A Recommendation Engine based on Adaptive Automata

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Abstract: The amount of information available nowadays is huge and in raw state; systems have to act proactively on selecting and presenting context-relevant information, but such feature is time-consuming an exhaustive. This paper presents a recommendation engine based on an adaptive rule-driven device – namely, an adaptive automata – as a lightweight scalable alternative to usual approaches on resource recommendation. The technique employed here is based on frequency analysis instead of relying on usual machine learning.

1 INTRODUCTION

The growth of social media and the diffusion of the Internet itself brought several challenges to the way data are traditionally analyzed; the amount of information available is huge and in raw state. In order to enhance browsing and learning experience, systems have to be proactive by selecting and presenting context-relevant information, for example, offering related subjects in an e-learning environment or by suggesting movies based on customer's history records; such feature is usually time-consuming and exhaustive for the whole computational infrastructure (Cereda and José Neto, 2014).

Adaptivity is the term used to denote the ability of a device to modify its own behavior without external interference (José Neto, 1994). For example, in a chess game, such modifications are triggered as the application of a rule pattern given a certain situation, like a pawn that advances all the way to the opposite side of the chess board and triggers a rule which promotes it to another piece of that player's choice; the pawn now has its own behavior changed to another piece and may act like so. Any rule-driven device can exploit the self-modification feature by adding an adaptive layer on top of its underlying rule set. In this paper, we will use an adaptive automata as computational model, which is proven to be Turing-complete (Rocha and José Neto, 2000).

We present here a simple and fast recommendation engine that uses a well-known computational model enhanced with an adaptive mechanism as a lightweight alternative to usual approaches for tackling raw data and trying to extract patterns and behaviors in situations for which absolute answers are too costly, and suboptimal solutions can be accepted. The use of an adaptive rule-driven device allows a compact yet expressive model which escalates on demand based on the current usage scenario (Cereda and José Neto, 2014).

2 BACKGROUND

There is a vast literature on how to identify and recommend resources that are relevant for a person or a group of people based on a couple of criteria. One of the most known methods for this purpose is called a *recommender system* (Resnick and Varian, 1997).

Recommender systems usually rely on two techniques known as collaborative and content-based filtering. The former is preference-oriented, recommending resources according to information obtained from groups of people that share similar trends and behaviors (Su and Khoshgoftaar, 2009). The latter is profile-oriented, which classifies resources and recommends similar ones based on interests of some person (Lops et al., 2011). Both techniques do have shortcomings, such as data sparsity and scalability (Cacheda et al., 2011); hybrid versions are usually employed in order to explore the strongest points of each original approach without ignoring the current context being considered (Adomavicius and Tuzhilin, 2005).

More recently, machine learning algorithms have been used for extracting association rules based on

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available data and finding patterns and trends (Gotardo et al., 2013). The main purpose is to establish correlation rules amongst resources. Although being extremely powerful, such techniques are very expensive in terms of computational efforts and might demand an impractical time, depending on the size of the data and how resources are represented in the system (Yahia and Murtada, 2010).

Cereda et al. (Cereda et al., 2009) describe an alternative approach for recommender systems, relying on discrete metrics and adaptive techniques. The recommendation process was managed by an adaptive rule-driven recognizer; by submitting two resources r_i and r_j to the recognizer M as an input string w, for example, if $w \in L(M)$ means that r_j could be a good recommendation given r_i and vice versa. One of the most interesting aspects pointed out by that early work was the model efficiency, since it could handle queries on a pair of related resources in polinomial time based on the length of the input string.

The main shortcoming of this approach, however, is the lack of proactivity, that is, the recognizer accepts/rejects queries about related resources, but it does not answer which resource could be a recommendation. Besides, the model suffers from data sparsity, leading to a problem known as cold start (Basiri et al., 2010). Inspired by this initial work, we propose here a new model, built from scratch, which aims at minimizing the effects of data sparsivity and cold start and offering a lightweight scalable alternative to usual approaches on resource recommendation.

It is worth noting that most approaches so far take the artificial intelligence path (Adomavicius and Tuzhilin, 2005), including graph-based recommender systems using an n-layer approach in order to establish correlation rules amongst relevant resources (Huang et al., 2004); however, the number of layers and resources might greatly increase data sparsity and increase computational processing. Our goal in this paper is an attempt to provide a new model based on an adaptive rule-driven device – namely, an adaptive automaton – that escalates on demand according to the current scenario, reducing the effects of data sparsity and handling queries in polinomial time in order to recommend context-relevant resources. Such features are desirable specially when dealing with a huge amount of raw data.

3 THE RECOMMENDATION ENGINE

In this section, we present an adaptive rule-driven device being used to implement a recommendation engine. We opted for an adaptive automaton (José Neto, 1994; José Neto, 2001), which consists of a traditional automaton as underlying device with the addition of an adaptive mechanism, as seen in Fig. 1; such mechanism allows the device to change its own configuration on runtime by invoking adaptive functions which can modify the underlying set of rules.

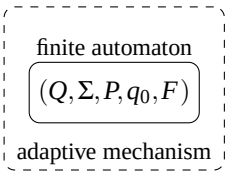


Figure 1: An adaptive automaton.

We provide a list of elements used in this section for quick reference; refer to Table 1 for a complete description of the symbols used in the text.

Let us consider a set R of resources. A resource might be any object relevant to a given context, e.g, books in a bookstore or dishes in a restaurant. For our example, the number of elements in R is fixed, although it is easy to change this model in order to obtain a recommendation engine that considers resources added on-the-fly.

The adaptive automaton of our model has all available resources from R represented as states (Q_R subset), but only related resources are connected through transitions. Connection between two resources may contain intermediate states indicating the strength of the connection; the first occurrence of a pair of resources triggers the adaptive mechanism which adds transitions from one to another, and later occurrences will increase this path by adding intermediate states. The number of intermediate states in a path is used to discover the best resource r_j given r_i. It is worth noting that paths are established if and only if there is an occurrence of pairs of resources, greatly reducing the model size.

A resource r_i may establish connection with an arbitrary number of other resources from R; such connections indicate possible trends from a group of people or even describe mutual dealings among resources (set T of special symbols). Our choice was modeling resource connections not as a single two-way symbol but as a pair of unidirectional ones, that is, a link between r_i and r_j will result in both $\tau_{(r_i,r_j)}$ and $\tau_{(r_j,r_i)}$. This is helpful if we want to keep track of the path to follow when analyzing possible recommendations or if we do not want to consider commutativity between two resources. For the scope of our paper, we are considering that commutativity is allowed.

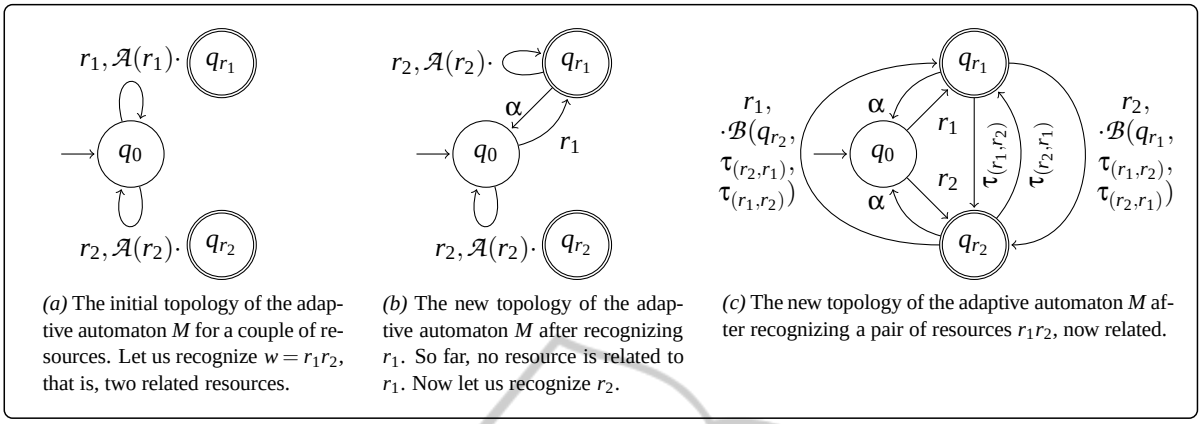
Fig. 2 represents the adaptive automaton M of our recommendation engine. For illustration purposes,

Table 1: List of elements for quick reference.

Element	Meaning	Example
Q	set of states	$Q = \{q_0, q_{\text{pizza}}, q_{\text{chips}}\}$
$F \subset Q$	subset of accepting states	$F = \{q_{\text{pizza}}, q_{\text{chips}}\}$
$q_0 \in Q$	initial state	—
R	set of resources	$R = \{\text{pizza}, \text{chips}\}$
$Q_R \subset Q$	subset of states associated with resources, $\lvert Q_R\rvert = \lvert R\rvert$	$Q_R = \{q_{\text{pizza}}, q_{\text{chips}}\}$
T	set of special symbols representing links amongst resources, $\lvert T\rvert = {}^{\lvert R\rvert!}/_{(\lvert R\rvert-2)!}$	$T = \{\tau_{(\text{pizza,chips})}, \tau_{(\text{chips,pizza})}\}$
$\tau_{(r_i,r_j)} \in T$	link between two resources r_i and r_j, with $r_i, r_j \in R$, $i, j \in \mathbb{N}$, $i \neq j$	$\tau_{(\text{pizza,chips})}$
D	set of adaptive functions	$D = \{\mathcal{A}, \mathcal{B}\}$
Σ	input alphabet	$\Sigma = \{\alpha, \text{pizza}, \text{chips}\}$
α	resource pair delimiter	—
P	$P\colon D \cup \{\varepsilon\} \times Q \times \Sigma \mapsto Q \times \Sigma \cup \{\varepsilon\} \times D \cup \{\varepsilon\}$, mapping relation	$P = \{(\mathcal{A}(\text{pizza}), q_0, \text{pizza}) \mapsto (q_0, \varepsilon, \varepsilon), (\mathcal{A}(\text{chips}), q_0, \text{chips}) \mapsto (q_0, \varepsilon, \varepsilon)\}$
$\mathcal{A}(r)\cdot$	adaptive function $\mathcal{A} \in D$ with argument r_i triggered before the symbol consumption	—
$\cdot\mathcal{B}(q,x,z)$	adaptive function $\mathcal{B} \in D$ with arguments q, x, z triggered after the symbol consumption	—
$f_Q\colon R \mapsto Q_R$	function that takes a resource $r_i \in R$ and returns its associated state $q_{r_i} \in Q_R$	$f_Q(\text{pizza}) \mapsto q_{\text{pizza}}$
$G\colon Q_R \mapsto R$	output relation that maps each state $q_{r_i} \in Q_R$ representing a resource $r_i \in R$ into a resource $r_j \in R - \{r_i\}$	$G(\text{pizza}) \mapsto \text{chips}$
$\arg\max A \subseteq R$	$y_{\max} = \max_{(x,y)\in A} y$, then $\arg\max A = \{x \in R \mid (x, y_{\max}) \in A\}$ is the set of x on which y is maximized	$\arg\max A = \{(\text{egg}, 7), (\text{pizza}, 5), (\text{bacon}, 7), (\text{spam}, 6)\} = \{\text{egg}, \text{bacon}\}$
$?(a,b,c) \to (d,e,f)$	rule-searching elementary adaptive action that searches P for rules matching the given pattern $(a, f \subseteq D \cup \{\varepsilon\}, b, d \subseteq Q, c \subseteq \Sigma, e \subseteq \Sigma \cup \{\varepsilon\})$	—
$-(a,b,c) \to (d,e,f)$	rule-erasing elementary adaptive action that removes rules matching the given pattern from P $(a, f \subseteq D \cup \{\varepsilon\}, b, d \subseteq Q, c \subseteq \Sigma, e \subseteq \Sigma \cup \{\varepsilon\})$	—
$+(a,b,c) \to (d,e,f)$	rule-inserting elementary adaptive action that adds rules with a specified pattern to P $(a, f \subseteq D \cup \{\varepsilon\}, b, d \subseteq Q, c \subseteq \Sigma, e \subseteq \Sigma \cup \{\varepsilon\})$	—

we wrote a very simple automaton with just a pair of resources, $R = \{r_1, r_2\}$, so the recommendation here is quite obvious; nevertheless, it is enough for allowing the observation of how the adaptive layer operates when changing the automaton topology.

As seen in Fig. 2 (a), the initial state q_0 has a loop for each resource r_i with an associated parametric adaptive function $\mathcal{A}$ with argument r_i triggered before the symbol consumption from the string of resource names. The call to the adaptive function $\mathcal{A}(r_i)$



(a) The initial topology of the adaptive automaton M for a couple of resources. Let us recognize $w = r_1 r_2$, that is, two related resources.

(b) The new topology of the adaptive automaton M after recognizing r_1. So far, no resource is related to r_1. Now let us recognize r_2.

(c) The new topology of the adaptive automaton M after recognizing a pair of resources $r_1 r_2$, now related.

Figure 2: An adaptive automaton M being used as a recommendation engine for a set of resources R containing r_1 and r_2.

(from set D of adaptive functions) will evoke a new configuration, with a transition from q_0 targeting state q_{r_i} consuming the symbol r_i. In our example, q_0 has now a transition to q_{r_1} consuming r_1 (Fig. 2 (b)); according to the input string format, r_2 is related to r_1, so a call to $\mathcal{A}(r_2)$ in q_{r_1} will evoke a new configuration (Fig. 2 (c)), where these two resources are now related.

If a resource has not been considered in the recommendation engine yet (Fig. 2 (a) with resource r_1), a modification is performed in the automaton topology in order to accommodate the newly considered resource; that is done through a call to the adaptive function $\mathcal{A}$ (Algorithm 1), which will remove and add transitions based on a set of elementary adaptive actions defined in the adaptive function body. Similarly, if an unconsidered resource is related to an existing one, not only this resource must be considered, but the recommendation path will also be built between them (as seen in Fig. 2 (b) with the loop in q_{r_1}, and the resulting recommendation path in (c) between r_1 and r_2). Adaptive function $\mathcal{A}$ takes one parameter denoting the resource to be considered. The syntax used in the function body and a complete description of elementary adaptative actions can be found in (José Neto, 1994).

If both resources r_i and r_j have been considered in the engine before, there will be a transition from q_0 to q_{r_i} consuming r_i and from q_{r_i} to q_{r_j} consuming r_j with a call to the adaptive function $\mathcal{B}$. Adaptive function $\mathcal{B}$ increments the number of transitions and intermediate states between two resources by adding a newly inserted state (chosen by a generator $g^\star$ in the function body) and modifying existing transitions in order to accommodate such new element in the recommendation path. The function takes three parameters denoting the source state followed by two link symbols $\tau_1, \tau_2 \in T$.

Algorithm 1: Adaptive function $\mathcal{A}(r)$.

Summary: this function modifies the automaton topology in order to accommodate the newly considered resource r; it creates recommendation paths between r and each considered resource; at last, it removes the selected transition from the mapping.

adaptive function $\mathcal{A}(r)$
variables: $?v, ?x, ?y, ?z$
$-(q_0, r) \rightarrow q_0, \mathcal{A}(r)\cdot$
$+(q_0, r) \rightarrow f_Q(r)$
$?(q_0, ?v) \rightarrow ?x$
$+(f_Q(r), ?v) \rightarrow f_Q(?v), \cdot\mathcal{B}(?v, \tau_{(r,?v)}, \tau_{(?v,r)})$
$+(f_Q(?v), r) \rightarrow f_Q(r), \cdot\mathcal{B}(r, \tau_{(?v,r)}, \tau_{(r,?v)})$
$-(f_Q(r), r) \rightarrow f_Q(r), \cdot\mathcal{B}(r, \tau_{(r,r)}, \tau_{(r,r)})$
$+(f_Q(r), \tau_{(r,?v)}) \rightarrow f_Q(?v)$
$+(f_Q(?v), \tau_{(?v,r)}) \rightarrow f_Q(r)$
$-(f_Q(r), \tau_{(r,r)}) \rightarrow f_Q(r)$
$?(q_0, ?y) \rightarrow q_0, \mathcal{A}(?y)\cdot$
$+(f_Q(?v), ?y) \rightarrow f_Q(?v), \mathcal{A}(?y)\cdot$
$-(f_Q(?v), r) \rightarrow f_Q(?v), \mathcal{A}(r)\cdot$
$?(f_Q(?v), ?z) \rightarrow f_Q(?v), \mathcal{A}(?z)\cdot$
$+(f_Q(r), ?z) \rightarrow f_Q(r), \mathcal{A}(?z)$
$+(f_Q(r), \alpha) \rightarrow q_0$
end adaptive function

An example of how adaptive function $\mathcal{B}$ modifies the automaton topology is illustrated in Fig. 3. For simplicity, only relevant parts of the automaton are shown.

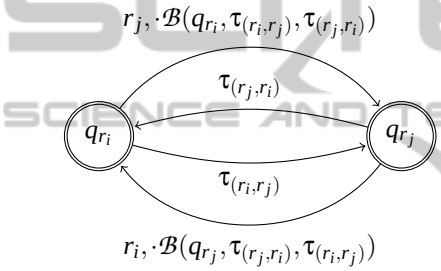
As seen in Fig. 3, $\mathcal{B}$ inserts the new state q_1 between r_i and q_j, rearranges existing transitions and adds new ones. When any transition holding an associated adaptive function $\mathcal{B}$ is executed, the corresponding recommendation path will increase in number of intermediate states.

Resources r_i and r_j are connected via a recommendation path, composed by their associated states, q_{r_i} and q_{r_j}, and an intermediate state q_k with transi-

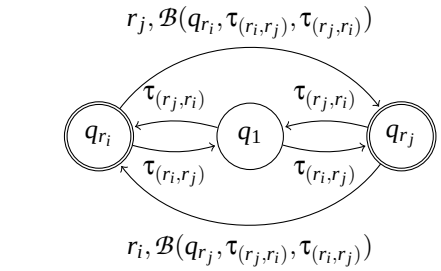
Algorithm 2: Adaptive function $\mathcal{B}(q,\tau_1,\tau_2)$.

Summary: this function adds a new element in the recommendation path between two resources. The higher the number of elements, the stronger the path.

adaptive function $\mathcal{B}(q,\tau_1,\tau_2)$
variables: $?v$
generators: $g^\star$
$?(q,\tau_1) \rightarrow ?v$
$-(q,\tau_1) \rightarrow ?v$
$-(?v,\tau_2) \rightarrow q$
$+(q,\tau_1) \rightarrow g^\star$
$+(g^\star,\tau_2) \rightarrow q$
$+(g^\star,\tau_1) \rightarrow ?v$
$+(?v,\tau_2) \rightarrow g^\star$
end adaptive function



A transition $(q_{r_i}, r_j) \rightarrow q_{r_j}$ will trigger an adaptive function $\mathcal{B}$ that will create a new state in the recommendation path between q_{r_i} and q_{r_j}.



The new automaton topology after the execution of the adaptive function $\mathcal{B}$, with a new state q_2 added in the recommendation path between q_{r_i} and q_{r_j}.

Figure 3: An example of the adaptive function $\mathcal{B}$ being triggered during the transition from q_{r_i} to q_{r_j} consuming r_j, resulting on adding a new state q_1 and a couple of new transitions.

tions consuming $\tau_{(r_i,r_j)}$ and $\tau_{(r_j,r_i)}$. Intermediate states act as a counter. At the beginning, this path contains no intermediate state from q_{r_i} to q_{r_j}; resources are directly connected through transitions consuming $\tau_{(r_i,r_j)}$ and $\tau_{(r_j,r_i)}$, as seen in Fig. 2 (c); this is by design and indicates the strength of the connection between these resources. The number of intermediate states in the path from q_{r_i} to q_{r_j} will be used as a parameter for deciding whether r_j should be recommended given r_i; the more states, the higher chance for r_j to be selected. If we go the other way in the path, that is, from q_{r_j} to q_{r_i}, the decision changes to whether r_i should be recommended given q_j. Alternatively, recommendation paths could be represented by a global counter associated with each pair of resources and an adaptive function that triggers an increment operation on demand.

It is important to observe that r_i and r_j share the same recommendation path (but of course, not the same transitions as q_{r_i} reaches q_{r_j} through $\tau_{(r_i,r_j)}$ and q_{r_j} reaches q_{r_i} through $\tau_{(r_j,r_i)}$), so our model may end up with at most $\binom{|R|}{2}$ recommendation paths, one for each $\{r_i,r_j\}$ subset, considering that all resources are related and thus connected. If commutativity does not hold between a pair of resources, every ordered pair (r_i,r_j) should have its own recommendation path, thus, the maximum number of recommendation paths should be $|T|$; the link set T already offers symbols to support non-shared recommendation paths, if this rule is chosen.

The adaptive automaton M of our recommendation engine accepts strings over the alphabet $\Sigma = R \cup T \cup \{\alpha\}$, $w \in \Sigma^*$, with $L(M) = \{w \in \Sigma^* \mid w = r_i | r_i r_j (\alpha r_i r_j)^*, r_i, r_j \in R, r_i \neq r_j\}$, in one of the forms presented as follows.

The first form, $w \in R$, denotes w as a single resource for which we want to get a recommendation. Here the idea is to submit w to our automaton and get an output string $w' \in R \cup \{\varepsilon\}$, with $w' \neq w$. For example, with $R = \{\text{egg}, \text{bacon}, \text{spam}\}$, and submitting $w = \text{egg}$ to the automaton, we should get an output string $w' = \text{bacon}$, meaning that bacon, based on our recommendation engine, is a good side dish for eggs. The occurrence of ε in the output string w' indicates that no recommendation was found based on the input string w. For practical purposes, the output relation always returns a resource $r_i \in R$, but that is a domain-specific decision.

The second form, $w = r_i r_j (\alpha r_k r_l)^*$, with $r_i, r_j, r_k, r_l \in R, r_i \neq r_j$, $\alpha \in \Sigma$ and $r_k \neq r_l$, denotes that w has at least one pair of resources, or a list of pairs separated by a delimiter α. A string in this form leads the automaton to change its topology according to the frequency of each pair of resources; modifications are possible due to the adaptive mechanism action triggered by a call to a parametric adaptive function $\mathcal{B}$ associated to specific transitions.

The string w is built from a subset of resources $R' \subseteq R$, $|R'| \geq 2$, in a transaction, for example, a basket containing grocery items in a purchase or a café tab.

In order to build a proper string to denote occurrences of each pair of resources from R', we need to obtain all subsets of two elements of R', that is, $\mathcal{P}_2(R')$, and separate them by using a special symbol α. Algorithm 3 illustrates the building process of the string w from a subset $R' \subseteq R$. For instance, let us consider a set of resources $R = \{\text{egg}, \text{sausage}, \text{bacon}, \text{spam}\}$ from a café menu and $R' = \{\text{egg}, \text{bacon}, \text{spam}\}$ as a breakfast order; a call to BUILD(R') would give us the string $w = \langle\text{egg}\rangle\langle\text{spam}\rangle\alpha\langle\text{egg}\rangle\langle\text{bacon}\rangle\alpha\langle\text{bacon}\rangle\langle\text{spam}\rangle$.

Algorithm 3: Building string w of shape $r_i r_j(\alpha r_k r_l)^*$ from $R' \subseteq R, |R'| \geq 2$.

Summary: this procedure builds an input string w to be recognized by the adaptive automaton of our recommendation engine from a subset R' of resources; it basically iterates through all subsets of two elements of R' and concatenates the intermediate results with the resource pair delimiter.

procedure BUILD(R')
  $w \leftarrow \varepsilon$
  $R'' \leftarrow \mathcal{P}_2(R')$
  $X \leftarrow r \in R''$
  for $x \in X$ **do**
    $w \leftarrow w \cdot x$
  end for
  $R'' \leftarrow R'' - X$
  if $R'' \neq \emptyset$ **then**
    for $X' \in R''$ **do**
      $w \leftarrow w \cdot \langle\alpha\rangle$
      for $x' \in X'$ **do**
        $w \leftarrow w \cdot x'$
      end for
    end for
  end if
  return w
end procedure

Special symbol α plays the role of a pair separator when building the input string w in the second form; since all transitions consuming this symbol target the initial state, the automaton behaves exactly the same with all pairs. The set of accepting states F is the union of the set of states Q_R representing resources from R, $F = Q_R, F \subset Q$.

One of the goals of the proposed recommendation engine is to submit an input string w in the first form, that is, $w \in R$, to our automaton and get an output string $w' \in R \cup \{\varepsilon\}$, with $w' \neq w$, as a recommended resource. In order to achieve that, we need to define an output relation G associated to each state $q_r \in Q_R$.

In order to determine which resource r_j to recommend in terms of resource r_i, we rely on counting the number of intermediate states for every recommendation path from r_i as a metric to indicate a suitable option. The number of intermediate states between two resources r_k and r_l (dynamically added by adaptive function $\mathcal{B}$) gives us the occurrences of the pair $\{r_k, r_l\}$; the higher that number, the more frequent the pair is, and thus, resource r_l can be a recommendation for resource r_k and vice versa. Alternately, an approach using global counters would simplify the comparison step since all values are directly available.

In order to count the intermediate states between r_i and r_j and choose the longest recommendation path, we present a procedure RECOMMEND(r) that takes a resource r and return its best recommendation, according to the highest pair frequency; this is done by inspecting the current automaton shape. The algorithm relies on counting specific transitions, so the number of intermediate states from r_i to r_j is $t-1$, with t being the number of transitions in T which consume $\tau_{(r_i,r_j)}$. Algorithm 4 illustrates the steps taken by such procedure in order to get the most suitable resource.

Algorithm 4: Obtaining the best resource as recommendation for $r \in R$.

Summary: this procedure that takes a resource r and return its best recommendation, according to the highest pair frequency; this is done by counting specific intermediate states

procedure RECOMMEND(r)
  $X \leftarrow \{\}$
  for $r_i \in R, r_i \neq r$ **do**
    $X' \leftarrow \{(q', \tau_{r,r_i}) \rightarrow q'' \in P \mid q', q'' \in Q\}$
    $X \leftarrow X \cup \{(r_i, |X'|)\}$
  end for
  $X'' \leftarrow \arg\max X'$
  return $x \in X''$
end procedure

Using the procedure presented in Algorithm 4, the output relation G maps every state $q_{r_i} \in Q_R$ representing resource r_i into a call to RECOMMEND(q_{r_i}) which returns a resource $r_j \neq r_i$ as recommendation; in other words, we get $G = \{(q_r) \rightarrow \text{RECOMMEND}(q_r) \mid q_r \in Q_R\}$,

4 EXPERIMENTS AND DISCUSSIONS

We developed two experiments in order to illustrate an evaluation of the recommendation engine proposed in this paper. First, we generated a data sample from a set R of 5 resources, $R = \{\text{egg}, \text{sausage}, \text{bacon}, \text{beans}, \text{spam}\}$, simulating several breakfast orders in a café; the data sample size ranged from 10 to 1000 entries. It is important to

mention that orders with just one item were discarded since you cannot establish a connection with other items in the same order.

First Experiment — The first experiment consisted of checking the hits of our recommendation engine [#1] compared to traditional association rule algorithms, namely Apriori [#2] (Agrawal and Srikant, 1994), PredictiveApriori [#3] (Scheffer, 2001), FP-Growth [#4] (Han et al., 2000) and Tertius [#5] (Flach and Lachiche, 1999). For this experiment, we used a sample size of 100 entries. All algorithms were executed in a 64-bit Linux environment with the help of the WEKA data mining software (Hall et al., 2009). The results are presented in Table 2. The parameters for each algorithm were automatically set by WEKA.

Table 2: Hits in the first experiment.

1	2	3	4	5
egg	bacon	–	spam	–	–
sausage	egg	–	egg	–	egg
bacon	spam	spam	spam	–	beans
beans	bacon	–	bacon	–	bacon
spam	bacon	–	beans	–	bacon

1. Our model, 2. Apriori, 3. PredictiveApriori, 4. FPGrowth, 5. Tertius

According to Table 2, Apriori and FPGrowth could not provide valid association rules based on the sample data (note that some rules are not valid in our context and were discarded, for example, if a customer doesn't order bacon, he won't order spam; we want to recommend resources solely based on positive input); by increasing the sample size, both algorithms start converging to the rules obtained from our model. PredictiveApriori and Tertius had a very similar output, although the latter had one miss when trying to extract a rule for an certain order.

It is also worth noting that the number of resources in R plays an important role in our experiment, since traditional association rule algorithms extract rules based on the power set of R, that is, $\mathcal{P}(R)$, and this set might become huge with many elements in R. Our model simply tries to establish rules based on one resource in terms of another, using just all subsets of two elements of R, that is, $\mathcal{P}_2(R)$, which is quite sufficient for our domain-specific problem.

In general, the results were significant since the design of our model employs an optimized straightforward technique (namely, frequency analysis) and at some extent the outcome came very close to more sophisticated algorithms such as the ones used in the experiment. We were able to extract meaningful connections at a low cost, minimizing the cold start problem. The key point for a recommendation context is that suboptimal answers are also valid, and thus a more balanced model in terms of hits and performance might be an interesting approach.

Second Experiment — The second experiment consisted of measuring the execution time of our recommendation engine compared to traditional association rule algorithms (the ones used in the first experiment). We tested the performance of each approach with the data sample size ranging from 10 to 1000 entries, for 1000 times.; the overview of the second experiment is in Table 3.

Table 3: Execution time in seconds of all approaches in the second experiment, with the data sample size ranging from 10 to 1000 entries. Values are represented in scientific notation, $\times 10^{-3}$.

Size	1	2	3	4	5
10	0.2	3.5	72.1	0.1	11.2
50	0.7	3.6	203.0	2.5	16.2
100	1.8	3.9	336.0	1.4	29.2
250	2.3	4.2	454.5	3.8	40.9
500	4.3	8.7	821.9	6.3	120.1
750	6.4	16.8	1187.6	9.5	180.6
1000	8.7	18.3	1110.4	9.1	178.6

1. Our model, 2. Apriori, 3. PredictiveApriori, 4. FPGrowth, 5. Tertius

According to Table 3, and based on data from Table 2, the algorithms with better predictions were also the more time-consuming ones. This is quite understandable, since several calculi are employed in order to get the best possible association rule. We can observe that our model had one the best performances amongst all approaches and still with a significant prediction rate. Perhaps the most important fact from this experiment is that our model does not suffer from data sparsity, since resource connections are only established when needed.

5 CONCLUSIONS

In this paper, we presented a recommendation engine that uses an ad-hoc adaptive automaton specially designed as a lightweight alternative to existing approaches on resource recommendation. The model is compact, efficient and offers suboptimal answers which are good enough for several specific contexts (Hatem and Ruml, 2014).

As a result of this work, we have achieved a recommendation engine based on a formalism that can be easily modified or extended in order to cover sev-

eral contexts (Cereda and José Neto, 2014). We have reached an interesting balance between performance and prediction, as seen in the two experiments in Section 4, with no significant effects of data sparsity and cold start. As future work, an additional adaptive function $\mathcal{C}$ can be used to modify recommendation paths on higher levels (for example, r_i to r_j through r_k).

The use of an adaptive rule-driven device provides simplicity and representation power; the recommendation engine shown here has a wide scope and may also be used along with usual artificial intelligence techniques, exploring the strongest points of both sides, and achieving good results when solving real world problems(José Neto, 2001; Cereda and José Neto, 2014).

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