Optimizing Web Content Presentation: a online PSO approach

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***Abstract*— In this paper we propose an approach to optimization of web marketing content based on online discrete particle swarm optimization (PSO) model. The idea behind online PSO is to evaluate the collective user feedback as the PSO objective function which drive particles velocities in the hybrid continuous-discrete space of web content features. The PSO coordinate the process of sampling collective user behavior in order to optimize the web marketing metric. Experiments in the online banner optimization scenario show that the method converges faster than other methods and avoid some common drawbacks such as local optimal and hybrid discrete/continuous features management. The proposed online optimization method is general and can be applied to other web marketing or business intelligent contexts.**

Keywords: web marketing optimization, collective behavior mining, collaborative intelligence

I. Introduction and Related Work

Optimization of web content presentation [11][12] is a very hot issue for e-commerce application. Whether considering web pages, advertising banners or any other content presentation media on the web, choosing the right structure and appearance with respect to the given audience can obtain more effective and successful impact on users, such as gathering more readers to web sites or customers to online shops.

Let consider an advertising banner scenario, where a designer has to compose a web banner considering a variety of options such as different background colors, available pictures of the product, presentation phrases, font types, and sizes. Usually the banner designer employs his own skills and his model of the target customer in order to design what he consider the best eye catching or attention catching advertising. The only way for the designer to know if the banner is effective is to submit it to the web and consider users reactions. Managing this interactive process for a large number of users is nearly impossible for a banner designer, on the other hand an automatic optimization [13] of the content presentation can exploit the feedback of a large number of online users. Some applications [1][13] has been proposed which try to select the optimal presentation using a voting mechanism (i.e. user feedback, such as number of clicks) among a fixed set of candidate ones, e.g. a set of candidate banners, or by tuning some features parameters by randomly generating candidates to vote [2]. The limit in the first case is that the optimal solution could not be in the fixed set of candidates, while a purely random strategy can hardly find an optimal solution because of combinatorial explosion, especially in presence of features with nearly continuous values, such as colors or image sizes.

Recently particle swarm optimization (PSO) [3][4] has emerged as an effective strategy for a variety of optimization problems. PSO uses the algorithmic metaphor of the dynamic of swarm behaviors in order to coordinate a set of particles, i.e. computational units, which move thru a given domain space. PSO combines cognitive and social strategies to focus the search of the swarm toward the most promising area.

The idea of our approach is to exploit the collective user feedback, as a swarm, in order to adapt and optimize the presentation features of web content with respect to the online audience. We devise a strategy based on PSO for generating candidates presentation instances which eventually converge to the optimal content presentation. A single particle submit a candidate presentation to a set of online users which provide a (implicit) feedback on it. Experiments show that the PSO strategy for web content presentation is effective and converges very fast, minimizing the number of sampled candidates, i.e. minimizing the number of non optimal presentations delivered.

To the best of our knowledge this is the first proposal of application of PSO to the online optimization of content presentation, i.e. using an interactive approach where the user feedback is used as an objective function. Moreover an hybrid approach is proposed which combines continuous and discrete dimension in PSO also if the discrete PSO has not been much addressed in the literature.

Other evolutionary approaches to adaptive web content selection has been proposed in the field of web newspapers [5][6] and multimedia information retrieval [7]. In [6] newspapers layouts are adapted to a user web browser configuration by a PSO offline approach.

II. PSO for Web Marketing

PSO has been introduced by Kennedy and Eberhart [3]. The metaphor got its inspiration from particles models of objects and simulation of collective behavior of flocks of birds. In PSO, a swarm is composed of a set of particles $P=\{p_1,p_2,\ldots,p_k\}$. The position of a particle corresponds to a candidate solution of a given optimization problem represented by an objective function $f\colon \Theta\rightarrow\Re$, with $\Theta\subseteq\Re^n$, to be maximized (or minimized).

At any step t, each particle p_i has associated a position $x_{i,t}$, a velocity $v_{i,t}$, where position and velocity are n-dimensional

vectors, and $b_{i,t}$ the particle personal best, i.e. the best position of p_i has ever visited until time step t. Moreover, particles are interconnected in a network and can communicate only with their neighbors l_i; in this way each particle can maintains the best position ever found among his l_i's neighbors denoted by $l_{i,t}$.

Each particle in the swarm moves according to its velocity. Position is updated by the vector expression

$$x_{i,t+1} = x_{i,t} + v_{i,t+1} \tag{1}$$

while velocity is updated by

$$v_{i,t+1} = \omega v_{i,t} + \varphi_1 \beta_{1,t} (b_{i,t} - x_{i,t}) + \varphi_2 \beta_{2,t} (l_{i,t} - x_{i,t}) \tag{2}$$

where the weights respectively represent the inertia ω, the acceleration factors φ_1, φ_2 and the random factors $\beta_{1,t}$, $\beta_{2,t}$ which are distributed in [0,1]. The contribution $(b_{i,t} - x_{i,t})$, the distance from the personal best, has been interpreted as a cognitive component, while $(l_{i,t} - x_{i,t})$ is a social component.

A number of variations to PSO has been proposed for velocity updating or other aspects. A very common one assumes that particles are connected by a complete network and in this case $l_{i,t}$ are substituted by a global l which can be maintained more efficiently. This simple variation is the one used in our approach.

Discrete PSO has been proposed since [8] and more recently [9], these methods emphasize the randomized contribution in order to obtain explorative behavior of the swarm in combinatorial search spaces. As pointed out in [10] and [3] PSO seems to benefit from the local monotony of objective function in continuous search spaces, but the same property does not hold in the discrete space generated by combinatorial problems. In other words, in a contour of a particle position, in a n-dimensional space, objective function is pleasant that is continuous, while in general this is not true for a discrete problem. On the other hand the distinction between continuous and discrete search space is not so sharp, since there are discrete spaces where the elements of the discrete domain can be ordered according to some notion of distance. Although this notion of "distance" does not have all the properties of a metric space but an approximation of continuity properties of objective function f can hold. Suppose for instance that f depends from different parameters such as temperature, and let the search space has a dimension T containing a finite set of ordered elements, say D_T={*very_cold, cold, cool, mild, warm, very_warm, hot, very_hot*}, and suppose that the best value so far of f has been found in position T=*very_warm* then it is possible, and likely, to define an appropriate discretization of velocity and position update to make the other particles moving from their positions toward *very_warm* on dimension T.

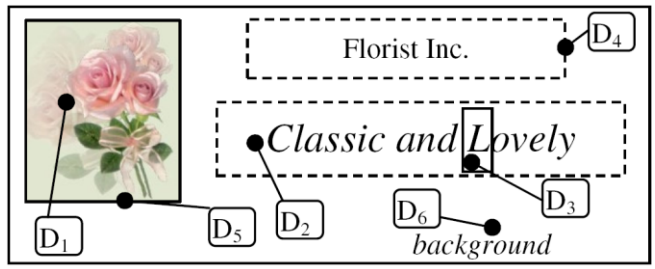

Figure 1. Content presentation structure and domains

III. An Online PSO model for Web Marketing Content Presentation

A. Web Marketing Content Presentation Search Space

The search space consists of admissible content presentations.

The content presentation search space is described by a feature vector $C=[c_1,\ldots,c_n]$ with $c_i \in D_i$, where D_i are possible alternatives provided by the content presentation designer.

In content presentation problems, the domains D_i are, in general, a mix of continuous, discretized and pure combinatorial domains. Let consider for example the banner scenario where a designer is proposing a web banner for advertising a florist shop. The banner consists of a fixed structure (see fig. 1) with a picture on the left hand side, the shops logo, a slogan phrase and a background which a uniform color. The designer has selected 10 different candidate pictures of roses, 7 of tulips and 12 of lilies (D_1); he is undecided among 10 different candidate phrases (D_2); he has decided the font types for the catching phrase but not the font size which has to be among a range from 8 to 14 points (D_3); moreover the size of the corporate logo and of the picture can also vary in given ranges (D_4, D_5) and the background color has to be decided in a shade of red (D_6). Summarizing the banner search space is $D=D_1 \times D_2 \times D_3 \times D_4 \times D_5 \times D_6$ where D_4, D_5, D_6, are continuous domains, D_2 is purely combinatorial, D_3 is discretized and D_1 is discretized internally to each group of flowers, the pictures are ordered in each group for increasing number of flowers.

B. Online PSO for Web Content Presentation

The particle swarm algorithm proposed here uses a fully connected particle swarm.

At each iteration each particle generates a new candidate presentation configuration by moving to a new position $x_{i,t}$ in the search space D. The evaluation of the objective function $f(x_{i,t})$ is realized by submitting the candidate presentation to web users and measuring their feedback.

The feedback is used in order to determine the personal best, absolute best and in order to perform velocity update. The algorithm aims at maximizing the feedback function. A scheme of the online algorithm is shown in fig. 2.

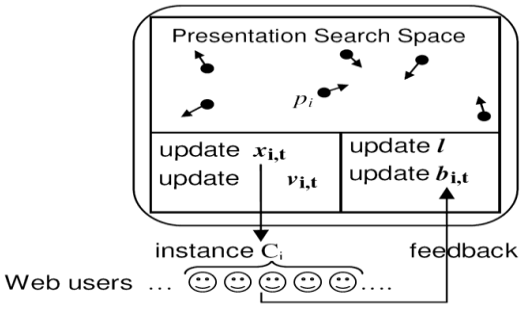

Figure 2. Online PSO for Web Content Presentation

The set P of particles is initially distributed in a random way in the search space. If the content designer has his own preferred or best candidate it is directly assigned to one particle. Personal best and global best are initially assigned to zero for all particles (i.e. no feedback observed).

Velocity updating has an important role in the proposed algorithm. Since it is supposed to have an hybrid continuous/discrete features space, different update functions are used for different classes of dimensional domains. The purpose is to exploit the local continuity for continuous and discretized domains and emphasize the exploration for pure combinatorial domains.

In the following is described the update phase of velocity and position which varies, as mentioned above, depending on the domain to which the feature belongs.

1) Continuous Feature

Position and velocity of continuous features, such as picture size, are updated according to the classical updating functions (1) and (2). Out of bound exceptions are managed by randomly restarting the particle dimension.

2) Ordered Discretized Feature

Discretized features are content features for which an order, or a similar notion, exists (i.e. domains D_3 and D_1 of the florist banner example).

The elements of an ordered discretized domain D_j are mapped into the integers $[0,1,2,\ldots|D_j|-1]$ and velocity/position updating is done as an integral approximation of a continuous position and velocity in the integral interval $[0, |D_j|-1]$.

$$x_{i,j,t+1} = \begin{cases} \lfloor x_{i,j,t} + v_{i,j,t+1} \rfloor & if \lfloor x_{i,j,t} + v_{i,j,t+1} \rfloor \in [0, |D_j| - 1] \\ |D_j| - 1 & if \lfloor x_{i,j,t} + v_{i,j,t+1} \rfloor > |D_j| - 1 \\ 0 & if \lfloor x_{i,j,t} + v_{i,j,t+1} \rfloor < 0 \end{cases}$$

It is worth noticing that we do not use $Z_{|D_j|}$ arithmetic which has the unlikely property of "wrapping" on the interval extremes, instead, a "bouncing back" approach has been preferred since it seems to better preserve the local continuity of f.

When the particle goes out of the discrete bounds, its velocity is reset to a magnitude of 1 with direction towards inside the interval.

Let $v_{new} = \lfloor \omega\, v_{i,j,t} + \varphi_1 \beta_{1,t} (b_{i,j,t} - x_{i,j,t}) + \varphi_2 \beta_{2,t} (l - x_{i,j,t}) \rfloor$ then

$$v_{i,j,t+1} = \begin{cases} v_{new} & if \quad x_{i,j,t+1} \in (0, |D_j| - 1) \\ 1 & if \quad x_{i,j,t+1} = 0 \\ -1 & if \quad x_{i,j,t+1} = |D_j| - 1 \end{cases}$$

The experiments have shown that for very small discrete domain size, ω is usually 1 and the parameters φ_i should be less than 0.2.

3) Pure Combinatorial Feature

In the case of pure combinatorial features (i.e. alternative phrases), where an ordering is not defined, we use a randomized approach which guarantees domain exploration. Position is updated like for discretized domain while velocity is computed as

$$v_{i,j,t+1} = \begin{cases} \lfloor \beta_{3,t} \rfloor & if \ \lfloor \beta_{1,t} \rfloor = \lfloor \beta_{2,t} \rfloor = 1 \ or \ \lfloor \beta_{1,t} \rfloor = \lfloor \beta_{2,t} \rfloor = 0 \\ b_{i,j,t} - x_{i,j,t} & if \ \lfloor \beta_{1,t} \rfloor = 1 \ and \ \lfloor \beta_{2,t} \rfloor = 0 \\ l - x_{i,j,t} & if \ \lfloor \beta_{1,t} \rfloor = 0 \ and \ \lfloor \beta_{2,t} \rfloor = 1 \end{cases}$$

where $\beta_{3,t}$ is uniformily distributed in $[0,|D_j|-1]$, $\beta_{1,t}$ and $\beta_{2,t}$ are uniformly distributed in [0,2).

C. Online particle feedback evaluation

In order to perform a correct evaluation, each $f(x_{i,t})$ should be obtained impressing with the $x_{i,t}$ banner the same number of users, that is the sample size s must be constant. The cost of n iterations with $|P|$ particles is then the number $s \cdot n \cdot |P|$ of contacted users. In other words the flow of users is divided into n sets u_i, $i=1,\ldots,n$, each of the same size s; an u_i represents the users assigned to evaluate f on the candidate solution currently found by particle p_i. The underlying assumption is that in all the user sample sets, f has an homogeneous behavior, i.e. the user are uniformly distributed in the n sets. Typical web marketing performance measure can be used, such as *#clicks / #impression*, *average_time_before_click / #impression*, *#finalized_orders / #impression* or a combination of the latters.

IV. Experiments

Experiments for the banner scenario with 6 hybrid features have been held using the hidden values technique developed in [5].

Optimal banner feature configurations are randomly generated and a simulated feedback function f is produced by using these values and the common euclidean distance for measuring the optimality of a candidate banner. Note that the optimal solution randomly generated is invisible to the PSO algorithm which only access to the evaluation function f.

For each randomly generated optimal configuration the online PSO has been run for at most 1000 iterations, and the generation in which the optimal is first discovered has been considered the convergence limit. Moreover artificial cases have been generated for comparison of different features mix: content presentation with only continuous features, discretized features and pure combinatorial features.

TABLE I. EXPERIMENTS

Search Space Type	#Domains × Size	Average convergence	Best	Worst
Mixed Banner	6 (3+2+1)	318	132	457
Continuous	8	75	60	93
Discretized	6×2^8	452	321	600
Discretized	8×2^8	654	443	742
Discretized	10×2^8	821	505	960
Pure Combinatorial	3×2^8	842	700	>1000
Pure Combinatorial	4×2^8	880	830	>1000
Pure Combinatorial	5×2^8	>1000	>1000	>1000

The results of the experiments for the different categories are summarized in the following table, the convergence limit are averaged over 200 random optimal configurations. Results show as expected that pure combinatorial problem domain easily become intractable while the best performances are obtained with continuous features. The mixed banner configuration used in the experiments is composed from 3 continuous features, 2 discretized features and 1 pure combinatorial features; for obtaining best performances the pure combinatorial feature of this mixed banner are weighted proportionally to their size in the evaluation function *f*. Moreover, note that the results are computed with a population of 20 particles.

Although more experiments and parameters tuning are needed, the technique seem to be viable for online optimization of content presentation when the number of features is relatively small such as in many web content scenario.

V. CONCLUSIONS

A web marketing optimization model based on online PSO [3] has been presented. The method search the optimal configuration in the hybrid feature search space of web marketing content presentation. The online approach is based on collective user feedback [5] in order to guide the particle swarm toward the selection of the optimal presentation. Different kind of velocity updates are used in the hybrid multi-dimensional domains in order to exploit the local continuity of the objective function.

It is worth noticing that the collective user behavior technique can be used to optimize in the same framework the web content presentation and some typical web marketing parameters such as adsense keywords to associate to marketing campaigns.

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