Medical Cost Pricing

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Prezentarea setului de date

Setul de date "insurance.csv" contine 7 coloane si 1338 de randuri si reprezinta datele care afectează costurile medicale ale unui beneficiar facturate de asigurarea de sanatate.

Caracteristici

- age: Vârsta beneficiarului principal
- sex: Sexul contractantului de asigurare, femeie, bărbat
- bmi: Indicele de masă corporală, care oferă o înțelegere a corpului, greutăți care sunt relativ mari sau mici în raport cu înălțimea,indice obiectiv al greutății corporale (kg / m ^ 2), folosind raportul dintre înălțime și greutate, în mod ideal între 18,5 și 24,9
- children: Numărul de copii acoperiți de asigurarea de sănătate / Numărul de persoane aflate în întreținere
- fumător: Beneficiarul este sau nu fumator
- region: Zona de reședință a beneficiarului în SUA: nord-est, sud-est, sud-vest, nord-vest.
- taxe: Costuri medicale individuale facturate de asigurarea de sănătate

Etapele proiectului:

1. Importarea librariilor si crearea sesiunii spark
2. Importarea setului de date din fisierul CSV aflat in Google Drive
3. Prezentarea datelor (coloane, numar de intrari, cateva statistici)
4. Verificarea, prelucrarea si pregatirea datelor
5. Verificarea pe coloane a existentei valorilor null
    - Verificarea datelor din coloanele 'region' si 'smoker'
    - Transformarea variabilelor 'region' si 'smoker' de tip string in variabila categoriala
    - Creearea unui vector de 'features' folosind VectorAssembler

    Selectia modelelor: Linear Regression Random Forest + creearea si utilizarea unui pipeline Gradient-boosted tree regression + creearea si utilizarea unui pipeline Utilizarea unui model DL - utilizand Tensorflow

In [1]:
```
from time import time
from pyspark import SparkContext
from pyspark.sql import SparkSession
```

In [6]:
```
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from pyspark.sql import functions
import pyspark.sql.functions as f
from pyspark.sql.functions import col
from pyspark.ml.feature import VectorAssembler,VectorIndexer,OneHotEncoder,StringIndexer
```

```
from pyspark.ml.linalg import Vectors
from pyspark.ml import Pipeline
from pyspark.ml.regression import LinearRegression, RandomForestRegressor, GBTRegressor
from pyspark.ml.evaluation import RegressionEvaluator
from sklearn.model_selection import train_test_split
from pyspark.sql.types import *
from sklearn.preprocessing import MinMaxScaler
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense
from sklearn.metrics import mean_squared_error, mean_absolute_error, mean_squared_log_er
```

2. Incărcarea datelor

In [7]:
```
spark = SparkSession.builder.appName('StrokePrediction').getOrCreate()
df = spark.read.csv('insurance.csv', inferSchema=True, header=True)
```

3. Prezentarea datelor

Se vor afișa: schema datelor, numarul de intrari din setul de date, coloanele existente, afisare aprimelor 20 de intrari, o statistica si cateva ploturi (matricea de corelatii si histograme). Primulplot reprezinta matricea de corelatii si va contine toate atributele din setul de date, al doilea plot va fi o histograma ce va prezenta distributia variabilei 'charges'.

In [8]:
```
# Se afiseaza schema datelor
df.printSchema()
```

```
root
 |-- age: integer (nullable = true)
 |-- sex: string (nullable = true)
 |-- bmi: double (nullable = true)
 |-- children: integer (nullable = true)
 |-- smoker: string (nullable = true)
 |-- region: string (nullable = true)
 |-- charges: double (nullable = true)
```

Spark nu detectează schema în mod corespunzător, așa că trebuie să definim și schema pentru setul de date. Tipul de date incorect poate produce probleme greu de depistat și erori de execuție. Prin urmare, se redifiește schema setului.

In [9]:
```
Schema=StructType([
  StructField('age',IntegerType(),nullable=True),
  StructField('sex',StringType() ,nullable=True),
  StructField('bmi',DoubleType(),nullable=True),
  StructField('children', IntegerType(),nullable=True),
  StructField('smoker',StringType() ,nullable=True),
  StructField('region',StringType() ,nullable=True),
  StructField('charges',DoubleType() ,nullable=True),


])
df = spark.read.option('header',True).schema(Schema).csv('insurance.csv')
df.printSchema()
```

```
root
 |-- age: integer (nullable = true)
 |-- sex: string (nullable = true)
 |-- bmi: double (nullable = true)
 |-- children: integer (nullable = true)
```

```
 |-- smoker: string (nullable = true)
 |-- region: string (nullable = true)
 |-- charges: double (nullable = true)
```

In [10]:
```
# Se afiseaza numarul de intrari din setul de date
df.count()
```

Out[10]:
```
1338
```

In [11]:
```
# Se afiseaza coloanele din setul de date
df.columns
```

Out[11]:
```
['age', 'sex', 'bmi', 'children', 'smoker', 'region', 'charges']
```

In [12]:
```
# Se afiseaza datele (primele 20 de randuri)
df.show()
```

```
+---+------+------+--------+------+---------+-----------+
|age|   sex|   bmi|children|smoker|   region|    charges|
+---+------+------+--------+------+---------+-----------+
| 19|female|  27.9|       0|   yes|southwest|  16884.924|
| 18|  male| 33.77|       1|    no|southeast|  1725.5523|
| 28|  male|  33.0|       3|    no|southeast|   4449.462|
| 33|  male|22.705|       0|    no|northwest|21984.47061|
| 32|  male| 28.88|       0|    no|northwest|  3866.8552|
| 31|female| 25.74|       0|    no|southeast|  3756.6216|
| 46|female| 33.44|       1|    no|southeast|  8240.5896|
| 37|female| 27.74|       3|    no|northwest|  7281.5056|
| 37|  male| 29.83|       2|    no|northeast|  6406.4107|
| 60|female| 25.84|       0|    no|northwest|28923.13692|
| 25|  male| 26.22|       0|    no|northeast|  2721.3208|
| 62|female| 26.29|       0|   yes|southeast| 27808.7251|
| 23|  male|  34.4|       0|    no|southwest|   1826.843|
| 56|female| 39.82|       0|    no|southeast| 11090.7178|
| 27|  male| 42.13|       0|   yes|southeast| 39611.7577|
| 19|  male|  24.6|       1|    no|southwest|   1837.237|
| 52|female| 30.78|       1|    no|northeast| 10797.3362|
| 23|  male|23.845|       0|    no|northeast| 2395.17155|
| 56|  male|  40.3|       0|    no|southwest|  10602.385|
| 30|  male|  35.3|       0|   yes|southwest|  36837.467|
+---+------+------+--------+------+---------+-----------+
only showing top 20 rows
```

In [13]:
```
#Statistica asupra setului de date
df.summary().show()
```

```
+-------+------------------+------+------------------+-----------------+------+---------
+------------------+
|summary|               age|   sex|               bmi|         children|smoker|   region
|           charges|
+-------+------------------+------+------------------+-----------------+------+---------
+------------------+
|  count|              1338|  1338|              1338|             1338|  1338|     1338
|              1338|
|   mean| 39.20702541106129|  null|30.663396860986538|  1.0949177877429|  null|     null
|13270.422265141257|
| stddev|14.049960379216147|  null| 6.098186911679012|1.205492739781914|  null|     null
|12110.011236693992|
|    min|                18|female|             15.96|                0|    no|northeast
|         1121.8739|
|    25%|                27|  null|             26.29|                0|  null|     null
|         4738.2682|
|    50%|                39|  null|              30.4|                1|  null|     null
```

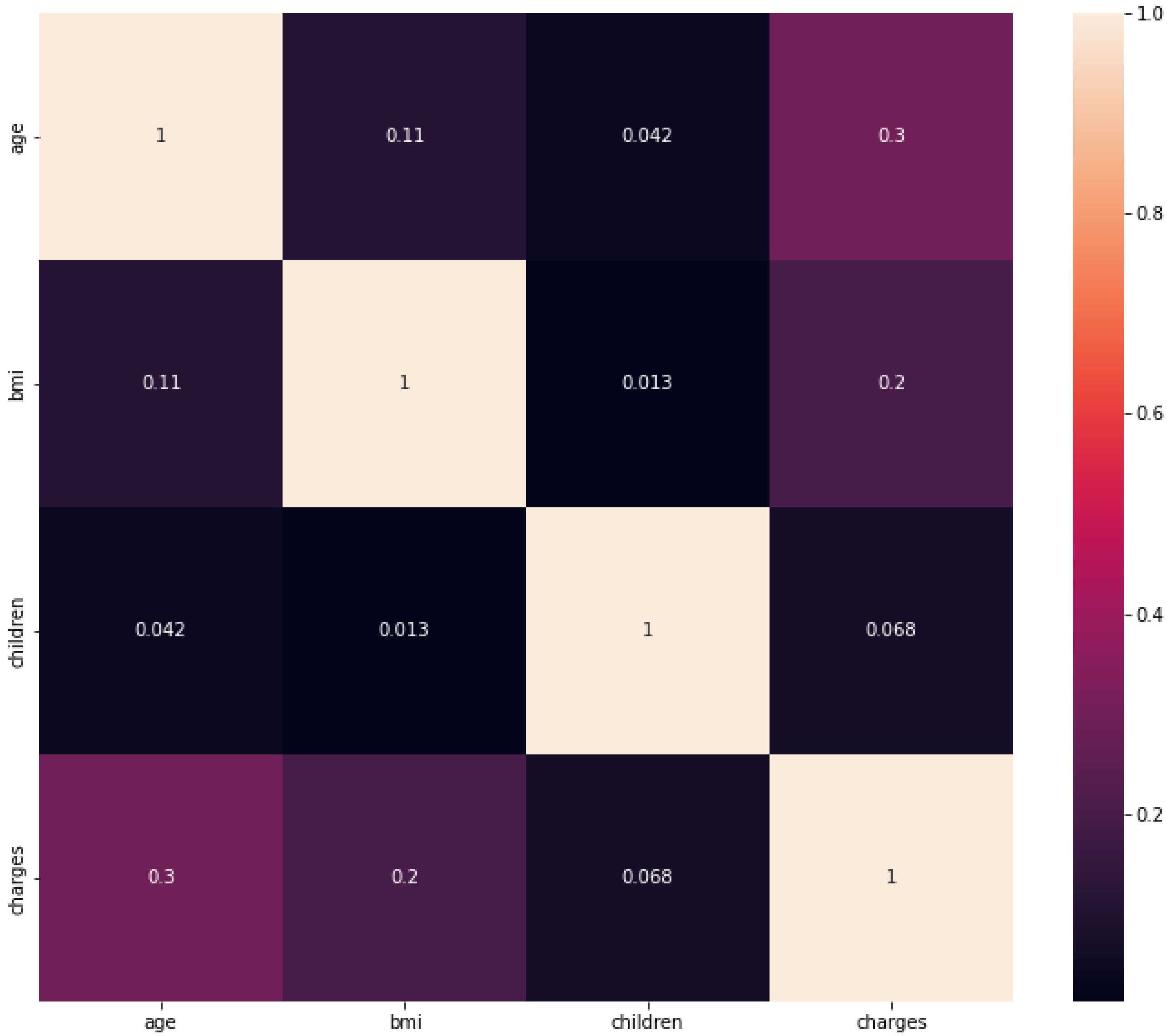
```
|          9377.9047|
|    75%|                 51|  null|              34.7|                2|  null|     null
|        16657.71745|
|    max|                 64|  male|             53.13|                5|   yes|southwest
|        63770.42801|
+-------+------------------+------+------------------+-----------------+------+---------
+------------------+
```

In [14]:
```python
# Se face transformarea dataframe-ului in Pandas pentru a putea crea plot-uri
df_pandas = df.toPandas()
```

In [15]:
```python
# Se afiseaza matricea de corelatii

plt.figure(figsize=(12,10))
sns.heatmap(df_pandas.corr(),annot=True)
```

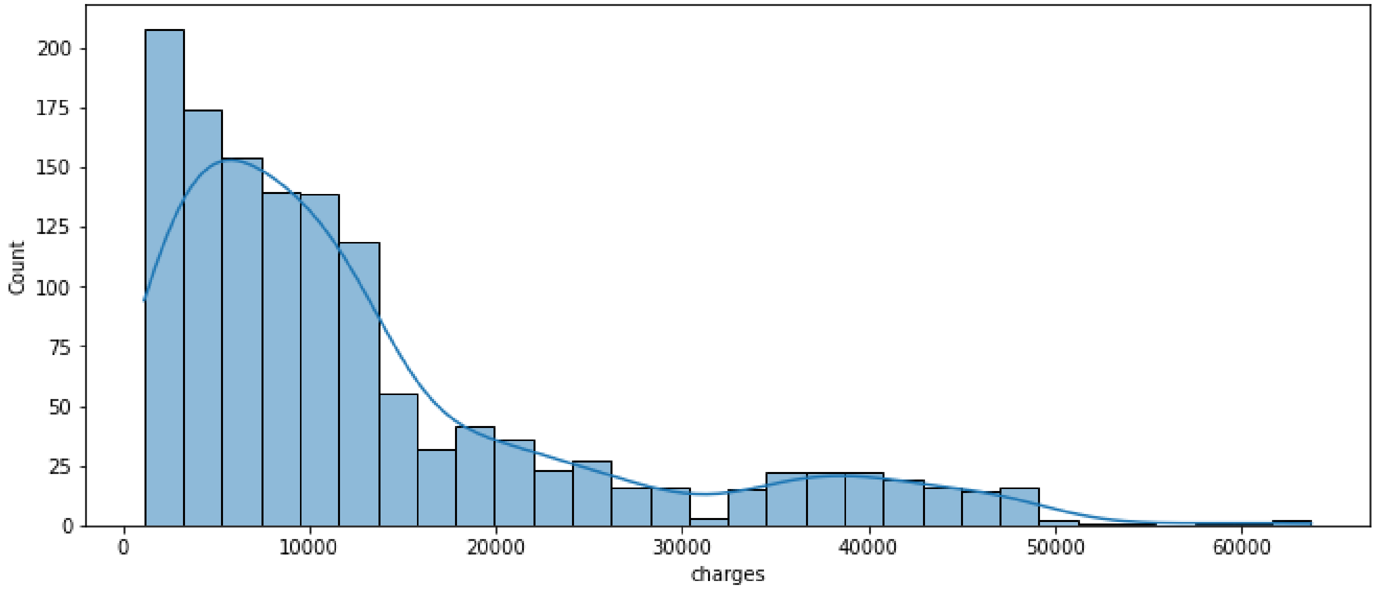
Out[15]: <AxesSubplot:>



In [16]:
```python
# Histograma pentru distributia coloanei 'charges'

plt.figure(figsize=(12, 5))
sns.histplot(df_pandas['charges'], kde=True)
```

Out[16]: <AxesSubplot:xlabel='charges', ylabel='Count'>



4.Verificarea si prelucrarea datelor

Se verifica fiecare coloana ramasa pentru a vedea daca exista valori null. De asemenea, se afiseaza valorile din coloanele 'region', 'smoker' si 'sex' si se ia o decizie asupra modului in care vor fi utilizate datele pe care le contin. Se va folosi StringIndexer pentru transformarea in variabile categoriale, variabilele string 'smoker', 'region', 'sex' si se va crea un vector denumit "features", format din coloanele relevante, folosind VectorAssembler.

In [17]:
```
# Se verifica daca exista valori null si se afiseaza cate valori null sunt pentru fiecar

df_agg= df.agg(*[f.count(f.when(f.isnull(c), c)).alias(c) for c in df.columns])
df_agg.show()
```

```
+---+---+---+--------+------+------+-------+
|age|sex|bmi|children|smoker|region|charges|
+---+---+---+--------+------+------+-------+
|  0|  0|  0|       0|     0|     0|      0|
+---+---+---+--------+------+------+-------+
```

Se observa ca nu sunt valori null, deci nu trebuie sterse intrari din setul de date, sau inlocuite in vreun fel datele din coloana respectiva.

In [18]:
```
# Se obtine numarul de valori pentru coloana region
df2 = df.groupBy('region').count()
df2.orderBy(col("count").desc(),col("region").asc()).show(60)

# Se obtine numarul de valori pentru coloana smoker
df2 = df.groupBy('smoker').count()
df2.orderBy(col("count").desc(),col("smoker").asc()).show(60)

# Se obtine numarul de valori pentru coloana sex
df2 = df.groupBy('smoker').count()
df2.orderBy(col("count").desc(),col("smoker").asc()).show(60)
```

```
+---------+-----+
|   region|count|
+---------+-----+
|southeast|  364|
|northwest|  325|
|southwest|  325|
```

```
|northeast|  324|
+---------+-----+

+------+-----+
|smoker|count|
+------+-----+
|    no| 1064|
|   yes|  274|
+------+-----+

+------+-----+
|smoker|count|
+------+-----+
|    no| 1064|
|   yes|  274|
+------+-----+
```

Varaibilele region, sex si smoker fiind de tip string vor trebui transformate in variabile categoriale pentru a putea fi utilizata mai departe.

In [19]:
```
from pyspark.ml.feature import StringIndexer, OneHotEncoder

# Crearea unui obiect StringIndexer, specificarea coloanelor de intrare și ieșire
SI_smoker = StringIndexer(inputCol='smoker',outputCol='smoker_cat')
SI_region = StringIndexer(inputCol='region',outputCol='region_cat')
SI_sex = StringIndexer(inputCol='sex',outputCol='sex_cat')

# Transformarea datelor
df = SI_smoker.fit(df).transform(df)
df = SI_region.fit(df).transform(df)
df = SI_sex.fit(df).transform(df)
# Afișarea datelor transformate
df.select('smoker', 'smoker_cat', 'region', 'region_cat', 'sex', 'sex_cat').show(10)
```

```
+------+----------+---------+----------+------+-------+
|smoker|smoker_cat|   region|region_cat|   sex|sex_cat|
+------+----------+---------+----------+------+-------+
|   yes|       1.0|southwest|       2.0|female|    1.0|
|    no|       0.0|southeast|       0.0|  male|    0.0|
|    no|       0.0|southeast|       0.0|  male|    0.0|
|    no|       0.0|northwest|       1.0|  male|    0.0|
|    no|       0.0|northwest|       1.0|  male|    0.0|
|    no|       0.0|southeast|       0.0|female|    1.0|
|    no|       0.0|southeast|       0.0|female|    1.0|
|    no|       0.0|northwest|       1.0|female|    1.0|
|    no|       0.0|northeast|       3.0|  male|    0.0|
|    no|       0.0|northwest|       1.0|female|    1.0|
+------+----------+---------+----------+------+-------+
only showing top 10 rows
```

In [20]:
```
# crearea obiectului si specificarea coloanelor de intrare si iesire
OHE = OneHotEncoder(inputCols=['smoker_cat', 'region_cat', 'sex_cat'],outputCols=['smoke

# transformarea datelor
df = OHE.fit(df).transform(df)

# vizualizarea si transformarea datelor
df.select('smoker', 'smoker_cat', 'smoker_OHE', 'region', 'region_cat', 'region_OHE', 's
```

```
+------+----------+-------------+---------+----------+-------------+------+-------+-----
--------+
|smoker|smoker_cat|   smoker_OHE|   region|region_cat|   region_OHE|   sex|sex_cat|
sex_OHE|
```

```
+------+----------+------------+--------+----------+------------+------+-------+-----
--------+
|   yes|       1.0|    (1,[],[])|southwest|       2.0|(3,[2],[1.0])|female|    1.0|
(1,[],[])|
|    no|       0.0|(1,[0],[1.0])|southeast|       0.0|(3,[0],[1.0])|  male|    0.0|(1,
[0],[1.0])|
|    no|       0.0|(1,[0],[1.0])|southeast|       0.0|(3,[0],[1.0])|  male|    0.0|(1,
[0],[1.0])|
|    no|       0.0|(1,[0],[1.0])|northwest|       1.0|(3,[1],[1.0])|  male|    0.0|(1,
[0],[1.0])|
|    no|       0.0|(1,[0],[1.0])|northwest|       1.0|(3,[1],[1.0])|  male|    0.0|(1,
[0],[1.0])|
|    no|       0.0|(1,[0],[1.0])|southeast|       0.0|(3,[0],[1.0])|female|    1.0|
(1,[],[])|
|    no|       0.0|(1,[0],[1.0])|southeast|       0.0|(3,[0],[1.0])|female|    1.0|
(1,[],[])|
|    no|       0.0|(1,[0],[1.0])|northwest|       1.0|(3,[1],[1.0])|female|    1.0|
(1,[],[])|
|    no|       0.0|(1,[0],[1.0])|northeast|       3.0|    (3,[],[])|  male|    0.0|(1,
[0],[1.0])|
|    no|       0.0|(1,[0],[1.0])|northwest|       1.0|(3,[1],[1.0])|female|    1.0|
(1,[],[])|
+------+----------+------------+--------+----------+------------+------+-------+-----
--------+
only showing top 10 rows
```

Mai departe se va forma un vector 'features' utilizand coloanele relevante. Vor fi incluse toate atributele numerice, deoarece, conform matricei de corelatie, nu se poate spune ca existau valori ce ar fi fost mult mai reprezentative decat altele in relatie cu variabila 'charges'.

In [21]:
```python
#Se va forma un vector denumit "features", format din coloanele relevante.

assembler = VectorAssembler(
  inputCols=['age',
              'bmi',
              'children',
             'region_cat',
             'smoker_cat',
             'region_OHE',
             'smoker_OHE',
             'sex_cat',
             'sex_OHE'
            ],
         outputCol="features")


# se completeaza valorile null
df = df.fillna(0)

# se transforma datele
output = assembler.transform(df)

# afisarea vectorului transformat
output.select("features", "charges").show()
```

```
+--------------------+-----------+
|            features|    charges|
+--------------------+-----------+
|(11,[0,1,3,4,7,9]...|  16884.924|
|(11,[0,1,2,5,8,10...|  1725.5523|
|(11,[0,1,2,5,8,10...|   4449.462|
|(11,[0,1,3,6,8,10...|21984.47061|
|(11,[0,1,3,6,8,10...|  3866.8552|
|(11,[0,1,5,8,9],[...|  3756.6216|
```

```
|(11,[0,1,2,5,8,9]...|  8240.5896|
|[37.0,27.74,3.0,1...|  7281.5056|
|(11,[0,1,2,3,8,10...|  6406.4107|
|(11,[0,1,3,6,8,9]...|28923.13692|
|(11,[0,1,3,8,10],...|  2721.3208|
|(11,[0,1,4,5,9],[...| 27808.7251|
|(11,[0,1,3,7,8,10...|   1826.843|
|(11,[0,1,5,8,9],[...| 11090.7178|
|(11,[0,1,4,5,10],...| 39611.7577|
|[19.0,24.6,1.0,2....|   1837.237|
|(11,[0,1,2,3,8,9]...| 10797.3362|
|(11,[0,1,3,8,10],...| 2395.17155|
|(11,[0,1,3,7,8,10...|  10602.385|
|(11,[0,1,3,4,7,10...|  36837.467|
+--------------------+-----------+
only showing top 20 rows
```

5. Alegerea și implementarea modelelor

Folosind setul de date ales, se doreste prezicerea costurilor medicale acoperita de asigurarea de sanatate a beneficiarilor in functie de anumite caracteristici. Pentru rezolvare, se vor folosi 3 modele ML. Deoarece problema pusa este de regresie, modelele ML alese si implementate vor fi de tip regresie.

1. Regresie Liniara

Primul pas va fi crearea unui data frame pentru regresie, folosid doar coloanele 'features' si 'charges' apoi se va face o diviziune asupra setului de date. Datele din setul de date vor fi impartite in doua subseturi: unul pentru antrenarea modelului si unul pentru testarea lui, procentele utilizate la impartire fiind 70% pentru cel de antrenare si 30% pentru cel de testare. Se va crea apoi un obiect de tip Linear Regresion, se antreneaza modelul si se testeaza.

1. Random Forest

Pentru acest model s-a creat un vector nou, numit 'features2'. Se creeaza un data frame nou, utilizand 'charges' si 'features2' si se imparte setul de date in date de antrenare si date de testare, folosind procentul 70% pentru datele de antrenare si 30% pentru cele de testare. Se creeaza un obiect de tip Random Forest Regressor cu coloanele 'charges' si 'features2' si un pipeline. Se antreneaza modelul utilizand pipeline-ul creat, apoi se testeaza si se evalueaza rezultatul obtinut.

1. Gradient-boosted tree regression

Pentru acest model se va folosi acelasi vector de features creat pentru Random Forest, anume 'features2', si aceleasi seturi de date de antrenament si de testare. Primul pas este crearea un obiect de tipul GBTRegressor si un nou pipeline, la pasul doi se antreneaza modelul folosind pipeline-ul. Se fac predictii pe baza setului de date de test, utilizand modelul antrenat si se evalueaza predictiile.

5.1 Linear Regression

In [22]:
```
# Se creeaza un dataframe doar cu aceste 2 coloane

df_linear_regression = output.select("features", "charges")
```

In [23]:
```
# Se face o diviziune a setului de date în subseturi pentru antrenare si testare testare
trainData,testData = df_linear_regression.randomSplit([0.7,0.3])
```

In [24]:
```python
#Se afiseaza statistici asupra datelor pentru training
trainData.describe().show()
```

```
+-------+------------------+
|summary|           charges|
+-------+------------------+
|  count|               935|
|   mean|13243.231118278076|
| stddev|12367.281649684883|
|    min|         1121.8739|
|    max|       63770.42801|
+-------+------------------+
```

In [25]:
```python
#Se afiseaza statistici asupra datelor pentru test
testData.describe().show()
```

```
+-------+------------------+
|summary|           charges|
+-------+------------------+
|  count|               403|
|   mean|13333.508424736969|
| stddev|11505.671134340035|
|    min|         1163.4627|
|    max|       55135.40209|
+-------+------------------+
```

In [26]:
```python
# Se creeaza un obiect de tip LinearRegression
lr = LinearRegression(labelCol='charges')
```

In [27]:
```python
# Se antreneaza modelul
lrModel = lr.fit(trainData)
```

In [28]:
```python
# Se afiseaza coeficientii si interceptia pentru regresia liniara
print("Coefficients: {} Intercept: {}".format(lrModel.coefficients,lrModel.intercept))
```

```
Coefficients: [270.11152620913185,329.5713468438745,530.0190240632434,177.2767396421288,
12205.015622722352,-251.6445033019465,215.8768703956481,-821.8871004269586,-12205.015622
722536,73.91570634420495,-73.91570634436678] Intercept: -712.7331915691593
```

In [29]:
```python
#Se evalueaza modelul pe datele de testare
results = lrModel.evaluate(testData)
```

In [30]:
```python
# Se afiseaza informatiile obtinute dupa evaluare
print("RMSE: {}".format(results.rootMeanSquaredError))
print("MSE: {}".format(results.meanSquaredError))
print("R2: {}".format(results.r2))
```

```
RMSE: 6100.115803046181
MSE: 37211412.81057376
R2: 0.71820632600281
```

In [31]:
```python
# Se afiseaza valorile reziduale
results.residuals.show()
```

```
+------------------+
|         residuals|
+------------------+
|  5370.120137146012|
|-11587.021087074627|
|-10532.034798612447|
|-10582.219569837496|
|-10741.075950556668|
|-10414.944294257544|
|  5417.395519547019|
```

```
|  5288.150218687806|
|-10731.391734042827|
|  7053.840234060168|
|-440.95390255170605|
| 19451.278100791722|
| -881.3102771447448|
| 11203.797097357181|
| 19492.614375859142|
|  2029.336335687277|
| 14158.087225557605|
| 1546.6809754123115|
|  659.1845866348913|
|  503.2984468840541|
+-------------------+
only showing top 20 rows
```

In [32]:

```
# Sa se afiseze corelatia intre 'charges' si 'age'
from pyspark.sql.functions import corr
df.select(corr('charges','age')).show()
```

```
+------------------+
|corr(charges, age)|
+------------------+
| 0.299008193330648|
+------------------+
```

In [33]:

```
# Sa se afiseze corelatia intre 'charges' si 'children'
from pyspark.sql.functions import corr
df.select(corr('charges','children')).show()
```

```
+-----------------------+
|corr(charges, children)|
+-----------------------+
|    0.06799822684790494|
+-----------------------+
```

In [34]:

```
# Sa se afiseze corelatia intre 'charges' si 'bmi'
from pyspark.sql.functions import corr
df.select(corr('charges','bmi')).show()
```

```
+-------------------+
| corr(charges, bmi)|
+-------------------+
|0.19834096883362906|
+-------------------+
```

In [35]:

```
#Aplicarea modelului pe datele de test neetichetate
unlabeled_data=testData.select("features")
predictions = lrModel.transform(unlabeled_data)
predictions.show()
```

```
+--------------------+------------------+
|            features|        prediction|
+--------------------+------------------+
|(11,[0,1,2,3,4,9]...|32331.756662853986|
|(11,[0,1,2,3,4,9]...|31181.830737074626|
|(11,[0,1,2,3,4,9]...| 33933.34054861245|
|(11,[0,1,2,3,4,9]...|  35455.6044698375|
|(11,[0,1,2,3,4,10...|23570.531050556667|
|(11,[0,1,2,3,4,10...|32876.988044257545|
|(11,[0,1,2,3,4,10...| 35616.82588045298|
|(11,[0,1,2,3,4,10...|36630.946781312196|
|(11,[0,1,2,3,4,10...| 35601.22853404283|
```

```
|(11,[0,1,2,3,4,10...|41495.338115939834|
|(11,[0,1,2,3,8,9]...| 5002.142402551706|
|(11,[0,1,2,3,8,9]...|2944.4661392082776|
|(11,[0,1,2,3,8,9]...| 5445.501727144745|
|(11,[0,1,2,3,8,9]...| 5592.614842642821|
|(11,[0,1,2,3,8,9]...|  3796.31402414086|
|(11,[0,1,2,3,8,9]...| 4723.701664312723|
|(11,[0,1,2,3,8,9]...|10756.959034442394|
|(11,[0,1,2,3,8,9]...| 5587.221524587689|
|(11,[0,1,2,3,8,9]...| 7326.630413365108|
|(11,[0,1,2,3,8,9]...| 7483.176803115946|
+--------------------+------------------+
only showing top 20 rows
```

In [36]:
```
testData.show()
```

```
+--------------------+-----------+
|            features|    charges|
+--------------------+-----------+
|(11,[0,1,2,3,4,9]...| 37701.8768|
|(11,[0,1,2,3,4,9]...|19594.80965|
|(11,[0,1,2,3,4,9]...|23401.30575|
|(11,[0,1,2,3,4,9]...| 24873.3849|
|(11,[0,1,2,3,4,10...| 12829.4551|
|(11,[0,1,2,3,4,10...|22462.04375|
|(11,[0,1,2,3,4,10...| 41034.2214|
|(11,[0,1,2,3,4,10...|  41919.097|
|(11,[0,1,2,3,4,10...| 24869.8368|
|(11,[0,1,2,3,4,10...|48549.17835|
|(11,[0,1,2,3,8,9]...|  4561.1885|
|(11,[0,1,2,3,8,9]...|22395.74424|
|(11,[0,1,2,3,8,9]...| 4564.19145|
|(11,[0,1,2,3,8,9]...|16796.41194|
|(11,[0,1,2,3,8,9]...| 23288.9284|
|(11,[0,1,2,3,8,9]...|   6753.038|
|(11,[0,1,2,3,8,9]...|24915.04626|
|(11,[0,1,2,3,8,9]...|  7133.9025|
|(11,[0,1,2,3,8,9]...|   7985.815|
|(11,[0,1,2,3,8,9]...| 7986.47525|
+--------------------+-----------+
only showing top 20 rows
```

5.2 Random Forest

In [38]:
```
#Se creeaza un nou vector, numit 'features2'

assembler = VectorAssembler(
  inputCols=['age',
              'bmi',
              'children',
             'region_cat',
             'smoker_cat',
             'sex_cat',
             'region_OHE',
             'smoker_OHE',
             'sex_OHE',

            ],
         outputCol="features2")

output2 = assembler.transform(df)
```

In [39]:
```
# Se creeaza un data frame nou

df_RandomForest = output2.select("features2", "charges")
```

In [40]:
```
# Se imparte  setul de date in date de antrenare si date de test, cu procente 70% si 30%

trainData,testData = df_RandomForest.randomSplit([0.7,0.3])
```

In [41]:
```
#Se afiseaza statistici asupra datelor pentru training

trainData.describe().show()
```

```
+-------+-----------------+
|summary|          charges|
+-------+-----------------+
|  count|              917|
|   mean|13131.53913172303|
| stddev|12047.26469417141|
|    min|        1121.8739|
|    max|      63770.42801|
+-------+-----------------+
```

In [42]:
```
#Se afiseaza statistici asupra datelor pentru test

testData.describe().show()
```

```
+-------+------------------+
|summary|           charges|
+-------+------------------+
|  count|               421|
|   mean| 13572.93018282423|
| stddev|12254.532155507519|
|    min|         1131.5066|
|    max|        48673.5588|
+-------+------------------+
```

In [43]:
```
# Se creeaza un obiect de tip Random Forest Regressor cu coloanele 'charges' si 'feature

rf = RandomForestRegressor(labelCol = 'charges',
                            featuresCol = 'features2')
```

In [44]:
```
featureIndexer =\
    VectorIndexer(inputCol="features2", outputCol="indexedFeatures").fit(trainData)

pipeline = Pipeline(stages=[featureIndexer, rf])
```

In [45]:
```
# Se antreneaza modelul

model = pipeline.fit(trainData)
```

In [46]:
```
# Se testeaza si se evalueaza modelul

predictions = model.transform(testData)

evaluator = RegressionEvaluator(
    labelCol="charges", predictionCol="prediction", metricName="mae")

mae = evaluator.evaluate(predictions)
print("MAE on test data = %g" % mae)

rfModel = model.stages[1]
print(rfModel)
```

```
MAE on test data = 2645.61
RandomForestRegressionModel: uid=RandomForestRegressor_109e2619e56b, numTrees=20, numFea
tures=11
```

6. Utilizarea unui model DL

Modelul DL va fi de tip regresie si va avea ca scop rezolvarea aceleiasi probleme: prezicerea costurilor medicale individuale facturate de asigurarea de sănătate. Pentru acesta se va folosi un data frame de tip pandas din care se vor sterge variabilele de tip string ('region','smoker', 'sex') si se vor separa caracteristicile variabilei tinta ('charges'), apoi se vor imparti datele in date de antrenare si date de testare. Se va aplica un feature scaling; acesta va invata pe datele de antrenare si va fi aplicat pe datele de antrenament si de test. Apoi se va crea o retea neuronala cu o arhitectura adaptata problemelor de tip regresie si se va compila modelul, avand parametrii de pe ultimul strat luati in calcul, aceasta fiind o problema de regresie si nu de clasificare. Se antreneaza modelul pentru 200 de epoci si o dimensiune a batch-ului de 128. La final, se va folosi un grafic pentru a analiza training loss-ul si validation loss-ul si se vor afisa valorile RMSE, MAE si MSLE.

In [47]:

```
# Se transforma data frame-ul intr-un dat frame de tip pandas
dfdl = df.toPandas()

# Se scoate coloana 'smoker' si coloana 'region' pentru a fi suprimate
dfdl = dfdl.drop('smoker', axis = 1)
dfdl = dfdl.drop('region', axis = 1)
dfdl = dfdl.drop('sex', axis = 1)
dfdl = dfdl.drop('smoker_OHE', axis = 1)
dfdl = dfdl.drop('region_OHE', axis = 1)
dfdl = dfdl.drop('sex_OHE', axis = 1)
# Se separa caracteristicile variabilei 'popularity'
X = dfdl.drop('charges', axis = 1)
y = dfdl['charges']

# Se impart datele in date de antrenare si date de testare
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=10
print(X_train)
```

```
     age     bmi  children  smoker_cat  region_cat  sex_cat
405   52  38.380         2         0.0         3.0      1.0
835   42  35.970         2         0.0         0.0      0.0
483   51  39.500         1         0.0         2.0      1.0
319   32  37.335         1         0.0         3.0      0.0
956   54  30.800         1         1.0         0.0      0.0
..   ...     ...       ...         ...         ...      ...
575   58  27.170         0         0.0         1.0      1.0
973   19  40.500         0         0.0         2.0      1.0
75    57  34.010         0         0.0         1.0      0.0
599   52  37.525         2         0.0         1.0      1.0
863   36  19.855         0         0.0         3.0      1.0

[936 rows x 6 columns]
```

In [48]:

```
# feature scaling
scaler = MinMaxScaler()

X_train = scaler.fit_transform(X_train)
X_test = scaler.transform(X_test)


# Se afiseaza forma dataset-urilor de antrenament si de testare
```

```
print(X_train.shape)
print(X_test.shape)
```

```
(936, 6)
(402, 6)
```

In [54]:
```
# Se creeaza o retea neuronala ce are o arhitectura potrivita unei probleme de tip regre
model = Sequential()
model.add(Dense(6, activation='relu', input_shape=(6, )))
model.add(Dense(6, activation='relu'))
model.add(Dense(6, activation='relu'))
model.add(Dense(6, activation='relu'))
model.add(Dense(1, activation='linear'))

model.summary()
```

```
Model: "sequential_1"
_________________________________________________________________
 Layer (type)                Output Shape              Param #   
=================================================================
 dense_5 (Dense)             (None, 6)                 42        
                                                                 
 dense_6 (Dense)             (None, 6)                 42        
                                                                 
 dense_7 (Dense)             (None, 6)                 42        
                                                                 
 dense_8 (Dense)             (None, 6)                 42        
                                                                 
 dense_9 (Dense)             (None, 1)                 7         
                                                                 
=================================================================
Total params: 175
Trainable params: 175
Non-trainable params: 0
_________________________________________________________________
```

In [55]:
```
# Se compileaza modelul

model.compile(optimizer='adam', loss='mse')
```

In [56]:
```
# Se antreneaza modelul pentru 200 de epoci si o dimensiune a batch-ului de 128.

history = model.fit(x=X_train,
                    y=y_train,
                    validation_data=(X_test, y_test),
                    batch_size=128,
                    epochs=200)
```

```
Epoch 1/200
8/8 [==============================] - 1s 26ms/step - loss: 330293184.0000 - val_loss: 3
04835616.0000
Epoch 2/200
8/8 [==============================] - 0s 5ms/step - loss: 330291328.0000 - val_loss: 30
4833760.0000
Epoch 3/200
8/8 [==============================] - 0s 6ms/step - loss: 330289216.0000 - val_loss: 30
4831584.0000
Epoch 4/200
8/8 [==============================] - 0s 6ms/step - loss: 330286944.0000 - val_loss: 30
4829216.0000
Epoch 5/200
8/8 [==============================] - 0s 5ms/step - loss: 330284352.0000 - val_loss: 30
4826624.0000
Epoch 6/200
8/8 [==============================] - 0s 5ms/step - loss: 330281536.0000 - val_loss: 30
4823712.0000
```

```
Epoch 7/200
8/8 [==============================] - 0s 6ms/step - loss: 330278368.0000 - val_loss: 30
4820416.0000
Epoch 8/200
8/8 [==============================] - 0s 5ms/step - loss: 330274784.0000 - val_loss: 30
4816704.0000
Epoch 9/200
8/8 [==============================] - 0s 6ms/step - loss: 330270624.0000 - val_loss: 30
4812416.0000
Epoch 10/200
8/8 [==============================] - 0s 6ms/step - loss: 330265952.0000 - val_loss: 30
4807488.0000
Epoch 11/200
8/8 [==============================] - 0s 5ms/step - loss: 330260384.0000 - val_loss: 30
4801824.0000
Epoch 12/200
8/8 [==============================] - 0s 5ms/step - loss: 330254080.0000 - val_loss: 30
4795168.0000
Epoch 13/200
8/8 [==============================] - 0s 5ms/step - loss: 330246816.0000 - val_loss: 30
4787552.0000
Epoch 14/200
8/8 [==============================] - 0s 6ms/step - loss: 330238464.0000 - val_loss: 30
4778944.0000
Epoch 15/200
8/8 [==============================] - 0s 5ms/step - loss: 330228736.0000 - val_loss: 30
4769024.0000
Epoch 16/200
8/8 [==============================] - 0s 5ms/step - loss: 330217888.0000 - val_loss: 30
4757632.0000
Epoch 17/200
8/8 [==============================] - 0s 7ms/step - loss: 330205440.0000 - val_loss: 30
4744672.0000
Epoch 18/200
8/8 [==============================] - 0s 7ms/step - loss: 330191136.0000 - val_loss: 30
4730048.0000
Epoch 19/200
8/8 [==============================] - 0s 6ms/step - loss: 330175136.0000 - val_loss: 30
4713504.0000
Epoch 20/200
8/8 [==============================] - 0s 7ms/step - loss: 330157120.0000 - val_loss: 30
4694912.0000
Epoch 21/200
8/8 [==============================] - 0s 5ms/step - loss: 330136800.0000 - val_loss: 30
4673792.0000
Epoch 22/200
8/8 [==============================] - 0s 6ms/step - loss: 330113600.0000 - val_loss: 30
4650016.0000
Epoch 23/200
8/8 [==============================] - 0s 5ms/step - loss: 330087456.0000 - val_loss: 30
4623488.0000
Epoch 24/200
8/8 [==============================] - 0s 6ms/step - loss: 330058400.0000 - val_loss: 30
4593664.0000
Epoch 25/200
8/8 [==============================] - 0s 8ms/step - loss: 330025760.0000 - val_loss: 30
4560192.0000
Epoch 26/200
8/8 [==============================] - 0s 6ms/step - loss: 329988928.0000 - val_loss: 30
4522816.0000
Epoch 27/200
8/8 [==============================] - 0s 5ms/step - loss: 329948384.0000 - val_loss: 30
4481344.0000
Epoch 28/200
8/8 [==============================] - 0s 5ms/step - loss: 329902656.0000 - val_loss: 30
4435392.0000
```

```
Epoch 29/200
8/8 [==============================] - 0s 5ms/step - loss: 329852160.0000 - val_loss: 30
4384000.0000
Epoch 30/200
8/8 [==============================] - 0s 5ms/step - loss: 329796480.0000 - val_loss: 30
4327168.0000
Epoch 31/200
8/8 [==============================] - 0s 5ms/step - loss: 329734624.0000 - val_loss: 30
4264864.0000
Epoch 32/200
8/8 [==============================] - 0s 5ms/step - loss: 329666400.0000 - val_loss: 30
4196128.0000
Epoch 33/200
8/8 [==============================] - 0s 6ms/step - loss: 329591584.0000 - val_loss: 30
4119712.0000
Epoch 34/200
8/8 [==============================] - 0s 5ms/step - loss: 329508608.0000 - val_loss: 30
4035232.0000
Epoch 35/200
8/8 [==============================] - 0s 5ms/step - loss: 329415840.0000 - val_loss: 30
3944608.0000
Epoch 36/200
8/8 [==============================] - 0s 5ms/step - loss: 329316224.0000 - val_loss: 30
3844672.0000
Epoch 37/200
8/8 [==============================] - 0s 6ms/step - loss: 329209152.0000 - val_loss: 30
3733024.0000
Epoch 38/200
8/8 [==============================] - 0s 5ms/step - loss: 329087680.0000 - val_loss: 30
3614080.0000
Epoch 39/200
8/8 [==============================] - 0s 6ms/step - loss: 328959360.0000 - val_loss: 30
3485728.0000
Epoch 40/200
8/8 [==============================] - 0s 5ms/step - loss: 328818848.0000 - val_loss: 30
3344800.0000
Epoch 41/200
8/8 [==============================] - 0s 5ms/step - loss: 328665568.0000 - val_loss: 30
3189984.0000
Epoch 42/200
8/8 [==============================] - 0s 6ms/step - loss: 328499040.0000 - val_loss: 30
3022080.0000
Epoch 43/200
8/8 [==============================] - 0s 5ms/step - loss: 328316512.0000 - val_loss: 30
2840992.0000
Epoch 44/200
8/8 [==============================] - 0s 5ms/step - loss: 328120832.0000 - val_loss: 30
2644320.0000
Epoch 45/200
8/8 [==============================] - 0s 5ms/step - loss: 327906112.0000 - val_loss: 30
2434144.0000
Epoch 46/200
8/8 [==============================] - 0s 6ms/step - loss: 327677024.0000 - val_loss: 30
2209632.0000
Epoch 47/200
8/8 [==============================] - 0s 5ms/step - loss: 327439040.0000 - val_loss: 30
1962656.0000
Epoch 48/200
8/8 [==============================] - 0s 6ms/step - loss: 327171968.0000 - val_loss: 30
1703360.0000
Epoch 49/200
8/8 [==============================] - 0s 5ms/step - loss: 326889728.0000 - val_loss: 30
1420192.0000
Epoch 50/200
8/8 [==============================] - 0s 5ms/step - loss: 326579168.0000 - val_loss: 30
1118400.0000
```

```
Epoch 51/200
8/8 [==============================] - 0s 5ms/step - loss: 326250240.0000 - val_loss: 30
0789728.0000
Epoch 52/200
8/8 [==============================] - 0s 5ms/step - loss: 325899072.0000 - val_loss: 30
0439296.0000
Epoch 53/200
8/8 [==============================] - 0s 5ms/step - loss: 325521344.0000 - val_loss: 30
0065728.0000
Epoch 54/200
8/8 [==============================] - 0s 6ms/step - loss: 325115200.0000 - val_loss: 29
9665888.0000
Epoch 55/200
8/8 [==============================] - 0s 5ms/step - loss: 324687424.0000 - val_loss: 29
9235936.0000
Epoch 56/200
8/8 [==============================] - 0s 5ms/step - loss: 324220160.0000 - val_loss: 29
8785696.0000
Epoch 57/200
8/8 [==============================] - 0s 5ms/step - loss: 323732672.0000 - val_loss: 29
8296736.0000
Epoch 58/200
8/8 [==============================] - 0s 5ms/step - loss: 323213824.0000 - val_loss: 29
7773984.0000
Epoch 59/200
8/8 [==============================] - 0s 5ms/step - loss: 322649536.0000 - val_loss: 29
7225088.0000
Epoch 60/200
8/8 [==============================] - 0s 5ms/step - loss: 322055456.0000 - val_loss: 29
6645472.0000
Epoch 61/200
8/8 [==============================] - 0s 6ms/step - loss: 321435680.0000 - val_loss: 29
6032416.0000
Epoch 62/200
8/8 [==============================] - 0s 5ms/step - loss: 320770208.0000 - val_loss: 29
5393792.0000
Epoch 63/200
8/8 [==============================] - 0s 6ms/step - loss: 320083872.0000 - val_loss: 29
4710080.0000
Epoch 64/200
8/8 [==============================] - 0s 5ms/step - loss: 319358624.0000 - val_loss: 29
3990176.0000
Epoch 65/200
8/8 [==============================] - 0s 5ms/step - loss: 318585088.0000 - val_loss: 29
3234560.0000
Epoch 66/200
8/8 [==============================] - 0s 5ms/step - loss: 317767648.0000 - val_loss: 29
2435232.0000
Epoch 67/200
8/8 [==============================] - 0s 6ms/step - loss: 316899808.0000 - val_loss: 29
1597120.0000
Epoch 68/200
8/8 [==============================] - 0s 6ms/step - loss: 316015552.0000 - val_loss: 29
0709120.0000
Epoch 69/200
8/8 [==============================] - 0s 6ms/step - loss: 315058080.0000 - val_loss: 28
9795808.0000
Epoch 70/200
8/8 [==============================] - 0s 5ms/step - loss: 314070432.0000 - val_loss: 28
8839584.0000
Epoch 71/200
8/8 [==============================] - 0s 5ms/step - loss: 313036704.0000 - val_loss: 28
7809920.0000
Epoch 72/200
8/8 [==============================] - 0s 5ms/step - loss: 311937824.0000 - val_loss: 28
6747072.0000
```

```
Epoch 73/200
8/8 [==============================] - 0s 6ms/step - loss: 310795872.0000 - val_loss: 28
5627904.0000
Epoch 74/200
8/8 [==============================] - 0s 6ms/step - loss: 309585440.0000 - val_loss: 28
4460192.0000
Epoch 75/200
8/8 [==============================] - 0s 5ms/step - loss: 308319776.0000 - val_loss: 28
3232128.0000
Epoch 76/200
8/8 [==============================] - 0s 6ms/step - loss: 307025056.0000 - val_loss: 28
1938880.0000
Epoch 77/200
8/8 [==============================] - 0s 5ms/step - loss: 305631008.0000 - val_loss: 28
0591776.0000
Epoch 78/200
8/8 [==============================] - 0s 5ms/step - loss: 304180512.0000 - val_loss: 27
9223008.0000
Epoch 79/200
8/8 [==============================] - 0s 6ms/step - loss: 302724640.0000 - val_loss: 27
7766624.0000
Epoch 80/200
8/8 [==============================] - 0s 5ms/step - loss: 301149120.0000 - val_loss: 27
6254528.0000
Epoch 81/200
8/8 [==============================] - 0s 5ms/step - loss: 299523680.0000 - val_loss: 27
4680384.0000
Epoch 82/200
8/8 [==============================] - 0s 5ms/step - loss: 297861184.0000 - val_loss: 27
3039232.0000
Epoch 83/200
8/8 [==============================] - 0s 5ms/step - loss: 296081152.0000 - val_loss: 27
1367776.0000
Epoch 84/200
8/8 [==============================] - 0s 6ms/step - loss: 294294592.0000 - val_loss: 26
9617856.0000
Epoch 85/200
8/8 [==============================] - 0s 5ms/step - loss: 292445984.0000 - val_loss: 26
7800528.0000
Epoch 86/200
8/8 [==============================] - 0s 5ms/step - loss: 290488128.0000 - val_loss: 26
5966544.0000
Epoch 87/200
8/8 [==============================] - 0s 5ms/step - loss: 288521472.0000 - val_loss: 26
4059648.0000
Epoch 88/200
8/8 [==============================] - 0s 5ms/step - loss: 286488608.0000 - val_loss: 26
2092176.0000
Epoch 89/200
8/8 [==============================] - 0s 5ms/step - loss: 284382784.0000 - val_loss: 26
0069584.0000
Epoch 90/200
8/8 [==============================] - 0s 5ms/step - loss: 282212224.0000 - val_loss: 25
7944992.0000
Epoch 91/200
8/8 [==============================] - 0s 5ms/step - loss: 279915360.0000 - val_loss: 25
5798272.0000
Epoch 92/200
8/8 [==============================] - 0s 5ms/step - loss: 277639520.0000 - val_loss: 25
3559808.0000
Epoch 93/200
8/8 [==============================] - 0s 5ms/step - loss: 275260192.0000 - val_loss: 25
1277440.0000
Epoch 94/200
8/8 [==============================] - 0s 5ms/step - loss: 272798464.0000 - val_loss: 24
8948304.0000
```

```
Epoch 95/200
8/8 [==============================] - 0s 6ms/step - loss: 270327456.0000 - val_loss: 24
6565136.0000
Epoch 96/200
8/8 [==============================] - 0s 5ms/step - loss: 267748112.0000 - val_loss: 24
4164720.0000
Epoch 97/200
8/8 [==============================] - 0s 6ms/step - loss: 265148912.0000 - val_loss: 24
1673552.0000
Epoch 98/200
8/8 [==============================] - 0s 5ms/step - loss: 262512048.0000 - val_loss: 23
9098064.0000
Epoch 99/200
8/8 [==============================] - 0s 5ms/step - loss: 259764592.0000 - val_loss: 23
6464688.0000
Epoch 100/200
8/8 [==============================] - 0s 5ms/step - loss: 256917632.0000 - val_loss: 23
3810208.0000
Epoch 101/200
8/8 [==============================] - 0s 6ms/step - loss: 254056512.0000 - val_loss: 23
1098608.0000
Epoch 102/200
8/8 [==============================] - 0s 5ms/step - loss: 251203184.0000 - val_loss: 22
8311344.0000
Epoch 103/200
8/8 [==============================] - 0s 5ms/step - loss: 248242592.0000 - val_loss: 22
5513168.0000
Epoch 104/200
8/8 [==============================] - 0s 5ms/step - loss: 245232368.0000 - val_loss: 22
2697744.0000
Epoch 105/200
8/8 [==============================] - 0s 6ms/step - loss: 242231296.0000 - val_loss: 21
9845936.0000
Epoch 106/200
8/8 [==============================] - 0s 6ms/step - loss: 239105680.0000 - val_loss: 21
6963104.0000
Epoch 107/200
8/8 [==============================] - 0s 6ms/step - loss: 236026304.0000 - val_loss: 21
3964896.0000
Epoch 108/200
8/8 [==============================] - 0s 7ms/step - loss: 232770432.0000 - val_loss: 21
0985536.0000
Epoch 109/200
8/8 [==============================] - 0s 6ms/step - loss: 229587808.0000 - val_loss: 20
7989440.0000
Epoch 110/200
8/8 [==============================] - 0s 6ms/step - loss: 226371872.0000 - val_loss: 20
4983056.0000
Epoch 111/200
8/8 [==============================] - 0s 5ms/step - loss: 223194928.0000 - val_loss: 20
1946528.0000
Epoch 112/200
8/8 [==============================] - 0s 5ms/step - loss: 219880224.0000 - val_loss: 19
8891392.0000
Epoch 113/200
8/8 [==============================] - 0s 5ms/step - loss: 216632496.0000 - val_loss: 19
5805184.0000
Epoch 114/200
8/8 [==============================] - 0s 5ms/step - loss: 213312976.0000 - val_loss: 19
2766272.0000
Epoch 115/200
8/8 [==============================] - 0s 6ms/step - loss: 209990624.0000 - val_loss: 18
9713168.0000
Epoch 116/200
8/8 [==============================] - 0s 6ms/step - loss: 206757776.0000 - val_loss: 18
6703152.0000
```

```
Epoch 117/200
8/8 [==============================] - 0s 5ms/step - loss: 203505328.0000 - val_loss: 18
3720704.0000
Epoch 118/200
8/8 [==============================] - 0s 5ms/step - loss: 200259712.0000 - val_loss: 18
0706640.0000
Epoch 119/200
8/8 [==============================] - 0s 6ms/step - loss: 197033136.0000 - val_loss: 17
7694544.0000
Epoch 120/200
8/8 [==============================] - 0s 6ms/step - loss: 193808768.0000 - val_loss: 17
4745920.0000
Epoch 121/200
8/8 [==============================] - 0s 5ms/step - loss: 190640912.0000 - val_loss: 17
1853792.0000
Epoch 122/200
8/8 [==============================] - 0s 5ms/step - loss: 187511136.0000 - val_loss: 16
9005328.0000
Epoch 123/200
8/8 [==============================] - 0s 5ms/step - loss: 184387408.0000 - val_loss: 16
6209664.0000
Epoch 124/200
8/8 [==============================] - 0s 6ms/step - loss: 181342736.0000 - val_loss: 16
3477792.0000
Epoch 125/200
8/8 [==============================] - 0s 5ms/step - loss: 178305248.0000 - val_loss: 16
0706768.0000
Epoch 126/200
8/8 [==============================] - 0s 5ms/step - loss: 175344208.0000 - val_loss: 15
7897824.0000
Epoch 127/200
8/8 [==============================] - 0s 5ms/step - loss: 172332496.0000 - val_loss: 15
5214288.0000
Epoch 128/200
8/8 [==============================] - 0s 5ms/step - loss: 169410368.0000 - val_loss: 15
2696864.0000
Epoch 129/200
8/8 [==============================] - 0s 5ms/step - loss: 166717568.0000 - val_loss: 15
0170080.0000
Epoch 130/200
8/8 [==============================] - 0s 6ms/step - loss: 163970544.0000 - val_loss: 14
7814048.0000
Epoch 131/200
8/8 [==============================] - 0s 6ms/step - loss: 161386544.0000 - val_loss: 14
5556736.0000
Epoch 132/200
8/8 [==============================] - 0s 5ms/step - loss: 158896112.0000 - val_loss: 14
3363920.0000
Epoch 133/200
8/8 [==============================] - 0s 5ms/step - loss: 156443584.0000 - val_loss: 14
1200400.0000
Epoch 134/200
8/8 [==============================] - 0s 5ms/step - loss: 154085312.0000 - val_loss: 13
9140320.0000
Epoch 135/200
8/8 [==============================] - 0s 6ms/step - loss: 151781088.0000 - val_loss: 13
7182288.0000
Epoch 136/200
8/8 [==============================] - 0s 6ms/step - loss: 149648928.0000 - val_loss: 13
5281552.0000
Epoch 137/200
8/8 [==============================] - 0s 7ms/step - loss: 147524096.0000 - val_loss: 13
3497760.0000
Epoch 138/200
8/8 [==============================] - 0s 6ms/step - loss: 145537312.0000 - val_loss: 13
1746536.0000
```

```
Epoch 139/200
8/8 [==============================] - 0s 5ms/step - loss: 143599952.0000 - val_loss: 13
0133168.0000
Epoch 140/200
8/8 [==============================] - 0s 5ms/step - loss: 141811728.0000 - val_loss: 12
8591152.0000
Epoch 141/200
8/8 [==============================] - 0s 5ms/step - loss: 140048784.0000 - val_loss: 12
7160960.0000
Epoch 142/200
8/8 [==============================] - 0s 5ms/step - loss: 138423040.0000 - val_loss: 12
5792808.0000
Epoch 143/200
8/8 [==============================] - 0s 6ms/step - loss: 136851744.0000 - val_loss: 12
4493784.0000
Epoch 144/200
8/8 [==============================] - 0s 5ms/step - loss: 135318208.0000 - val_loss: 12
3268736.0000
Epoch 145/200
8/8 [==============================] - 0s 6ms/step - loss: 133943384.0000 - val_loss: 12
2110688.0000
Epoch 146/200
8/8 [==============================] - 0s 5ms/step - loss: 132612696.0000 - val_loss: 12
1073296.0000
Epoch 147/200
8/8 [==============================] - 0s 5ms/step - loss: 131428328.0000 - val_loss: 12
0058232.0000
Epoch 148/200
8/8 [==============================] - 0s 7ms/step - loss: 130220888.0000 - val_loss: 11
9144920.0000
Epoch 149/200
8/8 [==============================] - 0s 6ms/step - loss: 129168648.0000 - val_loss: 11
8273760.0000
Epoch 150/200
8/8 [==============================] - 0s 5ms/step - loss: 128055616.0000 - val_loss: 11
7503744.0000
Epoch 151/200
8/8 [==============================] - 0s 6ms/step - loss: 127207800.0000 - val_loss: 11
6726512.0000
Epoch 152/200
8/8 [==============================] - 0s 6ms/step - loss: 126203520.0000 - val_loss: 11
6061064.0000
Epoch 153/200
8/8 [==============================] - 0s 5ms/step - loss: 125419840.0000 - val_loss: 11
5419024.0000
Epoch 154/200
8/8 [==============================] - 0s 6ms/step - loss: 124660624.0000 - val_loss: 11
4851360.0000
Epoch 155/200
8/8 [==============================] - 0s 5ms/step - loss: 123943192.0000 - val_loss: 11
4314552.0000
Epoch 156/200
8/8 [==============================] - 0s 5ms/step - loss: 123253928.0000 - val_loss: 11
3805160.0000
Epoch 157/200
8/8 [==============================] - 0s 5ms/step - loss: 122593752.0000 - val_loss: 11
3356736.0000
Epoch 158/200
8/8 [==============================] - 0s 5ms/step - loss: 122004856.0000 - val_loss: 11
2923888.0000
Epoch 159/200
8/8 [==============================] - 0s 6ms/step - loss: 121451896.0000 - val_loss: 11
2528016.0000
Epoch 160/200
8/8 [==============================] - 0s 6ms/step - loss: 120967568.0000 - val_loss: 11
2145200.0000
```

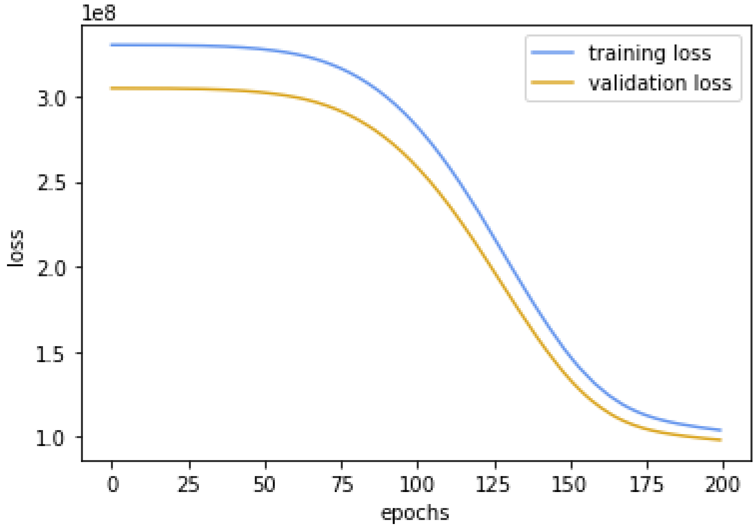
```
Epoch 161/200
8/8 [==============================] - 0s 6ms/step - loss: 120442416.0000 - val_loss: 11
1815856.0000
Epoch 162/200
8/8 [==============================] - 0s 6ms/step - loss: 120012448.0000 - val_loss: 11
1513904.0000
Epoch 163/200
8/8 [==============================] - 0s 5ms/step - loss: 119639520.0000 - val_loss: 11
1223392.0000
Epoch 164/200
8/8 [==============================] - 0s 6ms/step - loss: 119232120.0000 - val_loss: 11
0948200.0000
Epoch 165/200
8/8 [==============================] - 0s 5ms/step - loss: 118856680.0000 - val_loss: 11
0687512.0000
Epoch 166/200
8/8 [==============================] - 0s 6ms/step - loss: 118520984.0000 - val_loss: 11
0449824.0000
Epoch 167/200
8/8 [==============================] - 0s 6ms/step - loss: 118208776.0000 - val_loss: 11
0224408.0000
Epoch 168/200
8/8 [==============================] - 0s 5ms/step - loss: 117897904.0000 - val_loss: 11
0008632.0000
Epoch 169/200
8/8 [==============================] - 0s 5ms/step - loss: 117619560.0000 - val_loss: 10
9789544.0000
Epoch 170/200
8/8 [==============================] - 0s 5ms/step - loss: 117327496.0000 - val_loss: 10
9577432.0000
Epoch 171/200
8/8 [==============================] - 0s 6ms/step - loss: 117055576.0000 - val_loss: 10
9365184.0000
Epoch 172/200
8/8 [==============================] - 0s 5ms/step - loss: 116778560.0000 - val_loss: 10
9162272.0000
Epoch 173/200
8/8 [==============================] - 0s 5ms/step - loss: 116508744.0000 - val_loss: 10
8965752.0000
Epoch 174/200
8/8 [==============================] - 0s 5ms/step - loss: 116254016.0000 - val_loss: 10
8767000.0000
Epoch 175/200
8/8 [==============================] - 0s 5ms/step - loss: 116014848.0000 - val_loss: 10
8572048.0000
Epoch 176/200
8/8 [==============================] - 0s 6ms/step - loss: 115761320.0000 - val_loss: 10
8381384.0000
Epoch 177/200
8/8 [==============================] - 0s 5ms/step - loss: 115518176.0000 - val_loss: 10
8189728.0000
Epoch 178/200
8/8 [==============================] - 0s 6ms/step - loss: 115275368.0000 - val_loss: 10
7999232.0000
Epoch 179/200
8/8 [==============================] - 0s 6ms/step - loss: 115034584.0000 - val_loss: 10
7809936.0000
Epoch 180/200
8/8 [==============================] - 0s 5ms/step - loss: 114794576.0000 - val_loss: 10
7625488.0000
Epoch 181/200
8/8 [==============================] - 0s 6ms/step - loss: 114557464.0000 - val_loss: 10
7440904.0000
Epoch 182/200
8/8 [==============================] - 0s 5ms/step - loss: 114324160.0000 - val_loss: 10
7255256.0000
```

```
Epoch 183/200
8/8 [==============================] - 0s 6ms/step - loss: 114097024.0000 - val_loss: 10
7069240.0000
Epoch 184/200
8/8 [==============================] - 0s 5ms/step - loss: 113873208.0000 - val_loss: 10
6881144.0000
Epoch 185/200
8/8 [==============================] - 0s 5ms/step - loss: 113646064.0000 - val_loss: 10
6696288.0000
Epoch 186/200
8/8 [==============================] - 0s 5ms/step - loss: 113427744.0000 - val_loss: 10
6506832.0000
Epoch 187/200
8/8 [==============================] - 0s 5ms/step - loss: 113195552.0000 - val_loss: 10
6323224.0000
Epoch 188/200
8/8 [==============================] - 0s 6ms/step - loss: 112960624.0000 - val_loss: 10
6136768.0000
Epoch 189/200
8/8 [==============================] - 0s 5ms/step - loss: 112739688.0000 - val_loss: 10
5959912.0000
Epoch 190/200
8/8 [==============================] - 0s 5ms/step - loss: 112502288.0000 - val_loss: 10
5774168.0000
Epoch 191/200
8/8 [==============================] - 0s 5ms/step - loss: 112292832.0000 - val_loss: 10
5589000.0000
Epoch 192/200
8/8 [==============================] - 0s 5ms/step - loss: 112071792.0000 - val_loss: 10
5400360.0000
Epoch 193/200
8/8 [==============================] - 0s 5ms/step - loss: 111858256.0000 - val_loss: 10
5213608.0000
Epoch 194/200
8/8 [==============================] - 0s 5ms/step - loss: 111644384.0000 - val_loss: 10
5029776.0000
Epoch 195/200
8/8 [==============================] - 0s 5ms/step - loss: 111428416.0000 - val_loss: 10
4838088.0000
Epoch 196/200
8/8 [==============================] - 0s 5ms/step - loss: 111207208.0000 - val_loss: 10
4651272.0000
Epoch 197/200
8/8 [==============================] - 0s 5ms/step - loss: 110993416.0000 - val_loss: 10
4460696.0000
Epoch 198/200
8/8 [==============================] - 0s 5ms/step - loss: 110782824.0000 - val_loss: 10
4266504.0000
Epoch 199/200
8/8 [==============================] - 0s 5ms/step - loss: 110577640.0000 - val_loss: 10
4074296.0000
Epoch 200/200
8/8 [==============================] - 0s 5ms/step - loss: 110366136.0000 - val_loss: 10
3877304.0000
```

In [79]:

```python
# Se analizeaza pe grafic training loss-ul si validation loss-ul

plt.plot(history.history['loss'], c='cornflowerblue', label='training loss')
plt.plot(history.history['val_loss'], c='goldenrod', label='validation loss')
plt.legend()
plt.xlabel('epochs')
plt.ylabel('loss');
```

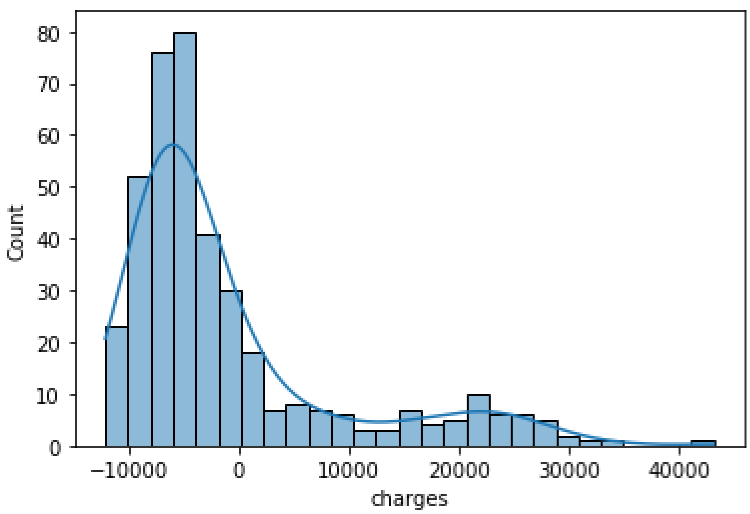


In [57]:
```
# Calcularea si afisarea valorilor RMSE, MAE, MSLE
from sklearn.metrics import mean_squared_log_error
y_pred = model.predict(X_test).reshape((-1, ))
mae = mean_absolute_error(y_test, y_pred)
rmse = np.sqrt(mean_squared_error(y_test, y_pred))
msle = mean_squared_log_error(y_test, y_pred)
print(f'RMSE: {rmse} - MAE: {mae} - MSLE: {msle}')
```

```
13/13 [==============================] - 0s 1ms/step
RMSE: 10192.021681607994 - MAE: 7857.906569790888 - MSLE: 0.7486421148908423
```

In [58]:
```
# Se calculeaza vectorul de valori reziduale (valori reale - predictii)
errors = y_test - y_pred

# Histograma cu estimarea densitatii acestor erori.
sns.histplot(x=errors, kde=True);
```



In [ ]: