Deep Learning from an IT perspective Industry session @ 6th Richmond IT Forum, Bad Ragaz, Sep 28, 2020



Thilo Stadelmann

What is AI and DL? Examples for successful DL deployments Lessons learned from an IT perspective



Image source: https://www.resortragaz.ch/de/aktivitaeten-und-events/erlebnisse

What → Examples? → Lessons learned





What is AI and Deep Learning?

What is AI?



thinking

"The exciting new effort to make computers think... machines with minds. in the full and literal sense."

"[The automation of] activities that we associate with human thinking, activities such as decision-making, problem solving,

"The study of how to make computers

"The study of mental faculties through the use of **computational models**.

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humanly

rationally

acting

What belongs to AI? An incomplete view of its subdisciplines





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Why is Al big *now*?



What's the big deal about deep learning? Adding depth to learn features automatically





What → Examples? → Lessons learned





Examples for successful DL deployments



Neural I Frightening Halloween Costume Ideas

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Use case 1: print media monitoring

Task



Challenge



Nuisance





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Print media monitoring – deployment



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Use case 2: symbol detection

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Symbol detection – challenges & solutions

a solutions



Tuggener, Elezi, Schmidhuber, Pelillo & Stadelmann (2018). «DeepScores – A Dataset for Segmentation, Detection and Classification of Tiny Objects». ICPR'2018.

Tuggener, Elezi, Schmidhuber & Stadelmann (2018). «Deep Watershed Detector for Music Object Recognition». ISMIR'2018.



Symbol detection – industrialization





Current results on class imbalance and robustness challenges

1. Added sophisticated data augmentation in every page's margins





- 2. Put additional effort (and compute) into hyperparameter tuning and longer training
- 3. Trained also on scanned (more real-worldish) scores

Sufficient condition: lots of tuning

→ Improved our mAP from 16% (on purely synthetic data) to 73% on more challenging real-world data set (additionally, using Pacha et al.'s evaluation method as a 2nd benchmark: SotA from 24.8% to 47.5%)

Elezi, Tuggener, Pelillo & Stadelmann (2018). «DeepScores and Deep Watershed Detection: current state and open issues». WoRMS @ ISMIR'2018. Pacha, Hajic, Calvo-Zaragoza (2018). «A Baseline for General Music Object Detection with Deep Learning». Appl. Sci. 2018, 8, 1488, MDPI.

What → Examples? → Lessons learned





Lessons learned from an IT perspective

ALPHAGO

AI

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Basis for disruption: automation ,,at scale" Or: "digital transformation" refers to a shift in all aspects of society, driven/enabled by this small set of technologies

Massively enhanced automation depth No need through progress in pattern recognition anymore

CLOUD COMPUTING

No need to invest into (IT) infrastructure anymore before entering the market

End Users

Application

Developers

Infrastructure &

Network Architects







One Implication: new opportunities ...through decoupling



size of idea \neq size of implementing organization

...small organizations can build whatever they want (given know-how, data and an interesting business case)

the technology is sector-independent

...enabling new alliances and co-operations

Risks through AI?

- AI per definition is a "dual use technology"
 → see report by Brundage et al., 2018
- But: "natural stupidity" is the more imminent threat
- Al ethics and explainable Al became mainstream and hot research topics in the recent years – not because of intolerable risks, but because of:



GREAT RESPONSIBILIT





The risk of natural stupidity ...or the problem of customer satisfaction





Cylance, I Kill You!

Read about our Journey of dissecting the brain of a leading Al based Endpoint Protection Product, culminating in the creation of a universal bypass

TL;DR

Al applications in security are clear and potentially useful, however Al based products offer a new and unique attack surface. Namely, if you could truly understand how a certain model works, and the type of features it uses to reach a decision, you would have the potential to fool it consistently, creating a universal bypass.

By carefully analyzing the engine and model of Cylance's Al based antivirus product, we identify a peculiar bias towards a specific game. Combining an analysis of the feature extraction process, its heavy reliance on strings, and its strong bias for this specific game, we are capable of crafting a simple and rather amusing bypass. Namely, by appending a selected list of strings to a malicious file, we are capable of changing its score significantly, avoiding detection. This method proved successful for 100% of the top 10 Malware for May 2019, and close to 90% for a larger sample of 384 malware.

Application-dependent risks

... or the problem of feasibility and market conformity





AND THE VIRTUALLY IMPOSSIBLE.

The problem of data Not big, but high-quality



Data is key

- Many real-world projects miss the required quantity & quality of data
 → even though «big data» is not needed
- Class imbalance needs careful dealing
 → special loss, resampling (also in unorthodox ways)
- Unsupervised methods need to be used creatively
- Users & label providers need to be trained



The problem of compute Training time GPT3 vs. at the edge





Sources: https://lambdalabs.com/blog/demystifying-gpt-3/, Tuggener et al. (2929), «Design Patterns for Resource Constrained Automated Deep Learning Methods», submitted to MDPI AI

The problem of deployment Introducing MLOps







Source: INNOQ / https://ml-ops.org/content/mlops-principles

Conclusions

- Deep learning is applied and deployed in «normal» businesses (non-AI, SME)
- It does not need big-, but some data (effort usually underestimated)
- IT needs to consider: specific **risks in procurement** / customization, **computational resources**, continued development after deployment (**MLOps**),

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➔ Happy to answer questions & requests



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Martin Braschler · Thilo Stadelmann

Kurt Stockinger Editors

Applied

Science

Lessons Learned for the Data-Driven Business

Data

Braschler - Stade Stockinger Eds.

2

Applied Data Science

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APPENDIX



Outlook: recent work in progress

- Learning to reduce motion artifacts in 3D CT scans
- Learning an artificial communication language for multi-agent reinforcement learning in logistics (notable rank in Flatland 2019 competition)
- Automated deep learning (top rank in AutoDL 2020 challenge)

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- Learning to segment and classify food waste in professional kitchens under adversarial conditions
- Improving robotic vision through active vision and combined supervised and reinforcement learning (Dr. Waldemar Jucker Award 2020)

Roost, Meier, Huschauer, Nygren, Egli, Weiler & Stadelmann (2020). «Improving Sample Efficiency and Multi-Agent Communication in RL-based Train Rescheduling». SDS'2020. Tuggener, Amirian, Benites, von Däniken, Gupta, Schilling & Stadelmann (2020). «Design Patterns for Resource Constrained Automated Deep Learning Methods». Submitted to MDPI AI. Roost, Meier, Toffetti Carughi & Stadelmann (2020). «Combining Reinforcement Learning with Supervised Deep Learning for Neural Active Scene Understanding». AVHRC 2020







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Foundation Inductive supervised learning

Assumption

- A model fitted to a *sufficiently large* sample of data...
- ...will generalize to unseen data

Method

- Searching for optimal parameters of a function...
- ...such that all sample inputs (images) are mapped to the correct outputs (e.g., «car»)



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Quelle: http://lear.inrialpes.fr/job/postdoc-large-scale-classif-11-img/attribs_patchwork.jpg



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What does the neural network «see»? Hierarchy of more complex features





Source: <u>https://www.pinterest.com/explore/artificial-neural-network/</u> Olah, et al., "Feature Visualization", Distill, 2017, <u>https://distill.pub/2017/feature-visualization/</u>.