MACHINE LEARNING & INDUSTRY

Review and trends

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AGENDA

- 1. Introduction
- 2. Machine Learning and Industry, European and Swedish context
- 3. ML approaches (hands-on)
- 4. Industry 4.0
- 5. ML in two industrial sectors (cases)
- 6. Concluding remarks
- 7. Activity: co-analysis of ML+IND scenarios



DR. ESTEBAN GUERRERO

- Current position: Researcher
- Industrial experience:
 - 4 years R&D engineer in a Colombian telecommunications company. Role: support back-end services.
- Education:
 - Ph.D. in Computing Science, Umeå University. Sweden.
 - Ph. Licentiate in Computing Science, Umeå University.
 - M.Sc. Master's degree in Computer Science, Malmö University. Sweden.
 - M.Sc. Master's studies in Telematics Engineering, University of Cauca. Colombia.
 - B.Eng. Bachelor degree in Electronic and Telecommunications Engineering, University of Cauca. Colombia.







Intelligent skiing coach Partners: Computing Science dept. and Umeå School of Sport Sciences, Umeå University



Towards a *trusted* intelligent coach

STAR-C: Sustainable behaviour change for health supported by person-Tailored, Adaptive, Riskaware digital Coaching in a social context

Partners: Department of Computing Science, Department of Epidemiology and Global Health, Department of Culture and Media Studies and Department of Social Work Umeå University

> Project period. 2018-12-01 - 2024-11-30

> > Funding agency FORTE

Budget: 14'940.000 SEK (Swedish krona)

Research subject: Public health and community medicine Psychology, Umeå Universit Key words: multi-agent system; argun theory; coalitions; stress; psycho 2017-2019

Jonglera - an agent-b

coaching system for s

management Partners: Computing Science dept. ar

Autonomous adar software agents support of human Partners: Computing Scienc University Sweden and Huma and Technology Lab, National raiwan

University, Taiwan

2016-2017

https://people.cs.umu.se/esteban/





EUROPEAN CONTEXT

Main source: https://ec.europa.eu/info/index_sv







https://ec.europa.eu/info/sites/info/files/research_and_innovation/knowledge_publications_t_ools_and_data/documents/ec_rtd_radical-innovation-breakthrough_052019.pdf







- Summary of "recent progress directions" in artificial intelligence:
 - Duelling networks, also called generative adversarial networks (GANs)
 - Capsule Networks
- Long term perspectives:

"In the next decade and beyond, one can expect significant research around *one-shot* and *zero-shot learning models* involving knowledge transfer."

https://ec.europa.eu/info/sites/info/files/research_and_innovation/knowledge_publications_t_ools_and_data/documents/ec_rtd_radical-innovation-breakthrough_052019.pdf











SWEDISH CONTEXT

Main sources: Vinnova, Regeringskansliet



2. Context



SMART INDUSTRY - A STRATEGY FOR NEW INDUSTRIALISATION FOR SWEDEN

Four focus areas have been chosen:

- Industry 4.0 Exploit the potential of digitalisation
- Sustainable production Improve the industrial sector's capacity for sustainable and resourceefficient production
- Industrial skills boost Ensure the supply of skil to the industrial sector
- Test bed Sweden Create attractive innovation environments

https://www.government.se/information-material/2016/04/smart-industry---a-strategy-for-new-industrialisation-for-sweden/ 2. Context https://www.regeringen.se/







und 1 million jobs

4a7ad75f2f54/nist_a4_faktablad

UMEA. UNIXX



Artificiell intelligens: tekniker, tillämpningar och applikationsområden

Källa: WIPO, Technology trends Artificial Intelligence (2019).

2. Context

Svenska AI-miljöer med geografisk hemvist.



UMEA. UNEA. UNEA. UNEA. UNEA.

Centers with focus on Machine Learning

39 AI-miljöer som arbetar för utveckling av artifciell intelligens

https://www.vinnova.se/globalass ets/mikrosajter/ai/vr_19-05_190704.pdf



ML APPROACHES (BRIEF) + HANDS-ON



MACHINE LEARNING IS NOT ONLY PYTHON





SUPERVISED LEARNING

- What is: "Supervised learning is a learning model built to make prediction, given an unforeseen input instance."
- How it works: "With supervised learning you use <u>labeled</u> data, which is a data set that has been classified, to infer a learning algorithm. The data set is used as the basis for predicting the classification of other <u>unlabeled</u> data" [Talabis,et.al.2014].
- Two important approaches (among many):
 - Linear Regression (many sub-mechanisms)
 - Classification Techniques: Logistic regression, Linear discriminant analysis, etc. ...(among many).

Talabis, M., McPherson, R., Miyamoto, I., & Martin, J. (2014). *Information Security Analytics: Finding Security Insights, Patterns, and Anomalies in Big Data*. Syngress.

Sugiyama, M. (2015). *Introduction to statistical machine learning*. Morgan Kaufmann.



SUPERVISED LEARNING



- We assume the equation: $Y_e = \varepsilon + \beta X$
- Y_e is the estimated or predicted value of Y based on our linear equation. **Goal**: find statistically significant values of the **parameters** ε and β that minimize the difference between Y and Y_e.

If we are able to determine the optimum values of these two parameters, then we will have the **line of best fit** that we can use to predict the values of *Y*, given the value of *X*.

SUPERVISED LEARNING

- Example 0: Linear regression, a diabetes dataset with Pythor
 - Jupyter notebook using Python3, scikit-learn



https://colab.research.google.com/drive/1Ey0_E-fCtggCNxdd96v8gxbCnAKh7_ug

	AGE	SEX	BMI	BP		Serum	Meas	suren	nents		Response
Patient	x1	$\mathbf{x}2$	$\mathbf{x3}$	$\mathbf{x4}$	$\mathbf{x5}$	$\mathbf{x6}$	$\mathbf{x}7$	$\mathbf{x8}$	$\mathbf{x9}$	x10	У
1	59	2	32.1	101	157	93.2	38	4	4.9	87	151
2	48	1	21.6	87	183	103.2	70	3	3.9	69	75
3	72	2	30.5	93	156	93.6	41	4	4.7	85	141
4	24	1	25.3	84	198	131.4	40	5	4.9	89	206
5	50	1	23.0	101	192	125.4	52	4	4.3	80	135
6	23	1	22.6	89	139	64.8	61	2	4.2	68	97
:	:	÷	:	÷	÷	÷	÷	÷	÷	÷	:
441	36	1	30.0	95	201	125.2	42	5	5.1	85	220
442	36	1	19.6	71	250	133.2	97	3	4.6	92	57

 Table 1. Diabetes study.
 442 diabetes patients were measured on 10 baseline variables. A prediction model was desired for the response variable, a measure of disease progression one year after baseline.

https://web.stanford.edu/~hastie/Papers/LARS/LeastAngle_2002.pdf https://www4.stat.ncsu.edu/~boos/var.select/diabetes.tab.txt



t [938.23786125] Mean squared error: 2548.07 Variance score: 0.47

learn



UNSUPERVISED LEARNING

- What is: "Unsupervised learning finds structures in the data."
- How does it work?: "Labels for the data instances or other forms of guidance for training are not necessary. This makes unsupervised learning attractive in applications where data is cheap to obtain, but labels are either expensive or not available." [Wittek. 2014].
- Two important approaches (among many):
 - Clustering (many sub-mechanisms)
 - Principal Components Analysis (among many).

Wittek, P. (2014). Quantum machine learning: what quantum computing means to data mining. Academic Press.







UNSUPERVISED LEARNING

Example 1: K-means with Python + Scikit-learn

Iris flower data set clustering

	Sepal length	Sepal width	Petal length	Petal width	Class
1	5.1	3.5	1.4	0.2	setosa
2	4.9	3.0	1.4	0.2	setosa
3	4.7	3.2	1.3	0.2	setosa
:	:	• •	:	:	:
150	5.9	3.0	5.1	1.8	virginica



Iris Versicolor

Iris Setosa

Iris Virginica

https://scikit-learn.org/stable/auto_examples/cluster/plot_cluster_iris.html#sphx-glr-auto-examples-cluster-plot-cluster-iris-py



UNSUPERVISED LEARNING

Example 1: K-means with Python + Scikit-learn

Jupyter notebook:

https://colab.research.google.com/drive/1dCb2q2ONQA3ge g2VBZ03bvxSdmGV_JF0



https://scikit-learn.org/stable/auto_examples/cluster/plot_cluster_iris.html#sphx-glr-auto-examples-cluster-plot-cluster-iris-py









DEEP LEARNING



DEEP LEARNING

Example 2: <u>Fashion MNIST</u> dataset + TensorFlow + Python

Goal: Classify images.

How: Train a network with 60000 examples. Evaluate with 10000.



Reference: https://www.tensorflow.org/tensorboard/tensorboard_in_notebooks



DEEP LEARNING

Example 2: <u>Fashion MNIST</u> dataset + TensorFlow + Python

See Jupyter notebook:



https://colab.research.google.com/drive/13YG9iSbbDRDKPOr D4sEoG8w_Vd2Q-_sF

Reference: <u>https://www.tensorflow.org/tensorboard/tensorboard_in_notebooks</u>



- Basic idea:
 - Agent receives feedback in the form of rewards
 - $_{\circ}~$ Agent's utility is defined by the reward function
 - Must (learn to) act so as to maximize expected rewards
 - All learning is based on observed samples of outcomes



See CS188 Artificial Intelligence UC Berkeley. Prof. Pieter Abbeel <u>https://www.youtube.com/watch?v=ifma8G7LegE</u>





Time step t is incremented after each iteration



- 1 ENVIRONMENT
- You are in state 3 with 4 possible actions

2 Agent

- I'll take action 2
- 3 ENVIRONMENT
- ► You received a reward of 5 units
- You are in state 1 with 2 possible actions

Goal: Find an optimal behaviour $\tau_{r_{t+1}}$ Learn optimal behavior π based on past actions. Maximize the expected cumulative reward over time



$$\Pr(s_{t+1} = s' \mid s_t = s, a_t = a)$$

...and we know that the action is determined by

$$\Pr(s_{t+1}=s'\mid s_t=s) \;\; \pi(s)$$

$$\sum_{s'} P_{\pi(s)}(s,s') \left(R_{\pi(s)}(s,s') + \gamma V(s') \right)$$

$$Markov$$

$$Decision$$

$$\pi(s) := \operatorname{argmax}_{a} \left\{ \sum_{s'} P(s' \mid s, a) \left(R(s' \mid s, a) + \gamma V(s') \right) \right\}$$

Markov Decision Process

50

0.5

https://en.wikipedia.org/wiki/File:Markov Decision Process.svg

0.10

0.95

0.05

S₁

0.70

0.20

1.0

0.4





 Example 3:OpenAI Gym <u>https://gym.openai.com/</u>

Gym is a toolkit for developing and comparing reinforcement learning algorithms. It supports teaching agents everything from walking to playing games like Pong or Pinball.

```
import gym
env = gym.make("CartPole-v1")
observation = env.reset()
for _ in range(1000):
    env.render()
    action = env.action_space.sample() # your agent here (this takes random actions)
    observation, reward, done, info = env.step(action)
```

```
if done:
    observation = env.reset()
env.close()
```

Lubuntu Python 3.7



INDUSTRY 4.0



INDUSTRIE 4.0

The Fourth Industrial Revolution aims to leverage differences between the physical, digital, and biological sphere. It integrates cyber-physical systems and the Internet of Things, big data_and cloud computing, robotics, artificialintelligence based systems and additive manufacturing

Expected effects:

- On the business side: it drastically modifies customer expectations, product enhancement, collaborative innovation and organisational forms.
- On people: one of the greatest challenges is on privacy, on the notion of ownership, consumer patterns and how we devote time to develop skills.

European Commission, strategy on digitising the European industry. <u>https://ec.europa.eu/digital-single-market/en/fourth-industrial-revolution</u>



Interpretability

One ML Algorithmic Trade-Off





Industrial Machine Learning (at GE)

Joshua Bloom, Professor at UC Berkeley, CTO Wise/GE





Sector	Core use cases:			
Asset Management	Investment strategy	Portfolio construction	Risk management	Client service
Healthcare	Diagnostics	Drug discovery	Monitoring	
Insurance	Risk assessment	Claims processing	Fraud detection	Customer service
Law & compliance	Case law	Discovery and due diligence	Litigation strategy	Compliance
Manufacturing	Predictive maintenance	Asset performance	Utility optimisation	
Retail	Customer segmentation	Content personalisation	Price optimisation	Churn prediction
Transport	Autonomous vehicles	Infrastructure optimisation	Fleet management	Control applications
Utilities	Supply management	Demand optimisation	Security	Customer experience

Source: MMC Ventures

https://www.mmcventures.com/wp-content/uploads/2019/02/The-State-of-AI-2019-Divergence.pdf

4. Industry 4.0

Challenges in industrial cyber-physical systems



Area	Key Challenges	Difficulty	Priority	Maturity in
CPS Capabilities	Real-time control of CPS systems	High	High	4–7 years
	Real-time CPS SoS	High	Medium	3–5 years
	Optimization in CPS and their application	High	Medium	4–7 years
	On-CPS advanced analytics	Medium	High	3–5 years
	Modularization and servification of CPS	Iow	High	3–5 years
	Energy efficient CPS	Medium	Medium	3–5 years
CPS Management	Lifecycle management of CPS	Medium	Medium	5–8 years
	Management of (very) large scale CPS and CPS-SoS	High	High	5–8 years
	Security and trust management for heterogeneous CPS	High	High	5–8 years
CPS Engineering	Safe programming and validation of CPS SoS	High	High	5–10+ years
	Resilient risk-mitigating CPS	High	High	5–10+ years
	Methods and tools for CPS lifecycle support	High	High	3–7 years
	New operating systems and programming languages for CPS and CPS SoS	Medium	Low	3–6 years
	Simulation of CPS and of CPS-SoS	Medium	High	3–6 years
CPS Infrastructures	Interoperable CPS services	Medium	High	2–5 years
	Migration solutions to emerging CPS infrastructures	Medium	High	3–6 years
	Integration of heterogeneous/mobile hardware and software technologies in CPS	Low	Medium	2–4 years
	Provision of ubiquitous CPS services	Medium	Medium	3–5 years
	Economic impact of CPS Infrastructure	High	High	3–6 years
CPS Ecosystems	Autonomic and self-* CPS	High	Medium	7–10+ years
	Emergent behavior of CPS	High	Medium	7–10+ years
	CPS with humans in the loop	High	High	2–5 years
	Collaborative CPS	Medium	Medium	5–8 years
CPS Information Systems	Artificial intelligence in CPS	High	High	7–10+ years
	Cross-domain large-scale information integration to CPS infrastructures	Medium	Low	6–9 years
	Transformation of CPS data and information analytics to actionable knowledge	High	High	4–8 years
	Knowledge-driven decision making/management	High	Medium	6–10+ years

Leitão, P., Colombo, A. W., & Karnouskos, S. (2016). Industrial automation based on cyber-physical systems technologies: Prototype implementations and challenges. *Computers in Industry*, *81*, 11-25.

4. Industry 4.0



REVIEW OF ML IN TWO SPECIFIC SECTORS

Oil and Gas 4.0

Cybersecurity



Case: Cybersecurity (1/3)

- <u>Spam detection</u>: "The detection of spam is based on the use of filters that analyse the content and decide whether or not they are spam or legitimate messages, blogs or websites" Two main strategies can be followed to detect spam: 1) textual analysis and 2) image-based analysis.
- Major technologies: Bayesian classifiers: Naive Bayes classifiers, Boolean Naive Bayes, etc.; Support vector machines (SVM), back-propagation neural networks, among others, Deep Belief Networks

Berman, D. S., Buczak, A. L., Chavis, J. S., & Corbett, C. L. (2019). A survey of deep learning methods for cyber security. *Information*, *10*(4), 122.



Case: Cybersecurity (2/3)

- <u>Malware detection</u>: "The detection of spam is based on the use of filters that analyse the content and decide whether or not they are spam or legitimate messages, blogs or websites" Two main strategies can be followed to detect spam: 1) textual analysis and 2) image-based analysis.
- Main technologies: Bayesian classifiers: Naive Bayes classifiers, Boolean Naive Bayes, etc.; Support vector machines (SVM), convolutional neural networks (CNNs) and recurrent neural networks (RNNs)

Berman, D. S., Buczak, A. L., Chavis, J. S., & Corbett, C. L. (2019). A survey of deep learning methods for cyber security. *Information*, *10*(4), 122.



Case: Cybersecurity (3/3)

- <u>Phishing detection</u>: "The detection of spam is based on the use of filters that analyse the content and decide whether or not they are spam or legitimate messages, blogs or websites" Two main strategies can be followed to detect spam: 1) textual analysis and 2) imagebased analysis.
- Main technologies: Bayesian classifiers, SVMs, neural networks

Berman, D. S., Buczak, A. L., Chavis, J. S., & Corbett, C. L. (2019). A survey of deep learning methods for cyber security. *Information*, *10*(4), 122.



Datasets for cybersecurity:

- Knowledge Discovery and Dissemination (KDD) 1999 dataset: <u>https://kdd.ics.uci.edu/databases/kddcup99/kddcup99.html</u>
- NSL-KDD dataset: <u>https://www.unb.ca/cic/datasets/nsl.html</u>
- CTU-13 Dataset: <u>https://www.stratosphereips.org/datasets-ctu13/</u>
- Others: Contagio, Comodo, the Genome Project, Virus Share, VirusTotal, DREBIN, and Microsoft Malware Classification

		Application scenarios of big data	a in the oil and gas industry (Mohammadpoor and Torabi, 2018).	.UN
		Domain	Application scenario	Z L
Application scenario	Benefit	Exploration	Seismic data Micro-seismic data	
Drilling	Reduce the safety risk a	n	1D, 2D, and 3D geological maps	
		Drilling	Drilling rig efficiency Drilling performance Invisible non-production time Reduce the risk of drilling operations Characterize the drill string dynamics	
Diagnosis and detection	With the help of unman	r Reservoir engineering	Reservoir management application Closed-Loop Reservoir Management (CLRM) and Integrated Asset Modeling (IAM)	
Weather monitoring system	Automatic weather sens reduce construction risk	0 S	Improve the CO ₂ sequestration Optimization on heavy oil reservoirs Reservoir modeling for unconventional oil and gas resources Improve the modeling of hydraulically fractured reservoirs Optimize the application of EOR projects	/ance,
Metering system	The intelligent sensor is according to the data.	Production engineering	Conduct automated decline analysis Production allocation technique Optimize the performance of electric submersible pumps (ESPs) Optimize the performance of rod pump wells Improve hydraulic fracturing projects Conduct field development	tically
Lu, H., Guo, I Huang, K. (20	L., Azimi, M., &	Refining	Petroleum asset management Management optimization of a comprehensive refinery in Spain Workflow to study the impact of well completion parameters on well productivity	r
era: A system	era: A systematic review and		Improve shipping performance	
111, 68-90.	puters in Industry,	Health and Safety Executive (HSE)	Develop an energy efficiency model during ship operations Improve the occupational safety of the oil and gas industry	



GAMING INDUSTRY

 See Al Copen

https://www m/watch?v= LQQ&featur



Other algorithms, methods and examples

- Curiosity
- Memory Enhanced Agents
- Curriculum Learning
- On-Demand Decision Making
- Concurrent Unity instances
- Training Generalized Agents
- Multi-GPU training
- Pre-training
- GAIL



All included in the Unity Machine Learning Agents Toolkit

Unite Copenhagen 2019

Gunity



CONCLUDING



WHY DO BUSINESSES FAIL AT MACHINE LEARNING? CHECKLIST

□ Know what business you're in.

- Do things in the right order. (don't start with the algorithms; solve: what business problem I am solving?)
- Don't reinvent the wheel
- Data is not the most important part (data not Data)
- To scale using ML in Industry, more humans are needed (more than data scientists / engineers; from: statistics, ethics, social work, etc.)

 $\hfill\square$ Simplify where is possible

- Focus more in information data than the algorithms
- Design incentives that cannot be gamed (for reward functions in Reinforcement Learning: what you want the thing to learn?; and maybe for some Deep Learning approaches)

Cassie Kozyrkov Head of Decision Intelligence, Google.

https://www.youtube.com/watch?v=dRJGyhS6gA0

Recommendations

Executives

- Familiarise yourself with the concepts of rules-based software, machine learning and deep learning.
- Explore why AI is important and its many applications
- Identify sources of AI expertise, and existing AI projects, within your organisation.

Entrepreneurs

- To identify opportunities for value creation, explore the many applications for Al
- Familiarise yourself with current developments in AI technology techniques offer new possibilities.

New approaches and novel

6. Conclusions

https://www.ai-playbook.com/introduction

END

Questions?





ACTIVITY

- 1. Individually or in group
- 2. Choose an industrial use case (it can be anonymized or hypothetical)
- 3. Simplify the case to I/ML/O
 - 1. Output: ? (key: think in business model)
 - 2. Input: data, human resources, infrastructure, etc.
 - 2. ML approach?
- 4. Take some minutes to reflect.
- 5. Group analysis





PROGRAMMING WITH PYTHON

Programming with Python

The best way to learn how to program is to do something useful, so this introduction to Python is built around a common scientific task: data analysis.

Arthritis Inflammation

We are studying inflammation in patients who have been given a new treatment for arthritis, and need to analyze the first dozen data sets of their daily inflammation. The data sets are stored in comma-separated values (CSV) format:

- · each row holds information for a single patient,
- columns represent successive days.

The first three rows of our first file look like this:

Code

0,0,1,3,1,2,4,7,8,3,3,3,10,5,7,4,7,7,12,18,6,13,11,11,7,7,4,6,8,8,4,4,5,7,3,4,2,3,0,0 0,1,2,1,2,1,3,2,2,6,10,11,5,9,4,4,7,16,8,6,18,4,12,5,12,7,11,5,11,3,3,5,4,4,5,5,1,1,0,1 0,1,1,3,3,2,6,2,5,9,5,7,4,5,4,15,5,11,9,10,19,14,12,17,7,12,11,7,4,2,10,5,4,2,2,3,2,2,1,1

So, we want to:

1. Calculate the average inflammation per day across all patients.

2. Plot the result to discuss and share with colleagues.

To do all that, we'll have to learn a little bit about programming.

Prerequisites

You need to understand the concepts of **files** and **directories** and how to start a Python interpreter before tackling this lesson. This lesson sometimes references Jupyter Notebook although you can use any Python interpreter mentioned in the Setup.

The commands in this lesson pertain to Python 3.

https://www8.cs.umu.se/kursmaterial/ws-python-scientific-computing/

With twice as many AI startups as any other country, the UK is the powerhouse of European AI entrepreneurship





Source: MMC Ventures, Beauhurst, Crunchbase, Tracxn

https://www.mmcventures.com/wp-content/uploads/2019/02/The-State-of-AI-2019-Divergence.pdf



EVENT

Program of the event

Digitising European Indu Stakeholder Forum 2019

- 13 November 2019 to mic^{13:00 Welcome coffee} November 2019
- "The focus of the 2019 DEI S Forum will be on the Europea_{14:45} The future of European industry is digital (panel) for Digital Innovation Hubs, A Intelligence and industrial par beyond 2020, including the re funding instruments and oppo

13/11 afternoon:

14:00 Keynote speeches

"We are all feeling the concrete effects of digitalisation" (Ursula von der Leyen) and EU industry needs to be digital. High level speakers from Spanish government, European Commission and EU Finnish presidency will discuss the overall political context and the future actions.

Digitalisation is no longer a question of whether it will take place or not, but a question of how best to accompany businesses in their digital transformation. Speakers will explore how to reinforce the offer of digital innovations across the EU, how to strengthen European industrial ecosystems of IoT, data, cloud, and AI in and across sectors, and how to reinforce the European network of Digital Innovation Hubs to support SMEs in their digital transformation.

16:15 Coffee break

16:45 The rise of Artificial Intelligence: opportunities for industry (panel)

In the industrial domain the potential impact of AI is extremely important, and can help industry to address the long-term challenges of competitiveness and sustainability. Stakeholders will showcase actual use cases in different industry sectors discussing legal considerations and challenges they had to overcome to make AI a cost effective solution to their business.

https://ec.europa.eu/digital-single-market/en/news/orgnising-european-industry-stakenoider-forum-2019



NEW REPORT (OCTOBER)

http://sip-piia.se/wp-content/uploads/2019/10/AI-rapport_2019-low.pdf



EN SYSTEMANALYS FRÂN PIIA OCH BLUE INSTITUTE

Swedish IndTech

Hur Artificiell Intelligens & Digitala Plattformar förändrar industri