## Bayesian Data Analysis, class 1b

Andrew Gelman

Chapter 1: Probability and inference

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  - Traditional likelihood
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- $ightharpoonup N( heta|\mu,\sigma^2)$ , etc., are precise mathematical expressions
- Details of distributions in Appendix A
- Check out our clean notation (compare to other books)
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 random  $7.60 \times 10^{-5}$  radon  $6.05 \times 10^{-6}$  radom  $3.12 \times 10^{-7}$ 

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► Likelihood:

$\theta$	$p(\text{"radom"} \theta)$
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radon	0.000143
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radon	$6.05 \times 10^{-6}$	0.000143	$8.65 \times 10^{-10}$	0.002
radom	$3.12 \times 10^{-7}$	0.975	$3.04 \times 10^{-7}$	0.673

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- ► Model checking
- Model improvement

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- Equally likely events
- Calibration on events defined by physical symmetry
- "Suppose a coin having probability 0.7 of coming up heads is tossed"
- ▶ I'm unsatisfied by axiomatic or betting rationales for Bayes
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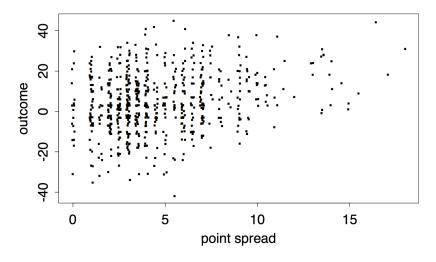
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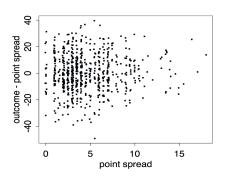
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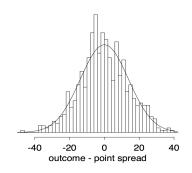
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# 1.6. Example of probability assignment: football point spreads

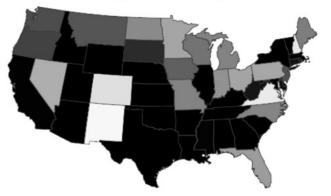




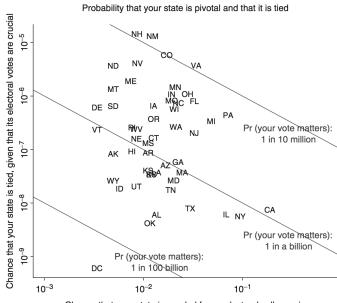


### Estimating the probability a vote is decisive

States where your vote is most likely to matter



#### The numbers



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### 1.7. Example: estimating the accuracy of record linkage

► Another example of empirical probability assignment

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- Being able to read an expression and separate constants from variables:

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### Mixture distribution for congressional elections

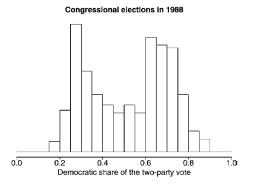


Figure 1. Histogram of Democratic Share of the Two-Party Vote in Congressional Elections in 1988. Only districts that were contested by both major parties are shown here.

### Separating into Republicans, Democrats, and open seats

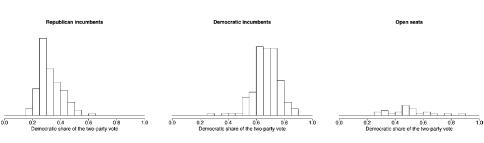


Figure 2. Histogram of Democratic Share of the Two-Party Vote in Congressional Elections in 1988, in Districts With (a) Republican Incumbents, (b) Democratic Incumbents, and (c) Open Seats. Combined, the three distributions yield the bimodal distribution in Figure 1.

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# Summarizing inferences by simulation

Simulation	Pa	ramet	$\operatorname{ers}$	Predictive quantities			
$\operatorname{draw}$							
	$ heta_1$	• • •	$ heta_k$	$ ilde{y}_1$	• • •	$\tilde{y}_n$	
1	$ heta_1^1$		$ heta_k^1$	$ ilde{y}_1^1$		$\tilde{y}_n^1$	
:	:	٠.	:	:	٠.	:	
${f L}$	$ heta_1^S$		$ heta_k^S$	$ ilde{y}_1^S$		$\tilde{y}_n^S$	

# Example: a regression model for forecasting elections

sim	$\sigma$	$\beta_0$	$eta_1$	$eta_2$	$ ilde{y}_1$	$ ilde{y}_2$	• • •	$ ilde{y}_{55}$	• • •	$ ilde{y}_{435}$	$\sum_{i} I(\tilde{y}_i > 0.5)$
1	.065	.19	.62	.067	.69	.57		NA		.79	251
2	.069	.25	.50	.097	.75	.63	• • •	NA	• • • •	.76	254
:	÷	÷	÷	÷	÷	÷	÷	÷	٠.	÷	:
1000	.067	.23	.51	.089	.73	.57		NA	• • •	.69	251
median	.068	.20	.58	.077	.73	.65		NA		.72	253
mean	.067	.20	.58	.078	.73		• • •		• • • •		252.4
$\operatorname{sd}$	.003	.02	.04	.007	.07	.07		NA	• • •	.07	3.1

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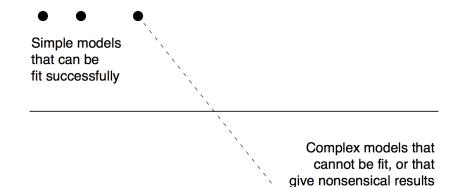
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#### Debugging



- Flexibility
- Combine multiple sources of information
- Uncertainty and variation

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- ▶ 3 steps of Bayesian data analysis
- Bayesian inference for simple discrete probabilities
- Assigning probabilities from data
- Simulation and software

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