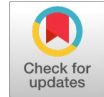


Chatbots Employing Deep Learning for Big Data

Prince Verma, Kiran Jyoti



Abstract: *With the evolution of artificial intelligence to deep learning, the age of perspicacious machines has pioneered that can even mimic as a human. A Conversational software agent is one of the best-suited examples of such intuitive machines which are also commonly known as chatbot actuated with natural language processing. The paper enlisted some existing popular chatbots along with their details, technical specifications, and functionalities. Research shows that most of the customers have experienced penurious service. Also, the inception of meaningful cum instructive feedback endure a demanding and exigent assignment as enactment for chatbots builtout reckon mostly upon templates and hand-written rules. Current chatbot models lack in generating required responses and thus contradict the quality conversation. So involving deep learning amongst these models can overcome this lack and can fill up the paucity with deep neural networks. Some of the deep Neural networks utilized for this till now are Stacked Auto-Encoder, sparse auto-encoders, predictive sparse and denoising auto-encoders. But these DNN are unable to handle big data involving large amounts of heterogeneous data. While Tensor Auto Encoder which overcomes this drawback is time-consuming. This paper has proposed the Chatbot to handle the big data in a manageable time.*

Keywords: Chatbot, Big Data Analytics, Artificial Intelligence, Deep Learning, Auto Encoder, Tensor flow, Neural Networks, Deep Neural Networks, Feed-Forward Networks.

I. INTRODUCTION

Deep Learning has been forged accordingly for various Natural language processing problems and outperforms with marvelous results in semantics, modeling of sentences, classification, prediction, and other NLP tasks. It has also been employed for image recognition as well as in the medical field. For example, to identify possible cures deep learning assists for the communication between molecules and biological proteins. It also accomplishes the task of superior training in a non-sequential manner with non-sequential data.

Big Data is currently the need of science and is the upcoming trend. This guides for the stipulation with mining of Big Data in every engineering and research domain [11]. The Big Data decipher the authentic tribulations in the domains of accomplishing assembly and safeguard of expansive sizes of data required for data analysis. Technical Corporations like Microsoft, Yahoo, and Google have composed and retained larger proportion of information. Furthermore, Twitter, Facebook, and YouTube, the

officialdoms of social media provide amenity to their users. Their users can engender a gigantic amount of data which is heterogeneous and unstructured in nature. Only Big Data analytics has the competence to analyze this gigantic amount of data. Big Data Analytics performs summarization, organizing, transforming and analyzing these data sets for the discovery of patterns and unrevealed correlations in the data. This can serve as profitable and valuable business information, such as customer preferences and usage statistics.

Big information constitutes large volumes of facts with different relative velocities and unbounded range. The latter holds heterogeneous and excessive data emerging from various independent assets. A most vital constituent of huge records personation is Variety in data[11]. It can precipitate with the support of perception which constitutes all guises of records favorable for an enterprise as well as for technological know-how. So, Big data take on with magnificent chances with a transformative perspective for healthcare, manufacturing, commerce, social media, educational services and many more [1].

With the leap up of deep learning trainable deep neural chatbots have substituted the traditional chatbot models very swiftly. Deep Learning mechanisms has dominated Conversational modeling to a great extend. The Convolution Neural Network(CNN) and Recurrent Neural Network (RNN) are Deep Neural Network (DNN) architectures can be adapted from the neural machine translation domain, where it already outperforms extremely well.

Deep computation is an innovative area that engrossed scientists in the latest years. It is denoted as a systematical model for illustration of big data, then storing, mining and analyzing accompanied by a theory of tensor. Numerous technologies are used in deep learning to fetch data from big data. Stacked Auto-Encoders (SDAEs) are fundamentally multilayer feedforward networks in which weights are adjusted according to the requirement. Here, the weights initialization is accomplished with the help of a generative learning algorithm. An Auto-Encoder for the single-layer network is a feed-forward network instructed to replicate the equivalent inputs at the output. Knowledge extraction is attained from data that can be circulated and hierarchical represented with managing weights in Auto-Encoders. One of the greatest software libraries for the arithmetical computation of mathematical expression to implement deep learning is Tensor Flow. For effectuating this purpose it wields data flow graphs. Among these graphs, Nodes exemplify mathematical operations while multidimensional data arrays called tensors are denoted by edges. It was contrived for Machine Learning and Google fabricated it. It is being widely used to develop solutions with Deep Learning [5]. Multimedia is one of its applications, therefore this model is also known as Multi-Modal Deep Learning. Video constitutes rich information such as audio, presence, and motion to appreciate its content.

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Current trends have manifested the amalgamation of spatial and temporal traces of any anthropoid action remembrance in the videos. Furthermore a framework has been suggested for action recognition in the multimedia demonstration of the video. Thus it proposes the learning of multimedia representations among video and audio data [7]. CNN constitutes primarily several layers of convolutions with nonlinear activation functionality. In this, to compute the output-input layer exploits the convolutions. As its emanation Local connections are devised, where neuron in the output are delineated with every single input. In the network different hundreds or thousands of filters are coupled with every layer to out-turn their results. There are also known as pooling layers. In a conventional neural network, it is assumed that all stakeholders i.e. outputs and inputs are self-standing. While RNNs are irreconcilable as these use consecutive information. RNNs as defined as recurrent as it deploys the indistinguishable task upon every element in the sequence, while the output is ascendant by the precursory computations. And for the perpetuation of that sole purpose, a "memory" is deployed to store pre-captured information. So, theatrically RNNs can utilize the information in random long sequences.

II. LITERATURE REVIEW

A. Definition of Chatbot

At present most serenity and extensively buoyant technologies to incorporate virtual assistants are Chatbots. Currently, to mediate access to data, the pile of web premiers is using chatbots as virtual assistants to carry out generic tête-à-tête with the user. So, a Chabot formally called Conversational Agent is application software that handles human communication employing natural (or Informal) language as human does. For a Chatbot, to model, the conversation is a predominant and cardinal venture of Natural Language Processing (NLP) and Artificial Intelligence (AI). Formerly, tactics for the fabrication of chatbot architectures eminently counted on hand-written rules, simple statistical methods and/or templates. All conventional chatbot's communication proficiency is immoderately intransigent. As per it, the user can be responded with the answer only if there is existence of some matching pattern amongst the divulgence from user and predefined communication sequence repertoire inside the plinth of knowledge [36]. Traditional chatbots deficits in the instinctive capacity like that of intellectual beings for perceiving the elucidation, associations and potential abilities afar from its own inventory extend.

B. Classification of Chatbot Applications

Chatbot applications can be categorized into four groups such as output-driven, information- driven, program- driven and feedback- driven [Figure 1]. Information-driven chatbots are materialized hinge on the type of data source and information they are trained on. It can be an open or closed domain. Program-driven chatbots are amalgamated to provide service to the customer of an organization. While a chatbot rooted on the type of action performed at time of response generation is feedback-driven chatbots. And when a Chatbot is dependent upon the outcome, then it's figured as Output-driven chatbots.

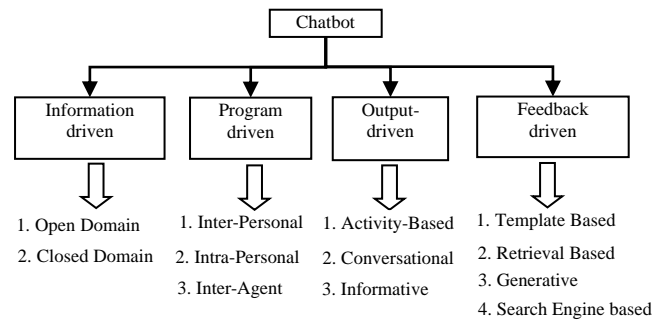


Fig. 1. Chatbot Classification

Amongst them, feedback-driven chatbot acts as the cornerstone for chatbot foundation nowadays as the information provided by them is responsible for the expansion of utterances and intents. Classification of Feedback-driven Models is tremendously administered by the kind of action performed during their response generation. The feedback driven models are using natural language text to clutch input for advancement to output. The dialogue manager oversees the amalgamation of feedback driven models for that sole purpose. For Chatbot's impetus, the dialogue manager necessitates three steps. First, is feedback generation by examining all the available response models. Second, return a feedback/response grounded on priority. Third, if there is an absence of any priority, the response is assorted with assistance from the model selection policy.

C. Existing Chatbots

Plenty of chatbots have been materialized as per in market requisition. All Chatbots that emerged have their features along with their effective uses as per their pros and cons stated in Table 1. So, the mass favored chatbot systems along with their details i.e. technical or non-technical, serviceability, advantages and disadvantages are listed below in Table 1.

Table- I: Chatbot Taxonomy

Chatbot	Year	Founder	Open Source/ Proprietary	Technique Used	Technical Process	Advantages	Drawbacks
Eliza [39]	1966	Joseph Weizenbaum	Open-source	Template Based Pattern Matching and Keyword Searching	A psychiatrist Program: Input key uses decomposition rules and Responses uses Pattern Matching for associated reassembly rules	Conversational interaction with people and behave as an information retrieval system	No logical reasoning capabilities, inappropriate responses, the knowledge base of 200 categories

PARRY [44]	1972	Kenneth Colby	Proprietary	Parsing, Interpretation- action module with Pattern Matching	Eliza with Attitude (paranoid schizophrenic) Written in LISP language recognition involves pattern-matching rules, and responses involve Interpretation- action	robust, never broke down, always provide a response	Provides idiosyncratic, partial and idiolect responses as a paranoid schizophrenic
ALICE [42]	1995	Richard Wallace	Open-source	Template Based Recursive Technique	Extension to Eliza. Botmaster creates AIML files for creating accurate responses. Responses are generated using Pattern Matching for new inputs.	Supervised Learning, knowledge base of more than 40000 categories. Information Retrieval through natural language. Can answer complex inputs due to recursion	Grammatical analysis to structure sentences
Cleverbot [45,46]	1997	Rollo Carpenter	Proprietary	Rule-Based, mapping input to output	Basic learning strategy, i.e. learning from human interactions	Constantly learning and increasing in data size with more than 4 million interactions per second with no restriction on its growth	Unpredictable responses without context
Elizabeth [40,41]	2002	Peter Millican as an adaptation to Joseph Weizenbaum's Eliza	Open-source	Template Based Pattern Matching with Iterative approach	Chatbot Creation System. Uses Input rules, keywords, perform transformation and output rules to generate a feedback response It's behavior is based on a 'Script' file.	Uses increasingly complex rules, Syntactic analysis to fabricated sentences	Cannot part the input and merge the outputs, Iteration in some Elizabeth rules, complex rules need Input transformation
Watson [50]	2006	IBM	Proprietary	Rule-Based NLP, UIMA	Uses DeepQA Software along with UIMA of Apache. Hadoop framework is used for distributed processing	Automated reasoning, Information retrieval, Knowledge representation,	Can't process structured data. No relational databases
Chat Script [49]	2009	Bruce Wilcox	Open-source	Script-Based. NLP with the dialogue management system	A rule has a type, a label, a pattern, and an output. the rule may fire based on conditions that Patterns portray	Rules are categorized topics i.e. keywords for pertinent rule search. Can be used as a solitary application i.e. help desk	Laborious to understand and installation over a web page
Dialog Flow [52]	2010	Ilya Gelfenbeyn (Google)	Proprietary	NLP, ML	Cloud-based chatbot platform which figures out the intents and entities to answer in any context.	Support more than 20 platforms and more than 14 languages. Supports all devices from wearables to phones to devices	Lack of two way communication in UI and does not brace over smart-phones, tablets, etc
Mitsuku [43]	2012	Steve Worswick	Proprietary	NLP with Heuristic Patterns	AIML files are used for responding. Using Pattern Matching for supervised learning	It contains all Alice's AIML files. It is continuously learning by inclusions from conversations with user that is still in progression	Failed to provide dialogue components
Chat Fuel [47]	2015	Dmitry Dumik	Open-source	Rule-Based mapping input to output with dialog flow	Provides block builder interface which uses pick and drop service, is user-friendly, permits feedback popups. It has combination with administrations like third-party CRM, and social media.	It provides analytical capacity and has dedicated conversational rules. Provides clients with the ability to make chatbots for their messengers Allow third-party integration with JSON API. Can handle Live Chat and have template marketplace	Inflexible communication and lacks in employment of knowledge-base
Many Chat	2015	Mikael Yang	Open-source	Rule-based Visual bot builder for Facebook Messenger	Provide flow builder interface which uses pick and drop service which is user-friendly to allows response prompts	Provides broadcasts, analytics, scheduled posting. Allow third party integration i.e. Zapier, Dev tool. Can handle Live Chat	Have Private template which needs to be shared
LUIS [51]	2015	Luis von Ahn	Proprietary	NLU with the prebuilt domain, Active learning	Cloud-based chatbot platform which uses utterances to get trained and figure out the intents cum entities.	Provides Active learning, and continuing to train on new utterances. Supports SDK for Android, Node.JS, Python, and Windows.	Required Azure subscription
Amazon Lex [53]	2017	Amazon	Proprietary	NLU, AWS Lambda	It can construct, test, as well as send your chatbots legitimately from the Amazon Lex console, Can incorporate conversational interfaces with any application utilizing voice and content.	Easy to use and cost-effective Gives Voice Interaction. In-built integration with AWS	Not multilingual, mapping entities & utterances are troublesome

III. RELATED WORK

Qingchen Zhang et al.[1] exploits a tensor-based deep learning model for heterogeneous data correlation. In proposed model output layer uses sum-of-squares error evaluated through tensor distance to completely study the emphasized data dispensation. In place of vector space, the high-order tensor space has been utilized for training the parameters in this model. The back-propagated algorithm of high-order has been harmonized in this process. Experimental datasets INEX, SANE, CUAVE and STL-10

are used by stacking multimodal deep learning with auto-encoders for evaluation of performance. From results, it has been demonstrated that the model has been proposed as feature learning capability when evaluated using the above-enlisted datasets. Maryam M Najafabadi et al.[2] has propounded that in what way some important Big Data Analytics issues can be considerate with intricate Deep Learning can.

The techniques it involves help in fast information retrieval from extensive data volumes with the extraction of composite patterns, tagging the data, enlisting of semantics and discriminative task simplification. The paper also concluded some challenges in research of Big Data Analytics using Deep Learning which comprises of model scalability, streaming data and distributed computation in high-dimensional data. For solution paper presented cognizance into pertinent future works by relevant questions constituting defining the semi-supervised and active learning, modeling for domain transformation, data sampling criteria and attainment of functional data generalizations and possibly enhancing semantic information.

Yibin Li et al.[3] has propounded a novel approach named 2SBM i.e. Intercrossed Secure Big Multimedia Model to bestow secure commercial services of multimedia big data for cloud computing. The approach is a Semantic-Based Control (SBAC) which is backed by the Semantic Information Matching (SIM) algorithm to identify semantically related information. For extracting high-quality knowledge, the projected approach also employs the Ontology-Based Access Recognition (OBAR) Algorithm based on automatic reasoning. The fundamental task of this approach is to contribute to secure cloud media access through multiple platforms.

Keke Gai et al.[4] elaborated on the prospective perils of sharing data between monetary favored organizations. The Risk Prediction algorithm based on decision tree (DTRP) has been postulated for such predictions. The technique uses a Secure Information Classification model based on supervised learning (SEB-SIC). As per experimental evaluations, the performance of the scheme used is good but on the cost of the additional computational workload. The confidentiality either financial service providers or customers have not drained as the information is classified with supervised learning techniques combination.

Liwei KUANG et al.[5] elaborated multi-source large scale heterogeneous data. The first process consolidates semi-structured, structured data and unstructured data using a tensor flow-based model. Then, the reduction of big data dimensions with singular value decomposition in incremental high order (IHOSVD) method. The theoretic examined and investigational outcome of the chronicle delivered the shreds of evidence that the suggested portrayal model for data and progressive dimensionality pruning procedure are talented. It poses a course of action for analyzing and methodical mining among big data.

Li Zhu et.al [6] researched on CBTC systems for the optimization of both control and communication. The paper focused on to minimization of Linear Quadratic Cost, energy consumption and the optimal profile tracking operation error. The train actions are bounded in constraints to confirm train operation safety. The real field measurements are overlooked for general simulation. The proposed optimization method spare improved the train control to ensure system safety by sacrificing part of the performance in CBTC systems.

R.Krishana et.al [7] examined applications involving predictions using big data with deep neural network (DNN). It is perceived that when DNN is employed for fault divination with preprocessing step then the process can be more proficient. The paper proposes Hierarchical Dimension Reduction (HDR) method for this purpose. The bi-step method outstood for value extrication from undetermined big data. This comprehensive approach is settled for ease of

forecast and predictions. Simulation responses are contained to control the all-inclusive method involving big data. The paper presumed that the utilization of HDR before DNN prompts a decrease in model size without a reduction of accuracy.

Y. Tamura et.al [8], proposed a valuable strategy dependent on profound training for OSS upgrading exercises with unwavering quality. Moreover, the paper established line of code as software for the unsatisfactory data envisaging among OSS recorded information and several numeral sketches utilized in the OSS projects. Moreover, OSS project's erroneous information is consumed for the result investigation utilizing the settled application software.

RidhaSoua et.al [9] reports prediction of traffic flow (short-term) by presenting a foundation established upon big-data. The multi-origin data is utilized with technique called Data Fusion in this framework. Two types of data has been considered here. First one is data stream and later data is event-based. Though the presented proposal individually prediction in traffic flow has been done in Deep Belief Networks by the use of heterogeneous input streams of data like weather data, prior traffic flow and tweet extracted event-based data. The Dempster's temporary standard has been utilized for the fulfillment of upgraded expectations. It has been done by fusing the corroboration imminent through data streams and modular data which are event-based. It is demonstrated that it beats the fundamental Dempster-Shafer rule.

H. Vizcaíno et.al [10] explained that Big Data can deal with an aggregate amount of data produced every second of time available from multiple sources and in various formats. Various approaches and skills have been established to make good use of these data, but their acceptance by organizations is complex in many respects. A survey of the best in class shows a few frameworks and methodologies. The recommendations are based on some of these aspects, in a punctual but not integral form. Therefore, it is suggested a methodology for the adoption of Big Data and a model of maturity for it.

Xindong Wu et al. [11] talked about the subtleties of the issues for the usage of the mining on Big Data. To help to mine upon Big Data, elite processing stages are required to force efficient structures for releasing the brimful potency in Big Data. Muddled conditions happen at the information level, here and there. For example, uncertain and missing values /as there are independent data sources and the assortment of information gathering conditions frequently utilized. Moreover, information accompanies issues like security concerns, noise and mistakes prompting adjusted information duplicates. For the situation, building up a sheltered data sharing convention is a noteworthy test. To execute the Data Mining calculation on Big Data, the key test is to produce a model by finding the examples to shape a brought together view. Accordingly, a deliberately structured calculation is required to dissect and combine the multi-sourced conclusions to get the Big Data based prime model. The paper inferred that Big Data as a developing pattern and its mining requirement is emerging in technological and building spaces.

Xue-Wen Chen et al. [12], has examined the Deep Learning to profit the Big Data for transfer learning with profound designs. Even though applying profound figuring out how to this stream is generally and substantially new and need to be accomplished for ameliorated execution. The paper reasoned that Big Data presents huge difficulties to profound learning like loud marks, heterogeneous and a lot of information. To tap the capacity of Big Data to the maximum, these specialized moves should be taken care of with better approaches for intuition and transformative arrangements.

Yisheng Lv et al. [13], has proposed a profound deep-learning approach for traffic stream prediction to consider characteristically the temporal and spatial connections. SAE (Stacked Auto Encoder) model is utilized to assimilate the conventional traffic stream attributes. After that training of the profound deep network system in a greedy unsupervised layerwise design is done. It has been out for the first time that a profound engineering model has been connected utilizing auto-encoders for the presentation of predictions on traffic stream features. The paper assessed that the proposed strategy beats SVM, RBF NN, RW, and BP NN model.

IV. RESEARCH GAPS

Deep learning application for Big Data is respectively recent and there is propensity for its performance enhancement. [12]. Deep Neural Networks got highlighted and attained ubiquitous recognition by transcending the substitutive method like kernel machine learning instead of machine learning [2]. It is a better option for Big Data as it accounts for reduced cost or energy in two ways. Firstly, only a limited number of neurons are active which have overpowered other neurons. Secondly, most of the neurons are connected sparsely by many minuscule to extended span connections. Also, to reduce communication costs the task is allocated to the neighboring neurons so as [14]. For designing Deep Learning Algorithm involving Big Data, one must consider the following.

The utilization areas for algorithms of Deep Learning and architectures of Big Data Analytics.

Deep learning algorithms adaptation for those applications involving Big Data Analytics.

Deep architectures with successive layers are employed in algorithms of Deep learning. In the chain process, the first layer is fed with data. The ascending output is yielded to its next layer as input. These nonlinear transformations get convoluted, as the data flows through deep architecture layers. The extremely non-collinear input data function comes out of the final transformation which can be wielded for indexing data or as classifier's features builder. Both recurrent (cyclic) NNs and feedforward (acyclic) NNs are better options in deep learning [14].

The backpropagation approach requires pre-training, so it works well only for labeled data in a limited amount for deep learning. But if data is unlabelled then Auto-encoders are overlooked. Predictive sparse coding [18], denoising auto-encoders [17] sparse auto-encoders [16], and Restricted Boltzmann Machines [15] are some stockpiled auto-encoders that entrenched Stacked Auto-Encoder. But these deep learning models involving big data containing enormous amounts of heterogeneous data are ineffective in performing feature learning [1,5]. For feature learning, Tensor Auto-Encoder has been proposed in data that is

heterogeneous. Useful demonstrations with multiple levels of big data make can be learned by a tensor deep learning model by compiling such tensor auto-encoders. But feature learning on heterogeneous data and for parameter training, it is time-consuming model[1].

Effortless to train and generally which is ahead of fully connected neural networks, Convolution Neural Networks (CNNs) is a feed-forward deep neural network. The series of stages are involved in CNN and among those; the beginning stages have two-layer types. First layer is the convolution and the later one is pooling[20]. On CNN, Rectification Logic Unit (ReLU) are used in all hidden layers [19]. CNN uses efficiently ReLUs and GPUs which makes it the ascendant approach among other detection and recognition tasks [20]. Also, an increase in depth leads to a better performance of CNN [19].

Recurrent (cyclic) NNs (RNNs) are the fathomless of all neural networks. These are powerful than feedforward deep neural networks and acts as a general computer that can help to create and process memories with abundant input pattern sequences. RNNs imitate the brain by allocating adjoining RNN that amalgamates the related behaviors, and less related ones to distant RNN parts. Thus instead of conventional FNNs which are self-located maps, the RNNs curtail self-extensible and the non-distinguishable potential. Also undeviating foraging in the application program can lead to diminished communication complexity. [14].

REFERENCES

1. Qingchen Zhang, Laurence T. Yang, Zhikui Chen, "Deep Computation Model for Unsupervised Feature Learning on Big Data", IEEE Transactions on Services Computing, Vol. 9, Issue 1, pp. 161-171, 2016.
2. Maryam M Najafabadi, Flavio Villanustre, Taghi M Khoshgoftaar, Naeem Seliya, Randall Wald and Edin Muharemagic, " Deep learning applications and challenges in big data analytics", Journal of Big Data 2:1, Springer, 2015.
3. Li, Yibin, "Intercrossed Access Controls for Secure Financial Services on Multimedia Big Data in Cloud Systems", ACM Transactions on Multimedia Computing, Communications, and Applications, Vol.12, Issue 4, November 2016.
4. Gai, Keke, Meikang Qiu, and Sam Adam Elnagdy, "Security-aware information classifications using supervised learning for cloud-based cyber risk management in financial big data, Big Data Security on Cloud", IEEE 2nd International Conference on Big Data Security on Cloud (BigDataSecurity), IEEE International Conference on High Performance and Smart Computing (HPC), and IEEE International Conference on Intelligent Data and Security (IDS), 2016.
5. L. Kuang, F. Hao, L. T. Yang, M. Lin, C. Luo, and G. Min, "A Tensor-Based Approach for Big Data Representation and Dimensionality Reduction," IEEE Transactions on Emerging Topics in Computing, Vol. 2, Issue. 3, pp. 280-291, Sept. 2014.
6. L. Zhu; F. R. Yu; Y. He; B. Ning; T. Tang; N. Zhao, "Communication-Based Train Control System Performance Optimization Using Deep Reinforcement Learning," IEEE Transactions on Vehicular Technology, Vol. PP, Issue. 99, pp.1-1, July 2017.
7. R. Krishnan, S. Jagannathan, and V. A. Samaranyake, "Deep learning inspired prognostics scheme for applications generating big data", Proceedings of International Joint Conference on Neural Networks (IJCNN), Anchorage, AK, USA, 2017, IEEE, pp. 3296-3302, 2017.
8. Y. Tamura, S. Ashida, and S. Yamada, "Fault Identification Tool Based on Deep Learning for Fault Big Data", Proceedings for International Conference on Information Science and Security (ICISS), Pattaya, 2016, IEEE, pp. 1-4, March 2017.

9. R. Soua, A. Koesdwiady and F. Karray, "Big-data-generated traffic flow prediction using deep learning and Dempster-Shafer theory," Proceedings for International Joint Conference on Neural Networks (IJCNN), Vancouver, BC, IEEE, pp. 3195-3202, Nov 2016.
10. Abhilasha Naidu, A.Y. Deshmukh, VipinBhure, "Design of High Throughput and Area Efficient Advanced Encryption System Core", Proceedings of International Conference on Communication and Signal Processing, IEEE, April 2014.
11. X. Wu, X. Zhu, G.-Q. Wu, and W. Ding, "Data mining with big data", IEEE Transactions on Knowledge and Data Engineering, vol. 26, no. 1, pp. 97-107, Jan 2014.
12. X. -W. Chen and X. Lin, "Big data deep learning: challenges and perspectives," IEEE Access, vol. 2, pp. 514-525, 2014.
13. Yisheng Lv, Yanjie Duan, Wenwen Kang, Zhengxi Li, and Fei-Yue Wang, "Traffic flow prediction with big data: A deep learning approach", IEEE Transactions on Intelligent Transportation Systems, vol.16, Issue 2, pp.865- 873, April 2015.
14. Jürgen Schmidhuber, "Deep learning in neural networks: An overview", Journal of Neural Networks, vol. 61, Pages 85-117, Elsevier, January 2015.
15. G. E. Hinton and R. R. Salakhutdinov, "Reducing the dimensionality of data with neural networks", Science, vol. 313, no. 5786, pp. 504- 507, 2006.
16. Y.-L. Boureau and Y. L. Cun, "Sparse feature learning for deep belief networks", Proceedings of 20th International Conference on Neural Information Processing Systems, ACM, pp. 1185-1192., 2007.
17. P. Vincent, H. Larochelle, Y. Bengio, and P.-A. Manzagol, "Extracting and composing robust features with denoising autoencoders", Proceedings of 25th International Conference on Machine Learning, ACM, pp. 1096-1103, 2008.
18. H. Lee, A. Battle, R. Raina, and A. Y. Ng, "Efficient sparse coding algorithms", Advances in Neural Information Processing Systems, IEEE Xplore, pp. 801-808., 2007.
19. Simonyan, K. & Zisserman, "A. Very deep convolutional networks for large-scale image recognition", International Conference on Learning Representations, pp 1-14, 2014.
20. Yann LeCun, Yoshua Bengio & Geoffrey Hinton, " Deep learning", Nature, Vol 521, pp 436-444, May 2015.
21. N. Srivastava and R. Salakhutdinov, "Multimodal learning with deep Boltzmann machines," The Journal of Machine Learning Research, Vol 15, Issue 1, pp 2949-2980, 201.
22. H. Lee, A. Battle, R. Raina, and A. Y. Ng, "Efficient sparse coding algorithms." Advances in Neural Information Processing Systems, pp. 801-808, Springer, 2006.
23. S. Rifai, G. Mesnil, P. Vincent, X. Muller, Y. Bengio, Y. Dauphin, and X. Glorot, "Higher-order contractive auto-encoder," Machine Learning and Knowledge Discovery in Databases, pp. 645-660, Springer, 2011.
24. A. Coates, A. Y. Ng, and H. Lee, "An analysis of single-layer networks in unsupervised feature learning", Proceedings of 14th International Conference on Artificial Intelligence and Statistics, pp. 215-223, PMLR, 2011.
25. Yankai Lin, Shiqi Shen, Zhiyuan Liu, Huanbo Luan, and Maosong Sun, "Neural relation extraction with selective attention over instances", Proceedings of the 54th Annual Meeting of the Association for Computational Linguistics, Vol 1, pp 2124-2133, 2016.
26. Tomas Mikolov, Ilya Sutskever, Kai Chen, Greg S Corrado, and Jeff Dean, "Distributed representations of words and phrases and their compositionality", Proceedings of the 26th International Conference on Neural Information Processing Systems, ACM, pp 3111-3119, 2013.
27. Xiaotian Jiang, Quan Wang, Peng Li, and Bin Wang., "Relation extraction with multi-instance multilabel convolutional neural networks", Proceedings of 26th International Conference on Computational Linguistics: Technical Papers, pp 1471-1480, 2016.
28. P. Vincent, H. Larochelle, I. Lajoie, Y. Bengio, and P.-A. Manzagol, "Stacked denoising autoencoders: Learning useful representations in a deep network with a local denoising criterion," The Journal of Machine Learning Research, Vol 11, Issue 1, pp. 3371-3408, 2010.
29. S. Rifai, P. Vincent, X. Muller, X. Glorot, and Y. Bengio, "Contractive auto-encoders: Explicit invariance during feature extraction," Proceedings of 28th International Conference on Machine Learning, pp. 833-840, 2011.
30. G. Hinton, S. Osindero, and Y. Teh, "A fast learning algorithm for deep belief nets", Neural Computation, ACM, vol. 18, issue 7, pp. 1527-1554, 2006
31. Wenyuan Zeng, Yankai Lin, Zhiyuan Liu, and Maosong Sun, "Incorporating relation paths in neural relation extraction", arXiv preprint arXiv:1609.07479, 2016.
32. Yin Wenpeng, Kann Katharina, Yu Mo & Schutze Hinrich, "Comparative Study of CNN and RNN for Natural Language Processing" arXiv preprint arXiv:1702.01923, 2017.
33. Kumar, Shantanu. "A Survey of Deep Learning Methods for Relation Extraction", arXiv preprint arXiv:1705.03645, 2017.
34. <http://www.wildml.com/2015/11/understanding-convolutional-neural-networks-for-nlp/#more-348>.
35. Steven E. Stemler, "Content Analysis", Emerging Trends in the Social and Behavioral Sciences, pp1-14, May 2015.
36. Abbate, M.L., U. Thiel, and T. Kamps. "Can proactive behavior turn chatterbots into conversational agents?" in IEEE/WIC/ACM International Conference on Intelligent Agent Technology. pp. 173-179, 2005.
37. <http://www.cleverbot.com/>.
38. Reshmi,S, Kannan Balakrishnan, "Empowering chatbots with business intelligence by Big data integration", International Journal of Advanced Research in Computer Science, Vol 9, No. 1, 2018,
39. Weizenbaum, J., "ELIZA: A computer program for the study of natural language communication between man and machine" Communications of the ACM, volume 9, number 6, pp 36-45, 1966.
40. Weizenbaum, J. "A response to Donald Michie. International Journal of Man-Machine Studies", Vol. 9, Issue 4, p. 503-505, 1977.
41. Shawar, BA and Atwell, E "A comparison between Alice and Elizabeth chatbot systems" The University of Leeds, School of Computing research report, 2002.
42. Wallace, R.S. "The Anatomy of A.L.I.C.E. in Parsing the Turing Test: Philosophical and Methodological Issues in the Quest for the Thinking Computer", R. Epstein, G. Roberts, and G. Beber, Editors, Springer Netherlands: Dordrecht. pp 181-210, 2009.
43. Worswick, S. "Mitsuku Chatbot: Mitsuku now available to talk on Kik messenger". 2010 Retrieval on 04/05/2018.
44. Masche, J and Le, N-T, N "A Review of Technologies for Conversational Systems", Advanced Computational Methods for Knowledge Engineering, Advances in Intelligent Systems and Computing book series (AISC, Vol. 629, Springer International Publishing, pp 212-225, 2017.
45. Carpenter, R. "Cleverbot 1997 13 November 2011.
46. Robert W. Gehl. "Teaching to the Turing Test with Cleverbot." Transformations: The Journal of Inclusive Scholarship and Pedagogy, Vol. 24, No. 1-2, pp. 56-66. JSTOR, 2014.
47. Janarthanam, S., "Hands-On Chatbots and Conversational UI Development: Build chatbots and voice user interfaces with Chatfuel, Dialog flow, Microsoft Bot Framework, Twilio, and Alexa Skills". Packt Publishing, 2017.
48. Mohammad, N. and Hussain O.K. "A Survey on Chatbot Implementation in Customer Service Industry through Deep Neural Networks", 15th International Conference on e-Business Engineering, IEEE, pp 54-61, 2018.
49. Wilcox, B. "ChatScript Basic User's Manual", Revision 11/18/2013 cs3.73, <http://chatscript.sourceforge.net/Documentation/ChatScript%20Basic%20User%20Manual.pdf>
50. Nay, C., "Knowing what it knows: selected nuances of Watson's strategy", in IBM Research News 2011, IBM.
51. Microsoft. Microsoft Cognitive Services: LUIS. 2015 [cited 24/04/2018.
52. Google. Dialog flow 2010 23/04/2018]; Available from <https://dialogflow.com/>.
53. Amazon Web Services, I. Amazon Lex – Build Conversation Bots. 2017 23/04/2018]; Available from <https://docs.aws.amazon.com/lex/latest/dg/what-is.html>.

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