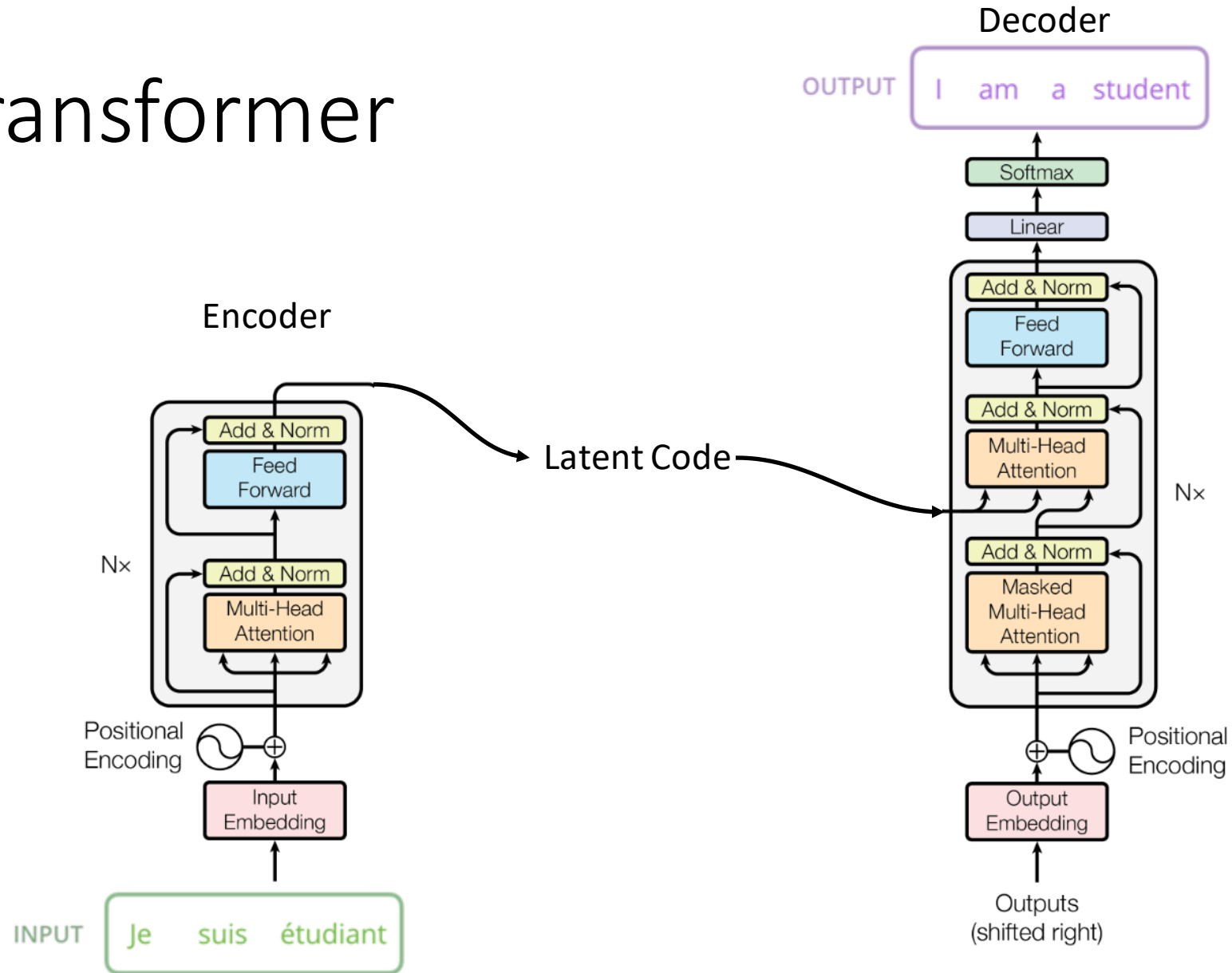


Neural Computation

The Decoder - Part 1

Autoregressive Generative Models

The Transformer



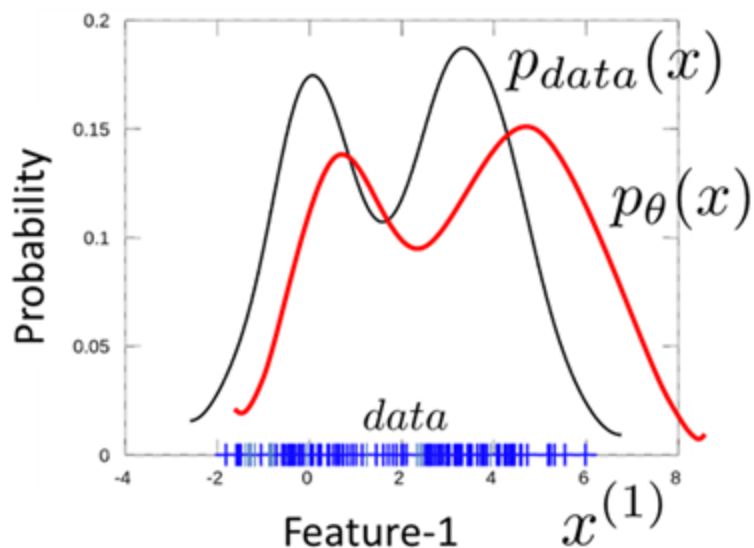
Probability Density Estimation

One of the main aims of unsupervised approaches and Generative Modelling.

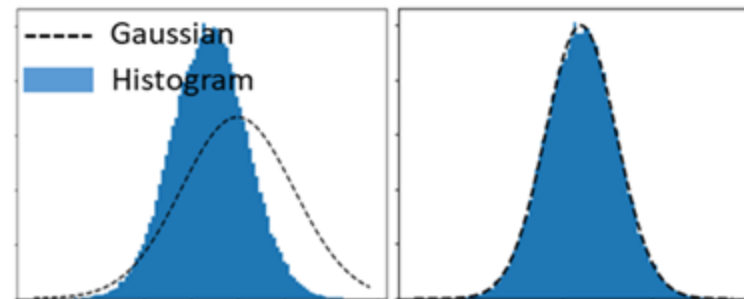
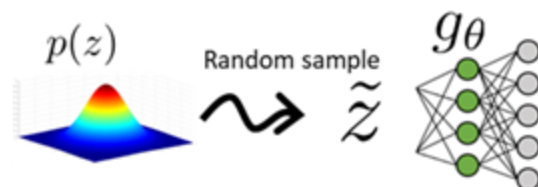
Goal of Density Estimation:

We could try to fit a probabilistic model $p_{\theta}(x)$ to the data, to learn their underlying distribution $p_{data}(x)$.

How? By learning its parameters θ so that: $p_{\theta}(x) \approx p_{data}(x)$



But we cannot always do that directly. Perhaps we cannot compute $p_{data}(x)$ or $p_{\theta}(x)$. Instead, we could do PDE *indirectly*: Enforce samples from model to be similar to real data instead:



$$x \sim p_{data}(x)$$

7	3	4	6	1	8	1	0
9	8	0	3	1	3	7	0
2	9	6	0	1	6	7	1
9	7	6	5	5	8	8	3
4	4	8	7	3	6	4	6
6	3	6	8	9	9	4	4
0	7	8	1	0	0	1	8
5	7	1	7	5	5	9	9



$$\tilde{x} \sim p_{\theta}(x)$$

1	1	1	2	1	1	7	
5	7	6	7	7	1	7	
7	6	9	1	3	3	1	
8	7	5	9	3	1	7	
7	7	5	0	7	7	7	
5	0	4	5	7	8	7	0
5	5	1	1	5	1	1	
6	1	2	1	2	4	1	

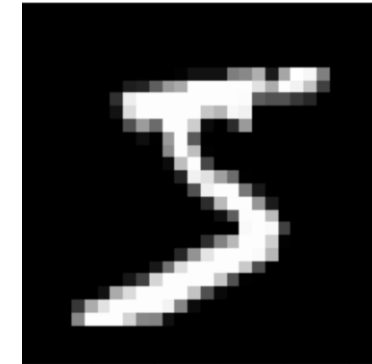
Both VAEs and GANs can be seen as following this approach.

Autoregressive Models

Problem:

- Model high dimensional difficult distribution

$$p_{\theta}(\mathbf{x}) = p_{\text{data}}(\mathbf{x}), \text{ with } \mathbf{x} = (x_1, \dots, x_n)$$



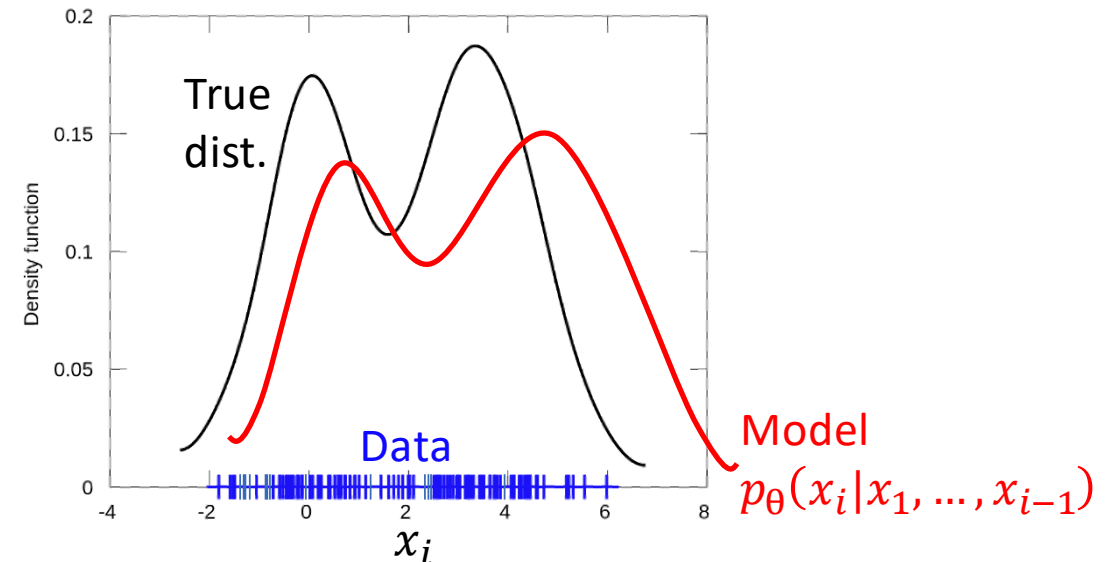
Idea:

- Factorise distribution

$$p_{\theta}(\mathbf{x}) = \prod_{i=1}^n p_{\theta}(x_i | x_1, \dots, x_{i-1})$$

Neural network:

- Parameters θ
- Input x_1, \dots, x_{i-1}
- Output dist. over x_i



WAVENET: A GENERATIVE MODEL FOR RAW AUDIO

Aäron van den Oord

Sander Dieleman

Heiga Zen[†]

Karen Simonyan

Oriol Vinyals

Alex Graves

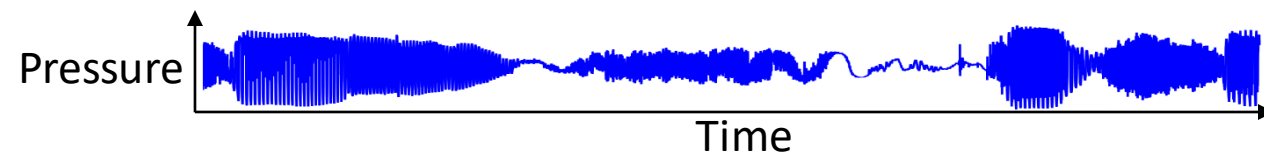
Nal Kalchbrenner

Andrew Senior

Koray Kavukcuoglu

{avdnoord, sedielem, heigazen, simonyan, vinyals, graves, nalk, andrewsenior, korayk}@google.com
Google DeepMind, London, UK

[†] Google, London, UK



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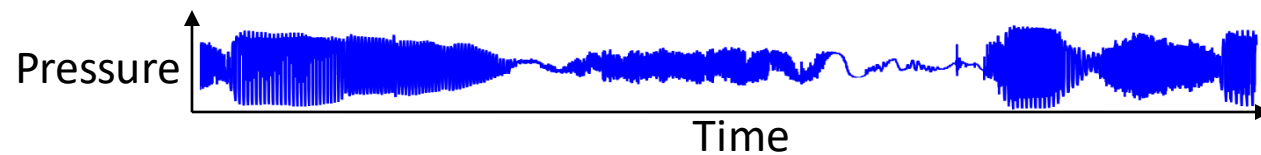
Andrew Senior

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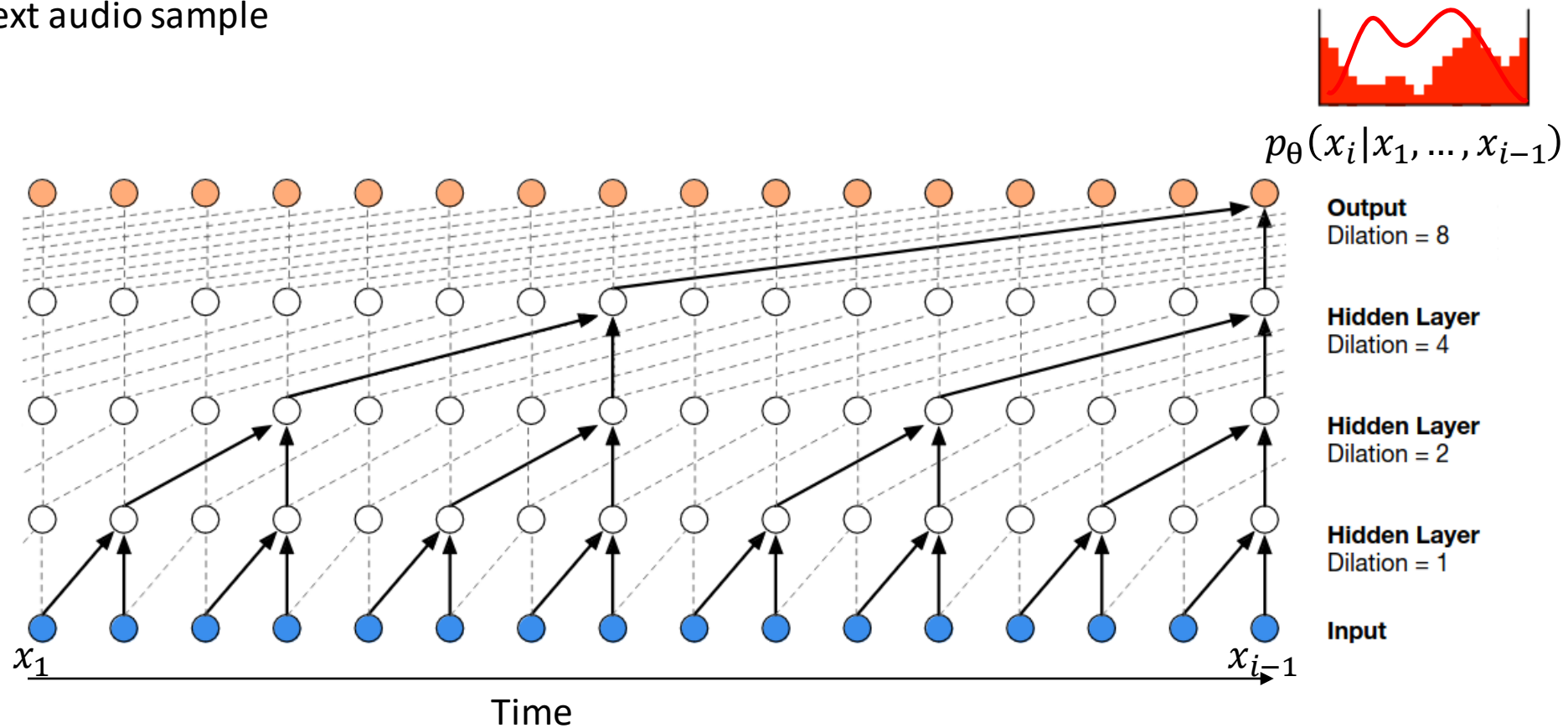
{avdnoord, sedielem, heigazen, simonyan, vinyals, graves, nalk, andrewsenior, korayk}@google.com

Google DeepMind, London, UK

[†] Google, London, UK



- Predict dist. for next audio sample



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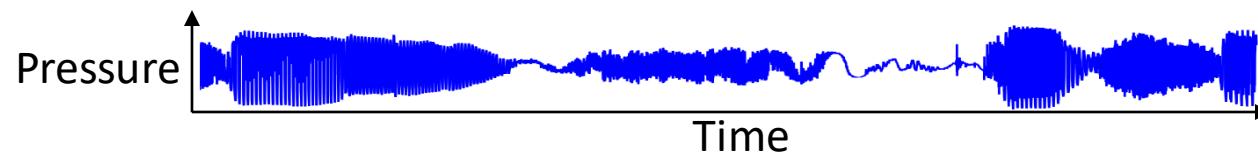
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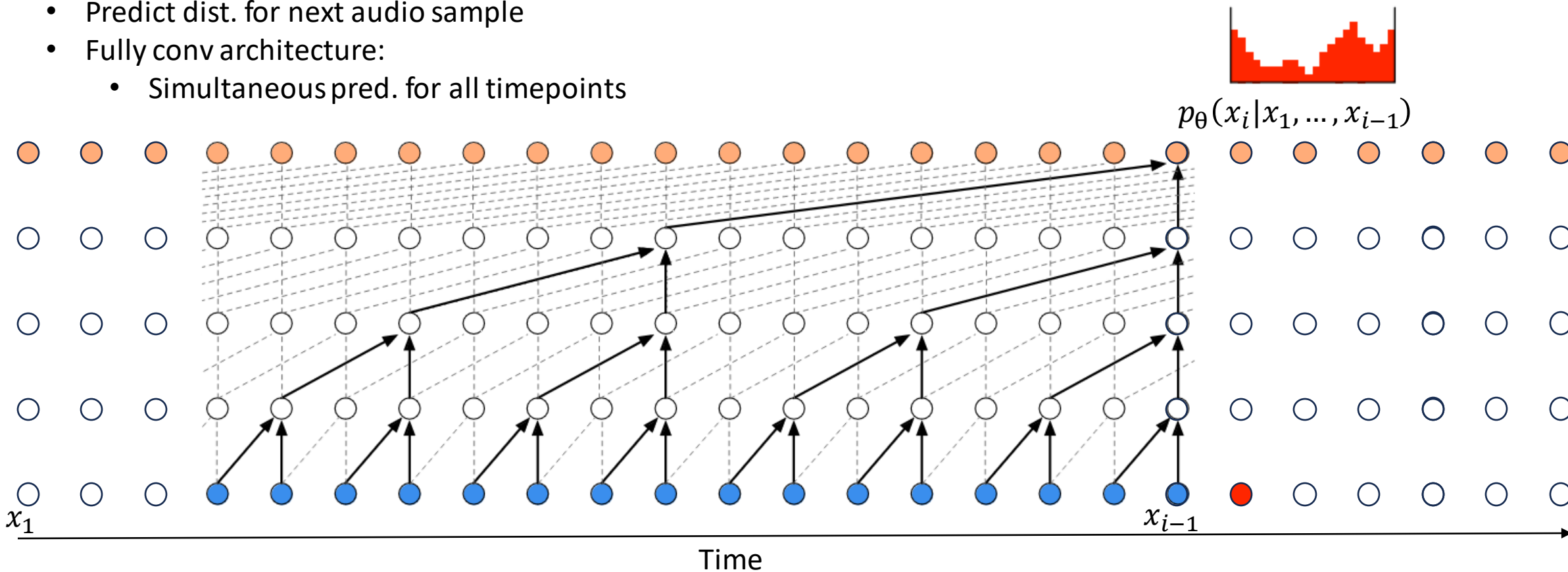
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[†] Google, London, UK



- Predict dist. for next audio sample
- Fully conv architecture:
 - Simultaneous pred. for all timepoints



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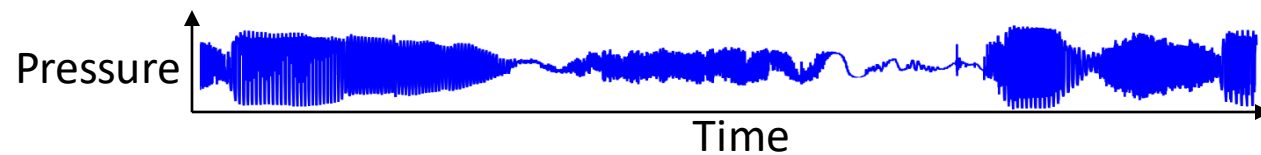
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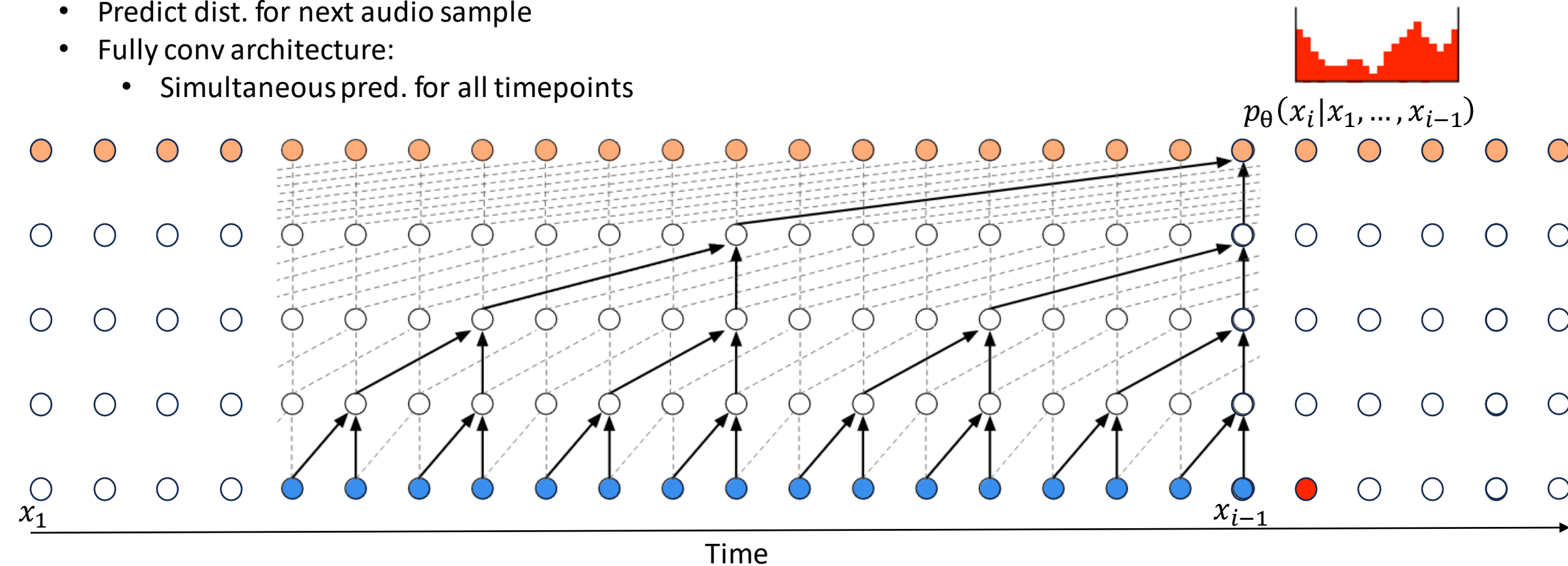
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Google DeepMind, London, UK

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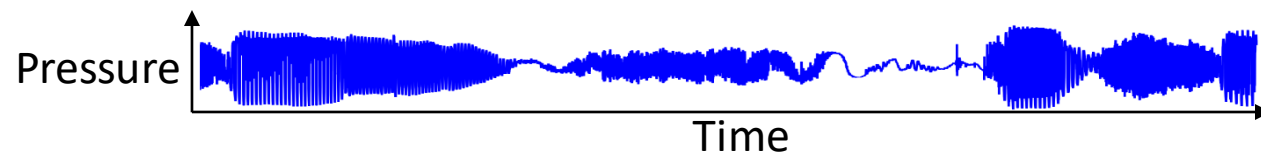
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Google DeepMind, London, UK

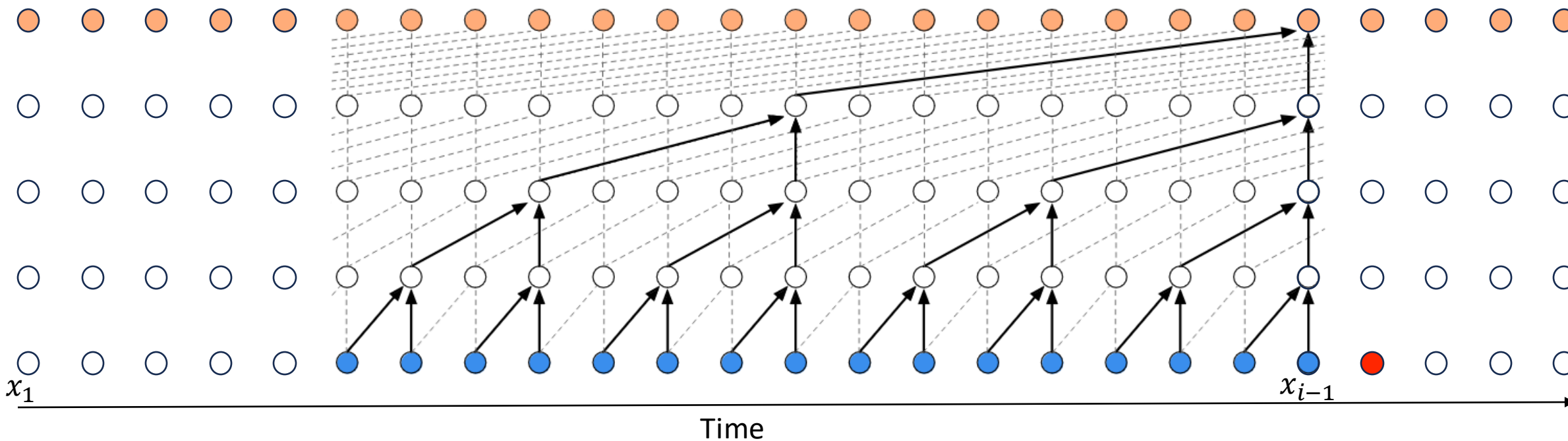
[†] Google, London, UK



- Predict dist. for next audio sample
- Fully conv architecture:
 - Simultaneous pred. for all timepoints

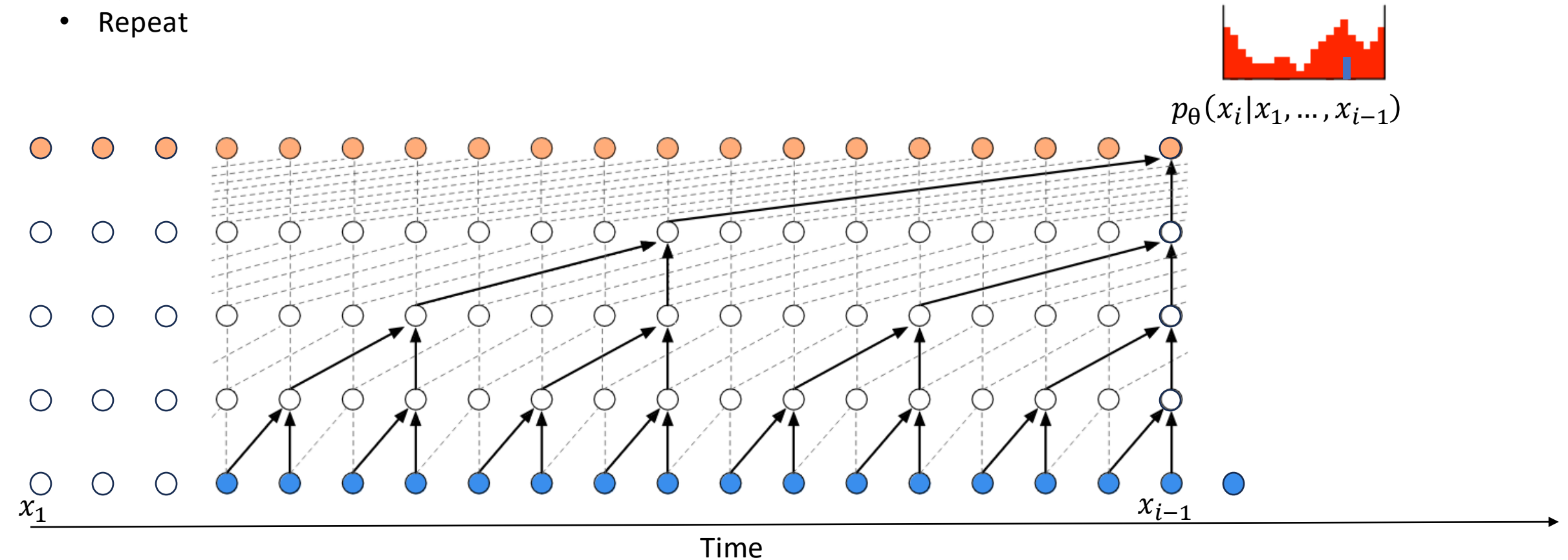


$$p_{\theta}(x_i | x_1, \dots, x_{i-1})$$



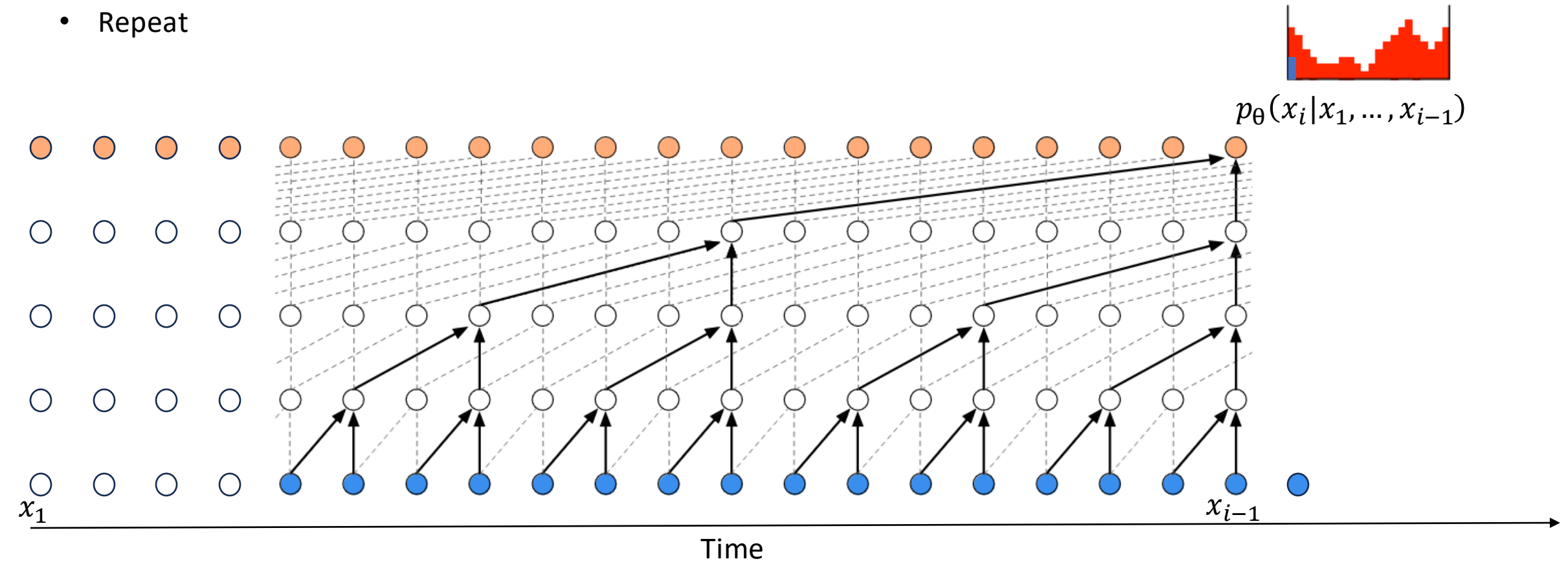
Sampling from the Model

- Predict dist. for next audio sample
- Sample from distribution
- Append new sample
- Repeat



Sampling from the Model

- Predict dist. for next audio sample
- Sample from distribution
- Append new sample
- Repeat

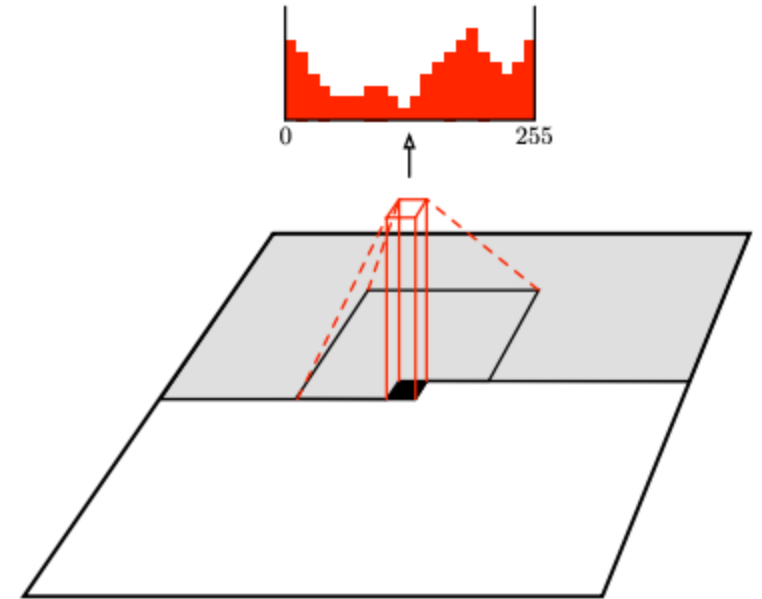
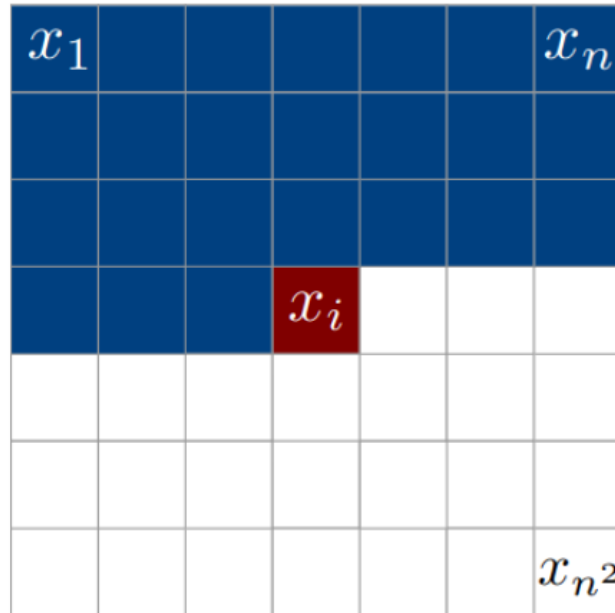


Pixel Recurrent Neural Networks

Aäron van den Oord
Nal Kalchbrenner
Koray Kavukcuoglu

Google DeepMind

AVDNOORD@GOOGLE.COM
NALK@GOOGLE.COM
KORAYK@GOOGLE.COM



Pixel Recurrent Neural Networks

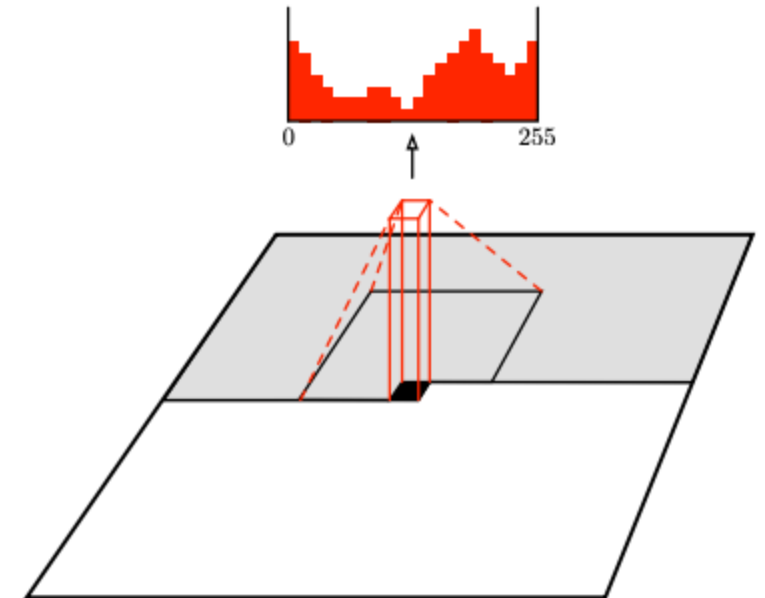
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Nal Kalchbrenner
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Image Generation:

- Sample one pixel
- Apply network
- Repeat

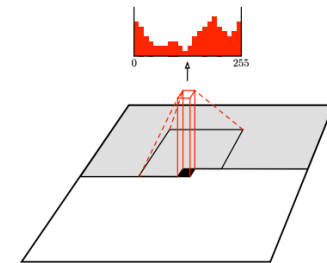
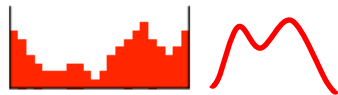
AVDNOORD@GOOGLE.COM
NALK@GOOGLE.COM
KORAYK@GOOGLE.COM



Summary

- Interpret data as sequence
- Train neural network
 - Input: previous values (x_1, \dots, x_{i-1})
 - Distribution of possible next values $p_\theta(x_i | x_1, \dots, x_{i-1})$
 - E.g. as histogram
 - Or Parametric dist.
 - Ensure correct receptive field, e.g. special convolutions
- Sampling:
 - One sample at a time
 - Slow, involves repeated application of model

$$p_\theta(\mathbf{x}) = \prod_{i=1}^n p_\theta(x_i | x_1, \dots, x_{i-1})$$



The Transformer

