

```
In [15]: import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.linear_model import LinearRegression
from sklearn.model_selection import train_test_split
from sklearn.metrics import r2_score, mean_absolute_error

plt.style.use("ggplot")
np.random.seed(42)
```

```
In [16]: n = 100

data = pd.DataFrame({
    "date": pd.date_range(start="2025-01-01", periods=n, freq="D"),
    "source": np.random.choice(["Google", "Facebook", "LinkedIn", "Email"], n),
    "campaign": np.random.choice(["Winter", "Spring", "Summer", "Brand"], n),
    "country": np.random.choice(["USA", "UK", "Canada", "India"], n),
    "sessions": np.random.randint(50, 300, n),
    "conversions": np.random.randint(5, 80, n),
    "cost": np.random.uniform(500, 3000, n)
})

data["revenue"] = data["conversions"] * np.random.uniform(100, 600, n)

data.head()
```

Out[16]:

	date	source	campaign	country	sessions	conversions	cost	revenue
0	2025-01-01	LinkedIn	Summer	Canada	274	29	1977.083151	14599.103719
1	2025-01-02	Email	Spring	India	178	22	576.250625	13095.556562
2	2025-01-03	Google	Spring	Canada	196	70	593.370472	21441.618692
3	2025-01-04	LinkedIn	Brand	USA	175	58	2556.501402	16588.524488
4	2025-01-05	LinkedIn	Spring	India	179	39	1400.476604	19040.052734

In [17]:

```
data["conversion_rate"] = (data["conversions"] / data["sessions"]) * 100
data["cpa"] = data["cost"] / data["conversions"]
data["roas"] = data["revenue"] / data["cost"]
data["revenue_per_session"] = data["revenue"] / data["sessions"]

data.describe()
```

Out[17]:

	date	sessions	conversions	cost	revenue	conversion_rate	cpa	roas	revenue_per_s
count	100	100.000000	100.000000	100.000000	100.000000	100.000000	100.000000	100.000000	100.000000
mean	2025-02-19 12:00:00	186.100000	41.260000	1646.923827	15151.605734	26.771134	53.686314	11.732328	94.0
min	2025-01-01 00:00:00	51.000000	6.000000	535.983722	634.060934	3.389831	8.476721	0.628890	4.5
25%	2025-01-25 18:00:00	145.750000	26.000000	933.178019	7535.923859	12.886636	25.204300	5.001835	43.0
50%	2025-02-19 12:00:00	195.000000	38.000000	1707.237130	14767.443959	23.347684	40.917849	8.510549	77.2
75%	2025-03-16 06:00:00	234.500000	58.000000	2240.412365	21292.034546	33.612440	66.624677	13.598306	125.9
max	2025-04-10 00:00:00	298.000000	73.000000	2939.630199	41157.285466	125.000000	235.735641	65.403731	398.8
std	NaN	63.602697	19.000595	732.647523	9487.075506	20.190896	45.120494	11.378049	72.7



In [18]:

```
total_revenue = data["revenue"].sum()
total_cost = data["cost"].sum()
overall_roas = total_revenue / total_cost

print("Total Revenue:", round(total_revenue,2))
```

```
print("Total Cost:", round(total_cost,2))
print("Overall ROAS:", round(overall_roas,2))
```

Total Revenue: 1515160.57

Total Cost: 164692.38

Overall ROAS: 9.2

```
In [19]: campaign_summary = data.groupby(["source","campaign"]).agg({
    "sessions":"sum",
    "conversions":"sum",
    "revenue":"sum",
    "cost":"sum"
}).reset_index()

campaign_summary["roas"] = campaign_summary["revenue"] / campaign_summary["cost"]

campaign_summary.sort_values("revenue", ascending=False)
```

Out[19]:

	source	campaign	sessions	conversions	revenue	cost	roas
15	LinkedIn	Winter	1971	503	223573.472327	17388.574972	12.857493
2	Email	Summer	2750	452	160123.815016	18214.841188	8.790843
5	Facebook	Spring	1575	291	142805.389534	17320.304312	8.244970
9	Google	Spring	933	234	116958.993583	5032.267313	23.241809
8	Google	Brand	1440	286	106674.910330	13954.351654	7.644562
4	Facebook	Brand	1063	282	104615.249467	11431.398449	9.151571
3	Email	Winter	751	217	102427.215537	10477.483334	9.775937
6	Facebook	Summer	843	291	94386.810951	9752.137770	9.678576
7	Facebook	Winter	1248	373	94169.331543	11264.308908	8.359974
13	LinkedIn	Spring	768	162	65082.650388	5198.953044	12.518415
0	Email	Brand	1267	275	63397.194544	7769.019539	8.160257
12	LinkedIn	Brand	640	181	62248.061864	6217.584117	10.011616
10	Google	Summer	909	135	60521.889035	9692.525845	6.244181
1	Email	Spring	534	130	47999.084487	4680.914613	10.254211
14	LinkedIn	Summer	1229	196	38297.513067	8054.174105	4.754989
11	Google	Winter	689	118	31878.991754	8243.543546	3.867147

In [20]:

```
country_summary = data.groupby("country").agg({
    "revenue": "sum",
    "cost": "sum"
}).reset_index()
```

```
country_summary["roas"] = country_summary["revenue"] / country_summary["cost"]
```

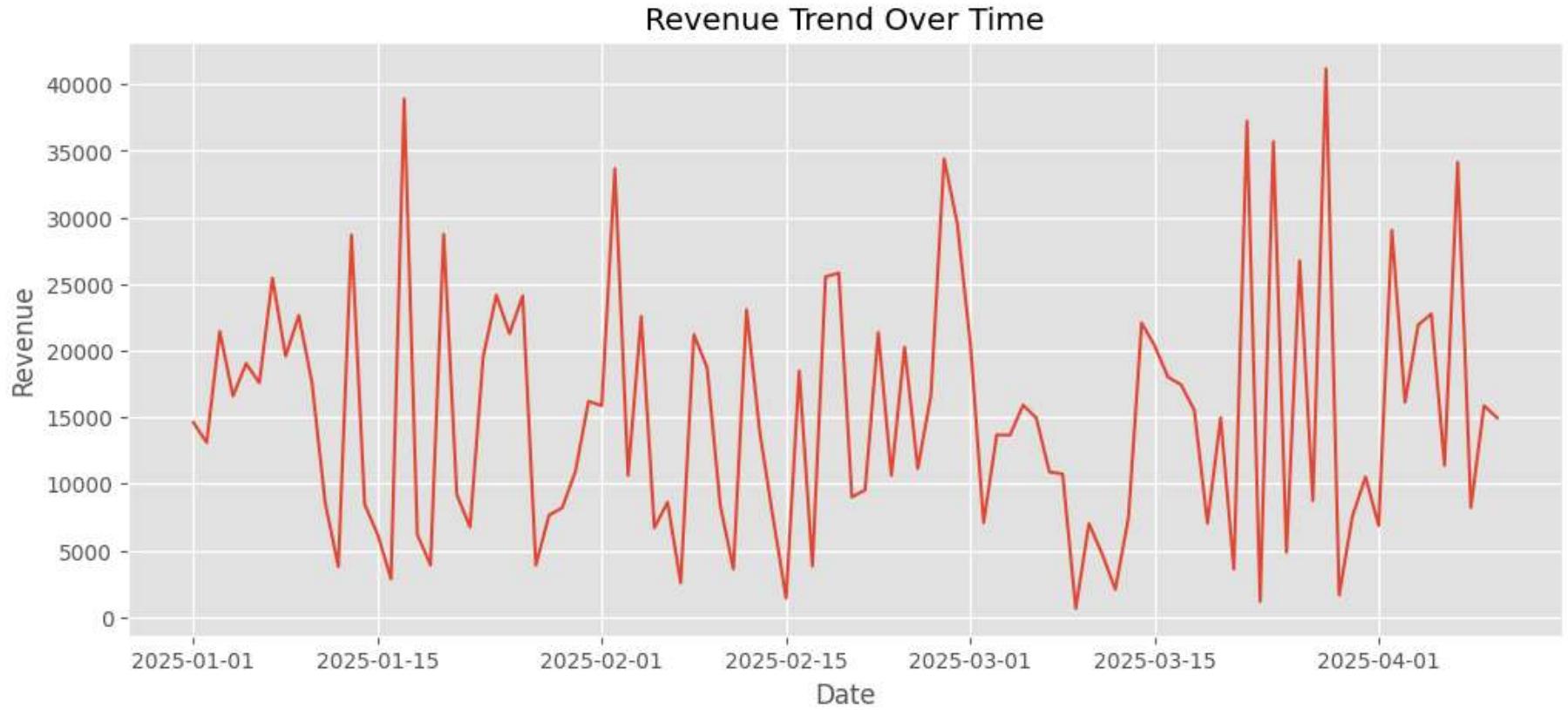
```
country_summary
```

Out[20]:

	country	revenue	cost	roas
0	Canada	291655.047564	33124.860315	8.804718
1	India	480165.938350	47081.320271	10.198651
2	UK	354351.356148	36970.748678	9.584641
3	USA	388988.231363	47515.453447	8.186563

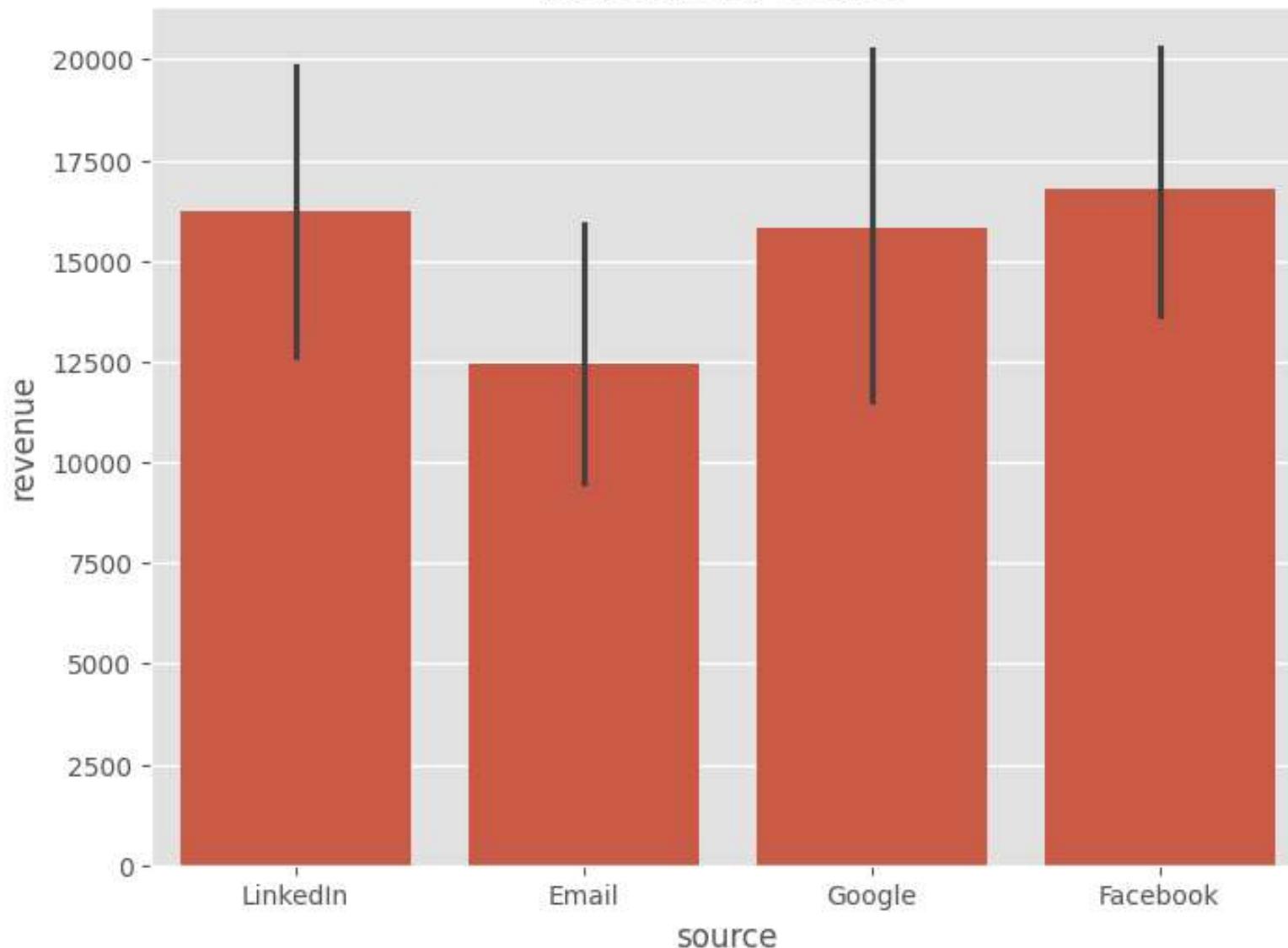
In [21]:

```
plt.figure(figsize=(12,5))
plt.plot(data["date"], data["revenue"])
plt.title("Revenue Trend Over Time")
plt.xlabel("Date")
plt.ylabel("Revenue")
plt.show()
```



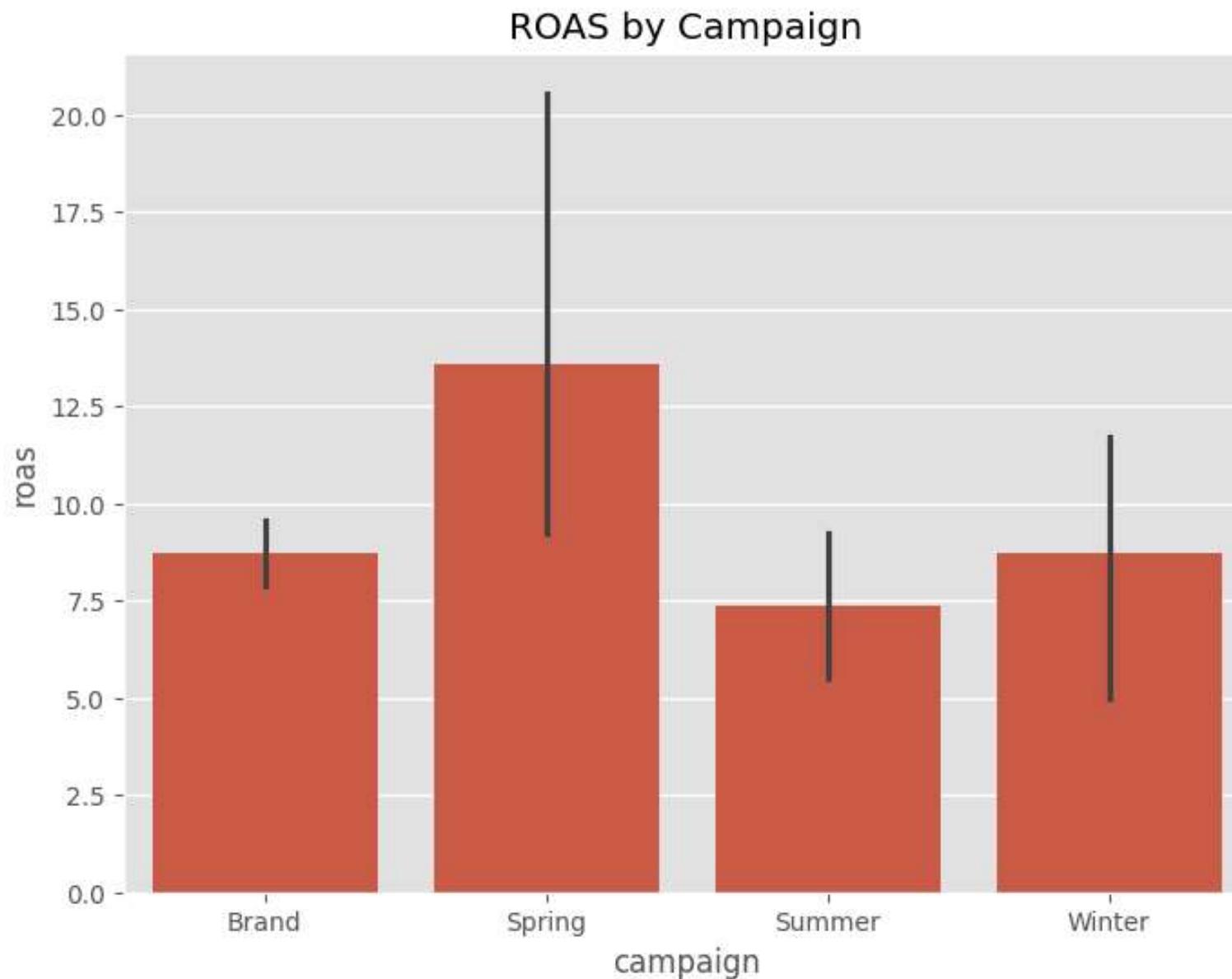
```
In [22]: plt.figure(figsize=(8,6))
sns.barplot(data=data, x="source", y="revenue")
plt.title("Revenue by Source")
plt.show()
```

Revenue by Source



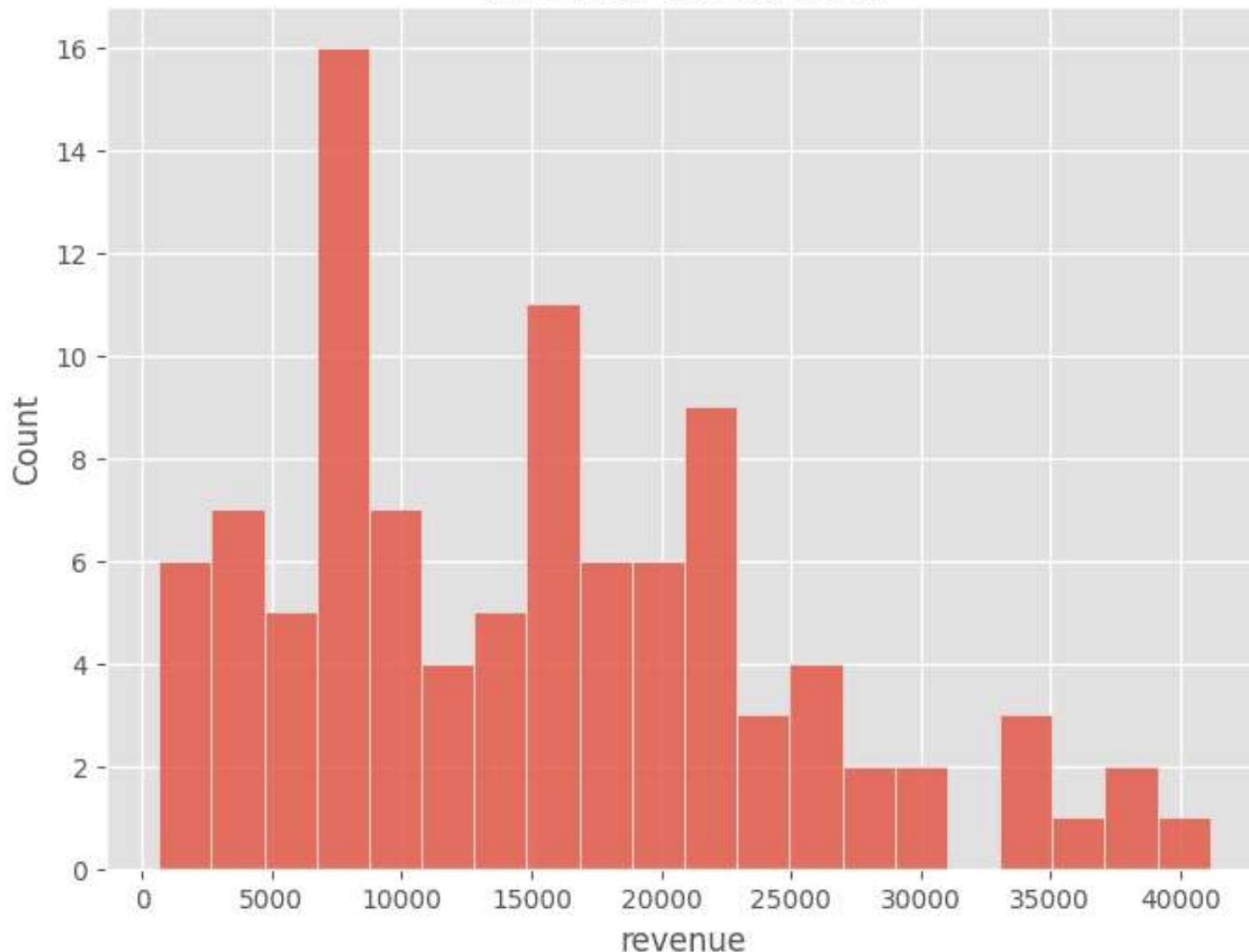
```
In [23]: plt.figure(figsize=(8,6))
sns.barplot(data=campaign_summary, x="campaign", y="roas")
```

```
plt.title("ROAS by Campaign")  
plt.show()
```



```
In [24]: plt.figure(figsize=(8,6))
sns.histplot(data["revenue"], bins=20)
plt.title("Revenue Distribution")
plt.show()
```

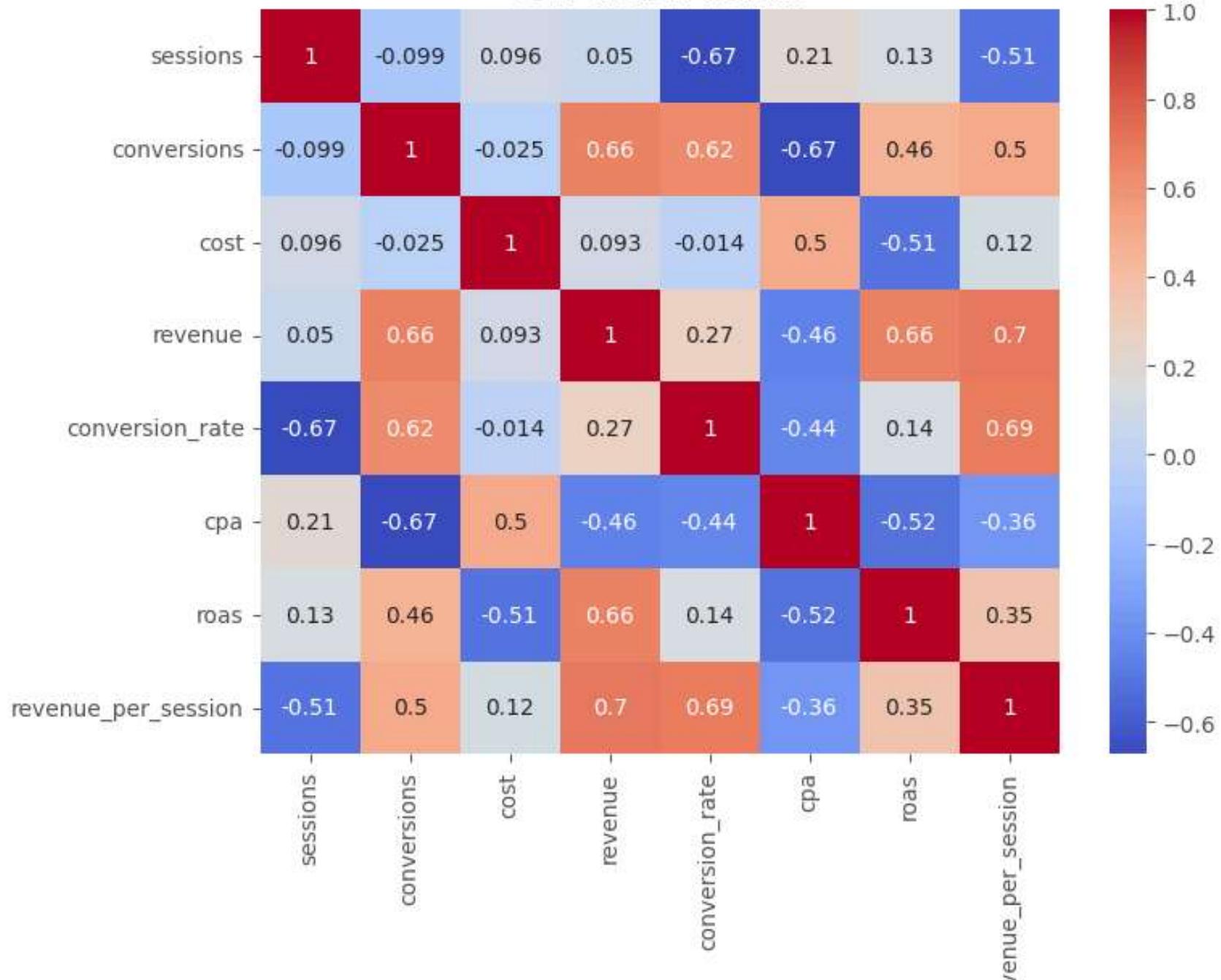
Revenue Distribution



```
In [25]: plt.figure(figsize=(8,6))
sns.heatmap(data.corr(numeric_only=True), annot=True, cmap="coolwarm")
```

```
plt.title("Correlation Matrix")
plt.show()
```

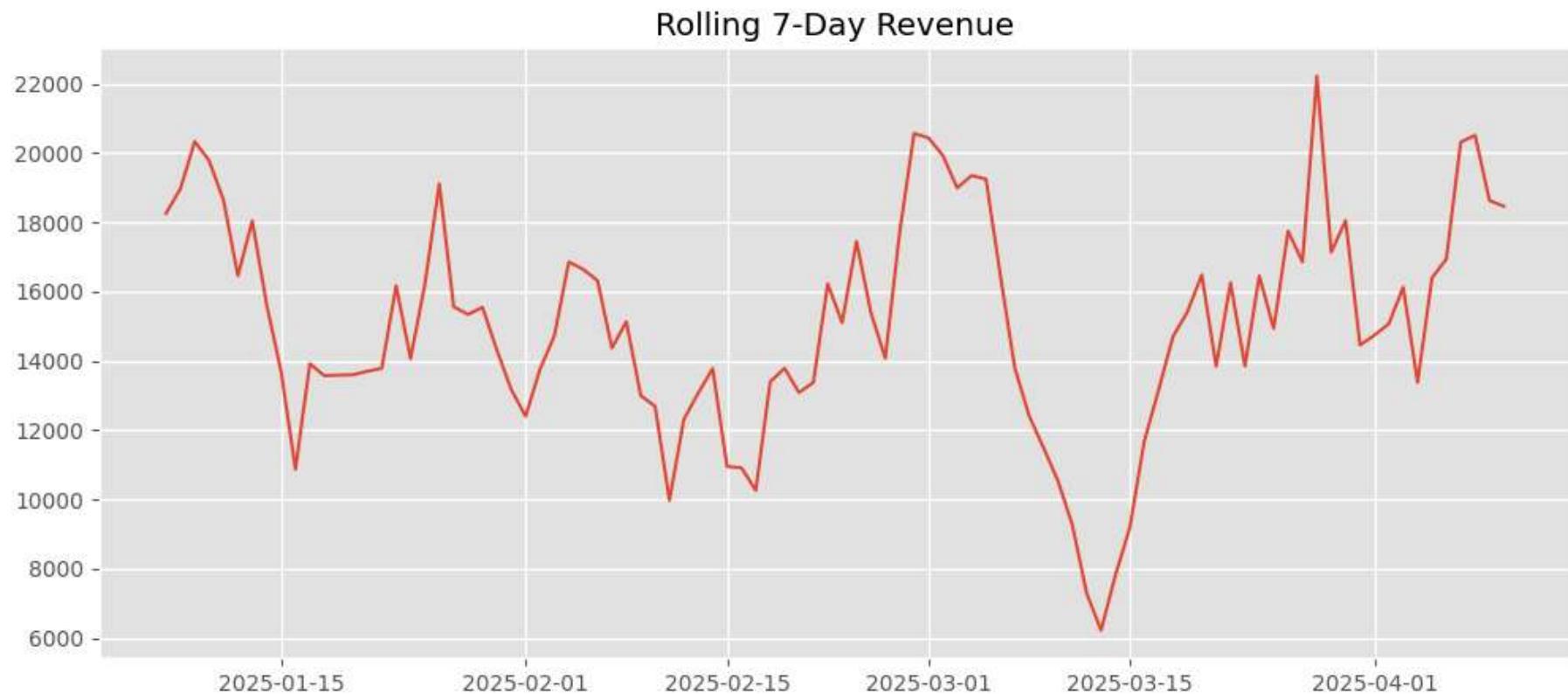
Correlation Matrix



re

```
In [26]: data["rolling_7day_revenue"] = data["revenue"].rolling(7).mean()

plt.figure(figsize=(12,5))
plt.plot(data["date"], data["rolling_7day_revenue"])
plt.title("Rolling 7-Day Revenue")
plt.show()
```



```
In [27]: data["previous_revenue"] = data["revenue"].shift(1)
data["growth_%"] = ((data["revenue"] - data["previous_revenue"]) / data["previous_revenue"]) * 100

data.tail()
```

Out[27]:

	date	source	campaign	country	sessions	conversions	cost	revenue	conversion_rate	cpa
95	2025-04-06	Facebook	Spring	India	124	29	2337.677610	11372.557523	23.387097	80.609573
96	2025-04-07	Facebook	Spring	UK	162	62	2508.702326	34135.898325	38.271605	40.462941
97	2025-04-08	Email	Brand	Canada	249	67	1205.086431	8222.453741	26.907631	17.986365
98	2025-04-09	Facebook	Winter	USA	213	66	943.598859	15871.785257	30.985915	14.296952
99	2025-04-10	Google	Summer	India	215	26	2376.536879	14955.349293	12.093023	91.405265

In [28]: `data.sort_values("revenue", ascending=False).head(10)`

Out[28]:

	date	source	campaign	country	sessions	conversions	cost	revenue	conversion_rate	cpa
86	2025-03-28	Facebook	Spring	USA	257	69	1297.439076	41157.285466	26.848249	18.803465
16	2025-01-17	Email	Winter	India	172	71	2939.630199	38891.074612	41.279070	41.403242
80	2025-03-22	LinkedIn	Winter	India	296	64	673.403252	37223.121262	21.621622	10.521926
82	2025-03-24	Google	Spring	UK	282	61	545.554564	35681.304215	21.631206	8.943517
57	2025-02-27	Google	Spring	UK	234	58	2087.734127	34394.030851	24.786325	35.995416
96	2025-04-07	Facebook	Spring	UK	162	62	2508.702326	34135.898325	38.271605	40.462941
32	2025-02-02	Email	Winter	India	119	68	2286.489807	33647.016855	57.142857	33.624850
58	2025-02-28	LinkedIn	Winter	India	266	62	613.260024	29554.723743	23.308271	9.891291
91	2025-04-02	Email	Summer	Canada	169	70	795.412069	29028.952335	41.420118	11.363030
19	2025-01-20	LinkedIn	Winter	Canada	73	52	2487.965487	28739.931387	71.232877	47.845490



In [29]:

```
data["day_number"] = np.arange(len(data))

X = data[["day_number", "sessions", "cost"]]
y = data["revenue"]
```

```
X_train, X_test, y_train, y_test = train_test_split(X,y,test_size=0.2, random_state=42)

model = LinearRegression()
model.fit(X_train,y_train)

predictions = model.predict(X_test)

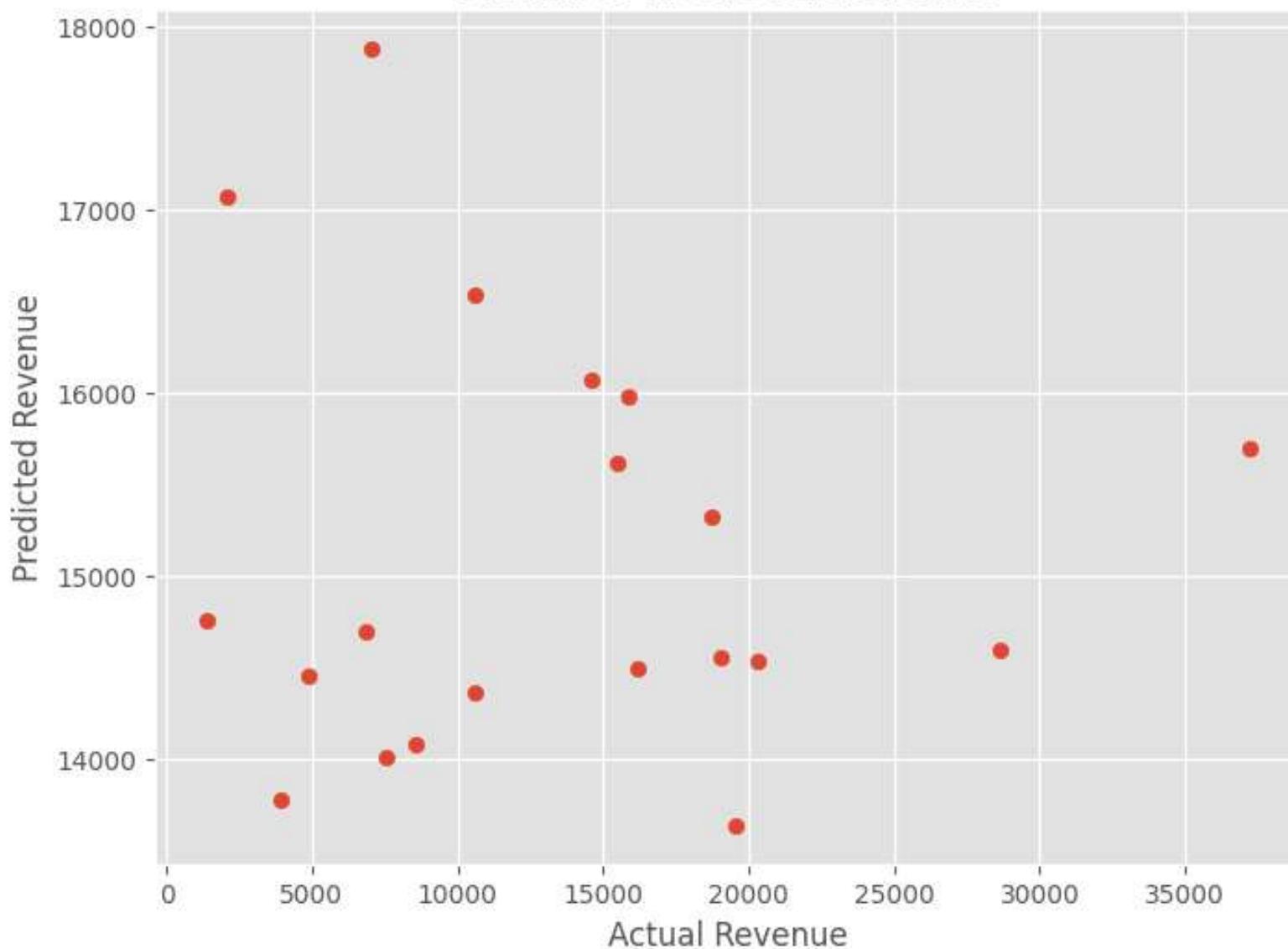
print("R2 Score:", r2_score(y_test,predictions))
print("MAE:", mean_absolute_error(y_test,predictions))
```

R2 Score: -0.06466019919586108

MAE: 7332.063516605073

```
In [30]: plt.figure(figsize=(8,6))
plt.scatter(y_test, predictions)
plt.xlabel("Actual Revenue")
plt.ylabel("Predicted Revenue")
plt.title("Actual vs Predicted Revenue")
plt.show()
```

Actual vs Predicted Revenue



~\Downloads\Market Campaign Attribution.sql

```
1 WITH base_sessions AS (
2     SELECT
3         s.session_id,
4         s.user_id,
5         s.source,
6         s.campaign,
7         u.country,
8         DATE(s.session_date) AS day
9     FROM sessions s
10    JOIN users u ON s.user_id = u.user_id
11 ),
12
13 session_counts AS (
14     SELECT
15         source,
16         campaign,
17         country,
18         day,
19         COUNT(session_id) AS total_sessions
20     FROM base_sessions
21     GROUP BY source, campaign, country, day
22 ),
23
24 conversion_details AS (
25     SELECT
26         bs.session_id,
27         bs.user_id,
28         bs.source,
29         bs.campaign,
30         bs.country,
31         bs.day,
32         c.conversion_id,
33         c.revenue
34     FROM base_sessions bs
```

```
35     JOIN conversions c
36         ON bs.user_id = c.user_id
37         AND bs.day <= DATE(c.conversion_date)
38 ),
39
40 conversion_counts AS (
41     SELECT
42         source,
43         campaign,
44         country,
45         day,
46         COUNT(conversion_id) AS total_conversions,
47         SUM(revenue) AS total_revenue,
48         AVG(revenue) AS avg_revenue_per_conversion
49     FROM conversion_details
50     GROUP BY source, campaign, country, day
51 ),
52
53 daily_spend AS (
54     SELECT
55         source,
56         campaign,
57         spend_date AS day,
58         SUM(cost) AS total_cost
59     FROM ad_spend
60     GROUP BY source, campaign, spend_date
61 ),
62
63 combined_metrics AS (
64     SELECT
65         cc.source,
66         cc.campaign,
67         cc.country,
68         cc.day,
69         sc.total_sessions,
70         cc.total_conversions,
71         cc.total_revenue,
```

```
72     cc.avg_revenue_per_conversion,
73     ds.total_cost
74   FROM conversion_counts cc
75   JOIN session_counts sc
76     ON cc.source = sc.source
77     AND cc.campaign = sc.campaign
78     AND cc.country = sc.country
79     AND cc.day = sc.day
80   JOIN daily_spend ds
81     ON cc.source = ds.source
82     AND cc.campaign = ds.campaign
83     AND cc.day = ds.day
84 ),
85
86 kpi_calculations AS (
87   SELECT
88     *,
89     ROUND(total_conversions::numeric / total_sessions * 100, 2) AS conversion_rate_percent,
90     ROUND(total_cost / total_conversions, 2) AS cpa,
91     ROUND(total_revenue / total_cost, 2) AS roas,
92     ROUND(total_revenue / total_sessions, 2) AS revenue_per_session
93   FROM combined_metrics
94 ),
95
96 rolling_metrics AS (
97   SELECT
98     *,
99     SUM(total_revenue) OVER (
100       PARTITION BY source, campaign, country
101       ORDER BY day
102       ROWS BETWEEN 6 PRECEDING AND CURRENT ROW
103     ) AS rolling_7day_revenue,
104
105     AVG(total_revenue) OVER (
106       PARTITION BY source, campaign, country
107       ORDER BY day
108       ROWS BETWEEN 6 PRECEDING AND CURRENT ROW
```

```
109      ) AS rolling_7day_avg_revenue
110  FROM kpi_calculations
111 ),
112
113 growth_metrics AS (
114     SELECT
115         *,
116         LAG(total_revenue) OVER (
117             PARTITION BY source, campaign, country
118             ORDER BY day
119         ) AS previous_day_revenue
120     FROM rolling_metrics
121 ),
122
123 final_growth AS (
124     SELECT
125         *,
126         ROUND(
127             (total_revenue - previous_day_revenue)
128             / NULLIF(previous_day_revenue, 0) * 100,
129             2
130         ) AS revenue_growth_percent
131     FROM growth_metrics
132 ),
133
134 ranking_metrics AS (
135     SELECT
136         *,
137         RANK() OVER (
138             PARTITION BY source
139             ORDER BY total_revenue DESC
140         ) AS revenue_rank_within_source,
141
142         DENSE_RANK() OVER (
143             ORDER BY roas DESC
144         ) AS overall_roas_rank
145     FROM final_growth
```

```
146 ),
147
148 percentage_contribution AS (
149     SELECT
150         *,
151         ROUND(
152             total_revenue /
153             SUM(total_revenue) OVER () * 100,
154             2
155         ) AS revenue_contribution_percent
156     FROM ranking_metrics
157 )
158
159 SELECT *
160 FROM percentage_contribution
161 WHERE
162     total_sessions > 0
163     AND total_conversions > 0
164     AND total_revenue > 0
165     AND total_cost > 0
166 ORDER BY day DESC, total_revenue DESC
167 LIMIT 500;
168
169
170
171
172
173
174
175
176
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182
```

	source text	campaign text	country text	day date	total_sessions bigint	total_conversions bigint	total_revenue numeric	avg_revenue_per_conversion numeric	total_cost numeric	conversion_rate_percent numeric	cpa numeric
1	Facebo...	Summer	UK	2026-02-...	5	4	3503.97	875.99250000000000000000	232.77	80.00	58.19
2	Email	Spring	India	2026-02-...	2	2	1406.07	703.03500000000000000000	430.17	100.00	215.09
3	Facebo...	Brand	India	2026-02-...	3	2	1271.79	635.89500000000000000000	134.00	66.67	67.00
4	Google	Spring	India	2026-02-...	3	3	1138.13	379.3766666666666667	119.38	100.00	39.79
5	Email	Winter	India	2026-02-...	3	2	1103.85	551.92500000000000000000	512.89	66.67	256.45
6	LinkedIn	Spring	USA	2026-02-...	2	1	894.11	894.11000000000000000000	124.86	50.00	124.86
7	LinkedIn	Summer	India	2026-02-...	4	1	880.87	880.87000000000000000000	229.87	25.00	229.87
8	LinkedIn	Brand	USA	2026-02-...	1	1	854.07	854.07000000000000000000	571.23	100.00	571.23
9	Facebo...	Brand	USA	2026-02-...	1	1	853.48	853.48000000000000000000	134.00	100.00	134.00
10	Google	Winter	UK	2026-02-...	3	1	830.76	830.76000000000000000000	493.76	33.33	493.76
11	LinkedIn	Winter	India	2026-02-...	2	1	792.66	792.66000000000000000000	348.41	50.00	348.41
12	LinkedIn	Summer	USA	2026-02-...	3	1	756.70	756.70000000000000000000	229.87	33.33	229.87
13	Google	Spring	USA	2026-02-...	1	1	749.88	749.88000000000000000000	119.38	100.00	119.38
14	LinkedIn	Spring	Canada	2026-02-...	2	1	738.91	738.91000000000000000000	124.86	50.00	124.86
15	Facebo...	Brand	Canada	2026-02-...	1	1	738.91	738.91000000000000000000	134.00	100.00	134.00
16	Email	Brand	Canada	2026-02-...	1	1	719.91	719.91000000000000000000	243.87	100.00	243.87
17	Facebo...	Summer	India	2026-02-...	1	1	465.96	465.96000000000000000000	232.77	100.00	232.77
18	Email	Brand	India	2026-02-...	1	1	465.96	465.96000000000000000000	243.87	100.00	243.87
19	Email	Winter	Canada	2026-02-...	1	1	455.50	455.50000000000000000000	512.89	100.00	512.89
20	Google	Summer	Canada	2026-02-...	3	2	453.36	226.68000000000000000000	435.56	66.67	217.78
21	LinkedIn	Winter	USA	2026-02-...	4	6	3870.15	645.02500000000000000000	566.24	150.00	94.37
22	LinkedIn	Spring	India	2026-02-...	2	3	2612.57	870.8566666666666667	359.35	150.00	119.78
23	Facebo...	Spring	USA	2026-02-...	2	3	1985.08	661.6933333333333333	436.21	150.00	145.40
24	Google	Summer	USA	2026-02-...	1	3	1749.62	583.2066666666666667	199.52	300.00	66.51

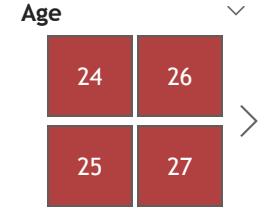
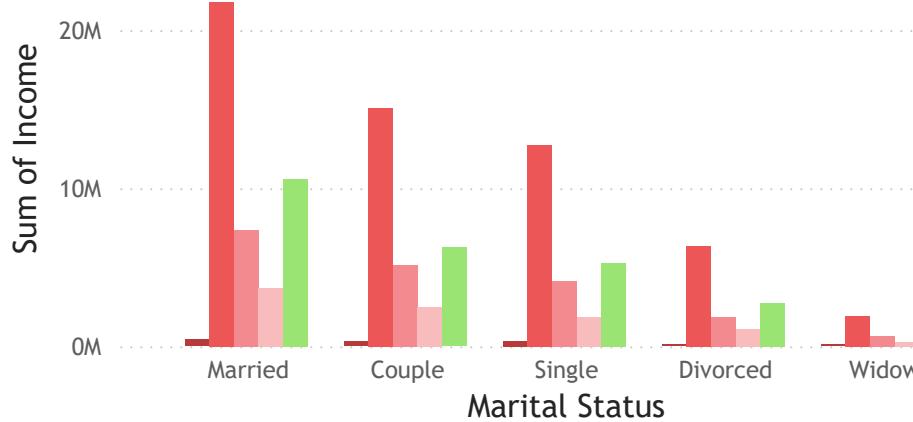
25	Email	Summer	India	2026-02-	2	2	1671.30	835.6500000000000000	269.31	100.00	134.66
26	Facebo...	Winter	USA	2026-02-	1	2	1568.28	784.1400000000000000	181.79	200.00	90.90
27	LinkedIn	Brand	India	2026-02-	2	3	1499.05	499.68333333333333	493.65	150.00	164.55
28	Google	Brand	Canada	2026-02-	3	2	1349.04	674.5200000000000000	163.71	66.67	81.86
29	Email	Summer	Canada	2026-02-	2	3	1285.60	428.53333333333333	269.31	150.00	89.77
30	LinkedIn	Spring	Canada	2026-02-	2	2	1228.32	614.1600000000000000	359.35	100.00	179.68
31	Email	Brand	Canada	2026-02-	3	1	995.00	995.0000000000000000	333.05	33.33	333.05
32	Google	Brand	USA	2026-02-	1	1	973.16	973.1600000000000000	163.71	100.00	163.71
33	Facebo...	Spring	India	2026-02-	1	1	948.99	948.9900000000000000	436.21	100.00	436.21
34	Facebo...	Winter	UK	2026-02-	2	1	807.06	807.0600000000000000	181.79	50.00	181.79
35	Email	Winter	USA	2026-02-	1	1	804.98	804.9800000000000000	203.81	100.00	203.81
36	LinkedIn	Summer	UK	2026-02-	2	1	767.54	767.5400000000000000	197.23	50.00	197.23
37	Facebo...	Brand	UK	2026-02-	3	1	767.54	767.5400000000000000	379.15	33.33	379.15
38	LinkedIn	Brand	UK	2026-02-	5	1	767.54	767.5400000000000000	493.65	20.00	493.65
39	Email	Summer	USA	2026-02-	1	1	749.88	749.8800000000000000	269.31	100.00	269.31
40	Google	Summer	Canada	2026-02-	1	1	699.28	699.2800000000000000	199.52	100.00	199.52
41	Google	Spring	Canada	2026-02-	2	1	502.49	502.4900000000000000	166.45	50.00	166.45
42	Facebo...	Winter	India	2026-02-	2	1	424.53	424.5300000000000000	181.79	50.00	181.79
43	Google	Summer	India	2026-02-	3	1	373.01	373.0100000000000000	199.52	33.33	199.52
44	Google	Winter	India	2026-02-	2	1	356.80	356.8000000000000000	446.65	50.00	446.65
45	LinkedIn	Winter	India	2026-02-	1	1	355.38	355.3800000000000000	566.24	100.00	566.24
46	LinkedIn	Winter	Canada	2026-02-	2	1	248.35	248.3500000000000000	566.24	50.00	566.24
47	LinkedIn	Summer	Canada	2026-02-	2	1	248.35	248.3500000000000000	197.23	50.00	197.23
48	Facebo...	Brand	Canada	2026-02-	2	1	248.35	248.3500000000000000	379.15	50.00	379.15

50	Google	Brand	UK	2026-02-	1	1	234.05	234.05000000000000000000	163.71	100.00	163.71
51	Google	Summer	USA	2026-02-	2	4	3480.28	870.07000000000000000000	344.14	200.00	86.04
52	Email	Summer	UK	2026-02-	3	4	3145.95	786.48750000000000000000	290.54	133.33	72.64
53	Email	Spring	UK	2026-02-	1	3	2818.11	939.37000000000000000000	184.33	300.00	61.44
54	LinkedIn	Brand	UK	2026-02-	3	3	2818.11	939.37000000000000000000	547.94	100.00	182.65
55	LinkedIn	Winter	USA	2026-02-	3	3	2749.04	916.3466666666666667	226.52	100.00	75.51
56	Facebo...	Spring	USA	2026-02-	1	3	2684.14	894.7133333333333333	142.66	300.00	47.55
57	Facebo...	Brand	India	2026-02-	3	4	2095.40	523.85000000000000000000	298.11	133.33	74.53
58	Facebo...	Summer	Canada	2026-02-	2	3	1937.22	645.74000000000000000000	582.28	150.00	194.09
59	LinkedIn	Winter	Canada	2026-02-	5	2	1933.21	966.60500000000000000000	226.52	40.00	113.26
60	Email	Winter	UK	2026-02-	3	2	1925.58	962.79000000000000000000	555.95	66.67	277.98
61	Email	Spring	USA	2026-02-	1	2	1818.90	909.45000000000000000000	184.33	200.00	92.17
62	Google	Winter	India	2026-02-	2	2	1717.62	858.81000000000000000000	418.51	100.00	209.26
63	LinkedIn	Summer	India	2026-02-	3	3	1695.87	565.29000000000000000000	553.42	100.00	184.47
64	Email	Brand	Canada	2026-02-	2	2	1616.12	808.06000000000000000000	269.88	100.00	134.94
65	Email	Winter	Canada	2026-02-	2	3	1382.95	460.9833333333333333	555.95	150.00	185.32
66	Google	Summer	UK	2026-02-	1	2	1322.68	661.34000000000000000000	344.14	200.00	172.07
67	LinkedIn	Brand	USA	2026-02-	2	2	1162.80	581.40000000000000000000	547.94	100.00	273.97

Customer Analysis for Marketing

Sum of Income by Marital Status and Education

Education ● Basic ● Graduate ● Masters ● None ● PhD



33K

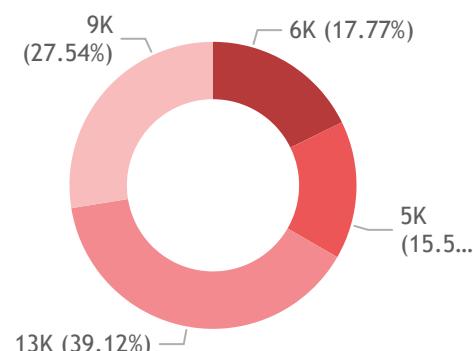
Total Purchase

51.62K

Average of Income

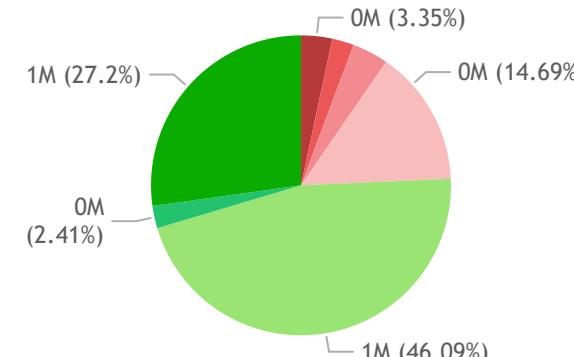
Means of Purchase

Catalog ● Deals ● In-Store ● Online



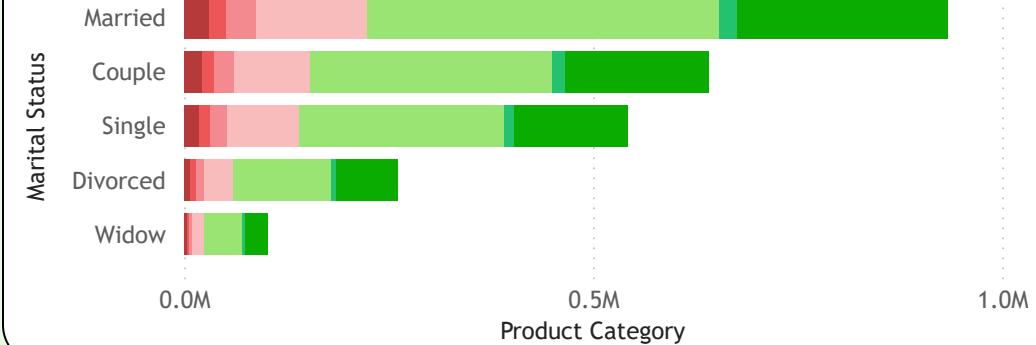
Product Sales

Fish ● Fruits ● Gold ● Meat ● Regular ● Sweets



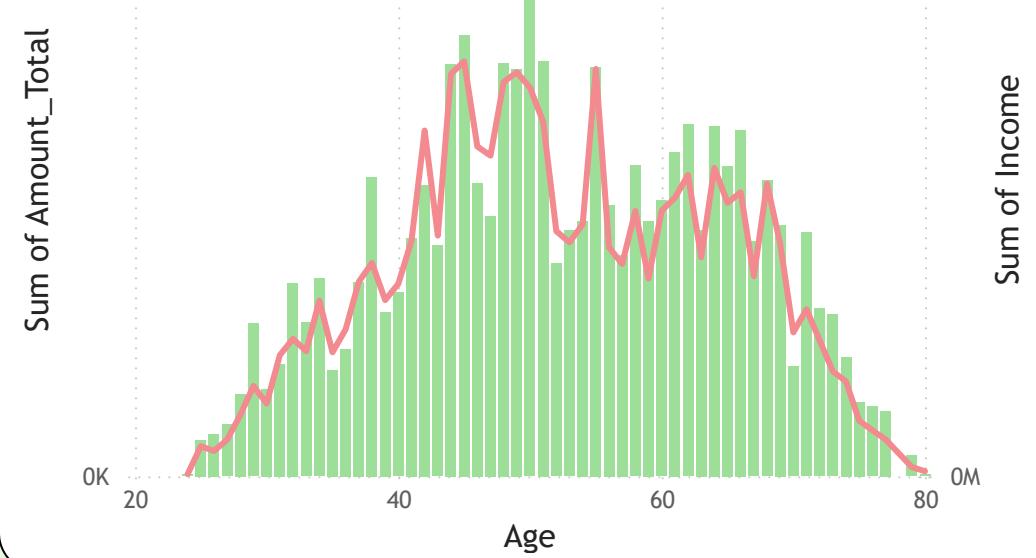
Products by Marital Status

Fish ● Fruits ● Gold products ● Meat ● Regular products ● Sweets ● Wines

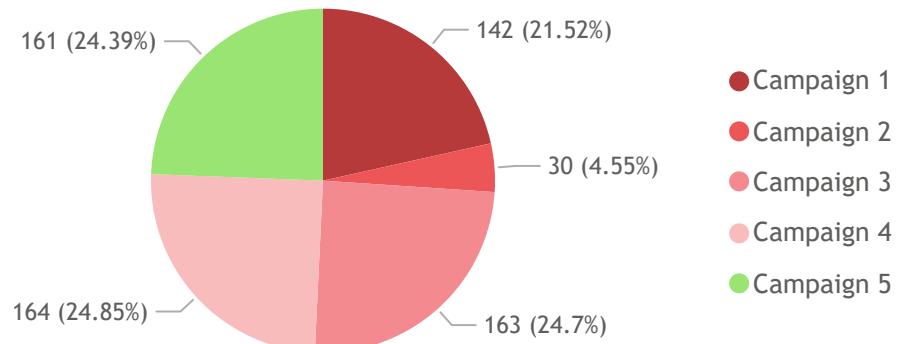


Age vs Expenditure

● Sum of Amount_Total ● Sum of Income

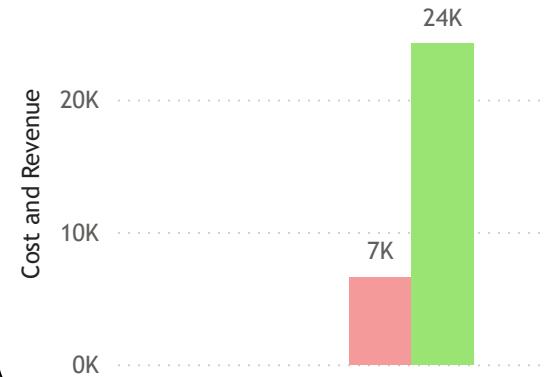


Campaign Acceptance

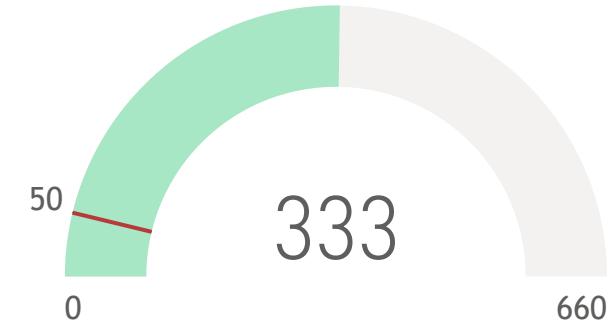


Cost vs Revenue of Campaign

Cost ● Revenue



Campaign Response



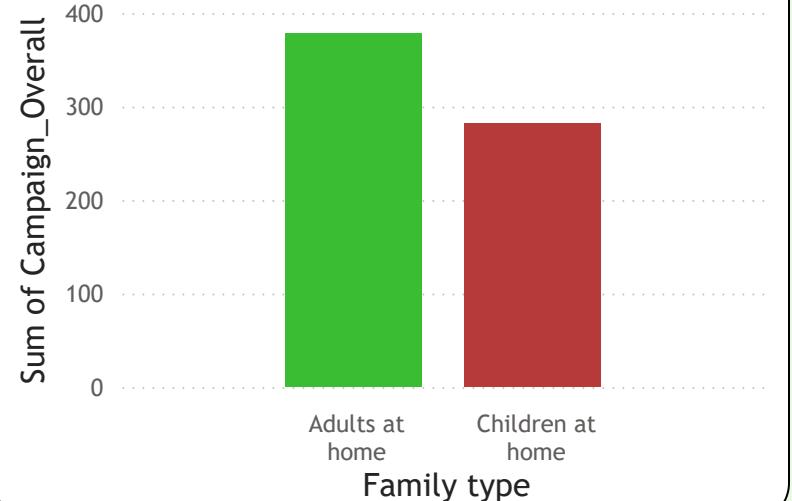
50.45%
% Success

18K
Campaign Profit

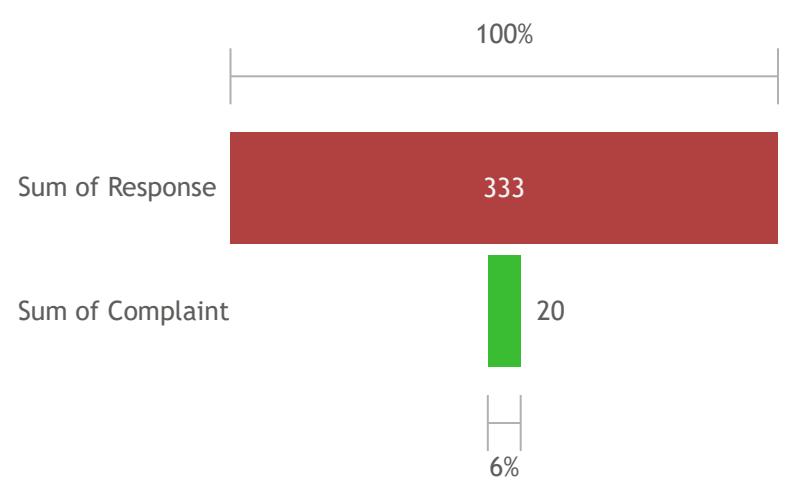
Insights

- The campaign response has exceeded the anticipated target amount.
- Revenue from the campaigns is 3x the cost of the campaigns.
- Families with no children responded better to the campaign.
- Lesser the complaints, higher the campaign response.

Sum of Campaign_Overall by Family type



Sum of Response and Sum of Complaint



Marketing Campaign Insights