Import libraries

In [1]:
```
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]:
```
warnings.filterwarnings("ignore") # Ignore Warnings
```

Load Data

In [4]:
```
df=pd.read_csv("insurence_clear.csv")
```

Drop Columns

In [5]:
```
df=df.drop(["Unnamed: 0"],axis="columns")
```

Split Inputs and Outputs

In [6]:
```
def load_inputs_outputs():

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

X,y=load_inputs_outputs()
```

Split data

In [7]:
```
from sklearn.model_selection import train_test_split
```

In [8]:
```
X_train,X_test,Y_train,Y_test=train_test_split(X,y,
                                               test_size=0.33, # 33% for testing
                                               random_state=42)
```

In [9]:
```
X_train.shape[0],X_test.shape[0]
```

Out[9]:
```
(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.

In [10]:
```
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)

        return self.X_data
    def multinomial(self):

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

Preprocessing Training Data

In [11]:
```
X_train_preprocesing=Preprocessing_OHE(X_train)
X_train_ohe=X_train_preprocesing.binary()
X_train_ohe=X_train_preprocesing.multinomial()
```

In [12]:
```
X_train_ohe.head()
```

Out[12]:

	age	sex	bmi	children	smoker	region_northeast	region_northwest	region_southeast	region_southwest
1046	59	1	37.400	0	0	0	0	0	1
682	55	0	26.980	0	0	0	1	0	0
1037	58	0	41.910	0	0	0	0	1	0
490	41	1	28.405	1	0	0	1	0	0
39	29	0	38.830	3	0	0	0	1	0

Preprocessing Testing Data

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

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

Out[14]:

	age	sex	bmi	children	smoker	region_northeast	region_northwest	region_southeast	region_southwest
764	56	0	33.82	2	0	0	1	0	0
887	51	1	37.00	0	0	0	0	0	1
890	54	0	23.00	3	0	0	0	0	1
1293	19	0	32.49	0	1	0	1	0	0
259	22	0	27.10	0	0	0	0	0	1

XGBOOST

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

In [16]:
```
xgb_reg=XGBRegressor(max_depth=2,
                     learning_rate=0.01,
                     n_estimators=650,
                     random_state=42)
```

Train Model

In [17]:
```
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=2, max_leaves=0, min_child_weight=1,
             missing=nan, monotone_constraints='()', n_estimators=650, n_jobs=0,
             num_parallel_tree=1, predictor='auto', random_state=42,
             reg_alpha=0, reg_lambda=1, ...)
```

Model Evaluation

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

In [19]:
```
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)

    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()
```

In [20]:
```
mse_xgb_train=Evaluete(X_train_ohe,Y_train).mse()
mse_xgb_test=Evaluete(X_test_ohe,Y_test).mse()

r2_xgb_train=Evaluete(X_train_ohe,Y_train).r2()
r2_xgb_test=Evaluete(X_test_ohe,Y_test).r2()

cv_xgb=Evaluete(X_test_ohe,Y_test).cv_score()
```

Evaluation Dataframe

In [21]:
```
df_evaluate=pd.DataFrame({"MSE train ":mse_xgb_train.flatten(),
                          "MSE test":mse_xgb_test.flatten(),
                          "R2 train":r2_xgb_train.flatten(),
                          "R2 test":r2_xgb_test.flatten(),
                         "CV":cv_xgb})
```

In [22]:
```
df_evaluate
```

Out[22]:

	MSE train	MSE test	R2 train	R2 test	CV
0	1.998535e+06	2.514030e+06	0.985183	0.981887	0.979176

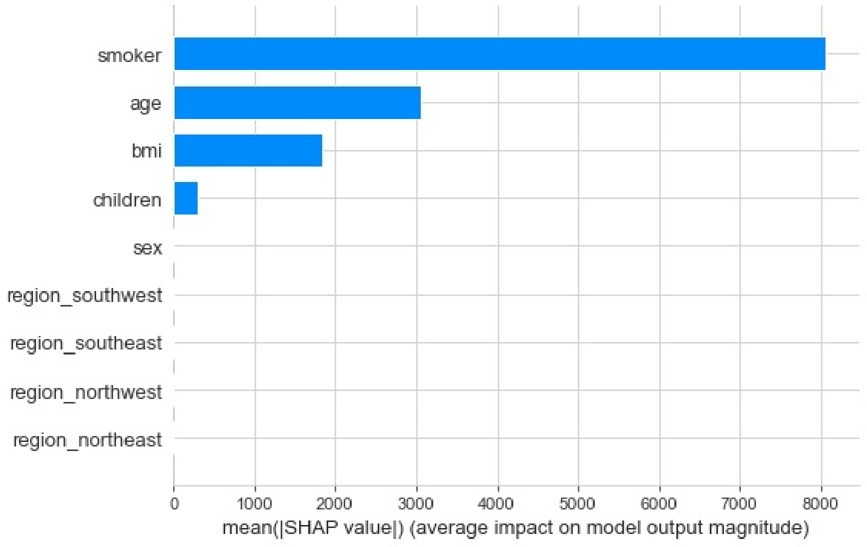
In [39]:
```
sorted_idx = xgb_reg.feature_importances_.argsort()
sorted_idx=sorted_idx.flatten()
```

In [23]:
```
explainer = shap.TreeExplainer(xgb_reg)
shap_values = explainer.shap_values(X_test_ohe)
```

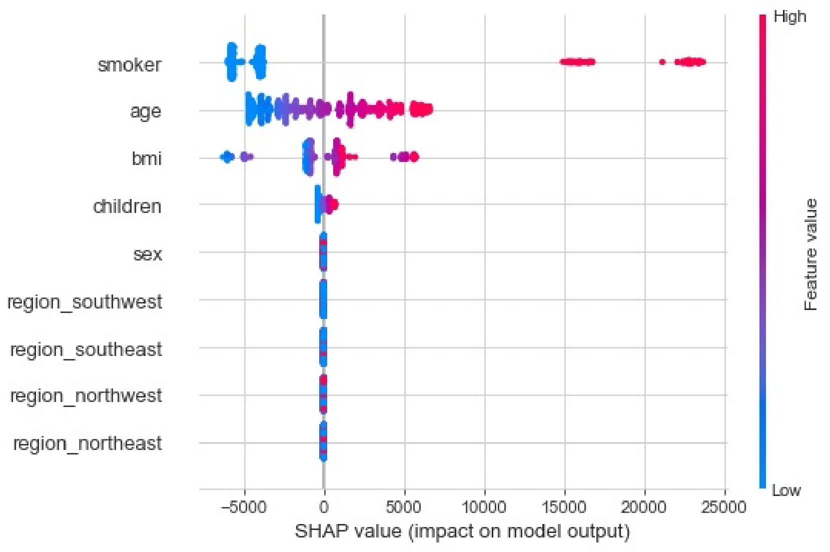
Plot Importance

In [29]:
```python
def plot_importance():

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

    return plt.show()
```

In [30]:
```python
if __name__ == "__main__":
    plot_importance()
```



In [31]:
```python
shap.summary_plot(shap_values, X_test_ohe)
```



We observe that the smoker variable has great weight when it comes to predictions. Followed by BMI and age. The children variable has negligible weight just like the user's region.

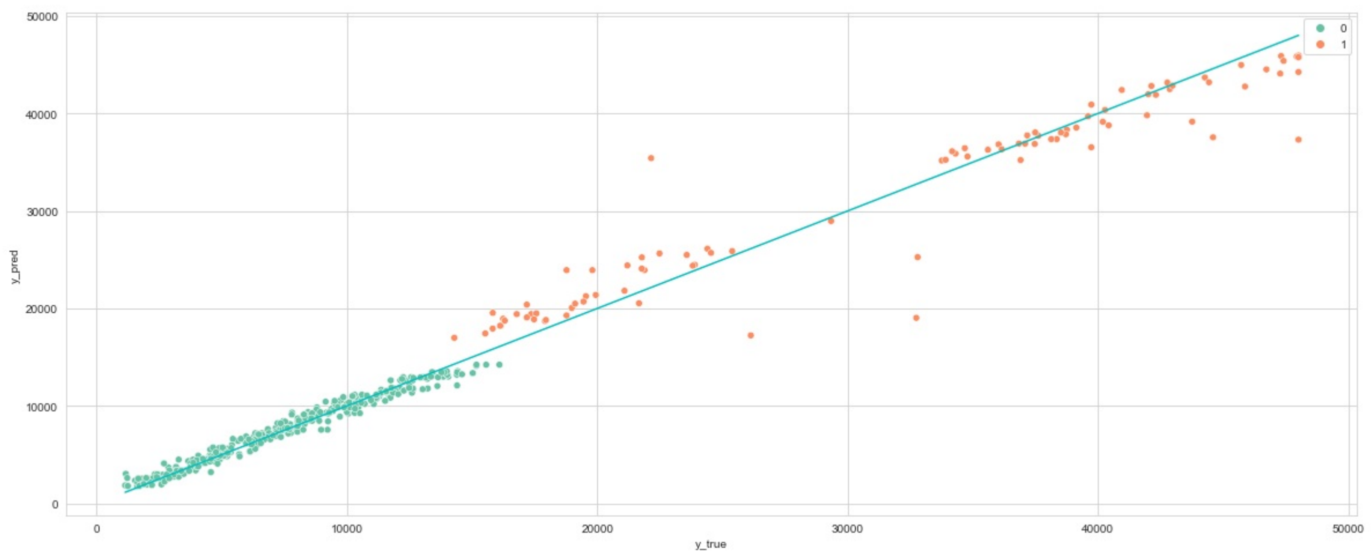
But they complement the predictions. Since the difference between algorithms and humans. It is we humans base our predictions on features of stronger variables. On the other hand, computers base their estimates on strong variables that are not so important. But that complement the value to predict giving closer results. That only using only the most significant variables.

In [32]:
```python
y_pred=xgb_reg.predict(X_test_ohe)
y_pred=y_pred.flatten()
```

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))
    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 [60]:
```python
df_test.query("smoker==0").sample(n=10,random_state=42)
```

Out[60]:

	y_true	y_pred	smoker
435	8342.908750	8693.538086	0
629	5116.500400	5577.990234	0
332	5028.146600	5741.529297	0
987	11067.917387	10184.244141	0
744	12029.286700	11362.739258	0
875	9487.644200	10311.553711	0
370	9432.925300	9477.511719	0
282	3732.625100	3691.402588	0
348	6610.109700	7017.916992	0
1055	10450.755883	9851.967773	0

In [36]:
```python
df_test.query("smoker==1").sample(n=10,random_state=42)
```

Out[36]:

	y_true	y_pred	smoker
1302	37465.34375	36863.539062	1
1127	17179.52200	20383.900391	1
1235	15817.98570	17926.035156	1
1128	42856.83800	42489.253906	1
1293	36898.73308	35210.808594	1
1122	33750.29180	35163.371094	1
1242	19798.05455	23922.166016	1
1283	33907.54800	35239.062500	1
1228	36021.01120	36820.976562	1
1078	34303.16720	35872.996094	1

As we can see, the predictions are very close to the original value. This indicates that the model is very reliable and generalizes very well. eL XGBOOST is quite a powerful algorithm, capable of giving interesting results in a short period of time. No wonder he is the winner of several Kaggle competitions.

Save Model

In [37]:
```
import joblib
```

In [38]:
```
joblib.dump(xgb_reg,"xgb_insurence.pkl") # Save Model
```

Out[38]:
```
['xgb_insurence.pkl']
```

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