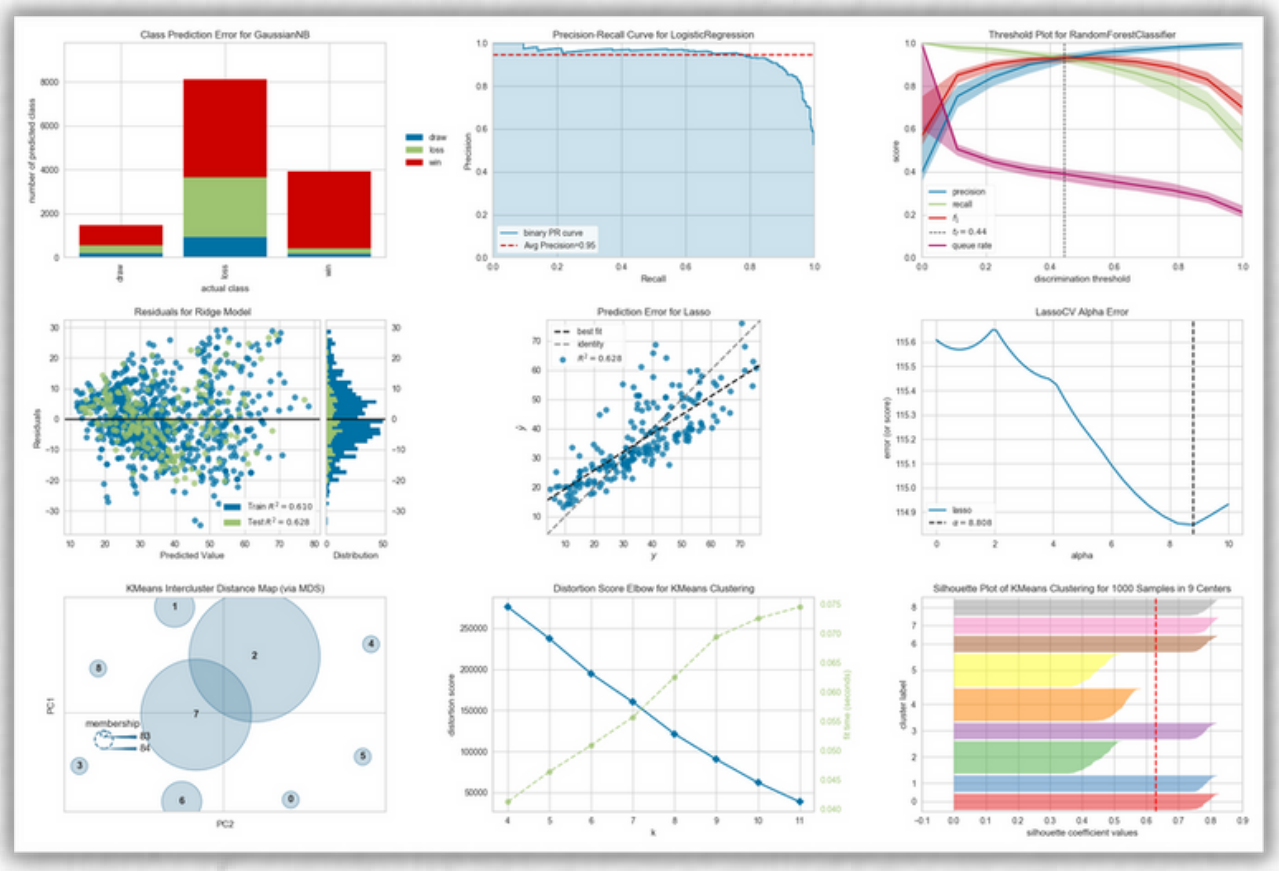
30 Python Libraries to Boost Your Data Science Productivity

Data Science is much more than Pandas, NumPy and Sklearn.

Here are 30 open-source libraries to upgrade your data game.

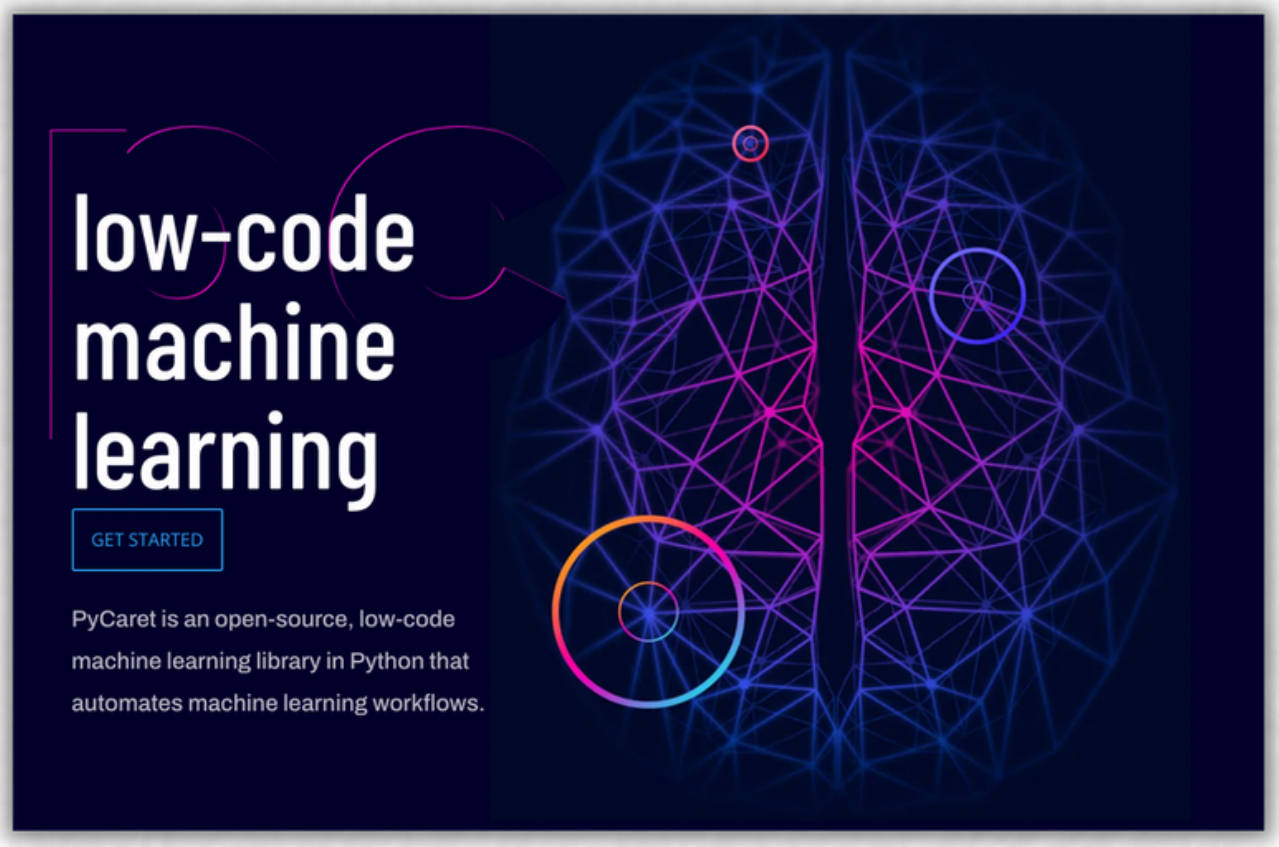
1. YellowBrick



A suite of visualization and diagnostic tools for **faster model selection**.

Matplotlib Sklearn

2. PyCaret



Automate ML workflows with this **low-code library**.

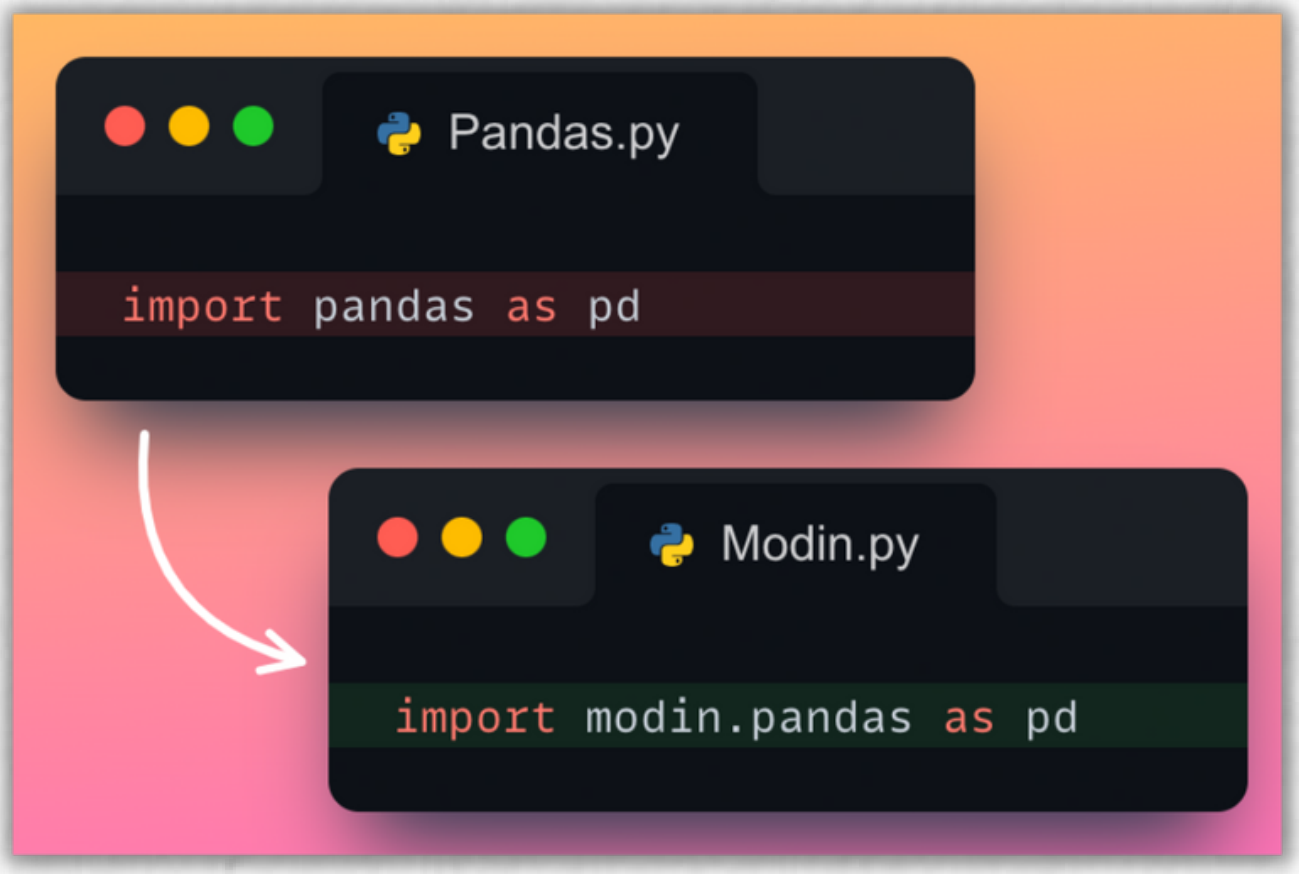
3. imbalanced-learn

```
target.value_counts()
1        548
0        352
```

```
from imblearn.over_sampling import SMOTE

os = SMOTE()

X_new, y_new = os.fit_resample(data, target)

y_new.value_counts()
1        548
0        548
```

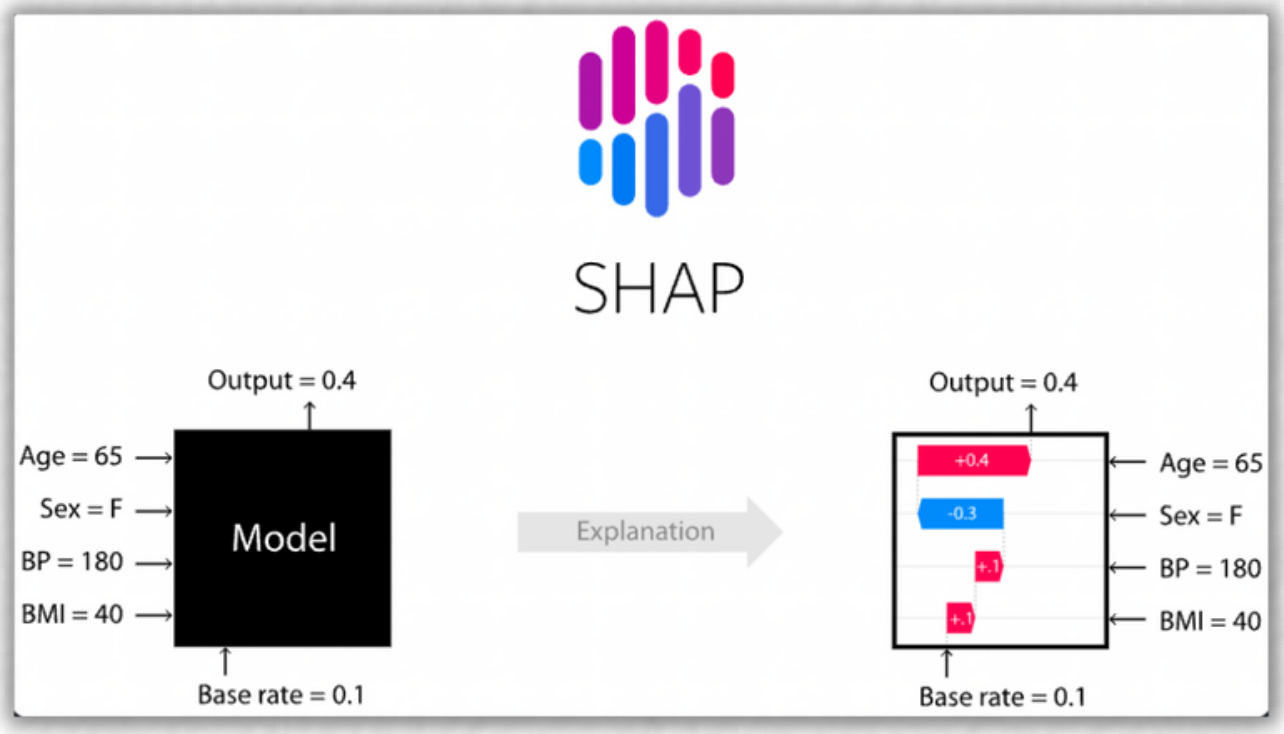
A variety of methods to handle **class imbalance**.

4. Modin



Boost Pandas' performance **up to 70x** by modifying the import.

5. SHAP

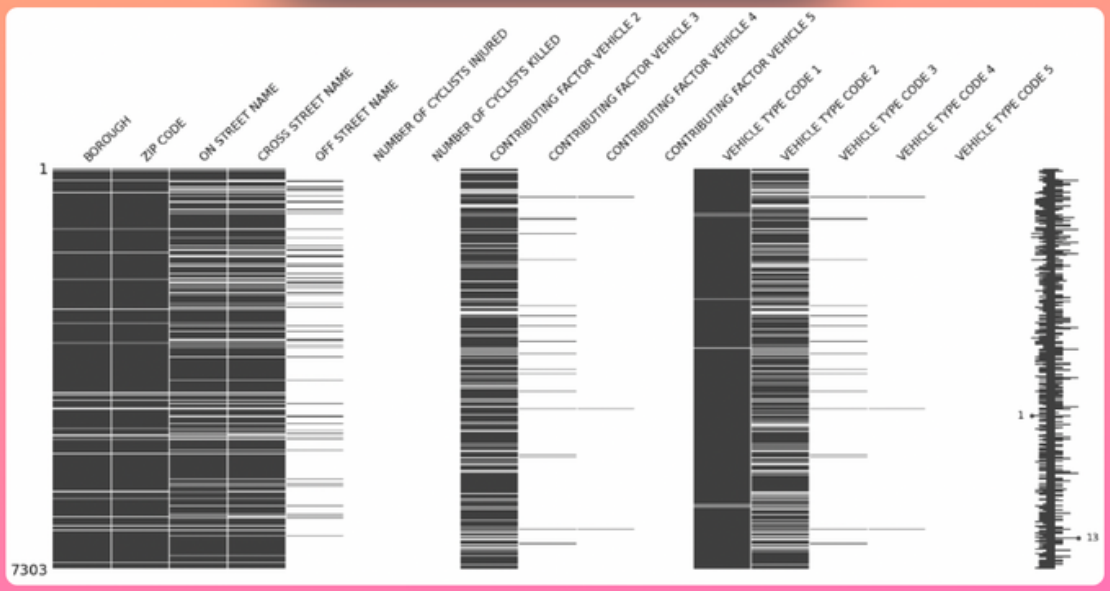


Explain the output of any ML model in few lines of code.

6. Missingno

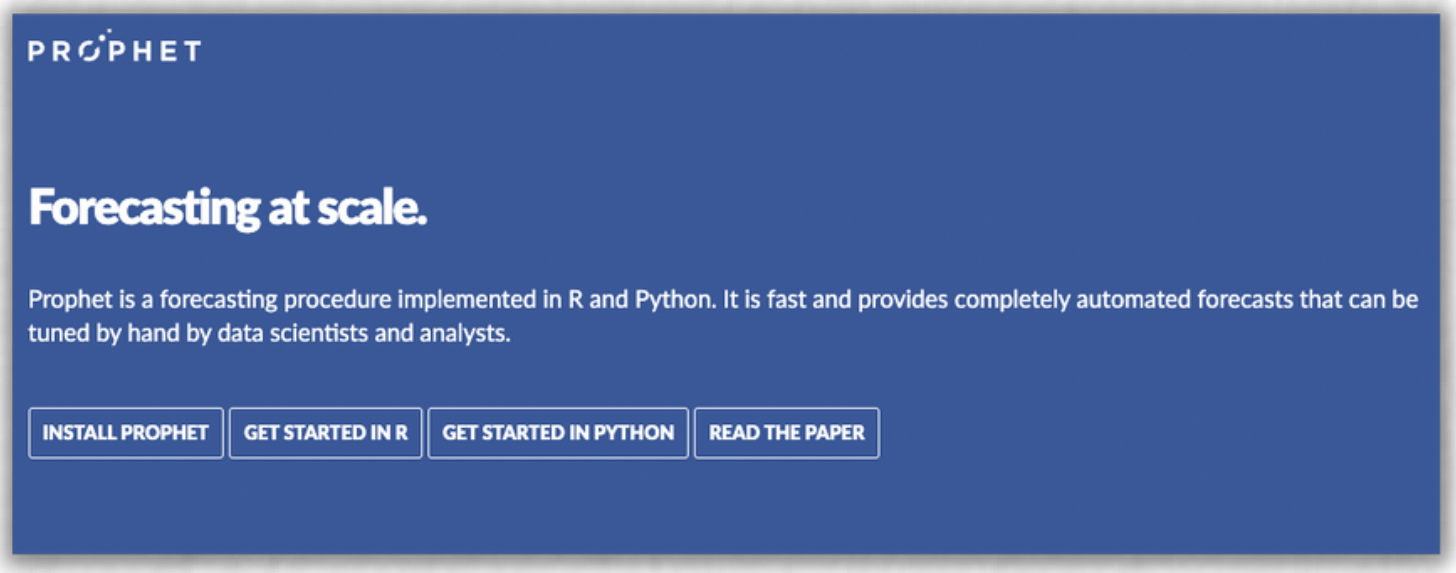
Missing Data

```
import missingno as msno

msno.matrix(df)
```



Visualize missing values
in your dataset
with ease.

7. Prophet



Produce **high-quality forecasts** on time-series data.

8. Parallel-Pandas

```
from parallel_pandas import ParallelPandas

ParallelPandas.initialize()
```

```
- df.apply()    #Pandas
+ df.p_apply() #Parallel
```

```
- df.map()    #Pandas
+ df.p_map() #Parallel
```

```
- df.mean()    #Pandas
+ df.p_mean() #Parallel
```

```
- df.describe()    #Pandas
+ df.p_describe() #Parallel
```

Parallelize Pandas across all CPU cores for **faster computation**.

9. Featuretools

Automated feature engineering for ML models.

10.Lazy Predict

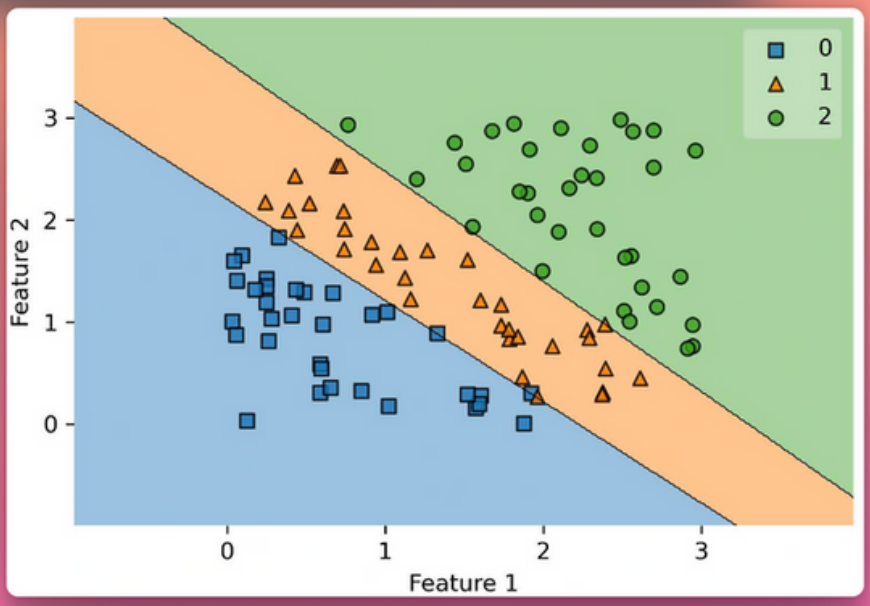
```python
from lazypredict.Supervised import LazyRegressor

reg = LazyRegressor()
reg.fit(X_train, X_test, y_train, y_test)
```

```
| Model                | R-Squared |   RMSE   | Time Taken |
|:---------------------|----------:|---------:|-----------:|
| SVR                  | 0.877199  | 2.62054  |  0.0330021 |
| KNeighborsRegressor  | 0.826307  | 3.1166   |  0.0179954 |
| MLPRegressor         | 0.750536  | 3.73503  |  0.725997  |
                            ...
                            ...
| LinearRegression     | 0.71753   | 3.97444  |  0.0190051 |
| DummyRegressor       |-0.02157   | 7.55832  |  0.0140116 |
```

Train 30 machine learning models in one line of code.

11. mlxtend

```
from mlxtend.plotting import plot_decision_regions

model = LogisticRegression().fit(X, y)

plot_decision_regions(X, y, model)
```



A collection of utility functions for **processing, evaluating, visualizing** models.

12. Vaex

```
%%time
df
```

```
CPU times: user 8 µs, sys: 0 ns, total: 8 µs
Wall time: 16.7 µs
```

#	vendor_id	pickup_datetime	dropoff_datetime	passenger_count	payment_type	trip_distance	pickup_longitude	pickup_latitude
0	VTS	2009-01-04 02:52:00.000000000	2009-01-04 03:02:00.000000000	1	CASH	2.630000114440918	-73.99195861816406	40.72156524658203
1	VTS	2009-01-04 03:31:00.000000000	2009-01-04 03:38:00.000000000	3	Credit	4.550000190734863	-73.98210144042969	40.736289978027344
2	VTS	2009-01-03 15:43:00.000000000	2009-01-03 15:57:00.000000000	5	Credit	10.350000381469727	-74.0025863647461	40.73974609375
3	DDS	2009-01-01 20:52:58.000000000	2009-01-01 21:14:00.000000000	1	CREDIT	5.0	-73.9742660522461	40.79095458984375
4	DDS	2009-01-24 16:18:23.000000000	2009-01-24 16:24:56.000000000	1	CASH	0.4000000059604645	-74.00157928466797	40.719383239746094
...	...	...	...	...	...	...	...	...
1,173,057,922	VTS	2015-12-31 23:59:56.000000000	2016-01-01 00:08:18.000000000	5	1	1.2000000476837158	-73.99381256103516	40.72087097167969
1,173,057,923	CMT	2015-12-31 23:59:58.000000000	2016-01-01 00:05:19.000000000	2	2	2.0	-73.96527099609375	40.76028060913086
1,173,057,924	CMT	2015-12-31 23:59:59.000000000	2016-01-01 00:12:55.000000000	2	2	3.799999952316284	-73.98729705810547	40.739078521728516
1,173,057,925	VTS	2015-12-31 23:59:59.000000000	2016-01-01 00:10:26.000000000	1	2	1.9600000381469727	-73.99755859375	40.72569274902344
1,173,057,926	VTS	2015-12-31 23:59:59.000000000	2016-01-01 00:21:30.000000000	1	1	1.059999942779541	-73.9843978881836	40.76725769042969

High performance package for **lazy Out-of-Core DataFrames.**

13. SweetViz

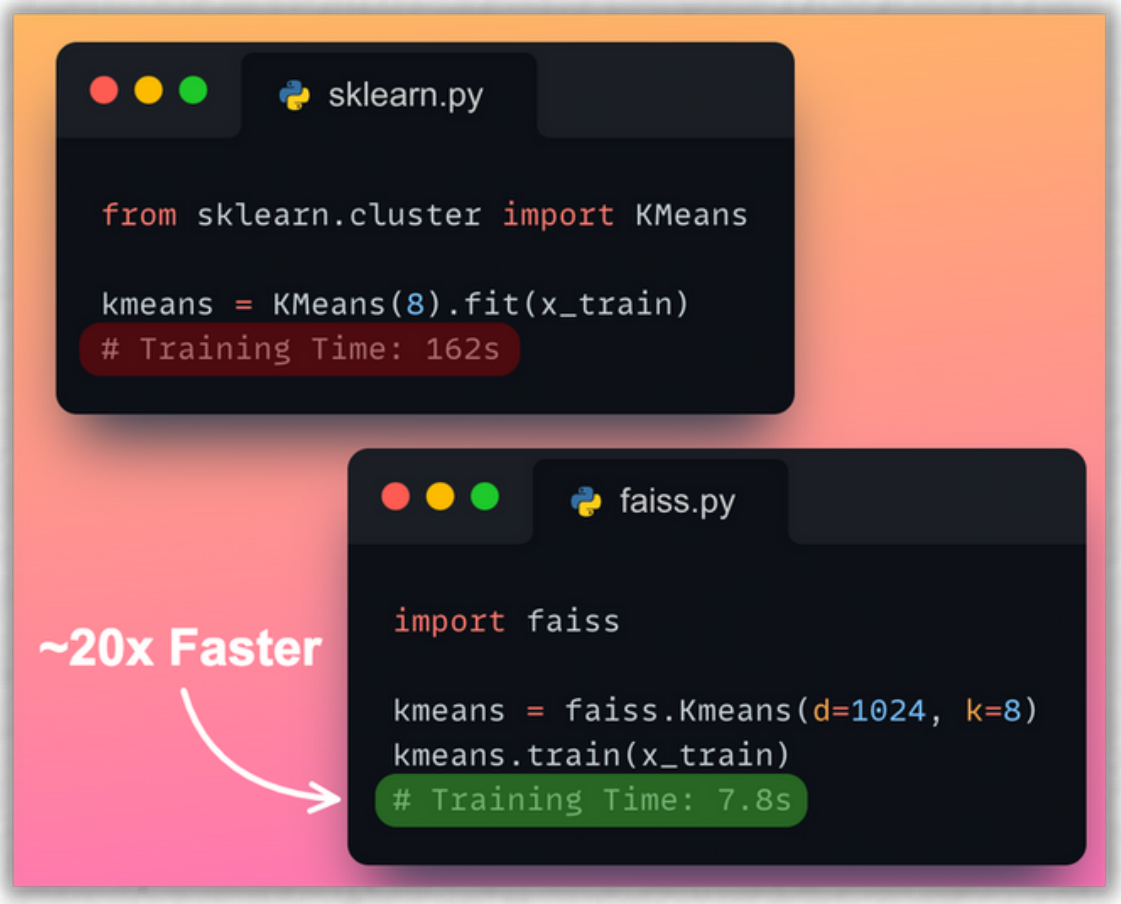
In-depth EDA report
in two lines
of code.

14. Skorch

PyTorch Sklearn

Leverage the power of PyTorch with the elegance of sklearn.

15. Faiss



Efficient algorithms for **similarity search** and **clustering** dense vectors.

16. statsmodel

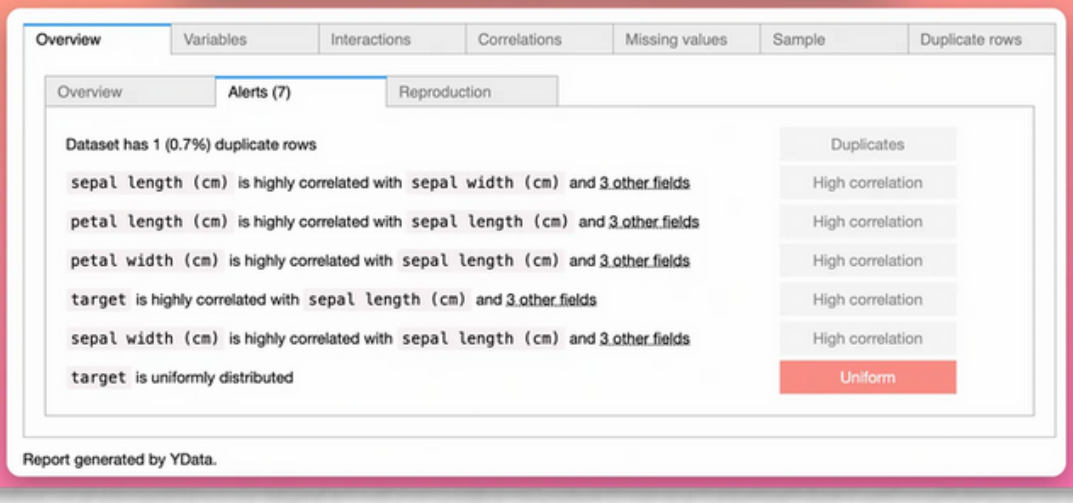
```python
import statsmodels.api as sm

results = sm.OLS(y, X).fit()
print(results.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                      y   R-squared:                       0.178
Model:                            OLS   Adj. R-squared:                  0.161
Method:                 Least Squares   F-statistic:                     10.51
Date:                Wed, 02 Nov 2022   Prob (F-statistic):           7.41e-05
Time:                        17:12:45   Log-Likelihood:                -20.926
No. Observations:                 100   AIC:                             47.85
Df Residuals:                      97   BIC:                             55.67
Df Model:                           2
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const          1.4713      0.075     19.579      0.000       1.322       1.620
x1             0.1045      0.105      1.000      0.320      -0.103       0.312
x2             0.4831      0.107      4.503      0.000       0.270       0.696
==============================================================================
Omnibus:                       39.684   Durbin-Watson:                   1.848
Prob(Omnibus):                  0.000   Jarque-Bera (JB):                6.503
Skew:                           0.096   Prob(JB):                       0.0387
Kurtosis:                       1.766   Cond. No.                         5.09
==============================================================================
```

Statistical testing and data exploration at fingertips.

17. Pandas-Profiling

```python
from pandas_profiling import ProfileReport

profile = ProfileReport(iris_data,
          title="Pandas Profiling Report")

profile.to_widgets()
```



Generate a high-level **EDA report** of your data in no time.

18. Streamlit

Create and host data-based Python web apps in few lines of code.

19. Category-encoders

```
import category_encoders as ce

ce_be = ce.BinaryEncoder(cols=['class'])

ce_be.fit_transform(data["class"])

   class_0  class_1  class_2
0        0        0        1
1        0        1        0
2        0        1        1
3        1        0        0
4        0        0        1
```

Binary

	gender	class
0	Male	A
1	Female	B
2	Male	C
3	Female	D
4	Female	A

Over 15 categorical data encoders.

20. DuckDB

Filter-Pandas.ipynb

```
df[df.city == "New Delhi"]
```

Pandas

Filter-SQL.ipynb

```
%%sql

select * from df
where city = 'New Delhi';
```

DuckDB

Run SQL queries on DataFrame.

21. PandasML

```
import pandas_ml as pdml

df = pdml.ModelFrame(X, y)

train, test = df.model_selection.
              train_test_split()

reg = df.linear_model.LinearRegression()

train.fit(reg)

test.predict(reg)
```

Pandas data wrangling + Sklearn algorithms + Matplotlib visualization.

22. Pytest

An **elegant testing framework** to test your code.

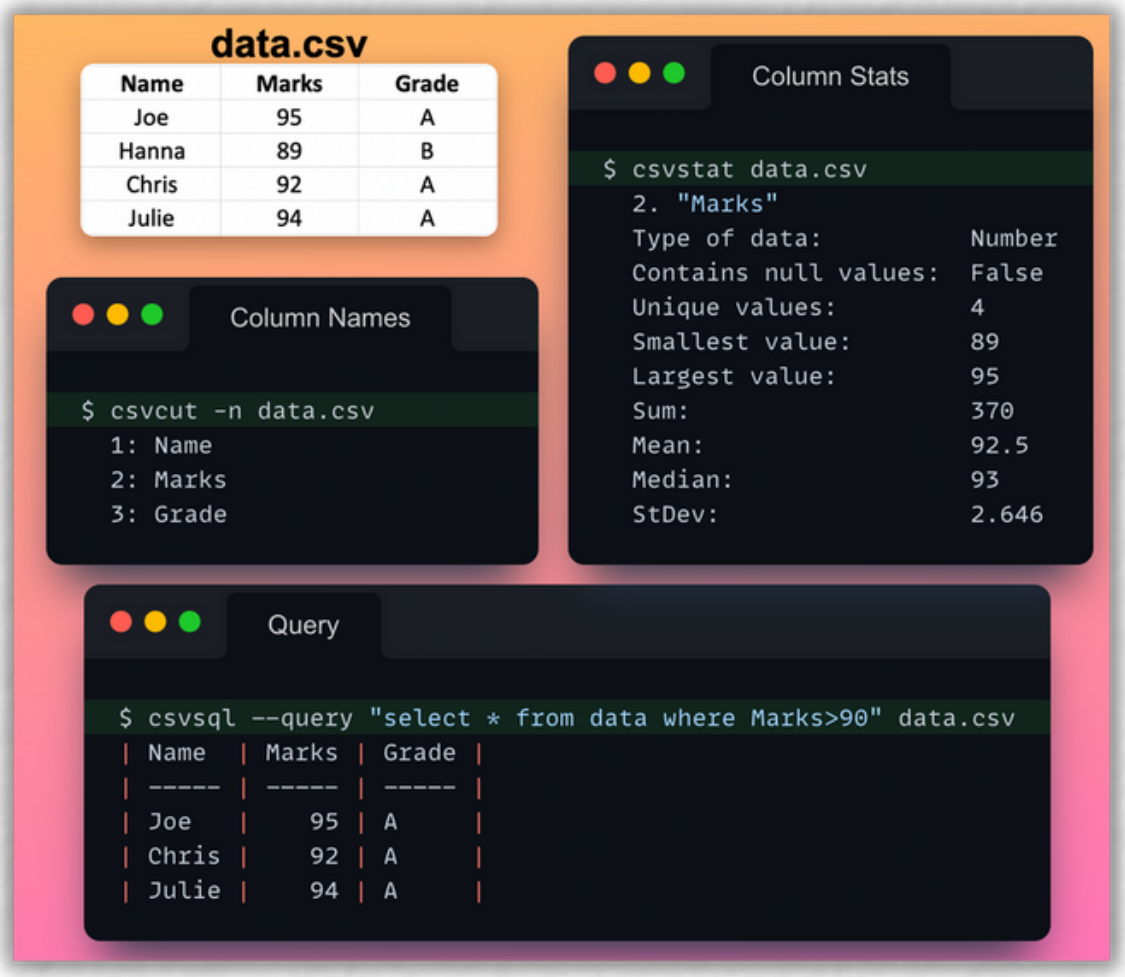
23. Numexpr

```
import numpy as np
import numexpr as ne

a = np.random.random(10**7)
b = np.random.random(10**7)

%timeit np.cos(a) + np.sin(b)

142 ms ± 257 µs per loop

%timeit ne.evaluate("cos(a) + sin(b)")

32.5 ms ± 229 µs per loop
```

~5x Faster

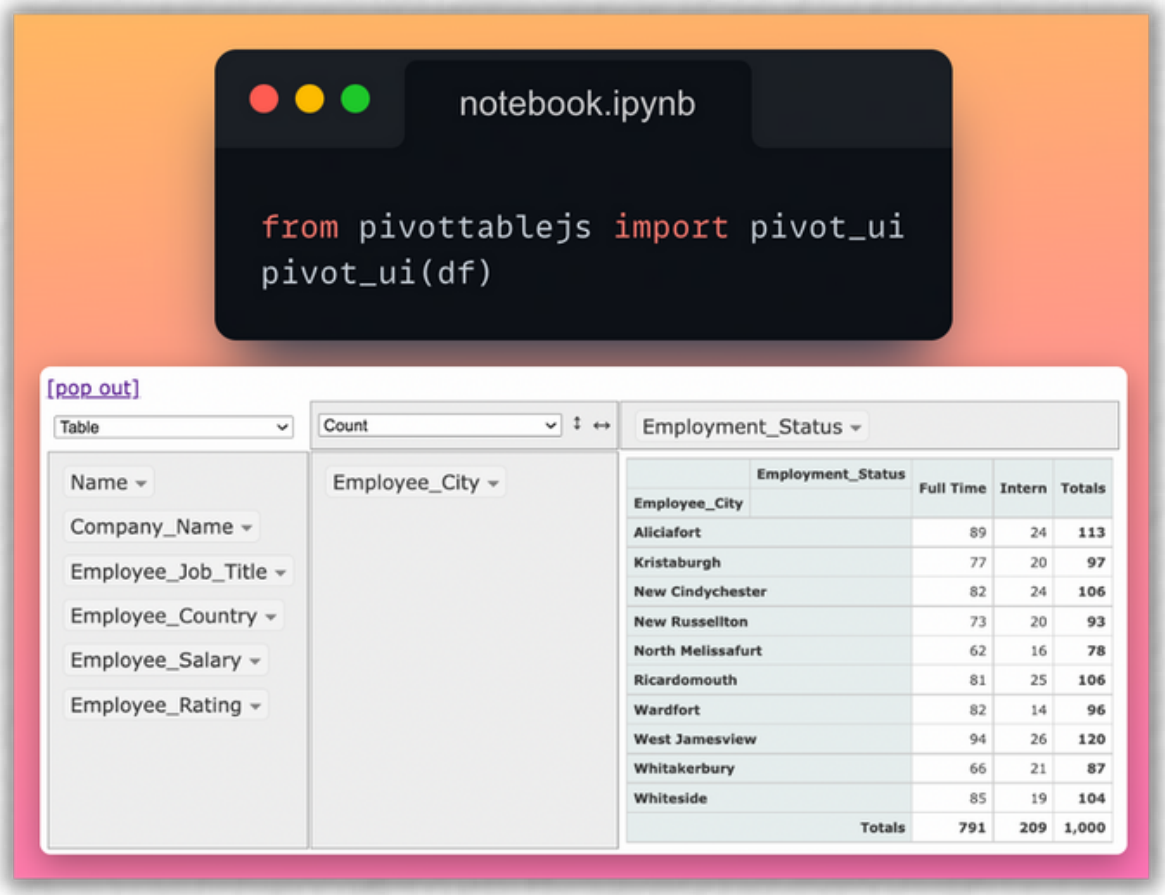
Parallelize NumPy to all CPU cores for **20x speedup**.

24. CSV-Kit



Explore, query and describe CSV files from terminal.

25. PivotTableJS



Drap-n-drop tools to group, pivot, plot dataframe.

26. Faker

fake_data.py

```
from faker import Faker
fake = Faker()

>>> fake.name()
'Darrell Alexander'

>>> fake.email()
'ryanrichard@example.com'

>>> fake.address()
'205 Brown Point, West Melissaport, MN 93828'
```

Generate **fake yet meaningful data** in seconds.

27. Icecream

Print

```python
def func(arr, n):
    print("arr =", arr, "n =", n)

func([1,2,3], 2)
## arr = [1, 2, 3] n = 2
```

Icecream

```python
from icecream import ic

def func(arr, n):
    ic(arr, n)

func([1,2,3], 2)
## ic| arr: [1, 2, 3], n: 2
```

Don't debug with print(). Use icecream.

28. Pyforest

```python
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import sys

from sklearn.linear_model import LinearRegression
```

```python
from pyforest import *

pd.read_csv("file.csv") ✅
np.array([1,2,3])       ✅
sys.path                ✅
LinearRegression()      ✅
```

No need to write imports. **Automatic package import**.

29. PySnooper

Profile your code. **Track new variables, and their updates**.

30. Sidetable

sidetable.py

```python
import sidetable

df.stb.freq(["City"],
            style=True)
```

value_counts()

```
City
West Jamesview        120
Aliciafort            113
New Cindychester      106
Ricardomouth          106
Whiteside             104
Kristaburgh            97
Wardfort               96
New Russellton         93
Whitakerbury           87
North Melissafurt      78
```

	City	count	percent	cumulative_count	cumulative_percent
0	West Jamesview	120	12.00%	120	12.00%
1	Aliciafort	113	11.30%	233	23.30%
2	Ricardomouth	106	10.60%	339	33.90%
3	New Cindychester	106	10.60%	445	44.50%
4	Whiteside	104	10.40%	549	54.90%
5	Kristaburgh	97	9.70%	646	64.60%
6	Wardfort	96	9.60%	742	74.20%
7	New Russellton	93	9.30%	835	83.50%
8	Whitakerbury	87	8.70%	922	92.20%
9	North Melissafurt	78	7.80%	1,000	100.00%

Supercharge Pandas' **value_counts()** method.