Introduction to Data Science

TITLE:

POKEMON DATASET ANALYSIS

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Problem Statement :

Applying ML Classification algorithms on the data set and getting inferences from the data. You may use the appropriate ML algorithm packages available in R or Python. But know which algorithm you use and know the concept behind it.

Data Set :

This dataset include the name,type,different physical attributes like attack,defense,speed,etc. of different pokemons.

Data Set Source: Kaggle(https://www.kaggle.com/abcsds/pokemon)

Number of Instances :

800

Number of Attributes :

13

Attribute Information :

1) #
2) Name
3) Type 1
4) Type 2
5) Total
6) HP
7)Attack
8)Defense
9)Sp. Atk
10)Sp. Def
11)Speed
12)Generation
13)Legendary

Terminologies:-

Data preprocessing:- Data preprocessing is a data mining technique that involves transforming raw data into an understandable format. Real-world data is often incomplete, inconsistent, and/or lacking in certain behaviours or trends, and is likely to contain many errors. Data preprocessing is a proven method of resolving such issues.

Real world data are generally

- Incomplete: lacking attribute values, lacking certain attributes of interest, or containing only aggregate data
- Noisy: containing errors or outliers
- Inconsistent: containing discrepancies in codes or names.

Tasks in data preprocessing

- Data cleaning: fill in missing values, smooth noisy data, identify or remove outliers, and resolve inconsistencies.
- Data integration: using multiple databases, data cubes, or files.
- Data transformation: normalization and aggregation.
- Data reduction: reducing the volume but producing the same or similar analytical results.
- Data discretization: part of data reduction, replacing numerical attributes with nominal ones.

Data cleaning

1. Fill in missing values (attribute or class value):
   - ❑ Ignore the tuple: usually done when the class label is missing.
   - ❑ Use the attribute mean (or majority nominal value) to fill in the missing value.
   - ❑ Use the attribute mean (or majority nominal value) for all samples belonging to the same class.
   - ❑ Predict the missing value by using a learning algorithm: consider the attribute with the missing value as a dependent (class) variable and run a learning algorithm (usually Bayes or decision tree) to predict the missing value.

2. Identify outliers and smooth out noisy data:

- Binning
  - Sort the attribute values and partition them into bins (see "Unsupervised discretization" below);
  - Then smooth by bin means, bin median, or bin boundaries.

- Clustering: group values in clusters and then detect and remove outliers (automatic or manual)
- Regression: smooth by fitting the data into regression functions.

3.Correct inconsistent data: use domain knowledge or expert decision.

Data transformation

- Normalization:
  - Scaling attribute values to fall within a specified range.
    - Example: to transform V in [min, max] to V' in [0,1], apply V'=(V-Min)/(Max-Min).
  - Scaling by using mean and standard deviation (useful when min and max are unknown or when there are outliers): V'=(V-Mean)/StDev.
- Aggregation: moving up in the concept hierarchy on numeric attributes.
- Generalization: moving up in the concept hierarchy on nominal attributes.
- Attribute construction: replacing or adding new attributes inferred by existing attributes.

Data reduction

- Reducing the number of attributes
  - Data cube aggregation: applying roll-up, slice or dice operations.
  - Removing irrelevant attributes: attribute selection (filtering and wrapper methods), searching the attribute space.
  - Principle component analysis (numeric attributes only): searching for a lower dimensional space that can best represent the data.
- Reducing the number of attribute values
  - Binning (histograms): reducing the number of attributes by grouping them into intervals (bins).
  - Clustering: grouping values in clusters.
  - Aggregation or generalization
- Reducing the number of tuples
  - Sampling

KNN

KNN can be used for both classification and regression predictive problems. However, it is more widely used in classification problems in the industry. To evaluate any technique we generally look at 3 important aspects:

1. Ease to interpret output

2. Calculation time

3. Predictive Power

Importing necessary libraries:

```
In [79]: import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns

import helper

from sklearn.preprocessing import StandardScaler
sc = StandardScaler()

from sklearn.neighbors import KNeighborsClassifier

from sklearn.preprocessing import LabelEncoder
le = LabelEncoder()

import scipy
```

Observing first ten samples of our dataset:

```
In [56]: data = pd.read_csv('Pokemon.csv')
data.head(n = 10)
```

Out[56]:

	#	Name	Type 1	Type 2	Total	HP	Attack	Defense	Sp. Atk	Sp. Def	Speed	Generation	Legendary
0	1	Bulbasaur	Grass	Poison	318	45	49	49	65	65	45	1	False
1	2	Ivysaur	Grass	Poison	405	60	62	63	80	80	60	1	False
2	3	Venusaur	Grass	Poison	525	80	82	83	100	100	80	1	False
3	3	VenusaurMega Venusaur	Grass	Poison	625	80	100	123	122	120	80	1	False
4	4	Charmander	Fire	NaN	309	39	52	43	60	50	65	1	False
5	5	Charmeleon	Fire	NaN	405	58	64	58	80	65	80	1	False
6	6	Charizard	Fire	Flying	534	78	84	78	109	85	100	1	False
7	6	CharizardMega Charizard X	Fire	Dragon	634	78	130	111	130	85	100	1	False
8	6	CharizardMega Charizard Y	Fire	Flying	634	78	104	78	159	115	100	1	False
9	7	Squirtle	Water	NaN	314	44	48	65	50	64	43	1	False

Checking for null values in the dataset:

```
In [57]: data.isnull().sum()

Out[57]: #              0
         Name           0
         Type 1         0
         Type 2       386
         Total          0
         HP             0
         Attack         0
         Defense        0
         Sp. Atk        0
         Sp. Def        0
         Speed          0
         Generation     0
         Legendary      0
         dtype: int64
```

Replacing null values in “Type 2” with “missing”:

```
In [58]: data.loc[data['Type 2'].isnull(), 'Type 2'] = 'missing'
```

Dropping unnecessary columns from the dataset:

```
In [59]: data.drop(labels = ['Name', '#'], inplace = True, axis = 1)
```

Rechecking for null values in the dataset:

```
In [60]: data.isnull().sum()

Out[60]: Type 1        0
         Type 2        0
         Total         0
         HP            0
         Attack        0
         Defense       0
         Sp. Atk       0
         Sp. Def       0
         Speed         0
         Generation    0
         Legendary     0
         dtype: int64
```

Looking for the Data types of our features:

In [45]:
```
data.dtypes
```

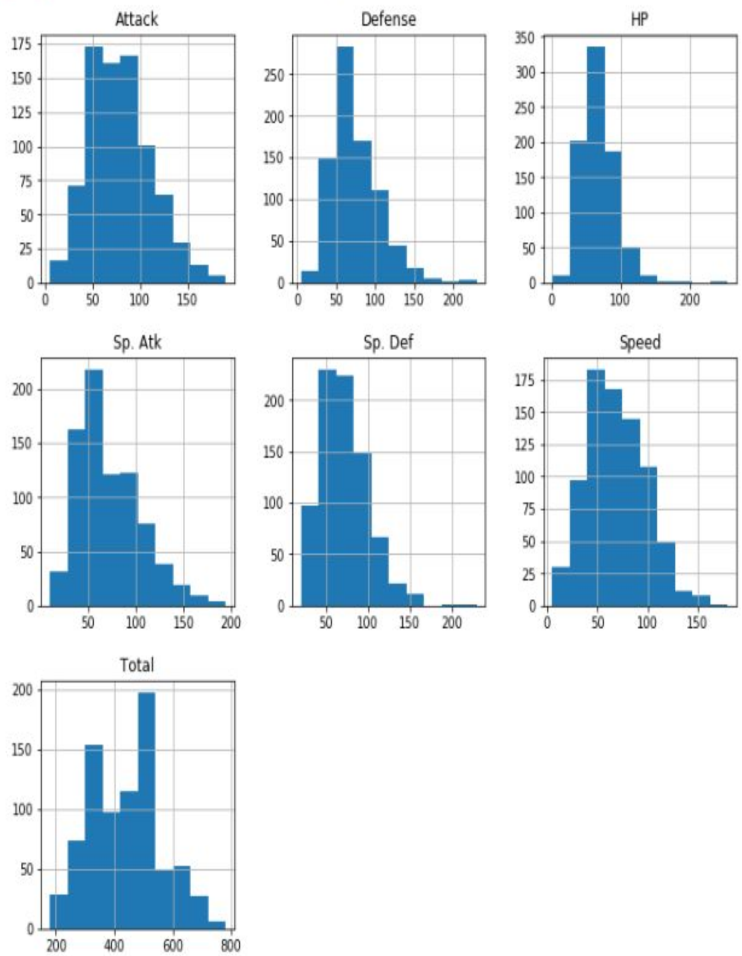
Out[45]:
```
Type 1        object
Type 2        object
Total          int64
HP             int64
Attack         int64
Defense        int64
Sp. Atk        int64
Sp. Def        int64
Speed          int64
Generation     int64
Legendary       bool
dtype: object
```

Univariate Analysis of continuous variables:

In [52]:
```
#Univariate Analysis
def uni_con_dist(data, to_leave = None):
  data.drop(to_leave, axis = 1, inplace = True)
  data[data.dtypes[((data.dtypes=="float64")|(data.dtypes=="int64"))].index.values].hist(figsize=[11,11])

  hist_data = {}
  for col in data[data.dtypes[((data.dtypes=="float64")|(data.dtypes=="int64"))].index.values].columns.values:
    hist_data[col + '_count'], hist_data[col + '_division'] = np.histogram(data[col])

uni_con_dist(data.copy(deep = False), to_leave = 'Generation')
```



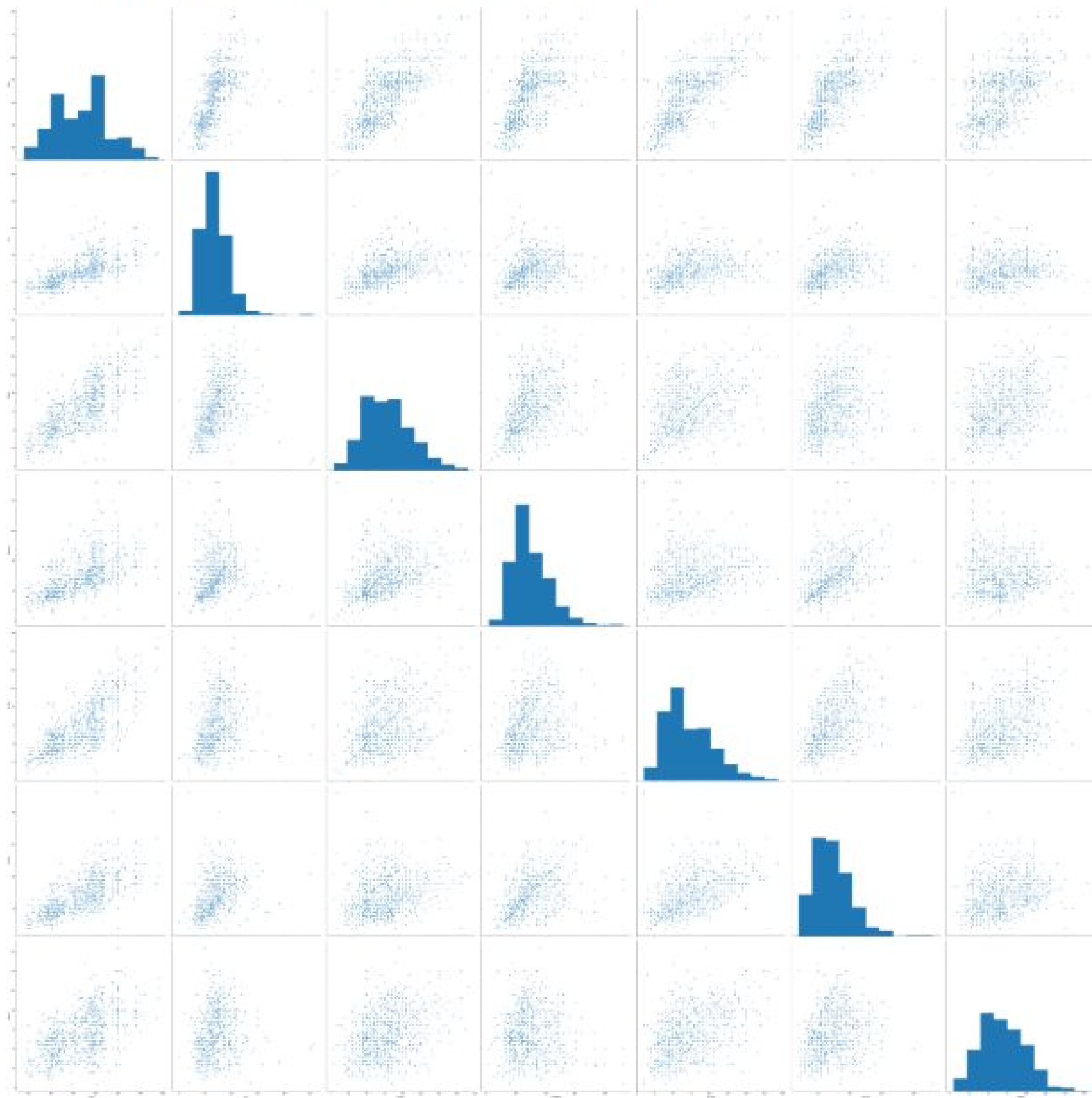
Bivariate analysis of continuous features :

In [71]:

```
#Biavariate Con-Con
def bi_con_con(data, to_leave, size = 10):
    data.drop(to_leave, axis = 1, inplace = True)
    sns.pairplot(data.loc[:, data.dtypes[((data.dtypes=="float64")|(data.dtypes=="int64"))].index.values], size = size)
    data_corr = data.loc[:, data.dtypes[((data.dtypes=="float64")|(data.dtypes=="int64"))].index.values].corr()
    print(data_corr)

bi_con_con(data.copy(deep = False), to_leave = ['Generation'])
```

	Total	HP	Attack	Defense	Sp. Atk	Sp. Def	Speed
Total	1.000000	0.618748	0.736211	0.612787	0.747250	0.717609	0.575943
HP	0.618748	1.000000	0.422386	0.239622	0.362380	0.378718	0.175952
Attack	0.736211	0.422386	1.000000	0.438687	0.396362	0.263990	0.381240
Defense	0.612787	0.239622	0.438687	1.000000	0.223549	0.510747	0.015227
Sp. Atk	0.747250	0.362380	0.396362	0.223549	1.000000	0.506121	0.473018
Sp. Def	0.717609	0.378718	0.263990	0.510747	0.506121	1.000000	0.259133
Speed	0.575943	0.175952	0.381240	0.015227	0.473018	0.259133	1.000000



Two way table of categorical variables:

In [76]:
```python
#Biavariate Cat-Cat Two Way table
def bi_cat_cat_2way(label1, label2, data):
  two_way = {}
  two_way['normal'] = pd.crosstab(index=data[label1], columns=data[label2], margins=True)# Usual 2 way table b/w 2 categorical var
  two_way['total_prop'] = two_way['normal']/two_way['normal'].loc["All","All"] #to get the total proportion of counts in each cell
                                                                                  #divide the table by the grand total
  two_way['col_prop'] = two_way['normal']/two_way['normal'].loc["All", :]
  two_way['row_prop'] = (two_way['normal'].T/two_way['normal']['All']).T
  return two_way

two_way_normal = bi_cat_cat_2way(label1 = 'Type 1', label2 = 'Type 2', data = data.copy(deep = False))['normal']
two_way_normal
```

Out[76]:

Type 2 Type 1	Bug	Dark	Dragon	Electric	Fairy	Fighting	Fire	Flying	Ghost	Grass	Ground	Ice	Normal	Poison	Psychic	Rock	Steel	Water	missing	All
Bug	0	0	0	2	0	2	2	14	1	6	2	0	0	12	0	3	7	1	17	69
Dark	0	0	3	0	0	2	3	5	2	0	0	2	0	0	2	0	2	0	10	31
Dragon	0	0	0	1	1	0	1	6	0	0	5	3	0	0	4	0	0	0	11	32
Electric	0	0	1	0	1	0	1	5	1	1	0	1	2	0	0	0	3	1	27	44
Fairy	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0	0	0	15	17
Fighting	0	1	0	0	0	0	0	1	0	0	0	0	0	0	3	0	2	0	20	27
Fire	0	0	1	0	0	7	0	6	0	0	3	0	2	0	2	1	1	1	28	52
Flying	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	4
Ghost	0	1	2	0	0	0	3	2	0	10	0	0	0	4	0	0	0	0	10	32
Grass	0	3	1	0	2	3	0	5	0	0	1	3	0	15	2	0	2	0	33	70
Ground	0	3	2	1	0	0	1	4	2	0	0	0	0	0	2	3	1	0	13	32
Ice	0	0	0	0	0	0	0	2	1	0	3	0	0	0	2	0	0	3	13	24
Normal	0	0	0	0	5	2	0	24	0	2	1	0	0	0	2	0	0	1	61	98
Poison	1	3	1	0	0	2	0	3	0	0	2	0	0	0	0	0	0	1	15	28
Psychic	0	1	0	0	6	3	1	6	1	1	0	0	0	0	0	0	0	0	38	57
Rock	2	2	2	0	3	1	0	4	0	2	6	2	0	0	2	0	3	6	9	44
Steel	0	0	1	0	3	1	0	1	4	0	2	0	0	0	7	3	0	0	5	27
Water	0	6	2	2	2	3	0	7	2	3	10	3	0	3	5	4	1	0	59	112
All	3	20	18	6	23	26	12	97	14	25	35	14	4	34	33	14	22	14	386	800

Cramer's V of categorical variables:

In [84]:
```python
#Bivariate Cat-Cat Chi Square and Cramers'V #Used when 2 Way table > 2 X 2
def bi_cat_cat_cramerV(two_way_normal):
  observed = two_way_normal.iloc[0:-1,0:-1]
  chi_stat, p_val, df, expected = scipy.stats.chi2_contingency(observed)
  cramers_v = np.sqrt(chi_stat/(two_way_normal['All'].iloc[-1] *(min(observed.shape)-1)))
  chi2_contingency = {}
  for name in ['chi_stat','p_val','df','expected', 'cramers_v']:
    chi2_contingency[name] = eval(name)
  #chi2_contingency = dict((name,eval(name)) for name in ['chi_stat','p_val','df','expected'])
  #chi2_contingency['cramers_v'] = cramers_v
  return chi2_contingency

bi_cat_cat_cramerV(two_way_normal)['cramers_v']
```

Out[84]: 0.24797228513443442

Cramer's V suggests a moderate correlation between the two categories

Applying a Classification Model(KNN Model)

Getting dummy features of categorical variables:

```
In [20]: data = pd.get_dummies(data, columns = ['Type 1', 'Type 2'])
```

Label encoding of the predictive variable:

```
In [21]: data['Legendary'] = le.fit_transform(data['Legendary'])
```

Rechecking the database:

```
In [22]: data.head(n = 10)
```

Out[22]:

	Total	HP	Attack	Defense	Sp. Atk	Sp. Def	Speed	Generation	Legendary	Type 1_Bug	...	Type 2_Grass	Type 2_Ground	Type 2_Ice	Type 2_Normal	Type 2_Poison	Type 2_Psychic	Type 2_Rock	T 2_S
0	318	45	49	49	65	65	45	1	0	0	...	0	0	0	0	1	0	0	
1	405	60	62	63	80	80	60	1	0	0	...	0	0	0	0	1	0	0	
2	525	80	82	83	100	100	80	1	0	0	...	0	0	0	0	1	0	0	
3	625	80	100	123	122	120	80	1	0	0	...	0	0	0	0	1	0	0	
4	309	39	52	43	60	50	65	1	0	0	...	0	0	0	0	0	0	0	
5	405	58	64	58	80	65	80	1	0	0	...	0	0	0	0	0	0	0	
6	534	78	84	78	109	85	100	1	0	0	...	0	0	0	0	0	0	0	
7	634	78	130	111	130	85	100	1	0	0	...	0	0	0	0	0	0	0	
8	634	78	104	78	159	115	100	1	0	0	...	0	0	0	0	0	0	0	
9	314	44	48	65	50	64	43	1	0	0	...	0	0	0	0	0	0	0	

10 rows × 46 columns

Seperating features and target variable from the dataset:

```
In [23]: x = data.drop(labels = 'Legendary', axis = 1)
         y = data['Legendary']
```

Spliting the dataset into traning and test set:

```
In [24]: from sklearn.model_selection import train_test_split
x_train, x_test, y_train, y_test = train_test_split(x,y, test_size = 0.125, random_state = 0)
```

Normalising the features:

```
In [25]: x_train = sc.fit_transform(x_train)
x_test = sc.transform(x_test)
```

Applying the KNN model:

```
In [26]: classifier = KNeighborsClassifier()

classifier.fit(x_train, y_train)
prediction = classifier.predict(x_test)
```

Generating the accuracy from confusion matrix:

```
In [27]: #Making the Confusion Matrix - Evaluation Metric
from sklearn.metrics import confusion_matrix
cm= confusion_matrix(y_test, prediction)
print(cm)

print('Accuracy')
```

```
[[92  0]
 [ 8  0]]
```

Accuracy : 92%