

```
# File location and type
file_location = "/FileStore/tables/exportcol.csv"
file_type = "csv"

# CSV options
infer_schema = "true"
first_row_is_header = "true"
delimiter = ","

# The applied options are for CSV files. For other file types, these will be ignored.
df = spark.read.format(file_type) \
    .option("inferSchema", infer_schema) \
    .option("header", first_row_is_header) \
    .option("sep", delimiter) \
    .load(file_location)

display(df)
```

product_id	product_description_lenght	product_photos_qty	product_weight_g	product_length_cm
6782d593f63105318f46bbf7633279bf	487	1	200	16
e95ee6822b66ac6058e2e4aff656071a	1153	1	180	17
e9a69340883a438c3f91739d14d3a56d	1912	5	3000	33
036734b5a58d5d4f46b0616ddc047ced	751	5	300	17
b1434a8f79cb3528540d9b21e686e823	184	1	13500	55
d86a6c48f83b045cbba6df84926a1f25	1150	2	3900	45
aa8d88eb4b9cb38894e33fa624c4287f	335	4	250	16
aa6746e94490239d3d9ee6ab89779aba	90	1	500	16
5cc739dd646d1ba52ccc4c2e000a052	800	2	1200	52

Showing the first 1000 rows.



5/3/2019  
# Create a view or table

temp\_table\_name = "linreg\_csv"

df.createOrReplaceTempView(temp\_table\_name)

%sql

/\* Query the created temp table in a SQL cell \*/

**select \* from `linreg\_csv`**

product_id	product_description_lenght	product_photos_qty	product_weight_g	product_length_cm
6782d593f63105318f46bbf7633279bf	487	1	200	16
e95ee6822b66ac6058e2e4aff656071a	1153	1	180	17
e9a69340883a438c3f91739d14d3a56d	1912	5	3000	33
036734b5a58d5d4f46b0616ddc047ced	751	5	300	17
b1434a8f79cb3528540d9b21e686e823	184	1	13500	55
d86a6c48f83b045cbba6df84926a1f25	1150	2	3900	45
aa8d88eb4b9cb38894e33fa624c4287f	335	4	250	16
aa6746e94490239d3d9ee6ab89779aba	90	1	500	16
5cc720dd4646d1be52ccc4e2e000e052	800	2	1200	50

Showing the first 1000 rows.



5/3/2019

Linear Regression - Databricks

```
# With this registered as a temp view, it will only be available to this particular notebook. If you'd like other users to be able to
query this table, you can also create a table from the DataFrame.
# Once saved, this table will persist across cluster restarts as well as allow various users across different notebooks to query this
data.
# To do so, choose your table name and uncomment the bottom line.
```

```
permanent_table_name = "linreg_csv"

# df.write.format("parquet").saveAsTable(permanent_table_name)
```

```
dfLinReg = sqlContext.sql("select product_description_lenght, product_photos_qty, product_weight_g, product_length_cm, product_height_cm,
product_width_cm, freight_value from linreg_csv")
display(dfLinReg)
```

product_description_lenght	product_photos_qty	product_weight_g	product_length_cm	product_height_cm
487	1	200	16	14
1153	1	180	17	11
1912	5	3000	33	12
751	5	300	17	4
184	1	13500	55	25
1150	2	3900	45	33
335	4	250	16	2
90	1	500	16	35
882	2	1200	52	12

Showing the first 1000 rows.



```
dfLinReg = dfLinReg.dropna(how='any')
```

```
from pyspark.sql.types import IntegerType
```

```
dfLinReg1 = dfLinReg.withColumn("freight_value", dfLinReg["freight_value"].cast(IntegerType()))
```

```
from pyspark.ml.regression import LinearRegression
```

```
from pyspark.ml.feature import VectorAssembler
```

```
dfAssemblerFeature = VectorAssembler(  
    inputCols=["product_description_lenght", "product_photos_qty", "product_weight_g", "product_length_cm",  
    "product_height_cm", "product_width_cm"],  
    outputCol="features")
```

```
transformed2 = dfAssemblerFeature.transform(dfLinReg1)
```

```
# dfLinReg.show()
```

```
(training, test) = transformed2.randomSplit([0.8, 0.2])
```

```
# training.show()
```

```
from pyspark.ml.regression import LinearRegression
```

```
lr = LinearRegression( maxIter=10, regParam=0.3, elasticNetParam=0.8, featuresCol="features", labelCol="freight_value")
```

```
# Fit the model
```

```
lrModel = lr.fit(training)
```

```
# Print the coefficients and intercept for linear regression
```

```
print("Coefficients: %s" % str(lrModel.coefficients))
```

```
print("Intercept: %s" % str(lrModel.intercept))
```

5/3/2019 11:04:04 AM  
Coefficients: [0.00107671160962,0.0,0.00230846925771,0.0256164301797,0.0562146962413,0.0123737770178]  
Intercept: 11.899274513653877

```
dfRatingCount = lrModel.transform(test)
dfRatingCount.show(10)
```

product_description_lenght	product_photos_qty	product_weight_g	product_length_cm	product_height_cm	product_width_cm	freight_value	
features	prediction						
23	1	200	16	2	11	15	[23.0,
1.0,200.0,1...	13.044136554769029						
27	1	300	21	11	13	8	[27.0,
1.0,300.0,2...	13.938052298083473						
27	1	300	21	11	13	8	[27.0,
1.0,300.0,2...	13.938052298083473						
27	1	300	21	11	13	15	[27.0,
1.0,300.0,2...	13.938052298083473						
30	1	1400	16	33	18	17	[30.0,
1.0,1400.0,...	17.65110866788902						
30	1	1400	16	33	18	17	[30.0,
1.0,1400.0,...	17.65110866788902						
33	2	400	20	20	20	15	[33.0,
2.0,400.0,2...	14.74229176862804						
35	1	300	16	6	16	7	[35.0,
1.0,300.0,1...	13.574631689909095						
40	1	562	20	13	17	11	[40.0,
1.0,562.0,2...	14.693176564901815						
41	1	150	20	3	18	7	[41.0,
1.0,150.0,2...	13.193390756941028						

only showing top 10 rows

```
# Summarize the model over the training set and print out some metrics
trainingSummary = lrModel.summary
print("RMSE: %f" % trainingSummary.rootMeanSquaredError)
print("r2: %f" % trainingSummary.r2)
```

RMSE: 13.343608

r2: 0.353158

So from the predictions and rsme value we can see that the accuracy of the model is very bad. To increase the predictions of the model further analysis can be done through random forests.