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The application of graphical databases and machine learning to flaw tracing and prediction in beer production

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Abstract

Latent flaws and contaminations, undetectable by most sensory and chemical based quality control programs, pose an existential risk to breweries – how can you detect and fix the cause of a flaw that has not yet developed? In this research, we present a novel approach to predicting latent flaws and tracing their creation back to the root cause in the beer brewing process. Furthermore, we show that the process may be able to predict flaws which occur in beer after packaging and distribution – increasing the actionability of any quality control program. At Analytical Flavor Systems, machine learning and artificial intelligence are used to build quality control and flavor profiling tools for the food and beverage industry. By applying our algorithms to production data and human sensory data collected with the Gastrograph™ Review application, predictions can be made as to the likelihood of a flaw appearing and how to prevent, delay, or mitigate these flaws.

Introduction

Quality control and assurance are important in a brewery. Knowing if a batch is flawed or deviant is indispensable. Nobody wants to ship a bad batch of product and risk losing customers. What if the beer is fine as it leaves the brewery but a flaw arises by the time it's in the consumer's hand? A novel system has been introduced for the root-cause analysis and prediction of flaws.

Gastrograph Review for iOS and Android is used for the collection of 24 sensory variables shown in **Figure 1**. In addition the app collects environmental data during beer tastings. This system uses a sensory data collection app (Gastrograph Review™). The data collected by this app is used to build flavor profiles and graphical databases depicting production pathways. The Gastrograph system is able to make predictions and models even in low data situations (i.e. less than 7 reviews).

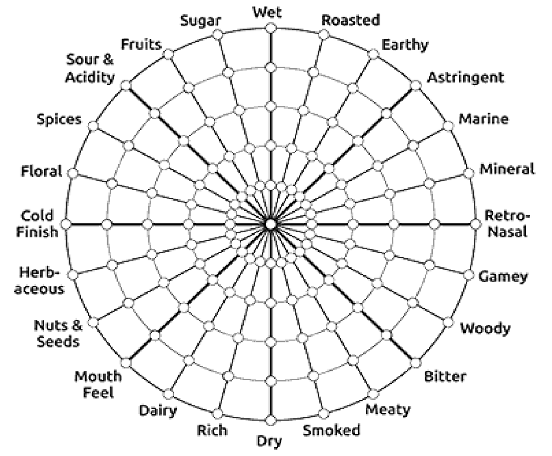

Figure 1: A visualization of the Gastrograph. The Gastrograph application by Analytical Flavor Systems measures 24 flavor variables as well as an overall perceived quality. All reviews in this study were done using this flavor wheel.

Our graphical databases are composed of neural networks which model the formation of flavor attributes throughout beer production (including flaw formation). The combination of these tools can be used to identify flaws, predict flaws, find the causes of flaws, and suggest mitigations for these flaws.

Flaw Identification

Flaw identification is necessary to find the root cause of a flaw and also to start predicting flaws. To illustrate flaw identification, a dataset is used that includes data from non-flawed beer and beer contaminated with mercaptan (ethanethiol), butyric acid, DMS, ethyl hexanoate and trans-2-nonenal. The five different flaws mentioned above can then be classified as one of five different classes plus one class for unflawed beer. **Figure 2** is the visualization of the training and test sets for the recognition of a flaw. This visualization clearly shows the use of metric learning increases the difference between the classes (different flaws). The flaws in the beer are then identified by the model and the beer is placed into one of the six classes. The accuracy for these techniques is illustrated in **Table 1**.

It has been shown that this model works for the identification of these flaw compounds at a high degree of accuracy. Furthermore, this model should be understood as a proof of concept. This portion of the project is a starting point for the baseline application of the model, and a greater number of iterations will dramatically increase the accuracy of the models for flaw detection. This method can be applied to the flaws illustrated as well as 15 other other common flaws. Basic steps to further improve accuracy include applying other metric learning or pre-processing methods, collecting more data for each flaw, using an ensemble approach, combining multiple models and model-chaining, and more data for different styles and types of beer. By increasing the amount of training data, the models will become more accurate in aggregate. By increasing the brands and styles of beer used in testing, the models will become more robust and usable for more styles and brands.

Flaw Classification Step	Training Accuracy	Test Accuracy
General flaw detection	0.921	0.917
Identification of mercaptan	0.940	0.917
Classification as one of five flaws	0.921	0.943
Classification as one of five flaws and non-flawed beer	0.915	0.900

Table 1: Accuracies for each step of flaw detection and classification

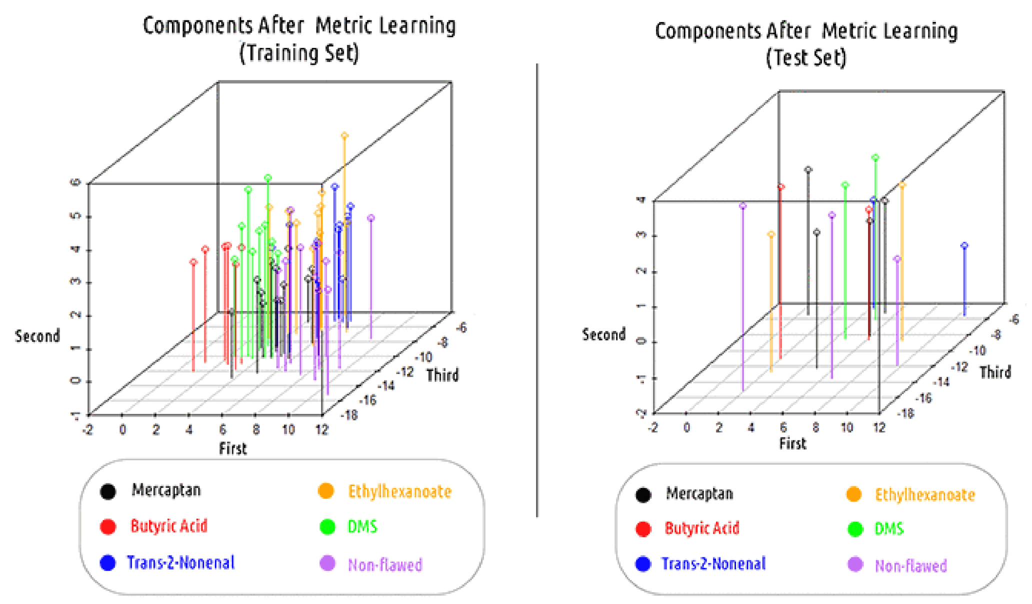

Figure 2: A visualization of model training and testing for classifying beers into one of six flaw categories

Graphical Databases and Flaw Tracing

Our flaw tracing and prediction is based on a graphical database that is constructed from neural networks (pictured in **Figure 4**). The database is comprised of nodes and links. Each node represents either a production process, an issue that can arise during a production process, a flaw that could appear, or a mitigation technique. The links represent possible paths that might be taken during production. Also, which link is followed changes the probability of other links being followed. These paths can result in any different combinations of issues, flaws, and mitigation steps. Each link has a function associated with it that represents the probability that this path will be followed in production. The independent variables in these probability functions are measurements that are taken during production (e.g. temperatures, times, pH, what equipment is used, ingredient lots, etc.). This means that changes in production cause the probability of a link being followed to change as well.

Algorithms are applied to the functions to assure maximum accuracy. The neural network learns not only how different processes change the way a beer develops and changes throughout production but also how these changes are different depending on the beer being brewed. As more and more data is collected, these probability functions change themselves to become more accurate. This means that the neural network becomes more powerful the more it is used.

There is one downside to the neural network that is being used for this tool. All of the models are built empirically. This means two things; the models are not explanatory, and the program does not know the difference between correlation and causation. By running a few production experiments based on new correlations, the amount of non correlation can be kept to a minimum.

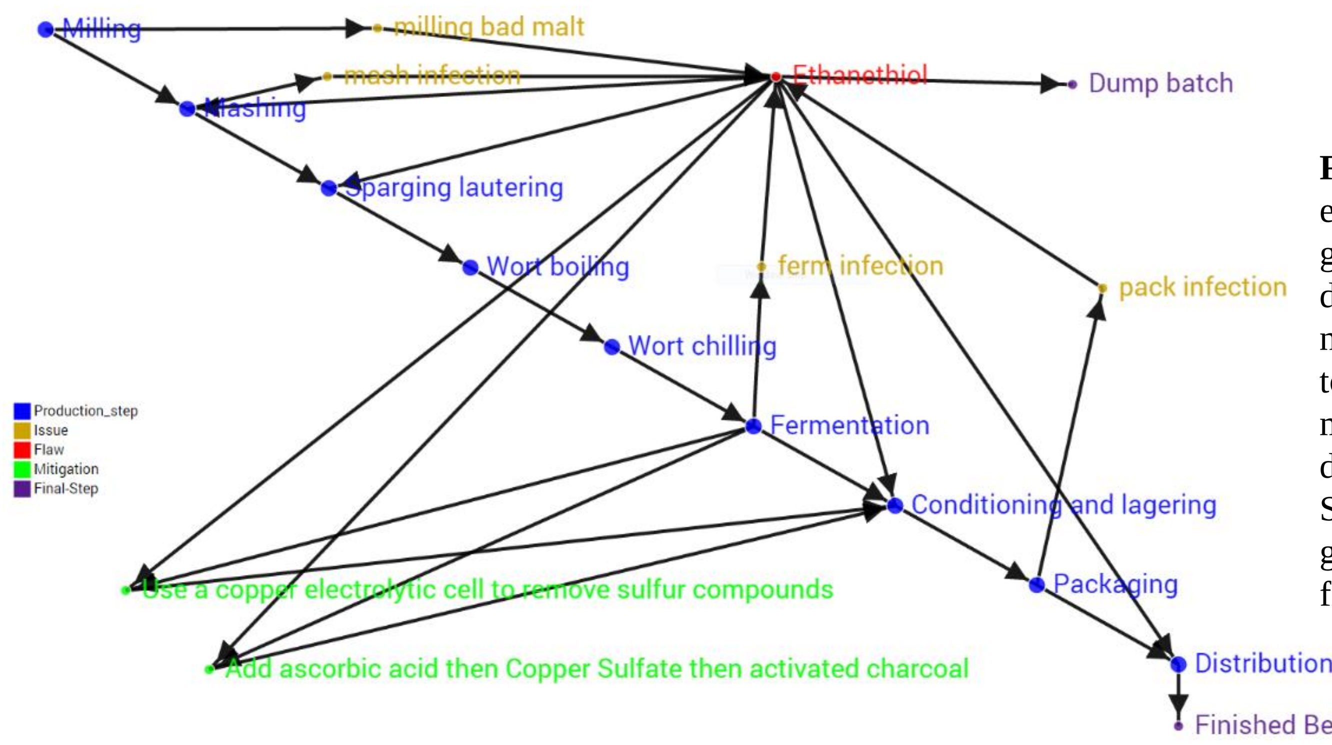

Figure 4: An excerpt from the graphical database/neural network that is used to trace, predict, and mitigate flaws and deviations. Specifically this graph represents the flaw ethanethiol.

Results and Discussion

Using a novel sensory data collection tool in combination with collecting production variables, flaws can be identified, traced, and predicted. Though the system may not work perfectly for a specific beer right away, it will be able to correct for any brand-to-brand differences encountered. This problem is quickly mitigated as data is gathered on the production variables and flavor profiles for this beer. Because of the nature of beer production, a graphical database is an ideal network to use for the model. Because as production proceeds, processes don't proceed in reverse, and likewise we can set up the graphical database so links only go in one direction. Also flaws can arise from more than one issue during brewing. This may be difficult to represent using some systems, but graphical databases easily represent this issue with converging several one-directional links onto one flaw node.

Overall this is a highly robust and reliable analytical system after baseline data has been collected. It could be used to change the face of quality control and quality assurance in beer.

Resources and Acknowledgements

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