In [1]:
```python
import pandas as pd
import warnings
warnings.filterwarnings("ignore")

df = pd.read_csv('data.csv')
df.dropna(inplace=True)
df.head()
```

Out[1]:

| | revenue | reach | local_tv | online | instore | person | event |
|---|---|---|---|---|---|---|---|
| 0 | 45860.28 | 2 | 31694.91 | 2115 | 3296 | 8 | non_event |
| 1 | 63588.23 | 2 | 35040.17 | 1826 | 2501 | 14 | special |
| 2 | 23272.69 | 4 | 30992.82 | 1851 | 2524 | 6 | special |
| 3 | 45911.23 | 2 | 29417.78 | 2437 | 3049 | 12 | special |
| 4 | 36644.23 | 2 | 35611.11 | 1122 | 1142 | 13 | cobranding |

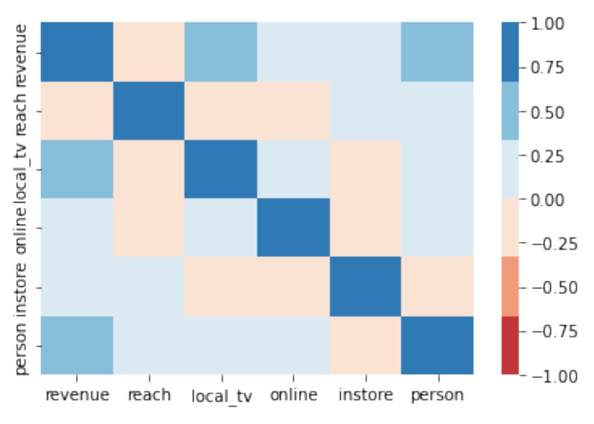
## 特征对销售额的关联性

reach(微信推送次数)与revenue(门店销售额)有负相关的关系，微信推动次数越多，销售额反而越低。
其余变量与销售额都是正相关关系。其中local_tv(本地电视广告投入)和person(门店销售人员投入)与销售额的正相关性较大。

In [2]:
```python
df.corr()['revenue']
```

Out[2]:
```
revenue     1.000000
reach      -0.165286
local_tv    0.602114
online      0.174198
instore     0.307361
person      0.557475
Name: revenue, dtype: float64
```

In [3]:
```python
import seaborn as sns
from matplotlib import pyplot as plt
sns.heatmap(df.corr(),vmin=-1,vmax=1,cmap=sns.color_palette('RdBu'))
plt.show()
```



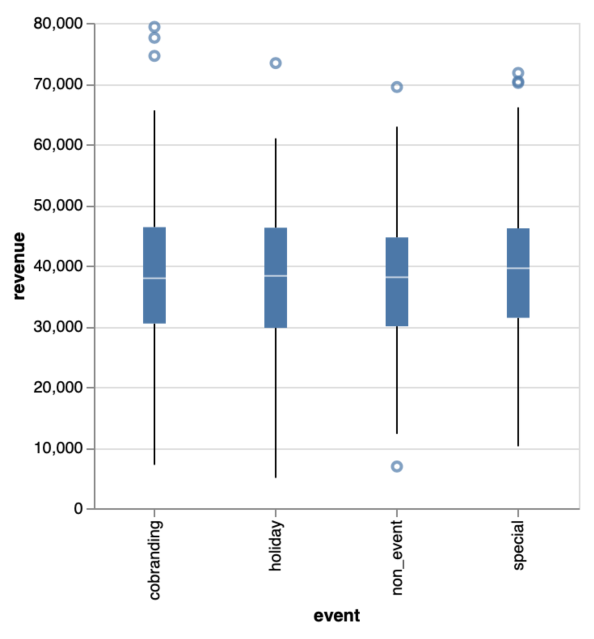

event(门店促销事件)为离散变量，计算其correlation ratio [https://zhuanlan.zhihu.com/p/362258222] 。门店促销事件类型与销售额的关联性低。

In [4]:
```python
import numpy as np
events = df[['event','revenue']]
events_mean = events.groupby(by='event', as_index=False)['revenue'].mean()
events_mean.columns = ['event','group_avg']
events = pd.merge(events, events_mean, on='event', how='left')
events['total_avg'] = df['revenue'].mean()
events['square_diff'] = (events['revenue']-events['total_avg'])**2
events_count = pd.DataFrame(df['event'].value_counts()).reset_index()
events_count.columns = ['event','count']
events_sum = events_count.merge(events_mean, on='event', how='inner')
events_sum['total_avg'] = df['revenue'].mean()
numerator = 0
for i in range(len(events_sum)):
    numerator += events_sum['count'][i]*(events_sum['group_avg'][i]-events_sum['total_avg'][i])**2
np.sqrt(numerator/sum(events['square_diff']))
```

Out[4]:
```
0.04368009601916971
```

In [5]:
```python
import altair as alt
alt.Chart(events, width=300).mark_boxplot(
).encode(
    x = 'event', y ='revenue'
)
```

Out[5]:




## 特征筛选

DictVectorizer结果为9个特征都应该保留

In [6]:
```python
X = df.drop('revenue', axis=1)
y = df['revenue']
from sklearn.feature_extraction import DictVectorizer
vec = DictVectorizer()
X = vec.fit_transform(X.to_dict(orient='record'))
len(vec.feature_names_), vec.feature_names_
```

Out[6]:
```
(9,
 ['event=cobranding',
  'event=holiday',
  'event=non_event',
  'event=special',
  'instore',
  'local_tv',
  'online',
  'person',
  'reach'])
```

使用SelectKBest保留最主要的4个特征。结果显示最主要的4个特征为local_tv(本地电视广告投入)、online(线上广告投入)、person(门店销售人员投入)、和reach(微信推送次数)。

In [7]:
```python
from sklearn.feature_selection import SelectKBest, f_classif
selector = SelectKBest(f_classif, k=4)
selector.fit(X,y)
X_new = selector.transform(X)
X_new = pd.DataFrame(X_new.toarray())
X_new
```

Out[7]:

| | 0 | 1 | 2 | 3 |
|---|---|---|---|---|
| 0 | 31694.91 | 2115.0 | 8.0 | 2.0 |
| 1 | 35040.17 | 1826.0 | 14.0 | 2.0 |
| 2 | 30992.82 | 1851.0 | 6.0 | 4.0 |
| 3 | 29417.78 | 2437.0 | 12.0 | 2.0 |
| 4 | 35611.11 | 1122.0 | 13.0 | 2.0 |
| ... | ... | ... | ... | ... |
| 924 | 30527.57 | 1407.0 | 12.0 | 3.0 |
| 925 | 31233.04 | 1849.0 | 18.0 | 2.0 |
| 926 | 34346.13 | 1200.0 | 8.0 | 3.0 |
| 927 | 30215.90 | 1532.0 | 16.0 | 3.0 |
| 928 | 30535.26 | 2381.0 | 12.0 | 4.0 |

929 rows × 4 columns

In [8]:
```python
X_new.columns = ['local_tv','online','person','reach']
X_new
```

Out[8]:

| | local_tv | online | person | reach |
|---|---|---|---|---|
| 0 | 31694.91 | 2115.0 | 8.0 | 2.0 |
| 1 | 35040.17 | 1826.0 | 14.0 | 2.0 |
| 2 | 30992.82 | 1851.0 | 6.0 | 4.0 |
| 3 | 29417.78 | 2437.0 | 12.0 | 2.0 |
| 4 | 35611.11 | 1122.0 | 13.0 | 2.0 |
| ... | ... | ... | ... | ... |
| 924 | 30527.57 | 1407.0 | 12.0 | 3.0 |
| 925 | 31233.04 | 1849.0 | 18.0 | 2.0 |
| 926 | 34346.13 | 1200.0 | 8.0 | 3.0 |
| 927 | 30215.90 | 1532.0 | 16.0 | 3.0 |
| 928 | 30535.26 | 2381.0 | 12.0 | 4.0 |

929 rows × 4 columns

## 训练数据测试数据划分

In [9]:
```python
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X_new, y, test_size=0.2, random_state=42, shuffle=True)
```

## 随机森林

In [10]:
```python
from sklearn.ensemble import RandomForestRegressor
from sklearn.metrics import mean_squared_error as mse

rf = RandomForestRegressor(random_state=42)
rf.fit(X_train, y_train)
score_rf = rf.score(X_train, y_train)
score_rf
```

Out[10]:
```
0.9476181488347754
```

In [11]:
```python
MSE_rf = mse(y_test, rf.predict(X_test))
MSE_rf
```

Out[11]:
```
53635433.91058462
```

In [12]:
```python
MAE_rf = np.mean(abs(y_test - rf.predict(X_test)))
MAE_rf
```

Out[12]:
```
5876.683041935483
```

## SVM

In [13]:
```python
from sklearn.pipeline import Pipeline
from sklearn.preprocessing import StandardScaler
from sklearn import svm

# svr = Pipeline([
#     ('scaler', StandardScaler()),
#     ('linear_svr', svm.SVR(kernel='linear'))
# ])
svr = svm.SVR(kernel='linear')
svr.fit(X_train, y_train)
score_svr = svr.score(X_train, y_train)
score_svr
```

Out[13]:
```
0.5988046494640198
```

In [14]:
```python
MSE_svr = mse(y_test, svr.predict(X_test))
MSE_svr
```

Out[14]:
```
61664671.877914995
```

In [15]:
```python
MAE_svr = np.mean(abs(y_test - svr.predict(X_test)))
MAE_svr
```

Out[15]:
```
6306.673476991544
```

## xgboost

In [16]:
```python
import xgboost

xgb = xgboost.XGBRegressor(random_state=42)
xgb.fit(X_train, y_train)
score_xgb = xgb.score(X_train, y_train)
score_xgb
```

Out[16]:
```
0.9915167351137204
```

In [17]:
```python
MSE_xgb = mse(y_test, xgb.predict(X_test))
MSE_xgb
```

Out[17]:
```
58501712.41569456
```

In [18]:
```python
MAE_xgb = np.mean(abs(y_test - xgb.predict(X_test)))
MAE_xgb
```

Out[18]:
```
6201.112864163306
```

## ANN

In [19]:
```python
from sklearn.neural_network import MLPRegressor

nn = MLPRegressor(random_state=42)
nn.fit(X_train, y_train)
score_nn = nn.score(X_train, y_train)
score_nn
```

Out[19]:
```
0.34259222301466274
```

In [20]:
```python
MSE_nn = mse(y_test, nn.predict(X_test))
MSE_nn
```

Out[20]:
```
89252423.91407908
```

In [21]:
```python
MAE_nn = np.mean(abs(y_test - nn.predict(X_test)))
MAE_nn
```

Out[21]:
```
7661.942534641474
```

## 模型对比

In [22]:
```python
scores = [score_rf, score_svr, score_xgb, score_nn]
MSEs = [MSE_rf, MSE_svr, MSE_xgb, MSE_nn]
MAEs = [MAE_rf, MAE_svr, MAE_xgb, MAE_nn]
summary = pd.DataFrame([scores, MSEs, MAEs], index = ['score','MSE','MAE']).apply(lambda x:round(x,2))
summary.columns = ['随机森林','SVM','XGBoost','Neural Nets']
summary
```

Out[22]:

| | 随机森林 | SVM | XGBoost | Neural Nets |
|---|---|---|---|---|
| score | 0.95 | 0.60 | 0.99 | 0.34 |
| MSE | 53635433.91 | 61664671.88 | 58501712.42 | 89252423.91 |
| MAE | 5876.68 | 6306.67 | 6201.11 | 7661.94 |

对比这四个模型，随机森林的结果最好。虽然随机森林的R^2没有XGBoost高，但其MSE（均方误差）和MAE（平均绝对误差）都是四个模型中最低的。

In [ ]: