Multi-attribute Preference Models for Computational Creativity

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Computational Creativity

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

Robert Caplin for The New York Times

I.B.M. plans to serve a breakfast pastry devised by Watson and the chef James Briscione at its meeting on Thursday.

By STEVE LOHR
Published: February 27, 2013

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I.B.M.'s Watson beat "Jeopardy" champions two years ago. But can it whip up something tasty in the kitchen?

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That is just one of the questions that I.B.M. is asking as it tries to expand its artificial intelligence technology and turn Watson into something that actually makes commercial sense.

SCIENCE | food | wired magazine

Digital Gastronomy

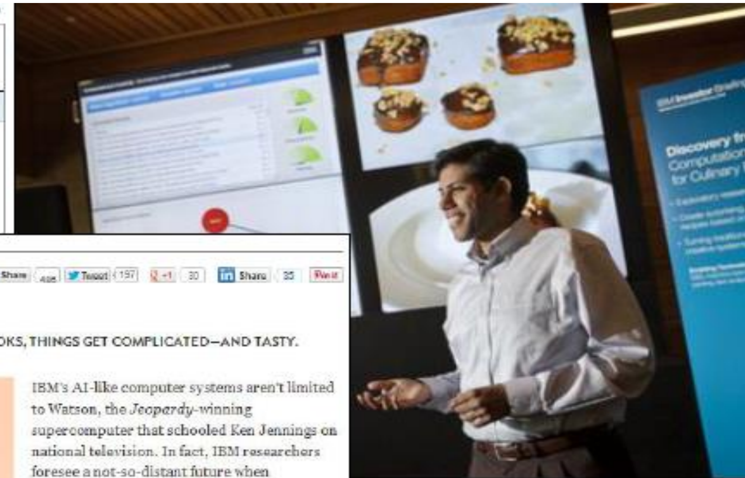
WHEN AN IBM ALGORITHM COOKS, THINGS GET COMPLICATED—AND TASTY.

Prop styling: Laurie Raab | Justin Fantl

IBM's AI-like computer systems aren't limited to Watson, the *Jeopardy*-winning supercomputer that schooled Ken 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.

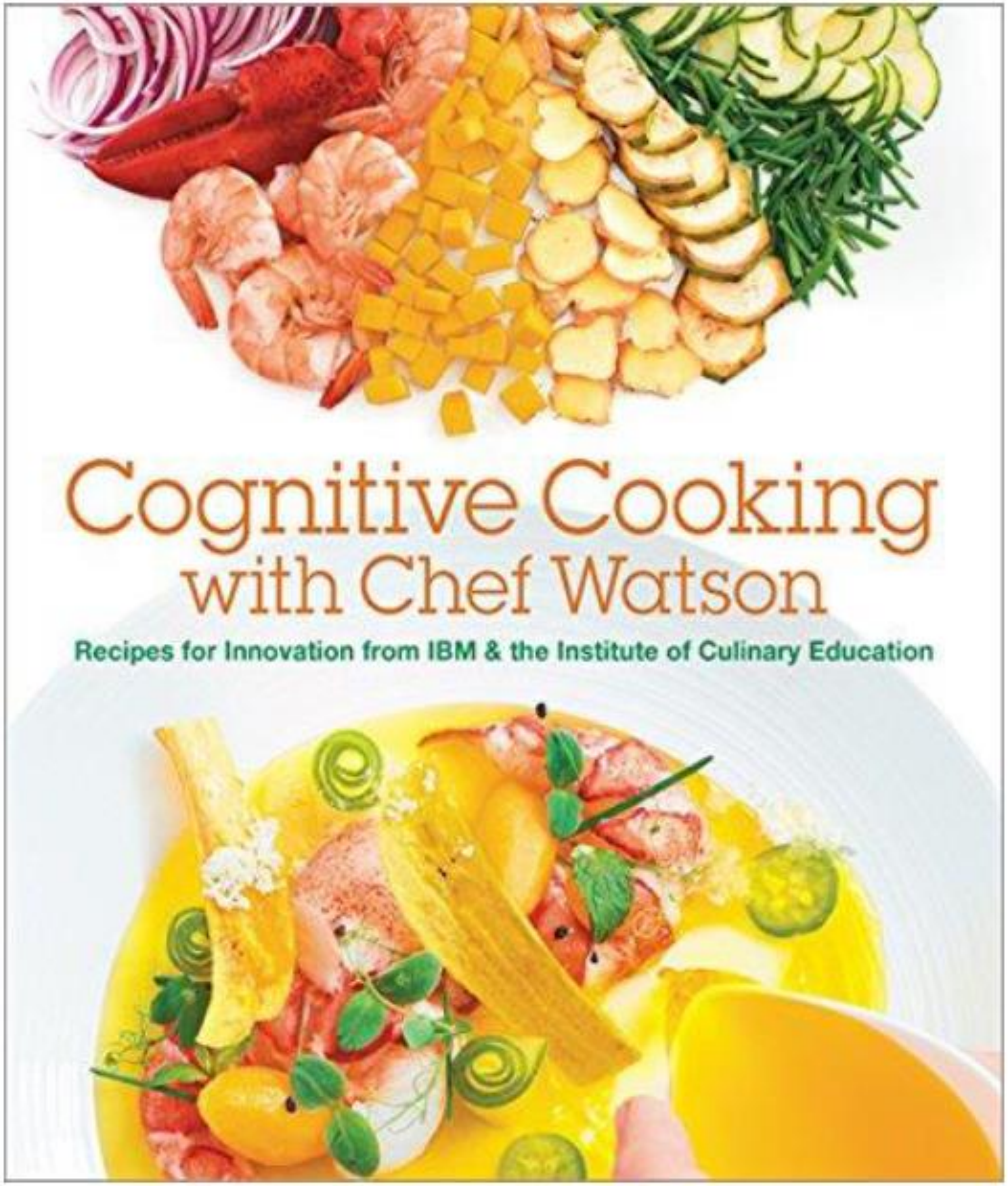
Researcher Lav Varshney has already built an algorithm that creates recipes from parameters like cuisine type, dietary restrictions, and course. The system determines optimal mixtures based on three things: tens of thousands of recipes taken from sources like the Institute of Culinary Education or the Internet, a database of hedonic psychophysics (what humans like to eat), and food chemistry. Right now, the result is like 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 WIRED's parent company, Condé Nast). We searched the site for a Caribbean plantain dessert and found a tasty concoction 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 Florian Pinel developed a mind-blowing Caymanian parfait. While the IBM dessert tasted better, it was also insanely elaborate, so we'll call it a draw.
—Allison P. Davis



IBM'S TASTE MASTER

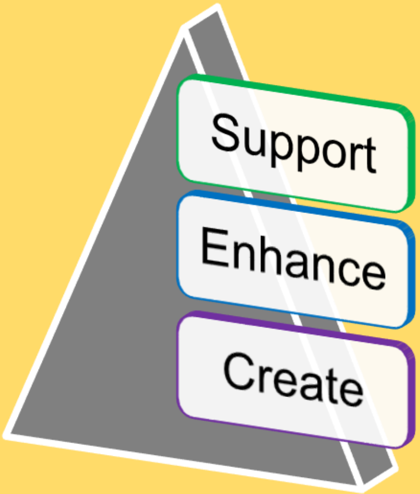
[*The New York Times*, 27 Feb. 2013]
[*San Jose Mercury News*, 28 Feb. 2013]
[*IEEE Spectrum*, 31 May 2013]
[*Wired*, 1 Oct. 2013]


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)

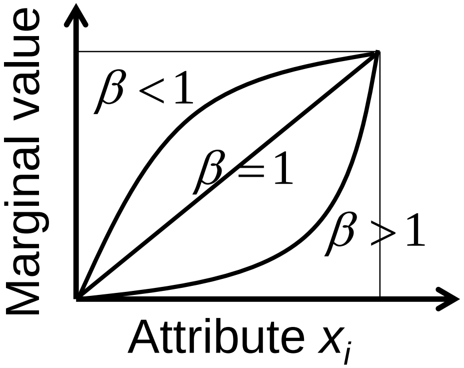
- Creativity assessment research goes back a far ways (Cattell et al. 1918)

Brief Terminology Review

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

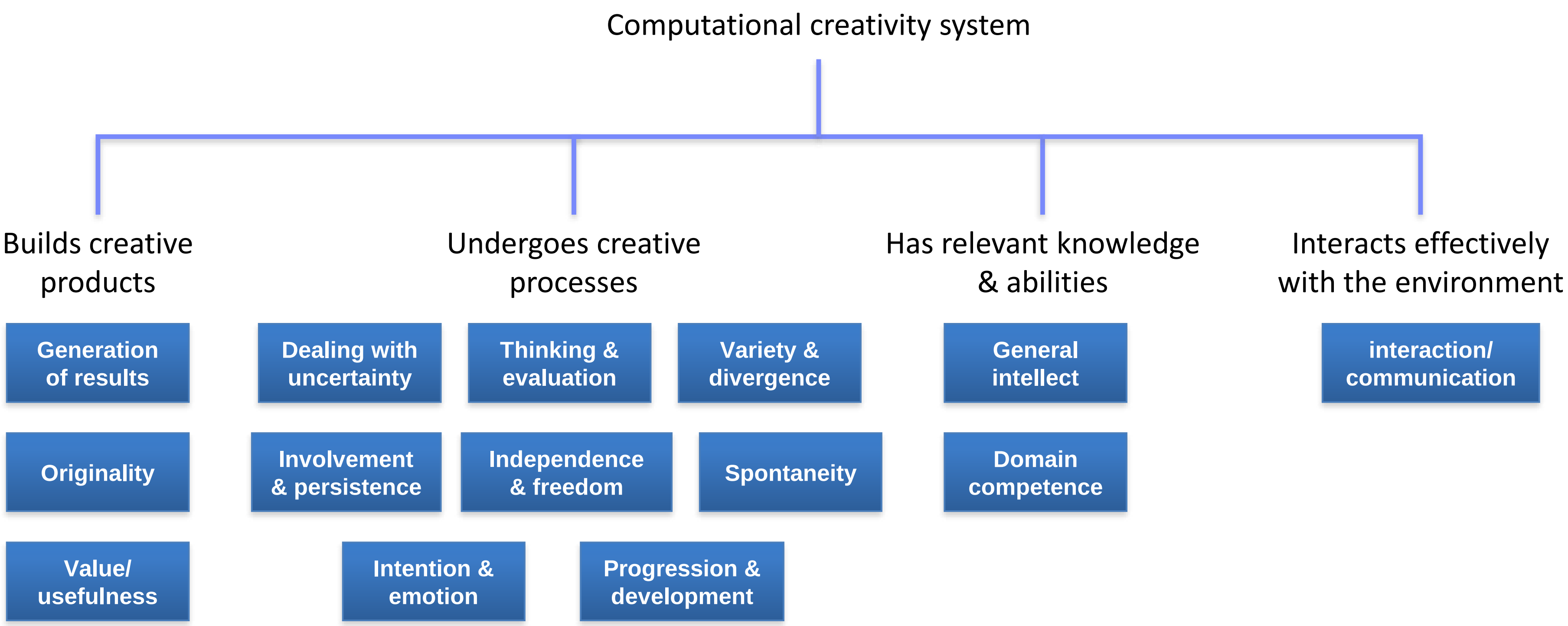
- **Preference functions** are mathematical representations of a person's preferences over the domain of attributes (Keeney and Raiffa 1976).
  - ❑ *Value functions* represent preferences under certainty
  - ❑ *Utility functions* represent preferences under uncertainty

- **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* $v_i(x_i)=x_i^{\beta}$



An Example Objectives Hierarchy

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

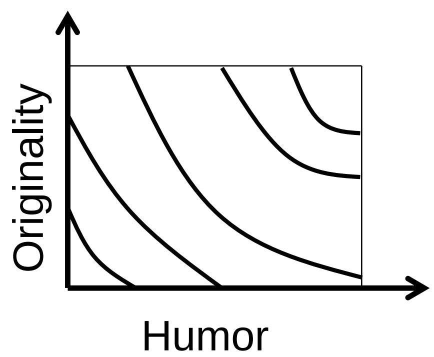


Implications of Mutual Preferential Independence

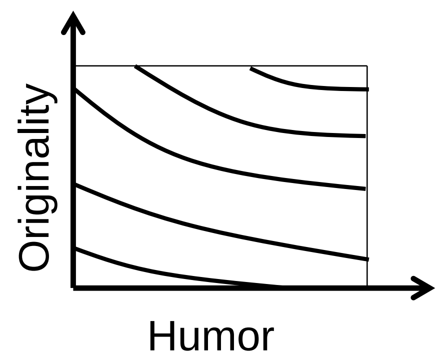
Example (Sternberg et al. 2006)

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

<u>Q:</u> Is the additive function appropriate?



Low cleverness score (0)



High cleverness score (5)

Value Copulas

Copulas combine one-dimensional functions (Sklar 1959). They were introduced for joint probabilities but recently they have also been used for multi-attribute utilities (Abbas 2009).

$$v\left(x_1,\dots,x_M\right)=C_\lambda\left(v_1\left(x_1\mid \bar{x}_1^{\lambda_1}\right),\dots,v_M\left(x_M\mid \bar{x}_M^{\lambda_M}\right)\right),$$

where $C_\lambda\left(z_1,\dots,z_M\right)\colon [0,1]^M \to [0,1]$ with specific properties and

conditional value functions $v_i\left(x_i\mid \bar{x}_i^{\lambda_i}\right)=\dfrac{v_i\left(x_i,\bar{x}_i^{\lambda_i}\right)-v_i\left(x_i^0,\bar{x}_i^{\lambda_i}\right)}{v_i\left(x_i^*,\bar{x}_i^{\lambda_i}\right)-v_i\left(x_i^0,\bar{x}_i^{\lambda_i}\right)}$

An Example Copula: Extended Archimedean

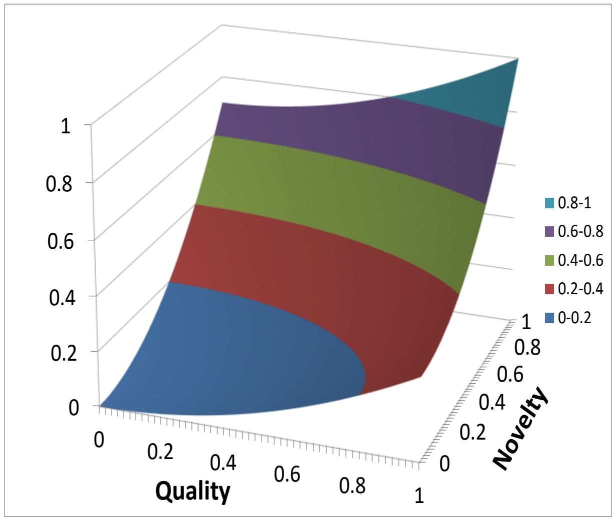
$$E\left(z_1,\dots,z_M\right)=a\psi^{-1}\left[\prod_{i=1}^{M}\psi\left(l_i+\left(1-l_i\right)z_i\right)\right]+b,$$

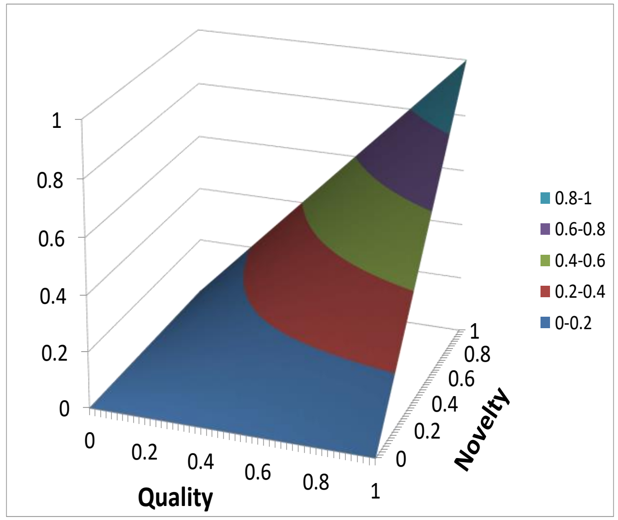
where $l_i\in[0,1), a=1\Big/\left(1-\psi^{-1}\left[\prod_{i=1}^{M}\psi\left(l_i\right)\right]\right), b=1-a,$ and ψ has cdf like properties

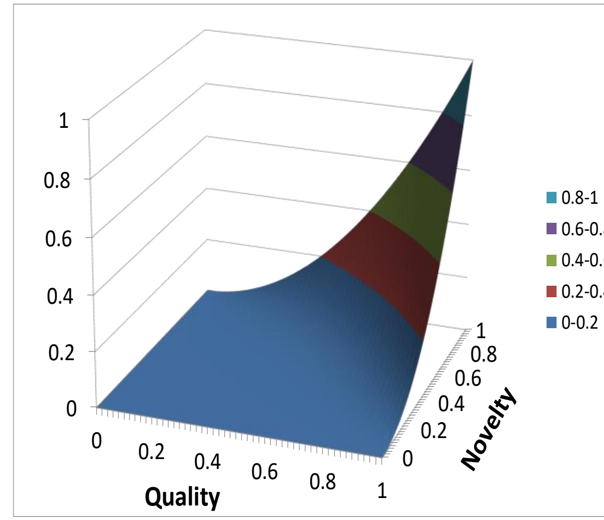
A special case: $l_i=0\ \forall i,\ \psi\left(z_i\right)=z_i$ results in the **multiplicative** form: $v\left(x_1,\dots,x_M\right)=\prod_{i=1}^{M}v_i\left(x_i\mid \bar{x}_1^*\right)$

Additive Value Functions vs. Value Copulas

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)

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

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

Extended Archimedean (copula)

$$v = E\left(v_N(x_N \mid x_Q^*), v_Q(x_Q \mid x_N^*)\right)$$

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

$$v_i(x_i) = x_i^{\beta_i};\ i = N,Q;\ \delta = -5$$

A CC Recommender Scenario: Setup

CC system generates N artifacts

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

$$\textbf{Metric : Loss} = \max_i \left[v\left(x_N{}^i, x_Q{}^i\right) \right] - v\left(x_N{}^{i*}, x_Q{}^{i*}\right),$$

$$\text{where } i^* = \arg\max_i \left[\frac{x_N{}^i + x_Q{}^i}{2} \right]$$

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

$$\textbf{Metric : Rank distance} = D\left[r\left(i : v\left(x_N{}^i, x_Q{}^i\right)\right), r\left(i : \frac{x_N{}^i + x_Q{}^i}{2} \right) \right],$$

$$\text{for rank } r\left(i : C^i\right), \text{ condition } C_i, \text{ metric } D$$

A CC Recommender Scenario: Numerical Example (1/2)

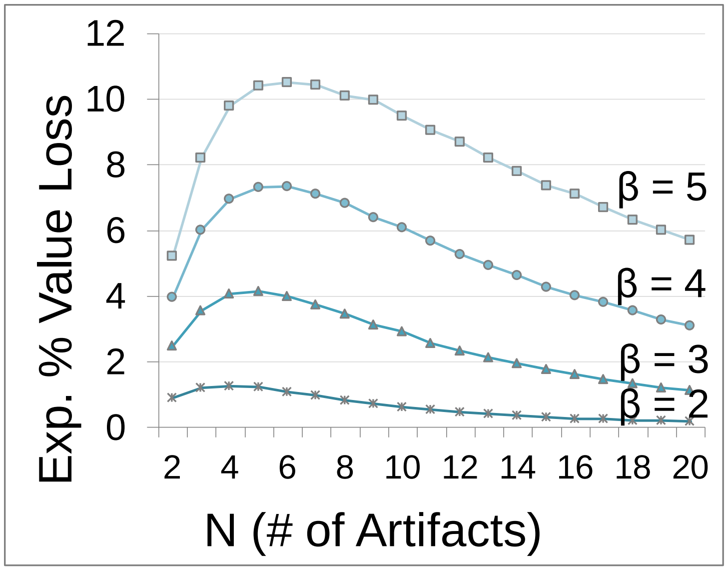
CC system generates N artifacts

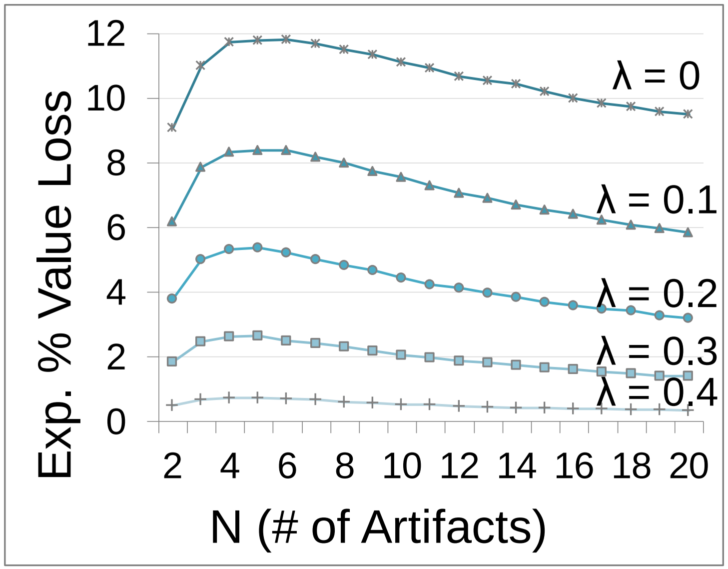
Suppose N artifacts are generated by: $X_N^{\,i}, X_Q^{\,i} \sim U\left(0,1\right)^2 \quad \forall i$

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

1 2 3 4 5

Case 1: System recommends the "best" artifact to the user





a) Metric: Exp. % value loss

A CC Recommender Scenario: Numerical Example (2/2)

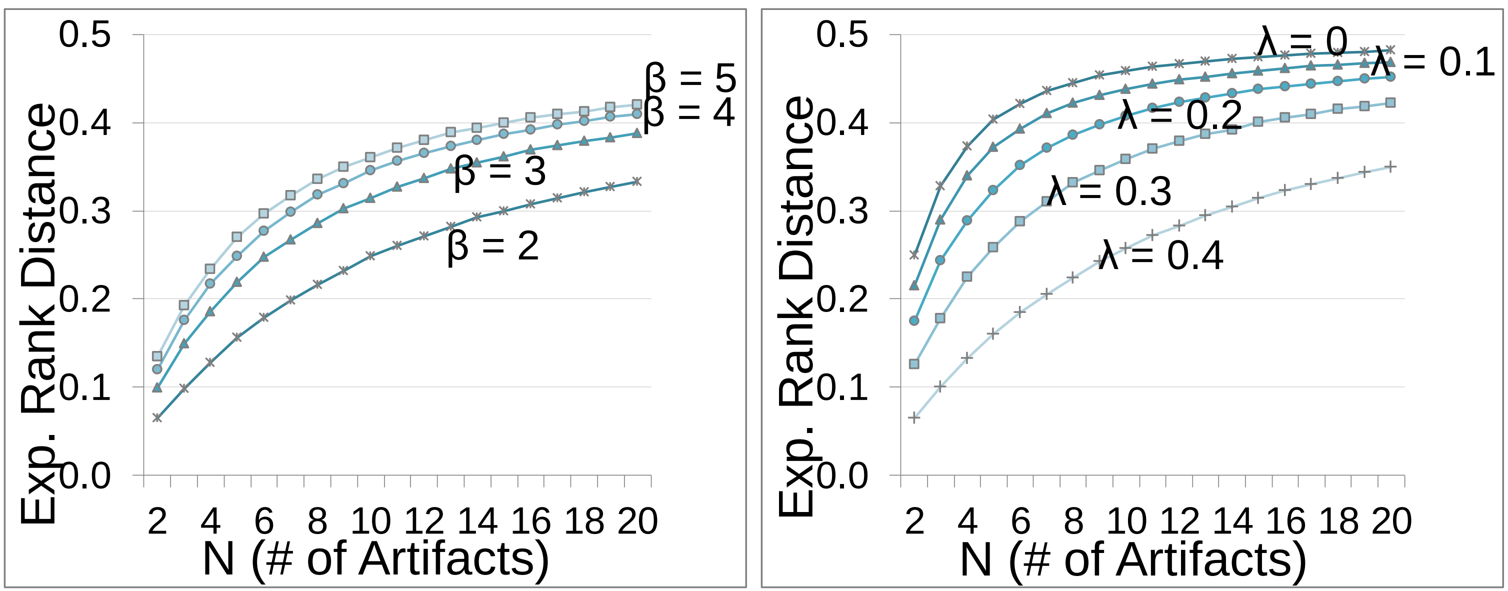
CC system generates N artifacts

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

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

1 2 3 4 5

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: $X_N \approx \int_0^{\alpha_N} f_T(t)\,dt$
  - Conformance: $X_C \approx \int_{\alpha_C}^{1} f_T(t)\,dt$
  - Quality: $X_Q \approx \int_{\alpha_Q}^{1} f_Q(q)\,dq$

- 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:

Attribute	GAmprovising	GenJam	Voyager
"Product"	0.41	0.73	0.48
"Process"	0.34	0.70	0.38
"Person"	0.36	0.72	0.45
"Press"	0.40	0.55	0.57

*** 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!

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