2. Bayesian workflow

- Building and improving models, gaining confidence in results
- 3 examples:
  - Birthdays
  - Sex ratios
  - Spell checking

Bayesian data analysis: (1) Modeling

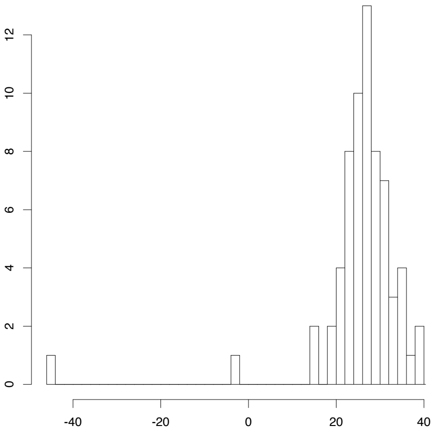
- "Generative models"
  - Data are a realization from a (multivariate) probability distribution
  - Data vector y, probability model $p(y|\theta)$, parameter vector θ
- Prior distributions
  - In Bayes inference, the parameter vector θ is a realization from a prior distribution, $p(\theta|\phi)$
  - Vector of hyperparameters ϕ is specified or itself modeled

Bayesian data analysis: (2) Inference

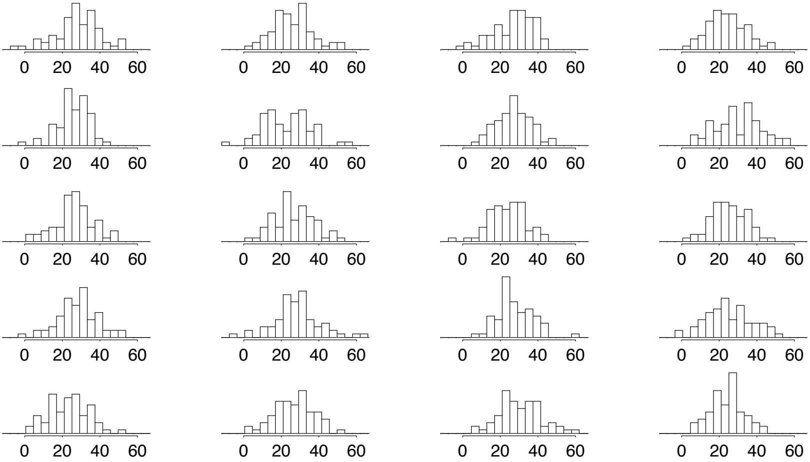
- Inference is represented by a matrix of posterior simulations
  - 1000 simulations of 90 parameters: a 1000×90 matrix
- Postprocessing
  - Inference for qoi's
  - Decision analysis

Bayesian data analysis: (3) Model checking/improvement

- A normal distribution is fit to the following data:

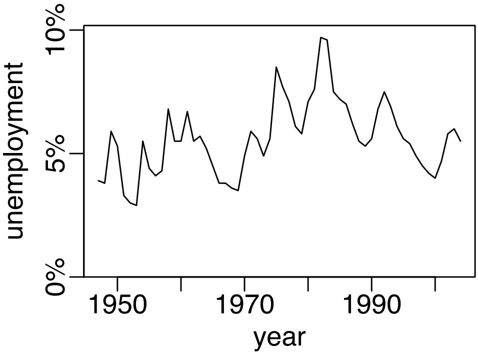


20 replications under the fitted model

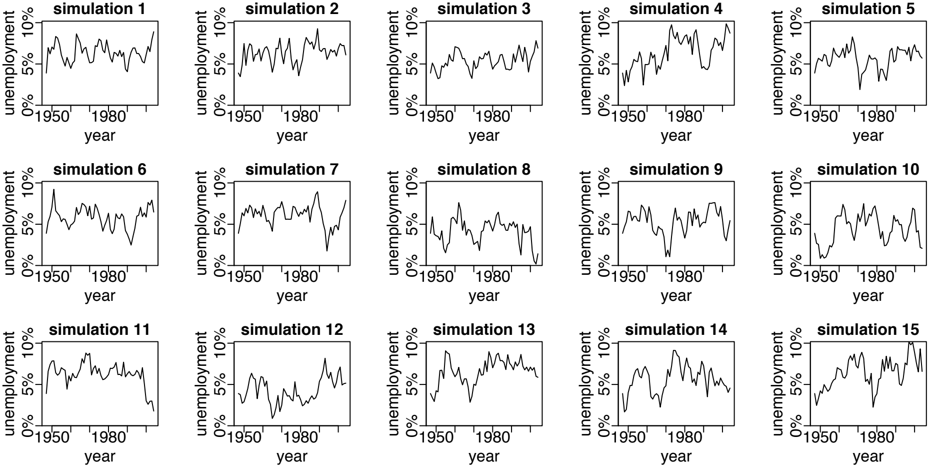


(Old) U.S. unemployment series

- Fit a first-order autoregression to these data:



15 replications under the fitted model



Birthdays!

Social Science & Medicine 73 (2011) 1246–1248

Contents lists available at SciVerse ScienceDirect

Social Science & Medicine

journal homepage: www.elsevier.com/locate/socscimed

Short report

Influence of Valentine's Day and Halloween on Birth Timing

Becca R. Levy*, Pil H. Chung, Martin D. Slade

Yale University, School of Public Health, Division of Social & Behavioral Sciences, 60 College Street, New Haven, CT 06520-8034, United States

A R T I C L E I N F O

Article history:
Available online 28 July 2011

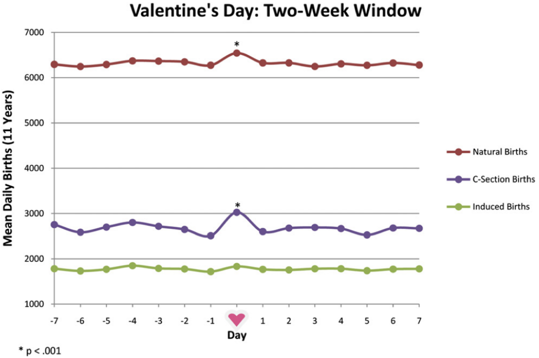
Keywords:
United States
Culture
Birth timing
Holidays
Pregnancy
Biocultural
Birth

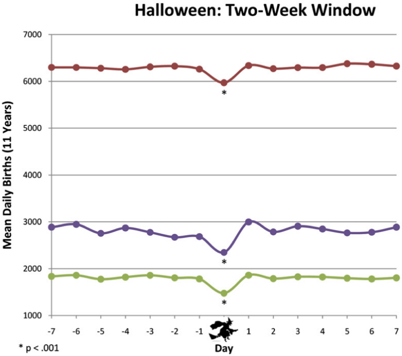
A B S T R A C T

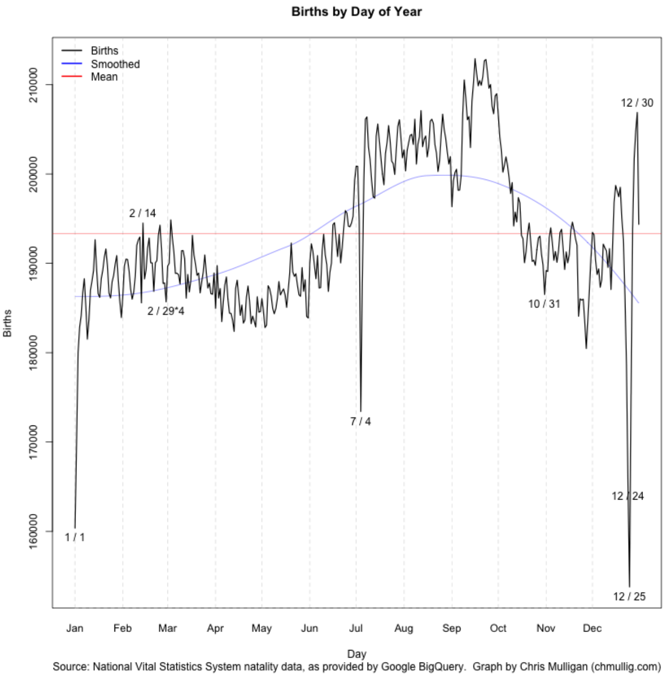
It is known that cultural representations, in the form of stereotypes, can influence functional health. We predicted that the influence of cultural representations, in the form of salient holidays, would extend to birth timing. On Valentine's Day, which conveys positive symbolism, there was a 3.6% increase in spontaneous births and a 12.1% increase in cesarean births. Whereas, on Halloween, which conveys negative symbolism, there was a 5.3% decrease in spontaneous births and a 16.9% decrease in cesarean births. These effects reached significance at $p < .0001$, after adjusting for year and day of the week. The sample was based on birth-certificate information for all births in the United States within one week on either side of each holiday across 11 years. The Valentine's-Day window included 1,676,217 births and the Halloween window included 1,809,304 births. Our findings raise the possibility that pregnant women may be able to control the timing of spontaneous births, in contrast to the traditional assumption, and that scheduled births are also influenced by the cultural representations of the two holidays.

© 2011 Elsevier Ltd. All rights reserved.

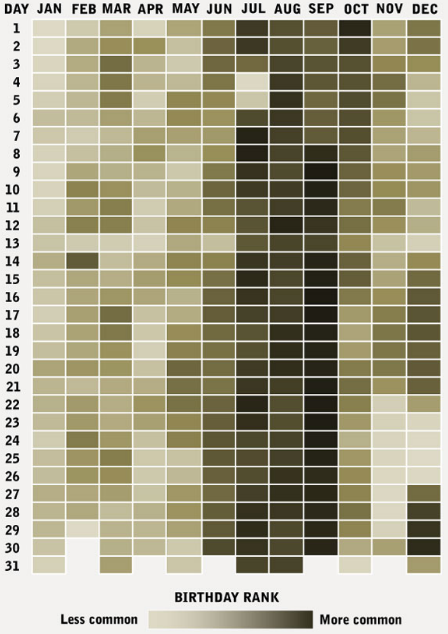
The published graphs show data from 30 days in the year

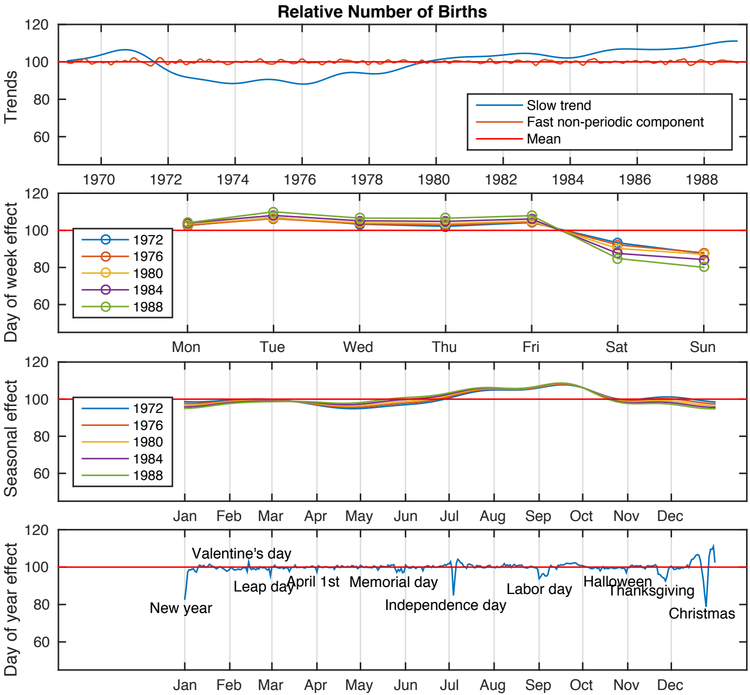




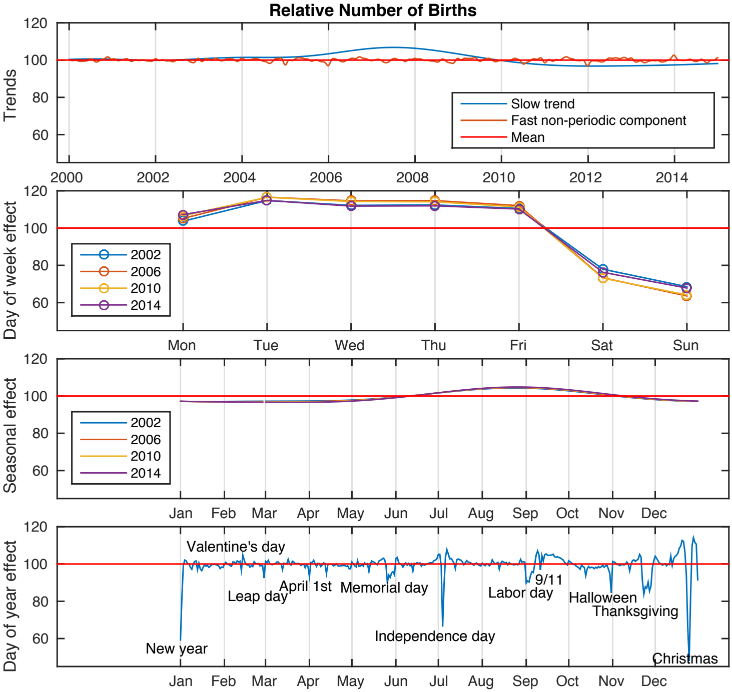

Births by Day of Year
Births
Smoothed
Mean
210000
200000
190000
180000
170000
160000
Births
2 / 14
2 / 29*4
7 / 4
10 / 31
12 / 30
12 / 24
12 / 25
1 / 1
Jan
Feb
Mar
Apr
May
Jun
Jul
Aug
Sep
Oct
Nov
Dec
Day
Source: National Vital Statistics System natality data, as provided by Google BigQuery. Graph by Chris Mulligan (chmullig.com)

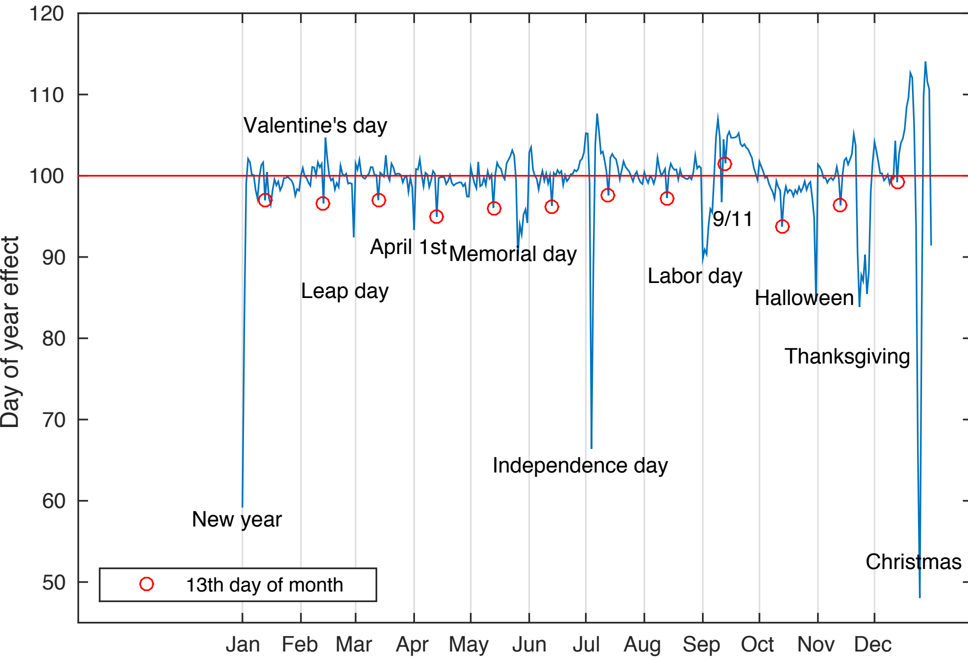
Which Birth Dates Are Most Common?





Relative Number of Births
Trends
Slow trend
Fast non-periodic component
Mean
1970
1972
1974
1976
1978
1980
1982
1984
1986
1988
Day of week effect
1972
1976
1980
1984
1988
Mon
Tue
Wed
Thu
Fri
Sat
Sun
Seasonal effect
Jan
Feb
Mar
Apr
May
Jun
Jul
Aug
Sep
Oct
Nov
Dec
Day of year effect
New year
Valentine's day
Leap day
April 1st
Memorial day
Independence day
Labor day
Halloween
Thanksgiving
Christmas

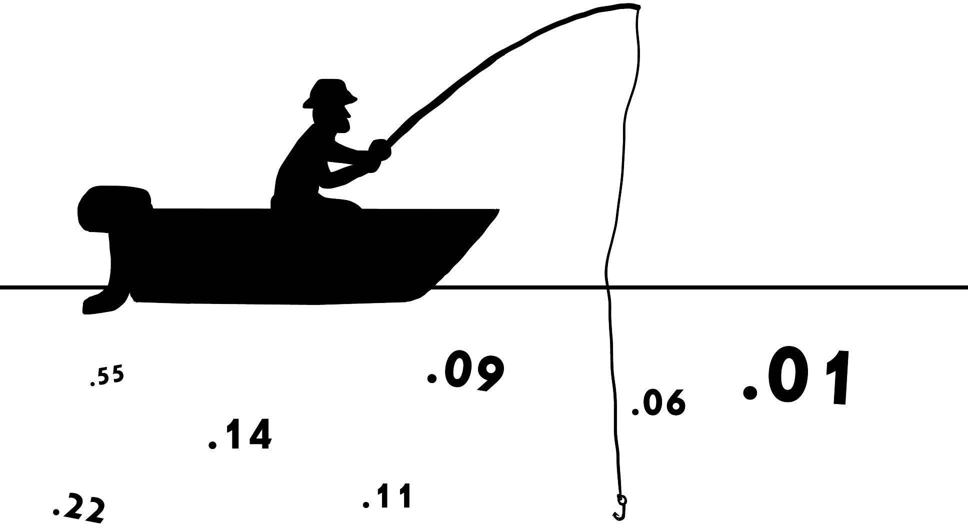

Relative Number of Births
Trends
Slow trend
Fast non-periodic component
Mean
2000
2002
2004
2006
2008
2010
2012
2014
Day of week effect
2002
2006
2010
2014
Mon
Tue
Wed
Thu
Fri
Sat
Sun
Seasonal effect
Day of year effect
Jan
Feb
Mar
Apr
May
Jun
Jul
Aug
Sep
Oct
Nov
Dec
Valentine's day
Leap day
April 1st
Memorial day
New year
Independence day
9/11
Labor day
Halloween
Thanksgiving
Christmas
120
100
80
60



Day of year effect
120
110
100
90
80
70
60
50
Jan
Feb
Mar
Apr
May
Jun
Jul
Aug
Sep
Oct
Nov
Dec
Valentine's day
April 1st
Memorial day
Leap day
Labor day
9/11
Halloween
Thanksgiving
Independence day
New year
Christmas
13th day of month

The blessing of dimensionality

- We learned by looking at 366 questions at once!
- Consider the alternative . . .



.55

.09

.06

.01

.14

.22

.11

.03

.34

The Fluctuating Female Vote: Politics, Religion, and the Ovulatory Cycle

P
X
©
R
sa
D
p

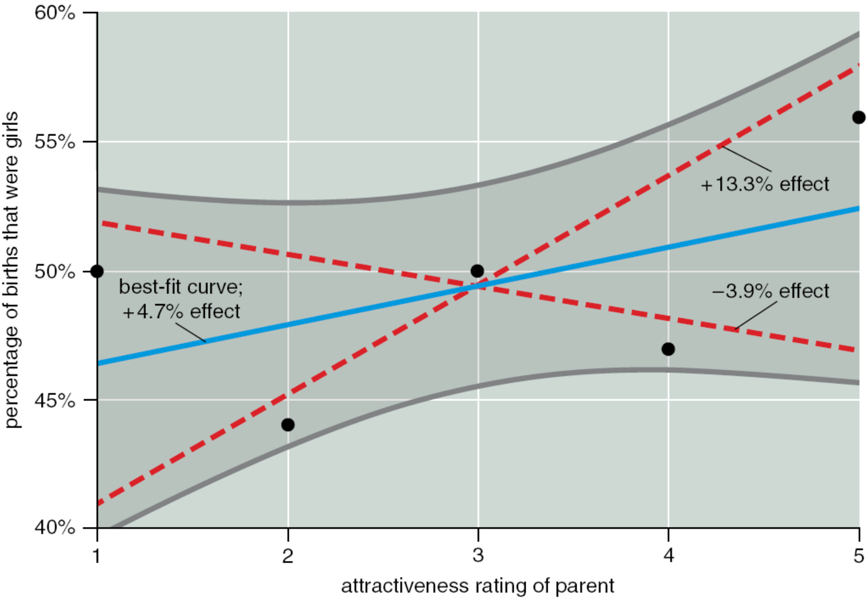
Kristina M. Durante[1], Ashley Rae[1], and Vladas Griskevicius[2]
[1]College of Business, University of Texas, San Antonio, and [2]Carlson School of Management, University of Minnesota

Abstract
Each month, many women experience an ovulatory cycle that regulates fertility. Although re
cycle influences women's mating preferences, we proposed that it might also change wome
views. Building on theory suggesting that political and religious orientation are linked to rep
how fertility influenced women's politics, religiosity, and voting in the 2012 U.S. presidenti
with large and diverse samples, ovulation had drastically different effects on single women
relationships. Ovulation led single women to become more liberal, less religious, and more
Obama. In contrast, ovulation led women in committed relationships to become more co
and more likely to vote for Mitt Romney. In addition, ovulation-induced changes in poli
women's voting behavior. Overall, the ovulatory cycle not only influences women's politics
differently for single women than for women in relationships.

Beautiful parents have more daughters?

- S. Kanazawa (2007). Beautiful parents have more daughters: a further implication of the generalized Trivers-Willard hypothesis. *Journal of Theoretical Biology*.
- Attractiveness was measured on a 1–5 scale ("very unattractive" to "very attractive")
  - 56% of children of parents in category 5 were girls
  - 48% of children of parents in categories 1–4 were girls
- Statistically significant (2.44 s.e.'s from zero, $p = 1.5\%$)
- But the simple regression of sex ratio on attractiveness is not significant (estimate is 1.5 with s.e. of 1.4)
- Multiple comparisons problem: 5 natural comparisons $\times$ 4 possible time summaries!

The data and fitted regression line



The larger statistical questions

- The questions
  - How to think about findings that are not “statistically significant”?
  - How to estimate small effects?
- The answers
  - Interpret the estimates in light of how large you think they might be (compared to your previous experience)
  - Estimate the pattern of effects rather than considering each individually

Prior information!

- Pr (boy birth) $\approx 51.5\%$
  - Boys die at a higher rate than girls
  - At age 20, the number of boys and girls is about the same
  - Evolutionary story
- What can affect Pr (boy births)?
  - Race, parental age, birth order, maternal weight, season of birth: effects of about 1% or less
  - Extreme poverty and famine: effects as high as 3%
- We expect any effects of beauty to be less than 1%

Another try: data from *People* magazine

The children of each year's "50 most beautiful people"

- We collected data from 1995–2000
- 1995: 32 girls and 24 boys: 57.1% girls (standard error 8.6)
- 1996: 45 girls and 35 boys: $56.2\% \pm 7.8\%$
- $1995 + 1996$: $56.6\% \pm 4.3\%$: almost statistically significant!
- 1997: 24 girls and 35 boys, ...
- Pooling 1995–2000: $47.7\% \pm 2.8\%$: not statistically significantly different from 48.5%

Why is this happening?

- Statistical theory and education are focused on estimating one effect at a time
- "Statistical significance" is a useful idea, but it doesn't work when studying very small effects
- Methods exist for including prior knowledge of effect sizes, but these methods are not well integrated into statistical practice

Bayesian approach

- Data: difference in Pr(girl) estimated from 3000 respondents
  - 0.08 ± 0.03 (selected comparison)
  - 0.047 ± 0.043 (linear regression)
- Prior distribution: $\mathrm{N}(0, 0.003^2)$
- Equivalent sample size:
  - Consider a survey with n parents
  - Compare sex ratio of prettiest $n/3$ to ugliest $n/3$
  - s.e. is $\sqrt{0.5^2/(n/3) + 0.5^2/(n/3)} = 0.5\sqrt{6/n}$
  - Equivalent info: $0.003 = 0.5\sqrt{6/n} \ldots n = 166{,}000$
- A study with $n = 166{,}000$ people would be weighted equally with the prior

Example: Spell checking

- The typed word "Radom" is actually Random ($\theta = 1$), Radon ($\theta = 2$), or Radom ($\theta = 3$)
- Prior distribution:

θ	$p(\theta)$
random	7.60×10^{-5}
radon	6.05×10^{-6}
radom	3.12×10^{-7}

- Likelihood:

θ	$p(\text{"radom"} \mid \theta)$
random	0.00193
radon	0.000143
radom	0.975

Spell checking

- Prior, likelihood, posterior distributions:

θ	$p(\theta)$	$p(y\|\theta)$	$p(\theta)p(y\|\theta)$	$p(\theta\|\mathrm{y})$
random	7.60×10^{-5}	0.00193	1.47×10^{-7}	0.325
radon	6.05×10^{-6}	0.000143	8.65×10^{-10}	0.002
radom	3.12×10^{-7}	0.975	3.04×10^{-7}	0.673

- Decision making
- Model checking
- Model improvement