Learning experts' preferences from informetric data

Marek Gagolewski^{1,2} Jan Lasek³

¹Systems Research Institute, Polish Academy of Sciences, ul. Newelska 6, 01-447 Warsaw, Poland, gagolews@ibspan.waw.pl

²Faculty of Mathematics and Information Science, Warsaw University of Technology, ul. Koszykowa 75, 00-662 Warsaw, Poland

> ³Interdisciplinary PhD Studies Program, Institute of Computer Science, Polish Academy of Sciences j.lasek@phd.ipipan.waw.pl

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Introduction and motivation









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Introduction and motivation

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Introduction and motivation

The field of *informetrics* deals with measurable aspects of information processes. So far, a number of tools has been suggested to quantify the value of information.

In this exposition we will investigate the efficacy of a set of chosen off-the-shelf solutions in an exemplary setup.

Producer Assessment Problem (PAP)

Let us formally definite the problem under our consideration [Gagolewski and Grzegorzewski 2011].

Producer Assessment Problem

Let $P = \{p_1, \ldots, p_k\}$ be a finite set consisting of k producers. The *i*-th producer outputs n_i products. Additionally, each product is given some kind of quantitative rating, e.g. concerning its overall quality. The state of p_i may be described by a sequence

$$\mathbf{x}^{(i)} = \left(x_1^{(i)}, \dots, x_{n_i}^{(i)}
ight) \in \mathbb{I}^{1,2,\dots} = \bigcup_{n \ge 1} \mathbb{I}^n$$

with elements in I, e.g. $I = [0, \infty)$. Most importantly, we should note that the numbers of products may vary from producer to producer. The goal is to design tools for producers' evaluation (rankings, preference relations, etc.) and their impact measurement.

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Producer Assessment Problem visually



Figure: Illustration of PAP definition for two example output vectors $\mathbf{x} = (10, 9, 8, 4, 2, 1)$ and $\mathbf{y} = (7, 7, 6, 5, 4, 4, 3, 2, 1, 1)$.

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Image: Image:

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These are examples of so-called impact indexes.

There are also tools from the domain of fuzzy systems. For example, the following fuzzy preference relation was suggested [Gagolewski and Lasek 2015]. For two output vectors \mathbf{x} and \mathbf{y} , the membership function of fuzzy preference relation $\mathbf{x} \prec \mathbf{y}$ is given by

$$\mu(\mathbf{x}, \mathbf{y}) = \begin{cases} \frac{\pi_{yx}}{\pi_{xy} + \pi_{yx}} & \text{if } \pi_{xy} + \pi_{yx} > 0, \\ 0.5 & \text{otherwise,} \end{cases}$$



In this exposition, our research question is which of the proposed functions (if any) is effective in describing experts' preferences in an exemplary instance of Producer Assessment Problem. In other words: ¿Do these tools effectively compress information contained in data?

We prepared generated data for PAP for an on-line questionnaire. The participants' (experts') responses serve us as evidence for validation purposes.

Questionnaire

In the questionnaire, participants were asked to provide answers for a series of questions.



Image: A matrix and a matrix

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Validation of hypothesis

To validate the hypothesis we confront two approaches:

• compare vectors on each coordinate and equalize their lengths by padding the shorter ones with zeros

$$(x_1, x_2, \cdots, x_n) \rightarrow (x_1, x_2, \ldots, x_n, 0, 0, \ldots, 0)$$

• extract certain features of output vectors using the discussed tools

$$(x_1, x_2, \cdots, x_n) \rightarrow (f_1(\mathbf{x}), f_2(\mathbf{x}), \dots, f_k(\mathbf{x}))$$

We use several prediction models:

- Ordinal Logistic Regression,
- k-Nearest Neighbours classifier and
- Random Forest model.

The models are trained on 80% of data and evaluated on 20% (\approx 1000 instances). In consecutive slides we discuss evaluation metrics used.

Evaluation metrics (1)

For *i*th example in the data set, $i=1,2,\ldots,N$ let

- $I_t^{(i)}, \ t \in \{-2, -1, 0, 1, 2\}$ denote true preference label,
- a given model assign probability $\mathbb{P}(I_k^{(i)})$ to label I_k ,
- a classifier assign labels according to $\hat{l}_{p}^{(i)} = \operatorname{argmax}_{k} \mathbb{P}(l_{k}^{(i)})$.

We considered the following evaluation measures:

Missclassification rate

$$\textit{Misscl} = \frac{1}{N} \sum_{i=1}^{N} \mathbb{1}(l_t^{(i)} \neq \hat{l}_p^{(i)}).$$

• average distance between labels for $d(l_t^{(i)}, l_p^{(i)}) = |t - p|$

$$AvgDist = \frac{1}{N}\sum_{i=1}^{N} d(I_t^{(i)}, \hat{I}_p^{(i)}).$$

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Evaluation metrics (2)

• Rank Probability Score

$$RPS = \frac{1}{4N} \sum_{i=1}^{N} \sum_{j=-2}^{2} \left(\hat{F}^{(i)}(j) - F^{(i)}(j) \right)^{2},$$

with $\hat{F}^{(i)}(\cdot)$ and $F^{(i)}(\cdot)$ being observed and estimated cumulative distribution function for labels

• Concordance Index

$$C = \frac{1}{M} \sum_{i: \ l_t^{(i)} \neq 0} \mathbb{1}(l_t^{(i)}, \ \hat{l}_p^{(i)} \text{ concordant}) + 0.5 \cdot \mathbb{1}(\hat{l}_p^{(i)} = 0).$$

with M being the number of "usable pairs" (i.e., $I_t^{(i)} \neq 0$)

Results - evaluation of models

Below we present the results of experiment for the two approaches (marked with superscript i and c for the "index" and "coordinate" approach respectively).

	Misscl	AvgDist	RPS	<i>C</i> ′
OLR _i	0.409	0.465	0.086	0.08
OLR _c	0.394	0.454	0.082*	0.075
kNN_i	0.401*	0.457*	0.085*	0.083*
kNN_c	0.453	0.548	0.099	0.122
RF_i	0.385*	0.452*	0.076*	0.078
RF_c	0.434	0.537	0.094	0.092
Equal	0.865	1.255	0.202	0.5

Table: Results of classification.

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Results - feature importance (1)

For OLR model and different versions of kNN model (for various values of parameter k) we calculated how many times a given feature was picked by the employed feature selection procedure for different respondents. In this way, we obtain that the most important for classification are:

- i_G (picked 42 times)
- 2 Σ(x) (30)
- Image: Second state of the second state of
- x₁ (16)
- Section 5 (15)

Results - feature importance (2)

In case of Random Forest model we derived ranking of features aggregating individual importance rankings for 32 participants by Borda count. The following ranking of features was obtained (top 5):

- I FP
- 0 i_G
- S(x)
- 4 x
- 5 x₁

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- The emphasis was put on quality rather than productivity during the evaluation process.
- The available tools are effective in compressing information from producers' output vectors.
- Among the best performing aggregation tools in our experiment we identified Egghe's g-index i_G , sum of product qualities $\Sigma(\mathbf{x})$, the fuzzy preference relation FP, mean quality of a product $\bar{\mathbf{x}}$ and the maximal quality of a product x_1 .

Thank you for your attention!

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