

Health Care Cost Prediction with:

- ★ Linear Regression
- ★ Logistic Regression
- ★ Linear Mixed model
- ★ Generalized Mixed Models

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Introduction

Medical expenses are difficult to estimate because the most costly conditions are rare and seemingly random. Still, some conditions are more prevalent for certain segments of the population. For instance, lung cancer is more likely among smokers than non-smokers, and heart disease may be more likely among the obese.

Goal

The goal of this analysis is to use patient data to estimate the average medical care expenses for such population segments. These estimates can be used to create actuarial tables that set the price of yearly premiums higher or lower, depending on the expected treatment costs.

Dataset

For this analysis, we will use a simulated dataset containing hypothetical medical expenses for patients in the United States. This data was created for using demographic statistics from the US Census Bureau, and thus, approximately reflect real-world conditions. And got this from Kaggle.

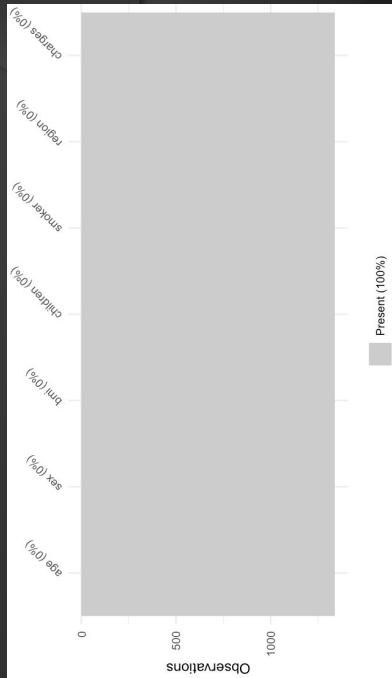
The insurance.csv file includes 1,338 examples of beneficiaries currently enrolled in the insurance plan, with features indicating characteristics of the patient as well as the total medical expenses charged to the plan for the calendar year. The features are:

- *age*: An integer indicating the age of the primary beneficiary (excluding those above 64 years, since they are generally covered by the government).
- *sex*: The policy holder's gender, either male or female.
- *bmi*: The body mass index (BMI), which provides a sense of how over- or under-weight a person is relative to their height. BMI is equal to weight (in kilograms) divided by height (in meters) squared. An ideal BMI is within the range of 18.5 to 24.9.
- *children*: An integer indicating the number of children/dependents covered by the insurance plan.
- *smoker*: A yes or no categorical variable that indicates whether the insured regularly smokes tobacco.
- *region*: The beneficiary's place of residence in the US, divided into four geographic regions: northeast, southeast, southwest, or northwest.

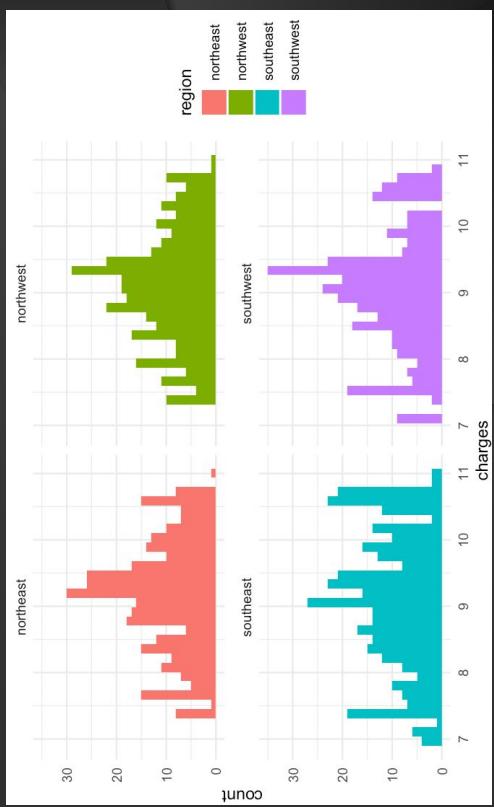
DATA EXPLORATION

```
'data.frame': 1338 obs. of 7 variables:  
 $ age : int 19 18 28 33 32 31 46 37 37 60 ...  
 $ sex : chr "female" "male" "male" "male" ...  
 $ bmi : num 27.9 33.8 33 22.7 28.9 ...  
 $ children: int 0 1 3 0 0 0 1 3 2 0 ...  
 $ smoker : chr "yes" "no" "no" "no" ...  
 $ region : chr "southwest" "southeast" "southeast" "northwest" ...  
 $ charges : num 16885 1726 4449 21984 3867 ...
```

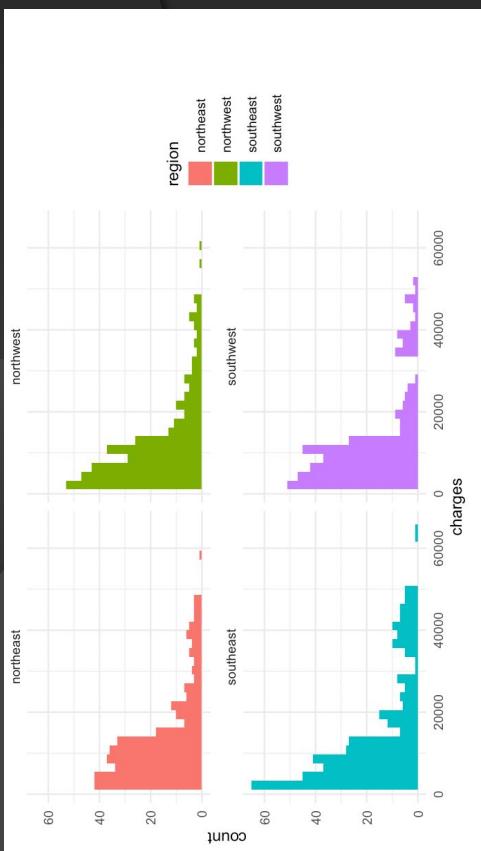
Checking for missingness in the dataset



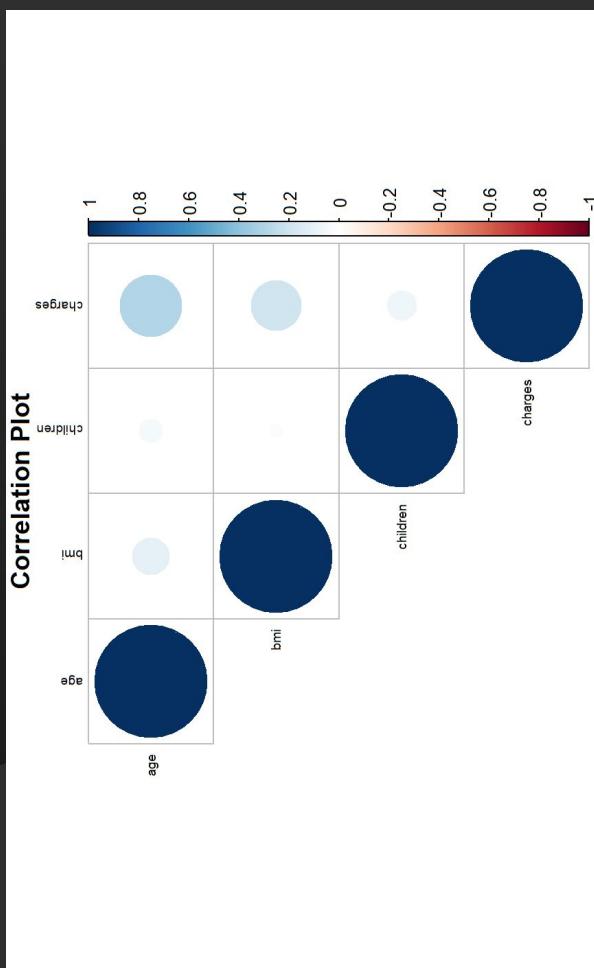
From this we can conclude that it is not normally distributed and is skewed right.



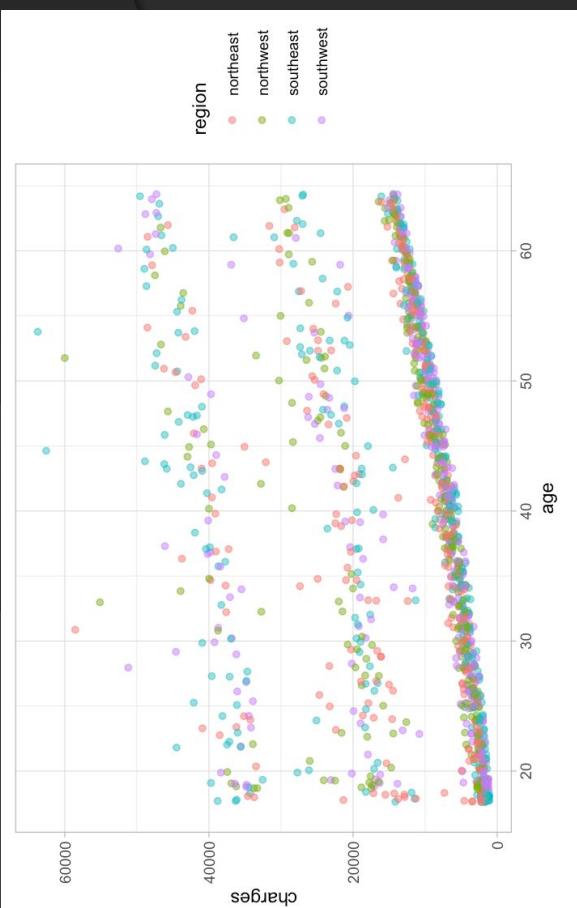
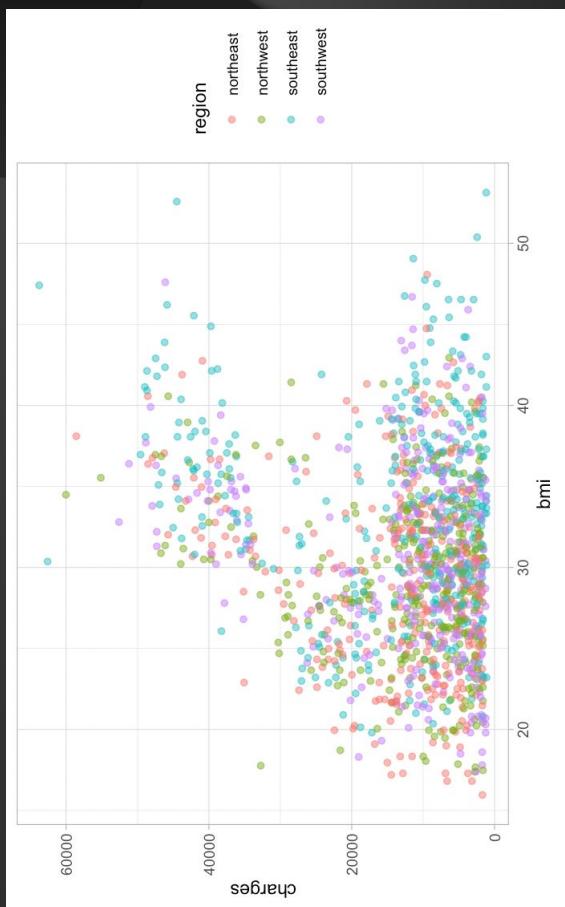
After adding log function to the variable



Correlation between the variables.

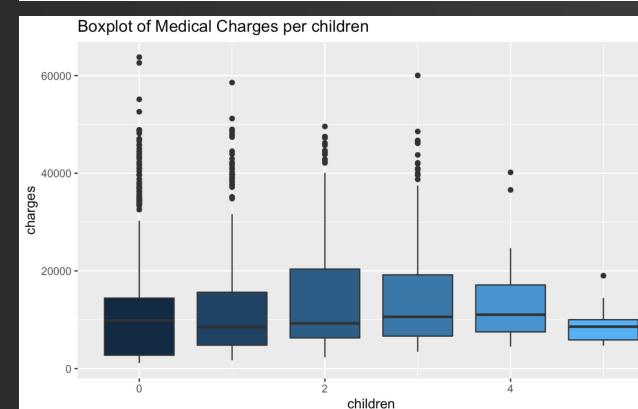
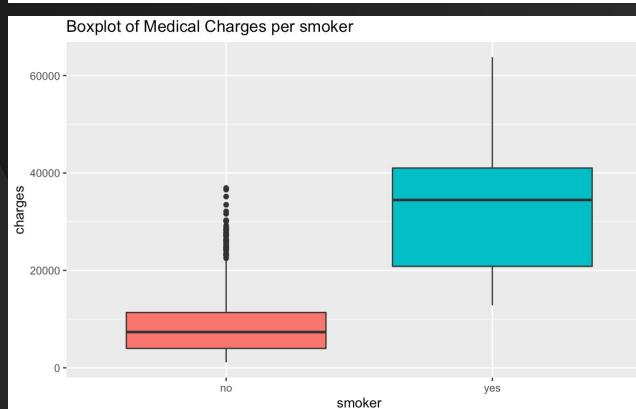
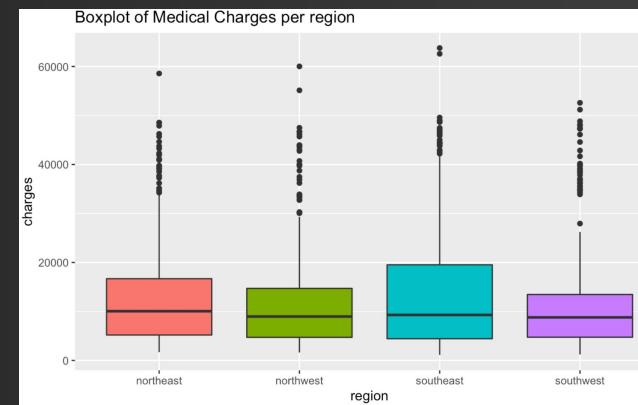
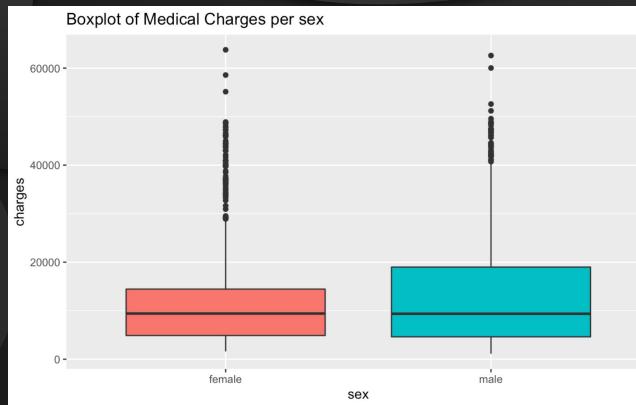


Looking into the correlation between charges and age, charges and bmi based on the region



As Age go up Charges for health insurance also trends up.

Dependent vs. Independent Variables



Linear Regression

```
Call:  
lm(formula = charges ~ age + bmi + region + children + sex +  
    smoker, data = insurance)  
  
Residuals:  
    Min      1Q  Median      3Q     Max  
-11304.9 -2848.1 - 982.1 1393.9 29992.8  
  
Coefficients:  
            Estimate Std. Error t value Pr(>|t|)  
(Intercept) -11938.5    987.8 -12.086 < 2e-16 ***  
age           256.9     11.9  21.587 < 2e-16 ***  
bmi          339.2     28.6 11.860 < 2e-16 ***  
regionnorthwest -353.0    476.3 -0.741 0.458769  
regionsoutheast -1035.0    478.7 -2.162 0.030782 *  
regionsouthwest -960.0    477.9 -2.009 0.044765 *  
children       475.5    137.8  3.451 0.000577 ***  
sexmale        -131.3   332.9 -0.394 0.693348  
smokeryes     23848.5   413.1 57.723 < 2e-16 ***  
---  
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```

Residual standard error: 6062 on 1329 degrees of freedom
Multiple R-squared: 0.7509, Adjusted R-squared: 0.7494
F-statistic: 500.8 on 8 and 1329 DF, p-value: < 2.2e-16

Dependent variable: Insurance charges

Independent variable: Age, BMI, Region, Children, Sex, Smoker

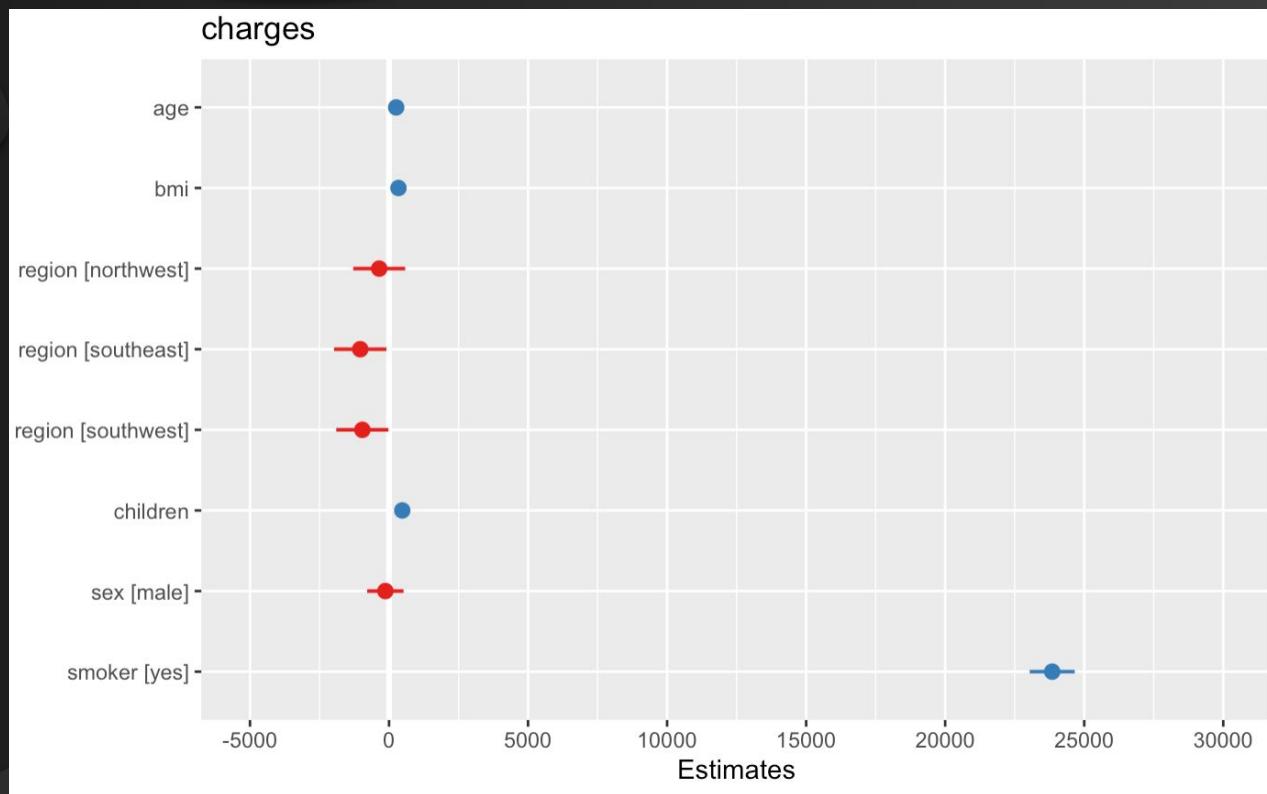
P value < 0.05 → significant

Top significant variables:

Age, BMI, Children, Smoker

R-squared: 0.75 → 75% variance explained by the model

Linear Regression



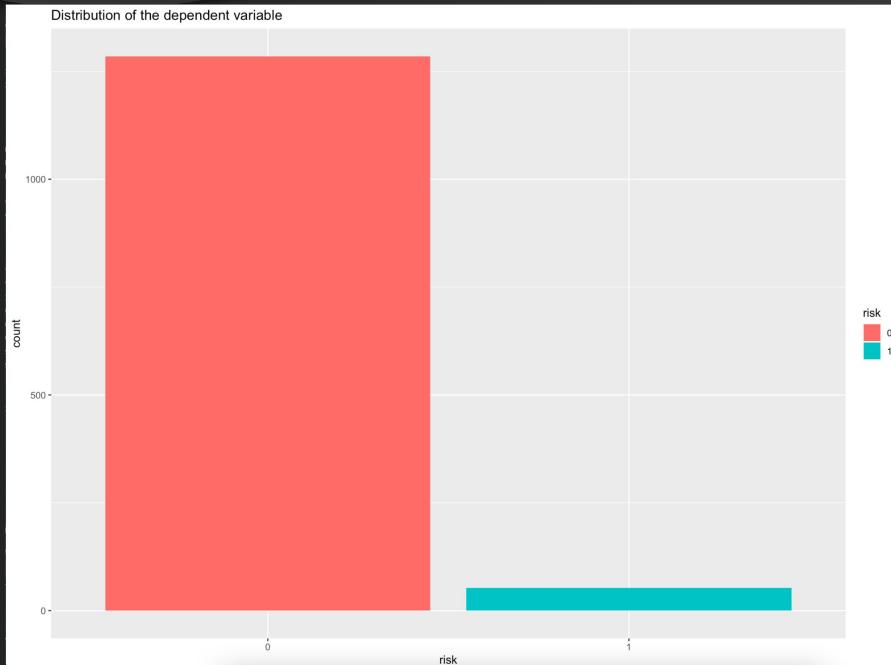
Logistic Regression

Intuition : Health care companies and High Risk Applicants

For the purpose of Logistic Regression we categorised each individual as a High Risk Applicant if he has attributes :

- BMI > 25
- Smoker Status : Yes
- Age > 50

Logistic Regression



Logistic Regression

Imbalance in classification problem

- Oversample (eg SMOTE)
- Downsample

Divide into Training and Test set (80-20)

Logistic Regression

```
```{r}
model_glm <- glm(risk~age+sex+bmi+children+smoker+region,
 family=binomial,
 data=training_data)
````|
```

Logistic Regression

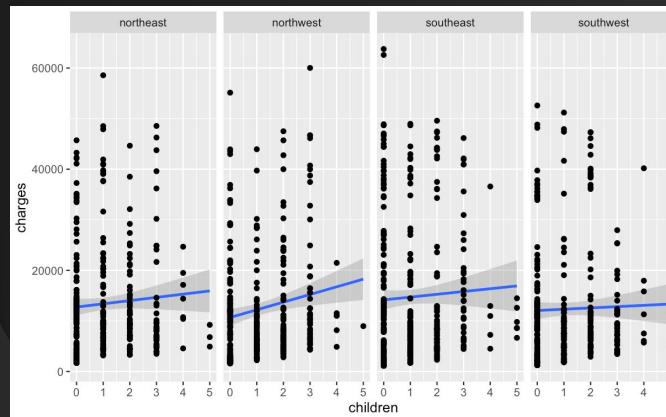
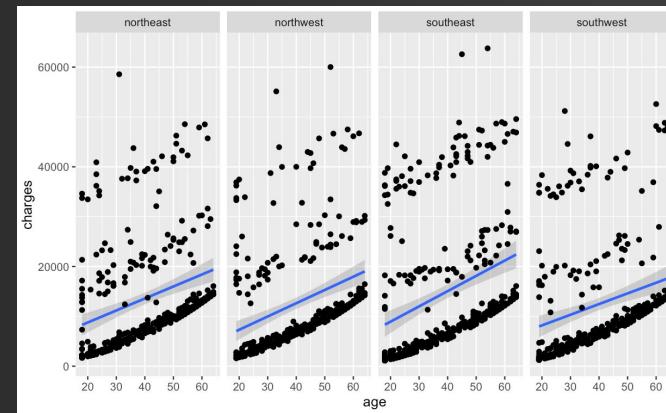
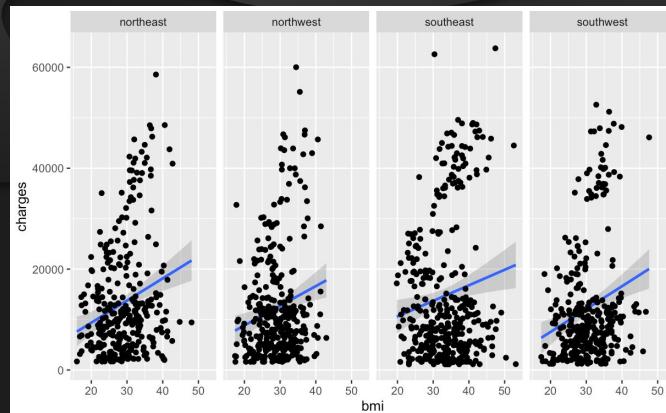
Confusion Matrix

```
> confusion_matrix  
risk  
pred  0  1  
  0 17  2  
  1  1 14  
. . .
```

Accuracy : 91.17 %

Recall : 87.5%

Linear Mixed-Effects Model (LMM)



Different intercept and slopes on each region for different variables

Not an ideal case for LMM because these trends have same direction (positive slope, upwards)

Linear Mixed-Effects Model (LMM)

```
Linear mixed model fit by REML ['lmerMod']
Formula: charges ~ sex + age + bmi + (1 | region)
Data: insurance
```

REML criterion at convergence: 28737.7

Scaled residuals:

Min	1Q	Median	3Q	Max
-1.3301	-0.6210	-0.4400	0.5972	4.1444

Random effects:

Groups	Name	Variance	Std. Dev.
region	(Intercept)	232625	482.3
Residual		129135439	11363.8

Number of obs: 1338, groups: region, 4

Fixed effects:

	Estimate	Std. Error	t value
(Intercept)	-6873.71	1794.59	-3.830
sexmale	1341.20	622.25	2.155
age	243.57	22.27	10.938
bmi	323.17	52.17	6.194

Correlation of Fixed Effects:

(Intr)	sexmale	age
sexmale	-0.145	
age	-0.390	0.026
bmi	-0.827	-0.048
	-0.113	

1

```
Data: insurance
Models:
model_lr: charges ~ sex + age + bmi
model_llmer: charges ~ sex + age + bmi + (1 | region)
npar      AIC    BIC logLik deviance Chisq Df Pr(>Chisq)
model_lr     5 28794 28820 -14392     28784
model_llmer   6 28796 28827 -14392     28784  0.0541  1     0.816
```

2

```
$region
(Intercept)
northeast   225.7956
northwest   -131.7809
southeast    256.8350
southwest   -350.8496

with conditional variances for "region"
```

3

Conclusion:

There is not much difference in variance happened between different regions, hence LMM is NOT needed and LM is better fit for this case

- (1 | region) as random effect to handle non-independence by introducing different intercepts for each region
- After running ANOVA between LR and LMM, the AIC BIC values *increase* between LMM compared to LR -> the model unnecessarily increase the complexity without improving the fit to the data

Generalized Linear Mixed Model (GLMM) on logistic regression

- Why are we using the method?
 - Provides information about whether individual variation amongst regions is significant.
 - To see if there is a different trends compared to overall in the regions.
- What variables used in the model
 - Fixed - effect variables: Sex, Age, Children, Smoker
 - Random - effect variables: Region

Generalized Linear Mixed Model (GLMM) on logistic regression

```
RStudio: Notebook Output
```

```
Generalized linear mixed model fit by maximum likelihood (Laplace Approximation) ['glmerMod']
  Family: binomial ( logit )
  Formula: charges_cat ~ sex + age + children + smoker + (1 | region)
  Data: insurance

    AIC      BIC  logLik deviance df.resid
  797.8    829.0   -392.9     785.8     1332

  Scaled residuals:
        Min      1Q  Median      3Q     Max
  -1.4752 -0.2996 -0.0371  0.2940 12.3914

  Random effects:
    Groups Name        Variance Std.Dev.
  region (Intercept) 0.05713  0.239
  Number of obs: 1338, groups: region, 4

  Fixed effects:
    Estimate Std. Error z value Pr(>|z|)
  (Intercept) -7.707e+00  5.033e-01 -15.314 <2e-16 ***
  sexmale     -3.338e-01  1.804e-01  -1.850  0.0643 .
  age         1.671e-01  9.954e-03  16.788 <2e-16 ***
  children    1.440e-01  7.435e-02   1.937  0.0528 .
  smokeryes   2.299e+05  4.054e+06   0.057  0.9548
  ---
  Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

  Correlation of Fixed Effects:
            (Intr) sexmale age    chldrn
  sexmale  -0.104
  age       -0.920 -0.075
  children  -0.365 -0.012  0.198
  smokeryes  0.000  0.000  0.000  0.000
  optimizer (Nelder_Mead) convergence code: 0 (ok)
  unable to evaluate scaled gradient
  Hessian is numerically singular: parameters are not uniquely determined
```

Generalized Linear Mixed Model (GLMM) on logistic regression

Random effects:

Groups	Name	Variance	Std.Dev.
region	(Intercept)	0.05713	0.239
Number of obs: 1338, groups: region, 4			

Fixed effects:

	Estimate	Std. Error	z value	Pr(> z)	
(Intercept)	-7.707e+00	5.033e-01	-15.314	<2e-16	***
sexmale	-3.338e-01	1.804e-01	-1.850	0.0643	.
age	1.671e-01	9.954e-03	16.788	<2e-16	***
children	1.440e-01	7.435e-02	1.937	0.0528	.
smokeryes	2.299e+05	4.054e+06	0.057	0.9548	

Generalized Linear Mixed Model (GLMM) on logistic regression

R RStudio: Notebook Output

```
$region
  (Intercept)
northeast  0.29605410
northwest  0.04043428
southeast -0.16775093
southwest -0.16823272

with conditional variances for "region"
```

Conclusion:

There is not much difference in variance happened between different regions, hence GLMM is NOT needed and GLM is better fit for this case

Conclusion

- We have figured out the features or variables which play vital role in the amount of health insurance as well as the prediction model to help the companies and the customers.
- For further analysis, dataset with more features will provide comparatively more accurate outputs.

**Thank You
Any questions :)?**