```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
Start coding or generate with AI.
Start coding or generate with AI.
sns.get_dataset_names()
     ['anagrams',
'anscombe',
      'attention',
      'brain_networks',
      'car_crashes',
      'diamonds',
      'dots',
      'dowjones',
      'exercise',
      'flights',
      'fmri',
      'geyser',
       'glue',
      'healthexp',
      'iris',
      'mpg',
      'penguins',
       'planets',
      'seaice',
      'taxis',
      'tips',
      'titanic']
df = sns.load_dataset('planets')
df
```

	method	number	orbital_period	mass	distance	year
0	Radial Velocity	1	269.300000	7.10	77.40	2006
1	Radial Velocity	1	874.774000	2.21	56.95	2008
2	Radial Velocity	1	763.000000	2.60	19.84	2011
3	Radial Velocity	1	326.030000	19.40	110.62	2007
4	Radial Velocity	1	516.220000	10.50	119.47	2009
1030	Transit	1	3.941507	NaN	172.00	2006
1031	Transit	1	2.615864	NaN	148.00	2007
1032	Transit	1	3.191524	NaN	174.00	2007
1033	Transit	1	4.125083	NaN	293.00	2008
1034	Transit	1	4.187757	NaN	260.00	2008
1035 rc	ws × 6 columns					

```
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Start coding or <u>generate</u> with AI.

col_num = df.select_dtypes(exclude='category')
col_num
```

	method	number	orbital_period	mass	distance	year
0	Radial Velocity	1	269.300000	7.10	77.40	2006
1	Radial Velocity	1	874.774000	2.21	56.95	2008
2	Radial Velocity	1	763.000000	2.60	19.84	2011
3	Radial Velocity	1	326.030000	19.40	110.62	2007
4	Radial Velocity	1	516.220000	10.50	119.47	2009
1030	Transit	1	3.941507	NaN	172.00	2006
1031	Transit	1	2.615864	NaN	148.00	2007
1032	Transit	1	3.191524	NaN	174.00	2007
1033	Transit	1	4.125083	NaN	293.00	2008
1034	Transit	1	4.187757	NaN	260.00	2008

1035 rows × 6 columns

df = sns.load_dataset('iris')
df

	sepal_length	sepal_width	petal_length	petal_width	species
0	5.1	3.5	1.4	0.2	setosa
1	4.9	3.0	1.4	0.2	setosa
2	4.7	3.2	1.3	0.2	setosa
3	4.6	3.1	1.5	0.2	setosa
4	5.0	3.6	1.4	0.2	setosa
145	6.7	3.0	5.2	2.3	virginica
146	6.3	2.5	5.0	1.9	virginica
147	6.5	3.0	5.2	2.0	virginica
148	6.2	3.4	5.4	2.3	virginica
149	5.9	3.0	5.1	1.8	virginica

150 rows × 5 columns

```
df['species'].unique()
```

array(['setosa', 'versicolor', 'virginica'], dtype=object)

num_col = df.select_dtypes(exclude = 'object')
num_col

	sepal_length	sepal_width	petal_length	petal_width
0	5.1	3.5	1.4	0.2
1	4.9	3.0	1.4	0.2
2	4.7	3.2	1.3	0.2
3	4.6	3.1	1.5	0.2
4	5.0	3.6	1.4	0.2
145	6.7	3.0	5.2	2.3
146	6.3	2.5	5.0	1.9
147	6.5	3.0	5.2	2.0
148	6.2	3.4	5.4	2.3
149	5.9	3.0	5.1	1.8

150 rows × 4 columns

num_col.corr()

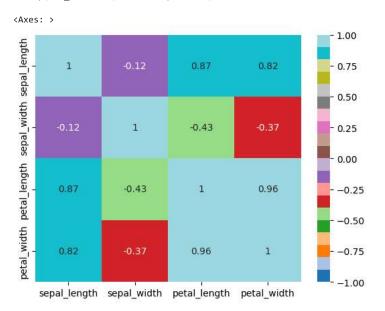
	sepal_length	sepal_width	petal_length	petal_width
sepal_length	1.000000	-0.117570	0.871754	0.817941
sepal_width	-0.117570	1.000000	-0.428440	-0.366126
petal_length	0.871754	-0.428440	1.000000	0.962865
petal_width	0.817941	-0.366126	0.962865	1.000000

num_col.corr(method = 'pearson')

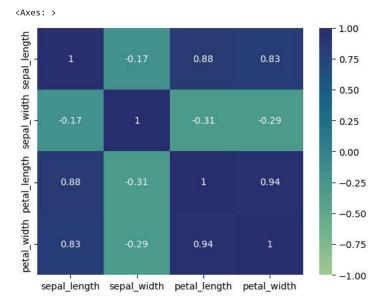
	sepal_length	sepal_width	petal_length	petal_width
sepal_length	1.000000	-0.117570	0.871754	0.817941
sepal_width	-0.117570	1.000000	-0.428440	-0.366126
petal_length	0.871754	-0.428440	1.000000	0.962865
petal_width	0.817941	-0.366126	0.962865	1.000000

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sns.heatmap(num_col.corr(method = 'pearson'),vmin = -1,vmax=1,annot = True,cmap = 'tab20')



sns.heatmap(num_col.corr(method = 'spearman'),vmin=-1,vmax=1,annot = True,cmap='crest')



Start coding or generate with AI.

Statistics are 3 types

- 1. univariate
- 2. bivariate
- 3. multivariate

#univariate - single column visualization
import seaborn as sns
df = sns.load_dataset('glue')
df

64 rows × 5 columns

df.head(15)

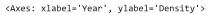
	Model	Year	Encoder	Task	Score
0	ERNIE	2019	Transformer	CoLA	75.5
1	T5	2019	Transformer	CoLA	71.6
2	RoBERTa	2019	Transformer	CoLA	67.8
3	BERT	2018	Transformer	CoLA	60.5
4	BiLSTM+ELMo	2018	LSTM	CoLA	32.1
59	BERT	2018	Transformer	RTE	70.1
60	BiLSTM+ELMo	2018	LSTM	RTE	57.4
61	BiLSTM+CoVe	2017	LSTM	RTE	52.7
62	BiLSTM+Attn	2017	LSTM	RTE	58.4
63	BiLSTM	2017	LSTM	RTE	57.4

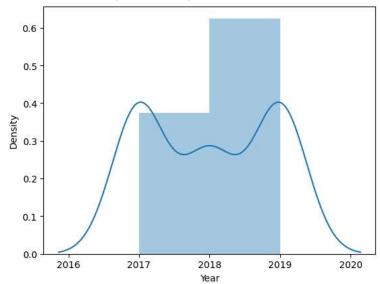
	Model	Year	Encoder	Task	Score
0	ERNIE	2019	Transformer	CoLA	75.5
1	T5	2019	Transformer	CoLA	71.6
2	RoBERTa	2019	Transformer	CoLA	67.8
3	BERT	2018	Transformer	CoLA	60.5
4	BiLSTM+ELMo	2018	LSTM	CoLA	32.1
5	BiLSTM+CoVe	2017	LSTM	CoLA	18.5
6	BiLSTM+Attn	2017	LSTM	CoLA	18.6
7	BiLSTM	2017	LSTM	CoLA	11.6
8	ERNIE	2019	Transformer	SST-2	97.8
9	T5	2019	Transformer	SST-2	97.5
10	RoBERTa	2019	Transformer	SST-2	96.7
11	BERT	2018	Transformer	SST-2	94.9
12	BiLSTM+ELMo	2018	LSTM	SST-2	89.3
13	BiLSTM+CoVe	2017	LSTM	SST-2	81.9
14	BiLSTM+Attn	2017	LSTM	SST-2	83.0

Start coding or generate with AI.

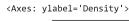
import warnings
warnings.filterwarnings('ignore')

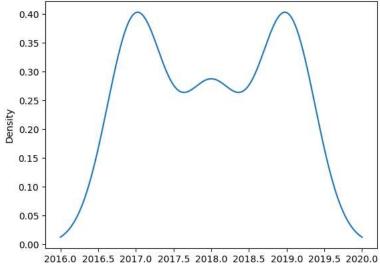
sns.distplot(df['Year'])





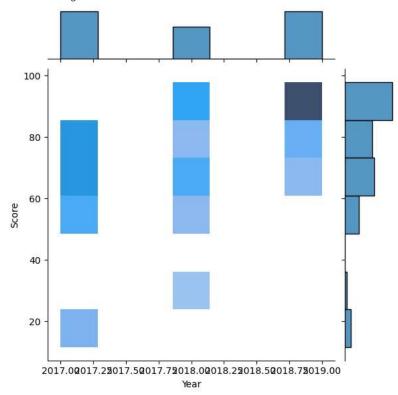
df['Year'].plot(kind = 'kde')



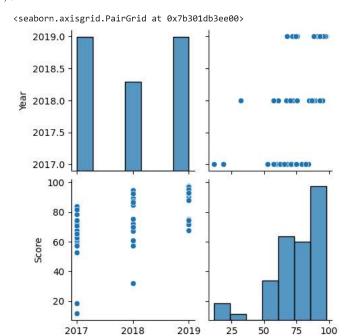


sns.jointplot(x=df['Year'],y=df['Score'],kind = 'hist')

<seaborn.axisgrid.JointGrid at 0x7b301ff76680>

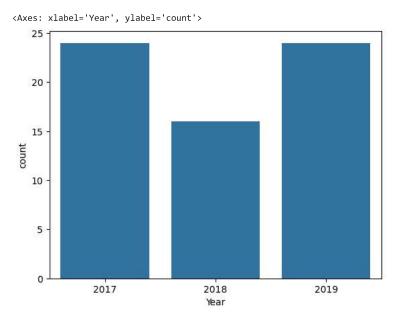


sns.pairplot(df)



Year

sns.countplot(x=df['Year'])



Score

import seaborn as sns

```
sns.get_dataset_names()

['anagrams',
    'anscombe',
    'attention',
    'brain_networks',
    'car_crashes',
    'diamonds',
    'dots',
    'dowjones',
    'exercise',
    'flights',
    'fmri',
    'geyser',
    'glue',
    'healthexp',
    'iris',
```

'mpg',

```
'penguins',
'planets',
'seaice',
'taxis',
'tips',
'titanic']
```

sns.load_dataset('mpg')

	mpg	cylinders	displacement	horsepower	weight	acceleration	model_year	origin
0	18.0	8	307.0	130.0	3504	12.0	70	usa
1	15.0	8	350.0	165.0	3693	11.5	70	usa
2	18.0	8	318.0	150.0	3436	11.0	70	usa
3	16.0	8	304.0	150.0	3433	12.0	70	usa
4	17.0	8	302.0	140.0	3449	10.5	70	usa
				•••				
393	27.0	4	140.0	86.0	2790	15.6	82	usa
4								•

df = sns.load_dataset('mpg')
df

	mpg	cylinders	displacement	horsepower	weight	acceleration	model_year	origin
0	18.0	8	307.0	130.0	3504	12.0	70	usa
1	15.0	8	350.0	165.0	3693	11.5	70	usa
2	18.0	8	318.0	150.0	3436	11.0	70	usa
3	16.0	8	304.0	150.0	3433	12.0	70	usa
4	17.0	8	302.0	140.0	3449	10.5	70	usa
393	27.0	4	140.0	86.0	2790	15.6	82	usa
4								>

Start coding or generate with AI.

```
kk = df.select_dtypes(exclude = 'object')
kk
```

	mpg	cylinders	displacement	horsepower	weight	acceleration	model_year
0	18.0	8	307.0	130.0	3504	12.0	70
1	15.0	8	350.0	165.0	3693	11.5	70
2	18.0	8	318.0	150.0	3436	11.0	70
3	16.0	8	304.0	150.0	3433	12.0	70
4	17.0	8	302.0	140.0	3449	10.5	70
393	27.0	4	140.0	86.0	2790	15.6	82
394	44.0	4	97.0	52.0	2130	24.6	82
395	32.0	4	135.0	84.0	2295	11.6	82
396	28.0	4	120.0	79.0	2625	18.6	82
397	31.0	4	119.0	82.0	2720	19.4	82

398 rows × 7 columns

kk.cov()

accele	weight	horsepower	displacement	cylinders	mpg	
9.	-5505.211745	-233.857926	-655.402318	-10.308911	61.089611	mpg
-2.	1290.695575	55.348244	168.623214	2.893415	-10.308911	cylinders
-156.	82368.423240	3614.033744	10872.199152	168.623214	-655.402318	displacement
- 73.	28265.620231	1481.569393	3614.033744	55.348244	-233.857926	horsepower
-974.	717140.990526	28265.620231	82368.423240	1290.695575	-5505.211745	weight
7.	-974.899011	-73.186967	-156.332976	-2.370842	9.058930	acceleration
2.	-959.946344	-59.036432	-142.717137	-2.193499	16.741163	model vear

kk.corr()

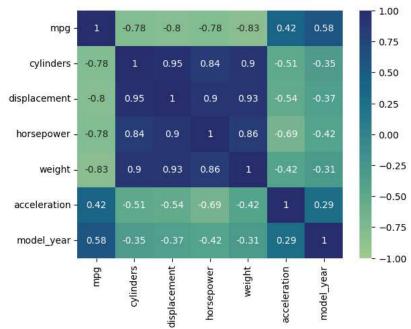
	mpg	cylinders	displacement	horsepower	weight	acceleration	mod
mpg	1.000000	-0.775396	-0.804203	-0.778427	-0.831741	0.420289	(
cylinders	-0.775396	1.000000	0.950721	0.842983	0.896017	-0.505419	-(
displacement	-0.804203	0.950721	1.000000	0.897257	0.932824	-0.543684	-(
horsepower	-0.778427	0.842983	0.897257	1.000000	0.864538	-0.689196	-(
weight	-0.831741	0.896017	0.932824	0.864538	1.000000	-0.417457	-(
acceleration	0.420289	-0.505419	-0.543684	-0.689196	-0.417457	1.000000	(
model vear	0.579267	-0.348746	-0.370164	-0.416361	-0.306564	0.288137	

kk.corr(method = 'pearson')

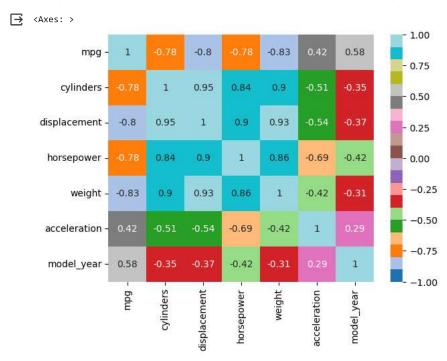
mod	acceleration	weight	horsepower	displacement	cylinders	mpg	
(0.420289	-0.831741	-0.778427	-0.804203	-0.775396	1.000000	mpg
-(-0.505419	0.896017	0.842983	0.950721	1.000000	-0.775396	cylinders
-(-0.543684	0.932824	0.897257	1.000000	0.950721	-0.804203	displacement
-(-0.689196	0.864538	1.000000	0.897257	0.842983	-0.778427	horsepower
-(-0.417457	1.000000	0.864538	0.932824	0.896017	-0.831741	weight
(1.000000	-0.417457	-0.689196	-0.543684	-0.505419	0.420289	acceleration
	0.288137	-0.306564	-0.416361	-0.370164	-0.348746	0.579267	model vear

sns.heatmap(kk.corr(method = 'pearson'),vmin = -1,vmax = 1,annot = True,cmap='crest')





sns.heatmap(kk.corr(method = 'pearson'),vmin = -1,vmax = 1,annot = True,cmap='tab20')



#univariate analysis

sns.distplot(x = df['weight'])

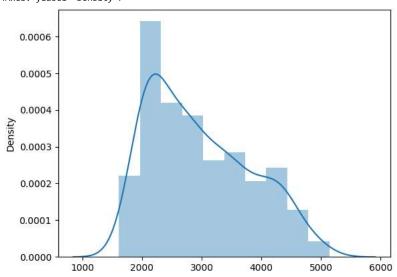
<ipython-input-17-93c64b9801d3>:4: UserWarning:

`distplot` is a deprecated function and will be removed in seaborn v0.14.0.

Please adapt your code to use either `displot` (a figure-level function with similar flexibility) or `histplot` (an axes-level function for histograms).

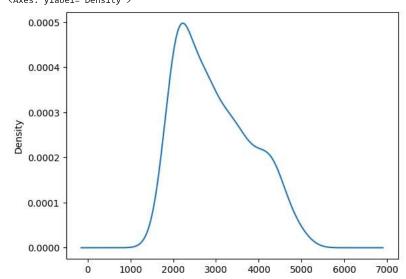
For a guide to updating your code to use the new functions, please see https://gist.github.com/mwaskom/de44147ed2974457ad6372750bbe5751

sns.distplot(x = df['weight'])
<Axes: ylabel='Density'>



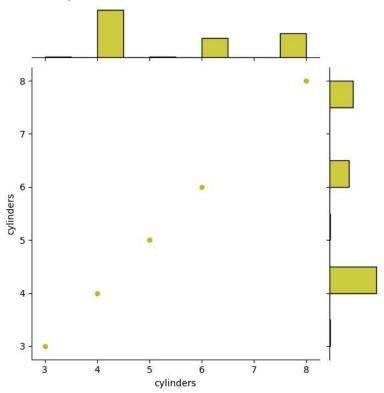
df['weight'].plot(kind = 'kde')

<Axes: ylabel='Density'>



sns.jointplot(x = kk['cylinders'], y = kk['cylinders'],color = 'y')

<seaborn.axisgrid.JointGrid at 0x7da434a0bc40>



sns.pairplot(kk)

