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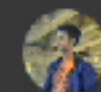
```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import classification_report, confusion_matrix, accuracy_score
```

```
train = pd.read_csv("fraudTrain.csv")
test = pd.read_csv("fraudTest.csv")

data = pd.concat([train, test])
data.describe()
```



	Unnamed: 0	cc_num	amt	zip	lat	long	city_pop	unix_time	merch_lat	merch_long	is_
count	1.852394e+06	1.852394e+06	1.852394e+06	1.852394e+06	1.852394e+06	1.852394e+06	1.852394e+06	1.852394e+06	1.852394e+06	1.852394e+06	1.852394e+06
mean	5.371934e+05	4.173860e+17	7.006357e+01	4.881326e+04	3.853931e+01	-9.022783e+01	8.864367e+04	1.358674e+09	3.853898e+01	-9.022794e+01	5.21001e+00
std	3.669110e+05	1.309115e+18	1.592540e+02	2.688185e+04	5.071470e+00	1.374789e+01	3.014876e+05	1.819508e+07	5.105604e+00	1.375969e+01	7.19921e+00
min	0.000000e+00	6.041621e+10	1.000000e+00	1.257000e+03	2.002710e+01	-1.656723e+02	2.300000e+01	1.325376e+09	1.902742e+01	-1.666716e+02	0.000000e+00
25%	2.315490e+05	1.800429e+14	9.640000e+00	2.623700e+04	3.466890e+01	-9.679800e+01	7.410000e+02	1.343017e+09	3.474012e+01	-9.689944e+01	0.000000e+00
50%	4.630980e+05	3.521417e+15	4.745000e+01	4.817400e+04	3.935430e+01	-8.747690e+01	2.443000e+03	1.357089e+09	3.936890e+01	-8.744069e+01	0.000000e+00
75%	8.335758e+05	4.642255e+15	8.310000e+01	7.204200e+04	4.194040e+01	-8.015800e+01	2.032800e+04	1.374581e+09	4.195626e+01	-8.024511e+01	0.000000e+00



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```
print(train.shape)
print(test.shape)
```

```
(1296675, 23)
(555719, 23)
```

```
[ ] display(data.head())
print(data.describe())
print(data.isnull().sum())
```

	Unnamed: 0	trans_date_trans_time	cc_num	merchant	category	amt	first	last	gender	street	...	lat	long	city
0	0	2019-01-01 00:00:18	2703186189652095	fraud_Rippin, Kub and Mann	misc_net	4.97	Jennifer	Banks	F	561 Perry Cove	...	36.0788	-81.1781	
1	1	2019-01-01 00:00:44	630423337322	fraud_Heller, Gutmann and Zieme	grocery_pos	107.23	Stephanie	Gill	F	43039 Riley Greens Suite 393	...	48.8878	-118.2105	
2	2	2019-01-01 00:00:51	38859492057661	fraud_Lind-Buckridge	entertainment	220.11	Edward	Sanchez	M	594 White Dale Suite 530	...	42.1808	-112.2620	
3	3	2019-01-01 00:01:16	3534003764340340	fraud_Kutch,	grocery_pos	45.00	Jeremy	White	M	9443 Cynthia Court	...	46.2206	-112.1128	



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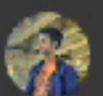


```
city_pop      0
job           0
dob           0
trans_num     0
unix_time     0
merch_lat     0
merch_long    0
is_fraud      0
dtype: int64
```

[] test.info

```
<bound method DataFrame.info of      Unnamed: 0  trans_date_trans_time      cc_num  \
0              0   2020-06-21 12:14:25   2291163933867244
1              1   2020-06-21 12:14:33   3573030041201292
2              2   2020-06-21 12:14:53   3598215285024754
3              3   2020-06-21 12:15:15   3591919803438423
4              4   2020-06-21 12:15:17   3526826139003047
...           ...           ...           ...
555714         555714  2020-12-31 23:59:07   30560609640617
555715         555715  2020-12-31 23:59:09   3556613125071656
555716         555716  2020-12-31 23:59:15   6011724471098086
555717         555717  2020-12-31 23:59:24   4079773899158
555718         555718  2020-12-31 23:59:34   4170689372027579
```

```
      merchant      category  amt  first  \
0  fraud_Kirlin and Sons  personal_care   2.86   Jeff
1  fraud_Sporer-Keebler  personal_care  29.84  Joanne
2  fraud_Swaniawski, Nitzsche and Welch  health_fitness  41.28  Ashley
3  fraud_Haley Group      misc_pos   60.05   Brian
4  fraud_Johnston-Casper      travel    3.19  Nathan
...
```



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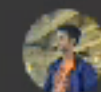


```
555714      519      Town planner  1966-02-13
555715      28739     Futures trader 1999-12-27
555716      3684      Musician      1981-11-29
555717      129       Cartographer  1965-12-15
555718      116001     Media buyer   1993-05-10
```

```
      trans_num  unix_time  merch_lat  merch_long \
0      2da90c7d74bd46a0caf3777415b3ebd3  1371816865  33.986391  -81.200714
1      324cc204407e99f51b0d6ca0055005e7  1371816873  39.450498  -109.960431
2      c81755dbbbea9d5c77f094348a7579be  1371816893  40.495810  -74.196111
3      2159175b9efe66dc301f149d3d5abf8c  1371816915  28.812398  -80.883061
4      57ff021bd3f328f8738bb535c302a31b  1371816917  44.959148  -85.884734
...      ...      ...      ...      ...
555714  9b1f753c79894c9f4b71f04581835ada  1388534347  39.946837  -91.333331
555715  2090647dac2c89a1d86c514c427f5b91  1388534349  29.661049  -96.186633
555716  6c5b7c8add471975aa0fec023b2e8408  1388534355  46.658340  -119.715054
555717  14392d723bb7737606b2700ac791b7aa  1388534364  44.470525  -117.080888
555718  1765bb45b3aa3224b4cdcb6e7a96cee3  1388534374  36.210097  -97.036372
```

```
      is_fraud
0      0
1      0
2      0
3      0
4      0
...      ...
555714      0
555715      0
555716      0
555717      0
555718      0
```

[555719 rows x 23 columns]>



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1296673 fraud_Reinger, Weissnat and Strosin food_dining 74.90



1296674 fraud_Langosh, Wintheiser and Hyatt food_dining 4.30

	first	last	gender	street	...	\
0	Jennifer	Banks	F	561 Perry Cove	...	
1	Stephanie	Gill	F	43039 Riley Greens Suite 393	...	
2	Edward	Sanchez	M	594 White Dale Suite 530	...	
3	Jeremy	White	M	9443 Cynthia Court Apt. 030	...	
4	Tyler	Garcia	M	408 Bradley Rest	...	
...	
1296670	Erik	Patterson	M	162 Jessica Row Apt. 072	...	
1296671	Jeffrey	White	M	8617 Holmes Terrace Suite 651	...	
1296672	Christopher	Castaneda	M	1632 Cohen Drive Suite 639	...	
1296673	Joseph	Murray	M	42933 Ryan Underpass	...	
1296674	Jeffrey	Smith	M	135 Joseph Mountains	...	

	lat	long	city_pop	job	\
0	36.0788	-81.1781	3495	Psychologist, counselling	
1	48.8878	-118.2105	149	Special educational needs teacher	
2	42.1808	-112.2620	4154	Nature conservation officer	
3	46.2306	-112.1138	1939	Patent attorney	
4	38.4207	-79.4629	99	Dance movement psychotherapist	
...	
1296670	37.7175	-112.4777	258	Geoscientist	
1296671	39.2667	-77.5101	100	Production assistant, television	
1296672	32.9396	-105.8189	899	Naval architect	
1296673	43.3526	-102.5411	1126	Volunteer coordinator	
1296674	45.8433	-113.8748	218	Therapist, horticultural	

	dob	trans_num	unix_time	merch_lat	\
0	1988-03-09	0b242abb623afc578575680df30655b9	1325376018	36.011293	
1	1978-06-21	1f76529f8574734946361c461b024d99	1325376044	49.159047	
2	1962-01-19	a1a22d70485983eac12b5b88dad1cf95	1325376051	43.150704	
3	1967-01-12	6b849c168bdad6f867558c3793159a81	1325376076	47.034331	



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```
data['transaction_month'] = data['trans_date_trans_time'].dt.month
data['transaction_day'] = data['trans_date_trans_time'].dt.day
data['transaction_hour'] = data['trans_date_trans_time'].dt.hour

data['birth_year'] = data['dob'].dt.year
data['birth_month'] = data['dob'].dt.month
data['birth_day'] = data['dob'].dt.day
data.drop(['trans_date_trans_time', 'dob'], axis=1, inplace=True)
train['trans_date_trans_time'] = pd.to_datetime(train['trans_date_trans_time'])
train['dob'] = pd.to_datetime(train['dob'])

train['transaction_year'] = train['trans_date_trans_time'].dt.year
train['transaction_month'] = train['trans_date_trans_time'].dt.month
train['transaction_day'] = train['trans_date_trans_time'].dt.day
train['transaction_hour'] = train['trans_date_trans_time'].dt.hour

train['birth_year'] = train['dob'].dt.year
train['birth_month'] = train['dob'].dt.month
train['birth_day'] = train['dob'].dt.day

train.drop(['trans_date_trans_time', 'dob'], axis=1, inplace=True)

test['trans_date_trans_time'] = pd.to_datetime(test['trans_date_trans_time'])
test['dob'] = pd.to_datetime(test['dob'])

test['transaction_year'] = test['trans_date_trans_time'].dt.year
test['transaction_month'] = test['trans_date_trans_time'].dt.month
test['transaction_day'] = test['trans_date_trans_time'].dt.day
test['transaction_hour'] = test['trans_date_trans_time'].dt.hour
test['birth_year'] = test['dob'].dt.year
test['birth_month'] = test['dob'].dt.month
```



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```
[ ] print(train.shape)
    print(test.shape)
    print(data.shape)
```

```
(1296675, 23)
(555719, 23)
(1852394, 23)
```

```
print(data.head(0))
print(data.head())
print(data.describe())
print(data.isnull().sum())
```

```
max    1.000000e+00  5.000000e+01  9.992100e+04  6.669330e+01 -6.795030e+01
```

	...	merch_lat	merch_long	is_fraud	transaction_year \
count	...	1.852394e+06	1.852394e+06	1.852394e+06	1.852394e+06
mean	...	3.853898e+01	-9.022794e+01	5.210015e-03	2.019501e+03
std	...	5.105604e+00	1.375969e+01	7.199217e-02	4.999996e-01
min	...	1.902742e+01	-1.666716e+02	0.000000e+00	2.019000e+03
25%	...	3.474012e+01	-9.689944e+01	0.000000e+00	2.019000e+03
50%	...	3.936890e+01	-8.744069e+01	0.000000e+00	2.020000e+03
75%	...	4.195626e+01	-8.024511e+01	0.000000e+00	2.020000e+03
max	...	6.751027e+01	-6.695090e+01	1.000000e+00	2.020000e+03

	transaction_month	transaction_day	transaction_hour	birth_year \
count	1.852394e+06	1.852394e+06	1.852394e+06	1.852394e+06
mean	7.152067e+00	1.585076e+01	1.280612e+01	1.973289e+03
std	3.424954e+00	8.876245e+00	6.815753e+00	1.739057e+01
min	1.000000e+00	1.000000e+00	0.000000e+00	1.924000e+03
25%	4.000000e+00	8.000000e+00	7.000000e+00	1.962000e+03



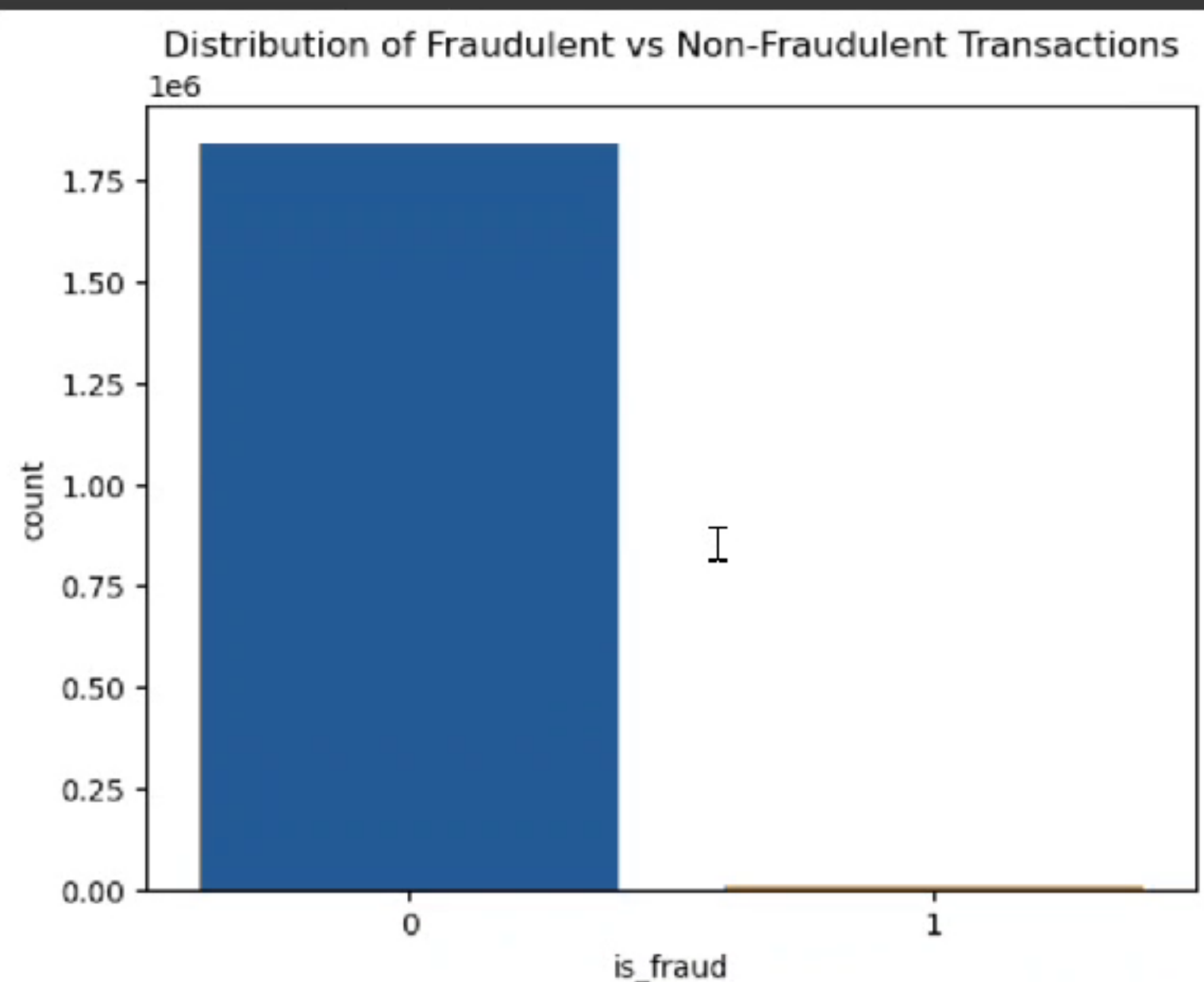
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```
sns.countplot(data=data, x='is_fraud')  
plt.title('Distribution of Fraudulent vs Non-Fraudulent Transactions')  
plt.show()
```

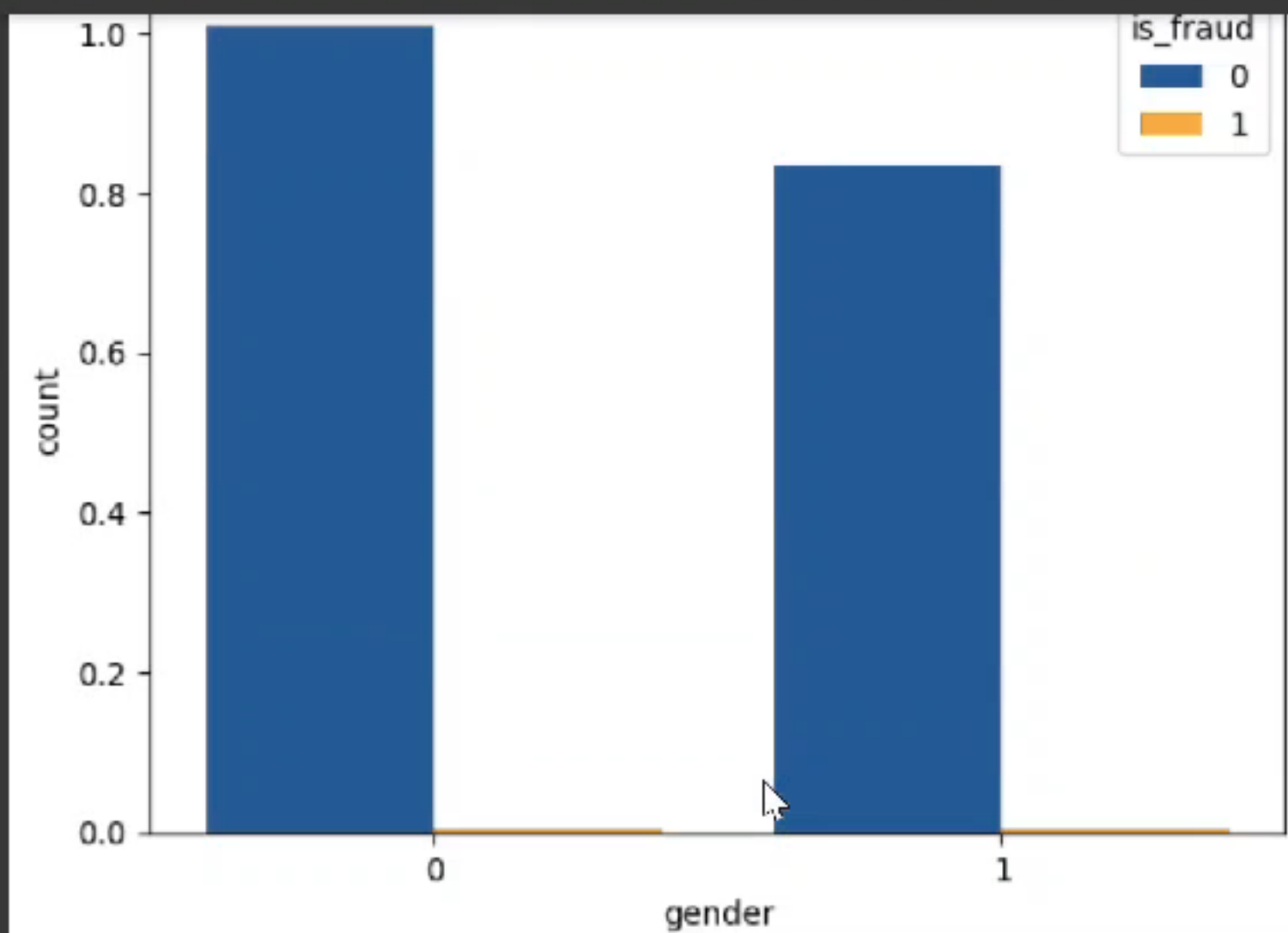




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```
[ ] plt.figure(figsize=(20,10))
sns.heatmap(data.corr(), annot=True, cmap='Blues')
plt.title('Correlation Heatmap')
plt.show()
```



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```
[ ] X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
```

```
# Training the model for LogisticRegression
log_model = LogisticRegression(max_iter=1000)
log_model.fit(X_train, y_train)
y_pred = log_model.predict(X_test)
print(classification_report(y_test, y_pred))
print(confusion_matrix(y_test, y_pred))
print("Accuracy:", accuracy_score(y_test, y_pred))
```

```
C:\Users\chatt\anaconda3\Lib\site-packages\sklearn\linear_model\_logistic.py:460: ConvergenceWarning: lbfgs failed to converge (status=2):
ABNORMAL_TERMINATION_IN_LNSRCH.
```

Increase the number of iterations (max_iter) or scale the data as shown in:

<https://scikit-learn.org/stable/modules/preprocessing.html>

Please also refer to the documentation for alternative solver options:

https://scikit-learn.org/stable/modules/linear_model.html#logistic-regression

```
n_iter_i = _check_optimize_result(
```

```
C:\Users\chatt\anaconda3\Lib\site-packages\sklearn\metrics\_classification.py:1469: UndefinedMetricWarning: Precision and F-score are ill-defined and
_warn_prf(average, modifier, msg_start, len(result))
```

```
C:\Users\chatt\anaconda3\Lib\site-packages\sklearn\metrics\_classification.py:1469: UndefinedMetricWarning: Precision and F-score are ill-defined and
_warn_prf(average, modifier, msg_start, len(result))
```

	precision	recall	f1-score	support
--	-----------	--------	----------	---------

0	0.99	1.00	1.00	368526
---	------	------	------	--------

1	0.00	0.00	0.00	1953
---	------	------	------	------

accuracy			0.99	370479
----------	--	--	------	--------

macro avg	0.50	0.50	0.50	370479
-----------	------	------	------	--------

weighted avg	0.99	0.99	0.99	370479
--------------	------	------	------	--------

```
[[368526 0]
```