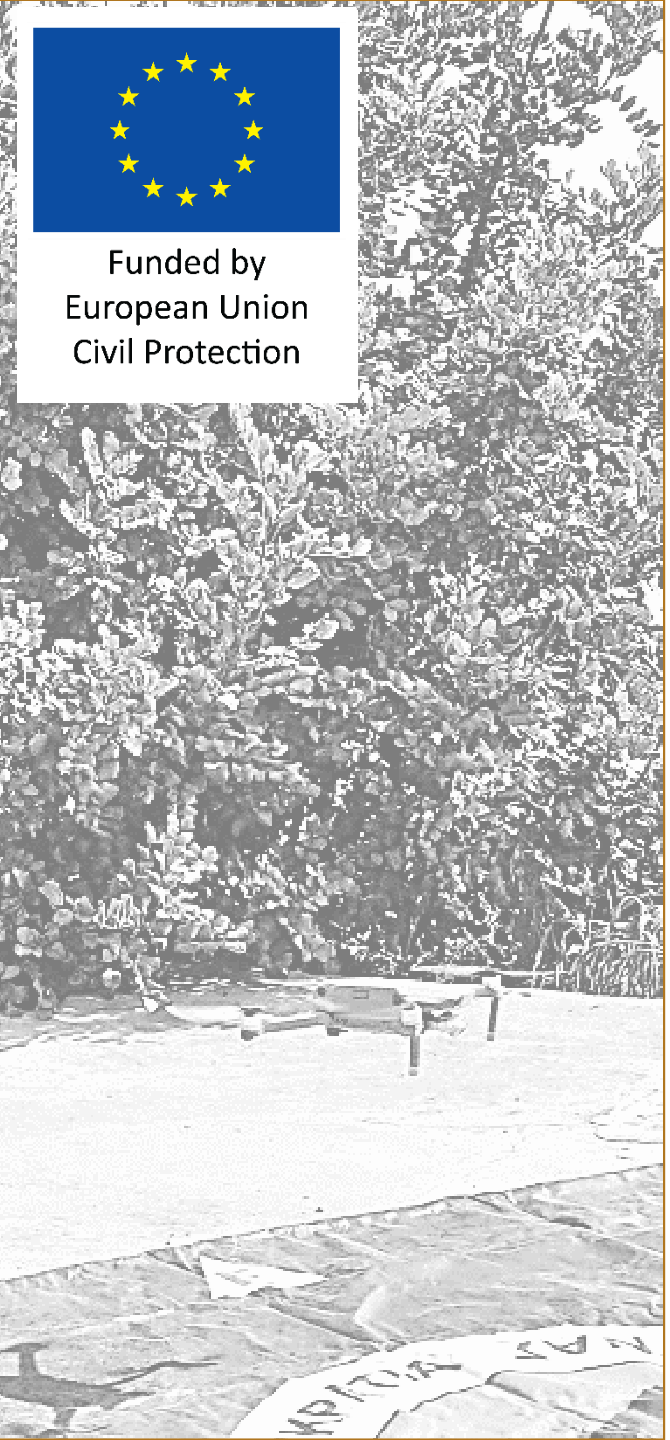

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European Union
Civil Protection

ARTION

Part I
Employing Artificial Intelligence in Disaster Management

Training Workshop

Disclaimer

The project has received funding from the European Union's Call for proposals in the field of Civil Protection under the Union Civil Protection Knowledge Network under grant agreement 101017763.

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Content

- Introduction
- Introduction to Artificial Intelligence
  - Machine Learning
- Artificial Intelligence in Disaster Management
  - AI and the Stages of Disaster Management
  - Prerequisites for Employing AI in Disaster Management
  - AI-powered Autonomous Robot Devices
  - Computer Vision Technologies
  - Modelling of Natural Disasters
  - Applications of AI in Disaster Management
- Realistic Field Exercises Using AI Tools

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Content

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Introduction

A few words about the training workshop

About this Training Workshop

- This training workshop is part of the activities of the project ARTION: Disaster Management Artificial Intelligence Knowledge Network
- It is a project funded from the European Union’s Call for proposals in the field of Civil Protection under the Union Civil Protection Knowledge Network.
- The duration of the project is 18 months

About this Training Workshop

- Purpose of this workshop
  - To share knowledge on the topic
    - To give all interested stakeholders an understanding of the broad scope and numerous applications of artificial intelligence in emergency response
  - To gather, consolidate and assess the needs of disaster management actors
    - In order to be used by researchers in the further development of AI tools for disaster management

Project Consortium

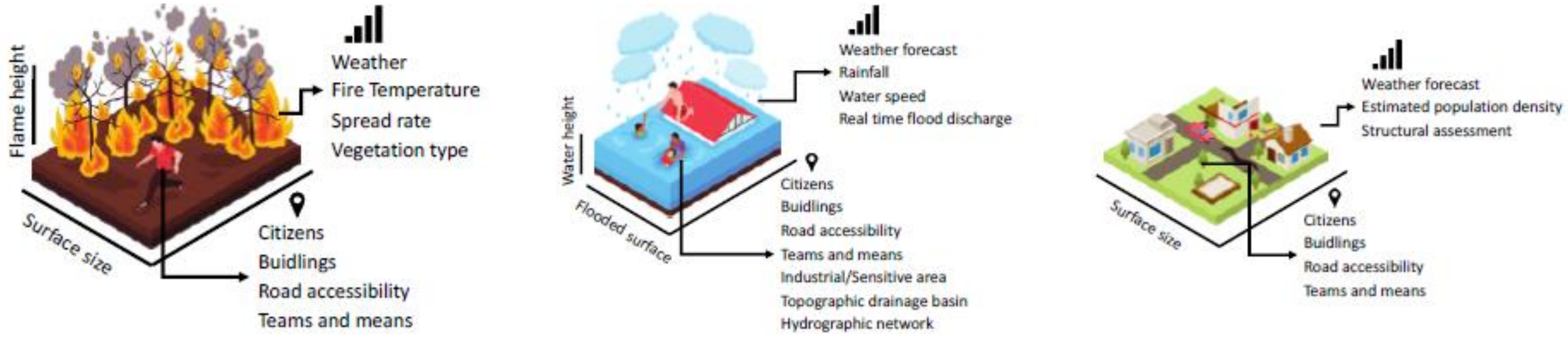
- ❑ KIOS Research and Innovation Center of Excellence of the University of Cyprus, in Cyprus
- ❑ Cyprus Civil Defense, in Cyprus
- ❑ Civil Protection of the Autonomous Region of Sardinia, in Italy
- ❑ CRIStAL (Research center in Computer Science, Signal and Automatic Control of Lille) of the University of Lille, in France
- ❑ Space Research Centre of the Polish Academy of Sciences

University of Cyprus
KOIOS Research and Innovation Center of Excellence
CYPRUS CIVIL DEFENCE
ΠΟΛΙΤΙΚΗ ΑΜΥΝΑ ΚΥΠΡΟΥ
REGIONE AUTÒNOMA DE SARDIGNA
REGIONE AUTONOMA DELLA SARDEGNA
Université de Lille
CRIStAL
Centre de Recherche en Informatique, Signal et Automatique de Lille
C!K Centrum Informacji Kryzysowej
CBK PAN
ARTION

The ARTION project

❑Creating a Knowledge Network

- The main goal of the proposed project is to establish the Disaster Management Artificial Intelligence Knowledge Network (ARTION), with the vision to become a world-class network for knowledge sharing in the area of artificial intelligence for disaster management that will transform the development and use of AI tools by first responders across Europe.

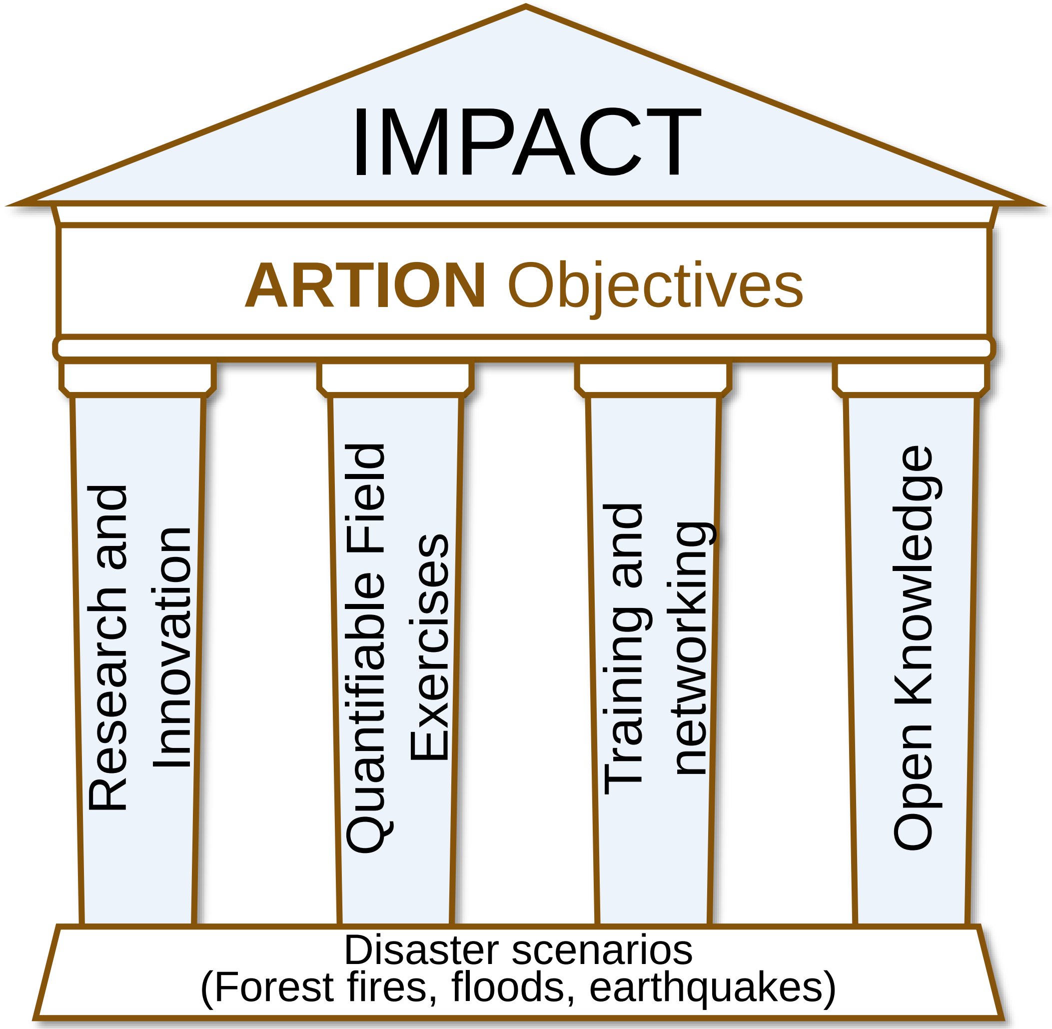


Forest fires Floods Earthquakes

General Objectives of ARTION

- To bridge across knowledge holders relevant to the UCPM
- To enhance coordination, cooperation, compatibility and complementarity between capacities and improve the competence of experts
- To collect and share knowledge, experience, expertise, skills, competence, lessons learnt, and best practices in close cooperation with civil protection authorities and disaster management authorities and knowledge centres
- To stimulate research and innovation and encourage the introduction and use of relevant new technologies
- To strengthen the links between civil protection and disaster risk management actors and develop a shared understanding and a common culture of prevention, preparedness and response
- Contribute to the implementation of the EU's international commitments towards disaster risk reduction, in particular those in the Sendai Framework for Disaster Risk Reduction 2015-20305

ARTION Strategic Pillars



Content

ARTION

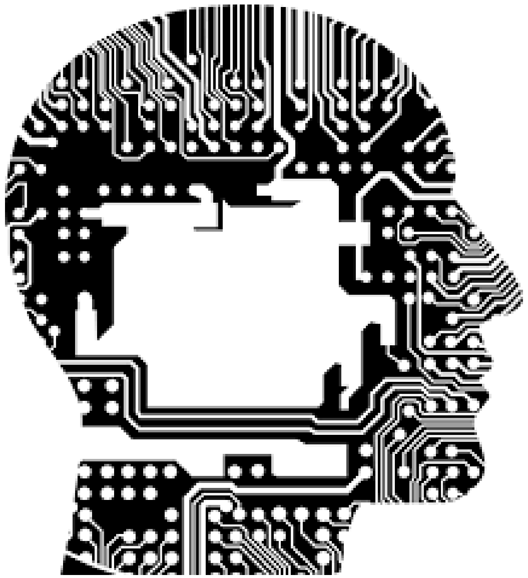
Artificial Intelligence

A brief introduction

What is Artificial Intelligence

- Intelligence is "the ability to learn, understand, and make judgments or have opinions that are based on reason" (according to online Cambridge dictionary).

- Artificial Intelligence (AI) is "the branch of computer science that is concerned with the automation of intelligent behavior" (Luger's and Stubblefield's definition, 1993).



What is Artificial Intelligence

- AI is the simulation of human intelligence by machines in order to have:
  - The ability to understand/discover meaning
  - The ability to learn
  - The ability to solve problems
  - The ability to act rationally

- The central principles of AI include:
  - Perception, Learning, Reasoning, Knowledge, Planning, Learning, Communication

What is Artificial Intelligence

AI		Robot
Programmed to think	**Vs.**	Programmed to do
Social Interaction		Low Level Interaction
Learns		Only as smart as initially programmed

Branches of AI

Branches of AI

Introduction to Machine Learning

- A type of artificial intelligence that provides computer the ability to learn without being explicitly programmed.
- Mitchell 1997
  - Learn from past experiences
  - A computer program is said to learn from experience E with respect to some class of tasks T and performance measure P, if its performance at the tasks improves with the experiences.
- Example Applications
  - Chess playing

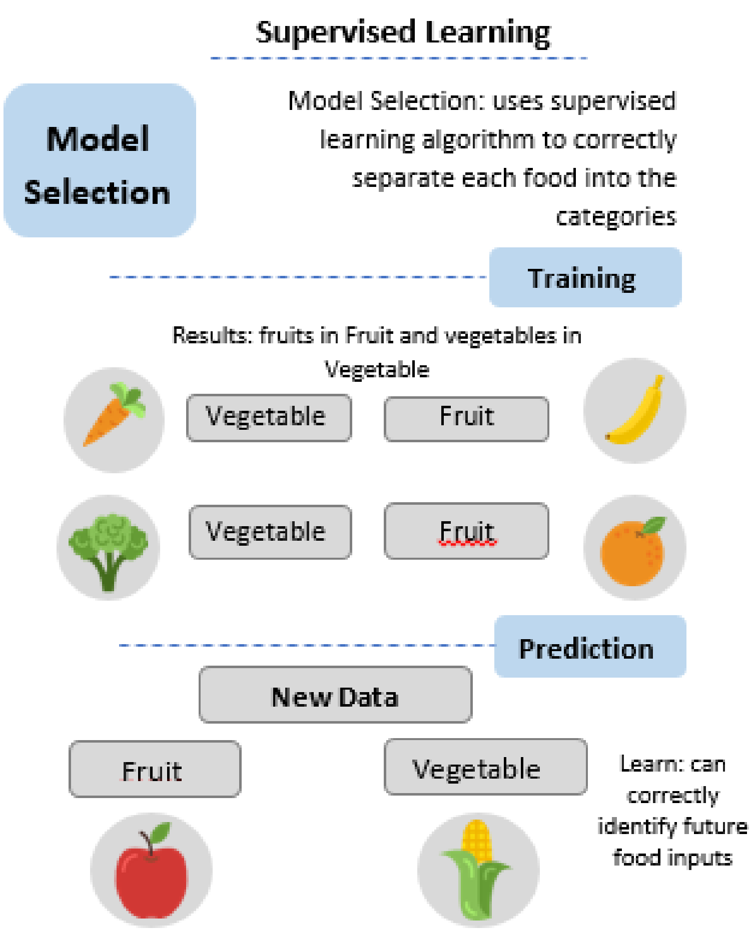
Applications of ML

- Examples of ML applications from every day life
  - Chess playing
  - Traffic Prediction
  - Personalize suggested content in social media / Internet
  - Fire Detection from video surveillance systems
  - Assisting identification of diseases which are considered hard-to-diagnose
  - Automatic Speech-to-Text converters (e.g., for hands-free SMS sending and emailing)

Classification of ML Algorithms

- **MACHINE LEARNING**
  - **Supervised Learning**
    - **Classification**
      Predict class from observations
    - **Regression**
      (Prediction)
      Predict value from observations
  - **Unsupervised Learning**
    - **Clustering**
      Group observations into 'meaningful' groups
    - ***Association***
      Finds relationships between variables
    - ***Anomaly Detection***
      Reduces the number of features
  - **Reinforcement Learning**
    Learn how to act based on feedback from the environment on previous actions

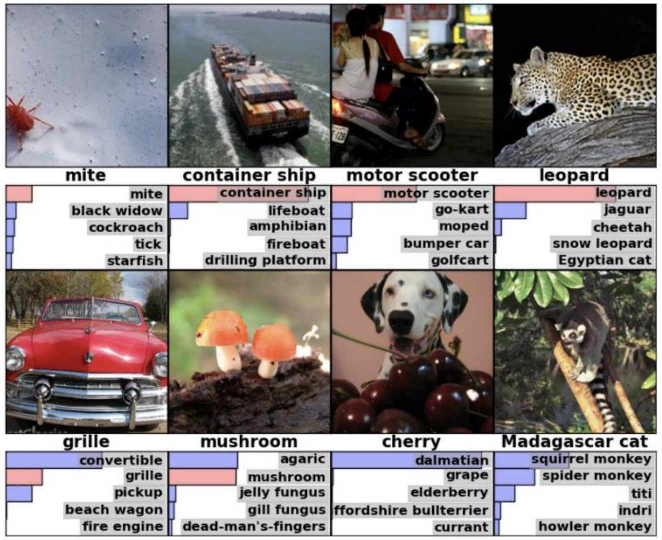
An example of how ML works



- ❑Learn from examples
- ❑Iterative process
  - Reduce the error i.e., mistakes
- ❑GPUs
- ❑Lots of labelled data

IMAGENET

- 1,000 object classes (categories).
- Images:
  - 1.2 M train
  - 100k test.



Supervised Learning

- Supervised learning is a machine learning approach that builds on labeled datasets.
- These datasets are designed to train algorithms into classifying data (classification) or predicting outcomes accurately (regression).
- Using labeled inputs and outputs, the model can measure its accuracy and learn over time.
- Supervised learning can be separated into two types of problems when data mining: classification and regression.

Supervised Learning

- ❑Train an algorithm on a labeled data set to predict the correct output value for unseen input.
  - Labelled Data
  - Replicate the right answers / Receiving direct feedback
  - Predict outcome/future for new data
  - Classification/Prediction
  - Example Applications: image recognition, email spam filtering, forecasting

Supervised Learning: Example

Training Data **(labeled)**

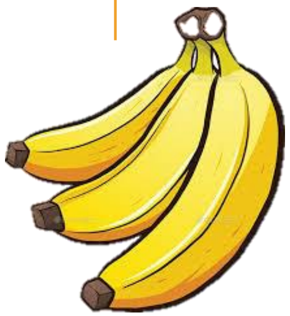
Apples

Bananas

Training ML algorithm

ML model

Unseen and unlabeled data



Class of unknown data: banana

Classification

- Classification problems use supervised algorithms to accurately assign objects (input data) into identified categories based on each object’s characteristics
- Classes are called *labels* or *categories*
- The objects (input data) are analyzed into a set of quantifiable characteristics, called *features*
  - *The selected features should be sufficient and appropriately chosen in order to classify objects into the correct category*

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Classification

- Classification examples:
  - Classifying spam in a separate folder from the inbox
  - Given a handwritten character, classify it as one of the known alphabet characters
  - Tumor classification from medical images as benign or malignant

- Examples of classification algorithms:
  - Support vector machines
  - Decision trees
  - Random forest
  - Neural Networks

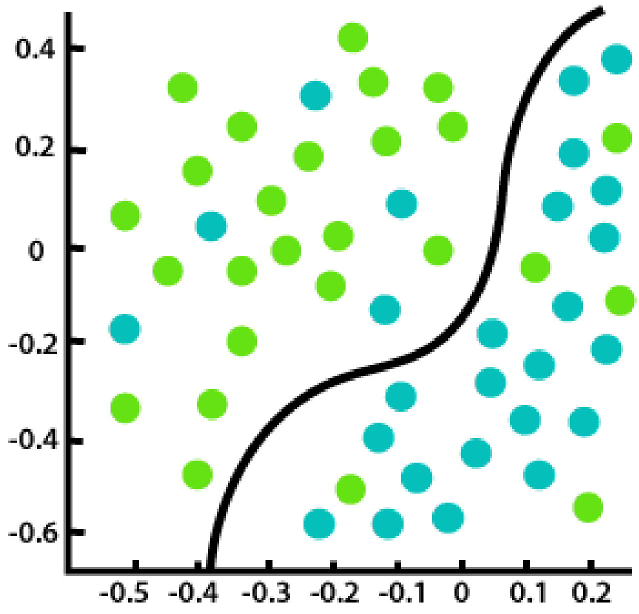
Regression

- Regression is another type of supervised learning method that understands the relationship between dependent and independent variables.
- Regression models predict continuous numerical values based on different input data points.
- The task of the Regression algorithm is to find the mapping function to map the input variable (x) to the continuous output variable (y).

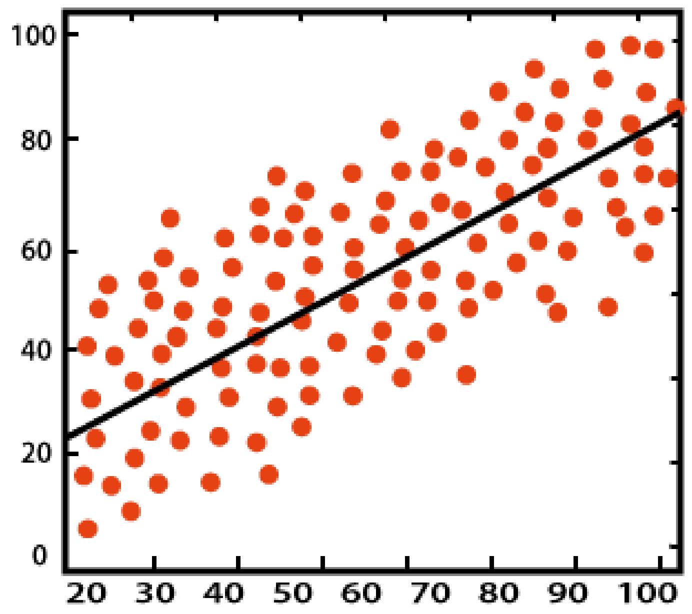
Regression

- Regression examples:
  - Predict sales revenue projections for a given business,
  - Predict weather based on recorded data like temperature, humidity, air quality, etc.
  - Predict data traffic in a communication network based on previous recorded data rates.
- Example of Regression algorithms:
  - Linear Regression
  - Polynomial Regression
  - Support Vector Regression
  - Decision Tree Regression
  - Random Forest Regression

Classification Vs. Regression



Classification



Regression

Classification Vs. Regression

Regression	Classification
The output variable must be of continuous nature or real value.	The output variable must be a discrete value.
The task is to map the input value (x) with the continuous output variable(y).	The task is to map the input value(x) with the discrete output variable(y).
Regression Algorithms are used with continuous data.	Classification Algorithms are used with discrete data.
We try to find the best fit line, which can predict the output more accurately.	We try to find the decision boundary, which can divide the dataset into different classes.

Classification Vs. Regression

Regression	Classification
Can be used to solve regression problems such as Weather Prediction, House price prediction, etc.	Can be used to solve classification problems such as Identification of spam emails, Speech Recognition, Identification of cancer cells, etc.
The regression Algorithm can be further divided into Linear and Non-linear Regression.	The Classification algorithms can be divided into Binary Classifier and Multi-class Classifier.

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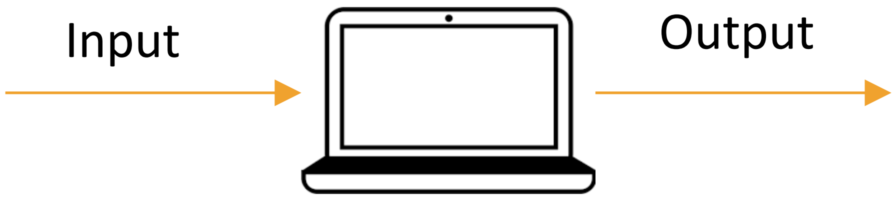
Unsupervised Learning

- Unsupervised learning uses machine learning algorithms to analyze and cluster unlabeled data sets.
- These algorithms are intended to discover hidden data patterns with no human intervention.
- Unsupervised learning models are used for three main tasks: clustering, association, and dimensionality reduction.

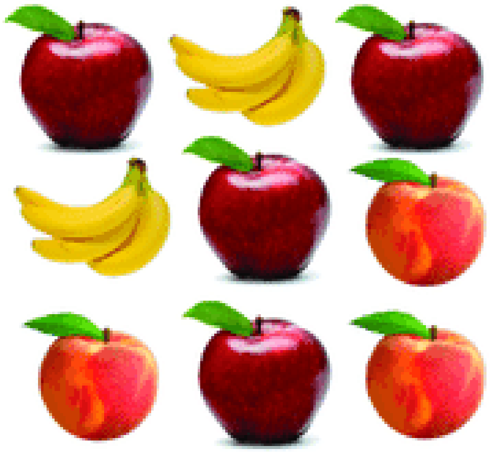
Unsupervised Learning



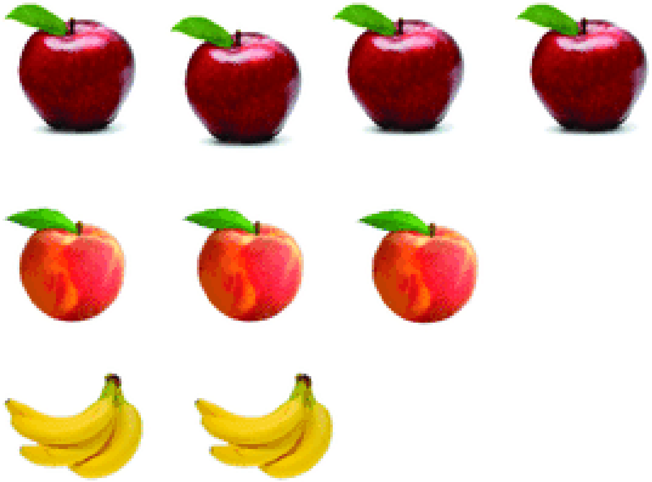
- Find similarities, identifies patterns and structures in a data set
    - Unlabeled data
    - Find patterns in data
    - Clustering association
    - Example Applications: Anomaly detection, customer segmentation, etc.

Unsupervised Learning: Example

Input data



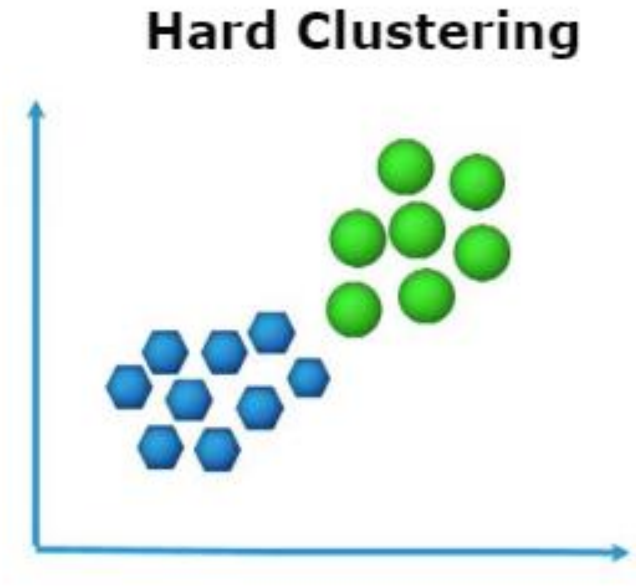
ML algorithm

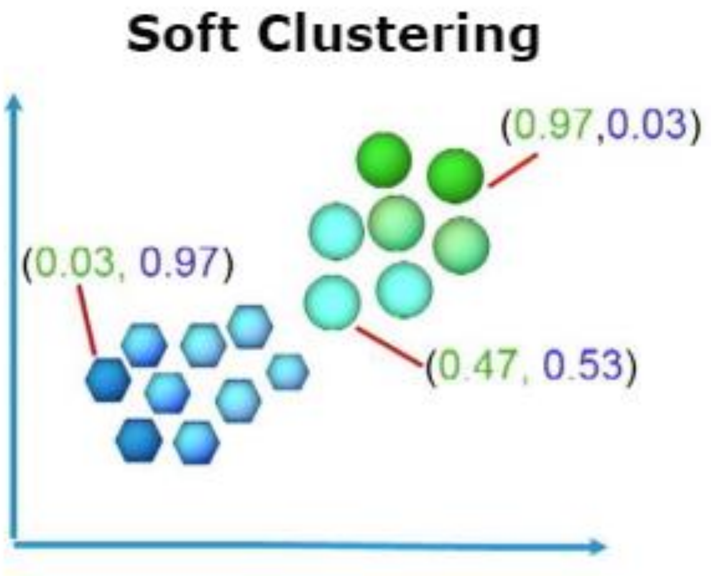


Clustering

- Clustering is a data mining technique for grouping unlabeled data into groups, called *clusters*, based on their similarities or differences.
- Data points in the same cluster are more similar to other data points in the same cluster than those in other clusters.
- Clustering algorithms fall into two broad groups:
  - Hard clustering, where each data point belongs to one cluster
  - Soft clustering, where each data point can belong to more than one clusters. Examples include phonemes in speech, which can be modeled as a combination of multiple base sounds.

Hard Vs. Soft Clustering





In soft clustering, each data point is assigned a probability of belonging to each cluster

Clustering

- Clustering examples:
  - Group organisms by genetic information into a taxonomy.
  - Group YouTube videos in order to produce recommendations for users similar to what they like
  - Group areas in a video to discriminate burned and healthy vegetation after a fire

- Examples of Clustering algorithms
  - K-means
  - Hierarchical clustering
  - Mean-shift clustering

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Association

- Association is another type of unsupervised learning method that uses different rules to find relationships between variables in a given dataset.
- These methods are frequently used for market basket analysis and recommendation engines, along the lines of “Customers Who Bought This Item Also Bought” recommendations.

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Dimensionality Reduction

- Dimensionality reduction is a learning technique used when the number of features in a given dataset is too high.
- It reduces the number of data dimensions to a manageable size while also preserving the data integrity.
- Often, this technique is used in the preprocessing data stage, such as when auto-encoders remove noise from visual data to improve picture quality.

Supervised Vs. Unsupervised Learning

- The main distinction between the two approaches is the use of labeled datasets. Supervised learning uses labeled input and output data, while an unsupervised learning algorithm does not.
- In supervised learning the algorithm “learns” from a training dataset by iteratively making predictions on the data and adjusting for the correct answer.
  - For example, a supervised learning algorithm can be trained with forest fire image samples to learn how to detect smoke and fire from a standard camera.

Supervised Vs. Unsupervised Learning

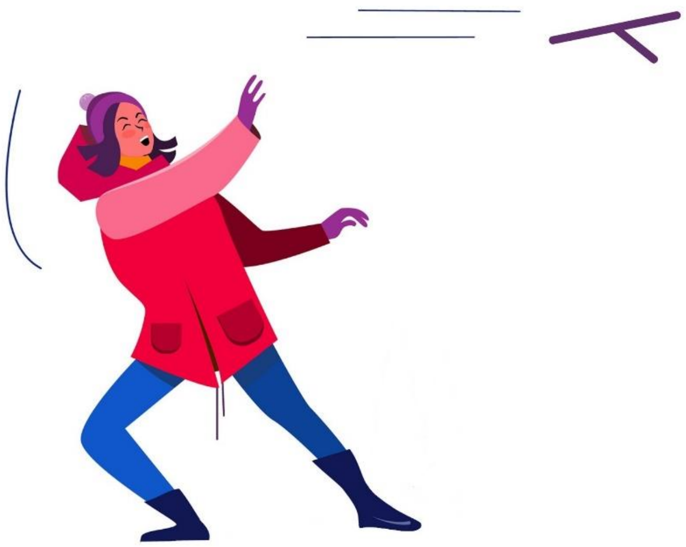
- While supervised learning models tend to be more accurate than unsupervised learning models, they require upfront human intervention to label the data appropriately.
  - For example, a supervised learning model can predict how long your commute will be based on the time of day, weather conditions and so on. But first, you have to train it to know that rainy weather extends the driving time.
- Unsupervised learning models, in contrast, work on their own to discover the inherent structure of unlabeled data.
  - Note that they still require some human intervention for validating output variables. For example, an unsupervised learning model can identify that online visitors often purchase groups of products at the same time.

Reinforcement Learning

- We learn by interacting with the environment
- Learn to make a good sequences of decisions
- For example
  - An infant learning to walk
  - A dog learning to fetch a branch
- The Reinforcement Learning Problem: learn what to do –what actions to take – so as to maximize a numerical reward signal
- Learner tries out actions to discover rewards
- Fundamental Idea: Learn from interactions

The Reinforcement Learning Problem

environment



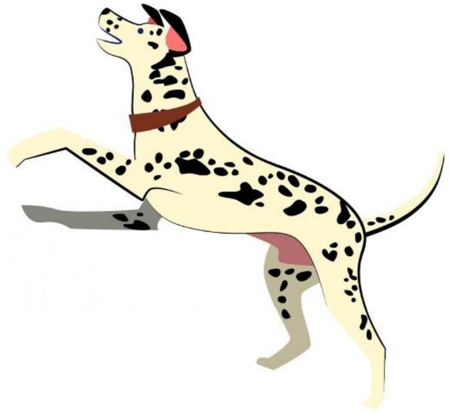
Designed by pch.vector / Freepik

actions ←

rewards →

observations →

agent



Designed by pch.vector / Freepik

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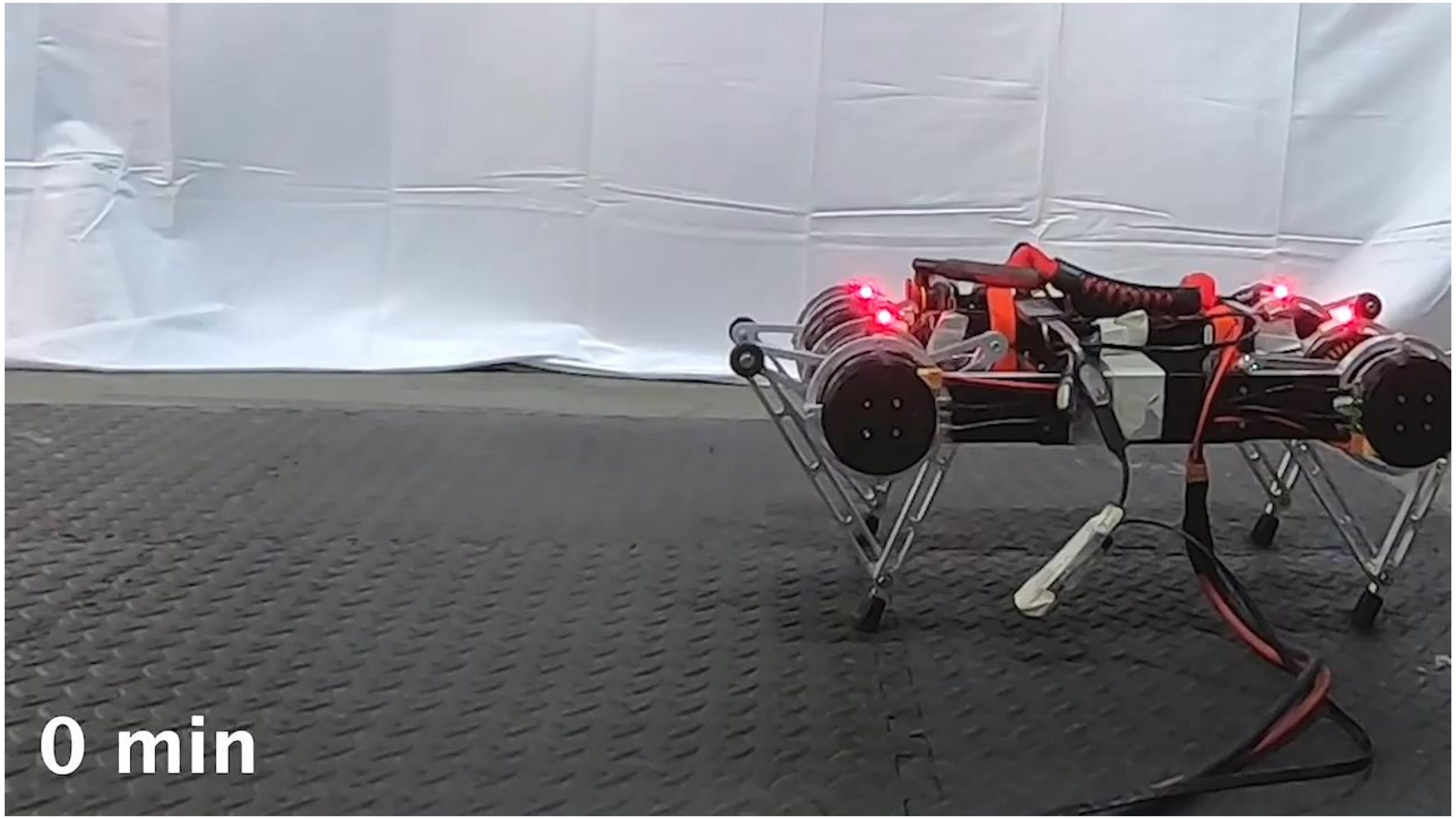
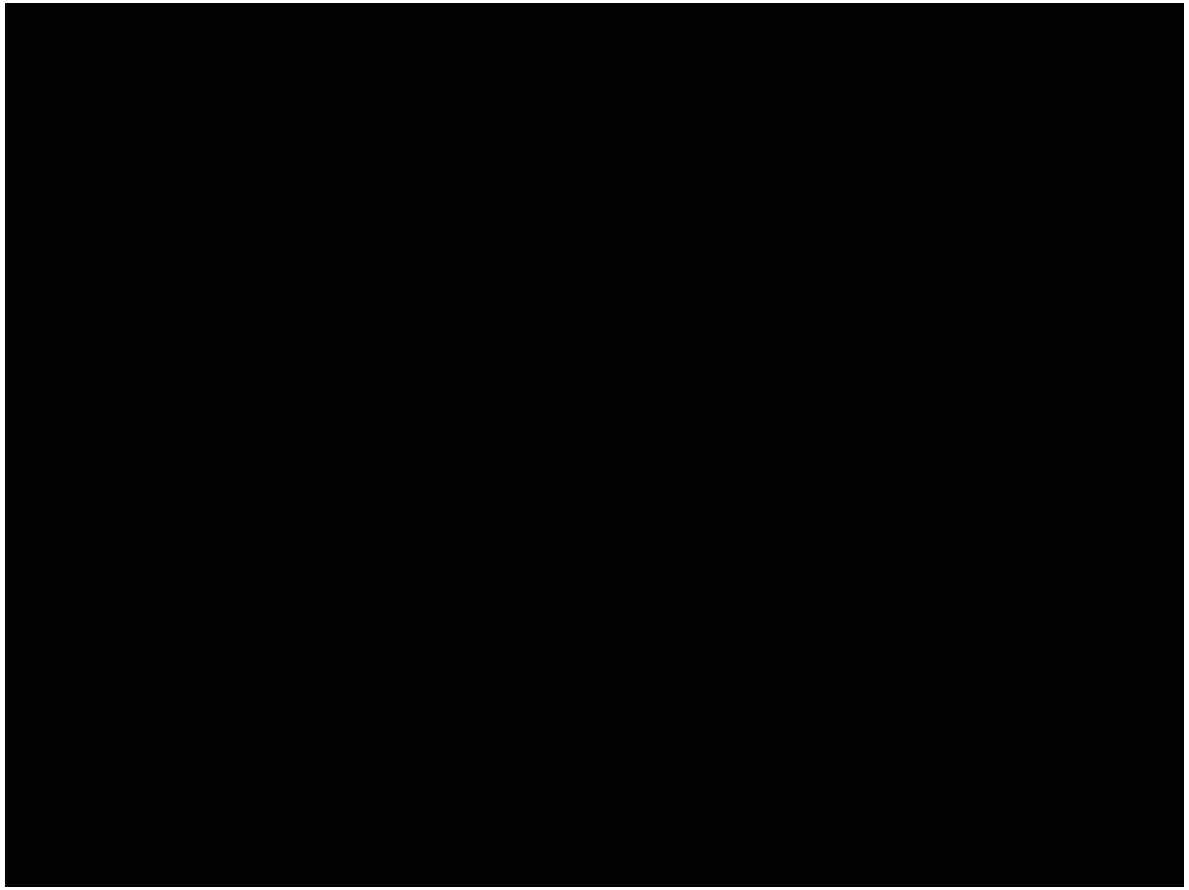
Learning to Walk



Tuomas Haarnoja, Sehoon Ha, Aurick Zhou, Jie Tan, George Tucker and Sergey Levine, 2019.

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

Atari Games



DeepMind, 2015.

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

Reinforcement Learning: Key Elements

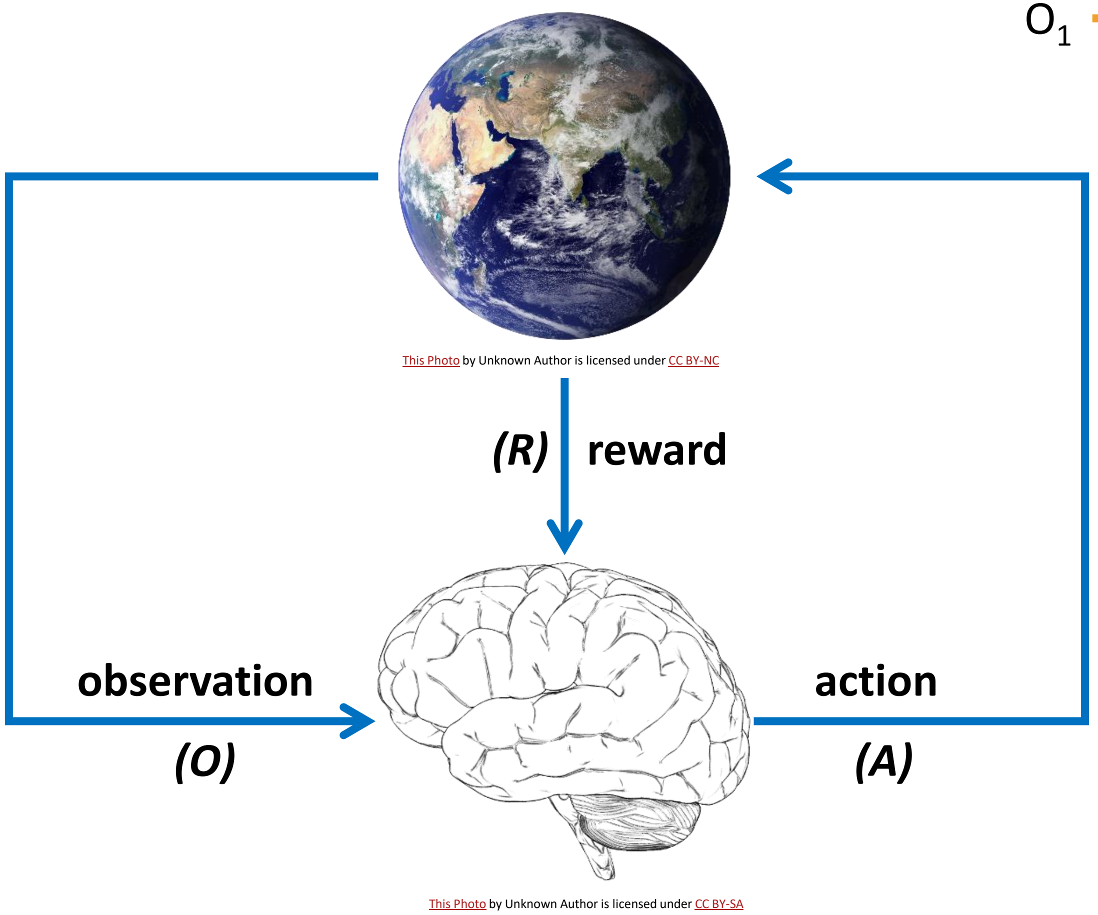
- **Policy:** agent's behavior function
  - It is a map from state to action
- **Reward Signal *R*:** indicates how well agent is doing
  - It is a scalar feedback signal
- **Value function:** how good is each state and/or action
  - It is a prediction of future reward
- **Model:** agent's representation of the environment
  - It predicts what the environment will do next

Sequential Decision Making

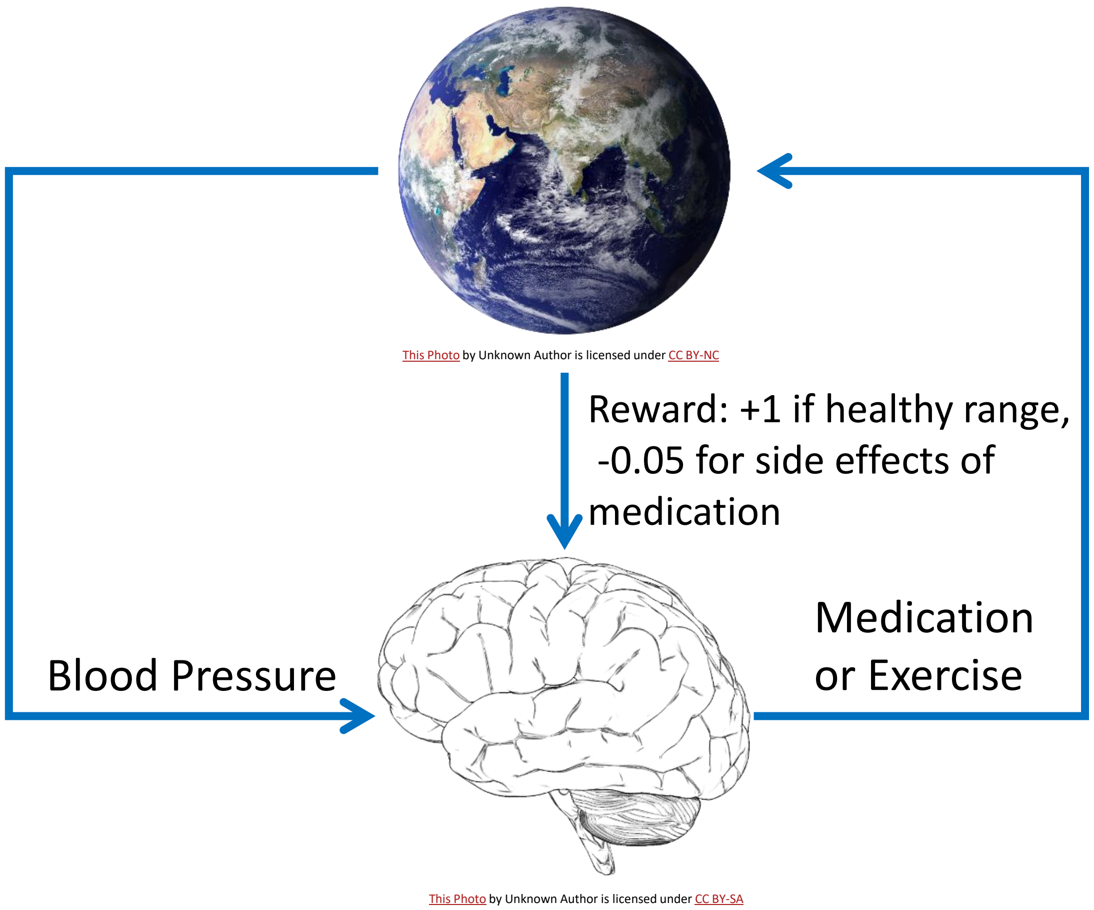
- Goal: select actions to maximize total future reward
- Actions may have long term consequences
- Reward may be delayed
- It may be better to sacrifice immediate reward to gain more long-term reward

RL: Sequential Decision Making

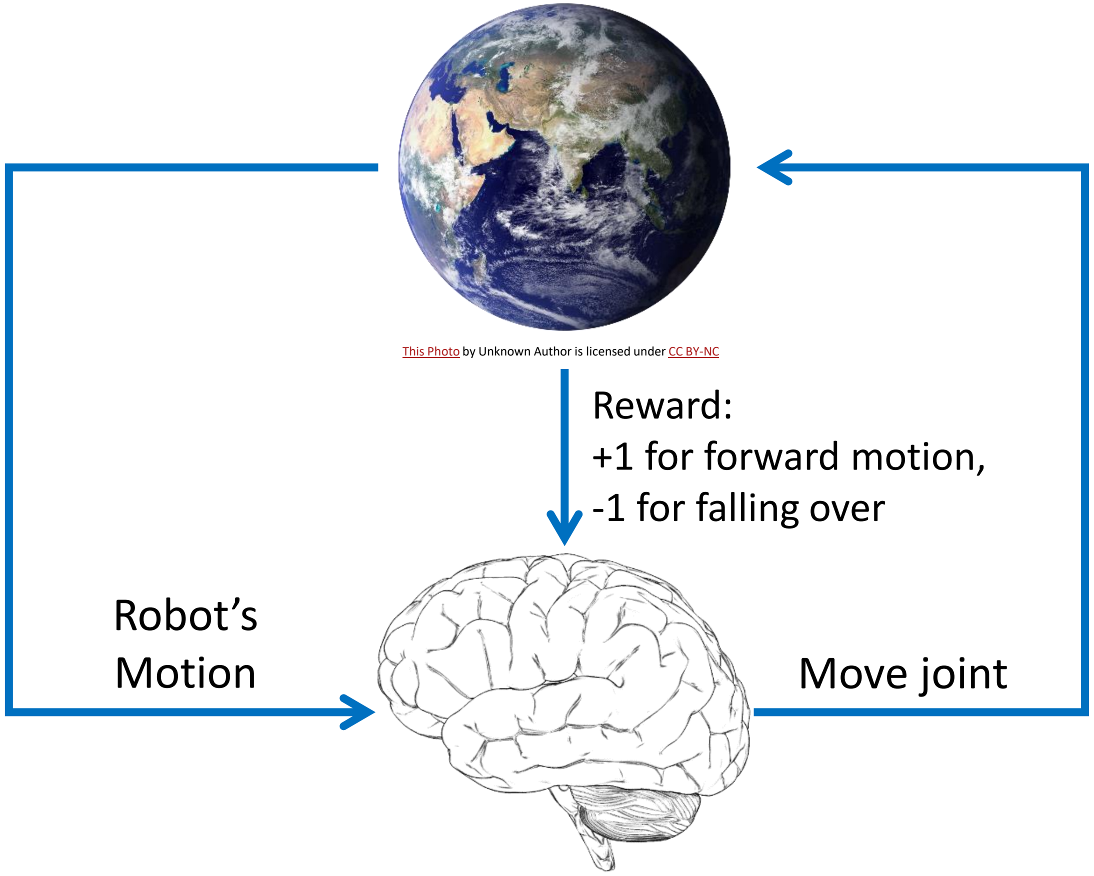
$$O_1 \xrightarrow[R_1]{A_1} O_2 \xrightarrow[R_2]{A_2} O_3 \xrightarrow[R_3]{A_3} \dots$$



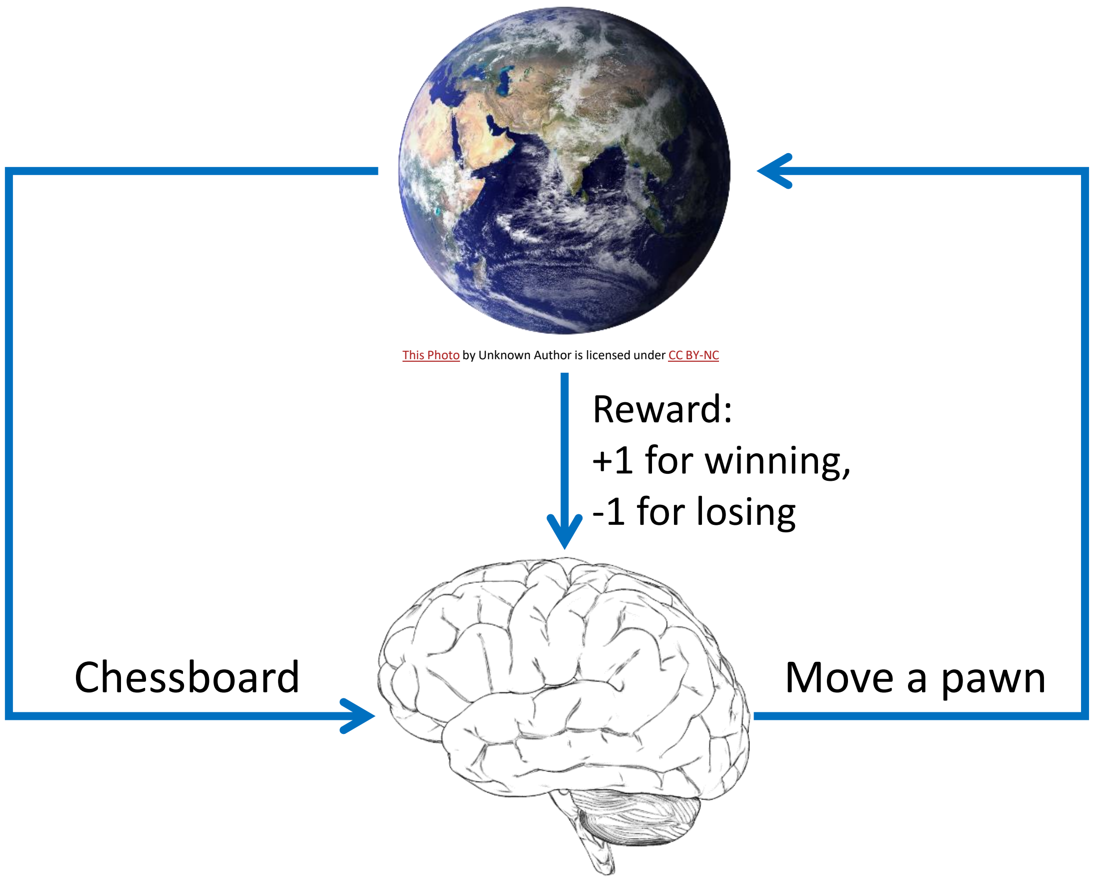
Example: Blood Pressure Control



Example: Make a humanoid robot walk



Example: Develop a computer chess master



Exploration vs Exploitation Dilemma

- Try a new restaurant (explore) or go to your favorite restaurant (exploit)
- To receive high rewards, the agent should prefer actions that has tried in the past and found to be effective in producing high rewards
- However, to discover such actions, it needs to try actions it has not selected before
- Need to find a balance between exploiting known actions and exploring new actions

Online Machine Learning

- Data becomes available in a sequential order.
- The available data is used to update the best predictor for future data at each step, as opposed to batch learning techniques which generate the best predictor by learning on the entire training data set at once.
- Online learning is a common technique used in areas of machine learning where it is computationally infeasible to train over the entire dataset, requiring the need of out-of-core algorithms.
- It is also used in situations where it is necessary for the algorithm to dynamically adapt to new patterns in the data, or when the data itself is generated as a function of time—e.g., stock price prediction.
- Online learning algorithms may be prone to catastrophic interference, a problem that can be addressed by incremental learning approaches.

Incremental Learning

- Incremental learning is a method of machine learning in which input data is continuously used to extend the existing model's knowledge—i.e., to further train the model.
- It is a dynamic technique of supervised and unsupervised learning.
- Can be applied when training data becomes gradually available over time (like data streams) or when its size reaches out of system memory limits (because of hardware constraints). Also, applying incremental learning to big data aims to produce faster classification or forecasting times.

Incremental Learning

- Learning the model to adapt to new data without forgetting its existing knowledge.
- Many traditional machine learning algorithms inherently support incremental learning. Other algorithms can be adapted to facilitate incremental learning.
- Some incremental learners have built-in some parameter or assumption that controls the relevancy of old data, while others, called stable incremental machine learning algorithms, learn representations of the training data that are not even partially forgotten over time.

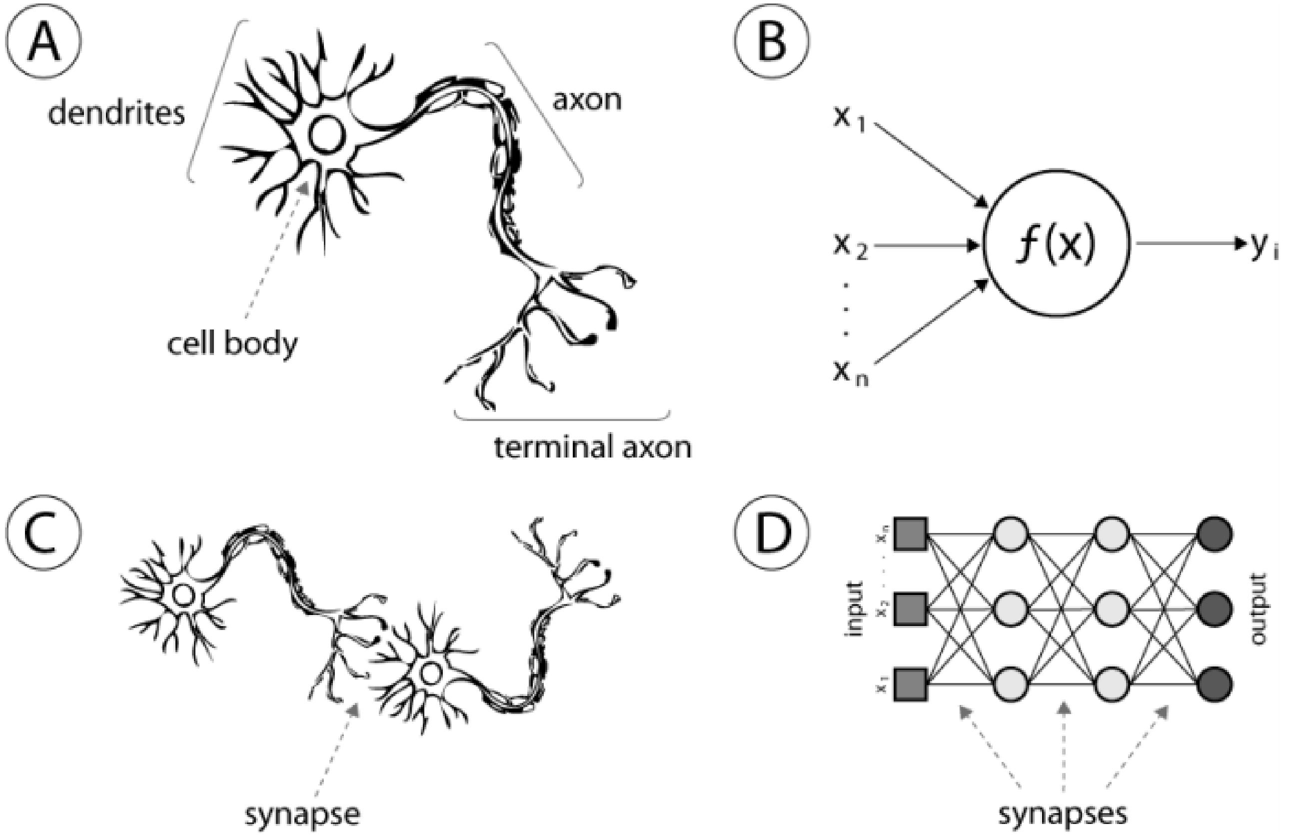
Artificial Neural Networks (ANNs)

- Neural networks is a subset of machine learning algorithms. They are vaguely inspired by the biological neural networks and modelled after the human brain.
- They are nowadays the most widely used machine learning algorithms.
- They can be applied to almost any type of problem in machine learning, either for supervised or unsupervised learning.

The concept behind ANNs

- Our brain is based on a complex network of interconnected *neurons.*
- Neurons are entities that receive information through a set of synapses, perform some sort of calculation, and pass the result to other neurons through its outgoing synapses.
- ANNs are computational algorithms that try to mimic this behaviour.
- They consist of artificial neurons, i.e., a mathematical function that seeks to simulate the behavior of a biological neuron.
    - Each neuron receives a set of input signals, combines them in some way and passes the information along.
- An ANN is a complex network of interconnected artificial neurons.

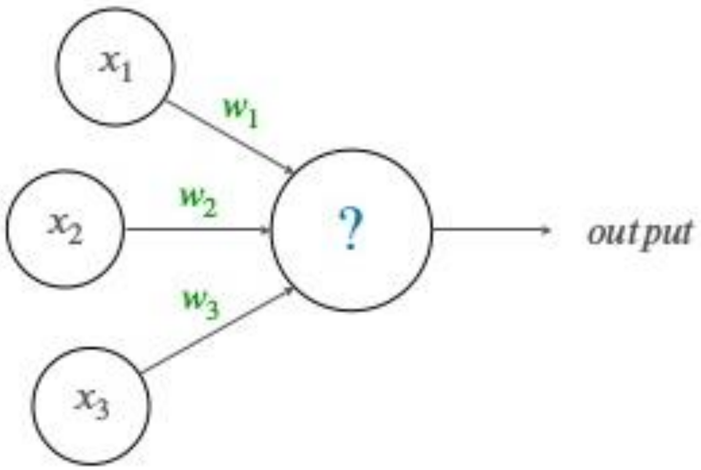
The concept behind ANNs



(A) Human neuron; (B) artificial neuron or hidden unity; (C) biological synapse; (D) ANN synapses.

Source: Vinícius Gonçalves Maltarollo, Káthia Maria Honório and Albérico Borges Ferreira da Silva (January 16th 2013). Applications of Artificial Neural Networks in Chemical Problems, Artificial Neural Networks - Architectures and Applications, Kenji Suzuki, IntechOpen, DOI: 10.5772/51275.

A simple artificial neuron



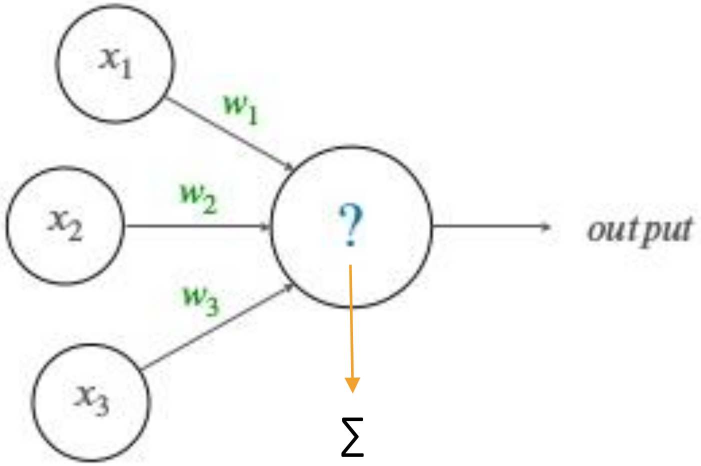
Shall I go to the beach this weekend?

x_1 → Will the weather be good?

x_2 → I am in the mood to drive?

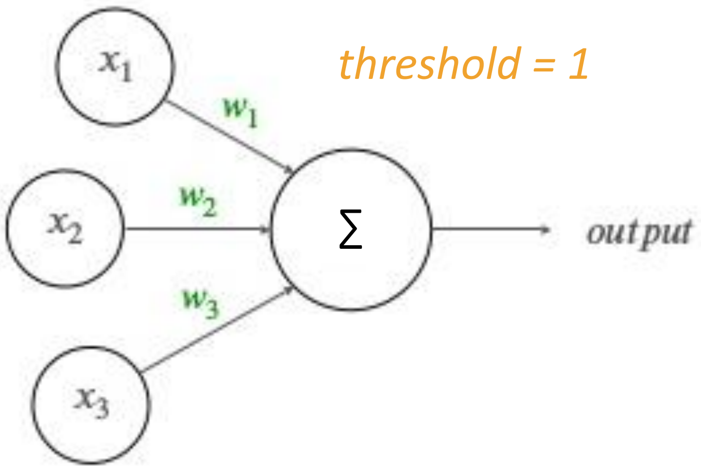
X_3 → Will a friend want to come with me?

A simple artificial neuron



$$output = \begin{cases} 0, & \sum_{j=0}^{n} w_j x_j \leq threshold \\ 1, & \sum_{j=0}^{n} w_j x_j > threshold \end{cases}$$

A simple artificial neuron



Shall I go to the beach this weekend?

x_1 = 1 (good weather)

x_2 = 0 (don't like driving)

x_3 = 1 (my best friend is coming along)

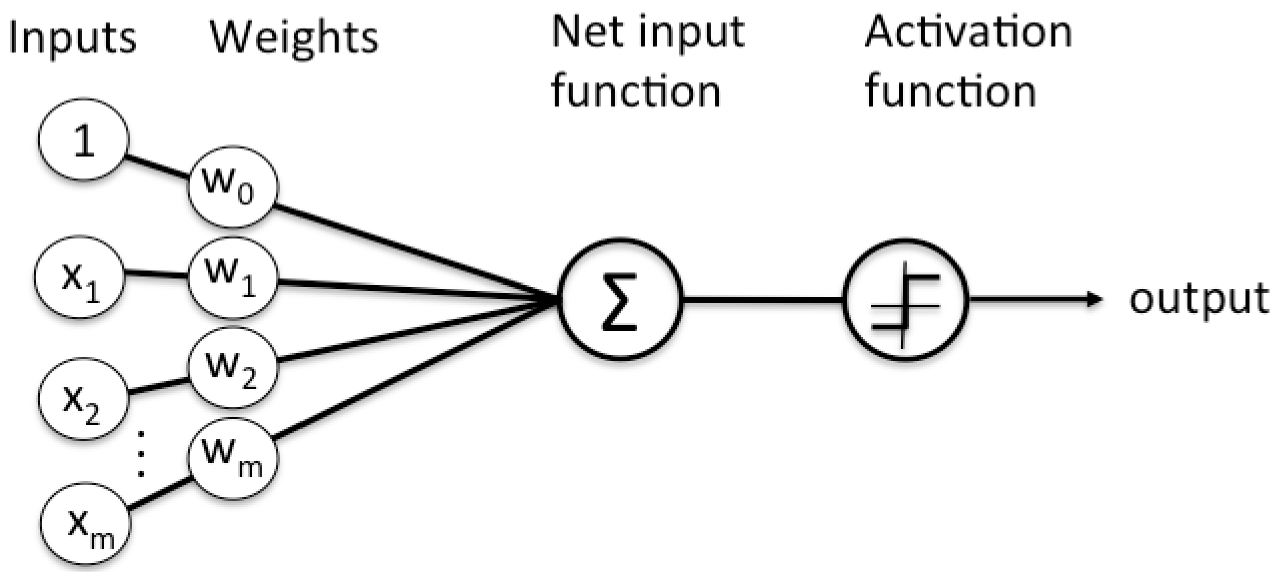
No weights, i.e., $w_1 = w_2 = w_3 = 1$,

$\sum_j w_j x_j = 2 > threshold$ → shall go

With weights, i.e., $w_1 = 2, w_2 = 1, w_3 = 3$,

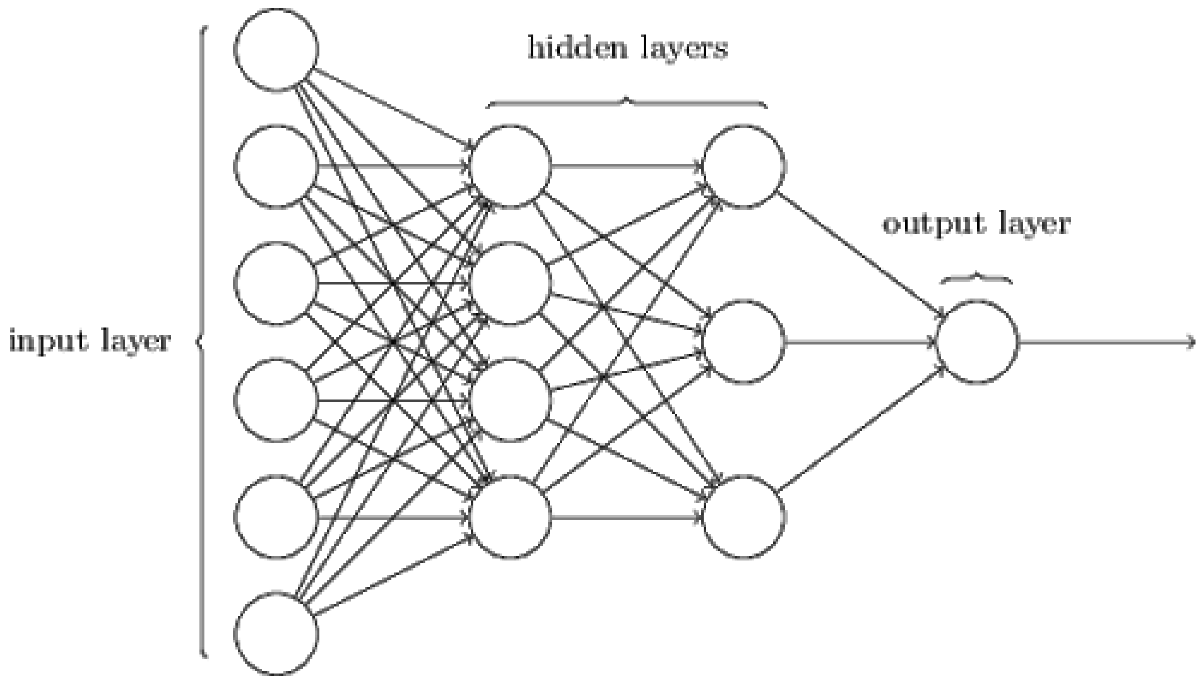
$\sum_j w_j x_j = 2 + 0 + 3 = 5 > threshold$ → shall go

Structure of an Artificial Neuron



Interconnected Network of Neurons

- A neural network is formed by a network of artificial neurons



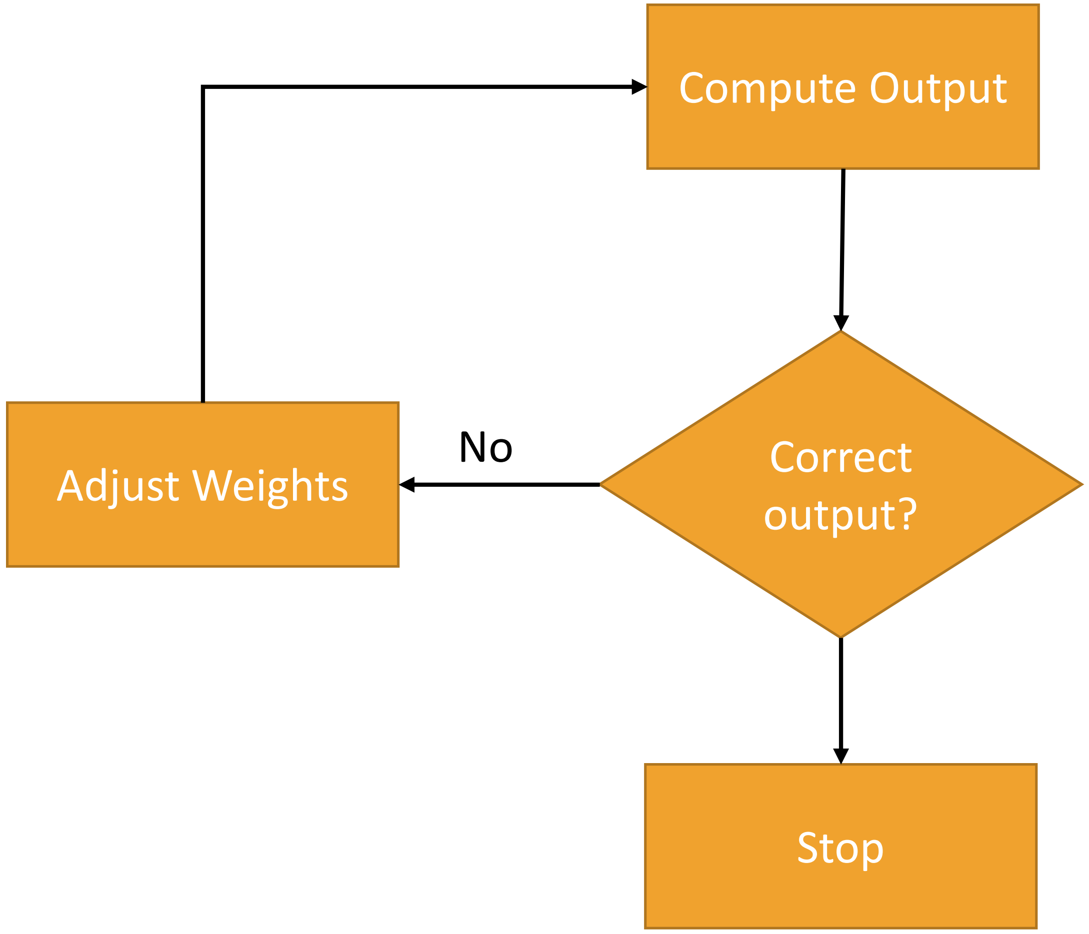
Deep Neural Networks: ANNs with multiple layers between the input and output layers

Neural Networks Intuition

- ANNs are trained to do specific tasks.
  - They are teached, like children. If you show a child several trees, he will then be able to identify other trees.
  - If we want our network to tell whether an image depicts a cat or a dog.
    - We first feed an image of a cat or a dog to the network. The network then does its internal computations and produces and output.
    - This output is compared with the truth. If the network thinks it was given a picture of a dog when in reality the picture was of a cat, it will alter the behaviour of its neurons slightly (by modifying the weights of the connections) in order to make a better prediction of a cat in the future.

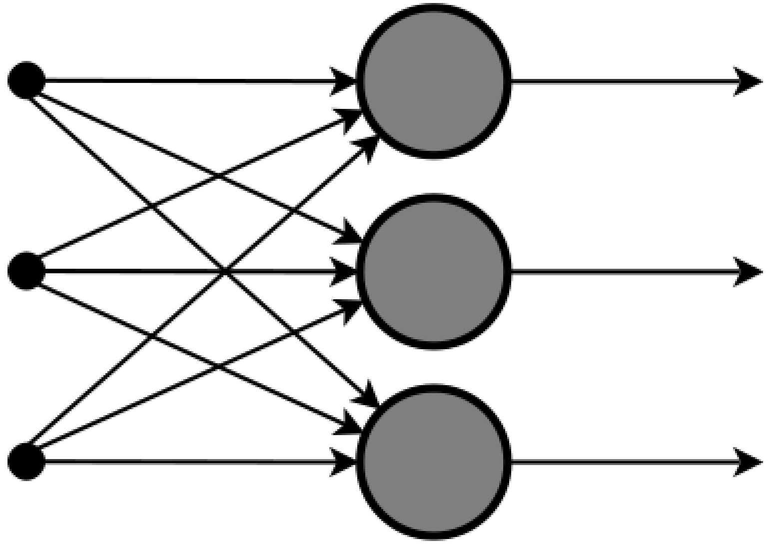
Supervised Learning in ANNs

- Training an ANN means adjusting its weights so that it produces correct outputs



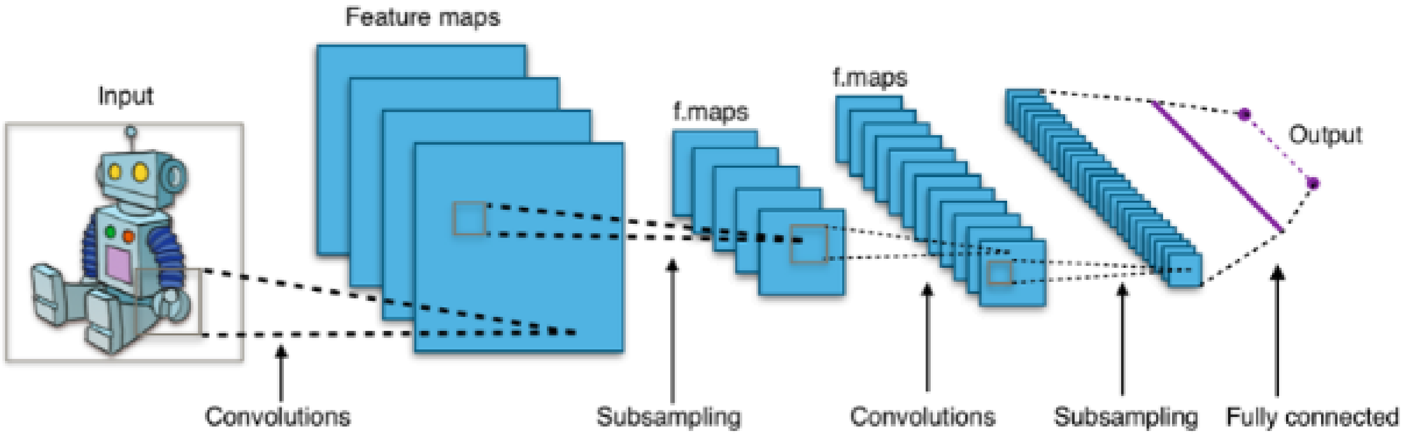
Types of ANNs

- Feedforward networks
  - The simplest structure
  - They are composed of layers of neurons, where a weighted output from one layer is the input to the next layer.
  - The data passes through the different input nodes until it reaches the output node. In other words, data moves in only one direction from the first tier onwards until it reaches the output node.



Types of ANNs

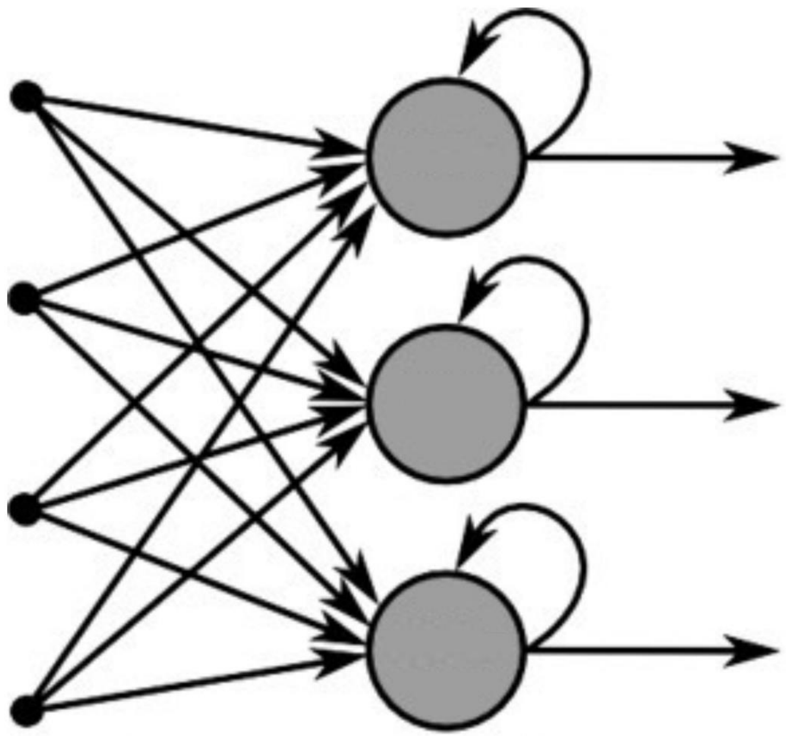
- Convolutional Neural Networks
  - They contain one or more convolutional layers, which can be either completely interconnected or pooled.
  - Before passing the result to the next layer, the convolutional layer uses a convolutional operation on the input, due to which the network can be much deeper with fewer parameters.



Types of ANNs

❑Recurrent Neural Networks

- The output of a particular layer is saved and fed back to the input.
- Helps predict the outcome of the layer.
- From each time-step to the next, each node will remember some information that it had in the previous time-step. In other words, each node acts as a memory cell while computing and carrying out operations.



Content

- Introduction
- Introduction to Artificial Intelligence
- Artificial Intelligence in Disaster Management
  - AI and the Stages of Disaster Management
  - Prerequisites for Employing AI in Disaster Management
  - AI-powered Autonomous Robot Devices
  - Computer Vision Technologies
  - Modelling of Natural Disasters
  - Applications of AI in Disaster Management
- Realistic Field Exercises Using AI Tools

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AI for Disaster Management

A selection of topics

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Types of Disasters

- ❑Artificial Intelligence can provide useful tools in any type of disaster

Natural Disasters	Man-made disasters
Wildfire	Fires (Urban, Industrial)
Earthquakes	Oil spills (Water Contamination)
Floods	Explosions
Landslide	Bioterrorism
Typhoon/Hurricane	Transportation Accidents (e.g., airplane crash)
Tsunami	

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To get an idea

- Possible examples of AI applications for Disaster Management:
  - Fire Detection from video surveillance systems for building an early warning system
  - Deploying drones with cameras in Search-and-Rescue operations using an AI algorithm for detection and tracking of objects (humans, animals, cars)
  - Prediction of disaster evolution, e.g., fire, oil spill in water, etc. in order to support decision-making procedures.
  - Building structure evaluation in order to estimate risk of further collapse after an earthquake
  - Real-time deployment of evacuation plans taking into account aspects like traffic prediction, disaster evolution, area map, etc.

What can AI do?

❑What kind of help can AI provide in the Disaster Management cycle?

- Systems that forecast events in order to take actions before a disaster
- Decision-support systems
- Decision-making systems
- AI-powered automated robotic devices

Who can AI help?

- From first-line rescuers to administrative authorities, all stakeholders that are involved in the cycle of disaster management can take advantage of AI-powered tools.
  - First-line responders like firefighters
    - e.g., predict fire temperature: to know the intensity and assess extension risk while approaching the fire
  - Rescue Teams
    - e.g., Real-time route finder to reach victims: Safe and quick route
  - Emergency Management Officers
    - e.g., A system that indicates good location for vehicles and aerial ladders (for safety and rescue efficiency)
  - Triage officers
    - e.g., A system that performs automatically real-time victim allocation to the nearest hospitals
  - Administrative authorities
    - e.g., A system that forecasts disasters and estimates their occurrence probability in order to issue an alert

Stages of Disaster Management

Mitigation

Prevent or reduce disasters and prevent or reduce the negative effects of disasters

- Long-term risk assessment and reduction
- Develop and compare disaster mitigation strategies
- Evaluate possible impacts due to hazards

Preparedness

Plan an effective response to minimize damage caused by a disaster

- Real-time forecasting and prediction
- Early warning and monitoring systems
- Develop emergency plans, e.g., evacuation plans
- Carry-out evacuation plans if necessary
- Training

Before the event

Response

Respond to immediate needs, e.g., search-and-rescue, medical care, food and water, etc.

- Event Mapping
- Damage assessment
- Identifying and responding to immediate needs
- Emergency rescue and relief teams: Coordination, Support, Resource allocation
- Triage

Recovery

Build back better (infrastructure, economic growth, healthcare, etc.)

- Develop recovery and reconstruction plans
- Evaluate loss and repair cost
- Infrastructure repair
- Track recovery status

After the event

Matching User Requirements with AI Algorithms

Forest Fires	
AI Algorithm	User Requirement / Purpose
Fire Temperature Prediction	Indication of the thermal power of the fire. This information is useful in determining the need for additional ground means and for aerial reinforcements.
Real-time prediction of fire evolution	To identify the required means and actions.
Real-time rescue planner for rescuers	Combination of safest and quickest route to reach victims.
Recommending positioning of teams, ground and aerial means	In order to maximize coverage with the available means.
Finding the access roads to the forest	In order to cut the access in all roads as early as possible.

Matching User Requirements with AI Algorithms

Flooding	
AI Algorithm	User Requirement / Purpose
Altimetry calculation of the submerged area	The knowledge of these values helps in anticipating an area that can be flooded with its level of exposure but also to estimate the required pumping equipment to be committed.
Average flow calculation from all water courses and forecast of flow for the next hours	To have a global vision of all involved flows as well as the forecasts for the next hours in order to take appropriate actions.
Recommending pump capacity based on overflow or leakage rate.	Employing an adequate pump capacity is critical in flooding management, otherwise situation can deteriorate.
Detection of landslides	This is a soil liquefaction indicator which causes building, bank and hydraulic structure destruction and should be monitored.

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Matching User Requirements with AI Algorithms

Earthquakes	
AI Algorithm	User Requirement / Purpose
Detection of surface and burried victims	This is the priority of the first rescuers on spot; assistance of victims
Structure evaluation: Measuring future collapse risks and anticipating evacuations	In order to prevent additional victims
Gas leakage detection and estimation of the probability of explosions	In order to prevent explosions or the occurrence of victims due to explosions.
Analysis of collapse types	This enables to assess potential voids for survival, small voids and big voids
Measuring the altimetric variation at T time or minute ground movements and estimating probability of aftershocks or landslides or additional collapses	It is to prevent possible aftershocks and to prevent a landslide or additional collapse.

Employing AI in Disaster Management

Prerequisites

? High Computing Power and Storage

? Input Data

? AI Algorithms

Employing AI in Disaster Management

Prerequisites

- ✓ High Computing Power and Storage
- ? Input Data
- ? AI Algorithms

Processing and Data Storage

- Latest computing devices having high computing power and storage capacity
- This offers the ability to process large amounts of data and execute complex algorithms fast.
- By means of AI algorithms and modern computers, it is possible to process large inputs providing a human-like interpretation of the situation.
  - Perception, Prediction, Learning, Reasoning, Knowledge, Planning, Communication
- It is impossible for the human brain to receive the amount of information an AI algorithm can analyze in a couple of minutes !!!

Employing AI in Disaster Management

Prerequisites

- ✓ High Computing Power and Storage
- ✓ Input Data
- ? AI Algorithms

Input data are available

- **The output of any AI algorithm is as good as the input data set.**
  - The data must be enough in terms of quantity and quality (accuracy).
- Reliable devices that can collect large amounts of data are now available in reasonable cost
  - Drones / Remotely Piloted Aircraft System (RPASs) / Unmanned Aerial Vehicles (UAVs)
  - Autonomous Underwater Vehicles (AUVs)
  - Sensors and cameras deployed statically
  - Wearable devices for first responders equipped with sensors
  - Other data sources, e.g., social media posts, online data acquisition systems, etc.

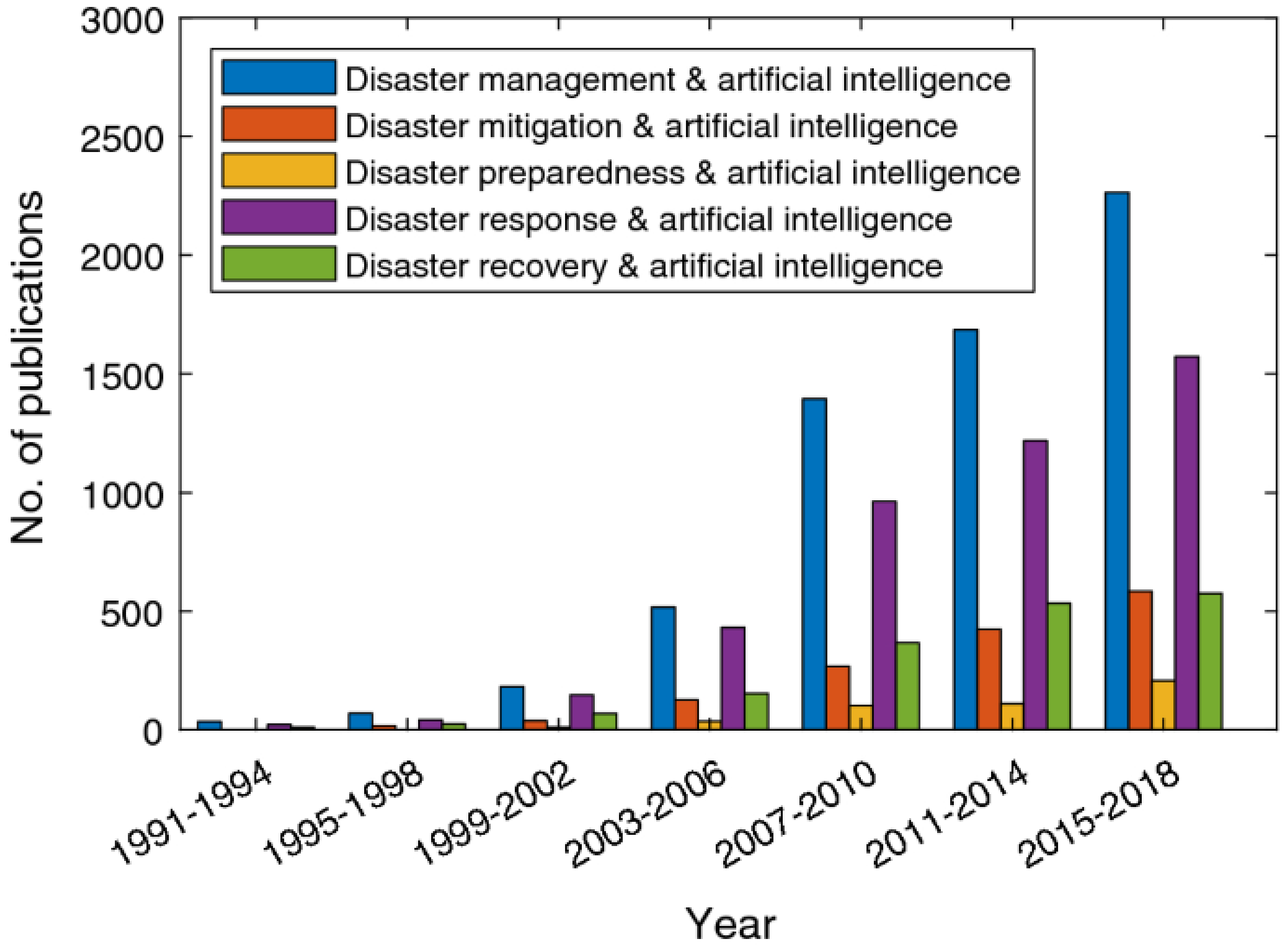
Employing AI in Disaster Management

Prerequisites

- ✓ High Computing Power and Storage
- ✓ Input Data
- ✓ AI Algorithms

AI algorithms

- Having the first two prerequisites nowadays (processing power and input data), the interest of the scientific community is increasing during the past few years.



Source: Sun, Wenjuan & Bocchini, Paolo & Davison, Brian. (2020). Applications of artificial intelligence for disaster management. Natural Hazards. 103. 2631-2689. 10.1007/s11069-020-04124-3.

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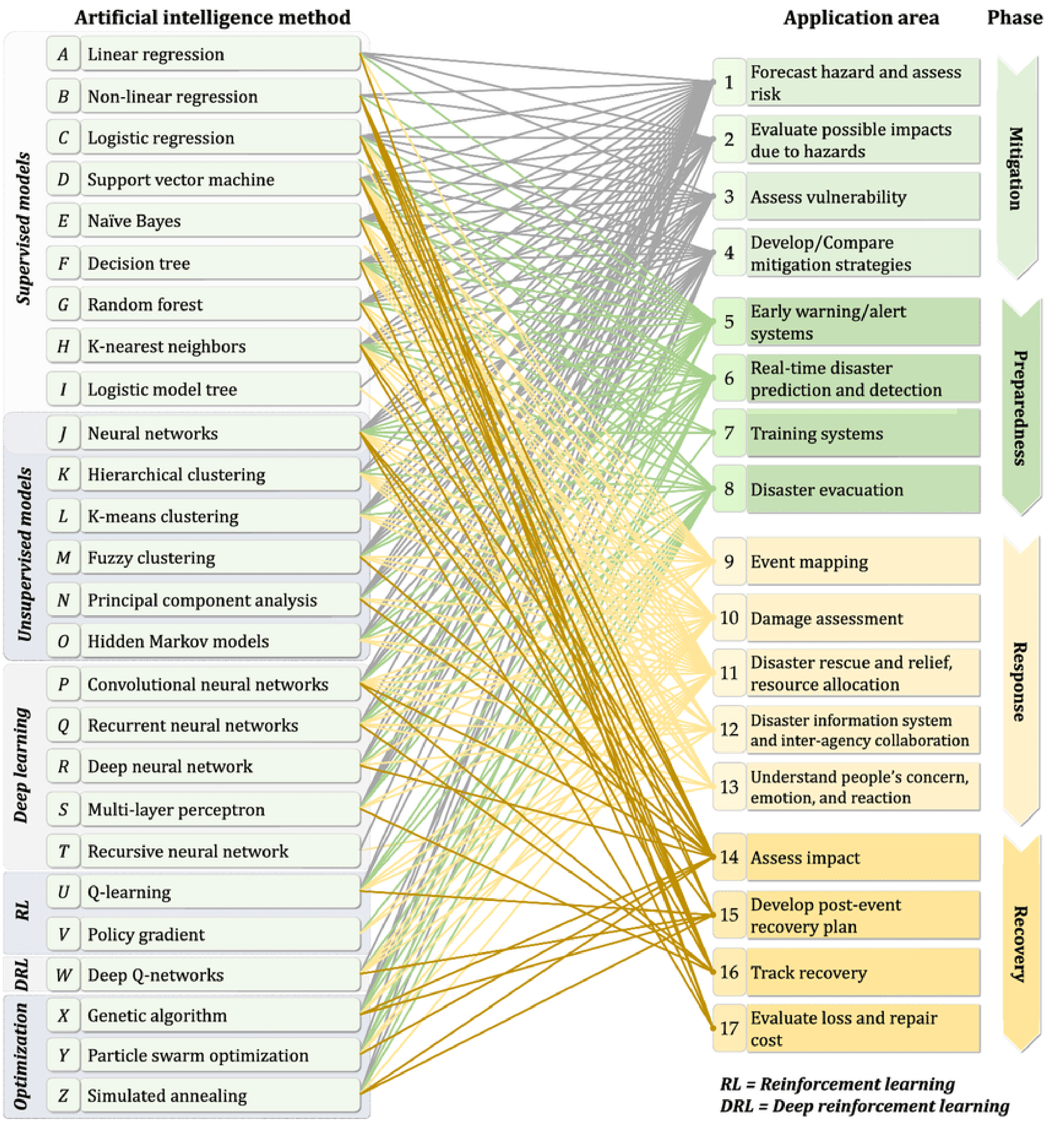
AI Algorithms

- Each algorithm is not specific to solving a few problems, if employed appropriately it can handle almost any type of problem.

Source: Sun, Wenjuan & Bocchini, Paolo & Davison, Brian. (2020). Applications of artificial intelligence for disaster management. Natural Hazards. 103. 2631-2689. 10.1007/s11069-020-04124-3.



AI-powered Automated Robot Devices

- Automated Robot Devices → for instance, UAVs (drones)
- Motivation
  - Provide greater probability of mission success without the risk of loss or injury of persons
  - Can be exposed to dangerous environments
  - Manned aircrew can lose concentration after many hours spent on watch; therefore loss of mission effectiveness
    - Too much information to process
    - Under stress
    - Limited Personnel
    - None ideal conditions to operate in

Jonathan Murray , 2012, “Securing Critical Infrastructure: Perimeter protection strategy at key national security sites including transport hubs, power facilities, prisons and correctional centres”.

Operational Needs

Mapping &
Reconnaissance

Monitoring
& Tracking

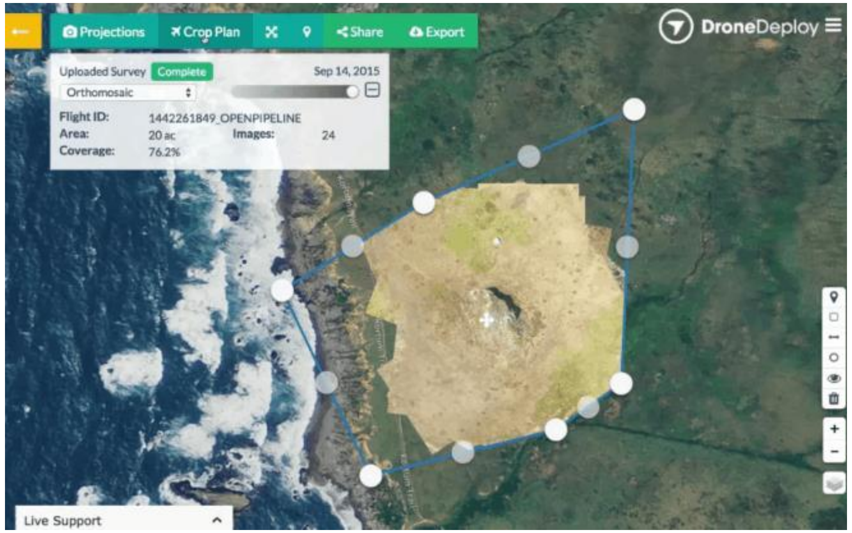
Temporary Utility
Infrastructure

Delivery of
Help-Aid

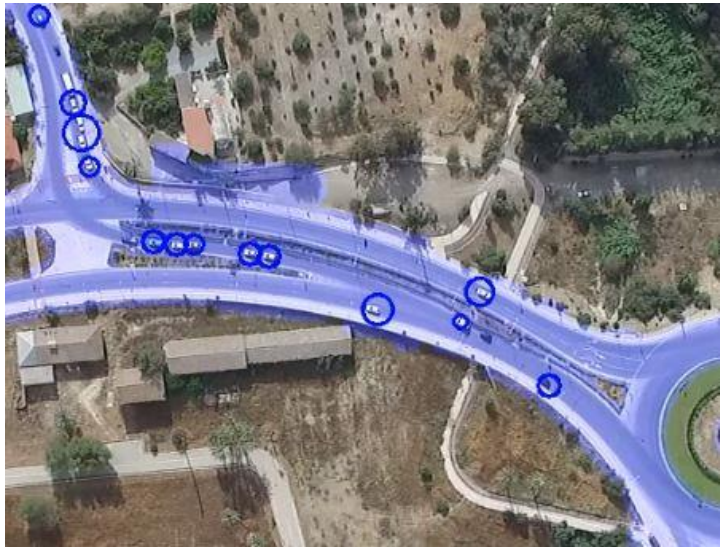
Safety
& Security

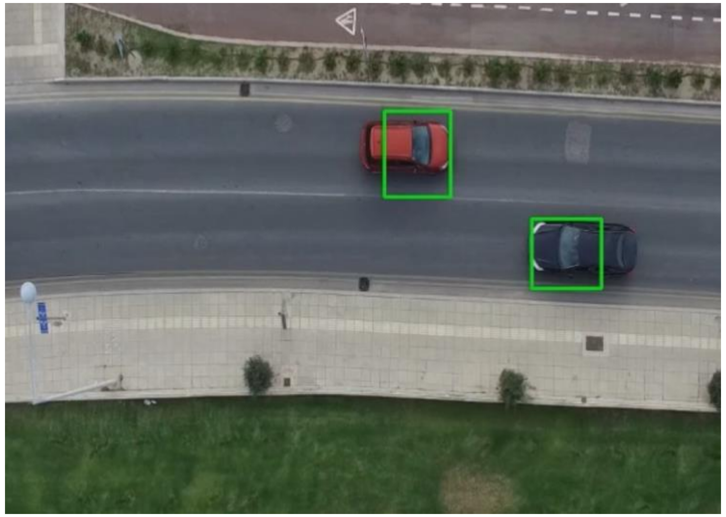
Mapping & Reconnaissance

- ❑Manually
- ❑DroneDeploy
- ❑Pix4D

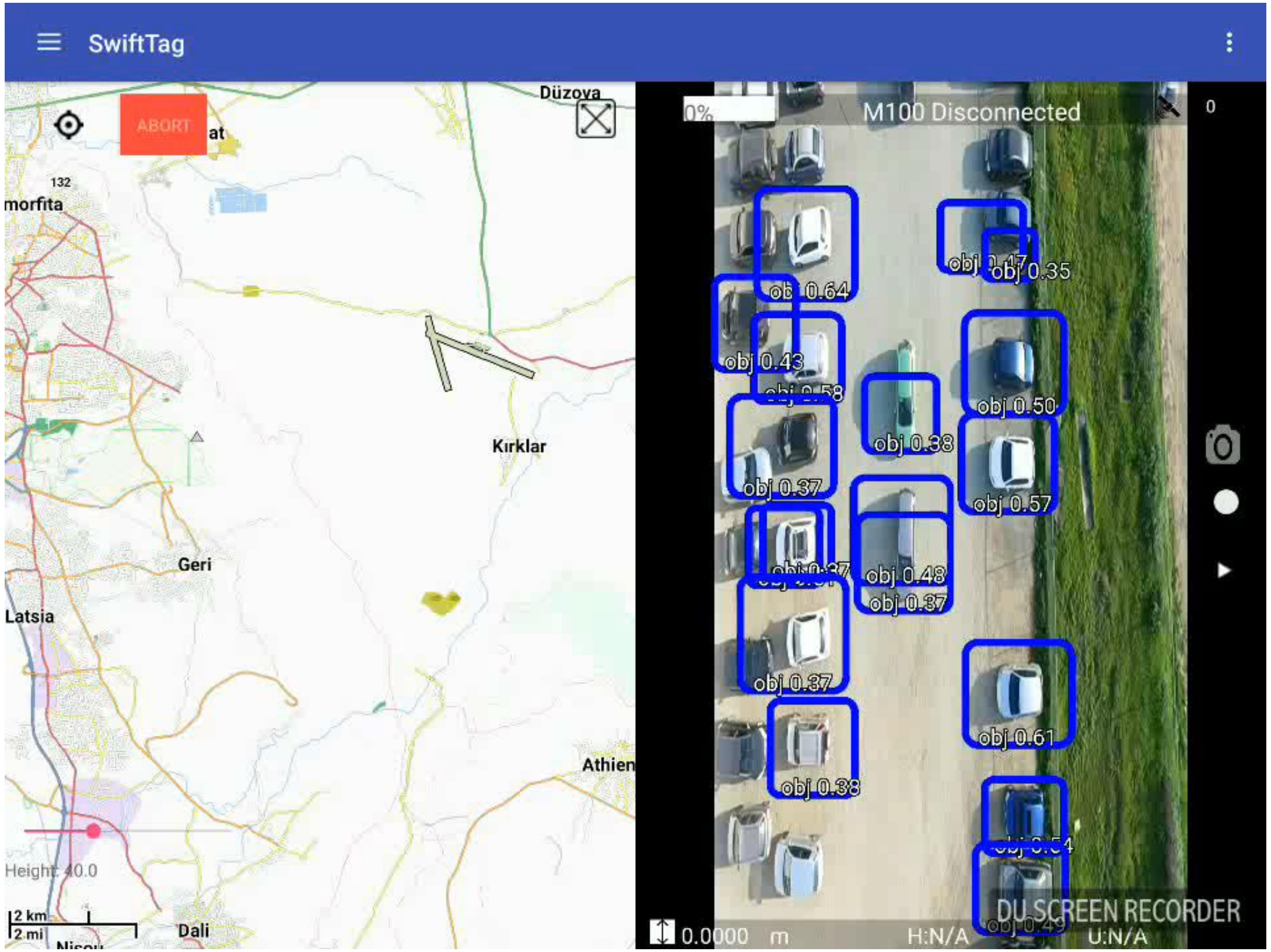


Monitoring & Tracking

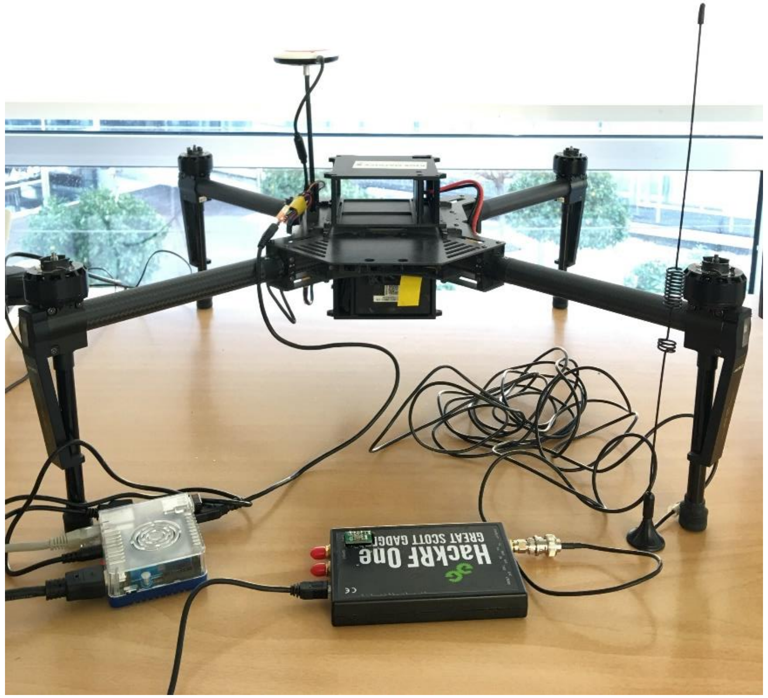




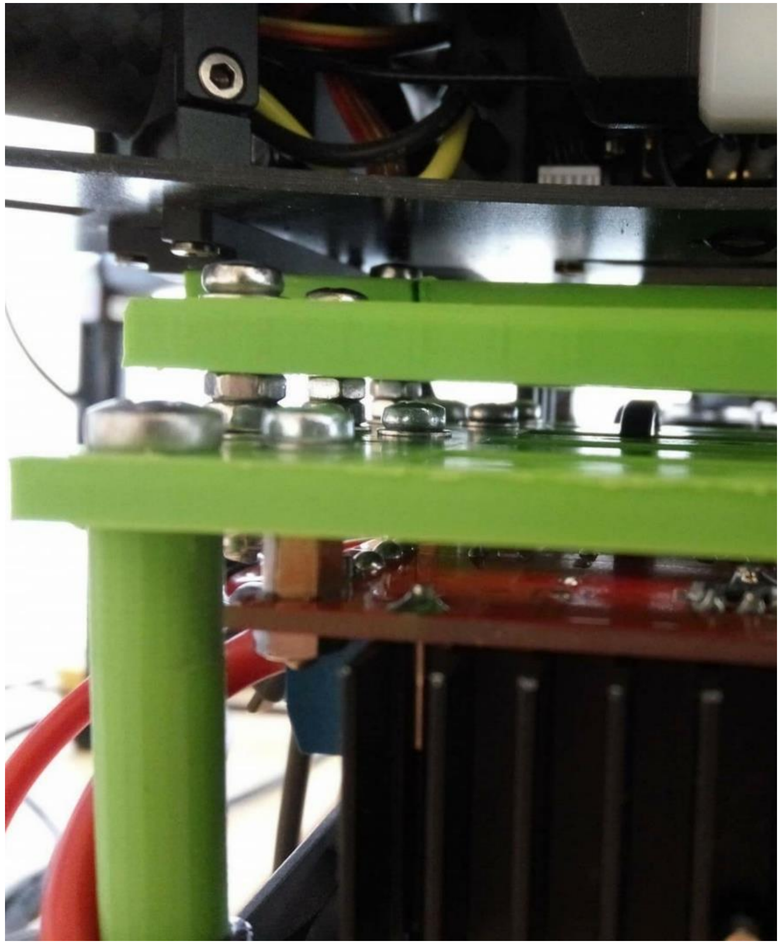
Monitoring & Tracking



Temporary Utility Infrastructure



Delivery of Help-Aid



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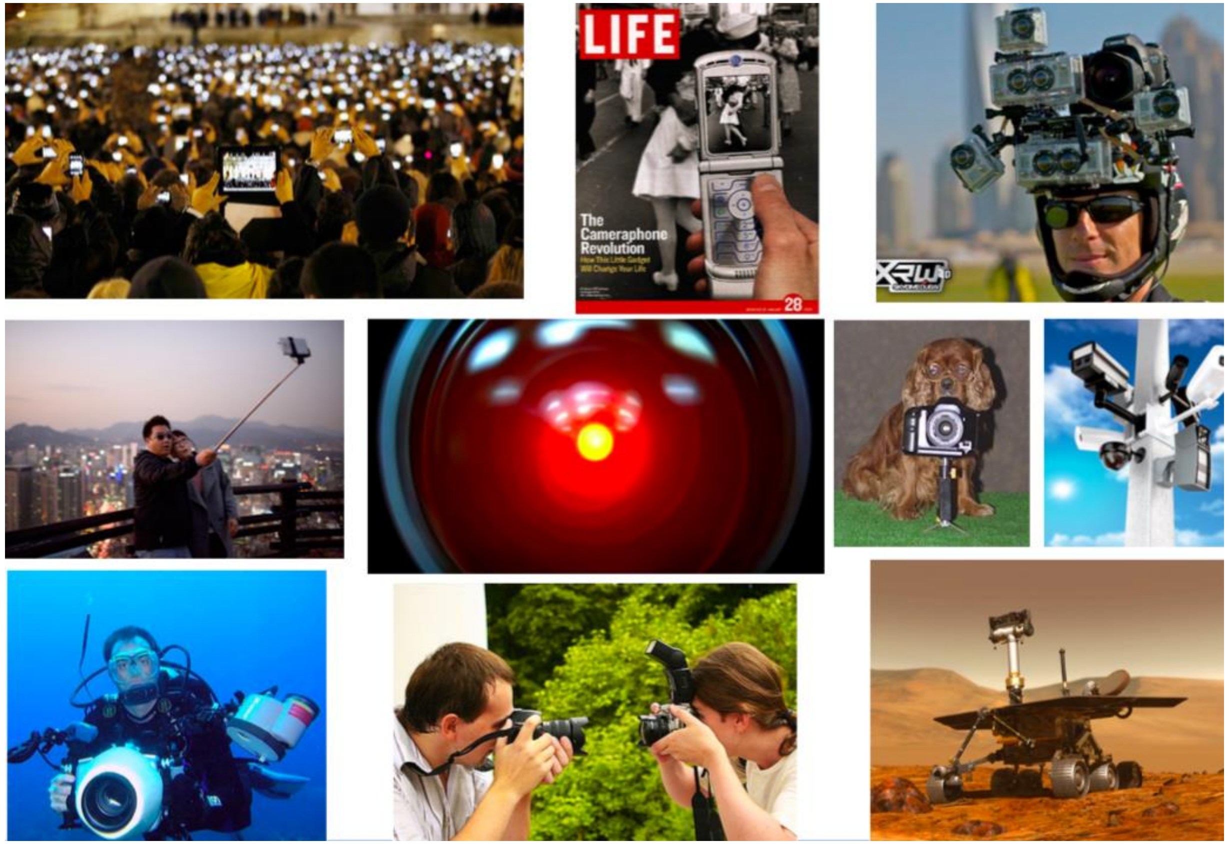
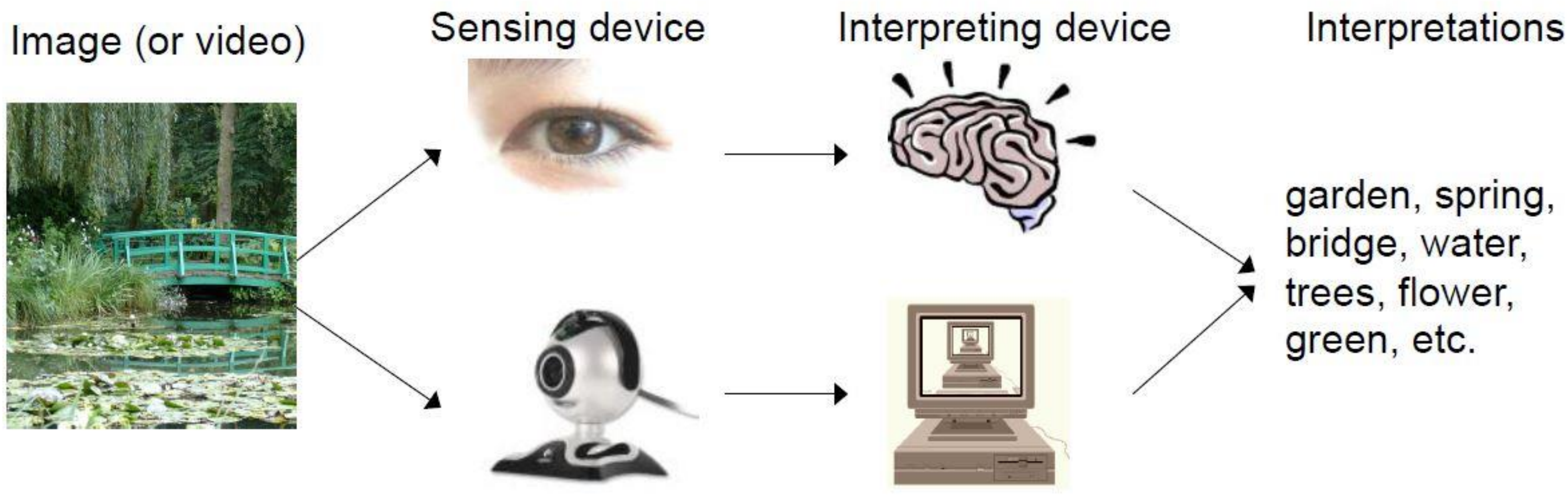
Computer Vision Technologies

- Computer Vision is a powerful branch of AI with numerous applications for emergency response.
- It deals with how computers can gain high-level understanding from digital images and videos.



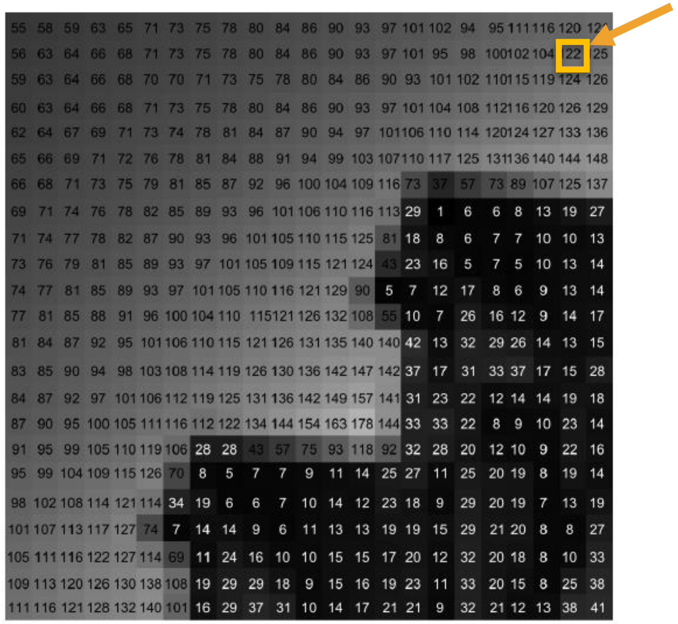
What is (Computer) Vision



The goal of computer vision

- To bridge the gap between pixels and “meaning”.

What we see



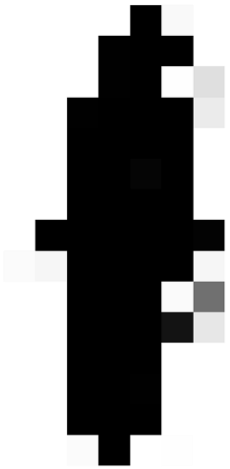
Pixel

What a computer sees

Understanding an image

- Human or machine-based detection

Detection



(Something is there)

Identification

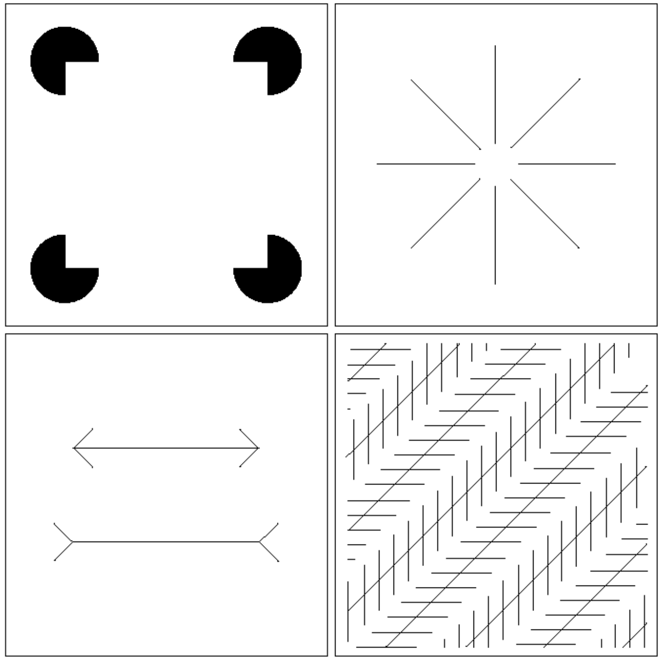
(A person is there)

Recognition

(A fireman is there)

Vision is Really Hard

- Vision is an amazing feature of natural intelligence
- More percentage of the human brain devoted to vision than any other task



Digital Image Processing
Book by Rafael C. Gonzalez and Richard Eugene Woods

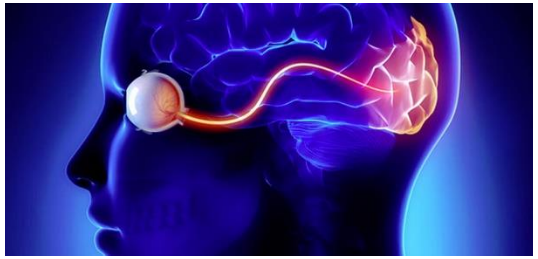
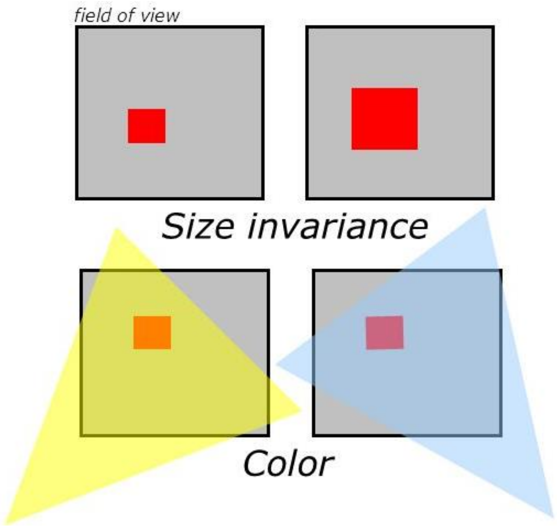
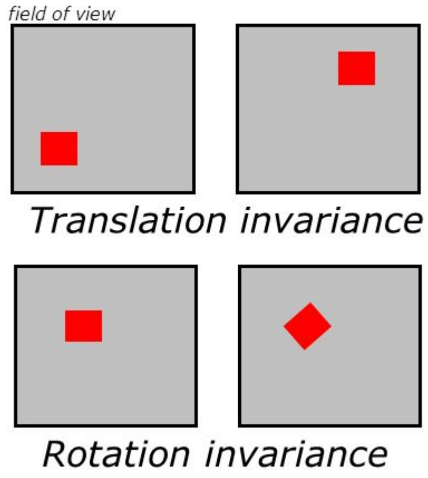


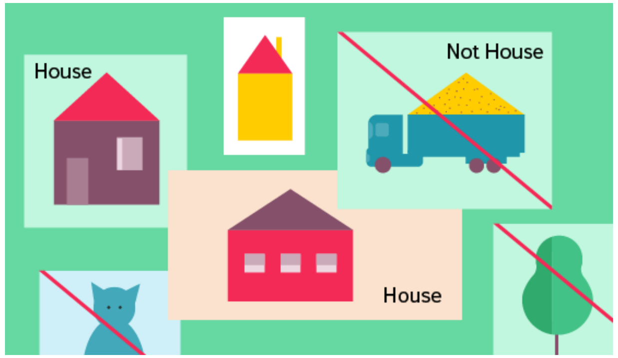
Photo credit: CLIPAREA.com/Folotia

Why Vision is a hard problem?

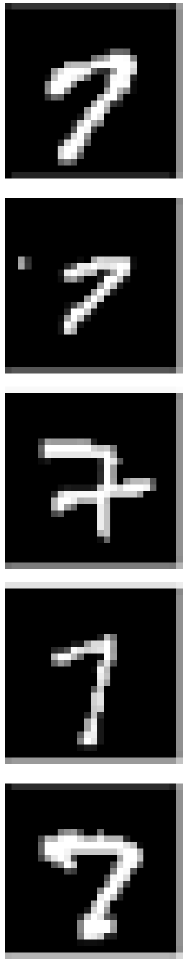


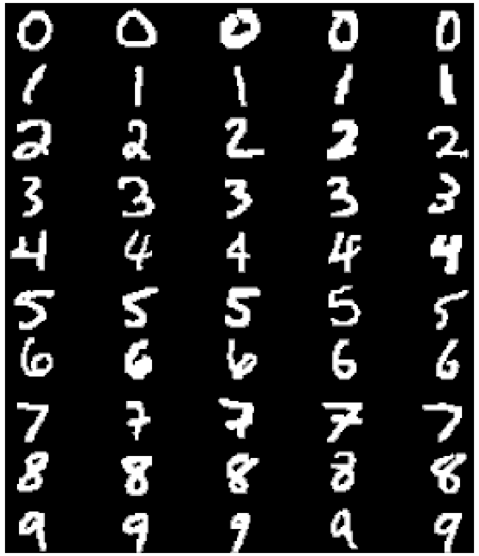
- ❑ Objects in rich categories exhibit significant variability
  - Photometric variation
  - Viewpoint variation
  - Occlusions
  - Intra-class variability
- ❑ Increased complexity → Difficult to hardcode rules
  - Cars come in a variety of shapes (sedan, minivan, etc)
  - People wear different clothes and take different poses

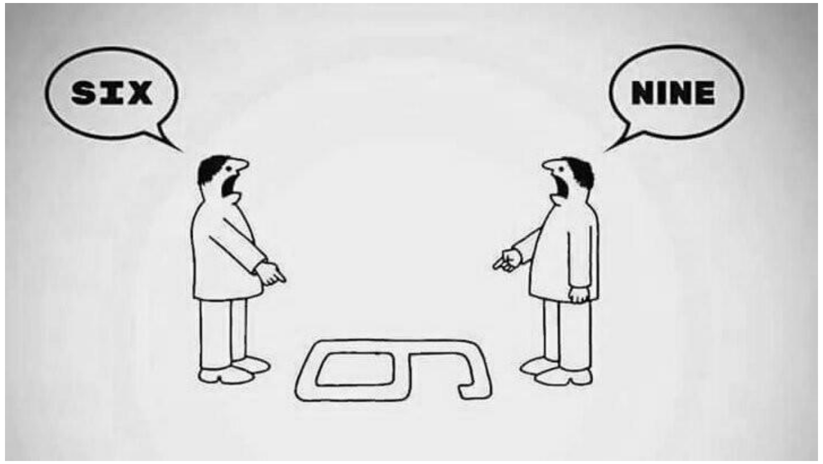




Example: Character Recognition







Potential sources for images and videos

- Video from cameras deployed for other purposes, like, security surveillance cameras (CCTV).
- Static cameras deployed for a specific disaster management applications
- Drone-mounted cameras (or robot-mounted cameras in general)
- Photos uploaded by users to social media.

On-Board Computer Vision

- The combination of computer vision and IMU data (altitude, acceleration, etc.) can improve the precision and robustness of drone navigation.
- Vision-based solutions are interesting for small drones (< 2 Kg) for indoor navigation, obstacle avoidance and other problems.

Mission Critical Aspects

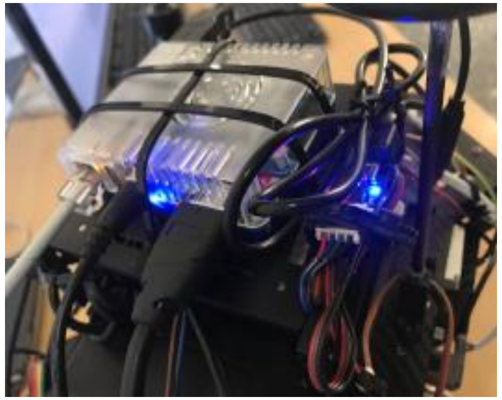
- Navigation
  - Path Planning
  - Localization
- Environment
  - GPS-Denied
  - Obstacle avoidance
  - Swarming
- Automatic Landing and takeoff
- Toward increasing autonomy

Application related processing

- Environment mapping
- Object Detection
- Anomaly Detection
- Video Enhancement
  - De-hazing
  - Image Stabilization
  - Super-resolution
  - Contrast Enhancement
- Data Compression

From Theory to Practice

Tablet

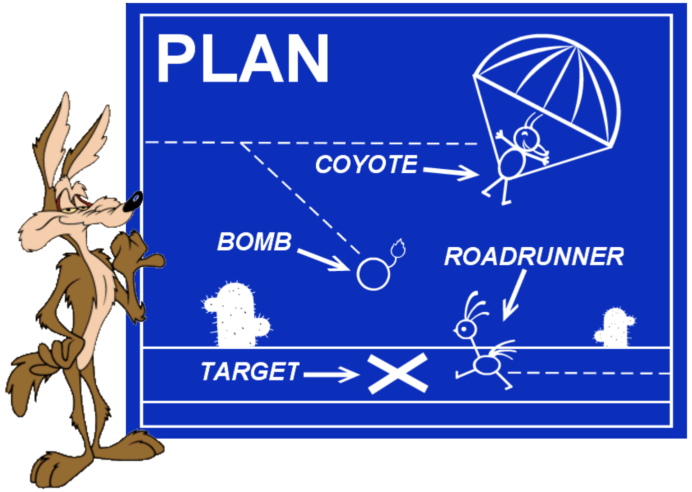


Embedded Processing Unit

From Theory to Practice (2)

- State of the art CV algorithms often require extensive hardware: limited payload

Contradiction!



- Remote processing of images: solution?
  - Use of ground station
  - High bandwidth, minimal latency, ultra reliable connection
  - Severe limitations!
  - (especially when targeting autonomous UAVs)

Challenges for UAVs

- ❑ Computer Vision Algorithms are Expensive
  - Limited memory footprint
  - Limited compute resources
- ❑ Batteries don't last that long
  - Computer Vision Algorithm can drain significant amounts
  - Need long endurance for long missions
- ❑ Does not play well with thermo
  - Burst in computation and intense use of cores

Challenges for UAVs

- Computer Vision Algorithms are Expensive
  - Limited memory footprint
  - Limited compute resources
- Batteries don’t last that long
  - Computer Vision Algorithm can drain significant amounts
  - Need
- Does no
  - Burst

ES related constraints:

Power Efficiency, Cooling, Battery, Cost (overheads), Reliability, Speed (latency), Size…

Implementation – Prototyping

Real-World Deployment

Requirements

- High Accuracy
  - Understand generalized object representation
- Real-Time Performance
  - As close to the camera frame-rate as possible
  - Will allow the UAV to reach maximum speed
  - Low Latency
  - Deterministic Processing Time
- Able to run on low-end hardware
  - Have as little impact on the weight and battery of the UAV

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Requirements

- High Accuracy
  - Understand generalized object representation
- Real-Time Performance
  - As close to the camera frame-rate as possible
  - Will allow the UAV to reach maximum speed
  - Low Latency
  - Dete
- Able to
  - Have

Customize Computer Vision Algorithms for:

Real-Time Performance
Low Memory Footprint
Low-end Hardware
Reliability, Speed (latency)

Image Understanding

- Different ways to describe what is in an image
  - **Classification:** Assign a label to the whole image
  - **Classification+Localization**: Find a single region that corresponds to the label and enclose in a bounding box
  - **Object Detection:** Find all instances of different object classes and enclose them in a bounding box
  - **Instance Segmentation:** Mark all the pixels that correspond to a specific class instance

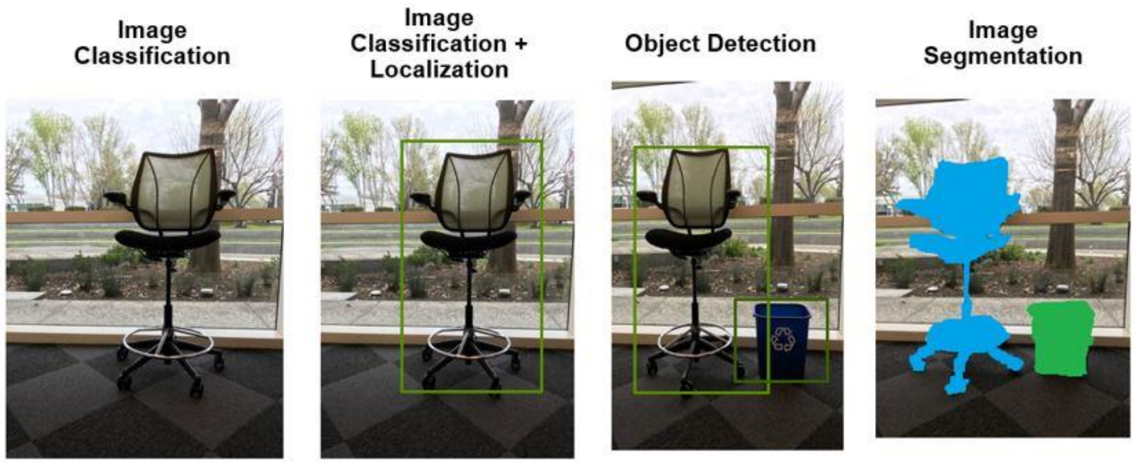


Image Classification

❑What does an image depict?

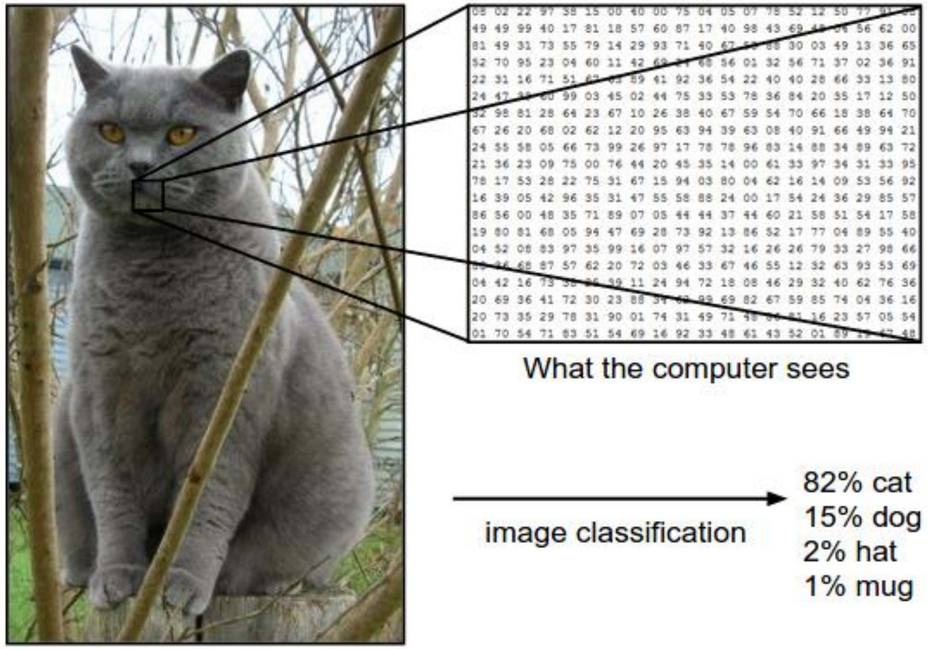
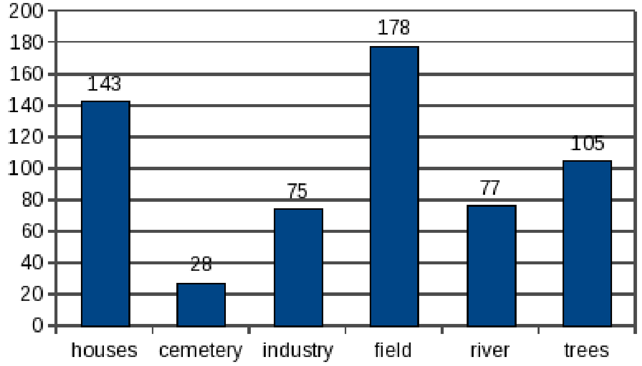
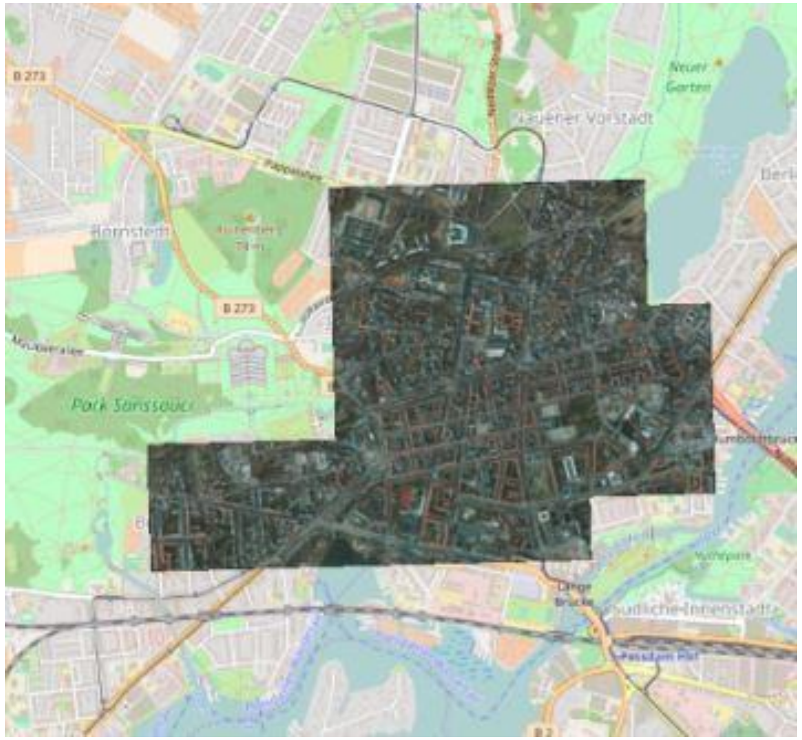


Image from the Stanford CS231 Course



Increasing Situational Awareness in Disaster Events

- A drone can scan the area in case of a disaster and report on events that have occurred
- Can be combined with GIS technologies



Automated detection of disasters

- ❑A training set of various images
  - > 8000 images
- ❑4 disaster events

Class	Set			Total Per Class
	Train	Validation	Testing	
Collapsed Building /Rubble	400	100	200	700
Fire/Smoke	420	110	210	740
Flood	400	100	200	700
Traffic Accidents	400	100	200	700
Normal	2700	1000	2000	5700
Total Per Set	4320	1410	2810	**Overall: 8540**

Collapsed Building/ Rubble

Fire/Smoke

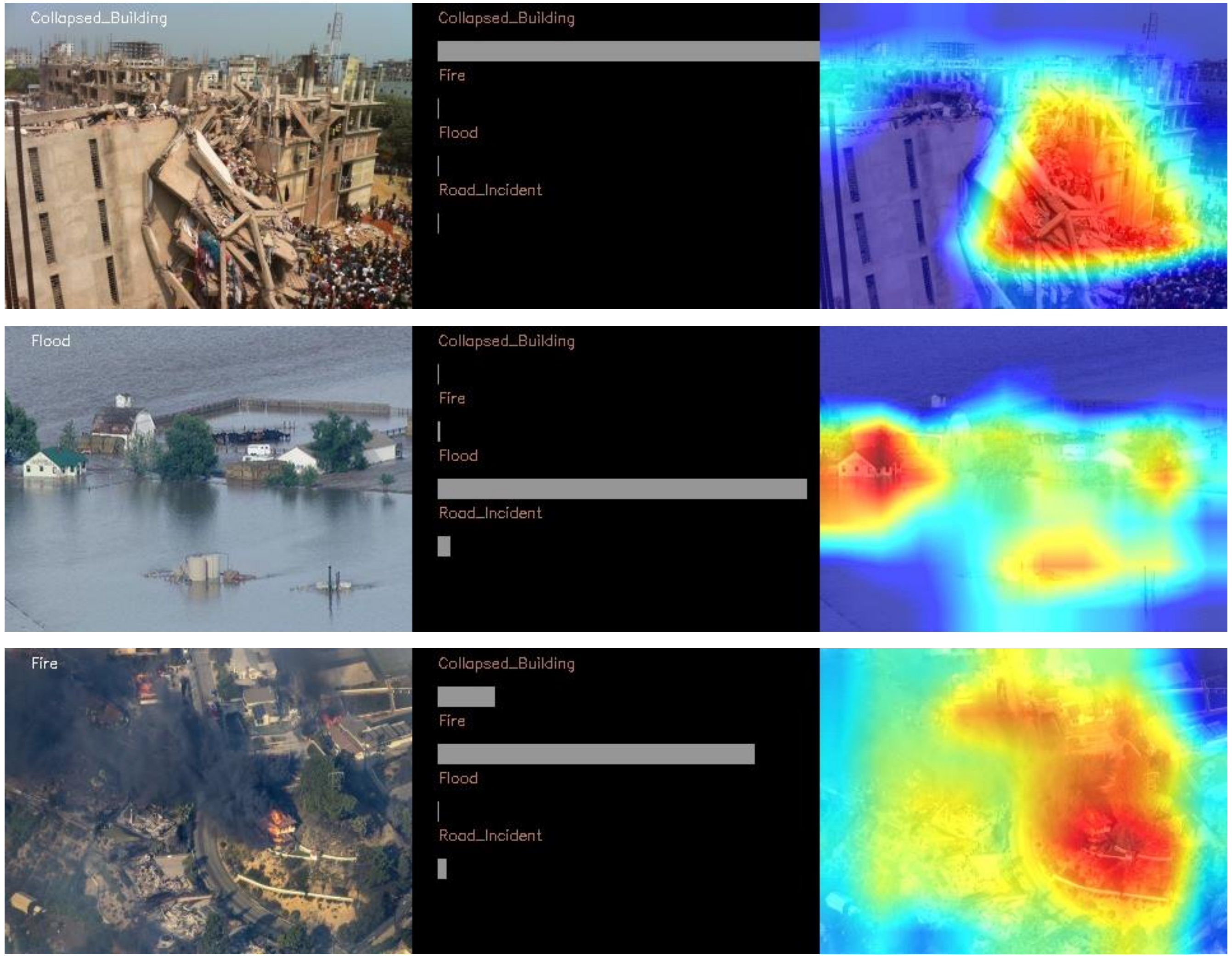
Flood

Traffic Accidents

Normal

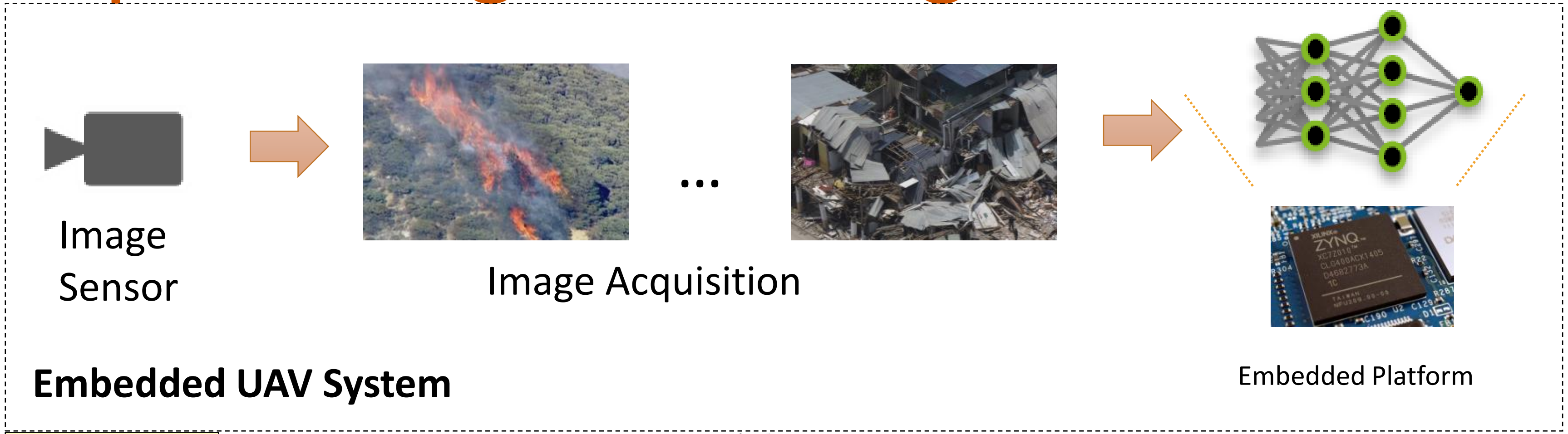
ARTION

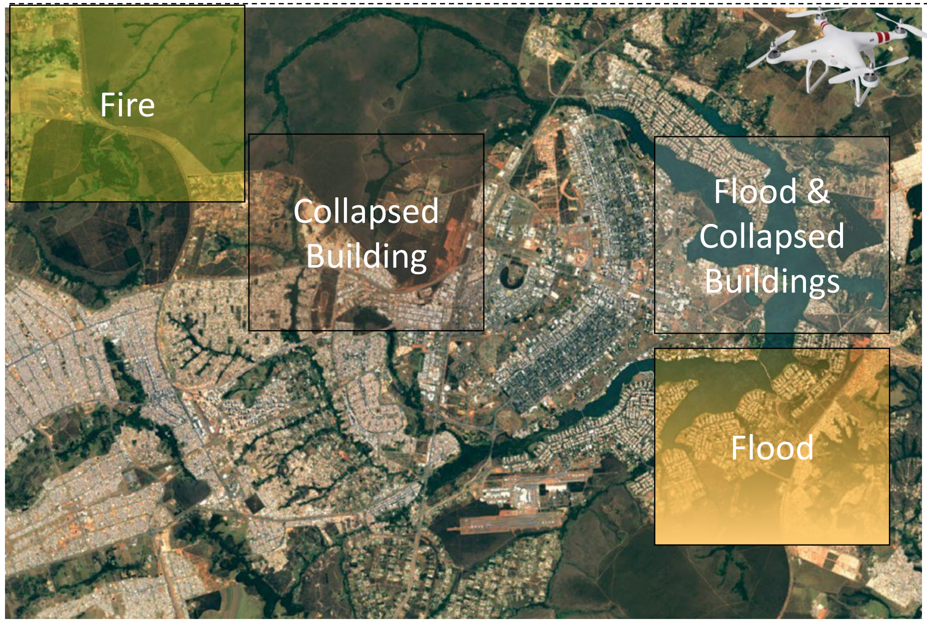
Example of operational system

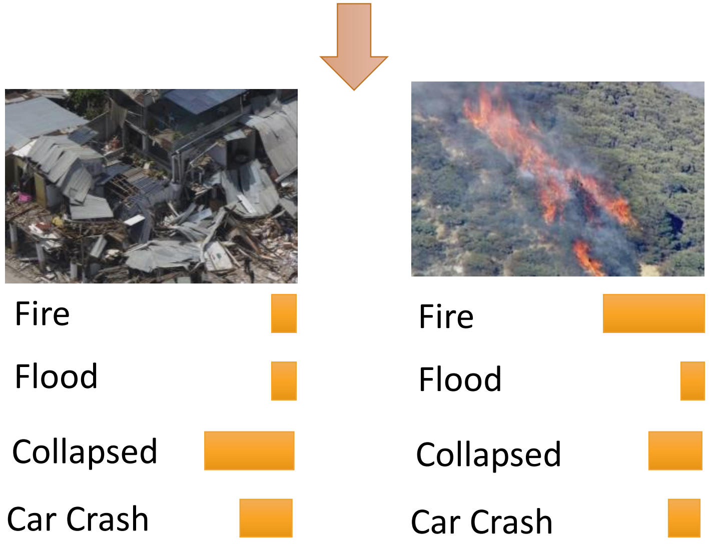


Autonomous patrolling and recognition

Automated Path Planning Software







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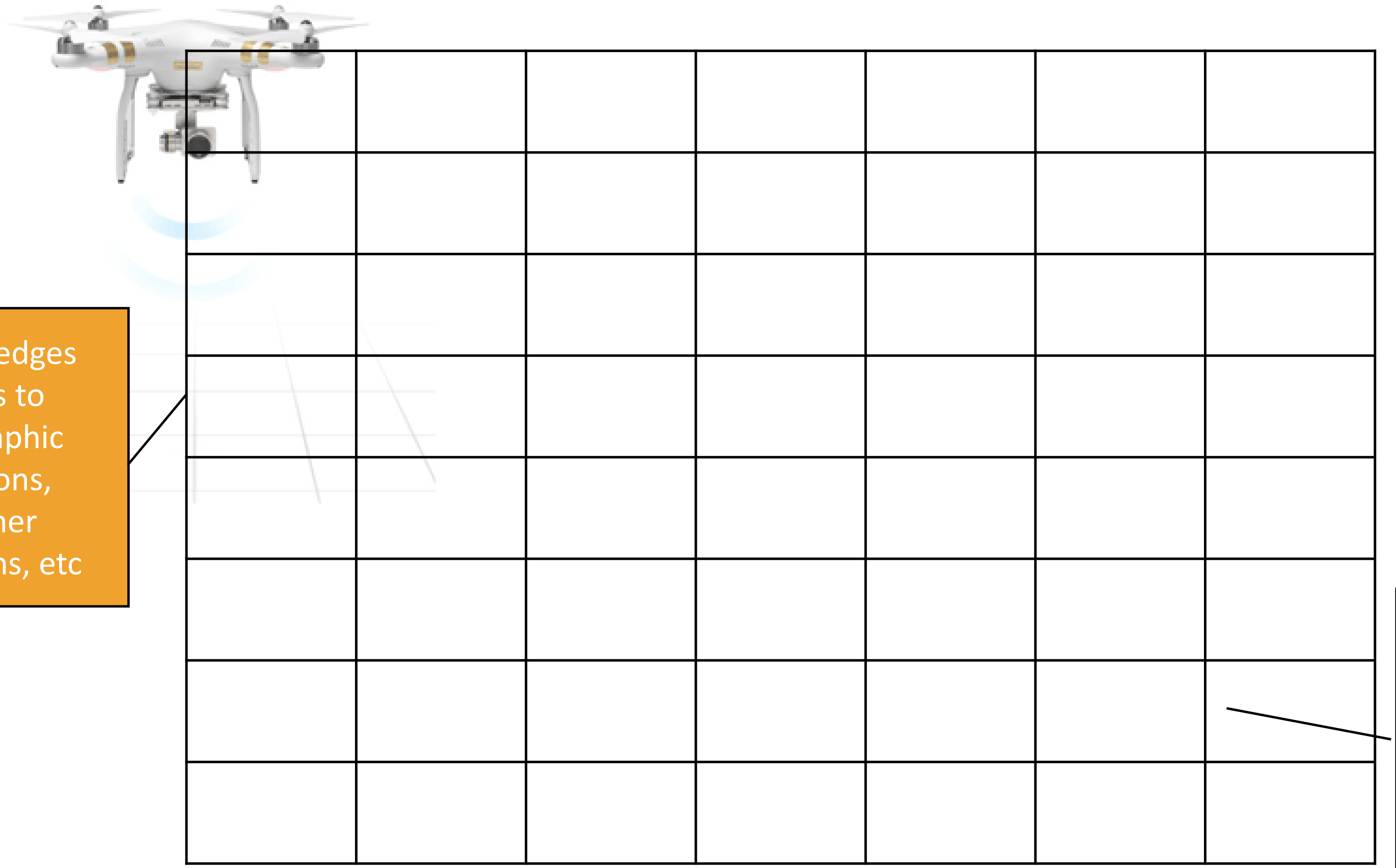
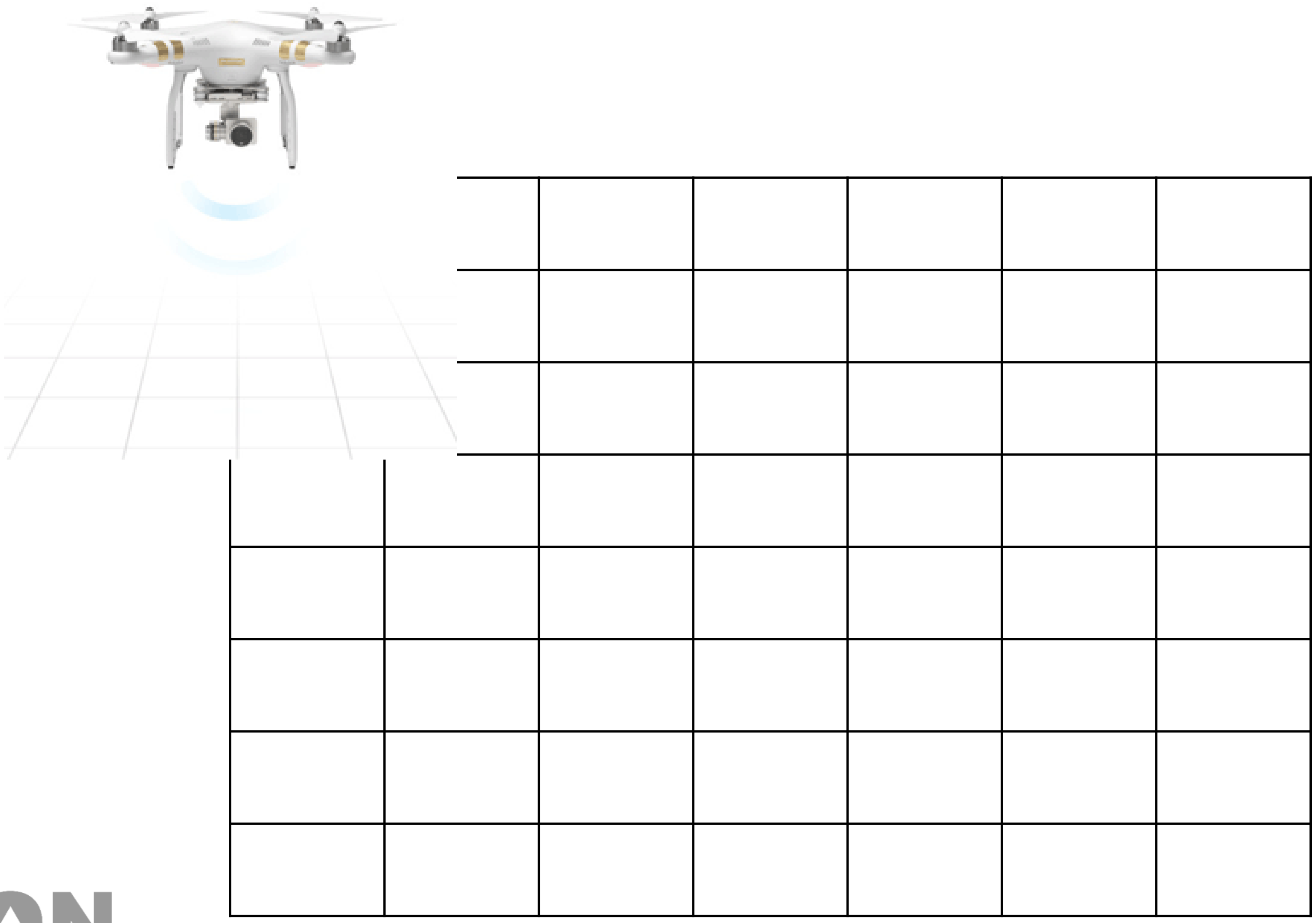
Path Planning



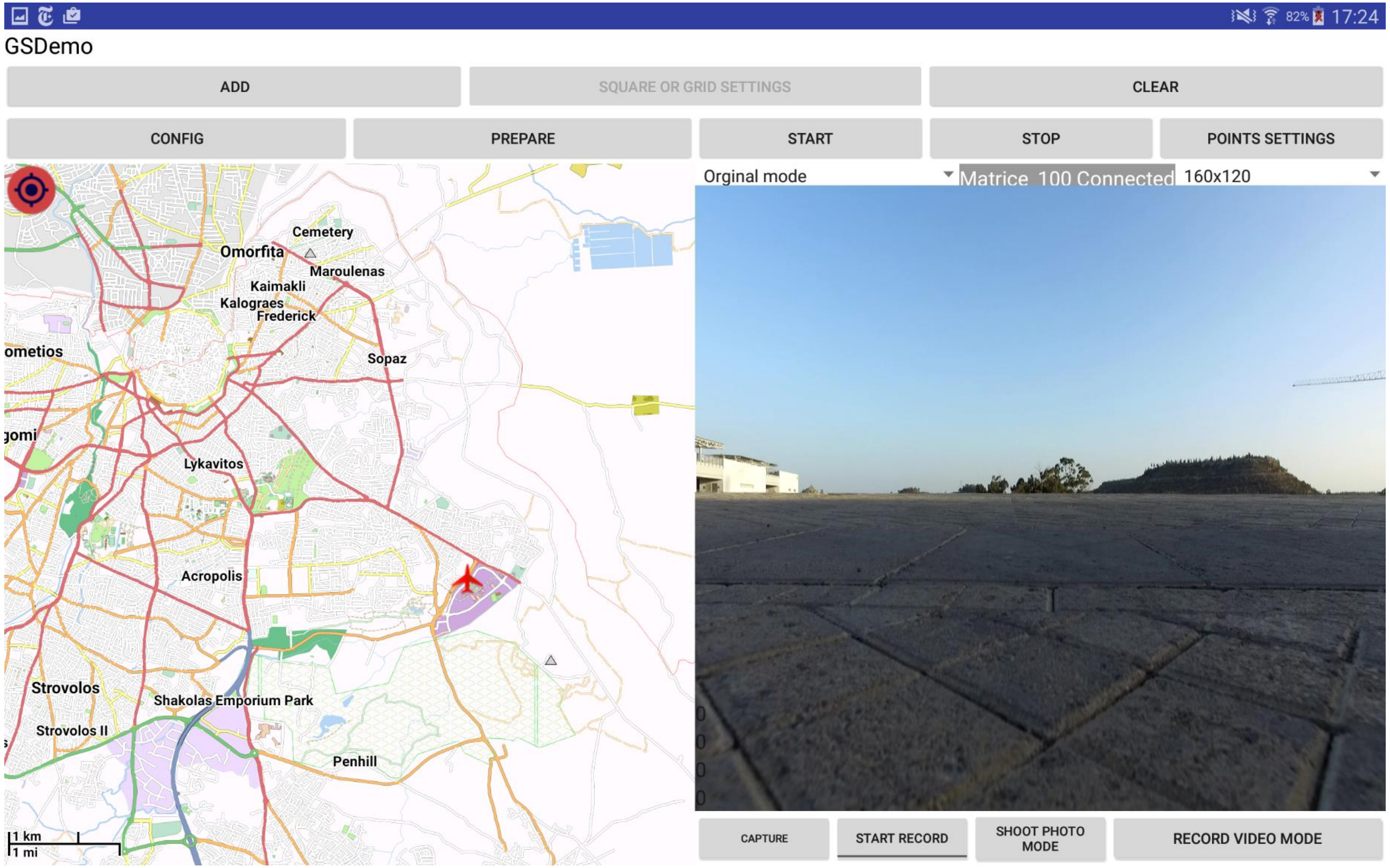
Cost on edges relates to topographic variations, weather conditions, etc

Path chosen to scan the RoI most efficiently and return to home – Hamiltonian Cycle

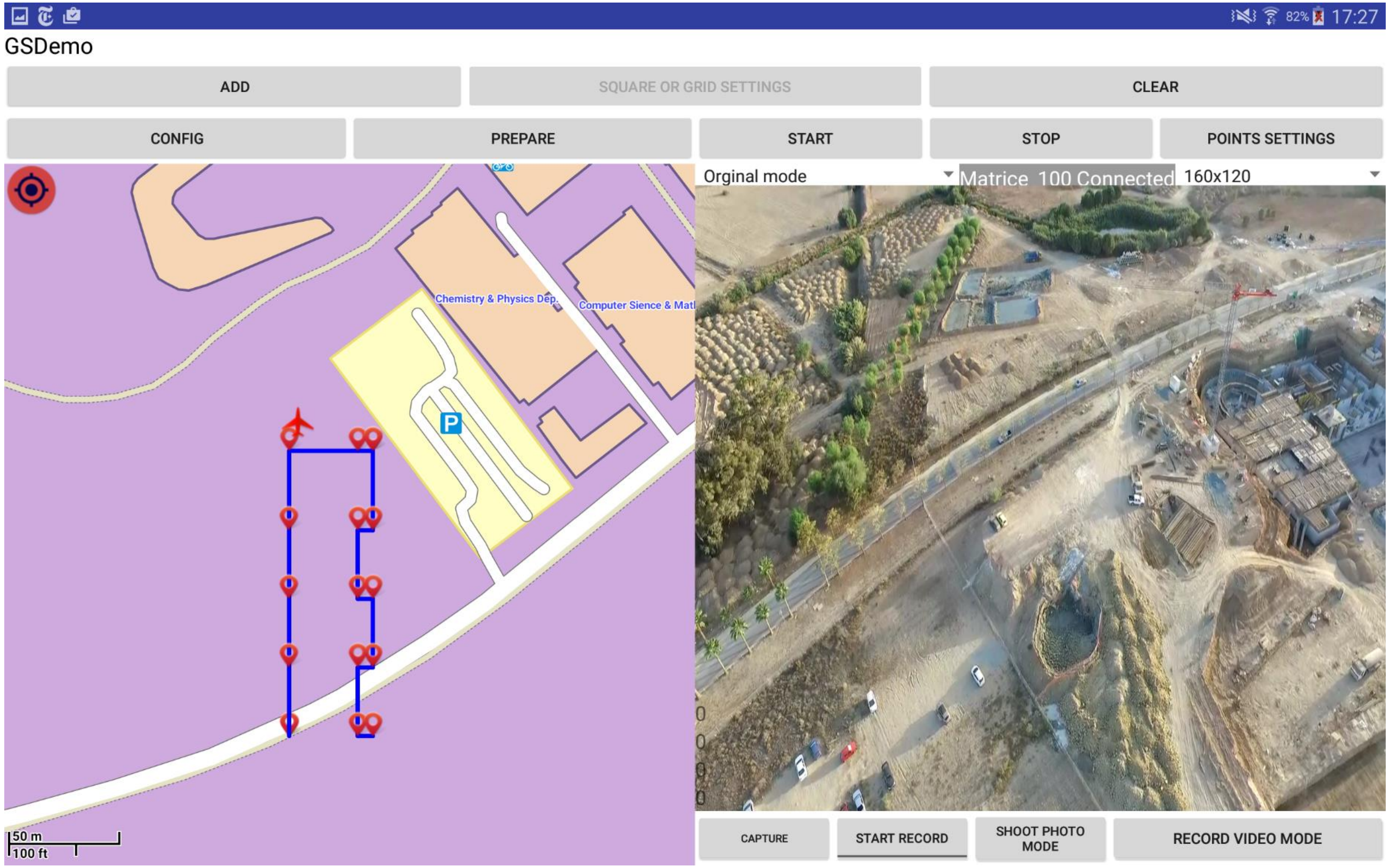
Path Planning



Automated watch-keeping and patrolling



Automated watch-keeping and patrolling



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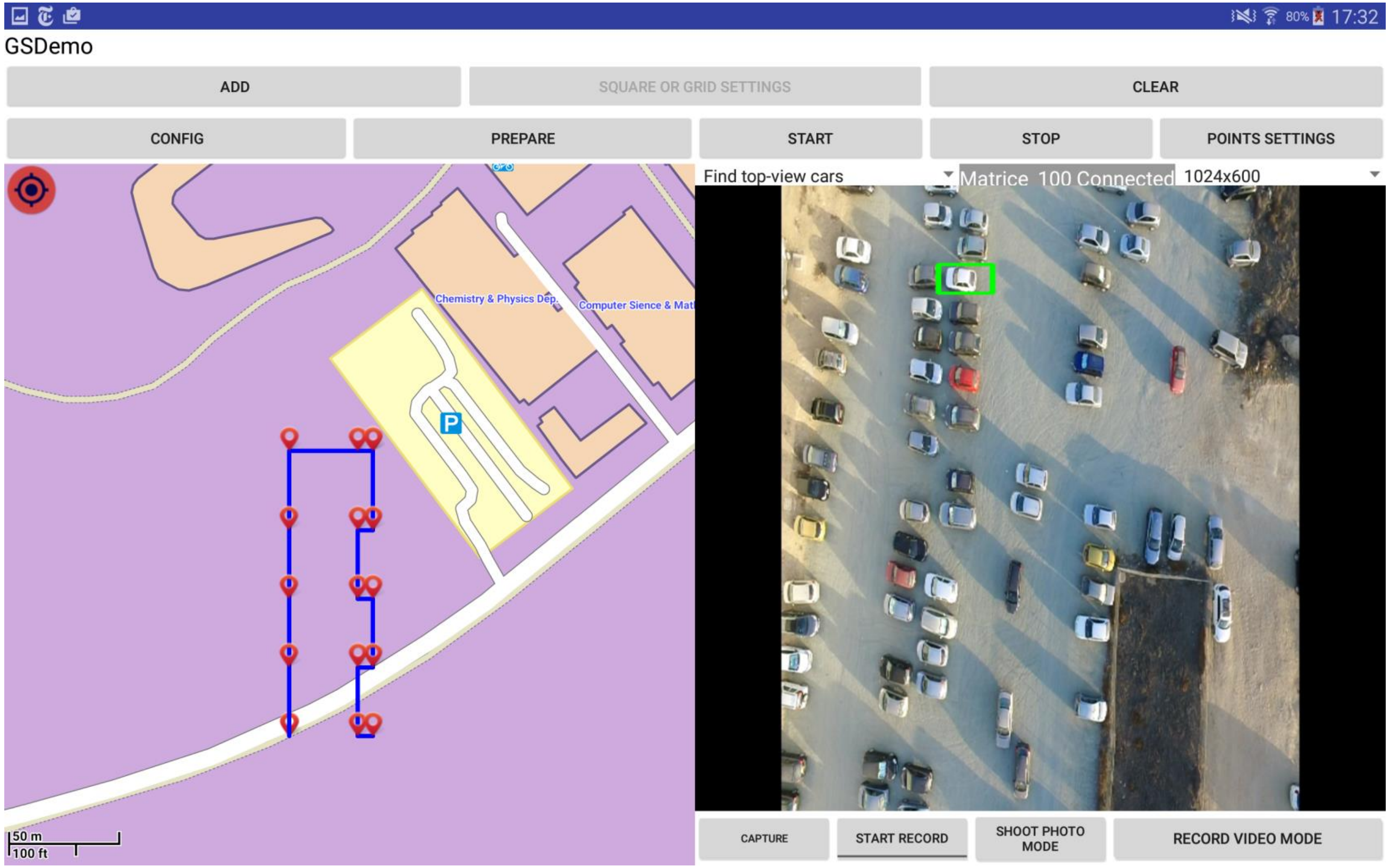
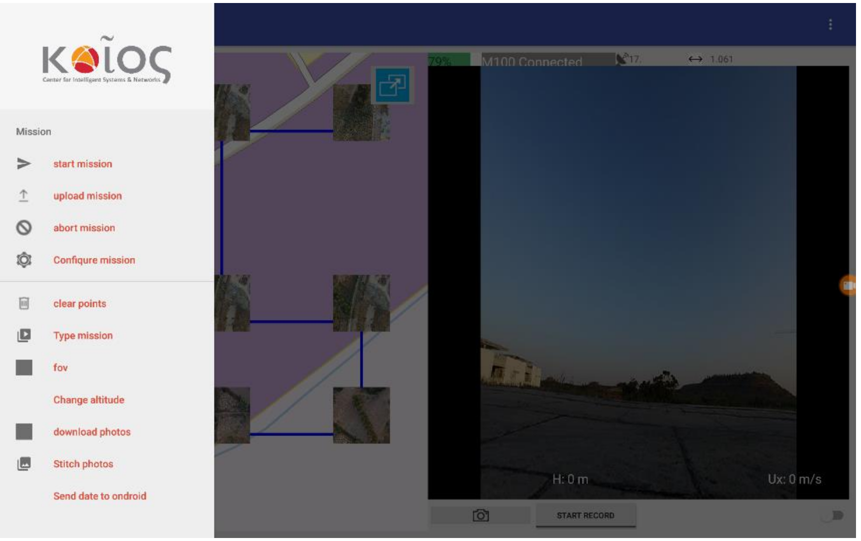
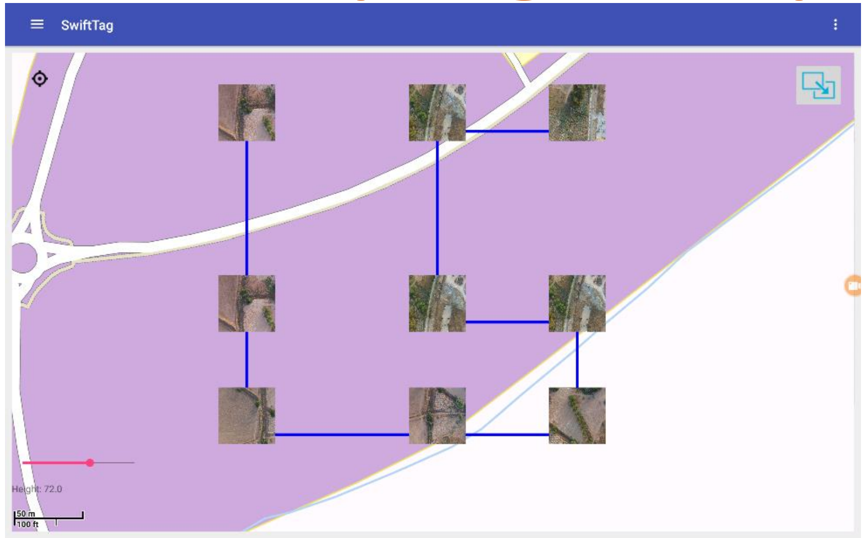
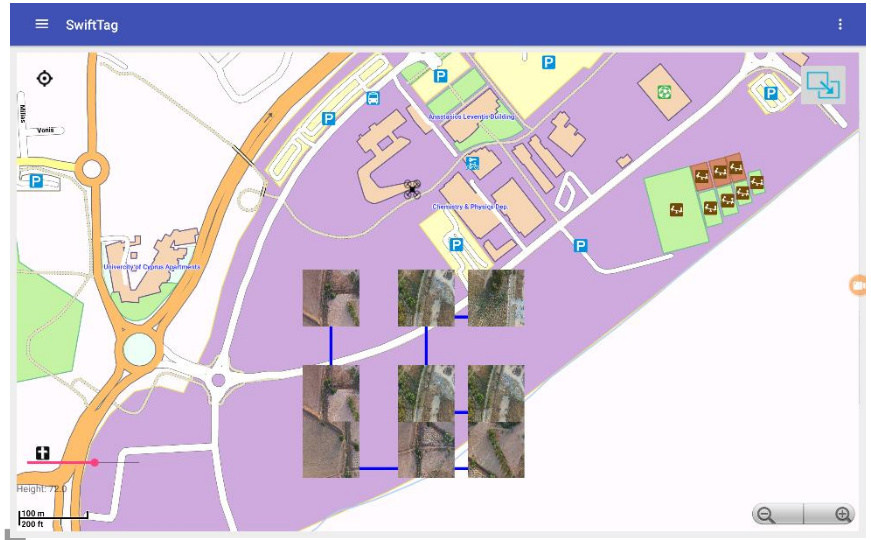
Automated watch-keeping and patrolling

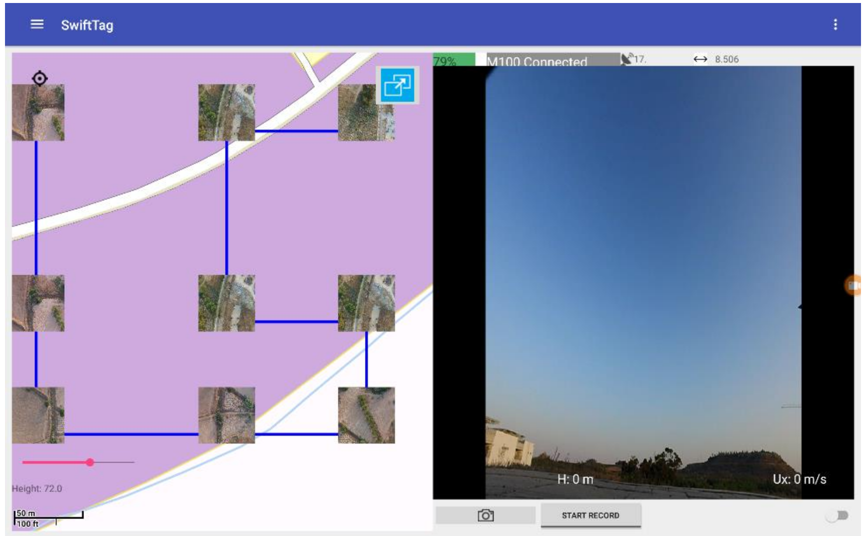


Automated watch-keeping and patrolling (2)





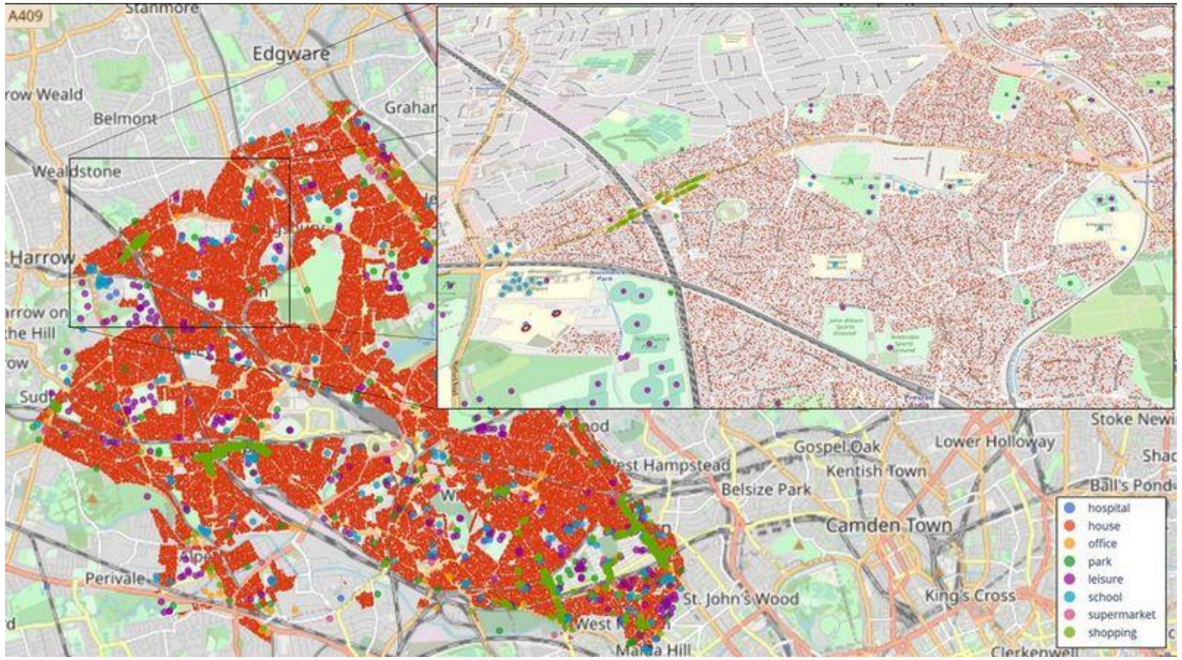




Modelling of Natural Disasters

- Computer Modelling is the process of constructing computer-based mathematical, graphical or algorithmic representations of real life systems of phenomena.
- A computer-based model consists of a set of algorithms or equations used to capture the behaviour of a system.
- Computer-based modelling is nowadays used in the context of pretty much all scientific fields
  - Some examples are traffic modelling, building structural modelling, car crash modelling, weather modelling, hurricane modelling, epidemic modelling.

Modelling of Natural Disasters

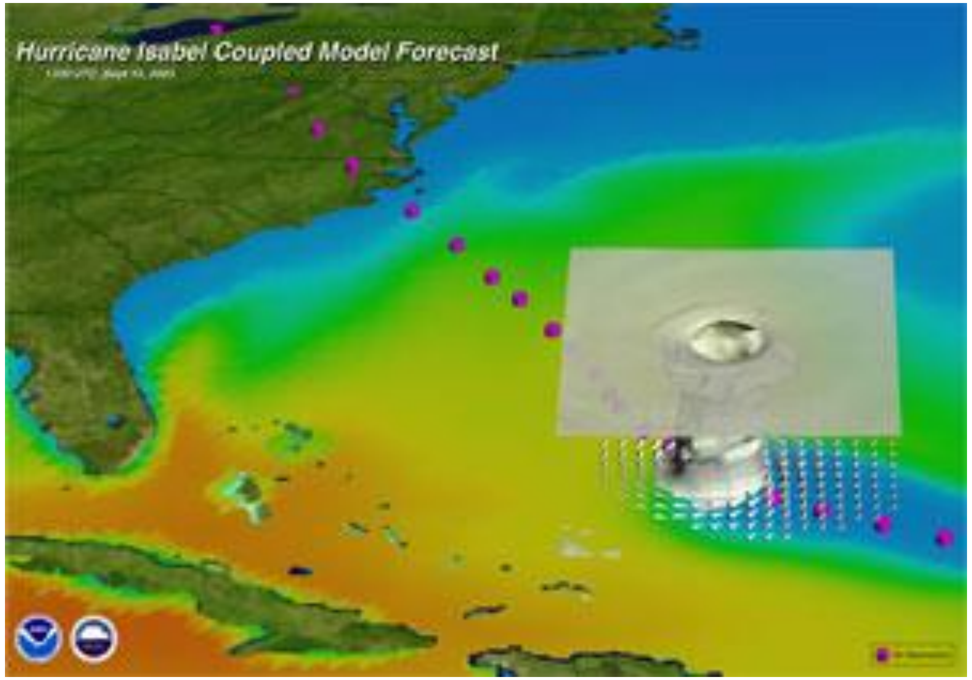


Graphical representation of a COVID-19 spread model across the London borough of Brent in UK. The image shows all the buildings that are incorporated into the model.

Source: https://hidalgo-project.eu/success-stories/covid-19-modelling

A 3-dimensional view of Hurricane Isabel (2005) approaching the East Coast of the United States provided by the GFDL model developed at NOAA's Geophysical Fluid Dynamic Laboratory. The white arrows indicate wind speed and direction near the earth's surface, and the pink dots indicate observations made every 6 hours along the hurricane's track.

Source: http://hurricanescience.net/science/forecast/models/



Modelling of Natural Disasters

- The major benefits of using computer-based models include, but are not limited, to the following:
  - Gain greater understanding of a process
  - Identify problems and bottlenecks in processes
  - Evaluate effect of system changes
  - Identify actions needed upstream or downstream relative to a certain operation, organization, or activity to either improve or mitigate events
  - Evaluate impact of changes in policy prior to implementation

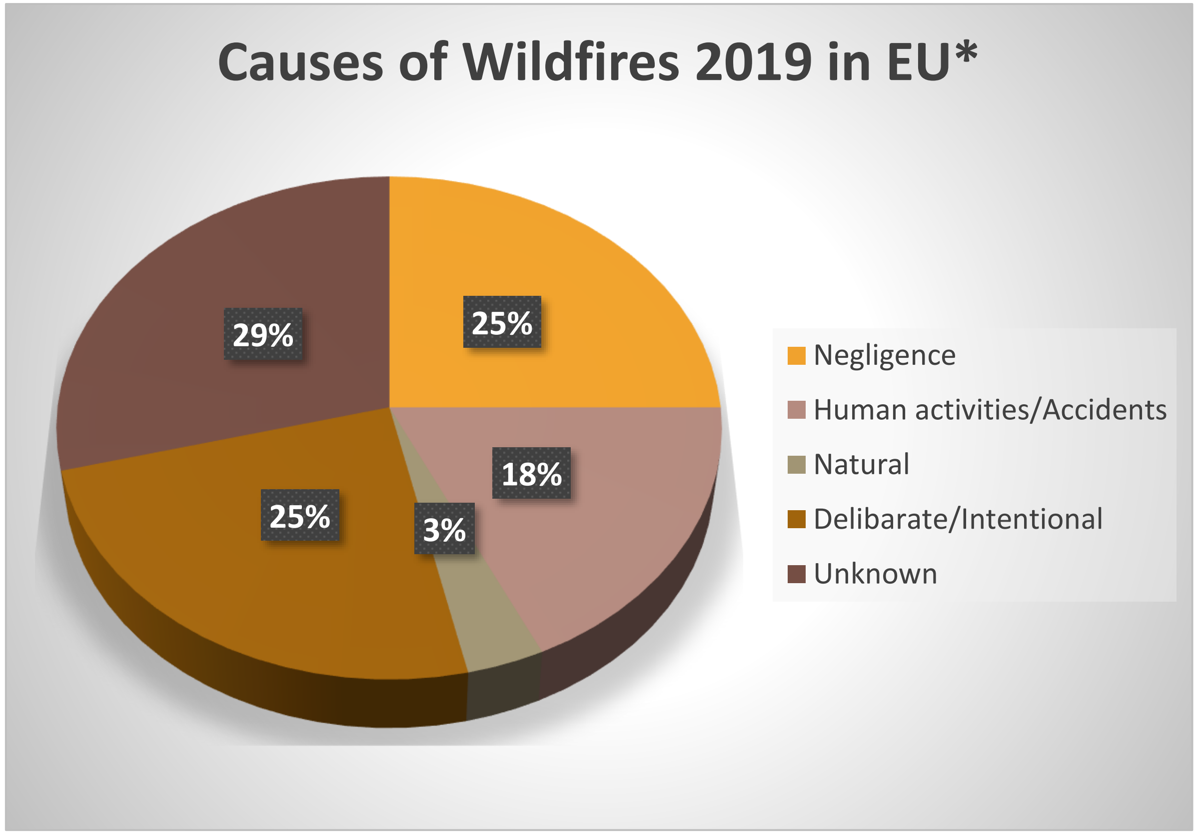
Modelling of Natural Disasters

- In disaster management, computer models of hazards and disasters are a key element in developing AI tools.

- A model of a disaster event, like a fire, a hurricane or a flood, is what provides the system with a machine-interpretable understanding of the situation.

- Examples presented in this workshop: modelling of wildfires and floods.

Motivation for Wildfire Modelling



- Wildfires remain one of the most common types of disaster with severe consequences
- ***50000*** fires in EU during 2019

*San-Miguel-Ayanz et al., Forest Fires in Europe, Middle East and North Africa 2019, EUR 30402 EN, Publications Office of the European Union, Luxembourg, 2020

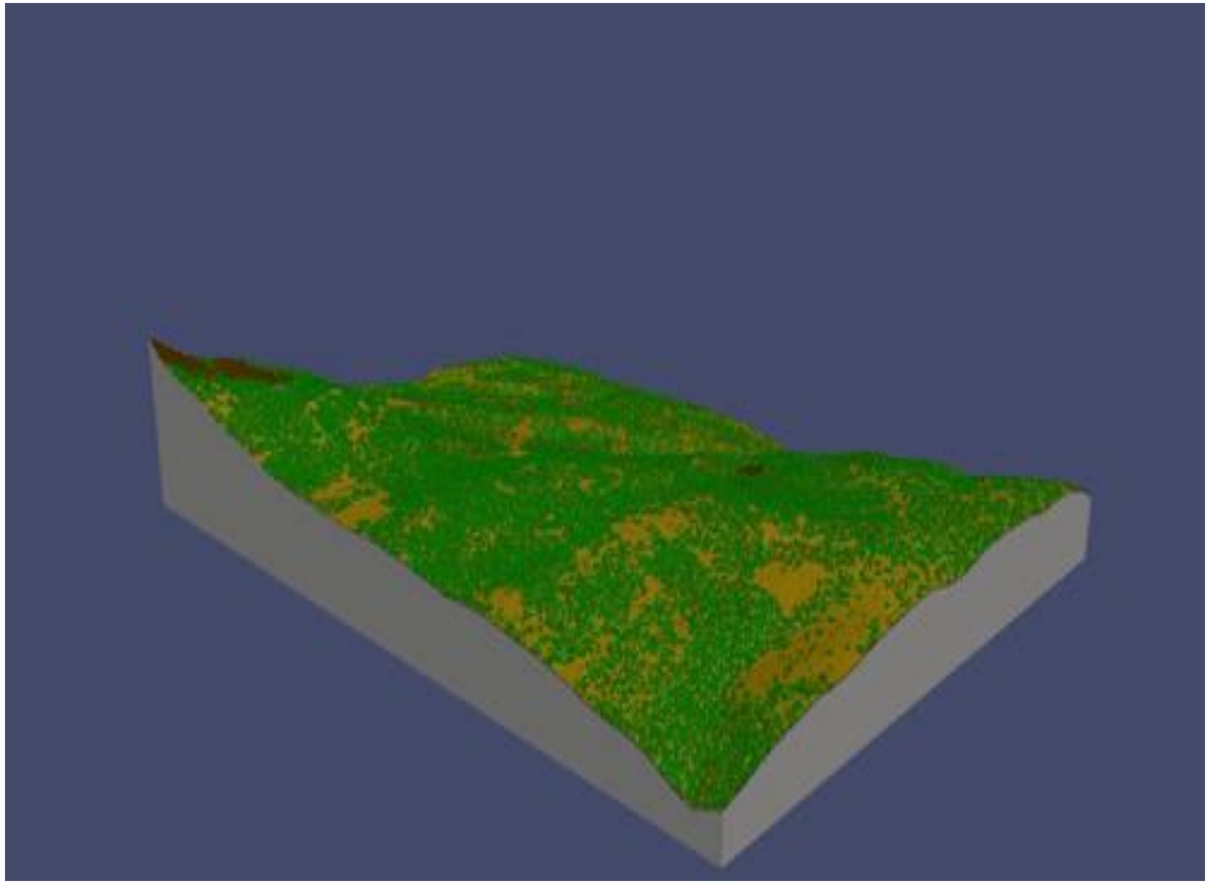
Motivation for Wildfire modelling

- Fighting Wildfires
  - Dangerous and high risk job
  - Firefighters need trementous skill and precise timing to keep the fire under control
  - Key drivers for compacting wildfires:
    - Effective planning
    - Early detection
    - Continuous monitoring

All of these requirements can be effectively facilitated by wildfire modelling

Motivation for Wildfire Modeling

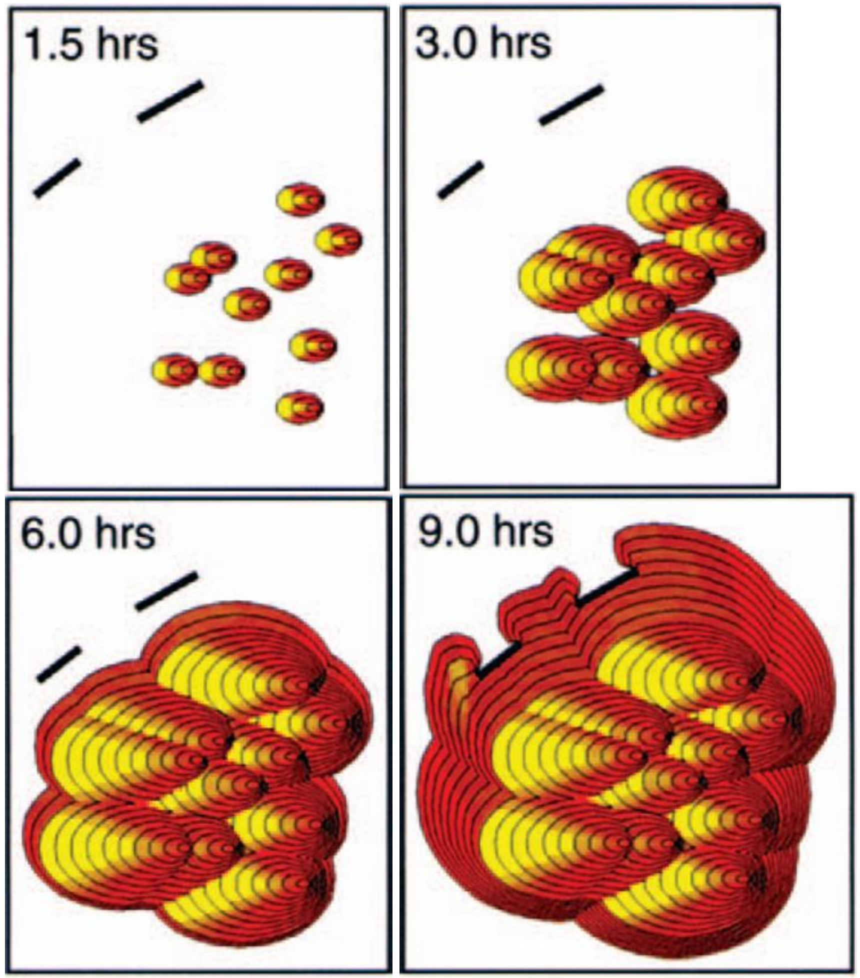
- Wildfire modeling enables the understanding and ultimately predicting the fire behaviour to:
  - Devise plans to effectively compact the fire
  - Improve the safety of firefighters and the public
  - Reduse risk and minimize damage
  - Protect ecosystems, watersheds, and air quality



QUIC-Fire model (https://wifire.ucsd.edu/next-generation-models)

What is Fire Modeling?

- Fire modeling denotes the **mathematical representation** of wildfire than allows its **numerical simulation** in order to understand and predict its spatio-temporal behaviour.
- Although fire models have been developed since 1940 due to their complexity they remain still an active research area.
- Fire models can be classified to:
  - Empirical models
  - Physical models
  - New generation models

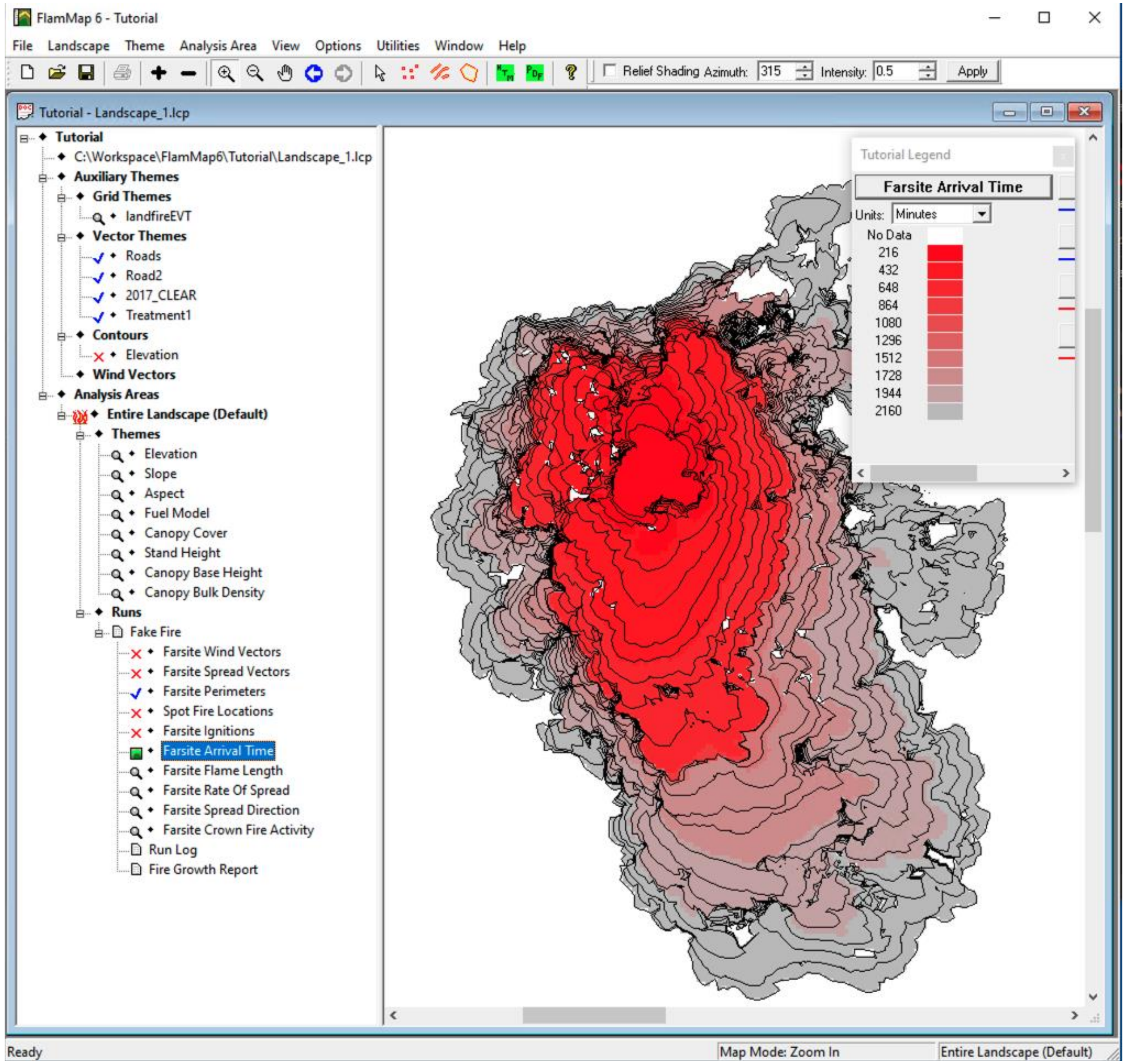


Empirical Fire Models

- Rely upon a top-level model to determine the magnitude of heat exchanges.
- They depend on a simplified analytical rate of spread (ROS) to predict the propagation of a fire as a function of time.
- Due to their simplified mathematically based models they can solve the fire propagation problem faster than real time for operational purposes.
- Examples of empirical fire models include:
  - Rothermel's (1972) surface fire spread model
  - Van Wagner's (1977) crown fire initiation model
  - Rothermel's (1991) crown fire spread model
  - Finney’s (1998) or Scott and Reinhardt’s (2001) crown fire calculation method

Empirical Fire Models - FlamMap

- FlamMap is a fire analysis application that simulates fire behaviour incorporating various empirical fire models.
- It creates a variety of vector and raster maps of potential fire behaviour characteristics (e.g., spread rate, flame length, crown fire activity) and environmental conditions that can be used for decision support and planning.

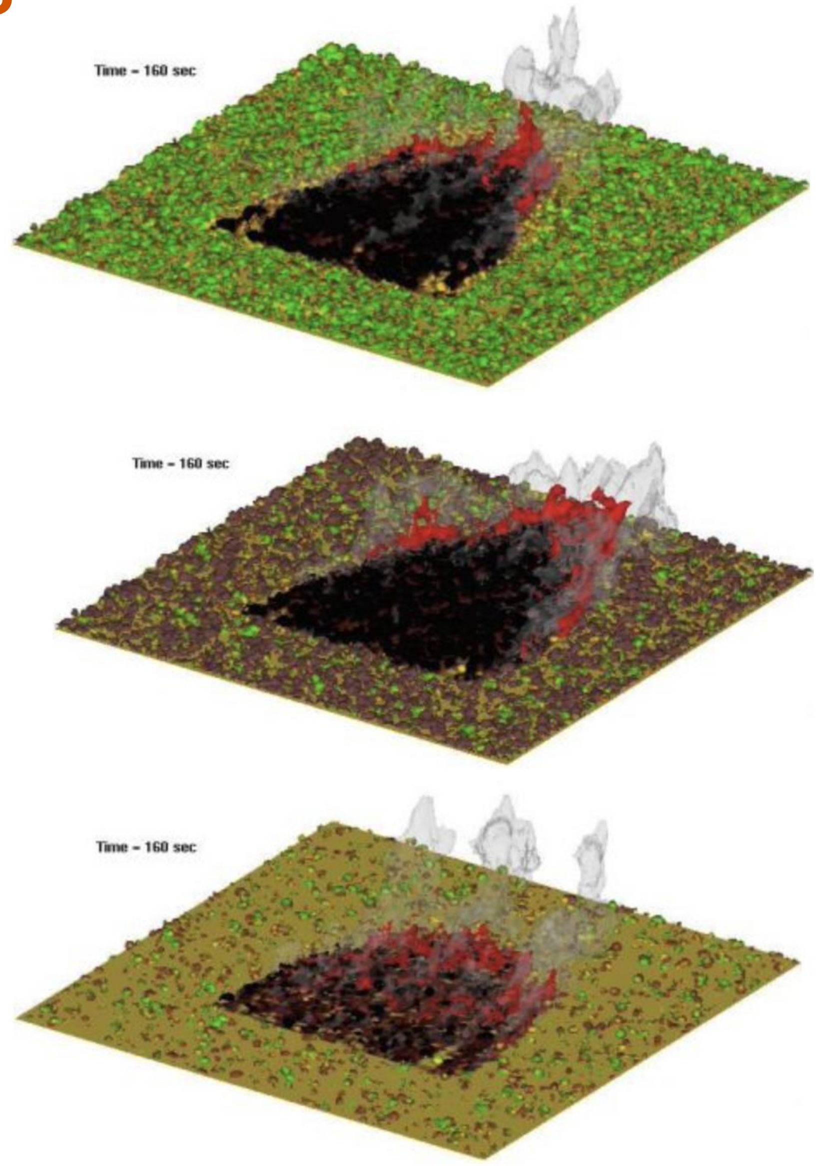


Physically based Fire Models

- Physically based fire models consider the fire behaviour in presence of combustion chemistry, heat transfer, and fluid dynamics.
- These models determine the heat, mass, and momentum fluxes released from the burn fuel that are transferred to surrounding unburnt fuel and the atmosphere.
- Physical fire models numerically solve equations for the fluid dynamics and thermochemistry of fires. Accurate physical equations can be formulated but all require numerical solutions that are generally slower than real-time.

Physically based Fire Models – HIGRAD/FIRETEC

- HIGRAD/FIRETEC is a physics-based, 3-D computer code designed to simulate the constantly changing, interactive relationship between fire and its environment.
- It combines computational fluid-dynamics model and physics models.
- Need huge computational resources and iscurrently a research tool only.

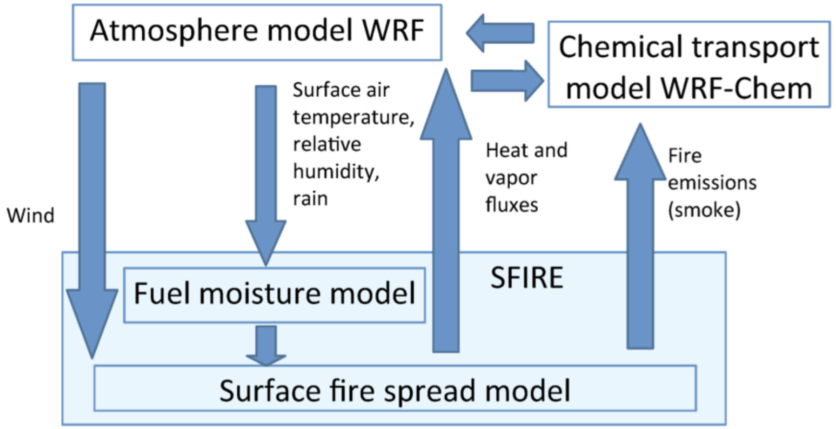


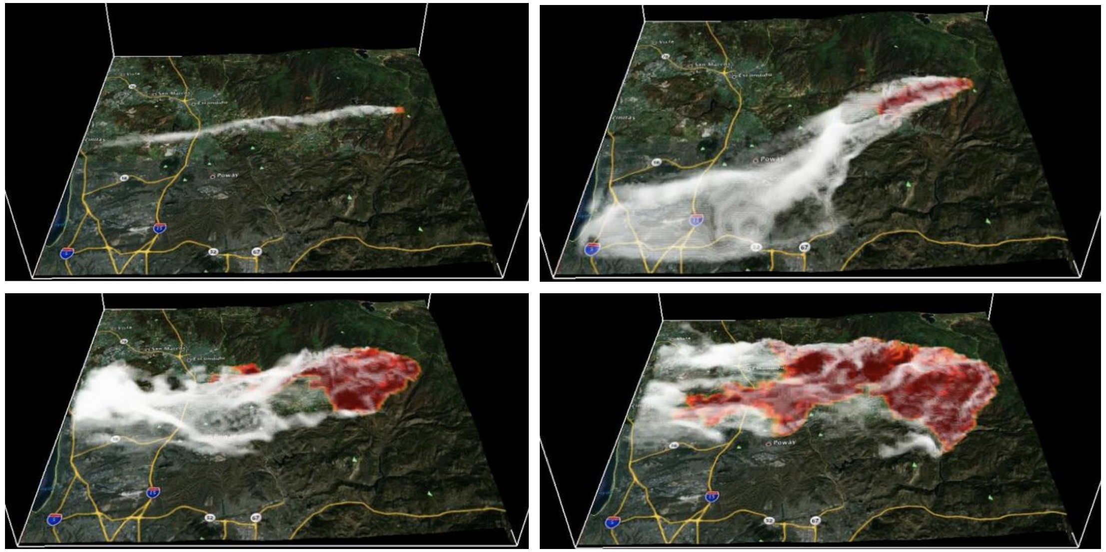
New generation fire-models

- They combine both physical and empirical fire models coupled to a numerical weather prediction (NWP) model or a computational fluid dynamics model (CFD).
- The coupled models include the interaction of wildfire with the sur-rounding atmosphere by means of changing the fire environment via humidity, temperature, and wind speed and direction.
- These models are four-dimensional models (three dimensions in space and one in time). Wildfire can impact the atmosphere directly via its heat and moisture fluxes or smoke.

New generation fire-models - WRF-Fire

- WRF-Fire (SFIRE) allows users to model the growth of a wildland fire in response to environmental conditions of terrain slope, fuel characteristics, and atmospheric conditions, and the dynamic feedbacks with the atmosphere.
- Its two-way coupling between the fire behaviour and the atmospheric environment allows the heat released by the fire to alter the atmosphere surrounding it.





WRF-Fire simulation from 2007 Santa Ana fires

Future Expectations

- Current approaches in wildfire modelling are very promising but can be further improved based on better knowledge on how wildfires ignited, spread, and were extinguished.

- Advancements in high-performance computing and satellite platforms would enable the operational use of the promising wildfire-weather models.

Motivation for Flood Modelling

- Flood events are one of the most destructive events that can happen. They can cause loss of life, severe damage to properties and adverse economic and environmental impact.
- As a natural disaster, flood risks cannot be completely eliminated, but flood modeling is a base for the development of many tools that can support decision-making in order to take precautions and minimize the consequences of a potential flood.

Flood modelling

- Flooding models are developed to predict the floodplain of a flood.
  - These models provide flow and level forecasts at selected key locations. Exploiting the results of a flooding model, such as water height 2-dimensional velocity, it is for example possible to develop algorithms that can identify and monitor closely the most hazardous areas.
- Three main model types exist:
  - Empirical models,
  - Hydrodynamic models
  - Simplified models.

Characteristics of model types

Empirical models	Hydrodynamic models	Simplified models
Assets		
Relatively quick and easy to implement Based on observation	Direct linkage to hydrology Detailed flood risk mapping Can account for hydraulic features/ structures Quantify timing and duration of inundation with high accuracy	Computationally efficient

Characteristics of model types

Empirical models	Hydrodynamic models	Simplified models
Limitations		
Non-predictive No/indirect linkage to hydrology (difficult to use in scenario modelling)	High data requirements Computationally intensive Input errors can propagate in time	No inertia terms (not suitable for rapid varying flow) No/little flow dynamics representation

Characteristics of model types

Empirical models	Hydrodynamic models	Simplified models
Application Range		
Flood monitoring Flood damage assessment	Flood risk assessment Flood damage assessment Real-time flood forecasting Water resources planning	Flood risk assessment Water resources planning Floodplain ecology River system hydrology Catchment hydrology Scenario modelling

Applications of AI to Disaster Management

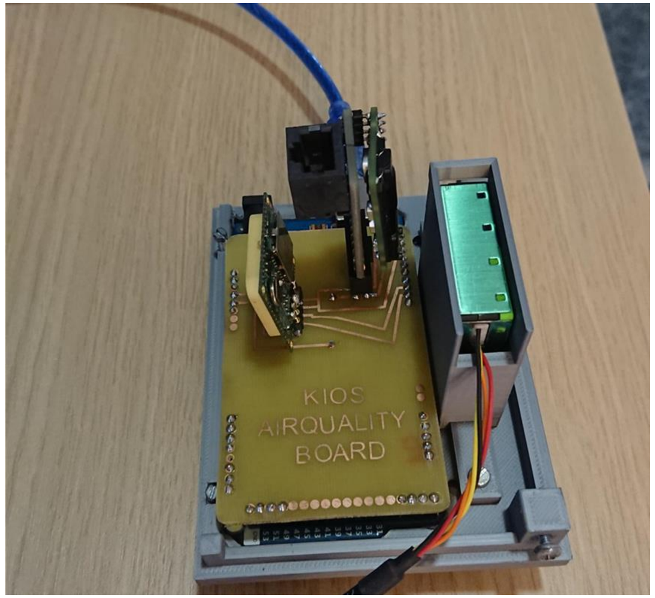
A selection of specific AI applications

Air Quality Monitoring Using UAVs

- Motivation
  - Air quality monitoring in urban areas is developed at high level by means of fixed stations accompanied with appropriate air quality sensors
    - They detect the air pollutant levels and warn the people in case of an emergency.
  - In rural areas this method in not developed yet, so this application developed a solution by flying an Unmanned Aerial Vehicle (UAV) having onboard air quality sensors to detect air pollution levels and warn the community in case of a disaster.

Air Quality Monitoring Using UAVs

- Design and Implementation of a hardware board containing air quality sensors to detect pollutants from fire smoke, like Particulate Matter (PM), Carbon Dioxide (CO_2) and also Humidity and Temperature levels (left)
- The hardware board is attached to an UAV (right)



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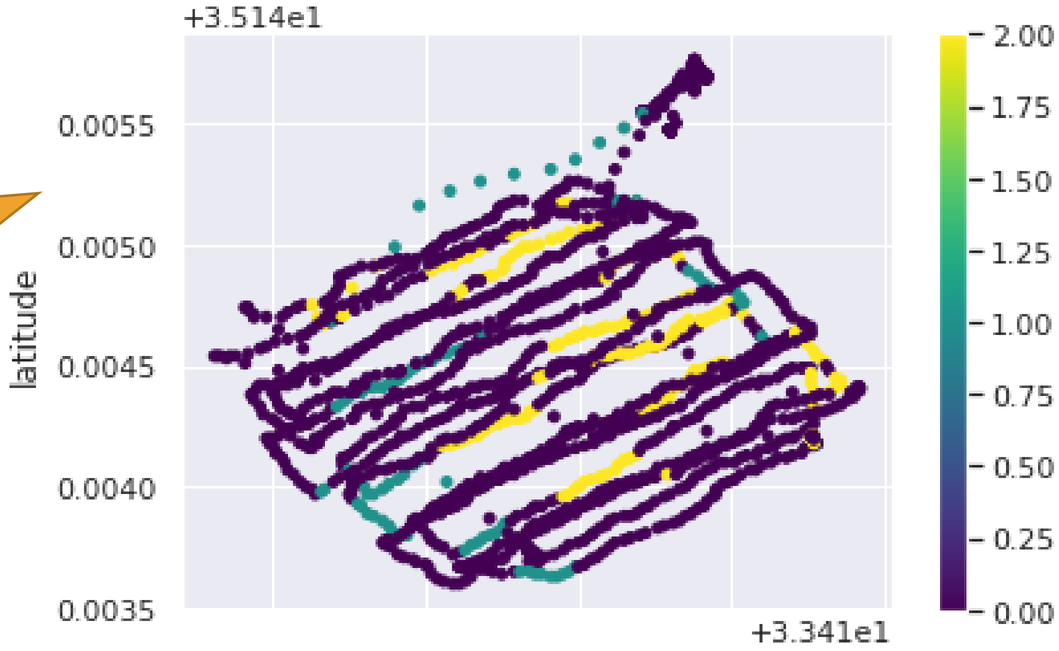
Air Quality Monitoring Using UAVs

- Design a software using Machine Learning algorithms to:
  - Navigate autonomously the UAV with the onboard sensor board
  - Cluster the area into small clusters based on pollution levels
  - Track the plume of the pollutant
  - Localize the source

- Clustering of an area by means of k-means clustering algorithm based on the CO_2 pollutant concentration
- Clustering is executer during the flight

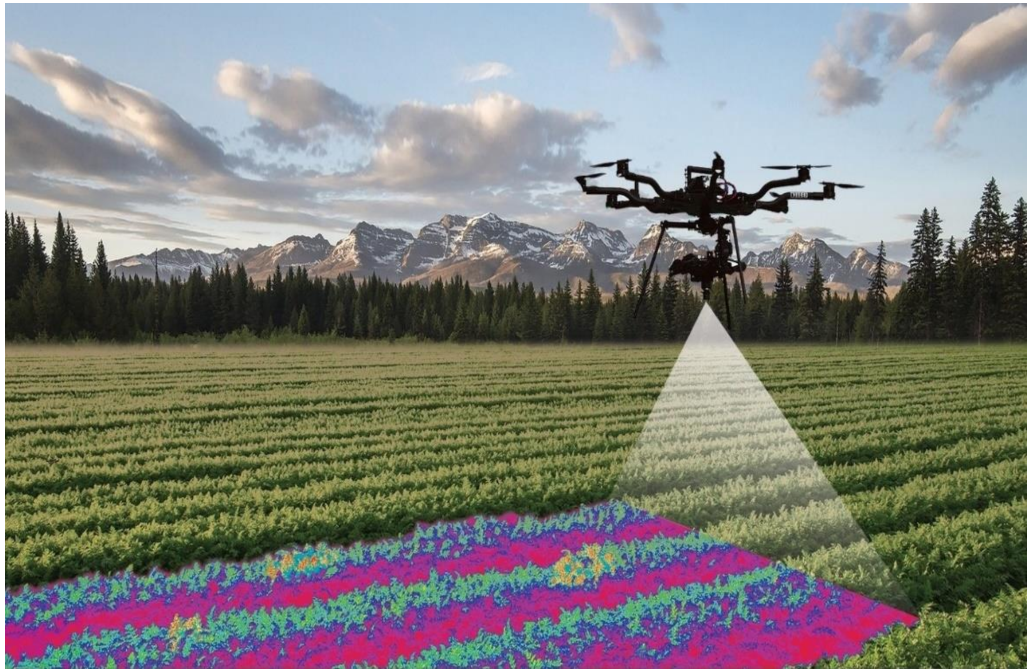


Calculation of Burned Area Index Using UAVs

- AIDERS: A multi-drone web-based platform that aims to assist first responders in taking actionable decisions during emergency situations.
- This helps in understanding better the characteristics of the ground, the vegetation or the atmosphere, and therefore assist the First Responders in taking better decisions.

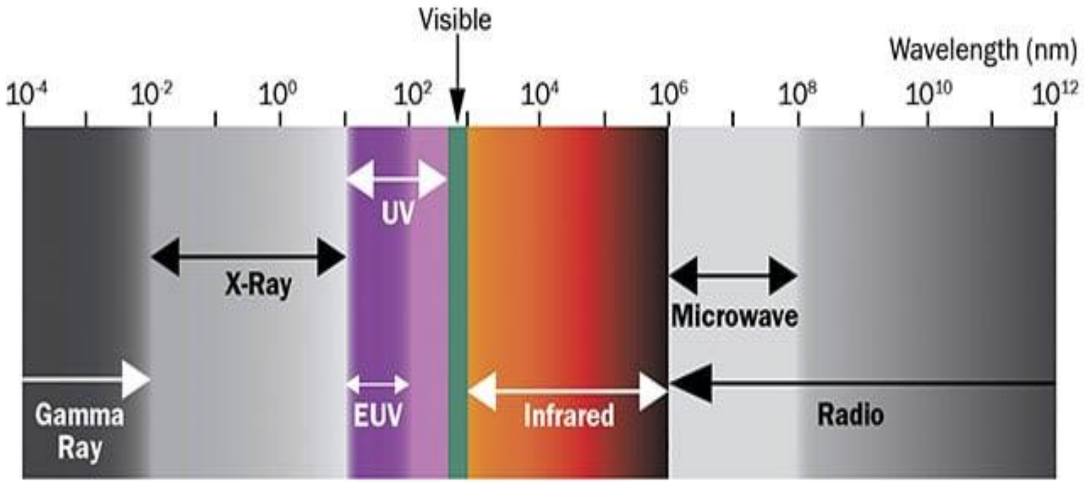
Calculation of Burned Area Index Using UAVs

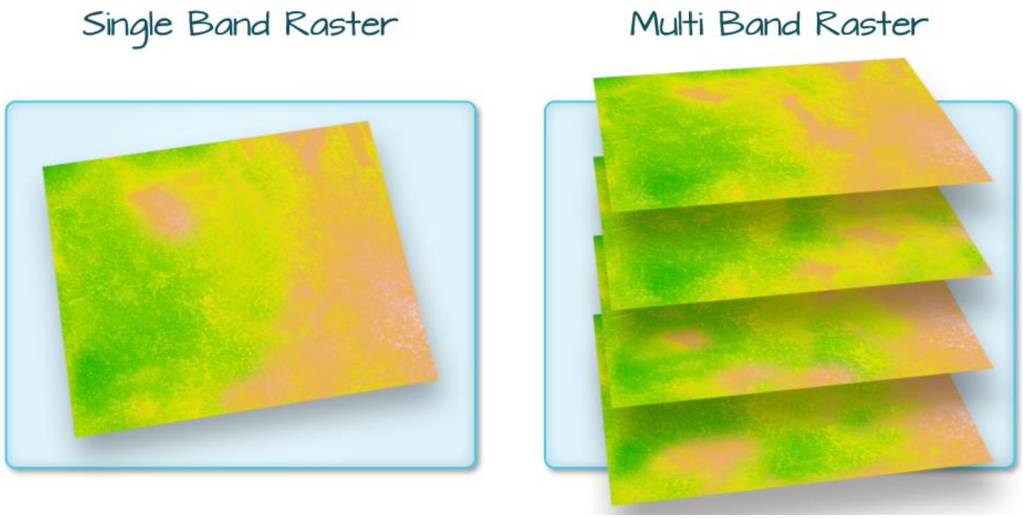
- Remote Sensing
  - The science of obtaining information about areas from distance
  - Helps in understanding better the characteristics of the ground, the vegetation or the atmosphere
  - Helps First Responders in taking better decisions



Calculation of Burned Area Index Using UAVs

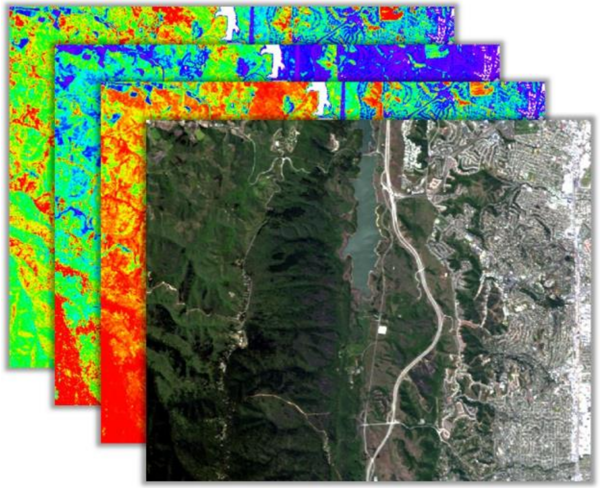
- Multispectral Bands
  - High quality Multispectral Cameras are used to capture bands
  - Image data captured at specific frequencies or specific bands, across the electromagnetic spectrum
  - Spectral images allow for extraction of information which the human eye fails to capture

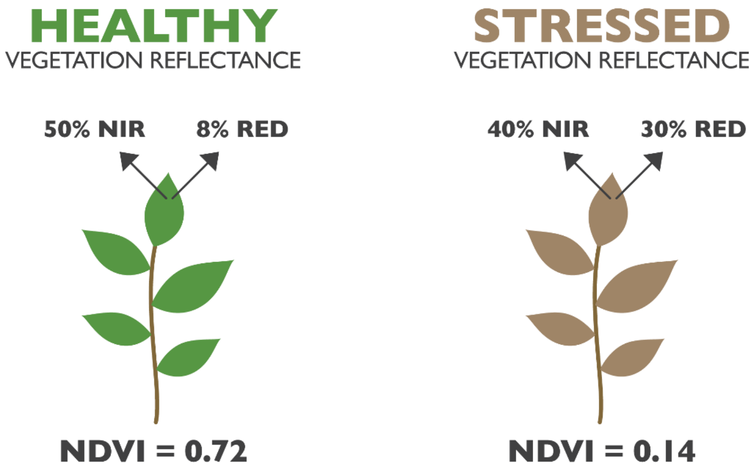




Calculation of Burned Area Index Using UAVs

- Multispectral Indices
  - A mathematical equation applied on multispectral bands
  - Helps to extract information about the area
  - e.g., NDVI: Values above 0.5 indicate a healthy plant.

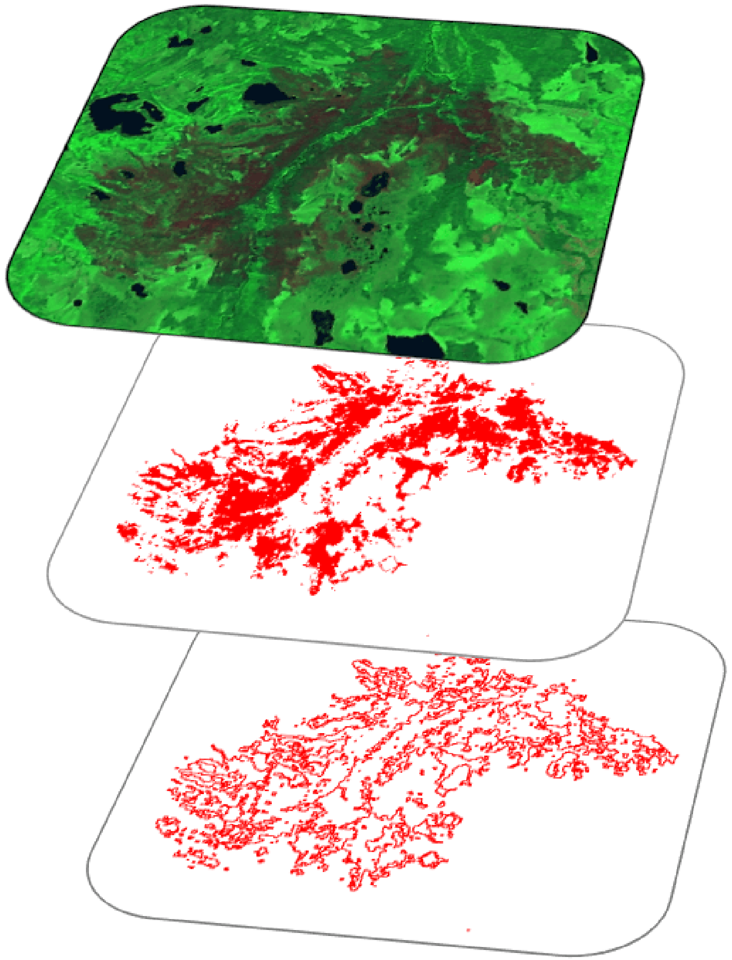




$$\mathbf{NDVI} = \frac{\mathbf{NIR - RED}}{\mathbf{NIR + RED}}$$

Calculation of Burned Area Index Using UAVs

- Burned Area Index (BAI)
  - Uses the Red and Near-infrared bands to identify burned areas
  - Useful for First Responders who need immediate situational awareness of the affected terrain
  - Images will be captured from drone equipped with multispectral camera and will be processed in real time.

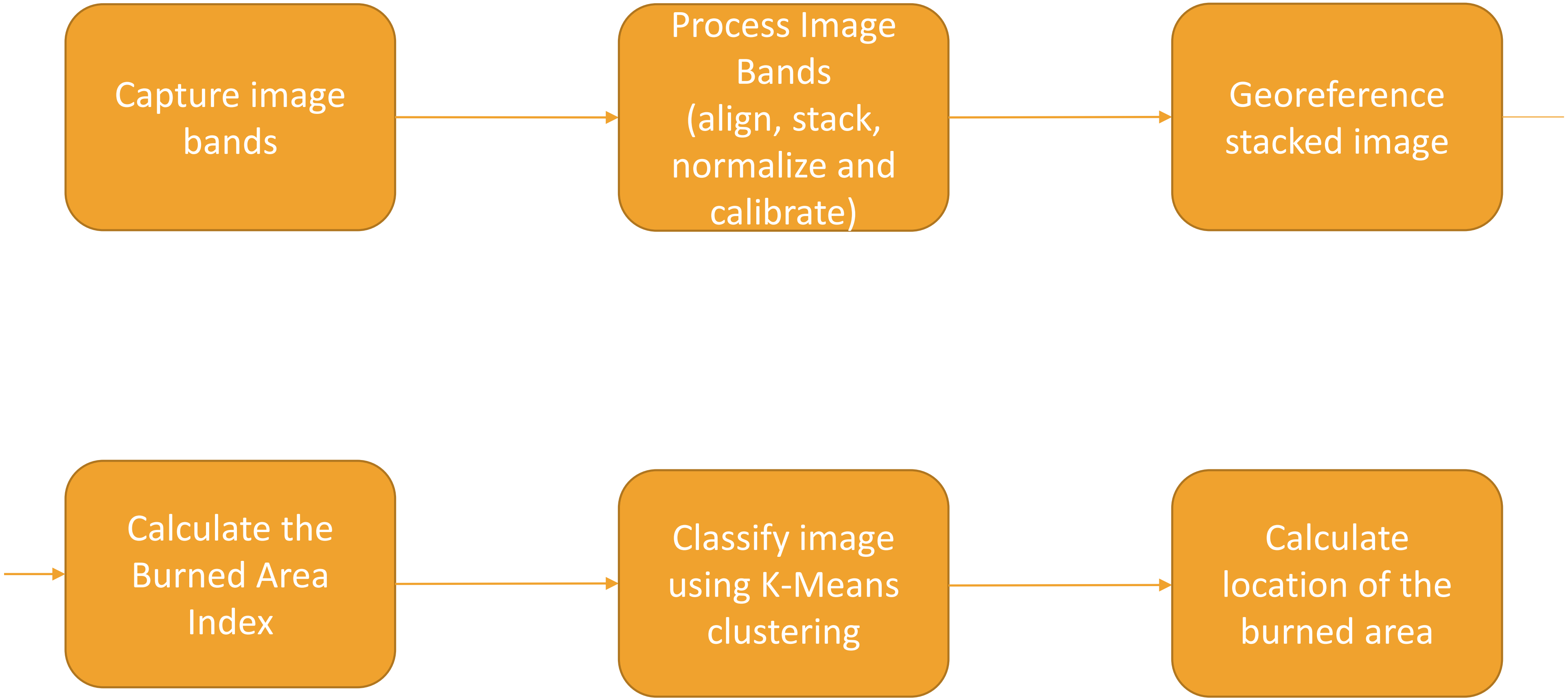


Calculation of Burned Area Index Using UAVs

- ❑ Georeferencing images after calculating BAI
- ❑ Calculating and highlighting on the image the location of the Burned Area as red polygons
- ❑ Helps a lot First Responders as they can acquire the exact location of a burned area and take actionable decisions.

Calculation of Burned Area Index Using UAVs

Workflow



Calculation of Burned Area Index Using UAVs

This is the result after following the workflow for BAI calculation.
The image is georeferenced, and is attached on the map, at the location that was initially captured.
The red polygons are also Georeferenced and therefore allow first Responders
be aware of the exact location of burned terrain.

Person Detection and Tracking Using UAVs

- Two main components: detection and tracking
- This is achieved by utilizing:
  - Footage captured from various test missions using UAV (Unmanned Aerial Vehicles)
  - Computer vision (a Convolutional Neural Network for the detection, and several algorithms for the tracking)
- Person Tracking
  - Track Moving Persons
  - Track Standing Persons
- Data Export (in CSV files)
  - Trajectories of Persons
  - Location of Persons
  - Direction of Persons

Person Detection and Tracking Using UAVs

❑Person Detection

- For the person detection algorithm, YOLOv4* was trained, that is a real-time object recognition system that can recognize multiple objects in a single frame.
- In order to increase the accuracy of the detector and to increase the dataset size, some image augmentations are implemented on several images and used as separate images for the training dataset. It helps enhancing details of the images since the altitude is usually high and the details are not clear.
  - Augmentations applied: Brightness, contrast, sharpening, saturation.

*A. Bochkovskiy, C.-Y. Wang, and H.-Y. M. Liao, "Yolov4: Op-timal speed and accuracy of object detection,"arXiv preprintarXiv:2004.10934, 2020

Person Detection and Tracking Using UAVs

Original image from a test mission.

Augmented image from a test mission.

Person Detection and Tracking Using UAVs

- Persons Tracking
  - Upon detecting the persons in a frame
  - Matching Detections in consecutive frames
  - More complex than detection: a combination of algorithms is employed
    - Hungarian Algorithm *
      - IoU (Intersection over Union) Scores
    - Distance Matching
      - If Hungarian has no match
      - Euclidean distance of latest person's position
      - Matches nearest detected person if distance in threshold
    - Kalman Filter **
      - Predicting movements if person is not detected.
      - Dealing with Occlusions (trees, buildings etc.)

* G. A. Mills-Tettey, A. Stentz, and M. B. Dias, "The dynamic Hungarian algorithm for the assignment problem with
changing costs,"Robotics Institute, Pittsburgh, PA, Tech. Rep. CMU-RI-TR-07-27, 2007.
** G. Welch, G. Bishopet al., "An introduction to the kalman filter,"1995.

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Person Detection and Tracking Using UAVs

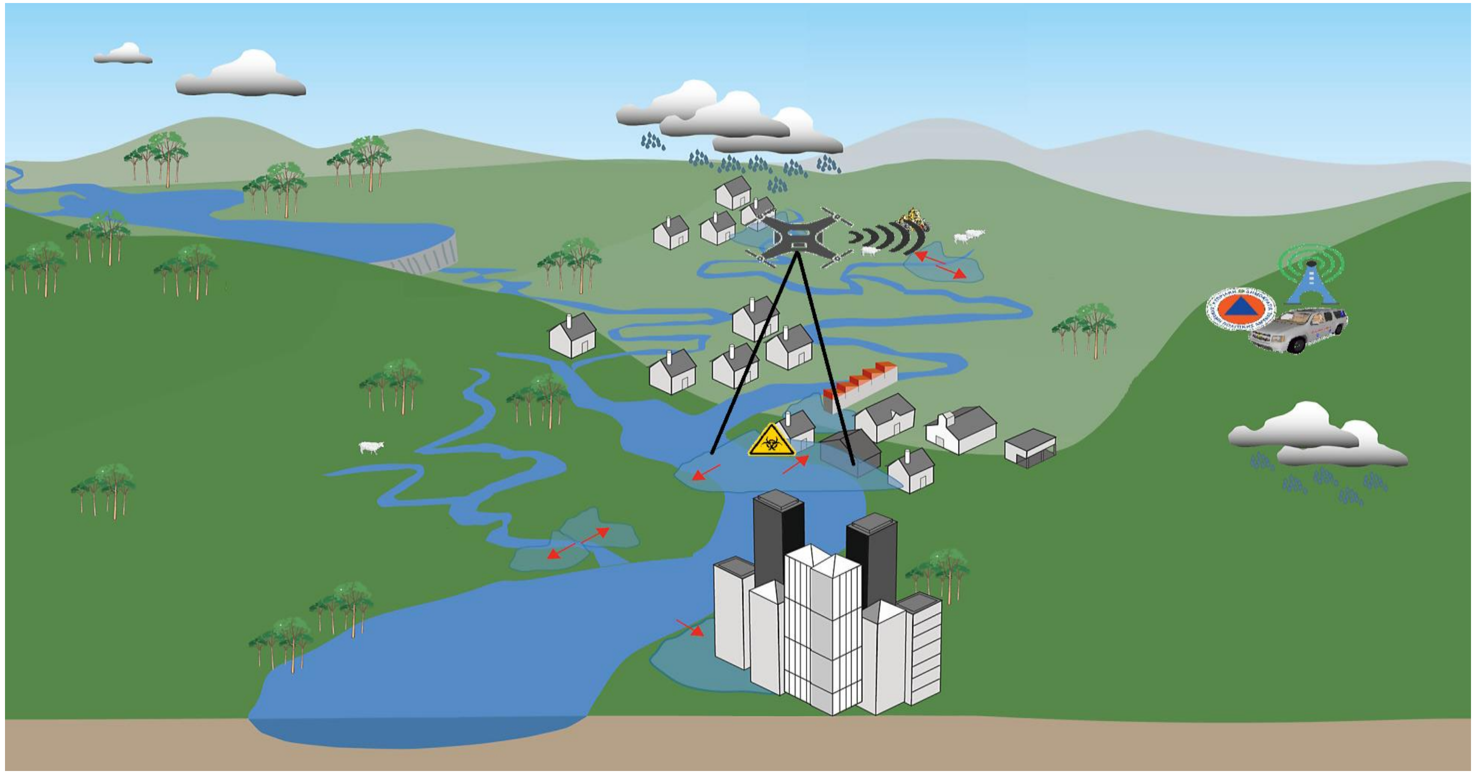
Monitoring Water Contamination Events Using UAVs

❑ Motivation and General Objective

- Pathogens can easily spread via water, leading to serious health complications or even death. Due to the nature of their work, first responders are more likely to become contaminated when they need to operate in areas where water is present.
- The general objective is to develop AI-based technologies to extract knowledge and suggest recommendations to manage the contamination event, assess its risk and forecast its evolution, as well as to develop forensic investigation tools.
- An integrated system will be developed and linked to a first responder control center aiming to enhance their ability to make effective decisions making assessing risk.

Monitoring Water Contamination Events Using UAVs

- Development of an AI algorithm for UAVs so that the drone chooses targets and monitor them as fast as possible
- A flood prediction model is used to help the drone arrive at the hazardous area on time



Drone arriving above the target to monitor a hazardous area and sending information to the first responders for better decisionmaking

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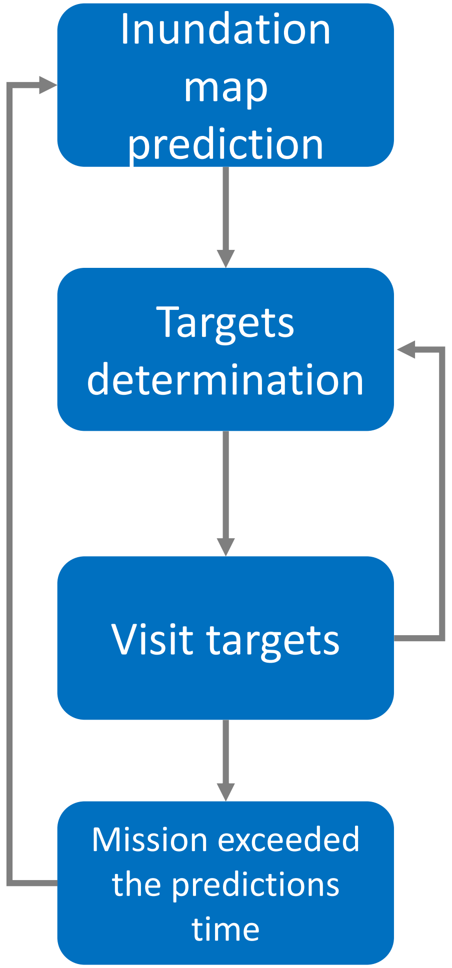
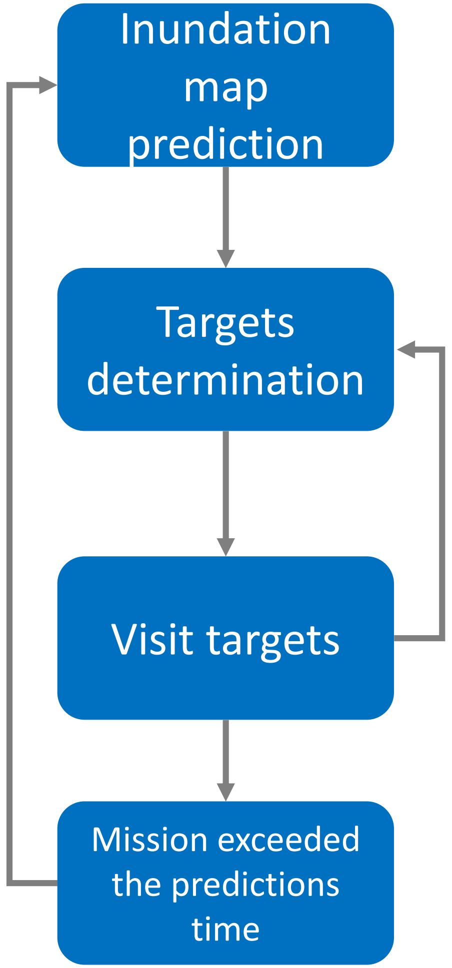
Monitoring Water Contamination Events Using UAVs

- After a flooding event has occurred in an area the flooding prediction software will be employed.
- A hydrodynamic model is used to predict the state of water for approximately 1 hour and presents it a grid map with cell size about 50m
  - Hydrodynamic models can simulate the height of water depths and the velocities in x and y directions.
  - Considering the velocities and the water depths, waypoints could be extracted so that the drone would be able to monitor the more dangerous locations.



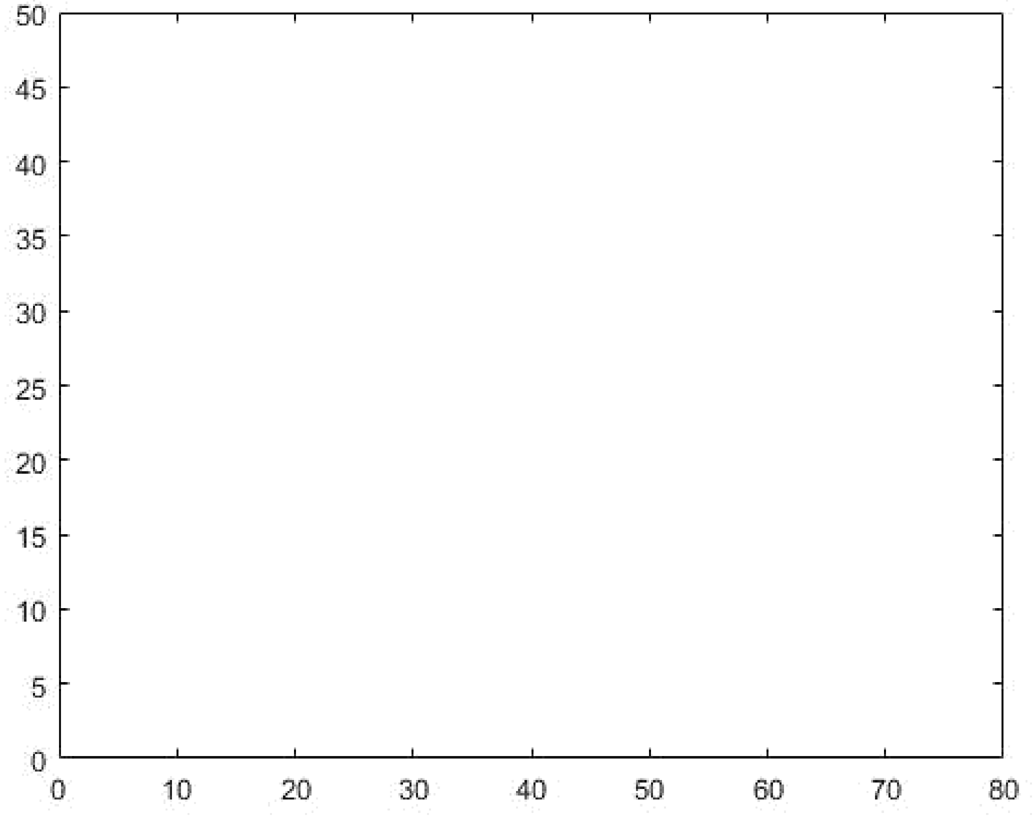
Monitoring Water Contamination Events Using UAVs

- ❑ Every minute all the targets that worth to be visited, based on the momentum of the water are selected for further monitoring.
- ❑ At each time step the drone will compute online its trajectories in order to visit the targets in the minimum time.
- ❑ With the prediction factor first responders would be able to extract information on the potential hazardous areas before the water reaches that area.



Monitoring Water Contamination Events Using UAVs

- Simulation of the momentum of a flood. The video shows the change of the momentum every second.



Reinforcement Learning in disaster emergency response

- The concept of Reinforcement Learning
  - We learn by interacting with the environment
  - Learn to make a good sequence of decisions
- The Reinforcement Learning Problem
  - Problem: learn what to do, i.e., what actions to take, so as to maximize a numerical reward signal
  - Learner tries out actions to discover rewards
  - Fundamental Idea: Learn from interactions

Reinforcement Learning in disaster emergency response

- Reinforcement Learning has a strong potential in disaster management applications
  - Finds an optimal strategy by means of learning from its own past experience (i.e., actions) without requiring any prior knowledge of the system behavior. It can be, therefore, used to model systems whose behavior exhibits changes and uncertainties.
  - Can be trained for objectives that are hard to optimize directly because of the lack of precise model, a feature that is very useful when addressing an emergency, unpredicted situation.

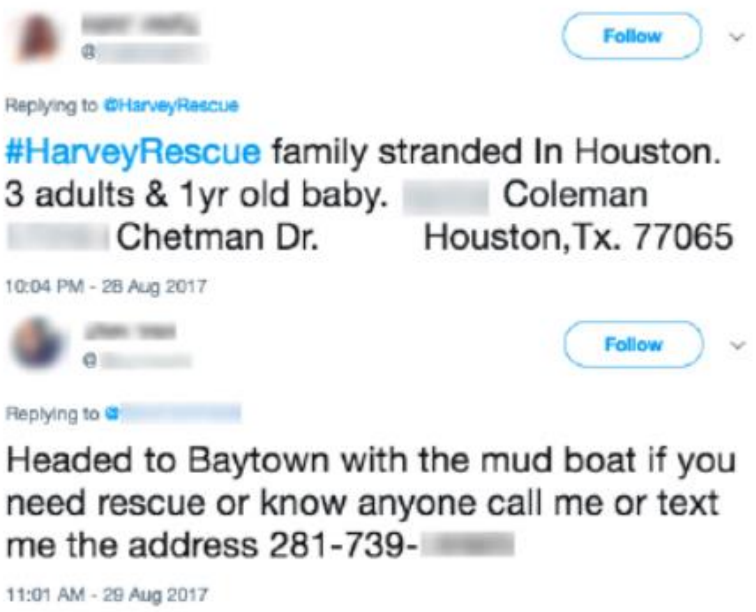
Reinforcement Learning in disaster emergency response

- Solving a large-scale disaster rescue problem by means of a reinforcement learning problem using massive social network data.
- A scheduling algorithm based on reinforcement learning to organize the rapid deployment of volunteers to rescue victims in dynamic settings.
  - Quickly identify victims and volunteers from social network data and then schedule the rescue teams for helping the victims.

L. Nguyen, Z. Yang, J. Zhu, J. Li, and F. Jin, “Coordinating Disaster Emergency Response with Heuristic Reinforcement Learning”, arXiv e-prints, 2018

Reinforcement Learning in disaster emergency response

- The algorithm has been demonstrated in a case study using Twitter data collected during Hurricane Harvey in 2017.



Sample tweets requesting and offering help (left) and the distribution of volunteers and victims in the Houston area on August 28, 2017 (right).

Reinforcement Learning in disaster emergency response

- The approach aims to match volunteers and victims for faster relief and efficient use of limited public resources.
- Introduces a new disaster relief channel that can serve as a backup plan when traditional helplines are not sufficient.
- Experimental results have shown that the proposed framework can respond to dynamic requests and achieve an optimal performance in terms of both space and time.

Content

- Introduction
- Introduction to Artificial Intelligence
- Artificial Intelligence in Disaster Management
  - AI and the Stages of Disaster Management
  - Prerequisites for Employing AI in Disaster Management
  - AI-powered Autonomous Robot Devices
  - Computer Vision Technologies
  - Modelling of Natural Disasters
  - Applications of AI in Disaster Management
- Realistic Field Exercises Using AI Tools

Field Exercises

Using AI tools in realistic field exercise

Civil Protection Field Exercises

- We continuously demonstrate and test AI tools for disaster management through field exercises.
- Exercises showcased in the following slides are conducted in Cyprus by the Cyprus Civil Defense in collaboration with the KIOS Research and Innovation Center of Excellence of the University of Cyprus.

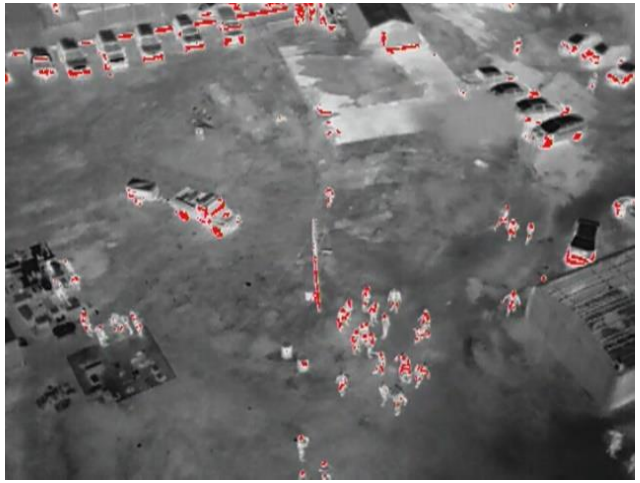
Exercise: Eggelados 2017

Lageia, Saturday 11 March 2017

Exercise: Eggelados 2017

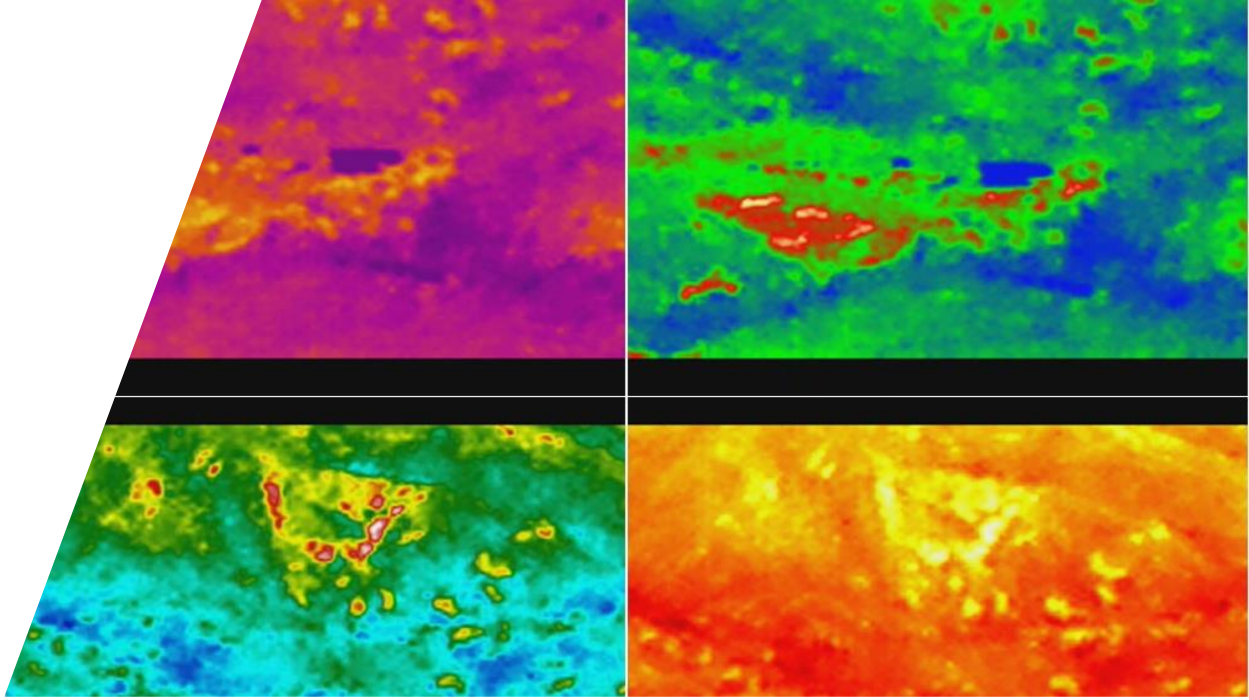
Zygi, Monday 13 March 2017
(Aerial Information Team)



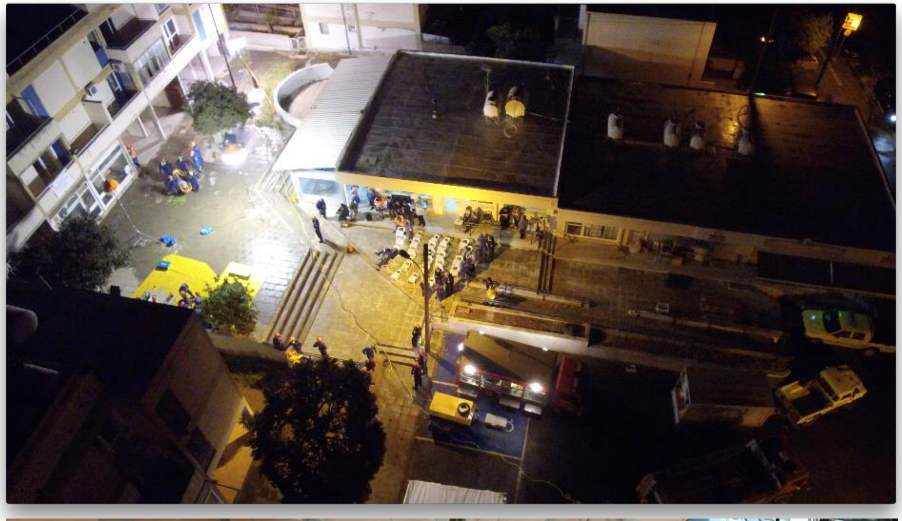



Ora Village Fire, 2017

- ❑ Use of drones at midnight of 19 July 2017 to assess danger to houses



Exercise: Eggelados 2018



Exercise: Lellapa 2018

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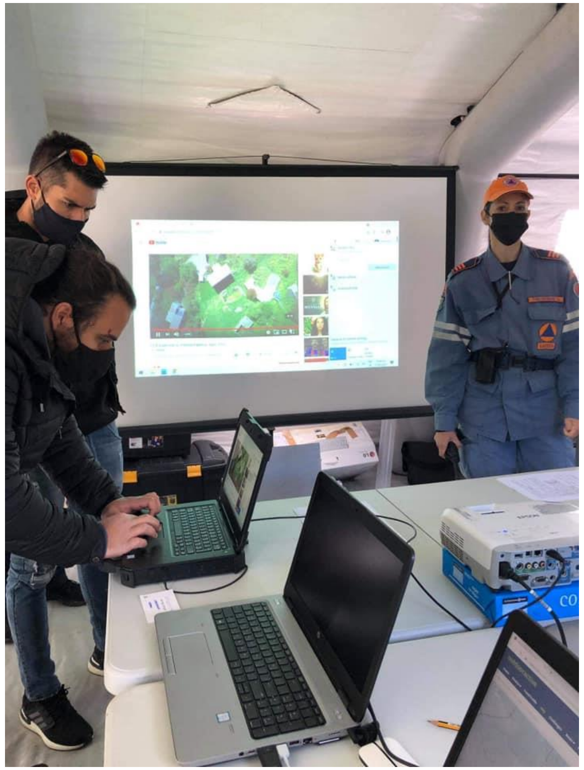
Civil Protection Field Exercises

- Data Collection
  - Field Exercises can be also executed for the collection of realistic data sets that will be used as training and test data in order to develop AI algorithms.
  - Such exercises were conducted as part of the ARTION project activities.



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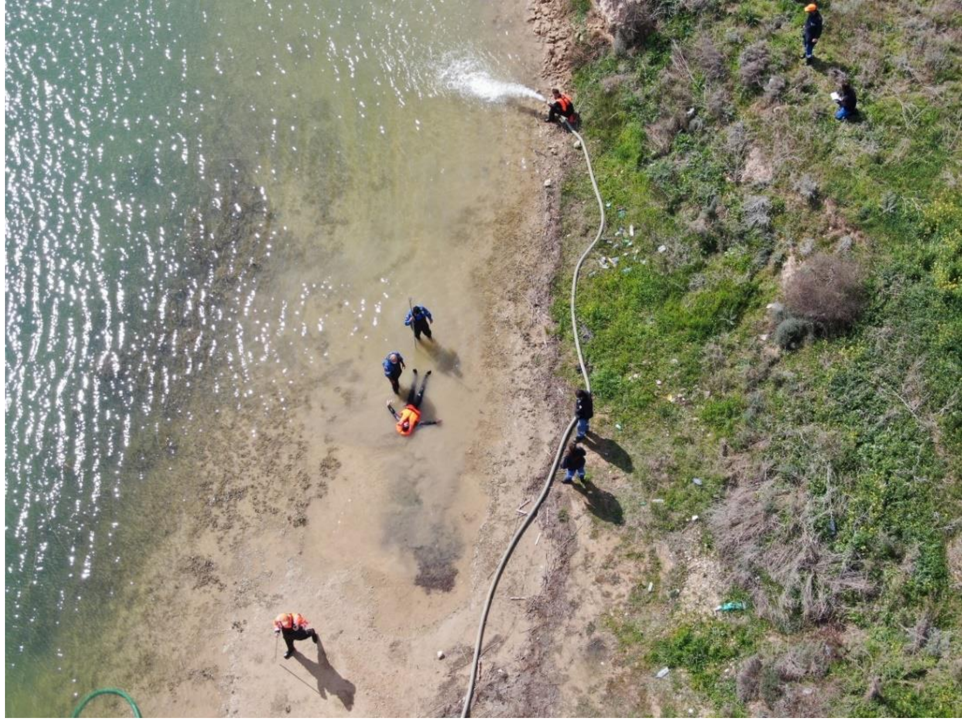
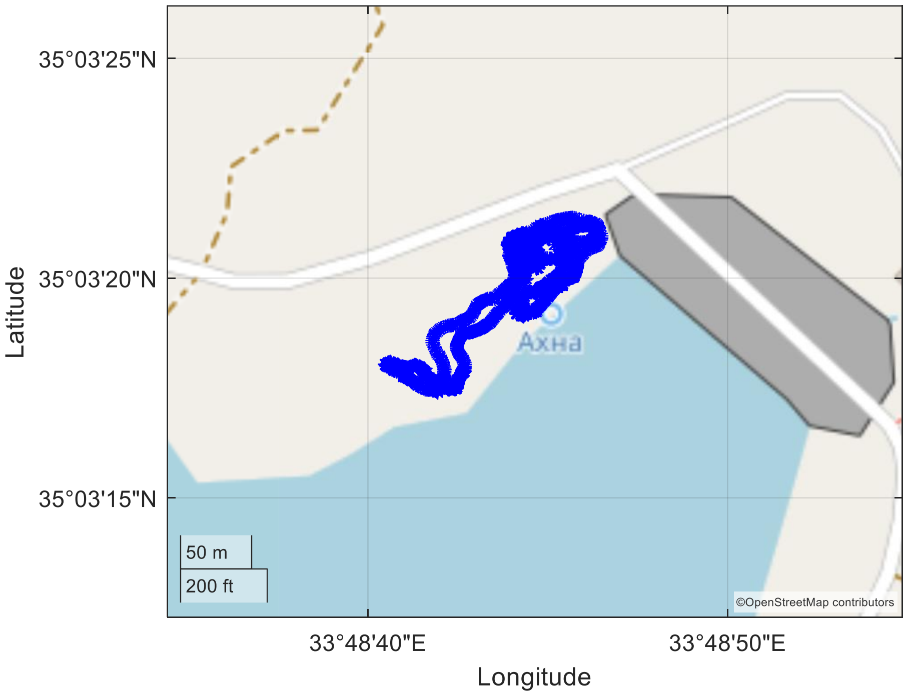
Exercise: Promitheas 2021

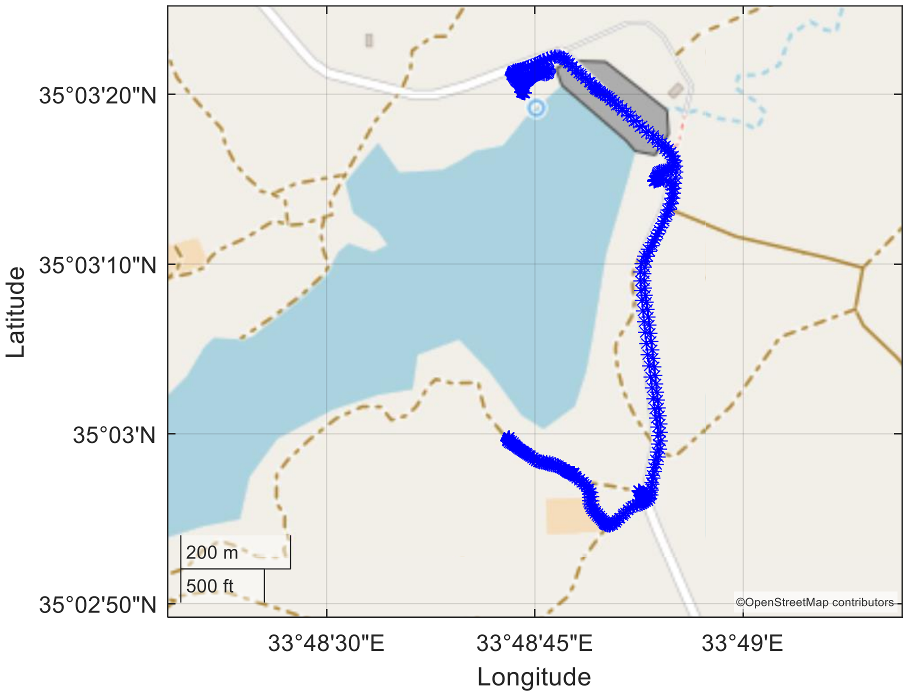
- Flooding scenario at the shore of an artificial lake in Achna
  - Water pumping
  - Establishment and Operation of an Emergency Operation Center and First aid station.
  - Search and Rescue of missing persons.
- Data collected by:
  - Videos captured by drones
  - GPS traces captured by a mobile app (mobile phones)



Exercise: Promitheas 2021

- GPS traces collected by mobile application





Exercise: Promitheas 2021

- Tracking people (video captured by drone)

Exercise: Search-and-Rescue in Paphos

- Search-and-Rescue exercise in the abandoned village of Vretsia in Paphos
  - After a tornado several people are missing. Some are lost and some are healivy injured
- Data collected by:
  - Videos captured by drones
  - GPS traces captured by a mobile app (mobile phones)

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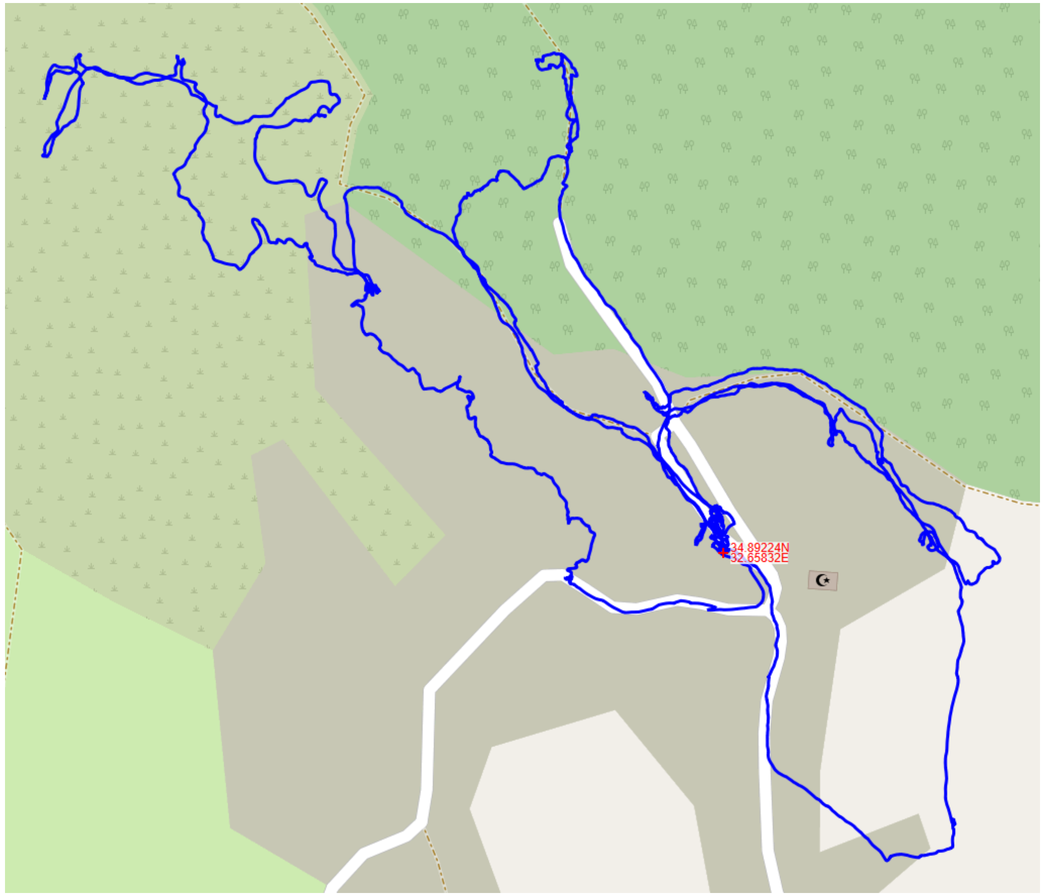
Exercise: Search-and-Rescue in Paphos

- Example of a GPS trace from a mobile phone



Exercise: Search-and-Rescue in Pathos

- ❑Tracking people (video captured by drone)

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