```
In [1]:
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
In [2]:
df = pd.read csv('data.csv')
In [3]:
df.head()
Out[3]:
   feature1
            feature2
                    feature3
                                target
                             -9.763182
0 -0.570563
           1.420342 0.495580
1 -0.990563
            0.556965
                    1.045064 -24.029355
2 -0.674728
            0.150617
                    1.774645
                            45.616421
3 0.388250 -0.387127 -0.110229
                            34.135737
4 1.167882 -0.024104 0.145063 86.663647
In [4]:
X = df.iloc[:,0:3].values
y = df.iloc[:,-1].values
In [5]:
from sklearn.model selection import train test split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random state=1)
In [6]:
from sklearn.linear model import LinearRegression
model = LinearRegression()
model.fit(X train, y train)
Out[6]:
LinearRegression()
In [7]:
# Residual
y_pred = model.predict(X_test)
residual = y_test - y_pred
```

1. Linear Relationship

In [8]:

```
fig, (ax1, ax2, ax3) = plt.subplots(ncols=3, figsize=(12, 2.5))
ax1.scatter(df['feature1'], df['target'])
ax1.set_title("Feature1")
ax2.scatter(df['feature2'], df['target'])
ax2.set_title("Feature2")
ax3.scatter(df['feature3'], df['target'])
```

```
ax3.set_title("Feature3")
plt.show()

Feature1

Feature2

Feature3

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```

In []:

2. Multicollinearity

```
In [9]:
```

```
from statsmodels.stats.outliers_influence import variance_inflation_factor

vif = []
for i in range(X_train.shape[1]):
    vif.append(variance_inflation_factor(X_train, i))
```

```
In [10]:
```

```
pd.DataFrame({'vif': vif}, index=df.columns[0:3]).T
```

Out[10]:

	feature1	feature2	feature3
vif	1.010326	1.009871	1.01395

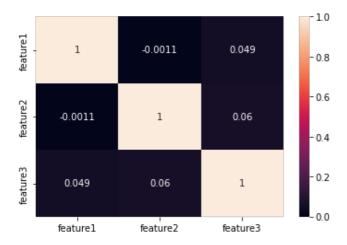
Our result is came for every feature is 1 then we can consider here is not any multicollinearity is present

In [11]:

```
# Another Technique
sns.heatmap(df.iloc[:,0:3].corr(),annot=True)
```

Out[11]:

<AxesSubplot:>



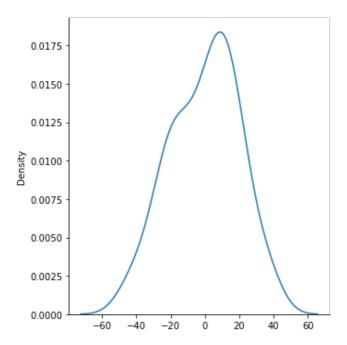
3. Normality of Residual

```
In [12]:
```

```
sns.displot(residual, kind='kde')
```

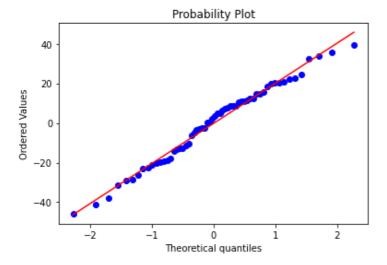
Out[12]:

<seaborn.axisgrid.FacetGrid at 0x25cdb9d8fa0>



In [13]:

```
# QQ Plot
import scipy as sp
fig, ax = plt.subplots(figsize=(6,4))
sp.stats.probplot(residual, plot=ax, fit=True)
plt.show()
```



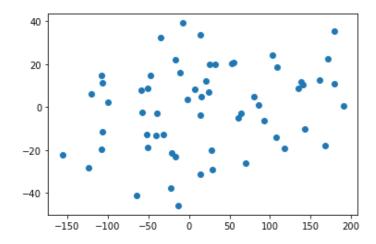
4. Homoscedasticity

```
In [14]:
```

```
plt.scatter(y_pred,residual)
```

Out[14]:

<matplotlib.collections.PathCollection at 0x25cdc27d250>



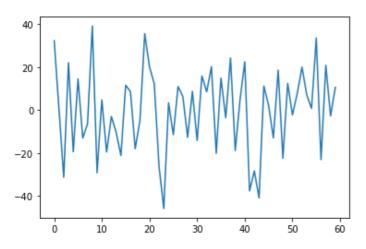
5. Autocorrelation of Residuals

In [15]:

plt.plot(residual)

Out[15]:

[<matplotlib.lines.Line2D at 0x25cdc2d9d90>]



In []:

In []:

In []: