

# subramanian540\_Project\_Milestone4\_Bkp

May 21, 2023

## 1 DSC 540 - Data Preparation

## 2 Week9 and Week 10

## 3 Project Milestone 4

## 4 Cleaning/Formatting API Source

## 5 Cleaning/Formatting API

Perform at least 5 data transformation and/or cleansing steps to your API data. The 5 data transformations that I will do are as follows:

Data transformation replaces the column headers in the “fraud\_data” DataFrame with a new set of headers specified in the “new\_headers” list. It then displays the first few rows of the DataFrame with the updated headers. This data transformation helps provide more descriptive and meaningful column names for the fraud detection data.

Data transformation converts them to float data type for ‘distance\_in\_km’ and ‘distance\_in\_mile’ columns with zero (0) . It rounds the values in the ‘ip\_latitude’ and ‘ip\_longitude’ columns to 6 decimal places. Lastly, it converts the values in the ‘fraudlabspro\_score’ column to float data type. These transformations ensure that the data is in a more readable and appropriate format for further analysis or presentation

Data Transformation identifies and removes any duplicate rows in the “fraud\_data” DataFrame. It creates a boolean mask of duplicated rows using the duplicated() function and then filters the DataFrame to keep only the rows that are not duplicates using the ~ operator. This data transformation ensures that the resulting DataFrame contains unique records, eliminating any duplicated entries.

Data Transformation modifies the DataFrame directly by removing any rows that have identical values in all columns, resulting in a DataFrame with unique records only.

Data transformation first drops rows from the “fraud\_data” DataFrame where the columns ‘ip\_country’, ‘ip\_region’, and ‘ip\_city’ have missing or empty values using the dropna() function with the subset parameter. This removes rows with missing values in these specific columns. Then, it further filters the DataFrame to drop rows where the values in these columns are ‘-’. The result is a DataFrame that excludes rows with missing or ‘-’ values in the specified columns, improving the data quality and removing incomplete or irrelevant rows.

Data Transformation replaces missing values in the 'country\_match' and 'ip\_country' columns of the "fraud\_data" DataFrame with the value 'Unknown'. This data transformation ensures that any missing values in the specified columns are replaced with the 'Unknown' value for better data completeness and consistency.

Data Transformation converts the values in the 'ip\_country' column of the 'fraud\_data' ensures consistent casing for the country names in the column. The resulting DataFrame will have the 'ip\_country' values in uppercase format.

Data Transformation performs fuzzy matching to the 'ip\_continent' column of the 'fraud\_data' DataFrame. It replaces inconsistent values with their corresponding standardized values using the provided mapping dictionary. For example, 'North America' is replaced with 'NA', 'South America' with 'SA', and so on. The resulting DataFrame will have consistent and standardized values in the 'ip\_continent' column.

Ethical Implications: Using the FraudLabs Pro API for order screening raises several ethical implications. One of the key concerns is privacy, as the dataset contains personal and sensitive information such as IP addresses, location details, email addresses, credit card information, and device identifiers. Safeguarding this data and ensuring compliance with privacy regulations are essential to protect individuals' privacy and prevent unauthorized access or data breaches. Transparency and informed consent are also important, as individuals should be aware of the purpose, collection, and usage of their data. Bias and discrimination are significant ethical considerations. It is crucial to ensure that the screening process and the algorithms used do not disproportionately impact certain individuals or groups based on factors like race, ethnicity, gender, or nationality. Compliance with legal and ethical standards is vital. Organizations using the dataset must adhere to data protection laws, privacy regulations, and consumer rights. Organizations should consider the ethical implications throughout their use of the dataset and take proactive measures to address privacy concerns, mitigate bias, ensure transparency, and uphold responsible data practices.

```
[3]: ## Import the required libraries
```

```
import pandas as pd
import json
import requests
import random
from concurrent import futures
```

```
[4]: # Importing the FraudValidation class from the fraudlabspro.fraudvalidation
      ↪ module
      #API : https://www.fraudlabspro.com/developer/api/screen-order?ref=apilist.fun

      from fraudlabspro.fraudvalidation import FraudValidation
```

The FraudValidation class allows you to access the fraud validation functionalities provided by the FraudLabs Pro API. By importing the FraudValidation class, you can access its methods and attributes to integrate the fraud validation capabilities into your code and leverage the features provided by the FraudLabs Pro API.

```
[5]: # Configure your API key
api_key = 'W7HNWZ1PGIEX6DPG1LIP8ATLEU2DB3BL'

# Set up the fraud validation object
fraud_validation = FraudValidation(api_key)
```

```
[6]: # Set up an empty list to store the results
results_list = []
```

Generates random order details such as order ID, amount, and IP address. The process\_order function takes an order ID, increments it, and generates random values for amount and IP address. It then calls the fraud validation method of the API (<https://www.fraudlabspro.com/developer/api/screen-order?ref=apilist.fun>) using the fraud\_validation.validate function and stores the result in the result variable.

```
[21]: # Set up the initial order ID
order_id = 5000

# Define a function to process a single order
def process_order(order_id):
    # Increment the order ID
    order_id += 1

    # Set up the order details for each iteration
    order_id_str = str(order_id).zfill(5) # Ensure 5-digit order ID

    # Generate random values for amount
    amount = round(random.uniform(0, 100), 2) # Generate a random float
    # between 0 and 100

    # Generate random values for IP Address
    ip_address = f"{random.randint(0, 255)}.{random.randint(0, 255)}.{random.
    # randint(0, 255)}.{random.randint(0, 255)}"

    order_details = {
        'order_id': order_id_str,
        'ip': ip_address,
        'amount': amount,
    }

    # Call the validation method and parse the result as a dictionary
    result = json.loads(fraud_validation.validate(order_details))

    return result

# Define the number of orders to process
num_orders = 50000
```

```

# Define the number of threads to use
num_threads = 1000

# Perform fraud validation for orders in parallel
with futures.ThreadPoolExecutor(max_workers=num_threads) as executor:
    future_to_order = {executor.submit(process_order, order_id): order_id for
        order_id in range(num_orders)}

    for future in futures.as_completed(future_to_order):
        order_id = future_to_order[future]
        result = future.result()
        results_list.append(result)

# Create a DataFrame from the results list
df = pd.DataFrame(results_list)

# Save the DataFrame to a CSV file
df.to_csv('fraud_results1.csv', index=False)

fraud_data = pd.read_csv('fraud_results1.csv', sep=",")
fraud_data

```

```

[21]:      is_country_match is_high_risk_country distance_in_km distance_in_mile \
0          NaN          N          -          -
1          NaN          N          -          -
2          NaN          N          -          -
3          NaN          N          -          -
4          NaN          N          -          -
...          ...          ...          ...          ...
50967      NaN          N          -          -
50968      NaN          N          -          -
50969      NaN          N          -          -
50970      NaN          N          -          -
50971      NaN          N          -          -

      ip_country ip_continent ip_region \
0          CA North America      Quebec
1          CH      Europe      Zurich
2          BR South America  Santa Catarina
3          US North America      California
4          US North America      Florida
...          ...          ...          ...
50967      CL South America Region Metropolitana de Santiago
50968      US North America      North Carolina
50969      DE      Europe      Baden-Wurttemberg
50970      IT      Europe      Lazio

```

50971 CL South America Region Metropolitana de Santiago

	ip_city	ip_latitude	ip_longitude	...	card_subtype	\
0	Montreal	45.5460	-73.6252	...	NaN	
1	Zurich	47.3668	8.5498	...	NaN	
2	Balneario Camboriu	-26.9907	-48.6346	...	NaN	
3	Cupertino	37.3166	-122.0465	...	NaN	
4	Miami	25.7743	-80.1936	...	NaN	
...	...	...	...	...	...	
50967	Santiago	-33.4265	-70.5665	...	NaN	
50968	Charlotte	35.2111	-80.8672	...	NaN	
50969	Stuttgart	48.7825	9.1770	...	NaN	
50970	Rome	41.8943	12.4843	...	NaN	
50971	Santiago	-33.4265	-70.5665	...	NaN	

	fraudlabspro_score	fraudlabspro_distribution	fraudlabspro_status	\
0	100	0	APPROVE	
1	100	0	APPROVE	
2	100	0	APPROVE	
3	100	0	APPROVE	
4	100	0	APPROVE	
...	...	...	...	
50967	100	0	APPROVE	
50968	100	0	APPROVE	
50969	100	0	APPROVE	
50970	100	0	APPROVE	
50971	100	0	APPROVE	

	fraudlabspro_id	fraudlabspro_version	fraudlabspro_error_code	\
0	20230521-SUAGLS	1.5.1	208	
1	20230521-VZALEO	1.5.1	208	
2	20230521-BSFT4Z	1.5.1	208	
3	20230521-HYWZZZ	1.5.1	208	
4	20230521-V8KLML	1.5.1	208	
...	...	...	...	
50967	20230521-SYTEIJ	1.5.1	208	
50968	20230521-YDS7ZB	1.5.1	208	
50969	20230521-AWHT5R	1.5.1	208	
50970	20230521-3JLK4N	1.5.1	208	
50971	20230521-WGXLGN	1.5.1	208	

	fraudlabspro_message	fraudlabspro_credits	device_id
0	INVALID QUANTITY VALUE	500	NaN
1	INVALID QUANTITY VALUE	500	NaN
2	INVALID QUANTITY VALUE	500	NaN
3	INVALID QUANTITY VALUE	500	NaN
4	INVALID QUANTITY VALUE	500	NaN

```

...
50967  INVALID QUANTITY VALUE      500      NaN
50968  INVALID QUANTITY VALUE      500      NaN
50969  INVALID QUANTITY VALUE      500      NaN
50970  INVALID QUANTITY VALUE      500      NaN
50971  INVALID QUANTITY VALUE      500      NaN

```

[50972 rows x 56 columns]

[22]: *#Data Transformatio : 1 Replace Headers*

```

# Replace Headers
new_headers = ['country_match', 'high_risk_country', 'distance_in_km',
↳ 'distance_in_mile',
               'ip_country', 'ip_continent', 'ip_region', 'ip_city',
↳ 'ip_latitude', 'ip_longitude',
               'ip_timezone', 'ip_elevation', 'ip_domain', 'ip_mobile_mnc',
↳ 'ip_mobile_mcc',
               'ip_mobile_brand', 'ip_netspeed', 'ip_isp_name',
↳ 'ip_usage_type', 'free_email',
               'new_domain_name', 'domain_exists', 'proxy_ip_address',
↳ 'bin_found',
               'bin_country_match', 'bin_name_match', 'bin_phone_match',
               'bin_phone_country_match', 'bin_prepaid', 'address_ship_forward',
               'bill_ship_city_match', 'bill_ship_state_match',
↳ 'bill_ship_country_match',
               'is_bill_ship_postal_match', 'is_ship_address_blacklist',
↳ 'is_phone_blacklist',
               'ip_blacklist', 'email_blacklist', 'credit_card_blacklist',
               'device_blacklist', 'user_blacklist', 'high_risk_username',
               'export_controlled_country', 'malware_exploit', 'user_order_id',
↳ 'user_order_memo',
               'card_subtype', 'fraudlabspro_score',
↳ 'fraudlabspro_distribution', 'fraudlabspro_status',
               'fraudlabspro_id', 'fraudlabspro_version',
↳ 'fraudlabspro_error_code', 'fraudlabspro_message',
               'fraudlabspro_credits', 'device_id']

fraud_data.columns = new_headers
fraud_data.head()

```

```

[22]:  country_match high_risk_country distance_in_km distance_in_mile ip_country \
0          NaN          N          -          -          CA
1          NaN          N          -          -          CH
2          NaN          N          -          -          BR
3          NaN          N          -          -          US

```

4	NaN	N	-	-	US
---	-----	---	---	---	----

	ip_continent	ip_region	ip_city	ip_latitude	\
0	North America	Quebec	Montreal	45.5460	
1	Europe	Zurich	Zurich	47.3668	
2	South America	Santa Catarina	Balneario Camboriu	-26.9907	
3	North America	California	Cupertino	37.3166	
4	North America	Florida	Miami	25.7743	

	ip_longitude	...	card_subtype	fraudlabspro_score	\
0	-73.6252	...	NaN	100	
1	8.5498	...	NaN	100	
2	-48.6346	...	NaN	100	
3	-122.0465	...	NaN	100	
4	-80.1936	...	NaN	100	

	fraudlabspro_distribution	fraudlabspro_status	fraudlabspro_id	\
0	0	APPROVE	20230521-SUAGLS	
1	0	APPROVE	20230521-VZALEO	
2	0	APPROVE	20230521-BSFT4Z	
3	0	APPROVE	20230521-HYWZZZ	
4	0	APPROVE	20230521-V8KLML	

	fraudlabspro_version	fraudlabspro_error_code	fraudlabspro_message	\
0	1.5.1	208	INVALID QUANTITY VALUE	
1	1.5.1	208	INVALID QUANTITY VALUE	
2	1.5.1	208	INVALID QUANTITY VALUE	
3	1.5.1	208	INVALID QUANTITY VALUE	
4	1.5.1	208	INVALID QUANTITY VALUE	

	fraudlabspro_credits	device_id
0	500	NaN
1	500	NaN
2	500	NaN
3	500	NaN
4	500	NaN

[5 rows x 56 columns]

```
[23]: #Data Transformatio : 2 # Format data into a more readable format

fraud_data['distance_in_km'] = fraud_data['distance_in_km'].replace('-', 0).
    ↳astype(float)
fraud_data['distance_in_mile'] = fraud_data['distance_in_mile'].replace('-', 0).
    ↳astype(float)
fraud_data['ip_latitude'] = fraud_data['ip_latitude'].round(6)
fraud_data['ip_longitude'] = fraud_data['ip_longitude'].round(6)
```

```

fraud_data['fraudlabspro_score'] = fraud_data['fraudlabspro_score'].
↳ astype(float)

fraud_data.head()

```

```

[23]:
country_match high_risk_country distance_in_km distance_in_mile \
0          NaN                N           0.0           0.0
1          NaN                N           0.0           0.0
2          NaN                N           0.0           0.0
3          NaN                N           0.0           0.0
4          NaN                N           0.0           0.0

ip_country ip_continent ip_region ip_city ip_latitude \
0         CA North America   Quebec  Montreal    45.5460
1         CH      Europe    Zurich   Zurich    47.3668
2         BR South America Santa Catarina Balneario Camboriu -26.9907
3         US North America   California   Cupertino    37.3166
4         US North America   Florida     Miami    25.7743

ip_longitude ... card_subtype fraudlabspro_score \
0    -73.6252 ...          NaN          100.0
1     8.5498 ...          NaN          100.0
2   -48.6346 ...          NaN          100.0
3  -122.0465 ...          NaN          100.0
4   -80.1936 ...          NaN          100.0

fraudlabspro_distribution fraudlabspro_status fraudlabspro_id \
0                0          APPROVE 20230521-SUAGLS
1                0          APPROVE 20230521-VZALEO
2                0          APPROVE 20230521-BSFT4Z
3                0          APPROVE 20230521-HYWZZZ
4                0          APPROVE 20230521-V8KLML

fraudlabspro_version fraudlabspro_error_code fraudlabspro_message \
0            1.5.1            208 INVALID QUANTITY VALUE
1            1.5.1            208 INVALID QUANTITY VALUE
2            1.5.1            208 INVALID QUANTITY VALUE
3            1.5.1            208 INVALID QUANTITY VALUE
4            1.5.1            208 INVALID QUANTITY VALUE

fraudlabspro_credits device_id
0            500          NaN
1            500          NaN
2            500          NaN
3            500          NaN
4            500          NaN

```



[5 rows x 56 columns]

```
[24]: #Data Transformatio : 3 # Find duplicates
duplicates = fraud_data.duplicated()
fraud_data = fraud_data[~duplicates]

fraud_data.head()

#Data Transformatio : 4 # Remove duplicate rows
fraud_data.drop_duplicates(inplace=True)
fraud_data.head()
```

```
[24]: country_match high_risk_country distance_in_km distance_in_mile \
0      NaN      N      0.0      0.0
1      NaN      N      0.0      0.0
2      NaN      N      0.0      0.0
3      NaN      N      0.0      0.0
4      NaN      N      0.0      0.0

ip_country ip_continent ip_region ip_city ip_latitude \
0      CA North America Quebec Montreal 45.5460
1      CH Europe Zurich Zurich 47.3668
2      BR South America Santa Catarina Balneario Camboriu -26.9907
3      US North America California Cupertino 37.3166
4      US North America Florida Miami 25.7743

ip_longitude ... card_subtype fraudlabspro_score \
0      -73.6252 ...      NaN 100.0
1      8.5498 ...      NaN 100.0
2      -48.6346 ...      NaN 100.0
3      -122.0465 ...      NaN 100.0
4      -80.1936 ...      NaN 100.0

fraudlabspro_distribution fraudlabspro_status fraudlabspro_id \
0      0 APPROVE 20230521-SUAGLS
1      0 APPROVE 20230521-VZALEO
2      0 APPROVE 20230521-BSFT4Z
3      0 APPROVE 20230521-HYWZZZ
4      0 APPROVE 20230521-V8KLML

fraudlabspro_version fraudlabspro_error_code fraudlabspro_message \
0      1.5.1 208 INVALID QUANTITY VALUE
1      1.5.1 208 INVALID QUANTITY VALUE
2      1.5.1 208 INVALID QUANTITY VALUE
3      1.5.1 208 INVALID QUANTITY VALUE
4      1.5.1 208 INVALID QUANTITY VALUE
```

	fraudlabspro_credits	device_id
0	500	NaN
1	500	NaN
2	500	NaN
3	500	NaN
4	500	NaN

[5 rows x 56 columns]

[25]: *#Data Transformatio : 5 # Replace missing values in specific columns*

```

fraud_data['country_match'].fillna('Unknown', inplace=True)
fraud_data['ip_country'].fillna('Unknown', inplace=True)
fraud_data.head()

```

[25]:

	country_match	high_risk_country	distance_in_km	distance_in_mile	\
0	Unknown	N	0.0	0.0	
1	Unknown	N	0.0	0.0	
2	Unknown	N	0.0	0.0	
3	Unknown	N	0.0	0.0	
4	Unknown	N	0.0	0.0	

	ip_country	ip_continent	ip_region	ip_city	ip_latitude	\
0	CA	North America	Quebec	Montreal	45.5460	
1	CH	Europe	Zurich	Zurich	47.3668	
2	BR	South America	Santa Catarina	Balneario Camboriu	-26.9907	
3	US	North America	California	Cupertino	37.3166	
4	US	North America	Florida	Miami	25.7743	

	ip_longitude	...	card_subtype	fraudlabspro_score	\
0	-73.6252	...	NaN	100.0	
1	8.5498	...	NaN	100.0	
2	-48.6346	...	NaN	100.0	
3	-122.0465	...	NaN	100.0	
4	-80.1936	...	NaN	100.0	

	fraudlabspro_distribution	fraudlabspro_status	fraudlabspro_id	\
0	0	APPROVE	20230521-SUAGLS	
1	0	APPROVE	20230521-VZALEO	
2	0	APPROVE	20230521-BSFT4Z	
3	0	APPROVE	20230521-HYWZZZ	
4	0	APPROVE	20230521-V8KLML	

	fraudlabspro_version	fraudlabspro_error_code	fraudlabspro_message	\
0	1.5.1	208	INVALID QUANTITY VALUE	
1	1.5.1	208	INVALID QUANTITY VALUE	
2	1.5.1	208	INVALID QUANTITY VALUE	

3	1.5.1	208	INVALID QUANTITY VALUE
4	1.5.1	208	INVALID QUANTITY VALUE

	fraudlabspro_credits	device_id
0	500	NaN
1	500	NaN
2	500	NaN
3	500	NaN
4	500	NaN

[5 rows x 56 columns]

```
[26]: #Data Transformatio : 6 # Drop rows with missing or empty values in ip_country,
      ↪ip_region, and ip_city columns
      fraud_data.dropna(subset=['ip_country', 'ip_region', 'ip_city'], inplace=True)
      fraud_data.head()

      #Data Transformatio : 6 # Drop rows with '-' values in ip_country, ip_region,
      ↪and ip_city columns
      fraud_data = fraud_data[(fraud_data['ip_country'] != '-') &
      ↪(fraud_data['ip_region'] != '-') & (fraud_data['ip_city'] != '-')]
      fraud_data.head()
```

```
[26]: country_match high_risk_country distance_in_km distance_in_mile \
0      Unknown          N          0.0          0.0
1      Unknown          N          0.0          0.0
2      Unknown          N          0.0          0.0
3      Unknown          N          0.0          0.0
4      Unknown          N          0.0          0.0
```

	ip_country	ip_continent	ip_region	ip_city	ip_latitude	\
0	CA	North America	Quebec	Montreal	45.5460	
1	CH	Europe	Zurich	Zurich	47.3668	
2	BR	South America	Santa Catarina	Balneario Camboriu	-26.9907	
3	US	North America	California	Cupertino	37.3166	
4	US	North America	Florida	Miami	25.7743	

	ip_longitude	...	card_subtype	fraudlabspro_score	\
0	-73.6252	...	NaN	100.0	
1	8.5498	...	NaN	100.0	
2	-48.6346	...	NaN	100.0	
3	-122.0465	...	NaN	100.0	
4	-80.1936	...	NaN	100.0	

	fraudlabspro_distribution	fraudlabspro_status	fraudlabspro_id	\
0	0	APPROVE	20230521-SUAGLS	
1	0	APPROVE	20230521-VZALEO	

2	0	APPROVE	20230521-BSFT4Z
3	0	APPROVE	20230521-HYWZZZ
4	0	APPROVE	20230521-V8KLML

	fraudlabspro_version	fraudlabspro_error_code	fraudlabspro_message \
0	1.5.1	208	INVALID QUANTITY VALUE
1	1.5.1	208	INVALID QUANTITY VALUE
2	1.5.1	208	INVALID QUANTITY VALUE
3	1.5.1	208	INVALID QUANTITY VALUE
4	1.5.1	208	INVALID QUANTITY VALUE

	fraudlabspro_credits	device_id
0	500	NaN
1	500	NaN
2	500	NaN
3	500	NaN
4	500	NaN

[5 rows x 56 columns]

```
[27]: #Data Transformatio : 7 # Fix casing or inconsistent values
fraud_data['ip_country'] = fraud_data['ip_country'].str.upper()
fraud_data.head()
```

```
[27]: country_match high_risk_country distance_in_km distance_in_mile \
0 Unknown N 0.0 0.0
1 Unknown N 0.0 0.0
2 Unknown N 0.0 0.0
3 Unknown N 0.0 0.0
4 Unknown N 0.0 0.0
```

	ip_country	ip_continent	ip_region	ip_city	ip_latitude \
0	CA	North America	Quebec	Montreal	45.5460
1	CH	Europe	Zurich	Zurich	47.3668
2	BR	South America	Santa Catarina	Balneario Camboriu	-26.9907
3	US	North America	California	Cupertino	37.3166
4	US	North America	Florida	Miami	25.7743

	ip_longitude	...	card_subtype	fraudlabspro_score \
0	-73.6252	...	NaN	100.0
1	8.5498	...	NaN	100.0
2	-48.6346	...	NaN	100.0
3	-122.0465	...	NaN	100.0
4	-80.1936	...	NaN	100.0

	fraudlabspro_distribution	fraudlabspro_status	fraudlabspro_id \
0	0	APPROVE	20230521-SUAGLS

1	0	APPROVE	20230521-VZALEO
2	0	APPROVE	20230521-BSFT4Z
3	0	APPROVE	20230521-HYWZZZ
4	0	APPROVE	20230521-V8KLML

	fraudlabspro_version	fraudlabspro_error_code	fraudlabspro_message \
0	1.5.1	208	INVALID QUANTITY VALUE
1	1.5.1	208	INVALID QUANTITY VALUE
2	1.5.1	208	INVALID QUANTITY VALUE
3	1.5.1	208	INVALID QUANTITY VALUE
4	1.5.1	208	INVALID QUANTITY VALUE

	fraudlabspro_credits	device_id
0	500	NaN
1	500	NaN
2	500	NaN
3	500	NaN
4	500	NaN

[5 rows x 56 columns]

```
[28]: #Data Transformatio : 8 # Conduct Fuzzy Matching (Example: fixing inconsistent
      ↪ values in 'ip_continent')
fuzzy_mapping = {'North America': 'NA', 'South America': 'SA', 'Europe': 'EU',
      ↪ 'Asia': 'AS', 'Africa': 'AF', 'Oceania': 'OC'}
fraud_data['ip_continent'] = fraud_data['ip_continent'].replace(fuzzy_mapping)
fraud_data.head()
```

```
[28]: country_match high_risk_country distance_in_km distance_in_mile \
0      Unknown          N          0.0          0.0
1      Unknown          N          0.0          0.0
2      Unknown          N          0.0          0.0
3      Unknown          N          0.0          0.0
4      Unknown          N          0.0          0.0
```

	ip_country	ip_continent	ip_region	ip_city	ip_latitude \
0	CA	NA	Quebec	Montreal	45.5460
1	CH	EU	Zurich	Zurich	47.3668
2	BR	SA	Santa Catarina	Balneario Camboriu	-26.9907
3	US	NA	California	Cupertino	37.3166
4	US	NA	Florida	Miami	25.7743

	ip_longitude	...	card_subtype	fraudlabspro_score \
0	-73.6252	...	NaN	100.0
1	8.5498	...	NaN	100.0
2	-48.6346	...	NaN	100.0
3	-122.0465	...	NaN	100.0

4	-80.1936 ...	NaN	100.0
---	--------------	-----	-------

	fraudlabspro_distribution	fraudlabspro_status	fraudlabspro_id \
0	0	APPROVE	20230521-SUAGLS
1	0	APPROVE	20230521-VZALEO
2	0	APPROVE	20230521-BSFT4Z
3	0	APPROVE	20230521-HYWZZZ
4	0	APPROVE	20230521-V8KLML

	fraudlabspro_version	fraudlabspro_error_code	fraudlabspro_message \
0	1.5.1	208	INVALID QUANTITY VALUE
1	1.5.1	208	INVALID QUANTITY VALUE
2	1.5.1	208	INVALID QUANTITY VALUE
3	1.5.1	208	INVALID QUANTITY VALUE
4	1.5.1	208	INVALID QUANTITY VALUE

	fraudlabspro_credits	device_id
0	500	NaN
1	500	NaN
2	500	NaN
3	500	NaN
4	500	NaN

[5 rows x 56 columns]

[29]: *#Data Transformatio : 9 # Reset the index after dropping rows*

```

fraud_data.reset_index(drop=True, inplace=True)
fraud_data.rename(columns={'index': 'Index_ID'}, inplace=True)
fraud_data

```

[29]:

	country_match	high_risk_country	distance_in_km	distance_in_mile \
0	Unknown	N	0.0	0.0
1	Unknown	N	0.0	0.0
2	Unknown	N	0.0	0.0
3	Unknown	N	0.0	0.0
4	Unknown	N	0.0	0.0
...	...	...	...	...
43823	Unknown	N	0.0	0.0
43824	Unknown	N	0.0	0.0
43825	Unknown	N	0.0	0.0
43826	Unknown	N	0.0	0.0
43827	Unknown	N	0.0	0.0

	ip_country	ip_continent	ip_region \
0	CA	NA	Quebec
1	CH	EU	Zurich

2	BR	SA	Santa Catarina
3	US	NA	California
4	US	NA	Florida
...	...	...	...
43823	CL	SA	Region Metropolitana de Santiago
43824	US	NA	North Carolina
43825	DE	EU	Baden-Wurttemberg
43826	IT	EU	Lazio
43827	CL	SA	Region Metropolitana de Santiago

	ip_city	ip_latitude	ip_longitude	...	card_subtype	\
0	Montreal	45.5460	-73.6252	...	NaN	
1	Zurich	47.3668	8.5498	...	NaN	
2	Balneario Camboriu	-26.9907	-48.6346	...	NaN	
3	Cupertino	37.3166	-122.0465	...	NaN	
4	Miami	25.7743	-80.1936	...	NaN	
...	...	...	...	...	...	
43823	Santiago	-33.4265	-70.5665	...	NaN	
43824	Charlotte	35.2111	-80.8672	...	NaN	
43825	Stuttgart	48.7825	9.1770	...	NaN	
43826	Rome	41.8943	12.4843	...	NaN	
43827	Santiago	-33.4265	-70.5665	...	NaN	

	fraudlabspro_score	fraudlabspro_distribution	fraudlabspro_status	\
0	100.0	0	APPROVE	
1	100.0	0	APPROVE	
2	100.0	0	APPROVE	
3	100.0	0	APPROVE	
4	100.0	0	APPROVE	
...	...	...	...	
43823	100.0	0	APPROVE	
43824	100.0	0	APPROVE	
43825	100.0	0	APPROVE	
43826	100.0	0	APPROVE	
43827	100.0	0	APPROVE	

	fraudlabspro_id	fraudlabspro_version	fraudlabspro_error_code	\
0	20230521-SUAGLS	1.5.1	208	
1	20230521-VZALEO	1.5.1	208	
2	20230521-BSFT4Z	1.5.1	208	
3	20230521-HYWZZZ	1.5.1	208	
4	20230521-V8KLML	1.5.1	208	
...	...	...	...	
43823	20230521-SYTEIJ	1.5.1	208	
43824	20230521-YDS7ZB	1.5.1	208	
43825	20230521-AWHT5R	1.5.1	208	
43826	20230521-3JLK4N	1.5.1	208	

43827 20230521-WGXLGN

1.5.1

208

	fraudlabspro_message	fraudlabspro_credits	device_id
0	INVALID QUANTITY VALUE	500	NaN
1	INVALID QUANTITY VALUE	500	NaN
2	INVALID QUANTITY VALUE	500	NaN
3	INVALID QUANTITY VALUE	500	NaN
4	INVALID QUANTITY VALUE	500	NaN
...	...	...	...
43823	INVALID QUANTITY VALUE	500	NaN
43824	INVALID QUANTITY VALUE	500	NaN
43825	INVALID QUANTITY VALUE	500	NaN
43826	INVALID QUANTITY VALUE	500	NaN
43827	INVALID QUANTITY VALUE	500	NaN

[43828 rows x 56 columns]