#2018107115 고지영

인공지능 발표

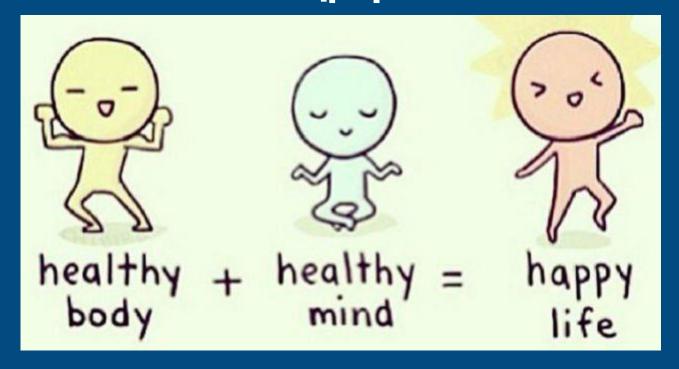


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여러 요인에 따라 달라지는 치료비용 예측



#1 사용한 데이터



Context

Machine Learning with R by Brett Lantz is a book that provides an introduction to machine learning using R. As far as I can tell, Packt Publishing does not make its datasets available online unless you buy the book and create a user account which can be a problem if you are checking the book out from the library or borrowing the book from a friend. All of these datasets are in the public domain but simply needed some cleaning up and recoding to match the format in the book.

Content

Columns

- · age: age of primary beneficiary
- · sex: insurance contractor gender, female, male
- bmi: Body mass index, providing an understanding of body, weights that are relatively high or low relative to height, objective index of body weight (kg / m ^ 2) using the ratio of height to weight, ideally 18.5 to 24.9
- · children: Number of children covered by health insurance / Number of dependents
- · smoker: Smoking
- · region: the beneficiary's residential area in the US, northeast, southeast, southwest, northwest.
- · charges: Individual medical costs billed by health insurance

Acknowledgements

The dataset is available on GitHub here.

Inspiration

Can you accurately predict insurance costs?

의료비 개인 데이터 세트 (선형회귀를 통한 보험료 예측)

컬럼

- 나이
- 성별(남,여)
- Bmi(체질량 지수 정상:18.5~24.9)
- 자녀(자녀의 수)
- 지역(미국)
- 흡연(흡연자,비흡연자)
- 비용(개인 의료비)

BMI(체질량지수) 계산



체중(kg) ÷
$$\frac{\Im(cm)}{100}$$

ВМІ	정상 여부
18.5 미만	저체중
18.5 - 24.9	정상
25 – 29.9	과체중
30 이상	비만

#2 데이터 읽어오기

```
import numpy as np
import pandas as pd
import os
import matplotlib.pyplot as pl
import seaborn as sns
import warnings
warnings.filterwarnings('ignore')
data = pd.read_csv('../input/insurance.csv')
```

모듈 import 데이터 읽어 오기

age sex bmi children smoker region charges 0 19 female 27.900 0 yes southwest 16884.92400 1 18 male 33.770 1 no southeast 1725.55230 2 28 male 33.000 3 no southeast 4449.46200 3 33 male 22.705 0 no northwest 21984.47061 4 32 male 28.880 0 no northwest 3866.85520 5 31 female 25.740 0 no southeast 3756.62160 6 46 female 33.440 1 no southeast 8240.58960 7 37 female 27.740 3 no northwest 7281.50560 8 37 male 29.830 2 no northwest 6406.41070 9 60 female <th colspan="9">data.head(10)</th>	data.head(10)								
1 18 male 33.770 1 no southeast 1725.55230 2 28 male 33.000 3 no southeast 4449.46200 3 33 male 22.705 0 no northwest 21984.47061 4 32 male 28.880 0 no northwest 3866.85520 5 31 female 25.740 0 no southeast 3756.62160 6 46 female 33.440 1 no southeast 8240.58960 7 37 female 27.740 3 no northwest 7281.50560 8 37 male 29.830 2 no northwest 6406.41070		age	sex	bmi	children	smoker	region	charges	
2 28 male 33.000 3 no southeast 4449.46200 3 33 male 22.705 0 no northwest 21984.47061 4 32 male 28.880 0 no northwest 3866.85520 5 31 female 25.740 0 no southeast 3756.62160 6 46 female 33.440 1 no southeast 8240.58960 7 37 female 27.740 3 no northwest 7281.50560 8 37 male 29.830 2 no northeast 6406.41070	0	19	female	27.900	0	yes	southwest	16884.92400	
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4 32 male 28.880 0 no northwest 3866.85520 5 31 female 25.740 0 no southeast 3756.62160 6 46 female 33.440 1 no southeast 8240.58960 7 37 female 27.740 3 no northwest 7281.50560 8 37 male 29.830 2 no northeast 6406.41070	2	28	male	33.000	3	no	southeast	4449.46200	
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8 37 male 29.830 2 no northeast 6406.41070	6	46	female	33.440	1	no	southeast	8240.58960	
	7	37	female	27.740	3	no	northwest	7281.50560	
9 60 female 25.840 0 no northwest 28923.13692	8	37	male	29.830	2	no	northeast	6406.41070	
	9	60	female	25.840	0	no	northwest	28923.13692	

상위 10개 데이터

[labelEncoder] 을 사용하여 성별, 흡연여부,지역과 같은 데이터를 수치로 바꿔준다.

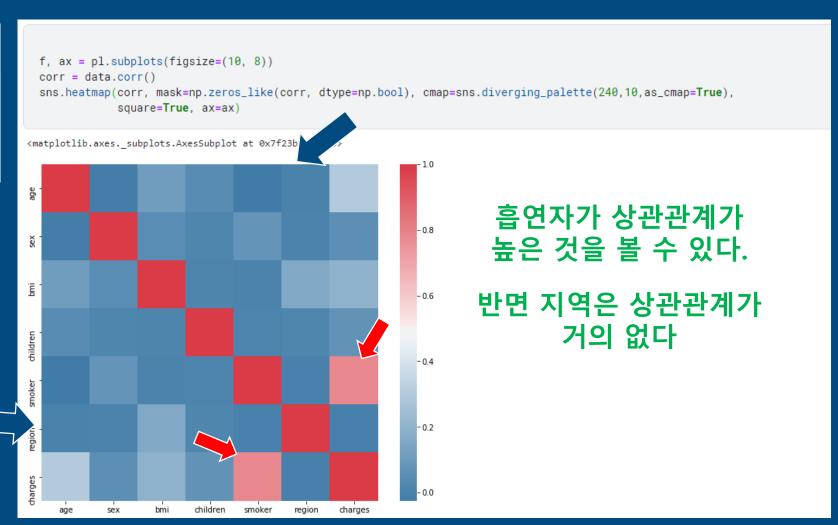
```
from sklearn.preprocessing import LabelEncoder
  #sex
 le = LabelEncoder()
 le.fit(data.sex.drop_duplicates())
 data.sex = le.transform(data.sex)
  # smoker or not
 le.fit(data.smoker.drop_duplicates())
 data.smoker = le.transform(data.smoker)
  #region
 le.fit(data.region.drop_duplicates())
 data.region = le.transform(data.region)
 + Code
             + Markdown
 print(data.region[:10])
 print(le.classes_)
Name: region, dtype: int64
['northeast' 'northwest' 'southeast' 'southwest']
```

```
print(data.smoker[:10])
      ◆──-흡연자
      ← 비흡연자
5
Name: smoker, dtype: int64
 print(data.sex[:10])
            여성
6
Name: sex, dtype: int64
```

#3 읽어온 데이터 표시-히트맵



널값이 있는지 확인



#3 읽어온 데이터 표시-히스토그램

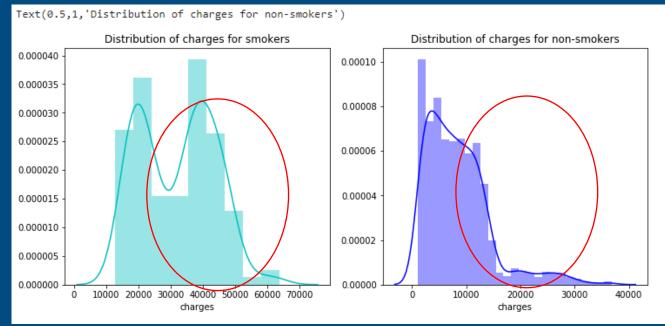
```
from bokeh.io import output_notebook, show
from bokeh.plotting import figure
output_notebook()
import scipy.special
from bokeh.layouts import gridplot
from bokeh.plotting import figure, show, output_file

f= pl.figure(figsize=(12,5))

ax=f.add_subplot(121)
sns.distplot(data[(data.smoker == 1)]["charges"],color='c',ax=ax)
ax.set_title('Distribution of charges for smokers')

ax=f.add_subplot(122)
sns.distplot(data[(data.smoker == 0)]['charges'],color='b',ax=ax)
ax.set_title('Distribution of charges for non-smokers')
```

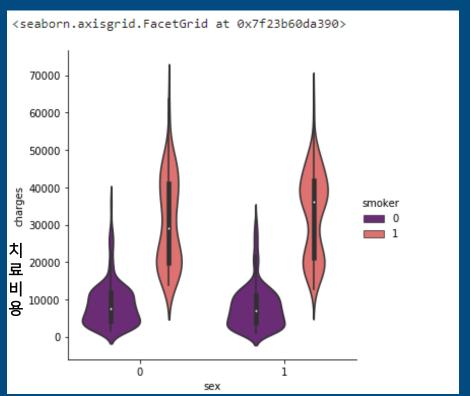
흡연자 vs 비흡연자



흡연자중에 의료비용이 높은 사람이 많다

#3 읽어온 데이터 표시-catplot, violin

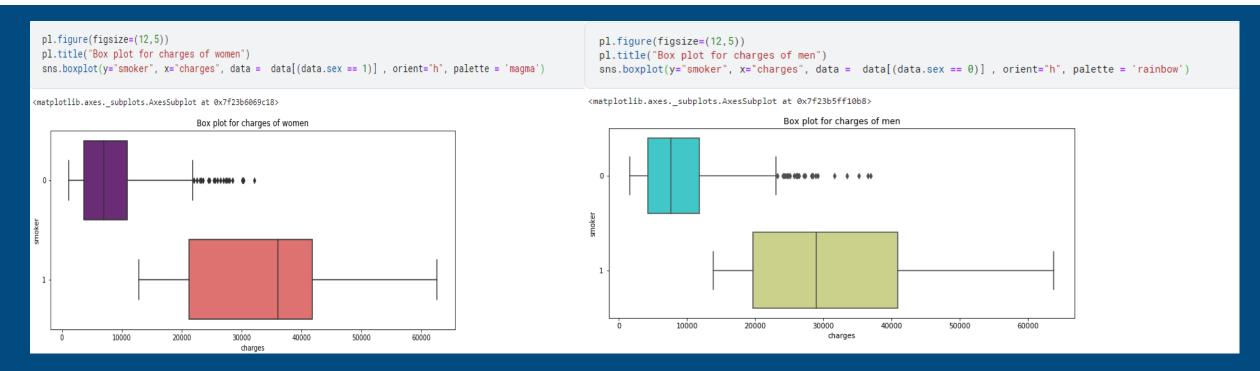




< 성별에 따른 흡연자 > 여성보다 남성흡연자의수가 많다

흡연자가 치료비용이 더 높다

#3 읽어온 데이터 표시-boxplot

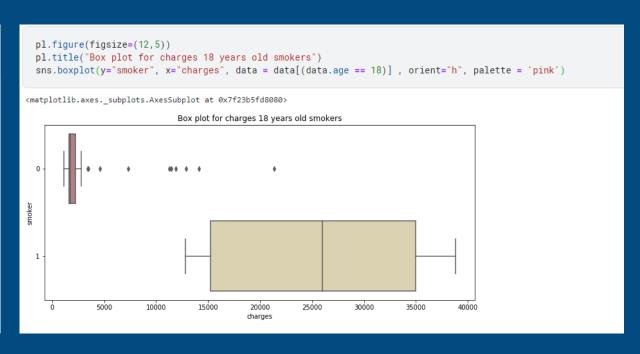


<여성>

<남성>

둘 다 흡연자의 의료 비용의 평균이 더 높다

#3 18세의 데이터

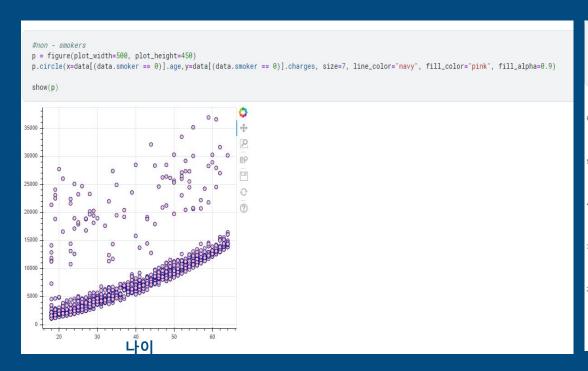


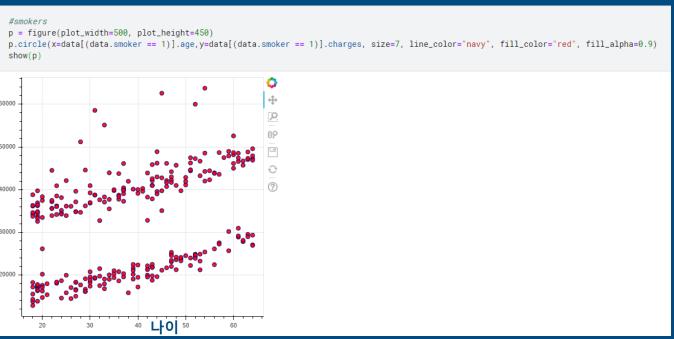
18살 흡연자의 비

⇒ 성인과 비슷

흡연자와 비흡연장의 <u>의료비용 차이가</u> 크다

#3 비흡연자 vs 흡연자 – 나이에 따른 의료비용



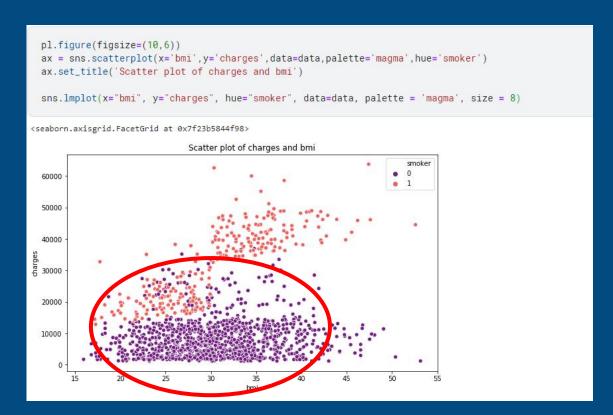


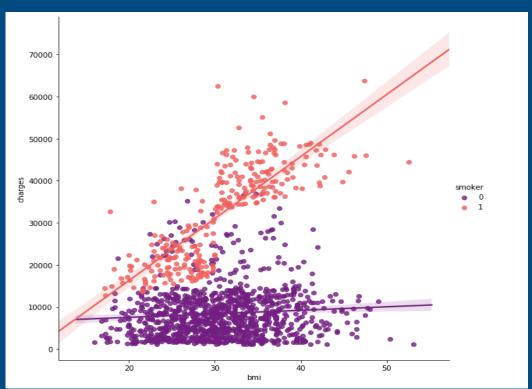
<비흡연자>

<흡연자>

둘 다 나이에 따라 의료비용 증가 흡연자가 의료비용 더 높음

#3 Bmi(체질량 지수) 에 따른 의료 비용





Bmi보다는 흡연여부가 더 큰 영향을 미침

#4 학습 및 테스트(LinearRegression)

```
from sklearn.linear_model import LinearRegression
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import PolynomialFeatures
from sklearn.metrics import r2_score, mean_squared_error
from sklearn.ensemble import RandomForestRegressor
```

```
x = data.drop(['charges'], axis = 1) #문제부분
y = data.charges #답부분

x_train,x_test,y_train,y_test = train_test_split(x,y, random_state = 0)
lr = LinearRegression().fit(x_train,y_train) #학습

y_train_pred = lr.predict(x_train)
y_test_pred = lr.predict(x_test)

print(lr.score(x_test,y_test))
```

0.7962732059725786

#점수

#4 학습 및 테스트(RandomForestRegressor)

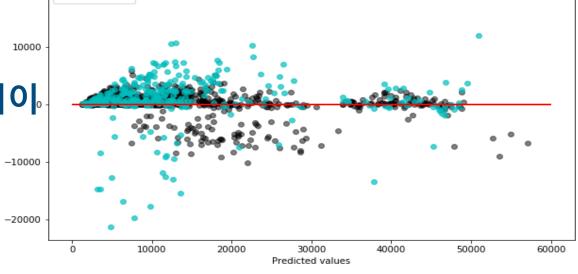
```
RF = RandomForestRegressor(random_state = 0)
RF.fit(x_train,y_train) #학습

score = RF.score(x_train,y_train)
print('Score:', format(score,'.3f'))

pred = RF.predict(x_test)
print('Predicted:', pred)
print('Correct answer:\n', y_test)
```

Score: 0.964 #점수

<결과>학습용데이터와 테스트데이 터가 거의 비슷하다



Train data

Test data

20000

#4 느낀점

- 이번 발표를 준비하면서 머신러닝 학습시키는데 필요한 데이터와 그렇지 않은 데이터를 구분하는 과정을 알게 되었고 이 주제를 찾기까지 다양한 주제들이 있었는데 머신러닝으로 정말 다양한 것을 할 수 있다는 것을 알게 되었습니다.
- 알고리즘마다 정확도가 다르다는 것을 알게 되었고 데이터를 직접 시각화 하는 과 정에서 그래프가 어떤 의미를 갖는지에 대해서 생각해보고 컬럼 간에 어떤 관계가 있는지도 알 수 있게 되었습니다.

감사합니다.