In [1]:
```
from sklearn.model_selection import RandomizedSearchCV, train_test_split, K
from sklearn import tree
from sklearn import ensemble
from sklearn.preprocessing import StandardScaler, OneHotEncoder
from sklearn.compose import ColumnTransformer, make_column_selector
from sklearn.pipeline import Pipeline
from sklearn.metrics import accuracy_score, confusion_matrix, ConfusionMatr
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
import random
import sys
import dtreeviz
from xgboost import XGBClassifier
import statistics

seed = 7112947496748021886
random.seed(seed)
```

In [2]:
```
# load full dataset
NBA_full = pd.read_csv("STAT841WorkingDataset.csv")

NBA_full.columns
```

Out[2]:
```
Index(['Unnamed: 0', 'player_name', 'position', 'season', 'team_city',
       'team_name', 'person_id', 'height_wo_shoes', 'weight', 'wingspan',
       'standing_reach', 'standing_vertical_leap', 'max_vertical_leap',
       'lane_agility_time', 'three_quarter_sprint', 'bench_press', 'draft
ed',
       'Id', 'team', 'conf', 'GP', 'Min_per', 'Ortg', 'usg', 'eFG', 'TS_p
er',
       'ORB_per', 'DRB_per', 'AST_per', 'TO_per', 'FTM', 'FTA', 'FT_per',
       'twoPM', 'twoPA', 'twoP_per', 'TPM', 'TPA', 'TP_per', 'blk_per',
       'stl_per', 'ftr', 'yr', 'ht', 'num', 'porpag', 'adjoe', 'pfr', 'ye
ar',
       'pid', 'type', 'ast.tov', 'rimmade', 'rimmade.rimmiss', 'midmade',
       'midmade.midmiss', 'rimmade..rimmade.rimmiss.',
       'midmade..midmade.midmiss.', 'dunksmade', 'dunksmiss.dunksmade',
       'dunksmade..dunksmade.dunksmiss.', 'drtg', 'adrtg', 'dporpag', 'st
ops',
       'bpm', 'obpm', 'dbpm', 'gbpm', 'mp', 'ogbpm', 'dgbpm', 'oreb', 'dr
eb',
       'treb', 'ast', 'stl', 'blk', 'pts', 'X', 'X.1', 'most_recent'],
      dtype='object')
```

In [3]:
```
# Take out the columns that are specifically not needed for analysis
cols_to_exclude = ["Unnamed: 0", "Id", "player_name", "season", "team_city"
                   "team", "conf", "ht", "year", "type", "team_name", "pers
                   "most_recent", "X", "rimmade", "rimmade.rimmiss", "midma
                   "midmade.midmiss", "rimmade..rimmade.rimmiss.", "midmade
                   "dunksmade", "dunksmiss.dunksmade", "dunksmade..dunksmad

# Exclude the columns
NBA_ready = NBA_full.loc[:, ~NBA_full.columns.isin(cols_to_exclude)].dropna
```

In [4]:
```
NBA_ready_numeric = NBA_ready.select_dtypes(exclude=['object'])
```

In [5]:
```
# The order of the columns is still a little strange from previous work don
# for easier processing down the line.

feature_names = list(NBA_ready.columns)
feature_names.pop(feature_names.index("drafted"))

# Take out the drafted status column, and reorder the dataset to put in the
# extraction with the columntransformer later down the line
feature_names = ["drafted"] + feature_names

NBA_ready = NBA_ready[feature_names]

# This is a simple comparison series object to ensure that we are extractin
compare = NBA_ready["drafted"]

NBA_ready
```

Out[5]:

	drafted	position	height_wo_shoes	weight	wingspan	standing_reach	standing_vertical_leap	n
0	0	PG	72.75	191.6	74.00	94.5	29.0	
1	1	PF	79.50	220.1	83.75	105.0	32.5	
2	0	SG	76.50	209.2	80.25	100.5	28.5	
3	0	SF	76.50	209.6	82.75	103.5	29.0	
4	1	PG	71.75	187.0	79.50	97.0	25.5	
...	...	...	...	...	...	...	...	
658	1	PG	76.50	180.9	80.25	100.0	33.5	
659	0	SG	76.50	206.4	78.00	101.0	24.0	
660	1	PF-C	81.25	246.8	86.00	105.5	33.0	
661	1	SF-SG	74.75	198.6	81.75	100.0	33.0	
662	1	SF	80.25	188.4	82.25	106.5	34.0	

623 rows × 59 columns

In [6]:
```
# Since the response variable is already 0-1-encoded, we actually need to s
# Note the use of the values property, since pandas Series preserve the ind
NBA_ready["drafted"] = pd.Series(np.where(NBA_ready["drafted"].values == 0,
```

In [7]:
```
# Show the columns we will be using
NBA_ready.columns
```

Out[7]:
```
Index(['drafted', 'position', 'height_wo_shoes', 'weight', 'wingspan',
       'standing_reach', 'standing_vertical_leap', 'max_vertical_leap',
       'lane_agility_time', 'three_quarter_sprint', 'bench_press', 'GP',
       'Min_per', 'Ortg', 'usg', 'eFG', 'TS_per', 'ORB_per', 'DRB_per',
       'AST_per', 'TO_per', 'FTM', 'FTA', 'FT_per', 'twoPM', 'twoPA',
       'twoP_per', 'TPM', 'TPA', 'TP_per', 'blk_per', 'stl_per', 'ftr',
'yr',
       'num', 'porpag', 'adjoe', 'pfr', 'pid', 'ast.tov', 'drtg', 'adrt
g',
       'dporpag', 'stops', 'bpm', 'obpm', 'dbpm', 'gbpm', 'mp', 'ogbpm',
       'dgbpm', 'oreb', 'dreb', 'treb', 'ast', 'stl', 'blk', 'pts', 'X.
1'],
      dtype='object')
```

In [8]:
```
# Notice that drafted status has been changed to yes/no, and that the only
# are position played and the year of college each player played their last
NBA_ready.dtypes
```

Out[8]:
```
drafted                    object
position                   object
height_wo_shoes           float64
weight                    float64
wingspan                  float64
standing_reach            float64
standing_vertical_leap    float64
max_vertical_leap         float64
lane_agility_time         float64
three_quarter_sprint      float64
bench_press               float64
GP                          int64
Min_per                   float64
Ortg                      float64
usg                       float64
eFG                       float64
TS_per                    float64
ORB_per                   float64
DRB_per                   float64
AST_per                   float64
TO_per                    float64
FTM                         int64
FTA                         int64
FT_per                    float64
twoPM                       int64
twoPA                       int64
twoP_per                  float64
TPM                         int64
TPA                         int64
TP_per                    float64
blk_per                   float64
stl_per                   float64
ftr                       float64
yr                         object
num                       float64
porpag                    float64
adjoe                     float64
pfr                       float64
pid                         int64
ast.tov                   float64
drtg                      float64
adrtg                     float64
dporpag                   float64
stops                     float64
bpm                       float64
obpm                      float64
dbpm                      float64
gbpm                      float64
mp                        float64
ogbpm                     float64
dgbpm                     float64
oreb                      float64
dreb                      float64
treb                      float64
ast                       float64
stl                       float64
blk                       float64
```

```
pts                          float64
X.1                          float64
dtype: object
```

In [9]:
```
# The position column contains primary and secondary positions, leading to
# categories. As a result, I will be categorizing based on players' primary
NBA_ready["position"] = NBA_ready["position"].str[:2]

# Note that since centers (C) sometimes have split positions, there is a da
NBA_ready["position"].value_counts()
```

Out[9]:
```
SG    166
PF    147
PG    131
SF    118
C      50
C-     11
Name: position, dtype: int64
```

In [10]:
```
# To address this, we simply take out the dashes
NBA_ready["position"] = NBA_ready["position"].replace('-', '', regex=True)

NBA_ready["position"].value_counts()
```

Out[10]:
```
SG    166
PF    147
PG    131
SF    118
C      61
Name: position, dtype: int64
```

In [11]:
```
NBA_ready.columns
```

Out[11]:
```
Index(['drafted', 'position', 'height_wo_shoes', 'weight', 'wingspan',
       'standing_reach', 'standing_vertical_leap', 'max_vertical_leap',
       'lane_agility_time', 'three_quarter_sprint', 'bench_press', 'GP',
       'Min_per', 'Ortg', 'usg', 'eFG', 'TS_per', 'ORB_per', 'DRB_per',
       'AST_per', 'TO_per', 'FTM', 'FTA', 'FT_per', 'twoPM', 'twoPA',
       'twoP_per', 'TPM', 'TPA', 'TP_per', 'blk_per', 'stl_per', 'ftr',
'yr',
       'num', 'porpag', 'adjoe', 'pfr', 'pid', 'ast.tov', 'drtg', 'adrt
g',
       'dporpag', 'stops', 'bpm', 'obpm', 'dbpm', 'gbpm', 'mp', 'ogbpm',
       'dgbpm', 'oreb', 'dreb', 'treb', 'ast', 'stl', 'blk', 'pts', 'X.
1'],
      dtype='object')
```

In [12]:
```
# Apply a column transformer that employs one-hot encoding to categorical v
ct = ColumnTransformer([
    ('onehot',
        OneHotEncoder(drop="first"),
        make_column_selector(dtype_include=object)),
    ('scale', StandardScaler(),
        make_column_selector(dtype_include=np.number))
    ],
    verbose_feature_names_out=False)
```

In [13]:
```
# To ensure we have acceptable data, we can see that we have a good mix of
# scaled and normalized variables
nba_trans = ct.fit_transform(NBA_ready)

ct.get_feature_names_out()
```

Out[13]:
```
array(['drafted_yes', 'position_PF', 'position_PG', 'position_SF',
       'position_SG', 'yr_Jr', 'yr_So', 'yr_Sr', 'height_wo_shoes',
       'weight', 'wingspan', 'standing_reach', 'standing_vertical_leap',
       'max_vertical_leap', 'lane_agility_time', 'three_quarter_sprint',
       'bench_press', 'GP', 'Min_per', 'Ortg', 'usg', 'eFG', 'TS_per',
       'ORB_per', 'DRB_per', 'AST_per', 'TO_per', 'FTM', 'FTA', 'FT_per',
       'twoPM', 'twoPA', 'twoP_per', 'TPM', 'TPA', 'TP_per', 'blk_per',
       'stl_per', 'ftr', 'num', 'porpag', 'adjoe', 'pfr', 'pid',
       'ast.tov', 'drtg', 'adrtg', 'dporpag', 'stops', 'bpm', 'obpm',
       'dbpm', 'gbpm', 'mp', 'ogbpm', 'dgbpm', 'oreb', 'dreb', 'treb',
       'ast', 'stl', 'blk', 'pts', 'X.1'], dtype=object)
```

In [14]:
```
# To ensure that we're actually preserving the outputs we want, we can chec
# from earlier
sum(nba_trans[:, 0] != compare)
```

Out[14]:
```
0
```

Bootstrap Feature Importance

In [15]:
```
# Since there are so many features, it may be in our best interest to perfo
# First, using 10-fold CV, we will select an optimal value for either L1 or

# XGBoost performs well on a small number of highly important variables. We
# selection implied by a model trained on the entirety of a training set to
# then we can perform some selection of a number of important variables, sa

train = nba_trans[:, 1:]
test = nba_trans[:, 0]
```

In [18]:

```
# CV_XGB takes a train and a test set and conducts 5-fold CV for each pair
# (XGBoost tuning parameters). While it is not very flexible as a function,
def CV_XGB(train, test):
    # Using 5-fold CV since the dataset isn't very large
    n_fold = 5

    # Split up the dataset into calibration and test sets
    X_calib, X_test_final, y_calib, y_test_final = train_test_split(train,

    cv = KFold(
        n_splits=n_fold,  # number of folds
        shuffle=True  # protects against data being ordered, e.g., all succ
        )

    # Our eta and gamma values to iterate through
    eta_vals = np.arange(0.1, 0.6, 0.1)
    gamma_vals = np.arange(0.2, 1.2, 0.2)

    # A container to record our hyperparameter values and their respective
    cv_errors = {}

    for i in range(0, len(eta_vals)):
        for j in range(0, len(gamma_vals)):
            # Set up a list container so we can calculate average test erro
            cv_loss = []
            for (train_id, test_id) in cv.split(X_calib):
                # foldwise training and test data
                X_train = X_calib[train_id, 1:]
                y_train = y_calib[train_id]
                X_test = X_calib[test_id, 1:]
                y_test = y_calib[test_id]

                # Create a binary classifier XGBoost model for each combina
                cv_model = XGBClassifier(eta = i, gamma = j, objective = 'b
                # Train on our data
                cv_model.fit(X_train, y_train)

                cv_loss.append(1.0 - cv_model.score(X_test, y_test))

            cv_error = np.mean(cv_loss)
            # Record our average CV error for each (eta, gamma) pair
            cv_errors[(i, j)] = cv_error

    return(cv_errors)
```

In [19]:
```
total_cv_errors = CV_XGB(train, test)
# We can see that we that the errors are different, and have been recorded
total_cv_errors
```

Out[19]:
```
{(0, 0): 0.6205252525252526,
 (0, 1): 0.6203838383838384,
 (0, 2): 0.6205252525252525,
 (0, 3): 0.6203636363636363,
 (0, 4): 0.6204444444444444,
 (1, 0): 0.33131313131313134,
 (1, 1): 0.3792929292929293,
 (1, 2): 0.36947474747474746,
 (1, 3): 0.35131313131313135,
 (1, 4): 0.39155555555555555,
 (2, 0): 0.3655757575757576,
 (2, 1): 0.37143434343434345,
 (2, 2): 0.3614343434343434,
 (2, 3): 0.3996363636363637,
 (2, 4): 0.4174949494949495,
 (3, 0): 0.4015959595959596,
 (3, 1): 0.5022020202020201,
 (3, 2): 0.44761616161616163,
 (3, 3): 0.4595757575757576,
 (3, 4): 0.3835151515151515,
 (4, 0): 0.445979797979798,
 (4, 1): 0.4741212121212121,
 (4, 2): 0.4900404040404041,
 (4, 3): 0.4136969696969697,
 (4, 4): 0.4659191919191919}
```

In [20]:
```
params = min(total_cv_errors, key = total_cv_errors.get)

# record our best eta and gamma values
params
```

Out[20]:
```
(1, 0)
```

Now that we have cross-validated for our ideal step size shrinkage and minimum loss reduction, we can perform nonparametric bootstrap samples to determine which of the features are the most important

Feature importance is a good indicator of whether or not a feature should be considered for an XGBoost model, since it determines how much an individual feature contributes to the 'decision' made by the XGBoost model.

In [22]:
```
# Conduct 1000 bootstrap samples to determine bootstrap-averaged feature im
# final 8-10 highest importance features

n_boot = 1000
n = nba_trans.shape[0]
keyList = [i for i in range(0, train.shape[1])]

feature_importance_container = []


for i in range(n_boot):
    random.seed(i)
    # Use nonparametric bootstrap to generate feature importance for each m
    boot_sample = np.random.choice(range(n), replace = True, size = n)

    # Conduct an XGBoost classification model using our optimal hyperparame
    # scores (particulary, total gain scores, which are the most similar to
    # forest models)
    boot_model = XGBClassifier(eta = 1, gamma = 0, objective = 'binary:logi

    boot_model.fit(train[boot_sample, :], test[boot_sample])

    feature_importances = boot_model.get_booster().get_score(importance_typ

    feature_importance_container += [feature_importances]
```

In [23]:
```
# Extract each feature to calculate bootstrap mean, SE, and confidence inte

# Takes the
def extract_feature_imp(lst, index):
    return [item[index] for item in lst]

boot_importance_by_feature = []

feature_importance_container[0]
```

Out[23]:
```
{'f0': 0.5259504914283752,
 'f3': 2.224379777908325,
 'f4': 2.723571300506592,
 'f5': 0.7016599774360657,
 'f6': 23.09351921081543,
 'f7': 18.434967041015625,
 'f8': 19.681264877319336,
 'f9': 14.504170417785645,
 'f10': 0.485105961561203,
 'f11': 42.552364349365234,
 'f12': 4.053670406341553,
 'f13': 24.0333194732666,
 'f14': 14.424583435058594,
 'f15': 1.816743016242981,
 'f16': 29.89222526550293,
 'f17': 28.48514747619629,
 'f18': 8.235798835754395,
 'f19': 14.38315200805664,
 'f20': 1.897722840309143,
 'f21': 4.2743706703186035,
 'f22': 18.13797378540039,
 'f23': 2.481764793395996,
 'f24': 0.7078239917755127,
 'f25': 12.08775806427002,
 'f26': 0.3456229567527771,
 'f27': 7.26711893081665,
 'f28': 2.3661837577819824,
 'f29': 9.355968475341797,
 'f30': 6.237644195556641,
 'f31': 10.07938003540039,
 'f32': 7.863998889923096,
 'f33': 1.2624510526657104,
 'f34': 16.727825164794922,
 'f35': 9.449917793273926,
 'f36': 1.8355551958084106,
 'f37': 5.461122035980225,
 'f38': 16.90018081665039,
 'f39': 0.9678099155426025,
 'f40': 0.9605807065963745,
 'f41': 9.930109024047852,
 'f42': 21.905624389648438,
 'f43': 15.028340339660645,
 'f44': 7.594355583190918,
 'f45': 7.746654987335205,
 'f46': 9.496835708618164,
 'f47': 9.366103172302246,
 'f48': 50.93415069580078,
 'f49': 5.601943016052246,
 'f50': 9.075593948364258,
 'f51': 21.572879791259766,
 'f52': 5.500296592712402,
 'f53': 6.325451850891113,
 'f54': 2.4817276000976562,
 'f55': 13.577906608581543,
 'f56': 5.994830131530762,
 'f57': 11.235276222229004,
 'f58': 0.23344402015209198,
```

```
 'f59': 1.1007022857666016,
 'f60': 24.61969757080078,
 'f61': 19.28888511657715,
 'f62': 8.701416969299316}
```

In [24]:

```
# This is a basic function that generates dictionary items in the form of l
# of a different dictionary
def dict_updater(dictionary, new_dict):
    for key in new_dict.keys():
        if key not in dictionary.keys():
            dictionary[key] = [new_dict[key]]
        else:
            dictionary[key] = dictionary.get(key, None) + [new_dict[key]]
    return(dictionary)
```

In [25]:

```
# Since the XGBoost models have regularization effects on each bootstrapped
# potentially different subsets of the total feature space every time. Ther
# gather the bootstrapped feature importance by the recorded feature index
final_dict = {}

for i in range(1000):
    final_dict = dict_updater(final_dict, feature_importance_container[i])
```

In [31]:

```
final_dict['f0']
```

```
 0.14536869525909424,
 2.4535160064697266,
 0.12104437500238419,
 0.21783509850502014,
 0.2496570348739624,
 9.64913558959961,
 0.4935193955898285,
 0.9649374485015869,
 1.5715930461883545,
 13.319684982299805,
 0.3734707832336426,
 2.4284210205078125,
 0.2968277931213379,
 0.15150374174118042,
 0.7140457630157471,
 1.028571367263794,
 7.084194183349609,
 8.855742454528809,
 0.11418592929840088,
```

In [32]:
```
# This takes the values associated with each feature and takes bootstrap me
def extract_boot_metrics(dictionary):
    means = {}
    SE_container = {}
    for key, value in dictionary.items() :
        means[key] = sum(value) / 1000

        difference = np.subtract(np.asarray(dictionary[key]), np.asarray(me
        SE_container[key] = np.sqrt((1 / 999) * sum(np.square(difference)))
    return(means, SE_container)

boot_means, boot_SEs = extract_boot_metrics(final_dict)
```

In [33]:
```
# We can now sort the mean and Standard Error values by feature
sortable_means = [[int(key[1:]), value] for key, value in boot_means.items(
sortable_SEs = [[int(key[1:]), value] for key, value in boot_SEs.items()]
sortable_means = sorted(sortable_means)
sortable_SEs = sorted(sortable_SEs)

# Simply sorting by index to make sure we can preserve the feature numbers,
# for analysis.
means_df = pd.DataFrame(sortable_means)
SEs_df = pd.DataFrame(sortable_SEs)
#SEs_df
means_df
```

Out[33]:

	0	1
0	0	0.975917
1	1	0.448010
2	2	0.817783
3	3	1.151687
4	4	2.264457
...	...	...
58	58	4.528564
59	59	7.288277
60	60	8.539052
61	61	6.967784
62	62	7.267767

63 rows × 2 columns

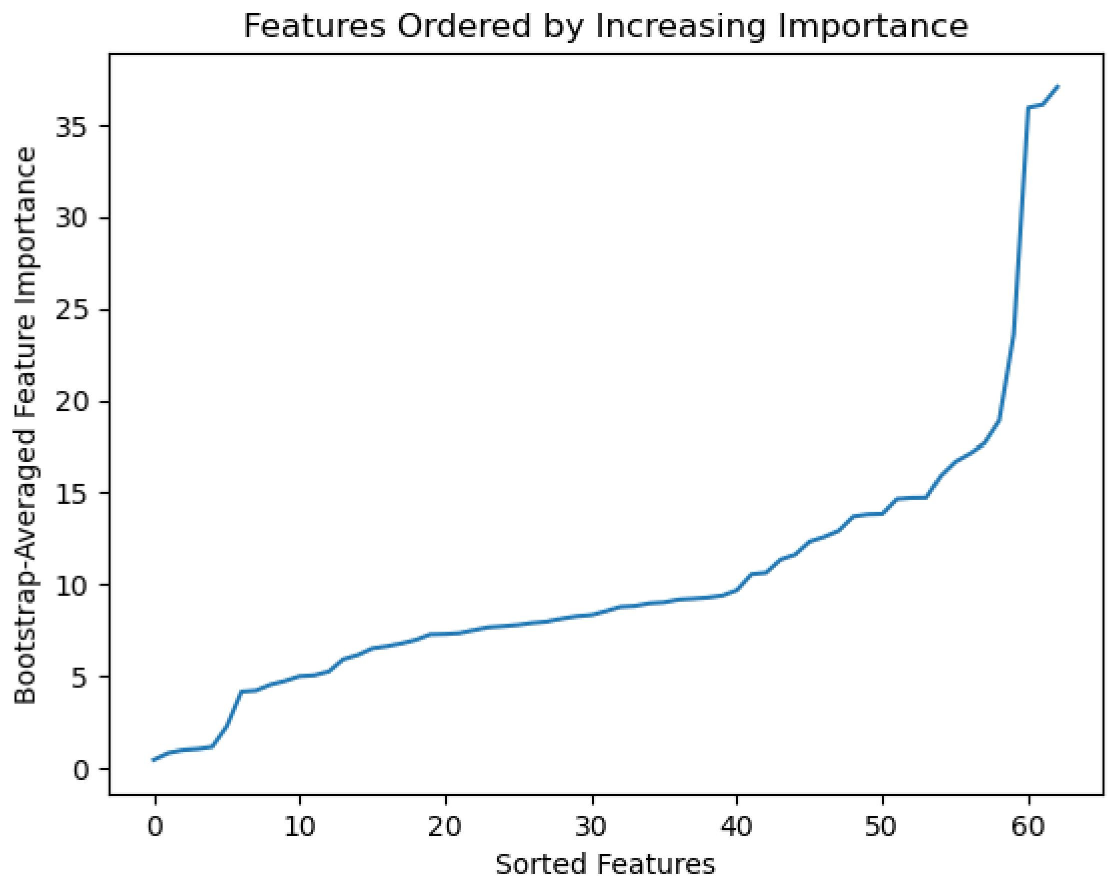
In [36]:
```
means_df["SEs"] = SEs_df.iloc[:, 1]

# We can now sort the dataset by increasing feature importance
means_df = means_df.sort_values(by = 1)
means_df
```

Out[36]:

	0	1	SEs
1	1	0.448010	1.847285
2	2	0.817783	2.070838
0	0	0.975917	2.124031
5	5	1.035069	2.443229
3	3	1.151687	2.597858
...	...	...	...
12	12	18.890914	14.641442
48	48	23.595675	22.001413
11	11	35.933441	17.253486
16	16	36.106949	27.792147
42	42	37.067921	18.227182

63 rows × 3 columns

In [52]:
```
plt.plot(range(63), means_df[1])
plt.xlabel("Sorted Features")
plt.ylabel("Bootstrap-Averaged Feature Importance")
plt.title("Features Ordered by Increasing Importance")
plt.show()
#plt.savefig("Feature_Importance.png")
```




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

We can see the there is a steep rise in feature importance for the top 5 or so features. This would suggest that we can use a subset of the total possible predictors, and we could yield good, if not better results.

In [38]:
```
# We cho
feature_subset = means_df.iloc[52:63, :]

feature_subset
```

Out[38]:

	0	1	SEs
14	14	14.719750	10.532248
20	20	14.730796	11.999169
13	13	15.913430	10.754404
47	47	16.684435	21.751815
34	34	17.125305	11.174492
6	6	17.670576	9.846716
12	12	18.890914	14.641442
48	48	23.595675	22.001413
11	11	35.933441	17.253486
16	16	36.106949	27.792147
42	42	37.067921	18.227182

In [39]:
```
# Use this subset model by selecting the columns for use in a final XGBoost
final_features = nba_trans[:, 1:]
final_test = nba_trans[:, 0]

final_features = final_features[:, np.asarray(feature_subset[0])]
#final_features.shape
```

In [40]:
```
X_train_final, X_test_final, y_train_final, y_test_final = train_test_split
```

In [44]:
```
final_XGB = XGBClassifier(eta = 1, gamma = 0, objective = 'binary:logistic'

final_XGB.fit(X_train_final, y_train_final)
```

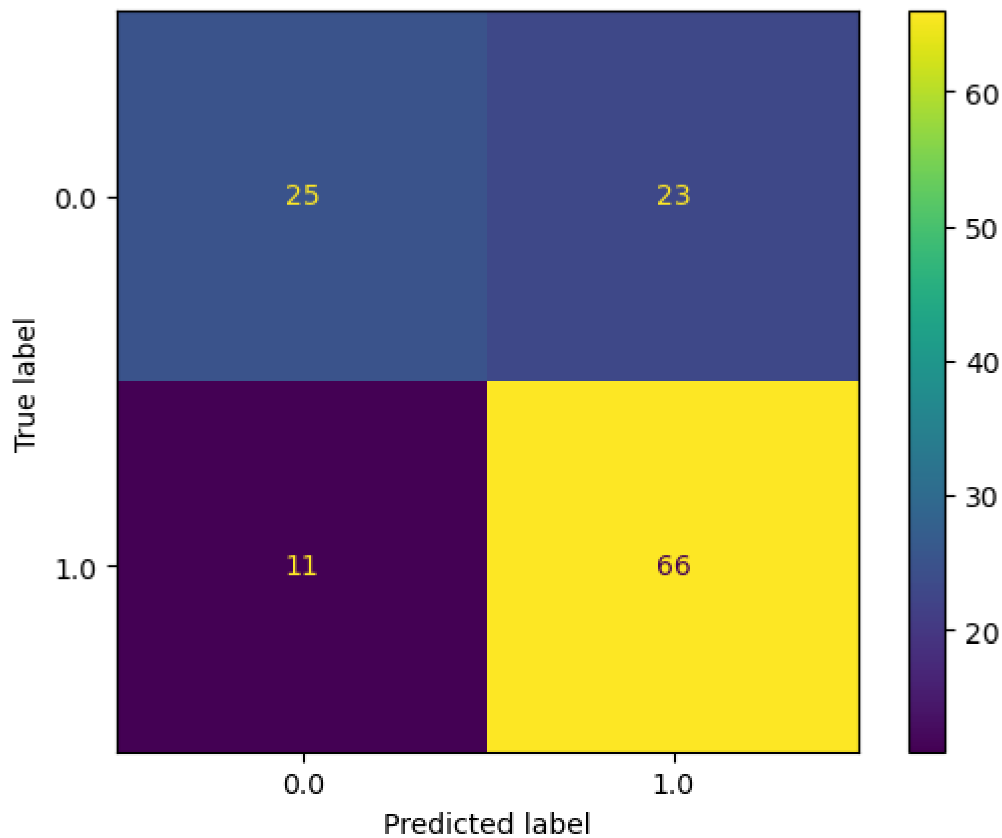
Out[44]:
```
XGBClassifier(base_score=0.5, booster='gbtree', callbacks=None,
              colsample_bylevel=1, colsample_bynode=1, colsample_bytree=
1,
              early_stopping_rounds=None, enable_categorical=False, eta=
1,
              eval_metric=None, feature_types=None, gamma=0, gpu_id=-1,
              grow_policy='depthwise', importance_type=None,
              interaction_constraints='', learning_rate=1, max_bin=256,
              max_cat_threshold=64, max_cat_to_onehot=4, max_delta_step=
0,
              max_depth=6, max_leaves=0, min_child_weight=1, missing=nan,
              monotone_constraints='()', n_estimators=100, n_jobs=0,
              num_parallel_tree=1, predictor='auto', ...)
```

In [45]:
```
print("XGBoost model test error: {}".format(
    1.0 - final_XGB.score(X=X_test_final, y=y_test_final)
))
```

```
XGBoost model test error: 0.272
```

We can see that by optimizing for the most important feature models, we get an error rate of 0.272, or an accuracy score of about 73%.

In [46]:
```
y_pred = final_XGB.predict(X_test_final)
cm = confusion_matrix(y_test_final, y_pred, labels=final_XGB.classes_)
disp = ConfusionMatrixDisplay(confusion_matrix=cm,
                              display_labels=final_XGB.classes_)
disp.plot()
disp.figure_.savefig('XGB_confusion.png')
```



Here we can see that this model is much better at predicting that a player gets drafted than if a player does not get drafted