nPlan

Man ~~vs~~ + Machine

The ultimate evaluation of schedule risk analysis

15 November 2021

What can you expect today?

1. What is nPlan?
2. Discussion on the traditional approach to QSRA
3. Artificial Intelligence and Machine Learning: how does it change inputs and outputs to QSRA?
4. Project context and schedule
5. Hands-on workshop
6. Machine Learning-supported analysis
7. Q&A
8. The accuracy comparison and awards

What is nPlan?

Who we are

nPlan is a data-driven risk analysis and assurance company; our AI forecasts project outcomes using historical data, making risk assurance easier, faster, and more reliable for project teams

Our Purpose

To inspire the world to forecast correctly and empower it to tackle risk

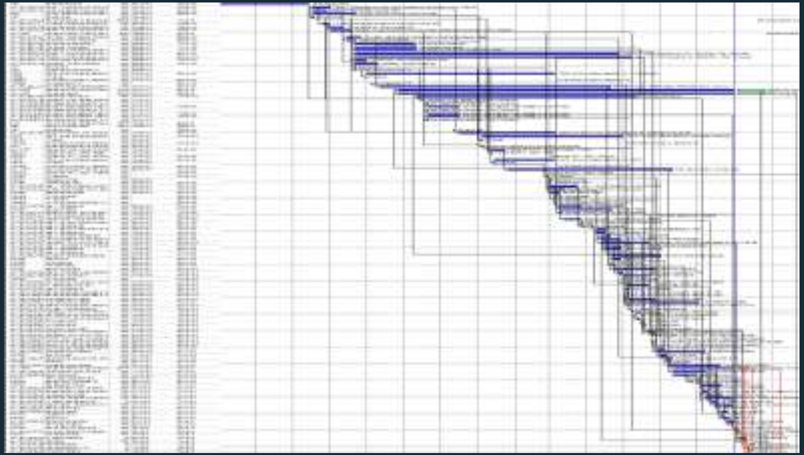
Our Mission

To unlock a trillion dollars of new project value through data-derived forecasting

Our Vision

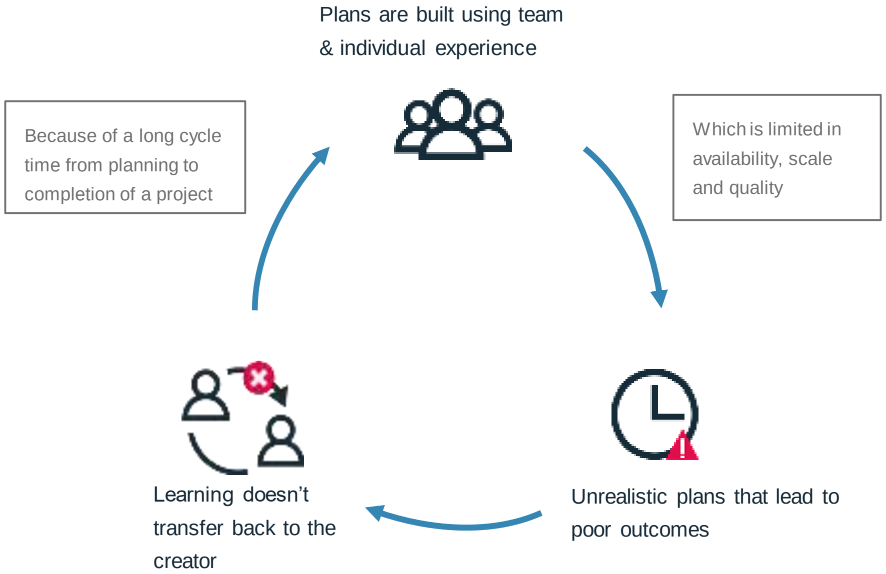
To build a world where ambitions are no longer limited by our understanding of risk

Project programmes are incredibly complex...



Programmes can have **thousands of activities** and accurate project planning is increasingly challenging as projects get more complex.

And learning from our mistakes is hard



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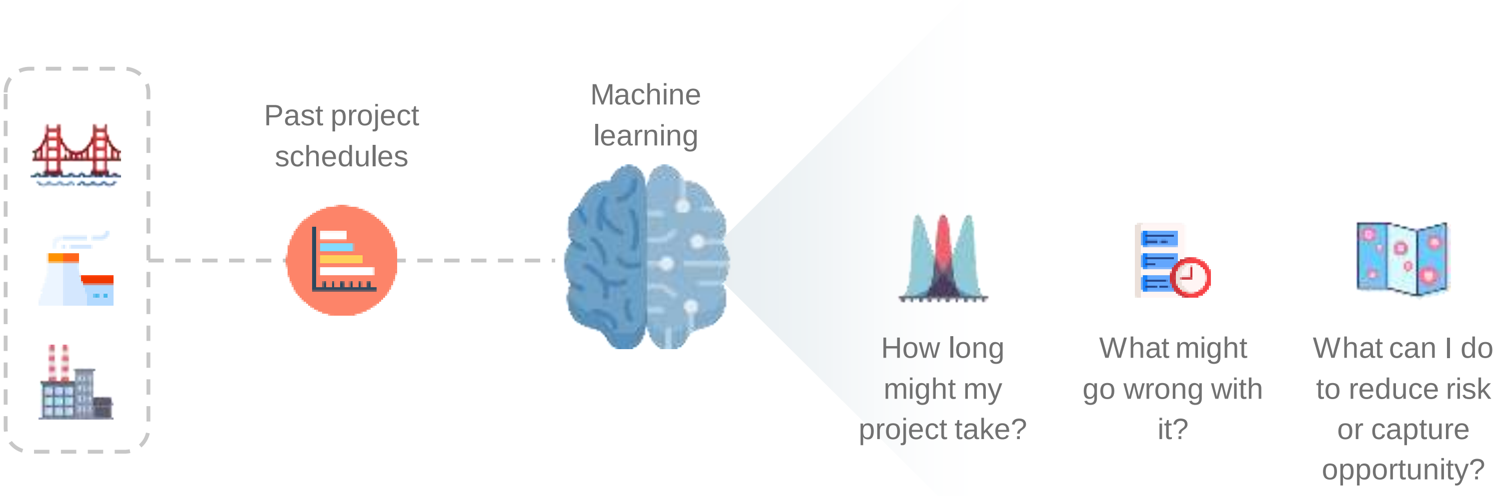
nPlan is a data-derived schedule and risk forecasting method that uses past project data and machine learning to generate unbiased forecasts of project outcomes.



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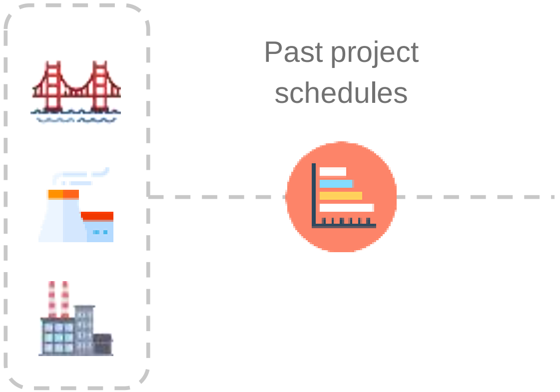
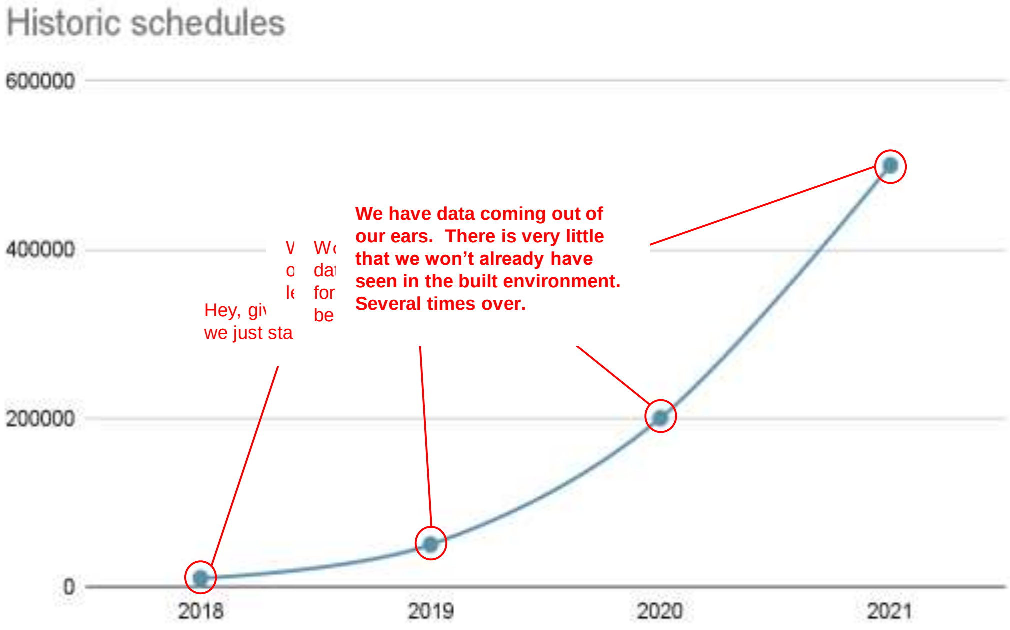




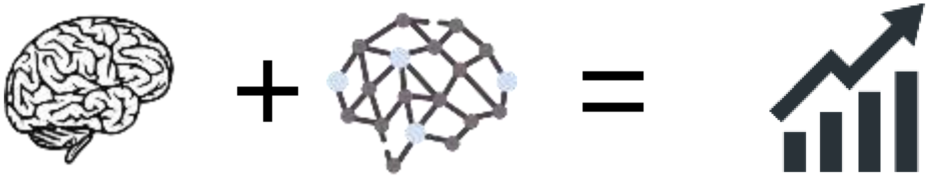
Man + Machine

Humans on their own struggle to objectively, efficiently and accurately forecast

BUT Machine Learning on its own will struggle to:

- understand the causality and as a result
- turn that accurate forecast into a mitigatory plan

SO, what we're going to establish today is whether risk identification and mitigation is improved by Machine Learning augmented by human intelligence



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QSRA: without the help of Machine Learning

Quantitative Schedule Risk Analysis (QSRA) overview

What is a quantitative schedule risk analysis (QSRA)?

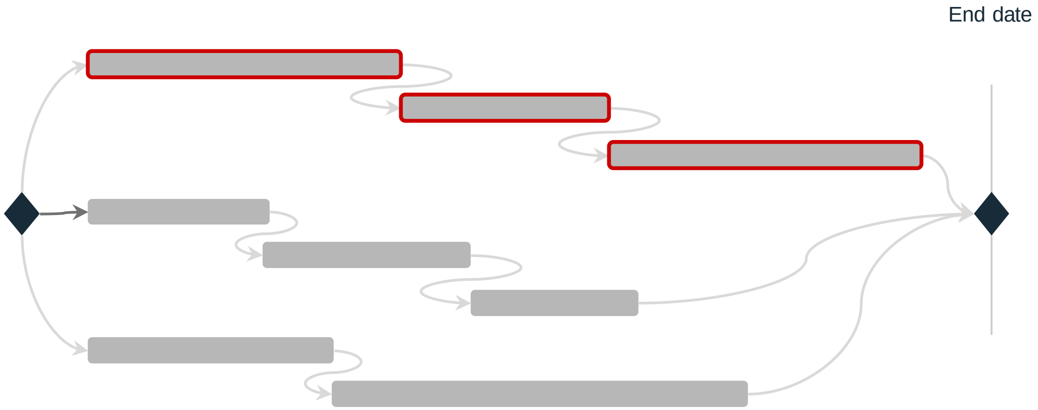
- QSRA is a method to evaluate the potential impact of uncertainties on the final duration of a schedule (project/programme/portfolio)
- Risks and uncertainties are quantified, and then applied to a base schedule and simulated on (Monte-Carlo simulation)

Why do people use QSRA?

- Understand the probability of meeting the key milestone dates
- Understand the potential range of dates of key milestones
- Understand the sensitivity of the key milestones to uncertainties in the schedule.
- Prioritise risk management activity to minimise the exposure to threats and capitalise on the opportunities

Understanding quantitative schedule risk analysis (QSRA)

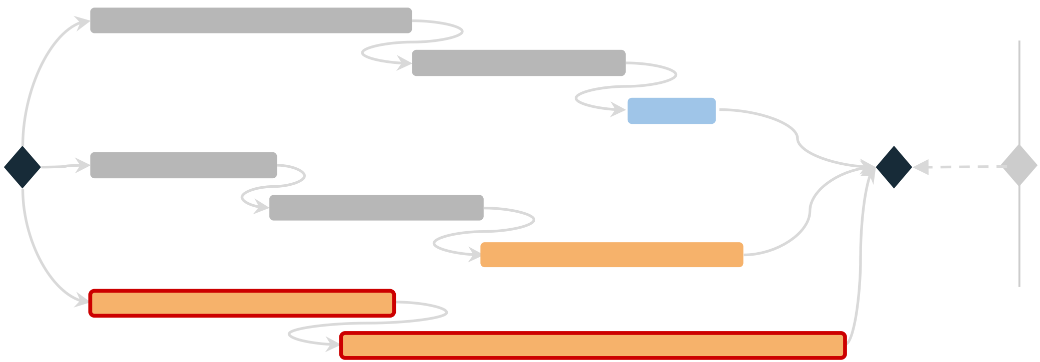
This is your ‘deterministic’ schedule



Understanding quantitative schedule risk analysis (QSRA)

First iteration

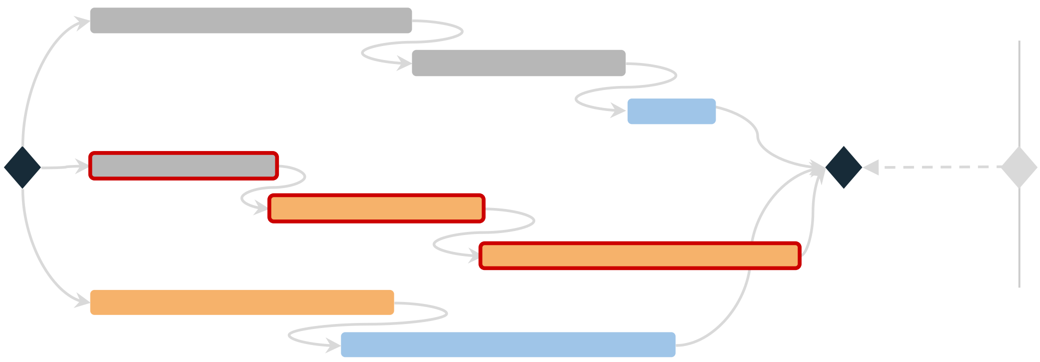
- Predicted to take longer than planned
- Predicted to take shorter than planned
- Predicted as planned



Understanding quantitative schedule risk analysis (QSRA)

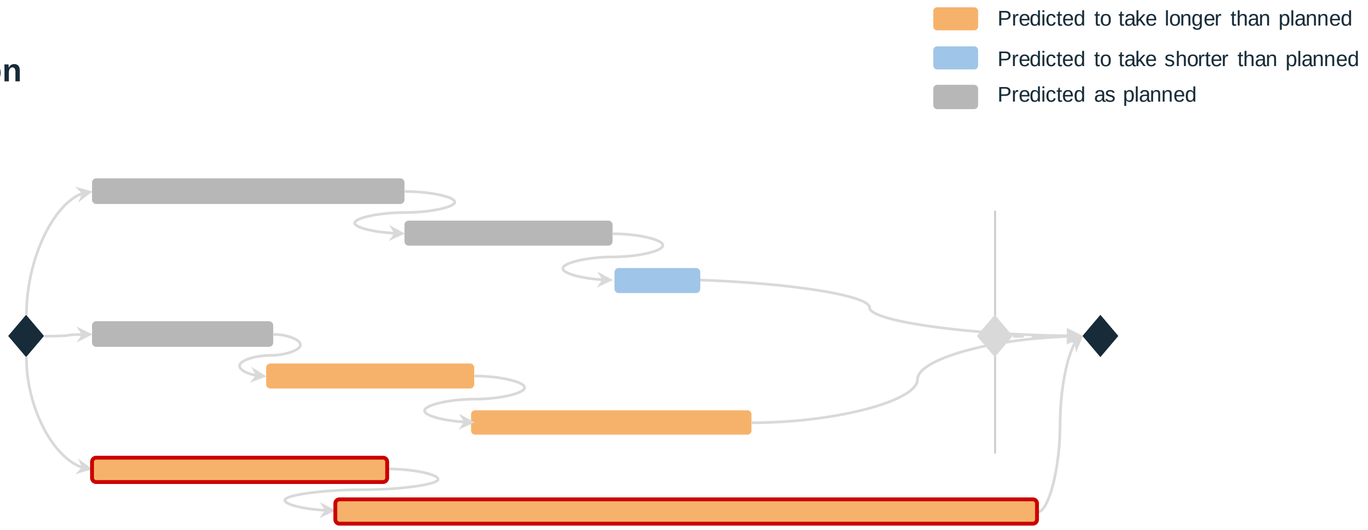
Second iteration

Predicted to take longer than planned
Predicted to take shorter than planned
Predicted as planned

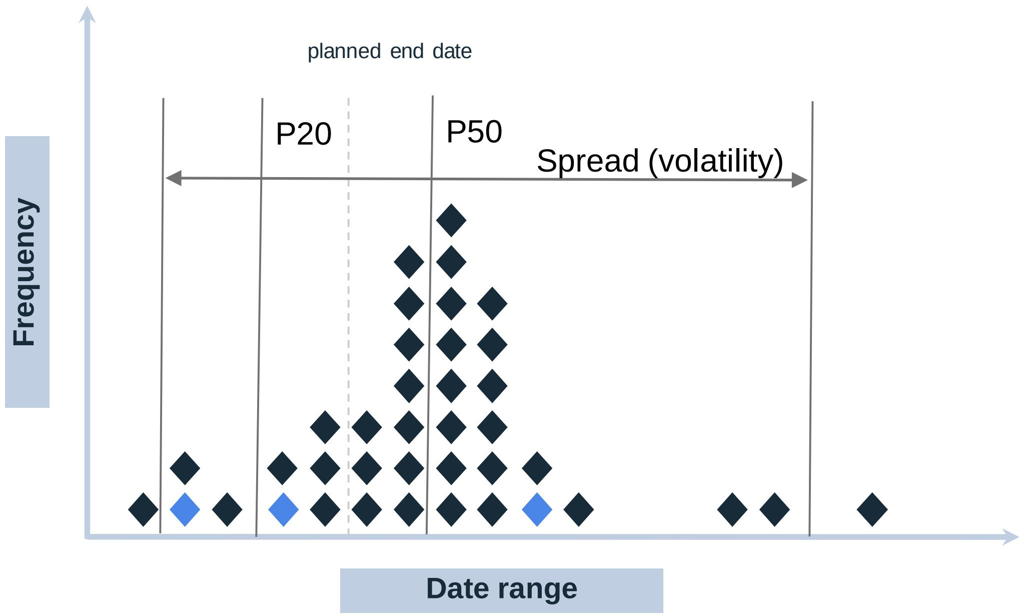


Understanding quantitative schedule risk analysis (QSRA)

n-th iteration



Understanding quantitative schedule risk analysis (QSRA)



The light blue diamonds represent the 3 iterations from previous slides.
We then simulate 1000s of times to find patterns.

From this example we can see:

- Most simulations finished after the planned end date (highest frequency of diamonds is after the dashed line)
- In some cases the project could finish earlier (diamonds left of the dashed line)
- In some extreme cases the project could be much later (diamonds on the far right)

The QSRA process in practice

- **Gather information** about the project, context, objectives etc.
- **Generate** comprehensive list of discrete risks
- Reach **consensus** on probability and impact
- **Identify** activities in schedule to apply discrete risks
- **Apply** uncertainties to activities
- Run the **simulation**
- **Analyse** outputs

But how do we *generate* a list of risks, and how do we *quantify* them?

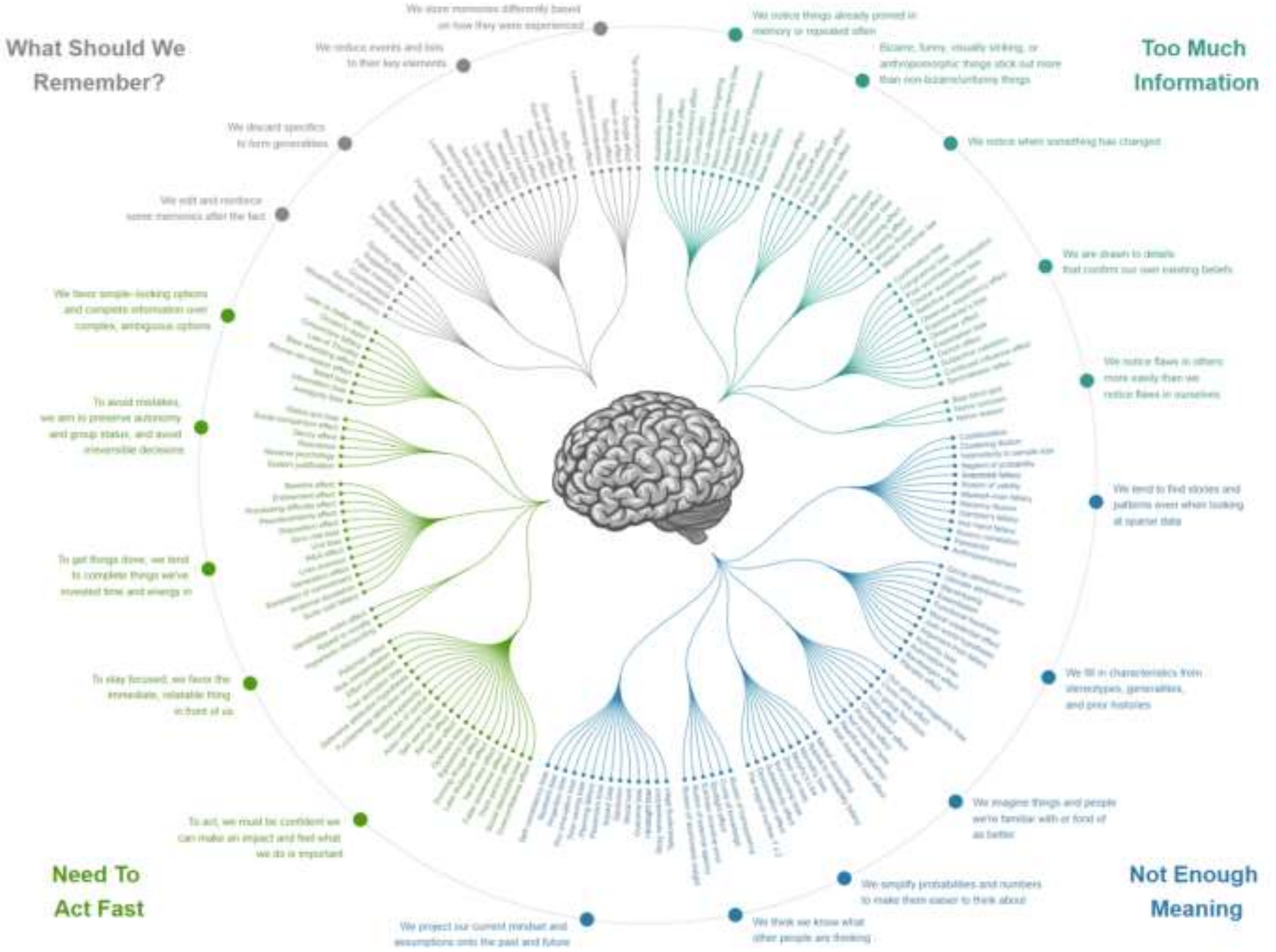
A risk practitioner would typically:

- Reach out to key stakeholders
- Conduct workshops/interviews with subject matter experts
- Review similar projects (if they exist)

The common denominator here is that these are **human** based inputs and interpretations:

- Biases
- Consensus hard to reach
- Motivations/pressures to ‘massage’ inputs

180+ cognitive biases!



Role play: a real project, a real QSRA

Gather information: A new hospital in a city centre

Scope includes:

- Demolishing existing building
- 15 floors
- 300 car parking spaces beneath
- All structure work (including roofing, facade etc)
- Footbridge over the road to health centre
- All HVAC, electrical and plumbing
- Fit out - MRI/imaging suites
- Landscaping

4.5 years in duration

Generate a list of discrete risks: A (very) high level risk brainstorm

Demolition:

- Potential asbestos
- Unexpected services requiring diversion

15 floors and 300 car parking spaces beneath:

- Ground conditions
- Undocumented buried services

Roofing and facade:

- Material delivery delays

Footbridge over the road to health centre:

- Interface unknown/agreement with third parties

All HVAC, electrical and plumbing

- Specialist trades (unexpected absence, competing project work)
- Cable pulls/damage, pipe and duct leaks, design errors

+

- Many more!

Reach consensus: Let's *quantify* and agree

Demolition: Potential asbestos

What do we know?

Probability assessment

- Existing building (office block) is from 1962
- Office is currently occupied
- Asbestos survey not conducted
- Project manager: "we haven't come across asbestos on a project since I started 3 years ago"
- Construction manager: "asbestos was used in lots of buildings between 1950s-1970s"

Impact Assessment

- 4.5 year project
- Demolition activities are planned for 64 days
- City code requires licensed specialist removal prior to demolition
- 4 local companies are licensed to remove and dispose of commercial asbestos waste
- Clear air certification 14 days post asbestos removal required prior to allowing people back in

Apply risks to base plan

Activity ID	Activity Name	Original Duration	Remaining Duration	Start	Finish
123456	Sample project	1453	1453	06-Feb-17	17-Nov-22
123456.2	MILESTONES	1399	1399	06-Feb-17	30-Aug-22
123456.3	CONSTRUCTION	1453	1453	06-Feb-17	17-Nov-22
123456.3.1	Sitework	451	451	20-Mar-17	03-Jan-19
123456.3.15	Roofing	367	367	16-Oct-19	06-Apr-21
123456.3.18	WP2 - Tie-Ins	801	801	24-Jun-19	30-Aug-22
123456.3.2	Demo	46	46	28-Sep-18	05-Dec-18
123456.3.3	Garden Expansion	1329	1329	02-Aug-17	17-Nov-22
123456.3.3.1	Enabling	185	185	06-Feb-17	27-Oct-17
123456.3.3.10	Infrastructure Summary	503	503	24-Jun-19	23-Jun-21
123456.3.3.11	Interior Rough-Ins and Finishes	1276	1276	06-Feb-17	08-Mar-22
123456.3.3.12	Landscaping, Site Improvements	1209	1209	06-Feb-17	29-Nov-21
123456.3.3.2	Bridge Footing	122	122	06-Feb-17	01-Aug-17
123456.3.3.3	Temp Electrical Service	124	124	07-Feb-17	02-Aug-17
123456.3.3.4	Col Line 11 Mini-Pile Work	219	219	06-Feb-17	18-Dec-17
123456.3.3.6	Foundations/Structure	1023	1023	07-Nov-17	08-Dec-21
123456.3.3.7	Exterior Enclosure	715	715	27-Oct-17	01-Sep-20
123456.3.3.8	Elevators	370	370	30-Dec-19	17-Jun-21
123456.3.3.9	Mechanical Floors	449	449	26-Sep-19	12-Jul-21
123456.3.5	COMMISSIONING	281	281	05-Oct-20	17-Nov-21
123456.3.6	Library	307	307	22-Aug-18	12-Nov-19
123456.3.7	Hoisting	345	345	17-Aug-18	04-Jan-21
123456.4	PROCUREMENT	550	550	22-Feb-17	30-Apr-19
PR-500	Procurement Complete	0	0		28-Jul-17
123456.4.10	05 - Metals	20	20	02-May-17	30-May-17
123456.4.11	Equipment Support	91	91	22-Feb-17	29-Jun-17
123456.4.2	08 - Openings	88	88	22-Feb-17	26-Jun-17
123456.4.27	23 - HVAC	550	550	22-Feb-17	30-Apr-19
123456.4.3	03 - Concrete	18	18	22-Feb-17	17-Mar-17
123456.4.4	21 - Fire Protection	14	14	02-May-17	19-May-17
123456.4.5	26 - Electrical	20	20	28-Jun-17	28-Jul-17
123456.4.6	22 - Plumbing	20	20	02-May-17	30-May-17
123456.4.7	07 - Thermal and Moisture Protection	29	29	02-May-17	12-Jun-17
123456.8	COMPLETION	243	243	29-Apr-21	18-Apr-22

Asbestos Risk

Probability

40%

Impact

30-120 days delay to demolition

Cause

Presence of asbestos is uncertain

Risk event

Asbestos may be discovered during asbestos survey

Effect

Licenced removal and standstill period required prior to any demolition activity

What's left to finish our QSRA?

- Continue **generating** discrete risks
  - How do we know we have thought of everything?
- Quantify and **apply** each risk
  - Do we have the data/experience/expertise to accurately estimate these risks?
  - Do we know which parts of the schedule are most sensitive to the risks?
  - What if our estimates are incorrect?
- Apply **uncertainties** to activities
  - How do we select activities and uncertainty ranges to apply?
- Run the **simulation**
- **Analyse** the outputs
  - Find probability and range for all key milestones
  - Sensitivity analysis to identify top risks (threats and opportunities) and uncertainties
  - *But…..*our model can tell us <u>only</u> about the risks and uncertainties we put in ourselves

Frequently asked questions

Q	My project is unique: how can you forecast that?	A	By looking at the project bottom-up from the activity level, where activities will be emulated across many projects
Q	My schedule has thousands of activities, can nPlan cope?	A	Because nPlan generates unique inputs for each activity, the number of activities in a schedule doesn't matter. There is no need to summarise a schedule!
Q	Is nPlan just another way of doing a QSRA?	A	No! The inputs are fundamentally different from a QSRA, and consequently so are the outputs. You can think of nPlan as an 'MLSRA'.

Artificial Intelligence and Machine Learning: how does it change inputs and outputs to QSRA?

From basic AI to Deep Learning

Accuracy

Artificial intelligence
~1950

- Rule-based (expert) systems.
- **Limited** accuracy, only worked in very predictable environments
- Useful for simpler, programmable tasks

Machine learning
~1980

- Introduction of the concept of "learning" from data. Order of 1000s of data points.
- **Good** accuracy, still limited to largely predictable environments
- The main limitation was computational capabilities and quantity of data

Deep learning
~2010

- Ability to "learn" complex relationships from millions of data points
- **Very accurate**, capable of generalising in uncertain environments
- Used for complex problems with lots of variables that have intricate relationships

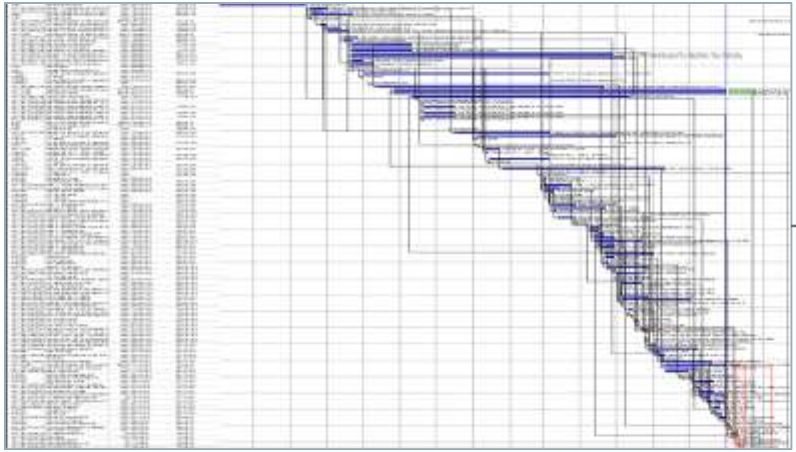
Time

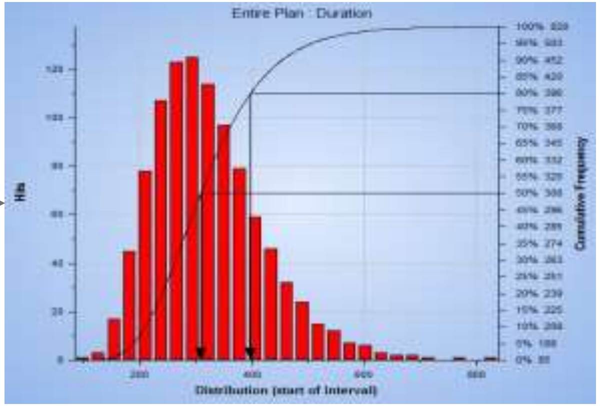
Source: IBM (Cloud Education Blog)

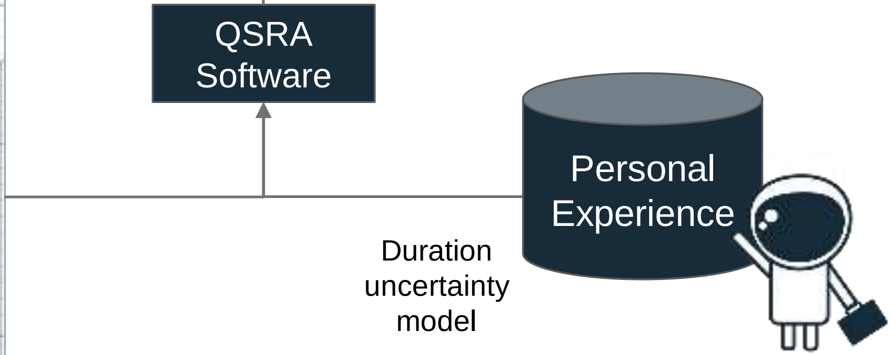
How a deep learning model doesn't "learn"

Traditional modelling for problem-solving

- Observe the problem and define what are the results you want
- Create a model that produces a result given the input data
- Possibly backtest your rules for accuracy



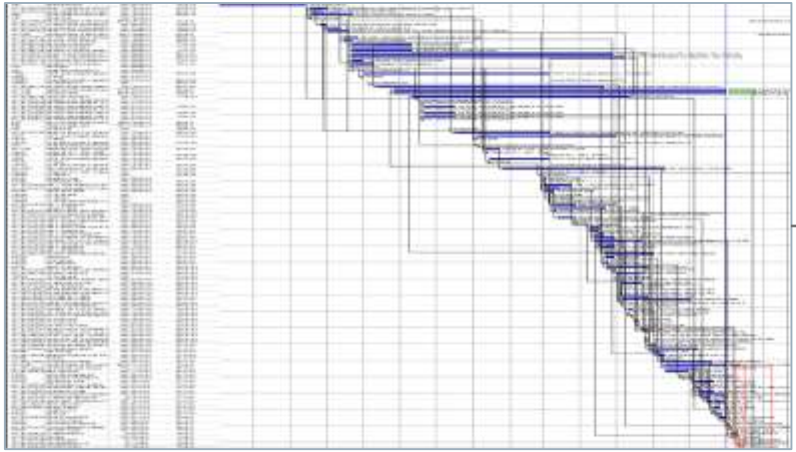


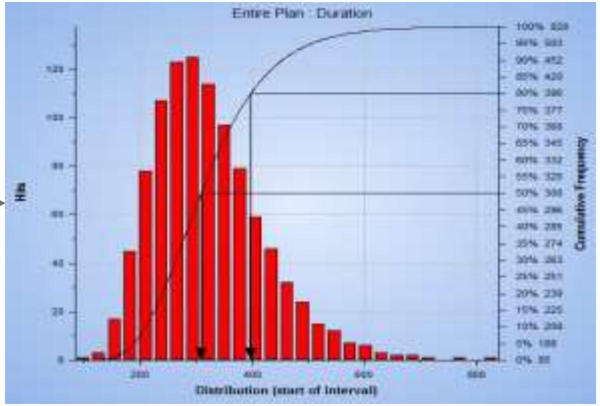


How a deep learning model doesn't "learn"

Drawbacks from the "traditional" approach

- Only data points known to the team are taken into account
- Volatility and long tails are usually under-estimated
- The further into the future, the worse we are at forecasting events
- Time consuming





QSRA Software

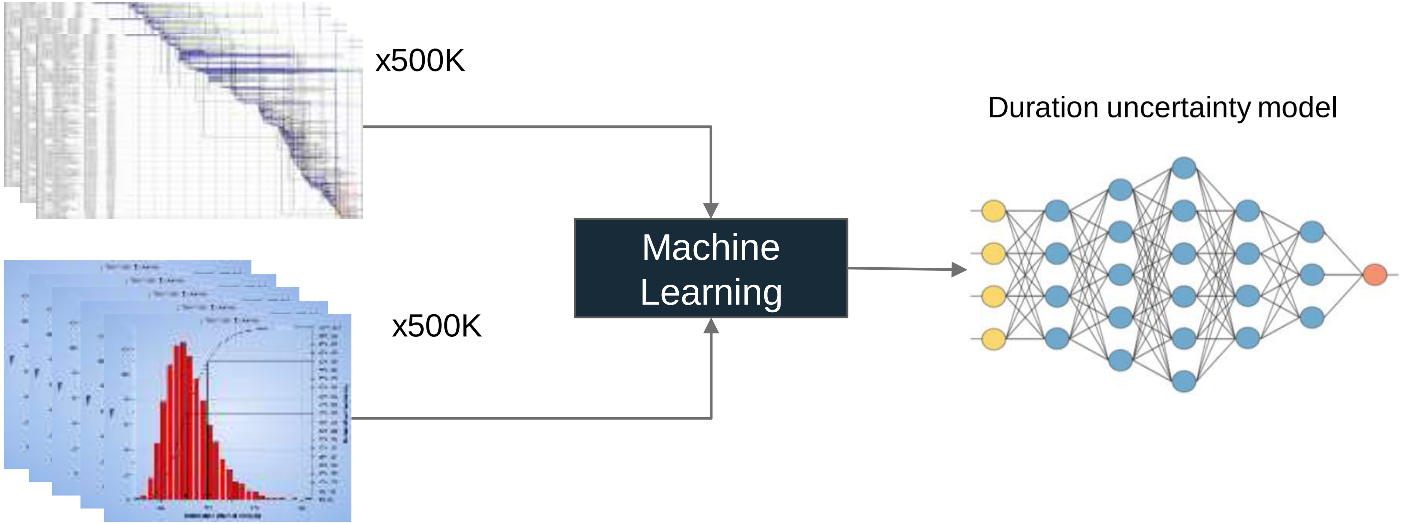
Personal Experience

Duration uncertainty model

How a deep learning model does ”learn”

Machine learning modelling for problem-solving

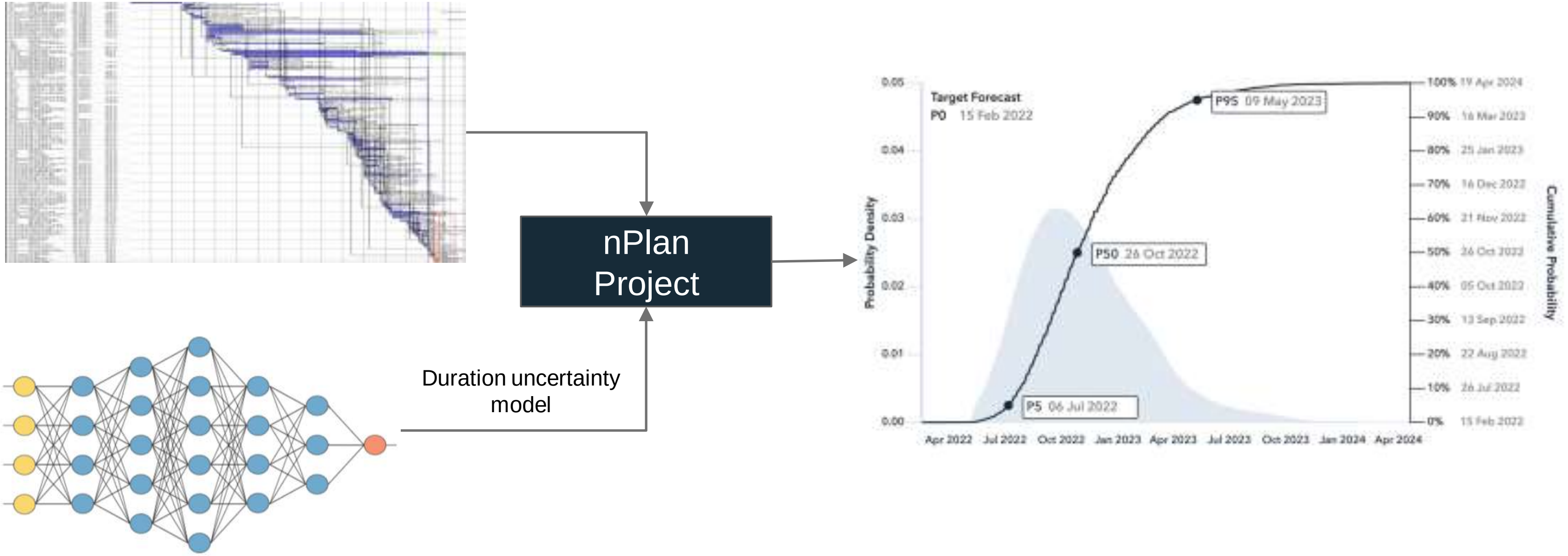
- Define a group of tunable models that could (possibly) solve the problem
- The ML algorithm observes the data and “ground truth” results and tunes the models
- The resulting model is the one that would have produced the best accuracy in observed data



How does a deep learning model does ”learn”

Machine learning modelling for problem-solving

Once the model has been “trained”, it can be deployed in the same way you would a “traditional” model



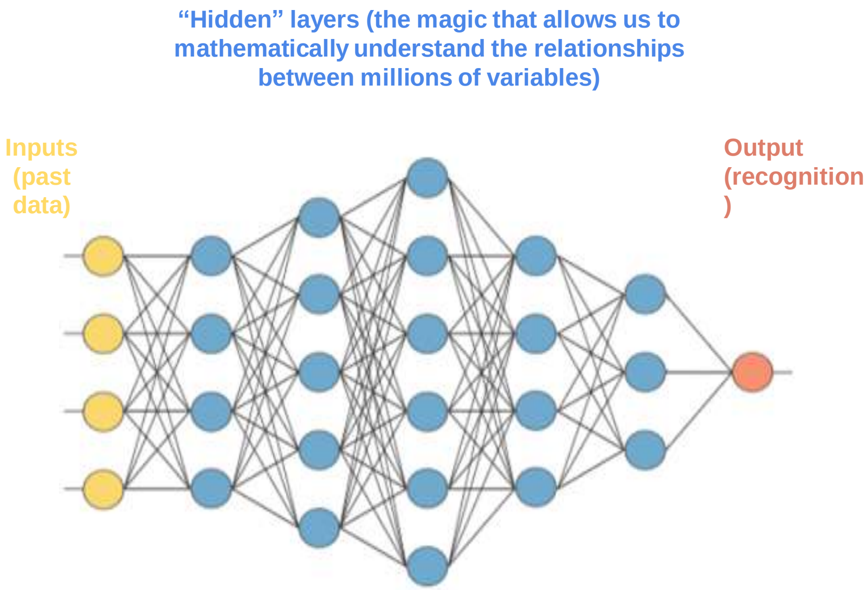
Why use Deep Learning?

A DL model will create connections between input features. During training, the model will "tune" the connections such it can accurately predict the output. These connections can be thought of as building complex features from a simpler input. The model "learns" how much these features should influence the output. Advantages to this approach include:

- **Data-points** - The DL model observes and learns these connections from millions of diverse data.

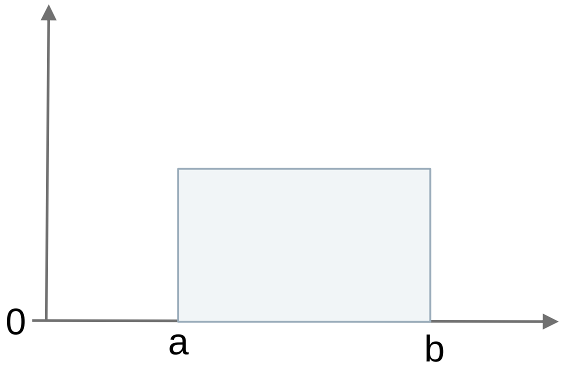
- **Objective performance** - DL takes a strict mathematical, performance-led approach, avoiding any biases in forecasts. This approach has theoretical guarantees that traditional programming does not.

- **Empirically tested** - DL models have been shown to outperform all other methods of modelling (including human expert decision-making) in any environment with plentiful data.

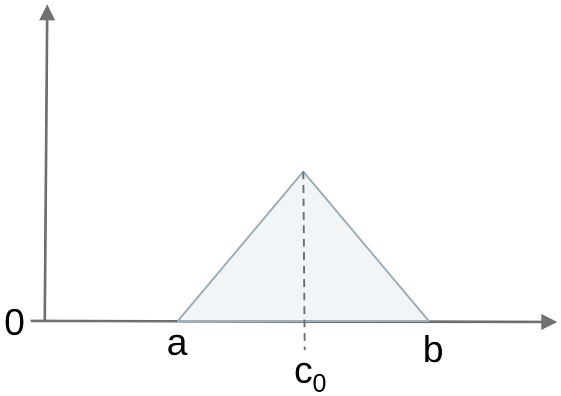


Model Outputs

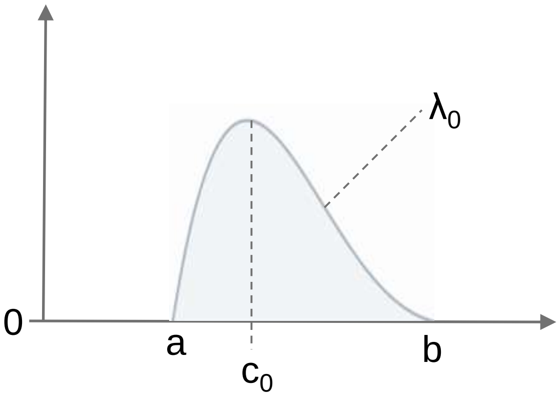
In traditional QSRA there are three common distributions used for uncertainty estimates



Uniform



Triangular



Beta-pert

As the number of parameters increase;

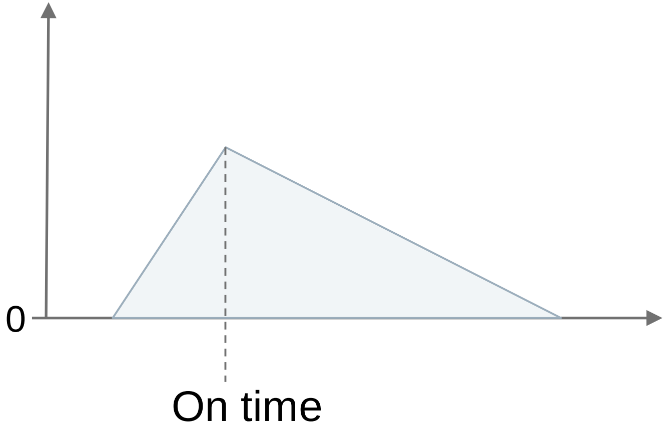
- Difficult to come up with a justifiable systematic process for hand-tuning parameters
- It becomes very time consuming

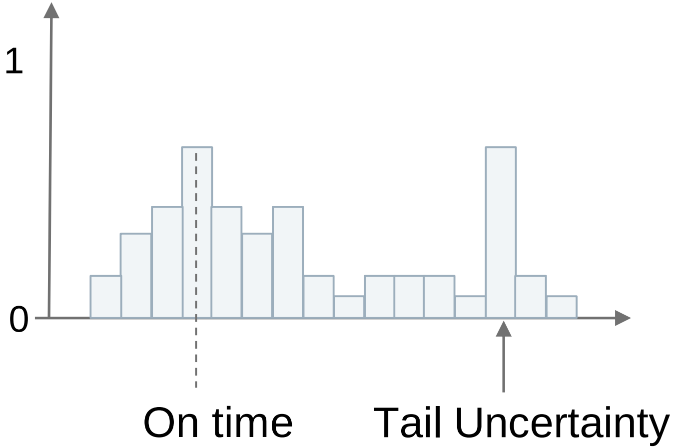
But

- You can model can capture many more types of uncertainty i.e. tail uncertainty

Why is that useful?

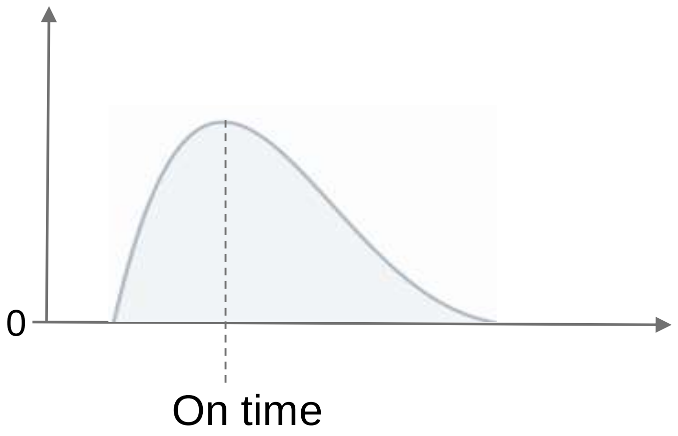
Case 1: Tail Risks >> focus on hazards that could cause severe delays

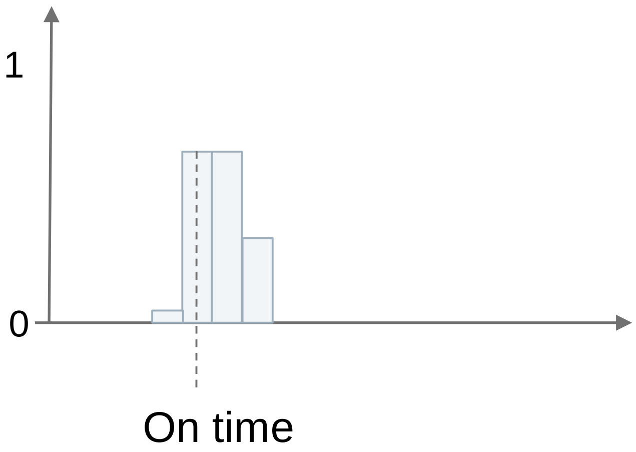




Why is that useful?

Case 2: Additional Uncertainty >> Exclude irrelevant tasks from mitigating strategy





Frequently asked questions

Q	How does the model know which data to use to forecast in future projects?	A	The ML model learns mathematical relationships between inputs and outputs, so past data doesn’t need to be consulted, only the rules learned from it.
Q	How is data from other industry sectors relevant to my project?	A	The ML process guarantees that the model will learn relevant relationships even when data is heterogeneous.
Q	Will the ML model tell me why my project will be delayed?	A	The ML model highlights the likelihood of delay, we work closely with those who know the specifics of each project to understand why those delays could happen.

Frequently asked questions

Q	Is the ML model perfect? If not, how can we trust the results?	A	The model is not perfect, but both in other fields and for this specific task, we have strong evidence to suggest it outperforms humans. The model will also provide more accurate uncertainty estimates than a human would.

That was a lot of information, let’s take a 5 minute break.
Please come back promptly!

Hands-on Workshop

Task

- Identify the most critical risks in the ‘new hospital in a city centre (UK)’ project using a nPlan
- Up to 10 selected activities

Time

- 40 minutes

How do we test it?

- Scenario testing to set the selected activities to be completed on-time

Main topic

- Each group would have 4-6 people
- Each break-out room would have an nPlan helper

Group with the most improvement in the final forecast would win a grand prize!

Hands-on Workshop

Group specific URL

- Group 1: shorturl.at/cjxIU
- Group 2: shorturl.at/qIST2
- Group 3: shorturl.at/kwJT5
- Group 4: shorturl.at/ajxzM

Login detail

- Username: pce-workshop@nplan.io
- Password: pce-workshop

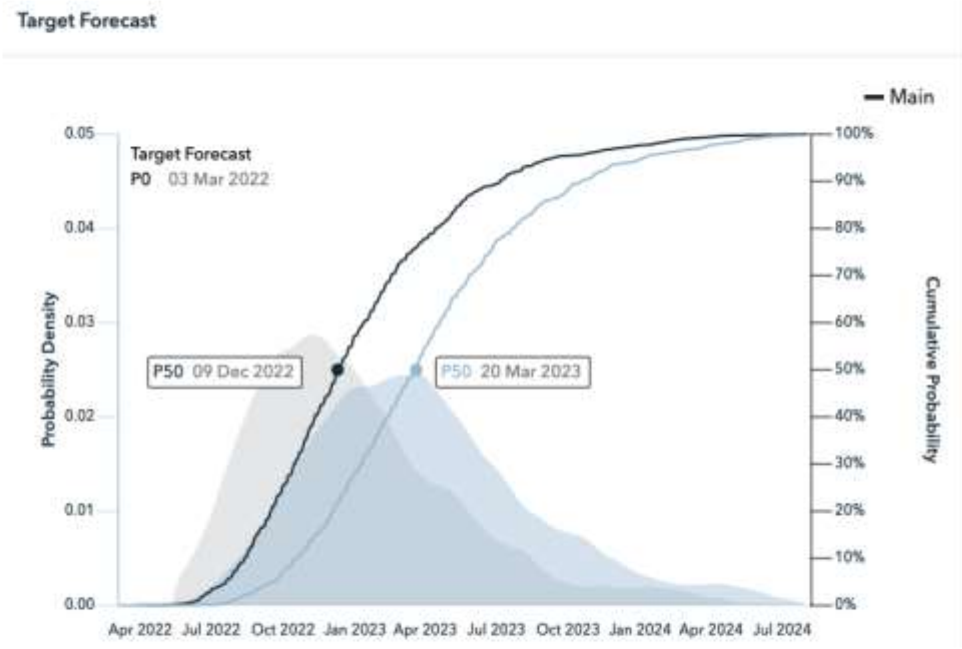
...and here’s one we prepared earlier

Example 10 choice of mitigation - Greatest effect

Showing all activities for: **Top 10 DC given criticality >10%**

Search by activity name or ID

ID	Activity
LVL7-810	Sheetrock Bottoms
LVL4-780	Install high piping above AHU's
COM120	Priority 1 Equipment (Level 12) - Supply AHU's a
A3-Lvl7-840	Install Electrical Wall Finishes
A2030	Reinforce, Place, Finish SOMD - L12-P1 (15,680
A1-Lvl8-710	Wall and Floor Ceramic Tile
A1-Lvl7-230	Wall and Floor Ceramic Tile
A12930	Reinforce, Place, Finish SOMD - L12-P2 (13,215
A12840	Reinforce, Place, Finish SOMD - L2-P2 (11,402 s
14140	Podium and Bracing Pin Piles

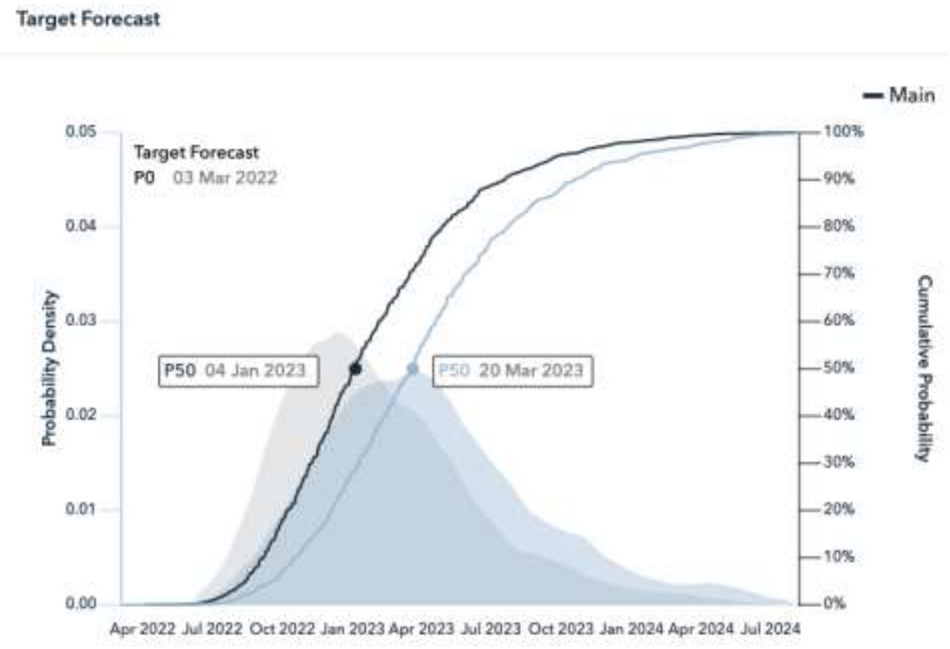


Example 10 choice of mitigation - Practical considerations

Showing all activities for: **3 Commissioning WBS + 7 Finishes WBS**

Search by activity name or ID

ID	Activity
LVL7-810	Sheetrock Bottoms
LVL7-3010	Bottoms - Tape/Sand
LST-420	Final ISD Walkthru
COM530	Balancing Punchlist
COM120	Priority 1 Equipment (Level 12) - Supply AH
A3-Lvl7-840	Install Electrical Wall Finishes
A2-Lvl7-750	Wall and Floor Ceramic Tile
A1-Lvl9-710	Wall and Floor Ceramic Tile
A1-Lvl8-710	Wall and Floor Ceramic Tile
A1-Lvl7-230	Wall and Floor Ceramic Tile



Audience Q&A

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Wrap-up

Human intelligence and Machine Learning both have their their strengths. And both have their risks.

Human intelligence runs the risk of noise and bias.

Machine Learning runs the risk of misinterpretation and inaction.

Today we have seen that successfully marrying the two mitigates those risks and amplifies their strengths so that we can produce a data-driven, human-acted-upon result that improves a project outcome.

And that was just in 60 minutes.

Few thoughts to finish

- We will send out the award vouchers to the email address with which you registered: please do flag to hello@nplan.io if it needs to go elsewhere!
- We're going to drop you a line with our details so that you can share any feedback on today's workshop along with focal questions in our Typeform Questionnaire
- Please do follow us at https://www.linkedin.com/company/nplan/ and via www.nplan.io as we will undoubtedly have more events of interest coming up.

nPlan

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