HW2

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In [1]:
```
import matplotlib.pyplot as plt
import numpy as np
import pandas as pd
from sklearn.datasets import fetch_openml
```

Task 1

In [2]:
```
data = fetch_openml("credit-g",as_frame=True)
df = data.data
df["target"]=data.target
df.head()
```

Out[2]:

	checking_status	duration	credit_history	purpose	credit_amount	savings_status	em
0	<0	6.0	critical/other existing credit	radio/tv	1169.0	no known savings	
1	0<=X<200	48.0	existing paid	radio/tv	5951.0	<100	
2	no checking	12.0	critical/other existing credit	education	2096.0	<100	
3	<0	42.0	existing paid	furniture/equipment	7882.0	<100	
4	<0	24.0	delayed previously	new car	4870.0	<100	

5 rows × 21 columns

In [3]:
```
continuous_f = ['duration','credit_amount','installment_commitment','res
idence_since','age','existing_credits','num_dependents']
categorical_f = ['checking_status','credit_history','purpose','savings_s
tatus','employment','personal_status','other_parties','property_magnitud
e','other_payment_plans','housing','job','own_telephone','foreign_worke
r']
```

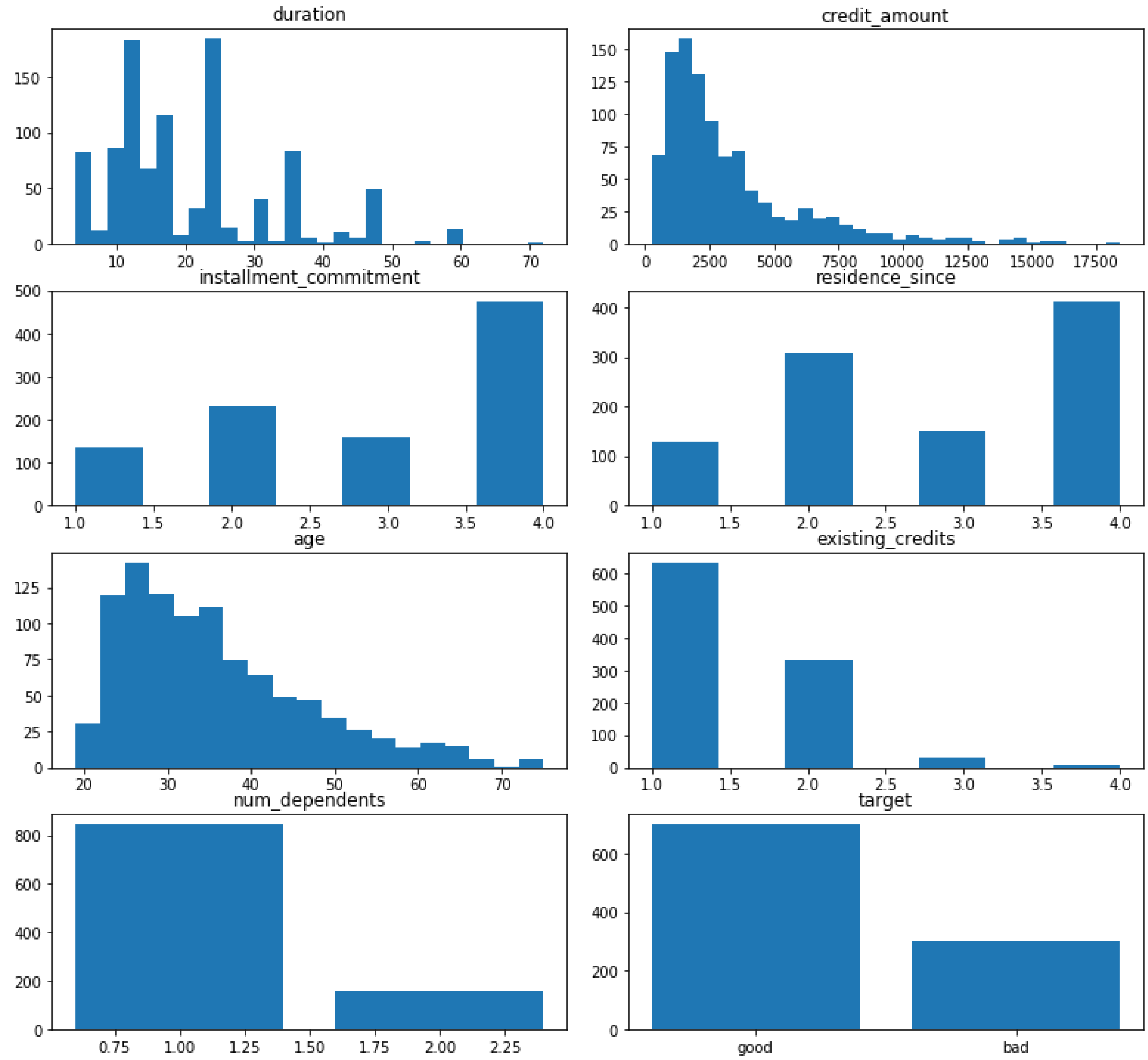
1.1

In [4]:
```
print("\033[1mContinuous:\033[0m")
for x in range(0,len(continuous_f)):
    print(continuous_f[x])
print("\n\033[1mCategorical:\033[0m")
for x in range(0,len(categorical_f)):
    print(categorical_f[x])
```

```
Continuous:
duration
credit_amount
installment_commitment
residence_since
age
existing_credits
num_dependents

Categorical:
checking_status
credit_history
purpose
savings_status
employment
personal_status
other_parties
property_magnitude
other_payment_plans
housing
job
own_telephone
foreign_worker
```

1.2

In [5]:
```
fig, ax = plt.subplots(4,2, figsize=(11, 10))
fig.tight_layout()

ax[0,0].set_title(continuous_f[0])
ax[0,0].hist(df[continuous_f[0]], bins='auto')

ax[0,1].set_title(continuous_f[1])
ax[0,1].hist(df[continuous_f[1]], bins='auto')

ax[1,0].set_title(continuous_f[2])
ax[1,0].hist(df[continuous_f[2]], bins=7)

ax[1,1].set_title(continuous_f[3])
ax[1,1].hist(df[continuous_f[3]], bins=7)

ax[2,0].set_title(continuous_f[4])
ax[2,0].hist(df[continuous_f[4]], bins='auto')

ax[2,1].set_title(continuous_f[5])
ax[2,1].hist(df[continuous_f[5]], bins=7)

ax[3,0].set_title(continuous_f[6])
ax[3,0].bar(df[continuous_f[6]].unique(), df[continuous_f[6]].value_coun
ts())

ax[3,1].set_title("target")
ax[3,1].bar(df["target"].unique(), df["target"].value_counts())

plt.show()
```



1.3

```
In [6]: from sklearn.model_selection import train_test_split

In [7]: train, test = train_test_split(df, test_size=0.2)

In [8]: y_train = train["target"]
        X_train = train.loc[:, train.columns != "target"]

In [9]: X_train_ohe = pd.get_dummies(X_train, columns=categorical_f)
        #X_train_ohe.head()

In [10]: y_train = y_train.map(dict(good=1, bad=0))
         #y_train
```

In [11]:
```
from sklearn.linear_model import LogisticRegression
from sklearn import metrics
from sklearn.model_selection import cross_val_predict
```

In [12]:
```
X_train_np = X_train_ohe.to_numpy()
y_train_list = y_train.values.tolist()
```

In [13]:
```
evaluate = cross_val_predict(LogisticRegression(max_iter=5000), X_train_
np, y_train_list, cv=5)
print("Evaluated on cross validation:",metrics.accuracy_score(y_train_li
st, evaluate))
```

```
Evaluated on cross validation: 0.765
```

1.4

In [14]:
```
from sklearn.pipeline import make_pipeline
from sklearn.compose import make_column_transformer
from sklearn.preprocessing import OneHotEncoder
from sklearn.preprocessing import LabelBinarizer
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import cross_val_score
```

In [15]:
```
#categorical = df.dtypes == object
preprocess = make_column_transformer(
    (OneHotEncoder(), categorical_f)
)
```

In [16]:
```
model1_pipe = make_pipeline(preprocess, LogisticRegression(max_iter=5000
))
scores = cross_val_score(model1_pipe, X_train, y_train_list)
print("Logistic Regression evaluated on cross validation:", np.mean(scor
es))
```

```
Logistic Regression evaluated on cross validation: 0.73875
```

In [17]:
```
from sklearn.svm import LinearSVC

model2_pipe = make_pipeline(preprocess, LinearSVC(max_iter=5000))
scores2 = cross_val_score(model2_pipe, X_train, y_train_list)
print("Linear SVM evaluated on cross validation:", np.mean(scores2))
```

```
Linear SVM evaluated on cross validation: 0.7324999999999999
```

In [18]:
```
from sklearn.neighbors import KNeighborsClassifier

model3_pipe = make_pipeline(preprocess, KNeighborsClassifier(n_neighbors
=3))
scores3 = cross_val_score(model3_pipe, X_train, y_train_list)
print("K Nearest Neighbors evaluated on cross validation:", np.mean(scor
es3))
```

```
K Nearest Neighbors evaluated on cross validation: 0.70625
```

In [19]:
```
preprocess2 = make_column_transformer(
    (StandardScaler(), continuous_f),
    (OneHotEncoder(), categorical_f)
)

model4_pipe = make_pipeline(preprocess2, LogisticRegression(max_iter=500
0))
scores4 = cross_val_score(model4_pipe, X_train, y_train_list)
print("Logistic Regression (scaling) evaluated on cross validation:", np
.mean(scores4))

model5_pipe = make_pipeline(preprocess2, LinearSVC(max_iter=5000))
scores5 = cross_val_score(model5_pipe, X_train, y_train_list)
print("Linear SVM (scaling) evaluated on cross validation:", np.mean(sco
res5))

model6_pipe = make_pipeline(preprocess2, KNeighborsClassifier(n_neighbor
s=3))
scores6 = cross_val_score(model6_pipe, X_train, y_train_list)
print("K Nearest Neighbors (scaling) evaluated on cross validation:", np
.mean(scores6))
```

```
Logistic Regression (scaling) evaluated on cross validation: 0.76499999
99999999
Linear SVM (scaling) evaluated on cross validation: 0.76
K Nearest Neighbors (scaling) evaluated on cross validation: 0.70375
```

It looks like Logistic Regression had the best evaluated cross val score in both without and with scaling. The other two were not that much off, but Linear SVM was slightly better than Nearest Neighbors.

StandardScaling the continuous features helped improve the scores across all 3 models.

1.5

In [29]:
```
from sklearn.model_selection import GridSearchCV
import warnings
warnings.filterwarnings(action='ignore')
```

In [123]:
```
param_grid_lr = {"logisticregression__penalty":['l1','l2','none'],
                 "logisticregression__C":np.logspace(-4, 4, 20)}
grid1 = GridSearchCV(model4_pipe, param_grid=param_grid_lr, cv=10)
best_lr = grid1.fit(X_train, y_train_list)
```

In [124]:
```
print(best_lr.best_params_)
print("Best LogReg val score:", best_lr.best_score_)
```

```
{'logisticregression__C': 0.08858667904100823, 'logisticregression__pen
alty': 'l2'}
Best LogReg val score: 0.76
```

In [36]:
```
y_test = test["target"]
X_test = test.loc[:, test.columns != "target"]
```

In [38]:
```
from sklearn.metrics import accuracy_score
pred_lr = best_lr.predict(X_test)
```

In [40]:
```
y_test = y_test.map(dict(good=1, bad=0))
```

In [54]:
```
lr_test_score = accuracy_score(y_test,pred_lr)
print("Best LogReg test score:",lr_test_score)
```

```
Best LogReg test score: 0.745
```

In [53]:
```
param_grid_lsvm = {'linearsvc__C': np.logspace(-3, 2, 6),
              'linearsvc__penalty': ['l1','l2']}
grid2 = GridSearchCV(model5_pipe, param_grid=param_grid_lsvm, cv=10)
best_lsvm = grid2.fit(X_train, y_train_list)

print(best_lsvm.best_params_)
print("Best Linear SVM val score:", best_lsvm.best_score_)
```

```
{'linearsvc__C': 0.01, 'linearsvc__penalty': 'l2'}
Best Linear SVM val score: 0.75625
```

In [55]:
```
pred_lsvm = best_lsvm.predict(X_test)
lsvm_test_score = accuracy_score(y_test,pred_lsvm)
print("Best Linear SVM test score:",lsvm_test_score)
```

```
Best Linear SVM test score: 0.735
```

In [60]:
```
param_grid_nn = {'kneighborsclassifier__n_neighbors': [1,2,3,4,5,6,7,8,9
]}
grid3 = GridSearchCV(model6_pipe, param_grid=param_grid_nn, cv=10)
best_nn = grid3.fit(X_train, y_train_list)

print(best_nn.best_params_)
print("Best KNN val score:", best_nn.best_score_)
```

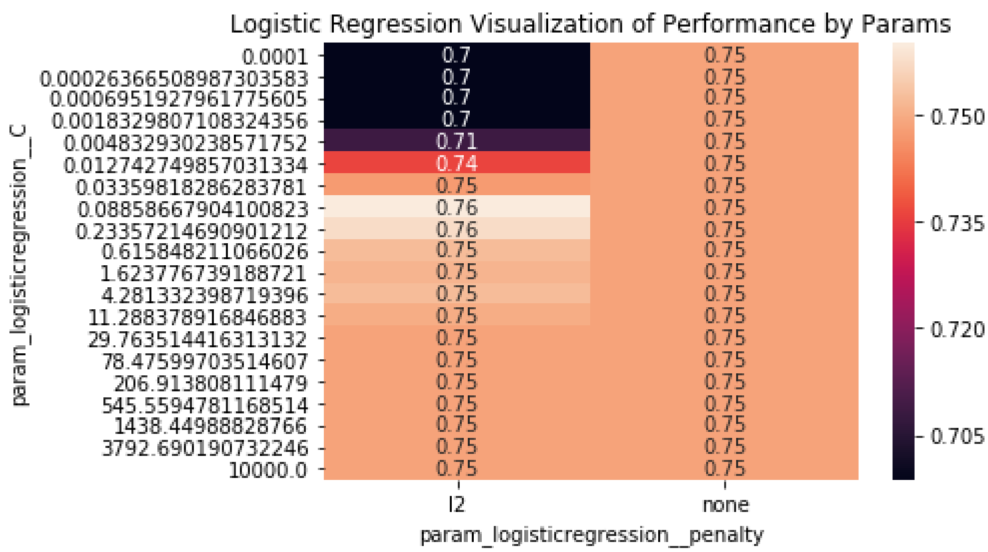
```
{'kneighborsclassifier__n_neighbors': 7}
Best KNN val score: 0.7337499999999999
```

In [61]:
```
pred_nn = best_nn.predict(X_test)
nn_test_score = accuracy_score(y_test,pred_nn)
print("Best KNN Test score:",nn_test_score)
```

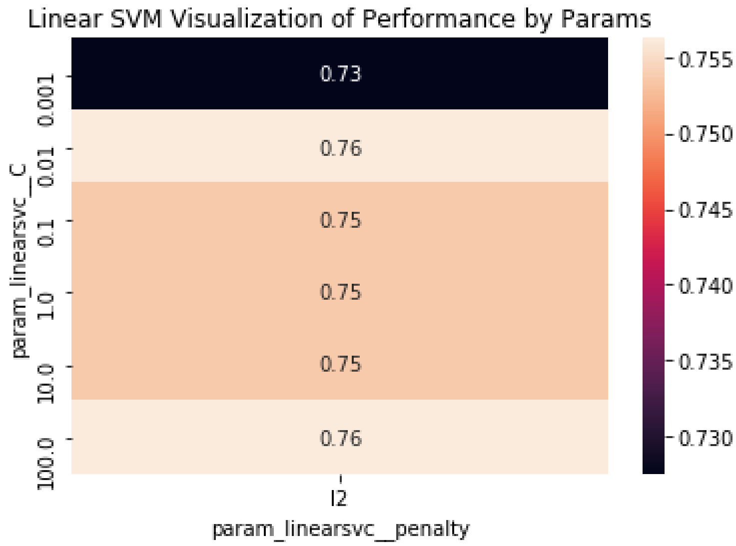
```
Best KNN Test score: 0.775
```

In [67]:
```
import seaborn as sns
```

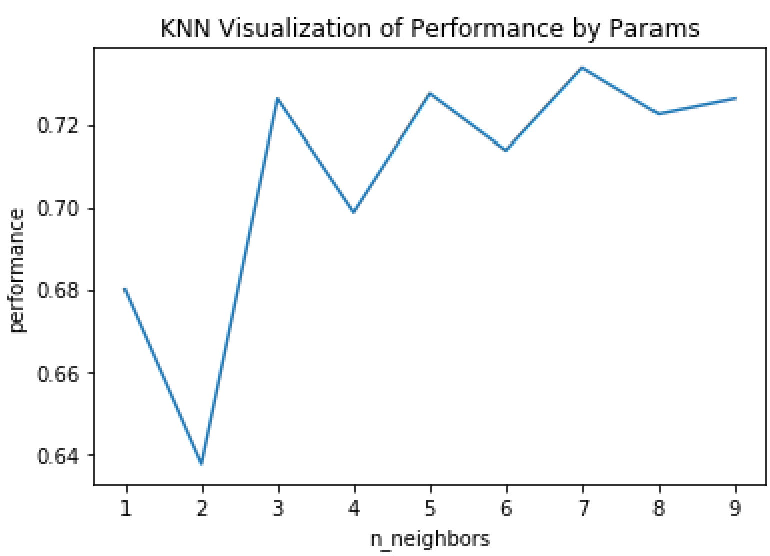
In [72]:
```
res_lr = pd.pivot_table(pd.DataFrame(grid1.cv_results_),
    values='mean_test_score', index='param_logisticregression__C', colum
ns='param_logisticregression__penalty')
ax = plt.axes()
ax.set_title("Logistic Regression Visualization of Performance by Param
s")
sns.heatmap(res_lr, annot=True)
plt.show()
```



In [73]:
```
res_lsvm = pd.pivot_table(pd.DataFrame(grid2.cv_results_),
    values='mean_test_score', index='param_linearsvc__C', columns='param
_linearsvc__penalty')
ax = plt.axes()
ax.set_title("Linear SVM Visualization of Performance by Params")
sns.heatmap(res_lsvm, annot=True)
plt.show()
```



In [101]:
```
nn_x = grid3.cv_results_['param_kneighborsclassifier__n_neighbors'].toli
st()
nn_y = grid3.cv_results_['mean_test_score'].tolist()
ax = plt.axes()
ax.set_title("KNN Visualization of Performance by Params")
ax.set_xlabel("n_neighbors")
ax.set_ylabel("performance")
plt.plot(nn_x, nn_y)
plt.show()
```



The results did improve for some and were about the same for others. For example, KNN went from 0.704 to 0.734 val score. Please see and compare results as printed above.

The test score was 0.745 on the best model (based on val score it was Log Reg).

1.6

In [102]:
```
from sklearn.model_selection import KFold
```

In [103]:
```
k_fold_s = KFold(shuffle=True, random_state=1)
```

KFold Shuffle random state 1

In [105]:
```
warnings.filterwarnings(action='ignore')
lr_kf_grid = GridSearchCV(model4_pipe, param_grid=param_grid_lr, cv=k_fo
ld_s)
best_lr_kf = lr_kf_grid.fit(X_train, y_train_list)

print(best_lr_kf.best_params_)
print("Best Log Reg val score using KFold shuffle:", best_lr_kf.best_sco
re_)
```

```
{'logisticregression__C': 0.08858667904100823, 'logisticregression__pen
alty': 'l2'}
Best Log Reg val score using KFold shuffle: 0.75
```

In [106]:
```
lsvm_kf_grid = GridSearchCV(model5_pipe, param_grid=param_grid_lsvm, cv=
k_fold_s)
best_lsvm_kf = lsvm_kf_grid.fit(X_train, y_train_list)

print(best_lsvm_kf.best_params_)
print("Best Linear SVM val score using KFold shuffle:", best_lsvm_kf.bes
t_score_)
```

```
{'linearsvc__C': 0.01, 'linearsvc__penalty': 'l2'}
Best Linear SVM val score using KFold shuffle: 0.75
```

In [107]:
```
nn_kf_grid = GridSearchCV(model6_pipe, param_grid=param_grid_nn, cv=k_fo
ld_s)
best_nn_kf = nn_kf_grid.fit(X_train, y_train_list)

print(best_nn_kf.best_params_)
print("Best KNN val score using KFold shuffle:", best_nn_kf.best_score_)
```

```
{'kneighborsclassifier__n_neighbors': 7}
Best KNN val score using KFold shuffle: 0.71875
```

KFold Shuffle random state 200

In [108]:
```
k_fold_s2 = KFold(shuffle=True, random_state=200)

lr_kf_grid2 = GridSearchCV(model4_pipe, param_grid=param_grid_lr, cv=k_f
old_s2)
best_lr_kf2 = lr_kf_grid2.fit(X_train, y_train_list)

print(best_lr_kf2.best_params_)
print("Best Log Reg val score using KFold shuffle:", best_lr_kf2.best_sc
ore_)

lsvm_kf_grid2 = GridSearchCV(model5_pipe, param_grid=param_grid_lsvm, cv
=k_fold_s2)
best_lsvm_kf2 = lsvm_kf_grid2.fit(X_train, y_train_list)

print(best_lsvm_kf2.best_params_)
print("Best Linear SVM val score using KFold shuffle:", best_lsvm_kf2.be
st_score_)

nn_kf_grid2 = GridSearchCV(model6_pipe, param_grid=param_grid_nn, cv=k_f
old_s2)
best_nn_kf2 = nn_kf_grid2.fit(X_train, y_train_list)

print(best_nn_kf2.best_params_)
print("Best KNN val score using KFold shuffle:", best_nn_kf2.best_score_
)
```

```
{'logisticregression__C': 0.23357214690901212, 'logisticregression__pen
alty': 'l2'}
Best Log Reg val score using KFold shuffle: 0.7512500000000001
{'linearsvc__C': 0.1, 'linearsvc__penalty': 'l2'}
Best Linear SVM val score using KFold shuffle: 0.7525000000000001
{'kneighborsclassifier__n_neighbors': 3}
Best KNN val score using KFold shuffle: 0.7224999999999999
```

New random train test split

In [110]:
```
train2, test2 = train_test_split(df, test_size=0.2)

y_train2 = train["target"]
X_train2 = train.loc[:, train.columns != "target"]
y_train2 = y_train2.map(dict(good=1, bad=0))
```

In [111]:
```
lr_kf_grid3 = GridSearchCV(model4_pipe, param_grid=param_grid_lr, cv=k_f
old_s2)
best_lr_kf3 = lr_kf_grid3.fit(X_train2, y_train2)

print(best_lr_kf3.best_params_)
print("Best Log Reg val score using KFold shuffle:", best_lr_kf3.best_sc
ore_)

lsvm_kf_grid3 = GridSearchCV(model5_pipe, param_grid=param_grid_lsvm, cv
=k_fold_s2)
best_lsvm_kf3 = lsvm_kf_grid3.fit(X_train2, y_train2)

print(best_lsvm_kf3.best_params_)
print("Best Linear SVM val score using KFold shuffle:", best_lsvm_kf3.be
st_score_)

nn_kf_grid4 = GridSearchCV(model6_pipe, param_grid=param_grid_nn, cv=k_f
old_s2)
best_nn_kf4 = nn_kf_grid4.fit(X_train2, y_train2)

print(best_nn_kf4.best_params_)
print("Best KNN val score using KFold shuffle:", best_nn_kf4.best_score_
)
```

```
{'logisticregression__C': 0.23357214690901212, 'logisticregression__pen
alty': 'l2'}
Best Log Reg val score using KFold shuffle: 0.7512500000000001
{'linearsvc__C': 0.1, 'linearsvc__penalty': 'l2'}
Best Linear SVM val score using KFold shuffle: 0.7525000000000001
{'kneighborsclassifier__n_neighbors': 3}
Best KNN val score using KFold shuffle: 0.7224999999999999
```

Changing to KFold with shuffling did not change the best parameters found but changing the shuffle random_state did change the parameters found in the C value and n_neighbors as shown above. Changing the train/test split random state did not change the parameters.

1.7

In [ ]:
```
plt.scatter()
```

In [177]:
```
lr_coef = best_lr.best_estimator_.steps[1][1].coef_
lsvm_coef = best_lsvm.best_estimator_.steps[1][1].coef_
```

Get feature names

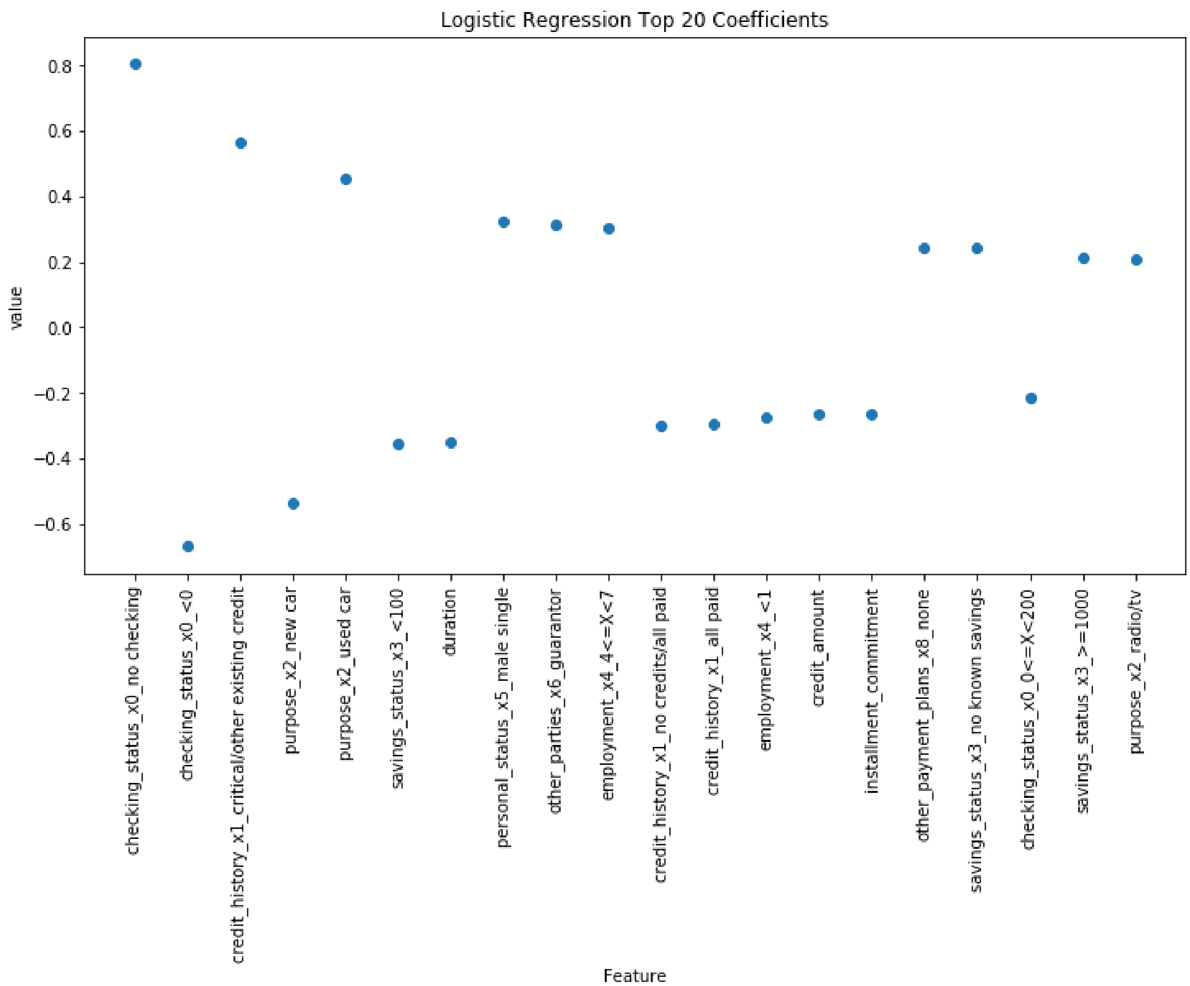
In [234]:
```
ohe_cat = OneHotEncoder()
ohe_cat.fit(X_train[categorical_f])
cat_f = []
for val in ohe_cat.get_feature_names().tolist():
    cat_f.append(categorical_f[int(val[1:val.index("_")])]+"_"+val)
```

In [236]:
```
final_feature_names = continuous_f + cat_f
```

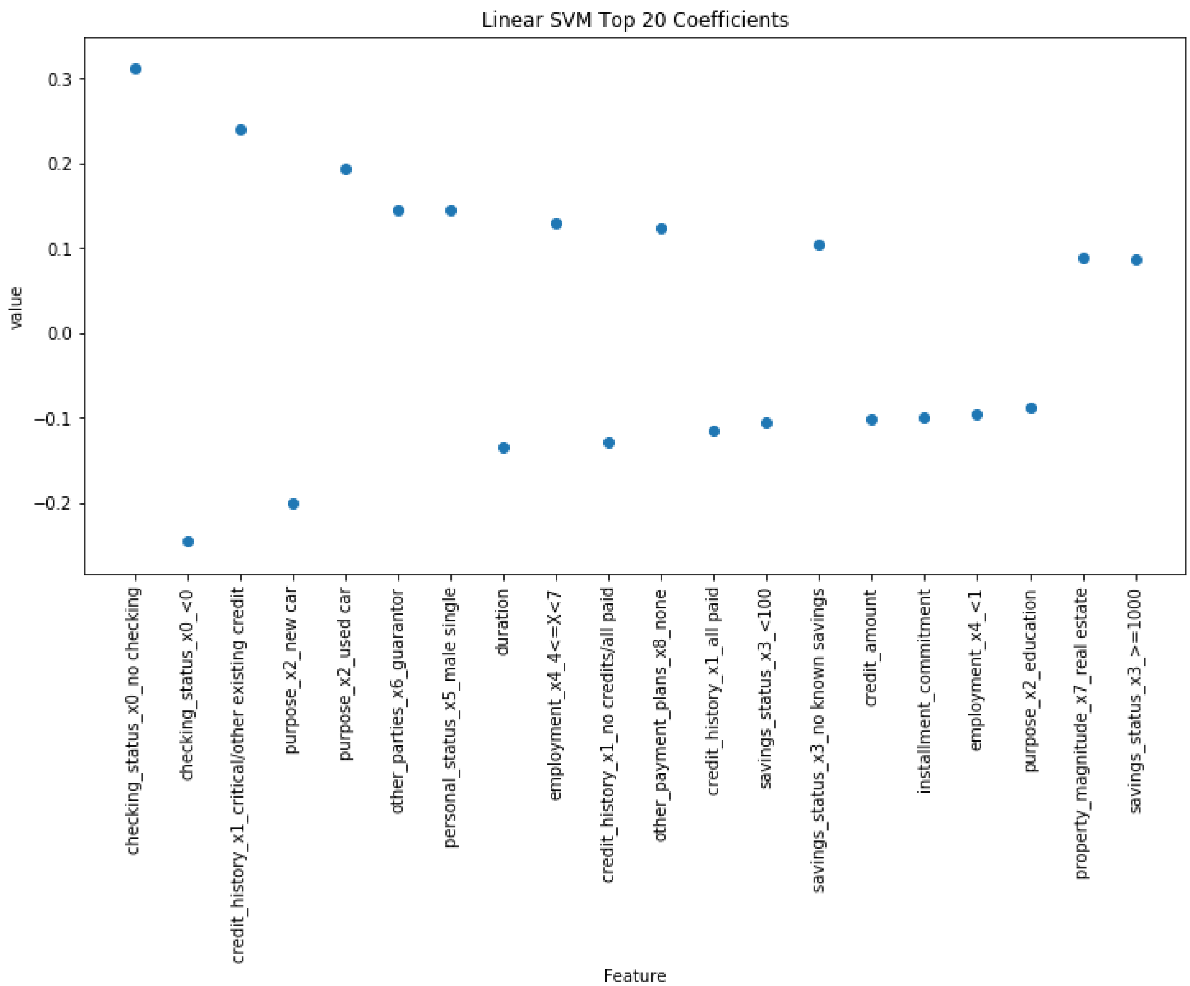
In [237]:
```
lr_coef_df = pd.DataFrame(list(zip(lr_coef[0], final_feature_names)),columns=['coef_value','feature_nm'])
lsvm_coef_df = pd.DataFrame(list(zip(lsvm_coef[0], final_feature_names)),columns=['coef_value','feature_nm'])
```

In [238]:
```
lr_df2 = lr_coef_df['coef_value'].abs().sort_values(ascending=False).index
lsvm_df2 = lsvm_coef_df['coef_value'].abs().sort_values(ascending=False).index
```

In [246]:
```
plt.figure(figsize=(12,6))
plt.scatter(lr_coef_df['feature_nm'].iloc[lr_df2[0:20]], lr_coef_df['coe
f_value'].iloc[lr_df2[0:20]])
plt.xticks(rotation=90)
plt.title("Logistic Regression Top 20 Coefficients")
plt.xlabel("Feature")
plt.ylabel("value")
plt.show()
```



In [247]:
```
plt.figure(figsize=(12,6))
plt.scatter(lsvm_coef_df['feature_nm'].iloc[lsvm_df2[0:20]], lsvm_coef_d
f['coef_value'].iloc[lsvm_df2[0:20]])
plt.xticks(rotation=90)
plt.title("Linear SVM Top 20 Coefficients")
plt.xlabel("Feature")
plt.ylabel("value")
plt.show()
```



In [ ]: