

FOSTERING ECONOMIC MOBILITY

In the city of Charlotte

BY TEAM49ERS

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WHAT WE DID - PREDICTIVE ANALYTICS

Who?



What?



Why?



DATA WE CHOSE AND WHY

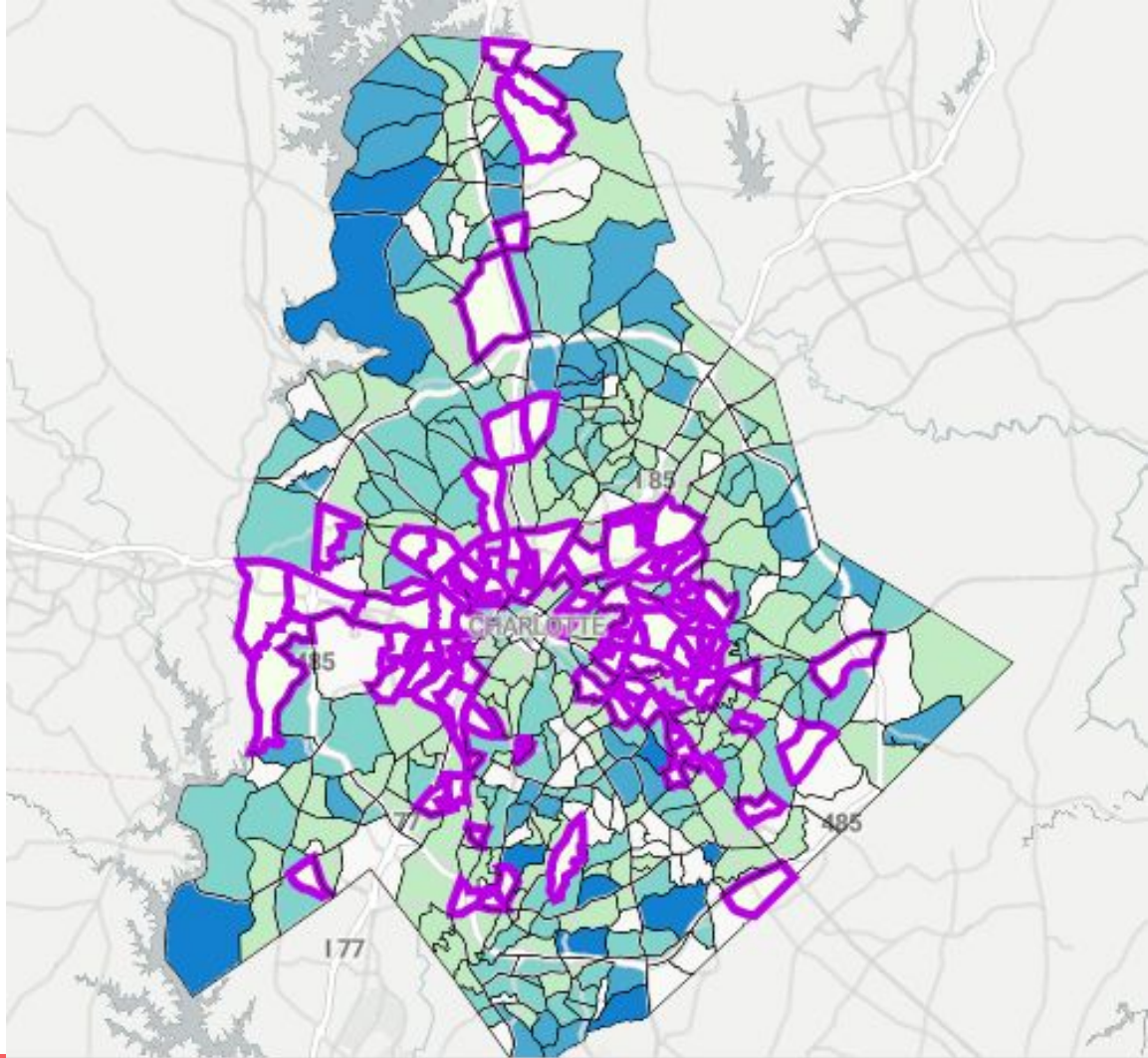


Consumer Financial
Protection Bureau

- Rich Dataset
- Comprises of all aspects that have direct impact
- Gives an idea about causal relationships
- Focus is House Sale Prices and Housing Loan Policies

CONCENTRATED REGIONS

- Neighborhood Segregation from 2011 to 2017
- Highlighted Regions show area of low economic development.



CORRELATION

Before Correlation Analysis

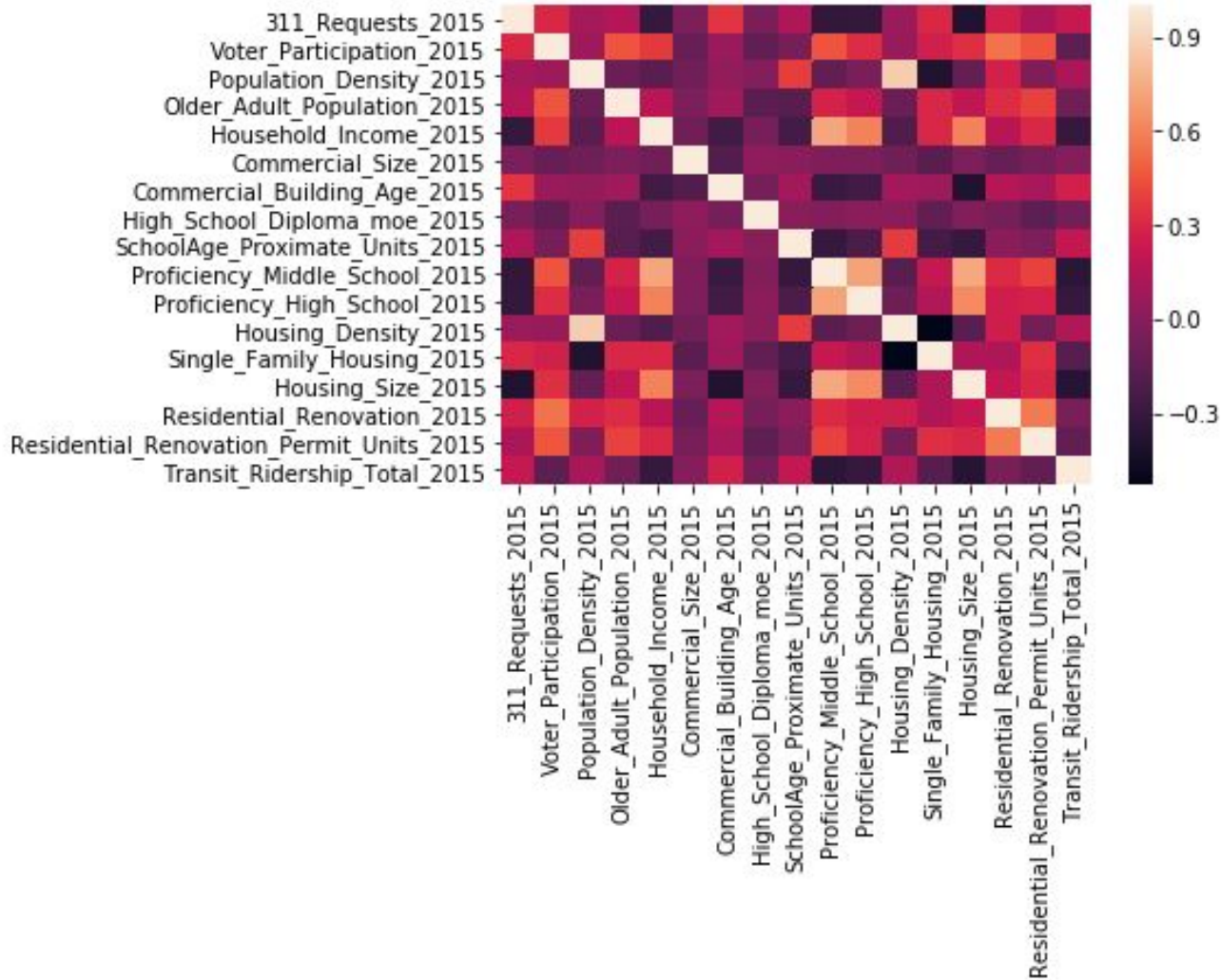
No of attributes : 97

After analysis :

No of attributes : 95

On applying stepwise reg:

No of attributes : 17



OLS Regression Results

```

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Dep. Variable:          y      R-squared:          0.927
Model:                  OLS    Adj. R-squared:       0.924
Method:                 Least Squares    F-statistic:       330.9
Date:                   Sat, 24 Mar 2018    Prob (F-statistic): 5.91e-240
Time:                   09:15:44    Log-Likelihood:    -5749.6
No. Observations:       462    AIC:               1.153e+04
Df Residuals:           445    BIC:               1.160e+04
Df Model:                17
Covariance Type:        nonrobust
=====

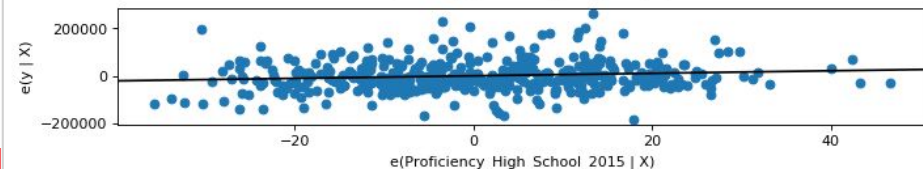
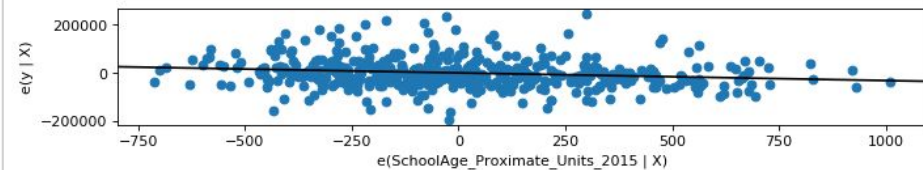
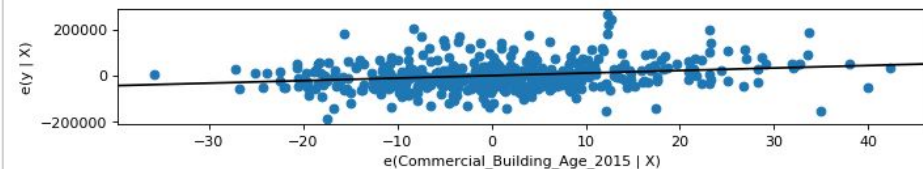
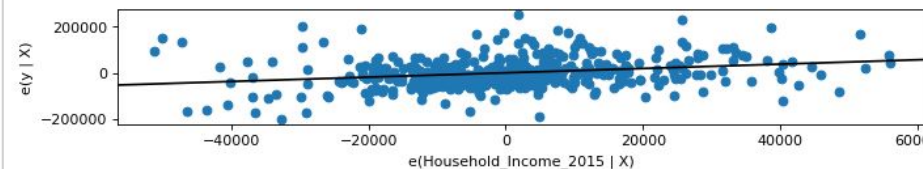
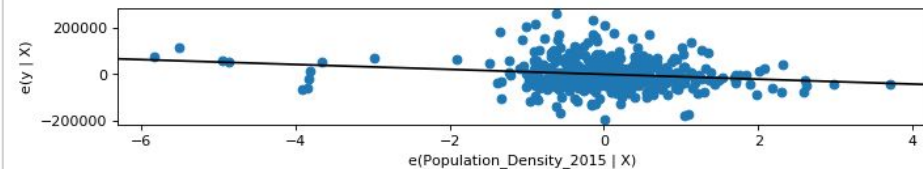
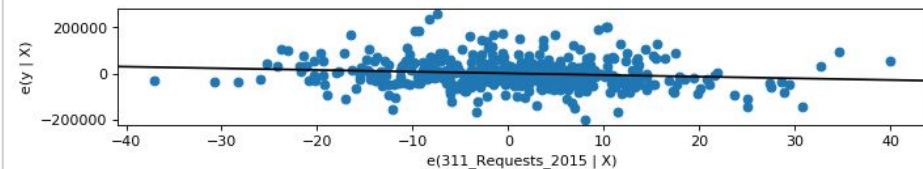
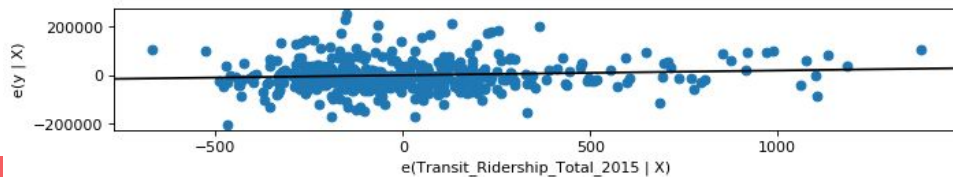
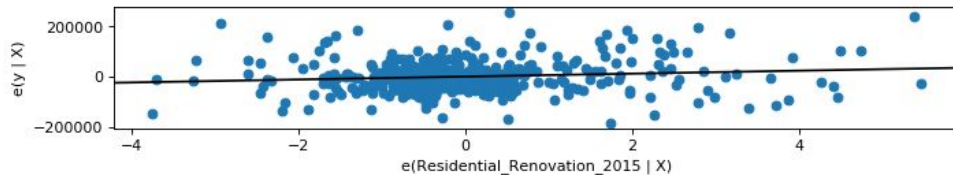
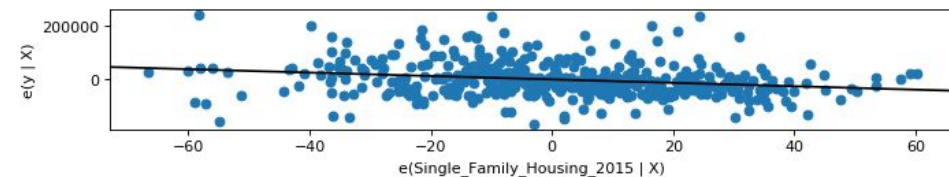
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	coef	std err	t	P> t	[0.025	0.975]
311_Requests_2015	-724.1362	269.291	-2.689	0.007	-1253.376	-194.896
Voter_Participation_2015	1711.4598	607.011	2.819	0.005	518.495	2904.425
Population_Density_2015	-1.056e+04	2961.409	-3.567	0.000	-1.64e+04	-4742.496
Older_Adult_Population_2015	-1430.2504	712.623	-2.007	0.045	-2830.775	-29.726
Household_Income_2015	0.9401	0.170	5.520	0.000	0.605	1.275
Commercial_Size_2015	0.5722	0.248	2.309	0.021	0.085	1.059
Commercial_Building_Age_2015	1094.9031	234.062	4.678	0.000	634.899	1554.908
High_School_Diploma_moe_2015	1966.4990	762.825	2.578	0.010	467.313	3465.685
SchoolAge_Proximate_Units_2015	-31.8987	9.039	-3.529	0.000	-49.664	-14.134
Proficiency_Middle_School_2015	554.0817	242.716	2.283	0.023	77.069	1031.094
Proficiency_High_School_2015	532.4864	198.902	2.677	0.008	141.582	923.391
Housing_Density_2015	1.642e+04	6443.153	2.549	0.011	3762.014	2.91e+04
Single_Family_Housing_2015	-639.7008	130.863	-4.888	0.000	-896.887	-382.515
Housing_Size_2015	37.3086	6.406	5.824	0.000	24.719	49.899
Residential_Renovation_2015	5892.2767	2254.224	2.614	0.009	1462.029	1.03e+04
Residential_Renovation_Permit_Units_2015	1573.4489	475.665	3.308	0.001	638.619	2508.279
Transit_Ridership_Total_2015	19.5556	9.633	2.030	0.043	0.623	38.488

PARTIAL REGRESSION PLOTS

R-SQUARE : 0.93

Omnibus:	55.763	Durbin-Watson:	1.915
Prob(Omnibus):	0.000	Jarque-Bera (JB):	106.428
Skew:	0.704	Prob(JB):	7.75e-24
Kurtosis:	4.883	Cond. No.	1.61e+05



LOGISTIC REGRESSION

Data Split: Train: 75% (3,89,922) Test: 25% (1,29,975)

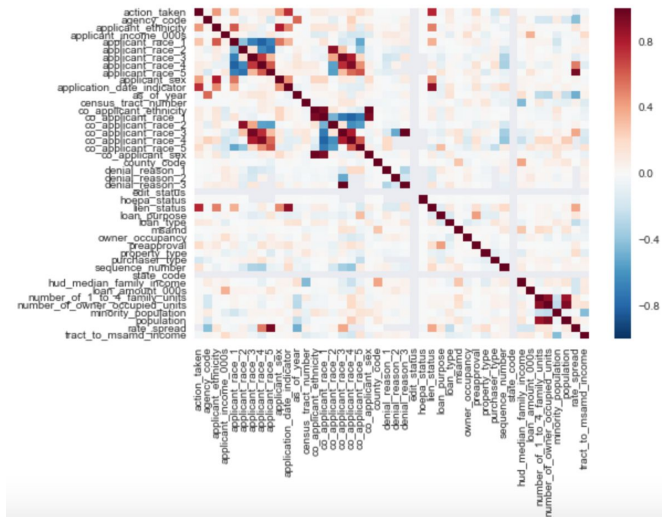
Accuracy: 60.49%

```
from sklearn.linear_model import LogisticRegression
classifier = LogisticRegression(random_state = 0)
classifier.fit(x, y)
```

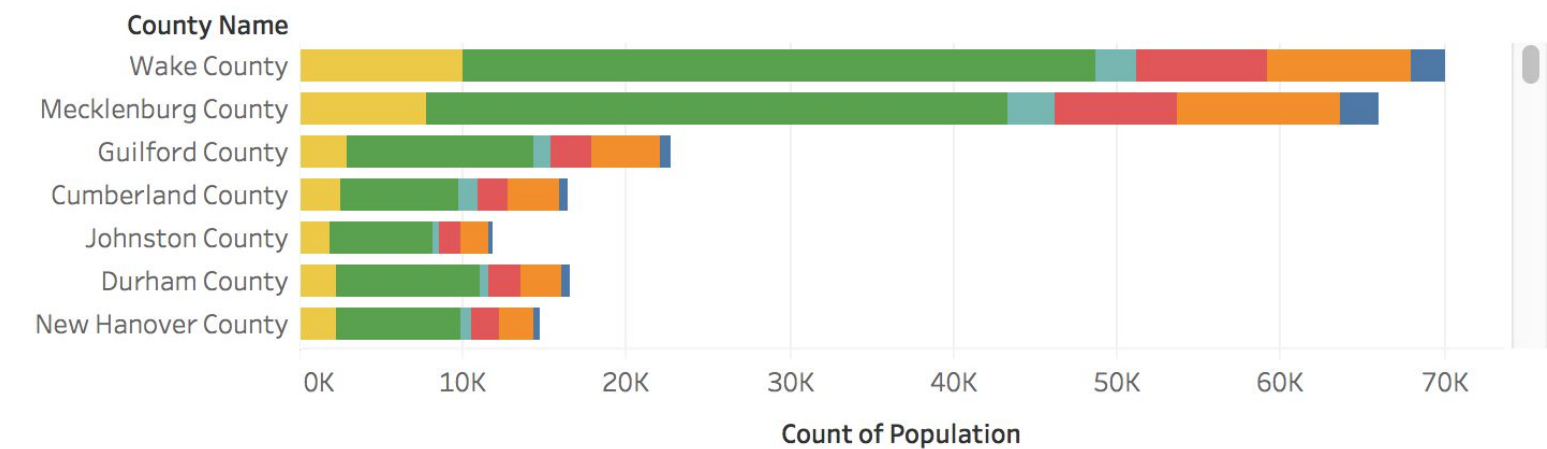
```
LogisticRegression(C=1.0, class_weight=None, dual=False,
fit_intercept=True,
                    intercept_scaling=1, max_iter=100, multi_class='ovr',
n_jobs=1,
                    penalty='l2', random_state=0, solver='liblinear',
tol=0.0001,
                    verbose=0, warm_start=False)
```

```
accuracy_score(np.array(y_test), np.array(y_pred))
```

0.60490863627620695

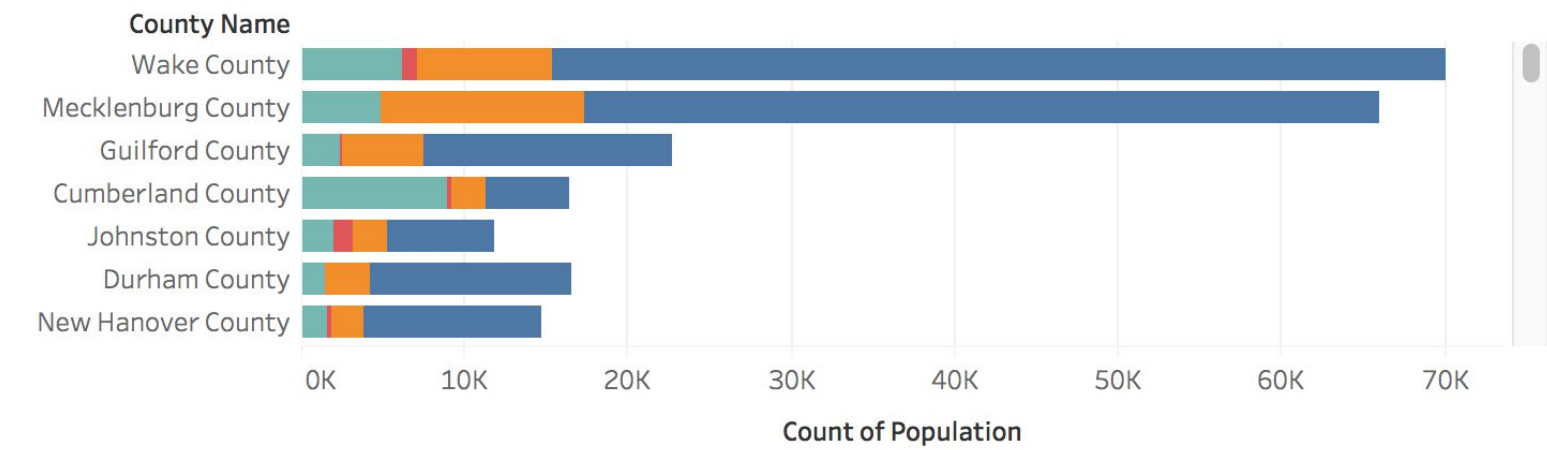


LOAN DECISIONS PER COUNTY



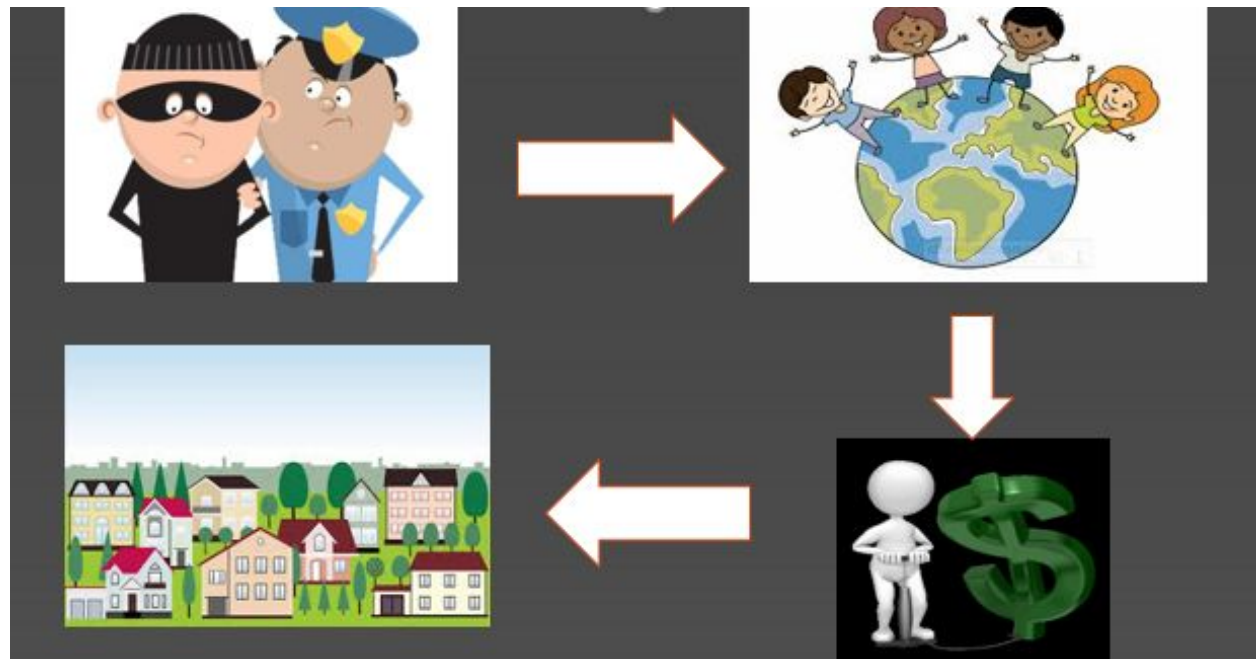
- Action Taken Name
- Application approve..
 - Application denied b..
 - Application withdra..
 - File closed for incom..
 - Loan originated
 - Loan purchased by t..
 - Preapproval request ..
 - Preapproval request ..

LOAN TYPES FAVOURED BY COUNTIES



- Loan type Name
- Conventional
 - FHA-insured
 - FSA/RHS-guaranteed
 - VA-guaranteed

CONNECTING THE DOTS...



*Thank you,
By Team49ers!*