Machine Learning presentation

07-09-2017



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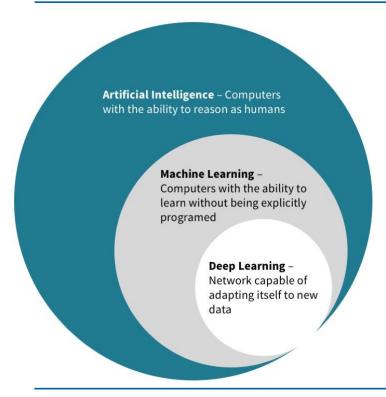
Videos in French

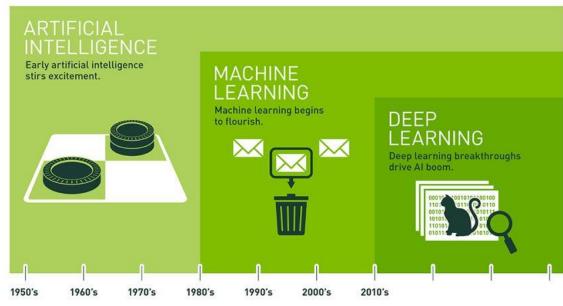
- ▶ Intro
 - https://www.youtube.com/watch?v=c7mIXLJESOk&feature=youtu.be
- Deep Learning for CNAF
 - https://www.youtube.com/watch?v=1DZkdrGwSSE&feature=youtu.be
- Feedback Deep Learning school
 - https://youtu.be/vjtVkDFVbNE
- Feedback Sophia conf AI
 - https://www.youtube.com/watch?v=Ad77CAYFr2U&feature=youtu.be

Introduction to Deep Learning

Deep learning?

Part of Artificial Intelligence

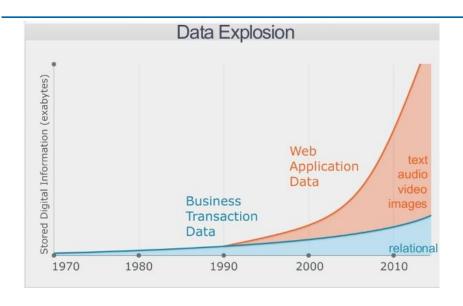




Since an early flush of optimism in the 1950s, smaller subsets of artificial intelligence – first machine learning, then deep learning, a subset of machine learning – have created ever larger disruptions.

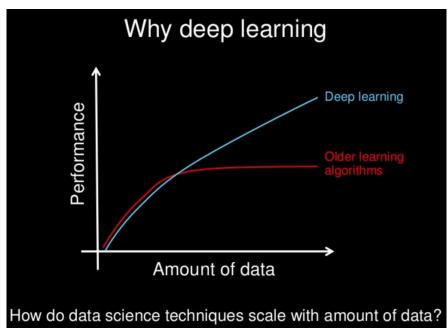


Why deep learning?







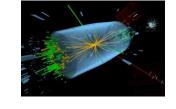




Applications



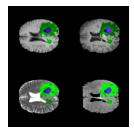


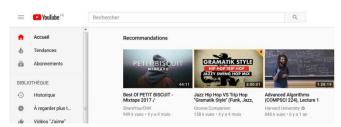






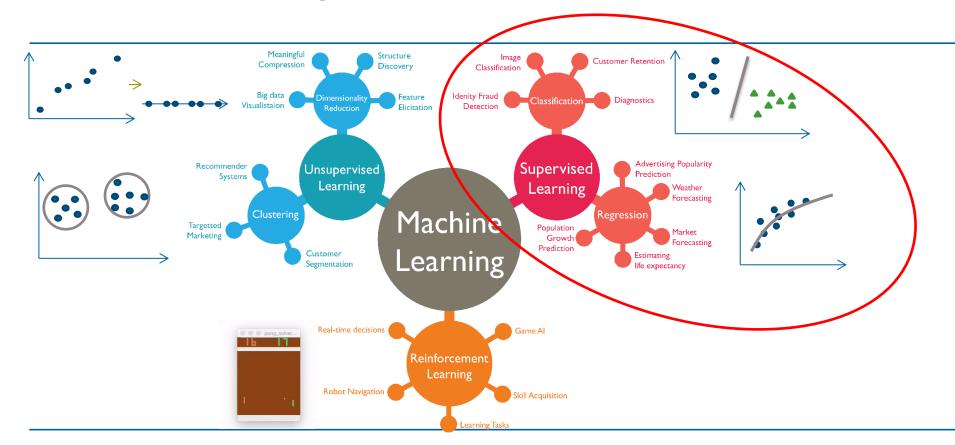




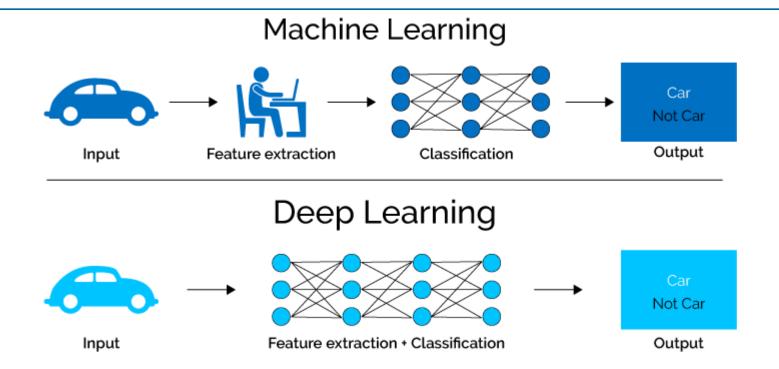




Machine learning basics

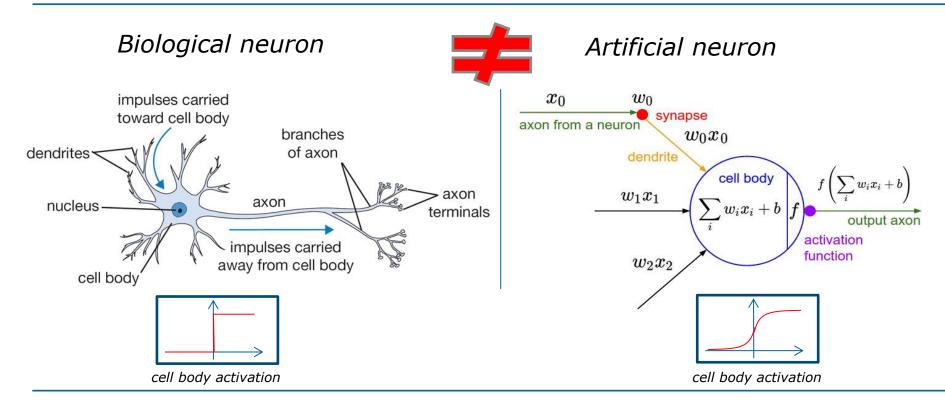


Machine Learning vs Deep Learning

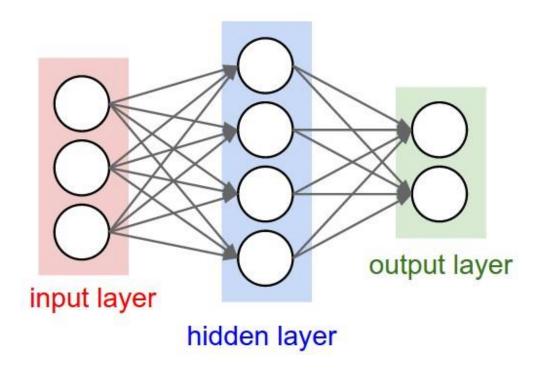


Basics in deep learning

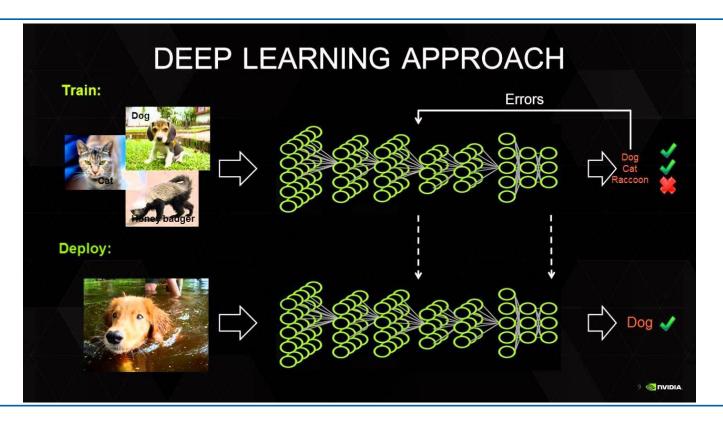
Neuron, called Perceptron



Neural network



Deep learning

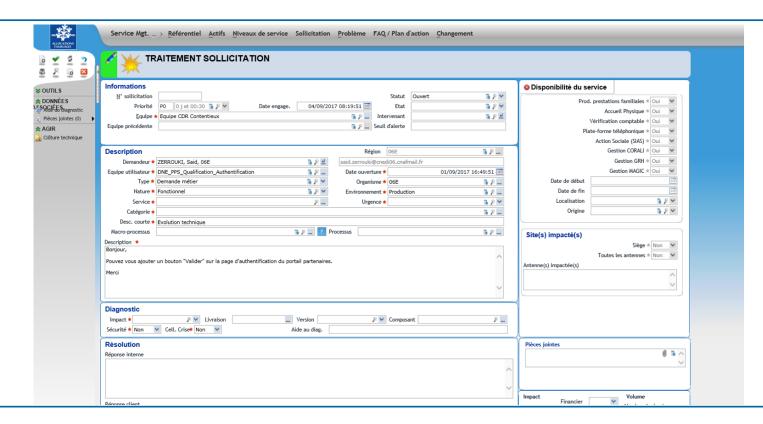






Text analysis on CNAF ticketing system

Ticketing system



Problem identified

- ▶ 300 000 tickets on 5 years
- ► Multiple duplicates and not always identified or sometimes late in the process Solution → SIMILARITY PREDICTION
- Process to redirect ticket to team able to solve the ticket.
- ▶ Redirection is not always easy and some tickets are long to solve because of it.

Solution → TEAM PREDICTION

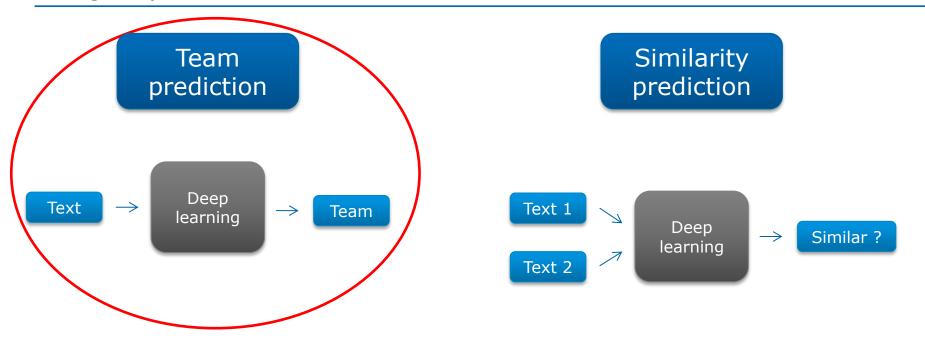
The purpose of every solution suggested is to help decision

Using only text of a ticket

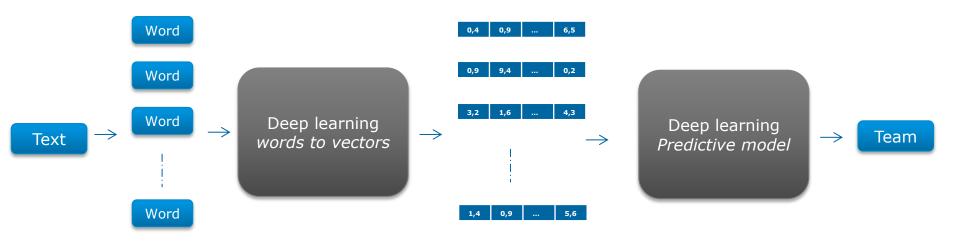
- ▶ One challenge → use only text
- Makes it reusable for other applications at CNAF
- Another approach in progress which is not presented here uses also categorical variables
- Scientific approach:
 - My method using Deep Learning will be compared with a classical approach in Machine learning (and Natural Language Processing)

Solutions proposed

Using only text



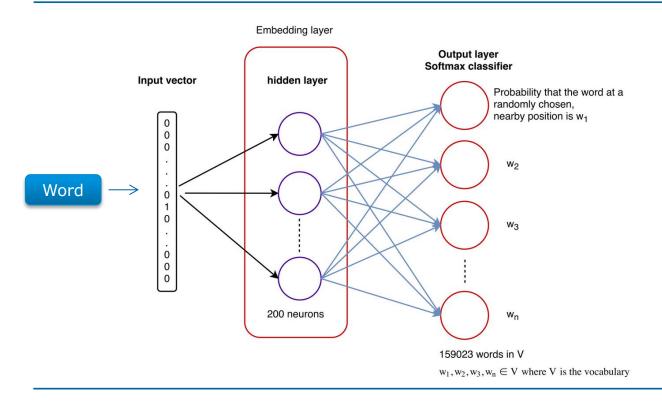
Deep learning solution proposed



From words to vectors

Embedding model (Skip gram)



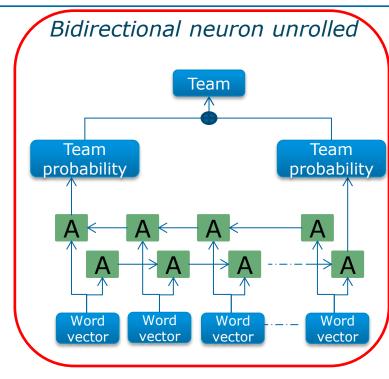


- Fake task: predict surrounding words of the input
- hidden layer is the representation by a vector of reals of the input word

Predictive model

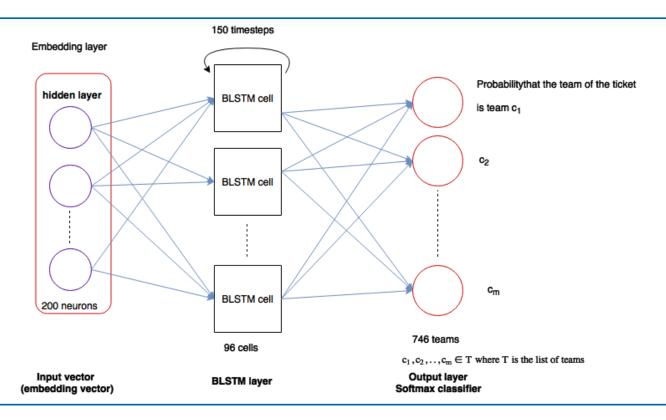
Recurrent Neural Network (RNN) and bidirectional RNN

Recurrent neuron Recurrent neuron unrolled Team **Team** probability Word Word Word Word vector vector vector vector



Team prediction





Results

▶ +700 teams

| Model | Test accuracy (%) | | |
|---|-------------------|--|--|
| Hazard following distribution | 1.21 | | |
| Most represented team | 4.54 | | |
| Traditional approach (no deep learning) | 23.26 | | |
| Proposed approach | 47.12 | | |

► Good results and research project to be continued...

Traditional method?

NOT DETAILED IN THIS PRESENTATION

$$tf-idf_{(t,d)} = tf_{(t,d)} x idf_{(t)}$$

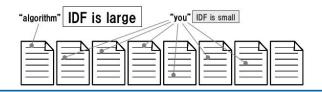
t = term d = document

| Term-Frequency Metric | Term(1) | Term(2) | Term(3) | Term(4) | Term(5) | Term(6) | Term(n) |
|--------------------------|---------|---------|---------|---------|---------|---------|---------|
| Document(1) | 225 | 300 | 0 | 0 | 0 | 25 | 0 |
| Document(2) | 78 | 87 | 0 | 92 | 0 | 175 | 0 |
| Document(3) | 58 | 137 | 0 | 0 | 237 | 0 | 21 |
| Document(4) | 0 | 12 | 101 | 0 | 0 | 0 | 0 |
| Document(5) | 3 | 15 | 0 | 24 | 0 | 48 | 87 |
| Document(6) | 0 | 0 | 71 | 0 | 0 | 0 | 0 |
| Document(n) | 109 | 0 | 901 | 221 | 331 | 441 | 551 |

Inverse Document Frequency (IDF)

Give more weight to a term occurring in less documents

$$IDF(t) = \log rac{|D|}{df(t)}$$
 $\frac{t: Term}{df(t): Document frequency of t}$ $\frac{df(t): Document frequency of t}{|D|: Number of documents in D}$



Project conclusion

- ► Github in progress (soon available): https://github.com/turpaultn/CnafSAXO
- Research report available (deep learning basic knowledge required) send a mail to: <u>turpaultn@gmail.com</u>

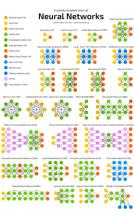


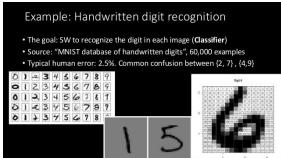
Deep Learning School June, 12-15

Lundi 12 Juin

Introduction and getting started workshop

- Presented by Stéphane CANU and Frédéric PRECIOSO
- Mathematical basics
- Deep learning concepts with presentation of Convolutional Neural Network (CNN)
- Workshop already using a neural network
- Good introduction and gives basics to rapidly come on deep learning



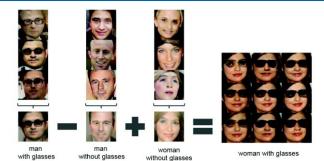




Mardi 13 Juin

Deep architectures

- Soufiane BELHARBI & Mélanie DUCOFFE
- Presentation of some of their thesis work
- Presentation of GANs and Autoencoders with applications
- From basics to research applications
- Gives better understanding of some architectures with some tricky points
- Lab on medical data segmentation with GAN





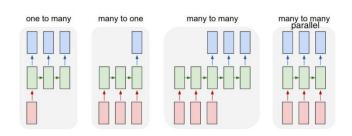
Fictional celebrity faces generated by a variational autoencoder.

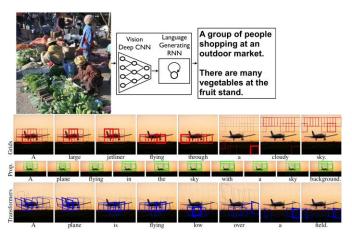


Mercredi 14 Juin

Dealing with time

- Rémi CADENE and Jakob VERBEEK
- ► Introduction to Recurrent Neural Network
- Annotate content of an image
- Using CNN and RNN
- Presentations which represent research work, good vulgarization for beginners and some details for others
- Lab on modelling time series with RNN

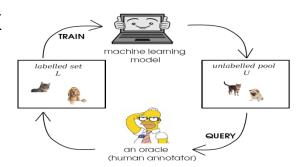


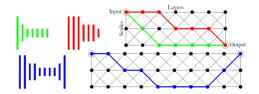


Jeudi 15 Juin

Building and training a Deep Network

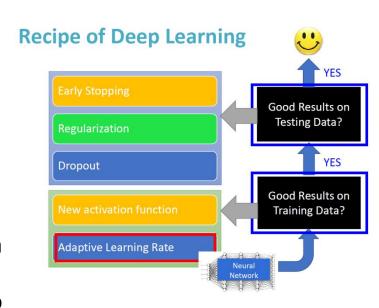
- ► Frédéric Précioso, Mélanie Ducoffe and Jakob VERBEEK
- Active learning presentation
- Explanation of research experiments
- Optimization process with techniques and tricks
- Good conclusion explaining some difficulties to train deep networks.
- It needs time to find good parameters on the optimization process





Conclusion and resources

- http://univ-cotedazur.fr/events/deep-learningschool
- Mostly industrial public
- Good initiation for beginners
- And labs designed for them
- Good levels of details for others
- Big success for this 1st Deep learning school in France
- ▶ To be reproduced next year and extended to other cities



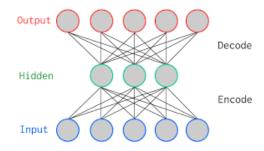




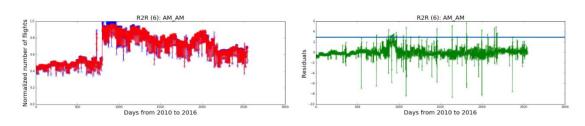
Anomaly detection

Asmaa FILLATRE - Amadeus

- http://www.telecom-valley.fr/wp-content/uploads/2017/05/FILLATRE.pdf
- Autoencoder for anomaly detection



▶ Unsupervised learning



Anomaly detection in sound for security

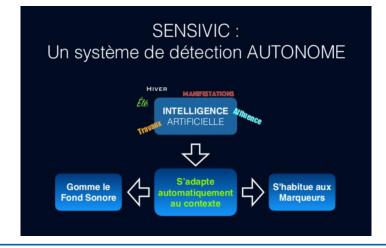
Jean DEMARTINI – USS SENSIVIC

► http://www.telecom-valley.fr/wp-content/uploads/2017/05/DEMARTINI-20170705 Sophia Conf DAAS IA pratique.pdf

▶ Add microphone with camera in security to detect anomalies camera can not

see.

No algorithm given



Language identification in (very) short texts

Mathieu LACAGE - Alcméon

- http://www.telecom-valley.fr/wp-content/uploads/2017/05/LACAGE.pdf
- Classification problem using ngrams
- No deep learning
- Learning by examples available on github



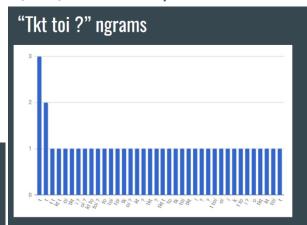
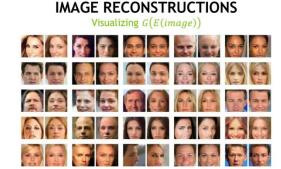


Photo editing with GANs

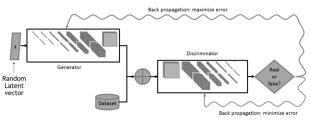
Greg HEINRICH - Nvidia

- http://www.telecom-valley.fr/wp-content/uploads/2017/05/HEINRICH.pdf
- ► GANs: Generative Adversarial Network
- Basics of the algorithm very well explained
- Famous algorithm
- Learning to generate the right data, in this case images



THE GAN SET-UP

Connecting the Discriminator to the Generator and the Dataset

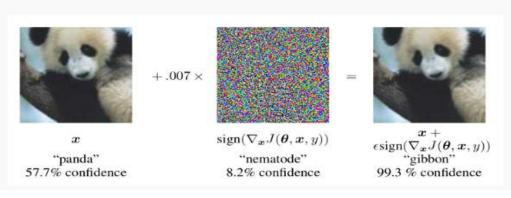




Fooling Deep Netwoks

Guillaume DEBARD – Laboratoire I3S

- http://www.telecom-valley.fr/wp-content/uploads/2017/05/DEBARD.pdf
- More technical
- ▶ Show some limitations of GANs
- How to attack a GAN
- Very good presentation which reduces the claim of Deep learning

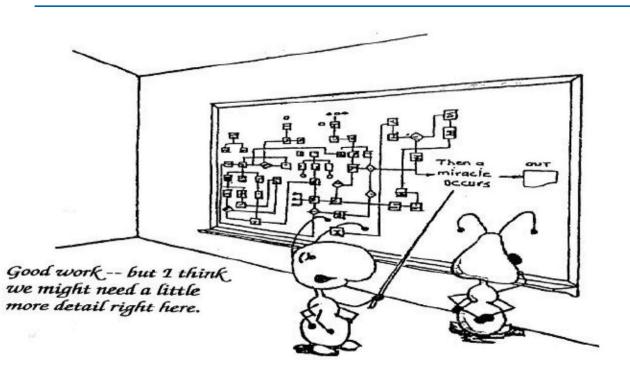


Conclusion

Deep learning

- ► First steps easy to implement
- Can solve new problems our outperforms previous method
- Not only for robots
- ▶ It is an **optimization process** relevant for many applications
- Why don't you try?

Any questions?



GIVEN THE PACE OF TECHNOLOGY, I PROPOSE WE LEAVE MATH TO THE MACHINES AND GO PLAY OUTSIDE.



References

References

Images

- https://leverton.de/blog/2016/12/21/3-deep-learning-trends-2017/
- https://www.mongodb.com/blog/post/deep-learning-and-the-artificial-intelligence-revolution-part-2
- ▶ https://blogs.nvidia.com/blog/2016/07/29/whats-difference-artificial-intelligence-machine-learning-deep-learning-ai/
- https://www.technologyreview.com/s/535201/the-face-detection-algorithm-set-to-revolutionize-image-search/
- https://www.analyticsvidhya.com/blog/2017/01/introduction-to-reinforcement-learning-implementation/
- http://med.stanford.edu/gevaertlab.html
- http://cs231n.github.io/neural-networks-1/
- https://www.youtube.com/watch?v=4A14mOsT6vQ
- http://www.businesswire.com/news/home/20170118005301/en/Neurala-Announces-14-Million-Series-Bring-Deep
- https://www.singularityweblog.com/alphago-deepmind-intelligence/
- https://www.linkedin.com/pulse/text-mining-deep-learning-part-1-shamane-siriwardhana
- https://www.ibm.com/blogs/insights-on-business/government/watson-in-defense-not-just-for-trivia/
- http://www.asimovinstitute.org/neural-network-zoo/
- https://www.youtube.com/watch?v=XNZIN7Jh3Sg
- https://www.slideshare.net/RoiBlanco/big-datasantiagov2
- https://www.linkedin.com/pulse/term-frequency-inverse-document-sanjay-singh-1
- https://www.slideshare.net/MasumiShirakawa/www-48698138
- http://keetmalin.wixsite.com/keetmalin/single-post/2017/06/05/TF-IDF-in-the-Field-of-Information-Retrieval

Thanks

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