DATA GEDREVEN BESLUITEN

Data-driven decision making with predictive analytics: a study on incident and traffic management

PROJECT REPORT

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A project for:

Rijkswaterstaat
Ministerie van Infrastructuur en Milieu

Contents

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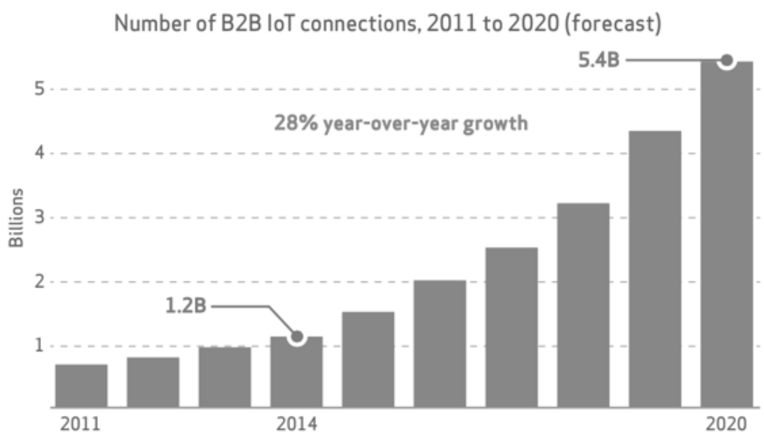
PROJECT RATIONALE

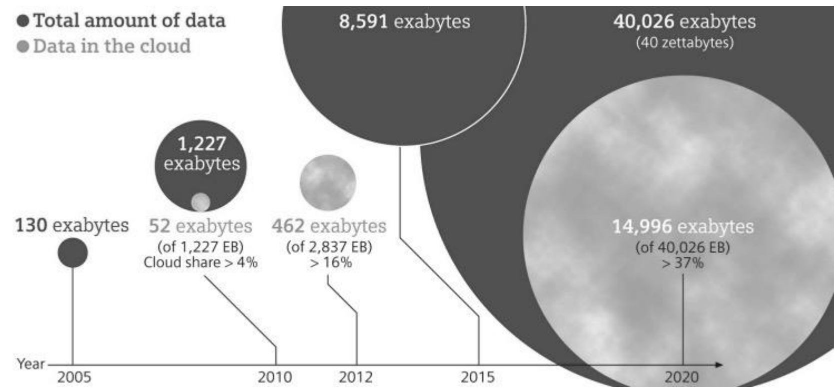
Convergence of multiple trends

Internet of Things grows exponentially



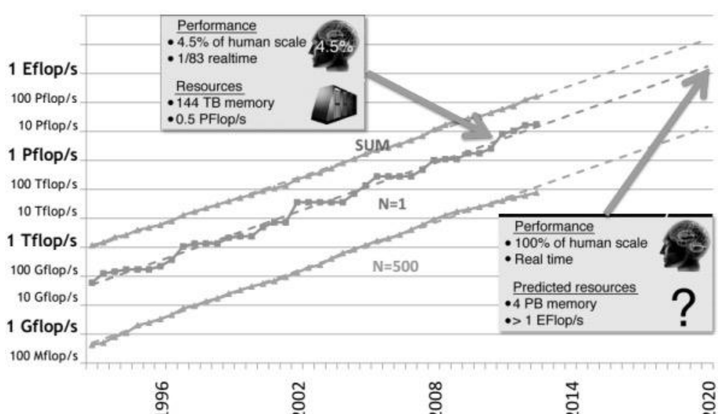
Source: ABI Research

Data production grows exponentially

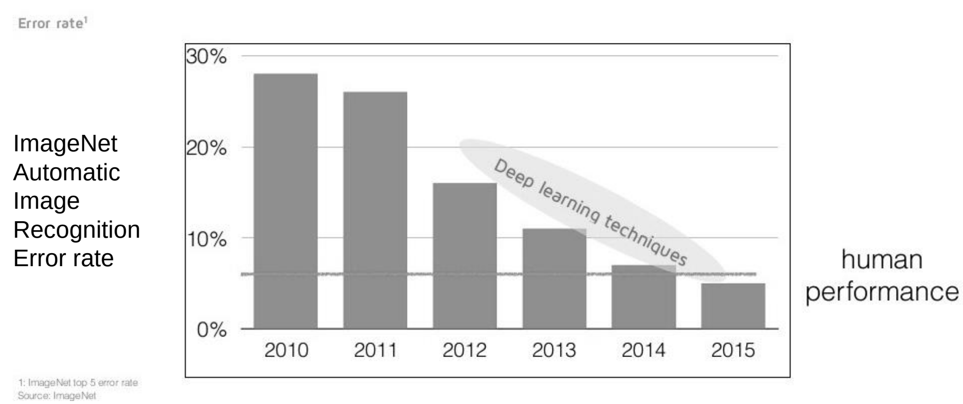


Source: IDC

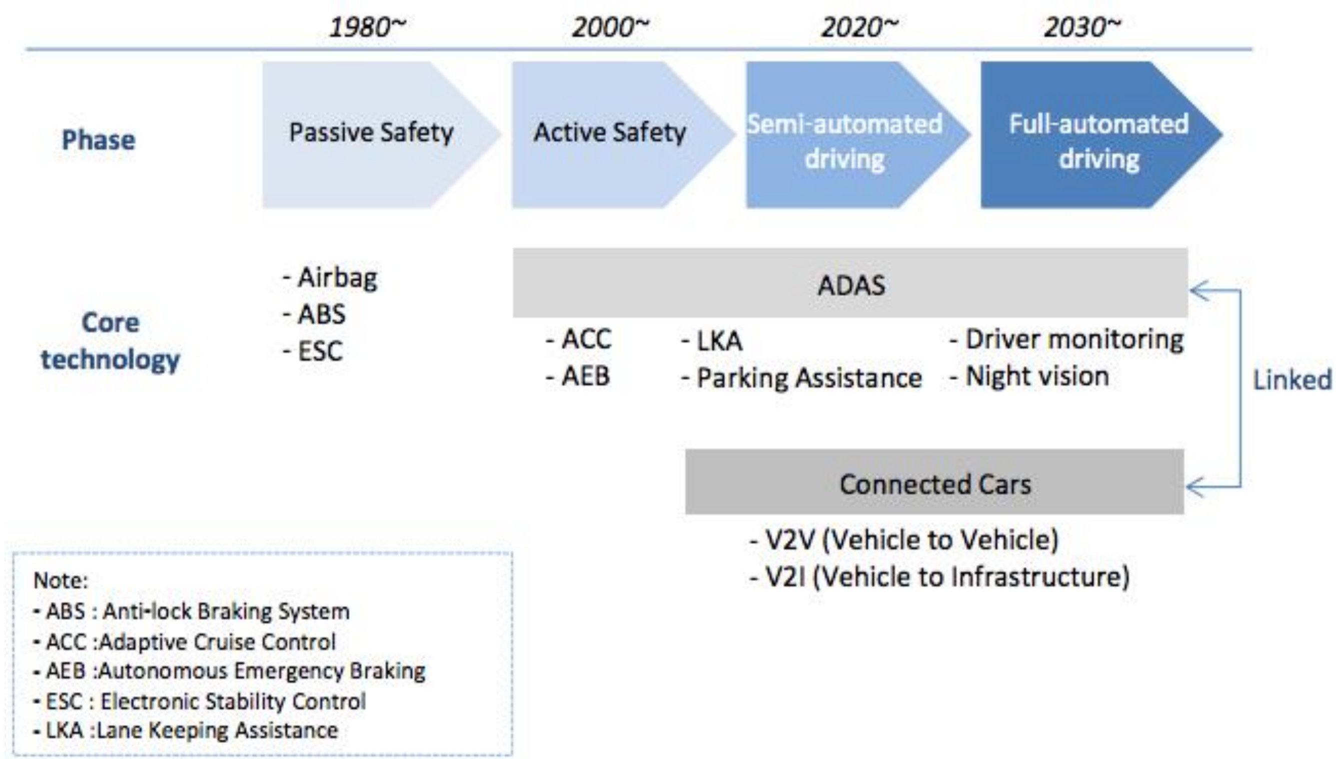
Computing power is reaching exascale (human brain) performance



AI models exceed human capacity at selected tasks.



From Monitoring to Autonomy: the car transformation



Autonomous driving is a process of gradual augmentation of driver decisions with machine decisions.

The automation are likely to unfold in the next 15 years, in parallel with capabilities that make cars connect with each other and with the infrastructure.

V2I (vehicle to infrastructure) capabilities are expected to be generally available in the 2020s.

Source: Goldman Sachs

Some observations

The emergence of traffic incident prediction is contextual to the emergence of similar capabilities in other industries (see section on use cases) and correspond to:

- The increasing availability of data
- The growing practice of cloud computing
- The growth of the internet of things and sensor networks

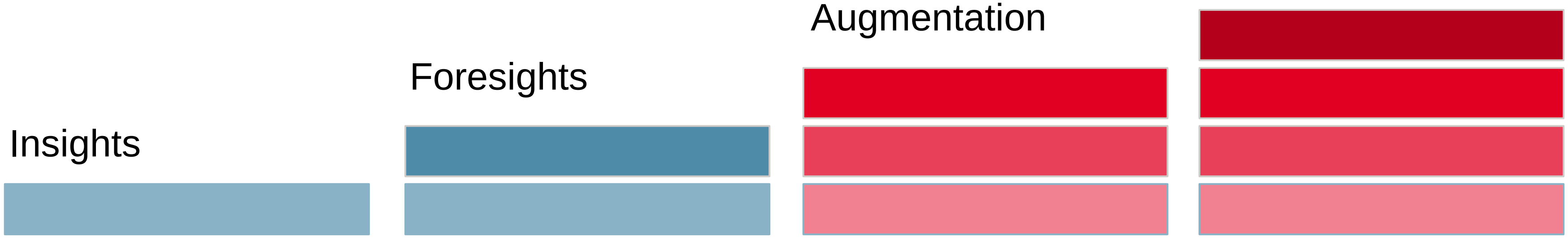
At the same time, improved methods, such as Deep Learning Neural Networks, enable predictive analytics. Foresights, rather than insights, are the focus of emerging management practices in every sector.

Specifically, methods of Artificial Intelligence developed over the last 30 years suddenly become viable and usable, giving rise to one of the fastest growing IT sectors.

The mobility sector is impacted in two main ways. On the one hand, and just like any other sector, it has an opportunity of leveraging IoT, analytics and computing to a larger than ever scale to create transparency on the way the system works, to provide real-time insights and to start predicting complex phenomena such as incidents.

On the other hand, the same technologies are disrupting the car (with autonomous vehicles) but also the consumption of transportation (car sharing, hile a ride, uber etc.) altering the context for traffic and incident management.

The general path from monitoring to autonomy



Insights

IoT and Big Data provide new sources of insights to decision makers.

Decisions are made by humans looking at data, values, experience and models that guide actions.

Foresights

The decision making style (tactical and strategic) changes to include predictions about what may happen in the future.

Decisions take into account future events, so that current decisions alter the course of action to achieve better outcomes.

Augmentation

Algorithms are capable of interpreting insight and foresight data better than humans and of suggesting optimal courses of action.

Human decision making regularly takes them into account. Decision making is human but with significant machine support.

Autonomy

Machines coordinate multiple systems and are capable of making complex decisions autonomously.

Humans have full oversight of machine decisions, but they intervene on request when essential, unknown tradeoffs have to be made.

The general path from monitoring to autonomy (cont.)

INSIGHTS

Focus on collection of real-time data from multiple synchronized sources to create a basis for decision making.

Typical uses:
- Monitoring equipment
- Monitoring infrastructure
- Real-time alerts
- Environmental conditions

Example:
- Detect ice on the road
- Weather alerts

Traditional decision making based on past and present evidence.

FORESIGHTS

Models estimate the future state of the system and predict status and events.

Typical uses:
- Incident prediction
- Anomaly detection
- Future capacity demand

Example:
- Predict traffic levels
- Predict incidents
- Predict resource needs

Traditional decision making, but based on what's likely to happen, rather than what normally happens.

AUGMENTATION

Algorithms use insights and foresights to advise decisions that help human capabilities.

Typical uses:
- Traffic manag. advise
- Inspection planning
- Coordination between partners in the traffic management chain

Example:
- Road inspector schedules are fully dynamic and designed by algorithms

Decision making is based on the collaboration man-machine: the decision is a joint effort.

AUTONOMY

Machines are able of governing the entire system, with selected supervision from humans.

Typical uses:
- Traffic management automation
- Road-vehicle collaboration
- Self-organizing roads

Example:
- Alter travel patterns of AVs based on weather conditions

Decision making is fully automated, with human supervision limited to exceptions raised by the machines.

Machine learning and incident prediction: project rationale

Rijkswaterstaat (RWS) has experimented with AI-methods in the context of incident management and incident prediction.

Recent projects have showed that predictive analytics, based on deep learning neural networks, are able to increase the predictability of incidents above traditional statistic methods. These methods are at an early stage but are developing very rapidly up to the point where predicting a future incident becomes of practical relevance.

Prediction means estimating the chance of a specific incident type (or class of incidents) for a section of the road network (e.g. 20km or 30km) for some time window in the future (e.g. the next 30 minutes).

In the case of RWS there is a significant value at stake. On the one hand, the ability to better predict mobility patterns and anomalies can lead to a much more effective role of RWS overall. At the same time, predictive analytics tend to increase the role of machines and algorithms in decision making, altering tasks that until now have been considered as intrinsically human tasks.

In this transformation of the traditional decision-making processes there are risks and opportunities, such as:

- How should traffic management use predictive insights in decision making?
- Which workflows and processes are affected most?
- Once autonomous vehicles start operating, can RWS use this opportunity to inform drivers and vehicles, and manage traffic through algorithms?
- How does the role of traffic managers and dispatchers change?
- What are the risks and opportunities that must be addressed in the traffic management process?

This project provides a basic framework to shape the questions that an organization needs to address, to identify opportunities of machine learning and AI, and to understand unknowns.

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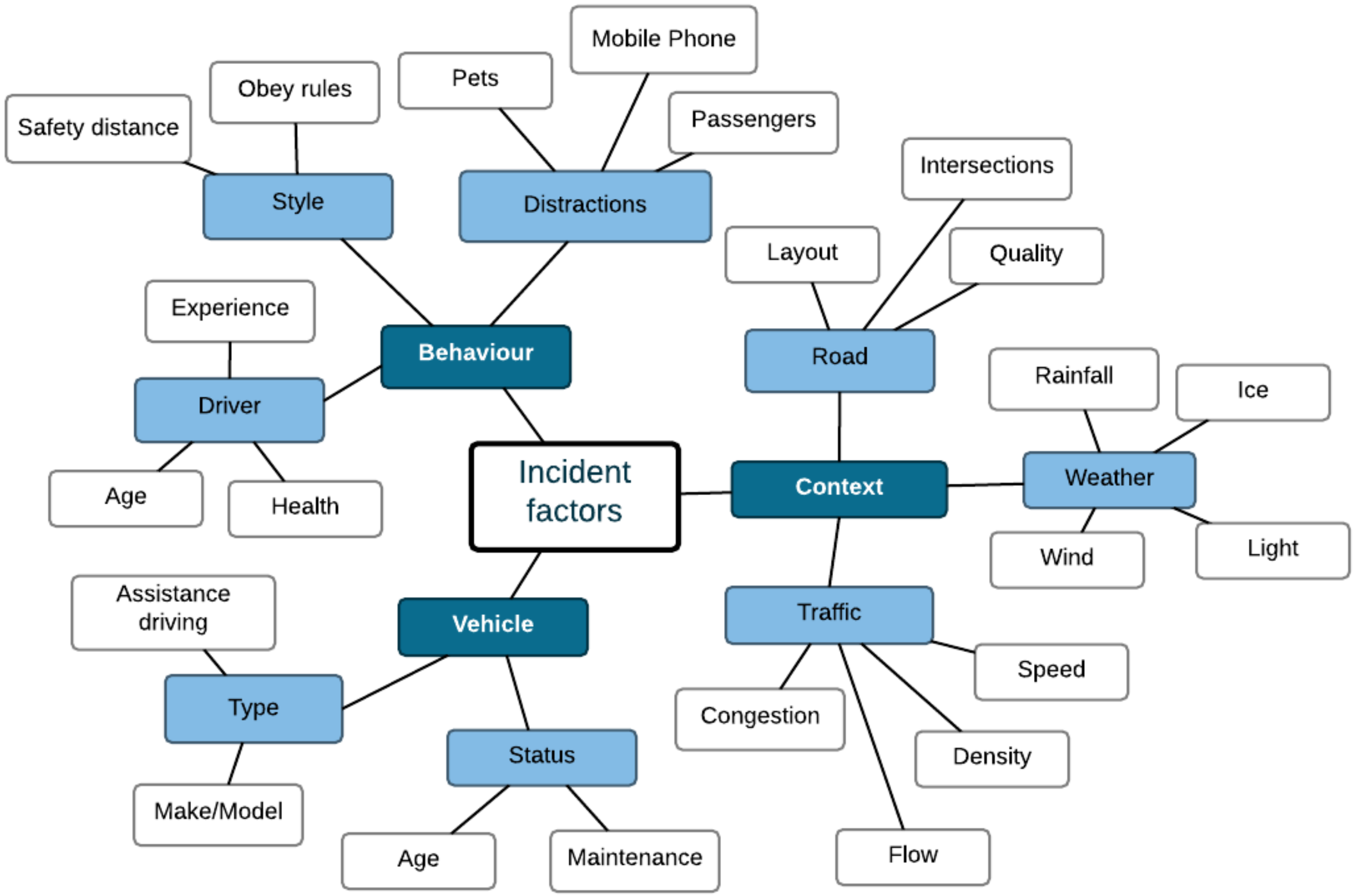
TRAFFIC AND INCIDENT PREDICTIONS

Factors linked to incidents

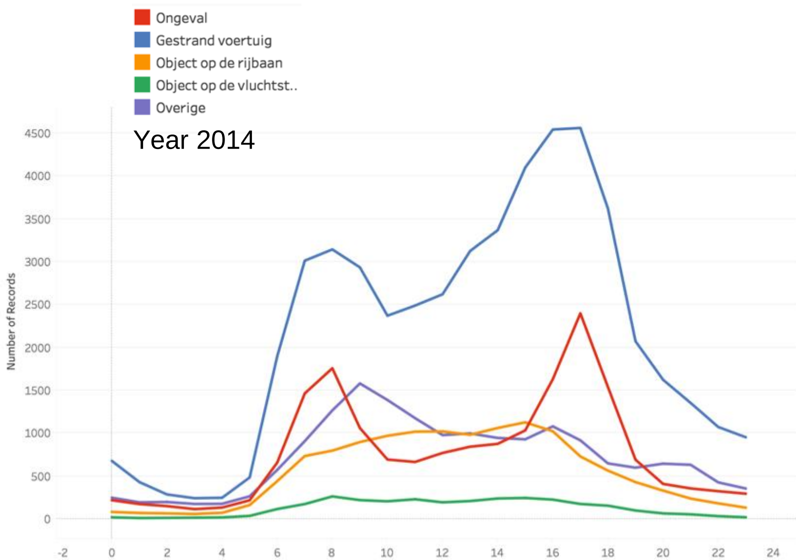


The graph summarizes factors that are likely or plausibly associated to incidents. In principle, if there is a relationship between an influencing factor and an incident type, then it is reasonable to assume that it is possible to identify the onset of influencing factors leading to an incident, thus predicting.

Some relationships in this diagram are well known, while others are speculative.

Neural networks are useful to infer the overall relationship between factors and incidents, although the relationship may be complex and only partly understood as a cause-effect link.

Hotspots: incidents concentrate in time and place



Hotspots: number of incidents per hour per sections of 5km, A12, year 2014

		Tijdstart																							
Incidenttype	Hectometer..	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23
Ongeval	0							2		5	8	1			2	1	1		5	3				1	1
	5								3	11	5	4	3	4	1	4	1	6	8	5	4	2	1	1	1
	10					1			7	5	1		1		1		3		10	4	1	1	1	2	1
	15					1	1	2	4		2		1	1	2	3	2	3	2		2	3			
	20	1	1				1	2			2	1	2		2		2	3	5				1		
	25	1						1	8	8	11	2	1		1	3	2	11	29	30	4	1	1		2
	30	1						2	7	5	4	1		2	1	2	6	6	3	3	3		1		2
	35		2	2				1	4	4	1		1			4	2	2	6	5	4	2		1	
	40		1	1			4	1	11	4	3	1		5	5		3	5	6	3	2	3	2		1
	45			2		1	1		2	1	4	2		3		2		1	6	2			2	1	1
	50			1		1		1	1	3	1	1	2	1	4		1	4	3	2	2	1	1		2
	55	1	1	1	1				14	16	10	6	9	4	2	3	10	17	24	8	6	3	3		4
	60			1	1			5	12	10	10	9	7	3	8	2	7	8	17	11	5	2	1	6	2
	65				2			2		2		1		2			1	3	4	3				1	
	70			1					1	4	2	1		1	1	1	1	2	2		1				1
	75		2					1	1	1					1		2	1		2	1	1	3		
	80			1	2			1	3			1			1	1		1				2			
	85	1	1	1		1			1			1		1	1					1	1				
	90		1							1				1				1		1					
	95																								
	100						1			2					1		1	1	2	2			1		
	105			2			1	1	2	4		2	2	1	2		4	6	9	12	4	1	1		1
	110								2	3	1	2	1	2			1	6	2	5	1			1	
	115	1	1	1		2	1	6	9	14	7	5	1	3	3	1	3	7	8	3	1		1		
	120	2		1			1	4	6	12	1	4	4	1	3	2	5	8	9	3	2	1	2		
	125					1		3	1	6	2	3	2	1	2	2	3	2	2	4		1	1	1	
	130		1			1		3	2	4	2	6	5	1	2	1	3	2	10	7	2		2		
	135								1	5	2	3	3	3	1	1	1	4	9	5			2		
	140		1				1	1	2	6	2	2	2	5	6	3		3	3	1	2	1	1	2	1
	145								3	4			2	2	3	2	2		2						

Hotspots: Average number of ongeval per hour per sections of 20km, A12, year 2015

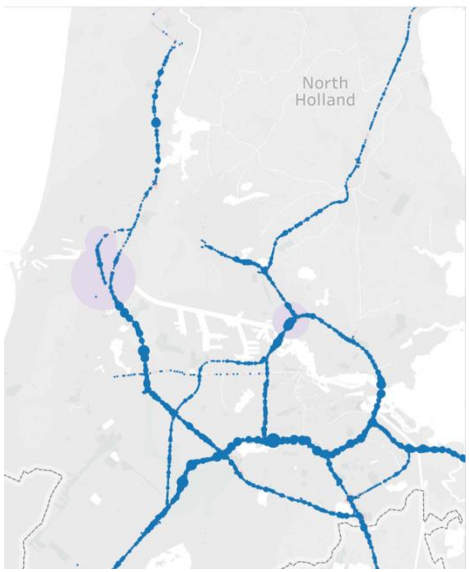
	UUR																							
Hectometerv..	**0**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**
0	2	1	2	1		5	6	20	25	15	5	3	4	15	9	13	23	25	25	7	3	9	4	9
20	1		1	3	1	3	3	31	28	15	8	4	4	8	10	4	37	53	39	9	4	5	3	3
40	5	1	1	3	1	2	11	26	20	9	12	5	11	15	12	5	31	42	26	6	2	6	1	8
60	2	4	2		2	1	3	18	22	10	8	6	4	6	12	8	21	29	18	10	2	3	2	1
80		2	1	1		1		7	3	1	1		1		1	6	1	3	2		1	1		1
100	2	1	1	2	2	3	9	18	20	10	10	2	7	4	7	7	18	34	17	14	4	2	1	8
120	1	2				2	11	22	16	16	14	9	7	13	14	10	27	43	18	5	6	7	5	4
140	1				1		4	8	11	6	3	6	6	2	7	3	5	4	6	3	2	2	1	

CSRESEARCH

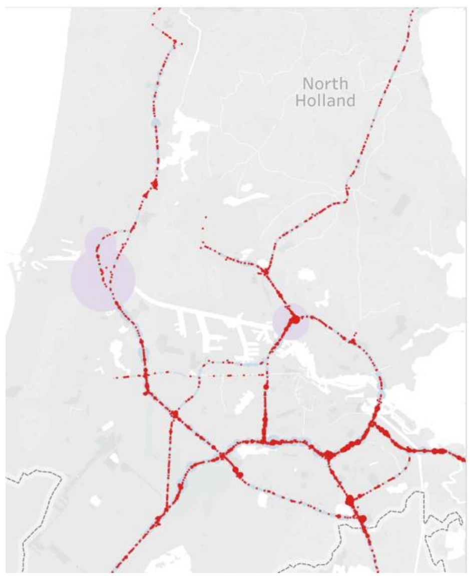
Hotspots and predictions

Incidents tend to distribute around time-space hotspots, which are the current planning basis for traffic and incident management. However, the probability of an incident at any single point in time and space is small. For instance, on the A12 in 2015 the highest frequency of incidents is recorded between km 20 and km 40 between 5pm and 6 pm. The probability of incident in this section for this time block is 14.7%: on average there will is one incident every 7 days.

Machine learning can detect factors that produce time-space dependent forecasts of incident and indicate for each road-section if an incident is likely *in the next time block*.



Gestrande voertuigen, North Holland, year 2014



Ongevallen, North Holland, year 2014

These systems are good candidates for augmenting human ability to inform, predict and manage incidents. Previous studies of RWS indicate that significant correlations between loop data and traffic incidents can be detected by Machine Learning algorithms. At an aggregated level, the studies indicate that the network can detect patterns of traffic that increase the probability of an incident.

A general model for incident prediction

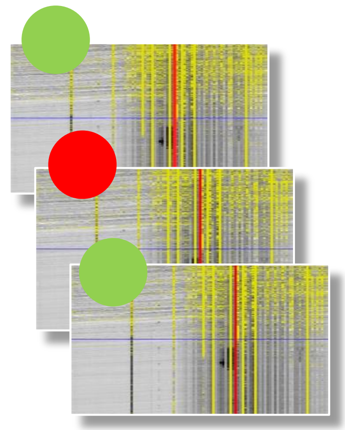
TRAINING

1

Historical incident data, traffic, weather and other data are split into training and test sets (to validate the training).

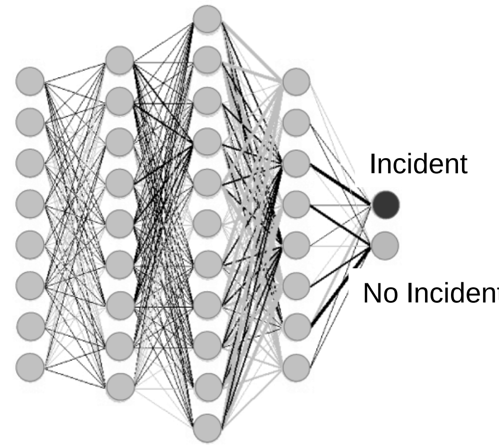
2

Data is modeled into the input format for the the neural network. Data is labeled as “incident” or “no incident”).



3

The training set is labelled 1 or 0 if an incident occurs (or not) in a specific time window in the future. The network learns to associate data patterns to labels.



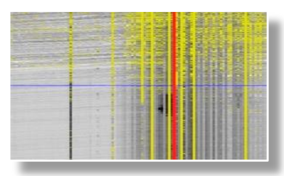
PREDICTING

A

Real-time incident data, traffic, weather and other data is captured by sensor networks.

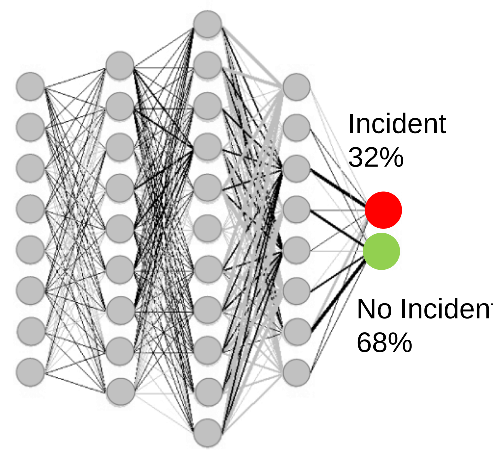
B

Data is modeled into the input format for the the neural network.



C

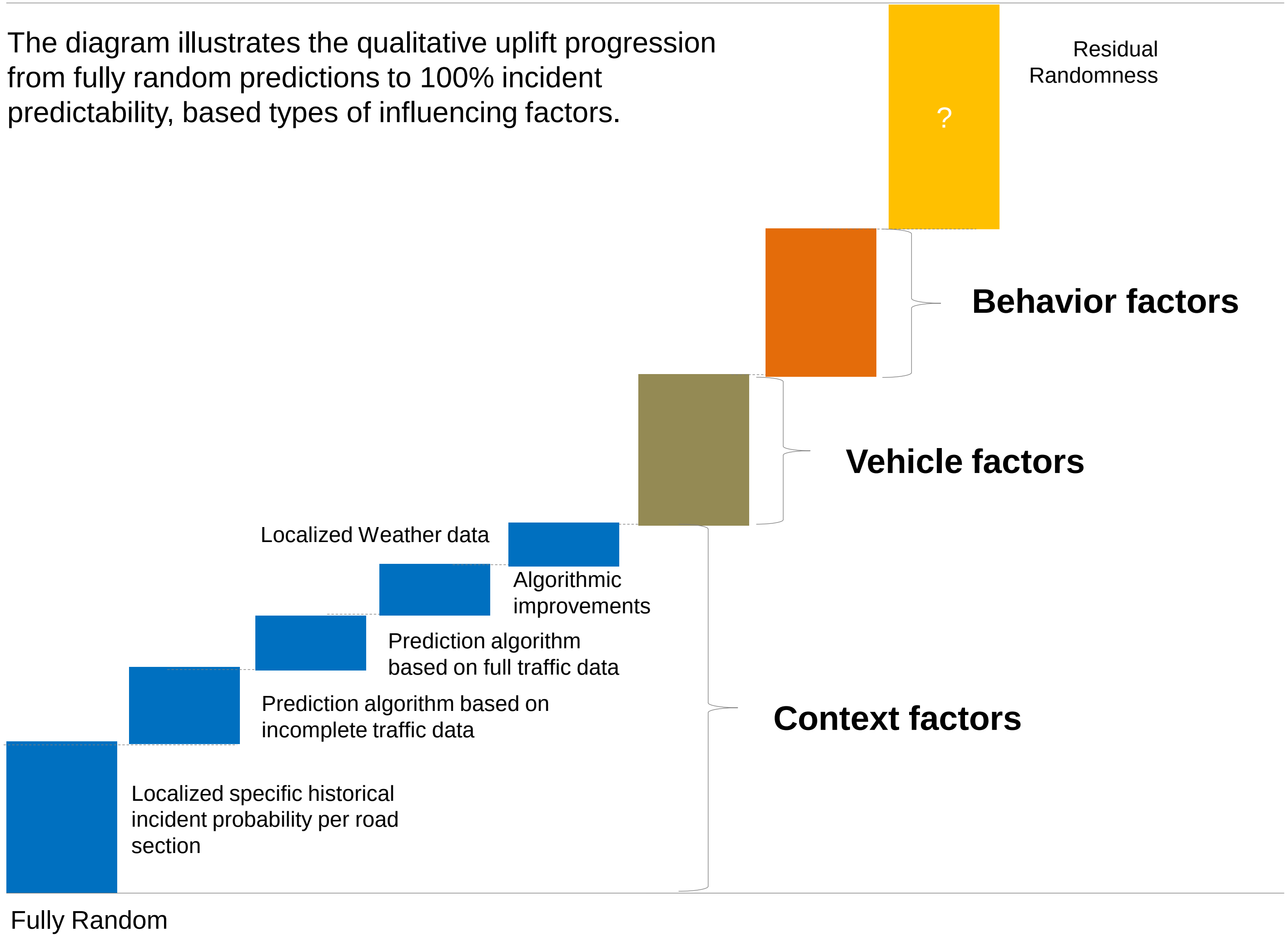
The network labels the image based on the training and offers incident probability for the road section and time window specified.



The path to operational incident foresights

THEORETICAL UPPER BOUND: 100% PREDICTABILITY

The diagram illustrates the qualitative uplift progression from fully random predictions to 100% incident predictability, based types of influencing factors.

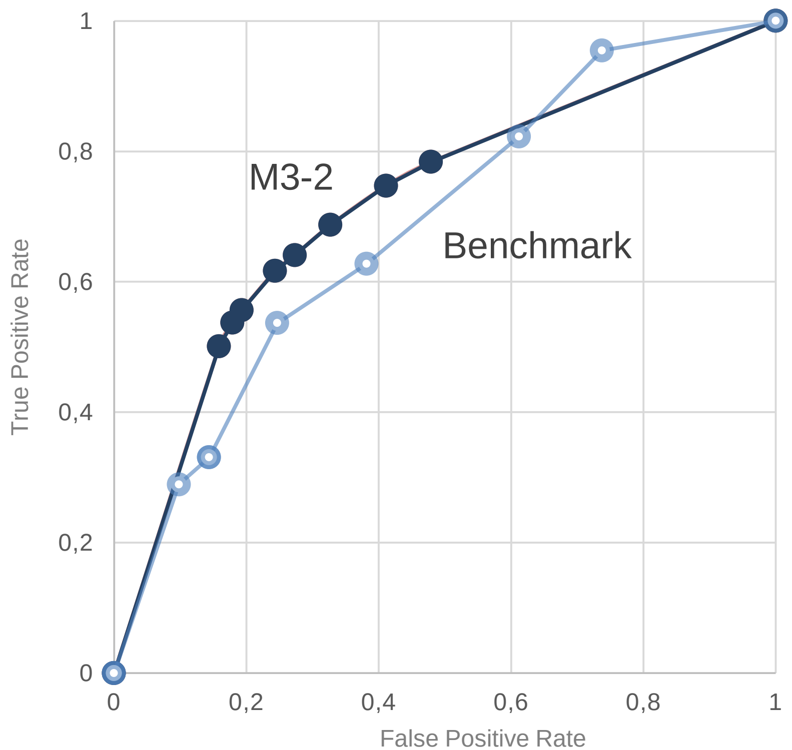


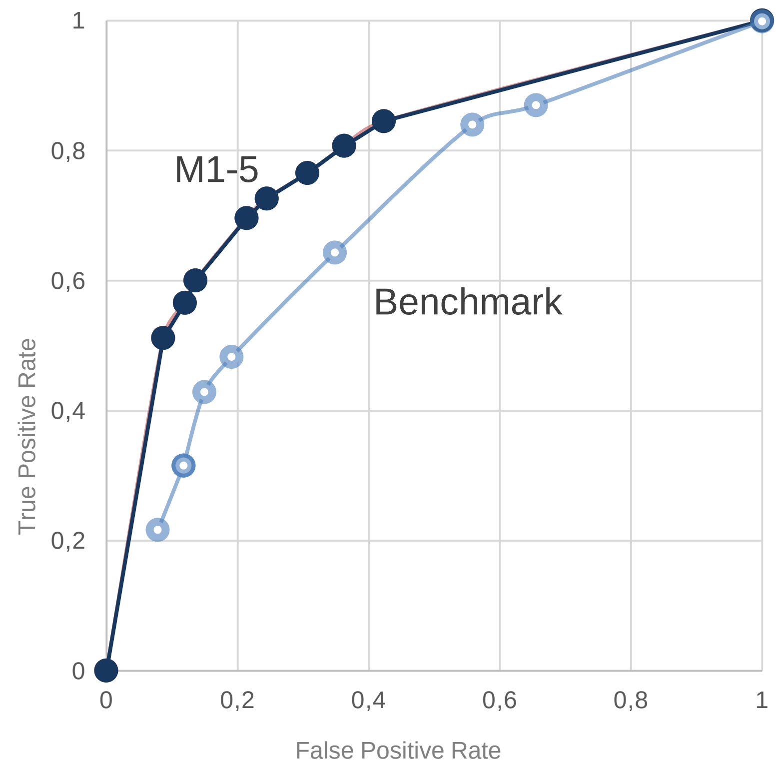
Full incident predictability is only a theoretical possibility: the myriad of simultaneous factors that cause an incident make full predictability practically impossible.

Nonetheless, many factors are known to contribute to increasing the incident probability.

By modeling these factors we can obtain a partial incident predictability, which nonetheless can significantly help decision making.

Incident predictions: sample results

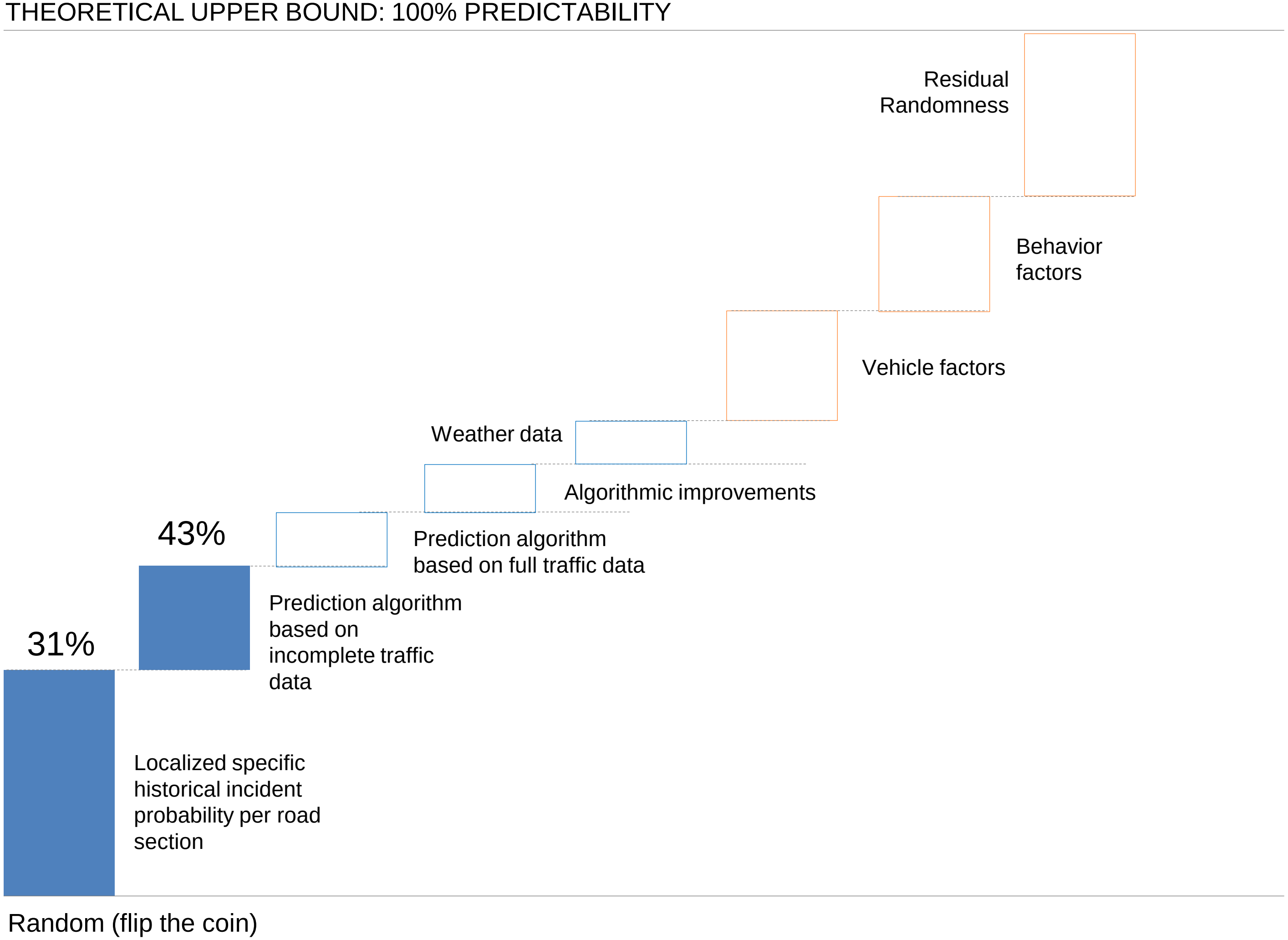




The diagrams above show two example of results for incident prediction along A12 (30km of the A12 road section) for 30 minutes in the future (the two models are called M3-2 and M1-5). These examples are based on a small training set (± 300 incidents) over a period of 18 months,

The benchmark is the most accurate prediction that can be obtained with incident probability only. The curves show the performance of the models and of the benchmark for various thresholds, which lead to different degrees of false positives and false negatives. The area between the model curve and the benchmark curve is a measure of the uplift: the larger the area the higher the improvement provided by the prediction model.

Uplift progression: early results



The studies carried out so far indicate a significant improvement of predictability compared to statistical data only.

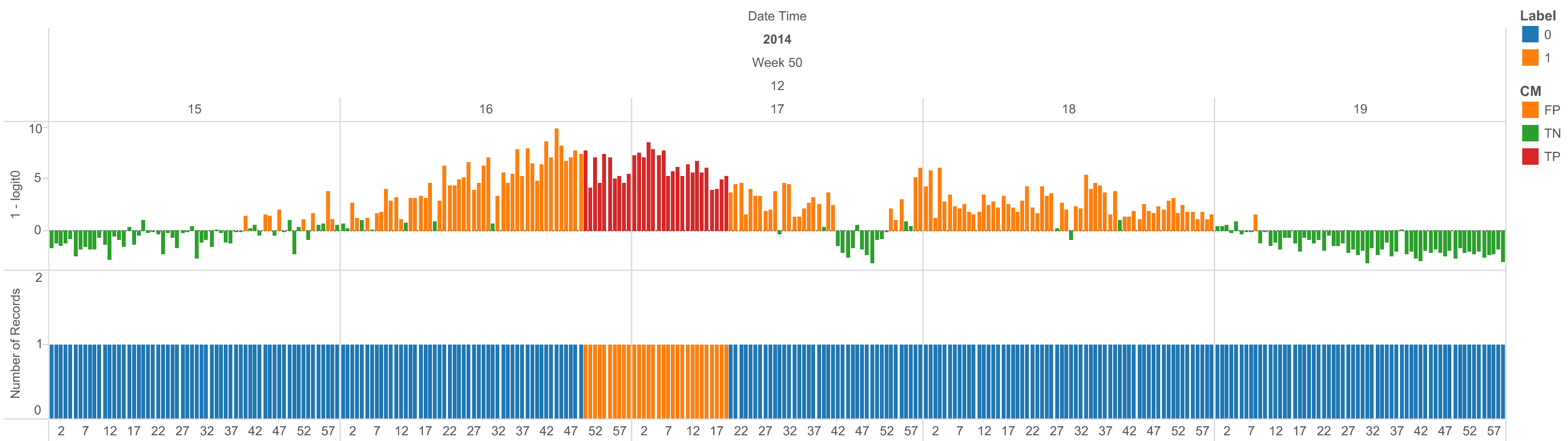
Considering that these results are obtained with very limited training sets, it is realistic to expect major improvements with better/more complete data.

Note that the score cannot be interpreted as “% of incidents predicted”, which is specific of every configuration of every method.

The output of incident prediction: example

The examples below illustrates a typical output of a prediction system. The top diagram shows the incident probability over time as predicted by the model. The diagram below shows the actual incident and a 30-minutes duration.

The prediction system in this case indicates a higher and sustained probability of the event in the period before the incident happened and during its unfolding. It also detects an increased probability after the event, which has not led to a secondary event.



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PREDICTIVE ANALYTICS, A.I.: BACKGROUND

The value of incident prediction

The value of incident prediction unfolds incrementally from incident prediction, to interpretation of incident factors, to suggestion of appropriate actions.

1 **PREDICT: Provide incident probability for sections or the road and for specific time windows.**

Example "There is a high chance of incident on A12, between km 34.2R and 48.2R between 10:30am and 11:00am"

Tools Deep learning neural networks applied to traffic, weather, behavior, etc.

2 **INTERPRET: Identify the data features that lead to increased (or decreased) incident probability to discover causal links between incidents and the underlying influencing factors.**

Example "Rain showers, speed gradients and pockets of heavy vehicles raise the incident probability"

Tools Feature interpretation and categorization of neural network layers.

3 **ADVISE: Suggest actions that can be implemented to alter the incident probability or mitigate the incident consequences.**

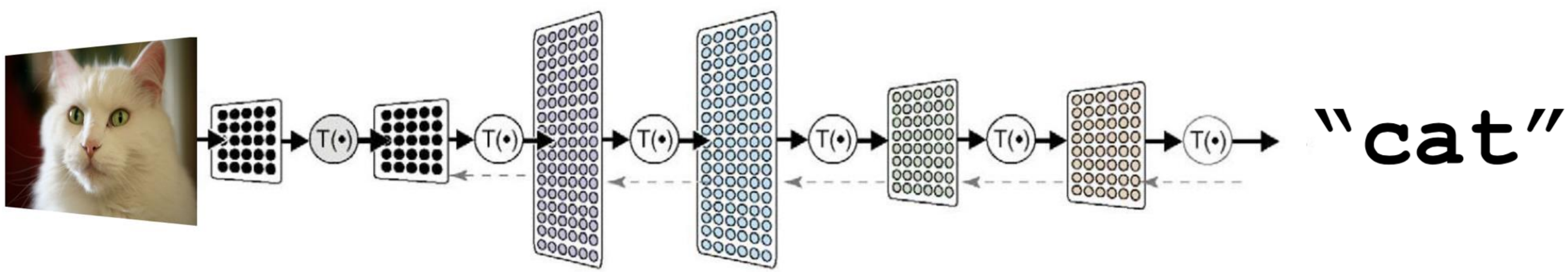
Example "Relocate inspector to Esso station km 36R, reduce speed to 75kmh on VMS at km 26R"

Tools Reinforced learning based on incident and action data.

* Gartner, January 2016

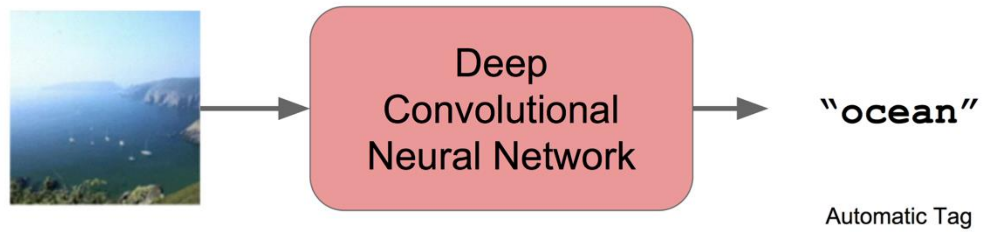
Predict: Deep Learning

- Deep learning (DL) is a modern version of neural networks that has proven very successful in Artificial Intelligence tasks, like speech and image recognition.
- Loosely based on the connectivity and function of neurons in the human brain. A DL network includes “neurons” (variables that can be activated) organized as layers connected in a stack.
- The network must be “trained” on a large dataset before it can be used, to understand the relationship between the data features and the “tag” associated to the data.
- Once trained, the DL can be used to label datasets. DL is a very general concept and can be utilized in very diverse applications.

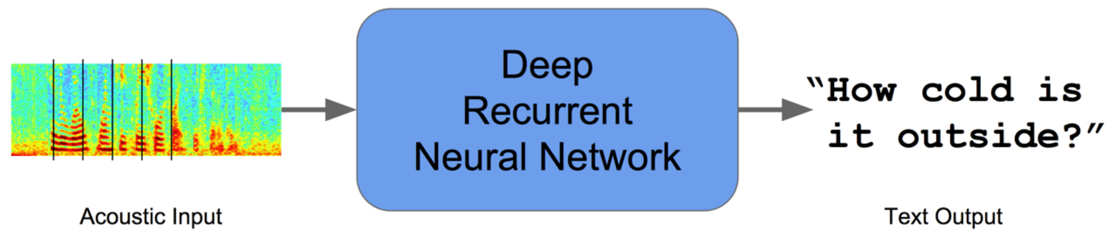


Deep learning most common applications

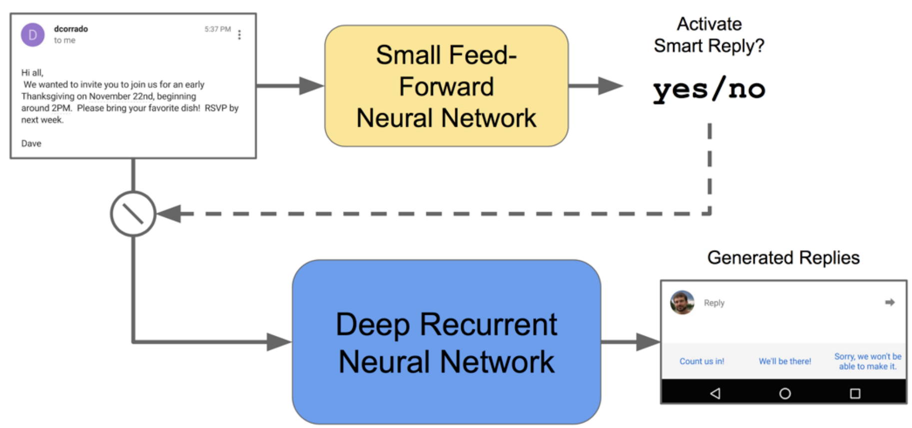
Image Recognition
(automatic tagging)



Speech Recognition



Automation



Interpret: Feature interpretation

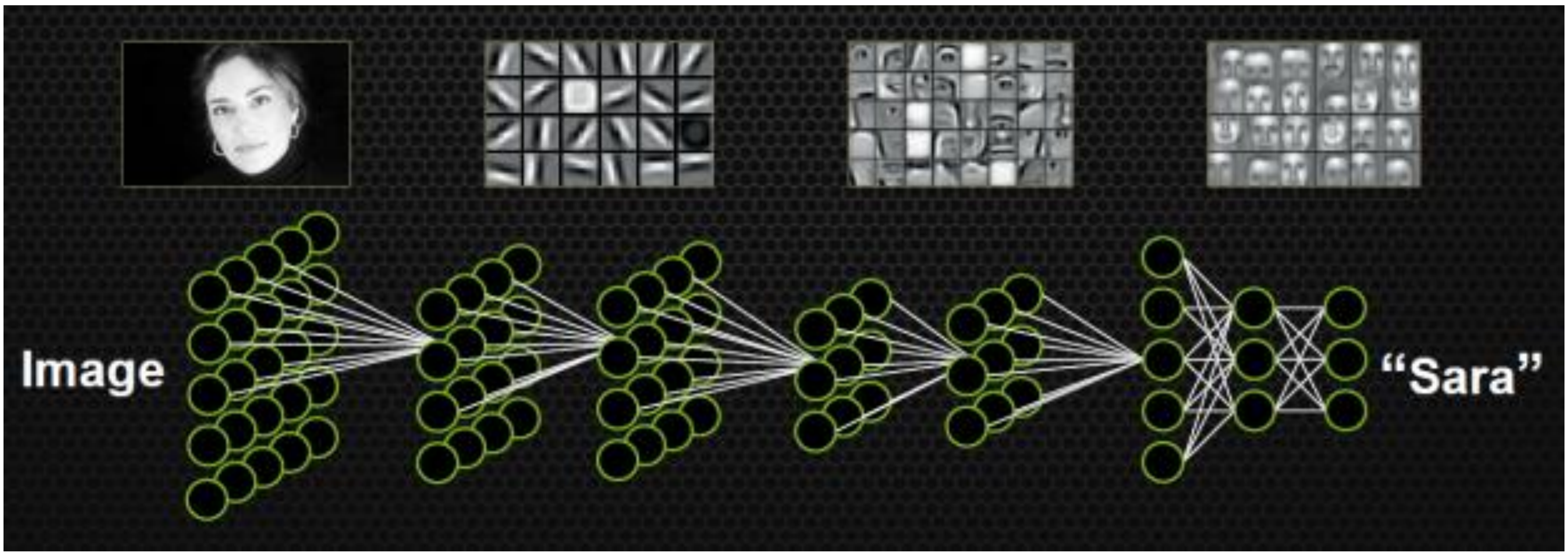
- Much of the power of Deep Learning derives from its ability to encode a hierarchy of features in the input data
- Many types of data samples are composed of a structured collection of features:
  - Objects in images are composed of elements of increasing specification. At the lower level one has lines, then partial features, like e.g. the eyes or the nose for a face, then the object itself among other objects in the image.
  - Speech sounds are composed of phonemes organized in words and phrases.
  - Sensor array data are usually structured in quasi-periodic sub-patterns as the system goes through operating cycles.
- A Deep Learning network encodes the hierarchy of features in its successive layers of neurons:
  - Layers closer to the input encode simple, more universal features (like lines of various orientations in the example below)
  - Middle layers encode more complex features that together compose the target object
  - Layers close to the output are trained to recognize specifically the combination of features that correspond to the target object

Feature interpretation: example of face recognition

Early layers detect low-level features, such as edges.

Deeper layers detect increasingly complex feature, such as face elements.

Final layers capture full examples of the face, leading to labeling.



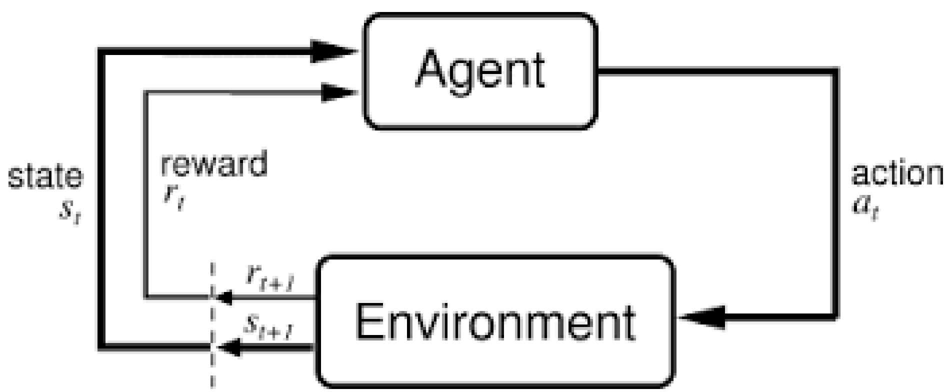
Source: Nvidia

Advise: Reinforcement Learning

- Deep learning (e.g. used to predict incidents) learns to pair data and incidents from past data and to predict future incidents based on real-time data. It does not suggest however which actions are appropriate on the basis of the prediction, a task left to human interpretation.
- Reinforced Learning (RL) extends the model to include actions and their impacts. By measuring the effects of the actions the system learns to suggest actions that are best suited to a specific situation.
- The mechanics of training are essentially the same as in regular neural networks, with the main difference being that the input to the network (state of the environment) is influenced by the network’s decisions (the network acts as an agent in the system).
- The actions decided by the network are graded by a reward function associated with a predetermined goal (e.g. maximize points won in a game).
- The network trains to learn (series of) actions that maximize the reward function over time. When a series of actions leads to high reward, the network reinforces this behavior in future decisions. The opposite happens for actions that result in low rewards. They are avoided in similar future situations.

Reinforcement Learning (cont.)

- At each time step t, the network (Agent) takes as input the state of the system (Environment) and the current value of the reward function.
- The network decides on an action, which is then implemented on the Environment.
- This results in a new state of the Environment and a new value of the reward function
- The network can learn from its rewards when it is in training mode, or simply decide actions based on previous training.



Actions can be, for example:
- Locate inspectors on certain places
- Change dynamic speed
- Open-close lanes
- Etc.

The environment includes:
- Traffic
- Incident
- Resources
- Etc.

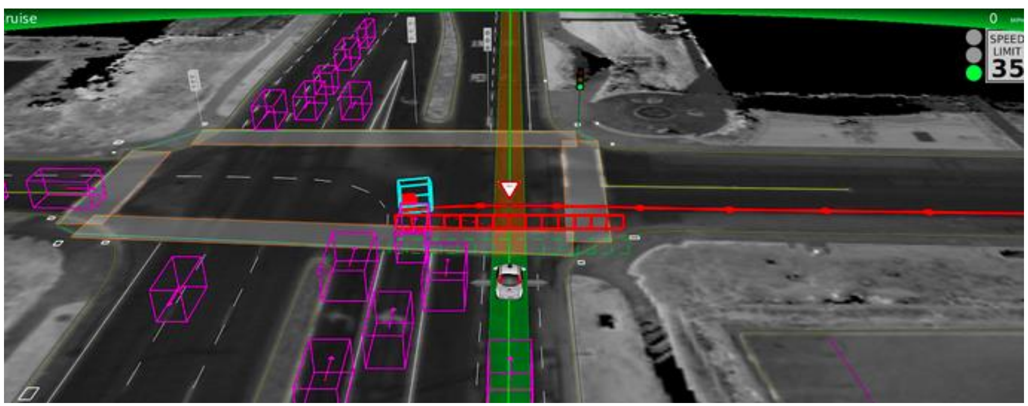
Reinforced learning: most common applications

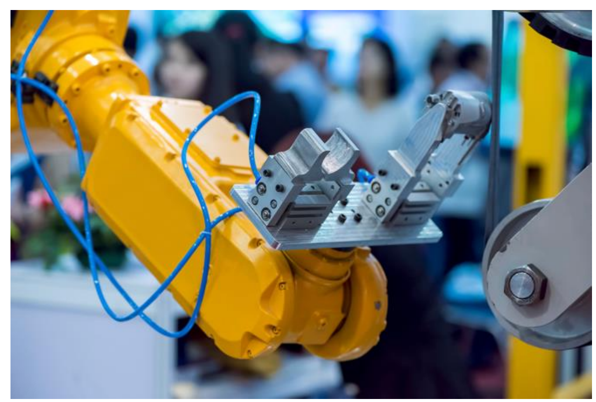
RL is a viable strategy in cases when:

- Learning by doing is viable in the real environment or on a simulated version of it
- There is a comprehensive data history on the environment and its response to actions to learn from
- Learning is continuous and the system needs to adapt to changing circumstances

Typical applications include:

- Autonomous Vehicles: learns motion and controls from environmental status and signals
- Finance: adapt transaction choices based and real-time feedbacks
- Robotics: teach movement by trial and error or mimicking human movement
- Games: learn from real and synthetic games and implement strategies that increase chance of winning





4

PREDICTIVE ANALYTICS, A.I.: SELECTED USE CASES

WHAT MACHINE LEARNING CAN DO: YEAR 2016

Input	Response	Application
Picture	Are there vehicles in the picture?	Automatic/streaming image tagging
Loan application	Will applicant repay the loan?	Credit card, loan approval
Advertisement plus user information	Will the user click on the ad?	Targeted commercials
Text in language A	Text in language B	Translation
Audio in language A	Audio in language B	Simultaneous translation
Sensors from machines	Is it about to break?	Preventive maintenance
Car camera and car sensors	Is the car free to move or likely to hit obstacle?	Self-driving car

In spite of the remarkable progress, Machine learning and AI have so far developed only for a small area of possible applications. In this subset they typically achieve better than human performances, and in spite of the narrow domain of applications, the technology will have significant economic and societal impact even at this stage.

Although Deep Learning was developed with some analogies with human cognition as guide, it derives its power from simple statistics, data availability and computation power.

Neural Networks can, given enough data, become very good at tasks for which a human brain would not be that good (or even hopeless), regardless of the task complexity and time available to resolve it. Incident prediction is a case in point, as it requires to make sense of numerical measurements coming from large arrays of sensors in real time.

Source: HBR, Andrew Ng

STATE OF MACHINE INTELLIGENCE APPLICATIONS: YEAR 2016

ENTERPRISE INTELLIGENCE

Many organizations combine internal and external data that can be analyzed using Machine/Artificial Intelligence (AI) to aid with both short term and strategic decisions. AI functions both to interpret raw data inputs (audio, video, sensor), as well as to combine multiple inputs into actionable intelligence.

ENTERPRISE FUNCTIONS

An increasing number of functions in large organizations can be automated or aided by AI. Layers of operation that are very repetitive or require parsing large amounts of data for their optimization can be effectively aided by AI systems.

AUTONOMOUS SYSTEMS

Together with the continuous improvement in the abilities of robotic systems, or precisely because of it, 3-D real world autonomous navigation on a large scale is around the corner. Self driving cars and drones have become a focus for regulators and stakeholders.

AGENTS

Although the promise of human-like intelligence is still projected to an unknown future, many narrower aspects of every-day and professional human interactions can be simulated and facilitated by AI assistants. The focus of big AI players such as Google and Facebook to put assistants into focus means that such applications will evolve significantly in medium term.

INDUSTRIES

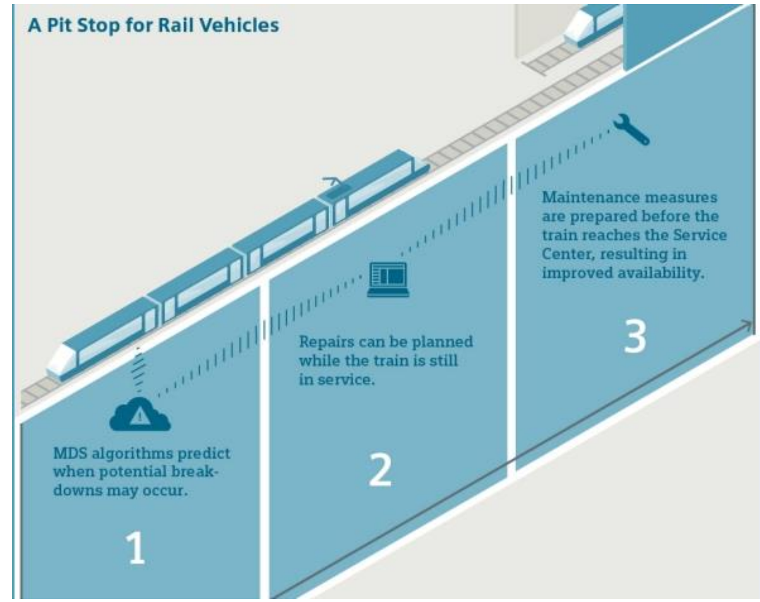
Across many core industries, AI applications are increasingly driving the facilitation of standard operations, and at the same time opening up new possibilities, as for example in the ability to speed up the design of new types of materials with pre-specified specs.

HEALTH CARE

Already having a deep impact in biology, through its applications in biochemistry, DNA analysis, and drug design, AI techniques are starting to be applied in personal health services and public health functions, putting new powerful tools in the hands of health care professionals, such as image recognition algorithms that can help evaluate scans.

Use case: predictive Maintenance

General concepts	• By collecting rich sensor information from machinery (vehicles, trains, engines) and infrastructure (roads, railways, etc.) it is possible to relate past incidents with sensor data patterns that led to them, and the sensor profiles that indicated future incidents. • This provides an opportunity of optimizing maintenance (fix what's broken) and preventive maintenance (replace parts on schedule even if they are not broken).
Example use cases	• Siemens has a collaboration with Spanish train company Renfe. An array of sensors on trains and tracks collects data which is transmitted to an analysis center in Allach, near Munich, where pattern analysis reveals possible malfunctions that could cause delays and outages before they happen. • In the UK, Network Rail collects data from sensors in the ground along the tracks. Pattern analysis indicates points in danger of deformations so that they are repaired timely, enhancing the safety of the network
Benefit	• It allows to reduce delays significantly • Incident and malfunction prevention • Cost reduction (maintenance is implemented on need, not on schedule)
Workflows impacted	• Maintenance scheduling • Inventory management for repairs • Incident management (data meta-analysis to inform predictive system)

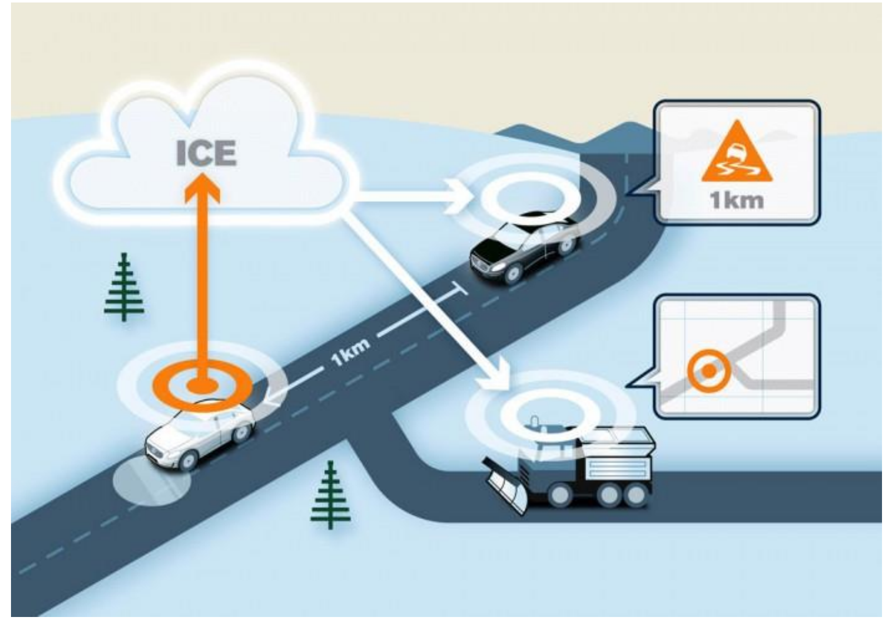


Source: Siemens

Source: IBM

Use case: Distributed Intelligent Transport Systems

General concepts	• Advances in peer-to-peer communications (ad hoc networks) and distributed computing (low energy chips, mobile devices) allow the formation of real-time networks based on locality. • Information can be shared among vehicles and hubs installed along the highway infrastructure. Data can be quickly analyzed in the hubs or vehicles to offer real time diagnostics to drivers and traffic managers.
Example use cases	• Volvo is developing a system that will estimate road friction and share information about icing conditions to other nearby vehicles and maintenance services. • In Lisbon and Pisa experimental distributed ITS systems use hubs along main roads that analyze real-time data from a variety of sensors, using Machine Learning algorithms to categorize traffic conditions and incidents and distribute messages to drivers locally. The hubs communicate important information to traffic control centers.
Benefit	• Latency and scalability issues addressed by modular architecture • Customization to local parameters (e.g. weather conditions, road details) • Lowers barrier for testing and rolling out new features
Workflows impacted	• Traffic/Incident Management • Infrastructure Maintenance • Data Warehousing

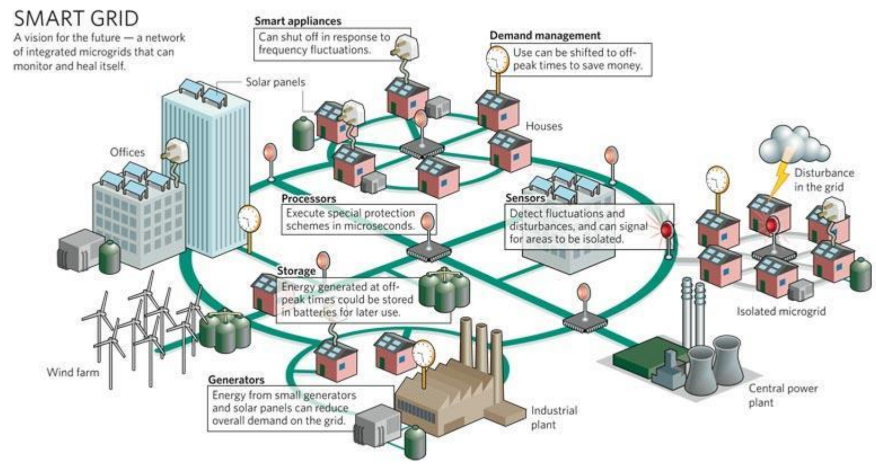


Source: Thenewswheel

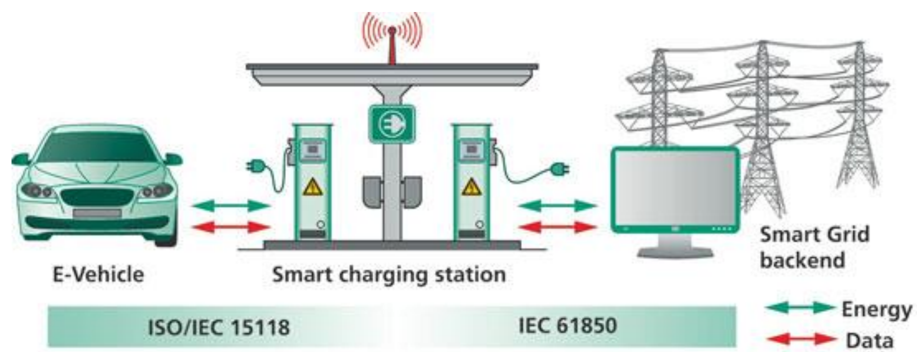
Source: PubMed

Use case: Smart Grid

General concepts	• Production of electricity is decentralized and diversified by the move to renewables, as consumption keeps growing. To stabilize delivery and optimize consumption vs. production, the network is managed in real time, using data from smart meters and home devices, stations and infrastructure sensors that is continuously analyzed by algorithms. • Electric Vehicles will eventually contribute significantly to the smart grid function, as directing them to recharging stations can be optimized to absorb excess energy production in the grid.
Example use cases	• In NYC, ConEdison in partnership with Columbia University have deployed a system of smart meters and device condition sensors that allows the prediction of outages using statistical and machine learning tools. The system can alter the distribution of loads to relieve pressures on the network and allow for preventive maintenance. • Several US states have run successful pilots using price incentives to shift EV recharge load to off peak hours and areas.
Benefit	• Optimized consumption patterns reduce need for building up expensive peak capacity. • Disruptive outages mostly prevented • Environmental benefits from production efficiencies
Workflows impacted	• Maintenance scheduling • Network management • Inventory management for repairs



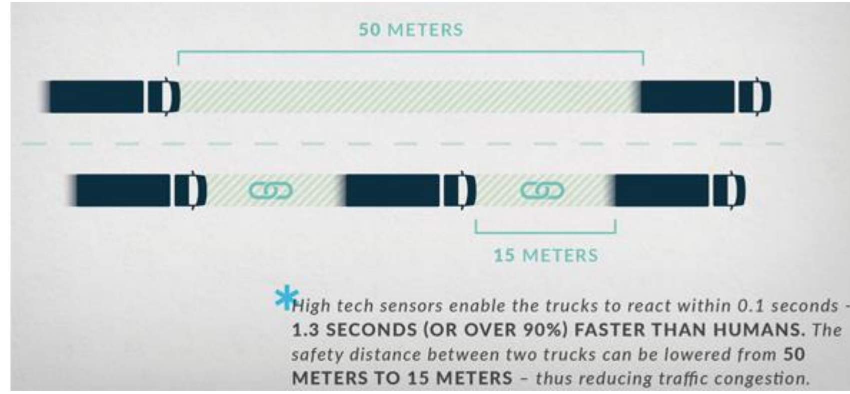
Source: 21centech blog



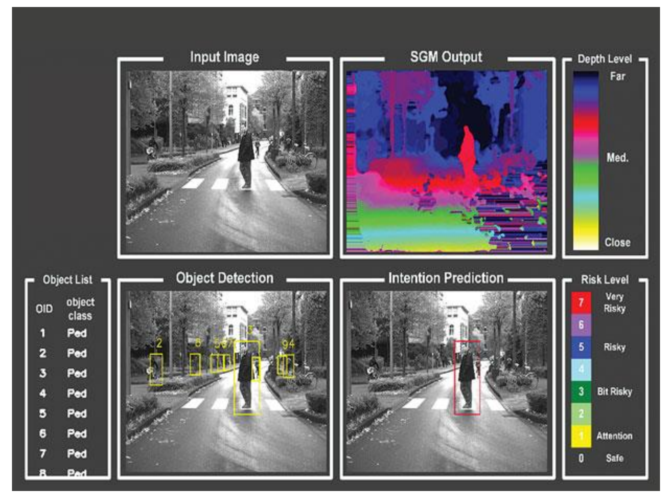
Source: Nanowerk

Use case: Autonomous Vehicles

General concepts	• Driving a vehicle is too complicated to describe by a finite set of rules. To advance self-driving technology, manufacturers have turned to “learn by example” using deep neural networks and reinforcement learning algorithms that can learn from human driving data. • Autonomous vehicles use neural networks both to recognize objects and sounds in their environment and to make decisions on the state of the vehicle. Most of the analysis is run hardwired on specially designed chips that allow for millisecond-time evaluations and decisions.
Example use cases	• Car manufacturers, regulators and large technology companies are actively developing frameworks for the rollout of autonomous technologies. Although most major manufacturers already include some kind of driver assistance, the integration of fully autonomous vehicles in the flow is expected for the next decade. • The technique known as “platooning” in which several vehicles with autonomous capabilities travel as a tight group in short distances (to minimize space and fuel consumption and improve safety) is being tested in the EU by a consortium of truck manufacturers.
Benefit	• Energy/Vehicle use Efficiency • Improved Safety • Improved traffic conditions
Workflows impacted	• Traffic/Incident Management • Commercial driving • Logistics chains



Source: Traffic Technology Today



Source: IEEE Spectrum

5

WORKFLOWS AND IMPACTS

Traffic management desired effects

Road Network Sections	Key Desired Effects
Major metropolitan areas	• Safety • Functionality and predictability of travel and transport chains • Attractiveness of alternative travel modes (public, pedestrian and bicycle traffic) • Contain traffic increase
Urban areas	• Safety • Functionality and predictability of travel and transport chains • Attractiveness of alternative travel modes (public, pedestrian and bicycle traffic)
Main highway and interconnecting network	• **Safety** • **Reliable 24/7 access** • **Incident-free** • **Predictable travel and transport**
Other road sections	• Safety • Reliable travel and transport
Special sites	• Reliable access • Travel and transport is incident-free and safe

Adapted from: Finnish Transportation Agency

Traffic management is designed to achieve some specific effects at various scales.

RWS mandate is specific for a portion of the national transportation network (in bold). The desired effects of traffic management are nonetheless similar at all scales.

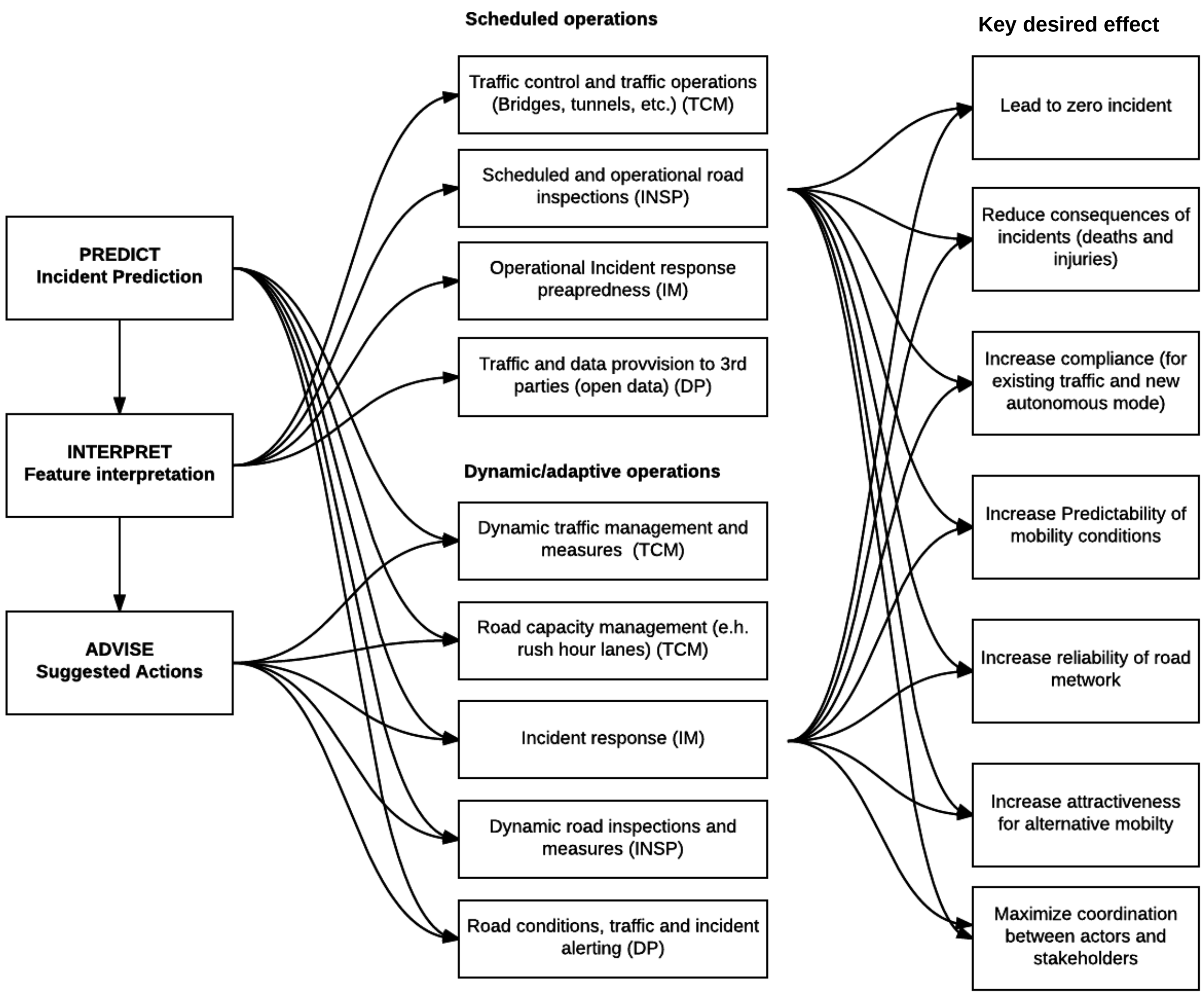
RWS Traffic management areas of activity

Area	Example activity
Traffic control and management (TCM)	• Traffic control in regular conditions (e.g. operate bridges and tunnels) • Traffic control during events • Dynamic traffic management (e.g. speed control, inflow lanes) • Capacity management (e.g. rush hour lanes)
Incident management (IM)	• Incident preparedness • Incident response: all activities triggered by an event, with the goal of reducing impacts on people, assets and the traffic flow • Cooperation with ambulances, police, fire brigades and other authorities
Crisis management CM)	• Preparedness and response to large events, that require escalation of management and resources • Floods, large incidents, explosions, etc.
Road and infrastructure inspections and management (INSP)	• Ensuring roads are in good, safe conditions, remove obstacles • Measures to prevent incidents, such as in case of icing • Fines and tickets
Data and Information provision to 3rd parties (DP)	• NDW (national data warehouse for traffic) – deliver traffic information to the public and other organizations

RWS Traffic management (Verkeersmanagement) comprises a specific set of activities, as described in the table.

Predictive capabilities are potentially affecting the majority of tasks of RWS.

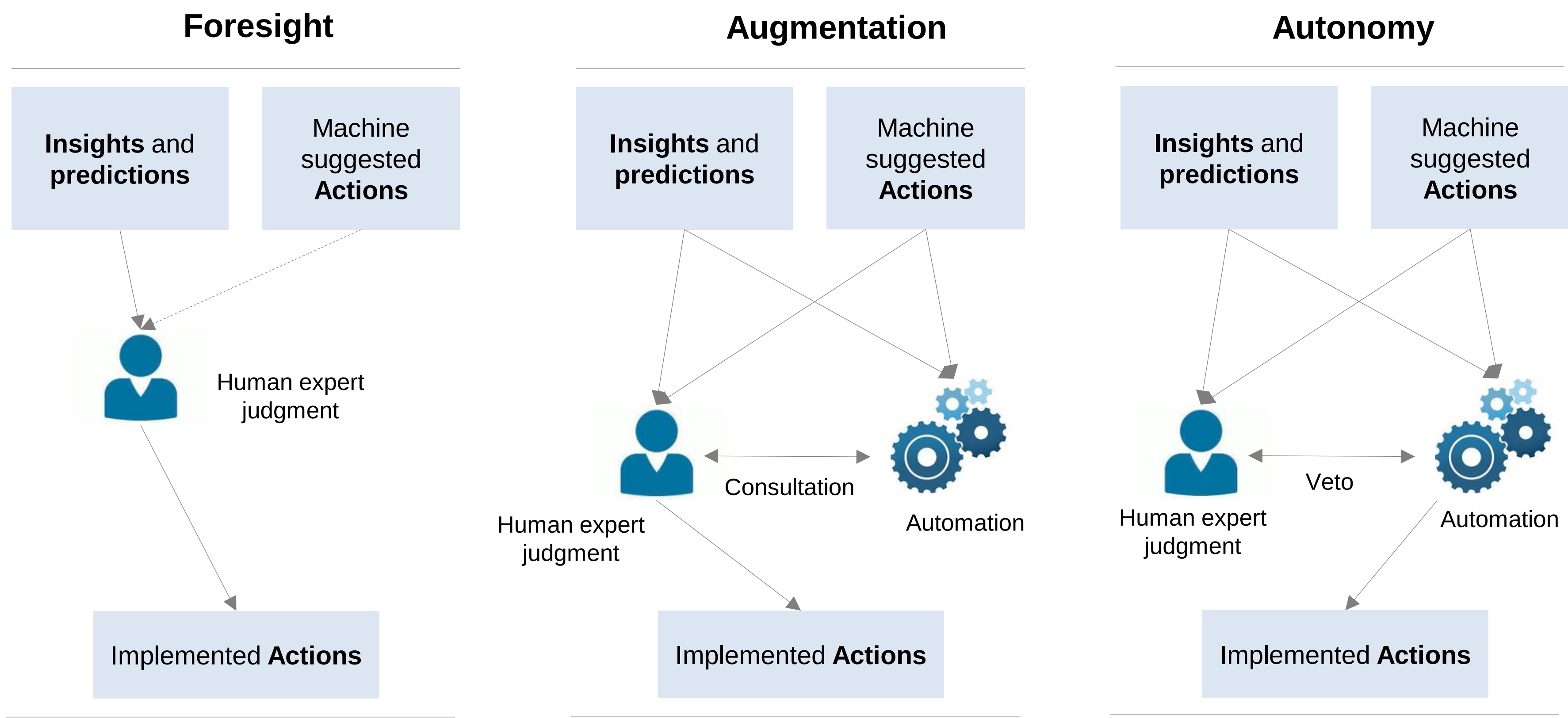
Linking predictive analytics to traffic management goals



The logical path between predictions, interpretation and advise leads to the desired effects of traffic management through the core workflows of traffic and incident management.

This diagram serves as a reference for specifying the relationship between prediction-interpretation-action and key desired effects.

Traffic management: from monitoring to autonomy



All actions implemented are based on human decisions. Decisions are taken considering insights and foresights available. Machine suggested actions are used as a reference.

All actions implemented are human responsibility but are based on consultation between humans and automations. Humans regularly accepts machine suggestions.

All actions implemented are the results of automations based on insights, predictions and machine suggested actions. Human role is veto and supervision.

Impacts of predictive analytics on traffic management

Area	Example activity	Foresights	Augmentation	Autonomy
Traffic control and management (TCM)	• Regular traffic control • Traffic control – events • Dynamic traffic management (e.g. speed control, inflow lanes) • Capacity management (e.g. rush hour lanes)	• Bridges, signs, lanes are operated as usual, consulting time-space specific incident predictions	• Some decisions are automated based on predictions (e.g. dynamic speed). • Machine suggested actions are consulted before making other decisions	• Most information-based actions are automated, under supervision • Human intervention is limited to anomalies and special cases
Incident management (IM)	• Incident preparedness • Incident response • Cooperation with ambulances, police, fire brigades and other authorities	• Location and planning of inspectors and resources are based on predicted need	• Location and planning of inspectors and resources are intrinsically dynamic and made on the fly based on needs	• Location and planning of inspectors and resources is delegated to intelligent systems
Crisis management CM)	• Preparedness and response to large events (Floods, large incidents, explosions, etc.)	• Predictions help create context awareness, for instance on traffic and people flows	• Some basic functions can be automated (e.g. road management) reducing burden for response teams	• NA
Road and infrastructure inspections and management (INSP)	• Ensuring roads are in good, safe conditions • Measures to prevent incidents • Fines and tickets	• Inspections can be scheduled accounting for predicted needs	• Location and planning of inspectors and resources are intrinsically dynamic and made on the fly based on needs	• Location and planning of inspectors and resources is delegated to intelligent systems
Data and Information provision to 3rd parties (DP)	• NDW (national data warehouse for traffic) – deliver traffic information to the public and other organizations	• Provide data and predictions to partners and end-users	• Provides insights on actions that will be taken in the near future by RWS	• Automate information provision to partners, end-users and autonomous vehicles

6

SELECTED OPPORTUNITIES

Three opportunities for the short term

	Dynamic inspection planning	Foresight-based road management	Open prediction data
Current status	Inspections are planned and scheduled on expected needs. Static areas of responsibility are assigned to traffic inspectors.	Speed limits as well as lane open/close decisions are based on monitoring the current situation and on expert judgment.	Vast amounts of open traffic data are shared with transportation partners and end users. The interpretation of data is done by end users.
Role of predictive analytics	Information on when and where future incidents will take place offers the opportunity of revising schedules and planning based on dynamic needs rather than history and expectations.	Incident predictions and data feature interpretation provide additional evidence on future road status. Road management tools can be used to selectively reduce the chance of incidents, as well as to maximize the travel flow.	Data interpretation in the form of real-time incident prediction and additional foresights enhance the value of RWS open data.
Implications	Schedules can be made dynamic and agile: the baseline (current method) can be compared with real-time predictions and lead to schedules and allocations based on expected needs.	Road management measures can combine experience with machine learning. Decisions can be based more precisely on local conditions.	The existing data stream can be complemented by a stream of interpreted data, for instance the chance of incidents, increasing the value and relevance of open data provision.

Dynamic inspection planning

Basis for decision

- Historical data – statistical data
- Peak hour demand
- Weather and other contingent factors
- Status of the road
- Feedback from the operations/partners
- ..

- Experience form operations
- Team available
- Resources available
- …

Inputs from Predictive Analytics

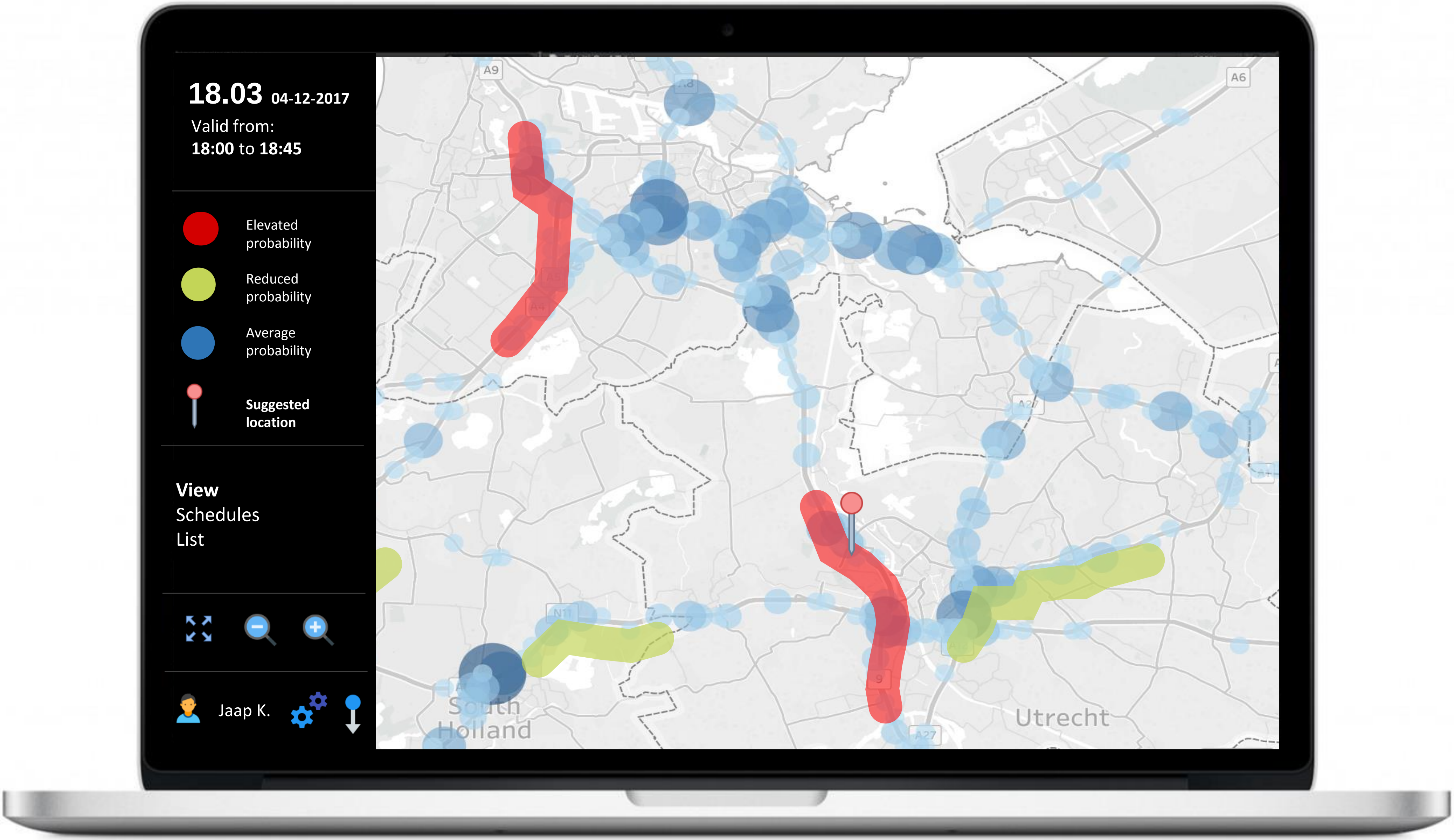
- Probability of events in sections of the road in a specific time window
- Data features explaining the basis for the predictions
- Accuracy of predictions recorded over time

Workflow

- Schedule and team size is based on experience, expected conditions, such as peak hours
- Resources are allocated to cover sections of the road network
- The allocation is static and changes ad hoc with top-down decisions

Workflow augmentations

- Demand for resources at specific times and places can be fed to the allocation practice
- Scheduling can gradually change from static to adaptive to fully dynamic without pre-defined arrangements
- The schedules are not individual, but collective, and change for the team as a whole (one schedule can be changed as a result of a change in another inspector's schedule)


18.03 04-12-2017
Valid from:
18:00 to 18:45
Elevated probability
Reduced probability
Average probability
Suggested location
View
Schedules
List
Jaap K.
A9
A6
South Holland
Utrecht
A27

Foresight-based road management

Basis for decision

- Historical data – statistical data
- Current road status, road works and incidents
- Traffic speed and flow data
- Weather and other contingent factors
- ..

- Experience form operations
- Resources deployed to manage traffic and incidents
- …

Workflow

- Speed boards are updated to force speed limits
- Lane sign (lane close-open) are updated to force flow structure
- Board text and alerts are updated for informing travelers and altering behaviour

Inputs from Predictive Analytics

- Probability of events in sections of the road in a specific time window
- Data features explaining the basis for the predictions
- Accuracy of predictions recorded over time

Workflow augmentations

- Speed boards, lane signs, board text and alerts are updated based on predictions to alter the change of incident
- Speed boards, lane signs, board text and alerts are updated based on interpretations of data features, to alter the chance of incident


RING-NOORD 3km file
RING-ZUID: HOGE KANS ONGEVAL
70
70
70


RIJ VOORZICHTIG!
HOGE WAARSCHIJNLIJKHEID INCIDENT VOORUIT.

Open prediction data

Status

- NDW publishes open traffic data for the Netherlands
- Data is structured in themes and provided to partners for uses in traffic information, traffic management and R&D
- Data is available in real-time and for historical datasets

Workflow

- Data is collected by a variety of public authorities and consolidated by NDW: data is captured by multiple systems and processed in a national data warehouse
- Data is distributed to partners through online or batch channels
- Data is cleaned and validated, but not interpreted in terms of incidents, travel risks etc.

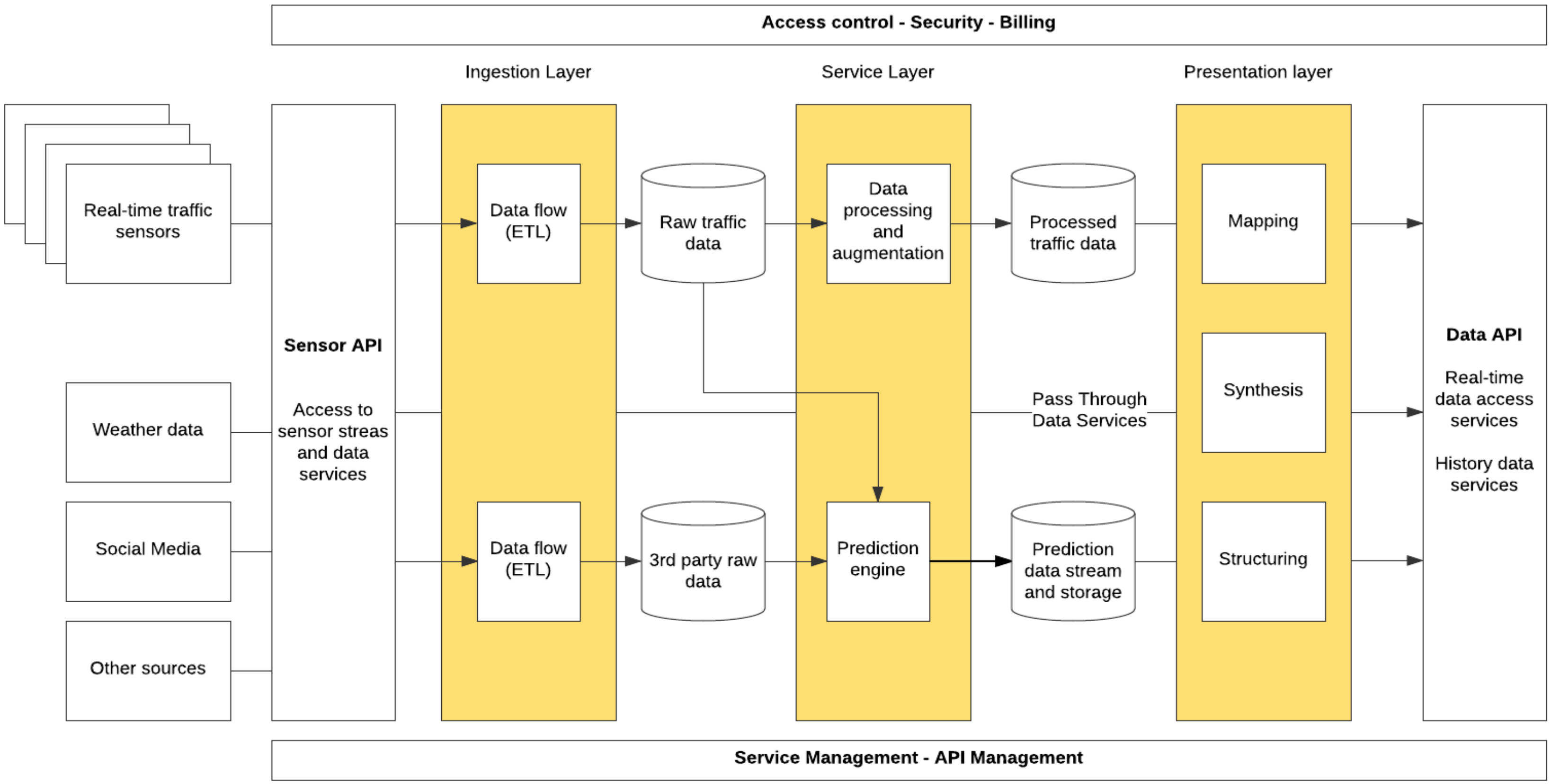
Inputs from Predictive Analytics

- Probability of events in sections of the road in a specific time window
- Data features explaining the basis for the predictions
- Accuracy of predictions recorded over time

Workflow augmentations

- Additional data themes are available real-time and batch, such as:
    - Incident probability
    - Status of data features increasing incident probability (e.g. road status)
    - Additional data sets related to safety (e.g. weather)

Extended architecture open prediction data



Navigation Apps
Infotainment
Data brokers
Media
Radio
Smart Cities
Info channels
Traffic Links
R&D
Local governments
Policy makers

MESSY WINTRY TRAFFIC AHEAD!
SafetyPLUS ACTIVATED
70
54
mph
Lawler Ranch Rd
Moore Rd
200 mi
Always Keep Your Hands on the Wheel
Be Prepared to Take Over at Any Time
P R N D

7

OBSERVATIONS AND CONCLUSIONS

Summary

The project provides a first assessment of the implications of predictive analytics applied to traffic and incident management. The main goals of the project are to assess:

- Which workflows and processes are likely to be affected most?
  - How does the role of traffic managers and dispatchers change?
  - Once autonomous vehicles start operating, can RWS use this opportunity to inform drivers and vehicles, and manage traffic through algorithms?
- What are the risks and opportunities that must be addressed in the traffic management process?

The project provides a basic framework to shape these questions.

The premise of the project is that predictive analytics should be seen in the context of a staged development that starts with making the mobility system transparent eventually leading to a degree of automation on traffic management.

Furthermore, predictions are interpreted in a broad sense, as “probability that something happens somewhere at some time” but also in terms of which data features lead to the prediction. In addition, the systems can be naturally extended to suggest actions and not only to provide foresights.

Based on conversations with experts within an outside of RWS, it emerges that three workflows are natural short term candidates for testing the implementation of predictive analytics:

- Traffic management resource allocation
- Traffic management measurements and information to travelers
- Open data and access to traffic and value added services

For each of them the project has elaborated a high level implementation scenario as well as some visual representations of what the system may imply in practice.

Observations

The key premise for the application of A.I. to incident prediction is to validate the ability of machine learning to produce superior insights compared to statistics alone. This has been proven.

However, there are several open questions that need to be addressed for the system to be used in operations, such as:

- Which “prediction” and which “quality” provide most value to traffic and incident Management ?
- How far should the system predict events or suggest courses of action?
- How can the system be tested in practice to experiment with its use and with its applicability?
- What level of machine automation is acceptable and useful to achieve the desired effects of traffic management?
- What is the operational path from making the traffic system more transparent to enabling autonomous decisions? Where should the organization aim to?

The reliability and accuracy of predictions is a key determinant to the extent of utilization of predictions. However, value to traffic management can be added even with partial predictions capabilities to augment human judgement.

In the use cases explored there are however several open questions which require additional work and research:

- What is the level of reliability and accuracy that would make traffic managers comfortable with considering predictive analytics?
- What are the implications of using this data in operations, such as in terms of liability?
- What is the degree of acceptance from experience traffic managers? Is the system considered an aid or a threat?

Linking predictions with actions

A natural progression of A.I. applied to traffic management relates to advising actions. A machine trained in this way would be able not only to predict incidents but also to suggest which actions are more appropriate to anticipate them. This closed-loop mechanism alters the state of the system and the the predictions through actions. It is meant to lead to the best achievable state of the system given the variables that cannot be controlled (e.g. weather) through selecting the most valid actions that can be controlled (e.g. traffic management measures taken in real time) with two complementary goals:

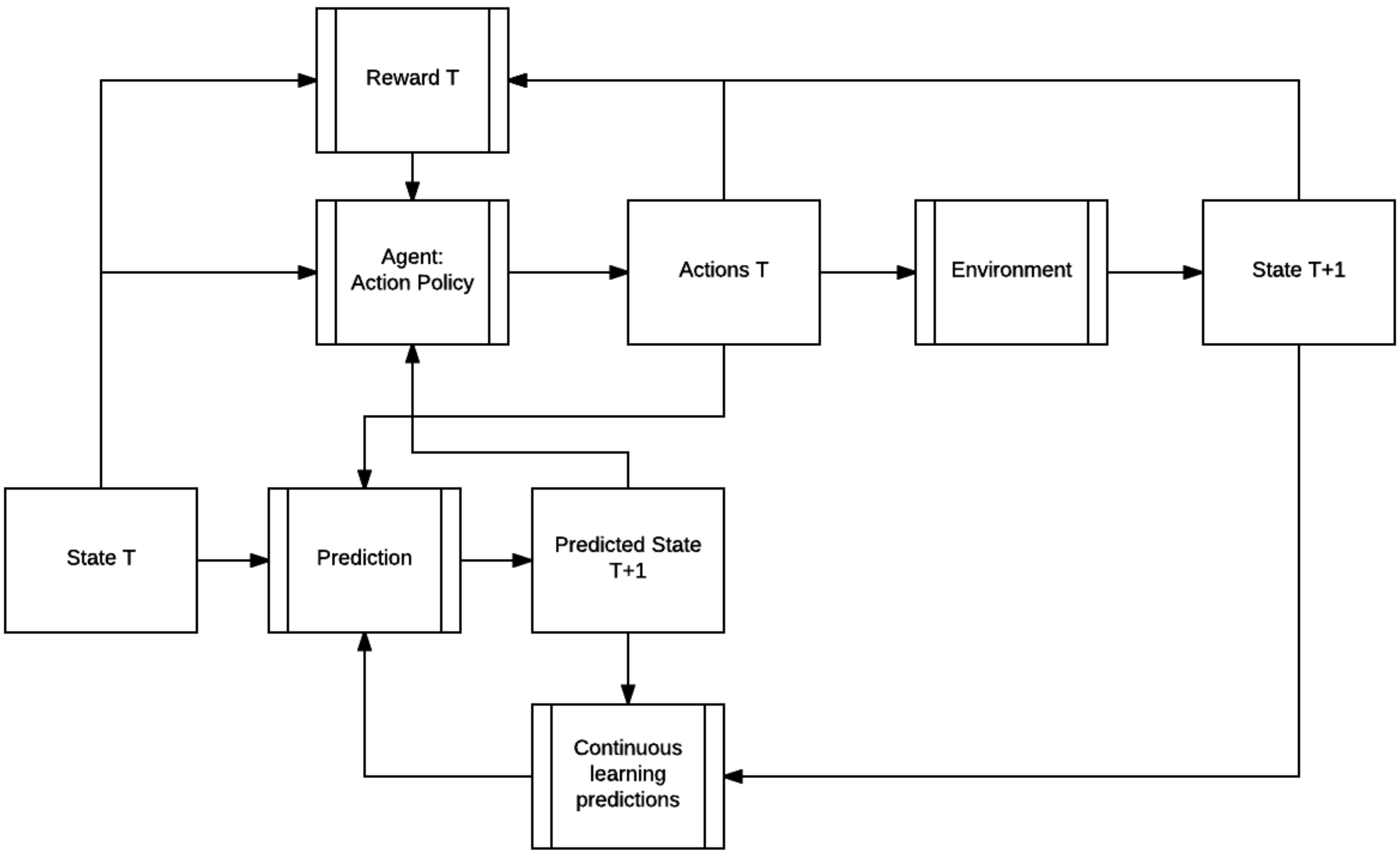
- To minimize the chance of incidents
- To minimize the disruption to the traffic flow

A possible implementation of the approach is through reinforced learning, whereby the system learns from past data, incidents and actions that were taken by RWS or partners, to pinpoint which actions are more likely to be effective in real-time. The system would thus not act on system status and actions. With state we include traffic, incidents, resources in use, road woks, weather, lanes operational etc.

With actions we include: information to drivers, information to AVs, speed limit changes, lane opened/closed, location and scheduling of inspections etc.

The general schema is illustrated in the next chart. In general terms, the idea is that by capturing (in some digital form) the set of actions that can be implemented and by linking their success to predictions, the system can be used to recommend which action to take at which point in time, augmenting or automating human decision making.

Linking predictions with actions: a general schema for reinforced learning in traffic management



Actions:
- Info to drivers
- Info to AV
- Speed limit changes
- Lane opened/closed
- Inspector relocation
- Etc.

State:
- Traffic
- Incidents
- Resources
- Inspectors
- Road works
- Lanes operational
- Etc.

A path forward

To address some of the open questions and opportunities described in the project, below a possible series of actions:

- Address the reliability and use in operations of a predictive system. It is useful to identify a test area, for instance A10, A12 or A15-A16 around Rotterdam, and create a program of incremental updates of the prediction system to validate accuracy and consistency over time in collaboration with the local traffic center.
- Explore the feasibility of reinforced learning. This is in order to understand the technical needs (for instance, which actions can be classified and digitized as a form of “catalogue” of possible actions) and the degree to which the system is practical, possibly for subset of use cases such as automatic speed change or road open-close.
- Develop the three use cases. There is a need to develop them to the point at which it becomes clear:
  - How they can implemented technically, for instance through demos and POCs
  - Which are the specific workflow changes that are introduced
  - What is the ROI and along which dimensions
  - What is the trigger for adoption and the organizations measures needed.

A

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