

Novelty Detection for Modeling User's Profile

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Abstract

This paper presents an original mechanism for modeling user profile based on a novelty detector filter model. This model enables to learn possibly evolving user need by means of positive and negative user's relevance feedback.

1. Introduction

In this paper, we present an original mechanism for modeling user profile in a content-based filtering system. This mechanism enables to learn possibly evolving user need by means of positive and negative user's relevance feedback. The feedback information is provided by the user following to voting process on a web sites set supplied by the system. In this process the sites are classified in two main categories: accepted sites, rejected sites.

The proposed mechanism is based on the novelty detector filter model derived from the works of [Kohonen 1984] and [Lamirel 1995]. In this mechanism we managed to overcome the defects of classic relevance feedback mechanisms [Ide 1971] [Rocchio 1971] under the vector space model [Salton 1975]. These defects could be summarized as follows; the feedback is a short-range process without memory and thus cannot manage cumulative building and recording of user profile. Moreover, the classic mechanisms show a significant imbalance in the treatment of positive and negative feedback, and in some condition, negative feedback has a paradoxical behavior and so makes incoherent the general performance of relevance feedback [Dunlop 1991].

In the next section, we introduce the basic concepts of the novelty detector filter and its use in a content-based web sites filtering system.

2. Novelty detector filter

The role of the novelty detector filter is to characterize, after its learning on a reference data set, the novel

properties of a data relatively to the reference data, i.e. the properties of the data that are not represented in the reference data. It also allows to characterize the common properties of this data relatively to the reference data set. Thus, the novelty detector filter defines at the same time the vector space ϕ which synthesizes the novelty compared to the reference data and the complementary space $I-\phi$ which synthesizes the habituation compared to these data.

The learning of the novelty detector filter is based on the theorem of Greville [Kohonen 1984] which yields a recursive expression for calculating a filter matrix ϕ_k . After simplification the theorem can be expressed as:

$$\phi_k = \phi_{k-1} - \frac{x'_k x'^T_k}{\|x'_k\|^2}$$

where:

$X_k = [x_1, x_2, \dots, x_k]$ is a reference data set; $x'_k = \phi_{k-1} x_k$ represents the orthogonal projection of the vector x_k on the novelty space ϕ_{k-1} that is orthogonal to the space spanned by the $k-1$ reference data; $\|x\|$ represents the length of the vector x ; and the recursion starts with $\phi_0 = I$.

2.1. Novelty proportion

The novelty proportion associated to a data x , relatively to a reference data set, can be obtained from the length of the novelty vector $\phi \cdot x$ associated to this data:

$$N_x = \frac{\|\phi \cdot x\|}{\|x\|}$$

Since the novelty and the habituation spaces are orthogonal, it is also possible to calculate the complementary proportion, namely the habituation proportion.

$$H_u = 1 - N_u$$

2.2. Using the novelty detector filter for modeling user's profile

As mentioned previously, the user's votes are classified in two main categories: acceptance and rejection. That leads us naturally to structure the component intended for modeling the user's need, in the form of two novelty

detector filters: acceptance filter and rejection filter. Their role is to treat the votes associated to their respective types so as to extract their synthetic properties in term of habituation and novelty. The learning on the accepted and rejected web sites produces two filters whose content is representative of the properties of web sites which got the same judgment by the user. Each filter could generate two vectors: habituation vector and novelty vector. The habituation vector generated by the acceptance filter and the novelty vector generated by the rejection filter provide two representation of the user's need. The creation of these vectors is presented hereafter.

Learning elementary synthesis

The construction of a novelty detector filter based on the user's votes does not yield directly the synthesis of these votes in terms of learned descriptors. Such synthesis can be obtained by projecting all descriptors of the web sites description space on the habituation space of the filter. The values obtained that correspond to the descriptors habituation proportions enable to divide the whole descriptor set into three distinct subsets:

- The subset of novel descriptors S_N , that is made up of the descriptors for which the habituation proportion is lower than a given threshold t_N .
- The subset of the habituated, or learned descriptors S_H , that is made up of the descriptors for which the habituation proportion is higher than a threshold t_H .
- The subset of the neutral descriptors S_n , that is made up of the descriptors for which the habituation proportion fall between the thresholds t_H and t_N .

Profile construction

The partition of the descriptors in three subsets permits to directly form habituation and novelty vectors generated by each novelty detector filter.

- The habituation vector can be described as follows:

$$V_H = \sum_{t \in S_H} H_t \bar{t}$$

where \bar{t} represents the directing unit vector associated with the descriptor t .

The habituation vector created by the acceptance filter can be used as profile when the user's votes consist only of accepted sites (positive relevance feedback).

- The novelty vector is given by:

$$V_N = \sum_{t \in S_N} N_t \bar{t}$$

The novelty vector created by the rejection filter can be used as profile when the user's votes consist only of rejected sites (negative relevance feedback).

Treating independently positive and negative user votes is very important, since each type of these votes can intervene in an autonomous way. However, the complementary behavior of these two types of feedback is

also very important, since they intervene mostly simultaneously.

In the classic relevance feedback mechanisms, the formulation functions stick to the same basics [Ide 1971] [Rocchio 1971] and have incoherent behavior, as pointed out in our introduction. Contrary to the classical mechanisms, our novelty detector filter allows us to propose a new formulation function whose behavior is homogeneous. It consists in combining the vectors obtained from our two filters in a way that the profile is moved towards both accepted sites (habituation vector generated by acceptance filter) and alternatives of rejected sites (novelty vector generated by rejection filter). This function is defined as follows:

$$P' = P + \beta \frac{\|V_{HA}\|}{\|V_{NR}\|} V_{NR}$$

where:

P represents initial user's predefined profile (optional), V_{HA} represents the habituation vector generated by acceptance filter, V_{NR} represents the novelty vector generated by rejection filter; β and γ represent positive parameters that control the influence of positive and negative feedback on the profile formulation.

3. Conclusion

We have introduced a novelty detector filter for modeling user profile. Our first experiment on the behavior of this filter has been applied on a corpus of several thousands of web sites, taken from one of the main categories of the open directory project DMOZ. It has enabled us to demonstrate the superiority of our filter over the classic relevance feedback mechanisms. Future experiments will be achieved to examine the effect of indexing methods on the behavior of the filter.

References

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