Overview

Motivation:
- Exploding demand for craft beer
- Designing new beers relies on trial and error

Goal:
- Optimize beer recipe generation to design better tasting beers, with less effort

Approach:
- Use deep and recurrent neural networks to learn (and map between) representations of beer in different domains

Background

Long Short Term Memory Networks
- Specializes in modeling sequential data
- Memory cells store relevant long-term info

\[
\begin{align*}
    i_t &= \sigma(W_i x_t + U_i h_{t-1} + b_i) \\
    \tilde{c}_t &= \tanh(W_c x_t + U_c h_{t-1} + b_c) \\
    f_t &= \sigma(W_f x_t + U_f h_{t-1} + b_f) \\
    C_t &= i_t \odot \tilde{c}_t + f_t \odot C_{t-1} \\
    o_t &= \sigma(W_o x_t + U_o h_{t-1} + V_o C_t + b_o) \\
    h_t &= o_t \odot \tanh(C_t) \\
    y &= \text{softmax}(h)
\end{align*}
\]

Beer Recipes
- Fermentables: affect sweetness, body, color, alcohol content
- Hops: give bitter, zesty, citric flavors
- Yeasts: affect alcohol content, flavor, aroma
- Miscellaneous: affects clarity and flavor

Models

DNN
- Uses a deep neural network to learn representations of beer

LSTM-DNN
- Combines the memory cells of LSTM with the learning capabilities of DNN

Encoder-Decoder
- Maps between representations of beer in different domains

Experimental Setup

Data
- Top frequencies of fermentables, hops, yeasts, and miscellaneous ingredients (left to right, top-down)

Training
- Developed using TensorFlow, Scikit-learn
- Bayesian hyperparameter tuning
- Stochastic gradient-based optimization

Results

Name
- Accuracies for 80-way classification of beer names

Type
- Accuracies for 3-way classification of beer types

Style
- Root mean squared errors for predicting beer attributes, lower RMSE is better

Future Work
- Generate meaningful representations of beer recipes using encoder-decoder model
- Create combined model of recipes and reviews
- Generate beer recipes and reviews