Machines, Algorithms and Humans:

shall we expect from the third Al wave to reshuffle the cards in the world of engineering and simulation?

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école — — — normale — — supérieure — — paris — saclay — —

The painter

Work of human or machine?



The cost of the « Next Rembrandt »

- A blend (and intensity!) of expertise:
 - 20 people: art experts, developers, Machine Learning experts, engineers
 - 18 months of collective effort
- Data collection:
 - 150Gb for 160,000 fragments extracted from Rembrandt's paintings
 - 346 paintings studied to determine demographics and presentation of the subject
- Feature engineering:
 - dozens of features for rendering face details
 - more than 500 hundred hours of computation
- 3D Printing
 - Model texture patterns and print layers
 - Build a heigh map of 148m pixels
 - 13 layers of ink



Wisdom

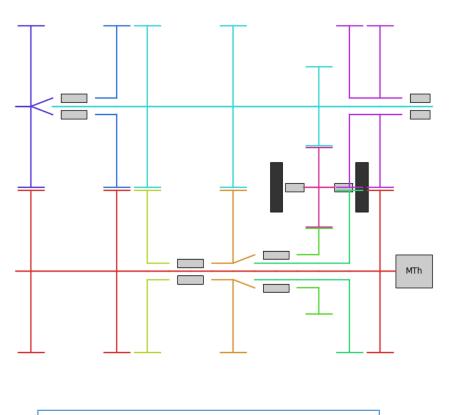
"We're like a father teaching a kid how to write—you still need the father. "

"I think Rembrandt would laugh himself silly if he saw there was a team of 20 people, really clever people, working for 18 months and this is what they come up with."

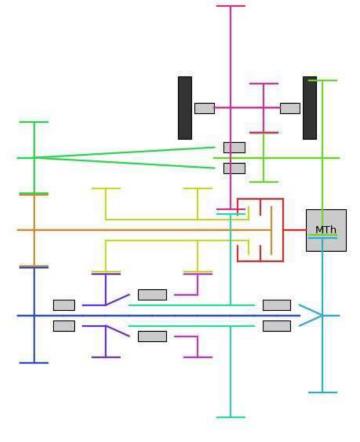
Bas Korsten, co-leader of the "Next Rembrandt" team

The gearbox engineer

Skecth of human or machine?



2D model of a six gearbox ratios of a manual transmission



2D model of a five gearbox ratios of a dual-clutch transmission

What does it take to sample and screen the space of gearbox architectures

- 992 architectural schemes scanned
- 1.5 x 10⁹ architectures generated
- 1.5 x 10⁸ architectures tested
- 1,390 viable architectures extracted
- 13,600 CPU-hours on Intel Xeon E5-1620v2
- Further screening based on price and mass constraints
- Expert assessment to evaluate plausibility regarding to volume optimization
 - 2D model of a six gearbox ratios of a manual transmission

- 142 architectural schemes scanned
- 2.5 x 10⁸ architectures generated
- 2.5 x 10⁷ architectures tested
- 320 viable architectures extracted
- 13,600 CPU-hours on Intel Xeon E5-1620v2
- Further screening based on price and mass constraints
- Expert assessment to evaluate plausibility regarding to volume optimization

2D model of a five gearbox ratios of a dual-clutch transmission

What we learned from innovative gearbox design

- There might be an Alpha-Go for gearbox design
 - Not clear what is is the complexity ceiling to extend it to engine design for instance
 - Requires the potential of HPC to sample and screen architectures in order to scale up
- Need to embark field expertise together with modeling ability:
 - Gearbox engineering, mechanical systems, optimization, graph sampling...
- Contribution of machine learning?
 - Not obvious at this stage, but...
 - ... it may help to better select high level design parameters and save brute force exploration time
- How to embrace such a design process disruption?
 - Mindset of the organization
 - Mindset of field experts

What it takes to make Machine Learning work

Big data? ... Well, quite big... and labelled

- Supervised learning algorithms outperform human performance in many pattern recognition tasks
 - LeCun et al. (1989): Handwritten zip code digit recognition
 - → USPS database; about 10,000 digits
 - → 10 categories; 7000 training data (16x16 gray level images)

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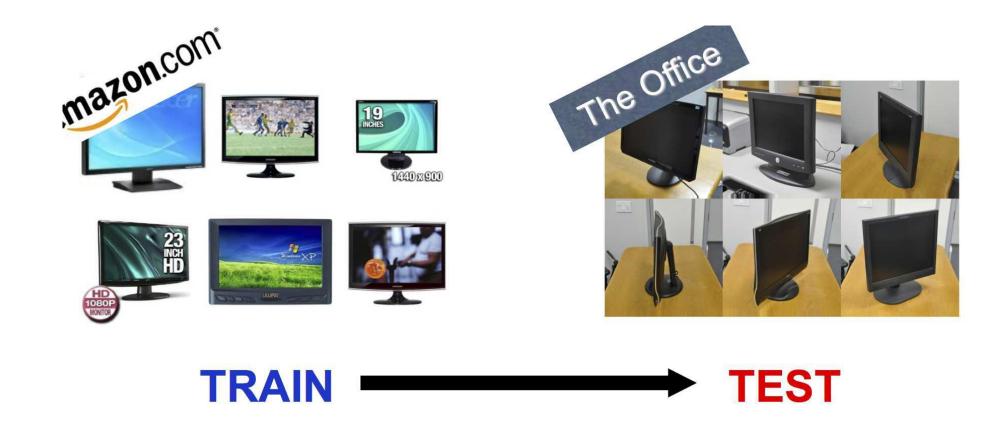


- Lu and Tang (2015): Face recognition
 - → Life Faces in the Wild (LFW) data set
 - → 5749 public figures; 13,233 uncontrolled face images
 - → Training on 40,000 pairs of images (matched/mismatched)
- Zhang et al. (2017): Pedestrian recognition
 - → Caltech pedestrian data set
 - → 10hours video at 30Hz:10⁶ frames
 - → 10% contain pedestrians; 2300 unique pedestrians
 - → Some trouble with partial occlusions...



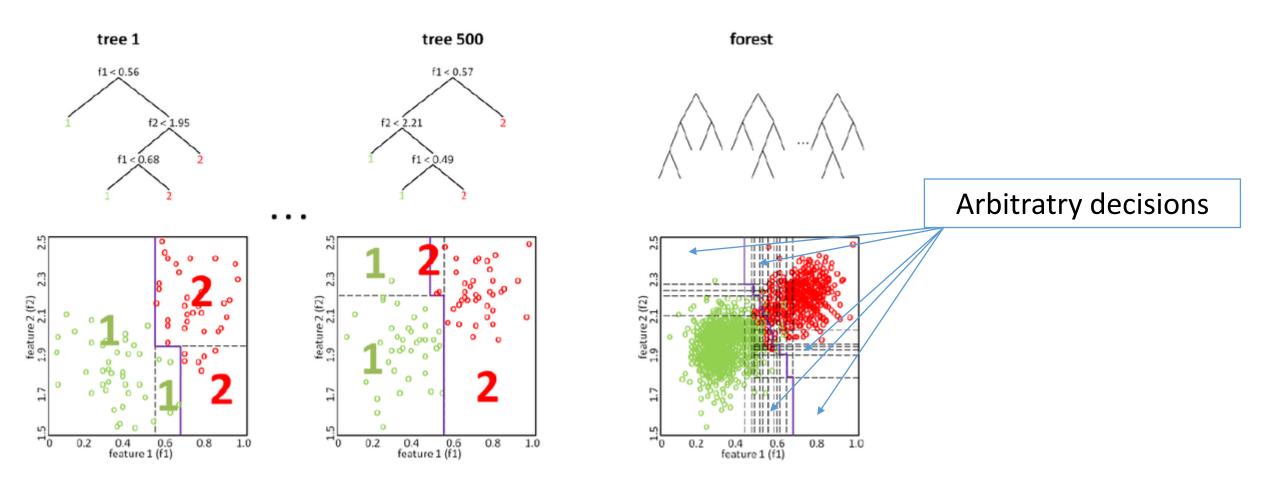
• But remember! Discriminant information is more important than massiveness of training data sets...

... but need to cover the input domain



This will probably not work with plain supervised learning (deep or shallow)...

Artefacts in decision rules based on supervised learning Random Forest example



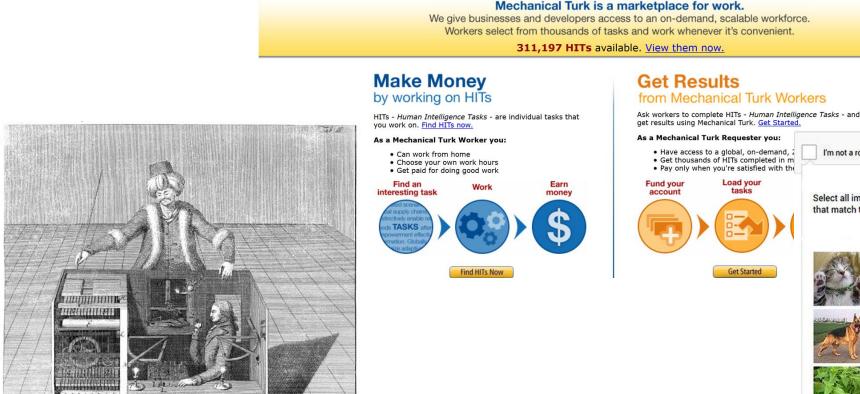
→ Need to learn with a reject option (see work by Marten Wegkamp, 2005-2008- 2011)

... and also needs human supervision

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amazon mechanical turk



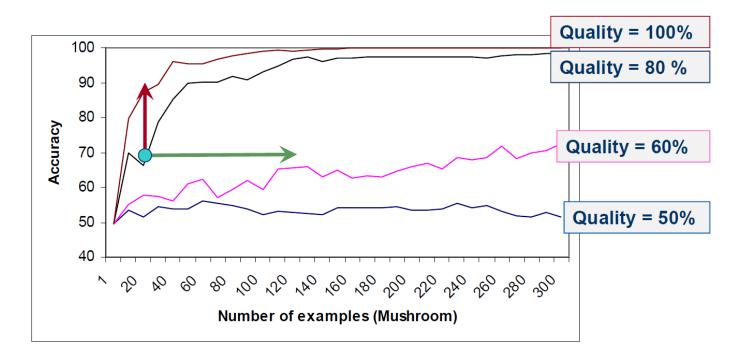
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Quality labels better than big data

- Get more examples → Improve classification
- Get more labels → Improve label quality → Improve classification



Source: Get Another Label? Improving Data Quality and Data Mining Using Multiple, Noisy Labelers. By V. S. Sheng, F. Provost, P. G. Ipeirotis. Proceedings of KDD, 2008

See also: Quality management on Amazon Mechanical Turk. By P. Ipeirotis, F. Provost, J. Wang. Proceedings of the ACM SIGKDD, 2010.

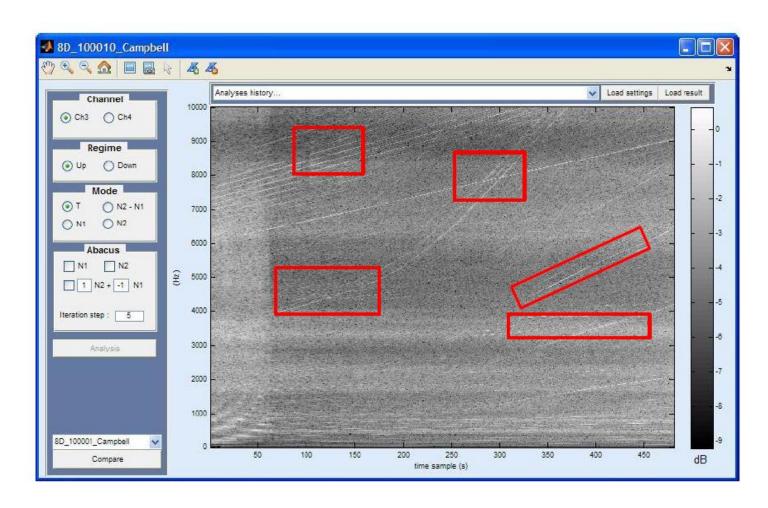
Why Machine Learning works so well in pattern recognition applications?

- Pattern recognition is a standard problem
- Image data have standard formats
- Image databases on www applications are massive
- Performance heavily relies on humans tagging images 'manually'
- Deep Learning is so fancy, mysterious and cool...

Not clear this line of thought will lead to a safe journey in the real world...

From marketing to industry: getting the job done...

An example of anomaly detection objective Benchmark assessment of aircraft engine



Source: Confidential report (2012) - Mathilde Mougeot, NV

- What we see? Time-frequency representation of vibration signals (Campbell diagram) wrt to speed during acceleration and decelaration regimes.
- Nature of anomalies
 Tiny details in those images. Require a lot of expertise to tag.
- Databases are small
 Only a few hundreds engines have been recorded with a very limited number of anomalies reported.
- But image structure helps! Anomaly detectors can be built using adapted representations of such signals and basic nearest neighbors in feature space.

B2C vs. B2B

- Standardized data
- Large data sets
- Cheap supervision
- Standard problems
- End user IS NOT an expert
- Performance is not critical



Search engines
Recommender systems
Targeting
Image tagging, ...

- Not always standardized data
- Small data sets
- Supervision ? Say again?
- Usually not standard problems
- End user IS an expert
- Performance is often critical

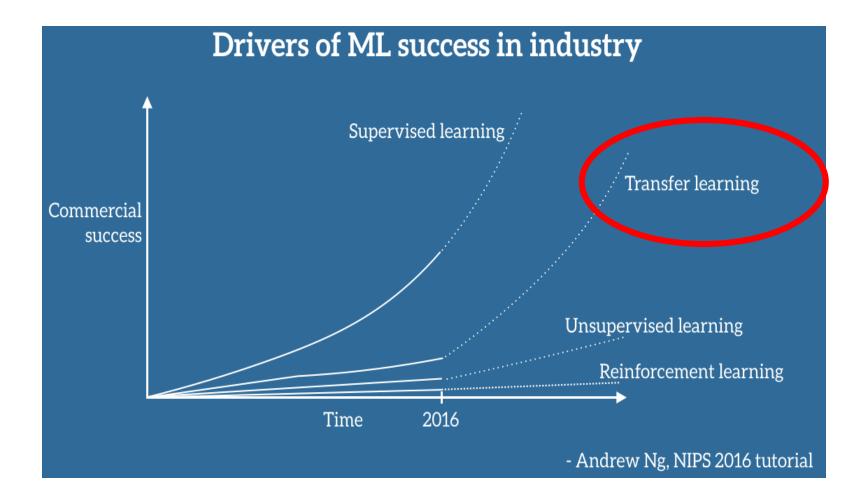
System design
Fraud detection
Predictive maintenance
Clinical decisions...

Challenges in the B2B industry

- Re-learn with small cost
 - Domain adaptation
 - Zero-shot learning
- Machine Learning pipelines have to face process improvement and novelty
 - Machine Learning algorithms require Lifecycle Management: Continuous learning
 - A possible asset: Learning from simulations and combine with field data
- Take into acount the human factor at the design stage
 - Most important! an AI project is a software project!
 - Annotation requires commitment of field experts
 - Acceptability relies on robust and explainable decision rules
 - Implementation of AI technologies may/will lead to revisiting business processes
 - Interfacing experts with 'intelligent' software is THE challenge

Conclusion

Expected impact of computational IA in the industry



NB: Andrew Ng is VP & Chief Scientist of Baidu, Co-Chairman and Co-Founder of Coursera, and an Adjunct Professor at Stanford University.

Main messages

- The third AI wave is computationaland relies on the advances of Machine Learning
 - Data-driven, similar to regression modeling with many variants
 - Heavily relies on mathematics to model complex data and formulate the task-related optimization problem
 - May/Will lead to industrial disasters (think of HAL)
 - The main risk: to be driven by a method and not by the problem to be solved in *its* context
 - Secondary risk: believe too much in training data
- Computational AI achieves nonlinear interpolation in high dimensional spaces
 - Al-based technologies may then outperform humans in certain well-defined tasks: detection, recognition, planning, etc.
 - Strong AI not for tomorrow...
- Al for B2B is very different from Al for B2C
 - Energy, healthcare, banking, defense... will not benefit of Computational AI 'as-is'
 - Scaling up and industrialization of AI modules in B2B raises scientific challenges
 - Main issue: conduct a cultural change
 - train AI-enhanced experts, bring social sciences in industrial design, render accessible scientific SOA to engineers...

Research:

http://nvayatis.perso.math.cnrs.fr/
http://www.cmla.ens-cachan.fr/

Training / M2 Master MVA: http://www.math.ens-cachan.fr/version-francaise/formations/master-mva/

French AI strategy:

FrancelA
 Rapport Villani
 https://www.economie.gouv.fr/France-IA-intelligence-artificielle
 https://www.aiforhumanity.fr

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