Multiple Viewpoint Melodic Prediction with Fixed-Context Neural Networks

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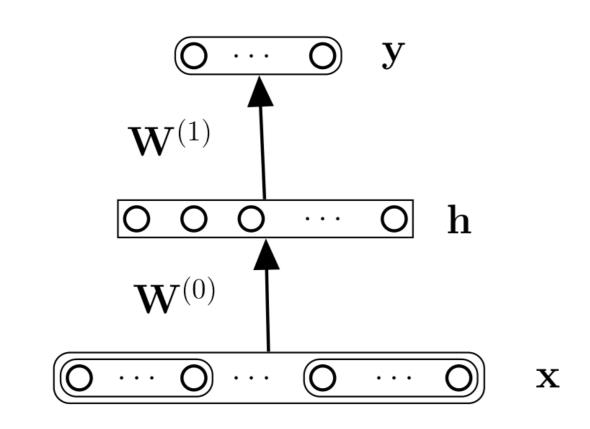
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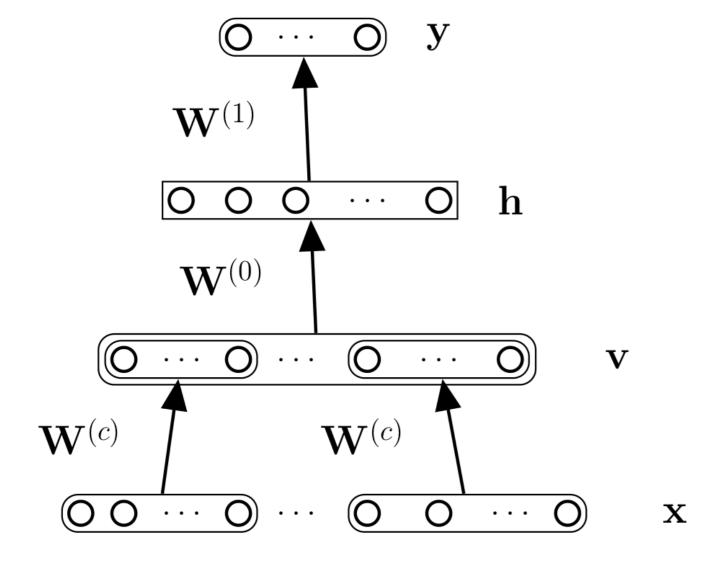
1. Introduction

- Modelling statistical regularities in melodies.
- A note based approach Multiple Viewpoint Systems.
- Predict a probability distribution over possible values of pitch of next note given the notes immediately preceding it: $p(s_t|s_{(1,...,t-1)})$.
- **Applications:** Music generation, studying melodic expectation, solo instrument/singing voice transcription.

3. Prediction Models



(a) Feed-forward Neural Network



- (b) Neural Probabilistic Melody Model
- Two non-recurrent neural network prediction models.
- Context events in one-hot representation given as input.
- Multiple input type one-hot vectors concatenated.
- Networks have softmax output layer to predict p(y|x).
- The feedforward neural network has a single logistic sigmoid hidden layer.
- The neural probabilistic melody model [2] has a hyperbolic tangent hidden layer and an additional linear *embedding* layer.
- Both networks trained using the backpropagation and mini-batch gradient descent [3].

References

[1] Conklin, Darrell, and Ian H. Witten. "Multiple viewpoint systems for music prediction." *Journal of New Music Research 24.1 (1995): 51-73.*[2] Bengio, Yoshua, et al. "Neural probabilistic language models." *Innovations in Machine Learning*. Springer Berlin Heidelberg, 2006. 137-186.

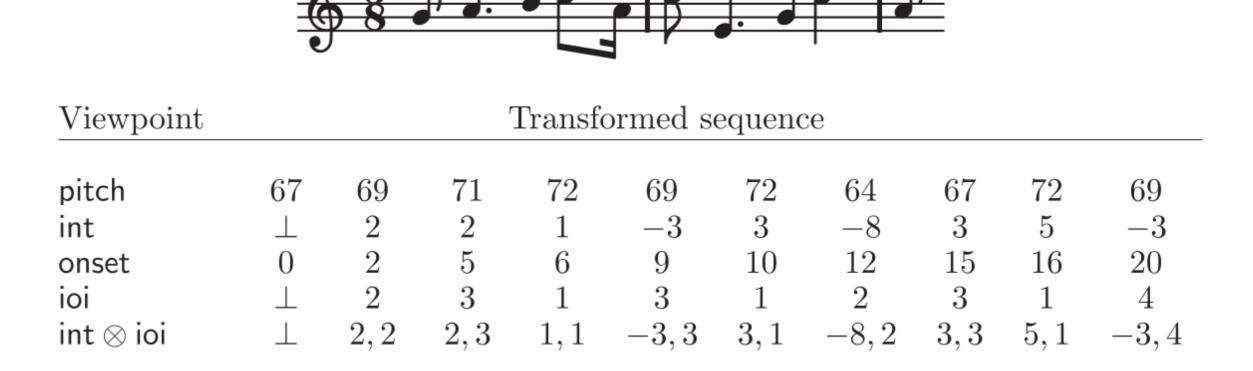
[3] Rumelhart, David E., Geoffrey E. Hinton, and Ronald J. Williams. "Learning representations by back-propagating errors." *Cognitive modeling* (1988).

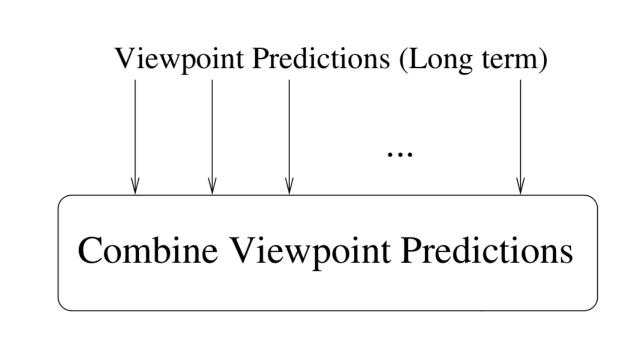
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2. Multiple Viewpoints Representation of Melody

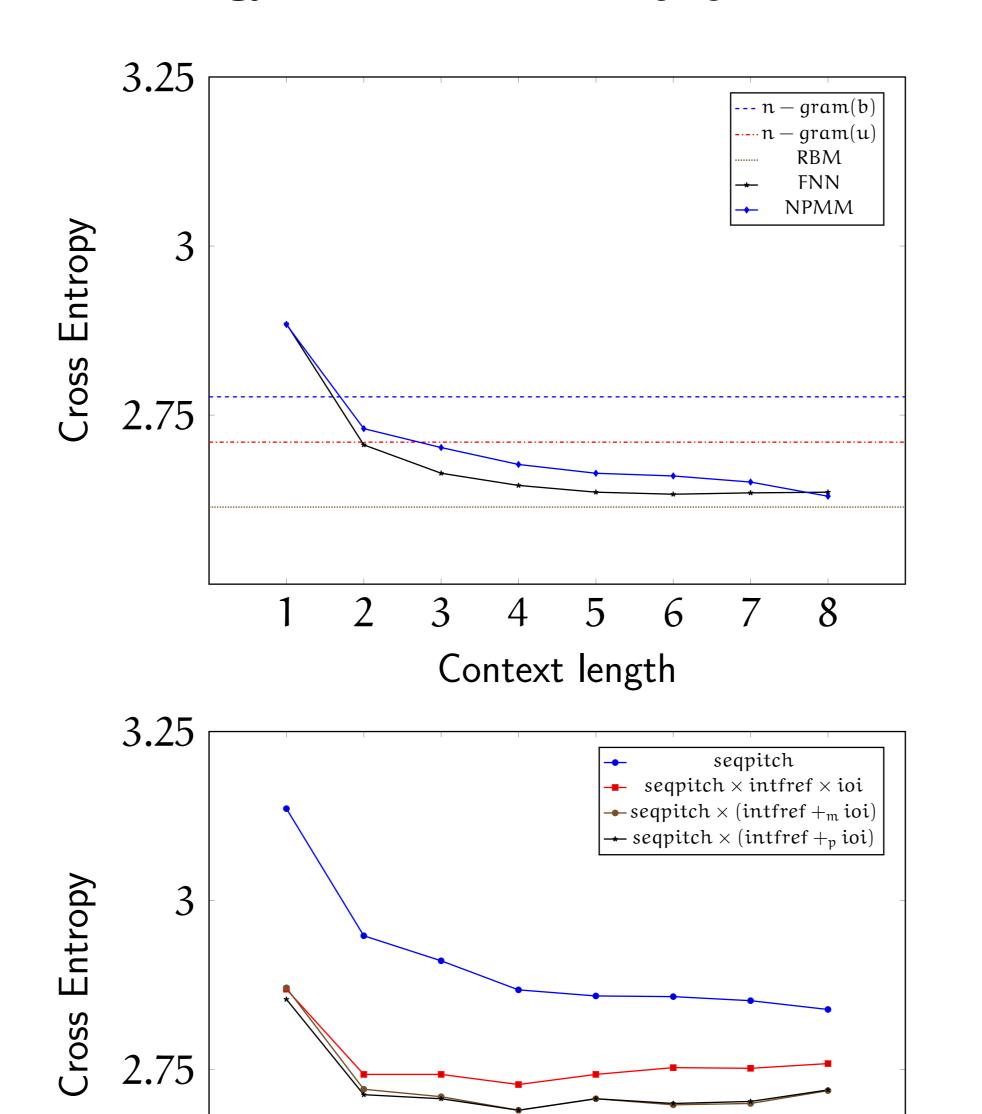




- A framework for analysis and generation of music in symbolic form (MIDI, Kern, etc.) [1].
- Melody broken down into parallel viewpoint type sequences.
- Viewpoint types can be linked via Cartesian product.
- One n-gram model per viewpoint type to overcome data sparsity.
- Multiple models combined using entropy-weighted mixture- or product-of-experts.
- Input types: Types in the context; Target type: Type being predicted.

4. Experiments & Evaluation

- **Dataset:** Bach chorales (9,227 notes), and Folk melodies of Canada (8,553 notes), China (11,056 notes) and Germany (8,393 notes) from the Essen Folk Song Collection [6].
- Criterion: Cross Entropy A measure of the divergence between model predictions and the true data distribution.
- Methodology: Model selection through grid search, with each model evaluated on folds identical to those in [4].



Experiments

- Predict pitch, given a context of...
 - pitch.
- pitch, inter-onset interval, scale-degree.
- Multiple viewpoint types combined via...
- a single model.
- a combination of multiple models.
- Compared with previous n-gram and restricted Boltzmann machine prediction models [4, 5].

Observations

- Predictions improve with context length.
- The respective best cases of both neural network models better than $n\text{-}\mathrm{grams}$ but worse than RBMs.
- Additional viewpoint types (in the present case) improve predictions.
- A combination of multiple models better than a single model particularly for longer contexts.
- Both MoE and PoE model combinations improve predictions. PoE only slightly better in some cases.

5. Future Work

• Neural network "tricks" and better optimization to improve existing results.

Context length

• Recurrent models to limit increase in the input space with context length.

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- Online learning to update model parameters while it predicts unseen sequences.
- Application to melody segmentation, voice separation and singing-voice transcription.

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