Project Controls Expo, Australia – 26th November 2019

Melbourne Cricket Ground, Melbourne

Improving project predictability with AI

Alan McFadyen

CEO & Founder, BitWinder

BitWinder | Project Controls EXPO Melbourne, Australia

About the Speaker

Alan McFadyen, CEO & Founder, BitWinder

Alan is a chartered engineer with 25 years' experience in project management and engineering. His career began in Scotland where he studied artificial intelligence. His experience includes senior management roles on multibillion-dollar mining projects and the management of large project portfolios in excess of one billion dollars. Most recently he led a technology project delivery function for BHPs Coal business. Alan continued to maintain a keen interest in artificial intelligence, leading him to identify an opportunity in project management. The result was BitWinder, the company which Alan founded to innovate with AI in project management.

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About the Topic

Poor predictability in projects is destroying value unnecessarily. With poor predictability, we blindly follow our forecasts until the evidence suggests otherwise. Yet, improved predictability allows our project teams to take early corrective action, when its least expensive and when options are plentiful. Artificial intelligence can significantly improve upon the current situation. Unlike us, artificial intelligence can learn from huge datasets giving it thousands of years of experience from which to draw upon when making forecasts. In this presentation, Alan McFadyen shares the results and new possibilities of using artificial intelligence to make projects more predictable.

What’s the problem?

$US15bn blowout sets off alarms

…needs another $20 billion of public money to finish rollout

… builders battle claimed $2bn blowout

The problem with projects

McKinsey

"On average, projects with budgets above $1 billion are delivered one year behind schedule, and run 30 percent over budget.",

Asvadurov et al., 2017, The art of project leadership: Delivering the world's largest projects, McKinsey

The problem with projects

EY

Of 365 oil and gas projects:

- 64% in cost overrun
- 73% in schedule delay

2014, Spotlight on oil and gas megaprojects, EY

Australian research

Grattan Institute conducted largest study into Australian transport infrastructure projects (*836 projects, 15 years*)

1

Projects > $20M

34% of projects overrun their budget

The average overrun is 24% - 43%

2

Projects > $100M

65% of projects overrun their budget

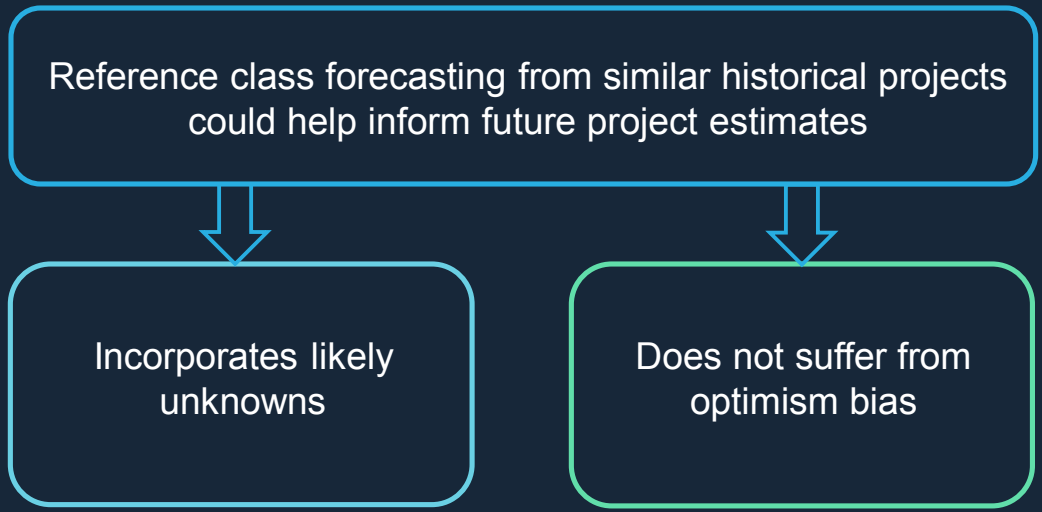
The average overrun is 52%

3

Average P90 – P50 estimate difference in samples of large projects was 9.2%, reality is 26%

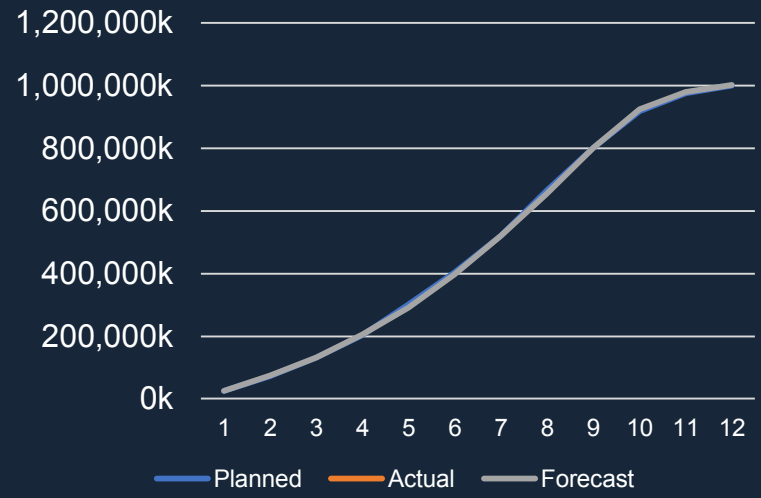
Reference: Terrill, M. and Danks, L., 2016, Cost overruns in transport infrastructure, Grattan Institute
https://grattan.edu.au/report/cost-overruns-in-transport-infrastructure/

Findings of research relevant to AI



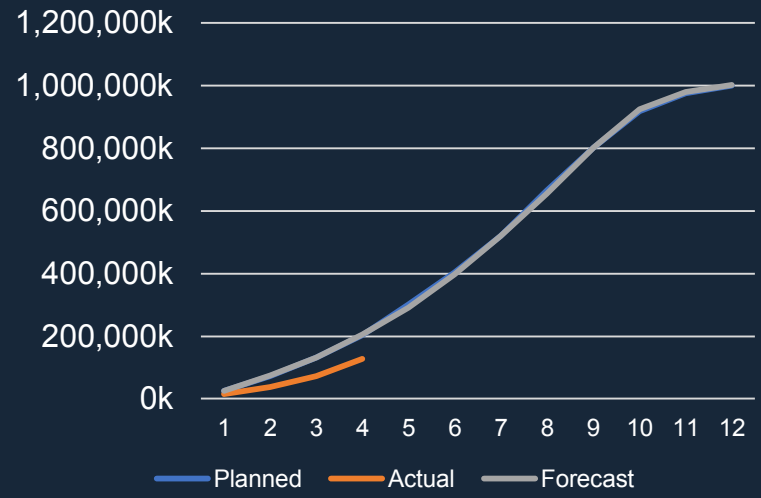
Reference: Terrill, M. and Danks, L., 2016, Cost overruns in transport infrastructure, Grattan Institute
https://grattan.edu.au/report/cost-overruns-in-transport-infrastructure/

Example: delivering $1 billion over 12 months



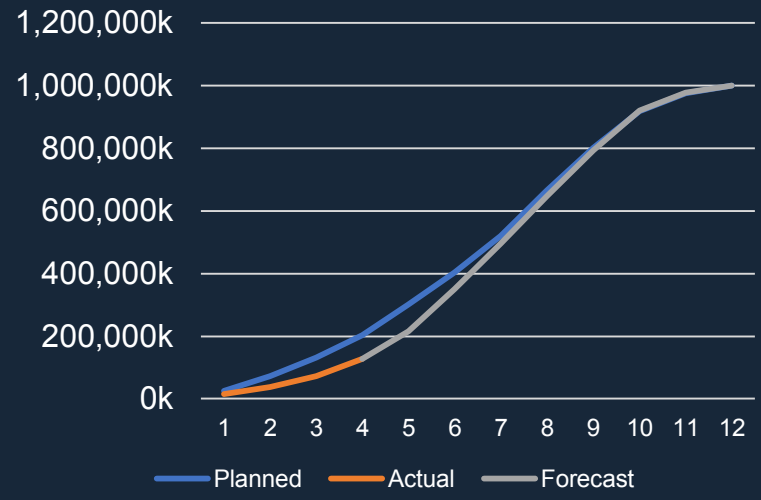
Plan for the year

Example: delivering $1 billion over 12 months



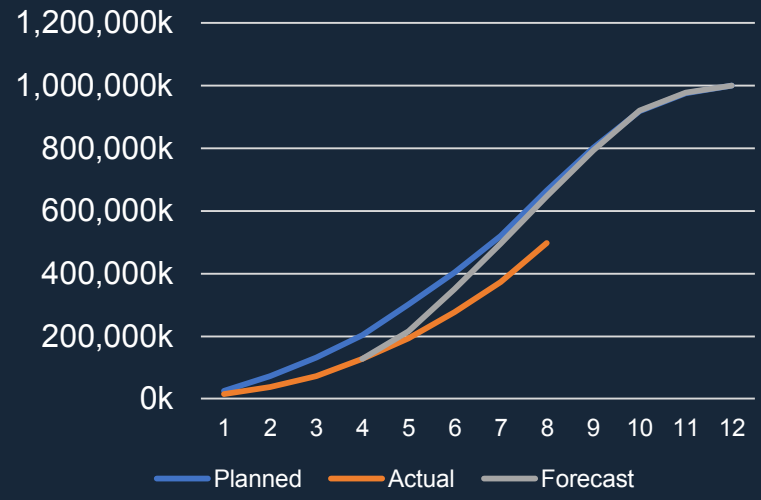
Underrun/late

Example: delivering $1 billion over 12 months



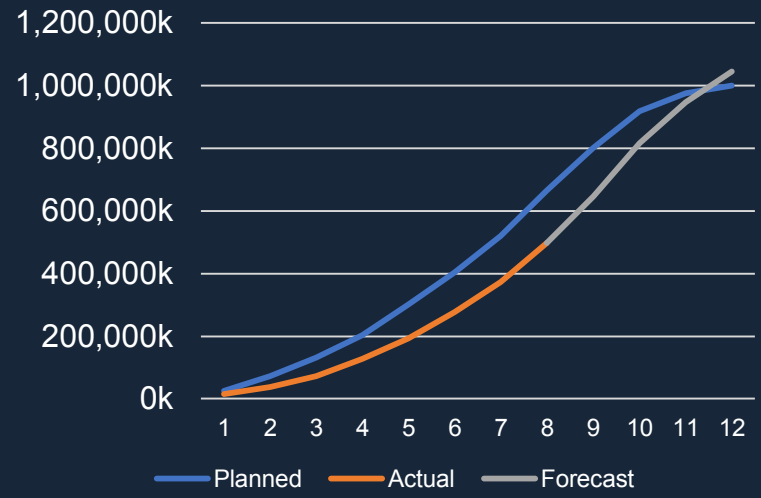
Re-forecast

Example: delivering $1 billion over 12 months



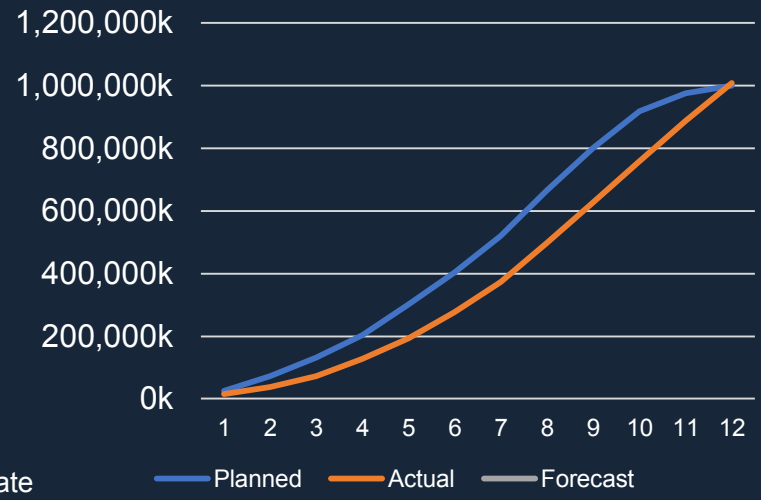
Still late

Example: delivering $1 billion over 12 months



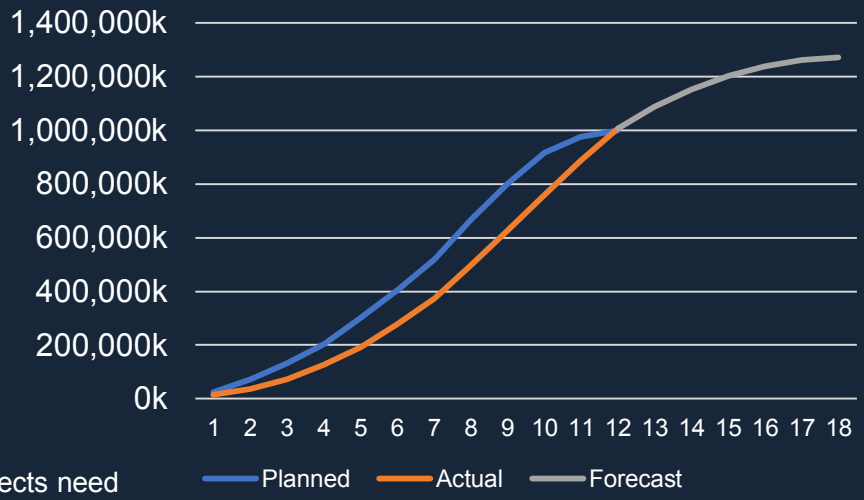
Re-forecast

Example: delivering $1 billion over 12 months



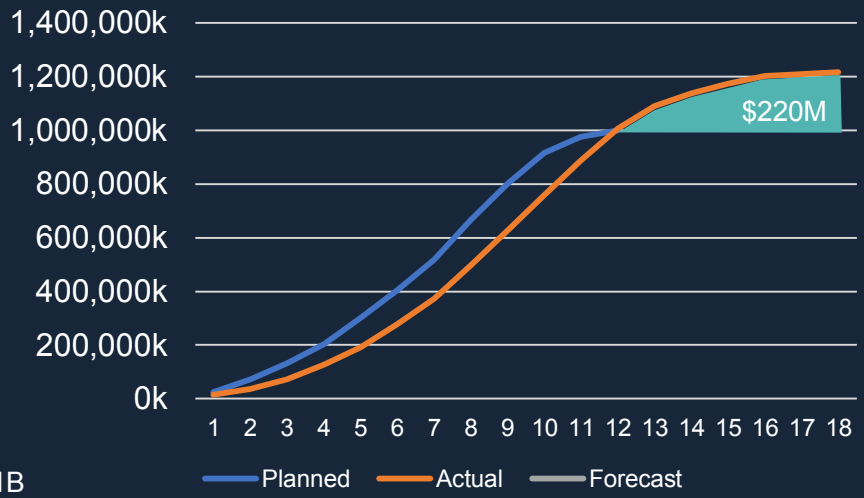
Spent budget - Late projects in underrun lent to overruns

Example: delivering $1 billion over 12 months



Late projects need funded - overruns used their budget

Example: delivering $1 billion over 12 months

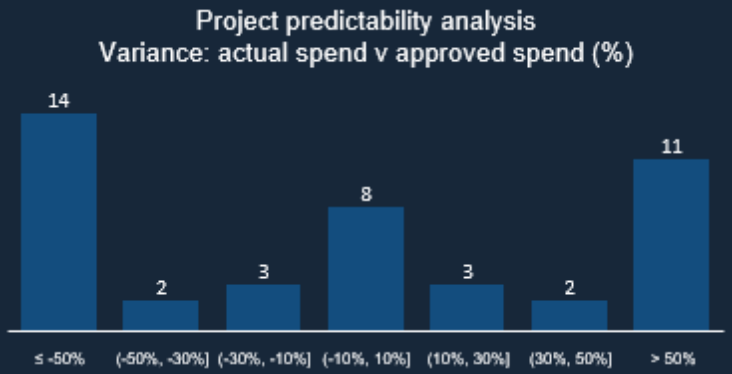


- Extension costs
- Overrun costs

Value: $1B
Cost: $1.22B

Real data example

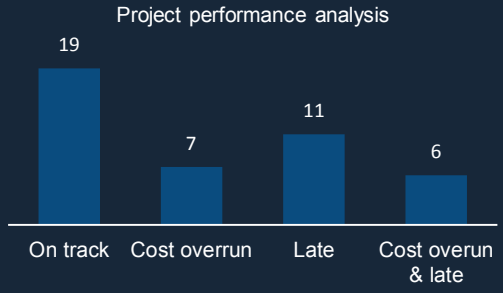
Program of 43 projects: 2017 – 2018



- Large spread of variance indicating low forecast accuracy
- 8 projects from 43 are within +/- 10% of approved spend for 2017/18

Real data example

43 projects: 2017 – 2018



Approved total spend	$267,361,000
Actual total spend	$335,831,000
Total variance $	-$68,470,000
Total variance %	-26%

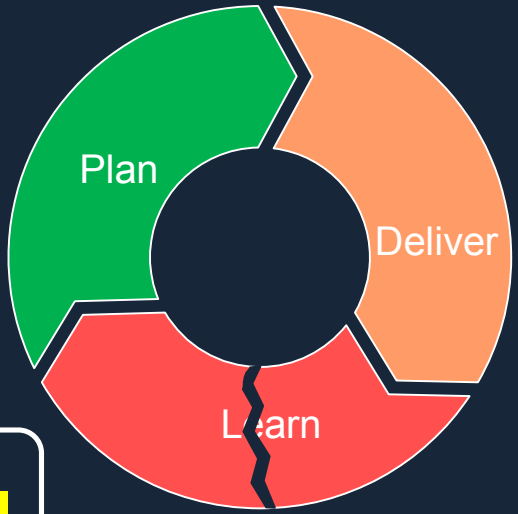
Overruns and underruns don't cancel each other out because they destroy value differently:

1. Overruns deliver the same value for a higher price than expected.
2. Underruns usually mean less value is being delivered than planned, which leads to extension costs. They are often future overruns in the making

Notes:
- Cost overrun – actual spend above approved spend which corresponds with an increase in total project estimated cost
- Late – actual spend below approved spend which doesn't correspond with a reduction in total project estimated cost
- Cost overrun & late – cost below approved spend which corresponds with an increase in total project estimated cost

The problem

Estimated $112B of capital spend in Australia FY19



15% over budget (34% x 43% x 112) = $16B (or 10 hospitals)

$16B worth of lessons not learned

What happens when you learn?

	Mapping applications	Project software
	Predicts journey time and route	Forecasts time and cost
	Learns from previous journeys	Doesn't consider previous projects
	Predictive modelling	Schedule based forecast
	Measured average error of 6%	Measured average error of 34% (>$100m)

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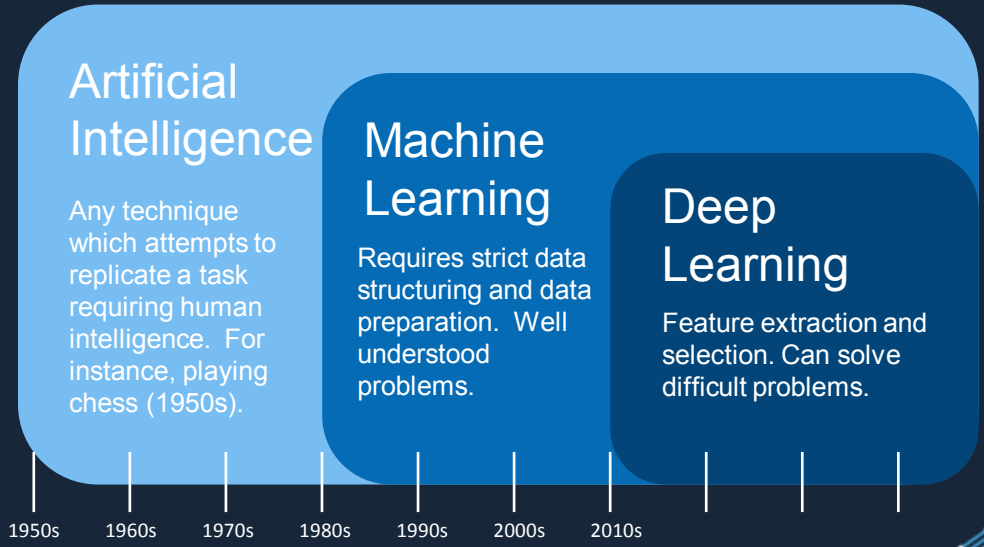
Artificial intelligence – a few basics

Artificial intelligence – why now?



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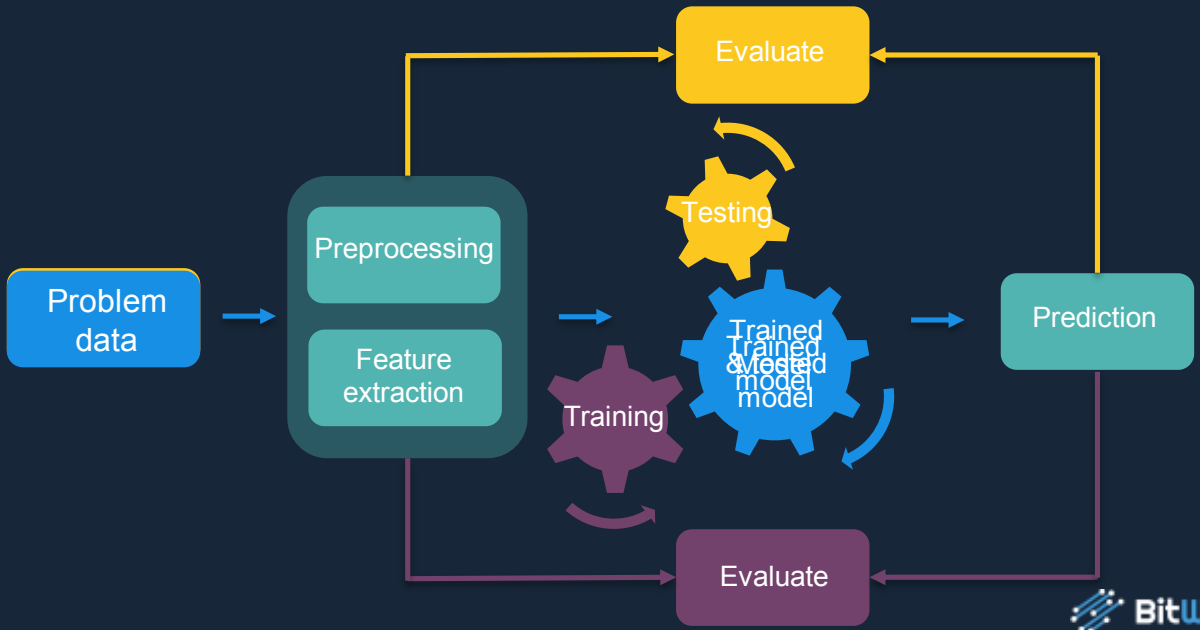
The machine learning pipeline



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A journey into using AI in projects

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First steps in AI for project management
(classification)

Can we learn from historical data and determine if projects in execution will end “good” or “bad”?

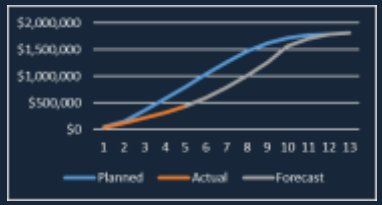
What is a good or bad project?

Good – at completion:

- Cost is within +/- 10%
- Schedule is within +/- 10%

Classification of projects

Sample project



Trained Classifier

Good

Bad

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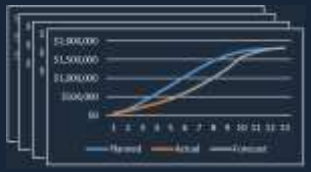
Training (learning) the neural network

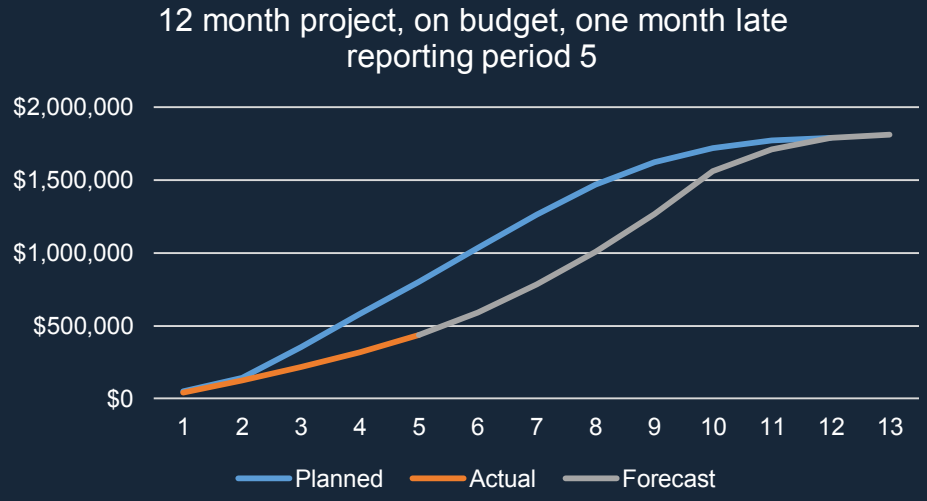


Raw cost charts

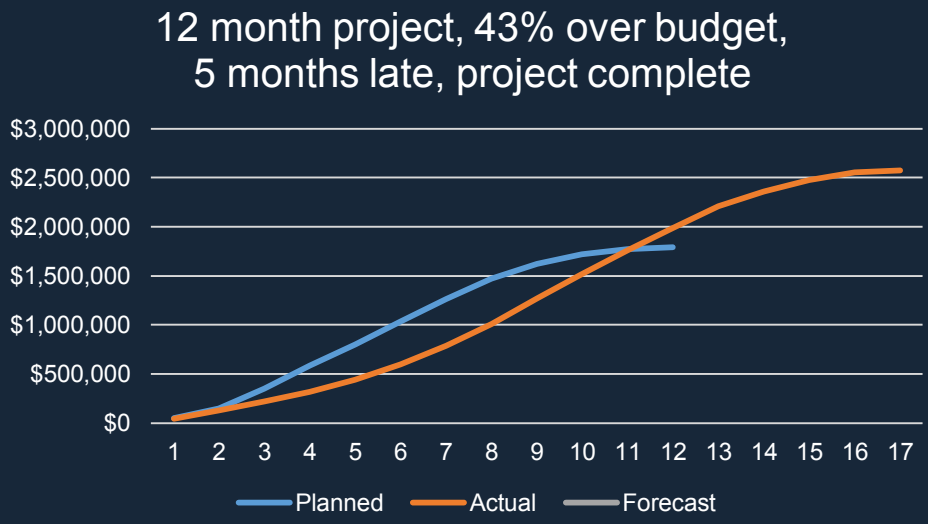
Feature engineering

Deep learning
Image classifier

An example: good or bad?



Bad, we've learned how this usually ends

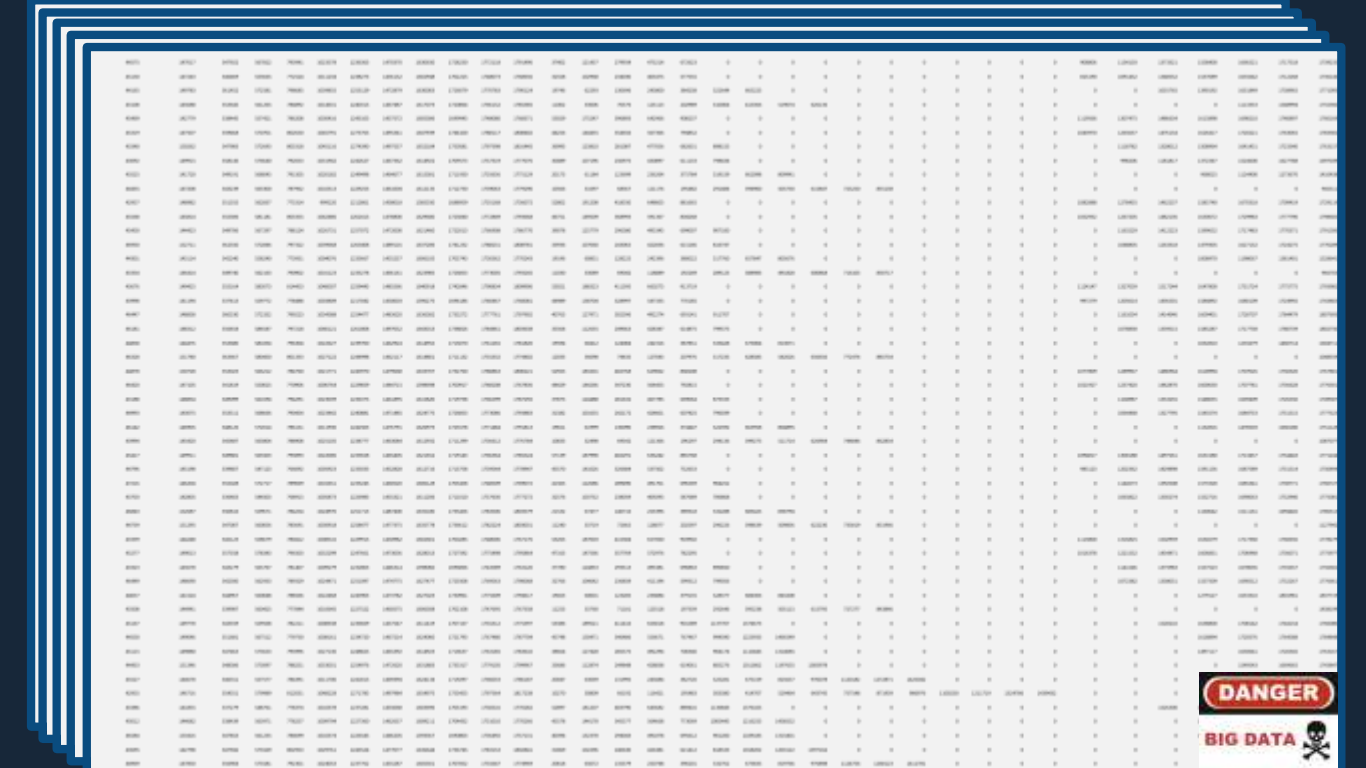


The overall classification result

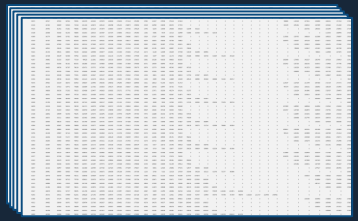
Correct classification with under 10% error over sample of 80 projects

Next step, can we predict periodic costs?
(regression)

Can we learn from historical cost data and generate a more accurate predicted forecast for projects in execution?


DANGER
BIG DATA

Training a regression neural network

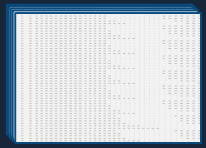


Historical cost & meta data

Feature engineering

Deep learning regressor

Forecast prediction with AI



Snapshot of projects in execution

Trained deep learning regressor

So how well does AI perform?

Validating performance – test data setup

38,000 project snapshots at progress mark: 20%, 30%, 40%

Unique combination of plan type, total cost and duration,

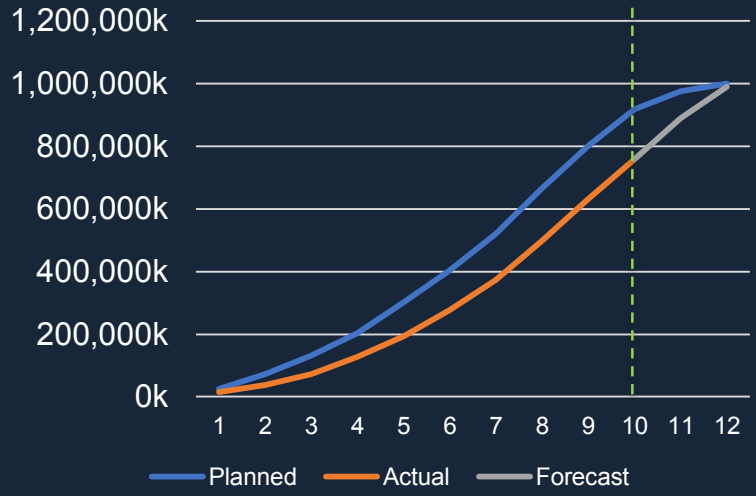
Unique combination of CPI, SPI and forecast variance

Summary of results at 20% progress

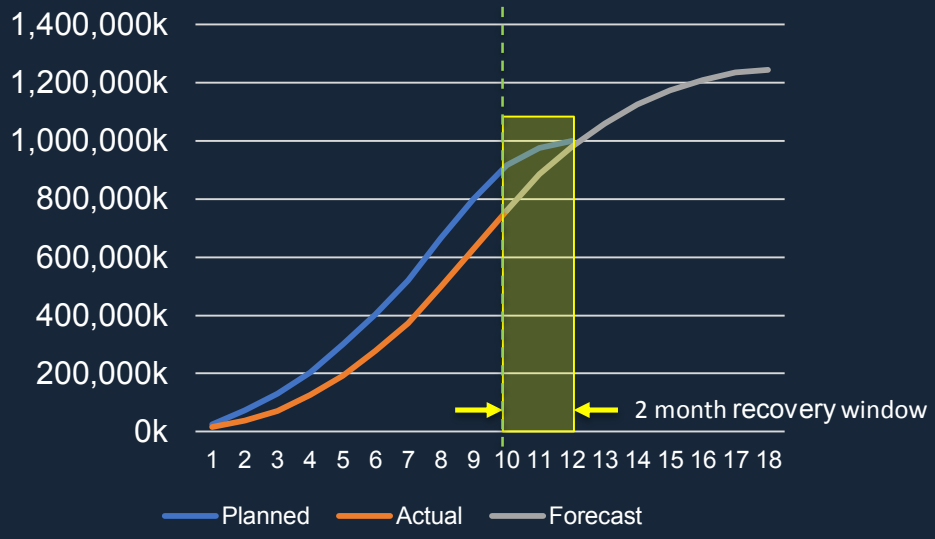
- Prediction error of 7.55% on cost & 4.70% on time
- 81.15% of predictions are more accurate than the forecast
- Prediction better on average by 15.32% over forecast error

How can we apply this in the real world?

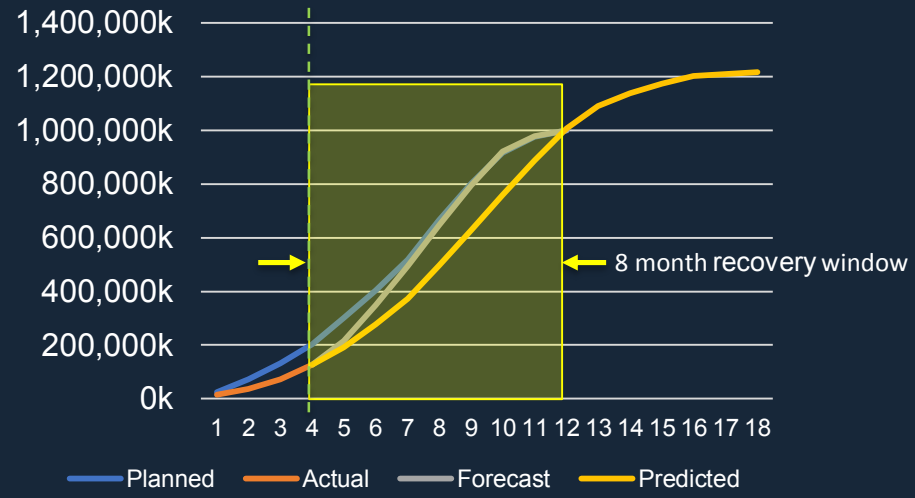
12 month project - 2 months remaining



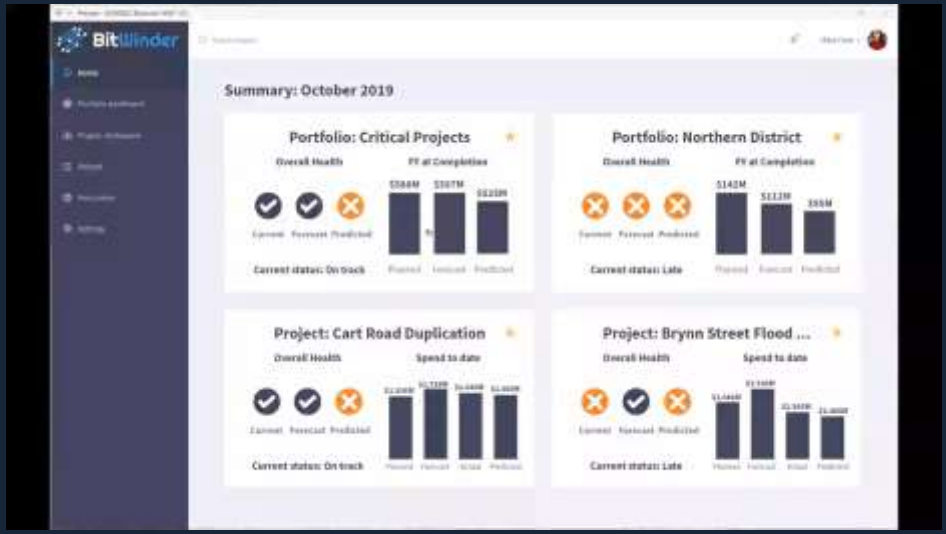
2 months to remaining, 6 months overrun



8 months remaining - 6 months overrun



Dashboard - predictive analytics



In **conclusion**

Challenges

- Security
- Desensitisation / privacy
- Data availability and quality
- Cost / benefit of customisation

Where to from here?

1. Improve explainability & the drivers behind the why
2. Schedule, risk and contract deliverables
3. Bring AI into the visualisation

Questions?

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