



# Assur'aimant Insurance Charges Prediction

Using Python with Sklearn

Brief : Prédire une prime d'assurance grâce l'IA

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# Insurance Charges Prediction

## 1 Introduction

### *Assur'aimant proposal*

- Perform data analysis to better understand Assur'aimant's customers
- Create a solution that would allow Assur'aimant to estimate the insurance premiums of its subscribers in the US market





# Insurance Charges Prediction

## 1 Introduction

Our objective is twofold:

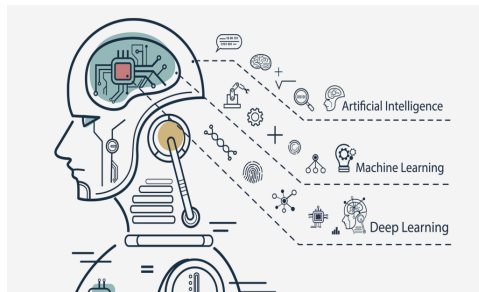
### Data analysis

Conduct an exploratory data analysis to better understand Assur'aimant's customers



### Modeling

Create a machine learning model that estimates customers' insurance charges based on their demographic data.





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## 2 Data analysis

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# Dataset

## Descriptive statistics

The file Dataset contains:

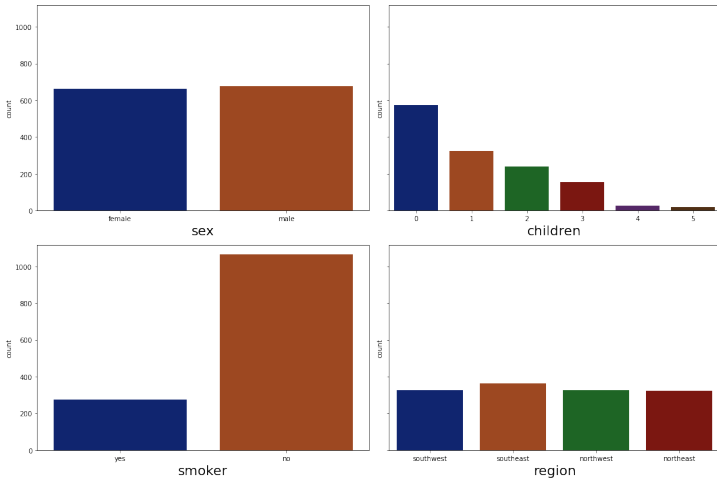
- 1338 observations
- 7 features  
4 numerical features (age, bmi, children and charges)  
and 3 categorical features (sex, smoker and region)
- no missing values
- and only one duplicate Rows

age	sex	bmi	children	smoker	region	charges
19	male	30.59	0	no	northwest	1639.5631
19	male	30.59	0	no	northwest	1639.5631



# Dataset

## Categorical features





## Dataset

### Categorical features

Frequency tables :

children	n	f	F
0	574	0.428999	0.428999
1	324	0.242152	0.671151
2	240	0.179372	0.850523
3	157	0.117339	0.967862
4	25	0.018685	0.986547
5	18	0.013453	1.000000

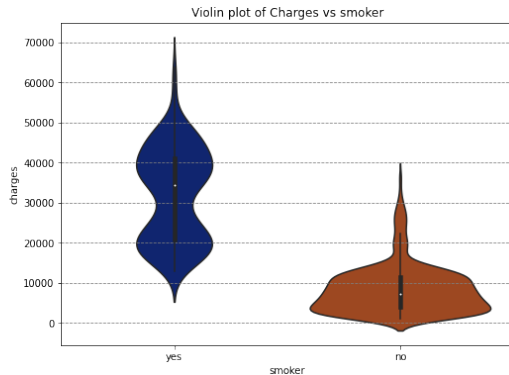
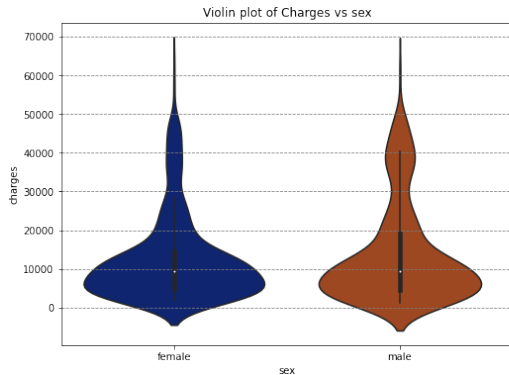
smoker	no	yes
sex		
female	547	115
male	517	159





# Dataset

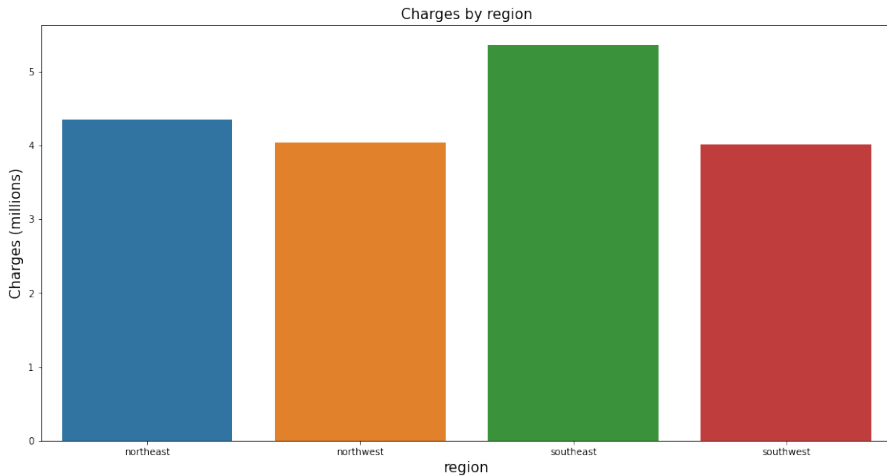
## Categorical feature by charges





# Dataset

Categorical feature by charges





# Dataset

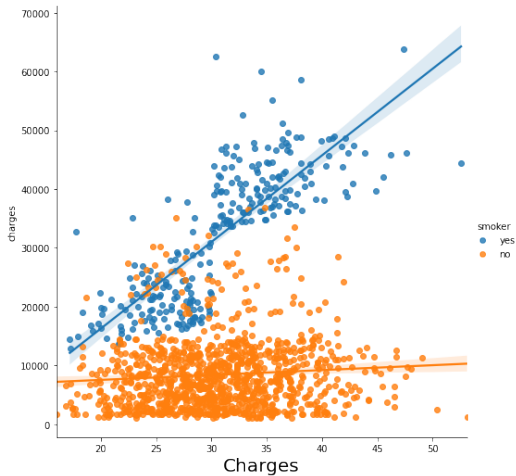
Categorical features by charges





# Dataset

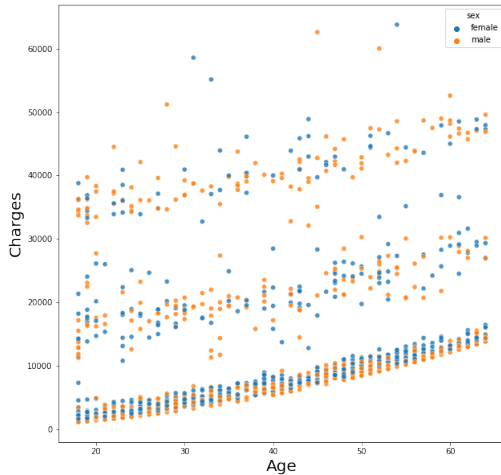
## Categorical features by charges





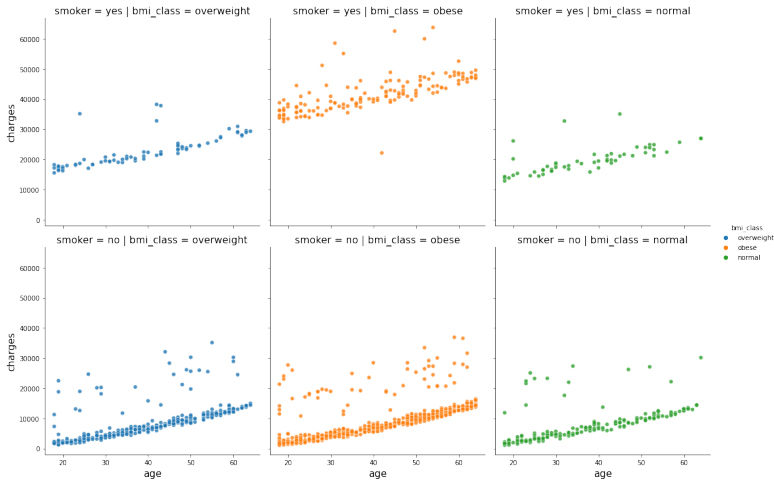
# Dataset

Categorical feature by charges



# Dataset

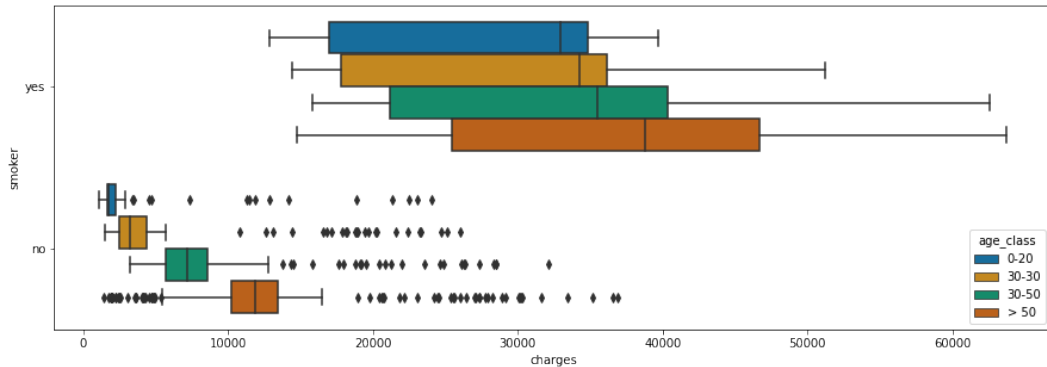
## Categorical features by charges





# Dataset

Categorical feature by charges

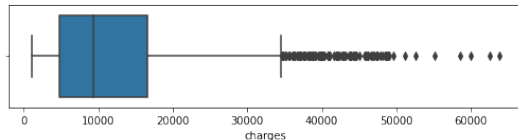
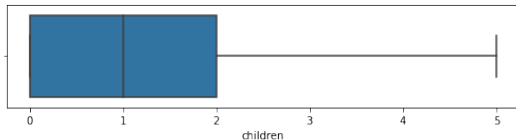
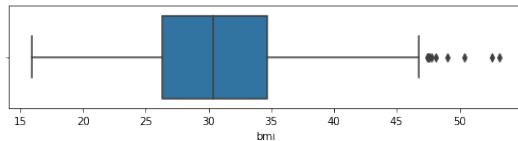
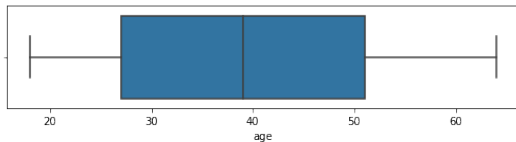




## Dataset

### Numerical features

Only bmi and charges have outliers



- bmi has 9 outliers
- charges has 139 outliers





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# Univariate analysis

## 2 Data analysis

- Testing normality graphically
- Apply log-transformations
- Normality test

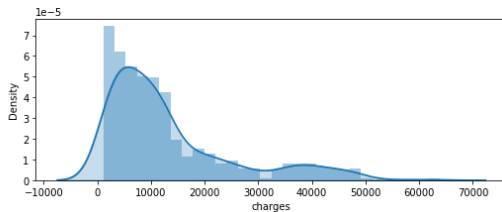
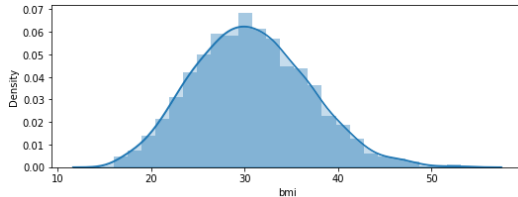
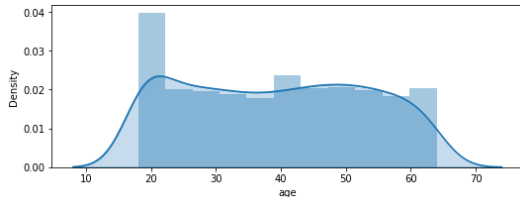


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# Univariate analysis

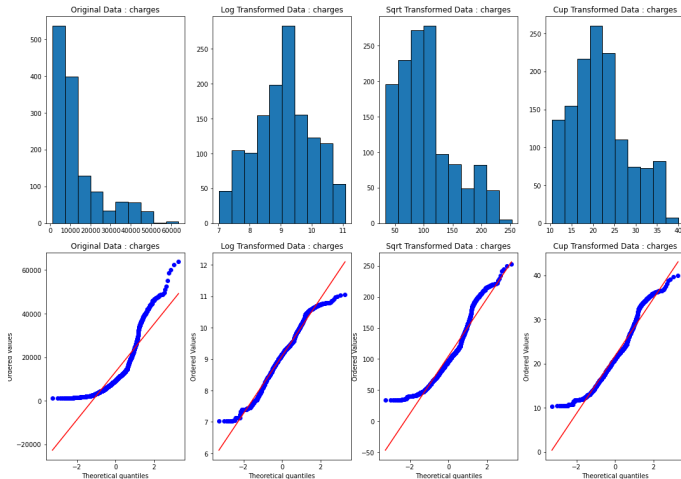
## Numerical features



	age	bmi	charges
skew	0.055673	0.284047	1.515880
kurt	-1.245088	-0.050732	1.606299

# Univariate analysis

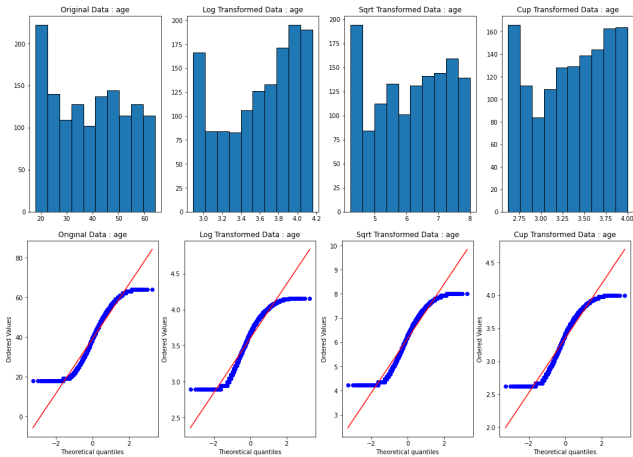
## Numerical features : charges





# Univariate analysis

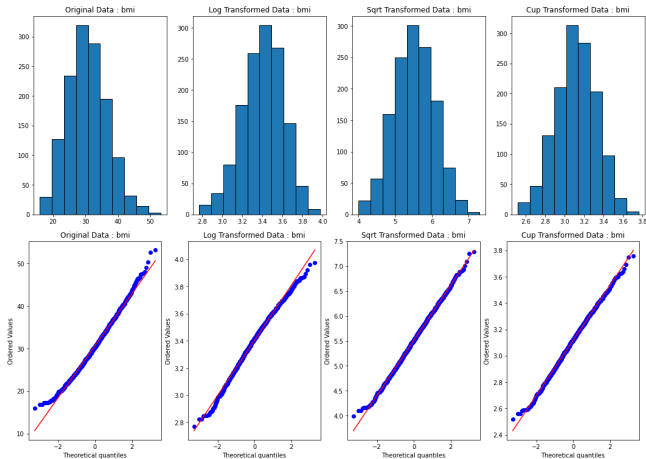
Numerical features : age





# Univariate analysis

Numerical features : bmi





# Univariate analysis

Numerical features : bmi

charges	ORIGIN.		log transf.		sqrt transf.		Cube R transf.	
	stat	pvalue (5%)	stat	pvalue (5%)	stat	pvalue (5%)	stat	pvalue (5%)
Agostino and Pearson	336.885	0.000	52.717	0.000	112.461	0.000	69.040	0.000
Shapiro-Wilk	0.815	0.000	0.983	0.000	0.934	0.000	0.962	0.000
Kolmogorov-Smirnov	1.000	0.000	1.000	0.000	1.000	0.000	1.000	0.000

age	ORIGIN.		log transf.		sqrt transf.		Cube R transf.	
	stat	pvalue (5%)	stat	pvalue (5%)	stat	pvalue (5%)	stat	pvalue (5%)
Agostino and Pearson	1557.821	0.000	593.282	0.000	1349.019	0.000	1067.809	0.000
Shapiro-Wilk	0.945	0.000	0.930	0.000	0.942	0.000	0.939	0.000
Kolmogorov-Smirnov	1.000	0.000	0.998	0.000	1.000	0.000	0.996	0.000

bmi	ORIGIN.		log transf.		sqrt transf.		Cube R transf.	
	stat	pvalue (5%)	stat	pvalue (5%)	stat	pvalue (5%)	stat	pvalue (5%)
Agostino and Pearson	17.581	0.000	15.400	0.000	2.851	0.240	4.127	0.127
Shapiro-Wilk	0.994	0.000	0.995	0.000	0.999	0.345	0.998	0.169
Kolmogorov-Smirnov	1.000	0.000	0.997	0.000	1.000	0.000	0.994	0.000

sqrt transf.  $(y) = y^{\frac{1}{2}}$       Cube Root transformation  $(y) = y^{\frac{1}{3}}$

Here we test the null hypothesis that a sample comes from a normal distribution



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# Correlation

## 2 Data analysis

- Pearson correlation
- Point Biserial test for correlation
- $\chi^2$  test for correlation
- ANOVA

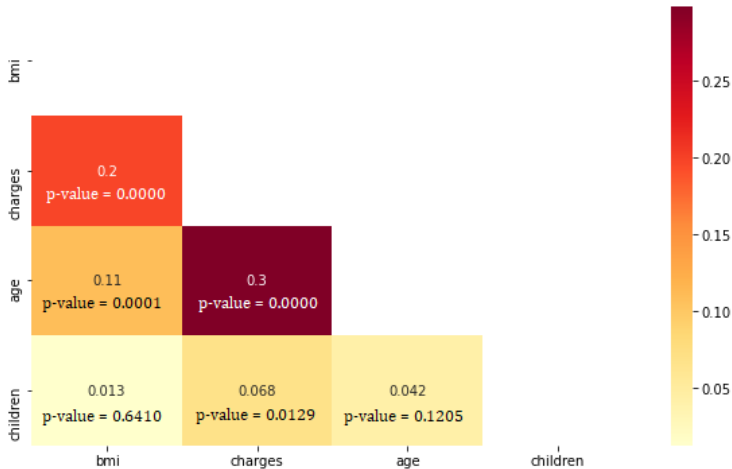


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# Correlation

## Pearson correlation



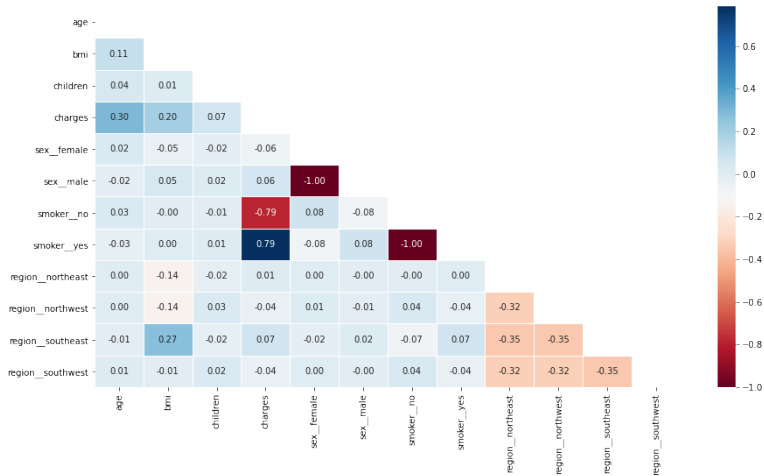
Here we test the null hypothesis that there is a statistically significant association between groups





# Correlation

## Pearson correlation





## Correlation

Point Biserial correlation

### Corr. : "charges" and "sex"

Point Biserial corr. : 0.057

t-value: -2.098

p-value: 0.036

### Corr. : "charges" and "smoker"

Point Biserial corr. : -0.787

t-value: 46.665

p-value: 0.000

Here we test the null hypothesis that the correlation is statistically significant.



## Correlation

$\chi^2$  test for correlation

p-value	sex	region	smoker	bmi class
sex				
region	0,9239			
smoker	0.0062	0,063548		
bmi class	0.2251	0.00005	0,609511	

Ho: The variables are not correlated with each other (Independent).



# Correlation

## ANOVA

| ANOVA between "charges" and "children" |

F-value: 3.297

p-value: 0.006

H0: there is no difference in means

H1: at least two means differ by comparing two groups.

### ASSUMPTION CHECK (Normality - Shapiro)

The assumption of normality is tested on the residuals  
Residuals are not normal (stat (W) =0.812, p=0.000)

### Kruskal-Wallis test

statistic : 29.4871                      pvalue : 0.0  
No significant differences between categories

### Multiple Comparison of Means - Tukey HSD, FWER=0.05

group1	group2	meandiff	p-adj	lower	upper	reject
0	1	365.1962	0.9	-2026.0598	2756.4522	False
0	2	2707.5881	0.0413	62.3365	5352.8398	True
0	3	2989.3428	0.0662	-109.9976	6088.6831	False
0	4	1484.6807	0.9	-5546.1043	8515.4657	False
0	5	-3579.9404	0.7925	-11817.2428	4657.3621	False
1	2	2342.3919	0.2025	-588.3514	5273.1352	False
1	3	2624.1465	0.2211	-722.1665	5970.4596	False
1	4	1119.4845	0.9	-6023.6128	8262.5817	False
1	5	-3945.1366	0.7286	-12278.5064	4388.2332	False
2	3	281.7546	0.9	-3250.5338	3814.0431	False
2	4	-1222.9074	0.9	-8454.9949	6009.18	False
2	5	-6287.5285	0.2705	-14697.3027	2122.2458	False
3	4	-1504.6621	0.9	-8914.9012	5905.577	False
3	5	-6569.2831	0.2432	-15132.7437	1994.1775	False
4	5	-5064.6211	0.7242	-15702.2375	5572.9954	False

Reject = True, means statistically significant difference.



# Correlation

## ANOVA

| ANOVA between "charges" and "children" |

F-value: 27.952

p-value: 0.000

H0: there is no difference in means

H1: at least two means differ by comparing two groups.

ASSUMPTION CHECK (Normality - Shapiro)

The assumption of normality is tested on the residuals  
Residuals are not normal (stat (W) =0.862, p=0.000)

Kruskal-Wallis test

statistic : 15.8076                      pvalue : 0.0004  
No significant differences between categories

Multiple Comparison of Means - Tukey HSD, FWER=0.05

group1	group2	meandiff	p-adj	lower	upper	reject
normal	obese	5270.111	0.0	3204.8498	7335.3722	True
normal	overweight	705.2854	0.7474	-1570.2691	2980.8399	False
obese	overweight	-4564.8256	0.0	-6327.8405	-2801.8107	True

Reject = True, means statistically significant difference.



# Correlation

## ANOVA

| ANOVA between "charges" and "region" |

F-value: 2.970

p-value: 0.031

H0: there is no difference in means

H1: at least two means differ by comparing two groups.

ASSUMPTION CHECK (Normality - shapiro)

The assumption of normality is tested on the residuals  
Residuals are not normal (stat (W) =0.827, p=0.000)

Kruskal-Wallis test

statistic : 4.7342                      pvalue : 0.1923  
No significant differences between categories

Multiple Comparison of Means - Tukey HSD, FWER=0.05

group1	group2	meandiff	p-adj	lower	upper	reject
northeast	northwest	-988.8091	0.7245	-3428.9343	1451.3161	False
northeast	southeast	1329.0269	0.4745	-1044.9417	3702.9955	False
northeast	southwest	-1059.4471	0.6792	-3499.5723	1380.6781	False
northwest	southeast	2317.8361	0.0583	-54.1994	4689.8716	False
northwest	southwest	-70.638	0.9999	-2508.8826	2367.6066	False
southeast	southwest	-2388.4741	0.0477	-4760.5096	-16.4386	True

Reject = True, means statistically significant difference.



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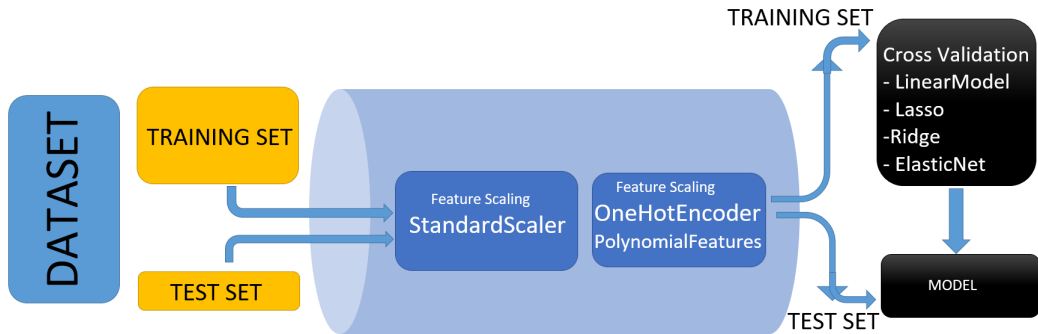
► Data analysis

► **Modeling**

► Conclusion



# Machine Learning Pipeline







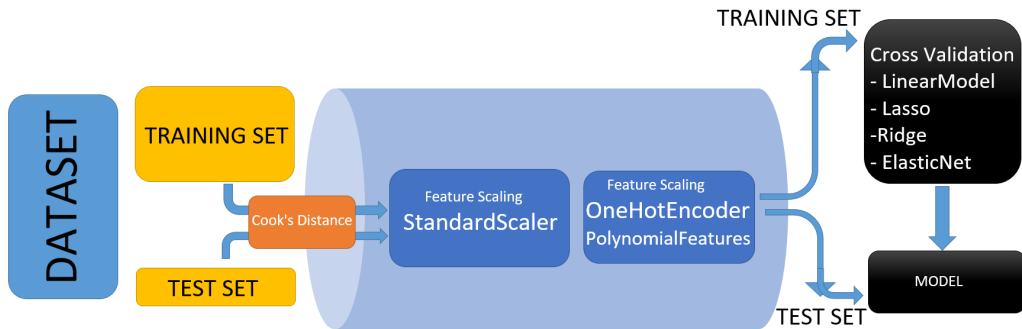
# Machine Learning

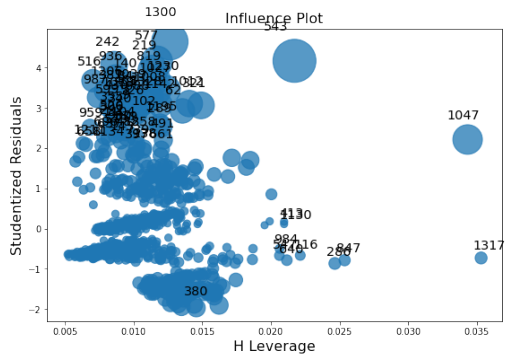
## Models

Model	R2	MAE	RMSE	Score (test)	Score (training)	Score (CV)
LASSO (Polynomial=2)	0.9124	1957.294489	3340.68227	0.92258252	0.858246217	0.8488 (+/- 0.04)
ElasticNet (Polynomial=2)	0.9124	1960.457382	3335.03664	0.92284396	0.857777099	0.8488 (+/- 0.04)
Ridg (Polynomial=2)	0.9088	2029.465675	3419.33535	0.91889416	0.861147147	0.8432 (+/- 0.04)
LR (Polynomial=2)	0.908	2059.129706	3441.72265	0.91782865	0.861231494	0.8395 (+/- 0.04)
LASSO (Polynomial=1)	0.7717	3655.59983	5092.51496	0.8200991	0.739238658	0.7286 (+/- 0.04)
ElasticNet (Polynomial=1)	0.7724	3662.001424	5094.07174	0.81998909	0.739370553	0.7285 (+/- 0.04)
LR (Polynomial=1)	0.7759	3708.067361	5107.96534	0.81900583	0.739694812	0.7282 (+/- 0.04)
Ridg (Polynomial=1)	0.7743	3706.798635	5107.54383	0.8190357	0.739682407	0.7282 (+/- 0.04)



# Machine Learning Pipeline







# Machine Learning

## Models

Model	R2	MAE	RMSE	Score (test)	Score (training)	Score (CV)
LASSO (Polynomial degree=2)	0.9167	1406.28958	3284.14811	0.92518061	0.93174224	0.9289 (+/- 0.03)
ElasticNet (Polynomial degree=2)	0.9163	1418.11301	3286.18929	0.92508757	0.93147991	0.9289 (+/- 0.03)
Ridg (Polynomial degree=2)	0.9156	1405.07355	3316.22355	0.92371199	0.93386043	0.9260 (+/- 0.03)
LR (Polynomial degree=2)	0.9156	1422.81265	3316.64098	0.92369278	0.93393518	0.9076 (+/- 0.05)
LASSO (Polynomial degree=1)	0.7717	3862.59891	5146.51752	0.81626342	0.82742769	0.8217 (+/- 0.02)
ElasticNet (Polynomial degree=1)	0.7723	3870.75378	5149.93451	0.81601936	0.82752003	0.8217 (+/- 0.02)
Ridg (Polynomial degree=1)	0.774	3909.13092	5166.05096	0.81486604	0.8277796	0.8211 (+/- 0.02)
LR (Polynomial degree=1)	0.7756	3916.18802	5168.88797	0.81466265	0.82779611	0.8210 (+/- 0.02)



# Machine Learning

## Models

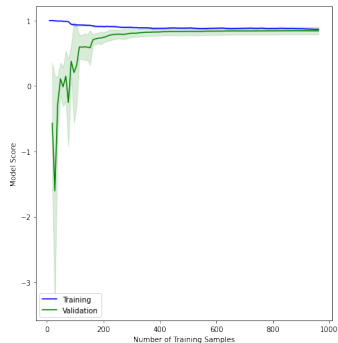
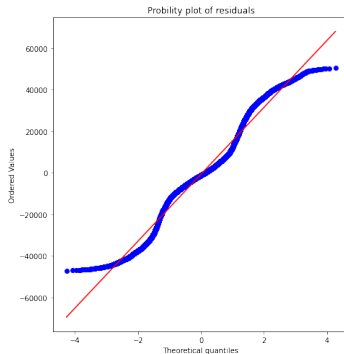
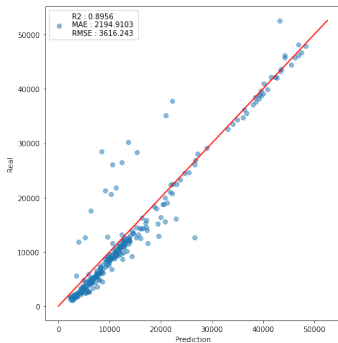
Model	Score (CV)	Score (CV Cook)	
LASSO (Polynomial degree=2)	0.8488	0.9289	+0.0801
ElasticNet (Polynomial degree=2)	0.8488	0.9289	+0.0801
Ridg (Polynomial degree=2)	0.8432	0.926	+0.0828
LR (Polynomial degree=2)	0.8395	0.9076	+0.068
LASSO (Polynomial degree=1)	0.7286	0.8217	+0.0931
ElasticNet (Polynomial degree=1)	0.7285	0.8217	+0.0932
Ridg (Polynomial degree=1)	0.7282	0.8211	+0.0929
LR (Polynomial degree=1)	0.7282	0.821	+0.0928



# Machine Learning

## Results analysis

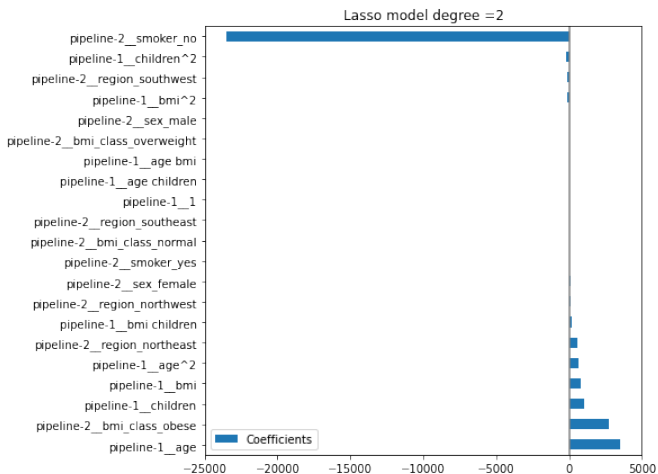
LASSO (Polynomial degree=<class 'sklearn.preprocessing.\_polynomial PolynomialFeatures'>)





# Machine Learning

## Results analysis





# Machine Learning

## Streamlit Application



### Insurance prediction

Age :

 - +

Sex :

☒ male  
☐ female

N Children :

 - +

Smoker ? :

☐ yes  
☒ no

Region:

 ▾

Height in cm? :

 - +

Weight in kg? :

 - +

Predict

Lasso Charges prediction : 6337 \$

Ridg2

7193 \$

↓ -856 \$

LR2

7193 \$

↓ -856 \$

Lasso1

6337 \$

↓ -856 \$

ElasticNet1

6316 \$

↑ 21 \$

Ridg1

6228 \$

↑ 109 \$

LR1

6178 \$

↑ 159 \$





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## 4 Conclusion

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- Smoking impact on health
- More observations
- More features (Alcohol consumption, ...)



# Assur'aimant Insurance Charges Prediction

*Thank you for listening!*  
*Any questions?*