Regularization Techniques for RNN-Generated Melodies

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Objectives

This project aims to characterize and compare three "regularization" strategies for recurrent neural networks used for token sequence generation:

- Dropout Regularization [1]
- Scheduled Sampling [2]
- Professor Forcing [3]

In particular, this project aims to implement each of these four strategies in Tensorflow. Then, this project aims to apply and evaluate these strategies using a MelodyRNN (an RNN for generation of single-note melodies) [4] trained on the Yamaha Piano E-Competition Dataset.

Motivation

- *Overfitting:* Learned model fits training data too well
- Two sources of overfitting in generative RNNs:
  - Neurons adapt *too well* to patterns in input data
  - Training and inference mismatch: in training, token likelihood conditioned on previous *actual* token, but during inference, token likelihood condition on previous *generated* token
- Goal: **Determine which regularization strategies best prevent overfitting** in order to generate better sequences
- One token sequence generation problem of interest: melody composition

Background: Regularization Methods

Dropout Regularization [1]

- Idea: remove units from neural network with probability p at training time; scale weights by p during generation
- Mathematical characterization for hidden unit i in layer l:

$$r_j^l \sim \text{Bernoulli}(p)$$
$$\tilde{\mathbf{y}}^l = \mathbf{y}^l * \mathbf{r}^l$$
$$z_i^{l+1} = \mathbf{w}_i^{l+1}\tilde{\mathbf{y}}^l + b_i^{l+1}$$
$$y_i^{l+1} = f\left(z_i^{l+1}\right)$$

Scheduled Sampling [2]

- Idea: to estimate previous token at iteration i of training time, use true token with probability ϵ_i and use generated token with probility $1 - \epsilon_i$
- Inverse sigmoidal ϵ_i decay schedule:

$$\epsilon_i = \frac{k}{(k + \exp(i/k))}, k > 1$$

Professor Forcing [3]

- [5]: [2] yields biased estimator of previous token
- Idea: train discriminator to differentiate between true and generated samples; train generator to maximize data likelihood and fool generator

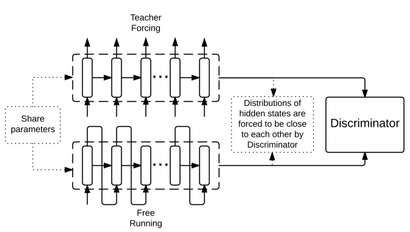
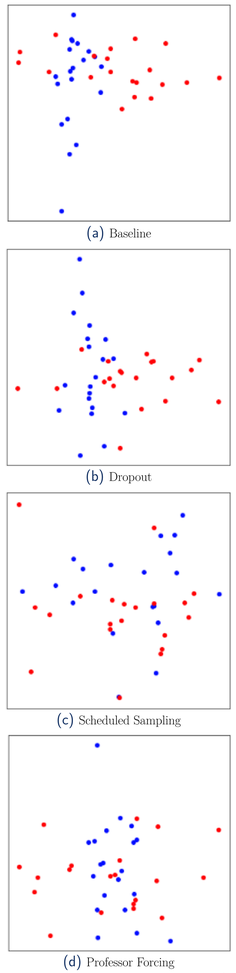


Figure 1: Network architecture used for professor forcing [3]

Experiments

- Model: MelodyRNN [4]
- Dataset: Yamaha Piano E-Competition Dataset
  - 1,400 performances
  - Randomly selected 90:10 training-evaluation split
- Implemented scheduled sampling and professor forcing; dropout implicitly available within MelodyRNN
- Architecture: 2-layers [64,64]
- Batch Size: 32
- Number of Iterations: 5,000
- After training: generated 10 128-step melodies primed at middle C
- Evaluation:
  - Hidden state discrepancy between training and generated sequences
  - Training and evaluation loss
  - Log likelihood

Results: Hidden State Analysis



(a) Baseline

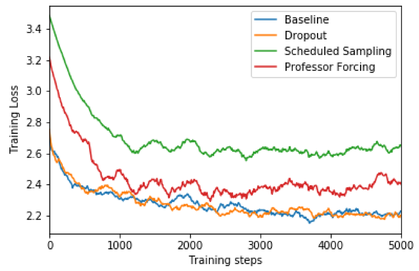
(b) Dropout

(c) Scheduled Sampling

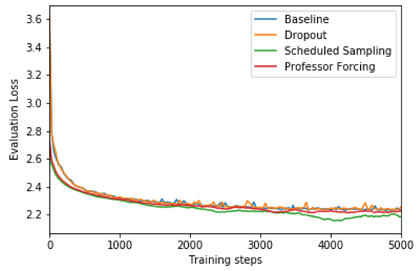
(d) Professor Forcing

Figure 2: T-SNE plots of RNN hidden states during training (red) and generation (blue)

Results: Training and Evaluation Loss



(a) Training loss for different regularization techniques



(b) Evaluation loss for different regularization techniques

Figure 3: Computed training and evaluation loss

Results: Log Likelihood

Strategy	Log Likelihood
Baseline	-280.3
Dropout	-235.5
Scheduled Sampling	-205.4
Professor Forcing	-226.2

Discussion

- Hidden State Analysis:
  - Clear disparity between training and generation states for baseline and dropout
  - Scheduled sampling and professor forcing show closer similarity in hidden states between training and generation
- Training and Evaluation Loss:
  - Minimal difference between baseline and dropout performance
  - Scheduled sampling and professor forcing do *worse* in training, but scheduled sampling performs slightly better in evaluation, indicating a regularizing effect
- Log Likelihood:
  - Best performing strategy: scheduled sampling
- Comparing Strategies:
  - Order of magnitude of training/generation mismatch in RNNs seems larger than that of units directly memorizing training data
  - Scheduled sampling and professor forcing outperform baseline/dropout
  - Bias in estimator shown by [5] is not an issue here (potential confounder: inadequate discriminator training)
  - Overall: scheduled sampling appears to be the best regularization strategy; also, faster runtime than professor forcing

Limitations

- All evaluations performed with the same training network architecture as the originally chosen baseline network
- Results show effects of different regularization techniques when network structure is held constant
- Results do not explain behavior when architecture for each strategy is tuned separately

Future Work

- *Evaluation of SeqGAN [6]*:
  Generative model: RL agent trained on a reward signal from discriminator; discriminator trained to distinguish between real and generated sequences
- *Application to long-term structure models*:
  Extend regularization methods described here to 'lookback' and attention mechanisms used to induce long-term structure in melodies

Conclusion

- Scheduled sampling generated melodies with the highest log likelihood
- Scheduled sampling demonstrated highest similarity between the hidden states observed during training and generation
- **Scheduled sampling is the most effective regularization method for this MelodyRNN architecture**

References

[1] Nitish Srivastava, Geoffrey E Hinton, Alex Krizhevsky, Ilya Sutskever, and Ruslan Salakhutdinov.
Dropout: a simple way to prevent neural networks from overfitting.
Journal of machine learning research, 15(1):1929–1958, 2014.

[2] Samy Bengio, Oriol Vinyals, Navdeep Jaitly, and Noam Shazeer.
Scheduled sampling for sequence prediction with recurrent neural networks.
In *Advances in Neural Information Processing Systems*, pages 1171–1179, 2015.

[3] Alex M Lamb, Anirudh GOYAL, Ying Zhang, Saizheng Zhang, Aaron C Courville, and Yoshua Bengio.
Professor forcing: A new algorithm for training recurrent networks.
In *Advances In Neural Information Processing Systems*, pages 4601–4609, 2016.

[4] Magenta: Music and art generation with machine intelligence.
`https://github.com/tensorflow/magenta`, 2017.

[5] Ferenc Huszár.
How (not) to train your generative model: Scheduled sampling, likelihood, adversary?
arXiv preprint arXiv:1511.05101, 2015.

[6] Lantao Yu, Weinan Zhang, Jun Wang, and Yong Yu.
Seqgan: Sequence generative adversarial nets with policy gradient.
In *AAAI*, pages 2852–2858, 2017.

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Additional Information

- Code: www.github.com/nalinimsingh/9.520-MelodyRnn-Regularization
- Contact Email: nmsingh@mit.edu