import pandas as pd
import numpy as np
from matplotlib import pyplot as plt
%matplotlib inline
import matplotlib

Out[2]:		R&D Spend	Administration	Marketing Spend	Profit
	0	165349.20	136897.80	471784.10	192261.83
	1	162597.70	151377.59	443898.53	191792.06
	2	153441.51	101145.55	407934.54	191050.39
	3	144372.41	118671.85	383199.62	182901.99
	4	142107.34	91391.77	366168.42	166187.94
	5	131876.90	99814.71	362861.36	156991.12
	6	134615.46	147198.87	127716.82	156122.51
	7	130298.13	145530.06	323876.68	155752.60
	8	120542.52	148718.95	311613.29	152211.77
	9	123334.88	108679.17	304981.62	149759.96
	10	101913.08	110594.11	229160.95	146121.95
	11	100671.96	91790.61	249744.55	144259.40
	12	93863.75	127320.38	249839.44	141585.52
	13	91992.39	135495.07	252664.93	134307.35
	14	119943.24	156547.42	256512.92	132602.65
	15	114523.61	122616.84	261776.23	129917.04
	16	78013.11	121597.55	264346.06	126992.93
	17	94657.16	145077.58	282574.31	125370.37
	18	91749.16	114175.79	294919.57	124266.90
	19	86419.70	153514.11	0.00	122776.86
	20	76253.86	113867.30	298664.47	118474.03
	21	78389.47	153773.43	299737.29	111313.02
	22	73994.56	122782.75	303319.26	110352.25
	23	67532.53	105751.03	304768.73	108733.99
	24	77044.01	99281.34	140574.81	108552.04
	25	64664.71	139553.16	137962.62	107404.34
	26	75328.87	144135.98	134050.07	105733.54
	27	72107.60	127864.55	353183.81	105008.31
	28	66051.52	182645.56	118148.20	103282.38

	R&D Spend	Administration	Marketing Spend	Profit
29	65605.48	153032.06	107138.38	101004.64
30	61994.48	115641.28	91131.24	99937.59
31	61136.38	152701.92	88218.23	97483.56
32	63408.86	129219.61	46085.25	97427.84
33	55493.95	103057.49	214634.81	96778.92
34	46426.07	157693.92	210797.67	96712.80
35	46014.02	85047.44	205517.64	96479.51
36	28663.76	127056.21	201126.82	90708.19
37	44069.95	51283.14	197029.42	89949.14
38	20229.59	65947.93	185265.10	81229.06
39	38558.51	82982.09	174999.30	81005.76
40	28754.33	118546.05	172795.67	78239.91
41	27892.92	84710.77	164470.71	77798.83
42	23640.93	96189.63	148001.11	71498.49
43	15505.73	127382.30	35534.17	69758.98
44	22177.74	154806.14	28334.72	65200.33
45	1000.23	124153.04	1903.93	64926.08
46	1315.46	115816.21	297114.46	49490.75
47	0.00	135426.92	0.00	42559.73
48	542.05	51743.15	0.00	35673.41
49	0.00	116983.80	45173.06	14681.40

In [3]: data.head() # To get the first 5 rows

Out[3]:		R&D Spend	Administration	Marketing Spend	Profit
	0	165349.20	136897.80	471784.10	192261.83
	1	162597.70	151377.59	443898.53	191792.06
	2	153441.51	101145.55	407934.54	191050.39
	3	144372.41	118671.85	383199.62	182901.99
	4	142107.34	91391.77	366168.42	166187.94

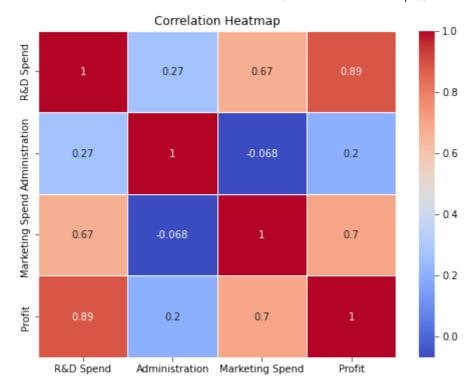
In [4]: data.shape # shows number of rows and columns in a dataset

Out[4]: (50, 4)

In [6]: data

Out[6]:		R&D Spend	Administration	Marketing Spend	Profit
-	0	165349.2000	136897.80	471784.1000	192261.83
	1	162597.7000	151377.59	443898.5300	191792.06
	2	153441.5100	101145.55	407934.5400	191050.39
	3	144372.4100	118671.85	383199.6200	182901.99
	4	142107.3400	91391.77	366168.4200	166187.94
	5	131876.9000	99814.71	362861.3600	156991.12
	6	134615.4600	147198.87	127716.8200	156122.51
	7	130298.1300	145530.06	323876.6800	155752.60
	8	120542.5200	148718.95	311613.2900	152211.77
	9	123334.8800	108679.17	304981.6200	149759.96
	10	101913.0800	110594.11	229160.9500	146121.95
	11	100671.9600	91790.61	249744.5500	144259.40
	12	93863.7500	127320.38	249839.4400	141585.52
	13	91992.3900	135495.07	252664.9300	134307.35
	14	119943.2400	156547.42	256512.9200	132602.65
	15	114523.6100	122616.84	261776.2300	129917.04
	16	78013.1100	121597.55	264346.0600	126992.93
	17	94657.1600	145077.58	282574.3100	125370.37
	18	91749.1600	114175.79	294919.5700	124266.90
	19	86419.7000	153514.11	211025.0978	122776.86
	20	76253.8600	113867.30	298664.4700	118474.03
	21	78389.4700	153773.43	299737.2900	111313.02
	22	73994.5600	122782.75	303319.2600	110352.25
	23	67532.5300	105751.03	304768.7300	108733.99
	24	77044.0100	99281.34	140574.8100	108552.04
	25	64664.7100	139553.16	137962.6200	107404.34
	26	75328.8700	144135.98	134050.0700	105733.54
	27	72107.6000	127864.55	353183.8100	105008.31
	28	66051.5200	182645.56	118148.2000	103282.38
	29	65605.4800	153032.06	107138.3800	101004.64
	30	61994.4800	115641.28	91131.2400	99937.59
	31	61136.3800	152701.92	88218.2300	97483.56
	32	63408.8600	129219.61	46085.2500	97427.84
	33	55493.9500	103057.49	214634.8100	96778.92
	34	46426.0700	157693.92	210797.6700	96712.80
	35	46014.0200	85047.44	205517.6400	96479.51

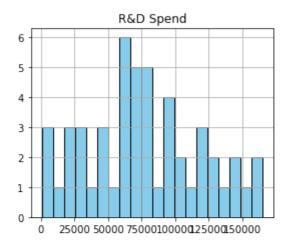
		nas spena	Administration	Marketing Spend	Profit	
	36	28663.7600	127056.21	201126.8200	90708.19	
	37	44069.9500	51283.14	197029.4200	89949.14	
	38	20229.5900	65947.93	185265.1000	81229.06	
	39	38558.5100	82982.09	174999.3000	81005.76	
	40	28754.3300	118546.05	172795.6700	78239.91	
	41	27892.9200	84710.77	164470.7100	77798.83	
	42	23640.9300	96189.63	148001.1100	71498.49	
	43	15505.7300	127382.30	35534.1700	69758.98	
	44	22177.7400	154806.14	28334.7200	65200.33	
	45	1000.2300	124153.04	1903.9300	64926.08	
	46	1315.4600	115816.21	297114.4600	49490.75	
	47	73721.6156	135426.92	211025.0978	42559.73	
	48	542.0500	51743.15	211025.0978	35673.41	
	49	73721.6156	116983.80	45173.0600	14681.40	
11]:	fr #	om sklearn. Replacing to r column in column_me	he zero values ['R&D Spend'; an = data[colu	<pre>import Standard: s with column med , 'Administration</pre>	ns '', 'Marketing Spend', 'Profit']:
11]:	fr # # fo sc. sc. # #	<pre>om sklearn. Replacing t. r column in column_me data[column] Performing aler = Standaled_data = Displaying</pre>	preprocessing he zero values ['R&D Spend', an = data[column] = data[column] Feature Scalin dardScaler() pd.DataFrame the first few	<pre>import Standard! s with column med , 'Administration umn].mean() lumn].replace(0, ng (Standardizate)</pre>	<pre>cons column_mean) con con con con con con con con con con</pre>	
11]:	frofo	<pre>om sklearn. Replacing to r column in column_me data[column] Performing aler = Standaled_data = Displaying int(scaled_</pre>	preprocessing he zero values ['R&D Spend'] an = data[column] = data[column] Feature Scalin dardScaler() pd.DataFrame the first few data.head()) Administration 0.560753 1.082803 -0.728253	import Standard: s with column med column].mean() lumn].replace(0, and (Standardizate color fit_trans a rows of the pro- a Marketing Spe 3 2.2816 6 2.0251 7 1.6944 6 1.4669	column_mean) on) eform(data), columns=data.colum	
[7]:	# # sc sc sc # pr 0 1 2 3 4	om sklearn. Replacing to recolumn in column_me data[column] Performing aler = Standaled_data = Displaying int(scaled_ R&D Spend	preprocessing he zero values ['R&D Spend'] an = data[column] = data[column] Feature Scalin dardScaler() pd.DataFrame the first few data.head()) Administration 0.56075: 1.08280: -0.72825: -0.09636: -1.079919	import Standard: s with column med s with column	column_mean) con) form(data), columns=data.colum processed data dd Profit 1 2.011203 10 1.999430 15 1.980842 19 1.776627	

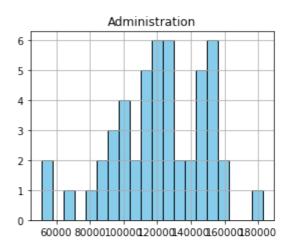


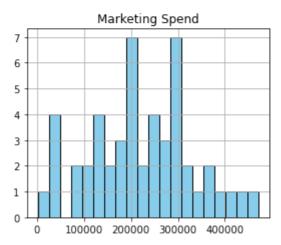
Using Matplotlib Histogram for the Distribution of features that Shows how data is
plt.figure(figsize=(10, 6))
data.hist(bins=20, figsize=(10, 8), color='skyblue', edgecolor='black')
plt.suptitle("Distribution of Features", size=16)
plt.show()

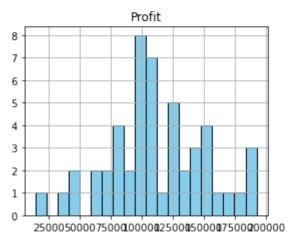
<Figure size 720x432 with 0 Axes>

Distribution of Features



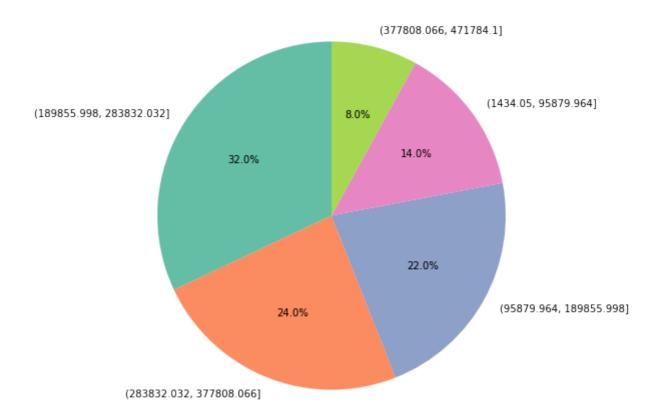






In [10]:

Marketing Spend Distribution



```
In [24]:
          from sklearn.model_selection import train_test_split
          from sklearn.linear_model import LinearRegression
          from sklearn.preprocessing import PolynomialFeatures
          from sklearn.tree import DecisionTreeRegressor
          from sklearn.ensemble import RandomForestRegressor
          from sklearn.svm import SVR
          from sklearn.neighbors import KNeighborsRegressor
          from sklearn.metrics import mean_absolute_error, mean_squared_error, r2_score
          from sklearn.preprocessing import StandardScaler
In [25]:
          # Generate synthetic data for demonstration
          np.random.seed(42)
          X = np.random.rand(100, 3) * 100 # 100 samples and 3 features
          y = 2.5 * X[:, 0] + 0.5 * X[:, 1]**2 - 1.5 * X[:, 2] + np.random.randn(100) * 10
In [26]:
          # Split the data into training and testing sets
          X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_stat
In [27]:
          X_train
         array([[83.53024956, 32.0780065, 18.65185104],
Out[27]:
                [87.73730719, 74.07686178, 69.7015741],
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                 [79.8295179 , 64.99639308, 70.19668773],
                [48.94527603, 98.56504541, 24.20552715]])
In [28]:
          y train, y test
         (array([ 701.23026982, 2859.45159173,
                                                  31.71730731, 3897.93147015,
Out[28]:
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                 2100.9407432 , 1713.85015316,
                                                9.21473352, 3027.95804636]))
In [29]:
          # Standardize the feature set
          scaler = StandardScaler()
          X_train_scaled = scaler.fit_transform(X_train)
          X_test_scaled = scaler.transform(X_test)
In [30]:
          X train scaled
         array([[ 1.30326424, -0.56944729, -1.01640827],
Out[30]:
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```

```
In [31]: X_test_scaled
```

```
array([[ 1.3657622 , -0.654041 , -0.3292868 ],
Out[31]:
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                [-1.22192137, -0.51536143, 1.60084764],
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                [ 0.12909833, 0.25339737, 0.0424065 ],
                [-0.56983891, -1.28622243, 0.70577764],
                 [ 0.3360727 , 0.87686124, 0.04682829]])
In [32]:
          # Initialize a DataFrame to store metrics
          metrics_df = pd.DataFrame(columns=['Model', 'MAE', 'MSE', 'RMSE', 'R2'])
In [33]:
          # Linear Regression
          linear_regressor = LinearRegression()
          linear_regressor.fit(X_train_scaled, y_train)
          y_pred_linear = linear_regressor.predict(X_test_scaled)
In [34]:
          y_pred_linear
         array([ 875.69788101, 1246.43315835, 2807.80322477, 1867.41773083,
Out[34]:
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                 100.0804251 , 4056.09572476, 3865.41369998, 2777.9192008 ,
                2730.38031038, -667.13688696, 3539.43996886, 416.06087492,
                2658.89355797, 2182.76533954, -252.98423419, 3176.93809866])
In [35]:
          # Calculate metrics
          metrics df = metrics df.append({
              'Model': 'Linear Regression',
              'MAE': mean_absolute_error(y_test, y_pred_linear),
              'MSE': mean_squared_error(y_test, y_pred_linear),
              'RMSE': np.sqrt(mean_squared_error(y_test, y_pred_linear)),
              'R2': r2 score(y test, y pred linear)
          }, ignore index=True)
          metrics df
                                             MSE
                                                                 R^2
Out[35]:
                    Model
                                MAE
                                                      RMSE
          0 Linear Regression 356.024429 151402.204487 389.104362 0.936473
In [36]:
          # Polynomial Regression
          poly features = PolynomialFeatures(degree=2)
          X_train_poly = poly_features.fit_transform(X_train_scaled)
          X_test_poly = poly_features.transform(X_test_scaled)
```

```
In [37]:
          X_train_poly
         array([[ 1.00000000e+00, 1.30326424e+00, -5.69447289e-01,
Out[37]:
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 1.15029990e-01],
[ 1.00000000e+00, -2.79985030e-01, 1.40940461e+00,
-1.18594908e+00, 7.83916169e-02, -3.94612192e-01,
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 1.40647521e+00],
[ 1.00000000e+00, -7.91359952e-01, -1.30090229e+00,
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 2.08149290e+00],
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 -1.07532062e+00, 1.84729436e+00, -7.90811777e-01,
-1.46152425e+00, 3.38540128e-01, 6.25666715e-01,
 1.15631444e+00],
[ 1.00000000e+00, -1.07595274e+00, 1.38681194e+00,
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-1.22061589e+00, 1.92324736e+00, 1.57327048e+00,
 1.28697954e+00],
[ 1.00000000e+00, 6.05309281e-01, 1.25032139e+00,
```

```
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 7.75338382e-04],
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 1.25894465e+00],
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 7.04805240e-01],
[ 1.00000000e+00, -3.85808674e-01, -6.97458431e-01,
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-6.02163560e-01, 1.39886793e+00, 4.94589664e-01,
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-9.74203766e-01, 3.37931810e+00, 1.61947240e+00,
-1.79087115e+00, 7.76100616e-01, -8.58240131e-01,
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 1.73503529e-02],
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 5.40862516e-03],
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 2.17382856e-01],
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 1.67250908e+00, 1.78726341e-02, -2.01273974e-01,
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 2.79728664e+00],
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[ 1.00000000e+00, -4.41176957e-01, -1.23545752e+00,
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 2.36487976e+00],
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 7.07063917e-01],
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 -7.66369981e-01, 2.32141151e+00, -2.01322687e+00,
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 5.87322948e-01],
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 8.99582481e-01, 2.38257374e-01, 3.74453473e-01,
 5.88503940e-01],
[ 1.00000000e+00, 8.25632989e-02, 1.56657056e+00,
```

In [38]:

```
EXPOSYS DATA LABS - startups50
       -8.24240626e-01, 6.81669832e-03, 1.29341234e-01,
       -6.80520252e-02, 2.45414333e+00, -1.29123110e+00,
        6.79372610e-01]])
X_test_poly
```

```
array([[ 1.00000000e+00, 1.36576220e+00, -6.54041003e-01,
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        -4.49727460e-01, 4.27769634e-01, 2.15367068e-01,
        1.08429795e-01],
       [ 1.00000000e+00, 9.25296157e-01, -4.18441329e-01,
         5.26099770e-01, 8.56172979e-01, -3.87182153e-01,
        4.86798096e-01, 1.75093145e-01, -2.20141887e-01,
         2.76780968e-01],
       [ 1.00000000e+00, 2.91799856e-01, 6.22828020e-01,
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        1.73361578e-01, 3.87914742e-01, 3.70029136e-01,
         3.52968182e-01],
       [ 1.00000000e+00, -5.04227149e-01, 6.66978768e-02,
         7.70780505e-01, 2.54245018e-01, -3.36308803e-02,
        -3.88648457e-01, 4.44860677e-03, 5.14094232e-02,
        5.94102587e-01],
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         2.56271317e+00],
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        4.17909108e-02],
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        -1.40383817e+00, 1.31696889e+00, -1.12141915e+00,
        1.61103437e+00, 9.54905557e-01, -1.37182040e+00,
        1.97076161e+00],
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         2.51800219e+00, 2.14522371e+00, 2.20256121e+00,
         2.26143121e+00],
       [ 1.00000000e+00, 4.99377632e-01, -1.05217201e+00,
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       -7.17459177e-01, 1.10706594e+00, 1.51166255e+00,
         2.06412607e+00],
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        -1.35559672e+00, 2.16537012e-01, 6.33636842e-01,
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        1.83764246e+00],
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         9.42184815e-01],
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         3.04657317e-01,
        4.12018276e-01, 2.62850869e-01, 1.56194710e-01,
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         2.91926675e-01],
       [ 1.00000000e+00, 1.21170245e+00, 1.00262562e+00,
```

```
1.33843601e+00,
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                  1.79141096e+00],
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                 -1.33539065e+00, 8.42418717e-01, 9.47799893e-01,
                  1.06636358e+00],
                 [ 1.00000000e+00, 1.50354638e+00, 4.27636410e-01,
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                  1.18461303e+00],
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                  4.24065027e-02, 1.66663782e-02, 3.27131772e-02,
                  5.47460859e-03, 6.42102288e-02, 1.07456964e-02,
                  1.79831147e-03],
                 [ 1.00000000e+00, -5.69838905e-01, -1.28622243e+00,
                  7.05777643e-01, 3.24716378e-01, 7.32939581e-01,
                 -4.02179560e-01, 1.65436814e+00, -9.07787034e-01,
                  4.98122081e-01],
                 [ 1.00000000e+00, 3.36072696e-01, 8.76861239e-01,
                  4.68282861e-02, 1.12944857e-01, 2.94689121e-01,
                  1.57377084e-02, 7.68885633e-01, 4.10619090e-02,
                  2.19288838e-03]])
In [39]:
          poly_regressor = LinearRegression()
          poly_regressor.fit(X_train_poly, y_train)
          y_pred_poly = poly_regressor.predict(X_test_poly)
In [40]:
          y_pred_poly
         array([ 594.30466217, 768.72445078, 2435.82136751, 1325.25364233,
Out[40]:
                 466.19628761, 3950.28248561, 3241.12327764, 4657.62056776,
                 288.75422355, 4504.60085412, 4378.96697334, 2466.1206863 ,
                2294.65804252, -62.46205755, 3361.84687331, 410.47227271,
                2105.31378629, 1717.43419977, 22.1034541, 3038.23703586])
In [41]:
          # Calculate metrics
          metrics_df = metrics_df.append({
              'Model': 'Polynomial Regression',
              'MAE': mean_absolute_error(y_test, y_pred_poly),
              'MSE': mean_squared_error(y_test, y_pred_poly),
              'RMSE': np.sqrt(mean_squared_error(y_test, y_pred_poly)),
              'R2': r2_score(y_test, y_pred_poly)
          }, ignore index=True)
In [42]:
          metrics df
                        Model
                                   MAE
                                                 MSE
                                                                     R^2
Out[42]:
                                                          RMSE
         0
                Linear Regression 356.024429 151402.204487 389.104362 0.936473
         1 Polynomial Regression
                               11.098949
                                            210.607707
                                                       14.512329 0.999912
In [43]:
          # Decision Tree Regression
          decision_tree_regressor = DecisionTreeRegressor(random_state=42)
          decision_tree_regressor.fit(X_train_scaled, y_train)
          y pred decision tree = decision tree regressor.predict(X test scaled)
```

```
In [44]:
          y_pred_decision_tree
          array([ 508.14190614, 783.70325364, 2562.57988349, 1279.83374083,
Out[44]:
                  776.75969032, 4023.69412845, 3232.90774568, 4669.04040869,
                  207.5895722 , 4476.90022639, 4242.08329451, 2562.57988349,
                 2196.4841459 , -12.28611862, 3232.90774568, 223.32133506,
                                                 31.71730731, 3158.64767309])
                 2196.4841459 , 1669.66782416,
In [45]:
           # Calculate metrics
          metrics_df = metrics_df.append({
               'Model': 'Decision Tree Regression',
               'MAE': mean_absolute_error(y_test, y_pred_decision_tree),
               'MSE': mean_squared_error(y_test, y_pred_decision_tree),
               'RMSE': np.sqrt(mean_squared_error(y_test, y_pred_decision_tree)),
               'R2': r2_score(y_test, y_pred_decision_tree)
           }, ignore_index=True)
In [46]:
          metrics df
                                                     MSE
                                                                          R^2
Out[46]:
                           Model
                                       MAE
                                                              RMSE
          0
                  Linear Regression
                                 356.024429 151402.204487
                                                          389.104362 0.936473
                                   11.098949
          1
              Polynomial Regression
                                                210.607707
                                                           14.512329 0.999912
          2 Decision Tree Regression
                                   90.346365
                                             12832.074622 113.278747 0.994616
In [47]:
           # Random Forest Regression
          random_forest_regressor = RandomForestRegressor(n_estimators=100, random_state=42)
           random_forest_regressor.fit(X_train_scaled, y_train)
          y pred random forest = random forest regressor.predict(X test scaled)
In [48]:
          # Calculate metrics
          metrics_df = metrics_df.append({
               'Model': 'Random Forest Regression',
               'MAE': mean_absolute_error(y_test, y_pred_random_forest),
               'MSE': mean_squared_error(y_test, y_pred_random_forest),
               'RMSE': np.sqrt(mean_squared_error(y_test, y_pred_random_forest)),
               'R2': r2_score(y_test, y_pred_random_forest)
           }, ignore index=True)
In [49]:
          metrics df
                                                                            \mathbb{R}^2
Out[49]:
                            Model
                                        MAE
                                                      MSE
                                                                RMSE
          0
                    Linear Regression
                                   356.024429 151402.204487 389.104362 0.936473
                Polynomial Regression
                                    11.098949
          1
                                                 210.607707
                                                             14.512329 0.999912
          2
              Decision Tree Regression
                                    90.346365
                                               12832.074622 113.278747 0.994616
          3 Random Forest Regression
                                    91.127631
                                               13059.691346 114.279007 0.994520
In [50]:
          # Support Vector Regression (SVR)
           svr_regressor = SVR(kernel='rbf')
```

```
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          svr_regressor.fit(X_train_scaled, y_train)
          y_pred_svr = svr_regressor.predict(X_test_scaled)
In [51]:
          # Calculate metrics
          metrics_df = metrics_df.append({
               'Model': 'Support Vector Regression',
               'MAE': mean_absolute_error(y_test, y_pred_svr),
               'MSE': mean_squared_error(y_test, y_pred_svr),
```

In [52]:

metrics df

```
R^2
Out[52]:
                               Model
                                             MAE
                                                            MSE
                                                                        RMSE
           0
                      Linear Regression
                                        356.024429 1.514022e+05
                                                                   389.104362
                                                                                0.936473
                                         11.098949 2.106077e+02
                                                                               0.999912
           1
                  Polynomial Regression
                                                                    14.512329
           2
                Decision Tree Regression
                                         90.346365 1.283207e+04
                                                                   113.278747
                                                                                0.994616
                                         91.127631 1.305969e+04
                                                                   114.279007
           3 Random Forest Regression
                                                                                0.994520
           4 Support Vector Regression 1460.631351 3.035555e+06 1742.284512 -0.273687
```

'RMSE': np.sqrt(mean_squared_error(y_test, y_pred_svr)),

'R2': r2_score(y_test, y_pred_svr)

}, ignore_index=True)

```
In [53]:
          # 6. K-Nearest Neighbors Regression (KNN)
          knn_regressor = KNeighborsRegressor(n_neighbors=5)
          knn_regressor.fit(X_train_scaled, y_train)
          y_pred_knn = knn_regressor.predict(X_test_scaled)
```

```
In [54]:
           y_pred_knn
```

```
array([ 602.95947739, 877.40558535, 3450.63479677, 1313.25833697,
Out[54]:
                 658.81038107, 3554.95290667, 2664.38956125, 3829.45054917,
                 449.2128915 , 4148.47085509, 3748.13969395, 2821.81297042,
                2276.31803766, 145.78386853, 3633.82241526, 586.18230446,
                2276.31803766, 1030.67852241, 106.47551861, 3671.59090151])
```

```
In [55]:
          # Calculate metrics
          metrics_df = metrics_df.append({
               'Model': 'K-Nearest Neighbors Regression',
              'MAE': mean_absolute_error(y_test, y_pred_knn),
              'MSE': mean_squared_error(y_test, y_pred_knn),
              'RMSE': np.sqrt(mean_squared_error(y_test, y_pred_knn)),
              'R2': r2_score(y_test, y_pred_knn)
          }, ignore index=True)
```

In [56]: metrics df

Out[56]:		Model	MAE	MSE	RMSE	R ²
	0	Linear Regression	356.024429	1.514022e+05	389.104362	0.936473
	1	Polynomial Regression	11.098949	2.106077e+02	14.512329	0.999912
	2	Decision Tree Regression	90.346365	1.283207e+04	113.278747	0.994616

	Model	MAE	MSE	RMSE	R ²
3	Random Forest Regression	91.127631	1.305969e+04	114.279007	0.994520
4	Support Vector Regression	1460.631351	3.035555e+06	1742.284512	-0.273687
5	K-Nearest Neighbors Regression	349.056282	2.005883e+05	447.870838	0.915835

```
In [57]: # Print the metrics DataFrame
print("Model Comparison Metrics:")
```

Model Comparison Metrics:

print(metrics_df)

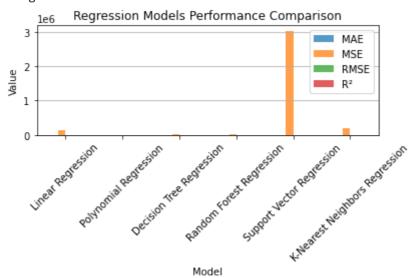
```
RMSE
                           Model
                                          MAE
                                                        MSE
0
                Linear Regression
                                   356.024429 1.514022e+05
                                                              389.104362
1
            Polynomial Regression
                                    11.098949
                                               2.106077e+02
                                                               14.512329
2
         Decision Tree Regression
                                    90.346365 1.283207e+04
                                                              113.278747
                                    91.127631 1.305969e+04
3
         Random Forest Regression
                                                              114.279007
4
       Support Vector Regression 1460.631351 3.035555e+06 1742.284512
  K-Nearest Neighbors Regression
                                  349.056282 2.005883e+05
                                                              447.870838
```

R²
0 0.936473
1 0.999912
2 0.994616
3 0.994520
4 -0.273687
5 0.915835

```
In [58]:
```

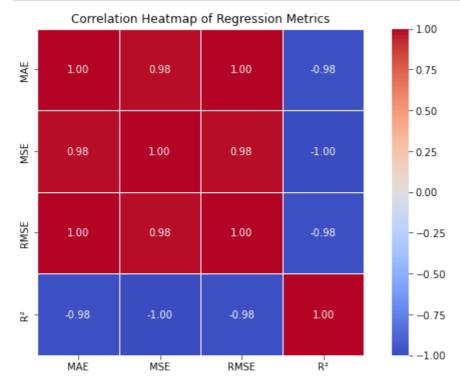
```
# Plot the metrics comparison
plt.figure(figsize=(14, 8))
metrics_df.set_index('Model').plot(kind='bar', alpha=0.75)
plt.title('Regression Models Performance Comparison')
plt.ylabel('Value')
plt.xticks(rotation=45)
plt.grid(axis='y')
plt.tight_layout()
plt.show()
```

<Figure size 1008x576 with 0 Axes>



```
In [62]:
# Create a heatmap for the metrics
plt.figure(figsize=(10, 6))
sns.heatmap(metrics_df.set_index('Model').corr(), annot=True, cmap='coolwarm', fmt="
```

```
plt.title('Correlation Heatmap of Regression Metrics')
plt.show()
```



```
In [63]: # Determine the best model based on R²
best_model_index = metrics_df['R²'].idxmax()
best_model = metrics_df.loc[best_model_index]
In [64]:
```

```
print("\nBest Model:")
print(best_model)
Best Model:
```

 Model
 Polynomial Regression

 MAE
 11.098949

 MSE
 210.607707

 RMSE
 14.512329

 R²
 0.999912

Name: 1, dtype: object

```
In [65]:
# Function to predict profit
def predict_profit(model, scaler, poly_features, r_and_d_spend, admin_cost, marketin
    input_data = np.array([[r_and_d_spend, admin_cost, marketing_spend]])
    input_data_scaled = scaler.transform(input_data)

# If using polynomial features, transform the input data
    if poly_features is not None:
        input_data_scaled = poly_features.transform(input_data_scaled)

predicted_profit = model.predict(input_data_scaled)
    return predicted_profit[0]
```

```
In [69]:
# Take user Input for prediction
r_and_d_spend = float(input("Enter the R&D Spend: "))
admin_cost = float(input("Enter the Administration Cost: "))
marketing_spend = float(input("Enter the Marketing Spend: "))
```

```
In [70]:
# Use the best model for prediction
if best_model['Model'] == 'Linear Regression':
    predicted_profit = predict_profit(linear_regressor, scaler, None, r_and_d_spend,
    elif best_model['Model'] == 'Polynomial Regression':
        predicted_profit = predict_profit(poly_regressor, scaler, poly_features, r_and_d
    elif best_model['Model'] == 'Decision Tree Regression':
        predicted_profit = predict_profit(decision_tree_regressor, scaler, None, r_and_d
    elif best_model['Model'] == 'Random Forest Regression':
        predicted_profit = predict_profit(random_forest_regressor, scaler, None, r_and_d
    elif best_model['Model'] == 'Support Vector Regression':
        predicted_profit = predict_profit(svr_regressor, scaler, None, r_and_d_spend, ad
    elif best_model['Model'] == 'K-Nearest Neighbors Regression':
        predicted_profit = predict_profit(knn_regressor, scaler, None, r_and_d_spend, ad
```

In [71]: # predicted the profit value of the Company
print(f"\nPredicted Profit: \${predicted_profit:.2f}")

Predicted Profit: \$1304876064.32

Enter the R&D Spend: 150000

Enter the Administration Cost: 50000