main.bib

## RETENTION BASED AUTOREGRESSIVE MODELS FOR MODELLING NEURAL DYNAMICS

by

Abhinav Muraleedharan

A thesis submitted in conformity with the requirements for the degree of Masters in Engineering

Graduate Department of Institute for Aerospace Studies

University of Toronto

© Copyright 2023 by Abhinav Muraleedharan

Retention based autoregressive models for modelling neural dynamics

Abhinav Muraleedharan Masters in Engineering Graduate Department of Institute for Aerospace Studies University of Toronto 2023

#### Abstract

In this work, we present Retention, a novel autoregressive model for generative modelling of sequences. Unlike Transformer based autoregressive models, retention scales linearly with respect to context size. We apply retention based models for modelling neural dynamics and achieve SOTA performance in neural modelling and behaviour decoding.

To Mom

### Acknowledgments

Thanks Mom

## Contents

## List of Tables



# List of Figures



### Chapter 1

### Introduction

The brain, as a complex dynamical system, governs a diverse range of behaviors and cognitive processes, presenting a fundamental challenge in neuroscience. Unraveling the dynamics of the brain holds the key to understanding the neural mechanisms underlying these processes. Beyond modeling neural activity, elucidating how such activity correlates with an organism's behavior is crucial for developing Brain-Computer Interfaces, clinical treatments for conditions like epilepsy, depression, and other neurodegenerative diseases.

Machine learning techniques have played a pivotal role in modeling brain dynamics, and modeling the correlation between neural dynamics and behavior of an animal. In [?], Pandarinath et al. introduced LFADS, an RNN-based method to infer latent dynamics from neural data. More recently, transformer-based models [?, ?], have been applied to learn neural dynamics and behaviour model. In [?], Pandarinath et al applied transformer-based models to learn neural dynamics without an explicit dynamical model. While LFADS and NDT (Neural Data Transformers) were focused on learning neural dynamics from single trial recordings, Azabou et.al recently introduced POYO [?], a transformer-based model to learn neural dynamics from multi-session neural recordings.

Although transformer-based models have shown remarkable success in general language modelling tasks and more recently in learning population dynamics of neurons, they exhibit poor scaling properties especially when applied to neural spiking data. Furthermore, unlike text data, neural recording probes sample on the order of kHz, and hence are characterized by high temporal resolution. This unique temporal aspect of neural spiking data presents a challenge for transformers, which are originally designed for sequential data but may struggle with the high-frequency nature of neural

signals. The transformer's poor scaling properties become particularly evident when recording from a large number of neurons simultaneously, as the number of potential firing patterns exponentially increases with the number of neurons.

In this work, we introduce a new class of autoregressive models to overcome limitations imposed by the architecture of attention-based transformer models. Our model has an unbounded context length and hence can capture long-range dependencies in the time series dataset. Furthermore, the complexity of training and inference of the parametrized model is independent of the context length, and hence our approach is computationally more efficient when compared to transformer-based autoregressive models.

### Chapter 2

### Methods

#### 2.1 Problem Statement

This is a text citation [?]. Prediction Transduction. Imagine we are recording data from D neurons distributed across different regions of the brain. Let  $x(t_i) \in \mathbb{R}^D$  denote the observed neural activity at timestep  $t_i$  and let  $y_i$  denote the observed behaviour of the animal at timestep  $t_i$ . From the time series dataset  $\mathcal{D} = \{(x_i, y_i, t_i)\}_{i=1}^N$  of neural recordings, our goal is to construct:

- A predictive model of underlying brain dynamics
- A probabilistic model to predict behaviour of the organism at time t + 1 given brain recordings until timestep t.

More formally, let's assume that the spiking activity is generated by an underlying non-stationary stochastic process defined by  $p_t(x)$ .

$$x(t) \sim p_t(x) \tag{2.1}$$

The probability of observing a sequence of neural recordings and behavior can be expressed as:

$$p(\lbrace x_1, y_1 \rbrace, \lbrace x_2, y_2 \rbrace, \lbrace x_3, y_3 \rbrace, ..) = \lim_{N \to \infty} \prod_{i=1}^{N} p(\lbrace x_i, y_i \rbrace | \lbrace x_1, y_1 \rbrace, \lbrace x_2, y_2 \rbrace, .. \lbrace x_{i-1}, y_{i-1} \rbrace)$$
(2.2)

In the context of neural recordings, it is convenient to assume that the neural recording data and behavior can be modelled with separate probability distributions of the form:

$$\prod_{i=1}^{N} p_d(\{x_i\} | \{x_1\}, \{x_2\}, ..\{x_{i-1}\})$$
(2.3)

4 CHAPTER 2. METHODS

$$\prod_{i=1}^{N} p_b(\{y_i\} | \{x_1\}, \{x_2\}, ... \{x_{i-1}\})$$
(2.4)

Specifically, we assume that that the neural observed neural spiking data at timestep  $t_i$  is not dependent on the behavior variables in the preceding timesteps. Probability distributions of this nature have been extensively investigated in the field of language modeling. In conventional autoregressive frameworks, the approximation of conditional distributions often involves the utilization of parameterized models constrained by a finite context limit [?]. While autoregressive models of this kind have been extremely successful in generating plausible language [?], they still struggle to capture long-range dependencies due to the finite context length limit[?]. Furthermore, the complexity of training and inference of transformer-based models is  $\mathcal{O}(N^2)$ , where N is the context length of the transformer model.

#### 2.2 Theory

#### 2.2.1 Retention

Mathematically, retention is defined as an exponentially weighted sum of a sequence of discrete vectors. If the vectors are drawn from a continuous space, then we perform thresholding operation to discretize the vectors. Specifically, given a sequence of vectors  $\{x_i\}_{i=1}^N$ ,  $x_i \in \mathbb{R}^d$ , Retention variable  $\zeta_k$  as:

$$\zeta_i = \sum_{k=1}^{i-1} 2^{-k} \sigma_{\theta}(x_{i-k}) \tag{2.5}$$

Here,  $x_k \in \mathbb{R}^D$  is the observed neural activity at timestep  $t_k$ , and  $\sigma_{\theta} : \mathbb{R}^D \to \{0, 1, 2, M\}^D$  is a thresholding function, where  $\sigma_{\theta}(x_i^j) = 1, \forall x_i^j > \theta$ . (We use the notation  $x_i^j$  to denote j th element of the vector  $x_i$ .)

Now, note that  $\zeta_k$  has a recursive property, specifically:

$$\zeta_{i+1} = 2^{-1}\zeta_i + 2^{-1}\sigma_{\theta}(x_i) \tag{2.6}$$

#### 2.2.2 Modelling Conditional Distributions with Retention Variables

Now, we approximate the conditional distribution defined in eq(3) with

$$\prod_{i=1}^{N} p_d(\{x_i\} | \{x_1\}, \{x_2\}, ..\{x_{i-1}\}) \approx \prod_{i=1}^{N} p_d(\{x_i\} | \zeta_i)$$
(2.7)

To learn the dynamics of the brain from neural recordings in an unsupervised manner, we maximize the following likelihood:

$$\mathcal{L}(X,\theta) = \sum_{i} log(p_d(\lbrace x_i \rbrace \vert \zeta_i; \theta))$$
 (2.8)

Here,  $X = \{x_1, x_2, .... x_M\}$ , the dataset of neural recordings.

Note that in this approach, the context window is not bounded, and the complexity of learning the parametrized model  $p_d(\lbrace x_i \rbrace | \zeta_i; \theta)$  is independent of the length of the context window. While training the model, we apply eq(6) to recursively update  $\zeta_i$  in an online fashion, instead of pre-computing and storing  $\lbrace \zeta_i \rbrace_{i=1}^N$  separately.

To learn the correlation between neural dynamics and behavior, we follow a similar approach and approximate the conditional distribution defined in eq(4) with:

$$\prod_{i=1}^{N} p_b(\{y_i\} | \{x_1\}, \{x_2\}, ..\{x_{i-1}\}) \approx \prod_{i=1}^{N} p_b(\{y_i\} | \zeta_i)$$
(2.9)

We define the loss function associated with this approach as the negative log-likelihood of the observed behavioral outcomes given the estimated neural activity states. Formally, the loss function  $\mathcal{L}$  is expressed as:

$$\mathcal{L}(X, Y, \phi) = -\sum_{i} \log p_b(\{y_i\} | \zeta_i; \phi)$$

#### 2.3 Model Architecture

#### 2.4 Data

#### 2.5 Training

Etiam euismod. Fusce facilisis lacinia dui. Suspendisse potenti. In mi erat, cursus id, nonummy sed, ullamcorper eget, sapien. Praesent pretium, magna in eleifend

6 CHAPTER 2. METHODS

Table 2.1: The quick brown fox

symbol	definition
$\overline{x}$	variable

egestas, pede pede pretium lorem, quis consectetuer tortor sapien facilisis magna. Mauris quis magna varius nulla scelerisque imperdiet. Aliquam non quam. Aliquam porttitor quam a lacus. Praesent vel arcu ut tortor cursus volutpat. In vitae pede quis diam bibendum placerat. Fusce elementum convallis neque. Sed dolor orci, scelerisque ac, dapibus nec, ultricies ut, mi. Duis nec dui quis leo sagittis commodo. Aliquam lectus. Vivamus leo. Quisque ornare tellus ullamcorper nulla. Mauris porttitor pharetra tortor. Sed fringilla justo sed mauris. Mauris tellus. Sed non leo. Nullam elementum, magna in cursus sodales, augue est scelerisque sapien, venenatis congue nulla arcu et pede. Ut suscipit enim vel sapien. Donec congue. Maecenas urna mi, suscipit in, placerat ut, vestibulum ut, massa. Fusce ultrices nulla et nisl.

#### 2.5.1 Data Collection

Nulla mattis luctus nulla. Duis commodo velit at leo. Aliquam vulputate magna et leo. Nam vestibulum ullamcorper leo. Vestibulum condimentum rutrum mauris. Donec id mauris. Morbi molestie justo et pede. Vivamus eget turpis sed nisl cursus tempor. Curabitur mollis sapien condimentum nunc. In wisi nisl, malesuada at, dignissim sit amet, lobortis in, odio. Aenean consequat arcu a ante. Pellentesque porta elit sit amet orci. Etiam at turpis nec elit ultricies imperdiet. Nulla facilisi. In hac habitasse platea dictumst. Suspendisse viverra aliquam risus. Nullam pede justo, molestie nonummy, scelerisque eu, facilisis vel, arcu.

#### 2.6 Model

#### 2.7 Conclusion

Nulla ac nisl. Nullam urna nulla, ullamcorper in, interdum sit amet, gravida ut, risus. Aenean ac enim. In luctus. Phasellus eu quam vitae turpis viverra pellentesque. Duis feugiat felis ut enim. Phasellus pharetra, sem id porttitor sodales, magna nunc aliquet nibh, nec blandit nisl mauris at pede. Suspendisse risus risus, lobortis eget, semper at, imperdiet sit amet, quam. Quisque scelerisque dapibus nibh. Nam enim. Lorem ipsum dolor sit amet, consectetuer adipiscing elit. Nunc ut metus. Ut metus justo,

2.7. CONCLUSION 7

auctor at, ultrices eu, sagittis ut, purus. Aliquam aliquam.

$$y = mx + b \tag{2.10}$$

Etiam suscipit aliquam arcu. Aliquam sit amet est ac purus bibendum congue. Sed in eros. Morbi non orci. Pellentesque mattis lacinia elit. Fusce molestie velit in ligula. Nullam et orci vitae nibh vulputate auctor. Aliquam eget purus. Nulla auctor wisi sed ipsum. Morbi porttitor tellus ac enim. Fusce ornare. Proin ipsum enim, tincidunt in, ornare venenatis, molestie a, augue. Donec vel pede in lacus sagittis porta. Sed hendrerit ipsum quis nisl. Suspendisse quis massa ac nibh pretium cursus. Sed sodales. Nam eu neque quis pede dignissim ornare. Maecenas eu purus ac urna tincidunt congue.

Donec et nisl id sapien blandit mattis. Aenean dictum odio sit amet risus. Morbi purus. Nulla a est sit amet purus venenatis iaculis. Vivamus viverra purus vel magna. Donec in justo sed odio malesuada dapibus. Nunc ultrices aliquam nunc. Vivamus facilisis pellentesque velit. Nulla nunc velit, vulputate dapibus, vulputate id, mattis ac, justo. Nam mattis elit dapibus purus. Quisque enim risus, congue non, elementum ut, mattis quis, sem. Quisque elit.

Maecenas non massa. Vestibulum pharetra nulla at lorem. Duis quis quam id lacus dapibus interdum. Nulla lorem. Donec ut ante quis dolor bibendum condimentum. Etiam egestas tortor vitae lacus. Praesent cursus. Mauris bibendum pede at elit. Morbi et felis a lectus interdum facilisis. Sed suscipit gravida turpis. Nulla at lectus. Vestibulum ante ipsum primis in faucibus orci luctus et ultrices posuere cubilia Curae; Praesent nonummy luctus nibh. Proin turpis nunc, congue eu, egestas ut, fringilla at, tellus. In hac habitasse platea dictumst.

Vivamus eu tellus sed tellus consequat suscipit. Nam orci orci, malesuada id, gravida nec, ultricies vitae, erat. Donec risus turpis, luctus sit amet, interdum quis, porta sed, ipsum. Suspendisse condimentum, tortor at egestas posuere, neque metus tempor orci, et tincidunt urna nunc a purus. Sed facilisis blandit tellus. Nunc risus sem, suscipit nec, eleifend quis, cursus quis, libero. Curabitur et dolor. Sed vitae sem. Cum sociis natoque penatibus et magnis dis parturient montes, nascetur ridiculus mus. Maecenas ante. Duis ullamcorper enim. Donec tristique enim eu leo. Nullam molestie elit eu dolor. Nullam bibendum, turpis vitae tristique gravida, quam sapien tempor lectus, quis pretium tellus purus ac quam. Nulla facilisi.

### Chapter 3

### Results

Duis aliquet dui in est. Donec eget est. Nunc lectus odio, varius at, fermentum in, accumsan non, enim. Aliquam erat volutpat. Proin sit amet nulla ut eros consectetuer cursus. Phasellus dapibus aliquam justo. Nunc laoreet. Donec consequat placerat magna. Duis pretium tincidunt justo. Sed sollicitudin vestibulum quam. Nam quis ligula. Vivamus at metus. Etiam imperdiet imperdiet pede. Aenean turpis. Fusce augue velit, scelerisque sollicitudin, dictum vitae, tempor et, pede. Donec wisi sapien, feugiat in, fermentum ut, sollicitudin adipiscing, metus.

Donec vel nibh ut felis consectetuer laoreet. Donec pede. Sed id quam id wisi laoreet suscipit. Nulla lectus dolor, aliquam ac, fringilla eget, mollis ut, orci. In pellentesque justo in ligula. Maecenas turpis. Donec eleifend leo at felis tincidunt consequat. Aenean turpis metus, malesuada sed, condimentum sit amet, auctor a, wisi. Pellentesque sapien elit, bibendum ac, posuere et, congue eu, felis. Vestibulum mattis libero quis metus scelerisque ultrices. Sed purus.

Donec molestie, magna ut luctus ultrices, tellus arcu nonummy velit, sit amet pulvinar elit justo et mauris. In pede. Maecenas euismod elit eu erat. Aliquam augue wisi, facilisis congue, suscipit in, adipiscing et, ante. In justo. Cras lobortis neque ac ipsum. Nunc fermentum massa at ante. Donec orci tortor, egestas sit amet, ultrices eget, venenatis eget, mi. Maecenas vehicula leo semper est. Mauris vel metus. Aliquam erat volutpat. In rhoncus sapien ac tellus. Pellentesque ligula.

Cras dapibus, augue quis scelerisque ultricies, felis dolor placerat sem, id porta velit odio eu elit. Aenean interdum nibh sed wisi. Praesent sollicitudin vulputate dui. Praesent iaculis viverra augue. Quisque in libero. Aenean gravida lorem vitae sem ullamcorper cursus. Nunc adipiscing rutrum ante. Nunc ipsum massa, faucibus sit amet, viverra vel, elementum semper, orci. Cras eros sem, vulputate et, tincidunt id, ultrices eget, magna. Nulla varius ornare odio. Donec accumsan mauris sit amet augue. Sed ligula lacus, laoreet non, aliquam sit amet, iaculis tempor, lorem. Sus-

10 CHAPTER 3. RESULTS

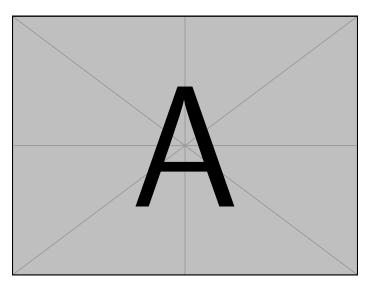


Figure 3.1: Jumping over the lazy dog

pendisse eros. Nam porta, leo sed congue tempor, felis est ultrices eros, id mattis velit felis non metus. Curabitur vitae elit non mauris varius pretium. Aenean lacus sem, tincidunt ut, consequat quis, porta vitae, turpis. Nullam laoreet fermentum urna. Proin iaculis lectus.

Sed mattis, erat sit amet gravida malesuada, elit augue egestas diam, tempus scelerisque nunc nisl vitae libero. Sed consequat feugiat massa. Nunc porta, eros in eleifend varius, erat leo rutrum dui, non convallis lectus orci ut nibh. Sed lorem massa, nonummy quis, egestas id, condimentum at, nisl. Maecenas at nibh. Aliquam et augue at nunc pellentesque ullamcorper. Duis nisl nibh, laoreet suscipit, convallis ut, rutrum id, enim. Phasellus odio. Nulla nulla elit, molestie non, scelerisque at, vestibulum eu, nulla. Ut odio nisl, facilisis id, mollis et, scelerisque nec, enim. Aenean sem leo, pellentesque sit amet, scelerisque sit amet, vehicula pellentesque, sapien.

## Appendix A

# Code

Lorem ipsum dolor sit amet, consectetuer adipiscing elit. Ut purus elit, vestibulum ut, placerat ac, adipiscing vitae, felis. Curabitur dictum gravida mauris. Nam arcu libero, nonummy eget, consectetuer id, vulputate a, magna. Donec vehicula augue eu neque. Pellentesque habitant morbi tristique senectus et netus et malesuada fames ac turpis egestas. Mauris ut leo. Cras viverra metus rhoncus sem. Nulla et lectus vestibulum urna fringilla ultrices. Phasellus eu tellus sit amet tortor gravida placerat. Integer sapien est, iaculis in, pretium quis, viverra ac, nunc. Praesent eget sem vel leo ultrices bibendum. Aenean faucibus. Morbi dolor nulla, malesuada eu, pulvinar at, mollis ac, nulla. Curabitur auctor semper nulla. Donec varius orci eget risus. Duis nibh mi, congue eu, accumsan eleifend, sagittis quis, diam. Duis eget orci sit amet orci dignissim rutrum.

Nam dui ligula, fringilla a, euismod sodales, sollicitudin vel, wisi. Morbi auctor lorem non justo. Nam lacus libero, pretium at, lobortis vitae, ultricies et, tellus. Donec aliquet, tortor sed accumsan bibendum, erat ligula aliquet magna, vitae ornare odio metus a mi. Morbi ac orci et nisl hendrerit mollis. Suspendisse ut massa. Cras nec ante. Pellentesque a nulla. Cum sociis natoque penatibus et magnis dis parturient montes, nascetur ridiculus mus. Aliquam tincidunt urna. Nulla ullamcorper vestibulum turpis. Pellentesque cursus luctus mauris.

Nulla malesuada porttitor diam. Donec felis erat, congue non, volutpat at, tincidunt tristique, libero. Vivamus viverra fermentum felis. Donec nonummy pellentesque ante. Phasellus adipiscing semper elit. Proin fermentum massa ac quam. Sed diam turpis, molestie vitae, placerat a, molestie nec, leo. Maecenas lacinia. Nam ipsum ligula, eleifend at, accumsan nec, suscipit a, ipsum. Morbi blandit ligula feugiat magna. Nunc eleifend consequat lorem. Sed lacinia nulla vitae enim. Pellentesque tincidunt purus vel magna. Integer non enim. Praesent euismod nunc eu purus. Donec bibendum quam in tellus. Nullam cursus pulvinar lectus. Donec et mi. Nam vulputate metus eu enim. Vestibulum pellentesque felis eu massa.

Quisque ullamcorper placerat ipsum. Cras nibh. Morbi vel justo vitae lacus tincidunt ultrices. Lorem ipsum dolor sit amet, consectetuer adipiscing elit. In hac habitasse platea dictumst. Integer tempus convallis augue. Etiam facilisis. Nunc elementum fermentum wisi. Aenean placerat. Ut imperdiet, enim sed gravida sollicitudin, felis odio placerat quam, ac pulvinar elit purus eget enim. Nunc vitae tortor. Proin tempus nibh sit amet nisl. Vivamus quis tortor vitae risus porta vehicula.

Fusce mauris. Vestibulum luctus nibh at lectus. Sed bibendum, nulla a faucibus semper, leo velit ultricies tellus, ac venenatis arcu wisi vel nisl. Vestibulum diam. Aliquam pellentesque, augue quis sagittis posuere, turpis lacus congue quam, in hendrerit risus eros eget felis. Maecenas eget erat in sapien mattis portitior. Vestibulum

14 APPENDIX A. CODE

porttitor. Nulla facilisi. Sed a turpis eu lacus commodo facilisis. Morbi fringilla, wisi in dignissim interdum, justo lectus sagittis dui, et vehicula libero dui cursus dui. Mauris tempor ligula sed lacus. Duis cursus enim ut augue. Cras ac magna. Cras nulla. Nulla egestas. Curabitur a leo. Quisque egestas wisi eget nunc. Nam feugiat lacus vel est. Curabitur consectetuer.

Suspendisse vel felis. Ut lorem lorem, interdum eu, tincidunt sit amet, laoreet vitae, arcu. Aenean faucibus pede eu ante. Praesent enim elit, rutrum at, molestie non, nonummy vel, nisl. Ut lectus eros, malesuada sit amet, fermentum eu, sodales cursus, magna. Donec eu purus. Quisque vehicula, urna sed ultricies auctor, pede lorem egestas dui, et convallis elit erat sed nulla. Donec luctus. Curabitur et nunc. Aliquam dolor odio, commodo pretium, ultricies non, pharetra in, velit. Integer arcu est, nonummy in, fermentum faucibus, egestas vel, odio.