Multi-attribute Preference Models for Computational Creativity

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Computational Creativity
And Now, From I.B.M., Chef Watson

IBM’s AI-like computer systems aren’t limited to Watson, the Jeopardy-winning supercomputer that schooled Alex Jennings on national television. In fact, IBM researchers foresee a not-so-distant future when algorithms will be a replacement for inefficient customer service models, a diagnostic tool for doctors, and believe it or not, chefs.

Researcher Lav Varshney has already built an algorithm that creates recipes from parameters like cuisine type, dietary restrictions and course. The system determines optimal mixtures based on three things: tens of thousands of recipes taken from sources like the Institute of Culinary Education or the Internet, a database of human psychophysics (what humans like to eat), and food chemistry.

Right now, the result is a pre-Julia Child cookbook, providing chefs who already know cooking basics, with suggestions for billions of ingredient combinations but no instructions.

To test its skill, we pitted IBM’s algorithm against go-to-recipe resource Epicurious (owned by WYD’s parent company, Condé Nast). We searched the site for a Caribbean plantain dessert and found a tasty connection with rum and coconut sauce. With the same parameters, IBM’s computer generated a list of about 50 ingredients, including orange, papaya, and cayenne pepper, from which IBM researcher and professional chef Morten Pedel developed a mind-blowing Cayambari parfait.

While the IBM dessert tasted better, it was also insanely elaborate, so we’ll call it a draw.

—Allan P. Davis

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[San Jose Mercury News, 28 Feb. 2013]
[IEEE Spectrum, 31 May 2013]
[Wired, 1 Oct. 2013]
Cognitive Cooking with Chef Watson

Recipes for Innovation from IBM & the Institute of Culinary Education
Computational Creativity

Computational Creativity Community

- Artificial Intelligence
- Cognitive Science/ Psychology
- Design
- Arts
- OR/DA? ...

Computational Creativity: Goals

- Support human creativity
- Enhance human creativity
- Build artifacts perceived as creative by humans
An Example Application

AARON (the robot painter)

- Developed by Harold Cohen since the 1970s

"AARON can make paintings of anything it knows about, but it actually knows about very little -- people, potted plants and trees, simple objects like boxes and tables, decoration."

-- Harold Cohen
Preference Modeling
Perspective
Motivation

“Novelty & More”

- Creativity involves novelty and value (Newell et al. 1958, Boden 1990)

- Mayer (1999) reviews other terms:
  - Novelty: originality
  - Value: usefulness, utility, adaptiveness, appropriateness, significance

- We will use the terms: novelty & quality (Ritchie 2001, Pease et al. 2001)

Subjectivity in Evaluation

- Relationship b/w creator/creation and observer (Wiggins 2006)

- Creative artifact must be judged or deemed to be creative (Sawyer 2012)

- Creativity assessment research goes back a far ways (Cattell et al. 1918)
Brief Terminology Review

• **Objective** indicates the direction in which one strives to do better and **attributes** are measures that determine how well objectives have been met.

• **Preference functions** are mathematical representations of a person’s preferences over the domain of attributes (Keeney and Raiffa 1976).
  - *Value functions* represent preferences under certainty
  - *Utility functions* represent preferences under uncertainty

• **Additive value functions** are most pervasive.
  - *Weighted sum of marginal value functions:* \( v(x_1, \ldots, x_M) = \sum_{i=1}^{M} \lambda_i v_i(x_i) \)
  - *Mutual preferential independence* is assumed
  - Marginal value functions can take any form, such as the *power function* \( v_i(x_i) = x_i^{\beta} \)

![Graph showing marginal value functions with different values of \( \beta \)]
An Example Objectives Hierarchy

- Example of an objectives hierarchy using attributes from Jordanous (2012) based on the 4 Ps model (Rhodes 1961):

  - Builds creative products:
    - Generation of results
    - Originality
    - Value/usefulness
  - Undergoes creative processes:
    - Dealing with uncertainty
    - Involvement & persistence
    - Intention & emotion
  - Has relevant knowledge & abilities:
    - Thinking & evaluation
    - Independence & freedom
    - Spontaneity
  - Interacts effectively with the environment:
    - Variety & divergence
    - Progression & development
    - General intellect
    - Domain competence
    - Interaction/communication
Implications of Mutual Preferential Independence

Example (Sternberg et al. 2006)

- Students provide captions for cartoons from the New Yorker
- Judges evaluate cleverness, humor & originality (5 point scale)
- Total score is the sum

Q: Is the additive function appropriate?

Low cleverness score (0)                 High cleverness score (5)
An Example Copula: Extended Archimedean

$$E(z_1,...,z_M) = a\psi^{-1}\left[\prod_{i=1}^{M} \psi\left(l_i + (1-l_i)z_i\right)\right] + b,$$

where $l_i \in [0,1), a = 1/\left(1-\psi^{-1}\left[\prod_{i=1}^{M} \psi\left(l_i\right)\right]\right), b = 1-a$, and $\psi$ has cdf like properties

A special case: $l_i = 0 \ \forall \ i$, $\psi(z_i) = z_i$ results in the multiplicative form: $v(x_1,...,x_M) = \prod_{i=1}^{M} v_i\left(x_i \mid \lambda_i\right)$
Consider the following value functions for an artifact with two attributes: **novelty** $x_N$ & **quality** $x_Q$

**Additive**

$$v = \lambda_N v_N (x_N) + (1 - \lambda_Q) v_Q (x_Q)$$

$$v_i(x_i) = x_i^{\beta_i}; \ i = N, Q$$

$\lambda_N = 0.4; \beta_N = \beta_Q = 2$

**Multiplicative (copula)**

$$v = v_N (x_N | x_Q^*) . v_Q (x_Q | x_N^*)$$

$$v_i(x_i | \bar{x}_i^*) = x_i; \ i = N, Q$$

**Extended Archimedean (copula)**

$$v = E(v_N (x_N | x_Q^*), v_Q (x_Q | x_N^*))$$

$$\psi(z_i) = (1 - e^{-\delta z_i})/(1 - e^{-\delta})$$

$$v_i(x_i) = x_i^{\beta_i}; \ i = N, Q; \delta = -5$$
Suppose the system considers “mean rating” (mean of novelty and quality scores) but the user’s preferences are best represented by $v(.)$

**Question:** What is the impact of mischaracterization of the user’s preferences?

**Case 1:** System recommends the “best” artifact to the user

**Metric:** Loss =

$$\max_i v(x^i_N, x^i_Q) - v(x^i_{i*}, x^i_{i*}),$$

where $i* = \arg \max_i \left[ \frac{x^i_N + x^i_Q}{2} \right]$.

**Case 2:** System recommends a rank order of artifacts to the user

**Metric:** Rank distance =

$$D \left[ r(i: v(x^i_N, x^i_Q)), r(i: \frac{x^i_N + x^i_Q}{2}) \right],$$

for rank $r(i: C^i)$, condition $C^i_i$, metric $D$. 
Case 1: System recommends the “best” artifact to the user

Suppose $N$ artifacts are generated by: $X_N^i, X_Q^i \sim U((0,1)^2)$ $\forall i$

Suppose user's value function: $v(x_N, x_Q) = \lambda x_N^\beta + (1-\lambda) x_Q^\beta$

**a) Metric: Exp. % value loss**
A CC Recommender Scenario: Numerical Example (2/2)

CC system generates N artifacts

Suppose $N$ artifacts are generated by: $X_N^i, X_Q^i \sim U(0,1)^2 \ \forall i$

Suppose user's value function: $v(x_N, x_Q) = \lambda x_N^{\beta} + (1 - \lambda) x_Q^{\beta}$

Case 2: System recommends a rank order of artifacts to the user

b) Metric: Exp. rank distance
Other Formulations (in the Paper*): Summary

Sets of Artifacts

- Set of artifacts with typicality \( T \), quality \( Q \) (Ritchie 2001) generated by probability density function \( f_{T,Q}(t,q) \).

- Three-attribute formulation for the set:
  - Novelty: \( X_N \approx \int_0^1 f_T(t)\,dt \)
  - Conformance: \( X_C \approx \int f_T(t)\,dt \)
  - Quality: \( X_Q \approx \int f_Q(q)\,dq \)

- For copula-based preferences, a generating system that balances typicality and quality is optimal.

Computational Creativity Systems

- Objectives are context-dependent in general.

- Illustration comparing three jazz improvisation systems (Jordanous 2012); four-attribute formulation:

<table>
<thead>
<tr>
<th>Attribute</th>
<th>GAmprovising</th>
<th>GenJam</th>
<th>Voyager</th>
</tr>
</thead>
<tbody>
<tr>
<td>“Product”</td>
<td>0.41</td>
<td>0.73</td>
<td>0.48</td>
</tr>
<tr>
<td>“Process”</td>
<td>0.34</td>
<td>0.70</td>
<td>0.38</td>
</tr>
<tr>
<td>“Person”</td>
<td>0.36</td>
<td>0.72</td>
<td>0.45</td>
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<tr>
<td>“Press”</td>
<td>0.40</td>
<td>0.55</td>
<td>0.57</td>
</tr>
</tbody>
</table>

* Bhattacharjya, D., 2016, Preference models for creative artifacts and systems, *In Proceedings of the 7th International Conference on Computational Creativity (ICCC).*
Conclusions

• An *explicit study of attributes* (and preference functions) is recommended for understanding preferences for artifacts and systems.

• Functions with *dependence* (like copulas) may be more appropriate than additive functions in creativity-related assessments.

• Formulating better preference models could have *operational benefits* (e.g., better search and optimization methods) as well as *strategic* ones (e.g., more effective design of computational creativity systems).

• There are *limitations* to using preference models here – it can be hard!
References


