



### The P-value Problem: Basis Statistics

Basic statistics under large sample size:

$$Z_1, ..., Z_n \sim N(\mu, \sigma^2) \Rightarrow \bar{Z} \sim N\left(\mu, \frac{\sigma^2}{n}\right)$$

Hypothesis testing for the mean:

$$H_0$$
:  $\mu = 0$  vs.  $H_A$ :  $\mu \neq 0$ 

• P-value and sample size:

$$p-value = 2P(Z > \sqrt{n}|\frac{\overline{Z}-0}{\sigma}|)$$
 is approximately 0 with  $n$  very large

#### "Inflated" Significance:

Conclusions based on smallsample statistical inferences using large samples can be misleading.

Samples Can Make the Insignificant...Significant!

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## The P-value Problem: Regression Analysis

 Hypothesis testing for the statistical significance of the regression coefficients:

$$H_0$$
:  $\beta_i = 0$  vs.  $H_A$ :  $\beta_i \neq 0$ 

P-value and sample size:

$$p-value = 2P(T_{n-p-1} > |t-value|)$$
 is approximately 0 with  $n$  very large

 Misleadingly, reject the null hypothesis of zero coefficient – all or most relationship are statistically significant. "Inflated" Statistical
Significance: Conclusions
based on small-sample
statistical inferences on the
regression coefficients using
large samples can be
misleading.

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### The P-value Problem: Approach

- <u>Sub-sampling</u>: Sample the observed data, e.g. 10-20% of the sample size
- Apply the regression model to each sub-sampled data
- Repeat for B times, e.g. B=100
- Output:

Sub-sample 1:  $\hat{\beta}_{0,1},\hat{\beta}_{1,1},\dots,\hat{\beta}_{p,1}$  & corresponding p-values  $pv_{0,1},pv_{1,1},\dots,pv_{p,1}$ 

Sub-sample 2:  $\hat{\beta}_{0,2}$ ,  $\hat{\beta}_{1,2}$ , ...,  $\hat{\beta}_{p,2}$  & corresponding p-values  $pv_{0,2}$ ,  $pv_{1,2}$ , ...,  $pv_{p,2}$ 

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Sub-sample B:  $\hat{\beta}_{0,B}$ ,  $\hat{\beta}_{1,B}$ , ...,  $\hat{\beta}_{p,B}$  & corresponding p-values  $pv_{0,B}$ ,  $pv_{1,B}$ , ...,  $pv_{p,B}$ 

 Empirical distributions of the regression coefficients and the p-values

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Sub-sample 2:  $\hat{\beta}_{0,2}$ ,  $\hat{\beta}_{1,2}$ , ...,  $\hat{\beta}_{p,2}$  & corresponding p-values  $pv_{0,2}$ ,  $pv_{1,2}$ , ...,  $pv_{p,2}$ 

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Sub-sample B:  $\hat{\beta}_{0,B}$ ,  $\hat{\beta}_{1,B}$ , ...,  $\hat{\beta}_{p,B}$  & corresponding p-values  $pv_{0,B}$ ,  $pv_{1,B}$ , ...,  $pv_{p,B}$ 

• Empirical distributions of the regression coefficients and the p-values

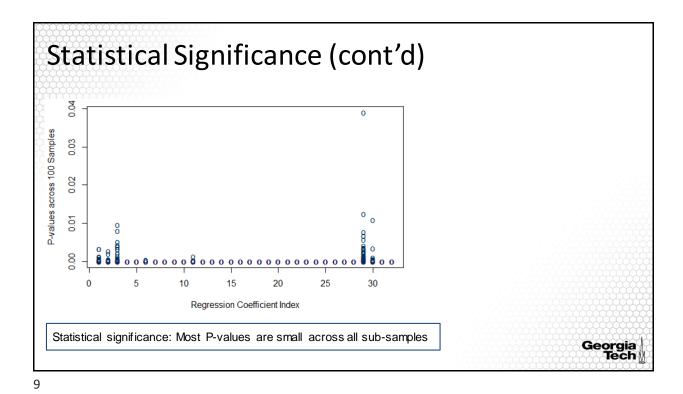
#### Theoretical Underpinning:

- Statistical significance (or lack of it)
  can be identified based on the
  distribution of the p-values;
  specifically, if the empirical distribution
  is approximately uniform between 0
  and 1, then we don't have statistical
  significance.
- Statistical significance (or lack of it) can be identified based on the confidence interval of the regression coefficient derived from the empirical distribution.

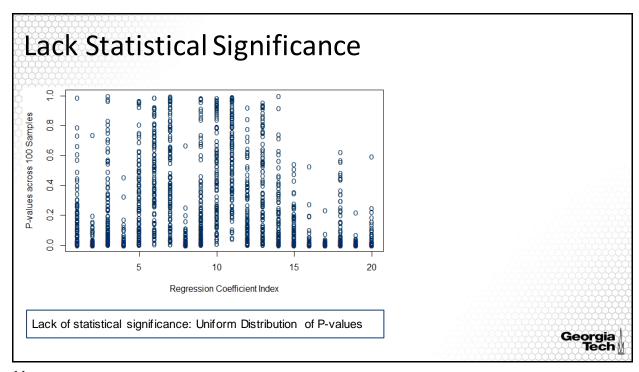


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The P-value Problem: Approach (cont'd)
## Approach: Subsample 40% of the initial data sample & repeat 100 times
count = 1
n = nrow(train)
B = 100
ncoef = dim(summary(model1)$coeff)[1]
pv_matrix = matrix(0, nrow = ncoef, ncol = B)
while (count <= B) {
    #40% random sample of indices
    subsample = sample(n, floor(n*0.4), replace=FALSE)
    # Extract the random subsample data
    subdata = train[subsample,]
    # Fit the regression for each subsample
    submod = Im(sqrt(cnt)\sim.,data=subdata)
    # Save the p-values
    pv_matrix[,count] = summary(submod)$coeff[,4]
    # Increment to the next subsample
    count = count + 1
# Count pv alues smaller than 0.01 across the 100 (sub)models
pv_significant = row Sums(pv_matrix < alpha)
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#### Statistical Significance Estimate Pr(>|t|)Freq ## Which regression coefficients are statistically significant? (Intercept) 1.670 $idx_scoef = which(pv_significant >= 95)$ 100 100 season3 1.380 ## Show the p-v alues of the significant coefficients in model2 100 100 cbind(summary(model2)\$coeff[idx\_scoef,c(1,4)], 2.800 Freq=pv\_significant[idx\_scoef]) -2.570 ## Plot the 100 p-v alues of the significant coefficients -3.770 -4.190 100 100 matplot(pv\_matrix[idx\_scoef,], -2.360xlab="Regression Coefficient Index", 100 100 100 1.480 ylab="P-values across 100 Samples", 6.820 10.700 type="p", 7.500 pch="o", 100 100 6.210 col=gtblue) 100 100 100 hr13 7.310 6.770 hr14 7.090 hr16 9.020 100 12.700 hr18 12,100 100 100 hr20 7.020 5.380 hr21 3.860 100 hr23 98 99 weekday5 0.723 weathersit3 Georgia



| Which regression coefficients are not statistically significant? |             | Estimate | Pr(> t ) | Freq |  |
|--|-------------|----------|----------|------|--|
| dx_icoef = which(pv_significant<85)                              | mnth2       | 0.379    | 0.005    | 12   |  |
| Show the p-v alues of the significant coefficients in model2     | mnth3       | 0.676    | 0.000    | 68   |  |
| bind(summary(model2)\$coeff[idx_icoef,c(1,4)],                   | mnth4       | 0.516    | 0.021    | 11   |  |
| Freq=pv_significant[idx_icoef])                                  | mnth5       | 1.108    | 0.000    | 66   |  |
| Plot the 100 p-v alues of the significant coefficients           | mnth6       | 0.499    | 0.043    | 7    |  |
|  | mnth7       | -0.326   | 0.240    | 1    |  |
| ratplot(pv_matrix[idx_icoef,],                                   | mnth8       | 0.300    | 0.267    | 2    |  |
| xlab="Regression Coefficient Index",                             | mnth9       | 1.052    | 0.000    | 64   |  |
| ylab="P-values across 100 Samples",                              | mnth10      | 0.516    | 0.020    | 7    |  |
| type="p",  | mnth11      | -0.241   | 0.260    | 1    |  |
| pch="o",   | mnth12      | -0.038   | 0.826    | 0    |  |
| col=gtblue)  | weekday 1   | 0.229    | 0.024    | 9    |  |
|  | weekday 2   | 0.174    | 0.080    | 4    |  |
|  | weekday3    | 0.283    | 0.004    | 16   |  |
|  | weekday 4   | 0.344    | 0.001    | 35   |  |
|  | weekday 6   | 0.530    | 0.000    | 79   |  |
|  | weathersit2 | -0.346   | 0.000    | 74   |  |
|  | temp        | 3.847    | 0.000    | 38   |  |
|  | atemp       | 4.879    | 0.000    | 84   |  |
|  | windspeed   | -1.101   | 0.000    | 59   |  |



# Statistical Significance Summary

- Most regression coefficients remain statistically significant for 95% of the sub-samples, supporting statistical significance for these factors
- Statistical significance is not supported for most of months and weekdays as well as for temperature and windspeed factors given that other relevant factors, such as season and weather situation are in the model.
- While the 85% cutoff was used for the frequency of p-values being smaller than the significance level 0.01, other lower cut-offs, such as 50%, can be used.



