x_k, \omega_j) + 1)}$$

$$= \frac{counts(x_i,\omega_j)+1}{(\sum_{k=1}^{d} counts(x_k,\omega_j))+d}$$

☐ is the number of unique words in all training data

LDA

2024年2月26日 17:17

To simplify the classifier, use a line rather than a curve.
It is a 2 class question.

Linear discriminant function/ or hyperplane

The func g(x)

$$g(\mathbf{x}) = \mathbf{w}^T\mathbf{x} + w_0$$

$$r = \frac{g(\mathbf{x})}{||\mathbf{w}||}$$

Is related to distance r(to the hyperplane)

in page 11, we try to find the g(x):
we hope intraclass projection more concentrated,
while interclass more separated.

The Fisher linear discriminant attempts to find such **w** that the following criterion is maximized:

$$J(\mathbf{w}) = \frac{|\tilde{m}_1 - \tilde{m}_2|^2}{\tilde{s}_1^2 + \tilde{s}_2^2} = \frac{(\tilde{m}_1 - \tilde{m}_2)^2}{\tilde{s}_1^2 + \tilde{s}_2^2}$$

so we have:

Scatter matrix

$$\mathbf{S}_i = \sum_{\mathbf{x} \in D_i} (\mathbf{x} - \mathbf{m}_i)(\mathbf{x} - \mathbf{m}_i)^T$$

$$\boldsymbol{S}_W = \boldsymbol{S}_1 + \boldsymbol{S}_2$$

W denotes withinclass
B denotes betweenclass

Thus, the maximization criterion $J(\mathbf{w})$ can be expressed as:

$$J(\mathbf{w}) = \frac{\mathbf{w}^T \mathbf{S}_B \mathbf{w}}{\mathbf{w}^T \mathbf{S}_W \mathbf{w}}$$

17

the final result is:

$$\mathbf{S}_i = \sum_{\mathbf{x} \in D_i} (\mathbf{x} - \mathbf{m}_i)(\mathbf{x} - \mathbf{m}_i)^T$$

and

$$\boldsymbol{S}_W = \boldsymbol{S}_1 + \boldsymbol{S}_2$$

15

$$\mathbf{w} = \mathbf{S}_W^{-1}(\mathbf{m}_1 - \mathbf{m}_2)$$

If matrix $\mathbf{S}_W$ is singular, i.e.

$$|\mathbf{S}_W| \approx 0$$

Then we can use the so-called regularization technique:

$$\mathbf{w} = (\mathbf{S}_W + \beta \mathbf{I})^{-1}\,(\mathbf{m}_1 - \mathbf{m}_2)$$

$$w_0 = -\frac{\mathbf{w}^T(\mathbf{m}_1 + \mathbf{m}_2)}{2}$$

MDA in 36

2024年2月26日 星期一 20:58

Pca dimensional reduction is unsupervised
Here we need reduction supervised

multiple classification need many discrimination function gi(x).

SVM

2024年1月12日 23:45

2class with label +1 -1
Optimal hyperplane when margin of separation is maximized.

对于任何一个输入的向量x，计算判别函数g（X）后除以W的模得到距离判别超平面的距离r

$$r = \frac{g(\mathbf{x})}{||\mathbf{w}||}$$

支持向量是指距离正负1决策边界最近的数据点（向量）。也就是支持向量是最难分类的点，最重要的点

此时为一个限制条件的最优化问题，限制条件为

$$d(i) \times [\mathbf{w}^T \mathbf{x}(i) + b] \geq 1$$

$$i = 1,2, \dots N$$

Where $d(i)$ is the class label of sample $\mathbf{x}(i)$. It takes the value of $+1$ or -1 for class 1 and 2, respectively.

优化W的2范数为最小

$$\rho = \frac{2}{||\mathbf{w}||}$$

that they satisfy the constraints

$$d(i) \times [\mathbf{w}^T \mathbf{x}(i) \ + b] \geq 1 \quad \text{for } i = 1,2, \dots, N$$

that they satisfy the constraints

$$d(i) \times [\mathbf{w}^T \mathbf{x}(i) \ + b] \geq 1 \qquad \text{for } i = 1,2, \dots, N$$

and the weight vector minimizes the following cost function:

$$J(\mathbf{w}) = \frac{1}{2}\mathbf{w}^T \mathbf{w}$$

根据拉格朗日乘数法得到的损失函数L(w,b,a)函数的偏w导等于0我们有

$$\mathbf{w} = \sum_{i=1}^{N} \alpha(i) d(i) \mathbf{x}(i)$$

相较于上节课的LDA计算特征向量，SVM只需要计算这些输入的线性和。

对于b的偏导得0有

$$\sum_{i=1}^{N} \alpha(i) d(i) = 0$$

+1分类的所有a(i)和等于所有-1分类的。

根据KKT理论，就能得知那些支持向量的a(i)才能大于0，不是支持向量的，a(i)等于0.

最后在p21得到一个不用w表示的损失函数L，由此可以替换为对偶问题

工具计算出最优化w

$$\mathbf{w}^* = \sum_{i=1}^{N} \alpha(i) d(i) \mathbf{x}(i)$$

由此得到b

$$b^* = \frac{1}{d(i)} - (\mathbf{w}^*)^T \mathbf{x}(i) = d(i) - (\mathbf{w}^*)^T \mathbf{x}(i)$$

$$b^* = \frac{1}{N_s} \sum_{\alpha(i) \neq 0} [d(i) - (\mathbf{w}^*)^T \mathbf{x}(i)]$$

P24，根据算出来优化的W，然后根据一个输入x就能得到b，可以算他们的平均来确定b

P32， 很多情况下这两类数据并不是线性可分的。

Classification trees

2024年1月12日 23:45

Euclidean distance used for measure similarity

A nonmetric method, classification tree

Pros: interpretability
Incorporate prior knowledge

分类树的节点问题选择：大道致简

定义杂质impurity指标：

Entropy impurity

$$i_E(N) = -\sum_j P(\omega_j)\log_2 P(\omega_j)$$

Variance and gini impurity

Var for 2class gini for multiclass(actually covariance matrix)

$$i_{Var}(N) = P(\omega_1)P(\omega_2)$$

ralization of the variance impurity, applicable to
e category, is the *Gini impurity*:

$$i_{Gini}(N) = \sum_{j\neq k} P(\omega_j)P(\omega_k) = \frac{1}{2}\left[1 - \sum_j P^2(\omega_j)\right]$$

Misclassification impurity

$$i_{MC}(N) = 1 - \max_j P(\omega_j)$$

when splitting, branch impurity is weighted gini and sum. choose the lowest splitting method.

stop iteration threshold, trade off

$$J = \alpha \times size + \sum_{N \in leaf\ node} i(N)$$

typical trees:
CART/ ID3/ C4.5/ Random forest

random forest:
n subsets, use of each subsets m features less than original d features, sample with replacement
when predicting, use all trees, vote for result.

Metrics

2024年1月12日 23:45

19:50讲了一句话

Regression

2024年3月25日 星期一 20:15

Feature selection

2024年1月12日 23:45

Last topic on supervised learning

Curse of dimensionality: 1. data sparsity 2. distance concentration

Select subset of features: 1. better generalization

Feature selection: just subset of original features
Feature extraction: create new feature hyperspace

Peaking Phenomenon: there is a critical point to get best performance in selecting L features.

2 method in individually feature evaluation: only to find bad features.
Based on separability: Fisher ratio, for continuous variables
Based on relevance: Mutual information, use x entropy and y entropy and joint entropy, for discrete features.

fisher

$$R = \frac{(m_1 - m_2)^2}{\sigma_1^2 + \sigma_2^2}$$

MI:

$$MI(x,y) = E(x) + E(y) - E(x,y)$$

Feature subset selection:

1. Search algorithm
2. Evaluation criterion

Search: 1. exhaustive search 2.sequential forward selection 3.sequential backward elimination

Evaluation criterion for feature subsets:

1. Use performance after training and test
2. Use separability measures, not related to classifiers, mahalanlbis measure/ scatter measure/

mahalanibis

$$J_{1,2} = (\mathbf{m}_1 - \mathbf{m}_2)^T \mathbf{C}^{-1} (\mathbf{m}_1 - \mathbf{m}_2)$$

c is cov

scatter

$$J = \mathrm{Tr}(\mathbf{S}_W^{-1} \mathbf{S}_B)$$

$$J = \frac{\mathrm{Tr}(\mathbf{S}_B)}{\mathrm{Tr}(\mathbf{S}_W)}$$

3 methods in subset selection:

Filter method: use separability measure and no classifier in loop
Wrapper method: use classifier
Embedded method: lasso regression use L1 norm shrinks the coefficients associated with the least important features to zero. Also need to train a model to predict label y_hat. Many models.

10.Clustering

2024年1月12日 23:45

Types: centroids-based, hierarchical, distribution-based, density-based

Centroids-based:

K-means:

WCSS define total squared distance(error)
WCSS can be used as criterian as long WCSS minimized.
WCSS suitable when samples seperated well.

$$WCSS = \sum_{i=1}^{k} \sum_{\mathbf{x} \in D_i} \|\mathbf{x} - \mathbf{m}_i\|^2$$

Iteration:

1. Set K
2. Random K centroids
3. Traverse all samples assign to nearest centroids.
4. Calc new centroids.
5. Repeat 3-4 until no change to centroids.
6. Try other K, repeat 1-5 use Elbow Method to decide best K

Hierarchical clustering:

Agglomerative: bottom-up

1. Each sample as a cluster
2. Compute Euclidean distance
3. Merge 2 nearest samples
4. Compute Euclidean distance and single linkage (nearest neighbour) or complete linkage or centroid linkage or average linkage

Divisve: top-down

Distribution-based clustering:

GMM model:

1. Set m clusters
2. Init a,u,y
3. EM
4. Mean of GMM is cluster centres.
5. Gmm = fitgmdst(data, m);

Density-based clustering:

DBSCAN:

minPts, can be choosed at least 3, D+1 , better 2D
Eps , should small, elbow

Step1: set minPts, eps, random start point
Step2: find density connected points
Step3: Choose another start point
Step4: finish when no further change

Pros: reduce noise, no K hyperparameter, arbitrary shape
Cons: rely density, rely init, hard esp

11.clustering evaluation

2024年4月8日 星期一　　20:43

silhouette coefficient

$$S_i = \frac{d_{bi} - d_{si}}{max\{s_{bi}, d_{si}\}}$$

$$S_{overall} = \frac{1}{N}\sum_{i=1}^{N} S_i$$

Dunn Index:

$$DI = \frac{\min\limits_{k,l\in m} d_{kl}}{\max\limits_{k\in m} \delta_k}$$

Davies-Bouldin index:

Calinski-Harabasz Index:

Rand Index:

Use for vote, for compare 2 clustering method.

quiz

2024年1月12日 23:45

1. kfold
2. cluster

Q&A

2024年4月8日 星期一 20:43

Expectation-Maximization:
After searching some related papers, I found most of the implementations use a diagonal matrix as initial covariance matrix, but I tried some random positive definite matrices, and still have an acceptable convergence speed. When I try the matrix in lecture note lecture note 3.4.2, sigma_hat_21, I can't get a result, I think this mat has a negative determination if I'm not mistaken. Could you please check that? And what's the best choice of initial value?

review

2024年4月15日 4:05

7.Performance Evaluation

hold out method, use 75% training, 25% testing
or 70% training, 15% validation, 15% testing
imbalance problem, use stratified random sampling

K fold: LOOCV, one sample/fold
repeated K fold

metric:

Acc	correct ratio
Sensitivity	in positive, correct ratio
Specificity	in negative, correct ratio
Precision	in prediction, correct p ratio
recall	in prediction, find p ratio

F score= 2pr/p+r

ROC: even having a model, dealing with some problem still need to add other scaling, so we can find a best result
ROC is tpr/fpr
AUC

8.Regression

least square estimation:

We have:

$$\mathbf{y} = \mathbf{\Phi} \times \mathbf{\theta} + \mathbf{\varepsilon}$$

Define the following loss function:

$$J = \frac{1}{2}\sum_{i=1}^{N} \varepsilon_i^2 = \frac{1}{2}\mathbf{\varepsilon}^T \mathbf{\varepsilon}$$

find the best theta

$$\hat{\boldsymbol{\theta}} = (\boldsymbol{\Phi}^T\boldsymbol{\Phi})^{-1}\boldsymbol{\Phi}^T\mathbf{y}$$

L2-norm: ridge estimation

$$\hat{\boldsymbol{\theta}}_{ridge} = (\boldsymbol{\Phi}^T\boldsymbol{\Phi} + \lambda\mathbf{I})^{-1}\boldsymbol{\Phi}^T\mathbf{y}$$

Where $\mathbf{I}$ is a $(m+1) \times (m+1)$ identity matrix.

L1-norm: Lasso, produce sparse model, eliminating unimportant var coefficient
large lambda make sparse model.

regression metric:

MSE, RMSE, MAE, R-squared(1-RSS/TSS) residual sum square total sum square

$$Adjusted\ R^2 = 1 - \frac{(1-R^2)(n-1)}{(n-m-1)}$$

validation:

linear, NORMAL error, error mean 0, multivariate normal, Homoscedasticity

9.Feature Selection

Feature selection

10.Clustering

10.Clustering

11.Cluster Evaluation

11.clustering evaluation

Genetic Algorithms

2024年4月23日 21:48

1. Evolutionary computing

4 problems:

black box:
when unknown inputs, black box optimization question, timetable/ TSP/ satellite
when unknown model, modelling problems, can be transformed into optimisation problems.
when unknown outputs, simulation,

search problems: simulation// optimization modeling(search space)

optimization constraint satisfaction

	Objective function	
Constraints	Yes	No
Yes	Constrained optimisation problem	Constraint satisfaction problem
No	Free optimisation problem	No problem

NP problems: P NP NPC NPH
EA: reproduction/ mutation

2. EA components:

representation, evaluation(fitness function), population, selection mechanism, variation operators(mutation crossover), initialization termination,

GA is the algorithm for binary string.

8Queens problem: phenotype and genotype

simple GA:

1	2	3	4	5	6	7	8	9	10	11	12
String No.	Initial Popn.	x	$f(x)$	% of Total	No. Sel.	Mating Pool	Mate	C'over Site	New Popn.	x	$f(x)$
1	01101	13	169	14.4	1	01101	2	4	01100	12	144
2	11000	24	576	49.2	2	11000	1	4	11001	25	625
3	01000	8	64	5.5	0	11000	4	2	11011	27	729
4	10011	19	361	30.9	1	10011	3	2	10000	16	256
Sum			1170	100.0	4						1754
Average			293								439

representation: float to L binary, in order to perform crossover and mutation.

Ackley is used to test how good is your GA program.

$$f(x) = -20 \cdot \exp\left(-0.2\sqrt{\frac{1}{n} \cdot \sum_{i=1}^{n} x_i^2}\right)$$
$$-\exp\left(\frac{1}{n}\sum_{i=1}^{n}\cos(2\pi x_i)\right) + 20 + e$$

$$\Gamma(a_1, \dots, a_L) = x + \frac{y-x}{2^L - 1} \cdot \left(\sum_{j=0}^{L-1} a_{L-j} \cdot 2^j\right) \in [x, y]$$

mutation: uniform mutation, self-adaptive mutation

crossover: Single arithmetic crossover, Simple arithmetic crossover, Whole arithmetic crossover, blend crossover,

multiparent recombination:
n-1 point, diagonal.
arithmetic crossover

representation: permutation,
swap mutation, insert mutation, Scramble mutation, Inversion mutation,
order 1 crossover: 1. substring copy to offspring, permutate other numbers in origin order, 2 parents 2 children
PMX crossover:
Cycle crossover:
edge recombination:

Element	Edges	Element	Edges
1	2,5,4,9	6	2,5+,7
2	1,3,6,8	7	3,6,8+
3	2,4,7,9	8	2,7+, 9
4	1,3,5,9	9	1,3,4,8
5	1,4,6+		

Choices	Element selected	Reason	Partial result
All	1	Random	[1]
2,5,4,9	5	Shortest list	[1 5]
4,6	6	Common edge	[1 5 6]
2,7	2	Random choice (both have two items in list)	[1 5 6 2]
3,8	8	Shortest list	[1 5 6 2 8]

Element	Edges	Element	Edges
1	2,5,4,9	6	2,5+,7
2	1,3,6,8	7	3,6,8+
3	2,4,7,9	8	2,7+, 9
4	1,3,5,9	9	1,3,4,8
5	1,4,6+		

Choices	Element selected	Reason	Partial result
All	1	Random	[1]
2,5,4,9	5	Shortest list	[1 5]
4,6	6	Common edge	[1 5 6]
2,7	2	Random choice (both have two items in list)	[1 5 6 2]
3,8	8	Shortest list	[1 5 6 2 8]
7,9	7	Common edge	[1 5 6 2 8 7]
3	3	Only item in list	[1 5 6 2 8 7 3]
4,9	9	Random choice	[1 5 6 2 8 7 3 9]
4	4	Last element	[1 5 6 2 8 7 3 9 4]

representation: tree

Machine Learning

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   Data preparation
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