

Постановка задач и выбор моделей в машинном обучении

Вадим Викторович Стрижов

Московский физико-технический институт

Осенний семестр 2019

Preference learning problem

The goal of research

To provide a method for preference estimation on a set of objects described by a set of ordinal features

The challenges

1. To propose a partial order cone concept to describe a finite partially ordered set.
2. To investigate properties of a composition of partial order cones.
3. To develop a method of ordinal-scaled dependency recovering.

History of problem

1. **Social choice theory** (K. Arrow, 1951)
2. Preference aggregation (J. Kemeny, 1959)
3. Ordinal regression (P. McCullagh, 1980)
4. Expert estimations (B. Litvak, 1996)
5. **Learning to rank** (W. Cohen, R. Shapiro, 1999)
6. Ranking SVM (R. Herbrich et al., 1999)
7. **Cones usage** (V. Strijov, 2006)
8. Criteria importance theory (V. Podinovskiy, 2007)
9. Decision theory (F. Aleskerov, 2007)
10. **Preference learning** (J. Fuernkranz, 2011)

Illustrative example: categorization of threatened species

There are given an ordinal description and categories of species

Species	Population size	Habitat structure	Structure variation	Category
Green sturgeon	small	spotty	stable	extinct in the wild
Ladoga coregonus	small	solid	segmented	critically endangered
long-finned charr	high	dispersion	segmented	endangered
Polar bear	high	solid	unknown	vulnerable

The goal: to construct a model of categorization by the expert-given ordinal object description

Problem setting

Input data

There given a set of pairs $D = \{(\mathbf{x}_i, y_i)\}_{i=1}^m$ such that an object $\mathbf{x}_i = [x_{i1}, \dots, x_{in}]^T$,

x_{ij} is an element of a non-numeric matrix \mathbf{X} with columns X_j :

$$\mathbf{X} = [X_1, \dots, X_n].$$

Elements

$$x_{ij} \in \mathbb{L}_j \text{ and } y_i \in \mathbb{Y}$$

belong to sets with given partial order relations.

The problem

To construct a model $f : \mathbb{L}_1 \times \dots \times \mathbb{L}_n \rightarrow \mathbb{R}$ such that

- ▶ f is a monotone function, $\mathbf{x}_i \succeq \mathbf{x}_k \rightarrow f(\mathbf{x}_i) \geq f(\mathbf{x}_k)$.
- ▶ \mathbf{f} optimally estimates a preference relation given by a vector \mathbf{y} .

The optimality condition is

$$y_i \succeq y_k \rightarrow f(\mathbf{x}_i) \geq f(\mathbf{x}_k).$$

Basic concepts

- ▶ **Partial order relation** \succeq is a reflexive, antisymmetric, and transitive binary relation.
- ▶ **Partial order matrix** \mathbf{Z} is a matrix describing pairwise dominance relation of objects:

$$\mathbf{Z}(i, k) = \begin{cases} 1, & \text{if } x_i \succeq x_k, \\ 0, & \text{if } x_i \not\succeq x_k. \end{cases}$$

- ▶ \mathcal{X}_0 is a **partial order cone** corresponding to a finite poset X , if

$$\mathcal{X}_0 = \{\chi \in \mathbb{R}_+^m \mid x_i \succeq x_k \rightarrow \chi_i \geq \chi_k \quad i, k = 1, \dots, m\}.$$

Partial order cone

\mathcal{X}_0 is a polyhedral partial order cone given by a matrix \mathbf{A} of size $m^2 \times m$:

$$\mathcal{X}_0 = \{\boldsymbol{x} \mid \mathbf{A}\boldsymbol{x} \leq \mathbf{0}\},$$

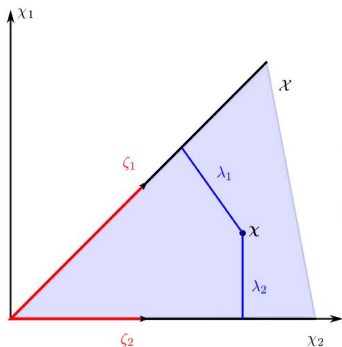
such that a string of matrix \mathbf{A} has the form

$[0, \dots, 0, -1_i, 0, \dots, 0, 1_k, 0, \dots, 0]$ and corresponds to an inequality $x_i \succeq x_k$.

Theorem [Minkowski, Weyl]

Each polyhedral cone \mathcal{X}_0 is non-empty and finitely generated,

$$\mathcal{X}_0 = \left\{ \sum_{k=1}^r \lambda_k \zeta_k \mid \lambda_k \geq 0 \right\}.$$



Explicit form of cone generators

Let a cone \mathcal{X} be generated with the columns of matrix \mathbf{Z} :

$$\mathcal{X} = \{\mathbf{Z}\boldsymbol{\lambda} \mid \boldsymbol{\lambda} \geq \mathbf{0}\}.$$

Theorem [Kuznetsov: 2013]

The following statements are valid for the cone \mathcal{X} and the partial order cone $\mathcal{X}_0 = \{\boldsymbol{\chi} \mid \mathbf{A}\boldsymbol{\chi} \leq \mathbf{0}\}$.

1. The cone \mathcal{X} is a subset of the cone \mathcal{X}_0 ,

$$\mathcal{X} \subseteq \mathcal{X}_0.$$

2. In the case of linear order on X , the cones \mathcal{X} and \mathcal{X}_0 are equal:

$$\mathcal{X} = \mathcal{X}_0$$

Polyhedral model with ordinal features

The problem

To construct a monotone function $f : \mathbb{L}_1 \times \dots \times \mathbb{L}_n \rightarrow \mathbb{R}$, optimally estimating a preference relation given by a vector \mathbf{y} ,

$$y_i \succeq y_k \rightarrow f(\mathbf{x}_i) \geq f(\mathbf{x}_k).$$

To solve a problem, define a class of models.

Linear polyhedral model

A set of values for a model $\mathbf{f}(\mathbf{X})$ on the sample D is a Minkowski sum of the cones $\mathcal{X}_1, \dots, \mathcal{X}_n$:

$$\mathbf{f}(\mathbf{X}) \in \mathcal{X} = \mathcal{X}_1 \oplus \dots \oplus \mathcal{X}_n.$$

Polyhedral model parameter optimization

Parametrization theorem [Kuznetsov: 2013]

A point $\mathbf{f}(\mathbf{X})$ of the cone \mathcal{X} is defined by a formula:

$$\mathbf{f}(\mathbf{X}) = \sum_{j=1}^n \mathbf{Z}_j \lambda_j, \quad \lambda_j \geq 0,$$

where \mathbf{Z}_j is a partial order matrix for the cone \mathcal{X}_j .

Optimal parameters

We construct a solution $\hat{\mathbf{f}}$ as a projection of a vector $\mathbf{y} \in D$ to the cone \mathcal{X} :

$$\hat{\mathbf{f}} = P_{\mathcal{X}}(\mathbf{y}).$$

Optimal parameters $\hat{\lambda}$ minimize the expression:

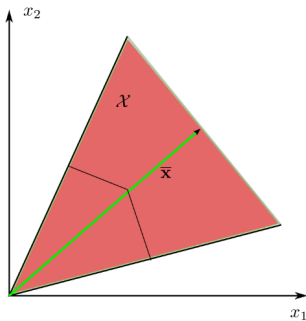
$$\hat{\lambda} = \arg \min_{\lambda_j \geq 0} \left\| \mathbf{y} - \sum_{j=1}^n \mathbf{Z}_j \lambda_j \right\|_2^2.$$

Reduction of parameter space

Polyhedral model:

$$\mathbf{f}(\mathbf{X}) = \sum_{j=1}^n \mathbf{z}_j \lambda_j, \quad \lambda_j \geq 0.$$

In the cone \mathcal{X} we consider a central point $\bar{\mathbf{x}} = \frac{1}{n} \sum_{j=1}^n \mathbf{z}_j$.



Theorem [Kuznetsov: 2014]

By replacing each cone $\mathcal{X}_k = \{\sum \lambda_{jk} \mathbf{z}_{jk} \mid \boldsymbol{\lambda}_k \geq \mathbf{0}\}$ with its central point, the polyhedral model can be expressed as

$$\mathbf{f}(\mathbf{X}) = \hat{\mathbf{Z}} \boldsymbol{\lambda},$$

where $\hat{\mathbf{Z}} = \sum_{j=1}^n w_j \mathbf{z}_j$ is a matrix of pairwise object dominance.

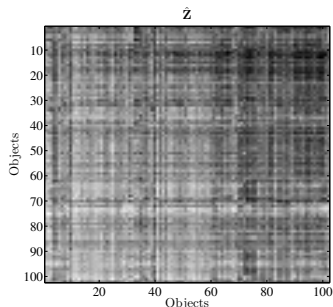
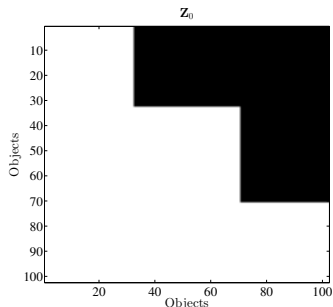
Algorithm of parameter optimization

Input: a sample $D = \{(\mathbf{x}_i, y_i)\}$.

Output: optimal parameters $\hat{\mathbf{w}}, \hat{\lambda}$.

Algorithm:

1. Construct matrices $\mathbf{Z}_1, \dots, \mathbf{Z}_n, \mathbf{Z}_Y$.
2. Estimate a matrix $\hat{\mathbf{Z}}$: $\hat{\mathbf{Z}}(i, k) = \sum_{j=1}^n w_j \mathbf{Z}_j(i, k)$.



3. Estimate parameters λ : $\hat{\lambda} = \arg \min_{\lambda_j \geq 0} \|\mathbf{y} - \hat{\mathbf{Z}}\lambda\|_2^2$.

Parameter optimization for a concordance problem [Kuznetsov: 2012]

- ▶ To find optimal parameters we solve consecutive problems of non-negative least squares with a matrix $\mathbf{X}_w = \mathbf{X}\mathbf{Z}_w$:

Problem $2k$:	Problem $2k + 1$:
$\hat{\lambda}_y = \min_{\lambda_y \geq 0} \ \mathbf{Z}_y \lambda_y - \mathbf{X}_w \hat{\lambda}_w\ _2^2$	$\hat{\lambda}_w = \min_{\lambda_w \geq 0} \ \mathbf{Z}_y \hat{\lambda}_y - \mathbf{X}_w \lambda_w\ _2^2$

- ▶ Theorem: an algorithm finds an optimal solution for not more than $m + n$ iterations.

Partial order matrix properties

$\mathbf{r}_1, \mathbf{r}_2$ — ordinal vectors, $\mathbf{Z}_1, \mathbf{Z}_2$ — corresponding matrices.

Theorem: ordinal metrics generalization

The following expressions hold.

1. Spearman correlation:

$$\rho_s(\mathbf{r}_1, \mathbf{r}_2) \propto \sum_i^m \left(\sum_k^m \mathbf{z}_1(i, k) - \mathbf{z}_2(i, k) \right)^2.$$

2. Kendall correlation:

$$\tau(\mathbf{r}_1, \mathbf{r}_2) \propto \sum_i \sum_k (\mathbf{z}_1(i, k) - \mathbf{z}_2(i, k))^2.$$

3. Multiclass AUC:

$$\text{AUC} = \frac{1}{M} \sum_{k,i=1}^m [\mathbf{z}(k, i) = 0][\hat{\mathbf{z}}(k, i) = 0], \quad M = \sum_{k_1 \prec k_2} m_{k_1} m_{k_2}.$$

Categorization of threatened species of the IUCN Red List

Expert-given data

Species	Population size	habitat square	Genetic diversity	Category
Green sturgeon	2	2	0	1
Ladoga whitefish	0	2	1	2
Long-finned charr	3	1	0	3
Polar bear	3	3	0	4
Buff-breasted sandpiper	2	1	0	3
Azovian beluga	1	3	1	1
Water chestnut	3	3	2	2
Omphalina hudsoniana	2	2	0	3
Sakhalin sturgeon	1	2	1	1
Dinnik's viper	3	3	2	2
Siberian tiger	2	2	1	2
Tropical lichens	2	1	1	5

Features description

Feature	scale
Population size	3 — large
	2 — small
	1 — critically small
	0 — unknown
Habitat square	3 — big
	2 — limited
	1 — very limited
	0 — unknown
Genetic diversity	3 — high
	2 — low
	1 — unknown
Category	5 — least concern
	4 — vulnerable
	3 — endangered
	2 — critically endangered
	1 — extinct in the wild

Pairwise feature dominance

	Population size	Habitat square	Genetic diversity
Population size	1	1	1
Habitat square	0	1	0
Genetic diversity	0	0	1

Categorization results

Error function – Hamming loss, $S(\mathbf{y}, \hat{\mathbf{y}}) = \frac{1}{m} \sum_{i=1}^m |y_i - \hat{y}_i|$.

Algorithm	Learning error	Testing error
Conic	0.29	0.58
Decision tree	0.25	0.69
GLM	0.57	0.71

