Import libraries

In [1]:
```python
import pandas as pd # Data Manupulation
import matplotlib.pyplot as plt # Plots
import seaborn as sns # Plots
import warnings # Ignore Warnings
import shap # Feature importances
```

In [2]:
```python
warnings.filterwarnings("ignore") # Ignore Warnings
```

Load Data

In [3]:
```python
df=pd.read_csv("insurence_clearv2.csv")
```

Split Inputs and Outputs

In [4]:
```python
def load_inputs_outputs():

    return df.drop(["charges"],axis="columns"),df.charges.values

X,y=load_inputs_outputs()
```

Split data

In [5]:
```python
from sklearn.model_selection import train_test_split
```

In [6]:
```python
X_train,X_test,Y_train,Y_test=train_test_split(X,y,
                                               test_size=0.33, # 33% for testing
                                               random_state=42)
```

In [7]:
```python
X_train.shape[0],X_test.shape[0]
```

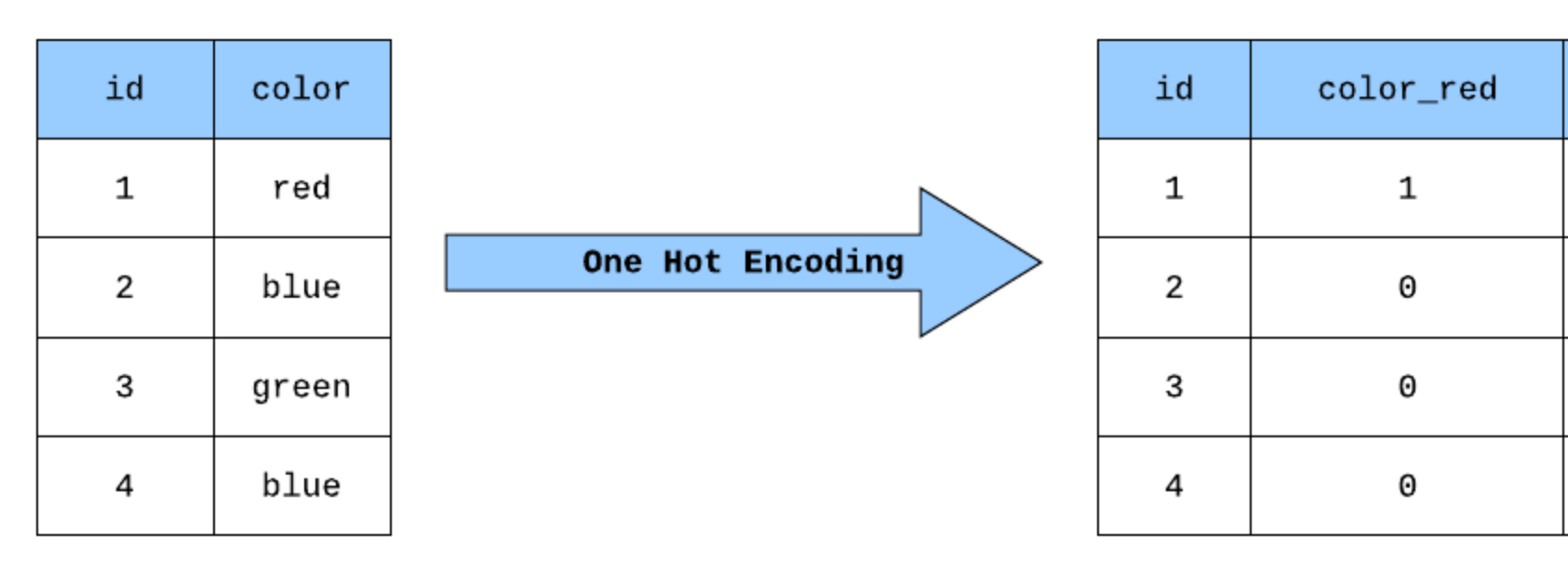
Out[7]:
```
(896, 442)
```

Data preprocessing

Note Decision trees do not require normalization of their inputs; and since XGBoost is essentially an ensemble algorithm comprised of decision trees, it does not require normalization for the inputs either.

We will only perform **One Hot Encoding transformation** for categorical variable.

One Hot Encoding



It is used for qualitative categorical variables, for example in the image the color variable. Where dummy variables are created according to the number of categories of the variables, a 1 is assigned where it complies with the condition and the others are filled with 0.

Instead of just replacing the labels with random numbers it can affect the performance of the model, for this type of variables. Since we would be giving more weight to the categories that have the highest value. In addition, the One Hot Encoding transformation has the advantage at the geometric level, since there is already the same distance between the categories.

In [8]:
```python
class Preprocessing_OHE():

    def __init__(self,X_data):
        self.X_data=X_data


    def binary(self):

        self.X_data["sex"]=self.X_data["sex"].apply(lambda x: 1 if x == "male"  else 0)
        self.X_data["smoker"]=self.X_data["smoker"].apply(lambda x: 1 if x == "yes"  else 0)
        self.X_data["medical_problem"]=self.X_data["medical_problem"].apply(lambda x: 1 if x == "severe"  else 0)

        return self.X_data

    def multinomial(self):

        return pd.get_dummies(self.X_data,columns=["region"])
```

Preprocessing Training Data

In [9]:
```python
X_train_preprocesing=Preprocessing_OHE(X_train)
```

In [10]:
```python
X_train_ohe=X_train_preprocesing.binary()
X_train_ohe=X_train_preprocesing.multinomial()
```

In [11]:
```python
X_train_ohe.head()
```

Out[11]:

	age	sex	bmi	children	smoker	medical_problem	region_northeast	region_northwest	region_southeast	region_southwest
1046	18	1	48.950	0	0	0	0	0	1	0
682	55	1	32.775	0	0	0	0	1	0	0
1037	19	0	25.745	1	0	0	0	1	0	0
490	38	0	34.800	2	0	0	0	0	0	1
39	18	0	35.625	0	0	0	1	0	0	0

Preprocessing Testing Data

In [12]:
```python
X_test_preprocesing=Preprocessing_OHE(X_test)
```

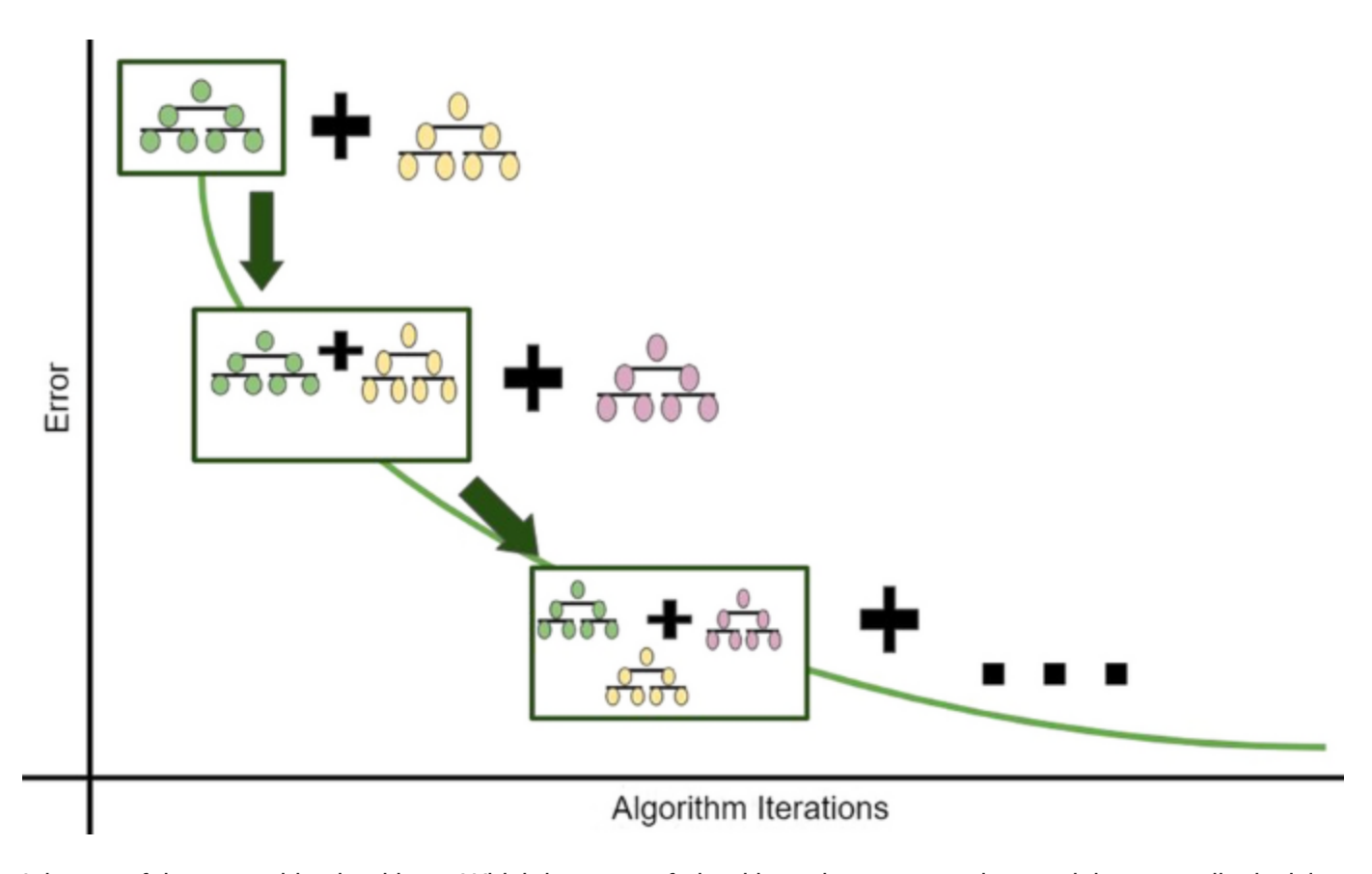
In [13]:
```python
X_test_ohe=X_test_preprocesing.binary()
X_test_ohe=X_test_preprocesing.multinomial()
```

In [14]:
```python
X_test_ohe.head()
```

Out[14]:

	age	sex	bmi	children	smoker	medical_problem	region_northeast	region_northwest	region_southeast	region_southwest
764	57	1	18.335	0	0	0	1	0	0	0
887	45	1	20.350	3	0	0	0	0	1	0
890	23	1	24.510	0	0	0	1	0	0	0
1293	19	0	32.490	0	1	1	0	1	0	0
259	24	0	27.600	0	0	1	0	0	0	1

XGBOOST



It is part of the assembly algorithms. Which is a type of algorithms that uses weaker models, generally decision trees. The functioning of this model can be summed up with the following phrase: **"Unity is strength".**

Unlike its brother the random forest which is another ensemble algorithm, it will improve each estimator in such a way that each estimator becomes better than the previous one according to the learning rate.

For this particular problem, which is regression, that is, to predict values with a decimal, each estimator performs the prediction to subsequently obtain the average prediction for each estimator.

In [15]:
```python
from xgboost import XGBRegressor
```

Explanation parameters

- max_depth: Maximum depth of each decision tree.
- n_estimators: Number of estimators,that is base algorithms.
- learning_rate: Room for improvement for each decision tree, this parameter goes from 0 to 1.
- random_state: For example, if I want to run this algorithm again, it will give me a different result, due to the random state

Creation of Model

In [16]:
```python
xgb_reg=XGBRegressor(max_depth=3,
                     learning_rate=0.01,
                     n_estimators=596,
                     random_state=42)
```

We assign the same parameters that we use to choose the ideal model.

Train Model

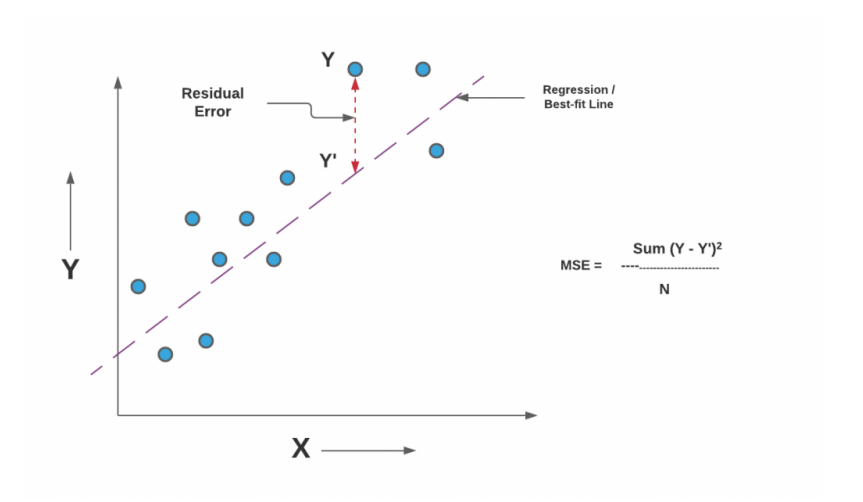
In [17]:
```python
xgb_reg.fit(X_train_ohe,Y_train)
```

Out[17]:
```
XGBRegressor(base_score=0.5, booster='gbtree', callbacks=None,
             colsample_bylevel=1, colsample_bynode=1, colsample_bytree=1,
             early_stopping_rounds=None, enable_categorical=False,
             eval_metric=None, gamma=0, gpu_id=-1, grow_policy='depthwise',
             importance_type=None, interaction_constraints='',
             learning_rate=0.01, max_bin=256, max_cat_to_onehot=4,
             max_delta_step=0, max_depth=3, max_leaves=0, min_child_weight=1,
             missing=nan, monotone_constraints='()', n_estimators=596, n_jobs=0,
             num_parallel_tree=1, predictor='auto', random_state=42,
             reg_alpha=0, reg_lambda=1, ...)
```

Model Evaluation

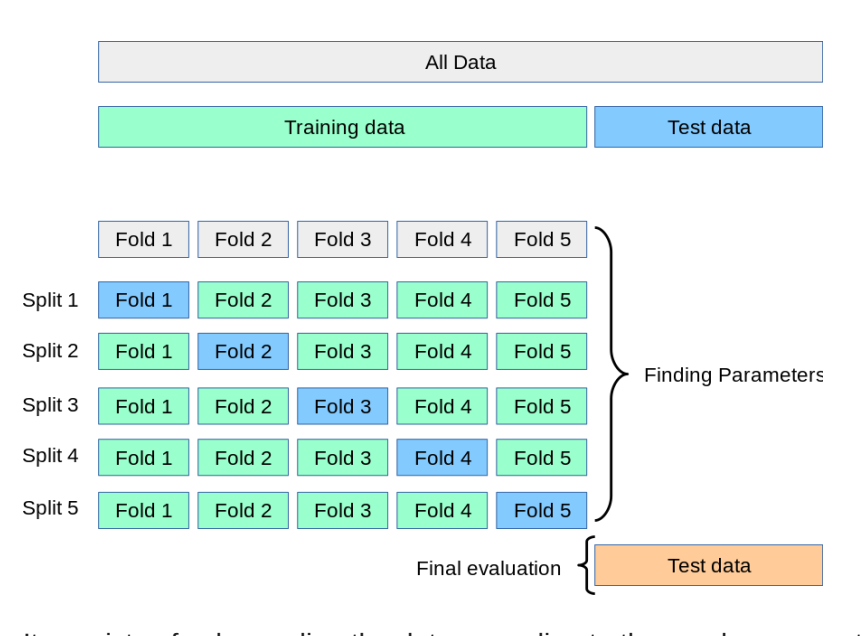
In [18]:
```python
from sklearn.model_selection import cross_val_score
from sklearn.metrics import r2_score,mean_squared_error
```

Mean Square Error



It is the average error between the value predicted by the model with respect to the model.

Cross Validation



It consists of subsampling the data according to the number requested by the user. In order to obtain an average of generalization of the data.

In [19]:
```python
class Evaluete():

    def __init__(self,X_data,y_true):



        self.X_data=X_data
        self.y_true=y_true

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

    def mse(self):

        return mean_squared_error(self.y_true,self.predict).flatten()

    def r2(self):

        return r2_score(self.y_true,self.predict).flatten()

    def cv_score(self):

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

Train Evaluation

In [20]:
```python
train_eval=Evaluete(X_train_ohe,Y_train)
```

In [21]:
```python
mse_train=train_eval.mse()
r2_train=train_eval.r2()
cv_train=train_eval.cv_score()
```

Test Evaluation

In [22]:
```python
test_eval=Evaluete(X_test_ohe,Y_test)
```

In [23]:
```python
mse_test=test_eval.mse()
r2_test=test_eval.r2()
cv_test=test_eval.cv_score()
```

Evaluation Dataframe

In [24]:
```python
features_df={"mse_train":mse_train,
         "mse_test":mse_test,
         "r2_train":r2_train,
         "r2_test":r2_test,
         "cv_train":cv_train,
         "cv_test":cv_test}
```

In [25]:
```python
df_evaluate=pd.DataFrame(features_df)
```

In [26]:
```python
df_evaluate
```

Out[26]:

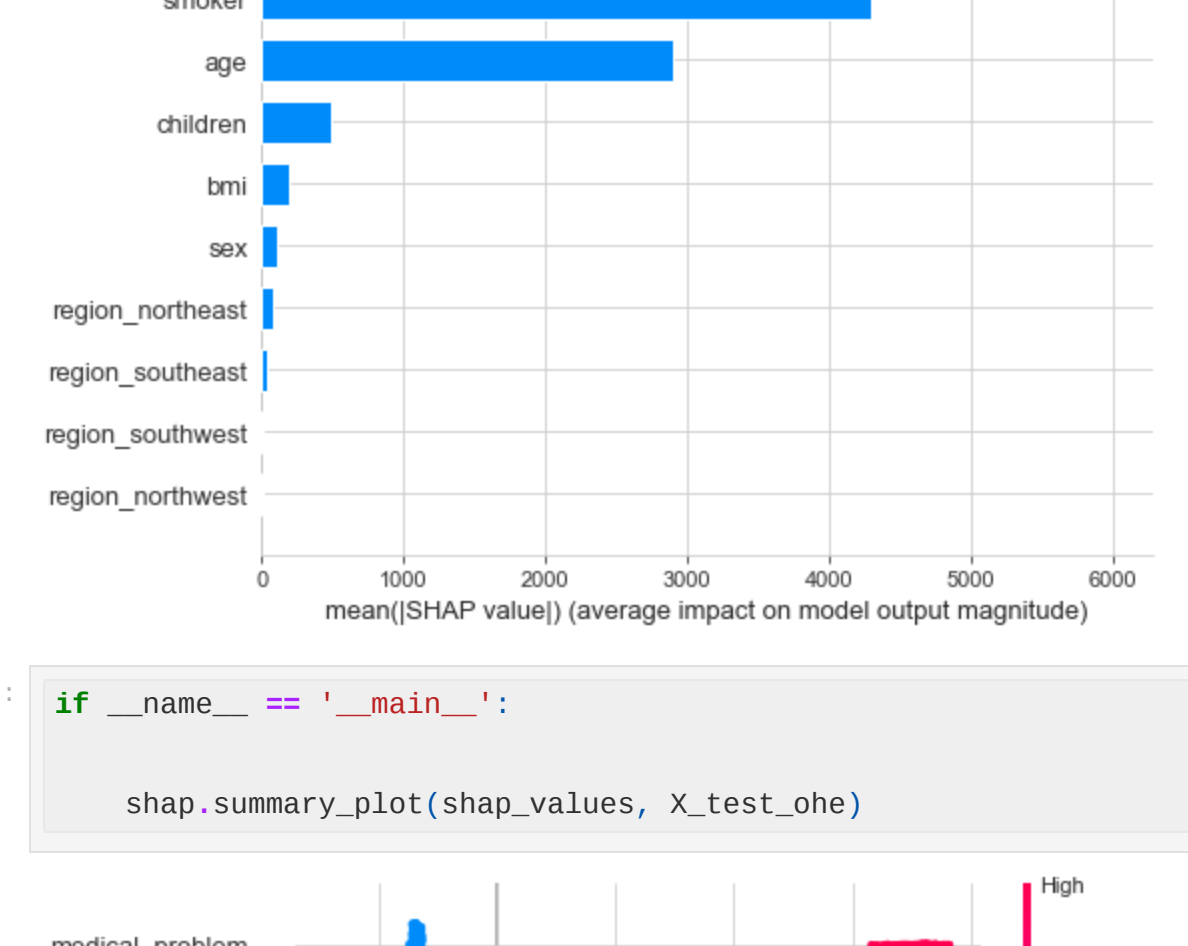
	mse_train	mse_test	r2_train	r2_test	cv_train	cv_test
0	2.351711e+06	3.023848e+06	0.983162	0.979416	0.975549	0.974433

In [27]:
```python
explainer = shap.TreeExplainer(xgb_reg)
shap_values = explainer.shap_values(X_test_ohe)
```

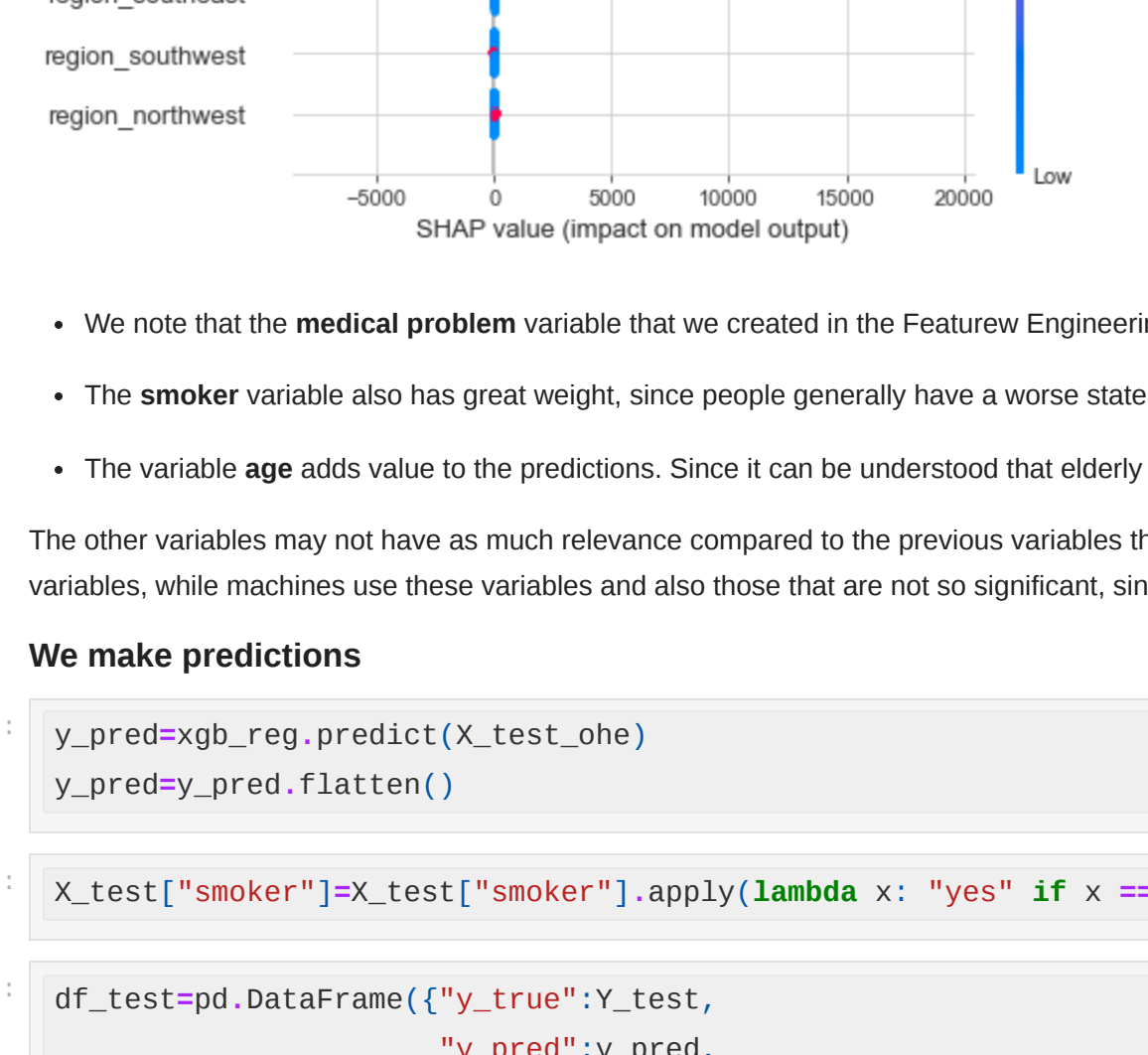
Plot Importance

In [28]:
```python
def plot_importance():

    sns.set_style(style="whitegrid")
    shap.summary_plot(shap_values, X_test_ohe, plot_type="bar")

    return plt.show()
```

In [29]:
```python
if __name__ == "__main__":
    plot_importance()
```



In [30]:
```python
if __name__ == '__main__':

    shap.summary_plot(shap_values, X_test_ohe)
```



- We note that the **medical problem** variable that we created in the Featurew Engineering section. It has great weight when estimating the price of the insurance, since if we have a very serious problem, the cost of the insurance will not increase more.
- The **smoker** variable also has great weight, since people generally have a worse state of health.
- The variable **age** adds value to the predictions. Since it can be understood that elderly people require more medical care.

The other variables may not have as much relevance compared to the previous variables that I mentioned earlier. But they can complement the value of the prediction. And that the difference between humans and machines when making predictions is that we rely on only relevant variables, while machines use these variables and also those that are not so significant, since they look for patterns unknown to the naked eye .

We make predictions

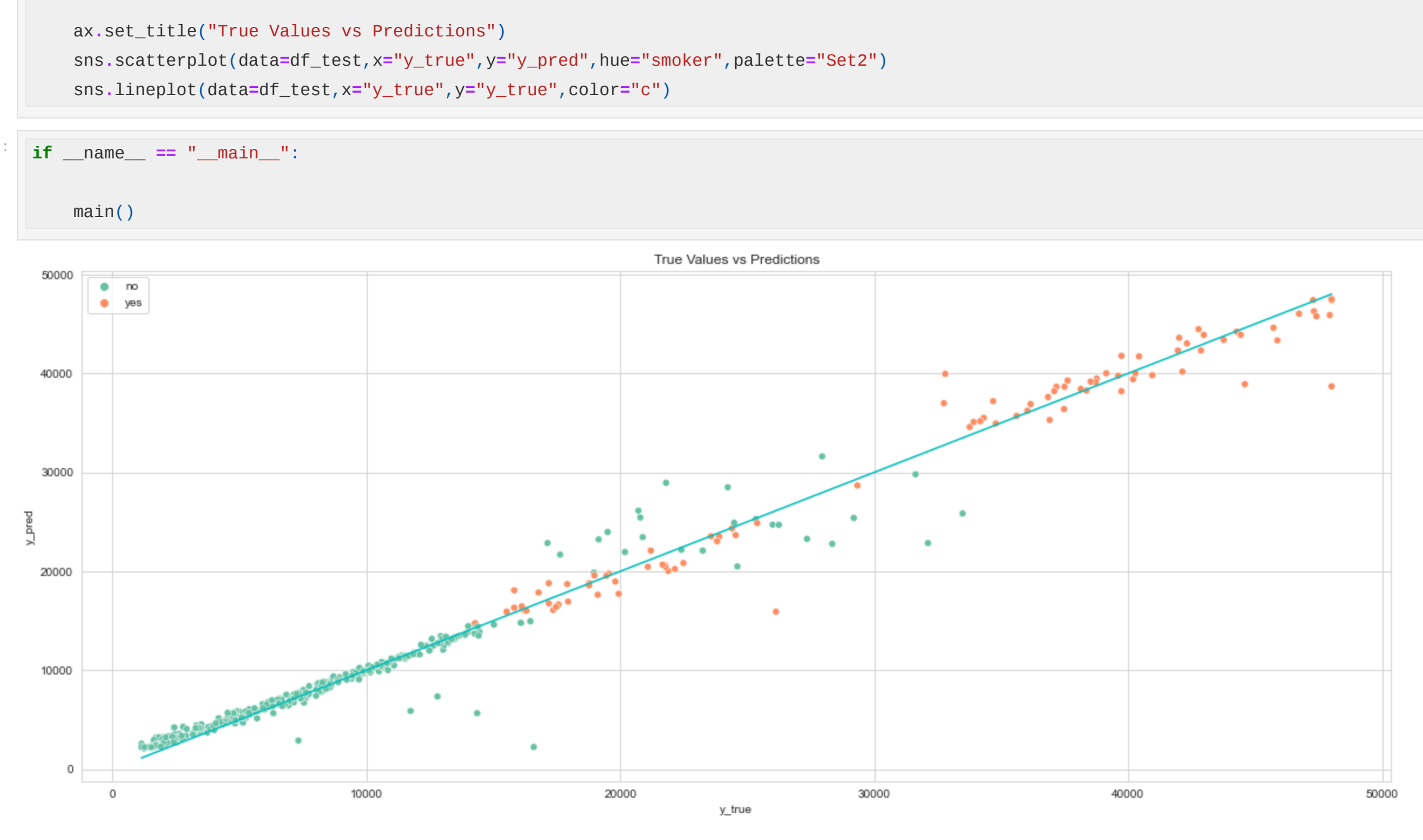
In [31]:
```python
y_pred=xgb_reg.predict(X_test_ohe)
y_pred=y_pred.flatten()
```

In [32]:
```python
X_test["smoker"]=X_test["smoker"].apply(lambda x: "yes" if x ==1 else "no")
```

In [33]:
```python
df_test=pd.DataFrame({"y_true":Y_test,
                      "y_pred":y_pred,
                      "smoker":X_test["smoker"]})
```

In [34]:
```python
def main():

    fig,(ax)=plt.subplots(1,1,figsize=(20,8))

    ax.set_title("True Values vs Predictions")
    sns.scatterplot(data=df_test,x="y_true",y="y_pred",hue="smoker",palette="Set2")
    sns.lineplot(data=df_test,x="y_true",y="y_true",color="c")
```

In [35]:
```python
if __name__ == "__main__":

    main()
```



In [36]:
```python
df_test.query("smoker=='no'").sample(n=20,random_state=42)
```

Out[36]:

	y_true	y_pred	smoker
435	11538.421000	11405.943359	no
629	4350.514400	4753.903320	no
332	7323.734819	2895.726562	no
987	2699.568350	3137.377686	no
744	13470.804400	13154.744141	no
875	4561.188500	5020.006348	no
370	2201.097100	3332.743408	no
282	3180.510100	3602.754883	no
348	7345.084000	7451.192871	no
1055	22395.744240	22174.378906	no
664	16069.084750	14824.206055	no
427	8825.086000	8889.758789	no
984	12479.708950	11993.656250	no
81	11881.358000	11811.742188	no
1032	11931.125250	11788.847656	no
312	9264.797000	9379.272461	no
695	13129.603450	13375.526367	no
755	9487.644200	9834.326172	no
1048	7201.700850	7080.818848	no
919	2203.735950	2895.726562	no

In [37]:
```python
df_test.query("smoker=='yes'").sample(n=20,random_state=42)
```

Out[37]:

	y_true	y_pred	smoker
1302	37465.34375	36379.675781	yes
1127	17179.52200	18797.785156	yes
1235	15817.98570	16316.422852	yes
1128	42856.83800	42300.078125	yes
1293	36898.73308	35282.058594	yes
1122	33750.29180	34576.773438	yes
1242	19798.05455	18954.109375	yes
1283	33907.54800	35073.332031	yes
1228	36021.01120	36221.644531	yes
1078	34303.16720	35501.222656	yes
1159	37079.37200	38193.539062	yes
1175	23807.24060	23034.773438	yes
1173	48000.00000	47527.250000	yes
1207	40419.01910	41705.316406	yes
1280	34672.14720	37186.882812	yes
1253	41999.52000	43585.941406	yes
1314	37607.52770	39269.695312	yes
1299	23887.66270	23491.943359	yes
1133	16297.84600	16030.650391	yes
1158	39125.33225	40006.363281	yes

The algorithm generates quite robust predictions, very close to the original value. Which this model is apt to solve the problem.

As a curious fact, XGBOOST is one of the most powerful algorithms within Machine Learning, it will generate interesting results in such a short time. He is the winner of multiple competitions on the kaggle platform. It has the advantage that we can use a GPU for training, speeding up the training process, something it shares with Deep Learning frameworks.

Save Model

In [38]:
```python
xgb_reg.save_model("xgb_insurence.json")
```

We save the model in json format. Since its operation in production will be faster and more efficient.