

Bayesian data analysis and Stan

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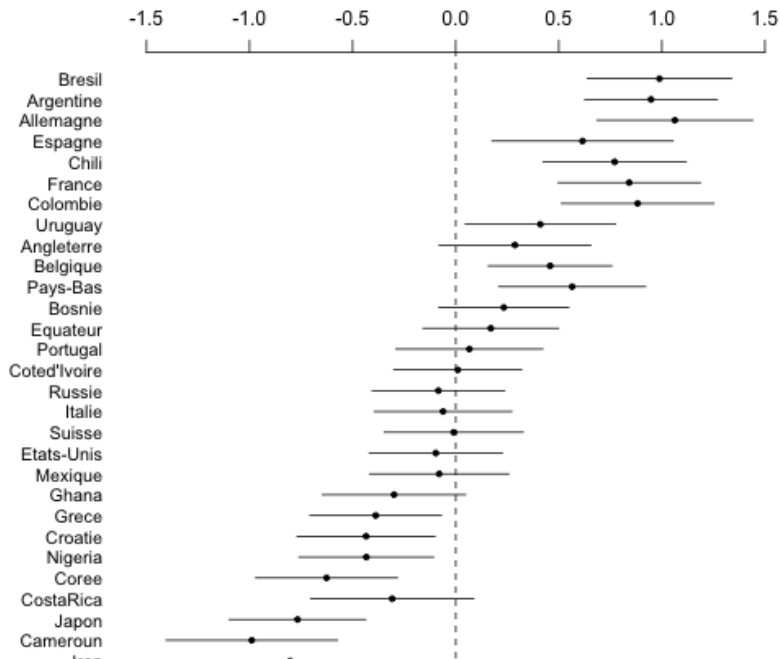
Dept of Statistics and Dept of Political Science
Columbia University, New York

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1. Real-life Stan

- ▶ Soccer
- ▶ Golf
- ▶ “Global climate challenge”

Team quality (estimate +/- 1 s.e.)



worldcup2012.txt

Bresil 3 Croatie 1
Mexique 1 Cameroun 0
Bresil 0 Mexique 0
Cameroun 0 Croatie 4
Cameroun 1 Bresil 4
Croatie 1 Mexique 3
Espagne 1 Pays-Bas 5
Chili 3 Australie 1
Espagne 0 Chili 2
Australie 2 Pays-Bas 3
Australie 0 Espagne 3
Pays-Bas 2 Chili 0
Colombie 3 Grece 0
Coted'Ivoire 2 Japon 1
Colombie 2 Coted'Ivoire 1
Japon 0 Grece 0
Japon 1 Colombie 4
Grece 2 Coted'Ivoire 1
Uruguay 1 CostaRica 3
Angleterre 1 Italie 2
Uruguay 2 Angleterre 1

soccerpowerindex.txt

Bresil
Argentine
Allemagne
Espagne
Chili
France
Colombie
Uruguay
Angleterre
Belgique
Pays-Bas
Bosnie
Equateur
Portugal
Coted'Ivoire
Russie
Italie
Suisse
Etats-Unis
Mexique

The model in Stan

```
parameters {  
  real b;  
  real<lower=0> sigma_a;  
  real<lower=0> sigma_y;  
  vector[nteams] eta_a;  
}  
transformed parameters {  
  vector[nteams] a;  
  a = b*prior_score + sigma_a*eta_a;  
}  
model {  
  eta_a ~ normal(0,1);  
  sqrt_dif = student_t(df, a[team1]-a[team2],sigma_y);  
}
```

Stan program (part 1)

```
data {  
  int nteams;  
  int ngames;  
  vector[nteam] prior_score;  
  int team1[ngames];  
  int team2[ngames];  
  vector[ngames] score1;  
  vector[ngames] score2;  
  real df;  
}  
transformed data {  
  vector[ngames] dif;  
  vector[ngames] sqrt_dif;  
  dif = score1 - score2;  
  sqrt_dif = (step(dif)-.5)*sqrt(fabs(dif));  
}
```

Stan program (part 2)

```
parameters {  
  real b;  
  real<lower=0> sigma_a;  
  real<lower=0> sigma_y;  
  vector[nteams] eta_a;  
}  
transformed parameters {  
  vector[nteams] a;  
  a = b*prior_score + sigma_a*eta_a;  
}  
model {  
  eta_a ~ normal(0,1);  
  sqrt_dif ~ student_t(df, a[team1]-a[team2],sigma_y);  
}
```

Fitting the model

- ▶ Go into R
- ▶ Read in the data
- ▶ Fit the Stan model
- ▶ Check convergence
- ▶ Graph the estimated team abilities
- ▶ Re-fit without prior information
- ▶ Compare to model with prior information

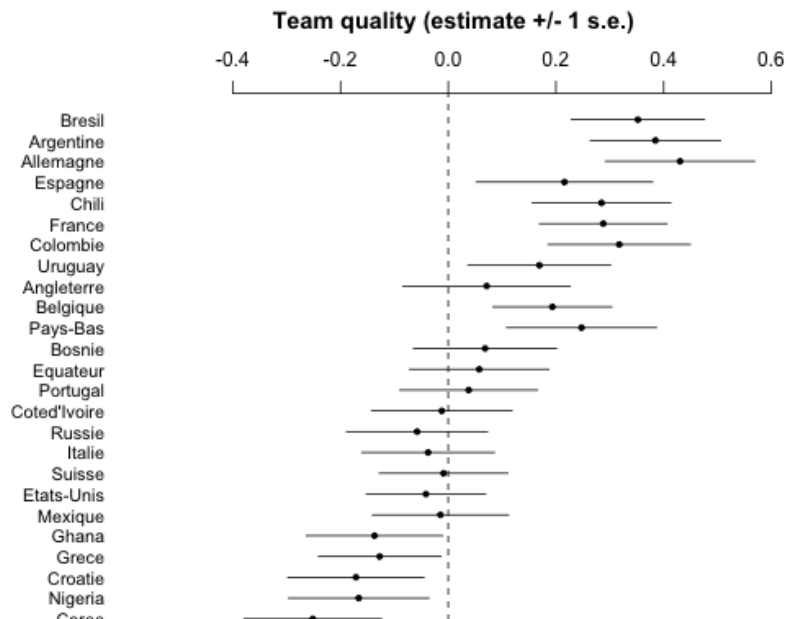
Load Stan into R

```
> setwd("~/AndrewFiles/teaching/stan_short_course/worldcup")
> library("rstan")
Loading required package: ggplot2
rstan (Version 2.9.0-3, packaged: 2016-02-11 15:54:41 UTC, GitRe
For execution on a local, multicore CPU with excess RAM we recom
rstan_options(auto_write = TRUE)
options(mc.cores = parallel::detectCores())
> rstan_options(auto_write = TRUE)
> options(mc.cores = parallel::detectCores())
```

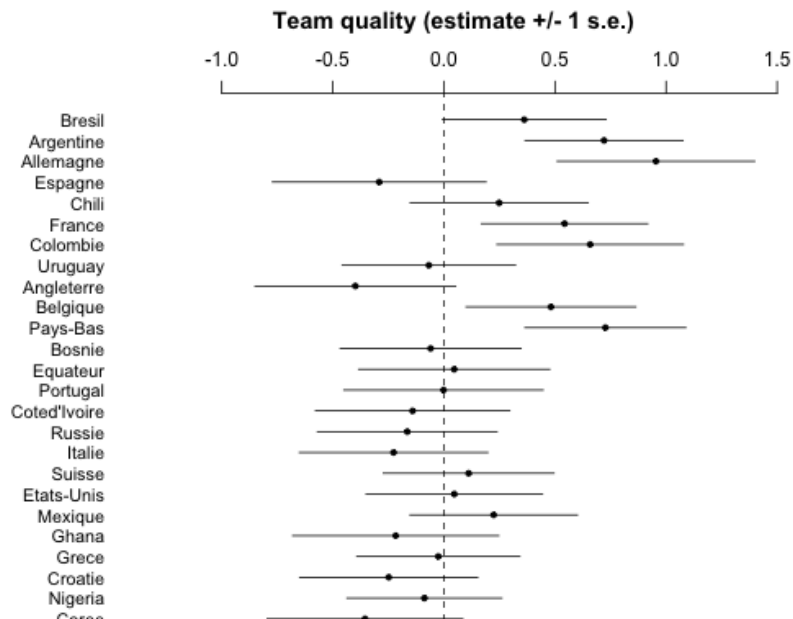
Fit the model

```
teams <- as.vector(unlist(read.table("soccerpowerindex.txt",  
  header=FALSE)))  
nteam <- length(teams)  
prior_score <- rev(1:nteam)  
prior_score <- (prior_score - mean(prior_score))/  
  (2*sd(prior_score))  
  
data2014 <- read.table("worldcup2014.txt", header=FALSE)  
nrow <- nrow (data2014)  
  
team1 <- match (as.vector(data2014[[1]]), teams)  
score1 <- as.vector(data2014[[2]])  
team2 <- match (as.vector(data2014[[3]]), teams)  
score2 <- as.vector(data2014[[4]])  
  
df <- 7  
fit <- stan("worldcup_first_try.stan", iter=100, chains=4)
```


Graph the estimates



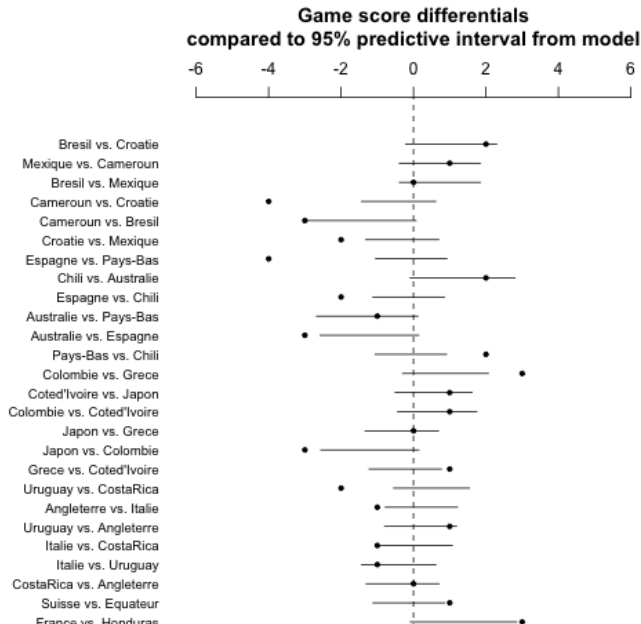
Re-fit the model without prior rankings

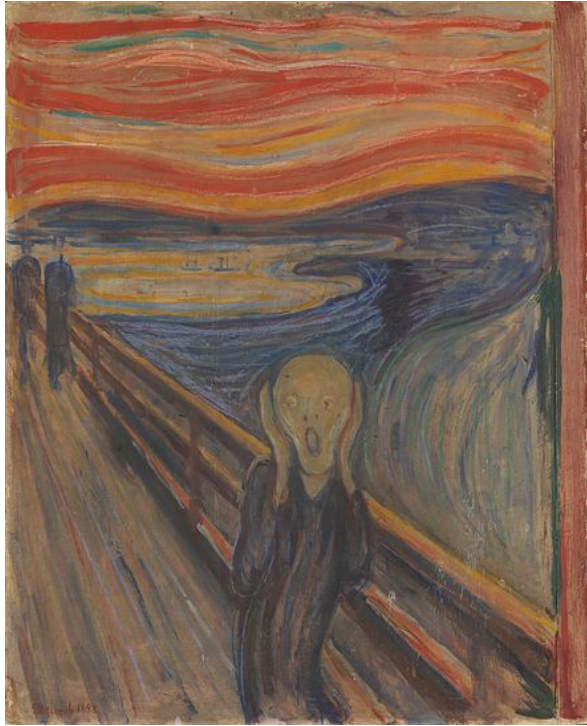


Checking model fit

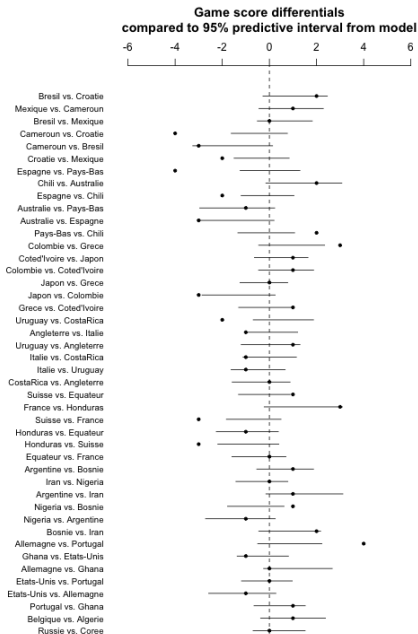
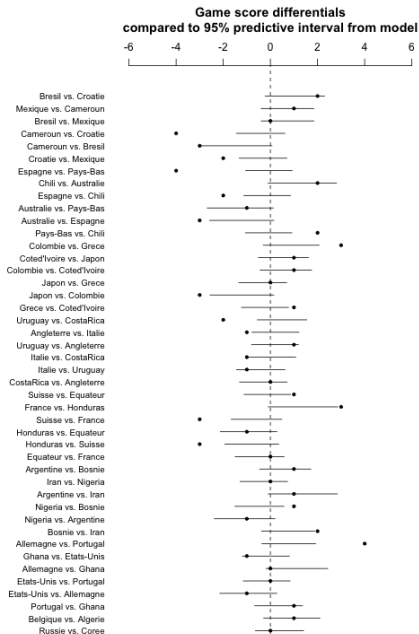
- ▶ Still inside R
- ▶ For each game, plot actual score differential and 95% predictive intervals
 - ▶ Not cross-validated but no big deal in this case because n is large
- ▶ The predictions don't fit the data!!
- ▶ Redoing the predictive intervals
- ▶ Re-plot, still a problem!

Compare model to predictions

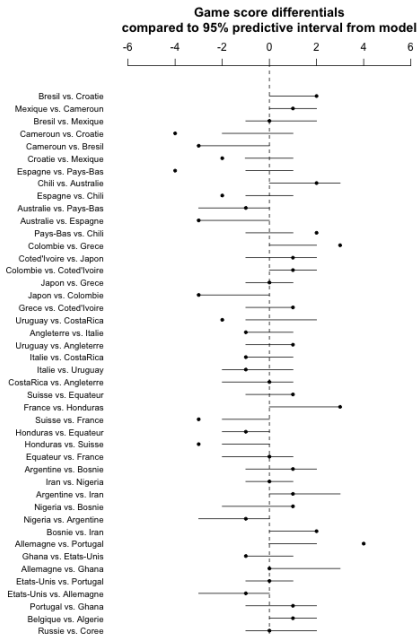
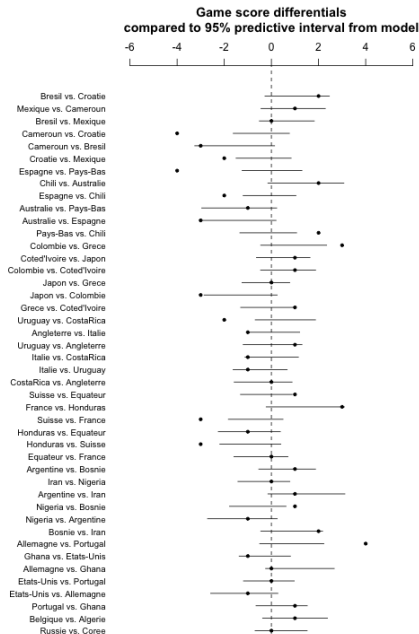




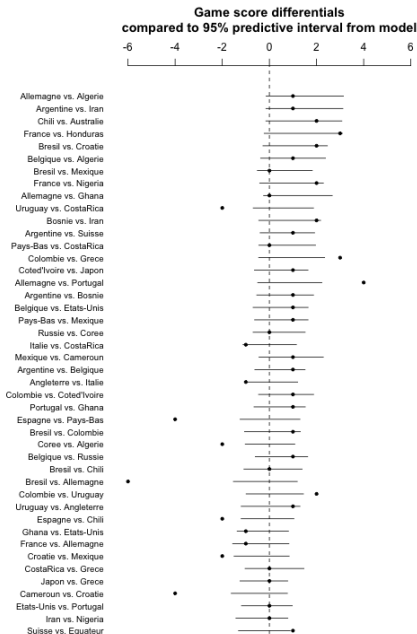
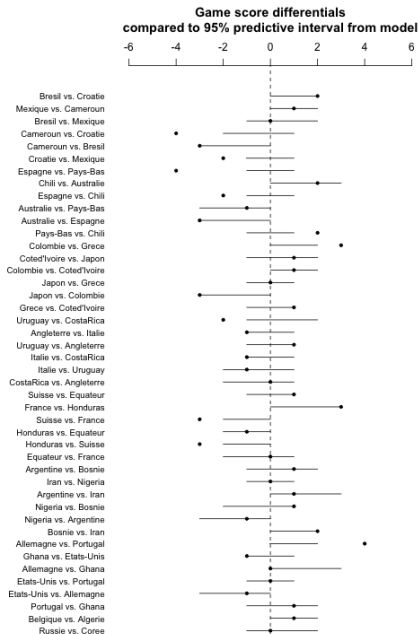
Use posterior simulations rather than point estimates



Round the predictions to integer score differentials



Plot in order of predicted score differential



Sign so expected outcomes are always positive

Game score differentials
compared to 95% predictive interval from model



Allemagne vs. Algerie
 Argentine vs. Iran
 Chili vs. Australie
 France vs. Honduras
 Bresil vs. Croatie
 Belgique vs. Algerie
 Bresil vs. Mexique
 France vs. Nigeria
 Allemagne vs. Ghana
 Uruguay vs. CostaRica
 Bosnie vs. Iran
 Argentine vs. Suisse
 Pays-Bas vs. CostaRica
 Colombie vs. Grece
 Coted'Ivoire vs. Japon
 Allemagne vs. Portugal
 Argentine vs. Bosnie
 Belgique vs. Etats-Unis
 Pays-Bas vs. Mexique
 Russie vs. Coree
 Italie vs. CostaRica
 Mexique vs. Cameroun
 Argentine vs. Belgique
 Angleterre vs. Italie
 Colombie vs. Coted'Ivoire
 Portugal vs. Ghana
 Espagne vs. Pays-Bas
 Bresil vs. Colombie
 Coree vs. Algerie
 Belgique vs. Russie
 Bresil vs. Chili
 Bresil vs. Allemagne
 Colombie vs. Uruguay
 Uruguay vs. Angleterre
 Espagne vs. Chili
 Ghana vs. Etats-Unis
 France vs. Allemagne
 Croatie vs. Mexique
 CostaRica vs. Grece
 Japon vs. Grece
 Cameroun vs. Croatie
 Etats-Unis vs. Portugal
 Iran vs. Nigeria
 Suisse vs. Equateur

Game score differentials
compared to 95% predictive interval from model



Allemagne vs. Algerie
 Espagne vs. Australie
 Argentine vs. Iran
 Chili vs. Australie
 Bresil vs. Cameroun
 France vs. Honduras
 Bresil vs. Croatie
 Argentine vs. Nigeria
 Belgique vs. Algerie
 Pays-Bas vs. Australie
 Colombie vs. Japon
 Bresil vs. Mexique
 France vs. Nigeria
 Allemagne vs. Ghana
 Uruguay vs. CostaRica
 Bosnie vs. Iran
 Equateur vs. Honduras
 Angleterre vs. CostaRica
 Argentine vs. Suisse
 Allemagne vs. Etats-Unis
 Pays-Bas vs. CostaRica
 Russie vs. Algerie
 Belgique vs. Coree
 Colombie vs. Grece
 Suisse vs. Honduras
 France vs. Suisse
 Coted'Ivoire vs. Japon
 Bosnie vs. Nigeria
 Allemagne vs. Portugal
 Argentine vs. Bosnie
 Belgique vs. Etats-Unis
 Pays-Bas vs. Mexique
 Argentine vs. Pays-Bas
 Russie vs. Coree
 Uruguay vs. Italie
 Italie vs. CostaRica
 Mexique vs. Cameroun
 Argentine vs. Belgique
 Angleterre vs. Italie
 Colombie vs. Coted'Ivoire
 Portugal vs. Ghana
 France vs. Equateur
 Coted'Ivoire vs. Grece
 Espagne vs. Pays-Bas

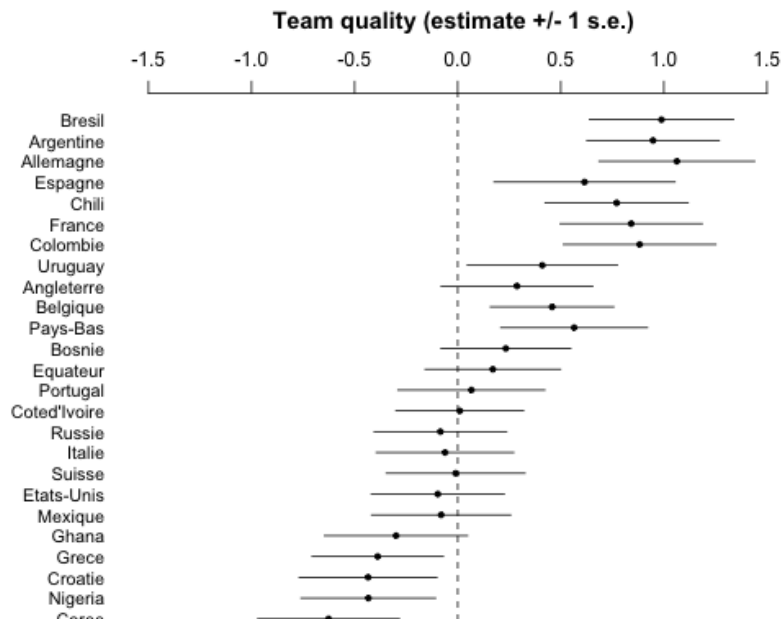
I found the bug!

- ▶ Still inside R
- ▶ Re-fit the model on the original scale
- ▶ Display the estimated team abilities
- ▶ Updated plot of data with predictive intervals—now it's ok!
- ▶ Go back and find the bug in the square-root-scale model
- ▶ Re-fit the debugged model

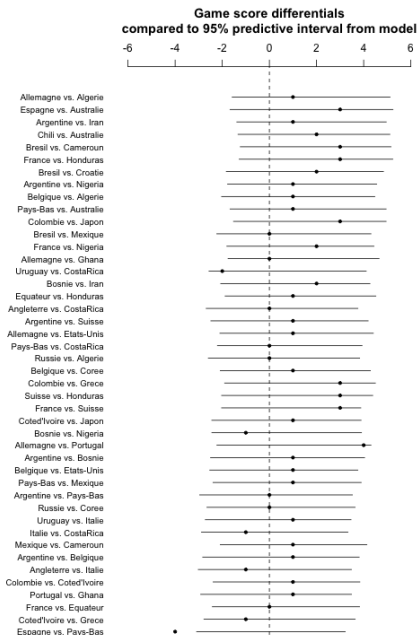
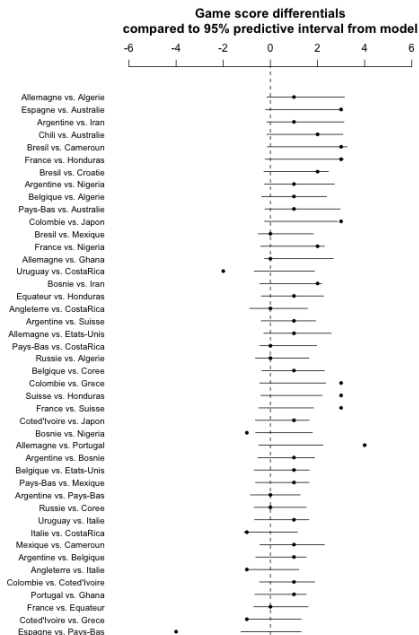
Our original model in Stan

```
parameters {  
  real b;  
  real<lower=0> sigma_a;  
  real<lower=0> sigma_y;  
  vector[nteams] eta_a;  
}  
transformed parameters {  
  vector[nteams] a;  
  a = b*prior_score + sigma_a*eta_a;  
}  
model {  
  eta_a ~ normal(0,1);  
  sqrt_dif ~ student_t(df, a[team1]-a[team2],sigma_y);  
}
```

Model fit to data on raw scale



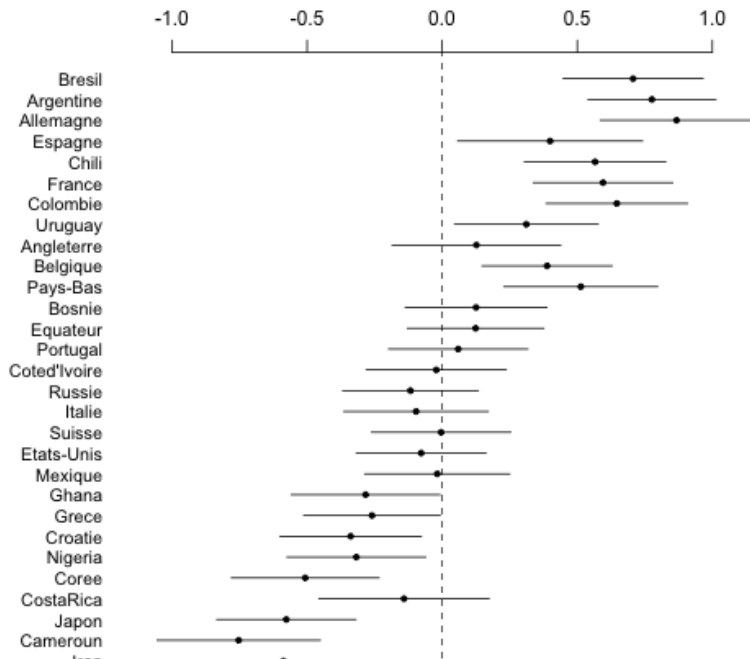
Compare data to predictive intervals



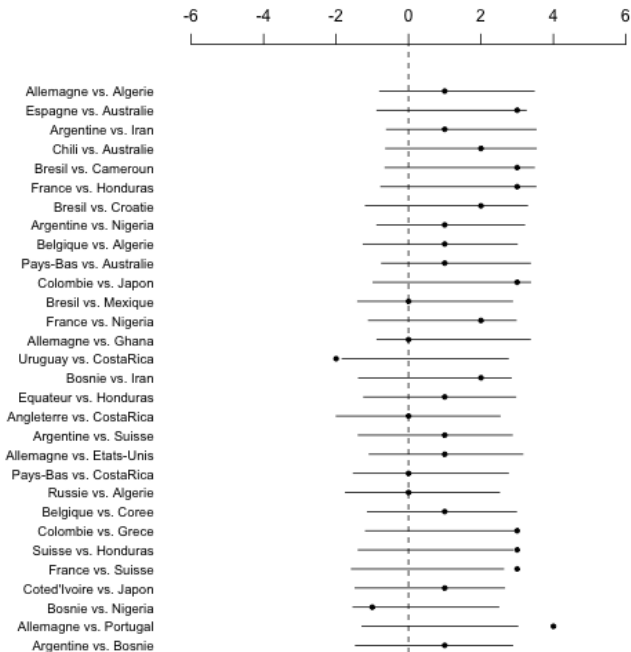
Our original Stan program (part 1)

```
data {  
  int nteams;  
  int ngames;  
  vector[nteam] prior_score;  
  int team1[ngames];  
  int team2[ngames];  
  vector[ngames] score1;  
  vector[ngames] score2;  
  real df;  
}  
transformed data {  
  vector[ngames] dif;  
  vector[ngames] sqrt_dif;  
  dif = score1 - score2;  
  sqrt_dif <- (step(dif)-.5)*sqrt(fabs(dif));  
}
```

Team quality (estimate +/- 1 s.e.)



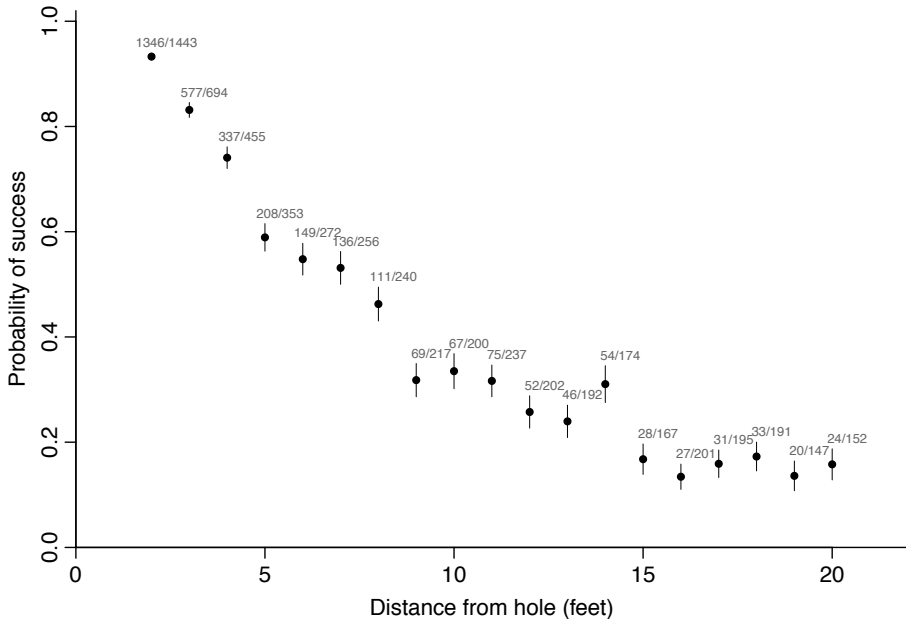
Game score differentials compared to 95% predictive interval from model



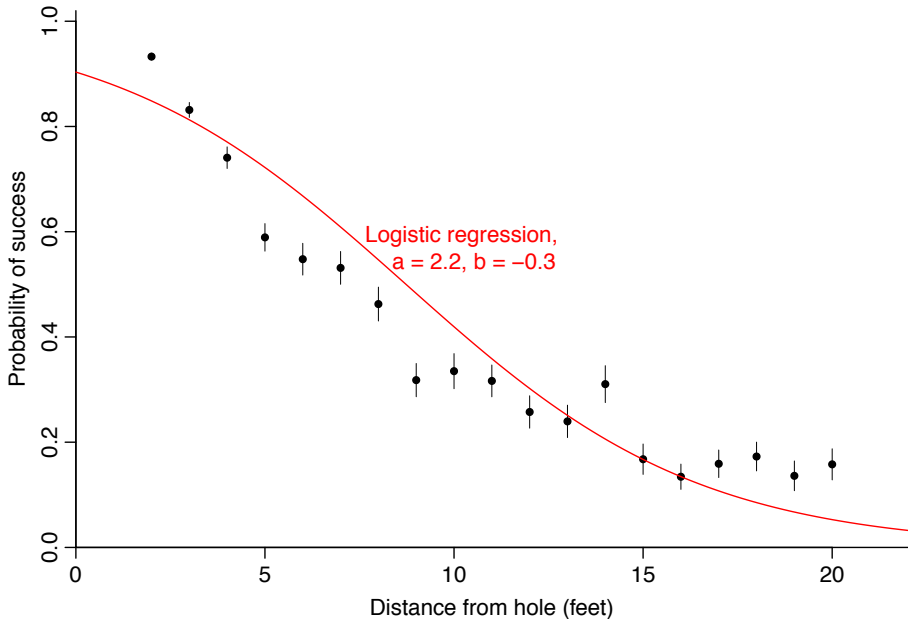
Lessons from World Cup example

- ▶ Model score differential, not simple wins and losses—even if your only goal is to predict wins and losses
- ▶ Same thing in education (model test scores rather than pass/fail) and elections (model vote share not win/loss)
- ▶ Jump in and fit a model, then check its fit to data
- ▶ Combine sources of information
- ▶ Compare different fits graphically

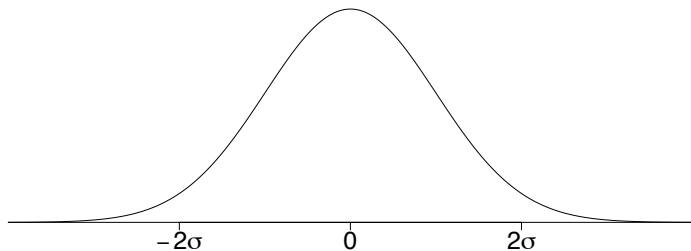
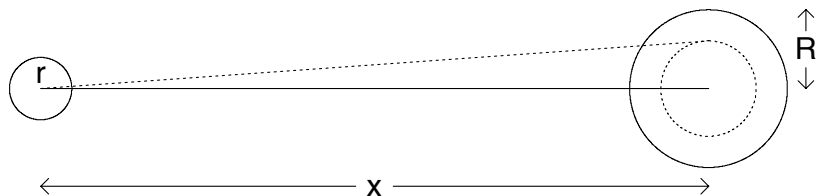
Data on putts in pro golf



What's the probability of making a golf putt?



Geometry-based model



```
data {  
  int J;  
  int n[J];  
  real x[J];  
  int y[J];  
  real r;  
  real R;  
}  
parameters {  
  real<lower=0> sigma;  
}  
model {  
  real p[J];  
  p = 2*Phi(asin((R-r)/x) / sigma) - 1;  
  y ~ binomial(n, p);  
}
```


Fit the model

```
golf <- read.table("golf.txt", header=TRUE, skip=2)
x <- golf$x
y <- golf$y
n <- golf$n
J <- length(y)
r <- (1.68/2)/12
R <- (4.25/2)/12
se <- sqrt((y/n)*(1-y/n)/n)

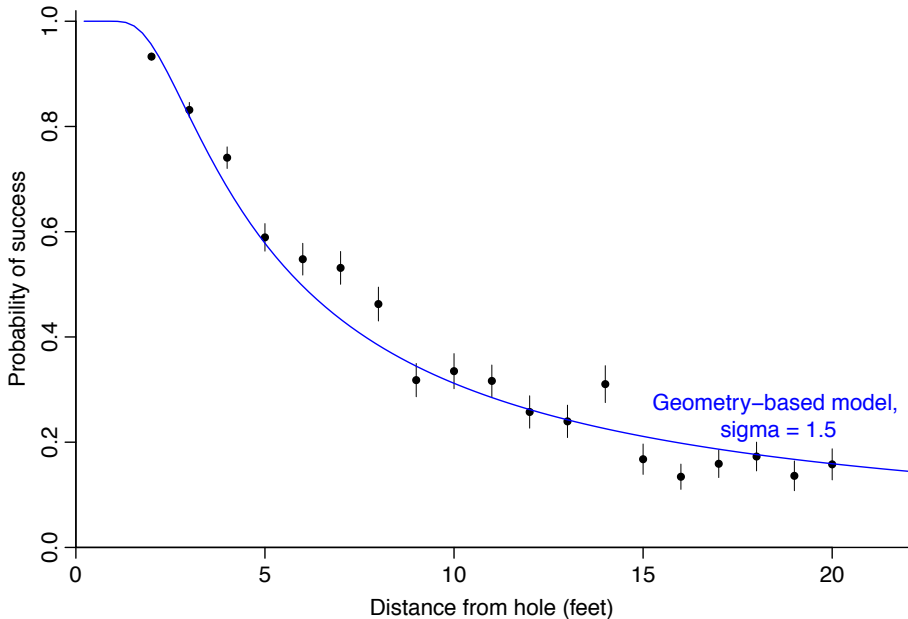
fit1 <- stan("golf1.stan")
```

Check convergence

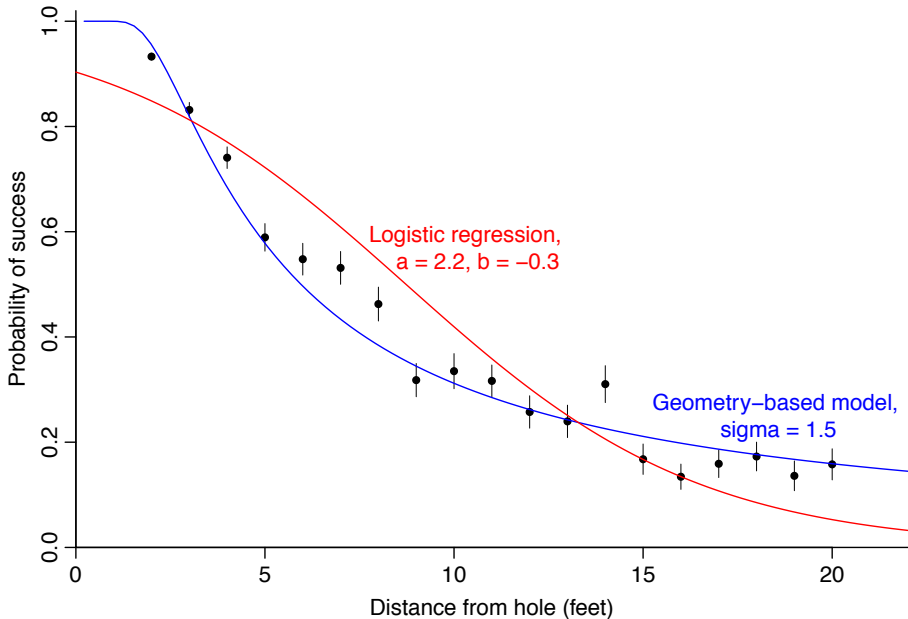
```
> print(fit1)
Inference for Stan model: golf1.
4 chains, each with iter=2000; warmup=1000; thin=1;
post-warmup draws per chain=1000, total post-warmup draws=4000.
```

	mean	se_mean	sd	25%	50%	75%	n_eff	Rhat
sigma	0.03	0.00	0.00	0.03	0.03	0.03	1692	1
sigma_degrees	1.53	0.00	0.02	1.51	1.53	1.54	1692	1

What's the probability of making a golf putt?



Two models fit to the golf putting data



“Global climate challenge”

On Dec 7, 2015, at 11:16 AM, Tom Daula|<***@***.com> wrote:

Interesting applied project for your students, or as a warning for decisions under uncertainty / statistical significance. Real money on the line so the length of time and number of entries required to get a winner may be an interesting dataset after this is all done.

<http://www.informath.org/Contest1000.htm>

Terms of the Contest

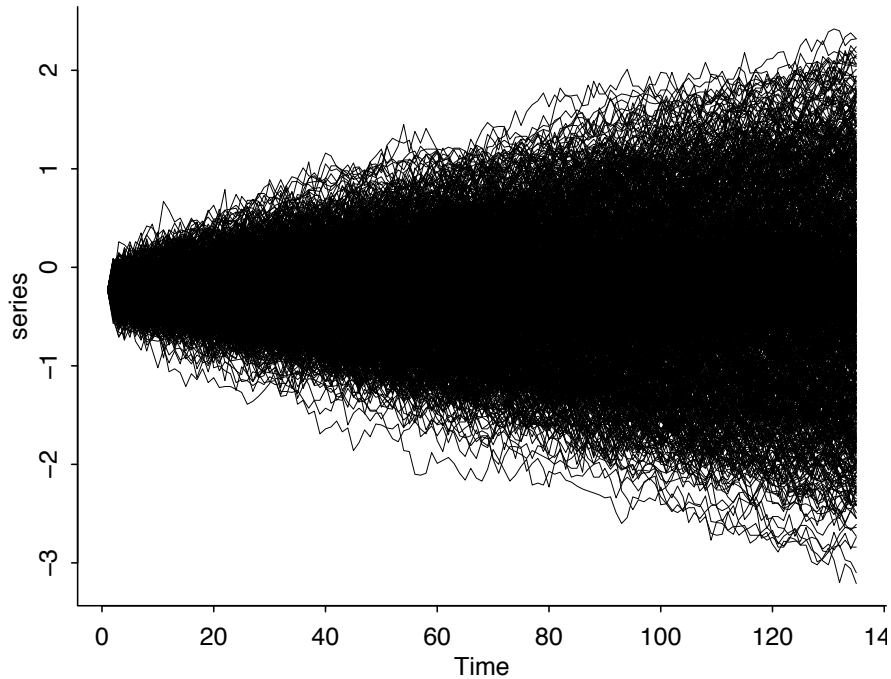
The file [Series1000.txt](#) contains 1000 simulated time series. Each series has length 135: the same length as that of the most commonly studied series of global temperatures (which span 1880-2014). The 1000 series were generated as follows. First, 1000 random series were obtained (for more details, see below). Then, some of those series were randomly selected and had a trend added to them. Each added trend was either $1^{\circ}\text{C}/\text{century}$ or $-1^{\circ}\text{C}/\text{century}$. For comparison, a trend of $1^{\circ}\text{C}/\text{century}$ is greater than the trend that is claimed for global temperatures.

A prize of \$100 000 (one hundred thousand U.S. dollars) will be awarded to the first person who submits an entry that correctly identifies at least 900 series: which series were generated without a trend and which were generated with a trend.

For instructions on how to submit an entry, see the [Contest Entry page](#). Each entry must be accompanied by a payment of \$10; this is being done to inhibit non-serious entries. There is a limit of one entry per person.

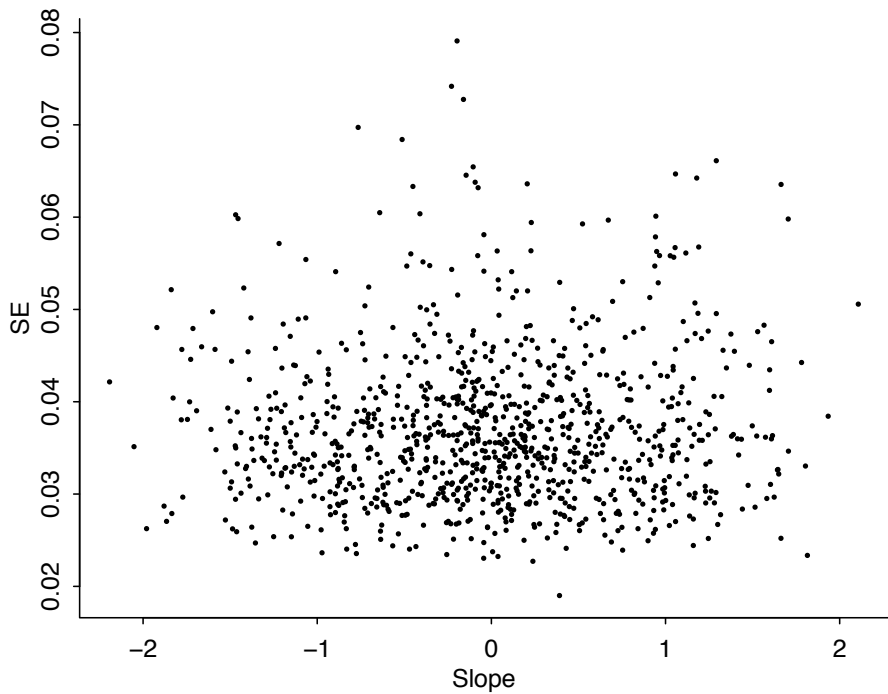
Download and graph the data

```
series <- matrix(scan("Series1000.txt"), nrow=1000, ncol=135,  
  byrow=TRUE)  
T <- 135  
N <- 1000  
  
pdf("series_1.pdf", height=5, width=6)  
par(mar=c(3,3,2,0), tck=-.01, mgp=c(1.5,.5,0))  
plot(c(1,T), range(series), bty="l", type="n",  
  xlab="Time", ylab="series")  
for (n in 1:N)  
  lines(1:T, series[n,], lwd=.5)  
dev.off()
```

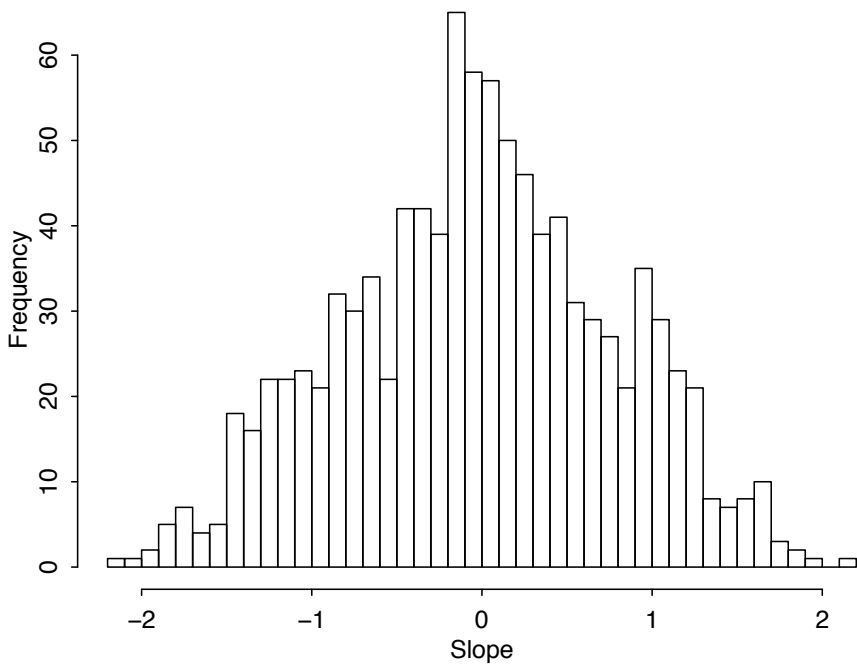


Fit a regression to each line and plot the estimated slopes

```
library("arm")
slope <- rep(NA, N)
se <- rep(NA, N)
for (n in 1:N){
  data <- series[n,]
  time <- 1:T
  fit <- lm(data ~ time)
  slope[n] <- 100*coef(fit)[2]
  se[n] <- 100*se.coef(fit)[2]
}
pdf("series_2.pdf", height=5, width=6)
par(mar=c(3,3,2,0), tck=-.01, mgp=c(1.5,.5,0))
plot(slope, se, bty="l", xlab="Slope", ylab="SE", pch=20, cex=.5)
dev.off()
```



Histogram of slope



Program a mixture model in Stan

```
data {  
  int K;  
  int N;  
  real y[N];  
  real mu[K];  
}  
parameters {  
  simplex[K] theta;  
  real<lower=0> sigma;  
}  
model {  
  real ps[K];  
  sigma ~ cauchy(0,2.5);  
  mu ~ normal(0,10);  
  for (n in 1:N) {  
    for (k in 1:K)  
      ps[k] = log(theta[k]) + normal_log(y[n], mu[k], sigma);  
    increment_log_prob(log_sum_exp(ps));  
  }  
}
```

Fit the model in R

```
y <- slope  
K <- 3  
mu <- c(0,-1,1)  
mix <- stan("mixture.stan")  
print(mix)
```

Inference for Stan model: mixture.

4 chains, each with iter=2000; warmup=1000; thin=1;

post-warmup draws per chain=1000, total post-warmup draws=4000.

	mean	se_mean	sd	25%	50%	75%	n_eff	Rhat
theta[1]	0.54	0	0.02	0.52	0.54	0.55	2449	1
theta[2]	0.24	0	0.02	0.23	0.24	0.25	2537	1
theta[3]	0.22	0	0.02	0.21	0.22	0.23	2444	1
sigma	0.40	0	0.02	0.39	0.40	0.42	2078	1

For each series, compute probability of it being in each component

```
generated quantities {  
  matrix[N,K] p;  
  for (n in 1:N){  
    vector[K] p_raw;  
    for (k in 1:K)  
      p_raw[k] = theta[k]*exp(normal_log(y[n], mu[k], sigma));  
    for (k in 1:K)  
      p[n,k] = p_raw[k]/sum(p_raw);  
  }  
}
```

Results

	[,1]	[,2]	[,3]
[1,]	0.09	0.00	0.91
[2,]	0.41	0.59	0.00
[3,]	0.93	0.01	0.06
[4,]	0.83	0.17	0.00
[5,]	0.82	0.17	0.00
[6,]	0.95	0.01	0.05
[7,]	0.74	0.00	0.26
[8,]	0.86	0.14	0.00
[9,]	0.11	0.00	0.89
[10,]	0.87	0.00	0.13
[11,]	0.94	0.01	0.06
[12,]	0.29	0.71	0.00
[13,]	0.09	0.91	0.00
[14,]	0.67	0.33	0.00
[15,]	0.93	0.01	0.06
[16,]	0.95	0.01	0.04
[17,]	0.16	0.84	0.00
[18,]	0.95	0.04	0.01
[19,]	0.77	0.23	0.00

Summaries

- ▶ Best guess for each series:

```
1    2    3
559 232 209
```

- ▶ Expected # correct and sd:

```
854.1  10.3
```

- ▶ Probability of getting at least 900 correct:

```
> pnorm(expected_correct, 899.5, sd_correct)
[1] 5.421277e-06
```

- ▶ Ummmmm ...

```
> 1/pnorm(expected_correct, 899.5, sd_correct)
[1] 184458.4
```


Should I play the \$100,000 challenge?

- ▶ From the discussion thread:

[Richard Tol \(@RichardTol\)](#) says:

November 20, 2015 at 8:31 pm

Why don't you guys just pay £10 to win £100,000? You don't need to accept that the challenge has any bearing on climate change — it has not — but it is a great opportunity to make £99,990.

- ▶ Expected return on \$10 bet:

$$(5.4 * 10^{-6}) * 10^5 = \$0.54$$

- ▶ What would *you* do?