
IGLOO: Slicing the Feature Space to Represent Long Sequences

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Abstract

Up until recently Recurrent neural networks (RNNs) have been the standard go-to component when processing sequential data with neural networks. Issues relative to vanishing gradient have been partly addressed by Long short-term memory (LSTM) and gated recurrent unit (GRU), but in practice experiments show that very long terms dependencies (beyond 1000 time steps) are difficult to learn. We introduce IGLOO, a new neural network architecture which aims at being faster than both LSTM and GRU but also their respective CuDNN optimized versions when convergence happens and provide an alternative in the case when there is no convergence at all. IGLOO's core idea is to use the relationships between patches sliced out of the features maps of convolution layers at different levels of granularity to build a representation for the sequence. We show that the model can deal with dependencies of more than 25,000 steps in a reasonable time frame. Beyond the well bench-marked copy-memory and addition problems which show good results, we also achieve best recorded accuracy on permuted MNIST (98.4%). IGLOO is also applied on the IMDB set and on the TUH Abnormal EEG Corpus.

1 Introduction

Until recently RNNs were deemed to be the reference structure to use in a neural network as soon as there was a notion of sequence. Beyond the usual Long short-term memory (LSTM) (Hochreiter et al., 1997) and the gated recurrent unit (GRU) (Cho et al., 2014) a plethora of other variations have been studied (Jozefowicz et al., 2015), with no candidate showing a clear advantage according to those studies. Dealing with very long term dependencies is a current area of research and recent papers have introduced new variations which aim at fixing this issue and improve on the historical models: IndRNN (Shai et al., 2018), RNN with auxiliary losses (Trinh et al., 2018). Earlier works also include the uRNN (Arjovsky et al., 2016), Quasi-Recurrent Neural Networks (Q-RNN) (Bradbury et al., 2016), Dilated RNN (Chang et al., 2017), Recurrent additive networks (Lee et al., 2017), ChronoNet (Roy et al., 2018), EUNN (Jing et al., 2016), Kronecker Recurrent Units – KRU (Jose et al., 2017) and Recurrent Weight Average (J. Ostmeier et al, 2017).

Besides RNNs, convolutional networks have also been used recently to tackle sequences. Convincing results have been achieved in audio synthesis by (van den Oord et al., 2016) using dilated causal convolutions. More generally the discussion in (Bai et al., 2018) presents a general structure based on convolutions, the Temporal Convolutional Network (TCN). It aims at learning sequences by using layers of convolutions stacked together and using different dilatation factors to allow cells in the higher regions to have a large receptive field, hence capturing information from the whole input space. Typically the earliest layer (the one closest to the input) doesn't not have any dilatation, while subsequent layers have exponentially increasing dilatations factors.

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Another approach to deal with sequences is the Transformer model proposed in (Vasvani et al., 2017) where an attention mechanism is used to find representations.

While the TCN is savvy in terms of model parameters, it relies on a pyramidal structure to propagate the information higher up the convolutional layers stack (like most CNNs). We propose a different approach which while in some cases having more parameters is still efficient in terms of computing time since the main operation is one large pointwise multiplication. In this document we present this structure in details and use it on several standard benchmark tasks such as the addition task, the copy memory task and sequential and permuted MNIST. We compare IGLOO to the TCN structure as well as the GRU, its Nvidia optimized version and some of the newly introduced RNNs. We find that IGLOO can outperform other structures in terms of convergence speed for very long sequences, managing to solve tasks with inputs 25,000 units long. We accomplish this by looking at a sequence as a whole rather than painstakingly looking at elements sequentially like RNNs do in the recurrent paradigm. While elements are fed to the model one after the other just like in a RNN, IGLOO takes global snapshots of the sequence and therefore doesn't suffer some of the drawbacks of RNNs.

The contribution of the paper is to present a new approach to generate long (as well as short) sequences representations by using the relationships between patches sliced out of feature maps extracted by a Conv1D layer from sequences. Especially, those patches are chosen as to not necessarily be contiguous so as to represent various parts of the feature space. We show that a quasi-randomly selected set of patches can be used to give a good representation and we present the process to accomplish this.

2 IGLOO

Sequential data usually comes in (T, M) shape. We examine two different cases: The first one is when the output of the structure is a vector of shape (L), when we want one final representation for the whole sequence. The second case is where we need the output to be of shape (T, L) which is the case when each time step gets its own output representation. The approach is different in each case in order to improve efficiency and minimize the number of parameters used.

2.1 Finding a sequence representation

We know that 1D convolutions applied to sequences return feature maps indicating how the sequence reacts to various filter. Given a kernel size K^* , K filters and using a causal 1D convolution (so that at time T , only data up to time T is available) each time step finds a representation with a vector $\in R^K$. Each item in this vector represents the activations for each filters for this time step. The full feature map $F1 \in R^{T \times K}$.

Usual Convolutional Networks then apply another convolution to this initial convolution and returns a second, deeper (in the sense that it is further away from the input) feature map. This second convolutional can be seen as learning relationships between contiguous patches of the feature map. Usual Convnets continue stacking layers this way. The Temporal Convolution Network (TCN) structure for example, uses dilated convolutions to reduce the overall depth of the network while aiming at having the deeper layers as large a receptive field as possible, i.e. get higher layers to have as global a view as possible with respect to the initial input. Since the higher layers are connected to all the inputs, it is then up the training process to make the information flow upwards.

The IGLOO structure (Figure 1.) works differently. After the initial convolution, rather than applying a second convolution layer to $F1$, we gather p slices on the first axis out of the T available (a typical value of p is 4) which we then concatenate to obtain a matrix $\in R^{p \times K}$. Those p slice can come from nearby areas or from far away areas, therefore bringing together information from different parts of the feature map. As such one can say that IGLOO exploits non-local relationships in the initial feature map $F1$. An amount L of those large patches is collected to produce a matrix $\in R^{p \times K \times L}$. This matrix is then multiplied point-wise by a trainable filter of the same size. One way to look at this operation is that the filter learns relationships between non-contiguous slices of $F1$. We then add up together each elements resulting from the point-wise multiplication on the last and the penultimate axis to find a vector $\in R^L$. We also add a bias to this output. As such there will be L biases. A non-linearity such as ReLU is applied (this step is not necessary). As a result we obtain a vector $U \in R^L$ which will represent the sequence and can then be fed to a Dense Layer and be used for

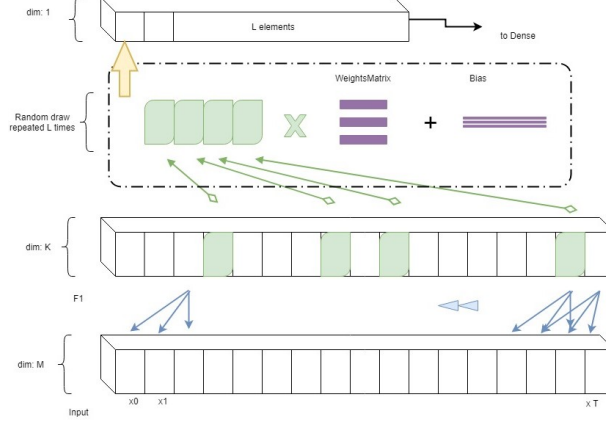


Figure 1: Basic IGLOO architecture.

classification or regression. In total, we train $O(L.K.p + L)$ parameters (not including the initial convolution C1). Some remarks:

- Each element of U can be seen as a representation of the relationship between p non-necessarily contiguous randomly chosen slices of the feature map $F1$. The nature of the relationship is given by the unique filter trained for this patch.
- Given a large enough L , U has a complete receptive field and is connected to each element of the input vector, as such it can be used as a representation vector for this sequence. This is not absolutely necessary for convergence since some input points may not contribute to an effective representation. CNN architectures do not always have this characteristic.
- Where traditional CNNs rely on network depth to bring together information from far away parts of the input, IGLOO directly samples patches from far away parts of the input so that it doesn't need depth. One layer can be enough in some cases. Nevertheless, since CNNs offer different levels of granularity at each layer depth it can be interesting to use patches from different levels too, which we implement.

2.2 Returning a sequence

Some tasks require to find a representation $U^* = (U_0, U_1, \dots, U_{T-1}) \in R^{T \times L}$, i.e. for each step rather than a representation for the whole sequence. Doing this naively would require to repeat the process described above T times and to use $T(L.K.p + L)$ parameters, which can still make sense for smallish values of T (< 20) but becomes burdensome for larger values.

The solution to this is to re-use some of the elements $U(k)$. After defining a stretch factor φ which divides T exactly, we shall only generate vectors $U(k)$ for $k \in [0, (T/\varphi) - 1]$ and find the others by reusing the weight in the corresponding $U(k)$ nearest to the left. The process happens in two stages:

- At the first stage, we generate the (T/φ) base $U(k)$ elements, with $U(k) \in R^\nu$ and repeat the sequence φ times to generate a vector $W \in R^{\nu \times T}$.
- At the second stage, we generate T other elements $V(k)$, with $V(k) \in R^\Sigma$ with $\Sigma : 0.15 \times L$ to obtain a vector $Q \in R^{\Sigma \times T}$.
- Lastly we concatenate W and Q along the first dimension to get the vector $U^* \in R^{L \times T}$, assuming $L = \Sigma + \nu$

We make sure that patches generated at the second stage are only collected in a range of the previous (φ) -elements. This way, the first stage generates filters for the global environment and the second stage generates filters for the local environment. Global environment filters can be reused (φ) -elements at a time to reduce the number of parameters. Using this method, the numbers of parameters is: $O((T/(\varphi))(L.K.p + L))$

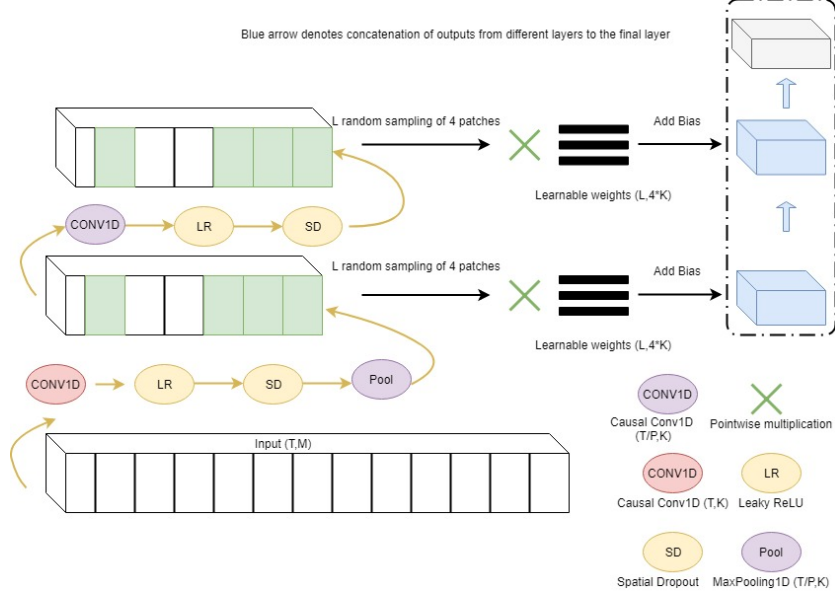


Figure 2: Stacked IGLOO architecture.

Using a two stages approach allows to keep the number of parameters of the model in check. It should be noted that the whole structure is basically made up of two large matrix point-wise multiplications, which means that while the number of parameters can be large, it is still computationally efficient.

3 Extensions

3.1 Stacking

In the case of standard CNNs, several layers of convolutions are applied. Each deeper layer represents activations for larger and larger objects in the inputs. For example in the case of images, filters in earlier layers represent basic shapes and filters in deeper layers represent more complex shapes. Using this analogy, IGLOO with a single layer only looks at combinations of filters representing basic shapes. Therefore we could add more stacks to IGLOO by using feature maps from deeper layers of some backbone CNN (Figure 2). IGLOO will then be able to give a representation of how slices of the feature maps interact at different levels of granularity, i.e. for basic shapes and for more complicated shapes. This increases the number of parameters but also increases accuracy and can be a good trade-off depending on the task.

3.2 Max Pooling

When looking for a global sequence representation, it is in some cases possible to reduce the dimension of the problem by applying max pooling with a given poolsize P to the output of the initial conv1D layer so that the patches are generated over a vector length of T/P rather than T . This reduces the number of parameters and can make sense as long as the information in the filters can be squeezed laterally which can be the case depending on the task. Tasks like copy memory below work well with max-pooling.

3.3 Residual Connections

Residuals connections can be added if looking to output a sequence. In practice we notice that a residual connection usual helps to improve convergence.

Table 1: **Copy Memory T=30**. Time to reach accuracy > 0.99

Model (Hidden)	Time (s)	Params
CuDNNGRU (128)	>1000	51K
CuDNNLSTM (128)	>1000	68K
indRNN (2X128)	>1000	51K
RWA (168)	>1000	58K
TCN (6X16)	21	70K
IGLOO (100)	6	22K

Table 2: **Copy Memory - IGLOO model**. Time to reach accuracy > 0.99

T size (L)	Time (s)	Params
T=100 (300)	12	80K
T=1,000 (500)	21	145K
T=5,000 (2,500)	52	370K
T=10,000 (7,000)	61	1520K
T=20,000 (10,000)	84	2180K
T=25,000 (15,000)	325	3270K

4 Applications

4.1 Copy Memory task

Dataset This task was initially introduced in (Hochreiter and J. Schmidhuber, 1997). We are given a vector of size $T+20$, where the first 10 elements $G=[G_0, G_1, \dots, G_9]$ are random integers between 1 and 8, the next $T-1$ elements are 0's, the following element is a 9 (which serves as a marker), and the following 10 elements are 0's again. The task is to generate a sequence which is zero everywhere except for the last 10 items which should be able to reproduce G . The task A can be considered a classification problem and the loss used will be categorical cross entropy (across 8 categories). The model will output 8 classes which will be compared to the actual classes.

Setup The metric we keep track of is the wall time needed to reach a certain accuracy on the test set. This makes more sense than comparing number of epochs required to reach those targets since epochs have a different durations for those various structures. We use a Batch size of 128 for all models. We use 128 hidden states for Vanilla GRU, Vanilla LSTM, CuDNNGRU and CuDNNLSTM. Models may differ in terms of parameters size but we are mostly interested in convergence speed in those experiments. Experiments are run in Keras with Tensorflow backend on GTX1060 GPU. For IGLOO, we use $K=5$ and causal padding along with varying number of patches L . All values are averaged over 10 runs.

Results As can be seen in Table 1, for a small value of T , we find that the optimized version of the GRU cell converges but very slowly. The vanilla version is even slower. Other cells except the TCN also take a long time to converge. Above 1000 steps the TCN sometimes gets stuck in a local minimum. From Table 2 it appears that for more than 1,000 steps, the IGLOO is an order of magnitude faster for this task. There is still convergence for up to **25,000 steps** which to our knowledge is longer than for any other structure in the literature. After 25,000 steps convergence can still happen in some cases. To the best of our knowledge no other method in the literature achieves convergence for that many steps on this benchmark.

4.2 Addition Task

Dataset This task (Task B) also tests the structure capacity to deal with long term memory. Given an input vector of shape $(2, T)$, with the first row being random numbers and the second row being 0 everywhere except at 2 random locations where it is 1, the purpose is to generate the result of adding the two numbers marked by the locations where there is a 1. This is a regression task and we shall investigate results for different size of T and different models. MSE is used as the loss function.

Table 3: **Addition task T=200.** Time to reach loss < 0.01

Model (Hidden)	Time (s)	Params
Vanilla GRU (128)	153	50K
Vanilla LSTM (128)	>1500	67K
CuDNNGRU (128)	24	50K
CuDNNLSTM (128)	99	67K
IndRNN (2*128)	1111	50K
RWA (164)	235	55K
TCN (18)	82	46K
IGLOO (L=500)	8	11K

Table 4: **Addition task T=1000.** Time to reach loss < 0.01

Model (Hidden)	Time (s)	Params
Vanilla GRU (226)	1298	155K
Vanilla LSTM (196)	>2000	155K
CuDNNGRU (226)	903	156K
CuDNNLSTM (196)	>2000	156K
IndRNN (2*256)	>2000	160K
RWA (276)	442	155K
TCN 24)	171	142K
IGLOO (L=2000)	17	133K

Setup We use 22,500 samples for the training, and 2,500 for the training set. For T=200, the IGLOO structure used has 500 patches. Since we only output the last time step rather than the whole sequence, the number of parameters is small compared to other structures. A learning rate of 0.005 is used throughout. Batch size is 100. We also use L=5 and a patch size of 4. We use a causal padding style and a learning rate of 0.005. We use the Adam optimizer with clip norm =1. The hidden dimensions for other cells are shown in the results table. They are used so that the number of parameters is similar for all cells in the experiment. For T=1,000, We use an IGLOO cell with 2,000 patches, a patch size of 4, and 3 stacks of those. We use a causal padding style and a learning rate of 0.005. We use the Adam optimizer with clip norm =1. For IGLOO with 5,000 steps, we use L=5,000 patches, 3 stacks and max pooling of 4. For 10,000 steps, we use the same configuration. For 20,000 steps, we use L=15,000 patches. All values are averaged over 10 runs.

Results For T=200 (Table 3), the vanilla LSTM takes much longer than other structures to converge, whereas the CuDNNLSTM and CuDNNGRU cells show competitive convergence. The Igloo cell is the fastest in this experiment. For 1000 time steps, some of the cells take more than 2000 seconds to converge and the igloo cell is still the fastest. For 5,000 steps IGLOO converges under 94 seconds, for 10,000 steps, under 125 seconds and for **20,000 steps**, it converges under 1000 seconds. To the best of our knowledge no other method in the literature achieves convergence for that many steps on this benchmark.

4.3 Artificial Grammar

Dataset Closely following (Ostemeyer et al., 2017), we use this task to make sure that IGLOO can represent sequences efficiently and not just sets. To be successful at this task, any neural net needs to be able to extract information about the order in which the elements of the sequence appear. Based on an artificial grammar generator (Figure 3), we generate a training set which includes sequences which follow all the predefined grammar rules and are classified as correct and we generate sequences with an error, which should be identified as invalid. As a result of the grammar generator, sequences such as: BPVVE, BTSSSXSE and BPTVPXVVE would be classified as valid and sequences such as: BTSXXSE, TXXTTVVE and BTSSSE would be classified as invalid.

Setup We generate 100,000 sequences and split 80/20 between the train and test sets. Half of the sequences are classified as valid. The maximum sequence length is 50 and there are 7 possible characters. We test different neural network structures and record the wall time to reach above 95

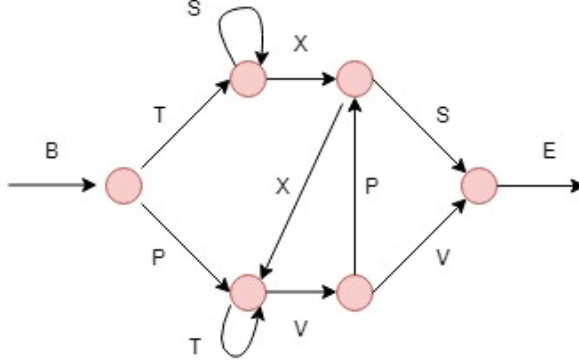


Figure 3: Grammar rules generator.

Table 5: **Grammar Task.** Time in seconds to reach accuracy > 95%

Model (Hidden)	Time (s)	Params
RWA (128)	1025	71K
LSTM (128)	384	70K
CuDNNLSTM (128)	90	71K
CuDNNGRU (148)	NC	70K
IndRNN (2X154)	59	73K
TCN (7X14)	NC	68K
IGLOO (L=500,2 stacks)	14	76K

Results From table 5 it appears that while the CuDNNLSTM manages to converge to the target accuracy quickly, the CuDNNGRU cannot converge at all. The TCN is also struggling on this task and cannot converge for the standard settings or even for a larger filter size of 34. In terms of convergence speed IGLOO performs better on this task than the other cells. From this experiment, we can conclude that IGLOO can successfully deal with a task where the order in which the elements appear is critical.

4.4 Sequential MNIST and permuted MNIST

Dataset Another dataset to benchmark the ability of a network to learn long term dependencies is the sequential MNIST task. In this task pixels are fed into a recurrent model before making a prediction. Since the MNIST dataset consists of 28*28 pixels sized images, once flattened they essentially amount to 784-long sequences. A variation is to randomly permute the pixels (the same way across all samples). This breaks the local structure of the image and should result in more complexity for the task. We report the results from the literature and compare them to applying IGLOO to this task.

Setup We use results from previous works as reported in the notes and compare the results to the IGLOO structure. For all results except IGLOO we just report what has been claimed in terms of performance in those various papers. For the pMNIST we use L=2500 patches, a patch size of 4, a spatial dropout of 0.15, 4 stacks and an initial Conv1D convolution of size K=8. For MNIST we use L=2500 patches, a patch size of 4, a spatial dropout of 0.2, 6 stacks and an initial Conv1D convolution of size K=8. Batch size of 128 is used and we run the net over 200 epochs.

Results It appears in Table 5 that IGLOO is competitive on the sequential MNIST set with a performance above the LSTM but slightly below the TCN and IndRNN (those performances are reported in the original papers and have not been reproduced here). For the pMNIST task, **IGLOO is performing the best across all reported results in the literature.** We see that the pMNIST and MNIST performances are very similar. IGLOO may be less impacted by permutation than RNN style structures because it is finding a representation for a sequence not by looking at each element sequentially but as a whole, taking patches from the whole input space.

Table 6: **MNIST - pMNIST**. Accuracy in %

Model (reference)	MNIST	pMNIST
iRNN (Le et al., 2015)	97.0	82.0
uRNN (Arjovsky et al., 2016)	95.1	91.4
LSTM	98.3	89.4
EURNN(Jing et al.,2016)	-	93.7
TCN (Bai et al., 2018)	99.0	97.2
r-LSTM (Trinh et al., 2018)	98.4	95.2
IndRNN (Li et al., 2018)	99.0	96.0
KRU(Jose et al.,2017)	96.4	94.5
Dilated GRU (Chang et al., 2018)	99.2	94.6
IGLOO - ours	98.6	98.4

Table 7: **IMDB Dataset**. %

Model (reference)	Peak Accuracy	Time to reach (s)
GRU (153K)	90.06	1624
CuDNNGRU (153K)	89.69	171
IGLOO (177K)	90.27	156

We note that while IGLOO and CuDNN LSTM run at similar speed of 30 seconds per epoch, the LSTM is much slower and takes about 540 seconds per epoch for a 128 hidden layers cell. Therefore we achieve superior accuracy for the pMNIST benchmark with speed levels (per epoch) similar to the fast NVIDIA optimized CuDNN LSTM cell. IGLOO is also competitive in terms of pure wall time just as for previous experiments.

4.5 IMDB Dataset

Dataset Following (Bradbury et al., 2000) we use the IMDB dataset for task D to see how IGLOO fares out in the wild with an example closer to what can be used in production. The IMDB task uses 50K examples of positive and negative reviews and the network should be able to determine the nature of each review in the test set, as such this is a sentiment classification task. The dataset is split equally in half for the training and the testing. As a classification task, we shall test IGLOO capacity to generate a good representation for a sentence that can be then classified with a feed forward network easily.

Setup The procedure is to run a baseline model using GRU (164 cells) and the CuDNN optimized version available in Keras, CuDNNGRU (164 cells) and compare this to IGLOO. The baseline neural network just includes an initial Conv1D layer with 64 hidden parameters followed by one instance of the cell we are studying. As a classification task, the loss used will be binary cross-entropy and we shall consider the accuracy for our benchmark as well as the time required to reach peak accuracy. We do not use all the enhancement to make it a state of the art performance, our purpose is to emphasize the differences in performance between the different methods rather than try to beat the state of the art. For our baseline we use a model with inputs I of dimension (800,300). We use 300 dimensional GloVe (Pennington et al., 2014) word embeddings limiting the number of words to 125k. The sequence length is capped at 800 (231 is the average sequence-length) and sequences are tiled until 800 for shorter sequences. For IGLOO we use L=300 patches, K=30 internal dimensions, L2 regularization of 0.05. We use 2 IGLOO stacks so that we can apply different layers of granularity. We add dropout of 0.15. We use a maxpool size of 4 which allows to reduce the sequence length from 800 to 200 and therefore reduce the number of parameters accordingly.

Results From Table 7, IGLOO appears competitive on this task compared to GRU and Nvidia optimized GRU, while being faster to reach its peak accuracy than the other methods. All the results here are fairly close to each other in terms of accuracy performance so rather than singling out a clear winner it is fair to say that IGLOO performs as well as the other cells.

Table 8: **TUH Abnormal EEG Corpus task.** %

Model (Params)	Peak Accuracy(%)	Time per epoch (s)
GRU (4.6M)	85.51	433
CuDNNGRU (4.6M)	85.87	70
IGLOO (4.6M)	85.87	46

4.6 TUH Abnormal EEG Corpus

Dataset We use the TUH abnormal EEG Corpus which is a subset of the TUH EEG Corpus (Obeid et al., 2016). The purpose of the task is to distinguish between normal and abnormal EEG sessions. The training set and test set is fairly small so we shall examine if IGLOO tends to overfit or not for those more complicated tasks. The total number of sessions in the training set is 2707 and there are 276 sessions in the test set split 127/150 as abnormal and normal. Convolutional networks can be used to tackle this task (R. Schirrmeyer et al., 2017). ChronoNet on the other hand is a new neural network architecture (Roy et al., 2018) which established the current state of the art result on this dataset with an 86.57% accuracy using a mixture of Conv1D dilatations and GRU layers. In this experiment we shall try to reproduce a baseline result using an architecture similar to ChronoNet and will then replace the GRU part with an IGLOO for comparison. With this experiment we are looking to validate that IGLOO can be in some cases used as a (faster) RNN drop-in replacement.

Setup Contrary to the architecture in (Roy et al., 2018) we will not apply the neural network directly on the EEG data. We will first use the raw EEG data from the dataset and change the 10/20 configuration to the transverse central parietal (TCP) montage system for accentuating spike activity. Resampling the data to 100Hz and using the first 5 minutes of data for each sequence, we obtain a matrix M of dimensions (22,30000). We transform this data to get a MFCC matrix of dimensions (22,834,40). We reshape this matrix to obtain a matrix of dimensions (834,880). The data we shall work on can be considered as 834 (times-steps) vectors of dimension 880. We would like to check whether on a more complicated problem IGLOO can still perform well and converge to a competitive result against the baseline in a shorter amount of time. We shall test 3 possible cells: the IGLOO, the GRU and the CuDNNGRU optimized cell. We use 360 hidden dimensions for the RNNs cells. The IGLOO which return sequences is set to use L:60 patches, an internal convolution size of 40, a stretch factor of 23 and a L2 regularization factor of 0.08. We find that using the regularization for IGLOO is important to reduce over-fitting. We use a drop out of 0.45 inside the IGLOO structure as well. Between the dropout and the L2 regularization we find that overfitting is not an issue. Figure 4 in the Appendix presents the neural network architecture we use, which is largely inspired from (Roy et al., 2018).

Results Results are reported in Table 8. All 3 structures allow to reach similar accuracies on this task. The main differentiation is with respect to the time it takes to converge. IGLOO converges faster than the two baseline models while having around 50 percent more parameters. It is clear that when a model requires to return sequences IGLOO will usually have more parameters than a baseline GRU model, but because of the nature of the operations used inside IGLOO it still runs faster. The peak accuracy obtained with IGLOO does not allow to beat the state of the art result (86.57%) presented in (Roy et al., 2018), but using ensembling would probably allow to do that. We leave it for further study.

5 Analysis

We have proposed to tackle sequences task by looking at them as a whole rather than in a recurrent manner. We think that there is no prize in keeping the old paradigm of recurrence if alternative methods can do as well or better depending on the case. In the light of experiments above a few questions arise

Does it solve the core problem? The core problem was to find an accurate and fast method to represent long sequences. Experiments show that this method allows to solve that issue better than alternative methods for the given benchmarks.

Is there an advantage only for long sequences? Experiments show that for the given benchmark tasks IGLOO performs very well on short sequences too.

Why does it work? The method works because it borrows for battle tested CNNs. CNNs are used for image processing by applying successive groups of filters and keeping those filters local across successive layers. We are taking away this locality restriction and adapting the image processing case to the sequential data case.

Does it not massively overfit? Experiments show that if no regularization is applied then the method can overfit for more complicated tasks. We also find that it is easily resolved by applying batch normalization layers and especially L2 regularization. We are happy that with L2 regularization overfitting is not an issue.

Does it work for sequences only? It is our view that this method can be applied to different format of data (including images) and this is a point we shall explore in the near future.

Overall, while providing good results for long sequences, the method is also as competitive as traditional methods for short length sequences and can be seamlessly included into larger architectures. Since IGLOO can fit aggressively to the sequence it is important to keep in mind all the tools which can prevent overfitting.

While working on the vanilla IGLOO cell it already appears that several improvements are possible. For example, it would be possible to introduce a multi-head component to IGLOO whereby the random patches would be reused but different set of filters would be applied to them. That would allow to get different “perspectives” as to how the different patches are correlated. Having several perspectives could eventually lead to better accuracy. We leave it open for further study.

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6 Appendix

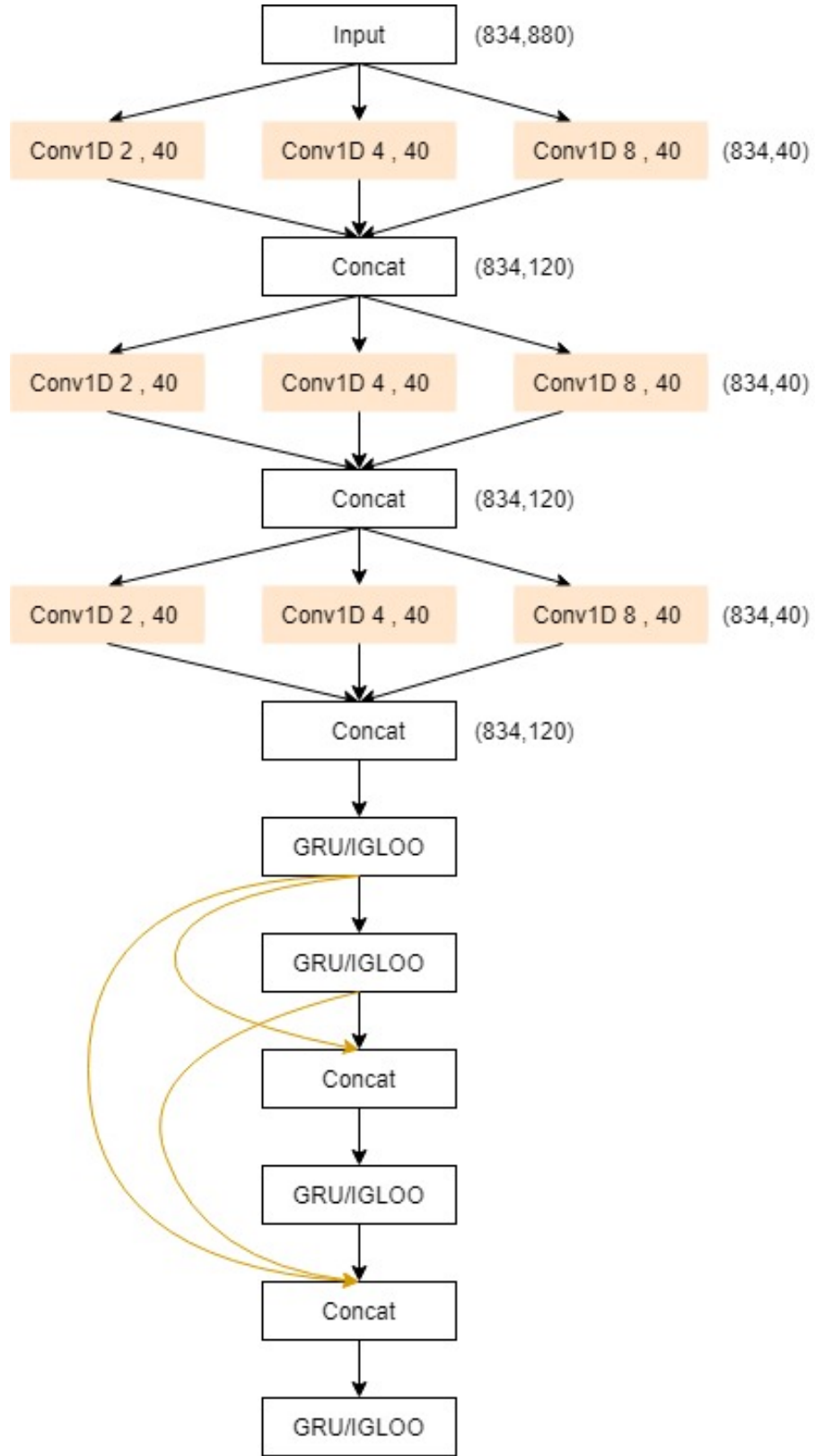


Figure 4: Baseline Structure used for the TUH Abnormal Corpus.