Towards Crafting Beer with Artificial Intelligence

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***Abstract*—The art of brewing beer has a long tradition that dates back to the very dawn of civilization. While the brewing process has been automated to a great extent, the creation of new beer recipes remains the result of creativity and human expertise with only minor support from software to validate chemical constraints. We collected a dataset of 157,000 publicly available recipes from all over the world and created a transformer-based model to support the creative process in brewing by suggesting new beer recipe templates. As a proof of concept, we crafted the IPA "Deeper" along a recipe generated by our model. Over 100 international newspapers and radio stations have reported on the first Artificial Intelligence (AI)-crafted beer from Switzerland over the past few months. For the first time, this paper reveals the underlying pipeline architecture of seven transformer networks trained end-to-end that made this remarkable success possible.**

***Index Terms*—beer, recipe generation, machine learning, natural language processing, transformers, sequence models**

I. Introduction

With a tradition of many thousands of years, brewing beer is a prototypical example of a production process where technological progress has greatly improved efficiency and reliability of the process, while the creation of new and tasty recipes remained the purview of human creativity and experience. At the same time, innovation is key, especially for micro-breweries when competing with large manufacturers. Commercial software is available for fine-tuning mixing ratios, temperatures, etc. of a previously human-created beer recipe, but the innovation process is only subject to human creativity, knowledge and experience. More recently, home-brewing has become an emerging trend with people sharing beer recipes on public internet platforms. With all this data available, we trained a beer recipe generator that automatically suggests ingredients along with their respective amounts and cooking times.

II. Related Work

Machine learning has been applied in breweries to improve the production process (Sugar Creek Brewing[1]), predict flavors and aromas from a fermentation process (Carlsberg Group[2]), and adapt beer recipes according to user feedback (IntelligentX[3]). Moreover, generative deep learning approaches have been used for generating recipes or ingredient combinations of dishes [1, 2]. To the best of our knowledge, this is the first attempt to create new beer recipes of variable size starting from a partial or even empty list of ingredients.

[1]https://www.ibm.com/blogs/think/2019/04/ai-and-iot-help-perfect-the-brew-at-sugar-creek-brewing-company/, accessed at 28.01.2021

[2]https://www.carlsberggroup.com/newsroom/carlsberg-research-laboratory-behind-beer-research-project-based-on-artificial-intelligence/, accessed at 28.01.2021

[3]https://www.forbes.com/sites/bernardmarr/2019/02/01/how-artificial-intelligence-is-used-to-make-beer, accessed at 28.01.2021

TABLE I
An example recipe template from the dataset

Title	Simtra IPA
Category	IPA
Malts	Marris Otter Pale, Caramel/Crystal, Pale 2-Row
Amounts	45.45%, 9.09%, 45.45%
Hops	Citra (13-14 AA), Simcoe (13-14 AA)
Boiling Times	100%, 8.33%
Dry Hops	Citra (13-14 AA)
Other Ingredients	Irish Moss
Boiling Times	25%

III. Beer Dataset

We collected 157,663 beer recipes from a popular brewing platform that features international recipes from professional and hobby brewers. Each recipe contains a title, meta-information such as the category, brewing information like processing steps and boiling time, and the ingredients with their respective amounts and cooking times. There are in total 58 different beer categories. With support from professional brewers, we identified the minimum components to make a beer recipe unique and producible by an expert, subsequently referred to as *template*. Additionally, we removed all recipes that contain rare ingredients and have a boiling time of more than 60 minutes, which was imposed by the brewery. In total, the cleaned dataset consists of 67,345 recipes with 315 unique malts, 1,648 hops, and 1,041 other ingredients such as spices for example. The amounts of each component were normalized. Table I shows a recipe template from our final dataset. Even though such recipes are incomplete (e.g., yeasts are missing), they feature sufficient information for stimulating the innovation process of a master brewer.

IV. Beer Recipe Generator

We decompose a beer recipe template into components (e.g., malts, hops) and treat each as an individual sequence generation problem. Our model consists of eight stacked transformer [3] decoders containing 4 layers, 8 attention heads, an embedding dimension of size 512 and feed-forward layers with 2,048 neurons. Each decoder is conditioned on the outputs of its predecessor and produces one subsequence of the recipe. Since, for example, the selection of hops highly depends on the selected malt, we want the attention to refer

TABLE II
THE PERPLEXITY COMPUTED ON UNSEEN TEST DATA

	Malt	Hops	Dry Hops	Miscs
Perplexity	12.04	13.56	3.58	3.72

to all previously generated modalities in order to successfully guide the recipe generation process. To that end, we employ the feature concatenation strategy that has been explored by [4] to allow the model to reason over multiple modalities simultaneously.

After training, a complete recipe can be generated in a hierarchical manner. First, the model requires a category as input, which can either be selected or randomly chosen. Based on the category, it predicts the malt and the respective amounts. Next, the hops and boiling times are generated by conditioning on both the category and malt. This is done by concatenating both into one feature vector. Once the hops are predicted, the dry hops are generated by extending the feature vector with the hop information. Then, further ingredients like spices are predicted based on all previously generated ingredients. Finally, the last decoder suggests a recipe title.

V. Results

Evaluation of generative models is not straightforward, and metrics such as the optimization criterion lack interpretability. We propose a threefold evaluation process by 1/ reporting model perplexity as the standard metric for sequence model in the literature; 2/ designing an evaluation metrics along a widely used definition of creativity in innovation processes and 3/ conducting a blinded experiment with a professional master brewer.

From the cleaned dataset we split off a test set of 6,136 recipe templates unseen during the training process. Table II reports model perplexity on different recipe components for the test set, which intuitively hints at how certain the model is when generating templates. According to [5], creativity includes two defining characteristics: "the ability to produce work that is both novel (i.e., original, unexpected) and appropriate (i.e., useful, adaptive concerning task constraints)". To assess the model's ability to produce novel recipe templates, we generated 10,000 recipes and computed the average maximum Jaccard similarity between the generated templates and the training set. To control for comparable entities, we first added the binned amounts to the ingredients and then concatenate all recipe components (except the title) to a single list. We interpret the average maximum Jaccard similarity between such lists as the degree of novelty. For comparison, the same procedure was applied to the test set. The results in table III show that the generated recipes are on average more novel than the ones from the test set. Thirdly, a blind test was conducted with a set of 140 recipes consisting of 70 human templates (randomly sampled from the test set) and the same number of generated templates. A professional master brewer evaluated producibility of each template in random order along technical and economical aspects (e.g. costs of ingredients in relation to shelf price). 87.1% of all human recipes were

TABLE III
THE RESULTS OF THE NOVELTY EVALUATION

	Generated	Test Set
Num Recipes	10,000	6,136
Average Similarity	0.194	0.514
Std. Similarity	0.132	0.243

considered producible, whereas only 32.9% of the generated recipes were considered producible.

Finally, the ultimate feasibility test for the project team was to actually brew one of the generated recipes. To this end, we granted a local micro-brewery access to our generator. According to the master brewer's statement, they requested the generator to create a recipe template for an India Pale Ale (IPA) and selected the second suggestion with only minor adaptions, i.e. one hop type that is not available in Switzerland was replaced by an equivalent type. The crafted IPA called *Deeper* is tasty with a fresh grapefruit flavor. Over 100 international newspapers and radio stations reported on the first beer crafted along a recipe from an AI approach. Currently, *Deeper* is subject to a consumer study at the University of Lucerne and can be purchased on the brewery's web-shop and soon from a large Swiss online retailer.

The evaluated metrics cannot assess the models' creativity directyly. However, it can be concluded that it is sufficient to support the creativity process of human experts.

VI. Conclusion and Future Work

We trained a beer recipe generator based on a pipeline architecture of eight transformer networks. Evaluation confirms that the generator is able to produce recipes with a high degree of novelty; about one third of the recipes were considered producible by a master brewer with respect to technical and economical aspects. The ultimate proof of concept was delivered by the manufacturing of *Deeper*, the first beer crafted along a recipe from an AI approach with extensive international media coverage.

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