McCormick: Augmenting creativity in R&D through AI-directed exploration

Summary

AI is often used to make recommendations based on what has worked well in the past, but this can result in solutions that are simply more of the same. McCormick's experience shows that AI can also be used to explore a solution space and result in new, creative combinations that may not otherwise have been attempted. In this way, AI can help augment and accelerate a process of creative experimentation.

Opportunity: Use AI to accelerate development of new flavor profiles

MKC creates a variety of products including seasonings, sauces, and flavors (some of which may also be sold B2B to clients for incorporation into third party products). A formula is a combination of specific ingredients in precise proportions that is standardized for consistency, and delivers a flavor profile, which describes the eating experience. Flavor creation for B2B products can be a competitive process, with several companies producing formulas in response to client requests. To improve the success of new flavors, McCormick looked at two important factors:

- **Scaling the experience of food scientists**. A junior flavorist typically apprentices for 7 years, during which they build experience and glean valuable insights. It is this cumulative experience that enables creativity; through an understanding of what works, what doesn't, and what are the degrees of freedom in between.

- **Improving the efficiency of the experimentation process**. To produce a single candidate flavor for a client, several steps are involved. Flavorists formulate a range of different flavor profiles, produce samples of the flavors, test them (both in isolation and after cooking in a test kitchen) and iterate until they have something worth submitting to the client[1]. Improving the efficiency of this process means a quicker time to market, and better leverage for food-scientists time.

McCormick wondered if AI could help. If flavorists can intuit insights from empirical experience, then there was probably more that could be extracted, more rapidly, through analytics. If these insights could be captured and systematized, then it could help flavorists better explore the flavor space, both by finding optimal flavors within an area around what is known well and by

[1] McCormick has observed that each 5-10 years of experience halves the number of iterations

finding promising new areas in the flavor space that have not been explored. Ultimately this would result in faster development and better quality.

Challenge: Credit assignment and large search space

The company leveraged data on around 350,000 formulas created over more than a decade, covering product attributes such as category (e.g., baked goods, salty snacks), format (e.g., seasoning, condiment, wet sauce, dried), amounts, type (e.g., variety of garlic) and success metrics such as product tasting scores. They also captured functional (e.g., shelf stability, flow rate), and non-functional (e.g., grain size, sodium content and FEMA[2] numbers) attributes on 40,000 raw materials. With such a high dimensionality in the dataset, the team needed a way to condense the problem to keep it manageable.

Solution: Graph representations and reduced dimensionality

A new deep learning system, named SAGE™ was developed, to generate the new flavor profiles. It accepts two principal user-defined inputs: (1) a seed formula (e.g., a flavor profile for Korean BBQ), and (2) any specific constraints desired in the output formulas (e.g., "must have mango"). The system then generates formulas with varying levels of deviation from the seed; 4 with only minor tweaks that optimize for anticipated performance, 4 with greater freedom but still subject to the constraints, and 4 that differed significantly. This gave the flavorists a range of options to iterate from, depending on the desired level of novelty.

To enable this effort, the team needed a few tricks. Firstly, they reduced the dimensionality of the data by e.g., aggregating 40,000 distinct raw materials into 3000 groupings. Secondly, they sampled 3000 formulas for training from the 350,000 corpus, each labeled with a "success" ratings. Lastly, they formulated the model as graph problem, defining distance metrics between materials where each formula was represented as a vector.

Outcomes: Performance equivalent to 20 years of experience

McCormick observed that junior food scientists, using the system, could achieve performance like that of a food scientist with 20 years of experience, significantly reducing the number of trials required. They also found that the system enabled greater use of global knowledge; in one case the system recommended a flavor profile from Canada to a flavorist in the US who had no prior experience of the Canadian market. The system therefore enabled an increase in creative output, while also better targeting their experimentation effort.

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[2] The Flavor Extract Manufacturer's Association of the United States. FEMA numbers refer to ingredients generally recognized as safe and allowed in the United States https://www.femaflavor.org/