RED BeeTL: Recipe Encoder Decoder Beer Translator LSTM

Gracie Ermi, Ellyn Ayton, Nolan Price and Brian Hutchinson

Computer Science Department, Western Washington University

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

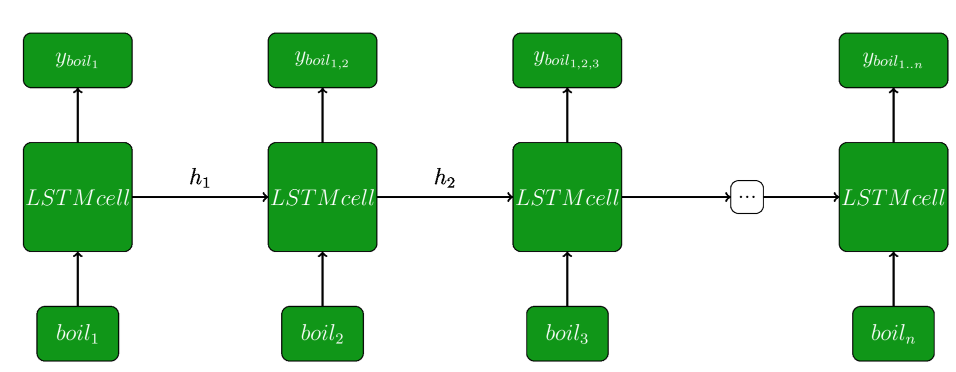
Approach:

- 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



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

Beer Recipes

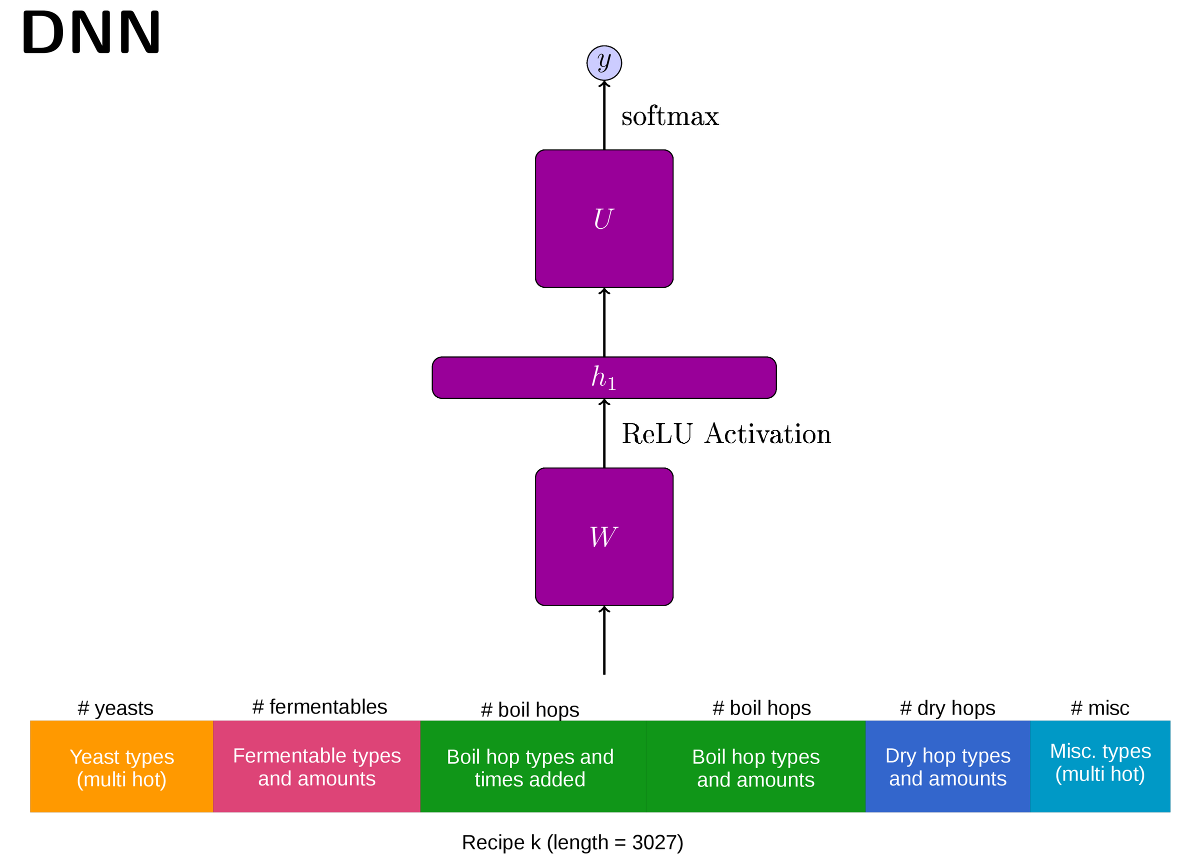
- Fermentables: affect sweetness, body, color, alcohol content
- Hops: give bitter, zesty, citric flavors
- Yeasts: affect alcohol content, flavor, aroma
- Miscellaneous: affects clarity and flavor

```
<RECIPE>
        <NAME>Citra Double IPA</NAME>
        <TYPE>Ale</TYPE>
        <FERMENTABLES>
                <FERMENTABLE>
                        <NAME>Caramel Malt</NAME>
                        <AMOUNT>2.3 lb</AMOUNT>
                <FERMENTABLE>
                . . .
        </FERMENTABLES>
        <HOPS>
                <HOP>
                        <NAME>Citra</NAME>
                        <AMOUNT>0.455 oz</AMOUNT>
                        <USE>Boil</USE>
                        <TIME>20</TIME>
                </HOP>
                <HOP>
                        <NAME>Amarillo</NAME>
                        <AMOUNT>0.5 oz</AMOUNT>
                        <USE>Dry</USE>
                </HOP>
                . . .
        </HOPS>
        <YEASTS>
                <YEAST>
                        <NAME>California Ale Yeast</NAME>
                </YEAST>
                . . .
        </YEASTS>
        <MISCS>
                <MISC>
                        <NAME>Irish Moss</NAME>
                </MISC>
                . . .
        </MISCS>
</RECIPE>
```

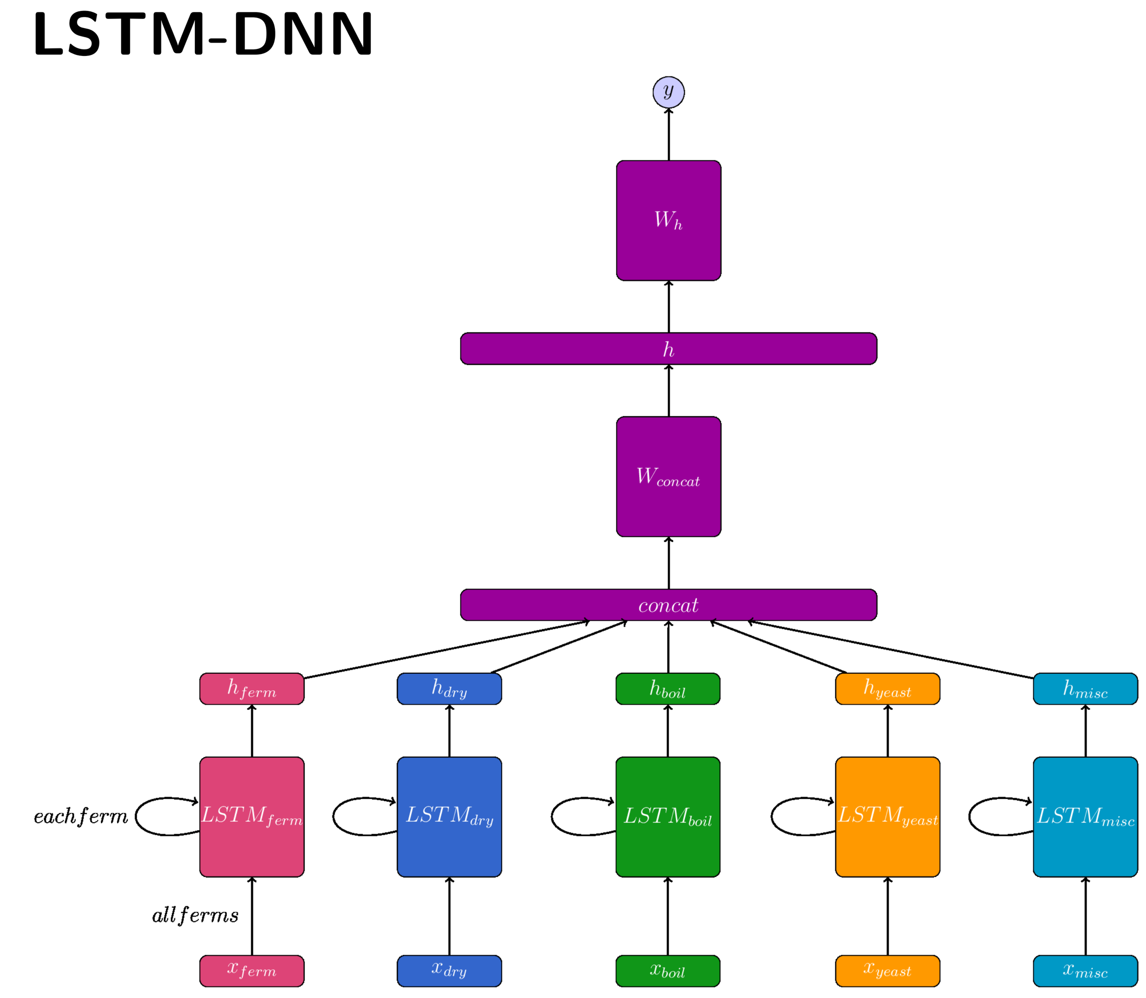
An example recipe from the Brewtoad dataset (in BeerXML format)

Models

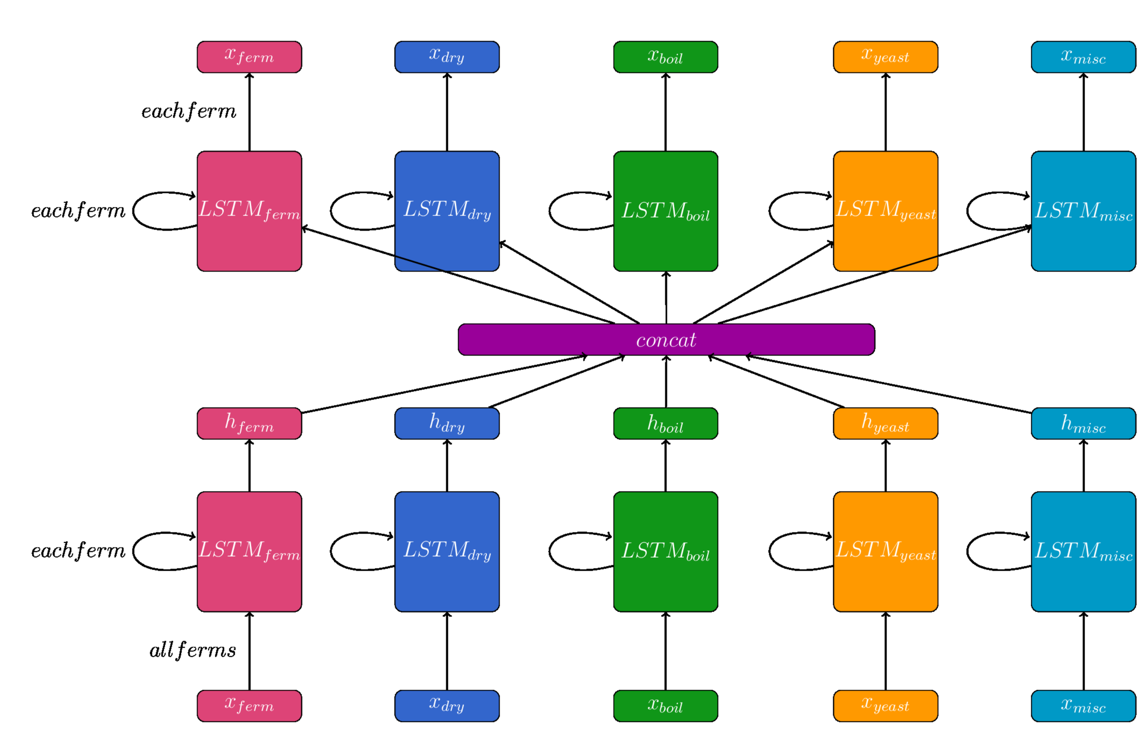
DNN



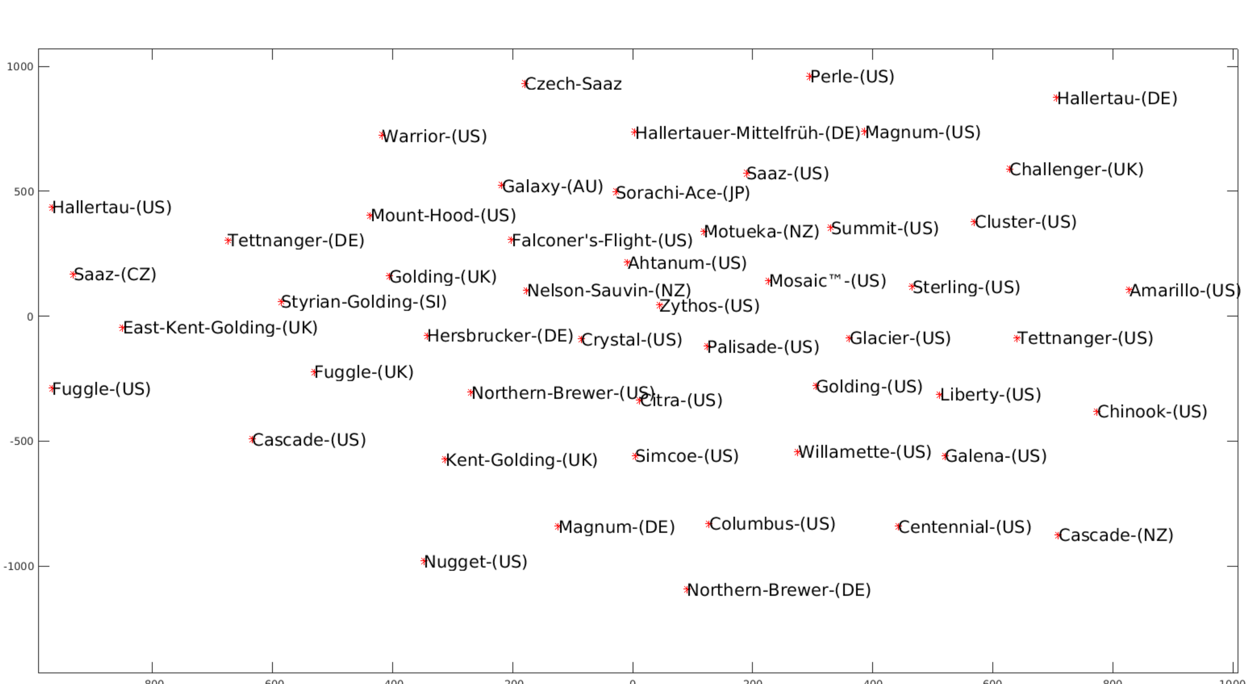
LSTM-DNN



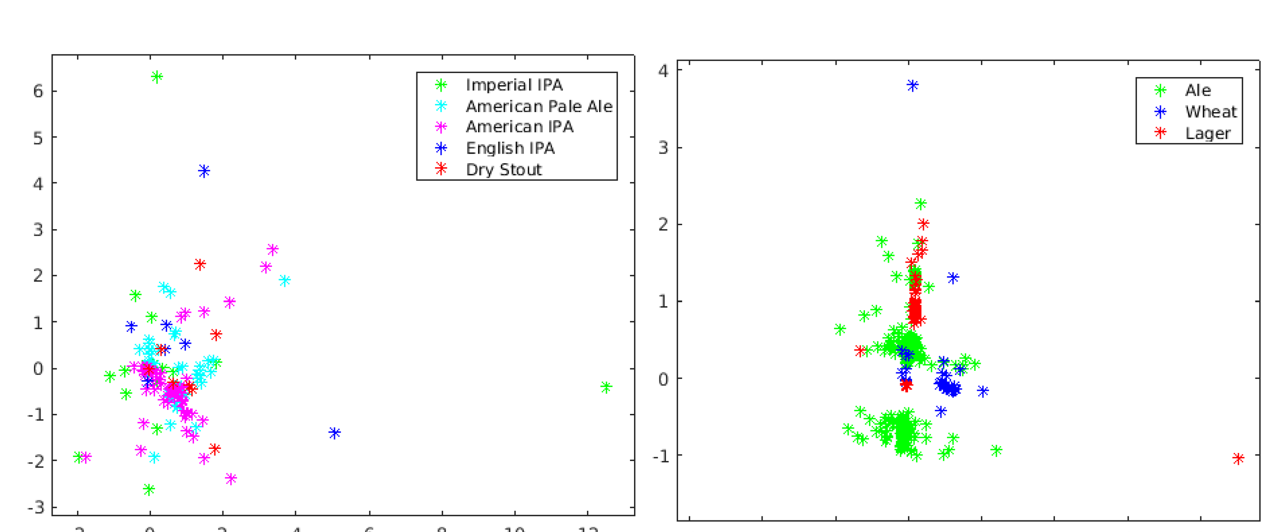
Encoder-Decoder



Embeddings



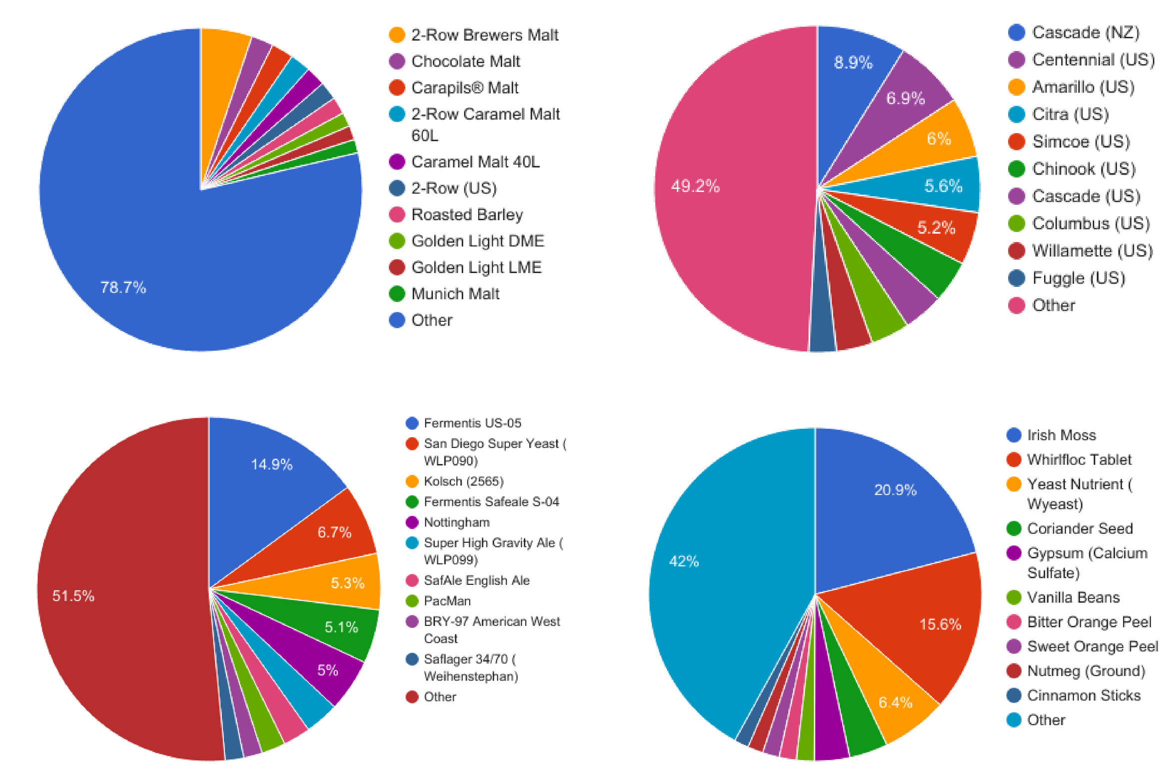
Plot of hop embedding vectors from encoder-decoder model



Left: Plot of names in fixed vector format; Right: Plot of types in fixed vector format

Experimental Setup

Data



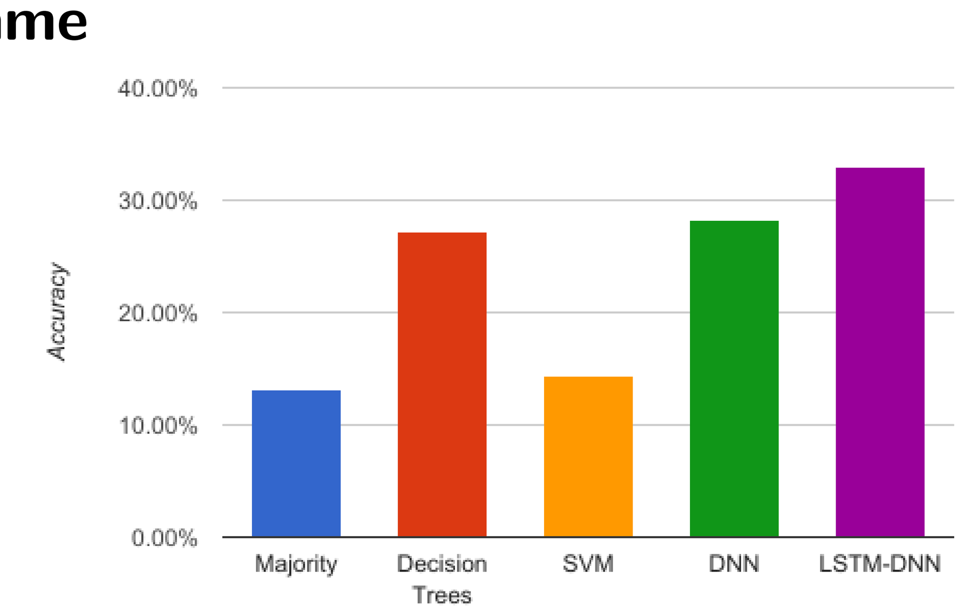
Top frequencies of fermentables, hops, yeasts, and miscellaneous ingredients (left to right, top down)

Training

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

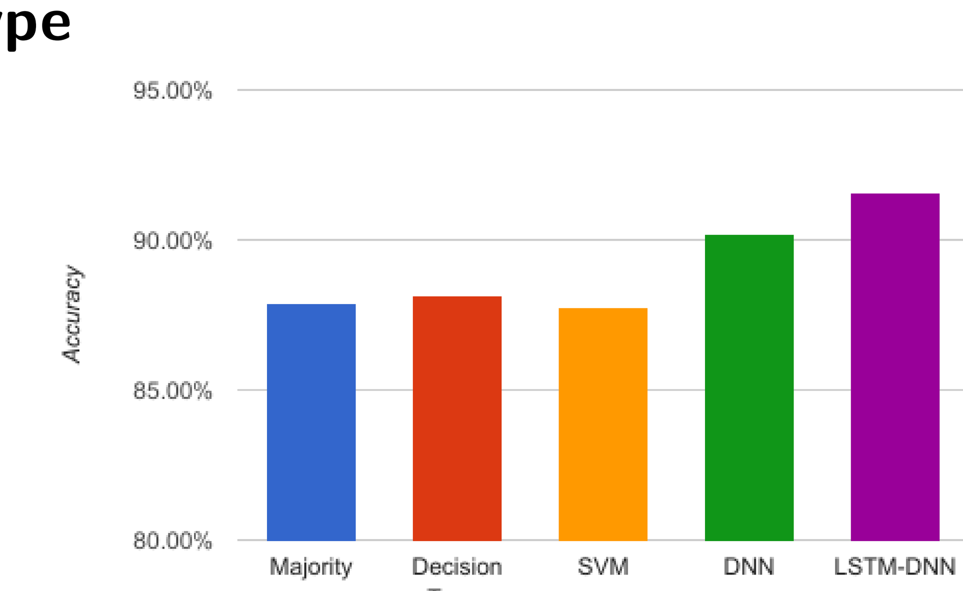
Results

Name



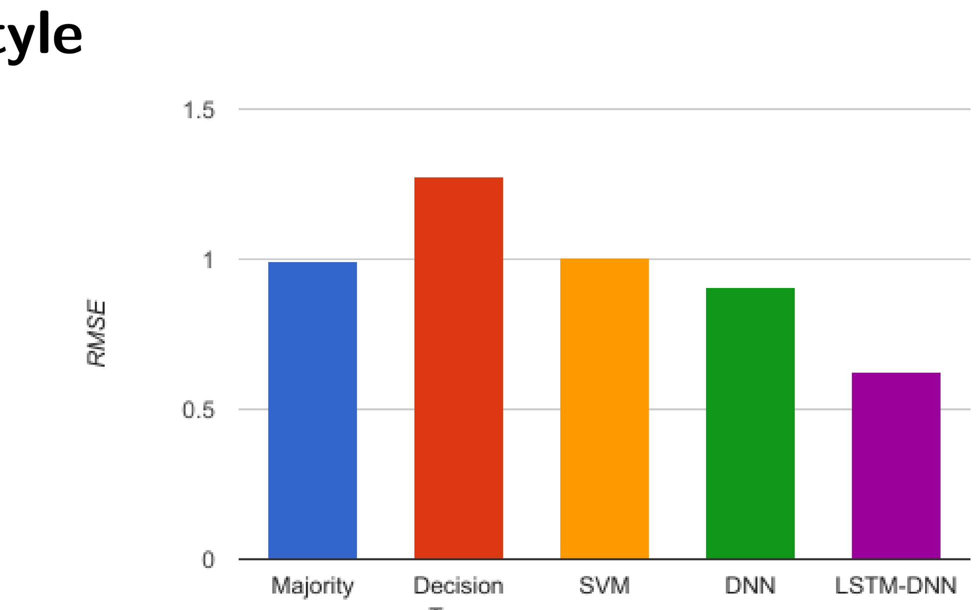
Accuracies for 80-way classification of beer names

Type



Accuracies for 3-way classification of beer types

Style



Root mean squared errors for predicting beer attributes, **small RMSE is better**

- Neural network models outperform standard baselines in all tasks

Future Work

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