Problem Statement:

Sales Channel Prediction Case Study:-

When a company enters a market, the distribution strategy and channel it uses are keys to its success in the market, as well as market know-how and customer knowledge and understanding. Because an effective distribution strategy under efficient supply-chain management opens doors for attaining competitive advantage and strong brand equity in the market, it is a component of the marketing mix that cannot be ignored . The distribution strategy and the channel design have to be right the first time. The case study of Sales channel includes the detailed study of TV, radio and newspaper channel. The predict the total sales generated from all the sales channel.

Importing required libraries

In [1]:
```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
import pickle
from scipy.stats import zscore
from sklearn.model_selection import train_test_split, GridSearchCV, cross_val_sco
from sklearn.preprocessing import StandardScaler
import statsmodels.formula.api as smf
from sklearn.metrics import r2_score, mean_squared_error
from sklearn.linear_model import LinearRegression, LassoCV, Lasso
from sklearn.neighbors import KNeighborsRegressor
from sklearn.tree import DecisionTreeRegressor
from sklearn.ensemble import RandomForestRegressor
from sklearn.svm import SVR
%matplotlib inline

import warnings
warnings.filterwarnings('ignore')
```

Reading data

In [2]:
```
df = pd.read_csv(r"C:\Users\Kushal Arya\Desktop\Data Analysis With Python\Adverti
df.head()
```

Out[2]:

	Unnamed: 0	TV	radio	newspaper	sales
0	1	230.1	37.8	69.2	22.1
1	2	44.5	39.3	45.1	10.4
2	3	17.2	45.9	69.3	9.3
3	4	151.5	41.3	58.5	18.5
4	5	180.8	10.8	58.4	12.9

Droping Unwanted Column

In [3]:
```
df = df.drop(columns = 'Unnamed: 0', axis = 1)
df.head()
```

Out[3]:

	TV	radio	newspaper	sales
0	230.1	37.8	69.2	22.1
1	44.5	39.3	45.1	10.4
2	17.2	45.9	69.3	9.3
3	151.5	41.3	58.5	18.5
4	180.8	10.8	58.4	12.9

Check no of row and column

In [4]:
```
print('No of Rows and Columns ----->', df.shape )
```

```
No of Rows and Columns -----> (200, 4)
```

Checking for Null values

In [5]:
```
print('----------------------\n')
print(df.isnull().sum())
print('\n----------------------')
```

```
----------------------

TV           0
radio        0
newspaper    0
sales        0
dtype: int64

----------------------
```

There is no null value

Information about dataset

In [6]:
```
print('-----------------------------------------------------\n')
print(df.info())
print('\n-----------------------------------------------------')
```

```
-----------------------------------------------------

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 200 entries, 0 to 199
Data columns (total 4 columns):
 #   Column     Non-Null Count  Dtype  
---  ------     --------------  -----  
 0   TV         200 non-null    float64
 1   radio      200 non-null    float64
 2   newspaper  200 non-null    float64
 3   sales      200 non-null    float64
dtypes: float64(4)
memory usage: 6.4 KB
None

-----------------------------------------------------
```

All features are in float

Statistic of Dataset

In [7]:
```
# We use describe command to extracte statistical infomation about dataset.
df.describe()
```

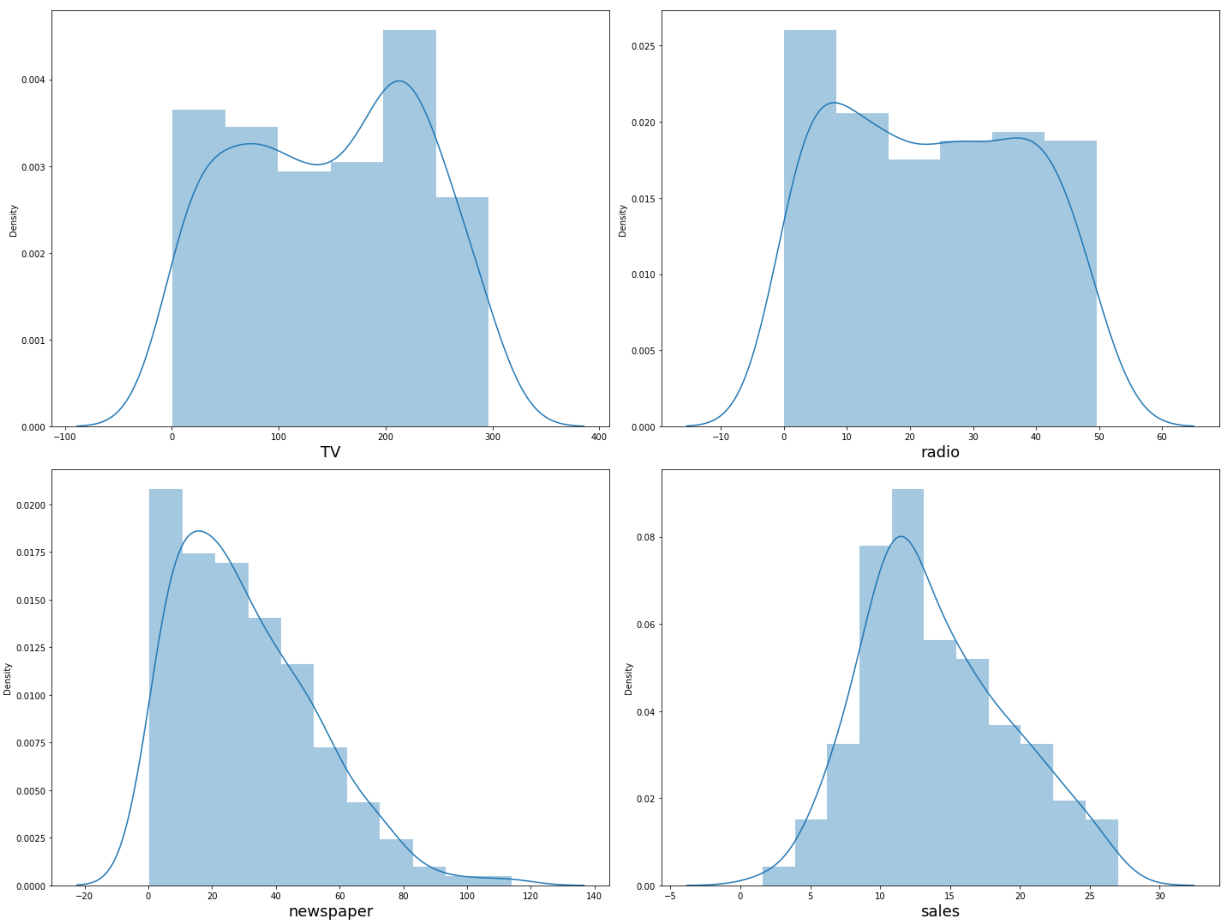
Out[7]:

	TV	radio	newspaper	sales
count	200.000000	200.000000	200.000000	200.000000
mean	147.042500	23.264000	30.554000	14.022500
std	85.854236	14.846809	21.778621	5.217457
min	0.700000	0.000000	0.300000	1.600000
25%	74.375000	9.975000	12.750000	10.375000
50%	149.750000	22.900000	25.750000	12.900000
75%	218.825000	36.525000	45.100000	17.400000
max	296.400000	49.600000	114.000000	27.000000

Plot graph to visualize how data is distributed in every column

In [8]:
```
# Let' see how data is distributed in every columns.
print('\nDistribution Plot :-\n')

plt.figure(figsize = (20,15), facecolor = 'white')
plotnumber = 1
for column in df:
    if plotnumber <=4:
        ax = plt.subplot(2,2, plotnumber)
        sns.distplot(df[column])
        plt.xlabel(column, fontsize = 18)
    plotnumber += 1
plt.tight_layout()
```

```
Distribution Plot :-
```



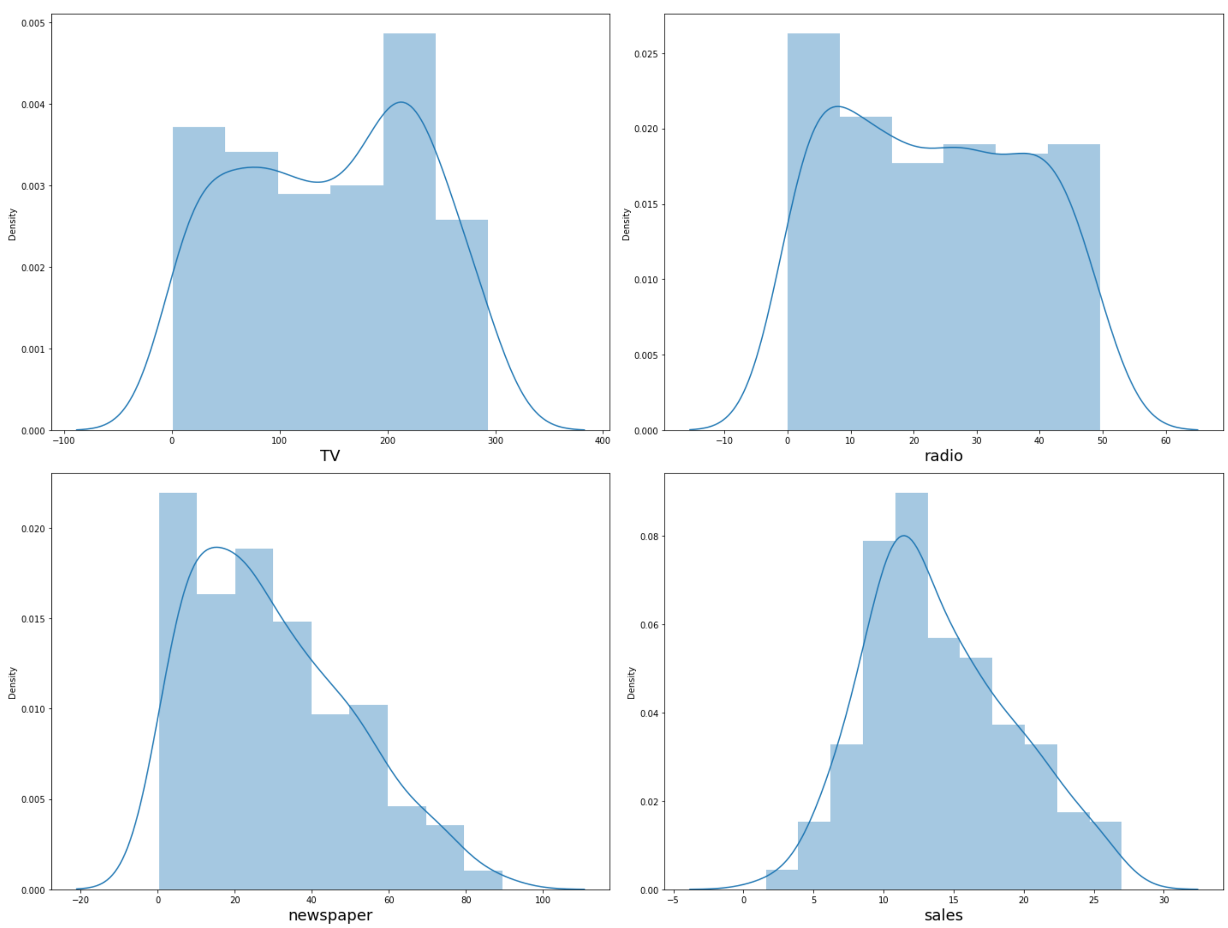
some column are skewed

Removing outliers and verify it

In [9]:
```
# with std 3 Lets see the stats

z_score = zscore(df[['TV', 'radio', 'newspaper']]) # use only continous data
abs_z_score = np.abs(z_score)

filtering_entry = (abs_z_score < 3).all(axis = 1)

df = df[filtering_entry]
```

In [10]:
```
# Let' see outliers remove or not.
print('\nDistribution Plot :-\n')

plt.figure(figsize = (20,15), facecolor = 'white')
plotnumber = 1
for column in df:
    if plotnumber <=4:
        ax = plt.subplot(2,2, plotnumber)
        sns.distplot(df[column])
        plt.xlabel(column, fontsize = 18)
    plotnumber += 1
plt.tight_layout()
```

```
Distribution Plot :-
```



In [11]:
```
print('Checking No of Rows and Columns After Removing Outliers ----->', df.shape
```

```
Checking No of Rows and Columns After Removing Outliers -----> (198, 4)
```

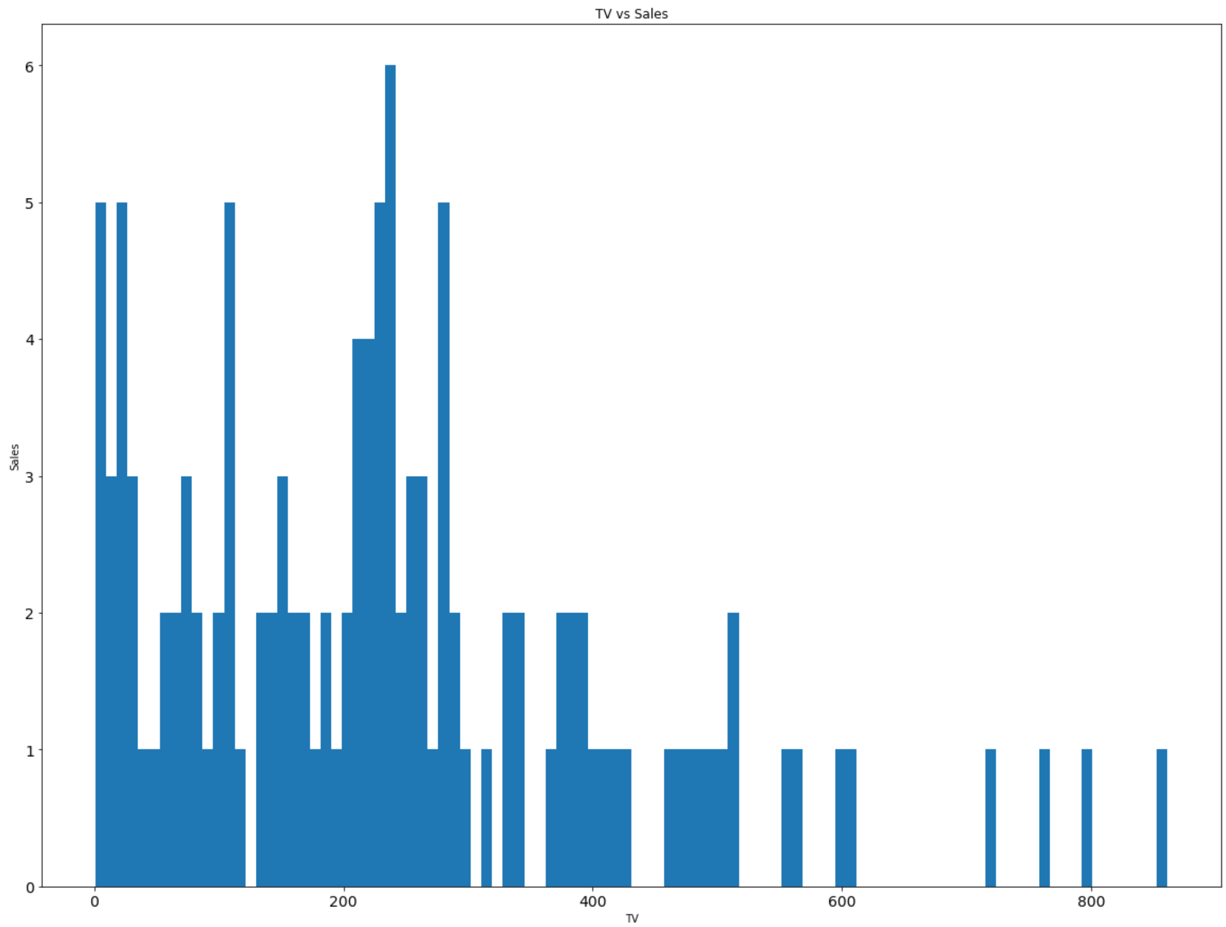
Outliers are removed

Visualizing relationship

In [12]:
```
TV= df.groupby('sales')['TV'].sum()
TV
```

Out[12]:
```
sales
1.6       0.7
3.2       4.1
4.8       8.6
5.3      18.5
5.5       7.3
        ...
24.7    220.3
25.4    799.8
25.5    283.6
26.2    287.6
27.0    276.9
Name: TV, Length: 121, dtype: float64
```

```
In [13]: TV.plot.hist(figsize = (20,15), fontsize = 14, bins = 100)
         plt.xlabel('TV')
         plt.ylabel('Sales')
         plt.title('TV vs Sales')
         plt.show()
```

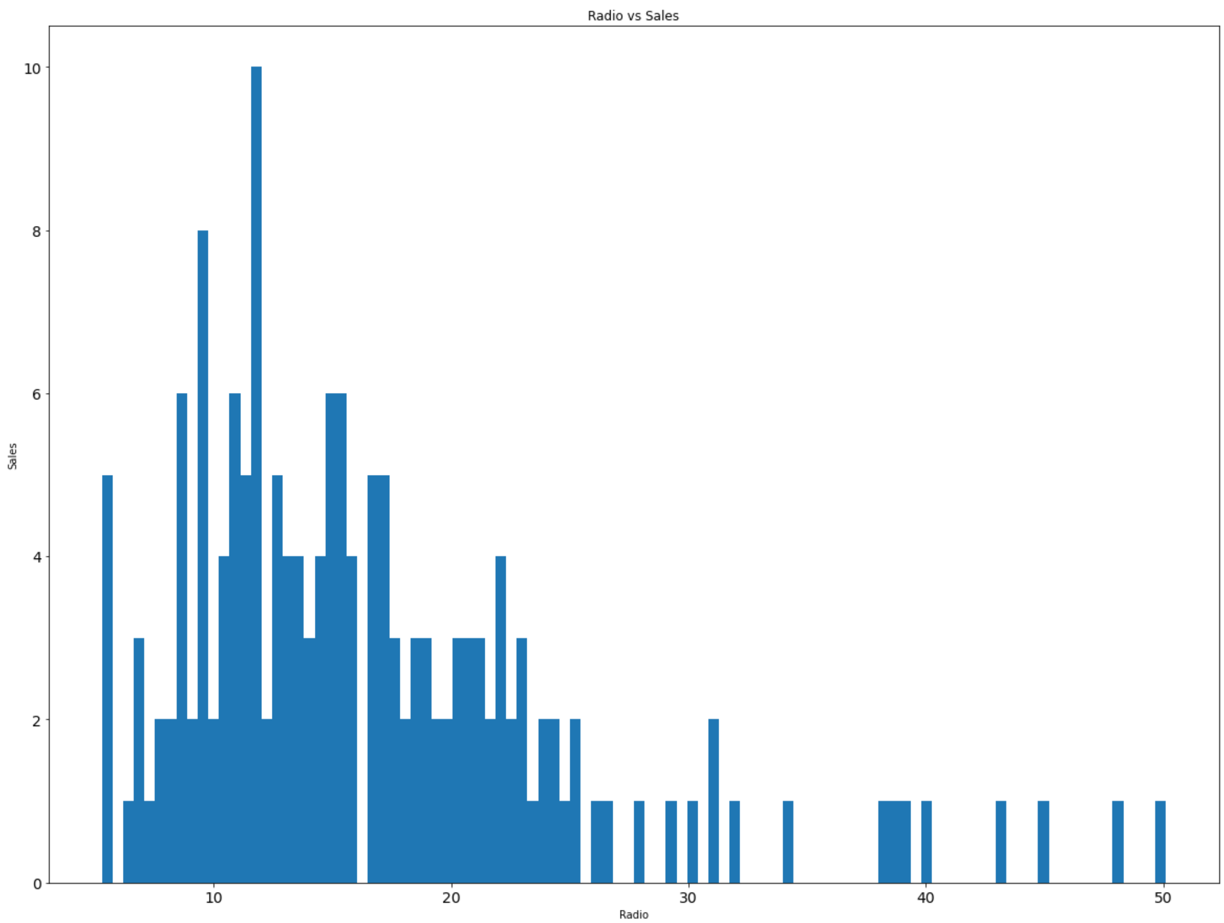


Range 10 to 15 highest sales

```
In [14]: radio = df.groupby('radio')['sales'].sum()
         radio
```

```
Out[14]: radio
         0.0      8.8
         0.3      8.7
         0.4      5.3
         0.8      9.4
         1.3     10.1
                 ...
         47.8    16.7
         48.9    34.2
         49.0    50.1
         49.4    38.4
         49.6    23.8
         Name: sales, Length: 165, dtype: float64
```

In [15]:
```
radio.plot.hist(figsize = (20,15), fontsize = 14, bins = 100)
plt.xlabel('Radio')
plt.ylabel('Sales')
plt.title('Radio vs Sales')
plt.show()
```

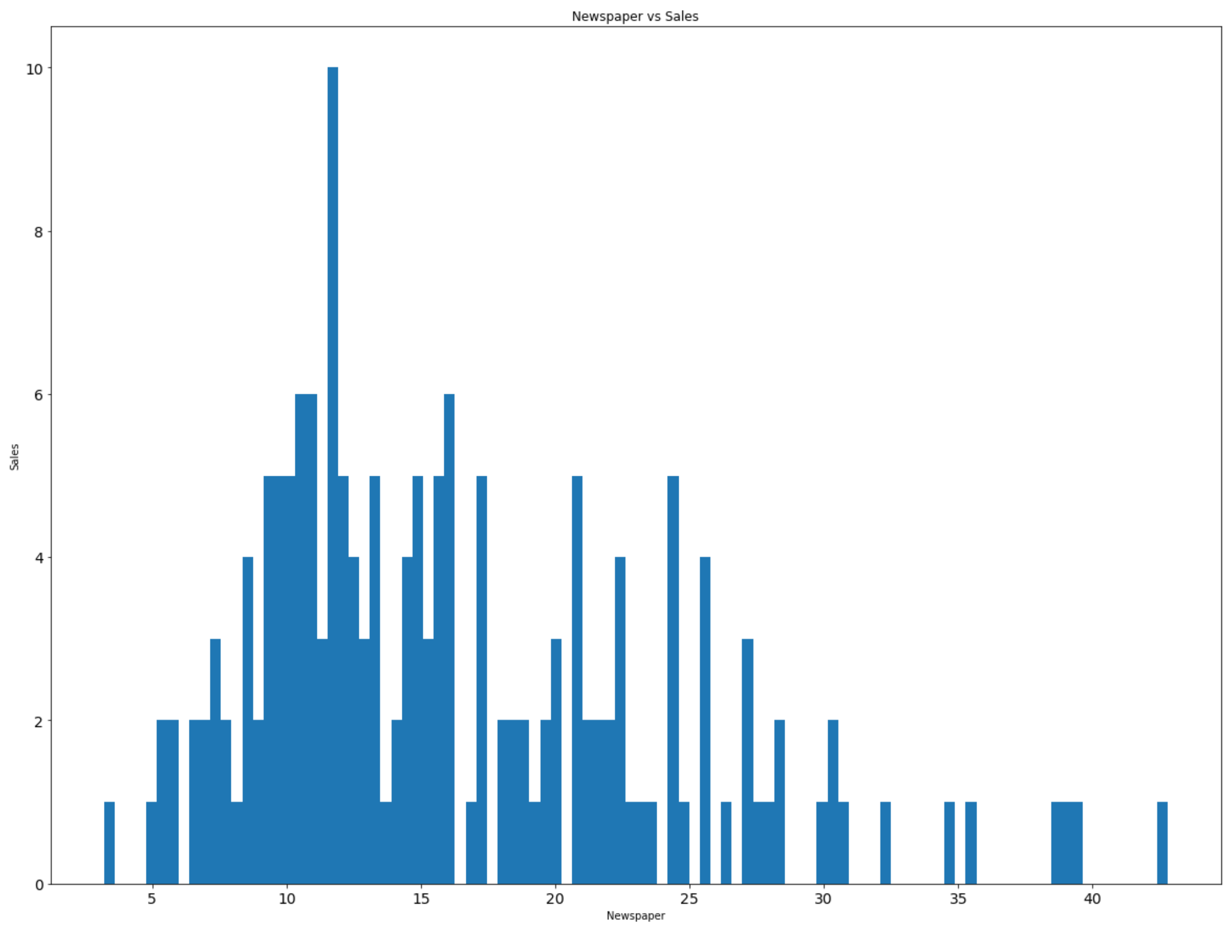


Range of 5 to 15 highest sales

In [16]:
```python
newsp= df.groupby('newspaper')['sales'].sum()
newsp
```

Out[16]:
```
newspaper
0.3     17.4
0.9      9.3
1.0      4.8
1.7     20.7
1.8     20.7
        ...
75.0     7.2
75.6    19.2
79.2    15.9
84.8    11.9
89.4     8.7
Name: sales, Length: 170, dtype: float64
```

In [17]:
```python
newsp.plot.hist(figsize = (20,15), fontsize = 14, bins = 100)
plt.xlabel('Newspaper')
plt.ylabel('Sales')
plt.title('Newspaper vs Sales')
plt.show()
```



Range 10 to 12 highest sales

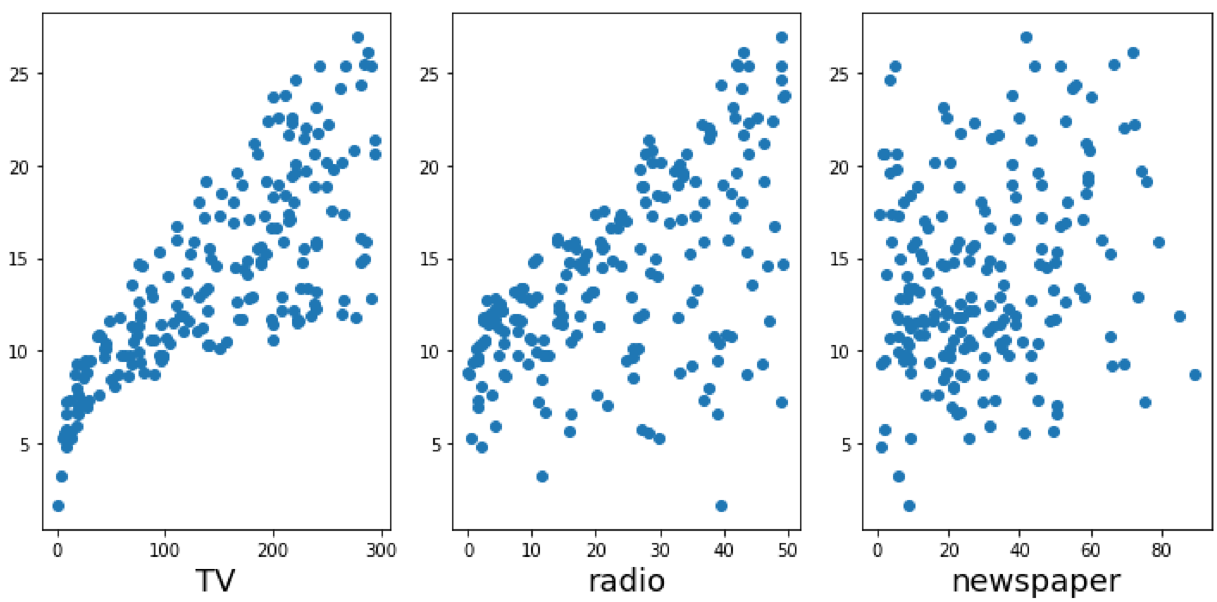
Spliting data into features and label

Spliting data into features and label

```
In [18]: x = df.drop('sales', axis = 1)
         y = df['sales']
```

```
In [19]: # Let' see how data is related to label .
         print('\nRelationship Plot :-\n')

         plt.figure(figsize = (10,5), facecolor = 'white')
         plotnumber = 1
         for column in x:
             if plotnumber <=4:
                 ax = plt.subplot(1,3, plotnumber)
                 plt.scatter(x[column], y)
                 plt.xlabel(column, fontsize = 18)
             plotnumber += 1
         plt.tight_layout()
```

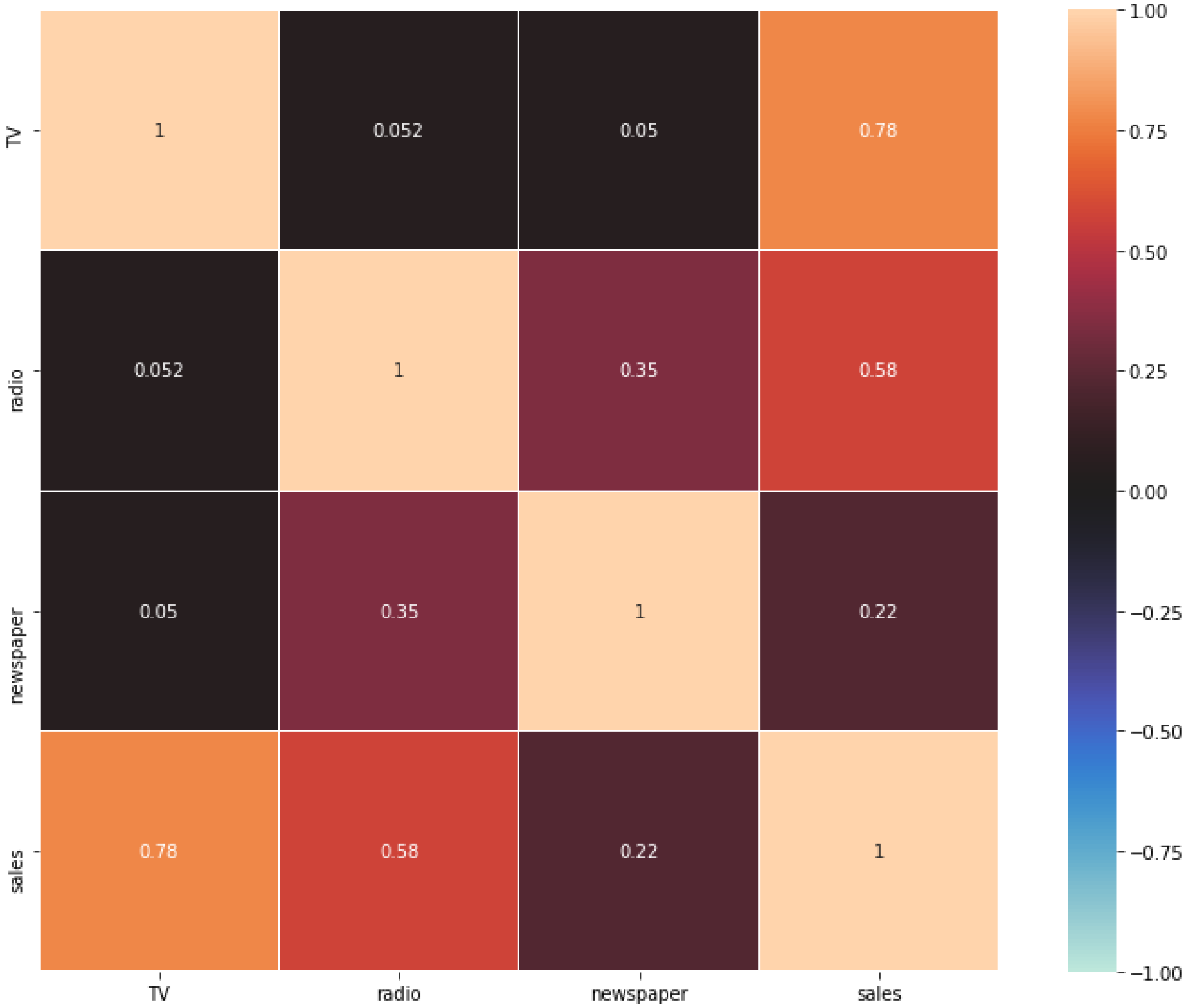
```
Relationship Plot :-
```



Newspaper not showing positive trends

Plotting Heatmap

In [20]:
```
df_corr = df.corr().abs()

plt.figure(figsize = (11,8))
sns.heatmap(df_corr, vmin = -1, annot = True, square = True, center = 0, fmt = '.
plt.tight_layout()
```



Observation : TV show maximum relation and newspaper show minimum relation with sales.

Checking for skewness

In [21]:
```
x.skew()
```

Out[21]:
```
TV           -0.082332
radio         0.114842
newspaper     0.650112
dtype: float64
```

Observation : No skewness is present in dataset

Data Scaling

In [22]:
```
scaler = StandardScaler()
x_scaled = scaler.fit_transform(x)
x_scaled
```

Out[22]:
```
array([[ 0.97869734,  0.98952135,  1.93299778],
       [-1.19901165,  1.09070498,  0.75131275],
       [-1.51933199,  1.53591293,  1.93790103],
       [ 0.05645636,  1.22561648,  1.40834924],
       [ 0.40024339, -0.83178391,  1.40344598],
       [-1.61906543,  1.73828018,  2.2173867 ],
       [-1.04647815,  0.6522426 , -0.30779084],
       [-0.31079737, -0.23817331, -0.89127846],
       [-1.62023876, -1.41864895, -1.41102374],
       [ 0.62317696, -1.38492107, -0.42056576],
       [-0.94557138, -1.16906267, -0.27346804],
       [ 0.79800381,  0.05863199, -1.26392602],
       [-1.44189191,  0.80739083,  1.77119028],
       [-0.57714432, -1.04764232, -1.10702179],
       [ 0.67363035,  0.65898817,  0.79544207],
       [ 0.57155024,  1.65733328,  1.13376683],
       [ 1.58061798,  1.1109417 ,  1.27596129],
       [-0.90919801, -0.17746313, -0.56276022],
       [ 0.0071763 ,  0.05188642, -0.52353416],
```

OLS Result

In [23]:
```
lm = smf.ols(formula = 'sales ~ TV + radio + newspaper', data = df).fit()
lm.summary()
```

Out[23]:

OLS Regression Results

Dep. Variable:	sales	**R-squared:**	0.895
Model:	OLS	**Adj. R-squared:**	0.894
Method:	Least Squares	**F-statistic:**	553.5
Date:	Mon, 12 Jul 2021	**Prob (F-statistic):**	8.35e-95
Time:	17:13:34	**Log-Likelihood:**	-383.24
No. Observations:	198	**AIC:**	774.5
Df Residuals:	194	**BIC:**	787.6
Df Model:	3		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
Intercept	2.9523	0.318	9.280	0.000	2.325	3.580

Split data into train and test. Model will be bulit on training data and tested on test data

In [24]:
```
x_train, x_test, y_train, y_test = train_test_split(x, y, test_size = 0.25, rando
print('Data has been splited.')
```

```
Data has been splited.
```

Model Building

Linear Regression model instantiaing, training and evaluating

In [25]:
```
Lr = LinearRegression()
Lr.fit(x_train, y_train)
y_pred = Lr.predict(x_test)
```

```
In [26]: print('=========================================================')
         print('R2 Score ----->', r2_score(y_test, y_pred))
         print('=========================================================')
         print('RMSE of Model ------->', np.sqrt(mean_squared_error(y_test, y_pred)))
         print('=========================================================')
         print('MSE of Model ------->', mean_squared_error(y_test, y_pred))
         print('=========================================================')
         print('Score of test data ---->', Lr.score(x_test, y_test))
         print('=========================================================')
```

```
=========================================================
R2 Score -----> 0.8532243062942227
=========================================================
RMSE of Model -------> 2.1658462808214387
=========================================================
MSE of Model -------> 4.690890112148059
=========================================================
Score of test data ----> 0.8532243062942227
=========================================================
```

Here we use Lasso Regularization to avoid overfitting

```
In [27]: # LassoCV will return best alpha after max itratation.
         # Normalize is subtracting the mean and dividing by the L2-norm.

         lassocv = LassoCV(alphas = None, max_iter = 1000, normalize = True)
         lassocv.fit(x_train,y_train)
```

```
Out[27]: LassoCV(normalize=True)
```

```
In [28]: alpha = lassocv.alpha_
         alpha
```

```
Out[28]: 0.006607312321213054
```

```
In [29]: lasso_reg = Lasso(alpha)
         lasso_reg.fit(x_train, y_train)
```

```
Out[29]: Lasso(alpha=0.006607312321213054)
```

```
In [30]: print('Lasso Score =======>', lasso_reg.score(x_train, y_train))
```

```
Lasso Score =======> 0.9069044644990196
```

Conclusion : Linear Regression model has 90% score

Knn model instantiaing, training and evaluating

In [31]:
```python
Knn = KNeighborsRegressor()
Knn.fit(x_train, y_train)
y_pred = Knn.predict(x_test)
```

In [32]:
```python
print('=========================================================')
print('R2 Score ----->', r2_score(y_test, y_pred))
print('=========================================================')
print('RMSE of Model ------->', np.sqrt(mean_squared_error(y_test, y_pred)))
print('=========================================================')
print('MSE of Model ------->', mean_squared_error(y_test, y_pred))
print('=========================================================')
print('Score of test data ---->', Knn.score(x_test, y_test))
print('=========================================================')
```

```
=========================================================
R2 Score -----> 0.9296055918625223
=========================================================
RMSE of Model -------> 1.4999253314748706
=========================================================
MSE of Model -------> 2.2497760000000007
=========================================================
Score of test data ----> 0.9296055918625223
=========================================================
```

Here we use Lasso Regularization to avoid overfitting

In [33]:
```python
# LassoCV will return best alpha after max itratation.
# Normalize is subtracting the mean and dividing by the L2-norm.

lassocv = LassoCV(alphas = None, max_iter = 1000, normalize = True)
lassocv.fit(x_train,y_train)
```

Out[33]:
```
LassoCV(normalize=True)
```

In [34]:
```python
alpha = lassocv.alpha_
alpha
```

Out[34]:
```
0.006607312321213054
```

In [35]:
```python
lasso_reg = Lasso(alpha)
lasso_reg.fit(x_train, y_train)
```

Out[35]:
```
Lasso(alpha=0.006607312321213054)
```

In [36]:
```python
print('Lasso Score =======>', lasso_reg.score(x_train, y_train))
```

```
Lasso Score =======> 0.9069044644990196
```

Conclusion : Knn model has 90% score

Decision Tree model instantiaing, training and evaluating

In [37]:
```
DT = DecisionTreeRegressor()
DT.fit(x_train, y_train)
y_pred = DT.predict(x_test)
```

In [38]:
```
print('=========================================================')
print('R2 Score ----->', r2_score(y_test, y_pred))
print('=========================================================')
print('RMSE of Model ------->', np.sqrt(mean_squared_error(y_test, y_pred)))
print('=========================================================')
print('MSE of Model ------->', mean_squared_error(y_test, y_pred))
print('=========================================================')
print('Score of test data ---->', DT.score(x_test, y_test))
print('=========================================================')
```

```
=========================================================
R2 Score -----> 0.9318451704502787
=========================================================
RMSE of Model -------> 1.4758726232300674
=========================================================
MSE of Model -------> 2.1782000000000004
=========================================================
Score of test data ----> 0.9318451704502787
=========================================================
```

Here we use Lasso Regularization to avoid overfitting

In [39]:
```
# LassoCV will return best alpha after max itratation.
# Normalize is subtracting the mean and dividing by the L2-norm.

lassocv = LassoCV(alphas = None, max_iter = 1000, normalize = True)
lassocv.fit(x_train,y_train)
```

Out[39]:
```
LassoCV(normalize=True)
```

In [40]:
```
alpha = lassocv.alpha_
alpha
```

Out[40]:
```
0.006607312321213054
```

In [41]:
```
lasso_reg = Lasso(alpha)
lasso_reg.fit(x_train, y_train)
```

Out[41]:
```
Lasso(alpha=0.006607312321213054)
```

In [42]:
```
print('Lasso Score =======>', lasso_reg.score(x_train, y_train))
```

```
Lasso Score =======> 0.9069044644990196
```

Conclusion : Decision Tree model has 90% score

Random Forest model instantiaing, training and evaluating

In [43]:
```
Rn = RandomForestRegressor()
Rn.fit(x_train, y_train)
y_pred = Rn.predict(x_test)
```

In [44]:
```
print('==========================================================')
print('R2 Score ----->', r2_score(y_test, y_pred))
print('==========================================================')
print('RMSE of Model ------->', np.sqrt(mean_squared_error(y_test, y_pred)))
print('==========================================================')
print('MSE of Model ------->', mean_squared_error(y_test, y_pred))
print('==========================================================')
print('Score of test data ---->', Rn.score(x_test, y_test))
print('==========================================================')
```

```
==========================================================
R2 Score -----> 0.9590715210811256
==========================================================
RMSE of Model -------> 1.14370326571187
==========================================================
MSE of Model -------> 1.3080571599999964
==========================================================
Score of test data ----> 0.9590715210811256
==========================================================
```

Here we use Lasso Regularization to avoid overfitting

In [45]:
```
# LassoCV will return best alpha after max itratation.
# Normalize is subtracting the mean and dividing by the L2-norm.

lassocv = LassoCV(alphas = None, max_iter = 1000, normalize = True)
lassocv.fit(x_train,y_train)
```

Out[45]:
```
LassoCV(normalize=True)
```

In [46]:
```
alpha = lassocv.alpha_
alpha
```

Out[46]:
```
0.006607312321213054
```

In [47]:
```
lasso_reg = Lasso(alpha)
lasso_reg.fit(x_train, y_train)
```

Out[47]:
```
Lasso(alpha=0.006607312321213054)
```

In [48]:
```
print('Lasso Score =======>', lasso_reg.score(x_train, y_train))
```

```
Lasso Score =======> 0.9069044644990196
```

Conclusion : Random Forest model has 90% score

SVM model instantiaing, training and evaluating

In [49]:
```
svr = SVR()
svr.fit(x_train, y_train)
y_pred = svr.predict(x_test)
```

In [50]:
```
print('=========================================================')
print('R2 Score ----->', r2_score(y_test, y_pred))
print('=========================================================')
print('RMSE of Model ------->', np.sqrt(mean_squared_error(y_test, y_pred)))
print('=========================================================')
print('MSE of Model ------->', mean_squared_error(y_test, y_pred))
print('=========================================================')
print('Score of test data ---->', svr.score(x_test, y_test))
print('=========================================================')
```

```
=========================================================
R2 Score -----> 0.8431536609343284
=========================================================
RMSE of Model -------> 2.2389157528727637
=========================================================
MSE of Model -------> 5.012743748461815
=========================================================
Score of test data ----> 0.8431536609343284
=========================================================
```

Here we use Lasso Regularization to avoid overfitting

In [51]:
```
# LassoCV will return best alpha after max itratation.
# Normalize is subtracting the mean and dividing by the L2-norm.

lassocv = LassoCV(alphas = None, max_iter = 1000, normalize = True)
lassocv.fit(x_train,y_train)
```

Out[51]:
```
LassoCV(normalize=True)
```

In [52]:
```
alpha = lassocv.alpha_
alpha
```

Out[52]:
```
0.006607312321213054
```

In [53]:
```
lasso_reg = Lasso(alpha)
lasso_reg.fit(x_train, y_train)
```

Out[53]:
```
Lasso(alpha=0.006607312321213054)
```

In [54]:
```
print('Lasso Score =======>', lasso_reg.score(x_train, y_train))
```

```
Lasso Score =======> 0.9069044644990196
```

Conclusion : SVM model has 90% score

Looking R2 score we found Random Forest has best model so we do Hyperparameter Tuning on it.

In [55]:
```
param_grid = {'n_estimators': [100,200,300,400,500],
              'max_features': ['auto', 'squrt'],
              'max_depth': [5, 10, 15, 20, 25, 30],
              'min_samples_split': [2, 5, 10, 15, 100],
              'min_samples_leaf': [1, 2, 5, 10]}
```

In [57]:
```
grid_search = GridSearchCV(estimator = Rn, param_grid = param_grid, cv = 5,n_jobs
```

In [58]:
```
grid_search.fit(x_train, y_train)
```

Out[58]:
```
GridSearchCV(cv=5, estimator=RandomForestRegressor(), n_jobs=-1,
             param_grid={'max_depth': [5, 10, 15, 20, 25, 30],
                         'max_features': ['auto', 'squrt'],
                         'min_samples_leaf': [1, 2, 5, 10],
                         'min_samples_split': [2, 5, 10, 15, 100],
                         'n_estimators': [100, 200, 300, 400, 500]})
```

In [59]:
```
best_parameters = grid_search.best_params_
print(best_parameters)
```

```
{'max_depth': 25, 'max_features': 'auto', 'min_samples_leaf': 1, 'min_samples_s
plit': 2, 'n_estimators': 300}
```

In [61]:
```
hRn = RandomForestRegressor(max_depth = 25, max_features = 'auto', min_samples_le
hRn.fit(x_train, y_train)
hRn.score(x_test, y_test)
```

Out[61]:
```
0.9591851892273268
```

In [62]:
```
y_pred = hRn.predict(x_test)
```

In [63]:
```python
print('=========================================================')
print('R2 Score ----->', r2_score(y_test, y_pred))
print('=========================================================')
print('RMSE of Model ------->', np.sqrt(mean_squared_error(y_test, y_pred)))
print('=========================================================')
print('MSE of Model ------->', mean_squared_error(y_test, y_pred))
print('=========================================================')
print('Score of test data ---->', hRn.score(x_test, y_test))
print('=========================================================')
```

```
=========================================================
R2 Score -----> 0.9591851892273268
=========================================================
RMSE of Model -------> 1.1421139931431339
=========================================================
MSE of Model -------> 1.3044243733333547
=========================================================
Score of test data ----> 0.9591851892273268
=========================================================
```

After Hyperparameter Tuning model accuracy score 95%.

Saving The Model

In [64]:
```python
# saving the model to the Local file system
filename = 'Advertising Sales Channel Prediction.pickle'
pickle.dump(hRn, open(filename, 'wb'))
```

Final Conclusion : Random Forest is our best model.

In [ ]:
```python

```