



# BAYESIAN STATISTICS

CLASS 3



Sampling distribution is  
Lognormal – there are two  
parameters for a Lognormal:  
 $\mu, \sigma^2$

$$\mu \sim \text{Uniform}(0,80)$$
$$\sigma^2 \sim \text{Uniform}(0,80)$$



# STAN

```
data{
  int <lower=0> n ;
  real y[n];
}

parameters {
  real mu;
  real <lower=0> sigma;
}

model {
  mu ~uniform(0,80);
  sigma~uniform(0,80);
  for (i in 1:n)
    y[i] ~ lognormal(mu,sigma);
}
```

# R Code

```
library(lmtest)
library(rstan)
lognorm.dat<-list(y=unemployment[,1],n=length(unemployment[,1]))
log.stan=stan(file='Q:\\My
Drive\\Bayesian\\Code\\lognormal_model.stan',data=lognorm.dat,seed=10678)
log.extract=extract(log.stan)
new.mu=log.extract$mu
new.sigma=log.extract$sigma
mean(new.mu)
mean(new.sigma)
mean(new.sigma/new.mu)
```

```
mu.sigma=cbind(new.mu,new.sigma)
head(mu.sigma)
```

	new.mu	new.sigma
[1,]	1.780556	0.5457839
[2,]	1.663109	0.6653600
[3,]	1.646789	0.5786628
[4,]	1.606961	0.5906967
[5,]	1.698649	0.5329611
[6,]	1.765465	0.6531658

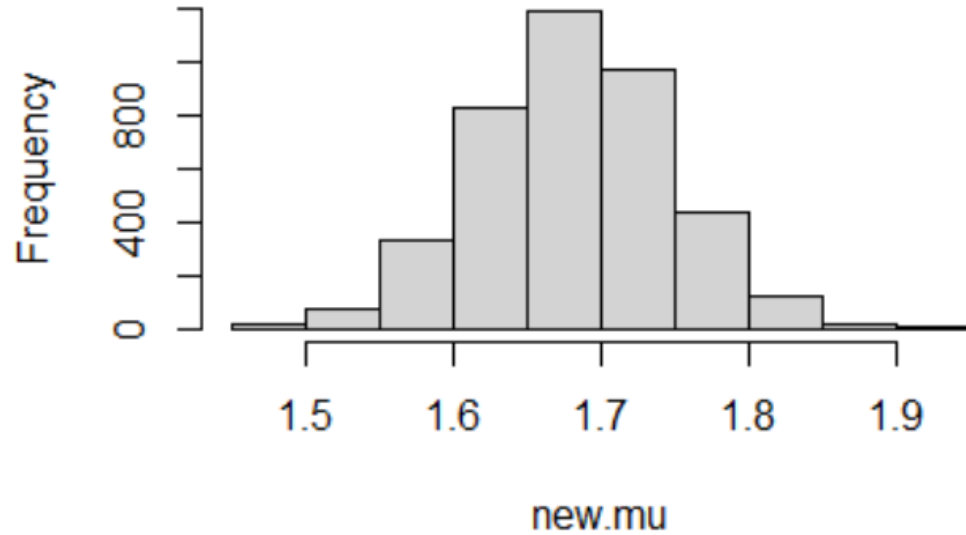
Posterior Joint distribution:  
 $P(\mu, \sigma | Y)$

Posterior Marginal distribution of mean:  
 $P(\mu | Y)$

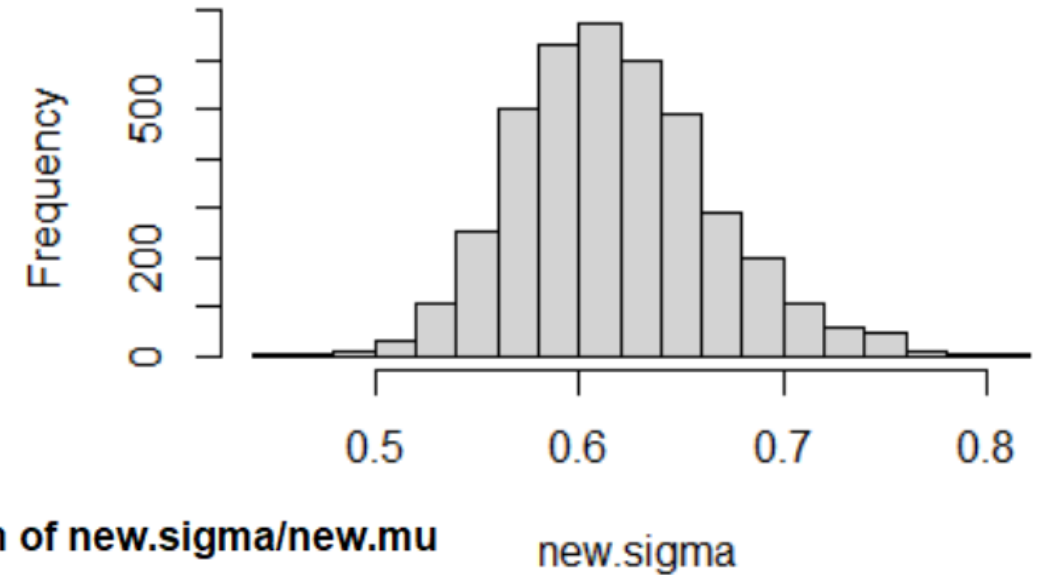
Posterior Marginal distribution of std dev:  
 $P(\sigma | Y)$

Together, these are the posterior joint distribution,  
however, you can just use one column for the posterior  
marginal distribution

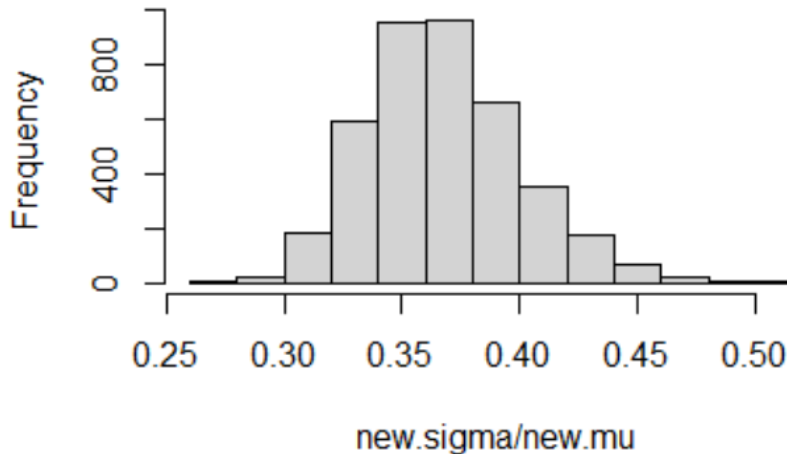
Histogram of new.mu



Histogram of new.sigma



Histogram of new.sigma/new.mu




NOTE: SIGMA is the **standard deviation** (not variance)

```
> summary(y)
  Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
1.226   3.858   5.233   6.478   7.527  22.981

> summary(new.mu)
  Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
1.455   1.638   1.681   1.682   1.727   1.934

> summary(new.sigma)
  Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
0.4535  0.5836  0.6141  0.6177  0.6478  0.8078
```



```
> summary(new.mu)
```

Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
1.455	1.638	1.681	1.682	1.727	1.934

```
> summary(new.sigma)
```

Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
0.4535	0.5836	0.6141	0.6177	0.6478	0.8078

```
> sd(log(y))
```

```
[1] 0.610505
```

```
> mean(log(y))
```

```
[1] 1.682152
```





```
> summary(y)
```

Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
1.226	3.858	5.233	6.478	7.527	22.981

```
> summary(exp(new.mu+0.5*new.sigma^2))
```

Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
5.049	6.207	6.500	6.530	6.820	8.607

```
> summary(sqrt((exp(2*new.mu+new.sigma^2)*(exp(new.sigma^2)-1))))
```

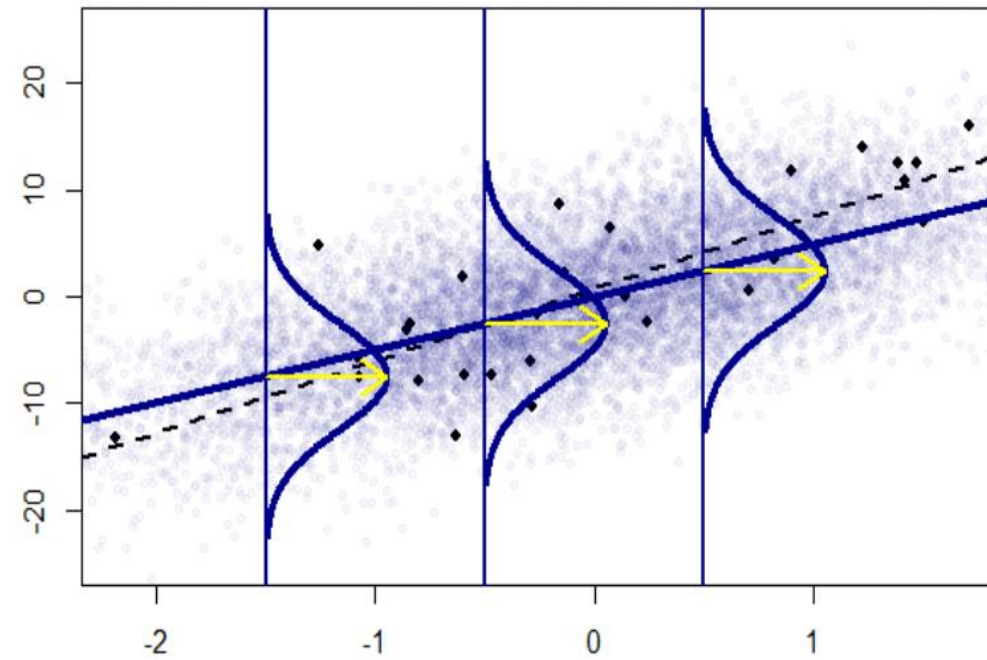
Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
2.978	4.038	4.380	4.473	4.827	7.552

```
> sd(y)
```

```
[1] 4.338271
```

Linear Regression assumes Normal distribution with a mean of  $X\beta$  and constant standard deviation

**Gaussian Distribution of Residuals across OLS in the Population**





'Liv.Area','Base.Area','Garage.Area','Porch.Area','Age

Recall Ames Housing data....trying to predict Y (sales price of house)

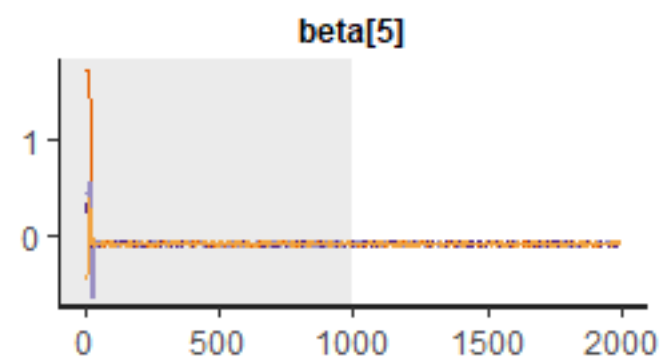
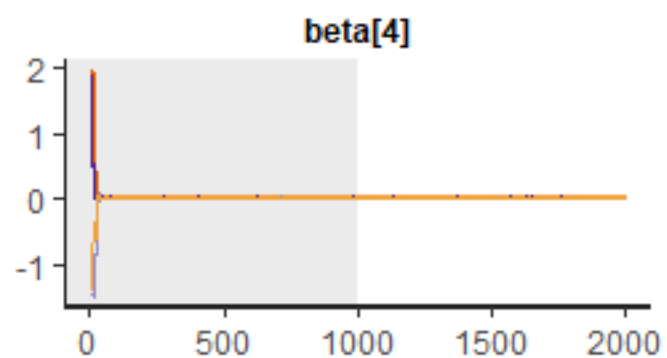
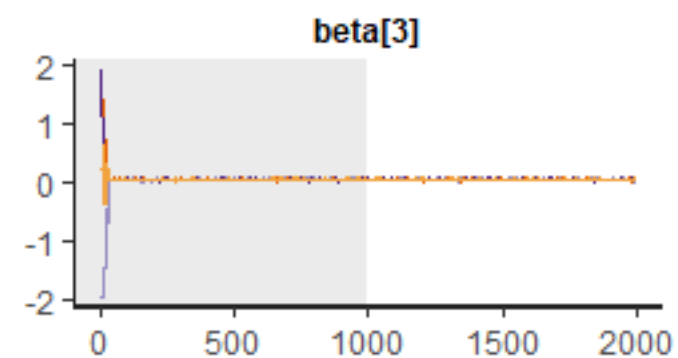
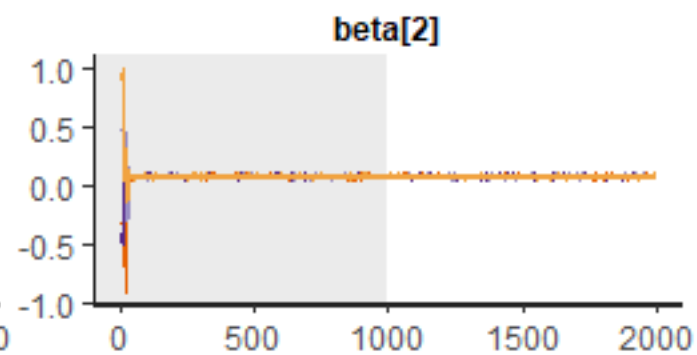
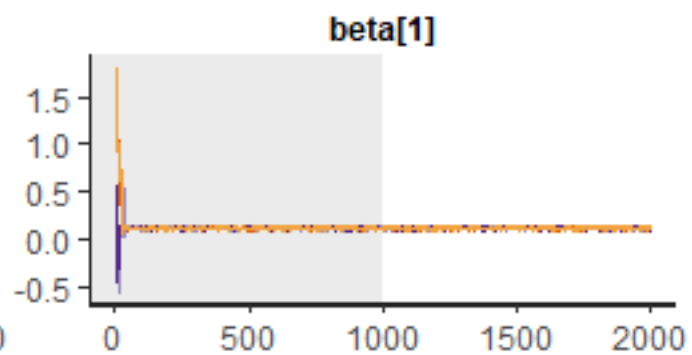
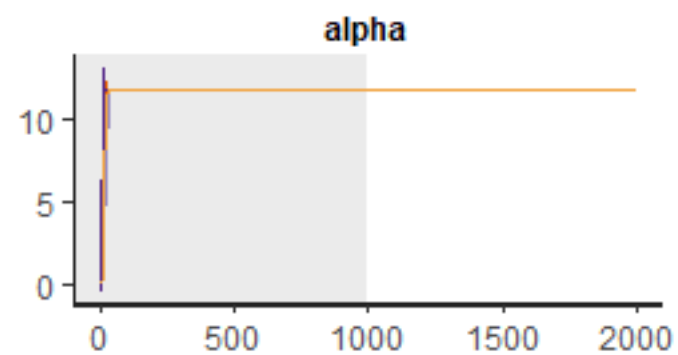
We will use the following predictor variables:  $X_1$  = Living Area,  $X_2$  = Basement Area,  $X_3$  = Garage Area,  $X_4$  = Porch Area and  $X_5$  = Age of house

$$\text{Log}(Y) = \alpha + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \beta_4 x_4 + \beta_5 x_5 + \varepsilon$$

# Regression in stan

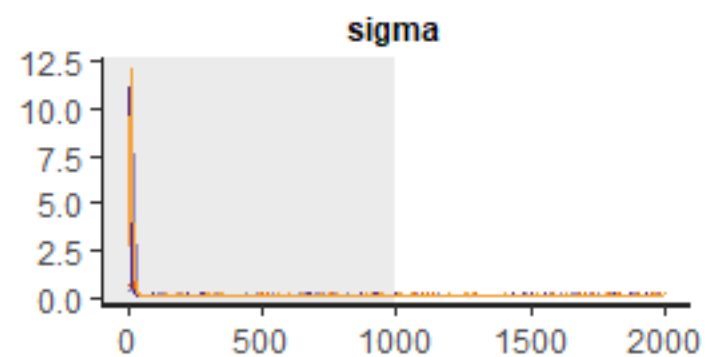
```
data{
  int <lower=0> n;
  vector[n] y;
  matrix[n,5] x;
}
parameters{
  real alpha;
  vector[5] beta;
  real<lower=0> sigma;
}
model {
  y ~normal(alpha + x*beta, sigma);
}
```

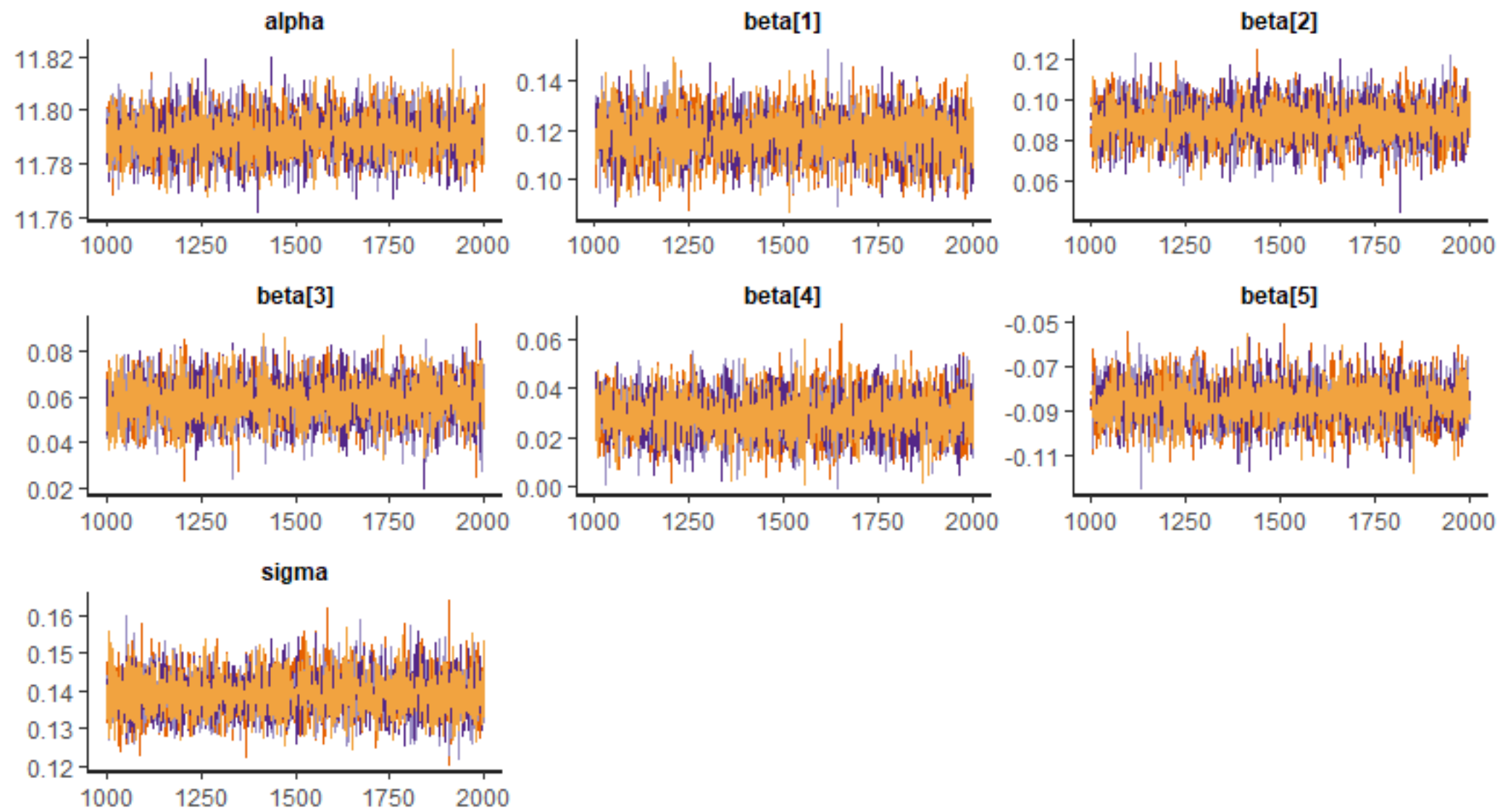
```
library(sas7bdat)
ameshousing<-read.sas7bdat('Q:\\My Drive\\Summer II - Statistics Bootcamp\\Bootcamp
Data\\ameshousing3.sas7bdat')
x=cbind(ameshousing$Gr_Liv_Area, ameshousing$Basement_Area,
ameshousing$Garage_Area, ameshousing$Deck_Porch_Area, ameshousing$Age_Sold)
x=as.data.frame(scale(x))
colnames(x)=c('Liv.Area','Base.Area','Garage.Area','Porch.Area','Age')
regress.dat=list(n=nrow(x),x=x,y=ameshousing$Log_Price)
regress.stan=stan(file='Q:\\My
Drive\\Bayesian\\Code\\ameshousing.stan',data=regress.dat,seed=93457)
output.stan=extract(regress.stan)
traceplot(regress.stan,inc_warmup=T)
```



chain

- 1
- 2
- 3
- 4





```
print(regress.stan, probs=c(.025,.975))
```

	mean	se_mean	sd	2.5%	97.5%	n_eff	Rhat
alpha	11.79	0.00	0.01	11.78	11.81	6588	1
beta[1]	0.12	0.00	0.01	0.10	0.14	5907	1
beta[2]	0.09	0.00	0.01	0.07	0.11	5643	1
beta[3]	0.06	0.00	0.01	0.04	0.08	5779	1
beta[4]	0.03	0.00	0.01	0.01	0.05	6864	1
beta[5]	-0.09	0.00	0.01	-0.10	-0.07	5316	1
sigma	0.14	0.00	0.01	0.13	0.15	5456	1
lp__	440.42	0.05	1.89	435.92	443.12	1744	1