

IMPLEMENTATION OF EXTRACTING UNIVERSITY STUDENT DETAILS THROUGH DATA ANALYSIS

*M. Mahesh, Dr.G. Sindhu

*UG Scholar, Saveetha School of Engineering, Saveetha Institute of Medical and Technical Sciences, Chennai Assistant Professor, Saveetha School of Engineering, Saveetha Institute of Medical and Technical Sciences,

Chennai

*mannammahesh30@gmail.com, sindhudhara@gmail.com

Abstract

Article Info Volume 83 Page Number: 574 - 585 Publication Issue: July-August 2020

Article History Article Received: 25 April 2020 Revised: 29 May 2020 Accepted: 20 June 2020 Publication: 10 August 2020 University dropout will outcomes the all universities college students in the world, with results which include reduced registratation, lessen the revenue for the college, lossing the cash for state that budget the studies, and joining the constitutes a social outcomes for college students, their families, and also society. The importance of predicting college dropout is locating the dropout college students earlier than leaving the university, with the intention to stlye strategies to tackle the results of it. By proofing the large knowledge technology to store the scholars attendance, checking marks, verbal exchange abilities to find the exact students destiny marks who has got the highest marks from the dropout college students. We are seeking to use different types of learning system to take away the most choices of being dropout. This may reduce the dropout pieces of the university students and their general marks. As well as discover and detailing the performance of comparative look at with locating the maximum effective accurancy practice in numerous supervised device learning method through the given dataset with interface based on the whole application through given dataset.Decades of analysis on artificial neural networks (ANNs) have published the thought that ANNs square measure per sensitive to missing/incomplete inputs at prediction time. Studies on dependable ANNs show that a neural network can't be thought of in and of itself fault tolerant, and it's unimaginable to induce complete error masking once a fault occurred, even within the presence of learning. Specific methodologies and neural design have thus been planned to enforce fault tolerance, however largely restricted to failure in hidden neurons.

Keywords: University Dropout, ANNs, Social Outcomes;

INTRODUCTION

The information that's on the far side to the storage capability and on the far side to the method power such a knowledge is termed massive knowledge. Massive knowledge suggests that extremely data; it's a group of giant datasets that can't be processed victimization of old computing techniques. Massive knowledge isn't simply a data'; rather it's become a whole subject, that involves in several tools, techniques and framework. Knowledge that area unit terribly in size termed massive knowledge. Unremarkable we tend to figure on



knowledge of size MB (wordbook, Excel) or most GB (Movies, Codes) however knowledge in petabytes i.e. 10^15 memory unit size is termed massive knowledge. It's explicit that almost 19th knowledge has been generated within the past six years ago.

LITERATURE SURVEY

Student's feedback is crucial for tutorial institutions so as to gauge faculty performance. Handling the qualitative opinions of scholars efficiently while automatic report generation may be a challenging task. Indeed, most of the organizations affect quantitative feedback effectively, whereas qualitative feedback is either processed manually or ignored altogether. This research proposes a supervised aspect based opinion mining system supported two layered LSTM model. The primary layer predicts the aspects described within the feedback and later specifies the orientation (positive, negative, neutral) of these predicted aspects. The model was tested on a manually tagged dataset constructed from the last five years student's comments from Sukkur IBA University also as on a typical SemEval – 2014 dataset. Unlike many other LSTM models proposed for other domains, the proposed model is sort of simple in terms of architecture which ends up in less complexity. The system attains good accuracy using the domain embedding layer in both tasks: aspect extraction (91%) and sentiment polarity detection (93%). To the simplest of our knowledge, this study may be a first attempt that uses deep learning approach for performing aspect based sentiment analysis on student's feedback for evaluating faculty teaching performance.

Gaussian mixture model (GMM) is employed for soft detector modeling of multimode industrial processes. However, it's been recognized that the performance of GMM deteriorates with the presence of outliers that normally exist in industrial datasets. Additionally, Samples with legendary labels in soft detector applications square measure typically rare as a results of big-ticket sampling instruction or long laboratory analysis. Shortage of labelled samples may lead GMMbased models to seek out information distributions; notwithstanding, with the virtual of the long tail property of Student's distribution, the SSMM possesses stronger lustiness against outliers compared with the GMM. Moreover, the semi-supervised model structure of SSMM allows exploiting unlabeled samples of the SSMM, specified the issues caused by skimpy labelled samples could also be tackled. To identify model parameters of the SSMM, we tend to additionally develop an expectation-maximization based coaching formula. Experimental results on numerical and industrial examples demonstrate that the planned technique is effective such as:

1) Modelling multimode characteristics

2) Exploiting unlabeled samples for performance improvement

3) Handling distinct outliers (in artificial dataset) and indistinct outliers (in industrial dataset).

Higher education in other countries has got to affect constant troubles and uncertainties thanks to the depression, high rates of unemployment in children, lack for study habits in lyceum and legal fluctuations. This uncertain environment doesn't foster student effort and it's behind the important rates of abandon in education. The Bologna process was thought to make a replacement paradigm in education within the European Union. However, the changes came from the highest(governments) to rock bottom (lectures and students) in order that they weren't properly supported by specialized training oriented to lectures. It didn't include the acceptable changes in lower education stages (secondary education) to organize student when facing university. Therefore, within the past decade several new teaching methodologies have seemed to affect student demotivation and to fight against dropouts. Those methodologies attempt to keep the



scholars engaged during the entire course paying more attention to their learning process, attitudes, motivations and expectations. Consequently, during this paper, we present a four -year experiment whose main objective is to stay students engaged during the entire year and to foster their motivation so as to extend their learning outcomes. The experiment is predicted on the appliance of gamification to the assessment process emulating a standard platform video-game, like super mario. The results show that this experiment was positive for many students who achieved good marks and good rates of task completion.

A redesign of the Moodle platform to adapt digital educational content [learning objects (Los)] to precise needs of scholars with disabilities. The approach, extendable to a variety of disciplines, was empirically tested with blind and deaf engineering students. With the arrival of the web and therefore the development of latest technologies, society has changed. People now interact and communicate differently. Sites and online applications have spread rapidly, transforming human activities. Education is not any exception during this regard: the emergence of online or e- learning has facilitated the event of latest learning methods wherein educational resources are presented via the online. During this paper, e-learning is broadly defined as "all sorts of electronic supported learning and teaching, which are procedural in character and aim to effect the development of data with regard to individual experience, practice and knowledge of the learner.

"we don't receive procedures; strategies embrace us." The investigation of the dissemination of advancements is worried about the reception and spreading of latest items, procedures, calculations, and thoughts by means of certain correspondence channels among people and associations, as a rule out the precise circumstance of an off-the-cuff community. Having an advancement spread rapidly during a social framework is certifiably not a minor issue. Numerous social researchers and market analysis have created hypotheses to advance equal showcasing procedures for advancing advancements. Among such examinations, three components of the dissemination procedure are regularly viewed as: the properties of the event, the correspondence channel, and therefore the informal community structure. Extensive exertion in dissemination cares has been given to both displaying the massive scale dispersion process and demonstrating the conduct of individual clients. Concentrates on the complete scale level typically center on displaying the event of a populace's system thoughtfulness regarding advancement. Different works investigate the auxiliary qualities of relational systems what's more; catch the effect of social impact. Dissemination ponders with reference to singular client's conduct have clothed to be progressively documented by exploiting of recently rose informal organization information, for instance, Facebook, Twitter, and live Journal, and additionally scholastic coordinated effort systems, for instance, coinitiation systems and reference systems. These examinations have uncovered furthermore. reconfirmed the elemental associations between social impact and therefore the results of dissemination.

PROBLEM STATEMENT:

To make a scientific review of literature on the prediction of college student dropout through data processing techniques. Methods/Analysis: The study was developed as a scientific review of the literature of inquiry results regarding the prediction of university dropout. During this phase, the review protocol, the choice requirements for potential studies and therefore the method for analyzing the content of the chosen studies were provided. The classification presented in section 3 allowed answering the most research question. What are the aspects considered within the prediction of college student desertion through data mining? Findings: University dropout may be a problem which affects universities round the world, with consequences like reduced enrolment, reduced



revenue for the university, and financial losses for the state which funds the studies, and also constitutes a social problem for college kids, their families, and society generally. Hence the important of predicting university dropout, that's to mention identify dropout students beforehand, so as to style strategies to tackle this problem. Novelty/Improvement: this is often the primary work to perform an integral systematic literature review about university dropout prediction through data processing, with studies.

PROPOSED SYSTEM:

Proposed concept deals with providing database by using Hadoop tool we will analyze no limitation of

knowledge and straightforward add number of machines to the cluster and that we get results with less time, high throughput and maintenance cost is extremely less and that we are using joins, partitions and bucketing techniques in Hadoop.

TECHNIQUES USED:

HADOOP TOOL:

Hadoop tool is opensource framework which as overseen by the apache software foundation and it's used for storing and processing huge datasets with a cluster of commodity hardware. We use Hadoop tool contains two things one is hdfs and map reduce. We also use Hadoop ecosystems like sqoop, hive and pig.



Figure 1: . System Architecture

MODULES:

- Existing Application (MySql)
- Connector (Sqoop)
- Analysis Query Langauge (Hive)

• Analysis Latin Script (Pig)

• Processing (Map Reduce)

DESCRIPTION FOR MODULES:

Published by: The Mattingley Publishing Co., Inc.



1. Existing Application (My Sql):

In My Sql may be a electric database management system. RDMS uses relations portables to store University data as a matrix of rows by columns with primary key. With My Sql language, University data in tables are often collected, stored, and processed, retrieved, extracted and manipulated mostly for business purpose. Existing concept deals with providing backend by using My Sql which contains lot of drawbacks i.e. data limitation is that time interval is high when the info is large and once data is lost we can't recover so thus we proposing concept by using Hadoop tool.



Fig 2. My SQL Architecture

2. Connector (Sqoop):

Sqoop may be a command-line interface application for transferring University data between relational databases (MySQL) and Hadoop. Here in MySQL database having University data need to import it to HDFS using Sqoop. University data often moved into HDFS/Hive from MySQL then it'll generate the java classes. In previous cases, flow of knowledge was from RDMs to HDFS. Using "export" tool, we will import data from HDFS to RDMs. Before performing export, Sqoop fetches table metadata from MySQL database. Thus we first got to create a table with required metadata.



Fig 3. Sqoop Architecture

3. Analysis Query Language (Hive):

Hive may be a data ware house system for Hadoop that runs SQL like queries called HQL (Hive query Language) which gets internally converted to map reduce jobs. In Hive, University data tables and data bases are created first then data is loaded into these tables. Hive organizes university data tables into partitions. It's how of dividing a table into related parts supported the values of partitioned columns. Using partition, it's easy to question some of the given dataset. Tables or partitions are sub-divided into buckets, to supply extra structure to the University data which will be used for more efficient querying. Bucketing works supported the worth of hash function of some column of a table.



Fig 4. Hive Architecture

4. Analysis Latin Script (pig):

To the research University data using Pig, programmers got to write scripts using Pig Latin language and execute them in interactive mode using the Grunt shell



of these scripts are internally converted to Map and Reduce tasks. After invoking the Grunt shell, you will run your pig scripts within the shell. Except LOAD and STORE, while performing all other operations, Pig Latin statements take a relation as input and produce another relation as output. As soon as you enter a Load statement within the Grunt Shell, its semantic checking are going to be administered to ascertain the contents of the schema, you would like to use the dump operator. Only after performing the dump operation, the Map Reduce job for loading the info into the filing system are going to be administered. Pig provides many builtin operators to support data operations like grouping, filters, ordering etc.



Fig 5. Pig Architecture

5.Processing (Map Reduce):

Map Reduce may be a framework using which we will write applications to process huge amounts of University data, in parallel, on large clusters of commodity hardware during a reliable manner. Map Reduce may be a processing technique and a program model for distributed computing supported java. The Map Reduce algorithm contains two important tasks, namely Map and Reduce stage. The map or namely mapper's job is to process the input file. Generally the input file is within the sort of file directory and is stored within the Hadoop filing system (HDFS). The input data is passed to the mapper function line by line. The mapper processes the info and creates several small chunks of knowledge. This stage is that the combination of the shuffle stage and therefore the Reduce stage. The Reducer's job is to process the info that comes from the mapper. After processing, it produce a replacement set of output, which can be stored within the HDFS.



Fig 6. Map Reduce Architecture

RESULT:

Main scope of this paper, Here no missing inputs of students details won't be there because of we are using Hadoop tool while predicting university student details. If we are using My SQL some missing inputs will be there because of processing time is high and moreover data is more. For transferring the university data between My SQL and Hadoop tool, it has been converted through Sqoop tool.

University Dropout Student's Details Through Data Analysis



Implementation Screenshot:



1	-	Inert	Page	Layos		Farmular	Deta	faire		Hilp :		Tell ros w	het yna ware n				
Ka			Celler		v	11 V A	1 10	-10	8- 1	t was	Tet	1	General	~	围	199	100
ELC.	η														Confiten	al Frend	
550	mat Pa	rter		* *	1.8	1. × 1.	A : =		CH 54 6	in Mary	ence		Sec. West.	36.45	Formatting	· Takle	Styles
Option	10	12			Ford		. 6		Alignmen			- 5	Nanber	- 4		Styles	
	1.0				1.44	the Brown											
				~	30	ALM_NEATTON											
- A-			· C		D	1		4			1	1		- E - 1	M	N	0
Statie_Na	Destrie	T.NO	op Yea	Seas	son.	Crop	Area	rainfall	Average	t h Me	an Ter	Cost of C	UCost of Phil	rield (Carl	cest of prov	fuction p	ersieh
Andaman	NICO	LAR!	2000	Khar	nit.	Arecanut	1254	0.01236	1 3	57	62	29076.7	6 1941.55	9.83	19085.44		
Andaman	NICOL	LAR:	2001	the	nit .	Arecanut	125	0.00411	9. 5	56	58	12630.8	5 1691.66	6.83	11554.04		
Andaman	NICOL	LAR	2002	Who	de Ye	Anecanut	1258	0.09006	4 3	16	53	32683.4	6 3207.35	9.33	29924.58		
Andamian	NICO	ARS	2005	Whi	tio Ye	Arecariut	1261	0.18105	1 1	5.7	58	13209.3	2 2228.97	5.9	13150.92		
Andaman	NICOE	AAR!	2004	Who	de Ye	Anecanut	1264.3	0.03544	6 6	63	67	22560.	3 1595.56	13.57	21451.75		
Andaman	NICO4	LAR!	2005	Who	ile Ye	Arecanut	795.63	0.10853	6 3	27	64	15423.4	8 804.8	39.63	32055.18		
Andaman	NICO	18.Ad	2006	Who	da Te	Arecenut	89	0.21128	5 1	18	58	28144.	5 2529.47	8.72	22544.18		
Andaman	NICOL	SAR:	2050	Rabi		Arecanut		0.24275	8 3	52	- 75	\$5801.9	5 1918.92	11.96	22388.66		
Andaman	NORT	1AH	2000	Khai	n#	Arecanut	310	0.23189	6 3	36	81	45291.3	4 715.04	36.61	26177.61		
Andaman	NORT	HAT	2001	Khar	nt	Arecarut	3100	0.0	5 2	21	75	89025.2	7 119.72	985.21	118069.1		
Andaman	NORT	MAR	2006	Who	ile Ye	Arecanut	1100	0.01387	9 I	14	72	28344	5 3670.54	2.47	27414.88		
Andaman	NORT	NAT .	2010	Rabi		Arecanut	1294	0.01387	9. 4	80	34	89025.2	7 2358	4.75	11106.18		
Andamian	SOUTH	AA.	2002	Who	de re	Anadanut	5105		D 1	19	26	19083.5	5 789.9	33.04	30837.7		
Andamian	SOUT	AA H	2005	Who	de re	N Arecanut	3110	i (0 3	17	93	29676.3	6 85.79	757.92	65021.96		
Andeman	SOUTH	4A3	2004	Who	te re	s Arecanut	8140.67		D 3	16	91	17705.9	9 2003.76	6.42	12864.14		
Andeman	SOUT	4AN	2005	Who	de Te	s Arecanut	3250.70	() (0; 3	27	94	22489.7	5 2554.91	8.05	20547.03		
Andaman	SOUT	AA.	2006	Who	1. 74	Arecanud	2000		5 d	54	80	17705.9	3 2261.24	4.03	9138-022		
Andaman	SOUT	(Ah	2010	Rabi		Anecanut	1913	0.03233	8)	54	83	9185.5	9 107.56	448.89	48282.61		
Andaman	NORT	HAP.	2010	Rabi		Actor_Tu	294.5	0.09954	5 3	34	54	22489.7	5 1918.92	11.97	22565.47		
Andaman	SOUT	44.1	2010	Rabi		Acher_Tut	20.5	6.02107	8. d	58	85	7868.6	4 85.79	986.23	84506.96		
Andaman	NICO	SAR!	2000	Who	de 7e	s Benana	17	0.03174	7 6	12	56	24171.6	5 3670.54	6.42	23564.87		
Andeman	NICOL	SAR!	2002	(Mho	de Ye	Barrana	211	0.07767	6	16		19857.	7 404.43	42.95	17170.27		
	He H	Lane Lane Lane Lane Lane Lane Lane Lane	Itaria Itaria Itaria Itaria Itaria Itaria Itaria Itaria Itaria Itaria Itaria Itaria Itaria Itaria Itaria Itaria Itaria Itaria Itaria Itaria Itaria Itaria Itaria Itaria Itaria Itaria Itaria Itaria Itaria Itaria Itaria Itaria Itaria Itaria Itaria Itaria Itaria Itaria Itaria Itaria Itaria Itaria Itaria Itaria Itaria Itaria Itaria Itaria Itaria Itaria Itaria Itaria Itaria Itaria Itaria Itaria Itaria Itaria Itaria Itaria Itaria Itaria Itaria Itaria Itaria Itaria Itaria Itaria Itaria Itaria Itaria Itaria Itaria Itaria Itaria Itaria Itaria Itaria Itaria Itaria Itaria Itaria Itaria Itaria Itaria Itaria Itaria Itaria Itaria Itaria Itaria Itaria Itaria Itaria Itaria Itaria Itaria Itaria Itaria Itaria Itaria Itaria Itaria Itaria Itaria Itaria Itaria Itaria Itaria Itaria Itaria Itaria Itaria Itaria Itaria Itaria Itaria Itaria Itaria Itaria Itaria Itaria Itaria Itaria Itaria Itaria Itaria Itaria Itaria Itaria Itaria Itaria Itaria Itaria Itaria Itaria Itaria Itaria Itaria Itaria Itaria Itaria Itaria Itaria Itaria Itaria Itaria Itaria Itaria Itaria Itaria Itaria Itaria Itaria Itaria Itaria Itaria Itaria Itaria Itaria Itaria Itaria Itaria Itaria Itaria Itaria Itaria Itaria Itaria Itaria Itaria Itaria Itaria Itaria Itaria Itaria Itaria Itaria Itaria Itaria Itaria Itaria Itaria Itaria Itaria Itaria	te Hann Collar 200 Collar Collar Col	Hannel Hannel Poper Layor I Garge - St Garge - St Famma Pairter Caller II. J. M Descent I Garge - St Garge -	Norme Norme Zoge Loyof If Group - St Gr	News Yeart Page Layort Fermulai Image Copy Image Image	Name Junit Digit Lipod Familia Oto Image Carp Image Image <td< td=""><td>Name Name Name Page Logot Learnal Outo Page Logot Learnal Outo Page Logot Learnal Outo Page Logot Learnal Outo Page Logot Page</td><td>Name Name Degle Laynut Family and the second Defense Name Name </td><td>Items Item Topic Local Family and the second Early and</td><td>Norme Norme Zege Loyod Familie Order Norme Norme Norme Opp Distance Norme Norme</td><td>Name Yand Opp Layor Family Value Page Layor Family Value Value</td><td>Name Vent Page Layort Landon Odd Name Vent Page Layort Cannot Odd Name Vent Page Layort General</td><td>Norme Norme Sign Logon, T Famme And Other Norme Vision V</td><td>Name Name Age Loyof Faire data Otes Name Year <thyear< th=""> <thyear< th=""> <thyear< th=""></thyear<></thyear<></thyear<></td><td>Norme Norme Sign Local Earned Norme Norme Norme Norme Norme Norme Coll Coll</td></td<>	Name Name Name Page Logot Learnal Outo Page Logot Learnal Outo Page Logot Learnal Outo Page Logot Learnal Outo Page Logot Page	Name Name Degle Laynut Family and the second Defense Name Name 	Items Item Topic Local Family and the second Early and	Norme Norme Zege Loyod Familie Order Norme Norme Norme Opp Distance Norme Norme	Name Yand Opp Layor Family Value Page Layor Family Value Value	Name Vent Page Layort Landon Odd Name Vent Page Layort Cannot Odd Name Vent Page Layort General	Norme Norme Sign Logon, T Famme And Other Norme Vision V	Name Name Age Loyof Faire data Otes Name Year Year <thyear< th=""> <thyear< th=""> <thyear< th=""></thyear<></thyear<></thyear<>	Norme Norme Sign Local Earned Norme Norme Norme Norme Norme Norme Coll Coll

CONCLUSION:

In this paper, we presented a study on data and prediction regarding research paper about university dropout's data, to research the info in Hadoop ecosystem and to enhance the student's mark standard supported marks on internals, attendance, extracurricular etc. Hadoop ecosystem is using hive, pig, map reduce tools for processing whether output will take less time to process and result are going to be in no time. Hence during this project, University student's data which is traditionally getting to store in RDMS getting to less performance, hence by using Hadoop tool the data's are going to be faster and efficiently processed.

We have shown how a widely known regularization technique, dropout, often effectively won't to train neural networks that are resilient to missing inputs at test time. The proposed approach is straightforward and computationally efficient. It doesn't use any external or companion learning model to supply advanced input imputation functionalities. Rather it works on the model itself, making it robust intentionally with only a minimal change to the training process. The approach is additionally general and applicable to any neural model, even those that we typically don't use dropout regularization, likes RC models. We have also discussed the connection between DropIn and data augmentation techniques, providing empirical evidence that DropIn isn't like perform data augmentation in input space, a minimum of from the purpose of view of the performance of the trained model. Furthermore, one can expect that exhaustive data augmentation can quickly become computationally unfeasible non trivial input space sizes.

REFERENCES

- 1. A. Kumar and R. Jain, "Faculty Evaluation System", Procedia Computer Science, 125, pp.533-541, 2018.
- B. Wang, and M. Liu, "Deep Learning for sentiment analysis," Stanford University report, vol. 10, no. 12, pp.701-719, 2016.
- 3. L. M. Rojas-Barahona, "Deep learning for sentiment analysis, " Language and linguistics compass, vol. 10, no.12 pp.
- J. Schmidhuler, "Long Short-Term Memory," Neural Computation, vol. 9,no. 8, pp. 1735-1780, 1997.
- Y. Ding, J. Yu, & J. Jiang, "Recurrent Neural Networks with Auxiliary Labels for crossdomain opinion target extraction", Aaai, 3436-3442, 2017.
- D. A. Kaufmann, "Reflection: Benefits of gamification in online higher education." Journal of Instructional Research, vol. 7, pp. 125-132, 2018.
- 7. D. Chalmers and R. Fuller, Teaching for learning at university. Routledge, 2012.
- I. Barker, "Find the time for slow education, "The times educational Supplement Scotland, vol. 2290, pp. 26, 2012.
- 9. A. Veiga and A. Amaral, "Soft law and the implementation problems of the bologna process." Educacaco, Sciedade & Culturals, vol.36, 2012.
- 10. D. Dicheva, C.Dicheva, G.Agre, G.Angelova et al., "Gamification in education: A systematic



mapping study." Educational Technology &Society, vol.18, no. 3,pp. 75-88, 2015.

- H. Jaeger and H. Haas, "Harnessing nonlinearity: Predicting chaotic systems and saving energy in wireless communication," Science, vol. 304, no. 5667, pp. 78–80, Apr. 2004.
- D. Bacciu, F. Crecchi, and D. Morelli, "DropIn: Making reservoir computing neural networks robust to missing inputs by dropout," in Proc. Int. Joint Conf. Neural Netw., May 2017, pp. 2080–2087.
- X. Bouthillier, K. Konda, P. Vincent, and R. Memisevic. (Jun. 2015). "Dropout as data augmentation," [Online]. Available: https://arxiv.org/abs/1506.08700
- J. L. Elman, "Finding structure in time," Cognit. Sci., vol. 14, no. 2, pp. 179–211, Mar. 1990.
- W. Gao and Z.-H. Zhou, "Dropout Rademacher complexity of deep neural networks," Sci. China Inf. Sci., vol. 59, Jul. 2016, Art. no. 072104.
- 16. Y. Wu et al. (2016). "Google's neural machine translation system: Bridging the gap between human and machine translation." [Online]. Available:

https://arxiv.org/abs/1609.08144

- 17. P. J. Werbos, "Backpropagation through time: What it does and how to do it," Proc. IEEE, vol. 78, no. 10, pp. 1550–1560, Oct. 1990.
- C. Gallicchio and A. Micheli. (2017). "Deep echo state network (DeepESN): A brief survey." [Online]. Available: https://arxiv.org/abs/1712.04323
- 19. D. Bacciu, A. Carta, and A. Sperduti. (2018)."Linear memory networks." [Online]. Available: https://arxiv.org/abs/1811.03356
- 20. D. Bacciu, P. Barsocchi, S. Chessa, C. Gallicchio, and A. Micheli, "An experimental characterization of reservoir computing in

ambient assisted living applications," Neural Comput. Appl., vol. 24, no. 6, pp. 1451–1464, May 2014.

- 21. D. Bacciu, C. Gallicchio, A. Micheli, M. D. Rocco, and A. Saffiotti, "Learning context aware mobile robot navigation in home environments," in Proc. 5th Int. Conf. Inf., Intell., Syst. Appl., Jul. 2014, pp. 57–62.
- D. Bacciu, "Unsupervised feature selection for sensor time-series in pervasive computing applications," Neural Comput. Appl., vol. 27, no. 5, pp. 1077–1091, Jul. 2016.
- I. Silva, G. Moody, J. S. Daniel, L. A. Celi, and R. G. Mark, "Predicting in-hospital mortality of ICU patients: The PhysioNet/Computing in cardiology challenge 2012," Comput. Cardiol., vol. 39, pp. 245–248, Sep. 2012.
- 24. Z. Che, S. Purushotham, K. Cho, and D. Sontag, "Recurrent neural networks for multivariate time series with missing values," Sci. Rep., vol. 8, Apr. 2018, Art. no. 6085.