MACHINE LEARNING: PROJECT APPROACH

Jochem Grietens
System Engineer – A.I. passionate
Jochem.Grietens@verhaert.com

15TH ANNIVERSARY
INNOVATION DAY 19.10.2018
CONFERENCE BY MASTERS IN INNOVATION
ON NEW PRODUCTS AND BUSINESS INNOVATION

Introduction

Goal

AI and ML ?

To situate the question: Two different aims of AI:

Long term aim:

➔ develop systems that achieve a level of 'intelligence' similar / comparable / better? than that of humans.

- not achievable in the next 20 to 30 years

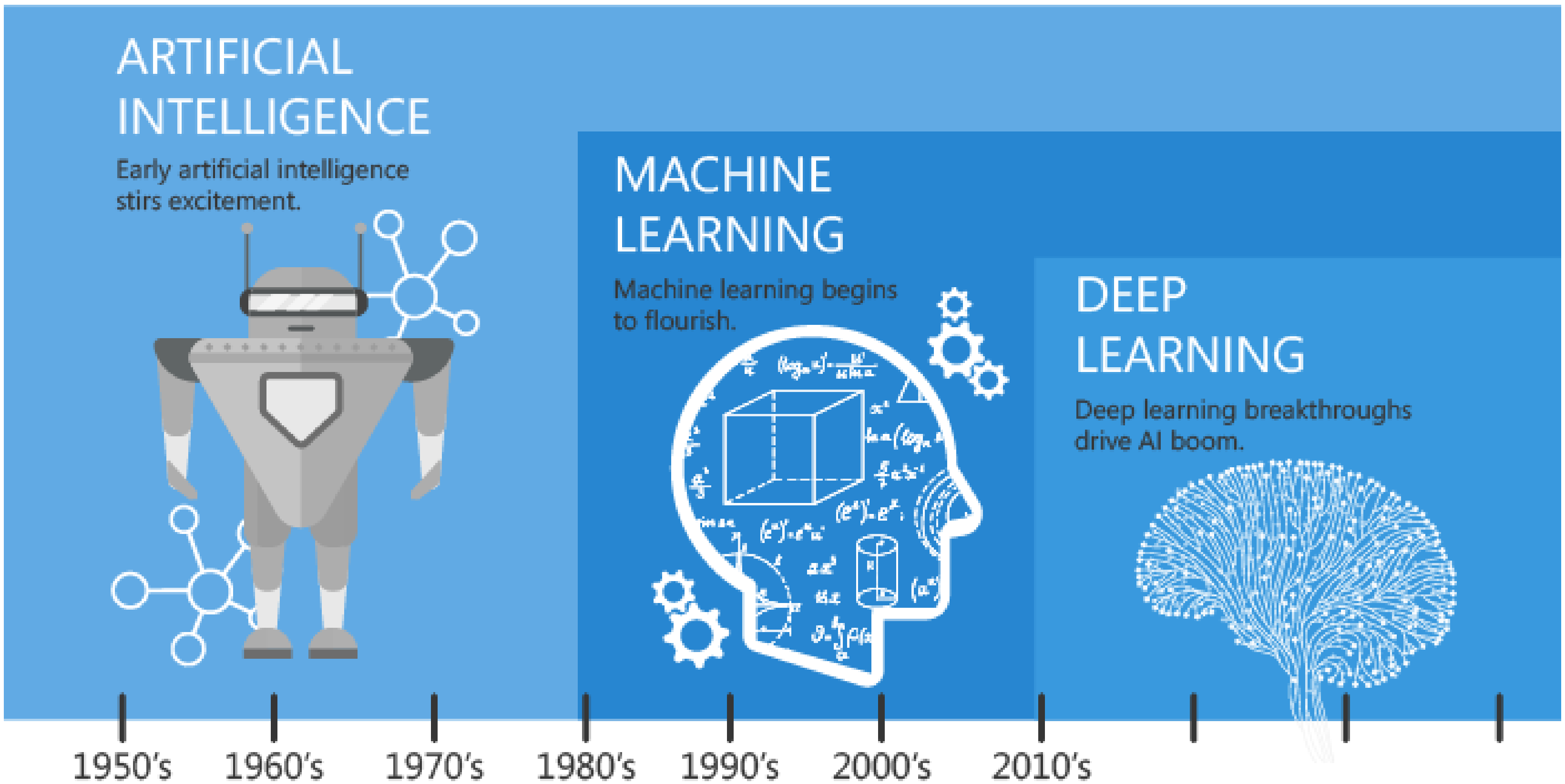
Short term aim:

➔ on specific tasks that seem to require intelligence: develop systems that achieve a level of 'intelligence' similar / comparable / better? than that of humans.

- achieved for very many tasks already

15

AI and ML ?



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

AI and ML ?

ML

- Unstructured data → structured data
- Learn from data
- Pattern recognition/detection
- …

AI

- Reasoning systems
- Planning, searching, …
- Expert systems
- Understanding ?
- …

Why now

Biggest drivers

1. Data availability
2. Computational performance.

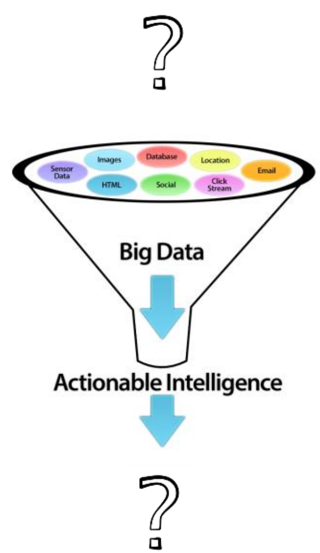
Framing the A.I. roadmap

Framing the A.I. roadmap

"Let's collect as much data as possible and apply A.I. later"

"We have a bunch of data laying around … "

"A.I. as a solution to everything…"

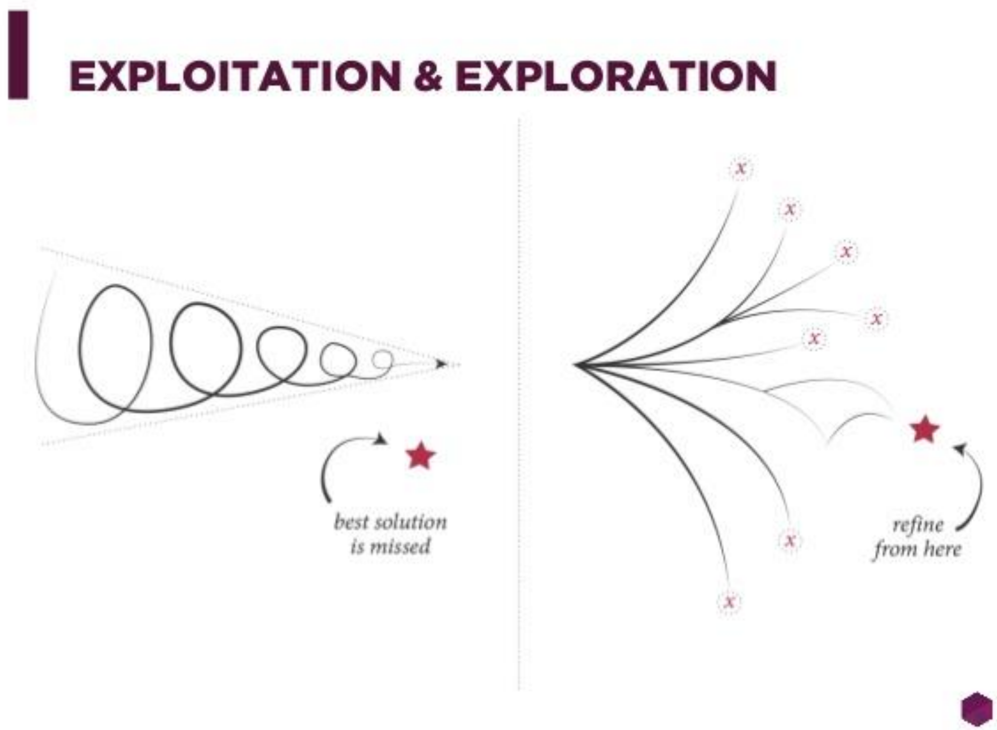


Framing the A.I. roadmap

"Goal oriented"

Vs

"Explorative"

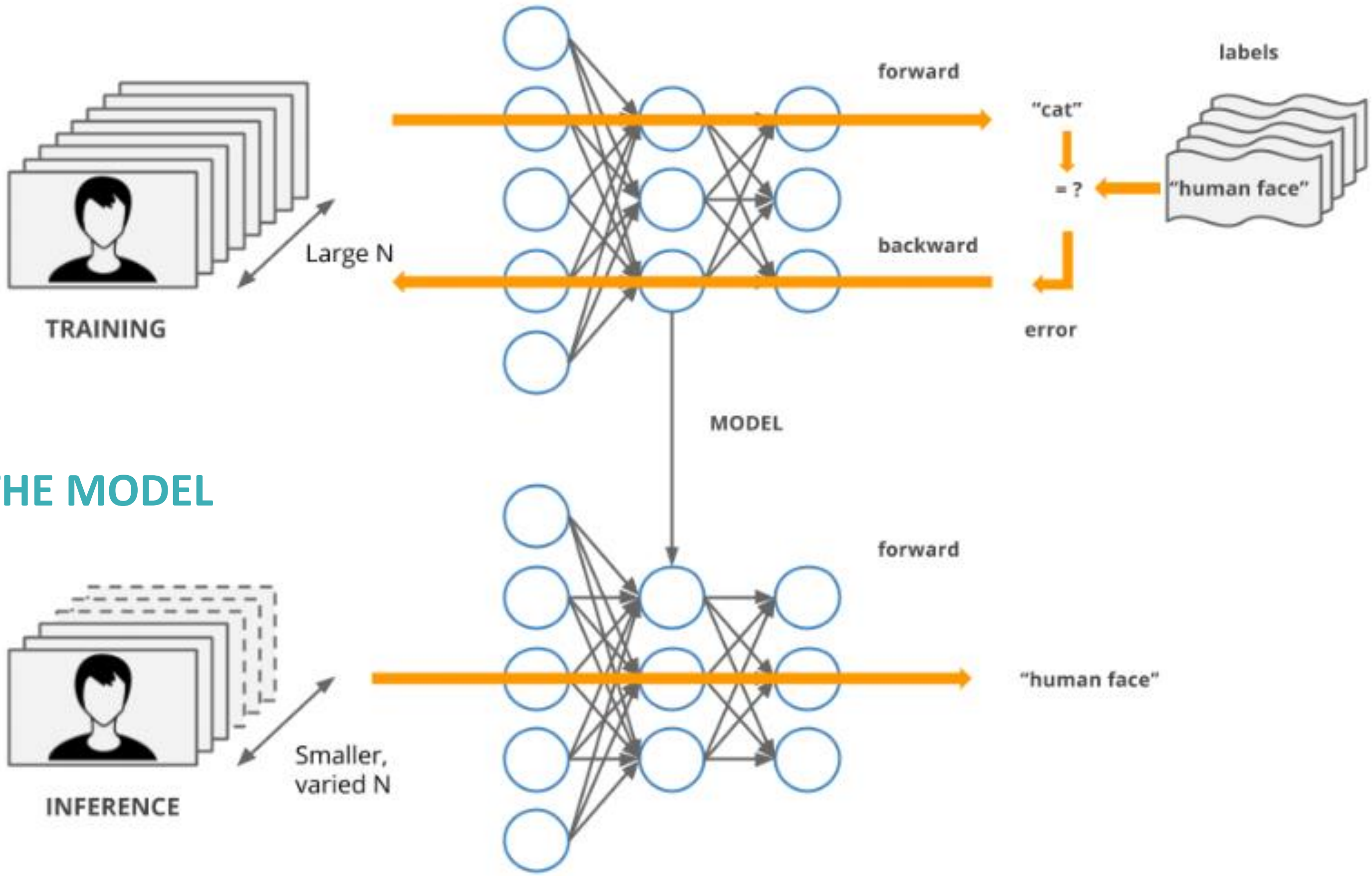


ML, where do we begin ?

Machine learning process

TRAINING THE MODEL

USING THE MODEL



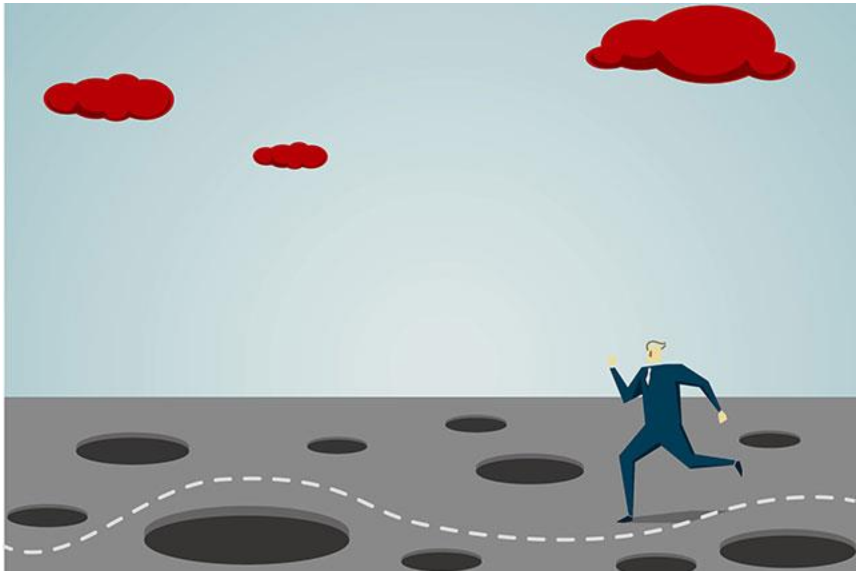
Machine learning – The new kid on the block

Unfamiliar technology

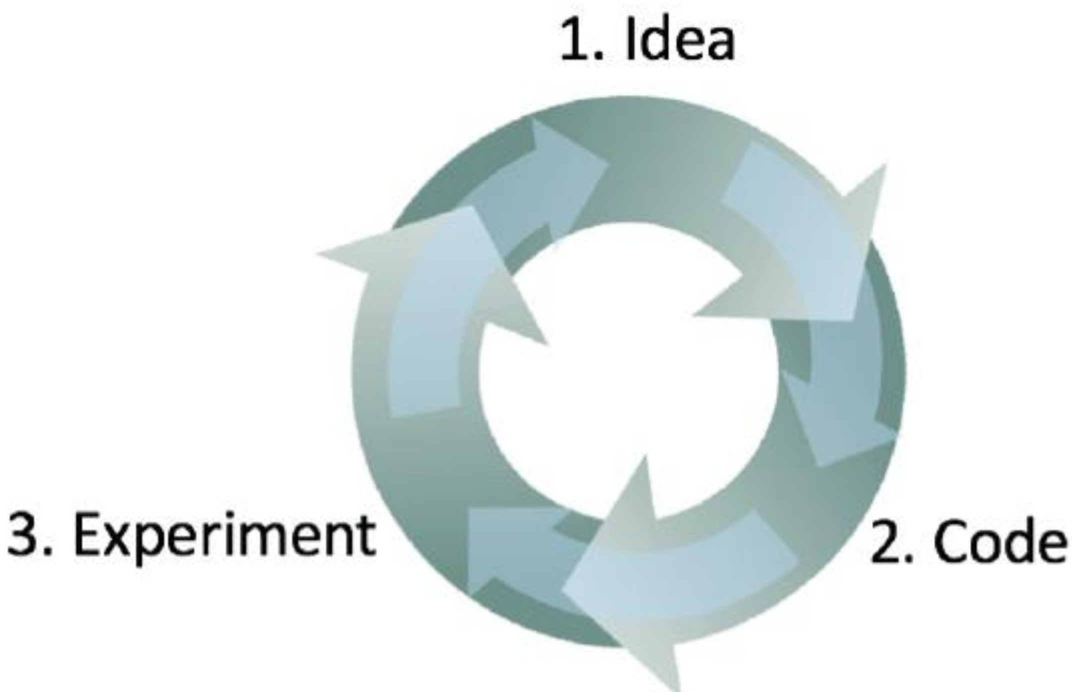
→ Risk project failure

→ Having the right team with the right skills

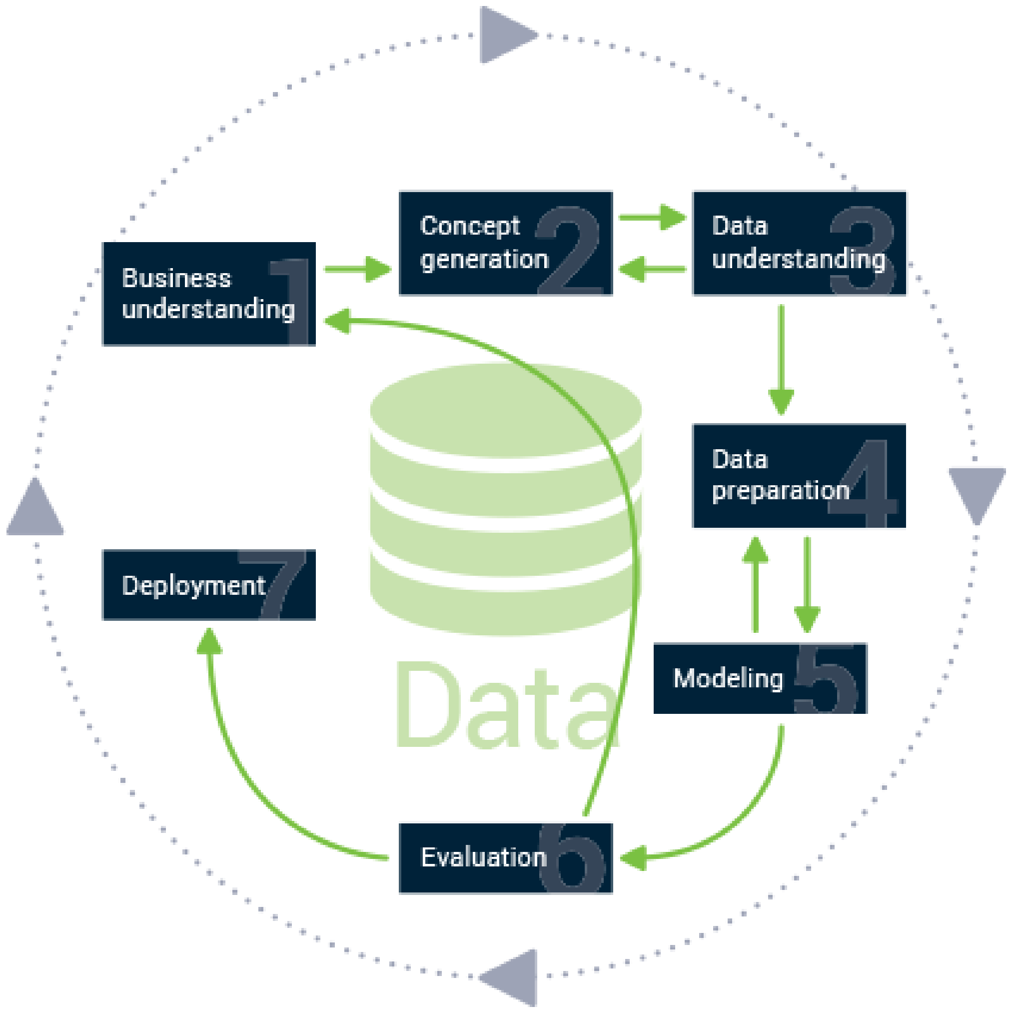
→ Careful execution



Development cycle

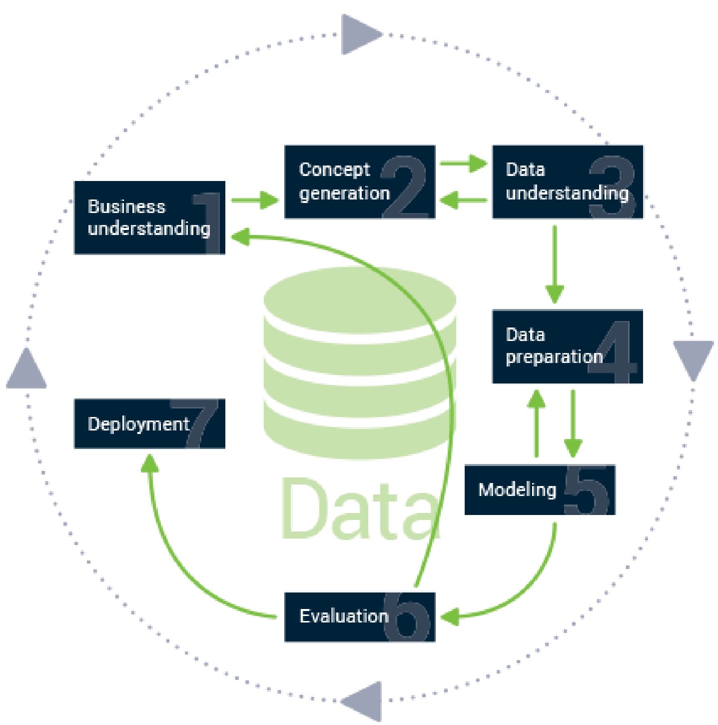


Machine learning project steps



Verhaert project flow:
based on CRISP-DM

1. Business understanding



Business understanding

- “Tech driven” vs “business driven”
- **Analyse the opportunity** first before investing resources and infrastructure.

Rules of ML

Concept on product level & Model level

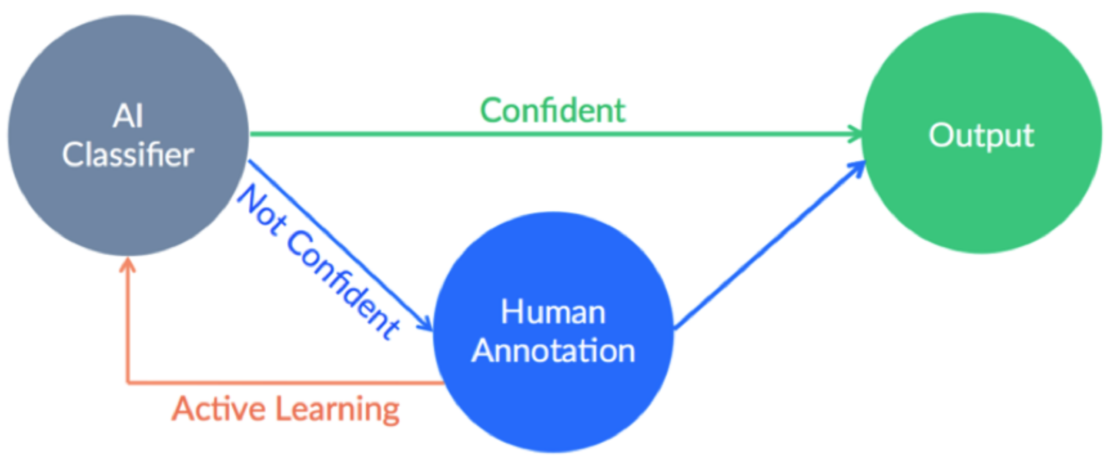
Algorithms don’t live in a box

A.I. failure and human interaction

"Sometimes A.I. isn't up for the job"

- *Problem too complex*
- *Never seen something like this before*

Human in the loop (HITL)

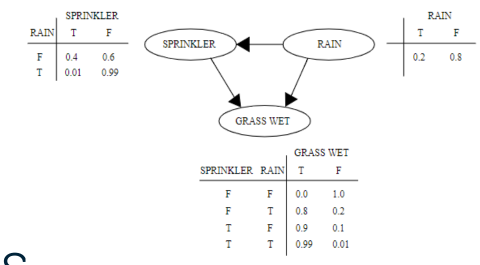


HITL + Active (incremental) Learning

Human interaction

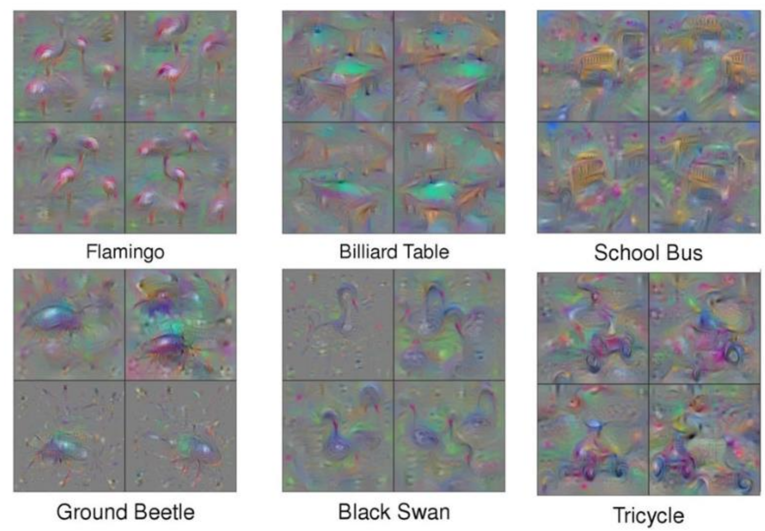
Level	Name	Narrative Definition	Execution of Steering and Acceleration/ Deceleration	Monitoring of Driving Environment	Fallback Performance of Dynamic Driving Task	System Capability (Driving Modes)
Human driver **monitors the driving environment**						
0	**No Automation**	the full-time performance by the *human driver* of all aspects of the *dynamic driving task*, even when enhanced by warning or intervention systems	Human driver	Human driver	Human driver	n/a
1	**Driver Assistance**	the *driving mode*-specific execution by a driver assistance system of either steering or acceleration/deceleration using information about the driving environment and with the expectation that the *human driver* perform all remaining aspects of the *dynamic driving task*	Human driver and system	Human driver	Human driver	Some driving modes
2	**Partial Automation**	the *driving mode*-specific execution by one or more driver assistance systems of both steering and acceleration/ deceleration using information about the driving environment and with the expectation that the *human driver* perform all remaining aspects of the *dynamic driving task*	**System**	Human driver	Human driver	Some driving modes
Automated driving system **("system") monitors the driving environment**						
3	**Conditional Automation**	the *driving mode*-specific performance by an *automated driving system* of all aspects of the dynamic driving task with the expectation that the *human driver* will respond appropriately to a *request to intervene*	System	**System**	Human driver	Some driving modes
4	**High Automation**	the *driving mode*-specific performance by an automated driving system of all aspects of the *dynamic driving task*, even if a *human driver* does not respond appropriately to a *request to intervene*	System	System	**System**	Some driving modes
5	**Full Automation**	the full-time performance by an *automated driving* system of all aspects of the *dynamic driving task* under all roadway and environmental conditions that can be managed by a *human driver*	System	System	System	**All driving modes**

Lack of transparency



Explainable AI (XAI)

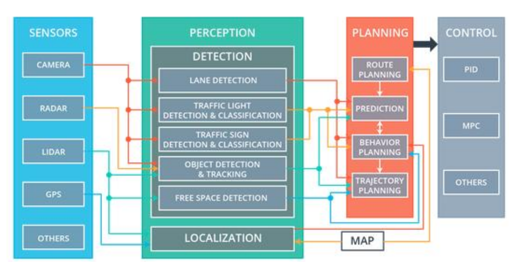
- Decision trees
- Bayesian reasoning systems
- Expert systems



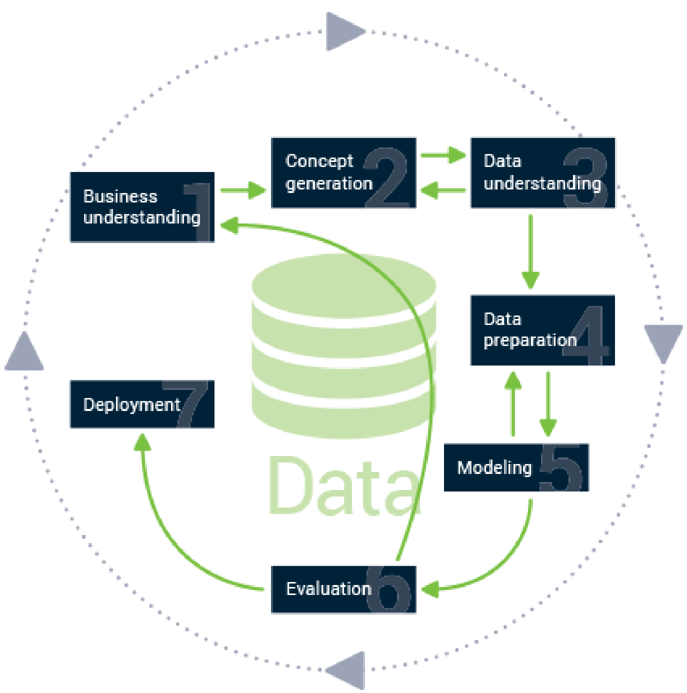
Reverse engineering

- Internal state reflection
- Parameter variation

Divide and conquer



2. Concept generation

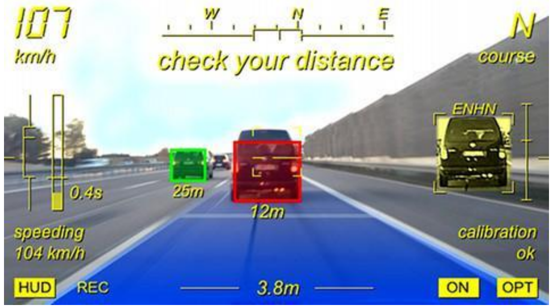


Explore the problem

Before understanding → explore the problem

Automated car:

Traffic sign detection, Free Road detection, Traffic lights, object recognition, Traffic rules, Distance, ….



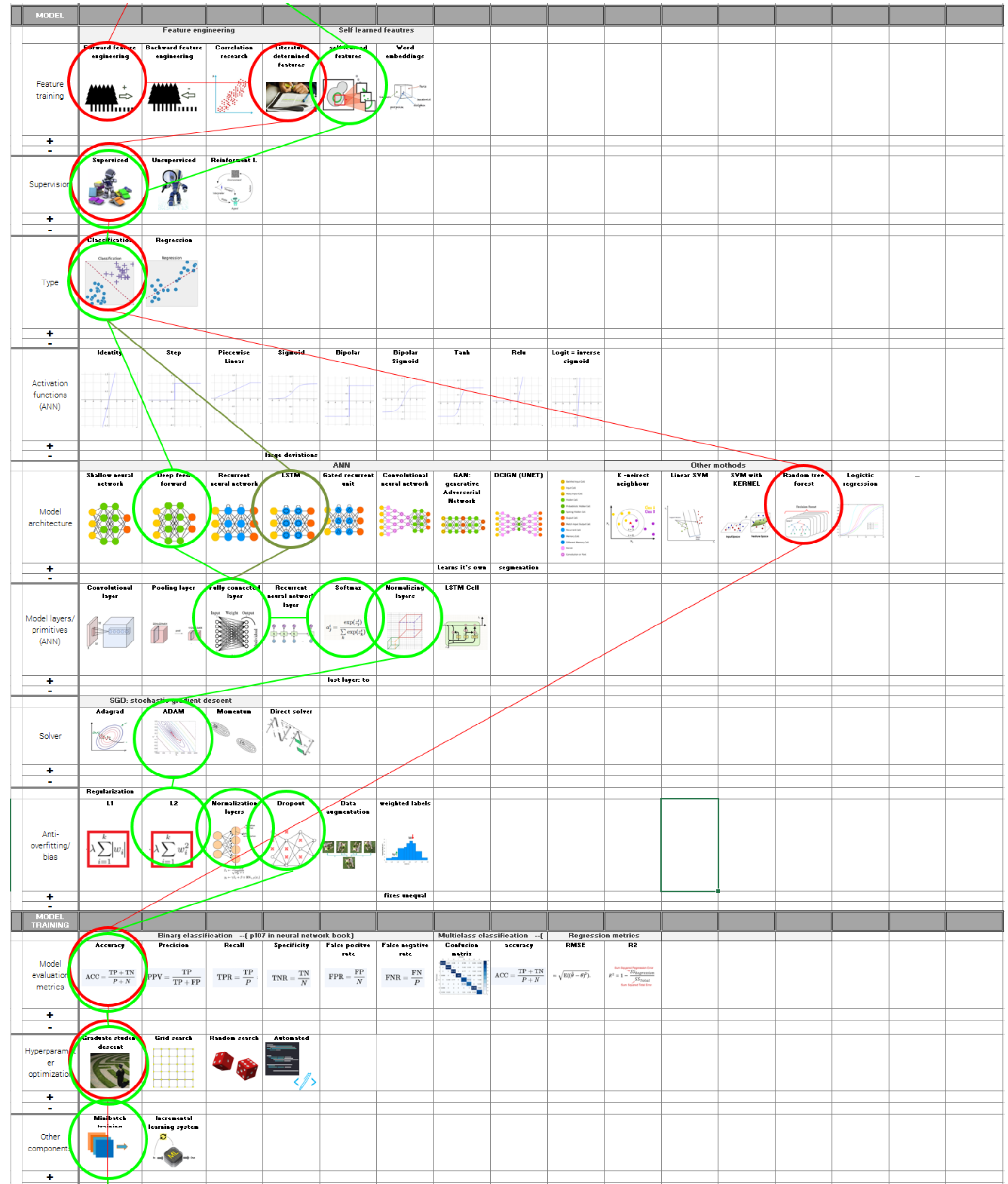
Input data:

Visual, Lidar, HD maps, traffic rules, gps, …

Output data: steering, breaking and driving, …

→ Understanding of the problem

Concept generation



Deep reinforcement **learning framework** for **autonomous driving**
AEL Sallab, M Abdou, E Perot... - Electronic ..., 2017 - ingentaconnect.com
... This can lead to potential extension of the **framework** to real **driving** scenarios ... He has over 10 years of experience in computer vision and **machine learning** including 8 years of ... IS&T International Symposium on Electronic Imaging 2017 **Autonomous** Vehicles and **Machines** 2017
☆ 99 Geciteerd door 38 Verwante artikelen Alle 6 versies

[HTML] **Autonomous driving** in urban environments: Boss and the urban challenge
C Urmson, J Anhalt, D Bagnell, C Baker... - Journal of Field ..., 2008 - Wiley Online Library
... **Autonomous driving** in urban environments: Boss and the Urban Challenge. Chris Urmson E-mail address:curmson@ri.cmu.edu. Carnegie Mellon University, Pittsburgh, Pennsylvania 15213. Search for more papers by this author. Joshua Anhalt ...
☆ 99 Geciteerd door 1196 Verwante artikelen Alle 25 versies

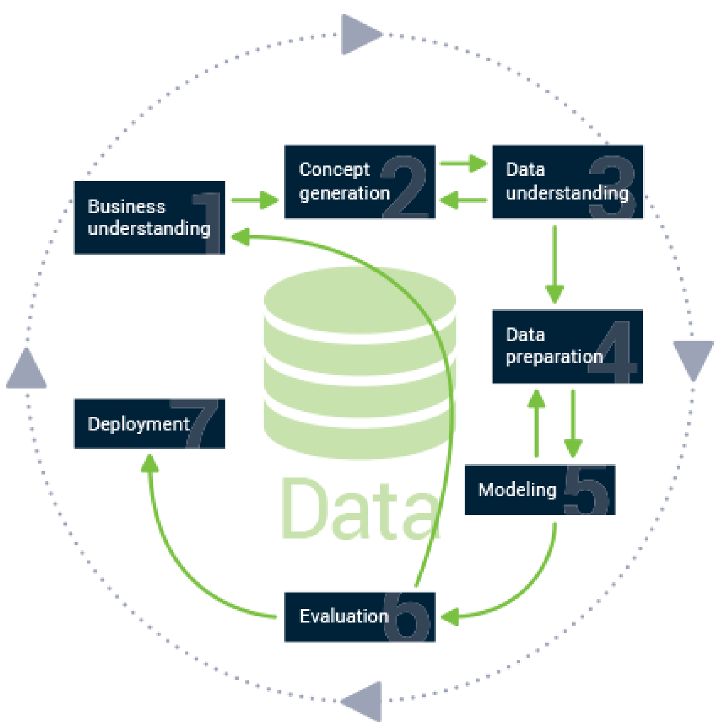
Graphical models for **driver** behavior recognition in a smartcar
N Oliver, AP Pentland - ... , 2000. IV 2000. Proceedings of the ..., 2000 - ieeexplore.ieee.org
... simulators, specially the lack of realism of the computer generated **automated** cars, the ... 1. SmartCar physical **self**-state: information sensed from the speedometer, acceleration throttle, steering ... data acquisition system in a real car and a **machine learning framework** for modeling ...
☆ 99 Geciteerd door 308 Verwante artikelen Alle 14 versies

Deepdriving: **Learning** affordance for direct perception in **autonomous driving**
C Chen, A Seff, A Kornhauser... - Proceedings of the IEEE ..., 2015 - cv-foundation.org
... When all these scenar- ios exist in the training data, a **machine learning** model will have difficulty ... is built upon the state-of-the-art deep Convo- lutional Neural Network (ConvNet) **framework** to automat ... We choose an initial **learning** rate of 0.01, and each mini-batch consists of 64 ...
☆ 99 Geciteerd door 363 Verwante artikelen Alle 18 versies »

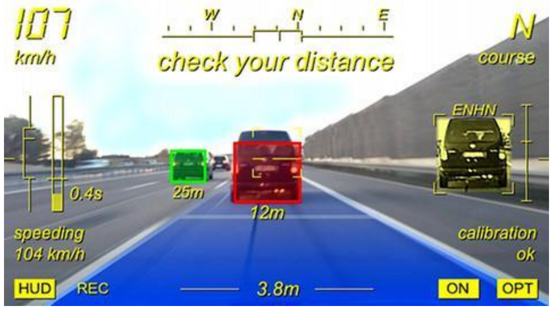
Are we ready for **autonomous driving**? the kitti vision benchmark suite
A Geiger, P Lenz, R Urtasun - Computer Vision and Pattern ..., 2012 - ieeexplore.ieee.org
Are we ready for **Autonomous Driving**? The KITTI Vision Benchmark Suite ... In this paper, we take advantage of our **autonomous driving** platform to develop novel chal- lenging benchmarks for the tasks of stereo, optical flow, vi- sual odometry / SLAM and 3D object detection ...
☆ 99 Geciteerd door 2453 Verwante artikelen Alle 20 versies

Safe, multi-agent, reinforcement **learning** for **autonomous driving**
S Shalev-Shwartz, S Shammah, A Shashua - arXiv preprint arXiv ..., 2016 - arxiv.org
... we will introduce a specific discrete action space for selecting "desires" tailored to the domain of **autonomous driving** ... section is to give a sense of how a challenging negotiation scenario is handled by our **framework** ... The Journal of **Machine Learning** Research, 3:213–231, 2003 ...
☆ 99 Geciteerd door 63 Verwante artikelen Alle 6 versies »

3. Data understanding



Explore the problem



Before understanding → explore the problem

Automated car:

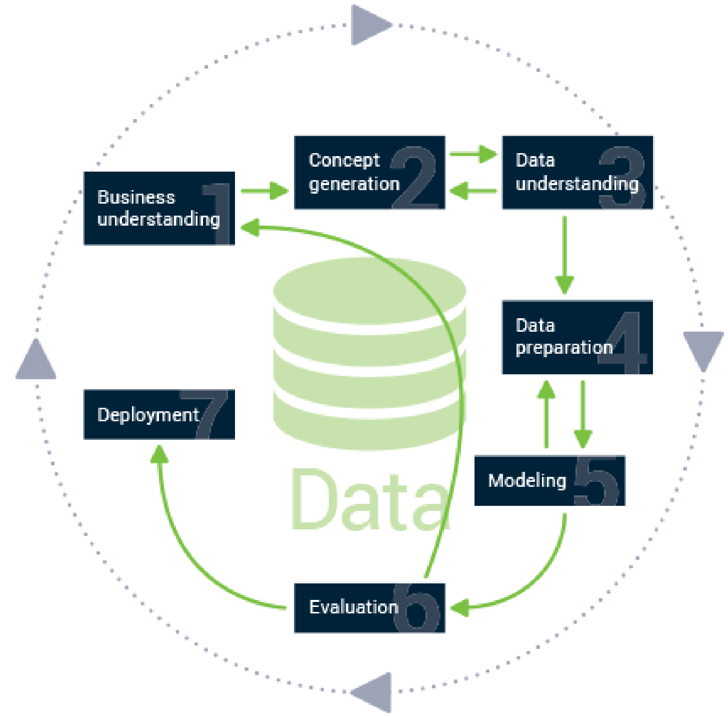
Traffic sign detection, Free Road detection, Traffic lights, object recognition, Traffic rules, Distance, ….

Traffic sign detection:

Lighting, surroundings, color, angle, image sharpness , ….

→ Understanding of the problem AND data

Data Gathering – First Runs



Creating data = expensive

→Gathering low cost data & learn

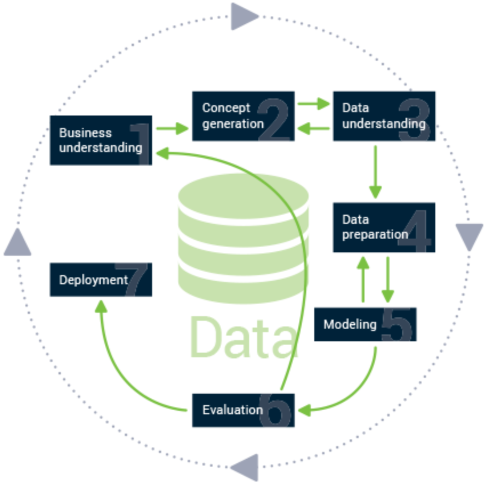
- Create toy datasets
- Use existing (online) databases
- Augment limited databases

Learn as much as you can this way.

- What's missing in the database ?
- Which are the hard cases ?

...

Data gathering – AI engineering



So you need more data…

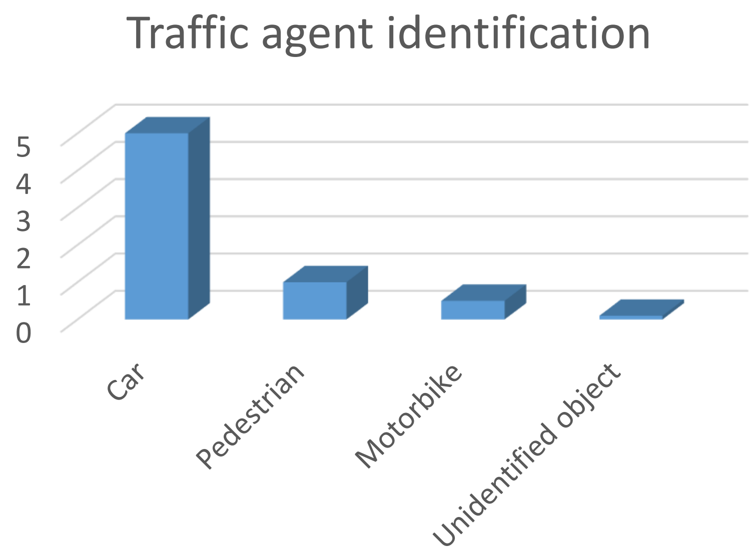
Questions:

- Is the **needed information present** in the data provided ?
- What data input could provide this information

→ Recruit expert knowledge.

→ This requires engineering/system/physics insight.

Training data balance



"Learning from a dataset that is skewed will predict skewed"

Fixes:

- Over sampling
- Under sampling
- Create new data
- Weighting techniques
- ...

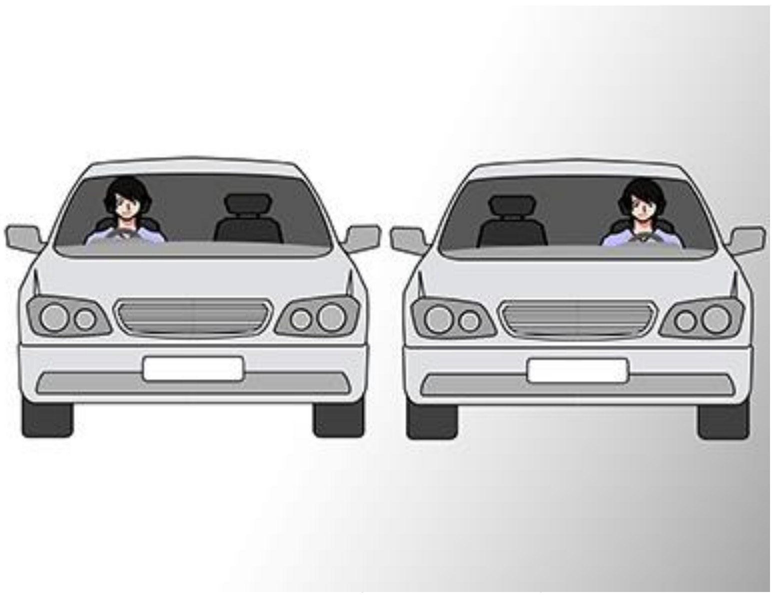
Data understanding

Data Veracity = Accuracy

Data fidelity

- Quality in context
- Unintended Bias

Quality in the context it's being used



Unintended Bias

Explaining overtraining

Learning by heart vs. learning general features

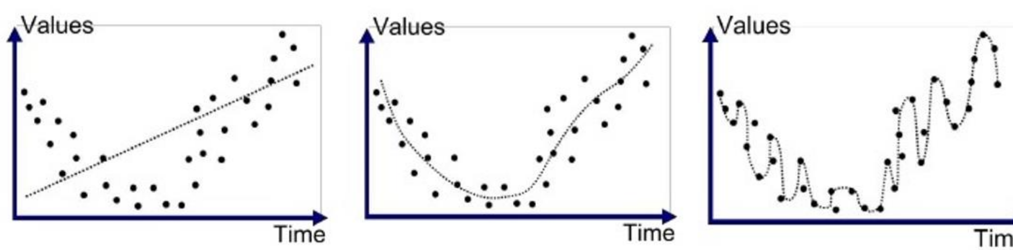



Algorithm should have learned general features :

- Recognizing 4 wheels vs 2 wheels
- Shape of person
- size vs environment

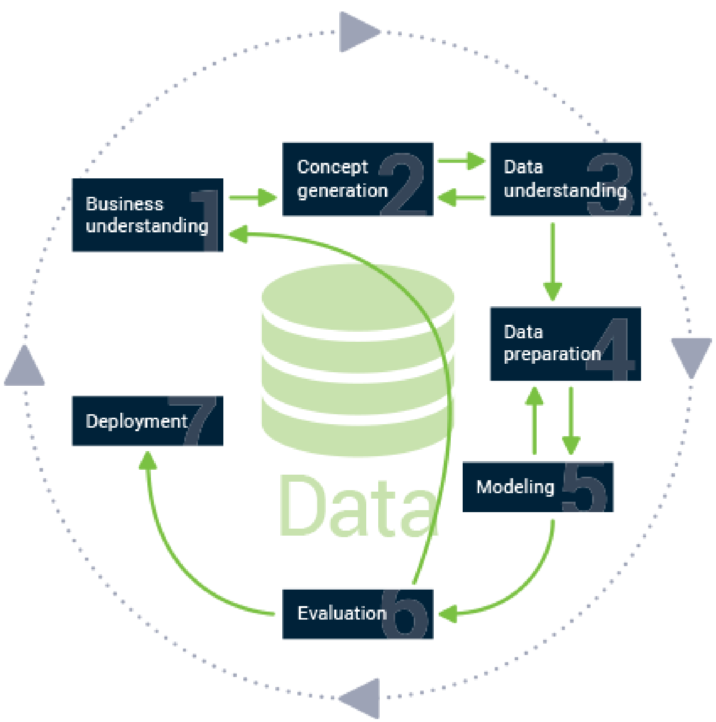
Instead it learned:

- Red/blue = car
- Tree in the background

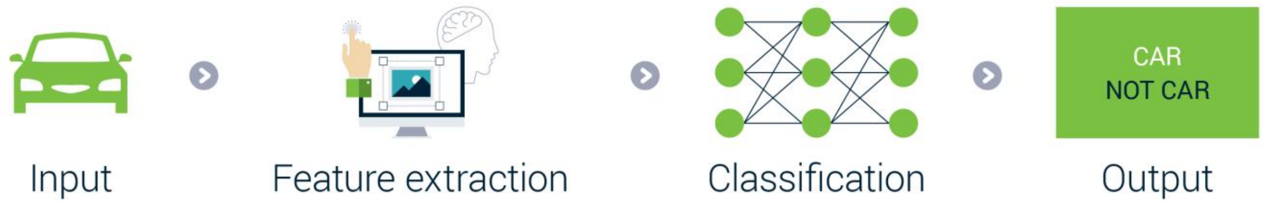


Underfitted Good Fit/Robust Overfitted

4. Data Preparation



Machine Learning



Deep Learning

Machine Learning

- (+) Good results with small data sets
- (+) Quick to train a model
- (−) Need to try different features and classifiers to achieve best results
- (−) Accuracy plateaus

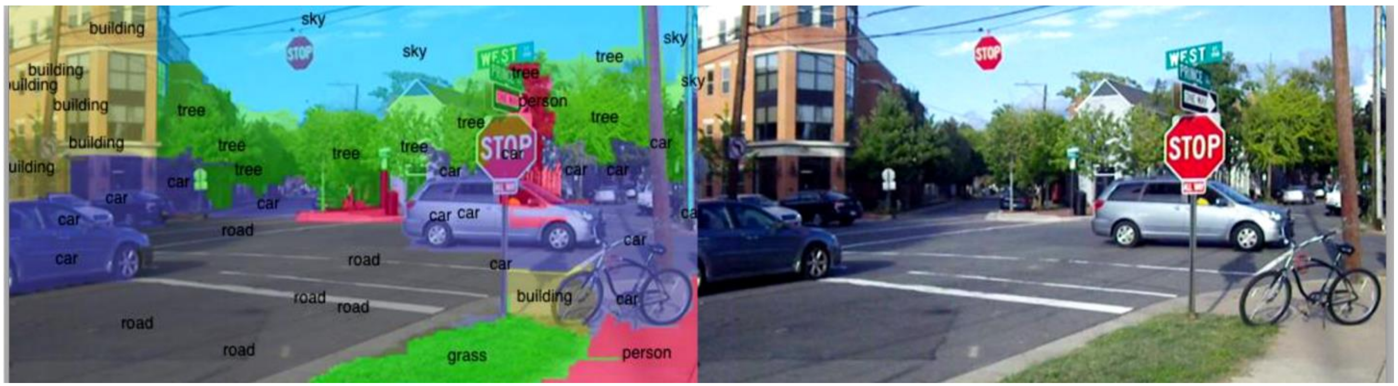
Deep Learning

- (−) Requires very large data sets
- (−) Computationally intensive
- (+) Learns features and classifiers automatically
- (+) Accuracy is unlimited

Data labeling

33,Jogging,49106652389000,-0.50395286,13.947236,7.0553403
33,Jogging,49106762313000,-8.430995,11.413852,5.134871
33,Jogging,49106872299000,0.95342433,1.3756552,1.6480621
33,Jogging,49106982315000,-8.19945,19.57244,2.7240696
33,Jogging,49107092330000,1.4165162,5.7886477,2.982856
33,Jogging,49107202316000,-1.879608,-2.982856,-0.29964766
33,Jogging,49107312332000,-6.1291566,6.851035,-8.158588
33,Jogging,49107422348000,5.829509,18.0061,8.539958
33,Jogging,49107522293000,6.2789803,2.982856,2.9147544
33,Jogging,49107632339000,-1.56634,8.308413,-1.4573772
33,Jogging,49107742355000,3.5276701,13.593107,9.425281
33,Jogging,49107852340000,-2.0294318,-5.706926,-10.18802
33,Jogging,49107962326000,2.7649305,10.337844,-9.724928
33,Jogging,49108062271000,3.568531,13.6748295,1.5390993
33,Jogging,49108172348000,-0.50395286,3.8681788,3.718355
33,Jogging,49108272262000,-2.3018389,1.6889231,0.08172209
33,Jogging,49108382370000,-3.568531,19.57244,6.510526
33,Jogging,49108492294000,-0.8036005,-3.2961242,-4.630918
33,Jogging,49108602371000,0.50395286,10.841797,13.525005
33,Jogging,49108702285000,5.706926,15.595298,6.1700177
33,Jogging,49108812332000,-8.662541,7.273266,4.0180025
33,Jogging,49108922378000,-1.334794,1.2258313,2.3699405
33,Jogging,49109022293000,-4.5900574,19.57244,4.7126403
33,Jogging,49109132308000,3.8681788,3.759216,0.84446156
33,Jogging,49109242355000,-1.7978859,1.5390993,8.730643
33,Jogging,49109352310000,7.668256,11.264028,-1.3075534
33,Jogging,49109462295000,-2.3699405,14.2877445,8.281172
33,Jogging,49109562271000,2.7240696,1.4573772,0.88532263
33,Jogging,49109672348000,-3.5957718,18.659876,-0.6537767
33,Jogging,49109782333000,3.9499009,4.140586,3.990762
33,Jogging,49109892349000,0.46309182,-2.4108016,2.4108016
33,Jogging,49109992263000,3.7864566,14.137921,-3.1463003
33,Jogging,49110102371000,3.336985,19.231932,6.5513873
33,Jogging,49110212326000,5.6660647,3.7864566,0.53119355
33,Jogging,49110263595000,0.23154591,0.7627395,0.7627395

Labeling is expensive!



Crowd sourcing: HUMAN INTELLIGENCE

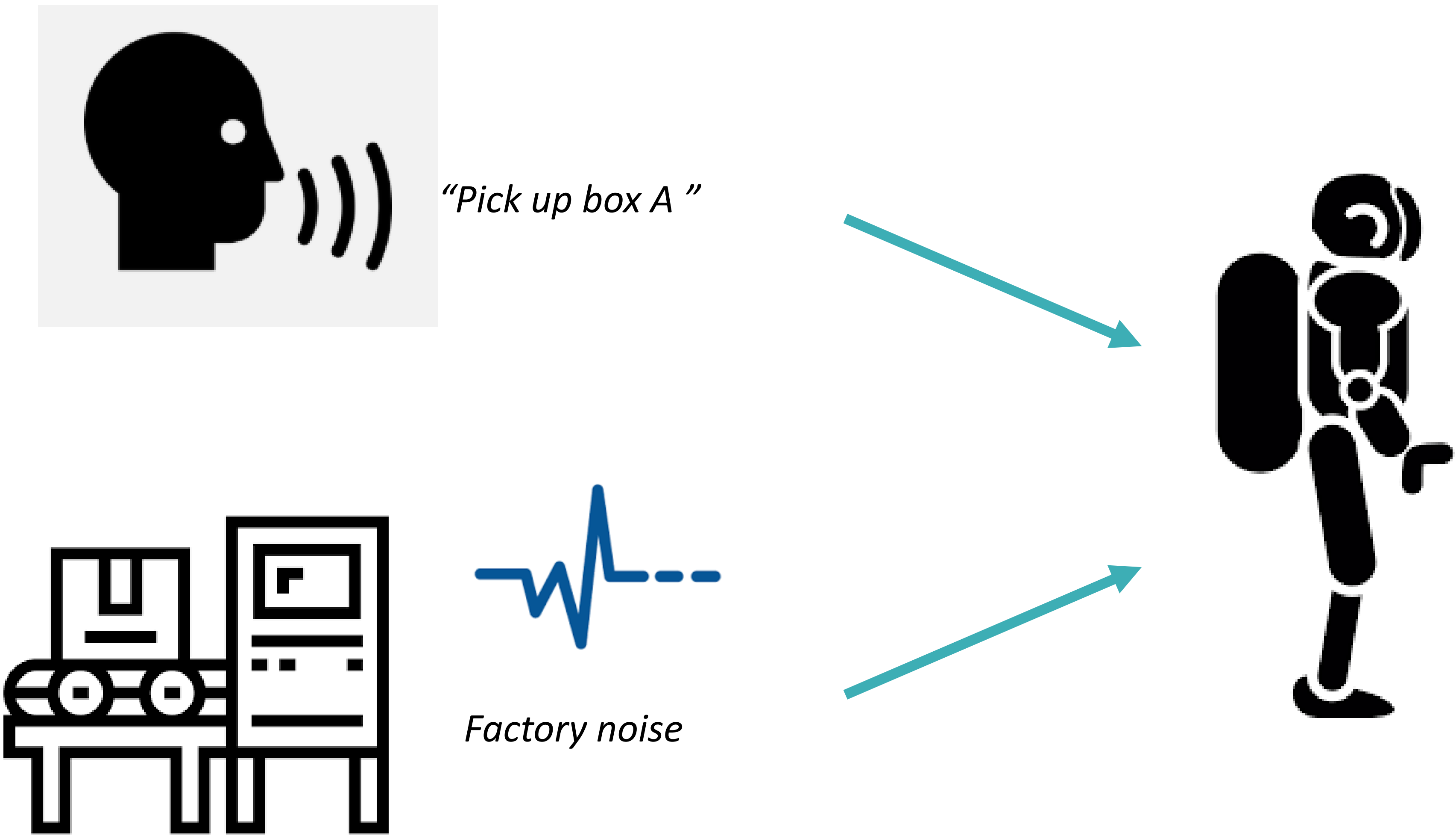
Data preparation

4 C = Clean, Correct, Consistent, Complete

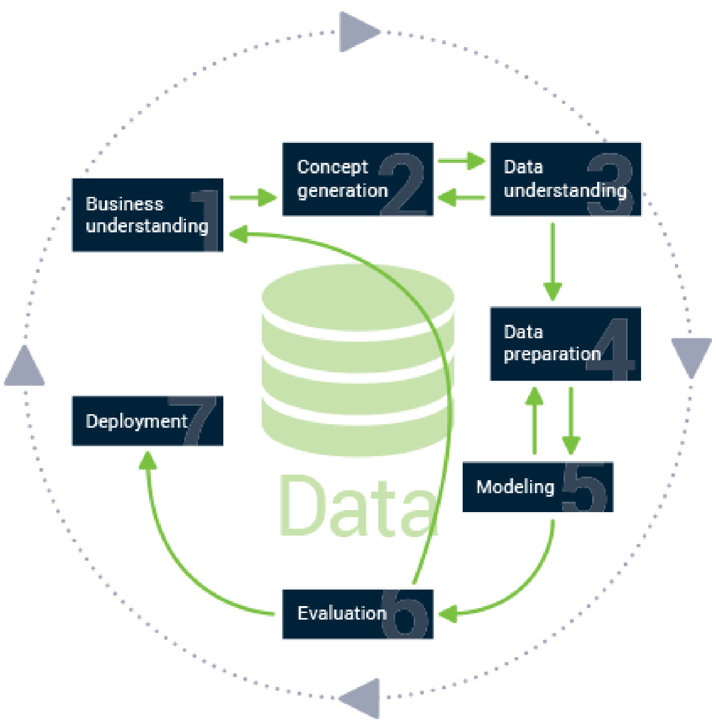
1. Data formatting
2. Data cleaning (usually 90% of the job),
3. **Data anonymization** (i.e. when working with healthcare and banking data)
4. **Data augmentation**
5. Feature engineering
6. …

Data augmentation

Artificial data synthesis

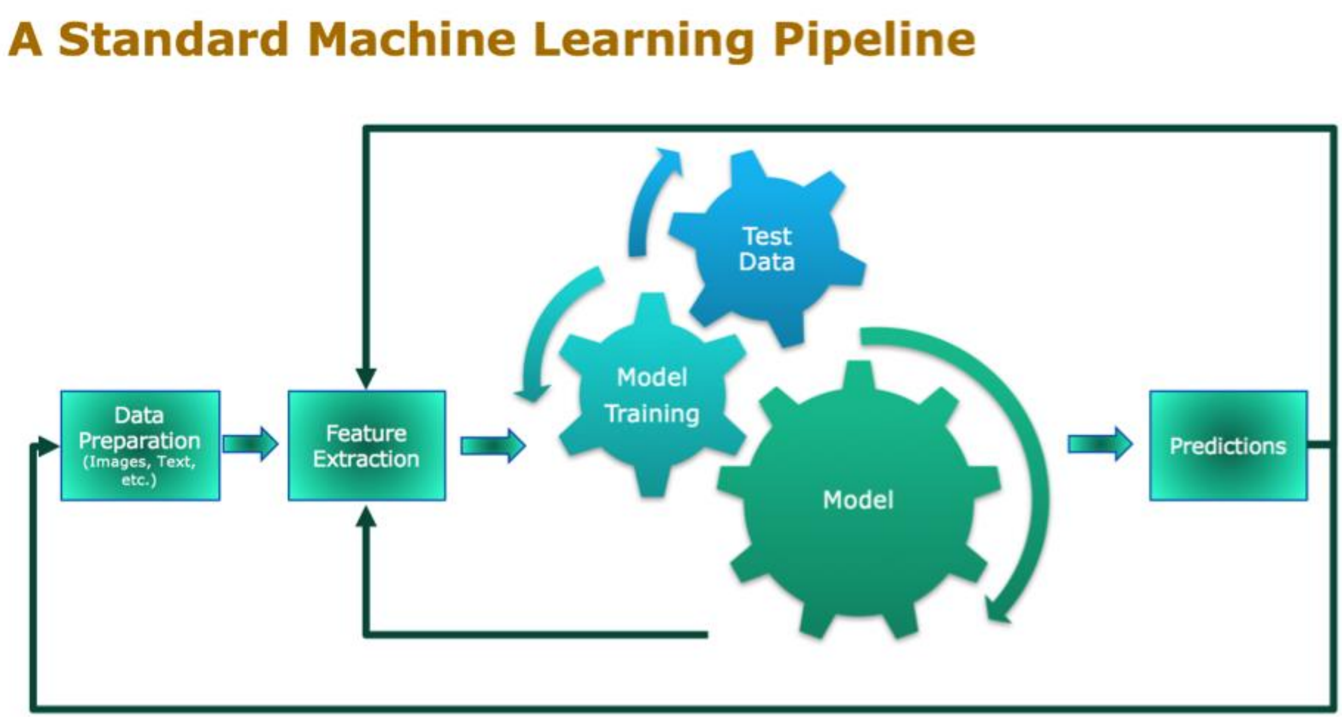


5. Modeling


Business understanding 1
Concept generation 2
Data understanding 3
Data preparation 4
Modeling 5
Evaluation 6
Deployment 7
Data

Build a simple model

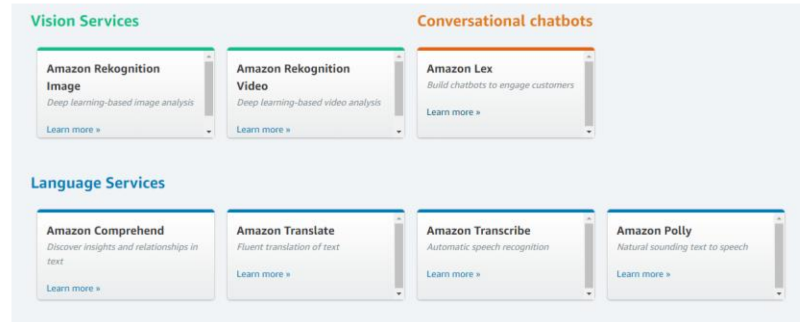
1. Determine ML algorithm performance metrics
2. Create a Data pipeline
3. Build a simple model first
4. Compare models

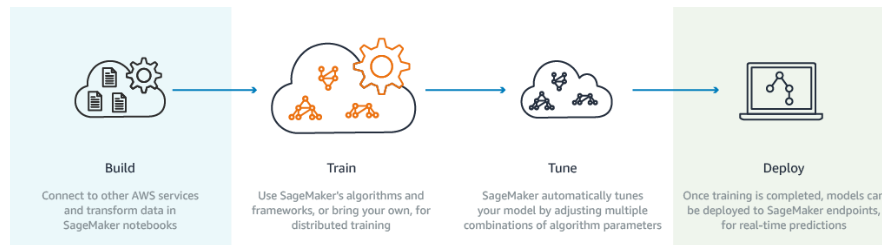


BUILD vs. BUY vs. PLATFORM

Off the shelf A.I. software

- From open source to pay-per-use
- Vendor support
- Clean and supply data
- Capabilities match
- Beware: Ideas with a website



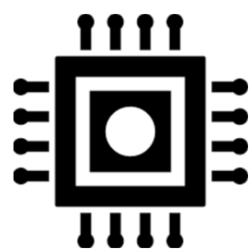


AI PLATFORMS

- IBM, Amazon, Google
- off the shelf → AI building tools for researchers.

Custom build

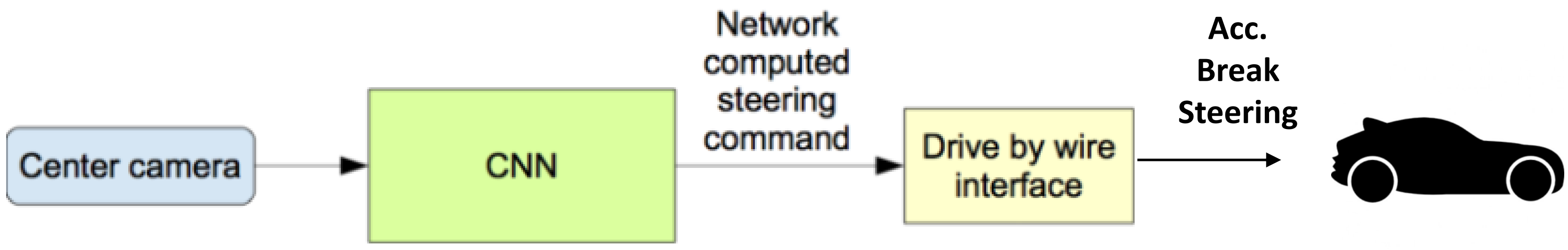
- Only when needed
- Great flexibility

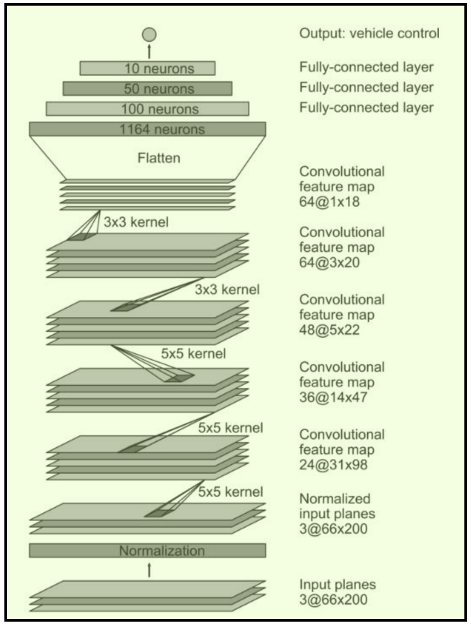


INNOVATION DAY 19.10.2018

End-to-end vs Ensembling

End-To-End vs Ensemble learning

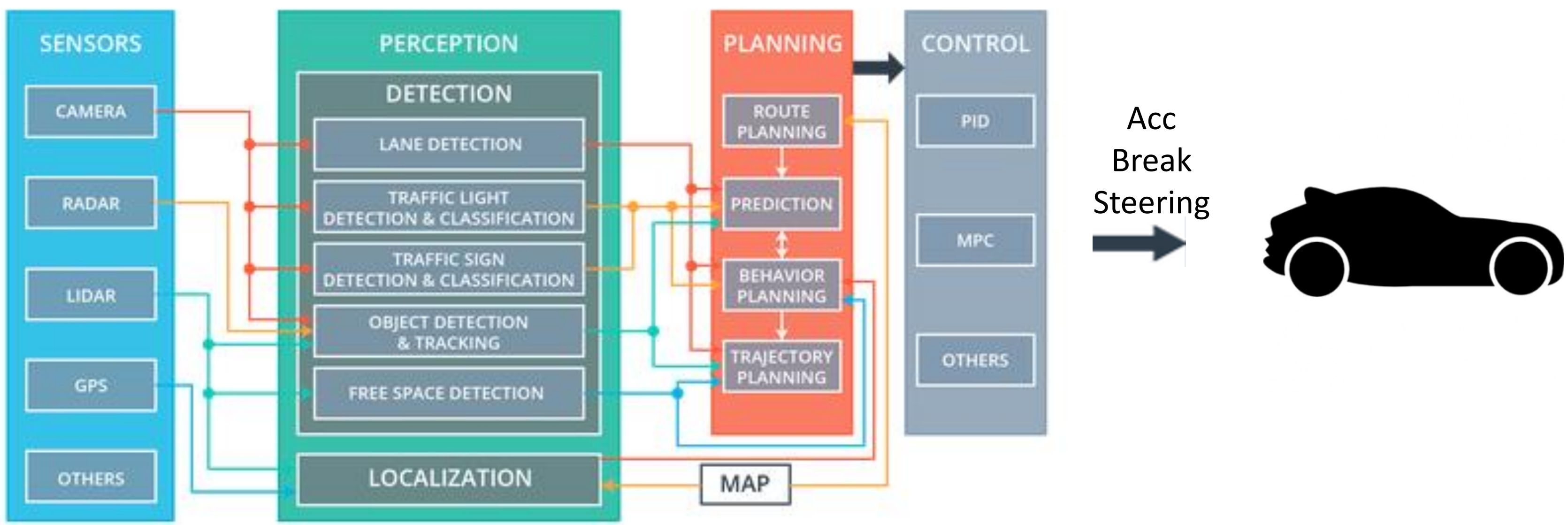




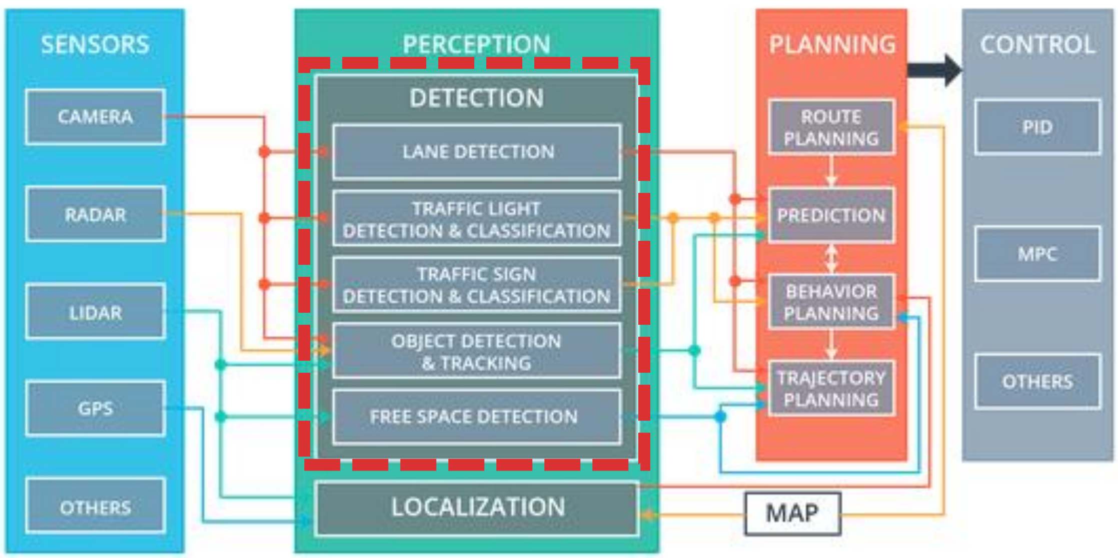
End-To-End vs Ensemble learning

Autonomous vehicles

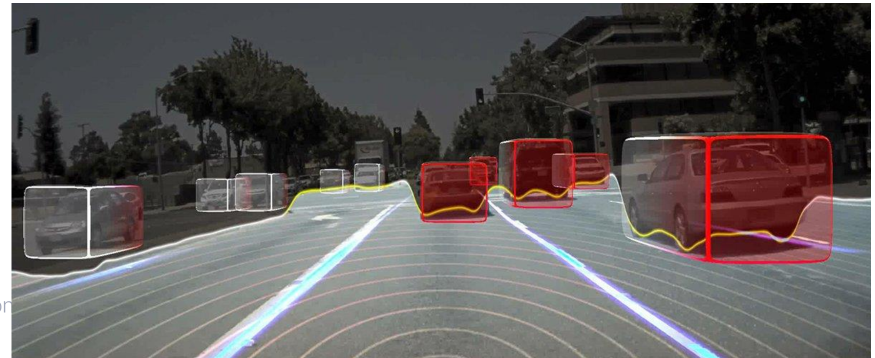
Subdivide the problem in to many subcomponents



Perception

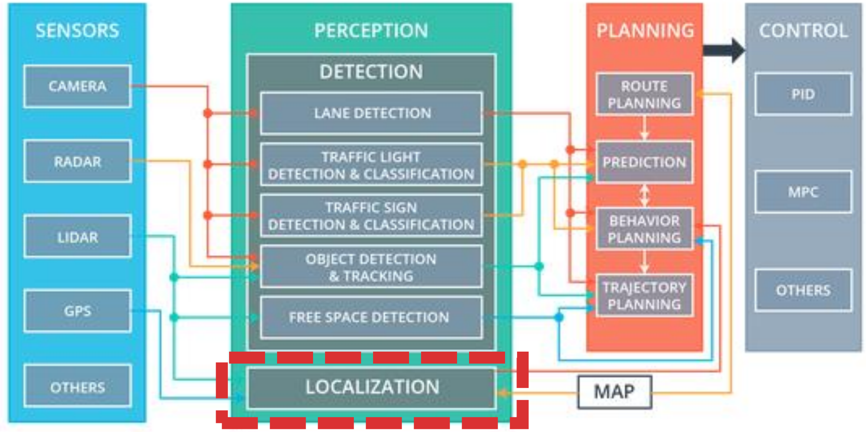


Acc
Break
Steering

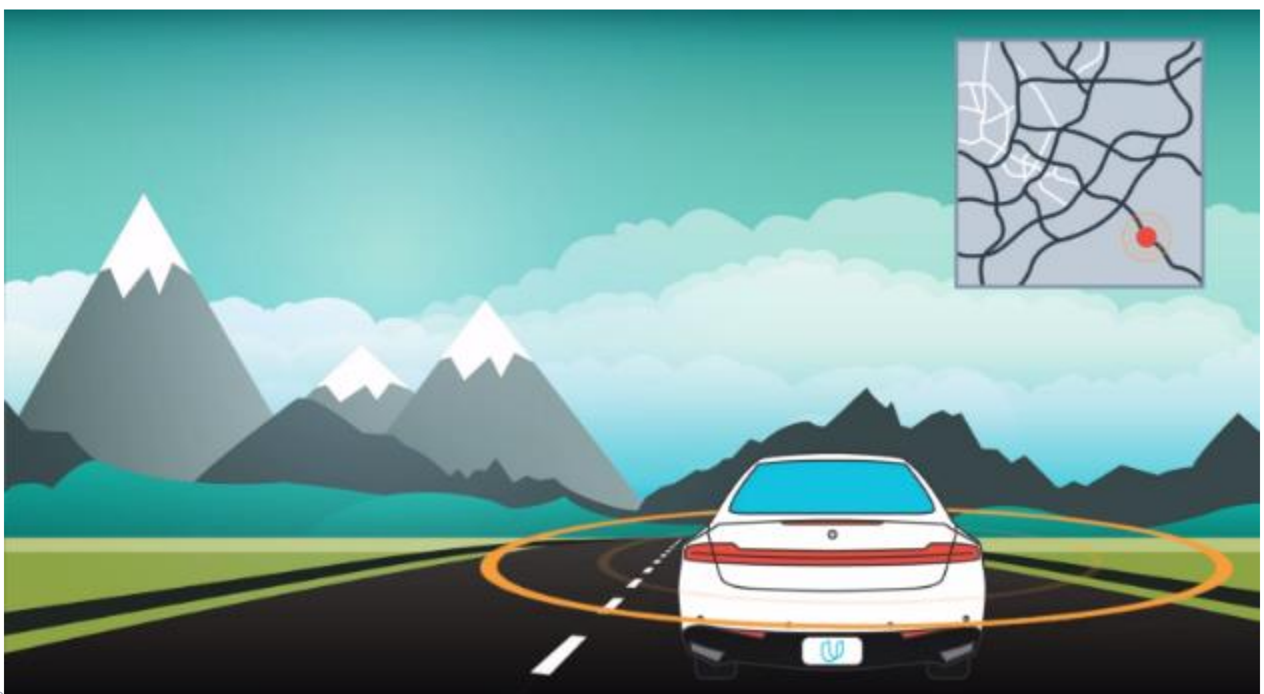


INNOVATION DAY 19.10.2018

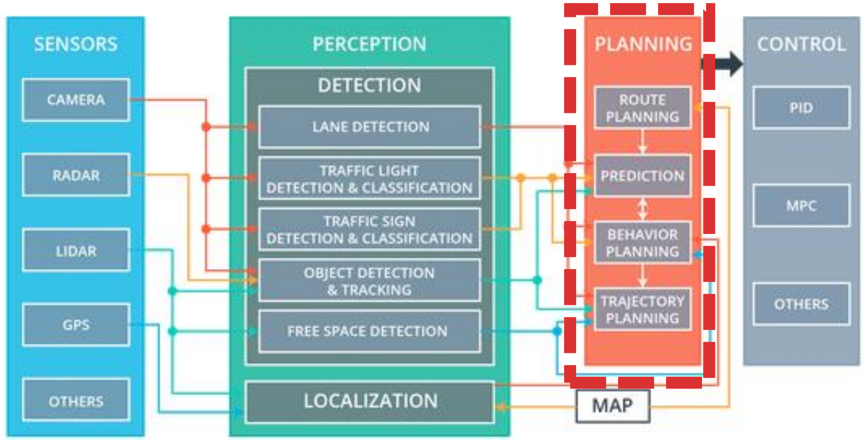
Localization



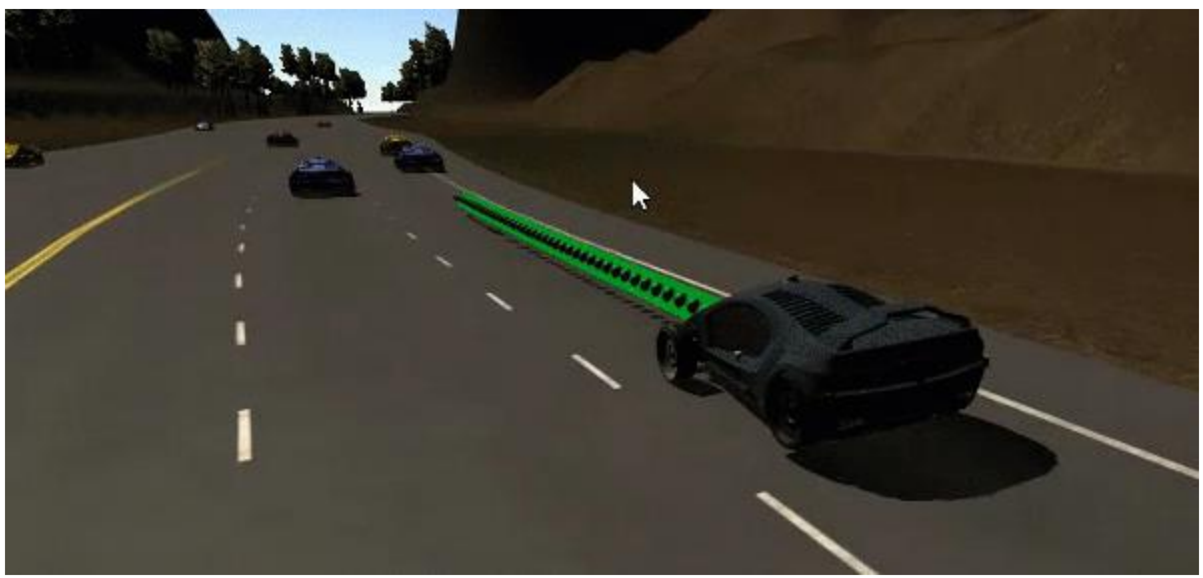
Acc.
Break
Steering



Planning



Acc.
Break
Steering



End-to-End vs Ensemble methods

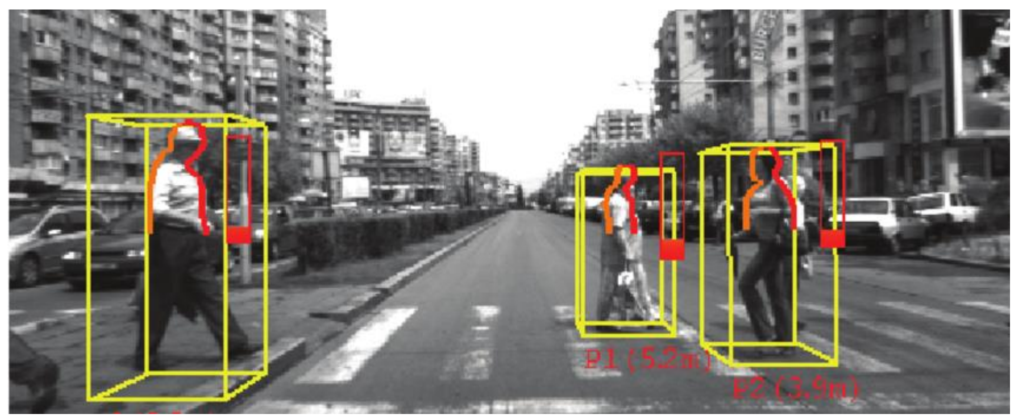
End-to-end

- Let the machine figure the problem out…
- More data needed
- Can improve performance

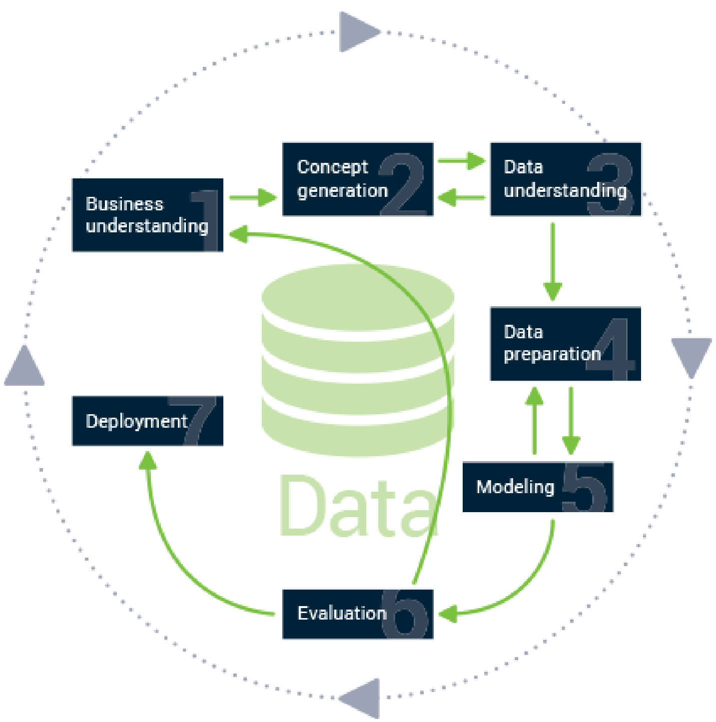
Ensemble methods

- Systems can be trained separately
- Less data needed
- Algorithm insight
- Levels of abstraction allow freedom:

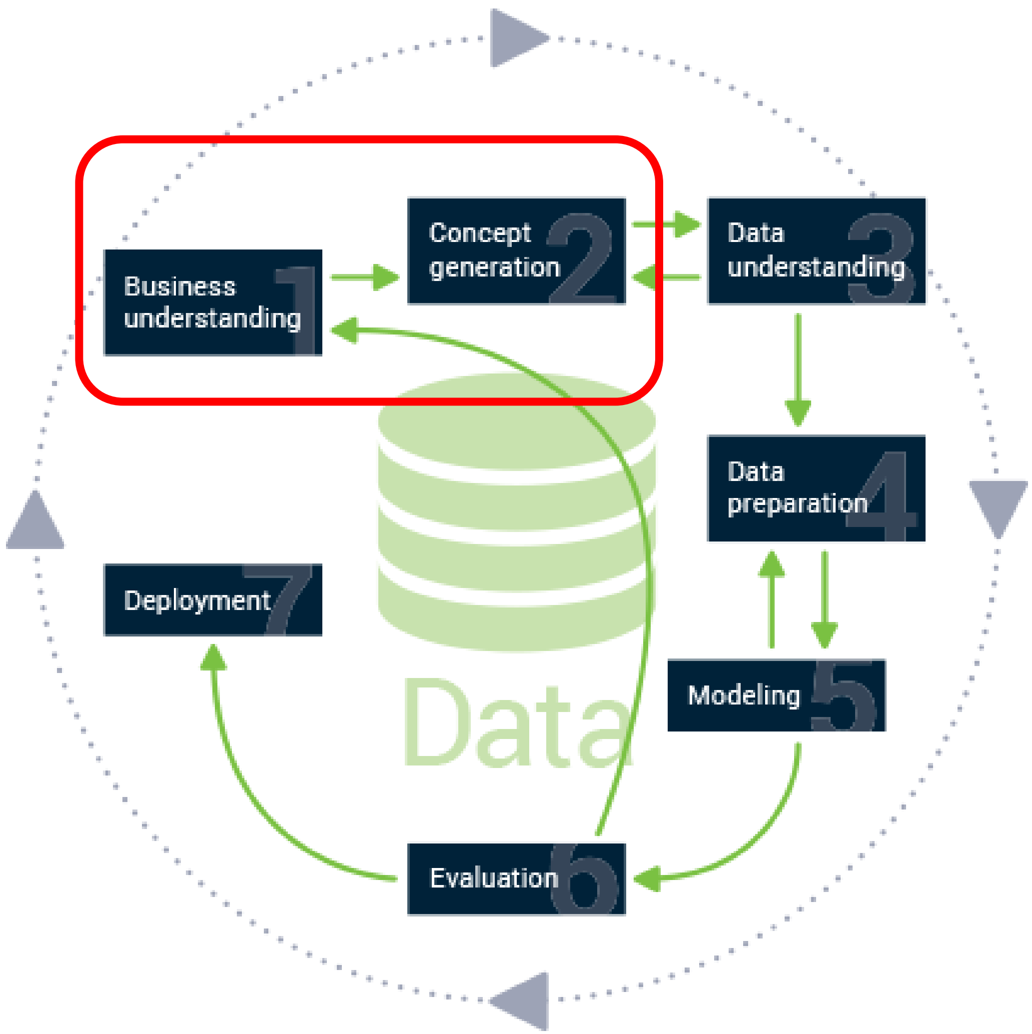
Person



5. Evaluation



Defining evaluation metrics



Success metrics

Define success metrics @ 2 levels

Business Level

→i.e. Decrease # interventions of driver in assisted driving.

Model (ML) Level

→Comparing models

→i.e. Accuracy object detection, Accuracy lane detection

Guard relation between the two !

Model level success metric

Find a metric that **represents your goal** & **easy to compare**

Multiple metrics

Classifier	Precision	Recall
A	95%	90%
B	98%	85%

$$\text{Precision} = \frac{\text{True Positive}}{\text{True Positive} + \text{False Positive}}$$

$$\text{Recall} = \frac{\text{True Positive}}{\text{True Positive} + \text{False Negative}}$$

Single metric: Accuracy = 50 %

$$2 \cdot \frac{\text{precision} \cdot \text{recall}}{\text{precision} + \text{recall}}.$$

Single metric combo

Classifier	Precision	Recall	F1 score
A	95%	90%	92.4%
B	98%	85%	91.0%

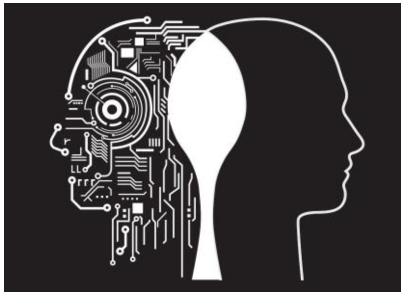
Comparing to human level performance

When ML automates things humans do well.

1. Humans are good labelers
2. Error analysis can draw on human intuition

"This recipe calls for a *pear* of apples"
mistaking "pair" for "pear."

3. Use human-level performance is often a good first goal.

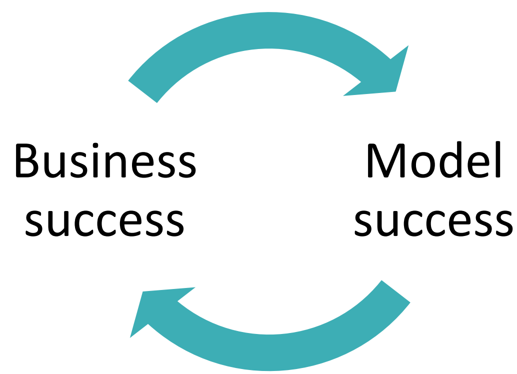


→ Automating things humans don't do well don't have these advantages to draw from – Creativity needed !

Business Level

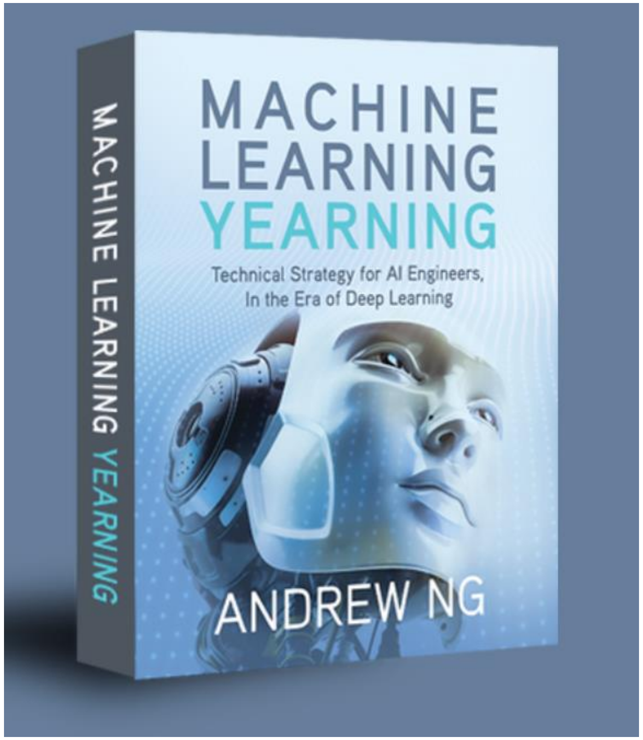
Acceptance level of a solution ?

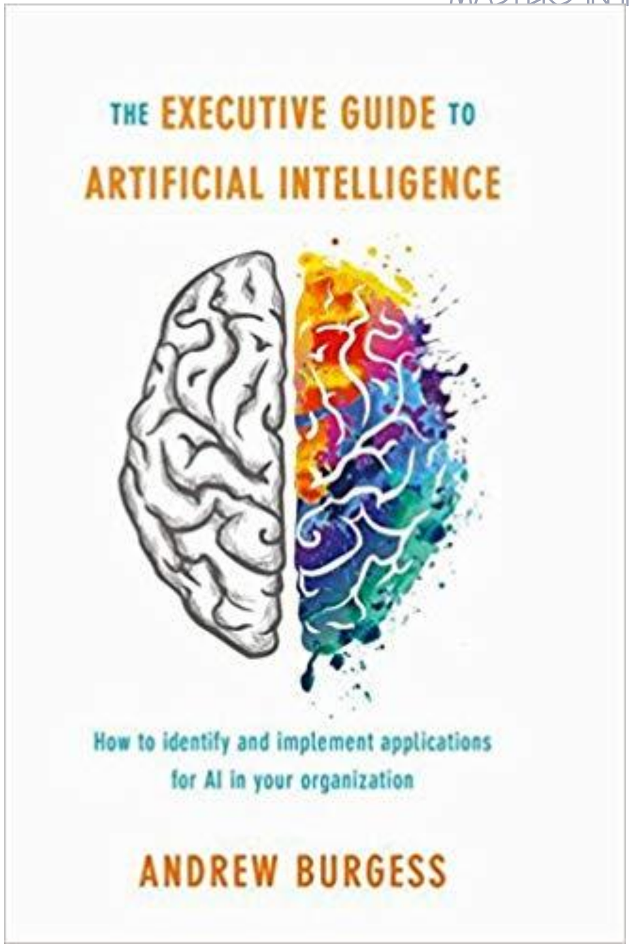
- Rational threshold ?
- Consumer acceptance threshold ?
- Legal context ?



Guard relation between the two !

Recommendations





Rules of Machine Learning:
Best Practices for ML Engineering

Martin Zinkevich

MASTERS IN INNOVATION®

One group, five brands

Our services are marketed through 5 brands each addressing specific missions in product development.

INTEGRATED PRODUCT DEVELOPMENT

VERHAERT
MASTERS IN INNOVATION

ON-SITE PRODUCT DEVELOPMENT

MOEBIUS DESIGN
MASTERS IN INNOVATION

DIGITAL PRODUCTS DEVELOPMENT

load
MASTERS IN INNOVATION

PEGUSAPPS
MASTERS IN INNOVATION

OPTICAL PRODUCTS DEVELOPMENT

LAMBDA-X
MASTERS IN INNOVATION

VENTURING