Scalability Analysis of Mini-Cluster Jetson TX2 for Training DNN Applied to Healthcare

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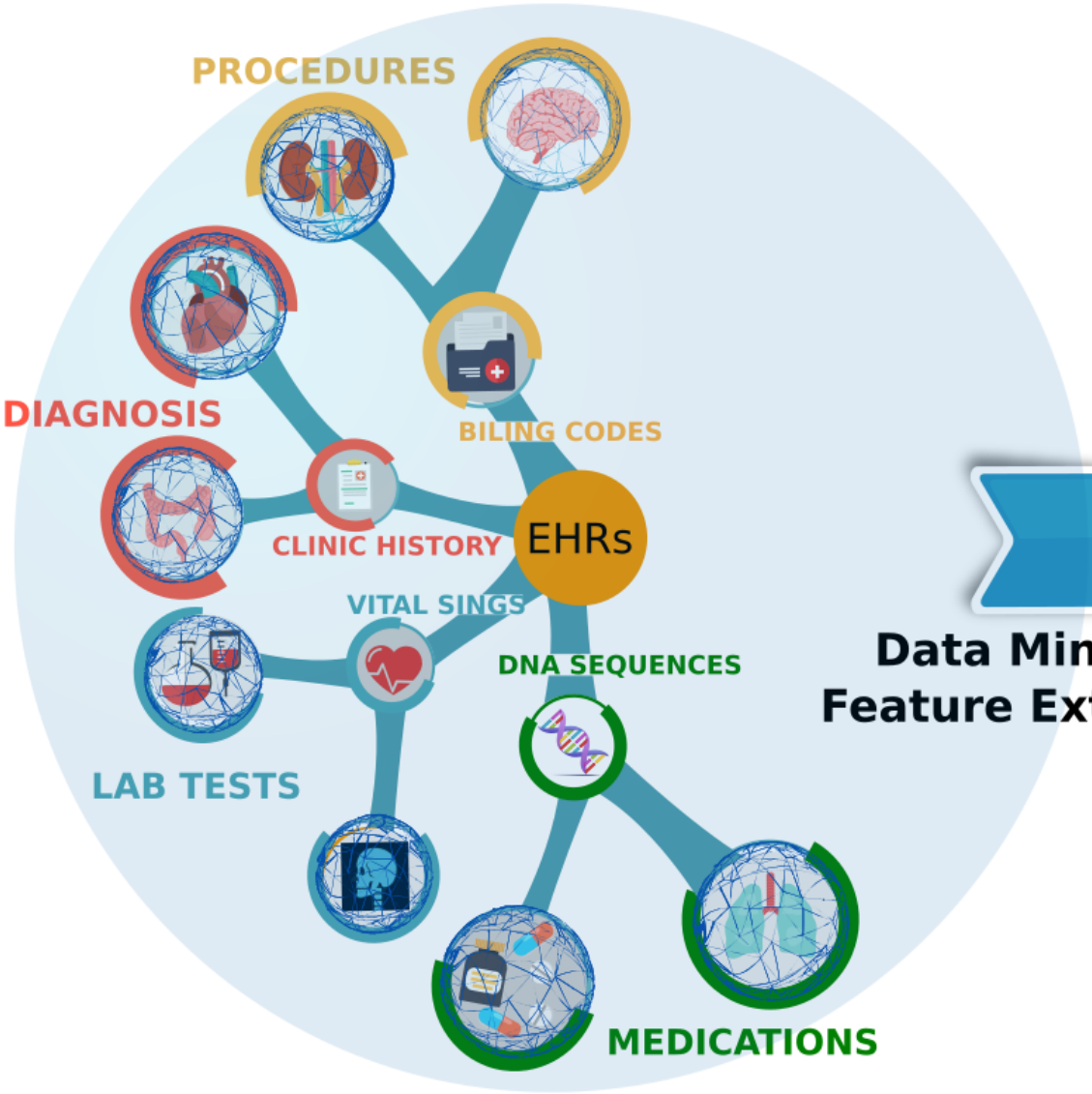
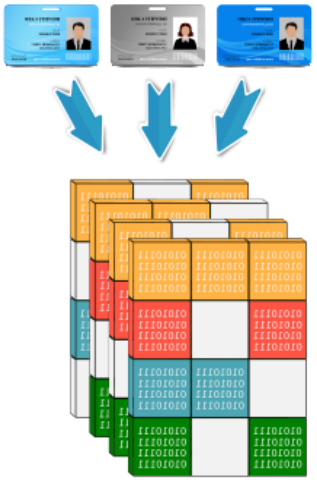
Motivation: Health Care Decision-Making



Data Mining & Feature Extraction



General Patient Phenotype Representation

Predictive Modeling

Challenges

- *A common challenge in healthcare today is that physicians have access to massive amounts of data on patients, but have short time to analyze all of them.*

- *One limitation is that hospitals without robust computational systems for processing, storing and drawing conclusions requires to outsource the clinical tasks and that is a risk for privacy clinical data.*

Developing a Green Intelligence Medical System to derivate a patient representation for predict general medical targets and improving the computational resources usage.

DiagnoseNET

Green Intelligence Medical System

Provides three high-level features:

1) A framework to build full Deep Neural Networks (DNN) workflow;

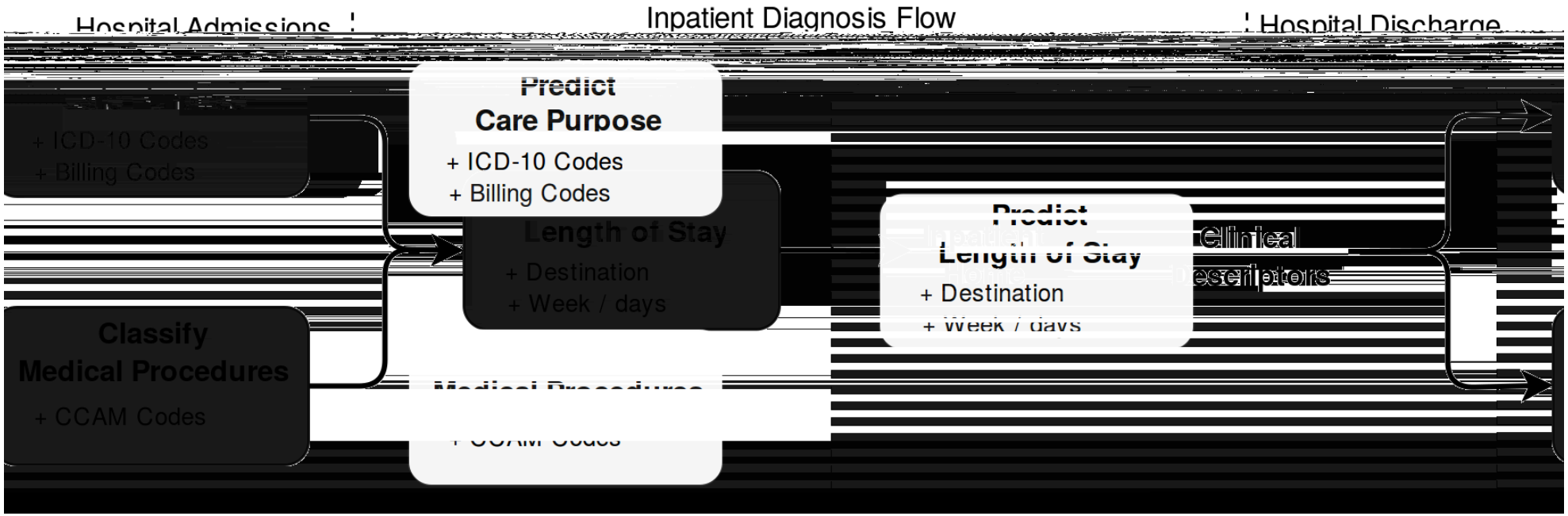
2) An energy-monitoring tool for workload characterization;

3) A distributed processing for training DNN on Jetson TX2 Mini-Clusters.

It is part of the **IADB Project**
Integration and Analysis of Biomedical Data: http://www.i3s.unice.fr/~riveill/IADB/

Case Study: Predict the Medical Future of Hospitalized Patients

Medical Target Pipeline



Case Study: Predict the Medical Future of Hospitalized Patients

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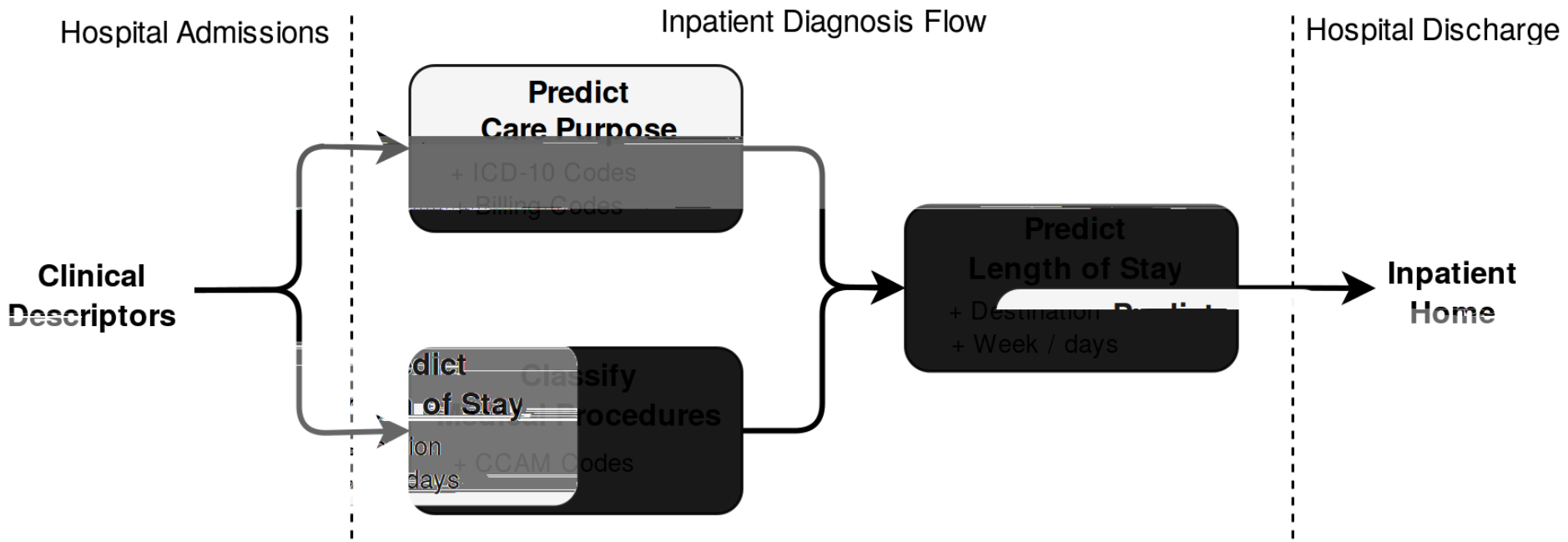
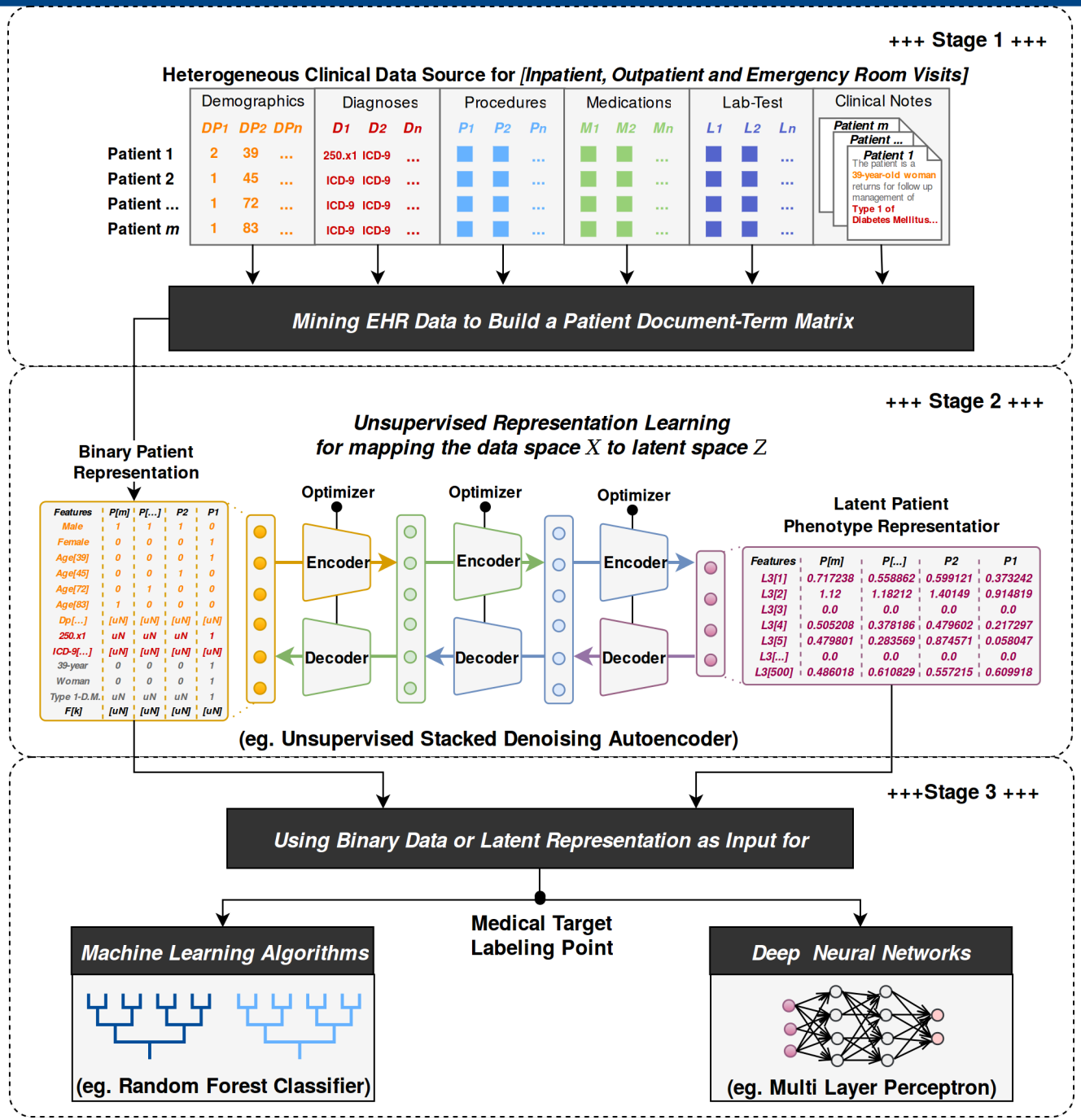


	Diagnosis related Group	ICD-10 Codes	Definition
	Patient 1	Morbidity Principal	R402	Unspecified coma
		Etiology	I619	Nontraumatic intracerebral hemorrhage, uns
	Medical Target	Care Purpose	Z515	Encounter for palliative care
	Label used	Clinical Major Category	20	Palliative care
	Patient 2	Morbidity Principal	R530	Neoplastic (malignant) relate fatigue
		Etiology	C20	Malignant neoplasm of rectum
	Medical Target	Care Purpose	Z518	Encounter for other specified aftercar
	Label used	Clinical Major Category	60	Other disorders

DiagnoseNET: Framework to automize the Patient Phenotype Representation

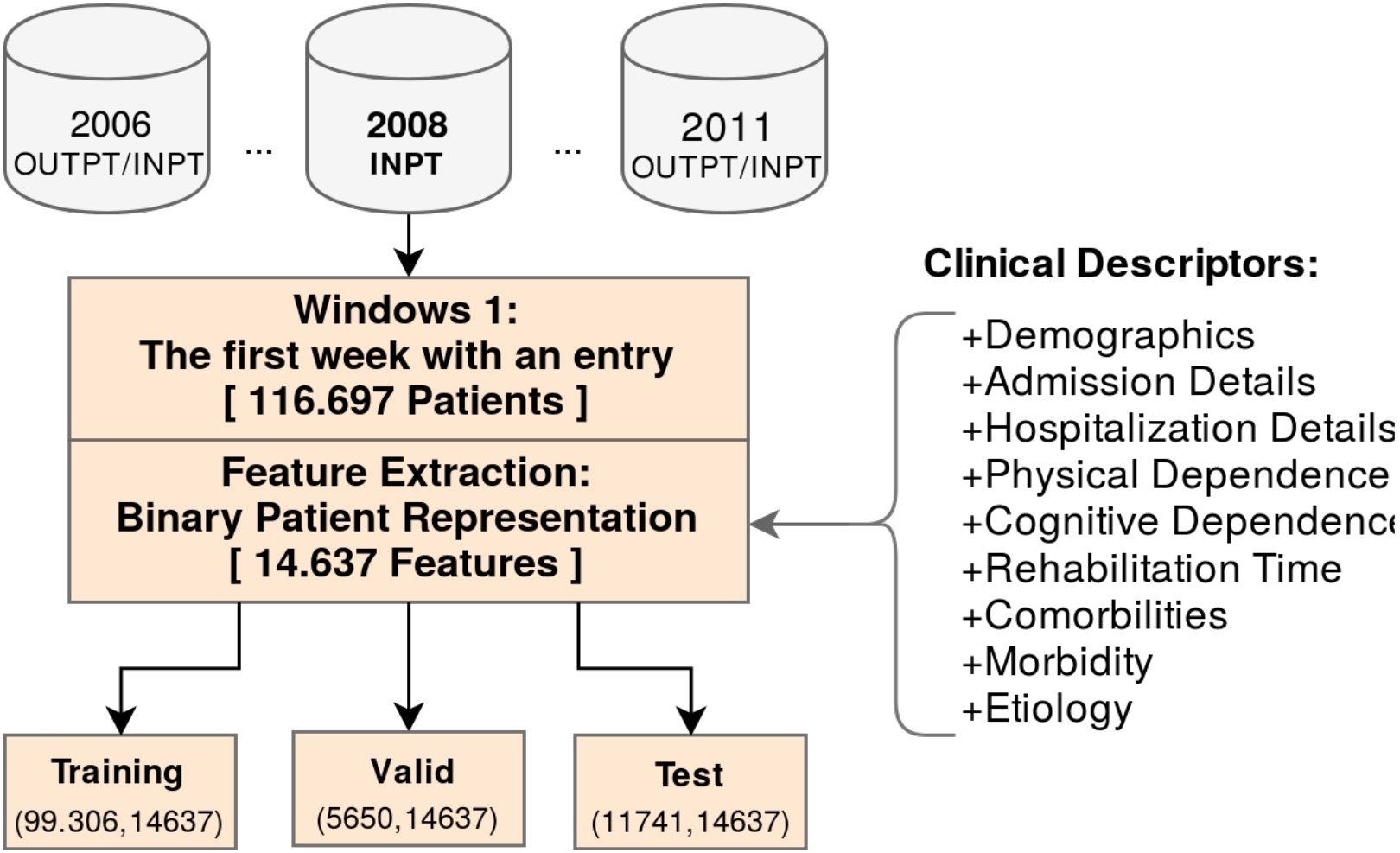


3. Adapted from: ! " #"$ " $% & ' ("( ) & *% % *& % $" . By Riccardo Miotto et al. SCIENTIFIC REPORTS, 2016.

Mining Electronic Health Records To Build A Patient Entity-Term Matrix

PMSI-PACA Clinical Dataset

As Input we are using result features *that describe the patient clinical descriptors to predict the medical targets.*



Data-mining: Feature Extraction From Electronic Health Records

Serialized a Patient Record in a Clinical Document Architecture Schema

Patients	x1_demographics			x4_physical_dependance			x7_related_diagnoses		
	gender	...	age	feeding	...	displacement	Das1	...	Das 3
Patient 1	2	...	61	4	...	2	Z431	...	Z501
Patient 2	2	..	65	4	...	2	J459	...	F322
....	...	...	...	...	...	...	...	...	...
Patient m	1	...	95	1	...	2	C259	...	F322

Build a Term-Document Matrix or Binary Patient Representation

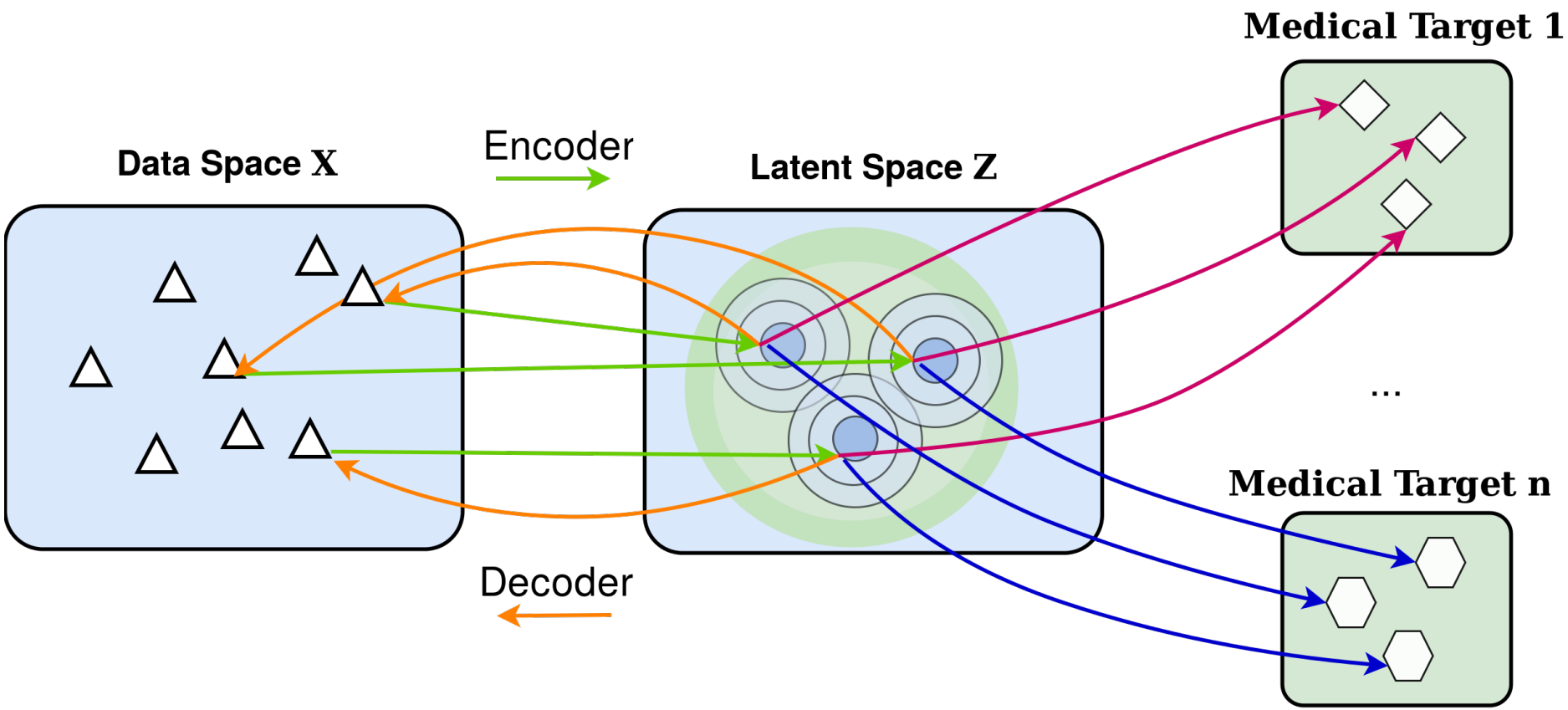
Patients	x1 :demographics			x4 :physical_dependance			x7 :related_diagnoses		
	[1 :male]	[2 :female]	60-74	[4 :Assistance]		[2 :normal_transfer]	Z431	...	F322
Patient 1	0	1	1	1	...	1	1	...	0
Patient 2	0	1	1	1	...	1	0	...	1
....	...	...	...	...	...	...	...	...	...
Patient m	1	0	0	0	...	1	0	...	1

Unsupervised Patient Phenotype Representation

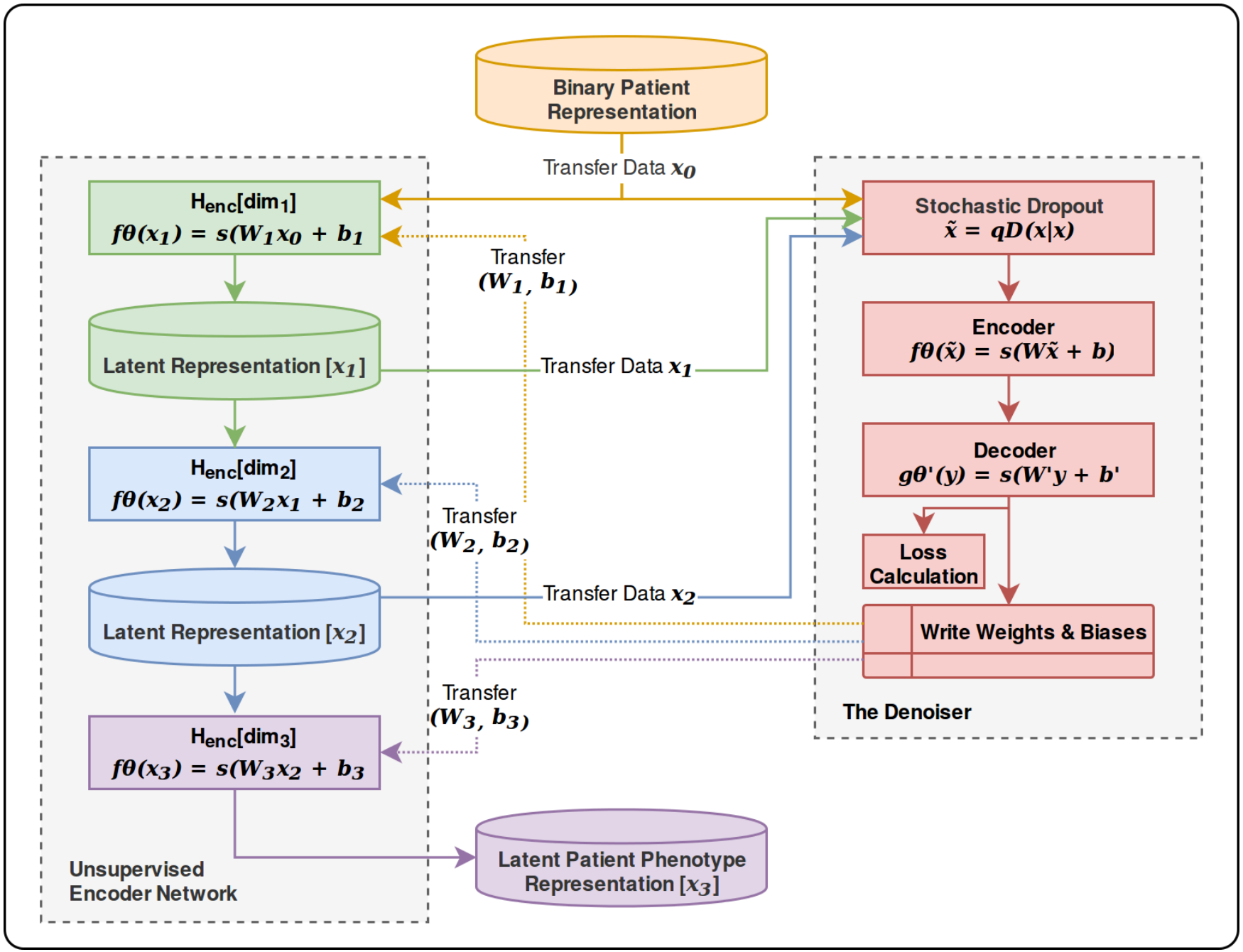
Unsupervised Patient Phenotype Representation

+ From a binary patient representation **{X}** derive a latent patient representation **{Z}.**

+ Once the general representation is obtained mapping it for the different medical targets.



Unsupervised Stacked Denoising Autoencoder Network



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By GARCÍA H. John et al. 2018

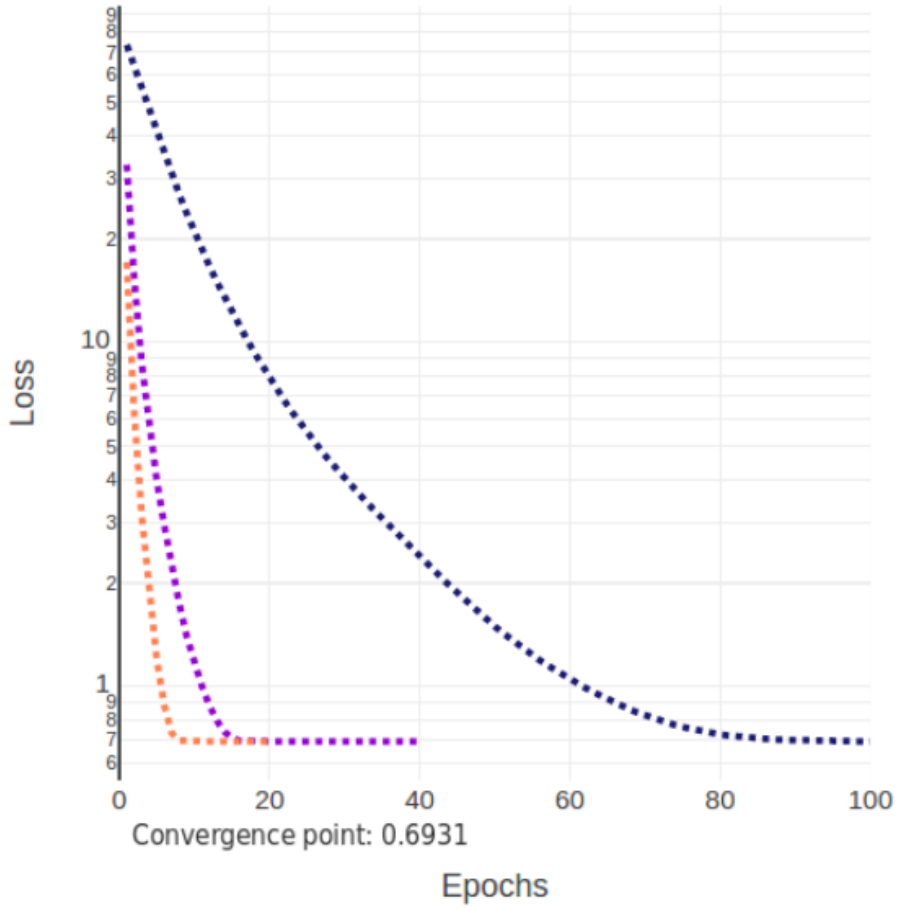
Experiment Analysis

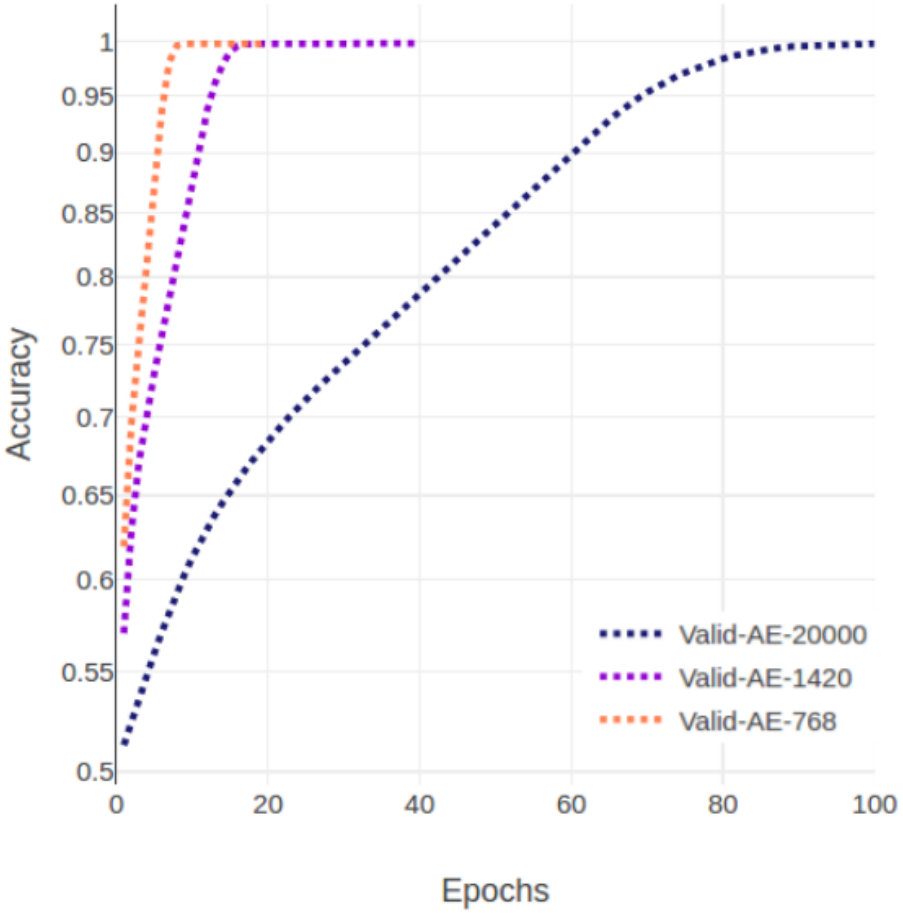
)(#um*er of Gradient pdates as Factor to %arly Model +onvergence.

1) Number of Gradient Updates as Factor to Early Model Convergence

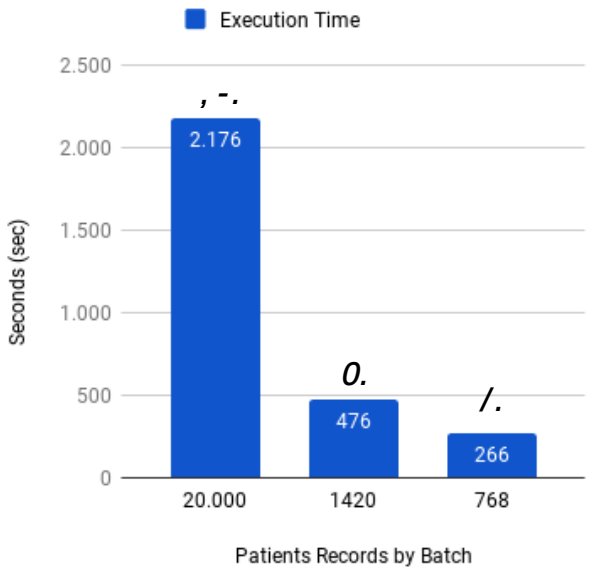
	1-Layer1	2-Layer2	3-Layer3	4-Activation_funct	5-GD_Optimizer	6-Learning_rate	7-Dropout-rate
0	2048	2048	768	relu	adam	0.0001	0.5

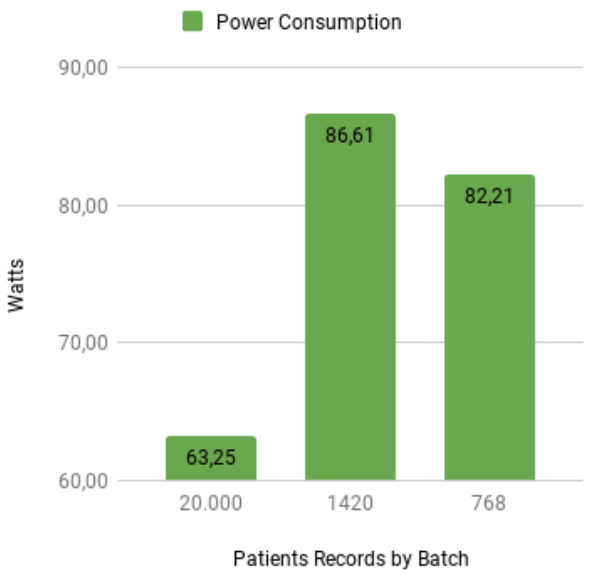
Network convergence using batch partitions of [20000, 1420, 768] records to generate [4, 59, 110] gradient updates by epoch respectively.

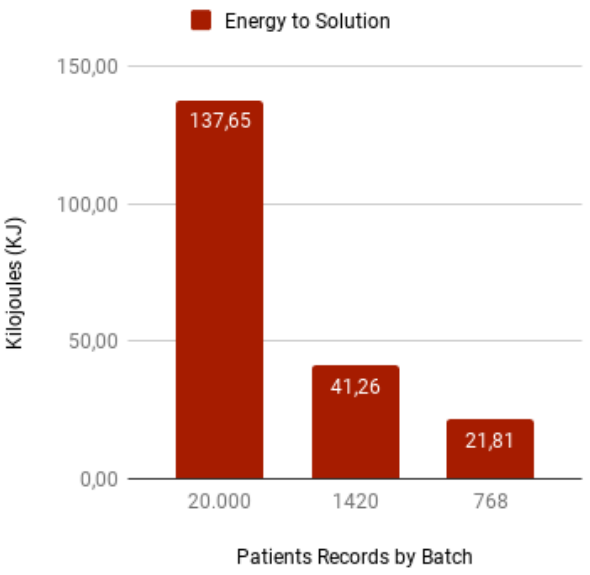




Number of Gradient Updates Impact the Energy to Solution







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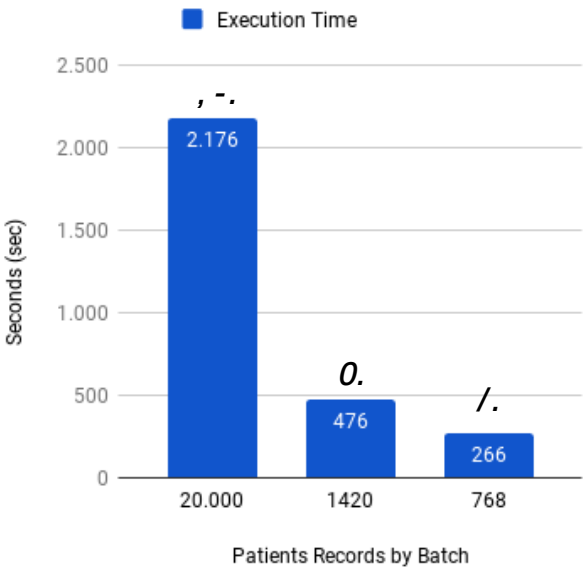
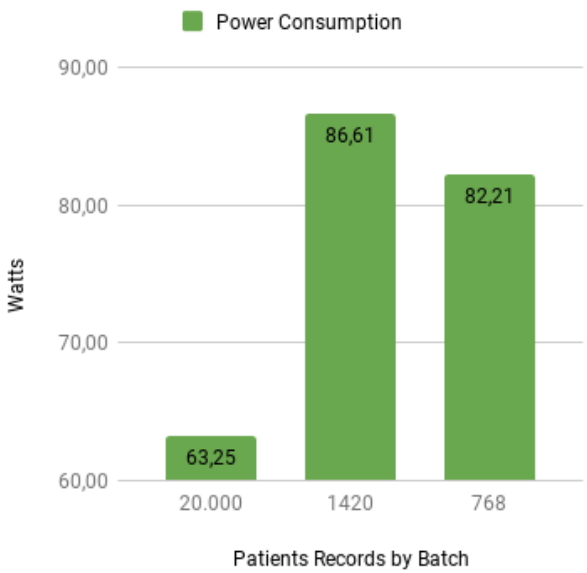
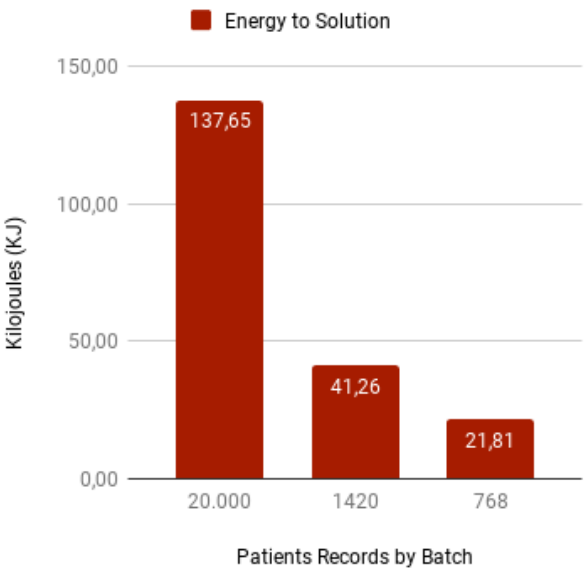
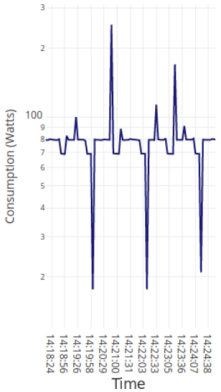






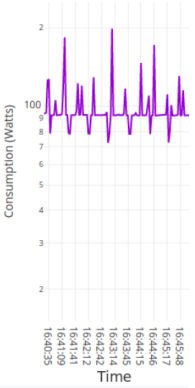
Power consumption in a window of 6 minutes



BF2 *34.444*

)1 %pochs

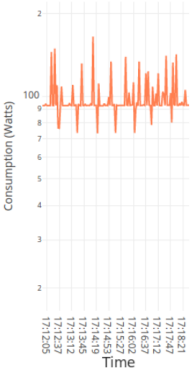
-0 GR "D PD



BF2 *) /34*

)5 %pochs

005 GR "D PD



BF2 *1-0*

) / %pochs

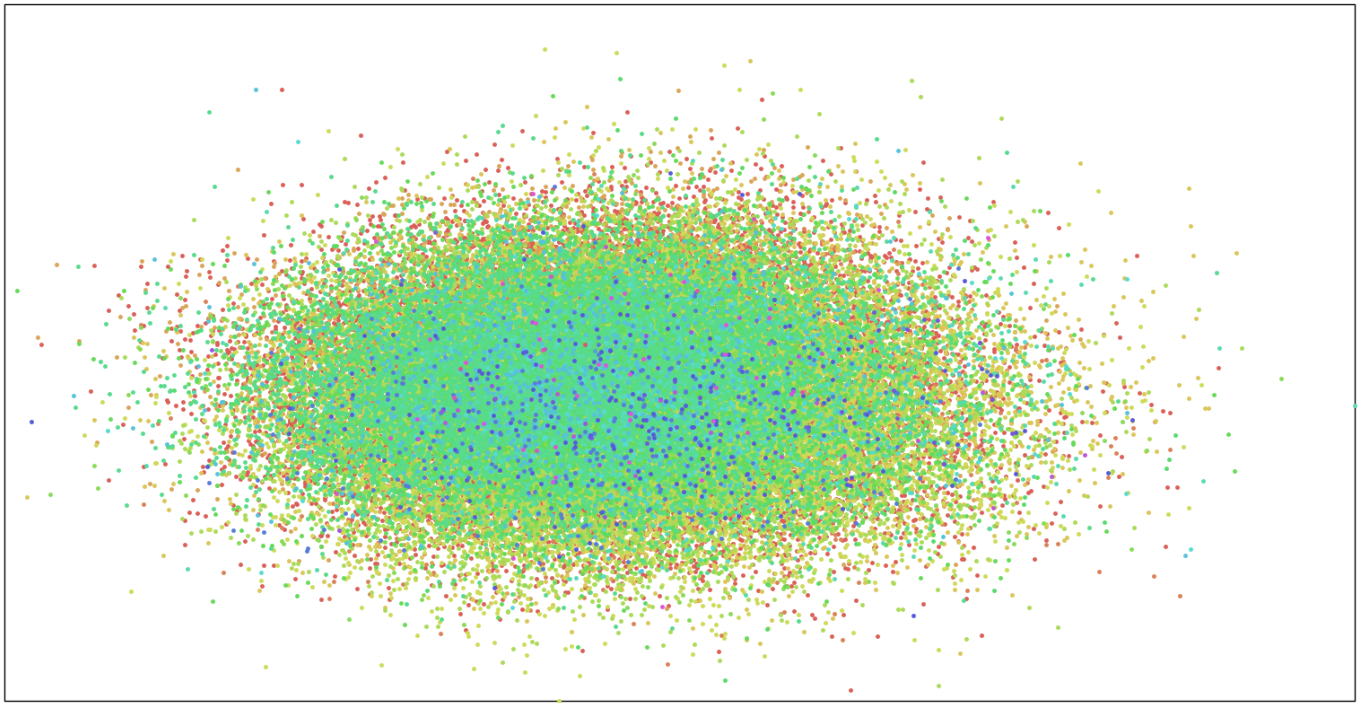
)5/4 GR "D PD

Number of Gradient Updates as Factor to Generate Quality Latent Representation

BF2 *34.444*

)44 %pochs

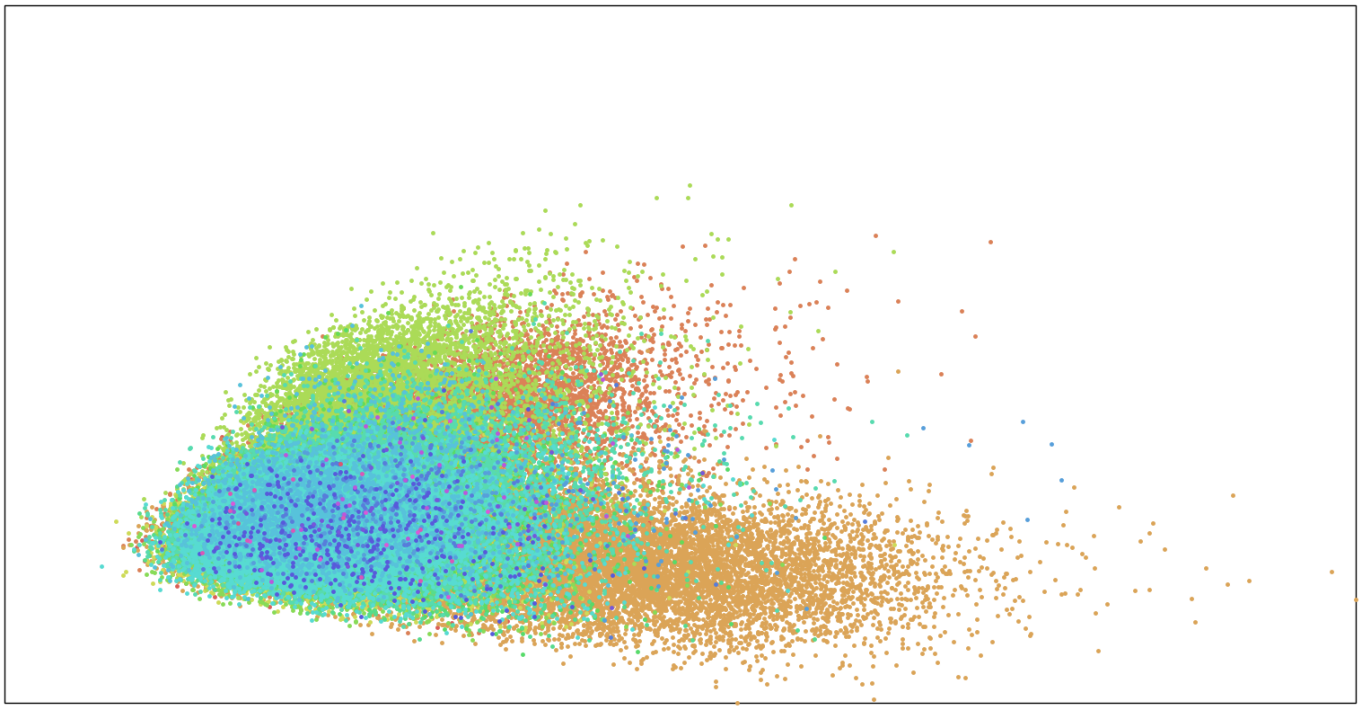
/44 GR "D PD



BF2 *) /34*

34 %pochs

)454 GR "D PD



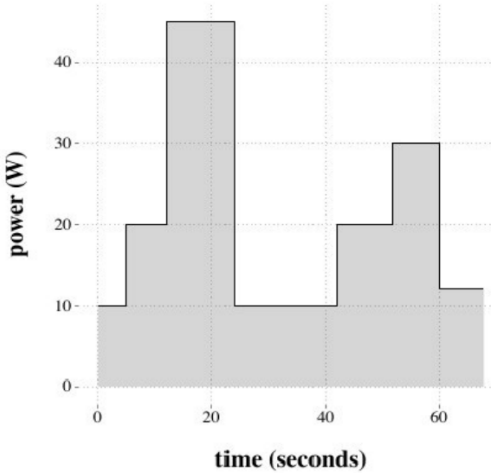
Energy Monitoring tool for Workload Characterization

Energy Consumption Metrics

1) Discretization of Energy Consumption per Time-Unit:

$$Energy = \int Power(t)\ dt$$

$$Energy = \sum_{i=1}^{N} Power(i) * \Delta t(i)$$



2) Energy to Solution (E2S):

$$E2S = \sum_{i=1}^{N} Power_{Node}(i) * max\ (\Delta t_{CPU}(i), \Delta t_{GPU}(i))$$

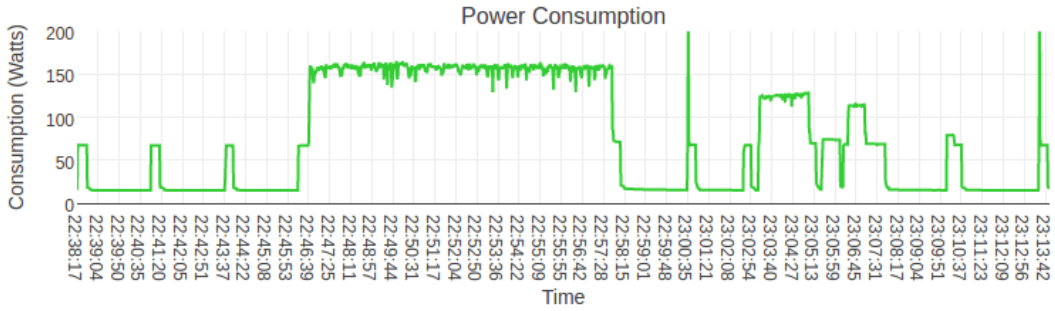
3) Instantaneous Power Consumption per Node:

$$Power_{Node}(i) = \sum_{j=1}^{nc} P^{j}_{CPU}(i) + \sum_{j=1}^{ng} P^{j}_{GPU}(i) + \sum_{j=1}^{nm} P^{j}_{RAM}(i)$$

5. Source - $ -& (/ ") $ ( ) % #* #$ "* $ *0 &. By GARCÍA H. John et al. 2016

Analysis of Energy Efficiency for Training the USDA on 1-GPU

S-1: Full Batch with 84.999 Patients Records



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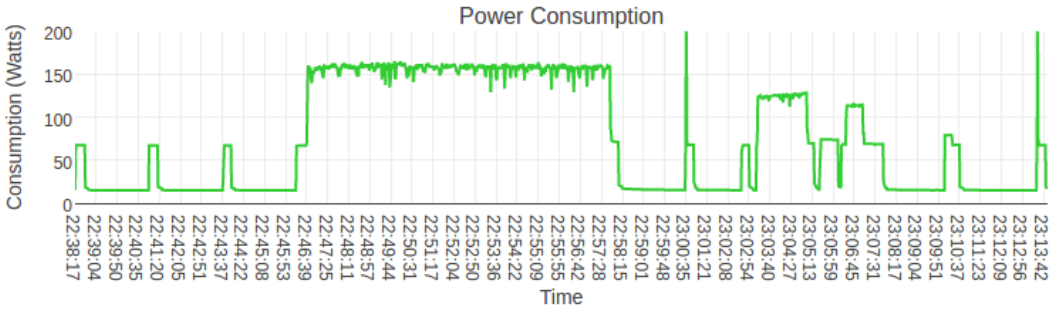
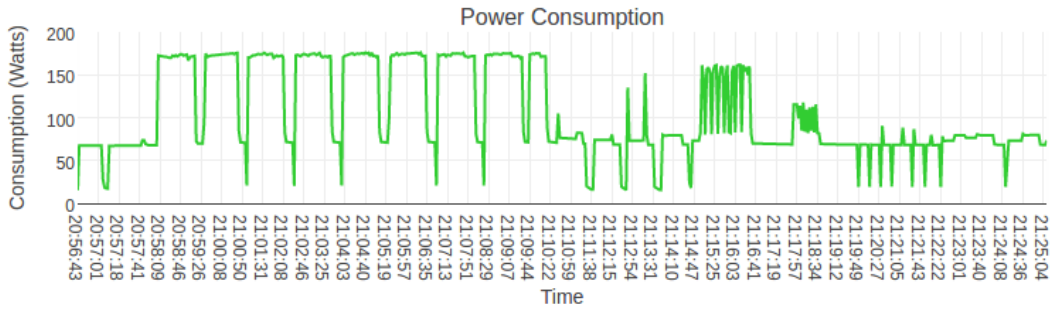


S-2: 9 Batches that Contain 10.000 Patients Records



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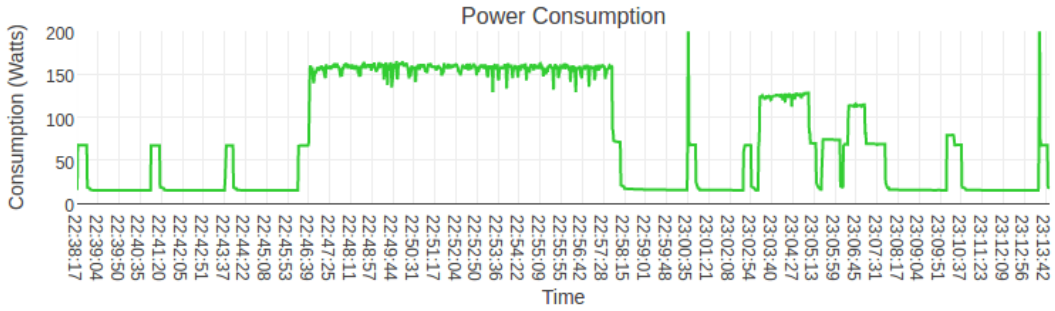

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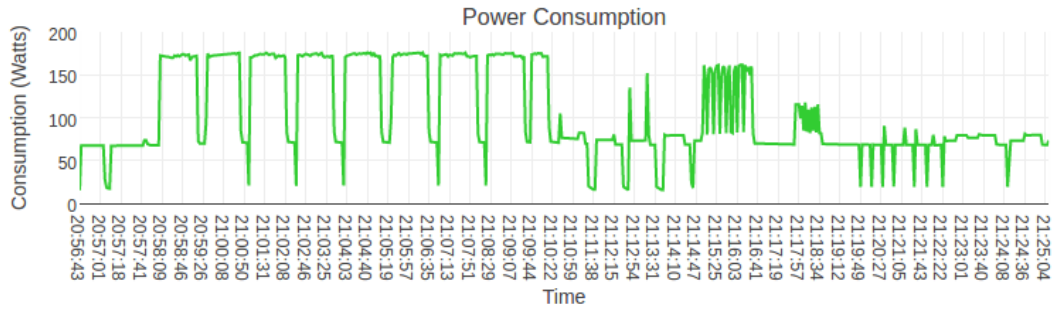
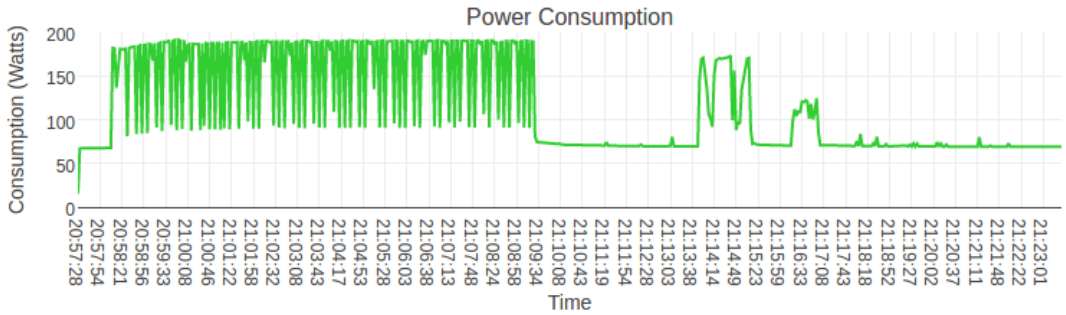


S-3: 85 Batches that Contain 1000 Patients Records



Analysis of Energy Efficiency for Training the USDA on 1-GPU

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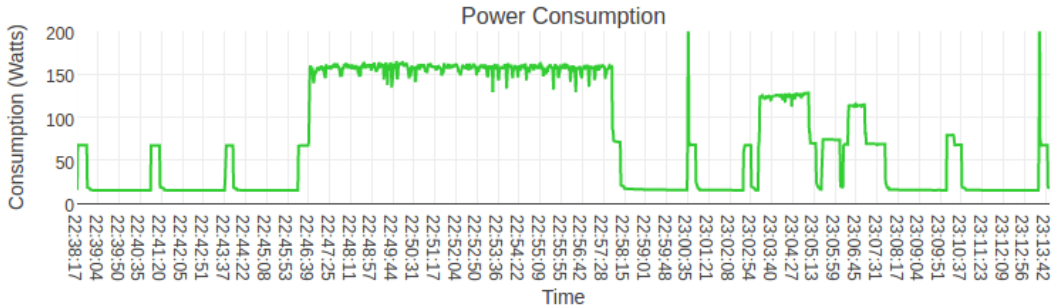

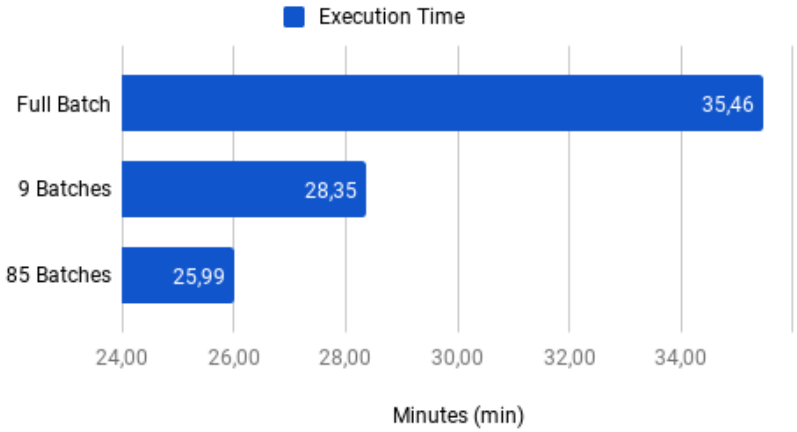

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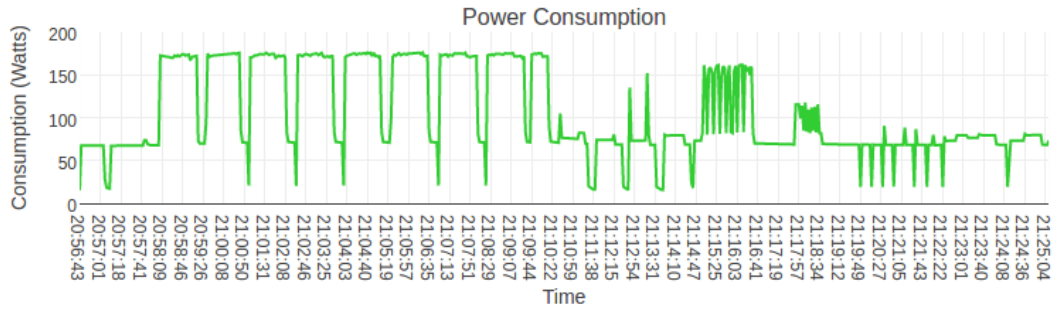

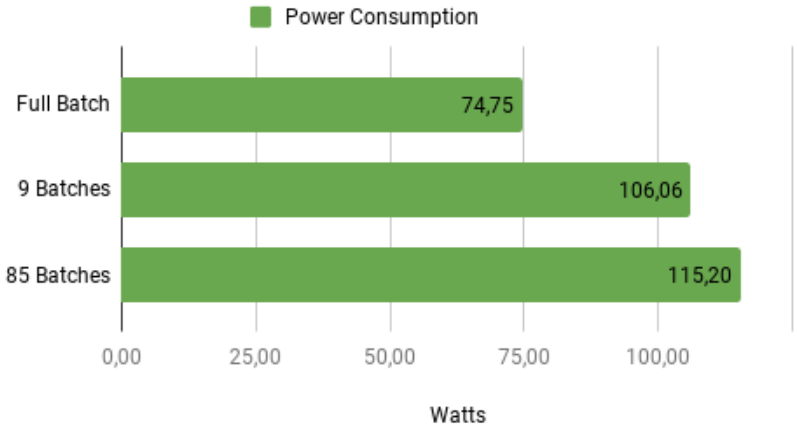

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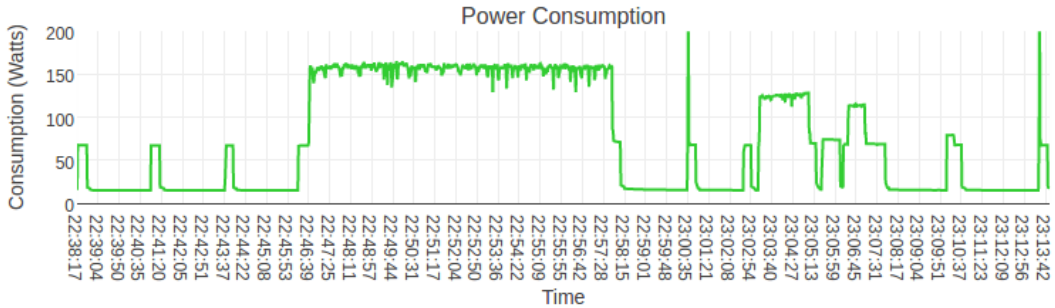

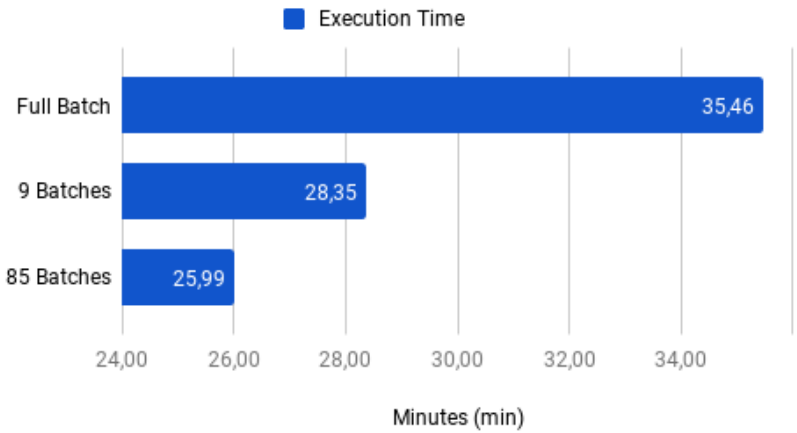

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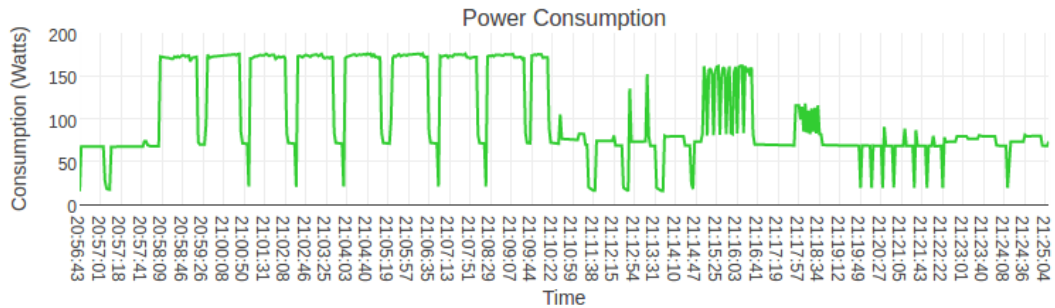

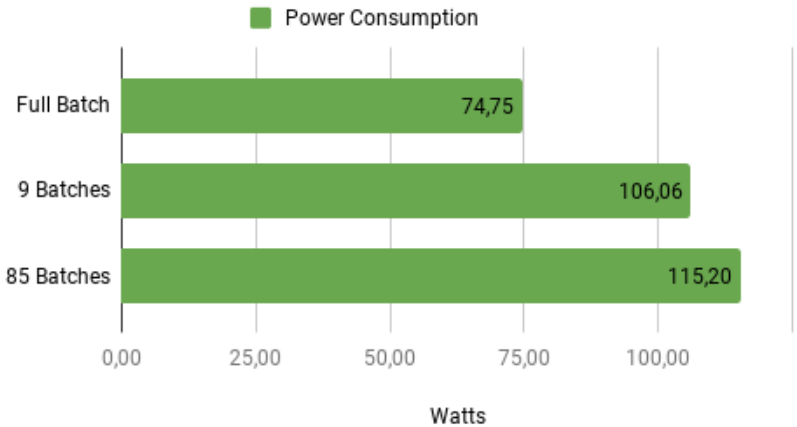

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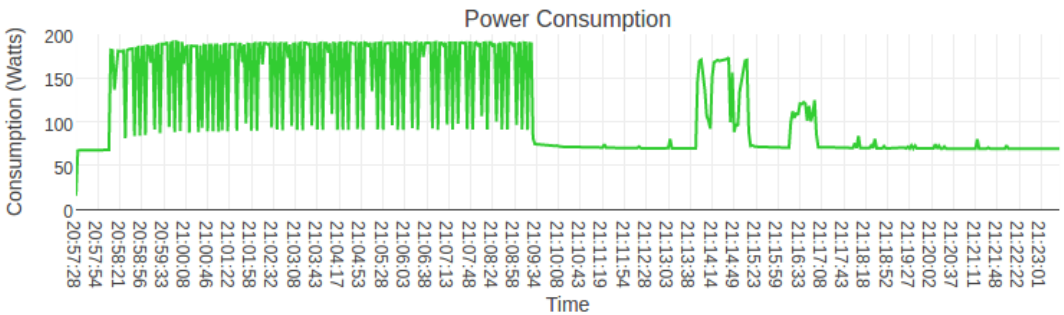
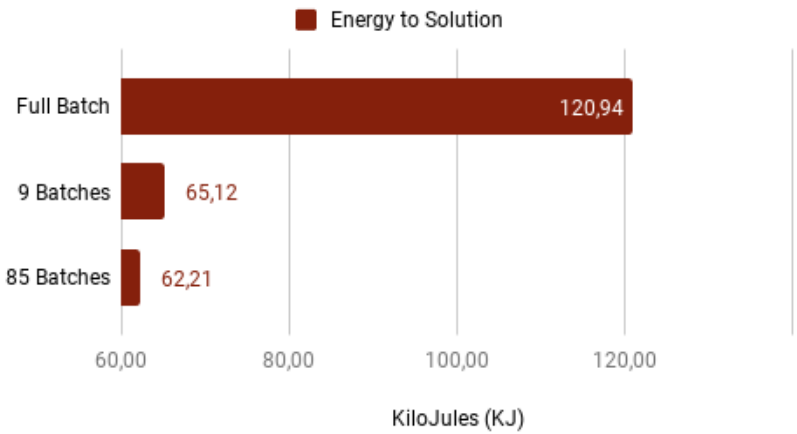
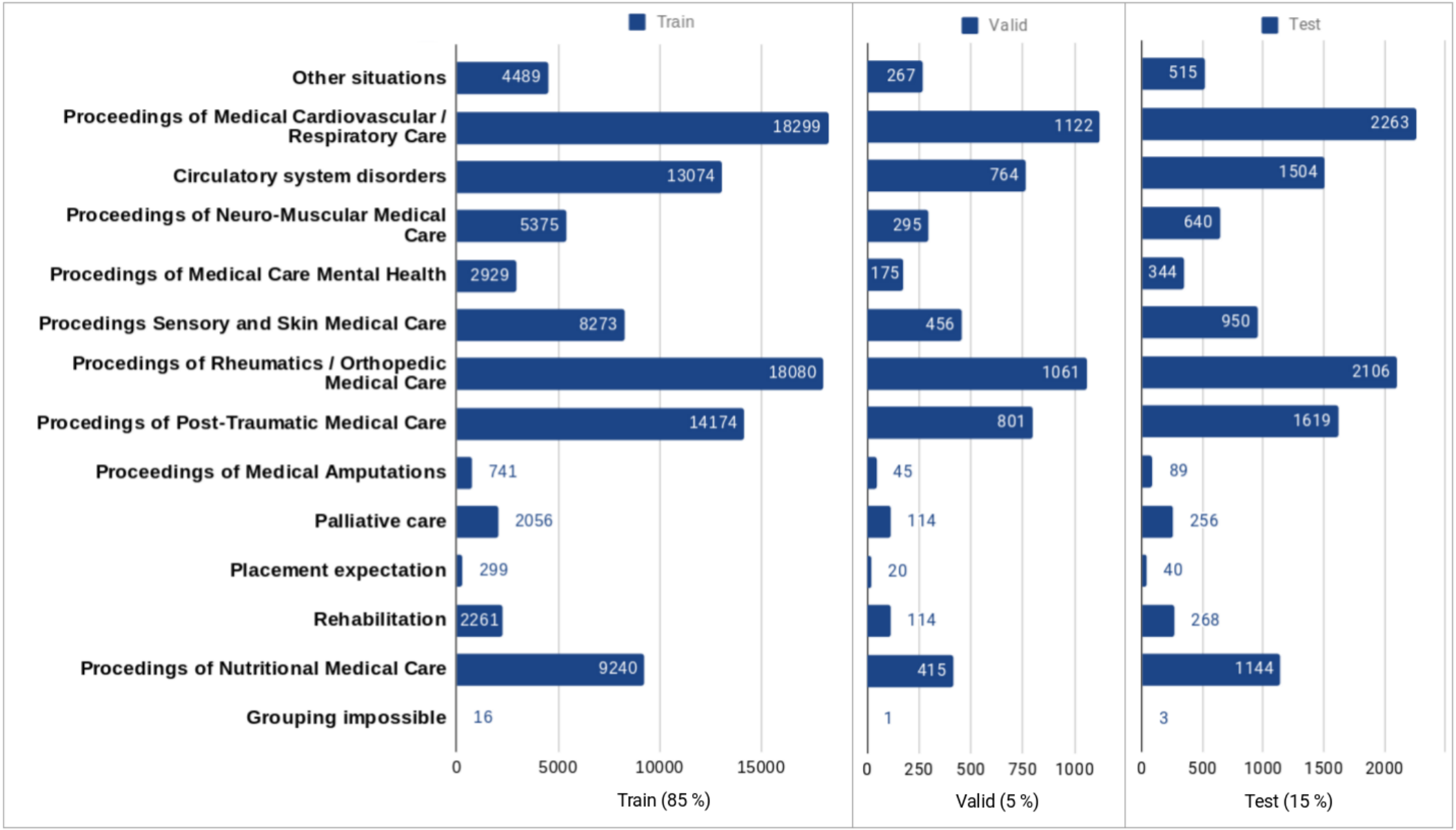




Supervised Learning

Medical Target 1

Medical Target 1: Care Purpose Description Labels at ICU



Supervised Learning

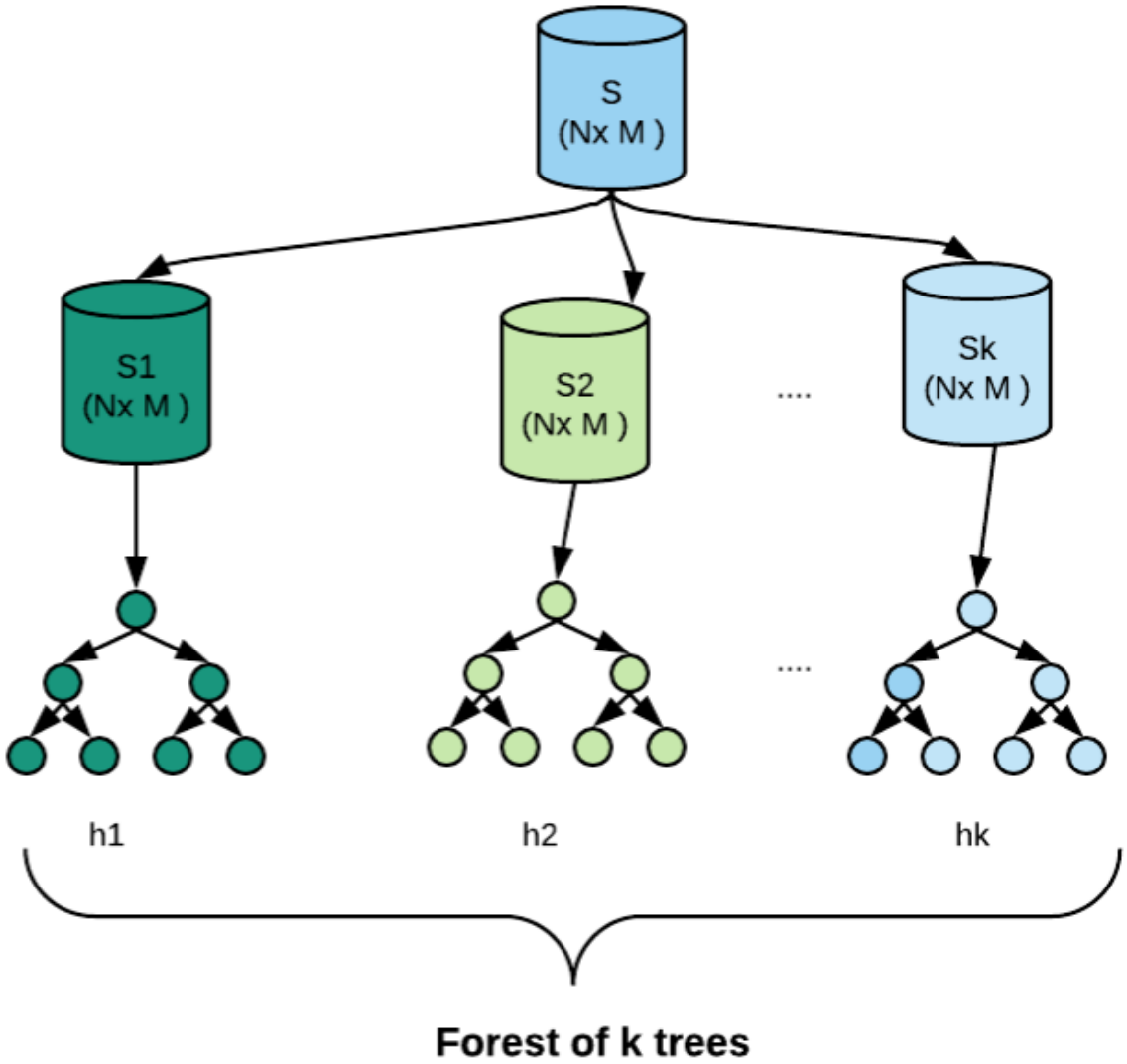
Random Forest Classifier

Ensemble Algorithm Based on Decision Tree Model

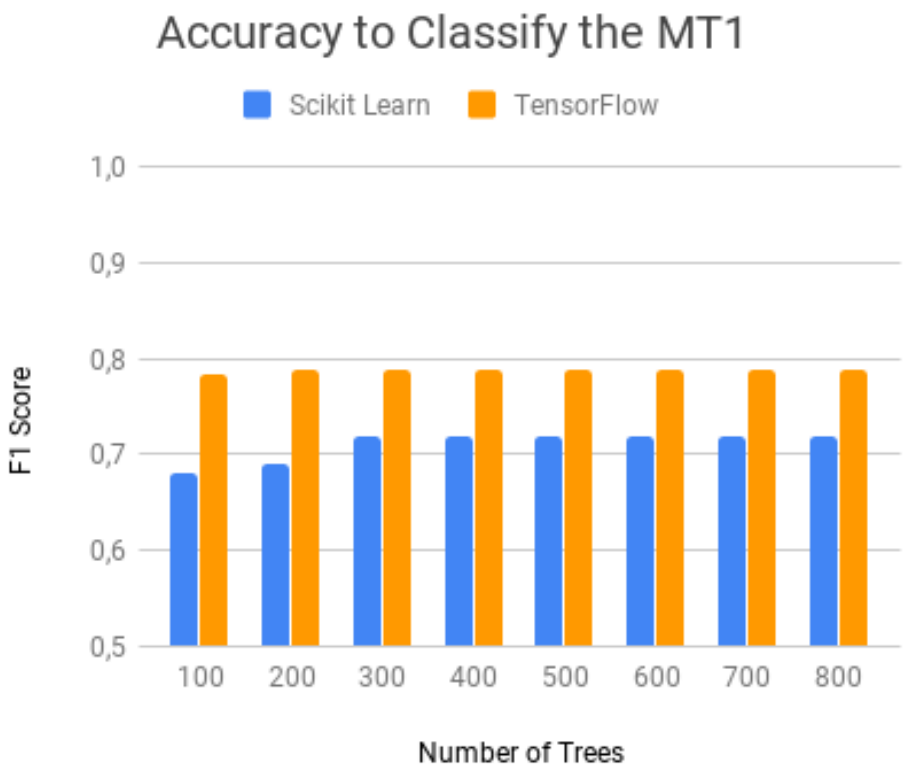
Step 1: Bootsrap sampling

Step 2: Construction of trees

Step 3: Collectiong trees in a forest model

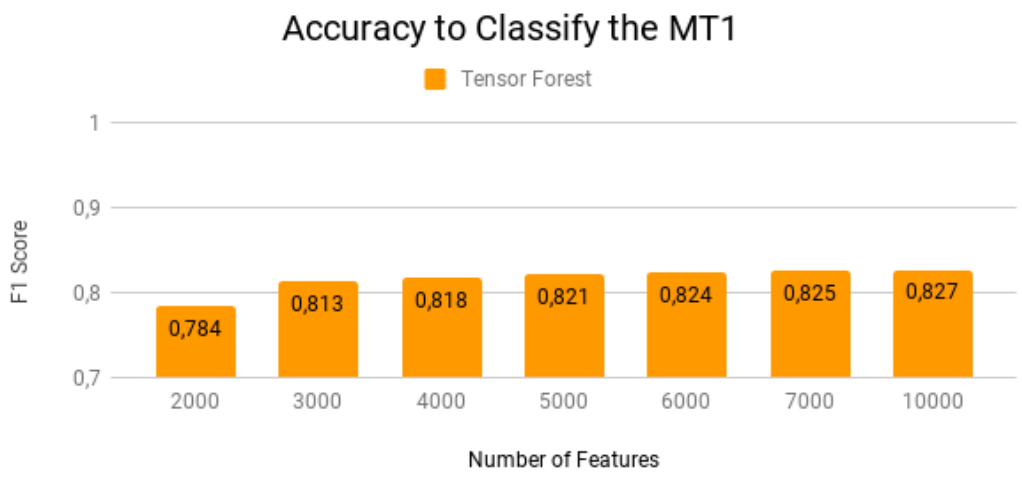


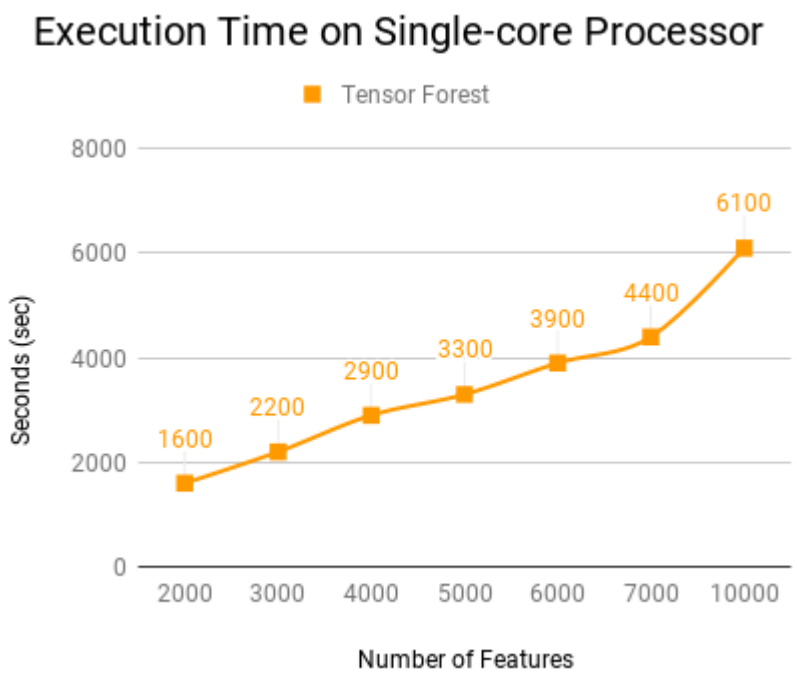
Experiments: Comparison of Random Forest off-Line Vs on-Line



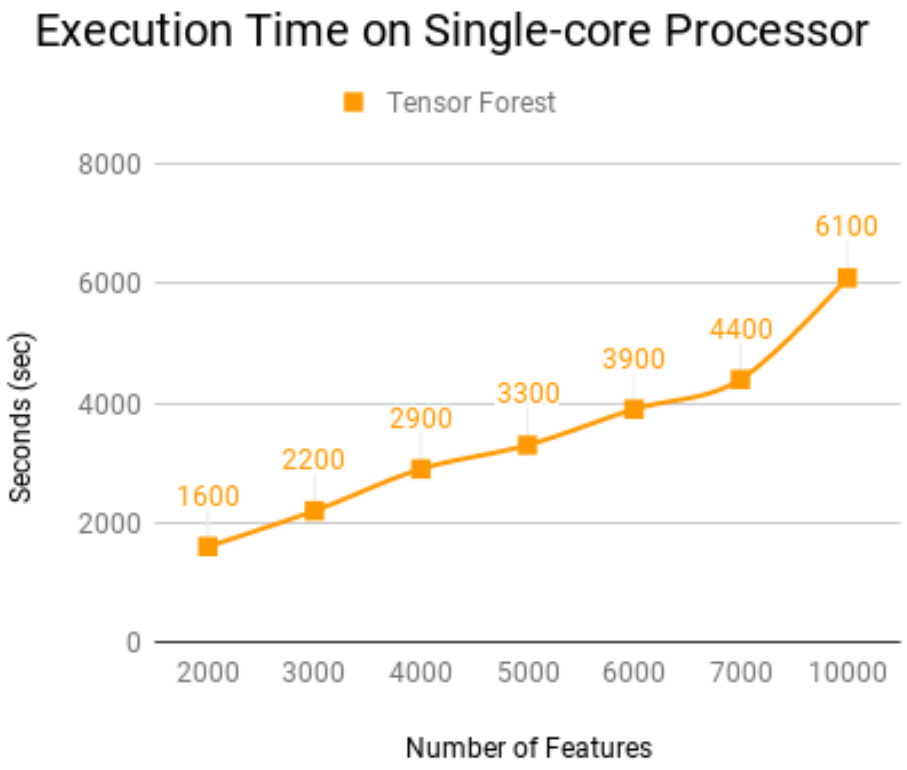
6. Source " ' " 1% * +* $)' "" " '*/. By Colthurst, Tomas et al. 2016

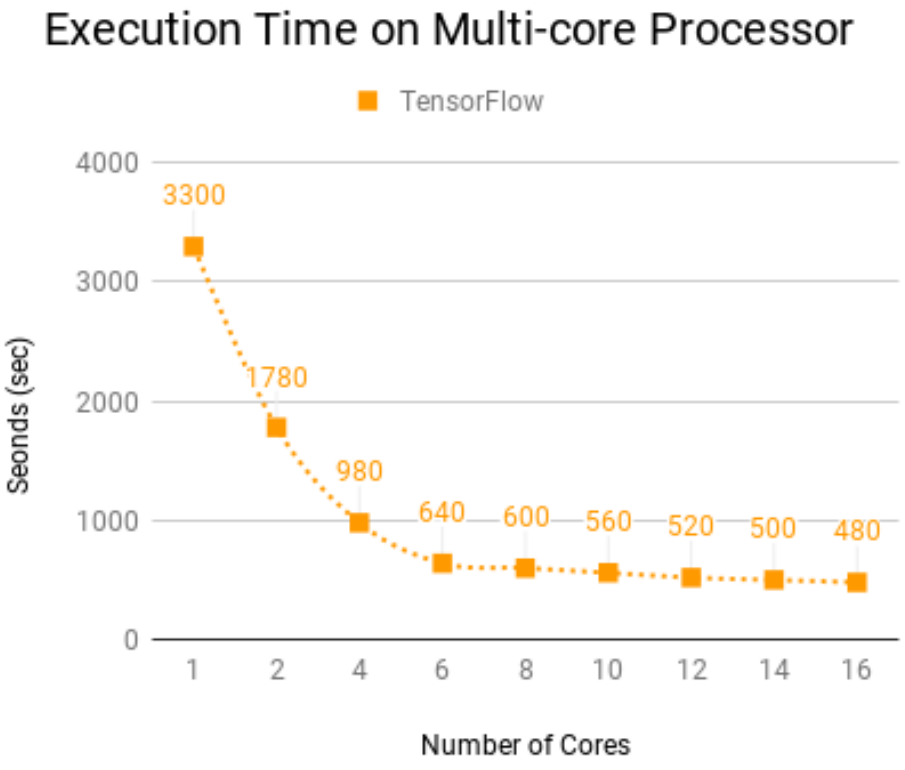
Experiments: Tensor Forest Analysis on Different Number of Features





Experiments: Tensor Forest Analysis on Multi-Core Processor

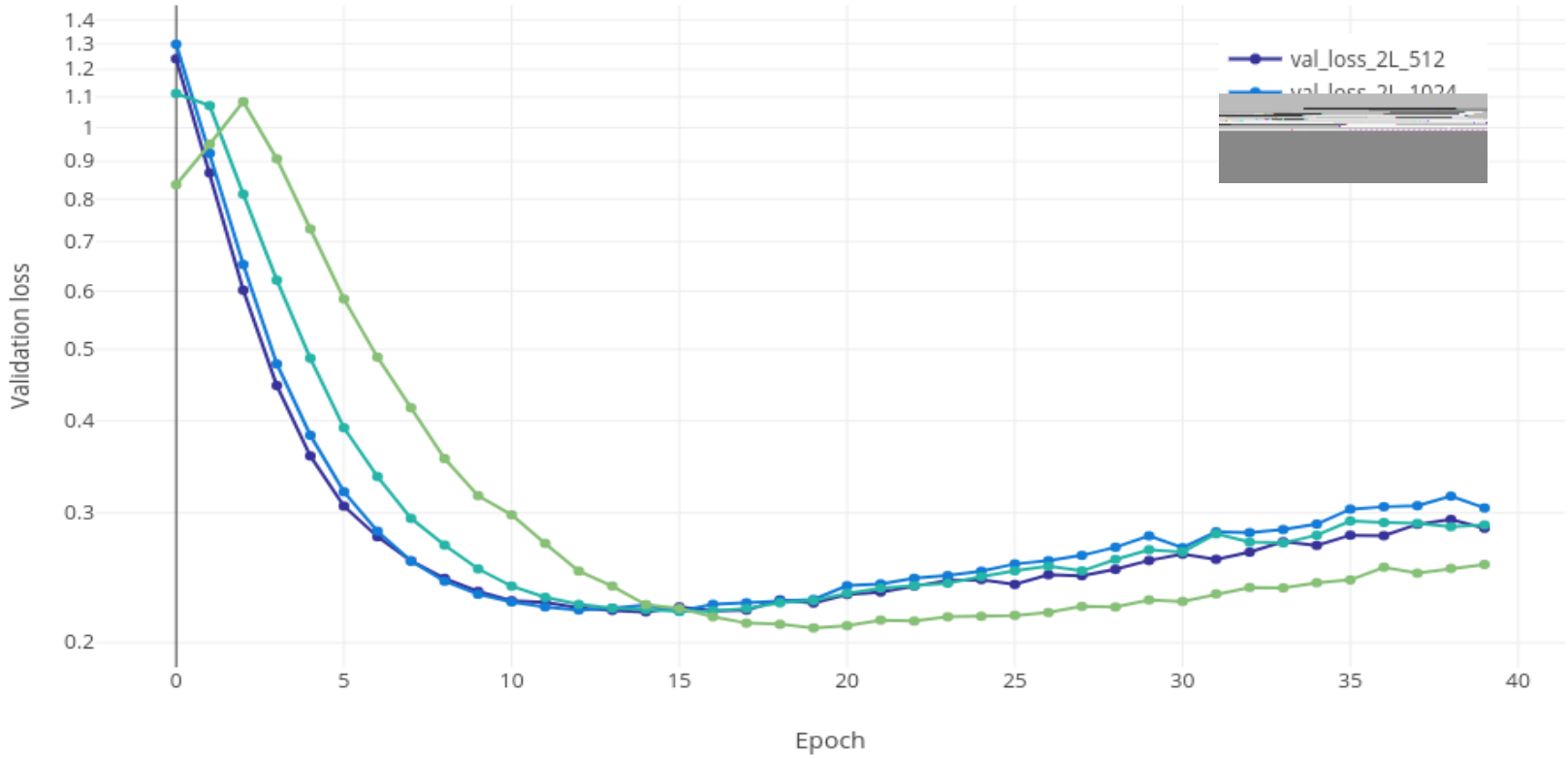




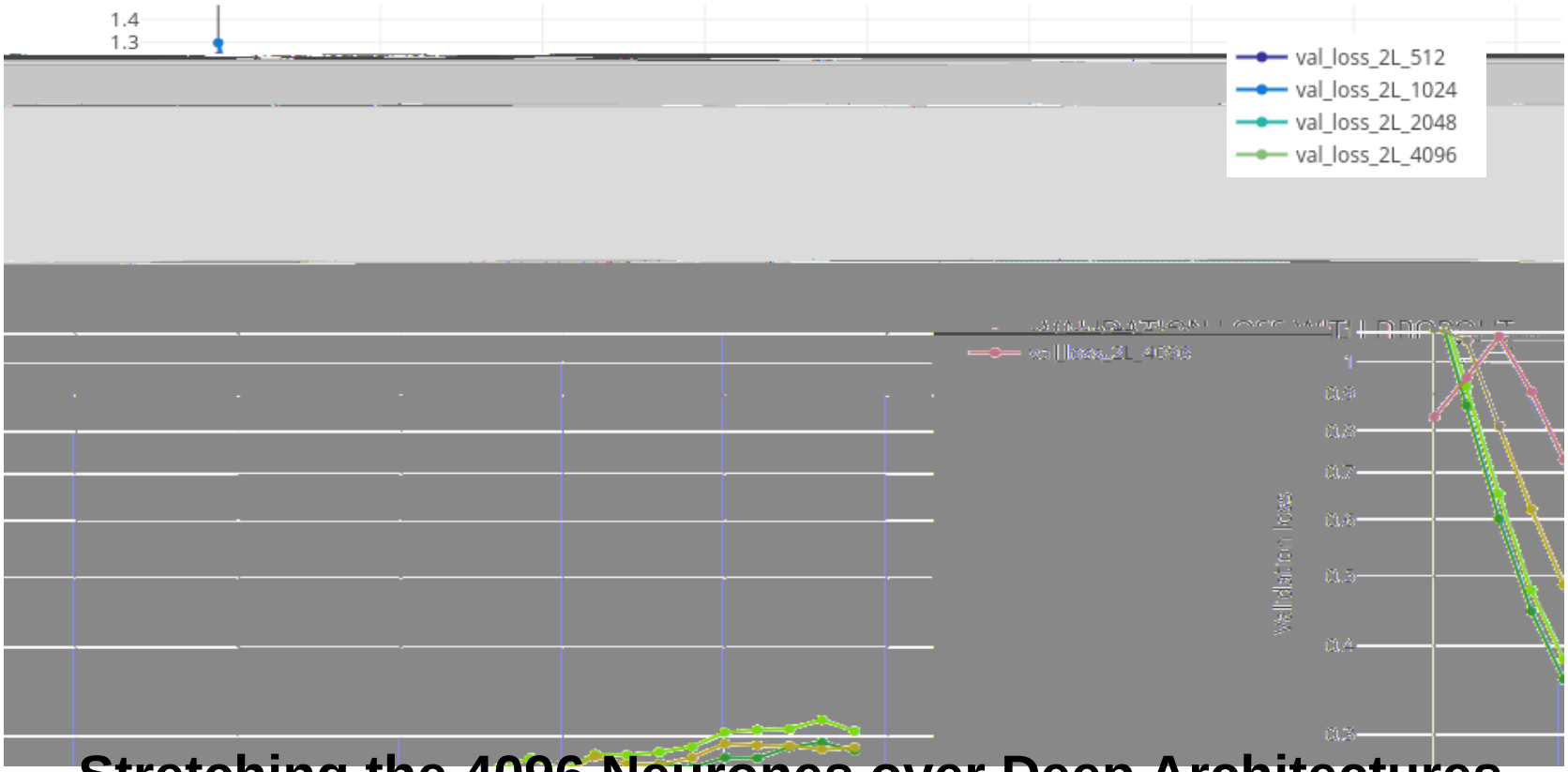
Supervised Learning

Feed-forward Multilayer Perceptron

Experiments: Feed-forward Multilayer Perceptron



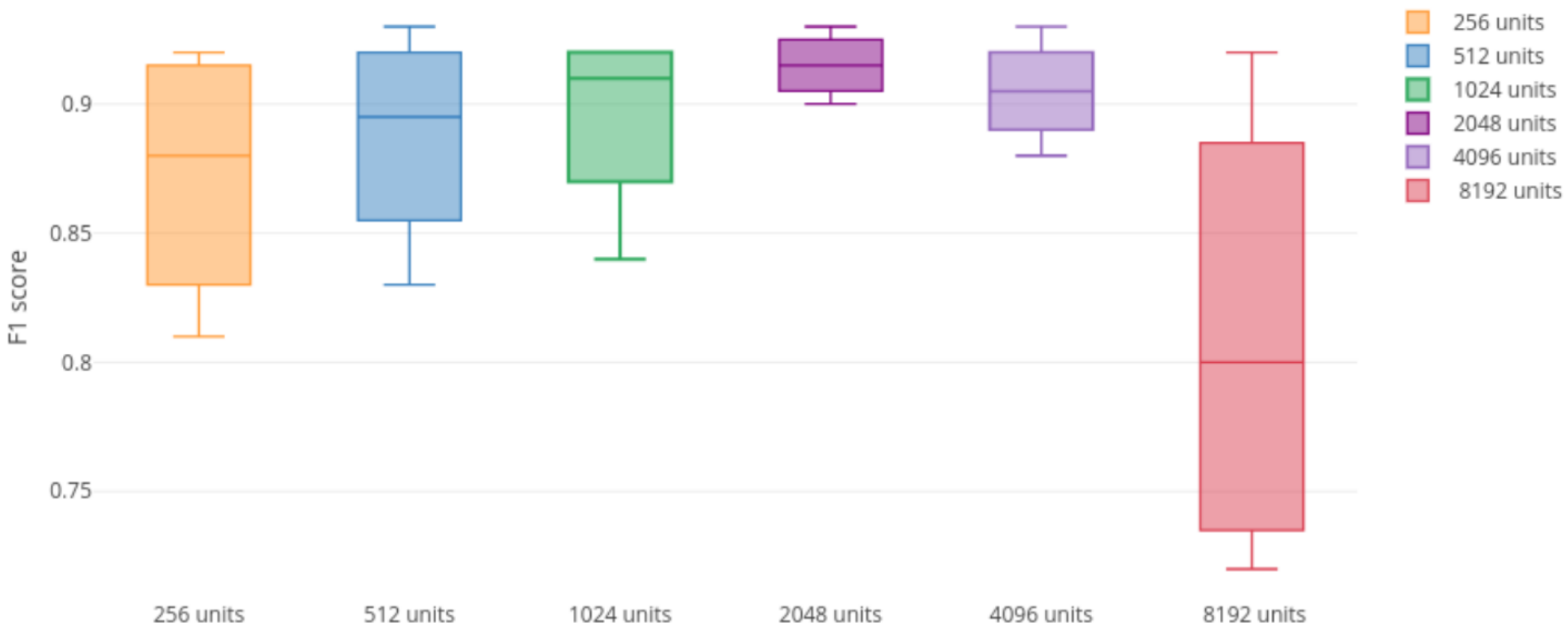
Experiments: Feed-forward Multilayer Perceptron



Stretching the 4096 Neurones over Deep Architectures

Number of units = 4096	F1 score	execution time (hours)	power consumption (watts)	energy consumption Mj
2 layers - 4096 units	0.92	4.85	214.86	3.75
4 layers - 2048 units	0.85	4.8	173.17	32.99
8 layers - 1024 units	0.72	4.76	153.43	2.68
16 layers - 512 units	0.75	4.72	130.95	2.23

Preliminary Results: F1-score for Different Stretching Configurations



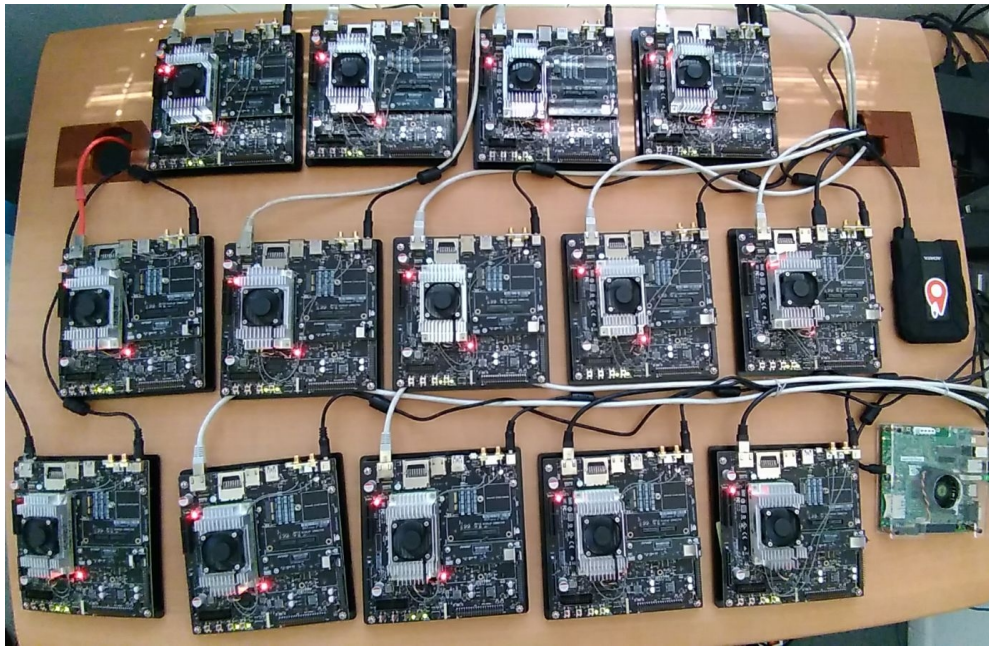
Architecture	F1 score	execution time (hours)	power consumption (watts)	energy consumption Mj
256 units - 2 layers - 128 units	0.91	4.71	92.27	1.57
2048 units - 8 layers - 256 units	0.91	4.73	101.68	1.73
8192 - 2 layers - 4096 units	0.92	4.85	214.86	3.75

Performance Results By class to Classify the Medical Target 1

Classes	True positives	False positives	False negatives	precision	recall	f1 score	occurence de la classe
0	424	54	122	0.89	0.78	0.83	546
1	2089	136	59	0.94	0.97	0.96	2148
2	1382	98	79	0.93	0.95	0.94	1461
3	598	72	34	0.89	0.95	0.92	632
4	211	73	153	0.74	0.58	0.65	364
5	861	136	141	0.86	0.86	0.86	1002
6	2086	96	105	0.96	0.95	0.95	2191
7	1574	115	74	0.93	0.96	0.94	1648
8	76	9	10	0.89	0.88	0.89	86
9	101	74	122	0.58	0.45	0.51	223
10	36	1	3	0.97	0.92	0.95	39
11	275	31	20	0.90	0.93	0.92	295
12	1088	44	16	0.96	0.99	0.97	1104
13	0	2	3	0.0	0.0	0.0	3

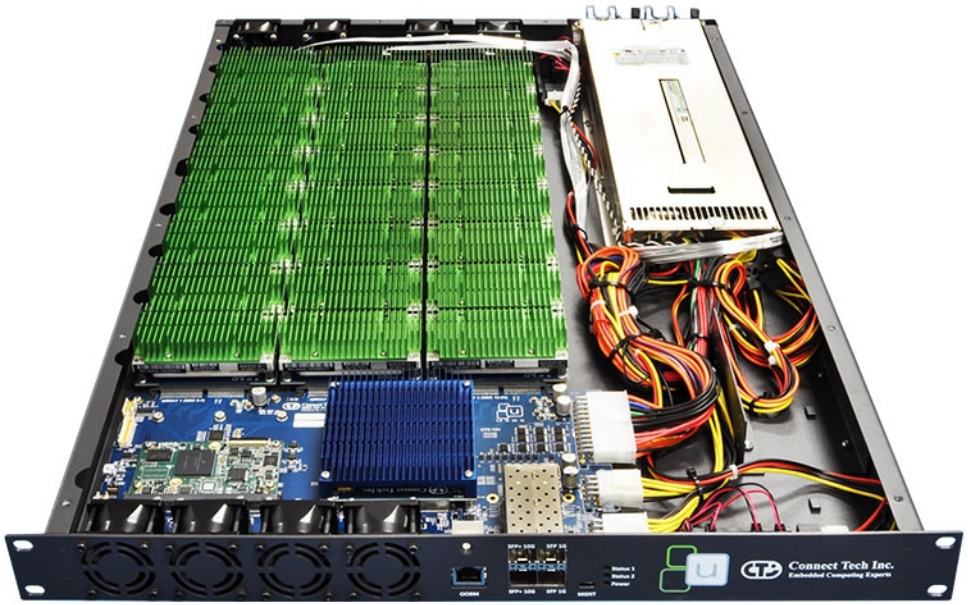
Distributed Processing for Training DNN on Jetson TX2 Mini-Clusters

Computational Resources



Mini-Cluster Jetson TX2

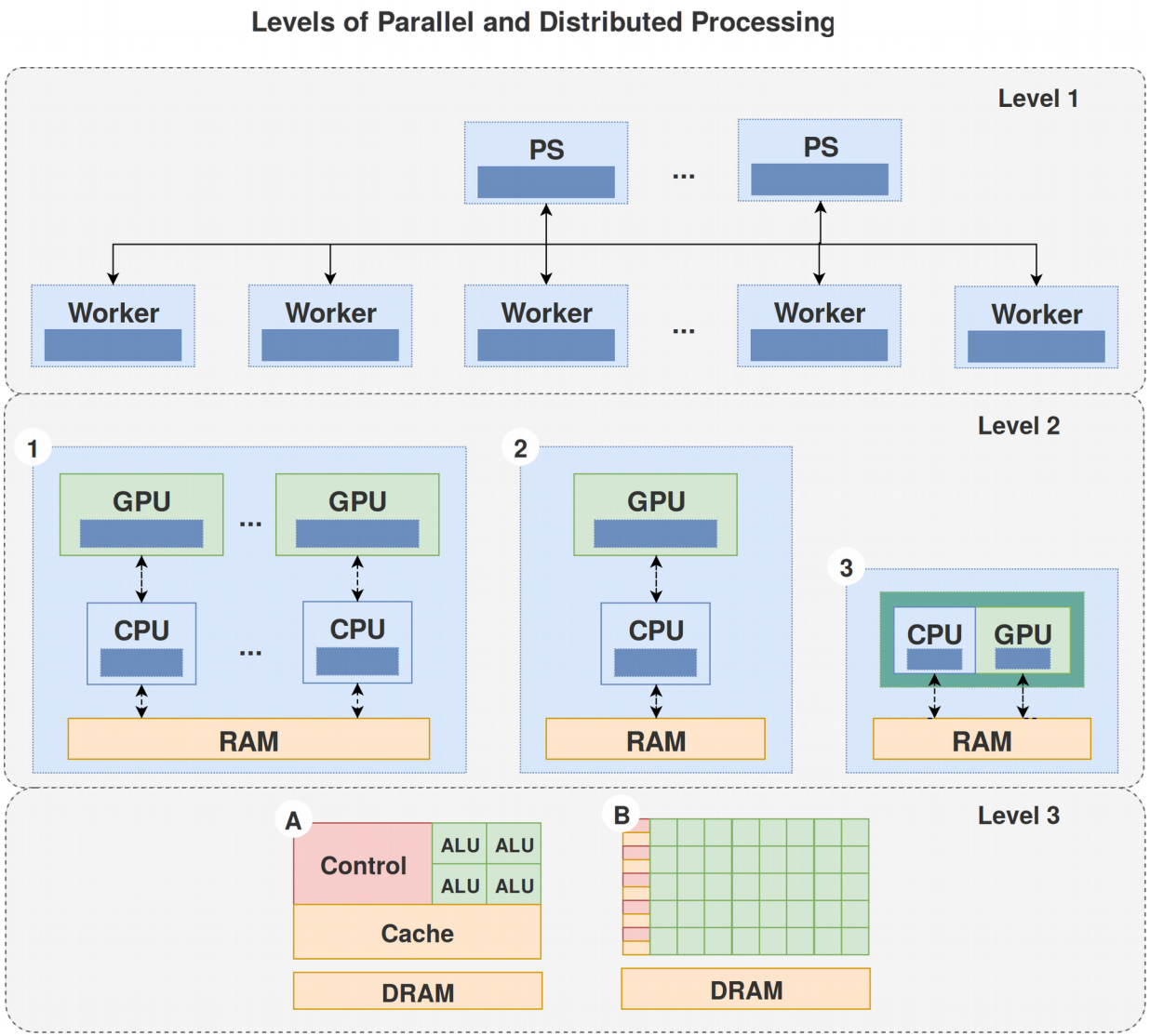
(Distributed Memory)

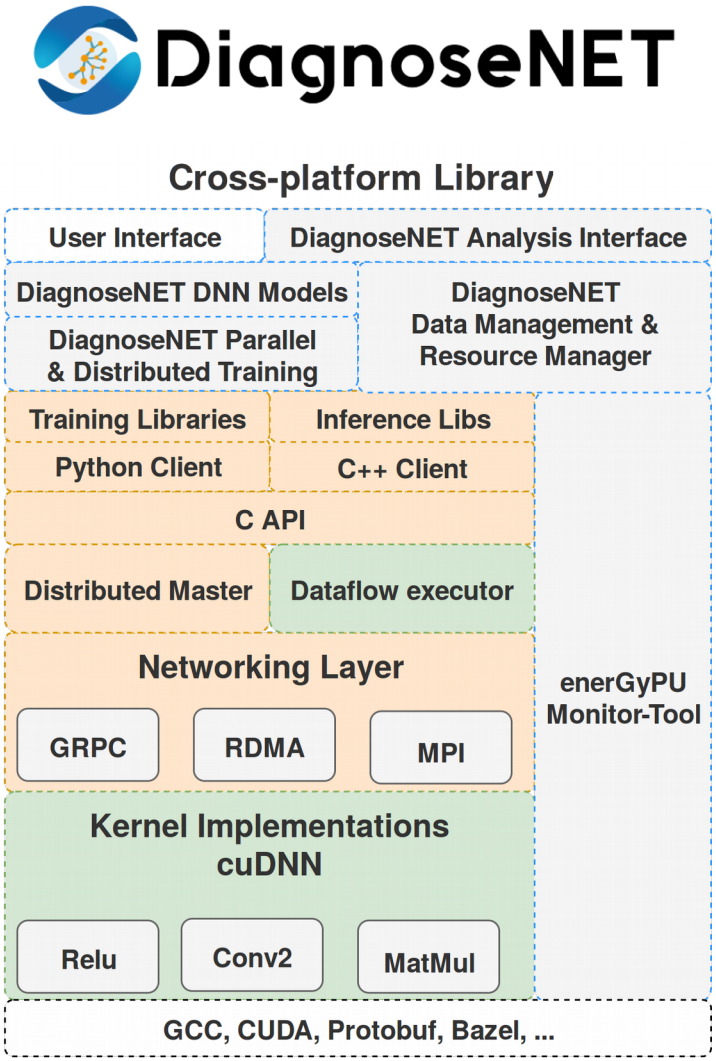


Array Node with 24 Jetson TX2

(Hybrid Memory)

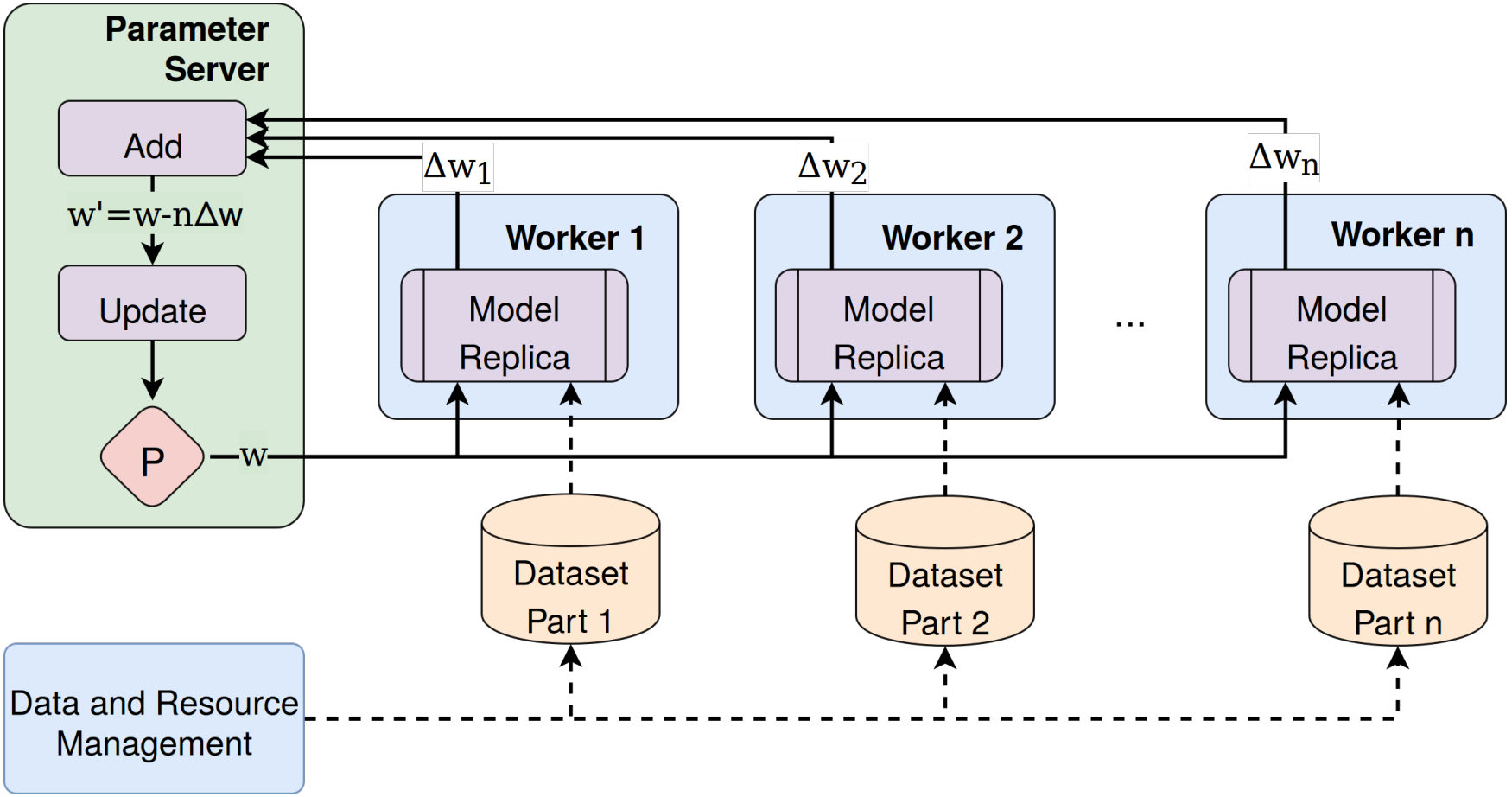
Develop DiagnoseNET for Training Large-Scale DNN on Distributed Systems





7. Adapted from Snap Machine Learning. By IBM Research et al. 2018
8. Adapted from TensorFlow Architecture. By Google Research.

Task-Based Data Parallelism: Synchronous



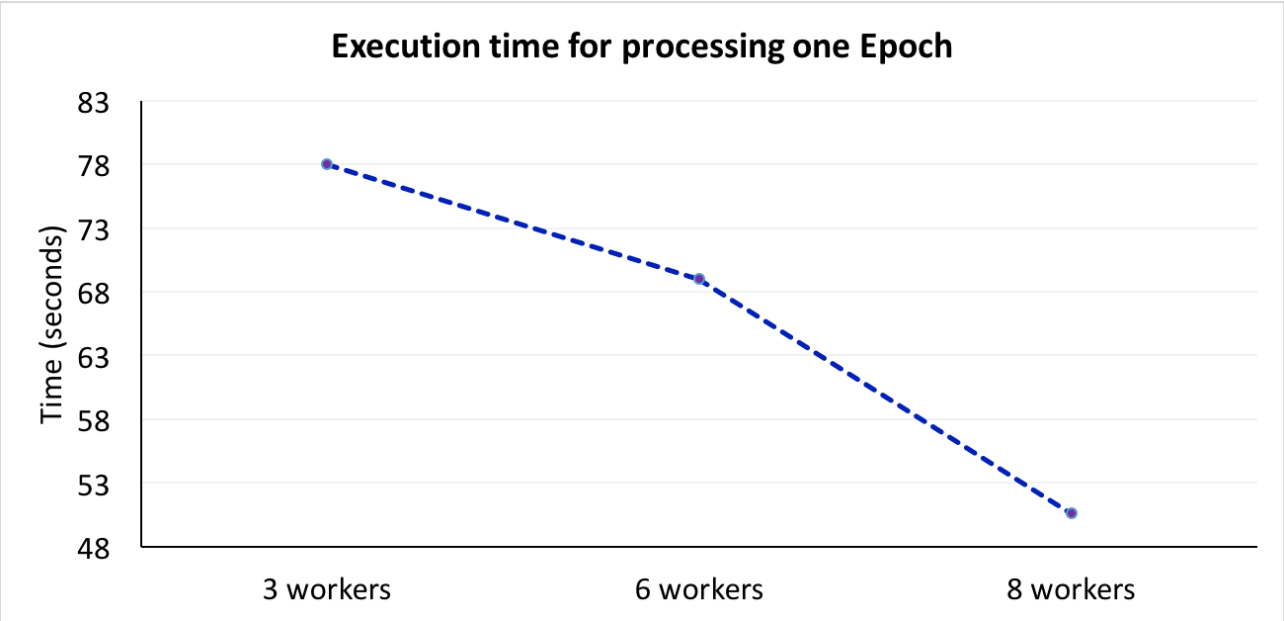
(Data Size):

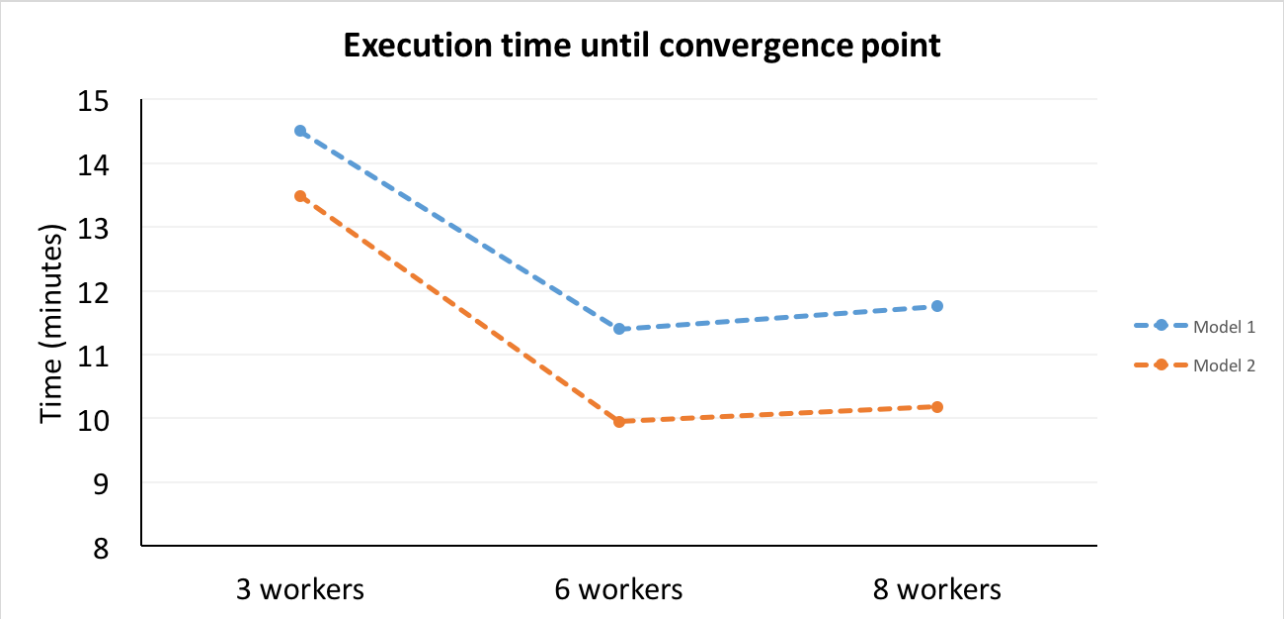
+ Setting the number of workers and micro batch.
+ Fine-tuning DNN hyperparameters.
+ Speeds up the training.
+ I/O Intensive.

9. Adapted from TensorFlow: Large-Scale Machine Learning on Heterogeneous Distributed Systems. By Google Research. 2015.

Preliminary Results to Scale the Unsupervised Representation Learning

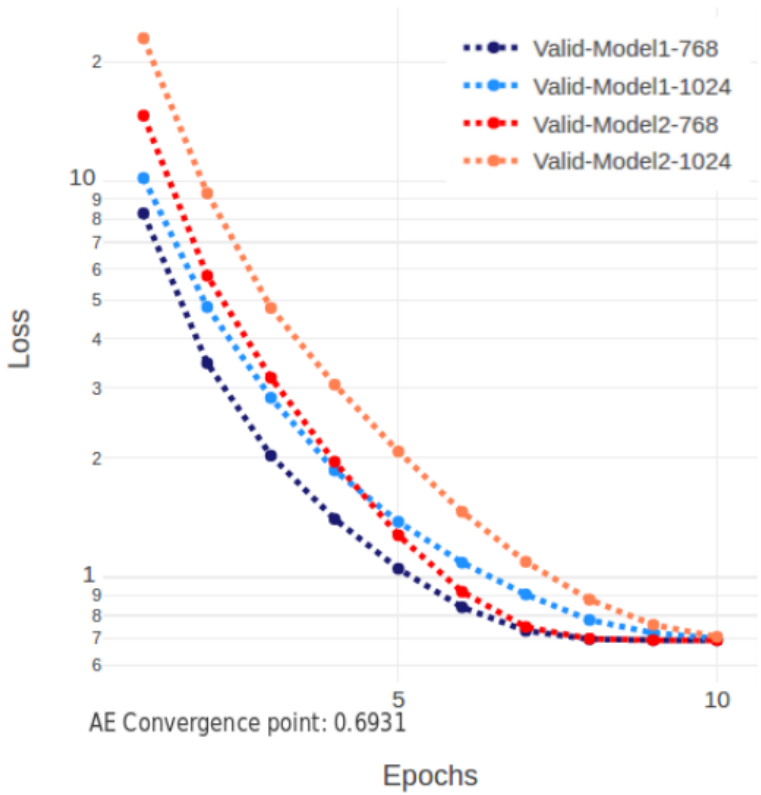
Preliminary results using: 10.000 records and 11.466 features.



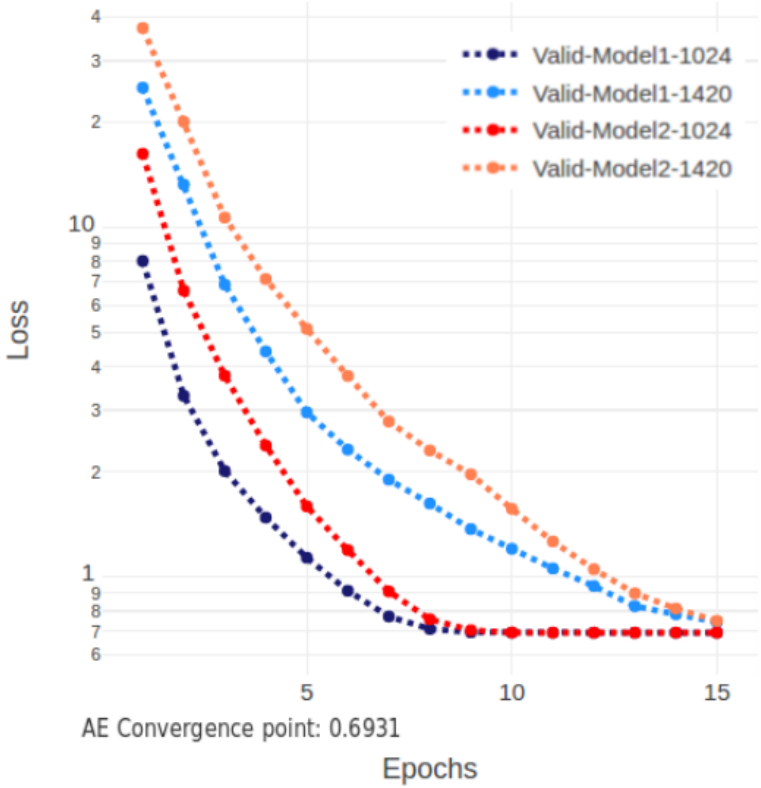


Number of Workers and Task Granularity as Factor to Early Model Convergence

- *Early convergence comparison between different groups of workers and task granularity for distributed training with 10.000 records and 11.466 features.*



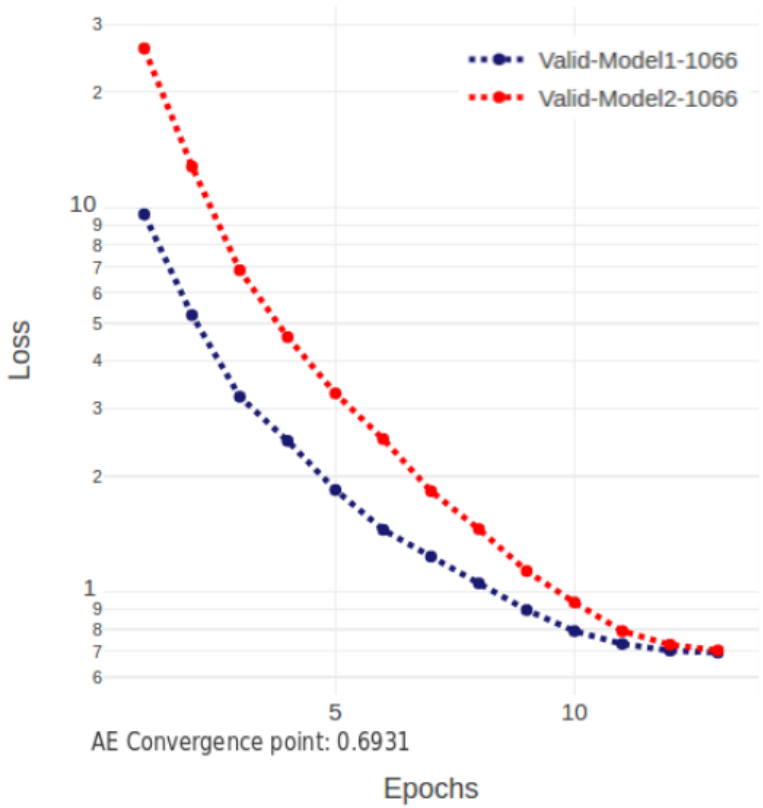
1.30 mins in avergange for processing one epoch on 1 PS 3 workers.



1 min in avergange for processing one epoch on 1 PS 6 workers.

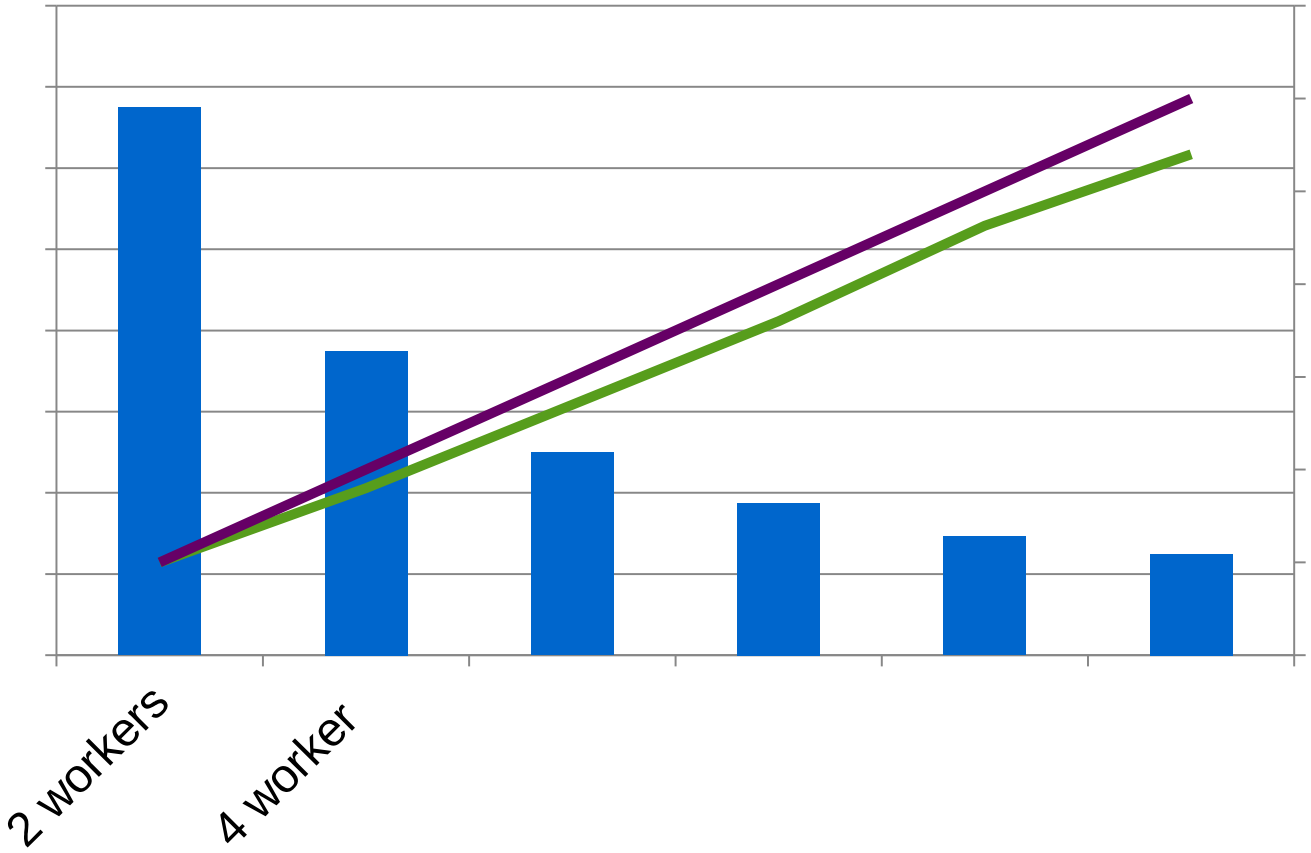
Number of Workers and Task Granularity as Factor to Early Model Convergence

- *Early convergence comparison between different groups of workers and task granularity for distributed training with 10.000 records and 11.466 features.*



50.6 secs in avergange for processing one epoch on 1 PS 8 workers.

Preliminary Results to Scale the Feed-forward Multilayer Perceptron



Conclusions

Using hundreds of **Gradient Updates by Epochs** with synchronous data parallelism offer an efficient distributed DNN training to early convergence.

Adapting the **Number of Records by Batch** or the **Model dimensionality** to minimize the bottleneck of data transfer from host memory to device memory reducing the GPU idle status.

Use a mini-Cluster of Jetson TX2 presents good results in distributed training using synchronous data parallelism.

Therefore, this can be used as a learning center with minimal infrastructure requirements and low power consumption and brings the opportunity to use a dataset with more patient's features.

Latent Representation:

- Reduces the number of sparse features without loss of precision in future classification.
- Reduces training time (41 %) to classify the first medical target.

Next Work on DiagnoseNET

- Distributed others kind of DNN architectures Like (CNN, RNN) and Tensor Forest.

- Compare several architecture:
    - multi-GPU (share memory)
    - vs Cluster (distributed memory)
    - vs Array (hybrid memory)

- For several medical task:

  MT-1: Predict the ‘Care Purpose or Major Clinical Category’ of patients in (coarse grain CMC / fine grain GHJ) from inpatients features recorded at the admission time.

  MT-2: Predict the ‘Clinical Procedures’ from Inpatients features recorded at the admission time and the Primary Morbidity.

  MT-3: Predict the ‘Inpatient Destination’ (home, transfer, death) and length of hospitalization stay from inpatients features recorded at the admission time and Primary Morbidity and Clinical Procedures.

Thanks for your attention

Scalability Analysis of Mini-Cluster Jetson TX2 for Training DNN Applied to Healthcare

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Département d'Informations Médicales DIM – CHU Nice

DiagnoseNET: Green Intelligence System Criteria

1) Select optimal computational resources and make good mapping of task granularity for training one model in less time and less power consumption give a mini-batch size factor.

2) Minimize the number of different trained models to converge the optimal generalization-accuracy model.

3) Management the queue of models to training and determine optimal combination of computational resources to use in each model training.