In [222]:

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
%matplotlib inline
```

In [223]:

```
import io
%cd "C:\Users\deepe\OneDrive\Desktop\Python Datasets\House Price Advanced Regression Tec
```

```
C:\Users\deepe\OneDrive\Desktop\Python Datasets\House Price Advanced Regre
ssion Techniques
```

In [224]:

```
housetrain=pd.read_csv("train.csv")
```

In [225]:

```
housetest=pd.read_csv("test.csv")
```

In [226]:

```
housetrain.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1460 entries, 0 to 1459
Data columns (total 81 columns):
 #   Column         Non-Null Count  Dtype  
---  ------         --------------  -----  
 0   Id             1460 non-null   int64  
 1   MSSubClass     1460 non-null   int64  
 2   MSZoning       1460 non-null   object 
 3   LotFrontage    1201 non-null   float64
 4   LotArea        1460 non-null   int64  
 5   Street         1460 non-null   object 
 6   Alley          91 non-null     object 
 7   LotShape       1460 non-null   object 
 8   LandContour    1460 non-null   object 
 9   Utilities      1460 non-null   object 
 10  LotConfig      1460 non-null   object 
 11  LandSlope      1460 non-null   object 
 12  Neighborhood   1460 non-null   object 
 13  Condition1     1460 non-null   object 
 14  Condition2     1460 non-null   object 
 15  BldgType       1460 non-null   object 
 16  HouseStyle     1460 non-null   object 
 17  OverallQual    1460 non-null   int64  
 18  OverallCond    1460 non-null   int64  
 19  YearBuilt      1460 non-null   int64  
 20  YearRemodAdd   1460 non-null   int64  
 21  RoofStyle      1460 non-null   object 
 22  RoofMatl       1460 non-null   object 
 23  Exterior1st    1460 non-null   object 
 24  Exterior2nd    1460 non-null   object 
 25  MasVnrType     1452 non-null   object 
 26  MasVnrArea     1452 non-null   float64
 27  ExterQual      1460 non-null   object 
 28  ExterCond      1460 non-null   object 
 29  Foundation     1460 non-null   object 
 30  BsmtQual       1423 non-null   object 
 31  BsmtCond       1423 non-null   object 
 32  BsmtExposure   1422 non-null   object 
 33  BsmtFinType1   1423 non-null   object 
 34  BsmtFinSF1     1460 non-null   int64  
 35  BsmtFinType2   1422 non-null   object 
 36  BsmtFinSF2     1460 non-null   int64  
 37  BsmtUnfSF      1460 non-null   int64  
 38  TotalBsmtSF    1460 non-null   int64  
 39  Heating        1460 non-null   object 
 40  HeatingQC      1460 non-null   object 
 41  CentralAir     1460 non-null   object 
 42  Electrical     1459 non-null   object 
 43  1stFlrSF       1460 non-null   int64  
 44  2ndFlrSF       1460 non-null   int64  
 45  LowQualFinSF   1460 non-null   int64  
 46  GrLivArea      1460 non-null   int64  
 47  BsmtFullBath   1460 non-null   int64  
 48  BsmtHalfBath   1460 non-null   int64  
 49  FullBath       1460 non-null   int64  
 50  HalfBath       1460 non-null   int64  
 51  BedroomAbvGr   1460 non-null   int64  
 52  KitchenAbvGr   1460 non-null   int64  
 53  KitchenQual    1460 non-null   object 
 54  TotRmsAbvGrd   1460 non-null   int64  
 55  Functional     1460 non-null   object 
```

```
 56  Fireplaces     1460 non-null   int64
 57  FireplaceQu    770 non-null    object
 58  GarageType     1379 non-null   object
 59  GarageYrBlt    1379 non-null   float64
 60  GarageFinish   1379 non-null   object
 61  GarageCars     1460 non-null   int64
 62  GarageArea     1460 non-null   int64
 63  GarageQual     1379 non-null   object
 64  GarageCond     1379 non-null   object
 65  PavedDrive     1460 non-null   object
 66  WoodDeckSF     1460 non-null   int64
 67  OpenPorchSF    1460 non-null   int64
 68  EnclosedPorch  1460 non-null   int64
 69  3SsnPorch      1460 non-null   int64
 70  ScreenPorch    1460 non-null   int64
 71  PoolArea       1460 non-null   int64
 72  PoolQC         7 non-null      object
 73  Fence          281 non-null    object
 74  MiscFeature    54 non-null     object
 75  MiscVal        1460 non-null   int64
 76  MoSold         1460 non-null   int64
 77  YrSold         1460 non-null   int64
 78  SaleType       1460 non-null   object
 79  SaleCondition  1460 non-null   object
 80  SalePrice      1460 non-null   int64
dtypes: float64(3), int64(35), object(43)
memory usage: 924.0+ KB
```

In [227]:

```
housetest.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1459 entries, 0 to 1458
Data columns (total 80 columns):
 #   Column         Non-Null Count  Dtype  
---  ------         --------------  -----  
 0   Id             1459 non-null   int64  
 1   MSSubClass     1459 non-null   int64  
 2   MSZoning       1455 non-null   object 
 3   LotFrontage    1232 non-null   float64
 4   LotArea        1459 non-null   int64  
 5   Street         1459 non-null   object 
 6   Alley          107 non-null    object 
 7   LotShape       1459 non-null   object 
 8   LandContour    1459 non-null   object 
 9   Utilities      1457 non-null   object 
 10  LotConfig      1459 non-null   object 
 11  LandSlope      1459 non-null   object 
 12  Neighborhood   1459 non-null   object 
 13  Condition1     1459 non-null   object 
 14  Condition2     1459 non-null   object 
 15  BldgType       1459 non-null   object 
 16  HouseStyle     1459 non-null   object 
 17  OverallQual    1459 non-null   int64  
 18  OverallCond    1459 non-null   int64  
 19  YearBuilt      1459 non-null   int64  
 20  YearRemodAdd   1459 non-null   int64  
 21  RoofStyle      1459 non-null   object 
 22  RoofMatl       1459 non-null   object 
 23  Exterior1st    1458 non-null   object 
 24  Exterior2nd    1458 non-null   object 
 25  MasVnrType     1443 non-null   object 
 26  MasVnrArea     1444 non-null   float64
 27  ExterQual      1459 non-null   object 
 28  ExterCond      1459 non-null   object 
 29  Foundation     1459 non-null   object 
 30  BsmtQual       1415 non-null   object 
 31  BsmtCond       1414 non-null   object 
 32  BsmtExposure   1415 non-null   object 
 33  BsmtFinType1   1417 non-null   object 
 34  BsmtFinSF1     1458 non-null   float64
 35  BsmtFinType2   1417 non-null   object 
 36  BsmtFinSF2     1458 non-null   float64
 37  BsmtUnfSF      1458 non-null   float64
 38  TotalBsmtSF    1458 non-null   float64
 39  Heating        1459 non-null   object 
 40  HeatingQC      1459 non-null   object 
 41  CentralAir     1459 non-null   object 
 42  Electrical     1459 non-null   object 
 43  1stFlrSF       1459 non-null   int64  
 44  2ndFlrSF       1459 non-null   int64  
 45  LowQualFinSF   1459 non-null   int64  
 46  GrLivArea      1459 non-null   int64  
 47  BsmtFullBath   1457 non-null   float64
 48  BsmtHalfBath   1457 non-null   float64
 49  FullBath       1459 non-null   int64  
 50  HalfBath       1459 non-null   int64  
 51  BedroomAbvGr   1459 non-null   int64  
 52  KitchenAbvGr   1459 non-null   int64  
 53  KitchenQual    1458 non-null   object 
 54  TotRmsAbvGrd   1459 non-null   int64  
 55  Functional     1457 non-null   object 
```

```
 56  Fireplaces     1459 non-null   int64
 57  FireplaceQu    729 non-null    object
 58  GarageType     1383 non-null   object
 59  GarageYrBlt    1381 non-null   float64
 60  GarageFinish   1381 non-null   object
 61  GarageCars     1458 non-null   float64
 62  GarageArea     1458 non-null   float64
 63  GarageQual     1381 non-null   object
 64  GarageCond     1381 non-null   object
 65  PavedDrive     1459 non-null   object
 66  WoodDeckSF     1459 non-null   int64
 67  OpenPorchSF    1459 non-null   int64
 68  EnclosedPorch  1459 non-null   int64
 69  3SsnPorch      1459 non-null   int64
 70  ScreenPorch    1459 non-null   int64
 71  PoolArea       1459 non-null   int64
 72  PoolQC         3 non-null      object
 73  Fence          290 non-null    object
 74  MiscFeature    51 non-null     object
 75  MiscVal        1459 non-null   int64
 76  MoSold         1459 non-null   int64
 77  YrSold         1459 non-null   int64
 78  SaleType       1458 non-null   object
 79  SaleCondition  1459 non-null   object
dtypes: float64(11), int64(26), object(43)
memory usage: 912.0+ KB
```

In [228]:

```
# Temporarily add dependent variable Saleproce intest data - For concatination
housetest["SalePrice"]="test"
```

In [229]:

```
# Row wise concatenation of dataframes fro preprocessing
combinedf=pd.concat([housetrain,housetest],axis=0)
```

In [230]:

```
pd.set_option("display.max_rows",82)
combinedf.isnull().sum().sort_values(ascending=False)
# Data size is 2919 rows or observations
```

Out[230]:

```
PoolQC          2909
MiscFeature     2814
Alley           2721
Fence           2348
FireplaceQu     1420
LotFrontage      486
GarageFinish     159
GarageQual       159
GarageCond       159
GarageYrBlt      159
GarageType       157
BsmtExposure      82
BsmtCond          82
BsmtQual          81
BsmtFinType2      80
BsmtFinType1      79
MasVnrType        24
MasVnrArea        23
MSZoning           4
Functional         2
Utilities          2
BsmtHalfBath       2
BsmtFullBath       2
GarageArea         1
BsmtFinSF1         1
SaleType           1
GarageCars         1
BsmtUnfSF          1
Electrical         1
Exterior2nd        1
Exterior1st        1
KitchenQual        1
TotalBsmtSF        1
BsmtFinSF2         1
TotRmsAbvGrd       0
Fireplaces         0
Id                 0
BedroomAbvGr       0
PavedDrive         0
WoodDeckSF         0
OpenPorchSF        0
EnclosedPorch      0
3SsnPorch          0
ScreenPorch        0
PoolArea           0
MiscVal            0
MoSold             0
YrSold             0
SaleCondition      0
KitchenAbvGr       0
HeatingQC          0
HalfBath           0
FullBath           0
LotArea            0
Street             0
LotShape           0
LandContour        0
LotConfig          0
LandSlope          0
Neighborhood       0
Condition1         0
```

In [231]:

```
# split data in to object and numeric calls for pre-processing
objcols=combinedf.select_dtypes(include=["object"])
numcols=combinedf.select_dtypes(include=np.number)
# np.number will select both int64 & float64
```

```
Condition2      0
BldgType        0
HouseStyle      0
OverallQual     0
OverallCond     0
YearBuilt       0
YearRemodAdd    0
RoofStyle       0
RoofMatl        0
ExterQual       0
ExterCond       0
Foundation      0
Heating         0
MSSubClass      0
CentralAir      0
1stFlrSF        0
2ndFlrSF        0
LowQualFinSF    0
GrLivArea       0
SalePrice       0
dtype: int64
```

In [232]:

```
# %missing values in each variable/columns
objcols.isnull().sum().sort_values(ascending=False)/objcols.shape[0]
```

Out[232]:

```
PoolQC           0.996574
MiscFeature      0.964029
Alley            0.932169
Fence            0.804385
FireplaceQu      0.486468
GarageCond       0.054471
GarageQual       0.054471
GarageFinish     0.054471
GarageType       0.053786
BsmtCond         0.028092
BsmtExposure     0.028092
BsmtQual         0.027749
BsmtFinType2     0.027407
BsmtFinType1     0.027064
MasVnrType       0.008222
MSZoning         0.001370
Utilities        0.000685
Functional       0.000685
Exterior2nd      0.000343
Electrical       0.000343
SaleType         0.000343
Exterior1st      0.000343
KitchenQual      0.000343
RoofStyle        0.000000
Neighborhood     0.000000
SaleCondition    0.000000
ExterQual        0.000000
LotShape         0.000000
LandContour      0.000000
ExterCond        0.000000
PavedDrive       0.000000
LotConfig        0.000000
LandSlope        0.000000
Condition1       0.000000
HouseStyle       0.000000
Condition2       0.000000
Foundation       0.000000
RoofMatl         0.000000
Street           0.000000
CentralAir       0.000000
HeatingQC        0.000000
Heating          0.000000
BldgType         0.000000
SalePrice        0.000000
dtype: float64
```

In [233]:

```
objcols.columns
```

Out[233]:

```
Index(['MSZoning', 'Street', 'Alley', 'LotShape', 'LandContour', 'Utilitie
s',
       'LotConfig', 'LandSlope', 'Neighborhood', 'Condition1', 'Condition
2',
       'BldgType', 'HouseStyle', 'RoofStyle', 'RoofMatl', 'Exterior1st',
       'Exterior2nd', 'MasVnrType', 'ExterQual', 'ExterCond', 'Foundatio
n',
       'BsmtQual', 'BsmtCond', 'BsmtExposure', 'BsmtFinType1', 'BsmtFinTyp
e2',
       'Heating', 'HeatingQC', 'CentralAir', 'Electrical', 'KitchenQual',
       'Functional', 'FireplaceQu', 'GarageType', 'GarageFinish', 'GarageQ
ual',
       'GarageCond', 'PavedDrive', 'PoolQC', 'Fence', 'MiscFeature',
       'SaleType', 'SaleCondition', 'SalePrice'],
      dtype='object')
```

In [234]:

```
# variables that have very high missing values which wil be imputed with word 'missing'
nacols=["PoolQC","MiscFeature","Alley","Fence","FireplaceQu"]
for col in nacols:
    objcols[col]=objcols[col].fillna("Missing")
```

In [235]:

```
# Selecting coloumns with similar names
garagecols=objcols[[x for x in objcols.columns if "Garage" in x]]
```

In [236]:

```
# Printing frequency counts if multiple variables
for col in garagecols.columns:
    freq=objcols[col].value_counts(dropna=False)
    print(freq)
```

```
Attchd     1723
Detchd      779
BuiltIn     186
NaN         157
Basment      36
2Types       23
CarPort      15
Name: GarageType, dtype: int64
Unf    1230
RFn     811
Fin     719
NaN     159
Name: GarageFinish, dtype: int64
TA     2604
NaN     159
Fa      124
Gd       24
Po        5
Ex        3
Name: GarageQual, dtype: int64
TA     2654
NaN     159
Fa       74
Gd       15
Po       14
Ex        3
Name: GarageCond, dtype: int64
```

In [237]:

```
bsmtcols=objcols[[x for x in objcols.columns if "Bsmt" in x] ]
```

In [238]:

```
for col in bsmtcols.columns:
    freq=objcols[col].value_counts(dropna=False)
    print(freq)
```

```
TA     1283
Gd     1209
Ex      258
Fa       88
NaN      81
Name: BsmtQual, dtype: int64
TA     2606
Gd      122
Fa      104
NaN      82
Po        5
Name: BsmtCond, dtype: int64
No     1904
Av      418
Gd      276
Mn      239
NaN      82
Name: BsmtExposure, dtype: int64
Unf    851
GLQ    849
ALQ    429
Rec    288
BLQ    269
LwQ    154
NaN     79
Name: BsmtFinType1, dtype: int64
Unf    2493
Rec     105
LwQ      87
NaN      80
BLQ      68
ALQ      52
GLQ      34
Name: BsmtFinType2, dtype: int64
```

In [239]:

```
# After going through data description NA in bsmtcols & garagecols means nogarage or nob
for col in garagecols.columns:
    objcols[col]=objcols[col].fillna('No')
```

In [240]:

```
for col in bsmtcols.columns:
    objcols[col]=objcols[col].fillna('No')
```

In [241]:

```
# Remaining variables very few missing values -  most_frequent imputation can be done
for cols in objcols.columns:
    objcols[col]=objcols[col].fillna(objcols[col].value_counts().idxmax())
```

In [242]:

```
# %missing values in numcols
numcols.isnull().sum().sort_values(ascending=False)/objcols.shape[0]
```

Out[242]:

```
LotFrontage      0.166495
GarageYrBlt      0.054471
MasVnrArea       0.007879
BsmtHalfBath     0.000685
BsmtFullBath     0.000685
BsmtFinSF2       0.000343
GarageCars       0.000343
GarageArea       0.000343
TotalBsmtSF      0.000343
BsmtUnfSF        0.000343
BsmtFinSF1       0.000343
KitchenAbvGr     0.000000
3SsnPorch        0.000000
EnclosedPorch    0.000000
OpenPorchSF      0.000000
WoodDeckSF       0.000000
ScreenPorch      0.000000
PoolArea         0.000000
MiscVal          0.000000
MoSold           0.000000
Fireplaces       0.000000
TotRmsAbvGrd     0.000000
Id               0.000000
BedroomAbvGr     0.000000
HalfBath         0.000000
FullBath         0.000000
MSSubClass       0.000000
GrLivArea        0.000000
LowQualFinSF     0.000000
2ndFlrSF         0.000000
1stFlrSF         0.000000
YearRemodAdd     0.000000
YearBuilt        0.000000
OverallCond      0.000000
OverallQual      0.000000
LotArea          0.000000
YrSold           0.000000
dtype: float64
```

In [243]:

```
numcols.columns
```

Out[243]:

```
Index(['Id', 'MSSubClass', 'LotFrontage', 'LotArea', 'OverallQual',
       'OverallCond', 'YearBuilt', 'YearRemodAdd', 'MasVnrArea', 'BsmtFinS
F1',
       'BsmtFinSF2', 'BsmtUnfSF', 'TotalBsmtSF', '1stFlrSF', '2ndFlrSF',
       'LowQualFinSF', 'GrLivArea', 'BsmtFullBath', 'BsmtHalfBath', 'FullB
ath',
       'HalfBath', 'BedroomAbvGr', 'KitchenAbvGr', 'TotRmsAbvGrd',
       'Fireplaces', 'GarageYrBlt', 'GarageCars', 'GarageArea', 'WoodDeckS
F',
       'OpenPorchSF', 'EnclosedPorch', '3SsnPorch', 'ScreenPorch', 'PoolAr
ea',
       'MiscVal', 'MoSold', 'YrSold'],
      dtype='object')
```

In [244]:

```
catcols=numcols[['OverallQual','OverallCond', 'YearBuilt', 'YearRemodAdd','GarageYrBlt',
```

In [245]:

```
numcols=numcols.drop(['OverallQual','OverallCond', 'YearBuilt', 'YearRemodAdd','GarageYr
```

In [246]:

```
# create a numeric missing code like 9999
catcols.GarageYrBlt=catcols.GarageYrBlt.fillna(9999)
```

In [247]:

```
#impute missing values in in numcols with median
for col in numcols.columns:
    numcols[col]=numcols[col].fillna(numcols[col].median())
```

In [248]:

```
from sklearn.preprocessing import LabelEncoder
```

In [249]:

```
numcols['SalePrice']=objcols.SalePrice
```

In [250]:

```
objcols=objcols.drop('SalePrice',axis=1)
```

In [251]:

```
# dummy variable encoding
objcols_encode=objcols.apply(LabelEncoder().fit_transform)
```

In [252]:

```
# dummy variable encoding
catcols_encode=catcols.apply(LabelEncoder().fit_transform)
```

In [253]:

```
numcols=numcols.drop('SalePrice',axis=1)
```

In [254]:

```
from sklearn.preprocessing import StandardScaler
```

In [255]:

```
numcols_scaled=StandardScaler().fit_transform(numcols)
```

In [256]:

```
numcols_scaled=pd.DataFrame(numcols_scaled,columns=numcols.columns)
```

In [257]:

```
numcols_scaled=numcols_scaled.reset_index()
```

In [258]:

```
objcols_encode=objcols_encode.reset_index()
```

In [259]:

```
catcols_encode=catcols_encode.reset_index()
```

In [260]:

```
# columns concatenation of all 3 dataframes into 1
combinedf_clean=pd.concat([numcols_scaled,catcols_encode,objcols_encode,],axis=1)
```

In [261]:

```
combinedf_clean=combinedf_clean.drop('index',axis=1)
```

In [262]:

```
combinedf=combinedf.reset_index()
```

In [263]:

```
combinedf_clean['SalePrice']=combinedf.SalePrice
```

In [264]:

```
housetrain_df=combinedf_clean[combinedf_clean.SalePrice!='test']
```

In [265]:

```
housetest_df=combinedf_clean[combinedf_clean.SalePrice=='test']
```

In [266]:

```
housetest_df=housetest_df.drop('SalePrice',axis=1)
```

In [267]:

```
housetest_df.shape
```

Out[267]:

```
(1459, 80)
```

In [268]:

```
combinedf_clean.shape
```

Out[268]:

```
(2919, 81)
```

In [269]:

```
y=housetrain_df.SalePrice
X=housetrain_df.drop(['Id',"SalePrice"],axis=1)
```

In [270]:

```
X.shape
```

Out[270]:

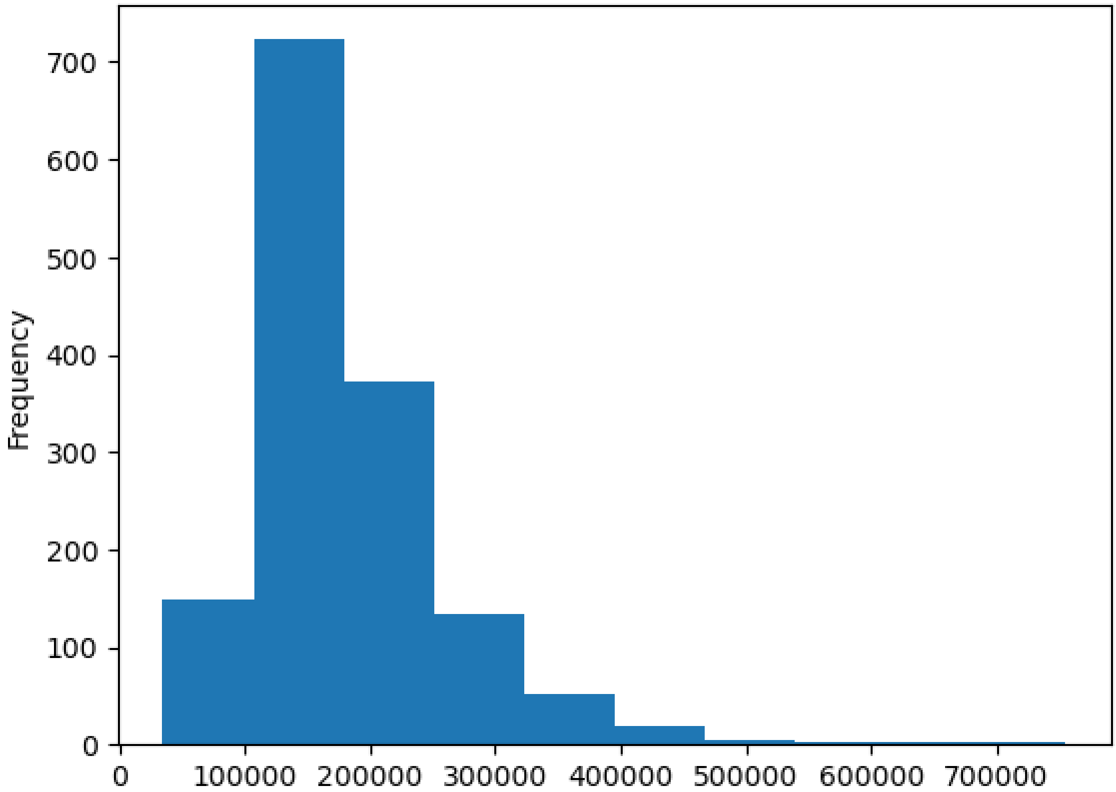
```
(1460, 79)
```

In [271]:

```
# create histogram, boxplot and destiny plot y and interpret
y.plot(kind='hist')
```

Out[271]:

```
<Axes: ylabel='Frequency'>
```

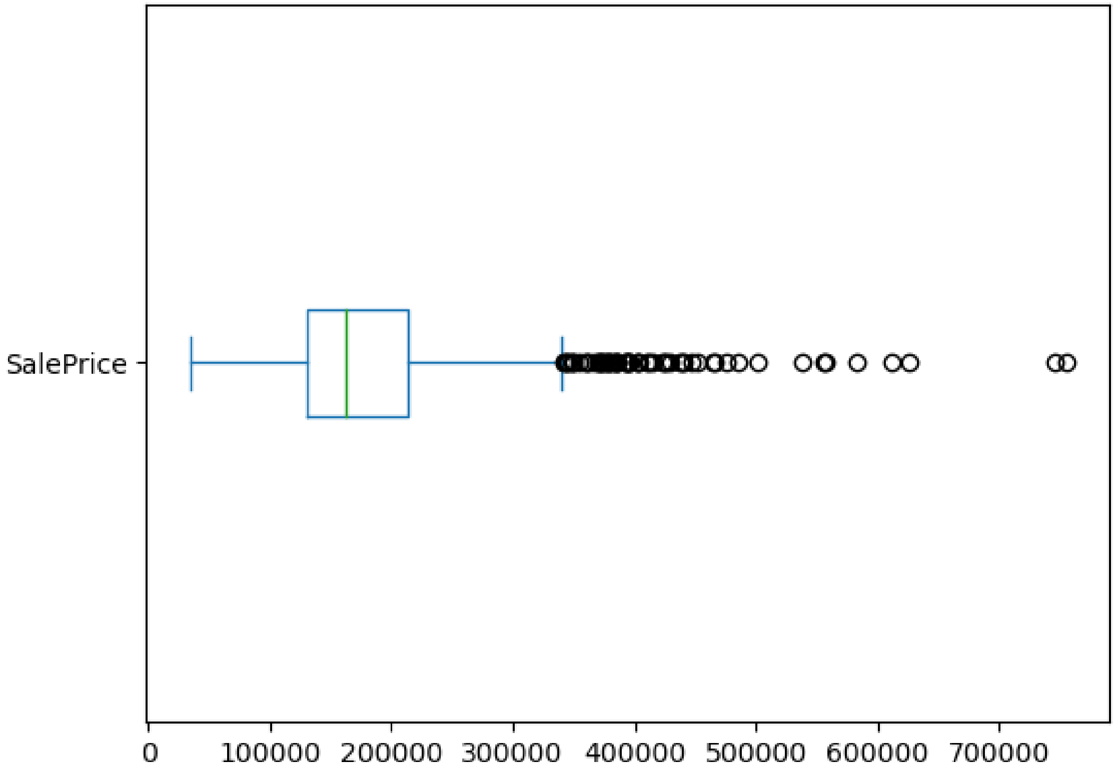


In [272]:

```
y.plot(kind='box',vert=False)
```

Out[272]:

<Axes: >

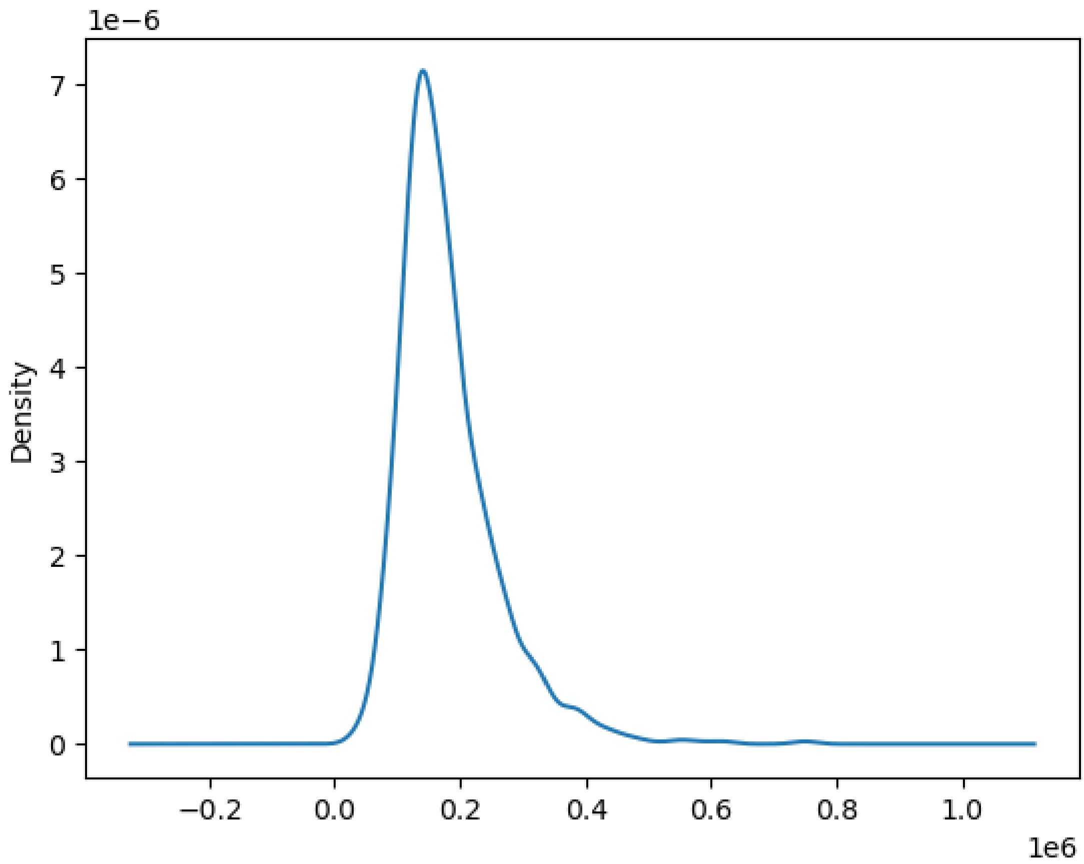


In [273]:

```
y.plot(kind='density')
```

Out[273]:

```
&lt;Axes: ylabel='Density'&gt;
```



In [274]:

```
y=y.astype('int64')
```

In [275]:

```
y.dtype
```

Out[275]:

```
dtype('int64')
```

In [276]:

```
print(y.skew())
print(y.kurt())
```

```
1.8828757597682129
6.536281860064529
```

In [277]:

```
y=np.log1p(y) #logarathemic transformation
```

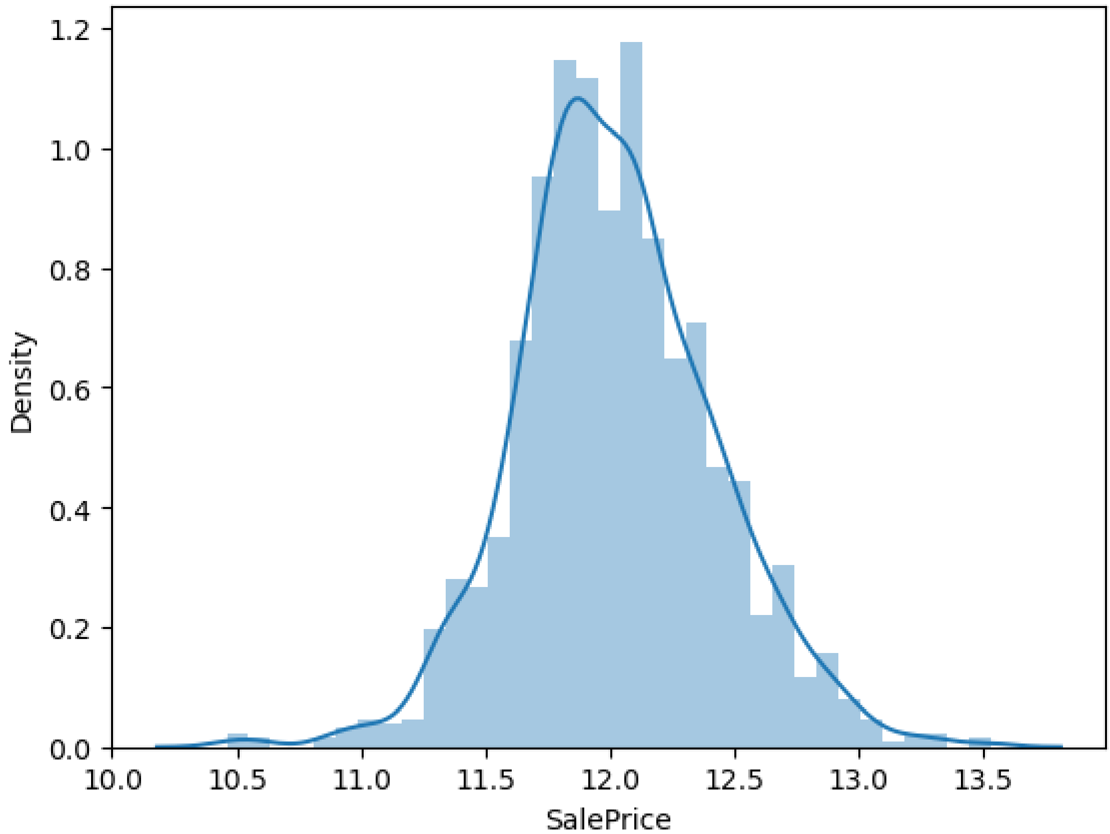
In [278]:

```
import seaborn as sns
sns.distplot(y)
```

```
C:\Users\deepe\AppData\Local\Temp\ipykernel_10408\3881980836.py:2: UserWar
ning:

`distplot` is a deprecated function and will be removed in seaborn v0.14.
0.

Please adapt your code to use either `displot` (a figure-level function wi
th
similar flexibility) or `histplot` (an axes-level function for histogram
s).

For a guide to updating your code to use the new functions, please see
https://gist.github.com/mwaskom/de44147ed2974457ad6372750bbe5751 (https://
gist.github.com/mwaskom/de44147ed2974457ad6372750bbe5751)

  sns.distplot(y)
```

Out[278]:

```
<Axes: xlabel='SalePrice', ylabel='Density'>
```



In [279]:

```
for col in objcols:
    freq=objcols[col].value_counts()
    print(freq)
```

```
RL         2265
RM          460
FV          139
RH           26
C (all)      25
Name: MSZoning, dtype: int64
Pave    2907
Grvl      12
Name: Street, dtype: int64
Missing    2721
Grvl        120
Pave         78
Name: Alley, dtype: int64
Reg    1859
IR1     968
IR2      76
IR3      16
Name: LotShape, dtype: int64
Lvl    2622
```

In [280]:

```
# Test Null Average SalePrice of different Street Equal
housetrain.SalePrice.groupby(housetrain.Street).mean()
```

Out[280]:

```
Street
Grvl    130190.500000
Pave    181130.538514
Name: SalePrice, dtype: float64
```

In [281]:

```
from scipy.stats import ttest_ind
```

In [282]:

```
# Split
streetp=housetrain[housetrain.Street=='Pave']
streetg=housetrain[housetrain.Street=='Grvl']
```

In [283]:

```
ttest_ind(streetp.SalePrice,streetg.SalePrice,equal_var=False)
# Since pvalue=0.11504797250476277 is greater than 0.05, Fail to Reject Null
```

Out[283]:

```
Ttest_indResult(statistic=1.900787855911007, pvalue=0.11504797250476277)
```

In [284]:

```
# Test Null Average SalePrice of different CentralAir Equal
housetrain.SalePrice.groupby(housetrain.CentralAir).mean()
```

Out[284]:

```
CentralAir
N    105264.073684
Y    186186.709890
Name: SalePrice, dtype: float64
```

In [285]:

```
# Split
Cy=housetrain[housetrain.CentralAir=='Y']
Cn=housetrain[housetrain.CentralAir=='N']
```

In [286]:

```
ttest_ind(Cy.SalePrice,Cn.SalePrice,equal_var=False)
# Since pvalue=2.280814388186851e-37 is less than 0.05, Reject Null
```

Out[286]:

```
Ttest_indResult(statistic=17.267772563668995, pvalue=2.280814388186851e-3
7)
```

In [287]:

```
# Test Null Average SalePrice of different LandSlope Equal
housetrain.SalePrice.groupby(housetrain.LandSlope).mean()
```

Out[287]:

```
LandSlope
Gtl    179956.799566
Mod    196734.138462
Sev    204379.230769
Name: SalePrice, dtype: float64
```

In [288]:

```
from scipy.stats import f_oneway
```

In [289]:

```
# Split
lg=housetrain[housetrain.LandSlope=='Gtl']
lm=housetrain[housetrain.LandSlope=='Mod']
ls=housetrain[housetrain.LandSlope=='Sev']
```

In [290]:

```
f_oneway(lg.SalePrice,lm.SalePrice,ls.SalePrice)
# Since pvalue=0.1413963584114019 is greater than 0.05, Fail to Reject Null
```

Out[290]:

```
F_onewayResult(statistic=1.9588170374149438, pvalue=0.1413963584114019)
```

In [291]:

```
# Test Null Averaage SalePrice of Different LotShape Equal
housetrain.SalePrice.groupby(housetrain.LotShape).mean()
```

Out[291]:

```
LotShape
IR1    206101.665289
IR2    239833.365854
IR3    216036.500000
Reg    164754.818378
Name: SalePrice, dtype: float64
```

In [292]:

```
# Split
lot1=housetrain[housetrain.LotShape=='IR1']
lot2=housetrain[housetrain.LotShape=='IR2']
lot3=housetrain[housetrain.LotShape=='IR3']
lotreg=housetrain[housetrain.LotShape=='Reg']
```

In [293]:

```
f_oneway(lot1.SalePrice,lot2.SalePrice,lot3.SalePrice,lotreg.SalePrice)
# Since pvalue=6.447523852011766e-25 is less than 0.05, Reject Null
```

Out[293]:

```
F_onewayResult(statistic=40.132851662262944, pvalue=6.447523852011766e-25)
```

In [294]:

```
# 3 ChiSquare test
# Test Null No Association between LotShape and Utilities
pd.crosstab(housetrain.LotShape,housetrain.Utilities)
```

Out[294]:

Utilities	AllPub	NoSeWa
LotShape		
IR1	483	1
IR2	41	0
IR3	10	0
Reg	925	0

In [295]:

```
from scipy.stats import chi2_contingency
```

In [296]:

```
chi2_contingency(pd.crosstab(housetrain.LotShape,housetrain.Utilities))
# Since pvalue=0.5686975328576362 is greater than 0.05, Fail to Reject Null
```

Out[296]:

```
Chi2ContingencyResult(statistic=2.0179110564804374, pvalue=0.5686975328576
362, dof=3, expected_freq=array([[4.83668493e+02, 3.31506849e-01],
       [4.09719178e+01, 2.80821918e-02],
       [9.99315068e+00, 6.84931507e-03],
       [9.24366438e+02, 6.33561644e-01]]))
```

In [297]:

```
# Test Null No Association between LandSlope and Neighbourhood
pd.crosstab(housetrain.LandSlope,housetrain.Neighborhood)
```

Out[297]:

Neighborhood	Blmngtn	Blueste	BrDale	BrkSide	ClearCr	CollgCr	Crawfor	Edwards	Gilb
LandSlope									
Gtl	17	2	16	56	14	145	39	94	
Mod	0	0	0	2	7	5	12	5	
Sev	0	0	0	0	7	0	0	1	

3 rows × 25 columns

In [298]:

```
chi2_contingency(pd.crosstab(housetrain.LandSlope,housetrain.Neighborhood))
# Since pvalue=3.7125473825660215e-45 is less than 0.05, Reject Null
```

Out[298]:

```
Chi2ContingencyResult(statistic=337.60875449650007, pvalue=3.7125473825660
215e-45, dof=48, expected_freq=array([[1.60917808e+01, 1.89315068e+00, 1.5
1452055e+01, 5.49013699e+01,
        2.65041096e+01, 1.41986301e+02, 4.82753425e+01, 9.46575342e+01,
        7.47794521e+01, 3.50232877e+01, 1.60917808e+01, 4.63821918e+01,
        2.12979452e+02, 8.51917808e+00, 6.91000000e+01, 3.88095890e+01,
        7.28863014e+01, 1.06963014e+02, 2.36643836e+01, 7.00465753e+01,
        5.58479452e+01, 8.14054795e+01, 2.36643836e+01, 3.59698630e+01,
        1.04123288e+01],
       [7.56849315e-01, 8.90410959e-02, 7.12328767e-01, 2.58219178e+00,
        1.24657534e+00, 6.67808219e+00, 2.27054795e+00, 4.45205479e+00,
        3.51712329e+00, 1.64726027e+00, 7.56849315e-01, 2.18150685e+00,
        1.00171233e+01, 4.00684932e-01, 3.25000000e+00, 1.82534247e+00,
        3.42808219e+00, 5.03082192e+00, 1.11301370e+00, 3.29452055e+00,
        2.62671233e+00, 3.82876712e+00, 1.11301370e+00, 1.69178082e+00,
        4.89726027e-01],
       [1.51369863e-01, 1.78082192e-02, 1.42465753e-01, 5.16438356e-01,
        2.49315068e-01, 1.33561644e+00, 4.54109589e-01, 8.90410959e-01,
        7.03424658e-01, 3.29452055e-01, 1.51369863e-01, 4.36301370e-01,
        2.00342466e+00, 8.01369863e-02, 6.50000000e-01, 3.65068493e-01,
        6.85616438e-01, 1.00616438e+00, 2.22602740e-01, 6.58904110e-01,
        5.25342466e-01, 7.65753425e-01, 2.22602740e-01, 3.38356164e-01,
        9.79452055e-02]]))
```

In [299]:

```
# Test Null No Association between RoofMatl and Exterior1st
pd.crosstab(housetrain.RoofMatl,housetrain.Exterior1st)
```

Out[299]:

Exterior1st	AsbShng	AsphShn	BrkComm	BrkFace	CBlock	CemntBd	HdBoard	ImStucc
RoofMatl								
ClyTile	0	0	0	0	0	0	0	0
CompShg	19	1	1	49	1	61	221	1
Membran	0	0	0	0	0	0	0	0
Metal	0	0	0	0	0	0	0	0
Roll	1	0	0	0	0	0	0	0
Tar&Grv	0	0	1	0	0	0	0	0
WdShake	0	0	0	0	0	0	0	0
WdShngl	0	0	0	1	0	0	1	0

In [300]:

```
chi2_contingency(pd.crosstab(housetrain.RoofMatl,housetrain.Exterior1st))
# Since pvalue=9.011149230024665e-47 is less than 0.05, Reject Null
```

Out[300]:

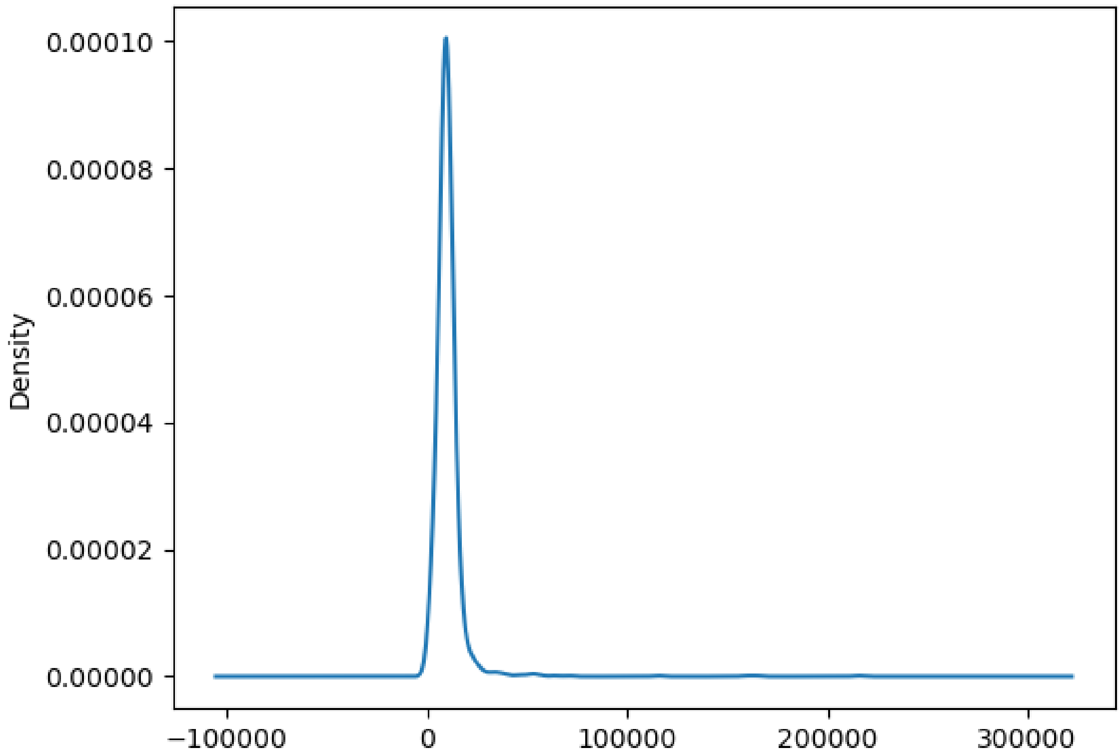
```
Chi2ContingencyResult(statistic=451.4219302226709, pvalue=9.01114923002466
5e-47, dof=98, expected_freq=array([[1.36986301e-02, 6.84931507e-04, 1.369
86301e-03, 3.42465753e-02,
        6.84931507e-04, 4.17808219e-02, 1.52054795e-01, 6.84931507e-04,
        1.50684932e-01, 7.39726027e-02, 1.36986301e-03, 1.71232877e-02,
        3.52739726e-01, 1.41095890e-01, 1.78082192e-02],
       [1.96438356e+01, 9.82191781e-01, 1.96438356e+00, 4.91095890e+01,
        9.82191781e-01, 5.99136986e+01, 2.18046575e+02, 9.82191781e-01,
        2.16082192e+02, 1.06076712e+02, 1.96438356e+00, 2.45547945e+01,
        5.05828767e+02, 2.02331507e+02, 2.55369863e+01],
       [1.36986301e-02, 6.84931507e-04, 1.36986301e-03, 3.42465753e-02,
        6.84931507e-04, 4.17808219e-02, 1.52054795e-01, 6.84931507e-04,
        1.50684932e-01, 7.39726027e-02, 1.36986301e-03, 1.71232877e-02,
        3.52739726e-01, 1.41095890e-01, 1.78082192e-02],
       [1.36986301e-02, 6.84931507e-04, 1.36986301e-03, 3.42465753e-02,
        6.84931507e-04, 4.17808219e-02, 1.52054795e-01, 6.84931507e-04,
        1.50684932e-01, 7.39726027e-02, 1.36986301e-03, 1.71232877e-02,
        3.52739726e-01, 1.41095890e-01, 1.78082192e-02],
       [1.36986301e-02, 6.84931507e-04, 1.36986301e-03, 3.42465753e-02,
        6.84931507e-04, 4.17808219e-02, 1.52054795e-01, 6.84931507e-04,
        1.50684932e-01, 7.39726027e-02, 1.36986301e-03, 1.71232877e-02,
        3.52739726e-01, 1.41095890e-01, 1.78082192e-02],
       [1.50684932e-01, 7.53424658e-03, 1.50684932e-02, 3.76712329e-01,
        7.53424658e-03, 4.59589041e-01, 1.67260274e+00, 7.53424658e-03,
        1.65753425e+00, 8.13698630e-01, 1.50684932e-02, 1.88356164e-01,
        3.88013699e+00, 1.55205479e+00, 1.95890411e-01],
       [6.84931507e-02, 3.42465753e-03, 6.84931507e-03, 1.71232877e-01,
        3.42465753e-03, 2.08904110e-01, 7.60273973e-01, 3.42465753e-03,
        7.53424658e-01, 3.69863014e-01, 6.84931507e-03, 8.56164384e-02,
        1.76369863e+00, 7.05479452e-01, 8.90410959e-02],
       [8.21917808e-02, 4.10958904e-03, 8.21917808e-03, 2.05479452e-01,
        4.10958904e-03, 2.50684932e-01, 9.12328767e-01, 4.10958904e-03,
        9.04109589e-01, 4.43835616e-01, 8.21917808e-03, 1.02739726e-01,
        2.11643836e+00, 8.46575342e-01, 1.06849315e-01]]))
```

In [301]:

```
# Numerical Variables  - Skewness & outleiers
# LotFrontSpace, Living Area, 1stFlrsft,
housetrain.LotArea.plot(kind='density')
```

Out[301]:

```
<Axes: ylabel='Density'>
```

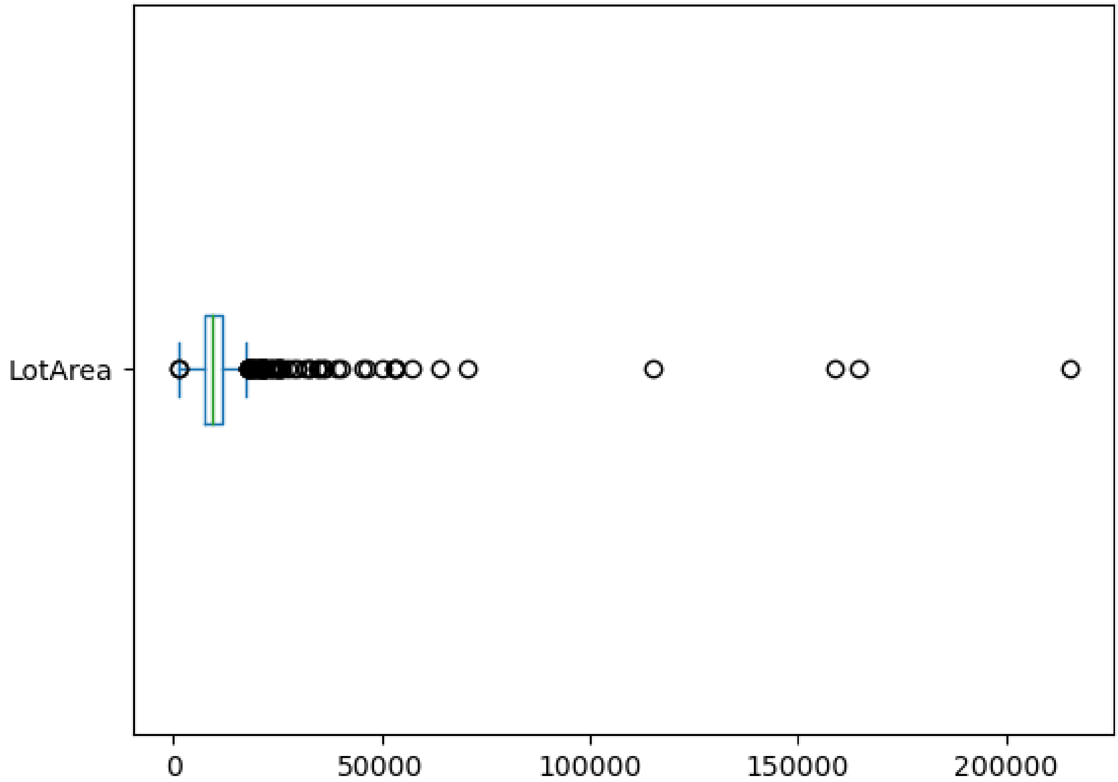


In [302]:

```
housetrain.LotArea.plot(kind='box',vert=False)
```

Out[302]:

<Axes: >

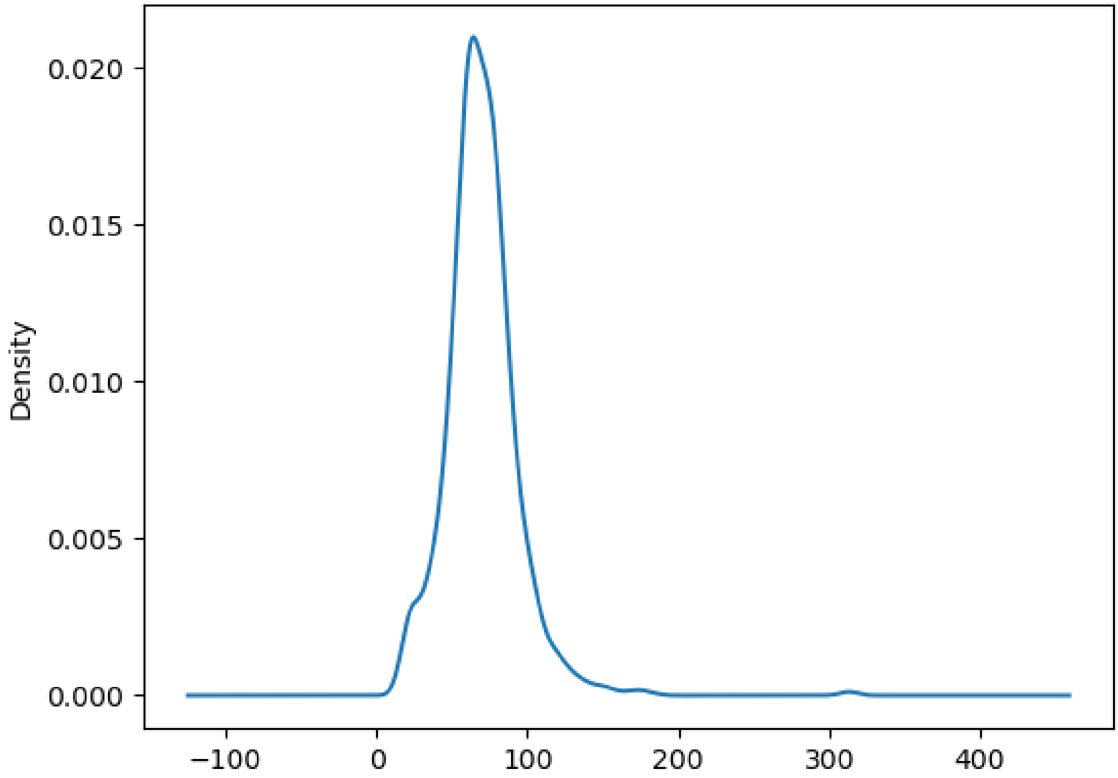


In [303]:

```
housetrain.LotFrontage.plot(kind='density')
```

Out[303]:

<Axes: ylabel='Density'>

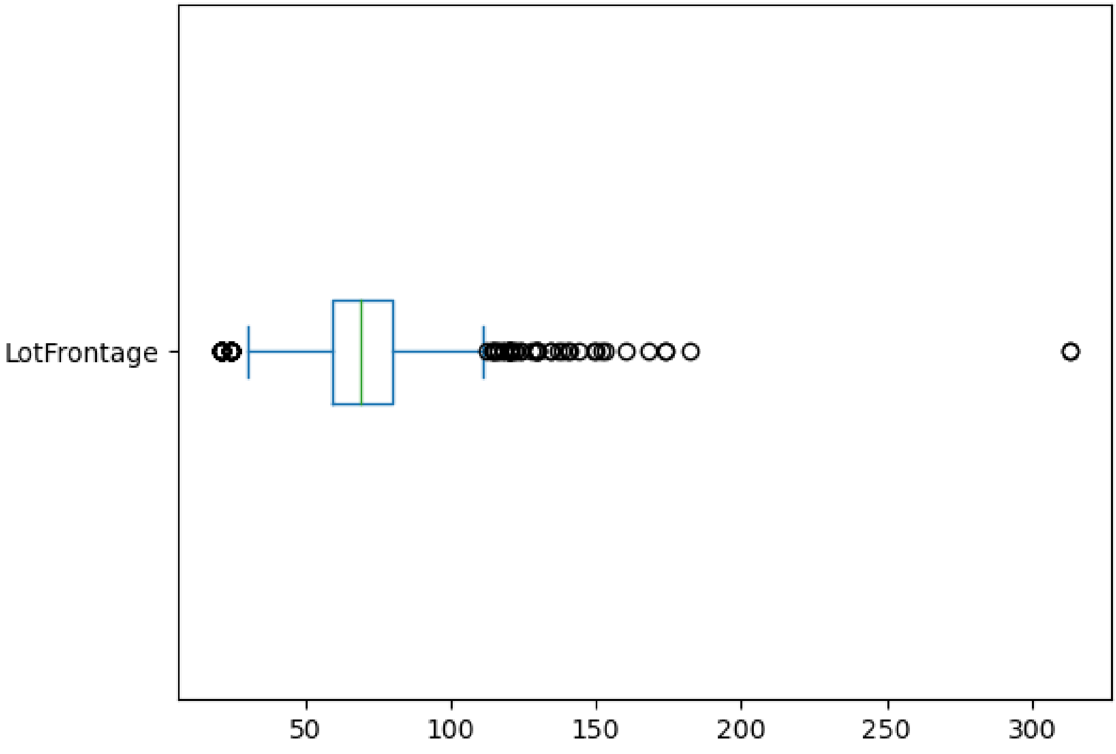


In [304]:

```
housetrain.LotFrontage.plot(kind='box',vert=False)
```

Out[304]:

```
<Axes: >
```



In [305]:

```
numcols.columns
```

Out[305]:

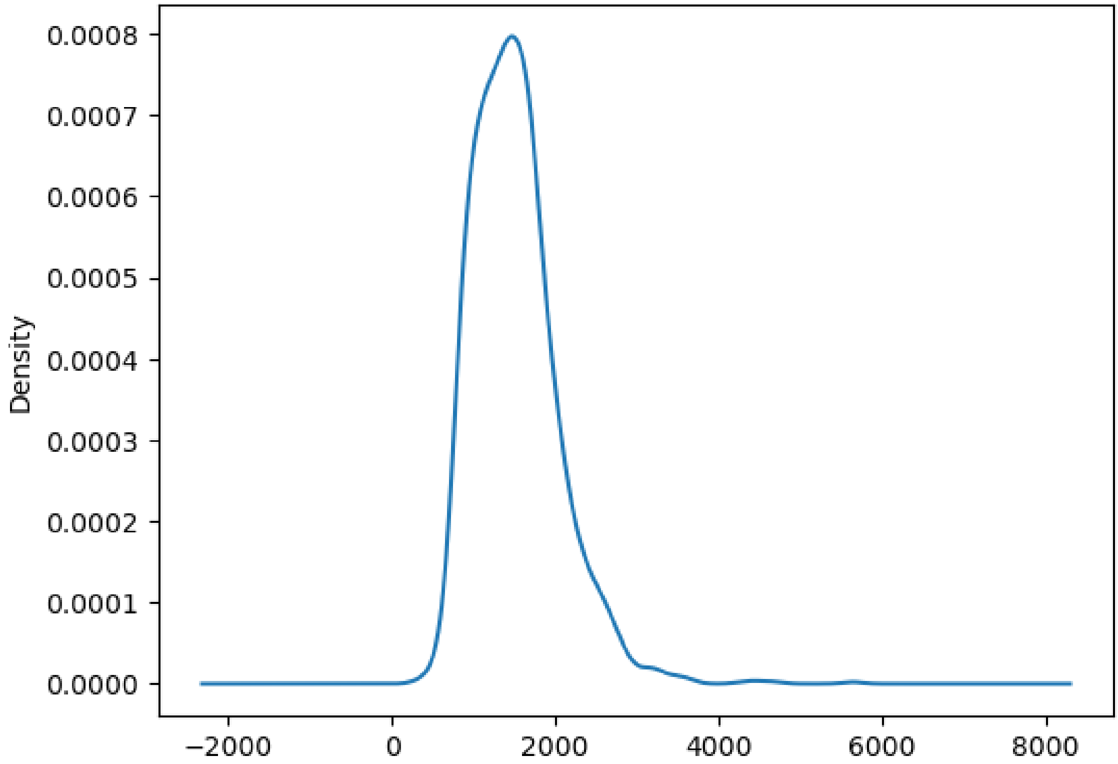
```
Index(['Id', 'MSSubClass', 'LotFrontage', 'LotArea', 'MasVnrArea',
       'BsmtFinSF1', 'BsmtFinSF2', 'BsmtUnfSF', 'TotalBsmtSF', '1stFlrSF',
       '2ndFlrSF', 'LowQualFinSF', 'GrLivArea', 'BsmtFullBath', 'BsmtHalfB
ath',
       'FullBath', 'HalfBath', 'BedroomAbvGr', 'KitchenAbvGr', 'TotRmsAbvG
rd',
       'Fireplaces', 'GarageCars', 'GarageArea', 'WoodDeckSF', 'OpenPorchS
F',
       'EnclosedPorch', '3SsnPorch', 'ScreenPorch', 'PoolArea', 'MiscVa
l'],
      dtype='object')
```

In [306]:

```
housetrain.GrLivArea.plot(kind='density')
```

Out[306]:

<Axes: ylabel='Density'>

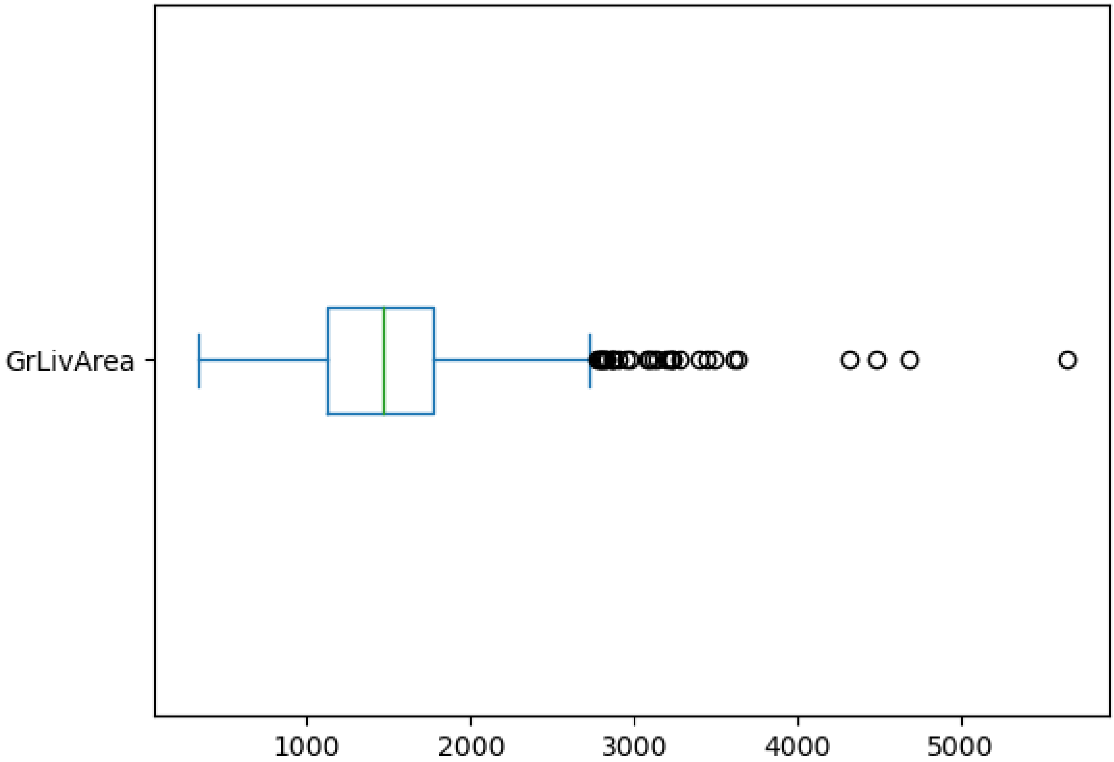


In [307]:

```
housetrain.GrLivArea.plot(kind='box',vert=False)
```

Out[307]:

<Axes: >

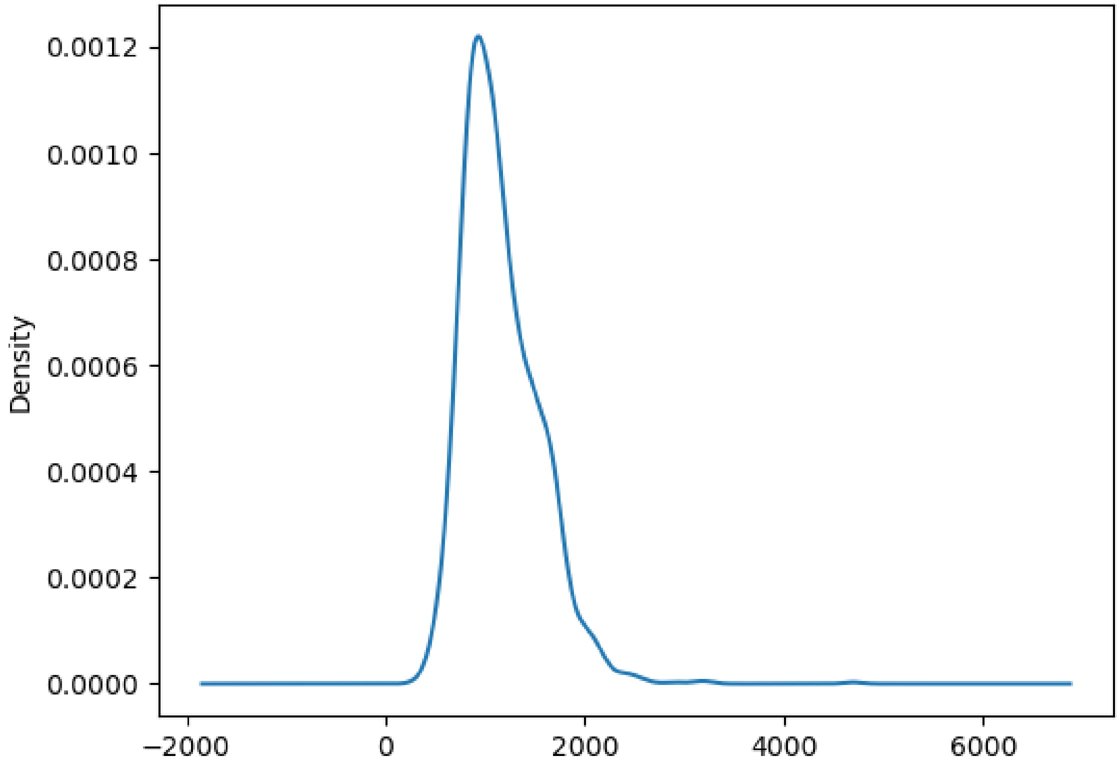


In [308]:

```
housetrain['1stFlrSF'].plot(kind='density')
```

Out[308]:

<Axes: ylabel='Density'>

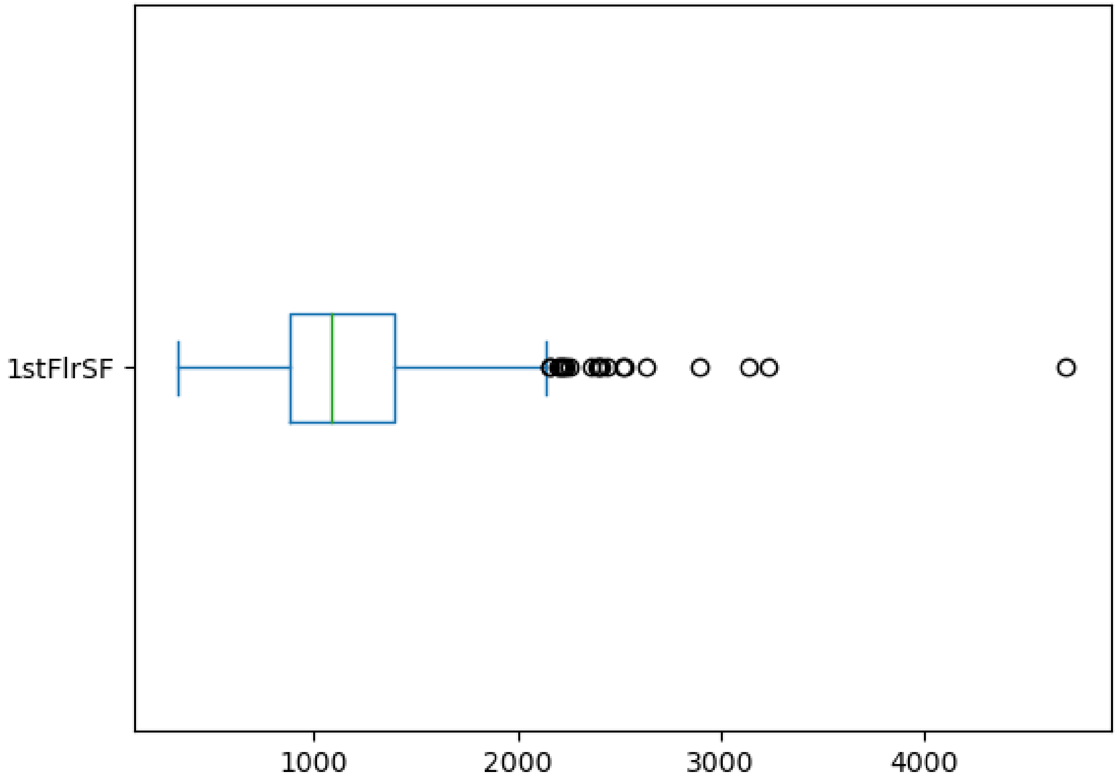


In [309]:

```
housetrain['1stFlrSF'].plot(kind='box',vert=False)
```

Out[309]:

<Axes: >



In [310]:

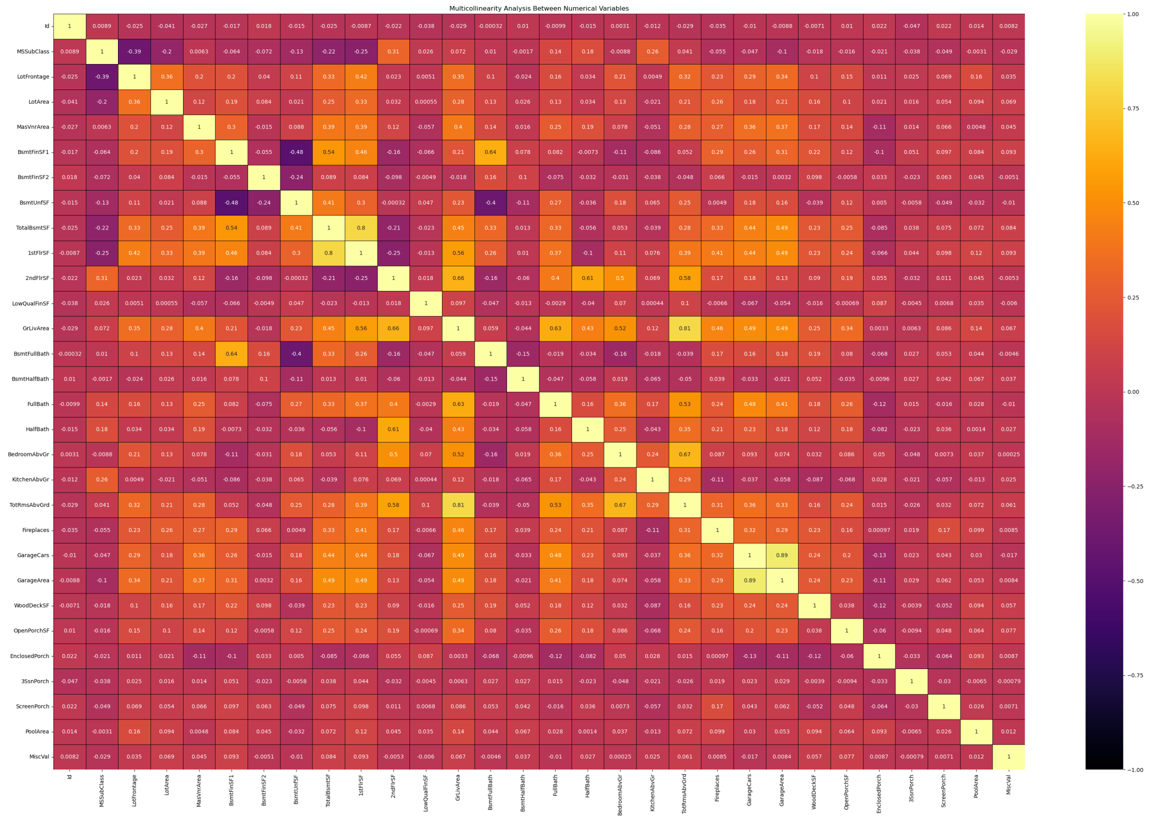
```
import seaborn as sns
```

In [311]:

```
# Multicollinearity Analysis Numerical Variables
plt.figure(figsize=(40,25))
sns.heatmap(numcols.corr(),annot=True,cmap='inferno',vmin=-1,vmax=1,linewidths=0.5,
            linecolor='black').set(title="Multicollinearity Analysis Between Numerical V
```

Out[311]:

```
[Text(0.5, 1.0, 'Multicollinearity Analysis Between Numerical Variables')]
```



In [312]:

```
from sklearn.linear_model import LinearRegression
```

In [313]:

```
reg=LinearRegression()
```

In [314]:

```
regmodel=reg.fit(X,y)
```

In [315]:

```
regmodel.score(X,y) # R Square
```

Out[315]:

```
0.8875703843513274
```

In [316]:

```
housetest_df=housetest_df.drop('Id',axis=1)
```

In [317]:

```
regtestpred=regmodel.predict(housetest_df)
```

In [318]:

```
pd.DataFrame(np.exp(regtestpred)).to_csv("reg.csv")
```

In [319]:

```
from sklearn.tree import DecisionTreeRegressor
```

In [320]:

```
tree=DecisionTreeRegressor(max_depth=8)
```

In [321]:

```
treemodel=tree.fit(X,y)
```

In [322]:

```
treemodel.score(X,y)
```

Out[322]:

```
0.9465046848167863
```

In [323]:

```
from sklearn.model_selection import cross_val_score
```

In [324]:

```
cross_val_score(tree,X,y)
```

Out[324]:

```
array([0.74132983, 0.73691948, 0.79284658, 0.75584489, 0.75122959])
```

In [325]:

```
treepredict=treemodel.predict(housetest_df)
```

In [326]:

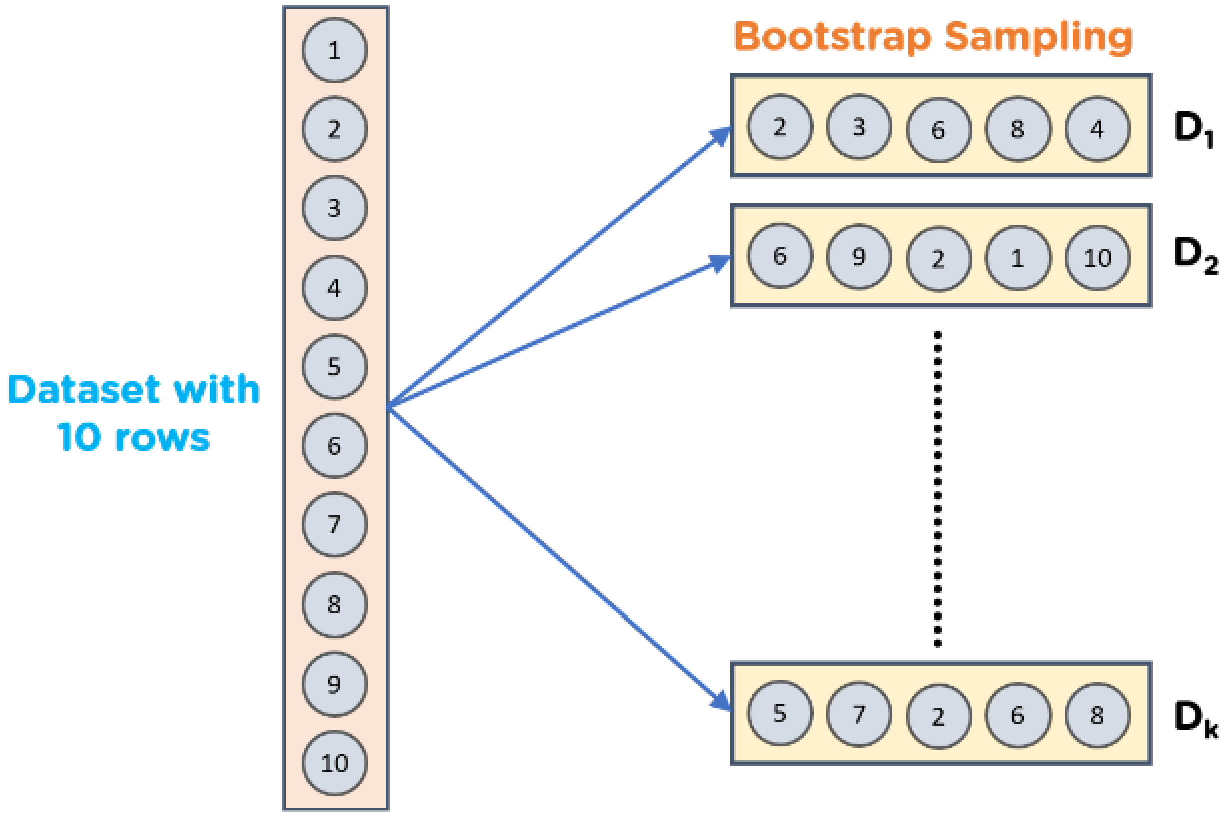
```
pd.DataFrame(np.exp(treepredict)).to_csv("tree.csv")
```

In [327]:

```
# machine learning - supervised learning - multitree models - ensemble techniques - bagg
# bagging also called as bootstrap aggregating
# Bagging, also known as Bootstrap aggregating, is an ensemble learning technique that h
#                    accuracy of machine learning algorithms. Particularly it overcomes t
# Bagging avoids overfitting of data and is used for both regression and classification 
#                                                                                      sp
```

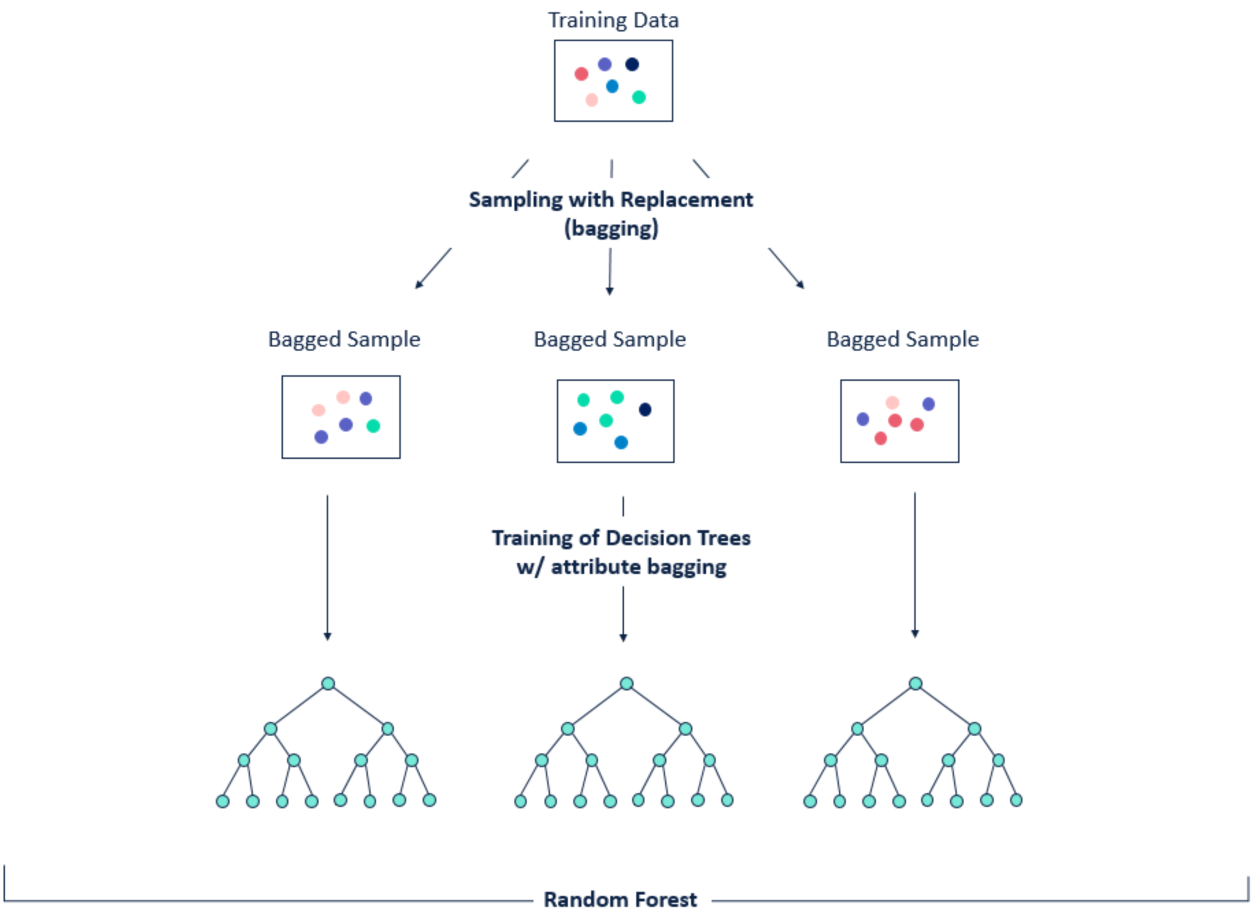
In [328]:

```
# Bagging or Bootstrapping is sampling technique
# Bootstrapping is the method of randomly creating samples of data out of a population w
#
```



In [329]:

```
# Random (sampling) forest (multiple trees)
# random forest is an iterative algorith,
# step 1 - specify the number of tress to be built n_estimators = 1000 (1000 decision tr
# srep 2 - create 1000 ssamples of data from original data and each sample will have 65%
#                  observations and sqrt(numof variables) randomly selected. if data is la
# step 3 - upon creating 1000 samples of data decision tree are parallely built as each
#
# step 4 - prediction will also be done for each tree.
# step 5 - all prediction are aggregated and classification - majority voting    regress

# tree splitting methods
# 1) gini (default) - 1-Σ(prob)^2
# 2) entropy & information gain
# 3) standard deviation reduction (regression)

# feature/variable importance is provided as part of output

# only disadvantage is computing power.
```



In [330]:

```
from sklearn.ensemble import RandomForestRegressor
```

In [331]:

```
RF=RandomForestRegressor(n_estimators=1000)
```

In [332]:

```
RFmodel=RF.fit(X,y)
```

In [333]:

```
RFmodel.score(X,y)
```

Out[333]:

```
0.9833938642398456
```

In [334]:

```
cross_val_score(RF,X,y)
```

Out[334]:

```
array([0.87666802, 0.86847937, 0.87683589, 0.88639551, 0.85673369])
```

In [335]:

```
np.mean([0.8761259 , 0.86893819, 0.87563819, 0.88688285, 0.8572662])
```

Out[335]:

```
0.872970266
```

In [336]:

```
RFpredict=RFmodel.predict(housetest_df)
```

In [338]:

```
pd.DataFrame(np.exp(RFpredict)).to_csv("RF.csv")
```

In [339]:

```
# machine - learning - supervised learning - ensemble methods - boosting method - gradie
# boosting algorithms are developed to improve the accuracy of the machine learning mode
#
# gradient boosting machine algorithm is both classification and regression algorithm
# step 1 - specify the number of trees to be built n_esstimators =1000
# step 2 - create sample 1 which 65% of observations randomly sampled and sqrt (num of v
#
# step 3 - build decision tree for sample 1 & predic
# step 4 - identify wrong predictions and move them to sample 2 and replenish the sample
# step 5 - build decision tree 2 and predict
# step 6 - identify wrong predictions and move them to sample 3.

# sequential building of trees as each tree is dependent on previous trees for sample.
# weak learners or wrong predictions are given weightage in trees
```

In [342]:

```
from sklearn.ensemble import GradientBoostingRegressor
```

In [343]:

```
gbm=GradientBoostingRegressor(n_estimators=3000)
```

In [345]:

```
gbmmodel=gbm.fit(X,y)
```

In [346]:

```
gbmmodel.score(X,y)
```

Out[346]:

```
0.9999405524254801
```

In [347]:

```
gbmpredict=gbmmodel.predict(housetest_df)
```

In [348]:

```
pd.DataFrame(np.exp(gbmpredict)).to_csv("gbm.csv")
```

In [351]:

```
n_trees=[100,200,300,400,500,600,800,1000]
```

In [355]:

```
for tree in n_trees:
    gb_clf= RandomForestRegressor(
        n_estimators=tree)
    gb_clf.fit(X,y)
    pred=gb_clf.predict(X)
    print("n_tree: ", tree)
    print("Rsquare:",gb_clf.score(X,y))
    print("RMSE:",np.sqrt(np.mean((np.exp(y-pred))**2)))
```

```
n_tree:  100
Rsquare: 0.9819402143765815
RMSE: 1.0020774081491917
n_tree:  200
Rsquare: 0.9828065336744494
RMSE: 1.0025913022009025
n_tree:  300
Rsquare: 0.9830044801263098
RMSE: 1.0025805560174235
n_tree:  400
Rsquare: 0.9834148465061464
RMSE: 1.0021676332820362
n_tree:  500
Rsquare: 0.9837492549955437
RMSE: 1.0025688556716097
n_tree:  600
Rsquare: 0.9831707341815927
RMSE: 1.0024061659304733
n_tree:  800
Rsquare: 0.9830271309700911
RMSE: 1.0023996105190554
n_tree:  1000
Rsquare: 0.9833119685243932
RMSE: 1.0025674190561187
```

In [ ]:

```

```