In [1]:
```
import os
import glob
import pandas as pd
import matplotlib.pyplot as plt
import datetime as dt
from concurrent import futures
import numpy as np
import pandas_datareader.data as web
from scipy.stats import gaussian_kde
from scipy.cluster.hierarchy import linkage, dendrogram, fcluster, set_link_color
from sklearn.manifold import TSNE
from sklearn.cluster import DBSCAN
from sklearn.cluster import KMeans
data_dir = "./data/stock_data_for_clustering"
os.makedirs(data_dir, exist_ok=True)
```

In [3]:
```
tables = pd.read_html('https://en.wikipedia.org/wiki/List_of_S%26P_500_companies'
first_table = tables[0]
print(first_table.shape)
first_table["Symbol"] = first_table["Symbol"].map(lambda x: x.replace(".", "-"))
sp500_tickers = list(first_table["Symbol"])
first_table.head()
```

```
(504, 9)
```

Out[3]:

	Symbol	Security	SEC filings	GICS Sector	GICS Sub-Industry	Headquarters Location	Date first added	CIK	Founded
0	MMM	3M	reports	Industrials	Industrial Conglomerates	Saint Paul, Minnesota	1976-08-09	66740	1902
1	AOS	A. O. Smith	reports	Industrials	Building Products	Milwaukee, Wisconsin	2017-07-26	91142	1916
2	ABT	Abbott	reports	Health Care	Health Care Equipment	North Chicago, Illinois	1964-03-31	1800	1888
3	ABBV	AbbVie	reports	Health Care	Pharmaceuticals	North Chicago, Illinois	2012-12-31	1551152	2013 (1888)
4	ABMD	Abiomed	reports	Health Care	Health Care Equipment	Danvers, Massachusetts	2018-05-31	815094	1981

In [4]:
```python
def download_stock(stock):
    try:
        print(stock)
        stock_df = web.DataReader(stock,'yahoo', start_time, end_time)
        stock_df['Name'] = stock
        output_name = f"{data_dir}/{stock}.csv"
        stock_df.to_csv(output_name)
    except:
        bad_names.append(stock)
        print('bad: %s' % (stock))
""" set the download window """
start_time = dt.datetime(2021, 12, 1)
end_time = dt.datetime(2022, 3, 1)
bad_names =[] #to keep track of failed queries
#set the maximum thread number
max_workers = 20
now = dt.datetime.now()
workers = min(max_workers, len(sp500_tickers)) #in case a smaller number of stock
with futures.ThreadPoolExecutor(workers) as executor:
    res = executor.map(download_stock, sp500_tickers)
""" Save failed queries to a text file to retry """
if len(bad_names) > 0:
    with open(f'{data_dir}/failed_queries.txt','w') as outfile:
        for name in bad_names:
            outfile.write(name+'\n')
finish_time = dt.datetime.now()
duration = finish_time - now
minutes, seconds = divmod(duration.seconds, 60)
print(f'The threaded script took {minutes} minutes and {seconds} seconds to run.'
print(f"{len(bad_names)} stocks failed: ", bad_names)
```

```
MMMAOS
ABT

ABBV
ABMD
ACN
ATVI
ADM
ADBE
ADP
AAP
AES
AFL
A
AIG
APD
AKAM
ALK
ALB
```

In [5]:
```python
historical_stock_data_files = glob.glob(f"./{data_dir}/*.csv")
reference_day = "2021-12-31"
start_day = "2022-01-03"
midterm_day = "2022-01-18"
end_day = "2022-01-31"
price_change_list = []
tickers_to_ignore = []
for files in historical_stock_data_files:
    df = pd.read_csv(files, index_col=["Date"])
    ticker = os.path.splitext(os.path.basename(files))[0]
    try:
        price_close = df[reference_day: end_day][["Close"]]
        price_change = (price_close / price_close.loc[reference_day, "Close"] - 1
        price_change = price_change.iloc[1: ,:]
        price_change = price_change.rename(columns={"Close": ticker})
        price_change_list.append(price_change)
    except KeyError as e:
        # some stocks started trading after 2021-12-31
        print(ticker)
        tickers_to_ignore.append(ticker)

df = pd.concat(price_change_list, axis=1)
print(df.shape)
df.head()
```

```
CEG
(20, 503)
```

Out[5]:

Date	A	AAL	AAP	AAPL	ABBV	ABC	ABMD	ABT	
2022-01-03	-1.985592	4.398669	-1.292315	2.500415	0.014774	-0.203179	1.982347	-1.207910	-1.77
2022-01-04	-5.299087	5.902012	-1.179757	1.199521	-0.177245	-1.151327	0.673771	-3.531335	-2.47
2022-01-05	-6.921383	4.008916	-1.429885	-1.492374	0.347121	-0.293475	-5.838461	-3.964759	-4.19
2022-01-06	-6.595678	3.396440	0.737864	-3.136795	-0.125553	-1.836107	-6.328482	-3.978972	-8.81
2022-01-07	-9.082368	7.349675	-0.746210	-3.041059	-0.384039	0.173072	-11.106165	-3.680551	-10.56

5 rows × 503 columns

```
In [6]: data_1 = df.loc[[end_day], :]
        display(data_1.head())
        data_2 = df.loc[[start_day, midterm_day, end_day], :]
        display(data_2.head())
        data_3 = df
        display(data_3.head())
```

Date	A	AAL	AAP	AAPL	ABBV	ABC	ABMD	ABT	
2022-01-31	-12.734098	-8.296213	-3.489249	-1.571216	1.100447	2.49078	-17.623971	-9.435843	-14.707

1 rows × 503 columns

Date	A	AAL	AAP	AAPL	ABBV	ABC	ABMD	ABT	
2022-01-03	-1.985592	4.398669	-1.292315	2.500415	0.014774	-0.203179	1.982347	-1.207910	-1.
2022-01-18	-12.013776	-0.334073	-0.821244	-4.375741	1.019206	0.692301	-18.595653	-10.068215	-15.
2022-01-31	-12.734098	-8.296213	-3.489249	-1.571216	1.100447	2.490780	-17.623971	-9.435843	-14.

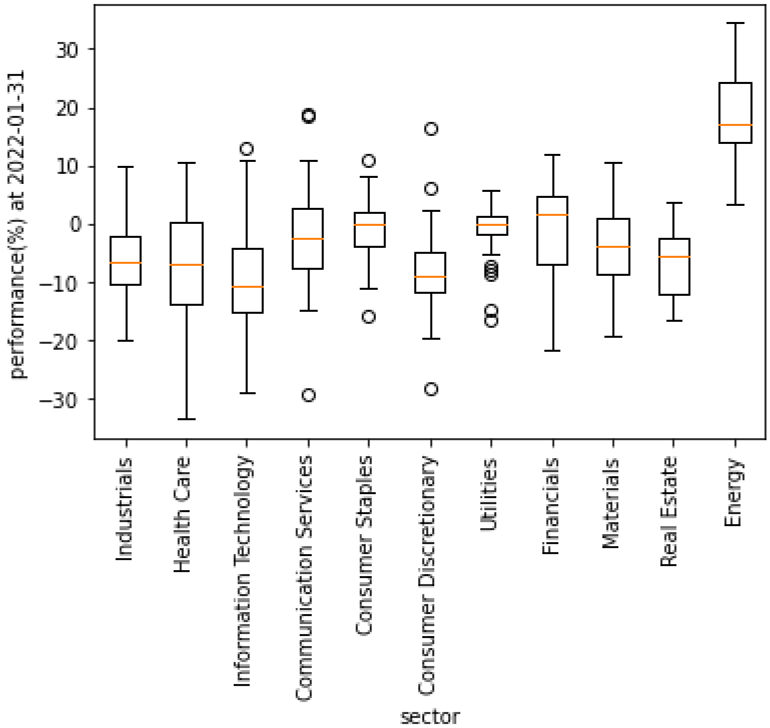
3 rows × 503 columns

Date	A	AAL	AAP	AAPL	ABBV	ABC	ABMD	ABT	
2022-01-03	-1.985592	4.398669	-1.292315	2.500415	0.014774	-0.203179	1.982347	-1.207910	-1.77
2022-01-04	-5.299087	5.902012	-1.179757	1.199521	-0.177245	-1.151327	0.673771	-3.531335	-2.47
2022-01-05	-6.921383	4.008916	-1.429885	-1.492374	0.347121	-0.293475	-5.838461	-3.964759	-4.19
2022-01-06	-6.595678	3.396440	0.737864	-3.136795	-0.125553	-1.836107	-6.328482	-3.978972	-8.81
2022-01-07	-9.082368	7.349675	-0.746210	-3.041059	-0.384039	0.173072	-11.106165	-3.680551	-10.56

5 rows × 503 columns

Exploratory Data Analysis(EDA) January is usually a month when the market tends to rise, but January 2022 was a difficult month. Here is a quick analysis of how stocks performed.

In [7]:
```
first_table = first_table[~first_table["Symbol"].isin(tickers_to_ignore)]
industry_list = list(first_table["GICS Sector"].unique())
performance_by_industry = [data_1.loc[:, first_table[first_table["GICS Sector"]==
plt.boxplot(performance_by_industry, labels=industry_list)
plt.xticks(rotation=90)
plt.xlabel("sector")
plt.ylabel(f"performance(%) at {end_day}")
plt.show()
```

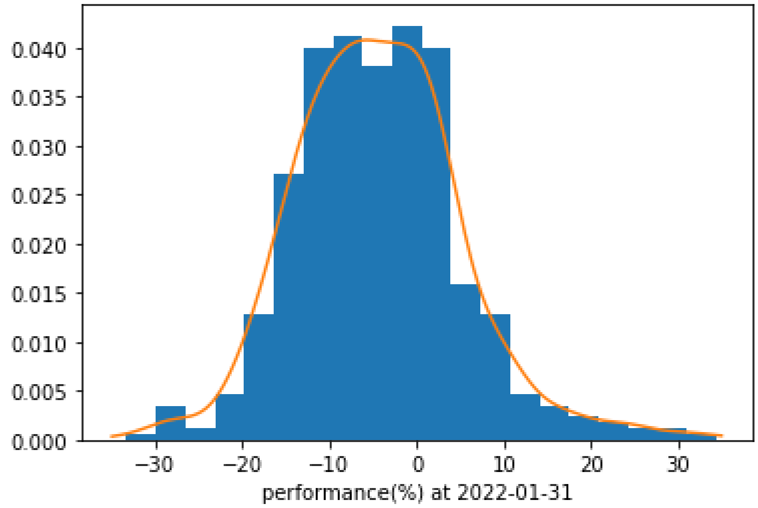


Clustering

One-dimentional data We will first perform clustering using Type 1 data.

Before clustering, we first check the distribution of the data

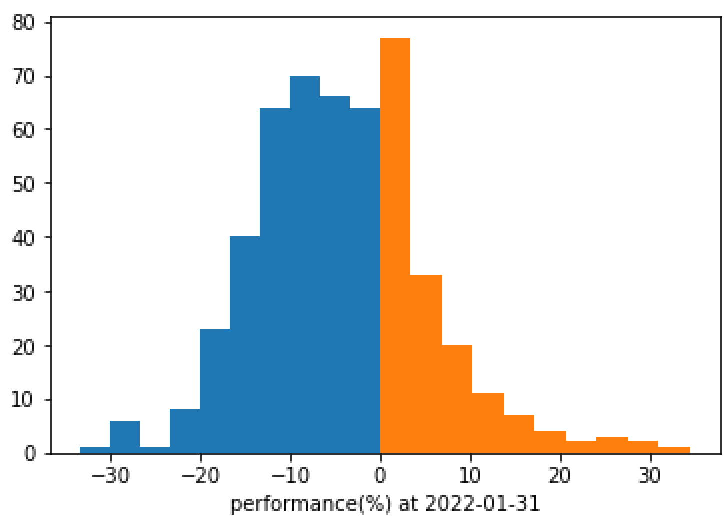
In [8]:
```
# Kernel density estimation
x = np.linspace(-35, 35, 1000)
kde = gaussian_kde(data_1.values)
y = kde(x)
plt.hist(data_1.loc[end_day, :], bins=20, density=True)
plt.plot(x, y)
plt.xlabel(f"performance(%) at {end_day}")
plt.show()
```



You don’t think clustering is particularly necessary because the data is nicely distributed around -5 and there is no cluster.

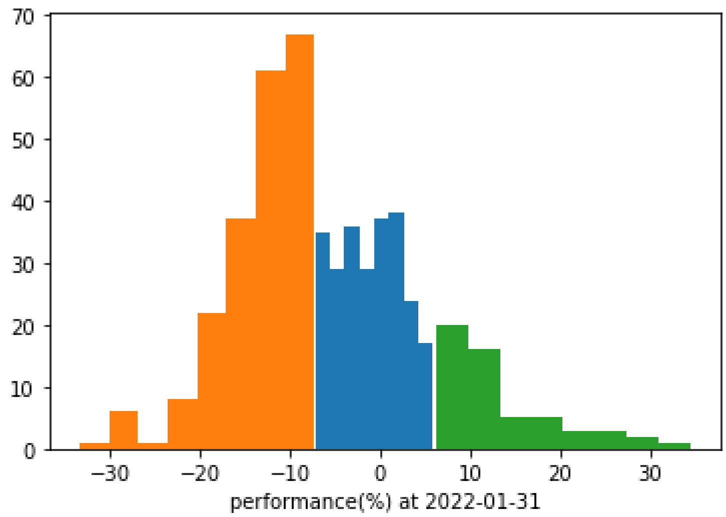
If you dare to do clustering, you can, for example, arbitrarily divide the data into clusters smaller than 0 and clusters greater than 0.

In [9]:
```
plt.hist(data_1[data_1 < 0].loc[end_day, :], bins=10)
plt.hist(data_1[data_1 >= 0].loc[end_day, :], bins=10)
plt.xlabel(f"performance(%) at {end_day}")
plt.show()
```

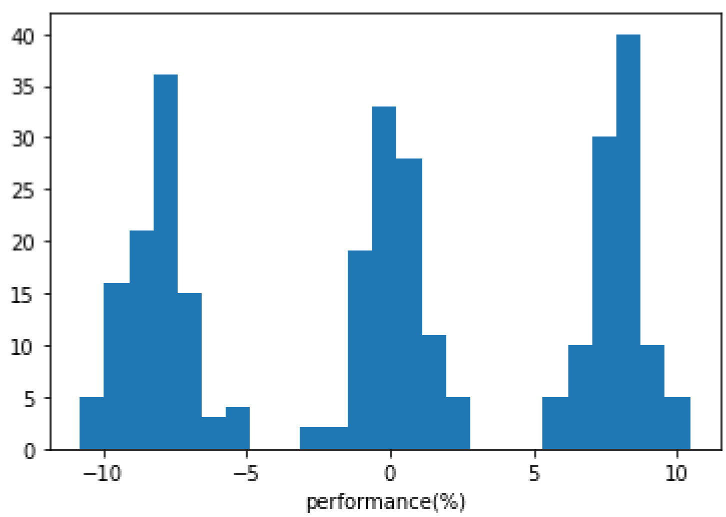


Here we will use KMeans clustering to divide the data into three clusters as a test. We could indeed divide them into three, but the boundaries of the clusters are not appropriate.

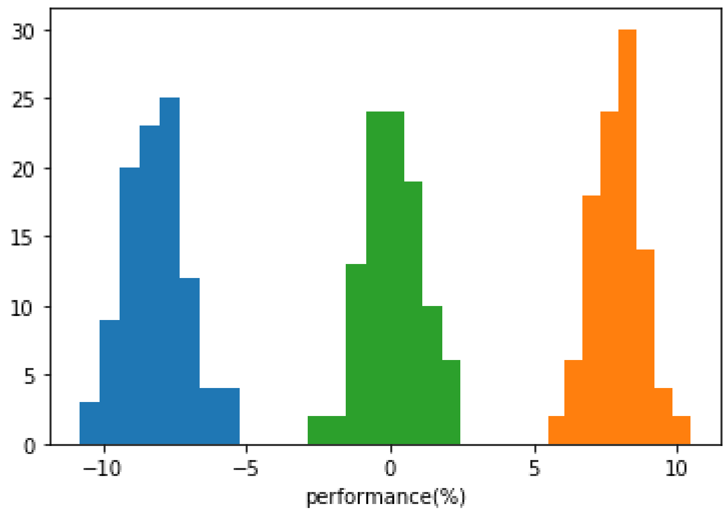
In [10]:
```
n_clusters = 3
kmeans = KMeans(n_clusters=n_clusters, random_state=0).fit(data_1.T.values)
for i in range(n_clusters):
    plt.hist(data_1.loc[end_day, kmeans.labels_ == i], bins=8)
plt.xlabel(f"performance(%) at {end_day}")
plt.show()
```



In [11]:
```
dummy_zero = np.random.normal(0,1,100)
dummy_minus = np.random.normal(-8,1,100)
dummy_plus = np.random.normal(8,1,100)
dummy = np.concatenate([dummy_zero, dummy_minus, dummy_plus])
plt.hist(dummy, bins=25)
plt.xlabel("performance(%)")
plt.show()
```



In [12]:
```python
n_clusters = 3
kmeans = KMeans(n_clusters=n_clusters, random_state=0).fit(dummy.reshape(-1,1))
for i in range(n_clusters):
    plt.hist(dummy[kmeans.labels_ == i], bins=8)
plt.xlabel("performance(%)")
plt.show()
```



Two-dimentional data What if the data is two-dimensional? The distribution of the data becomes a bit more complex.

Let’s check the distribution of type 2 data.

Note that type 2 data has three dimensions. So we are going to slice the data and plot the two-dimensional data.

We first plot performance on January 18 and January 31.

In [16]:
```python
def scatter_hist(x, y, ax, ax_histx, ax_histy):
    # no labels
    ax_histx.tick_params(axis="x", labelbottom=False)
    ax_histy.tick_params(axis="y", labelleft=False)
# the scatter plot:
    ax.scatter(x, y, alpha=0.5)
```

In [18]:
```python
# now determine nice limits by hand:
binwidth = 0.25
xymax = max(np.max(np.abs(x)), np.max(np.abs(y)))
lim = (int(xymax/binwidth) + 1) * binwidth
```