



UPTAKE<sup>®</sup>

# Applications of Industrial AI

**Jake Bartolone**  
Engineering Manager, AI/ML Platform  
[Jake.Bartolone@uptake.com](mailto:Jake.Bartolone@uptake.com)



# Overview of IoT

The Internet of Things is a system where physical things are connected to the Internet. Connectivity is enabled by sensors within or attached to the items

Bringing this kind of “super visibility” to industries provides endless business possibilities – imagine utility companies that can predict service outages, airlines that can remotely monitor plane performance and healthcare organizations than can base treatment on real-time genome analysis.

IoT market will be **\$14.4 Trillion by 2022** (Cisco), additional areas of investment include:

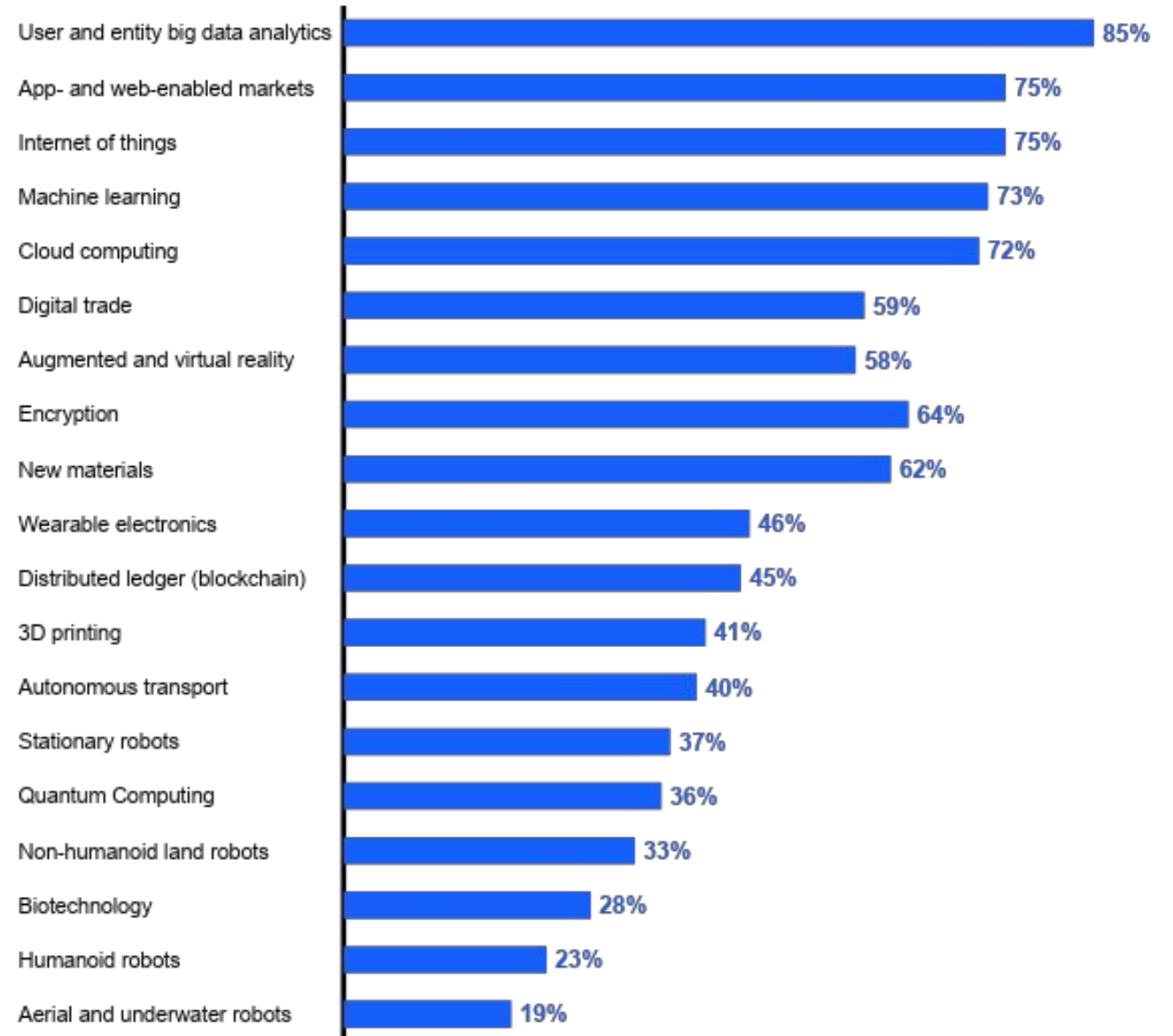
- Reducing The Time-to-market: **\$3T**
- Improving supply chain and logistics: **\$2.7T**
- Cost reduction strategies: **\$2.5T**
- Increasing employee productivity: **\$2.5T**





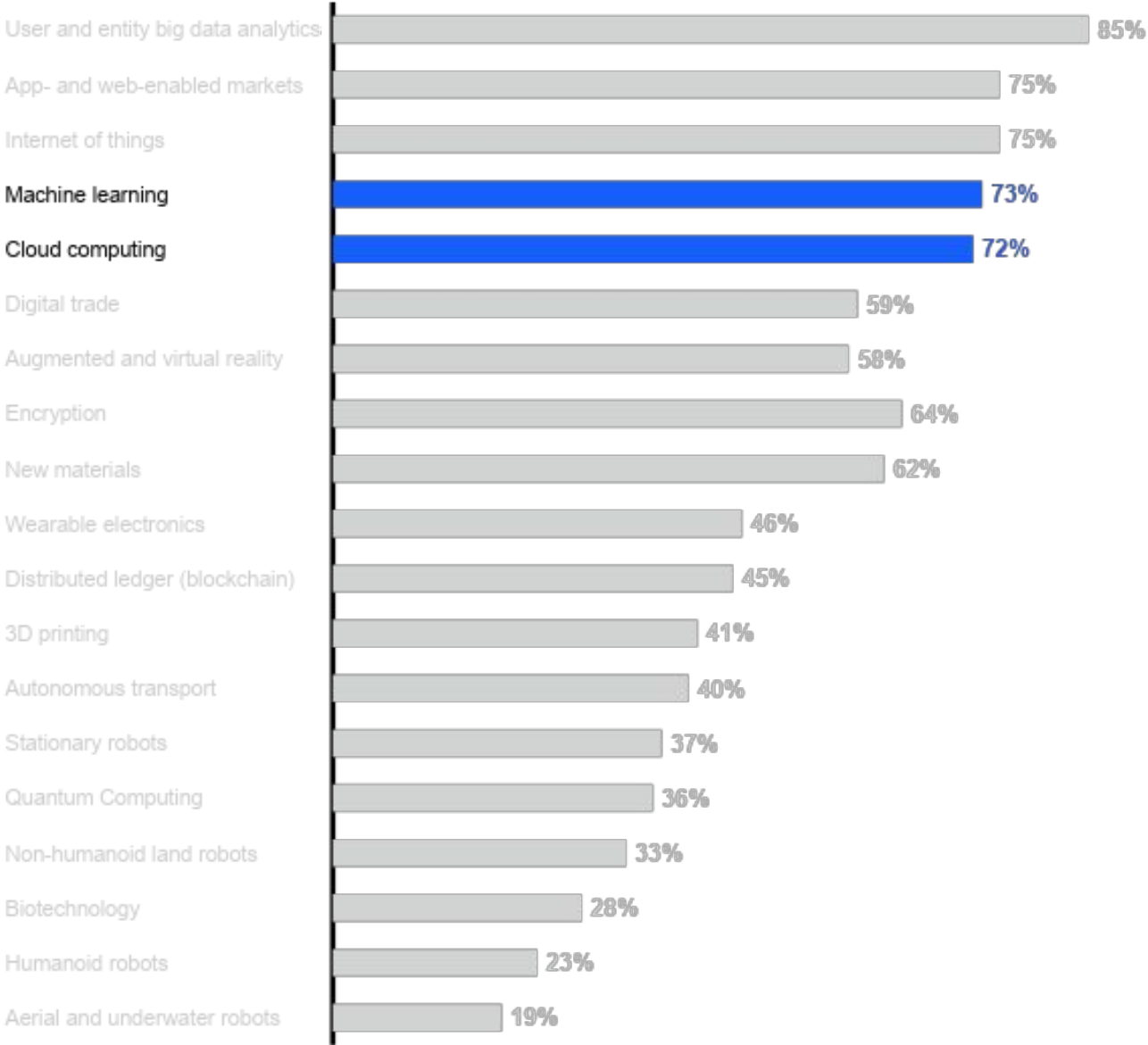
# AI Adoption

Technologies by proportion of companies likely to adopt them by 2020 (projects)





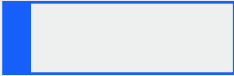




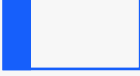


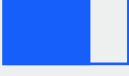

# AI, IOT & ML Hand in Hand





# Buckets of Use Cases

Potential economic impact of IoT in 2025, including consumer surplus, is \$3.9 trillion to \$11.1 trillion.

Settings	Size in 2025 <sup>1</sup> \$ billion, adjusted to 2015 dollars	Major Applications
Human	 170-1,590	Monitoring and managing illness, improving wellness
Home	 200-350	Energy management, safety and security, chose automation, usage-based design of appliances
Retail environments	 410-1,160	Automated checkout, layout opination, smart CRM, in-store personalized promotions, inventory shrinkage prevention
Offices	 170-1,590	Organizational redesign and worker monitoring, augmented reality for training, energy monitoring, building security
Factories	 1,210-3,700	Operations optimization, equipment maintenance, health and safety, IoT-enabled R&D
Worksites	 160-930	Condition-based maintenance, reduced insurance
Vehicles	 210-740	Public safety and health, traffic control, resource management
Cities	 930-1,660	Public safety and health, traffic control, resource management
Outside	 560-850	Logistics routing, autonomous cars and trucks, navigation
TOTAL - \$3.0 TRILLION – 11.1 TRILLION		

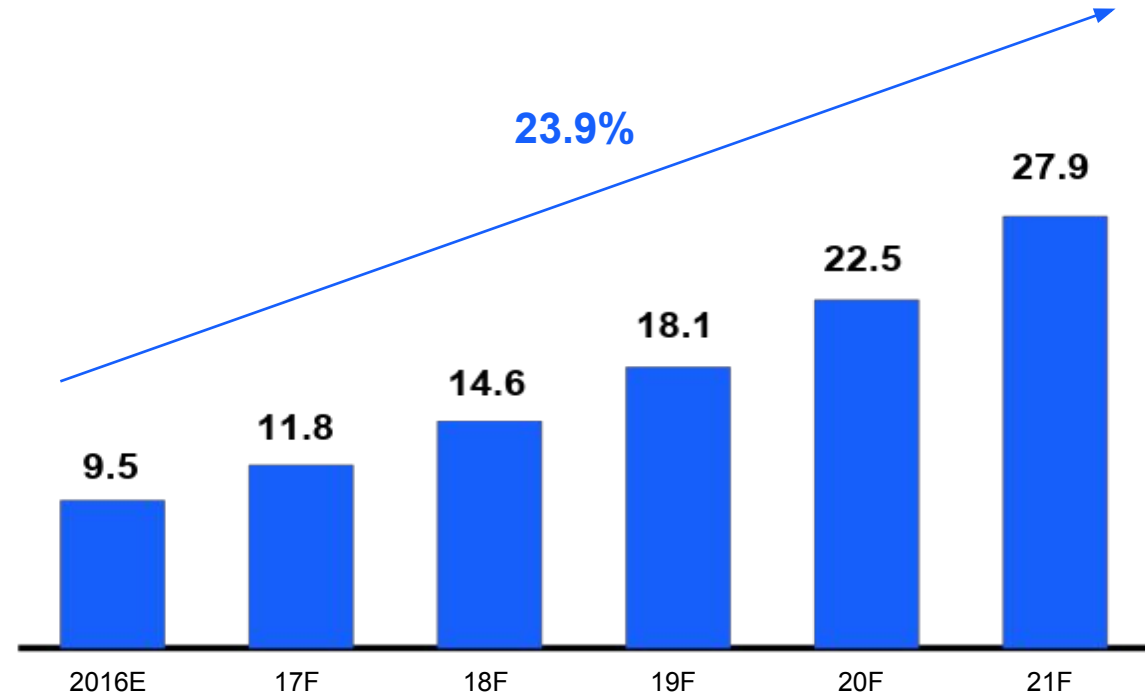
# Use case: fleet management



Improve productivity, reliability, and safety of supplier fleets

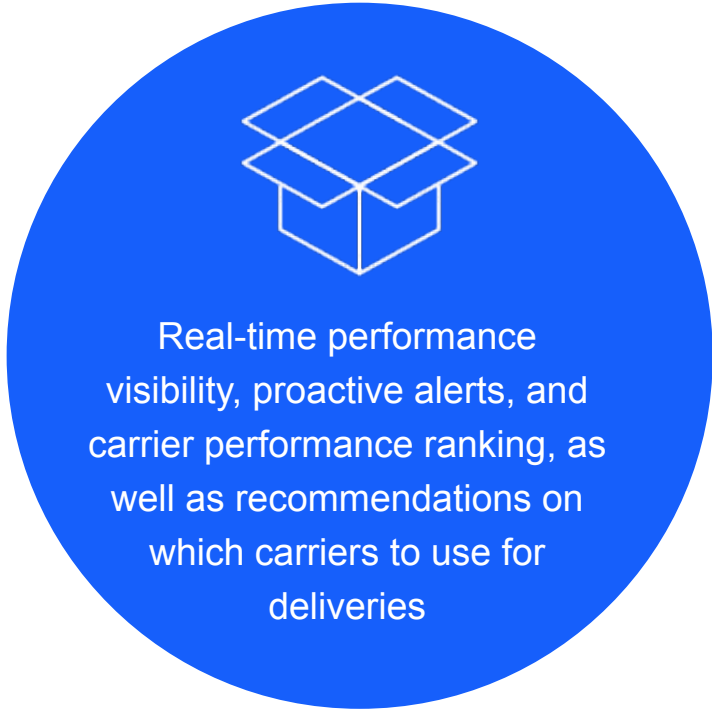
## Fleet management global TAM forecast (2017E - 21F)

Billions of dollars

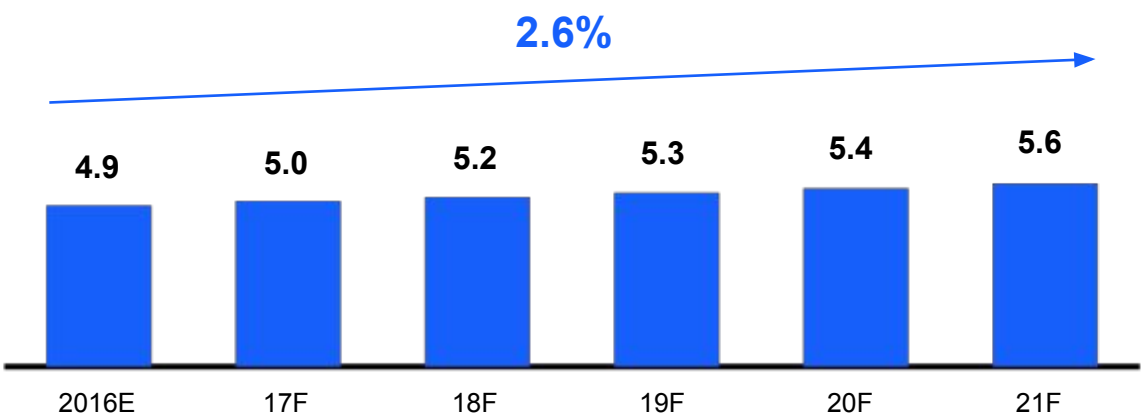


The fleet management market, which includes all operation, asset, and driver management technologies and services, is **projected to grow 24% p.a. to 2021, reaching \$28B**

# Use case: on-time-in-full shipping



OTIF penalties global TAM forecast (2017E - 21F)  
Billions of dollars



When scaling current Conagra Brands OTIF penalties to the global consumer packaged goods market, penalties are projected to grow **2.6% p.a. to 2021, reaching \$5.6B**



# Failure prediction and prognostics across industries



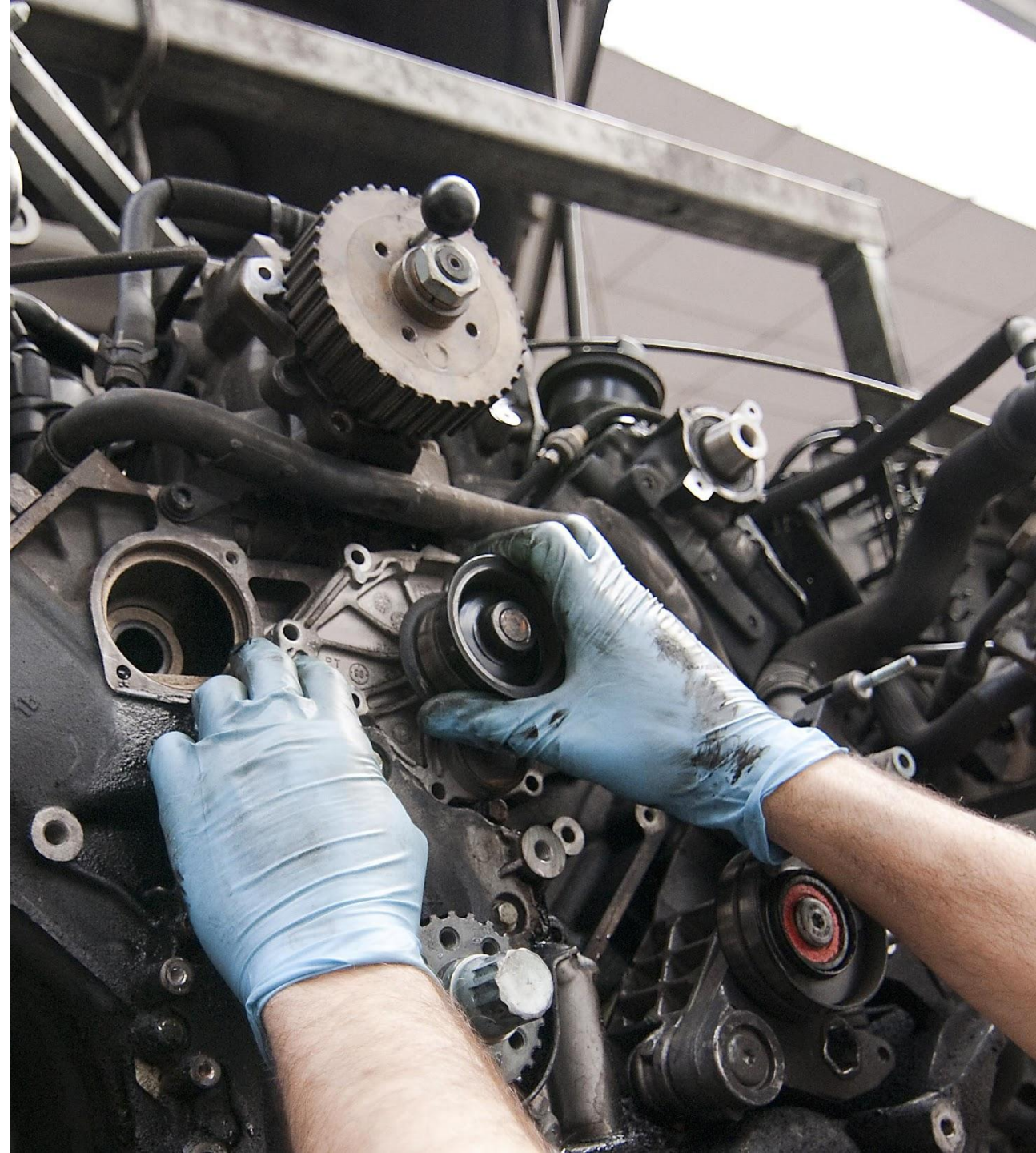


# Failure Prediction

## What is it?

Leading up to machine failure, it is usually possible to identify a decrease in performance that indicates an impending problem. The **prognostic/failure prediction model detects these decreases as soon as possible** and alerts analysts, who can then take preventive actions and minimize repair costs.

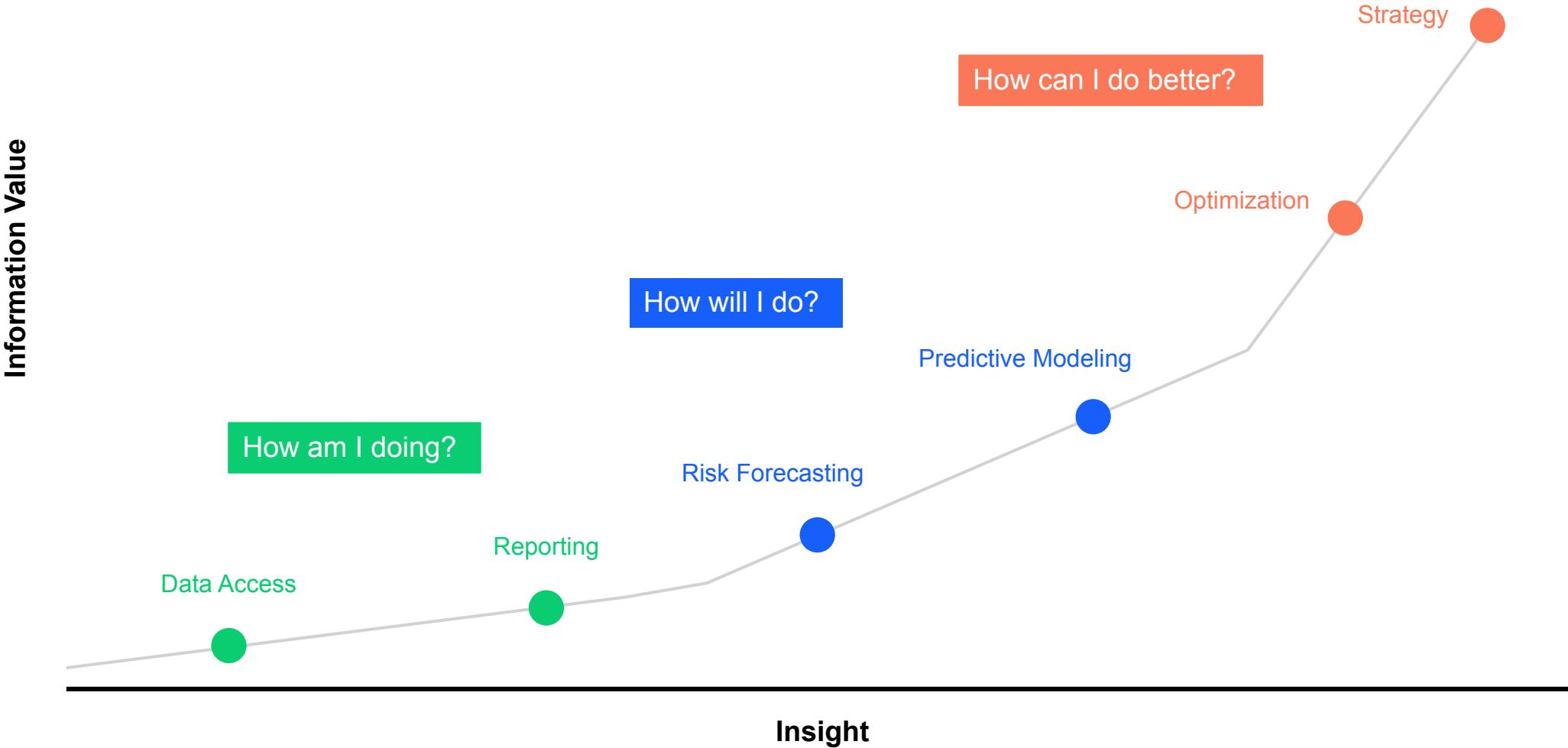
- When a machine is no longer able to perform its intended function, the cost of repair as well as the network disruption from machine downtime can be significant.
- If caught early enough, the repairs may be minor and the downtime can be planned, minimizing costs. However, the longer the potential failure goes undetected, the more expensive it becomes to repair, ultimately hitting its peak in cost when the machine fails.





# Analytics value curve

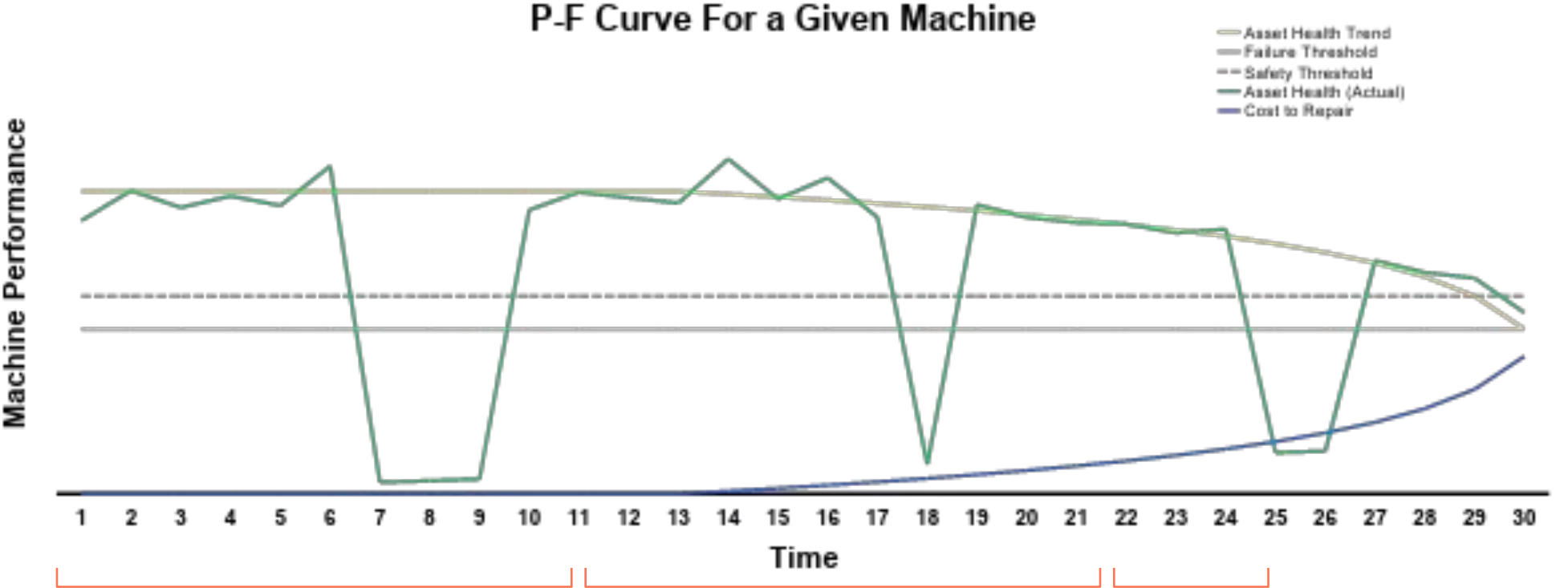
## Levels of Analytics





# P-F curve for a given machine

The P-F Curve shows how a machine fails and how early detection of a failure provides time to plan and schedule the replacement or repair of a failing part



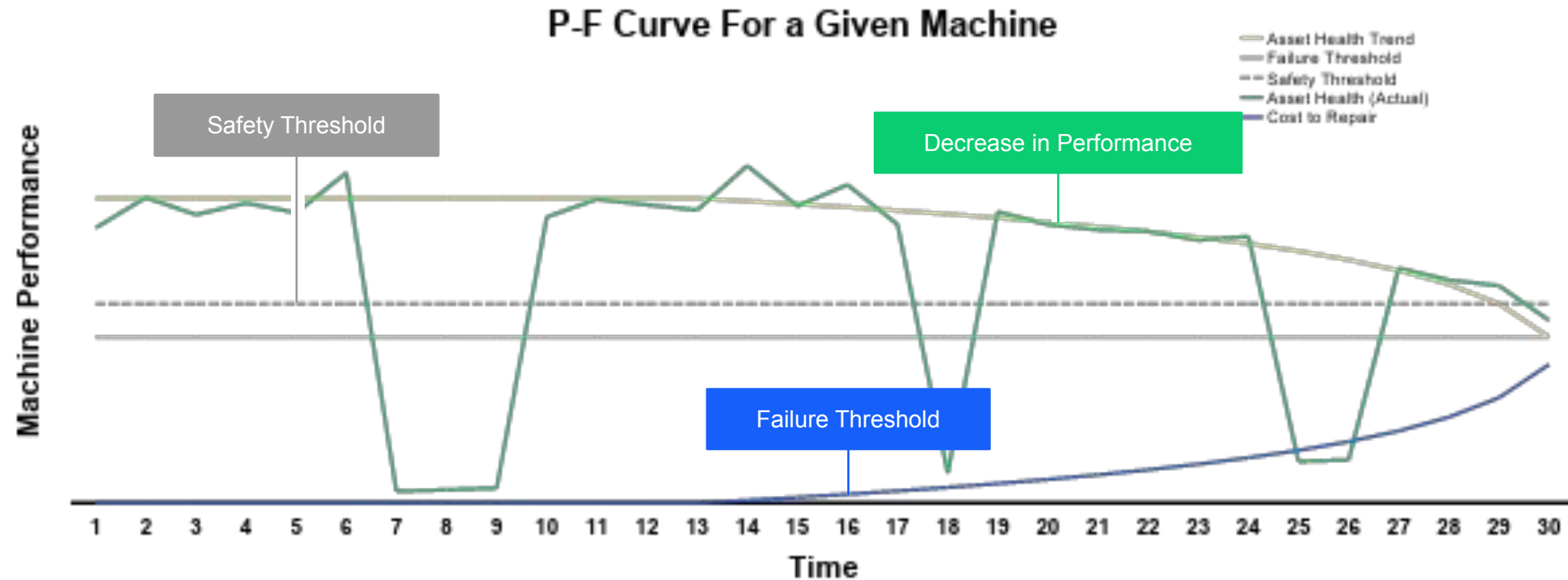
- Machine is operating normally, subject to random noise
- Failure threshold is known
- Safety critical thresholds have been established
- Machine starts to show signs of decreased performance
- At this point machine can still be repaired for low-cost
- Machine hits safety critical level
- Cost to repair is SIGNIFICANTLY higher than if early intervention had taken place



## P-F curve for a given machine

12

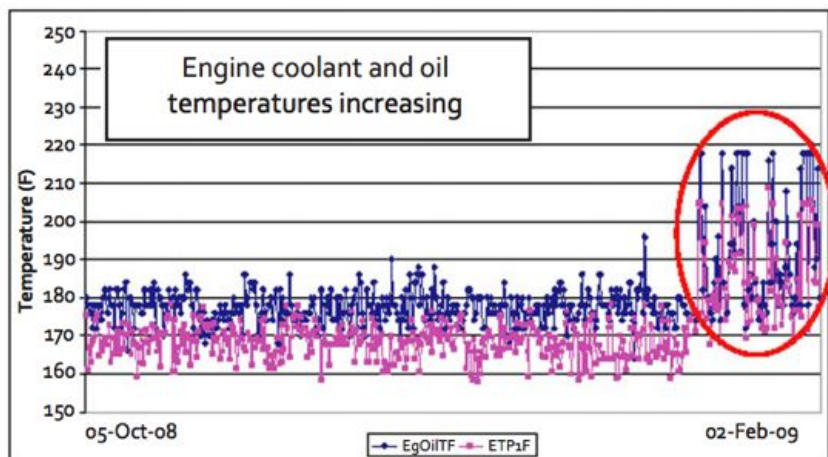
The objective of the model is to catch the decrease in performance as soon as possible.  
It also seeks to establish safety and failure thresholds, a non-trivial problem.



**Note:** This example is univariate and ignores the effects of ambient conditions, operating modes, drivers, etc.

# Failure prediction example

The deviation (in this case, increase) in engine coolant and oil temperature was detected, resulting in a coolant fan issue being identified. The failure of the coolant fan was prevented, avoiding engine shutdown and locomotive downtime.



On the Track

\$20K

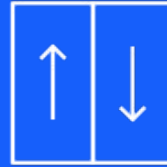
(per locomotive per year)

Prevention of road failures

Optimization of asset performance

Asset tracking to inform rail network planning





# Transfer learning

Class of algorithms that apply learning from related, but not identical tasks, to make predictions on previously unseen data sets



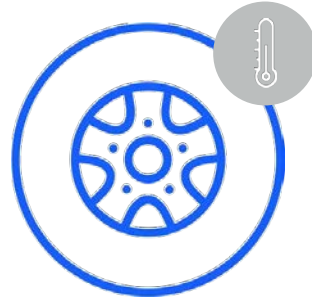
# Transfer learning: example

**Tire failures are very rare.** Most industries will only see a few incidents per year making predicting tire failures very difficult.

**Transfer Learning is able to help with these problems.**

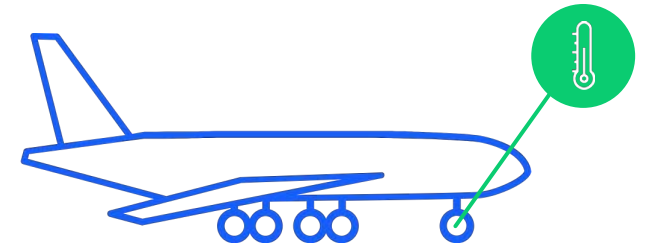


Catastrophic Mining Tire Failure



Machine Learning Related To Tires

Problem Detected

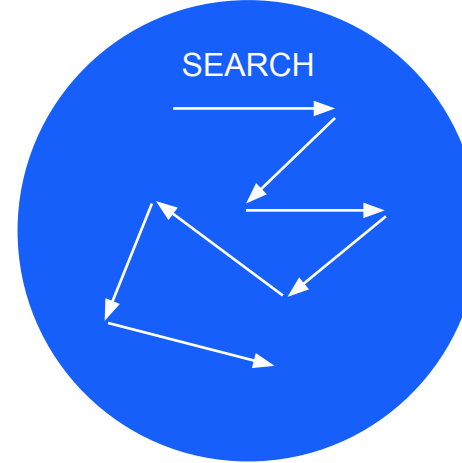


Insights Applied To New Verticals

Crisis Averted!

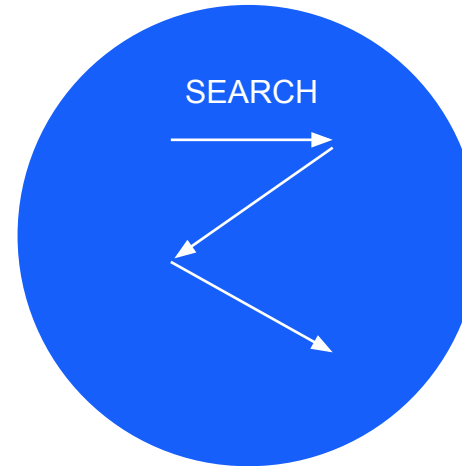


# Transfer learning



## Inductive Learning

Induce predictive model from set of training examples



## Inductive Transfer

Applying learnings from source tasks to create a directed search through a hypothesis space

*Allowable hypothesis are both reduced AND expanded based on previous experience*






# Transfer learning

## Neural Networks

Standard gradient-descent algorithms can be supplemented by information from previous tasks

## Benefits

- Speeds up parameter search
- Biases model towards parameters from previous tasks



*Hmmm...the last few times I was climbing a similar hill, I found the top was in this direction!*

# Transfer learning

## Bayesian Transfer

- Derives prior distribution from source tasks
- Theoretical bounds on convergence and prediction errors are available for some applications of this approach

Prior  
Distribution

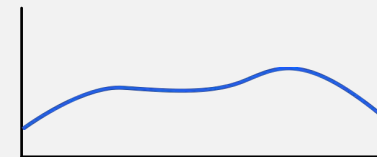
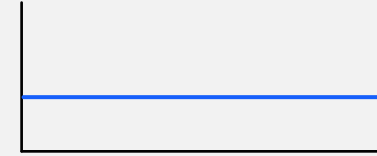
+

Data

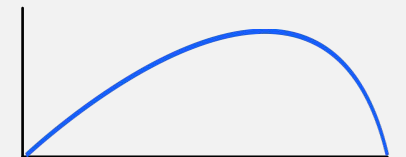
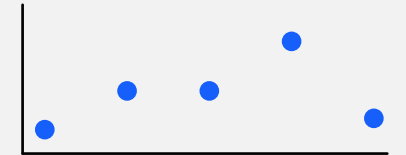
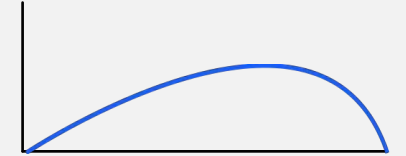
=

Posterior  
Distribution

## Bayesian Learning



## Bayesian Transfer





**What is the  
value of failure  
prediction and  
prognostics?**



# What is the value of prognostics?

## Locomotive

- \$160k per locomotive maintenance per year
- Unplanned downtime results in \$322k in lost revenue per locomotive per year
- Average Class-I railroad could realize annual savings of \$86M if 10% of unplanned maintenance was converted to planned maintenance







# What is the value of prognostics?

## Mining

Mining industry has moved to progressively larger machines, resulting in higher costs of failure

### CAT 797F

- \$5 Million price tag
- Equivalent to 250 Ford F-150 trucks
- 0.3 MPG
- Hauls 400 tons per load at up to 40 mph
- \$1.5M cost per day of downtime
- 6 tires, costing \$42,500 per tire





# What is the value of prognostics?

## Wind Turbine

**High failure rates:** Blades, Electrical, Gear Box, Generator

- 33,250 turbines installed between 2007 and 2015
- Total parts cost of blade replacement is \$150M annually (1-3% annual failure rate)
- Gearbox part cost \$250k





**What are the  
challenges?**





# Not all anomalies are meaningful

## Locomotive Case Study

- Repeated anomaly: elevated engine temperature and several other unusual signals
- Occurred in specific locations
- Feedback from customer: normal behavior ... when going through tunnels
- Added tunnel locations to model







# Not all failures are predictable

## Power Transmission Case Study

- Transformer outages are very rare
- #2 cause of outages: squirrels (APPA, 2017)
- No sensor data on a transformer helps predict a squirrel-based outage
- Identify and remove wildlife outages from training set





# Not all sensors are reliable

## Sensor Calibration Case Study

- Assets outperforming manufacturer specs
- Model and calculations seem fine
- Examine the inputs
- Customer agrees to A/B test
- Proper calibration improves output





# Questions?

[Jake.Bartolone@uptake.com](mailto:Jake.Bartolone@uptake.com)



**Copyright © 2019 by Uptake Technologies Inc.** All rights reserved. No parts of this document may be distributed, reproduced, transmitted, or stored electronically without Uptake's prior written permission. This document contains Uptake's confidential and proprietary information. If a pre-existing contract containing disclosure and use restrictions exists between your company and Uptake, you and your company will use the information in this document subject to the terms of the pre-existing contract. If no such pre-existing contract exists, you and your Company agree to protect the information in this document and agree not to reproduce or disclose the information in any way. Uptake makes no warranties, express or implied, in this document. Uptake shall not be liable for damages of any kind arising out of use of this document. Any discussion of potential features is not a promise of future functionality.