- YZUP Ara Proje-4.
 - SOURCE CODE ==> = https://github.com/ilkerCoder/Pyspark-Predict-housing.csv/blob/main/house-pricing.ipynb

```
In [ ]: import pyspark
In [ ]: #PySpark 1 import etmek ve and pyspark1 kullanabilmek icin sparksession ' u baslatma
       from pyspark.sql import SparkSession
       spark=SparkSession.builder.appName("DatawithPySpark").getOrCreate()
In [ ]: """ SİMDİ SPARK CALISIYOR ,VERI KONUMUNU VE DIGER DETAYLARI BELIRTEBILIRIZ: """
       file location = "./housing.csv"
       file_type = "csv"
       #inferSchema seçeneğine True değeri verildiğinde, Spark, veri kümesindeki değerlerin veri
       #tiplerini otomatik olarak çıkarmaya çalışır.
       infer_schema = "true"
       first_row_is header = "true"
       delimiter = ","
In [ ]: """
       spark.read.format() yöntemi kullanılıyor. Bu yöntem, belirtilen dosya türüne göre uygun bir
       okuma biçimi sağlar (örneğin: CSV, JSON, parquet, metin dosyası vb.).
       df=spark.read.format(file type).option("inferSchema",infer schema).option("header", first row is header).option
In [ ]: """
       VERİLERİMİZİ TABULAR DATA OLARAK GOREBİLMEK İCİN. İLK 5 SATIR GOSTERİLİYOR .
       0.00
       df.show(5)
      -----+
      |longitude|latitude|housing_median_age|total_rooms|total_bedrooms|population|households|median_income|median_hou
      se value|ocean_proximity|
      | -122.23| 37.88|
                                  41.0|
                                          880.0|
                                                       129.0|
                                                                 322.0|
                                                                          126.0|
                                                                                      8.32521
      452600.0|
                  NEAR BAY
                                 21.0| 7099.0|
      | -122.22| 37.86|
                                                      1106.0| 2401.0| 1138.0|
                                                                                      8.3014|
                 NEAR BAY
      358500.0|
      | -122.24| 37.85|
                                  52.0| 1467.0|
                                                       190.0|
                                                                 496.0|
                                                                          177.0|
                                                                                      7.2574|
      352100.0|
                 NEAR BAY|
      | -122.25| 37.85|
                                  52.0|
                                         1274.0|
                                                       235.0|
                                                                 558.0|
                                                                          219.0|
                                                                                     5.6431|
      341300.0|
                  NEAR BAY
                                                       280.0|
                                                                  565.0|
                                                                          259.0|
      | -122.25| 37.85|
                                  52.0|
                                          1627.0|
                                                                                      3.84621
      342200.0|
                  NEAR BAY
      ----+
      only showing top 5 rows
In [ ]: """
       BURADA .DTYPES , COLUMNS GİBİ OZELLİKLERİ DE KULLANABİLİRDİK FAKAT KONUMUZ SPARK OLDUĞU İCİN
       HEP SPARK BU KONULARDA NASIL OZELLESTİRMELER YAPMIS ONU ARASTIRIP BUNU GOSTERMEK İSTİYORUM.
       O YUZDEN PREPROCESSİNG ONCESİ PRİNTSCHEMA İLE BİR VERİ CSV KEŞFİNE DEVAM EDELİM .
       df.printSchema()
       |-- longitude: double (nullable = true)
       |-- latitude: double (nullable = true)
       |-- housing_median_age: double (nullable = true)
       |-- total rooms: double (nullable = true)
       |-- total_bedrooms: double (nullable = true)
       |-- population: double (nullable = true)
       |-- households: double (nullable = true)
       |-- median_income: double (nullable = true)
       |-- median_house_value: double (nullable = true)
       |-- ocean_proximity: string (nullable = true)
In [ ]: print("TOPLAM COLUMN SAYISI ==>" , len(df.columns))
print("TOPLAM KAYIT SAYISI ==>" , df.count())
       df.describe().show()
```

```
TOPLAM COLUMN SAYISI ==> 10
      TOPLAM KAYIT SAYISI ==> 20640
                 longitude| latitude|housing_median_age| total_rooms| total_bedrooms|
households| median_income|median_house_value|ocean_proximity|
      |summarv|
      population|
      20640 | 20640 | 20640 |
20640 | 20640 | 20640 | 20640 |
      | count|
                                                                        20640|
                                                                                        204331
      20640|
        mean | -119.56970445736148 | 35.6318614341087 | 28.639486434108527 | 2635.7630813953488 | 537.8705525375618 | 1425.476
      7441860465|499.5396802325581|3.8706710029070246|206855.81690891474| NULL|
      | stddev| 2.003531723502584|2.135952397457101| 12.58555761211163|2181.6152515827944|421.38507007403115| 1132.4
      6212176534|382.3297528316098| 1.899821717945263|115395.61587441359| NULL|
         min| -124.35| 32.54| 1.0| 2.0|
| 1.0| 0.4999| 14999.0| <1H OCEAN|
| max| -114.31| 41.95| 52.0| 39320.0|
32.0| 6082.0| 15.0001| 500001.0| NEAR OCEAN|
                                                                                      6445.01
      35682.0|
In [ ]: # ARTIK VERİ İSLEMEYE BASLAYABİLİRİZ . ONCE DUPLİCATE DEGERLERİ SİLEREK BASLAYALIM :
       df.count()
       df=df.dropDuplicates()
       df.count()
Out[]: 20640
In []: #BURADA TAHMİN EDİLMEK İSTENEN DEGER(label) MEDIAN HOUSE VALUE OLDUĞU İCİN YENIDEN ADLANIRALIM:
       df=df.withColumnRenamed('median_house_value','label')
       print(df.show(3))
       #LINEAR REGRESSION YAPACAGIMIZ ICIN BIR KORELASYON ANALIZI YAPALIM :
       from pyspark.sql.functions import corr
       correlations = []
       for col in df.columns:
          #OCEAN_PROX. STRING OLDUGU İCİN O VE label HARİC DİGER SUTUNLARIN KORELASYONLARINI ALALIM
          if col != 'label' and col != "ocean_proximity": # 'label' sütunu hariç
             correlation = df.stat.corr(col, 'label')
             correlations.append((col, correlation))
       correlations
       #EN GUCLU KORELASYON MEDİAN İNCOME , TOTAL ROOMS , HOUSİNG MEDİAN AGE OLARAK GİDİYOR.
      |longitude|latitude|housing_median_age|total_rooms|total_bedrooms|population|households|median_income| label|o
      cean_proximity|
                    +----
      ----+
      | -122.28| 37.81|
                                52.0| 340.0|
                                                       97.0| 200.0| 87.0|
                                                                                    1.5208|112500.0|
      NEAR BAY|
      | -122.13| 37.67|
                                 40.0| 1748.0|
                                                       318.0| 914.0| 317.0|
                                                                                     3.8676|184000.0|
      NEAR BAY|
      | -122.07| 37.67|
                                 27.0|
                                         3239.0|
                                                       671.0| 1469.0| 616.0|
                                                                                     3.2465|230600.0|
      NEAR BAY|
      only showing top 3 rows
('housing median age', 0.10562341249320963),
        ('total\_rooms', 0.13415311380656358),
        ('total_bedrooms', 0.049148219599425405),
        ('population', -0.024649678888894945),
        ('households', 0.06584265057005599),
        ('median_income', 0.6880752079585519)]
In []: #PYSPARK DA PANDAS OZELLİKLERİNİ KULLANABİLMEK İCİN PYSPARK DAKİ TOPANDAS OZELLİĞİNİ KULLANALIM.
       import pandas as pd
       pandas df = df.toPandas()
       print("TOPLAM NULL DEGERLER ----- \n" , pandas df.isnull().sum())
       #ORTALAMA DEGER ILE DOLDURACAGIZ . FONKSİYONUMUZU EKLEYELİM
       from pyspark.sql.functions import mean
       # TOTAL BEDROOMS ORTALAMA DEGERINI BUL
       mean_value = df.select(mean(df["total_bedrooms"])).collect()[0][0]
```

```
# ORTALAMA DEGERLE DOLDUR
        df_filled = df.fillna(mean_value, subset=["total_bedrooms"])
       TOPLAM NULL DEGERLER -----
        longitude
       latitude
                                 0
       housing_median_age
       total_rooms
                                 0
       total bedrooms
                               207
       population
                                0
       households
                                 0
       median income
                                0
       label
                                 0
       ocean proximity
                                0
       dtype: int64
In [ ]: # BIR TANE KATEGORİK DEGİSKENIMIZ VAR(OCEAN_PROXİMİTY). BU ATTRİBUTE ORDİNAL OLMADIGI İCİN
        # ONE HOT ENCODING YAPALIM :
        print(df_filled.show(5))
        from pyspark.ml.feature import OneHotEncoder , StandardScaler , StringIndexer , VectorAssembler
        from pyspark.ml import Pipeline
        # Pyspark OneHotEncoder STRING DEGERLERLE ISLEM YAPAMADIGI ICIN ONCE INDEXER ILE SAYISAL
        #DEGERLERE DONUSTURUP DAHA SONRA ONE HOT ENCODING YAPACAGIZ
        indexer = StringIndexer(inputCol="ocean_proximity", outputCol="ocean_proximity_index")
encoder = OneHotEncoder(inputCol="ocean_proximity_index", outputCol="ocean_proximity_encoded")
        pipeline = Pipeline(stages=[indexer, encoder])
        # Pipeline'ı veri üzerinde uygulama
        model = pipeline.fit(df_filled)
        encoded df = model.transform(df filled)
        encoded_df = encoded_df.drop("ocean_proximity" , "ocean_proximity_index")
        # Sonuçları gösterme
        encoded_df.show()
```

```
|longitude|latitude|housing median age|total rooms|total bedrooms|population|households|median income| label|o
      cean_proximity|
      | -122.28| 37.81|
                                       52.0|
                                                 340.0|
                                                                97.0|
                                                                          200.0|
                                                                                     87.0|
                                                                                                 1.5208|112500.0|
      NEAR BAY
      | -122.13|
                   37.67|
                                       40.0|
                                                1748.0|
                                                               318.0|
                                                                          914.0|
                                                                                    317.0|
                                                                                                 3.8676|184000.0|
      NEAR BAY
      | -122.07|
                   37.67
                                       27.0|
                                                3239.0|
                                                               671.0|
                                                                         1469.0|
                                                                                    616.0|
                                                                                                 3.2465 | 230600.0 |
      NEAR BAY
      | -122.13|
                   37.66|
                                       19.0|
                                                 862.0|
                                                               167.0|
                                                                          407.0|
                                                                                    183.0|
                                                                                                 4.3456|163000.0|
      NEAR BAY|
      | -121.85|
                   39.73|
                                       52.0|
                                                 444.0|
                                                                80.0|
                                                                         1107.0|
                                                                                     98.0|
                                                                                                 3.4191|137500.0|
      INLANDI
                  ----+
      only showing top 5 rows
      None
       |longitude|latitude|housing_median_age|total_rooms|total_bedrooms|population|households|median_income| label|o
      cean proximity encoded|
                                | -122.28| 37.81|
                                       52.0|
                                                 340.0|
                                                                97.01
                                                                          200.01
                                                                                     87.0|
                                                                                                 1.5208|112500.0|
      (4,[3],[1.0])|
                   37.67|
       | -122.13|
                                       40.01
                                                1748.01
                                                               318.01
                                                                          914.01
                                                                                    317.01
                                                                                                 3.8676|184000.0|
       (4,[3],[1.0])|
                   37.67|
                                       27.0|
                                                                                                 3.2465 | 230600.0 |
                                                3239.01
                                                               671.01
                                                                         1469.01
                                                                                    616.01
       | -122.07|
       (4,[3],[1.0])|
                   37.661
                                       19.01
                                                 862.0|
                                                               167.01
                                                                          407.01
                                                                                    183.01
                                                                                                 4.3456 | 163000.0 |
         -122.13|
      (4,[3],[1.0])|
                   39.73|
                                                 444.0|
                                                                                                 3.4191|137500.0|
         -121.85|
                                       52.0|
                                                                80.01
                                                                         1107.0|
                                                                                     98.0|
      (4,[1],[1.0])|
                    38.01
                                                               570.01
                                                                         1806.01
                                                                                                 4.2647 | 133400.0 |
       | -121.85|
                                       26.0|
                                                3364.01
                                                                                    566.01
       (4,[1],[1.0])|
                   37.991
                                       15.0|
                                                                         1051.0|
                                                                                                 4.9783 | 163900.0 |
       | -121.87|
                                                2203.0
                                                               312.0|
                                                                                    311.0|
       (4,[1],[1.0])|
                   38.93|
                                                                                                 2.6607| 90400.0|
         -119.98|
                                       25.01
                                                1262.01
                                                               293.01
                                                                          534.01
                                                                                    226.01
       (4,[1],[1.0])|
                   36.761
                                                                                                 1.7344| 51300.0|
         -119.781
                                       47.01
                                                1425.0|
                                                               323.0|
                                                                          949.0|
                                                                                    325.0|
       (4,[1],[1.0])|
                   36.57|
                                                                                                 2.5556| 69700.0|
          -119.61
                                       42.01
                                                2311.01
                                                               439.01
                                                                         1347.01
                                                                                    436.01
       (4,[1],[1.0])|
                    40.85|
                                       31.0|
                                                                         1005.0|
                                                                                                 3.5156|143000.0|
       l -124.05l
                                                2414.01
                                                               428.01
                                                                                    401.01
       (4,[2],[1.0])|
                                                                                                 2.1038 | 62000.0|
         -119.77|
                    36.31
                                       24.01
                                                2202.0|
                                                               471.01
                                                                         1052.01
                                                                                    439.01
       (4,[1],[1.0])|
                   38.76|
                                                                                                 2.3125 | 67900.0 |
         -122.681
                                       29.01
                                                 994.0|
                                                               226.01
                                                                          302.01
                                                                                    117.01
       (4,[1],[1.0])|
                   34.16|
                                       45.0|
                                                               335.0|
                                                                                                 5.1423|322900.0|
       I -118.36I
                                                1755.01
                                                                          822.01
                                                                                    342.01
      (4,[0],[1.0])|
       | -118.35|
                   34.09|
                                       47.0|
                                                1800.0|
                                                               546.0|
                                                                          921.0|
                                                                                    478.0|
                                                                                                 2.8021|280600.0|
       (4,[0],[1.0])|
         -118.19|
                   34.08|
                                       35.0|
                                                1554.0|
                                                               381.0|
                                                                         1487.0|
                                                                                    374.0|
                                                                                                 1.9038|139500.0|
      (4,[0],[1.0])|
         -118.33|
                   34.03|
                                       46.0|
                                                2312.0|
                                                               625.0|
                                                                         1552.0|
                                                                                    603.0|
                                                                                                 1.6429|125000.0|
       (4,[0],[1.0])|
         -118.31|
                   34.02|
                                       46.0|
                                                1976.0|
                                                               469.0|
                                                                         1409.0|
                                                                                    431.0|
                                                                                                 2.2981|112100.0|
       (4,[0],[1.0])|
       | -118.25|
                   34.011
                                       45.0|
                                                 782.0|
                                                               270.0|
                                                                         1030.0|
                                                                                    235.0|
                                                                                                 1.0898 | 93400.0 |
       (4,[0],[1.0])
         -118.28|
                   33.97|
                                       31.0|
                                                2017.0|
                                                               566.0|
                                                                         2063.0|
                                                                                    521.0|
                                                                                                 1.9219|107000.0|
       (4,[0],[1.0])|
      +----
       -----+
      only showing top 20 rows
In [ ]: train_df, test_df = encoded_df.randomSplit([.75, .25] , seed=100)
```

```
features = ["longitude" ,"latitude" , "housing_median_age", "total_rooms" ,"total_bedrooms", "population" , "housing_median_age", "total_rooms" ,"total_bedrooms", "population" , "housing_median_age", "total_rooms" ,"total_bedrooms", "population" , "housing_median_age", "total_rooms" ,"total_bedrooms", "population" , "housing_median_age", "total_rooms" ,"total_bedrooms", "population" , "housing_median_age", "total_rooms" ,"total_bedrooms", "population" , "housing_median_age", "total_rooms" ,"total_bedrooms", "population" , "housing_median_age", "total_rooms" ,"total_bedrooms", "population" , "housing_median_age", "total_rooms" ,"total_bedrooms", "population" , "housing_median_age", "total_rooms" ,"total_bedrooms", "population" , "housing_median_age", "total_rooms" ,"total_bedrooms", "population" , "housing_median_age", "total_rooms" ,"total_bedrooms", "population" , "housing_median_age", "total_rooms" ,"total_bedrooms", "population" , "housing_median_age", "total_rooms" ,"total_bedrooms", "population" , "housing_median_age", "total_rooms" ,"total_bedrooms", "population" , "housing_median_age", "total_rooms" ,"total_bedrooms", "population" , "housing_median_age", "total_rooms" ,"total_bedrooms", "population" , "housing_median_age", "total_rooms" ,"total_bedrooms", "population" ,"housing_median_age", "total_rooms", "total_bedrooms", "total_bedrooms", "population" ,"housing_median_age", "total_rooms", "total_bedrooms", "total_bedrooms", "total_bedrooms", "total_bedrooms", "total_bedrooms", "total_bedrooms", "total_bedrooms", "total_rooms", "total_bedrooms", "total_rooms", "total_rooms", "total_rooms", "total_rooms", "total_rooms", "total_rooms", "total_rooms", "total_rooms", "total_rooms", "total_rooms", "total_rooms", "total_rooms", "total_rooms", "total_rooms", "total_rooms", "total_rooms", "total_rooms", "total_rooms", "total_rooms", "total_rooms", "total_rooms", "total_rooms", "total_rooms", "total_rooms", "total_rooms", "total_rooms", "total_rooms", "total_rooms", "total_rooms", "total_rooms", "total_rooms", "
```

```
stages = [stage 1, stage 2, stage 3]
  pipeline = Pipeline(stages=stages)
  model = pipeline.fit(train_df)
  pred result= model.transform(test df)
  pred result.show(5)
.-----+
|longitude| latitude| housing\_median\_age| total\_rooms| total\_bedrooms| population| households| median\_income| label| occupant of the longitude and the longitude and the longitude and the longitude and the longitude and the longitude and the longitude and the longitude and the longitude and the longitude and the longitude and the longitude and the longitude and the longitude and the longitude and the longitude and the longitude and the longitude and the longitude and the longitude and the longitude and the longitude and the longitude and the longitude and the longitude and the longitude and the longitude and the longitude and the longitude and the longitude and the longitude and the longitude and the longitude and the longitude and the longitude and the longitude and the longitude and the longitude and the longitude and the longitude and the longitude and the longitude and the longitude and the longitude and the longitude and the longitude and the longitude and the longitude and the longitude and the longitude and the longitude and the longitude and the longitude and the longitude and the longitude and the longitude and the longitude and the longitude and the longitude and the longitude and the longitude and the longitude and the longitude and the longitude and the longitude and the longitude and the longitude and the longitude and the longitude and the longitude and the longitude and the longitude and the longitude and the longitude and the longitude and the longitude and the longitude and the longitude and the longitude and the longitude and the longitude and the longitude and the longitude and the longitude and the longitude and the longitude and the longitude and the longitude and the longitude and the longitude and the longitude and the longitude and the longitude and the longitude and the longitude and the longitude and the longitude and the longitude and the longitude and the longitude and the longitude and the longitude and the longitude and the longitude and the longitude and the longitude and the lon
ean proximity encoded | out features | features | prediction |
-----+
                                        36.0| 2349.0| 528.0| 1194.0| 465.0|
| -124.27| 40.69|
                                                                                                                                                          2.5179|79000.0|
(4,[2],[1.0])|[-124.27,40.69,36...|[-62.004759084060...|197851.07491546567|
    -124.21| 40.75|
                                                     32.0| 1218.0| 331.0| 620.0| 268.0|
                                                                                                                                                          1.6528|58100.0|
(4,[2],[1.0])|[-124.21,40.75,32...|[-61.974821966935...|156920.35540752695|
                                                     20.0| 3810.0| 787.0| 1993.0|
                                                                                                                                 721.0|
                                                                                                                                                          2.0074|66900.0|
    -124.21| 41.75|
(4,[2],[1.0])|[-124.21,41.75,20...|[-61.974821966935...|149568.51469413703|
                                                                                                                                    583.0|
| -124.19| 40.77|
                                                     30.0| 2975.0| 634.0| 1367.0|
                                                                                                                                                            2.442|69000.0|
(4,[2],[1.0])|[-124.19,40.77,30...|[-61.964842927894...|194327.39536100044|
| -124.18| 40.78| 37.0| 1453.0| 293.0| 867.0|
                                                                                                                                    310.0| 2.5536|70200.0|
(4,[2],[1.0])|[-124.18,40.78,37...|[-61.959853408373...| 185712.5337922892|
-----+
only showing top 5 rows
```

ARTIK TEST DATAMIZDA PREDİCTİON SÜTUNU MEVCUT, DOLAYISIYLA EVALUATE EDEBILIRIZ LINEAR REGRESYON MODELİ R2 VE RMSE 'Yİ KULLANIYOR

```
In []: from pyspark.ml.evaluation import RegressionEvaluator
    regeval = RegressionEvaluator(labelCol="label",
    predictionCol="prediction", metricName="rmse")
    acc = regeval.evaluate(pred_result, {regeval.metricName: "r2"})
    print(acc)
    rmse = regeval.evaluate(pred_result)
    print(rmse)
```

0.6394263010189293 68925.24178667089

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