Recipe for Disaster: A Seq2Seq Model for Recipe Generation

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Background

- RNNs have had success at producing locally coherent text.
- Recipe instruction generation is particularly challenging: references specific ingredients, global coherence.
- Globally coherent recipe generation relatively unexplored.
- Polmaridi et al. (2015): Cuisine classification and generation with MDPs.
- Brewe et. al. (2015): Recipe generation with charm.
- Choi et. al. (2016): Globally coherent text generation.

Problem Statement

- Input a set of ingredients
- Output a sequence of instructions that govern the combination of these ingredients
- Mimic the style and syntax of a human-written recipe
- Incorporate all ingredients into instructions

Dataset

- The dataset used in our model was the MIT Recipe1M database.
- Consists of over 1 million recipes consisting of a list of ingredients and instructions.
- We split the data as follows:
  - Train: 95% of recipes
  - Development: 2.5% of recipes
  - Test: 2.5% of recipes

![Diagram of model architecture]

\[ E_{pred} = \sum_{i} CE(y_i, \hat{y}_i) \]

Results

- Dev Loss:
  - Vanilla Seq2Seq: 3.00
  - Attention: 3.00
  - Dropout: 4.42
  - Attention + Dropout: 4.42

Experiments

- Regularization/Dropout
- Luong Attention
- Beam Search
- Pretrained word embeddings

Conclusion

- We were successfully able to minimize the training loss and generate novel recipes for ingredients.
- More work is needed to generalize more effectively to unseen examples.
- Dev loss is not strictly predictive of performance.
- Categorical inference.
- Further work:
  - Dependency parsing
  - Checklist specialized attention
  - Bidirectional encoder
  - RNN Cell type (GRU vs Vanilla vs LSTM)
  - Specialized metrics for model evaluation.