

# A Neural Probabilistic Model for Music Prediction

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# Outline

Introduction: Language Modelling & Music Prediction

Background: Computing Music

Approach: Learning pitch sequences with RBMs

Initial Results: Improved pitch prediction

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# Statistical Language Modelling

lún er bæði í landsliðinu U 20 og í a  
agsýnilega ekki upp við velgengnina c  
st ekki. Margrét stundar nám við V  
estu af frítíma sínum í fótboltaefing  
að sé svona heillandi við fótboltan  
fér finnst svo gaman að spila fótboli  
að fer auðvitað mikill tími í æfingar  
ð vini mína. . . .’ Margrét sér framt  
oltanum. Hana langar að fara til útlar  
skalanda eða Norðurlöndin eru ofar

- ▶ Modelling sequences of words in text.
- ▶ Understanding properties of language through documents.
- ▶ Applied in speech recognition, document analysis & classification.

# Music Prediction



- ▶ Modelling sequences of *musical events* (musical pitch, note duration, etc.).
- ▶ Understanding properties of music through scores.

## Scientific:

- ▶ Analysis of
  - ▶ Compositional practices
  - ▶ Musical style
- ▶ Music Education & Training
- ▶ Organizing music data
- ▶ Aiding music transcription
- ▶ Music & emotion

## Creative:

- ▶ Generative music
- ▶ Compositional assistance

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# Notable Approaches

- ▶ Markov models to carry out a “musical conversation”.
- ▶ Rule-based systems to imitate classical composers.
- ▶ Neural networks to play like Charlie Parker.
- ▶ Genetic Algorithms to improvise Jazz solos.
- ▶ Hidden Markov models to harmonize chorales like Bach.



Introduction: Language Modelling & Music Prediction

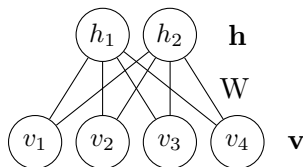
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# Restricted Boltzmann Machine

- ▶ A bipartite graphical model for learning probability distributions
- ▶ Adjusts weights according to data while learning.
- ▶ Data presented at visible layer. Features learned in hidden layer.
- ▶ Generative model.



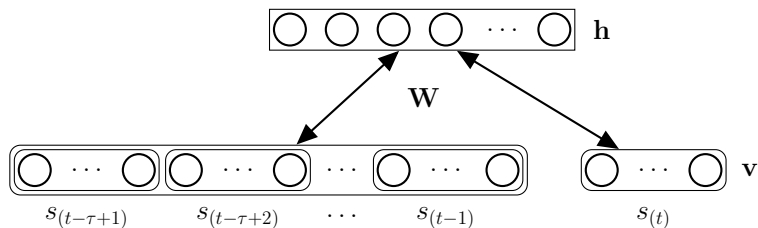
# Why RBMs?

RBMs have some desirable qualities for learning from music data

- ▶ Reasonable predictions for unseen cases.
- ▶ Non-exponential scaling with sequence length.
- ▶ Efficient learning algorithms.
- ▶ Scalable to deeper architectures.
- ▶ Generative properties.

# Neural Probabilistic Music Prediction

A simple model based on the Restricted Boltzmann Machine for learning sequences of musical pitch.



The present approach motivated by previous work in language modelling.

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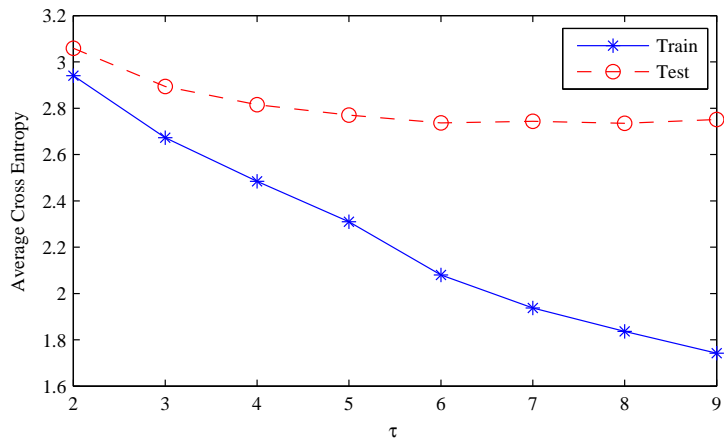
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# Sequence Length

Makes use of information in longer pitch sequences.



# Prediction Performance

Better cross entropy estimates.

ID	Markov-3	Markov*	RBM-2	RBM-3	RBM-4	RBM-5	RBM-6	RBM-7	RBM-8	RBM-9
0	2.885	2.861	3.062	2.895	2.812	2.787	2.783	2.770	2.772	2.793
1	2.544	2.444	2.732	2.554	2.510	2.465	2.442	2.442	2.455	2.465
2	3.110	3.115	3.174	3.030	2.935	2.894	2.852	2.865	2.848	2.849
3	2.791	2.721	2.886	2.738	2.666	2.672	2.641	2.703	2.741	2.802
4	3.192	3.010	3.202	3.069	2.974	2.867	2.822	2.826	2.838	2.829
5	3.385	3.340	3.475	3.286	3.203	3.140	3.107	3.117	3.026	3.070
6	2.596	2.428	2.740	2.597	2.519	2.461	2.432	2.411	2.379	2.383
7	3.083	3.105	3.196	2.980	2.899	2.878	2.815	2.812	2.817	2.817
<b>Av.</b>	<b>2.948</b>	<b>2.878</b>	<b>3.059</b>	<b>2.894</b>	<b>2.815</b>	<b>2.771</b>	<b>2.737</b>	<b>2.743</b>	<b>2.734</b>	<b>2.751</b>

# Case Study: Folk Melody Classification

Overall accuracy of 59.93%

	<i>Nova-Scotia</i>	<i>Alsace</i>	<i>Yugoslavia</i>	<i>Switzerland</i>	<i>Austria</i>	<i>Germany</i>	<i>China</i>
Nova-Scotia	74.83%	5.96%	0.00%	2.65%	4.63%	4.63%	7.28%
Alsace	13.19%	29.67%	7.69%	10.99%	19.78%	16.48%	2.19%
Yugoslavia	10.08%	10.08%	42.02%	14.29%	14.29%	8.40%	0.84%
Switzerland	6.45%	17.20%	6.45%	35.48%	22.58%	7.53%	4.30%
Austria	10.58%	19.23%	4.81%	12.50%	41.35%	9.62%	1.92%
Germany	11.27%	11.74%	2.35%	9.86%	8.92%	53.99%	1.88%
China	6.75%	1.27%	0.00%	0.84%	3.80%	0.00%	87.34%



# Conclusions & Future Work

## Conclusion

- ▶ RBMs are a good starting point for music prediction.
  - ▶ Use longer contexts.
  - ▶ Handle unseen contexts.
  - ▶ Scale gracefully.

## Some interesting directions for future work

- ▶ Extensions to harmonic sequences.
- ▶ Predicting other musical dimensions.
- ▶ Learning higher-level structure.
- ▶ Other applications.

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Dr. Marcus Pearce (QMUL)  
Son Tran (City)

Thank you!

Questions?

