Computation World 2019

May 5-9, Venice, Italy

Panel:
Achievements and Challenges in Cognition and Machine Learning

Theme: Advanced Adaptive Systems

Adina Aniculaisei, TU Clausthal, Germany

Charlotte Sennersten, CSIRO Mineral Resources, Australia

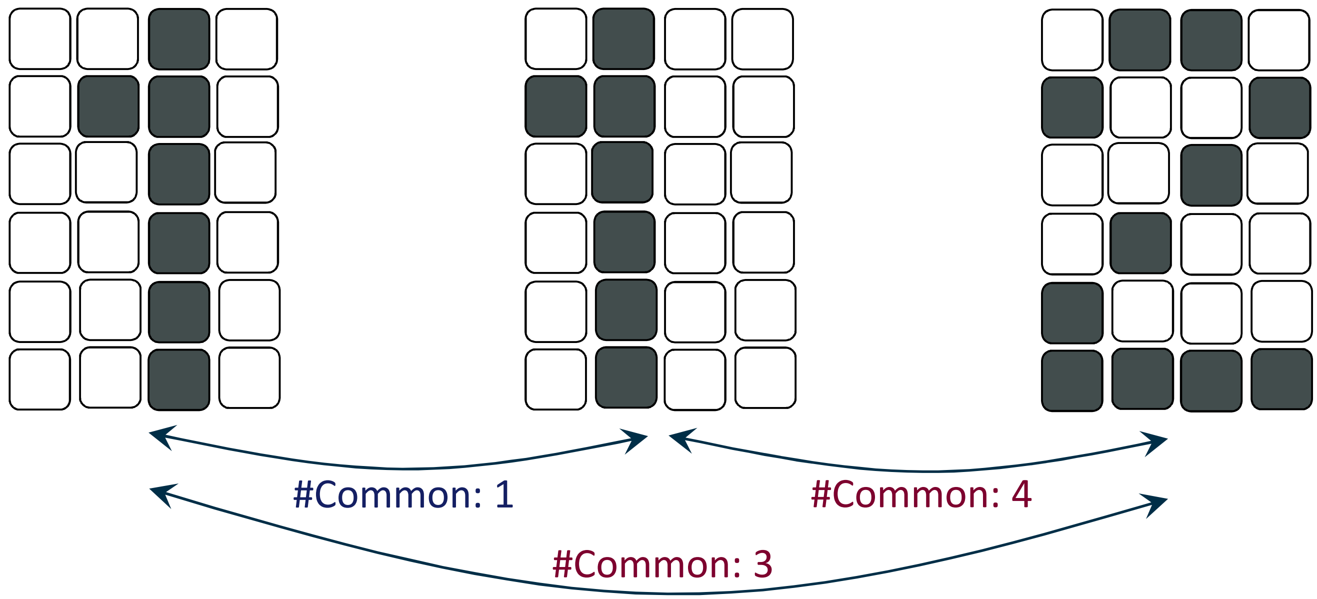
Sebastian Lawrenz, TU Clausthal, Germany

Herwig Mannaert, University of Antwerp, Belgium

Achievements and Challenges in Cognition and Machine Learning

- Adina Aniculaesei
  - Major tech companies have established presence of AI and machine learning in safety-critical applications
  - This impacts correct behavior and system development process
- Charlotte Sennersten
  - DARPA outlines 3 waves of AI: handcrafted knowledge, statistical learning, and contextual adaptation
  - What can we learn from those waves ?
- Sebastian Lawrenz
  - Data is the new oil, you need a data exchange marketplace
  - You need possibilities to measure and check the data quality
- Herwig Mannaert
  - What about preprocessing to make the data worth learning ?
  - How about the fact that we turn everybody into a data scientist ?

Have we got data that's worth learning ?



I see sensory preprocessing as a way to get data that's worth learning.

- Carver Mead, IJCANN 1990

I am sad to report that we still don't have data that's worth learning.

- Carver Mead, Oral History of Neural Networks, 2000

Should we learn features instead of clusters ?

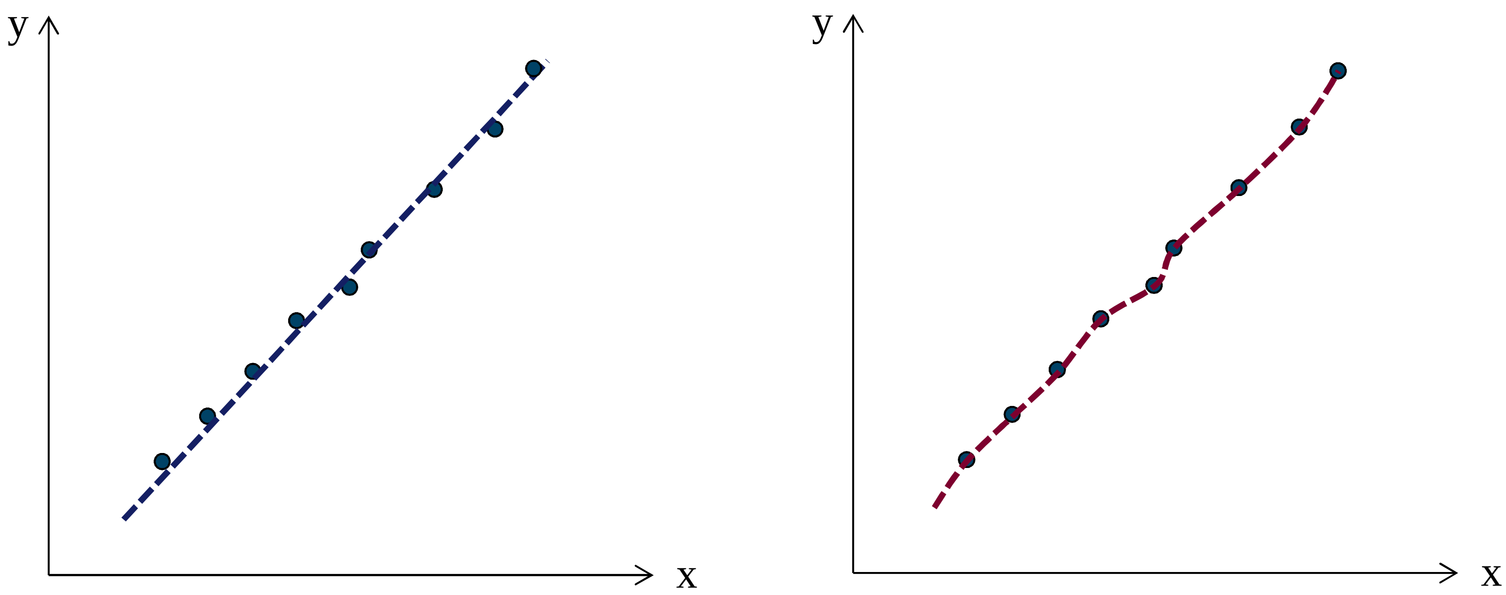
- We are trying to train machines to learn/classify clusters
  - *Pattern classification*
  - *Artificial intelligence*
  - *Artificial neural networks*
  - *Business intelligence, data mining, big data, data science*

- How about trying to *learn to discover features* ?

In the first layers of human visual processing,
connectivity is limited to a spatial spread of 2.5%.

- David Van Essen, Charles Anderson, 1989

Should we look for structure instead of values ?



Through any N points, you can fit a polynomial of degree n-1.

Counting corresponding genes gives sometimes surprising results.

Compare two Shakespeare plays and a Borat movie on a bit-per-bit basis.

Should we turn everybody into a data scientist ?

- We are turning lots of people into data scientists
  - *Biologists*
  - *Finance experts*
  - *Marketeers*
  - …

- Should we unleash unqualified people to the delicate profession of pattern analysis and classification ?

Not every correlation is causal.
Consider the one between grey hair and falling down the stairs.

- Belgian statistics professor, 1984

Questions, Comments, Opinions, …

Correctness of AI systems: Can we do it?

Panel Discussion

Adina Aniculaesei, ISSE, Technische Universität Clausthal
Venice - ADAPTIVE 2019, 8th May 2019

Motivation

Autonomous tranport robots

Growing user demand

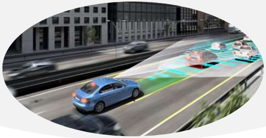
Expansion of the theory in artificial intelligence

Personal assistants

Smart Home Automation

Improvement in the area of data aquisition

Autonomous driving



Development of self – X features

Challenge 1: Uncertain and Unknown Environments

Tesla driving at 65mph crashed into a firefighter truck which responded to a freeway accident in the USA. The driver reported the vehicle was on autopilot (Jan 22, 2018).

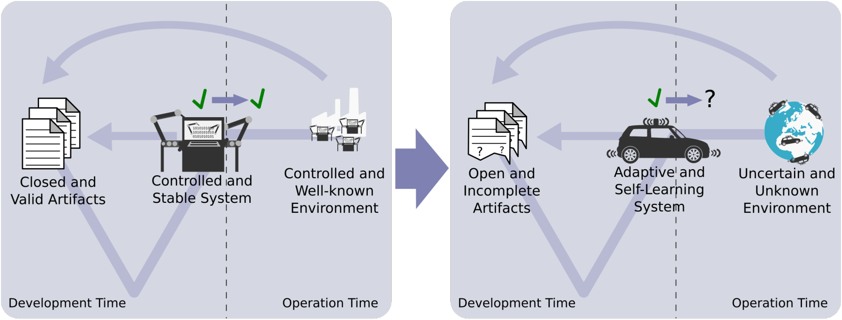
Source:
https://www.wired.com/story/tesla-autopilot-crash-dui
Twitter: @CC_Firefighters

Challenge 2: Adaptive and Self-Learning Systems

Tay is the Twitter Bot created by Microsoft to learn from users. It ended up displaying unwanted behavior, e.g. racist comments (2016).

Source: nytimes.com

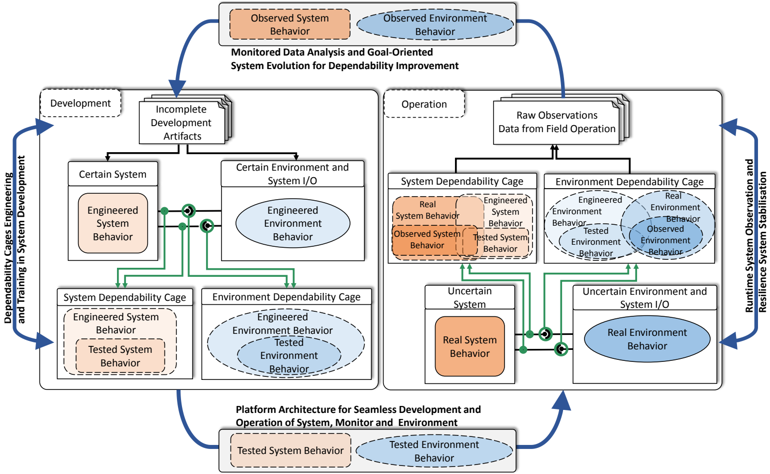
Challenge 3: Open and Incomplete Artifacts



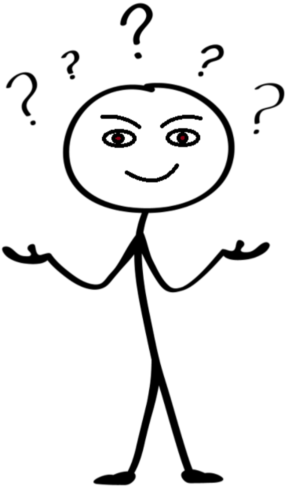
Lifecycle Model of CPS

Lifecycle Model of Autonomous Systems

Our Approach: Hierarchical Dependability Cages

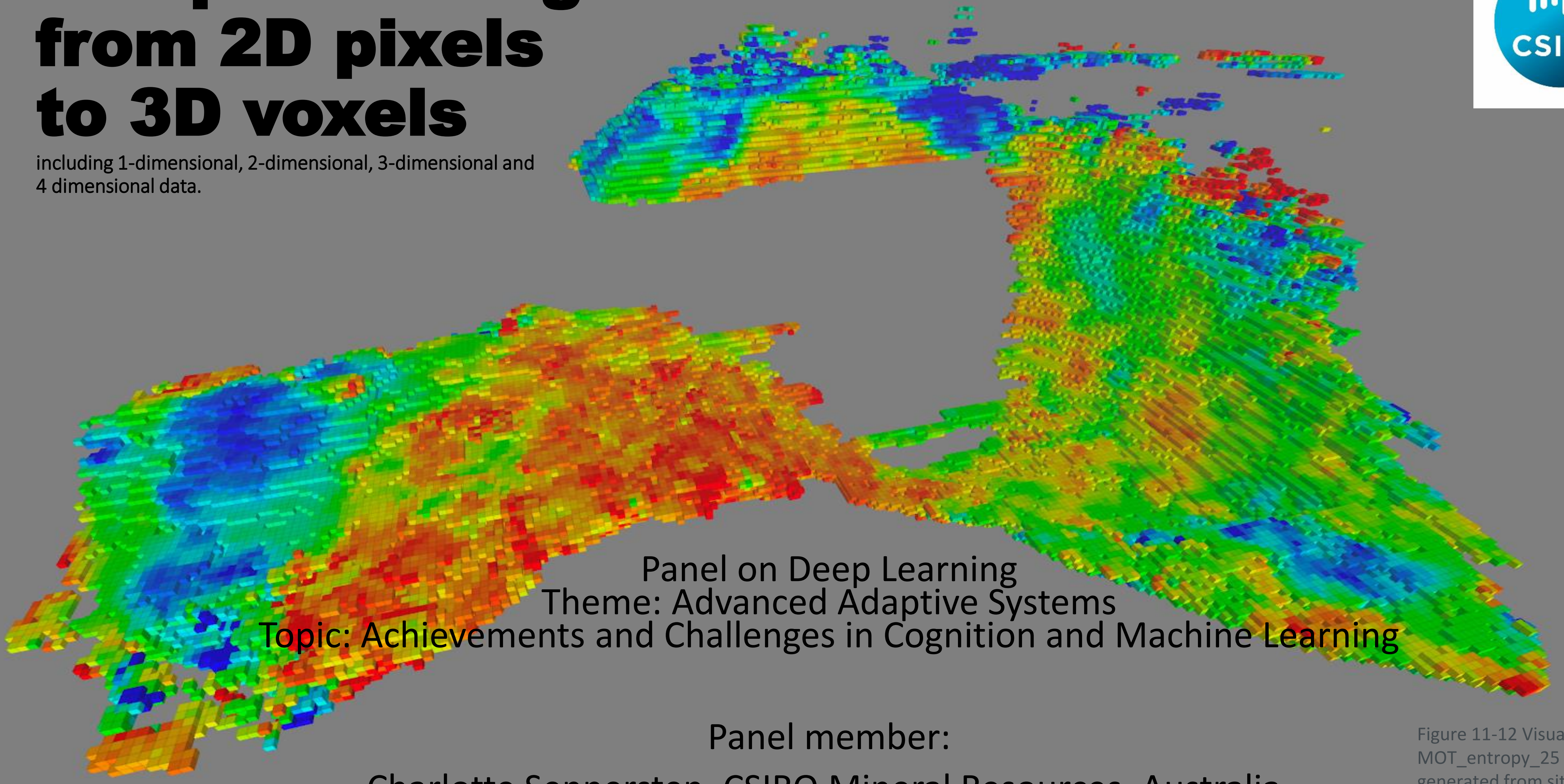


Thank you for your attention!



'Deep' Learning from 2D pixels to 3D voxels

including 1-dimensional, 2-dimensional, 3-dimensional and 4 dimensional data.



Panel on Deep Learning

Theme: Advanced Adaptive Systems

Topic: Achievements and Challenges in Cognition and Machine Learning

Figure 11-12 Visualisation of MOT_entropy_25 attribute generated from site 1 dataset

Panel member:

Charlotte Sennersten, CSIRO Mineral Resources, Australia.

A Quick Background browsing Internet:

Deep Learning *is a subfield of machine* ***learning*** *concerned with algorithms inspired by the structure and function of the brain called artificial* ***neural networks****.*

Deep learning *is a subset of* ***machine learning*** *in artificial intelligence (AI) that has networks capable of* ***learning*** *unsupervised from data that is unstructured or unlabeled. Also known as* ***deep*** *neural* ***learning*** *or* ***deep neural network****.*

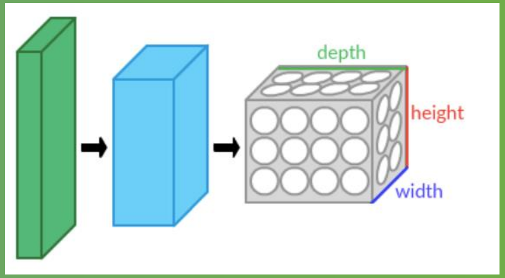
Deep Learning *is being widely* ***used*** *in industries to solve large number of problems like computer vision, natural language processing and pattern recognition. Following are some of the applications of* ***Deep Learning****: Image Recognition:* ***Deep*** *Neural Nets are* ***used*** *to identify objects in an image.*

In ***deep learning****, a convolutional* ***neural network*** *(****CNN****, or ConvNet) is a class of* ***deep neural networks****, most commonly applied to analyzing visual imagery.*

The ***neural network*** *itself is not an algorithm, but rather a framework for many different* ***machine learning*** *algorithms to work together and process complex data inputs. ... An* ***ANN*** *is based on a collection of connected units or nodes called artificial neurons, which loosely model the neurons in a biological brain.*

Deep learning *is getting lots of attention lately and for good reason. ...* ***Deep learning*** *models can achieve state-of-the-art accuracy, sometimes exceeding human-level performance. Models are trained by using a large set of labelled data and* ***neural network*** *architectures that contain many layers.*

To combine two approaches to create new knowledge, call it all 'objective knowledge':



CNN layers arranged in 3 dimensions

ORE BODY DNA

Machine Learning

Numerical Analytics Bottom-Up

Human Interpretation

Volumetric Search Top-Down

Interpretation *A*

Interpretation *B*

Interpretation *C*

Search Patterns *A, B, and C*

CRC ORE Project Report P2–003: Volumetric Analytics for Grade Engineering – searching for Ore Body DNA (2017/18)

Charlotte Sennersten, CSIRO Mineral Resources, QCAT Pullenvale, Australia

A pixel/2D network architecture does not take into account the spatial structure of data, treating input pixels which are far apart in the same way as pixels that are close together. This ignores locality of reference in image data, both computationally and semantically. Thus, full connectivity of neurons is wasteful for purposes such as image recognition that are dominated by spatially local input patterns.

Convolutional neural networks are biologically inspired variants of multilayer perceptrons that are designed to emulate the behavior of a visual cortex.[citation needed] These models mitigate the challenges posed by the MLP architecture by exploiting the strong spatially local correlation present in natural images. As opposed to MLPs, CNNs have the following distinguishing features:

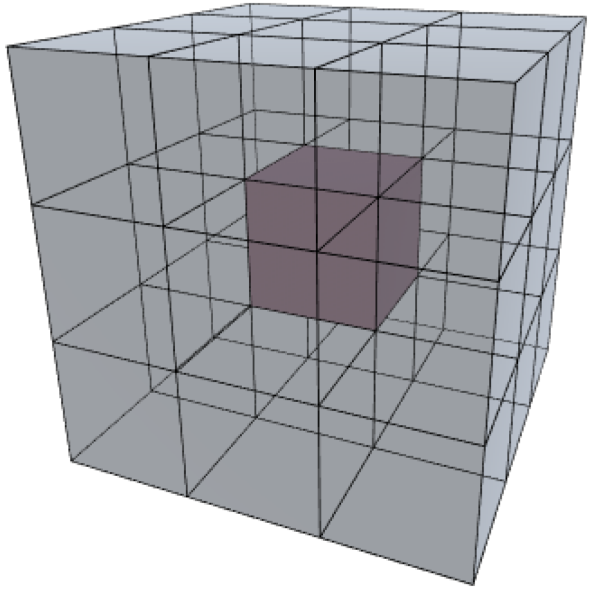
•**3D volumes of neurons**. The layers of a CNN have neurons arranged in 3 dimensions: width, height and depth. The neurons inside a layer are connected to only a small region of the layer before it, called a receptive field. Distinct types of layers, both locally and completely connected, are stacked to form a CNN architecture.
•**Local connectivity**: following the concept of receptive fields, **CNNs exploit spatial locality by enforcing a local connectivity pattern between neurons of adjacent layers.**

The architecture thus ensures that the learned "filters" produce the strongest response to a spatially local input pattern. Stacking many such layers leads to non-linear filters that become increasingly global (i.e. responsive to a larger region of pixel space) so that the network first creates representations of small parts of the input, then from them assembles representations of larger areas.
•**Shared weights**: In CNNs, each filter is replicated across the entire visual field. These replicated units share the same parameterization (weight vector and bias) and form a feature map. This means that all the neurons in a given convolutional layer respond to the same feature within their specific response field. Replicating units in this way allows for features to be detected regardless of their position in the visual field, thus constituting a property of translation invariance.

Together, these properties allow CNNs to achieve better generalization on vision problems. Weight sharing dramatically reduces the number of free parameters learned, thus lowering the memory requirements for running the network and allowing the training of larger, more powerful networks.

https://en.wikipedia.org/wiki/Convolutional_neural_network#Poo

Extending to 3D



Edge detect kernel

1	1	1
1	-8	1
1	1	1

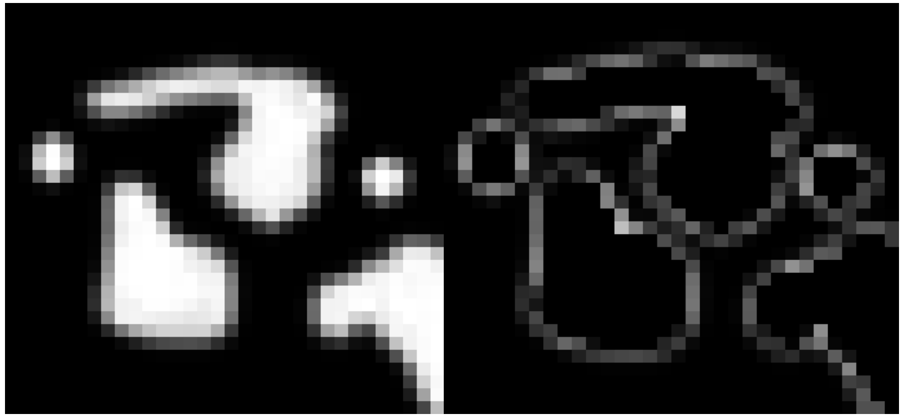
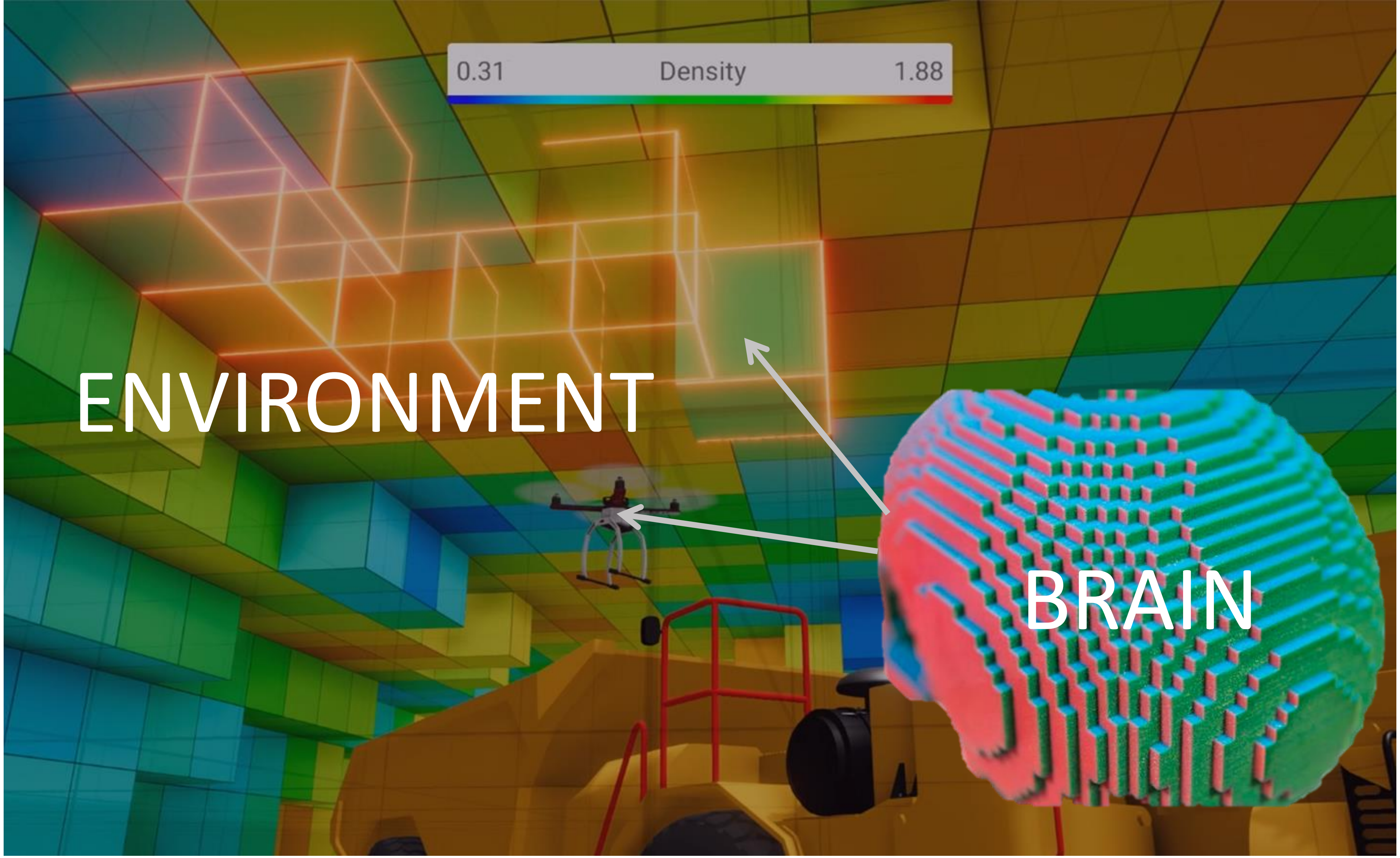


Image convolution example, edge detection.

- Instead of a 2D kernel, we use a 3D kernel.
- Instead of processing a 2D image we process a 3D voxelised dataset.

"To test machine learning methods for their ability to automatically extract rules from data for detecting and predicting heterogeneity features in the rock mass; these rules including shape relationships with respect to ore body attributes, an opportunity not attainable using current resource modelling approaches."

Charlotte Sennersten, CSIRO Mineral Resources, QCAT Pullenvale, Australia



We can fuse environment with brain regions via gaze to understand how to create AI algorithms for people and robots so we understand/share the algorithm patterns and their source/provenance in an intuitive way!

Charlotte Sennersten, CSIRO Mineral Resources, QCAT Pullenvale, Australia
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Data Quality and Data Sources for Deep Learning Applications

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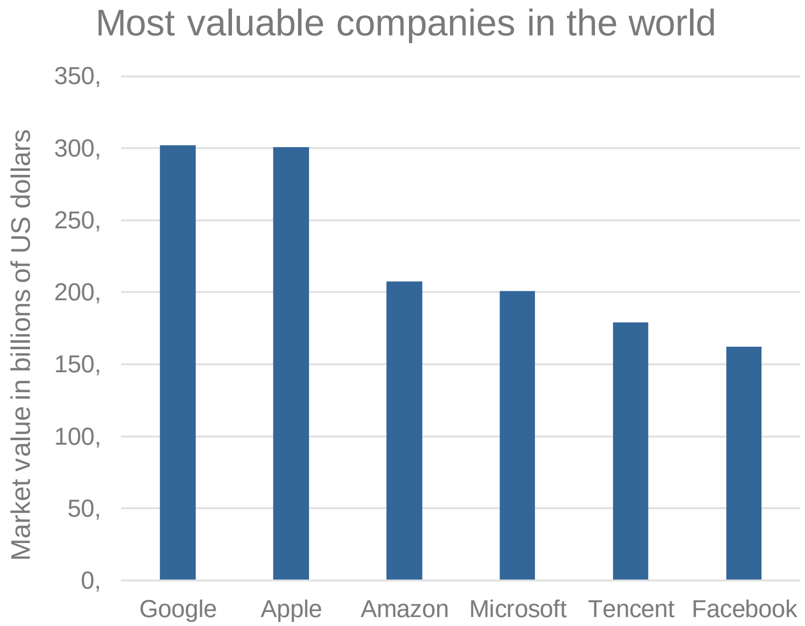
Motivation

- *Data is the new Oil*
- Collecting Data becomes easier and easier
  - Mobile devices
  - Internet of Things

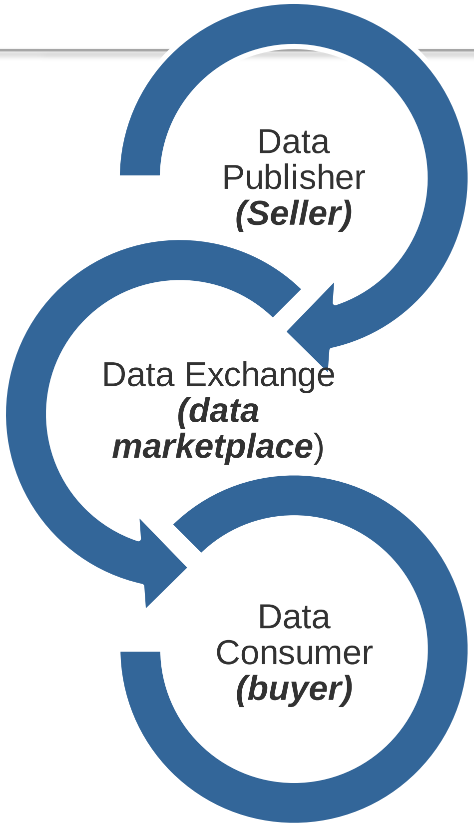
- Data driven business
  - Big Data
  - Data Science & AI

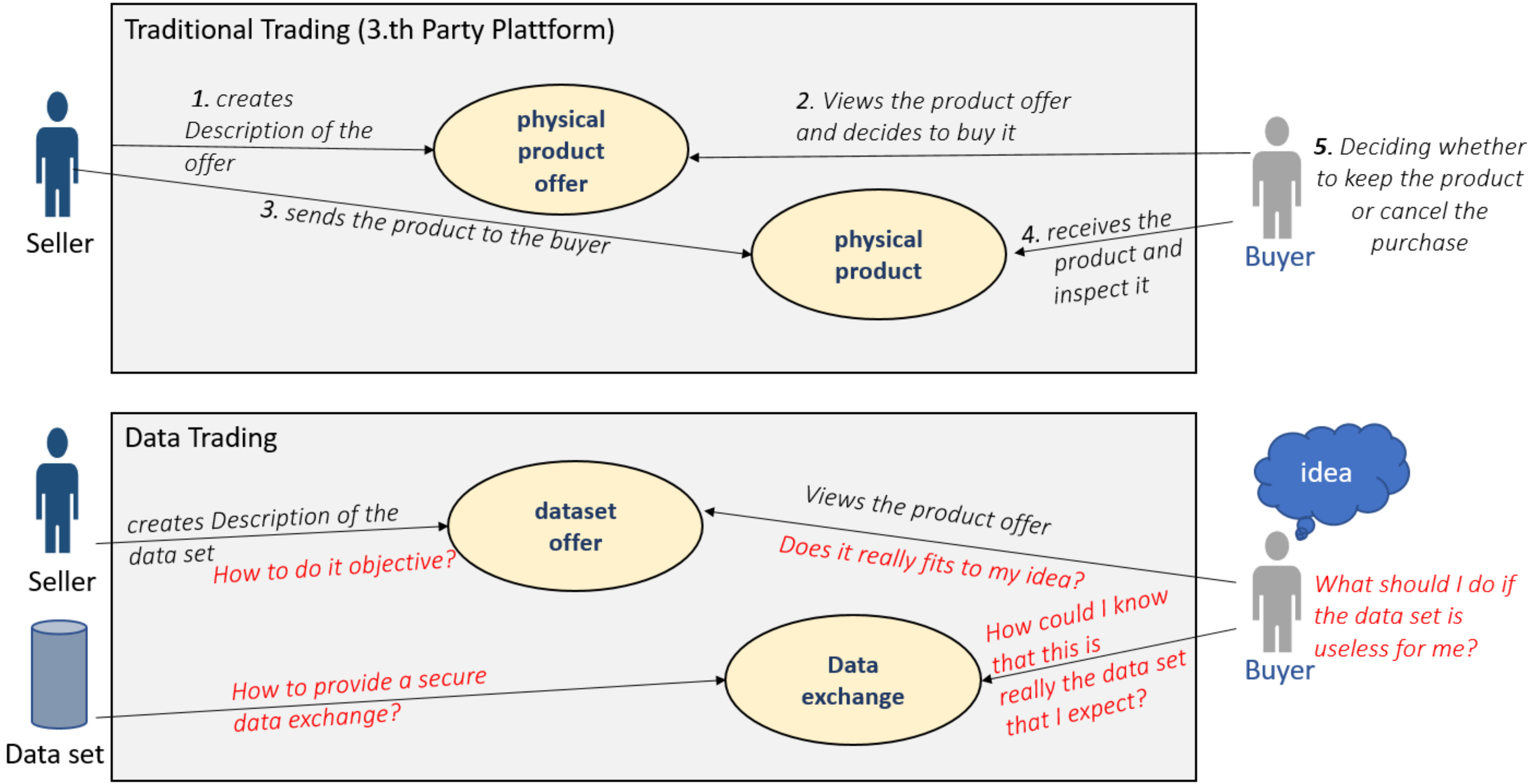
- Methods for **Data Trading** and Exchange are required



Introduction

- Data marketplaces as an approach for safe data exchange
- Stakeholders:
  - *Seller*: produces data and wants to sell it
  - *Buyer*: Has an business model and needs data to realize it



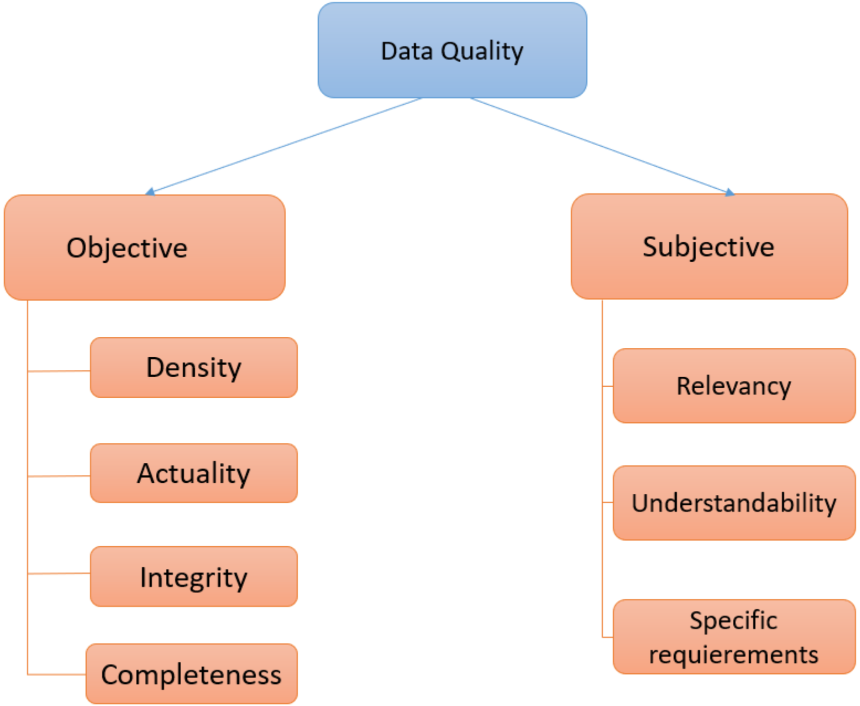

Traditional Trading (3.th Party Plattform)
Seller
1. creates Description of the offer
physical product offer
2. Views the product offer and decides to buy it
3. sends the product to the buyer
physical product
4. receives the product and inspect it
Buyer
5. Deciding whether to keep the product or cancel the purchase
Data Trading
Seller
creates Description of the data set
How to do it objective?
dataset offer
Views the product offer
Does it really fits to my idea?
idea
Buyer
What should I do if the data set is useless for me?
Data set
How to provide a secure data exchange?
Data exchange
How could I know that this is really the data set that I expect?

Main Challenges in a Data marketplace

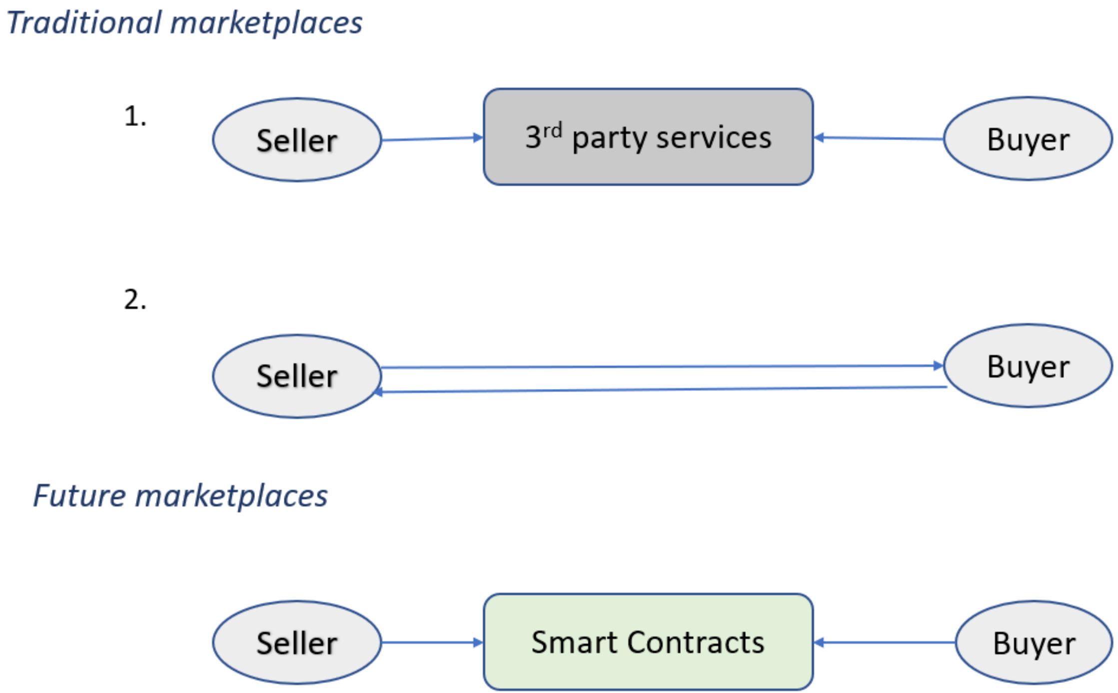
- ***Establishment of a secure platform**: Providing a secure platform for transactions and the data exchange*
- ***Establishment of data integrity**: Ensuring that the source of the data is legitimate and has not been modified.*
- ***Ensuring data quality**: The *buyer* should be able to check the quality of data before buying it. The *seller* should be able to create an objective description of the data set

Data Quality

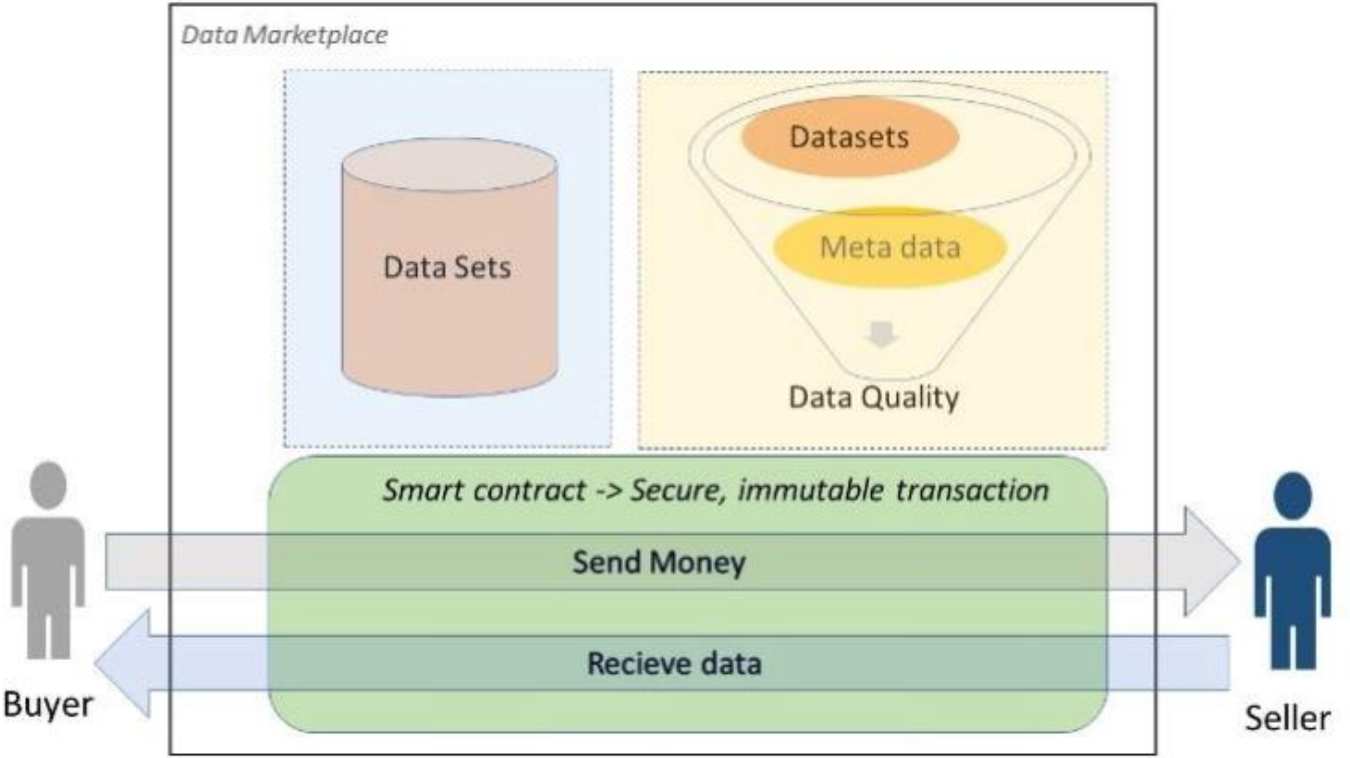
- **Data**: data are just symbols, just as a list of String or integer values
- **Information**: data that are processed to be useful, providing
- answers to ‘who’, ‘what’, ‘where’, and ‘when’ questions



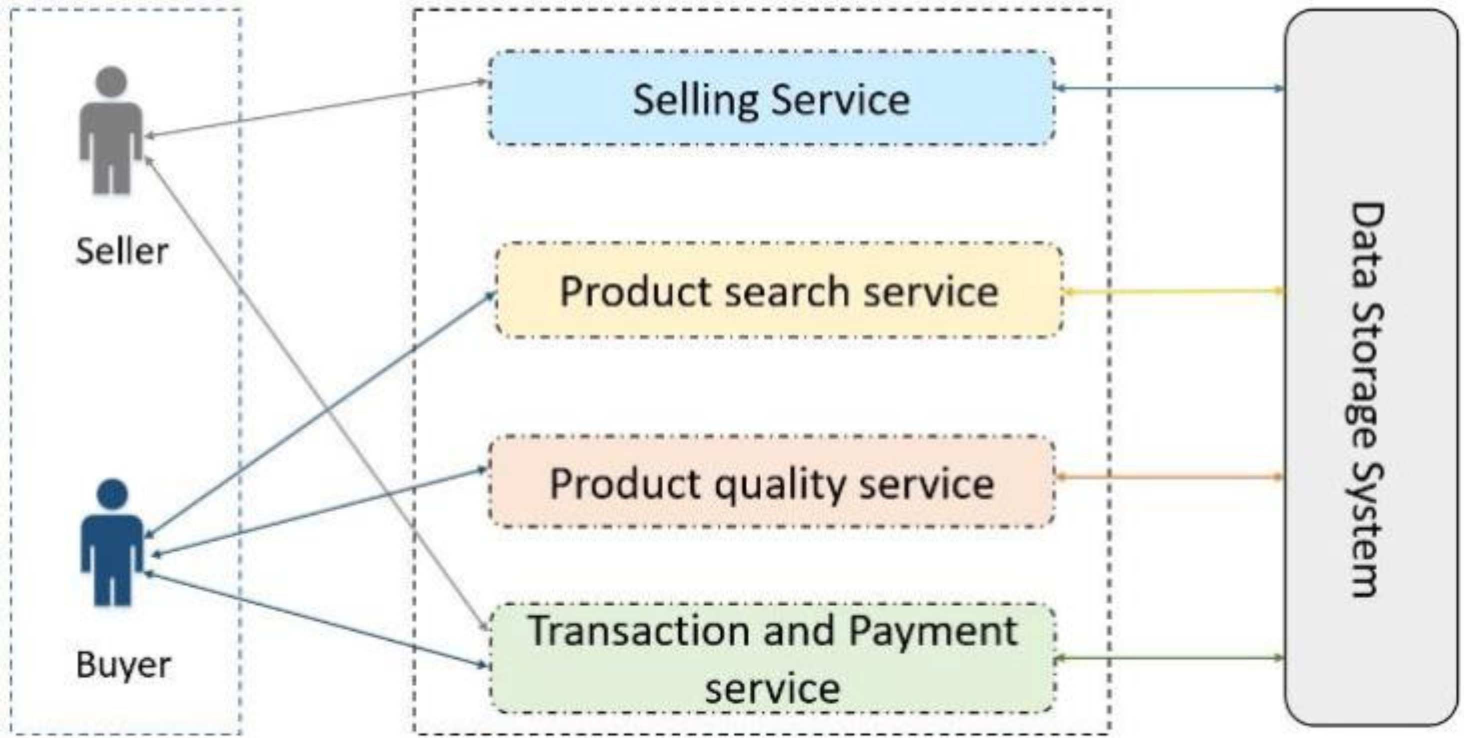
Solutions and Approach



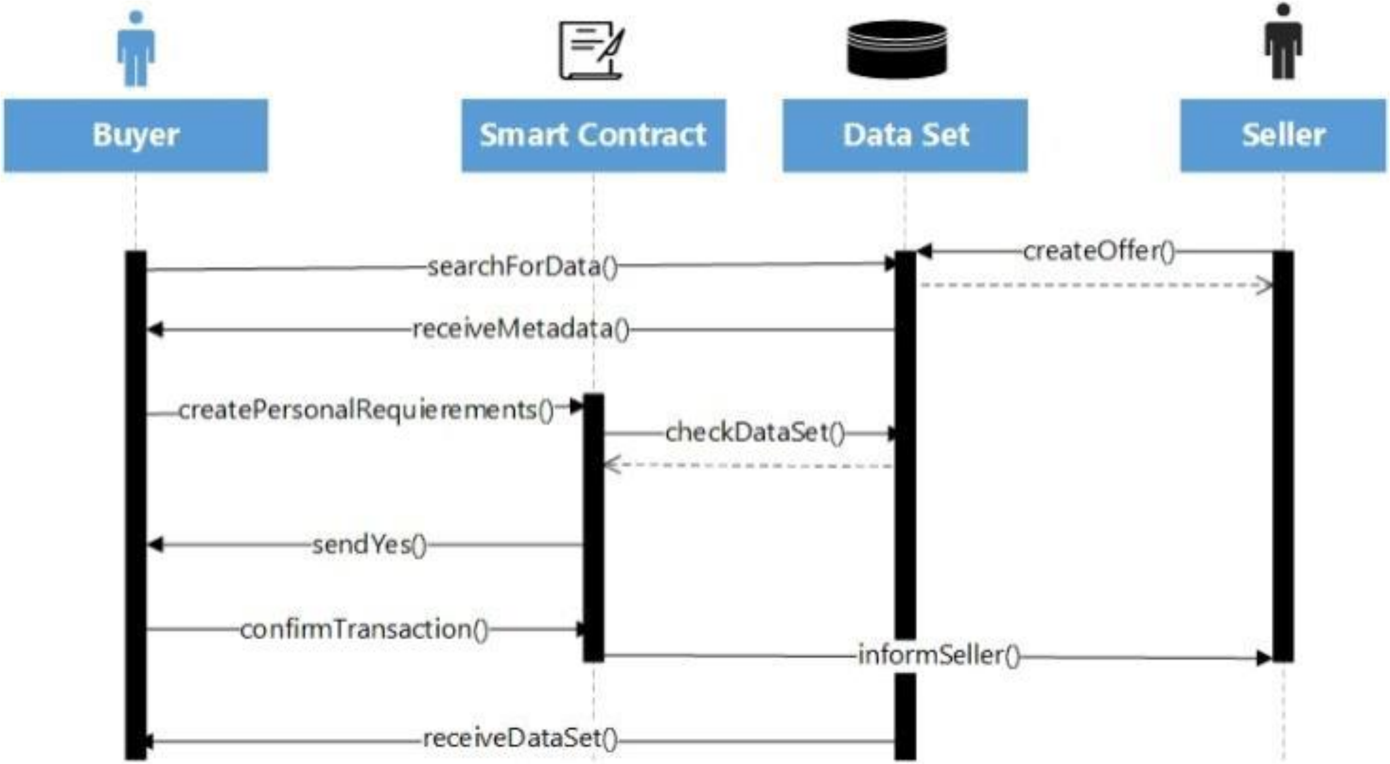
Proposed Solution



Architectural Overview



Smart and Secure Data Exchange



Conclusion and Outlook

- BlockChain Technology provides:
  - A secure decentralized Platform without a 3.th Party
  - Supports data integrity
  - A technical realization to check the data quality based on smart Contracts
- Outlook:
  - Still evaluating different existing BlockChain Technologies

Thank you for your attention!

Thank you for joining this presentation!