Abstract

Ongoing title:
Interactive user modelling for human-in-the-loop machine learning

Abstract

En puhu suomea.

Preface

To fill.

Espoo, August 2, 2019,

Pedram Daee

Contents

List of Publications

This thesis consists of an overview and of the following publications which are referred to in the text by their Roman numerals.

I Pedram Daee, Joel Pyykkö, Dorota Głowacka, and Samuel Kaski. Interactive Intent Modeling from Multiple Feedback Domains. In *Proceedings of the 21st International Conference on Intelligent User Interfaces*, Sonoma, California, USA, 71–75, March 2016.

II Pedram Daee*, Tomi Peltola*, Marta Soare*, and Samuel Kaski. Knowledge elicitation via sequential probabilistic inference for high-dimensional prediction. *Machine Learning*, 106, 9-10, 1599–1620, 2017.

III Iiris Sundin*, Tomi Peltola*, Luana Micallef, Homayun Afrabandpey, Marta Soare, Muntasir Mamun Majumder, Pedram Daee, Chen He, Baris Serim, Aki Havulinna, Caroline Heckman, Giulio Jacucci, Pekka Marttinen, and Samuel Kaski. Improving genomics-based predictions for precision medicine through active elicitation of expert knowledge. *Bioinformatics*, 34, 13, i395–i403, 2018.

IV Pedram Daee*, Tomi Peltola*, Aki Vehtari, and Samuel Kaski. User Modelling for Avoiding Overfitting in Interactive Knowledge Elicitation for Prediction. In *Proceedings of the 23rd International Conference on Intelligent User Interfaces*, Tokyo, Japan, 305–310, March 2018.

V Giulio Jacucci, Oswald Barral, Pedram Daee, Markus Wenzel, Baris Serim, Tuukka Ruotsalo, Patrik Pluchino, Jonathan Freeman, Luciano Gamberini, Samuel Kaski, Benjamin Blankertz. Integrating Neurophysiological Relevance Feedback in Intent Modeling for Information Retrieval. *Journal of the Association for Information Science and Technology*, 2019.

Author's Contribution

Publication I: "Interactive Intent Modeling from Multiple Feedback Domains"

The author had the main responsiblity in problem formulation and modeling. The author designed and implemented the simulation experiment. Joel Pyykkö and the author built the system for user studies and conducted them together. The author wrote the initial draft of the manuscript, after which all co-authors joined for revisions.

Publication II: "Knowledge elicitation via sequential probabilistic inference for high-dimensional prediction"

The ideas and experiments in this article were designed jointly (the first three authors contributed equally). The author had the main responsibility in the derivation of the sequential experimental design and implementation of the experiments. Dr. Tomi Peltola derived and implemented the posterior approximation. The manuscript was written jointly.

Publication III: "Improving genomics-based predictions for precision medicine through active elicitation of expert knowledge"

The author contributed on formulation of the sequential experimental design and implementation of a portion of the early version of the experiments. The author made comments to the manuscript in preparation.

Publication IV: "User Modelling for Avoiding Overfitting in Interactive Knowledge Elicitation for Prediction"

The ideas and experiments in this article were designed jointly (the first two authors contributed equally). The author designed and implemented the user study. Dr. Tomi Peltola had the main responsibility of the model formulation. The first two authors wrote the initial draft of the manuscript, after which all co-authors joined for revisions.

Publication V: "Integrating Neurophysiological Relevance Feedback in Intent Modeling for Information Retrieval"

The author had the main responsibility in design and implementation of the interactive intent modelling and information retrieval system, and writing of the correspnding sections. All the authors contributed to paper revisions.

1. Introduction

Whether it is an everyday user searching for an application in her mobile phone or a doctor working with a cancer diagnostic system, humans and machines are increasingly interacting with each other. The goal of the thesis is to improve this interaction by incorporating a model of the human user in the system they are interacting with. In particular, the thesis considers the family of problems where the human and machine interact to solve a prediction problem. Such problems can include personalized search activity or medical prediction about the response of a cancer drug. An important common factor in both these scenarios is that the number of labeled data (training data) that the machine can use to make predictions, is usually very few compared to the dimension of search space. This results in ill-posed statistical learning since there are limits in how low in sample size statistical methods can go [1].

1.1 Motivation

1.2 Research questions and contributions

This thesis investigates methods to tackle the limited user interaction challenge in interactive machine learning for prediction. The thesis focuses on scenarios where there is few labeled data available compared to the dimension of the problem, or when a human user is provider of the labeled data. The core idea of the thesis is to jointly model the human user with the data as part of a unified probabilistic model and use the model to improve the interaction.

RQ1 – *Can we exploit new sources of interaction as additional learning signals from human user to improve interactive intent modelling?*

Publications I and V contribute to this research question by proposing models to incorporate new types of user feedback to amend the limited feedback in exploratory information seeking tasks. The tasks considered are document search scenarios where a user needs to sequentially provide relevance feedback to suggested keywords in order to find the targeted document. This is modelled as a multi-armed bandit problem with the goal of finding the most relevant document with minimum interaction. In particular, Publication I couples user relevance feedback on both documents and keywords by assuming a shared underlying latent model connected through a probabilistic model of the relationship between keywords and documents. Thompson sampling on the posterior of the latent intent was then used to recommend new documents and keywords in each iteration. Publication V investigates the use of implicit relevance feedback from neurophysiology signals for effortless information seeking. The work contributes by demonstrating how to integrate this inherently noisy and implicit feedback source with scarce explicit interaction. A model for controlling the accuracy of the feedback given its nature (implicit or explicit) was introduced. Similar to Publication I, Thompson sampling was used to control the exploration and exploitation balance of the recommendations. Both publications were evaluated by user studies in realistic information seeking tasks.

RQ2 – *Can expert knowledge about high dimensional data models be elicited to improve the prediction performance?*

Publications II and III contribute to this research question. Publication II proposes a framework for user knowledge elicitation as a probabilistic inference process, where the user knowledge is sequentially queried to improve predictions. In particular, sparse linear regression is considered as the data model with access to only few high-dimensional training data. It is assumed that there are experts who have knowledge about the relevance of the covariates, or of values of the regression coefficients and can provide this information to the data model if queried. The work contributes by an algorithm and computational approximation for fast and efficient interaction, which sequentially identifies the most informative queries to ask from the user. Publication III, builds on Publication II by adding user knowledge about direction of relevance of covariates and applying the method in important applications of precision medicine with the goal of predicting the effects of different treatments using high-dimensional genomic measurements. Both publications were evaluated by extensive simulations and user studies. Source codes for methods presented in Publications II and III, and user study data from Publication II are available at `https://github.com/HIIT/knowledge-elicitation-for-linear-regression` and `https://github.com/AaltoPML/knowledge-elicitation-for-precision-medicine`.

RQ3 – *Is it enough to incorporate human knowledge directly in the data model as explained in RQ2, or could it be beneficial to account for rational knowledge updates that humans may undergo during the interaction?*

Publication IV contributes to this research question by modelling the knowledge provider, here the human user, as a rational agent that updates its knowledge about the underlying prediction task during the interaction. In particular, certain aspects of training data may be revealed to the user during knowledge elicitation. The design of the system is then critical, since the elicited user knowledge cannot be assumed to be independent from the data model knowledge coming from the training data. If not accounted properly, knowledge elicitation can lead to double use of data and overfitting, if the user reinforces noisy patterns in the data. We propose a user modelling methodology, by assuming simple rational behaviour, to correct the problem and evaluate the method in a user study. Source code and user study data are available at `https://github.com/HIIT/human-overfitting-in-IML`.

1.3 Organization of the thesis

The organization of the thesis is as follows. Chapter 2 provides an overview of probabilistic modelling and introduces our approach of modelling the user and data as a joint probabilistic model. Chapter three investigates the purpose of interactions and reviews different utility functions designed to minimize the effort of the user. The fourth chapter summarizes Publications I-IV. Chapter five concludes the thesis and provides discussions for future works.

2. Probabilistic modelling of data and user

This chapter provides a brief introduction to probabilistic modelling as the main statistical framework that is used through the thesis. After some preliminaries, Section 2.2 briefly reviews the type of linear models that are used in Publication I-IV for prediction. Section 2.3 introduces different types of user interaction with the linear model and explains how user knowledge about the model can be incorporated as observational feedback. Finally, the key components for modelling observational data and user feedback as a joint probabilistic model is introduced in Section 2.4.

2.1 Preliminaries

The core idea of probabilistic modelling is to describe all the unobserved parameters and observed data as random variables from probability distributions. The unobserved parameters include the unknown quantity of interest or other parameters that affect the data or the quantity of interest. Bayesian inference provides a powerful framework to fit the described probabilistic model to observational data [2]. A core feature of Bayesian inference is that it provides probability distributions as the solution, compared to deterministic methods which provide a single outcome. This uncertainty quantification is of particularly high interest in cases where few observational data are available or when the data acquisition scheme is controlled by the model. Both of these constrains are prominently present in the tasks investigated by this thesis.

We follow the notation of [2] and use $p(.)$ to denote a probability distribution and $p(.|.)$ a conditional distribution. Consider the case where there are a set of observations $\mathscr{D} = \{y_1, ..., y_n\}$ generated from a probabilistic model with an unobserved parameter of interest θ. The observational model for an observation y describes the conditional density of y given the parameter θ and is denoted as $y \sim p(y \mid \theta)$. It is usually assumed that the observations are conditionally independent given θ, enabling us to write the model for all observations as $p(\mathscr{D} \mid \theta) = \prod_{i=1}^{n} p(y_i \mid \theta)$. The observational model is called likelihood function if perceived as a function of θ with fixed observation y. One of the core questions in statistical inference is to estimate the parameter of interest θ based on observations $\mathscr{D}$. Bayesian inference answers this question by computing the conditional distribution of θ given $\mathscr{D}$ following the Bayes rule

$$p(\theta \mid \mathscr{D}) = \frac{p(\mathscr{D} \mid \theta)p(\theta)}{p(\mathscr{D})}. \tag{2.1}$$

Where $p(\theta)$ represents the prior belief about θ and $p(\mathscr{D})$ is called the marginal likelihood and acts as a normalization factor as it does not depend on θ. The marginal likelihood can be computed using the marginalization rule, i.e., $p(\mathscr{D}) = \int_\theta p(\mathscr{D},\theta)d\theta = \int_\theta p(\mathscr{D} \mid \theta)p(\theta)d\theta$ [1]. $p(\theta \mid \mathscr{D})$ is called the posterior and it expresses the uncertainty surrounding the true value of θ, after updating the prior assumptions about θ (i.e., the prior distribution) with the knowledge coming from the observations through the likelihood.

In many cases, we may be more interested to make a prediction about an unknown observable data point $\hat{y}$ rather than the parameter θ. Bayesian inference allows us to compute the conditional distribution of this unknown observable data given the observed data point as

$$p(\hat{y} \mid \mathscr{D}) = \int_\theta p(\hat{y} \mid \theta)p(\theta \mid \mathscr{D})d\theta. \tag{2.2}$$

$p(\hat{y} \mid \mathscr{D})$ is known as the posterior predictive distribution and represents the uncertainty about a potential new observation. An example usage of this distribution could be when we want to predict the value of a test data. Since test data is not observed, we can use posterior predictive distribution as our best guess. However, in many applications, only a value (and not a distribution) is required as the prediction. This can be handled by using some statistics of the distribution (for example mean or median) as the prediction. Still, the quantified uncertainty in the distribution can be useful as it provides knowledge about how certain we are about our estimate. Particularly, this uncertainty can help us to design more efficient interaction with a user, as will be discussed in Section 3.

2.2 Modelling data for prediction

Prediction is one of the core problems in statistical analysis and supervised machine learning. Given a set of n input and output pairs, called training data and denoted by $\mathscr{D} = \{(\boldsymbol{x}_i, y_i)\}_{i=1}^n$, the goal is to find a mapping from inputs to outputs. Here, $\boldsymbol{x}_i \in \mathbb{R}^d$ is a d-dimensional vector representing the values of i^{th} data point and y_i is the corresponding response (or target) variable which can be anything depending on the underlying problem. In this thesis, we consider the regression tasks, meaning that we model response variables by real values, i.e., $y_i \in \mathbb{R}$[2]. The dimensions of the inputs are commonly called feature, covariates,

[1]The integral turns to summation for discrete θ.

[2]The problem is called classification in supervised learning if the response variable is restricted to categorical values (sometimes called classes).

or attribute.

A well-studied and widely practical type of regression, known as linear regression, assumes that the relationship between all inputs and their corresponding response variables is linear. This relation ship can be written as

$$y_i = \sum_{j=1}^{d} x_i^j w^j + \epsilon_i = \boldsymbol{x}_i^\top \boldsymbol{w} + \epsilon_i, \qquad i = 1, \ldots, n,$$

where $\boldsymbol{w} \in \mathbb{R}^d$ is the regression coefficients or the model's weight (we use superindex to refer to an element of the vector) and ϵ_i is the residual error between linear prediction $\boldsymbol{x}_i^\top \boldsymbol{w}$ and the response value y_i.

EXPLAIN ERROR MODEL AND THEN MENTION HOW IT CAN BE SOLVED BY FREQUIENTICE APPROACH AND THEN INTRODUCE THE BAYES APPROACH AND MENTION THAT WE WILL GO THROUGH THE STEPS..

$$\boldsymbol{y} \sim \mathrm{N}(\boldsymbol{X}\boldsymbol{w}, \sigma^2 \mathbf{I}), \tag{2.3}$$

ALSO EXPLAIN BRIEFLY THE NON BAYESIAN TREATMENT AND EXPLAIN WHY WE GO WITH BAYES/

2.2.1 Bayesian Linear regression

2.2.2 Sparse priors

2.3 Modelling the user

2.4 Key components of the joint model

Let y and x denote the outputs (target variables) and inputs (covariates), and θ and ϕ_y the model parameters. Let f encode input (*feedback*) from the user, presumably a domain expert, and ϕ_f be model parameters related to the user input. We identify the following key components:

1. An observation model $p(y \mid x, \theta, \phi_y)$ for y.

2. A feedback model $p(f \mid \theta, \phi_f)$ for the expert's knowledge.

3. A prior model $p(\theta, \phi_y, \phi_f)$ completing the hierarchical model description.

4. A query algorithm and user interface that facilitate gathering f iteratively

from the expert.

5. Update process of the model after user interaction.

The observation model can be any appropriate probability model. It is assumed that there is some parameter θ, possibly high-dimensional, that the expert has knowledge about. The expert's knowledge is encoded as (possibly partial) feedback f that is transformed into information about θ via the feedback model. Of course, there could be a more complex hierarchy tying the observation and feedback models, and the feedback model can also be used to model more user-centric issues, such as the quality of or uncertainty in the knowledge or user's interests.

3. User interaction with the probabilistic model

3.1 Active learning and experimental design

3.2 Multi-armed bandits and Bayesian optimization

4. Summary of the Contributions

This chapter briefly summarizes the contributions of Publications I-V with emphasize on answering the research questions of the thesis.

4.1 Interactive intent modelling from multiple feedback domains (Publications I and V)

4.2 Expert knowledge elicitation for high-dimensional prediction (Publications II and III)

4.3 User modelling for avoiding overfitting in knowledge elicitation (Publication IV)

5. Discussion

References

[1] David Donoho and Jared Tanner. Observed universality of phase transitions in high-dimensional geometry, with implications for modern data analysis and signal processing. *Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences*, 367(1906):4273–4293, 2009.

[2] Andrew Gelman, John B Carlin, Hal S Stern, David B Dunson, Aki Vehtari, and Donald B Rubin. *Bayesian data analysis*. Chapman & Hall/CRC, 3rd edition, 2014.

Publication I

Pedram Daee, Joel Pyykkö, Dorota Głowacka, and Samuel Kaski. Interactive Intent Modeling from Multiple Feedback Domains. In *Proceedings of the 21st International Conference on Intelligent User Interfaces*, Sonoma, California, USA, 71–75, March 2016.

Interactive Intent Modeling from Multiple Feedback Domains

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ABSTRACT
In exploratory search, the user starts with an uncertain information need and provides relevance feedback to the system's suggestions to direct the search. The search system learns the user intent based on this feedback and employs it to recommend novel results. However, the amount of user feedback is very limited compared to the size of the information space to be explored. To tackle this problem, we take into account user feedback on both the retrieved items (documents) and their features (keywords). In order to combine feedback from multiple domains, we introduce a *coupled multi-armed bandits* algorithm, which employs a probabilistic model of the relationship between the domains. Simulation results show that with multi-domain feedback, the search system can find the relevant items in fewer iterations than with only one domain. A preliminary user study indicates improvement in user satisfaction and quality of retrieved information.

Author Keywords
Exploratory search; intent modeling; multi-armed bandits; relevance feedback; probabilistic user models.

ACM Classification Keywords
H.3.3 Information Search and Retrieval: Relevance feedback; I.2.6 Learning.

INTRODUCTION
The dominant information retrieval paradigm relies on the user's ability to form a precise query, which is difficult at least in the about 50% of search sessions where the user is uncertain about her information need [17]. Furthermore, the information need can shape throughout the search session. For instance, when the user prepares for writing a summary about a particular topic, the search process typically takes several iterations in which the user directs the search by tuning the initial query and the initial search intent, after observing the results. This important type of a search scenario is called *exploratory search* [10, 12, 18].

There is a wide variety of qualitative definitions of exploratory search [19]. Marchionini [12] illustrated exploratory and lookup tasks as an overlapping cloud and suggested that lookup tasks are embedded in exploratory tasks and vice versa. The problem context that motivates the search process is typically characterized in definitions of exploratory search [18]. Imprecise task requirements or open-ended search goals are the two primary attributes often used to define exploratory search with respect to the problem context [11]. The exploratory search process is considered to be cognitively complex with the information seeker being uncertain about the search process [18].

To help the user in exploratory search, her interactions with the system can be employed to infer her search intent. This is challenging for two reasons. First, active interaction is required from the user; however, users are often not willing to invest in actively giving feedback to search systems. Second, even if the interface was appealing enough, the user can only provide a limited amount of feedback, which makes user intent modelling challenging. In this paper we make it easier for the user to give feedback in exploratory search, by allowing feedback on multiple domains, in this case keywords and documents. For this we formulate the user intent modelling task as a new coupled multi-armed bandit problem, instead of using only one multi-armed bandit for one modality as in earlier approaches [14].

The rest of the paper is organized as follows: First we model exploratory search as a learning problem with limited feedback. Next, we propose the *coupled multi-armed bandits* algorithm that employs Thompson sampling with a novel probabilistic user model. We conclude the paper by evaluating the proposed method in a simulation scenario and a user study.

PROPOSED APPROACH

Problem Setting
Let D be a set of documents in a corpus and K be a set of keywords extracted from these documents. For each user, it is assumed that the relevance of each document $d \in D$ is an unknown distribution over [0,1]. This distribution encodes the uncertainty of the user about the relevance of each item, which is a key element of exploratory search. The expected

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relevance of d for the user is denoted by $E_D[d]$. The document $d \in D$ is more relevant than $d' \in D$, if $E_D[d'] < E_D[d]$. Similarly, it is assumed that the relevance of each keyword $k \in K$ is an unknown distribution over [0,1] with its expected relevance denoted by $E_K[k]$. We call this set of distributions the user intent model. The expected relevances of keywords and documents are connected through a model of the data that defines how keywords belong to documents.

In each session, a user with a fixed but unknown intent model arrives. Each session consists of N iterations. In each iteration, the user provides input based on her intent model as relevance values to keywords and documents, and the algorithm provides a set of new documents and keywords. It is assumed that user feedback consists of samples from the relevance distributions.

The retrieval system should look for the most relevant document $d^* = \arg\max_{d \in D} E_D[d]$ and present it to the user. To solve this maximization the system needs to explore the document space to estimate the expected relevance of documents based on user feedback. At the same time it should exploit the estimates to show relevant documents as early as possible. This kind of a black box optimization problem, where the objective function is unknown and expensive to sample, has been studied in multi-armed bandit [6] and Bayesian optimization [4, 16] literature. A natural performance criterion for these problems is regret, which is the loss due to not presenting the most relevant documents to the user. The cumulative regret after receiving feedback for a set of documents n_D is $cum\_regret = |n_D| E_D[d^*] - \sum_{d \in n_D} E_D[d]$. The goal is to minimize the cumulative regret, which is equivalent to maximizing the sum of expected relevance feedback on documents in n_D. However, since the expected relevance of documents is hidden to the system, this measure cannot be calculated in practice.

In practice, an exploratory search system is successful if it presents to the user items, e.g. documents, that the user finds interesting. How we measure this "interest" is through maximizing the average number of clicks (or other types of positive relevance feedback) on documents in N iterations [15]. Since it is reasonable to assume that the user provides positive feedback mostly on relevant documents, this user behavior model also minimizes the cumulative regret defined from the theory point of view.

By modeling the problem as regret minimization, there is little hope to achieve a reasonable result by only considering the limited feedback on documents. In exploratory search, it is more convenient for the user to express the abstract understanding of her needs in terms of higher-level information, such as a set of keywords. In this paper we take advantage of both feedback on documents and on keywords in order to improve the regret of an exploratory search system. We tackle the problem by modeling it as coupled multi-armed bandits where it is possible to provide feedback both to the arms and the features defining the arms. In our exploratory search problem, the arms are documents and the features are keywords defining the documents.

Connecting Documents and Keywords

We assume there exists a document-keyword matrix M defined as

$$M = \begin{bmatrix} P(k_1|d_1) & \cdots & P(k_{|K|}|d_1) \\ \vdots & \ddots & \vdots \\ P(k_1|d_{|D|}) & \cdots & P(k_{|K|}|d_{|D|}) \end{bmatrix}_{|D| \times |K|}$$

where $P(k_i|d_j)$ specifies the likelihood of document d_j generating keyword k_i. This matrix is generated from the data model that expresses how keywords and the documents are related. An example, which we use, is to consider documents as bags of words and to use normalized *tf-idf* representations of documents. We make the simplifying assumption that the connection between expected relevance of a document and keywords is as follows:

$$E_D[d_j] = \sum_{i=1}^{|K|} E_K[k_i] P(k_i|d_j)$$

With the compact notation $E_D[D] = \left[E_D[d_1], \ldots, E_D\left[d_{|D|}\right]\right]^T$, and analogously for keywords, this becomes

$$E_D[D] = M E_K[K] \quad (1)$$

Note that we made the simplifying assumptions only for the expected relevances; the shapes of the relevance distributions can be different.

Coupled Bayesian Bandits

The user provides relevance feedback to both documents and keywords. The relevance (reward) distributions for document d and keyword k are denoted by $r_d \sim f^D(.|x_d, \theta)$ and $r_k \sim f^K(.|x_k, \theta)$, respectively. The x_d and x_k are the feature (context) vectors associated with d and k. The fixed but unknown parameter θ defines the shared link between these two relevance distributions. After the user has interacted with a set of documents n_D and a set of keywords n_K, we can write the posterior at time $t = |n_D| + |n_K|$ as

$$\pi_t(\theta) \propto \pi_0(\theta) \prod_{d \in n_D} f^D(r_d|x_d, \theta) \prod_{k \in n_K} f^K(r_k|x_k, \theta), \quad (2)$$

where $\pi_0(\theta)$ is the prior distribution for θ. In order to apply Bayesian bandit methods [1, 9] it is only necessary to be able to perform the following two steps: draw a sample from the posterior at time t, and after that score all the documents and keywords by $E_D[r_d|x_d, \theta^p]$ and $E_K[r_k|x_k, \theta^p]$.

These two steps are the minimum requirements for employing the Thompson sampling algorithm for bandits [1, 7, 9]. In Thompson sampling, the exploration and exploitation are controlled indirectly by the uncertainty in the posterior. We can easily draw a sample from the posterior by using any sampling method, after specifying the shared parameter θ that connects the relevance distributions, and the feature vectors x_d and x_k. These parameters are defined by the user model.

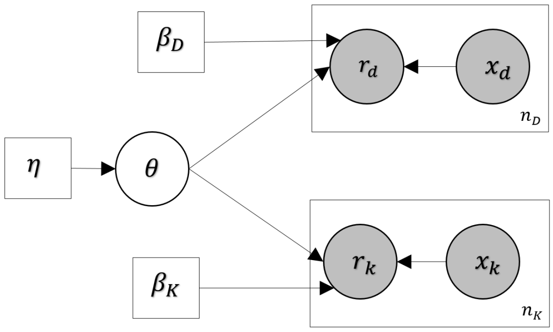

Figure 1. Probabilistic model for user feedback on documents and keywords.

Probabilistic User Model

We propose a simple model for received relevance feedback on documents and keywords. Since the amount of feedback from the user is limited, we need to impose a structure on the expected relevance of items to be able to generalize well. We assume that the expected relevance of keywords is linearly related to their feature vectors by the unknown weight vector θ, i.e. $E_K[K] = M^T\theta$. Based on this linearity assumption and our previous assumption in equation (1), we have $E_D[D] = ME_K[K] = MM^T\theta$. Using this feature transformation, we only need to estimate one set of unknown weights to specify expected relevance of both documents and keywords. Considering Gaussian distributions for relevance, we propose the following model (plate diagram in Figure 1):

$$f^K(r_k|x_k, \theta, \beta_K) = N(r_k; x_k^T\theta, \beta_K^2)$$

$$f^D(r_d|x_d, \theta, \beta_D) = N(r_d; x_d^T\theta, \beta_D^2)$$

$$\pi_0(\theta) = N(\theta; 0, \eta^2 \mathrm{I})$$

Here, x_k is the k^{th} column of M and x_d is the d^{th} column of MM^T; they define feature vectors for keyword k and document d, respectively. Since all the distributions are Gaussian, the posterior is also a Gaussian distribution, with:

$$\pi_t(\theta) = N(\theta; \mu_t, \Sigma_t)$$

$$\Sigma_t^{-1} = \beta_D^{-2} X_{n_D}^T X_{n_D} + \beta_K^{-2} X_{n_K}^T X_{n_K} + \eta^{-2}\mathrm{I} \qquad (3)$$

$$\mu_t = \Sigma_t\left(\beta_D^{-2} X_{n_D}^T R_{n_D} + \beta_K^{-2} X_{n_K}^T R_{n_K}\right)$$

where X_{n_D} is a $|n_D| \times D$ design matrix containing feature vectors for the observed documents in the set n_D, and R_{n_D} is a $|n_D| \times 1$ matrix of the corresponding observed relevance values. With the same logic, X_{n_K} is a $|n_K| \times D$ design matrix containing feature vectors for the observed keywords in the set n_K, and R_{n_K} is a $|n_K| \times 1$ matrix of the corresponding observed relevance values. The computational complexity of (3) comes from the covariance matrix inversion.

The coupled multi-armed bandits algorithm employing Thompson sampling for controlling exploration-exploitation tradeoff is as follows:

ALGORITHM 1: Coupled multi-armed bandits

At time step t

1. draw $\theta^p \sim \pi_t(\theta)$ from (3)
2. for document bandit: select $d^+ = \arg\max_{d \in D} x_d^T \theta^p$
3. for keyword bandit: select $k^+ = \arg\max_{k \in K} x_k^T \theta^p$
4. update the posterior (3) based on user feedback and observed feature vectors

SIMULATION

In each exploratory search session, the simulator considers a small set of documents and keywords as targets, and assumes their expected relevance to be 1. The simulated user employs Latent Semantic Indexing (LSI) and cosine similarity measure to calculate similarities to the targets for all documents and keywords. According to these similarities, an expected relevance value in [0,1] is assigned to each document and keyword, defining $E_D[D]$ and $E_K[K]$.

In each iteration, the algorithm presents five documents and five keywords to the user (by repeating steps 2 and 3 of Algorithm 1). We assume that the simulated user selects document d as relevant with probability equal to relevance value $r_d \sim N(E_D[d], \beta_D^2)$, and provides relevance feedback $r_k \sim N(E_K[k], \beta_K^2)$ for keyword k with probability proportional to $|r_k - 0.5|$. The motivation is that users usually give feedback to keywords that are highly relevant or irrelevant. We used a fixed pool of 750 computer science arXiv articles, with only 50 of them having high expected relevance in the user intent model. The model parameters were set to $\beta_D = \beta_k = 0.3$ and $\eta = 0.5$. We compared our method with variants that only consider feedback on keywords or documents to update the posterior (3).

Based on the simulation result in Figure 2, we can conclude that considering feedback on both documents and keywords will significantly increase the number of relevant items that the user can find with the same number of iterations.

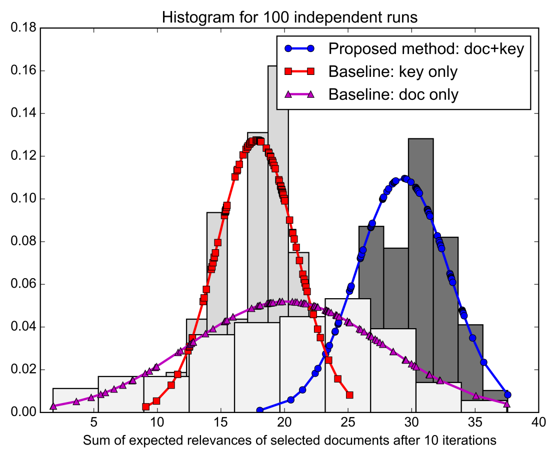

Figure 2. Histogram for 100 independent runs of the methods. The sum of expected relevances of selected documents after 10 iterations is significantly higher when both types of feedback (doc+key) are considered.

USER EXPERIMENTS AND RESULTS

We implemented the proposed method in an existing exploratory search system SciNet [8]. SciNet uses the LinRel algorithm [2] to learn the user intent model based on feedback on keywords visualized on a radar-like interface. In our implementation, we replaced LinRel with Algorithm 1. Furthermore, user interactions with documents, i.e. clicks or bookmarks, are considered as relevance feedback on documents, in addition to feedback on keywords. The computational complexity of both algorithms is the same.

We conducted a preliminary user study on 10 university students and researchers. All the participants were fluent in English and had some background in computer science or a related field. Each participant performed two exploratory tasks in which they had to do a literature survey on a topic and answer three questions in a fixed amount of time. The topics were reinforcement learning and neural networks. The participants reported their knowledge of the topics on 1-5 Likert scale (with 2.2 on average). The user interface and real time performance of the systems were identical, and the participants were naïve about which exploratory search engine was used for each task. In each iteration, five documents were shown to the user and the user could bookmark the relevant ones. All user interactions were logged by the system including the typed query, documents and keywords presented to the user, and documents and keywords that the user interacted with. After each task the participants answered a questionnaire containing SUS [5] and a short version of ResQue [13] using 1-5 Likert scale, where 1 indicates “strongly disagree”. A short interview with each participant was conducted after the tasks.

Answers to all the tasks and the bookmarked documents were rated by experts in a double-blind assessment using a scale from 0 (no answer) to 5 (perfect answer). All the shown documents were assessed on a binary scale based on their relevance to the search topic. The inter-rater agreement between the experts showed that the rankings overlapped more than 80%. One of the users was excluded from the analysis because he did not bookmark any article.

Table 1 summarises different performance measures for the proposed algorithm and the baseline system. The percentage of all the shown articles that were labelled as relevant by the experts was calculated as a measure of the quality of the shown information. For the proposed system this value was 5 percent better compared to the baseline. However, the difference was not statistically significant.

Performance measure	Proposed	Baseline
Average SUS score	**75**	67.2
Average ResQue score	**54.7**	52.3
% of relevant documents	**84.6**	79.1
User task performance	3.45	3.45

Table 1. Performance measures for the proposed and baseline systems. The better value on each row is shown in bold.

The proposed algorithm had better SUS and ResQue scores compared to the baseline. However, due to the small sample size these differences were not statistically significant. It should be noted that most of the questions in SUS and ResQue target areas such as user interface, which was the same in both systems. There are two questions in ResQue that measure the *novelty* and *diversity* of search results [13]: *The recommender system helped me discover new items* and *The items recommended to me are diverse*. In both questions the proposed method scored higher (4.1 and 3.7) against the baseline system (3.5 and 3.3).

User task performance was measured by averaging the expert assessments of the answers for the three questions in each task. The users were hard pressed to gather a report in time, which was also evident in their answers. In these reports both systems achieved the same average performance.

In the interviews, 6 out of 9 users reported higher satisfaction with the proposed system (more diversity and better results), one reported that he could not tell the difference, and two said that the baseline was better.

Overall, the preliminary results indicate that the proposed system gave the users a more satisfying image of the topic they were exploring. Furthermore, the usability of the total system has also improved.

DISCUSSION AND CONCLUSION

In this paper we introduced the *coupled multi-armed bandits* algorithm as the exploratory search method that employs the user feedback on both the retrieved items and their features. Our approach is based on two main ideas. First, we model user behavior as a generative probabilistic model. Second, we couple different sources of feedback in a unified model. Our simulation results and preliminary user study indicate that considering these two sources of feedback can improve the performance and quality of the exploratory search.

From the practical point of view, our algorithm provides the opportunity to exploit several types of relevance feedback that are available for documents, in addition to relevance feedback available for individual keywords. For example in [3] it was shown that it is possible to detect implicit relevance feedback from physiological signals such as electrodermal activity and facial electromyography on documents. We believe that this is an important step for the future of exploratory search applications since an increasing amount of research studies the feasibility of performing information retrieval based on novel types of relevance signals both on keywords and on documents.

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REFERENCES

1. Agrawal, S., and Goyal, N. Thompson Sampling for Contextual Bandits with Linear Payoffs. In *Proc. of ICML,* (2013), 127-135.
2. Auer, P. Using confidence bounds for exploitation-exploration trade-offs. *The Journal of Machine Learning Research*, (2003), 397-422.
3. Barral, O., Eugster, M. J., Ruotsalo, T., Spapé, M. M., Kosunen, I., Ravaja, N., ... and Jacucci, G. Exploring Peripheral Physiology as a Predictor of Perceived Relevance in Information Retrieval. In *Proc. of IUI,* ACM (2015), 389-399.
4. Brochu, E., Cora, V. M., and De Freitas, N. A tutorial on Bayesian optimization of expensive cost functions, with application to active user modeling and hierarchical reinforcement learning. *arXiv preprint arXiv:1012.2599*, 2010.
5. Brooke, J. SUS-A quick and dirty usability scale. *Usability evaluation in industry 189*, (1996), 4-7.
6. Bubeck, S., and Cesa-Bianchi, N. Regret analysis of stochastic and nonstochastic multi-armed bandit problems. *Foundations and Trends in Machine Learning*, (2012), 5(1), 1-122.
7. Chapelle, O., and Li, L. An empirical evaluation of thompson sampling. In *Advances in Neural Information Processing Systems,* (2011), 2249-2257.
8. Glowacka, D., Ruotsalo, T., Konuyshkova, K., Kaski, S., and Jacucci, G. Directing exploratory search: Reinforcement learning from user interactions with keywords. In *Proc. of IUI,* ACM (2013), 117-128.
9. Hoffman, M. D., Shahriari, B., and de Freitas, N. On correlation and budget constraints in model-based bandit optimization with application to automatic machine learning. In *Proc. of AISTATS,* (2014), 365-374.
10. Kammerer, Y., Nairn, R., Pirolli, P. and Chi, E.H. Signpost from the masses: learning effects in an exploratory social tag search browser. In *Proc. of the SIGCHI Conference on Human Factors in Computing Systems*, ACM (2009), 625-634.
11. Kim, J. Describing and predicting information-seeking behavior on the web. *Journal of the American Society for Information Science and Technology*, (2009), 679–693.
12. Marchionini, G. Exploratory search: from finding to understanding. *Communications of the ACM* (2006), 41–46.
13. Pu, P., Chen, L., and Hu, R. A user-centric evaluation framework for recommender systems. In *Proc. of RecSys,* ACM (2011), 157-164.
14. Ruotsalo, T., Jacucci, G., Myllymäki, P. and Kaski, S. Interactive intent modeling: Information discovery beyond search. *Communications of the ACM*, (2014), 58(1), 86-92.
15. Slivkins, A., Radlinski, F., and Gollapudi, S. Ranked bandits in metric spaces: learning diverse rankings over large document collections. *The Journal of Machine Learning Research*, (2013), 14(1), 399-436.
16. Srinivas, N., Krause, A., Kakade, S. M., and Seeger, M. Gaussian process optimization in the bandit setting: No regret and experimental design. In *Proc. of ICML,* (2010).
17. Teevan, J., Alvarado, C., Ackerman, M. S., and Karger, D. R. The perfect search engine is not enough: a study of orienteering behavior in directed search. In *Proc. of CHI,* ACM (2004), 415-422.
18. White, R. W., and Roth, R. A. Exploratory search: Beyond the query-response paradigm. *Synthesis Lectures on Information Concepts, Retrieval, and Services*, (2009), 1-98.
19. Wildemuth, B. M., and Freund, L. Assigning search tasks designed to elicit exploratory search behaviors. In *Proc. of HCIR*. ACM (2012), 1–10

Publication II

Pedram Daee*, Tomi Peltola*, Marta Soare*, and Samuel Kaski. Knowledge elicitation via sequential probabilistic inference for high-dimensional prediction. *Machine Learning*, 106, 9-10, 1599–1620, 2017.

Publication III

Iiris Sundin*, Tomi Peltola*, Luana Micallef, Homayun Afrabandpey, Marta Soare, Muntasir Mamun Majumder, Pedram Daee, Chen He, Baris Serim, Aki Havulinna, Caroline Heckman, Giulio Jacucci, Pekka Marttinen, and Samuel Kaski. Improving genomics-based predictions for precision medicine through active elicitation of expert knowledge. *Bioinformatics*, 34, 13, i395–i403, 2018.

Publication IV

Pedram Daee*, Tomi Peltola*, Aki Vehtari, and Samuel Kaski. User Modelling for Avoiding Overfitting in Interactive Knowledge Elicitation for Prediction. In *Proceedings of the 23rd International Conference on Intelligent User Interfaces*, Tokyo, Japan, 305–310, March 2018.

Publication V

Giulio Jacucci, Oswald Barral, Pedram Daee, Markus Wenzel, Baris Serim, Tuukka Ruotsalo, Patrik Pluchino, Jonathan Freeman, Luciano Gamberini, Samuel Kaski, Benjamin Blankertz. Integrating Neurophysiological Relevance Feedback in Intent Modeling for Information Retrieval. *Journal of the Association for Information Science and Technology*, 2019.