Application of Machine learning

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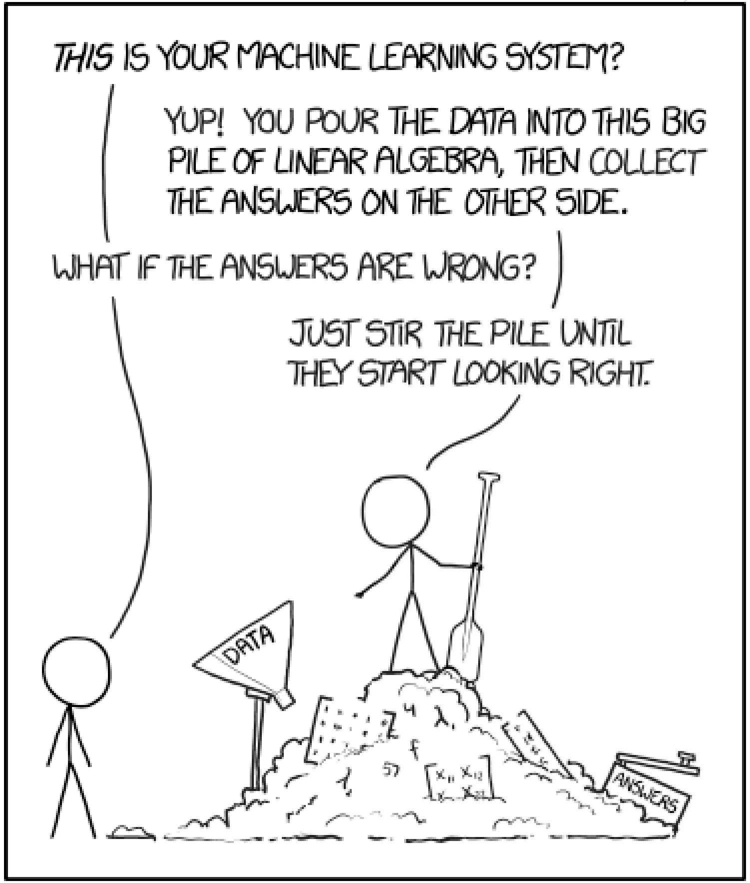
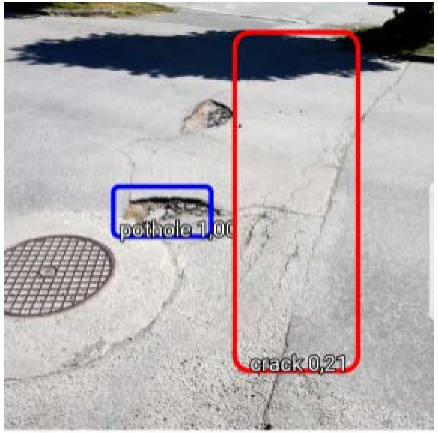
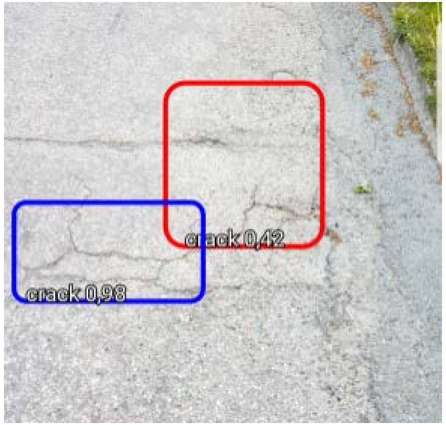
Machine Learning

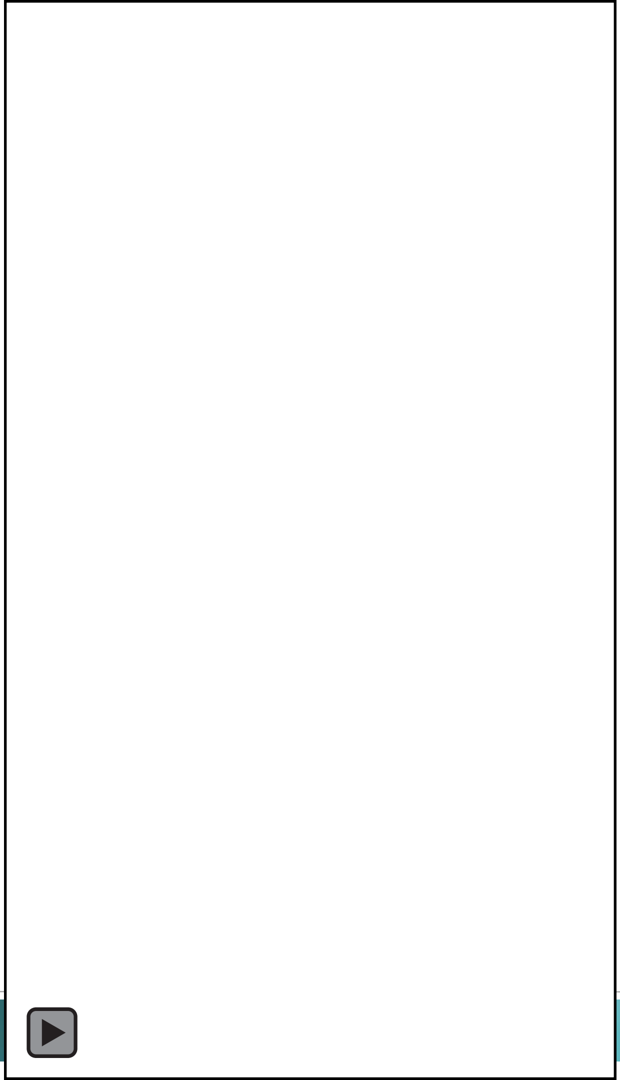
- Uses data to learn without explicit programming
- Tries to estimate a function that maps input to output data
- Use test data to verify that the model can generalize to unseen data
- Output labels, real values or actions depending on the task
  - Classification, Regression, Reinforcement Learning



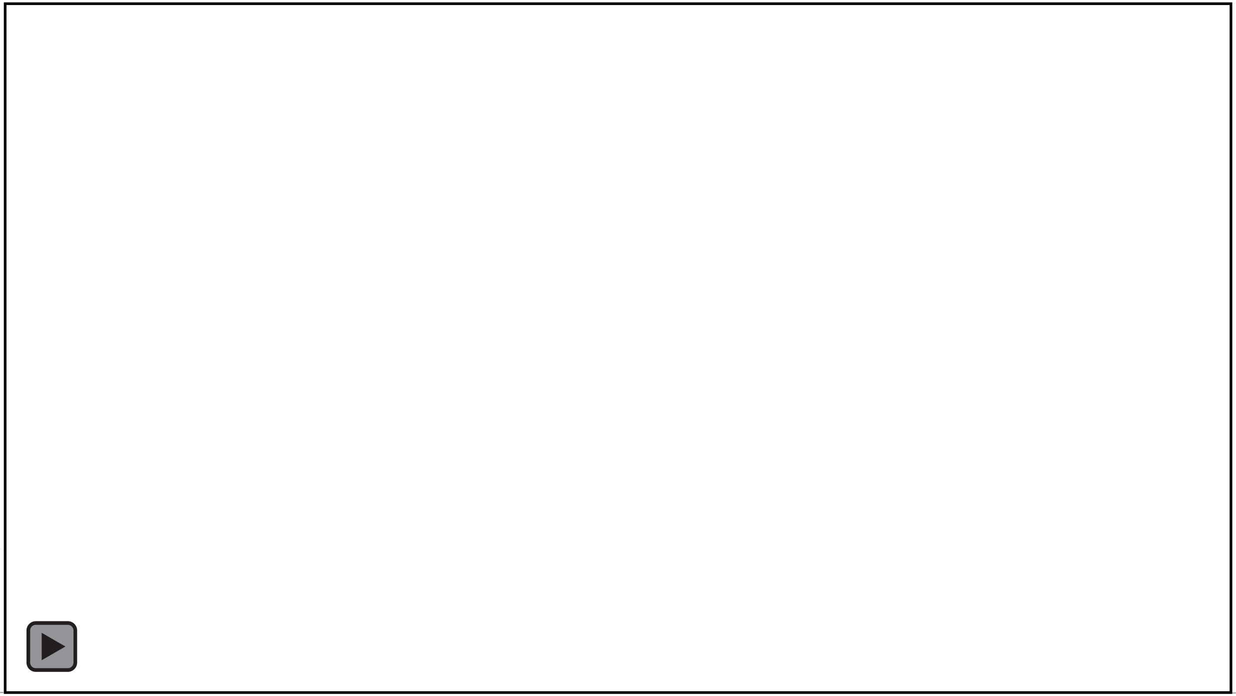
Road Damage Detection Model







ReClass



Supervised Learning

- Train using a labelled dataset with input and output pairs
  - E.g. Rust detection

Rust

No Rust

- Use the trained model to know if an image contains rust or not
- Great when large amounts of **labelled** data is available

Supervised Learning

- Visual inspection of the quality of produced radiopharmaceuticals

The need for data

- Supervised learning requires a substantial amount of **labelled** data
  - Collected/Generated
  - Labelled
  - Cleaned/Processed

AI Bench: Training AI models in Virtual Reality

Define camera paths to take sample photos

The application automatically labels the training sets

You can vary environmental conditions

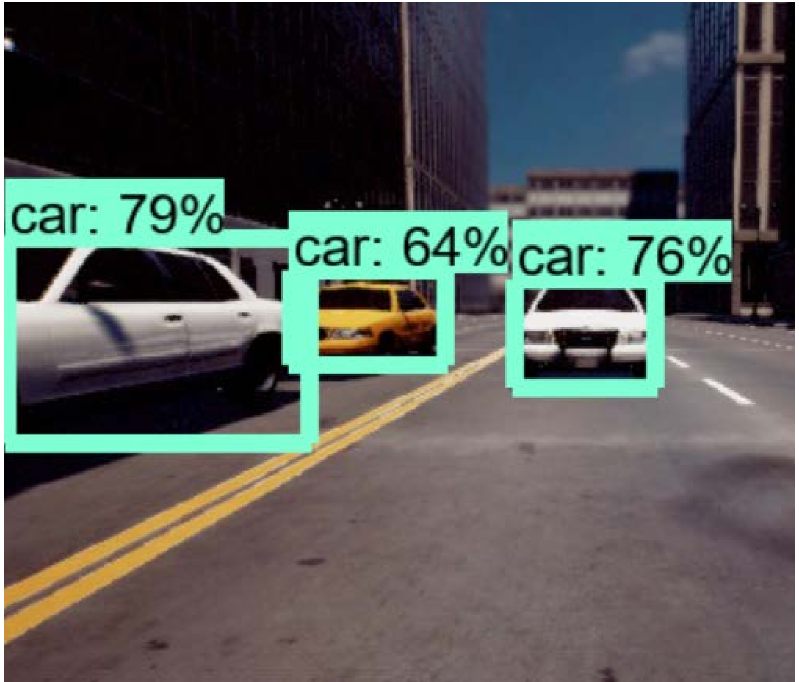
Classification outputs

Virtual

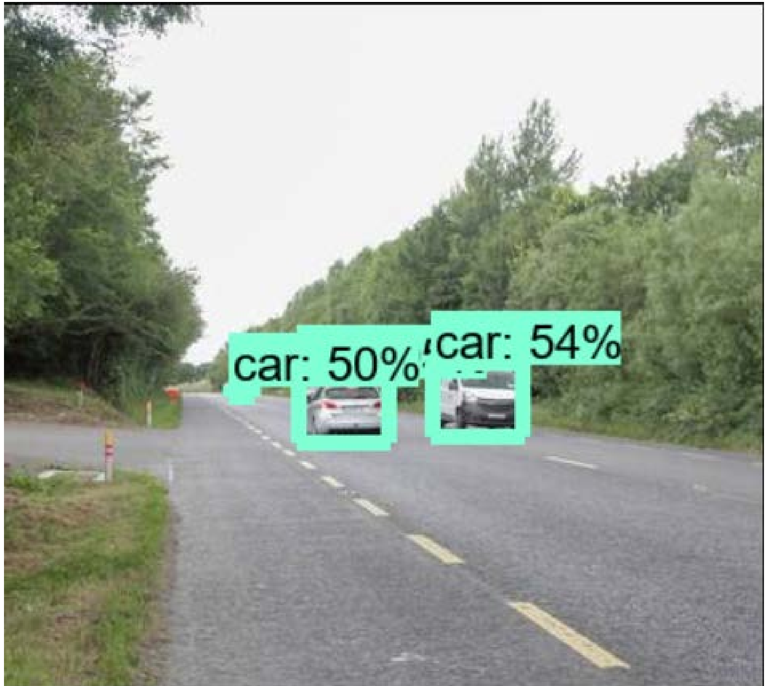
Real

Classification outputs

Virtual



Real

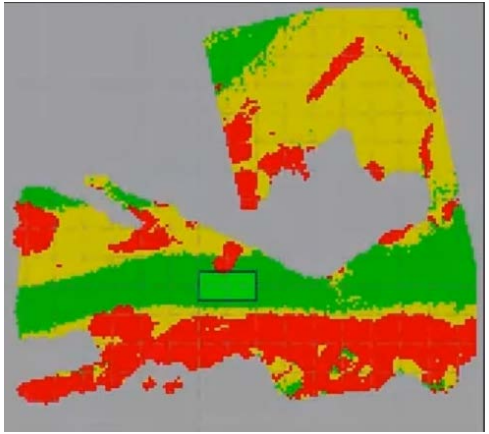


Reinforcement Learning

- Actions, Goal
- Penalty / Reward based learning
- Learn through feedback
- Great if you have a safe environment to explore (driving track, simulated environment).

Reinforcement Learning

- Teach a machine learning system to control a robot and move it in an environment in order to take measurements of radiation levels and map out radiation in the environment.
- Teach the system to avoid areas with high radiation levels by penalizing it for being in those areas.



Questions?

Barriers to assuring of autonomous systems

- Based on the Assuring Autonomy International Programme at University of York
- https://www.york.ac.uk/assuring-autonomy/
- Scope: assurance of Robotics and Autonomous Systems (RAS)
- Critical Barrier to Assurance and Regulation (C-BAR) is a problem that must be solved for a particular system or domain, in order to avoid one or more of the risks presented next.

Risks (to be avoided by coping with C-BARs)

- a safe system cannot be deployed (losing the benefit of the technology)
- an unsafe system is deployed (lack of clear evidence to assure operation)
- the adoption of safe technology is slow
- there is a lack of progress in adoption in a particular domain
- the level of accidents and incidents leads to a backlash

C-BARs

- Adaptation – of behaviour in operation
- Bounding Behaviour – safe operation within known bounds
- Cross-Domain Usage – known to be effective in one domain, how can it be assessed for adequacy in another environment
- Explanations – of decisions made by a RAS
- Handover – handing (back) control to a human
- Human-Robot Interaction – in sight of potential for physical harm to humans
- Incident and Accident Investigation – information needed to be provided to support incident/accident investigations

C-BARs – cont.

- Monitoring – retain sufficient levels of attention and concentration of operators
- Risk Acceptance – how can risk be estimated, communicated and accepted?
- Role of Simulation – how can it enable assurance and regulation, and when does it provide sufficient evidence to allow controlled use of the RAS?
- Systems of Systems –when given SoSs which are ‘individually safe’ how can safe interaction be assured, in their intended operational environment?
- Training and Testing AI – how can it be shown that the training sets (and test sets) give enough coverage of the environment to provide sufficient evidence (in itself or in combination with other means of V&V) to allow controlled use of the RAS?
- Validation & Verification – effective means of RAS/AI V&V