

UNIVERSITY OF ZAGREB  
FACULTY OF ELECTRICAL ENGINEERING AND COMPUTING

MASTER THESIS num. 1572

# **End-to-End Deep Learning Model for Base Calling of MinION Nanopore Reads**

Neven Miculinić

Zagreb, June 2018.

*Umjesto ove stranice umetnite izvornik Vašeg rada.*  
*Kako biste uklonili ovu stranicu, obrišite naredbu \izvornik.*

*I would like to thank my mentor, Mile Šikić, for his patient guidance, encouragement and advice provided over the years.*

*I would also like to thank my family and friends for their continuous support.*

*In the end, honorable mentions go to Marko Ratković for his help with this thesis.*

# CONTENTS

<b>1. Introduction</b>	<b>1</b>
1.1. Organization . . . . .	1
<b>2. Background</b>	<b>2</b>
2.1. Oxford Nanopore MinION . . . . .	3
2.2. Existing basecallers . . . . .	5
2.2.1. Official . . . . .	5
2.2.2. Third-party basecallers . . . . .	7
<b>3. Methods</b>	<b>8</b>
<b>4. System architecture</b>	<b>9</b>
4.1. Data Preparation . . . . .	9
4.2. Training pipeline . . . . .	9
4.3. Hyperparameter optimization . . . . .	9
<b>5. Results</b>	<b>11</b>
<b>6. Conclusion</b>	<b>12</b>
<b>Bibliography</b>	<b>13</b>

# LIST OF FIGURES

2.1. Depiction of the sequencing process. Taken from (Ratković, 2017) with authors permission . . . . .	3
2.2. DNA strain being pulled through a nanopore . . . . .	4
2.3. Structure of FAST5 file and raw signal plot show in <i>HDFView</i> . . . . .	4
4.1. dataset protobuf description . . . . .	10

# LIST OF TABLES

# 1. Introduction

In recent years, deep learning methods significantly improved the state-of-the-art in multiple domains such as computer vision, speech recognition and natural language processing (Lecun and Bengio, 1998; Krizhevsky et al., 2012) In this paper, we present application of deep learning for DNA basecalling problem.

Oxford Nanopore Technology's MinION nanopore sequencing platform Mikheyev and Tin (2014) is the first portable DNA sequencing device. It produces longer reads than competing technologies. In addition, it enables real-time data analysis which makes it suitable for various applications. Although MinION is able to produce long reads, even up to 882 kb Loman (a,b), they have an error rate of 10% or higher. This master thesis uses R9.4 pore model and compares previous techniques with novel auto-encoder multi-task training.

## 1.1. Organization

[TODO]: Write some fancy stuff once completed.

## 2. Background

Due to technical constraints, it's infeasible to sequence whole DNA in single strand. Every sequencing technology to date have an upper limit how big strand can it precisely sequence. This limit is considerably smaller than size of genome. For example E.Coli has 4.5 million base pairs in its DNA, while Sanger's sequencing maximum output is around 1000 base pairs max. To make DNA basecalling feasible technique called shotgun sequencing was invented. The strand is cloned number of times, then via chemical agent broken down into smaller fragments of appropriate length. Sequenced fragments are called reads.

Genome assembly is the process of reconstructing the original genome from reads and usually starts with finding overlaps between reads. The quality of reconstruction heavily depends on the length and the quality (accuracy) of the reads produced by the sequencer.

If we have reference sequence we usually align the reads on the reference to aid us into genome assembly. Otherwise we have to use many de novo assembly techniques.

The right analogy would be building a puzzle. Since we cannot scan the whole puzzle because our camera is too small or imprecise, we are scanning pieces of the whole picture. Puzzle pieces would represent fragments in this analogy. If we have a map, even a rough one, it shall aid us into assembling those puzzle pieces into complete pictures. Otherwise we're fiddling in the dark and using de novo assembly techniques.

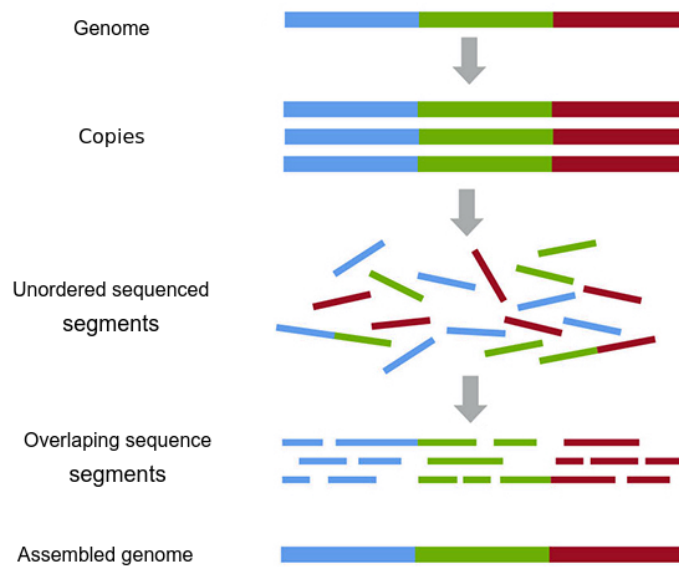
Figure 2.1 depicts process of sequencing visually.

In 1977, Frederick Sanger (Mile Šikić, 2013)(Pettersson et al., 2009) started development of sequencing technologies. It allowed read lengths up to 1000 bases with very high accuracy(99.9%) at the cost of 1\$ per 1000 bases. Later, second generation sequencing, like IAN Torrent and Illumina devices, reduced the price while keeping the accuracy high. However, they had a cost of shorter read lengths, about a few hundred base pairs, which makes resolving repetitive regions practically impossible.

Third generation sequencing technologies have longer read lengths at the accuracy's expense. PacBio, for example, developed technology with a few thousand bases with error rates of ~10-15%.

MinION sequences, which this master thesis use, made sequencing less expensive and even portable.





**Figure 2.1:** Depiction of the sequencing process. Taken from (Ratković, 2017) with authors permission

## 2.1. Oxford Nanopore MinION

The MinION device by Oxford Nanopore Technologies is the first portable DNA sequencing device. Its small weight, low cost, and long read length combined with decent accuracy yield promising results in various applications including full human genome assembly Jain et al. (2017) what could potentially lead to personalized genomic medicine. It weights only 87 grams, and its portability lead to uses on international space station and the antarctic among other places.

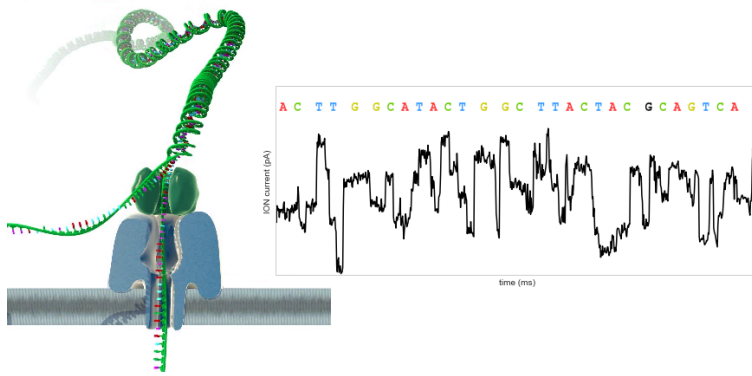
Under the hood, it has numerous nano-meter sized pores, thus a names Nanopore. Each pore has width of around 6 nucleotied. Under electric current DNA strand passed through the pore and changes its electric resistance. The sensor measures current through the pore multiple times a second <sup>1</sup>. This signal varies depending which k-mer is occupying the pore, and on its basis we're performing the basecalling. On figure 2.2 this process is visually depicted.

Official software called MinKNOW outputs sequencing data in FAST5 (a variant of the HDF5 standard) file format. It is a hierarchical file format with data arranged in a tree-structure of groups. Metadata are stored in group and dataset attributes. The same file format is during used different stages of analyses and groups, datasets and attributes are added incrementally. Figure 2.3 shows raw signal being present in the FAST5 file.

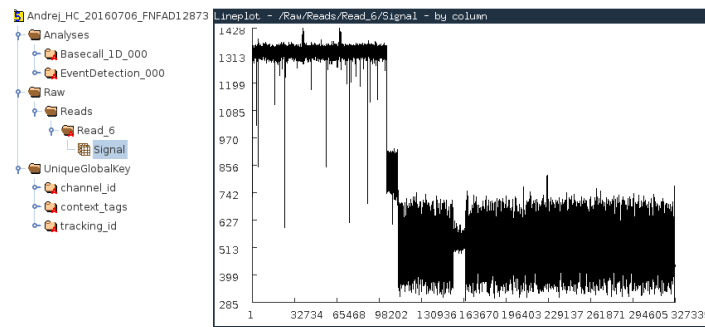
<sup>1</sup>The model we worked with had 4000 samples per seconds

<sup>2</sup>Figure adapted from <https://nanoporetech.com/how-it-works>

<sup>3</sup><https://support.hdfgroup.org/products/java/hdfview/>



**Figure 2.2:** DNA strain being pulled through a nanopore <sup>2</sup>



**Figure 2.3:** Structure of FAST5 file and raw signal line plot show in *HDFView* <sup>3</sup>

Minion offers the possibility of sequencing one or both strands of DNA. Sequencing both strands and combining information results in reads of higher quality. Those reads are called 2D (two-dimensional) reads. Otherwise, if the only single strand is sequenced 1D (one-dimensional) reads are produced.

MinION devices can produce long reads, usually tens of thousand base pairs (with reported reads lengths of 100 thousand Loman (a) and even recently above 800 thousand base pairs Loman (b)), but with high sequencing error than older generations of sequencing technologies. Switch from older R7.3 to R9 chemistry in 2016 increased accuracy of produced data. With this change, the accuracy of 1D data increased from 70% to 85% and the accuracy of 2D reads from 88% to 94% Brown. This increase of accuracy makes 1D reads usable for analysis with benefits over 2D reads being faster sample preparation and faster sequencing. Developed tool in this thesis focuses on base calling 1D reads.

## 2.2. Existing basecallers

### 2.2.1. Official

Oxford Nanopore has, with the R9 version of the platform, introduced a variety of base calling options. Some of those are production ready and some experimental. The majority of information regarding differences, specifications and similar is only available through Nanoporetech Community <sup>4</sup>.

*Metrichor* is an Oxford Nanopore company that offers cloud-based platform *EPI2ME* for analysis of nanopore data. Initially, base calling was only available by uploading data to the platform - that being the reason why this basecaller is often called Metrichor even though it is a name of the company.

The older version of Metrichor relied on *hidden Markov models* (HMM) to find the biological sequence corresponding to the signal. Preprocess included segmentation of the signal into smaller chunks called events defined by start location of the chunk, length, mean value and variance of the signal in the chunk. Metrichor then assumed that each event usually corresponds to a context of 6 bases being present in the pore and that the context is typically shifted by one base in each step. The states of HMM are modeled as a context present in the pore and transition correspond to change of bases in the pore. During the transition from one state to another, an event is emitted. Base calling is performed using the Viterbi algorithm which determines the most likely sequence of states for the observed sequence of events. This approach showed poor results when calling long homopolymer stretches as the context in the pore remains the same Goodwin et al. (2016) Ip et al. (2015).

With the release of R9 chemistry, this model was replaced by a more accurate recurrent neural network (RNN) implementation. Currently, Oxford Nanopore offers several RNN-based local basecaller versions under different names: Albacore, Nanonet and basecaller integrated into MinKNOW Community.

*Albacore* is basecaller by Oxford Nanopore Technologies ready for production and actively supported. It is available to the Nanopore Community served as a binary. The source code of Albacore was not provided and is only available through the ONT Developer Channel. Tool supports only R9.4 and future R9.5 version of the chemistry.

*Nanonet*<sup>5</sup> uses the same neural network that is used in Albacore but it is continually under development and does contain features such as error handling or logging needed for production use. It uses *CURRENNT* library for running neural networks. It supports basecalling of both R9 and R9.4 chemistry versions.

---

<sup>4</sup><https://community.nanoporetech.com/>

<sup>5</sup><https://github.com/nanoporetech/nanonet/>

*Scrappie*<sup>6</sup> is another basecaller by Oxford Nanopore Technologies. Similar to Nanonet, it is the platform for ongoing development. Scrappie is reported to be the first basecaller that specifically address homopolymer base calling. It became publicly available just recently in June, 2017 and supports R9.4 and future R9.5 data.

---

<sup>6</sup><https://github.com/nanoporetech/scrappie>

### 2.2.2. Third-party basecallers

*Nanocall* David et al. (2016) was the first third-party open source basecaller for nanopore data. It uses HMM approach like the original R7 Metrichor. Nanocall does not support newer chemistries after R7.3.

*DeepNano* Boža et al. (2017) was the first open-source basecaller based on neural networks. It uses bidirectional recurrent neural networks implemented in Python, using the Theano library. When released, originally only supported R7 chemistry, but support for R9 and R9.4 was added recently.

## **3. Methods**

In this chapter all key deep learning concepts shall be described.

## 4. System architecture

### 4.1. Data Preparation

DEBUG was off

title Data has been downloaded from [https://data.genomicsresearch.org/Projects/online\\_dataset/train\\_set\\_all/](https://data.genomicsresearch.org/Projects/online_dataset/train_set_all/). The following species were provided there by the Chiron team:

- Human
- E. Coli
- Lambda Phage

The raw dataset is transformed using my repo, `minion-data`<sup>1</sup>. It defines common dataset training structure in the protobuf (Google) interface description language (IDL). The whole definition can be seen in figure 4.1.

For the concrete Chiron dataset, the re-squiggled preparation method was used. (The data was re-squiggled, that is after aligning the read on the reference, the read data is improved and each base pairs place on the raw signal is calculated.)

The re-squiggled basecalled data is located at `/Analyses/RawGenomeCorrected_000/BaseCa`. The interesting code fragments are in function `processDataPoint` of file `minion_data/preperation/` from `minion-data` python package.

After the gzipped dataset is prepared, it goes into the training pipeline. The whole training & testing pipeline is available open source on <https://github.com/nmiculenic/minion-basecaller>

### 4.2. Training pipeline

### 4.3. Hyperparameter optimization

---

<sup>1</sup><https://github.com/nmiculenic/minion-data>

```

1 syntax = "proto3";
2
3 package dataset;
4
5 enum BasePair {
6     A = 0;
7     C = 1;
8     G = 2;
9     T = 3;
10    BLANK = 4;
11 }
12
13 enum Cigar {
14     MATCH = 0;
15     MISMATCH = 1;
16     INSERTION = 2; // Insertion, soft clip, hard clip
17     DELETION = 3;  // Deletion, N, P
18 }
19
20 message DataPoint {
21     message BPConfidenceInterval {
22         uint64 lower = 1;
23         uint64 upper = 2;
24         BasePair pair = 3;
25     }
26     repeated float signal = 1;
27     repeated BasePair basecalled = 2; // What we basecalled
28     repeated BPConfidenceInterval labels = 3; // labels describe ←
        corrected basecalled signal for training
29 }
30

```

**Figure 4.1:** dataset protobuf description



## **5. Results**

## **6. Conclusion**

# BIBLIOGRAPHY

- Marko Ratković. Deep learning model for base calling of minion nanopore reads, 2017.
- Yann LeCun and Yoshua Bengio. The handbook of brain theory and neural networks. chapter Convolutional Networks for Images, Speech, and Time Series, pages 255–258. MIT Press, Cambridge, MA, USA, 1998. ISBN 0-262-51102-9. URL <http://dl.acm.org/citation.cfm?id=303568.303704>.
- Alex Krizhevsky, Ilya Sutskever, and Geoffrey E Hinton. Imagenet classification with deep convolutional neural networks. In F. Pereira, C. J. C. Burges, L. Bottou, and K. Q. Weinberger, editors, *Advances in Neural Information Processing Systems 25*, pages 1097–1105. Curran Associates, Inc., 2012. URL <https://goo.gl/UpFBv8>.
- Alexander S Mikheyev and Mandy MY Tin. A first look at the oxford nanopore minion sequencer. *Molecular ecology resources*, 14(6):1097–1102, 2014.
- Nick Loman. *Nanopore R9 rapid run data release*, a. URL <http://lab.loman.net/2016/07/30/nanopore-r9-data-release/>. [Online; posted 30-July-2016].
- Nick Loman. *Thar she blows! Ultra long read method for nanopore sequencing*, b. URL <http://lab.loman.net/2017/03/09/ultrareads-for-nanopore/>. [Online; posted 9-March-2017].
- Mirjana Domazet-Lošo Mile Šikić. *Bioinformatika*. Bioinformatics - course materials, Faculty of Electrical Engineering and Computing, University of Zagreb, 2013.
- Erik Pettersson, Joakim Lundeberg, and Afshin Ahmadian. Generations of sequencing technologies. *Genomics*, 93(2):105–111, feb 2009. doi: 10.1016/j.ygeno.2008.10.003. URL <https://doi.org/10.1016/j.ygeno.2008.10.003>.
- Miten Jain, Sergey Koren, Josh Quick, Arthur C Rand, Thomas A Sasani, John R Tyson, Andrew D Beggs, Alexander T Dilthey, Ian T Fiddes, Sunir Malla, Hannah Marriott, Karen H Miga, Tom Nieto, Justin O’Grady, Hugh E Olsen, Brent S Pedersen, Arang Rhie, Hollian Richardson, Aaron Quinlan, Terrance P Snutch, Louise Tee, Benedict Paten, Adam M.

- Phillippy, Jared T Simpson, Nicholas James Loman, and Matthew Loose. Nanopore sequencing and assembly of a human genome with ultra-long reads. *bioRxiv*, 2017. doi: 10.1101/128835. URL <http://biorxiv.org/content/early/2017/04/20/128835>.
- C Brown. *YouTube Technology Focus Live Stream No thanks, I've already got one*. URL <https://www.youtube.com/watch?v=nizGyutn6v4>. [Online; posted 8-March-2016].
- Sara Goodwin, John D. McPherson, and W. Richard McCombie. Coming of age: ten years of next-generation sequencing technologies. *Nat Rev Genet*, 17(6):333–351, Jun 2016. ISSN 1471-0056. URL <http://dx.doi.org/10.1038/nrg.2016.49>. Review.
- Camilla L.C. Ip, Matthew Loose, John R. Tyson, Mariateresa de Cesare, Bonnie L. Brown, Miten Jain, Richard M. Leggett, David A. Eccles, Vadim Zalunin, John M. Urban, Paolo Piazza, Rory J. Bowden, Benedict Paten, Solomon Mwaigwisya, Elizabeth M. Batty, Jared T. Simpson, Terrance P. Snutch, Ewan Birney, David Buck, Sara Goodwin, Hans J. Jansen, Justin O’Grady, and Hugh E. Olsen and. Minion analysis and reference consortium: Phase 1 data release and analysis. *F1000Research*, oct 2015. doi: 10.12688/f1000research.7201.1. URL <https://doi.org/10.12688/f1000research.7201.1>.
- Nanopore Community. *Basecalling overview*. URL [https://community.nanoporetech.com/technical\\_documents/data-analysis/v/datd\\_5000\\_v1\\_reve\\_22aug2016/basecalling-overvi](https://community.nanoporetech.com/technical_documents/data-analysis/v/datd_5000_v1_reve_22aug2016/basecalling-overvi). [Accessed; 12-July-2017].
- Matei David, Lewis Jonathan Dursi, Delia Yao, Paul C Boutros, and Jared T Simpson. Nanocall: An open source basecaller for oxford nanopore sequencing data. *bioRxiv*, 2016. doi: 10.1101/046086. URL <http://biorxiv.org/content/early/2016/03/28/046086>.
- Vladimír Boža, Broňa Brejová, and Tomáš Vinař. DeepNano: Deep recurrent neural networks for base calling in MinION nanopore reads. *PLOS ONE*, 12(6):e0178751, jun 2017. doi: 10.1371/journal.pone.0178751. URL <https://doi.org/10.1371/journal.pone.0178751>.
- Google. Protocol buffers. <https://github.com/google/protobuf>.

## **End-to-End Deep Learning Model for Base Calling of MinION Nanopore Reads**

### **Abstract**

In the MinION device, single-stranded DNA fragments move through nanopores, which causes drops in the electric current. The electric current is measured at each pore several thousand times per second. Each event is described by the mean and variance of the current and by event duration. This sequence of events is then translated into a DNA sequence by a base caller. Develop a base-caller for MinION nanopore sequencing platform using a deep learning architecture such as convolutional neural networks and recurrent neural networks. Instead of events, use current waveform at the input. Compare the accuracy with the state-of-the-art basecallers. For testing purposes use publicly, available datasets and Graphmap or Minimap 2 tools for aligning called reads on reference genomes. Implement method using TensorFlow or similar library. The code should be documented and hosted on a publicly available Github repository.

**Keywords:** base calling, Oxford Nanopore Technologies, MinION, deep learning, seq2seq, convolutional neural network, residual network, CTC loss

### **S kraja na kraj model dubokog učenja za određivanje očitanih baza dobivenih uređajem za sekvenciranje MinION**

#### **Sažetak**

Unutar uređaja MinION, fragmenti jednostruke DNA prolaze kroz nanopore, što uzrokuje promjene u električnoj struji. Struja proizvedena na svakoj nanopori mjeri se nekoliko tisuća puta u sekundi. Svaki događaj opisan je srednjom vrijednosti i varijancom struje te svojim trajanjem. Postupak kojim se takav slijed događaja prevodi u niz nukleotida naziva se određivanje očitanih baza. Razviti alat za prozivanje baza za uređaj za sekvenciranje MinION koristeći modele dubokog učenje kao što su konvolucijske i povratne neuronske mreže. Umjesto događaja na ulazu koristi valni oblik struje. Usporediti dobivenu točnost s postojećim rješenjima. U svrhu testiranja koristiti javno dostupne skupove podataka i alate GraphMap ili Minimap 2 za poravnanje očitavanja na referentni genom. Alat implementirati koristeći programsku biblioteku TensorFlow (ili neku sličnu). Programski kod treba biti dokumentiran i javno dostupan preko repozitorija GitHub. **Ključne riječi:** određivanje

baza, Oxford Nanopore Technologies, MinION, duboko učenje, prevođenje, konvolucijske neuronske mreže, rezidualne mreže, CTC gubitak