Analysis Health Related Expenses to Age, BMI, number of Children, and Smoker Status

Overview

Analysis fcused on health expenses on cohort of individuals. Dependencies were # of children, BMI, age and Smoker or not. Insights were generated individuals health expenses on these dependencies. Finally a LogisticRegression(LR) with solver at lbfgs, classification ML model was trained to predict an individuals propensity for health costs above $40,000 to asses for risk on the dependencies.

Findings:

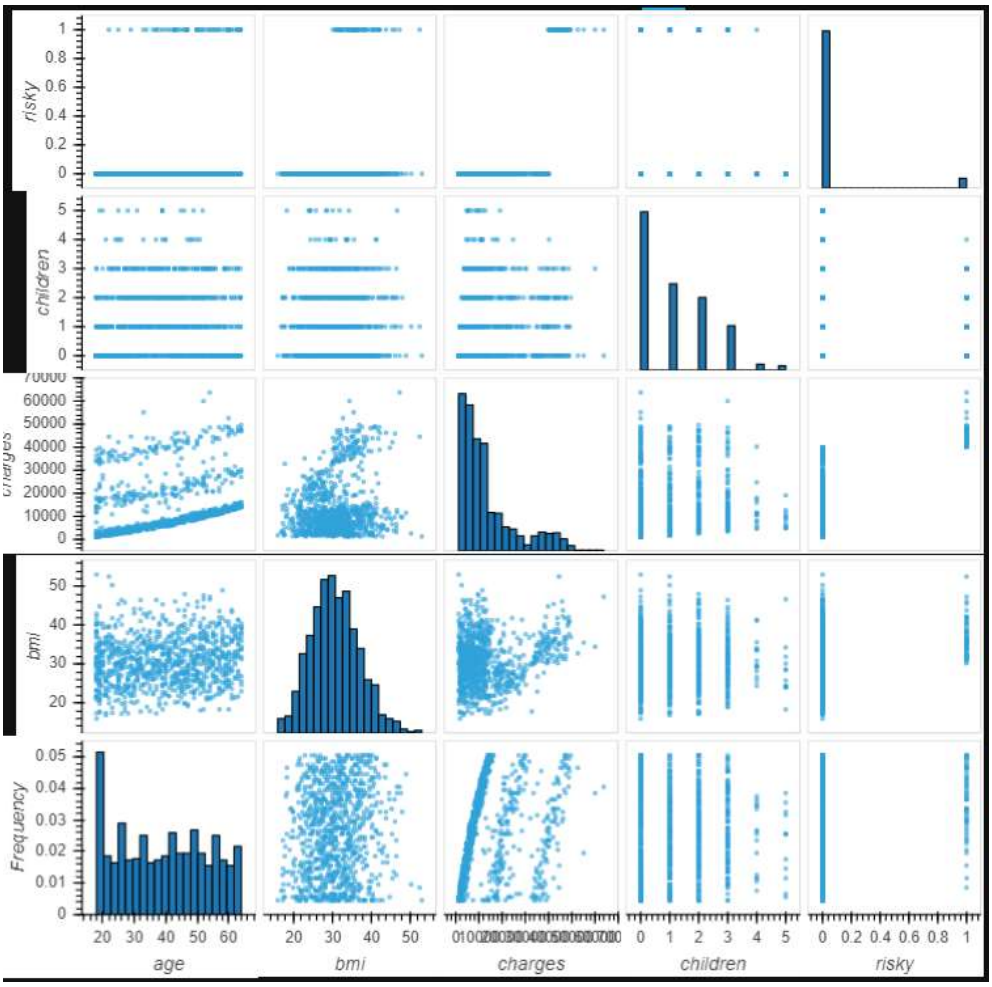
1. Summary Statistics for Medical Charges data set
    a. Total rows: 1004 (=data points= individuals)
    b. Units assumed: Age: years; BMI in kg/m^2; Charges: US$:

	Units	Mean	Std	Min	Median	Max
Age	Years	39.30	13.97	18.00	39.00	64.00
BMI	kgm^{-2}	30.79	6.19	15.96	30.50	53.13
Children		1.10	1.19	0	1	5
Charges	US$	13,408	12,146	1,122	9,440	63,770

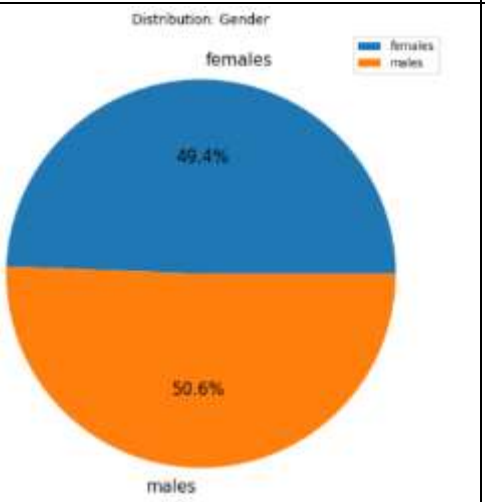
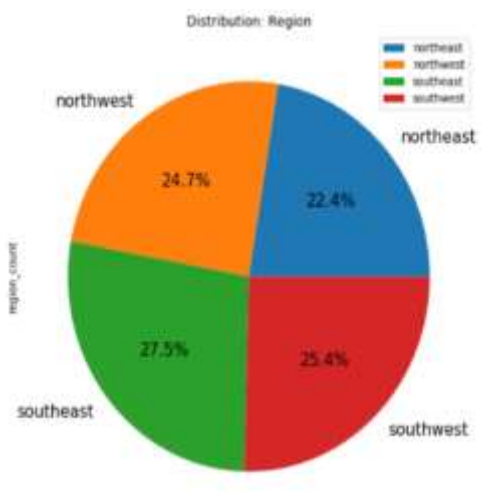
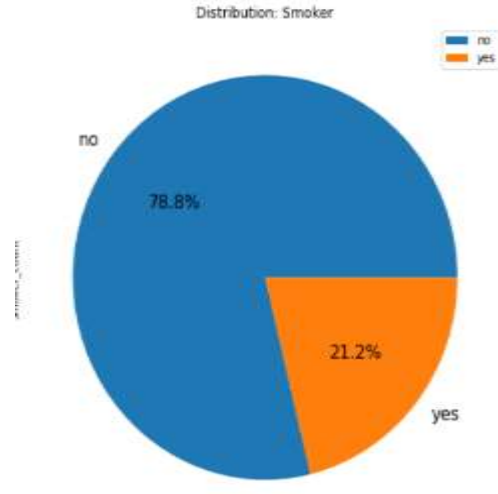
    c. Categorical:

	Value-Counts (numbers of individuals)
Sex	Male: 508; Female: 496
Smoker	Smoker: 312; Non-Smoker: 791
Region	NE: 225; NW: 248; SE: 276; SW: 255

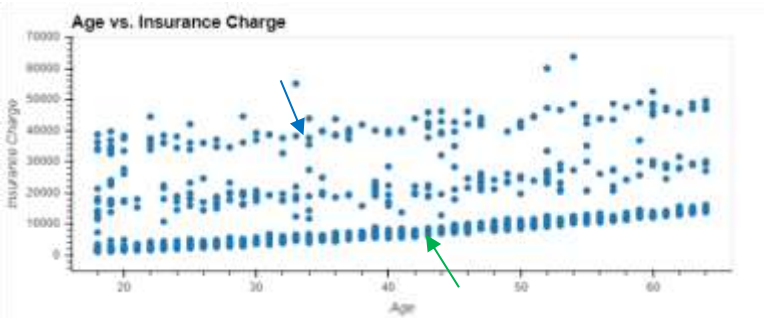
d. Scatter Matrix :



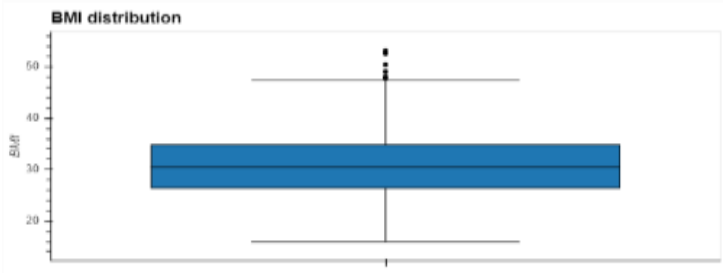
e. Distributions:

Gender	Region	Smoker
		

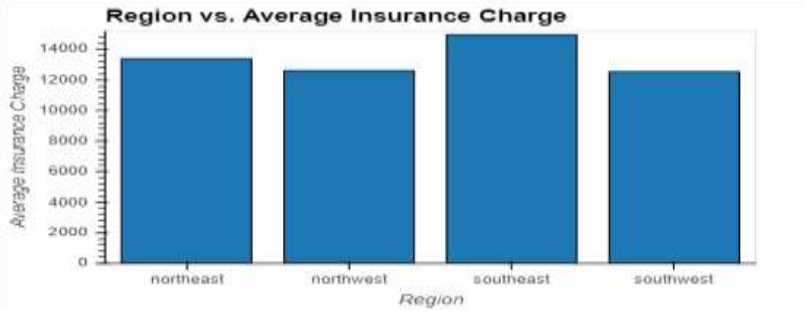
2. The sample that represents the population shows the following characteristics:
    a. Individuals in terms of numbers are distributed evenly, females to males' demographics and between 4 regions [see above].
    b. ~1/5th of the individuals are smokers [see above].
    c. There are 3 distinct classes (bands) of individuals, as seen in the Insurance Charge vs. Age plot. The lowest band (green) is the cohort cheapest to serve, while the one on top (blue) is the costliest. [see below]
    d. There are 2 distinct classes (bands) of individuals, as seen in the Insurance Charge vs. BMI plot. The lowest flat band (orange) is the cohort cheapest to serve while the band gradually rising (red) behaves as generally expected (higher the BMI, higher the medical costs). [see below]

Age vs. Insurance Charge	BMI vs. Insurance Charge
	

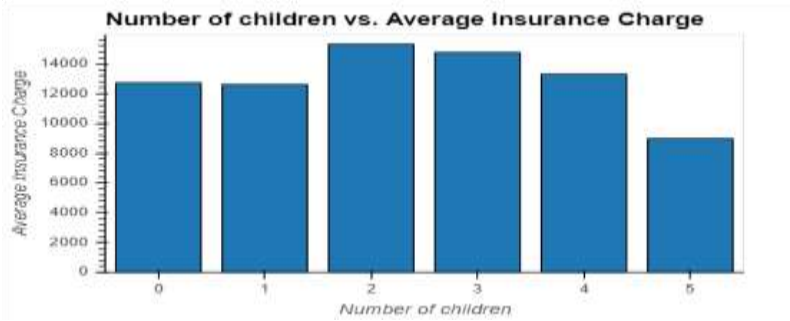
    e. The distribution of insurance charges shows skewed data set with few very high outliers (above 75% percentile). BMI has few outliers, while age has no outliers. They are both distributed evenly to the median. [Charges and BMI plots are seen below]

Charges box and whiskers	BMI box and whiskers
	

    f. On average non-smoking males in the southwest has the lowest medical charges at $7,251, while the most expensive were smoking males in the southwest with charges at $35,230. [on the pdf code]
    g. The highest charge on an individual on average per region is for southwest with $14,953. [see below]
    h. On average the highest cost per individual depending on the number of children occurs at 2 children ($15,312) and the lowest ($8976) at 5 children. However, the latter case is suspect because of lack of data (numbers) for individuals with 4 and 5 children, as shown in the scatter matrix plot above. [see below]



region	charges
northeast	13387.630722
northwest	12609.897092
southeast	14952.589649
southwest	12530.708516



children	charges
0	12722.185056
1	12603.476238
2	15312.137788
3	14758.296242
4	13302.770644
5	8976.244817

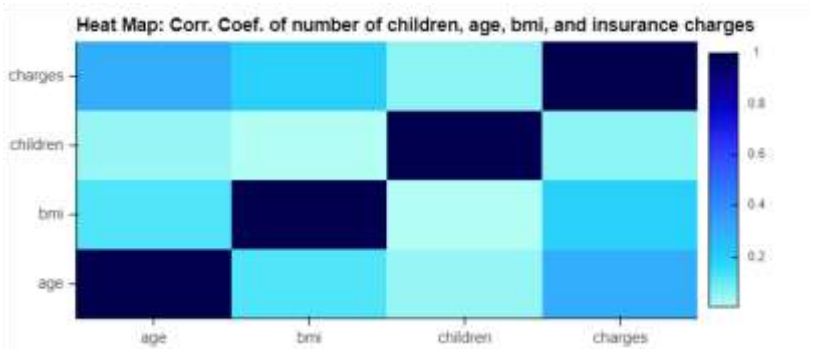
3. The average age of the female is 40.00 years while for males it is 38.60 years. [see below]

sex	age	bmi	children	charges	risky
female	40.004032	30.430252	1.066532	12641.380864	0.042339
male	38.606299	31.143917	1.141732	14156.676964	0.074803

4. The smoking rate for those of who have kids = (47+45+26+2+1)/(186+47+151+45+94+26+14+2+11+1) = 20.97%
   Smoking rate for those without kids = 92/(335+92) = 21.55%
   Therefore, it is higher for those with kids. [see below]

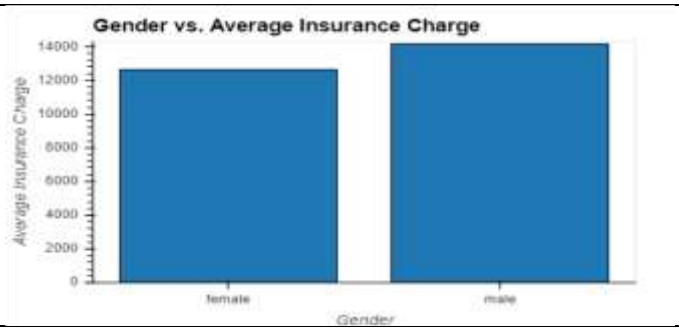
children	smoker	age
0	no	335
	yes	92
1	no	186
	yes	47
2	no	151
	yes	45
3	no	94
	yes	26
4	no	14
	yes	2
5	no	11
	yes	1

5. There is very low collinearity between variables (age, BMI, number of children) given by the correlation values and the heat map. [see below]



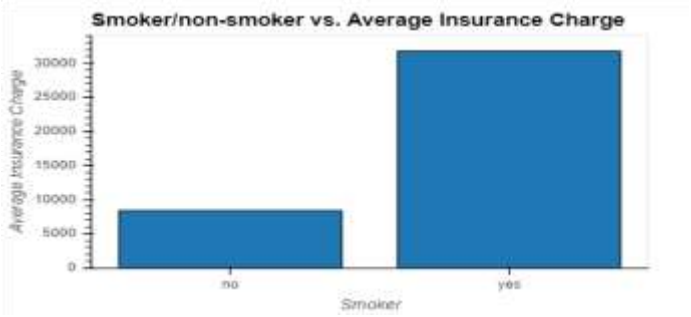
	age	bmi	children	charges
age	1.000000	0.122592	0.039342	0.300724
bmi	0.122592	1.000000	0.003464	0.191917
children	0.039342	0.003464	1.000000	0.053132
charges	0.300724	0.191917	0.053132	1.000000

6. a. Being male increases medical costs by on average $ 1,515. [see below]



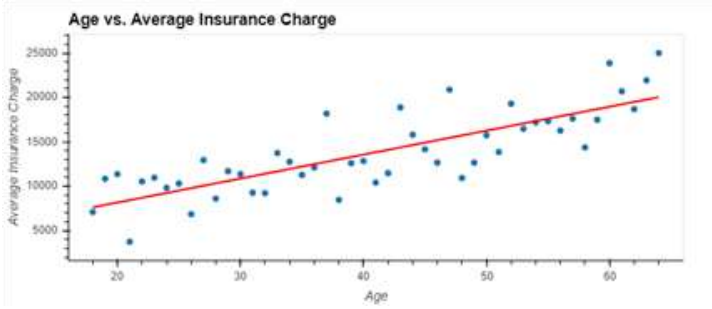
sex	charges
female	12641.380864
male	14156.676964

b. Being a smoker increases medical costs significantly by, on average, $ 23,364. [see below]



smoker	charges
no	8451.303856
yes	31815.659419

c. Each additional year adds medical costs by $ 261. But this has a significant RMSE of $2,682.54. I've used average charges per year to reduce noise in this calculation as such there maybe some error associated, compared to raw data. [see below]

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Slope:  [[269.89612532]]
Intercept:  [2768.27652013]

R-squared (R2 ): 0.6506671776730499
Root Mean Squared Error (RMSE): 2682.5375368008604
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Predicting Health Expense Risk from the Dependencies

A predictive classification ML model was used where a patient's healthcare cost above $40,000 being high risk (likely should be excluded). I've selected $40,000 as the cutoff because this is an imbalanced data set and will get highly imbalanced if the cutoff is set at $50,000. At $50,000, only 4 individuals would place themselves above the cutoff. At $40,000, the number of individuals above cutoff gets increased to 59. To mitigate this, we could use imbalanced learn classification ML algorithm such as one of the oversampling techniques: SMOTE or hybrid such as SMOTTEEN.

Data sets were separated: train (75%) and test (25%) using Scikit-Learn, train_test_split. They were then scaled using StandardScaler. LogisticRegression(LR) model with solver at lbfgs (Limited Memory Broyden–Fletcher–Goldfarb–Shanno algorithm (BFGS)) was used for modeling the system. Predicted values obtained and compared them with test (y_test) values, and obtained LR classification report, the accuracy score is a respectable 98%. Also, the Precision and Recall scores were reasonable.

Of particularly important is the high-risk [1] recall score at 81%. This compared to Precision scores for both cases (high-risk[1] and low-risk[0]) is not as good. Since Recall scores have False Negatives (FN) (high-risk folks identified as low-risk), there is room for improvement. Of the test set (True 235 Low-Risk and True 16 High-Risk) of the low-risk predictions, 3 were misidentified as low risk (FN, which is costly to say an insurance provider) of the predicted high-risk 2 were True low-risk (False Positives FP), i.e., provider would drop them by which they'll lose revenue (profit too since they are True low risk). But the actual financial losses are significant with the high-risk cohort, which means the model need to improve the Recall Scores. These metrics are seen on the Classification Report and Confusion Matrix.

Once trained, if an individual (or a cohort) applies, what must be done is to get the parameters for the individual (or the cohort) and see what the predicted risk (y_pred from the code). As it stands, if the cutoff is at $40,000, the model would have an accuracy score of 98%.

Logistic Regression Classification Report:

	precision	recall	f1-score	support
Low Risk [0]	0.99	0.99	0.99	235
High Risk [1]	0.87	0.81	0.84	16
accuracy			0.98	251
macro avg	0.93	0.90	0.91	251
weighted avg	0.98	0.98	0.98	251

Confusion Matrix:

	Predicted 0	Predicted 1
Low Risk [0]	233	2
High Risk [1]	3	13