In [1]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns
```

In [42]:
```
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score, classification_report, confusion_matrix,
from sklearn.tree import DecisionTreeClassifier
from sklearn.linear_model import LogisticRegression, LinearRegression
from sklearn.ensemble import RandomForestClassifier, GradientBoostingClassifier, Ada
from sklearn.naive_bayes import GaussianNB
from sklearn.svm import SVC
from sklearn import metrics
```

In [3]:
```
train = pd.read_csv('trainset.csv')
test = pd.read_csv('testset.csv')
```

In [4]:
```
train.head()
```

Out[4]:

	age	job	marital	education	housing	loan	contact	month	day_of_wee
0	41	blue-collar	divorced	basic.4y	yes	no	telephone	may	mo
1	49	entrepreneur	married	university.degree	yes	no	telephone	may	mo
2	49	technician	married	basic.9y	no	no	telephone	may	mo
3	41	technician	married	professional.course	yes	no	telephone	may	mo
4	45	blue-collar	married	basic.9y	yes	no	telephone	may	mo

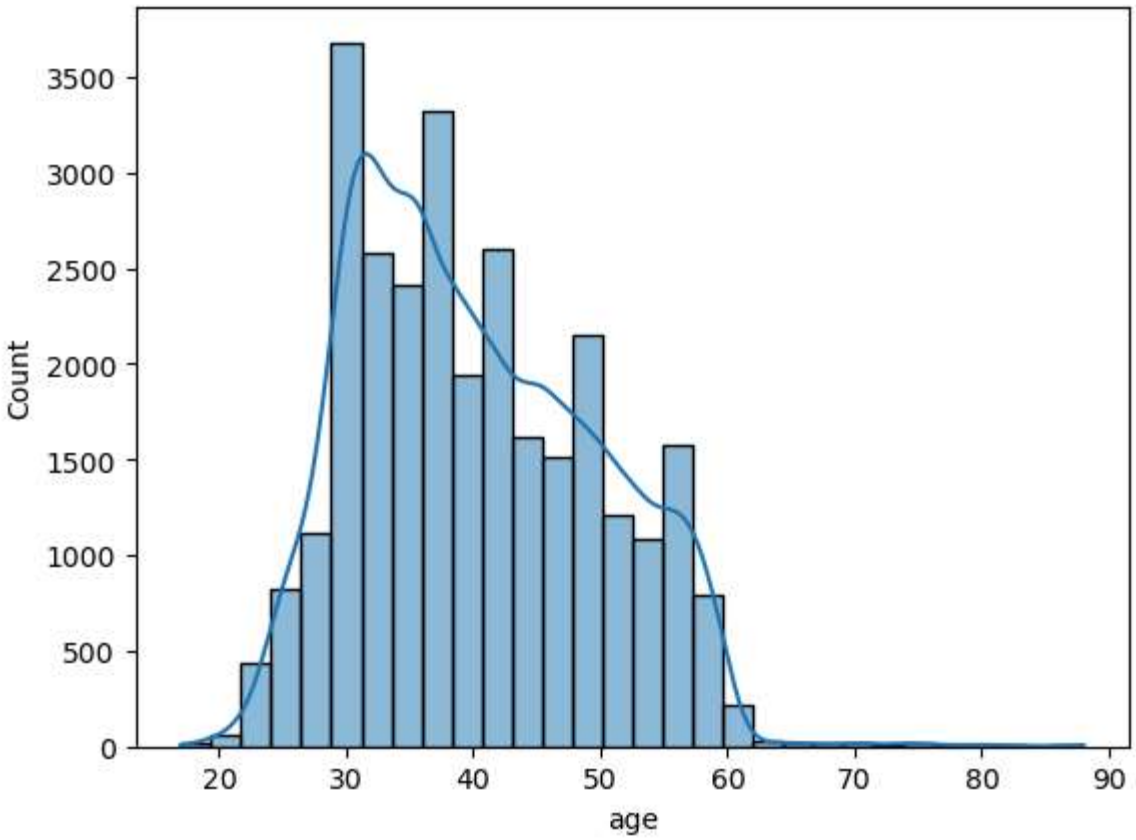
In [5]:
```
train.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 29271 entries, 0 to 29270
Data columns (total 15 columns):
 #   Column         Non-Null Count  Dtype  
---  ------         --------------  -----  
 0   age            29271 non-null  int64  
 1   job            29271 non-null  object 
 2   marital        29271 non-null  object 
 3   education      29271 non-null  object 
 4   housing        29271 non-null  object 
 5   loan           29271 non-null  object 
 6   contact        29271 non-null  object 
 7   month          29271 non-null  object 
 8   day_of_week    29271 non-null  object 
 9   duration       29271 non-null  int64  
 10  campaign       29271 non-null  int64  
 11  pdays          29271 non-null  int64  
 12  poutcome       29271 non-null  object 
 13  nr.employed    29271 non-null  float64
 14  Subscribed     29271 non-null  object 
dtypes: float64(1), int64(4), object(10)
memory usage: 3.3+ MB
```

First Park--data exploration

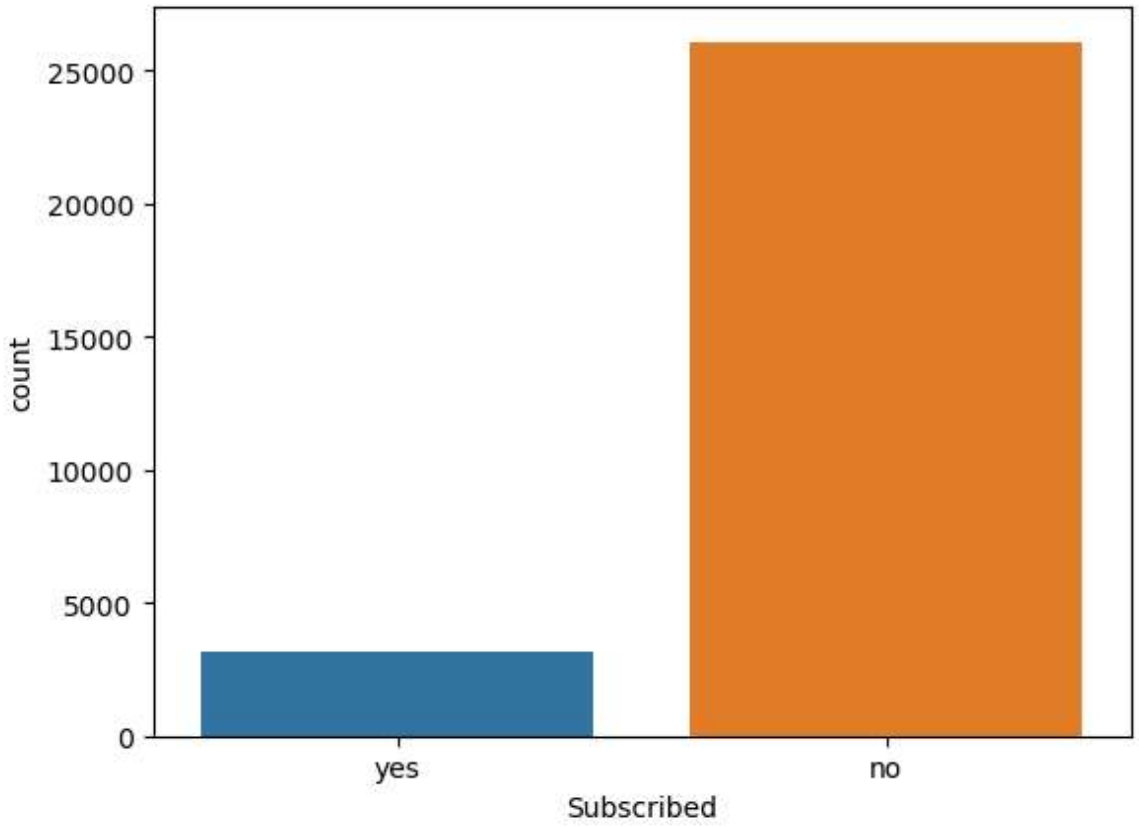
In [6]:
```
sns.histplot(train['age'], bins=30, kde=True)
```

Out[6]: <Axes: xlabel='age', ylabel='Count'>



In [7]:
```
sns.countplot(x='Subscribed', data=train)
```

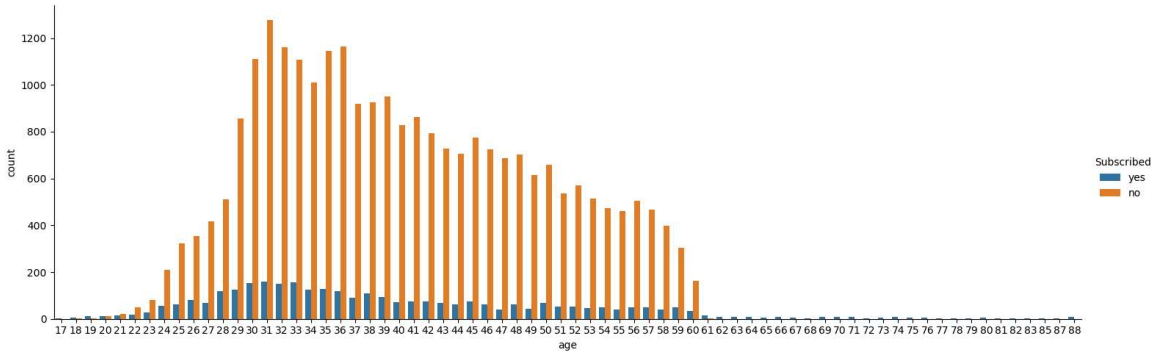
Out[7]: <Axes: xlabel='Subscribed', ylabel='count'>



In [8]:
```
sns.catplot(x='age', data=train, kind='count', hue='Subscribed',height=5, aspect=3)
```

```
E:\anaconda\Lib\site-packages\seaborn\axisgrid.py:118: UserWarning: The figure lay
out has changed to tight
  self._figure.tight_layout(*args, **kwargs)
```

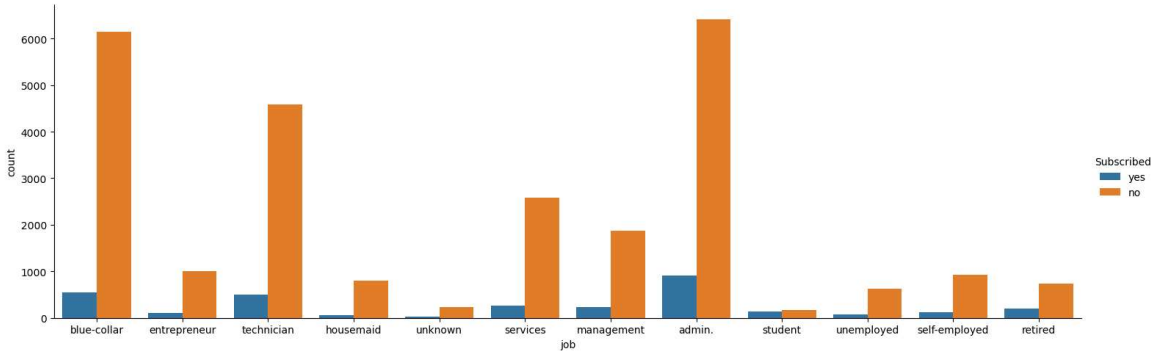
Out[8]: <seaborn.axisgrid.FacetGrid at 0x2164fcaeb50>



In [9]:
```
sns.catplot(x='job', data=train, kind='count', hue='Subscribed' ,height=5, aspect=3)
```

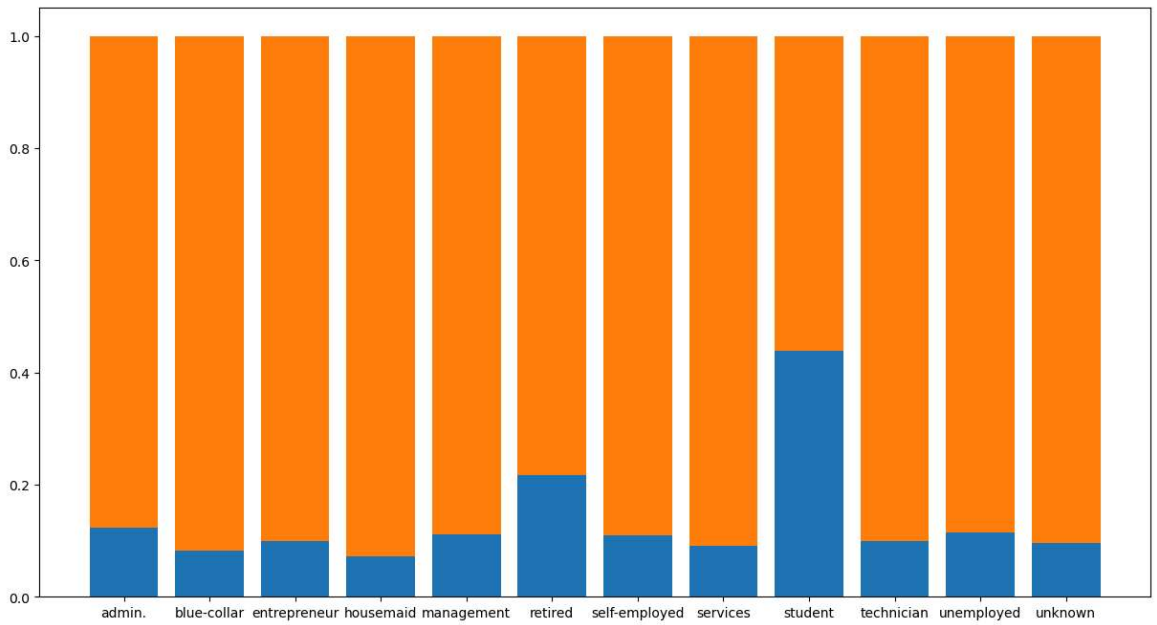
```
E:\anaconda\Lib\site-packages\seaborn\axisgrid.py:118: UserWarning: The figure lay
out has changed to tight
  self._figure.tight_layout(*args, **kwargs)
```

Out[9]: <seaborn.axisgrid.FacetGrid at 0x21650800050>



In [10]:
```
job_counts = train.groupby(['job', 'Subscribed']).size().unstack(fill_value=0)

job_counts['total'] = job_counts['yes'] + job_counts['no']
job_counts['yes_percentage'] = job_counts['yes'] / job_counts['total']
job_counts['no_percentage'] = job_counts['no'] / job_counts['total']

plt.figure(figsize=(15, 8))
plt.bar(job_counts.index, job_counts['yes_percentage'], label='Subscribed')
plt.bar(job_counts.index, job_counts['no_percentage'], bottom=job_counts['yes_percent
```

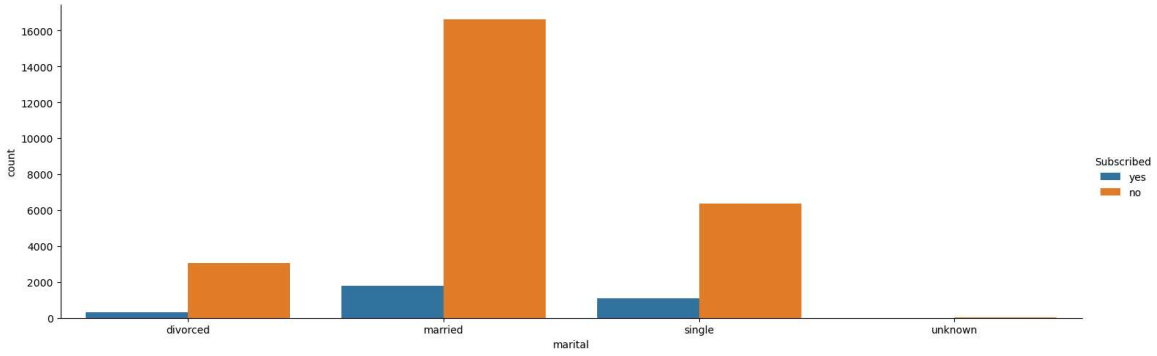
Out[10]: <BarContainer object of 12 artists>



In [11]:
```
sns.catplot(x='marital', data=train, kind='count', hue='Subscribed' ,height=5, aspect
```

```
E:\anaconda\Lib\site-packages\seaborn\axisgrid.py:118: UserWarning: The figure lay
out has changed to tight
  self._figure.tight_layout(*args, **kwargs)
```

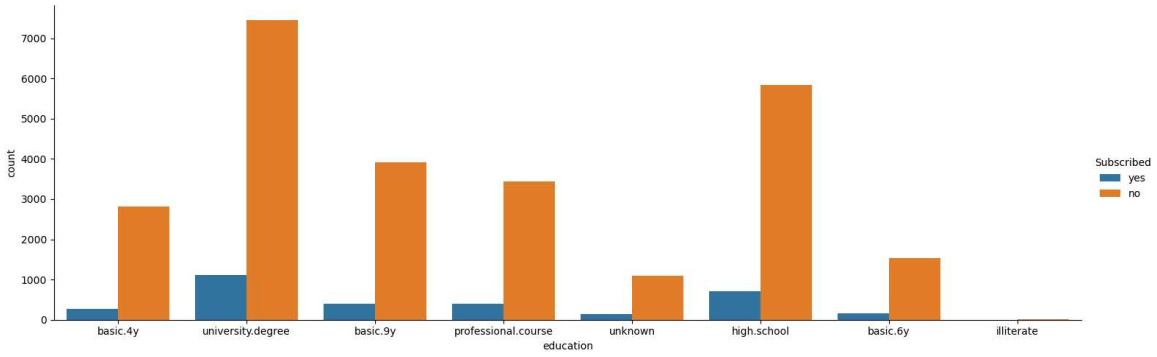
Out[11]: <seaborn.axisgrid.FacetGrid at 0x216504cb610>



In [12]:
```
sns.catplot(x='education', data=train, kind='count', hue='Subscribed' ,height=5, aspe
```

```
E:\anaconda\Lib\site-packages\seaborn\axisgrid.py:118: UserWarning: The figure lay
out has changed to tight
  self._figure.tight_layout(*args, **kwargs)
```

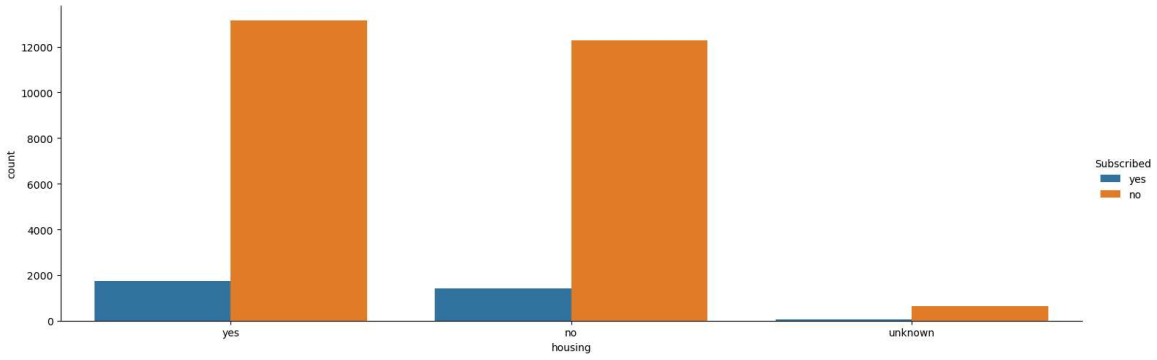
Out[12]: <seaborn.axisgrid.FacetGrid at 0x2165078f890>



In [13]:
```
sns.catplot(x='housing', data=train, kind='count', hue='Subscribed' ,height=5, aspect
```

```
E:\anaconda\Lib\site-packages\seaborn\axisgrid.py:118: UserWarning: The figure lay
out has changed to tight
  self._figure.tight_layout(*args, **kwargs)
```

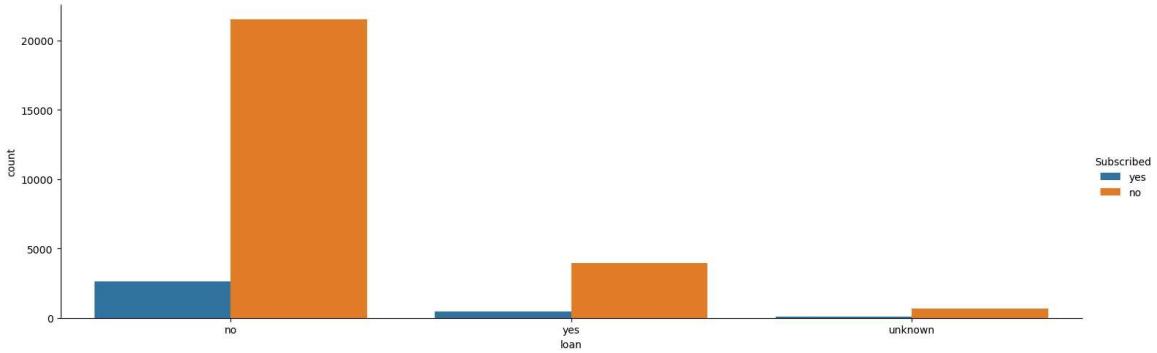
Out[13]: <seaborn.axisgrid.FacetGrid at 0x216505b5cd0>



In [14]:
```
sns.catplot(x='loan', data=train, kind='count', hue='Subscribed' ,height=5, aspect=3)
```

```
E:\anaconda\Lib\site-packages\seaborn\axisgrid.py:118: UserWarning: The figure lay
out has changed to tight
  self._figure.tight_layout(*args, **kwargs)
```

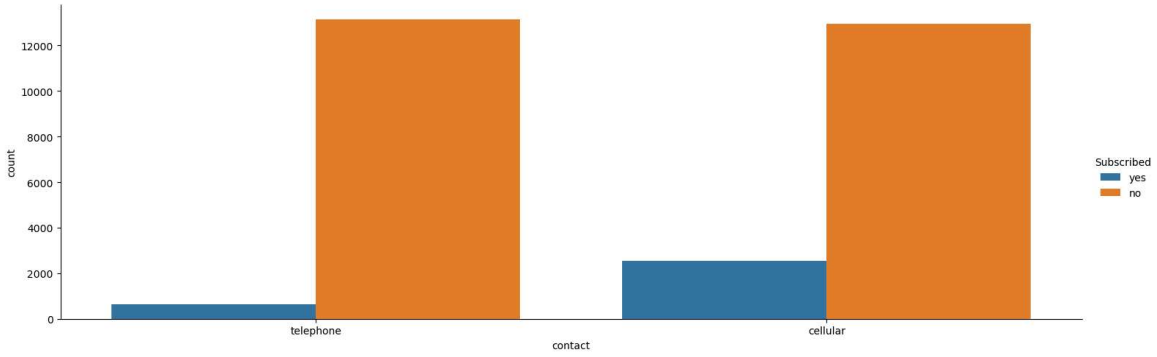
Out[14]: <seaborn.axisgrid.FacetGrid at 0x21650f55910>



In [15]:
```
sns.catplot(x='contact', data=train, kind='count', hue='Subscribed' ,height=5, aspect
```

```
E:\anaconda\Lib\site-packages\seaborn\axisgrid.py:118: UserWarning: The figure lay
out has changed to tight
  self._figure.tight_layout(*args, **kwargs)
```

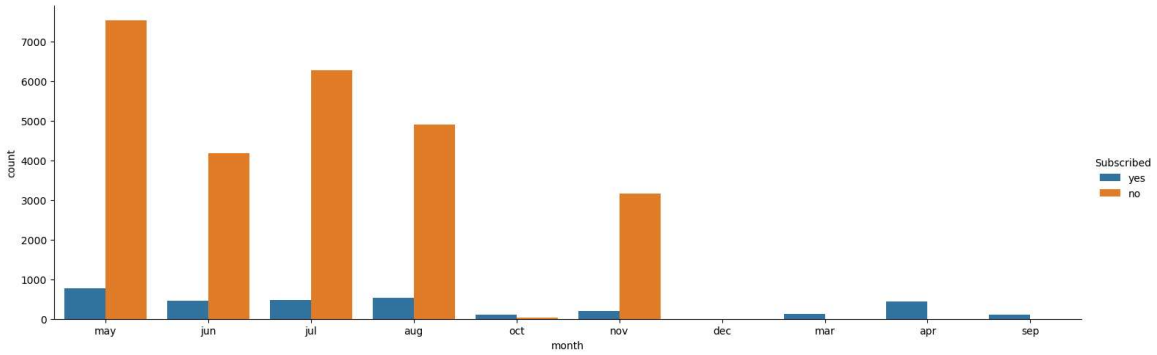
Out[15]: <seaborn.axisgrid.FacetGrid at 0x21651064490>



In [16]:
```
sns.catplot(x='month', data=train, kind='count', hue='Subscribed' ,height=5, aspect=
```

```
E:\anaconda\Lib\site-packages\seaborn\axisgrid.py:118: UserWarning: The figure lay
out has changed to tight
  self._figure.tight_layout(*args, **kwargs)
```

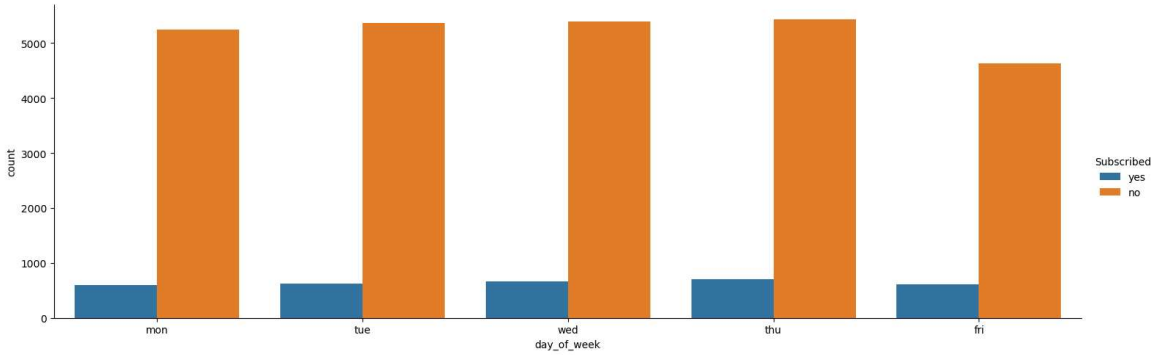
Out[16]: <seaborn.axisgrid.FacetGrid at 0x21650ffb090>



In [17]:
```
sns.catplot(x='day_of_week', data=train, kind='count', hue='Subscribed',height=5, as
```

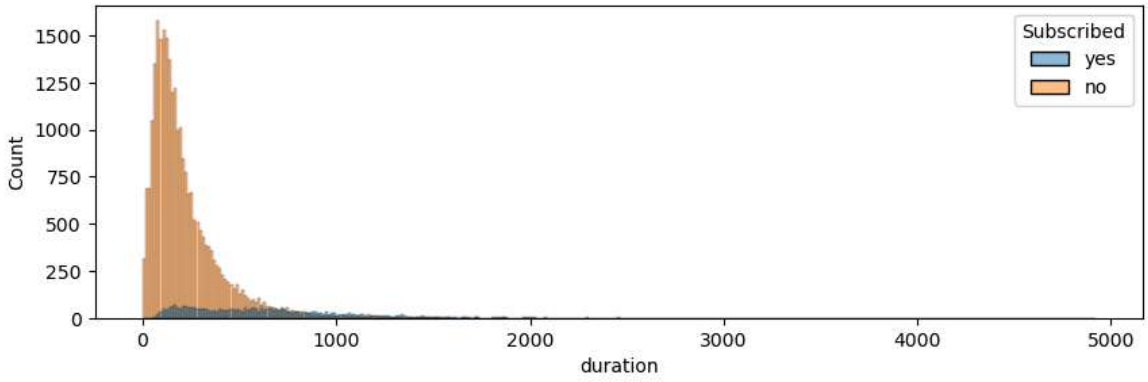
```
E:\anaconda\Lib\site-packages\seaborn\axisgrid.py:118: UserWarning: The figure lay
out has changed to tight
  self._figure.tight_layout(*args, **kwargs)
```

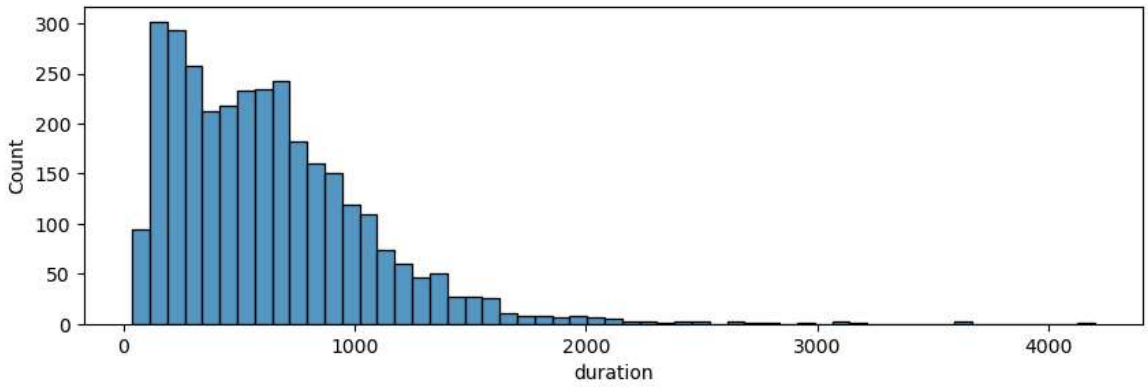
Out[17]: <seaborn.axisgrid.FacetGrid at 0x21651185910>

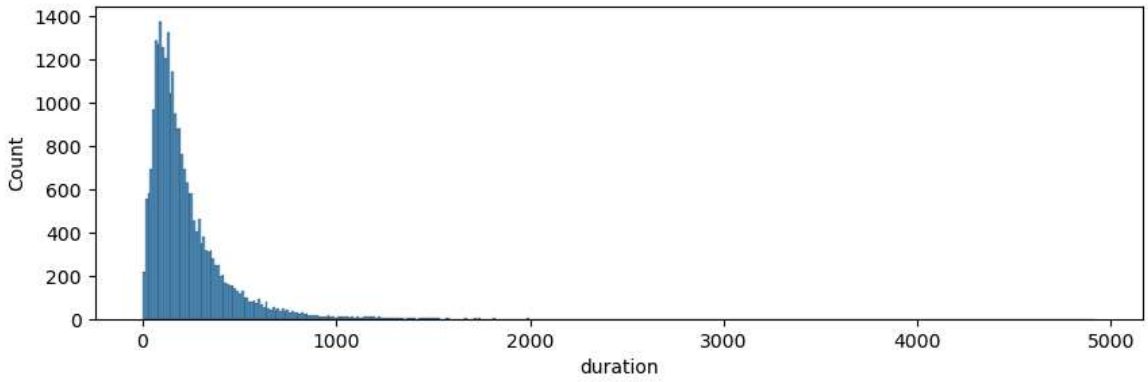


In [18]:
```
plt.figure(figsize=(10, 3))
sns.histplot(x='duration', data=train, hue='Subscribed')
plt.figure(figsize=(10, 3))
sns.histplot(x='duration', data=train[train['Subscribed'] == 'yes'])
plt.figure(figsize=(10, 3))
sns.histplot(x='duration', data=train[train['Subscribed'] == 'no'])
```

Out[18]: <Axes: xlabel='duration', ylabel='Count'>



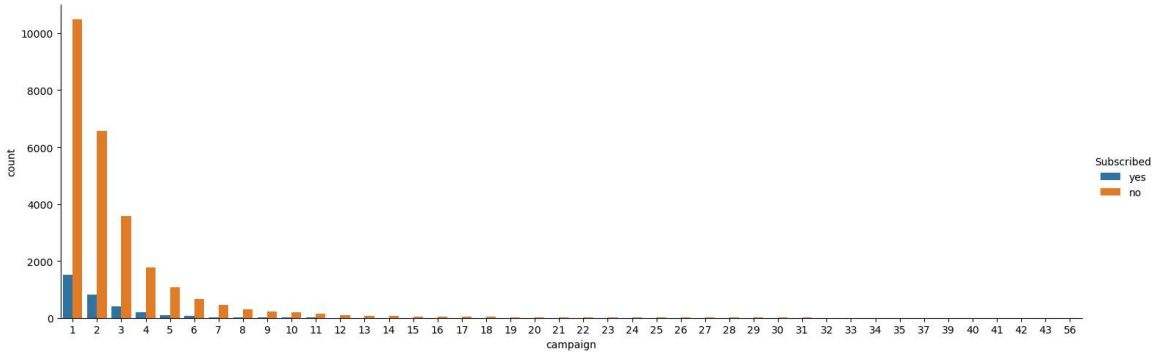




In [19]:
```
sns.catplot(x='campaign', data=train, kind='count', hue='Subscribed' ,height=5, aspec
```

```
E:\anaconda\Lib\site-packages\seaborn\axisgrid.py:118: UserWarning: The figure lay
out has changed to tight
  self._figure.tight_layout(*args, **kwargs)
```

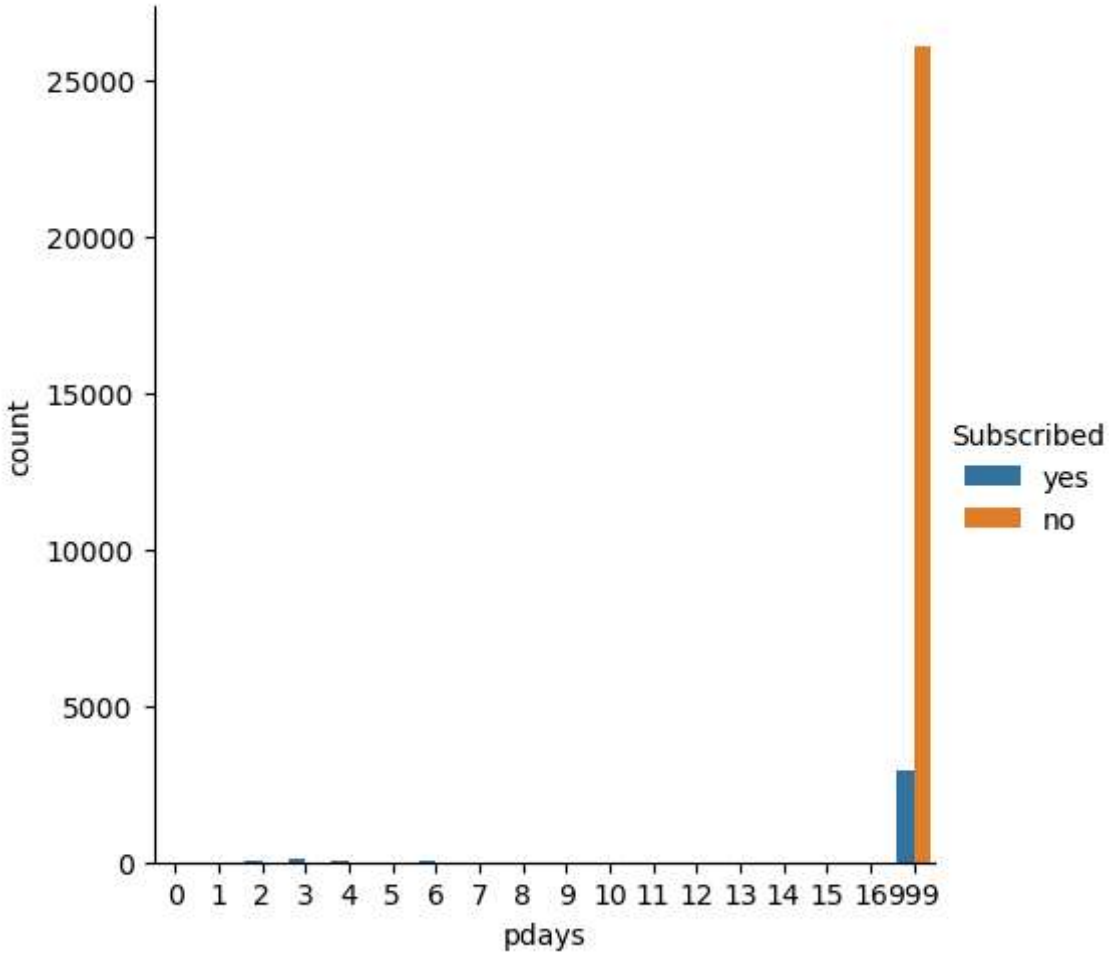
Out[19]: <seaborn.axisgrid.FacetGrid at 0x216552fa9d0>



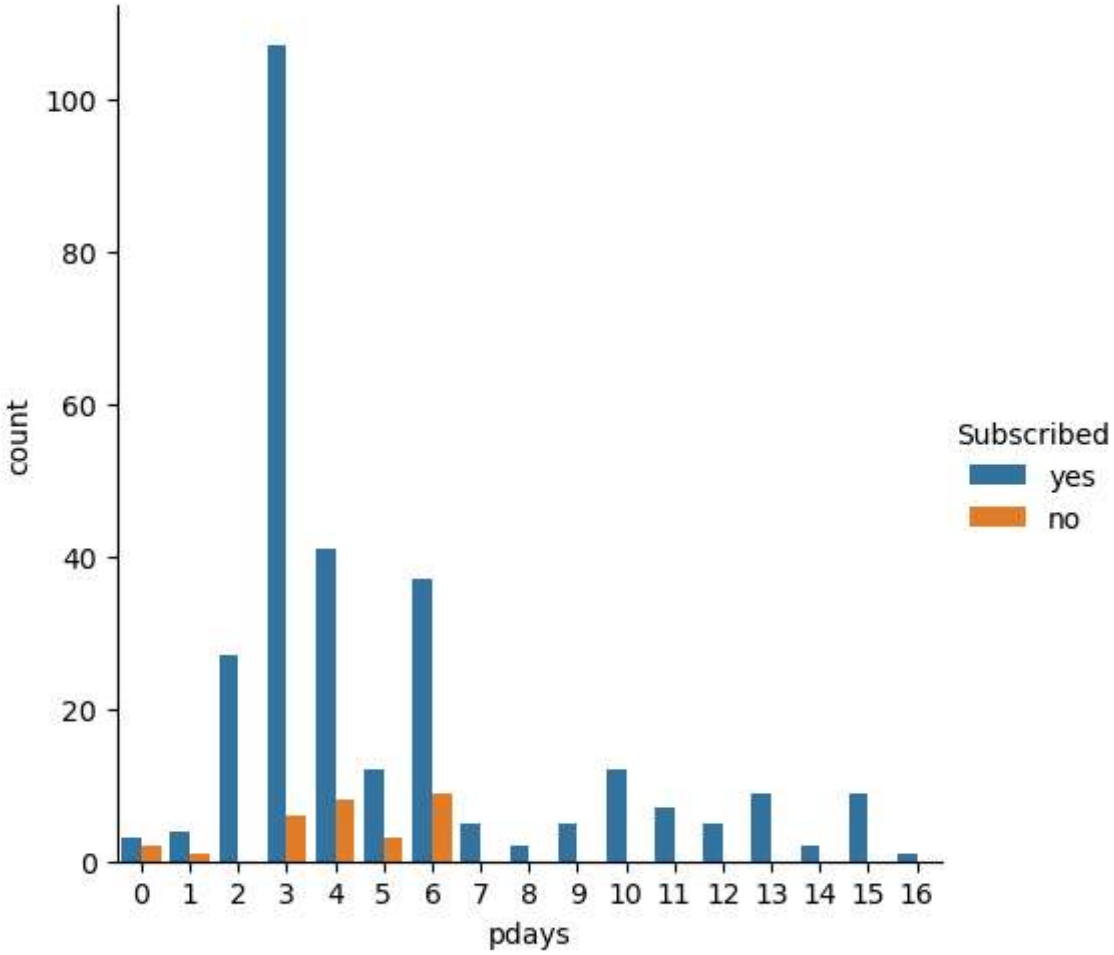
In [20]:
```
plt.figure()
sns.catplot(x='pdays', data=train, kind='count', hue='Subscribed')
plt.figure()
sns.catplot(x='pdays', data=train[train['pdays']!=999], kind='count', hue='Subscribe
```

```
E:\anaconda\Lib\site-packages\seaborn\axisgrid.py:118: UserWarning: The figure lay
out has changed to tight
  self._figure.tight_layout(*args, **kwargs)
E:\anaconda\Lib\site-packages\seaborn\axisgrid.py:118: UserWarning: The figure lay
out has changed to tight
  self._figure.tight_layout(*args, **kwargs)
```

Out[20]:
```
<seaborn.axisgrid.FacetGrid at 0x21655325850>

<Figure size 640x480 with 0 Axes>
```




```
<Figure size 640x480 with 0 Axes>
```

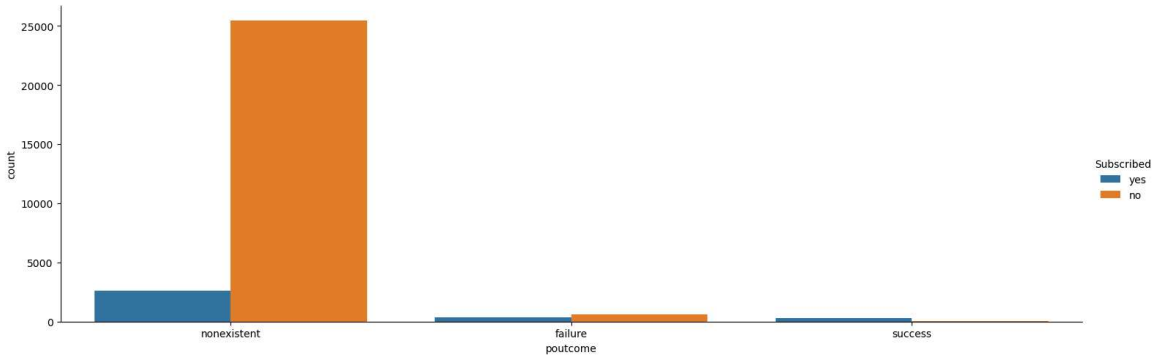

count
100
80
60
40
20
0
0 1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16
pdays
Subscribed
yes
no

In [21]:
```
plt.figure()
sns.catplot(x='poutcome', data=train, kind='count', hue='Subscribed' ,height=5, aspec
plt.figure()
sns.catplot(x='poutcome', data=train[train['poutcome']!='nonexistent'], kind='count',
```

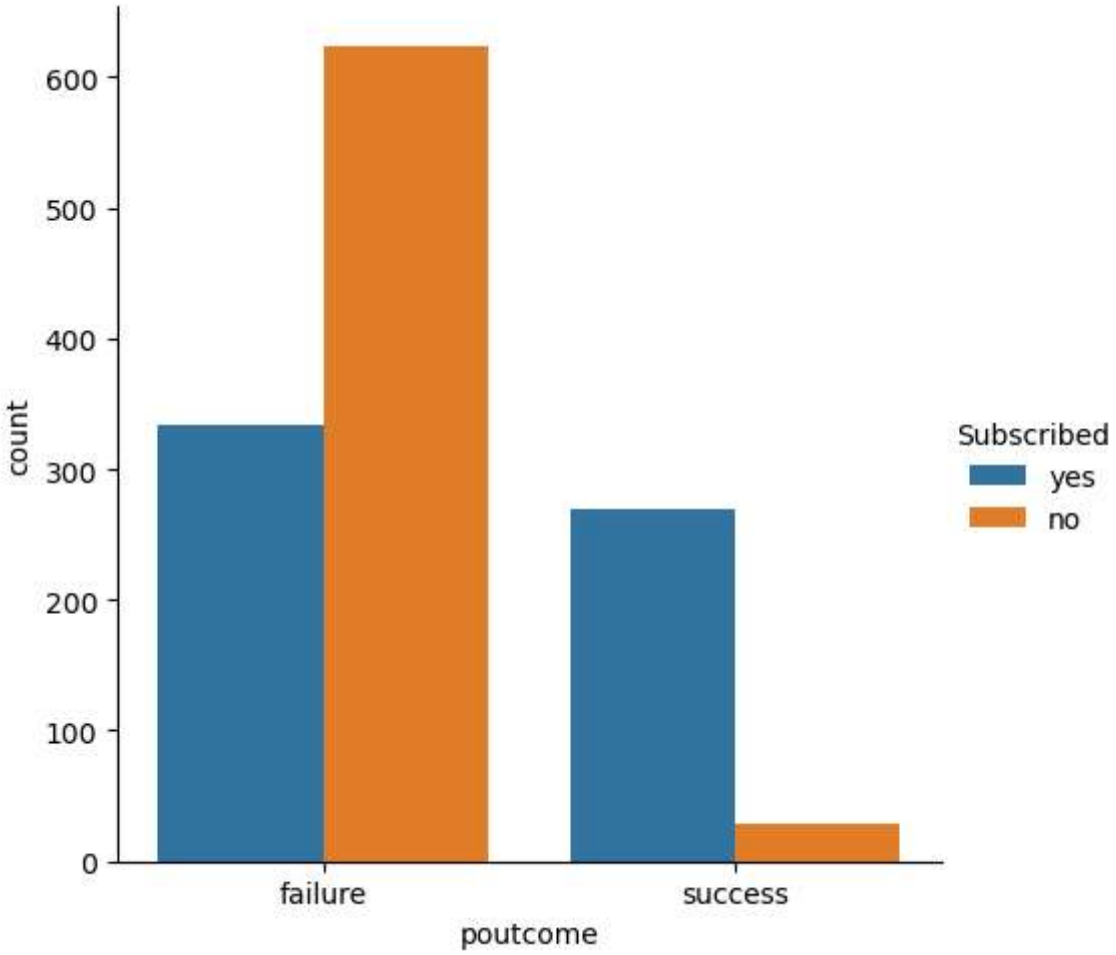
```
E:\anaconda\Lib\site-packages\seaborn\axisgrid.py:118: UserWarning: The figure lay
out has changed to tight
  self._figure.tight_layout(*args, **kwargs)
E:\anaconda\Lib\site-packages\seaborn\axisgrid.py:118: UserWarning: The figure lay
out has changed to tight
  self._figure.tight_layout(*args, **kwargs)
```

Out[21]: <seaborn.axisgrid.FacetGrid at 0x21656b62450>

<Figure size 640x480 with 0 Axes>



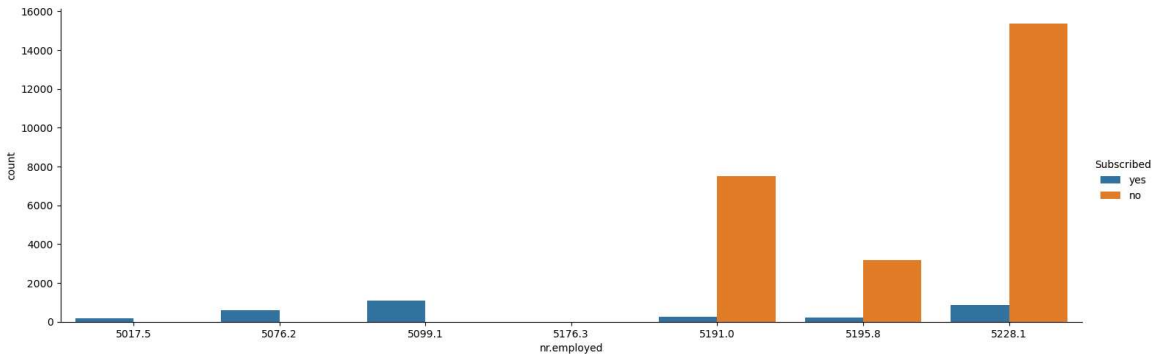
<Figure size 640x480 with 0 Axes>



In [22]:
```
sns.catplot(x='nr.employed', data=train, kind='count', hue='Subscribed' ,height=5, as
```

```
E:\anaconda\Lib\site-packages\seaborn\axisgrid.py:118: UserWarning: The figure lay
out has changed to tight
  self._figure.tight_layout(*args, **kwargs)
```

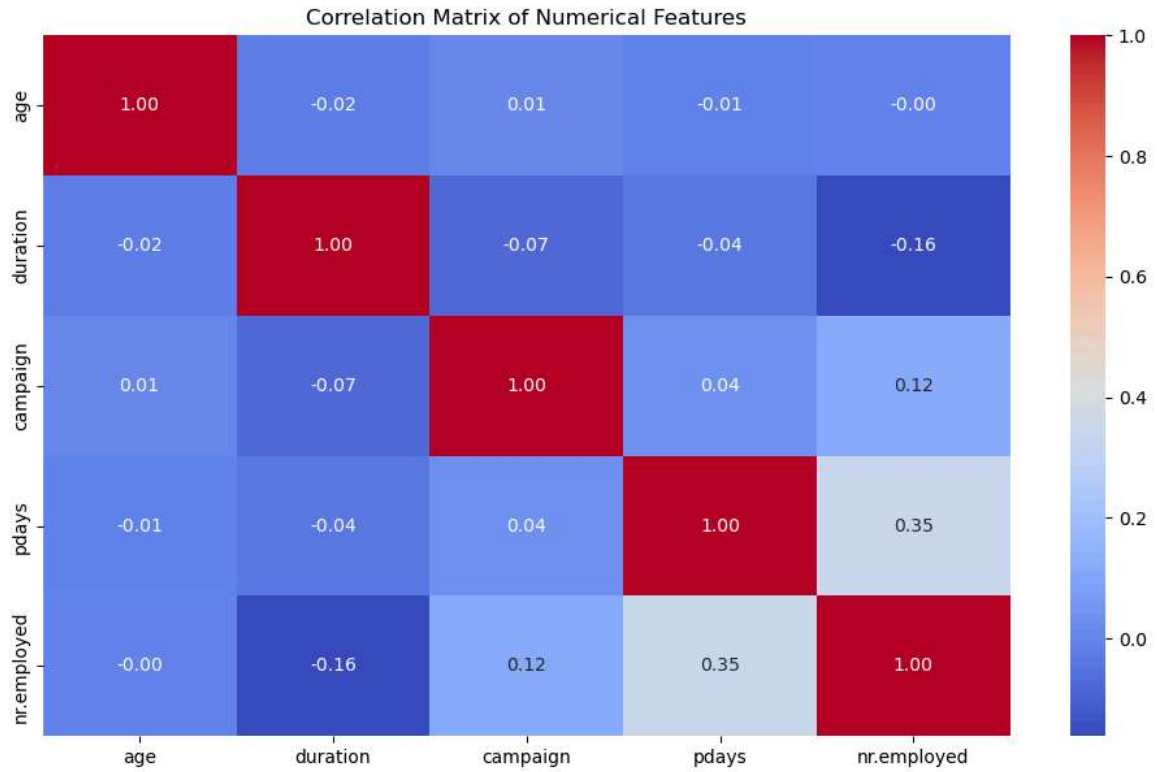
Out[22]: <seaborn.axisgrid.FacetGrid at 0x21656a02510>



Useless--correlation matrix

In [23]:
```
num_features = train.select_dtypes(include=[np.number])
correlation_matrix = num_features.corr()
plt.figure(figsize=(12,7))
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm', fmt=".2f")
plt.title('Correlation Matrix of Numerical Features')
```

Out[23]: Text(0.5, 1.0, 'Correlation Matrix of Numerical Features')



Second part--Preprocessing the data

In [24]:
```
cat_features = train.select_dtypes(include=['object']).columns
train = pd.get_dummies(train, columns=cat_features, drop_first=True)
train.head()
```

Out[24]:

	age	duration	campaign	pdays	nr.employed	job_blue-collar	job_entrepreneur	job_housemaid
0	41	1575	1	999	5191.0	True	False	False
1	49	1042	1	999	5191.0	False	True	False
2	49	1467	1	999	5191.0	False	False	False
3	41	579	1	999	5191.0	False	False	False
4	45	461	1	999	5191.0	True	False	False

5 rows × 47 columns

In [25]:
```
cat_features = test.select_dtypes(include=['object']).columns
test = pd.get_dummies(test, columns=cat_features, drop_first=True)
test.head()
```

Out[25]:

	age	duration	campaign	pdays	nr.employed	job_blue-collar	job_entrepreneur	job_housemaid
0	62	717	2	999	5017.5	False	False	False
1	49	136	2	999	5017.5	False	False	False
2	36	342	1	999	5017.5	False	False	False
3	70	131	1	999	5017.5	False	False	False
4	60	98	1	999	5017.5	False	False	False

5 rows × 47 columns

In [26]:
```
encoded_correlation_matrix = train.corr()
encoded_correlation_matrix.head()
```

Out[26]:

	age	duration	campaign	pdays	nr.employed	job_blue-collar	job_entrepren
age	1.000000	-0.023490	0.011435	-0.010726	-0.004494	-0.006121	0.032
duration	-0.023490	1.000000	-0.074162	-0.038289	-0.161586	0.016979	0.005
campaign	0.011435	-0.074162	1.000000	0.036038	0.123702	-0.004492	-0.005
pdays	-0.010726	-0.038289	0.036038	1.000000	0.351073	0.031841	0.006
nr.employed	-0.004494	-0.161586	0.123702	0.351073	1.000000	0.034969	-0.006

5 rows × 47 columns

In [27]:
```
high_corr = np.where(encoded_correlation_matrix.abs() > 0.75)
high_corr_pairs = [(encoded_correlation_matrix.columns[x], encoded_correlation_matrix
                    for x, y in zip(*high_corr) if x != y and x < y]
high_corr_pairs
```

Out[27]:
```
[('pdays', 'poutcome_success', -0.9710796102201944),
 ('marital_married', 'marital_single', -0.7607539807601534),
 ('housing_unknown', 'loan_unknown', 1.0)]
```

clean unknown value

In [28]:
```
train = train[~train.isin(['unknown']).any(axis=1)]
test = test[~test.isin(['unknown']).any(axis=1)]
```

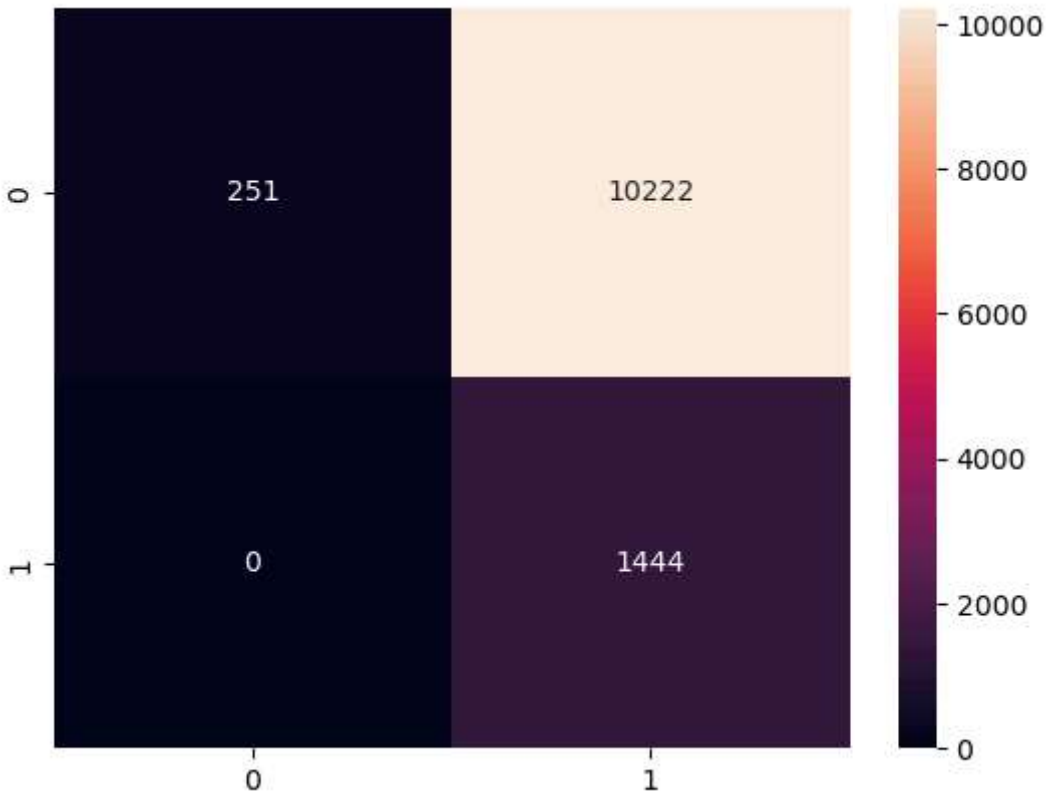
Third part-- using classification model and test

In [29]:
```
X_train = train.drop('Subscribed_yes', axis=1)
y_train = train['Subscribed_yes']

X_test = test.drop('Subscribed_yes', axis=1)
y_test = test['Subscribed_yes']
```

In [31]:
```
Dtc_model = DecisionTreeClassifier()
Dtc_model.fit(X_train, y_train)
Dtc_prediction = Dtc_model.predict(X_test)

print(accuracy_score(y_test, Dtc_prediction))
print(classification_report(y_test, Dtc_prediction))

cm = confusion_matrix(y_test, Dtc_prediction)
sns.heatmap(cm, annot=True, fmt="d")
```

```
0.14223378367038683
              precision    recall  f1-score   support

       False       1.00      0.02      0.05     10473
        True       0.12      1.00      0.22      1444

    accuracy                           0.14     11917
   macro avg       0.56      0.51      0.13     11917
weighted avg       0.89      0.14      0.07     11917
```

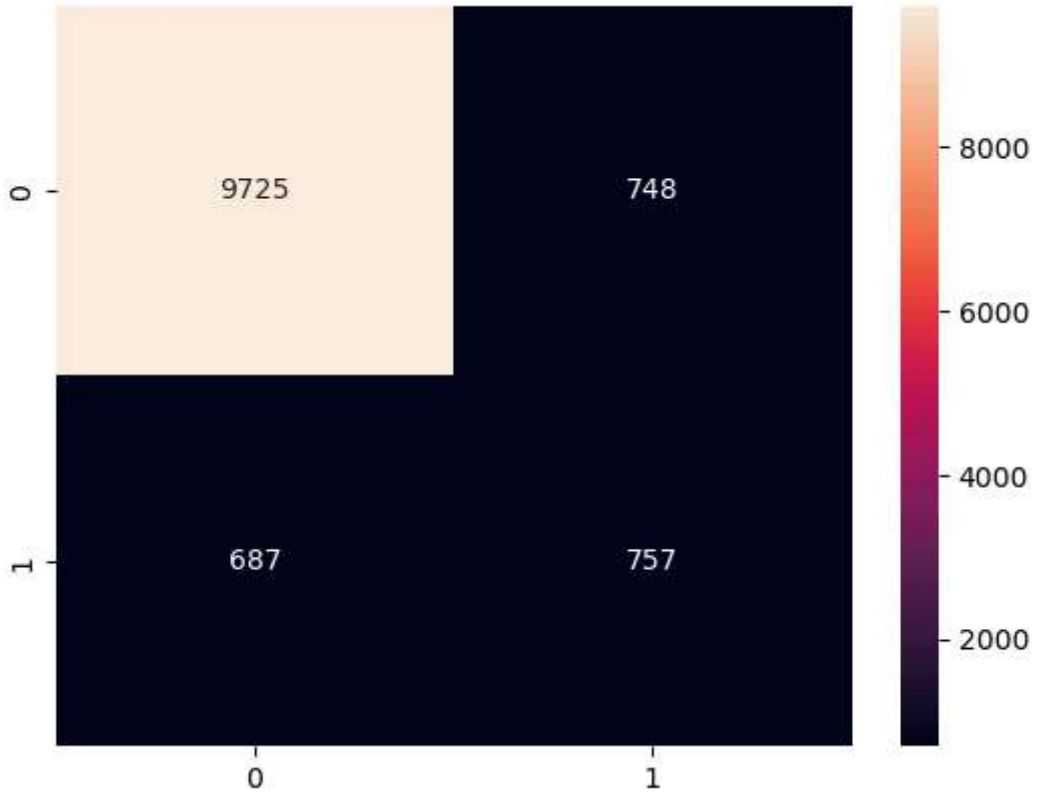
Out[31]: <Axes: >



In [32]:
```
logmodel = LogisticRegression()
logmodel.fit(X_train, y_train)
log_prediction = logmodel.predict(X_test)

print(accuracy_score(y_test, log_prediction))
print(classification_report(y_test, log_prediction))

cm = confusion_matrix(y_test, log_prediction)
sns.heatmap(cm, annot=True, fmt="d")
```

```
0.8795837878660737
              precision    recall  f1-score   support

       False       0.93      0.93      0.93     10473
        True       0.50      0.52      0.51      1444

    accuracy                           0.88     11917
   macro avg       0.72      0.73      0.72     11917
weighted avg       0.88      0.88      0.88     11917


E:\anaconda\Lib\site-packages\sklearn\linear_model\_logistic.py:460: ConvergenceWa
rning: lbfgs failed to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html (https://scikit-lea
rn.org/stable/modules/preprocessing.html)
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-regression
(https://scikit-learn.org/stable/modules/linear_model.html#logistic-regression)
  n_iter_i = _check_optimize_result(
```

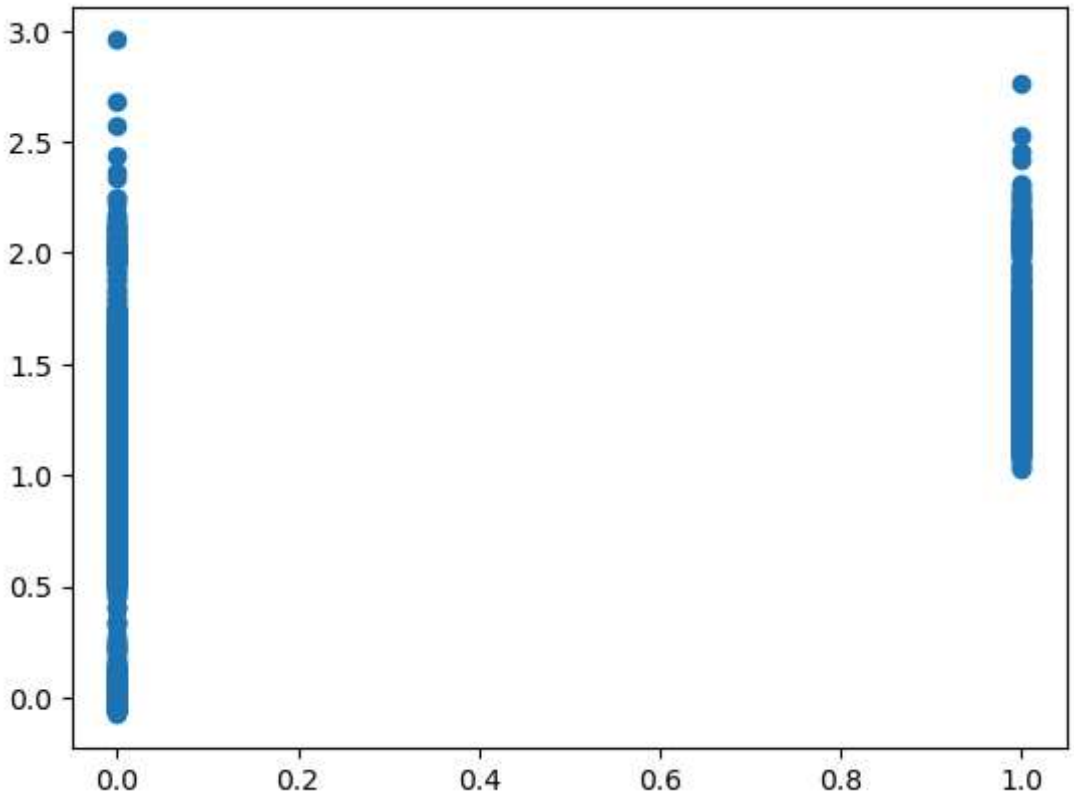
Out[32]: <Axes: >



In [41]:
```
lmodel = LinearRegression()
lmodel.fit(X_train, y_train)
lmodel_prediction = lmodel.predict(X_test)

print('Mean Absolute Error: ', metrics.mean_absolute_error(y_test, lmodel_prediction)
print('Mean Squared Error: ', metrics.mean_squared_error(y_test, lmodel_prediction))
print('Root Mean Squared Error: ', np.sqrt(metrics.mean_squared_error(y_test, lmodel_

plt.scatter(y_test, lmodel_prediction)
```

```
Mean Absolute Error:  0.7917191902144544
Mean Squared Error:  0.737641171816545
Root Mean Squared Error:  0.8588603913422396
```

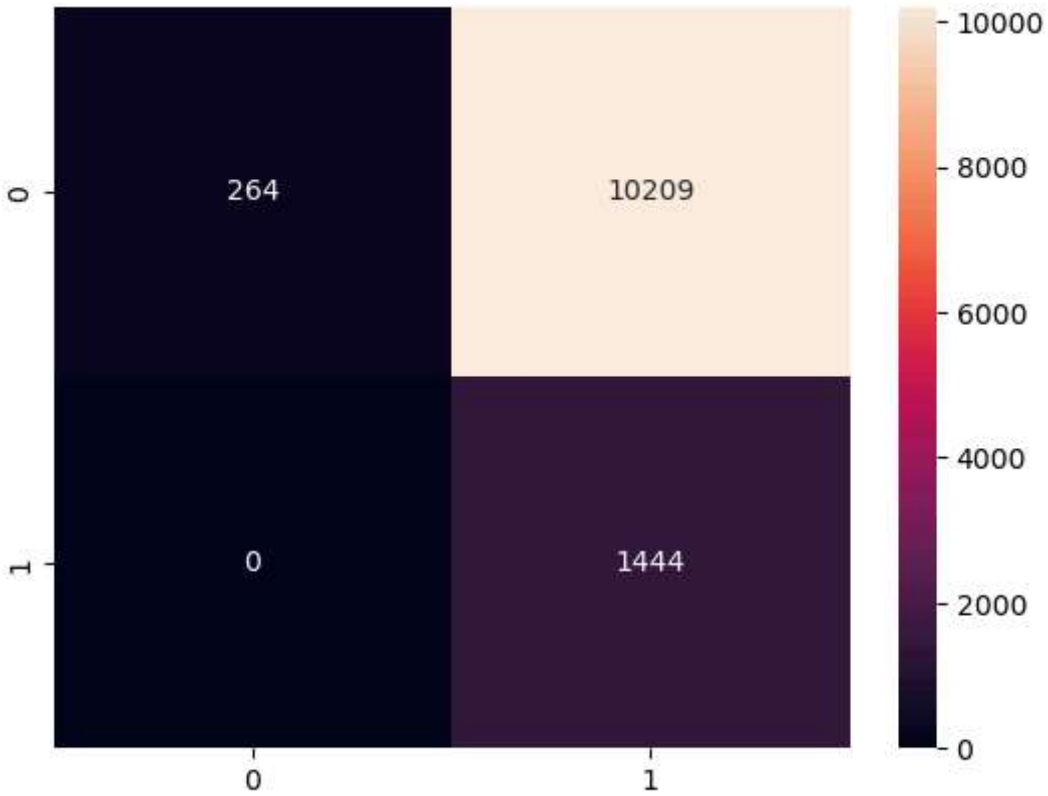
Out[41]: <matplotlib.collections.PathCollection at 0x216598d6990>



In [34]:
```
rfmodel = RandomForestClassifier()
rfmodel.fit(X_train, y_train)
rfmodel_prediction = rfmodel.predict(X_test)

print("Random Forest Accuracy:", accuracy_score(y_test, rfmodel_prediction))
print("Random Forest Classification Report:\n", classification_report(y_test, rfmodel

cm = confusion_matrix(y_test, rfmodel_prediction)
sns.heatmap(cm, annot=True, fmt="d")
```

```
Random Forest Accuracy: 0.14332466224720986
Random Forest Classification Report:
              precision    recall  f1-score   support

       False       1.00      0.03      0.05     10473
        True       0.12      1.00      0.22      1444

    accuracy                           0.14     11917
   macro avg       0.56      0.51      0.13     11917
weighted avg       0.89      0.14      0.07     11917
```

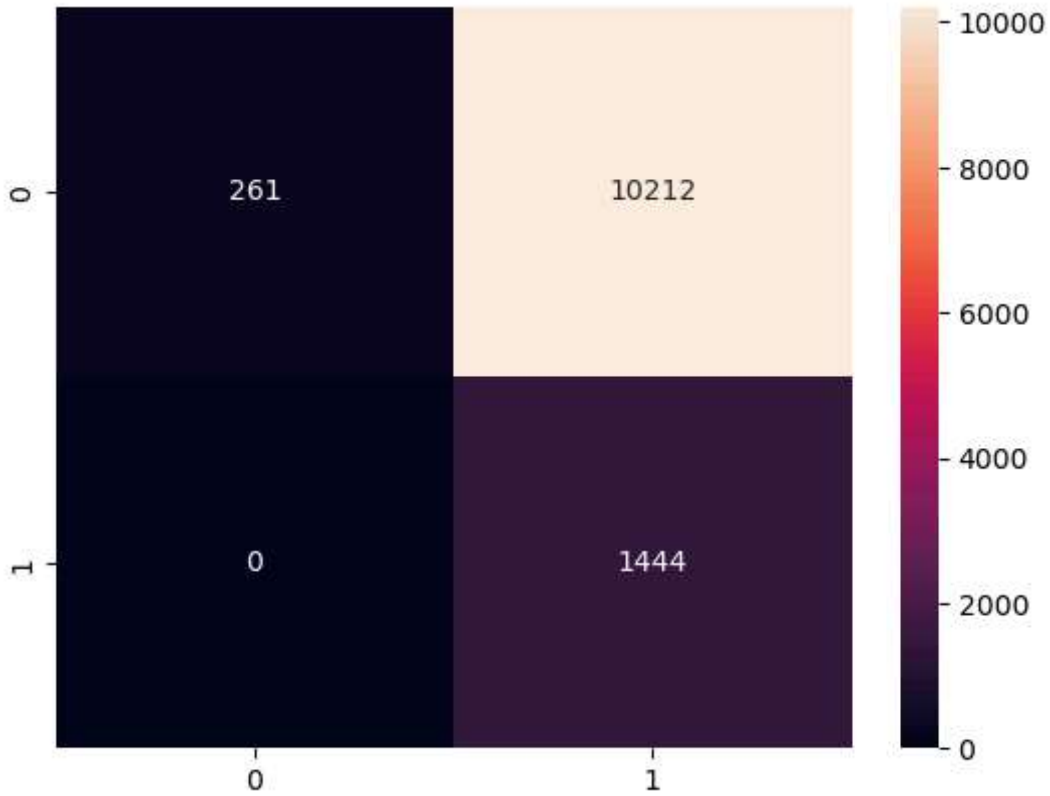
Out[34]: <Axes: >



In [35]:
```
gbm_model = GradientBoostingClassifier()
gbm_model.fit(X_train, y_train)
gbm_model_prediction = gbm_model.predict(X_test)

print("Gradient Boosting Classifier Accuracy:", accuracy_score(y_test, gbm_model_pred
print("Gradient Boosting Classifier Classification Report:\n", classification_report(

cm = confusion_matrix(y_test, gbm_model_prediction)
sns.heatmap(cm, annot=True, fmt="d")
```

```
Gradient Boosting Classifier Accuracy: 0.14307292103717378
Gradient Boosting Classifier Classification Report:
              precision    recall  f1-score   support

       False       1.00      0.02      0.05     10473
        True       0.12      1.00      0.22      1444

    accuracy                           0.14     11917
   macro avg       0.56      0.51      0.13     11917
weighted avg       0.89      0.14      0.07     11917
```

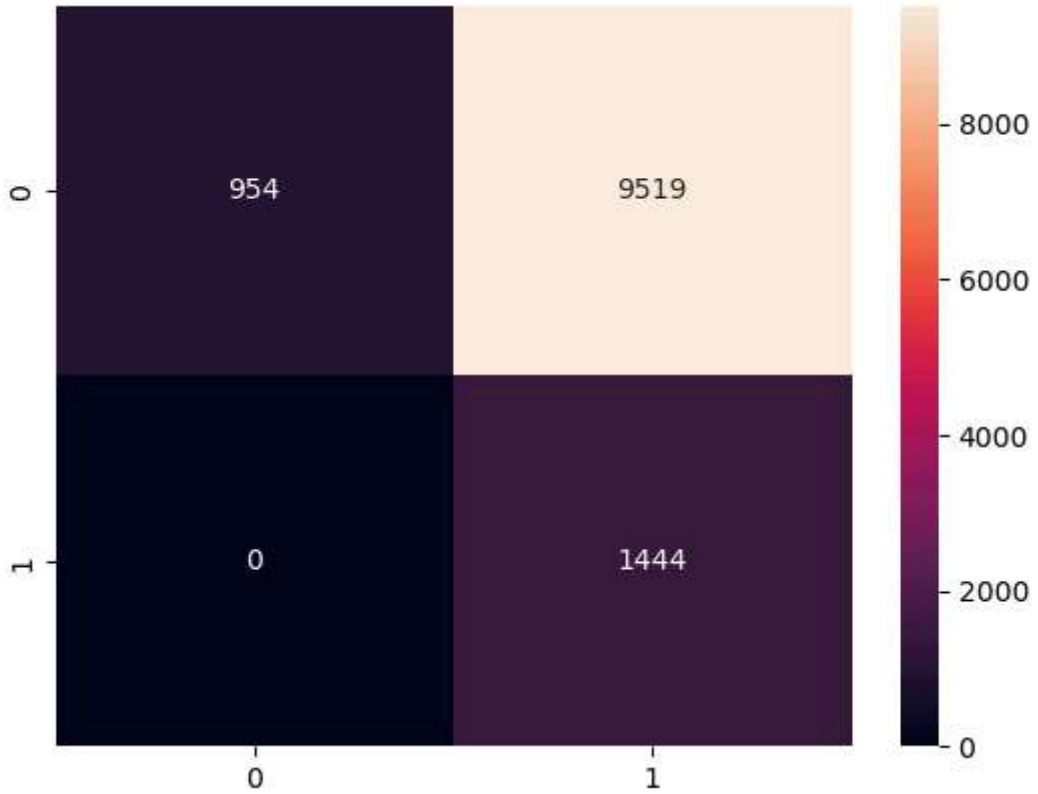
Out[35]: <Axes: >



In [36]:
```
nb_model = GaussianNB()
nb_model.fit(X_train, y_train)
nb_predictions = nb_model.predict(X_test)

print('Naive Bayes Accuracy:', accuracy_score(y_test, nb_predictions))
print('Naive Bayes Classification Report:\n', classification_report(y_test, nb_predic

cm = confusion_matrix(y_test, nb_predictions)
sns.heatmap(cm, annot=True, fmt="d")
```

```
Naive Bayes Accuracy: 0.20122514055550894
Naive Bayes Classification Report:
              precision    recall  f1-score   support

       False       1.00      0.09      0.17     10473
        True       0.13      1.00      0.23      1444

    accuracy                           0.20     11917
   macro avg       0.57      0.55      0.20     11917
weighted avg       0.89      0.20      0.17     11917
```

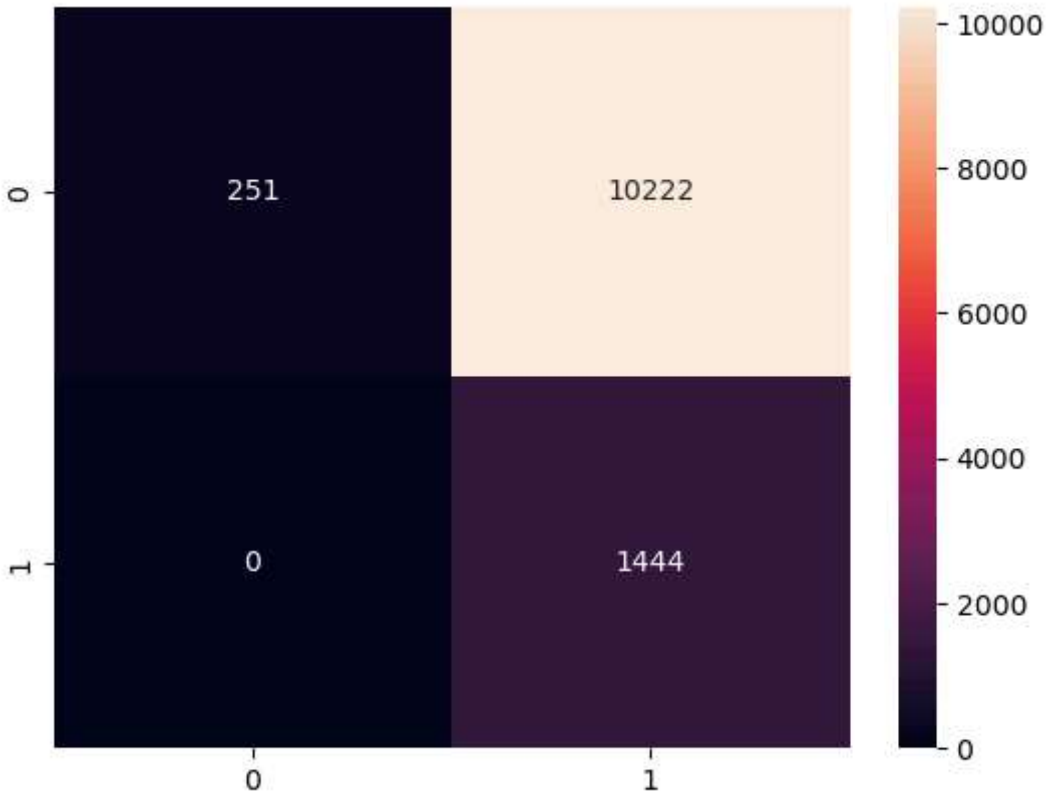
Out[36]: <Axes: >



In [37]:
```
ada_model = AdaBoostClassifier()
ada_model.fit(X_train, y_train)
ada_predictions = ada_model.predict(X_test)

print('AdaBoost Accuracy:', accuracy_score(y_test, ada_predictions))
print('AdaBoost Classification Report:\n', classification_report(y_test, ada_predicti

cm = confusion_matrix(y_test, ada_predictions)
sns.heatmap(cm, annot=True, fmt="d")
```

```
AdaBoost Accuracy: 0.14223378367038683
AdaBoost Classification Report:
              precision    recall  f1-score   support

       False       1.00      0.02      0.05     10473
        True       0.12      1.00      0.22      1444

    accuracy                           0.14     11917
   macro avg       0.56      0.51      0.13     11917
weighted avg       0.89      0.14      0.07     11917
```

Out[37]: <Axes: >



In [38]:
```
svm_model = SVC()
svm_model.fit(X_train, y_train)
svm_predictions = svm_model.predict(X_test)

print('SVM Accuracy:', accuracy_score(y_test, svm_predictions))
print('SVM Classification Report:\n', classification_report(y_test, svm_predictions))

cm = confusion_matrix(y_test, svm_predictions)
sns.heatmap(cm, annot=True, fmt="d")
```

```
SVM Accuracy: 0.6504153729965595
SVM Classification Report:
              precision    recall  f1-score   support

       False       1.00      0.60      0.75     10473
        True       0.26      1.00      0.41      1444

    accuracy                           0.65     11917
   macro avg       0.63      0.80      0.58     11917
weighted avg       0.91      0.65      0.71     11917
```

Out[38]: <Axes: >