In [1]:
```python
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns
import warnings
warnings.filterwarnings('ignore')
```

In [2]:
```python
data= pd.read_csv(r"H:\Data\......\bank+marketing\bank\bank-full.csv")
```

Dropping unrelated columns.

In [3]:
```python
data= data.drop('contact', axis=1)
```

In [4]:
```python
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 45211 entries, 0 to 45210
Data columns (total 16 columns):
 #   Column     Non-Null Count  Dtype 
---  ------     --------------  ----- 
 0   age        45211 non-null  int64 
 1   job        45211 non-null  object
 2   marital    45211 non-null  object
 3   education  45211 non-null  object
 4   default    45211 non-null  object
 5   balance    45211 non-null  int64 
 6   housing    45211 non-null  object
 7   loan       45211 non-null  object
 8   day        45211 non-null  int64 
 9   month      45211 non-null  object
 10  duration   45211 non-null  int64 
 11  campaign   45211 non-null  int64 
 12  pdays      45211 non-null  int64 
 13  previous   45211 non-null  int64 
 14  poutcome   45211 non-null  object
 15  y          45211 non-null  object
dtypes: int64(7), object(9)
memory usage: 5.5+ MB
```

In [5]:
```python
data.head()
```

Out[5]:

	age	job	marital	education	default	balance	housing	loan	day	month	durati
0	58	management	married	tertiary	no	2143	yes	no	5	may	2
1	44	technician	single	secondary	no	29	yes	no	5	may	1
2	33	entrepreneur	married	secondary	no	2	yes	yes	5	may	
3	47	blue-collar	married	unknown	no	1506	yes	no	5	may	
4	33	unknown	single	unknown	no	1	no	no	5	may	1

In [6]:
```python
columns= list(data.columns)
```

In [7]:
```python
from sklearn.preprocessing import LabelEncoder
le= LabelEncoder()
```

In [8]:
```python
for col in columns:
    if data[col].dtype == 'object':
        data[col]= le.fit_transform(data[col])
```

In [9]:
```python
data
```

Out[9]:

	age	job	marital	education	default	balance	housing	loan	day	month	duration
0	58	4	1	2	0	2143	1	0	5	8	261
1	44	9	2	1	0	29	1	0	5	8	151
2	33	2	1	1	0	2	1	1	5	8	76
3	47	1	1	3	0	1506	1	0	5	8	92
4	33	11	2	3	0	1	0	0	5	8	198
...	...	...	...	...	...	...	...	...	...	...	...
45206	51	9	1	2	0	825	0	0	17	9	977
45207	71	5	0	0	0	1729	0	0	17	9	456
45208	72	5	1	1	0	5715	0	0	17	9	1127
45209	57	1	1	1	0	668	0	0	17	9	508
45210	37	2	1	1	0	2971	0	0	17	9	361

45211 rows × 16 columns

In [10]:
```python
data.isna().sum()
```

Out[10]:
```
age          0
job          0
marital      0
education    0
default      0
balance      0
housing      0
loan         0
day          0
month        0
duration     0
campaign     0
pdays        0
previous     0
poutcome     0
y            0
dtype: int64
```

In [11]:
```
data.describe()
```

Out[11]:

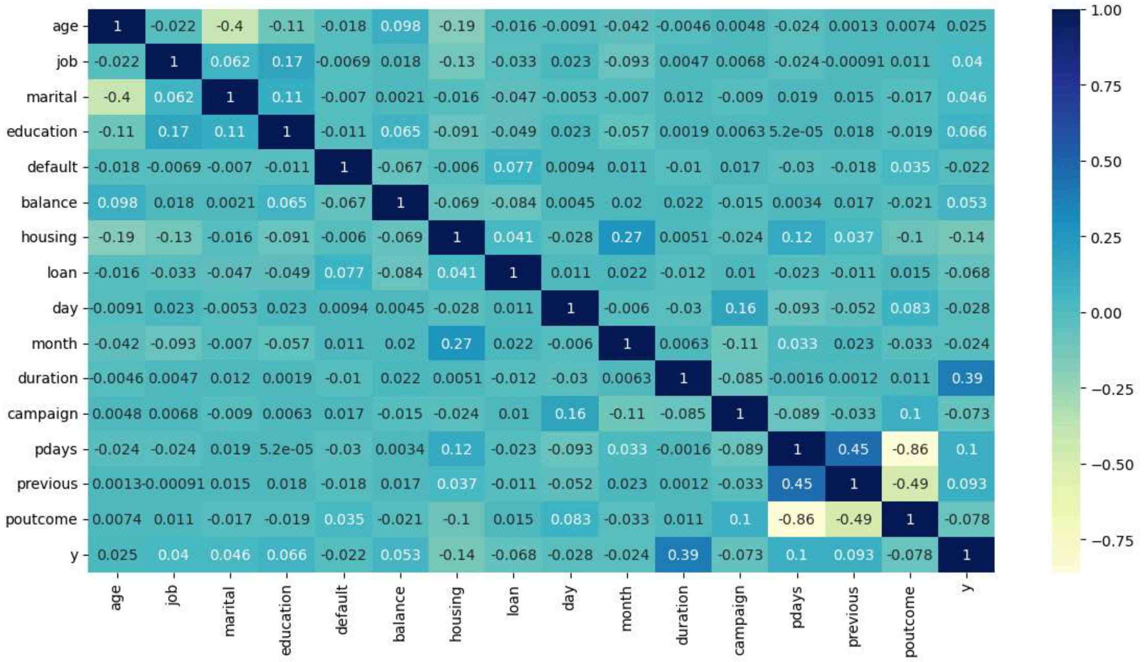
	age	job	marital	education	default	balance
count	45211.000000	45211.000000	45211.000000	45211.000000	45211.000000	45211.000000
mean	40.936210	4.339762	1.167725	1.224813	0.018027	1362.272058
std	10.618762	3.272657	0.608230	0.747997	0.133049	3044.765829
min	18.000000	0.000000	0.000000	0.000000	0.000000	-8019.000000
25%	33.000000	1.000000	1.000000	1.000000	0.000000	72.000000
50%	39.000000	4.000000	1.000000	1.000000	0.000000	448.000000
75%	48.000000	7.000000	2.000000	2.000000	0.000000	1428.000000
max	95.000000	11.000000	2.000000	3.000000	1.000000	102127.000000

The positive correlation (+0.39) between "duration" and "y" suggests that longer conversations during the last contact are associated with a higher likelihood of the client subscribing to the term deposit.

Note: 1. The variable "y" indicates whether the client subscribed to a term deposit (binary outcome: "yes" or "no").

2. "duration" refers to the length of the last contact with a client during a marketing campaign, measured in seconds.

In [12]:
```
plt.figure(figsize=(14,7))
sns.heatmap(data.corr(), cmap= 'YlGnBu', annot= True)
plt.show()
```



In [13]:
```
x= data.iloc[:, :-1]
y= data['y']
print(x.shape)
print(y.shape)
```

```
(45211, 15)
(45211,)
```

In [14]:
```
from sklearn.model_selection import train_test_split
from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import accuracy_score, confusion_matrix
```

In [15]:
```
x_train, x_test, y_train, y_test= train_test_split(x, y, train_size= 0.70,
```

In [16]:
```
dt= DecisionTreeClassifier()
dt.fit(x_train, y_train)
```

Out[16]:
```
DecisionTreeClassifier()
```

In [17]:
```
preds= dt.predict(x_test)
```

In [18]:
```
acc= accuracy_score(preds, y_test)
print(f'Accuracy score:', acc)
```

```
Accuracy score: 0.870023591860808
```

In [19]:
```
confusion_matrix(preds, y_test)
```

Out[19]:
```
array([[11065,   862],
       [  901,   736]], dtype=int64)
```

In [20]:
```
depths= [1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15]
df= pd.DataFrame(columns= ['Max_depths', 'Accuracy'])
df
```

Out[20]:

Max_depths	Accuracy

In [21]:

```
for input_parameter in depths:
    model= DecisionTreeClassifier(max_depth= input_parameter)
    model.fit(x_train, y_train)
    Mpreds= model.predict(x_test)
    Macc= accuracy_score(Mpreds, y_test)*100
    df= df.append({'Max_depths': input_parameter, 'Accuracy': Macc}, ignore_
df
```

Out[21]:

	Max_depths	Accuracy
0	1.0	88.218815
1	2.0	88.712769
2	3.0	88.823356
3	4.0	89.184606
4	5.0	89.567974
5	6.0	89.663816
6	7.0	89.877617
7	8.0	89.752285
8	9.0	89.634326
9	10.0	89.450015
10	11.0	89.354173
11	12.0	89.332055
12	13.0	89.177234
13	14.0	88.933943
14	15.0	88.602182

The decision tree classifier achieved optimal performance on this dataset when the maximum depth was set to 7.0.