Structured Object Recommendation

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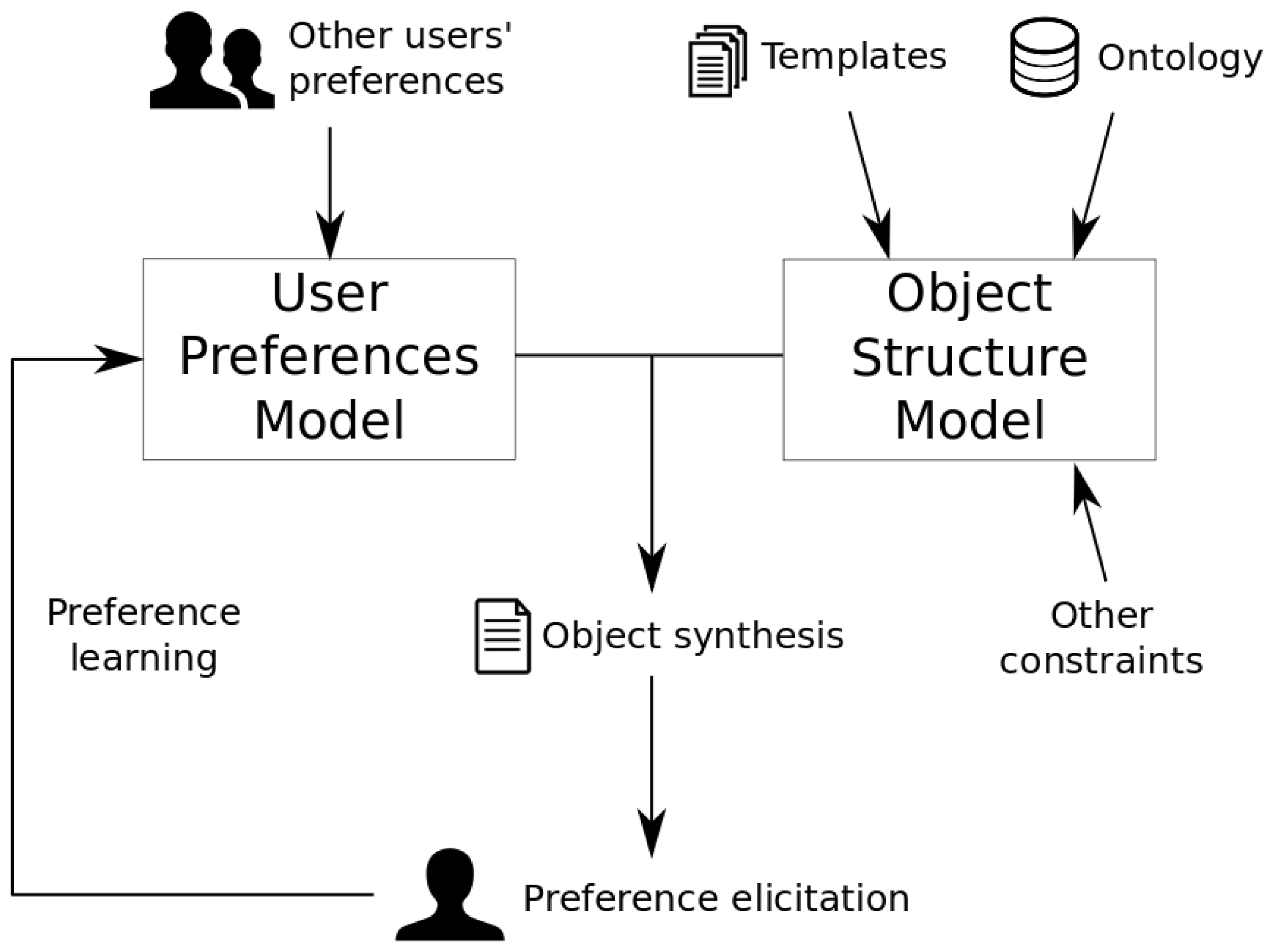
1. Structured objects

Complex objects having several components linked by boolean and numerical constraints. Some examples:

Class of objects	**Components**	**Constraints**
Recipes	Ingredients	Presence of ingredients, quantity proportions, ...
PC configurations	Processor, graphic card, RAM, hard drive, ...	Minimum requirements, performance, price, ...
Furniture arrangements	Pieces of furniture, walls, doors, windows, ...	Arrangement constraints, e.g. no wooden table close to the fireplace, no tall cabinet close to the window, ...

2. Recommendation + Object Synthesis



- Represent objects as a combination of boolean and numerical features, imposing arbitrary constraints on their structure;
- Recommend existing objects and unseen objects, created from scratch (object synthesis);
- Objects created modifying templates and personalized on the basis of the user's preferences;
- User's preferences learned from interaction (preference elicitation) and other users' similar preferences;
- Flexible method that can generalize many existing approaches;
- Possibility of extending the approach to perform *structure learning*.

3. Learning Modulo Theories (LMT)

Structured prediction via Optimization Modulo Theories (OMT) [1]:

$$x^* = \mathrm{argmax}_x \ f(x) = \mathrm{argmax}_x \ w^T \psi(x)$$

OMT optimizes a linear function over an arbitrary set of boolean and numeric constraints.

Weight learning by max-margin, formulation depending on the type of evidence acquired, usually a ranking problem:

$$\begin{array}{rl} \min & |w| + C \sum \xi_{i,j} \\ \text{subj to} & \\ \forall x_i \prec x_j & w^T(\psi(x_i) - \psi(x_j)) \geq \Delta(x_i, x_j) - \xi_{i,j} \end{array}$$

4. The user & structure model

The synthesis model is a weighted combination of the user model and the structure model.

$$\mathrm{argmax}_x \ f(x) = \mathrm{argmax}_x \ \alpha f_u(x) + (1-\alpha) f_s(x)$$

$$f_u(x) = \langle w_u, \psi(x) \rangle + \beta \sum_{u' \in \mathcal{U} : u' \neq u} \langle w_{u'}, \psi(x) \rangle \langle w_{u'}, w_u \rangle$$

The structure model $f_s(x)$ can be any linear function expressible by OMT, constraining the predicted objects to proper "shapes", e.g. a similarity measure with existing templates.

5. Preference elicitation

- Binary comparison with suboptimal solution:

$$x^{**} = \mathrm{argmax}_{x : x \neq x^*} f(x)$$

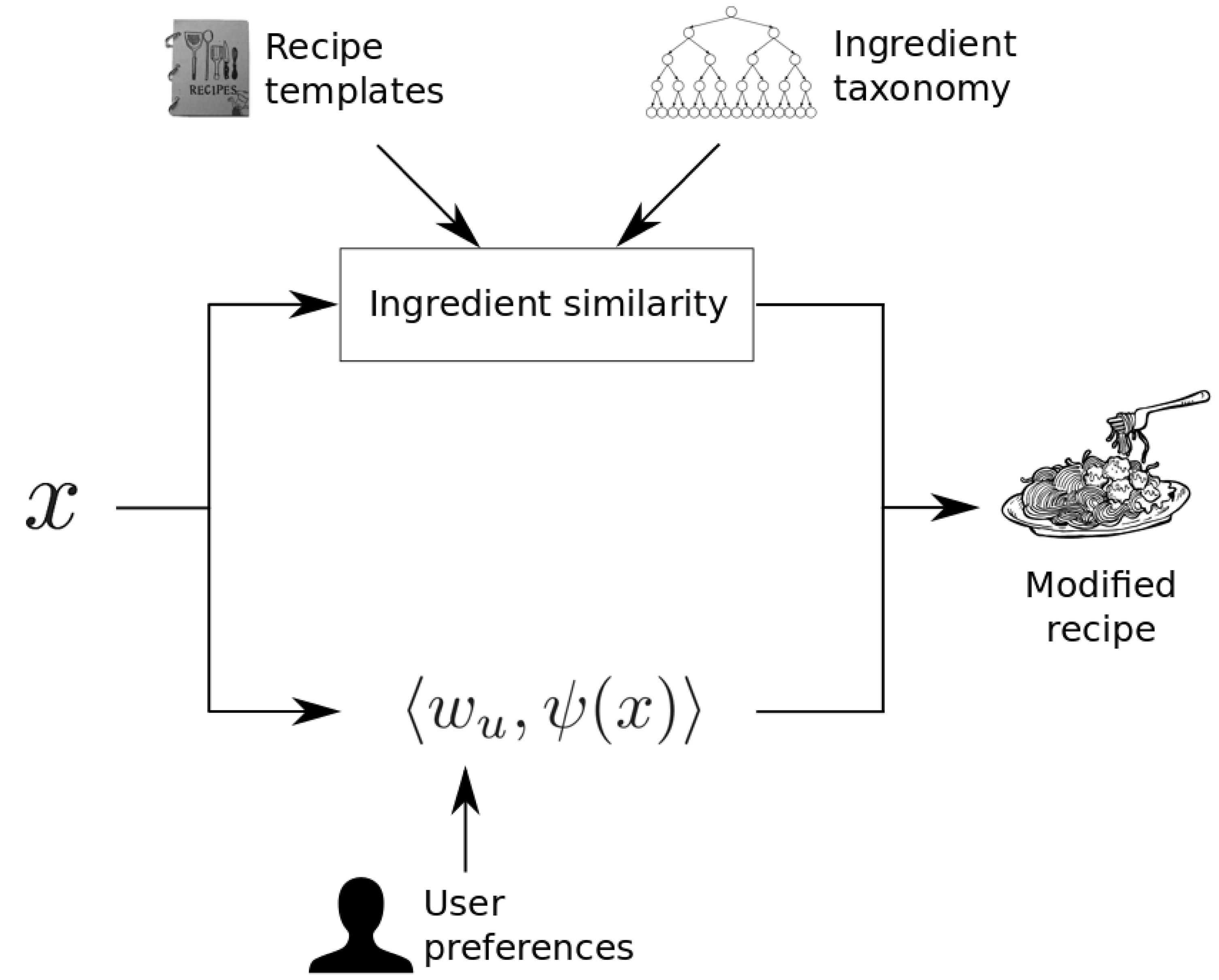
- Suggestion of an undesired value for feature i by the user:

$$x^{**} = \mathrm{argmax}_{x : x_i \neq x_i^*} f(x)$$

- Suggestion of a correction by the user (according to his unknown preference h):

$$x^{**} = \mathrm{argmax}_{x : x_i \neq x_i^*} h(x)$$

6. Example: Recipe modification



- The system creates recipes (set of ingredients) starting from a pool of existing templates of recipes;
- The recipes are modified according to the user's preferences, e.g. vegetarian versions of existing recipes;
- The structure model measures the similarity of the object x with the recipe templates, e.g.:

$$\mathrm{ingsim}(x) = \max_{T \in \mathcal{T}} \langle \psi(x), \psi(T) \rangle$$

where $\mathcal{T}$ is the set of templates;
- A taxonomy of ingredients can be used to make more accurate predictions, by substituting ingredients only with similar ones;
- Existing recipes modification methods (such as [2]) can be used as structure model in our formulation.

7. References

[1] Teso, Stefano, Sebastiani, Roberto, and Passerini, Andrea. Structured learning modulo theories. *Artificial Intelligence Journal*, 2014.

[2] Teng, Chun-Yuen, Lin, Yu-Ru, and Adamic, Lada A. Recipe recommendation using ingredient networks. *4th Annual ACM Web Science Conference.*, 2012.