In [1]:
```python
import pandas as pd
import numpy as np
from matplotlib import pyplot as plt
import folium
from sklearn.model_selection import train_test_split, GridSearchCV
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import accuracy_score, roc_curve, auc, plot_confusion_mat
rix
from sklearn.metrics import confusion_matrix, precision_recall_curve, f1_score
, recall_score
from sklearn.preprocessing import OneHotEncoder
from sklearn import tree
import warnings
warnings.filterwarnings('ignore')
%matplotlib inline
from xgboost import XGBClassifier, plot_importance
import seaborn as sns
import shap
sns.set(style="white")
```

Data Preparation & EDA

In [2]:
```python
# import data
df = pd.read_csv('data/churn_data.csv')
df.head()
```

Out[2]:

	state	account length	area code	phone number	international plan	voice mail plan	number vmail messages	total day minutes	total day calls	total day charge	...	tc e ca
0	KS	128	415	382-4657	no	yes	25	265.1	110	45.07	...	
1	OH	107	415	371-7191	no	yes	26	161.6	123	27.47	...	
2	NJ	137	415	358-1921	no	no	0	243.4	114	41.38	...	
3	OH	84	408	375-9999	yes	no	0	299.4	71	50.90	...	
4	OK	75	415	330-6626	yes	no	0	166.7	113	28.34	...	

5 rows × 21 columns

In [3]:
```python
# clean up column names
df.columns = df.columns.str.replace(' ', '_')
```

In [4]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3333 entries, 0 to 3332
Data columns (total 21 columns):
state                     3333 non-null object
account_length            3333 non-null int64
area_code                 3333 non-null int64
phone_number              3333 non-null object
international_plan        3333 non-null object
voice_mail_plan           3333 non-null object
number_vmail_messages     3333 non-null int64
total_day_minutes         3333 non-null float64
total_day_calls           3333 non-null int64
total_day_charge          3333 non-null float64
total_eve_minutes         3333 non-null float64
total_eve_calls           3333 non-null int64
total_eve_charge          3333 non-null float64
total_night_minutes       3333 non-null float64
total_night_calls         3333 non-null int64
total_night_charge        3333 non-null float64
total_intl_minutes        3333 non-null float64
total_intl_calls          3333 non-null int64
total_intl_charge         3333 non-null float64
customer_service_calls    3333 non-null int64
churn                     3333 non-null bool
dtypes: bool(1), float64(8), int64(8), object(4)
memory usage: 524.2+ KB
```

In [5]:
```
# Change data types to 'category' and change yes/no to 1 or 0
df['state'] = df['state'].astype('category')
df['international_plan'] = df['international_plan'].replace(('yes', 'no'), (1,
0))
df['international_plan'] = df['international_plan'].astype('int')
df['voice_mail_plan'] = df['voice_mail_plan'].replace(('yes', 'no'), (1, 0))
df['voice_mail_plan'] = df['voice_mail_plan'].astype('int')
df['churn'] = df['churn'].replace((True, False), (1, 0))
df['churn'] = df['churn'].astype('int')
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3333 entries, 0 to 3332
Data columns (total 21 columns):
state                     3333 non-null category
account_length            3333 non-null int64
area_code                 3333 non-null int64
phone_number              3333 non-null object
international_plan        3333 non-null int32
voice_mail_plan           3333 non-null int32
number_vmail_messages     3333 non-null int64
total_day_minutes         3333 non-null float64
total_day_calls           3333 non-null int64
total_day_charge          3333 non-null float64
total_eve_minutes         3333 non-null float64
total_eve_calls           3333 non-null int64
total_eve_charge          3333 non-null float64
total_night_minutes       3333 non-null float64
total_night_calls         3333 non-null int64
total_night_charge        3333 non-null float64
total_intl_minutes        3333 non-null float64
total_intl_calls          3333 non-null int64
total_intl_charge         3333 non-null float64
customer_service_calls    3333 non-null int64
churn                     3333 non-null int32
dtypes: category(1), float64(8), int32(3), int64(8), object(1)
memory usage: 488.0+ KB
```

In [6]:
```
# Count no. of churns per state
df_statechurns = df[['state','churn']]
df_statechurns = df_statechurns.groupby(['state'], as_index=False).sum()
df_statechurns.head(3)
```

Out[6]:

	state	churn
0	AK	3
1	AL	8
2	AR	11

In [7]:
```
# Create map of churns per state
url = (
    'https://raw.githubusercontent.com/python-visualization/folium/master/exam
ples/data'
)
state_geo = f'{url}/us-states.json'
m = folium.Map(location=[48, -102], zoom_start=3)

folium.Choropleth(
    geo_data=state_geo,
    name='choropleth',
    data=df_statechurns,
    columns=['state', 'churn'],
    key_on='feature.id',
    fill_color='YlOrRd',
    fill_opacity=0.7,
    line_opacity=0.2,
    legend_name='Churn Count',
).add_to(m)

folium.LayerControl().add_to(m)
m.save('images/map.html')
m
```

Out[7]: Make this Notebook Trusted to load map: File -> Trust Notebook

It looks like there may be some trends, however to avoid creating a dummy column for each of 50 states, categorize each into one of 4 regions as defined by the US Census Bureau.

In [8]:
```
# import data for states and their regions
df_regions = pd.read_csv('data/state-geocodes.csv')
df_regions.head()
```

Out[8]:

	Region	RegionName	Division	State (FIPS)	StateName	StateCode
0	3	South	6	1	Alabama	AL
1	4	West	9	2	Alaska	AK
2	4	West	8	4	Arizona	AZ
3	3	South	7	5	Arkansas	AR
4	4	West	9	6	California	CA

In [9]:
```
# Drop unnecessary columns and rename columns
df_regions = df_regions.drop(columns=['Region', 'Division', 'State (FIPS)', 'S
tateName'])
df_regions = df_regions.rename({'StateCode': 'state', 'RegionName': 'region'},
axis=1)
df_regions['state'] = df_regions['state'].astype('category')
df_regions.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 51 entries, 0 to 50
Data columns (total 2 columns):
region    51 non-null object
state     51 non-null category
dtypes: category(1), object(1)
memory usage: 3.5+ KB
```

In [10]:
```
# Merge region data with original data
df = df.merge(df_regions, on='state', how='left')
```

In [11]:
```
df.head()
```

Out[11]:

	state	account_length	area_code	phone_number	international_plan	voice_mail_plan	number
0	KS	128	415	382-4657	0	1	
1	OH	107	415	371-7191	0	1	
2	NJ	137	415	358-1921	0	0	
3	OH	84	408	375-9999	1	0	
4	OK	75	415	330-6626	1	0	

5 rows × 22 columns

In [12]:
```
# create region dummies
region = pd.get_dummies(df['region'], prefix='region', drop_first=True)
df = df.join(region)
df.drop(['region'], axis=1, inplace=True)
df.head()
```

Out[12]:

	state	account_length	area_code	phone_number	international_plan	voice_mail_plan	number
0	KS	128	415	382-4657	0	1	
1	OH	107	415	371-7191	0	1	
2	NJ	137	415	358-1921	0	0	
3	OH	84	408	375-9999	1	0	
4	OK	75	415	330-6626	1	0	

5 rows × 24 columns

Model 1 - Logistic Regression - SKlearn

In [13]:
```
# Create independent and dependent sets
y = df['churn']

# drop y column 'churn' and phone number
# drop state and area code in favor of region column
X = df.drop(columns=['churn', 'phone_number', 'state', 'area_code'], axis=1)
```

In [14]:
```
# standardize the X dataframe using min max
X = (X - X.min()) / (X.max() - X.min())
X.head()
```

Out[14]:

	account_length	international_plan	voice_mail_plan	number_vmail_messages	total_day_minute
0	0.524793	0.0	1.0	0.490196	0.75570
1	0.438017	0.0	1.0	0.509804	0.46066
2	0.561983	0.0	0.0	0.000000	0.69384
3	0.342975	1.0	0.0	0.000000	0.85347
4	0.305785	1.0	0.0	0.000000	0.47520

In [15]:
```
# Create test and train splits
X_train, X_test, y_train, y_test = train_test_split(
    X, y, test_size=0.2, random_state=42)
```

In [16]:
```
# Create the model
logreg = LogisticRegression(fit_intercept=False, C=1e12, solver='liblinear')

# Fit the model
logreg.fit(X_train, y_train)
```

Out[16]:
```
LogisticRegression(C=1000000000000.0, fit_intercept=False, solver='liblinea
r')
```

In [17]:
```
# Generate predictions
y_hat_train = logreg.predict(X_train)
y_hat_test = logreg.predict(X_test)
```

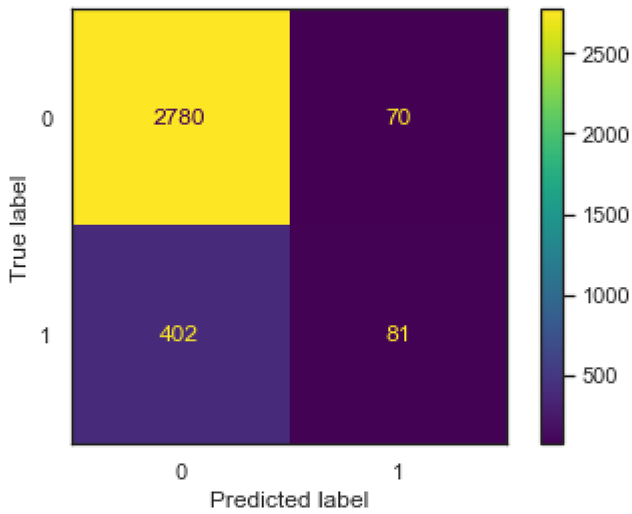
In [18]:
```
# Caclulate accuracy and AUC for train data
accuracy = accuracy_score(y_train, y_hat_train)
print('Accuracy is: {0}'.format(round(accuracy, 2)))

# Check the AUC
false_positive_rate, true_positive_rate, thresholds = roc_curve(y_train, y_hat
_train)
roc_auc = auc(false_positive_rate, true_positive_rate)
print('\nAUC is: {0}'.format(round(roc_auc, 2)))
```

```
Accuracy is: 0.86

AUC is: 0.58
```

In [19]:
```
# Calculate accuracy and AUC for test data
accuracy = accuracy_score(y_test, y_hat_test)
print('Accuracy is: {0}'.format(round(accuracy, 3)))

# Check the AUC
false_positive_rate, true_positive_rate, thresholds = roc_curve(y_test, y_hat_
test)
roc_auc = auc(false_positive_rate, true_positive_rate)
print('\nAUC is: {0}'.format(round(roc_auc, 3)))
```

```
Accuracy is: 0.843

AUC is: 0.545
```

In [20]:
```
# Look at confusion matrix
plot_confusion_matrix(logreg, X, y)
plt.show()
```



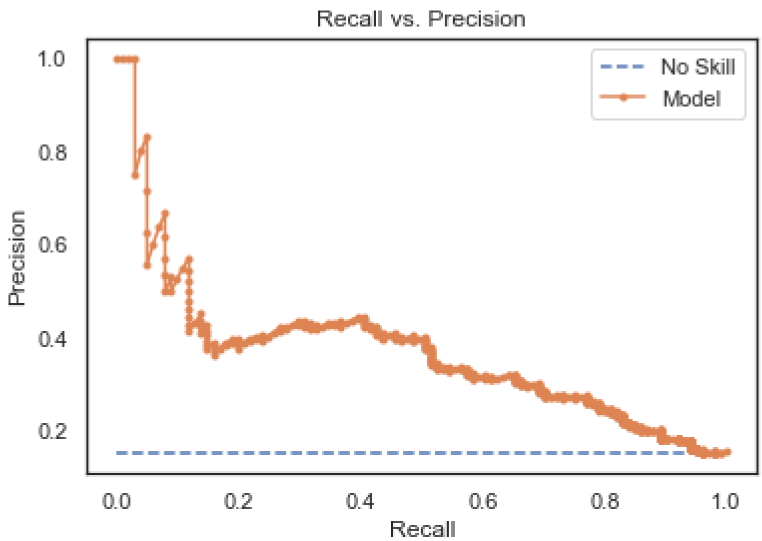
In [21]:
```
# Calculate Recall
recall = recall_score(y, logreg.predict(X))
print('Recall: {:.4}%'.format(recall * 100))
```

```
Recall: 16.77%
```

In [22]:
```
# Classes imbalanced--use Precision-Recall Curves instead ROC curve
def pr_curve(model):
    # predict probabilities
    lr_probs = model.predict_proba(X_test)
    # keep probabilities for the positive outcome only
    lr_probs = lr_probs[:, 1]
    # predict class values
    y_hat = model.predict(X_test)
    lr_precision, lr_recall, _ = precision_recall_curve(y_test, lr_probs)
    lr_f1, lr_auc = f1_score(y_test, y_hat), auc(lr_recall, lr_precision)
    # summarize scores
    print('XG Boost: f1=%.3f auc=%.3f' % (lr_f1, lr_auc))
    # plot the precision-recall curves
    no_skill = len(y_test[y_test==1]) / len(y_test)
    plt.plot([0, 1], [no_skill, no_skill], linestyle='--', label='No Skill')
    plt.plot(lr_recall, lr_precision, marker='.', label='Model')
    # axis labels
    plt.xlabel('Recall')
    plt.ylabel('Precision')
    plt.title('Recall vs. Precision')
    # show the legend
    plt.legend()
```

In [23]:
```
# Precision-Recall Curves for Logistic Regression Tree
pr_curve(logreg)
# save plot
plt.savefig('images/pr_curve_lr.png', dpi=150)
# show the plot
plt.show()
```

```
XG Boost: f1=0.186 auc=0.372
```



Model 2 - Decision Tree Classifier via Gini

In [24]:
```
# Train a DT classifier
classifier = DecisionTreeClassifier(random_state=10)
classifier.fit(X_train, y_train)
```

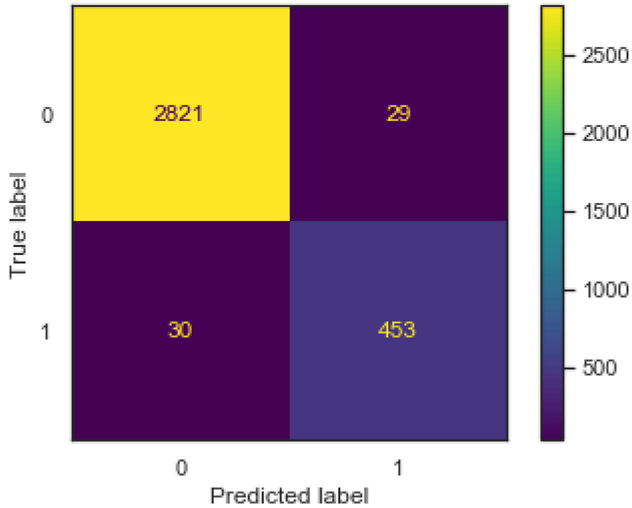
Out[24]:
```
DecisionTreeClassifier(random_state=10)
```

In [25]:
```
# Make predictions for test data
y_hat_train = classifier.predict(X_train)
y_pred = classifier.predict(X_test)
```

In [26]:
```
# Caclulate accuracy and AUC for test data
accuracy = accuracy_score(y_test, y_pred)
print('Accuracy is: {0}'.format(round(accuracy, 3)))

# Check the AUC
false_positive_rate, true_positive_rate, thresholds = roc_curve(y_test, y_pred
)
roc_auc = auc(false_positive_rate, true_positive_rate)
print('\nAUC is: {0}'.format(round(roc_auc, 3)))
```

```
Accuracy is: 0.912

AUC is: 0.826
```

In [27]:
```
# Look at confusion matrix
plot_confusion_matrix(classifier, X, y)
plt.show()
```

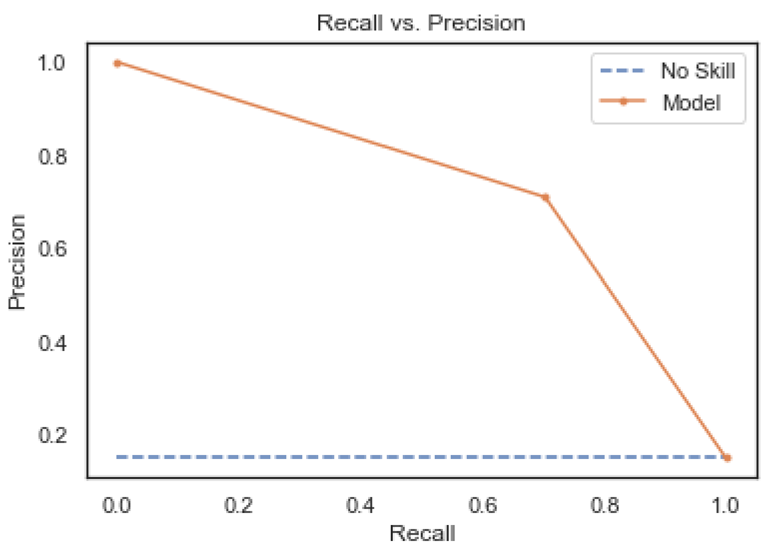


In [28]:
```
# Calculate Recall
recall = recall_score(y, classifier.predict(X))
print('Recall: {:.4}%'.format(recall * 100))
```

```
Recall: 93.79%
```

In [29]:
```
# Precision-Recall Curves for Gini Tree
pr_curve(classifier)
# save plot
plt.savefig('images/pr_curve_dt_gini.png', dpi=150)
# show the plot
plt.show()
```

```
XG Boost: f1=0.706 auc=0.729
```



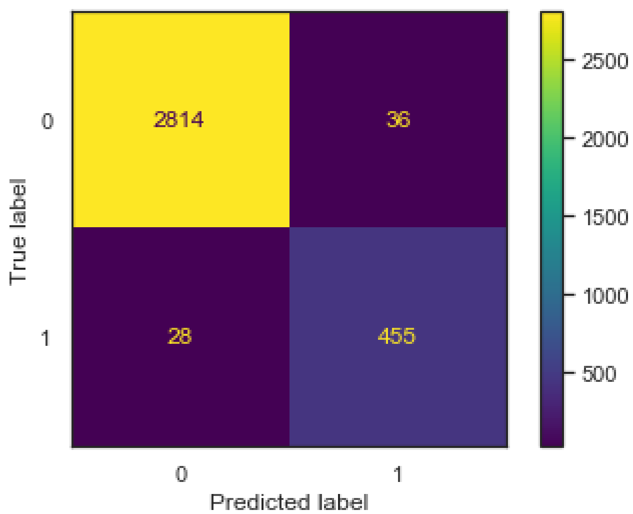
Model 2b - Decision Tree Classifier via Entropy

In [30]:
```
# Use entropy
classifier_2 = DecisionTreeClassifier(random_state=10, criterion='entropy')
classifier_2.fit(X_train, y_train)

# Make predictions for test data
y_pred = classifier_2.predict(X_test)
```

In [31]:
```
# Calculate accuracy
acc = accuracy_score(y_test,y_pred)
print('Accuracy is :{0}'.format(round(acc, 3)))

# Check the AUC for predictions
false_positive_rate, true_positive_rate, thresholds = roc_curve(y_test, y_pred
)
roc_auc = auc(false_positive_rate, true_positive_rate)
print('\nAUC is :{0}'.format(round(roc_auc, 3)))
```

```
Accuracy is :0.904

AUC is :0.83
```

In [32]:
```
# Look at confusion matrix
plot_confusion_matrix(classifier_2, X, y)
plt.show()
```

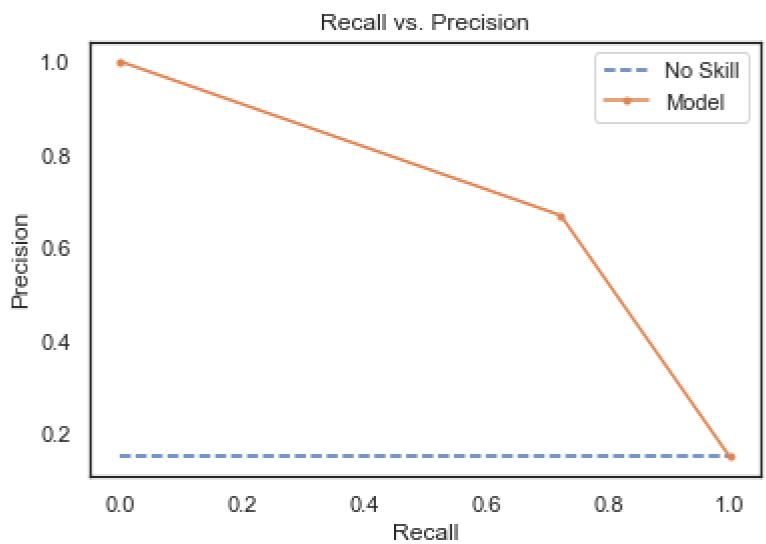


In [33]:
```
# Calculate Recall
recall = recall_score(y, classifier_2.predict(X))
print('Recall: {:.4}%'.format(recall * 100))
```

```
Recall: 94.2%
```

In [34]:
```
# Precision-Recall Curves for Entropy Tree
pr_curve(classifier_2)
# save plot
plt.savefig('images/pr_curve_dt_entropy.png', dpi=150)
# show the plot
plt.show()
```

```
XG Boost: f1=0.695 auc=0.717
```

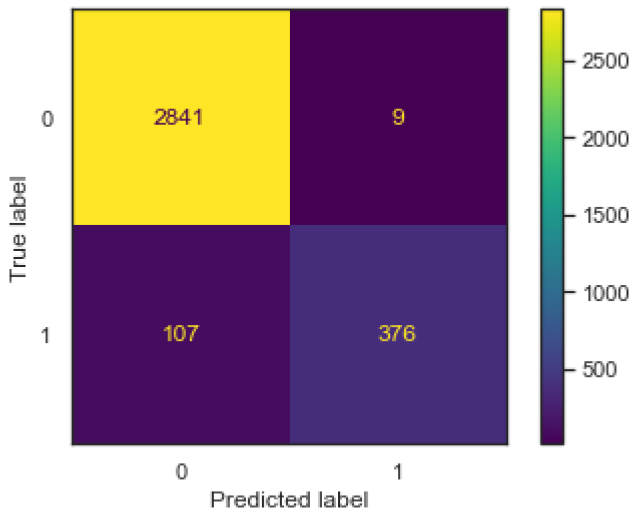


Model 3 - XG Boost

In [35]:
```
# Instantiate XGBClassifier
clf = XGBClassifier()

# Fit XGBClassifier
clf.fit(X_train, y_train)

# Predict on training and test sets
training_preds = clf.predict(X_train)
test_preds = clf.predict(X_test)

# Accuracy of training and test sets
training_accuracy = accuracy_score(y_train, training_preds)
test_accuracy = accuracy_score(y_test, test_preds)

print('Training Accuracy: {:.4}%'.format(training_accuracy * 100))
print('Validation accuracy: {:.4}%'.format(test_accuracy * 100))
```

```
Training Accuracy: 97.0%
Validation accuracy: 94.6%
```

In [36]:
```
# Look at confusion matrix
plot_confusion_matrix(clf, X, y)
plt.show()
```

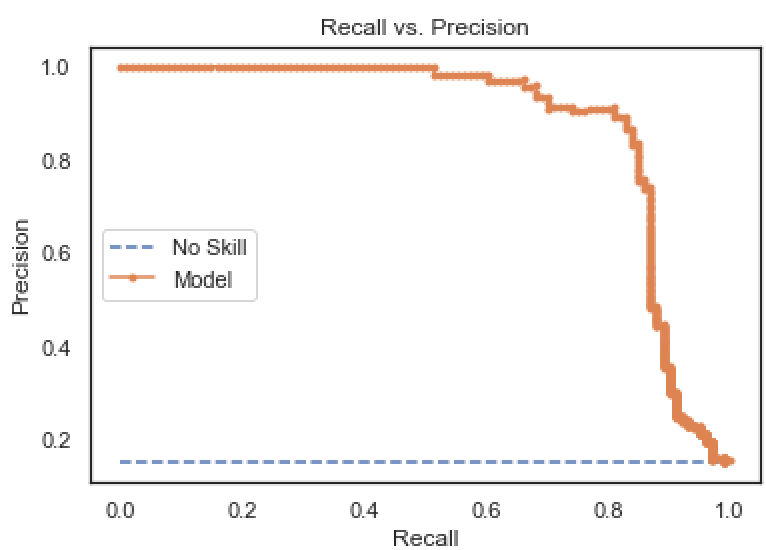


In [37]:
```
# Calculate Recall
recall = recall_score(y, clf.predict(X))
print('Recall: {:.4}%'.format(recall))
```

```
Recall: 0.7785%
```

In [38]:
```
# Precision-Recall Curves for XGBoost
pr_curve(clf)
# save plot
plt.savefig('images/pr_curve_xgboost.png', dpi=150)
# show the plot
plt.show()
```

```
XG Boost: f1=0.800 auc=0.880
```



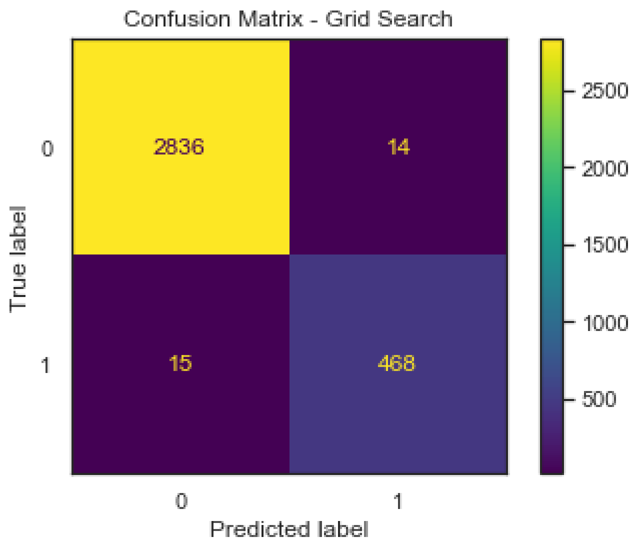
Model 3b - Grid Search

In [39]:
```
# Goal is to increase recall
param_grid = {
    'learning_rate': [0.1, 0.2],
    'max_depth': [5, 6],
    'min_child_weight': [1, 2],
    'subsample': [0.5, 0.7],
    'n_estimators': [100],
    'scale_pos_weight': [5] # impose greater penalties for errors on the minor class, sum(negative instances) / sum(positive instances)
}
```

In [40]:
```
# Grid Search based on previous XG Boost classifier
grid_clf = GridSearchCV(clf, param_grid, scoring='accuracy',
                        cv=None, n_jobs=1)

grid_clf.fit(X_train, y_train)
best_parameters = grid_clf.best_params_

print('Grid Search found the following optimal parameters: ')
for param_name in sorted(best_parameters.keys()):
    print('%s: %r' % (param_name, best_parameters[param_name]))

training_preds = grid_clf.predict(X_train)
test_preds = grid_clf.predict(X_test)
training_accuracy = accuracy_score(y_train, training_preds)
test_accuracy = accuracy_score(y_test, test_preds)
grid_clf
print('')
print('Training Accuracy: {:.4}%'.format(training_accuracy * 100))
print('Validation accuracy: {:.4}%'.format(test_accuracy * 100))
```

```
Grid Search found the following optimal parameters:
learning_rate: 0.1
max_depth: 6
min_child_weight: 1
n_estimators: 100
scale_pos_weight: 5
subsample: 0.7

Training Accuracy: 99.92%
Validation accuracy: 95.95%
```

In [41]:
```
# Look at confusion matrix
plot_confusion_matrix(grid_clf, X, y)
plt.title('Confusion Matrix - Grid Search')

# save plot
plt.savefig('images/conf_matrix_gridsearch.png', dpi=150)

plt.show()
```

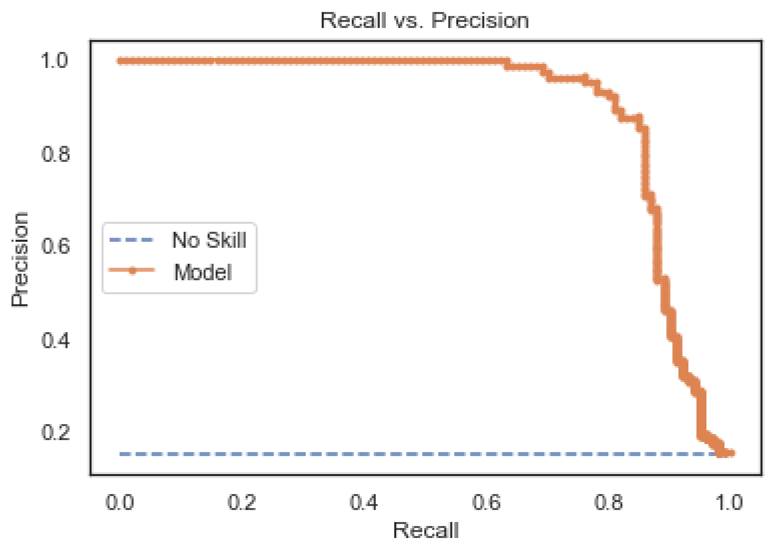


In [42]:
```
# Calculate Recall
recall = recall_score(y, grid_clf.predict(X))
print('Recall: {:.4}%'.format(recall * 100))
```

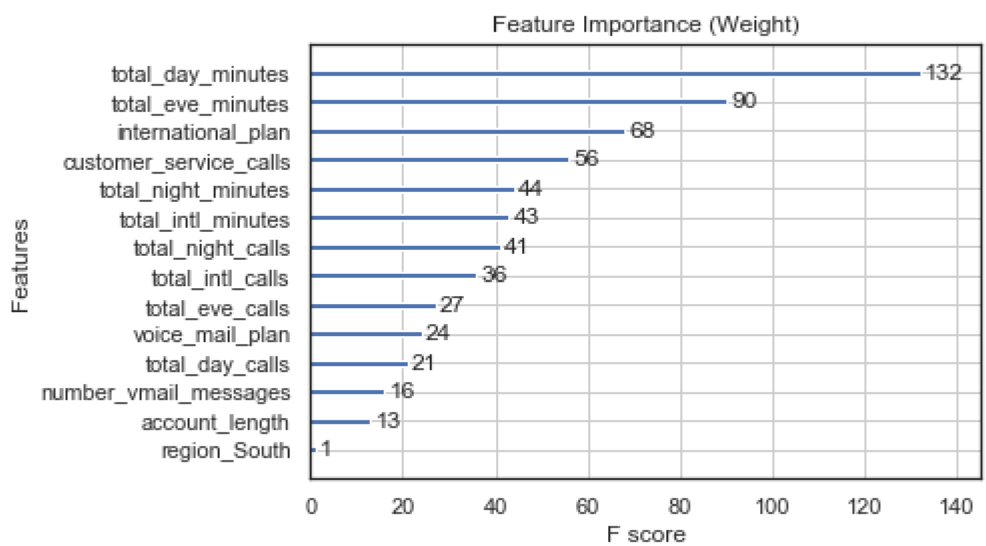
```
Recall: 96.89%
```

In [43]:
```
# Precision-Recall Curves for Grid Search
pr_curve(grid_clf)
# save plot
plt.savefig('images/pr_curve_gridsearch.png', dpi=150)
# show the plot
plt.show()
```

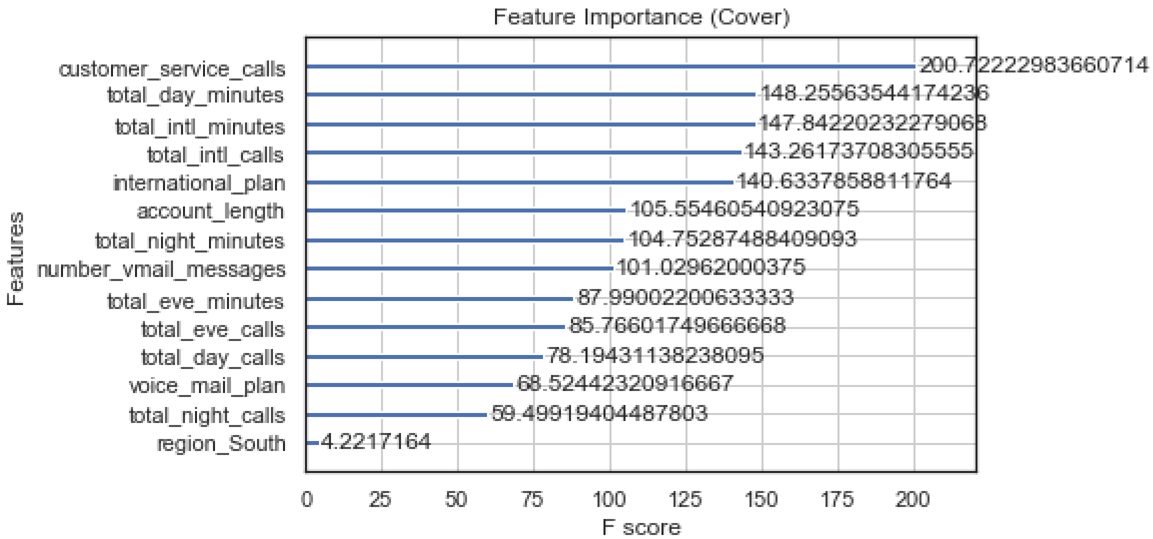
```
XG Boost: f1=0.864 auc=0.897
```



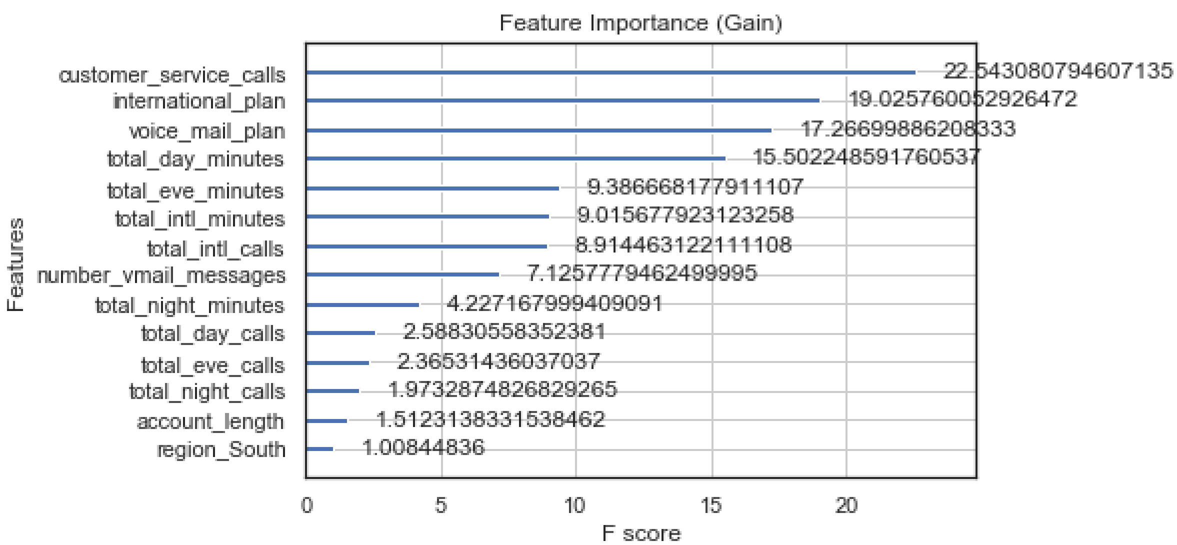
In [44]:
```
# plot feature importance
plot_importance(clf, importance_type='weight')
plt.title('Feature Importance (Weight)')
plt.show()
```



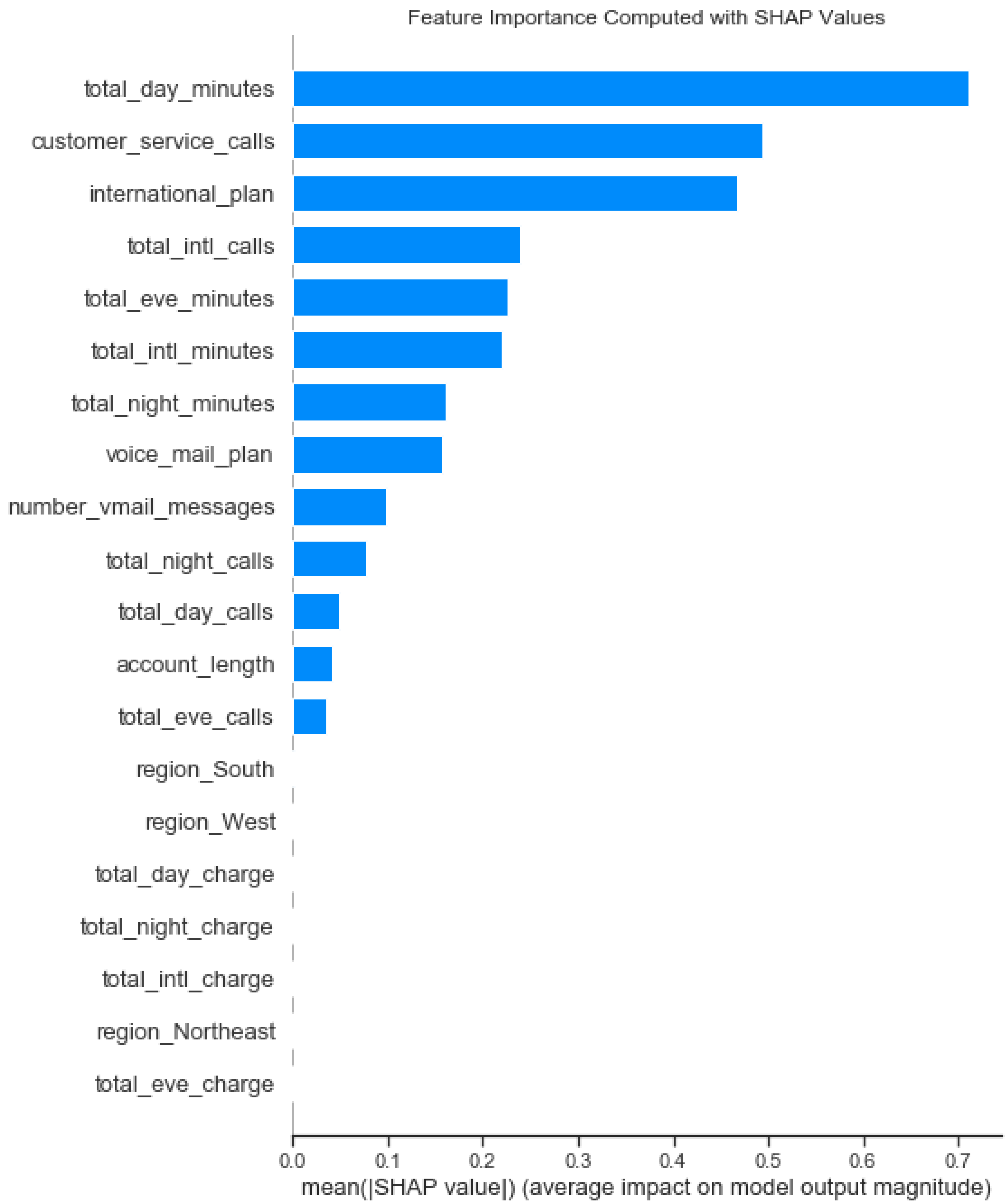
In [45]:
```
plot_importance(clf, importance_type='cover')
plt.title('Feature Importance (Cover)')
plt.show()
```



In [46]:
```
plot_importance(clf, importance_type='gain')
plt.title('Feature Importance (Gain)')
plt.show()
```



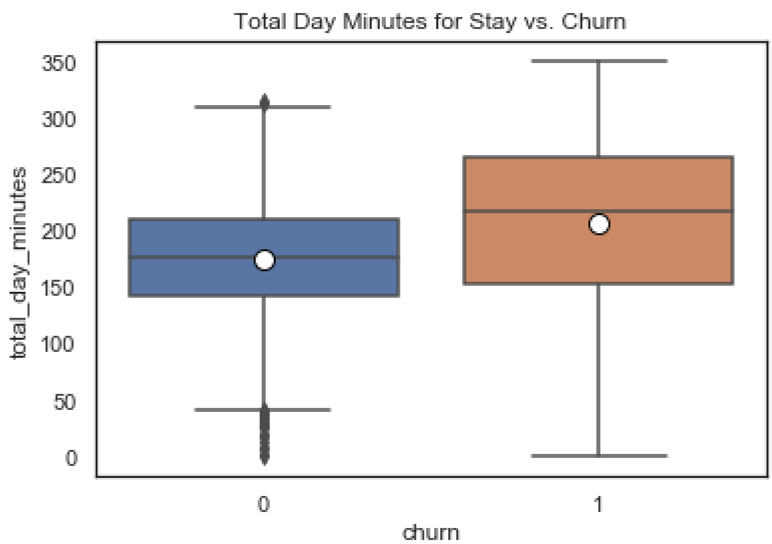
In [47]:
```
# Feature Importance Computed with SHAP Values (Game Theory)
explainer = shap.TreeExplainer(clf)
shap_values = explainer.shap_values(X_test)
shap.summary_plot(shap_values, X_test, plot_type="bar", show=False)
plt.title('Feature Importance Computed with SHAP Values')
plt.tight_layout()
# save plot
plt.savefig('images/shap_importance.png', dpi=300)
plt.show()
```



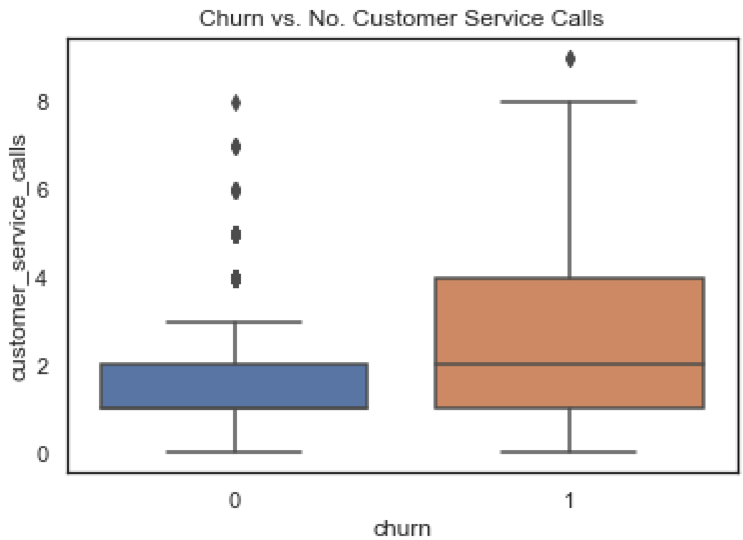
In [48]:
```
# split data into customers that stayed or churned
yes_churn = df[df['churn']==1]
no_churn = df[df['churn']==0]
```

In [49]:
```
# Look at boxplots for
bp = sns.boxplot(x='churn', y='total_day_minutes', data=df,
                 showmeans=True,
                 meanprops={"marker":"o",
                        "markerfacecolor":"white",
                        "markeredgecolor":"black",
                       "markersize":"10"})
bp.set_title('Total Day Minutes for Stay vs. Churn')

print('No Churn Median: {:.4} mins'.format(no_churn['total_day_minutes'].media
n()))
print('No Churn Mean: {:.4} mins'.format(no_churn['total_day_minutes'].mean
()))

print('Churn Median: {:.4} mins'.format(yes_churn['total_day_minutes'].median
()))
print('Churn Mean: {:.4} mins'.format(yes_churn['total_day_minutes'].mean()))

# save plot
plt.savefig('images/boxplot_day_minutes.png', dpi=150)

plt.show()
```

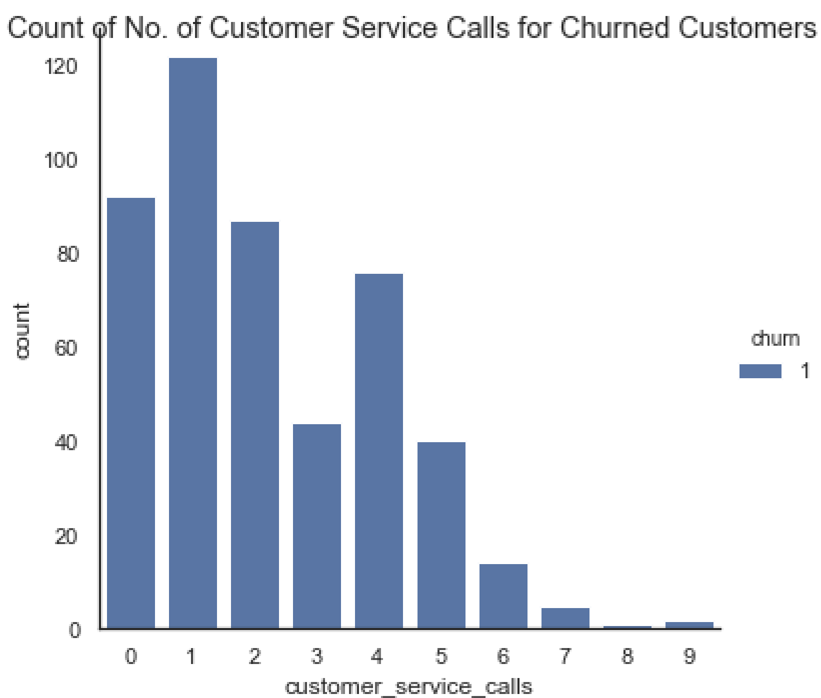
```
No Churn Median: 177.2 mins
No Churn Mean: 175.2 mins
Churn Median: 217.6 mins
Churn Mean: 206.9 mins
```



In [50]:
```
bp = sns.boxplot(x='churn', y='customer_service_calls', data=df)
bp.set_title('Churn vs. No. Customer Service Calls')

# save plot
plt.savefig('images/boxplot_no_service_calls.png', dpi=150)

plt.show()
```

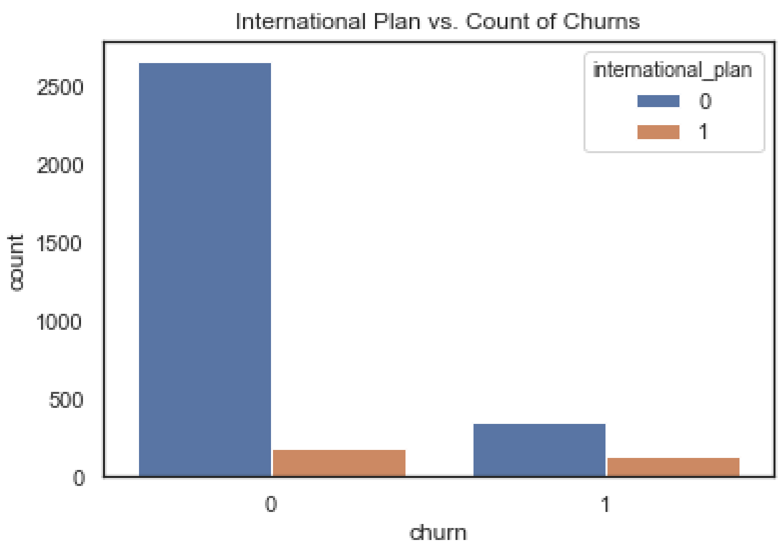


In [51]:
```
ax = sns.catplot(x="customer_service_calls", hue="churn", data=yes_churn, kind
="count")
ax.fig.suptitle('Count of No. of Customer Service Calls for Churned Customers'
)

# save plot
plt.savefig('images/bar_service_calls.png', dpi=150)

plt.show()
```

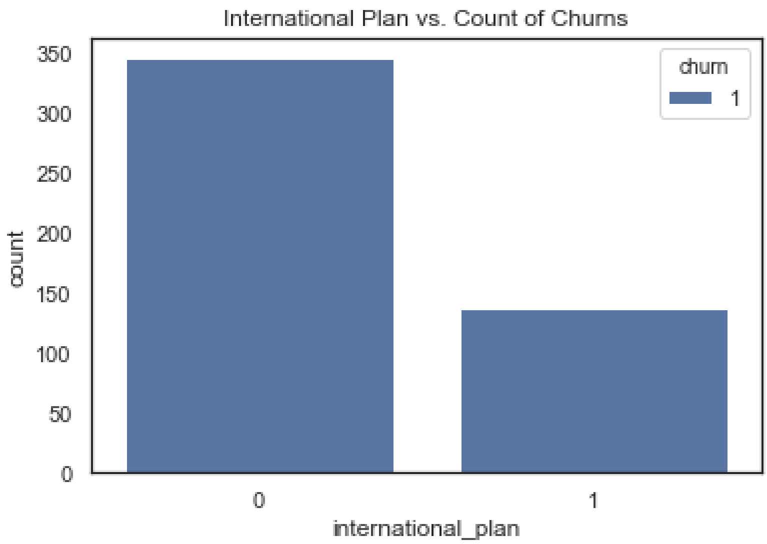


In [52]:
```
ax = sns.countplot(x="churn", hue="international_plan", data=df)
ax.set_title('International Plan vs. Count of Churns')

# save plot
plt.savefig('images/bar_intl_plan.png', dpi=150)

print('No Churn with Plan: {} customers'.format(no_churn['international_plan']
.sum()))
print('No Churn wout Plan: {} customers'.format(no_churn['international_plan']
.count()-no_churn['international_plan'].sum()))
print('Churn with Plan: {} customers'.format(yes_churn['international_plan'].s
um()))
print('Churn wout Plan: {} customers'.format(yes_churn['international_plan'].c
ount()-no_churn['international_plan'].sum()))

plt.show()
```

```
No Churn with Plan: 186 customers
No Churn wout Plan: 2664 customers
Churn with Plan: 137 customers
Churn wout Plan: 297 customers
```



In [53]:
```
ax = sns.countplot(x="international_plan", hue="churn", data=yes_churn)
ax.set_title('International Plan vs. Count of Churns')

# save plot
plt.savefig('images/bar_intl_plan_churns.png', dpi=150)

plt.show()
```



In [ ]: