In [1]:

```
import numpy as np
import matplotlib.pyplot as plt
import pandas as pd
import seaborn as sns
```

In [2]:

```
df = pd.read_csv('Telco-Customer-Churn.csv')
```

In [3]:

```
df.head()
```

Out[3]:

	customerID	gender	SeniorCitizen	Partner	Dependents	tenure	PhoneService	MultipleLines	InternetService	OnlineSecuri
0	7590-VHVEG	Female	0	Yes	No	1	No	No phone service	DSL	N
1	5575-GNVDE	Male	0	No	No	34	Yes	No	DSL	Y
2	3668-QPYBK	Male	0	No	No	2	Yes	No	DSL	Y
3	7795-CFOCW	Male	0	No	No	45	No	No phone service	DSL	Y
4	9237-HQITU	Female	0	No	No	2	Yes	No	Fiber optic	N

5 rows × 21 columns

In [4]:

```
# Confirm that there are no NaN cells by displaying NaN values per feature column.

df.isna().sum()
```

Out[4]:

```
customerID          0
gender              0
SeniorCitizen       0
Partner             0
Dependents          0
tenure              0
PhoneService        0
MultipleLines       0
InternetService     0
OnlineSecurity      0
OnlineBackup        0
DeviceProtection    0
TechSupport         0
StreamingTV         0
StreamingMovies     0
Contract            0
PaperlessBilling    0
PaymentMethod       0
MonthlyCharges      0
TotalCharges        0
Churn               0
dtype: int64
```

In [5]:

```
#df.dropna()
```

In [6]:

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 7032 entries, 0 to 7031
Data columns (total 21 columns):
 #   Column            Non-Null Count  Dtype  
---  ------            --------------  -----  
 0   customerID        7032 non-null   object 
 1   gender            7032 non-null   object 
 2   SeniorCitizen     7032 non-null   int64  
 3   Partner           7032 non-null   object 
 4   Dependents        7032 non-null   object 
 5   tenure            7032 non-null   int64  
 6   PhoneService      7032 non-null   object 
 7   MultipleLines     7032 non-null   object 
 8   InternetService   7032 non-null   object 
 9   OnlineSecurity    7032 non-null   object 
 10  OnlineBackup      7032 non-null   object 
 11  DeviceProtection  7032 non-null   object 
 12  TechSupport       7032 non-null   object 
 13  StreamingTV       7032 non-null   object 
 14  StreamingMovies   7032 non-null   object 
 15  Contract          7032 non-null   object 
 16  PaperlessBilling  7032 non-null   object 
 17  PaymentMethod     7032 non-null   object 
 18  MonthlyCharges    7032 non-null   float64
 19  TotalCharges      7032 non-null   float64
 20  Churn             7032 non-null   object 
dtypes: float64(2), int64(2), object(17)
memory usage: 1.1+ MB
```

In [7]:

```
df.describe()
```

Out[7]:

	SeniorCitizen	tenure	MonthlyCharges	TotalCharges
count	7032.000000	7032.000000	7032.000000	7032.000000
mean	0.162400	32.421786	64.798208	2283.300441
std	0.368844	24.545260	30.085974	2266.771362
min	0.000000	1.000000	18.250000	18.800000
25%	0.000000	9.000000	35.587500	401.450000
50%	0.000000	29.000000	70.350000	1397.475000
75%	0.000000	55.000000	89.862500	3794.737500
max	1.000000	72.000000	118.750000	8684.800000

In [8]:

```
df['Churn'].value_counts()
```

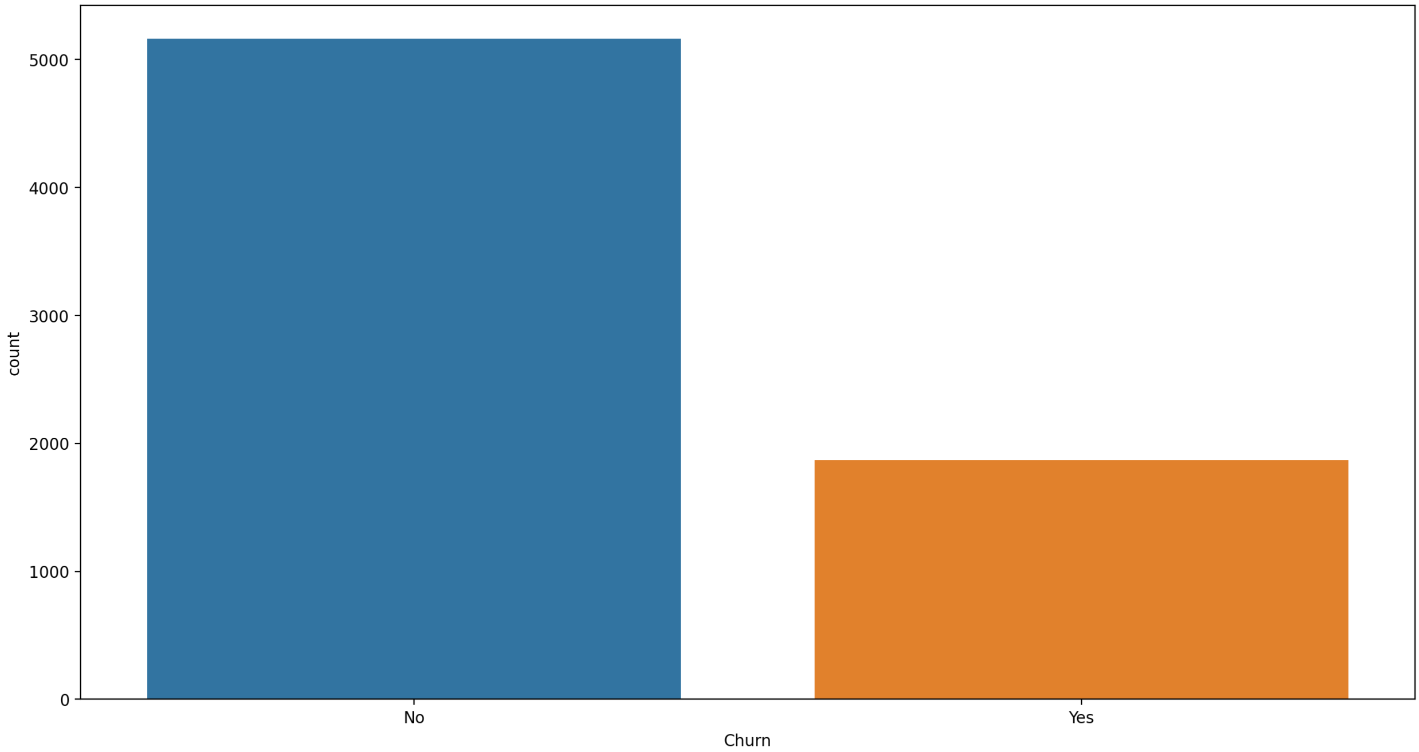
Out[8]:

```
No     5163
Yes    1869
Name: Churn, dtype: int64
```

In [9]:

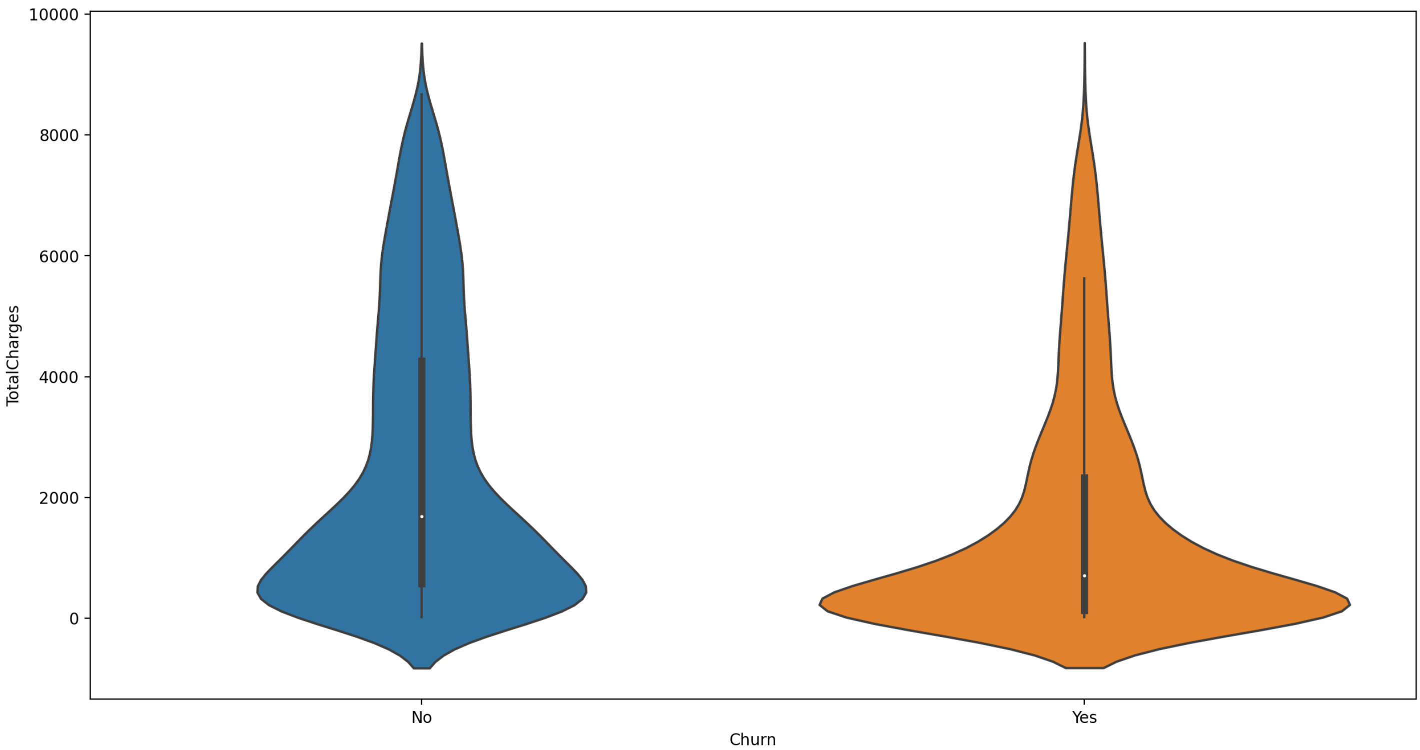
```
plt.figure(figsize =(15,8), dpi = 200)
```

```
sns.countplot(data = df, x = 'Churn')

plt.savefig('fig1.png')
```



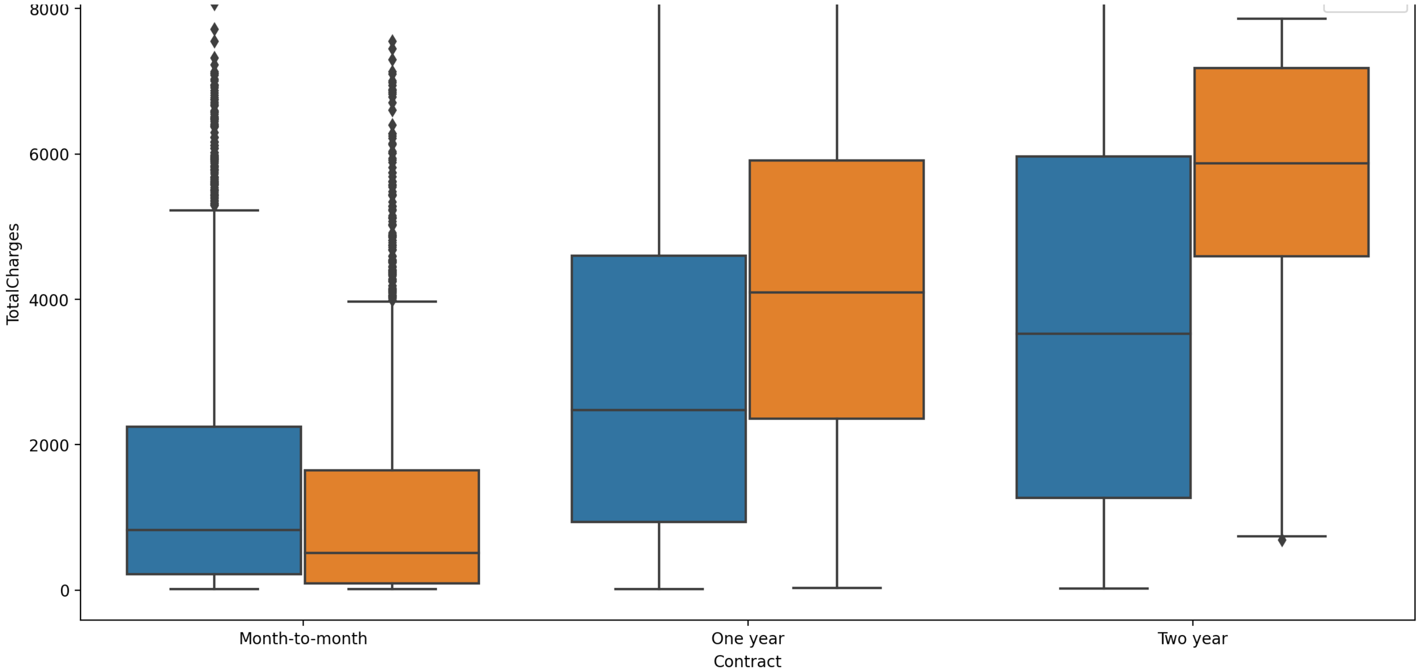
In [10]:

```
plt.figure(figsize =(15,8), dpi = 200)
sns.violinplot(data = df, x = 'Churn' , y = 'TotalCharges')

plt.savefig('fig2.png')
```



In [11]:

```
plt.figure(figsize =(15,8), dpi = 200)
sns.boxplot(data = df, y = 'TotalCharges', x = 'Contract', hue = 'Churn')

plt.savefig('fig3.png')
```



In [12]:

```
df.columns
```

Out[12]:

```
Index(['customerID', 'gender', 'SeniorCitizen', 'Partner', 'Dependents',
       'tenure', 'PhoneService', 'MultipleLines', 'InternetService',
       'OnlineSecurity', 'OnlineBackup', 'DeviceProtection', 'TechSupport',
       'StreamingTV', 'StreamingMovies', 'Contract', 'PaperlessBilling',
       'PaymentMethod', 'MonthlyCharges', 'TotalCharges', 'Churn'],
      dtype='object')
```

In [13]:

```
corr_df = pd.get_dummies(df[['customerID', 'gender', 'SeniorCitizen', 'Partner', 'Depend
ents',
        'tenure', 'PhoneService', 'MultipleLines', 'InternetService',
        'OnlineSecurity', 'OnlineBackup', 'DeviceProtection', 'TechSupport',
        'StreamingTV', 'StreamingMovies', 'Contract', 'PaperlessBilling',
        'PaymentMethod', 'MonthlyCharges', 'TotalCharges', 'Churn']]).corr()
```

In [14]:

```
corr_df
```

Out[14]:

	SeniorCitizen	tenure	MonthlyCharges	TotalCharges	customerID_0002-ORFBO	customerID_0003-MKNFE	cus
SeniorCitizen	1.000000	0.015683	0.219874	0.102411	-0.005251	-0.005251	
tenure	0.015683	1.000000	0.246862	0.825880	-0.011381	-0.011381	
MonthlyCharges	0.219874	0.246862	1.000000	0.651065	0.000318	-0.001942	
TotalCharges	0.102411	0.825880	0.651065	1.000000	-0.008892	-0.009160	
customerID_0002-ORFBO	-0.005251	-0.011381	0.000318	-0.008892	1.000000	-0.000142	
...	...	...	...	...	...	...	
PaymentMethod_Credit card (automatic)	-0.024359	0.232800	0.030055	0.182663	-0.006265	-0.006265	
PaymentMethod_Electronic check	0.171322	-0.210197	0.271117	-0.060436	-0.008490	-0.008490	
PaymentMethod_Mailed check	-0.152987	-0.232181	-0.376568	-0.294708	0.021939	0.021939	

	SeniorCitizen	tenure	MonthlyCharges	TotalCharges	customerID_0002-ORFBO	customerID_0003-MKNFE	cus
Churn_No	-0.150541	0.354049	-0.192858	0.199484	0.007175	0.007175	
Churn_Yes	0.150541	-0.354049	0.192858	-0.199484	-0.007175	-0.007175	

7079 rows × 7079 columns

In [15]:

```
corr_df['Churn_Yes'].sort_values()
```

Out[15]:

```
Churn_No                                -1.000000
tenure                                  -0.354049
Contract_Two year                       -0.301552
StreamingMovies_No internet service     -0.227578
StreamingTV_No internet service         -0.227578
                                           ...
InternetService_Fiber optic              0.307463
TechSupport_No                           0.336877
OnlineSecurity_No                        0.342235
Contract_Month-to-month                  0.404565
Churn_Yes                                1.000000
Name: Churn_Yes, Length: 7079, dtype: float64
```

In [16]:

```
corr_df['Churn_Yes'].sort_values().iloc[1:-1]
```

Out[16]:

```
tenure                                  -0.354049
Contract_Two year                       -0.301552
StreamingMovies_No internet service     -0.227578
StreamingTV_No internet service         -0.227578
InternetService_No                      -0.227578
                                           ...
PaymentMethod_Electronic check           0.301455
InternetService_Fiber optic              0.307463
TechSupport_No                           0.336877
OnlineSecurity_No                        0.342235
Contract_Month-to-month                  0.404565
Name: Churn_Yes, Length: 7077, dtype: float64
```

Churn Analysis

Now we focus on segmentating customers based on their tenure, creating 'cohorts', allowing us to examine differene between customer cohort segments

In [17]:

```
df['tenure'].unique()
```

Out[17]:

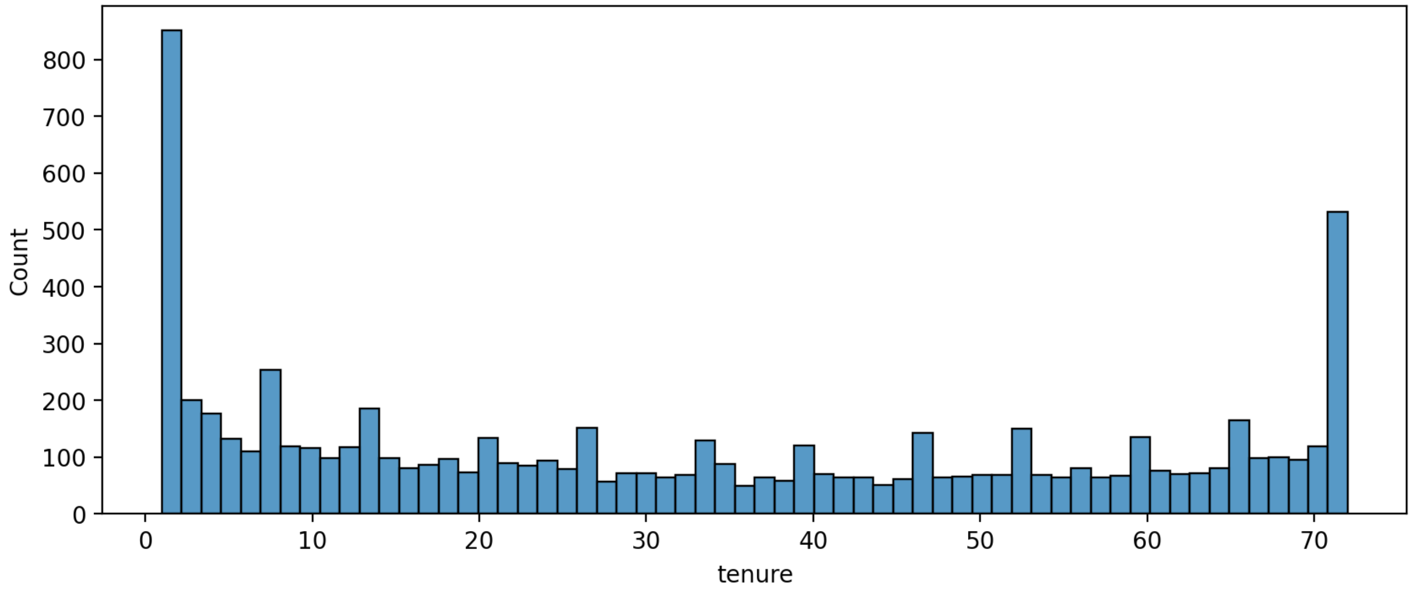
```
array([ 1, 34,  2, 45,  8, 22, 10, 28, 62, 13, 16, 58, 49, 25, 69, 52, 71,
       21, 12, 30, 47, 72, 17, 27,  5, 46, 11, 70, 63, 43, 15, 60, 18, 66,
        9,  3, 31, 50, 64, 56,  7, 42, 35, 48, 29, 65, 38, 68, 32, 55, 37,
       36, 41,  6,  4, 33, 67, 23, 57, 61, 14, 20, 53, 40, 59, 24, 44, 19,
       54, 51, 26, 39])
```

Create a histogram displaying the distribution of 'tenure' column, which is the amount of months a customer was or has been on a customer.

In [18]:

```
plt.figure(figsize=(10,4),dpi=200)
```

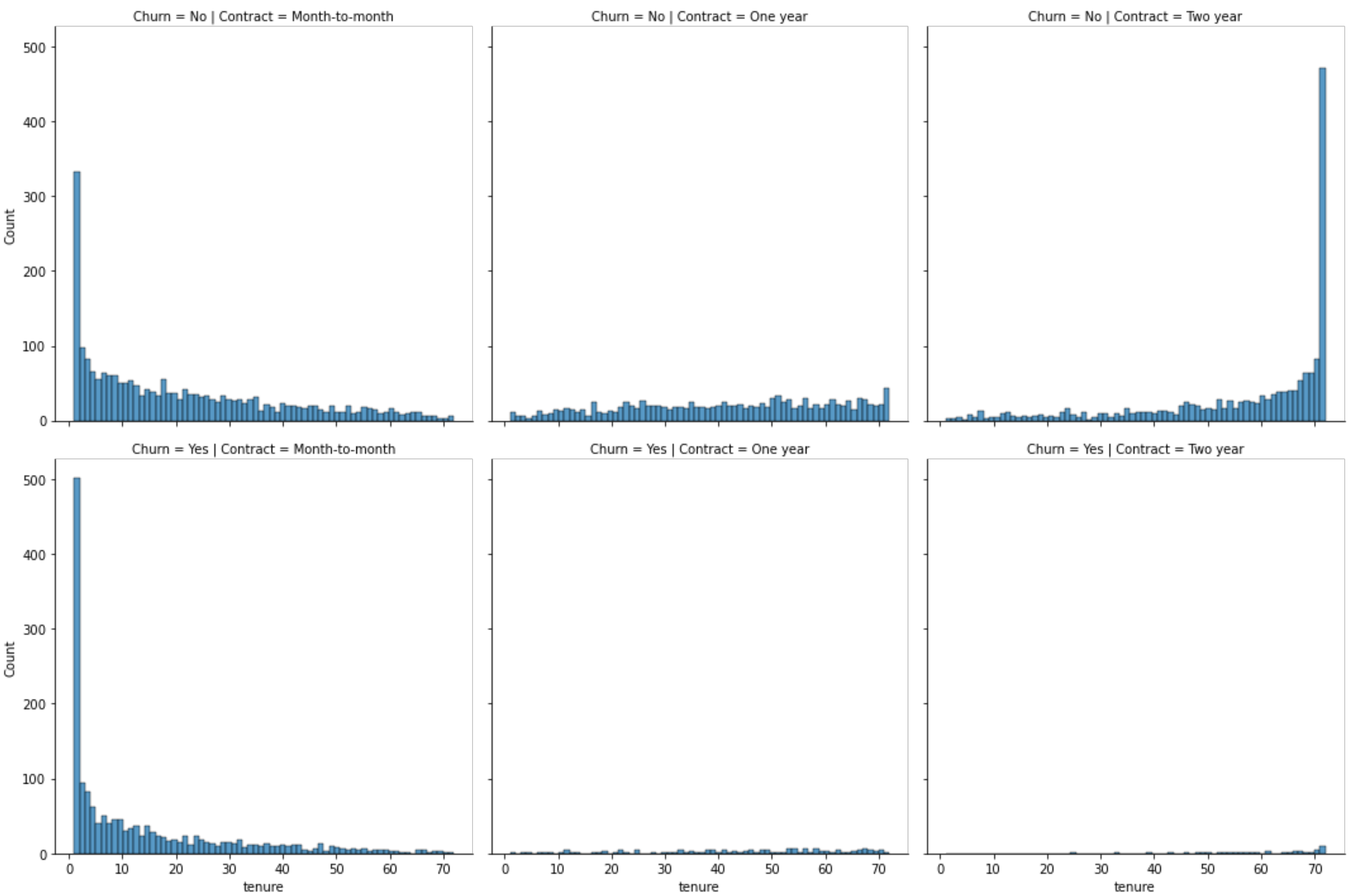
```
sns.histplot(data=df,x='tenure',bins=60)

plt.savefig('fig4.png')
```



In [19]:

```
plt.figure(figsize=(10,3),dpi=200)
sns.displot(data=df,x='tenure',bins=70,col='Contract',row='Churn');
plt.savefig('fig5.png')
```

<Figure size 2000x600 with 0 Axes>

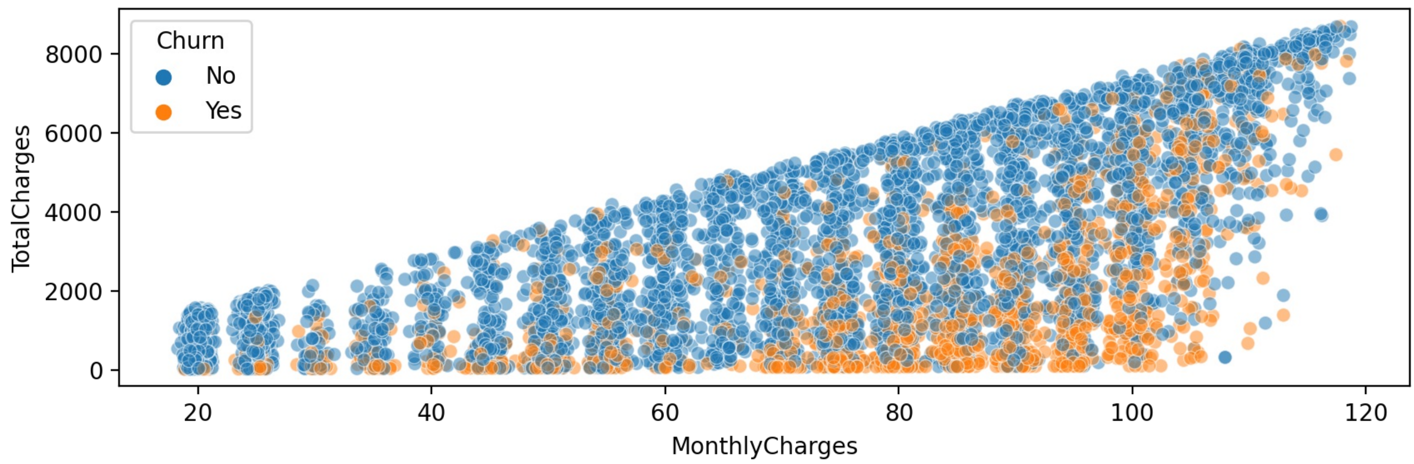


Display a scatter plot of Total Charges versus Monthly Charges, and color hue by Churn.

In [22]:

```
plt.figure(figsize=(10,3),dpi=200)
```

```
sns.scatterplot(data = df, x = 'MonthlyCharges', y = 'TotalCharges', hue = 'Churn',
                linewidth=0.5,alpha=0.5)
plt.savefig('fig6.png')
```



Creating Cohorts based on Tenure

Let's begin by treating each unique tenure length, 1 month, 2 month, 3 month...N months as its own cohort.

In [36]:

```
yes_churn =  df.groupby(['Churn' , 'tenure']).count().transpose()['Yes']
no_churn = df.groupby(['Churn','tenure']).count().transpose()['No']
```

In [37]:

```
churn_rate = 100 * yes_churn / (no_churn+yes_churn)
```

In [39]:

```
churn_rate.transpose()
```

Out[39]:

	customerID	gender	SeniorCitizen	Partner	Dependents	PhoneService	MultipleLines	InternetService	OnlineSec
tenure									
1	61.990212	61.990212	61.990212	61.990212	61.990212	61.990212	61.990212	61.990212	61.99
2	51.680672	51.680672	51.680672	51.680672	51.680672	51.680672	51.680672	51.680672	51.68
3	47.000000	47.000000	47.000000	47.000000	47.000000	47.000000	47.000000	47.000000	47.00
4	47.159091	47.159091	47.159091	47.159091	47.159091	47.159091	47.159091	47.159091	47.15
5	48.120301	48.120301	48.120301	48.120301	48.120301	48.120301	48.120301	48.120301	48.12
...	...	...	...	...	...	...	...	...	
68	9.000000	9.000000	9.000000	9.000000	9.000000	9.000000	9.000000	9.000000	9.00
69	8.421053	8.421053	8.421053	8.421053	8.421053	8.421053	8.421053	8.421053	8.42
70	9.243697	9.243697	9.243697	9.243697	9.243697	9.243697	9.243697	9.243697	9.24
71	3.529412	3.529412	3.529412	3.529412	3.529412	3.529412	3.529412	3.529412	3.52
72	1.657459	1.657459	1.657459	1.657459	1.657459	1.657459	1.657459	1.657459	1.65

72 rows × 19 columns

In [42]:

```
##churn_rate.transpose()['customerID'].plot()
```

In [43]:

```
df['tenure']
```

Out[43]:

```
0        1
1       34
2        2
3       45
4        2
        ..
7027    24
7028    72
7029    11
7030     4
7031    66
Name: tenure, Length: 7032, dtype: int64
```

Based on the tenure column values, create a new column called Tenure Cohort that creates 4 separate categories:

'0-12 Months'

'24-48 Months'

'12-24 Months'

'Over 48 Months'

In [49]:

```
def cohort(tenure):
    if tenure < 13:
        return '0-12 Months'
    elif tenure < 25:
        return '12-24 Months'
    elif tenure < 49:
        return '24-48 Months'
    else:
        return "Over 48 Months"
```

In [51]:

```
cohort(17)
```

Out[51]:

```
'12-24 Months'
```

In [53]:

```
df ['Tenure Cohort'] = df['tenure'].apply(cohort)
```

In [55]:

```
df.head(10)[['tenure','Tenure Cohort']]
```

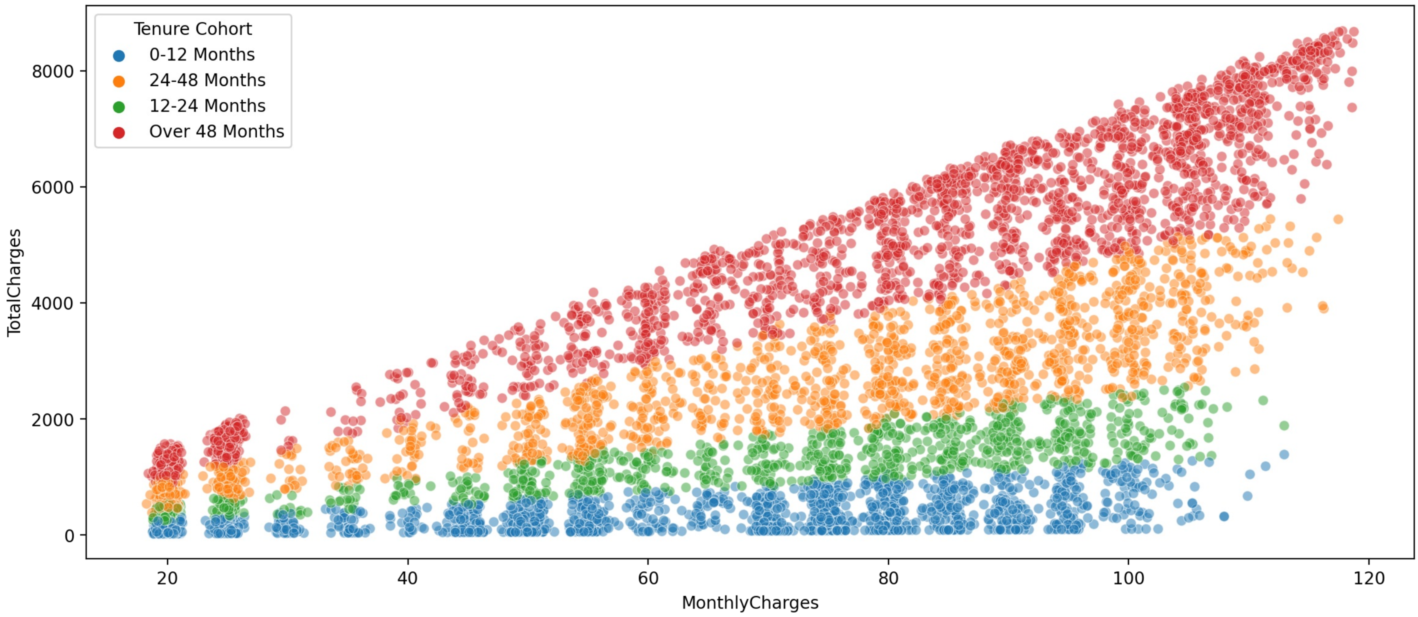
Out[55]:

	tenure	Tenure Cohort
0	1	0-12 Months
1	34	24-48 Months
2	2	0-12 Months

	tenure	Tenure Cohort
3	45	24-48 Months
4	2	0-12 Months
5	8	0-12 Months
6	22	12-24 Months
7	10	0-12 Months
8	28	24-48 Months
9	62	Over 48 Months

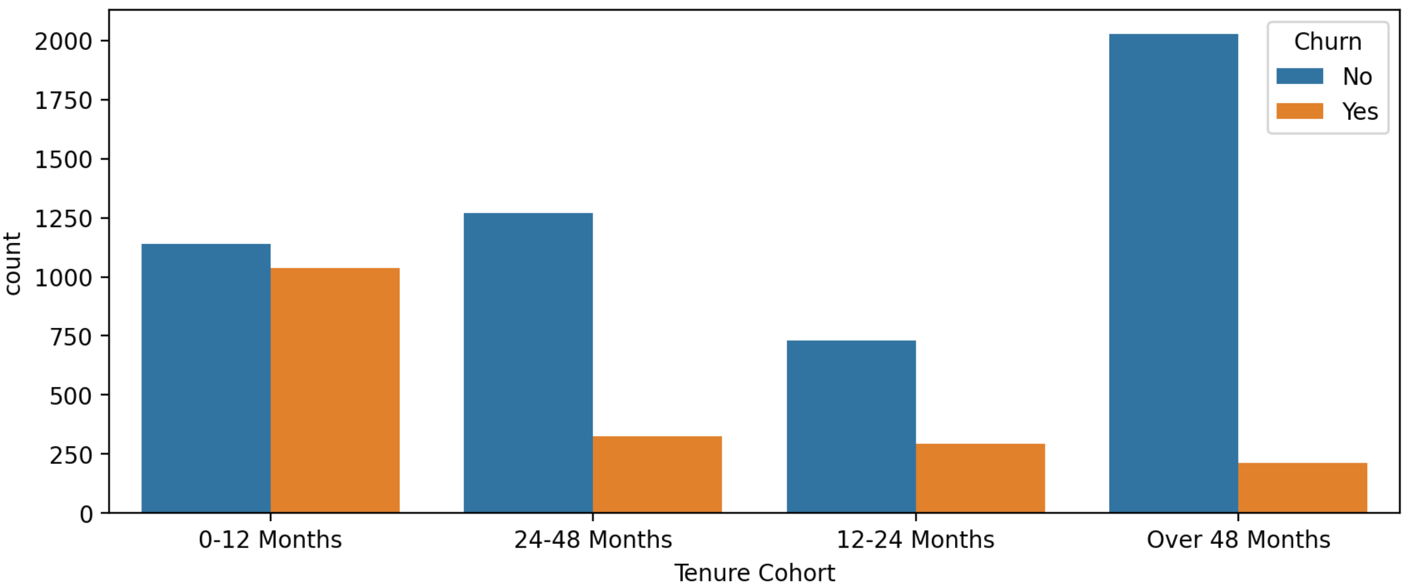
In [64]:

```
## Now create a scatter plot between monthly charge and total charge
plt.figure(figsize=(14,6), dpi = 200)
sns.scatterplot(data = df, x = 'MonthlyCharges', y = 'TotalCharges', hue = 'Tenure Cohor
t',
                linewidth = 0.5, alpha = 0.5)

plt.savefig('fig7.png')
```



In [65]:

```
## Create a count plot the churn count per cohort
plt.figure(figsize=(10,4),dpi=200)
sns.countplot(data=df,x='Tenure Cohort',hue='Churn')

plt.savefig('fig8.png')
```



Now Lets discuss our Predictive Modeling

Let's explore 4 different tree based methods: A Single Decision Tree, Random Forest, AdaBoost, Gradient Boosting.

In [70]:

```
df.head(10)
```

Out[70]:

	customerID	gender	SeniorCitizen	Partner	Dependents	tenure	PhoneService	MultipleLines	InternetService	OnlineSecuri
0	7590-VHVEG	Female	0	Yes	No	1	No	No phone service	DSL	N
1	5575-GNVDE	Male	0	No	No	34	Yes	No	DSL	Y
2	3668-QPYBK	Male	0	No	No	2	Yes	No	DSL	Y
3	7795-CFOCW	Male	0	No	No	45	No	No phone service	DSL	Y
4	9237-HQITU	Female	0	No	No	2	Yes	No	Fiber optic	N
5	9305-CDSKC	Female	0	No	No	8	Yes	Yes	Fiber optic	N
6	1452-KIOVK	Male	0	No	Yes	22	Yes	Yes	Fiber optic	N
7	6713-OKOMC	Female	0	No	No	10	No	No phone service	DSL	Y
8	7892-POOKP	Female	0	Yes	No	28	Yes	Yes	Fiber optic	N
9	6388-TABGU	Male	0	No	Yes	62	Yes	No	DSL	Y

10 rows × 22 columns

In [72]:

```
X = df.drop(['Churn' , 'customerID'],axis= 1)
```

In [73]:

```
X = pd.get_dummies(X,drop_first=True)
```

In [74]:

```
y = df['Churn']
```

In [75]:

```
from sklearn.model_selection import train_test_split
```

In [76]:

```
X_train, X_test, y_train,y_test = train_test_split(X,y,test_size = 0.1, random_state = 1
01)
```

In [77]:

```
## Decision Tree Perfomance
from sklearn.tree import DecisionTreeClassifier
```

In [78]:

```
dt = DecisionTreeClassifier(max_depth = 8)
```

In [79]:

```
dt.fit(X_train,y_train)
```

Out[79]:

```
DecisionTreeClassifier(max_depth=8)
```

In [80]:

```
pred = dt.predict(X_test)
```

In [82]:

```
from sklearn.metrics import plot_confusion_matrix,classification_report
```

In [84]:

```
print(classification_report(y_test,pred))
```

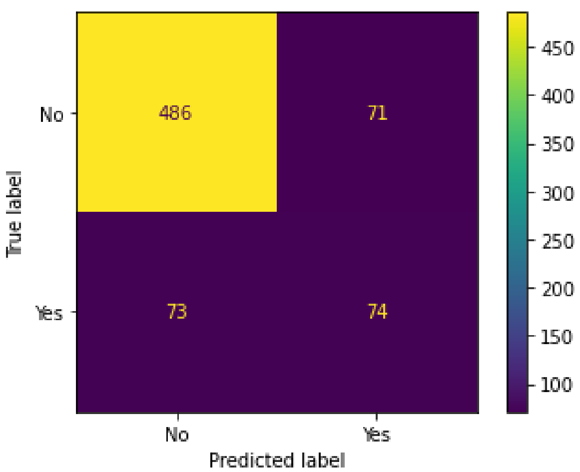
```
              precision    recall  f1-score   support

          No       0.87      0.87      0.87       557
         Yes       0.51      0.50      0.51       147

    accuracy                           0.80       704
   macro avg       0.69      0.69      0.69       704
weighted avg       0.79      0.80      0.79       704
```

In [85]:

```
plot_confusion_matrix(dt,X_test,y_test)
```

Out[85]:

```
<sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay at 0x7fe6ad830d00>
```

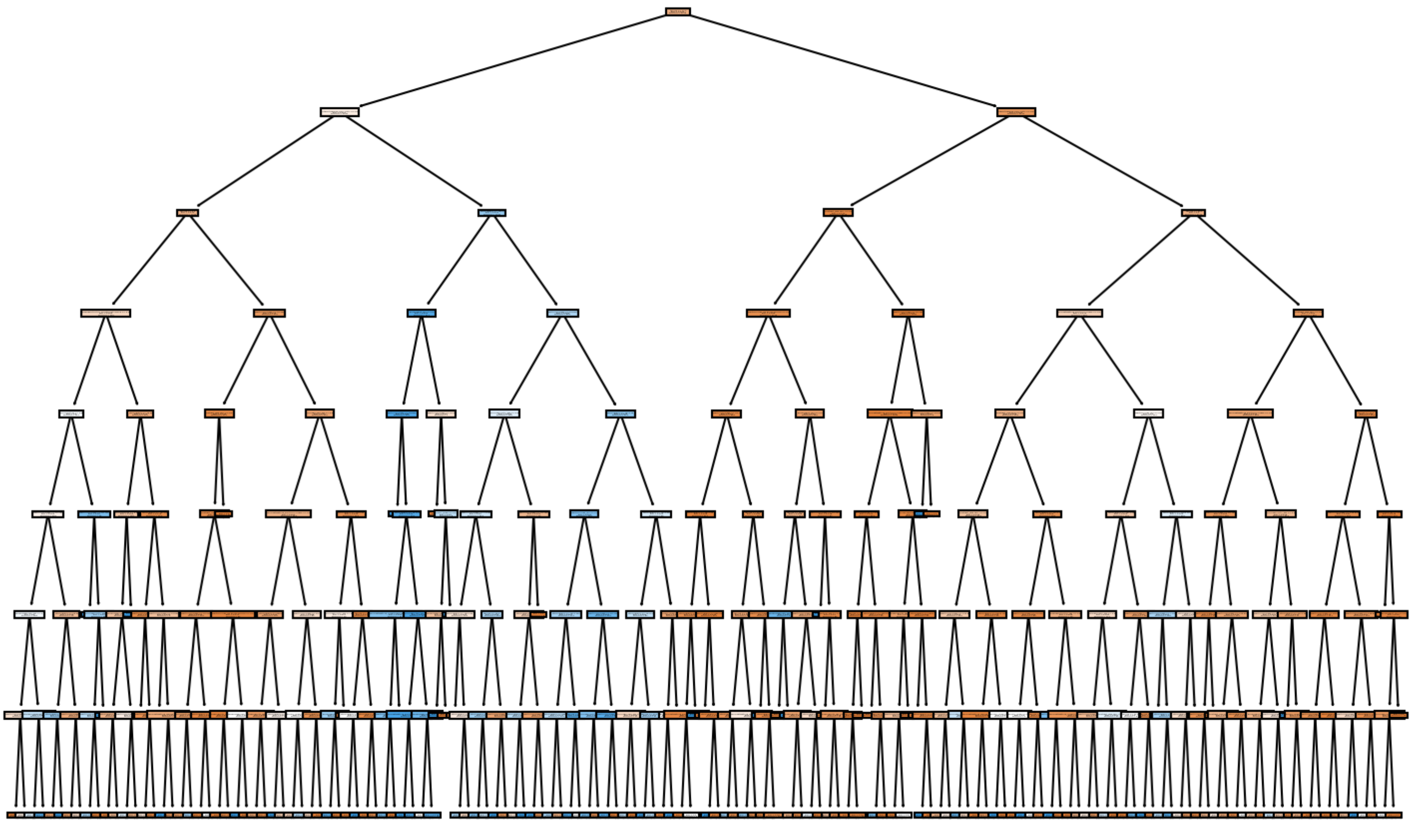


In [86]:

```
from sklearn.tree import plot_tree
```

In [88]:

```
plt.figure(figsize=(12,8),dpi=150)
plot_tree(dt,filled=True,feature_names=X.columns)

plt.savefig('fig9.png')
```



Random Forest

Now determine aRandom Forest model and create a classification report and confusion matrix from its predicted results on the test set.**

In [89]:

```
from sklearn.ensemble import RandomForestClassifier
```

In [95]:

```
rf = RandomForestClassifier(n_estimators= 100, max_depth=8)
```

In [96]:

```
rf.fit(X_train,y_train)
```

Out[96]:

```
RandomForestClassifier(max_depth=8)
```

In [97]:

```
predts = rf.predict(X_test)
```

In [98]:

```
print(classification_report(y_test,predts))
```

```
              precision    recall  f1-score   support

          No       0.87      0.92      0.89       557
```

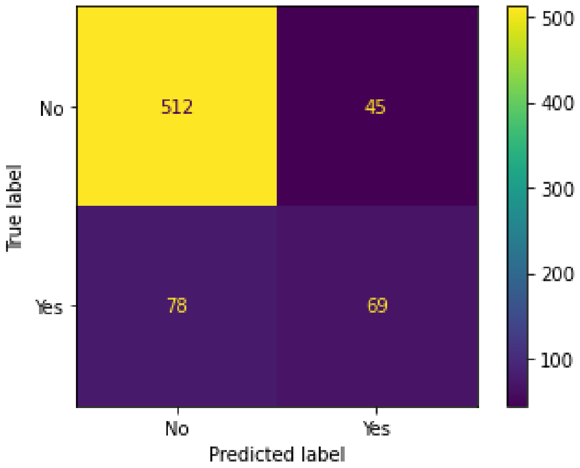
```
         Yes       0.61      0.47      0.53       147

    accuracy                           0.83       704
   macro avg       0.74      0.69      0.71       704
weighted avg       0.81      0.83      0.82       704
```

In [112]:

```
plot_confusion_matrix(rf,X_test,y_test)
```

Out[112]:

```
<sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay at 0x7fe6b1844790>
```



Boosted Trees

We are trying Ada Boost and gredient Boost to create a model and report back the classification report and plot a confusion matrix for its predicted results

In [114]:

```
from sklearn.ensemble import GradientBoostingClassifier,AdaBoostClassifier
```

In [115]:

```
ada_model = AdaBoostClassifier()
```

In [116]:

```
gb_model = GradientBoostingClassifier()
```

In [117]:

```
ada_model.fit(X_train,y_train)
```

Out[117]:

```
AdaBoostClassifier()
```

In [118]:

```
gb_model.fit(X_train,y_train)
```

Out[118]:

```
GradientBoostingClassifier()
```

In [119]:

```
ada_preds = ada_model.predict(X_test)
```

In [120]:

```python
gb_preds = gb_model.predict(X_test)
```

In [121]:

```python
print(classification_report(y_test,ada_preds))
```

```
              precision    recall  f1-score   support

          No       0.88      0.90      0.89       557
         Yes       0.60      0.54      0.57       147

    accuracy                           0.83       704
   macro avg       0.74      0.72      0.73       704
weighted avg       0.82      0.83      0.83       704
```

In [122]:

```python
print(classification_report(y_test,gb_preds))
```

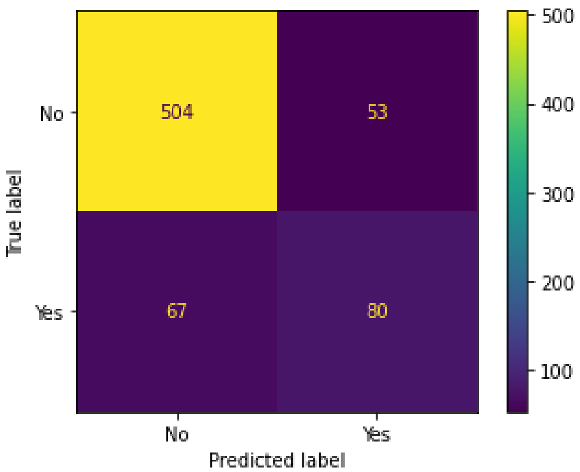
```
              precision    recall  f1-score   support

          No       0.87      0.90      0.89       557
         Yes       0.57      0.50      0.53       147

    accuracy                           0.82       704
   macro avg       0.72      0.70      0.71       704
weighted avg       0.81      0.82      0.81       704
```

In [123]:

```python
plot_confusion_matrix(ada_model,X_test,y_test)
```

Out[123]:

```
<sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay at 0x7fe6ad7e8400>
```

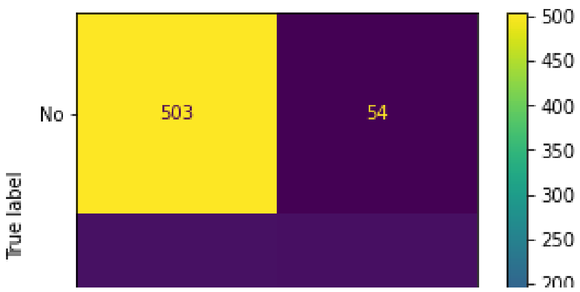


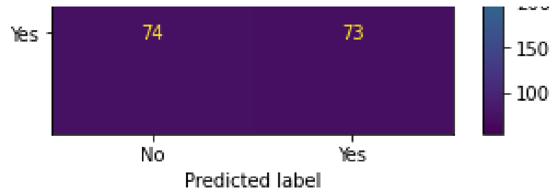
In [124]:

```python
plot_confusion_matrix(gb_model,X_test,y_test)
```

Out[124]:

```
<sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay at 0x7fe6ad7e80a0>
```





With base models, we got best performance from an AdaBoostClassifier, but note, we didn't do any gridsearching AND most models performed about the same on the data set.

Great Job!!

In [ ]: