Open in Colab

In [1]:
```
import warnings # ignore warnings
import pandas as pd # data manipulation
import numpy as np # linear algebra
import matplotlib.pyplot as plt # plots
import seaborn as sns # plots
```

In [2]:
```
warnings.filterwarnings("ignore")
```

In [3]:
```
df=pd.read_csv("/content/insurence_clear.csv")
df=df.drop(["Unnamed: 0"],axis="columns")
```

In [4]:
```
df.head()
```

Out[4]:

	age	sex	bmi	children	smoker	region	charges
0	18	male	33.77	1	no	southeast	1725.5523
1	28	male	33.00	3	no	southeast	4449.4620
2	25	male	26.22	0	no	northeast	2721.3208
3	23	male	34.40	0	no	southwest	1826.8430
4	19	male	24.60	1	no	southwest	1837.2370

In [5]:
```
def dataset():
    return df.drop(["charges"],axis="columns"),df.charges.values

X,y=dataset()
```

Split data

In [6]:
```
from sklearn.model_selection import train_test_split

X_train,X_test,Y_train,Y_test=train_test_split(X,
                                               y,
                                               test_size=0.33,
                                               random_state=42)
```

Data preprocessing

- **MinMaxScaler** It consists of adjusting the data on a scale from 0 to 1. With the aim that the variables are comparable to each other.
- **OneHotEncoding** It is used for qualitative variables. For example the geographical location or the color of a car. It consists of creating several fictitious variables according to the number of categorical variables. Where a 1 is indicated if said observation belongs to the class. It's a similar thing with truth tables if you're familiar with programming.
- **PolynomialFeatures** It consists of raising to a certain power. To break the linearity of the data. Since sometimes a linear regression is not enough to solve the problem.

In [7]:
```
from sklearn.preprocessing import MinMaxScaler,OneHotEncoder,PolynomialFeatures
```

In [9]:
```
poly=PolynomialFeatures(degree=2) # degree polynomial
rescale=MinMaxScaler()
def poly_transform(x):

    x=pd.get_dummies(x,drop_first=True,columns=["sex","smoker","region"]) # dummy variables
    x[["age","bmi","children"]]=rescale.fit_transform(x[["age","bmi","children"]]) # reescale

    return poly.fit_transform(x) # polynomial transform
```

In [10]:
```
X_train_poly=poly_transform(X_train)
X_test_poly=poly_transform(X_test)
```

Creation of the polynomial model

In [11]:
```
from sklearn.linear_model import LinearRegression
```

In [12]:
```
poly.fit(X_train_poly,Y_train) # we give the training data
```

Out[12]:
```
PolynomialFeatures()
```

In [13]:
```
lm=LinearRegression()
```

In [14]:
```
lm.fit(X_train_poly,Y_train) #  we give the training data
```

Out[14]:
```
LinearRegression()
```

In [15]:
```
lm.score(X_train_poly,Y_train) # evaluate with training data
```

Out[15]:
```
0.9634029455648855
```

In [16]:
```
lm.score(X_test_poly,Y_test) # evaluate with testing data
```

Out[16]:
```
0.9534487395422595
```

Data transform

In [17]:
```
from sklearn.compose import make_column_transformer
from sklearn.pipeline import Pipeline
```

In [18]:
```
tf_colummns=make_column_transformer((MinMaxScaler(),["age","bmi","children"]), # Reescale
                                    (OneHotEncoder(drop="if_binary"),["region","sex","smoker"])) # OneHotEncoding
```

Mean square error

Measures the average error between the original and predicted values.

In [19]:
```
from sklearn.metrics import mean_squared_error
```

Gradient Boosting

It is an algorithm that uses such complex algorithms. That is perfected according to the learning rate assigned by the user. In such a way that each tree will become better than the previous one. And the predicted value is going to average the predictions of the weakest algorithms.

In [20]:
```
from sklearn.ensemble import GradientBoostingRegressor
```

In [21]:
```
def evaluate(max_depth,lr):

    estimator_list=[]
    mse_train_list=[]
    mse_test_list=[]

    estimators=np.arange(100,1000,step=2)
    for estimator in estimators:

        model=GradientBoostingRegressor(max_depth=max_depth,n_estimators=estimator,learning_rate=lr,random_state=42)
        model=Pipeline([("transform",tf_colummns),("model",model)])
        model.fit(X_train,Y_train)
        pred_train=model.predict(X_train)
        pred_test=model.predict(X_test)

        mse_train=mean_squared_error(Y_train,pred_train)
        mse_test=mean_squared_error(Y_test,pred_test)

        estimator_list.append(estimator)
        mse_test_list.append(mse_test)
        mse_train_list.append(mse_train)


    return estimator_list,mse_test_list,mse_train_list
```

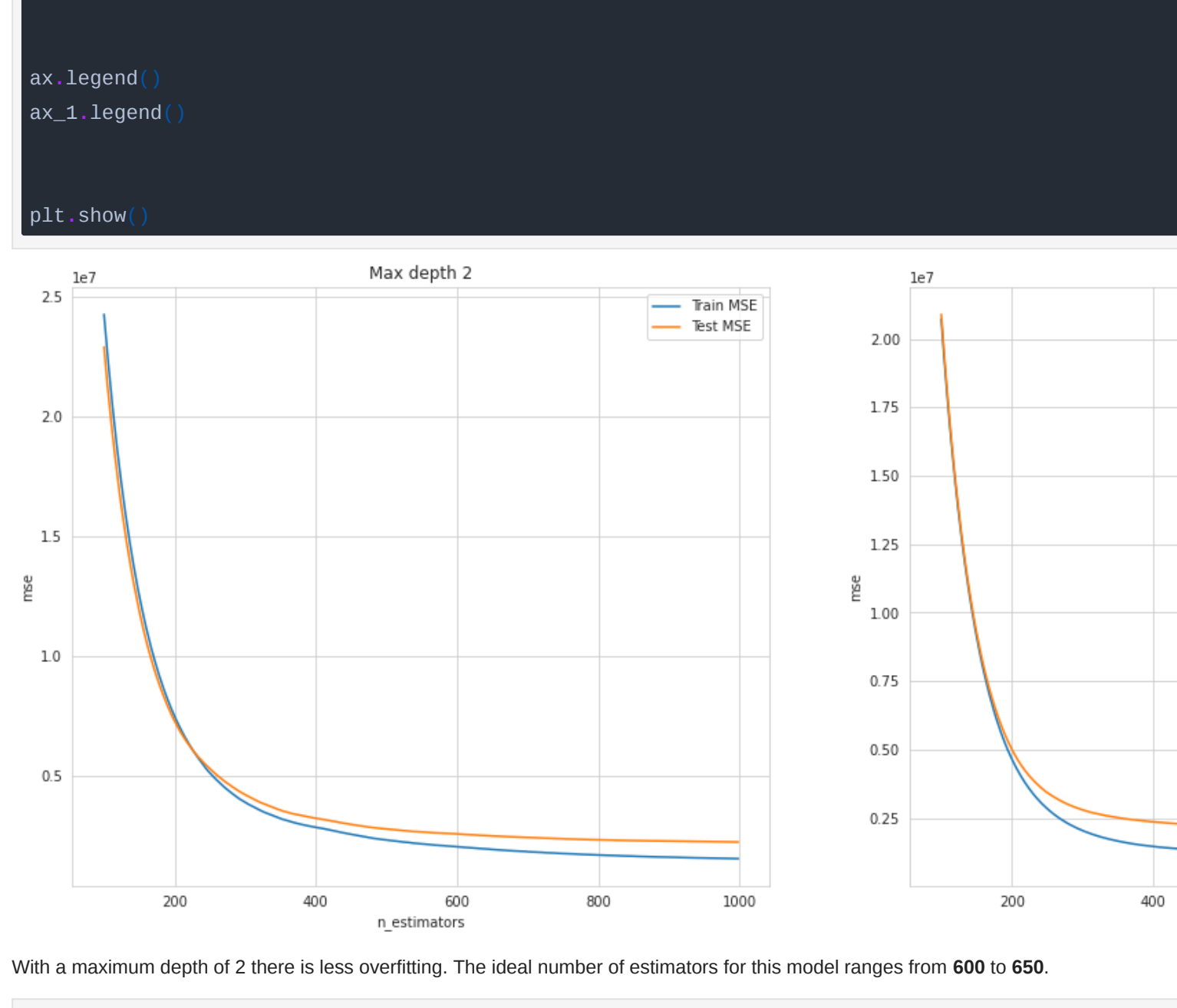
In [22]:
```
def dataframe_evaluate_trees(max_depth,lr):

    n_trees,mse_test,mse_train=evaluate(max_depth=max_depth,lr=lr)

    df_evaluate=pd.DataFrame({"n_trees": n_trees,"mse_test":mse_test,"mse_train":mse_train})

    return df_evaluate
```

In [23]:
```
first_evaluete=dataframe_evaluate_trees(max_depth=2,lr=0.01)
```

In [24]:
```
second_evalue=dataframe_evaluate_trees(max_depth=3,lr=0.01)
```

Ideal number of estimators

In [25]:
```
sns.set_style(style="whitegrid")
fig,(ax,ax_1)=plt.subplots(1,2,figsize=(20,8))

ax.set_title("Max depth 2")
ax.plot(first_evaluete["n_trees"],first_evaluete["mse_train"],label="Train MSE")
ax.plot(first_evaluete["n_trees"],first_evaluete["mse_test"],label="Test MSE")
ax.set_xlabel("n_estimators")
ax.set_ylabel("mse")

ax_1.set_title("Max depth 3")
ax_1.plot(second_evalue["n_trees"],second_evalue["mse_train"],label="Train MSE")
ax_1.plot(second_evalue["n_trees"],second_evalue["mse_test"],label="Test MSE")
ax_1.set_xlabel("n_estimators")
ax_1.set_ylabel("mse")



ax.legend()
ax_1.legend()


plt.show()
```



With a maximum depth of 2 there is less overfitting. The ideal number of estimators for this model ranges from **600** to **650**.

In [26]:
```
first_evaluete.query("n_trees>=610 and n_trees<=650")
```

Out[26]:

	n_trees	mse_test	mse_train
255	610	2.573382e+06	2.035120e+06
256	612	2.569730e+06	2.030027e+06
257	614	2.567193e+06	2.027725e+06
258	616	2.563711e+06	2.020486e+06
259	618	2.562565e+06	2.017820e+06
260	620	2.558399e+06	2.012292e+06
261	622	2.555605e+06	2.009786e+06
262	624	2.550161e+06	2.004448e+06
263	626	2.547803e+06	1.999737e+06
264	628	2.545697e+06	1.996426e+06
265	630	2.539644e+06	1.989649e+06
266	632	2.535433e+06	1.984598e+06
267	634	2.534456e+06	1.982152e+06
268	636	2.531520e+06	1.978980e+06
269	638	2.529817e+06	1.973510e+06
270	640	2.525128e+06	1.968694e+06
271	642	2.522637e+06	1.966628e+06
272	644	2.519831e+06	1.963609e+06
273	646	2.518178e+06	1.955914e+06
274	648	2.514168e+06	1.951191e+06
275	650	2.509063e+06	1.944993e+06

Starting from the estimator number 630 there is no longer an improvement for the test data.

In [27]:
```
gbr=GradientBoostingRegressor(max_depth=2,
                              learning_rate=0.01,
                              n_estimators=630,
                              random_state=42)
```

In [42]:
```
gbr_pipeline=Pipeline([('preprocess',tf_colummns),
                      ('gbr',gbr)])
```

In [43]:
```
gbr_pipeline.fit(X_train,Y_train)
```

Out[43]:
```
Pipeline(steps=[('preprocess',
                 ColumnTransformer(transformers=[('minmaxscaler',
                                                  MinMaxScaler(),
                                                  ['age', 'bmi', 'children']),
                                                 ('onehotencoder',
                                                  OneHotEncoder(drop='if_binary'),
                                                  ['region', 'sex',
                                                   'smoker'])])),
                ('gbr',
                 GradientBoostingRegressor(learning_rate=0.01, max_depth=2,
                                           n_estimators=630,
                                           random_state=42))])
```

In [44]:
```
gbr_pipeline.score(X_train,Y_train) # evaluate with training data
```

Out[44]:
```
0.9852488568613742
```

In [45]:
```
gbr_pipeline.score(X_test,Y_test) # evaluate with test data
```

Out[45]:
```
0.9817020077116009
```

XGBOOST

It is similar to adaboost. With the difference that xgboost can be used with GPU. Which training will be faster.

In [32]:
```
from xgboost import XGBRegressor
```

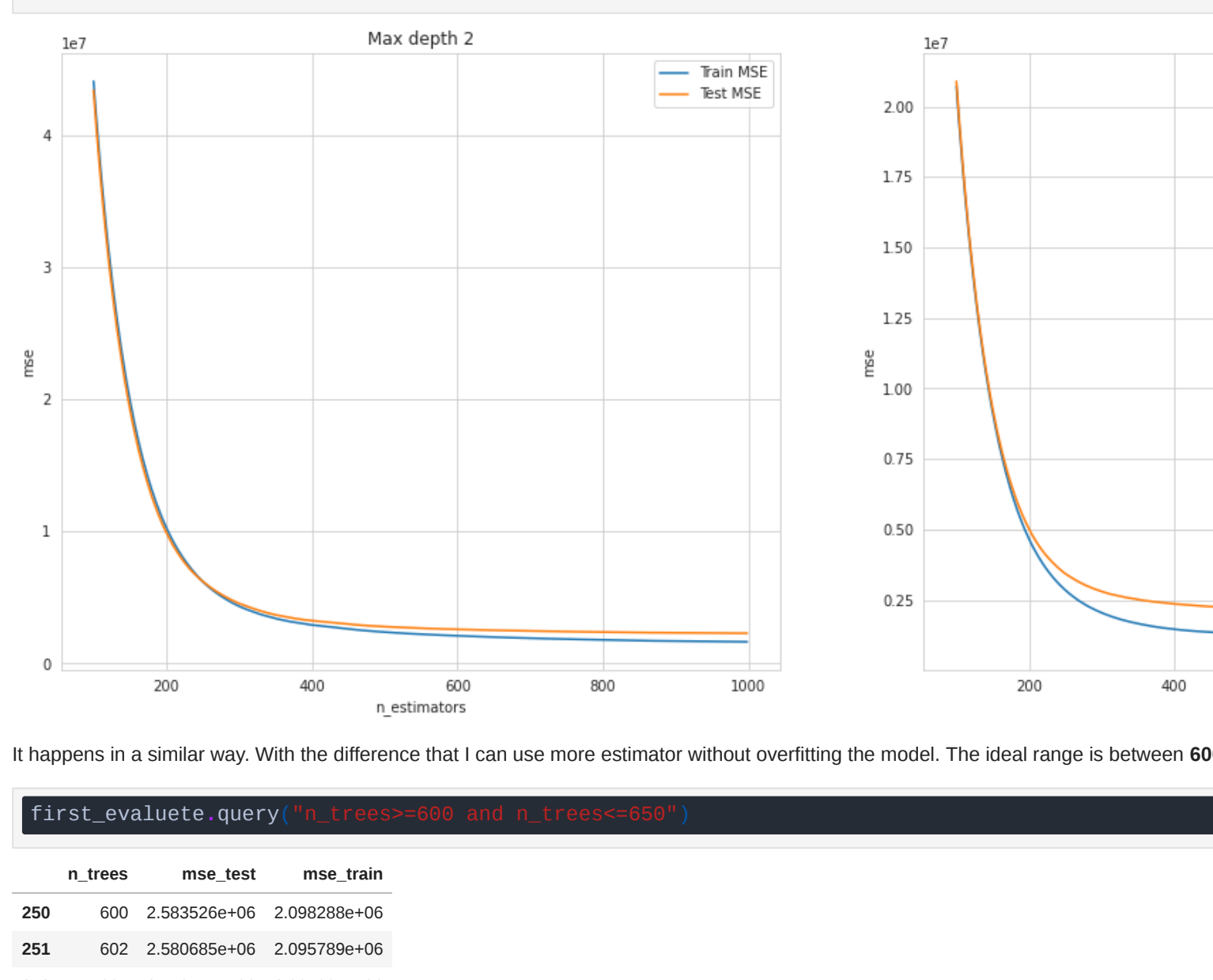
Selection number of estimators XGBOOST

In [33]:
```
def evaluate(max_depth,lr):

    estimator_list=[]
    mse_train_list=[]
    mse_test_list=[]

    estimators=np.arange(100,1000,step=2)
    for estimator in estimators:

        model=XGBRegressor(max_depth=max_depth,n_estimators=estimator,learning_rate=lr,random_state=42,verbosity=0)
        model=Pipeline([("transform",tf_colummns),("model",model)])
        model.fit(X_train,Y_train)
        pred_train=model.predict(X_train)
        pred_test=model.predict(X_test)

        mse_train=mean_squared_error(Y_train,pred_train)
        mse_test=mean_squared_error(Y_test,pred_test)

        estimator_list.append(estimator)
        mse_test_list.append(mse_test)
        mse_train_list.append(mse_train)


    return estimator_list,mse_test_list,mse_train_list
```

In [34]:
```
first_evaluete=dataframe_evaluate_trees(max_depth=2,lr=0.01)
```

In [35]:
```
second_evaluete=dataframe_evaluate_trees(max_depth=3,lr=0.01)
```

In [36]:
```
sns.set_style(style="whitegrid")
fig,(ax,ax_1)=plt.subplots(1,2,figsize=(20,8))

ax.set_title("Max depth 2")
ax.plot(first_evaluete["n_trees"],first_evaluete["mse_train"],label="Train MSE")
ax.plot(first_evaluete["n_trees"],first_evaluete["mse_test"],label="Test MSE")
ax.set_xlabel("n_estimators")
ax.set_ylabel("mse")

ax_1.set_title("Max depth 3")
ax_1.plot(second_evalue["n_trees"],second_evalue["mse_train"],label="Train MSE")
ax_1.plot(second_evalue["n_trees"],second_evalue["mse_test"],label="Test MSE")
ax_1.set_xlabel("n_estimators")
ax_1.set_ylabel("mse")



ax.legend()
ax_1.legend()


plt.show()
```



It happens in a similar way. With the difference that I can use more estimator without overfitting the model. The ideal range is between **600** to **650** estimators. Since from this amount, the error does not decrease drastically for the test data.

In [81]:
```
first_evaluete.query("n_trees>=600 and n_trees<=650")
```

Out[81]:

	n_trees	mse_test	mse_train
250	600	2.583526e+06	2.098288e+06
251	602	2.580685e+06	2.095789e+06
252	604	2.579417e+06	2.091601e+06
253	606	2.575930e+06	2.086473e+06
254	608	2.573907e+06	2.083187e+06
255	610	2.568440e+06	2.077505e+06
256	612	2.566746e+06	2.071262e+06
257	614	2.565072e+06	2.068420e+06
258	616	2.562253e+06	2.065196e+06
259	618	2.558028e+06	2.059896e+06
260	620	2.555405e+06	2.056877e+06
261	622	2.553836e+06	2.051443e+06
262	624	2.549749e+06	2.046255e+06
263	626	2.546846e+06	2.043204e+06
264	628	2.544266e+06	2.040766e+06
265	630	2.541228e+06	2.036212e+06
266	632	2.537496e+06	2.030277e+06
267	634	2.534912e+06	2.028028e+06
268	636	2.532498e+06	2.025265e+06
269	638	2.530372e+06	2.019497e+06
270	640	2.526840e+06	2.014488e+06
271	642	2.524499e+06	2.012323e+06
272	644	2.522096e+06	2.010106e+06
273	646	2.518522e+06	2.005413e+06
274	648	2.515825e+06	2.001244e+06
275	650	2.514029e+06	1.998535e+06

We select 650. Since from ciho estimator there is no significant improvement.

In [46]:
```
xgb_reg=XGBRegressor(max_depth=2,
                     learning_rate=0.01,
                     n_estimators=650,
                     verbosity=0,
                     random_state=42)

xgb_pipeline=Pipeline([("transform",tf_colummns),("xgb",xgb_reg)])
```

In [47]:
```
xgb_pipeline.fit(X_train,Y_train)
```

Out[47]:
```
Pipeline(steps=[('transform',
                 ColumnTransformer(transformers=[('minmaxscaler',
                                                  MinMaxScaler(),
                                                  ['age', 'bmi', 'children']),
                                                 ('onehotencoder',
                                                  OneHotEncoder(drop='if_binary'),
                                                  ['region', 'sex',
                                                   'smoker'])])),
                ('xgb',
                 XGBRegressor(learning_rate=0.01, max_depth=2, n_estimators=650,
                              random_state=42, verbosity=0))])
```

In [48]:
```
xgb_pipeline.score(X_train,Y_train)
```

Out[48]:
```
0.9851829733145766
```

In [49]:
```
xgb_pipeline.score(X_test,Y_test)
```

Out[49]:
```
0.9818865587018973
```

In [59]:
```
from sklearn.metrics import r2_score
from sklearn.model_selection import cross_val_score
```

In [73]:
```
class Evaluete():

  def __init__(self,model,X_data,y_true):

    self.X_data=X_data
    self.y_true=y_true

    self.model=model
    self.predict=self.model.predict(self.X_data)


  def mse(self):

    return mean_squared_error(self.y_true,self.predict)

  def r2(self):

    return r2_score(self.y_true,self.predict)

  def cv_score(self):

    return cross_val_score(self.model,self.X_data,self.y_true,cv=10).mean()
```

MSE

Measures the average error between the original and predicted values.

In [65]:
```
mse_poly_train=Evaluete(lm,X_train_poly,Y_train).mse()
mse_poly_test=Evaluete(lm,X_test_poly,Y_test).mse()

mse_gbr_train=Evaluete(gbr_pipeline,X_train,Y_train).mse()
mse_gbr_test=Evaluete(gbr_pipeline,X_test,Y_test).mse()

mse_xgb_train=Evaluete(xgb_pipeline,X_train,Y_train).mse()
mse_xgb_test=Evaluete(xgb_pipeline,X_test,Y_test).mse()
```

R^2

It measures the degree of fit between the original value and the predictions. The closer it is to 1, the closer the original and predicted values will be.

In [77]:
```
r2_poly_train=Evaluete(lm,X_train_poly,Y_train).r2()
r2_poly_test=Evaluete(lm,X_test_poly,Y_test).r2()

r2_gbr_train=Evaluete(gbr_pipeline,X_train,Y_train).r2()
r2_gbr_test=Evaluete(gbr_pipeline,X_test,Y_test).r2()

r2_xgb_train=Evaluete(xgb_pipeline,X_train,Y_train).r2()
r2_xgb_test=Evaluete(xgb_pipeline,X_test,Y_test).r2()
```

Cross Validation

It measures the degree of generalization of the model. It divides the data into several subsets by the amount said by the user. To subsequently obtain the average value of generalization.

In [74]:
```
cv_poly=Evaluete(lm,X_test_poly,Y_test).cv_score()
cv_gbr=Evaluete(gbr_pipeline,X_test,Y_test).cv_score()
cv_xgb=Evaluete(xgb_pipeline,X_test,Y_test).cv_score()
```

Dataframe evaluation

In [78]:
```
models_names=["Polynomial Regression","Gradient Boosting","XGBOOST"]

mse_train=[mse_poly_train,mse_gbr_train,mse_xgb_train]
mse_test=[mse_poly_test,mse_gbr_test,mse_xgb_test]

r2_train=[r2_poly_train,r2_gbr_train,r2_xgb_train]
r2_test=[r2_poly_test,r2_gbr_test,r2_xgb_test]

cv=[cv_poly,cv_gbr,cv_xgb]

evaluate_df=pd.DataFrame({"Model":models_names,
                          "MSE train":mse_train,
                          "MSE test":mse_test,
                          "R2 train":r2_train,
                          "R2 test":r2_test,
                          "CV":cv})
```

In [79]:
```
evaluate_df
```

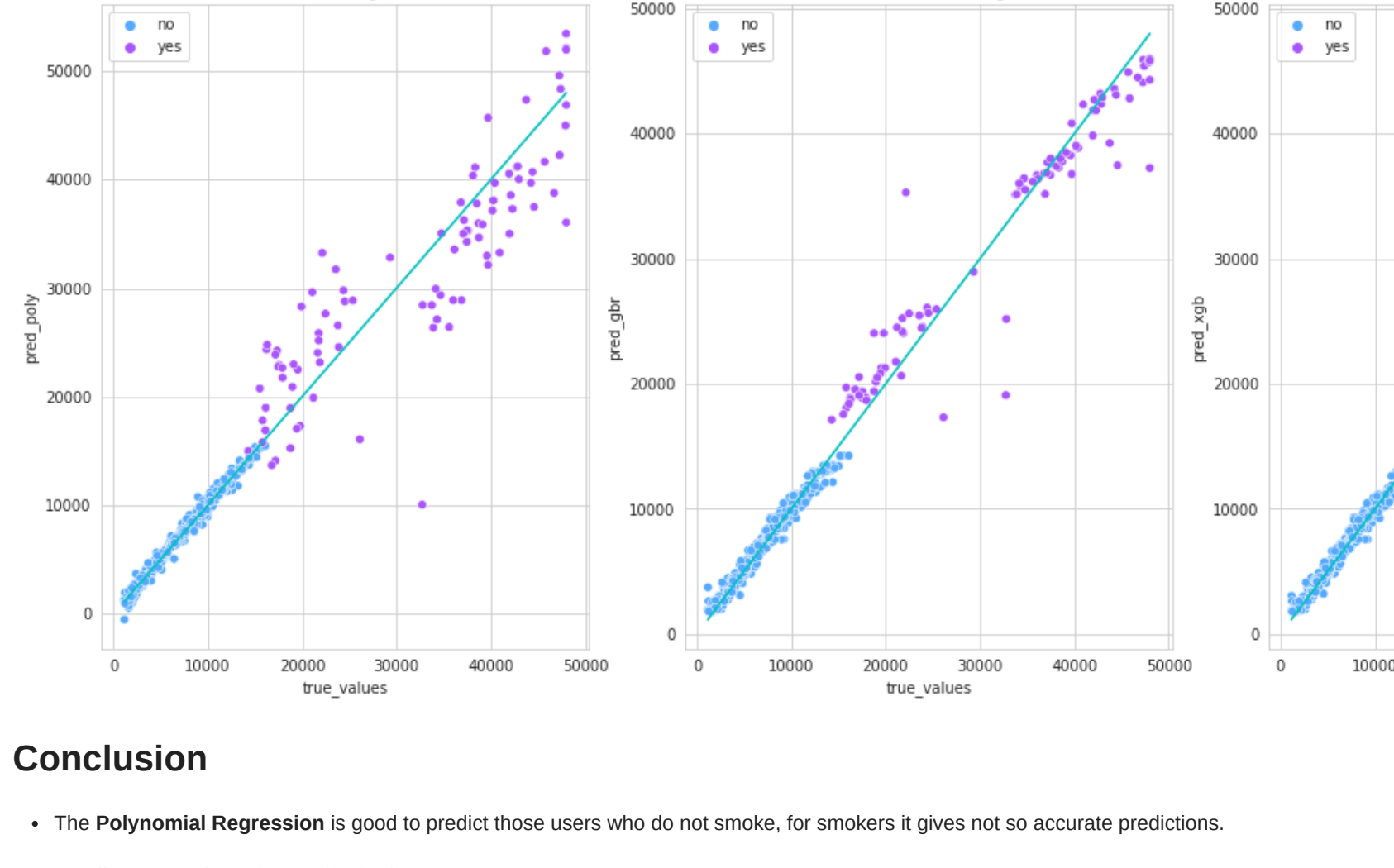
Out[79]:

	Model	MSE train	MSE test	R2 train	R2 test	CV
0	Polynomial Regression	4.936247e+06	6.461016e+06	0.963403	0.953449	0.950897
1	Gradient Boosting	1.989649e+06	2.539644e+06	0.985249	0.981702	0.978221
2	XGBOOST	1.998535e+06	2.514029e+06	0.985183	0.981887	0.979176

XGBOOST and gradient Boosting have very similar metrics to gradient boosting. But **XGBOOST** performs better for test data.

In [83]:
```
df_test=pd.DataFrame({"true_values":Y_test,
                        "pred_poly":pred_poly_test,
                       "pred_gbr":pred_gbr_test,
                       "pred_xgb":pred_xgb_test,
                       "smoker":X_test["smoker"]
                      })
```

In [85]:
```
fig,(ax_0,ax_1,ax_2)=plt.subplots(1,3,figsize=(20,8))
sns.set_style(style="whitegrid")

ax_0.set_title("Polinomial Regression")
sns.scatterplot(data=df_test,x="true_values",y="pred_poly",color="red",hue="smoker",ax=ax_0,palette="cool")
sns.lineplot(data=df_test,x="true_values",y="true_values",color="c",ax=ax_0)


ax_1.set_title("GradientBoosting")
sns.scatterplot(data=df_test,x="true_values",y="pred_gbr",color="red",hue="smoker",ax=ax_1,palette="cool")
sns.lineplot(data=df_test,x="true_values",y="true_values",color="c",ax=ax_1)

ax_2.set_title("XGBOOST")
sns.scatterplot(data=df_test,x="true_values",y="pred_xgb",color="red",hue="smoker",ax=ax_2,palette="cool")
sns.lineplot(data=df_test,x="true_values",y="true_values",color="c",ax=ax_2)

plt.show()
```



Conclusion

- The **Polynomial Regression** is good to predict those users who do not smoke, for smokers it gives not so accurate predictions.
- **Gradient Boosting** It is good for both cases.
- **XGBOOST** Has a better root mean square error than using gradient boosting. In turn, it is faster to train and presents fewer symptoms of overfitting.