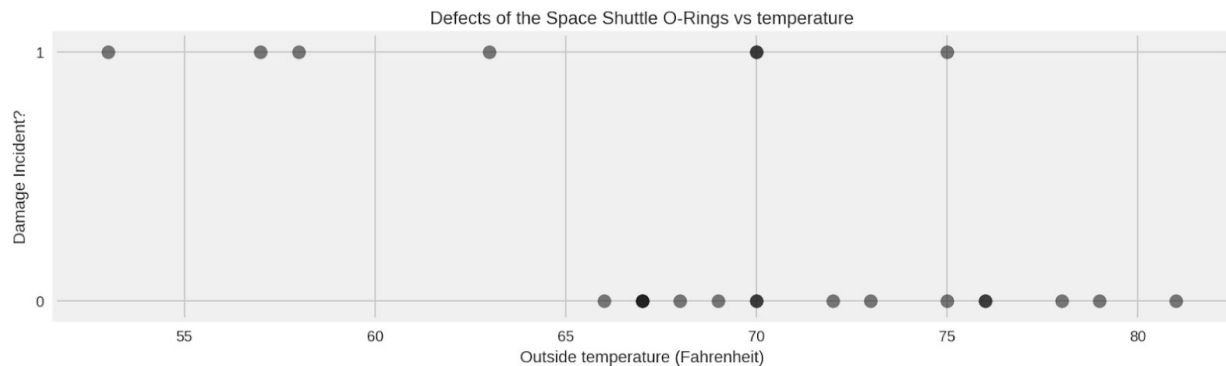


# Bayesian inference real life example

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Challenger example:-



$$p(t) = \frac{1}{1 + e^{\beta t + \alpha}},$$

$$\beta = \text{Normal}(\mu, \sigma^2)$$

$$\alpha = \text{Normal}(\mu, \sigma^2)$$

```
def challenger_joint_log_prob(D, temperature_, alpha, beta):  
    rv_alpha = tfd.Normal(loc=0., scale=1000.)  
    rv_beta = tfd.Normal(loc=0., scale=1000.)  
    logistic_p = 1.0 / (1. + tf.exp(beta * tf.to_float(temperature_) + alpha))  
    rv_observed = tfd.Bernoulli(probs=logistic_p)  
  
    return (rv_alpha.log_prob(alpha) +  
            rv_beta.log_prob(beta) + tf.reduce_sum(rv_observed.log_prob(D)))
```

---

Also, note that `rv_alpha` and `rv_beta` represent the random variables for our prior distributions for  $\alpha$  and  $\beta$ . By contrast, `rv_observed` represents the conditional distribution for the likelihood of observations in temperature and O-ring outcome, given a logistic distribution parameterized by  $\alpha$  and  $\beta$ . `tf.reduce_sum(rv_observed.log_prob(D))` represents the likelihood.

Next, we take our `joint_log_prob` function, and send it to the `tfp.mcmc` module. Markov chain Monte Carlo (MCMC) algorithms make educated guesses about the unknown input values, computing the likelihood of the set of arguments in the `joint_log_prob` function. By repeating this process many times, MCMC builds a distribution of likely parameters. Constructing this distribution is the goal of probabilistic inference.

