

2 - Methods for special structured quadratic constrained quadratic programmings

Cong Sun, Yaxiang Yuan

Consider a kind of quadratic constrained quadratic programmings (QCQP) which come from wireless communications. The problems have nonconvex objective functions while the constraints have only positive definite second-order terms. By approximating the problem as a series of trust region subproblems, we achieve a feasible solution of QCQP. This point acts as the starting point of the nonconvex Sequential Quadratic Programming (SQP) method, to achieve a stationary point of the QCQP problem. Such methods allow us to solve these QCQP problems with low complexity and achieve considerable solutions.

3 - Trajectory-based Method for Nonlinear Constrained Optimization

Terry-leigh Oliphant, Montaz Ali

The trajectory-based method for solving constrained nonlinear programming problems is proposed. The augmented Lagrangian problem reformulation is used to convert the constrained problem into an equivalent unconstrained problem and a new scheme for updating the penalty parameter is discussed.

4 - Direct Search Based on Probabilistic Descent

Zaikun Zhang, Serge Gratton, Clément Royer, Luis Nunes Vicente

Direct search methods are a class of derivative-free algorithms based on evaluating the objective function along polling directions. It is typical to assume that the directions form a positive spanning set, so that at least one of them is descent. We study a more general framework where the directions are only required to be probabilistic descent, meaning that with a certain probability at least one of them is descent. This framework enjoys almost-sure global convergence and a global rate of 1 over the squareroot of k for the gradient norm with overwhelmingly high probability.

■ HB-15

Thursday, 10:30-12:00 - Room 125

Contemporary Issues in Revenue Management

Stream: Revenue Management II

Invited session

Chair: Fredrik Odegaard

1 - Exponential Approximations for Network Revenue Management

Christiane Barz, Dan Adelman, Canan Uckun

We consider a new approximation architecture for the network revenue management problem using exponential functions to express concavity. We address a number of technical challenges in fitting parameters and demonstrate numerical performance compared against other approximations.

2 - Dynamic Pricing with Strategic Consumers and Social Learning

Tatsiana Levina, Yuri Levin, Mikhail Nediak, Jue Wang

We present a dynamic pricing model for a monopolist offering a durable product to multiple segments of strategic consumers. Consumers use social learning to determine the true quality of the product in order to make their purchase decision. The network structure is captured by weighting the impact of the consumers' reviews of the product with their level of influence in the social network. The firm's objective is to maximize the expected profits. We study the structure of the optimal pricing policy of the monopolist in relation to consumer preference for quality and network parameters.

3 - Revenue Management with Ancillary Services

John Wilson, Fredrik Odegaard

Motivated by the growing prevalence for airlines to charge for checked baggage, we consider the pricing of ancillary products. We assume there are two types of customers: those that only demand a primary item and will not consume the ancillary service and those that demand a primary item provided they also receive the ancillary service. The objective is to determine optimal prices both primary and ancillary products and derive structural properties for when it is optimal not to charge separately for ancillary services.

4 - Bundle Pricing of Ancillary Services with Dependent Valuations

Fredrik Odegaard, Mihai Banciu

This paper introduces a novel approach to bundle pricing of products or services when consumers' valuations exhibit dependence. We model the joint density of valuations using copula theory and provide analytical derivations for the prices under different bundling strategies. We also provide sharp bounds for the profit function regardless of the dependence functions and analyze how the typical assumption of independence impacts the seller's profits. Specifically, we find that the relative gap in profitability, which we call the "price of independence", can be arbitrarily bad.

■ HB-16

Thursday, 10:30-12:00 - Room 127

Topic Modeling and Information Retrieval with Applications

Stream: Intelligent Optimization in Machine Learning and Data Analysis

Invited session

Chair: Anton Khritankov

1 - Finding Scientific Topics and Similarity Search

Anton Khritankov

Finding relevant scientific results is a common problem for researchers. It usually requires a researcher to know exactly what to look for, which might not be the case when research starts. We propose a feasible solution to this problem based on similarity search using topic models. In this report, we present a software system we built for a major library where it is used to search a collection of over 800 thousand full-text Ph.D. theses and other documents. We demonstrate the system and topic search on several examples.

2 - Topic Profiles - Applications of Topic Models

Časlav Božić

Topic Models are statistical language models based on LDA. Instead of assigning only one 'language' to the document, they use a distribution across 'topics' which are in turn defined as distributions over words. This corresponds with the intuitive notion of a document containing a mixture of distinct topics, which can appear in different combinations and proportions. The presented results of method's novel applications include creation of 'Topic Profiles' for scholarly authors by analyzing texts of their publications, and using the profiles for quantitative matching with funding opportunities.

3 - Thematic Classification for EURO/IFORS Conference Using Expert Model

Arsestii Kuzmin, Alexander Aduenko, Vadim Strijov

The decision support system predicts the areas, streams and sessions for the abstracts of a major conference. Abstract collections from the previous EURO/IFORS (2010, 2012, 2013) conferences and their expert thematic models are considered. The terminological dictionary of the conference and the global thematic model of these collections are constructed. A similarity function between two abstracts is proposed. The non-metric hierarchical clustering algorithm which considers a constructed global thematic model is used to construct the thematic model of a new conference without an expert model.

Thematic classification for
EURO/IFORS conference
using expert model

Arsenty Kuzmin, Alexander Aduenko, and Vadim Strijov

Moscow Institute of Physics and Technology
Department of Control and Applied Mathematics

IFORS 2014, Barcelona
17.06.2014

Offer a Decision Support System

The goal:

- to construct a thematic model of the conference

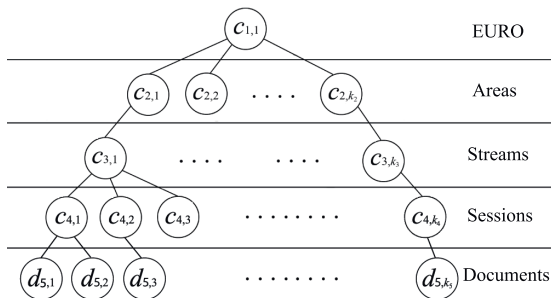
What we have:

- thematic models of the previous conferences
- participants abstracts for the upcoming conference

The main idea:

- to unite all thematic models into one,
- to calculate the similarity of a new abstract and each Stream of the United model
- to show the most similar Streams to the Experts

EURO/IFORS conference hierarchical model



- 1 A group of experts is responsible for an Area,
- 2 participants submit their Abstracts to the collection,
- 3 the experts distribute the Abstracts over the Streams,
- 4 the Abstracts are organised into the Sessions.

Challenges

Causes of the problems

- 1 Great number of the experts (more than 200),
- 2 expert classification could be controversial,
- 3 there is no base thematic model.

The terms of the document determine its theme

$W = \{w_1, \dots, w_n\}$ is the terms dictionary of the conference

Let the document be the bag of words

The document d of the collection D is an unordered set of words of the dictionary W , $d = \{w_j\}$, $j \in \{1, \dots, n\}$.

The more documents contain some term, the less information this term gives us about clustering.

Terms significance matrix Λ :

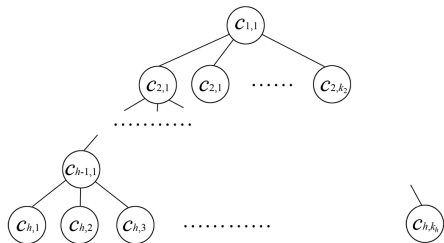
$$\Lambda = \text{diag}\{\lambda_{1,1}, \dots, \lambda_{n,n}\}, \text{ normalization: } \mathbf{x}_s \mapsto \frac{\mathbf{x}_s}{\sqrt{\mathbf{x}_s^T \Lambda \mathbf{x}_s}}$$

Hierarchical representation of the thematic model

Each leaf (h, i) of the tree corresponds to the document d_i .

Each node (l, i) , $l \neq h$ corresponds to the cluster $c_{l,i}$, which consists of corresponding documents.

Here l is a conference level, $h = 5$ is the number levels and i is the index of a node given level.



Similarity function

Define the similarity function $s(\cdot, \cdot)$ between documents x_i and x_j as:

$$s(x_i, x_j) = \frac{x_i^T \Lambda x_j}{\sqrt{x_i^T \Lambda x_i} \sqrt{x_j^T \Lambda x_j}} = x_i^T \Lambda x_j.$$

Define the similarity function $S(\cdot, \cdot)$ between clusters $c_{l,i}$ and $c_{l,j}$ as the mean $s(x, y)$ between their documents $x \in c_{l,i}, y \in c_{l,j}$

$$S(c_{l,i}, c_{l,j}) = \frac{1}{|A|} \sum_{(x, y) \in A} s(x, y),$$

where A is the set of all document pairs from clusters $c_{l,i}$ and $c_{l,j}$, $x \in c_{l,i}, y \in c_{l,j}, x \neq y$.

Similarity function

Define the similarity function $s(\cdot, \cdot)$ between the document \mathbf{x}_i and the cluster $c_{\ell,j}$ on the one hierarchy level as:

$$s(\mathbf{x}_i, c_{\ell,j}) = \mathbf{x}_i^T \Lambda \bar{\mathbf{x}}_{\ell,i},$$

where $\bar{\mathbf{x}}_{\ell,i}$ is the mean vector of the cluster $c_{\ell,i}$.

Document to cluster of the h level similarity

$$s(\mathbf{x}, c_{h,i}) = \sum_{j=0}^{h-1} \theta_{h-j} s(\mathbf{x}, B^j(c_{h,i})),$$

where θ_{h-j} is the significance of the level $h-j$ and B^j is the operator of the precedence that associate cluster $c_{h,i}$ with its predecessor on the level j .

The clustering quality function

Suppose F_0 is a mean intra-cluster similarity: $F_0 = \frac{1}{k_\ell} \sum_{i=1}^{k_\ell} S(c_{\ell,i}, c_{\ell,i})$,

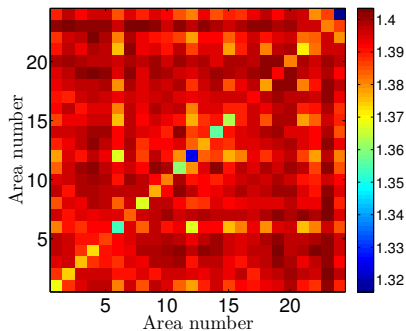
and F_1 is a mean inter-cluster similarity: $F_1 = \frac{2}{k_\ell(k_\ell - 1)} \sum_{i < j} S(c_{\ell,i}, c_{\ell,j})$

Clustering quality criterion

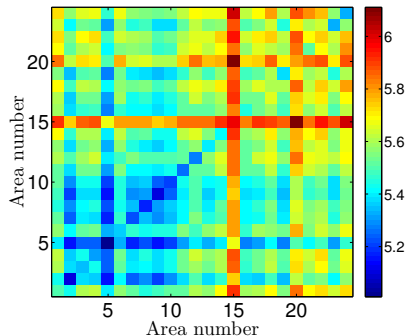
$$F = \frac{F_1}{F_0} \rightarrow \min$$

The expert hierarchical model is the origin for the algorithmic thematic model.

Distance and similarity functions comparison

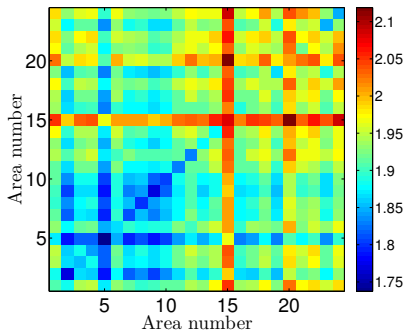


Euclidean distance

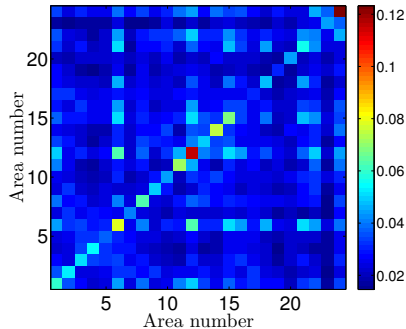


Hellinger distance

Distance and similarity functions comparison



Jenson-Shannon distance



Proposed similarity function

The relevance operator R

Let S^{k_h} be the permutation of the level h clusters

The clusters in this permutation are sorted by the similarity to an object x in the descending order, k_h is the clusters quantity.

$$S^{k_h} = \{3, 1, \dots, 6\}$$

Let $R : \mathbb{R}^n \rightarrow S^{k_h}$ be the relevance operator

It maps the document $x \in \mathbb{R}^n$ to the permutation of the lowest hierarchy level clusters

Let $\text{pos}(s, j) : S^q \times \{1, 2, \dots, q\} \rightarrow \{1, 2, \dots, q\}$ be the position function

It returns the position of the given number in the permutation.

The baseline relevance operator R_1

Sort all clusters of the h hierarchy level by their size.

Let $c_{h,i_1}, \dots, c_{h,i_{k_h}}$ be the corresponding order of level h clusters:

$$|c_{h,i_1}| \geq |c_{h,i_2}| \geq \dots \geq |c_{h,i_{k_h}}|.$$

Clusters of the equal size have some fixed order.

Let $R_1(\cdot) = (i_1, i_2, \dots, i_{k_h})$ be the baseline relevance operator

R_1 returns the permutation S^{k_h} of the ordered-by-size level h clusters for all documents.

Quality criteria $Q(R)$ and $AUC(R)$

$Q(R)$ quality criterion

Denote $Q(R)$ by the average position of the expert cluster $z_{j,h}$ in the permutation $R(\mathbf{x}_j)$:

$$Q(R) = \frac{1}{|D|} \sum_{j=1}^{|D|} \text{pos}(R(\mathbf{x}_j), z_{j,h}).$$

$AUC(R)$ quality criterion

$AUC(R) \in [0, 1]$ is the area under the top curve for a histogram $\#\{\text{pos}(R(\mathbf{x}_j), z_{j,h}) \leq i\}$, where $i \in [1, k_h]$.

$$AUC(R) = \frac{1}{k_h |D|} \sum_{i=1}^{k_L} \#\{\text{pos}(R(\mathbf{x}_j), z_{j,h}) \leq i\}.$$

Terms significance

Denote by \mathbf{p}_ℓ^j the vector of j -th components of mean vectors $\bar{\mathbf{x}}_{\ell,i}$

$$\mathbf{p}_\ell^j = [\bar{x}_{\ell,1}^j, \dots, \bar{x}_{\ell,k_\ell}^j]^T \text{ and normalize it: } \mathbf{p}_\ell^j \mapsto \frac{\mathbf{p}_\ell^j}{\sum_{i=1}^{k_\ell} p_\ell^{j,i}}$$

The word entropy

Define the entropy $I_\ell(w_j)$ of the word w_j for hierarchy level ℓ as

$$I_\ell(w_j) = \sum_{i=1}^{k_\ell} -p_\ell^{ji} \log(p_\ell^{ji}).$$

Term w_j significance according to its entropy

$$\lambda_j = 1 + \alpha_\ell \log(1 + I_\ell(w_j))$$

Optimization using the collection with the expert model

$$\alpha_\ell^* = \arg \min_{\alpha_\ell} Q(R)$$

The documents collections

The purpose of the experiment

Construct a thematic model of the conference EURO 2013

The collection D^1 :

We matched the Areas and the Streams from collections:

- EURO 2012, $|D| = 1342$, 26 Areas, 141 Streams.
- EURO 2013, $|D| = 2313$, 24 Areas, 137 Streams.

The united structure has 24 Areas, 178 Streams.

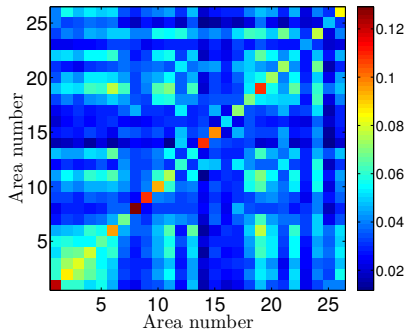
The collection D^2 :

- EURO 2010, $|D| = 1663$, 26 Areas, 113 Streams.

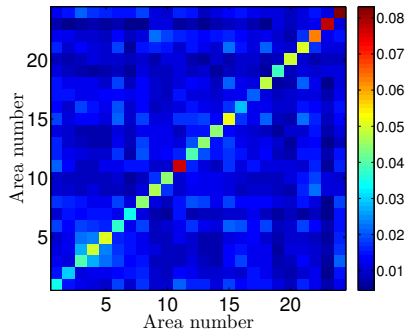
15 out of 178 streams are present only in the year 2010.

Size of the dictionary:

- $|W| = 1675$ terms.

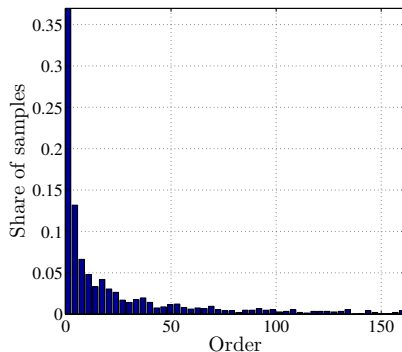


Areas similarity, $\lambda_i = 1$

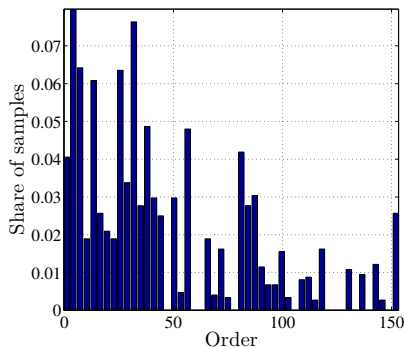


Areas similarity, optimized λ

Quality comparison $Q(R)$

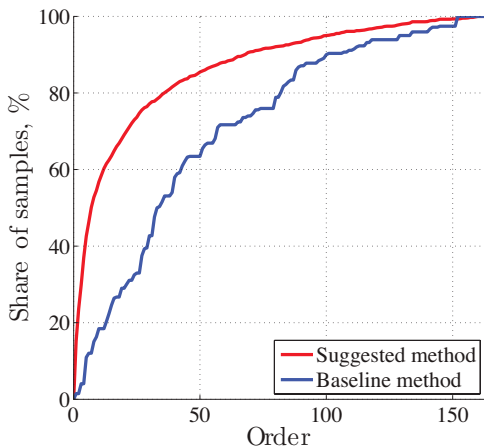


Proposed relevance operator,
 $Q = 22.54$



Baseline relevance operator
 $R_1(\cdot)$, $Q = 46.86$

Quality comparison AUC(R)



$$\text{AUC}(R) = 0.868, \text{AUC}(R_1) = 0.719$$

Implementation: <http://europrogramadvisor.com>

Conference program validation for EURO/INFORMS abstract collection

Paste title and abstract here

Title:

Abstract:

The talk is devoted to the problem of the thematic hierarchical model construction. One must to construct a hierarchcal model of a scientific conference abstracts using machine learning clustering approach, to check the adequacy of the expert models and to visualize hierarchical differences between the algorithmic and expert models. An algorithms of hierarchical thematic model constructing is developed. It uses the notion of terminology similarity to construct the model. The obtained model is visualized as the plane graph.

Search results (page 1 of 18)

Area: Emerging Applications of OR Stream: Models of Embodied Cognition	<input type="button" value="Select"/>
Area: OR in Health, Life Sciences & Sports Stream: Medical Decision Making	<input type="button" value="Select"/>
Area: Discrete Optimization, Geometry & Graphs Stream: Graphs and Networks	<input type="button" value="Select"/>
Area: Data Science, Business Analytics, Data Mining Stream: Machine Learning and its Applications	<input type="button" value="Select"/>
Area: Discrete Optimization, Geometry & Graphs Stream: Boolean and Pseudo-Boolean Optimization	<input type="button" value="Select"/>
Area: Discrete Optimization, Geometry & Graphs Stream: Geometric Clustering	<input type="button" value="Select"/>
Area: Multiple Criteria Decision Making and Optimization Stream: Preference Learning	<input type="button" value="Select"/>
Area: Multiple Criteria Decision Making and Optimization Stream: Innovative Software Tools for MCDA	<input type="button" value="Select"/>

Conclusion

- The weighted cosine similarity function is proposed.
- The entropy-based method to calculate terms significance is proposed.
- The relevance operator is proposed.