CONSTRUCTIVE SOCIAL CHOICE WITH SETWISE MAX-MARGIN

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Trento , Italy

December 20, 2017

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1.1 Background and Motivation

- The *social choice problem* is essentially the problem of choosing or recommending an item combining individual opinions, preferences, interests, or welfares.
- To reach a collective decision or social welfare satisfying some notion of societal consensus.
- Social choice has been the subject of intense investigation within
  - *computer science*
  - *Artificial Intelligence*
  - *operations research*

Preference Elicitation

- Preference elicitation is defined as the problem of developing a decision support system by an interactive way (i.e asking informative queries)

Constructive Recommendation

- Constructive recommendation is the task of recommending structured objects, i.e. configurations of several components, assembled on the basis of the **user preferences**.
    - planning a trip around Italy involves deciding which city visit, in which order, how long stay and which activity to do in each city, subject to the available time and budget

How does constructive recommendation work?

- "Synthesis" of new objects from scratch (i.e. assemble them from their components) on the basis of the user preferences.
- User preferences are represented by a *utility function* $\mathcal{X} \times \mathcal{Y} \rightarrow$ R that maps structured objects $y \in \mathcal{Y}$ to a ranking score, which can also depend on contextual information $x \in \mathcal{X}$ (e.g. a user query).
- Object synthesis is performed by maximizing the utility function over the constrained domain of feasible configurations.

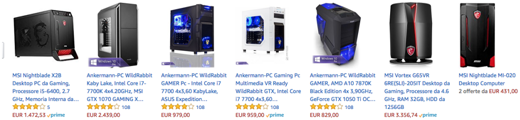
Query ranking

- Interaction with user $\Rightarrow$ Asking pairwise queries
- Feedback $\Rightarrow$ Ranking constraint either
    - x is preferred over x' (written as $x \succ x'$)
    - x' is preferred over x ($x' \succ x$) or
    - There is no clear preference between the two items ($x \approx x'$)
- Recommendation $\Rightarrow$ by solving a constrained MILP optimization problem over a very large domain of feasible configurations.

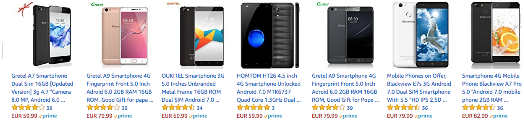
Constructive Social choice

- Classical social choice focuses neither on **learning** nor on **recommendation** but only on analyzing **voting protocols**, and no existing ”social preference learner” is constructive.
- Constrictive social choice $\Rightarrow$ Recommending a synthesized object by solving a constrained optimization problem (Group-wise recommendation)

Application Domains



- personal computers or mobile phone recommendation.



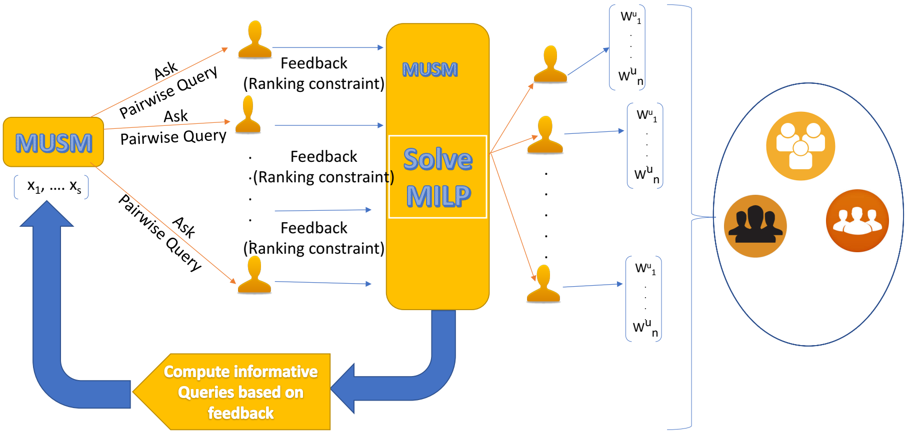
- Sets of exam schedules shared by many professors.
- Family home furniture arrangement
- Recipes recommendation
- Travel planing...etc.

- Making a first step towards extending constructive preference elicitation to social choice domains.
- A single best item synthesized by **constructive approach** to be recommended for a group of people or a society.
  - Different users may give different contributions to the aggregate utility (group satisfaction)

    $\Rightarrow$ Here our main focus is learning the user contributions

How to achieve it?

Constructive preference elicitation



Constructive Social choice

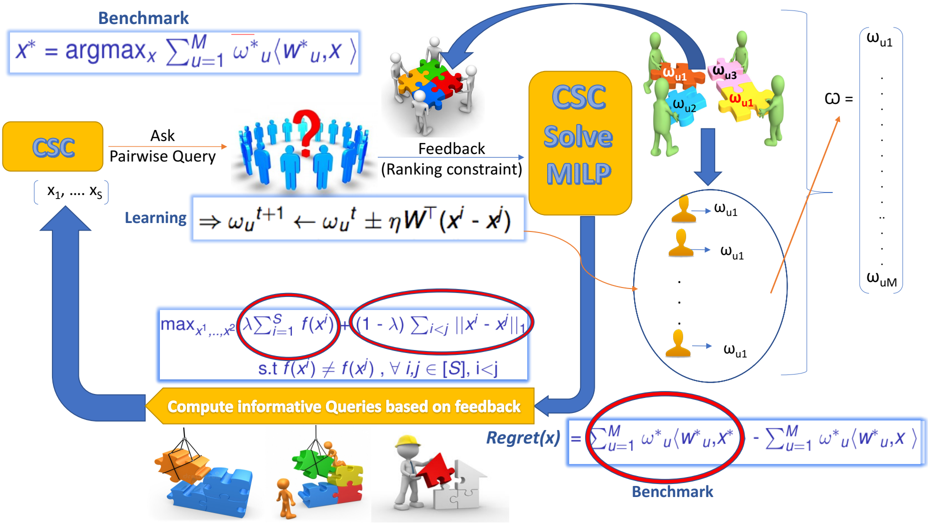
Setting

- User preferences are represented by weight vector $w \in R^N$
- $x = (x_1, . . . ,x_N)$ represents configurations over N feature space (N attributes).
- $X_z \in \{0,1\}$ for all $z \in$ [n] assuming a one-hot encoding of categorical features.
- $\langle . , . \rangle$represent the usual dot product
- $\langle x,w \rangle = \sum_{z=1}^{n} w_z x_z$ for utility of a configuration x.

- A set of users $u \in \{1,....M\}$
- $w^*_u \in R^N_+$ representing true preferences of user $u \in [M]$
- $w^u_1, \ldots, w^u_K \in R^N_+$ (learned)estimated preferences of user u.
- $x^* \in \mathcal{X}$ representing one of the configurations most preferred by the *group*.
- $W \in R^{N\times M}_+$ is the matrix obtained by stacking the learned preference vectors of all users side-by-side(aggregation). W_* is the analogue for the true preferences.
- $\omega \in R^M$ parameters representing the contribution of different users to the overall utility of configurations from collective, group-wise feedback
- The aggregate Preference of the users as a group are defined as a function f of W.

$$\Rightarrow f(x;W) := \sum_{u=1}^{M} \omega_u \langle w_i, x \rangle$$

Constructive Social Choice (CSC)



Algorithm 1 The CONSTRUCTIVE-SOCIALCHOICE algorithm; it uses the MUSETMARGIN algorithm as first step to receive the individual user information. Here M is the number of users, S is the set size, and T is the number of iterations. The hyperparameter λ is left implicit.

procedure CONSTRUCTIVE-SOCIALCHOICE(m, w^u, S, T)

    ; Initialization

    for $u = 1, \ldots, m$ **do**

        $MUSM(MultiUserSetMargin)$

    ; Main loop

    $\mathcal{D}_u \leftarrow \varnothing$

    for $t = 1, \ldots, T$ **do**

        $\{\omega^i, \boldsymbol{x}^i\}_{i=1}^{S} \leftarrow$ SOLVE($\mathcal{D}, S, \lambda$)

        for $\boldsymbol{x}^i, \boldsymbol{x}^j \in \{\boldsymbol{x}^1, \ldots, \boldsymbol{x}^m\}$ **s.t.** $i < j$ **do**

            THE GROUP SELECTS($\boldsymbol{x}^+$from$\{\boldsymbol{x}^i\}$)

            $\mathcal{D} \leftarrow \mathcal{D} \cup$ QUERYGROUP($\boldsymbol{x}^i, \boldsymbol{x}^j$)

        $\omega^*, \boldsymbol{x}^* \leftarrow$ SOLVE($\mathcal{D}, 1, \lambda$)

    return $\omega^*, \boldsymbol{x}^*$

Experimental Results

Experimental setup

- 20 groups of M = 20 users were randomly generated each using a hierarchical sampling procedure.
- **Sparse Users** = Users with preference information about some of the attributes. (realistic)
- **Dense Users** = users with preference information about all or most of the attributes.(unlikely)
- Noiseless implementation

$\Rightarrow$ We implemented the CONSTRUCTIVE SOCIAL CHOICE algorithm using Python, leveraging Gurobi 7.5.0 for solving the core MILP problem.

Dataset description

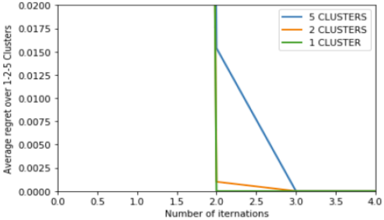
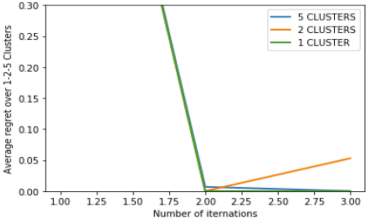
- The first experiment is performed on the synthetic problem. In this setting:
  - The space of products $\mathcal{X}$ is taken to be the Cartesian product of r categorical attributes.
  - Each having r possible values.
  - Represented using a one hot encoding for a total of r^2 0-1 variables.
  - We used the $r = 4$ case, with $r^2 = 16$ variables and $r^r = 256$ total products.

- In the second experiment we consider a realistic PC recommendation task $\Rightarrow$ suggest a fully customized PC.
- PC configuration is defined by 7 categorical attributes:
  - Computer type , Manufacturer (8 choices), CPU model (37choices), Monitor size (8), RAM amount (10), storage size (10), Price.
- The PC dataset includes 16 Horn constraints leading to a search product space of about 700,000 distinct configurations.

- The performance is measured by ranking loss as:

$$\text{Regret}(x) = \sum_{u=1}^{M} \omega^{*}{}_{u} \langle w^{*}{}_{u}, x^{*} \rangle - \sum_{u=1}^{M} \omega^{*}{}_{u} \langle w^{*}{}_{u}, x \rangle$$

- Cluster $\Rightarrow$ diverge or may be conflicting interests with in a group.
- Experimental results demonstrated that the constructive social choice algorithm converges earlier for decreasing number of clusters both for synthetic and PC experiments.

<table>
<tr><th colspan="3">Performance over 1,2,5 clusters</th></tr>
<tr><th></th><th>Normal</th><th>Uniform</th></tr>
<tr><td>Synthetic</td><td>
</td><td>
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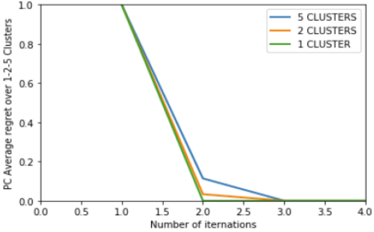
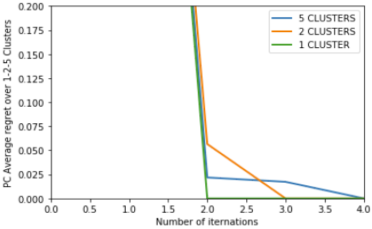
<tr><td>PC</td><td>
</td><td>
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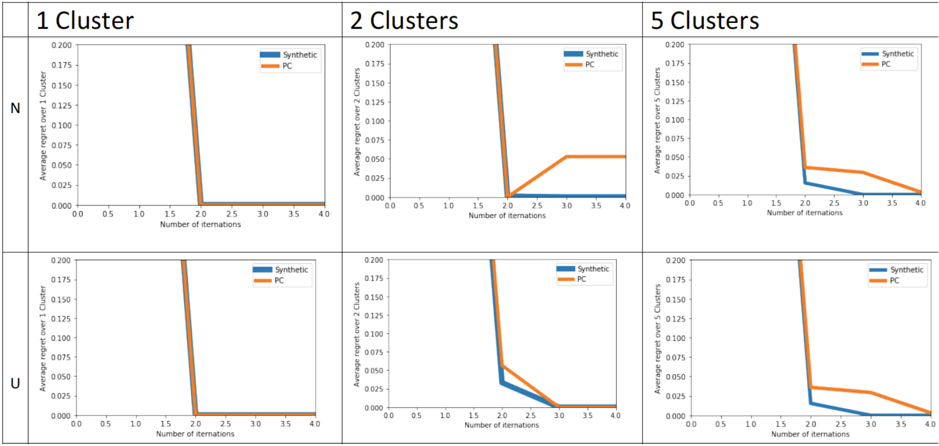
Performance over 1,2,5 clusters



Comparison between Synthetic and PC experiment

Limitation (Addressing Dense users)

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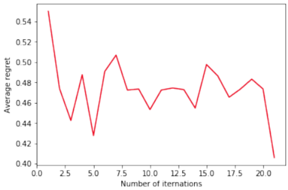
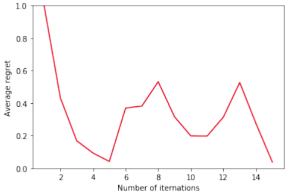
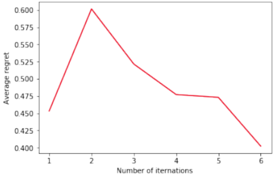
N</td><td>
</td><td>
</td><td>
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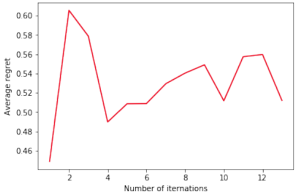
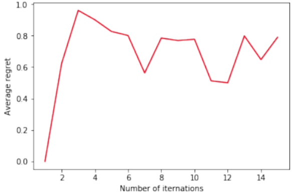
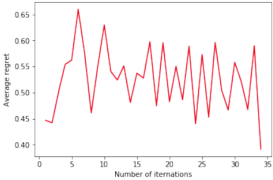
U</td><td>
</td><td>
</td><td>
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Performance on Dense User groups

Conclusion

- We presented an approach to make a first step towards extending constructive preference elicitation to social choice domains.
- Constructive learning in social choice is a natural extension and many problems can be measured in it.
- A key idea is that, by asking informative questions and collecting group wise feedback to iteratively elicit societal preference and make the best recommendation to the society according to the learned feedback.

Future Work

- As a future work we propose an extension to
  - Learning both the preferences of individual users and their contributions (W and ω)
  - Further refinement of the algorithm to address dense users.
  - A deep experimental evaluation of more realistic and complex datasets like the PC dataset.

- Thank You.