Data Preprocessing

In [1]:

```
# Importing the libraries
import numpy as np
import matplotlib.pyplot as plt
import pandas as pd
```

In [2]:

```
# Importing the dataset
df = pd.read_csv('RL_EXAM_10.csv', sep=",")
```

In [3]:

```
df
```

Out[3]:

	User ID	Gender	Age	EstimatedSalary	Purchased
0	15624510	Male	19	19000	0
1	15810944	Male	35	20000	0
2	15668575	Female	26	43000	0
3	15603246	Female	27	57000	0
4	15804002	Male	19	76000	0
...	...	...	...	...	...
395	15691863	Female	46	41000	1
396	15706071	Male	51	23000	1
397	15654296	Female	50	20000	1
398	15755018	Male	36	33000	0
399	15594041	Female	49	36000	1

400 rows × 5 columns

In [7]:

```
# Function Encoding
def encoding_char(x):
    char_var = list(set(x.columns) - set(x._get_numeric_data().columns))
    for Gender in char_var:
        f = pd.factorize(x[Gender])
        x[Gender] = pd.factorize(x[Gender])[0]
    return(x)


# Encoding categorical data
df = encoding_char(df)
df
```

Out[7]:

	User ID	Gender	Age	EstimatedSalary	Purchased
0	15624510	0	19	19000	0
1	15810944	0	35	20000	0
2	15668575	1	26	43000	0
3	15603246	1	27	57000	0
4	15804002	0	19	76000	0
...	...	...	...	...	...
395	15691863	1	46	41000	1
396	15706071	0	51	23000	1
397	15654296	1	50	20000	1
398	15755018	0	36	33000	0
399	15594041	1	49	36000	1

400 rows × 5 columns

In [8]:

```
df.describe()
# Критических выбросов не наблюдается
```

Out[8]:

	User ID	Gender	Age	EstimatedSalary	Purchased
count	4.000000e+02	400.000000	400.000000	400.000000	400.000000
mean	1.569154e+07	0.510000	37.655000	69742.500000	0.357500
std	7.165832e+04	0.500526	10.482877	34096.960282	0.479864
min	1.556669e+07	0.000000	18.000000	15000.000000	0.000000
25%	1.562676e+07	0.000000	29.750000	43000.000000	0.000000
50%	1.569434e+07	1.000000	37.000000	70000.000000	0.000000
75%	1.575036e+07	1.000000	46.000000	88000.000000	1.000000
max	1.581524e+07	1.000000	60.000000	150000.000000	1.000000

In [10]:

```
# mean()-3*std
# Let's check how much the data are spread out from the mean.
mean_User_ID = np.mean(df['User ID'], axis=0)
sd_User_ID = np.std(df['User ID'], axis=0)

mean_Gender = np.mean(df['Gender'], axis=0)
sd_Gender = np.std(df['Gender'], axis=0)

mean_Age = np.mean(df['Age'], axis=0)
sd_Age = np.std(df['Age'], axis=0)

mean_EstimatedSalary = np.mean(df['EstimatedSalary'], axis=0)
sd_EstimatedSalary = np.std(df['EstimatedSalary'], axis=0)

mean_Purchased = np.mean(df['Purchased'], axis=0)
sd_Purchased = np.std(df['Purchased'], axis=0)

counter_User_ID = 0
counter_Gender = 0
counter_Age = 0
counter_EstimatedSalary = 0
counter_Purchased = 0

for User_ID, Gender, Age, EstimatedSalary, Purchased in zip(df['User ID'], df['Gender'], d
f['Age'], df['EstimatedSalary'], df['Purchased']):
    if not mean_User_ID - 3*sd_User_ID <= User_ID <= mean_User_ID + 3*sd_User_ID:
        counter_User_ID += 1
    if not mean_Gender - 3*sd_Gender <= Gender <= mean_Gender + 3*sd_Gender:
        counter_Gender += 1
    if not mean_Age - 3*sd_Age <= counter_Age <= mean_Age + 3*sd_Age:
        counter_Age += 1
    if not mean_EstimatedSalary - 3*sd_EstimatedSalary <= counter_EstimatedSalary <= mean_
EstimatedSalary + 3*sd_EstimatedSalary:
        counter_EstimatedSalary += 1
    if not mean_Purchased - 3*sd_Purchased <= counter_Purchased <= mean_Purchased + 3*sd_P
urchased:
        counter_Purchased += 1

counter_dicts = {'counter_User_ID': counter_User_ID,
                'counter_Gender': counter_Gender,
                'counter_Age': counter_Age,
                'counter_EstimatedSalary': counter_EstimatedSalary,
                'counter_Purchased': counter_Purchased}
print(counter_dicts)
```

```
{'counter_User_ID': 0, 'counter_Gender': 0, 'counter_Age': 7, 'counter_Estima
tedSalary': 0, 'counter_Purchased': 0}
```

In [11]:

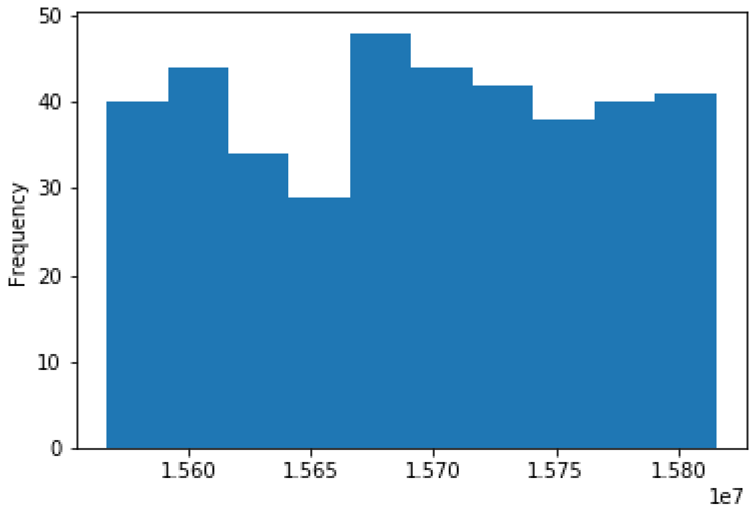
```
# Outliers
User_ID = []
for ap in df['User ID']:
    if ap > df['User ID'].mean() + 3 * df['User ID'].std():
        ap = df['User ID'].mean() + 3*df['User ID'].std()
    elif ap < df['User ID'].mean() - 3 * df['User ID'].std():
        ap = df['User ID'].mean() - 3*df['User ID'].std()
    User_ID.append(ap)
df['User ID']  = User_ID

Gender = []
for m in df['Gender']:
    if m > df['Gender'].mean() + 3 * df['Gender'].std():
        m = df['Gender'].mean() + 3*df['Gender'].std()
    elif m < df['Gender'].mean() - 3 * df['Gender'].std():
        m = df['Gender'].mean() - 3*df['Gender'].std()
    Gender.append(m)
df['Gender']  = Gender

Age = []
for loc in df['Age']:
    if loc > df['Age'].mean() + 3 * df['Age'].std():
        loc = df['Age'].mean() + 3*df['Age'].std()
    elif loc < df['Age'].mean() - 3 * df['Age'].std():
        loc = df['Age'].mean() - 3*df['Age'].std()
    Age.append(loc)
df['Age'] = Age

EstimatedSalary = []
for loc in df['EstimatedSalary']:
    if loc > df['EstimatedSalary'].mean() + 3 * df['EstimatedSalary'].std():
        loc = df['EstimatedSalary'].mean() + 3*df['EstimatedSalary'].std()
    elif loc < df['EstimatedSalary'].mean() - 3 * df['EstimatedSalary'].std():
        loc = df['EstimatedSalary'].mean() - 3*df['EstimatedSalary'].std()
    EstimatedSalary.append(loc)
df['EstimatedSalary'] = EstimatedSalary

Purchased = []
for loc in df['Purchased']:
    if loc > df['Purchased'].mean() + 3 * df['Purchased'].std():
        loc = df['Purchased'].mean() + 3*df['Purchased'].std()
    elif loc < df['Purchased'].mean() - 3 * df['Purchased'].std():
        loc = df['Purchased'].mean() - 3*df['Purchased'].std()
    Purchased.append(loc)
df['Purchased'] = Purchased
```

In [12]:

```
# User_ID distribution
df['User ID'].plot(kind = 'hist')
```

Out[12]:

<matplotlib.axes._subplots.AxesSubplot at 0x1f452e88af0>

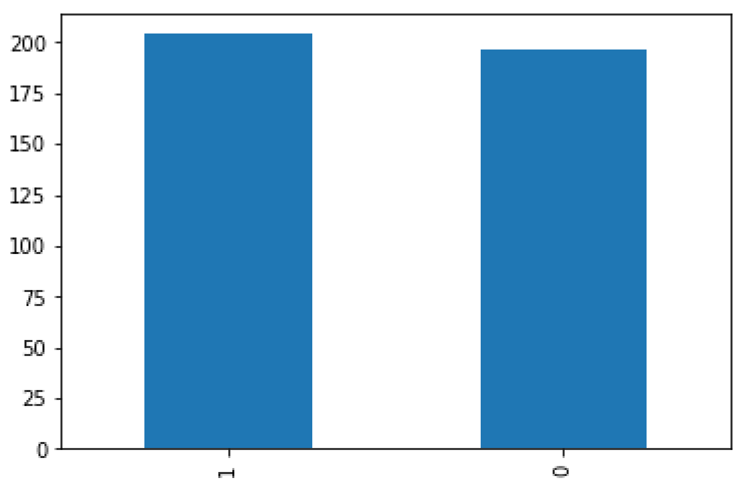


In [13]:

```
# Gender distribution
distribution = df['Gender'].value_counts()
distribution.plot(kind='bar')
```

Out[13]:

<matplotlib.axes._subplots.AxesSubplot at 0x1f454f5ab20>

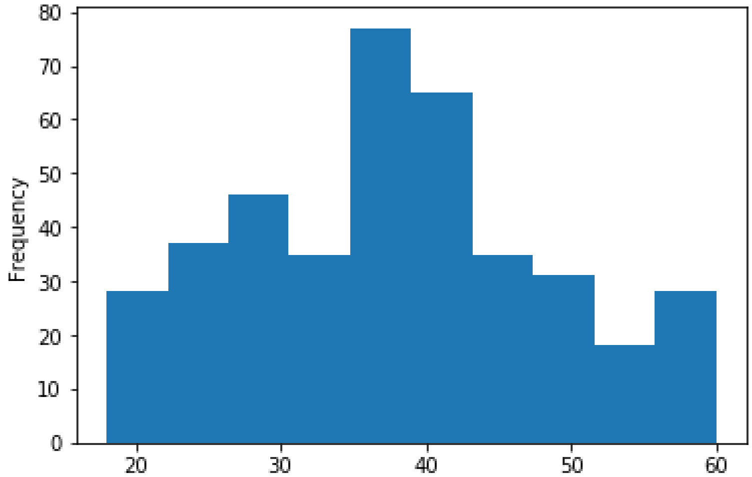


In [14]:

```
# Age distribution
df['Age'].plot(kind = 'hist')
```

Out[14]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x1f454fb73d0>
```

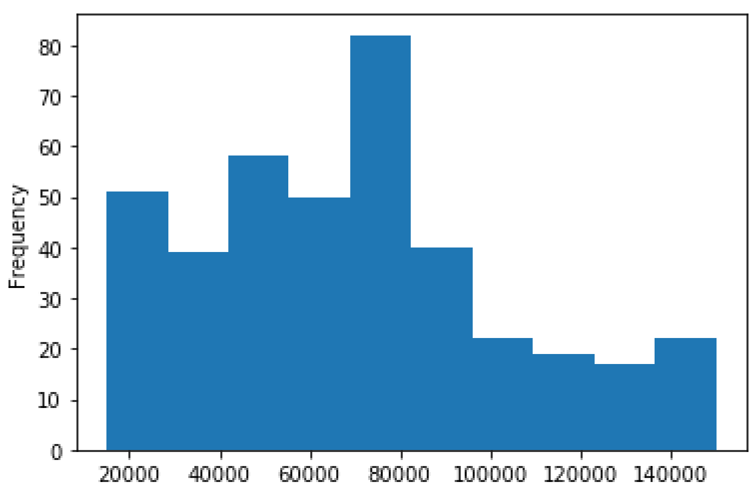


In [15]:

```
# EstimatedSalary distribution
df['EstimatedSalary'].plot(kind = 'hist')
```

Out[15]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x1f455039a00>
```

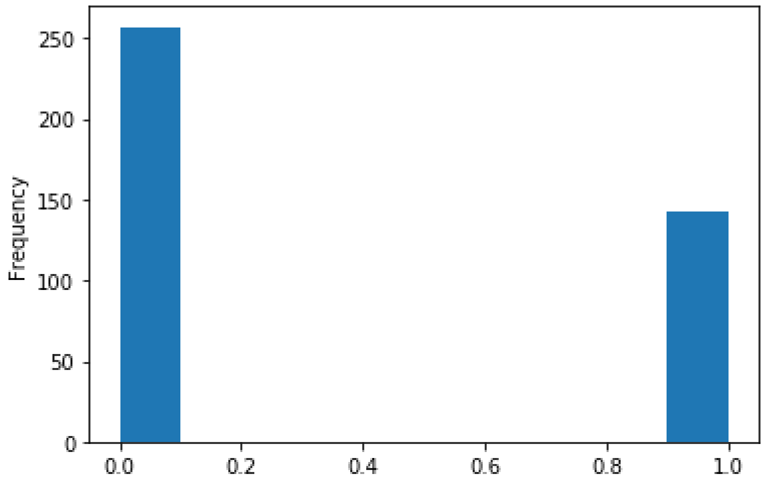


In [16]:

```
# Purchased distribution
df['Purchased'].plot(kind = 'hist')
```

Out[16]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x1f455089700>
```



In [17]:

```
df.isnull().sum()
# Таким образом мы имеем пропущенные значения в таких колонках:
```

Out[17]:

```
User ID            0
Gender             0
Age                0
EstimatedSalary    0
Purchased          0
dtype: int64
```

In [20]:

```
# Taking care of missing data
# https://scikit-learn.org/
from sklearn.impute import SimpleImputer
#numeric
df[['User ID']] = SimpleImputer(missing_values=np.nan, strategy='mean').fit_transform(df[[
'User ID']]).round()
df[['Gender']] = SimpleImputer(missing_values=np.nan, strategy='mean').fit_transform(df[[
'Gender']]).round()
df[['EstimatedSalary']] = SimpleImputer(missing_values=np.nan, strategy='mean').fit_transf
orm(df[['EstimatedSalary']]).round()
```

Classification Tree

In [22]:

```
def max_leaf_nodes(X_train, X_test, y_train, y_test, n):
    mse_train = []
    mse_test = []
    for i in n:
        rf = DecisionTreeClassifier(max_leaf_nodes = i, random_state=10).fit(X_train, y_tr
ain)
        mse_train.append(mean_squared_error(y_train, rf.predict(X_train)))
        mse_test.append(mean_squared_error(y_test, rf.predict(X_test)))
    fig, ax = plt.subplots(figsize=(8, 4))
    ax.plot(n, mse_train, alpha=0.5, color='blue', label='train')
    ax.plot(n, mse_test, alpha=0.5, color='red', label='test')
    ax.set_ylabel("MSE")
    ax.set_xlabel("max_leaf_nodes")
```

In [26]:

```
# Splitting the dataset into the Training set and Test set
from sklearn.model_selection import train_test_split
X = df.iloc[:, :-1].values
y = df.iloc[:, -1].values

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=0)
```

In [24]:

```
df
```

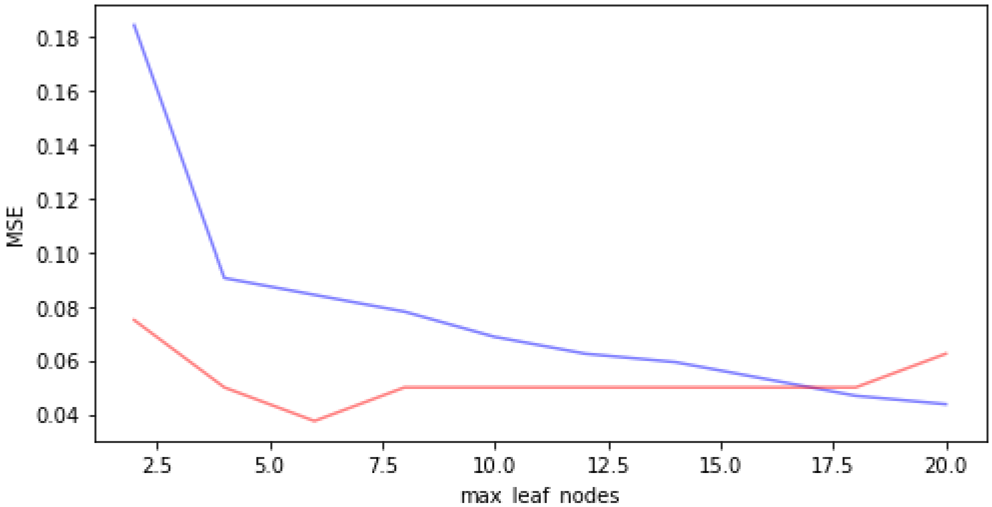
Out[24]:

	User ID	Gender	Age	EstimatedSalary	Purchased
0	15624510.0	0.0	19	19000.0	0
1	15810944.0	0.0	35	20000.0	0
2	15668575.0	1.0	26	43000.0	0
3	15603246.0	1.0	27	57000.0	0
4	15804002.0	0.0	19	76000.0	0
...	...	...	...	...	...
395	15691863.0	1.0	46	41000.0	1
396	15706071.0	0.0	51	23000.0	1
397	15654296.0	1.0	50	20000.0	1
398	15755018.0	0.0	36	33000.0	0
399	15594041.0	1.0	49	36000.0	1

400 rows × 5 columns

In [28]:

```
# The optimal number of max_leaf_nodes
from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import mean_squared_error
max_leaf_nodes(X_train, X_test, y_train, y_test, [2, 4, 6, 8, 10, 12, 14, 16, 18, 20])
```



Выберем leaf_nodes = 17

In [29]:

```
# Fitting Classification Tree to the Training set
ct = DecisionTreeClassifier(max_leaf_nodes = 17, criterion = 'entropy', random_state = 10)
.fit(X_train, y_train)

# Predicting the Test set results
y_pred = ct.predict(X_test)
ct.score(X_test,y_test)
```

Out[29]:

```
0.95
```

In [30]:

```
# Making the Confusion Matrix
from sklearn.metrics import confusion_matrix
cm = confusion_matrix(y_test, y_pred)
print(cm)
```

```
[[56  2]
 [ 2 20]]
```

Вывод: данная модель отлично подходит для целей прогнозирования, т.к. ее точность = 95%. Так же мы имеем 4 ложных предсказания.