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Prediction of Aircraft Safety events using Bayesian inference and Hierarchical structures

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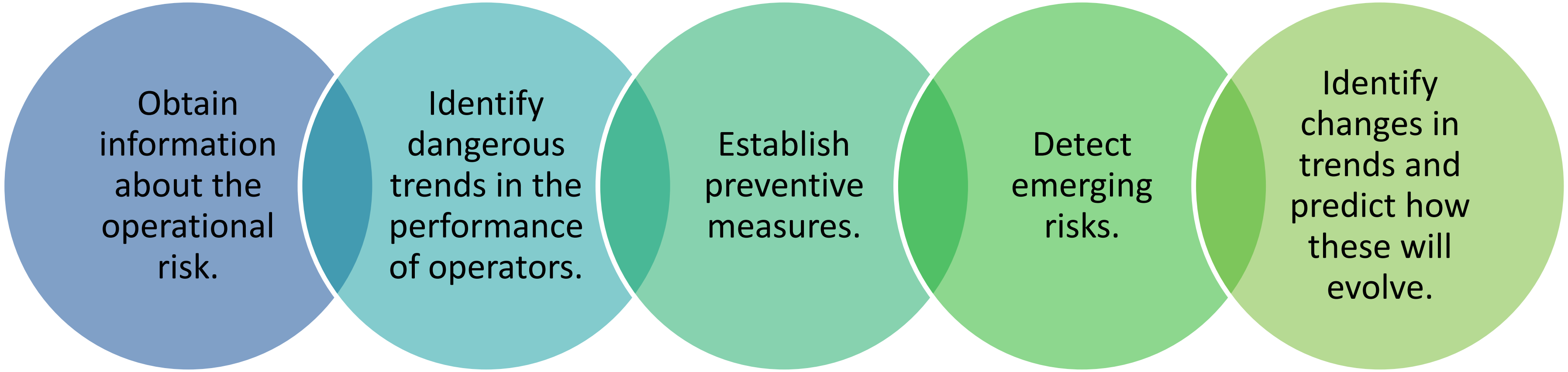
Contents

Need of Bayesian predictive analytics in aviation safety



- Conventional statistic approaches are inadequate when risks are rare or novel because there is insufficient relevant data.
- Organizations are often asked to make inference using sparse data. Waiting to obtain the "long run" objective frequency before making a decision is in many cases simply not possible.
- Additional information (beyond data) usable in the Bayesian inference framework should not be ignored.

Introduction to model base Bayesian inference I

Posterior		Likelihood	Prior
$P(H\|D)$	$\propto$	$P(D\|H)$	$P(H)$

Posterior $P(H|D)$

Probability that the hypothesis is true given the evidence/data

Plausibility of a hypothesis conditional upon our knowledge and applicable data

Likelihood $P(D|H)$

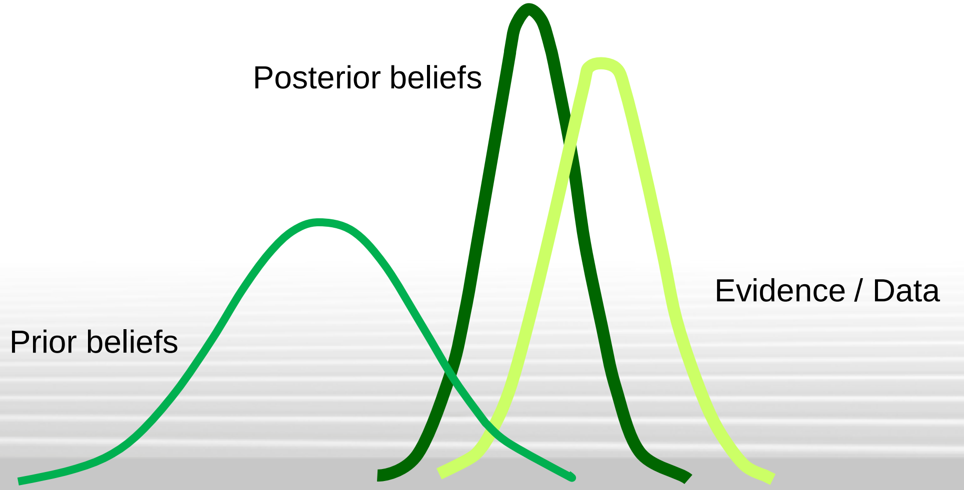
Probability this evidence/data if this hypothesis were true

Aleatory model representing the process providing the data

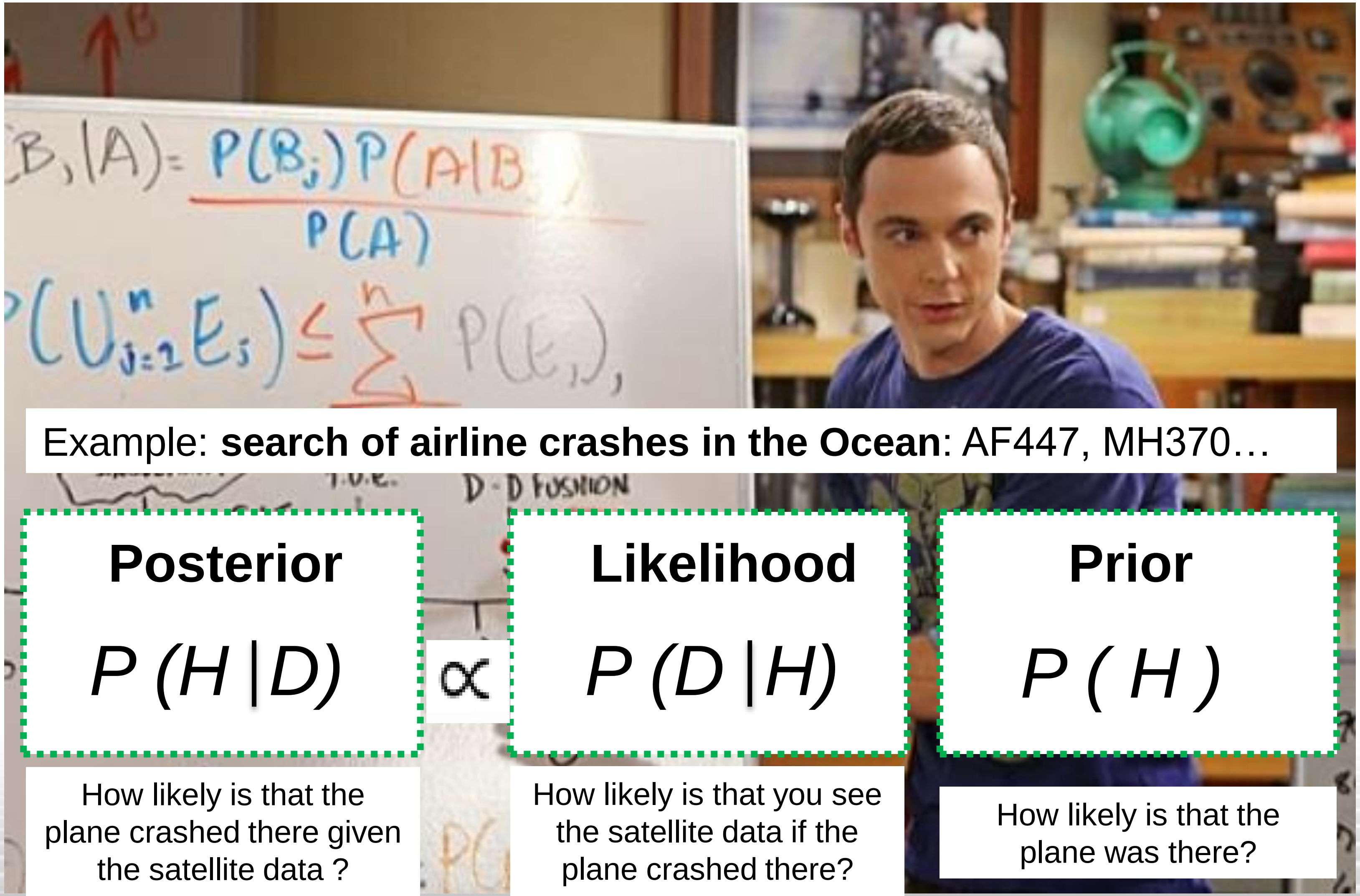
Prior $P(H)$

Probability of H being true, before gathering evidence

Our knowledge of the problem beyond what we call "data"



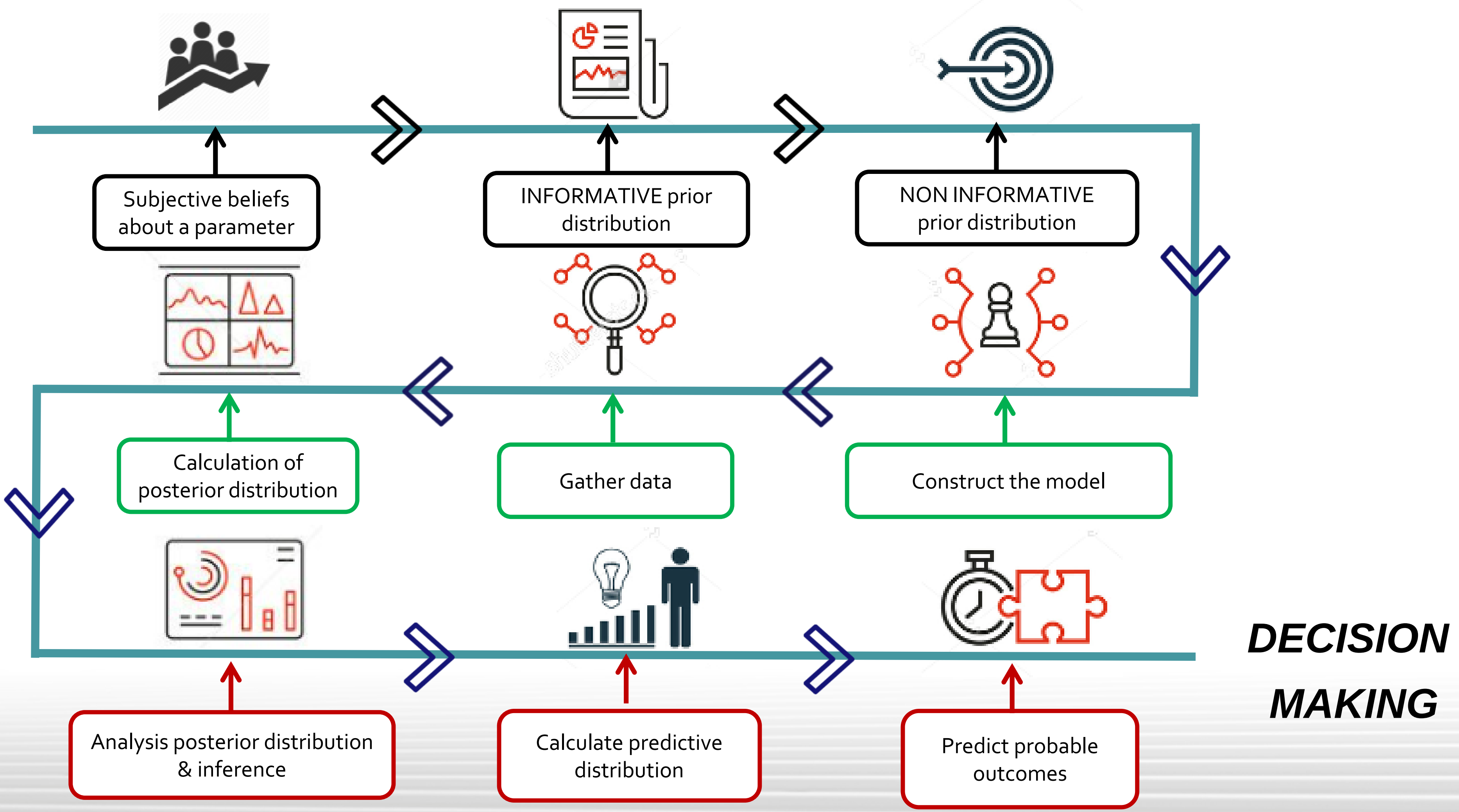
Introduction to model base Bayesian inference II



Example: **search of airline crashes in the Ocean**: AF447, MH370…

Posterior		**Likelihood**	**Prior**
$P(H \mid D)$	$\propto$	$P(D \mid H)$	$P(H)$
How likely is that the plane crashed there given the satellite data ?		How likely is that you see the satellite data if the plane crashed there?	How likely is that the plane was there?

Introduction to model base Bayesian inference III



Safety events data and information

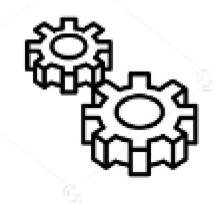
- Analysis of air operators safety incidents registered in MOR System.
- Usually precursors to more serious incidents or even accidents.

Monthly incidents

4 fleets of different models of aircraft

Generic Company A

PILOT REPORTS



DEFERRED ITEMS

IN FLIGHT SHUTDOWN

IN FLIGHT TURN-BACK

DELAY & CANCELATIONS

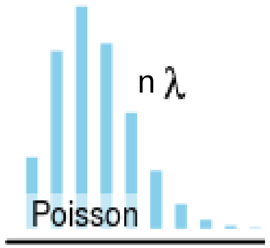
REJECTED TAKE-OFF

NON STABLISED APPROACH

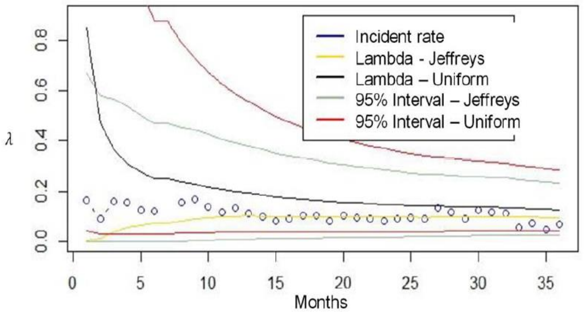
FLIGHT TIME LIMITATIONS

Basic models for estimating the rate of incidents

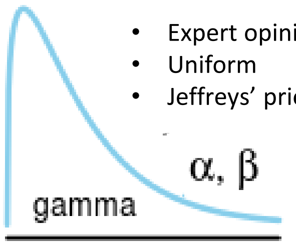
Gamma-Poisson model



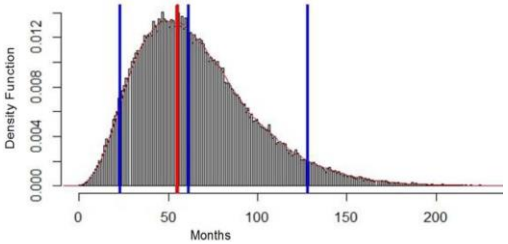
Likelihood



- Expert opinion
- Uniform
- Jeffreys' prior

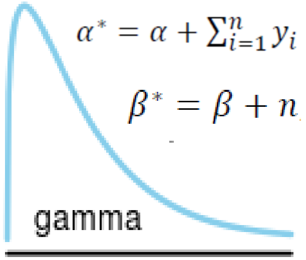


Prior

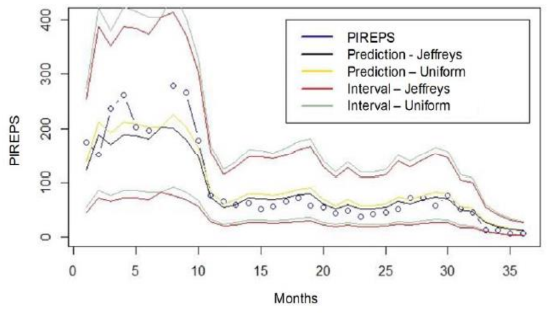


$\alpha^* = \alpha + \sum_{i=1}^{n} y_i$

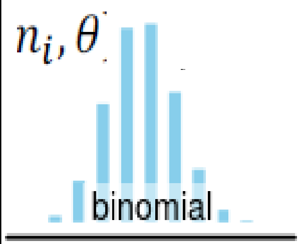
$\beta^* = \beta + n$



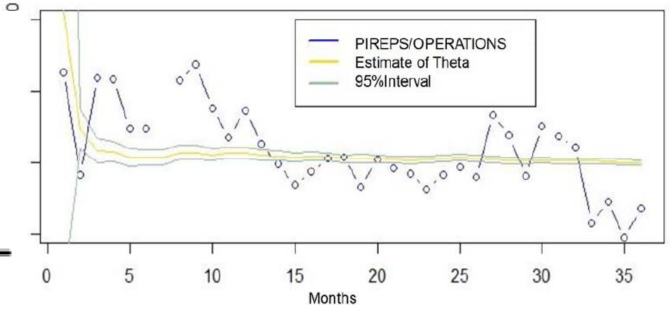
Posterior

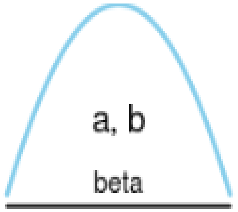


Beta-Binomial model

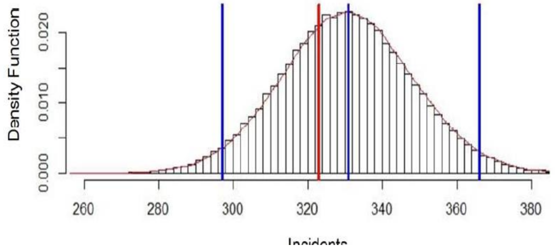


Likelihood



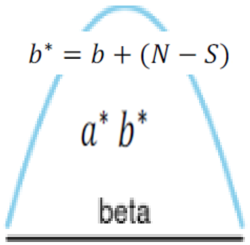


Prior

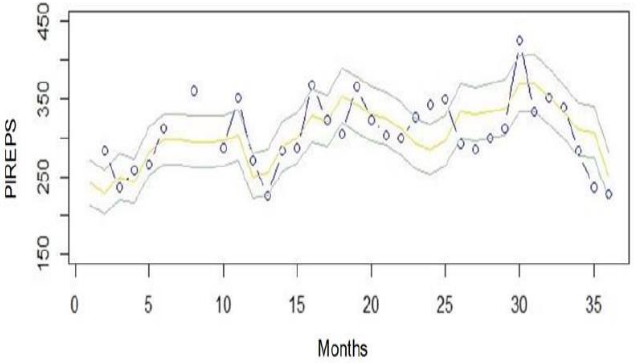


$a^* = a + S$

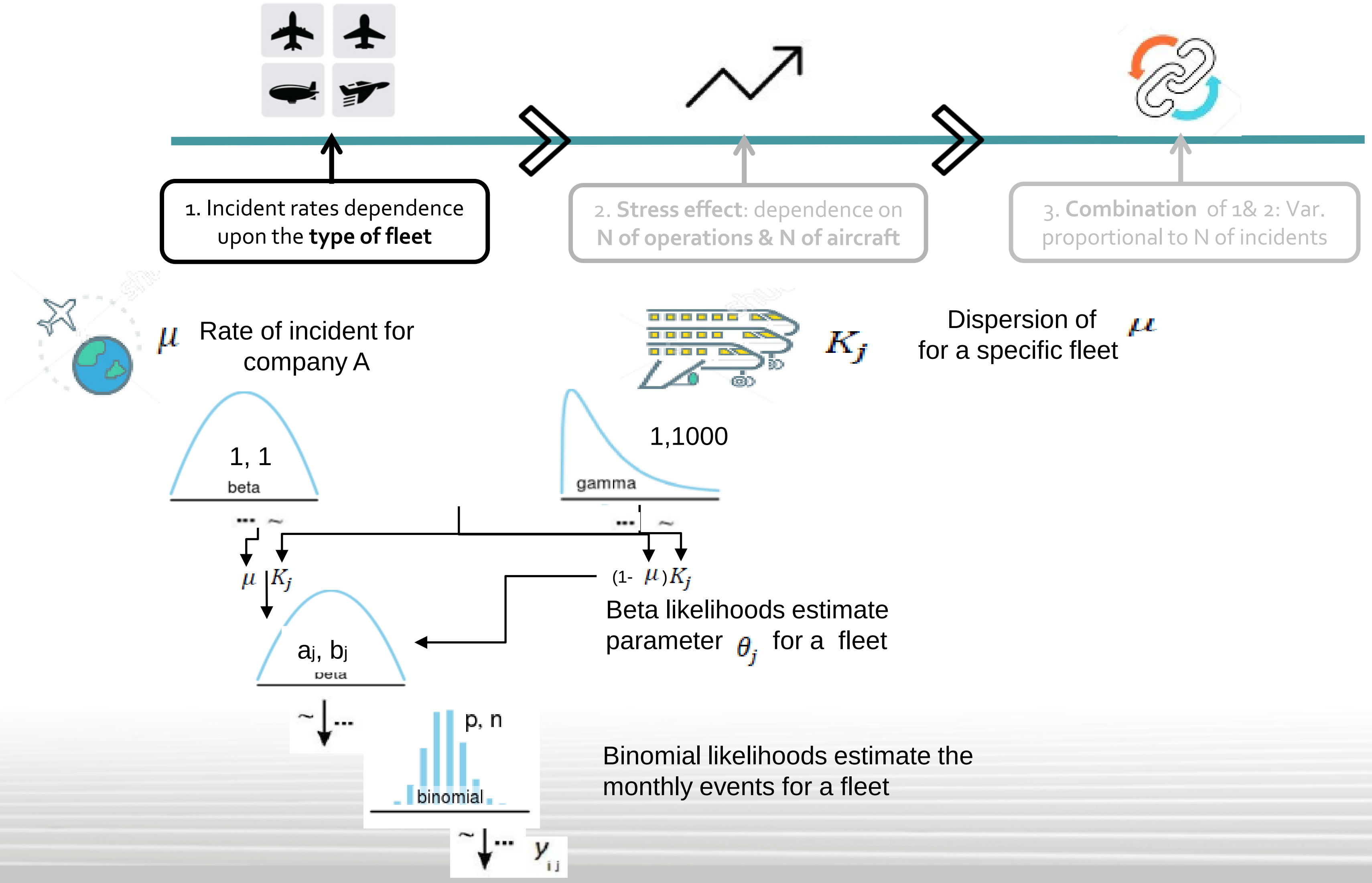
$b^* = b + (N - S)$



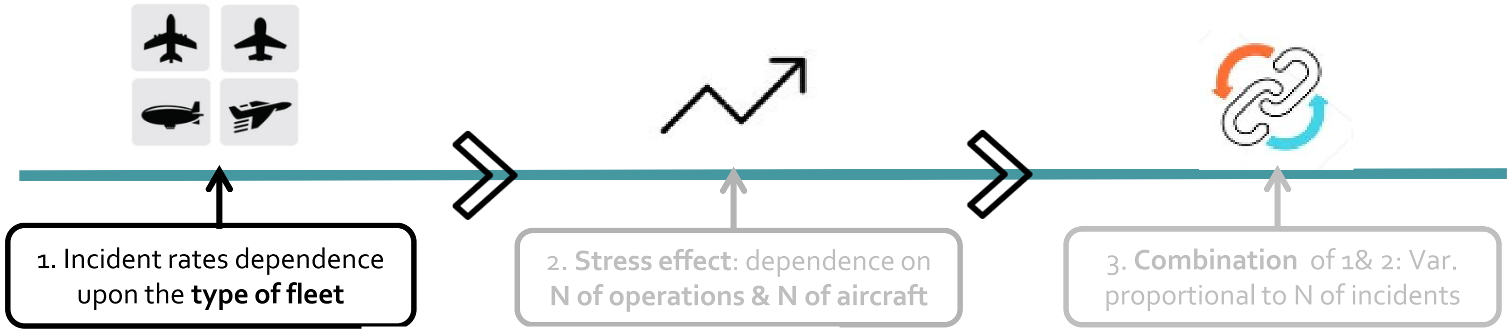
Posterior



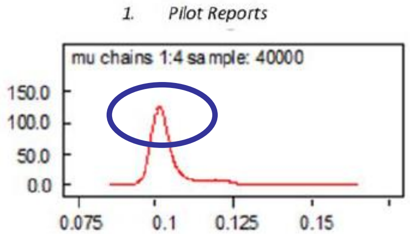
Hierarchical models I: concept



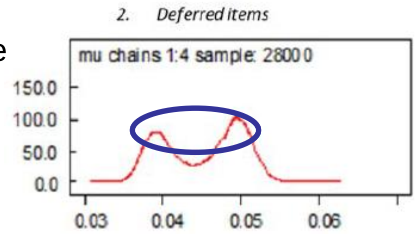
Hierarchical model I: results



- Identifies the orders of magnitude characteristic for each category of incidents, and allows company benchmarking.

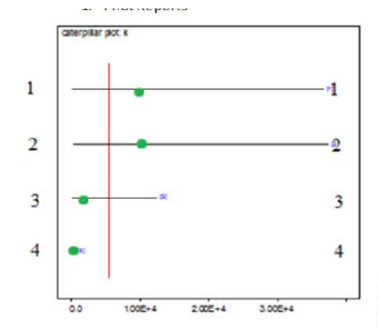


Identifies changes in the value of the incident rate for the company: "two clearly defined maxima."

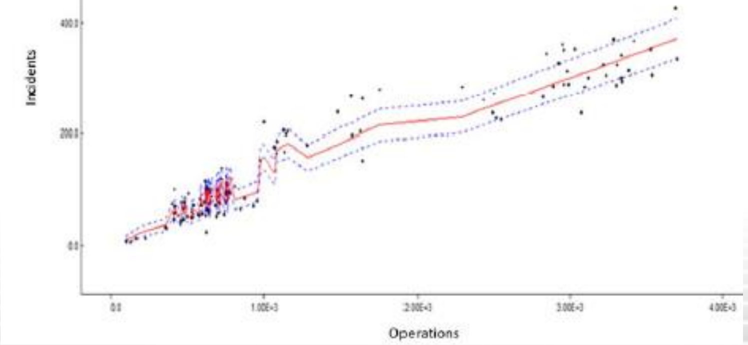


- Median values of K are generally high. Incident rates for the different fleets (θ_j) are of the same order and similar to the company μ

- Exception/Extreme values of K identifies atypical incident rates in fleets

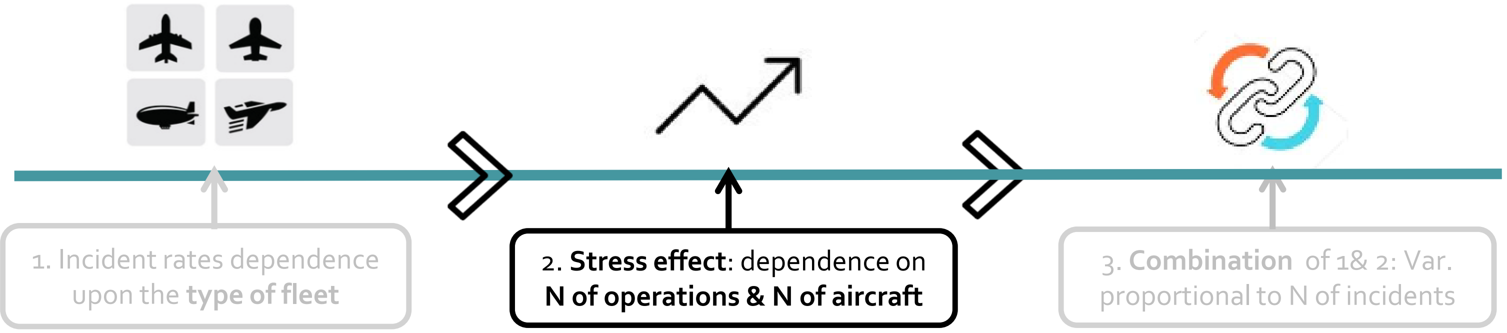


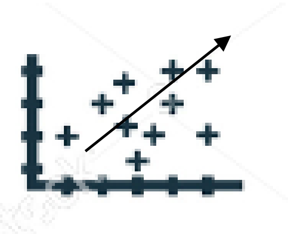
- A good fit to the data and predictions



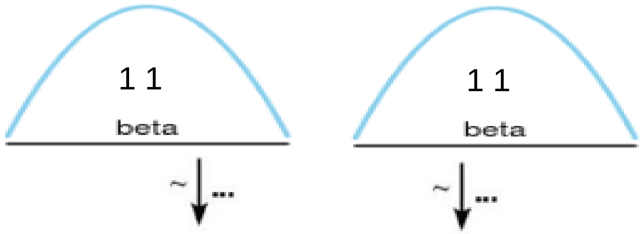
- Useful tool for evaluating and comparing fleets, types of incidents and different companies.

Hierarchical model II: concept





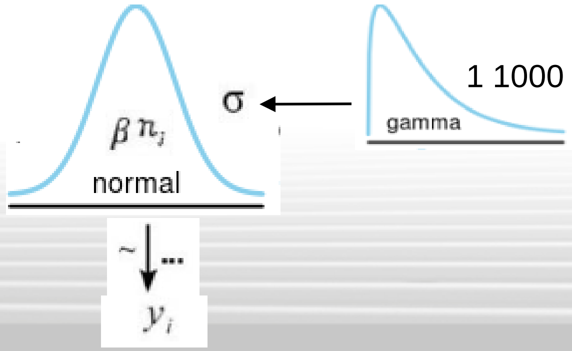
Model a linear relationship between incidents and operations via parameter



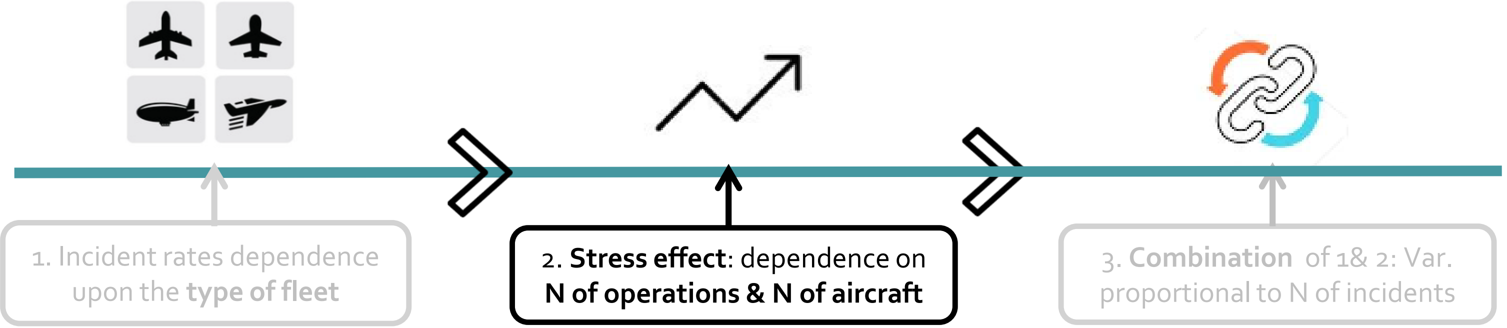
$$\beta = \alpha_{1j} * n_i + \alpha_{2j}$$

Each fleet may be characterised by two parameters, α_1 and α_2 , to which we assign prior Beta (1,1) distribution.

Incident data modelled as a Normal distribution

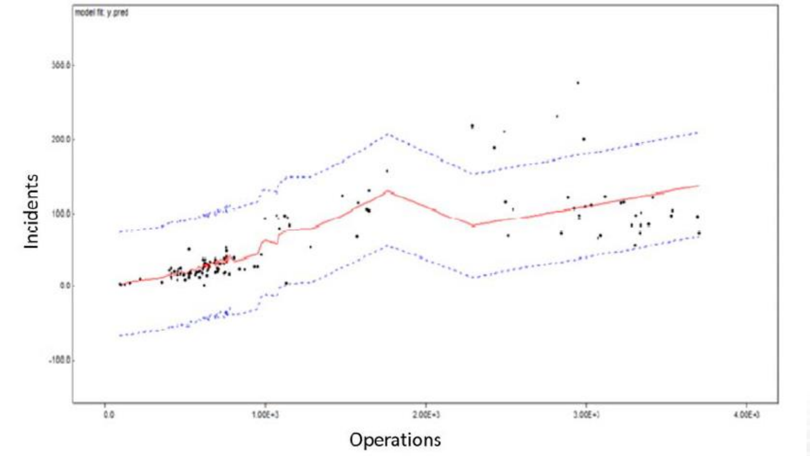


Hierarchical model II: results



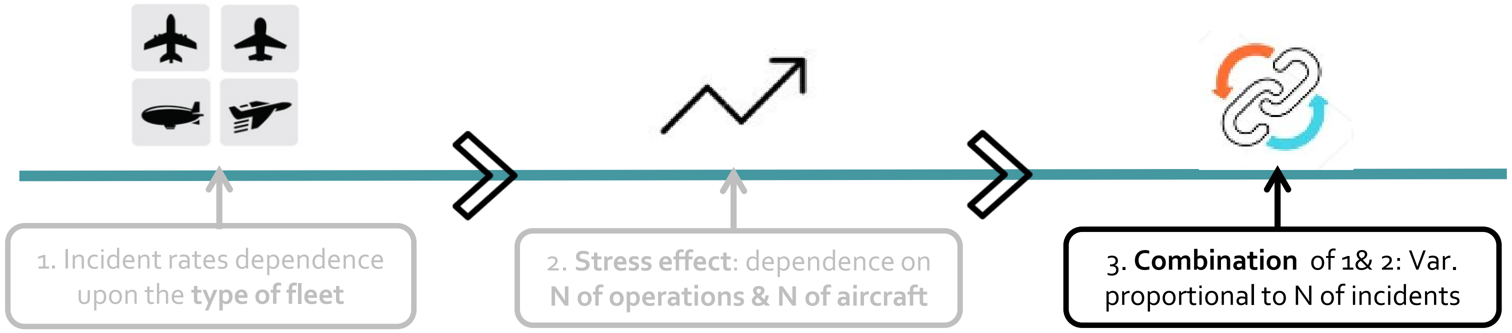
α_1
- Values very small, <10−5. It is difficult to quantify the stress for events that are highly unlikely.
- Distributions depends on the fleet and event being analyzed. The less likely the event, the greater the similarity between the distributions.

α_2
- Analogous to the incident rate. The less the incident rate is influenced by the number of operations, the greater the similarity with the incident rates calculated using the other methods.



- The model gives a better fit to the data for this category of event.
- It is useful when there is a change in the incident rate for all fleets.

Hierarchical models III: concept

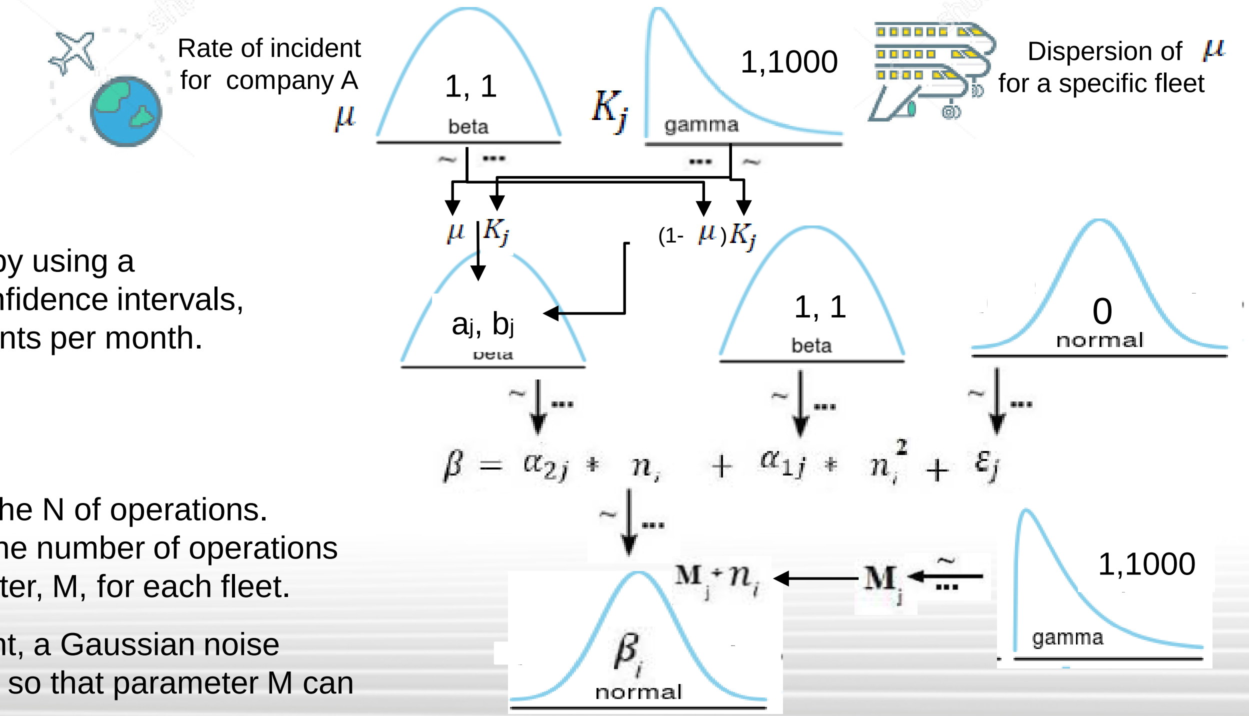


1º level has a structure similar to that in Hierarchical Model 1. Function of parameters μ and K is very like Model 1.

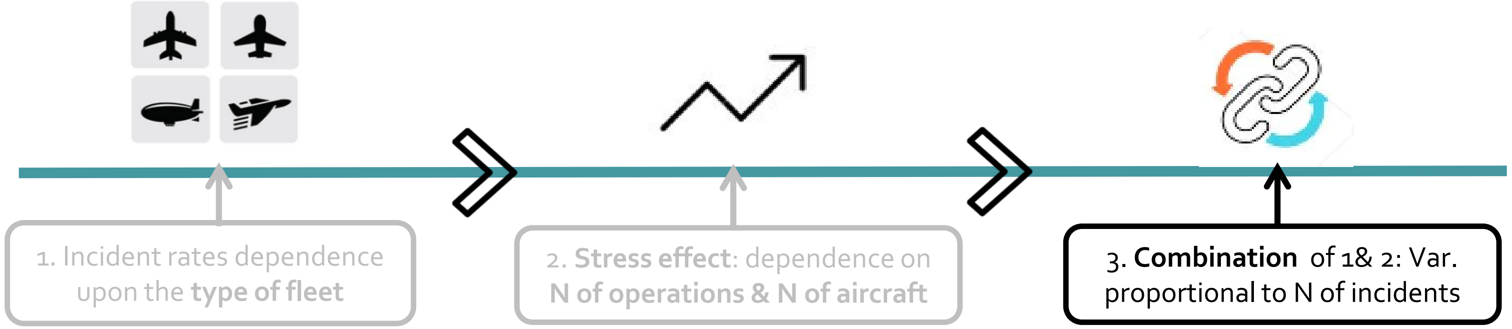
2º level incorporates the stress effect by using a **quadratic regression** to establish confidence intervals, especially when there are many incidents per month.

3º level uses a Normal dependent on the N of operations. It makes the variance proportional to the number of operations by estimating a proportionality parameter, M, for each fleet.

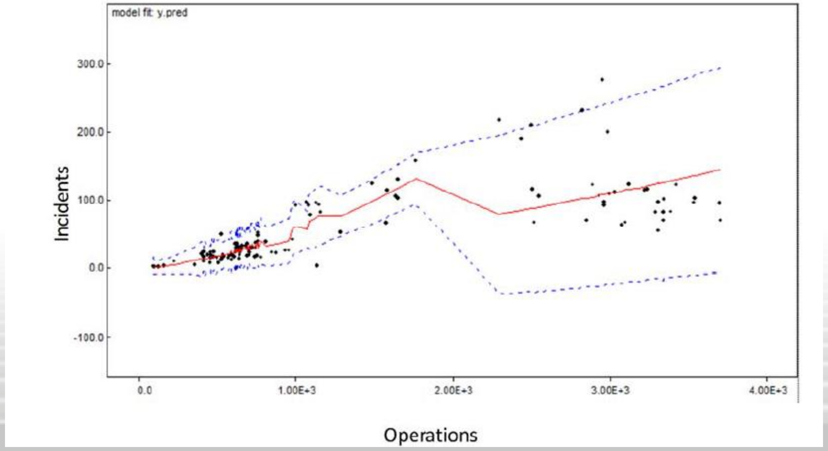
When the variance of a fleet is constant, a Gaussian noise component is added to the regression, so that parameter M can be set to 0, if required.



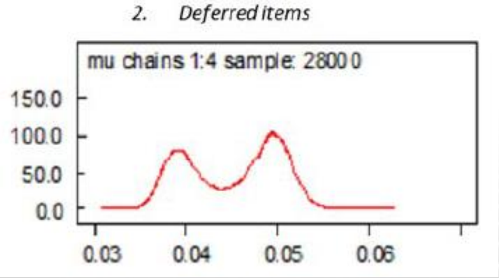
Hierarchical models III: results

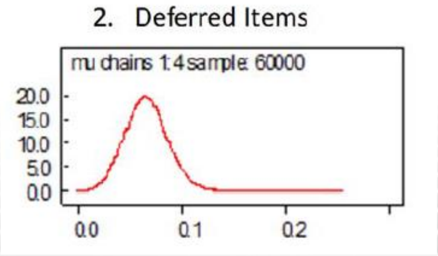


- Confidence levels show a very good fit to the data and the predictions are, in all cases, in line with the initial data.
- The "Deferred Items" of Company A is specific case where there is a drastic change in the incident rate, despite which the model still gives a good fit.



- Many parameters. Flexible and capable of quantifying the data spread. However, they do not have that same significance and are more difficult to interpret.
- The distributions are of a similar order of magnitude to those of parameter mu in Hierarchical Model 1. However, they are less precise .
- For example, the distributions of mu no longer capture the changes in the parameter.





Conclusions and utility

- Usefulness of hierarchical Bayesian structures effectively quantify risk.
  - Good estimates of incident rate per operation, trends and orders of magnitude of the incidents. It detects changes in trends.
  - Estimates parameter representing the performance of the entire set of fleets of a Company. Good tool for comparing the performance of different companies.
  - Measures the spread of the incident rate of a fleet, for a particular incident category, compared to the overall rate for the entire Company. Rapid alert of fleets that require more in-depth analysis, due to their behaviour deviating from the ideal.
  - Calculates how much the rate of incidents varies with the number of operations due to the so-called stress effect. Quantitatively compare the stress effect in one fleet compared to that in others. Quantify stress effect in the different incident categories.
  - Good fit to the data and confidence intervals with respect to the spread of the data series for any order of magnitude.
- Provides simple means of performing many different types of analysis that typically form part of the risk assessment carried out by aircraft operators.

Reference

"*Prediction of aircraft safety incidents using Bayesian inference and hierarchical structures*", Safety Science Vol. 104 (2018), pp. 216-230. https://doi.org/10.1016/j.ssci.2018.01.008

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Prediction of aircraft safety incidents using Bayesian inference and hierarchical structures

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ABSTRACT

Today, aviation is immersed in a shift from old-fashioned reactive and compliance-based safety approaches towards proactive and performance-based methods and tools. Stakeholders have to monitor, gather and analyse safety-related data and information in order to anticipate and predict actual and emerging safety risks. In this context safety analytics and statistics need to evolve to forecast future safety performances and risks.

This research adopts an innovative statistical approach involving the use of Bayesian inference and Hierarchical structures to develop statistical estimation and prediction models with different complexities and objectives. The study develops and analyses five Bayesian models of increasing difficulty, two basic and three Hierarchical models, which allows us to explore safety incident data, efficiently identify anomalies, assess the level of risk, define an objective framework for comparing air carriers, and finally predict and anticipate incidents.

EASA European Aviation Safety Agency

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THANK YOU VERY MUCH FOR YOUR ATTENTION

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