EDA

In [1]:
```
# import necessary packages

#preprocessing
import numpy as np
import pandas as pd

import matplotlib.pyplot as plt
import seaborn as sns
from scipy.stats import binned_statistic
import pickle5 as pickle
from tqdm import tqdm

# modeling
import statsmodels.api as sm
from sklearn import linear_model as lm
from sklearn.model_selection import GridSearchCV, train_test_split,KFold
import sklearn.naive_bayes as nb
from sklearn.metrics import plot_confusion_matrix, mean_squared_error
from sklearn.neighbors import KNeighborsClassifier
from sklearn.neighbors import KNeighborsRegressor
from sklearn.preprocessing import LabelEncoder
from sklearn.preprocessing import StandardScaler
from sklearn.linear_model import LogisticRegression
from sklearn.naive_bayes import GaussianNB
from sklearn.svm import LinearSVC
from sklearn.tree import DecisionTreeClassifier, plot_tree
from sklearn.ensemble import RandomForestClassifier, AdaBoostClassifier, Stackin
import xgboost as xgb
from sklearn import metrics
```

In [2]:
```
# figure set-up

sns.set(rc = {'axes.titlesize': 15,
              'axes.labelsize': 15,
              'xtick.labelsize': 10,
              'ytick.labelsize': 10,
              'figure.figsize': (16, 9)})
```

In [3]:
```
# import pickle file
df = pickle.load(open('hmda_2017_il_data_all_records.pkl', "rb"))
```

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

Out[4]:

respondent_id	loan_type	loan_amount_000s	preapproval	action_taken	applicant_ethnicity	bla
76-0503625	Conventional	8.0	0	withdrawn	0	
81-5294275	Conventional	206.0	0	withdrawn	0	
0000917742	Conventional	550.0	0	denied	0	

respondent_id	loan_type	loan_amount_000s	preapproval	action_taken	applicant_ethnicity	bla
36-3987946	Conventional	259.0	1	denied	0	
36-4327855	Conventional	219.0	0	withdrawn	0	

In [5]:
```
df.shape
```

Out[5]:
```
(19460, 12)
```

In [6]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 19460 entries, 76-0503625 to 48-1148159
Data columns (total 12 columns):
 #   Column                          Non-Null Count  Dtype  
---  ------                          --------------  -----  
 0   loan_type                       19460 non-null  object 
 1   loan_amount_000s                19460 non-null  float64
 2   preapproval                     19460 non-null  int64  
 3   action_taken                    19460 non-null  object 
 4   applicant_ethnicity             19460 non-null  int64  
 5   black                           19460 non-null  int64  
 6   applicant_sex                   19460 non-null  int64  
 7   applicant_income_000s           19460 non-null  float64
 8   hud_median_family_income        19460 non-null  float64
 9   tract_to_msamd_income           19460 non-null  float64
 10  number_of_owner_occupied_units  19460 non-null  float64
 11  number_of_1_to_4_family_units   19460 non-null  float64
dtypes: float64(6), int64(4), object(2)
memory usage: 1.9+ MB
```

In [7]:
```
# action_taken is the label variable(categorical)
# show the amount of observation under each category
df['action_taken'].value_counts()
```

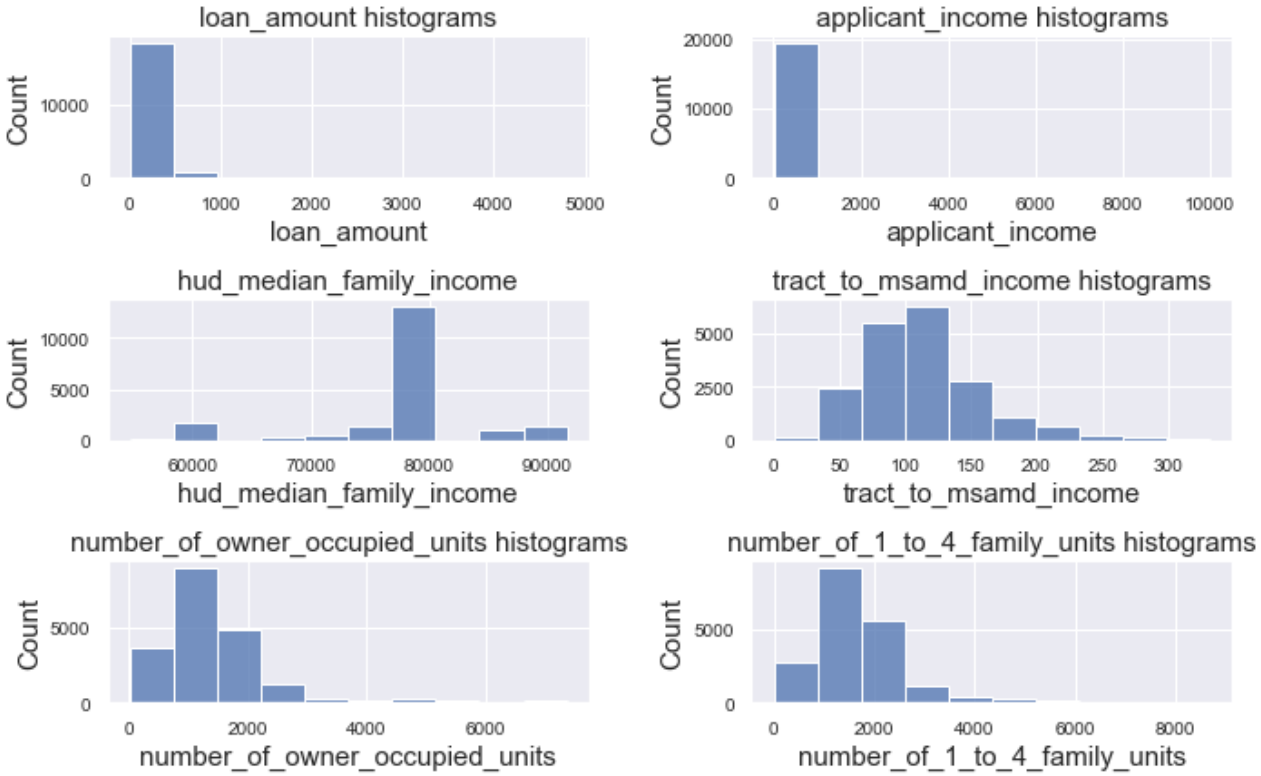
Out[7]:
```
withdrawn    10410
denied        7194
approved      1856
Name: action_taken, dtype: int64
```

In [8]:
```
# the histogram of label variable - action_taken
sns.set(rc = {'axes.titlesize': 15,
              'axes.labelsize': 15,
              'xtick.labelsize': 10,
              'ytick.labelsize': 10,
              'figure.figsize': (10, 6.2)})
plt.hist(df['action_taken'])
plt.title('Frequency of `action_taken` variable')
plt.xlabel('action_taken categories')
plt.ylabel('frequency')
```

Out[8]:
```
Text(0, 0.5, 'frequency')
```

In [9]:

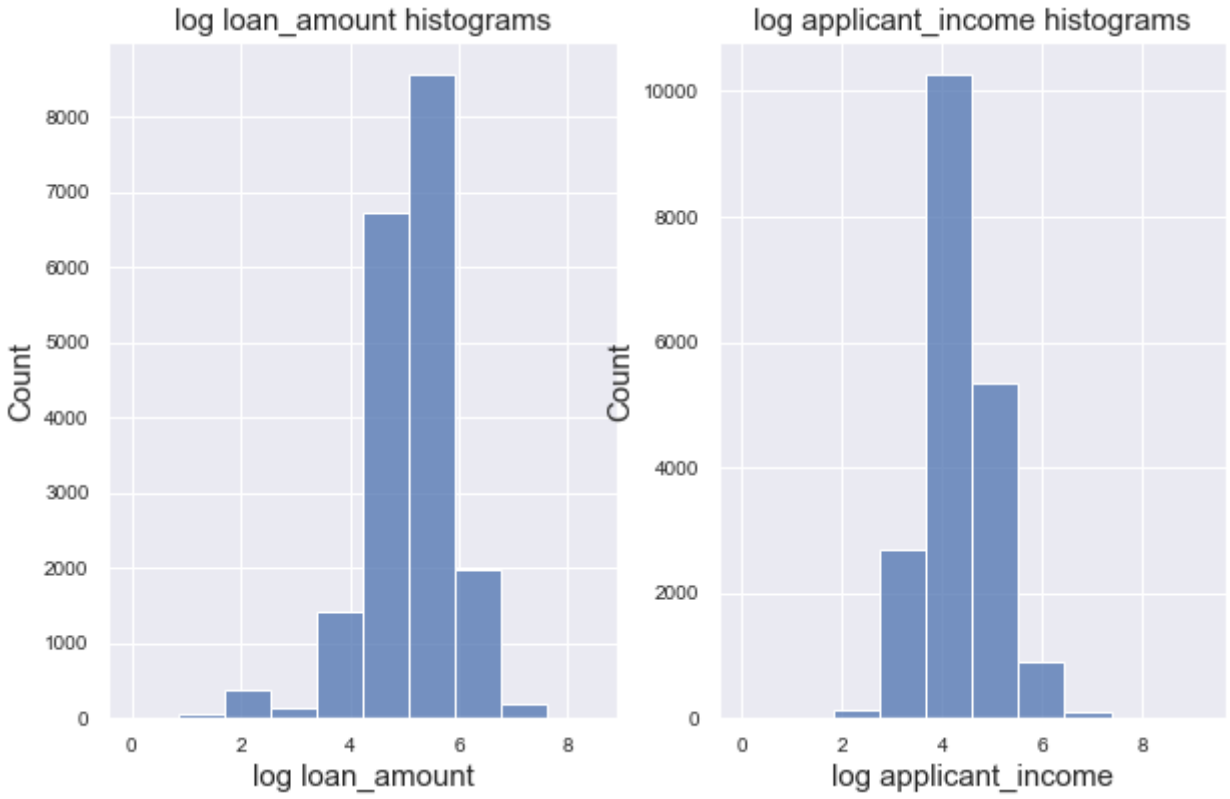
```
# feature transformation
# plotting all the continuous variables
plt.subplot(3,2,1)#n_rows, n_columns, index
sns.histplot(data = df, x = 'loan_amount_000s', bins = 10)
plt.xlabel('loan_amount')
plt.title("loan_amount histograms")
plt.subplot(3,2,2)#n_rows, n_columns, index
sns.histplot(data = df, x = 'applicant_income_000s', bins = 10)
plt.xlabel('applicant_income')
plt.title("applicant_income histograms")
plt.subplot(3,2,3)#n_rows, n_columns, index
sns.histplot(data = df, x = 'hud_median_family_income', bins = 10)
plt.xlabel('hud_median_family_income')
plt.title("hud_median_family_income")
plt.subplot(3,2,4)#n_rows, n_columns, index
sns.histplot(data = df, x = 'tract_to_msamd_income', bins = 10)
plt.xlabel('tract_to_msamd_income')
plt.title("tract_to_msamd_income histograms")
plt.subplot(3,2,5)#n_rows, n_columns, index
sns.histplot(data = df, x = 'number_of_owner_occupied_units', bins = 10)
plt.xlabel('number_of_owner_occupied_units')
plt.title("number_of_owner_occupied_units histograms")
plt.subplot(3,2,6)#n_rows, n_columns, index
sns.histplot(data = df, x = 'number_of_1_to_4_family_units', bins = 10)
plt.xlabel('number_of_1_to_4_family_units')
plt.title("number_of_1_to_4_family_units histograms")
plt.tight_layout()
```



I believe the variable `loan_amount` and `applicant_income` need transformation since the histogram of the two variables are right-skewed. So I did log transformation as the following:

In [10]:
```
df['log_loan_amount_000s'] = np.log(df['loan_amount_000s'])
df['log_applicant_income_000s'] = np.log(df['applicant_income_000s'])
plt.subplot(1,2,1)#n_rows, n_columns, index
sns.histplot(data = df, x = 'log_loan_amount_000s', bins = 10)
plt.xlabel('log loan_amount')
plt.title("log loan_amount histograms")
plt.subplot(1,2,2)#n_rows, n_columns, index
sns.histplot(data = df, x = 'log_applicant_income_000s', bins = 10)
plt.xlabel('log applicant_income')
plt.title("log applicant_income histograms")
```

Out[10]:
```
Text(0.5, 1.0, 'log applicant_income histograms')
```



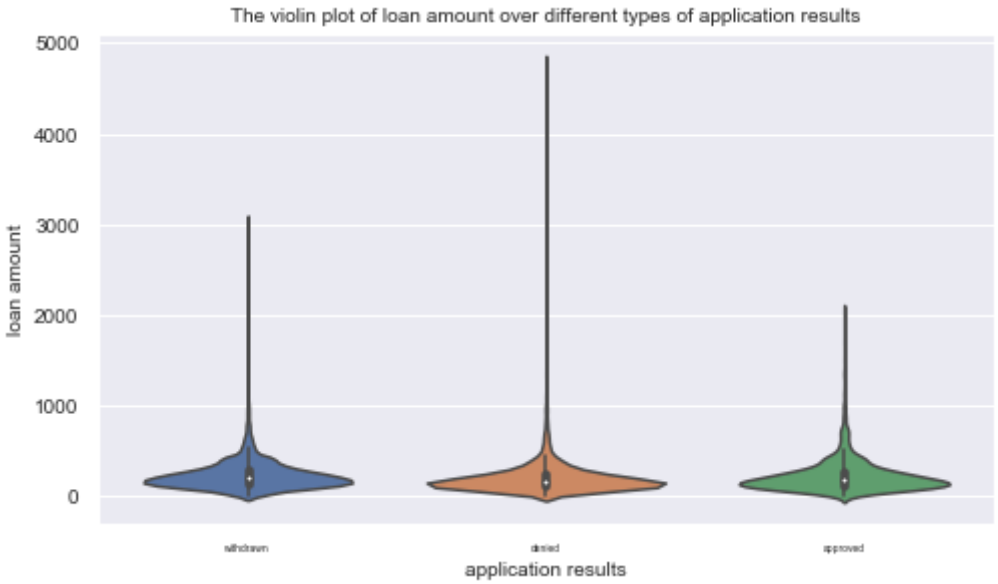
In [11]:

```
## scatter plots between continuous features
sns.set(rc = {'axes.titlesize': 10,
              'axes.labelsize': 10,
              'xtick.labelsize': 10,
              'ytick.labelsize': 10,
              'figure.figsize': (24, 13.5)})
sns.pairplot(df[['loan_amount_000s','applicant_income_000s',
                 'hud_median_family_income','tract_to_msamd_income','number_of_owne
                  'number_of_1_to_4_family_units']])
plt.tight_layout()
```

Yes. I have found a linear relationship between the variables `number_of_owner_occupied_units` and `number_of_1_to_4_family_units`. I may exclude one of them when starting to build model.

In [12]:
```
## the violin plot between action_taken(label variable) and loan_amount_000s
sns.set(rc = {'axes.titlesize': 10,
              'axes.labelsize': 10,
              'xtick.labelsize': 5,
              'ytick.labelsize': 10,
              'figure.figsize': (8, 4.5)})
ax = sns.violinplot(x='action_taken', y='loan_amount_000s', data=df)
plt.title('The violin plot of loan amount over different types of application re
plt.xlabel('application results')
plt.ylabel('loan amount')
```

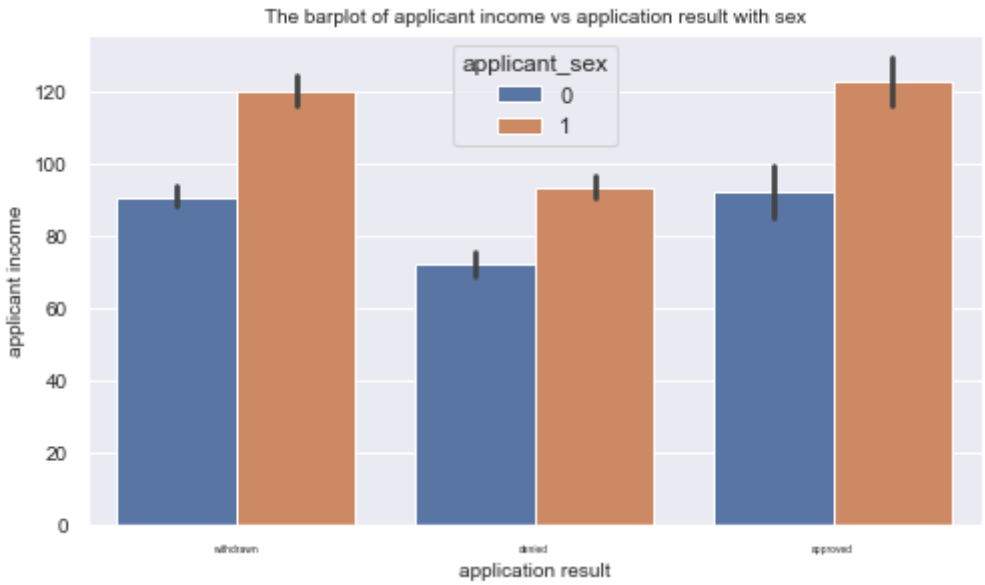
Out[12]:
```
Text(0, 0.5, 'loan amount')
```



I found the distribution of loan amount is very right-skewness, especially for the application result is `denied` , and I believe the reason why application is denied is partially caused by too large loan amount.

In [13]:
```
#bar plot of income across sex over different categories of action_taken(label v
ax = sns.barplot(x="action_taken", y="applicant_income_000s", hue="applicant_sex
plt.title('The barplot of applicant income vs application result with sex')
plt.xlabel('application result')
plt.ylabel('applicant income')
```

Out[13]:
```
Text(0, 0.5, 'applicant income')
```



Please be noted that `0` stands for female and `1` stands for male. I found for each application result, female's income is lower than male. Also, The avreage income of applicants whose applications are approved is higher than that of whose applications are denied.

Inference

In [15]:
```
## data preparation
df = df.reset_index()
df_prepped = df.drop(columns = ['loan_type','respondent_id']).join(
    pd.get_dummies(df['loan_type'], drop_first = True)
)
df_prepped['action_taken'] = df_prepped['action_taken'].astype('category')
y = df_prepped['action_taken']
x = df_prepped.drop(columns = ['action_taken'])
x_train, x_test, y_train, y_test = train_test_split(x, y,
                                                    train_size = 0.8,
                                                    random_state = 432)
ss = StandardScaler()
x_train_std = pd.DataFrame(ss.fit(x_train).transform(x_train),
                           columns = x_train.columns,
                           index = x_train.index)

x_test_std = pd.DataFrame(ss.fit(x_test).transform(x_test),
                          columns = x_test.columns,
                          index = x_test.index)
x_train_std = sm.add_constant(x_train_std)
x_test_std  = sm.add_constant(x_test_std)
x_train     = sm.add_constant(x_train)
x_test      = sm.add_constant(x_test)
```

In [16]:
```

## MNLogit Regularization
param_grid = {
    'C': 10.0**np.arange(-5, 1, step = 1),
}

lr_cv = lm.LogisticRegression(penalty = 'l1', solver = 'saga',
                              max_iter = 1e3, random_state = 490)
grid_search = GridSearchCV(lr_cv, param_grid,
                          cv = 5,
                          scoring = 'accuracy')
grid_search.fit(x_train_std, y_train)
best = grid_search.best_params_
best
```

```
/Users/juli/opt/miniconda3/lib/python3.7/site-packages/sklearn/linear_model/_sa
g.py:329: ConvergenceWarning: The max_iter was reached which means the coef_ did
not converge
  "the coef_ did not converge", ConvergenceWarning)
/Users/juli/opt/miniconda3/lib/python3.7/site-packages/sklearn/linear_model/_sa
g.py:329: ConvergenceWarning: The max_iter was reached which means the coef_ did
not converge
  "the coef_ did not converge", ConvergenceWarning)
/Users/juli/opt/miniconda3/lib/python3.7/site-packages/sklearn/linear_model/_sa
g.py:329: ConvergenceWarning: The max_iter was reached which means the coef_ did
not converge
  "the coef_ did not converge", ConvergenceWarning)
/Users/juli/opt/miniconda3/lib/python3.7/site-packages/sklearn/linear_model/_sa
g.py:329: ConvergenceWarning: The max_iter was reached which means the coef_ did
not converge
  "the coef_ did not converge", ConvergenceWarning)
```

Out[16]:
```
{'C': 0.01}
```

	action_taken = 0
loan_amount	0.0451

	action_taken = 0
	(0.0268)
black	0.1184
	(0.0177)
family_income	-0.0478
	(0.0285)
Features	15
Observations	15568
Pseudo R-squared	0.028

	action_taken = 1
preapproval	-0.0848
	(0.0257)
applicant_income	-0.0064
	(0.0201)
family_income	0.0968
	(0.0274)
Features	15
Observations	15568
Pseudo R-squared	0.028

In [17]:
```
## Refit MNLogit Model with selected features
fit_logit_reg = sm.MNLogit(y_train, x_train_std
                           ).fit_regularized(alpha = 1/best['C'],
                                             L1_wt = 1,
                                             qc_tol = 1e3)
## show the summary of MNLogit Model
fit_logit_reg.summary2()
```

```
Optimization terminated successfully    (Exit mode 0)
            Current function value: 0.9259210852222489
            Iterations: 51
            Function evaluations: 52
            Gradient evaluations: 51
```

Out[17]:

Model:	MNLogit	Pseudo R-squared:	0.028
Dependent Variable:	action_taken	AIC:	28131.2596
Date:	2021-05-14 21:23	BIC:	28261.3602
No. Observations:	15568	Log-Likelihood:	-14049.
Df Model:	15	LL-Null:	-14446.
Df Residuals:	15551	LLR p-value:	9.8761e-160
Converged:	1.0000	Scale:	1.0000
No. Iterations:	51.0000		

action_taken = 0	Coef.	Std.Err.	t	P>|t|	[0.025	0.975]
const	1.1793	0.0280	42.0760	0.0000	1.1244	1.2342
loan_amount_000s	0.0451	0.0268	1.6844	0.0921	-0.0074	0.0977
preapproval	0.0008	0.0265	0.0286	0.9772	-0.0512	0.0527
applicant_ethnicity	0.0419	0.0179	2.3412	0.0192	0.0068	0.0770
black	0.1184	0.0177	6.7020	0.0000	0.0838	0.1530
applicant_sex	0.0011	0.0174	0.0622	0.9504	-0.0331	0.0353
applicant_income_000s	0.0000	nan	nan	nan	nan	nan
hud_median_family_income	-0.0478	0.0285	-1.6770	0.0935	-0.1037	0.0081
tract_to_msamd_income	0.0000	nan	nan	nan	nan	nan
number_of_owner_occupied_units	0.0000	nan	nan	nan	nan	nan
number_of_1_to_4_family_units	0.0000	nan	nan	nan	nan	nan
log_loan_amount_000s	0.0000	nan	nan	nan	nan	nan
log_applicant_income_000s	-0.3158	0.0251	-12.6017	0.0000	-0.3649	-0.2667
FHA	0.1159	0.0183	6.3436	0.0000	0.0801	0.1517
FSA/RHS	0.0001	0.0169	0.0079	0.9937	-0.0331	0.0333
VA	0.0057	0.0175	0.3270	0.7436	-0.0285	0.0400

action_taken = 1	Coef.	Std.Err.	t	P>|t|	[0.025	0.975]
const	1.5747	0.0268	58.7948	0.0000	1.5222	1.6272
loan_amount_000s	0.0000	nan	nan	nan	nan	nan
preapproval	-0.0848	0.0257	-3.2988	0.0010	-0.1352	-0.0344
applicant_ethnicity	0.0000	nan	nan	nan	nan	nan
black	0.0000	nan	nan	nan	nan	nan
applicant_sex	0.0000	nan	nan	nan	nan	nan
applicant_income_000s	-0.0064	0.0201	-0.3164	0.7517	-0.0458	0.0331
hud_median_family_income	0.0968	0.0274	3.5295	0.0004	0.0431	0.1506
tract_to_msamd_income	0.0071	0.0191	0.3731	0.7091	-0.0303	0.0446
number_of_owner_occupied_units	0.0000	nan	nan	nan	nan	nan
number_of_1_to_4_family_units	0.0000	nan	nan	nan	nan	nan
log_loan_amount_000s	0.0194	0.0225	0.8594	0.3901	-0.0248	0.0635
log_applicant_income_000s	0.0000	nan	nan	nan	nan	nan
FHA	0.0000	nan	nan	nan	nan	nan
FSA/RHS	0.0000	nan	nan	nan	nan	nan
VA	0.0000	nan	nan	nan	nan	nan

In [18]:
```
# get marginal effect summary of MNLogit Model
```

```
fit_logit_reg.get_margeff().summary()
```

Out[18]:

MNLogit Marginal Effects

Dep. Variable: action_taken

Method: dydx

At: overall

action_taken=approved	dy/dx	std err	z	P>|z|	[0.025	0.975]
loan_amount_000s	-0.0017	nan	nan	nan	nan	nan
preapproval	0.0049	nan	nan	nan	nan	nan
applicant_ethnicity	-0.0016	nan	nan	nan	nan	nan
black	-0.0046	nan	nan	nan	nan	nan
applicant_sex	-4.179e-05	nan	nan	nan	nan	nan
applicant_income_000s	0.0004	nan	nan	nan	nan	nan
hud_median_family_income	-0.0038	nan	nan	nan	nan	nan
tract_to_msamd_income	-0.0004	nan	nan	nan	nan	nan
number_of_owner_occupied_units	0	nan	nan	nan	nan	nan
number_of_1_to_4_family_units	0	nan	nan	nan	nan	nan
log_loan_amount_000s	-0.0011	nan	nan	nan	nan	nan
log_applicant_income_000s	0.0122	nan	nan	nan	nan	nan
FHA	-0.0045	nan	nan	nan	nan	nan
FSA/RHS	-5.167e-06	nan	nan	nan	nan	nan
VA	-0.0002	nan	nan	nan	nan	nan
action_taken=denied	**dy/dx**	**std err**	**z**	**P>|z|**	**[0.025**	**0.975]**
loan_amount_000s	0.0100	nan	nan	nan	nan	nan
preapproval	0.0157	nan	nan	nan	nan	nan
applicant_ethnicity	0.0093	nan	nan	nan	nan	nan
black	0.0263	nan	nan	nan	nan	nan
applicant_sex	0.0002	nan	nan	nan	nan	nan
applicant_income_000s	0.0012	nan	nan	nan	nan	nan
hud_median_family_income	-0.0284	nan	nan	nan	nan	nan
tract_to_msamd_income	-0.0013	nan	nan	nan	nan	nan
number_of_owner_occupied_units	0	nan	nan	nan	nan	nan
number_of_1_to_4_family_units	0	nan	nan	nan	nan	nan
log_loan_amount_000s	-0.0036	nan	nan	nan	nan	nan
log_applicant_income_000s	-0.0702	nan	nan	nan	nan	nan
FHA	0.0258	nan	nan	nan	nan	nan
FSA/RHS	2.982e-05	nan	nan	nan	nan	nan

VA	0.0013	nan	nan	nan	nan	nan
action_taken=withdrawn	**dy/dx**	**std err**	**z**	**P>|z|**	**[0.025**	**0.975]**
loan_amount_000s	-0.0083	nan	nan	nan	nan	nan
preapproval	-0.0207	nan	nan	nan	nan	nan
applicant_ethnicity	-0.0077	nan	nan	nan	nan	nan
black	-0.0217	nan	nan	nan	nan	nan
applicant_sex	-0.0002	nan	nan	nan	nan	nan
applicant_income_000s	-0.0015	nan	nan	nan	nan	nan
hud_median_family_income	0.0322	nan	nan	nan	nan	nan
tract_to_msamd_income	0.0017	nan	nan	nan	nan	nan
number_of_owner_occupied_units	0	nan	nan	nan	nan	nan
number_of_1_to_4_family_units	0	nan	nan	nan	nan	nan
log_loan_amount_000s	0.0047	nan	nan	nan	nan	nan
log_applicant_income_000s	0.0580	nan	nan	nan	nan	nan
FHA	-0.0213	nan	nan	nan	nan	nan
FSA/RHS	-2.465e-05	nan	nan	nan	nan	nan
VA	-0.0011	nan	nan	nan	nan	nan

Prediction

null model

In [19]:
```
## null model accuracy
y_hat_dic = {}
for (k,v) in zip(np.unique(y_train, return_counts = True)[0],
                 np.unique(y_train, return_counts = True)[1]):
    y_hat_dic[k] = v
null_acc = np.mean(y_test == max(y_hat_dic))
null_acc
```

Out[19]: 0.5382836587872559

MNLgoit ACC

In [20]:
```
## MNLogit model accuracy
yhat = y_test.cat.categories[fit_logit_reg.predict(x_test_std).idxmax(axis = 1)]
#yhat
acc_logit = np.mean(yhat == y_test)
acc_logit
```

Out[20]: 0.5680883864337102

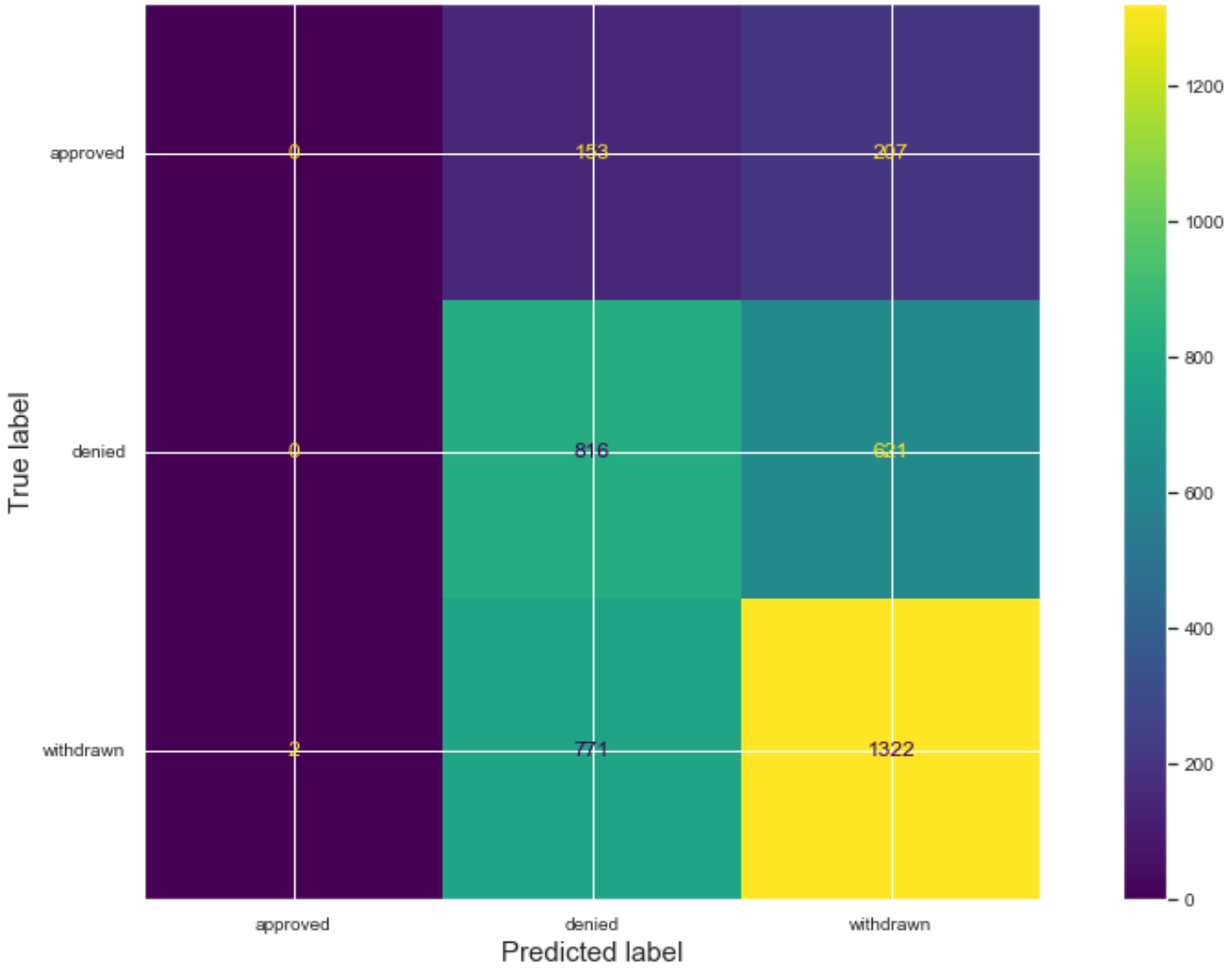
Naive Bayes

In [21]:
```
## naive bayes model accuracy
sns.set(rc = {'axes.titlesize': 15,
              'axes.labelsize': 15,
              'xtick.labelsize': 10,
              'ytick.labelsize': 10,
              'figure.figsize': (16, 9)})
gnb = nb.GaussianNB()
gnb.fit(x_train, y_train)

nb_acc = gnb.score(x_test, y_test)
print(nb_acc)

plot_confusion_matrix(gnb, x_test, y_test)
plt.show()
```

```
0.5493319630010277
```



KNN

In [23]:
```
## KNN model accuracy
kf = KFold(n_splits = 5, random_state = 490, shuffle = True)
k_nbrs = [5, 10, 15, 20, 25, 30, 35, 40, 45, 50,60,70,80,90,100, 110, 120,130,14
accuracy = {}


for k in tqdm(k_nbrs):
    acc = []
```

```
    for trn, tst in kf.split(x_train_std):
        yhat = KNeighborsClassifier(n_neighbors = k
        ).fit(x_train_std.iloc[trn], y_train.iloc[trn]
        ).predict(x_train_std.iloc[tst])
        acc.append(np.mean(yhat == y_train.iloc[tst]))
    accuracy[k] = np.mean(acc)
```

```
100%|██████████| 20/20 [01:57<00:00,  5.87s/it]
```

In [24]:

```
best_k = max(accuracy, key = accuracy.get)
print(best_k)
```

```
100
```

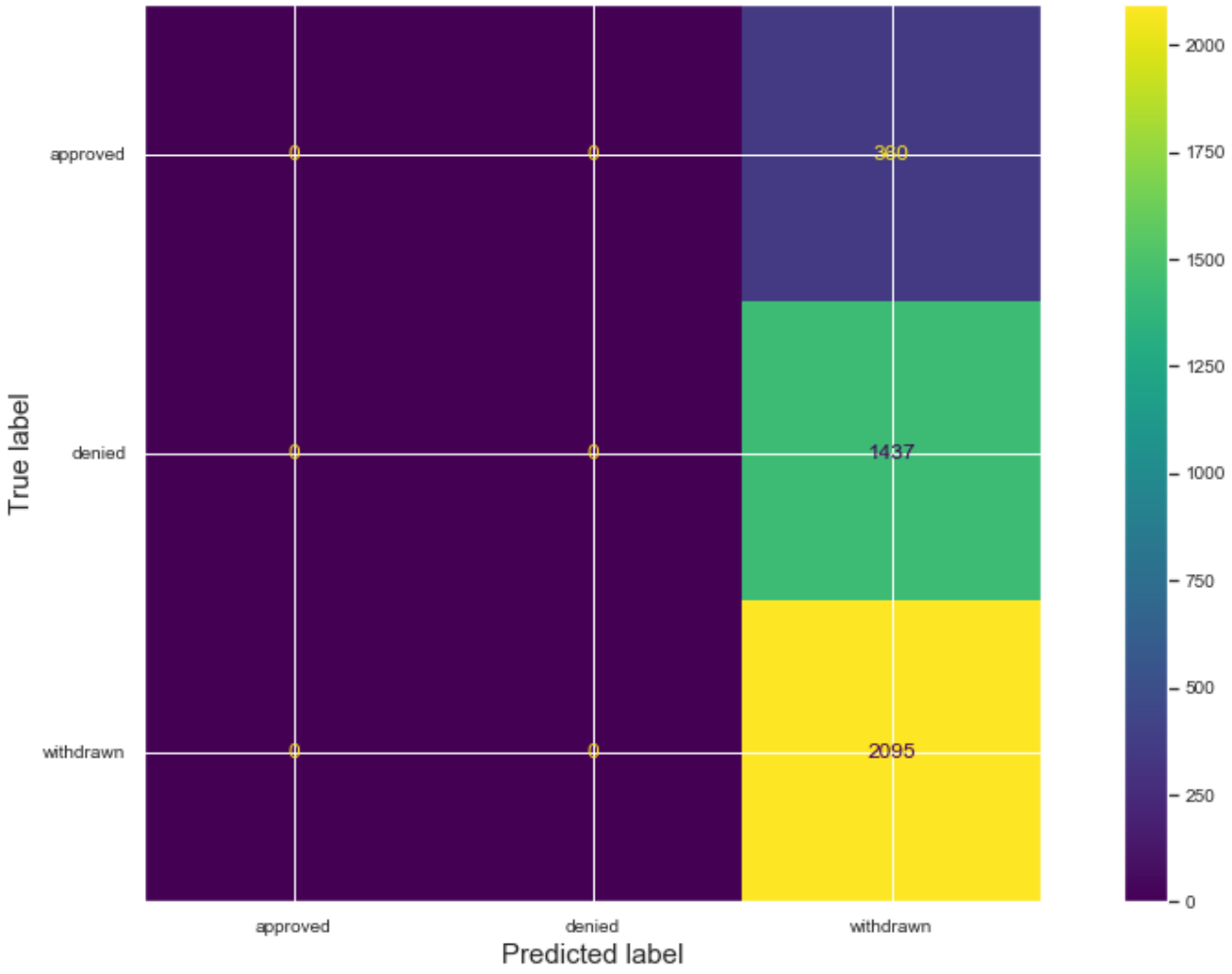
In [25]:

```
%%time
knn = KNeighborsClassifier(n_neighbors = best_k)
knn.fit(x_train_std, y_train)
acc_knn = knn.score(x_test_std, y_test)
print(acc_knn)
```

```
0.5688591983556013
CPU times: user 2.23 s, sys: 835 ms, total: 3.06 s
Wall time: 1.82 s
```

In [26]:

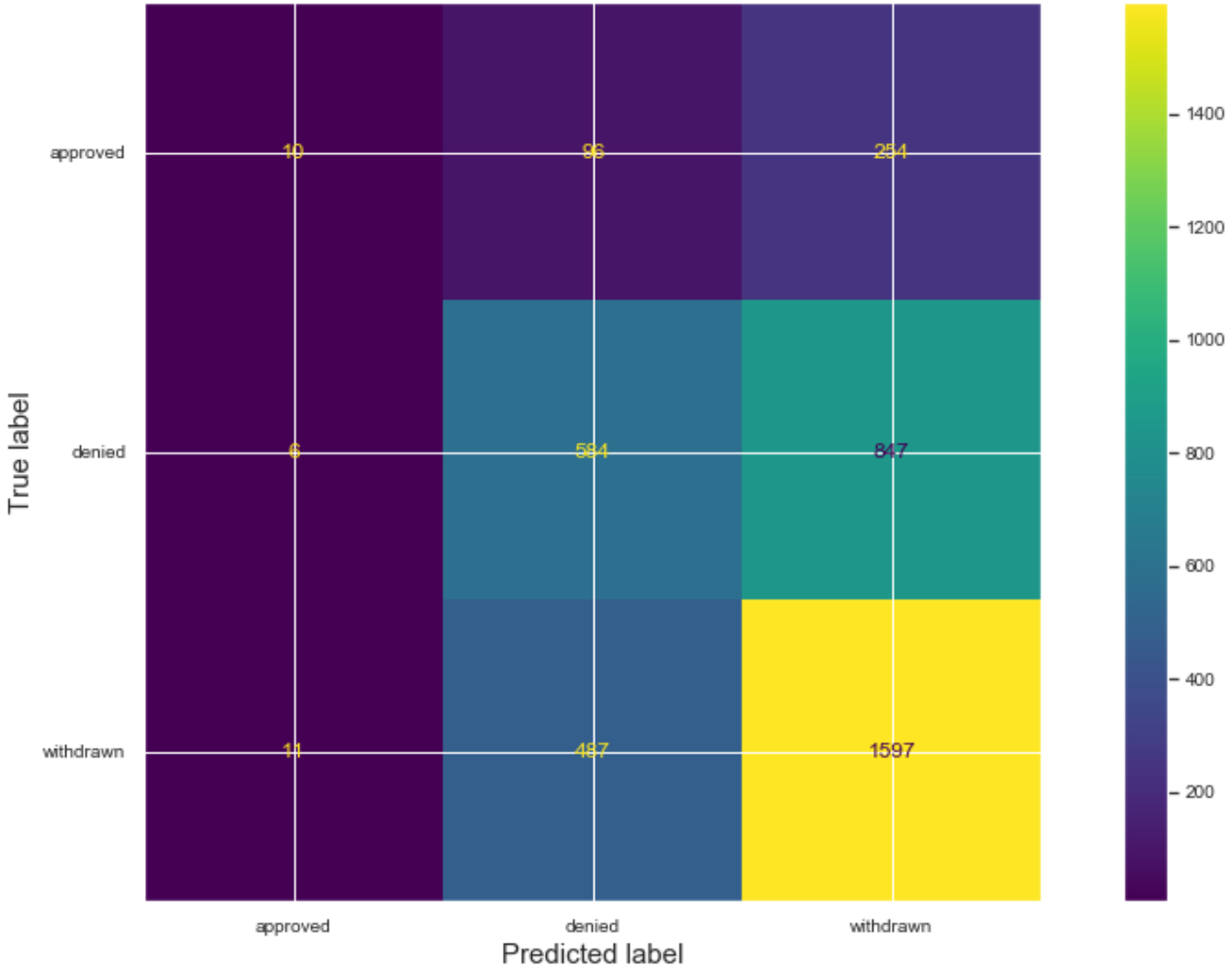
```
plot_confusion_matrix(knn, x_test, y_test)
plt.show()
```



Random Forest Model

In [27]:
```
## random forest model accuracy and confusion matrix
clf_rf = RandomForestClassifier(n_estimators = 500,
                                random_state = 432,
                                max_features = 'sqrt',
                                oob_score = True,
                                verbose = 1)
clf_rf.fit(x_train, y_train)
rf_acc = clf_rf.score(x_test, y_test)
print(rf_acc)
plot_confusion_matrix(clf_rf, x_test, y_test)
plt.show()
```

```
[Parallel(n_jobs=1)]: Using backend SequentialBackend with 1 concurrent workers.
[Parallel(n_jobs=1)]: Done 500 out of 500 | elapsed:   17.0s finished
[Parallel(n_jobs=1)]: Using backend SequentialBackend with 1 concurrent workers.
[Parallel(n_jobs=1)]: Done 500 out of 500 | elapsed:    0.6s finished
[Parallel(n_jobs=1)]: Using backend SequentialBackend with 1 concurrent workers.
0.5629496402877698
[Parallel(n_jobs=1)]: Done 500 out of 500 | elapsed:    0.6s finished
```



Adaboosting Model

In [28]:
```
param_grid = {
    'n_estimators': [25, 50, 75, 100],
```

```
    'learning_rate': [0.1,0.5,1,1.5]
}

ada_cv = AdaBoostClassifier(base_estimator = DecisionTreeClassifier(
                             max_depth = 1),
                            random_state = 490)
grid_search = GridSearchCV(ada_cv, param_grid,
                           cv = 5,
                           scoring = 'accuracy'
                           ).fit(x_train, y_train)

best_e_lr = grid_search.best_params_
best_e_lr
```

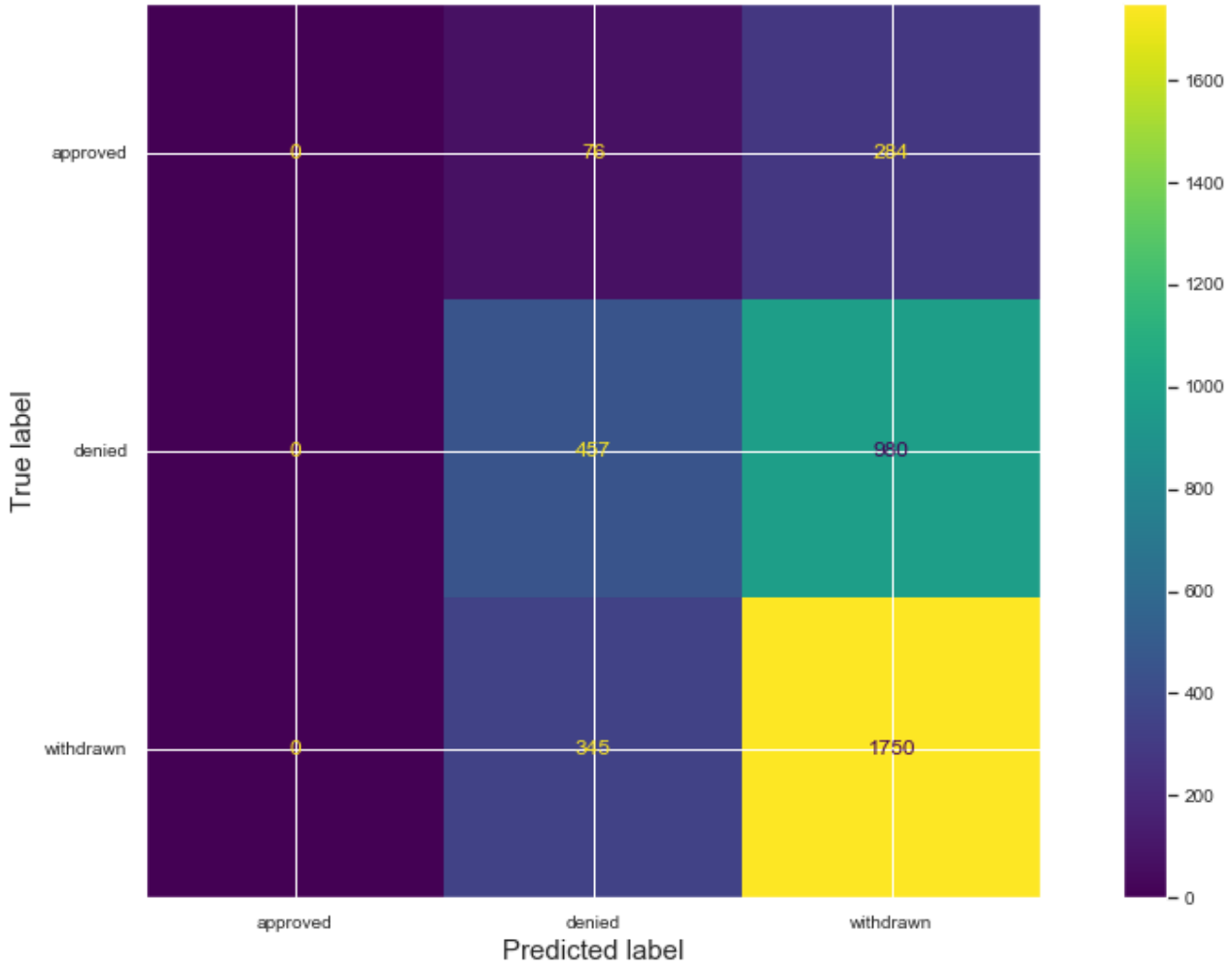
Out[28]:
```
{'learning_rate': 0.5, 'n_estimators': 50}
```

In [29]:
```
clf_ada = AdaBoostClassifier(base_estimator = DecisionTreeClassifier(
                             max_depth = 1),
                            random_state = 490,
                            n_estimators = best_e_lr['n_estimators'],
                            learning_rate = best_e_lr['learning_rate'])
clf_ada.fit(x_train, y_train)

ada_acc = clf_ada.score(x_test, y_test)
ada_acc
```

Out[29]:
```
0.567060637204522
```

In [30]:
```
plot_confusion_matrix(clf_ada, x_test, y_test)
plt.show()
```



Stacking

In [31]:
```
print("Naive Bayes", nb_acc)
print("rf acc: ", rf_acc)
print("ada acc: ", ada_acc)
```

```
Naive Bayes 0.5493319630010277
rf acc:  0.5629496402877698
ada acc:  0.567060637204522
```

In [32]:
```
estimators = [
    ('knn',gnb),
    ('rf', clf_rf),
    ('ada', clf_ada)
]
stack_clf = StackingClassifier(
    estimators=estimators,
    final_estimator=LogisticRegression(solver = 'saga'), cv = 5
)
stack_clf.fit(x_train, y_train)
```

```
[Parallel(n_jobs=1)]: Using backend SequentialBackend with 1 concurrent workers.
[Parallel(n_jobs=1)]: Done 500 out of 500 | elapsed:   18.6s finished
[Parallel(n_jobs=1)]: Using backend SequentialBackend with 1 concurrent workers.
[Parallel(n_jobs=1)]: Done 500 out of 500 | elapsed:   13.3s finished
[Parallel(n_jobs=1)]: Using backend SequentialBackend with 1 concurrent workers.
```

```
[Parallel(n_jobs=1)]: Done 500 out of 500 | elapsed:    0.4s finished
[Parallel(n_jobs=1)]: Using backend SequentialBackend with 1 concurrent workers.
[Parallel(n_jobs=1)]: Done 500 out of 500 | elapsed:   13.2s finished
[Parallel(n_jobs=1)]: Using backend SequentialBackend with 1 concurrent workers.
[Parallel(n_jobs=1)]: Done 500 out of 500 | elapsed:    0.5s finished
[Parallel(n_jobs=1)]: Using backend SequentialBackend with 1 concurrent workers.
[Parallel(n_jobs=1)]: Done 500 out of 500 | elapsed:   12.9s finished
[Parallel(n_jobs=1)]: Using backend SequentialBackend with 1 concurrent workers.
[Parallel(n_jobs=1)]: Done 500 out of 500 | elapsed:    0.4s finished
[Parallel(n_jobs=1)]: Using backend SequentialBackend with 1 concurrent workers.
[Parallel(n_jobs=1)]: Done 500 out of 500 | elapsed:   13.1s finished
[Parallel(n_jobs=1)]: Using backend SequentialBackend with 1 concurrent workers.
[Parallel(n_jobs=1)]: Done 500 out of 500 | elapsed:    0.4s finished
[Parallel(n_jobs=1)]: Using backend SequentialBackend with 1 concurrent workers.
[Parallel(n_jobs=1)]: Done 500 out of 500 | elapsed:   12.9s finished
[Parallel(n_jobs=1)]: Using backend SequentialBackend with 1 concurrent workers.
[Parallel(n_jobs=1)]: Done 500 out of 500 | elapsed:    0.4s finished
```

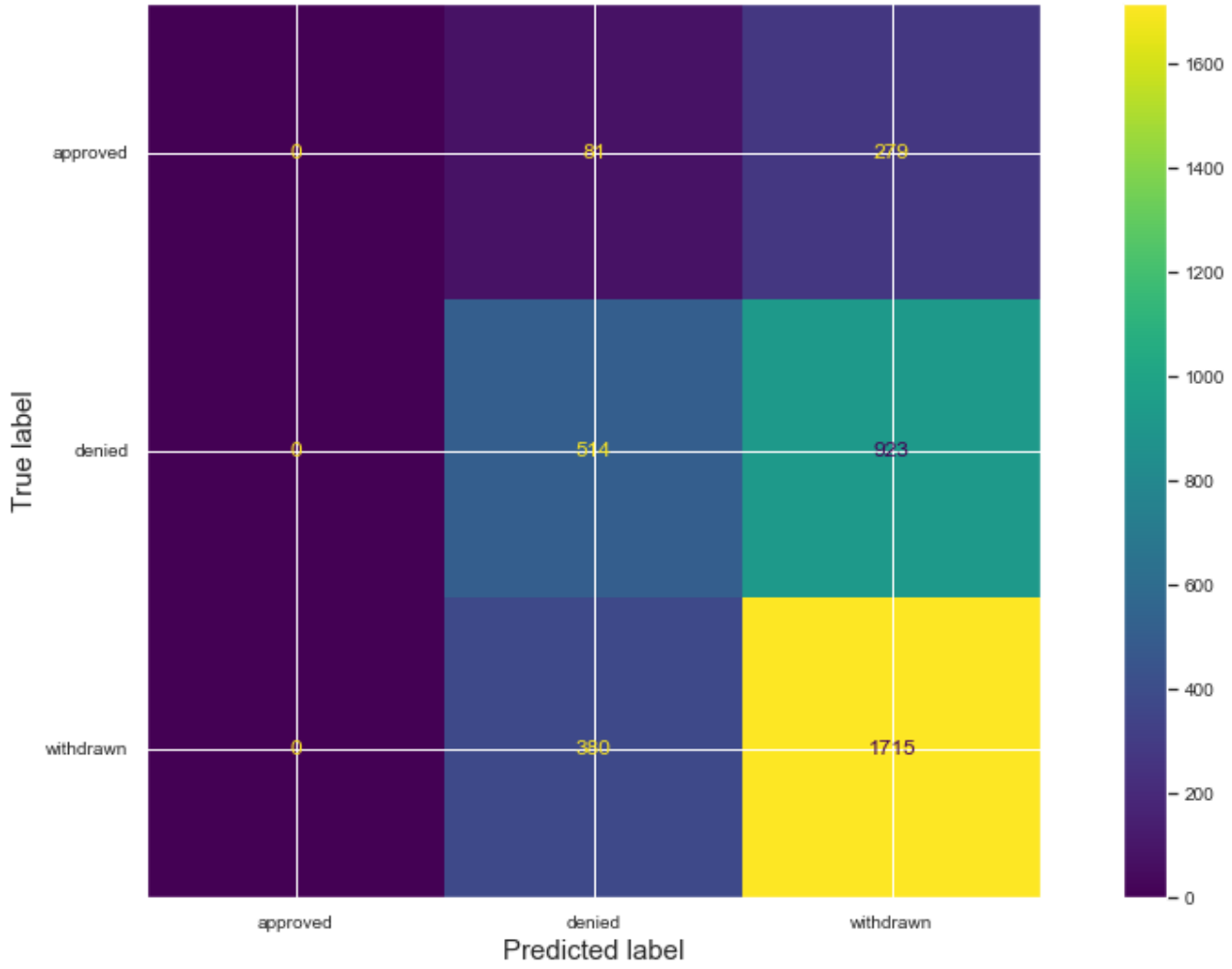
Out[32]:

```
StackingClassifier(cv=5,
                   estimators=[('knn', GaussianNB()),
                               ('rf',
                                RandomForestClassifier(max_features='sqrt',
                                                       n_estimators=500,
                                                       oob_score=True,
                                                       random_state=432,
                                                       verbose=1)),
                               ('ada',
                                AdaBoostClassifier(base_estimator=DecisionTreeCl
assifier(max_depth=1),
                                                   learning_rate=0.5,
                                                   random_state=490))],
                   final_estimator=LogisticRegression(solver='saga'))
```

In [33]:

```
plot_confusion_matrix(stack_clf, x_test, y_test)
plt.show()
```

```
[Parallel(n_jobs=1)]: Using backend SequentialBackend with 1 concurrent workers.
[Parallel(n_jobs=1)]: Done 500 out of 500 | elapsed:    0.6s finished
```



In [34]:
```
stack_acc = stack_clf.score(x_test, y_test)
stack_acc
```

```
[Parallel(n_jobs=1)]: Using backend SequentialBackend with 1 concurrent workers.
[Parallel(n_jobs=1)]: Done 500 out of 500 | elapsed:    0.5s finished
```

Out[34]: 0.5727132579650566

Comparison

Model	Accuracy
Null Model	0.5383
MNLogit Model	0.5527
Naive Bayes Model	0.5470
KNN	0.5689
Random Forest Model	0.5632
Adaboosting Model	0.5671
Stacking Model	0.5725

MNLogit Model has the strongest interpretation power and flexibility. I will choose stacking model combining Naive Nayes model, Random Forest model and Adaboosting model given the

metric of accuracy.

In [ ]: